Graphs and Information Retrieval

Proefschrift

ter verkrijging van de graad van doctor
aan de Radboud Universiteit Nijmegen
op gezag van de rector magnificus prof. dr. J.H.J.M. van Krieken,
volgens besluit van het college van decanen
in het openbaar te verdedigen

op woensdag 22 maart 2023

om 12:00 uur precies

door

Chris Frans Henri Kamphuis
geboren op 22 maart 1993
te Oldenzaal, Nederland

Promotor:

prof. dr. ir. A.P. (Arjen) de Vries

Manuscriptcommissie:

Person A	(Affiliation)
Person B	(Affiliation)
Person C	(Affiliation)
Person D	(Affiliation)
Person E	(Affiliation)

This work is part of the research program Commit2Data with project number 628.011.001 (SQIREL-GRAPHS), which is (partly) financed by the Netherlands Organisation for Scientific Research (NWO).

Printed by a drukkerij met een naam

Typeset using LaTeX

ISBN: 111-11-11111-11-1

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Chapter 1

Introduction

> I *propose* to consider the question, "Can machines think?"
>
> Alan Turing - 1950

I also propose to consider the question, "Can machines think?" Instead of approaching this through a thought experiment as Turing did, nowadays, one can approach this question by asking it to a search engine. When issuing this query to popular web search systems, we get varying results: the first result on Google is a passage generated from the article written by Turing, while the first result on Bing is a passage generated from a website that concludes machines cannot think.[1,2]

We use systems that process queries daily when looking for *information*. While Google and Bing are all-purpose web engines that mainly focus on finding and retrieving information from the internet, people also use specialized search systems in their day-to-day lives: Amazon and eBay when we are looking for a product to buy, Scholar and ResearchGate for scientific resources, Youtube and TikTok for Videos, or Facebook and LinkedIn when we are searching for people. It might even be possible that you are reading this text after you found this document through search.

When searching for the query, "Can machines think?", searching

[1] However, if a machine cannot think, can we trust the result presented by this algorithm?

[2] These results were retrieved in October of 2022

through text documents only might be sufficient for the person who searches. However, more than considering the text is needed when searching today. For example, when one wants to buy a product on Amazon, aspects other than text also need to be considered. Let us say you want to buy an iPhone; information on the price, which edition is the most recent, or which color it has are all essential to determine which one you want. You may also want to consider the rating provided by people that previously bought an iPhone.

If someone searches for people on LinkedIn, they are generally more interested in persons they are connected to than strangers. If you are looking for someone to do a job, it is ideal that a shared connection can vouch for them. In this case, how people relate to each other in their network might indicate *relevance*. Not only the structure of how people relate to each other determines relevance; other examples are their experience, where they work, or reviews of their previous work might matter.

Although it might be possible to encode all this information as written text, often, it is more convenient to save this information in a more structured approach. Where information retrieval researchers research the retrieval of "information" through text data, data management researchers research the retrieval of structured data. This thesis considers both methods simultaneously: systems that can work with structured and unstructured information are investigated.

1.1 Problem Description and Research Questions

Although information retrieval and data retrieval are research fields investigated by different disciplines, they are closely related, and systems that use both have been researched and developed in the past (In later parts of this thesis, examples are provided). Also, techniques developed in one community might help the other, as things like storing and quickly retrieving data are essential for information and data retrieval.

In recent years there has been much exciting research in the database community studying graph databases. What these databases exactly are will be described in chapter 2. As these databases are becoming more popular for data retrieval tasks where the data is highly inter-

connected, they might also benefit similar tasks in the information retrieval field where data is often highly interconnected. This thesis will investigate how these databases, with dedicated graph query languages, can be used for information retrieval tasks. This leads us to this thesis's main research question: **Research Question: How can information retrieval benefit from graph databases and graph query languages?**

Three sub-research questions are defined to guide us in answering the main research question:

1. *Research Question 1: What are the benefits of using relational databases for information retrieval?*

2. *Research Question 2: Can we extend the benefits from using relational databases for information retrieval to using graph databases while being able to express graph-related problems easier?*

3. *Research Question 3: When does information retrieval research benefit from graph data?*

Chapters 3, 4 and 6 will take these research questions and try to answer them. Then in Chapter 7, we will try to take the answers to these questions and use them to answer the main research question.

1.2 Thesis Contributions and Structure

- Chapter 2 will describe all necessary background information to provide context to the other chapters. The background that is described in this chapter concerns the "general" background knowledge for this thesis. Individual chapters will also have related work sections that concern the background knowledge in those chapters. The information described in those related work sections might contain overlapping information, i.e., the knowledge needed to understand the context of those chapters. This is done to make it possible to understand a chapter without first reading the chapters that come before it.

- Chapter 3 concerns information retrieval research using relational databases. Although, traditionally, inverted indexes are used

for information retrieval, we show that by employing relational databases, some advantages are gained. First, attempts to use relational databases for information retrieval through the years will be described. One of the latter attempts used a column-oriented relational database system for information retrieval, achieving competitive efficiency compared to a traditional system built using inverted indexes. This approach is re-implemented as a prototype system used, which is then used for a reproduction study. This chapter establishes the usefulness of relational databases for information retrieval by demonstrating its benefits. The content in this chapter is based on the following published works:

  - C. Kamphuis and A. P. de Vries. The OldDog Docker Image for OSIRRC at SIGIR 2019. In *Proceedings of the Open-Source IR Replicability Challenge co-located with 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval, OSIRRC@SIGIR 2019, Paris, France, July 25, 2019*, pages 47–49, Aachen, 2019b. CEUR-WS.org. URL `http://ceur-ws.org/Vol-2409/docker07.pdf`
  - C. Kamphuis, A. P. de Vries, L. Boytsov, and J. Lin. Which BM25 Do You Mean? A Large-Scale Reproducibility Study of Scoring Variants. In *Advances in Information Retrieval*, ECIR '20, pages 28–34, Cham, 2020. Springer International Publishing. ISBN 978-3-030-45442-5

- Chapter 4 takes the concept of employing relational databases for information retrieval and extends the relational model to the graph model. GeeseDB is introduced, a graph database prototype system built on top of an embedded column-oriented relational engine. Using the graph model makes it possible to express more complex information retrieval problems than when the relational model is used. These more complex models often use multi-stage retrieval approaches. GeeseDB is built on top of an embedded database system, so moving data between ranking stages can be done efficiently. The content of this chapter has previously been described in the following published works:

  - C. Kamphuis and A. P. de Vries. Reproducible IR needs an (IR) (graph) query language. In *Proceedings of the Open-Source IR Replicability Challenge co-located with 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval, OSIRRC@SIGIR 2019, Paris, France, July 25, 2019*, pages 17–20, Aachen, 2019a. CEUR-WS.org. URL `http://ceur-ws.org/Vol-2409/position03.pdf`
  - C. Kamphuis and A. P. de Vries. GeeseDB: A Python Graph Engine for Exploration and Search. In *Proceedings of the 2nd International Conference on Design of*

Experimental Search & Information REtrieval Systems, DESIRES '21, pages 10–18, Aachen, 2021. CEUR-WS.org. URL `http://ceur-ws.org/Vol-2950/paper-11.pdf`

- Chapter 5 introduces the concept of entity linking. Specifically, the Radboud Entity Linker [van Hulst et al., 2020] system is discussed. When trying to utilize REL to annotate a large corpus with entity linking, issues were found that prohibited the annotations process to such an extent that it was not possible to do within a reasonable time. In order to be able to annotate the corpus, the REL toolkit internals were upgraded, and a batch extension was developed. Altogether this led to more efficient software such that REL can annotate larger corpora. The content in this chapter has previously been described in the following published work:

  – C. Kamphuis, F. Hasibi, J. Lin, and A. P. de Vries. REBL: Entity Linking at Scale. In *Proceedings of the 3rd International Conference on Design of Experimental Search & Information REtrieval Systems*, DESIRES '22, Aachen, 2022. CEUR-WS.org. URL `https://desires.dei.unipd.it/2022/papers/paper-08.pdf`

- Chapter 6 will employ the software described in the chapter before it and uses it to annotate a large web corpus. We developed a specification of how entity link annotations can be shared for these annotations. Following this specification, we made the annotations for the MS MARCO [Bajaj et al., 2016] corpora publicly available. Using these annotations, we show that, through query expansion, we can increase recall effectiveness for first-stage rankers on this dataset. Next, a demonstration shows how entity links can also be used for geographical information applications. This content has been described in the following work, accepted for publication;

  – C. Kamphuis, A. Lin, S. Yang, J. Lin, A. P. de Vries, and F. Hasibi. MMEAD: MS MARCO Entity Annotations and Disambiguations. In *Proceedings of the 46th International ACM SIGIR Conference on Research & Development in Information Retrieval*, SIGIR '23, New York, NY, USA, 2023. Association for Computing Machinery. ISBN 978-1-4503-9408-6. doi: 10.1145/3539618.3591887

- Chapter 7 will serve as a conclusion and tries to summarize the content discussed in the book. Here we will reflect on the research question and discuss what future research is needed.

1.3 Other Publications

During the employment at Radboud University, the following work was also published:

- C. Kamphuis, F. Hasibi, A. P. de Vries, and T. Crijns. Radboud University at TREC 2019. In *NIST Special Publication 1250: The Twenty-Eighth Text REtrieval Conference Proceedings (TREC 2019)*, TREC '19, Gaithersburg, Maryland, 2019. [Sl]: NIST. URL `https://trec.nist.gov/pubs/trec28/papers/RUIR.N.C.pdf`

- J. Lin, J. Mackenzie, C. Kamphuis, C. Macdonald, A. Mallia, M. Siedlaczek, A. Trotman, and A. P. de Vries. Supporting Interoperability Between Open-Source Search Engines with the Common Index File Format. In *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*, SIGIR '20, page 2149–2152, New York, NY, USA, 2020a. Association for Computing Machinery. ISBN 9781450380164. doi: 10.1145/3397271.3401404

- P. Boers, C. Kamphuis, and A. P. de Vries. Radboud University at TREC 2020. In *NIST Special Publication 1266: The Twenty-Ninth Text REtrieval Conference Proceedings (TREC 2020)*, TREC'20, Gaithersburg, Maryland, 2020. [Sl]: NIST. URL `https://trec.nist.gov/pubs/trec29/papers/RUIR.N.pdf`

- T. Schoegje, C. Kamphuis, K. Dercksen, D. Hiemstra, T. Pieters, and A. P. de Vries. Exploring task-based query expansion at the TREC-COVID track. *CoRR*, abs/2010.12674, 2020. URL `https://arxiv.org/abs/2010.12674`

- C. Kamphuis. Graph Databases for Information Retrieval. In *Advances in Information Retrieval*, pages 608–612, Cham, 2020. Springer International Publishing. ISBN 978-3-030-45442-5

Although this work relates to the main subject of the thesis, it is not used as source material for the work described in this thesis.

Chapter 2

Background

> Machines take me by surprise with great frequency.
>
> Alan Turing - 1950

2.1 Introduction

This chapter aims to provide the context in which this work is written. By introducing the related scientific fields, this chapter sketches a broader context wherein this research exists.

First, the field of information retrieval is introduced. Within the field of information retrieval, different approaches to *retrieving information* have been used throughout the decades. These approaches will be introduced such that the reader understands what works in the field. The work described in this thesis would also be considered information retrieval research.

Secondly, techniques from different research areas are also used for this research. Specifically, the research described in this thesis extensively uses techniques typically investigated by the *data management* community. This field will also be introduced, especially the techniques used for the research described in this work are highlighted.

Then, the concept of *graphs* will be explained. Graphs themselves are just mathematical structures that model the relations between objects. The objects are modeled as *nodes* and relations between them

as *edges*. Many kinds of graphs exist; they are helpful for modeling problems that can be expressed formally through this framework. Different kinds of graphs will be explained, and examples of how to use them will be provided.

Finally, we will describe the idea of *reproducible science*. In general, scientific work must be reproducible. In our research, we spend additional effort on reproducible science. What reproducibility exactly entails will be introduced.

2.2 Information Retrieval

The research described in this thesis is *information retrieval* research. Colloquially, one can refer to information retrieval as the science of everything relating to search engines. This field encompasses all aspects: from user experiences of search systems to storage algorithms and fast retrieval of the information items users search. Baeza-Yates et al. [1999] introduce information retrieval as the following:

Information retrieval (IR) deals with the representation, storage, organization of, and access to information items.

Following this description, an information retrieval system, i.e., a search engine, is a system that allows users to access information items that they are looking for. How this works internally is typically not interesting for the user, they want to find the information they seek. Typically, and also in this thesis, the term *document* refers to information items, even though the item the user seeks is not necessarily a document literally.

Consider the following situation; someone wants to know whether it will rain in the coming half an hour. They might query a web search engine with the text *weather*. In this case, the user does not care how the search engine works but only about the result. In order to satisfy the user's information need, the search engine needs to (1) present the correct weather forecast and (2) do this quickly. The user will be dissatisfied if the search engine presents the incorrect weather forecast or cannot do this in seconds.

In order to answer this inquiry for information correctly, the information retrieval system needs more context. It can only correctly know the weather if it is known where the user resides. Typically, when

accessing search engines through a telephone or computer, this information is sent along with the query as metadata. This way, the search engine can correctly answer even though the user did not explicitly give this information.

Then when the user's location is known, the search engine needs to find a webpage that correctly provides the weather for that particular location. As there are billions of web pages in the search engine's index, correctly identifying which one contains information about the weather at that particular location and time and then retrieving it in seconds is the next challenge.

Search engines must smartly organize the data because it is infeasible to iterate over all web pages to check if the correct information is available. Typically, documents within a search engine are organized through a data structure called an inverted index.

2.2.1 Inverted Indexes

Inverted indexes have been used for decades in the field of information retrieval. They are designed to access documents quickly. If a system cannot provide the data quick enough, the user would use a different system. Documents are typically structured through words that form sentences, which form paragraphs, and, eventually, stories. When considering a document in its standard form, it is not trivial to quickly know whether it contains a specific word. When searching for something, it is paramount that the search engines know what documents contain the keywords in the query. Documents are *inverted* to store this information. Instead of storing documents as is; a mapping from documents to words, search engines store the inverted information; a mapping from words to documents. To provide an example, consider the following three short documents:

1. Cats and dogs are animals.
2. Cats are smart animals.
3. Dogs are great at tricks.

Then the inverted index looks something like this:

animal: [1 2], **cat:** [1 2], **dog:** [1 3], **great:** 3, **smart:** 2, **trick:** 3

There are a couple of interesting observations that can be made here. Not all words appear in the inverted index. Typically words without "meaning", or so-called stop words, are dropped. These words tend to contain no semantic information and can therefore be dropped. This process is called stopword removal or *stopping*. Then, words are sometimes shortened to their *stem*. Let us say we have a query only mentioning the word "dog", so not plural, then we still want to be able to find the documents that mention the plural form. This shortening to the word's stem is called *stemming*. In this case, the words are ordered alphabetically. When the number of documents in a collection increases, the number of unique words also increases. By storing the words alphabetically, a computer can find the entries for that particular word easier.

When someone queries the search engine with the following query: "dog tricks", the search engine can directly find which documents contain these words using the inverted index. It can then automatically discard all documents that do not contain these words. For the keywords, the search engine retrieves the lists associated with them. These lists are called *posting lists* in information retrieval. Entries in such lists are referred to as *postings*. In this case, the postings only contain the document identifiers as data. Generally, however, information like how often a word appears in a document or its location is also stored in the posting. In practice, posting lists are often compressed, and instead of storing the direct identifiers, the gaps between them are stored such that the index becomes smaller. In literature, these gaps are referred to as delta gaps.

In this case, the posting lists of the words "dog" and "trick" are retrieved: [1 3] and [3]. Then some scoring method can process these lists and assign a score to the documents present in these lists. As document 3 is the only document containing both words, it makes sense to consider this document the most relevant. However, assessing relevance ordering is more complex when multiple documents contain both words with different frequencies. In order to create orderings based on relevancy, different models for scoring documents have been proposed in the past. In the following sections, these models are presented.

2.2.2 Ranking Models

Boolean Retrieval

The boolean retrieval model was used in the early days of information retrieval. Boolean retrieval can be formulated as the following; let,

$$T = \Big\{t_1, \quad t_2, \quad \ldots, \quad t_n\Big\} \tag{2.1}$$

be the set of all index terms that appear in the collection. Let,

$$D = \Big\{d_1, \quad d_2, \quad \ldots, \quad d_m\Big\} \tag{2.2}$$

be the set of all documents, where every document is a subset of T. Specifically, the terms that appear in that document. Then a query can be any boolean expression over T. All documents that adhere to the boolean expression formed by the query are considered relevant. To give an example, consider the same three documents as before:

1. Cats and dogs are animals.
2. Cats are smart animals.
3. Dogs are great at tricks.

Then, D is formulated as $\{ d_1, d_2, d_3 \}$ with,

$$d_1 : \Big\{cat, \quad dog, \quad animal\Big\} \tag{2.3}$$

$$d_2 : \Big\{cat, \quad smart, \quad animal\Big\} \tag{2.4}$$

$$d_3 : \Big\{dog, \quad great, \quad trick\Big\} \tag{2.5}$$

One could be interested in finding all documents that mention dogs but not cats. Then we can formulate the following boolean query:

$$Q = dog \wedge \neg cat \tag{2.6}$$

Then if we find all subsets that adhere to the individual terms in this conjunction, we get the following set expression:

$$Q = \{d_1, d_3\} \ \cap \{d_3\} = \{d_3\} \tag{2.7}$$

This shows that document d_3 is the only document about dogs, not cats. Although it is possible to express complicated expressions with boolean logic, a document either satisfies the expression or does not. All documents that satisfy the expression are considered relevant; creating a ranking between them cannot be done with this approach alone.

With this approach, there is no apparent difference between data retrieval and information retrieval; there is only one correct solution: all documents that satisfy the restrictions imposed by the query.

Vector Space Models

In 1975, the vector space model was introduced by Salton et al. [1975]. The idea behind the vector space model is to represent documents and queries as vectors. Consider a collection that has t unique terms, then we can represent a document in the collection as a t dimensional vector:

$$D_j = \Big(w_0, \cdots, w_t\Big) \tag{2.8}$$

where D_j is the j-th document in the collection, and w_i represents the weight associated with the i-th term in the collection. These weights can be binary, or if one only wants to consider the importance of the term in the document, they can be the term frequency or any weight that considers the "general" term importance.

Then if we have a query q, we can represent it in the same way:

$$q = \Big(q_0, \cdots, q_t\Big) \tag{2.9}$$

where q_i represents the weight of the i-th term in the collection. Most values in these vectors will be zero.

Now it is possible to calculate a similarity score between the query and every document. This similarity is typically calculated by calculating the cosine similarity between the two vectors, which between a document d and a query q is defined as:

$$\cos(d, q) = \frac{\mathbf{d} \cdot \mathbf{q}}{||\mathbf{d}||\ ||\mathbf{q}||} \tag{2.10}$$

Then, calculating this for the documents in the collection gives a relevance score value for all of them. Ordering them based on relevance then produces a ranked list where the highest is presumed to be the most interesting for the user. As mentioned before, the

weights represented in the document vector do not necessarily have to be binary. Salton et al. showed that the product of the term frequency with a general measure of term importance worked best. The measure they used for term importance was the inverse document frequency proposed by Spärck Jones [1972] three years earlier.

Probabilistic Relevance Models

In 1976, Robertson and Spärck Jones developed the probabilistic ranking framework. Within this framework, it is assumed that a document has a certain probability of being relevant given a query. Then, a search system that implements models within this framework ranks documents. Documents with the highest probability of being relevant are ranked the highest.

Within this framework, with the assumption of binary independence, which is nicely explained by Robertson and Zaragoza [2009], the Robertson-Spärck Jones weight can be derived. When assuming no relevance labels are available, this leads to an approximation of the classical inverse document frequency.

Then by extending this function to include within-document term frequency information and document length normalization, the well-known BM25 function can be derived. Chapter 3 will focus on this model, and additional information explaining this model will be presented there.

Language Models

Later, language models were proposed [Song and Croft, 1999, Hiemstra, 2001, Zhai and Lafferty, 2002]. The idea behind language models is that documents are considered language samples. These samples can be used for a generative process. This process generates terms in the sample by randomly selecting one of the words from that sample. Let the probability of a document d generating a term t_i be:

$$P(t_i|d) = \frac{tf_{t_i,d}}{\sum_t^d tf(t,d)} \tag{2.11}$$

with $tf_{t_j,d}$ being the term frequency of term t_j in document d.

Then, if we have a query Q. It is possible to calculate the likelihood that the document samples generated this query, as we know for every

term in the query what the probability is that one of the document samples generates that term:

$$P(d|Q) = \prod_{q \in Q} P(q|d) \tag{2.12}$$

There are some issues when we take the document with the maximum likelihood. First, if a query contains multiple terms, a document can only get a non-zero likelihood of generating that query if all query terms exist in that document. If this is not the case, the probability of generating that term would be 0. As we calculate the maximum likelihood, we take the product of the individual probabilities of the query terms. Then the second issue is that there is no term-independent specificity weighting. Terms with a higher degree of specificity should increase the resulting probabilities more than "filler" words. The previously described inverse document frequency took care of this in the vector space model.

In order to overcome these issues, a smoothing technique is used. Instead of only considering the samples formed by the documents, a collection-wide sample is also being used. This collection-wide sample generates terms according to the frequency in which the terms appear in the collection:

$$P(t_i|C) = \frac{df(t_i)}{\sum_t df(t)} \tag{2.13}$$

With C being the collection, and $df(t_i)$ the document frequency of term t_i; i.e., the number of documents in the collection in which term t_i appears. Then, the probability generated by the document sample is interpolated by the probability generated by the collection sample:

$$P(d|Q) = \prod_{q \in Q} \omega \cdot P(q|d) + (1 - \omega) \cdot P(q|C) \tag{2.14}$$

with ω being the smoothing factor, i.e., how much is the collection sample weighted against the document sample?

