Modeling Human-Like Rates of Learning via Analogical Generalization

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Introduction

A significant problem with many computational models of learning is that they require a cognitively implausible number of inputs and training trials. Recently both Peter Stone and Leslie Kaelbling have advocated a push towards "no zeros learning," referring to the size of the dataset. In other words, learning from fewer than ten examples is an important goal. We believe that the ability to do efficient learning from a few examples is important in computational models of classification. There is clear psychological evidence that people do not require hundreds or even tens of examples to learn many categories. This phenomenon repeats across domains from spatial language learning (e.g., Casasola, 2005) to image classification (Gentner and Namy, 1999; Nosofsky *et al.*, 1996).

Gentner and Loewenstein (2002) have argued that individuals learn categories through a process of *progressive abstraction,* wherein instances of a category are compared and the commonalities are abstracted out as a direct result of the comparison. In many cases, the commonalities resulting from comparison appear to be in the relational structure of the cases being compared. For example, in (Gentner and Namy, 1999), subjects who compared a bicycle to a skateboard appeared to form a generalization based on the functional relationship between the wheels of a vehicle and the vehicle's purpose, rather than basic perceptual features, such as the shape and number of wheels.

This paper discusses SEQL, a computational model of progressive abstraction. We present results from two studies that show how SEQL has been successfully applied to learning concrete object categories and more abstract spatial relations. In both domains, SEQL is capable of learning from a small number of examples, similar to the training set sizes that would be required by a person. We conclude by considering further work to more fully evaluate SEQL as an approach to category learning.

The SEQL Model

We compare structured descriptions using SME, the Structure Mapping Engine (Falkenhainer *et al.*, 1989), a computational model based on Gentner's (1983) structure-mapping theory of analogy and similarity in humans. Given two descriptions, a base case and a target case, SME computes one or more mappings between the cases by aligning their common structure. One of the key insights of structure-mapping theory is that when humans compare two cases, they seek out mappings which maximize *systematicity*. That is, they prefer mappings that align interconnected, higher-order relations to more superficial mappings, which only align first-order relations and attributes. When SME computes a mapping between two cases, it returns a set of correspondences between the elements in the two cases, along with a structural evaluation score, a numerical estimate of the systematicity of the mapping. The structural evaluation score estimates the similarity of the cases.

We use SEQL (Kuehne *et al.*, 2000; Halstead & Forbus, 2005) as our model of categorization. In SEQL, category learning is modeled as a process of progressive abstraction in which comparison promotes generalization and abstraction. Each incoming exemplar is compared to existing generalizations and stand-alone exemplars using SME. If the exemplar is considered "close enough" to a current generalization it is merged into that generalization. The merging process involves using SME to find correspondences between expressions in the new exemplar and expressions in the generalization. Generalizations consist of all those expressions which have been found in a reasonable proportion of their exemplars, along with probabilities for each expression that indicate how many of the exemplars contained that expression.

SEQL is capable of performing unsupervised category learning by grouping those exemplars that SME finds to be sufficiently similar into the same generalization. However, when SEQL is working from labeled data, it can also perform supervised learning by constructing a single generalization from the set of exemplars that have been given the same label.

Our approach to learning using SEQL differs from traditional cased-based reasoning (CBR) approaches in two ways. Traditional CBR typically uses application-specific matching and retrieval mechanisms whereas SEQL is a domain-independent cognitive simulation of human processing. This makes our technique more powerful, as we are able to use the same set of cognitively plausible processes to model learning across domains and input modalities without tailoring our retrieval and matching methods to each individual task. Another important difference is that CBR typically solves a problem by adapting a single, previously seen case. SEQL, on the other hand, constructs generalizations from multiple cases.

Experiments

Sketch Recognition

We believe that an important first step in showing that SEQL is a viable model of progressive abstraction is to demonstrate that it can be used to build concrete generalizations based on sets of highly similar objects. We have used sketch recognition as a representative task. By sketch recognition, we mean, given a sketch drawn by a person, identifying the object the sketch is meant to represent. Learning by generalization is important in sketch recognition because different people, or even the same person at different times, may vary in the way they draw an object. A recognition system needs to learn classifiers that are sufficiently robust to operate across many different sketches of the same object.

There have been several previous systems which learn to recognize hand-drawn sketches from examples. However, they generally require large numbers of examples to construct their sketch classifiers. For example, Liwicki and Knipping (2005) built a system for recognizing five different symbols typically found in circuit diagrams. Despite the simplicity of these symbols, the system was trained on 500 images, 50 for each of two possible orientations for each symbol. Sharon and van de Panne (2006) built a more general system for recognizing objects drawn by a user. However, their system utilized a training set of a comparable size: 20-60 examples of each object. While these systems have proven capable in the domains for which they were built, they clearly cannot be considered reasonable models of human learning.

