Learning Spatial Terms Without Explicit Negative Evidence

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Abstract

A method is presented for learning to associate simple scenes with spatial terms, in the absence of explicit negative evidence. A straightforward approach, in the learning of a given term, is to take all positive instances for any other term to be implicit negative instances for the term in question. While this approach is inadequate as it stands, a variation on it is shown to work well: positive instances for other concepts are taken as only weak negative evidence for the concept being learned. In the back-propagation framework used here, this idea is implemented through attenuation of the error signals from implicit negative instances. This notion of weakened implicit negative evidence is a very general one, applicable to other learning schemes, as well as other domains. It is also shown that knowledge of which pairs of spatial terms are antonyms facilitates the learning process.
1 The Problem

Researchers in child language acquisition have often observed that the child learns language apparently without the benefit of negative evidence [Braine, 1971; Bowerman, 1983; Pinker, 1989]. While these researchers have focused on the "no negative evidence" problem as it relates to the acquisition of grammar, the problem is a general one, and appears in several different aspects of language acquisition. This report approaches the "no negative evidence" problem specifically in the context of the learning of the semantics of lexemes for spatial relations. The methods used to solve the problem here are of general applicability, however, and are not restricted to this particular domain.

This work is a part of the $L_0$ language learning project at the International Computer Science Institute. [Weber and Stolcke, 1990] present an overview of this project, which seeks to provide an account of language acquisition in the simple domain of geometrical objects. Within this domain, the current work addresses the task of learning to associate scenes, containing several simple objects, with terms to describe the spatial relations among the objects in the scenes. This is illustrated in Figure 1.

For each scene, the system is supplied with an indication of which object is the reference object (we call this object the landmark, or LM), and which object is the one being located relative to the reference object (this is the trajector, or TR).

The system is to learn in the absence of negative instances. This condition is imposed so that the conditions under which the system learns will be similar in this respect to those under which children learn.

The "no negative evidence" problem surfaces here, as it is not clear just how to generalize from the positive examples seen. Consider Figure 2. Given the landmark (labeled "LM"), the task is to learn the concept "above". We have been given four positive instances, marked as small dotted circles in the figure, and no negative instances. The problem is that we want to generalize so that we can recognize new instances of "above" when they are presented, but since there are no negative instances, it is not clear where the boundaries of the region "above" the LM should be. One possible generalization is the white region containing the four instances. Another possibility is the union of that white region with the dark region surrounding the LM. Yet another is the union
of the light and dark regions with the interior of the LM. And yet another is the correct one, which is not closed at the top. In the absence of negative examples, we have no obvious reason to prefer one of these generalizations over the others.

One possible approach would be to take the smallest region that encompasses all the positive instances. It should be clear, however, that this will always lead to closed regions, which are incorrect characterizations of such spatial concepts as "above" and "outside". Thus, this cannot be the answer.

And yet, humans do learn these concepts, apparently in the absence of negative instances. The computational work presented in this report indicates how that learning might take place.

The basic ideas that are embodied in the system are presented first, and are followed by the results. After that, a full explanation of the system's technical details is presented.

2 A Possible Solution: Mutual Exclusivity

One solution to the "no negative evidence" problem which suggests itself is to take every positive instance for one concept to be an implicit negative instance for all other spatial concepts being learned. There are problems with this approach, as we shall see, but they are surmountable.

There are related ideas present in the child language literature, which support the work presented here. [Markman, 1987] posits a "principle of mutual exclusivity" for object naming, whereby a child assumes that each object may only have one name. This is to be viewed more as a learning strategy than as a hard-and-fast rule: clearly, a given object may have many names (an office chair, a chair, a piece of furniture, etc.). The method being suggested really amounts to a principle of mutual exclusivity for spatial relation terms: since each spatial relation can only have one name, we take a positive instance of one to be an implicit negative instance for all others.

In a related vein, [Johnston and Slobin, 1979] note that in a study of children learning locative
terms in English, Italian, Serbo-Croatian, and Turkish, terms were learned more quickly when there was little or no synonymy among terms. They note that children seem to prefer a one-to-one meaning-to-morpheme mapping; this is similar to, although not quite the same as, the mutual exclusivity notion put forth here.¹

In linguistics, the notion that the meaning of a given word is partly defined by the meanings of other words in the language is a central idea of structuralism. This has been recently reiterated by [MacWhinney, 1989]: “the semantic range of words is determined by the particular contrasts in which they are involved”. This is consonant with the view taken here, in that contrasting words will serve as implicit negative instances to help define the boundaries of applicability of a given spatial term.

