Optimization of Natural Language Processing Components for Robustness and Scalability

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Optimization of Natural Language Processing Components for Robustness and Scalability

by

Jinho D. Choi

B.A., Coe College, 2002
M.S.E., University of Pennsylvania, 2003

A thesis submitted to the
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This thesis entitled:
Optimization of Natural Language Processing Components for Robustness and Scalability
written by Jinho D. Choi
has been approved for the Department of Computer Science

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The final copy of this thesis has been examined by the signatories, and we find that both the content and the form meet acceptable presentation standards of scholarly work in the above mentioned discipline.
This thesis focuses on the optimization of NLP components for robustness and scalability. Three kinds of NLP components are used for our experiments, a part-of-speech tagger, a dependency parser, and a semantic role labeler. For part-of-speech tagging, dynamic model selection is introduced. Our dynamic model selection approach builds two models, domain-specific and generalized models, and selects one of them during decoding by comparing similarities between lexical items used for building these models and input sentences. As a result, it gives robust tagging accuracy across corpora and shows fast tagging speed. For dependency parsing, a new transition-based parsing algorithm and a bootstrapping technique are introduced. Our parsing algorithm learns both projective and non-projective transitions so it can generate both projective and non-projective dependency trees yet shows linear time parsing speed on average. Our bootstrapping technique bootstraps parse information used as features for transition-based parsing, and shows significant improvement for parsing accuracy. For semantic role labeling, a conditional higher-order argument pruning algorithm is introduced. A higher-order pruning algorithm improves the coverage of argument candidates and shows improvement on the overall F1-score. The conditional higher-order pruning algorithm also noticeably reduces average labeling complexity with minimal reduction in F1-score.

For all experiments, two sets of training data are used; one is from the Wall Street Journal corpus, and the other is from the OntoNotes corpora. All components are evaluated on 9 different genres, which are grouped separately for in-genre and out-of-genre experiments. Our experiments show that our approach gives higher accuracies compared to other state-of-the-art NLP components, and runs fast, taking about 3-4 milliseconds per sentence for processing all three components. All components are publicly available as an open source project, called ClearNLP. We believe that this project is beneficial for many NLP tasks that need to process large-scale heterogeneous data.
This thesis is dedicated to my parents, Youngsang Choi and Kyungsook Lee, my American grandparents, Thomas and Elizabeth Janik, and my sister, Jeany Choi, who have loved, supported, and encouraged me ever since I was born. It is also dedicated to my prayer partner, Kyungshim Lee, and my future wife, Juyoung Choi, who have prayed for me constantly.
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# Contents

## Chapter

1 Introduction

1.1 Research questions and objectives .............................................. 1

1.2 Background .............................................................................. 3

1.2.1 Part-of-speech tagging ......................................................... 3

1.2.2 Dependency parsing ............................................................. 3

1.2.3 Semantic role labeling ......................................................... 5

1.3 Overall framework ............................................................... 6

1.4 Thesis statement ................................................................. 8

2 Dependency Conversion

2.1 Introduction ........................................................................... 9

2.1.1 Motivation .......................................................................... 9

2.1.2 Background ........................................................................ 11

2.1.3 Overview ............................................................................ 13

2.2 Mapping empty categories .................................................... 15

2.2.1 Wh-movement .................................................................... 15

2.2.2 Topicalization ..................................................................... 17

2.2.3 Right node raising .............................................................. 18

2.2.4 Discontinuous constituent .................................................. 20
2.3 Finding dependency heads .............................................................. 21
  2.3.1 Head-finding rules ................................................................. 21
  2.3.2 Apposition ................................................................. 23
  2.3.3 Coordination ................................................................. 24
  2.3.4 Small clauses ................................................................. 29

  2.4 Assigning dependency labels .......................................................... 31
  2.4.1 CLEAR dependency labels .................................................... 31
  2.4.2 Dependency label heuristics .................................................. 32
  2.4.3 Comparison to the Stanford dependency approach ......................... 34

  2.5 Adding secondary dependencies .................................................... 36
  2.5.1 GAP: gapping ................................................................. 36
  2.5.2 REF: referent ................................................................. 37
  2.5.3 RNR: right node raising ...................................................... 39
  2.5.4 XSUBJ: open clausal subject ............................................... 40

  2.6 Adding function tags ................................................................. 42
  2.6.1 SEM: semantic function tags ............................................... 42
  2.6.2 SYN: syntactic function tags .............................................. 43

  3 Experimental setup ........................................................................ 44
  3.1 Corpora .................................................................................. 45
  3.2 Machine learning ....................................................................... 47

  4 Part-of-speech Tagging .................................................................. 50
  4.1 Overview ............................................................................... 50
  4.2 Background ........................................................................... 52
  4.3 Dynamic model selection ............................................................ 53
    4.3.1 Training ........................................................................ 53
    4.3.2 Decoding ........................................................................ 54
<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.4</td>
<td>Tagging algorithm</td>
<td>56</td>
</tr>
<tr>
<td>4.5</td>
<td>Features</td>
<td>56</td>
</tr>
<tr>
<td>4.6</td>
<td>Related work</td>
<td>57</td>
</tr>
<tr>
<td>4.7</td>
<td>Experiments</td>
<td>58</td>
</tr>
<tr>
<td>4.7.1</td>
<td>Accuracy comparisons</td>
<td>58</td>
</tr>
<tr>
<td>4.7.2</td>
<td>Speed comparisons</td>
<td>61</td>
</tr>
<tr>
<td>5</td>
<td>Dependency Parsing</td>
<td>62</td>
</tr>
<tr>
<td>5.1</td>
<td>Overview</td>
<td>62</td>
</tr>
<tr>
<td>5.2</td>
<td>Transition-based dependency parsing</td>
<td>64</td>
</tr>
<tr>
<td>5.2.1</td>
<td>Transition decomposition</td>
<td>64</td>
</tr>
<tr>
<td>5.2.2</td>
<td>Transition recomposition</td>
<td>66</td>
</tr>
<tr>
<td>5.2.3</td>
<td>Parsing algorithm</td>
<td>69</td>
</tr>
<tr>
<td>5.3</td>
<td>Bootstrapping</td>
<td>72</td>
</tr>
<tr>
<td>5.3.1</td>
<td>Bootstrapping parse history</td>
<td>72</td>
</tr>
<tr>
<td>5.3.2</td>
<td>Related work</td>
<td>74</td>
</tr>
<tr>
<td>5.4</td>
<td>Post-processing</td>
<td>75</td>
</tr>
<tr>
<td>5.5</td>
<td>Features</td>
<td>77</td>
</tr>
<tr>
<td>5.6</td>
<td>Experiments</td>
<td>78</td>
</tr>
<tr>
<td>5.6.1</td>
<td>Accuracy comparisons</td>
<td>78</td>
</tr>
<tr>
<td>5.6.2</td>
<td>Speed comparisons</td>
<td>83</td>
</tr>
<tr>
<td>6</td>
<td>Semantic Role Labeling</td>
<td>86</td>
</tr>
<tr>
<td>6.1</td>
<td>Overview</td>
<td>86</td>
</tr>
<tr>
<td>6.2</td>
<td>Semantic roles in dependency structure</td>
<td>88</td>
</tr>
<tr>
<td>6.2.1</td>
<td>Predicate argument structures in PropBank</td>
<td>88</td>
</tr>
<tr>
<td>6.2.2</td>
<td>Syntactic and semantic dependencies</td>
<td>89</td>
</tr>
<tr>
<td>6.2.3</td>
<td>Adding semantic roles to dependency trees</td>
<td>91</td>
</tr>
<tr>
<td>Section</td>
<td>Page</td>
<td></td>
</tr>
<tr>
<td>------------------------------------------------------------------------</td>
<td>------</td>
<td></td>
</tr>
<tr>
<td>6.3 Argument pruning</td>
<td>94</td>
<td></td>
</tr>
<tr>
<td>6.3.1 First-order argument pruning</td>
<td>94</td>
<td></td>
</tr>
<tr>
<td>6.3.2 Higher-order argument pruning</td>
<td>94</td>
<td></td>
</tr>
<tr>
<td>6.3.3 Conditional higher-order argument pruning</td>
<td>97</td>
<td></td>
</tr>
<tr>
<td>6.4 Features</td>
<td>102</td>
<td></td>
</tr>
<tr>
<td>6.4.1 Feature templates</td>
<td>102</td>
<td></td>
</tr>
<tr>
<td>6.4.2 Positional feature separation</td>
<td>103</td>
<td></td>
</tr>
<tr>
<td>6.5 Experiments</td>
<td>104</td>
<td></td>
</tr>
<tr>
<td>6.5.1 Accuracy comparisons</td>
<td>104</td>
<td></td>
</tr>
<tr>
<td>6.5.2 Speed comparisons</td>
<td>106</td>
<td></td>
</tr>
<tr>
<td>7 Conclusion</td>
<td>109</td>
<td></td>
</tr>
<tr>
<td>Bibliography</td>
<td>112</td>
<td></td>
</tr>
<tr>
<td>Appendix</td>
<td></td>
<td></td>
</tr>
<tr>
<td>A Constituent Treebank Tags</td>
<td>119</td>
<td></td>
</tr>
<tr>
<td>A.1 Function tags</td>
<td>119</td>
<td></td>
</tr>
<tr>
<td>A.2 Part-of-speech tags</td>
<td>120</td>
<td></td>
</tr>
<tr>
<td>A.3 Clause and phrase level tags</td>
<td>121</td>
<td></td>
</tr>
<tr>
<td>B Semantic Role Labels</td>
<td>122</td>
<td></td>
</tr>
<tr>
<td>B.1 PropBank semantic role labels</td>
<td>122</td>
<td></td>
</tr>
<tr>
<td>B.2 VerbNet thematic role labels</td>
<td>123</td>
<td></td>
</tr>
<tr>
<td>C Dependency Labels</td>
<td>124</td>
<td></td>
</tr>
<tr>
<td>C.1 CoNLL dependency labels</td>
<td>124</td>
<td></td>
</tr>
<tr>
<td>C.2 Stanford dependency labels</td>
<td>125</td>
<td></td>
</tr>
</tbody>
</table>
D The CLEAR Dependency Labels

D.1 Arguments: subject related
  D.1.1 AGENT: agent
  D.1.2 CSUBJ: clausal subject
  D.1.3 CSUBJPASS: clausal passive subject
  D.1.4 EXPL: expletive
  D.1.5 NSUBJ: nominal subject
  D.1.6 NSUBJPASS: nominal passive subject

D.2 Arguments: object related
  D.2.1 ATTR: attribute
  D.2.2 DOBJ: direct object
  D.2.3 IOBJ: indirect object
  D.2.4 OPRD: object predicate

D.3 Auxiliaries
  D.3.1 AUX: auxiliary
  D.3.2 AUXPASS: passive auxiliary

D.4 Complements
  D.4.1 ACOMP: adjectival complement
  D.4.2 CCOMP: clausal complement
  D.4.3 XCOMP: open clausal complement
  D.4.4 COMPLM: complementizer

D.5 Modifiers: adverbial related
  D.5.1 ADVCL: adverbial clause modifier
  D.5.2 ADVMOD: adverbial modifier
  D.5.3 MARK: maker
  D.5.4 NEG: negation modifier
  D.5.5 NPADVMOD: noun phrase as adverbial modifier
D.6  Modifiers: coordination related .................................................. 138
    D.6.1  CONJ: conjunct ................................................................. 138
    D.6.2  CC: coordinating conjunction ......................................... 138
    D.6.3  PRECONJ: pre-correlative conjunction ............................... 139
D.7  Modifiers: noun phrase related .................................................... 140
    D.7.1  APPOS: appositional modifier ........................................... 140
    D.7.2  DET: determiner ............................................................... 141
    D.7.3  INFMOD: infinitival modifier ........................................... 141
    D.7.4  NMOD: modifier of nominal .............................................. 142
    D.7.5  NN: noun compound modifier ............................................ 142
    D.7.6  NUM: numeric modifier ................................................... 142
    D.7.7  PARTMOD: participial modifier ......................................... 142
    D.7.8  POSSESSIVE: possessive modifier ..................................... 142
    D.7.9  PREDET: predeterminer .................................................. 142
    D.7.10 RC ModiD.10ers: relative clause modifier ............................ 143
D.8  Modifiers: prepositional phrase related ....................................... 143
    D.8.1  PCOMP: complement of a preposition ................................ 144
    D.8.2  POBJ: object of a preposition ......................................... 144
    D.8.3  PREP: prepositional modifier ......................................... 144
D.9  Modifiers: quantifier phrase related ......................................... 145
    D.9.1  NUMBER: number compound modifier ................................ 145
    D.9.2  QUANTMOD: quantifier phrase modifier .............................. 145
D.10  Modifiers: miscellaneous ......................................................... 145
    D.10.1 AMOD: adjectival modifier .............................................. 146
    D.10.2 DEP: unclassified dependent .......................................... 146
    D.10.3 INTJ: interjection .................................................... 146
    D.10.4 META: meta modifier .................................................. 146
D.10.5 PARATAxis: parenthetical modifier ............................................. 147
D.10.6 POSS: possession modifier ......................................................... 147
D.10.7 PRT: particle ........................................................................... 148
D.10.8 PUNCT: punctuation ................................................................. 148
D.10.9 ROOT: root ............................................................................. 148
Tables

Table

2.1 A list of empty categories used in constituent Treebanks for English. 13
2.2 Head-finding rules. 21
2.3 A list of the CLEAR dependency labels. 31
2.4 A list of the CLEAR dependency labels unclassified by the Stanford approach. 34
2.5 Mappings between the CLEAR and the Stanford dependency labels. 35
3.1 Evaluation methods for different tasks. 45
3.2 Distributions of training sets for the OntoNotes models. 45
3.3 Distributions of evaluation sets. 46
3.4 Lexical similarities between the evaluation sets in Table 3.3. 46
3.5 Unix commands for listing the evaluation sets in Table 3.3. 47
3.6 Liblinear learning parameters for each task. 48
3.7 The number of features and the amount of memory used for training and decoding. 49
4.1 Mappings between Google’s universal POS tags and the Penn POS tags. 52
4.2 An example of the Penn POS tags and Google’s universal POS tags. 52
4.3 Feature templates for POS tagging. 56
4.4 Tagging accuracies of all tokens from the WSJ models. 58
4.5 Tagging accuracies of all tokens from the OntoNotes models. 58
4.6 Tagging accuracies of unknown tokens from the WSJ models. 59
4.7 Tagging accuracies of unknown tokens from the OntoNotes models. . . . . . . . . 59
4.8 Tagging accuracies achieved by the medical model. . . . . . . . . . . . . . . . 60
4.9 Tagging speeds. . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 61

5.1 Decomposed transitions grouped into the Arc and List operations. . . . . . . . 64
5.2 Preconditions of the decomposed transitions in Table 5.1. . . . . . . . . . . . . . 64
5.3 Transitions in different dependency parsing algorithms. . . . . . . . . . . . . . 66
5.4 Parsing states generated by Algorithm 5.1 for the example. . . . . . . . . . . . . 71
5.5 Feature templates for dependency parsing. . . . . . . . . . . . . . . . . . . . . . . . 77
5.6 Labeled attachment scores for all trees from the WSJ models. . . . . . . . . . . 79
5.7 Labeled attachment scores for all trees from the OntoNotes models. . . . . . . 79
5.8 Unlabeled attachment scores for all trees from the WSJ models. . . . . . . . . . 80
5.9 Unlabeled attachment scores for all trees from the OntoNotes models. . . . . . 80
5.10 Labeled attachment scores for non-projective trees from the WSJ models. . . . 81
5.11 Labeled attachment scores for non-projective trees from the OntoNotes models. . 81
5.12 Unlabeled attachment scores for non-projective trees from the WSJ models. . . . 82
5.13 Unlabeled attachment scores for non-projective trees from the OntoNotes models. . 82
5.14 Parsing speeds. . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 84

6.1 Mapping between semantic and syntactic dependencies. . . . . . . . . . . . . . . 90
6.2 Feature templates for semantic role labeling. . . . . . . . . . . . . . . . . . . . . . . 103
6.3 F1-scores of semantic role labeling from the WSJ models. . . . . . . . . . . . . 104
6.4 F1-scores of semantic role labeling from the OntoNotes models. . . . . . . . . . 104
6.5 Precisions and recalls for in-genre and out-of-genre experiments. . . . . . . . . . 105
6.6 F1-scores of numbered arguments and modifiers. . . . . . . . . . . . . . . . . . . . 106
6.7 Labeling speeds. . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 107

A.1 A list of function tags for English. . . . . . . . . . . . . . . . . . . . . . . . . . . . 119
Figures

Figure

1.1 An example of constituent and dependency structures. .......................... 4
1.2 An example of constituent and dependency trees labeled with semantic roles. ... 5
1.3 An example of English and Chinese parallel sentences labeled with semantic roles. . 6
1.4 The overall framework. ............................................................................ 7
2.1 Structural differences in the Penn Treebank and the OntoNotes Treebank. ....... 10
2.2 An example of a projective dependency graph. ........................................ 12
2.3 An example of a non-projective dependency graph. ................................. 12
2.4 The overview of constituent to dependency conversion. ........................... 14
2.5 An example of *wh*-movement. ............................................................... 15
2.6 A dependency tree converted from the constituent tree in Figure 2.5 ............... 15
2.7 Another example of *wh*-movement. ....................................................... 16
2.8 A dependency tree converted from the constituent tree in Figure 2.7. .............. 16
2.9 An example of topicalization. ................................................................. 17
2.10 A dependency tree converted from the constituent tree in Figure 2.9. ............. 17
2.11 An example of topicalization, where a topic movement creates a cyclic relation. . 18
2.12 A dependency tree converted from the constituent tree in Figure 2.11. ............ 18
2.13 An example of right node raising. .......................................................... 19
2.14 A dependency tree converted from the constituent tree in Figure 2.13. ............ 19
2.15 A CoNLL style dependency tree converted from the constituent tree in Figure 2.13. . 19
2.16 An example of discontinuous constituents. . . . . . . . . . . . . . . . . . . . . . . . . 20
2.17 A dependency tree converted from the constituent tree in Figure 2.16. . . . . . . . . 20
2.18 An example of a noun phrase modifying another noun phrase. . . . . . . . . . . . . . 22
2.19 Different ways of representing coordination in dependency structure. . . . . . . . . 24
2.20 Examples of small clauses with internal and external subjects. . . . . . . . . . . . . . 29
2.21 Dependency trees converted from the constituent trees in Figure 2.20. . . . . . . . . 29
2.22 An example of a small clause in a passive construction. . . . . . . . . . . . . . . . . . 30
2.23 An example of a gapping relation. . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 36
2.24 The CLEAR dependency tree converted from the constituent tree in Figure 2.23. . . 37
2.25 The CoNLL dependency tree converted from the constituent tree in Figure 2.23. . . 37
2.26 An example of a referent relation. . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 38
2.27 An example of right node raising where the raised constituent is the head. . . . . . . 39
2.28 The dependency tree converted from the constituent tree in Figure 2.27. . . . . . . . 39
2.29 An example of an open clausal subject caused by a subject raising. . . . . . . . . . . 40
2.30 A dependency tree converted from the constituent tree in Figure 2.29. . . . . . . . . 40
2.31 An example of an open clausal subject caused by an object raising. . . . . . . . . . . 41
2.32 A dependency tree converted from the constituent tree in Figure 2.31. . . . . . . . . 41
2.33 An example of exceptional case marking. . . . . . . . . . . . . . . . . . . . . . . . . . 41
2.34 A dependency tree converted from the constituent tree in Figure 2.33. . . . . . . . . 41
2.35 A constituent tree with semantic function tags. . . . . . . . . . . . . . . . . . . . . . . 42
2.36 A dependency tree converted from the constituent tree in Figure 2.35. . . . . . . . . 42
2.37 Another dependency tree converted from the constituent tree in Figure 2.35. . . . . 43
2.38 A constituent tree with syntactic function tags. . . . . . . . . . . . . . . . . . . . . . . 43
2.39 A dependency tree converted from the constituent tree in Figure 2.38. . . . . . . . . 43

4.1 The overview of POS tagging using dynamic model selection. . . . . . . . . . . . . 51
4.2 Cosine similarity distributions. ................................. 55

5.1 The average number of transitions performed by each algorithm in Table 5.3. ... 68
5.2 The range of subtree and head information. ......................... 72
5.3 An automatically generated tree for the example in Table 5.4. .......... 73
5.4 A flowchart of our bootstrapping technique. ......................... 74
5.5 Average parsing speeds with respect to sentence lengths. ............... 85

6.1 Three senses of the verb open and their argument structures in PropBank. ... 88
6.2 An example of a PropBank predicate argument structure. ................. 88
6.3 A dependency tree annotated with the semantic arguments in Figure 6.2 ... 89
6.4 An example of a continuous argument. ................................ 91
6.5 An example of discontinuous constituents. ............................. 92
6.6 An example of a referent argument. ................................... 93
6.7 Argument coverage rates achieved by different pruning algorithms and input trees. 96
6.8 An example of a down-path. .......................................... 98
6.9 An example of an up-path. ............................................ 99
6.10 The average number of argument candidates for different pruning algorithms. ... 101
6.11 Average labeling speeds with respect to sentence lengths. ............... 108
Chapter 1

Introduction

1.1 Research questions and objectives

Unlike earlier stages of Natural Language Processing (NLP) where it was used by certain groups of people for specific purposes (e.g., DARPA using NLP for machine translation),\(^1\) the application of NLP has expanded to everyday computing and has also broadened to a general audience. For example, Google and Bing Translators are developed using an NLP technique called statistical machine translation, and they provide an online service that instantly translates texts and web pages.\(^2\) IBM Watson is based on an NLP application called question-answering, and has shown outstanding performance in answering Jeopardy type questions (www.watson.ibm.com). NLP is no longer in the future; it has become a present-day reality.

As NLP components mature, more attention is drawn to the practical aspects of these components. In this respect, two things must be evaluated. First, NLP components should be tested for robustness in handling heterogeneous data.\(^3\) Many recent NLP components take statistical learning approaches, which usually perform well when training and testing data are from similar sources. However, the performance degrades increasingly as the discrepancy between the training and testing data becomes larger. Thus, NLP components need to be evaluated on data from several different sources to ensure their robustness. Second, NLP components should be tested for scalability in handling a large amount of data. Lately, these components have been used for processing data

---

2. Google Translator: translate.google.com, Bing Translator: translator.bing.com
3. The term “heterogeneous data” is used to indicate a mixture of data collected from several different sources.
that are not fixed but growing indefinitely. The scope of this data type can be as large as the entire content of the web. Thus, NLP components need to be evaluated for speed and complexity to ensure their scalability.

The objective of this thesis is to answer the following research question: “how can NLP components be optimized for better robustness and scalability”. Three NLP components are used in experiments to answer this question: a part-of-speech tagger, a dependency parser, and a semantic role labeler. A part-of-speech tagger assigns lexical categories to word tokens, a dependency parser finds dependency relations between word pairs, and a semantic role labeler finds semantic arguments of predicates. Since there are many NLP tasks highly dependent on output generated by these components (e.g., information retrieval, machine translation, question-answering), it is important to optimize them for robustness as well as scalability so that they can provide reliable information without becoming bottlenecks for other tasks.

Three goals are to be accomplished in this research. First, to prepare gold-standard data from several different sources, which can be used to evaluate system performance for both in-genre and out-of-genre experiments. This step involves automatic generation of dependency trees with semantic roles. Second, to develop a part-of-speech tagger, a dependency parser, and a semantic role labeler showing robust results across this data. This step involves dynamic model selection for part-of-speech tagging, feature bootstrapping for dependency parsing, and higher-order argument pruning for semantic role labeling. Third, to reduce the expected running time of these components while retaining good accuracy. This step involves optimization of tagging, parsing, and labeling algorithms.

Although experiments are done in English, all three components use statistical, data-driven learning approaches so they can be easily ported to other languages with some feature engineering. Moreover, they already have been used for several projects and are publicly available as an open source project called ClearNLP (clearnlp.googlecode.com). We believe this research helps make NLP components available for more applications and brings these components closer to a greater number of users.
1.2 Background

1.2.1 Part-of-speech tagging

Part-of-speech tagging is the task of assigning a lexical category known as a “part-of-speech” (e.g., noun, verb) to a word. Part-of-speech tagging is useful for two reasons. First, it can disambiguate meanings of words belonging to multiple lexical categories. For example, a word *spring* belongs to two lexical categories, noun and verb, and means either *the season of growth* or *to move forward by leaps and bounds* when used as a noun or a verb, respectively.\(^4\) Thus, the meaning of *spring* can only be disambiguated by identifying its part-of-speech in the context of the current sentence. Second, part-of-speech tagging provides back-off features of lexical items for NLP components. Lexical items are perhaps the most important features for many NLP components; however, they are often biased to the source data. Using only lexical items as features can be problematic when NLP components, trained on this particular source data, are used to process data from different sources where lexical items are very different from ones in the training data. Part-of-speech tags group lexical items into certain grammatical categories and provide more generalized features to NLP components, which improves robustness in handling new data.

Part-of-speech tagging is performed as a preprocessing step to many NLP tasks such as named entity recognition, NP chunking, dependency parsing, etc. It has been used widely for various applications and is considered one of the most useful NLP techniques in existence.\(^5\)

1.2.2 Dependency parsing

Dependency parsing is the task of finding a dependency structure for an input sentence. A dependency refers to either a syntactic or semantic relation between a pair of word tokens. There are syntactic dependencies like subject or object and semantic dependencies like locative or temporal (see Appendix D for more details about dependency labels). Dependency parsing is often compared to constituent parsing, which groups word tokens into constituents and groups these constituents

\(^4\) The definitions of *spring* are captured from WordNet ([http://wordnet.princeton.edu](http://wordnet.princeton.edu)).

\(^5\) See Table A.2 for a list of Penn part-of-speech tags.
again into bigger constituents (e.g., phrases, clauses); thus, the final output becomes a syntactic tree (a constituent structure). Figure 1.1 shows an example of constituent and dependency structures. Unlike a constituent structure, also known as a phrase structure, there is no phrasal node in a dependency structure: each node in a dependency structure represents a word token, and each node is dependent on exactly one other node except for the root (e.g., *bought* in Figure 1.1).

![Figure 1.1: An example of constituent (left) and dependency (right) structures. Tables A.3 and 2.3 show more details about these phrase level tags and dependency labels, respectively.](image)

Dependency structures have several advantages over phrase structures. First, phrase structures are more affected by word order in that different phrase structure rules need to be generated for phrases with the same meaning but a different word order. Dependency structures are less affected by word order, which makes them more suitable for representing flexible word order languages (e.g., Bulgarian, Czech, Hindi, Korean). Second, many dependencies are applicable cross-linguistically such that a similar set of dependencies can be applied to multiple languages with minor modifications. This language independent aspect was one of the main reasons for CoNLL to choose dependency parsing as a multilingual parsing task (Buchholz and Marsi, 2006; Nivre et al., 2007; Hajič et al., 2009). Third, automatic dependency parsing is much faster than automatic constituent parsing, which makes it more applicable for systems requiring fast processing of large-scale data.6

These advantages have resulted in considerable recent interest in applying dependency parsing to many NLP tasks such as machine translation (Shen et al., 2008), sentiment analysis (Councill et al., 2010), question-answering (Cui et al., 2005), etc. It is especially beneficial for those who need to deal with a vast amount of data in many different languages.

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6 Dependency parsing takes about 0.003 ~ 0.157 seconds per sentence whereas constituent parsing takes about 0.25 ~ 0.77 seconds per sentence (Cer et al., 2010).
1.2.3 Semantic role labeling

Semantic role labeling is the task of identifying arguments of a predicate and labeling the arguments with the semantic roles they play with respect to the predicate. In theory, a predicate can be any lexical category (e.g., verb, noun) that forms its own predicate argument structure. An argument is a participant of an event (or state) denoted by the predicate. Semantic roles, also known as thematic roles, are the underlying relations between the predicate and its arguments. In Figure 1.2, a verb predicate \textit{open} forms an argument structure that consists of two arguments, \textit{He} as an agent and \textit{the door} as a theme, and two adjuncts, \textit{with his foot} as instrumental and \textit{at ten} as temporal (see Appendix B for more details about semantic roles).

Semantic role labeling has sparked much interest because it provides helpful information for several NLP tasks (Shen and Lapata, 2007; Liu and Gildea, 2010). For example, to answer a question like “How did he open the door?”, analyzing the syntactic trees in Figure 1.2 can only give a clue to the answer (e.g., the answer may be found from one of PPs or PREP dependencies), but not the exact answer. Semantic roles can give more fine-grained information with respect to the focus of the question, in this case, the instrument of the event, \textit{with his foot}.

![Figure 1.2: An example of constituent (top) and dependency (bottom) trees labeled with semantic roles. See Table B.2 for more details about these semantic role labels.](image)

In the context of machine translation resources, parallel sentences from different languages, which are translations of each other, often form the same predicate argument structures even when their
syntactic structures appear to be different. In Figure 1.3, the surface locations of the agent *him* and the recipient *her* are reversed between English and Chinese, but their semantic roles stay the same. This implies that predicate argument structures can provide more generalizations useful for multilingual tasks such as machine translation than syntactic structures.

![Figure 1.3: An example of English and Chinese parallel sentences labeled with semantic roles. The lines show many-to-many (block) word alignments between the parallel sentences.](image)

For our experiments, we use the PropBank style semantic role labels, which are coarse-grained on a surface level (e.g., ARG0, ARG1) but can be mapped to more fine-grained labels (e.g., agent, theme) through predefined mappings (Palmer et al., 2005).

### 1.3 Overall framework

Figure 1.4 shows the overall framework of this research. Prior to the development of the NLP components, manually annotated constituent trees are taken from Treebanks and automatically converted to dependency trees (Chapter 2). Semantic roles from PropBanks are added to dependency trees during this conversion (Section 6.2.3). Once the conversion is done, dependency trees with semantic roles are divided into training and evaluation sets. Given the training set, three models are built in pipelines: part-of-speech tagging (Chapter 4), dependency parsing (Chapter 5), and semantic role labeling (Chapter 6). During training, models in later pipelines are trained on automatic outputs generated by previous models. For example, a semantic role labeling model is trained on data consisting of automatic outputs from both part-of-speech tagging and dependency parsing models. Finally, all models are tested on the evaluation set for their robustness and scalability (Chapter 3).
Figure 1.4: The overall framework.
1.4 Thesis statement

The goal of this thesis is to improve the robustness and scalability of three NLP components, a part-of-speech tagger, a dependency parser, and a semantic role labeler. The term ‘robustness’ is used here to indicate how well NLP components respond to test data that varies from their training data. Robustness is evaluated by measuring accuracies on both in-genre and out-of-genre data. By building a generalized model for part-of-speech tagging, bootstrapping parse information for dependency parsing, and applying higher-order argument pruning for semantic role labeling, we improve the robustness of these three NLP components. The term ‘scalability’ is used here to indicate how fast NLP components run when processing large scale data. Scalability is evaluated by measuring the expected running times and speeds.\(^7\) By adapting dynamic model selection for part-of-speech tagging, optimizing the engineering of transition-based parsing algorithms for dependency parsing, and applying conditional higher-order argument pruning for semantic role labeling, we improve the scalability of these three components.

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\(^7\) The expected running time is how fast an algorithm is expected to run on average in terms of complexity and the speed is how fast a system actually runs on a real machine.
2.1 Introduction

2.1.1 Motivation

Most current state-of-the-art dependency parsers take various statistical learning approaches (McDonald and Pereira, 2006; Nivre, 2008; Huang and Sagae, 2010; Rush and Petrov, 2012). The biggest advantage of statistical parsing is found in the ability to adapt to new data without modifying the parsing algorithm. Statistical parsers can be trained on data from new domains, genres, or languages as long as they are provided with sufficiently large training data from the new sources. On the other hand, this is also the biggest drawback for statistical parsing because annotating such large training data is manually intensive work that is costly and time consuming.

Although a few manually annotated dependency Treebanks are available for English (Rambow et al., 2002; Čmejrek et al., 2004), constituent Treebanks are still more dominant (Marcus et al., 1993; Weischedel et al., 2011). It has been shown that the Penn Treebank style constituent trees can reliably be converted to dependency trees using head-finding rules and heuristics (Johansson and Nugues, 2007; de Marneffe and Manning, 2008a; Choi and Palmer, 2010b). By automatically converting these constituent trees to dependency trees, statistical dependency parsers have access to a larger amount of training data. Few tools are available for constituent to dependency conversion. Two of the most popular ones are the LTH and the Stanford dependency converters.¹

¹ The LTH dependency converter: http://nlp.cs.lth.se/software/treebank_converter/
The LTH converter had been used to provide English data for the CoNLL’07-09 shared tasks (Nivre et al., 2007; Surdeanu et al., 2008; Hajič et al., 2009). The LTH converter makes several improvements over its predecessor, Penn2Malt,\(^2\) by adding syntactic and semantic dependencies retained from function tags (e.g., PRD, TMP) and producing long-distance dependencies caused by empty categories or gapping relations.\(^3\) The Stanford converter was used for the SANCL’12 shared task (Petrov and McDonald, 2012), and is perhaps the most widely used dependency converter at the moment. The Stanford converter gives fine-grained dependency labels useful for many NLP tasks. Appendix C shows descriptions of the CoNLL and the Stanford dependency labels generated by these two tools.

Both converters perform well for most cases; however, they are somewhat customized to the Penn Treebank (mainly to the Wall Street Journal corpus; see Marcus et al. (1993)), so do not work as well when applied to different corpora. For example, the OntoNotes Treebank (Weischedel et al., 2011) contains additional constituent tags not used by the Penn Treebank (e.g., EDITED, META), and shows occasional departures from the Penn Treebank guidelines (e.g., inserting NML phrases, separating hyphenated words; see Figure 2.1). These new formats affect the ability of existing tools to find correct dependencies, motivating us to aim for a more resilient approach.

![Figure 2.1: Structural differences in the Penn Treebank (left) and the OntoNotes Treebank (right). The hyphenated word is tokenized, HYPH, and the nominal phrase is grouped, NML, in the OntoNotes.](http://stp.lingfil.uu.se/~nivre/research/Penn2Malt.html)

Producing more informative trees provides additional motivation. The Stanford converter generates dependency trees without using information such as function tags (Section A.1), empty categories (Section 2.2), or gapping relations (Section 2.5.1), which is provided in manually annotated but not in automatically generated constituent trees. This enables the Stanford converter to generate

\(^2\) Penn2Malt: [http://stp.lingfil.uu.se/~nivre/research/Penn2Malt.html](http://stp.lingfil.uu.se/~nivre/research/Penn2Malt.html)

\(^3\) The term “long-distance dependency” is used to indicate dependency relations between words that are not within the same domain of locality.
the same kind of dependencies given either manually or automatically generated constituent trees. However, it sometimes misses important details such as long-distance dependencies, which can be retrieved from empty categories, or produces unclassified dependencies that can be disambiguated by function tags. This becomes an issue when this converter is used for generating dependency trees for training because statistical parsers trained on these trees would not reflect these details.

The dependency conversion described here takes the Stanford dependency approach as the core structure and integrates the CoNLL dependency approach to add long-distance dependencies, to enrich important relations like object predicates, and to minimize unclassified dependencies. The Stanford dependency approach is taken for the core structure because it gives more fine-grained dependency labels and is currently used more widely than the CoNLL dependency approach. For our conversion, head-finding rules and heuristics are completely reanalyzed from the previous work to handle constituent tags and relations not introduced by the Penn Treebank. Our conversion has been evaluated with several different constituent Treebanks (Marcus et al., 1993; Nielsen et al., 2010; Weischedel et al., 2011; Verspoor et al., 2012) and showed robust results across these corpora.

2.1.2 Background

2.1.2.1 Dependency graph

A dependency structure can be represented as a directed graph. For a given sentence $s = w_1, \ldots, w_n$, where $w_i$ is the $i$'th word token in the sentence, a dependency graph $G_s = (V_s, E_s)$ can be defined as follows:

$$V_s = \{w_0 = \text{root}, w_1, \ldots, w_n\}$$

$$E_s = \{(w_i \xrightarrow{r} w_j) : i \neq j, w_i \in V_s, w_j \in V_s - \{w_0\}, r \in R_s\}$$

$$R_s = \text{A subset of all dependency relations in } s$$

$w_i \xrightarrow{r} w_j$ is a directed edge from $w_i$ to $w_j$ with a label $r$, which implies that $w_i$ is the head of $w_j$ with a dependency relation $r$. A dependency graph is considered well-formed if it satisfied all of the following properties:
• **Root**: there must be a unique vertex, \( w_0 \), with no incoming edge.
\[
\neg \exists k. (w_0 \leftarrow w_k)
\]

• **Single head**: each vertex \( w_{i>0} \) must have at most one incoming edge.
\[
\forall i. (i > 0 \Rightarrow \forall j. ((w_i \leftarrow w_j) \Rightarrow \neg \exists k. (k \neq j) \land (w_i \leftarrow w_k)))]
\]

• **Connected**: there must be an undirected path between any two vertices.\(^4\)
\[
[\forall i,j. (w_i \rightarrow w_j)], \text{ where } w_i - w_j \text{ indicates an undirected path between } w_i \text{ and } w_j.
\]

• **Acyclic**: a directed path between any two vertices must not be cyclic.
\[
\neg [\exists i,j. (w_i \leftarrow w_j) \land (w_i \rightarrow w_j)], \text{ where } w_i \rightarrow w_j \text{ indicates a directed path from } w_i \text{ to } w_j.
\]

Sometimes, *projectivity* is also considered a property of a well-formed dependency graph. When projectivity is considered, no crossing edge is allowed when all vertices are lined up in linear-order and edges are drawn above the vertices (Figure 2.2). Preserving projectivity can be useful because it enables regeneration of the original sentence from its dependency graph without losing the word order. More importantly, it reduces parsing complexity to \( O(n) \) (Nivre and Scholz, 2004).

