

Distributional Semantics

Distributional semantics develops theories and methods to represent the meaning of natural language expressions, with vectors encoding their statistical distribution in linguistic contexts. It is at once a theoretical model to express meaning, a practical methodology to construct semantic representations, a computational framework for acquiring meaning from language data, and a cognitive hypothesis about the role of language usage in shaping meaning. This book aims to build a common understanding of the theoretical and methodological foundations of distributional semantics. Beginning with its historical origins, the text exemplifies how the distributional approach is implemented in distributional semantic models. The main types of computational models, including modern deep neural language models, are described and evaluated, demonstrating how they address various types of semantic issues. Open problems and challenges are also analyzed. Students and researchers in natural language processing, artificial intelligence, and cognitive science will appreciate this book.

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– James Pustejovsky, Brandeis University

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Preface

What Is Distributional Semantics?

Language is used to convey *meaning*, and meaning is the quintessence of language. In fact, meaning is the “holy grail” (Jackendoff, 2002) of linguistics, philosophy, psychology, and neuroscience, as well as of Natural Language Processing (NLP) and Artificial Intelligence (AI). No research field that has at its center language and its use in communication by human or artificial agents can avoid inquiring into issues such as: What is the meaning of linguistic expressions at different levels of complexity (e.g., words, phrases, sentences, etc.)? How can meaning be represented? How is meaning structured and organized in language(s) and in the human mind? How does meaning represent the world? What meaning relations exist between words and sentences? How are word meanings combined to form the interpretation of sentences and discourses? How is meaning acquired? How does meaning interface with aspects of human cognition such as concepts, reasoning, perception, and action?

These and other similar questions are the object of study of *semantics*. This book is concerned with *distributional semantics*, an approach to meaning that develops theories and methods for quantifying and categorizing semantic properties of linguistic items based on their distributional properties in text corpora, as samples of language data. Grounded in the *Distributional Hypothesis*, according to which words with similar linguistic contexts tend to have similar meanings, the essence of distributional semantics can be described as follows:

The meaning of a linguistic expression is represented with a real-valued *vector* (nowadays commonly called *embedding*) that encodes its statistical distribution in contexts.

The continuous nature of its representations distinguishes distributional semantics from other theoretical frameworks that instead represent meaning with symbolic structures. Moreover, there is a large array of computational methods to learn semantic representations from corpus data, which are then used in NLP and AI applications, as well as for cognitive and linguistic analyses. We refer to such methods as *distributional semantic models* (DSMs).

Distributional semantics lies at the crossroad of computational linguistics, AI, and cognitive science. Therefore, it is the combination of various characters: (i) it is a theoretical model to represent meaning, (ii) a computational framework to acquire it from language data, (iii) a practical methodology to construct semantic representations, and (iv) a cognitive hypothesis about the role of language usage in shaping meaning. This makes distributional semantics a fascinating research area and a privileged vantage point to combine theoretical, cognitive, and computational perspectives on language.

The Need for a Common Ground

Distributional semantics is a relatively novel approach to the study of meaning, but it has undergone deep transformations since its outset. Three main generations of models have followed one another: (i) *count DSMs* that build distributional vectors by recording co-occurrence frequencies; (ii) *predict DSMs* that learn vectors with shallow neural networks trained to predict surrounding words; (iii) *contextual DSMs* that use deep neural language models to generate inherently contextualized vectors for each word token, and therefore radically depart from previous *static DSMs* that instead learn a single vector per word type. Across its history, the changes in distributional semantics involve the way to characterize linguistic contexts, the methods to generate word vectors, the nature of such vectors, and the model complexity itself, which has exponentially grown especially with the last generation of deep neural DSMs.

Though it has been extensively practiced since the 1990s, the popularity of distributional semantics has exploded only recently, thereby becoming the leading approach to meaning representation in computational linguistics and cognitive science. This has coincided with the advent of neural network methods as the dominant computational paradigm for AI and NLP, which has produced a proliferation of models to learn semantic vectors and has fostered their use in downstream applications. Several “off-the-shelf” pretrained vectors are nowadays available, and provide ready-to-use resources for experimentation and system development. The fast and unprecedented expansion of distributional semantics is surely a positive fact that has boosted research

in this area, but it also has its drawbacks. Like many novel scientific fields, distributional semantics lacks a common understanding of its theoretical and methodological foundations. This often prompts a rather opportunistic attitude, which not only fosters rapid development but also risks hindering progress by constantly “reinventing the wheel,” and encourages a strong tendency to focus on the last “trendy” model, without considering whether and to what extent it brings significant advances over the previous ones, whether it can address qualitatively different issues or simply provides some quantitative improvement on old problems. Moreover, pretrained distributional vectors are often used in a kind of “black box” fashion, with little awareness of the effects of the different training settings and of the general properties and limits of distributional representations. This leads to a dangerous polarization between enthusiastic and skeptical attitudes toward distributional approaches to meaning, which prevents a rational and critical analysis of their actual potentialities.

