A Generic Evaluation of a Categorical Compositional-distributional Model of Meaning

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Abstract

Until this research, the evaluation work on the categorical model of sentence meaning (Coecke et al.) [6] has only been limited to small datasets that contain simple phrases with no recursive grammatical structures. Each of them only considered limited language units individually [16][19][30][31]. In this project, the categorical framework is instantiated on some concrete distributional models. It is the first unified practical model that handles most language units (nouns, verbs, prepositions, adjectives, adverbs, relative pronouns, conjunctions, and disjunctions) and complex grammatical structures (arbitrary sentences of any lengths). This project also conducts the first large-scale generic evaluation for the categorical model, based on the "term-definition" classification method first introduced by (Kartsaklis et al.) [19]. Specifically, the experiment is divided into the following steps. First, how well the categorical model performs on different types of phrases, including simple subject/object/possessive relative pronoun phrases, prepositions, and adjective phrases. Here, the categorical model gives good results in general. The second step is to mix all simple phases of different types. In this case, the categorical model also gives better results than the bag-of-words baseline models. The last step is to introduce complex sentences with recursive grammatical structures, the experiment shows that categorical doesn't give better results than the baseline methods in this case. Based on the experiment and its results, a detailed discussion is given at the end to analyze the cause for all results obtained. Some insights into building practical categorical models are shared, and some potential future work is mentioned.

Chapter 1

Introduction

> But what is the meaning of the word 'five'? No such thing was in question here, only how the word 'five' is used.
>
> Ludwig Wittgenstein

Natural language is ambiguous and messy in its nature. People have been seeking ways to automate the process of understanding natural language for a long time. From the early ages, philosophers had been looking for frameworks of understanding natural language. Aristotle tried to compress the different types of "constructions" into truth statements, with words as terms of different types, and inference is made from terms [25]. Later Frege developed the mathematical framework of logic, and provided a way to represent and inference the truth theoretic system to reason about propositions [11], and Montague gave a framework to reason syntax using logic [9]. All of these are based on the idea that words have meaning and a sentence is a functional composition of words. On the other hand, Wittgenstein argued in his Philosophical Investigations [40] that a word's meaning depends on its context of use.

In modern age, enabling computers to understand natural language is one of the central tasks of machine intelligence. Based on different schools of thoughts, different approaches in computational linguistics have been invented. In particular, most of these methods can be classified into formal semantics and distributional semantics.

Formal semantic approaches model language using a type-logical framework. In this framework, semantics is from logical expressions derived from

syntax structures of a sentence. Distributional semantics provides a vector space model that enables similarity comparison between linguistic units.

In recent years, due to the availability of large amounts of text online, and an increase of computing power, distributional semantics gained great success in many applications, such as machine translation, text mining, synonym discovery and paraphrasing. In such models, vector spaces have been used to express the meaning of natural language. However, there is one problem of distributional semantics to build sentence vectors: it is hard to find a particular sentence in any corpus, even though a big corpus is used. Therefore, if sentences are considered as the basic units, their vectors will contain many zeros, which will make similarity comparison nearly impossible.

Thus incorporating compositional information into distributional models of word meaning is important to fix this problem and improve the practical results. Theoretically, Coecke et. al. [6] discovered that pregroups grammar and vector spaces with linear maps share a compact closed structure. Under this framework, a categorical model of sentence meaning was developed. Sadrzadeh et al. [30][31] further developed models for sentences involving subject, object and possessive relative pronouns. In all of these papers, toy experiments were performed, and a few other more formal but small scale evaluations on simple phrases were performed [16][19].

This research is to build a practical model and perform a generic, large scale evaluation on the categorical compositional-distributional model. The practical model is built based on some concrete distributional models, then a systematical evaluation is performed. The evaluation is divided into the following steps: the first step is to perform a larger scale experiment of relative pronouns, transitive verbs, intransitive verbs, adjectives, adverbs, and prepositions; the second step is to perform evaluations on sentences with recursive grammatical structures; lastly, an evaluation on a few mixed, relatively large datasets is performed. The dataset used for evaluation in this project is extracted from the Oxford Junior Dictionary, and the method is to classify definitions (sentences) to their corresponding terms (nouns), as first introduced in (Kartsaklis et al.) [19].

The results show that the categorical model gives better results on non-recursive sentences in general, but gives slightly lower accuracy on complex sentences with recursive structures, but not significantly worse. The background chapter will introduce the theories behind related models used in this

paper, the methodology chapter will give details about the ways different types of words are modeled, and how the practical model was built, as well as the evaluation methods. The experimental work chapter will introduce the term-definition classification work in this project, and list the results. In the discussion chapter, I will give some analysis of the results, and some insights into the practical model and the results obtained from the experiments. Some future work is mentioned at the end.

Chapter 2

Background

Expressing meaning is one of the core tasks in Computational Linguistics, because it is the slate of many important applications, including paraphrase identification, question-answering systems, text summarization, information retrieval, machine translation and so on.

There are two "camps" in Computational Linguistics for a long time: the formal semantic models, and the distributional semantic models. The former tells compositional information of a sentence but does not provide quantitative information such as similarity, while the latter is quantitative but does not contain compositional information [6].

In this chapter, an introduction to the background is given: the formal semantics and the distributional models. After that, I introduce the theoretical framework of the categorical model of meaning, which builds up a passage between the two seemingly orthogonal approaches.

2.1 Formal semantics

Rooted in Frege's view of language is the idea that the meaning of a sentence is some functional composition of the meaning of individual words it contains [11]. That is, given a sentence, the semantics of this sentence is composed of the meaning of the individual words and the rules of combining these words, just like a thought is a composition of senses [12]. Indeed, with the words and the grammars, a person can produce new sentences and use them to express what he/she wants to say. Later Montague gave a systematic way of formalizing natural language semantics in his revolutionary papers EFL, UG,

PTQ, in which he claimed that natural language is naturally incoherent; but the semantics of it can be represented using some well known tools from logic, such as type theory and lambda-calculus.(Barwise, Jon and Robin Cooper. 1981) [1].

To use Montague's method, there are two steps: first one needs to perform syntactic analysis over a sentence. Syntax can be represented based on a set of grammars, such grammars can be modeled in various ways, such as CFG (Context-free grammars), CCG (combinatory categorial grammar), PCCG (Probabilistic CCG), PCFG (Probabilistic CFG) [41][13]. The semantics can be represented by logical expressions: one widely used way is to use lambda calculus expressions combined with higher-order logic [26][17]. Usually, a sentence is firstly parsed based on some grammars first, then a logical expression can be assigned to each individual words (for a relational word, it will be a predicate). After this, each node in the parse tree can be assigned a logical expression. The logical expression at the root will represent the meaning of this sentence. For example, a sentence "men like football" can be analyzed in the following way:

Syntactic Analysis	Semantics
$S \rightarrow NP \;\; VP$	$VP(NP)$
$NP \rightarrow men, football$	$men, football$
$VP \rightarrow V \;\; NP$	$V(NP)$
$V \rightarrow like$	$\lambda xy, like(x, y)$

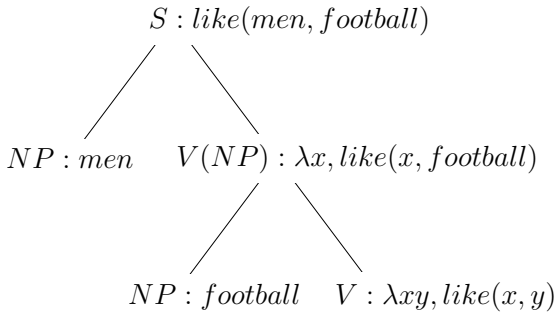


Figure 2.1: Syntactic analysis and parse tree and semantics of a sentence

More complicated sentences can also be analyzed using this method. The benefit of formal semantic approaches is that as long as the logical structure

of a sentence is obtained, the truth value of a sentence can be calculated. In real world applications, this greatly helps analyze the inference of a sentence.

However, formal semantics is not really quantitative, and simply using truth values cannot tell a lot of things, such as the similarity between words, which can be calculated from distributional models described below. Formal semantics also fails when a sentence is grammatically correct but has no sense in term of semantics. For example, Chomsky's example "colorless green ideas sleep furiously" in his *S*yntactic Structures [2]. In other cases, such as idioms and metaphors, where the semantic of a sentence is not exactly what it suggests literally, formal semantics also will not work well. Moreover, formal semantics approaches always suffer from ambiguity of sentence, lack of context data, and complexity issues in practice.

2.2 Distributional semantics

In his Philosophical Investigation, Wittgenstein states: "For a large class of cases–though not for all–in which we employ the word 'meaning' it can be defined thus: the meaning of a word is its use in the language" [40]. In general, "meaning" can refer to a number of things. For example, the meaning of "cup" can be considered in many aspects: a cup is for drinking, a cup is usually put on a table, it's usually made from glass, and when you drop a cup from your hand, it can break, etc. When you think about this word, its meaning is really only what its related context suggests to be.

The implication in practice is that a word's meaning can be largely determined by a collection of the co-occurring words within a certain window in a large corpora, such as ukWac (Ferraresi et al., 2008) [10], the British National Corpus, and Gigaword (Graff et al. 2003) [14]. A word has stronger relation to a word co-occurs with it frequently than a word does not appear many times with it in a large corpus. Normally, a semantic model is a vector space, and each word is a vector in this vector space. The basis of this vector space denotes some features of the semantic space.

The biggest benefit of vector space representation is similarity comparison. For example, with a proper vector space model, it is very easy to show that "dog" is close to "cat" and "mammal", but further from other words, such as "bank". The cosine distance between two word vectors represent their

similarity. Given two words "cat" and "dog", they can be expressed as $\overrightarrow{cat}$ and $\overrightarrow{dog}$ in some semantic vector space, and their distance is $\frac{\overrightarrow{cat}\cdot\overrightarrow{dog}}{\|\overrightarrow{cat}\|\|\overrightarrow{dog}\|}$. This model has already been useful in many fields, such as word clustering, automatic thesauri discovery, information retrieval and paraphrasing.

2.3 Compositionality in distributional models of meaning

The two camps are thought to be orthogonal methods, and either of them has pros and cons complementary to the other. In recent years, adding compositional information to distributional models had been investigated.

The three basic models introduced below will be the baseline models in the experiment later.

2.3.1 Additive models

The simplest idea is to add all word vectors in a sentence together, and produce a new vector representing the sentence. The vector for a sentence containing n words will be calculated as following:

$$\overrightarrow{W_1W_2\dots W_n} = \sum_{i=1}^{n} \overrightarrow{W_i}$$

A simple example:

$$\overrightarrow{Mike\ Studies\ Economies} = \overrightarrow{Mike} + \overrightarrow{Studies} + \overrightarrow{Economies}$$

The additive model has been proved to be very efficient in computing, and has given good results in experiments [24]. The main problem of the additive model is that the addition operation is commutative, therefore "cat catches mouse" will be equal to "mouse catches cat". However, this can be solved, as stated in [24], by adding scalar factors to different words: $\overrightarrow{W_1W_2\dots W_n} = \sum_{i=1}^{n} c_i\overrightarrow{W_i}$, where $\{c_i\}_i$ is a set of coefficients. In this case, the result is never

commutative anymore, but how to determine the values of those scalar factors is another problem.

2.3.2 Multiplicative models

The multiplicative model is also a so-called "bag of words" model. Instead of adding vectors, it point-wise multiplies all vectors in a sentence to produce sentence vector.

$$\overrightarrow{W_1 W_2 \dots W_n} = \prod_{i=1}^{n} \overrightarrow{W_i}$$

Again, a simple example can be:

$$\overrightarrow{Mike\ Studies\ Economies} = \overrightarrow{Mike} \odot \overrightarrow{Studies} \odot \overrightarrow{Economies}$$

The multiplicative model still suffers from the commutative problem; and by adding coefficients to weight the individual words (as shown in the additive model) will not solve this problem either. In addition, if the vectors are sparse, the sentence vectors computed from point-wise multiplications will contain a large number of zeros, which will make similarity comparison very imprecise. In most cases this is not a desired property. The use of some smoothing techniques can avoid too many zero entries in the resulted vectors [24]. Although the multiplicative method is commutative, Edward Grefenstette [15] pointed out that the multiplicative model evaluated in [24] shows better ability for disambiguation on verbs. This is mainly because multiplication is an information non-increasing process. As shown in the next chapter this property, and the information non-decreasing property of the additive method can help with modeling disjunctions and conjunctions.

