Abstract

Building machines that can understand text like humans is an AI-complete problem. A great deal of research has already gone into this, with astounding results, allowing everyday people to discuss with their telephones, or have their reading materials analysed and classified by computers. A prerequisite for processing text semantics, common to the above examples, is having some computational representation of text as an abstract object. Operations on this representation practically correspond to making semantic inferences, and by extension simulating understanding text. The complexity and granularity of semantic processing that can be realised is constrained by the mathematical and computational robustness, expressiveness, and rigour of the tools used.

This dissertation contributes a series of such tools, diverse in their mathematical formulation, but common in their application to model semantic inferences when machines process text. These tools are principally expressed in nine distinct models that capture aspects of semantic dependence in highly interpretable and non-complex ways. This dissertation further reflects on present and future problems with the current research paradigm in this area, and makes recommendations on how to overcome them.

The amalgamation of the body of work presented in this dissertation advances the complexity and granularity of semantic inferences that can be made automatically by machines.

Foreword

This document is a doktordisputats - a dissertation within the Danish academic system required to obtain the degree of Doctor Scientiarum, in form and function equivalent to the French and German Habilitation and the Higher Doctorate of the Commonwealth.
The dissertation contains my work in the field of semantic dependence for information retrieval, realised in the period January 2009 - April 2017.

The first chapter of this dissertation consists of an executive summary that introduces the general area and gives a compact overview of the specific contributions of this work. This chapter is aimed at readers with a broad background in computer science or related disciplines. The remainder of the dissertation consists of nine technical chapters that are slightly reformatted versions of previously published papers.

Publications

The following published papers have been included in the text of this dissertation. The papers are listed in the order they appear in the dissertation:

1. Roi Blanco and Christina Lioma. **Graph-based Term Weighting for Information Retrieval**. In: *Information Retrieval*. Springer, 2012. Vol. 15, no. 1, pp. 54–92. issn: 1386-4564. doi: 10.1007/s10791-011-9172-x. url: [http://dx.doi.org/10.1007/s10791-011-9172-x](http://dx.doi.org/10.1007/s10791-011-9172-x)

2. Christina Lioma, Jakob Grue Simonsen, Birger Larsen, and Niels Dalum Hansen. **Non-Compositional Term Dependence for Information Retrieval**. In: *Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval, Santiago, Chile, August 9-13, 2015*. Ed. by Ricardo A. Baeza-Yates, Mounia Lalmas, Alistair Moffat, and Berthier A. Ribeiro-Neto. ACM, 2015, pp. 595–604. isbn: 978-1-4503-3621-5. doi: 10.1145/2766462.2767717. url: [http://doi.acm.org/10.1145/2766462.2767717](http://doi.acm.org/10.1145/2766462.2767717)

3. Christina Lioma and Niels Dalum Hansen. **A Study of Metrics of Distance and Correlation Between Ranked Lists for Compositionality Detection**. In: *Journal of Cognitive Systems Research*. Elsevier, 2017, in press. doi: 10.1016/j.cogsys.2017.03.001.

4. Christina Lioma, Birger Larsen, and Wei Lu. **Rhetorical Relations for Information Retrieval**. In: *The 35th International ACM SIGIR conference on research and development in Information Retrieval, SIGIR’12, Portland, OR, USA, August 12-16, 2012*. Ed. by William R. Hersh, Jamie Callan, Yoelle Maarek, and Mark Sanderson. ACM, 2012, pp. 931–940. isbn: 978-1-4503-1472-5. doi: 10.1145/2348283.2348407. url: [http://doi.acm.org/10.1145/2348283.2348407](http://doi.acm.org/10.1145/2348283.2348407)
5. Casper Petersen, Christina Lioma, Jakob Grue Simonsen, and Birger Larsen. *Entropy and Graph Based Modelling of Document Coherence using Discourse Entities: An Application to IR*. In: *Proceedings of the 2015 International Conference on The Theory of Information Retrieval, ICTIR 2015, Northampton, Massachusetts, USA, September 27-30, 2015*. Ed. by James Allan, W. Bruce Croft, Arjen P. de Vries, and Chengxiang Zhai. ACM, 2015, pp. 191–200. isbn: 978-1-4503-3833-2. doi: 10.1145/2808194.2809458. url: [http://doi.acm.org/10.1145/2808194.2809458](http://doi.acm.org/10.1145/2808194.2809458).

6. Christina Lioma, Fabien Tarissan, Jakob Grue Simonsen, Casper Petersen, and Birger Larsen. *Exploiting the Bipartite Structure of Entity Grids for Document Coherence and Retrieval*. In: *Proceedings of the 2016 ACM on International Conference on the Theory of Information Retrieval, ICTIR 2016, Newark, DE, USA, September 12–6, 2016*. Ed. by Ben Carterette, Hui Fang, Mounia Lalmas, and Jian-Yun Nie. ACM, 2016, pp. 11–20. isbn: 978-1-4503-4497-5. doi: 10.1145/2970398.2970413. url: [http://doi.acm.org/10.1145/2970398.2970413](http://doi.acm.org/10.1145/2970398.2970413).

7. Christina Lioma, Roi Blanco, Raquel Mochales Palau, and Marie-Francine Moens. *A Belief Model of Query Difficulty That Uses Subjective Logic*. In: *Advances in Information Retrieval Theory, Second International Conference on the Theory of Information Retrieval, ICTIR 2009, Cambridge, UK, September 10-12, 2009, Proceedings*. Ed. by Leif Azzopardi, Gabriella Kazai, Stephen E. Robertson, Stefan M. Rüger, Milad Shokouhi, Dawei Song, and Emine Yilmaz. Vol. 5766. Lecture Notes in Computer Science. Springer, 2009, pp. 92–103. isbn: 978-3-642-04416-8. doi: 10.1007/978-3-642-04417-5. url: [http://dx.doi.org/10.1007/978-3-642-04417-5_9](http://dx.doi.org/10.1007/978-3-642-04417-5_9).

8. Christina Lioma, Birger Larsen, Hinrich Schütze, and Peter Ingwersen. *A Subjective Logic Formalisation of the Principle of Polyrepresentation for Information Needs*. In: *Information Interaction in Context Symposium, IIiX 2010, New Brunswick, NJ, USA, August 18–21, 2010*. Ed. by Nicholas J. Belkin and Diane Kelly. ACM, 2010, pp. 125–134. isbn: 978-1-4503-0247-0. doi: 10.1145/1840784.1840804. url: [http://doi.acm.org/10.1145/1840784.1840804](http://doi.acm.org/10.1145/1840784.1840804).

9. Christina Lioma, Birger Larsen, and Peter Ingwersen. *Preliminary Experiments using Subjective Logic for the Polyrepresentation of Information Needs*. In: *Information Interaction in Context: 2012, IIiX’12, Nijmegen, The Netherlands, August 21–24, 2012*. Ed. by Jaap
The papers presented below are published in the period January 2009 – April 2017 and are unrelated or marginally related to my research on semantic dependence for information retrieval. For this reason, they are not included in the dissertation. The list is shown here to outline the context of the research presented in this dissertation and to indicate the broadness of my research. The papers are presented in increasing chronological order:

1. Roi Blanco and Christina Lioma. Mixed Monolingual Homepage Finding in 34 Languages: the Role of Language Script and Search Domain. In: Journal of Information Retrieval, Special Issue on non-English Web Retrieval. Springer, 2009. vol. 12, no. 3, pp. 324–351. Full reference: [32].

2. Christina Lioma and Roi Blanco. Part of Speech Based Term Weighting for Information Retrieval. In: Advances in Information Retrieval, 31th European Conference on IR Research, ECIR 2009, Toulouse, France, April 6-9, 2009. Proceedings. Springer, 2009, pp. 412–423. Full reference: [190].

3. Christina Lioma, Roi Blanco, and Marie-Francine Moens. A Logical Inference Approach to Query Expansion with Social Tags. In: Advances in Information Retrieval Theory, Second International Conference on the Theory of Information Retrieval, ICTIR 2009, Cambridge, UK, September 10-12, 2009, Proceedings. Lecture Notes in Computer Science. Springer, 2009, pp. 358–361. Full reference: [191].

4. Charles Jochim, Christina Lioma, Hinrich Schütze, Steffen Koch, and Thomas Ertl. Preliminary Study into Query Translation for Patent Retrieval. In: Proceedings of the 3rd International Workshop on Patent Information Retrieval (PaIR '10). ACM, 2010. pp. 57–66. Full reference: [141].

5. Lukas Michelbacher, Alok Kothari, Martin Forst, Christina Lioma, and Hinrich Schütze. A Cascaded Classification Approach to Semantic Head Recognition. In: Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing, EMNLP 2011, pp. 793–803. Full reference: [221].