Our goal with this book is to contribute to establishing distributional semantics as a *unitary and general framework to represent and study meaning*, which is implemented in various computational models and applied to address different semantic issues. We aim at building a common understanding of the theoretical and methodological foundations of distributional semantics by:

- tracing its historical origins;
- discussing and clarifying what is meant by *distributional* and *semantic* in this discipline;
- exemplifying how the distributional approach is implemented in DSMs;
- identifying, distinguishing, and evaluating the main types of DSMs;
- presenting how various types of semantic issues are addressed with DSMs;
- analyzing the open problems and challenges.

Distributional semantics is a fast and continuously moving field. It would be as impossible as it is useless to provide an exhaustive account of all its variations. Therefore, some of them have been left out by necessity. Up-to-date details may be easily obtained by browsing online resources such as the *ACL Anthology* or *arXiv*. This book has a different and more ambitious aim: Abstracting from the wealth of works in this area a general view that may help the reader to understand and master the common methodological paradigm that lies behind the increasingly large number of studies in distributional semantics.

Outline of the Book

The book consists of three main parts. *Part I – Theory* presents the major methodological aspects of distributional semantics as a framework for meaning investigation. Chapter 1 deals with the epistemological principles of

distributional semantics, in particular the Distributional Hypothesis, its historical foundations, and its place in theoretical and computational linguistics. Chapter 2 introduces the basic notions to construct distributional semantic representations from corpora: various types of linguistic contexts, vectors, co-occurrence matrices and their dimensionality reduction to extract latent dimensions, vector similarity measures, and so on.

Part II – Models presents the most important families of static DSMs. Chapter 3 contains a synoptic view of the different types and generations of models. We then focus on static DSMs, since they are still the best-known and most widely studied family of models, and they learn context-independent distributional representations that are useful for several linguistic and cognitive tasks. Chapter 4 illustrates matrix models, which organize distributional information into co-occurrence matrices, Chapter 5 discusses models based on the use of random patterns to accumulate low-dimensional vectors in an incremental way, and Chapter 6 reviews predict DSMs that use shallow neural language models.

Part III – Practice explores how distributional semantics addresses different aspects of meaning. Chapter 7 focuses on the main methods and benchmarks to evaluate DSMs and analyzes the results of a comparative evaluation of the models described in Part II on a large range of tasks and datasets. Chapter 8 illustrates the most important applications of distributional semantics to the study of lexical meaning (e.g., word senses, paradigmatic relations, etc.). Chapter 9 discusses the main distributional approaches to the compositional interpretation of complex linguistic expressions and the last generation of deep neural language models that learn contextual embeddings and provide new tools to explore the context-sensitive nature of meaning.

Chapter 10 concludes the book with a general summary of the current state of distributional semantics, its future prospects, and challenges.

Distributional semantics is a multidisciplinary field. This book is intended for NLP and AI scholars and practitioners, linguists, and cognitive scientists. The background and interests of this potential audience are extremely heterogeneous, like the toolbox of distributional semantics, which includes notions from theoretical and computational linguistics, linear algebra, statistics, neural networks, and so on. We have tried to make this book as self-contained as possible, and we have added mathematical notes that introduce the key concepts. We expect the book to be accessible to a large number of readers from different fields, but of course it has been impossible to present all the mathematical and computational methods used by DSMs and their applications. However, gaps will be easily filled by consulting general handbooks or introductory texts, some of which have been listed in the further reading section at the end of each chapter.

Terminological Issues

Distributional semantics is mainly concerned with the *lexicon*, which includes *words* as well as complex *set phrases* and *constructions*, such as idioms and multiword expressions. In computational linguistics and information retrieval, words and set phrases are also referred to as *terms*. In this book, we use *lexeme*, *lexical item*, *term*, and *word* interchangeably, unless differently specified, because the concept of term has a strong overlap with the concept of lexeme, and words are the most typical targets of DSMs.

We distinguish between meaning and sense. We use *meaning* to refer to the general semantic content of a lexeme and *sense* to refer to a particular use of a lexeme in a context (or class of contexts). Theories of lexical meaning typically assume the notion of sense as their starting point. On the other hand, distributional semantics dispenses with senses as a primitive theoretical notion. In fact, distributional representations are primarily representations of the content (i.e., meaning) of a lexeme, rather than of its senses. Chapter 8 discusses how the notion of sense can be represented in DSMs.

The widespread adoption of neural networks in distributional semantics has popularized the term “embedding,” which is, however, used in different ways, sometimes to mean a vector learnt by neural models, sometimes as a generic equivalent of distributional representation. In this book, we use *distributional vector* to refer to any vector that encodes distributional information. Instead, we reserve *embedding* for all kinds of low-dimensional, dense vectors, independently of the method that creates them.

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Writing this book took much longer than we expected. However, this delay has also had positive effects because we have been able to witness the rapid and dramatic changes that distributional semantics has undergone in the last years.

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