3 Difficulties with Mutual Exclusivity

This report concentrates on the learning of the following eight English spatial terms:

- above
- below
- on
- off
- inside
- outside
- to the left of
- to the right of

Bearing this set of terms in mind, consider Figure 2 again. Under mutual exclusivity, if the four dotted circles are considered as positive instances of “above”, they are implicit negatives for all other spatial terms. It is certainly the case that a TR cannot be both “above” and “in” an LM; thus, it is reasonable for a positive instance of “above” to yield an implicit negative for “in” (and for “below”, among other terms). However, a TR can be both “above” and “outside” an LM, or both “above” and “off” an LM. As an example, all four positive instance for “above” shown in the figure could also be perfectly good positive instances of “outside”, and labeling them as implicit negatives through mutual exclusivity leaves us with a training set that has many false negatives in it, i.e. implicit negative instances which really should be positives.

“Outside” is a term that is particularly badly affected by this problem of false implicit negatives: all of the spatial terms listed above except for “in” (and “outside” itself, of course) will supply false negatives to the training set for “outside”.

The severity of this problem is illustrated in Figure 3. In these figures, which represent training data for the spatial concept “outside”, we have tall, rectangular landmarks, and training points²

¹They are not quite the same since a difference in meaning need not correspond to a difference in actual reference. When we call a given object both a “chair” and a “throne”, these are different meanings, and this would thus be consistent with a one-to-one meaning-to-morpheme mapping. It would not be consistent with the principle of mutual exclusivity, however.
²I.e. trajectories consisting of a single point each
relative to the landmarks. Positive training points (instances) are marked with circles, while negative instances are marked with X's. In (a), the negative instances were placed there by the teacher, showing exactly where the region not outside the landmark is. This gives us a "clean" training set, but the use of teacher-supplied explicit negative instances is precisely what we are trying to get away from. In (b), the negative instances shown were derived from positive instances for the other spatial terms listed above, through the principle of mutual exclusivity. Thus, this is the sort of training data we are going to have to use. Note that in (b) there are many false negative instances among the positives, to say nothing of the positions which have been marked as both positive and negative.

This issue of false implicit negatives is the main problem with mutual exclusivity, and it is this problem that this report addresses.

4 Salvaging Mutual Exclusivity

The basic idea used here, in salvaging the idea of mutual exclusivity, is to treat positive instances and implicit negative instances differently during training:

Implicit negatives are viewed as supplying only weak negative evidence.

The intuition behind this is as follows: since the implicit negatives are arrived at through the application of a fallible heuristic rule (mutual exclusivity), they should count for less than the positive instances, which are all assumed to be correct. Clearly, the implicit negatives should not be seen as supplying excessively weak negative evidence, or we revert to the original problem of learning in the (virtual) absence of negative instances. But equally clearly, the training set noise supplied by false negatives is quite severe, as seen in the figure above. So this approach is to be seen as a compromise, so that we can use implicit negative evidence without being overwhelmed by the noise it introduces in the training sets for the various spatial concepts.
The details of this method, and its implementation under back-propagation, are covered in Section 7. However, this is a very general solution to the "no negative evidence" problem, and can be understood independently of the actual implementation details. Any learning method which allows for weakening of evidence should be able to make use of it. In addition, it could serve as a means for addressing the "no negative evidence" problem in other domains. For example, a method analogous to the one suggested here could be used for object naming, the domain for which Markman suggested mutual exclusivity. This would be necessary if the problem of false implicit negatives is as serious in that domain as it is in this one.

5 Results

Figure 4 shows the results of learning the spatial term "outside", first without negative instances, then using implicit negatives obtained through mutual exclusivity, but without weakening the evidence given by these, and finally with the negative evidence weakened.

The landmark in each of these figures is the same one shown in the training sets in Figure 3, and is indicated by a tall rectangle made up of small squares, and angle brackets at the four corners. This is easiest to distinguish in (c).

The size of the black circles indicates the appropriateness, as judged by the trained network, of using the term "outside" to refer to a particular position, relative to the LM shown. Clearly, the concept is learned best when implicit negative evidence is weakened, as in (c). When no negatives at all are used, the system overgeneralizes, and considers even the interior of the LM to be "outside". When mutual exclusivity is used, but the evidence from implicit negatives is not weakened, the concept is learned very poorly, as the noise from the false implicit negatives hinders the learning of the concept. Having all implicit negatives supply only weak negative evidence greatly alleviates the problem of false implicit negatives in the training set, while still enabling us to learn without using explicit, teacher-supplied negative instances.

