Combinatorial Meta Search

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Abstract

Machine learning approaches to computational creativity learn a generative model from a set of exemplars. We introduce combinatorial meta search, an approach for manipulating and combining different learned generative models. We hypothesize that combinatorial meta search can discover new generative models for which data may never have existed and thus expand the space of possible creative artifacts that can be generated.

1 Introduction and Background

Machine learning (ML) has shown promise for many creative tasks such as music generation, image and painting generation, image style transfer, etc. In particular it has shown great success on creative tasks with large datasets [8]. Computational creativity techniques that use machine learning train on a corpus of existing examples and learn a function that can be used to approximate the examples. While modern ML approaches have shown some ability to generalize, they are largely designed to produce output close to a set of exemplars. This feature is an inherent limitation of modern machine learning methods when applied to creative aesthetic domains where one might expect greater novelty.

As an alternative, human creativity is intentional and goal-based. Skill learning and experience are important factors in human creativity. However, humans seem to be able to intentionally manipulate their internal models to produce output no one has ever seen. Consider for example George de Mestral's invention of velcro in the 1940's, based on reapplying his observations of the prickly seeds of a Xanthium plant to artificial materials. Instead of learning a model and sampling from a distribution over possible outputs, humans appear to learn a variety of knowledge and creatively recombine this knowledge to search through possibility spaces. In other words: by intentional manipulation of models, one is able to explore new models for which there might never have been training data, query those models ability to generate interesting and novel artifacts, and iteratively manipulate those models if necessary.

We propose a novel approach to machine learning based computational creativity, inspired by human creativity and research in the field of computational creativity: *combinatorial meta search*. Combinatorial meta search is a search over the space of possible generative models. In the next section we will propose a number of operators for manipulating the generative models to iterative expand the search space. The search process is guided by high-level metrics originally proposed by Boden [2]: *novelty*, *surprise*, and *value*.

2 The Case for Combinatorial Creativity

The term *combinatorial creativity* refers to creativity that takes the form of a combinatorial process joining familiar ideas in an unfamiliar way [2]. The field of computational creativity focuses on research questions formalizing creative problem solving. Within this field there exist many formalized techniques for achieving combinatorial creativity including concept blending [3], amalgamation [7], and adaption [9]. At a high level these techniques allow the recombination of items from within a knowledge base, while retaining some of the structure from the parent items.

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Figure 1 illustrates examples of output from three combinatorial creativity techniques given the two input concepts, represented as graphs, on the left. The inputs represent encodings for the concept of a house (Input 1) and a boat (Input 2) in terms of their uses and locations. *Concept blends* merge elements that are similar to one another according to the knowledge base, but can include non-merged elements as well, thus leading to the "Houseboat" blend [4]. *Amalgams* incorporate as much information as possible from both input spaces without merging, instead choosing between sufficiently similar elements. Amalgams can also perform a single manipulation of a single element, similar to the concept of mutation from evolutionary algorithms. *Compositional adaption* breaks apart the individual elements of each input and composes novel concepts piece-by-piece, which allows it to generate smaller, novel concepts [1]. The output concepts illustrated in Figure 1 are a single output of many possible combinations from each technique.

Combinatorial creativity techniques cannot create new knowledge out of thin air, they require a knowledge base of concepts or cases. This knowledge base is typically encoded by domain experts. Machine learning based computational creativity can be thought of as first learning this knowledge base from data Combinatorial meta-search introduces three new aspects. First, the models being combined are generative, meaning they are paired with algorithms that can produce creative artifacts; Second, instead of manipulating models using a single, given combinatorial algorithm (concept blending, amalgams, compositional adaptation), we introduce a search that tries all combination algorithms and inspects what they are capable of generating. Third, combinatorial algorithms can be chained to expand the space of possible models to those for which there may have never been training data.

3 Proposed Algorithm and Examples

Combinatorial meta search is an optimization search over the space of all possible generative models for the type of . The operators that allow the search algorithm to move around the space are the combinatorial algorithms enumerated above: concept blending, amalgams, and compositional adaptation. Consider Figure 2, which represents the space of all possible generative models for the type of artifact that we wish to generate. $M1$ and $M2$ represent models trained on different examples (e.g., a GAN trained to generate images of horses and a GAN trained to generate images of humans). All other points in space are hypothetical models representing training sets that do not exist. Each of the three combinatorial operators can only reach certain portions of the space of possible models. By chaining operations together, combinatorial meta search can reach unique parts of the space, such as the upper middle section of the figure by combining amalgamation and compositional adaption (e.g. a GAN that can generate images of centaurs). Combinatorial meta search can be implemented in the form of any number of optimization search algorithms including, but not limited to, hill-climbing, simulated annealing, genetic algorithm, or reinforcement learning.

Combinatorial meta search may be provided with more than two initial models. However, each combinatorial operator will only combine two models at a time. Notably, concept blending, amalgams, and compositional adaptation all require that components of the individual models must be comparable and a mapping between models must be computable.

The objective function for combinatorial meta search is the sum of three creativity measures originally proposed by Boden [2]: novelty, surprise, and value. Novelty and surprise can be measured by directly comparing generative model structures. Novelty is a measure of the difference between a new model and the two input models. Surprise is a measure of the difference between a new model and other non-input models in the space. Value, on the other hand, requires the generated output of the models to be measured, and requires domain-specific heuristics.