We believe there are two keys to fast learning of classifiers for sketch recognition: qualitative sketch representations and an efficient learning algorithm. Representations need to be qualitative so that the learner does not become distracted by irrelevant features that vary across even nearly identical sketches. For example, it should not matter whether a particular edge in a sketch is 3 inches long or 4 inches long, or whether an angle between two edges in 60 degrees or 75 degrees. On the other hand, it may matter whether one edge is longer than another, or whether two edges are parallel or perpendicular. In our sketch representation scheme, we decompose a sketch into edges and then represent these types of relative, qualitative relations between edges. This decreases the necessary amount of training considerably, as our system will not care if two sketches of an object are drawn at different scales, or if the edges in one sketch are slightly rotated.

Our representational vocabulary has three types of terms: *attributes*, *pairwise relations*, and *anchoring relations*. Attributes categorize an individual edge as straight, curved, or elliptical. Pairwise relations give basic qualitative relationships between pairs of edges. These include relative length, relative orientation, whether two edges are connected, and whether the connection between them is a concave or convex corner. Anchoring relations describe relationships between groups of three or more edges and contain greater structural depth. There are anchoring relations for edges that form a closed shape, such as a triangle or quadrilateral, and for edges whose endpoints meet to form a three-way junction. Please see (Lovett *et al.*, 2007) for a more detailed description of the representation scheme.

We use SEQL as our classification learner. For this study, we were primarily concerned with supervised learning, since a child may be told the names of objects, just as the training sketches for a recognition system can be labeled with the appropriate object names. Given a list of objects with the same label, SEQL compares the objects' representations and constructs a generalization consisting of the elements of the representations found in most or all of the sketches. New sketches can then be classified by comparing them to each generalization and returning the class name of the generalization which is most similar. We calculated similarity by using SME to find a mapping between a new exemplar and a known generalization. In order to choose the closest match, we normalized our similarity scores based on the size of both the exemplar and the generalization.

In our study (Lovett *et al.*, 2007), we built a library of sketches by having 9 subjects each sketch 8 everyday objects. See Figure 1 for example sketches of four of the objects. We gave the subjects an illustration of each object to use as a guide, to ensure that they would all draw similar versions of each object from the same viewpoint. However, we told them to only draw those features of the objects which they believed were necessary for someone to recognize their sketch. This allowed us to produce a set of similar sketches of each object that nonetheless contained a high degree of within-object variability, certainly more than was found in the previously mentioned studies on sketch recognition. Evaluating our system on this library, we found that it was able to learn generalizations from as few as two examples of each object that were sufficient for classifying the other examples of the objects. As the training set size increased to six examples of each object, the system's performance improved further; it correctly classified objects into one of eight classes 77.5% of the time. When we ignored confusion between three particularly similar classes of objects (cups, buckets, and cylinders), performance was at 94.2%.

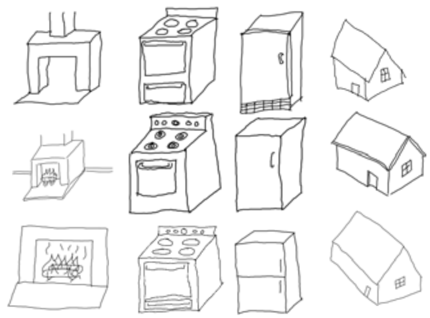

Figure 1. Examples of sketches drawn by subjects

Spatial Language

Another area of learning where abstraction from observed exemplars plays an important role is the learning of spatial preposition categories to describe relationships between objects. There has been much psychological research on how children learn to abstract away from the specific objects in a scene to the more general relationship between them (e.g. Casasola, 2005). There is also a large body of work examining which aspects of a scene are important to how an adult chooses a preposition to describe a scene. For example, the labels of the objects involved (Feist & Gentner, 1998), the control relationships between the objects (Coventry & Prat-Sala, 2001) and other functional relationships between the objects (Carlson-Radvansky *et al.*, 1999) have all been shown to play an important role in how English prepositions are used.