It should be noted that in general, when using mutual exclusivity without weakening the evidence given by implicit negatives, the results are not always identical with those shown in Figure 4(b), but are always of approximately the same quality.
The results for all eight concepts trained with weak implicit negative evidence are shown in Figure 5.

6 Antonyms

While the results of learning with weakened evidence from implicit negatives are significantly better than those obtained otherwise (recall Figure 4), they are still not perfect. The response is not uniformly strong across the region “outside” the landmark, and there is a very small response from some of the interior of the landmark.

One approach to remedying this situation is to assume that we know prior to training which pairs of spatial terms are antonyms. Since we know that a positive instance for a spatial term is always a reliable negative instance for its antonym, we can treat antonyms as special cases, and avoid weakening the evidence from an implicit negative of a term provided the implicit negative was caused by a positive instance for the term’s antonym.

For example, if we were currently viewing a positive instance of “above”, this would be taken as a weak implicit negative for all other terms except “below”, for which it would be taken as a strong (unweakened) implicit negative.

Regarding this notion of learning spatial terms assuming knowledge of which terms are antonyms, it is worth noting some psycholinguistic evidence that seems to support the validity of this assumption.

- [Clark, 1973] notes that when children have learned the the meaning of only one member of an antonym pair, their response to the unlearned term will be one that would have been appropriate to the learned one. I.e. they seem to know that the two terms are related, and to confuse them.

- [Tomasello, 1987] presents data covering a child’s acquisition of English prepositions. Spatial terms in oppositions such as in/out and over/under were learned earlier than the terms “by”, “with”, “for”, “at”, and “of”. In this latter list of prepositions, not all have clear antonyms. If there were knowledge of which terms were antonyms, and if this knowledge helped in the learning process, we might expect results similar to these.

This is clearly not conclusive evidence, but it suggests that the assumption of knowledge of antonyms should not be dismissed out of hand. In addition to this, there is some evidence that knowledge of antonyms does indeed help in the learning of the terms involved:

- [Lovelace, 1990] has noted that learning is facilitated by the presentation of spatial terms to children in antonym pairs.

Settling this question definitively is a matter best left to a developmental psycholinguist. Computationally however, as we shall see, the knowledge of antonym pairs helps immensely.

Figure 6 shows the results of learning the spatial term “outside” when all implicit negatives for “outside” are weakened except for those which are positive instances for “inside”. Comparing this with Figure 4(c), we find the knowledge of antonyms yields significant improvement, in that the larger circles indicate a higher degree of appropriateness. In addition, note that the interior of the landmark in Figure 6 is not marked as “outside” at all, whereas in Figure 4(c), parts of it are very slightly marked as “outside”.

The other terms were also learned to a high degree of accuracy using the antonym method.
Figure 5: Spatial Terms Learned with Weakened Evidence from Implicit Negatives
7 Detailed System Description

The system used in the above demonstrations learns the image based semantics for a set of spatial terms, using a point trajector (TR). This is the first step toward a more complete system which will eventually handle arbitrarily shaped TRs, polysemy, and other phenomena.

The eventual aim is to have the system learn closed-class spatial terms taken from arbitrary natural languages. This point is worth stressing, as it necessitates that the design reflect the sort of flexibility we would expect of a human being in this domain, and not be restricted to the spatial structure imposed by any single language or small subset of languages. The idea is to force oneself to work with primitives which are genuinely perceptual in nature, and thus essentially universal. The current version of the system does in fact work with such primitives.

This presentation begins with an exposition of the representation and architecture used, together with the basic ideas embodied in the architecture, and then discusses the weakening of evidence from implicit negative instances.

7.1 Representation of the LM and TR

Figure 7 illustrates the representations used for the LM and point TR.

The representation scheme for the LM comprises the following:

- The $x, y$ coordinates of several "key points" of the LM, where $x$ and $y$ each vary between 0.0 and 1.0, and indicate the location of the point in question as a fraction of the width or height of the image. The key points currently being used are the four corners of the LM's bounding

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3 The term "closed-class" is used to describe a set of linguistic elements that are fairly small in number and fixed in membership. For example, verbal prefixes and prepositions are considered to be closed-class forms. I focus on these as they can be seen as supplying the fundamental structure imposed on a domain (space, in this case) by a language. See [Talmy, 1983] for details.
box (UL: upper left, UR: upper right, LL: lower left, LR: lower right), and the LM's center of mass (CoM).

