A Geometric Method for Context Sensitive Distributional Semantics

by

Stephen McGregor

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First Supervisor: Prof. Geraint Wiggins
Second Supervisor: Dr. Matthew Purver

School of Electronic Engineering and Computer Science
Queen Mary, University of London
United Kingdom

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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

Introduction

“Words,” writes **?**, “are only an eye-twitch away from the things they stand for,” (p. 100). Words press right up against reality: they are always almost becoming the things that they point at, bleeding into thoughts and actions, taking on shapes or else pressing shapes onto the world of perceptions and experiences that they inhabit. Words are felt by the ear, on they eye, in the mouth, but also in the mind, on so many levels that the problem of disentangling words from thoughts and meanings has ruined some of the most fastidiously calculated analyses of the nature of cognition and existence. Language, in its vacillations, becomes so entwined with the way that we encounter reality that it is impossible to extract it without irreparably damaging the boundary between the world itself and the experience of being in the world. As Wittgenstein (1967) puts it, “philosophical problems arise when language goes on holiday,” (¶38).

In the almost-becoming of language, then, there lurks a treacherous encounter with the inscrutability of having-become—but also an opportunity for an interface with the actual mechanisms of knowing and believing, the exposure of the guts of the apparatus of cognition. In the very same inescapable closeness of words that has occasionally confounded philosophers, the data-minded scientist might hope to find a conduit for connecting a process of rules and reactions to the murky near-world of signs and meanings. Words port information from one system to another, traversing the passage from the lived-in world of a communicator to that of a communicant, but there is also information about words, and then, at some point, the information that words carry and the information that carries words bundles into a dynamic semiotic composite, and meaning happens. One of the principal theoretical commitments of this thesis is that language is in the world: language is experienced materially, and it is the structure of language, not just in a formal abstraction of syntax but in the way that symbols manifest themselves as components in the entire machinery of causes and intentions, that gives words their potency. So how much can we know about what is in words by knowing about the way that words are in the world?

In the pages that follow, I will describe the theory and application of a novel lexical semantic model, implemented through computational processes of word counting and representation building geared to map words into a dynamic space of contextually sensitive meaning-bearing structures. I will demonstrate how these spaces can be generated by an analysis of terms denoting some sort of conceptual continuum, and how they in turn lend themselves to a quantitative, geometric analysis of the relationships between the very words by which they are generated. This model is built upon a framework of established computational linguistic methodology, and will likewise be tested using data that has been developed and analysed by the natural language processing community. It also offers an opportunity for applying theoretical insight to quantitative techniques in natural language processing, and, finally, I will argue, a basis for considering ways in which computational models can in turn play a role in subsequent theoretical and philosophical investigations of the nature of language and cognition.

2.1 A Question and A Hypothesis

In my research I have sought to explore the question of the extent to which a data-driven, statistical mechanism, instantiated by an information processing, symbol manipulating machine, can achieve a lexical semantic model that is suited to capturing the protean nature of conceptualisation in a world of unstable and unpredictable situations. This line of enquiry follows from the idea that cognitive agents are fundamentally enmeshed in their environments, to such an extent that no model of cognition can be abstracted away from a corresponding model of the world without significant loss of efficacy.[1] This supposition presents a serious problem for the computational modelling of semantics, however: how can a machine which is by definition a system of processes unto themselves, with a carefully constrained mechanism for receiving input and offering output, be used to capture the embedded condition of cognition by which semantics arise in the first place? And here I will refrain from attempting a universal definition of the contentious term *semantics*, but I will broadly apply this word to describe the processes by which symbols or representations that are in some sense tangible commute with the immaterial realm of concepts and meaning.

I will take as a pretence the idea that there are far too many ways to conceptualise,

[1] As **?** has pointed out, the best model of the world is very often just the world, anyway.

and furthermore that the structures that support conceptualisation are far too complex and varied, to yield to a lexical or conceptual model based on rigid, static symbolic representations, however composite they may potentially be. Instead, I will seek to build a model which is contextual from the ground up, such that there is no base state that might be construed as standard, default, literal, or in some sense more true to a construct of the world as it is—precisely because *the world as it is* is always necessarily just that, an artefact constructed on the premise of some situation determining the units and levels of abstraction on which an analysis is to be performed. So I propose to seek computational methodologies which are prolific to the point of promiscuity in their capacity for generating conceptual relationships, and here I believe the procedures associated with the machine learning paradigm will in fact prove beneficial: rather than treat the proliferation of data that arises from the analysis of large scale corpora as, as it has sometimes been construed, a *curse*, I will embrace the combinatory immensity of a space of statistics about observations of language use as a feature affording perpetual contextualisation.