This smoothing solves both problems. As the collection sample contains all terms, it is no longer possible for probabilities generated by a specific term to be zero, so the resulting product will not be zero either. Then, words with a higher specificity also get a boost; words with a high specificity have a low probability of being generated by the collection sample, meaning that it is more important for a document

to contain that word to achieve a high probability of relevance. Words with a low specificity have a smaller effect; the probability of them being generated by the collection sample is already relatively high.

Learning to Rank

With the increase in computing power, learning to rank became a popular approach to ranking. The methods described in the previous sections can all be considered unsupervised learning methods if we look at them from a machine-learning perspective. Learning to rank models would be considered supervised or reinforcement learning methods.

The goal is to learn a model that, given a query, ranks documents relevant to that query higher than those not relevant to that query. In general, there are three ways to achieve this; for all these methods, relevance labels are assumed to be available from which the function can be learned. Learning-to-rank methods are usually categorized into the following three categories:

Pointwise. Pointwise methods are most comparable to standard regression methods. The idea is to learn a function that directly predicts a document's relevance label. Consider that we have n query-document pairs for which relevance labels are available, with m independent variables per pair. Then the relevance labels for these pairs can be expressed as a vector $\mathbf{y}$, and the independent variables as a matrix $\mathbf{X}$;

$$\mathbf{y} = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} \qquad (2.15) \qquad \mathbf{X} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,m} \\ \vdots & \ddots & \vdots \\ x_{n,1} & \cdots & x_{n,m} \end{bmatrix} \qquad (2.16)$$

Then, the goal is to learn a function $\hat{\mathbf{y}} = f(\mathbf{X})$ such that some distance measure between $\mathcal{L}(\hat{\mathbf{y}}, \mathbf{y})$ is minimized. Commonly used measures for this are mean square error or mean absolute error. The pointwise learning approach to ranking has some unwanted properties, however. Consider a situation where we have three documents; $[\, d_1, d_2, d_3 \,]$, with relevance labels $[\, 1, 0, 0 \,]$, i.e. document d_1 is relevant and the other documents are not. Then, two different ranking functions, a and b, might produce the following predicted relevance labels:

$a = [1, 0.9, 0.8]$ and $b = [0, 0.1, 0.2]$, which results in the following respective rankings: $[d_1, d_2, d_3]$ and $[d_3, d_2, d_1]$. The ranking produced by system a is objectively better. It ranks the relevant document as the most relevant. System b, however, ranks the relevant document as the least relevant. If we evaluate the two systems with a loss function, say mean absolute error, system b would seem better as the mean absolute error is smaller.

Pairwise. Pairwise ranking tries to deal with this by not directly learning from the relevance label but by looking at pairs of documents. The idea behind this is that it does not matter what the actual ranking score value is determined as long as it is higher for relevant documents than non-relevant ones.

Pairwise functions consider, given a query, two documents at a time. Then the function tries to determine which one of the two documents is more relevant than the other. If we consider the same set of relevance labels $\mathbf{y}$ and independent variables $\mathbf{X}$, then if we would take a pair of documents x_k and x_l, with their corresponding relevance labels y_k and y_l, assuming $y_k \neq y_l$, then we are trying to learn the following function:

$$f(x_k, x_l) = \begin{cases} 0 & \text{if } y_k < y_l \\ 1 & \text{if } y_k > y_l \end{cases} \tag{2.17}$$

This function can be learned by any binary classification method. After the method is learned, it can be used to determine an ordering of documents. Pairwise methods tend to be more expensive than pointwise methods, as the number of samples to train on for pointwise methods is n, with n being the number of documents for which relevance assessments are available per query. For pairwise methods, every document with a label can be compared with every other document, creating n^2 training samples per query.

A disadvantage of pairwise methods is that every pair is treated equally when training a model. There is no difference when comparing the two highest-ranked documents to comparing the two lowest-ranked documents, even though users typically care about the highest-ranked documents.

Listwise. Instead of only looking at pairs of documents, the listwise approach considers the whole ranking. This way, the top of the ranking can affect the function's learning more than the bottom of the ranking. Generally, when learning a listwise learning-to-rank method, the goal is to optimize some ranking metric quality directly. Examples of ranking metrics will be introduced in Section 2.2.3.

Multistage Ranking In many cases, applying inference to all documents in the collection is still impossible because of computational costs. A non-learning-to-rank approach is often used to create an initial ranking. Then it is assumed that the top-k documents probably contain all relevant documents. Then the learned method only has to reorder the top-k documents to present to the user.

In these cases, it can make sense to rank the top-k documents using an inverted index, while the reranking is done with another computer program.

Vector Space Models revisited

With the rise of large language models, the vector space model became more popular again due to what is called *dense* retrieval.

The basic idea is to predict the relevance of a document d for a query q:

$$rel(q, d) = \omega\left(\phi\left(q\right), \psi\left(d\right)\right) \tag{2.18}$$

Here, ψ and ϕ are learned functions using large language models that map the query and the document to vectors with low dimensionality. These functions map the query and the document to the same space. When documents are relevant to the query, the resulting vectors should be similar, while if the document is not relevant, they should be dissimilar. This similarity is measured through the function ω, often the dot-product or cosine similarity.

Finding the vectors closest to a query vector is the same as nearest neighbor search. In the case of dense retrieval, dedicated dense retrieval systems tend to be used instead of an inverted index.

2.2.3 Evaluation

In the previous section, all kinds of ranking approaches have been introduced. When comparing different ranking methods to each other, we need to be able to measure some ranking quality. In order to measure the quality of rankings produced by systems, many different metrics have been introduced. In this section, the most common evaluation metrics are introduced, among them all metrics used in this thesis.

All metrics introduced are @k metrics. We only evaluate the documents ranked up to rank k, i.e., if $k = 30$, we only consider the first 30 documents produced by the system.

Precision

A straightforward approach to evaluating a ranking produced by a system is through precision. The precision metric counts the number of relevant documents found by the system, which is then divided by the total number of documents found by the system:

$$P@k = \frac{\sum_{i=1}^{k} \text{rel}\,(d_i)}{k} \tag{2.19}$$

In this case, rel(.) is a function that returns 1 if the document is relevant; otherwise, 0. If $k = 30$, then only the first 30 documents are considered. If ten of these documents are relevant, then $P@30 = \frac{10}{30} = \frac{1}{3}$. Precision can, however, be somewhat limited in its use. In this example, the quality of the ranking might not seem good. Only a third of the produced documents are relevant. However, when only ten relevant documents are present in the collection, the $P@30$ could not have been higher.

Recall

To prevent the issue that the precision is low when there are few relevant documents in the collection, we could measure how many relevant documents were retrieved compared to the total number of documents. This measure is called recall:

$$R@k = \frac{\sum_{i=1}^{k} \text{rel}\,(d_i)}{\sum_{i=1}^{N} \text{rel}\,(d_i)} \tag{2.20}$$

Here N is the number of documents in the collection. If, again, $k = 30$ and we found 10 relevant documents, and if there are 15 relevant documents in the collection. Then $R@30 = \frac{10}{15} = \frac{2}{3}$.

F_1-measure

Where precision measures the share of documents found that are relevant, recall measures the number of relevant documents found compared to the total number of relevant documents. For precision, it makes sense to retrieve as few documents as possible; the probability of finding relevant documents decreases the more documents are returned. For recall, it makes sense to retrieve more documents, as when more documents are retrieved, it can only increase.

To find the correct balance between precision and recall, it is possible to use the F_1-measure. It is defined as the harmonic mean between precision and recall:

$$F_1@k = 2 \cdot \frac{P@k \cdot R@k}{P@k + R@k} \tag{2.21}$$

If either recall or precision is low, the F_1-measure suffers as well. To achieve a high F_1-measure, recall, and precision must be high.

Average Precision

Consider the situation where three documents are retrieved, and two systems might produce rankings with the following relevance labels: $[1, 0, 0]$ and $[0, 0, 1]$. Both rankings achieve the same $P@3$ and $R@3$ scores, and subsequently also the same $F_1@3$. The previously introduced metrics cannot distinguish between ranking quality in this situation. It is, however, clear that the first ranking is better than the second ranking. Instead of measuring the precision only at rank k, the average precision measure calculates it every time a relevant document is encountered. The sum of these values is divided by the number of relevant documents found up to k:

$$AP@k = \frac{1}{\sum_{i=1}^{N} \operatorname{rel}(d_i)} \sum_{i=1}^{k} P(i) \cdot \operatorname{rel}(d_i) \tag{2.22}$$

Looking back at the two rankings, $[1, 0, 0]$ and $[0, 0, 1]$, the rankings produce an $AP@3$ of 1 and $\frac{1}{3}$ respectively.

Discounted Cumulative Gain

Discounted cumulative gain is an evaluation metric developed after the observation that users often only look at the highest-ranked documents and that documents might not have binary relevance labels. If a document is ranked at, say, rank 5, it might already be possible that it is not considered by the user anymore and that they already reformulated the query. Plus, the metrics described before would rank the following two rankings to be of equal quality: $[2, 1, 0]$ and $[1, 2, 0]$ So discounted cumulative gain was developed with the intention that there should be a discounted gain every time a new relevant document is found, plus non-binary relevance labels can be taken into account. This discount is applied by dividing by the logarithm of the rank plus one:

$$DCG@k = \sum_{i=1}^{k} \frac{\text{rel}(d_i)}{\log_2(i+1)} \tag{2.23}$$

In this case, rel(.) does not return a binary value but the actual relevance assessment.

Normalized Discounted Cumulative Gain

A disadvantage of *DCG* is that the scores produced by this metric can vary greatly between rankings. If many relevant documents exist for a query, the values *DCG* takes can be much higher than if only one relevant label is available. Normalized discounted cumulative gain takes care of this by dividing by the highest possible *DCG* that can be achieved. So normalized discounted cumulative gain is calculated by dividing the *DCG* of the ranking, by the *DCG* of the ideal ranking:

$$NDCG@k = \frac{DCG@k}{IDCG@k} \tag{2.24}$$

with $IDCG@k$ being the $DCG@k$ for a perfect ranking.

Reciprocal Rank

The metrics described before score the whole ranking up to rank k. This might be unnecessary; if a document found is relevant, it should not matter anymore what the relevance assessment is of all documents after it. After all, the user would stop looking after document k, as

the relevant information is found. The reciprocal rank only takes the first found relevant document into account. It divides 1 by the index of the first found document:

$$RR@k = \frac{1}{\text{minrank}(d)} \tag{2.25}$$

where only the first k documents are considered. If the index of the first relevant is greater than k, the resulting score is 0.

2.2.4 Significance Testing

Some of the measures described above can still be problematic when they are used to compare different systems. Fuhr [2018] describes common mistakes when evaluating IR systems and how to avoid them.

2.3 Data Retrieval

In the case of information retrieval, the concept of *relevance* is critical. When someone issues a query, it does not necessarily have to be the case that words in the query must be present for the document to be relevant. Information retrieval has to deal with some uncertainty; if only some relevant documents are found, this does not necessarily have to be a problem. If we think about a search engine from a user's perspective, a document is only relevant if it contains the information they seek. In order to find this information, the user has to express their information need in a query, which the systems then have to interpret somehow in order to present the user (hopefully) the correct information. It might, however, be possible that two different users issue the same query, e.g., *the weather*. However, one user is interested in today's weather, while the other is interested in tomorrow's weather. Different documents will be relevant for the user in these cases: relevancy is tight to the user's expectations.

In the field of *data retrieval*, relevancy does not exist. When we speak about data retrieval, we are interested in retrieving all data that fulfills some predicate. It assumes that there is no ambiguity in the data. An example could be; to provide a list of all dog breeds. In this case, the system should return a list of all dog breeds known by the system. If it would accidentally forget to return one dog breed or includes an answer

that is not correct, the system works incorrectly. The most commonly used data retrieval systems are relational database management systems (RDBMS) or relational databases. Relational databases are used to represent tabular data as relations. The concept of a relation comes from relational algebra, where a relational is defined as a set of tuples. In a relational database, a table corresponds to the relation, a row is one of the tuples, and a column can be considered an attribute in the tuple. There are differences between the theoretic framework of relational algebra and its implementation in relational databases. For example, in practice, it is often possible to have duplicate rows in a relational database, which is not possible in a set.

Relational databases implement the operators as proposed by relational algebra, which means users can select columns from a table (projection), filter rows that fulfill certain predicates (selection), and combine tables (join). Typically, this is done through a structured query language (SQL). SQL is a declarative language; someone can express which data needs to be retrieved but not how. Depending on what a user expects from the program, choosing different database management systems for different applications makes sense. In the case of storing employee records for a company, it makes sense to store this data in a database suited for transactions. When data analysis for scientific studies is important, storing data in a database system focused on analytics makes more sense.

2.3.1 Physical vs. Logical models

As SQL is a declarative language, data management systems' physical and logical models are strongly separated. Although many dialects of SQL exist, basic SQL queries are system agnostic and can run on different types of SQL engines. The logical model of data management systems is the SQL queries; what should be done. The physical model is how this should be done. Depending on which system is used, things like join ordering and how the data is processed, can be very different. The logical model does not "mind" how the query is resolved as long as it is done correctly.

In the case of information retrieval, the physical and logical models are often more entangled. Model specification and query processing often co-exist. When this is the case, it can be harder to detect why

systems differ when they implement the same models. Chapter 3 will discuss this in more detail.

Lin [2022] discusses how information retrieval might benefit from separating physical and logical models in the context of dense retrieval models. Chapter 4 will discuss his proposal in more detail.

2.3.2 Columns vs Rows

Earlier database management systems were row oriented. Row-oriented means that when we look at how data is physically stored on the computer, all data within a tuple is represented near each other in memory. This orientation is especially well suited when a database needs to process many transactions. Some IR systems have been built on top of such databases. However, these were less efficient than when inverted indexes were used. Later, column-oriented databases were developed. These databases are more suited for analytical queries; transactions tend to be more costly. As these databases are more suited for analytics, they are also more suited for information retrieval systems. These systems are more suited for developing IR systems; this practice is used throughout this thesis.

2.3.3 NoSQL and Graphs

In recent years there has been interest in database systems that approach data retrieval differently than traditional relational database systems. These systems approach data retrieval not using the relational model. This could, for example, mean that joins are not possible within the system. This might seem limiting, but if certain operations are not supported, it might be possible to increase the efficiency of other operations. A very efficient key-value store could be an example of this.

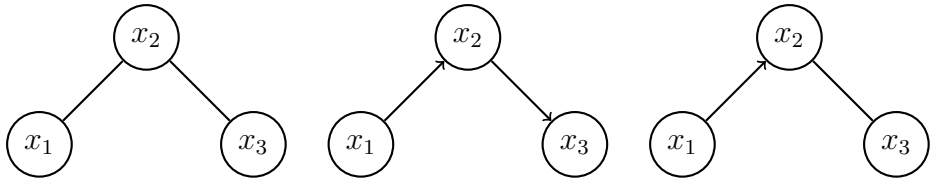
In particular, graph database systems are NoSQL database management systems that have been of interest in the database community in the last few years. The work in Chapter 4 works with these databases. The concept of graphs is explained in Section 2.4.

2.3.4 Embedded Database

Typically, databases run on dedicated database servers. It is, however, also possible to have so-called embedded database systems. These systems do not require a dedicated database server to be set up. They work within the application process itself. A massive advantage of embedded databases is that they work within the same memory space as the application process. This makes it possible to instantly move data from the database to a usable format for the application process. For information retrieval applications, this might be beneficial, especially in the case of multistage ranking as described in Section 2.2.2. However, embedded databases might not be the best solution in some cases. When a dedicated database server is run, it is possible to optimize the database better as it is less dependent on data representations in application processes.

2.3.5 Databases for Information Retrieval

As databases are designed for the purpose of data retrieval, they are suited for information retrieval in the case of boolean retrieval. However, it is harder to express models following a data retrieval approach when considering the concept of relevancy. When expressing models that model some uncertainty, much data must be processed efficiently—inverted indexes are used to select critical data quickly. Older (row-based) database systems were not efficient enough to quickly retrieve all the necessary data to create rankings and model uncertainty simultaneously. After columnar databases became prominent, it was possible to express simple ranking models that consider uncertainty somewhat efficiently. In this thesis, we will use, in some cases, columnar databases for information retrieval problems. Specifically, MonetDB [Boncz, 2002], a non-embedded columnar database, is used for the work presented in Chapter 3, and DuckDB [Raasveldt and Mühleisen, 2019], an embedded columnar database, is used for the work presented in Chapters 4 and 6.



(a) Basic Graph (b) Directed Graph (c) Mixed Graph

Figure 2.1: Example of (**a**) a simple graph, (**b**) a directed graph, and (**c**) a mixed graph.

2.4 Graphs

As mentioned in Section 2.3.3, in this thesis, we present work where we want to think about information retrieval using the concept of graphs and which kinds of graphs exist. The graphs follow the definitions described by Sakr et al. [2021].

Basic Graphs A *graph* is a structure consisting of a set of objects where pairs of these objects can be related. Typically, these objects are called nodes or vertices, and the relation between a pair of objects is referred to as an edge. So more formally, a graph G is a pair of vertices V and edges E;

$$G = (V, E) \tag{2.26}$$

where V is the set of vertices in the graph, and E a set of pairs (sets with two elements) of vertices:

$$E = \left\{ \{v_1, v_2\} \mid \{v_1, v_2\} \in V^2 \right\} \tag{2.27}$$

Typically, graphs are graphically illustrated as a set of circles, where every circle represents a vertex. If an edge exists between two vertices, a line is drawn between the two circles. Consider for example Figure 2.1a, the graph illustrates a graph with $V = \{x_1, x_2, x_3\}$ and $E = \{\{x_1, x_2\}, \{x_2, x_3\}\}$. It does not necessarily have to be that every vertex is included in at least one edge.

A graph is called *bi-partite* if it is possible to separate the set of vertices in two separate sets, so there exists only edges between vertices in the two separate sets. The graph's structure can be used to analyze how things relate. Considering geographical maps, we can

model countries as vertices and create an edge between two countries if they are neighboring. Then, we can use the graph structure to analyze the possible paths from one country to another where only a maximum of two other countries are crossed. For many use cases, however, it is helpful to let graphs contain data or have less restrictive rules on how a graph might be formed.

Directed Edges The most basic extension of graphs is that they are allowed directed edges. This means an edge can exist from one node to another, but this connection does not exist in the opposite direction. In the case of countries and their neighbors, this does not make sense; if one country borders another, the opposite is also true. However, on the internet, one website might contain a hyperlink to another, while the opposite does not have to be the case. We need directed graphs to properly model the situation. Again, we can use this model to see how many paths there are from one website to another, with the restriction of visiting two other websites. In this case, the E is a set of ordered pairs of vertexes:

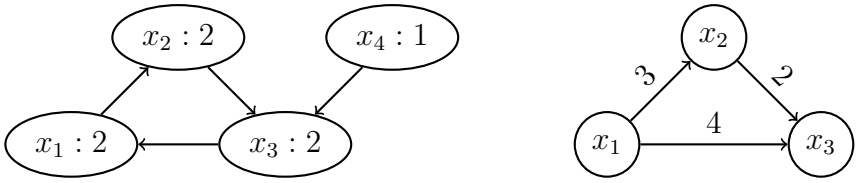
$$E = \left\{(v_1, v_2) \,|\, (v_1, v_2) \in V^2\right\} \tag{2.28}$$

Figure 2.1b shows an illustration of the following directed graph: $V = \{x_1, x_2, x_3\}$ and $E = \{(x_1, x_2), (x_2, x_3)\}$

Mixed Graphs Mixed graphs are graphs that accept both undirected and directed edges. In that case, a graph is defined with two sets of edges, where one set describes the undirected edges and the other the directed edges:

$$G = \{V, E_1, E_2\} \tag{2.29}$$

with E_1 and E_2 being defined as edges as presented in Equations (2.27) and (2.28) respectively. Figure 2.1c shows the illustration of a mixed graph: $V = \{x_1, x_2, x_3\}$, $E_1 = \{\{x_1, x_2\}\}$, and $E_2 = \{(x_2, x_3)\}$. Mixed graphs are sometimes used in applications where the direction of an edge is unclear but where a relation exists. Types of these graphs appear, for example, in causality research.



(a) Data Graph (b) Weighted Graph

Figure 2.2: Example of (**a**) a data graph, and (**b**) a weighted graph.

2.4.1 Labeled Graphs

The types of graphs we described are all graphs that do not contain data themselves; we can only reason about the structure of the graphs. Even though this already has many practical applications, graphs are attractive when they are allowed to contain data for the applications we are interested in. There are two ways to add data to graphs; it is possible to add data to the vertices or the edges.

Data Graph A data graph is a type of graph where vertices have data. Figure 2.2a shows an example of a (directed) graph where every vertex is labeled with a number. These graphs are, for example, used in the famous PageRank algorithm [Page et al., 1999]. In this algorithm, every vertex represents a webpage, and a directed edge exists between a node a to b if a link on website a points to website b. Then by randomly walking over this graph or visiting a new website randomly, it is possible to count how often a node has been visited. The number of visits corresponds to the PageRank score. The PageRank scores in a graph correspond to the probabilities found in a Markov process in equilibrium.

Weighed Graph A weighted graph is a type of graph where edges have data. Figure 2.2b shows an example of a (directed) graph where every edge is labeled with a number. For example, these kinds of graphs are used to calculate the shortest distance between nodes. These kinds of graphs are, for example, useful for navigation systems. There are two possible paths if we need to travel from location x_1 to location x_3. The path from x_1 directly to x_3 is shorter than going from x_1 to x_3 via x_2. When graphs are larger, algorithms like Dijkstra's algorithm can

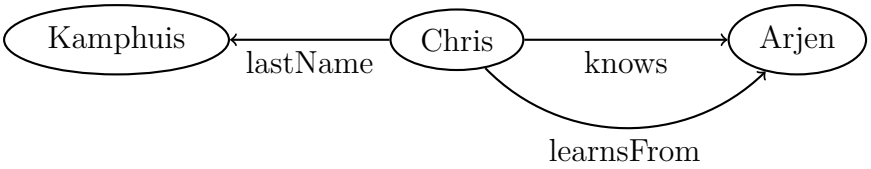


Figure 2.3: Example of a W3C RDF graph.

efficiently find the shortest path over weighted graphs.