- A bitmap in which those pixels corresponding to the interior of the LM are the only ones set. In the figure shown, we see the interior of a relatively large blob in this map.

No claim is made regarding the cognitive reality of the particular LM key points chosen. While there may be arguments to made for them, that issue lies outside the scope of this report. An understanding of the basic design ideas in the system can be reached without focusing on the actual key points used here. These particular points are adequate for the purposes of this report; others may be used in the future if needed. Note also that the general method of weakening evidence from implicit negatives is not in any way tied to a specific choice of key points.

The (punctate) TR is specified by the $x, y$ coordinates of the point.

The activation of an output node of the system, once trained for a particular spatial concept, represents the appropriateness of using the spatial term in describing the TR's location, relative to the LM.

### 7.2 Basic Idea

In learning simple spatial concepts such as "above", both the LM key points and the LM interior map are needed. This section should serve to give a feel for how the two representations are used together.

Consider the key points first. Part of the function of this system is the specification of half-planes in two-space, with the constraint that the line which defines each half-plane must pass through an LM key point.
Figure 8 illustrates how the concept "above" might be captured using such a combination of lines through points and knowledge about whether or not a particular point is part of the interior of the LM. Let the three lines which have arrows crossing them select the half planes pointed to by the arrows, and let the other lines be irrelevant. Further, let it be the case that any point which is part of the interior of the LM cannot be considered "above" it. This gives us the region above the LM. It is important to notice that both the LM key point representation and the LM interior map representation are used to arrive at this.

Note that in Figure 8, several of the lines are parallel to one another. As shown in Figure 9, the system imposes the constraint that the four angles labeled α all be equal. This is done to capture the fact that the regions picked out by spatial terms such as "above", "below", "to the right of", and so on, tend to be symmetrical and cone-like rather than lopsided. In addition, this constraint reduces the dimensionality of the search space.

The system learns spatial concepts such as "above" using the quickprop\(^4\) algorithm [Fahlman, 1988], a variant on back-propagation [Rumelhart and McClelland, 1986]. The learning algorithm is set up to incorporate the constraints that the lines pass through particular points, and that the slopes of the bounding box lines be related as shown in Figure 9.

### 7.3 Parameterized Regions

The representation used here makes it possible for us to learn a concept using one LM, and have this generalize to other LMs of different sizes and shapes, and in different positions. To give an idea of how this works, we focus on the notion of parameterized regions.

Consider Figure 10. The figure in (a) shows a region in 2-space learned using the intersection of three half-planes, as might be done using an ordinary perceptron. In (b), we see the same region, but learned relative to the key points of an LM. It should be clear that this region is the one that was used earlier in demonstrating how one might learn the concept "above". The critical part here is that now that this region is learned relative to the LM key points, it will change position and

\[4\text{Quickprop gets its name from its ability to quickly converge on a solution. In most cases, it exhibits faster convergence than that obtained using conjugate gradient methods [Fahlman, 1990].}\]
Figure 9: Equality Constraints on Line Slopes

Figure 10: Parameterized Regions
size when the LM key points change. This is illustrated in (c). Thus, the region is parameterized by the LM key points.

This is a useful idea in learning regions for terms such as “above”, “below”, “to the right of”, and so on. For once the term has been learned, it immediately generalizes to LMs in new positions, and of new sizes and shapes.

7.4 Details

A simple two-input perceptron unit defines a line in the \(x, y\) plane, and selects a half-plane on one side of it.\(^5\) Let \(w_x\) and \(w_y\) refer to the weights on the links from the \(x\) and \(y\) inputs to the perceptron unit. In general, if the unit’s function is a simple threshold, the equation for such a line will be

\[
xw_x + yw_y = 0,
\]

i.e. the net input to the perceptron unit will be

\[
net_{in} = xw_x + yw_y.
\]

Note that this line always passes through the origin \((0,0)\).

If we want to force the line to pass through a particular point \((x_t, y_t)\) in the plane, we simply shift the entire coordinate system so that the origin is now at \((x_t, y_t)\). This is trivially done by adjusting the input values such that the net input to the unit is now

\[
net_{in} = (x - x_t)w_x + (y - y_t)w_y.
\]

Given this, we can easily force lines to pass through the key points of an LM, as discussed above, by setting \((x_t, y_t)\) appropriately for each key point. Once the system has learned, the regions will be parameterized by the coordinates of the key points, so that the spatial concepts will be independent of the size and position of any particular LM.