2.3.3 Sentence living in tensor space

One elegant idea is to represent sentences as tensor products of words (Smolensky, 1990, [24]). A sentence of n words can be represented by:

$$\overrightarrow{W_1 W_2 \dots W_n} = W_1 \otimes W_2 \otimes \cdots \otimes W_n$$

$$\overrightarrow{Mike\ Studies\ Economies} = \overrightarrow{Mike} \otimes \overrightarrow{Studies} \otimes \overrightarrow{Economies}$$

In this approach, sentence vectors live in higher dimensional spaces. Also tensor product is non-commutative, so it does not have the bag-of-words models' problem of commutative property.

In addition, Clark and Pulman further proposed the idea to embed word types into the representation of vectors [3]. But long sentences produce higher dimensional vectors, and sentences of different lengths will fall into vector spaces of different orders. Therefore they will not be comparable to each other. Both of these problems make this approach not feasible in practice.

2.3.4 Other models

Some research makes use of the topological structures of sentences, especially in the applications where similarity comparison is important. In these methods, a sentence is firstly parsed by some dependency parser. The similarity of two sentences depends on the common edges of the trees (word-overlap) [39]. Remarkably, Vasile Rus, et al. (2008) used a graph based model [29]. In their paper, text is firstly converted into a graph according to some dependency-graph formalism (text $\rightarrow$ dependency graph). The graph is thus a representation of the sentence. After that, the sentence similarity problem is reduced to a graph isomorphism search (graph subsumption or containment). Rus' model obtained very positive results for paraphrasing.

Other feasible models have also been proposed. For example, many deep learning based models have been developed recently. Socher et al. [34][35][36] used recursive neural networks (RNN) that parse natural language sentences and produce vectors for sentences based on compositionality. The model works for sentences with variable sizes, and it works particularly well on identifying negations. Their recursive auto-encoder model has been applied to paraphrase detection and prediction of sentiment distribution, which also obtained very

good results [33][37].

Coecke et al. (2010) [6] proposed a categorical framework of meaning which takes advantage of the fact that both a pregroup grammar and the category of finite-dimensional vector spaces with linear maps share a compact closed structure. The construction of a sentence vector from word vectors is performed by tensor contraction. The framework preserves the order of words, and more importantly, does not suffer from the dimensionality expansion problems of other tensor-product approaches, since the tensor contraction process guarantees that every sentence vector will live in a basic vector space. And the following section will introduce the categorical model in details.

2.4 A categorical framework of meaning

The categorical model provides a mathematical foundation of a compositional distributional models of meaning. The essentiality of category theory here as a passage is described in (Coecke et. al.) [6].

First I will start with the basic components will be used in this paper.

2.4.1 Category

A category $\mathbb{C}$ can be defined as following:

1. a collection of objects
2. a collection of morphisms (or arrows)
3. each morphism has domain (dom) A and codomain (cod) B, therefore a morphism f can be written as $f : A \to B$
4. there is a composition operation $\circ$ for each pair of arrows f, g, with $cod(f) = dom(g), g \circ f : dom(f) \to cod(g)$, composition operation satisfies the associative law.
5. for each object A, there is an identity morphism $1_A : A \to A$. For any morphism $f : A \to B$, there is $f \circ 1_A = f$, $1_B \circ f = f$.

Based on this simple definition of category, many other categories can be constructed with some additional structures. They have strong expressive power to model many existing mathematical structures. For more details about Category Theory itself, one can refer to Benjamin Pierece's book [27].

2.4.2 Monoidal category

Another essential property we want to capture in natural language is the "parallel composition". A sentence "$W_1W_2...W_m$" can be represented by tensor $W_1 \otimes W_2 \otimes ... \otimes W_m$. Each of these words can be a vector, or a tensor of any order, and they are composed in parallel by monoidal tensor.

Here, each word can either live in a vector space of order 1, or live in a higher-order vector space. The resulted sentence vector is the tensor product of all words sequentially. To capture parallel composition, the feature of monoidal category is useful.

A monoidal category is a category that admits monoidal tensor: For each ordered pair of objects (A, B), there is a parallel composite object $A \otimes B$, where $\otimes$ is called the monoidal tensor. There is a unit object I in a monoidal category, satisfying the following property:

$$A \otimes I = A = I \otimes A$$

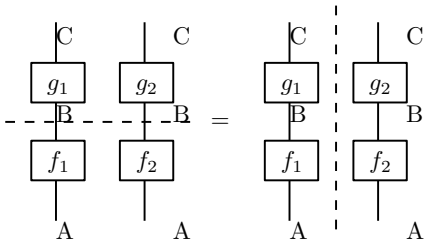
For each pair of morphisms $(f : A \to B, g : C \to D)$, there is a parallel composite morphism $f \otimes g : A \otimes C \to B \otimes D$.

Monoidal category further requires bifunctoriality for any pair of morphisms $(f : A \to B, g : B \to C)$ [6]:

$$(g_1 \otimes g_2) \circ (f_1 \otimes f_2) = (g_1 \circ f_1) \otimes (g_2 \circ f_2)$$

A Graphical Language for monoidal categories is useful to show many properties in simple ways. It is introduced in many articles and will be used directly in this paper, for details refer to [5][6][30]. In this graphical language, objects (types) are depicted by wires and morphisms (processes) are depicted by boxes.

For example, the bifunctoriality can be depicted by:



2.4.3 Compact closed categories

A compact closed category is a monoidal category, where every object A has left and right duals A^l, A^r, and satisfying:

$$(A \otimes B)^l \cong \left(B^l \otimes A^l\right)$$
$$(A \otimes B)^r \cong (B^r \otimes A^r)$$

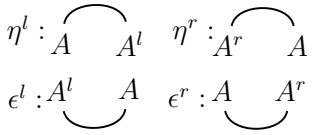
and there are morphisms ϵ and η, where

$$\epsilon^l : A^l \otimes A \to I$$
$$\epsilon^r : A \otimes A^r \to I$$
$$\eta^l : I \to A \otimes A^l$$
$$\eta^r : I \to A^r \otimes A$$

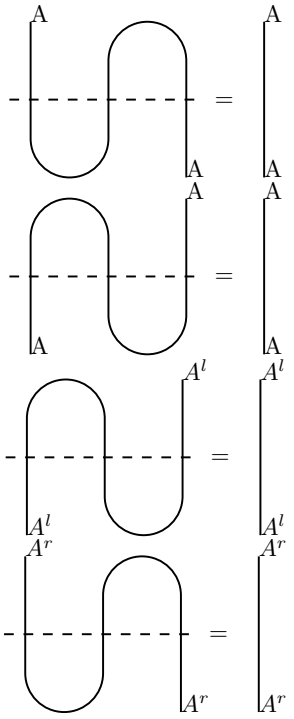
These morphisms satisfy the following equalities:

$$(1_A \otimes \epsilon^l) \circ (\eta^l \otimes 1_A) = 1_A$$
$$(\epsilon^r \otimes 1_A) \circ (1_A \otimes \eta^r) = 1_A$$
$$(\epsilon^l \otimes 1_{A^l}) \circ (1_{A^l} \otimes \eta^l) = 1_{A^l}$$
$$(1_{A^r} \otimes \epsilon^r) \circ (\eta^r \otimes 1_{A^r}) = 1_{A^r}$$

The graphical language for compact closed category is the "String Diagrams". A detailed introduction can be found in the categorical categorical quantum mechanics papers [4] and (Sadrzadeh et al.) [30]. Graphically, the ϵ and η maps are "bending" the wires:



And the morphisms' equalities can be depicted respectively as:

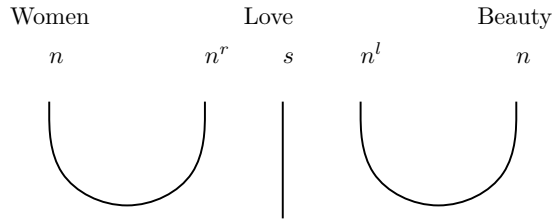


2.4.4 Pregroups grammar and FVect as compact closed categories

The original work of Lambek Calculus were found to be useful to introduce as a mathematical model for syntactic calculus in the categorical model here [6]. Using Lambek Calculus, a sentence with compound word types can be reduced based on the rules of partial order. A phrase or a sentence is grammatically correct if it can be reduced to a proper type it expects, and it is not grammatical if otherwise. For example, in a transitive sentence "women love beauty". The word "women" is a noun and has type n; the word "beauty" is a noun and has type n, the word "love" is a transitive verb and has type $(n^r s n^l)$, where n^r is the right adjoint of n, and n^l is the left adjoint of n. The type of the transitive verb "love" means that the verb expects a subject on its left (i.e. the subject) and expects an object on its right (i.e. the object). The type of this sentence can be reduced as following:

$$n(n^r s n^l)n \to (nn^r)s(n^l n) \to s$$

Graphically, this reduction can be depicted as:



For a formal definition, a pregroup is a partially ordered monoid $(P, \leq, \cdot, 1)$, and each object $p \in P$ has left and right adjoints p^l and p^r. It can be represented as $(P, \leq, \cdot, 1, (-)^l, (-)^r)$. To make it more specific, I explain each part in this six-tuple:

- P is a collection of primitive objects
- $\leq$ is the partial ordering relation on collection P
- $\cdot$ is monoid multiplication, for objects $a, b \in P$, $a \cdot b \in P$. Note that $\cdot$ is non-commutative and it is associative. An intuitive way to understand $\cdot$ is string concatenation on a set of strings.
- there is a unit $1 \in P$, and $1 \cdot a = a \cdot 1$
- For each element $a \in P$, there are left and right adjoints $a^l \in P$ and $a^r \in P$. The adjoints satisfy $a^l \cdot a \leq 1 \leq a \cdot a^l$ and $a \cdot a^r \leq 1 \leq a^r \cdot a$. Some other important properties of adjoints: The adjoints of an object are unique; $1^l = 1 = 1^r$; $(a \cdot b)^l = b^l \cdot a^l$, $(a \cdot b)^r = b^r \cdot a^r$; $a^{lr} = a = a^{rl}$; $a \leq b \Rightarrow b^l \leq a^l$ and $b^r \leq a^r$.

A Pregroup is a compact closed category because [6]:

- Objects in the category are posets.
- Morphisms in the category are partial orders in Lambek Calculus, that is a morphism of type $A \to B$, there is $A \leq B$. For each pair of objects, there is at most one morphism between them.
- The monoidal multiplication in pregroup is the monoidal tensor. Given any two morphisms $a \leq b$ and $c \leq d$, the tensor between two morphisms is $a \cdot c \leq b \cdot d$. The Bifunctoriality property is also satisfied. It worth noting that unlike the **FVect** described below, this is not a symmetrical monoid.

- Each object has left and right adjoints. The epsilon maps and eta maps are: $\epsilon^l : p^l \cdot p \leq 1$, $\epsilon^r : p \cdot p^r \leq 1$, $\eta^l : 1 \leq p \cdot p^l$ and $\eta^r : 1 \leq p^r \cdot p$. They correspondes to the "cups" and "caps" in the graphically language respectively.

FVect is the category where finite-dimensional vector spaces over $\mathbb{R}$ are objects, linear maps are morphisms and vector space tensor is monoidal tensor [6]. There is also inner product for the vector spaces. **FVect** is a compact closed category when vector spaces on $\mathbb{R}$ are objects, linear maps between vector spaces are morphisms, and vector space tensor product is monoidal tensor, the unit is the scalars in $\mathbb{R}$. There is also an isomorphism $V_1 \otimes V_2 \cong V_2 \otimes V_1$ for any tensor objects $V_1 \otimes V_2$ and $V_2 \otimes V_1$. This makes **FVect** a symmetrical monoidal category. Every vector space has a dual vector space (conjugate transpose) V^*. Since the vector space is over $\mathbb{R}$, the dual space is its transpose, and $V \cong V^*$. Because of the symmetrical property of **FVect**, the left adjoint and right adjoint of a vector space are the same, and they are equal to its dual: $V^l = V^* = V^r$. We also assume that the vector spaces have fixed basis $\{\overrightarrow{n_i}\}_i$, and there is inner product over a vector space. The epsilon and eta maps can be concretely defined as:

$$\epsilon^l = \epsilon^r : V \otimes V \to \mathbb{R} :: \sum_{ij} c_{ij} \overrightarrow{n_i} \otimes \overrightarrow{n_j} \to \sum_{ij} c_{ij} \langle \overrightarrow{n_i} | \overrightarrow{n_j} \rangle$$

$$\eta^l = \eta^r : \mathbb{R} \to V \otimes V :: 1 \to \sum_{ij} c_{ij} \overrightarrow{n_i} \otimes \overrightarrow{n_j}$$

The fact that **FVect** is a compact closed category can then be verified [6][15].