Pregel/Giraph Graph An obvious extension is, of course, adding data to both the vertices and edges. In this context, we refer to them as Pregel/Giraph graphs, as these systems implement these graphs. Some algorithms need graphs to have both edge and vertex data. An example is the node2vec algorithm, which generates vector representations of the vertices of the graph. These graphs are used for various machine learning applications.

Formally the data on the graph can be expressed by a labeling function:

$$\rho : (V \cup E) \to w \mid w \in \mathbb{R}^+ \tag{2.30}$$

In this case, we assume that the weights are positive numbers, as often it is a constrain imposed by algorithms. There are however no theoretical restrictions from graph theory that impose this constrain. For the data graph and weighted graphs we do not take the union of vertices and edges, but just the vertices or edges respectively as a valid input for the labeling function.

2.4.2 RDF graphs

Research Description Framework (RDF) graphs are directed graphs where edges have labels and where multiple edges may exist between a pair of nodes. Graphs that allow multiple edges between a pair of nodes are also called *multi-graphs*. They are a standard by the World Wide Web Consortium (W3C). The idea behind the RDF graphs is that they are a collection of so-called triples. These triples contain a *subject*, *predicate*, and *object*. The predicate describes the relation (edge) from the subject (node) to the object (node): a collection of triples forms a graph. Knowledge graphs are often represented by RDF

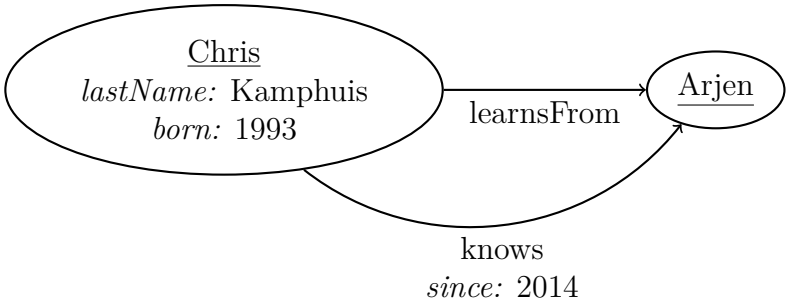


Figure 2.4: Example of a Property Graph.

triples, which have many applications in information retrieval. It is, for example, possible to generate entity cards on top of search engine result pages using knowledge graphs. Figure 2.3 shows an example of a small RDF graph.

2.4.3 Property Graphs

Then finally, we will discuss property graphs. Property graphs allow everything we described before, vertices might also have labels, and vertices and properties can have values (multiple values per property are even allowed). A property-value represents some named vertex or edge data. For example, if a node represents a person, the person's age can be a property of the node. Depending on the type of property graph, the graph might also contain multiple vertex or edge labels. Figure 2.4 shows an example of a property graph. The node with label *Chris* has the last name and birth year as properties. The edge with label *knows* from the node *Chris* to the node *Arjen* has a timestamp as a property. Property graphs are the graphs with the most expressive power. They are used as the data model for graph databases. Formally, to complement our previous definitions of vertices and edges, we assume the existence of three infinite sets; L, P, and A. L is an infinite set containing vertex/edge labels, P is an infinite set containing property names, and A is an infinite set of atomic values. Using these sets we can define the following two functions that assign labels, and property-value pairs:

$$\lambda : (V \cup E) \to l \mid l \subset L \tag{2.31}$$

$$\sigma : (V \cup E) \times P \to a \mid a \subset A \tag{2.32}$$

2.5 Reproducible Science

In order to establish experimental results in science, it is essential that they can independently be verified. Many fields have had problems where the reproducibility of scientific studies was lacking. In psychology, a large reproducibility study was carried out [Open Science Collaboration, 2015]. In this study, a selection of 100 published studies in 2008 was taken. The goal was to reproduce the findings of all these studies to determine how many were holding up. Of the original 100 studies, 97 presented significant results. When trying to reproduce these results, it was possible for only 35 out of 97 of these studies to reproduce significant results.

It is unclear why these many scientific studies were not reproducible. Nevertheless, many type II errors happened; failure to reject the null hypothesis while it is false. Scientific misconduct could explain some of these results, but it is unlikely that this is happening at such a large scale. All studies this project tried to reproduce were published in just three journals. These journals were peer-reviewed; only the scientific studies the reviewers thought were good enough were published. This process, of course, introduces a selection bias. Studies that show more impactful results have a higher probability of being published. This bias favors papers with type II errors, even though the scientific conduct was proper.

When a scientific study is published, people might interpret its results as fact. Something that should not be done. One should consider experimental results only as evidence of how the world might work. Then, whenever the results are reproduced, more evidence is gathered to support the findings. By reproducing science, our understanding of the world becomes more precise, and eventually, we can assume with high certainty that something is true.

In the field of information retrieval, reproducibility has also been a topic of interest. Throughout this thesis, the topic of reproducibility will come back, and here only some observations on the topic of reproducibility in our field are highlighted, plus some closely related issues. Before introducing these observations, it is important to clearly define what is meant by reproducibility. Within the Association for Computing Machinery (ACM), a clear distinction has been made between the concepts of; repeatability, replicability, and reproducibility.

- *Repeatability* is verification of results produced by the same research group, using the same resources. Confirming that when one reruns their experiments, the same results are produced. This might seem trivial, but it might happen that when software is updated to some newer version, e.g., upgrading from Lucene 7 to Lucene 8, the results software produces might slightly differ.

- *Replicability* is the verification of results produced by a different research group, but using the same resources. This could, for example, be done by running the publicly available code for a research project and verifying its results. This is already somewhat more tricky than it might look. Often, in scientific papers, the parameter settings of the software might be left out, making it hard to verify results correctly.

- *Reproducibility* is the verification of results produced by a different research group that uses its own (different) resources. Typically, in a reproduction study, the scientific study is done from scratch using the instructions presented in a paper. As many details might be left out, it is even harder to reproduce results exactly. However, if a reproduction study can confirm the results of previous work, this is a strong indication of the correctness of the results presented in that work.

In Chapter 3, we will present some scientific results about the BM25 algorithm. Many systems implement this algorithm, while the reported effectiveness results as measured through established metrics (a subset of metrics described in Section 2.2.3) are pretty different. How this can happen will be discussed. BM25, however, is a ranking method often used as a baseline method. When comparing newer algorithms to BM25, it makes quite a difference if its implementation reports a low score to a relatively high score.

Armstrong et al. [2009] showed that many improvements in ranking algorithms presented throughout the years did not add up. Significant improvements were presented in many cases, and they were compared against weak baselines. Also, there was no upward trend of retrieval effectiveness, which would be expected if we find an improvement repeatedly. More recently, Yang et al. [2019] showed this still happens. New methods are being compared against implementations of BM25

that have non-optimal hyperparameter settings. Leading to methods looking better than they are, and it is harder to compare methods against each other if the baseline that was compared against is different.

For this thesis, all software and data produced is publicly available and released on Zenodo[1] in order to facilitate reproducible science, following the guidelines of the research data management policy of the Institute for Computing and Information Science of the Radboud University.[2] Additionally, in some chapters, the importance of reproducibility will be highlighted and discussed in more detail.

[1] `https://zenodo.org`, last accessed - May 16th 2023

[2] `https://www.ru.nl/icis/research-data-management/`

Chapter 3

IR using Relational Databases

> "Is this new question a worthy one to investigate?" This latter question we investigate without further ado, thereby cutting short an infinite regress.
>
> Alan Turing - 1950

Abstract

There have been many attempts to express information retrieval problems using relational databases. This chapter will highlight one of the latter attempts that revived the idea of expressing bag-of-words ranking functions using SQL. A prototype system that uses these expressions is presented, dubbed OldDog, after the work by Mühleisen et al.. This system can be used for rapid IR prototyping and is especially helpful in the context of reproducible information retrieval research. Also, when researchers speak of BM25, it is not always clear which variant they mean since many tweaks to Robertson et al.'s original formulation have been proposed. Does this ambiguity "matter"? We attempt to answer this question with a large-scale reproducibility study of BM25, considering eight variants implemented in the

OldDog system. Experiments on three newswire collections show no significant effectiveness differences between them, not even for Lucene's (often maligned) approximation of document length.

3.1 Introduction

Where information retrieval researchers commonly use inverted indexes as data structures, there is also a rich history of researchers using relational databases to represent the data in information retrieval systems. Different approaches in the literature present varying successes. Given this context, we arrive at the first research question:

RQ1: What are the benefits of using relational databases for information retrieval?

In order to answer this question, first, we will look at the history of using database systems for IR. Then, one of the latter attempts of using a relational database for information retrieval will be highlighted. Using this work, a prototype system is built, dubbed "OldDog". This system will be used in a reproduction experiment, which compares several variants of BM25 which each other. This reproduction study confirms previous findings found in the literature and verifies that relational database systems are suited for running IR experiments.

3.2 Related work

3.2.1 Boolean retrieval

Perhaps the earliest work on using relational databases for information retrieval is the work by Schek and Pistor [1982]. In their work, the authors recognize that the relational data model is widely accepted as an interface to query structured data. However, it is inconvenient to use unstructured data like text. They proposed extending the relational model by allowing Non First Normal Form (NF^2) relations. This extension allows for text queries to be more easily expressed. However, the systems that can be built in this language are boolean retrieval systems. At the time, that worked well, but scoring was not a feature

implemented. Similarly, Macleod [1991] compared the inverted index approach to using the relational model. Macleod showed how queries of the IBM STAIRS system could be expressed using the relational model. These were, however, still boolean queries, so scoring using uncertainty was not considered.

3.2.2 Probabilistic Relational Algebra

Fuhr [1996] recognized that where databases contain structured/formatted data, IR systems deal with unformatted data requiring uncertain inference. They propose to express this uncertainty using a probabilistic relational algebra [Fuhr and Rölleke, 1997] (PRA). PRA can be considered an extension of standard relational algebra. The basic idea behind PRA is that tuples are assigned weights; the weight represents the probability that the tuple belongs to the relation. These probabilities give two advantages. Uncertain information can be expressed, and tuples representing answers to queries can be ordered by the weights representing the uncertainty. The most certain tuples are ranked at the top. Although these extensions give advantages over boolean retrieval, how to assign these probabilities to, for example, a document-term pair remains a question.

3.2.3 IR on top of a database cluster

Grabs et al. [2004] have proposed PowerDB-IR, developed to run IR applications on a scalable infrastructure. It should also be able to update the data quickly while retrieving up-to-date results. Grabs et al. achieve this by assigning every document to a category, e.g., sports or news, in their experiment. A dedicated node is created for every category, containing tables containing documents, inverted lists, and statistics tables. The system supports both single-category and multi-category searches. For a single query search, the following ranking score value is calculated:

$$\mathrm{RSV}(d,q) = \sum_{t \in q} tf(t,d) \cdot idf(t)^2 \cdot tf(t,q) \tag{3.1}$$

Here $tf(t,d)$ is the term frequency of term t in document d, $idf(t)$ is the inverted document frequency of term t (which is squared in this

formula), and $tf(t, q)$ is the term frequency of term t in the query text. Calculating this is straightforward: all statistics necessary are stored on a node. However, when one wants to search on multiple (or all) categories, subscores need to be calculated for all relevant nodes before they can be aggregated to a final score. The cost of this approach is high, but this work may have proposed the first real IR in SQL approach.

3.2.4 Integrating DB + IR

Chaudhuri et al. [2005] also identify the need for systems that integrate database and IR functionalities. In their view, database systems need to be more flexible for scoring and ranking, while IR systems cannot adequately handle structured data and metadata. Chaudhuri et al. put together a list of seven requirements that a DB + IR system should be able to support, of which they identify the following three requirements as the most important:

1. *Flexible scoring and ranking.* It should be possible to customize the ranking function for different applications; a news search system probably needs different ranking functions and settings than a web search system.

2. *Optimizability.* Following standard database approaches, queries in a DB+IR system should have a query optimizer that considers the workload and the data characteristics. For example, when only one relevant result is sufficient, the system should be able to abort when a relevant document is found.

3. *Metadata and ontologies.* Other than metadata that describes data sources, metadata that is used for understanding information demands might be needed. This metadata could be, for example, an ontology or a lexicon used for more effective ranking strategies.[1]

To build a system that can support these requirements, the authors identify four alternatives for designing a DB+IR system:

[1] Latent representations generated by large language models would have been a great example of this kind of metadata had their paper been written today.

1. *On-top-of-SQL.* The IR functionalities are built on top of a SQL engine. The disadvantage of this approach is that it is challenging to customize efficient access for both IR and DB functionalities.

2. *Middleware.* In this approach, SQL and IR engines run simultaneously. The two disadvantages of using this approach are that the API needs to talk to two systems, which can have very different design philosophies, and the data needs to be shared between systems, incurring a large overhead and making it harder to combine both functionalities.

3. *IR-via-ADTs.* The third approach is building an IR system using abstract data types. The authors argue that this approach makes the system more customizable than the previous approaches. However, the authors also note that optimization in the case of UDFs is complicated. Also, when programmers need to work with such a system, it has the full complexity of SQL plus the complexity of working with ADTs, making them efficient.

4. *RISC.* The final approach is what the authors prefer; IR functionalities build on top of a relational *storage* engine, as described in an earlier work by them [Chaudhuri and Weikum, 2000]. The DB+IR systems should then be built on top of this engine.

Although the approaches described in this work are interesting, they do not provide prototypes to compare them. (The goal of this paper was to present a theoretical framework for tackling this problem.) Even though it is not the preferred option of Chaudhuri et al., this PhD thesis research focuses on the *On-top-of-SQL* approach.

3.2.5 Handwritten plans and Array Databases

Héman et al. [2006] participated in the TREC TeraByte track using the relational engine MonetDB/X100 [Boncz et al., 2005]. They were able to express ranking functions efficiently and effectively in this system. In their participation, they used BM25 as a scoring function. In order to reduce the amount of computation necessary for every document-term pair, the BM25 score was precalculated. The disadvantage of this approach is that the query plans were not generated from SQL but were handwritten. Having to handwrite queries makes this system

more challenging to use for IR researchers. Also, because all BM25 scores were precalculated (albeit with some compression), more storage was needed than when only the term frequencies would be saved.

The same research group [Cornacchia et al., 2008] also ran experiments on the TREC TeraByte track using the array database SRAM (Sparse Relational Array Mapping). SRAM automatically translates BM25 queries to run them on a relational engine (particularly X100). However, SRAM is quite an exotic query language, only used by the researchers themselves, and no current (prototype) system offers support for this approach.

3.2.6 Retrieval models only using SQL

In more recent work, Mühleisen et al. [2014] showed that the commonly used BM25 ranking function could also be easily expressed using SQL. This is done similarly to Grabs et al. [2004]. In this work, the MonetDB [Boncz, 2002] and Vectorwise [Zukowski et al., 2012] systems were used, making the runtime much faster than Grabs et al.'s original results. Mühleisen et al. specifically focused on the retrieval efficiency of systems and compared the efficiency of inverted indexes with systems built on top of relational engines. They argue that instead of using a custom build IR system using an inverted index, researchers could store their data representations in a column-oriented relational database and formulate the ranking functions using SQL. They show that their implementation of BM25 in SQL is on par in efficiency and effectiveness compared to systems that use an inverted index.[2]

There was an interesting observation in the paper to highlight: All the systems evaluated in this paper implement BM25. However, there was a substantial difference between the effectiveness scores produced by these systems, as shown in Table 3.1. The only two systems that achieved the same effectiveness score were the two database systems (MonetDB and Vectorwise). Although the same research group developed these two systems, they were completely separate projects.

These results were surprising as the authors took specific care to keep document preprocessing identical for all systems. However, the

[2]In particular the Vectorwise system.

Table 3.1: Results presented by Mühleisen et al. [2014]. `MAP` and `P@5` on the ClueWeb12 collection are reported for five different systems that each claim to rank their documents using BM25. The table shows that only the two database systems (MonetDB and Vectorwise) achieve the same effectiveness score.

System	MAP	P@5
Indri [Strohman et al., 2005]	0.246	0.304
MonetDB [Boncz, 2002]	0.225	0.276
Vectorwise [Zukowski et al., 2012]	0.225	0.276
Lucene [Apache Software Foundation, 2013]	0.216	0.265
Terrier [Ounis et al., 2005]	0.215	0.272

Table 3.2: Results from the RIGOR workshop [Arguello et al., 2016]. `MAP@1000` on the .GOV2 collection is reported for four different systems that run BM25. The table shows that all four implementations report a different effectiveness score.

System	MAP@1000
ATIRE [Trotman et al., 2012]	0.290
Lucene [Apache Software Foundation, 2013]	0.303
MG4J [Boldi and Vigna, 2005]	0.299
Terrier [Ounis et al., 2005]	0.270

observed difference in `MAP` of 3% absolute was the largest deviation in the score reported.

3.2.7 Reproducibility

The paper by Mühleisen et al. [2014] is not the only one that reports the differences in effectiveness scores for BM25. In the SIGIR 2015 Workshop on Reproducibility, Inexplicability, and Generalizability of Results (RIGOR) [Arguello et al., 2016] and the Open-Source IR Replicability Challenge (OSIRRC) workshop [Clancy et al., 2019b] similar results are observed. See Tables 3.2 and 3.3, respectively.

It is unclear why the results between these systems differ this much; many explanations are possible. Examples include; differences

Table 3.3: Results from the OSIRRC workshop [Clancy et al., 2019b]. `AP`, `P@30`, and `NDCG@20` on the robust04 collection are reported for seven different systems that run BM25. As shown in the table, all implementations report (again) a different effectiveness score.

System	AP	P@30	NDCG@20
Anserini [Clancy et al., 2019a]	0.253	0.310	0.424
ATIRE [Trotman et al., 2012]	0.218	0.320	0.421
ielab [Scells and Zuccon, 2019]	0.183	0.261	0.348
Indri [Hauff, 2019]	0.239	0.300	0.404
OldDog [Kamphuis and de Vries, 2019b]	0.243	0.299	0.400
Pisa [Mallia et al., 2019]	0.253	0.312	0.422
Terrier [Câmara and Macdonald, 2019]	0.236	0.298	0.405

in preprocessing,[3] different hyperparameter settings, differences in the definition of the inverse document frequency (*idf*) used, or erroneous implementation of the ranking function. Using, for example, non-optimized hyperparameter settings can lead to considerable gaps in differences between effectiveness scores. Yang et al. [2019] showed that in many cases, new ranking methods had been proposed that compared the results of a newly proposed method to a non-fine-tuned version of BM25, making the results look better than they are. The choices for hyperparameters are often left out of papers, while BM25 is the baseline compared against. As BM25 is often used as a baseline, it is crucial to understand why these differences exist and how they arise.

3.3 Prototype OldDog

As shown in Table 3.3, one of the workshop's submissions was the prototype system developed for this PhD thesis research [Kamphuis and de Vries, 2019b]. This prototype is a software project to replicate and extend the database approach to information retrieval presented in Mühleisen et al. [2014]. The prototype was based on their work, so we dubbed it *OldDog*. OldDog uses column store database Mon-

[3]But this cannot explain the differences reported in Mühleisen et al., as they ensured preprocessing was the same for all systems.

Table 3.4: Example of tables representing the data in the OldDog system, the dict tables contains all term specific data, the terms table represents all the postings, and the docs table contains all document specific data.

(a) **dict**

termid	term	df
1	put	1
2	robe	1
3	wizard	1
4	hat	1

(b) **docs**

docid	term	df
1	doc1	8

(c) **terms**

termid	docid	tf
1	1	1
2	1	1
3	1	1
4	1	1

etDB [Boncz, 2002] for query processing. Mühleisen et al. produced the database tables to represent the data typically found in an inverted index using a custom program running on Hadoop. Instead, we created a Lucene index using the Anserini tool suite by Yang et al. [2018a]. From this index, we extracted the data necessary to fill the tables. Anserini takes care of standard document preprocessing. Three tables are constructed. One table contains the data that represents the documents, another one that represents the terms, and one that contains all data that relate terms to documents. To illustrate, for a document named "doc1" with the text "I put on my robe and wizard hat" is shown in Table 3.4.

Using these tables, we can easily express bag-of-word ranking functions in SQL queries. The default ranking function implemented in our implementation of OldDog is the version of BM25 that had been proposed by Robertson et al. [1994], which will be expanded upon in the next section.

3.3.1 Docker

For the submission to the OSIRRC workshop [Clancy et al., 2019b], we created a docker image of OldDog.[4] Mühleisen et al. implemented a conjunctive variant of BM25 (all query terms have to be present in a document in order for a document to be considered relevant). When

[4] `https://hub.docker.com/r/osirrc2019/olddog`

```
CREATE table dict AS SELECT * FROM odict WHERE df <= (
        SELECT 0.1 * COUNT(*) FROM docs
);
```

Figure 3.1: This code updates the `docs` table such that all terms with a document frequency greater than a tenth of the collection size are removed.

creating the submission for the workshop, we noticed that the effectiveness scores were substantially lower than those of other submissions. The retrieval effectiveness degraded more than we expected a priori, given the results in previous work. When removing the conjunctive constraint, the effectiveness results increased. So our prototype supports both conjunctive and disjunctive versions of BM25. Our entry in Table 3.3 presents the effectiveness scores of the disjunctive variant. The number of relevant documents per topic for this collection was likely relatively low.

3.3.2 Ease-of-Use

Having implemented BM25 in a database system enabled us to carry out some experiments quite easily that are more complicated when using an inverted index. Filtering out the terms with a large document frequency is easy, as all document frequencies are stored in one table. We updated the table removing the terms with large document frequency in only two lines of SQL, as shown in Figure 3.1. This approach could be an automatic way to remove stopwords from a collection. This filter was too strict to improve retrieval effectiveness but can easily be fine-tuned. For example, we could easily join against a table storing a traditional stopword list.

3.4 Variants of BM25

Having "OldDog" set up, we can quickly run retrieval experiments. As mentioned in the previous section, it is still unclear why the differences between the submissions were this big. Also, many different variants of BM25 that claim to be more effective have been proposed in the

literature. A study by Trotman et al. [2014] compared several variants and found that improvements presented in the literature do not add up. As we now have a system in which the BM25 formula is written directly in SQL, we can easily swap this version of BM25 with its proposed improvements. By using OldDog, we can ensure the data representation is the same when we compare these variants; the results will only reflect what the effects are applying a different variant of BM25. This way, we can easily confirm the findings of Trotman et al..

