Semantic Holism and Word Representations in Artificial Neural Networks

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Abstract. Artificial neural networks are a state-of-the-art solution for many problems in natural language processing. What can we learn about language and meaning from the way artificial neural networks represent it? Word representations obtained from the Skip-gram variant of the word2vec model exhibit interesting semantic properties. This is usually explained by referring to the general distributional hypothesis, which states that the meaning of the word is given by the contexts where it occurs. We propose a more specific approach based on Frege’s holistic and functional approach to meaning. Taking Tugendhat’s formal reinterpretation of Frege’s work as a starting point, we demonstrate that it is analogous to the process of training the Skip-gram model and offers a possible explanation of its semantic properties.

1 INTRODUCTION

Meaning is, therefore, something that words have in sentences; and it’s something that sentences have in a language. [8] On the other hand, meaning could also be something that words have on their own, with sentences being compositions and language a collection of words. This is the question of semantic holism versus atomism, which was important in the philosophy of language in the second half of the 20th century and has not been satisfyingly answered yet.

Artificial neural networks are the state-of-the-art solution for many problems in natural language processing (and machine learning in general). They produce word representation with interesting properties, but the way they work is little understood from the perspective of linguistics or the philosophy of language.

We believe that by finding parallels between concepts in AI and the philosophy of language, we can better understand both areas.

In this paper, we present an analogy between meaning defined as truth-value potential (a reformulation of Fregean holistic and functional approach) and a variant of language representation model, therefore pointing out a possibility that its striking syntactic and semantic properties [18] are formed due to adhering to holistic principles.

1.1 Related work

We have found only one work concerning the philosophical aspects of neural language models [14]. It is, however, concentrating on Self-Organizing Maps and Quine’s version of semantic holism.

There are papers showing that Skip-gram with negative sampling is implicitly a factorization of a word-context matrix (e.g. [15], although this result was later contested by various authors, such as [1] and [21]), or deriving the equations in an alternative way [11] (discussed more in Section 3). This may tell us something about the model, but it does not answer the principal question: why should the matrix factorized in a certain way contain semantic information?

2 SEMANTIC HOLISM AND ATOMISM

Semantic holism (or meaning holism) is the thesis that what a linguistic expression means depends on its relations to many or all other expressions within the same totality. […] The totality in question may be the language to which the expressions belong, or a theory formulation in that language. [19] The opposing view is called semantic atomism, and it claims that there are expressions (typically words), whose meaning does not depend on the meaning of other expressions. The meaning of these expressions is given by something outside language (e.g. their relation to physical or mental objects).

In the following sections, we will specify the implications of both alternatives for semantics. The question also plays a role in cognitive science (content identity and similarity), epistemology (commensurability of theories) and seems to be strongly connected with the analytic/synthetic distinction [8].

There are other positions in between these two, such as semantic molecularism or the belief that neither relations external nor internal are primary in forming meaning. However, to keep this text simple, we will only concentrate on extreme positions. We will also only talk about words, although the same argument can be used with smaller meaningful language units (e.g. parts of a compound word).

Our goal is not to assess whether the truth lies with holism, atomism or neither of them. We will only show that holism is a useful perspective when understanding neural language models is concerned.

Before we get into details of the two perspectives, let us point out two critical aspects of their difference: holism proclaims inter-dependence of meanings of words, contrary to their independence in atomism. And holism favours decomposition over composition.

2.1 Atomism

It is a widely held view that much of the history of the philosophy of language consists of a failed attempt to make semantic atomism work. [8 p. 32]

Atomism played an important role in analytic philosophy, starting with Bertrand Russell’s logical atomism and continuing with logical positivism, as exemplified in this quote by Carnap [3]:

A language consists of a vocabulary and a syntax, i.e. a set of words which have meanings and rules of sentence formation. These rules indicate how sentences may be formed out of the various sorts of words.
For logical positivists, words have meaning, because they refer to objects (be it physical, sensual, logical, mathematical or other). The rules of composition determine the meaning of sentences (and rule out senseless sequences of words).

Under this (or similar) view, the fact that words refer to the outside world is presupposed. Their references are independent of each other (that dog refers to dog is independent of that horse refers to horse). There is strong emphasis on compositionality, that reached its peak in Chomskian linguistics and is still relevant today.

Crucially, this means that a word can have meaning on its own (e.g. by referring to something). The meaning of larger units, such as sentences, is derived by the rules of composition from the meaning of words.

### 2.2 Holism

Semantic holism acccents the interdependence of meaning. The whole (language, theory, . . .) is the primary vehicle of meaning. The meaning of smaller units is derived by decomposition.

This view is motivated by the same word having a different meaning in a different context. Gottlob Frege has shown that even such seemingly unambiguous words as numbers play distinct roles in different situations: 5 is a prime number and there are 5 cows on the meadow are different at least in that the first 5 signifies a complete (abstract) object, while the second one needs to be supplemented with information that it is cattle of which there are 5 specimens, otherwise the expression would not be grammatical.