2.4.5 A passage from syntax to semantics

The previous subsection has shown that the Pregroups Grammars and Vector spaces with linear maps share the same compact closed structure. The categorical framework unites these two important aspects of natural language: compositional information represented by grammar and meaning represented by vector space. In practice, this means that a sentence's grammatical structure can be reduced based on the word types and rules in the grammar, and this can be a guidance of how the tensor of a sentence can be reduced to a

basic order-1 vector. This takes into account the composition information of a sentence, in the same time it reduces sentence vector into a basic vector (order 1), solved the dimensionality problem.

In the original work of (Coecke et al.) [6], the "meaning" of language is considered to be the product category **FVect** $\times P$, in which a pair of vector space and grammar type (V, a) is an object and a pair of linear map and pregroup order relation $(f, \leq)$ is a morphism. This product category is also a compact closed category. In particular, there are four morphisms: $(\epsilon^l, \leq)$, $(\epsilon^r, \leq)$, $(\eta^l, \leq)$ and $(\eta^r, \leq)$. The sentence's type can be reduced based on the grammar, and the corresponding vector space linear maps are applied to the words' vectors. Concrete examples of different types of phrases and sentences will be given in the Methodology Chapter.

2.4.6 Frobenius Algebra

Frobenius algebra is useful in modeling relative pronouns, as will be shown later. It will also be essential for building practical model in the experiment [30][19].

A Frobenius algebra over a symmetrical monoidal category $(\mathbb{C}, \otimes, I)$ can be defined as a tuple $(V, \sigma, \vartheta, \mu, \xi)$, where V is an object of $\mathbb{C}$, and $\sigma, \vartheta, \mu, \xi$ have types:

$$\begin{aligned} \sigma &: V \to V \otimes V \\ \vartheta &: V \to I \\ \mu &: V \otimes V \to V \\ \xi &: I \to V \end{aligned}$$

Moreover we require the Frobenius condition:

$$(1_V \otimes \mu) \circ (\sigma \otimes 1_V) = \sigma \circ \mu = (\mu \otimes 1_V) \circ (1_V \otimes \sigma)$$

If the category is **FVect** (finite-dimensional vector space and linear maps) as introduced before, the morphisms $\sigma, \vartheta, \mu, \xi$ are linear maps. Again, we assume the vector space N has a fixed basis $\{n_i\}_i$, the maps can be written as

[19][30]:

$$\sigma : N \to N \otimes N :: \overrightarrow{n_i} \to \overrightarrow{n_i} \otimes \overrightarrow{n_i}$$
$$\vartheta : N \to I :: \overrightarrow{n_i} \to 1$$
$$\mu : N \otimes N \to N :: \overrightarrow{n_i} \otimes \overrightarrow{n_i} \to \overrightarrow{n_i}$$
$$\xi : I \to N :: 1 \to \overrightarrow{n_i}$$

2.5 Progress of building practical models and evaluation of the categorical model

Since the theory does not imply how the word vectors should be built, nor how the reduction on vectors should be performed, this leaves experimental work in practice. There were several simple and small scale experiments available. Grefenstette et. al. [16] gave a set of useful practical way to build vectors for relational words including intransitive and transitive verbs from a large corpus, and evaluated a small set of simple phrases, concluded that the categorical model gave good results. Kartsaklis et. al. [19] further stipulated choices of sentence spaces, and introduced an interesting way of performing evaluation (term-definition classification on dictionary term-definition pairs), which was used in this project for large scale evaluation. Furthermore, in each of the papers of building categorical models, the authors usually performed small scale evaluations to prove effectiveness of the methods [6][16].

However, there was no unified, large scale evaluation on different types of words that can be modeled before this research. In addition, there was no practical model so far that can experiment with and evaluate complex sentences, with recursive grammatical structures. This project builds such a practical model, and performs a unified, large scale evaluation on different types of phrases, and moreover, on complex sentences. The experiment results will help with further research on practical construction of the categorical model.

Chapter 3

Methodology

In this section, a set of practical solutions of building the categorical model are provided. First different semantic word spaces are introduced, then the particular ways of creating vectors for different types of relational words in this paper. Lastly, I introduce the details of implementing the model, which will be used in the experimental work in the next chapter.

3.1 Semantic word spaces for the categorical model

Semantic word space is the basic building block of distributional semantic models, and the tensor spaces for relational words are built upon the basic semantic word spaces.

A semantic word space is a vector space of words' semantics, in which each word is represented by a vector. Each dimension of the vector space represents one certain feature. In a conventional vector space, each dimension of a word vector is the co-occurrence count of another word within a window over a large corpora. The vector space used in this project is from an experiment conducted by Kartsaklis et al. [18]. The vectors were trained from the ukWaC corpus (Ferraresi et al. 2008) [10], and used 2000 content words (excluding the 50 most frequent "stop" words) as the basis. The context is set up to be a 5-word window from each side of the target word. A vector is created for every content word that has at least 100 occurrences in the ukWaC corpus. The semantic space is scored 0.77 Spearman's rank correlation coefficient (i.e. Spearman's ρ) on a benchmark dataset of Rubenstein and Goodenough (1965)

[18][28]. In the vector space, each word has a tag to denote its type. There are four types of words: noun, verb, adjective, and adverb. All vectors contain only positive numbers.

There are also other types of semantic word spaces being built so far. One popular type of semantic vectors is the so called neural vectors using machine learning techniques, such as neural networks. These models usually produce decent word vector spaces of relatively low dimensions ($\leq$ 300). I experimented two neural vector spaces during a very early stage of this project: The vector space trained by Turian et al. [38], which implemented the model introduced by Collobert and Weston (2008) [7], as well as the Word2Vec tool developed by Mikolov et al. [23]. However, having negative values is not a desired property in the multiplicative model, and hence the categorical model. This result will be shown in the experiment chapter.

It was also experimented by Kartsaklis et al. [18] to reduce the original vector space to a 300 dimensional vector space using Singular Vector Decomposition (SVD). After the SVD process, the vector space has a much lower dimension (300), but introduces negative numbers as well. Thus in the experiment, I used the vector space before SVD, which is 2000-dimensional.

3.2 Sentence space

As the categorical framework actually does not imply a particular sentence space, Kartsaklis et. al. [19] gave a clear comparison of two feasible sentence spaces in practice: $S = N \otimes N$ and $S = N$ [19]. When sentences are instantiated on $S = N \otimes N$, it comes with the problem that sentences of different grammatical structure and different lengths will have vectors of different orders. This will cause troubles when comparing arbitrary sentences. In this project, sentence vectors of order 1 ($S = N$) will be preferred because of its ability to compare sentences of any grammatical structures in the basic vector space, by calculating the cosine distance between these vectors. In the later session "Implementation Details", I will explain how a an arbitrary sentence can be reduced to a basic vector based on the categorical framework with some simplification described below.

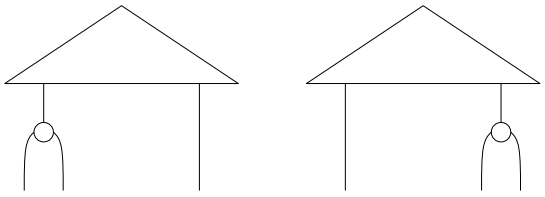
3.3 Create tensors for relational words

Another practical issue that the categorical framework does not specify is how the tensors for relational words are created. For example, the matrix for adjectives and the order-3 tensors ("cubes") for transitive verbs, etc. As the pregroup types of words show in the background chapter, there are basic order-1 vectors (usually the nouns), and there are multi-linear maps (the relational words, usually functional words such as verbs, adjectives, etc.). The relational words should be "applied" to other words, and they are tensors of higher orders.

This research focuses on creating tensor spaces directly from corpus. Grefenstette et. al. introduced a general way to create vectors for relational words in [16]. It specifically discussed how the tensors for intransitive words and transitive words can be trained from a corpus: in the intransitive case, the subjects of the intransitive words were added together in the corpus, in the transitive case, tensor of each subject-object pair of the transitive verb in a corpus is added.

It is worth noting that in the original theory, an intransitive verb is a matrix and a transitive verb is a tensor of order 3 ("a cube"). The method mentioned above creates tensors that are one-order less than it supposes to be. To solve this problem, one way is to directly construct higher-order vectors is to add the verb itself in the tensor product, another way is to use machine learning techniques to help construct the tensors. Considering the time and space required for the first approach, these two methods are not included in the scope of this experiment.

Instead, Frobenius algebra can help solve this problem. Applying the Frobenius σ map can copy one "wire" of the relational word's tensor, then produce a diagonal matrix or a order-3 tensor, then the tensors for relational words will have the right orders. In a transitive verb's case, based on which part to "copy", there are so called "CpSbj" and "CpObj" methods. "CpSbj" copies the "row" dimension of a transitive verb's matrix, and "CpObj" copies the "column" dimension os a transitive verb's matrix, using the σ map. These two methods can be depicted below:



CpSbj CpObj

However, we suspect later this simplification will affect the performance in practice.

Based on the models and techniques introduced so far, we can now extend the model to many other concrete types of words.

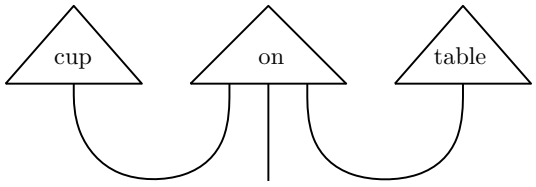
3.3.1 Noun-modifying prepositions

Noun modifying prepositions are taken into consideration in this research. A noun modifying preposition functions in a similar way as a transitive verb. Consider the phrase "cup on table": here "cup" is a noun, "table" is another noun, and "on" is connecting them. In this case, "cup" and "table" can be regarded as the subject and the object, just like in a transitive verb phrase. From this observation, noun-modifying prepositions can be modeled.

The Pregroup type of a noun modifying preposition is $n^r nn^l$, and the Pregroup type of a noun is simply n. Given a word vector space N, and a fixed basis $\{\overrightarrow{n_i}\}_i$, the linear map to produce sentence meaning vector is:

$$f = \epsilon_{\mathrm{N}} \otimes 1_{\mathrm{S}} \otimes \epsilon_{\mathrm{N}}$$

Applying the linear map to the vectors of words, the graphic calculus can be depicted as following:



Algebraically, the vector of "cup" and "table" can be expressed as $\overrightarrow{cup} = \sum_i w_{\mathrm{i}} \overrightarrow{n_{\mathrm{i}}}$ and $\overrightarrow{table} = \sum_k v_{\mathrm{k}} \overrightarrow{n_{\mathrm{k}}}$ respectively, and preposition "on" can be expressed as $\overrightarrow{on} = \sum_{ijk} P_{\mathrm{ijk}} \overrightarrow{n_{\mathrm{i}}} \otimes \overrightarrow{n_{\mathrm{j}}} \otimes \overrightarrow{n_{\mathrm{k}}}$, where w_i, v_k, P_{ijk} are corresponding coefficients.

