Mining the Semantic Similarity of Spatial Relations from Text

Niloofar Aflaki*[1], Christopher B. Jones[2], and Kristin Stock[1]

[1]Massey Geoinformatics Collaboratory, Massey University, Albany, New Zealand

[2]School of Computer Science & Informatics, Cardiff University

*Email: n.aflaki@massey.ac.nz

Abstract

Spatial relations are one of the most important components in a location description, conveying information about proximity, direction, adjacency and topology among other things. However, despite being studied for many years, the semantics of spatial relations are still not well understood, particularly given that the use of spatial relations can vary with context. In this paper we investigate whether it is possible to mine the semantics of spatial relations from text, particularly focusing on semantic similarity, but also exploring the extraction of richer semantic information about the relationships between spatial relations, with the long term goal of moving towards the automation of the interpretation and generation of locative expressions. We test three similarity methods, including a bag of words technique, with both general and geospatial corpora, and using word embeddings. We compare the results to ground truth data from human subjects experiments.

Keywords: corpus linguistics, spatial relations, semantic similarity.

1 Introduction

Spatial language is an essential aspect of communicating information about geographical locations whether in speech or in textual documents. The main distinctive component of such language is the use of words that describe spatial relationships between the location or object to be described and one or more reference objects, as in “I am standing in front of the cinema”. A major challenge in geographical information retrieval is the automated interpretation of locative expressions such as this, which is essential for translation of natural language expressions into georeferenced locations, allowing information about the location of people, objects or events in text documents to be located for applications such as emergency response or navigation. A related challenge is the automated generation of spatial language to provide descriptions of locations and navigational instructions. Many of the words that are used to communicate individual spatial relations are prepositions, though other parts of speech, such as verbs, can also play an important role. A widely acknowledged characteristic of prepositions used in a spatial sense is that they are often vague and ”overloaded” in meaning, in that a single word, such as *at* might imply different interpretations of the corresponding

*

geometric configuration to which they refer (Landau and Jackendoff, 1993). Thus *at* can mean inside, or next to, or just outside of a reference object. As a consequence, some spatial relation terms can be used interchangeably, while others, such as beneath and above, have much more specific meanings. Successful automated interpretation and generation of geo-spatial language depends on understanding factors including the geometric configuration to which a spatial relation refers in a given context and the semantic relationships, such as synonyms and hypernyms, between spatial relational terms. In this paper, as a step towards the creation of a semantic network of spatial relations, we present the results of some experiments to determine the degree of similarity between natural language spatial relational terms.

We investigate the use of three different text-based approaches to determine the semantic similarity between spatial relation terms. Two of our approaches use a bag of words method, where a bag of words is a vector of frequencies of occurrence of the words in the document collection (explained further below). The first approach employs a generic corpus (the British National Corpus) and the second a corpus that contains geospatial language (the Nottingham Corpus of Geospatial Language (Stock et al., 2013)). The third approach uses GloVe (Global Vectors) embeddings from the Stanford Common Crawl[1] which is a vector space representation of terms obtained using an unsupervised learning algorithm (Pennington et al., 2014). An embedding of an individual word is a reduced dimensionality representation of the co-occurrence of other words with that word. In the two bag of words approaches, the bag of words is a vector containing a dimension for every word used in a document collection, and the values of the vector are a function of the frequency of use of the respective word in the context of the represented spatial relation, using tf-idf, which attaches more weight to words that are specific to the spatial relation and less common throughout the document collection. Similarity between a pair of spatial relations is then measured by the cosine similarity between their vectors. In the case of the GloVe embeddings, we calculate the cosine similarity between GloVe embedding vectors for the spatial relations concerned.

We evaluate the similarity values by comparing each matrix of derived similarity values with a matrix of similarities that was created using the results of human subject experiments to measure the extent to which each of the spatial relation terms corresponds to each of a number of geometric configurations representing a variety of possible spatial relations. In addition to reporting the results of this evaluation we highlight a number of observations of the degree to which particular spatial relations were found, using these methods, to be similar to many other spatial relations, and hence of a generic nature, or different from most other spatial relations, and hence more specific in their meaning and usage.

In the remainder if the paper we review related work in section 2, before describing in section 3 the methods applied. In section 4 we present the results and their evaluation. The paper concludes in Section 5 with a summary of the conclusions and a discussion of future work .

2 Related Work

Spatial language is often regarded as serving the purpose of locating objects and places in space (Landau and Jackendoff, 1993; Coventry and Garrod, 2004). Descriptions of locations (locative expressions), typically use a spatial relation term or phrase to link a located object (or locatum) to a reference object (or relatum) (Talmy, 1983). The spatial relation, which often takes the form of a

[1]https://nlp.stanford.edu/projects/glove/

preposition (but can be other parts of speech, particularly verbs), can specify various aspects of the relation between the locatum and relatum, including geometry, orientation, space schematization, idealization, abstraction and topology (Talmy, 1983; Zwarts, 1997, 2005). Various categories of spatial relation have been identified. *Topological* relations can refer to aspects of connectivity between objects, such as containment, touching and overlap (Egenhofer and Franzosa, 1991), but the term topological is also used in a linguistics context to refer to relations that distinguish aspects of proximity such as *in*, *next to*, *at*, and *between* (Levinson, 2003). The spatial relation *on* can also be regarded as topological, but in three dimensions and with an interpretation of support (Herskovits, 1987). Another major category of spatial relations is *directional* relations, also at least partially referred to as *projective* relations when they depend upon the perspective of a viewer. These latter include *left*, *right*, *front*, *back*, *above* and *below* (Herskovits, 1987; Coventry and Garrod, 2004). *Metric* spatial relations can refer to topological or directional spatial relations that can be quantified.

Partly related to our longer term objective of understanding semantic relations between spatial relations is the concept of conceptual neighborhoods, which provides a graphical model of gradual transitions between relations. Links in the graph relate to high levels of similarity between similar but not equivalent relations. A general grouping of a large set of natural language spatial relation terms was provided by Bitters (2009), the groups being: basic, over/under, adjacency, proximity, containment, orientation, intersection, network and cluster, which appear to have been manually asserted by the author. Shariff et al. (1998) conducted human subjects experiments on the use of natural language terms for topological relations between a region and line objects that the subjects were asked to draw to represented given natural language spatial relations between a road and a park (i.e. a specific context). The relations varied aspects of the geometric ("metric") relations between the line object and the region and clustering found that the main groups represented predominantly topological as opposed to metric properties of the relations. Previous methods for determining semantic similarity between spatial relations include Schwering (2007), who measured "semantic" distances between the topological and metric configurations introduced in Shariff et al. (1998), based respectively on distances in a conceptual neighborhood graph and on spatial distances. Clustering of these distances revealed 4 groups of *inside*, *outside or disjoint*, *crosses* and *enters*. They conducted human subject experiments of perceived similarity between the configurations, finding a close match with these four groups. In contrast our work focuses on the use of contextual language of spatial relations to measure similarity. We also use human subject experiments for evaluation, in which people judged the applicability of natural language spatial relation terms to diagrams that represent various configurations of geometric objects.