![Figure 2.2: An example of a projective dependency graph.](image)

Figure 2.2: An example of a projective dependency graph.

![Figure 2.3: An example of a non-projective dependency graph. The dependency between *car* and *is* is non-projective because it crosses the dependency between *bought* and *yesterday.*](image)

Figure 2.3: An example of a non-projective dependency graph. The dependency between *car* and *is* is non-projective because it crosses the dependency between *bought* and *yesterday.*

Although preserving projectivity has a few advantages, non-projective dependencies are often required, especially in flexible word order languages, to represent correct dependencies (Nivre, 2008). Even in rigid word order languages such as English, non-projective dependencies are necessary to

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\(^4\) An ‘undirected path’ implies a path between two vertices, regardless of their directionality.
represent long-distance dependencies. In Figure 2.3, there is no way of describing the dependency relations for both “bought → yesterday” and “car → is” without having their edges cross. Because of such cases, projectivity is dropped from the properties of a well-formed dependency graph for this research.

A well-formed dependency graph, with or without the projective property, satisfies all of the conditions for a tree structure, so is called a ‘dependency tree’.

2.1.2.2 Types of empty categories

Empty categories are syntactic units, usually nominal phrases, that appear in the surface form to signal the canonical locations of syntactic elements in its deep structure (Cowper, 1992; Chomsky, 1995). Table 2.1 shows a list of empty categories used in constituent Treebanks for English. Some of these empty categories have overloaded meanings. For instance, *PRO* indicates empty subjects caused by different pro-drop cases (e.g., control, imperative, nominalization). See Bies et al. (1995); Taylor (2006) for more details about these empty categories.

<table>
<thead>
<tr>
<th>Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>PRO</em></td>
<td>Empty subject of pro-drop (e.g., control, ECM, imperative, nominalization)</td>
</tr>
<tr>
<td><em>T</em></td>
<td>Trace of wh-movement and topicalization</td>
</tr>
<tr>
<td>*</td>
<td>Trace of subject raising and passive construction</td>
</tr>
<tr>
<td>0</td>
<td>Null complementizer</td>
</tr>
<tr>
<td><em>U</em></td>
<td>Unit (e.g., $)</td>
</tr>
<tr>
<td><em>ICH</em></td>
<td>Pseudo-attach: Interpret Constituent Here</td>
</tr>
<tr>
<td><em>??</em></td>
<td>Placeholder for ellipsed material</td>
</tr>
<tr>
<td><em>EXP</em></td>
<td>Pseudo-attach: EXPletives</td>
</tr>
<tr>
<td><em>RNR</em></td>
<td>Pseudo-attach: Right Node Raising</td>
</tr>
<tr>
<td><em>NOT</em></td>
<td>Anti-placeholder in template gapping</td>
</tr>
<tr>
<td><em>PPA</em></td>
<td>Pseudo-attach: Permanent Predictable Ambiguity</td>
</tr>
</tbody>
</table>

Table 2.1: A list of empty categories used in constituent Treebanks for English.

2.1.3 Overview

Figure 2.4 shows the overview of our constituent to dependency conversion. Given a constituent tree, empty categories are mapped to their antecedents first (step 2; see Section 2.2). This step
relocates phrasal nodes regarding certain kinds of empty categories that may cause generation of non-projective dependencies. Once empty categories are mapped, special cases such as apposition, coordination, or small clauses are handled next (step 3; see Sections 2.3.2 to 2.3.4). Finally, general cases are handled using head-finding rules and heuristics (step 4; see Section 2.3.1 and Section 2.4).

Secondary dependencies are added as a separate layer of this dependency tree (step 5; see Section 2.5). Additionally, syntactic and semantic function tags in the constituent tree are preserved as features of individual nodes in the dependency tree (not shown in Figure 2.4; see Section A.1).

---

5 Although phrases in constituency trees are relocated, word order in dependency trees remains the same.
2.2 Mapping empty categories

Most long-distance dependencies can be represented without using empty categories in dependency structure. In English, long-distance dependencies are caused by certain linguistic phenomena such as *wh*-movement, topicalization, discontinuous constituents, etc. It is difficult to find long-distance dependencies during automatic parsing because they often introduce dependents that are not within the same domain of locality, resulting in non-projective dependencies (McDonald and Satta, 2007; Koo et al., 2010; Kuhlmann and Nivre, 2010).

Four types of empty categories are used to represent long-distance dependencies during our conversion: \*T*, \*RNR*, \*ICH*, and \*PPA* (see Table 2.1). Note that the CoNLL dependency approach used \*EXP* to represent extraposed elements in expletive constructions, which is not used in our approach because the annotation of \*EXP* is somewhat inconsistent across different corpora.

2.2.1 Wh-movement

![Diagram of wh-movement](image)

Figure 2.5: An example of *wh*-movement.

![Diagram of dependency tree](image)

Figure 2.6: A dependency tree converted from the constituent tree in Figure 2.5
Wh-movement is represented by *T* in constituent trees. In Figure 2.5, WHNP-1 is moved from the object position of the subordinate verb *liked* and leaves a trace, *T*-1, at its original position. Figure 2.6 shows a dependency tree converted from the constituent tree in Figure 2.5. The dependency of WHNP-1 is derived from its original position so that it becomes a direct object of *liked* (DOBJ; Section D.2.2).

![Figure 2.7: Another example of wh-movement.](image)

Wh-complementizers can be moved from several positions. In Figure 2.7, WHNP-1 is moved from the prepositional phrase, PP, so in Figure 2.8, the complementizer *what* becomes an object of the preposition *in* (POBJ; Section D.8.2). Notice that the POBJ dependency is non-projective; it crosses the dependency between *knew* and *was*. This is a typical case of a non-projective dependency caused by wh-movement.

![Figure 2.8: A dependency tree converted from the constituent tree in Figure 2.7. The dependency derived from the wh-movement, POBJ, is indicated by a dotted line.](image)
2.2.2 Topicalization

Topicalization is also represented by *T*. In Figure 2.9, S-1 is moved from the subordinate clause, SBAR, and leaves a trace behind. In Figure 2.10, the head of S-1, *liked*, becomes a dependent of the matrix verb *seemed* (ADVCL; Section D.5.1), and the preposition *like* becomes a dependent of the subordinate verb *liked* (MARK; Section D.5.3). The MARK dependency is non-projective such that it crosses the dependency between Root and *seemed*.

![Figure 2.9: An example of topicalization.](image)

There are a few cases where *T* mapping causes cyclic dependency relations. In Figure 2.11, *T*-1 is mapped to S-1 that is an ancestor of itself. Thus, the head of S-1, *bought*, becomes a dependent of the subordinate verb *said* while the head of the subordinate clause, *said*, becomes a dependent of the matrix verb *bought*. Since this creates a cyclic relation in the dependency tree, such traces are ignored during our conversion (Figure 2.12).

![Figure 2.10: A dependency tree converted from the constituent tree in Figure 2.9. The dependency derived from the topicalization, MARK, is indicated by a dotted line.](image)
2.2.3 Right node raising

Right node raising occurs in coordination where a constituent is governed by multiple parents that are not on the same level (Levine, 1985). Right node raising is represented by \(*_{RNR}\) in constituent trees. In Figure 2.13, NP-1 should be governed by both PP-1 and PP-2, where \(*_{RNR}\)-1’s are located. Making NP-1 dependents of both PP-1 and PP-2 breaks the **single head** property (Section 2.1.2.1); instead, the dependency of NP-1 is derived from its closest \(*_{RNR}\)-1 in our conversion. In Figure 2.14, *her* becomes a dependent of the head of PP-2, *in*. The dependency between *her* and the head of PP-1, *for*, is preserved as a secondary dependency, **REF** (referent; see Section 2.5). Thus, *her* is a dependent of only PP-2 in our dependency tree while the dependency to PP-2 can still be retrieved through the secondary dependency.\(^6\)

---

\(^6\)Secondary dependencies are not commonly used in dependency structures. These are dependencies derived from gapping relations, referent relations, right node raising, and open clausal subjects, which may break tree properties (Section 2.5). During our conversion, secondary dependencies are preserved in a separate layer so they can be learned either jointly or separately from other dependencies.
Note that the CoNLL dependency approach makes *her* a dependent of the head of PP-1, which creates a non-projective dependency (the dependency between *for* and *her* in Figure 2.15). This non-projective dependency is avoided in our approach without losing any referential information.

Figure 2.13: An example of right node raising.

Figure 2.14: A dependency tree converted from the constituent tree in Figure 2.13. The secondary dependency, RNR, is added to a separate layer to preserve tree properties.

Figure 2.15: A CoNLL style dependency tree converted from the constituent tree in Figure 2.13. The dependency caused by right node raising, PMOD, is indicated by a dotted line.
2.2.4 Discontinuous constituent

A discontinuous constituent is a constituent that is separated from its original position by some intervening material. The original position of a discontinuous constituent is indicated by *ICH* in constituent trees. In Figure 2.16, PP-1 is separated from its original position, *ICH*-1, by the adverb phrase, ADVP. Thus, in Figure 2.17, the head of the prepositional phrase, than, becomes a prepositional modifier (PREP; Section D.8.3) of the head of the adjective phrase (ADJP-2), expensive. The PREP dependency is non-projective; it crosses the dependency between is and now.

![Figure 2.16: An example of discontinuous constituents.](image)

![Figure 2.17: A dependency tree converted from the constituent tree in Figure 2.16. The dependency derived from the *ICH* movement, PREP, is indicated by a dotted line.](image)
2.3 Finding dependency heads

2.3.1 Head-finding rules

<table>
<thead>
<tr>
<th>Rule</th>
<th>ADJP</th>
<th>ADVP</th>
<th>CONJP</th>
<th>EDITED</th>
<th>EMBED</th>
<th>FRAG</th>
<th>INTJ</th>
<th>LST</th>
<th>META</th>
<th>NAC</th>
<th>NML</th>
<th>NP</th>
<th>NX</th>
<th>PP</th>
<th>PRN</th>
<th>PRT</th>
<th>QP</th>
<th>RRC</th>
<th>S</th>
<th>SBAR</th>
<th>SBARQ</th>
<th>SINV</th>
<th>SQ</th>
<th>UCP</th>
<th>VP</th>
<th>WHADJP</th>
<th>WHADVP</th>
<th>WHNP</th>
<th>WHPP</th>
</tr>
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<tbody>
<tr>
<td>ADJP</td>
<td>r</td>
<td>JJ*</td>
<td>VB*</td>
<td>IN</td>
<td>RB</td>
<td>ADVP</td>
<td>CD</td>
<td>QP</td>
<td>FW</td>
<td>NP</td>
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<tr>
<td>ADVP</td>
<td>r</td>
<td>VB*</td>
<td>RP</td>
<td>RB</td>
<td>JJ*</td>
<td>ADJP</td>
<td>ADVP</td>
<td>QP</td>
<td>IN</td>
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<td>CONJP</td>
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<td>NN*</td>
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Table 2.2: Head-finding rules. 1/r implies the search direction for the leftmost/rightmost constituent. */+ implies 0/1 or more characters and -TAG implies any POS tag with the specific function tag. | implies a logical OR and ; is a delimiter between POS tags. Each rule gives higher precedence to the left (e.g., VP takes the highest precedence in S).

Table 2.2 shows head-finding rules (henceforth, headrules) derived from various constituent Treebanks. For each phrase (or clause) in a constituent tree, the head of the phrase is found by using its headrules, and all other nodes in the phrase become dependents of the head. This procedure goes on recursively until every constituent in the tree becomes a dependent of one other constituent,
except for the top constituent, which becomes the root of the dependency tree. A dependency tree generated by this procedure is guaranteed to be well-formed (Section 2.1.2.1), and may or may not be non-projective, depending on how empty categories are mapped (Section 2.2).

Notice that the headrules in Table 2.2 give information about which constituents can be the heads, but do not show which constituents cannot be the heads. Some constituents are more likely to be dependents than heads. In Figure 2.18, both *Three times* and *a week* are noun phrases under another noun phrase. According to our headrules, the rightmost noun phrase, NP-TMP, is chosen to be the head of this phrase. However, NP-TMP is actually an adverbial modifier of NP-H (NPADVMOD; Section D.5.5); thus, NP-H should be the head of this phrase instead. This indicates that extra information is required to retrieve correct heads for this kind of phrases.

![Figure 2.18: An example of a noun phrase modifying another noun phrase.](image)

**Algorithm 2.1**: *getHead(N, R)*

- **Input**: An ordered list $N$ of constituent nodes that are siblings, The headrules $R$ of the parent of nodes in $N$.
- **Output**: The head constituent of $N$ with respect to $R$. All other nodes in $N$ become dependents of the head.

1. if the search direction of $R$ is $r$ then $N$.reverse() # the 2nd column in Table 2.2
2. for flag in \{0...3\} do
3. for tags in $R$ do # e.g., tags ← NN*|NML
4. for node in $N$ do
5. if (flag = getHeadFlag(node)) and (node is tags) then
6. head ← node
7. break the highest for-loop
8. for node in $N$ do
9. if node ≠ head then
10. node.head ← head
11. node.label ← getDependencyLabel(node, node.parent, head) # Section 2.4.2
12. return head
The $getHead(N, R)$ method in Algorithm 2.1 finds the head of a phrase (lines 2-7) and makes all other constituents in the phrase dependents of the head (lines 8-11). The input to the method is the ordered list of children $N$ and the corresponding headrules $R$ of the phrase. The $getHeadFlag(C)$ method in Algorithm 2.2 returns the head-flag of a constituent $C$, which indicates the dependency precedence of $C$: the lower the flag is, the sooner $C$ can be chosen as the head. For example, NP-TMP in Figure 2.18 is skipped during the first iteration (line 2 in Algorithm 2.1) because it has the adverbial function tag TMP, so gets a flag of 1 (line 1 in Algorithm 2.2). Alternatively, NP-H is not skipped because it gets a flag of 0. Thus, NP-H becomes the head of this phrase.

**Algorithm 2.2 : $getHeadFlag(C)$**

<table>
<thead>
<tr>
<th>Input:</th>
<th>A constituent $C$.</th>
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</thead>
<tbody>
<tr>
<td>Output</td>
<td>The head-flag of $C$, that is either 0, 1, 2, or 3.</td>
</tr>
</tbody>
</table>

1: if $hasAdverbialTag(C)$ return 1 # Section D.5
2: if $isMetaModifier(C)$ return 2 # Section D.10.4
3: if (C is an empty category) or $isPunctuation(C)$ return 3 # Section D.10.8
4: return 0

The following sections describe heuristics to resolve special cases such as apposition, coordination, and small clauses, where correct heads cannot always be retrieved by headrules alone.

### 2.3.2 Apposition

Apposition is a grammatical construction where multiple noun phrases are placed side-by-side and later noun phrases give additional information about the first noun phrase. For example, in a phrase “John, my brother”, both John and my brother are noun phrases such that my brother gives additional information about its preceding noun phrase, John. The $findApposition(C)$ method in Algorithm 2.3 makes each appositional modifier a dependent of the first noun phrase in a phrase (lines 8-9). An appositional modifier is either a noun phrase without an adverbial function tag (line 5), any phrase with the function tag HLN|TTL (headlines or titles; line 6), or a reduced relative clause containing a noun phrase with the function tag PRD (non-VP predicate; line 7).
Algorithm 2.3: findApposition(C)

Input: A constituent C.
Output: True if C contains apposition; otherwise, False.
1: if (C is not NP|NML) or (C contains NN*) or (C contains no NP) return False
2: let f be the first NP|NML in C that contains no POS  # skip possession modifier
3: b ← False
4: for s in all children of C preceded by f do
5: if ((s is NML|NP) and (not hasAdverbialTag(s))) # Section D.5
6: or (s has HLN|TTL)
7: or ((s is RRC) and (s contains NP-PRD)) then
8: s.head ← f
9: s.label ← APPOS
10: b ← True
11: return b

2.3.3 Coordination

Several approaches have been proposed for coordination representation in dependency structure. The Stanford dependency approach makes the leftmost conjunct the head of all other conjuncts and conjunctions. The Prague dependency approach makes the rightmost conjunction the head of all conjuncts and conjunctions (Čmejrek et al., 2004). The CoNLL dependency approach makes each preceding conjunct or conjunction the head of its following conjunct or conjunction.

Our conversion takes an approach similar to the CoNLL dependency approach, which had been shown to work better for transition-based dependency parsing (Nilsson et al., 2006). There is one small change in our approach such that conjunctions do not become the heads of conjuncts (CLEAR...
in Figure 2.19). This way, conjuncts are always dependents of their preceding conjuncts whether or not conjunctions exist in between.

Algorithm 2.4: `getCoordinationHead(C, R)`

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<tr>
<th>Line</th>
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<tr>
<td>1-4</td>
<td>Check if <code>C</code> is coordinated and return null if not.</td>
</tr>
<tr>
<td>5-20</td>
<td>For each child <code>c</code> of <code>C</code>, check if it is a coordinating conjunction or a comma or colon.</td>
</tr>
<tr>
<td>21</td>
<td>If a coordinating conjunction is found, set <code>isPatternFound</code> to True.</td>
</tr>
<tr>
<td>22</td>
<td>If <code>pHead</code> is null, return null.</td>
</tr>
<tr>
<td>23</td>
<td>If <code>S</code> is not empty, return the head of the leftmost conjunct in <code>S</code>.</td>
</tr>
</tbody>
</table>

The `getCoordinationHead(C)` method in Algorithm 2.4 finds dependencies between conjuncts and returns the head of the leftmost conjunct in `C`. The algorithm begins by checking if `C` is coordinated (line 1). For each constituent in `C`, the algorithm checks if it matches the conjunct head pattern of `C` (line 21), which varies by `C`’s phrase type. For instance, only a non-auxiliary verb or a verb phrase can be a conjunct head in a verb phrase (see `getConjunctHeadPattern(C)` in Algorithm 2.6). When a coordinator (a conjunction, comma, or colon) is encountered, a sub-span is formed (line 9). If the span includes at least one constituent matching the conjunct head pattern, it is considered a
new conjunct and the head of the conjunct is retrieved by the headrule of \( C \) (line 10). The head of the current conjunct becomes a dependent of the head of its preceding conjunct if it exists (see `getConjunctHead(S, R, pHead)` in Algorithm 2.8). If there is no constituent matching the pattern, all constituents within the span become dependents of the head of the previous conjunct if it exists (lines 16-19). This procedure goes on iteratively until all constituents in \( C \) are encountered. Note that the `getCoordinationHead(C, R)` method is called before the `findApposition(C)` method in Algorithm 2.3; thus, a constituent can be a conjunct or an appositional modifier, but not both.

The `containsCoordination(C)` method in Algorithm 2.5 decides whether a constituent \( C \) is coordinated. \( C \) is coordinated if it is an unlike coordinated phrase (line 1), a noun phrase containing a constituent with the function tag `ETC` as the rightmost child (line 2-4), or contains a conjunction followed by a conjunct (lines 5-9).

```plaintext
Algorithm 2.5 : containsCoordination(C)

Input: Constituent \( C \).
Output: True if \( C \) contains coordination; otherwise, False.
1: if \( C \) is UCP return True # unlike coordinated phrase
2: if \((C \text{ is NML} \mid \text{NP}) \text{ and } (C \text{ contains } -\text{ETC})\) then # et cetera (etc.)
3: let \( e \) be a child of \( N \) with -ETC
4: if \( e \) is the rightmost element besides punctuation return True
5: for \( f \) in all children of \( C \) do # skip pre-conjunctions
6: if not (isCoordinatingConjunction(f) or isPunctuation(f)) then # App. D.6.2, D.10.8
7: break
8: let \( N \) be all children of \( C \) preceded by \( f \)
9: return \( N \) contains CC|CONJP
```

The `getConjunctHeadPattern(C)` method in Algorithm 2.6 returns a pattern that matches potential conjunct heads of \( C \). In theory, a verb phrase should contain at least one non-auxiliary verb or a verb phrase that matches the pattern (\( \text{VP} \mid \text{VB}^{\prime} \) in line 9); however, this is not always true in practice (e.g., VP-ellipsis, randomly omitted verbs in web-texts). Moreover, phrases such as unlike coordinated phrases, quantifier phrases, or fragments do not always show clear conjunct head patterns. The default pattern of `*` is used for these cases, indicating that any constituent can be the potential head of a conjunct in these phrases.
Algorithm 2.6: getConjunctHeadPattern(C)

**Input:** A constituent C.

**Output:** The conjunct head pattern of C if exists; otherwise, the default pattern, *.

If C contains no child satisfying the pattern, returns the default pattern, *.

VB$^b$ implies a non-auxiliary verb (Section D.3).

S$^b$ implies a clause without an adverbial function tag (Section D.5).

1: if C is ADJP then $p \leftarrow$ ADJP|JJ*|VBN|VBG
2: elif C is ADVP then $p \leftarrow$ ADVP|RB*
3: elif C is INTJ then $p \leftarrow$ INTJ|UH
4: elif C is PP then $p \leftarrow$ PP|IN|VBG
5: elif C is PRT then $p \leftarrow$ PRT|RP
6: elif C is NML|NP then $p \leftarrow$ NP|NML|NN*|PRP|-NOM
7: elif C is NAC then $p \leftarrow$ NP
8: elif C is NX then $p \leftarrow$ NX
9: elif C is VP then $p \leftarrow$ VP|VB$^b$
10: elif C is S then $p \leftarrow$ S$^b$|SINV|SQ|SBARQ
11: elif C is SQ then $p \leftarrow$ S$^b$|SQ|SBARQ
12: elif C is SINV then $p \leftarrow$ S$^b$|SINV
13: elif C is SBAR* then $p \leftarrow$ SBAR*
14: elif C is WHNP then $p \leftarrow$ NN*|WP
15: elif C is WHADJP then $p \leftarrow$ JJ*|VBN|VBG
16: elif C is WHADVP then $p \leftarrow$ RB*|WRB|IN
17: if ($p$ is not found) or (C contains no $p$) return *
18: return $p$

A pattern $p$ retrieved by the getConjunctHeadPattern(C) method in Algorithm 2.6 is used in the isConjunctHead(C, P, p) method in Algorithm 2.7 to decide whether a constituent C is a potential conjunct head of its parent P. No subordinating conjunction is considered a conjunct head in a subordinate clause (line 1); this rule is added to prevent a complementizer such as whether from being the head of a clause starting with expressions like whether or not. When the default pattern is used, the method accepts any constituent except for a few special cases (lines 3-7). The method returns True if C matches $p$ (line 9).
Algorithm 2.7: \texttt{isConjunctHead}(C, P, p)

\begin{verbatim}
Input: Constituents C and P, where P is the parent of C, and the conjunct head pattern p of P.
Output: True if C matches the conjunct head pattern; otherwise, False.
1: if (P is SBAR) and (C is ID|DT) return False # Section D.5.3
2: if p is * then # the default pattern
3: if isPunctuation(C) return False # Section D.10.8
4: if isInterjection(C) return False # Section D.10.3
5: if isMetaModifier(C) return False # Section D.10.4
6: if isParentheticalModifier(C) return False # Section D.10.5
7: if isAdverbialModifier(C) return False # Section D.5.2
8: return True
9: if C is p return True
10: return False
\end{verbatim}

Finally, the \texttt{getConjunctHead}(S, R, pHead) method in Algorithm 2.8 finds the head of a conjunct S and makes this head a dependent of its preceding conjunct head, pHead. The head of S is found by the \texttt{getHead}(N, R) method in Algorithm 2.1 where R is the headrule of S’s parent. The dependency label CONJ is assigned to this head except for the special cases of interjections and punctuation (lines 4-6).

Algorithm 2.8 The \texttt{getConjunctHead}(S, R, pHead) method.

\begin{verbatim}
Input: A constituent C, a sub-span S of C, the headrule R of C, and the previous conjunct head pHead in C.
Output: The head of S. All other nodes in S become dependents of the head.
1: cHead ← getHead(S, R) # Section 2.3.1
2: if pHead ≠ null then
3:   cHead.head ← pHead
4:   if isInterjection(C) then cHead.label ← INTJ # Section D.10.3
5:   elif isPunctuation(C) then cHead.label ← PUNCT # Section D.10.8
6:   else cHead.label ← CONJ # Section D.6.1
7:   return cHead
\end{verbatim}
2.3.4 Small clauses

Small clauses are represented as declarative clauses without verb phrases in constituent trees. Small clauses may not contain internal subjects. In Figure 2.20, both S-1 and S-2 are small clauses but S-1 contains an internal subject, *me*, whereas the subject of S-2 is controlled externally. This distinction is made because S-1 can be rewritten as a subordinate clause such as “I am her friend” whereas such a transformation is not possible for S-2. In other words, *me her friend* as a whole is an argument of *considers* whereas *me* and *her friend* are separate arguments of *calls*.

![Figure 2.20: Examples of small clauses with internal (left) and external (right) subjects.](image)

Figure 2.20: Examples of small clauses with internal (left) and external (right) subjects.

Figure 2.21 shows dependency trees converted from the trees in Figure 2.20. A small clause with an internal subject is considered a clausal complement (CCOMP; the left tree in Figure 2.20) whereas one without an internal subject is considered an object predicate (OPRD; the right tree in Figure 2.20), implying that it is a non-VP predicate of the object. This way, although *me* has no direct dependency to *friend*, their relation can be inferred through this label.

![Figure 2.21: Dependency trees converted from the constituent trees in Figure 2.20.](image)

Figure 2.21: Dependency trees converted from the constituent trees in Figure 2.20.

Note that the CoNLL dependency approach uses the object predicate for both kinds of small clauses such that *me* and *her friend* become separate dependents of *considers*, as they are for *calls*. This analysis is not taken in our approach because we want our dependency trees to be consistent with the
original constituent trees. Preserving the original structure makes it easier to integrate additional information to the converted dependency trees that has been already annotated on top of these constituent trees (e.g., semantic roles in PropBank).

For passive constructions, OPRD is applied to both kinds of small clauses because a dependency between the object and the non-VP predicate is lost by the NP movement. In Figure 2.22, I is moved from the object position to the subject position of considered (NSUBJPASS; Section D.1.6); thus, it is no longer a dependent of friend. The dependency between I and friend can be inferred through OPRD without adding more structural complexity to the tree.
2.4 Assigning dependency labels

2.4.1 Clear dependency labels

Table 2.3 shows a list of dependency labels, called the Clear dependency labels, generated by our dependency conversion. These labels are mostly inspired by the Stanford dependency approach, partially borrowed from the CoNLL dependency approach, and newly introduced by the Clear dependency approach to minimize unclassified dependencies. Appendix D shows detailed descriptions of the Clear dependency labels. Section 2.4.3 shows a comparison between the Clear and the Stanford dependencies.

<table>
<thead>
<tr>
<th>Label</th>
<th>Description</th>
<th>Label</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACOMP</td>
<td>Adjectival complement</td>
<td>NEG</td>
<td>Negation modifier</td>
</tr>
<tr>
<td>ADVCL</td>
<td>Adverbial clause modifier</td>
<td></td>
<td>Modifier of nominal</td>
</tr>
<tr>
<td>ADVMOD</td>
<td>Adverbial modifier</td>
<td>NMOD*</td>
<td>Noun compound modifier</td>
</tr>
<tr>
<td>AGENT</td>
<td>Agent</td>
<td>NN</td>
<td>Noun phrase as ADVMOD</td>
</tr>
<tr>
<td>AMOD</td>
<td>Adjectival modifier</td>
<td>NSUBJ</td>
<td>Nominal subject</td>
</tr>
<tr>
<td>APPPOS</td>
<td>Appositional modifier</td>
<td>NSUBJPASS</td>
<td>Nominal subject (passive)</td>
</tr>
<tr>
<td>ATTR</td>
<td>Attribute</td>
<td>NUM</td>
<td>Numeric modifier</td>
</tr>
<tr>
<td>AUX</td>
<td>Auxiliary</td>
<td>NUMBER</td>
<td>Number compound modifier</td>
</tr>
<tr>
<td>AUXPASS</td>
<td>Auxiliary (passive)</td>
<td>OPRD*</td>
<td>Object predicate</td>
</tr>
<tr>
<td>CC</td>
<td>Coordinating conjunction</td>
<td></td>
<td>PARATAxis</td>
</tr>
<tr>
<td>CCOMP</td>
<td>Clausal complement</td>
<td>PARTMOD</td>
<td>Participial modifier</td>
</tr>
<tr>
<td>COMPLM</td>
<td>Complementizer</td>
<td>PCOMP</td>
<td>Complement of a preposition</td>
</tr>
<tr>
<td>CONJ</td>
<td>Conjunct</td>
<td>POBJ</td>
<td>Object of a preposition</td>
</tr>
<tr>
<td>CSUBJ</td>
<td>Clausal subject</td>
<td>POSS</td>
<td>Possession modifier</td>
</tr>
<tr>
<td>CSUBJPASS</td>
<td>Clausal subject (passive)</td>
<td>POSSESSIVE</td>
<td>Possessive modifier</td>
</tr>
<tr>
<td>DEP</td>
<td>Unclassified dependent</td>
<td>PRECONJ</td>
<td>Pre-correlative conjunction</td>
</tr>
<tr>
<td>DET</td>
<td>Determiner</td>
<td>PREDDET</td>
<td>Predeterminer</td>
</tr>
<tr>
<td>DOBJ</td>
<td>Direct object</td>
<td>PREP</td>
<td>Prepositional modifier</td>
</tr>
<tr>
<td>EXPL</td>
<td>Expletive</td>
<td>PRT</td>
<td>Particle</td>
</tr>
<tr>
<td>INFMOD</td>
<td>Infinitival modifier</td>
<td>PUNCT</td>
<td>Punctuation</td>
</tr>
<tr>
<td>INTJ**</td>
<td>Interjection</td>
<td>QUANTMOD</td>
<td>Quantifier phrase modifier</td>
</tr>
<tr>
<td>IOBJ</td>
<td>Indirect object</td>
<td>RCMOD</td>
<td>Relative clause modifier</td>
</tr>
<tr>
<td>MARK</td>
<td>Marker</td>
<td>ROOT</td>
<td>Root</td>
</tr>
<tr>
<td>META**</td>
<td>Meta modifier</td>
<td>XCOMP</td>
<td>Open clausal complement</td>
</tr>
</tbody>
</table>

Table 2.3: A list of the Clear dependency labels. Labels followed by * are borrowed from the CoNLL dependency approach. Labels followed by ** are newly introduced by the Clear dependency approach.
2.4.2 Dependency label heuristics

The $\text{getDependencyLabel}(C, P, p)$ in Algorithm 2.10 assigns a dependency label to a constituent $C$ by using function tags and inferring constituent relations between $C$, $P$, and $p$, where $P$ is the parent of $C$ and $p$ is the head constituent of $P$. Heuristics described in this algorithm are derived from careful analysis of several constituent Treebanks (Marcus et al., 1993; Nielsen et al., 2010; Weischedel et al., 2011; Verspoor et al., 2012) and manually evaluated case-by-case. All supplementary methods are described in Appendix D. The $\text{getSimpleLabel}(C)$ method in Algorithm 2.9 returns the dependency label of a constituent $C$ if it can be inferred from the POS tag of $C$; otherwise, null.

Algorithm 2.9: $\text{getSimpleLabel}(C)$

\begin{itemize}
    \item \textbf{Input:} A constituent $C$.
    \item \textbf{Output:} The dependency label of $C$ if it can be inferred from the POS tag of $C$; otherwise, null.
\end{itemize}

1: let $d$ be the head dependent of $C$
2: if $C$ is ADJP|WHADJP|JJ* return AMOD # Section D.10.1
3: if $C$ is PP|WHPP return PREP # Section D.8.3
4: if $C$ is PRT|RP return PRT # Section D.10.7
5: if $\text{isPreCorrelativeConjunction}(C)$ return PRECONJ # Section D.6.3
6: if $\text{isCoordinatingConjunction}(C)$ return CC # Section D.6.2
7: if $\text{isParentheticalModifier}(C)$ return PARATAxis # Section D.10.5
8: if $\text{isPunctuation}(C|d)$ return PUNCT # Section D.10.8
9: if $\text{isInterjection}(C|d)$ return INTJ # Section D.10.3
10: if $\text{isMetaModifier}(C)$ return META # Section D.10.4
11: if $\text{isAdverbialModifier}(C)$ return ADVMOD # Section D.5.2
12: return null
Algorithm 2.10: getDependencyLabel(C, P, p)

\[\textbf{Input:}\text{ Constituents }C, P, \text{ and } p.\] 
\[P \text{ is the parent of } C, \text{ and } p \text{ is the head constituent of } P.\]
\[\textbf{Output:}\text{ The dependency label of } C \text{ with respect to } p \text{ in } P.\]

1: let \(c\) be the head constituent of \(C\)
2: let \(d\) be the head dependent of \(C\)
3: if \(\text{hasAdverbialTag}(C)\) then \# Section D.5
4: if \(C\) is \(\text{S|SBAR|SINV}\) return \(\text{ADVCL}\)
5: if \(C\) is \(\text{NML|NP|QP}\) return \(\text{NPADVMOD}\)
6: if (label ← \(\text{getSubjectLabel}(C)\)) \(\neq\) null return label \# Section D.1
7: if \(C\) is \(\text{UCP}\) then
8: \(c\).add(all function tags of \(C\))
9: return getDependencyLabel\((c, P, p)\)
10: if \(P\) is \(\text{VP|SINV|SQ}\) then
11: if \(C\) is \(\text{ADJP}\) return \(\text{ACOMP}\)
12: if (label ← \(\text{getObjectLabel}(C)\)) \(\neq\) null return label \# Section D.2
13: if \(\text{isObjectPredicate}(C)\) return \(\text{OPRD}\) \# Section D.2.4
14: if \(\text{isClausalComplement}(C)\) return \(\text{CCOMP}\) \# Section D.4.2
15: if (label ← \(\text{getAuxiliaryLabel}(C)\)) \(\neq\) null return label \# Section D.3
16: if \(P\) is \(\text{ADJP|ADVP}\) then
17: if (label ← \(\text{getNonFiniteModifierLabel}(C)\)) \(\neq\) null return label \# Section D.7
18: if \(\text{isRelativeClauseModifier}(C)\) return \(\text{RCMOD}\) \# Section D.7.10
19: if \(\text{isClausalComplement}(C)\) return \(\text{CCOMP}\) \# Section D.4.2
20: if \(\text{isPossessionModifier}(C, P)\) return \(\text{POSS}\) \# Section D.10.6
21: if (label ← \(\text{getSimpleLabel}(C)\)) \(\neq\) null return label \# Section D.7
22: if \(\text{isOpenClausalComplement}(C)\) return \(\text{XCOMP}\) \# Section D.4.3
23: if \(\text{isObjectPredicate}(C)\) return \(\text{OPRD}\) \# Section D.2.4
24: if \(\text{isClausalComplement}(C)\) return \(\text{CCOMP}\) \# Section D.4.2
25: if \(\text{isRelativeClauseModifier}(C)\) return \(\text{RCMOD}\) \# Section D.7.10
26: if \(\text{isObjectPredicate}(C)\) return \(\text{OPRD}\) \# Section D.2.4
27: if (\(C\) is \(\text{SBAR}\)) or \(\text{isOpenClausalComplement}(C)\) return \(\text{ADVCL}\) \# Section D.4.3
28: if \(\text{isPossessionModifier}(C, P)\) then \(C\) is \(\text{S*}\) return \(\text{ADVCL}\)
29: if \(\text{isRelativeClauseModifier}(C)\) return \(\text{RCMOD}\) \# Section D.7.10
30: if \(\text{isOpenClausalComplement}(C)\) return \(\text{XCOMP}\) \# Section D.4.3
31: if \(\text{isRelativeClauseModifier}(C)\) return \(\text{RCMOD}\) \# Section D.7.10
32: return getNounModifierLabel\((C)\) \# Section D.7
33: if (label ← \(\text{getSimpleLabel}(C)\)) \(\neq\) null return label \# Section D.4.2
34: if \(d\) is \(\text{IN}\) return \(\text{PREP}\)
35: if \(d\) is \(\text{RB*}\) return \(\text{ADVMOD}\)
36: if \(\text{isRelativeClauseModifier}(C)\) then \(\text{ADVP}\) or \(\text{isJJS}\) \(\text{RB*}\) then
37: if \(\text{isRelativeClauseModifier}(C)\) then \(\text{ADVP}\) or \(\text{isJJS}\) \(\text{RB*}\) then
38: return \(\text{ADVMOD}\)
39: return \(\text{DEP}\)
2.4.3 Comparison to the Stanford dependency approach

Treating dependency trees generated by the Stanford dependency approach as gold-standard, the CLEAR dependency approach shows a labeled attachment score of 90.39%, an unlabeled attachment score of 95.39%, and a label accuracy of 93.01%. For comparison, the OntoNotes Treebank is used, which consists of various corpora in multiple genres (see Section 3.1 for more details about the OntoNotes Treebank). Out of 138K dependency trees generated by our conversion, 3.69% of them contain at least one non-projective dependency. Out of 2.6M dependencies, 3.62% are unclassified by the Stanford converter whereas 0.23% are unclassified by our approach, that is a 93.65% proportional reduction in error. A dependency is considered unclassified if it is assigned with the label, DEP (Section D.10.2). Table 2.4 shows a list of the top 40 dependency labels generated by our approach that are unclassified by the Stanford dependency approach.7

<table>
<thead>
<tr>
<th>Label</th>
<th>Proportion</th>
</tr>
</thead>
<tbody>
<tr>
<td>PUNCT</td>
<td>23.98</td>
</tr>
<tr>
<td>INTJ</td>
<td>14.18</td>
</tr>
<tr>
<td>APPOS</td>
<td>9.44</td>
</tr>
<tr>
<td>META</td>
<td>7.25</td>
</tr>
<tr>
<td>NADVMOD</td>
<td>6.86</td>
</tr>
<tr>
<td>CCOMP</td>
<td>6.71</td>
</tr>
<tr>
<td>ADVCL</td>
<td>4.98</td>
</tr>
<tr>
<td>DEP</td>
<td>4.75</td>
</tr>
</tbody>
</table>

Table 2.4: A list of the CLEAR dependency labels that are unclassified by the Stanford dependency approach. The first column shows the unclassified CLEAR dependency labels and the second column shows their proportions to unclassified dependencies in the Stanford dependency approach (in %).

