Automatic Categorization of Spatial Prepositions

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Abstract

Learning spatial prepositions is an important problem in spatial cognition. We describe a model for learning how to classify visual scenes according to what spatial preposition they depict. We use SEQL, an existing model of analogical generalization, to construct relational descriptions from stimuli input as hand-drawn sketches. We show that this model can distinguish between *in*, *on*, *above*, *below*, and *left*, after being trained on simple sketches exemplifying each preposition.

Introduction

Spatial reasoning is a skill central to many human tasks, as is being able to communicate about space. One way we share spatial information is through the use of prepositions to describe relationships between entities in the world. These utterances involve at minimum two objects: a reference object (the ground) and a located object (the figure) as well as the preposition that describes their relationship. The set of spatial prepositions in English is quite small when compared with other word categories; however computationally modeling the assignment of preposition labels to visual scenes remains a difficult and important problem.

Many recent psychological studies have focused on understanding which properties of the figure and ground objects play a role in the assignment of spatial prepositions. Some of the properties studied are extracted directly from the spatial arrangement of objects and surface features. Spatial language has garnered so much attention since it is considered to be an important organizing structure for conceptual information (Talmy, 1983). Studies have also shown that children learn how to use spatial language through interactions with objects in the world and without negative evidence.

In this paper, we automatically categorize simple geometric sketches based on the preposition that would describe them. Sketching is particularly suited to studying this domain as our understanding of spatial terms is grounded in perception. Perceptual features can be automatically computed using sketching systems, thus removing a source of tailorability in modeling. For these experiments, we used sKEA (Forbus, Ferguson & Usher, 2001), the first open-domain sketching system. sKEA sidesteps traditional recognition problems by allowing users to conceptually label the glyphs in a sketch. We use this conceptual information along with visual properties of the ink itself to focus on understanding the relationships in the sketch. The possibilities for conceptual labels are limited only by the underlying database (currently a subset of the Cyc database containing over 35,000 concepts). In addition to the conceptual label, users can give each glyph a name to reference it by. Basic qualitative spatial relationships are extracted from the ink in the sketch (Forbus, Tomai & Usher, 2003). In sKEA, the frame of reference is also specified by allowing the user to select the view of the sketch (i.e., "looking from side", "looking from another object").

We previously used sKEA as input into SpaceCase, a Bayesian model that assigned prepositions to individual sketches (Lockwood, Forbus, & Usher, 2005). In that model, update rules fired based on properties in the sketch such as animacy of the ground and figure objects. In that work, the rules were motivated by results from psychological studies indicating what properties of scenes were important for preposition assignment. In the experiments described here, we use sKEA to automatically compute a set of spatial relationships from sketches. These relationships are suggested by, and consistent with, those features which have been shown to influence spatial preposition judgments with human subjects. Analogical generalization is used to automatically create groupings based on the features we have extracted. The generalizations created group the sketches together based on the relationship (*in, on, above, below,* and *left)* between the two objects.

Analogical Generalization

We use SEQL (Skorstad, Gentner, & Medin, 1988; Kuehne, Forbus, Gentner, & Quinn, 2000) as our model of categorization. SEQL is a computer model of category learning that is based on Gentner's (1983) structure-mapping theory of analogy and similarity. In SEQL categories are created through a process of successive comparison with incoming exemplars. The comparisons are carried out with SME, the Structure-Mapping Engine (Falkenhainer, Forbus & Gentner, 1986; Forbus, Ferguson & Gentner, 1994). For each category, a set of generalizations and exemplars is maintained. Each new exemplar that arrives is compared against existing generalizations. If the comparison is very close, i.e. over a given threshold, the exemplar is merged into the generalization and the generalization is replaced with the overlap between them. If it is sufficiently similar to an existing exemplar, the overlap between the two exemplars is stored as a new generalization. Finally, if the incoming exemplar is not similar enough to any of the existing generalizations, it is maintained as a separate exemplar.

The determination of "similar enough" is controlled by the *match threshold* parameter, which is 1.0 when the two descriptions are identical. If this threshold is too high, it is difficult to find any exemplars that are similar enough to create generalizations. If too low, then the generalizations created are meaningless. Previous experiments suggest that a match threshold between 0.75 and 0.9 tends to yield the most useful results.