The idea of exploiting semantic networks in the context of natural language processing is well established. Their potential for disambiguation was recognised in Au (2010) who proposed a semantic network of words, giving examples of the use of informs and is-a links. Fellbaum (1998) proposed some semantic and lexical relations, or factors, that are influential in creating a semantic network of verbs. Some of these factors are entailment, hyponymy and opposition. WordNet (Miller et al., 1990) also provides a rich semantic network for some parts of speech such as nouns, but its support for semantic relations between terms, such as prepositions, that serve as spatial relations is very limited.

In recent years there has been interest in using vector space representations, to infer semantic relations between words. Word embeddings provide such a vector space representation, which can be regarded as form of conceptual space as proposed by Gardenfors (2004) in which similarity between concepts is a function of distance in the conceptual space. In word embeddings the dimensions correspond to meanings associated with the words that have been mapped to the respective dimension by a dimensionality reduction procedure. It was demonstrated in Mikolov et al. (2013) that cosine distances between word embeddings represent vector offsets that correspond to semantic relations (especially analogy) between the represented words. Subsequent studies (Fu et al., 2014; Attia et al., 2016) have also exploited word embeddings to determine semantic relations (e.g. synonyms, hypernyms) between words. In our work we present preliminary investigations of the use of word embeddings to measure similarity between spatial relation terms as well as investigating similarity between the textual contexts of spatial relations represented in bag of word vectors.

3 Method

In order to test the ability of text mining approaches to determine the semantic similarity of spatial relations, we compared three methods. Using these methods, we tested 25 spatial relations, 22 of which were single word prepositions, and the other 3 of which were prepositional phrases (*next to, adjacent to, close to*). The set of prepositions was selected from content obtained from the Geograph [2] and Foursquare web sites[3]. We manually identified the spatial relations present in a sample of 1010 expressions from these two sources from central London (780 expressions from Geograph and 230 expressions from Foursquare), excluding spatial relations that rely on verbs for their spatial interpretation. For example, prepositions like *to* and *from* usually require a verb for complete interpretation (e.g. "the road comes from the city centre"), and were thus excluded.

3.1 Method 1: Bag of Words with BNC

In the first method, we extract eight word windows (four words on either side of the spatial relation words or phrases), and build a bag of words model that contains the tf-idf value for the most frequently appearing 1000 words across all of the spatial relations. We then calculate the tf-idf sum for each word-spatial relation pair (summing across all expressions that include the spatial relation concerned), and thus producing a vector for each spatial relation, with each value in the vector being the sum of tf-idf values for one of the words in the bag. We then calculate the cosine similarity between pairs of vectors, to establish a measure of the semantic similarity between the corresponding spatial relations. We used the British National Corpus (BNC) [4] to create the model, searching only for the spatial relation word or phrase, and did not distinguish between spatial and non-spatial senses. This means that some of the expressions included for a given spatial relation are likely to contain non spatial senses (e.g. "not all children *in* the family are gifted" or "In the period *between* the first European landings and the First World War..."). Metaphoric, figurative and temporal uses of spatial relation words and phrases in text are common, and these are included in the bag of words alongside everything else.

3.2 Method 2: Bag of Words with NCGL

Method 2 is very similar to Method 1, except that is uses a geospatial corpus, rather than a general corpus, and thus we aim to reduce some of the non-spatial senses of the spatial relation words and

[2]https://www.geograph.org.uk/
[3]https://www. foursquare.com
[4]http://www.natcorp.ox.ac.uk/

phrases. The Nottingham Geospatial Corpus of Geospatial Language (Stock et al., 2013) contains 10,146 expressions (sentences or paragraphs), each of which contains geospatial content, including at least a location reference and a spatial relation (i.e. only a place name is not sufficient for addition to the Nottingham Corpus). The content of the Nottingham Corpus was harvested from a 46 different web sites, from a range of domains (e.g. local history, tourism, news).

We performed the same steps using the bag of words approach as for Method 1, producing a second set of similarity measures between the 25 spatial relation words and phrases. Since the Nottingham Corpus only includes geospatial expressions, the incidence of non-spatial uses of the spatial relation words and phrases is likely to be much lower than for the BNC. However, given that the Nottingham Corpus contains some complex expressions, occasional non-spatial senses are still likely to occur. For example, the following expression includes a temporal sense of *at*: "This is known as Stony balk and was *at* one time a paved way across the field". However, these non-spatial senses are in the minority.

3.3 Method 3: GloVe Embeddings

The third method uses the published GloVe embeddings from the Stanford Common Crawl[5] (Pennington et al., 2014). We extracted vectors for each of the 25 spatial relations from the 840B token, 2.2M vocabulary, cased, 300 dimension vector data set. For the three spatial relations that consist of two words (*close to, next to* and *adjacent to*), we used only the first word, as the data set did not include embedding vectors for bigrams. We tested the use of hyphenated bigrams, which do appear in the GloVe dataset, but these provided negative cosine similarities, in contrast to every other word in the matrix, and thus were not thought to be representative of the bigram spatial relation phrases concerned, so were excluded. We calculated the cosine similarity between pairs of embedding vectors to create a third similarity matrix.

3.4 Human Subjects Data

Data from a human subjects experiment (described in more detail in Stock and Yousaf (2018)) was used to calculate similarity between pairs of the 25 spatial relations for comparison with the similarity determined using the three methods described above. Human subjects were presented with a series of natural language expressions, each of which contained one of the 25 spatial relations, in the context of a particular pair of geographic features (locatum and relatum). The expressions were randomly selected from instances of the selected 25 spatial relations in the Nottingham Corpus of Geospatial Language, and then in some cases simplified to exclude non-spatial adjectives and create expressions conforming to a standard construction as described in Stock et al. (2013).