Robertson et al. [1994]

The original formulation of BM25 consists of two parts. The first part is derived from the binary independence relevance model [Robertson and Zaragoza, 2009], which results in an approximation of the classical inverse document frequency (idf) for a query term t:

$$w_i^{\text{IDF}} = \log\left(\frac{N - df_t + 0.5}{df_t + 0.5}\right) \tag{3.2}$$

where N is the collection size, and df_t are the number of collection documents containing query term t.

There is, however, a negative consequence of using this formula for weighing term importance. Let us say there is a collection with $10,000$ documents; then, it is possible to plot the idf for each term as shown in Figure 3.2. The figure shows that the idf score becomes negative when $df_t > \frac{N}{2}$. This happens for terms that appear in more than half of all documents, e.g.: "the" or "a". Many systems do not consider these terms when searching by keeping a list of common words that can be ignored (stop words). However, when these words are considered, a negative idf would decrease the relevance scores of documents with the query term in the document – variations of BM25 have been proposed to deal with this anomaly, which is discussed in the following sections.

The second part of BM25 can be considered as a term frequency weighting tf. These two parts are multiplied to get something like the traditional term frequency-inverse document frequency weighting $tf \times w_i^{\text{IDF}}$. However, the tf in BM25 is extended: every additional term occurrence does not increase the ranking score value as much as the previous one. For example, a term being present twice in a document versus once provides more information than a term being present ten

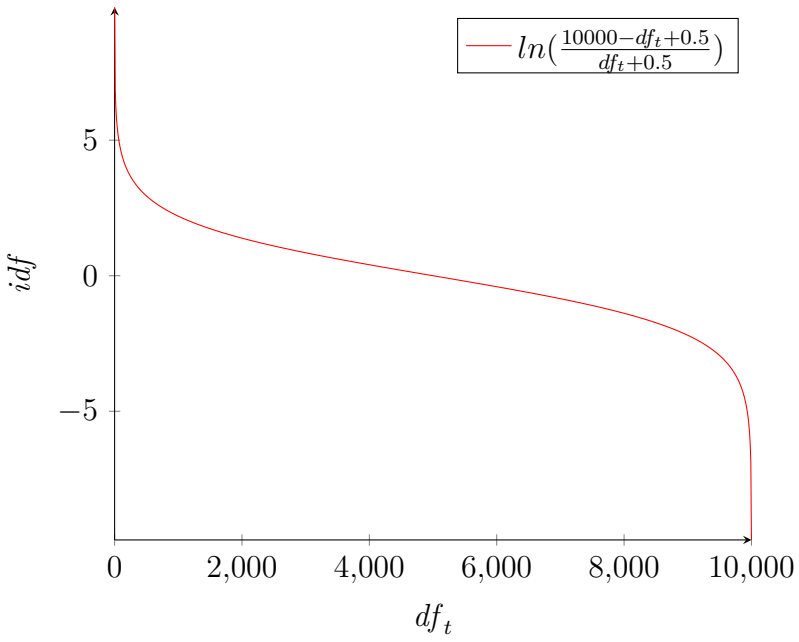


Figure 3.2: Inverse document frequency as used by Robertson et al. [1994]

times versus nine. To achieve this effect of "diminishing return" of additional occurrences, the following convenient formula was chosen to define the *tf* component of the ranking:

$$\frac{tf}{k + tf} \text{ where } k > 0 \tag{3.3}$$

This approach ensures that the term frequency does not increase linearly. In the final formulation of BM25, k is written as k_1. This is because earlier versions of this ranking formula also had a k_2 and k_3 parameter.

Then lastly, a second component is added that can correct for documents longer than others. It is, however, unclear how one should deal with documents being longer than others; the document's author can be verbose, in which case additional term occurrences do not provide extra information. On the other hand, a document can be lengthy because more relevant information is provided, and the document is more relevant than its shorter counterpart. For these reasons, the following soft-length normalization is introduced:

$$(1 - b) + b \times \left(\frac{L_d}{L_{avg}} \right) \text{ with } 0 <= b <= 1 \tag{3.4}$$

When setting $b = 1$, full-length normalization is used, while if $b = 0$, none is used. Combining these parts, including the correction for term frequency and the length normalization, we get BM25 as initially proposed by Robertson et al. [1994]:

$$\sum_{t \in q} \log \left(\frac{N - df_t + 0.5}{df_t + 0.5} \right) \cdot \frac{tf_{td}}{k_1 \cdot \left(1 - b + b \cdot \left(\frac{L_d}{L_{avg}}\right)\right) + tf_{td}} \tag{3.5}$$

Lucene (default)

The variant implemented in Lucene (as of version 8) introduces two main differences. As mentioned, the *idf* component of Robertson et al. [1994] is negative when $df_t > \frac{N}{2}$. To avoid negative values in all possible cases, Lucene adds a constant value of one before calculating the *log*

value. Second, the document length used in the scoring function is compressed (in a lossy manner) to a one-byte value, denoted $L_{d\text{lossy}}$. With only 256 distinct document lengths, Lucene can pre-compute the value of

$$k_1 \cdot \left(1 - b + b \cdot \left(\frac{L_{d\text{lossy}}}{L_{avg}}\right)\right) \tag{3.6}$$

for each possible length, resulting in fewer computations at query time. Then Equation (3.7) describes BM25 as implemented in Lucene:

$$\sum_{t \in q} \log\left(1 + \frac{N - df_t + 0.5}{df_t + 0.5}\right) \cdot \frac{tf_{td}}{k_1 \cdot \left(1 - b + b \cdot \left(\frac{L_{d\text{lossy}}}{L_{avg}}\right)\right) + tf_{td}} \tag{3.7}$$

Lucene (accurate)

Equation (3.8) represents our attempt to measure the impact of Lucene's lossy document length encoding. We implemented a variant that uses exact document lengths but is otherwise identical to the Lucene default.

$$\sum_{t \in q} \log\left(1 + \frac{N - df_t + 0.5}{df_t + 0.5}\right) \cdot \frac{tf_{td}}{k_1 \cdot \left(1 - b + b \cdot \left(\frac{L_d}{L_{avg}}\right)\right) + tf_{td}} \tag{3.8}$$

ATIRE [Trotman et al., 2012]

Equation (3.9) shows BM25 as implemented by ATIRE; it implements the *idf* component of BM25 as $\log(N/df_t)$, which also avoids negative values. The TF component is multiplied by $k_1 + 1$ to make it look more like the classic RSJ weight [Robertson and Spärck Jones, 1976]; this does not affect the resulting ranked list, as all scores are scaled linearly with this factor.

$$\sum_{t \in q} \log\left(\frac{N}{df_t}\right) \cdot \frac{(k_1 + 1) \cdot tf_{td}}{k_1 \cdot \left(1 - b + b \cdot \left(\frac{L_d}{L_{avg}}\right)\right) + tf_{td}} \tag{3.9}$$

BM25L [Lv and Zhai, 2011c]

BM25L builds on the observation that BM25 penalizes longer documents too much compared to shorter ones. The *idf* component differs to avoid negative values. The TF component is reformulated as follows:

$$\frac{(k_1 + 1) \cdot c_{td}}{k_1 + c_{td}} \tag{3.10}$$

with

$$c_{td} = \frac{tf_{td}}{1 - b + b \cdot \left(\frac{L_d}{L_{avg}}\right)} \tag{3.11}$$

The c_{td} component is further modified by adding a constant δ, boosting the score for longer documents. The authors report using $\delta = 0.5$ for the highest effectiveness. Equation (3.12) presents the final formulation of BM25L:

$$\sum_{t \in q} \log\left(\frac{N + 1}{df_t + 0.5}\right) \cdot \frac{(k_1 + 1) \cdot (c_{td} + \delta)}{k_1 + (c_{td} + \delta)} \tag{3.12}$$

BM25+ [Lv and Zhai, 2011a]

BM25+, as shown in Equation (3.13), encodes a general approach for dealing with the issue that ranking functions unfairly prefer shorter documents over longer ones. Lv and Zhai propose adding a lower-bound bonus when a term appears at least once in a document. The difference with BM25L is a constant δ to the TF component. The *idf* component is again changed to a variant that disallows negative values.

$$\sum_{t \in q} \log\left(\frac{N + 1}{df_t}\right) \cdot \left(\frac{(k_1 + 1) \cdot tf_{td}}{k_1 \cdot \left((1 - b) + b \cdot \left(\frac{L_d}{L_{avg}}\right)\right) + tf_{td}} + \delta\right) \tag{3.13}$$

BM25-adpt [Lv and Zhai, 2011b]

BM25-adpt is an approach that varies k_1 per term (i.e., uses term specific k_1 values). In the original formulation of BM25, k_1 can be considered a hyperparameter that regulates the increase of score for

additional occurrences of a term; k_1 ensures that every additional occurrence gets discounted as it provides less information than its previous. However, Lv and Zhai argued that this does not necessarily have to be the case. If there are much fewer documents with $t+1$ occurrences versus t, it should provide more information than when the number of documents is almost the same. In order to find the optimal term-specific k_1 value, the authors want to maximize the information gain for that particular query term. First, they identify the probability of selecting a document randomly from the collection that contains the term q at least once in a document as:

$$p(1|0,q) = \frac{df_t + 0.5}{N+1} \tag{3.14}$$

The probability of a term occurring one more time is defined as:

$$p(t+1|t,q) = \frac{df_{t+1} + 0.5}{df_t + 1} \tag{3.15}$$

In both these formulas, 1 and 0.5 are added for smoothing to avoid zero probabilities. Then the information gain from t to $t+1$ occurrences is computed as, subtracting the initial probability:

$$G_q^t = \log_2\left(\frac{df_{t+1} + 0.5}{df_t + 1}\right) - \log_2\left(\frac{df_t + 0.5}{N+1}\right) \tag{3.16}$$

Here df_t is not defined as a standard document frequency but based on the length normalized term frequency:

$$df_t = \begin{cases} |D_{t|c_{td} \geq t-0.5}| & t > 1 \\ df(q) & t = 1 \\ N & t = 0 \end{cases} \tag{3.17}$$

In this case $df(q)$ is the "normal" document frequency, and c_{td} is the same as in BM25L (pivoted method for length normalization Singhal et al. [1996]):

$$c_{td} = \frac{tf_{td}}{1 - b + b \cdot \left(\frac{L_d}{L_{avg}}\right)} \tag{3.18}$$

This means the following: df_t is equal to the number of documents in the collection when $t = 0$, and it is equal to the "normal" document

frequency when $t = 1$. Otherwise, it will be the number of documents with at least t occurrences of the term (rounded up) using the pivoted method c_{td}.

Then, the information gain is calculated for $t \in \{0, \cdots, T\}$,until $G_q^t > G_q^{t+1}$. This threshold is chosen as a heuristic: When t becomes large, the estimated information gain can be very noisy. So T is chosen as the smallest value that breaks the worst burstiness rule [Church and Gale, 1995] (the information gain starts decreasing). The optimal value for k_1 is then determined by finding the value for k_1 that minimizes the following equation:

$$k_1' = \arg\min_{k_1} \sum_{t=0}^{T} \left(\frac{G_q^t}{G_q^1} - \frac{(k_1+1)\cdot t}{k_1 + t} \right)^2 \tag{3.19}$$

Essentially, this gives a value for k_1 that maximizes information gain for that specific term; k_1 and G_q^1 are then plugged into the BM25-adpt formula:

$$\sum_{t \in q} G_q^1 \cdot \frac{(k_1'+1)\cdot tf_{td}}{k_1' \cdot \left((1-b) + \cdot \left(\frac{L_d}{L_{avg}}\right)\right) + tf_{td}} \tag{3.20}$$

We found that the optimal value of k_1 is not defined for about 90% of the terms. A unique optimal value for k_1 only exists when $t > 1$ while calculating G_q^t. For many terms, especially those with a low df, $G_q^t > G_q^{t+1}$ occurs before $t > 1$. In these cases, picking different values for k_1 has virtually no effect on retrieval effectiveness. For undefined values, we set k_1 to 0.001, the same as Trotman et al. [2014].

TF $l \circ \delta \circ p \times$IDF [Rousseau and Vazirgiannis, 2013]

TF$l \circ \delta \circ p \times$IDF, as shown in equation 3.23, models the non-linear gain of a term occurring multiple times in a document as:

$$1 + \log\left(1 + \log\left(tf_{td}\right)\right) \tag{3.21}$$

To ensure terms occurring at least once in a document get boosted, the approach adds a fixed component δ, following BM25+. These parts are combined into the TF component using the pivoted method for length normalization [Singhal et al., 1996]:

$$c_{td} = \frac{tf_{td}}{1 - b + b \cdot \left(\frac{L_d}{L_{avg}}\right)} \tag{3.22}$$

The same IDF component as in BM25+ is used, which gives us TF$l \circ \delta \circ p \times$IDF:

$$\sum_{t \in q} \log\left(\frac{N+1}{df_t}\right) \cdot (1 + \log(1 + \log(c_{td} + \delta))) \tag{3.23}$$

3.5 Experiments

This section presents an empirical evaluation of the impact of the different choices of BM25 as described in Section 3.4. Our experiments were conducted using Anserini (v0.6.0) on Java 11 to create an initial index, and subsequently using relational databases for rapid prototyping, using "OldDog" [Kamphuis and de Vries, 2019b] after Mühleisen et al. [2014]; following that work, we use MonetDB as well. Evaluations with Lucene (default) and Lucene (accurate) were performed directly in Anserini; the latter was based on previously-released code that we updated and incorporated into Anserini.[5] The inverted index was exported from Lucene to OldDog, ensuring that all experiments share the same document processing pipeline (e.g., tokenization, stemming, stopword removal). While exporting the inverted index, we precalculate all k_1 values for BM25-adpt as suggested by Lv and Zhai [2011b]. As an additional verification step, we implemented both Lucene (default) and Lucene (accurate) in OldDog and compared the results to the output from Anserini. We can confirm that the results are the same, setting aside unavoidable differences related to floating point precision. All BM25 variants are then implemented in OldDog as minor variations upon the original SQL query provided in Mühleisen et al.. The term-specific parameter optimization for the *adpt* variant was already calculated during the index extraction stage, allowing us to upload the optimal (t, k) pairs and directly use the term-specific k values in the SQL query. The advantage of our experimental methodology is

[5] `http://searchivarius.org/blog/accurate-bm25-similarity-lucene` (last accessed – March 3rd, 2023)

that we did not need to implement a single new ranking function from scratch.

The experiments use three TREC newswire test collections: TREC Disks 4 and 5, excluding Congressional Record, with topics and relevance judgments from the TREC 2004 Robust Track (Robust04); the New York Times Annotated Corpus, with topics and relevance judgments from the TREC 2017 Common Core Track (Core17); the TREC Washington Post Corpus, with topics and relevance judgments from the TREC 2018 Common Core Track (Core18). Following standard experimental practice, we assess ranked list output in terms of average precision (`AP`) and precision at rank 30 (`P@30`). The parameters shared by all models are set to $k_1 = 0.9$ and $b = 0.4$, Anserini's defaults. The parameter δ is set to the value reported as best in the corresponding source publication.

All experiments were run on a Linux desktop (Fedora 30, Kernel 5.2.18, SELinux enabled) with four cores (Intel Xeon CPU E3-1226 v3 @ 3.30 GHz) and 16 GB of main memory; the MonetDB 11.33.11 server was compiled from source using the `--enable-optimize` flag.

3.6 Results

Table 3.5 shows the effectiveness scores of the different BM25 variants. The observed differences in effectiveness are small and can be entirely attributed to variations in the scoring function; our methodology fixes all other parts of the indexing pipeline (e.g., tag cleanup, tokenization, and stopwords). Both an ANOVA and Tukey's HSD show no significant differences between any variant on all test collections. These results confirm the findings of Trotman et al. [2014]: effectiveness differences are unlikely an effect of the choice of the BM25 variant. Across the IR literature, we find differences due to more mundane settings (such as the choice of stopwords) tend to be larger than the differences we observe here. Although we find no significant improvements over the original [Robertson et al., 1994] formulation, using a variant of BM25 that avoids negative ranking scores might still be worthwhile.

You might have caught that the effectiveness scores of ATIRE and Lucene (accurate) are the same. This is not a mistake. As explained, the $k_1 + 1$ in ATIRE scales the scores linearly and does not affect the

Table 3.5: Effectiveness scores different BM25 variants. All were implemented as SQL queries, so the underlying data representations are the same.

	Robust04		Core17		Core18	
	AP	P@30	AP	P@30	AP	P@30
Robertson et al.	.2526	.3086	.2094	.4327	.2465	**.3647**
Lucene (default)	.2531	.3102	.2087	.4293	.2495	.3567
Lucene (accurate)	.2533	.3104	.2094	.4327	.2495	.3593
ATIRE	.2533	.3104	.2094	.4327	.2495	.3593
BM25L	.2542	.3092	.1975	.4253	**.2501**	.3607
BM25+	.2526	.3071	.1931	.4260	.2447	.3513
BM25-adpt	**.2571**	**.3135**	**.2112**	.4133	.2480	.3533
$\text{TF}_{lo\delta\circ p} \times \text{IDF}$	.2516	.3084	.1932	**.4340**	.2465	.3647

ranking. So the only difference that can change the effectiveness scores is the different *idf* functions. However, these are practically the same, especially when a collection has a large number of documents (N):

$$\log\left(\frac{N}{df_t}\right) = \log\left(\frac{N - df_t + df_t}{df_t}\right) \tag{3.24}$$

$$= \log\left(\frac{N - df_t}{df_t} + \frac{df_t}{df_t}\right) \tag{3.25}$$

$$= \log\left(\frac{N - df_t}{df_t} + 1\right) \tag{3.26}$$

$$\approx \log\left(\frac{N - df_t + 0.5}{df_t + 0.5} + 1\right) \tag{3.27}$$

Switching our attention from effectiveness to efficiency, Table 3.6 presents the average retrieval time per query in milliseconds (without standard deviation for Anserini, which does not report time per query). MonetDB uses all cores for inter- and intra-query parallelism, while Anserini is single-threaded.

Comparing Lucene (default) and Lucene (accurate), we find negligible differences in effectiveness. However, the differences in retrieval time are also negligible, which calls into question the motivation behind the

Table 3.6: Average retrieval time per query in ms: Anserini (top) and OldDog (bottom)

	Robust04	Core17	Core18
Lucene (default)	52	111	120
Lucene (accurate)	55	115	123
Robertson et al.	158 ± 25	703 ± 162	331 ± 96
Lucene (default)	157 ± 24	699 ± 154	326 ± 90
Lucene (accurate)	157 ± 24	701 ± 156	324 ± 88
ATIRE	157 ± 24	698 ± 159	331 ± 94
BM25L	158 ± 25	697 ± 160	333 ± 96
BM25+	158 ± 25	700 ± 160	334 ± 96
BM25-adpt	158 ± 24	700 ± 157	330 ± 92
$\text{TF}_{l \circ \delta \circ p} \times \text{IDF}$	158 ± 24	698 ± 158	331 ± 96

original length approximation. Currently, the similarity function and, thus, the document length encoding are defined at index time. Storing exact document lengths would allow for different ranking functions to be swapped at query time more effortlessly, as no information would be discarded at index time. Accurate document lengths might additionally benefit downstream modules that depend on Lucene. We suggest that Lucene might benefit from storing exact document lengths.

3.7 Conclusion

In summary, the previous sections describe a double reproducibility study. The study methodologically validated the usefulness of databases for IR prototyping and performed a large-scale study of BM25 to confirm the findings of Trotman et al. [2014]. It does not seem to matter which of the multitude of BM25 variants is used. Furthermore, to return to our research question, we can conclude that using relational databases for information retrieval is beneficial. Because data processing and storage are separated in relational databases, comparing different ranking functions in a relational system is much easier compared to a system that uses an inverted index. The work by Mühleisen et al. [2014] also confirmed that relational databases

could be as efficient as inverted indexes in retrieval tasks. In short, databases have use cases in which they are easier to work with, while it is possible to have efficient systems.

Chapter 4

From Tables to Graphs

> "The reader will have anticipated that I have no very convincing arguments of a positive nature to support my views. If I had I should not have taken such pains to point out the fallacies in contrary views.
>
> Alan Turing - 1950

Abstract

This chapter introduces GeeseDB. GeeseDB is a Python toolkit for solving information retrieval research problems that leverage graphs as data structures. It aims to simplify information retrieval research by allowing researchers to formulate graph queries through a graph query language quickly. GeeseDB is built on top of DuckDB, an embedded column-store relational database for analytical workloads. GeeseDB is available as an easy-to-install Python package. In only a few lines of code, users can create a first-stage retrieval ranking using BM25. Queries read and write Numpy arrays and Pandas dataframes at negligible data transformation cost. Therefore, the results of a first-stage ranker expressed in GeeseDB can be used in various stages in the ranking process, enabling all the power of Python machine learning libraries with minimal overhead.

4.1 Introduction

In recent years there has been a lot of exciting new information retrieval research that uses non-text data to improve the efficacy of search applications. All these research directions have improved search systems' effectiveness by using more diverse data. Although more diverse data sources are considered, these systems are often implemented through a coupled architecture. In particular, first-stage retrieval is often carried out with different software compared to later retrieval stages, where these novel reranking techniques tend to be used. In our view, researchers could benefit from a system where retrieval stages are more tightly coupled, which facilitates the exploration of how to use non-content data for ranking and serves the data in a format suitable for reranking with, e.g., transformers, tree-based methods or graph-based methods.

The previous chapter demonstrates how relational databases can be used for information retrieval problems. Integrating alternative data sources into search systems is easier when using a relational database instead of an inverted index. In the case of information retrieval, graph data can often be used to improve search effectiveness. One of the most famous examples where graphs help information retrieval is the PageRank algorithm [Page et al., 1999]. Although it might be possible to express this data in relational databases, they are not designed with graph structures in mind.