6. Charles Jochim, Christina Lioma, and Hinrich Schütze. Expanding Queries with Term and Phrase Translations in Patent Retrieval. In: Multidisciplinary Information Retrieval - Second Information Retrieval Facility Conference, IRFC 2011, pp. 16–29. Full reference: [140].
7. Radu Dragusin, Paula Petcu, Christina Lioma, Birger Larsen, Henrik Jørgensen and Ole Winther. Rare Disease Diagnosis as an Information Retrieval Task. In: Advances in Information Retrieval Theory - Third International Conference, ICTIR 2011, pp. 356–359. Full reference: [73].

8. Christina Lioma, Alok Kothari, and Hinrich Schütze. Sense Discrimination for Physics Retrieval. In: Proceeding of the 34th International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR 2011, pp. 1101–1102. Full reference: [194].

9. Christina Lioma, Birger Larsen, and Hinrich Schütze. User Perspectives on Query Difficulty. In: Advances in Information Retrieval Theory - Third International Conference, ICTIR 2011, pp. 3–14. Full reference: [199].

10. Wei Lu, Qikai Cheng, and Christina Lioma. Fixed Versus Dynamic Co-Occurrence Windows in TextRank Term Weights for Information Retrieval. In: The 35th International ACM SIGIR conference on research and development in Information Retrieval, SIGIR ’12, pp. 1079–1080. Full reference: [211].

11. Birger Larsen, Christina Lioma, Ingo Frommholz, and Hinrich Schütze. Preliminary Study of Technical Terminology for the Retrieval of Scientific Metadata Book Records. In: The 35th International ACM SIGIR conference on research and development in Information Retrieval, SIGIR ’12, pp. 1131–1132. Full reference: [173].

12. Peter Ingwersen, Christina Lioma, Birger Larsen, and Peiling Wang. An Exploratory Study into Perceived Task Complexity, Topic Specificity and Usefulness for Integrated Search. In: Information Interaction in Context: 2012, IIix’12, pp. 302–305. Full reference: [139].

13. Raf Guns, Christina Christina Lioma, and Birger Larsen. The Tipping Point: F-score as a Function of the Number of Retrieved Items. In: Journal of Information Processing & Management. Elsevier, 2012. Vol. 48, no. 6, pp. 1171–1180. Full reference: [109].

14. Radu Dragusin, Paula Petcu, Christina Lioma, Birger Larsen, Henrik Jørgensen, Ingemar J. Cox, Lars K. Hansen, Peter Ingwersen, and Ole Winther. Specialised Tools are Needed when Searching the Web for Rare Disease Diagnoses. In: Rare Diseases. 2013. Vol. 1, no. 2, pp: e25001-1–e25001-4. Full reference: [72].

15. Radu Dragusin, Paula Petcu, Christina Lioma, Birger Larsen, Henrik Jørgensen, Ingemar J. Cox, Lars K. Hansen, Peter Ingwersen, and Ole Winther. FindZebra: A Search Engine for Rare Diseases. In: International Journal of Medical Informatics. Elsevier, 2013. Vol. 82, no. 6, pp. 528–538. Full reference: [71].
16. Casper Petersen, Christina Lioma, and Jakob Grue Simonsen. **Comparative Study of Search Engine Result Visualisation: Ranked Lists Versus Graphs.** In: *Proceedings of the 3rd European Workshop on Human-Computer Interaction and Information Retrieval, Dublin, Ireland, August 1, 2013*, pp. 27–30. Full reference: [258].

17. Roi Blanco, Manuel Eduardo Ares Brea, and Christina Lioma. **User Generated Content Search.** In: *Mining of User Generated Content and its Applications*, 2013, pp.167–187. Full reference: [30].

18. Niels Dalum Hansen, Christina Lioma, Birger Larsen, and Stephen Alstrup. **Temporal Context for Authorship Attribution - A Study of Danish Secondary Schools.** In: *Multidisciplinary Information Retrieval - 7th Information Retrieval Facility Conference, IRFC 2014*, pp. 22–40. Full reference: [112].

19. Casper Petersen, Jakob Grue Simonsen, and Christina Lioma. **The Impact of Using Combinatorial Optimisation for Static Caching of Posting Lists.** In: *Information Retrieval Technology - 11th Asia Information Retrieval Societies Conference, AIRS 2015*, pp. 420–425. Full reference: [261].

20. Alessandro Sordoni, Yoshua Bengio, Hossein Vahabi, Christina Lioma, Jakob Grue Simonsen, and Jian-Yun Nie. **A Hierarchical Encoder-Decoder for Generative Context-Aware Query Suggestion.** In: *Proceedings of the 24th ACM International Conference on Information and Knowledge Management, CIKM 2015*, pp. 553–562. Full reference: [299].

21. Casper Petersen, Jakob Grue Simonsen, and Christina Lioma. **Power Law Distributions in Information Retrieval.** In: *Transactions on Information Systems (TOIS)*. ACM, 2016, Vol. 34, no. 2, pp. 1–37. Full reference: [262].

22. Christina Lioma, Birger Larsen, Wei Lu, and Yong Huang. **A Study of Factuality, Objectivity and Relevance: Three Desiderata in Large-Scale Information Retrieval?.** In: *Proceedings of the 3rd IEEE/ACM International Conference on Big Data Computing, Applications and Technologies, BDCAT 2016*, pp. 107–117. Full reference: [197].

23. Brian Brost, Ingemar J. Cox, Yevgeny Seldin, and Christina Lioma. **An Improved Multileaving Algorithm for Online Ranker Evaluation.** In: *Proceedings of the 39th International ACM SIGIR conference on Research and Development in Information Retrieval, SIGIR 2016*, pp. 745–748. Full reference: [38].

24. Christina Lioma, Birger Larsen, Casper Petersen, and Jakob Grue Simonsen. **Deep Learning Relevance: Creating Relevant Information (As Opposed to Retrieving It).** In: *Neu-IR’16 SIGIR Workshop on*
It is generally acknowledged that dismantling something is easier that putting it back together. From puzzles to LEGO structures, examples abound where it takes less time and mental effort to reduce some structure to its parts, than to combine parts to form a structure. One reason is that, when a structure is dismantled, it is no longer always obvious how its parts fit together. Or, to put it differently, dismantling causes information loss.

It follows that, to make a structure, one needs not only its individual components, but also knowledge about how to combine them. This little bit of common sense lies at the core of Frege’s Principle of Compositionality.

\footnote{Friedrich Ludwig Gottlob Frege is widely credited for the first modern formulation of the Principle of Compositionality in his Foundations of Arithmetic (1884), even though he never explicitly stated the principle. Precursors of this idea appear in the work of Plato and Boole, among others.}
Formulated more than 100 years ago, this principle posits, roughly, that:

The meaning of an expression is a function of the meanings of its constituent expressions and of the ways these constituents are combined [312].

**Principle of Compositionality**

Initially formulated in the context of mathematics, this principle has been since applied to several other domains, from linguistics (by Montague [312]) to programming languages [142, 274, 272], software engineering [61], geology [62], biology [282], and – indeed – LEGO.

The widespread application of the principle of compositionality across different disciplines is partially due to its appeal to our human inclination to dismantle in order to understand. Toddlers spend hours disassembling and reassembling structures; zoologists dissect animals; linguists tokenize language; physicists isolate atoms; geologists separate rock minerals. Common throughout these activities is the wish to learn, i.e., to determine the nature of some phenomenon by investigating its composing elements and their relationship to one another.

The role of this decomposing process to scientific analysis has been acknowledged at least since Aristoteles’ time, who referred to it as the dissecting method of achieving a solution (λύσις) through several layers (analýsis) of processing (analysis).

There are at least two interesting implications to this decomposing paradigm of scientific analysis:

I. The constituent parts of a structure that is being decomposed do not necessarily have the same properties as that structure.

II. Each constituent part of a structure can be itself a separate structure that is, in its turn, decomposable into its own constituent parts.

The above two implications practically mean that the task of modelling the properties of a structure by decomposing it into its constituent parts increases in complexity, the more one decomposes. One of the most illustrative examples of this increase in complexity is found in physics, and concerns the behaviour of atoms: the movement of a physical object is decided by its mass and the forces acting on it (understanding this requires basic physics); however, on a microscopic level, the movements of the atoms composing that object can only be given probabilistic estimates of behaving in a particular way, for at the heart of their behaviour is randomness. Understanding this requires quantum physics.

Generally, complex structures tend to be studied in science by restricting their representation to factors that can be reasonably computed, hence reducing part of the complexity. One of the most common analytical tools deployed for this is the so-called **Assumption of Independence**, which posits that:
The constituent parts composing a structure can be assumed to occur independently of one another \[55\].

