Towards Vector Space Models of Semantics and the Semiotic Textology

Some Relations between Recent Advances in Computational Linguistics and Semiotic Textology

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1 Introduction

One of the main characteristics of Semiotic Textology[1] (and, in general, all the theoretical framework developed by János S. Petöfi) is its integrative character. As he declared, his aim was always to establish and to elaborate "a conception that claims to represent an *integrative theoretical framework*" [17]. From the first works on co-textual text linguistics to the last developments of the Semiotic Textology, Petöfi was integrating in a single theoretical framework the last developments on linguistics, philosophy of language or semiotics.

The relationships between Petöfi's theory and computation are not strange nor extraordinary. As all of you probably know, his background was not only modern linguistics and literature but mathematics. From time to time, as Petöfi recognizes, he was "interested in the relationship between *computer linguistics and text theoretical research*". In fact, during the sixties and seventies he published several papers in the emerging field of Computational Linguistics [17].[2]

During the last years, a new computational approach to language interpretation and understanding has emerged: the Vector Space Models of Semantics [23]. From an engineering point of view, these models are computationally efficient and useful for many tasks ; from a linguistic point of view, they are based on a well-known linguistic framework: the distributional hypothesis [13]. Moreover, recent experiments are showing their reliability in psychology and cognitive science, as well as their usefulness in several applications as machine translations, automatic thesaurus construction or document retrieval [7, 1, 4].

The distributional approach based on vector space models is totally different from the traditional formal approach. Formal semantic approaches are based mainly on first-order logic and they are able to represent the meaning of complex expressions through the principle of compositionality. Distributional models are based on vectors, matrix and lineal algebra, and

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[1] I will follow [15] as main reference. In several sections, without claiming to be exhaustive, I will cite the Petöfi's original reference. I will assume that the reader knows the Semiotic Textology theory. Therefore, only specific aspects of the theory will be explained.

[2] For example, [16] is nowadays available at the ACL-Anthology: a web site that includes all the major papers presented at the Association of Computational Linguistics and related events from early years (1967) to the present: `https://www.aclweb.org/anthology/`.

they can properly deal with the contextual meaning of words in large corpora and the similarity between words.

Like other researchers, I am persuaded that both approaches are compatible. Indeed, during the last five years several proposals try to combine both approaches, developing compositional-distributional semantic models [14, 6, 5, 2, 1, 12].

Taking in mind the integrative nature of the Semiotic Textology, the question I want to deal with in this paper is whether it is possible to integrate vector space models of semantics in the formal framework of Semiotic Textology. Apart from the fact that Semiotic Textology follows the principle of compositionality, as far as I know none of the compositional-distributional models proposed thus far have taken into account textual structure: all of them are focused on sentences. Hence, if it is possible to develop this integration, Semiotic Textology could be seen as the general textual framework for Vector Space Models of (Distributional) Semantics.

In the next section I will present briefly the main features of vector space models. Then I will show how this integration works in three aspects of the Semiotic Textology: first, the distributional meaning in the component *sensus*; second, the similarity as an interpretation process and the bases of interpretation; and third, the vector space models and the multimediality of text. I will conclude with the main ideas.

2 A brief sketch of Vector Space Models of Semantics

In this section I will briefly introduce Vector Space Models of Semantics and explain how they represent the meaning of a text.[3]

Vector Space Models of Semantics are based on three theoretical assumptions [5]:[4]

1. The Wittgenstein (1953) idea that "meaning just is use" [24];

2. The concept of collocation of Firth (1957) [9] and the idea that "you shall know a word by the company it keeps";

3. and the distributional hypothesis of Harris (1968): words will occur in similar contexts if and only if they have similar meanings [13].

[3]See [23] for a survey.

[4]In this paper I will refer to this meaning (based on the use and the context) as "distributional meaning".

The main idea of Vector Space Models is to represent the context of words in real texts. The relation between context and word is carried out by a matrix. Each row of the matrix corresponds to a word and each column to a context. The value of the matrix is a number that measures the weight of each word in each context. See Figure 2

	drive	street
car	7	6
taxi	5	6
train	6	1

Table 1: Example of a toy vector space.