The data management community has shown much interest in graph databases in recent years. Graph databases are different from relational databases in that a relation is not the abstraction for representations, but a graph is. Graphs can be considered a better abstraction for real-world data than relations. Graphs focus much more on concepts (nodes in a graph) and how they relate to each other (edges in a graph), while in a relational database this information is more implicit. Many different graph types exist; one is called the *property graph model*. This type of graph contains nodes and directed edges, which can be labeled; nodes and edges can also have associated key-value pairs. In this chapter, we will work with the property graph model and see how it benefits IR research.

The research goal in this chapter is two-fold; firstly we want to develop a system that can search efficiently and handle graphs. In the

previous chapter, we showed that relational databases could search efficiently and help reproducible research. However, these systems do not support graph data structures well. Systems built on inverted indexes use coupled architectures, which can introduce unnecessary overhead.

Secondly, we want to create a system where both first and second-stage retrieval are directly supported. In IR research multi-stage retrieval systems contain components that are not ran in the same ecosystem; introducing overhead in retrieval efficiency. So in this chapter, the prototype system GeeseDB is introduced; it tries to leverage the same techniques for search as relational databases do while also naturally being able to support graphs. This leads to the main research question for this chapter:

RQ2: Can we extend the benefits from using relational databases for information retrieval to using graph-databases while being able to express graph-related problems easier?

In order to answer this research question, we will work with the prototype system GeeseDB, but before GeeseDB is discussed, first we will look into work that uses systems that try to combine two systems for two-stage retrieval experiments, and systems built for processing graphs.

4.2 Related work

In modern IR it is not uncommon to use coupled architectures. In many situations a ranking model is used that is efficient, but only reasonably effective. BM25 can be considered such a model, it can be calculated cheaply, while more advanced, but less efficient, retrieval models achieve higher effectiveness. In such cases, BM25 can be used to calculate an initial top-k ranking that contains (presumably) all relevant documents. Then, the more expensive model only has to calculate the final ranking scores over the top-k documents.

In this section, first some methods are introduced where such multi-stage approaches are used, then systems that implement these approaches are highlighted. In particular there will be a focus on the coupled-architectures aspect of these systems, and finally some

proposed methods will be discussed to deal with cons arising from coupled architectures.

4.2.1 Learning To Rank

In learning-to-rank multi-stage retrieval approaches tend to be used, often the models are not efficient enough to compute a relevance score value for all documents in the collection. Deveaud et al. [2014] showed that for the TREC Contextual Suggestion track [Dean-Hall et al., 2014], reranking using user-based features significantly improved retrieval effectiveness over a baseline language modeling approach. These features show that data not present in the document's text can help the retrieval effectiveness of systems; metadata helps to rank.

Macdonald et al. [2012] show examples of many features that are effective for learning to rank, many of these features are non-textual. Some influential features are: click count, click entropy, and the number of displayed results in a session.

Often, in these cases, a decision tree based ensemble like LambdaMART [Burges, 2010] tends to be trained. These models take input that's not typically produced by an inverted index. So, in order to use these models, the output from the inverted index needs to be converted.

4.2.2 Dense Retrieval

Where traditionally, search was carried out using inverted indexes, dense retrieval has become more prevalent in recent years. Consider, for example, the work by Gao et al. [2021]; in their work, they proposed `clear`, a model that aims to complement lexical models with a dense retrieval model. In their study, they use BM25 as the lexical model. The BM25 scores are calculated using an inverted index (Anserini [Yang et al., 2018a]), while the dense retrieval model is a fine-tuned BERT bi-encoder. This dense model calculates a score using a different maximum inner-product search (MIPS) system (Faiss [Johnson et al., 2019]) to calculate a similarity score for the query document pairs. Then scores are weighted and summed to calculate a new ranking score value.

In a similar study, Luan et al. [2021] compared several methods on

the MS Marco document en passage datasets. In their work, one of the two best models on the passage dataset was combining a lexical model and a BERT-based bi-encoder. The scores were combined by retrieving the top-n documents for both the lexical model and the bi-encoder. In order to do this, an inverted index (Anserini) is used to retrieve the documents for the lexical model, while the bi-encoder uses a MIPS system (ScaNN [Guo et al., 2020]).

Then to give a third example, Lin et al. [2020b] do experiments with distilled dense representations. They do an extensive comparison study, and in their work, the best results are reported by either multi-stage or hybrid dense + sparse retrieval methods. The multi-stage retrieval method was BM25 + BERT-large. Although effective, it is a method with a high latency because of the cross-encoder used. A TCT-ColBERT (Tightly-Coupled Teacher - ColBERT) bi-encoder with doc2query-T5 sparse retrieval was the best hybrid method. This sparse retrieval method is a BM25 retrieval method that expands the documents with T5 language model questions [Raffel et al., 2020]. These questions were generated by letting the T5 language model generate questions that the passage might answer. Sparse retrieval is carried out by Anserini, and dense retrieval by Faiss.

4.2.3 Knowledge Graphs and Entities

Knowledge graphs have been used a lot as well in IR research. Hasibi et al. [2016b] proposed the Entity Linking incorporated Retrieval (ELR) approach. The idea behind this concept is that when entity annotations are available for queries and documents, they can be incorporated into the ranking model. This study only focuses on entity retrieval, but it generalizes to retrieval. The entities are incorporated by creating a dedicated index for entities on which entity scores can be calculated. These are then merged by the document scores calculated using the regular index. By incorporating entity scores, ELR can increase effectiveness scores for multiple baseline methods.

Dalton et al. [2014] used entity features for query expansion. One of the features was calculated by tagging queries with an entity-linking system. When entities were found, information from the knowledge base linked to them was included in query expansion. Alternative names of the entity were also included in the query expansion. Then

this expanded query provided a score for all documents. Another feature they calculate is by ranking the entities in the knowledge base using the original query text. Then the data (e.g., words in the descriptions) included in the knowledge base can be included as terms for query expansion. Multiple other features using entities were also calculated,

Balog [2018] wrote a book on entity-oriented search, giving an excellent outline of methods that use entities for search. I recommend it if you want to read more about entity information for IR.

Basically, in order to include entities, a knowledge graph needs to be queried. This tends to be done by a different systems than the systems used for regular retrieval.

4.2.4 Current approaches

Some systems are used a lot for information retrieval research. These systems are typically built as inverted index systems. Recently, retrieval methods using neural networks have become state-of-the-art, mainly using large language models. Some systems will be described, and how they deal with these recent advances will be highlighted.

PyTerrier

PyTerrier by Macdonald et al. [2021], is a Python extension of Terrier [Ounis et al., 2005]. Terrier is an open-source search engine system written in Java. It implements state-of-the-art indexing and retrieval techniques on top of an inverted index. It is a system suited for rapidly developing retrieval experiments concerning document collections with many documents. The PyTerrier extension was developed to express complex IR pipelines in Python. Using Python operators directly, it is possible to set up an IR pipeline using PyTerrier in only a few lines of code.

PyTerrier was expanded to support state-of-the-art large language model reranking approaches and dense retrieval methods. As the PyTerrier framework is developed for the Python ecosystem, other (re-)ranking methods that are implemented in Python can readily work with PyTerrier. Because of these features, the PyTerrier system is ideal for modern information retrieval research that often concerns

reranking through learned methods, as they are often developed in Python.

Note, however, that PyTerrier uses a coupled architecture, first-stage retrieval is carried out using Terrier in Java (e.g., a bm25 run), and then the resulting top documents are reranked in Python. For this, some overhead is introduced because of data transfer between processes.

Pyserini

Pyserini was developed by Lin et al. [2021], which is a Python extension of Anserini [Yang et al., 2018a]. Pyserini and Anserini have a lot in common with PyTerrier and Terrier. Just like Terrier, Anserini is developed in Java, but on top of Apache Lucene. Anserini is developed as a system with solid support for reproducible research. Anserini provides reproducible baselines for many retrieval benchmarks that can be run with minimal setup.

Pyserini is developed as a Python wrapper around the Anserini retrieval system. Within the Python ecosystem, it is possible to access the Anserini internals and replicate the same experiments implemented in Anserini. Similarly to PyTerrier, Pyserini also contains features that are not available directly in Anserini; ranking methods that make use of large language models, such as dense retrievers and BERT-based cross encoders. As these methods are generally developed in Python, it is much easier to support them with Pyserini compared to Anserini.

Anserini is included in Pyserini as a JAR file, so when using Pyserini for first-stage retrieval, data needs to be retrieved from JAVA before it can be materialized in Python. The setup is similar to Pyterrier.

4.2.5 Proposed approaches

Separation of the Logical and Physical Model

As shown in the previous sections, dense and sparse retrieval methods are often implemented using different systems, which introduces the coupled architecture. Lin [2022] recognizes that sparse retrieval models are typically implemented in inverted indexes and dense retrieval methods with approximate nearest neighbor systems. Although these systems are different, the input and the output are the same: the input

is a query, and the output is a ranked list of the top-k documents the ranking methods deem the most relevant.

In order to be able to formalize these similarities and distinctions more clearly, Lin proposes a distinction between the logical and physical retrieval models. Logical models consists of encoders that maps documents and queries to a representation, and a comparison function that defines how a ranking score value can be computed from comparing these representations. Physical models define how to create a top-k ranking from a large corpus given a query. This could be applying the logical model to every query-document pair, but through optimizations it might not necessary to compare all documents to the query. For example, dense retrieval methods often make use of HNSW which prunes documents that have a low likelihood of being relevant.

A Graph Query Language for IR

We [Kamphuis and de Vries, 2019a] proposed to create graph query language for information retrieval problems. In the context of separating logical and physical models, a graph query language can be interpreted as a logical model, while the engine that implements the graph query language can be considered the physical model.

If it is possible to express both first stage and second stage retrieval in such a query language, both stages would be computed by the same physical model, automatically ensuring a coupled architecture is not necessary. Having a graph query language available, ensures that more complicated retrieval strategies can be expressed compared to when a relational query language is used.

So ideally we develop a system with the following two capabilities; the system supports first stage retrieval directly, and graph queries over the output of this first stage retrieval can be processed without a coupled architecture. In order to fulfill these needs, we developed GeeseDB in a follow up study.

4.3 GeeseDB

GeeseDB[1] is a prototype Python toolkit for information retrieval that leverages graphs as data structures, allowing metadata and graph-oriented data to be easily included in the ranking pipeline. The toolkit is designed to quickly set up first-stage retrieval and make it easy for researchers to explore new ranking models.

In short, GeeseDB aims to provide the following functionalities:

- GeeseDB is an easy-to-install, self-contained Python package available through `PyPI` with as few as possible dependencies. It contains topics and relevance judgments for several standard IR collections out-of-the-box, allowing researchers to develop new ranking models quickly.
- First stage (sparse) retrieval is directly supported. In only a few lines of code, it is possible to load documents and create BM25 rankings.
- Data is served in a usable format for later retrieval stages. GeeseDB allows directly running queries on Pandas data frames for efficient data transfer to sequential reranking algorithms.
- Easy data exploration is supported through querying data with SQL, but more interestingly, using a graph query language (based on the Cypher query language), making exploring new research avenues easier. This prototype supports a subset of the graph query language Cypher, similar to the property graph database model query language as described by Angles [2018].

4.4 Design

At the core of GeeseDB lies the full-text search design presented by Mühleisen et al. [2014]. This work proposes a column-store database for IR prototyping, which uses the database schema described in Figure 4.1, consisting of three database tables. These tables are exactly the same as the tables described in the previous chapter. Using these three tables, the authors show that BM25 can be easily expressed as a SQL

[1] `https://github.com/informagi/geesedb`

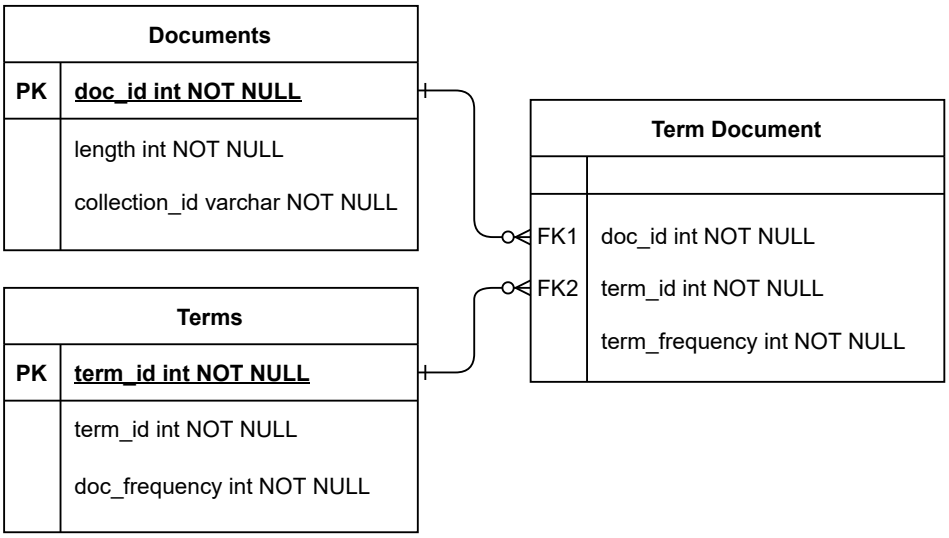


Figure 4.1: Database schema by Mühleisen et al. for full text search in relational databases

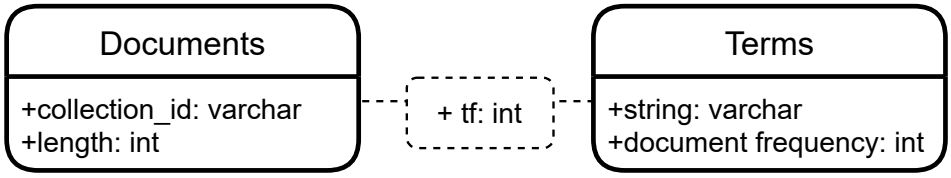


Figure 4.2: Graph schema representing bipartite document-term graph

query with latencies on par with custom-built IR engines. In GeeseDB, we use the same relational schema for full-text search. Instead of seeing the document data and term data as tables that relate to each other through a many-to-many join table, it is also possible to consider this schema as a bipartite graph. In this graph, documents and terms are considered nodes connected through edges. If a term occurs in a document, an edge exists between that term and the document. GeeseDB uses the data model of property graphs labeled multigraphs where both edges and nodes can have property-value pairs. The database schema, as described in Figure 4.1, would then translate to the property graph schema shown in Figure 4.2. A small example of a graph represented by this schema is shown in Figure 4.3. Document nodes contain document-specific information (i.e., document length and the

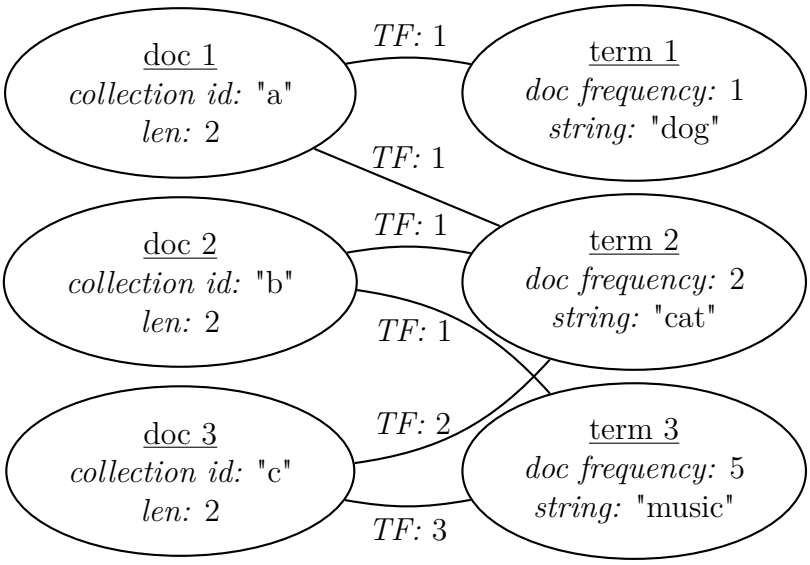


Figure 4.3: Example term-document graph that maps to relational database schema

collection identifier), term nodes contain information relevant to the term (i.e., the term string and the term's document frequency), and the edges between document and terms nodes contain term frequency information (i.e., how often is the term mentioned in the document represented the respective nodes it connects).

If one wants to, for example, also store position data, this graph can easily be changed to a graph where the edges store the position of a term. If a term appears multiple times in a document, the property graph model will allow multiple edges between two nodes. The graph schema that we described by Figure 4.2 maps one-to-one to the relational database schema described by Figure 4.1, so nodes are represented by standard relational tables that represent specific data units (terms, documents), while many-to-many join tables represent edges. So even though we think of the data as graphs, they are represented as relational tables in the backend. When using GeeseDB for search, we at least expect the document-term graph to be present. Of course, new node types can be introduced to explore new search strategies.

4.4.1 Backend

GeeseDB is built on top of DuckDB [Raasveldt and Mühleisen, 2019], an in-process SQL OLAP (analytics optimized) database management system. DuckDB is designed to support analytical query workloads. It aims explicitly to process complex, long-running queries where a significant portion of the data is accessed, conditions matching the case of IR research. DuckDB has a client Python API which can be installed using `pip`. Afterward, it can be used directly. DuckDB has a separate API built around NumPy and Pandas, providing NumPy/Pandas views over the same underlying data representation without incurring data transfer (usually referred to as "zero-copy" reading). Pandas DataFrames can be registered as virtual tables, allowing to query the data in Pandas DataFrames directly. GeeseDB inherits all these functionalities from DuckDB.

As DuckDB is a database management system, we can execute analytical SQL queries on tables containing our data, including the BM25 rankings described by Mühleisen et al. [2014]. By default, the BM25 implementation provided with GeeseDB implements the disjunctive variant of BM25 instead of the conjunctive variant they used. Although the conjunctive variant of BM25 can be calculated more quickly, we chose to use the disjunctive variant as IR researchers more commonly use it, and the differences between effectiveness scores are noticeable on smaller collections. For now, we only support the original formulation of BM25 by Robertson et al. [1994]. However, supporting other versions of BM25 as described in the previous chapter is trivial.

4.5 Graph Query Language

What distinguishes GeeseDB from alternatives, database-backed (OldDog) [Kamphuis and de Vries, 2019b], or native systems (Anserini [Yang et al., 2018a], Terrier [Ounis et al., 2005]) is the graph query language, based on Cypher [Francis et al., 2018]. For now, GeeseDB implements Cypher's basic graph pattern-matching queries for retrieving data. An example of a graph query supported by GeeseDB is presented in Figure 4.4. This query finds all documents written by the same authors as those who wrote document "96ab542e". For comparison, Figure 4.5

```
MATCH (d:docs)-[]-(:authors)-[]-(d2:docs)
WHERE d.collection_id = "96ab542e"
RETURN DISTINCT d2.collection_id
```

Figure 4.4: An example cypher query that finds all documents that were written by the same author that wrote the document with the `collecion_id` "96ab542e"

```
SELECT DISTINCT d2.collection_id
FROM docs AS d2
JOIN doc_author AS da2 ON (d2.collection_id = da2.doc)
JOIN authors AS a2 ON (da2.author = a2.author)
JOIN doc_author AS da3 ON (a2.author = da3.author)
JOIN docs AS d ON (d.collection_id = da3.doc)
WHERE d.collection_id = '96ab542e'
```

Figure 4.5: SQL query that corresponds to the graph query described in Figure 4.4.

illustrates the same query represented in SQL; much more complex than the Cypher version, due to the join conditions that have to be made explicit. In order to connect the "docs" table with the "authors" table 2 joins are needed; reconnecting the "docs" table again introduces two more joins.

At the moment of writing, GeeseDB supports the following Cypher keywords: `MATCH`, `RETURN`, `WHERE`, `AND`, `DISTINCT`, `ORDER BY`, `SKIP`, and `LIMIT`. Instead of using `WHERE` to filter data, it is also possible to use graph matching, as shown in Figure 4.6; the query returns the length of document "96ab542e". Everything that is not directly supported yet by our implementation can, of course, still be expressed in SQL, which

```
MATCH (d:docs {d.collection_id: "96ab542e"})
RETURN d.len
```

Figure 4.6: Graph query where the length of document with `collection_id` is returned.

is fully supported.[2] In order to know how to join nodes to each other if no edge information has been provided, GeeseDB stores information on the schema. This way, GeeseDB knows how nodes relate to each other through which edges. GeeseDB has a module for updating the graph schema, allowing researchers to quickly set up the graph they want to be represented in the database.

4.6 Usage

GeeseDB comes as an easy-to-install Python package that can be installed using pip, the standard package installer for Python:

```
$ pip install geesedb
```

After installing GeeseDB, we can immediately start using it. It is also possible to install the latest commit by installing the latest version directly from GitHub. As an example, we will show how to use GeeseDB for the background linking task of the TREC News Track [Soboroff et al., 2019]. The goal of this task is: *Given a news story, find other news articles that can provide meaningful context or background information.* These articles can then be recommended to the reader to help them understand the context in which these news articles occur. The collection used for this task is the Washington Post V3 collection[3] released for the 2020 edition of TREC. It contains 671,945 news articles published by the Washington Post published between 2012 and 2020 and 50 topics with relevance assessments (topics correspond to collection identifiers of documents for which relevant data has to be found). The articles in this collection contain valuable metadata; in particular, we will use authorship information. We extracted 25,703 unique article authors, where it is possible that multiple authors co-wrote a news article. We also annotate documents with entity information which was obtained by using the Radboud Entity Linker [van Hulst et al., 2020]. In total 31,622,419 references to 541,729 unique entities were found. The links also contain mention and location information, as well as the `ner_tag` found by the linker's entity recognition module

[2] GeeseDB supports the graph queries by translating them to their corresponding SQL queries. After all, both nodes and edges are just tables in the backend.

[3] `https://trec.nist.gov/data/wapost/`

(The `ner_tag` is part of a link, as the entity linker can assign different tags to the same entity). Figure 4.7 illustrates the data schema that we use for the background linking task using a small example graph.

4.6.1 Indexing and Search

In order to start, a database containing at least the document and term information needs to be created. Figure 4.8 shows how the data can be easily loaded using CSV files.

