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Caleb Phillips
University of Colorado Boulder

Lee Becker
University of Colorado Boulder

Elizabeth Bradley
University of Colorado Boulder

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Caleb Phillips, Lee Becker, and Elizabeth Bradley

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Department of Computer Science
Campus Box 430
University of Colorado
Boulder, Colorado 80309

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Abstract

This paper applies machine learning and the mathematics of chaos to the task of designing indoor rock-climbing routes. Chaotic variation has been used to great advantage on music and dance, but the challenges here are quite different, beginning with the representation. We present a formalized system for transcribing rock climbing problems, then describe a variation generator that is designed to support human route-setters in designing new and interesting climbing problems. This variation generator, termed STRANGE BETA, combines chaos and machine learning, using the former to introduce novelty and the latter to smooth transitions in a manner that is consistent with the style of the climbs[1]. This entails parsing the domain-specific natural language that rock climbers use to describe routes and movement and then learning the patterns in the results. We validated this approach with a pilot study in a small university rock climbing gym, followed by a large blinded study in a commercial climbing gym, in cooperation with experienced climbers and expert route setters. The results show that STRANGE BETA can help a human setter produce routes that are at least as good as, and in some cases better than, those produced in the traditional manner.

1 Introduction

Computer assistance in creative tasks, generally the domain of cognitive science or artificial intelligence research, is a well-established idea that has attained some success over the past decades. For instance, pseudo-random sequences have been used to create music and art [2, 13, 20, 8]. In this paper, we are concerned with the more-modest goal of assisting humans in a creative task: in particular, using machine learning and the mathematics of chaos to generate variations on indoor rock climbing routes. A similar approach has been successfully used for generating interesting variations in domains such as dance choreography and music composition [7, 10]. In these applications, the hallmark "sensitive dependence on initial conditions" of chaotic attractors is exploited to generate a variation that deviates sufficiently from the input to be unique and interesting, while at the same time maintaining its basic style. In this work, we adapt these techniques to the domain of indoor climbing routes and validate our approach via a large study in a commercial climbing gym. We show that computer-aided route setting can produce routes that climbers prefer to those set traditionally.

The key contributions of this work are as follows:

[1] This name stems from the fact that our system makes use of *strange* attractors in order to generate variations on climbing route information, which is colloquially called *beta* by climbers.

- A language for the representation of climbing problems
- A parsing framework for mapping the domain-specific natural language used by climbers to a succinct set of semantic symbols in that representation.
- A machine-learning approach to sequence generation that utilizes Variable Order Markov Models (VOMMs).
- A chaotic variation generator that is designed specifically for climbing problems.
- A user interface that allows human route setters to easily explore the space of possible variations and automatically generate easy-to-use route plans.
- Validation of the chaotic variations in a commercial climbing gym, using a robust research instrument, in cooperation with expert setters and experienced climbers.
- A publicly available implementation at `http://strangebeta.com`

The next section of this paper provides a discussion of the most-relevant related work. Section 3 introduces the problem domain and defines useful climbing-related concepts; section 4 gives an overview of how Strange Beta is used. Section 5 presents our language for describing climbing routes and discusses its strengths and limitations; section 6 reviews the mathematics of chaotic variation and our specific implementation of that strategy. Section 7 describes the Strange Beta tool and its results. Sections 8 and 9 describe the design, implementation, and analysis of our two evaluation studies, the first in the University of Colorado Outdoor Program's climbing gym and the second at the Boulder Rock Club commercial climbing gym. In section 10, we describe a parsing strategy for the natural language that rock climbers use to describe their movements. We then show how to train a VOMM on a corpus of climbs and demonstrate how the resulting model can be used to smooth awkward transitions that may be present in generated routes. In section 11, we discuss future directions and conclusions.

2 Related Work

As mentioned above, the use of computers in creative tasks—for independent generation and/or in assistance roles—is not a new idea. Computation has a particularly rich history in music composition, in both generative and assistant roles [13]. Route setting for indoor climbing is viewed by its practitioners as a creative task on par with music composition, requiring substantial expertise in order to create routes that are both of an appropriate difficulty and interesting to climb. A climbing route is a prescribed sequence of dynamic movements: a sequence of symbols from a complex language not unlike a dance or a tonal music composition, both of which can also be viewed as symbol sequences. All three of these domains—climbing, music, and dance—have strong notions of "style," but that notion is very hard to formalize, even for experienced practitioners.

The challenge in creating a variation on a sequence in any of these domains is to introduce novelty while maintaining stylistic consonance. The structure of a chaotic attractor can be exploited to accomplish this. Two projects that apply this idea to the realms of music composition and dance choreography are especially relevant to Strange Beta. In [10], Diana Dabby proposed the idea of exploiting the properties of chaos—the counterintuitive combination of the fixed structure of a chaotic attractor and the sensitivity of its trajectories to small changes—to generate variations on musical pieces. In her work, a musical piece is codified as a sequence of n pitches (symbols). A "reference trajectory" of length n is generated from the Lorenz equations, starting at some initial condition (often $(1, 1, 1)$, which is not actually on the attractor), and successive points on the trajectory are assigned to successive pitches in the musical piece. Next, a second trajectory is generated with a different initial condition—say, $(0.999, 1, 1)$. Dabby's variation generator steps through this new trajectory from start to end. It examines the x coordinate of the three-dimensional state-space vector at each point, and then finds the point in the reference trajectory whose x value is closest to but not greater than that value. The pitch assigned to this point is then played. Variations generated in this fashion are different from the original piece and yet reminiscent of its style. This technique is fairly straightforward, but the selection of good initial conditions can be quite a challenge, and that choice strongly affects the results.

Chaographer uses similar ideas to create variations on movement sequences, but with slightly different implementation of the mathematics and some necessary domain-specific changes [7]. In Chaographer, a symbol describes the state of 23 joints, which combine to articulate a body position. The nearest-neighbor calculation is generalized to the full dimension of the state space—without the directional restriction in Dabby's work—and care is taken that the initial condition falls on or near the attractor, which removes some of choice issues and their implications. The resulting movement sequence variations are essentially shuffled concatenations of subsequences of the original; the stylistic consonance derives from the subsequence structure, while the novelty derives from the chunking and shuffling. Chaographer's companion tool, MotionMind, uses simple machine-learning strategies to smooth the potential dissonance that can occur at the subsequence boundaries [23]. MotionMind uses transition graphs and Bayesian networks to capture the patterns in a corpus of human movement, then uses those data structures to find a series of movements that create stylistically consonant interpolations. In a simple Turing Test, the chaotic variations were found to be only marginally less aesthetically appealing to human judges than those created by human choreographers [6].

3 About Indoor Climbing

In this section, we give a brief overview of the mechanics of indoor climbing and climbing route setting. Appendix A extends this discussion with a glossary of terms. Additional information can be also be found in [1], which provides a detailed and practical guide to professional route setting.

While once just for training, indoor climbing has become a popular sport of its own, with at least one and sometimes several dedicated climbing gyms in most major cities. A survey conducted by Roper Research for the Recreation Roundtable reported that in 2003, approximately 3% of the US population[2], or 8.7 million people, participated in some sort of rock climbing [19].

Indoor climbing walls are designed to mimic rock formations. They are often textured, and are covered with embedded "t-nuts" so that hand holds or foot pieces ("jibs") can be bolted to the surface in different configurations and orientations. T-nuts can be arranged on a geometric grid or in some approximation of a uniform random distribution. Holds—generally

[2]According to US Census data, the US Population was 290,210,914 in July, 2003.

polyurethane, but sometimes made of wood, rock, or other materials—come in all shapes and sizes.

Climbers have an informal but fairly consistent language for describing holds, which involves a relatively small vocabularly of colloquial terms. The majority of handholds can be classified into large open upward-facing pockets ("jugs"), small edges ("crimps"), or convex rounded holds ("slopers"). There are also more esoteric shapes (e.g., "side-pulls" and "Gastons") and composite shapes. Despite the large number of possible shapes, climbers describe holds using a readily parseable domain-specific grammar—the topic of Section 10.1—that focuses on the holds' function, quality, and orientation.

Holds are placed on the wall by experienced route setters to form a "problem" or a "route"—a series of holds with designated start and ending holds. Between those endpoints, order is unspecified; part of the challenge for the climber is to find the right sequence of holds, which may not be at all obvious. Climbers use the word "beta" to refer to information about how to climb a given route. Routes differ in length; short ones that do not require a rope for protection are called "bouldering" problems. Longer routes that require mostly side-to-side movements are called "traverses." Since multiple problems coexist on a single wall—and can even share holds—route setters use colored tape to show which hold is part of which problem.