For example, if "car", "taxi" and "train" are words and "street" and "drive" represent contexts,[5] their distributional meaning could be represented as the matrix of Table 2. In this matrix there are three vectors of dimension two.[6]

One of the main advantages of vector spaces is that it is easy to calculate the similarity between two vectors. For example, Figure 1, which represents the same vector space in a cartesian plane, shows clearly how the distance between the vectors of "car" and "taxi" is smaller than the distance between "car" and "train". Mathematically, it is possible to know the distance between two vectors by the cosine of the angle formed by them.[7]

Therefore, the context in which "car" is used is more similar to the context of "taxi" than to the context of "train". In other words, due to the fact that these vectors represent distributional meanings, it is possible to conclude that the meaning of "car" has more similarity to "taxi" than to "train".

In Figure 1 it is easy to see the similarity between vectors because it represents only two possible contexts ("drive" and "street"). It is a 2-dimensional vector space. A real vector space is n-dimensional: there is one dimension for each possible context. As human beings, we cannot see more than three dimensions. However, mathematically we can know the similarity between two vectors in a n-dimensional space. Even though

[5] That is: they are words that could appear in the context of words like "car", "taxi" or "train".

[6] In order to clearly represent vectors, I will use not the weight but the words with a weight higher than 0. Therefore, the vector of the word "car" is `<street, drive>` and the vector of the word "train" is `<drive>`.

[7] This is the Cosine Distance. There are other distance metrics as Euclidean Distance.

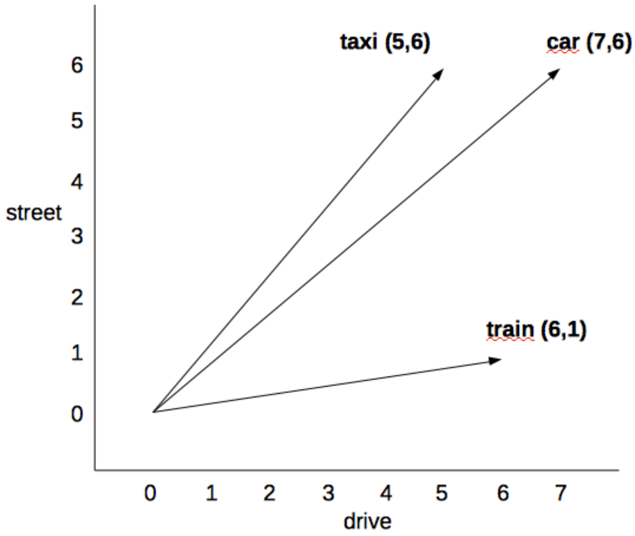

Figure 1: Graphical representation of a vector space.

we cannot see an n-dimensional space, we can know if two n-dimensional vectors are more or less similar applying the same similarity metrics.[8]

From a linguistic point of view, the main implications of vector space models of semantics are as follows:

- More than the meaning, vector spaces represent all the linguistic contexts (or cotext) in which a word could appear and where it is interpreted.
- An n-dimensional vector space is a representation, not the interpretation.
- The process of interpretation in a semantic vector model is based on the similarity (or distance) between two words or expressions.
- Unlike formal logic-based approaches to semantics, which use an atomic and unambiguous semantic representation of words or texts, vector

[8]From a linguistic point of view, it is relevant how the context is defined. It is possible to specify a large context as, for example, the document (term-document matrix) or more specific contexts as the paragraph, the sentence or even only the phrases [23]. In this paper I will assume that the context is the sentence, but there are other possibilities. It is also important how the weight of each word in each context is computed. It used to be the frequency of the word in the context normalized in a real number between 0 and 1, but there are other posibilites. This is a question about I will say nothing in this paper. See [23].

space models of semantics allow us to deal with diffuse aspects of meaning, with frequencies and probabilities.