**Assumption of Independence**

Making the assumption of independence bypasses the problem of accounting for the mode and degree of dependence of the constituent parts of a structure. This allows to build considerably less complex and more scalable models of the structure studied, compared to when modelling dependence. Often, to compensate for the information loss incurred by the assumption of independence, heuristics are introduced. However, in practice, theoretical explanations of these heuristics are seldom given or generalisable.

This dissertation presents a series of studies that replace the assumption of independence (and the heuristics that follow from its adoption), with principled methods for capturing semantic dependence in the context of information retrieval. We explain this next.

2 Semantic Dependence in Information Retrieval

**DEPENDENCE** (*noun*): the quality or state of being influenced or determined by or subject to another.

**CATENA** (*noun, plural catenae*): a connected series of related things.

Information retrieval is the scientific discipline studying how machines can infer the semantics of some information object, like a document\(^2\), so that they can approximate its relevance to some human or automatic request. The best known application of information retrieval is search engines.

Intuitively, one may expect that automatically inferring text semantics would require complex linguistic representations, expressive enough to capture as many facets of meaning in language as possible. Few such approaches have been presented. However, their high complexity is a serious challenge to both computational efficiency and human interpretation of the underlying processes. Consequently, the majority of information retrieval approaches today adopt some form of the assumption of independence when processing text. This allows to easily represent text as the multiset (or bag) of its words, disregarding grammar, word order, and in general any relation binding words together, but keeping multiplicity. These methods are collectively known as *bag of words* approaches\(^3\).

As old as bag of words approaches may be (they can be traced at least as far back as Zellig S. Harris’ 1954 article on Distributional Structure \[116\]), equally old is the criticism against them. Empirically, it is easy to see that important semantic distinctions, for instance the difference in meaning between the

\(^2\) In information retrieval terminology, *document* refers to any information object, e.g. text of any type or format (pdf, html, tweet, book, product review, etc.).

\(^3\) The divide between linguistic rigour and computational performance was famously captured by Frederick Jelinek at IBM in the 1980s, who anecdotally said: “every time we fire a linguist, system performance goes up” [paraphrased].
proposition *John loves Mary* and the proposition *Mary loves John*, cannot be captured by bag of words approaches. Nevertheless, despite the long and well argued criticism against these approaches, they continue to be the main paradigm in text processing because the benefits they yield (ease of computation, scalability, interpretability of results, robust processing) outrank their disadvantages (semantic inaccuracy, restricted analytical scope).

This dissertation presents:

(i) a series of studies showing that several benefits of bag of words approaches can be preserved when representing aspects of semantic dependence in principled, non-complex ways;

(ii) reflections on why the current *modus vivendi* of semantic processing in information retrieval is inadequate and should be revised;

(iii) recommendations on designing a new *modus operandi* that bridges the two extremes of shallow versus deep semantic processing, leading to more accurate and more expressive information retrieval inferences.

The common underlying objective in the body of work included in this dissertation is to model the dependence of textual constituents on three different levels of semantic analysis: *lexical, discourse*, and *cognitive*.

**Lexical level.** The units of analysis in lexical semantics are words.

**Discourse level.** The units of analysis in discourse semantics are sentences.

**Cognitive level.** The units of analysis in cognitive semantics are concepts.

For each of the above three levels, the type and strength of the dependence conjoining the constituent parts of text is examined in a principled manner, and different models are developed for processing the corresponding *semantic catenae* (of words, sentences, or concepts) in the context of information retrieval. These models capture part of the information loss that takes place when reasoning about text computationally by dismantling it into individual words, sentences, or concept representations. Collectively, these models replace the assumption of independence with non-complex representations of lexical, discourse, and cognitive dependence, using principles from graph theory, probability theory, logic and statistics.

A total of nine models of semantic dependence for information retrieval are presented in this dissertation (outlined in Table 1). The results contributed and conclusions drawn by each model are discussed next, separately for lexical, discourse and cognitive semantics.
3 Contributions to Lexical Semantics

Three models of lexical dependence (referred to as Model I, II, and III) are presented as Chapters 2, 3, and 4 of this dissertation. All three models are unsupervised (they incur no added computational cost for training on pre-annotated data). Each model uses principles of different formalisms: graph theory, probability, and statistics.

3.1 Model I: Unsupervised graph theoretic lexical dependence [33].

The essential idea of lexical semantics is that the meaning of a word correlates with the semantic entailments associated to this word. Following this, instead of assuming that words occur independently in text, Model I represents word dependencies as graph edges that connect vertices denoting unique words (see Figure 1 for an illustration). More simply, instead of representing text as a bag of words, text is represented as a graph of interconnected words. Analogies are then made between different aspects of word dependence and aspects of the graph’s topology (such as clustering or average path length).

Based on this graph representation of text, Model I contributes a novel term weighting approach for information retrieval. In addition to its theoretical novelty, Model I also makes the following two advances:

On an algorithmic level it is not subject to document length bias (because it replaces the currently dominating frequentist practice of word counts by vertex connectivity). Practically this makes the need for additional document length normalisation obsolete (unlike all other term weighting approaches).

On a theoretical level it allows aspects of lexical dependence, such as grammatical type, modification, or non-adjacent transition, to be seamlessly in-

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Tab. 1: The nine models of semantic dependence presented in this dissertation. The numbers inside square brackets point to the bibliographic references of the articles where each model was published.

| METHOD   | SEMANTIC LEVEL |
|----------|----------------|
|          | lexical        | discourse   | cognitive |
| graph theory | Model I [33]    | Models VI-VII [203, 259] |
| probabilistic | Model II [202] | Models IV-V [196, 259] |
| statistics  | Model III [193] |                          |
| logic      |                | Models VIII-IX [192, 200, 195] |

4 Term and word are used interchangeably in information retrieval and also in this dissertation.
Compatibility of systems of linear constraints over the set of natural numbers. Criteria of compatibility of a system of linear Diophantine equations, strict inequalities, and nonstrict inequations are considered.

Fig. 1: [Model I]. Graph representation of the above sample text: vertices denote words, edges denote co-occurrence within a fixed context window, and directionality denotes grammatical modification [33].

corporated into term weighting (because they are formulated as weights, labels or direction in the graph edges). Practically, this modularity allows generating instances of term weighting methods that capture different aspects of lexical dependence in the approximation of a term’s semantic salience. This has not been possible in any other term weighting approach.

The reliability and validity of Model I is supported by thorough experimental evaluation in two information retrieval tasks (ad hoc search and web blog search), using large-scale state of the art benchmark datasets (28.9GB in total), and measuring effectiveness (precision, binary preference), efficiency (overhead in milliseconds, running time of iterations), and parameter sensitivity against competitive state of the art baselines.

3.2 Models II & III: Unsupervised probabilistic & statistical lexical dependence [193, 202]

The most common approach for approximating the semantic dependence between words in information retrieval is through lexical frequency statistics of

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5 Throughout this chapter, state of the art refers to the year the corresponding article was first published.
their co-occurrence. The underlying rationale is that:

- If words co-occur often enough in some corpus, they are semantically dependent;
- The more often words co-occur, the more semantically dependent they are.

Model II reveals (for the first time in information retrieval) that this rationale is not always correct: the frequency of word co-occurrence can be separate from the strength of semantic dependence. Even though the former can be indicative to some extent of the latter, their relation is not symmetric. This miscalculation of semantic dependence in words is corrected by two models (one probabilistic, one statistical), which distinguish between frequency of co-occurrence and strength of semantic dependence as follows.

Model II represents word pairs as probability distributions of their distributional semantics (co-occurring words within fixed context windows extracted from corpora). These probability distributions are generated for word pairs and for perturbations of these pairs where one word at a time is replaced by its synonym. This is a modern implementation of Leibniz’ Principle of Intersubstitutivity (salva veritate) to detect irregular composition of meaning, which posits that words which can be substituted for one another without altering the truth of any statement are the same (eadem) or coincident (coincidentia). The divergence between the distribution of the original word pair and the distribution of its perturbation (illustrated as the Kullback-Leibler Divergence of \( p(x) \) and \( q(x) \) in Figure 2) is found by Model II to be an accurate approximation of the semantic strength of the words of the original word pair.

In addition to the theoretical novelty of Model II, the significance of its findings to information retrieval can be summarised as follows:

On a conceptual level it points out a significant error in the estimation of semantic strength between words that has gone so far undetected in this very well studied area of information retrieval (the relevant literature is outlined in Section 6).

On an algorithmic level it proposes a non-complex solution to this error that yields considerable gains in retrieval accuracy and that has increased interpretability.

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6. The Distributional Hypothesis posits that words used or occurring in the same contexts tend to purport similar meanings. John Rupert Firth famously captured this as: “you shall know a word by the company it keeps.”

7. Image by Nathan Mundhenk. Source: https://upload.wikimedia.org/wikipedia/en/a/a8/KL-Gauss-Example.png. Licensed under Creative Commons: CC BY-SA 3.0.