Difficulty is determined using a subjective scale. There are several competing scales in use; in this paper, we employ the widely used American scale called the Yosemite Decimal System (YDS). YDS is a subjective consensus-based scale, where the easiest problems requiring a rope are given 5.0 and there is no upper bound, with the currently "most difficult" climb rated 5.15. A postfixed minus or plus (e.g, 5.12-) indicates that the route is on the "easier end" or "harder end" of the grade. The more-common convention is to use the letters a, b, c, and d (where a is easier and d is harder) to more precisely grade a route (e.g., 5.10b).

4 Strange Beta: Overview

The rest of this paper describes the details of the design, implementation, and testing of Strange Beta. By way of context for that discussion, this section presents a prototypical scenario of its use by an experienced route setter. Such a setter might want Strange Beta's assistance for a host of reasons, foremost among which are creativity block (or simply looking for additional inspiration). We also imagine that such a tool could also assist in the training of novice setters.

The first step is to transcribe one or more routes using the computer-readable language described in section 5. In doing this, the route setter can make use of routes from any domain (i.e., outdoors, indoors, bouldering, etc.) These routes, which will serve as input to the variation generator, are stored by the software in a route database. Routes transcribed by others can be used as well, but this is not without problems, as we discuss below. Variations generated by Strange Beta can themselves be used to generate other variations, or mixed with additional routes to inject other styles.

When a route-setter is ready to create a new problem, she chooses one or more routes from the database. In the simplest scenario, she picks a single route, but we have found that it is often more interesting to pick two or more routes to "mix." If the chosen routes are of a consistent grade and style, then the generated variation will be of a similar style and grade. Combining vastly different routes—either in terms of style or grade—can have unexpected, but often very interesting, results.

```
Problem 13 from the CU–hosted RMR CCS
Climbing Competition in March, 2009.
A few large moves between moderate
crimps and slopers with thin/smeared
feet on a vertical wall. Set by Thomas Wong.
Intermediate Difficulty.
– – –
R slopey ledge
L match
R medium crimp sidepull
L diagonal sloper
R crimp (big move)
L sloper (bad) sidewaysish
R crack sidepull
L wide pinch
R match
```

Figure 1: An example CRDL file of a route set by Thomas Wong for a climbing competition at the University of Colorado. All the text up until the line containing three hyphens is a header that describes the context of the route for posterity, but is ignored (for now) by the variation generator.

Strange Beta has a variety of controls, which set the values of the free parameters in the chaotic variation algorithm that it applies to the chosen routes. In our implementation, these are presented to the user in the form of presets ("default" values and "more variation" values). A setter who is experienced with the software can choose to vary the initial conditions or parameters of the algorithm in order to explore alternatives or fine tune the results.

The resulting variation is presented as a "route plan," a sequence of moves expressed in the language of section 5. To help the setter make sense of the new route, this route plan includes a set of annotations that describe how the variation differs from the original(s). The setter can print this plan and use it for direction while setting a route. During that process, the setter may choose to make improvisations or corrections to the variation.

5 Route Description Language

The first challenge in this project was to create a descriptive language for climbing problems that accurately captures the salient features of the domain, in sufficient detail to produce interesting variations, while not being so complex as to form a barrier to use. Strange Beta's language, which we call CRDL ("climbing route description language"), is designed to match the epistemology of this domain. An example CRDL description of a short problem is given in figure 1.

In this formalization, we specifically model the sequence of the hand movements (L for left and R for right), but leave out the foot positions. This assumes that a route-setter could easily choose foothold placements that match the style of the upper-body movements and produce a route with the desired difficulty. Similarly, the wall's characteristics (e.g., steepness) are left out. As we show in section 9.5, these assumptions are reasonable; the steepness is closely associated with difficulty and foot holds can fairly simply be placed to support desired hand movements. The exception to this rule is for "heel-hook" and "toe-hook" moves, where the feet are used to hook larger holds.

It is worth noting that these design choices reflect a focus on the sequence of movements, rather than on the specific placements of holds on the wall. The effect of this is to encourage the person who performs the transcription of the route to record their subjective understanding of how the route should be climbed. This is exactly what climbers call "beta." This choice regarding the language design also means that in order to transcribe a route properly, the person doing the transcription needs to have a good grasp of the climb, and maybe have climbed or set it themselves. This, too, is implicit in climbers' use of the term "beta." CRDL's match to these understandings and conventions of the domain is intended to make STRANGE BETA easy for its target audience to use.

We evaluated the success of this language—and indirectly its accuracy and expressiveness—in two ways: interviews with users and the consistency of the results. We found that CRDL is a useful language for climbers and route setters. As compared to the work in [6, 7], where individual joint orientations are modeled explicitly, it is much more free-form and coarser grained. As a result, setters found that it is not a chore to transcribe a climbing problem in CRDL, whereas the notions of specifying individual joint angles was incomprehensible to human choreographers. However, this flexibility comes at the cost of specificity—routes transcribed with this system might contain a fair amount of ambiguity[3]. In [1], Anderson suggests another language for describing routes in climbing competitions. While similar to CRDL, Anderson's maps also document roughly where holds are placed in space relative to one another. Because of the complexity of implementing such a system, we have erred on the side of simplicity and omitted spatial information from CRDL. One could also impose more-stringent tests on this language, e.g.: *If a given route A is transcribed by one person into CRDL, and that transcription T is used by another person to set a second route B, is it true that A is sufficiently similar to B that an experienced climber would recognize them as being subtle variations on the same premise?.* This is a matter for future work.

6 Generating Chaotic Variations

To implement STRANGE BETA's chaotic variation generator, we follow the same basic design used in [7] and [10]. Given a set of ordinary differential equations (ODEs), some reference initial condition IC_r, variation initial condition IC_v, and sequence of input symbols $i = \{i_1, i_2, ..., i_n\}$—the n moves in the "seed" route(s)—we use a fourth-order Runge-Kutta solver to generate two n-point trajectories in the state space of that ODE system: one called $\vec{r}$ beginning at IC_r and one called $\vec{v}$ beginning at IC_v:

$$\vec{r} = \{r_1, r_2, ..., r_n\}, \ \vec{v} = \{v_1, v_2, ..., v_n\} \tag{1}$$

We then create the mapping that associates the sequence of input symbols to the sequence of points in the chaotic reference trajectory (i.e., $i_1 \rightarrow r_1$ and so on). Finally, we step through

[3]Students of classical dance notation may notice a similarity to Beauchamp-Feuillet notation, which purposely omits details under the assumption that a trained dancer would know them intuitively.

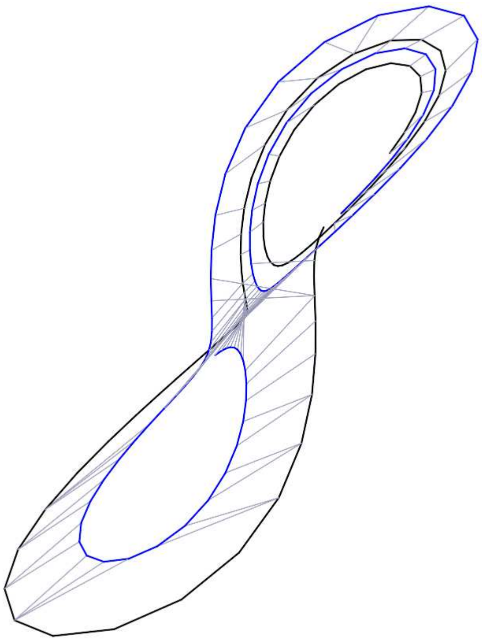


Figure 2: Reference (black) and Variation (blue) trajectories for $IC_r(-13, -12, 52)$ (black), $IC_v = (-16, -13.5, 52)$ (light blue) projected on the X-Z plane. The gray lines show the associations between reference and variation points that produce the corresponding variation sequence.

the variation trajectory point by point, using a Nearest Neighbor Algorithm (NNA) to find the nearest point in $\vec{r}$ for each v_k, then output the sequence of associated symbols $o = \{o_1, o_2, ..., o_n\}$:

$$o_j = i_k \ s.t. \ k = argmin_l\{d(v_l, r_j)\} \tag{2}$$

where $d(x, y)$ is some function that calculates the distance between two points x and y, typically a projected 2-norm (i.e., Euclidean distance). This algorithm is equivalent to the approach used in [7]. In [10], however, the NNA is unidimensional and directional: it will find the nearest neighbor in the x-axis if only and only if the neighbor is greater than or equal to the target. This causes the algorithm to find no neighbor for some inputs; it also disturbs the continuity of the variation because its projection can destroy neighbor relationships. Dabby suggests that in this case the user should "fill in the blanks"[10]. Although we implement both versions of the algorithm, our preference is for a strict Euclidean NNA of the sort presented in equation (2).