3 Towards an integration of Vector Space Models in a Semiotic Textology framework.

Assuming these ideas, I will now show how, in my opinion, vector space model of meaning could be integrated in the Semiotic Textology framework. I will present three connection points:

1. the relation between the distributional meaning based on vector spaces and the verbal conceptual *sensus* (both *sistemicus* and *contextualis*);
2. the relation between the similarity as an interpretative process and the bases of interpretation;
3. the relation between the vector space models and the *Relatum Imago* on one hand, and the multimediality of communication on the other hand.

3.1 The verbal conceptual *sensus* and the Vector Space Models of (Distributional) Semantics.

Vector Space Models assume that the distributional meaning is THE meaning of words: they establish a direct relation between word meaning and a point in the vector space. This idea appears in many proposals such as [6, 5, 8, 1].

Analyzing these models from the point of view of Semiotic Textology, we find out that they are ignoring the complex structure of the text. The model of meaning assumed in these approaches is quite (or too) simple, compared with the complex aspects of verbal and multimedia communication. It is true that, as these distributional vector space models do, it is not possible to specify the meaning of a word or expression without the distributional context facet of the meaning (represented formally as vector space). However, it is true too that with ONLY the distributional contextual facet of the meaning it is not possible to describe or analyze the meaning of words, expressions or texts, as Semiotic Textology shows[9]. The meaning of a word is more complex than a simple distribution of contexts.

In the definition of text as a complex relational sign, Petöfi identifies three facets of the verbal conceptual *sensus*: relational, inferential and configurational [22]. In the canonical language, they are represented as a tuple [20]:

$$L =< P, T, K >$$

The relational aspect P is a single or complex logical proposition. The inferential aspect T represents all the inferences that must be carried out in order to understand correctly an expression or text. Finally, configurational aspect K is related to the specific order in which words and information appear in the text and its implications in the interpretation.

From my point of view, Semantic Vector Models are related to the inferential aspect T. Petöfi explains that there are many types of inferences in the verbal conceptual *sensus* such as, for example, morfosyntactic inferences or syllogism inferences (see [22] for examples). Vector Space Models of Semantics are another example of these kinds of inferences. Therefore, the verbal conceptual *sensus* has a specific facet devoted to the logical formal meaning (P) and another devoted to the distributional meaning (vectors in a semantic space) as an inference (T_d).

In this regard, I think that there is not a direct link between a (single or complex) propositional meaning and a point in a distributional vector semantic space.[10] Rather than being directly linked, both facets of meaning must be compatible: they must be coherent.

All inference is produced from a previous knowledge. In this case, the previous knowledge is the vector space in which all the contexts of a word are represented.

Sensus sistemicus, ***sensus contextualis*** and the Vector Space Model of Semantics.

Petöfi specifies an important difference between *sensus sistemicus* and *sensus contextualis*.[11] *Sensus sistemicus* refers to the set of meanings that

[9]It seems that they have forgotten the linguistic textual model developed during the seventies.

[10]The figurative use of language shows clearly this indirect relationship. In a novel metaphor there is a clear inconsistence between the proposition/lexical meaning os a word and the distributional inference makes over the context.

[11]Also in the *formatio*

each textual element of each *media* can take from its semiotic system. *Sensus contextualis* refers to the specific meaning that a textual unit has in a specific communicative situation [18, 21].

In the vector space model it is possible to differentiate between these two facets of the *sensus*.

The distributional *sensus sistemicus* of a vector space model is an n-dimensional matrix formed by all the possible contexts in which words could appear. As I showed before, each vector in this n-dimensional space represents word contexts.

Theoretically, this matrix is infinite [5, 1]. Due to the fact that the dimensions of the vector space are the contexts in which words could appear, and the amount of possible contexts is theoretically infinite, the dimensions of the vector space are also infinite.