Frege promoted what we could call sentence holism: Only in the context of a sentence does a word have a meaning. We will later use its modern reformulation to show an analogy with certain neural language models and therefore their holistic character.

Another group of arguments for holism consist of variations on the theme of impossibility of knowing or using a word without being able to use other words. For example, it could be argued that a person could not correctly use the word mammal, without also knowing (at least some of) bird, animal and kinds of animals. Therefore the meaning of words cannot be formed in isolation.

Something that is harder to explain under holism than under atomism is the fact that words refer to objects. If the meaning of words is given by other words, how is it connected to the world around us? However, not all words refer to something. And even if subscribing to holism makes explaining reference harder, it may be because it is a hard problem to explain.

Another thing that is simpler under atomism is compositionality. While in atomism it plays a central role as one of the presupposed properties of language, holism may not need it. But it does not claim that words do not have meaning at all, only that it is derived (by some sort of decomposition) from the meaning of the whole.

### 3 WORD REPRESENTATIONS IN AI

Although all artificial neural networks that work with language must have some way of representing it, the most interesting representations come from neural language models. Language modelling is a task of predicting a missing word from a sequence or generating text. There is also a similar class of models that are designed specifically to produce representations of language units, which we will call neural language representation models.

The representations (also called embeddings) are high dimensional vectors of real numbers. They are either learned together with the rest of the network for the particular task or pretrained by a general language representation model (typically on a larger dataset not specific for the task).

Some neural language (representation) models produce representation with semantic properties, although the task of language modeling itself is not (at least at the first sight) directly connected with semantics and no explicit semantic annotation is given to the neural network.

These semantic properties became popular with the invention of the word2vec software and the Skip-gram model, whose author said about it:

The model itself has no knowledge of syntax or morphology or semantics. Remarkably, training such a purely lexical model to maximize likelihood will induce word representations with striking syntactic and semantic properties.

However, they did not present any explanation of the phenomenon. Goldberg and Levy present a detailed derivation of the central equation of the Skip-gram model. In the last section they say:

Why does this produce good word representations?

Good question. We don’t really know.

The distributional hypothesis states that words in similar contexts have similar meanings. The objective [of the Skip-gram model] clearly tries to increase the [dot product of the context and the word representations] for good word-context pairs, and decrease it for bad ones. Intuitively, this means that words that share many contexts will be similar to each other (note also that contexts sharing many words will also be similar to each other).

This is, however, very hand-wavy. Can we make this intuition more precise? We’d really like to see something more formal.

We believe that the implicit holistic component of this hand-wavy approach is central to the quality of Skip-gram representations and we can make the intuition more precise by analogy with the definition of the truth-value potential.

![Figure 1. Examples of embeddings semantic relations according to [13].](image)

#### 3.1 Semantic properties of the Skip-Gram model

The Skip-gram model was introduced by Tom Mikolov et al. as a method to efficiently train word embeddings. It exceeded state-of-the-art in various semantic tasks. The embeddings have interesting semantic properties, most notably the vector arithmetic illustrated by Figure and the following equation:

\[ v_{\text{king}} - v_{\text{man}} + v_{\text{woman}} \approx v_{\text{queen}}. \]

meaning that starting with the word king, if we subtract the vector for the word man and add the vector for the word woman, the nearest vector in the embedding space will be the one that corresponds to the word queen. This means that queen is to woman as king is to man.
Hollis et al. [13] show that it is possible to infer various psycholinguistic and semantic properties of words from the Skip-gram embeddings. Mikolov et al. [17] also trained the Skip-gram model with phrases, resulting in even simpler and more elegant equations, such as

\[ v_{\text{Germany}} + v_{\text{capital}} \approx v_{\text{Berlin}}. \]

Mikolov et al. [16] proposed another shallow neural language model, Continuous Bag of Words (CBOW). The main difference between CBOW and Skip-gram (see Figure 2) is that while Skip-gram predicts context words from a given word, CBOW predicts a word from a given context.

![Figure 2. CBOW and Skip-gram language models according to [16].](image)

## 4 RELEVANT THEORIES OF MEANING

In this section, we discuss theories of meaning that are relevant to word representations in artificial neural networks. Notice that even though they strictly speaking do not require meaning holism, they all lean towards it quite strongly.

### 4.1 The distributional hypothesis

Holism is generally a better alternative in cases where there is nothing beside language itself to anchor meaning to. This is the case of neural language (representation) models. If they represent meaning at all, it must be derived from the training corpus. This may be the reason behind the popularity of the distributional hypothesis in neural language model literature. The famous saying by Firth [7], “You shall know a word by the company it keeps!”, is quoted in majority of papers concerned with vector space models of language.

The general distributional hypothesis states that the meaning of a word is given by the contexts in which it occurs. It is, however, worth noticing that in Firth’s theory, collocation is just one among multiple levels of meaning and his text does not support the idea of meaning based on context alone.

A more suitable formulation of the distributional hypothesis (referred in connection to Skip-gram in [21]) is found in Distributional structure [12], where it is suggested that distribution may be used for comparing meanings and that difference of meaning correlates with difference of distribution.