8. Interpretability refers to how easy it is for humans to understand a process and its resulting outcome. The more abstract the features used, and the higher the dimension of spaces represented, the harder it is for humans to readily comprehend a process and explain its output.
Fig. 2: [Model II]. Illustration of Kullback-Leibler divergence ($D_{KL}$).

Model III follows the same rationale as Model II, but uses a different representation. Word pairs are represented not as probability distributions, but as lists of the term weights of their distributional semantics. These lists are ranked by term weight, and the distance or correlation between these lists is found to be an accurate approximation of the semantic strength between the words. The novelty of this approach is that, instead of considering all terms forming the distributional semantics of the input phrase, it ranks these terms by their contribution to the text semantics (approximated by their term weight) and considers only the most discriminative terms. This allows for more dense and discriminative representations.

In addition to the theoretical novelty of Model III, the significance of its findings can be summarised as follows:

On a theoretical level it proposes a simple, unsupervised solution to a problem that has been primarily addressed in increasingly complex ways (more recently deep learning). Any appropriate term weighting method and correlation or distance metric can be plugged into Model III, allowing for different aspects of term salience (and its ranking) to be considered in the computation of lexical dependence.

On an empirical level it yields the highest performance reported up to the date of publication for this task and benchmarks, outperforming the previous highly tuned supervised deep learning state of the art, while also having high interpretability (elements of which are exemplified in Figure 3 for the Pearson correlation coefficient).

Model II is a novel contribution to information retrieval. Model III is a novel contribution to natural language processing.

The reliability and validity of Models II & III is supported by thorough experimental evaluation. Model II is evaluated in two information retrieval tasks (ad hoc search and web search), using large-scale state of the art benchmark.
datasets (502.1GB in total), and measuring effectiveness (precision, normalised discounted cumulative gain) both on the whole dataset and also separately per query length. Model III is evaluated on the largest manually annotated compositionality dataset publicly available in 2016 (1048 phrases) \[89\] against competitive state of the art baselines.

4 Contributions to Discourse Semantics

Four models of discourse dependence (referred to as Models IV, V, VI, and VII) are presented in Chapters 5, 6, and 7 of this dissertation. All four models are unsupervised (hence they incur no added computational cost for tuning). Models IV & V are probabilistic, while Models VI & VII use principles from graph theory.

4.1 Models IV & V: Unsupervised probabilistic discourse dependence \([196, 259]\)

The essential idea of discourse semantics is that the meaning of a sentence is bounded by anaphoric elements in that sentence pointing to preceding or succeeding sentences (or elements thereof) that are collectively needed to interpret the discourse context. Following this, instead of assuming that text is an unordered set of sentences, Models IV & V represent the relations and transition between sentences in text when processing text semantics. Two different probabilistic models of discourse dependence are presented.

Model IV \([196]\) approximates the retrieval probability of different rhetorical relations (defined by Rhetorical Structure Theory \([214]\) and exemplified in Table 2) between sentences in text, and creates a novel ranking model that includes this probability in its computation. This retrieval probability of different rhetorical relations is found to be highly discriminative of topical relevance.

In addition to the theoretical novelty of Model IV, the significance of its findings can be summarised as follows:

On a theoretical level it proposes a novel ranking model that allows making inferences about which part of text is topically relevant to a query and why, as opposed to assuming that all parts in text are equally topically relevant to some query.
### Tab. 2: Examples of the rhetorical relations (in bold italics) inferred as part of Model IV

| Rhetorical Relation | Examples                                                                 |
|---------------------|--------------------------------------------------------------------------|
| attribution         | ... the islands now known as the Gilbert Islands were settled by Austronesian-speaking people ... |
| background          | ... many whites had left the country when Kenyatta divided their land among blacks ... |
| cause-result        | ... I plugged “wives” into the search box and came up with the following results ... |
| comparison          | ... so for humans, it is stronger than coloured to frustrate these unexpected numbers ... |
| condition           | ... Conditional money based upon care for the pet ... |
| consequence         | ... voltage drop with the cruise control switch could cause erratic cruise control operation ... |
| contrast            | ... Although it started out as a research project, the ARPANET quickly developed into ... |
| elaboration         | ... order accutane no prescription required ... |
| enablement          | ... The project will also offer exercise programs and make eye care services accessible ... |
| evaluation          | ... such advances will be reflected in an ever-greater proportion of grade A recommendations ... |
| explanation         | ... the concept called as “evolutionary developmental biology” or shortly “evo-devo” ... |
| manner-means        | ... Fill current path using even-odd rule, then paint the path ... |
| summary             | ... Safety Last, Girl Shy, Hot Water, The Kid Brother, Speedy (all with lively orchestral scores) ... |
| temporal            | ... Take time out before you start writing ... |
| topic-comment       | ... Director Mark Smith expressed support for greyhound adoption ... |
Fig. 4: [Model V]. Catenae of discourse entities (matrix rows) of the sample text shown above (example reproduced from [19]). s,o,x denote the syntactic role of subject, object, or other.

1 [The Justice Department]s is conducting an [anti-trust trial]o against [Microsoft corp.]s with [evidence]x that [the company]s is increasingly attempting to crush [competitors]o.
2 [Microsoft]o is accused of trying to forcefully buy into [markets]x where [its own products]s are not competitive enough to unseat [established brands]o.
3 [The case]s revolves around [evidence]o of [Microsoft]s aggressively pressing [Netscape]o into merging [browser software]o.
4 [Microsoft]s claims [its tactics]s are commonplace and good economically.
5 [The government]s may file [a civil suit]o ruling that [conspiracy]s to curb [competition]o through [collusion]x is [a violation of the Sherman Act]o.
6 [Microsoft]s continues to show [increased earnings]o despite [the trial]x.

On an empirical level it yields considerable gains in retrieval performance, while also having high interpretability.

Model V [259] represents the relations between core syntactic entities of different sentences in text as catenae of salient discourse entities (see Figure 4 for an example). Analogies are then made between the entropy of these catenae and the amount of semantic disorder in text. Entropy is found to be an accurate approximation of text coherence, and further, text coherence is found to be highly discriminative of topical relevance.

In addition to the theoretical novelty of this Model V, the significance of its findings can be summarised as follows:

On a theoretical level it proposes the first ever coherence ranking model for information retrieval, allowing to make inferences about which part of text is topically relevant to a query as a function of both its topical relevance and its coherence with respect to the rest of the text.

The reliability and validity of Models IV & V is supported by thorough experimental evaluation. Model IV is evaluated on ad hoc information retrieval, using large-scale state of the art benchmark datasets (500GB in total), and measuring effectiveness (precision, binary preference, normalised discounted cumulative gain) both on the whole dataset and also separately per query length,
against competitive state of the art baselines. Model V is evaluated both on text reordering (standard task in coherence modelling) and also on \textit{ad hoc} information retrieval. State of the art benchmark datasets are used for both text reordering and retrieval (500GB in total), and effectiveness (accuracy, mean reciprocal rank, expected reciprocal rank) is measured against state of the art baselines.

Models IV & V contribute novel, non-complex, unsupervised methods of processing two different aspects of discourse semantics in information retrieval: rhetorical relations between sentences, and entity transition across sentences for text coherence. Prior to this work, none of these two aspects had been integrated into information retrieval in non \textit{ad hoc} ways. Model IV is a novel contribution to information retrieval. Model V is a novel contribution to both natural language processing and information retrieval.

4.2 Models VI & VII: Unsupervised graph theoretic discourse dependence [203, 259]

Similarly to Models IV & V, Models VI & VII represent the relations and transition between sentences in text when processing text semantics. However, unlike Models IV & V (that are probabilistic), Models VI & VII use graph theory.

Two different graph theoretic models of sentence dependence are presented.

Model VI [259] represents the relations between different discourse entities across sentences in text as bipartite graphs whose vertex sets represent sentences and entities respectively. Analogies are then made between different aspects of sentence dependence and aspects of the topology of this bipartite graph when projected onto a one-mode graph\footnote{One-mode projection is a graph representation of the relation structure among only one of the two set of vertices of a bipartite graph.} (see Figure 5 for an illustration).

Model VII [203] uses the same representation of entities and sentences as a bipartite graph, but makes inferences about discourse semantics directly on the bipartite graph instead of its one-mode projections (this is significantly less trivial).

Both Models VI & VII are shown to be successful when ranking documents
in information retrieval with respect to both their topical relevance and their coherence.

In addition to the theoretical novelty of these models, the significance of their findings can be summarised as follows:

On a theoretical level they propose novel unsupervised modelling of both global and local text coherence\(^{11}\) (very few exist).

On a theoretical level Model VII proposes novel graph metrics on the bipartite graph without one-mode projection (very few exist in general, and none exist for coherence modelling).