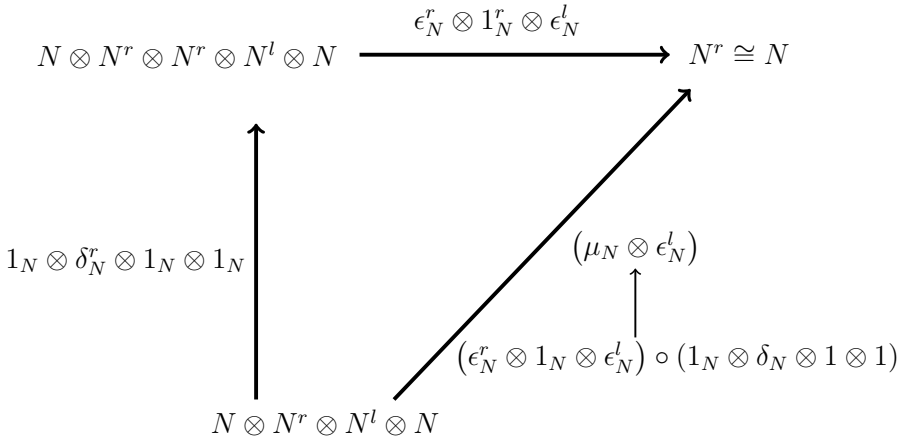
Applying the linear map f to the tensor of word vectors:

$$
\begin{aligned}
& f\left(\overrightarrow{cup} \otimes \overrightarrow{on} \otimes \overrightarrow{table}\right) \\
=& \epsilon_N^r \otimes 1_N \otimes \epsilon_N^l \left[\overrightarrow{cup} \otimes \overrightarrow{on} \otimes \overrightarrow{table}\right] \\
=& \epsilon_N^r \otimes 1_N \otimes \epsilon_N^l \left[\left(\sum_i m_i \overrightarrow{n_i}\right) \otimes \left(\sum_{ijk} P_{ijk} \overrightarrow{n_i} \otimes \overrightarrow{n_j} \otimes \overrightarrow{n_k}\right) \otimes \left(\sum_k v_k \overrightarrow{n_k}\right)\right] \\
=& \epsilon_N^r \otimes 1_N \otimes \epsilon_N^l \left[\sum_{ijk} P_{ijk} m_i v_k \overrightarrow{n_i} \otimes \overrightarrow{n_i} \otimes \overrightarrow{n_j} \otimes \overrightarrow{n_k} \otimes \overrightarrow{n_k}\right] \\
=& \sum_{ijk} P_{ijk} \epsilon_N^r \left(\overrightarrow{n_i} \otimes \overrightarrow{n_i}\right) \otimes 1_N \left(\overrightarrow{n_j}\right) \otimes \epsilon_N^l \left(\overrightarrow{n_k} \otimes \overrightarrow{n_k}\right) \\
=& \sum_{ijk} P_{ijk} m_i v_k \left\langle \overrightarrow{n_i} | \overrightarrow{n_i} \right\rangle \otimes \overrightarrow{n_j} \otimes \left\langle \overrightarrow{n_k} | \overrightarrow{n_k} \right\rangle \\
=& \sum_{ijk} P_{ijk} m_i v_k 1 \otimes \overrightarrow{n_j} \otimes 1 \\
\cong& \sum_{ijk} P_{ijk} m_i v_k \overrightarrow{n_j}
\end{aligned}
$$

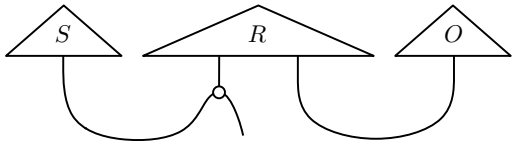
The above equation is exactly $\overrightarrow{cup} \times \left(\overrightarrow{on} \times \overrightarrow{table}\right)^T$. However, due to the difficulty of creating order-3 tensors for relational words, in practical, Frobenius models are used in this experiment. Since there is no particular emphasis on either using CpSbj or using CpObj, the final vector is the addition (hence average in cosine distance sense) of two vectors from CpSubj and CpObj. In the CpSubj case, the derivation of "cup on table" is:

$$
\begin{aligned}
&\mu_N \otimes \epsilon^l\big[\overrightarrow{cup} \otimes \overrightarrow{on} \otimes \overrightarrow{table}\big] \\
=&\mu_N \otimes \epsilon^l\Big[\Big(\sum_i m_{\mathrm{i}} \overrightarrow{n_i}\Big) \otimes \Big(\sum_{ijk} P_{ik} \overrightarrow{n_i} \otimes \overrightarrow{n_k}\Big) \otimes \sum_k v_k \overrightarrow{n_k}\Big] \\
&= \mu_N \otimes \epsilon^l\big[\sum_{ijk} P_{ik} m_i v_{\mathrm{k}} \overrightarrow{n_{\mathrm{i}}} \otimes \overrightarrow{n_{\mathrm{i}}} \otimes \overrightarrow{n_{\mathrm{k}}} \otimes \overrightarrow{n_{\mathrm{k}}}\big] \\
&= \sum_{ik} P_{ik} m_i v_k \mu_N\left(\overrightarrow{n_{\mathrm{i}}} \otimes \overrightarrow{n_{\mathrm{i}}}\right) \otimes \epsilon^l_N\left(\overrightarrow{n_k} \otimes \overrightarrow{n_k}\right) \\
&= \sum_{ik} P_{ik} m_k v_k \overrightarrow{n_i} \otimes 1 \\
&\cong \sum_{ik} P_{ik} m_i v_k \overrightarrow{n_i} \\
&= \overrightarrow{cup} \odot \left(\overrightarrow{on} \times \overrightarrow{table}\right)^T
\end{aligned}
$$

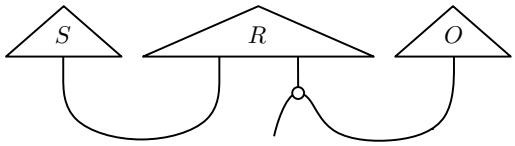
The commutative diagram is:



Graphically, CpSubj is depicted as below:



CpObj is very similar to CpSbj for prepositions. The only difference is that it is the object "wire" that gets copied. The detail of derivation is waived here because it is very similar, the graphical calculus is depicted below:



The final result is the addition of CpSubj vector and CpObj vector.

3.3.2 Transitive verbs

Following the original mathematical model for transitive verbs in [6], transitive sentences/phrases can be modeled in the following way.

First a transitive verb has Pregroup type $n^r s n^l$. It is a tensor of order-3 in **FVect**: $N_s \otimes S \otimes N_o$, where N_s is the vector space for subject, N_o is the vector space for object, and S is space for sentence. The linear map that transforms meaning of words to meaning of sentence is:

$$f = \epsilon_N^r \otimes 1_S \otimes \epsilon_N^l$$

Any transitive sentence's meaning, take an example, "cat likes milk", can be computed by applying the linear map f to the tensor of words.

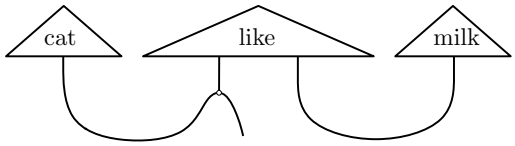
$$\begin{aligned}
&f\left(\overrightarrow{cat} \otimes \overrightarrow{like} \otimes \overrightarrow{milk}\right) \\
&= \left(\epsilon_N^r \otimes 1_N \otimes \epsilon_N^l\right) \left[\overrightarrow{cat} \otimes \overrightarrow{like} \otimes \overrightarrow{milk}\right] \\
&= \left(\epsilon_N^r \otimes 1_N \otimes \epsilon_N^l\right) \left[\left(\sum_i m_i \overrightarrow{n_i}\right) \otimes \left(\sum_{ijk} P_{ijk} \overrightarrow{n_i} \otimes \overrightarrow{n_j} \otimes \overrightarrow{n_k}\right) \otimes \left(\sum_k v_k \overrightarrow{n_k}\right)\right] \\
&= \left(\epsilon_N^r \otimes 1_N \otimes \epsilon_N^l\right) \left[\sum_{ijk} P_{ijk} m_i v_k \overrightarrow{n_i} \otimes \overrightarrow{n_i} \otimes \overrightarrow{n_j} \otimes \overrightarrow{n_k} \otimes \overrightarrow{n_k}\right] \\
&= \sum_{ijk} P_{ijk} m_i v_k \epsilon_N^r \left(\overrightarrow{n_i} \otimes \overrightarrow{n_i}\right) \otimes 1_N \left(\overrightarrow{n_j}\right) \otimes \epsilon_N^l \left(\overrightarrow{n_k} \otimes \overrightarrow{n_k}\right) \\
&= \sum_{ijk} P_{ijk} m_i v_k \left\langle \overrightarrow{n_i} | \overrightarrow{n_i} \right\rangle \otimes \overrightarrow{n_j} \otimes \left\langle \overrightarrow{n_k} | \overrightarrow{n_k} \right\rangle \\
&= \sum_{ijk} P_{ijk} m_i v_k 1 \otimes \overrightarrow{n_j} \otimes 1 \\
&\cong \sum_{ijk} P_{ijk} m_i v_k \overrightarrow{n_j}
\end{aligned}$$

Similarly, the final result is $\overrightarrow{cat} \times \left(\overrightarrow{like} \times \overrightarrow{milk}\right)^T$. In this experiment,

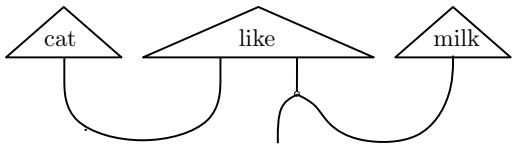
again, the Frobenius model are more suitable in practice. The final vector is the addition of two vectors from CpSubj and CpObj. In the CpSubj case, the derivation of "cat likes milk" is:

$$
\begin{aligned}
&\left(\mu_N \otimes \epsilon^l\right) \left[\overrightarrow{cat} \otimes \overrightarrow{like} \otimes \overrightarrow{milk}\right] \\
&= \left(\mu_N \otimes \epsilon_l\right) \left[\left(\sum_i m_{\mathrm{i}} \overrightarrow{n_i}\right) \otimes \left(\sum_{ik} P_{ik} \overrightarrow{n_i} \otimes \overrightarrow{n_k}\right) \otimes \left(\sum_k v_k \overrightarrow{n_k}\right)\right] \\
&= \left(\mu_N \otimes \epsilon^l\right) \left[\sum_{ijk} P_i k m_i v_{\mathrm{k}} \overrightarrow{n_{\mathrm{i}}} \otimes \overrightarrow{n_{\mathrm{i}}} \otimes \overrightarrow{n_{\mathrm{k}}} \otimes \overrightarrow{n_{\mathrm{k}}}\right] \\
&= \sum_{ik} P_{ik} m_i v_k \mu_N \left(\overrightarrow{n_{\mathrm{i}}} \otimes \overrightarrow{n_{\mathrm{i}}}\right) \otimes \epsilon_N^l \left(\overrightarrow{n_k} \otimes \overrightarrow{n_k}\right) \\
&= \sum_{ik} P_{ik} m_k v_k \overrightarrow{n_i} \otimes 1 \\
&\cong \sum_{ik} P_{ik} m_i v_k \overrightarrow{n_i} \\
&= \overrightarrow{cat} \odot \left(\overrightarrow{like} \times \overrightarrow{milk}\right)^T
\end{aligned}
$$

The graphical calculus is presented beblow:



The CpObj case is similar to CpSbj in that it is copying the object "wire". The detailed calculation is omitted, the graphical calculus is presented here:



3.3.3 Adjectives and intransitive verbs

An adjective can be thought as a noun modifier. It has the Pregroup type nn^l, which expects a noun on its right. Assuming the noun being modified lives in space N, then the linear map that produces the vector for the phrase from the vectors for the noun in an adjective phrase is:

$$f = 1_{\mathrm{N}} \otimes \epsilon_N^l$$

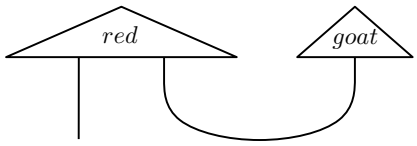
Take a very simple example phrase "red goat", given a fixed basis $\{\overrightarrow{n_i}\}_i$, the two words can be represented by:

$$\overrightarrow{red} = \sum_{ij} A_{ij} \overrightarrow{n_i} \otimes \overrightarrow{n_j}$$
$$\overrightarrow{goat} = \sum_{j} m_j \overrightarrow{n_j}$$

By applying the linear map f to the meaning space of the adjective phrase, the result can be derived in the following way:

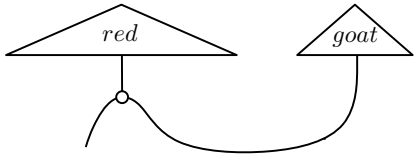
$$\begin{aligned}
&\left(I_N \otimes \epsilon_N^l\right) \left[\overrightarrow{red} \otimes \overrightarrow{goat}\right] \\
=&\left(I_N \otimes \epsilon_N^l\right) \left[\left(\sum_{ij} A_{ij} \overrightarrow{n_i} \otimes \overrightarrow{n_j}\right) \otimes \left(\sum_{j} m_j \overrightarrow{n_j}\right)\right] \\
=&\left(I_N \otimes \epsilon_N^l\right) \left[\sum_{ij} A_{ij} m_j \overrightarrow{n_i} \otimes \overrightarrow{n_j} \otimes \overrightarrow{n_j}\right] \\
=&\sum_{ij} A_{ij} m_j I_N\left(\overrightarrow{n_i}\right) \otimes \epsilon_N^l\left(\overrightarrow{n_j} \otimes \overrightarrow{n_j}\right) \\
=&\sum_{ij} A_{ij} m_j \overrightarrow{n_i} \otimes \langle \overrightarrow{n_j} | \overrightarrow{n_j} \rangle \\
=&\sum_{ij} A_{ij} m_j \overrightarrow{n_i} \otimes 1 \\
=&\overrightarrow{red} \times \overrightarrow{goat}^T
\end{aligned}$$

Graphically, it can be depicted as:

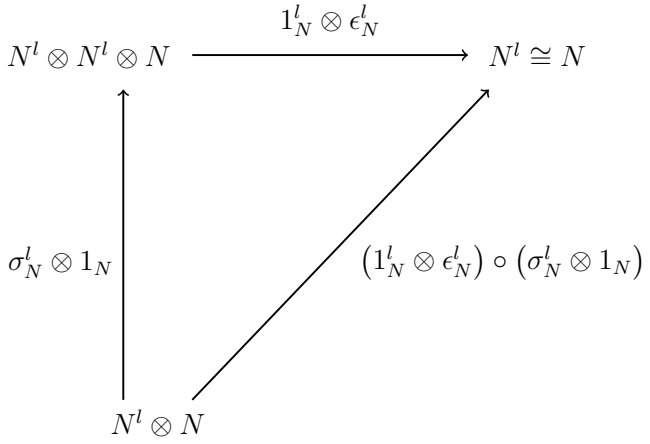


In the model, I created the adjectives using $\overrightarrow{adj} = \sum_i \overrightarrow{w_i}$, where each $\overrightarrow{w_i}$ is one word modified by this adjective in the corpus, and the equation is summing over all such word vectors. This will create a vector of order 1

for the adjective at the end. Therefore, in order to create a true "matrix" for adjectives, Frobenius operator σ map is used again to "copy" the vector and make it a diagonal matrix. Then the matrix can be applied to the noun. Graphically, this process can be depicted as following:



The details of derivation is not shown here, the reader can easily verify that the final result is $\overrightarrow{red} \times \overrightarrow{goat}$, where the vector $\overrightarrow{red}$ here is a diagonal matrix. Use a commutative diagram, this process is:



Intransitive verbs have the same rule as adjectives in a sentence or a noun phrase, except that it occurs on its subject's right, thus it has pregroup type $n^r n$. It modifies a noun and act as a linear map of order-2. The model for an intransitive verb can be easily drawn based on the adjective's model described above.

3.3.4 Adverbs

Adverbs are more "free" (and more complicated) because there are many positions in a sentence where an adverb can occur. Adverbs occupying different positions will have different types. For a specific example, see (Lambek 2008, page 32) [21]. In general, an adverb can be modifying an adjective, a verb,

a preposition or a sentence, depending on where the adverb occurs in that sentence.

Take an intransitive verb-modifying adverb for an example: the adverb has type $(n^r s)^r (n^r s) \to s^r n^{rr} n^r s$ if it is on the right side of the verb; it has type $(n^r s)(n^r s)^l \to n^r s s^l n$. Adjective-modifying adverbs have similar types. Here an adverb is a order-4 tensor in **FVect**. When an adverb is modifying a transitive verb, it is a order-6 tenor.

An adverb can also be a sentence modifier. In this case, an adverb can have type $s^r s$ or $s s^l$, depending on which side of the sentence this adverb appears. Since a sentence is instantiated on a basic vector, an adverb is a matrix in this case.

One interesting simplification that is worth noticing is from Lambek [20][22]. It assigns an adverb a basic type α. Any other word modified by an adverb is thus reduced to its own type: give a word of any type t, $t\alpha \leq t$ and $\alpha t \leq t$ [20]. However, this does not give us freedom in terms of vector spaces, since the type α can represent tensors of different orders in a real sentence depending on what it modifies.

A order-4 or a order-6 tensor is not feasible to build in practice because of the training time and space requirements. We need some simplification on adverbs. First of all, verb-modifying adverbs are not considered in this project. From the dataset, there are a few adjective-modifying adverbs and sentence-modifying adverbs. We will only consider these two here.

It is worth trying to create tensors of different orders for different types of adverbs. However, in this project, I took a simpler approach: use bag-of-words model locally. An adverb is "restristing" information because it usually confines the meaning of a word or a phrase it modifies. Therefore, I use the multiplicative model here because of its information non-increasing property. To train an adverb's vector $\overrightarrow{adv}$, simply add all words' vectors $\overrightarrow{w_i}$ this adverb modifies directly: $\overrightarrow{adv} = \sum_i \overrightarrow{w_i}$. In terms of an adjective modifying adverb, we can think of the process of multiplication a "matrix point-wise multiplication", where the adverb and adjective's matrices are both diagonal matrices. Thus it reduces to two vectors' point-wise multiplication. For example, a sentence "a very thin thread" has "very thin" first represented as a adverb modified adjective, a new adjective vector for "very thin" is first created by point-wise multiplying the two words' vectors, then it is used to modify the noun "thread". In terms of a sentence modifying adverb, we can think of the process

of multiplication a vector point-wise multiplication. For example, a sentence "Quickly, we believed him". In this case, the final sentence vector created can be point-wise multiplication of the adverb "quickly" and the vector of the sentence "we believed him".

3.3.5 Compound verb

In real sentences, compound verbs are often used. There are different types of compound verbs. Here I give a few examples:

- Prepositional verbs: "rely on", "climb over". Here the prepositions are acting as normal prepositions and they are used together with verbs to apply on particular objects.
- Phrasal verbs: "break down", "work out". Here the prepositions are acting like adverbs.
- A compound single word as a verb: "water-proof"
- Verbs with Auxiliaries: Examples are "am thinking", "have been doing".

In the first two cases, a transitive verb-modifying preposition has type $(n^r sn^l)^r(n^r sn^l)$. It is a order-6 tensor in **FVect**. Again I did a simplification by using the additive model on such cases locally. Both a transitive verb and a preposition live in the same order-3 tensor space as linear maps. Therefore, I treat a prepositional verb as a new verb that is close to both to the verb and the preposition. Similar to the adverbs, for simplification, vector addition is used here. For example, the vector for the prepositional verb "rely on" will be $(\overrightarrow{rely} + \overrightarrow{on})$. There are a few prepositional verbs and phrasal verbs in the experimental dataset.

A compound single word is treated as a single verb in this project. If such a verb occurs in the BNC corpus, it will be considered as one word, therefore it makes no difference from a normal verb.

Verbs with auxiliaries are not considered in this research.

3.3.6 Relative pronouns

The work of (Sadrzadeh et. al) [30][31] gave a very detailed explanation in their two papers to model relative pronouns. In the first paper, subject and

object relative pronouns were modeled [30], in the second paper, possessive relative pronouns were modeled [31]. In this research, I followed the models as these two papers suggested. Here I repeat the outline of how these models work, using the table below (Sbj refers to subject relative pronouns, Obj refers to object relative pronouns, Poss Subj refers to possessive subject relative pronouns, Poss Obj refers to possessive object relative pronouns, ϵ, η are maps of compact closed category and $\sigma, \mu, \vartheta, \xi$ are maps of Frobenius algebra introduced in the background chapter, 's is a map of type $N \to N$ that sends a subject/object to its owner):

	pregroup type	meaning space	corresponding morphism
Sbj	$n^r n s^l n$	$N \otimes N \otimes S \otimes N$	$(1_N \otimes \mu_N \otimes \xi_S \otimes 1_N)$ $\circ (\eta_N \otimes \eta_N)$
Obj	$n^r n n^{ll} s^l$	$N \otimes N \otimes N \otimes S$	$(1_N \otimes \mu_N \otimes 1_N \otimes \xi_S)$ $\circ (\eta_N \otimes \eta_N)$
Poss Subj	$n^r n s^l n n^l$	$N \otimes N \otimes S \otimes N \otimes N$	$\mu_N \circ (1_N \otimes' s)$ $\circ (1_N \otimes \mu_N \otimes \vartheta_S \otimes \epsilon_N)$
Poss Obj	$n^r n n^{ll} s^l n^l$	$N \otimes N \otimes N \otimes S \otimes N$	$\mu_N \circ ('s \otimes 1_N)$ $\circ (\epsilon_N \otimes \vartheta_S \otimes \mu_N \otimes 1_N)$

Table 3.1: Categorical models for relative pronouns

For details and graphical calculus, refer to (Sadrzadeh et. al) [30][31].

3.3.7 Disjunctions and conjunctions

Conjunctions are phrases connected by "and" or its equivalent words/notations, disjunctions are phrases connected by "or", comma or their equivalent words/ notations. Conjunction phrases are like "and" in logic, which is information restricting (non-increasing); disjunction phrases are like "or" in logic, which is information adding (non-decreasing). I created conjunction phrases' semantic vectors using vector point-wise multiplication, and disjunction phrases' semantic vectors using vector addition.

For example, vector for a phrase "dogs and cats" can be constructed in the following way:

$$\overrightarrow{dogs\ and\ cats} = \overrightarrow{dogs} \odot \overrightarrow{cats}$$

A disjunction phrase "year, month, hour" can be constructed in the following way:

$$\overrightarrow{year\ month\ hour} = \overrightarrow{year} + \overrightarrow{month} + \overrightarrow{hour}$$

I consider a conjunction/disjunction phrase as a "compound" word/phrase that is an average of all the individual components in it. Therefore, vector point-wise multiplication and addition for such phrases inside a categorical framework is reasonable in practice.

3.3.8 Sentence vs. phrase

In all the above discussions, we assumed that we were mostly working on sentences: the types finally reduce to sentence type s. In the experiment, all definitions from the dictionary are essentially noun phrases since they are defining nouns. The only difference we are going to make, is to replace s type with n type when it is necessary.

3.4 Implementation of a practical categorical model

This section will introduce how the relational word vectors were trained from the British National Corpus (BNC), then outline the specific way in this project to parse sentences/phrases so that the evaluation can be performed accurately. Lastly, I will introduce the algorithm that takes the parse information for a sentence, and computes the sentence vector.

3.4.1 Corpus for training

There are multiple large English corpus available for facilitating Computational Linguistics/NLP tasks. I adopted the British National Corpus (BNC), with CCG (combinatory categorial grammar) parsing information [1]. The BNC has about 100 million words, selected from a wide range of written and spoken

[1] This corpus data was given by Dimitri Kartsaklis and Edward Grefenstette from the Computational Linguistics Group of Oxford University Computer Science Department.

sources. The version I obtained is a CCG parsed BNC corpus available at the Computational Linguistics Group of Oxford Computer Science Department. CCG is very similar to pregoup grammars in structure, and additional information is given in the corpus to help identify the words' types and relations.

3.4.2 Train transitive verb matrices

A matrix for a transitive verb was trained by summing all subject/object tensors with which the transitive verb appeared in the corpus: $\sum_i subject_i \otimes object_i$. This can be achieved by a simple algorithm. However scanning through the BNC and constructing the matrices is time consuming. When the 2000-dimensional word vectors are used, the space for each verb's matrix is huge. Because the nature of this project is an evaluation of the categorical model, I only need to create matrices for less than 200 verbs. The strategy used in the training process was to store every verb's matrix in a separate file to avoid a single, oversized file (shelve file) for all verb matrices. However, this will not be practical in any real-world applications, thus reducing the dimensionality of the word vector space is a necessary task (e.g. performing non-negative matrix factorization). If the dimension of the word vectors is 300, then the size of a matrix is reduced from 2000^2 to 300^2 in terms of the number of entries.