The choice of the ODE system and the initial conditions are critical to Strange Beta's success, as are the parameters of the solver algorithm. As in [10] and [7], we use the Lorenz system:

$$\begin{aligned} x' &= a(y - x) \\ y' &= x(r - z) - y \\ z' &= xy - bz \end{aligned} \tag{3}$$

with $a = 16$, $r = 45$, and $b = 4$, arguably the canonical example of a chaotic system. We used a solver step size $h = 0.015$. We chose a reference initial condition near the attractor:

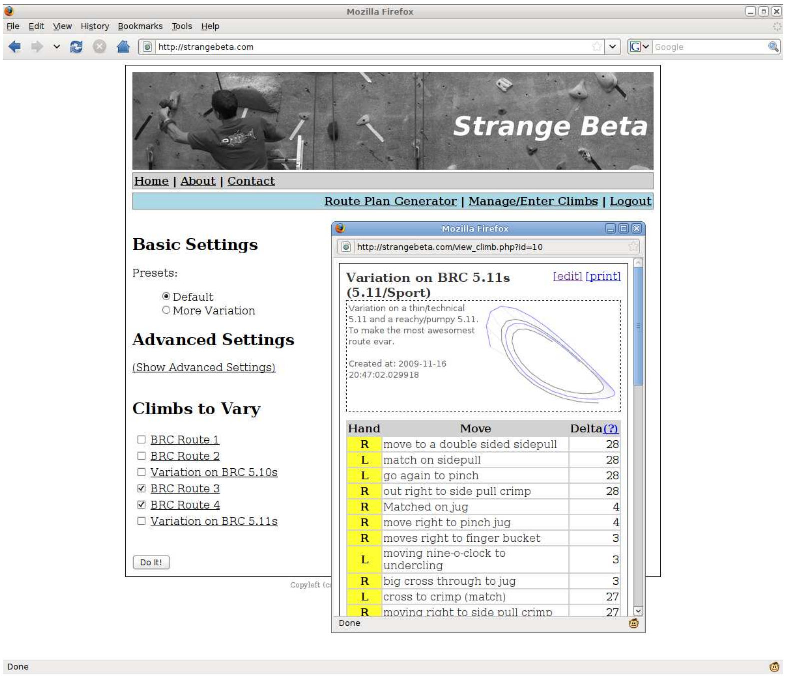


Figure 3: Screenshot of Strange Beta software being used to generate a variation on two input routes.

$IC_r = (-13, -12, 52)$. An example trajectory $\vec{r}$ from this initial condition is shown in figure 2, together with one of the variations $\vec{v}$ that we explored in this project. Dabby investigated other ODE systems, but found the Lorenz equations to be the "most desirable"[10]. Similarly, we considered a Rössler attractor, but were unable to convince ourselves that it generated more-interesting variations—especially given the short lengths of our trajectories, which are typically on the order of 30 symbols—so all of the results in this paper use the Lorenz system.

The choice of symbols is, as alluded to above, another key to the success of this strategy. We treated each move—i.e., each line in a CRDL input sequence like figure 1—as an individual symbol. It is not clear whether it makes more sense to vary the left and right hands separately or together. Here, we varied them together; we will explore the other approach in future work.

Strange Beta shares some of the challenges faced by previous chaotic variation generators. Route-setters, like musicians or dancers, are not necessarily familiar with computer-readable formats, ODE solvers, and chaotic dynamics, so the user interface requires some real thought. The software is web based; its output is a "Chaotic Route Plan" that reproduces the input route(s) alongside the variation. It specifically indicates which moves in the variation have been changed and identifies their provenance (i.e., which input sequence they came from and where). Figure 3 shows a screenshot made during the process of generating a variation on two input routes. The centerpiece of this figure is the chaotic route plan: the varied sequence together with the annotations about changes and provenance, a picture of the corresponding trajectories, and some details about how they were generated. This route plan can be printed and used by the route setter, as described in section 4.

Another challenge that Strange Beta shares with previous approaches to chaotic variation is novelty. In both [7] and [10], the varied trajectory can only contain a re-ordering of the specific set of unique symbols in the reference trajectory. Given the large language of possible climbing movements, this is an unnatural restriction. To relax it, we use simple machine-learning techniques to bring "new" or "unique" movements into a variation trajectory, as was done in [23]. Details of this approach are covered in section 10.3.

Climbing routes pose some new challenges for chaotic variations as well:

1. There are dependencies between some movements. The most obvious example is a "match," where a climber places both hands on the same hold simultaneously. How should these dependencies be enforced without reducing the chances for interesting variation?

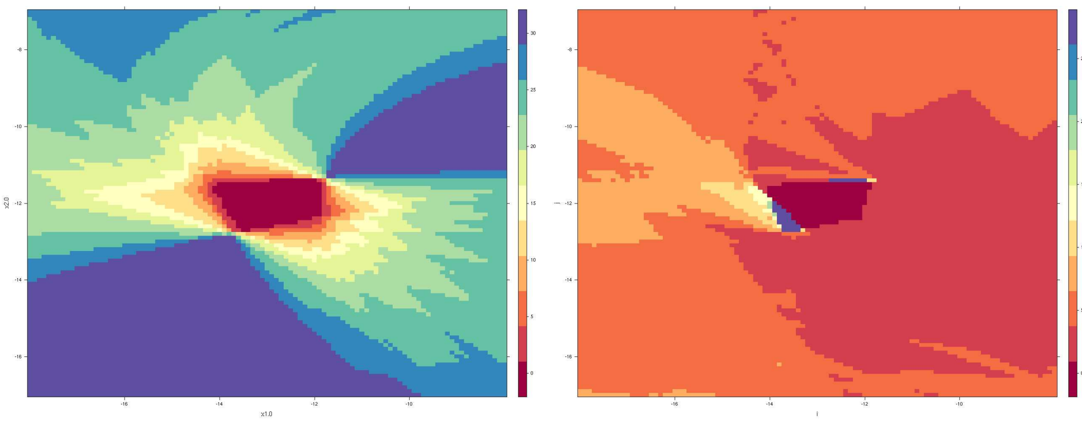
2. Dances and sonatas contain hundreds or thousands of notes and movements, but climbing routes are much shorter. What are the implications of this? How do we generate an interesting variation on a three- or five-move problem?

To address the first issue, we simply replace "match" moves with the previous movement of the other hand and add a note to the route plan: "(match?)" This is intended to let the setter know that this move was used as a match move in the input problem. We address the second issue by using multiple climbs as input. This has the effect of both increasing the trajectory length and incorporating more movement types. When doing this, we generally try to include routes that are both stylistically similar and of a compatible difficulty. The result is a variation that takes cues from both routes and is longer than both. In the scenario where radically different routes are mixed, the result can be unpredictable. For instance, if a setter chose to combine an "easy" route (e.g., 5.4) with a very difficult route (e.g., 5.13) the resulting varation is unlikely to be a successful climb, involving sections of intense difficulty and complexity surrounded by straight-forward movement requiring little effort (by an experienced climber). Over-long variations are not a problem; the setter can simply select a chunk of the variation or eliminate uninteresting sections.

7 Spelunking for Initial Conditions

With an effective chaotic variation generation algorithm in hand, our next challenge is to help the user choose an IC_v that creates a variation that is sufficiently different from the input while also preserving the style. To this end, Strange Beta takes a brute-force analysis approach. Given some IC_r, we place points on a $N \times N \times N$ point grid around it, spaced evenly on intervals of size s. N and s are free parameters of the algorithm; generally, $N = 100$ and $s = 0.01$ provide a sufficiently complex picture of the IC landscape, and so are set as the defaults. Experienced users can change these values if they wish.

To help users make sense of this space of possibilities, we color-code points in that space according to the characteristics of the variation. Specifially, we calculate two measures of difference between the reference trajectory and the variation trajectory: *effect* and *change*. Effect is the number of symbols that would be changed in a chaotic variation. Change is the average distance (in terms of index) that those changed symbols would be moved. Figure 4 plots these two metrics for a specific instance. The effect runs the gamut from no change (the red region) to having every move changed (the purple region). However, at those same points, the change metric tells a different story; instances are visible where every move is changed, but only by a small amount (purple effect, red change). The opposite situation also arises, where a



(a) Effect (b) Change

Figure 4: Effect and change for $IC_r = (-13, -12, 52)$, $N = 100$, $s = 0.1$ in the x-y plane (i.e., with z held constant at 52) using 2D Euclidean distance for nearest-neighbor calculation. In both maps, "cold" colors (e.g., blue and purple) indicate the largest amount of variation (effect or change) and "hot" colors indicate little or no change. Using this color map, neutral or average change is colored yellow.

small number of moves are varied by a large amount. In addition to these extremes, there are examples of just about every condition in between.