Table 2.5 shows mappings between the CLEAR and the Stanford dependency labels. Some labels in the Stanford dependency approach are not used in our conversion. For instance, multi-word expressions (MWE) are not used in our approach because it is not clear how to identify multi-word expressions systematically. Furthermore, purpose clause modifiers (PURPCL) and temporal modifiers (TMOD) are not included as dependencies but added as separate features of individual nodes in our dependency trees (see Section A.1 for more details about these additional features).

7 The following options are used for the Stanford dependency conversion, which is the same setup that was used for the SANCL’12 shared task (Petrov and McDonald, 2012): -basic -conllx -keepPunct -makeCopulaHead.
<table>
<thead>
<tr>
<th>CLEAR</th>
<th>Count</th>
<th>Stanford</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACOMP</td>
<td>20,325</td>
<td>ACOMP(98.19)</td>
</tr>
<tr>
<td>ADVCL</td>
<td>33,768</td>
<td>ADVCL(53.43), XCOMP(19.79), DEP(11.33), CCOMP(6.67), PARTMOD(6.04)</td>
</tr>
<tr>
<td>ADVMOD</td>
<td>101,134</td>
<td>ADVMOD(96.38)</td>
</tr>
<tr>
<td>AGENT</td>
<td>4,756</td>
<td>PREP(99.62)</td>
</tr>
<tr>
<td>AMOD</td>
<td>131,971</td>
<td>AMOD(97.93)</td>
</tr>
<tr>
<td>APPOS</td>
<td>17,869</td>
<td>APPOS(54.80), DEP(40.56), ATTR(15.41)</td>
</tr>
<tr>
<td>ATTR</td>
<td>22,597</td>
<td>ATTR(81.87), DEP(15.41)</td>
</tr>
<tr>
<td>AUX</td>
<td>106,428</td>
<td>AUX(99.98)</td>
</tr>
<tr>
<td>AUXPASS</td>
<td>19,289</td>
<td>AUXPASS(99.99)</td>
</tr>
<tr>
<td>ADVMOD</td>
<td>191,134</td>
<td>ADVMOD(96.38)</td>
</tr>
<tr>
<td>ADVPASS</td>
<td>101,134</td>
<td>ADVPASS(96.38)</td>
</tr>
<tr>
<td>AGENT</td>
<td>4,756</td>
<td>PREP(99.62)</td>
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<td>AMOD</td>
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<td>AMOD(97.93)</td>
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<tr>
<td>APPOS</td>
<td>17,869</td>
<td>APPOS(54.80), DEP(40.56), ATTR(15.41)</td>
</tr>
<tr>
<td>ATTR</td>
<td>22,597</td>
<td>ATTR(81.87), DEP(15.41)</td>
</tr>
<tr>
<td>AUX</td>
<td>106,428</td>
<td>AUX(99.98)</td>
</tr>
<tr>
<td>AUXPASS</td>
<td>19,289</td>
<td>AUXPASS(99.99)</td>
</tr>
</tbody>
</table>

Table 2.5: Mappings between the CLEAR and the Stanford dependency labels. The CLEAR column show the CLEAR dependency labels. The Count column shows the count of each label. The Stanford column shows labels generated by the Stanford converter in place of the CLEAR dependency label with probabilities (in %); labels with less than 3% occurrences are discarded.
2.5 Adding secondary dependencies

Secondary dependencies are additional dependency relations derived from gapping relations (Section 2.5.1), relative clauses (Section 2.5.2), right node raising (Section 2.5.3), and open clausal complements (Section 2.5.4). These are separated from the other types of dependencies (Section 2.4) because they can break tree properties (e.g., single head, acyclic) when combined with the others. Preserving tree structure is important because most dependency parsing algorithms assume their input to be trees. Secondary dependencies give deeper representations that allow extraction of more complete information from the dependency structure.

2.5.1 GAP: gapping

Gapping is represented by co-indexes (with the = symbol) in constituent trees. Gapping usually happens in forms of coordination where some parts included in the first conjunct do not appear in later conjuncts (Jackendoff, 1971). In Figure 2.23, the first conjunct, VP-3, contains the verb used, which does not appear in the second conjunct, VP-4, but is implied for both NP=1 and PP=2. The CoNLL dependency approach makes the conjunction, and, the heads of both NP=1 and PP=2, and adds an extra label, GAP, to their existing labels (ADV-GAP and GAP-OBJ in Figure 2.25). Although this represents the gapping relations in one unified format, statistical dependency parsers perform poorly on these labels because they do not occur frequently enough and are often confused with regular coordination.

Figure 2.23: An example of a gapping relation.
In our approach, gapping is represented as secondary dependencies; this way, it can be trained separately from the other types of dependencies. The GAP dependencies in Figure 2.24 show how gapping is represented in our structure: the head of each constituent involving a gap (road, as_{9}) becomes a dependent of the head of the leftmost constituent not involving a gap (railways, as_{4}).

Figure 2.24: The CLEAR dependency tree converted from the constituent tree in Figure 2.23. The gapping relations are represented by the secondary dependencies, GAP.

Figure 2.25: The CoNLL dependency tree converted from the constituent tree in Figure 2.23. The dependencies derived from the gapping relations, ADV-GAP, GAP-OBJ, are indicated by dotted lines.

2.5.2 REF: referent

A referent is the relation between a wh-complementizer in a relative clause and its referential head. In Figure 2.26, the relation between the complementizer which and its referent Crimes is represented by the REF dependency. Referent relations are represented as secondary dependencies because integrating them with other dependencies breaks the single-head tree property (e.g., which would have multiple heads in Figure 2.26). The linkReferent(C) method in Algorithm 2.11 finds a wh-complementizer and makes it a dependent of its referent. Note that referent relations are not provided in constituent trees; however, they are manually annotated in the PropBank as
LINK-SLC (Bonial et al., 2010, Chap. 1.8). This algorithm was tested against the PropBank annotation using gold-standard constituent trees and showed an F1-score of approximately 97%.

Figure 2.26: An example of a referent relation. The referent relation is represented by the secondary dependency, REF.

Algorithm 2.11: linkReferent(C)

**Input:** A constituent C.

1: if C is WHADVP|WHNP|WHPP then
2: let c be the wh-complementizer of C
3: let s be the topmost SBAR of C
4: if the parent of s is UCP then s ← s.parent
5: if isRelativizer(c) and (s has no NOM) then
6: let p be the parent of s
7: ref ← null
8: if p is NP|ADVP then
9: let ref be the previous sibling of s that is NP|ADVP, respectively
10: elif p is VP then
11: let t be the previous sibling of s that has PRD
12: if s has CLF then ref ← t
13: if (C is WHNP) and (t is NP) then ref ← t
14: if (C is WHPP) and (t is PP) then ref ← t
15: if (C is WHADVP) and (t is ADVP) then ref ← t
16: if ref ≠ null then
17: while ref has an antecedent do ref ← ref.antecedent
18: c.rHead ← ref
19: c.rLabel ← REF

Algorithm 2.12: isRelativizer(C)

**Input:** A constituent C.

**Output:** True if C is a relativizer linked to some referent; otherwise, False.

1: return C is 0|that| when| where| whereby| wherein| whereupon| which| who| whom| whose
2.5.3 **RNR: right node raising**

As mentioned in Section 2.2.3, missing dependencies caused by right node raising are preserved as secondary dependencies. In Figure 2.14 (page 19), *her* should be a dependent of both *for* and *in*; however, it is a dependent of only *for* in our structure because making it a dependent of both nodes breaks a tree property (e.g., *her* would have multiple heads). Instead, the dependency between *her* and *for* is preserved with the RNR dependency. Figure 2.28 shows another example of right node raising where the raised constituent, VP-2, is the head of the constituents that it is raised from, VP-4 and VP-5. In this case, *done* becomes the head of *can* with the dependency label, RNR.

![Figure 2.27: An example of right node raising where the raised constituent is the head.](image1)

![Figure 2.28: The dependency tree converted from the constituent tree in Figure 2.27. Right node raising is represented by the secondary dependency, RNR.](image2)
2.5.4 XSUBJ: open clausal subject

An open clausal subject is the subject of an open clausal complement (usually non-finite) that is governed externally. Open clausal subjects are often caused by raising and control verbs (Chomsky, 1981). In Figure 2.29, the subject of like is moved to the subject position of the raising verb seemed (subject raising) so that She becomes the syntactic subject of seemed as well as the open clausal subject of like (see Figure 2.30).

Figure 2.29: An example of an open clausal subject caused by a subject raising.

In Figure 2.31, the subject of wear is shared with the object of the control verb forced (object control) so that me becomes the direct object of forced as well as the open clausal subject of wear (Figure 2.32). Alternatively, me in Figure 2.33 is not considered the direct object of expected but the subject of wear; this is a special case called “exceptional case marking (ECM)”, which appears to be very similar to the object control case but is handled differently in constituent trees (see Taylor (2006) for more details about ECM verbs).
Figure 2.31: An example of an open clausal subject caused by an object raising.

Figure 2.32: A dependency tree converted from the constituent tree in Figure 2.31. The open clausal subject is represented by the secondary dependency, XSUBJ.

Figure 2.33: An example of exceptional case marking.

Figure 2.34: A dependency tree converted from the constituent tree in Figure 2.33.
2.6 Adding function tags

2.6.1 SEM: semantic function tags

When a constituent is annotated with a semantic function tag (BNF, DIR, EXT, LOC, MNR, PRP, TMP, and VOC; see Section A.1), the tag is preserved with the head of the constituent as an additional feature. In Figure 2.35, the subordinate clause SBAR is annotated with the function tag PRP, so the head of the subordinate clause, *is*, is annotated with the semantic tag in our representation (Figure 2.36). Note that the CoNLL dependency approach uses these semantic tags in place of dependency labels (e.g., the dependency label between *is* and *let* would be PRP instead of ADVCL). These tags are kept separate from the other kinds of dependency labels in our approach so they can be processed either during or after parsing. The semantic function tags can be integrated easily into our dependency structure by replacing dependency labels with semantic tags (Figure 2.37).

![Figure 2.35: A constituent tree with semantic function tags. The phrases with the semantic function tags are indicated by dotted boxes.](image)

![Figure 2.36: A dependency tree converted from the constituent tree in Figure 2.35. The function tags PRP, LOC, and TMP are preserved as additional features of *is*, *here*, and *tomorrow*, respectively.](image)
Figure 2.37: Another dependency tree converted from the constituent tree in Figure 2.35. The function tags, PRP, LOC, and TMP, replace the original dependency labels, ADVCL, ADVMOD, and NPADVMOD.

### 2.6.2 SYN: syntactic function tags

When a constituent is annotated with one or more syntactic function tags (ADV, CLF, CLR, DTV, NOM, PUT, PRD, RED, and TPC; see Section A.1), all tags are preserved with the head of the constituent as additional features. In Figure 2.38, the noun phrase NP-1 is annotated with the function tag PRD and TPC so the head of the noun phrase, `slap`, is annotated with both tags in our representation (Figure 2.39). Similarly to the semantic function tags (Section 2.6.1), syntactic function tags can also be integrated into our dependency structure by replacing dependency labels with syntactic tags.

![Figure 2.38](image)

**Figure 2.38:** A constituent tree with syntactic function tags. The phrase with the syntactic function tags is indicated by a dotted box.

![Figure 2.39](image)

**Figure 2.39:** A dependency tree converted from the constituent tree in Figure 2.38. The function tags, PRD and TPC, are preserved as additional features of `slap`. 
Chapter 3

Experimental setup

All experiments for POS tagging (Section 4.7), dependency parsing (Section 5.6), and semantic role labeling (Section 6.5) use the same setup. For each task, several systems are run for comparison and two models are built for each system; one is trained on the Wall Street Journal corpus in OntoNotes, called the WSJ model, and the other is trained on all corpora in OntoNotes, called the OntoNotes model. These models are evaluated on corpora from six genres in OntoNotes and three genres in medical domains (Section 3.1). The WSJ models demonstrate how the systems perform when they are trained and evaluated on data from different genres. The OntoNotes models demonstrate how the systems perform when they are trained on a mixture of genres and evaluated on genres that are the same or different from the ones used for training. These experiments provide insights for those who want to build a single model to process data from different sources.

All models are trained by a machine learning algorithm called Liblinear (Section 3.2). For each system, both accuracies and speeds are measured. Accuracies are measured by the standard methods generally used for evaluating each task (see Table 3.1). Speeds are measured by running each system five times, cutting off the top and the bottom speeds, and averaging the middle three. All systems are evaluated on an Intel Xeon 2.57GHz using a single core, a Linux v2.6.18-308.11.1.el5, and a 64-Bit Java virtual machine v1.6.0_33. Note that the model loading times are excluded for speed comparison because they are fixed costs that can be pre-processed, whereas the data reading and the feature extraction times are included because they play an important role during decoding. The accuracy and speed results demonstrate the robustness and scalability of each system.
### Task Measurement Equation

<table>
<thead>
<tr>
<th>Task</th>
<th>Measurement</th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pos tagging</td>
<td>Accuracy</td>
<td>( \text{Acc}_p = \forall i. \frac{</td>
</tr>
<tr>
<td>Dependency parsing</td>
<td>Labeled attachment score</td>
<td>( \text{LAS} = \forall i. \frac{</td>
</tr>
<tr>
<td></td>
<td>Unlabeled attachment score</td>
<td>( \text{UAS} = \forall i. \frac{</td>
</tr>
<tr>
<td>Semantic role labeling</td>
<td>Argument identification +</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Argument classification</td>
<td></td>
</tr>
<tr>
<td></td>
<td>- Precision</td>
<td>( \text{P}_{h&amp;l} = \forall i. \frac{</td>
</tr>
<tr>
<td></td>
<td>- Recall</td>
<td>( \text{R}_{h&amp;l} = \forall i. \frac{</td>
</tr>
<tr>
<td></td>
<td>- F1-score</td>
<td>( \text{F}<em>{h&amp;l} = 2 \cdot \frac{(\text{P}</em>{h&amp;l} \cdot \text{R}<em>{h&amp;l})}{(\text{P}</em>{h&amp;l} + \text{R}_{h&amp;l})} )</td>
</tr>
</tbody>
</table>

Table 3.1: Evaluation methods for different tasks. \( |w_i| \): the total \# of word tokens, \( |a_i|_s \): the total \# of system-generated arguments, \( |a_i|_g \): the total \# of gold-standard arguments, \( C_p(w_i) \): a token with the correct POS tag, \( C_h(w_i) \): a token with the correct dependency head, \( C_{h\&l}(w_i) \): a token with the correct dependency head and label, \( C_{h\&l}(a_i) \): an argument with the correct semantic head (predicate) and label (semantic role).

### 3.1 Corpora

For the WSJ models, the Wall Street Journal sections 2-21 from OntoNotes (Weischedel et al., 2011) are used for training. This training set consists of 30,060 sentences with 731,677 word tokens and 77,826 verb predicates. We use the WSJ corpus from OntoNotes instead of the original Penn Treebank (Marcus et al., 1993) because they use slightly different annotation guidelines which our evaluation data follow. Table 3.2 shows the distributions of all genres used for training the OntoNotes models. The latest version of OntoNotes, v4.99, is used for building these models.\(^1\)

<table>
<thead>
<tr>
<th></th>
<th>BC</th>
<th>BN</th>
<th>MZ</th>
<th>NW</th>
<th>TC</th>
<th>WB</th>
<th>ALL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tokens</td>
<td>214,178</td>
<td>228,019</td>
<td>165,400</td>
<td>1,047,377</td>
<td>89,278</td>
<td>238,760</td>
<td>1,983,012</td>
</tr>
<tr>
<td>Sentences</td>
<td>14,131</td>
<td>11,366</td>
<td>6,924</td>
<td>41,553</td>
<td>11,386</td>
<td>11,046</td>
<td>96,406</td>
</tr>
<tr>
<td>Predicates</td>
<td>27,860</td>
<td>27,187</td>
<td>18,898</td>
<td>106,295</td>
<td>13,720</td>
<td>19,735</td>
<td>213,695</td>
</tr>
</tbody>
</table>

Table 3.2: Distributions of training sets for the OntoNotes models. BC: broadcasting conversation, BN: broadcasting news, MZ: magazine, NW: newswire, TC: telephone conversion, WB: web-text, ALL: all genres combined.

For evaluation, six corpora from OntoNotes are used: the MSNBC broadcasting conversation (BC), the CNN broadcasting news (BN), the Sinorama news magazine (MZ), the WSJ newswire (NW), the Callhome telephone conversation (TC), and the GALE web-text (WB), and three corpora from

\(^1\) The religious texts in OntoNotes v4.99, the Bible, are excluded from our experiments because they come from a very specific domain that should be trained and evaluated separately.
medical domains are used (Nielsen et al., 2010): the Mipacq clinical notes (MP), the Medpedia articles (MD), and the Sharp clinical notes (SH). These corpora are first evaluated individually then grouped together to demonstrate in-genre and out-of-genre experiments. For the WSJ models, the WSJ corpus is used for in-genre and all other corpora are used for out-of-genre experiments. For the OntoNotes models, all OntoNotes corpora are used for in-genre and all medical corpora are used for out-of-genre experiments.


Table 3.4 shows lexical similarities between the evaluation sets in Table 3.3. Given two sets of lexical types, $S_i$ and $S_j$, collected from corpora $C_i$ and $C_j$, the lexical similarity of $C_i$ against $C_j$ is measured as $LS_{ij} = \frac{|S_i \cap S_j|}{|S_i|}$, where $i$ and $j$ indicate the indices of a column and a row in Table 3.4, respectively. For example, $LS_{14}$ (that is the value in the BC column and the NW row) implies that out of 3,677 lexical types in BC, 50.88% of them intersect with lexical types in NW.

Table 3.4: Lexical similarities between the evaluation sets in Table 3.3 (in %). The count row shows the total number of lexical types in each corpus.
Table 3.5 shows Unix commands for listing the evaluation sets in Table 3.3; this table is added for those who own these corpora and want to replicate our experimental setup. Note that some of these commands assume the Bash shell with extended globing, which require running the following command first: ‘bash; shopt -s extglob’.

<table>
<thead>
<tr>
<th>Source</th>
<th>Genre</th>
<th>Command</th>
</tr>
</thead>
<tbody>
<tr>
<td>OntoNotes</td>
<td>BC</td>
<td><code>ls bc/msnbc/00/msnbc_000[5-7]*</code></td>
</tr>
<tr>
<td></td>
<td>BN</td>
<td><code>ls bn/cnn/03/*</code></td>
</tr>
<tr>
<td></td>
<td>MZ</td>
<td>`ls mz/sinorama/10/ectb_10+(6[5-9]</td>
</tr>
<tr>
<td></td>
<td>NW</td>
<td><code>ls nw/hsj/23/*</code></td>
</tr>
<tr>
<td></td>
<td>TC</td>
<td><code>ls tc/ch/00/ch_00[4-5]*</code></td>
</tr>
<tr>
<td></td>
<td>WB</td>
<td><code>ls wb/eng/00/eng_001*</code></td>
</tr>
<tr>
<td>Medical</td>
<td>MD</td>
<td><code>ls mipacq2/0[1-2]/[4-9]*</code></td>
</tr>
<tr>
<td></td>
<td>MP</td>
<td><code>ls medpedia/02/*</code></td>
</tr>
<tr>
<td></td>
<td>SH</td>
<td>`ls sharp-clinical/02/rec+(29</td>
</tr>
</tbody>
</table>

Table 3.5: Unix commands for listing the evaluation sets in Table 3.3.

3.2 Machine learning

For machine learning, Liblinear L2-regularization, L1-loss support vector classification is used (Fan et al., 2008). This algorithm shares the same underlying approach as support vector machines: given a set of instance-label pairs \((x_i, y_i)\) where \(x_i \in \mathbb{R}^d, y_i \in \{-1, 1\}\), it finds a hyperplane \(w\) maximizing the margin between the two classes by solving the optimization problem in Equation (3.1) \((C\) is a penalty parameter).

\[
w = \arg \min_w \frac{1}{2} w^T w + C \sum_{i=1}^n \max(1 - y_i w^T x_i, 0) \tag{3.1}
\]

In our case, all features are binarized so \(x_i \in \{0, 1\}^d\), where \(d\) is the dimensionality of the feature space. Furthermore, since our tasks require predictions of multiple classes, a one-vs-all approach is adapted, which generates \(M\) numbers of hyperplanes, \([w_m : m \in \{1, \ldots, M\}]\), where \(m\) is a class and \(w_m\) is a hyperplane separating the class \(m\) from the other classes. During decoding, the one-vs-all approach uses Equation (3.2) to predict the class \(m\) given the instance \(x_i\).

\[
m = \arg \max_m w_m^T x_i \tag{3.2}
\]
The main difference between support vector machines and Liblinear is that support vector machines can handle non-linearly separable data using kernels (e.g., polynomial, gaussian) whereas Liblinear performs only linear classification without using any kernel. This aligns well with our data because our feature dimensionality is often very high (up to a few millions) so that classes essentially become linearly separable through different dimensions. As a result, Liblinear significantly reduces both the training and decoding times, yet performs very accurately (see Hsieh et al. (2008) for more details about how Liblinear computes weights using a dual coordinate descent method).

Table 3.6 shows the Liblinear learning parameters used for our experiments; $c$ is a cost, $e$ is a termination criterion, and $B$ is a bias. These parameters are found by running cross-validations on the WSJ training set\(^2\) with grid search on the hyper-parameters $c$ and $B$; no parameter turning is performed on $e$. It is possible to improve performance of the OntoNotes models by running separate cross-validations on the OntoNotes training set, which we will explore in the future.

<table>
<thead>
<tr>
<th>Task</th>
<th>Model</th>
<th>$c$</th>
<th>$e$</th>
<th>$B$</th>
</tr>
</thead>
<tbody>
<tr>
<td>POS tagging</td>
<td>Model(_D)</td>
<td>0.1</td>
<td>0.1</td>
<td>0.9</td>
</tr>
<tr>
<td></td>
<td>Model(_G)</td>
<td>0.2</td>
<td>0.1</td>
<td>0.4</td>
</tr>
<tr>
<td>Dependency parsing</td>
<td>-</td>
<td>0.1</td>
<td>0.1</td>
<td>0.0</td>
</tr>
<tr>
<td>Semantic role labeling</td>
<td>Model(^\leftarrow)</td>
<td>0.1</td>
<td>0.1</td>
<td>0.0</td>
</tr>
<tr>
<td></td>
<td>Model(^\rightarrow)</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
</tr>
</tbody>
</table>

Table 3.6: Liblinear learning parameters for each task; $c$: cost, $e$: termination criterion, $B$: bias. Model\(_D\) and Model\(_G\) are domain-specific and generalized models for POS tagging (Section 4.3.1). Model\(^\leftarrow\) and Model\(^\rightarrow\) are lefthand and righthand models for semantic role labeling (Section 6.4.2).

The \texttt{crossValidate}(CV, c, e, B) method in Algorithm 3.1 takes a list $CV$ of cross-validation sets and Liblinear parameters ($c$, $e$, $B$), and returns the average accuracy of all cross-validation sets. The \texttt{getModel}(trn\(_i\), c, e, B) method in line 4 takes a training set $trn\(_i\)$ and the hyper-parameters ($c$, $e$, $B$), and returns a Liblinear model $m\(_i\)$. The \texttt{getAccuracy}(tst\(_i\), m\(_i\)) method in line 5 takes an evaluation set $tst\(_i\)$ and the Liblinear model $m\(_i\)$, and returns the accuracy of $m\(_i\)$ on $tst\(_i\)$. This \texttt{crossValidate}(CV, c, e, B) method is performed several times with different combinations of the hyper-parameters and a combination with the highest average accuracy is used for the final model (ones in Table 3.6).

\(^2\) Each section in the WSJ training set is considered a cross-validation set.
Algorithm 3.1: crossValidate\((CV, c, e, B)\)

**Input:** A list \(CV\) of cross-validation sets, and Liblinear parameters \(c, e,\) and \(B\).

**Output:** The average accuracy of all cross-validation sets.

1: \(acc \leftarrow 0\)
2: for \(tst_i\) in \(CV\) do
3: \(trn_i \leftarrow \sum cv,\) where \(\forall cv. (cv \in CV) \land (cv \neq tst_i)\)
4: \(m_i \leftarrow getModel(trn_i, c, e, B)\)
5: \(acc \leftarrow acc + getAccuracy(tst_i, m_i)\)
6: return \(acc / |CV|\)

It is worth mentioning that we had previously tried several supervised machine learning algorithms for dependency parsing and found out that Liblinear worked the best for our experiments. Compared to maximum entropy (Ratnaparkhi, 1998), Liblinear trained as fast yet performed significantly more accurately. Compared to robust risk minimization (Zhang et al., 2002), Liblinear trained slightly faster and performed slightly more accurately. Compared to support vector machines using a linear kernel (Cortes and Vapnik, 1995), Liblinear trained significantly faster and performed as accurately. Given this previous experience, we decided to use Liblinear for all our experiments although it would be interesting to see the impact of other machine learning algorithms on different tasks.

<table>
<thead>
<tr>
<th>Model</th>
<th>WSJ Features</th>
<th>WSJ Train</th>
<th>WSJ Decode</th>
<th>OntoNotes Features</th>
<th>OntoNotes Train</th>
<th>OntoNotes Decode</th>
</tr>
</thead>
<tbody>
<tr>
<td>POS(_D)</td>
<td>435,462</td>
<td>2.4GB</td>
<td>0.7GB</td>
<td>1,063,175</td>
<td>6.5GB</td>
<td>1.5GB</td>
</tr>
<tr>
<td>POS(_G)</td>
<td>412,405</td>
<td>2.6GB</td>
<td>0.7GB</td>
<td>1,034,895</td>
<td>6.5GB</td>
<td>1.5GB</td>
</tr>
<tr>
<td>DEP</td>
<td>973,400</td>
<td>6.5GB</td>
<td>1.2GB</td>
<td>1,797,232</td>
<td>12GB</td>
<td>2.1GB</td>
</tr>
<tr>
<td>SRL(_-)</td>
<td>239,321</td>
<td>3.2GB</td>
<td></td>
<td>444,265</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SRL(_\rightarrow)</td>
<td>247,944</td>
<td>3.2GB</td>
<td></td>
<td>462,532</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3.7: The number of features and the amount of memory used for training and decoding the WSJ and OntoNotes models. The Features column shows the number of features, and the Train and Decode columns show the amount of RAM used for training and decoding, respectively.

Table 3.7 shows the number of features and the amount of memory used for training and decoding each of our final models, which are referred to ‘ClearNLP’ in the following sections. To run the WSJ models for all three tasks, 12.1GB and 2.4GB of RAM are required for training and decoding, respectively. To run the OntoNotes models for all three tasks, 25.3GB and 4.3GB of RAMs are required for training and decoding, respectively.
Part-of-speech Tagging

4.1 Overview

Most state-of-the-art POS taggers take statistical learning approaches, which perform very well when their training and testing data are from the same source, achieving over 97% accuracy (Toutanova et al., 2003; Giménez and Márquez, 2004; Shen et al., 2007). However, the performance drops when they are used for tagging data that varies from their training data. Several domain adaptation approaches have been proposed for the improvement of POS tagging in new domains (Daumé and Marcu, 2006; Daume III, 2007). Although these techniques work well, they are limited in three ways. First, they assume that target domains are already known, which is often not the case; especially when POS tagging is used for real-time systems such as online machine translators or search engines. Second, these approaches still require a relatively small but sufficient amount of manual annotation from target domains, which is not always available. Third, they build different models for handling new domains, which can be cumbersome when the number of target domains becomes large.

The dynamic model selection described in this chapter makes no assumption about the target domains. The objective is not to adapt a model to a specific domain different from existing training data, but to build a model that is general enough to work well for any domain. During training, two models are built; one is optimized for lexical items specific to the training data, called a domain-specific model, and the other is optimized for lexical items general to any domain, called a generalized model. Both models are derived from the same training data; no extra data is required for building either model. During decoding, one of these models is selected dynamically by measuring similarities
between input sentences and lexical items used for the models. Our hypothesis is that the domain-specific and generalized models perform better for sentences similar and dissimilar to the training data, respectively.

Figure 4.1: The overview of POS tagging using dynamic model selection.

Figure 4.1 shows the overview of POS tagging using our dynamic model selection approach. The following sections describe how to build both domain-specific and generalized models using the same training data (Section 4.3.1), and select an appropriate model for input sentences dynamically during decoding (Section 4.3.2). Each model uses a one-pass, left-to-right POS tagging algorithm (Section 4.4). Even with this simple tagging algorithm, our system shows tagging accuracy comparable to two other state-of-the-art POS taggers, the Stanford POS tagger and the SVMTool, when coupled with this dynamic model selection approach (Section 4.7.1). Furthermore, our system shows noticeably faster tagging speed compared to the other two systems (Section 4.7.2).
4.2 Background

The Penn Treebank project defined a set of POS tags (henceforth, the Penn POS tags) that has been used as the standard POS tagset for English (Marcus et al., 1993). The Penn POS tags were originally designed for annotating the Wall Street Journal corpus and later extended by the OntoNotes project to annotate corpora from several different sources (Weischedel et al., 2011). Table A.2 shows a list of the Penn POS tags.

<table>
<thead>
<tr>
<th>Google</th>
<th>Penn</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>.</td>
<td>$</td>
<td>:</td>
</tr>
<tr>
<td>ADJ</td>
<td>JJ</td>
<td>JJR</td>
</tr>
<tr>
<td>ADP</td>
<td>IN</td>
<td>Prepositions, postpositions</td>
</tr>
<tr>
<td>ADV</td>
<td>RB</td>
<td>RB</td>
</tr>
<tr>
<td>CONJ</td>
<td>CC</td>
<td>Conjunctions</td>
</tr>
<tr>
<td>DET</td>
<td>DT</td>
<td>EX</td>
</tr>
<tr>
<td>NOUN</td>
<td>NN</td>
<td>NNP</td>
</tr>
<tr>
<td>NUM</td>
<td>CD</td>
<td>Numerals</td>
</tr>
<tr>
<td>PRON</td>
<td>PRP</td>
<td>PRP$</td>
</tr>
<tr>
<td>PRT</td>
<td>AFX</td>
<td>POS</td>
</tr>
<tr>
<td>VERB</td>
<td>MD</td>
<td>VB</td>
</tr>
<tr>
<td>X</td>
<td>ADD</td>
<td>FW</td>
</tr>
</tbody>
</table>

Table 4.1: Mappings between Google’s universal POS tags and the Penn POS tags. The Google column shows Google’s universal POS tags and the Penn column shows lists of the Penn POS tags map to Google’s POS tags (delimited by ‘|’).

The Penn POS tags are fine-grained and reflect several linguistic phenomena such as pluralities of nouns, tenses of verbs, comparative forms of adjectives, etc. Recently, Google grouped the Penn POS tags into more coarse-grained ones that can be applied cross-linguistically (Petrov et al., 2012). Table 4.1 shows mappings between Google’s universal POS tags and the Penn POS tags.

<table>
<thead>
<tr>
<th>Sentence</th>
<th>He</th>
<th>bought</th>
<th>a</th>
<th>car</th>
<th>yesterday</th>
<th>that</th>
<th>is</th>
<th>red</th>
</tr>
</thead>
<tbody>
<tr>
<td>Penn</td>
<td>PRP</td>
<td>VBD</td>
<td>DT</td>
<td>NN</td>
<td>NN</td>
<td>WDT</td>
<td>VBZ</td>
<td>JJ</td>
</tr>
<tr>
<td>Google</td>
<td>PRON</td>
<td>VERB</td>
<td>DET</td>
<td>NOUN</td>
<td>NOUN</td>
<td>DET</td>
<td>VERB</td>
<td>ADJ</td>
</tr>
</tbody>
</table>

Table 4.2: An example of the Penn POS tags and Google’s universal POS tags. The Penn and Google rows show the Penn and Google’s POS tags with respect to the word tokens.
4.3 Dynamic model selection

4.3.1 Training

Consider training data as a collection of documents where each document contains sentences focusing on similar topics. For the Wall Street Journal corpus, a document can be an individual file or all files within each section. Alternatively, a document may contain sentences covering many different topics but written in similar styles. For instance, the OntoNotes Treebank consists of corpora from various sources such that each corpus can be considered a document following similar writing styles (see Section 3.1 for more details about the OntoNotes Treebank).

To build a generalized model, lexical features (e.g., $n$-gram word forms) that are too specific to individual documents should be avoided; this way, a classifier can place more weights on features general to any document. To filter out document-specific features, a threshold is set to the document frequency of each lowercase simplified word form in the training data. A simplified word form is derived by applying the following regular expressions sequentially to a word form, $w$. `replaceAll` is a function that replaces all matches of the regular expression in $w$ (the 1st parameter) with the specific string (the 2nd parameter). All numerical expressions are replaced with 0 in a simplified word form. A lowercase simplified word form is a decapitalized simplified word form.

1. $w.replaceAll(\d\%, 0)$ (e.g., $1\% \rightarrow 0$)
2. $w.replaceAll(\$\d, 0)$ (e.g., $\$1 \rightarrow 0$)
3. $w.replaceAll(\:\\.,\d, 0)$ (e.g., $.1 \rightarrow 0$)
4. $w.replaceAll(\d(\terminates\d|\d|\div\d|\div\d\div\d), 0)$ (e.g., $1,2|1:2|1-2|1/2|1.2 \rightarrow 0$)
5. $w.replaceAll(\d+, 0)$ (e.g., $1234 \rightarrow 0$)

Given a set of lowercase simplified word forms whose document frequencies are greater than a certain threshold, a model is trained by using non-lexical features (e.g., POS tags of previously tagged word tokens, ambiguity classes) and lexical features only associated with these lowercase simplified word forms. For a generalized model, a threshold of 2 is used, meaning that only lexical features whose
lowercase simplified word forms occur in at least 3 documents of the training data are used. For a domain-specific model, a threshold of 1 is used for our experiments. We have experimented with models using different thresholds (e.g., 0, 3), which did not improve tagging accuracy for our data.