Although this certainly describes a basic principle of neural language models, it is still rather vague.

### 4.2 The use theory of meaning

The use theory of meaning can be summed up as the meaning of a word is its use in the language [22] §43. It is associated with late Wittgenstein’s concept of language game. In *Philosophical Investigations* [22] §§499–500, he writes:

To say “This combination of words makes no sense” excludes it from the sphere of language and thereby bounds the domain of language. […] When a sentence is called senseless, it is not as if it were its sense that is senseless. But a combination of words is being excluded from the language, withdrawn from circulation.

This bounding of the domain of language is precisely what language model does, therefore the use theory may be one way to connect language modelling and semantics.

That knowledge of language emerges from language use is also one of main hypotheses of cognitive linguistics [4].

### 4.3 Structuralism

In structuralism [5], the meaning of a word is given by its relation to the other words of the language:

The elements of a structure have neither extrinsic designation, nor intrinsic signification. Then what is left? […] [N]othing other than a sense […] a sense which is necessarily and uniquely positional. [6]

This holds for word representations in artificial neural networks as well. The vectors representing the words do not have any other meaning than their position among the rest of the vectors and a single vector does not have any significance outside the model. This is also demonstrated by the vectors being different every time the model is trained because of random initialization.

### 5 SKIP-GRAM AND TRUTH-VALUE POTENTIAL

In this section, we introduce the truth-value potential and show that Skip-gram corresponds to it better than CBOW.

#### 5.1 The truth-value potential

Tugendhat’s compact reformulation of Frege’s sentence holism, the definition of meaning as truth-value potential is [20]:

\[ T(\phi) = T(\psi) \iff \forall x : T(x(\phi)) = T(x(\psi)), \]

where \( T \) is the truth-value potential (meaning), \( M \) is the truth-value of the sentence and \( x(\omega) \) is the result of completing the expression \( \omega \) by the expression \( x \) to form a sentence.

One important aspect of this definition is that, following Frege [10], it is based on an assumption that the sentence (or rather the corresponding judgement) is the basic unit of meaning.

#### 5.2 Word2vec models and semantic holism

The definition of meaning as truth-value potential is analogous to the process of training a model for word representations. One difference is that when we are training a model, we do not have the whole of language at our disposal. Even after approximating the language with a finite corpus, it still is not practical to compare all the contexts for
a given word at the same time, therefore the universal quantifier has to be replaced by an iterative process of examining the contexts one by one (or actually batch by batch, which is a step back towards the totality that is being estimated). And we have no means to assess whether the sentences from the corpus are true or false. We can either assume that they are mostly true, or try to replace the concept of truth with something else (maybe language use). Even the first option seems to be enough—imagine a corpus full of false sentences about cats, e.g. Cats can fly., Cats are cetaceans. etc. We cannot expect the representation of the word cats in a model trained on this corpus to be any good, therefore the requirement for the corpus to consist mostly of true sentences is not excessive.

The simplest model that corresponds to this analogy is the Skip-gram model. It does just what is described in the definition – it fixes a word and goes through all the possible contexts. It compares the words based on the context. The context words are predicted and their representations are fixed (in a single training step), while the representation of a single word is learned. By learning the representation of a word from the representation of the context, Skip-gram complies to the principles of semantic holism. The analogy between the definition of truth-value potential and the process of training the Skip-gram model is one possible explanation for its semantic properties and its performance in semantic tasks.

The complementary CBOW architecture (see Figure 2) performs much worse in the evaluation of the semantic tasks [19]. In CBOW, a missing word is predicted from its context. Therefore, in a single learning step, the representation of the missing word is fixed. What changes (and is learned) is the representation of the context words. By learning the representation of the context from the representation of the word, CBOW is implicitly conforming to semantic atomism: words are the basic units of meaning and the meaning of the broader context is derived from the atomic meaning of words. This may be the reason why CBOW does not exhibit the same semantic properties as Skip-gram and it performs worse in semantic tasks.

6 CONCLUSION AND FUTURE WORK

The distributional hypothesis as an explanation for the semantic properties of neural language models should be expanded into a more detailed account. We show one possible way to do that via a Fregean approach to meaning.

Both the distributional hypothesis itself and Tugendhat’s interpretation of Frege’s work are examples of holistic approaches to meaning, where the meaning of the whole determines the meaning of parts. As we demonstrated on the opposition between Skip-gram and CBOW models, the distinction between semantic holism and atomism may play an essential role in semantic properties of neural language representations models.

We have demonstrated the connection between the Skip-gram model and the definition of meaning as truth-value potential. Although this is an isolated observation of an analogy between a specific model and a specific theory about meaning, it is a crucial step towards finding a theory of meaning that would correspond to the current results of NLP research, increasing our understanding of NLP and ultimately the language itself.

The direction of research from successful language technologies to properties of language itself offers many opportunities for inquiry, with very few being explored so far.

Many state-of-the-art models for natural language processing use smaller units than words for their input and output. This analysis could be extended to take this into account.