SEQL can now use probabilities in producing generalizations (Halstead & Forbus, 2005). When generalizations are created or extended, the union of the descriptions is used, with the probability of an expression being in the generalization calculated by the frequency of occurrence in the exemplars that make up the generalization.

Experimental Design

Experiment 1

Input. Input was provided as sketches created using sKEA. Each sketch contained two geometric shapes named figure/ground and conceptually labeled with their common shape names (for example, in figure 1 below, the square was named figure and conceptually labeled "square"). The shapes used were circles, triangles, rectangles, and squares.

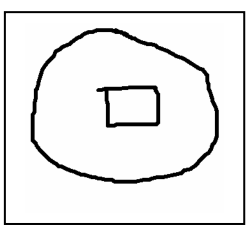

Figure 1. An example of the sketched input used in this experiment.

In the first experiment the library of sketches used contained 50 sketches. Each sketch was designed to be a good example of one of five spatial prepositions: *in*, *on*, *above*, *below*, or *left*, with 10 sketches created for each preposition. By "good example" we mean that it would be easily and unequivocally recognized as a good representative of the English use of that preposition. For example, in all of the *on* sketches, the figure object was smaller than the ground object and the entire bottom surface of the figure object was in contact with the top surface of the ground object. Each preposition had examples containing different shapes in the ground and figure roles. All sketches were 2D and drawn from the same side view perspective.

The sketches were drawn from stimuli in the psychological literature studying spatial prepositions, focusing on simple geometric shapes. The sketches for *above* and *on* were taken in part from examples provided in Regier (1995). Other sketches for *left* and *above* were created based on information from Gapp (1995a, 1995b), whose experiments explored the effect of distance and shape (extent)/size of the ground in judgments of applicability for projective spatial relationships. The sketches were also informed by a variety of experiments that discuss limitations on regions of acceptability for prepositions, such as Logan and Sadler (1996) and Regier and Carlson (2001).

Visual Processing. Initial processing is done on the sketch to extract visual information from the ink. This information is meant to approximate high-level visual processing. For example, RCC-8 relations (Cohn, 1996) are computed between the objects in the sketch to determine topological relationships such as touching (`RCC8-EC`) and inside (`RCC8-nTPP`). We use these qualitative spatial relations as one source of perceptually salient relationships in the sketches.

sKEA automatically computes a variety of other qualitative spatial relationships from the ink. For example, spatial processing identifies groups of glyphs that form connected glyph groups and contained glyph groups. In the latter case it also specifies which glyph acts as the container and which acts as the insider. sKEA computes positional relations (i.e., *above* and *to the right of* between all pairs of glyphs in a sketch that are disjoint from each other.

Our model does some minimal additional processing based on the spatial relationships computed from the sketch. For example, positional relations are always computed with the figure in the first argument and the ground in the second argument, i.e., `(above ground figure)` would be translated to `(below figure ground)`[1]. For each sketch, this visual information and any conceptual information about the objects in the sketches is recorded as an exemplar. Unnecessary information, like bookkeeping facts representing specifics of our implementation, are filtered out since we do not view them as psychologically relevant. All filtering and processing procedures were done over the entire case library of sketches. Individual sketches were never singled out for specific processing.

Classification. All 50 sketch cases were run through SEQL, using a match threshold of 0.9. Our goal in doing these experiments is to see whether we can achieve human-like classification results automatically, and what specific sets of relationships are needed to do so.

[1] *Above* as computed by sKEA is very different from its English language counterpart. The spatial relationship *above* in sKEA is derived by comparing the relative positions of the centers of area of the bounding boxes of the glyphs. This alone is not enough information to parse different prepositions. For example, the positional relationship *above* shows up in the generalizations for both *above* and *on*.