Effect and change plots change significantly for different parameter values. We generated similar plots for different s values, different NNAs, and in different projections (clearly we must project because these metrics are 4-dimensional). Each combination generates pictures with different geometry, but the patterns in figure 4 are generic and representative, so we chose this IC_r value as the default setting for Strange Beta, along with the $IC_v = (-16, -12, 52)$ that is drawn left of center in figure 4, and the 2-dimensional Euclidean NNA calculation.

To help users sift through these results and explore different IC_vs, we implemented an "IC picker" tool that preprocesses the data and finds candidate ICs, given a desired amount of change or effect. This automates the otherwise onerous process of varying parameter values and examining dozens of plots in order to find appropriate values for one's needs. This tool also makes it easy to find multiple—possibly disparate—conditions with similar change and effect characteristics.

Generating plots like this requires a great deal of computation and produces a substantial amount of data—$N = 100$ results in 1,000,000 unique ICs and as many runs of an ODE solver on equation (3), for instance. Thankfully, this problem is easily parallelizable. To compute the results in a tractable amount of time (30 minutes versus two days), we made use of a 16 node, 128 CPU cluster, with each of 100 nodes processing 10,000 trajectories. Although this is a tremendous amount of computation, it only must be performed once for each set of parameters and can be calculated offline. The resulting static map is then included with Strange Beta so that a user can fine-tune the amount and style of blending by selecting different ICs from the map.

8 Pilot Study

With route plans in hand, our next step was to analyze the effectiveness of the system. After negotiations with the route-setting staff at the University of Colorado Outdoor Program (CUOP) climbing gym, we were invited to join them in setting routes. The setters agreed to allow us to set a single route using the Strange Beta software, without interference or assistence from them.

On 24 April 2009 we set a 29-move traverse called "Green-13", which is based on a variation of two routes: the one in figure 1 and a longer roped route (a 5.12- at the Rock'n and Jam'n gym in Thornton, Colorado). These two routes are of similar fairly sustained intermediate difficultly and similar style, both making use of many crimpers. We used Strange Beta with $IC_v = (-16, -12, 52)$ and $IC_r = (-13, -12, 52)$, then printed out the resulting route plan and brought it to the gym. During route setting, we attempted to stay as true to the variation as possible. We did deviate from the route plan in a few places. For instance, if a move could be modified slightly[4] to make use of a hold that was already present on the wall, we were willing to make that modification instead of cluttering up the wall with another hold. We altered the first few moves of the variation for a different reason: Strange Beta placed the crux of the 5.12- at the beginning of the variation, which is not much fun for climbers. Finally, the order of the R and L hands had to be changed several times to make movements more interesting or avoid awkwardness.

The resulting climb still required a fair amount of human thinking by the setter, but with a very different flavor and focus than is typical for route setting. Typically, a setter approaches the creation of a new route by trying to think up a particularly interesting move or two and then building a problem around it. Strange Beta's route plan provided us with a useful, interesting skeleton with which to work. The staff setters who were present in the gym were clearly envious. In [10], Dabby describes her system as an "idea generator;" based on our experience in this pilot study, Strange Beta appears to succeed on that basis.

Assessing results is notoriously difficult in venues where intangibles like "style" play such important roles. To assess our results, we placed a questionnaire in the climbing gym. This questionnaire asked climbers to compare three routes on each of five metrics, using a scale from one to five (i.e., a weak Likert scale with a Likert-type response format). All three routes were of comparable length and difficulty; one is our Green-13 and the other two were set by expert human setters. The participants were not informed about the purpose of the survey or the difference between the routes. Six climbers chose to complete the voluntary questionnaire, one of which was not blind (one of the staff setters). Appendix B provides details about this questionnaire. Although the sample size is small, this pilot study provided some useful early feedback.

To analyze the consistency of the instrument, we computed Cronbach's $\alpha = 0.817$ on the responses. Doing a per-item consistency analysis, we determined that answers to question 5 ("Requires thought/non-obvious beta") were the least consistent, so we discarded that question from the analysis, producing a new overall $\alpha = 0.866$. Although this is a respectable α value, we will not claim great confidence in this instrument because it is only a five-item scale—far smaller than is recommended in the literature [11]. Treating the summed scale data as ordinal, we can report median attitude values, which are summarized in table 1 for the three routes. Climb

[4] In this case, by a "slight" modification, we mean without substantial change to the perceived "intent" of the variation.

Climb	Median Summed Scale Value	Chaotic
1	14	X
2	15	
3	16.5	

Table 1: Results of Pilot Survey

3—a traditionally set route—was rated as having the most appropriate, sustained difficulty, good flow, creativity and interest. To determine if the difference in these three medians is significant, we used a Wilcoxon rank sum test. The results show that the difference in medians between Strange Beta's climb and the other two climbs is marginally significant (p-values of 0.06 and 0.02 for climbs 2 and 3 respectively), but the difference between the two non-chaotic climbs is not significant (p-value = 0.37). Hence, we can conclude that at least for this (small) sample, the non-chaotic routes were preferred, but not by a substantial margin.

As is usually the case with pilot studies, these conclusions generated a host of new questions:

- Green-13 was set by an inexperienced route setter (author CP). How would an experienced route setter employ, and react to, setting routes using chaotic variations?
- What about setting routes at varying levels of difficulty, different styles, or different lengths?
- Is there a qualitative relationship between the choice of initial condition and the resulting variation? Can this be controlled, or quantified?
- Are there other description languages, perhaps more prescriptive, that result in more-interesting variations?

To explore some of these questions and to address limitations in survey apparatus, we performed a much larger study at a commercial climbing gym.

9 Experiment and Analysis

Building on the pilot study described in the previous section, we carried out a second experiment at a large climbing gym, the Boulder Rock Club (BRC), in collaboration with two expert setters, Tony Yao (T) and Jonathan Siegrist (J), and the editors of *Climbing* magazine.

9.1 Experimental Design and Instrument

After consultation with these experts and the other setters at the BRC, we decided to set four routes, two at a grade of 5.10 and two at a grade of 5.11. One route of each grade was set using our chaotic method and the other two were set traditionally. Using a questionnaire, we measured the attitude of climbers towards the four routes. Again, this study was blind: climbers were not aware of the research question. As input to the variation generator, we chose four existing routes in the gym, two of each grade, both well regarded. All four routes were transcribed by T. The two variations were generated by author CP, using Strange Beta with $IC_v = (-16, -13.5, 52)$ and the same IC_r as in the pilot. We also chose to skip the first 100

Climb	Setter	Grade	Med. Summed Value	Avg. Pos. Response %	Med. Rank	Chaotic
1	J	5.10	6	27.44	3	
2	J	5.10	4	25.58	3	X
3	T	5.11	9	37.23	1	X
4	T	5.11	4	26.21	3	

Table 2: Results of BRC Experiment

integrated points of the trajectory to further avoid transient behavior. These two changes from the pilot study were intended to produce routes with more variation.

On 30 September 2009, T and J set the four routes using the resulting chaotic route plans. Afterward, we interviewed them to record their thoughts on the experience, which we have summarized below. Questionnaires were made available at the front desk of the climbing gym for willing participants and fliers were posted throughout the gym to advertise the opportunity to participate. Incentives for participation were provided by *Climbing* magazine.

Over the course of approximately two weeks, 44 (presumably unique) climbers completed questionnaires with mean ability, in terms of typical upper-end outdoor climbing grade, of 5.11c. Minimum ability was 5.10; maximum was 5.12d. On average, participants reported that they climb indoors between two and three times per week and had been climbing 12 years, with a minimum of 6 months and maximum of 53 years. Although we believe this sample to be fairly unbiased and representative of the population of indoor climbers as a whole, we cannot claim that this sample is random and hence our analysis is constrained to making conclusions about the preferences of these 44 participants with regard to the specific four climbs we set.

The questionnaire that we designed to interpret climbers' reactions and preferences to these routes used standard, well-accepted techniques for construction of attitude surveys [15, 12, 5]. It was much more comprehensive than the one used in the pilot study, incorporating redundancy to enable external consistency checks and explore our concerns about scale robustness and consistency. Appendix B provides additional details about this questionnaire. In summary, participants were asked to rate each climb using a 14-item five-point summative Likert scale as well as a single direct ranking question. The five-point response format used the standard response categories (Strongly Agree, Agree, Neither Agree Nor Disagree, Disagree, and Strongly Disagree), to which we have assigned ordinal values of (2,1,0,-1,-2) respectively. Four of these questions were negatively keyed so that negative responses indicate positive attitudes. These four questions were inverted in post-processing. Internal consistency analysis showed that items 1, 9, 10, and 11 produced the greatest inconsistency and were eliminated from analysis, resulting in a 10-item summative scale with an overall Cronbach $\alpha = 0.834$ (versus 0.708 before censoring). This value indicates that the research instrument is strongly consistent [11, 22].