Instead of loading the data from CSV files, it is also possible to load the text data directly using the CIFF format for data exchange [Lin et al., 2020a]. GeeseDB also has functionalities to create CSV files from the CIFF format. Authorship information and entity links can be loaded similarly. After loading the data, we can quickly create a BM25 ranking for ad hoc search in the Washington Post collection, as shown in Figure 4.9.

For the background linking task, however, we do not have regular topics; we only have the collection identifiers of the documents for which we need to find relevant background info. In order to search for relevant background reading, queries that represent our information need have to be constructed. A common approach is to use the top-k TF-IDF terms of the source article. These can easily be found using the Cypher statement in Figure 4.10. Instead of using Cypher, it would also be possible to use SQL, as shown in Figure 4.11; however, this example shows again that the Cypher query is more elegant than SQL.

Processing Cypher queries depends on the schema information that must be loaded. We have a supporting class for this, and the schema data used in this paper will be available via GitHub. Using the terms found with Cypher, we can construct queries to pass to the searcher and create a BM25 ranking. The code that generates the rankings for all topics is presented in Figure 4.12. In only a few lines of Python code, it is easy to create rankings. From this point, writing the content of `hits` to a runfile and evaluating using `trec_eval` is trivial.
Instead of "just" ranking with BM25, using, e.g., the metadata to adapt the ranking is straightforward. In the case of background linking, it makes sense to consider authorship information when recommending articles that might be suitable as background reading. As journalists often specialize in specific news topics (e.g., politics, foreign affairs,

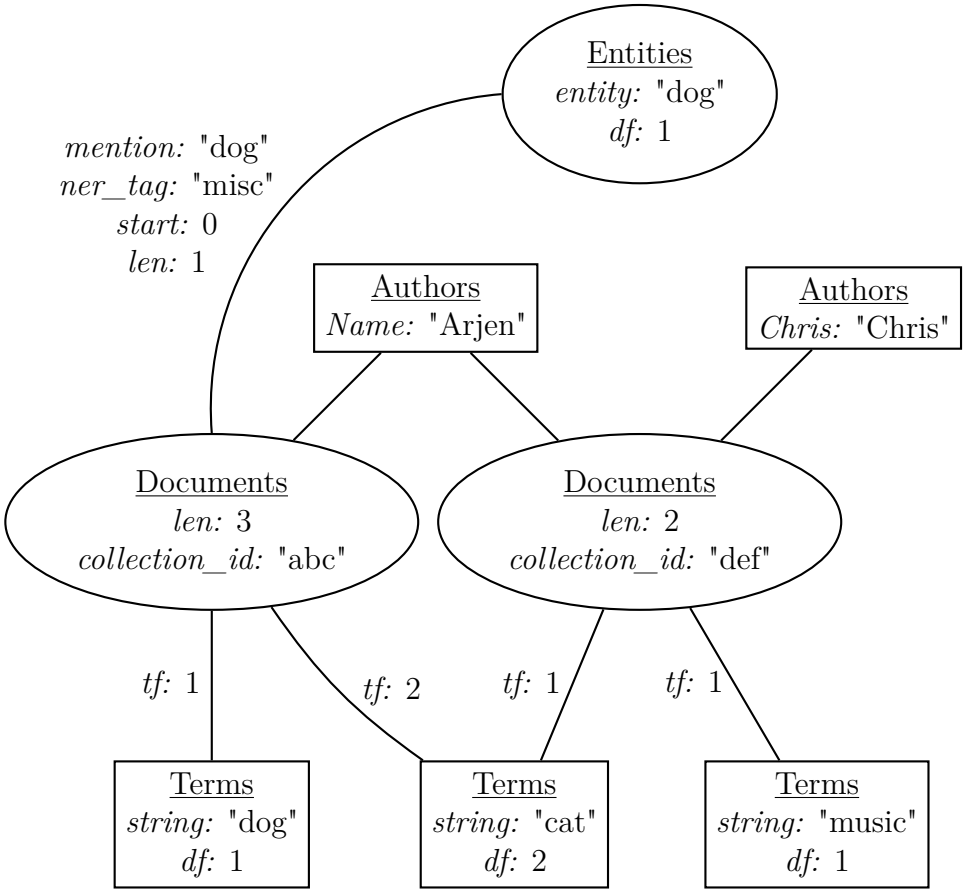


Figure 4.7: Example property graph for the TREC News Track's background linking task. The node types are authors, entities, terms, and documents. Edges connect document nodes to other types of nodes. Both edges and nodes can have properties (following the property graph model). Multiple edges may exist between one entity node and one document node, as one entity can be linked multiple times to one document.

```
from geesedb.index import FullTextFromCSV

index = FullTextFromCSV(
    database='/path/to/database',
    docs_file='/path/to/docs.csv',
    term_dict_file='/path/to/term_dict.csv',
    term_doc_file='/path/to/term_doc.csv'
)
index.load_data()
```

Figure 4.8: Load text data from the WashingtonPost collection formatted as CSV files in the format as described by Mühleisen et al. [2014]

```
from geesedb.search import Searcher

searcher = Searcher(
    database='/path/to/database',
    n=10
)
hits = searcher.search_topic('obama and trump')
```

Figure 4.9: Example on how to create a BM25 ranking for the query "obama and trump" that returns the top 10 documents.

```
MATCH (d:docs {collection_id: ?})-[]-(t:term_dict)
RETURN string
ORDER BY tf*log(671945/df)
DESC
LIMIT 5
```

Figure 4.10: Prepared Cypher statement that finds the top-5 TF-IDF terms in a document.

```
SELECT term_dict.string
FROM term_dict
JOIN term_doc ON (term_dict.term_id = term_doc.term_id)
JOIN docs ON (docs.doc_id = term_doc.doc_id)
WHERE docs.collection_id = ?
ORDER BY term_doc.tf * log(671945/term_dict.df
DESC
LIMIT 5;
```

Figure 4.11: Prepared SQL statement that finds the top-5 TF-IDF terms in a document.

tech), the stories they write often share context. Also, when journalists collaborate on stories, they write together on topics they specialize in. As authorship information is available to us, we can decide to use the information whether an article is written by the authors of the topic article or by someone they have collaborated with in the past. Finding the articles that this group of people writes can quickly be done using a graph query, the query that finds these articles is shown in Figure 4.13.

Depending on the number of documents this query finds, different rescoring strategies can be decided upon. If the set of documents written by the authors or their co-authors is large, it is possible only to consider these documents, but if the set is small, a score boost might be more appropriate. Figure 4.14 shows an example of how only to consider documents found with the query in Figure 4.13. In this case, we ensure that at least 2000 documents are found before filtering.

For another example, the graph query language is also valuable when considering entities. Journalists write news articles that relate to events concerning, e.g., people, organizations, or countries. In other words, the basis of news articles lay the entities as they are often the subject of news. So, instead of using the most informative terms in a news article, it is worthwhile to consider the entities identified in the article instead. Important entities tend to be mentioned at the beginning of a news article Kamphuis et al. [2019]; Figure 4.15 shows the Cypher query to retrieve the text mentions of the first five mentioned entities.

```python
from geesedb.search import Searcher
from geesedb.connection import get_connection
from geesedb.resources import
    get_topics_backgroundlinking
from geesedb.interpreter import Translator

db_path = '/path/to/database'
searcher = Searcher(
    database=db_path,
    n=1000
)

translator = Translator(db_path)
c_query = """cypher TFIDF query"""

query = translator.translate(c_query)
cursor = get_connection(db_path).cursor
topics = get_topics_backgroundlinking(
    '/path/to/topics'
)
for topic_no, collection_id in topics:
    cursor.execute(query, [collection_id])
    topic = ' '.join(cursor.fetchall()[0])
    hits = searcher.search_topic(topic)
```

Figure 4.12: Create a BM25 ranking for all background linking topics using the top-5 TFIDF terms. Note that a processed topic file was used where only the topic identifier and article id are available. The topic file in this format is provided on our GitHub.

```
MATCH (d:docs)-[]-(:authors)-[]-(:docs)-[]-(:authors)-
    []-(d2:docs {collection_id:
    ?})
RETURN DISTINCT d.collection_id
```

Figure 4.13: Cypher query to find documents written by co-authors of the authors of the topic article.

```
# import and first lines the same as previous example

author_c_query = """cypher authorship query"""
author_query = t.translate(author_c_query)

cursor = get_connection(db_path).cursor
topics = get_topics_backgroundlinking(
    '/path/to/topics'
)
for topic_no, collection_id in topics:
    cursor.execute(query, [collection_id])
    topic = ' '.join(cursor.fetchall()[0])
    hits = searcher.search_topic(topic)

    cursor.execute(author_query, [collection_id])
    docs_authors = {
        e[0] for e in cursor.fetchall()
    }
    if len(docs_authors) > 2000:
        hits =
        ↪ hits[hits.collection_id.isin(docs_authors)]
```

Figure 4.14: Find documents written by all authors that collaborated with the authors of the topic article, if there are more than 2000 documents found, only consider these documents as background reading candidates.

```
MATCH (d:docs {collection_id: ?})-[]-(e:entities)
RETURN mention
ORDER BY start
LIMIT 5
```

Figure 4.15: Retrieve the first five entities mentioned in the topic article, and return the terms used to mention the entity.

Before it is possible to search using the text describing the first five entity mentions, the text needs to be processed. The term data loaded in GeeseDB was already processed, as it was data loaded from CSV files built from a CIFF file created from an Anserini [Yang et al., 2018a] (Lucene) index. Pyserini [Lin et al., 2021] that can be used to tokenize the text the same way the documents were tokenized. Figure 4.16 shows the Python code where we extract the mentions, process them such that they become a usable query for GeeseDB, and then BM25 ranking is created with this query.

4.7 Conclusion

This chapter described the prototype implementation of GeeseDB, and how we envision graph databases can be used for information retrieval research. The GeeseDB system can be considered the question on our research question: *Can we extend the benefits from using relational databases for information retrieval to using graph databases, while being able to express graph-related problems easier?* As GeeseDB is built on top of a relational engine it automatically inherits the benefits of using relational databases for IR. As GeeseDB can process graph queries, we also are able to express graph related problems.

GeeseDB is still however a prototype system, and more functionalities need to be implemented. In particular, although the architecture is not coupled, it is not as efficient as traditional methods that do use coupled architectures. The overhead introduced introduce in coupled architectures is lower than the retrieval efficiency from methods that are state of the art but work coupled.

Also, not all graph operators are yet supported. In order to make GeeseDB a usable system for IR researchers, more operators need to be implemented and the system needs to be developed to be more robust.

```
from geesedb.search import Searcher
from geesedb.connection import get_connection
from geesedb.resources import
 ↪  get_topics_backgroundlinking
from geesedb.interpreter import Translator
from pyserini.analysis import Analyzer,
 ↪  get_lucene_analyzer

db_path = '/path/to/database'
searcher = Searcher(
    database=db_path,
    n=1000
)

analyzer = Analyzer(get_lucene_analyzer())

translator = Translator(db_path)
c_query = """cypher entity query"""
query = translator.translate(c_query)

cursor = get_connection(db_path).cursor
topics = get_topics_backgroundlinking(
    '/path/to/topics'
)

for topic_no, collection_id in topics:
    cursor.execute(query, [collection_id])
    topic = ' '.join([e[0] for e in cursor.fetchall()])
    topic = ' '.join(analyzer.analyze(topic))
    hits = searcher.search_topic(topic)
```

Figure 4.16: Create a BM25 ranking for all background linking topics using the mention text of the first five linked entities in the source article.

Chapter 5

Creation of the Entity Graph

Abstract

REBL is an extension of the Radboud Entity Linker (REL) for Batch Entity Linking. REBL is developed after encountering unforeseen issues when trying to link the large MS MARCO v2 document collection with REL. In this chapter we discuss the issues we ran into and our solutions to mitigate them. REBL makes it easier to isolate the GPU heavy operations from the CPU heavy operations, by separating the mention detection stage from the candidate selection and entity disambiguation stages. By improving the entity disambiguation module we were able to lower the time needed for linking documents by an order of magnitude.

5.1 Introduction

In the previous chapter we have introduced the GeeseDB system that can query IR graphs and create rankings. Using GeeseDB we expressed queries over the Washington Post news article collection. The examples we showed made use of entity annotations that were created by the Radboud Entity Linker (REL) [van Hulst et al., 2020]. Although, the Washington Post collection is used for retrieval experiments, it is mostly used as a benchmark for news retrieval. In recent years, the MS MARCO ranking collections became popular for IR research. They have become the de-facto benchmark for information retrieval experiments that employ deep learning. These collections are considerably larger

than the Washington Post collection; the Washington Post collection consists of 728,626 news articles and blog posts, while the MS MARCO v2 document collections consists of almost 12 million web documents. The MS MARCO v2 document collections has almost 20 times as many documents, which are also longer on average. When using REL, the Washington Post collection can be linked in a relatively short time. Using one GPU the linking time was about a day. As the documents in the MS MARCO v2 document collection are somewhat longer than those in the Washington Post collection, we expected it would be possible to link this collection in about a month time using one GPU. As it is possible to divide the workload over multiple machines, the time needed to link all documents can be decreased even more easily.

When starting to link the first segment of this collection, the time it took to link was however considerably larger than expected. In fact, after 72 hours there was a time-out after only linking 20 percent of the segment (200k documents) that should only take about 12 hours (following a rough estimation). Why the linking took much more time than expected was unclear.

The goal of the research described in this chapter concerns our approach to mitigate these issues such that we could link the MS MARCO v2 document collection in an exceptable runtime. When working on this research we ran in multiple issues that concerned the document collection specifically, but also issues when trying to deploy REL on larger collection with longer documents. These issues will be described and we will explain what we did to solve them.

For our approach we developed a batch extension for REL, dubbed REBL. REBL improves REL efficiency 9.5 times, decreasing the processing time per document (excluding mention detection) on a sample of 5000 MS MARCO documents from 1.23 seconds to 0.13 seconds. Given modest computational resources, we demonstrate that REBL enables the annotation of a large corpus like MS MARCO v2. We discuss potential improvements that can be made to further improve batch entity linking efficiency. The REBL code and toolkit are available publicly at `https://github.com/informagi/REBL`.

Our third research question;

RQ2: When does information retrieval research benefits from graph data?

is not directly answered by the research described in this chapter. The research in this chapter was needed in order to obtain a dataset that we wanted to approach the third question. So, it forms the basis for the research described in the next chapter that will try to answers this question. In order to give proper context for the research described in this chapter, first entity linking will be described in more depth, before explaining the Radboud Entity Linking system that was used for this research.

5.2 Related Work

Entity linking concerns identifying entity mentions in text and linking them to their corresponding entities in a knowledge graph. It fulfills a key role in the knowledge-grounded understanding of documents. It has been proven effective for diverse tasks in information retrieval [Gerritse et al., 2022, 2020, Xiong et al., 2017, Hasibi et al., 2016a, Balog et al., 2013, Reinanda et al., 2015, Chatterjee and Dietz, 2022], natural language processing [Lin et al., 2012, Ferrucci, 2012], and recommendation [Yang et al., 2018b]. Utilizing entity annotations in these downstream tasks depends upon the annotation of text corpora with a method for entity linking. Due to the complexity of entity linking systems, this process is often performed by a third-party entity linking toolkit, examples include DBpedia Spotlight [Mendes et al., 2011], TAGME [Ferragina and Scaiella, 2010], Nordlys [Hasibi et al., 2017], GENRE [De Cao et al., 2021], Blink [Wu et al., 2020], and REL [van Hulst et al., 2020].

A caveat in existing entity linking toolkits is that they are not designed for batch processing large numbers of documents. Existing entity linking toolkits are primarily optimized to annotate individual documents, one at a time. This severely restricts utilizing state-of-the-art entity linking tools, such as REL, Blink, and GENRE, that employ neural approaches and require GPUs for fast operation. Annotating millions of documents incurs significant computational overhead, to the extent that annotation of a large text corpus becomes practically infeasible using modest computational power resources, especially when tagging documents one by one. Batch entity linking is, however, necessary to build today's data-hungry machine learning models,

considering large text corpora like the MS MARCO v2 (12M Web documents) [Bajaj et al., 2016].

5.3 REL

This research specifically concerns the Radboud Entity Linking (REL) toolkit, in the context of processing large corpora. REL annotates individual documents efficiently, requiring only modest computational resources while performing competitively compared to the state-of-the-art methods on effectiveness. It considers entity linking as a modular problem consisting of three stages:

- *Mention Detection.* This step aims to identify all possible text spans in a document that might refer to an entity. If text spans that refer to entities are not appropriately identified, the system cannot correctly link the entity in later stages. REL is built to be a modular system, making it possible to use different named entity recognition (NER) systems for this stage. For REL the default system used is FLAIR, which is a state-of-the-art NER system that uses contextual word embeddings.

- *Candidate Selection.* For every detected mention, REL considers up to $k_1 + k_2 (= 7)$ candidate entities. $k_1 (= 4)$ candidate entities are selected based on their prior occurrence probability $p(e|m)$ (for entity e given mention m). These priors are pre-calculated by summing Wikipedia hyperlinks and priors from the Cross-Wiki [Spitkovsky and Chang, 2012] corpus. The other $k_2 (= 3)$ entities are chosen based on the similarity of their emtity embedding to the word embeddings of the context. (Considering a context of a maximum of 200-word tokens.)

- *Entity Disambiguation.* The final step aims to map the mention to the correct entity in a knowledge base. The candidate entities for each mention are obtained from the previous stage, and REL implements the Ment-norm method proposed by Le and Titov [2018].

After all entities have been found, REL produces a JSON object that contains all entities and their respective locations in the source text.

5.4 From REL to REBL

The MS MARCO v2 document collection contains 11,959,635 documents split into 60 compressed files, totaling roughly 33GB. Uncompressed, these files are in JSON line format (where every line represents a document, described by a JSON object). These JSON objects have five fields: *url*, *title*, *headings*, *body*, and *docid*. We wanted to link the documents' titles, headings, and bodies for our experiments. We link to the 2019-07 Wikipedia dump, one of the two dumps also used in the initial development of REL. It is, however, straightforward to take another dump of Wikipedia and develop another REL instance.

In order to ease linking this size of data, we separated the GPU-heavy mention detection stage from the CPU-heavy candidate selection and entity disambiguation stages; the modified code can be found on GitHub.[1] For REBL, the input for mention detection are the compressed MS MARCO v2 document files, and its output consists of the mentions found and their location in the document, in Apache Parquet format.[2] These files and the source text are the input for the subsequent phases (candidate selection and entity disambiguation). The final output consists of Parquet files containing spans of text and their linked entities. In the following, we discuss what is changed for mention detection, candidate selection, and entity disambiguation steps to make REL more suited to annotate the MS MARCO v2 collection with entity links.

5.4.1 Mention Detection

REL [van Hulst et al., 2020] uses Flair [Akbik et al., 2019] as the default method for mention detection, a state-of-the-art named entity recognition system. Flair uses the `segtok`[3] package to segment an (Indo-European) document in sentences, internally represented as `Sentence` objects. These sentences are split into words/symbols represented as `Token` objects. When creating these representations, however, it is not possible to recreate the source text properly, as Flair removes

[1] `https://github.com/informagi/REBL`

[2] `https://github.com/apache/parquet-format`, (last accessed – May 8th, 2023)

[3] `https://github.com/fnl/segtok`, (last accessed – May 8th, 2023)

multiple whitespace characters when occurring after each other. REL corrects for this to preserve the correct span data about its location in the source text, by counting the number of whitespace characters removed, a somewhat inefficient process prone to mistakes. We set out to construct the underlying data structures ourselves for REBL. To do this, we used the `syntok`[4] package, a follow-up version of `segtok`. Both packages were developed by the same author, who claims that the `syntok` package segments sentences better than `segtok`.

When constructing sentences from the token objects, we ran into another issue that originated from the data handling procedure in Flair. Flair removes various zero width Unicode characters from the source text: zero width space (`U+200B`), zero width non-joiner (`U+200C`), variation selector-16 (`U+FE0F0`), and zero width no-break space (`U+FEFF`). These characters occur rarely, but in a collection as large and diverse as MS MARCO v2, these characters are found in some documents. When encountering these characters using REBL, the token objects were constructed such that the span and offset of the token still referred to that of the source text: For the case of the zero width space, we updated the `syntok` package. While, according to the Unicode standard, zero width space is not a whitespace character, it should be considered a character that separates two words. For the other Unicode characters removed by Flair, we manually update the span in the `Token` objects created by Flair such that they refer correctly to the positions in the source text. Now, when Flair identifies a series of tokens as a possible mention, we can directly identify the location in the source text from the `Token` objects.

Flair supports named entity recognition in batches; this way, multiple pieces of text can be sent to the GPU for faster inference time. Because REL had been designed to tag one document at a time, it did not utilize this functionality. REBL exploits this feature, allowing users to specify the number of documents to be tagged simultaneously, increasing linking efficiency.

[4] `https://github.com/fnl/syntok`, (last accessed – May 8th, 2023)

5.4.2 Candidate Selection and Entity Disambiguation

For candidate selection, REL makes use of a $p(e|m)$ prior, where e is an entity, and m is a mention. These priors are saved in an (SQLite) database, and up to 100 priors per mention are considered. However, data conversion between the client and the representation stored in the database incurred a high serialization cost. We updated this to a format that is faster to load, with the additional benefit of a considerably decreased database size.[5] We experimented with data storage in the DuckDB column-oriented database as an alternative. However, we found that SQLite was (still) more efficient as a key-value store, at least in DuckDB's state of development when we ran the experiments.

We found that the entity disambiguation stage took much longer than reported in the original REL paper. This difference can partially be explained by the length of the documents to be linked. The documents evaluated by van Hulst et al. [2020] consisted of, on average, 323 tokens, with an average of 42 mentions to consider. The average number of tokens in an MS MARCO v2 document is about $1,800$, with 84 possible mentions per document.[6] Per mention, 100 tokens to the left and the right (so 200 total) are considered the context for the disambiguation model. The longer documents result in a higher memory consumption per context and document, with higher processing costs.

We improve the efficiency of the entity disambiguation step such that it can be run in a manageable time. REL recreated database cursors for every transaction, we rewrote the REL database code to create one database cursor for the entity disambiguation module. The same queries were issued to the database multiple times within a document. This happened when a mention occurs multiple times within a document. By caching the output of these queries, we could considerably lower the number of database calls needed. We cached all database calls per every segment in the collection, as we ran the process for every segment separately.

