A Geometric Method for Context Sensitive Distributional Semantics

by

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The text of this thesis, as well as the research it describes, is my own original work and has not been previously submitted for any other degree or qualification. In places where words or ideas have been adopted from others, I have clearly indicated this with quotations and citations as appropriate. Everything else, in both form and content, has been made by me and no one else.

My university requires me to make the following statement:

I add this:

Abstract

This thesis describes a novel methodology, grounded in the distributional semantic paradigm, for building context sensitive models of word meaning, affording an empirical exploration of the relationship between words and concepts. Anchored in theoretical linguistic insight regarding the contextually specified nature of lexical semantics, the work presented here explores a range of techniques for the selection of subspaces of word co-occurrence dimensions based on a statistical analysis of input terms as observed within large-scale textual corpora. The relationships between word-vectors that emerge in the projected subspaces can be analysed in terms of a mapping between their geometric features and their semantic properties. The power of this modelling technique is its ability to generate ad hoc semantic relationships in response to an extemporaneous linguistic or conceptual situation.

The product of this approach is a generalisable computational linguistic methodology, capable of taking input in various forms, including word groupings and sentential context, and dynamically generating output from a broad base model of word co-occurrence data. To demonstrate the versatility of the method, this thesis will present competitive empirical results on a range of established natural language tasks including word similarity and relatedness, metaphor and metonymy detection, and analogy completion. A range of techniques will be applied in order to explore the ways in which different aspects of projected geometries can be mapped to different semantic relationships, allowing for the discovery of a range of lexical and conceptual properties for any given input and providing a basis for an empirical exploration of distinctions between the semantic phenomena under analysis. The case made here is that the flexibility of these models and their ability to extend output to evaluations of unattested linguistic relationships constitutes the groundwork for a method for the extrapolation of dynamic conceptual relationships from large-scale textual corpora.

This method is presented as a complement and a counterpoint to established distributional methods for generating lexically productive word-vectors. Where contemporary vector space models of distributional semantics have almost universally involved either the factorisation of co-occurrence matrices or the incremental learning of abstract representations using neural networks, the approach described in this thesis preserves the connection between the individual dimensions of word-vectors and statistics pertaining to observations in a textual corpus. The hypothesis tested here is that the maintenance of actual, interpretable information about underlying linguistic data allows for the contextual selection of non-normalised subspaces with more nuanced geometric features. In addition to presenting competitive results for various computational linguistic targets, the thesis will suggest that the transparency of its representations indicates scope for the application of this model to various real-world problems where an interpretable relationship betweendata and output is highly desirable. This, finally, demonstrates a way towards the productive application of the theory and philosophy of language to computational linguistic practice.

Glossary

base space A high dimensional, sparse vector space of word-vectors, delineated in terms of dimensions of co-occurrence statistics.

context The situation – environmental, cognitive, perceptual, linguistic, and otherwise – in which an agent finds itself and applies language to meaning.

contextual input A set of words characteristic of a conceptual category or semantic relationship used to generate a subspace for the modelling of semantic phenomena.

dimension selection The process of contextually choosing a subset of dimensions in order to project a subspace from a base space.

co-occurrence The observation of one word in proximity to another in a corpus.

co-occurrence statistic A measure of the tendency for one word to be observed in proximity to another across a corpus.

co-occurrence window The boundary defining the proximity within which two words are considered to be co-occurring, typically a distance in terms of words within a sentence.

methodology The process of building base spaces from observations of co-occurrences within a corpus and contextually projecting subspaces through dimension selection.

model An application of methodology to a particular linguistic task or experiment, sometimes including task specific statistical analysis techniques.

subspace A context specific lower-dimensional projection from a base space, effectively mapping semantic relationships to a context by way of the geometric relationships between word-vectors.

word-vector A high-dimensional geometrically situated semantic representation of a word, constructed as an array of co-occurrence statistics.