The generalized and domain-specific models are trained separately. The domain-specific model is trained first; it is optimized by running $n$-fold cross-validation, where $n$ is the number of documents in the training data, and grid search on the Liblinear parameters $c$ and $B$ (Hsieh et al. (2008); see Section 3.2 for more details about Liblinear). The generalized model is trained in a similar way, $n$-fold cross-validation with grid search, except that it uses both the domain-specific model that is previously built and the generalized model that is currently built during cross-validation and selects either model for the best results guided by gold-standard annotation. It may be possible to improve tagging accuracy by optimizing both models simultaneously, which will be explored in the future.

4.3.2 Decoding

Once domain-specific and generalized models are built, two approaches can be adapted for decoding. One is to run both models and merge their outputs. This approach produces potentially more accurate output than either model, but takes longer to decode because the merging process may take a long time and cannot be started until both models are finished. Instead, an alternative approach is taken; that is to select one of the models dynamically based on input sentences. With an efficient model selection scheme, this approach can run as fast as a single model approach, yet give more robust results.

The premise of this dynamic model selection is that the domain-specific model performs better for sentences that are similar to its training space, whereas the generalized model performs better for ones that are dissimilar. During training, a set of simplified word forms, say $T$, used for building the domain-specific model is collected. During decoding, another set of simplified word forms, say $S$, is collected from each input sentence. If the cosine similarity between $T$ and $S$ is greater than a certain threshold, the domain-specific model is selected; otherwise, the generalized model is selected for decoding. The threshold is derived by running another cross-validation on the training data. For
each fold, both models are trained and evaluated simultaneously using the learning parameters found from the previous cross-validation (Section 4.3.1). During this cross-validation, cosine similarities are extracted for all testing sentences where the domain-specific model performs more accurately.

Figure 4.2: Cosine similarity distributions. The top and bottom distributions show cosine similarities extracted from the Wall Street Journal corpus and the OntoNotes corpora, respectively. The $y$-axis shows the number of occurrences of each cosine similarity during cross-validation.

Figure 4.2 shows the distributions of cosine similarities extracted from the Wall Street Journal corpus (top) and the OntoNotes corpora (bottom) during the cross-validation. From each distribution, the similarity at the first 5% area is chosen as the threshold; that is 0.025 for the Wall Street Journal corpus, and 0.018 for the OntoNotes corpora. This 5% area is not picked randomly but empirically derived during the cross-validation. It is possible to improve tagging accuracy by choosing different thresholds; we later found that picking the first 8% area, that is 0.022, gave the best results for the OntoNotes models. However, this threshold is not used for our experiments because it was not derived automatically, but rather ascertained by manual inspection.
4.4 Tagging algorithm

Each model uses a one-pass, left-to-right POS tagging algorithm. This algorithm tags the leftmost word token first and sequentially tags tokens on the right until all tokens are tagged. Each token is visited only once during tagging. The motivation is to analyze how our dynamic model selection works with a simple algorithm first then apply it to more sophisticated algorithms later (e.g., a bidirectional tagging algorithm). Even with this simple algorithm, our system shows comparable results against two other state-of-the-art POS taggers when coupled with the dynamic model selection.

4.5 Features

Table 4.3: Feature templates for POS tagging. \( i \): the index of the current word token, \( f \): simplified word form (e.g., \( f_i \) is the simplified word form of the \( i \)th word token), \( m \): lowercase simplified word form, \( p \): POS, \( a \): ambiguity class, \( c_\ast \): character sequence in \( w_i \) (e.g., \( c_2 \): the 1st and 2nd characters of \( w_i \), \( c_{n-1} \): the \( n-1 \)'th and \( n \)'th characters of \( w_i \)).

Table 4.3 shows the feature templates used for our POS tagging experiments. Our feature templates are mostly inspired by Giménez and Màrquez (2004) except for a few changes. For lexical features, either simplified word forms or lowercase simplified word forms are used instead of the actual word forms, which provide more generalization of these features. Furthermore, ambiguity classes are derived selectively in our approach. Given a word form, we count how often each POS tag is used with this word form in training data and keep only POS tags above a certain threshold for the
ambiguity class. For instance, if the threshold is 40% and a word form is used as a noun 50%, a verb 40%, and an adjective 10% in the training data, only the noun and verb POS tags are taken (e.g., NN, VB) and make up the ambiguity class of this word form, NN_VB. For the generalized model, a threshold of 90% is used, which favors precision more than recall. A threshold of 90% is sufficient to guarantee only one POS tag in the ambiguity class. Moreover, many forms end up not having ambiguity classes at all with this threshold. From our experiments, we find this to be more useful than expanding ambiguity classes with lower thresholds for the generalized model. For the domain-specific model, thresholds of 20% and 50% are used for the WSJ and the OntoNotes models, respectively.

4.6 Related work

Toutanova et al. (2003) introduced a tagging algorithm using bidirectional dependency networks, and showed improved results over other single directional model approaches. Giménez and Màrquez (2004) used a one-pass, left-to-right and right-to-left combined tagging algorithm and achieved near state-of-the-art performance. Shen et al. (2007) presented a tagging approach using guided learning for bidirectional sequence classification and showed current state-of-the-art performance against the other models trained and evaluated on the same data set. There are also semi-supervised learning approaches using external data that showed better performance than these supervised learning approaches (Spoustová et al., 2009; Søgaard, 2011).

Our individual models (generalized and domain-specific) are similar to Giménez and Màrquez (2004) in that we use a subset of their features and adapt a one-pass, left-to-right tagging algorithm, which is a simpler version of theirs. However, we use Liblinear for learning, which runs much faster than their classifier, Support Vector Machines, for both training and decoding. Furthermore, we use simplified word forms instead of the original word forms as features, which generalize more readily. Most importantly, we prune out lexical features using document frequencies for these individual models, which improves parsing accuracy (Section 4.7.1).
4.7 Experiments

4.7.1 Accuracy comparisons

Tables 4.4 and 4.5 show tagging accuracies of all tokens achieved by the WSJ and OntoNotes models. The Baseline and Baseline+ models are trained on features extracted from the original word forms and the lowercase simplified word forms in Section 4.5, respectively. These models take all lexical items as features regardless of their document frequencies. The Domain and General models are the domain-specific and generalized models in Section 4.3. The ClearNLP model is our dynamic model selection approach. The ClearNLP model is compared with two other state-of-the-art systems, the Stanford POS tagger (Toutanova et al., 2003) and the SVMTool (Giménez and Màrquez, 2004). Both systems are trained on the same training sets and use configurations optimized for their best results. The “G over D” row shows how often the generalized model is chosen over the domain-specific model during dynamic model selection.

Table 4.4: Tagging accuracies of all tokens from the WSJ models (in %).

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>93.53</td>
<td>94.06</td>
<td>88.44</td>
<td>83.50</td>
<td>91.61</td>
<td>76.74</td>
<td>86.70</td>
<td>92.22</td>
<td>96.93</td>
<td>88.25</td>
</tr>
<tr>
<td>Baseline+</td>
<td>93.70</td>
<td>94.37</td>
<td>88.51</td>
<td>83.79</td>
<td>91.69</td>
<td>77.47</td>
<td>88.08</td>
<td>92.39</td>
<td>96.98</td>
<td>88.64</td>
</tr>
<tr>
<td>Domain</td>
<td>93.07</td>
<td>95.23</td>
<td>90.91</td>
<td>87.57</td>
<td>93.78</td>
<td>82.07</td>
<td>87.22</td>
<td>94.08</td>
<td>97.39</td>
<td>90.43</td>
</tr>
<tr>
<td>General</td>
<td>93.13</td>
<td>95.09</td>
<td>91.18</td>
<td>87.95</td>
<td>93.14</td>
<td>84.15</td>
<td>87.01</td>
<td>93.68</td>
<td>97.24</td>
<td>90.61</td>
</tr>
<tr>
<td>ClearNLP</td>
<td><strong>93.21</strong></td>
<td>95.37</td>
<td><strong>91.32</strong></td>
<td>88.03</td>
<td><strong>93.74</strong></td>
<td><strong>84.05</strong></td>
<td><strong>87.05</strong></td>
<td><strong>94.01</strong></td>
<td>97.40</td>
<td><strong>90.79</strong></td>
</tr>
<tr>
<td>Stanford</td>
<td>87.72</td>
<td><strong>95.50</strong></td>
<td>90.77</td>
<td><strong>88.45</strong></td>
<td>92.79</td>
<td>84.03</td>
<td>86.24</td>
<td>94.00</td>
<td><strong>97.41</strong></td>
<td>89.92</td>
</tr>
<tr>
<td>SVMTool</td>
<td>87.82</td>
<td>95.13</td>
<td>90.54</td>
<td>87.86</td>
<td>92.95</td>
<td>81.87</td>
<td>85.96</td>
<td>93.98</td>
<td>97.31</td>
<td>89.49</td>
</tr>
<tr>
<td>G over D</td>
<td>52.12</td>
<td>40.99</td>
<td>42.65</td>
<td>71.23</td>
<td>23.28</td>
<td>85.51</td>
<td>81.00</td>
<td>38.20</td>
<td>10.98</td>
<td>61.15</td>
</tr>
</tbody>
</table>

Table 4.4: Tagging accuracies of all tokens from the WSJ models (in %).

Table 4.5: Tagging accuracies of all tokens from the OntoNotes models (in %).

<table>
<thead>
<tr>
<th>Model</th>
<th>BC</th>
<th>BN</th>
<th>MZ</th>
<th>NW</th>
<th>TC</th>
<th>WB</th>
<th>Avg.</th>
<th>Avg.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>97.20</td>
<td>97.00</td>
<td>95.78</td>
<td>97.33</td>
<td>95.35</td>
<td>94.66</td>
<td>92.18</td>
<td>86.40</td>
</tr>
<tr>
<td>Baseline+</td>
<td>97.24</td>
<td>97.08</td>
<td>95.88</td>
<td>97.48</td>
<td>95.39</td>
<td>94.76</td>
<td>92.16</td>
<td>87.29</td>
</tr>
<tr>
<td>Domain</td>
<td>97.34</td>
<td>97.27</td>
<td>96.22</td>
<td>97.61</td>
<td>95.49</td>
<td>95.43</td>
<td>92.37</td>
<td>88.65</td>
</tr>
<tr>
<td>General</td>
<td>97.29</td>
<td>97.09</td>
<td>95.93</td>
<td>97.49</td>
<td>95.48</td>
<td>95.06</td>
<td>92.61</td>
<td>88.97</td>
</tr>
<tr>
<td>ClearNLP</td>
<td><strong>97.32</strong></td>
<td>97.26</td>
<td><strong>96.20</strong></td>
<td>97.60</td>
<td><strong>95.43</strong></td>
<td><strong>95.42</strong></td>
<td><strong>92.58</strong></td>
<td><strong>89.05</strong></td>
</tr>
<tr>
<td>Stanford</td>
<td>97.13</td>
<td><strong>97.31</strong></td>
<td>96.07</td>
<td><strong>97.61</strong></td>
<td><strong>95.44</strong></td>
<td>95.42</td>
<td>92.53</td>
<td><strong>90.03</strong></td>
</tr>
<tr>
<td>SVMTool</td>
<td>97.15</td>
<td>96.81</td>
<td>95.69</td>
<td>97.43</td>
<td>94.71</td>
<td>95.18</td>
<td>91.55</td>
<td>88.49</td>
</tr>
<tr>
<td>G over D</td>
<td>26.69</td>
<td>27.58</td>
<td>13.13</td>
<td>6.89</td>
<td>68.50</td>
<td>27.10</td>
<td>30.76</td>
<td>62.15</td>
</tr>
</tbody>
</table>
The Avg\textsubscript{i} and Avg\textsubscript{o} columns show the micro average accuracies for in-genre and out-of-genre experiments. For the WSJ models, the accuracy of NW is measured for Avg\textsubscript{i} and the micro average of all other corpora are measured for Avg\textsubscript{o}. For the OntoNotes models, the micro averages of the OntoNotes and Medical corpora are measured for Avg\textsubscript{i} and Avg\textsubscript{o}, respectively. The Baseline+ models show improvements over the Baseline models for all experiments except for MD in Table 4.5. The improvements are greater for out-of-genre experiments (e.g., 0.96% improvement for Avg\textsubscript{o} in Table 4.5), which indicates that the lowercase simplified word forms give features that generalize better for heterogeneous data. The domain-specific and generalized models perform better for in-genre and out-of-genre experiments, respectively (as expected). The ClearNLP models show the most robust results across genres.

Compared to the state-of-the-art systems, our dynamic model selection approach gives higher tagging accuracies for Avg\textsubscript{o} in Table 4.4, and for both Avg\textsubscript{i} and Avg\textsubscript{o} in Table 4.5. The differences between the ClearNLP and Stanford models in Table 4.5 are marginal. However, the difference for Avg\textsubscript{o} in Table 4.4 is statistically significant (McNemar, $p < .0001$), which implies that our approach is more effective when the training data is small and is used for tagging data with many varieties. Considering that our model uses a simple one-pass, left-to-right tagging algorithm (Section 4.4), these results are very encouraging.

<table>
<thead>
<tr>
<th>Model</th>
<th>BC</th>
<th>BN</th>
<th>MD</th>
<th>MP</th>
<th>MZ</th>
<th>SH</th>
<th>TC</th>
<th>WB</th>
<th>Avg\textsubscript{i}</th>
<th>Avg\textsubscript{o}</th>
</tr>
</thead>
<tbody>
<tr>
<td>ClearNLP</td>
<td>69.78</td>
<td>83.26</td>
<td>66.90</td>
<td>68.29</td>
<td>74.80</td>
<td>68.21</td>
<td>26.18</td>
<td>76.08</td>
<td>89.11</td>
<td>66.80</td>
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<tr>
<td>Stanford</td>
<td>19.24</td>
<td>87.31</td>
<td>64.25</td>
<td>70.94</td>
<td>66.32</td>
<td>67.35</td>
<td>20.64</td>
<td>78.08</td>
<td>88.30</td>
<td>61.16</td>
</tr>
<tr>
<td>SVMTool</td>
<td>19.08</td>
<td>78.35</td>
<td>62.94</td>
<td>66.53</td>
<td>65.23</td>
<td>61.45</td>
<td>19.62</td>
<td>76.43</td>
<td>86.88</td>
<td>57.70</td>
</tr>
<tr>
<td>Tokens</td>
<td>3,077</td>
<td>1,284</td>
<td>4,755</td>
<td>6,077</td>
<td>2,663</td>
<td>10,163</td>
<td>2,452</td>
<td>2,609</td>
<td>983</td>
<td>33,080</td>
</tr>
</tbody>
</table>

Table 4.6: Tagging accuracies of unknown tokens from the WSJ models (in %).

<table>
<thead>
<tr>
<th>Model</th>
<th>BC</th>
<th>BN</th>
<th>MZ</th>
<th>NW</th>
<th>TC</th>
<th>WB</th>
<th>MD</th>
<th>MP</th>
<th>SH</th>
<th>Avg\textsubscript{i}</th>
<th>Avg\textsubscript{o}</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>ClearNLP</td>
<td>82.37</td>
<td>83.71</td>
<td>87.39</td>
<td>88.24</td>
<td>59.70</td>
<td>78.82</td>
<td>72.32</td>
<td>68.21</td>
<td>73.15</td>
<td>81.25</td>
<td>71.48</td>
<td></td>
</tr>
<tr>
<td>Stanford</td>
<td>84.75</td>
<td>86.36</td>
<td>87.28</td>
<td>90.48</td>
<td>64.48</td>
<td>82.42</td>
<td>72.11</td>
<td>72.48</td>
<td>69.22</td>
<td>83.76</td>
<td>70.79</td>
<td></td>
</tr>
<tr>
<td>SVMTool</td>
<td>80.34</td>
<td>80.87</td>
<td>84.27</td>
<td>85.85</td>
<td>55.42</td>
<td>75.34</td>
<td>65.95</td>
<td>64.62</td>
<td>63.92</td>
<td>78.12</td>
<td>64.54</td>
<td></td>
</tr>
<tr>
<td>Tokens</td>
<td>295</td>
<td>528</td>
<td>928</td>
<td>714</td>
<td>397</td>
<td>1,553</td>
<td>3,342</td>
<td>5,065</td>
<td>8,216</td>
<td>4,415</td>
<td>16,623</td>
<td></td>
</tr>
</tbody>
</table>

Table 4.7: Tagging accuracies of unknown tokens from the OntoNotes models (in %).
Tables 4.6 and 4.7 show tagging accuracies of unknown tokens achieved by the WSJ and OntoNotes models. The Tokens row shows the number of unknown tokens found in each genre. For both Avg$_i$ and Avg$_o$ in Table 4.6, the ClearNLP model shows higher accuracies than the other two systems; the difference for Avg$_o$ is statistically significant (McNemar, $p < .0001$). For Avg$_o$ in Table 4.7, the ClearNLP model also shows a higher accuracy that is statistically significant (McNemar, $p < .05$). However, the Stanford model shows an advantage over our model for Avg$_i$ in Table 4.7. We suspect that this is because the way we divide the OntoNotes training set into documents, treating each corpus as one document, does not work the best for our dynamic model selection approach such that a better document classification method is required to achieve better results. We will explore the possibility of using unsupervised clustering techniques that automatically group the training data into meaningful documents for dynamic model selection in the future.

For comparison, tagging accuracies of all tokens in MD, MP, and SH achieved by a model trained on a small amount of medical data are provided in Table 4.8. There is a total of 133,110 tokens in the training data. This model shows a micro average of 94.84% for the medical genres; the accuracy is higher for SH whose training data is larger. Notice that this model uses about $\frac{1}{15}$ the number of training instances used by the OntoNotes model, which shows an average of 89.26% on the same evaluation sets. This implies that even a small amount of training data in the same genre can significantly improve tagging accuracy.

<table>
<thead>
<tr>
<th></th>
<th>MD</th>
<th>MP</th>
<th>SH</th>
<th>ALL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tokens</td>
<td>30,367</td>
<td>16,122</td>
<td>86,621</td>
<td>133,110</td>
</tr>
<tr>
<td>Accuracy</td>
<td>93.93</td>
<td>93.38</td>
<td>97.34</td>
<td>94.84</td>
</tr>
</tbody>
</table>

Table 4.8: Tagging accuracies achieved by the medical model. The Tokens row shows the number of tokens in the training data of each genre. The Accuracy row shows the tagging accuracy of each genre. The ALL column indicates the mixture of all three genres.
4.7.2 Speed comparisons

Tagging speeds are measured by running each system on a mixture of all data. The ClearNLP and Stanford taggers are written in Java; the Stanford POS tagger provides APIs that allow us to make fair comparisons between these two systems. The SVMTool is written in Perl. Table 4.9 shows speed comparisons between all three systems; the top and bottom three rows show results from the WSJ and OntoNotes models, respectively. The T# columns show how many milliseconds each system takes for tagging one sentence in 5 trials, the Avg column shows the average tagging speeds of the middle three trials, and the Tokens column shows how many tokens are tagged per second. Our system tags about 39.5 - 39.9K tokens per second, including the runtime for both POS tagging and dynamic model selection, which is noticeably faster than the other systems.\footnote{There is a POS tagger faster than our system, called the TnT POS tagger (Brants, 2000); however, it is written in C++ and its tagging accuracy is significantly lower than these state-of-the-art systems; thus, the TnT POS tagger is not included in our experiments.}

<table>
<thead>
<tr>
<th>Model</th>
<th>T1</th>
<th>T2</th>
<th>T3</th>
<th>T4</th>
<th>T5</th>
<th>Avg</th>
<th>Tokens</th>
</tr>
</thead>
<tbody>
<tr>
<td>WSJ</td>
<td>ClearNLP</td>
<td>0.36</td>
<td>0.37</td>
<td>0.37</td>
<td>0.37</td>
<td>0.38</td>
<td>0.37</td>
</tr>
<tr>
<td></td>
<td>Stanford</td>
<td>57.47</td>
<td>58.01</td>
<td>58.03</td>
<td>58.13</td>
<td>60.12</td>
<td>58.06</td>
</tr>
<tr>
<td></td>
<td>SVMTool</td>
<td>13.10</td>
<td>13.40</td>
<td>13.83</td>
<td>13.91</td>
<td>14.07</td>
<td>13.71</td>
</tr>
<tr>
<td>ON</td>
<td>ClearNLP</td>
<td>0.36</td>
<td>0.36</td>
<td>0.37</td>
<td>0.37</td>
<td>0.37</td>
<td>0.36</td>
</tr>
<tr>
<td></td>
<td>Stanford</td>
<td>105.19</td>
<td>105.52</td>
<td>106.55</td>
<td>106.95</td>
<td>107.09</td>
<td>106.34</td>
</tr>
<tr>
<td></td>
<td>SVMTool</td>
<td>15.47</td>
<td>15.51</td>
<td>15.73</td>
<td>15.90</td>
<td>15.96</td>
<td>15.71</td>
</tr>
</tbody>
</table>

Table 4.9: Tagging speeds (in ms). The top and the bottom three rows show results from the WSJ and OntoNotes models, respectively.
Chapter 5

Dependency Parsing

5.1 Overview

Most current statistical dependency parsers take one of two parsing approaches. One is a transition-based approach that greedily searches for local optima (highest scoring transitions) and uses features based on parse history to predict the next transition (Nivre, 2008; Attardi and Dell’Orletta, 2009; Huang and Sagae, 2010; Goldberg and Elhadad, 2010). The other is a graph-based approach that searches for a global optimum (a maximum spanning tree) from a complete graph in which vertices represent word tokens and edges, directed and weighted, represent dependency relations (McDonald et al., 2005; Mcdonald and Pereira, 2006; Koo et al., 2010; Rush and Petrov, 2012). The transition-based approach searches for local optima, so it usually performs better on short-distance dependencies while the graph-based approach usually performs better on long-distance dependencies because it searches for a global optimum (Nivre and McDonald, 2008).1 Some ensemble approaches using integrated models of both transition-based and graph-based approaches had also shown improved parsing results (Nivre and McDonald, 2008; Zhang and Clark, 2008; Surdeanu and Manning, 2010).

Lately, the usefulness of transition-based parsing has drawn more attention because it generally performs noticeably faster than graph-based parsing (Cer et al., 2010). Transition-based parsing has worst-case parsing complexities as low as $O(n)$ and $O(n^2)$ for the generation of projective and non-projective dependency trees, respectively, where $n$ is the number of word tokens in

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1 The relation between far apart tokens considered in later parsing states and earlier mistakes make it harder for transition-based parsing to correctly establish long distance dependencies.
a sentence (Nivre, 2003; Covington, 2001). The parsing complexity is lower for the generation of projective dependency trees because it can deterministically drop tokens that can potentially violate the projective property from the search space (Section 2.1.2.1) whereas that is not advisable for the generation of non-projective dependency trees. Nevertheless, it is still possible to perform non-projective parsing in expected linear time because the amount of non-projective dependencies is notably smaller than the amount of projective dependencies (Nivre and Nilsson, 2005), so a parser can perform projective parsing for most cases and perform non-projective parsing only when it is needed (Choi and Nicolov, 2009; Nivre, 2009; Choi and Palmer, 2011a).

Another attractive aspect of transition-based parsing is that it can use features based on parse history for statistical learning, which helps make more accurate predictions (Nivre, 2006). Thus, many transition-based approaches incrementally build parsing states so that later parsing states can use parse history derived from earlier states as features. During training, this parse history is derived from gold-standard dependency trees. During decoding, however, it is derived from automatically generated dependency trees, which may not provide the same type of features as the ones used for training. By minimizing the gap between the features derived during training and decoding, it is possible to improve parsing accuracy; especially on new data where automatic parse output is poor.

This chapter focuses on the engineering of different aspects of transition-based, non-projective dependency parsing. To reduce the search space of non-projective dependency parsing, a new parsing algorithm is proposed, which combines transitions in both projective and non-projective dependency parsing algorithms (Section 5.2). To narrow down the gap between parse features derived from gold-standard and automatic dependency trees, a bootstrapping technique is introduced (Section 5.3). Additionally, a post-processing technique is suggested that guarantees an automatic parse output is a tree instead of a forest (Section 5.4). All of these approaches together show significant improvement for both in-domain and out-of-domain experiments. Our final model is evaluated on corpora from several different genres and shows comparable results in parsing accuracy and a clear advantage in parsing speed with respect to other state-of-the-art dependency parsers (Section 5.6). These results demonstrate the benefit of careful engineering that effectively leverages linguistic knowledge.
5.2 Transition-based dependency parsing

5.2.1 Transition decomposition

Table 5.1 shows functional decomposition of transitions used in Nivre’s arc-eager and Covington’s algorithms. Transition-based parsing can be viewed as a search problem with a very large branching factor. Nivre’s arc-eager algorithm is a projective parsing algorithm that shows a worst-case parsing complexity of $O(n)$ (Nivre, 2003). Covington’s algorithm is a non-projective parsing algorithm that shows a worst-case parsing complexity of $O(n^2)$ without backtracking (Covington, 2001). Covington’s algorithm was later formulated as a transition-based parsing algorithm by Nivre (2008), called Nivre’s list-based algorithm. Table 5.3 shows the relation between the decomposed transitions in Table 5.1 and the transitions from the original algorithms.

<table>
<thead>
<tr>
<th>Operation</th>
<th>Transition</th>
<th>Current state</th>
<th>⇒</th>
<th>Resulting state</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARC</td>
<td>LEFT-*l</td>
<td>( [$λ_1$], $l_2$, [$j$], $A$ )</td>
<td>$⇒$</td>
<td>( [$λ_1$], $l_2$, [$j$], $A$ ∪ { $l$ $→$ $j$ } )</td>
</tr>
<tr>
<td></td>
<td>RIGHT-*l</td>
<td>( [$λ_1$], $l_2$, [$j$], $A$ )</td>
<td>$⇒$</td>
<td>( [$λ_1$], $l_2$, [$j$], $A$ ∪ { $l$ $→$ $j$ } )</td>
</tr>
<tr>
<td></td>
<td>NO-*</td>
<td>( [$λ_1$], $l_2$, [$j$], $A$ )</td>
<td>$⇒$</td>
<td>( [$λ_1$], $l_2$, [$j$], $A$ )</td>
</tr>
<tr>
<td>LIST</td>
<td>*-SHIFT$_{d,in}$</td>
<td>( [$λ_1$], $l_2$, [$j$], $A$ )</td>
<td>$⇒$</td>
<td>( [$λ_1$], $l_2$, [$j$], $A$ )</td>
</tr>
<tr>
<td></td>
<td>*-REDUCE</td>
<td>( [$λ_1$], $l_2$, [$j$], $A$ )</td>
<td>$⇒$</td>
<td>( [$λ_1$], $l_2$, [$j$], $A$ )</td>
</tr>
<tr>
<td></td>
<td>*-PASS</td>
<td>( [$λ_1$], $l_2$, [$j$], $A$ )</td>
<td>$⇒$</td>
<td>( [$λ_1$], $l_2$, [$j$], $A$ )</td>
</tr>
</tbody>
</table>

Table 5.1: Decomposed transitions grouped into the ARC and LIST operations.

<table>
<thead>
<tr>
<th>Operation</th>
<th>Transition</th>
<th>Preconditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARC</td>
<td>LEFT-*l</td>
<td>$[i$ $≠$ $0$] $∧$ $¬$[$∃k$. ($i$ $→$ $k$) $∈$ $A$] $∧$ $¬$[$(i$ $*$ $→$ $j$) $∈$ $A$]</td>
</tr>
<tr>
<td></td>
<td>RIGHT-*l</td>
<td>$¬$[$∃k$. ($k$ $→$ $j$) $∈$ $A$] $∧$ $¬$[$(i$ $*$ $←$ $j$) $∈$ $A$]</td>
</tr>
<tr>
<td></td>
<td>NO-*</td>
<td>$¬$[$∃l$. LEFT-*l $∨$ RIGHT-*l]</td>
</tr>
<tr>
<td>LIST</td>
<td>*-SHIFT$_{d,in}$</td>
<td>$[λ_1$ $</td>
</tr>
<tr>
<td></td>
<td>*-REDUCE</td>
<td>$[∃h$. ($h$ $→$ $i$) $∈$ $A$] $∧$ $¬$[$∃k$. ($i$ $→$ $k$)]</td>
</tr>
<tr>
<td></td>
<td>*-PASS</td>
<td>$¬$[$*$-SHIFT$_{d,in}$ $∧$ <em>-REDUCE</em>]</td>
</tr>
</tbody>
</table>

Table 5.2: Preconditions of the decomposed transitions in Table 5.1.

Table 5.2 shows preconditions of the decomposed transitions in Table 5.1. Some preconditions need to be satisfied to ensure the properties of a well-formed dependency graph (Section 2.1.2.1). The parsing states are represented as tuples ($λ_1$, $l_2$, $β$, $A$), where $λ_1$, $l_2$ are lists of partially processed
tokens and $\beta$ is a list of the remaining unprocessed tokens. $A$ is a set of labeled arcs representing previously identified dependencies. $l$ is a dependency label, and $i$ and $j$ represent indices of their corresponding word tokens, $w_i$ and $w_j$. $[\lambda_1[i]$ implies $w_i$ is the last token in $\lambda_1$, and $[j|\beta]$ implies $w_j$ is the first token in $\beta$. The initial state is $([0], [, [1, \ldots, n], \emptyset)$. The 0 identifier corresponds to an initial token, $w_0$, introduced as the root of a dependency tree. The final state is $(\lambda_1, \lambda_2, [, A)$, i.e., parsing terminates when all tokens in $\beta$ are consumed (there is no remaining unprocessed token).

The decomposed transitions in Table 5.1 can be grouped into two operations, Arc and List. The Arc operation, consisting of the top three transitions, determines the dependency between the last token $w_i$ in $\lambda_1$ and the first token $w_j$ in $\beta$ using an oracle $O_d$. In our case, $O_d$ is a single multi-class classifier that predicts recomposed transitions in Section 5.2.2. It is possible to build two separate oracles for the Arc and List operations; we tried this approach, which did not lead to better parsing results than the single oracle approach. During training, $O_d$ consults parse information derived from gold-standard dependency trees, whereas such information is provided by a machine learning algorithm to $O_d$ during decoding. Left- $*$ is performed when $O_d$ predicts $w_j$ is the head of $w_i$ with a dependency label $l$ (notated as $i \xleftarrow{l} j$). Similarly, Right- $*$ is performed when $O_d$ predicts $w_i$ is the head of $w_j$ with a dependency label $l$ (notated as $i \xrightarrow{l} j$). No- $*$ is performed when $O_d$ predicts there is no dependency between $w_i$ and $w_j$. The Arc operation does not update a state of any list ($\lambda_1$, $\lambda_2$, or $\beta$); only $A$ gets updated after these transitions are performed.

The List operation, consisting of the bottom three transitions, determines which pair of word tokens is compared next for a dependency using $O_d$. $*$-SHIFT$^{d|n}$ is performed when $\lambda_1$ is empty ($*$-SHIFT$^{d}$: deterministic shift), or $O_d$ predicts there is no dependency between $w_j$ and any token in $\lambda_1$ other than $w_i$ ($*$-SHIFT$^{n}$: non-deterministic shift). After a $*$-SHIFT$^{d|n}$ transition, all tokens in $\lambda_2$ as well as $w_j$ are moved to $\lambda_1$. $*$-REDUCE is performed when $w_i$ has already found its head, and $O_d$ predicts $w_i$ is not the head of any token in $\beta$. After a $*$-REDUCE transition, $w_i$ is removed from $\lambda_1$. $*$-PASS is performed when the conditions for both $*$-SHIFT$^{d|n}$ and $*$-REDUCE fail. After a $*$-PASS transition, $w_i$ is moved to the front of $\lambda_2$ so it can be compared to other tokens in $\beta$ later. This transition is added for non-projective parsing where a long-distance dependency is present.
Transition decomposition as described here gives a clear distinction between the Arc and List operations as compared to transitions used in transition-based parsing algorithms. This decomposition makes it easier to integrate transitions from one algorithm into the other algorithm because all decomposed transitions now use the same data structures with uniform notation (e.g., Nivre’s arc-eager algorithm does not use $\lambda_2$, which makes it harder to integrate its transitions into Nivre’s list-based algorithm using $\lambda_2$). Section 5.2.2 shows how these decomposed transitions can be recomposed into transitions used in several different dependency parsing algorithms.

### 5.2.2 Transition recomposition

Any combination of two decomposed transitions in Table 5.1, one from each operation, can be recomposed into a new transition. For instance, the combination of $\text{LEFT-}*l$ and $\text{*-REDUCE}$ makes a transition, $\text{LEFT-REDUCE}_l$, which performs $\text{LEFT-}*l$ and $\text{*-REDUCE}$ sequentially; the Arc operation is always performed before the List operation. Table 5.3 shows how these decomposed transitions are recomposed into transitions used in different dependency parsing algorithms.

<table>
<thead>
<tr>
<th>Transition</th>
<th>Nivre’03</th>
<th>Covington’01</th>
<th>Nivre’08</th>
<th>C&amp;P’11</th>
<th>This work</th>
</tr>
</thead>
<tbody>
<tr>
<td>\text{LEFT-REDUCE}_l</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>\text{LEFT-PASS}_l</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>\text{RIGHT-SHIFT}^n</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>\text{RIGHT-PASS}_l</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>\text{NO-SHIFT}^d</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>\text{NO-SHIFT}^n</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>\text{NO-REDUCE}</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>\text{NO-PASS}</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

Table 5.3: Transitions in different dependency parsing algorithms. The last column shows transitions used in our parsing algorithm. The other columns show transitions used in Nivre (2003), Covington (2001), Nivre (2008), and Choi and Palmer (2011a), respectively.

Nivre’s arc-eager algorithm allows no combination of $\text{*-PASS}$, which removes or skips tokens that can violate the projective property (Nivre’03 in Table 5.3). As a result, this algorithm performs at most $2n - 1$ transitions during parsing, and can produce only projective dependency trees.\(^2\) Covington’s

\(^2\) The $\text{*-SHIFT}^d$ transitions are not counted because they do not require comparison between word tokens.
algorithm allows no combination of $\ast$-Shift$^n$ or $\ast$-Reduce, which inevitably compares each token with all tokens prior to it (Covington’01). Thus, this algorithm performs $\frac{n(n+1)}{2}$ transitions during parsing, and can produce both projective and non-projective dependency trees.

The last three algorithms in Table 5.3 show cumulative updates to Covington’s algorithm; they add one or two transitions from Nivre’s arc-eager algorithm to Covington’s algorithm. By adding these transitions, a fewer number of transitions needs to be performed during parsing, which reduces the expected running time of these approaches. Nivre (2008) introduced a concept of non-deterministic shift that could skip some tokens in $\lambda_1$ without comparing them to $w_j$ (NO-Shift$^n$). Choi and Nicolov (2009) implemented this algorithm and showed that it was possible to achieve a linear time parsing speed in practice for non-projective parsing using non-deterministic shift. Choi and Palmer (2010a) added LEFT-REDUCE$^l$ to this approach and reduced the search space more.

Our parsing algorithm makes another incremental update to Choi and Palmer (2010a) by adding RIGHT-SHIFT$^n_l$ and NO-REDUCE. During training, it checks for the preconditions of all transitions and generates training instances with corresponding labels. During decoding, the oracle $O_d$ predicts which transition to perform based on the current parsing state. With the addition of new transitions, $O_d$ can choose either projective or non-projective parsing: by choosing the combinations with $\ast$-Shift$^n$ or $\ast$-Reduce, the algorithm performs projective parsing, whereas it performs non-projective parsing by choosing the combinations with $\ast$-Pass. Our experiments show that these additional transitions can reduce the expected running time as well as the feature space without compromising performance in parsing accuracy (Section 5.6.1). The advantage derives from improving the efficiency of the choice mechanism; it is now simply a transition choice and requires no additional processing.

Figure 5.1 shows the average number of transitions performed by each parsing algorithm in Table 5.3 with respect to sentence lengths. For comparison, gold-standard dependency trees in the OntoNotes Treebank are used. Covington’s algorithm shows a quadratic growth in transitions as the sentence length increases while the other three approaches show more or less linear growths. The bottom figure in Figure 5.1 demonstrates reduction in the average number of transitions performed.
by our algorithm, in which the number of transitions grows linearly as the sentence length increases. This implies that our algorithm gives an expected linear time parsing speed for this data set although a worst-case parsing complexity is still $O(n^2)$.

![Graphs showing number of transitions vs sentence length for different algorithms](image)

Figure 5.1: The average number of transitions performed by each algorithm in Table 5.3 with respect to sentence lengths. Each sentence length indicates the number of word tokens in a sentence. The top and the bottom figures show comparisons between the last four and three approaches in Table 5.3.

Note that Nivre (2009) introduced another transition-based parsing algorithm that could perform non-projective parsing in expected linear time. This algorithm tries to resolve non-projectivity by reordering tokens that are not within the same domain of locality. Transitions in this algorithm are not integrated into our algorithm because it deviates from a different dependency parsing algorithm (Nivre, 2004), which makes the integration difficult. We also tried to include two other transitions, \textsc{Left-Shift}_i^n and \textsc{Right-Reduce}_t, which did not lead to better parsing results. Adding these transitions forces $w_j$ to have at most one dependent, which is often not the case in our data.
5.2.3 Parsing algorithm

Algorithm 5.1 shows our non-projective dependency parsing algorithm using all recomposed transi-
tions in Table 5.3.