The default setting of REL is to keep embeddings on the GPU after they are loaded. This, however, slowed down disambiguation

[5]The table that represents the priors shrank from 9.6GB to 2.2GB.

[6]These figures are calculated over the body field; we also tagged the shorter title and headers fields.

when many documents were being processed consecutively because operations like normalization were carried out over all embeddings on the GPU. A considerable speed-up has been achieved by clearing these embeddings as soon as a document is processed.

Finally, after retrieving the embeddings from the database, REL puts them in a Python list. We rewrote the REL code such that the binary data is directly loaded from NumPy, a data format that Pytorch can directly use.

5.5 Effects on Execution

In the mention detection stage, we improved tokenization and applied batching. In the MS MARCO v2 collection, 411,906 documents have tokens automatically removed by Flair, which are 3.4% of all documents. The MS MARCO v1 collection does not contain these characters; the documents in that version of the collection were sanitized before it was published. Batching documents in the mention detection stage decreased the average time for finding all named entities. We used batches of size 10, as the documents are relatively large. The optimal batch size will depend on the available GPU memory.

Some documents in the MS MARCO v2 collection cannot be linked. This happened only in extraordinary cases where linking with entities did not make sense in the first place, an example being a document consisting of numbers only. Here, the `syntok` package created one long `Sentence` object from this file that could not fit in GPU memory.

Table 5.1 shows our improvements to the candidate selection and entity disambiguation step and describes how much time is saved in REBL. The code improvements to create the database cursor only once and to load the data directly from NumPy had no noticeable effect on the overall run time of entity disambiguation and are not reported in this table. Note that the large standard deviations are primarily due to the differences in processing costs between long and short documents.

5.6 Conclusion and Discussion

This chapter described REBL, an extension for the Radboud Entity Linker. We utilized REL's modular design to separate the GPU-heavy

Table 5.1: Efficiency improvements for Candidate Selection and Entity Disambiguation. Improvements are calculated over a sample of 5000 documents using a machine with an Intel Xeon Silver 4214 CPU @ 2.20GHz using two cores with 187GB RAM and a GeForce RTX 2080 Ti (11GB) GPU. Improvements are cumulative; the times shown include the previous improvement as well.

Improvement	Seconds	Explanation
Old Candidate Selection + Entity Disambiguation	1.23 ± 2.09	Average time it takes to select candidates and disambiguate per document
No embedding reset	0.26 ± 1.60	The default setting of REL was to keep embeddings in GPU memory after they were loaded by clearing them from GPU memory after every document a speed up was achieved.
Cache database calls	0.15 ± 1.31	When an entity oc We will revisit DuckDB upon progress in the implementation of zero-cost positional joins. curs within a document, there is a high probability of it occurring multiple times. By caching the calls, we increase memory usage but can lower the time needed for candidate selection and entity disambiguation.
Representation change candidates	0.13 ± 1.19	By representing the candidates better in the database, we were able to save on conversion time, lowering the time needed for candidate selection.

mention detection stage from the CPU-heavy candidate selection and entity disambiguation stages. The mention detection module is now more robust and reliable, using a better segmenter and preserving location metadata correctly. The candidate selection and entity disambiguation steps were updated to improve their runtime Although it is now possible to run REL. [van Hulst et al., 2020] on MS MARCO v2 [Bajaj et al., 2016] in a (for us) somewhat reasonable time, we identified further improvements to implement.

Found mentions are compared to all other mentions during the candidate selection step. The complexity of this step is $O(n^2)$, with n being the number of mentions found in a document, which is especially problematic for longer documents. As we are only interested in similar mentions, we expect that it might be worthwhile to implement a locality-sensitive hashing algorithm to decrease the number of comparisons needed at this stage. Initial experiments have shown that for very long documents, which are present in the collection, this is a viable approach with only a limited decrease in effectiveness.

REBL now implements a two-step approach that writes intermediate results to the file system in Parquet format. A streaming variant would be preferable. We have kept SQLite as the database backend but will consider specialized key-value stores to speed up candidate selection and entity disambiguation. Dedicated key-value stores probably can speed up those stages even more.

The candidate selection stage considers the context of a mention. This context has to be constructed from the source document. As a result, we load the source data a second time during candidate selection. Alternatively, we could output the mention context in the mention detection stage, which could speed up the remaining. However, this would significantly increase the size of the mention detection output. More experiments are needed to strike the right balance here. Having a streaming approach would also mitigate this issue.

Overall, it has become clear that a data processing-oriented perspective on entity linking is necessary for efficient solutions. Having made several implicit design choices explicit, re-evaluating these might lead to more effective entity linking as well.

Chapter 6

MMEAD

Abstract

MMEAD, or MS MARCO Entity Annotations and Disambiguations, is a resource for entity links for the MS MARCO datasets. We specify a format to store and share links for both document and passage collections of MS MARCO. Following this specification, we release entity links to Wikipedia for documents and passages in both MS MARCO collections (v1 and v2). Entity links have been produced by the REL and BLINK systems. MMEAD is an easy-to-install Python package, allowing users to load the link data and entity embeddings effortlessly. Using MMEAD takes only a few lines of code. Finally, we show how MMEAD can be used for IR research that uses entity information. We show how to improve recall@1000 and MRR@10 on more complex queries on the MS MARCO v1 passage dataset by using this resource. We also demonstrate how entity expansions can be used for interactive search applications.

6.1 Introduction

The MS MARCO datasets [Bajaj et al., 2016] have become the *de facto* benchmark for evaluating deep learning methods for Information Retrieval (IR). The TREC deep learning track [Craswell et al., 2021], which has run since 2019, derives its datasets from the MS MARCO passage and document collections. The collections have been used in zero- and few-shot scenarios for diverse retrieval tasks and

domains [Thakur et al., 2021, 2022, Xu et al., 2022]. They also serve as primary resources for training deep learning models for downstream IR tasks such as conversational search [Dalton et al., 2021] and search over knowledge graphs [Gerritse et al., 2022] to achieve state-of-the-art results.

Purely text-based neural IR models, trained using MS MARCO collections, can generally not reason over complex concepts in the social and physical world [Bosselut et al., 2021, Sciavolino et al., 2021]. In response, recently proposed neuro-symbolic methods aim to combine neural models and symbolic AI approaches, e.g., by using knowledge graphs, which map concepts to symbols and relations. An essential step in developing neuro-symbolic models is connecting text to entities that represent the world's concepts formally. This step is mainly done using *Entity linking*, an intermediary between text and knowledge graphs, which detects entity mentions in the text and links them to the corresponding entries in a knowledge graph.

Despite the proven effectiveness of neuro-symbolic AI – and for IR models in particular [Tran and Yates, 2022, Gerritse et al., 2022, Chatterjee and Dietz, 2022] – the IR community has made limited efforts to develop such models. A primary hindrance is the annotation of large-scale collections with entities; entity linking methods are computationally expensive. Running them over a large text corpus (e.g., MS MARCO v2 with 12M documents and 140M passages) requires extensive resources. This work aims to fill this gap by making entity annotations of the MS MARCO ranking collections readily available and easy to use.

So, this chapter is a continuance of the previous chapter. In the previous chapter the batch extension for the Radboud Entity Linking system, REBL, is introduced. In this chapter MMEAD is presented, a resource that provides entity links for the MS MARCO document and passage ranking collections. Two state-of-the-art entity linking tools, namely REL [van Hulst et al., 2020], through REBL, [Kamphuis et al., 2022] and BLINK [Wu et al., 2020], are utilized for annotating the corpora. The annotations are stored in a DuckDB database, enabling efficient analytical operations and fast access to the entities. The resource is available as a Python package and can be installed from PyPI effortlessly. The resource also includes a sample demo, enabling queries with complex compositional structures about entities.

We envision that MMEAD will foster research in neuro-symbolic IR research and can be used to further improve neural retrieval models. In our experiments, we show significant improvements on recall for neural re-ranking IR models when using MMEAD annotations as bag-of-word expansions for queries and passages. Our experiments reveal that the difference in effectiveness is even greater (in terms of both recall and MRR) for complex queries that require further reasoning over entities.

To show the usefulness of our resource, we also present how to enrich interactive search applications. Specifically, we demonstrate how to obtain entities' geographical locations by relating the entities found in passages to their Wikidata entries. Plotting these entities on the world map shows that the MS MARCO passages can be geo-located all over the world. We can also move from location to web text by retrieving all passages associated with a geographical location that we present through an interactive demo.

To return to our last research question;

RQ3: When does information retrieval research benefit from graph data?

In this chapter attempts to demonstrate that graph data, in this case a graph of entities, can help retrieval by including metadata that can be included through graph operations. Although we do not use GeeseDB, the work described in Chapter 4, to carry out the query expansion methods described, it would be a natural application of GeeseDB.

In summary, this chapter makes the following contributions:

- We annotate the documents of the MS MARCO passage and document collections and share these annotations. By sharing these annotations, we ease future research in neuro-symbolic retrieval, which extensively uses entity information. We also provide useful metadata such as Wikipedia2Vec [Yamada et al., 2016] entity embeddings.

- We provide a Python library that makes our data easy to use. All data is stored in DuckDB tables, which can be loaded and queried quickly. The library is easy to install through PyPI, and the entity annotations are available with only a few lines of code.

- We experimentally show that retrieval effectiveness measured by recall significantly increases when using MMEAD. The improvement is even greater for hard queries, where we observe low retrieval effectiveness using text-only IR models.

- We demonstrate how the data can be used in geographical applications. For example, we can plot on a static map all entities found in the MS MARCO v2 passage collection for which geographical data is available. Additionally, through an interactive demo, one can retrieve all passages associated with a geographical location.

MMEAD is publicly available at `https://github.com/informagi/mmead`.

6.2 Background

In this section, we describe systems that are used for creating entity annotations on the MS MARCO collections for MMEAD. Some information presented in this section is also already presented in the previous chapter, as it is also important for the context of this chapter, it is presented again.

6.2.1 REL

REL (Radboud Entity Linker) [van Hulst et al., 2020] is a state-of-the-art open-source entity linking tool designed for high throughput and precision. REL links entities to a knowledge graph (Wikipedia) using a three-stage approach: (1) mention detection, (2) candidate selection, and (3) entity disambiguation. We briefly explain these three steps:

1. *Mention Detection.* REL starts the entity linking process by first identifying all text spans that might refer to an entity. In this stage, it is essential that all possible entities in the text are identified, as only the output of this stage can be considered an entity by REL. These spans are identified using a named entity recognition (NER) model based on contextual word embeddings. For our experiments, we use the NER model based on Flair embeddings.

2. *Candidate Selection.* Up to seven candidate entities are considered for every mention found by Flair. Part of these entities are selected according to the prior probability $P(e|m)$ of the mention m being linked to the entity e. Precisely, the top-4 ranked entities based on $P(e|m) = \min(1, P_{Wiki}(e|m) + P_{YAGO}(e|m))$ are selected, where $P_{YAGO}(e|m))$ is a uniform probability from the YAGO dictionary [Hoffart et al., 2011] and $P_{Wiki}(e|m)$ is computed based on the summation of hyperlink counts in Wikipedia and the CrossWikis corpus [Spitkovsky and Chang, 2012]. The remaining three candidate entities are determined according to the similarity of an entity and the context of a mention. For the top-ranked candidates based on $P(e|m)$ probabilities, the context similarity is calculated by $\mathbf{e}^T \sum_{w \in c} \mathbf{w}$. Here $\mathbf{e}$ is the entity embedding for entity e, and $\mathbf{w}$ are the word embeddings in context c, with a maximum length of 200-word tokens. The entity and word embeddings are jointly learned using Wikipedia2Vec [Yamada et al., 2016].

3. *Entity Disambiguation.* The final stage tries to select the correct entity from the candidate entities and maps it to the corresponding entry in a knowledge graph (Wikipedia). For this, REL assumes a latent relation between entities in the text and utilizes the Ment-norm method proposed by Le and Titov [2018].

6.2.2 BLINK

BLINK [Wu et al., 2020] is a BERT-based [Devlin et al., 2019] model for candidate selection and entity disambiguation, which assumes that entity mentions are already given. When utilized in an end-to-end entity linking setup, BLINK achieves similar effectiveness scores as REL. Below we describe the three steps of mention detection, candidate selection, and entity disambiguation for end-to-end entity linking using BLINK.

1. *Mention Detection.* The mention detection stage can be done using an NER model. Like REL, we use Flair [Akbik et al., 2019] for mention detection.

2. *Candidate Selection.* BLINK considers ten candidates for each

mention. The candidates are selected through a bi-encoder (similar to Humeau et al. [2019]) that embeds mention contexts and entity descriptions. The mention and the entity are encoded into separate vectors using the `[CLS]` token of BERT. The similarity score is then calculated using the dot-product of the two vectors representing the mention context and the entity.

3. *Entity Disambiguation.* For entity disambiguation, BLINK employs a cross-encoder to re-rank the top 10 candidates selected by the candidate selection stage. The cross-encoder usage is similar to the work by Humeau et al. [2019], which employs a cross-attention mechanism between the mention context and entity descriptions. The input is the concatenation of the mention text and the candidate entity description.

6.2.3 DuckDB

DuckDB [Raasveldt and Mühleisen, 2019] is an in-process column-oriented database management system. It is designed with requirements that are beneficial for the MMEAD resource:

1. *Efficient analytics.* DuckDB is designed for analytical (OLAP) workloads, while many other database systems are optimized for transactional queries (OLTP). DuckDB is especially suitable for cases where analytics are more important than transactions. As we release a resource, transactions (after loading the data) are unnecessary, making an analytics database more useful than a transactional-focused one.

2. *In-process.* DuckDB runs in-process, which means no database server is necessary, and all data processing happens in-process. This allows the database to be installed from PyPI without any additional steps.

3. *Efficient data transfer.* Because DuckDB runs in-process, it can transfer data from and to the database more easily, as the address space is shared. In particular, DuckDB uses an API built around NumPy and Pandas, which makes data (almost) immediately available for further data analysis within Python.

DuckDB also supports the JSON and parquet file formats, making data loading especially fast when data is provided in such formats.

6.3 MMEAD

MMEAD provides links for MS MARCO collections v1 and v2 created by the REL entity linker, and links for the MS MARCO v1 passage collection by the BLINK entity linker. For REL, we use its batch entity linking extension, REBL [Kamphuis et al., 2022]. The knowledge graphs used for the REL and BLINK entity linkers are Wikipedia dumps from 2019-07 and 2019-08, respectively. Both dumps are publicly available from the linking systems' Github pages.

6.3.1 Goals

The design criteria for MMEAD are based on the following goals:

- *Easy-to-use.* It should be easy to load and use the linked entities in experiments. With only a few lines of code, it should be possible to load entities and use them for analysis. Additional information should also be readily available, like where entities appear in the text and their latent representations.

- *High-quality entity links.* We wish to release high-quality entity links for the MS MARCO collections, so that applying neuro-symbolic models and reasoning over entities becomes feasible.

- *Extensibility.* It should be easy to link the collections with a different entity linking system and publish them in the same format as MMEAD. This way, we can integrate links produced by other entity linking systems and make them automatically available through the MMEAD framework.

- *Useful metadata.* Additional data that can help with experiments should be provided; this includes mapping entities to their respective identifiers and latent representations.

6.3.2 Design

Easy-to-use. To create an easy-to-use package, we make the MMEAD data publicly available as JSONL files, which is the same format as the MS MARCO v2 collections. Each line of JSON contains entity links for one of the documents or passages in the collections; see Figure 6.1. The corresponding document can be identified through the JSON field that represents the document/passage identifier: `docid` for documents and `pid` for passages. Then, for every section of a document, a separate JSON field is available to access the entities in that section. For passages, there is only one section containing the entity annotations of the passage, while for MS MARCO v2 documents, we link not only the `body` of the document but also the `header` and the `title`.

All essential information about the entity mentions and linked entities is stored in the JSON objects. Specifically, the following metadata is made available: `entity_id`, `start_pos`, `end_pos`, `entity`, and `details`. The field `entity_id` stores the identifier that refers to the entry in the knowledge graph (Wikipedia, in our case). The `start_pos` and `end_pos` fields store the start and end positions of the text span that refers to the linked entity (i.e., as a standoff annotation of the entity mention). The positions are UTF-8 indices into the text, ready to be used in Python to extract the relevant parts of the document. The field `entity` stores the text representation of the entity from the knowledge graph. We chose to store this field for convenience and human readability. The `details` field is a JSON object that stores linker-specific information; examples include the entity type available from the NER module and the confidence of the identified mention.

High-quality entity links. MMEAD provides entity links produced by state-of-the-art entity linking systems. For this paper, we provide links from REL for both MS MARCO v1 and v2 passages and docs, and links from BLINK for MS MARCO v1 passages. Both these systems have high precision, ensuring that identified mentions and their corresponding entities are likely correct. The knowledge graphs used by the entity linkers are the same as those used in the original studies; this way, extensive research has been done to confirm the precision of the linking systems.

Extensibility. We ensure extensibility by clearly describing the format in which the entity links are provided. If another system shares its links in the same format, the MMEAD Python library can work with the data directly. The `details` field per entity annotation enables inclusion of linker-specific information. REL provides specific instructions on updating the system to newer versions of Wikipedia in its documentation, making it possible to easily release links to newer versions of Wikipedia.

Useful metadata. Alongside the entity links, we also provide additional useful metadata. Specifically, we release Wikipedia2Vec [Yamada et al., 2016] embeddings (300d and 500d feature vectors). REL uses the 300d Wikipedia2Vec feature vectors internally for candidate selection. These feature vectors consist of word embeddings *and* entity embeddings mapped into the same high-dimensional feature space. These embeddings can be used directly for information retrieval research [Gerritse et al., 2020, 2022]. We also release a mapping of entities to their identifiers. The entity descriptions can change in different versions of Wikipedia, but their identifiers remain constant. The identifier can also be used to find the corresponding entity in other knowledge graphs such as Wikidata.

6.3.3 An Example

A passage from the MS MARCO v1 passage ranking collection is shown below.[1]

> *The Manhattan Project and its atomic bomb helped bring an end to World War II. Its legacy of peaceful uses of atomic energy continues to have an impact on history and science.*

A few text spans in this text can be considered as entities: "the Manhattan Project", "World War II", and "atomic energy." REL identifies two of these entities: the *Manhattan Project* and *World War II*. The output of the system is converted to our JSON specification, which results in the JSON object presented in Figure 6.1. The value of the `md_score` field shows that Flair is more certain about "World War II" being an entity than the "Manhattan Project."

[1]This is the second passage from the collection.

```
{
        "passage": [
        {
                "entity_id": 19603,
                "start_pos": 4,
                "end_pos": 21,
                "entity": "Manhattan Project",
                "details": {
                        "tag": "ORG",
                        "md_score": 0.613243
                }
        },
        {
                "entity_id": 32927,
                "start_pos": 65,
                "end_pos": 77,
                "entity": "World War II",
                "details": {
                        "tag": "MISC",
                        "md_score": 0.991474
                }
        }
        ],
        "pid": 1
}
```


Figure 6.1: Example of MMEAD annotations for a MS MARCO passage in JSON format. The field `tag` depicts the type of the entity and `md_score` shows the certainty of the mention detection component in identifying the text span as a mention.

Table 6.1: Number of entities linked by REL; we show the total number of entities found and how many entities there are per passage/document on average.

	passages	docs
MS MARCO v1	18,561,221 (2.10)	145,725,732 (45.34)
MS MARCO v2	233,254,024 (1.69)	661,183,287 (55.28)

```
from mmead import get_links
links = get_links('v1', 'passage', linker='rel')
```

Figure 6.2: Example of how to load MMEAD entity links for the MS MARCO v1 passage collection.

Table 6.1 shows the number of entities found in the collections by the REL system. Blink found 21,968,356 entity links for the v1 passage collection. For 11,177,904 entities, the two linking systems produced exactly the same output.

6.4 How To Use

MMEAD comes with easy-to-use Python code, allowing users to work with the resource effortlessly. To start, MMEAD can be installed from PyPI using pip:

```
$ pip install mmead
```

After installation, the entity links can be loaded into a DuckDB database [Raasveldt and Mühleisen, 2019] with only a couple of lines of code, as shown in Figure 6.2. When running this code for the first time, initialization will take some time, as all the data need to be downloaded and ingested into the DuckDB database. After loading the data for the first time, it is automatically stored on disk. Loading the persisted data for later usage will only take seconds.

Once the data is loaded, it is ready to use. We provide a simple interface to access the data. The code shown in Figure 6.3 loads the entity links available for a document in the MS MARCO v1 passage

```
>>> links.load_links_from_docid(123)
{"passage":[{"entity_id":"7954681", ... }
```

Figure 6.3: Example of how to load the entity links for a document. For formatting reasons, we do not show the full output.

ranking collection. When using this function, the data is provided in JSON format, making it easy to access the annotations.

We also provide word embeddings and entity embeddings generated by Wikipedia2Vec [Yamada et al., 2016] based on the 2019-07 Wikipedia dump. These embeddings are stored in DuckDB tables and are available as Numpy arrays after loading. Figure 6.4 shows how embeddings are loaded using MMEAD. The example demonstrates that the entity embedding of *Montreal* and the word embedding of "Montreal" are closer to each other than the word embeddings of the two words "Montreal" and "green" based on dot-product as a similarity function. The dimensionality of the embedding vectors (300 or 500) can be specified in the code.

The mapping between the official Wikipedia identifiers and entity text representations is extracted from the 2019-07 Wikipedia dump. If entity annotations from another version of Wikipedia are available, the MMEAD mappings can be used to match entities between the dumps. Needless to say, emerging entities in newer versions of Wikipedia cannot be mapped to the version that is available in MMEAD. However, existing entities in MMEAD can be mapped to newer versions of Wikipedia in a straightforward manner. Figure 6.5 shows how entity identifiers can be matched to their text and the other way around.

As DuckDB is used as a database engine for MMEAD, it is possible to directly access the underlying tables and issue structured queries in an efficient manner. Figure 6.6 shows an example, where a connection to the database is created, and the identifiers of passages containing the entity *Nijmegen* are retrieved.