From a cognitive point of view, this vector space is produced by the experience of the speaker [10, 11]. The experience is the cognitive process that allows us to store early linguistic contexts for each word, and register how the language has been used in each context. In this case, the experience stores in a vector space the words than tend to co-occur with other words in the same context.[12]

The *sensus contextualis* is established according to how similar a new contextual vector (a new sentence, for example) is compared to the vector space. The meaning related to the most similar vector in the semantic space is assigned to the new vector as distributional meaning. This is the process of inference as interpretation that I will explain in the next section.

[12]From a computational point of view, the *sensus sistemicus* is the matrix created from a large corpora. This matrix is considered as a sample of the theoretical infinite matrix. Despite the availability of very large corpora, it is impossible to develop a corpus large enough to represent all words and all context, because contexts are infinite. However, bearing in mind the evolution of the Big Data, maybe this practical problem will have a solution in the near future. Anyway, nowadays it is important to demarcate the corpus and its size correctly in order to develop a reliable application of vector space models to languages.

3.2 Similarity as interpretation at the first grade of the descriptive-explicative interpretation.

Similarity as co-textual interpretation.

During the interpretation, the interpreter infers the meaning of a word according to the similarity of its context compared to all the previous contexts in which this word has appeared. From a vectorial point of view, this inference is based on the similarity between the new contextual vector of the word and the previous vectors in the semantic space. The interpretation is coherent if the new context and the previous contexts are in some way similar.[13]

For example, Table 2 represents a possible contextual vector of the word "oasis".[14] When a sentence with the word "oasis" must be interpreted and one or more of these words (the words that constitute the vector) appear in the context, it is possible to infer that the word "oasis" means "an area in the dessert where there is water and where plants grow"[15], as in the sentence number 1.

`arena desierto pozo roca arenas hasta lugar forma dunas cal terreno cerca desiertos encuentran dentro duna grandes ...`

Table 2: Examples of vector for the word "oasis".

(1) En esta ciudad de pequeñas casas de adobe y ladrillo, que se levanta entre la *arena* del *desierto* y el *agua* del **oasis** de Tozeur y que antaño fue parada obligada de las caravanas, Don Juan Carlos y Doña Sofía visitaron el museo de Dar Cherait.

Formally, let $\overrightarrow{v_s}$ be the vector composed of the words in the context of the sentence (`<ladrillo, arena, caravanas, ...>`) and $\overrightarrow{v_w}$ the vector

[13]Similar in the sense of vector similarity. Some threshold θ must be specified in order to decide when a similarity value is strong enough to consider two vectors as similar or dissimilar.

[14]It is only a sample of the complete vector, that has been extracted applying the algorithm Lattent Dirichlet Allocation Topic Modeling [3] to the Spanish Wikipedia Corpus.

[15]*Oxford Advanced Learner's Dictionary* 6th edition

composed of the words of previous contexts in the semantic space (<arena, desierto, pozo, ...>), the inference process is thus based on the similarity (*sim*) between both vectors.

$$T_d = sim(\overrightarrow{v_s}, \overrightarrow{v_w})$$

Specifically, the distributional meaning inferred is the vector in the semantic space that maximized the similarity between the sentence vector $\overrightarrow{v_s}$ and each vector $\overrightarrow{v_{1-n}}$ in the semantic space:

$$T_d = argmax(sim(\overrightarrow{v_s}, \overrightarrow{v_{1-n}}))$$

Therefore, given a new contextual vector, its distributional meaning is the most similar vector in a semantic space. All the linguistic information related to this vector (lexical meaning, implications, etc.) will be assigned to the new vector.

There are several empirical experiments that show how only with the aid of the context of words, a computer is able to predict human similarity judgments between words, develop thesaurus automatically or even detect lexical entailment. From a cognitive point of view, it is related to the "fast mapping": the human capacity to learn (or infer) the meaning of a new word attending only to the word in its context. [1]

However, the meaning of a word or expression is not only its context. There are many other aspects that must be taken into account in a holistic and serious view of meaning, as Semiotic Textology does.[16] The final meaning of a word, expression, sentence or text must combine, between other aspects, the (simple or complex) propositional meaning P and the inferential distributional meaning T_d. I argue, then, that distributional semantics is not the whole meaning of words, phrases and sentences, but it is an important aspect of meaning. The distribution meaning has an important role in the *sensus* of a text.