Algorithm 5.1: \( \text{getDependencyArcSet}(S) \)

**Input:** A sentence \( S = w_1, \ldots, w_n \).

**Output:** A set \( A \) of labeled dependency arcs in \( S \).

1: \( (\lambda_1, \lambda_2, \beta, A) := ([0], [ ]), [1, 2, \ldots, n], \emptyset) \)
2: while \( \beta \neq [ ] \) do
3: if \( \lambda_1 = [ ] \) then
4: No-Shift
5: elif \( O_d \Rightarrow (i \xrightarrow{L} j) \) then
6: if \( i = 0 \) then No-Shift
7: elif \( (\exists k. (i \leftarrow k) \in A) \) or \( (i \rightarrow^{*} j) \in A \) then No-Pass
8: elif \( O_d \Rightarrow \neg(\exists k \in \beta. (i \rightarrow k)) \) then Left-Reduce
9: else Left-Pass
10: elif \( O_d \Rightarrow (i \xrightarrow{L} j) \) then
11: if \( (\exists k. (k \rightarrow j) \in A) \) or \( ((i \leftarrow^{*} j) \in A) \) then No-Pass
12: elif \( O_d \Rightarrow \neg(\exists k \in \lambda_1. (k \neq i) \land ((k \leftarrow j) \lor (k \rightarrow j))) \) then Right-Shift
13: else Right-Pass
14: else
15: elif \( O_d \Rightarrow \neg(\exists k \in \lambda_1. (k \leftarrow j) \lor (k \rightarrow j)) \) then No-Shift
16: elif \( (\exists h. (h \rightarrow i) \in A) \) and \( (O_d \Rightarrow \neg(\exists k \in \beta. (i \rightarrow k))) \) then No-Reduce
17: else No-Pass
18: return \( A \)

The algorithm takes a sentence as input and produces a set of labeled dependency arcs in the sentence
as output. It starts by initializing the parsing state (line 1) and terminates when \( \beta \) becomes empty (line 2). If \( \lambda_1 \) is empty, it performs No-Shift \( d \) (lines 3-4). If \( O_d \) predicts that \( w_j \) is the head of \( w_i \)
with a dependency label \( l \) (line 5), it performs either No-Shift \( d \) if \( w_i \) is the root (line 6), No-Pass
if \( w_i \) already has the head or is an ancestor of \( w_j \) (line 7), Left-Reduce \( l \) if \( O_d \) predicts that \( w_i \) is
not the head of any token in \( \beta \) (line 8), or Left-Pass \( l \) (line 9). If \( O_d \) predicts that \( w_i \) is the head
of \( w_j \) with a dependency label \( l \) (line 10), it performs either No-Pass if \( w_j \) already has the head or
is an ancestor of \( w_i \) (line 11), Right-Shift \( n \) if \( O_d \) predicts that there is no dependency between
\( w_j \) and any token in \( \lambda_1 \) other than \( w_i \) (line 12), or Right-Pass \( l \) (line 13). If \( O_d \) predicts that there
is no dependency between \( w_i \) and \( w_j \) (line 14), it performs No-Shift if \( O_d \) predicts that there is no dependency between \( w_j \) and any token in \( \lambda_1 \) (line 15), No-Reduce if \( w_i \) already has the head and is predicted not to be the head of any token in \( \beta \) by \( O_d \) (line 16), or No-Pass. Finally, the algorithm returns a set \( A \) containing all labeled dependency arcs in \( S \).

The root, single head, and acyclic properties of a well-formed dependency graph in Section 2.1.2.1 are ensured by the conditions in lines 6, 7, and 11. The connected property, on the other hand, is ensured during post-processing (Section 5.4). Note that this algorithm performs only non-projective parsing without lines 8, 12, 15, and 16, which is equivalent to Covington’s algorithm. It is worth mentioning the soundness and completeness of our parsing algorithm (Shieber et al., 1995). Let \( T_k(s) = \{t_1, \ldots, t_k\} \) be a transition sequence generated by our algorithm for a sentence \( s \), and \( G(T_k(s)) \) be the dependency graph derived by \( T_k(s) \). A transition-based dependency parsing algorithm is sound if and only if for every sentence \( s \) and every transition sequence \( T_k(s) \), the root, single head, and acyclic properties are satisfied in \( G(T_k(s)) \) (Nivre, 2008). The soundness of our algorithm can be proved by induction as follows:

- **Base:** \( G(T_0(s)) \) satisfies all three properties for \( T_1(s) \).

- **Inductive:** Assume that \( G(T_k(s)) \) satisfies all three properties for \( T_k(s) \), where \( k > 1 \). Let \( T_{k+1}(s) \) be \( \{t_1, \ldots, t_{k+1}\} \), where \( t_{k+1} \) is one of the transitions in Table 5.3. If \( t_{k+1} \) is either a LEFT-*l or RIGHT-*l transition, a dependency arc \( \delta \) generated by this transition preserves all three properties because of the preconditions in Table 5.2. If \( t_{k+1} \) is a No-*l transition, no dependency arc is generated. This makes \( G(T_{k+1}(s)) \) either \( G(T_k(s)) \) or \( G(T_k(s)) \cup \{\delta\} \); thus, \( G(T_{k+1}(s)) \) satisfies all three properties.

A transition-based dependency parsing algorithm is complete if and only if for every sentence \( s \) and every well-formed dependency graph \( G \) for \( s \), there is a transition sequence \( T(s) \) generated by the algorithm such that \( G = G(T(s)) \) (Nivre, 2008). The proof of completeness for our algorithm comes free from the proof of completeness for Nivre’s list-based algorithm (Nivre, 2008, 5.1) because our algorithm can generate any transition sequence that Nivre’s list-based algorithm generates.
Table 5.4: Parsing states generated by Algorithm 5.1 for the example.

Table 5.4 shows a list of parsing states generated by Algorithm 5.1 for the example, assuming that the oracle $O_d$ always makes correct decisions. After $w_3$ and $w_4$ are compared, $w_3$ is removed from $\lambda_1$ (state 4) so it is no longer compared to any other token in $\beta$ (states 9 and 13). If $w_3$ were the head of any token in $\beta$, LEFT-PASS would be performed, in which case, $w_3$ would be moved to $\lambda_2$ instead.

After $w_2$ and $w_4$ are compared, $w_2$ is moved to $\lambda_2$ (state 5) so it can be compared to other tokens in $\beta$ (state 10). After $w_1$ and $w_4$ are compared, $*$-SHIFT$^n$ is performed (state 6) because there is no dependency between $w_4$ and any other token in $\lambda_1$. On the other hand, $*$-PASS is performed after $w_4$ and $w_6$ are compared (state 9) because there is a dependency between $w_6$ and $w_2$ in $\lambda_1$ (state 10). After $w_6$ and $w_7$ are compared, $w_6$ is removed from $\lambda_1$ (state 12) because it is no longer needed for the later parsing states.
5.3  Bootstrapping

5.3.1  Bootstrapping parse history

Transition-based parsing, in comparison to graph-based parsing, has the advantage of using the parse history as features to make more accurate predictions without increasing parsing complexity. When $w_i$ and $w_j$ are compared in any parsing state ($w_i$ is the last token in $\lambda_1$ and $w_j$ in the first token in $\beta$; see Table 5.1), the subtree and head information of these tokens is partially provided by earlier parsing states. Figure 5.2 illustrates the range of subtree and head information given to $w_i$ and $w_j$.

![Figure 5.2: The range of subtree and head information, where $i < j$, and the dotted line indicates ancestors in the head relation.](image)

Graph-based parsing can also take advantage of using the parse history. This is done by performing higher-order parsing, which improves parsing accuracy but also increases parsing complexity (Carreras, 2007; Koo and Collins, 2010; Rush and Petrov, 2012). Transition-based parsing is attractive because it can use parse information from earlier parsing states without increasing parsing complexity. The qualification is that parse information provided by gold-standard dependency trees during training may not give the same type of features provided by automatically generated dependency trees during decoding. This can confuse a statistical model trained on features derived only from the gold-standard trees. The problem becomes more severe as the discrepancies between gold-standard and automatically generated trees get larger.

To reduce the gap between gold-standard and automatically generated trees, a bootstrapping technique is applied during training. First, a statistical parsing model is trained using gold-standard

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3 Higher-order, non-projective, graph-based dependency parsing is NP-hard without performing approximation.
trees. Next, the training data is parsed using this model. During parsing, new features are extracted for each parsing state, which consist of parse information derived from an automatically generated tree, then a training instance is created by joining these features with a gold-standard label. The gold-standard label is achieved by consulting the relation between $w_i$ and $w_j$ in the gold-standard tree. Figure 5.3 shows an automatically generated tree for the example in Table 5.4, where the **DOBJ** dependency is incorrectly predicted. Given a parsing state where $w_i = \text{wanted}$ and $w_j = \text{see}$, the oracle $O_d$ would predict a **RIGHT-SHIFT** transition. However, according to the gold-standard tree, this is not the correct transition to perform; a **RIGHT-PASS** transition should be performed given this parsing state (state 9 in Table 5.4). Thus, the gold-standard label, **RIGHT-PASS**, and features extracted from the tree in Figure 5.3 are joined to create a training instance for this state. The parsing state is then updated with the incorrectly predicted transition, **RIGHT-SHIFT**$, so the algorithm can continue parsing (with the incorrect parse).

![Figure 5.3: An automatically generated tree for the example in Table 5.4. The **DOBJ** dependency is incorrectly predicted compared to the gold-standard tree in Table 5.4.](image)

When the parsing is done, a different parsing model is built using the training instances induced by the previous model. This procedure is repeated until a certain stopping criterion is met, which is determined by cross-validation. For each iteration, cross-validation is performed to check if the average parsing accuracy of the current cross-validation set is higher than the one from the previous iteration. The procedure is stopped when the parsing accuracy on the cross-validation set starts decreasing. During decoding, only the last model is used for parsing. Figure 5.4 shows a flowchart of our bootstrapping technique.
The concept of using automatically generated data for training is not new; it is common to use automatically generated POS tags for training, which is known to be more useful than using gold-standard POS tags for dependency parsing. Here, we go one step farther by bootstrapping parse information. Our experiments show that this bootstrapping technique gives a significant improvement to parsing accuracy (Section 5.6.1). This technique is not limited to transition-based dependency parsing but can be applied to other NLP components such as a POS tagger or an NP chunker that make incremental updates in predictions.

![Flowchart of our bootstrapping technique.](image)

**Figure 5.4:** A flowchart of our bootstrapping technique.

### 5.3.2 Related work

Daumé et al. (2009) presented a learning algorithm, called SEARN, for integrating search and learning to solve complex structured prediction problems. Our bootstrapping technique can be viewed as a simplified version of SEARN. During training, SEARN iteratively creates a set of new cost-sensitive examples using a known policy. In our case, the new examples are training instances consisting of
parse information derived from automatically generated trees induced by the previous model. Our technique is simplified because the new examples are not cost-sensitive. Furthermore, Searn interpolates the current policy with the previous policy whereas we do not perform such interpolation. During decoding, Searn generates a sequence of decisions and makes a final prediction. In our case, the decisions are predicted dependency arcs and the final prediction is a dependency tree. Searn has been successfully adapted to several NLP tasks such as named entity recognition, syntactic chunking, and POS tagging. To the best of our knowledge, this is the first time that this idea has been applied to transition-based dependency parsing and shown improved results.

Brill (1995) introduced transformation-based learning that starts with simple rules for predicting certain values (e.g., POS tags, transitions) using baseline features, applies transformations to the features using a set of rule templates, reconstructs the rules using the transformed features, and selects transformations that derive the best rules for predicting the values. The transformations are applied repeatedly until they do not affect or hurt the performance. Transformation-based learning is similar to our bootstrapping approach in the sense that it iteratively transforms features to achieve better results and stops when no more benefit is found from the transformations.

Zhang and Clark (2008) suggested a transition-based projective dependency parsing algorithm that kept $B$ different sequences of parsing states and chose the one with the highest score. They used beam search and showed a worst-case parsing complexity of $O(n)$ given a fixed size of beam. Their learning mechanism, using the structured perceptron algorithm, involves training on automatically derived parsing states that closely resemble potential states encountered during our decoding.

5.4 Post-processing

Just like many other transition-based dependency parsing algorithms, our parsing algorithm does not guarantee that the parse output is a connected tree. This implies that after the algorithm is finished, there can be headless tokens. For each token $w_p$ for which the algorithm could not find the head during parsing, the same oracle $O_d$ is used again to predict the head of $w_p$ but this time, $w_p$ is compared to all other tokens which may have been skipped during parsing. For each comparison,
the oracle keeps track of the head candidate with the highest score and makes it the head of \( w_p \). Any dependency which creates a cyclic relation is avoided during post-processing. Although this post-processing technique is simple, it not only ensures the connected property (Section 2.1.2.1), but also improves parsing accuracy (Section 5.6.1).

The \texttt{postProcess}(D) method in Algorithm 5.2 takes a dependency forest \( D \) and adds dependency arcs for all headless tokens in \( D \). The head of each headless token is initialized to the artificial root, \( w_0 \) (line 3). If the oracle \( O_d \) predicts a dependency arc between \( w_i \) and \( w_j \) with a label \( l \) and a score \( s_i \) (\( 0 \leq i < j \)) and if \( w_j \) is not an ancestor of \( w_i \), a dependency arc with the highest score is kept (lines 4-8). Similarly, if \( O_d \) predicts a dependency arc between \( w_j \) and \( w_k \) with a label \( l \) and a score \( s_k \) (\( j < k \leq n \)) and if \( w_j \) is not an ancestor of \( w_k \), a dependency arc with the highest score is kept (lines 9-13). The dependency arc with the overall highest score is added to \( A \) as the head of \( w_j \). Notice that the \texttt{postProcess}(D) method process headless tokens left-to-right. The final parse output may vary if headless tokens are processed right-to-left, which we will explore in the future.

**Algorithm 5.2 : postProcess(D)**

**Input:** A dependency forest \( D \).

1. \( N \leftarrow \text{an ordered list of headless tokens in } D \) \# e.g., \( N \leftarrow [w_2, w_3, w_5] \)
2. \textbf{for} \( w_j \) \textbf{in} \( N \) \textbf{do}
3. \( (a_m, s_m) \leftarrow (0 \xrightarrow{l} j, 0) \), where \( l \leftarrow \text{ROOT} \)
4. \( i \leftarrow (j - 1) \)
5. \textbf{while} \( i \geq 0 \) \textbf{do} \# \( 0 \) is the ID of the artificial root
6. \( \text{if} \ (O_d \Rightarrow (i \xrightarrow{l} j, s_i)) \text{ and } ((i \xleftarrow{\ast} j) \notin A) \text{ and } (s_i > s_m) \text{ then} \)
7. \( (a_m, s_m) \leftarrow (i \xrightarrow{l} j, s_i) \)
8. \( i \leftarrow (i - 1) \)
9. \( k \leftarrow (j + 1) \)
10. \textbf{while} \( k \leq n \) \textbf{do} \# \( n \) is the ID of the rightmost token in \( D \)
11. \( \text{if} \ (O_d \Rightarrow (j \xrightarrow{l} k, s_k)) \text{ and } ((j \xleftarrow{\ast} k) \notin A) \text{ and } (s_k > s_m) \text{ then} \)
12. \( (a_m, s_m) \leftarrow (j \xrightarrow{l} k, s_k) \)
13. \( k \leftarrow (k + 1) \)
14. \( A \leftarrow (A \cup a_m) \)
5.5 Features

Table 5.5 shows the feature templates used for our dependency parsing experiments. \( \lambda_1[0] \) and \( \beta[0] \) are the last token in \( \lambda_1 \) and the first token in \( \beta \), which are equivalent to \( w_i \) and \( w_j \) in Table 5.1, respectively. \( \lambda_1[n] \) and \( \beta[n] \) are the \( n \)'th to the last token in \( \lambda_1 \) and the \( n \)'th token in \( \beta \), respectively. \( w_{x+n} \) is the token whose distance from \( w_x \) is \( n \). For instance, \( w_{i-1} \) and \( w_{i+1} \) are the tokens prior and next to \( w_i \), respectively. Note that \( w_{i-n} \) may or may not be equivalent to \( \lambda_1[n] \). It is possible that \( w_{i-n} \) is already removed by the \( *\text{-REDUCE} \) transition from a previous parsing state (Section 5.2.1), so it no longer exists in any list and can only be retrieved from the original sentence. \( hd(x) \) stands for the head of \( x \). \( ld(x) \) and \( rd(x) \) stand for the leftmost and rightmost dependents of \( x \), respectively.

<table>
<thead>
<tr>
<th>Token</th>
<th>Form</th>
<th>Lemma</th>
<th>POS</th>
<th>Deprel</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \lambda_1[0] )</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>( \lambda_1[1] )</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>( \lambda_1[2] )</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>( hd(\lambda_1[0]) )</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>( ld(\lambda_1[0]) )</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>( rd(\lambda_1[0]) )</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>( \beta[0] )</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>( \beta[1] )</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>( \beta[2] )</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>( \beta[3] )</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>( ld(\beta[0]) )</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>( w_{i-2} )</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>( w_{i-1} )</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>( w_{i+1} )</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>( w_{i+2} )</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>( w_{j-2} )</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>( w_{j-1} )</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
</tbody>
</table>

Table 5.5: Feature templates for dependency parsing.

The Form, Lemma, POS, and Deprel columns indicate the word form, lemma, POS tag, and dependency label features of the corresponding token. These features are used either individually or jointly (e.g., POS tags of both \( \lambda_1[0] \) and \( \beta[0] \) make one feature). Additionally, three binary features are used, which check if \( w_i \) is the leftmost token in the original sentence, if \( w_j \) is the rightmost token in the original sentence, and if \( w_i \) and \( w_j \) are adjacent.
5.6 Experiments

5.6.1 Accuracy comparisons

Tables 5.6 and 5.7 show labeled attachment scores for all trees achieved by the WSJ and OntoNotes models, respectively. The Baseline model uses the parsing algorithm in Section 5.2.3. The Baseline+ model is the Baseline model with the post-processing in Section 5.4. The ClearNLP model is the Baseline+ model with the bootstrapping technique in Section 5.3. The C&N’09 and C&P’11 models are the transition-based dependency parsing approaches introduced by Choi and Nicolov (2009) and Choi and Palmer (2011a), respectively (see Section 5.2.2). These models use the same machine learning algorithm (Liblinear L2-L1 svm, see Section 3.2), post-processing, and bootstrapping technique as the ClearNLP model. We use feature templates optimized for the best results achieved with the CoNLL’09 shared task data for English (Hajič et al., 2009).

The ClearNLP model is compared against two state-of-the-art dependency parsers, MaltParser and MSTParser. For MaltParser, a non-projective transition-based parsing algorithm using Swap transitions is used for parsing (Nivre, 2009) and Liblinear multi-class support vector classification is used for learning (Crammer and Singer, 2002). We use feature templates provided by the MaltParser team instead of their default templates, which show improved parsing accuracy. For MSTParser, a non-projective graph-based parsing algorithm, Chu-Liu-Edmonds algorithm, is used for parsing (McDonald et al., 2005) and the margin infused relaxed algorithm (MIRA) is used for learning (Crammer and Singer, 2003). Only 1st-order features are used for MSTParser; 2nd-order features create a huge feature space for building the OntoNotes model, requiring too much memory for our machine. Thus, only the 1st-order features are used for our experiments; therefore, one must consider that parsing accuracy is expected to be higher but parsing speed is expected to be slower with the 2nd order features for MSTParser. Note that neither MaltParser nor MSTParser have been optimized for our experiments. Their results are there to give a sense of how well our approach performs against these state-of-the-art parsers off-the-shelf but not for absolute comparisons.

4 See Mcdonald and Pereira (2006) for more details about the 2nd order features.
## Table 5.6: Labeled attachment scores for all trees from the WSJ models (in %).

<table>
<thead>
<tr>
<th>Model</th>
<th>BC</th>
<th>BN</th>
<th>MD</th>
<th>MP</th>
<th>MZ</th>
<th>SH</th>
<th>TC</th>
<th>WB</th>
<th>Avg.</th>
<th>Avg.o</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>75.38</td>
<td>80.75</td>
<td>78.34</td>
<td>71.49</td>
<td>80.19</td>
<td>60.50</td>
<td>68.58</td>
<td>78.68</td>
<td>86.94</td>
<td>74.18</td>
</tr>
<tr>
<td>Baseline+</td>
<td>75.73</td>
<td>81.13</td>
<td>78.69</td>
<td>72.10</td>
<td>80.64</td>
<td>60.77</td>
<td>69.82</td>
<td>78.98</td>
<td>87.18</td>
<td>74.68</td>
</tr>
<tr>
<td>ClearNLP</td>
<td>76.04</td>
<td>82.02</td>
<td>79.07</td>
<td>72.84</td>
<td>81.30</td>
<td>63.44</td>
<td>70.19</td>
<td>79.56</td>
<td>88.10</td>
<td>75.50</td>
</tr>
<tr>
<td>C&amp;N’09</td>
<td>75.85</td>
<td>81.54</td>
<td>78.76</td>
<td>72.84</td>
<td>80.86</td>
<td>63.61</td>
<td>70.19</td>
<td>79.56</td>
<td>88.10</td>
<td>75.23</td>
</tr>
<tr>
<td>C&amp;P’11</td>
<td>75.96</td>
<td>81.55</td>
<td>79.00</td>
<td>72.80</td>
<td>81.10</td>
<td>63.55</td>
<td>69.70</td>
<td>79.45</td>
<td>88.03</td>
<td>75.34</td>
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<td>79.77</td>
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<td>68.28</td>
<td>77.86</td>
<td>86.49</td>
<td>74.10</td>
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<tr>
<td>MSTParser</td>
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<td>79.84</td>
<td>77.34</td>
<td>72.39</td>
<td>79.31</td>
<td>63.44</td>
<td>70.19</td>
<td>79.56</td>
<td>88.10</td>
<td>75.50</td>
</tr>
</tbody>
</table>

## Table 5.7: Labeled attachment scores for all trees from the OntoNotes models (in %).

<table>
<thead>
<tr>
<th>Model</th>
<th>BC</th>
<th>BN</th>
<th>MZ</th>
<th>NW</th>
<th>TC</th>
<th>WB</th>
<th>Med.</th>
<th>Avg.</th>
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<td>Baseline</td>
<td>85.54</td>
<td>85.00</td>
<td>85.26</td>
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<td>81.36</td>
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<td>80.81</td>
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<td>Baseline+</td>
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<td>85.48</td>
<td>87.77</td>
<td>81.89</td>
<td>82.13</td>
<td>81.15</td>
<td>74.56</td>
<td>62.17</td>
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<tr>
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<td>86.33</td>
<td>89.00</td>
<td>83.39</td>
<td>82.58</td>
<td>81.72</td>
<td>75.57</td>
<td>64.98</td>
</tr>
<tr>
<td>C&amp;N’09</td>
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<td>85.84</td>
<td>88.66</td>
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<td>82.33</td>
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<td>82.31</td>
<td>81.53</td>
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<td>MaltParser</td>
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<td>81.76</td>
<td>80.87</td>
<td>80.27</td>
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<td>80.85</td>
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</tbody>
</table>

The Avg. and Avg.o columns show the micro average labeled attachment scores for in-genre and out-of-genre experiments. For the WSJ models, the score of NW is measured for Avg. and the micro average of all other corpora are measured for Avg.o. For the OntoNotes models, the micro averages of the OntoNotes and Medical corpora are measured for Avg. and Avg.o, respectively. The Baseline+ models show improvements over the Baseline models for all experiments. The ClearNLP models show additional improvements over the Baseline+ models; the improvements are greater for out-of-genre experiments (e.g., 1.45% improvement for Avg.o in Table 5.7), which indicates that our bootstrapping technique is more effective where automatic parse results are poor. The ClearNLP models show higher scores than the C&N’09 and C&P’11 models for both in-genre and out-of-genre experiments; all differences are statistically significant (McNemar, $p < 0.01$) except for the one between the C&P’11 and ClearNLP models for Avg. in Table 5.6. More importantly, the ClearNLP model uses about $\frac{1}{3}$ the number of features used by the C&N’09 and C&P’11 models (e.g., for the OntoNotes models, 5.43M, 4.84M, and 0.97M features are used by the C&N’09, C&P’11, and ClearNLP models, respectively), indicating that the ClearNLP model can perform as accurately as
the other two models using a much smaller set of features. Compared to MaltParser and MSTParser, the ClearNLP models again show higher scores for both in-genre and out-of-genre experiments. We believe that it is possible to improve MaltParser’s parsing accuracy by applying our bootstrapping and post-processing techniques, which can bring its performance closer to ours, whereas it is more difficult to apply these techniques to MSTParser, which is based on a graph-based parsing algorithm.

<table>
<thead>
<tr>
<th>Model</th>
<th>BC</th>
<th>BN</th>
<th>MD</th>
<th>MP</th>
<th>MZ</th>
<th>SH</th>
<th>TC</th>
<th>WB</th>
<th>Avg. i</th>
<th>Avg. o</th>
</tr>
</thead>
<tbody>
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<td>83.42</td>
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<td>81.46</td>
<td>88.57</td>
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<td>76.12</td>
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<td>89.68</td>
<td><strong>79.36</strong></td>
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<td>84.04</td>
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<td>89.50</td>
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</tr>
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<td>83.23</td>
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<td>74.69</td>
<td>81.14</td>
<td>88.23</td>
<td>78.29</td>
</tr>
<tr>
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<td>81.84</td>
<td><strong>77.91</strong></td>
<td>83.44</td>
<td><strong>68.74</strong></td>
<td><strong>77.15</strong></td>
<td>81.92</td>
<td>88.36</td>
<td>79.26</td>
</tr>
</tbody>
</table>

Table 5.8: Unlabeled attachment scores for all trees from the WSJ models (in %).

<table>
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<th>MZ</th>
<th>NW</th>
<th>TC</th>
<th>WB</th>
<th>MD</th>
<th>MP</th>
<th>SH</th>
<th>Avg. i</th>
<th>Avg. o</th>
</tr>
</thead>
<tbody>
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<td>66.60</td>
<td>86.54</td>
<td>76.26</td>
</tr>
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<td>87.68</td>
<td>89.11</td>
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<td>84.40</td>
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<td>78.87</td>
<td>66.90</td>
<td>86.83</td>
<td>76.65</td>
</tr>
<tr>
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<td><strong>87.86</strong></td>
<td><strong>88.49</strong></td>
<td>90.32</td>
<td><strong>86.17</strong></td>
<td><strong>84.87</strong></td>
<td><strong>84.32</strong></td>
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</tr>
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<td>90.06</td>
<td>85.61</td>
<td>84.67</td>
<td>83.75</td>
<td>78.96</td>
<td>69.32</td>
<td>87.48</td>
<td>77.43</td>
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<td>89.06</td>
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<td>83.47</td>
<td>83.10</td>
<td>79.59</td>
<td>69.67</td>
<td>86.40</td>
<td>77.54</td>
</tr>
<tr>
<td>MSTParser</td>
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<td>87.10</td>
<td>89.23</td>
<td>85.29</td>
<td>84.08</td>
<td>83.72</td>
<td>79.49</td>
<td><strong>70.36</strong></td>
<td>86.70</td>
<td>77.94</td>
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</tbody>
</table>

Table 5.9: Unlabeled attachment scores for all trees from the OntoNotes models (in %).

Tables 5.8 and 5.9 show unlabeled attachment scores for all trees achieved by the WSJ and OntoNotes models, respectively. The ClearNLP model shows the most robust results across genres. For all out-of-genre experiments, the ClearNLP models show higher scores than the other models. For in-genre experiments, the ClearNLP model shows a higher score than all other models in Table 5.9; however, the C&P’11 model shows a higher score than the ClearNLP model in Table 5.8. We suspect that this is because the additional features used by the C&P’11 model help make more accurate predictions for Avg. i in Table 5.8, which is trained and evaluated on the same corpus (WSJ), whereas they give less impact on other corpora. Notice that MSTParser consistently performs more accurately
than MaltParser except for MP in Table 5.9, which is not the case for labeled attachment scores in Tables 5.6 and 5.7. This implies that graph-based parsing has an advantage in finding arcs whereas transition-based parsing has an advantage in finding labels.

Tables 5.10 and 5.11 show labeled attachment scores and Tables 5.12 and 5.13 show unlabeled attachment scores for non-projective trees achieved by the WSJ and OntoNotes models, respectively. A non-projective tree is a dependency tree consisting of at least one non-projective dependency. The Trees row shows the number of non-projective trees in each genre. There are not many non-projective trees in our corpora; English is a rigid word-order language that does not contain many non-projective dependencies. In the future, we will explore the possibility of comparing parse results for non-projective trees with languages such as Czech (Hajič et al., 2000), Danish (Kromann, 2003), and Sloven (Džeroski et al., 2006) that contain more non-projective dependencies. Note that our previous approach, C&P’11, was evaluated on the CoNLL’09 shared task data for Czech and showed the second highest score against other parsers (Choi and Palmer, 2011a). Considering that our current approach, ClearNLP, gives comparative results to our previous approach, it is expected to perform well for Czech and other languages as well.

<table>
<thead>
<tr>
<th>Model</th>
<th>BC</th>
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<th>MD</th>
<th>MP</th>
<th>MZ</th>
<th>SH</th>
<th>TC</th>
<th>WB</th>
<th>Avg. i</th>
<th>Avg. o</th>
</tr>
</thead>
<tbody>
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<td>73.87</td>
</tr>
<tr>
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<td>72.95</td>
<td>82.83</td>
<td>73.41</td>
</tr>
<tr>
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<td>72.56</td>
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<td>61.90</td>
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<td>80.89</td>
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<tr>
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</table>

Table 5.10: Labeled attachment scores for non-projective trees from the WSJ models (in %).

<table>
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<tr>
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<th>WB</th>
<th>MD</th>
<th>MP</th>
<th>SH</th>
<th>Avg. i</th>
<th>Avg. o</th>
</tr>
</thead>
<tbody>
<tr>
<td>ClearNLP</td>
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<td><strong>86.47</strong></td>
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<td><strong>77.69</strong></td>
<td>78.74</td>
<td>76.13</td>
<td>76.09</td>
<td><strong>80.61</strong></td>
<td>77.10</td>
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<td>C&amp;N’09</td>
<td><strong>82.97</strong></td>
<td><strong>80.23</strong></td>
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<td>85.26</td>
<td>76.54</td>
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<td>80.11</td>
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<td>77.37</td>
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<td>76.04</td>
<td>75.68</td>
<td>80.42</td>
<td><strong>77.57</strong></td>
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<tr>
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<td>72.88</td>
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<td>77.88</td>
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</table>

Table 5.11: Labeled attachment scores for non-projective trees from the OntoNotes models (in %).
Table 5.12: Unlabeled attachment scores for non-projective trees from the WSJ models (in %).

<table>
<thead>
<tr>
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<th>BC</th>
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<th>MD</th>
<th>MP</th>
<th>MZ</th>
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<th>WB</th>
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<th>Avg,o</th>
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Table 5.13: Unlabeled attachment scores for non-projective trees from the OntoNotes models (in %).

<table>
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<th>NW</th>
<th>TC</th>
<th>WB</th>
<th>MD</th>
<th>MP</th>
<th>SH</th>
<th>Avg,</th>
<th>Avg,o</th>
</tr>
</thead>
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<td><strong>81.05</strong></td>
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<td>76.22</td>
<td><strong>79.63</strong></td>
<td>81.17</td>
<td>78.32</td>
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</table>

The ClearNLP model shows the highest score for Avg,o whereas the C&P’11 model shows the highest score for Avg,i in Tables 5.10 and 5.12. However, their results are reversed in Tables 5.11 and 5.13; the ClearNLP model shows the highest score for Avg,i whereas the C&P’11 model shows the highest score for Avg,o. This is probably because the ClearNLP model makes early *-SHIFT and *-REDUCE transitions that hurt performance in finding some non-projective dependencies, but more thorough study needs to be done to make sure which transitions help or hurt performance in finding what kind of non-projective dependencies.

5.6.2 Speed comparisons

Parsing speeds are measured by running each system on a mixture of all data. All systems are written in Java; C&N’09 and C&P’11 are implemented in the same project called ClearParser, and the other systems are implemented in their own projects. Table 5.14 shows speed comparisons between all five systems; the top and bottom five rows show results from the WSJ and OntoNotes models, respectively. The T# columns show how many milliseconds each system takes for parsing one sentence in 5 trials, and the Avg column shows the average parsing speeds of the middle three

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5 ClearParser: clearparser.googlecode.com
trials, and the Trees column shows how many trees are parsed per second. The transition-based
parsing approaches, the top four systems, take about 1 - 2 milliseconds per sentence, whereas the
graph-based parsing approach, MSTParser, shows over 30 times slower parsing speeds than the
transition-based parsing approaches. Our system takes about 1.16 - 1.28 milliseconds per sentence,
which is fast but not as fast as C&P’11. This contradicts our transition comparison in Figure 5.1; it
is caused by an implementation difference between ClearParser and ClearNLP. ClearParser assumes
input and output to be a tree so it is optimized for generating a tree structure whereas ClearNLP
does not make such an assumption so that it is designed for generating a graph structure, which is
more complicated and gives higher overheads during runtime.

<table>
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<tr>
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<td>1.28</td>
<td>1.28</td>
<td>1.28</td>
<td>1.29</td>
<td>1.30</td>
<td>1.28</td>
<td>780</td>
</tr>
<tr>
<td>C&amp;N’09</td>
<td>1.23</td>
<td>1.23</td>
<td>1.27</td>
<td>1.27</td>
<td>1.46</td>
<td>1.26</td>
<td>795</td>
</tr>
<tr>
<td>C&amp;P’T1</td>
<td>1.06</td>
<td>1.07</td>
<td>1.08</td>
<td>1.21</td>
<td>1.22</td>
<td>1.12</td>
<td>892</td>
</tr>
<tr>
<td>MaltParser</td>
<td>2.12</td>
<td>2.13</td>
<td>2.14</td>
<td>2.16</td>
<td>2.17</td>
<td>2.14</td>
<td>467</td>
</tr>
<tr>
<td>MSTParser</td>
<td>65.60</td>
<td>66.36</td>
<td>66.77</td>
<td>67.73</td>
<td>67.79</td>
<td>66.62</td>
<td>15</td>
</tr>
</tbody>
</table>

Table 5.14: Parsing speeds (in ms.). The top and the bottom five rows show results from the WSJ
and OntoNotes models, respectively.

Figure 5.5 shows average parsing speeds with respect to sentence lengths achieved by the WSJ (the
top figure) and OntoNotes (the bottom figure) models. MSTParser is excluded from this comparison
because its parsing speed is noticeably slower than the other four systems. All four systems show
similar growth rates that are close to linear although some systems begin to show curves towards
the end (e.g., sentence groups 70 and 80). Considering there are not many sentences in these groups,
all four systems show linear parsing speeds in practice. Notice that ClearNLP and MaltParser show
very similar growth rates with the OntoNotes models whereas that is not really the case with the
WSJ models. This is probably because they start performing a similar number of non-projective
transitions (∗-PASS for ClearNLP and SWAP for MaltParser) with the OnteNotes models where non-projective dependencies are classified more accurately.

Figure 5.5: Average parsing speeds with respect to sentence lengths. The top and the bottom figures show parsing speeds achieved by the WSJ and OntoNotes models, respectively. The bottom table shows the number of sentences in each group. ————: MaltParser, ———: C&N’09, ———: C&P’11, ————: ClearNLP.

<table>
<thead>
<tr>
<th>Group</th>
<th>≤10</th>
<th>≤20</th>
<th>≤30</th>
<th>≤40</th>
<th>≤50</th>
<th>≤60</th>
<th>≤70</th>
<th>≤80</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sentences</td>
<td>9,789</td>
<td>6,159</td>
<td>2,966</td>
<td>1,313</td>
<td>479</td>
<td>178</td>
<td>75</td>
<td>30</td>
</tr>
</tbody>
</table>
Chapter 6

Semantic Role Labeling

6.1 Overview

Recently, dependency-based semantic role labeling has demonstrated two advantages over constituent-based semantic role labeling. First, semantic role labeling is often performed after syntactic parsing, either dependency parsing or constituent parsing, because it uses syntactic parses as its input. Syntactic parsing is usually considered a bottleneck to semantic role labeling in terms of execution time; however, since dependency parsing is much faster than constituent parsing (Cer et al., 2010), this becomes less of an issue. Second, dependency structures are more similar to predicate argument structures than constituent structures because they can directly define relations between predicates and arguments with labeled arcs (see Figures 6.2 and 6.3). Unlike constituent-based SRL that maps phrases to semantic roles, dependency-based SRL maps head-tokens to semantic roles and considers the subtrees of the head-tokens as arguments. This may lead to a concern about getting the actual semantic chunks back, but previous studies have shown that it is possible to recover the original chunks from the head-tokens with minimal loss (Ekeklint and Nivre, 2007; Choi and Palmer, 2010a).