Alongside the expression, respondents were also presented with a matrix of diagrams, each showing a particular geometric configuration between two objects, indicating one of 50 different spatial relations (appendix A). To avoid overloading the respondents with many diagrams, the diagrams were divided into subsets so that each respondent was presented with only 16 diagrams for each expression. The 16 diagrams were randomly selected from the full set, ensuring that diagrams from the same class of spatial relation (e.g. topological, projective, etc.) were included. Figure 1 contains an example stimulus. Respondents were asked to select between 1 and 3 diagrams that best reflected the expression, and to rate the degree to which those 1 to 3 diagrams fitted the expression using a

[5]https://nlp.stanford.edu/projects/glove/

half-Likert scale (*agree somewhat, agree* and *agree strongly*). This approach was designed to force respondents to select the diagram/s that best matched the expression, and then indicate the degree of match.

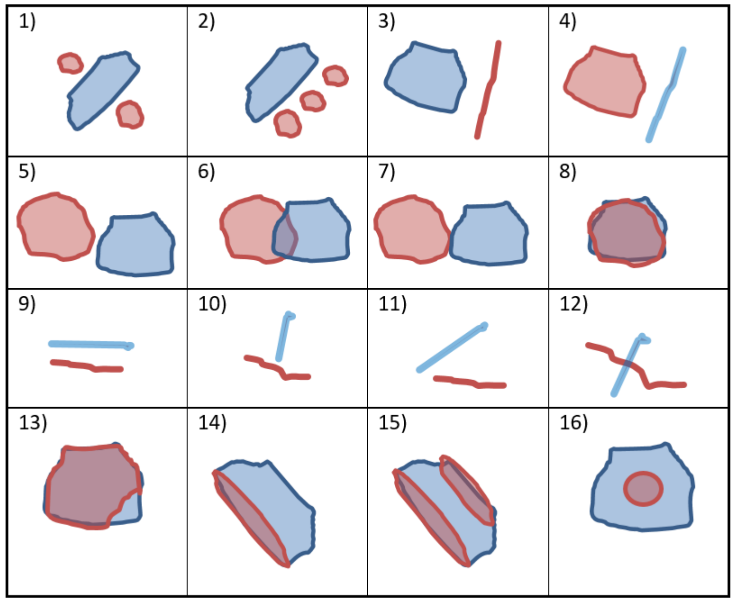


Figure 1: Example Stimulus for Human Subjects Experiment

In total, 1882 expressions were scored, with each respondent scoring 20 randomly selected expressions, each expression being scored by between 21 and 36 respondents recruited from Survey Monkey Audience. Following the experiment, a score was calculated for each of the 50 spatial relations, using Equation 1, where response k represents each individual response, which is multiplied by the weight, depending on the selection of the respondent for the given expression-spatial relation combination, and n is the total number of responses for the expression.

$$GCOscore_{expression,spatialrelation} = (\sum_{k=}^{n} response_k.weight_k)/n \qquad \text{Equation 1}$$

Weights were applied to each response (0.5, 0.75 and 1 for agree somewhat, agree and agree strongly respectively). The score for each expression-spatial relation combination was then calculated as the mean of all individual responses across all diagrams that depicted the relation.

We then created a single vector for each spatial relation term by calculating the mean of the values across all expressions that used the term. Table 1 shows the number of expressions that were used to calculate the mean, for each spatial relation, and as can be seen, there are wide variations in the number of expressions that were used to calculate the mean vectors, and some spatial relations have very few (or only one) expressions. Therefore those spatial relations that are included in many are likely to represent a broader range of contexts than those that are included in only one expression. This issue and its implications are discussed further in Section 4.1.

Spatial Relation	Nottingham Corpus	BNC	Human Subjects
beyond	46	782	1
opposite	68	408	1
close to	54	360	1
between	368	11178	2
toward	24	272	2
behind	56	828	3
off	245	1418	4
past	131	1729	8
outside	95	955	10
inside	49	522	11
near	518	526	13
adjacent	18	101	15
alongside	32	208	16
around	262	2266	19
over	413	6027	19
beside	23	40	20
next to	99	83	56
by	1325	39248	67
through	567	6876	84
along	411	1127	95
at	2259	21223	196
on	2507	36313	302
in	5185	8999	327

Table 1: Frequency of Spatial Relation Terms in Corpora

4 Results

4.1 How well do the three methods match the human subjects experiments, and which method matches most closely?

Our first analysis considers how well the text mining methods presented match the human subjects experiments. Table 2 presents the Pearson Product Moment Correlation Coefficient for each of the three methods when compared with the human subjects experiments (and between methods 2 and 3), calculated using the lower triangular half of the diagonally symmetrical matrix. As shown in Table 1, the numbers of expressions included in the mean calculations for each spatial relation vary widely, and we tested the inclusion of different subsets of spatial relations by expression frequency, to determine whether the lower number of expressions produced poorer correlations, given that spatial relations with few expressions would be expected to represent a smaller number of different contexts and therefore be less representative. Unexpectedly, the reverse was true, with the spatial relations with most expressions showing lower correlation between the text mined methods and the human subjects experiments, with moderate correlation (as defined in (Hinkle et al., 2003)) for spatial relations with fewer than 50 expressions in the human subjects comparison set, and high correlation with fewer than 15 expressions (around half of the spatial relations). This decreased correlation may be due to noise resulting from the multiple uses and meanings of expressions in many different contexts and situations, and therefore may have been matched to different spatial relations by respondents. We can see in the Nottingham corpus the results for all spatial relations are higher, due to the fact that most of the spatial relation terms appeared in spatial or geospatial senses. Notably prepositions that have the largest numbers of expressions are the most general, with a broad range of applications in different contexts (especially *in, at* and *on*), while most of those with fewer expressions, and higher correlations, are more specific spatial relations (e.g. *opposite, between and beyond*, although *close to* might be considered a counter example, that may be considered to have a general meaning, but fewer expressions in the human subjects data set).

Comparison	All Spatial Relations	Relations with <100 expressions	Relations with <50 expressions	Relations with <20 expressions	Relations with <15 expressions	Relations with <10 expressions	Relations with <5 expressions
n of spatial relations	25	22	18	16	12	9	8
BNC/Human Subjects	0.285	0.248	0.331	0.491	0.569	0.666	0.727
Nottingham/ Human Subjects	**0.468**	**0.482**	**0.517**	**0.596**	**0.716**	**0.746**	0.761
GloVe/Human Subjects	0.45	0.434	0.515	0.556	0.648	0.707	**0.77**
Nottingham/GloVe	0.701	0.763	0.818	0.835	0.825	0.889	0.902

Table 2: Pearson Product Moment Correlation Coefficients

Of the three methods, the bag of words (BoW) method using the Nottingham Corpus (Method 2) provided the best results, with GloVe (Method 3) slightly poorer and the BoW using the BNC (Method 1) noticeably worse. The only distinction between Methods 1 and 2 is the corpus from which the context words (the four words on either side of the spatial relation) were selected, and an additional potentially confounding factor in Method 1 is that multiple senses of the spatial relation words are likely to be included in the data, while for Method 2, non-geospatial senses are likely to be relatively infrequent. Since Method 3 also uses generic text but nevertheless provides a clear improvement over the BoW approach, we might expect that the use of embeddings trained on a geospatial rather than a generic corpus would result in additional improvements. This is an area for future work. Given that Method 2 produced the best results, our subsequent analysis focuses on the data produced using that Method.