Similarity and the bases of interpretation.

If we assume that the interpretation process in a vector space model is based on the similarity between vectors, it is necessary to integrate this similarity into the structural descriptive-explicative interpretation developed by

[16] There are some problems that must be deal with in this proposal. For example, the representation of polysemy or the textual implications. These are problems that will be deal with in Future Work.

Semiotic Textology. I will focus mainly on the interpretation at first grade. At the end I will present some aspects of the figurative interpretation.

Petöfi organizes the interpretation according to a set of bases [17, 21]. Each base is a conceptual unit in charge of developing some (general or specific) processes of the interpretation. Each base is formed by three sectors: a set of knowledge, a set of hypothesis and a set of preferences. These three sectors are needed in order to develop the interpretation.

The semantic vector space in which all the previous contexts are stored is a part of these bases. Together with the lexical knowledge (word senses, preference semantics, etc.), each word is associated with the set of contexts in which the word tends to appear. Initially, these contexts are represented by vectors of words.

Due to the fact that this theoretically infinite vector space is general knowledge about the languages (like a verbal semiotic system), it is stored in the General Typological Base (B_{Tp}). It is the first base, the most general one. It includes all the knowledge about communicative situations, *media*, social, cultural and pragmatic aspects, etc. that an interpreter needs in order to carry out any interpretative process. Other proposal assumes that the Vector Space of Semantics is an important part of the lexicon of a speaker [1, 5]. In the framework of Semiotic Textology, the vector space that represents distributional meanings is an important part of the General Typological Base B_{Tp}.

Once an interpreter must interpret a specific *vehiculum* in a specific communicative situation, the Central Base of Interpretation B_I is activated. This base takes from the General Typological Base B_{Tp} all the knowledge needed to interpret this specific *vehiculum*. In order to develop the distributional vector-based inference presented previously, the Central Base of Interpretation B_I must contain a subspace of the general theoretically infinite vector space. This subspace is formed by all the contextual vectors related to each word of the *vehiculum*. As a subspace of a general vector space, it has the same dimension n of the vector space, but only has the rows related to each word of the *vehiculum*. Accordingly, this subspace is also theoretically infinite.

The Central Base of Interpretation B_I controls the action of each local base. Each of them carries out a specific step of the interpretative process. The vector subspace with the distributional-contextual meaning of each word is used mainly by the ${}_sB_m$ base. From all the possible meanings of each textual unit (words, etc.), this base selects only those compatible and coherent according to the context (including linguistic context) and the communicative situation (in the opinion of the interpreter). This base creates the *interpretamentum* of the text [21].

Therefore, bearing in mind for now the word as an elemental unit, this base ${}_sB_m$ is the one that applies the inference process based in vector similarity that I pointed out before. It takes the contextual vector of a word in the text and looks for the most similar vector in the subspace that contains all the possible contextual vectors. The distributional meaning of the most similar vector will be assigned to the word in the text. It is a process of inference in the sense that it has been extracted from the previous knowledge about possible contexts stored in the vector space.

Following distributional-compositional models, these similarities are done not only with the words, but with other meso-units (2nd, 3rd degree, etc.) up to, at least, sentence level. The distributional-compositional status of textual units (macro-architecture units) remains open.

It is important to indicate that this distributional meaning inferred from the similarity between the context of a word and previous contexts must be compatible with the other facets of the *sensus*: propositional meaning, other inference or relations, etc. This compatibility is based also on previous experiences, in which specific distributional meaning is related to specific lexical o propositional meaning.

3.3 Vector space models for the representation of the *Relatum Imago* and multimediality

In this last section I will show the connection between Vector Space Models of Semantics as well as the *Relatum Imago* on one hand, and the multimedia aspects of the Semiotic Textology on the other hand. I will deal with both aspects together because both are related to the same (unresolved) problem.