Results. The fifty simple sketches were classified into the five generalizations expected (corresponding to *in, on, above, below*, and *left*). These results were stable over a variety of match threshold values between 0.8 and 0.9.

```
(enclosesHorizontally ground figure)
(connectedGlyphGroupTangentialConnection
       figure ground)
(connectedGlyphGroupTangentialConnection
       ground figure)
(rcc8-EC figure ground)
(above figure ground)
```

Figure 2. The SEQL generalization created for the preposition *on*.

Inspection of the generalizations generated shows the overlap between the sketches that creates the generalization. Figure 2 shows the generalization created for *on*.

The information included in the generalization is visual information based on the spatial arrangement of the glyphs in the sketch. Looking at the facts generalized, it makes sense that the salient perceptual information needed to assign the relationship *on* would be a combination of tangential connection between the figure and the ground and the figure being above the ground. Currently, every fact in a case is weighted the same as every other fact.

These are surprisingly good results considering that we only used 10 sketches for each preposition and no prior training was needed. Also, relatively few facts were needed in each case to determine which category a sketch fell into. The average number of facts per generalization was 5.6. The most facts needed was 7 for *on*.

It is important to note that not just any set of facts will result in a useful classification. If bookkeeping information is not filtered out, it will overwhelm the cases and categories that result are meaningless. Also, object-centric perceptual information had to be filtered out, as it ended up being irrelevant to the spatial preposition categories and was adding noise to the similarity comparisons. For example, the spatial properties that sKEA automatically computes includes an estimation of roundness of glyphs. If the roundness facts are left in the cases, they sometimes cause sketches to classify based on similar roundness facts instead of on the relationship between the glyphs. So the set of facts that ended up in each case ends up being focused on those facts that specifically related to the relationship between the two glyphs.

Likewise, while doing these experiments, we found several additional spatial relationships that had not previously been computed that were needed to create meaningful generalizations. In order to get the *above* and *below* cases to generalize, we added information about the grazing line. The grazing line is a horizontal line, that grazes (is tangential to) the very top of the ground object. Regier and Carlson (2001) suggest that *above* ratings are sensitive to the grazing line and we found the same result in our experiments.

The set of facts retained in generalizations is summarized in the table below along with the categories they appear in:

Relationship	Categories
Horizontal enclosure	below, above, on
Vertical enclosure	left
Left of	left
RCC8-DC (disjoint)	below, above, left
Above	above, on
Below	below
Above Grazing Line	above
Below Grazing Line	below
Contained Glyph Group	in
RCC8-NTPP/TPP (inside)	in
Connected Glyph Group	on
RCC8-EC (touching)	on

Figure 3. A summary of the spatial relationships used for generalization.

When glyphs partially overlap, a fact is also asserted based on percentage of total area overlap (LessThan10Overlap, DefiniteOverlap, or GreaterThan90Overlap). These facts are useful for disambiguating cases of partial overlap from those that are just poorly drawn examples of *in* or *on* and are computed for every sketch. Since none of the simple sketches had overlap cases, none of these facts shows up here. It is interesting that this small set of relationships is sufficient to distinguish between these prepositions. Efforts were made to remove redundant and unnecessary information. For example, in addition to designating contained glyph groups, sKEA also asserts information about which object is designated as the container and which is the insider. At this level of classification removing that information had no impact on the generalizations created. Keeping just the information that the ground and the figure form a contained glyph group is enough to ensure the correct generalization will form.

Experiment 2

Input. The input for Experiment 2 was very similar to that for Experiment 1. The same 50 sketches from Experiment 1 were used. In addition, 20 new sketches which were more complicated (non-standard) and/or ambiguous cases of spatial prepositions were used. Figure 4 below shows two sketches from the 20 added and illustrate two different reasons for inclusion. The sketch on the left shows an ambiguous case where the circle could be considered *above* or *to the left* of the square. The sketch on the right shows an instance of *in* where the figure is only partially contained within the boundaries of the ground (this is similar to the case "the flowers are *in* the vase"). For the rest of this discussion, the 50 original sketches from Experiment 1 will be referred to as the simple sketches and the 20 additional sketches from Experiment 2 will be referred to as the complex sketches.