9.2 Climb Preference

Interpreting the summed Likert scale data as ordinal, we can compute the median values for the four climbs, which are given in table 2. Applying a Wilcoxon rank-sum test to the 5.10 climb's scale data, we were unable to reject the null hypothesis that the medians are equal (p-value = 0.54). In the case of the 5.11 climbs, however, we were able to reject this null hypothesis: for this sample, the difference between medians is significant (p-value << 0.05). In other words, we can state with confidence that climb 3 is preferred by this sample over climb 4, but we cannot make a similar claim about the 5.10 climbs, about which the participants were more indecisive[5].

Because interpreting summative Likert scale data as ordinal may be viewed dimly by some conservative statisticians[6], we also carried out a similar analysis using a convincingly continuous variable: percentage of positive (*viz.*, Agree or Strongly Agree) responses to scale items—an approach common to marketing research, for example. Mean values for this variable are in table 2. A Welch 2-sample t-test on this data produced congruent conclusions to those described earlier in this paragraph: we were unable to reject the null hypothesis that the 5.10 climbs have equal means but we *were* able to reject this null hypothesis with high confidence in the case of the 5.11 climbs.

As a final indicator of climb preference, we asked participants to rank-order the four climbs. The median ranks (where smaller is better) are listed in table 2. We computed the inter-grade coefficient of concordance of these ranks using Kendall's method and found values of $W = 0.01$ with a p-value of 0.59 for the 5.10 climbs and $W = 0.38$ with p-value << 0.01 for the 5.11 climbs. These values further serve to indicate that raters are in agreement on their preference for climb 3 over climb 4, but are not clearly decided between climbs 1 and 2.

9.3 Possible Correlating Factors

In addition to determining climb preference, we also made use of correlation tests to answer a pair of secondary research questions:

1. Is preference affected by climb order (i.e., do participants rate climbs differently when they are tired)?

2. Is preference affected by climber ability (i.e., do better or worse climbers rate climbs differently)?

To address the first question, we used Kendall's τ on the ordinal variable and Pearson's r on the continuous variable. These results suggested a correlation that is very near zero, both with high p-values. From this we concluded that there was no obvious correlation between climb order and climb preference—or, more precisely, that we cannot reject the null hypothesis that they are uncorrelated. We confirmed this conclusion using the pure ranking data, which also produced a Kendall coefficient near zero and a large p-value (near 0.95). We used the same tests to answer the second question, producing correlation coefficients (on the order of 0.1) with p-values greater than $\alpha = 0.05$, indicating that there is no clear correlation in the data between climber ability and climb preference.

[5] It is worth noting that the setter of the 5.10 climbs, J, was displeased with his "chaotic" route and felt that Strange Beta had "helped" him produce a route that was below the standards he typically holds himself to (in fact, he was hesitant to sign his name to it). It is interesting to note that, while individual climbers may have preferred one route or another, they were generally ambivalent about the two 5.10 routes. One possible hypothesis, proposed by the setters with whom we worked, is that climbers are less decisive about the quality of less difficult routes.

[6] Indeed, any interpretation of Likert-scale data is a contentious issue [14, 9]. Although some researchers claim that a properly composed and applied summative Likert-scale with a sufficient number of questions can produce useful interval-scale data, we have erred on the side of statistical conservativism. To this end, we used non-parametric tests and treated the summed scale as ordinal, or parametric tests that are robust to skew, in order to analyze a continuous variable derived from the ordinal data.

These two questions correspond to the most obvious sources of data skew in our specific population. The τ and r results indicate that these concerns are unfounded.

9.4 Results Summary

It is clear that the participants of the survey preferred climb 3, which was set with the assistance of Strange Beta, over climb 4, a climb set without it. In the case of the 5.10 climbs, participants may have preferred the climb set without the software, but not by a significant margin. It is worth noting that the four climbs that were used as input to the variation generator were transcribed by T. From this, one could conjecture that the software performs best when used by the same setter as did the original transcription. Although more work would needed to confirm or deny this, we suspect that a flexible description format like the one we have chosen may allow setters to use personal idioms in their descriptions, preventing portability and reducing the effectiveness when these same descriptions are used by third parties. *In sum, we feel confident in making the claim that when used properly, in a scenario where an expert setter feels the use is appropriate, our software can assist in producing a route which is at least as well regarded as those routes produced without it. And, in some cases—indeed, in this study—*Strange Beta *can produce routes that are considered superior by climbers to those set purely by human experts.*

9.5 The Setters' Experience

The preferences of the climbers are only part of the assessment of Strange Beta; analyzing the opinions of the route-setters is also crucial to understanding the effectiveness of the system.

To this end, we interviewed the setters after they had finished setting the four routes. Although positive about the experience in general, both setters were hesitant to endorse anything that would lessen their creative control. Interestingly, this response is similar to that of the composers in [10], but at odds with the more-supportive response dancers had to a similar experiment [6]. One of the two setters, J, found using the generated route plan to be unwieldy and time-consuming. This may, again, be a result of having the other setter, T, transcribe all four input routes, or it may be a user-interface design issue. During the course of the experiment, we identified several ways to improve the route-plan format and route-transcription process in order to attend to problems that both setters encountered using the system. Both setters, for example, found some aspects of the output format to be confusing (principally the inclusion of the input data). We have since removed this feature from the output.

To address our initial assumptions about the design of the route description language, we asked the setters whether it was reasonable for variations to leave the placement of foot pieces, and the distance between holds, to their discretion. They agreed that this was a reasonable assumption, as usually foot pieces are placed to accommodate hand movements. In general, the setters found the flexibility of the format to be beneficial and allowed them more creative control overall.

10 The Grammar of Climbing

Movement "style" is easy for humans—even non-experts—to perceive, but it is devilishly hard to formalize. This issue, which was explored in the context of dance in [6, 23] and in a variety of

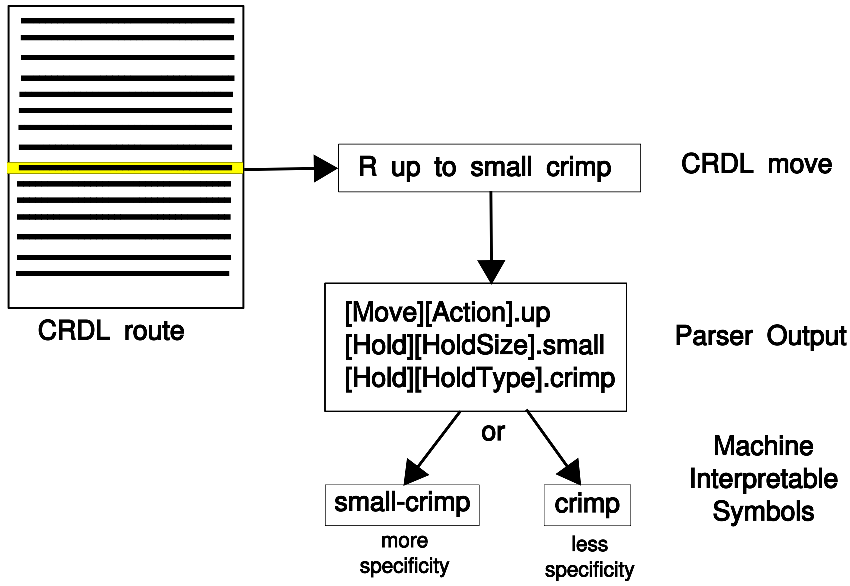


Figure 5: Schematic describing the parsing process...

good papers in the SIGGRAPH community, also arises in climbing. In this section, we present a machine-learning strategy for capturing the style of a climb.

The first and most critical step in this process is the definition of the representation. The CRDL language in section 5 is useful for generation of chaotic variations, but it is not rich or structured enough to support machine learning strategies for this domain. To address this problem, in this section we seek to parse the free-form natural language of the CRDL into a set of machine interpretable symbols. Figure 5 shows the strategy taken here: each CRDL movement line is parsed and then assigned to an unambiguous machine interpretable symbol. Section 10.1 describes climbers' free-form movement descriptions in a bit more depth and presents a strategy for translating those descriptions into well defined parses. Then, section 10.2 discusses how parser output can be translated into a set of symbols. By tuning the number of parsed features that are used, we can control the size and specificity of the resulting symbol set.

Once a corpus of climbing routes have been translated into symbols, the next question is how to model them. To this end, section 10.3 presents a variable-order Markov model that we have trained on a substantial corpus of climbing routes. As an example application of this model, we perform *de novo* movement generation ("forward simulation," in the parlance of the graphics/animation community) to interpolate between successive movements, inserting new movements that smooth awkward transitions that may have been created by Strange Beta's chaotic variation generator. Because the model is trained on the user-generated corpus of climbing routes, we can ensure that the resulting interpolation is stylistically consonant with respect to the data the model is trained on.