On an empirical level both models yield considerable gains in both coherence (Model VII in particular yields the highest accuracy reported at the time of publication, outperforming the previous highly tuned state of the art) and retrieval performance, while also having high interpretability.

The reliability and validity of Models VI & VII is supported by thorough experimental evaluation both in text reordering (standard task in coherence modeling) and also in ad hoc information retrieval. State of the art benchmark datasets are used for both text reordering and retrieval (500GB in total), and effectiveness (accuracy, mean reciprocal rank, expected reciprocal rank) is measured against state of the art baselines. Models VI & VII contribute non-complex, unsupervised ways of processing discourse flow in text, which are novel to both natural language processing and information retrieval.

5 Contributions to Cognitive Semantics

Two models of cognitive dependence (referred to as Models VIII and IX) are presented as Chapters 8, 9, and 10 of this dissertation. Both models use Sub-

\(^{11}\) Local versus global coherence refers to the well connectedness of adjacent versus remote text spans.
The essential idea of cognitive semantics is that language is part of a more general human cognitive ability, which describes the world as people conceive it. Different people may have different representations of the semantics of the same object. Modelling these representations is central to information retrieval, where a major challenge is to devise expressive methods for mapping written representations of meaning to their best fitting semantic concepts.

Models VIII & IX formally represent different concept representations of query and document semantics, and combine these representations in highly tractable and expressive ways that account for the different types and degrees of dependence between representations (graphically illustrated in Figures 6 & 7). Based on this, Model VIII contributes a novel query difficulty estimation approach, and Model IX contributes a novel polyrepresentation approach for information retrieval. Both models are novel to information retrieval.

In addition to the theoretical novelty of these models, the significance of their findings can be summarised as follows:

On a theoretical level they present a rich calculus for expressing impact, bias, and directionality between cognitive representations. This is the first mathematical expression of the Principle of Polyrepresentation.

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12 Subjective logic is a type of probabilistic logic that explicitly takes uncertainty and source trust into account [143].
13 The Principle of Polyrepresentation [138] posits that information retrieval effectiveness may improve through the consideration of multiple and diverse representations of information objects or processes.
14 together with the Quantum Model, presented in Section 6.
On a theoretical level they present mathematical means for quantifying the degree of uncertainty in probability estimates of concept representations that are used in information retrieval. Practically, this allows semantic inferences to be made even when the input arguments may be fraught with uncertainty.

The reliability and validity of Models VIII & IX is supported by thorough experimental evaluation in ad hoc information retrieval using rich human-assessed benchmark data and measuring different aspects of effectiveness (precision, normalised discounted cumulative gain, binary preference, mean reciprocal rank) on standard settings.

Collectively Models I - IX show that, in the analytical spectrum of deep (complex) versus shallow (naive) processing, there is a lot to be gained both empirically and theoretically, from a middle ground of principled, yet non-complex formalisations of text semantics.

6 Research Landscape of Semantic Dependence in Information Retrieval

This section contextualises the findings presented above by contributing a broad, comprehensive and up to date overview of the state of the art and major trends of semantic dependence in information retrieval. This overview includes the literature covered in Chapters 2 - 10, and further extends it with more recent advances. Details on the precise comparison and evaluation of the results presented in this dissertation to prior work are provided in the individual articles.

6.1 Lexical Dependence

Broadly speaking, efforts to model dependence on the level of lexical semantics (term dependence), also known as term co-occurrence, adjacency and lexical affinities in information retrieval, typically model phrases found in queries and/or documents, motivated by the intuition to consider as more relevant those documents in which terms appear in the same order and patterns as they appear in the query, and as less relevant those documents in which terms are separated. Lexical dependence is approximated using either statistical or linguistic information.

Research in this area began with the early work on statistical term associations and syntax-based approaches, continuing with work on probabilistic term dependence models, syntactic methods, and statistical approaches. From the mid-1990s onwards, research focused on hybrid methods combining syntactic and statistical approaches of phrase processing, phrase-based enhancement of the indexed term representations, and phrase-based term
weighting [241, 255, 305]. This was succeeded by a focus on statistical methods, primarily using language modelling [28, 219, 230, 240, 298, 302] but not exclusively [209], while attention has also been given to heuristics [309] and formalisations of term position [212].

A temporal listing of the major contributions in lexical dependence for information retrieval can be seen in Table 3. Efforts in this area intensified in the late 1990s, and peaked again relatively recently (see Figure 8), motivated, among others, by the often stated need to refine the state of semantic processing in information retrieval. However, despite this long and rich literature, no prior work on lexical dependence in information retrieval has contributed solutions to lexical dependence that account for semantic aspects such as modification and transitivity (contributed by Model I), or semantic non-compositionality (thus correcting the error of equating frequency to semantic strength) (contributed by Models II & III).

6.2 Discourse Dependence

Unlike the long-spanning and rich literature of lexical dependence in information retrieval, discourse dependence has been largely ignored in information retrieval prior to the date of publication of the articles in this dissertation. There was no prior work on automatically inferred discourse transitions for information retrieval, neither for rhetorical relations (contributed by Model IV), nor for coherence (contributed by Models V & VI). In that sense, Models IV – VI contribute not only improved semantic processing, but also completely new ways of thinking about text semantics in information retrieval.

Major prior work on discourse semantics outside information retrieval is displayed in Table 3. As Figure 8 graphically shows, advances in this area started emerging in the 1990s, peaked around 2010, and further again more recently. Most of the very recent work uses deep learning (corresponding to its emergence in recent years in Figure 9).

These trends support the reasoning put forward in this dissertation that discourse semantics should not be ignored. Efforts to integrate discourse semantics to information retrieval can benefit from the significant progress made in the field of natural language processing. This line of research has the potential to raise the bar of semantic inferences in search engines, that is required to push information retrieval further beyond searching, in the direction of simulating human intelligence (artificial intelligence - AI).

6.3 Cognitive Dependence

A common starting point when reasoning about cognitive dependence in information retrieval is the Principle of Polyrepresentation [136], which posits that the combination of various different cognitive representations of documents and information needs is likely to reveal cognitive overlaps, the semantics of which

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16 Prior to the first publication of the articles included in the dissertation.
Fig. 8: Number of publications on lexical, discourse, and cognitive dependence in information retrieval (y axis), versus publication year (x axis). The numbers of publications are smoothed by moving 3-year averages.

Fig. 9: Number of publications on the major paradigms used to model semantic dependence in information retrieval (y axis), versus publication year (x axis). The numbers of publications are smoothed by moving 3-year averages.
are discriminative indicators of topical relevance. Following the formulation of this principle in the mid-1990s, research in this area has been gaining traction (see Table 3), with a recent peak around 2010 (see Figure 8). This peak corresponds to a considerable advance in the field: the mathematical formulation of the (up until then) solely conceptual formalisation of the Principle of Polyrepresentation. Specifically, two very different mathematical formulations of the principle were presented in the same year and in the proceedings of the same conference: the Quantum model of Frommholz et al. [98], and Model IX [200] [195] of this dissertation.

In the Quantum model, cognitive representations are modelled in Hilbert spaces\(^{17}\) and combined by means of their tensor products. This differs from Model IX, where cognitive representations are modelled as subjective beliefs and combined using logical operators of Subjective Logic. Model IX is significantly more efficient and less complex than the Quantum model.

Overall, the landscape of research in cognitive dependence for information retrieval is different to that of lexical dependence and discourse dependence, in the sense that it is more uniform, characterised mainly by fewer, smaller peaks and relatively steady research interest throughout the years (see Figure 8). Table 3 highlights the major research in cognitive dependence for information retrieval.