4.2 Do some spatial relations correlate better with human subjects experiments than others?

In Figure 2, a matrix of cosine similarity between specific pairs of spatial relations using Method 2, four spatial relations show high similarity to each other: *at, in, on* and *by.* In addition to these specific, strong pairwise similarities, the sum of the cosine similarities between these four spatial relations and all others are also higher than the sums for other spatial relations (see Figure 3, which presents all spatial relations in order of their total similarity, being the sum of cosine similarities with all other relations). At the other end of the spectrum, *alongside, beside* and *toward* have particularly low sum of similarity. Thus there is a trend for the more general spatial relations, that can be used in different contexts and could often be substituted with more specific spatial relations, to have higher total correlation with other spatial relations. These spatial relations at the top of the list are relations of proximity, collocation and containment, while some more specific relations appear further down the list. Surprisingly, there are some spatial relations (*close to, beside, next to*), that might reasonably be expected to appear higher up the list, and be more similar to other spatial relations (e.g. *near* to *close to*).

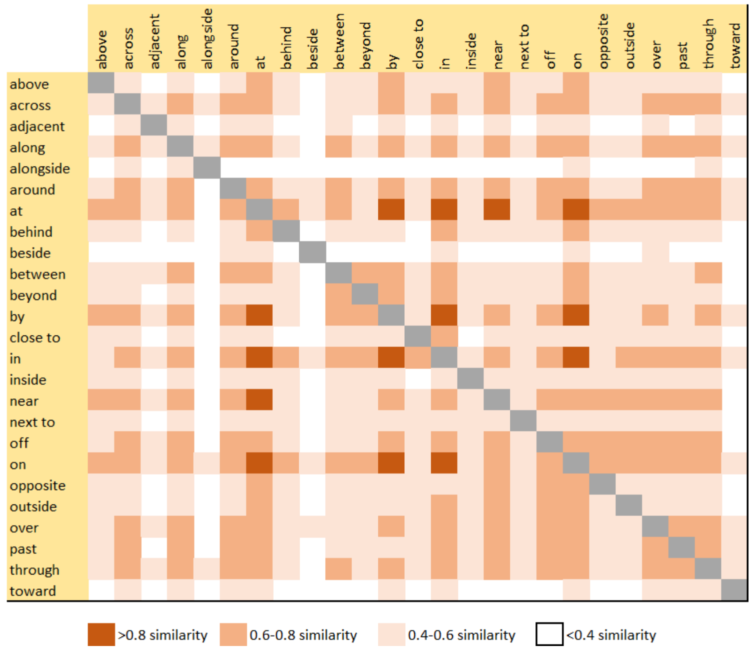


Figure 2: Matrix of Spatial Relation Cosine Similarity for Method 2

4.3 Do we see clusters among the spatial relations?

To answer this question, we used unsupervised clustering techniques to see whether meaningful groups of spatial relations could be extracted from the text. The following dendrogram (Figure 4) shows the clusters among spatial relations using Agglomerative Hierarchical Clustering. To calculate the distance among clusters, the complete linkage agglomeration method was selected which clustered the spatial relations in a similar manner to human subject spatial relations' similarity. Other methods such as Average and Ward were tested, but they produced sparse clusters that appeared less effective than those from the complete linkage method. The reason might be that the complete linkage method can perform well on dissimilar and distinct clusters and is sensitive to outliers (Manning et al., 2010). The dendrogram groups together the more general relations (*in, at, on*), discussed in Section 4.1. *Alongside* and *beside* also appear together, but some other relations that might be considered similar (e.g. *adjacent*, *next to*) do not. However, *next to* is grouped with *outside*, and in some contexts, this similarity is likely to be valid (e.g. "I am outside the post office" and "I am next to the post office"). Another collection of adjacency/proximity relations (*around, near, by*) appear

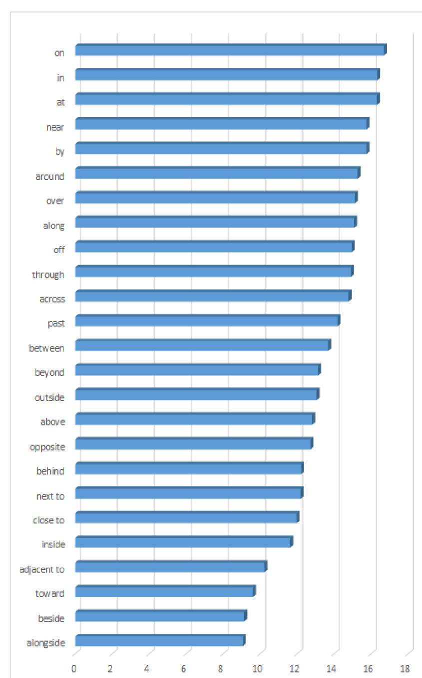


Figure 3: Total Cosine Similarity for Each Spatial Relation with all Others

together in another group. Spatial relations that are commonly used in route directions (e.g. *through, across, along, past*) also appear together.

The dendrogram identifies some particular sub-groupings of spatial relations, but also highlights the often ambiguous and context-sensitive nature of spatial relations, and it may be necessary for a more sophisticated semantic similarity measure to consider different senses of some commonly overloaded spatial relations.

4.4 Do we see patterns among the highly scoring words in the bag?

We extracted the highest ranked (by tf-idf) words in the bag of word matrix for each spatial relation and performed part of speech analysis on the top 30 words, classifying the words into 9 of the most frequently occurring parts of speech, accounting for 99% of the words (only 8 words did not fall into these 9 categories, across all spatial relations). Figure 5 shows the proportions of each part of speech for each spatial relation in their alphabetic order.

Nouns and prepositions were the most frequently occurring classes, covering 60% of the top 30 words across all spatial relations. There is a distinct negative correlation (-0.67 Pearson product moment coefficient) between the the frequency of nouns and prepositions across the 25 spatial relations. Table 3 ranks the spatial relations in order of the frequency of nouns and prepositions, with a group of proximity and adjacency related prepositions (*adjacent, beside, next to, near*) having the highest proportion of noun frequency, and the lowest proportion of preposition frequency. In contrast, the more general prepositions referred to in Section 4.1 have lower noun frequencies and higher preposition frequencies, with *in, on* and *at* all appearing near the top of the preposition frequency list. It is clear from these results that there are differences in the patterns of language used by different prepositions, and this analysis suggests some particular variations by level of specificity of spatial relations, and by particular classes of spatial relation meaning (e.g. topology, proximity, collocation).