3.4.3 "Direct tensor": another way to create transitive verb's tensor

Instead creating a transitive verb's tensor using the method introduced in previous subsection, there is a simple way. For each transitive verb v in the semantic word vector space, its matrix can be directly created by $v \otimes v$. This approach gave different but consistent results. As shown in the experimental work chapter, I will denote this method as "VT-Direct" and denote the method introduced in the previous section as "VT-BNC".

3.4.4 Train preposition matrices

Training noun-modifying preposition matrices was very much like training transitive verb matrices. The two nouns on the two sides of a preposition

have same rules as the subject and the object of a transitive verb. Thus training process was exactly the same as training transitive verb matrices.

3.4.5 Train adjective/adverb vectors

A vector for an adjective was trained by summing all nouns' vectors with which the adjective appears in the corpus: $\sum_i noun_i$. A vector for an adverb is trained by summing all words' vectors with which the adverb appears in the corpus: $\sum_i word_i$ [19].

3.4.6 Train intransitive verb vectors

An intransitive verb's vector is also trained in a similar way: summing all subjects with which the intransitive verb appears in the corpus: $\sum_i subject_i$.

3.4.7 Adding once vs. adding all

When training all these vector and tensor spaces for relational words, there are two different methods. Take a transitive verb's matrix as an example: a transitive verb's matrix is the sum over all the tensors of subject/object pairs in a corpus, $\sum_i subject_i \otimes object_i$. One approach is to add tensor of each pair $(subject_i, object_i)$ only once, the other approach is to add tensors of all pairs, regardless of how many times the pair appears in the corpus. I suspected that the first approach would give different results since the vectors created would be different. However some intermediate experiments showed that the two approaches gave very similar performance under this experimental setting. Thus in the final experiment, I used the second approach because it takes less time to train.

3.4.8 Parse arbitrary sentences for the categorical model

Before using the categorical model to produce the vector for a sentence, parsing is an essential step because the information of how a sentence is composed is required. In particular, the parse should reflect how the words should be composed so that the types in the sentence can be reduced grammatically. There are many parsers available, such as the C&C parser developed by Curran et al. [8], which can produce CCG parse tree for a given sentence. CCG

is very close to pregroups grammar, thus a CCG parse can be converted to pregroup grammar. However, all parsers suffer from inaccuracy, and in many cases they produce wrong parse.

As we need to carefully evaluate the performance of the categorical model, and compare it to other models, inaccurate/wrong parse for a sentence is not acceptable. Therefore, I used a simple notation to parse sentences, and later I parsed all definitions used in this experiment by hand to guarantee accuracy.

This part will provide an introduction to this notation. Based on the methodology introduced in the previous chapter, there are the following operations in this simple notation system:

1. Inner product as tensor contraction operation of an order-3 relational word. This is denoted by "|" in the sentence parse information.

2. Point-wise multiplication as tensor contraction operation of an order-2 relational word. This is denoted by "*" in the parse information. Notably, there is no "point-wise multiplication" in the theoretical framework, but under the Frobenius setting, a matrix for an order-2 relational word is essentially a diagonal matrix. Therefore, the inner product of such a matrix with a vector will be equal to point-wise multiplication of the diagonal vector for the relational word, and the order-1 word vector being modified. Point-wise multiplication for conjunctions and adverbs is also denoted by "*".

3. Addition for disjunctions and compound verbs, denoted by "+".

There are a few additional remarks on notations:

1. Every word is associated with a type, separated by "#"

2. Every sentence is recursively parsed. In the parse tree, the root is "Final", non-leaf nodes are named in capital characters, and leaf nodes are the words in the phrase.

3. Each node in the parse tree is separated by "!!".

4. Each string after "=" only contains one kind of operation.

5. Determinators and quantifiers are not taken into consideration.

Given a sentence, the parse of this sentence can be denoted as a recursive structure. Here is one simple example of an adjective phrase:

Term: *fibre (noun)*
Definition: *a thin thread*
Parse: *Final=very#d*thin#a*thread#n*

A more complicated example involves some recursive structure:

Term: *bank (noun)*
Definition: *the ground near the edge of a river, canal, or lake*
Parse: *A=river#n+canal#n+lake#n!!B=edge#n|of#p|A!!Final=ground#n|near#p|B*

3.4.9 Recursive sentences vs. non-recursive sentences

In this paper, a **recursive sentence** is a sentence which cannot be parsed without using the notation recursively; a **non-recursive sentence** is a sentence which can be parsed without using the notation recursively. The purpose of this differentiation to evaluate the categorical model's performance on simple and complex sentences later.

3.4.10 Algorithm to calculate a sentence vector

Based on the helper notation and methodologies introduced in section 3.4.8, the following algorithms are proposed to calculate a sentence's vector.

The algorithm ***p*arse** takes in a sentence's parse information, and a string of the parse of current node, denoted by the notation in the previous section, returns a vector. It assumes that a word semantic vector space and relational words' tensor spaces are ready to use. The body of this algorithm first looks at the input string, which is the compositional information of current level in a parse tree. For example, *A=river#n+canal#n+lake#n* in the previous example, or the root *Final=ground#n|near#p|B*. If it is a single word, then the algorithm returns a vector or a tensor according to its type; if it is a phrase, the algorithm will first determine which kind of phrase it is, then call itself recursively to return a proper vector. The algorithm follows the models

explained in the methodology chapter, except that I omitted the 's map in the cases of possessive subject relative pronoun and possessive object relative pronoun, because the training was not successful. However it will be shown in the experimental work chapter that the practical model still gave significantly better results.

Another algorithm ***s*enVec**, takes the string of a sentence's parse tree, and calls ***p*arse** on the root of this parse tree. It returns the vector for the sentence.

I used Python's numpy, scipy, and shelve libraries to construct this algorithm.

Algorithm: senVec

Data: A string of a sentence's parse *s*p
Result: the vector of the sentence
Body:
get a dictionary from the parse *s*p as pDic
return *parse(pDic['Final'], pDic)*

Algorithm 1: Construct a dictionary of parse information and return a vector for an arbitrary sentence

Algorithm: parse
Data: cStr: parse of current node in parse tree, pDic: dictionary of parse
Result: the vector at this level of parse tree
Body:
if *cStr is a primitive word type* **then**
  switch *cStr type* **do**
    According to the phrase's type, return the word's vector or tensor
  endsw
end
if *cStr represents a transitive verb phrase* **then**
  get subject phrase (subj), verb phrase (verb), object phrase (obj) from pDic
  return $parse\,(subj, pDic) \odot (parse\,(verb, pDic) \times parse\,(obj, pDic))^T +$
  $(parse\,(subj, pDic) \times parse\,(verb, pDic)) \odot parse\,(subj, pDic)^T$
end
if *cStr represents an adjective phrase* **then**
  get the adjective (adj) and the noun phrase (np) being modified by the adjective from pDic
  return $parse\,(np, pDic) \odot parse\,(adj, pDic)$
end
if *cStr represents an adverb phrase* **then**
  get the adverb (adv) and the verb phrase (vp) being modified by the adjective from pDic
  return $parse\,(vp, pDic) \odot parse\,(adv, pDic)$
end
if *cStr represents a preposition verb phrase* **then**
  get subject left phrase (psubj), preposition phrase (prep), right phrase (pobj) from pDic
  return $parse\,(psubj, pDic) \odot (parse\,(prep, pDic) \times parse\,(pobj, pDic))^T +$
  $(parse\,(psubj, pDic) \times parse\,(prep, pDic)) \odot parse\,(psubj, pDic)^T$
end
if *cStr represents a conjunction phrase* **then**
  get an array of sub phrases p_i from pDic
  return $\sum_i parse\,(p_i, pDic)$
end
if *cStr represents a disjunction phrase* **then**
  get an array of sub phrases p_i from pDic
  return $\prod_i parse\,(p_i, pDic)$
end
if *cStr represents a subject relative pronoun phrase* **then**
  get subject phrase (subj), verb phrase (verb), object phrase (obj) from pDic
  return $parse\,(subj, pDic) \odot (parse\,(verb, pDic) \times parse\,(obj, pDic))^T$
end
if *cStr represents an object relative pronoun phrase* **then**
  get subject phrase (subj), verb phrase (verb), object phrase (obj) from pDic
  return $(parse\,(subj, pDic) \times parse\,(verb, pDic)) \odot parse\,(subj, pDic)^T$
end
if *cStr represents a possessive subject relative pronoun phrase* **then**
  get possessor phrase (poss), subject noun phrase (subj), verb phrase (verb), object noun phrase (obj) from pDic
  return $parse\,(poss, pDic) \odot parse\,(subj, pDic) \odot$
  $(parse\,(verb, pDic) \times parse\,(obj, pDic))^T$
end
if *cStr represents a possessive object relative pronoun phrase* **then**
  get possessor phrase (poss), subject noun phrase (subj), verb phrase (verb), object noun phrase (obj) from pDic
  return $parse\,(poss, pDic) \odot (parse\,(subj, pDic) \times parse\,(verb, pDic)) \odot$
  $parse\,(subj, pDic)^T$
end

Algorithm 2: Parse and return vector on each level of parse tree

Chapter 4

Experimental work

4.1 A term-definition classification task

The experimental work of this research is based on a term-definition classification task first introduced by Kartsaklis et al. [19] to match terms with phrases. In their paper 112 terms from the Oxford Junior Dictionary were extracted. Each term in the dataset contains three definitions from the Oxford Junior Dictionary itself [32], the Oxford Concise School Dictionary, and the WordNet [19]. The task was to treat terms as classes, and use cosine distance as similarity. Finally, a definition is assigned to the term which is most similar (smallest cosine distance). The results were evaluated by calculating the accuracy of the classification task. Nouns and verbs with very simple definitions were evaluated in their experiment, and the categorical model was scored slightly higher than the baseline models.

In this experiment, I used the mean reciprocal rank (MRR) in addition to accuracy. MRR gives more objective results, it considers "how good" the vectors are instead of just looking at how many definitions are matched exactly. This experiment involves larger datasets, therefore MRR is necessary to give a good idea for each model's overall performance.

4.2 Extract datasets for evaluation

In this experiment, I extracted data only from the Oxford Junior Dictionary, and all terms are nouns; therefore all definitions are noun phrases. There are thousands of words in the dictionary; each word contains at least one

definition. I used a collection of 221 nouns' term-definition pairs randomly extracted from the dictionary, and each term only keeps one definition. I classified the definition phrases into two types: non-recursive phrases and recursive phrases as introduced in section 3.4.9.

Examples of non-recursive phrases are "a particular thing" and "woman who rules a country". They are non-recursive because "a particular thing" is a direct composition of an adjective "particular" and a noun "thing", where "particular" is an adjective that expects one argument on its right; and "woman who rules a country" is a direct composition of "woman", "rules" and "country", where "rules" is a transitive verb that expects two arguments. Examples of recursive phrases are "a lot of loud noise" and "a big party with a lot of dancing". The first phrase has "loud noise" and then "a lot of loud noise"; the second phrase has "a big party", "a lot of dancing", and the two parts get composed as "a big party with a lot of dancing".

There are 104 term-definition pairs containing non-recursive (simple) phrases and 77 term-definition pairs containing recursive (complex) phrases. Some additional term-definition pairs are added to this dataset to create a unified evaluation at the end.

I also created datasets for a few specific cases in order to evaluate the categorical model on different types of relational words under the current experimental setting. Specifically, subject/object relative pronoun phrases, preposition phrases, transitive verb phrases and adjective phrases. They are mostly simple (non-recursive) phrases. There are not enough non-recursive phrases for disjunctions, conjunctions and adverbs to extract from the dictionary dataset I obtained; therefore the specific evaluation on these three types of words is not performed in this experiment.

The datasets are available in the Appendix.

4.3 Baseline evaluation methods

This section introduces the baseline methods of creating vectors for phrases and sentences: the additive model, the multiplicative model, and a head word model.