\(^{17}\) **Hilbert spaces** are a generalisation of Euclidean space to spaces with any finite or infinite number of dimensions.
Tab. 3: Classification of related work on (a) lexical, (b) discourse, and (c) cognitive dependence in information retrieval (second column), according to the approach (third column) used to model dependence. The rows are sorted increasingly by year of publication.
| ARTICLE                            | TYPE OF Semantic DependeNce | TYPE OF APPROACH       |
|-----------------------------------|-----------------------------|------------------------|
| Baxendale 1958                   | lexical: term associations  | linguistic analysis    |
|                                   |                             | heuristics             |
| Stiles 1961                       | lexical: term associations  | heuristics             |
| Doyle 1962                        | lexical: term associations  | graphs/networks        |
| Guiliano & Jones 1963             | lexical: term associations  | graphs/networks        |
|                                   |                             | heuristics             |
| Salton 1966                       | lexical: term associations  | linguistic analysis    |
|                                   |                             | heuristics             |
| Lesk 1969                         | lexical: term associations  | vector space           |
| Earl 1972                         | lexical: term associations  | linguistic analysis    |
|                                   |                             | heuristics             |
| Halliday & Hasan 1976             | lexical: term associations  | graphs/networks        |
| van Rijsbergen 1977               | lexical: term associations  | heuristics             |
| Harper & van Rijsbergen 1978      | lexical: term associations  | heuristics             |
| Hopfield 1982                     | cognitive: document &      | graphs/networks        |
|                                   | query associations          |                        |
| Salton et al. 1982                | lexical: term dependence   | probabilistic          |
| Dillon & Gray 1983                | lexical: term associations  | heuristics             |
| Yu et al. 1983                    | lexical: term associations  | probabilistic          |
| Metzler et al. 1984               | lexical: term associations  | heuristics             |
| Sowa 1984                         | cognitive: concept         | graphs/networks        |
|                                   | associations                |                        |
| Smith & Devine 1985               | lexical: term associations  | heuristics             |
| Hopfield 1986                     | cognitive: document &      | graphs/networks        |
|                                   | query associations          |                        |
| van Rijsbergen 1986               | cognitive: document &      | logic                  |
|                                   | query associations          |                        |
| Smeaton 1986                      | lexical: term associations  | heuristics             |
| Huang & Lippmann 1987             | cognitive: document relations | graphs/networks    |
| Mann & Thompson 1988              | discourse: rhetorical      | heuristics             |
|                                   | relations                   |                        |
| Pearl 1988                        | cognitive: document &      | graphs/networks        |
|                                   | query associations          | probabilistic          |
| Saracevic & Kantor 1988           | cognitive: document &      | heuristics             |
|                                   | query associations          |                        |
| Smeaton & van Rijsbergen 1988     | lexical: term associations  | heuristics             |
| Belew 1989                        | cognitive: document &      | graphs/networks        |
|                                   | query associations          |                        |
| Fagan 1989                        | lexical: term associations  | heuristics             |
| Kwok 1989                         | cognitive: document &      | graphs/networks        |
|                                   | query associations          |                        |
| Dozkocs et al. 1990               | cognitive: document &      | graphs/networks        |
|                                   | query associations          |                        |
| Lewis & Croft 1990                | lexical: term associations  | heuristics             |
| Veronis & Ide 1990                | lexical: term associations  | graphs/networks        |

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Table 3 – continued from previous page

| ARTICLE                        | TYPE OF SEMANTIC DEPENDENCE            | TYPE OF APPROACH |
|-------------------------------|----------------------------------------|-----------------|
| Devlin 1991 [63]              | cognitive: document & query associations| logic           |
| Hoey 1991 [125]               | lexical & discourse: document cohesion | graphs/networks|
| Lin et al. 1991 [130]         | cognitive: document relations          | graphs/networks|
| Macleod & Robertson 1991 [213]| cognitive: document associations       | graphs/networks|
| Sinclair 1991 [288]           | lexical: term associations             | graphs/networks|
| Turtle & Croft 1991 [179]     | cognitive: document relevance          | graphs/networks|
| Wilkinson & Hingston 1991 [334]| lexical: related terms                 | graphs/networks|
| Bruza & van der Weide 1992 [40]| cognitive: document & query associations| logic           |
| Chevallet 1992 [45]           | cognitive: document & query associations| logic           |
| Chiaramella & Chevallet 1992 [19]| cognitive: document & query associations| logic           |
| Ingwersen 1992 [134]          | cognitive: document & query associations| heuristics      |
| Lewis 1992 [179]              | lexical: term associations             | heuristics      |
| Nie 1992 [244]                | cognitive: document & query associations| logic           |
| Belkin et al. 1993 [23]       | cognitive: document & query associations| heuristics      |
| Kozima 1993 [169]             | lexical: term associations             | graphs/networks|
| Meghini et al. 1993 [212]     | cognitive: document & query associations| logic           |
| Ingwersen 1994 [135]          | cognitive: document & query associations| heuristics      |
| Logan et al. 1994 [207]       | cognitive: document & query associations| logic           |
| Losse 1994 [209]              | lexical: term associations             | probabilistic   |
| Crestani & van Rijsbergen 1995[67]| cognitive: document & query associations| logic           |
| Groz et al. 1995 [102]        | discourse: document coherence          | heuristics      |
| Muller & Kutschkeukes 1995 [235]| cognitive: document & query associations| logic           |
| Evans & Zhai 1996 [87]        | lexical: term associations             | heuristics      |
| Huibers et al. 1996 [131]     | cognitive: document & query associations| logic           |
| Ingwersen 1996 [130]          | cognitive: document & query associations| heuristics      |
| Nie et al. 1996 [244]         | cognitive: document & query associations| logic           |
| Pederson et al. 1997 [255]    | lexical: term associations             | heuristics      |
| Strzalkowski & Lin 1997 [305] | lexical: term associations             | heuristics      |
| Tong et al. 1997 [315]        | lexical: term associations             | heuristics      |
| Crestani & van Rijsbergen 1998[59]| cognitive: document & query associations| graphs/networks|
| Foltz et al. 1998 [90]        | discourse: document coherence          | heuristics      |

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| ARTICLE | TYPE OF SEMANTIC DEPENDENCE | TYPE OF APPROACH |
|---------|-----------------------------|------------------|
| Lalmas 1998 | cognitive: document & query associations | logic |
| van Rijsbergen et al. 1998 | cognitive: document & query associations | logic |
| Ingwersen 1999 | cognitive: document & query associations | heuristics |
| Lin 1999 | lexical: term dependence | heuristics probabilistic |
| Song & Croft 1999 | lexical: term dependence | probabilistic |
| Narita & Ogawa 2000 | lexical: term associations | heuristics |
| Shin & Stach 2000 | discourse: document coherence | heuristics |
| Zhu & Gauch 2000 | discourse: document quality | heuristics |
| Dorogovtsev & Mendes 2001 | lexical: term associations | graphs/networks |
| Ferrer i Cancho & Sole 2001 | lexical: term associations | graphs/networks |
| Fujita 2001 | lexical: term associations | linguistic analysis heuristics |
| Kibble 2001 | discourse: document coherence | heuristics |
| Lin 2001 | lexical: term associations | heuristics |
| Losada & Barreiro 2001 | cognitive: document & query associations | logic |
| Mikk 2001 | discourse: document quality | heuristics |
| Barzilay et al. 2002 | discourse: document coherence | graphs/networks |
| Kehler 2002 | discourse: document heuristics | heuristics |
| Motter et al. 2002 | discourse, cognitive: term & concept associations | graphs/networks |
| Nallapati & Allan 2002 | lexical: term associations | graphs/networks probabilistic |
| Sigman & Cecchi 2002 | lexical: term associations | graphs/networks |
| Teufel & Moens 2002 | discourse: rhetorical relations | heuristics |
| Widdows & Dorrow 2002 | lexical: term associations | graphs/networks |
| Baldwin et al. 2003 | lexical: term compositionality | vector space |
| Bordag et al. 2003 | lexical: term associations | graphs/networks |
| Lapata 2003 | discourse: document coherence | probabilistic heuristics |
| McCarthy et al. 2003 | lexical: phrase compositionality | heuristics |
| Morato et al. 2003 | discourse: rhetorical relations | heuristics |
| Reddy et al. 2003 | lexical: term compositionality | vector space |
| Srikanth & Srihari 2003 | lexical: term dependence | probabilistic |
| Barzilay & Lee 2004 | discourse: topic order | probabilistic |
| Blondel et al. 2004 | lexical: term associations | graphs/networks |
| Erkan & Radev 2004 | lexical: term associations | graphs/networks |
| Ferrer i Cancho et al. 2004 | lexical: term associations | graphs/networks |
| He & Ounis 2004 | lexical: query difficulty | heuristics |
| Ho & Fairon 2004 | lexical: term associations | graphs/networks |
| Kibble & Power 2004 | discourse: document coherence | linguistic trees heuristics |
| Mihalcea & Tarau 2004 | lexical: term associations | graphs/networks |
| Milo et al. 2004 | lexical: term associations | graphs/networks |
| Miltsakaki & Kukich 2004 | discourse: document coherence | heuristics |