We use predicate argument structures in PropBank for our experiments (Palmer et al., 2005). For both constituent-based and dependency-based SRL, it is possible to reduce the search space by pruning argument candidates. This is because the PropBank guidelines generally restrict argument candidates to constituents within the same domain of locality as their predicates (e.g., siblings of the predicates in constituent trees, direct dependents of the predicates in dependency trees); thus, a
semantic role labeler does not need to search beyond these candidates for argument identification.\footnote{There are exceptional cases such as verb-particle constructions, prepositional phrases, coordinations, etc.} This pruning strategy works well when semantic role labeling is performed on gold-standard trees; however, it does not work as well when automatically generated trees are used. This motivates the development of an enhanced pruning algorithm that gives better recall for argument identification, yet effectively prunes out argument candidates.

Traditionally, semantic role labeling is done in two steps, argument identification and argument classification (Gildea and Jurafsky, 2002; Johansson and Nugues, 2008). Argument identification is the task of finding arguments of each predicate, and argument classification is the task of assigning a semantic role to each argument with respect to the predicate. This is from a general belief that each task requires a different set of features (Xue and Palmer, 2004), and training these tasks in a pipeline takes less time than training them as a joint-inference task. However, recent machine learning algorithms can train a large scale feature space quickly (Hsieh et al., 2008). Furthermore, Choi and Palmer (2011b) have shown that this joint-inference approach performs as accurately as the pipeline approach without using two separate sets of features. Thus, argument identification and classification is performed jointly in our approach.

This chapter first illustrates how PropBank predicate argument structures, annotated on constituent trees, can be mapped to dependency trees (Section 6.2). An enhanced argument pruning algorithm, called a conditional higher-order argument pruning algorithm, is introduced next (Section 6.3). Our experiments show that this new pruning algorithm improves both argument identification and classification, yet keeps the average number of argument candidates close to the original pruning algorithm (Section 6.5).
6.2 Semantic roles in dependency structure

6.2.1 Predicate argument structures in PropBank

PropBank is a corpus in which arguments are annotated with the semantic roles they play with respect to their predicates (Palmer et al., 2005). Predicates can be verbs, including light verbs (Hwang et al., 2010), nouns, or even adjectives (Hawwari et al., 2011). Each predicate encompasses one or more senses defining their own predicate argument structures in PropBank. For example, the verb predicate *open* contains three senses, \{open.01, open.02, open.03\}, and each sense defines its own argument structure (Figure 6.1). Thus, the verb *open* in “He *opened* the door with his foot at ten” takes the first sense, open.01, and forms the argument structure described in Figure 6.2.

![Figure 6.1: Three senses of the verb *open* and their argument structures in PropBank. The sense open.03 is for a verb-particle construction, *open up*.](image1)

![Figure 6.2: An example of a PropBank predicate argument structure. The verb predicate *open* is annotated with the sense open.01 and the argument structure containing three numbered arguments, ARG0, ARG1, and ARG2, and one modifier, ARGM-TMP.](image2)

PropBanks in most languages are annotated on top of constituent Treebanks except for Hindi where annotation is done on a dependency Treebank (Vaidya et al., 2011). When a constituent Treebank
is used, each argument is annotated on one or more phrasal nodes (indicated by dotted boxes in Figure 6.2). ARG0 and ARG1 represent an agent and a theme, respectively. ARG[0-4], called numbered arguments, are elements that frequently co-occur with their predicates. These numbered arguments do not always correspond to core arguments. For instance, PropBank annotates with his foot as a numbered argument, ARG2 (an instrument), which is considered an oblique argument in some other Linguistic theories (Van Valin, 1997, Chap. 3.2). Additionally, PropBank annotates general event modifiers such as a temporal adjunct with ARGM-* labels (e.g., ARGM-TMP). Section B.1 provides more details about the semantic role labels used in PropBank.

### 6.2.2 Syntactic and semantic dependencies

When a dependency Treebank is used for PropBanking, arguments are labeled on the head-tokens of the phrases instead. Head-tokens are retrieved by the headrules and heuristics described in Chapter 2. Figure 6.3 shows an example of a dependency tree annotated with the semantic arguments in Figure 6.2, where the top arcs show syntactic dependencies from the dependency conversion (Chapter 2) and the bottom arcs show semantic dependencies extracted from PropBank. The head-token of each argument phrase (indicated by a dotted box) has an incoming arc from its predicate with a PropBank label. For instance, door is the head-token of the NP, the door, so it becomes a semantic dependent of opened with the label, ARG1. This implies that the syntactic subtree of this head-token, the door, is a semantic argument of the predicate open with the semantic role, ARG1.

![Figure 6.3: A dependency tree annotated with the semantic arguments in Figure 6.2. The top arcs show syntactic dependencies from the dependency conversion in Chapter 2, and the bottom arcs show semantic dependencies extracted from PropBank.](image-url)
Semantic and syntactic dependencies are often aligned together. In Figure 6.3, *door* is a syntactic dependent, **DOBJ** (direct object), as well as a semantic dependent, **ARG1** (patient), of *opened*. Table 6.1 shows mappings between the semantic and syntactic dependencies in the OntoNotes Treebank. The **R-** and **C-** labels represent referent and continuous arguments, respectively (see Section 6.2.3 for more details about these labels).

<table>
<thead>
<tr>
<th>SRL</th>
<th>DEP</th>
<th>Diverge</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARG0</td>
<td>NSUBJ:66.13</td>
<td>30.31</td>
<td>158,931</td>
</tr>
<tr>
<td>ARG1</td>
<td>DOBJ: 34.88, NSUBJ: 21.71</td>
<td>12.69</td>
<td>245,924</td>
</tr>
<tr>
<td>ARG2</td>
<td>PREP:24.59, ACOMP:20.06</td>
<td>3.22</td>
<td>84,368</td>
</tr>
<tr>
<td>ARG3</td>
<td>PREP:41.78</td>
<td>6.07</td>
<td>5,572</td>
</tr>
<tr>
<td>ARG4</td>
<td>DIR:57.43, PREP:24.77</td>
<td>2.92</td>
<td>4,898</td>
</tr>
<tr>
<td>ARG5</td>
<td>NSUBJ:56.52</td>
<td>30.43</td>
<td>23</td>
</tr>
<tr>
<td>R-ARG0</td>
<td>NSUBJ:82.56</td>
<td>17.04</td>
<td>9,989</td>
</tr>
<tr>
<td>R-ARG1</td>
<td>NSUBJ:42.6, DOBJ:33.37</td>
<td>7.38</td>
<td>11,454</td>
</tr>
<tr>
<td>R-ARG2</td>
<td>ATTR:33.53</td>
<td>3.34</td>
<td>1,736</td>
</tr>
<tr>
<td>R-ARG3</td>
<td>NSUBJ:24.05</td>
<td>12.66</td>
<td>79</td>
</tr>
<tr>
<td>R-ARG4</td>
<td>DIR:78.46</td>
<td>0.00</td>
<td>65</td>
</tr>
<tr>
<td>C-ARG0</td>
<td>NSUBJ:34.91</td>
<td>23.08</td>
<td>169</td>
</tr>
<tr>
<td>C-ARG1</td>
<td>XCOMP:59.71</td>
<td>2.07</td>
<td>2,807</td>
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<tr>
<td>C-ARG2</td>
<td>PREP:38.14</td>
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<td>97</td>
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<tr>
<td>C-ARG3</td>
<td>PREP:42.86</td>
<td>7.14</td>
<td>14</td>
</tr>
<tr>
<td>C-ARG4</td>
<td>DIR:50, PREP:25</td>
<td>0.00</td>
<td>8</td>
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<tr>
<td>C-V</td>
<td>PRT:70.31</td>
<td>17.44</td>
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<tr>
<td>ARG-ADJ</td>
<td>AMOD:73.45</td>
<td>3.54</td>
<td>339</td>
</tr>
<tr>
<td>ARG-ADV</td>
<td>AVMOD:41.34, ADVCL:29.54</td>
<td>5.74</td>
<td>28,780</td>
</tr>
<tr>
<td>ARG-CAU</td>
<td>PRP:80.94</td>
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</tr>
<tr>
<td>ARG-COM</td>
<td>PREP:91.84</td>
<td>3.15</td>
<td>539</td>
</tr>
<tr>
<td>ARG-DIR</td>
<td>DIR:45.98, PRT:22.47</td>
<td>1.36</td>
<td>4,785</td>
</tr>
<tr>
<td>ARG-DIS</td>
<td>CC:34.24, INTJ:23.71, AVMOD:22.42</td>
<td>6.05</td>
<td>28,316</td>
</tr>
<tr>
<td>ARG-EXT</td>
<td>AVMOD:43.45</td>
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<td>1,802</td>
</tr>
<tr>
<td>ARG-GOL</td>
<td>PREP:61.73</td>
<td>3.23</td>
<td>1,147</td>
</tr>
<tr>
<td>ARG-LOC</td>
<td>LOC:78.38</td>
<td>10.42</td>
<td>18,352</td>
</tr>
<tr>
<td>ARG-MNR</td>
<td>MNR:56.42</td>
<td>7.65</td>
<td>17,509</td>
</tr>
<tr>
<td>ARG-MOD</td>
<td>AUX:92.3</td>
<td>7.41</td>
<td>28,357</td>
</tr>
<tr>
<td>ARG-NEG</td>
<td>NEQ:91.35</td>
<td>3.15</td>
<td>14,776</td>
</tr>
<tr>
<td>ARG-PRD</td>
<td>PRP:62.46, PREP:23.38</td>
<td>4.85</td>
<td>1,031</td>
</tr>
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<td>ARG-PRP</td>
<td>AVMOD:42.68, PREP:28.74</td>
<td>5.20</td>
<td>3,845</td>
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<td>ARG-PRP</td>
<td>PREP:80.22</td>
<td>5.02</td>
<td>5,304</td>
</tr>
<tr>
<td>ARG-REC</td>
<td>NPARMOD:51.95</td>
<td>3.90</td>
<td>154</td>
</tr>
<tr>
<td>ARG-TMP</td>
<td>TMP:85.61</td>
<td>7.93</td>
<td>50,528</td>
</tr>
</tbody>
</table>

Table 6.1: Mapping between semantic and syntactic dependencies. The SRL column shows semantic labels, the DEP column shows syntactic labels associated with the semantic labels with probabilities (in %), the Diverge column shows the probabilities of semantic dependents whose heads are not their syntactic heads (in %), and the Count column shows the count of each semantic label. The **R-** and **C-** labels represent referent and continuous arguments, respectively.
Note that the syntactic dependencies in Table 6.1 use the semantic function tags from constituent trees for dependency labels, as described in Figure 2.37 (page 43). This gives a clearer idea about how the semantic function tags in constituent trees correspond to the semantic role labels in PropBank. Our experiments show that the semantic and syntactic dependents are aligned about 86.44%.

6.2.3 Adding semantic roles to dependency trees

In principle, the head-token of each argument phrase becomes a semantic dependent of its predicate with the same PropBank label in a dependency tree (Figures 6.2 and 6.3). However, for numbered arguments containing discontinuous constituents, the same label is used for the leftmost constituent whereas the C-* labels, indicating continuous arguments, are used for the remaining pieces of the constituent in the parse tree. These continuous arguments are caused by linguistic phenomena such as subject raising or right node raising, represented by secondary dependencies like XSUBJ or RNR (Sections 2.5.4 and 2.5.3) in a dependency tree. In Figure 6.4, PropBank annotates S-2 as an ARG1 of the verb predicate allow, which is linked to NP-1 by the empty category *-1, representing subject raising (see the constituent tree on the left). As a result, the numbered argument ARG1 consists of the discontinuous constituents, NP-1 and S.

![Diagram]

Figure 6.4: An example of a continuous argument. The dependency tree on the right is converted from the constituent tree on the left, and the top and the bottom arcs show syntactic and semantic dependencies, respectively. The numbered argument ARG1 consists of discontinuous constituents, NP-1 and S. The secondary dependency XSUBJ is indicated by a dotted line.
When this constituent tree is converted into a dependency tree (the rightmost tree in Figure 6.4), there is no token whose subtree includes all tokens in both NP-1 and S; that is, He, to, and enter. At least two tokens, He and enter, are required to represent the ARG1 of allowed in this dependency tree. Note that the subtree of enter would have covered all of these tokens if the secondary dependency XSUBJ were assumed; however, this assumption cannot be generally made because most dependency parsers do not produce such secondary dependencies (Section 2.5). Labeling both He and enter as ARG1s of allowed creates the ambiguity of them being either two separate arguments or one argument with discontinuous constituents. Thus, only He is labeled as an ARG1 whereas enter is labeled as a C-ARG1, meaning that it is still an ARG1 of allowed but is a continuation from another ARG1, He.

Figure 6.5: An example of discontinuous constituents, repeated from Figures 2.16 and 2.17. The dependency tree at the bottom is converted from the constituent tree at the top with semantic roles.

Figure 6.5 shows the constituent and dependency trees in Figures 2.16 and 2.17 labeled with semantic roles. PropBank annotates the ADJP-2 as an ARG2 of the verb predicate be, which is linked to PP-1 by the empty category, *ICH*-1. Unlike the previous case, this dependency tree has the head-token, expensive, whose subtree contains all the tokens in both ADJP-2 and PP-1; that is, more, expensive, than, and before. Thus, only expensive is labeled as an ARG2 of is, and the head-token of PP-1, than,
is not labeled as a C-ARG2. Referent arguments are labeled as R-* when they are annotated in a dependency tree. In Figure 6.6, PropBank annotates NP-2 as an ARG1 of the verb predicate head, which is linked to WHNP-1 by the empty category *T*-1 representing wh-movement, then linked to NP-3 by the linkReferent(C) method in Algorithm 2.11 (Section 2.5.2). Although there is a head token, highway, whose subtree contains all tokens in NP-3 and WHNP-1, this subtree also contains other tokens including the predicate, which creates a cyclic relation. Thus, only the subtree of highway excluding the subtree of heads is considered an ARG0 in the dependency tree; that is, The and highway. This leaves out that as an argument, so it is labeled as a R-ARG0, meaning that it is an ARG0 of heads, and its referent, highway, is also an ARG0 of the same predicate.

![Figure 6.6: An example of a referent argument. The dependency tree at the bottom is converted from the constituent tree at the top with semantic roles.](image)

Figure 6.6: An example of a referent argument. The dependency tree at the bottom is converted from the constituent tree at the top with semantic roles.

Note that referent arguments can be applied to modifiers as well. For instance, wh-complementizers such as when or where are often labeled as a R-ARGM-TMP or a R-ARGM-LOC, meaning that it is a temporal or a locative modifier with a referent, respectively.
6.3 Argument pruning

6.3.1 First-order argument pruning

Xue and Palmer (2004) introduced a pruning algorithm for constituent-based semantic role labeling that reduces the size of argument candidates by visiting only phrases that are siblings of either the predicate or predicate’s ancestors. In Figure 6.2, NP-2, PP-3, and PP-4 are siblings of the predicate, open, and NP-1 is a sibling of the predicate’s parent, VP; thus, all of these four phrases would be considered argument candidates by this algorithm. Additionally, their algorithm considered direct children of prepositional phrases argument candidates as well; thus, INs and NPs under PP-3 and PP-4 would also be considered argument candidates.

Johansson and Nugues (2008) adapted this algorithm for dependency-based semantic role labeling by visiting only direct dependents of either the predicate or predicate’s ancestors. Let us term this first-order argument pruning since it takes only direct dependents into account. The term ‘n’th-order’ is borrowed from dependency parsing where only direct dependents are used for first-order parsing whereas indirect dependents such as grand-dependents are also used for higher-order parsing. In Figure 6.3, He, door, with, and at are direct dependents of opened, so these tokens are considered argument candidates by this algorithm. Coupled with their predicate-argument reranker, Johansson and Nugues (2008) achieved state-of-the-art performance for dependency-based semantic role labeling in the CoNLL’08 shared task (Surdeanu et al., 2008) using this pruning algorithm.

6.3.2 Higher-order argument pruning

Although first-order argument pruning works well and effectively reduces the number of argument candidates, it is based on a Linguistic theory called “domain of locality” (Joshi, 2004), which is most effectively applied to gold-standard dependency trees, but does not apply as well to automatically generated ones. Our experiments show that this first-order pruning algorithm visits over 99% of all arguments using gold-standard dependency trees in our evaluation data sets, but visits less than 93% using automatically generated trees (see Figure 6.7). Argument coverage is particularly low for
corpora whose automatic parse results are poor. This implies that the upper bound for recall for semantic role labeling using this pruning algorithm is lower than 93% when automatically generated dependency trees are used. Such a low upper bound in recall affects the overall F1-score; thus, a higher-order pruning algorithm is needed for better argument coverage.

Algorithm 6.1 shows a method that takes a dependency tree $T$ as input and produces a set of semantic dependency arcs in $T$ as output. This algorithm uses higher-order argument pruning, which significantly improves the argument coverage when automatically generated dependency trees are used for input (Figure 6.7). Note that all predicates are assumed to be identified in $T$; predicate identification is often not considered a part of semantic role labeling (Carreras and Màrques, 2004; Carreras and Màrquez, 2005; Hajič et al., 2009) although it is a necessary step. The difficulty of building a predicate identification model comes from incomplete annotation in PropBank. Currently, PropBank annotation in the OntoNotes v4.99 misses about 5% of verb instances, which brings enough noise to negatively impact training and evaluation. Thus, gold-standard predicate identification is used for our experiments.\footnote{The PropBank annotation is expected to be complete in v5.0. Once the OntoNotes v5.0 is released, we will train and evaluate models for predicate identification.}

\begin{algorithm}
\caption{getArgumentArcSet($T$)}
\begin{algorithmic}[1]
\Input A dependency tree $T$, where predicates are already identified.
\Output A set $A$ containing semantic dependency arcs in $T$.
\State $A \leftarrow \emptyset$
\For {$p$ in all predicates in $T$}
\State getArgumentArcSetDown($p, p, A$) \hfill \# Algorithm 6.2
\EndFor
\If {$p$ has the head $h$} getArgumentArcSetUp($p, h, A$) \hfill \# Algorithm 6.3
\EndIf
\State return $A$
\end{algorithmic}
\end{algorithm}

\begin{algorithm}
\caption{getArgumentArcSetDown($p, n, A$)}
\begin{algorithmic}[1]
\Input A predicate $p$, a dependency node $n$, and a set of dependency arcs $A$, where $n$ is either $p$ or a descendant of $p$.
\State for $d$ in all dependents of $n$ do
\State if $d$ is an argument of $p$ with a label $l$ then $A \leftarrow A \cup \{d \cong l p\}$
\State getArgumentArcSetDown($p, d, A$)
\end{algorithmic}
\end{algorithm}
Algorithm 6.3: \textit{getArgumentArcSetUp}(p, h, A)

\textbf{Input}: A predicate \(p\), a dependency node \(h\), and a set of dependency arc \(A\), where \(h\) is an ancestor of \(p\).

1: \textbf{if} \(h\) is an argument of \(p\) with a label \(l\) \textbf{then} \(A \leftarrow A \cup \{h \xleftarrow{l} p\}\)
2: \textbf{for} \(d\) in all dependents of \(h\) \textbf{do}
3: \textbf{if} \(d\) is an argument of \(p\) with a label \(l\) \textbf{then} \(A \leftarrow A \cup \{d \xleftarrow{l} p\}\)
4: \textbf{if} \(h\) has the head \(h'\) \textbf{then} \(\text{getArgumentArcSetUp}(p, h', A)\)

For each predicate in \(T\), the \textit{getArgumentArcSetDown}(p, d, A) method in Algorithm 6.2 is called first, which finds semantic dependencies between the predicate and all descendants of the predicate. This is where our algorithm is distinguished from the previous algorithm; only direct dependents of the predicate are considered argument candidates in the first-order pruning algorithm. Then, the \textit{getArgumentArcSetUp}(p, h, A) method in Algorithm 6.3 is called, which finds semantic dependencies between the predicate and predicate’s ancestors as well as their direct dependents. This time, only direct dependents of the predicate’s ancestors are considered argument candidates; our experiments show that visiting all descendants of the ancestors significantly increases the number of argument candidates (Figure 6.10) without giving much improvement in labeling accuracy (Section 6.5.1).

Figure 6.7: Argument coverage rates achieved by different pruning algorithms and input trees (in \%). \(W^*\) and \(O^*\) stand for pruning algorithms using trees automatically generated by the Wall Street Journal and the OntoNotes models, and \(G^*\) stands for algorithms using gold-standard trees, respectively. \(*-F\) and \(*-H\) stands for the first-order and the higher-order pruning algorithms.

Figure 6.7 shows argument coverage rates achieved by different pruning algorithms and input trees (in \%). Given gold-standard dependency trees, both first-order and higher-order pruning algorithms
show above 99% argument coverage rates. However, given automatically generated trees, the first-order pruning algorithm shows around 91-93% whereas the higher-order pruning algorithm shows around 97-98% argument coverage rates; the differences are statistically significant (McNemar’s test, \( p < .0001 \)). The argument coverage rates are higher for the OntoNotes model because it generates higher quality dependency trees than the WSJ model (Section 5.6.1).

6.3.3 Conditional higher-order argument pruning

Higher-order argument pruning gives better argument coverage to semantic role labeling; however, it also increases the number of argument candidates. To reduce the average number of argument candidates, conditional higher-order argument pruning is proposed, which brings the complexity close to the one achieved by the first-order argument pruning, yet still shows noticeably better argument coverage. During training, dependency paths between predicates and dependency nodes whose subtrees contain arguments of the predicates are collected. These paths are used to prune out argument candidates that are not likely to form predicate argument structures during decoding.

Algorithm 6.4: collectPathSets\((T, c_d, c_u)\)

<table>
<thead>
<tr>
<th>Line</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>((D_d, D_u) \leftarrow ({ }, { })) # initialize empty dictionaries</td>
</tr>
<tr>
<td>2</td>
<td>for all predicates in (T) do</td>
</tr>
<tr>
<td>3</td>
<td>for all grand-dependents of (p) do</td>
</tr>
<tr>
<td>4</td>
<td>collectPathsDown((p, d, D_d)) # Algorithm 6.5</td>
</tr>
<tr>
<td>5</td>
<td>if (p) has the grand-head (h) then collectPathsUp((p, h, D_u)) # Algorithm 6.6</td>
</tr>
<tr>
<td>6</td>
<td>(S_d \leftarrow D_d.getKeys(c_d))</td>
</tr>
<tr>
<td>7</td>
<td>(S_u \leftarrow D_u.getKeys(c_u))</td>
</tr>
<tr>
<td>8</td>
<td>return ((S_d, S_u))</td>
</tr>
</tbody>
</table>

Algorithm 6.4 shows a method that takes a dependency tree \(T\) and two cutoffs, \(c_d\) and \(c_u\), as input and produces two sets, \(S_d\) and \(S_u\), as output. The algorithm begins by initializing two dictionaries, \(D_d\) and \(D_u\), in which keys and values are dependency paths and their occurrences in \(T\), respectively (line 1). For each predicate, dependency paths between the predicate and its
descendants whose subtrees contain arguments of the predicate, called down-paths, are added to $D_d$ (lines 3-4). Note that dependency paths between the predicate and its direct dependents are not collected because they are always considered argument candidates regardless of their paths to the predicate. Similarly, dependency paths between the predicate and its ancestors whose dependents are arguments of the predicate, called up-paths, are added to $D_u$ (line 5). Again, dependency paths between the predicate and its head are not collected because the head and head’s dependents are always considered argument candidates. Once this procedure is done, two sets $S_d$ and $S_u$ are created by selecting only paths in $D_d$ and $D_u$ whose occurrences are greater than the cutoffs $c_d$ and $c_u$, respectively (lines 6-7). For our experiments, cutoffs of 5 and 0 are used for $c_d$ and $c_u$, respectively.

**Algorithm 6.5**: $\text{collectPathsDown}(p, n, D_d)$

**Input:** A predicate $p$, a dependency node $n$, and a dictionary $D_d$, where $n$ is a descendant of $p$, and keys and values in $D_d$ are down-paths and their occurrences, respectively.

1: if $n$ is an argument of $p$ then
2: for $a$ in getPathList($p$, n.head) do $D_d[a] ← D_d[a] + 1$  # Algorithm 6.7
3: for $d$ in all dependents of $n$ do
4: $\text{collectPathsDown}(p, d, D_d)$

Algorithm 6.5 shows a method that collects down-paths between a predicate $p$ and $p$’s descendant $n$, where $n$ is an argument of $p$ (lines 1-2). In Figure 6.8, $\text{what}$ is an R-ARG1 of the predicate $\text{see}$; thus, dependency paths are collected between $\text{saw}$ and $\text{what}$, ↓CONJ and ↓CONJ↓PREP, indicating that these are paths from $p$ to $p$’s descendants whose subtrees contain arguments of $p$. This procedure is repeated recursively until all descendants of $n$ are visited (lines 3-4).

![Figure 6.8: An example of a down-path. For the predicate see and its argument what, two dependency paths are collected, ↓CONJ and ↓CONJ↓PREP.](image-url)
Algorithm 6.6: \textit{collectPathsUp}(p, h, D_u)

\textbf{Input:} A predicate \(p\), a dependency node \(h\), and a dictionary \(D_u\), where \(h\) is an ancestor of \(p\), and keys and values in \(D_u\) are up-paths and their occurrences, respectively.

1: \textbf{if } \(h\) has a dependent that is an argument of \(p\) \textbf{then}
2: \hspace{1em} \textbf{for } \(a\) in \textit{getPathList}(h, p) \textbf{ do} \(D_u[a] \leftarrow D_u[a] + 1\) \# Algorithm 6.7
3: \textbf{if } \(h\) has the head \(h'\) \textbf{ then}
4: \hspace{1em} \textit{collectPathsUp}(p, h', D_u)

Algorithm 6.6 shows a method that collects up-paths between a predicate \(p\) and \(p\)'s ancestor \(h\) whose dependent is an argument of \(p\) (lines 1-2). In Figure 6.9, \(He\) is an \texttt{ARG0} of the predicate \textit{join}; thus, dependency paths are collected between \textit{saw} and \(He\), \(\uparrow\text{XCOMP}\) and \(\uparrow\text{XCOMP}\uparrow\text{CONJ}\), indicating that these are either intermediate or full paths from \(p\) to \(p\)'s ancestor whose dependent is an argument of \(p\). This procedure is repeated recursively until all ancestors of \(h\) are visited (lines 3-4).

![Diagram of dependency tree with up-paths](image)

Figure 6.9: An example of an up-path. For the predicate \textit{join} and its argument \(He\), two dependency paths are collected, \(\uparrow\text{XCOMP}\) and \(\uparrow\text{XCOMP}\uparrow\text{CONJ}\).

Algorithm 6.7 shows a method that takes dependency nodes \(t\) and \(b\) as input, where \(t\) is an ancestor of \(b\), and a list \(L\) of dependency paths between \(t\) and \(b\) as output. A dependency path can have a height of one (e.g., \(\downarrow\text{CONJ}\)) or many (e.g., \(\downarrow\text{CONJ}\downarrow\text{PREP}\)), depending on the hierarchy between \(t\) and \(b\).

Algorithm 6.7: \textit{getPathList}(t, b)

\textbf{Input:} Dependency nodes \(t\) and \(b\), where \(t\) is an ancestor of \(b\).
\textbf{Output:} A list \(L\) containing dependency paths between \(t\) and \(b\).

1: \(L \leftarrow [\ ]\)
2: \textbf{while } \(t \neq b\) \textbf{ do}
3: \hspace{1em} \(L.add\) (the dependency path between \(t\) and \(b\)) \# e.g., \(\downarrow\text{CONJ}, \uparrow\text{XCOMP}\)
4: \hspace{1em} \(b \leftarrow b\).head
5: \textbf{return } \(L\)
Given the sets of dependency paths collected by Algorithm 6.4, the higher-order pruning algorithm in Section 6.3.2 can be rewritten as a conditional higher-order pruning algorithm. Algorithm 6.8 shows a method that uses conditional higher-order argument pruning; it is similar to the method in Algorithm 6.1, except that it calls Algorithms 6.9 and 6.10, which prune out argument candidates more rigorously than Algorithms 6.2 and 6.3 called in Algorithms 6.1.

Algorithm 6.8: \textit{getArgumentArcSetCon}(T, S_d, S_u)

\begin{itemize}
\item \textbf{Input:} A dependency tree \( T \), a set of down-paths \( S_d \), and a set of up-paths \( S_u \), where predicates are already identified in \( T \).
\item \textbf{Output:} A set \( A \) containing semantic dependency arcs in \( T \).
\end{itemize}

1: \( A \leftarrow \emptyset \)
2: \textbf{for} \( p \) \textbf{in} all predicates in \( T \) \textbf{do}
3: \hspace{1em} \textit{getArgumentArcSetDownCon}(p, p, A, S_d) \hspace{1em} \# Algorithm 6.9
4: \hspace{1em} \textbf{if} \( p \) has the head \( h \) \textbf{then} \textit{getArgumentArcSetUpCon}(p, h, A, S_u) \hspace{1em} \# Algorithm 6.10
5: \textbf{return} \( A \)

Algorithm 6.9 shows a method that is similar to the method in Algorithm 6.2, except that it checks if the down-path from predicate \( p \) to its descendant \( d \) exists in \( S_d \), which contains down-paths collected by Algorithm 6.5 (line 3). If \( S_d \) does not contain the down-path between \( p \) and \( d \), all descendants of \( d \) are discarded from being argument candidates of \( p \).

Algorithm 6.9: \textit{getArgumentArcSetDownCon}(p, n, A, S_d)

\begin{itemize}
\item \textbf{Input:} A predicate \( p \), a dependency node \( n \), a set of dependency arcs \( A \), and a set of down-paths \( S_d \), where \( n \) is either \( p \) or a descendant of \( p \).
\end{itemize}

1: \textbf{for} \( d \) \textbf{in} all dependents of \( n \) \textbf{do}
2: \hspace{1em} \textbf{if} \( d \) is an argument of \( p \) with a label \( l \) \textbf{then} \( A \leftarrow A \cup \{d \xleftarrow{l} p\} \)
3: \hspace{1em} \textbf{if} \( S_d \) contains the dependency path between \( p \) and \( d \) \textbf{then} \hspace{1em} \# conditional
4: \hspace{1em} \textit{getArgumentArcSetDownCon}(p, d, A, S_d)

Algorithm 6.10 shows a method that is similar to the method in Algorithm 6.3, except that it checks if the up-path from predicate \( p \) to its ancestor \( h' \) exists in \( S_u \), which contains up-paths collected by Algorithm 6.6 (line 5). If \( S_u \) does not contain the up-path between \( p \) and \( h' \), all dependents and ancestors of \( h' \) as well as \( h' \) itself are discarded from being argument candidates of \( p \).
Algorithm 6.10: getArgumentArcSetUpCon(p, h, A, S_u)

**Input:** A predicate p, a dependency node h, a set of dependency arc A, and a set of up-paths S_u, where h is an ancestor of p.

1: if h is an argument of p with a label l then A ← A ∪ {h ↓ p}
2: for d in all dependents of h do
3: if d is an argument of p with a label l then A ← A ∪ {d ↓ p}
4: if (h has the head h') and
5: (S_u contains the dependency path between h' and p) then  # conditional
6: getArgumentArcSetUpCon(p, h', A, S_u)

---

Figure 6.10: The average number of argument candidates for different pruning algorithms with respect to sentence lengths. The top and the bottom figures show results achieved by the Wall Street Journal and OntoNotes models, respectively. *A stands for an algorithm considering all dependency nodes as argument candidates. *F, *H, and *H+ stand for the first-order, the higher-order, and the conditional higher-order pruning algorithms, respectively.

Figure 6.10 shows the average numbers of argument candidates compared by different pruning algorithms with respect to sentence lengths. For both the Wall Street Journal (W+) and OntoNotes (O+) models, the higher-order pruning algorithm (*H) consistently compares about twice as many argument candidates as the first-order pruning algorithm (*F), although it compares significantly
less than the algorithm comparing all dependency nodes (\(\ast A\)). The conditional higher-order pruning algorithm (\(\ast H^+\)) gives an average number of argument candidates close to the one achieved by the first-order pruning algorithm. The gap between these two algorithms becomes smaller as the sentence length increases, which implies that the conditional higher-order pruning algorithm is even more effective for longer sentences.

6.4 Features

6.4.1 Feature templates

Table 6.2 shows the feature templates used for our semantic role labeling experiments. Our feature templates are inspired by Johansson and Nugues (2008) although we combine their feature sets, one for argument identification and the other for argument classification, into one.\(^3\) \(w_p\) and \(w_a\) stand for the current predicate and the argument candidate, respectively. \(w_{x+n}\) stands for the word token whose distance from \(w_x\) is \(n\). \(hd(x)\) stands for the head of \(x\). \(ld(x)\) and \(rd(x)\) stand for the leftmost and rightmost dependents of \(x\). \(ls(x)\) and \(rs(x)\) stand for the left-nearest and right-nearest siblings of \(x\). The Form, Lemma, POS, Deprel, Depset, Subcat\(_L\), and Subcat\(_R\) columns indicate the word form, lemma, POS tag, dependency label, sub-dependency label set, left subcategorization, and right subcategorization features of the corresponding token, respectively. These features are used either individually or jointly (e.g., POS tags of both \(w_p\) and \(w_a\) make one feature).

The dependency label set is derived by collecting all dependency labels of \(w_{pred}\)'s direct dependents. For the predicate \(open\) in Figure 6.3, the dependency label set is \{\(\text{NSUBJ}, \text{DOBJ}, \text{PREP}\}\). Unlike Johansson and Nugues (2008), we decompose subcategorization features into two parts: one representing the left-hand side and the other representing the right-hand side dependencies of \(w_{pred}\). For the predicate \(open\) in Figure 6.3, the left-hand side subcategorization is \(\overleftarrow{\text{NSUBJ}}\) and the right-hand side subcategorization is \(\overrightarrow{\text{DOBJ-PREP-PREP}}\). Our experiments show that with this separation, the subcategorization features generalize better. In addition to the features in Table 6.2, three

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\(^3\) Johansson and Nugues (2008)’s feature templates are also inspired by previous work on constituent-based semantic role labeling (Gildea and Jurafsky, 2002; Pradhan et al., 2008).
kinds of path features are added: POS paths, dependency paths, and height paths. In Figure 6.9, the POS and dependency paths between the predicate *join* and its argument *He* are ↑VBD↑VBD↓PRP and ↑XCOMP↑CONJ↓NSUBJ, respectively. The height path, introduced by Choi and Palmer (2011b), indicates the height between a predicate and its argument. Let LCA be the lowest common ancestor of *join* and *He* in Figure 6.9; that is *came*. The height path between these two tokens is ↑2↓1, implying that the height between *join* and LCA is 2 and the height between *He* and LCA is 1.

<table>
<thead>
<tr>
<th>Token</th>
<th>Form</th>
<th>Lemma</th>
<th>POS</th>
<th>Deprel</th>
<th>Subset</th>
<th>Subcat&lt;sub&gt;L&lt;/sub&gt;</th>
<th>Subcat&lt;sub&gt;R&lt;/sub&gt;</th>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
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<td></td>
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<td>✓</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( hd(w_p) )</td>
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<td>✓</td>
<td></td>
<td></td>
<td>✓</td>
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<td></td>
</tr>
<tr>
<td>( ld(w_p) )</td>
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<td>✓</td>
<td></td>
<td></td>
<td>✓</td>
<td>✓</td>
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</tr>
<tr>
<td>( rd(w_p) )</td>
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<td>✓</td>
<td></td>
<td></td>
<td>✓</td>
<td></td>
<td></td>
</tr>
<tr>
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<td>✓</td>
<td>✓</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( w_{a-1} )</td>
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<td>✓</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( w_{a+1} )</td>
<td>✓</td>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
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<td></td>
<td></td>
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<tr>
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<td>✓</td>
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</tr>
<tr>
<td>( rd(w_a) )</td>
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<td>✓</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( ls(w_a) )</td>
<td>✓</td>
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<td></td>
</tr>
<tr>
<td>( rs(w_a) )</td>
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<td>✓</td>
<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

Table 6.2: Feature templates for semantic role labeling.

We also use the last two predicted numbered argument labels of the current predicate as features. Finally, two kinds of binary features are used: if \( w_{arg} \) is a syntactic head of \( w_{pred} \) and if \( w_{pred} \) is a syntactic head of \( w_{arg} \).