4.3.1 An additive model

In the additive model, a sentence vector is created by adding all the order-1 word vectors from the sentence. In practice, the additive model can add all word vectors in a sentence. However, because of the stop words (very frequent words) and some insignificant words (words not contributing to the meaning of a sentence, such as prepositions, logical words, etc.), adding all words might not give good results. The reason is that stop words occur so frequently that they can be with any other words. For example, "very", "is", and "of" can appear everywhere in an article. Their vectors will have similar numbers for each entry element, which means the they will not contribute much about the meaning of a sentence overall. Instead, adding these vectors could reduce the accuracy of the sentence vector produced.

In the actual experiment I conducted, the sentence was first preprocessed to remove all stop words and insignificant words (such as determinators). The model then adds the rest words' vectors to produce a sentence vector.

4.3.2 A multiplicative model

In the multiplicative model, a sentence vector is created by point-wise multiplying all the order-1 word vectors in the sentence. Again in practice, the multiplicative model can point-wise multiply all word vectors in a sentence. However, the stop words and insignificant words will not contribute to the sentence vector positively. In the actual experiment, stop words and insignificant words were dropped.

4.3.3 Head word of sentence

In some cases, the head word of a sentence is most significant and could stand in a position that best represents a sentence. One good example is a the term-definition pair, "coach" and "bus that takes people", where "bus" is already very close to "coach". This is obviously not always true. For example, consider the term-definition pair, "clerk" and "someone who writes letters". The word "someone" in some case would not be a good representative for the term "clerk". The head word model surely does not capture all the important information of the sentence. However, this method is nevertheless a trivial baseline method.

4.4 Experimental results

With all the theoretical preparations and experimental settings, this section presents the main results from the experiment. For all the tables presented in this section, "CM" is short for the categorical model, "AM" is short for the additive model, "HM" is short for the head-word model, "MM" is short for the multiplicative model. If the transitive verb tensors are created from the BNC (section 3.4.2), I denote it as "VT-BNC" in the table's caption; If the transitive verb tensors are created using the method in section 3.4.3, I denote it as "VT-Direct" in a table's caption.

4.4.1 Evaluate relative pronouns

The first experiment is about subject, object, and possessive relative pronouns. From the Oxford Junior Dictionary and (Sadrzadeh et al.) [30][31], 10 possessive relative pronoun phrases, 10 object relative pronoun phrases, and 16 subject relative pronoun phrases are extracted. They are all simple phrases and most of them don't have recursive sentence structures. The result is presented in the tables below. Results in Table 4.1 Table 4.2, and Table 4.3 show scores using verb vectors trained from the BNC. Table 4.4, Table 4.5, and Table 4.6 show the results using the method suggested in section 3.4.3.

	CM	AM	HM	MM
Accuracy	**6/10**	5/10	4/10	**6/10**
Accuracy	**0.60**	0.50	0.40	**0.60**
MRR	0.7458	0.6736	0.5025	**0.7750**

Table 4.1: Possessive relative pronoun, VT-BNC, 10 pairs

	CM	AM	HM	MM
Hits	3/10	6/10	2/10	**7/10**
Accuracy	0.30	0.60	0.20	**0.70**
MRR	0.5000	0.7144	0.4035	**0.8000**

Table 4.2: Object relative pronoun, VT-BNC, 10 pairs

	CM	AM	HM	MM
Hits	**7/16**	5/16	6/16	6/16
Accuracy	**0.44**	0.31	0.38	0.38
MRR	0.5699	0.5262	0.5051	**0.5563**

Table 4.3: Subject relative pronoun, VT-BNC, 16 pairs

	CM	AM	HM	MM
Hits	**7/10**	5/10	4/10	6/10
Accuracy	**0.70**	0.50	0.40	0.60
MRR	**0.8167**	0.6736	0.5025	0.7750

Table 4.4: Possessive relative pronoun, VT-Direct, 10 pairs

	CM	AM	HM	MM
Hits	**8/10**	6/10	2/10	7/10
Accuracy	**0.80**	0.60	0.20	0.70
MRR	**0.8750**	0.7144	0.4035	0.8000

Table 4.5: Object relative pronoun, VT-Direct, 10 pairs

	CM	AM	HM	MM
Hits	**6/16**	5/16	**6/16**	**6/16**
Accuracy	**0.38**	0.31	**0.38**	**0.38**
MRR	0.5509	0.5262	0.5051	**0.5563**

Table 4.6: Subject relative pronoun, VT-Direct, 16 pairs

4.4.2 Evaluate adjectives

An adjective's vector is trained from the BNC by adding all nouns modified by it. The result shows that with the current setting, the categorical model does not perform outstandingly from other models; instead, it gives similar results to the bag-of-words models. In addition, the categorical model, together with the additive and multiplicative models, outperform the head word model. This shows the non-triviality of the categorical model (Table 4.7).

	CM	AM	HM	MM
Hits	14/31	**15/31**	7/31	14/31
Accuracy	0.45	**0.48**	0.23	0.45
MRR	0.6079	**0.6169**	0.3866	0.6122

Table 4.7: Adjective vectors trained from the BNC, 31 pairs

4.4.3 Evaluate prepositions

Preposition vectors are trained from the BNC corpus, as described in the methodology chapter. The result shows that the accuracy and MRR of the categorical model is only slightly higher than other models, but the difference is not significant (Table 4.8).

	CM	AM	HM	MM
Hits	**9/37**	7/37	**9/37**	**9/37**
Accuracy	**0.24**	0.19	**0.24**	**0.24**
MRR	**0.4030**	0.3584	0.3140	0.4017

Table 4.8: Preposition vectors trained from the BNC, 37 pairs

4.4.4 A mixed evaluation on non-recursive phrases

This experiment is mixing all terms defined by relative pronoun phrases, adjective phrases, and preposition phrases. They are all simple phrases, and most of them do not contain any recursive structure.

The reason of this experiment is that, by mixing different types of words, the experiment shows whether the vectors computed from the models work as well as the case that only single type of phrases appear. The final result shows that the categorical model gives better overall results. Again, since there are verb phrases, two different ways of creating verb vectors are evaluated here, and they give similar results (Table 4.9, Table 4.10).

4.4.5 An evaluation on recursive phrases

77 pairs of terms and definitions are selected from the Oxford Junior Dictionary. All of these terms' definitions have recursive structures. Using the

	CM	AM	HM	MM
Hits	**25/104**	20/104	15/104	23/104
Accuracy	**0.24**	0.19	0.14	0.22
MRR	0.3445	0.3238	0.2128	**0.3461**

Table 4.9: Mixed evaluation on 104 simple phrases, VT-BNC

	CM	AM	HM	MM
Hits	**25/104**	20/104	15/104	23/104
Accuracy	**0.24**	0.19	0.14	0.22
MRR	**0.3481**	0.3238	0.2128	0.3461

Table 4.10: Mixed evaluation on 104 simple phrases, VT-Direct

algorithm introduced in section 3.4.10, a phrase of a definition can be decomposed recursively to build a vector for the definition phrase. In this section I show that although the categorical model has shown better performance (or at least non-trivial performance) on the simple phrases, it is outperformed by the bag-of-words models in this case (Table 4.11, Table 4.12). Also notably, the additive model has similar performance with the multiplicative model, given the word vector space in this experiment setting.

	CM	AM	HM	MM
Hits	10/77	**12/77**	10/77	**12/77**
Accuracy	0.13	**0.16**	0.13	**0.16**
MRR	0.2441	0.2585	0.2134	**0.2956**

Table 4.11: Recursive phrases, VT-BNC, 77 pairs

	CM	AM	HM	MM
Hits	9/77	**12/77**	10/77	**12/77**
Accuracy	0.12	**0.16**	0.13	**0.16**
MRR	0.2363	0.2585	0.2134	**0.2956**

Table 4.12: Recursive phrases, VT-Direct, 77 pairs

4.4.6 An overall evaluation

Finally, there is an overall evaluation involving all pairs mentioned above, and some additional pairs extracted from the dictionary. The result shows that the categorical model gives slightly lower results than the bag-of-word models in MRR, and gives lower accuracy. However it is not significant (Table 4.13, Table 4.14).

	CM	AM	HM	MM
Hits	21/221	**28/221**	24/221	26/221
Accuracy	0.10	**0.13**	0.11	0.12
MRR	0.1854	0.2150	0.1648	**0.2346**

Table 4.13: 221 terms, VT-BNC

	CM	AM	HM	MM
Hits	22/221	**28/221**	24/221	26/221
Accuracy	0.10	**0.13**	0.11	0.12
MRR	0.1870	0.2150	0.1648	**0.2346**

Table 4.14: 221 terms, VT-Direct

Chapter 5

Discussion

5.1 Overall performance of the categorical model

The primary objective of this research is to give a unified evaluation for the categorical compositional-distributional model. With the current experimental setting, there are a few observations:

1. The categorical model is non-trivial: the results show that the categorical model outperforms the head-word baseline. This is as expected because the head-word baseline model is only a vague and sometimes inaccurate approximation to the meaning of a whole phrase. It is expected that the categorical model, the additive model, and the multiplicative model give better results, because they take more information into account from a phrase.

2. The categorical model gives better performance on non-recursive phrases (i.e. simple phrases). I expected that the categorical model gives better results than any other bag-of-words baseline models because the categorical model not only considers individual words' meaning, but also considers the compositional information in the phrase. It treats relational words as multi-linear maps and compose the vectors in a meaningful way. The experiment also shows that the categorical model does not give significantly better results (rather, it is just a bit better than the additive model and the multiplicative model). I suspect that this is because of the simplification during the training of relational words' vectors: I used the Frobenius algebra operation σ to expand a vector

to a diagonal matrix, this matrix is obviously lack of information to represent because of the zero entries in the matrix.

3. The categorical model is outperformed by the baseline models on recursive phrases (i.e. complex phrases), the disadvantage is not significant as well. I suspect that the inaccuracy is amplified during the long chain of matrix/vector operations. This can be seen from the fact that unlike other experiments, the head-word model gives similar results to other models. The inaccuracy-amplification could make the additive/multiplicative/categorical models perform worse on these phrases than on the simple cases.

Besides these observations and analysis, there are also a few interesting discoveries worth mentioning. I will discuss them in the following sections.

5.2 Vectors with negative values

I conducted experiments on two neural vector spaces. The vector space developed by Turian gave very low accuracy and MRR on all models, therefore the result is not very suggestive. The Word2Vec vectors gave good results on additive model in the term-definition classification task. However, it gives bad results on multiplicative model. As the categorical model essentially involves a large amount of multiplication operations, it also gives bad results.

The table below shows one experiment using the Word2Vec vectors as semantic word vectors, relational word tensors are trained from the BNC. The dataset is a collection of 59 term-definition pairs. The result (Table 5.1) shows that the multiplicative model and the categorical model give poor accuracy and MRR.

	CM	AM	HM	MM
Hits	0/59	**27/59**	8/59	6/59
Accuracy	0.00	**0.46**	0.14	0.10
MRR	0.07	**0.60**	0.24	0.17

Table 5.1: Performance of the Word2Vec vectors

I suspect that the negative results these neural vectors give is because the neural vectors have negative values, and vectors with negative values cannot

present good results after vector point-wise multiplication, because the values are drastically changed after the multiplication. This is intuitive because the categorical model involves tensor contraction (inner product) and vector point-wise multiplication in this experimental setting. When the multiplications are performed, the sentence vectors after calculation are never accurate to represent the meaning of the phrases.

Thus with similar experiment settings, it is suggested to use semantic vectors that contain only positive numbers.

5.3 The role of abstract words

During the experiment, I suspected that the performance of the categorical model and other distributional models was affected negatively by the occurrence of abstract (or vague) words (such as "people", "someone", "thing"), because such a word is so frequent that its vector contains almost equal numbers. When such a vector is used in the models, it will not contribute to the results, instead, it lowers the performance.

To test this idea, two smaller datasets were extracted from the 221 pairs in the experiment. One dataset contains 21 terms that are defined by abstract (vague) words and frequent words. The other dataset contains 21 terms that are defined by very specific (but not very frequent) words. These two datasets are also available in the Appendix.

The result shows that my speculation is indeed the case. The following two tables (Table 5.2, Table 5.3) show that the models are sensitive to "vague" and "specific" words, and the categorical model gives more significantly better result on terms defined by "specific" words.