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Table 3 — continued from previous page

| ARTICLE                        | TYPE OF SEMANTIC DEPENDENCE | TYPE OF APPROACH   |
|-------------------------------|-------------------------------|-------------------|
| Pang & Lee 2004 [259]         | discourse:                   | heuristics        |
| Pedersen et al. 2004 [255]    | lexical: term associations   | graphs/networks  |
| Poesio et al. 2004 [260]      | discourse: document coherence| heuristics        |
| van Rijsbergen 2004 [221]     | cognitive: document & query  | quantum           |
| Tomlinson 2004 [313]          | lexical: query difficulty    | heuristics        |
| Tsikrika & Lalmas 2004 [171]  | discourse: document relevance| graphs/networks  |
| Caldeira et al. 2005 [12]     | lexical: term associations   | graphs/networks  |
| Ferrer i Cancho 2005 [50]     | discourse: syntactic         | associations      |
| Larsen 2005 [168]             | cognitive: document          | heuristics        |
| Larsen & Ingwersen 2005 [100] | cognitive: document          | query associations|
| Medeiros Soares et al. 2005   | lexical: term associations   | graphs/networks  |
| Metzler & Croft 2005 [210]    | lexical: term associations   | graphs/networks  |
| Mishne et al. 2005 [230]      | lexical: term associations   | heuristics        |
| Mothe & Tanguy 2005 [235]     | lexical: query difficulty    | heuristics        |
| Plachouras & Ounis 2005 [263] | discourse: document relevance| logic             |
| Popescu & Etzioni 2005 [266]  | lexical: phrase sentiment    | heuristics        |
| Reyna & Brainerd 2005 [273]   | lexical: term associations   | graphs/networks  |
| Steyvers & Tenenbaum 2005     | discourse, cognitive: term & | concept associations| graphs/networks  |
| Venkatapathy & Joshi 2005     | lexical: term compositionality| vector space      |
| Vitevitch & Rodriguez 2005    | lexical & cognitive:         | term associations |
|                               | term associations             | graphs/networks  |
| Wiebe et al. 2005 [333]       | discourse: document sentiment | heuristics        |
| Wilson et al. 2005 [334]      | discourse: document subjectivity| heuristics       |
| Yom-Tov et al. 2005 [341]     | lexical: query difficulty    | heuristics        |
| Zhou & Croft 2005 [149]       | discourse: document quality  | heuristics        |
| Fung & Ngai 2006 [100]        | discourse: topic cohesion    | probabilistic     |
| Gamon 2006 [101]              | lexical: term associations   | graphs/networks  |
| Goldberg & Zhu 2006 [100]     | discourse: document sentiment| graphs/networks  |
| Hassan & Banea 2006 [113]     | lexical: term associations   | graphs/networks  |
| Karamanis 2006 [147]          | discourse: document coherence| probabilistic     |
| Katz & Giesbrecht 2006 [150]  | lexical: term compositionality| vector space      |
| Larsen et al. 2006 [170]      | cognitive: document          | heuristics        |
|                               | query associations            | graphs/networks  |
| Leicht et al. 2006 [177]      | lexical: term associations   | graphs/networks  |
| Masucci & Rodgers 2006 [215]  | lexical: term associations   | graphs/networks  |
| Muller et al. 2006 [239]      | lexical: term associations   | graphs/networks  |
| Nastase et al. 2006 [242]     | lexical: noun associations   | graphs/networks  |
| Shanahan et al. 2006 [263]    | discourse: document aspect   | heuristics        |
| Soricut & Marcu 2006 [300]    | discourse: document coherence| graphs/networks  |
| Wang et al. 2006 [328]        | discourse: rhetorical types  | graphs/networks  |

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Table 3 – continued from previous page

| ARTICLE                                | TYPE OF SEMANTIC DEPENDENCE                      | TYPE OF APPROACH |
|----------------------------------------|-------------------------------------------------|------------------|
| Antiqueira et al. 2007 [165]           | discourse: author attribution graphs/networks    |                  |
| Blanco & Lioma 2007 [31]               | lexical: term associations graphs/networks       |                  |
| Chen et al. 2007 [44]                  | discourse: document structure heuristics         |                  |
| Choudhury et al. 2007 [51]             | lexical: term associations graphs/networks       |                  |
| Cook et al. 2007 [51]                  | lexical: term associations linguistics            |                  |
| Esuli & Sebastiani 2007 [85]           | lexical: term associations graphs/networks       |                  |
| Ferrer i Cancho et al. 2007 [91]       | lexical: term associations graphs/networks       |                  |
| Filippova & Strube 2007 [94]           | discourse: document coherence heuristics         |                  |
| Hughes & Ramage 2007 [130]             | lexical: term associations graphs/networks       |                  |
| Lioma & Ounis 2007 [201]               | lexical: term quality heuristics                 |                  |
| Minkov & Cohen 2008 [229]              | lexical: term associations graphs/networks       |                  |
| Oussalah et al. 2008 [248]             | cognitive: document & query associations logic    |                  |
| Plaza et al. 2008 [264]                | lexical: term associations graphs/networks       |                  |
| Radhouni & Falquet 2008 [268]          | cognitive: document & query associations logic    |                  |
| Shi et al. 2008 [281]                  | discourse: document & query associations logic    |                  |
| Simou et al. 2008 [287]                | cognitive: document & query associations logic    |                  |
| Skov et al. 2008 [289]                 | cognitive: document & query associations heuristics|                  |
| Zuccon et al. 2008 [352]               | cognitive: document & query associations logic    |                  |
| Agirre & Sorroa 2009 [7]               | lexical: term associations graphs/networks       |                  |
| Antiqueira et al. 2009 [11]            | lexical: term associations graphs/networks       |                  |
| Banik 2009 [17]                        | discourse: document coherence heuristics         |                  |
| Bicknell & Levy 2009 [20]              | discourse: document coherence probabilistic      |                  |

Continued on next page
Table 3 – continued from previous page

| ARTICLE | TYPE OF SEMANTIC DEPENDENCE | TYPE OF APPROACH |
|---------|----------------------------|-----------------|
| Chen et al. 2009 | discourse: document coherence | probabilistic |
| Crestani 2009 | cognitive: document & query associations | logic |
| Diriye et al. 2009 | cognitive: document & query associations | heuristics |
| Juffinger et al. 2009 | discourse: document credibility | heuristics |
| Karamanis et al. 2009 | discourse: document coherence | probabilistic heuristics |
| Korkontzelos & Manandhar 2009 | lexical: term associations | graphs/networks |
| Larsen et al. 2009 | cognitive: document & query associations | heuristics |
| Lecce & Amato 2009 | cognitive: document & query associations | logic |
| Lioma et al. 2009 | cognitive: document & query associations | logic |
| Lv & Zhai 2009 | lexical: term association | probabilistic heuristics |
| Park et al. 2009 | discourse: document bias | heuristics |
| Ramage et al. 2009 | lexical: term associations | graphs/networks |
| Sinha et al. 2009 | lexical: term associations | graphs/networks |
| Somasundaran et al. 2009 | discourse: discourse relations & opinion polarity | classification heuristics |
| Somasundaran et al. 2009 | discourse: discourse relations & opinion polarity | classification heuristics |
| du Verle & Prendinger 2009 | discourse: rhetorical relations | vector space |
| Wittek et al. 2009 | lexical: term associations | heuristics |
| Yu et al. 2009 | discourse: rhetorical relations | heuristics |
| Bendersky et al. 2010 | lexical: term associations | graphs/networks probabilistic |
| Burstein et al. 2010 | discourse: document coherence | probabilistic |
| Cheung & Penn 2010 | discourse: document coherence | heuristics |
| Clarke & Lapata 2010 | discourse: rhetorical relations | heuristics |
| Efron & Winget 2010 | cognitive: document & query associations | heuristics |
| Ennals et al. 2010 | discourse: document controversy | heuristics |
| Frommholz et al. 2010 | cognitive: document & query associations | quantum |
| Lex et al. 2010 | discourse: document objectivity | heuristics |
| Lipka & Stein 2010 | discourse: document quality | heuristics |
| Mitchell & Lapata 2010 | lexical: term compositionality | vector space |
| Suwandelatna & Perera 2010 | discourse: topic identification | graphs/networks |
| Yessenalina et al. 2010 | discourse: document subjectivity | heuristics classification |
| Bendersky et al. 2011 | discourse: document quality | heuristics |
| Celikyilmaz & Hakkani-Tur 2011 | discourse: document coherence | probabilistic heuristics |
| Elsner & Charniak 2011 | discourse: document coherence | probabilistic heuristics |
| Elsner & Charniak 2011 | discourse: document coherence | probabilistic heuristics |