The action of the previous local base ${}_sB_r$ achieves as a result the *interpretamentum*. It is a bi-front module ${}_sM_R$ connecting both the *sensus contextualis* and the *relatum imago*. This *relatum imago* is the mental image of the (real o not) referent expressed in a *vehiculum*. Both aspects of module ${}_sM_R$ must be compatible. The main difference between them is that, when the *sensus contextualis* is organized according to the verbal semiotic system (or any other *media*) (it has a linguistic-medial configuration), the *relatum imago* is organized according to the (real or imaginary) reality. The first one is a part of the *significatum* (a part of the textual sign), the second one is out of the text: it is a part of the image of the world of the interpreter.

Due to the fact that both aspects of this module ${}_{s}M_{R}$ must be compatible, the question is if Semantic Vector Models are able to represent both the *sensus contextualis* and the *relatum imago.* The answer is yes and no.

The specific vector space models I am talking about in this paper are vector spaces of words and word co-ocurrences. These vector spaces are formed by the amount of times two words appear in the same context. Therefore, these models are suitable to represent (a part of) the *sensus contextualis.* However, due to the fact that they use words as basic elements, they are not able to represent the *relatum imago.*

Nevertheless, the Vector Space Models of Semantics based in word co-ocurrence constitute only one option. Vector spaces are used to represent not only word co-ocurrence, but many other social and communicative aspects as well. For example, Peter Gärdenfors' work on Cognitive Science is specially interesting in this regard. He is developing a vector space approach to concepts. He argues that it is possible to model the mental representation of concepts by vector spaces. These vector spaces are not based on word co-ocurrence, but on other dimensions as color, taste, texture, etc. [10, 11]. As a vector space model, the similarity is also an important cognitive process in this proposal.

In this regard, vector spaces could be used as a formal representation of both the *sensus* and the *relatum imago.* The open question is how to combine a word-based vector space with a concept-based vector space.[17]

An important question that remains unanswered in Semiotic Textology is the development of a formal (or canonical) language capable of representing any kind of *media* (text, image, music, etc.) and any kind of *sensus* (*dictum, apperceptum* and *evocatum*) [19]. Vector space models could fulfill in part this *desideratum.*

In Computer Science it is common practice to represent digital images as matrixes (that is, as vector spaces). In fact, the application of vector spaces to texts comes from image processing. The application of vector spaces to music is not evident, but it is possible. The main problem is to define the basic unit of music: the note?, the bar?, the musical phrase? The same problem arises in the Semiotic Textology. Once the main unit is defined, it is possible to use vector space models to represent music.

As regarding the representation of any kind of *sensus* (*dictum, apperceptum* and *evocatum*) with semantic vectors, previously I have referred to the work of Gärdenfors about the representation of concepts with vector

[17] About the problem of how to represent the extensional meaning with vector spaces see also [1, 8]

spaces. This is a possible representation of conceptual *sensus appercetum.* As far as I know, there has not yet been any attempt to represent the non-conceptual*sensus evocatum* with vector spaces. I don't even know whether that is possible. Maybe, if it is possible to represent music with vectors, maybe it will be possible to represent evocations.

At any rate, semantic vectors constitute nowadays a powerful formal approach to different *media*. It is suitable from a computational point of view and flexible to represent different medial aspects from the semiotic point of view.

4 Conclusions

In this paper I have presented a first attempt to combine Vector Spaces Models of Semantics with the theoretical framework of Peöfi's Semiotic Textology. I have shown (I hope) that this integration is not only possible but also is an enrichment contribution both to Semiotic Textology and to Vector Space Models of Semantics.

I know that in this paper I have left many questions open: many aspects than must be developed deeply, both theoretically and empirically.

As a general theory of text and multimedia communication, Semiotic Textology is a suitable theoretical framework for the Vector Space Models of Semantics. It avoids the over-simplification in the definition of meaning of these models, showing the complexity of language in particular and multimedia communication in general. Specifically, Semiotic Textology shows the relations that distributional models must establish with propositional meaning, lexical meaning, inferences and relations, other *media* or other kinds of *sensus*, etc.

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