	CM	AM	HM	MM
Hits	**12/21**	10/21	6/21	11/21
Accuracy	**0.57**	0.48	0.29	0.52
MRR	**0.674**	0.601	0.478	0.639

Table 5.2: Phrases of "specific" words, VT-BNC

	CM	AM	HM	MM
Hits	**6/21**	5/21	2/21	6/21
Accuracy	**0.29**	0.24	0.10	**0.29**
MRR	0.411	0.388	0.226	**0.446**

Table 5.3: Phrases of "vague" words, VT-BNC

Chapter 6

Future work

6.1 Further investigation into phrases of "vague" and "specific" words

One immediate task that could be done is to expand datasets of phrases of "vague" words and phrases of "specific" words. A large scale evaluation of this could help the understanding of the performance of distributional models over different types of words, and especially how the categorical model reacts on the difference.

6.2 Negative phrases

Negative phrases and sentences are not discussed in this work. However negative phrases are not unusual. (Coecke et al.) [6] has already modeled negative sentences within the categorical framework. An effective way of evaluating how the categorical model performs on negative phrases and sentences is necessary.

6.3 Reduce size of semantic word vector space

As stated previously, under the experimental setting of this project, only vector spaces containing positive numbers can be used because they work on multiplication and inner product. The vector is 2000-dimension, taking more than 5Gb space on disk (as a shelve database). When training relational

word vectors, a matrix for one relational word can take up to 1Gb space on disk. Even for evaluation task, this is over sized. Any attempt to reduce the size of semantic word space is plausible. One possible attempt is to perform non-negative matrix factorization on the vector space to produce a word vector space of lower dimensionality while preserving its performance on word similarity comparison.

6.4 Other ways of training relational word vectors

The relational words' representations are created using a tensor based approach in this project, and the tensors are created directly from the BNC corpus. However, this approach only creates tensors that are 1-order less than it should be. For example, an adjective's vector is created by adding all nouns' vectors modified by the adjective in the corpus. The result is a order-1 vector instead of a matrix. The Frobenius algebra copy operation creates a diagonal matrix, which might not contain enough information for how the adjective is modifying other nouns. Same for a transitive verb, the outcome is a matrix instead of a "cube", hence Frobenius algebra copy operation is used to expand it to a cube. However the cube only has non-zero numbers on its diagonal plane, which again might not be a complete representation of a transitive verb.

However, the tensor-based approach in the experiment cannot create a adjective matrix or a transitive verb "cube" easily, because there is no information to represent the extra order. Some machine learning techniques can be used to create complete "matrices" and "cubes".

Chapter 7

Conclusion

A practical categorical model was instantiated on concrete distributional models in this research. It could compute vectors for complex sentences and phrases based on the categorical model of sentence meaning. A dataset for large-scale evaluation was extracted from the Oxford Junior Dictionary. Based on the practical model and the evaluation dataset, a large scale, generic evaluation was performed. The experimental results has been giving valuable insights into the practice of building distributional models and especially, building categorical models. Future practical models and experiments can be set up based on this work.

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Appendix

Dictionary data for evaluation

Table 1: Phrases with recursive structures

#	term	definition
1	annual	a plant which lives only one year
2	balloon	a small, coloured, rubber bag that you can blow up
3	band	a group of people who play music together
4	blast	a sudden wind, a rush of air
5	board	a long, thin piece of wood
6	bonnet	the part of a car that covers the engine
7	ball	a big party with a lot of dancing
8	bank	the ground near the edge of a river, canal, or lake
9	block	a thick piece of something hard and solid
10	calf	a young cow, elephant, or whale
11	chalk	a kind of soft, white rock
12	chapel	a kind of small church
13	cheek	rude behaviour or speech
14	chest	a big, strong box
15	churn	a large container for milk
16	circle	a round shape like a ring or a wheel
17	cloud	dust or smoke that looks like a cloud
18	conductor	someone who sells tickets on a bus
19	cone	a case for seeds of evergreen trees
20	country	a land with its own people and laws
21	crack	a sudden, loud noise
22	cricket	an insect that makes a shrill sound
23	crystal	a small, hard, shiny piece of something

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Table 1 – *Continued from previous page*

#	term	definition
24	enemy	the people fighting against you
25	energy	the power that comes from coal, electricity, and gas
26	eye	the small hole in a needle
27	fibre	a very thin thread
28	file	a collection of information on a computer
29	force	strength, power, violence
30	fraction	a small part of something
31	funnel	a chimney on a ship or steam engine
32	gear	part of a bicycle or car
33	hemisphere	one half of the earth
34	hip	a red berry on a rose
35	horn	a brass musical instrument that You blow into
36	jaw	the lower part of the face
37	joint	a large piece of meat
38	knight	a man in armour who rode into battle on a horse
39	mass	a large number or amount
40	needle	a very thin, pointed leaf
41	officer	a policeman or policewoman
42	orange	the colour of this fruit
43	pack	a group of dogs or wolves
44	patch	a small piece of something
45	peace	a time free for war
46	pilot	someone who steers a ship in narrow, difficult places
47	plan	a map of a building or a town
48	point	the sharp end of something
49	princess	the daughter of a king or queen
50	programme	a talk, play, or show on the radio or television
51	property	a house or other building with land around it
52	prophet	a great religious teacher
53	racket	a lot of loud noise
54	rally	a race for cars or motorcycles
55	result	the score or marks at the end of a game, competition, or test
56	roll	a very small loaf of bread
57	room	enough space for something
58	scent	a liquid with a sweet smell

Continued on next page

Table 1 – *Continued from previous page*

#	term	definition
59	scooter	a motorbike with a small engine
60	service	a meeting in church with prayers and singing
61	shower	a short fall of rain or snow
62	shutter	a wooden cover that fits over a window
63	skin	the outer covering of your body
64	space	the area or distance between things
65	station	a building for policemen or firemen
66	stick	a long, thin piece of wood
67	straw	dry stalks of corn
68	survey	a careful look at something
69	tank	a large container for liquid
70	tip	the part at the end of something
71	title	the name of a book, film, picture, or piece of music
72	tragedy	a play with a very sad ending
73	tube	a long, thin, round container
74	video	a videotape with a film or television programmes on it
75	volume	one of a set of books
76	wall	one of the sides of a building or room
77	youth	a boy or young man

Table 2: 104 simple phrases, mostly non-recursive

#	term	definition
1	article	a particular thing
2	beast	a big animal
3	boar	a male pig
4	break	a short rest
5	cabin	a small hut
6	card	thick paper
7	chart	a big map
8	fat	greasy meat
9	fiber	a thin thread
10	glory	great fame
11	hall	a big room
12	heaven	a happy place

Continued on next page

Table 2 – *Continued from previous page*

#	term	definition
13	hint	a useful idea
14	inspector	an important policeman
15	iron	a strong metal
16	jet	a fast aeroplane
17	labour	hard work
18	lane	a narrow road
19	line	a long mark
20	noise	an unpleasant sound
21	note	a short letter
22	perfume	a nice smell
23	place	a particular area
24	pouch	a small bag
25	shaft	a thin pole
26	sponge	a soft cake
27	spot	a round mark
28	star	a famous singer
29	stream	a small river
30	trail	a rough path
31	scrap	a small piece
32	article	a piece of writing
33	bazaar	a market in Africa
34	beam	a line of light
35	area	a part of a place
36	bar	a long piece of wood
37	bow	a knot with loops
38	brow	the top of a hill
39	character	someone in a story
40	chestnut	a kind of tree
41	child	a son or daughter
42	code	a set of rules
43	composition	a piece of music
44	cotton	thread for sewing
45	course	a series of lessons
46	dummy	a model of a person
47	entry	a way into place

Continued on next page

Table 2 – *Continued from previous page*

#	term	definition
48	figure	the shape of a body
49	foot	a measure of length
50	fortune	a lot of money
51	hardware	the machinery of a computer
52	head	the person in charge
53	lock	a piece of hair
54	machinery	the parts of a machine
55	peak	the top of a mountain
56	pound	a measure for weight
57	prisoner	someone in prison
58	pyramid	the shape of a pyramid
59	rock	a sort of music
60	sale	the selling of things
61	scene	part of a play
62	shot	the firing of a gun
63	speech	the power of speaking
64	stone	a measure for weight
65	vision	a kind of dream
66	yard	a measure for length
67	centre	the middle of something
68	charge	the cost of something
69	dance	a party where people dance
70	den	a place where an animal lives
71	gum	a sweet that you chew
72	idea	something that you have thought of
73	idol	a person that people love
74	sight	something that you see
75	sole	fish that you eat
76	view	everything that you see
77	football	game that boy like
78	skirt	garment that woman wear
79	boot	shoe that covers the ankle
80	clerk	someone who writes letters
81	coach	a bus that takes people
82	coat	the fur that covers an animal

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Table 2 – *Continued from previous page*

#	term	definition
83	draught	air that blows into a room
84	fan	something that blows air
85	groom	a person who looks after horses
86	group	people who play music
87	landlord	a person who looks after a hotel
88	mark	a stain, spot, or line that spoils something
89	ruler	someone who rules a country
90	writing	something that you have written
91	emperor	person who rule empire
92	queen	woman who reign country
93	plug	plastic which stop water
94	carnivore	animal who eat meat
95	widow	woman whose husband die
96	orphan	child whose parent die
97	teacher	person whose job educate children
98	comedian	artist whose joke entertain people
99	priest	clergy whose sermon people follow
100	commander	military whose order marine obey
101	clown	entertainer whose trick people enjoy
102	assistant	person whose job help boss
103	inspector	someone whose job check things
104	model	someone whose job wear clothes

Table 3: Some additional entires

#	term	definition
1	bill	a bird's leak
2	bug	an insect
3	cab	a taxi
4	cap	a lid
5	case	a container
6	choice	choosing
7	dash	a hurried rush
8	disc	a record
9	flight	an escape

Continued on next page

Table 3 – *Continued from previous page*

#	term	definition
10	fringe	an edge
11	ground	the earth
12	kid	a young goat
13	kiosk	a telephone box
14	land	a country
15	lord	a nobleman
16	lump	a swelling
17	marriage	a wedding
18	mate	a friend
19	mill	gentle
20	pace	a step
21	paper	a newspaper
22	plane	an aeroplane
23	power	strength
24	project	a plan
25	rail	a bar or rod
26	reception	a welcome
27	remain	ruins
28	ring	a circle
29	row	a quarrel
30	rubbish	nonsense
31	scholar	a pupil
32	score	twenty
33	side	an edge
34	spirit	a ghost
35	standard	a flag
36	sum	an amount
37	sweet	very pleasant
38	time	seconds, minutes, hours, days, weeks, months, years
39	term	a word or phrase
40	track	a path
41	unit	the number one
42	business	a shop or firm or industry

Table 4: Phrases that contain "vague words"

#	term	definition
1	article	a particular thing
2	place	a particular area
3	article	a piece of writing
4	area	a part of a place
5	character	someone in a story
6	chestnut	a kind of tree
7	dummy	a model of a person
8	entry	a way into place
9	fortune	a lot of money
10	head	the person in charge
11	lock	a piece of hair
12	machinery	the parts of a machine
13	prisoner	someone in prison
14	rock	a sort of music
15	scene	part of a play
16	vision	a kind of dream
17	centre	the middle of something
18	idol	a person that people love
19	sight	something that you see
20	view	everything that you see
21	clerk	someone who writes letters

Table 5: Phrases that contain "specific words"

#	term	definition
1	boar	a male pig
2	fiber	a thin thread
3	hint	a useful idea
4	iron	a strong metal
5	yet	a fast aeroplane
6	lane	a narrow road
7	perfume	a nice smell
8	bow	a knot with loops
9	cotton	thread for sewing

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Table 5 – *Continued from previous page*

#	**term**	**definition**
10	hardware	the machinery of a computer
11	shot	the firing of a gun
12	skirt	garment that woman wear
13	boot	shoe that covers the ankle
14	queen	woman who reign country
15	carnivore	animal who eat meat
16	widow	woman whose husband die
17	orphan	child whose parent die
18	comedian	artist whose joke entertain people
19	commander	military whose order marine obey
20	clown	entertainer whose trick people enjoy
21	model	someone whose job wear clothes