There is a basic geometric and computational insight to be had here. In spatial models of semantic relationships, semantics are generally quantified in terms of geometric relationships between the lexical representations projected into the space. To this well-known approach to semantic modelling I will simply add that geometric measures, when considered as observations from within a system, are relative to the position from which the observations are being made: angles vanish as shapes rotate into a plane that is perpendicular to an observer, and things that are distant from one another can seem close when they are aligned from a certain point of view. Given interrelated data points in a very high dimensional space, there are necessarily an astronomically large number of lower dimensional perspectives that can be taken on the data; given a choice of perspective, and assuming at least a degree of differentiation in terms of relationships across dimensions, we should be able to arbitrarily select some point of view by which the relationships between data points fall into a desired order. The trick of modelling semantic relationships in context then becomes the problem of finding a way to reliably select the correct perspective on data without prior recourse to the nature or validity of the affordances of that perspective. This then gives rise to my fundamental hypothesis:

> *In a distributional semantic space defined in terms of dimensions of co-occurrence statistics which are in some sense interpretable, it will be possible project lower dimensional subspaces based on an analysis of input terms in order to generate geometric relationships which can be used to train models to contextually predict semantic relationships.*

My approach to testing this hypothesis will involve generating base spaces of statistical relationships between words, developing mechanisms for taking lower dimensional perspectives on these base spaces, and then experimenting with the ways that the geometric features of these spaces can serve as input for the supervised learning of linear and logistic models for ranking and classifying semantic phenomena. Terminologically, I will describe the process of building a base space from the traversal of a corpus and then projecting subspaces from this base space as a *methodology*, in that it is a procedure that is applied to data in response to an input that leads to the output of a new configuration of data supplied for further analysis. I will then describe the application of machine learning techniques to concatenations of these projected subspaces, or more precisely to matrices of statistics derived from these subspaces, in terms of modelling, and the vectors of coefficients and biases which can be applied to subsequent geometric data will therefore be referred to as *models*. There is clearly room for variation here: my methodology, the subspaces it dynamically produces, and the feature-weighting models learned from these spaces can all be understood in terms of inputs, parameters, functions, and outputs, but hopefully these terminological commitments will serve to elucidate the descriptions of empirical research in the chapters that follow.

There are two crucial procedural features of my methodology. The first is the dynamic nature of the projection of contextual subspaces from the base space, which happens in an online way, in reaction to textual input as it arises. This aspect of the system's architecture has been designed to map, at least on a certain level of abstraction, to the dynamic and lateral nature of an cognitive agent's engagement with an environment, and likewise to the correspondingly productive nature of language by which a staggering multitude of expressions can be generated from a well-defined lexicon.

GEOMETRY DYNAMISM

2.2 Contributions to the Field

First and foremost, this thesis presents a novel computational methodology for using linguistic data to generate conceptually productive geometries of word-vectors. This methodology is grounded in the well known distributional semantic paradigm, which involves the representation of words (or other lexical units) as vectors in high dimensional spaces, constructed on the basis of observations of the way words occur with one another across large scale corpora. A fundamental characteristic of this approach is that it traffics in lexical representations which are structured in such a way as to be semantically productive: through their relative situation in space, through their composition by linear algebraic operations, and so forth, the representations themselves provide a handle on the way that words become implements of conceptualisation and vessels of meaning.

These representations are constructed through a process of corpus traversal, taking in a very large number of observations about the way in which words tend to co-occur with one another, resulting in a quantitative instantiation of signs as not only the indices but also the operons of meaning-making. The data-driven nature of this representation-building process means that this technique is naturally amenable to computation, and the advent of massive digitised textual resources combined with the availability of powerful hardware has seen the field flourish in the last several years.

Computers are, on the other hand, notoriously literal devices, not, in their application as strictly rule-abiding systems, particularly suited to feeling out the critical nuance that is inherent in human communication, the inherent looseness between what is said and what is meant. My contribution to this active area of research is to introduce, by way of a theoretical consideration of the relationship between language and cognition, an element of contextuality to the mechanisms of distributional semantic spaces. My approach seeks to move distributional semantics into the realm of

The consequence of this is that

In the case of metaphor classification, they are state-of-the-art, and components of the analogy completion results likewise in places offer at least a very promising outlook for future exploration. Elsewhere the results are in many cases competitive, and in all cases provide a valuable basis for a consideration of the special operation of my methodology as well as a reflection on the theoretical assumptions underpinning the model.

It is in terms of this last regard, concerning the theoretical contingencies and consequences of my empirical research, that I envision my second contribution to the field.

The second contribution of the work described here is to apply a noteworthy but under-represented current of theoretical work in linguistics and the philosophy of language to computational approaches to words and concepts.

In recent years this, thanks to the research from theoretically informed computer scientists such as **?** and **?**, has become a productive area

In particular, my methodology has been designed to be at least conversant with the idea that there is really no such thing as a stable conceptual scheme, but rather that concepts are always emerging, unfolding,

With this said, I've sought to be open enough in my methodological commitments to permit various theoretical preconditions to and interpretations of the empirical research that I'll describe here. This means that I would much rather describe the

2.3 Methods

As there are

I will offer an overview of the techniques for constructing, applying, and validating the models which will serve as the central empirical contribution of this work.

Representation Construction The mechanism by which

Model Learning I will present the geometric measurements produced using my methodology with, broadly, two categories of task: the rating or ranking of linguistic relationships, in the form of word pairs, in terms of their

(in particular *relatedness* and *similarity*, and similarly the classification of word pairs again in terms of whether they represent instances of

Hypothesis Testing SOMETHING

The tasks handled by my methodology will consist of broadly of two types, the ranking of

In the case of comparisons between correlations, the method for establishing the probability of results not invalidating the null hypothesis – which is to say, the chances of the results happening by pure chance given the hypothetical viccitudes of the data – will be calculated using the Fisher r-to-z transform. This equation takes as input a correlation coefficient between model output and target data

This is, appropriately, a computationally intense procedure that involves taking various cuts of the data and considering

2.4 The Layout of the Thesis

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