5 Conclusions and Future Work

This preliminary research suggests that text mining methods show some promise for the identification of semantic similarity and richer relationships among spatial relations, and are able to identify differences in the way that spatial relations are used. Specifically, we identify variations between the spatial relations that we consider to be more general (e.g. *at, in, on*) in the sense of being spatial relations that could be substituted with other more precise spatial relations, and those that have a much narrower meaning. The former, more general spatial relations exhibit a higher correlation with other spatial relations than the more specific spatial relations. We demonstrate that clustering methods can be used on text data to identify groups of words that have associated meanings, and we show that spatial relations vary in the parts of speech that they commonly co-occur with, with proximity spatial relations much more commonly co-occurring with nouns than spatial relations like (e.g. *at, in* and *on*), which more commonly co-occur with prepositions, potentially due to a need to clarify the spatial relation in a given context.

Our analysis compares bag of words and word embeddings models on different corpora to see which most closely reflect human cognition. Among the methods tested, the BoW approach with the Nottingham corpus was most highly correlated with the human subjects assessment, but GloVe

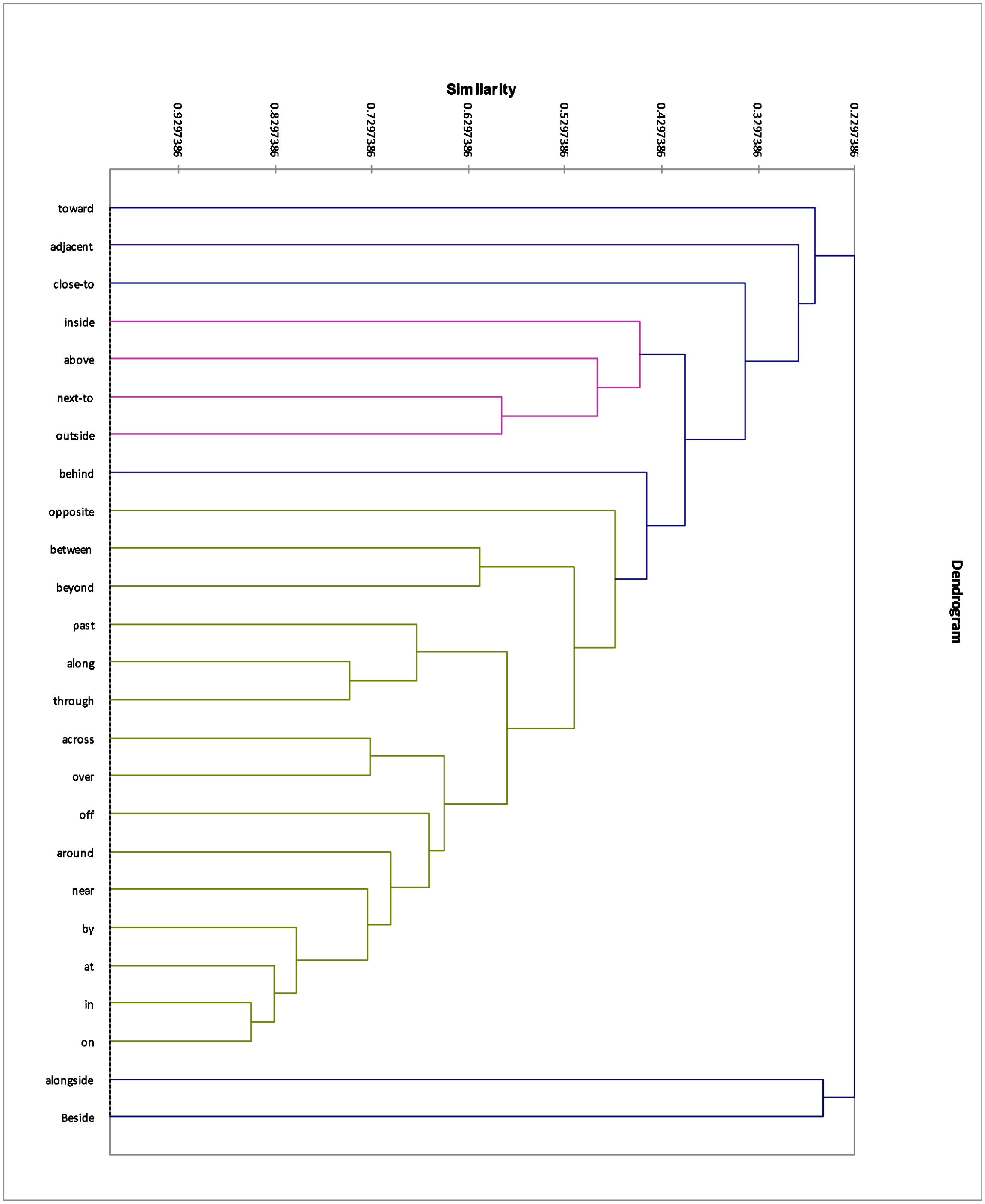


Figure 4: Nottingham Corpus (Method 2) Dendrogram

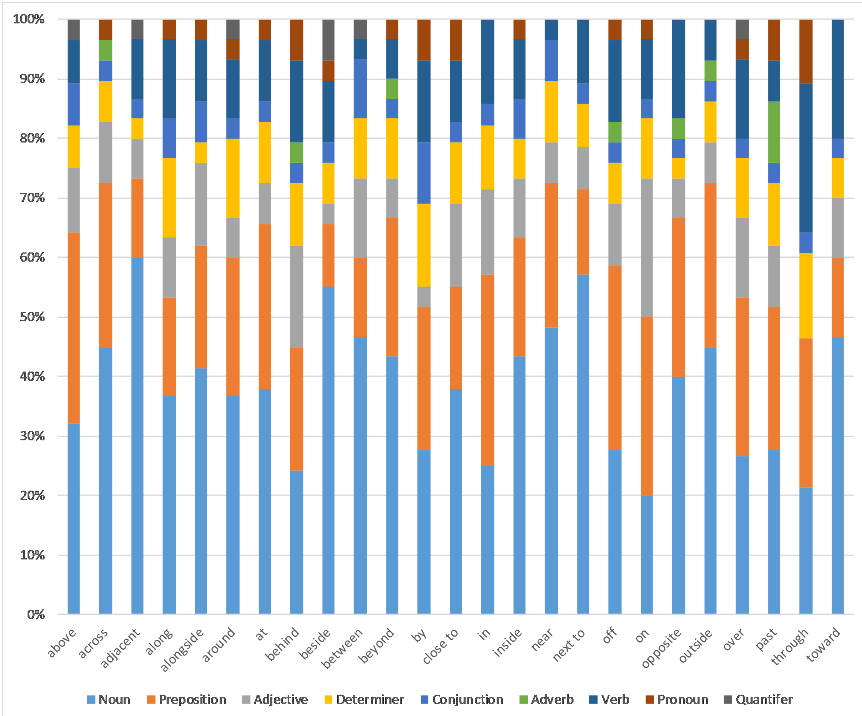


Figure 5: Frequency of Occurrence of Parts of Speech among Top 30 Words in the Bag