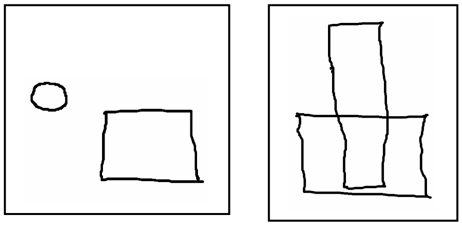

Figure 4. Two examples of the stimuli used for experiment 2.

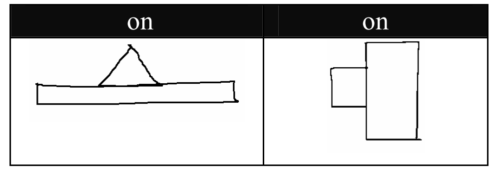

Figure 5. Two dissimilar examples, both instances of *on*. The sketch on the left is a simple example, and the one on the right is complex in that it involves vertical rather than horizontal support.

The 20 complex sketches obviously could not cover every possible arrangement of figure and ground, so we focused on the following deviations:

- Sketches where the figure overlaps the ground by varying amount (ambiguous between *in* and *on*)
- Sketches ambiguous between *above* and *left* (as in figure 2b above)
- Sketches where the figure is attached to the side of the ground – vertical as opposed to horizontal support (on as in "the picture is *on* the wall") or where the ground is sloped.
- *On* and *above* examples where the figure was larger (larger vertical extent) than the ground

The idea that some scenes are better examples of certain prepositions than others is common in the literature. For example, Logan and Sadler (1996) argue that for spatial templates, there are three regions of acceptability for spatial relationships: the good region, the region of examples that are not good, but are acceptable, and the region of unacceptable examples. These sketches are intended to fall into the acceptable but not good category.

Classification. First, the simple geometric sketches were classified using SEQL. Once the base generalizations were created, the complex sketch examples were added to SEQL and the generalization algorithm was run again. Several different runs were done with varying match thresholds. We good results were found at both the 0.8 and 0.9 levels.

Results. As mentioned above, the original 50 sketches created 5 generalizations, one corresponding to each relationship represented. This result was unchanged in this experiment. The ambiguous *above/left* sketches divided – the one that was most like the left sketches joined that generalization while the others created a separate generalization. The sketches where the figure overlapped the ground by varying amounts formed another generalization. The *on* category assimilated all of the other sketches that were meant as complex or ambiguous examples of that preposition. The incorporation of these instances into the overall generalization altered the facts that were considered part of the generalization as can be seen in the figures at the top of the next column.

```
--DEFINITE FACTS:
(connectedGlyphGroupTangentialConnection
             figure ground)
(connectedGlyphGroupTangentialConnection
             ground figure)
(rcc8-EC figure ground)
--POSSIBLE FACTS:
88% (above figure ground)
65% (enclosesHorizontally ground figure)
18% (enclosesHorizontally figure ground)
12% (leftOf figure ground)
12% (enclosesVertically ground figure)
6% (rightOf figure ground)
```

Figure 6. The new generalization created for *on* after the complex sketch examples are added.

Clearly this new generalization covers a wide variety of sketches. However, it is important to note that all sketches that were included in this generalization depict a relationship that would be classified using the preposition *on*. Another interesting result is that the sketches representing those cases where the figure overlaps the ground, but is not fully contained in it, formed a separate generalization. While they would most likely be labeled as *in* (although some might be *on* depending on the context of the scene) they did not join the generalization that contained the simple cases of *in*.

Although there were a variety of new sketches added, the group of facts used to create the generalizations did not change that much from Experiment 1. In addition to the facts listed in Figure 3, the following facts showed up in the generalizations created in Experiment 2:

- RCC8-PO (i.e., partially overlaps)
- DefiniteOverlap[2]
- rightOf
- The horizontal and vertical inclusion was expanded to include cases where the figure included the ground.

[2] For all sketches where an RCC8-PO relationship exists, one of {`DefiniteOverlap`, `LessThan10Overlap`, `GreaterThan90Overlap`} gets asserted based on the percentage of area overlap (<10%, between 10% and 90%, or >90%) between the figure and ground.