We now consider the architecture of the network for a point TR at \(x, y\), as shown in Figure 11.

For the time being, we focus on the part of the network which is responsible for defining the parameterized regions. This is the left hand part of the net, fed by \(x\) and \(y\) inputs from the LM and TR\(^6\).

The input to this part of the network consists of the coordinates of the current point TR, and the coordinates of the key points of the current LM. These LM key points are referred to as UL [upper left corner of the bounding box], UR [upper right], LL [lower left], LR [lower right], and CoM [center of mass]. Note that the LM and TR coordinate input is first fed to a set of nodes at which the LM value \((x\) or \(y\)) is subtracted from the corresponding TR value. Thus, we have 5 pairs of 2 nodes at this “subtraction” layer; these nodes are marked with “-” signs. The first pair contains the values \((x_{TR} - x_{UL}, y_{TR} - y_{UL})\), while the others contain analogous values for the other LM key points. It is important to note that the weights on the links from the input to this first subtraction layer are equal to \(1.0\), and are frozen; they do not learn.

There is a cluster of four hidden nodes surrounded by a dashed line, and labeled “BB”. This stands for “bounding box”, as the cluster has one hidden unit allocated for each corner of the LM’s bounding box. Similarly, the hidden unit cluster labeled “CoM” has three units allocated to the center of mass of the object, so that three different lines pass through that key point.

\(^5\)The values \(x\) and \(y\) are between 0.0 and 1.0 in the case of this system.

\(^6\)This excludes the cluster of hidden units labeled “I”, and their inputs from the LM interior map.
The input to each of these units has been shifted as described above, so that the half-plane each of them defines will pass through the corresponding LM key point. These are the units whose input is of the form shown in equation 3.

Recall that the slopes of the lines passing through the LM's bounding box corners are related as shown in Figure 9. To see how this constraint is implemented, note that from equation 1, we get

\[ y = -\left(\frac{w_x}{w_y}\right)x, \]  

i.e. the slope of the line is

\[ \text{Slope} = -\frac{w_x}{w_y}. \]  

Let \( r = w_x^{UL} \) and \( s = w_y^{UL} \) be the weights from the UL \( x \) and \( y \) subtraction nodes\(^7\) to the hidden node for the line through the upper left corner of the LM bounding box. \( r \) and \( s \) are marked in Figure 11. Given these two values, we can implement the slope equality constraints by simply requiring that

\[ w_{x}^{LR} = r, \]  
\[ w_{j}^{i} = -r, j \in \{LL, UR\}, \]  
\[ w_{k}^{x} = s, k \in \{UR, LL, LR\}, \]  

\(^7\)That is, the two nodes in the subtraction layer holding the values \( x_{TR} - x_{UL} \) and \( y_{TR} - y_{UL} \), respectively.
where these are the corresponding weights feeding into the other bounding box hidden units in the BB cluster. By doing this, we collapse eight dimensions of the search space down into two.

Thus, this constraint is easily enforced using a weight-sharing modification to back propagation [LeCun, 1989], such that

$$\Delta u_k = \epsilon \times \left( \sum_{i,j \in V(k)} \frac{-\partial E}{\partial w_{ij}} \frac{\partial w_{ij}}{\partial u_k} \right)$$

where $\epsilon$ is the learning rate, $u_k$ is a particular weight (such as $r$ or $s$ above), $V(k)$ is the set of all links that are tied to that weight, and $E$ is the usual cost function. Note that $\frac{\partial w_{ij}}{\partial u_k}$ is always either 1.0 or -1.0 here (recall equations 6, 7, and 8).

Now consider the remainder of the network in Figure 11, that is, the part below the node cluster labeled "I" (for "interior map"). Input to the network is arranged such that when the TR $x, y$ inputs are set to indicate a specific point in the image, the LM interior input units (the five rightmost input units in Figure 11) receive their input from the corresponding pixel in the LM interior map, along with its four nearest neighbors. This is illustrated in Figure 12. When the TR $x, y$ inputs change to indicate some new point in the image, these interior map nodes receive input from the corresponding new set of pixels, centered on the location of the point TR.

Thus we have two distinct representations interacting in the network: specifications of location in terms of $x, y$ coordinates, and presence (or lack thereof) of the LM interior region at that location.