Spatial Relation Rank by Noun Frequency	Spatial Relation Rank by Preposition Frequency
adjacent	above
beside	in
next to	off
between	on
near	across
toward	at
across	opposite
beyond	outside
inside	over
outside	around
alongside	beyond
opposite	by
along	near
around	past
at	through
close to	alongside
above	behind
by	inside
off	along
over	close to
past	adjacent
behind	between
in	next to
on	toward
through	beside

Table 3: Rank of Spatial Relations by Frequency of Parts of Speech in Top 30 Words in the Bag

embedding using vectors extracted from generic data were only slightly worse, and both were much more highly correlated than the BoW method with the BNC. Given that the use of a purely geospatial corpus showed significant improvement for the BoW method over a generic corpus, in future work, we propose to create embeddings from geospatial text, in the hope that this will result in further improvement in the results. This work is a first step towards a broader goal of creating a semantic network of spatial relations showing not just the degree of similarity, but also the nature of the relationship between spatial relations (e.g. hypernymy, hyponymy, synonymity). It also provides a glimpse of the ambiguous and context-sensitive nature of spatial relations, an aspect that must be accommodated in any semantic network.

6 Acknowledgements

This work was partially funded under a PhD scholarship from Ordnance Survey, UK, and their support is gratefully acknowledged.

7 References

Attia, M., S. Maharjan, Y. Samih, L. Kallmeyer, and T. Solorio
2016. CogALex-V Shared Task: GHHH - Detecting Semantic Relations via Word Embeddings. Pp. 86–91.

Au, L.
2010. Semantic network methods to disambiguate natural language meaning. US Patent 7,711,672.

Bitters, B.
2009. Spatial Relationship Networks: Network Theory Applied to GIS Data. *Cartography and Geographic Information Science*, 36(1):81–93.

Coventry, K. and S. Garrod
2004. *Saying, seeing and acting : the psychlogical semantics of spatial prepositions.* Hove, Sussex: Psychology Press.

Egenhofer, M. and R. D. Franzosa
1991. Point-set topological spatial relations. *International Journal of Geographical Information Systems*, 5(2):161–174.

Fellbaum, C.
1998. A semantic network of english verbs. *WordNet: An electronic lexical database*, 3:153–178.

Fu, R., J. Guo, B. Qin, W. Che, H. Wang, and T. Liu
2014. Learning Semantic Hierarchies via Word Embeddings. Pp. 1199–1209.

Gardenfors, P.
2004. Conceptual spaces as a framework for knowledge representation. *Mind and Matter*, 2:9–27.

Herskovits, A.
1987. *Language and Spatial Cognition.* New York, NY, USA: Cambridge University Press.

Hinkle, D. E., W. Wiersma, S. G. Jurs, and others
2003. *Applied statistics for the behavioral sciences.* Boston, MA: Houghton Mifflin.

Landau, B. and R. Jackendoff
1993. Whence and whither in spatial language and spatial cognition? *Behavioral and Brain Sciences*, 16(2):255–265.

Levinson, S. C.
2003. Space in Language and Cognition by Stephen C. Levinson.

Manning, C., P. Raghavan, and H. Schütze
2010. Introduction to information retrieval. *Natural Language Engineering*, 16(1):100–103.

Mikolov, T., W.-t. Yih, and G. Zweig
2013. Linguistic Regularities in Continuous Space Word Representations. In *HLT-NAACL*.

Miller, G. A., R. Beckwith, C. Fellbaum, D. Gross, and K. J. Miller
1990. Introduction to wordnet: An on-line lexical database. *International journal of lexicography*, 3(4):235–244.

Pennington, J., R. Socher, and C. Manning
2014. Glove: Global Vectors for Word Representation. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, Pp. 1532–1543, Doha, Qatar. Association for Computational Linguistics.

Schwering, A.
2007. Evaluation of a Semantic Similarity Measure for Natural Language Spatial Relations. In *Spatial Information Theory*, S. Winter, M. Duckham, L. Kulik, and B. Kuipers, eds., Lecture Notes in Computer Science, Pp. 116–132. Springer Berlin Heidelberg.

Shariff, A., M. Egenhofer, and Mark, D.
1998. Natural-Language Spatial Relations Between Linear and Areal Objects: The Topology and Metric of English-Language Terms. *International Journal of Geographical Information Science*, 12:215–246.

Stock, K.
2014. A geometric configuration ontology to support spatial querying. Castellon, Spain. AGILE Digital Editions.

Stock, K., R. C. Pasley, Z. Gardner, P. Brindley, J. Morley, and C. Cialone
2013. Creating a Corpus of Geospatial Natural Language. Pp. 279–298. Springer-Verlag New York, Inc.

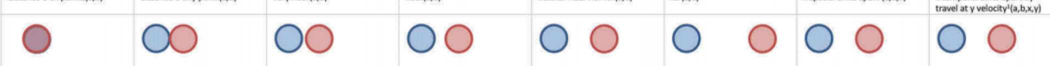
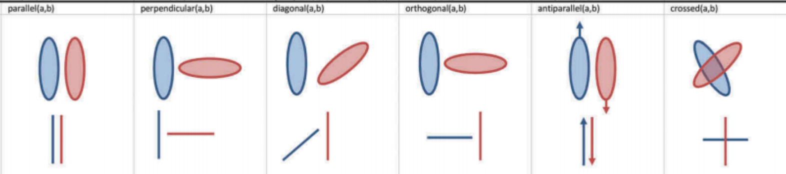
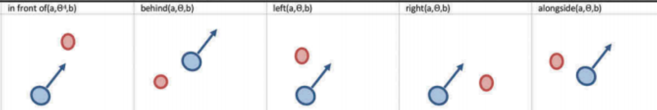
Stock, K. and J. Yousaf
2018. Context-aware automated interpretation of elaborate natural language descriptions of location through learning from empirical data. *International Journal of Geographical Information Science*, 32(6):1087–1116.