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Chapter 2

The Geometry of Conceptualisation: Analogies

In this chapter, as a final empirical investigation into the potentialities of context specific distributional semantic techniques, I will investigate the capacity of my methodologies to model analogy. For the purposes of the computational and geometric modelling of semantics, analogy can be seen as a kind of meta-phenomenon: an analogical equation involving two sets of lexical representations indicates that there is some underlying intensionality that conceptual binds the denotations of the representations. So, for instance, the metaphor "that surgeon is a butcher" can be extended through a mapping between the conceptual domains of SURGERY and BUTCHERY to arrive at semantic formulae such as *surgeon:scalpel::butcher:cleaver* or hospital:patient :: abattoir:carcass. Furthermore, if these relationships can be mapped geometrically in a semantic space, then we should have on our hands a productive mechanism for configuring a general semantic model—and one which may overcome some of the issues of interpretation and composition raised in the last chapter. If we can connect a general region of butchery to a region of surgery in a semantic space, for instance, then we might be able to extrapolate such metaphoric turns of speech as "the surgeon hacked at me with her scalpel" from a model without committing to the claim that the model (or, for that matter, and agent) has actually interpreted the metaphor in an online way.

The idea that there is a geometric component to analogy is at least hinted at by **?**, who, as discussed in Chapter 5.4, raises the issue of inequalities and asymmetries in relationships of synonymy. **?** extends Tversky's insights to a model explicitly targeting analogy through the application of isomorphic *structure mappings* that identify congruities between conceptual domains based on composite symbolic representations.

From a computational perspective, **?** describe a system that functions through a series of *spatial operators* which facilitate mappings between conceptual domains by way of a schema of collocations, containments, and orientations, though these operations do not involve the instantiation of Euclidean measures. Subsequent symbolic computational models of metaphor in particular have seized on the mechanism of modelling mappings between conceptual structures that are, to a greater or lesser extent, based on the identification of congruities and a corresponding geometrical logic of sorts, and a small sample of work in the field has been surveyed in Chapter 2.3.

The empirical work described here will, naturally, focus on a statistical rather than symbolic approach to modelling analogy by way of spatial mappings between domains—and, in this case, domains, in the spirit of **?**, are represented roughly as regions in a Euclidean space. It is important to note, though, that one of the primary components of the productive symbolic approaches to analogy mentioned above goes away once we move into distributional semantic spaces: where the features of symbolic representations are generally constructed to be interpreted as actual attributes of the denotations being modelled, the dimensions of distributional semantic spaces are simply indices to information about co-occurrences observed in a digital corpus (this has already been discussed in Chapter 3.3 in the context of **?**'s (**?**) work studying the relationship between co-occurrence overlap and entailment, and again in Chapter **??** by way of **?**'s (**?**) model treating directions in factorised distributional spaces as conceptual themes). So there is a trade-off between access to a continuous Euclidean space of lexical semantic representations with geometric measures facilitated by the statistical nature of the representation building process and the loss of interpretable features in a symbolic conceptual scheme. My hypothesis here, in line with experiments described in the previous two chapters, is that a process of contextualisation can generate spaces where collections of co-occurrence dimensions representing conceptually oriented profiles of language use will provide an appropriate ground for modelling analogy in terms of rigorous Euclidean relationships. And in the case of analogy in particular, as will be seen in the following section, there is already a body of work offering compelling evidence that distributional semantic statistics can map conceptual relationships onto the geometry of word co-occurrence.