As mentioned above, the representation used here lends itself to excellent generalization across LMs, in part due to the use of parameterized regions. In addition to this, the LM interior map is part of the input. Thus, we can simply substitute in new key point coordinates and the corresponding new interior map to get the learned region relative to a new LM. The learning itself can take place relative to a small number of LMs, and the results will generalize to any other LM.

### 7.5 Implementing “Weakened” Mutual Exclusivity

Now that the basic architecture and representations have been explained, we present the means by which the evidence from implicit negative instances is weakened. It is assumed that training
sets have been constructed using mutual exclusivity as a guiding principle, such that each negative instance in the training set for a given spatial term results from a positive instance for some other term.

- Evidence from implicit negative instances is weakened simply by attenuating the error caused by these implicit negatives.
- Thus, an implicit negative instance which yields an error of a given magnitude will contribute less to the weight changes in the network than will a positive instance of the same error magnitude.

This is done as follows:

Referring back to Figure 11, note that output nodes have been allocated for each of the spatial terms to be learned. For a network such as this, the usual error term in back-propagation is

\[ E = \frac{1}{2} \sum_{j,p} (t_{j,p} - o_{j,p})^2 \]  

(10)

where \( j \) indexes over output nodes, and \( p \) indexes over input patterns.

We modify this by dividing the error at each output node by some number \( \beta_{j,p} \), dependent on both the node and the current input pattern.

\[ E = \frac{1}{2} \sum_{j,p} \left( \frac{t_{j,p} - o_{j,p}}{\beta_{j,p}} \right)^2 \]  

(11)

The general idea is that for positive instances of some spatial term, \( \beta_{j,p} \) will be 1.0, so that the error is not attenuated. For an implicit negative instance of a term, however, \( \beta_{j,p} \) will be some value \( Atten \), which corresponds to the amount by which the error signals from implicit negatives are to be attenuated.

Assume that we are currently viewing input pattern \( p \), a positive instance of “above”. Then the target value for the “above” node will be 1.0, while the target values for all others will be 0.0, as they are implicit negatives. Here, \( \beta_{above,p} = 1.0 \), and \( \beta_{i,p} = Atten, \forall i \neq above \).

The value \( Atten = 8.0 \) was used successfully in the experiments reported here.

If we want to avoid weakening implicit negative evidence which was contributed by antonyms, this can be done easily by adjusting the \( \beta \) values. We set \( \beta_{j,p} = 1.0 \) if the input pattern \( p \) is either labeled as a positive instance of the spatial term indexed by \( j \), or if \( p \) is an implicit negative instance of that term, but contributed by its antonym. \( \beta_{j,p} = Atten \) for all other implicit negatives, as before.

7.6 Training and Generalization

The system was trained to learn the eight spatial concepts mentioned above. Training in all cases was done relative to two LMs: the tall rectangle shown in Figure 3, and another one just like it, rotated 90 degrees so that its major axis was horizontal.

Results of this training have already been presented (in Figure 5). That figure, however, showed the regions learned relative to one of the LMs that had been used in training. Figure 13 presents an example of the ability of the system to generalize to new LMs.
The region shown, like those in Figure 5, is obtained by using the system to determine the appropriateness of using the term “above” at each point on a 20x20 grid. I.e. for each point, we test to see whether a punctate TR at that location would be a good instance of “above”, relative to the current LM. The points are done in turn, sequentially, and the results saved in the map which is eventually displayed.

Two points of interest are that:

- The system had not been trained on an LM in exactly this position.
- The system had never been trained on a triangle of any sort.

The region shown encompasses areas far from the LM, which could not have been done by the very local receptive fields used for the interior map. At the same time, the interior of the LM is completely unactivated, and as the system had never seen a triangle before, the parameterized regions could not be responsible for this. Thus, we have both parts of the LM representation playing a role in the learning.

8 Conclusions

Markman’s principle of mutual exclusivity, by which a positive instance for one term is considered to be an implicit negative instance for all other terms, is inadequate as it stands in the learning of image-based semantics for spatial terms. However, through the refinement of having implicit negatives supply only weak negative evidence, the problem of false implicit negative instances in the resulting training set can be successfully addressed. This enables us to avoid the use of teacher-supplied explicit negative instances.

The learning of a set of spatial terms can be improved by making use of knowledge of which terms in the set are antonyms.

These ideas have been demonstrated through their implementation in a system which learns perceptually grounded semantics for spatial terms. The system exhibits excellent generalization across landmarks, correctly determining the appropriateness of using a learned term to describe novel situations involving previously unseen landmark objects.
References