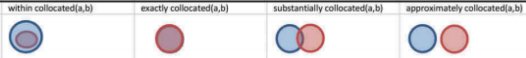
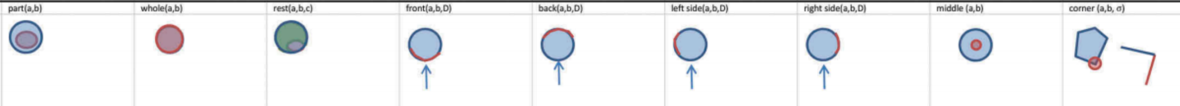
Talmy, L.
1983. How Language Structures Space. In *Spatial Orientation: Theory, Research, and Application*, H. L. Pick and L. P. Acredolo, eds., Pp. 225–282. Boston, MA: Springer US.

Zwarts, J.
1997. Vectors as Relative Positions: A Compositional Semantics of Modified PPs1. *Journal of Semantics*, 14(1):57–86.

Zwarts, J.
2005. Prepositional Aspect and the Algebra of Paths. *Linguistics and Philosophy*, 28(6):739–779.

Appendix A. Geometric Configurations Stock (2014)

Parameter		Values								
TOPOLOGY (t): Are the objects connected and how?	**Label**	overlap(a,b)	touch(a,b)	contain(a,b)	disjoint(a,b)	equal(a,b)				
	Illustration									
	Query	ST_Overlaps(a,b) = 1	ST_Touches(a,b) =1	ST_Contains(a,b) = 1	ST_Disjoint(a,b) = 1	ST_Equals(a,b) = 1				
	Axioms									
DISTANCE (ds): How close are the objects to each other?	**Label**	distance 0 all points(a,b)	distance 0 any point(a,b)	very near(a,b)	near(a,b)	neither near nor far(a,b)	far(a,b)	x spatial units apart (a,b,x)	x temporal units apart by travel at y velocity[1](a,b,x,y)	
	Illustration									
	Query (WHERE clause)	ST_Equals(a,b) = 1	ST_Touches(a,b) =1	ST_DWithin(a,b,σ)	ST_DWithin(a,b,2σ)	(ST_Distance(a,b) > 2σ) AND (ST_Distance(a,b) < 4σ)	NOT ST_DWithin(a,b,4σ)	ST_Distance(a,b) = x ST_Distance(ST_Centroid(a), ST_Centroid(b)) = x	ST_Distance(a,b) = xy ST_Distance(ST_Centroid(a), ST_Centroid(b)) = xy	
	Axioms	ds.zeroAllPoints(a,b) ≡ t.equal(a,b)	ds.zeroAnyPoint(a,b) ≡ t.touch(a,b)	ds.veryNear(a,b) ≡ (t.disjoint(a,b) V t.touch(a,b))	ds.near ≡ (t.disjoint(a,b) V t.touch(a,b))	ds.neitherNearNorFar(a,b) ≡ t.disjoint(a,b)	ds.far(a,b) ≡ t.disjoint(a,b)	ds.spatialUnitsApart(a,b) ≡ t.disjoint(a,b)	ds.temporalUnitsApart(a,b) ≡ t.disjoint(a,b)	
LINEAR ORIENTATION(lo): How are linear objects oriented relative to each other?	**Label**	parallel(a,b)	perpendicular(a,b)	diagonal(a,b)	orthogonal(a,b)	antiparallel(a,b)	crossed(a,b)			
	Illustration									
	Query (WHERE clause)	MaxAzimuth[2](ST_Boundary(SSRectangle[3](ST_ConvexHull(a)))) – MaxAzimuth[2] (ST_Boundary(SSRectangle[3] (ST_ConvexHull(b)))) = 0 ST_Azimuth(ST_StartPoint(a), ST_EndPoint(a)) - ST_Azimuth(ST_StartPoint(b), ST_EndPoint(b)) = 0	MaxAzimuth[2] (ST_Boundary(SSRectangle[3] (ST_ConvexHull(a)))) – MaxAzimuth[2] (ST_Boundary(SSRectangle[3] (ST_ConvexHull(b)))) IN (π/2, 3π/2) ST_Azimuth(ST_StartPoint(a), ST_EndPoint(a)) - (ST_Azimuth(ST_StartPoint(b), ST_EndPoint(b)) = IN (π/2, 3π/2)	MaxAzimuth[2] (ST_Boundary(SSRectangle[3] (ST_ConvexHull(a)))) – MaxAzimuth[2] (ST_Boundary(SSRectangle[3] (ST_ConvexHull(b)))) IN (π/4, 3π/4, 5π/4, 7π/4) ST_Azimuth(ST_StartPoint(a), ST_EndPoint(a)) - (ST_Azimuth(ST_StartPoint(b), ST_EndPoint(b)) = IN (π/4, 3π/4, 5π/4, 7π/4)	MaxAzimuth[2] (ST_Boundary(SSRectangle[3] (ST_ConvexHull(a)))) – MaxAzimuth[2] (ST_Boundary(SSRectangle[3] (ST_ConvexHull(b)))) IN (0, π/2, π , 3π/2) ST_Azimuth(ST_StartPoint(a), ST_EndPoint(a)) - (ST_Azimuth(ST_StartPoint(b), ST_EndPoint(b)) = IN (0, π/2, π , 3π/2)	MaxAzimuth[2] (ST_Boundary(SSRectangle[3] (ST_ConvexHull(a)))) – MaxAzimuth[2] (ST_Boundary(SSRectangle[3] (ST_ConvexHull(b)))) = π ST_Azimuth(ST_StartPoint(a), ST_EndPoint(a)) - (ST_Azimuth(ST_StartPoint(b), ST_EndPoint(b)) = π	MaxAzimuth[2] (ST_Boundary(SSRectangle[3] (ST_ConvexHull(a)))) – MaxAzimuth[2] (ST_Boundary(SSRectangle[3] (ST_ConvexHull(b)))) IN (π/2, 3π/2) AND ST_Overlaps(a,b) ST_Azimuth(ST_StartPoint(a), ST_EndPoint(a)) - (ST_Azimuth(ST_StartPoint(b), ST_EndPoint(b)) = IN (π/2, 3π/2) AND ST_Overlaps(a,b)			
	Axioms	lo.parallel(a,b)⇒lo.orthogonal (a,b)	lo.perpendicularl(a,b)⇒ lo.orthogonal(a,b)			lo.antiparallel(a,b)⇒ lo.orthogonal(a,b)	lo.crosses(a,b)⇒t.overlap(a,b)			
HORIZONTAL PROJECTIVE ORIENTATION(hpo): How are objects oriented to each other relative to a projected axis?	**Label**	in front of(a,θ[4],b)	behind(a,θ,b)	left(a,θ,b)	right(a,θ,b)	alongside(a,θ,b)				
	Illustration									
	Query	ST_Angle(ST_Azimuth(a,b), θ) < π/2	ST_Angle(ST_Azimuth(a,b), θ) > π/2	(ST_Azimuth(a,b) < θ) AND (ST_Azimuth(a,b) > θ±2 π)	(ST_Azimuth(a,b) > θ) AND (ST_Azimuth(a,b) < θ±2 π)	ST_Angle(ST_Azimuth(a,b), θ) IN (π, 3π/2)				
	Axioms									