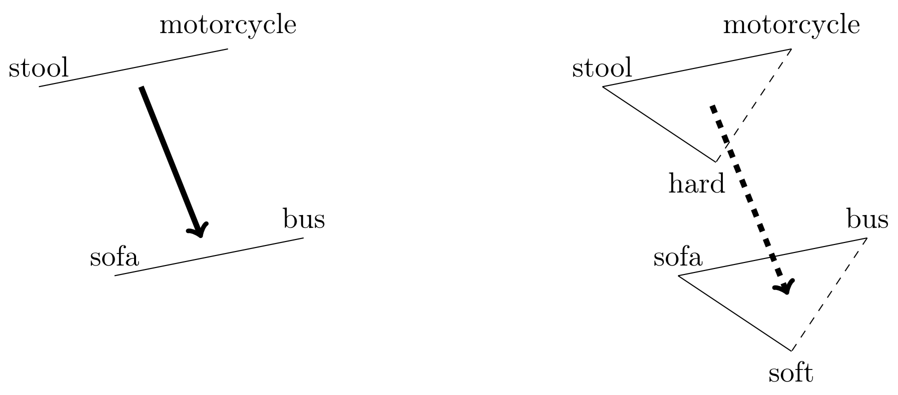
2.1 Analogies as Parallel Vectors

The `word2vec` distributional semantic modelling techniques, which have served as a point of comparison and discussion throughout this thesis, was originally presented with a test set of 19,544 four-word analogies, constructed by the model artchitects and devised to cover a range of relationships which the designers categorised as broadly *semantic* or *syntactic* (**??**).[1] So, for instance, the data presents relationships such as, on the one hand, *Bangkok:Thailand :: Paris:France* or *boy:girl :: man:woman*, and, on the other hand, *calm:calmly :: lucky:luckily* or *aware:unaware :: efficient:inefficient*. The task involves feeding a semantic model the first three terms and then measuring the rate at which it is able to accurately predict the fourth term.

The neural network architecture of the `word2vec` approach produces remarkably strong results on this task through the application of a simple geometric device. Within the normalised space of word-vectors generated over the course of iterative traversals of a large-scale digital corpus, given an unfinished analogy of form $A : B :: C : X$, the model simply finds the vector $\overrightarrow{x}$ most closely fulfilling the equation $\overrightarrow{b} + \overrightarrow{c} - \overrightarrow{a} \approx \overrightarrow{x}$, where $\overrightarrow{a}, \overrightarrow{b}, and \overrightarrow{c}$ are the word-vectors corresponding to the three known elements of the analogy, and returns the vocabulary word associated with $\overrightarrow{x}$. The original literature reports an accuracy rate of 0.61 for the CBoW model, which is all the more impressive when we consider how many ways there are to choose the wrong solution to an analogy from a vocabulary of one million words. (It should be noted that similarly strong results have been reported for the hybrid frequentist-neural model of **?**, .)

But the really remarkable thing about these results is that the models build these spaces in a completely unsupervised manner with respect to the actual task of analogy solution. This means that the arrangement of word-vectors plays out in a tidy conceptual geometry, interpretable through simple linear algebraic operations, simply by virtue of the way that words tend to come up in proximity to one another in the course of colloquial written language use (the original results were obtained from models trained on the Google News Corpus, and, as will be seen below, the same models trained on Wikipedia achieve comparable scores). Much has been made of this: **?** postulate about the procedural equivalence of iterative and statistical models mitigated by parameterisation issues, while AroraEA2016 have attempted to explain mathematically how the application of a random walk type algorithm to statistical models results in a recapitulation of the strong neural network results. At the time of writing, there is a generally accepted intuition afoot in the field that, along the lines of the distributional hypothesis itself, it makes sense that the gradual nudging of word-vectors by a neural network based on observations of co-occurrences should push words into situations where orientations and distances in space broadly map to conceptual relationships between representations; there is not, however, a well-formed mathematical explanation of why these techniques are so effective at projecting semantic relationships into space. At any rate, the import of all this is that, in `word2vec` type distributional semantic spaces, at least a certain type

[1] The analogy data is included in the package that can be downloaded at `https://code.google.com/archive/p/word2vec/source/default/source`.



(a) This makes sense.

(b) Does this make sense?