### 6.4.2 Positional feature separation

Features in Section 6.4.1 are divided into two sets and trained separately: one contains features for arguments on the left-hand side and the other contains features for arguments on the right-hand side of the predicate. From our experiments, we found that separating these features improves the overall F1-score of semantic role labeling, evaluated for both argument identification and classification, whereas having one combined set of features shows an advantage when semantic role labeling is evaluated for only argument identification.
6.5 Experiments

6.5.1 Accuracy comparisons

Tables 6.3 and 6.4 show F1-scores for semantic role labeling \( (F_{h,l} \text{ in Table 3.1}) \), achieved by the WSJ and OntoNotes models, respectively. The Baseline model uses the first-order pruning algorithm in Section 6.3.1. The Baseline+ model is the Baseline model with positional feature separation from Section 6.4.2; positional feature separation is also applied to all the other models. The High-order model uses the higher-order pruning algorithm in Section 6.3.2. The No-pruning model does not use any pruning algorithm. The ClearNLP model uses the conditional higher-order pruning algorithm in Section 6.3.3. The ClearNLP model is compared to another dependency-based semantic role labeler, ClearParser, which uses a transition-based semantic role labeling algorithm showing state-of-the-art performance on the CoNLL’09 shared task data for English (Choi and Palmer, 2011b). ClearParser uses the same positional feature separation and does not use any pruning algorithms.

<table>
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<tr>
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<tbody>
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<td>70.00</td>
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<td>70.38</td>
<td>72.02</td>
<td>82.28</td>
<td>71.64</td>
</tr>
<tr>
<td>No-pruning</td>
<td>73.63</td>
<td>76.87</td>
<td>70.47</td>
<td>70.08</td>
<td>73.99</td>
<td>62.18</td>
<td>70.46</td>
<td>72.25</td>
<td>82.48</td>
<td>71.95</td>
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<td>71.03</td>
<td>72.53</td>
<td>82.26</td>
<td>71.52</td>
</tr>
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</table>

Table 6.3: F1-scores of semantic role labeling from the WSJ models (in %).

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<tr>
<th>Model</th>
<th>BC</th>
<th>BN</th>
<th>MZ</th>
<th>NW</th>
<th>TC</th>
<th>WB</th>
<th>MD</th>
<th>MP</th>
<th>SH</th>
<th>Avg.</th>
<th>Avg.</th>
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<tbody>
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<td>82.90</td>
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<td>76.17</td>
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<td>62.67</td>
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<td>70.02</td>
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<td>Baseline+</td>
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<td>81.47</td>
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<td>77.28</td>
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<td>81.69</td>
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</table>

Table 6.4: F1-scores of semantic role labeling from the OntoNotes models (in %).

The Avg \(_i\) and Avg \(_o\) columns show the micro average F1-scores for in-genre and out-of-genre experiments. For the WSJ models, the F1-score of NW is measured for Avg \(_i\) and the micro average
of all other corpora are measured for \( \text{Avg}_o \). For the OntoNotes models, the micro averages of the OntoNotes and Medical corpora are measured for \( \text{Avg}_i \) and \( \text{Avg}_o \), respectively. The Baseline+ model shows higher scores than the Baseline model and the High-order model shows higher scores than the Baseline+ model for all experiments, which indicates that the positional feature separation and the higher-order pruning algorithm improve labeling accuracy for both in-genre and out-of-genre experiments. Although the High-order model performs better than the No-pruning model for all in-genre experiments, the No-pruning model performs better for all out-of-genre experiments; this is expected because the higher-order pruning algorithm performs less accurately when syntactic parse input is poor, which is the case for out-of-genre experiments.

The ClearNLP model shows lower scores than the High-order model for both \( \text{Avg}_i \) and \( \text{Avg}_o \) in Table 6.3; however, it shows similar or slightly higher scores than the High-order model for both \( \text{Avg}_i \) and \( \text{Avg}_o \) in Table 6.4. This is because the ClearNLP model could not learn enough conditions from the WSJ corpus whereas enough conditions are learned from the OntoNotes corpora so the ClearNLP model can perform as accurately as the High-order model. For both \( \text{Avg}_i \) and \( \text{Avg}_o \) in Table 6.3, the ClearNLP model shows higher scores than ClearParser. In Table 6.4, ClearParser performs better for \( \text{Avg}_i \) whereas the ClearNLP model performs significantly better for \( \text{Avg}_o \). This implies that our approach works more effectively for out-of-genre experiments.

<table>
<thead>
<tr>
<th>Model</th>
<th>WSJ: ( \text{Avg}_i )</th>
<th>WSJ: ( \text{Avg}_o )</th>
<th>Onto: ( \text{Avg}_i )</th>
<th>Onto: ( \text{Avg}_o )</th>
</tr>
</thead>
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<td>P</td>
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</tr>
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<td>Baseline</td>
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<td>72.39</td>
<td>69.79</td>
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<td>78.44</td>
<td>74.07</td>
<td>69.36</td>
</tr>
<tr>
<td>High-order</td>
<td>86.65</td>
<td>78.78</td>
<td>74.29</td>
<td>69.65</td>
</tr>
<tr>
<td>No-pruning</td>
<td><strong>86.94</strong></td>
<td><strong>78.45</strong></td>
<td><strong>74.70</strong></td>
<td><strong>69.40</strong></td>
</tr>
<tr>
<td>ClearNLP</td>
<td>86.47</td>
<td>78.73</td>
<td>74.13</td>
<td>69.70</td>
</tr>
<tr>
<td>ClearParser</td>
<td>84.45</td>
<td><strong>80.17</strong></td>
<td>71.74</td>
<td><strong>71.29</strong></td>
</tr>
</tbody>
</table>

Table 6.5: Precisions (P) and recalls (R) for in-genre (\( \text{Avg}_i \)) and out-of-genre (\( \text{Avg}_o \)) experiments (in %). The WSJ and Onto columns show scores achieved by the WSJ and OntoNotes models.

Table 6.5 shows precisions and recalls for in-genre and out-of-genre experiments. The No-pruning model shows the highest precisions whereas ClearParser shows the highest recalls for all experiments. The High-order model shows higher recalls than the Baseline+ model for all experiments, which
is expected. Interestingly, the ClearNLP model shows higher recalls than the No-pruning models for all experiments; the differences are statistically significant (McNemar, \( p < .01 \)). Furthermore, the ClearNLP models show higher recalls than the High-order models for most experiments even with the more aggressive pruning algorithm; the differences for the OntoNotes experiments are statistically significant (McNemar, \( p < .01 \)). We suspect that this is because the conditional higher-order pruning algorithm reduces more noise for recall than the naive higher-order pruning algorithm so it performs better even with fewer argument candidates. On the other hand, the ClearNLP models do not show high precision for all experiments. We will explore the possibility of improving precision for the ClearNLP models through error analysis in the future.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>85.81</td>
<td>71.14</td>
<td>84.69</td>
<td>71.76</td>
</tr>
<tr>
<td>Baseline+</td>
<td>86.27</td>
<td>71.18</td>
<td>85.40</td>
<td>71.93</td>
</tr>
<tr>
<td>High-order</td>
<td>86.49</td>
<td>71.43</td>
<td>85.51</td>
<td>72.28</td>
</tr>
<tr>
<td>No-pruning</td>
<td>86.54</td>
<td>71.08</td>
<td>85.53</td>
<td>72.10</td>
</tr>
<tr>
<td>ClearNLP</td>
<td>86.48</td>
<td>71.07</td>
<td>85.53</td>
<td>72.29</td>
</tr>
<tr>
<td>ClearParser</td>
<td><strong>86.66</strong></td>
<td>70.21</td>
<td>85.90</td>
<td>72.15</td>
</tr>
</tbody>
</table>

Table 6.6: F1-scores of numbered arguments (ARGN) and modifiers (ARGM) for in-genre and out-of-genre experiments (in %).

Table 6.6 shows F1-scores of numbered arguments and modifiers for in-genre and out-of-genre experiments. The ClearNLP model shows the highest scores for predicting both numbered arguments and modifiers for the OntoNotes in-genre experiment (Onto: Avg.\(_i\)), whereas the other models show advantages for other experiments.

### 6.5.2 Speed comparisons

Labeling speeds are measured by running each system on a mixture of all data. All systems are written in Java; ClearParser has its own implementation and the other models are implemented in the same system. Table 6.7 shows speed comparisons between five models; the top and bottom five rows show results from the WSJ and OntoNotes models, respectively. The T\# columns show how many milliseconds each model takes for labeling all arguments of each predicate in 5 trials, and the
Avg column shows the average labeling speeds of the middle three trials, and the Arguments column shows how many arguments are labeled per second. The ClearNLP models take about 0.42 - 0.45 milliseconds per predicate, which is slower than the Baseline+ model but faster than all the other models. The ClearNLP model labels over 1,500 more arguments per second than the high-order model, which is noticeably faster. Notice that ClearParser shows faster speeds than the No-pruning model even though neither of them uses any pruning algorithm. This comes from implementation differences between these two systems; ClearParser walks through an array for searching arguments whereas the No-pruning model traverses a tree. Since accessing an array is quicker than traversing a tree, the No-pruning model shows slower labeling speeds than ClearParser although they compare an equal number of argument candidates.

<table>
<thead>
<tr>
<th>Model</th>
<th>T1</th>
<th>T2</th>
<th>T3</th>
<th>T4</th>
<th>T5</th>
<th>Avg</th>
<th>Arguments</th>
</tr>
</thead>
<tbody>
<tr>
<td>WSJ</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline+</td>
<td>0.34</td>
<td>0.34</td>
<td>0.34</td>
<td>0.35</td>
<td>0.39</td>
<td>0.34</td>
<td>7,111</td>
</tr>
<tr>
<td>High-order</td>
<td>0.58</td>
<td>0.60</td>
<td>0.60</td>
<td>0.60</td>
<td>0.61</td>
<td>0.60</td>
<td>4,062</td>
</tr>
<tr>
<td>No-pruning</td>
<td>0.77</td>
<td>0.78</td>
<td>0.80</td>
<td>0.81</td>
<td>0.88</td>
<td>0.80</td>
<td>3,081</td>
</tr>
<tr>
<td>ClearNLP</td>
<td>0.41</td>
<td>0.42</td>
<td>0.42</td>
<td>0.42</td>
<td>0.42</td>
<td>0.42</td>
<td>5,856</td>
</tr>
<tr>
<td>ClearParser</td>
<td>0.60</td>
<td>0.61</td>
<td>0.63</td>
<td>0.66</td>
<td>0.69</td>
<td>0.63</td>
<td>3,877</td>
</tr>
<tr>
<td>ON</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline+</td>
<td>0.35</td>
<td>0.35</td>
<td>0.35</td>
<td>0.35</td>
<td>0.35</td>
<td>0.35</td>
<td>6,934</td>
</tr>
<tr>
<td>High-order</td>
<td>0.62</td>
<td>0.62</td>
<td>0.62</td>
<td>0.64</td>
<td>0.64</td>
<td>0.63</td>
<td>3,904</td>
</tr>
<tr>
<td>No-pruning</td>
<td>0.80</td>
<td>0.82</td>
<td>0.83</td>
<td>0.84</td>
<td>0.86</td>
<td>0.83</td>
<td>2,947</td>
</tr>
<tr>
<td>ClearNLP</td>
<td>0.45</td>
<td>0.45</td>
<td>0.45</td>
<td>0.45</td>
<td>0.46</td>
<td>0.45</td>
<td>5,410</td>
</tr>
<tr>
<td>ClearParser</td>
<td>0.61</td>
<td>0.63</td>
<td>0.63</td>
<td>0.63</td>
<td>0.66</td>
<td>0.63</td>
<td>3,882</td>
</tr>
</tbody>
</table>

Table 6.7: Labeling speeds (in ms.). The top and the bottom five rows show results from the WSJ and OntoNotes models, respectively.

Figure 6.11 shows labeling speeds with respect to sentence lengths achieved by the WSJ (the top figure) and OntoNotes (the bottom figure) models. ClearParser and the No-pruning models show almost complete linear growth whereas the other models show somewhat similar logarithm growth, implying that the pruning algorithms work more effectively for longer sentences. The ClearNLP model shows labeling speeds close to the Baseline+ model; especially for longer sentences. This implies that the ClearNLP model, using the conditional higher-order pruning algorithm, runs almost as fast as the Baseline+ model, using the first-order pruning algorithm, yet performs more accurately.
Figure 6.11: Average labeling speeds with respect to sentence lengths. The top and the bottom figures show parsing speeds achieved by the WSJ and OntoNotes models, respectively. The bottom table shows the number of sentences in each group. ---: No-pruning, ------: ClearParser, - - - -: High-order, -----: ClearNLP, --------: Baseline+.

<table>
<thead>
<tr>
<th>Group</th>
<th>≤ 10</th>
<th>≤ 20</th>
<th>≤ 30</th>
<th>≤ 40</th>
<th>≤ 50</th>
<th>≤ 60</th>
<th>≤ 70</th>
<th>≤ 80</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sentences</td>
<td>9,789</td>
<td>6,159</td>
<td>2,966</td>
<td>1,313</td>
<td>479</td>
<td>178</td>
<td>75</td>
<td>30</td>
</tr>
</tbody>
</table>
Chapter 7

Conclusion

This thesis focuses on the optimization of NLP components for robustness and scalability. All trees in constituent Treebanks are converted into dependency trees in the CLEAR dependency format and semantic roles in PropBanks are mapped accordingly to these dependency trees. For dependency conversion, new head-finding rules and heuristics are introduced to handle format changes in recent English Treebanks, allowing us to generate richer and more robust dependency representations than previous approaches. For POS tagging, dynamic model selection is introduced, which shows more robust tagging accuracy across different genres and runs noticeably faster than two other state-of-the-art POS taggers. Our selection approach is more effective when training data is small and is used for tagging data with many varieties. For dependency parsing, a new transition-based parsing algorithm and a bootstrapping technique are introduced. Our parsing algorithm shows linear time parsing speed for generating both projective and non-projective dependency trees and shows a lower average number of transitions performed compared to other transition-based parsing algorithms. Our bootstrapping technique gives significant improvement on parsing accuracy showing higher performance against two other state-of-the-art dependency parsers. For semantic role labeling, a conditional higher-order argument pruning algorithm is introduced. A higher-order argument pruning algorithm improves the coverage of argument candidates and shows improvement on the overall F1-score. The conditional higher-order argument pruning algorithm noticeably reduces the average number of argument candidates with little compromise of the F1-score.
To the best of our knowledge, this is the first time that these three components have been evaluated on such a wide variety of English data using the same experimental settings. Our results for in-genre and out-of-genre experiments give helpful feedback for many NLP tasks such as machine translation or information extraction that depend significantly on the outputs of these components and need to process large-scale heterogeneous data. Processing all three components takes about 2.49-2.69 milliseconds per sentence using our approaches and implementations (0.36-0.37 milliseconds for POS tagging, 1.16-1.28 milliseconds for dependency parsing, and 0.97-1.04 milliseconds for semantic role labeling), which handles over 370 sentences per second. Additionally, our dependency conversion is useful for those who want to generate gold-standard dependency trees for training. All components are implemented in an open source project called ClearNLP and are publicly available.\footnote{ClearNLP: \url{clearnlp.googlecode.com}, ClearParser: \url{clearparser.googlecode.com}} It is worth mentioning that the main advantage of ClearNLP over ClearParser comes from modular programming. ClearParser is designed specifically for dependency parsing and semantic role labeling and it runs fast for those tasks, but it is hard to extend its APIs to other components. ClearNLP is designed to be more modular and to interface easily with other NLP components in general i.e., it is easier to extend its APIs to other NLP components such as a POS tagger or a DAG (directed acyclic graph) parser.\footnote{ClearNLP includes a DAG parser that is still experimental.}

There is still much room for improvement. For all three tasks, no extensive feature engineering is performed, which needs to be done for optimum results. We will try to apply automatic feature selection techniques such as Chi-square (Liu and Setiono, 1995) that may improve the speed and accuracy of our NLP components. For POS tagging, we will try to integrate our dynamic model selection approach with more sophisticated tagging algorithms such as bidirectional dependency networks (Toutanova et al., 2003) in hopes of improve accuracy further. Moreover, we will explore the possibility of using unsupervised clustering techniques to automatically group training data into meaningful document sets for dynamic model selection. For dependency parsing, we will try to compare parse results for non-projective trees with languages containing more non-projective
dependencies such as Czech (Hajič et al., 2000), Danish (Kromann, 2003), Sloven (Džeroski et al., 2006), etc. and see which transitions help or hurt performance in non-projective parsing. We will also try to apply more exhaustive search techniques such as $k$-best parsing or beam search to improve our parsing accuracy further. For semantic role labeling, we plan to implement a predicate identification module in ClearNLP so the entire SRL process can be automated. We also plan to implement an argument spanning module in ClearNLP so it can produce the actual spans of semantic arguments instead of just head-tokens. Most importantly, we will analyze what types of errors made by our dependency parser hurt the most for semantic role labeling and try to improve labeling accuracy for these error cases.


Appendix  A

Constituent Treebank Tags

This appendix shows tags used in various constituent Treebanks for English (Marcus et al., 1993; Nielsen et al., 2010; Weischedel et al., 2011; Verspoor et al., 2012). Tags followed by * are not the typical Penn Treebank tags but used in some other Treebanks.

### A.1 Function tags

<table>
<thead>
<tr>
<th>Syntactic roles</th>
<th>Semantic roles</th>
<th>Text and speech categories</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADV  Adverbial</td>
<td>PUT Locative complement of put</td>
<td>ETC Et cetera</td>
</tr>
<tr>
<td>CLF  <em>It-cleft</em></td>
<td>PRD Non-VP predicate</td>
<td>FRM* Formula</td>
</tr>
<tr>
<td>CLR  Closely related constituent</td>
<td>RED* Reduced auxiliary</td>
<td>HLN Headline</td>
</tr>
<tr>
<td>DTV  Dative</td>
<td>SBJ Surface subject</td>
<td>IMP Imperative</td>
</tr>
<tr>
<td>LGS  Logical subject in passive</td>
<td>TPC Topicalization</td>
<td></td>
</tr>
<tr>
<td>NOM  Nominalization</td>
<td></td>
<td>UNF Unfinished constituent</td>
</tr>
</tbody>
</table>

Table A.1: A list of function tags for English.
### A.2 Part-of-speech tags

<table>
<thead>
<tr>
<th>Word level tags</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ADD</strong></td>
<td>Email</td>
</tr>
<tr>
<td><strong>AFX</strong></td>
<td>Affix</td>
</tr>
<tr>
<td><strong>CC</strong></td>
<td>Coordinating conjunction</td>
</tr>
<tr>
<td><strong>CD</strong></td>
<td>Cardinal number</td>
</tr>
<tr>
<td><strong>CODE</strong></td>
<td>Code ID</td>
</tr>
<tr>
<td><strong>DT</strong></td>
<td>Determiner</td>
</tr>
<tr>
<td><strong>EX</strong></td>
<td>Existential there</td>
</tr>
<tr>
<td><strong>FW</strong></td>
<td>Foreign word</td>
</tr>
<tr>
<td><strong>GW</strong></td>
<td>Go with</td>
</tr>
<tr>
<td><strong>IN</strong></td>
<td>Preposition or subordinating conjunction</td>
</tr>
<tr>
<td><strong>JJ</strong></td>
<td>Adjective</td>
</tr>
<tr>
<td><strong>JJR</strong></td>
<td>Adjective, comparative</td>
</tr>
<tr>
<td><strong>JJS</strong></td>
<td>Adjective, superlative</td>
</tr>
<tr>
<td><strong>LS</strong></td>
<td>List item marker</td>
</tr>
<tr>
<td><strong>MD</strong></td>
<td>Modal</td>
</tr>
<tr>
<td><strong>NN</strong></td>
<td>Noun, singular or mass</td>
</tr>
<tr>
<td><strong>NNP</strong></td>
<td>Proper noun, singular</td>
</tr>
<tr>
<td><strong>NNPS</strong></td>
<td>Proper noun, plural</td>
</tr>
<tr>
<td><strong>PDT</strong></td>
<td>Predeterminer</td>
</tr>
<tr>
<td><strong>POS</strong></td>
<td>Possessive ending</td>
</tr>
<tr>
<td><strong>PRP</strong></td>
<td>Personal pronoun</td>
</tr>
<tr>
<td><strong>PRP$</strong></td>
<td>Possessive pronoun</td>
</tr>
<tr>
<td><strong>RB</strong></td>
<td>Adverb</td>
</tr>
<tr>
<td><strong>RBR</strong></td>
<td>Adverb, comparative</td>
</tr>
<tr>
<td><strong>RBS</strong></td>
<td>Adverb, superlative</td>
</tr>
<tr>
<td><strong>RP</strong></td>
<td>Particle</td>
</tr>
<tr>
<td><strong>TO</strong></td>
<td>To</td>
</tr>
<tr>
<td><strong>UH</strong></td>
<td>Interjection</td>
</tr>
<tr>
<td><strong>VB</strong></td>
<td>Verb, base form</td>
</tr>
<tr>
<td><strong>VBD</strong></td>
<td>Verb, past tense</td>
</tr>
<tr>
<td><strong>VBG</strong></td>
<td>Verb, gerund or present participle</td>
</tr>
<tr>
<td><strong>VBN</strong></td>
<td>Verb, past participle</td>
</tr>
<tr>
<td><strong>VBP</strong></td>
<td>Verb, non-3rd person singular present</td>
</tr>
<tr>
<td><strong>VBZ</strong></td>
<td>Verb, 3rd person singular present</td>
</tr>
<tr>
<td><strong>WDT</strong></td>
<td>Wh-determiner</td>
</tr>
<tr>
<td><strong>WP</strong></td>
<td>Wh-pronoun</td>
</tr>
<tr>
<td><strong>WP$</strong></td>
<td>Possessive wh-pronoun</td>
</tr>
<tr>
<td><strong>WRB</strong></td>
<td>Wh-adverb</td>
</tr>
<tr>
<td><strong>XX</strong></td>
<td>Unknown</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Punctuation like tags</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>$</strong></td>
<td>Dollar</td>
</tr>
<tr>
<td><strong>:-</strong></td>
<td>Left bracket</td>
</tr>
<tr>
<td><strong>,:</strong></td>
<td>Right bracket</td>
</tr>
<tr>
<td><strong>,:</strong></td>
<td>Hyphen</td>
</tr>
<tr>
<td><strong>.:</strong></td>
<td>Superfluous punctuation</td>
</tr>
<tr>
<td><strong>&quot;</strong></td>
<td>Symbol</td>
</tr>
<tr>
<td><strong>&quot;&quot;</strong></td>
<td>General punctuation</td>
</tr>
</tbody>
</table>

Table A.2: A list of part-of-speech tags for English.
### A.3 Clause and phrase level tags

<table>
<thead>
<tr>
<th>Clause level tags</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>S</strong></td>
<td>Simple declarative clause</td>
</tr>
<tr>
<td><strong>SBAR</strong></td>
<td>Clause introduced by a subordinating conjunction</td>
</tr>
<tr>
<td><strong>SBARQ</strong></td>
<td>Direct question introduced by a <em>wh</em>-word or a <em>wh</em>-phrase</td>
</tr>
<tr>
<td><strong>SINV</strong></td>
<td>Inverted declarative sentence</td>
</tr>
<tr>
<td><strong>SQ</strong></td>
<td>Inverted yes/no question, or main clause of a <em>wh</em>-question</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Phrase level tags</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ADJP</strong></td>
<td>Adjective phrase</td>
</tr>
<tr>
<td><strong>ADVP</strong></td>
<td>Adverb phrase</td>
</tr>
<tr>
<td><strong>CAPTION</strong></td>
<td>Caption</td>
</tr>
<tr>
<td><strong>CIT</strong></td>
<td>Citation</td>
</tr>
<tr>
<td><strong>CONJP</strong></td>
<td>Conjunction phrase</td>
</tr>
<tr>
<td><strong>EDITED</strong></td>
<td>Edited phrase</td>
</tr>
<tr>
<td><strong>EMBED</strong></td>
<td>Embedded phrase</td>
</tr>
<tr>
<td><strong>FRAG</strong></td>
<td>Fragment</td>
</tr>
<tr>
<td><strong>HEADING</strong></td>
<td>Heading</td>
</tr>
<tr>
<td><strong>INTJ</strong></td>
<td>Interjection</td>
</tr>
<tr>
<td><strong>LST</strong></td>
<td>List marker</td>
</tr>
<tr>
<td><strong>META</strong></td>
<td>Meta data</td>
</tr>
<tr>
<td><strong>NAC</strong></td>
<td>Not a constituent</td>
</tr>
<tr>
<td><strong>NML</strong></td>
<td>Nominal phrase</td>
</tr>
<tr>
<td><strong>NP</strong></td>
<td>Noun phrase</td>
</tr>
<tr>
<td><strong>NX</strong></td>
<td>N-bar level phrase</td>
</tr>
<tr>
<td><strong>PP</strong></td>
<td>Prepositional phrase</td>
</tr>
<tr>
<td><strong>PRN</strong></td>
<td>Parenthetical phrase</td>
</tr>
<tr>
<td><strong>PRT</strong></td>
<td>Particle</td>
</tr>
<tr>
<td><strong>QP</strong></td>
<td>Quantifier Phrase</td>
</tr>
<tr>
<td><strong>RRC</strong></td>
<td>Reduced relative clause</td>
</tr>
<tr>
<td><strong>TITLE</strong></td>
<td>Title</td>
</tr>
<tr>
<td><strong>TYPO</strong></td>
<td>Typo</td>
</tr>
<tr>
<td><strong>UCP</strong></td>
<td>Unlike coordinated phrase</td>
</tr>
<tr>
<td><strong>VP</strong></td>
<td>Verb phrase</td>
</tr>
<tr>
<td><strong>WHADJP</strong></td>
<td><em>Wh</em>-adjective phrase</td>
</tr>
<tr>
<td><strong>WHADVP</strong></td>
<td><em>Wh</em>-adverb phrase</td>
</tr>
<tr>
<td><strong>WHNP</strong></td>
<td><em>Wh</em>-noun phrase</td>
</tr>
<tr>
<td><strong>WHPP</strong></td>
<td><em>Wh</em>-prepositional phrase</td>
</tr>
<tr>
<td><strong>X</strong></td>
<td>Unknown</td>
</tr>
</tbody>
</table>

Table A.3: A list of clause and phrase level tags for English.
Appendix B

Semantic Role Labels

B.1 PropBank semantic role labels

This appendix shows a list of the PropBank semantic role labels. See Bonial et al. (2010) for more details about the PropBank semantic role labels.

<table>
<thead>
<tr>
<th>Label</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARG0</td>
<td>Agent</td>
</tr>
<tr>
<td>ARG1</td>
<td>Patient, theme</td>
</tr>
<tr>
<td>ARG2</td>
<td>Instrument, benefactive, attribute</td>
</tr>
<tr>
<td>ARG3</td>
<td>Starting point</td>
</tr>
<tr>
<td>ARG4</td>
<td>Ending point</td>
</tr>
<tr>
<td>ARGA</td>
<td>External causer</td>
</tr>
<tr>
<td>ARGM-ADJ</td>
<td>Adjectival</td>
</tr>
<tr>
<td>ARGM-ADV</td>
<td>Adverbial</td>
</tr>
<tr>
<td>ARGM-CAU</td>
<td>Cause</td>
</tr>
<tr>
<td>ARGM-COM</td>
<td>Comitative</td>
</tr>
<tr>
<td>ARGM-DIR</td>
<td>Direction</td>
</tr>
<tr>
<td>ARGM-DIS</td>
<td>Discourse</td>
</tr>
<tr>
<td>ARGM-GOL</td>
<td>Goal</td>
</tr>
<tr>
<td>ARGM-EXT</td>
<td>Extent</td>
</tr>
<tr>
<td>ARGM-L0C</td>
<td>Location</td>
</tr>
<tr>
<td>ARGM-MNR</td>
<td>Manner</td>
</tr>
<tr>
<td>ARGM-MOD</td>
<td>Modal</td>
</tr>
<tr>
<td>ARGM-NEG</td>
<td>Negation</td>
</tr>
<tr>
<td>ARGM-PRD</td>
<td>Secondary predication</td>
</tr>
<tr>
<td>ARGM-PRP</td>
<td>Purpose (previously, ARGM-PNC)</td>
</tr>
<tr>
<td>ARGM-REC</td>
<td>Recipricol</td>
</tr>
<tr>
<td>ARGM-TMP</td>
<td>Temporal</td>
</tr>
</tbody>
</table>

Table B.1: A list of the PropBank semantic role labels.
B.2 VerbNet thematic role labels

This appendix shows a list of the VerbNet thematic role labels. See Bonial et al. (2011) for more details about the VerbNet thematic role labels.

<table>
<thead>
<tr>
<th>Label</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>actor1,2</td>
<td>pseudo-agents, used for some communication classes</td>
</tr>
<tr>
<td>agent</td>
<td>animate subject, volitional or internally controlled</td>
</tr>
<tr>
<td>asset</td>
<td>currency, used for Build/Get/Obtain Classes</td>
</tr>
<tr>
<td>attribute</td>
<td>changed quality of patient/theme</td>
</tr>
<tr>
<td>beneficiary</td>
<td>Entity benefiting from action</td>
</tr>
<tr>
<td>cause</td>
<td>entity causing an action, used for psychological/body verbs</td>
</tr>
<tr>
<td>destination</td>
<td>End point/target of motion</td>
</tr>
<tr>
<td>experiencer</td>
<td>Participant that is aware of experiencing something</td>
</tr>
<tr>
<td>extent</td>
<td>Range or degree of change</td>
</tr>
<tr>
<td>instrument</td>
<td>Objects/forces that come into contact and cause change in another object</td>
</tr>
<tr>
<td>location</td>
<td>Underspecified destination/source/place</td>
</tr>
<tr>
<td>material</td>
<td>Starting point of transformation</td>
</tr>
<tr>
<td>patient1,2</td>
<td>Affected participants, used for some combining/attaching verbs</td>
</tr>
<tr>
<td>predicate</td>
<td>Predicative complement</td>
</tr>
<tr>
<td>product</td>
<td>End result of transformation</td>
</tr>
<tr>
<td>recipient</td>
<td>Target of transfer</td>
</tr>
<tr>
<td>source</td>
<td>Spatial location, starting point</td>
</tr>
<tr>
<td>stimulus</td>
<td>Events/objects that elicit a response from an experiencer</td>
</tr>
<tr>
<td>theme</td>
<td>Participants in/undergoing a change of location</td>
</tr>
<tr>
<td>theme1,2</td>
<td>Indistinct themes, used for differ/exchange classes</td>
</tr>
<tr>
<td>patient</td>
<td>Affected participants undergoing a process</td>
</tr>
<tr>
<td>time</td>
<td>Class-specific, express temporal relations</td>
</tr>
<tr>
<td>topic</td>
<td>Topic of conversation, message, used for communication verbs</td>
</tr>
<tr>
<td>proposition</td>
<td>Complement clause indicating desired/requested action, used for order class</td>
</tr>
</tbody>
</table>

Table B.2: A list of the VerbNet thematic role labels.
Appendix C

Dependency Labels

C.1 CoNLL dependency labels

This appendix shows a list of the CoNLL dependency labels. See Johansson (2008, Chap. 4) for more details about the CoNLL dependency labels.

<table>
<thead>
<tr>
<th>Labels retained from function tags</th>
<th>Labels inferred from constituent relations</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADV</td>
<td>Unclassified adverbial</td>
</tr>
<tr>
<td>BNF</td>
<td>Benefactor</td>
</tr>
<tr>
<td>DIR</td>
<td>Direction</td>
</tr>
<tr>
<td>DTV</td>
<td>Dative</td>
</tr>
<tr>
<td>EXT</td>
<td>Extent</td>
</tr>
<tr>
<td>LGS</td>
<td>Logical subject</td>
</tr>
<tr>
<td>LOC</td>
<td>Locative</td>
</tr>
<tr>
<td>AMOD</td>
<td>Modifier of adjective or adverb</td>
</tr>
<tr>
<td>CONJ</td>
<td>Conjunct</td>
</tr>
<tr>
<td>COORD</td>
<td>Coordination</td>
</tr>
<tr>
<td>DEP</td>
<td>Unclassified dependency</td>
</tr>
<tr>
<td>EXTR</td>
<td>Extraposited element</td>
</tr>
<tr>
<td>GAP</td>
<td>Gapping</td>
</tr>
<tr>
<td>IM</td>
<td>Infinitive marker</td>
</tr>
<tr>
<td>NMOD</td>
<td>Modifier of nominal</td>
</tr>
<tr>
<td>OBJ</td>
<td>Object or clausal complement</td>
</tr>
</tbody>
</table>

Table C.1: A list of the CoNLL dependency labels.
### C.2 Stanford dependency labels

This appendix shows a list of the Stanford dependency labels. See de Marneffe and Manning (2008b) for more details about Stanford dependency labels.

<table>
<thead>
<tr>
<th>Label</th>
<th>Description</th>
<th>Label</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABBREV</td>
<td>Abbreviation modifier</td>
<td>NPAVDMOD</td>
<td>Noun phrase as ADVMOD</td>
</tr>
<tr>
<td>ACOMP</td>
<td>Adjectival complement</td>
<td>NSUBJ</td>
<td>Nominal subject</td>
</tr>
<tr>
<td>ADVCL</td>
<td>Adverbial clause modifier</td>
<td>NSUBJPASS</td>
<td>Nominal subject (passive)</td>
</tr>
<tr>
<td>ADVMOD</td>
<td>Adverbial modifier</td>
<td>NUM</td>
<td>Numeric modifier</td>
</tr>
<tr>
<td>AGENT</td>
<td>Agent</td>
<td>NUMBER</td>
<td>Element of compound number</td>
</tr>
<tr>
<td>AMOD</td>
<td>Adjectival modifier</td>
<td>PARATAxis</td>
<td>Parataxis</td>
</tr>
<tr>
<td>APPPOS</td>
<td>Appositional modifier</td>
<td>PARTMOD</td>
<td>Participial modifier</td>
</tr>
<tr>
<td>ATTR</td>
<td>Attribute</td>
<td>PCOMP</td>
<td>Prepositional complement</td>
</tr>
<tr>
<td>AUX</td>
<td>Auxiliary</td>
<td>POBJ</td>
<td>Object of a preposition</td>
</tr>
<tr>
<td>AUXPASS</td>
<td>Auxiliary (passive)</td>
<td>POSS</td>
<td>Possession modifier</td>
</tr>
<tr>
<td>CC</td>
<td>Coordination</td>
<td>POSSESSIVE</td>
<td>Possessive modifier</td>
</tr>
<tr>
<td>CCOMP</td>
<td>Clausal complement</td>
<td>PRECONJ</td>
<td>Preconjunct</td>
</tr>
<tr>
<td>COMPLM</td>
<td>Complementizer</td>
<td>PREDET</td>
<td>Predeterminer</td>
</tr>
<tr>
<td>CONJ</td>
<td>Conjunct</td>
<td>PREP</td>
<td>Prepositional modifier</td>
</tr>
<tr>
<td>COP</td>
<td>Copula</td>
<td>PREPC</td>
<td>Prepositional clausal modifier</td>
</tr>
<tr>
<td>CSUBJ</td>
<td>Clausal subject</td>
<td>PRT</td>
<td>Phrasal verb particle</td>
</tr>
<tr>
<td>CSUBJPASS</td>
<td>Clausal subject (passive)</td>
<td>PUNCT</td>
<td>Punctuation</td>
</tr>
<tr>
<td>DEP</td>
<td>Dependent</td>
<td>PURPCL</td>
<td>Purpose clause modifier</td>
</tr>
<tr>
<td>DET</td>
<td>Determiner</td>
<td>QUANTMOD</td>
<td>Quantifier phrase modifier</td>
</tr>
<tr>
<td>DOBJ</td>
<td>Direct object</td>
<td>RCMOD</td>
<td>Relative clause modifier</td>
</tr>
<tr>
<td>EXPL</td>
<td>Expletive</td>
<td>REF</td>
<td>Referent</td>
</tr>
<tr>
<td>INFMOD</td>
<td>Infinitival modifier</td>
<td>REL</td>
<td>Relative</td>
</tr>
<tr>
<td>IOBJ</td>
<td>Indirect object</td>
<td>ROOT</td>
<td>Root</td>
</tr>
<tr>
<td>MARK</td>
<td>Marker</td>
<td>TMOD</td>
<td>Temporal modifier</td>
</tr>
<tr>
<td>MWE</td>
<td>Multi-word expression</td>
<td>XCOMP</td>
<td>Open clausal complement</td>
</tr>
<tr>
<td>NEG</td>
<td>Negation modifier</td>
<td>XSUBJ</td>
<td>Controlling subject</td>
</tr>
<tr>
<td>NN</td>
<td>Noun compound modifier</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table C.2: A list of the Stanford dependency labels.
Appendix D

The CLEAR Dependency Labels

This appendix gives descriptions of the CLEAR dependency labels. Algorithms introduced here are called by the \textit{getDependencyLabel}(C, P, p) method in Algorithm 2.10. Algorithms followed by \textasteriskcentered (e.g., \textit{setPassiveSubject}(D, H)* in Algorithm D.2) are called after the \textit{getDependencyLabel}(C, P, p) method and applied to all dependency nodes.