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| ARTICLE | TYPE OF SEMANTIC DEPENDENCE | TYPE OF APPROACH |
|---------|-----------------------------|-----------------|
| Ghosh et al. 2011 [104] | discourse: argument segmentation | linguistic analysis classification |
| Heerschop et al. 2011 [120] | discourse: discourse relations opinion polarity | heuristics |
| Herzig et al. 2011 [122] | discourse: document bias | heuristics |
| Lin et al. 2011 [187] | discourse: document coherence | classification heuristics |
| Lioma et al. 2011 [194] | lexical: term associations | probabilistic heuristics |
| Michelbacher et al. 2011 [221] | lexical: term compositionality | classification heuristics |
| Reddy et al. 2011 [270] | lexical: term compositionality vector space | |
| Schwarz & Morris 2011 [281] | discourse: document credibility | heuristics |
| Socher et al. 2011 [295] | lexical: term compositionality deep learning | |
| Wang et al. 2011 [329] | discourse: discourse relations | heuristics |
| Wiebe & Riloff 2011 [332] | discourse: document subjectivity | classification heuristics |
| Zhang 2011 [346] | discourse: document coherence graphs/networks | |
| Zhou et al. 2011 [348] | discourse: rhetorical relations & document sentiment | heuristics |
| Li et al. 2012 [182] | lexical: phrase compositionality vector space | |
| Morris et al. 2012 [234] | discourse: document credibility | heuristics |
| Tan et al. 2012 [308] | discourse: document comprehensibility | heuristics |
| Guinaudeau & Strube 2013 [108] | discourse: document coherence graphs/networks | |
| Horn et al. 2013 [128] | discourse: document factuality | heuristics |
| Kiela & Clarke 2013 [154] | lexical: phrase compositionality vector space | |
| Krcmar et al. 2013 [162] | lexical: term compositionality vector space | |
| Mikolov et al. 2013 [225] | lexical: term compositionality deep learning | |
| Oh et al. 2013 [242] | discourse: document trustworthiness | heuristics |
| Rousseau & Vazirgiannis 2013 [275] | lexical: term associations | graph theory |
| Salehi & Cook 2013 [276] | lexical: phrase compositionality | heuristics |
| Schulte et al. 2013 [133] | lexical: term compositionality vector space | |
| Xiong et al. 2013 [137] | discourse: document cohesion | probabilistic |
| Banea et al. 2014 [149] | discourse: document subjectivity | heuristics |
| Chenlo et al. 2014 [156] | discourse: rhetorical relations | heuristics |
| Choi et al. 2014 [150] | discourse: rhetorical relations | probabilistic |
| Frommholz & Abbasi 2014 [177] | cognitive: document & query associations | heuristics statistics |
| Hill & Korhonen 2014 [123] | lexical: phrase subjectivity | heuristics |
| Kartsaklis 2014 [139] | lexical: term compositionality | logic |
| Li & Hovy 2014 [183] | discourse: document coherence deep learning | |
| Abbasi & Frommholz 2015 [16] | cognitive: document & query associations | heuristics statistics |

*Continued on next page*
Table 3 – concluded from previous page

| ARTICLE | TYPE OF SEMANTIC DEPENDENCE | TYPE OF APPROACH |
|---------|----------------------------|------------------|
| Dima 2015 [66] | lexical: term compositionality | vector space |
| Eickhoff et al. 2015 [74] | lexical: term dependence | logic |
| Hunter et al. 2015 [132] | discourse: rhetorical relations | graphs/networks, heuristics |
| Kuyten et al. 2015 [163] | discourse: rhetorical relations | probabilistic |
| Le & Zuidema 2015 [175] | lexical: term compositionality | deep learning |
| Lioma et al. 2015 [202] | lexical: term compositionality | vector space, probabilistic |
| Mineshima et al. 2015 [228] | lexical: term compositionality | logic |
| Neelakantan et al. 2015 [243] | lexical: term compositionality | vector space |
| Petersen et al. 2015 [259] | discourse: document coherence | graphs/networks, probabilistic |
| Qiu et al. 2015 [267] | lexical: term associations | vector space, deep learning |
| Salehi et al. 2015 [277] | lexical: term compositionality | deep learning |
| Voskarides et al. 2015 [327] | discourse: entity relations | graphs/networks |
| Xiong et al. 2015 [338] | discourse: document coherence | probabilistic |
| Yazdani et al. 2015 [339] | lexical: term compositionality | deep learning |
| Zellhoefer 2015 [344] | cognitive: query associations | heuristics |
| Zhang et al. 2015 [344] | discourse: document coherence | graphs/networks, probabilistic |
| Asher et al. 2016 [11] | lexical: term compositionality | semantic theory |
| Cordeiro et al. 2016 [53] | lexical: term compositionality | deep learning |
| Ermakova & Mothe 2016 [54] | discourse: document structure | probabilistic, heuristics |
| Gutierrez et al. 2016 [110] | lexical: term compositionality | vector space |
| Hashimoto & Tsuruoka 2016 [117] | lexical: term compositionality | deep learning |
| Lioma et al. 2016 [143] | discourse: document coherence | graphs/networks |
| Liu & Huang 2016 [206] | discourse: sentence dependence | deep learning |
| Monroe et al. 2016 [234] | lexical: term compositionality | deep learning |
| Nikolaev et al. 2016 [248] | lexical: term associations | heuristics |
| Paperno & Baroni 2016 [251] | lexical: term compositionality | vector space |
| Pavlick & Callison-Burch 2016 [253] | lexical: term compositionality | logic |
| Tian et al. 2016 [313] | lexical: term compositionality | vector space |
| Toutanova et al. 2016 [316] | lexical: term compositionality | deep learning |
| Zhang et al. 2016 [317] | lexical & discourse: term & sentence associations | deep learning |
| Zhu et al. 2016 [331] | lexical: term compositionality | deep learning |
| Lioma and Hansen 2017 [193] | lexical: term compositionality | distance metrics |
7 Conclusions

Building machines that can simulate understanding text like humans is an AI-complete problem\(^{18}\). A great deal of research has already gone into this, with astounding results, allowing everyday people to discuss with their telephones, or orally instruct their laptops to select and analyse their reading materials. A prerequisite for processing text semantics, common to all applications of information retrieval, is having some computational representation of text as an abstract object. Operations on this representation practically correspond to making semantic inferences, and by extension simulating understanding text. The complexity and granularity of semantic processing that can be realised is constrained by the mathematical and computational robustness, expressiveness, and rigour of the tools used.

This dissertation presents a series of such tools, diverse in their mathematical formulation, but common in their application to model the semantic dependence of words, sentences and concepts in textual information retrieval. These tools are principally expressed in nine distinct models that capture aspects of semantic dependence in highly interpretable and non-complex ways. This dissertation further expands beyond these separate nine contributions, and presents embracive reflections on the following two levels:

I. FUTURE ANALYTICAL METHODS. A great amount of research focus is directed towards refining and improving methods of semantic processing by training them on increasingly larger and more challenging data. This requires additional and powerful parameterised adaptation (this was traditionally manually controlled and interpretable, but is increasingly becoming self-adaptive and harder to interpret). While this practice is generally useful and attractive, it should not be the only one. Justified as its predominance may be, if unchallenged, it risks leading the area into a standstill (there is only so much parameterisation that can be sustained).

The amalgamation of the body of work presented in this dissertation shows an alternative way of thinking about our methods of analysis: there is a lot to be gained from taking a step back and considering alternative characterisations, representations and solutions to the general problem of text understanding in information retrieval. Above and beyond the specific methods presented in this dissertation, the overarching message is to start thinking about new methods. This is predicated on our capacity and our need to do so, or in more plain English, because we can and because we must.

- We can start thinking of new methods because, as fellow disciplines within and outside computer science and mathematics advance, their output is a stream of inspiration for reasoning about text semantics.

\(^{18}\) AI-complete refers to artificial intelligence problems whose solution is non-trivial and cannot be approximated by any simple specific algorithm.
Our capacity to think of new methods is anything but constrained by such advances.

- We must start thinking of new methods because, if we do not, the research in the area will eventually close in on itself and lose its innovative drive that has been so far pushing it forward.

II. FUTURE RESEARCH QUESTIONS. The amount of core research questions posed in information retrieval today seems notably smaller than the amount of scenarios (or tasks) within which these questions are examined, without this implying that we have arrived at general solutions of these research questions. There is a lot to be gained from asking new questions about text and its semantic interpretation by computers. Not asking new research questions cannot advance semantic processing. New inferences are required to address new and unexpected challenges, such as the novel problems pertaining to discourse dependence that this dissertation argues should be solved in textual information retrieval. After all, reliability and validity are properties of inferences, not of methods.

For an area that has been vigorously investigated for more than 50 years now, it is alarming to see how little reasoning is done outside word counts. Several of the advances described in this dissertation could, in principle, have been made 20 years ago, in the sense that the theoretical tools needed were already in place; it is just that no one thought of asking these questions before. The time is now ripe for new research questions, instead of continuing to hammer the proverbial same old hammer upon the same old nail.

Collectively, the above reflections pave the way for refined semantic processing in information retrieval systems, where shallow semantic processing is traditionally preferred. These insights have the potential to inspire new models of computational processing and analysis that can improve notably the performance of semantic inferences made by search engines and similar technologies. This type of refined semantic processing is expected to be particularly valuable in the emerging field of content-based retrieval that requires systems enabling people not only to access but also to assess the information they interact with, for instance in terms of its credibility, transparency, or bias [197].

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