10.1 A Parser for Climbing-Route Descriptions

After our experiment in the BRC and a subsequent article in *Climbing* magazine [17], Strange Beta gained a fair amount of exposure in the climbing community. As a result, a large number of climbers and route setters entered routes into our public web-based implementation. As of

19 April 2011, 250 users had created accounts on the site, entered 125 routes (comprising 1139 moves), and generated 210 variations (comprising 3800 moves). This represents a substantial corpus of human-generated movement sequences that can be used as the basis of a learning algorithm, but like most natural-language corpora, it presents some serious challenges to that process. As an example, consider the following moves entered by a variety of different users:

1. "moving right to a right angle crimp rail"
2. "bicycle on start and foot chip then match on crimp-jug"
3. "large horizontal iron cross to a pinch"
4. "Now move out left 5 feet to huge pinch which looks like a "F"
5. "Small Jug"
6. "cross topostive jug medium to large"
7. "Dynamic Reach Back Over Sholder About 2 Feet Up, Negitive Side Of An I-Beam, Could be Substituted With A Negitive Edge"

At first glance, decomposing these moves into an underlying knowledge representation seems a very difficult task. The website's unrestricted input provides no way to control the vocabulary, spelling, or syntax of the entries, yielding data with too little common structure for simple regular expression matching. The variance in word choice and descriptiveness proved to be too ambiguous for strict approaches like the LL-K algorithms that are used for parsing programming languages. Instead we turned to the Natural Language Processing (NLP) literature for techniques robust enough to handle the novelty and ambiguity found in descriptions of climbing routes.

Shallow semantic parsing refers to the process of analyzing a text for its basic semantic relationships and propositions. Current research in shallow semantic parsing centers on learning statistical models for semantic role labeling. While considered state-of-the-art, these models require large annotated corpora such as PropBank [16], an approximately one-million-word corpus annotated with predicate-argument structures. By comparison, the relatively small size of our corpus suggests that learning our own semantic parser from data is not feasible. Existing semantic role labelers are optimized for the newswire text found in PropBank and would be ill-suited for handling the non-standard vocabulary and word usages found in our data. Furthermore, we are more interested in decomposing user-entered moves into climbing specific semantics rather than the general semantics used by most semantic role labelers. Consequently, we found more-traditional, rule-based NLP techniques to be better suited to this corpus of climbing domain language.

For the purposes of parsing route descriptions like the ones in the list on page 17, we adapted an approach to natural language understanding that has successfully been employed in a variety of spoken dialogue systems: semantic frame parsing. In frame semantics, an object evokes some scene or related knowledge. It is represented as a collection of features or frame elements, which are in turned filled with values. In a travel domain, for example, the *Flight* frame might consist of frame elements such as *Origin*, *Destination*, *Departure Time*, and *Airline*. From a sentence, a frame semantic parser identifies the appropriate frame and extracts the words that fill the frame elements. Thus sentences like "I am flying from Seattle to Denver on August 20th on

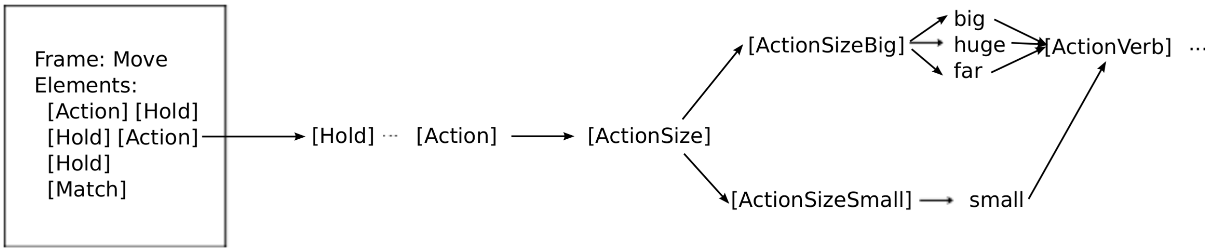


Figure 6: Illustration of a small part of the Phoenix Grammar

Frontier Airlines." and "I'm coming back to Denver from Seattle on the 20th of August via Frontier" would parse into an identical set of frame-elements. This approach is well suited for our task because its robustness in the face of ungrammatical constructions and the relative ease of authoring grammars makes it well suited for the domain-specific, fragmented, and variable descriptions generated by our user base.

Our key NLP task was to parse a description of a sequence of climbing moves into the appropriate frame semantic representation. To do this, we used the Phoenix Parser [24], a flexible semantic frame parser built using recursive transtion networks. We began by authoring a context-free grammar for recognizing different classes of moves, and then we iteratively refined it until the system was able to parse a large percentage of our user-generated text. At each step, we run the entire corpus of moves through the parser and inspect those move descriptions that failed to parse, and make small adjustments to the grammer to fix what is missing (or wrong). When the grammer is able to parse more than 95% of the input corpus, we stop making improvements. By stopping short of 100% acceptance, we avoid overfitting the grammar to the input data.

In designing the Phoenix grammar, we chose to use a single *Move* frame, which consists of *Action*, *Hold*, and *Match* frame elements to capture the salient features of the route descriptions. Figure 6 shows an illustration of a small part of the resulting grammar and appendix C provides the complete grammar. Given the larger goal of creating an assistance system, it is important that the frame elements' semantic decompositions reflect differences in climbing difficulty; consequently, the grammar rules were written to discriminate moves by hold quality, hold size, and action size. To illustrate this breakdown consider the phrase "large horizontal iron cross to a pinch". If the grammar is correctly defined, the parser would recognize "large . . . cross" as a big action and pinch as a type of hold. Using this grammar, we are able to successfully parse 95% of the free-form user-entered moves. Without a hand-parsed "oracle" corpus, validation must be done manually. To this end, we sanity check the parser's output, and make any final corrections to the grammar as necessary

As a complete example of how the parser functions, consider the following "noisy" CRDL move:

```
R moving right to a right angle crimp rail
```

Given this input, our parser generates the following output:

```
PARSE_0:
IsMove:[Move].[Action].[ActionVerb].[ActionVerbSmall].[ActionVerbSmallT].right
```

Symbol Set	Description	N	Example Symbol
1	Hold Types	68	sloper
2	Hold Types with Descriptors	182	edge-small-sloping
3	Hold Types with Quality Booleans	110	pinch-(big move)-(good hold)
4	Hold Types with Descriptors and Quality Booleans	220	pinch-small-sloping-(cross)

Table 3: Descriptions of the four symbol sets. N is the number of unique symbols present in our parsed data.

```
        [Hold].[HoldShape].[HoldShapeGood].[HoldShapeGoodT].right angle
        [HoldType].[HoldTypeT].crimp
IsMove:[Move].[Hold].[HoldType].[HoldTypeT].rail
END_PARSE
```

In this example, the parse is actually ambiguous, resulting in two matching `IsMove` frames: "right-right-angle-crimp" and "rail". In our application, this ambiguity is not a problem since these two parses clearly relate to different parts (or features) of the same move. Hence, in post-processing a script combines the two parses to acheive the hybrid move symbol: "right-right-angle-crimp-rail", which matches what the user was (presumably) attempting to describe[7]. Conveniently, our grammar does not need to include explicit information about hybrid holds, so long as it includes the basic vocabulary of which they can be composed.

10.2 Tuning Specifity with Symbol Set Size

In the previous section, we discussed how parser output can be used explicitly to generate machine interpretable symbols. In this section, we will consider using a subset of parsed features to generate multiple symbol sets at different levels of specificity. For instance, consider the final example from the previous section of the symbol: "right-right-angle-crimp-rail". In some applications it may be only useful to know the hold type ("crimp-rail") and not the direction ("right") or the positioning of the hold ("right-angle"), while some other applications may operate on these more specific features as well. By limiting the specificity of the resulting symbol set, we can provide more flexibility in the resulting model(s) and at the same time reduce the complexity of the modeling task by limiting the size of the input language.

To enable flexibility in modeling, we define four symbol sets of increasing specifity, which are described in table 3. Each symbol set focuses on a set of dinstinct features that we believe are likely to be most meaningful in this domain, and stem from the structure of the parser grammar. The first symbol set simply assigns a symbol to each type of hold, without any concern for attributes, position, orientation, or movement. The second set includes parsed size and shape attributes. The third and fourth are modifications of the first and the second, respectively, that incorporate a set of three special boolean attributes that explicitly describe the quality (difficulty) of the move:

[7] A "crimp rail" is how a climber might describe a long shallow hold that requires crimping. In this particular move, the hold appears to be vertical in orientation (right angle) and is located to the right.

- Is the move a cross?[8] This is set to true if that word appears in the data entry.
- Is the hold "good"? This is set to true if the sum of hold descriptors in the data entry is biased towards positive statements (i.e., "big," "good," etc.) and false otherwise.
- Is the move "big"? This is set to true if the movement verb in the data entry is modified with a size attribute.

