A Sub-symbolic Model of the Cognitive Processes of Re-representation and Insight

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ABSTRACT
We present a sub-symbolic computational model for effecting knowledge *re-representation* and *insight*. Given a set of data, manifold learning is used to automatically organize the data into one or more representational transformations, which are then learned with a set of neural networks. The result is a set of neural filters that can be applied to new data as re-representation operators.

Author Keywords
Re-representation, Insight, Cognitive Model

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General Terms
Theory, Algorithms

INTRODUCTION
A significant aspect of creative endeavor is the mechanism of analogy. Indeed, it has even been suggested that analogy-making may be *the* facilitator for creative endeavor [1]. A striking example of this is the case of Alan Turing's attempt to understand and automate the process of proof generation in mathematics. In order to facilitate this, he chose to draw an analogy between the human mathematician and a simple, abstract model that has become well-known as the Turing Machine. Turing was ultimately disappointed in his efforts to produce an automated mathematician, but the result of his (as well as others') analogy-making is surely one of history's most spectacular failures—the birth of the field of computer science.

One compelling instantiation of analogy making for problem solving is often termed *re-representation*—the reencoding of the problem at hand in a (usually quite) different way so that it (better) resembles something familiar or useful. For example, much of computer vision is concerned with re-representing raw pixel data (Figure 1(a)) in a way that facilitates image understanding in some form (Figure 1(b)). This process of discovering a useful re-representation has been identified in some theories as the essence of insight [4].

(a) (b)

Figure 1. *Re-representation in computer vision.* Raw pixel data in (a) is re-represented in (b) in a form that facilitates image analysis and understanding via computer vision algorithms, encoding such information as edge location, or, as in this case, a local point spread function.

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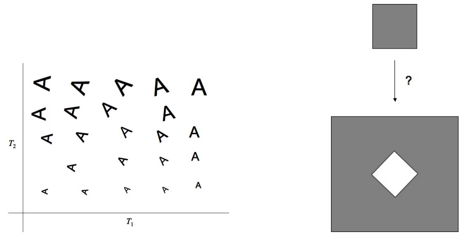
METHODOLOGY
We employ an "image"-based approach to discover a (re-)representation mechanism that is invariant to various transformations. We consider the general case where closed form analytical expressions for such transformations will not be derivable, and propose learning transformations inherent in the data by employing a neural approach as a (hopefully compact) representation.

In many cases, these transformations may occur on a lower-dimensional manifold, and we will have to discover that surface (see Figure 2) in order to produce an accurate (re-)representation (in the form of a neural filter). Combining (nonlinear) manifold learning with a sub-symbolic transformation representation will allow us to discover interesting transformations that can be used to re-represent data in a way that facilitates analogy making. To summarize, this implementation of knowledge (re-)representation is composed of two steps:

1. The discovery of the relevant manifold, and
2. Learning the transformation(s).



(a) (b)

Figure 2. ***Transformations that live on the manifold can be discovered and encoded as useful knowledge representations.*** **(a) 2-D manifold reveals two high-level concept transformations: rotation and scaling. (b) the puzzle requires the application of both transformations for its solution.**

Re-representation

Given a set $\mathcal{T}$ of learning task instances that are related through some transformation ξ, we require a clustering process p that (at least) induces an ordering on $\mathcal{T}$. To implement p, we apply an iterative manifold learning algorithm [3] to reduce our data to a single dimension whose ordering of the data (hopefully) faithfully represents the transformation ξ to be learned. (For example, from Figure 2, the A's should be ordered from largest to smallest or from smallest to largest in the scaling dimension.) Then, neighbors on the manifold act as input/output training patterns. For learning, we employ a standard multi-layer perceptron trained with backpropagation.

The result is a neural filter ζ that (hopefully) closely approximates the transformation ξ and can be applied to new tasks to facilitate their solution. In the puzzle example, the task of recognizing A's is represented with multiple instantiations. The manifold learner orders the A's from largest to smallest and produces a set of training pairs that encode this scaling transformation. These data are used to train a neural network that learns to scale its input. Similarly, the rotational transformation can also be learned as a neural filter. When the puzzle is encountered, the scaling and rotational transformations can be used to re-represent the large square as a small diamond, facilitating the puzzle's solution.

Insight

Insight can now be formulated as the solution to the problem of deciding, given a set of learned transformations, which will be useful. Given a set Ξ of such transformations, we can approach the question of which to use as a meta-learning problem, the solution to which will result in the system becoming better at having useful insights with experience. As more tasks and more representations are experienced, the system's insight into which re-representation will be most useful will improve. The end result is a *dynamic evaluation criterion*, one critical component for any system which might be attributed as creative [2].

DISCUSSION

It is interesting to note that this approach admits both discriminative and generative models. For example, we might construct a (discriminative) model that learns to recognize disguised voices by transferring knowledge of music transposition. Given various examples of transposed music, the system can learn a manifold that represents transposition, and then learn a sub-symbolic transformation that implements it. Later, when asked to recognize a disguised voice, the system can discover that the two tasks are related and apply the (inverse of the) transposition transformation to the disguised voice, producing something similar to a known voice.

We also might construct a (generative) model that creates unique aircraft designs by transferring knowledge of avian anatomy. Given various examples of birds, the system learns a manifold with dimensions representing concepts like wing size, center of mass relative to head, length of tail, feather type, etc., and each of these may be learned as a sub-symbolic transformation. Later, when faced with the task of aircraft design, the system discovers that planes and birds are similar and, given a basic prototype design, can generate novel variations to it by applying the various learned transformations. Indeed, given this approach the generative/discriminative dichotomy may be elucidated by whether we are applying learned transformations or their inverses.

Summarizing, we hypothesize that knowledge discovery can be accomplished via manifold learning, knowledge representation can be accomplished via learning transformations implicit in the manifold dimensions, insight can be facilitated by meta-learning that matches transformations to new tasks, and re-representation occurs through applying learned transformations to the new task (resulting in a system that creatively solves problems using insight and analogy).

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