Figure 2.1: The analogical components of overlapping conceptual frames do not necessarily map neatly into a singular space.

of analogy plays out along the lines illustrated in Figure **??**, as a close approximation of a parallelogram at the surface of a normalised hypersphere in a space delineated by abstract dimensions acting as handles for the backpropagating action of a neural network.

So, to put it in plain language, the line between two points representing a conceptual relationship in one region of the space should be parallel to and in the same direction as two points in another region representing an analogous conceptual relationship under a different overall conceptual scheme. There is, however, an objection to be raised here. Returning once again to **?**'s (**?**) observations about the asymmetry of similarity, there are problems once we begin to extend the geometry of analogy to more complex conceptual structures, as illustrated in Figure **??**: for any given mapping between anything other than the most trivial conceptual domains, there will be some intensional component of the denotation that does not conform to the presumed isomorphism of the analogy in a distributional semantic space.

2.2 Contextualising Analogical Geometry

2.2.1 Projecting Probability into Space

Before we engage with an exploration of the analogical potential of context specific subspaces, a brief review of the mathematics of distributional semantic spaces with literal co-occurrence dimensions will serve to reinforce the connection between the geometry of analogy and the probabilistic grounding of my methodology. Returning to the definition of a co-occurrence statistic outlined in Chapter 4.4, recall that the pointwise mutual information between a word w and a co-occurrence term c is the unexpectedness associated with an observation of c in proximity to w, which can be expressed in terms of joint and compound probabilities (and the equation is approximate because we're ignoring the skewing factor of 1 and the smoothing constant described in Chapter **??**:

$$PMI(w,c) \approx \log\left(\frac{p(w,c)}{p(w) \times p(c)}\right) \tag{2.1}$$

The basic assumption of the geometric approach to analogy, meanwhile, is that the components of an analogy map into a parallelogram sitting in some askance situation in a high dimensional space, a state of affairs which can be expressed using linear algebraic terms for a suppositional analogy $A : B :: C : D$ and the corresponding word-vectors:

$$\overrightarrow{a} - \overrightarrow{b} \approx \overrightarrow{c} - \overrightarrow{d} \tag{2.2}$$

For any arbitrary dimension i, this can then be reduced to a difference between logs:

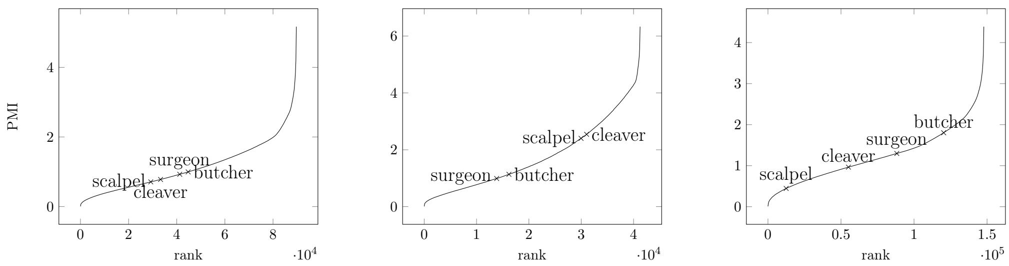
$$\log\left(\frac{p(a,i)}{p(a) \times p(i)}\right) - \log\left(\frac{p(b,i)}{p(b) \times p(i)}\right) \approx \log\left(\frac{p(c,i)}{p(c) \times p(i)}\right) - \log\left(\frac{p(d,i)}{d(a) \times p(i)}\right) \tag{2.3}$$

This expression can be significantly reduced by merging the arguments of the logarithms on either side of the equation into ratios:

$$\frac{p(a,i) \times p(b)}{p(b,i) \times p(a)} \approx \frac{p(c,i) \times p(d)}{p(d,i) \times p(c)} \tag{2.4}$$