D.1 Arguments: subject related

Subject-related labels consist of agents (AGENT), clausal subjects (CSUBJ), clausal passive subjects (CSUBJPASS), expletives (EXPL), nominal subjects (NSUBJ), and nominal passive subjects (NSUBJPASS).

\textbf{Algorithm D.1 : getSubjectLabel}(C, d)

\begin{itemize}
  \item \underline{Input:} Constituents $C$ and $d$, where $d$ is the head dependent of $C$.
  \item \underline{Output:} CSUBJ, NSUBJ, EXPL, or AGENT if $C$ is a subject-related argument; otherwise, null.
\end{itemize}

1: \textbf{if} $C$ has SBJ \textbf{then}
2: \quad \textbf{if} $C$ is S* \textbf{return} CSUBJ \quad \# Section D.1.2
3: \quad \textbf{if} $d$ is EX \textbf{return} EXPL \quad \# Section D.1.4
4: \quad \textbf{return} NSUBJ \quad \# Section D.1.5
5: \quad \textbf{if} $C$ has LGS \textbf{return} AGENT \quad \# Section D.1.1
6: \quad \textbf{return} null
Algorithm D.2: `setPassiveSubject(D, H)`

**Input:** Dependents $D$ and $H$, where $H$ is the head of $D$.

**Output:** If $D$ is a passive subject, append `PASS` to its label.

1: if $H$ contains `AUXPASS` then
2: if $D$ is `CSUBJ` then $D$.label $\leftarrow$ `CSUBJPASS`  # Section D.1.3
3: elif $D$ is `NSUBJ` then $D$.label $\leftarrow$ `NSUBJPASS`  # Section D.1.6

### D.1.1 AGENT: agent

An agent is the complement of a passive verb that is the surface subject of its active form. In our approach, the preposition *by* is included as a part of `AGENT`.

1. The car was bought [by John] `AGENT`(bought, by), `POBJ`(by, John)
2. The car bought [by John] is red `AGENT`(bought, by), `POBJ`(by, John)

### D.1.2 CSUBJ: clausal subject

A clausal subject is a clause in the subject position of an active verb. A clause with a `SBJ` function tag is considered a `CSUBJ`.

1. [Whether she liked me] doesn’t matter `CSUBJ`(matter, liked)
2. [What I said] was true `CSUBJ`(was, said)
3. [Who I liked] was you `CCOMP`(was, liked), `NSUBJ`(was, you)

In (3), *Who I liked* is topicalized such that it is considered a clausal complement (`CCOMP`) of *was*; *you* is considered a nominal subject (`NSUBJ`) of *was*.

### D.1.3 CSUBJPASS: clausal passive subject

A clausal passive subject is a clause in the subject position of a passive verb. A clause with the `SBJ` function tag that depends on a passive verb is considered a `CSUBJPASS`.

1. [Whoever misbehaves] will be dismissed `CSUBJPASS`(dismissed, misbehaves)
D.1.4 EXPL: expletive

An expletive is an existential there in the subject position.

(1) There was an explosion EXPL(was, There)

D.1.5 NSUBJ: nominal subject

A nominal subject is a non-clausal constituent in the subject position of an active verb. A non-clausal constituent with the SBJ function tag is considered a NSUBJ.

(1) [She and I] came home together NSUBJ(came, She)
(2) [Earlier] was better NSUBJ(was, Earlier)

D.1.6 NSUBJPASS: nominal passive subject

A nominal passive subject is a non-clausal constituent in the subject position of a passive verb. A non-clausal constituent with the SBJ function tag that depends on a passive verb is considered a NSUBJPASS.

(1) I [am] drawn to her NSUBJPASS(drawn, I)
(2) We will [get] married NSUBJPASS(married, We)
(3) She will [become] nationalized NSUBJPASS(nationalized, She)

D.2 Arguments: object related

Object-related labels consist of attributes (ATTR), direct objects (DOBJ), indirect objects (IOBJ), and object predicates (OPRD).

Algorithm D.3 : getobjectLabel(C)

Input: A constituent C whose parent is VP|SINV|SQ.
Output: DOBJ or ATTR if C is in an object or an attribute; otherwise, null.

1: if C is NP|NML then
2: if C has PRD return ATTR # Section D.2.1
3: return DOBJ # Section D.2.2
4: return null
D.2.1  **ATTR: attribute**

An attribute is a noun phrase that is a non-VP predicate usually following a copula verb.

(1) This product is [a global brand]  **ATTR(is, brand)**
(2) This area became [a prohibited zone]  **ATTR(became, zone)**

D.2.2  **DOBJ: direct object**

A direct object is a noun phrase that is the accusative object of a (di)transitive verb.

(1) She bought me [these books]  **DOBJ(bought, books)**
(2) She bought [these books] for me  **DOBJ(bought, books)**

D.2.3  **IOBJ: indirect object**

An indirect object is a noun phrase that is the dative object of a ditransitive verb.

(1) She bought [me] these books  **IOBJ(bought, me)**
(2) She bought these books [for me]  **PREP(bought, for)**
(3) [What] she bought [me] were these books  **DOBJ(bought, What), IOBJ(bought, me)**
(4) I read [them] [one by one]  **DOBJ(read, them), NPADVMOD(read, one)**

In (2), *for me* is considered a prepositional modifier although it is the dative object in an unshifted form. This information is preserved with a function tag **DTV** as additional information in our representation (Section 2.6.2). In (3), *What* and *me* are considered direct and indirect objects of *bought*, respectively. In (4), the noun phrase *one by one* is not considered an **IOBJ**, but an adverbial noun phrase modifier (**NPADVMOD**) because it carries an adverbial function tag, **MNR**. This kind of information is also preserved with semantic function tags in our representation (Section 2.6.1).

**Algorithm D.4:**  *setIndirectObject(C)*

**Input:** A dependent $D$.

**Output:** If $D$ is an indirect object, set its label to **IOBJ**.

1. **if** ($D$ is **DOBJ**) and ($D$ is followed by another **DOBJ**) **then** $D$.label ← **IOBJ**
**D.2.4 OPRD: object predicate**

An object predicate is a non-VP predicate in a small clause that functions like the predicate of an object. Section 2.3.4 describes how object predicates are derived.

(1) She calls [me] [her friend]  \(\text{DOBJ}\)\(\text{(calls, me)}, \text{OPRD}\)\(\text{(calls, friend)}\)

(2) She considers [[me] her friend]  \(\text{CCOMP}\)\(\text{(considers, friend)}, \text{NSUBJ}\)\(\text{(me, friend)}\)

(3) I am considered [her friend]  \(\text{OPRD}\)\(\text{(considered, friend)}\)

(4) I persuaded [her] [to come]  \(\text{DOBJ}\)\(\text{(persuaded, her)}, \text{XCOMP}\)\(\text{(persuaded, come)}\)

In (2), the small clause *me her friend* is considered a clausal complement (\(\text{CCOMP}\)) because we treat *me* as the subject of the non-VP predicate, *her friend*. In (4), the open clause *to come* does indeed predicate over *her* but is not labeled as an \(\text{OPRD}\) but rather an open clausal complement (\(\text{XCOMP}\)).

This is because the dependency between *her* and *come* is already shown in our representation as an open clausal subject (\(\text{XSUBJ}\)) whereas such information is not available for the non-VP predicates in (1) and (3); thus, without labeling them as object predicates, it can be difficult to infer the relation between the objects and object predicates.

---

**Algorithm D.5: isObjectPredicate\(\langle C\rangle\)**

<table>
<thead>
<tr>
<th>Input:</th>
<th>A constituent (C).</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output:</td>
<td>True if (C) is an object predicate; otherwise, False.</td>
</tr>
</tbody>
</table>

1: if \((C \text{ is } S) \text{ and } (C \text{ contains no VP}) \text{ and } (C \text{ contains both SBJ and PRD})\) then  
2: if the subject of \(C\) is an empty category return True  
3: return False

---

**D.3 Auxiliaries**

Auxiliary labels consist of auxiliaries (\(\text{AUX}\)) and passive auxiliaries (\(\text{AUXPASS}\)). The \(\text{getAuxiliaryLabel}\(\langle C\rangle\) method in Algorithm D.6 shows how auxiliary labels are distinguished. Note that a passive auxiliary is supposed to modify only a past participle (\(\text{VBN}\)), which is sometimes annotated as a past tense verb (\(\text{VBD}\)). The condition in lines 5 and 8 resolves such an erroneous case. Lines 6-7 are
added to handle the case of coordination where $vp_1$ is just an umbrella constituent that groups VP conjuncts together.

**Algorithm D.6 : getAuxiliaryLabel($C$)**

**Input:** A constituent $C$ whose parent is VP|SINV|SQ.

**Output:** AUX or AUXPASS if $C$ is an auxiliary or a passive auxiliary; otherwise, null.

```plaintext
1: if $C$ is MD|TO return AUX                      # Section D.3.1
2: if ($C$ is VB*) and ($C$ contains VP) then
3: if $C$ is be|become|get then
4: let $vp_1$ be the first VP in $C$
5: if $vp_1$ contains VBN|VBD return AUXPASS       # Section D.3.2
6: if ($vp_1$ contains no VB*) and ($vp_1$ contains VP) then  # for coordination
7: let $vp_2$ be the first VP in $vp_1$
8: if $vp_2$ contains VBN|VBD return AUXPASS
9: return AUX
10: return null
```

### D.3.1 AUX: auxiliary

An auxiliary is an auxiliary or modal verb that gives further information about the main verb (e.g., tense, aspect). The preposition to, used for infinitive, is also considered an AUX. Auxiliary verbs for passive verbs are assigned with a separate dependency label AUXPASS (Section D.3.2).

(1) I [have] [been] seeing her  
AUX(seeing, have), AUX(seeing, been)

(2) I [will] meet her tomorrow  
AUX(meet, will)

(3) I [am] [going] [to] meet her tomorrow  
AUX(meet, am), AUX(meet, going), AUX(meet, to)

### D.3.2 AUXPASS: passive auxiliary

A passive auxiliary is an auxiliary verb, be, become, or get, that modifies a passive verb.

(1) I [am] drawn to her  
AUXPASS(drawn, am)

(2) We will [get] married  
AUXPASS(married, get)

(3) She will [become] nationalized  
AUXPASS(nationalized, become)
D.4 Complements

Complement labels consist of adjectival complements (ACOMP), clausal complements (CCOMP), and open clausal complements (XCOMP). Additionally, complementizers (COMPLM) are included to indicate the beginnings of clausal complements.

D.4.1 ACOMP: adjectival complement

An adjectival complement is an adjective phrase that modifies the head of a VP|SINV|SQ, that is usually a verb.

(1) She looks [so beautiful] ACOMP(looks, beautiful)
(2) Please make [sure to invite her] ACOMP(make, sure)
(3) Are you [worried] ACOMP(Are, worried)
(4) [Most important] is your heart ACOMP(is, important), NSUBJ(is, heart)

In (4), Most important is topicalized such that it is considered an ACOMP of is although it is in the subject position; your heart is considered a nominal subject (NSUBJ) of is.

D.4.2 CCOMP: clausal complement

A clausal complement is a clause with an internal subject that modifies the head of an ADJP|ADVP|NML|NP|WHNP|VP|SINV|SQ. For NML|NP|WHNP, a clause is considered a CCOMP if it is neither a infinitival modifier (Section D.7.3), a participial modifier (Section D.7.7), nor a relative clause modifier (Section D.7.10).

(1) She said [(that) she wanted to go] CCOMP(said, wanted)
(2) I am not sure [what she wanted] CCOMP(sure, wanted)
(3) She left no matter [how I felt] CCOMP(matter, felt)
(4) I don’t know [where she is] CCOMP(know, is)
(5) She asked [should we meet again] CCOMP(asked, meet)
(6) I asked [why did you leave] \textsc{CCOMP}(asked, leave)

(7) I said [may God bless you] \textsc{CCOMP}(said, bless)

(8) The fact [(that) she came back] made me happy \textsc{CCOMP}(fact, came)

In (4), \textit{where she is} is considered a \textsc{CCOMP} although it carries arbitrary locative information. Clauses such as polar questions (5), \textit{wh}-questions (6), or inverted declarative sentences (7) are also considered \textsc{CCOMP}. A clause with an adverbial function tag is not considered a \textsc{CCOMP}, but an adverbial clause modifier (Section D.5.1).

\begin{algorithm}
\textbf{Algorithm D.7: } \textit{isClausalComplement}(C)
\begin{enumerate}
\item if $C$ is S|SQ|SINV|SBARQ return True
\item if $C$ is SBAR then
  \begin{enumerate}
  \item if $C$ contains a \textit{wh}-complementizer return True
  \item if $C$ contains a null complementizer, 0 return True
  \item if $C$ contains a complementizer, \textit{if}, \textit{that}, or \textit{whether} then
    \begin{enumerate}
    \item set the dependency label of the complementizer to COMPLM \# Section D.4.4
    \item return True
    \end{enumerate}
  \end{enumerate}
\item return False
\end{enumerate}
\end{algorithm}

(D.4.3) XCOMP: open clausal complement

An open clausal complement is a clause without an internal subject that modifies the head of an \textsc{ADJP}|\textsc{ADVP}|\textsc{VP}|\textsc{SINV}|\textsc{SQ}.

(1) I want [to go] \textsc{XCOMP}(want, go)

(2) I am ready [to go] \textsc{XCOMP}(ready, go)

(3) It is too soon [to go] \textsc{XCOMP}(soon, go)

(4) He knows [how to go] \textsc{XCOMP}(knows, go)

(5) What do you think [happend] \textsc{XCOMP}(think, happened)

(6) He forced [me] [to go] \textsc{DOBJ}(forced, me), \textsc{XCOMP}(forced, go)

(7) He expected [[me] to go] \textsc{CCOMP}(expected, go), \textsc{NSUBJ}(me, go)
In (7), *me to go* is not considered an XCOMP but a clausal complement (CCOMP) because *me* is considered a nominal subject (NSUBJ) of *go* (see Section 2.5.4 for more examples of open clauses).

**Algorithm D.8**: isOpenClausalComplement(C)

- **Input**: A constituent C whose parent is ADJP|ADVP|VP.
- **Output**: True if C is an open clausal complement; otherwise, False.

1: if C is S then
2: return (C contains VP) and (the subject of C is an empty category)
3: if (C is SBAR) and (C contains a null complementizer) then
4: let c be S in C
5: return isOpenClausalComplement(c)
6: return False

**D.4.4 COMPLM: complementizer**

A complementizer is a subordinating conjunction, *if, that,* or *whether,* that introduces a clausal complement (Section D.4.2). A COMPLM is assigned when a clausal complement is found (see the line 6 of isClausalComplement(C) in Section D.4.2).

1. She said [that] she wanted to go COMPLM(wanted, that)
2. I wasn’t sure [if] she liked me COMPLM(liked, if)
3. I wasn’t sure [whether] she liked me COMPLM(liked, whether)
D.5 Modifiers: adverbial related

Adverbial related modifiers consist of adverbial clause modifiers (ADVCL), adverbial modifiers (ADVMOD), markers (MARK), negation modifiers (NEG), and noun phrases as adverbial modifiers (NPADVMOD).

Algorithm D.9: hasAdverbialTag(C)

Input: A constituent C.
Output: True if C has an adverbial function tag; otherwise, False.

1: if C has ADV|BNF|DIR|EXT|LOC|MNR|PRP|TMP|VOC return True
2: return False

D.5.1 ADVCL: adverbial clause modifier

An adverbial clause modifier is a clause that acts like an adverbial modifier. A clause with an adverbial function tag (see hasAdverbialTag(C)) is considered an ADVCL. Additionally, a subordinate clause or an open clause is considered an ADVCL if it does not satisfy any other dependency relation (see Appendices D.4.2 and D.4.3 for more details about clausal complements).

(1) She came [as she promised] ADVCL(came, promised)
(2) She came [to see me] ADVCL(came, see)
(3) [Now that she is here] everything seems fine ADVCL(seems, is)
(4) She would have come [if she liked me] ADVCL(come, liked)
(5) I wasn’t sure [if she liked me] CCOMP(sure, liked)

In (2), to see me is an ADVCL (with a semantic role, purpose) although it may appear to be an open clausal complement of came (Section D.4.3). In (4) and (5), if she liked me is considered an ADVCL and a clausal complement (CCOMP), respectively. This is because if in (3) creates a causal relation between the matrix and subordinate clauses whereas it does not serve any purpose other than introducing the subordinate clause in (4), just like a complementizer that or whether.
D.5.2  ADVMOD: adverbial modifier

An adverbial modifier is an adverb or an adverb phrase that modifies the meaning of another word. Other grammatical categories can also be ADVMOD if they modify adjectives.

1. I did [not] know her  ADVMOD(know, not)
2. I invited her [[as] well]  ADVMOD(invited, well), ADVMOD(well, as)
3. She is [already] [here]  ADVMOD(is, already), ADVMOD(is, here)
4. She is [so] beautiful  ADVMOD(beautiful, so)
5. I’m not sure [any] more  ADVMOD(more, any)

In (5), any is a determiner but considered an ADVMOD because it modifies the adjective, more.

Algorithm D.10 : isAdverbialModifier(C)

Input: A constituent C.
Output: True if C is an adverbial function tag; otherwise, False.

1: if C is ADVP|RB*|WRB then
2: let P be the parent of C
3: if (P is SBAR) and (P is ADVCL) and (C is IN|DT|TO) and (C is the last child of P) return False
4: return True

D.5.3  MARK: maker

A marker is a subordinating conjunction (e.g., although, because, while) that introduces an adverbial clause modifier (Section D.5.1).

1. She came [as she promised]  MARK(promised, as)
2. She came [because she liked me]  MARK(liked, because)

Algorithm D.11 : setMarker(C, P)

Input: Constituents C and P, where P is the parent of C.
Output: If C is a marker, set its label to MARK.

1: if (P is SBAR) and (P is ADVCL) and (C is IN|DT|TO) then C.label ← MARK

The setMarker(C, P) method is called after P is identified as an adverbial modifier.
D.5.4 \textbf{NEG: negation modifier}

A negation modifier is an adverb that gives negative meaning to its head.

(1) She decided not to come  \textit{NEG}(come, not)
(2) She didn’t come  \textit{NEG}(come, n’t)
(3) She never came  \textit{NEG}(came, never)
(4) This cookie is no good  \textit{NEG}(is, no)

\begin{algorithm}
\textbf{Algorithm D.12:} \textit{setNegationModifier}(D) *
\begin{algorithmic}
\Input{A dependent $D$.}
\Output{If $D$ is a negation modifier, set its label to \texttt{NEG}.}
\State \textbf{if} ($D$ is \texttt{NEG}) and ($D$ is \texttt{never} $|$ \texttt{not} $|$ \texttt{n’t} $|$ \texttt{’nt} $|$ \texttt{no}) \textbf{then} $D$.label \leftarrow \texttt{NEG}
\end{algorithmic}
\end{algorithm}

D.5.5 \textbf{NPADVMOD: noun phrase as adverbial modifier}

An adverbial noun phrase modifier is a noun phrase that acts like an adverbial modifier. A noun phrase with an adverbial function tag (see \textit{hasAdverbialTag}(C)) is considered an \texttt{NPADVMOD}. Moreover, a noun phrase modifying either an adjective or an adverb is also considered an \texttt{NPADVMOD}.

(1) Three times \texttt{[a week]}  \texttt{NPADVMOD}(times, week)
(2) It is \texttt{[a bit]} surprising  \texttt{NPADVMOD}(surprising, bit)
(3) \texttt{[Two days]} ago  \texttt{NPADVMOD}(ago, days)
(4) It \texttt{[all]} feels right  \texttt{NPADVMOD}(feels, all)
(5) I wrote the letter \texttt{[myself]}  \texttt{NPADVMOD}(wrote, myself)
(6) I met her \texttt{[last week]}  \texttt{NPADVMOD}(met, week)
(7) She lives \texttt{[next door]}  \texttt{NPADVMOD}(lives, door)

In (6) and (7), both \textit{last week} and \textit{next door} are considered \texttt{NPADVMOD} although they have different semantic roles, temporal and locative, respectively. These semantic roles can be retrieved from function tags and preserved as additional information (Section 2.6.1).
D.6  Modifiers: coordination related

Coordination related modifiers consist of conjuncts (CONJ), coordinating conjunctions (CC), and pre-correlative conjunctions (PRECONJ).

D.6.1  CONJ: conjunct

A conjunct is a dependent of the leftmost conjunct in coordination. The leftmost conjunct becomes the head of a coordinated phrase. Section 2.3.3 describes how conjuncts are derived.

(1) John, [Mary], and [Sam]  CONJ(John, Mary), CONJ(John, Sam)
(2) John, [Mary], and [so on]  CONJ(John, Mary), CONJ(John, on)
(3) John, [Mary], [Sam], [etc.]  CONJ(John, Mary), CONJ(John, Sam), CONJ(John, etc.)

Although there is no coordinating conjunction in (3), the phrase is considered coordinated because of the presence of etc.

D.6.2  CC: coordinating conjunction

A coordinating conjunction is a dependent of the leftmost conjunct in coordination.

(1) John, Mary, [and] Sam  CC(John, and)
(2) I know John [[as] [well] as] Mary  CC(John, as), ADVMOD(as, as), ADVMOD(as, well)
(3) [And], I know you  CC(know, And)

In (1), and becomes a CC of John, which is the leftmost conjunct. In (2), as well as is a multi-word expression so the dependencies between as and the others are not so meaningful but there to keep the tree connected. In (3), And is supposed to join the following clause with its preceding clause; however, since we do not derive dependencies across sentences, it becomes a dependent of the head of this clause, know.
**Algorithm D.13 :** \textit{isCoordinatingConjunction}(C)

\begin{itemize}
  \item \textbf{Input:} A constituent \(C\).
  \item \textbf{Output:} True if \(C\) is a coordinating conjunction; otherwise, False.
\end{itemize}

1: return \(C\) is \texttt{CC|CONJP}

**D.6.3 \quad PRECONJ: pre-correlative conjunction**

A pre-correlative conjunction is the first part of a correlative conjunction that becomes a dependent of the first conjunct in coordination.

(1) [Either] John [or] Mary \quad \textbf{PRECONJ}(John, Either), \textbf{CC}(John, or), \textbf{CONJ}(John, Mary)
(2) [Not only] John [but also] Mary \quad \textbf{PRECONJ}(John, Not), \textbf{CC}(John, but), \textbf{CONJ}(John, Mary)

**Algorithm D.14 :** \textit{isPreCorrelativeConjunction}(C)

\begin{itemize}
  \item \textbf{Input:} A constituent \(C\).
  \item \textbf{Output:} True if \(C\) is a pre-correlative conjunction; otherwise, False.
\end{itemize}

1: if \((C\) is \texttt{CC}) and \((C\) is both|either|neither|whether) return True
2: if \((C\) is \texttt{CONJP}) and \((C\) is not only) return True
3: return False
D.7 Modifiers: noun phrase related

Noun phrase related modifiers consist of appositional modifiers (APPOS), determiners (DET), infinitival modifiers (INFMOD), modifiers of nominals (NMOD), noun compound modifiers (NN), numeric modifiers (NUM), participial modifiers (PARTMOD), possessive modifiers (POSSESSIVE), predeterminers (PREDET), and relative clause modifiers (RCMOD).

Algorithm D.15: getNonFiniteModifierLabel(C)

Input: A constituent C whose parent is NML|NP|WHNP.
Output: INFMOD or PARTMOD.

1: if isOpenClausalComplement(C) or (C is VP) then # Section D.4.3
2: if isInfinitivalModifier(C) return INFMOD # Section D.7.3
3: return PARTMOD # Section D.7.7

Algorithm D.16: getNounModifierLabel(C)

Input: A constituent C whose parent is NML|NP|NX|WHNP.
Output: AMOD, DET, NN, NUM, POSSESSIVE, PREDET, or NMOD.

1: if C is VBG|VBN return AMOD # Section D.10.1
2: if C is DT|WDT|WP return DET # Section D.7.2
3: if C is PDT return PREDET # Section D.7.9
4: if C is NML|NP|FW|NN* return NN # Section D.7.5
5: if C is CD|QP return NUM # Section D.7.6
6: if C is POS return POSSESSIVE # Section D.7.8
7: return NMOD # Section D.7.4

D.7.1 APPOS: appositional modifier

An appositional modifier of an NML|NP is a noun phrase immediately preceded by another noun phrase, which gives additional information to its preceding noun phrase. A noun phrase with an adverbial function tag (Section D.5.1) is not considered an APPOS. Section 2.3.2 describes how appositional modifiers are derived.
(1) John, [my brother] \(\text{APPOS}(\text{John}, \text{brother})\)
(2) The year [2012] \(\text{APPOS}(\text{year}, 2012)\)
(3) He [himself] bought the car \(\text{APPOS}(\text{He}, \text{himself})\)
(4) Computational Linguistics [(CL)] \(\text{APPOS}(\text{Linguistics, CL})\)
(5) The book, Between You and Me \(\text{APPOS}(\text{book, Between})\)

**D.7.2 DET: determiner**

A determiner is a word token whose POS tag is DT|WDT|WP that modifies the head of a noun phrase.

(1) [The] US military \(\text{DET}(\text{military, The})\)
(2) [What] kind of movie is this \(\text{DET}(\text{movie, What})\)

**D.7.3 INFMOD: infinitival modifier**

An infinitival modifier is an infinitive clause or phrase that modifies the head of a noun phrase.

(1) I have too much homework [to do] \(\text{INFMOD}(\text{homework, do})\)
(2) I made an effort [to come] \(\text{INFMOD}(\text{effort, come})\)

Algorithm D.17 : \(\text{isInfinitivalModifier}(C)\)

**Input:** A constituent \(C\) whose parent is NML|NP|WHNP.
**Output:** True if \(C\) is an infinitival modifier; otherwise, False.

1: if \(C\) is VP then \(vp \leftarrow C\)
2: else
3: let \(t\) be the first descendant of \(C\) that is VP
4: \(vp \leftarrow (t\text{ exists}) ? t : \text{null}\)
5: if \(vp \neq \text{null}\) then
6: let \(t\) be the first child of \(vp\) that is VP
7: while \(t\) exists do
8: \(vp \leftarrow t\)
9: if \(vp\)'s previous sibling is TO return True
10: let \(t\) be the first child of \(vp\) that is VP
11: if \(vp\) contains TO return True
12: return False
D.7.4 **NMOD: modifier of nominal**

A modifier of nominal is any unclassified dependent that modifies the head of a noun phrase.

D.7.5 **NN: noun compound modifier**

A noun compound modifier is any noun that modifies the head of a noun phrase.

(1) The [US] military  \textsc{PREDET}(military, US)
(2) The [video] camera  \textsc{PREDET}(camera, video)

D.7.6 **NUM: numeric modifier**

A numeric modifier is any number or quantifier phrase that modifies the head of a noun phrase.

(1) [14] degrees  \textsc{NUM}(degrees, 14)
(2) [One] nation, [fifty] states  \textsc{NUM}(nation, One), \textsc{NUM}(states, fifty)

D.7.7 **PARTMOD: participial modifier**

A participial modifier is a clause or phrase whose head is a verb in a participial form (e.g., gerund, past participle) that modifies the head of a noun phrase.

(1) I went to the party [hosted by her]  \textsc{PARTMOD}(party, hosted)
(2) I met people [coming to this party]  \textsc{PARTMOD}(people, coming)

D.7.8 **POSSESSIVE: possessive modifier**

A possessive modifier is a word token whose \textsc{POS} tag is \textsc{POS} that modifies the head of a noun phrase.

(1) John[’s] car  \textsc{NMOD}(John, ’s)

D.7.9 **PREDET: predeterminer**

A predeterminer is a word token whose \textsc{POS} tag is \textsc{PDT} that modifies the head of a noun phrase.

(1) [Such] a beautiful woman  \textsc{PREDET}(woman, Such)
(2) [All] the books we read  \textsc{PREDET}(books, All)
D.7.10  **RCMOD: relative clause modifier**

A relative clause modifier is a either relative clause or a reduced relative clause that modifies the head of an NML\(\mid\)NP\(\mid\)WHNP.

(1) I bought the car [(that) I wanted]  \(\text{RCMOD(car, wanted)}\)
(2) I was the first person [to buy this car]  \(\text{INFMOD(person, buy)}\)
(3) This is the car [for which I’ve waited]  \(\text{RCMOD(car, waited)}\)
(4) It is a car [(that is) worth buying]  \(\text{RCMOD(car, worth)}\)

In (2), *to buy this car* is considered an infinitival modifier (INFMOD) although it contains an empty *wh*-complementizer in the constituent tree. (4) shows an example of a reduced relative clause.

**Algorithm D.18 : isRelativeClauseModifier(C)**

1. if \(C\) is RRC return True  
2. if \((C\) is SBAR) and \((C\) contains a *wh*-complementizer) return True  
3. return False

D.8  **Modifiers: prepositional phrase related**

Prepositional phrase related modifiers consist of complements of prepositions, objects of prepositions, and prepositional modifiers.

**Algorithm D.19 : getPrepositionModifierLabel(C)**

1. if \(C\) is NP\(\mid\)NML return POBJ  \(\#\) Section D.8.2  
2. return PCOMP  \(\#\) Section D.8.1
D.8.1  **PCOMP: complement of a preposition**

A complement of a preposition is any dependent that is not a **POBJ** but modifies the head of a prepositional phrase.

(1) I agree with [what you said]  **PCOMP**(with, said)

D.8.2  **POBJ: object of a preposition**

An object of a preposition is a noun phrase that modifies the head of a prepositional phrase, which is usually a preposition but can be a verb in a participial form such as **VBG**.

(1) On [the table]  **POBJ**(On, table)
(2) Including us  **POBJ**(Including, us)
(3) Given us  **POBJ**(Given, us)

D.8.3  **PREP: prepositional modifier**

A prepositional modifier is any prepositional phrase that modifies the meaning of its head.

(1) Thank you [for coming [to my house]]  **PREP**(Thank, for),  **PREP**(coming, to)
(2) Please put your coat [on the table]  **PREP**(put, on)
(3) Or just give it [to me]  **PREP**(give, to)

In (1), *to my house* is a **PREP** carrying a semantic role, direction. These semantic roles are preserved as additional information in our representation (Section 2.6.1). In (2), *on the table* is a **PREP**, which is considered the locative complement of *put* in some linguistic theories. Furthermore, in (3), *to me* is the dative object of *give* in the unshifted form, which is also considered a **PREP** in our analysis. This kind of information is also preserved with syntactic function tags in our representation (Section 2.6.2).
D.9 Modifiers: quantifier phrase related

Quantifier phrase related modifiers consist of number compound modifiers (NUMBER) and quantifier phrase modifiers (QUANTMOD).

D.9.1 NUMBER: number compound modifier

A number compound modifier is a cardinal number that modifies the head of a quantifier phrase.

(1) [Seven] million dollars  NUMBER(million, Seven), NUM(dollars, million)
(2) [Two] to [three] hundred  NUMBER(hundred, Two), NUMBER(hundred, three)

D.9.2 QUANTMOD: quantifier phrase modifier

A quantifier phrase modifier is a dependent of the head of a quantifier phrase.

(1) [More] [than] five  AMOD(five, More), QUANTMOD(five, than)
(2) [Five] [to] six  QUANTMOD(six, Five), QUANTMOD(six, to)

Quantifier phrases often form a very flat hierarchy, which makes it hard to derive correct dependencies for them. In (1), More than is a multi-word expression that should be grouped into a separate constituent (e.g., [More than] one); however, this kind of analysis is not used in our constituent trees. Thus, More and than become an AMOD and a QUANTMOD of five, respectively. In (2), to is more like a conjunction connecting Five to six, which is not explicitly represented. Thus, Five and to become QUANTMODs of six individually. More analysis needs to be done to derive correct dependencies for quantifier phrases, which will be explored in future work.

D.10 Modifiers: miscellaneous

Miscellaneous modifiers consists of adjectival modifiers (AMOD), unclassified dependents (DEP), interjections (INTJ), meta modifiers (META), parenthetical modifiers (PARATAxis), possession modifiers (POSS), particles (PRT), punctuation (PUNCT), and roots (ROOT).
D.10.1 **AMOD: adjectival modifier**

An adjectival modifier is an adjective or an adjective phrase that modifies the meaning of another word, usually a noun.

1. A [beautiful] girl \ AMOD(girl, beautiful)
2. A [five year old] girl \ AMOD(girl, old)
3. [How many] people came \ AMOD(people, many)

D.10.2 **DEP: unclassified dependent**

An unclassified dependent is a dependent that does not satisfy conditions for any other dependency.

D.10.3 **INTJ: interjection**

An interjection is an expression made by the speaker of an utterance.

1. [Well], it is my birthday \ INTJ(is, Well)
2. I [um] will throw a party \ INTJ(throw, um)

Algorithm D.20: *isInterjection*(C)

<table>
<thead>
<tr>
<th>Input:</th>
<th>A constituent C.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output:</td>
<td>True if C is an interjection; otherwise, False.</td>
</tr>
</tbody>
</table>

1: return C is INTJ|UH

D.10.4 **META: meta modifier**

A meta modifier is code (1), embedded (2), or meta (3) information that is randomly inserted in a phrase or clause.

1. [choijd] My first visit \ META(visit, choijd)
2. I visited Boulder and {others} [other cities] \ META(Boulder, others), CONJ(Boulder, cities)
3. [Applause] Thank you \ META(Thank, Applause)
Algorithm D.21: \textit{isMetaModifier}(C)

\begin{itemize}
  \item \textbf{Input:} A constituent $C$.
  \item \textbf{Output:} True if $C$ is a meta modifier; otherwise, False.
\end{itemize}

1: \textbf{return} $C$ is \text{CODE|EDITED|EMBED|LST|META}

\section*{D.10.5 \textsc{Parataxis}: Parenthetical Modifier}

A parenthetical modifier is an embedded chunk, often but not necessarily surrounded by parenthetical notations (e.g., brackets, quotes, commas, etc.), which gives side information to its head.

\begin{enumerate}
  \item She[, I mean,] Mary was here \textsc{Parataxis}(was, mean)
  \item [That is to say,] John was also here \textsc{Parataxis}(was, is)
\end{enumerate}

Algorithm D.22: \textit{isParentheticalModifier}(C)

\begin{itemize}
  \item \textbf{Input:} A constituent $C$.
  \item \textbf{Output:} True if $C$ is a parenthetical modifier; otherwise, False.
\end{itemize}

1: \textbf{return} $C$ is \text{PRN}

\section*{D.10.6 \textsc{Poss}: Possession Modifier}

A possession modifier is either a possessive determiner (\textsc{PRP$\$}) or a \textsc{NML|NP|WHNP} containing a possessive ending that modifies the head of a \textsc{ADJP|NML|NP|QP|WHNP}.

\begin{enumerate}
  \item I bought [his] car \textsc{Poss}(car, his)
  \item I bought [John's] car \textsc{Poss}(car, John)
  \item This building is [Asia's] largest \textsc{Poss}(largest, Asia)
\end{enumerate}

Note that \textit{Asia's} in (3) is a \textsc{Poss} of \textit{largest}, which is an adjective. Such an expression does not occur often but we anticipate it to appear more when dealing with informal texts (e.g., text-messages, conversations, web-texts).
Algorithm D.23: isPossessionModifier(C)

**Input:** Constituents C and P, where P is the parent of C.

**Output:** True if C is a possession modifier; otherwise, False.

1: if C is PRP$ return True
2: if P is ADJP|NML|NP|QP|WHNP then
3: return C contains POS
4: return False

D.10.7 PRT: particle

A particle is a preposition in a phrasal verb that forms a verb-particle construction.

(1) Shut [down] the machine  PRT(Shut, down)
(2) Shut the machine [down]  PRT(Shut, down)

D.10.8 PUNCT: punctuation

Any punctuation is assigned the dependency label PUNCT.

Algorithm D.24: isPunctuation(C)

**Input:** A constituent C.

**Output:** True if C is punctuation; otherwise, False.

1: return (C is :|,|.|‘’|\-LRB-|\-RRB-\-HYPH\-NFP\-SYM\-PUNC)

D.10.9 ROOT: root

A root is the root of a tree that does not depend on any node in the tree but the artificial root node whose ID is 0. A tree can have multiple roots only if the top constituent contains more than one child in the original constituent tree (this does not happen with the OntoNotes Treebank but happens quite often with medical corpora).