Related Work

A number of models of spatial prepositions involve representational templates that are created by hand. For example, Herskovits (1980, 1986) categorizes spatial language into *use cases* based on object and contextual features as well as typicality, and Logan and Sadler (1996) classify geometric scenes using spatial templates. These models require an exhaustive list of the use cases/templates needed, mechanisms for selecting the correct one, and an account of what modifications can be made to fit an imperfect template to a scene. By contrast, our use of SEQL produces relational templates automatically, and reduces the imperfect fit problem to structural alignment.

Regier's (1995) connectionist model was able to learn spatial prepositions for a variety of languages. However, it required labeled training data, and a total of 3000 epochs of training on 126 movies. Since we do not label our stimuli, there are no cues for our system as to which sketches should be classified together.

Regier and Carlson's (2001) attentional vector sum (AVS) model is able to reproduce similar results to humans for several different prepositions. Recent extensions (Regier, Carlson, & Corrigan, 2005) modified the original AVS model to account for functional information. This is done by focusing attention on the functional parts of objects (such as the bristles of a toothbrush). This work predicts acceptability judgments of spatial terms as opposed to categorizing stimuli.

Coventry *et al*. (2004; Cangelosi *et al* 2005) have developed a model which implements the constraints of the *functional geometric framework* (Coventry & Garrod, 2004) for the prepositions *over/under/above/below*. The model has been shown to be consistent with human data on the appropriateness of these four prepositions in describing scenes involving both geometric and functional information. Martinez, Cangelosi, and Coventry (2001) describe another model that simulates the same set of data, using a neural network whose input is descriptions of visual scenes. These descriptions are created using variables to encode various factors that were found to influence *over/under/above/below* judgments in experiments (Coventry, Prat-Sala, & Richards, 2001): orientation, function, appropriateness, and object type. The encoding of variables is done by hand, however, unlike our automatic encoding scheme.

We find all of these projects to be complementary to our work; there are tradeoffs to the different approaches. The main benefit of our approach is the flexibility and extendibility of the system. Since the input is sketches, it is very quick and easy to create more stimuli and to test more arrangements of objects. Since conceptual labeling ties to the underlying off-the-shelf knowledge base, functional information can be added through inference. No information for any case needs to be hand coded or added individually.

Discussion

We have shown that we can successfully classify simple geometric sketches by the spatial preposition that would be used to describe them by extracting a sufficient set of spatial relationships. Our contribution is unique in two ways. The first is our use of sketch-based input. This allows us the flexibility to quickly and easily create a variety of stimuli, including being able to recreate similar examples to stimuli from different psychological experiments. Automatically extracting the salient perceptual information eliminates the need for hand coding of representations. The second unique aspect of our model is the use of analogical generalization to automatically create categories. By altering the contents of our case libraries, through variations of the automatic encoding process, we were able to explore what relationships are sufficient to create the correct generalizations.

Future Work

We plan to extend the corpus of sketches to include everyday objects in addition to abstract geometric shapes. Psychological studies show that functional information about objects in scenes contributes heavily to the choice of preposition used to describe them (Coventry, Prat-Sala, & Richards, 2001; Feist & Gentner, 1998; Carlson-Radvansky, Covey, & Lattanzi, 1999; Coventry & Mather, 2002; Coventry & Garrod, 2004). Since we are already conceptually labeling the objects in our sketches, we can use the knowledge base to infer the functional properties of figure and ground objects, and verify that the figure and ground are fulfilling their functional roles.

Another direction involves testing with human subjects. The sKEA interface provides an interesting opportunity to run human subjects with the exact same stimuli (sketches) provided to the computational model. For example, we plan to present people with a categorization task similar to what was given to SEQL, and determine how they classify the harder sketches to inform subsequent versions of our model.

Finally, we also plan to explore categorization of prepositions in other languages (cf. Regier, 1995; Bowerman, 1999). There are competing theories as to how spatial reasoning and spatial language develop. One theory is that all humans share a small set of spatial primitives that we then learn to map to prepositions. Some recent work suggests that these primitives may be more varied than previously suspected (Choi *et al*, 1999). By comparing the relationships necessary to correctly classify prepositions in different languages we hope to shed some light on this discussion.

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