We have shown (Lockwood *et al.*, 2006) that SEQL can classify sketches representing the relationships in, on, above, below, and left into the correct preposition categories. Not only can it correctly classify the sketches, but it can do so with only 50 total exemplars (10 for each of the 5 prepositions) and in only one pass over the training data. In contrast, many connectionist models attempting to model the same phenomenon require many more stimuli and a number of training trials that is simply not cognitively plausible. For example, Regier's (1995) model required a total of 3000 epochs of training on 126 movies to learn spatial prepositions.

Our study involved only simple sketches of pairs of geometric objects (circles, squares, rectangles and triangles) representing basic spatial relationships. These input were drawn from psychological studies and other computational models. The inputs were sketched using sKEA (Forbus, Ferguson & Usher, 2001) the first open-domain sketch understanding system. sKEA provides users with interface tools to conceptually label the glyphs drawn with the entity that glyph represents. These labels are drawn from a subset of the Cyc knowledge base (containing around 35,000 facts) allowing sKEA to infer a large amount of information about the objects in the sketch. The objects in each sketch were named *figure* and *ground* to clarify the relationship that we were interested in (this is consistent with psychological studies where subjects are asked to complete the sentence "object A is ___ object B"). For example, consider Figure 2 below:

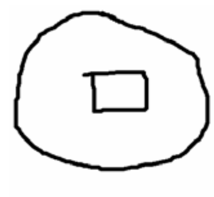

Figure 2. An example of the sketched input used in the spatial language

This figure shows an example of one of the sketched input examples for *in*. In this sketch, the circle is named *ground* to specify its role in the preposition, and it is conceptually labeled *circle*. Similarly the square is named *figure* and conceptually labeled *square.*

In addition to the object information from the knowledge base, sKEA computes a set of qualitative spatial relationships from the ink in the sketch. The information extracted is meant to approximate high-level visual processing. For example, RCC-8 relations (Cohn, 1996) are extracted to determine topological relationships. In Figure 2, sKEA would compute the RCC-8 relationship RCC8-nTPP (non-tangential proper part) to describe the topological relationship between the circle and the square. sKEA would also determine that the glyphs formed a contained glyph group with the circle filling the role of container and the square as the contained object. Although they do not appear in this example, sKEA also computes positional relations (i.e. *above, to the right of*) between all pairs of disjoint glyphs in a given sketch.

All of this information - both the perceptual information from the ink in the sketch and the object knowledge from the labels - is combined to form a case representation for each input object. Unnecessary information, like bookkeeping facts, is automatically filtered out of the cases before the experiment is run. The cases are then sent through SEQL, which automatically groups them based on similarity and forms a generalization for each group. Our goal in doing these experiments is two-fold. We are determining whether we can achieve human-like classification results automatically, and we are also interested in what specific sets of relationships are needed to do so.

We are currently creating a second sketch library containing real-world objects to conduct a second round of classification with SEQL. These objects are also drawn from the psychology literature and will allow us to examine which functional features are key to determining preposition use. Additionally, psychological work has addressed the variation in preposition usage across languages and cultures (e.g. Bowerman, 1999). We plan to also try to learn the prepositions of other languages using this new set of sketches.

Future Work

There are two main directions in which we will continue this work: improvements or enhancements to the SEQL system itself and the application of SEQL to new domains. SEQL has recently been enhanced by weighting the expressions in a generalization based on the proportion of exemplars that include that generalization, i.e. their probability (Halstead and Forbus, 2005). A further enhancement might be to also weight expressions based on their probability of appearing in the exemplars for alternative classes. An expression that appears in most exemplars for one class but few exemplars for other classes has the highest diagnostic strength and thus should receive more weight. This approach would be fairly easy to implement, but it is not clear that it is a plausible model of how people form generalizations. In particular, this approach depends on knowing the full set of generalizations for all alternative classes when one is constructing a generalization. It may be that people never consider all alternatives at once, but instead retrieve a small set of possible generalizations on the fly when faced with a classification task. These possibilities require further consideration.

The second direction for future work involves using SEQL to construct more abstract categories. Previous work (Halstead & Forbus, 2007) has shown that SEQL can be used in the more abstract domain of identifying the perpetrator of terrorist attacks. However, the initial representations used as input to SEQL were already quite abstract. In terms of modeling progressive abstraction, we would like to explore whether the same concrete, spatial representations from which SEQL learned entities (sketched objects) and simple relationships (spatial prepositions) can also be used to learn more abstract, higher-order relations. These could include mathematical concepts like monotonicity or functional concepts like the importance of having wheels on a vehicle. By demonstrating how analogical comparison might promote the construction of generalizations that can become increasingly abstract, we hope to put forth not only a model of efficient human learning, but also a potential explanation for how young children might begin to construct abstract concepts.

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