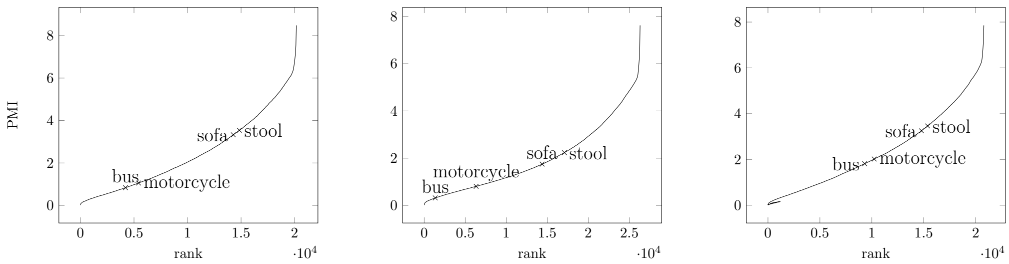
Or, converting the ratio of joint and independent probabilities to conditional probabilities and with a little more algebra:

$$p(i|a) \times p(i|d) \approx p(i|b) \times p(i|c) \tag{2.5}$$



dimension: *life* dimension: *hands* dimension: *known*

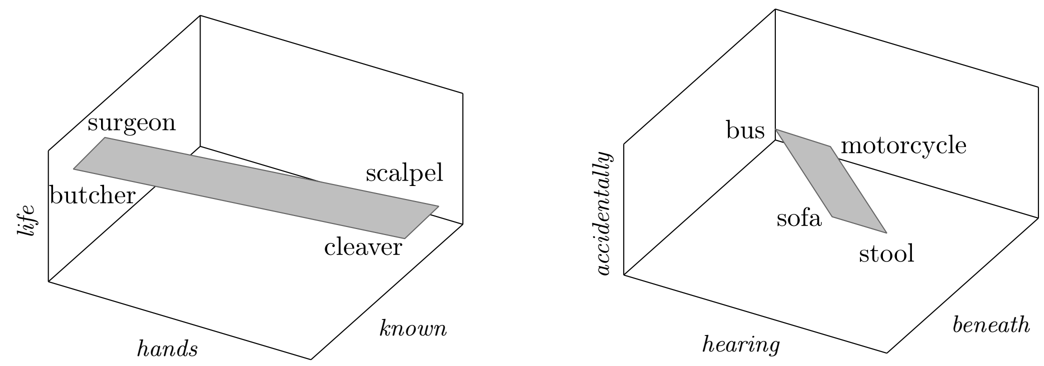
(a) SURGERY $\Longleftrightarrow$ BUTCHERY



dimension: *beneath* dimension: *hearing* dimension: *accidentally*

(b) FURNITURE $\Longleftrightarrow$ VEHICLES

Figure 2.2: Histograms of the top three co-occurrence dimensions satisfying the expected arithmetic of analogy.



SURGERY $\Longleftrightarrow$ BUTCHERY FURNITURE $\Longleftrightarrow$ VEHICLES

Figure 2.3: The geometry of two analogies projected into subspaces defined by the three most analogically accurate dimensions.