We lack the space for a full evaluation, but note that Guzdial and Riedl's 2016 work represents an instantiation of this technique in the domain of video game level design [5]. The work made use of concept blending to combine different learned models of level design trained on aesthetically different types of levels. A sketch of a proof that combinatorial meta search can generate a wider range of creative artifacts is given in [6].

Acknowledgments

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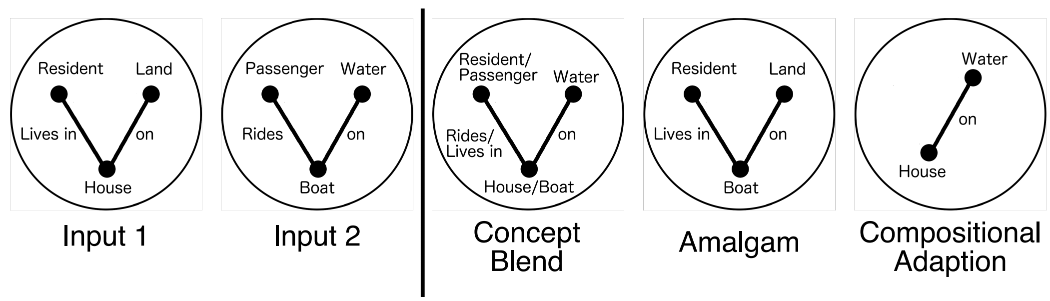

Figure 1: Example of three combinatorial creativity techniques. Two input spaces on left with example output from the three techniques on the right.

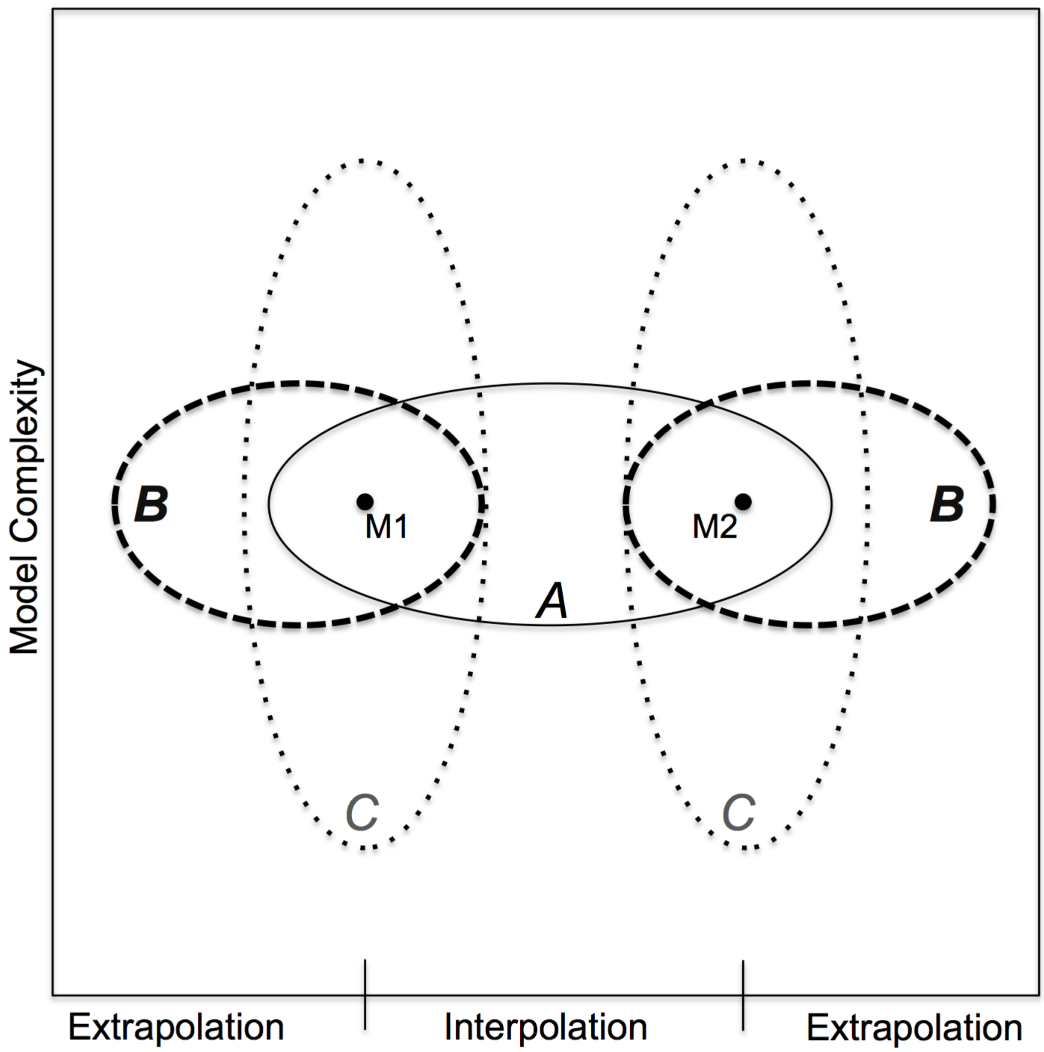

Figure 2: Abstraction of the space of models accessible to each technique individually given two inputs (M1 and M2) in terms of amalgamation (A), concept blending (B) and compositional adaption (C).