Parameter		Values								
DIRECTION (dr): What is the cardinal direction from one object to the other?	**Label**	north(a,b)	south(a,b)	west(a,b)	east(a,b)	northEast(a,b)	northWest(a,b)	southEast(a,b)	southWest(a,b)	
	Illustration									
	Query (WHERE clause)	MinY[5](ST_Envelope(b)) >= MaxY(ST_Envelope(a)) AND MinX(ST_Envelope(b)) >= MinX(ST_Envelope(a)) AND MaxX(ST_Envelope(b)) <= MaxX(ST_Envelope(a))	MaxY (ST_Envelope(b)) <= MinY(ST_Envelope(a)) AND MinX(ST_Envelope(b)) >= MinX(ST_Envelope(a)) AND MaxX(ST_Envelope(b)) <= MaxX(ST_Envelope(a))	MaxX (ST_Envelope(b)) <= MinX(ST_Envelope(a)) AND MinY(ST_Envelope(b)) >= MinY(ST_Envelope(a)) AND MaxY(ST_Envelope(b)) <= MaxY(ST_Envelope(a))	MinX (ST_Envelope(b)) >= MaxX(ST_Envelope(a)) AND MinY(ST_Envelope(b)) >= MinY(ST_Envelope(a)) AND MaxY(ST_Envelope(b)) <= MaxY(ST_Envelope(a))	MinX (ST_Envelope(b)) >= MaxX(ST_Envelope(a)) AND MinY(ST_Envelope(b)) >= MaxY(ST_Envelope(a))	MaxX (ST_Envelope(b)) <= MinX(ST_Envelope(a)) AND MinY(ST_Envelope(b)) >= MaxY(ST_Envelope(a))	MinX (ST_Envelope(b)) >= MaxX(ST_Envelope(a)) AND MaxY(ST_Envelope(b)) <= MinY(ST_Envelope(a))	MaxX (ST_Envelope(b)) <= MinX(ST_Envelope(a)) AND MaxY(ST_Envelope(b)) <= MinY(ST_Envelope(a))	
	Axioms									
ADJACENCY (a): Are objects adjacent to each other?	**Label**	adjacent(a,b)								
	Illustration									
	Query (WHERE clause)	(ST_DWithin(a,b,σ)) AND ((ST_Touches(a,b) =1) OR (ST_Disjoint(a,b) =1))								
	Axioms	a.adjacent(a,b) ⇒ ds.near								
COLLOCATION (cl): Are objects in the same place?	**Label**	within collocated(a,b)	exactly collocated(a,b)	substantially collocated(a,b)	approximately collocated(a,b)					
	Illustration									
	Query (WHERE clause)	ST_Contains(a,b) = 1	ST_Equals(a,b) = 1	(ST_Overlaps(a,b) = 1) AND (ST_Area(ST_Difference(a,b) > ST_Area(a)/2[6])	ST_DWithin(a,b,σ)					
	Axioms	cl.within collocated (a,b) ≡ t.contain(a,b)	cl.exactly collocated (a,b) ≡ t.equal(a,b)	cl.substantially collocated (a,b) ≡ t.overlap(a,b) cl.exactly collocated (a,b) ⇒ cl.substantially collocated (a,b)	cl.substantially collocated (a,b) cl.exactly collocated (a,b) cl.substantially collocated (a,b) ⇒ cl.approximately collocated (a,b) cl.exactly collocated (a,b) ⇒ cl.approximately collocated (a,b) cl.within collocated (a,b) ⇒ cl.approximately collocated (a,b)					
OBJECT PARTHOOD (op): Which part of the object is of interest?	**Label**	part(a,b)	whole(a,b)	rest(a,b,c)	front(a,b,D)	back(a,b,D)	left side(a,b,D)	right side(a,b,D)	middle (a,b)	corner (a,b, σ)
	Illustration									
	Query (WHERE clause)	ST_Contains(a,b) = 1	ST_Equals(a,b) = 1	ST_Equals(ST_Union(a,b),c) = 1	FrontGeometry[7](a, D) = b	BackGeometry (a, D) = b	LeftSideGeometry (a, D) = b	RightSideGeometry (a, D) = b	ST_Centroid(a) = b	PolygonAngle[8](ST_Intersection(a,b)) < σ AND PolygonAngle(ST_Intersection (a,b)) > 0 (ST_Touches(a,b) = 1) AND ST_Intersection(ST_Boundary(a), ST_Boundary(b) IS NOT NULL AND (ST_Azimuth(a) <> ST_Azimuth(b))
	Axioms	op.part(a,b) ≡ t.contain(a,b)	op.whole(a,b) ≡ t.equal(a,b)	op.rest(a,b,c) ⇒ op.part(a,c) Λ op.part(a,b) op.rest(a,b,c) ⇒ ¬t.overlap (a,b) op.rest(a,b,c) ⇒ t.touch (a,b)	op.front(a,b,D) ⇒ ¬ op.back (a,b,D) Λ ¬ op.left side (a,b,D) Λ ¬ op.right side(a,b,D)	op.back(a,b,D) ⇒ ¬ op.front(a,b,D) Λ ¬ op.left side (a,b,D) Λ ¬ op.right side(a,b,D)	op.left side(a,b,D) ⇒ ¬ op.back (a,b,D) Λ ¬ op.front (a,b,D) Λ ¬ op.right side(a,b,D)	op.right side(a,b,D) ⇒ ¬ op.back (a,b,D) Λ ¬ op.front (a,b,D) Λ ¬ op.left side(a,b,D)	op.middle (a,b,D) ⇒ ¬ op.back (a,b,D) Λ ¬ op.front (a,b,D) Λ ¬ op.left side(a,b,D) Λ ¬ op.right side(a,b,D)	op.corner (a,b,D) ⇒ ¬ op.junction (a,b,D)