2.2.2 Projecting Probability in Space

2.2.3 Finding Contexts for Analogies

2.3 A Note on the Data

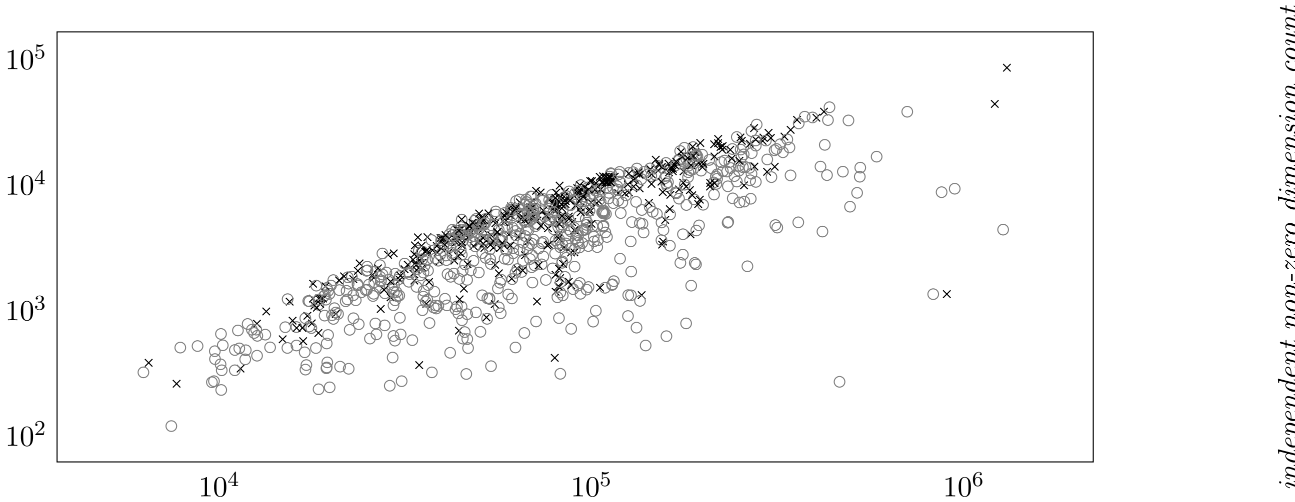
It must be mentioned that the data that has been analysed in this chapter is of a very specific character. The analogies put together by the team at Google are populated

	dimensions	5	10	20	50	100	200
2x2	JOINT	0.911	0.972	0.989	0.986	0.970	0.916
	INDY	0.722	0.908	0.976	0.985	0.967	0.873
	ZIPPED	0.921	0.975	0.991	0.987	0.970	0.919
5x5	JOINT	0.941	0.987	0.996	0.997	0.995	0.957
	INDY	0.697	0.908	0.973	0.984	0.962	0.895
	ZIPPED	0.934	0.987	0.999	0.998	0.997	0.968

Table 2-A: Accuracy rates for solving analogies when choosing subsets of optimal dimensions from 400 dimensional subspaces picked taking the first three elements of each analogy as input.

	dimensions	5	10	20	50	100	200
2x2	JOINT	0.654	0.814	0.896	0.930	0.881	0.466
	INDY	0.115	0.234	0.341	0.369	0.267	0.045
	ZIPPED	0.616	0.806	0.892	0.929	0.887	0.489
5x5	JOINT	0.657	0.828	0.901	0.921	0.835	0.402
	INDY	0.129	0.253	0.338	0.384	0.277	0.051
	ZIPPED	0.589	0.790	0.888	0.915	0.876	0.418

Table 2-B: Accuracy rates for solving randomly completed analogies when choosing subsets of optimal dimensions from 400 dimensional subspaces picked taking the first three elements of each analogy as input.



by a high percentage of proper names, in particular place names and also currencies, demonyms, and the like. This belies a particular view of language and indeed cognition which is at odds with the premise motivating the model described in this thesis, as outlined at the beginning of Chapter 3. Proper names are, as **?** has pointed out, particular kinds of words with peculiar denotational properties in that they refer to specific and unique entities or correspondingly specific classes of entities. This is not to say that they do not admit ambiguity – *Paris* is the name of, among other things, a classical character, and *Berlin* the name of a 1980s new wave band – but there tends to be a certain clarity of intent when these types of words are used. These types of analogies are exemplary of cases where language coalesces into a relatively stable conceptual representation, and, notwithstanding cases of polysemy, it's arguably not particularly surprising that these relationships emerge as commensurable directions in a likewise stable representational space.

Furthermore, it is telling that the designers of the dataset have chosen to refer to the variety of analogy typified by *slow:slowly::fast:quickly* as *syntactic*. With reference to **?** and more lately in the distributional semantic paradigm **?**, I would rather call this type of analogy *syntagmatic*, in that

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