The rationale behind this procedure is that a move that involves a "bad" hold, a "big" movement, or a cross, is almost always more difficult than a move without these features.

In any problem of this type, representational accuracy—and thus the results of any algorithms that operate on the resulting data—depends heavily on the user-friendliness of the formal language. Since the natural language used by climbers in describing their routes is so varied and unstructured, that issue is of critical importance here. Judging by the success of this strategy—successful parsing of more than 90% of inputs from hundreds of climbers distributed around the world—our grammar appears to be doing justice to this domain-specific language. However, a fuller evaluation of these issues will require more data, which we are in the process of gathering via the website.

10.3 Modeling the Grammar of Climbing

A "generative" model trained on a corpus of climbing routes that have been parsed as described in the previous sections, can be used to generate new climbs—or chunks of climbs—that have the same style as the others in that corpus. This has numerous applications, but here we will explore the problem of smoothing transitions between movement subsequences.

To capture the grammar of climbing, we look to Markov models. This amounts to viewing the climb-setting process as a state machine in which the probability of transitioning to the next state (move) is a function of the current state. While the state-based nature of this approach seems appropriate for our domain, we could not convince ourselves that a *single* move provided sufficient context to make a reasonable prediction. In order to consider more context, we used Variable Order Markov Models (VOMMs), which determine the probability of moving to successor states from the current state and a variable number of prior states. VOMMs have been used widely in compression algorithms (e.g, [4]), but only recently in the context of prediction. [3], for instance, use VOMMs to learn a sequence and predict the most likely next state. They study how several VOMM learning algorithms handle different types of input, finding the "decomposed" Context Tree Weighting (DE-CTW) to be a good general-purpose model. Significantly, DE-CTW was the best at learning music scores and predicting the next most likely note sequence—a task that bears substantial resemblance to what Strange Beta does.

Using the implementation from [3], we trained a VOMM on the symbol sequences generated by the parser described in section 10.1 from the entire corpus of user-entered data on the Strange Beta website. In order to study inter-user differences and allow users to request models that match their individual styles, we also trained a separate VOMM model for each user's data. (The full-corpus model, in contrast, captures some average of the overall style—an amalgam of the styles of all of the individuals who contributed.) There are other interesting

[8] Moves that involve a cross require the climber to cross one arm over (or under) the other to reach a given hold. This is a common movement in difficult climbs and we found it useful to model it explicitly.

cross sections that one might try: a model of climbs set by experts, models for different climb difficulties, models for different geographic regions[9], or models of different types of climbing (sport climbing, top-roping, bouldering or traversing), for instance.

A VOMM trained in this fashion can be used for a variety of interesting purposes, including recognition, forward simulation, and interpolation. Given a sequence of moves, it can provide a estimate of the likelihood that that climb was produced by that model:

$$L = -log_2(P(sequence|model) \tag{4}$$

Forward simulation is a matter of creating a sequence of moves from a given starting point that minimizes the negative log likelihood value L. Interpolation adds another constraint: given a starting move, an ending move, and the surrounding k-sized context of moves, is there some number of moves we can insert between the two that will minimize the negative log likelihood of the entire sequence?

We experimented with climbing-route interpolation using the VOMM model trained on the parsed corpus. To find an interpolation sequence, we performed an exhaustive search, looking for the set of inserted symbols that minimize the negative log likelihood. This search involves visiting N^j nodes, where j is the maximum-sized insertion considered and N is the size of the symbol set (from table 3). This search is exponential in j, but running it with $1 <= j <= 2$ is useful for this domain. (We found that when setters judge a route to be jerky or disconnected, for instance—which can arise in Strange Beta as a side effect of the chaotic variation strategy—they generally inserted only one or two extra holds to "smooth" the transition.) We have yet to perform a full formal evaluation of these results, but the preliminary results are promising. Like a human expert, this VOMM-based scheme inserts common movements—simple moves to a jug or crimp—to "fix" discontinuities. Whether or not this produces climbs that are actually more "pleasant" or "natural" to climbers is an open question.

11 Conclusions and Future Work

In this paper, we have applied chaotic variations and machine learning to a new domain with some unique and interesting challenges: indoor climbing route setting. We have proposed new ways of exploring the space of possible variations and validated the results in two user studies. We found that our chaotic variation strategy is a useful assistant to human experts, helping them produce routes that are at least as well regarded as those set traditionally. We proposed a formal representation for climbing route description and a parsing strategy for transforming the informal movement descriptions provided by users into a set of unambiguous symbols. We then trained a variable-order Markov model on a substantial corpus of data gathered from the broader climbing community and used it to create stylistically consonant climbing sequences.

Though Strange Beta's chaotic variation facilities have been fairly well worked out and assessed, the machine-learning work described in the previous section is only a beginning. There are particularly interesting opportunities for future work concerning representations, methodologies, and incorporation of domain knowledge. A formal evaluation of the symbol sets of table 3 and the parser framework of which they are targets could lead to a more-effective knowledge-representation framework, which would in turn support better models. It would also

[9] One might hypothesize that the style of climbing in a given region is affected by the style of climbing necessitated by the surrounding geology

be interesting to compare and contrast VOMMs to other learning algorithms for this application. Assessing how well Strange Beta works in different environments and for a large number of different setters will require a much more substantial experimental evaluation than we have done here.

Finally—and of most interest to us—is the incorporation of domain knowledge into Strange Beta's mathematics and models. Identification of the crux, the most difficult section of a route, is of particular importance. We know from our surveys that the quality of a crux is important to a climber's impression of the route. If we could identify the crux of a route, then we could determine whether or not a chaotic variation or a VOMM-generated route has one—and if it is of a reasonable size, shape, and position in the overall route. Ultimately, we would like to explicitly address the question of *how* human setters create interesting short sequences and use that understanding as a basis for a machine-learning solution. Existing research on biomechanical models for equilibrium acquisition while climbing [18] could support this endeavor, as it offers explicit models for climbing-related movement in route generation. These explicit mechanical models might be expanded with cognitive models for how climbers visualize climbs—a combination of not just movements, but also specific application of force and effort [21].

Gathering the data to support all of these research threads will require the continued interest and participation of the climbing community. To this end, we continue to prototype new features on the publicly facing implementation of the system at `strangebeta.com`. These data, and the associated results, would also contribute to existing academic research on rock climbing. Research on the exercise physiology of difficult climbing, for instance, has produced well-defined training guidelines for climbers [25]. Strange Beta could dovetail nicely with this, generating route variations aimed at specific training goals.

Overall, we believe that chaotic variations provide great promise in the realm of creative processes. Though there are many open questions and much to be done, the work described here serves two important purposes from the standpoint of the climbing community. Firstly, it is a large step forward in terms of creating a functional prototype of such a system. And secondly, and perhaps most importantly, it has convinced us and others that chaotic variations are a useful technique in this domain. We are uncertain whether our approach to route setting will be widely adopted, in large part because expert setters enjoy the creative challenges of setting unique and interesting problems from scratch. However, we see promising applications when creativity block strikes or when teaching novice setters.

Acknowledgements

We would like to thank the climbing gyms and route setters who supported this work for their help—particularly setters Tony Yao and Jonathan Siegrist at the BRC and Hana Dansky and Thomas Wong at the CUOP climbing wall. Their thoughtful feedback, and their help in setting routes, allowing us to access their facilities and solicit their patrons was essential to this project. Matt Samet, the Editor in Chief of *Climbing Magazine* was very helpful in the organization and design of the BRC experiment; without his enthusiasm for the project, we would not have been able to obtain the results we have presented here. Finally, Dr. Jeffrey Luftig provided crucial criticism and suggestions regarding the design of our experimental instrument and the subsequent statistical analysis, and Dan Knights provided early and useful insight on the possibility of applying machine learning to rock climbing sequences.

No.	Question	α
1	Appropriate Difficulty	0.725
2	Sustained Difficulty	0.727
3	Has Good Flow/Seems Consonant	0.810
4	Is Creative/Has Interesting Moves	0.755
5	Requires thought/Non-obvious Beta	0.866

Table 4: The pilot study instrument: a five-item Likert scale intended to assess participants' attitude towards a given climb. Cronbach's α is a measure of internal consistency.

A Glossary of Climbing Terms

- **Beta** - Information about how a route/problem must (or can) be climbed.
- **Crimper** - A shallow hold that may only support the tips of the fingers and hence might need to be "locked off" (where the thumb reinforces the position by pressing down on the forefingers)
- **Crux** - The most difficult move(s) of a route.
- **Gaston** - The opposite of a sidepull, with the gripping surface facing inward (*viz.*, the grip used to pry open an elevator door).
- **Jib** - A very small knob-like hold, usually used as a foot piece.
- **Jug** - A fairly deep hold whose geometry is similar to that of a steep-walled pot or jug.
- **Match** - A hold that is held with both hands simultaneously.
- **Problem** - Another term for a climbing route which more directly captures the often puzzling nature of climbing routes.
- **Redpoint** - To climb from start to finish without falling, typically placing protection on the way.
- **Sidepull** - When a hold is positioned so that its main grip ping surface is away from the climbers body (*viz.*, the grip one would use to close a sliding glass door).
- **Sloper** - A more-rounded hold that is gripped with the palm of the hand or pads of the fingers, to create friction.

B Questionnaire Design and Consistency

The questionnaire used in the pilot study at the University of Colorado climbing gym used a five-question Likert scale with a five-item Likert-type response format to determine the attitude of climbers regarding each climb. The questions are listed in table 4 along with Cronbach's α, a measure of internal consistency of the responses. The α reported in this table is the *overall* Cronbach's α, with the given question removed—hence a number larger than the overall $\alpha = 0.817$ (the α obtained for all questions, without any censored) indicates that censoring

No.	Question	τ	α	Neg.
1	Too easy for the grade	-0.108	0.750	X
2	Too difficult for the grade	0.184	0.703	X
3	Difficulty is consistent throughout the climb	0.220	0.696	
4	Requires thoughtful/nontrivial beta	0.117	0.707	
5	Has good flow throughout	0.536	0.661	
6	Appears to be well thought out	0.556	0.650	
7	Is creative/has interesting moves	0.480	0.657	
8	Climbs awkwardly	0.413	0.668	X
9	Good variety of handholds/types of grips	0.161	0.705	
10	Has a definite crux	-0.121	0.753	
11	Crux is technically engaging	0.043	0.719	
12	Has an unpleasant/stopper crux	0.173	0.701	X
13	Is a route I would climb again	0.560	0.645	
14	Is a route I would recommend to others	0.633	0.638	

Table 5: The BRC study instrument: a 14-item Likert scale intended to assess participants' attitude towards a given climb. Cronbach's α is a measure of internal consistency; τ is a measure of correlation, which is being used a secondary measure of consistency, and questions that are negatively keyed (i.e., a positive response indicates a negative attitude) are flagged.

this question would improve the scale's consistency [11, 22]. We also asked participants to state whether they were a Beginning, Intermediate, or Advanced climber, but did not use this information in our analysis.

The questionnaire used in the larger BRC study used a 14-question Likert scale with a five-item Likert response format. As compared to the 5-question survey used in the pilot study, this survey includes many more questions which are separated into the same basic categories tested in the survey. The reasoning here is that a larger number of questions allows for greater redundancy and ability to measure internal consistency. In addition, we also introduced a rank-ordering question to serve as an external consistency metric, to compare the the Likert-scale results, and expanded the demographic questions to allow for further investigation of possible correlating factors. Finally, we asked participants which order they climbed the routes in, since we hypothesized that the larger number of experimental routes (4 versus 1) might lead to ordering effects. Table 5 lists the questions along with their internal consistency metrics.

The α value, again, should be considered relative to the overall α of 0.708. τ is the Kendall's τ correlation coefficient for each question's rating, as correlated with the overall rating. Hence, a question with a large τ and large α relative to the mean, are generally consistent with the overall results [15]. Some questions are negatively keyed to avoid bias from having all questions be repetitively positive or negative. For instance, question 1 asks whether the route is too easy for the grade (a negative statement) and question 5 asks whether the route has good flor (a positive statement). In addition to the Likert scale, this questionnaire requested some domain-specific demographic information and asked participants to rank-order the climbs (which served as an external consistency check) and list the order in which they climbed them (which served to expose any ordering bias). These questions are listed in table 6.

Question
Years climbing?
Years climbing in a gym?
Hardest indoor redpoint?
Hardest outdoor redpoint?
Days per week climbing outside?
Days per week climbing at the BRC?
Typical indoor grade range?
Typical outdoor grade range?
In what order did you climb the routes (e.g., 1,4,3,2) ?
What is your overall ranking of the routes from best to worst (e.g., 4,2,1,3)?
What is your favorite ice cream flavor?

Table 6: Demographics and other questions from the BRC study. Climber ability, experience, and order were used to asses possible correlations with climb preference. Climb ranking was used as an external consistency metric. To the disasppointment of your authors, no significant correlation was found between ice cream preference and climber ability.

C Phoenix Grammar Specification for Climbing Routes

```
[Move]
    ([Action] [Hold])
    ([Hold] [Action])
    ([Hold])
    ([Match])
;

[Match]
    (match)
;

[Hold]
    ([HoldSize] [HoldShape] [HoldType])
    ([HoldShape] [HoldSize] [HoldType])
    ([HoldShape] [HoldType])
    ([HoldSize] [HoldType])
    ([HoldType])
;

[HoldSize]
    ([HoldSizeBig])
    ([HoldSizeSmall])
;

[HoldSizeBig]
    ([HoldSizeBigT])
    ([Not] [HoldSizeBig])
;

[HoldSizeBigT]
    (big)
    (good)
    (manageable)
    (managable)
    (deep)
    (positive)
    (goodish)
    (okay)
    (ok)
    (solid)
    (decent)
;

[HoldSizeSmall]
    ([HoldSizeSmallT])
    ([Not] [HoldSizeBig])
;

[HoldSizeSmallT]
    (mini)
    (shallow)
    (small)
    (bad)
    (razor)
    (shitty)
    (tiny)
    (micro-dick)
    (transition)
    (nonexistent)
;

[HoldShape]
   ([HoldShapeGood])
   ([HoldShapeBad])
;
   =20
[HoldShapeGood]
    ([HoldShapeGoodT])
    ([Not] [HoldShapeBad])
;

[HoldShapeGoodT]
    (starting)
    (vertical)
    (bulbous)
    (angle)
    (sideways)
    (double sided)
    (right angle)
    (left angle)
;

[Not]
    (not)
    (no)
;
```

```
[HoldShapeBad]
    (roof)
    (slopey)
    (sloping)
    (vertical)
    (finger)
    (diagonal)
    (angled)
    (gaston)
    (flat)
    (downward)
    (down ward)
    (open hand)
    (openhand)
    (reachy)
;

[HoldType]
    ([HoldTypeT])
    ([UnderCling])
    ([SidePull])
    ([FootHook])
    ([GenericHold])
    ([Layback])
    ([Mantle])
    ([Jib])
;

[HoldTypeT]
    (jug)
    (pocket)
    (crimp)
    (edge)
    (sloper)
    (cobble)
    (crimper)
    (crimpbeam)
    (beam)
    (layback)
    (horn)
    (ball)
    (boobies)
    (slope)
    (pinch)
    (bucket)
    (rail)
    (ear)
    (cup)
    (flake)
    (thumbcatch)
    (slot)
    (gaston)
    (dish)
    (ledge)
    (incut)
    (teeth)
    (arete)
    (tufa)
    (hand jam)
    (fist jam)
    (finger jam)
    (mono)
    (offwidth)
    (chicken head)
    (knob)
    (handle)
;

[Mantle]
   (topout)
   (top out)
   (mantle)
   (finishing hold)
   (top)
   (finish)
;

[GenericHold]
   (hold)
   (hand)
   (feature)
   (grip)
   (start)
;

[Layback]
   (lay back)
   (layback)
   (lie back)
   (lieback)
;
```

```
[Jib]
   (jib)
   (gib)
   (churd)
;

[SidePull]
    (sidepull)
    (side pull)
;

[UnderCling]
    (undercling)
    (under cling)
;

[FootHook]
    (heel hook)
    (heelhook)
    (toe hook)
    (toehook)
    (bicycle)
;

[Action]
    ([ActionSize] [ActionVerb])
    ([ActionVerb])
;

[ActionVerb]
    ([ActionVerbBig])
    ([ActionVerbSmall])
;

[ActionVerbSmall]
    ([ActionVerbSmallT])
    ([FootHook])
    ([Layback])
    ([Cross])
;

[ActionVerbSmallT]
    (bump)
    (out)
    (up)
    (left)
    (right)
    (fondle)
    (grab)
    (roll)
    (over)
    (diagonal)
    (slide)
    (grab)
    (drop)
    (go again)
    (go)
    (move)
;

[Cross]
    (cross over)
    (cross under)
    (crossover)
    (crossunder)
    (cross)
;


[ActionVerbBig]
    (throw)
    (dyno)
    (reach)
    (fall into)
    (huck)
    (deadpoint)
    (rock)
    (dead point)
;

[ActionSize]
    ([ActionSizeBig])
    ([ActionSizeSmall])
;

[ActionSizeBig]
    (big)
    (huge)
    (far)
;
```

```
[ActionSizeSmall]                        ;
    (small)
```

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