All data can be downloaded directly as well, and links to the data are provided on our Github page.[2]

[2] `https://github.com/informagi/mmead`

```
>>> from mmead import get_embeddings
>>> e = get_embeddings(300, verbose=False)
>>> montreal_word = e.load_word_embedding("Montreal")
>>> montreal_entity = e.load_entity_embedding("Montreal")
>>> green_word = e.load_word_embedding("green")

>>> montreal_word @ montreal_entity
31.83191792
>>> montreal_word @ green_word
5.55568354

>>> toronto_word = e.load_word_embedding("Toronto")
>>> toronto_word
array([-1.497e-01, -7.765e-01, -1.000e-02, ...])
>>> montreal_word @ toronto_word
21.62585146
```

Figure 6.4: Example code for loading word and entity embeddings. It shows that the dot-product between "Montreal" word and entity embeddings is greater than the dot-product of embedding vectors for the word "Montreal" and a random word. The word embeddings of Montreal and Toronto, two cities in Canada, are more similar.

```
>>> from mmead import get_mappings
>>> m = get_mappings(verbose=False)
>>> m.get_id_from_entity('Montreal')
7954681
>>> m.get_entity_from_id(7954681)
'Montreal'
```

Figure 6.5: Entity names and identifiers are accessible in MMEAD. Given an entity text, we can directly find its corresponding identifier and vice versa.

```
>>> from mmead import load_links
>>> cursor = load_links(
...     'msmarco_v1_passage_links',
...     verbose=False
... )
>>> cursor.execute("""
...     SELECT pid
...     FROM msmarco_v1_passage_links_rel
...     WHERE entity='Nijmegen'
... """)
[(771129,), (1273612,), (1418035,), ... ]
```

Figure 6.6: All data is stored in DuckDB tables, and thus it is possible to directly access the tables and issue queries. In this example, we extract the identifiers of passages that contain the city of Nijmegen.

6.5 Entity Expansion with MMEAD

To demonstrate the usefulness of MMEAD for (neural) retrieval models, we have conducted experiments that extend existing models with MMEAD annotations. These experiments serve a demonstrative purpose only, and the full potential of this resource is to be further explored in (neuro-)symbolic IR models [Gerritse et al., 2022, Tran and Yates, 2022].

6.5.1 Methods

BM25 expansion. We experimented with three retrieval methods to show the benefits of entity annotation for passage ranking: one baseline method and two methods that use query entity expansion [Shehata, 2022] using REL:

a **BM25 – No Expansion.** As a baseline method, we used BM25 as implemented in Anserini Kamphuis et al. [2020] using hyperparameters $k_1 = 0.82$ and $b = 0.68$, shown to be optimal for the MS MARCO dataset. MS MARCO was indexed normally, and no expansion was considered for the queries or the passages.

b BM25 – Entity Text Expansion. In this method, passages and queries are expanded with the text representation of their annotated entities (from REL). Once the passages and queries have been expanded with entities, we run BM25 with the same hyper-parameter settings as described in **a**.

c BM25 – Entity Hash Expansion. Instead of using the text representation of entities as an expansion, we expanded the passages and queries by the MD5 hash of the entity text (from REL). The use of MD5 hashing is to provide a consistent representation of multi-word terms and to avoid partial or incorrect matching between queries and non-relevant passages; e.g., passages that contain the word "united", do not benefit if the query contains "United States" as an entity. Again, after expansion, we run BM25 with the same hyper-parameter settings described in **a**.

In these experiments, the identified entities are deduplicated. As a demonstration of the proposed text expansion methods, Figure 6.7 shows how the query expansion is performed using explicit and hashed forms. The added entities provide more precise context and help eliminate ambiguous terms. Figure 6.8 shows the expansion methods on the relevant passage for this query. The relevant passage can be found through our expansion technique. The linking system recognizes that both the query and the passage contain a reference to the entity *Sacagawea*, even though they are spelled differently in the query and the passage.

Reciprocal Rank Fusion. As a second series of experiments, we applied Reciprocal Rank Fusion (RRF) [Cormack et al., 2009] to the runs described above. RRF is a fusion technique that can combine rankings produced by different systems. RRF creates a new ranking by only considering the rank of a document in the input. Given a set of documents D and a set of rankings R, RRF can be computed as:

$$RRF(d \in D) = \sum_{r \in R} \frac{1}{k + r(d)} \tag{6.1}$$

Here k is a hyperparameter that can be optimized, but we simply used a default value of $k = 60$ for all settings.

a. did sacajawea cross the pacific ocean with lewis and clark

b. The same text as shown in **a.** + *Sacagawea Clark Pacific Ocean C. S. Lewis*

c. The same text as shown in **a.** + `860324 a97fed 3e3b0e 3fe907`

Figure 6.7: Examples of queries for the three different experiments; (**a**) the non-expanded query, (**b**) the query with entity text expansion, and (**c**) the query with entity hash expansion. Text expansions are shown in italics. The MD5 hashes shown in (**c**) are shortened in this example for formatting.

a. Introduction. Sacagawea, as everyone knows, was the young Indian woman who, along with her baby, traveled with Lewis and Clark to the Pacific Ocean and back.She was a great help to the expedition and many organizations are preparing celebrations to commemorate the 200-year anniversary of the endeavor.y: M. R. Hansen. Sacagawea, as everyone knows, was the young Indian woman who, along with her baby, traveled with Lewis and Clark to the Pacific Ocean and back.

b. The same text as shown in **a.** + *Indian Ocean James Hansen Sacagawea India Oceania William Clark Meriwether Lewis Pacific Ocean*

c. The same text as shown in **a.** + `fe6fc8 860324 aa84e6 7847ef 3e3b0e 7d31e0 2d8836 e58bef`

Figure 6.8: The relevant passage for the query presented in Figure 6.7; (**a**) the non-expanded passage, (**b**) the passage with entity text expansion, and (**c**) the passage with entity hash expansion. Text expansions are in italics. The MD5 hashes shown in (**c**) are shortened in this example for formatting.

This provides us with four new rankings; the RRF of the pairwise combinations of the three rankings described above and the RRF of all three of these runs:

d. RRF – No Expansion + Entity Text. RRF fusion of runs **a** and **b**. The run with no expansions and the run with entity text expansions are considered.

e. RRF – No Expansion + Entity Hash. RRF fusion of runs **a** and **c**. The run with no expansions and the run with entity hash expansions are considered.

f. RRF – Entity Text + Entity Hash. RRF fusion of runs **b** and **c**. The run with entity text expansions and the run with entity hash expansions are considered.

g. RRF – No Expansion + Entity Text + Entity Hash. RRF fusion of runs **a**, **b**, and **c**. All three runs are considered.

6.5.2 Experimental Setup

In our experiments, we use MMEAD as a resource to expand queries and passages with entities. The experiments are performed using the MS MARCO v1 passage ranking collection, where only queries containing at least one entity annotation are used. We do not expect meaningful differences for queries without any linked entities, as the expanded query is identical to the original query in that case (due to the simplicity of the method applied here).

As we expect the linked entities to provide additional semantic information about the queries and passages, we conduct further testing on the obstinate query sets of the MS MARCO Chameleons [Arabzadeh et al., 2021], which consist of challenging queries from the original MS MARCO passage dataset. In general, ranking methods show poor effectiveness in finding relevant matches for these queries. Our testing focuses on the bottom 50% of the worst-performing queries from the subsets of Veiled Chameleon (Hard), Pygmy Chameleon (Harder), and Lesser Chameleon (Hardest), which represent increasing levels of difficulty.

This gives us four query sets on which we evaluate; (1) all queries that contain entity annotations (*dev* – 1984 queries), (2) all queries in

the hard subset that contain entity annotations (*hard* – 680 queries), (3) all queries in the harder subset that contain entity annotations (*harder* – 493 queries), and lastly, (4) all queries in the hardest subset that have entity annotations (*hardest* – 322 queries).

The experiments are evaluated using Mean Reciprocal Rank (MRR) at rank ten and Recall (R) at rank one thousand. MRR@10 is the official metric for the MS MARCO passage ranking task, while R@1000 gives an upper limit on how well re-ranking systems could perform. The Anserini [Yang et al., 2018a] toolkit is used to generate our experiments.

6.5.3 Results

Table 6.2 presents the results of our experiments. If we first look at lines **a-c** in the results table, we can examine the effects of our expansion methods compared to the baseline run. Looking at R@1000, we can see that more relevant passages are found using entity expansion for the *dev* collection and its harder subsets. We do not find additional relevant documents/passages on the *dev* set when we use the entity hashes, and entity text seems to be the better approach. There is, however, no increase in MRR@10 when using this expansion method. Entity expansions help when evaluating using R@1000, especially when the queries are more complex. The difference in recall effectiveness becomes larger the more complex the queries get. MRR@10 only improves when using entity text expansion.

The reciprocal rank fusion methods are presented in lines **d-g**. When using these methods, the R@1000 increases more. Again, the subsets that contain more complex queries tend to benefit more. Regarding R@1000 effectiveness, the best RRF method uses a ranking from the normal, not expanded index, with the index that has been expanded with the entity text. Again, entity text expansion helps recall more than using hash expansion. Although the RRF methods improve recall, MRR@10 does not benefit from RRF when compared to using only one of the expansion techniques.

6.6 Beyond Quantitative Results

In the previous section, we demonstrated the potential value of MMEAD using quantitative evaluations, where we leverage entities to improve

Table 6.2: Results on the MS MARCO v1 passage collection, using only the queries that have entity annotations. Bolded numbers are the highest achieved effectiveness. Scores with a dagger (†) are significantly better compared to BM25 with no expansion (run *a*), following a paired t-test with Bonferroni correction. For MRR, we have not calculated significance scores due to its ordinal scale [Fuhr, 2018].

			R@1000				MRR@10			
			dev	hard	harder	hardest	dev	hard	harder	hardest
a.	BM25	No Expansion	0.9111	0.7855	0.7444	0.6677	**0.2413**	0.0373	0.0137	0.0000
b.	BM25	Entity Text	0.9183	0.8240†	0.7951†	0.7298†	0.2202	0.0385	0.0173	**0.0057**
c.	BM25	Entity Hash	0.9105	0.7980	0.7576	0.6848	0.2199	0.0383	**0.0175**	0.0052
d.	RRF	No Expansion + Entity Text	**0.9338**†	**0.8436**†	**0.8124**†	**0.7500**†	0.2372	0.0385	0.0163	0.0019
e.	RRF	No Expansion + Entity Hash	0.9250†	0.8260†	0.7921†	0.7205†	0.2378	0.0367	0.0152	0.0034
f.	RRF	Entity Text & Hash	0.9231	0.8260†	0.7982†	0.7314†	0.2218	0.0375	0.0161	0.0053
g.	RRF	No Expansion + Entity Text & Hash	0.9313†	0.8370†	0.8043†	0.7376†	0.2358	**0.0391**	0.0156	0.0035

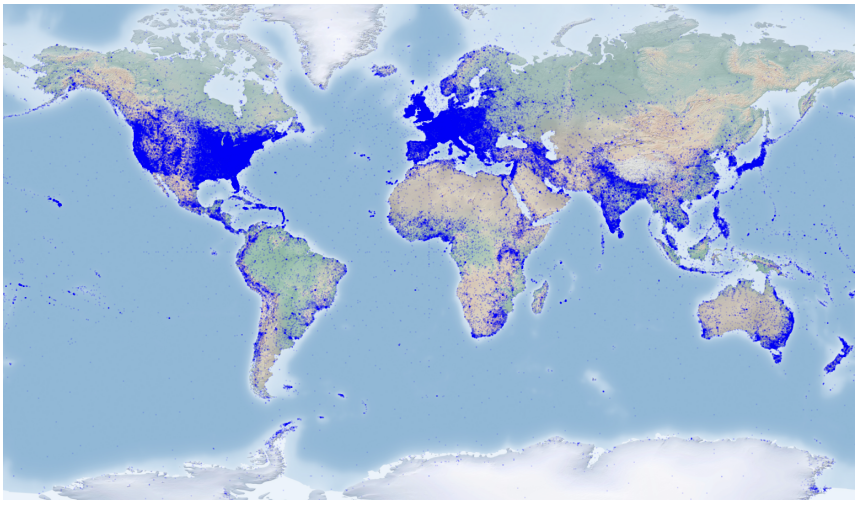


Figure 6.9: Locations of entities found in the MS MARCO v2 passage collection.

retrieval effectiveness in standard benchmark datasets. Beyond these quantitative results, MMEAD can also help enrich interactive search applications in various ways. This section describes a few such examples.

Entity links to Wikidata provide an entrée into the broader world of open-linked data, which enables integration with other existing resources. This allows us to build interesting "mashups" or support search beyond simple keyword queries. As a simple example, we can take the entities referenced in MS MARCO, look up the coordinates for geographic entities, and plot them on a map. Figure 6.9 shows a world map with all entities found in the MS MARCO v2 passage collection mapped onto it (each shown with a transparent blue dot). The results are as expected, where the blue dots' density largely mirrors worldwide population density, although (also as expected) we observe more representation from entities in North America, Europe, and other better-developed parts of the world.

Figure 6.9 is a static visualization, but we can take the same underlying data and principles to create interesting interactive demonstrations. Geo-based search is an obvious idea, where users can specify a geographic region – either by dragging a box in an interactive interface to encompass a region of interest, or specifying a geographic entity.

For example, the user might ask "Show me content about tourist sites in Paris" and receive passages about the Eiffel Tower in which Paris is not mentioned explicitly. Simple reasoning based on geographic containment relationships on open-linked data resources would be sufficient for answering this query. While it is possible that pretrained transformers might implicitly contain this information, they can never offer the same degree of fine-grained control provided by explicit entity linking.

As a simple demonstration, we have taken MMEAD, reformatted the entity links into RDF, and ingested the results into the QLever SPARQL engine [Bast and Buchhold, 2017].[3] By combining MMEAD with RDF data from Wikidata and OpenStreetMap, we can issue SPARQL queries such as "Show me all passages in MS MARCO about France".

The query is shown in Figure 6.10, which gives us 122,316 entities found in the collection that have a connection with France (most of them are located in France). Then we can automatically show the entities on a map, as presented in Figure 6.11 (showing the first 1000 entities found).

Not all linked entities are located in France, however. For example, some entities are related to France (entities for which France is mentioned in their Wikidata), but are located elsewhere in the world. One of the blue dots in Germany is the source of the river *Moselle*. This river starts in Germany by splitting off from the *Rhine*, and then goes through France. Instead of querying for France, we can also query for different countries. Table 6.3 shows the number of entities found for a sample of countries.

6.7 Conclusion and Future Work

This research presents the resource MMEAD, or MS MARCO Entity Annotations and Disambiguations. MMEAD contains entity annotations for the passages and documents in MS MARCO v1 and v2. These annotations simplify entity-oriented research on the MS MARCO collections. Links have been provided using the REL and BLINK entity linking systems. Using DuckDB, the data can quickly be queried,

[3] `https://github.com/ad-freiburg/qlever`, last accessed April 26th 2023

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX ex: <http://example.org/>
PREFIX schema: <https://schema.org/>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX passage: <http://example.org/passage>
PREFIX geo: <http://www.opengis.net/ont/geosparql#>
PREFIX wd: <http://www.wikidata.org/entity/>
PREFIX wdt: <http://www.wikidata.org/prop/direct/>
SELECT ?pid ?content ?entity ?label ?coord
WHERE {
        ?pid rdf:type passage: .
        ?pid schema:description ?content .
        ?pid passage:has ?entity .
        FILTER (regex(?entity, "wikidata", "i"))
        ?entity rdfs:label ?label .
        ?entity wdt:P625 ?coord .
        ?entity wdt:P17 wd:Q142 .
        FILTER (LANG(?label) = "en")
}
```

Figure 6.10: SPARQL query that produces all entities in the passages of the MS MARCO v2 collection that are related to the country of France.

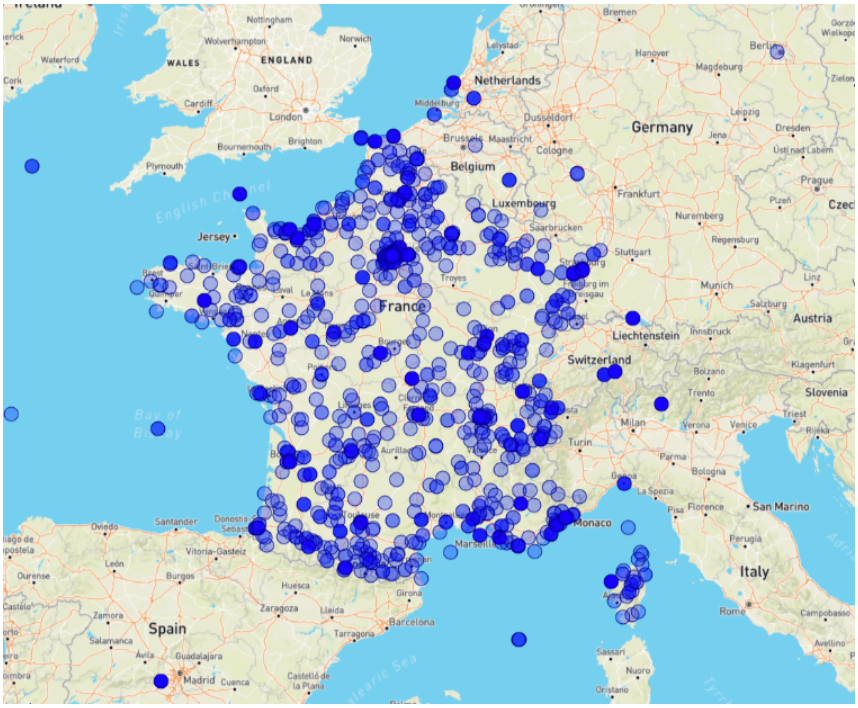


Figure 6.11: First 1000 entities found in that are connected to France. Entities are represented with a blue dot on the map.

making the resource easy to use.

To return to our third research question:

RQ3: When does information retrieval research benefits from graph data?

Entity links can be considered a bi-partite graph where entities and documents are nodes, that are connected when entities appear in documents. Using these entities for query and passage expansion, we showed experimentally a significant increase in recall effectiveness. Although in this chapter we used Anserini for our retrieval experiments, it is trivial to express the same problem using GeeseDB. When using reciprocal rank fusion, the effectiveness difference becomes even more prominent and new relevant passages are found. The question remains whether these passages can be ranked higher by new retrieval models. With MMEAD, we support information retrieval research that combines deep learning and entity graph information.

Table 6.3: Number of entities found per country for some example countries where the entity has an English label.

Country	WikiData ID	# Entities
United States	Q30	3,429,889
Canada	Q16	170,833
France	Q146	122,316
New Zealand	Q664	19,094
Peru	Q419	16,448
Iran	Q794	13,633
Ecuador	Q736	10,588
South Korea	Q884	9,718
Monaco	Q235	8,546
Singapore	Q334	6,597

We also demonstrated that our resource can enrich interactive search applications. In particular, we present an interactive demo where all entities related to geographical locations can be positioned on a map. Specifically we queried the data as a RDF triple graph.

Using the MMEAD format, releasing entity links for collections beyond MS MARCO is also possible. We already showed that using entity links improves recall when using the linked entities for query expansion. What the effects are when training, e.g., DPR methods that include the entity links, is yet to be investigated – an exciting research opportunity that lies ahead.

Chapter 7

Conclusion

> We can only see a short distance ahead, but we can see plenty there that needs to be done.
>
> Alan Turing - 1950

To conclude, I want to summarize the work described in the chapters following the research questions of this thesis. We will look once more at the work in the individual chapters, then try to tie it together following the main research question. Then, I want to reflect on the work described in this thesis and present research opportunities that follow the work described.

7.1 Contributions

Recall the main research question and its subquestions:

- **Research Question: How can information retrieval benefit from graph databases and graph query languages?**
- *Research Question 1: What are the benefits of using relational databases for information retrieval?*
- *Research Question 2: Can we extend the benefits from using relational databases for information retrieval to using graph databases while being able to express graph-related problems easier?*

- *Research Question 3: When does information retrieval research benefit from graph data?*

Chapter 3 introduces the history of using relational databases for information retrieval. One of the latter attempts, using columnar databases for retrieval, is highlighted. This approach is re-implemented as a prototype system; "OldDog". OldDog is used for a reproduction experiment, where many expressions of BM25 are compared against each other. Because OldDog was built using a relational database, we could express the logical model of the ranking functions separately from their physical models. This way, we could find the difference between the models while keeping the data the same. The work in the chapter demonstrates the usefulness of using relational databases for reproduction experiments in information retrieval. Looking at research question 1: *What are the benefits of using relational databases for information retrieval?*, we have demonstrated that relational databases provide a framework for easily comparing different ranking methods, as shown in the reproduction study. The system is reasonably efficient, making it easy to set up for new experiments.

Chapter 4 takes the data model for information retrieval using relational databases, as presented in Chapter 3, and extends this model to a graph data model. This model is implemented in the prototype system GeeseDB, a prototype graph database for information retrieval. GeeseDB is built on top of DuckDB and uses its column-oriented tables and the fact that it can be run in-process. With a robust backend, we can express graph queries for information retrieval and run them on GeeseDB. GeeseDB supports all functionalities that OldDog already supports, plus it makes the expression of more complicated problems through the graph framework easier. Considering research question 2: *Can we extend the benefits from using relational databases for information retrieval to using graph databases, while being able to express graph-related problems easier?*, we find that, with GeeseDB, it is possible to take all the benefits from using relational databases for information retrieval, while making it possible to express more complex problems through a graph query language.

Chapter 5 concerns the improvements on the Radboud Entity Linking (REL) system. Some unforeseen issues were encountered when trying to deploy this system to annotate a large document collection. The time it took to tag the whole collection was much larger than

expected, making it unfeasible to annotate the whole corpus in a reasonable time. By improving the efficiency of several components of the software and including a batch extension, it was possible to speed up parts of the software by a factor of ten. After deploying these improvements, it was possible to use the REL software for large corpora.

Chapter 6 continues with the system created in Chapter 5 and deploys it to annotate the large MS MARCO document and passage collections. A specification on how to share these annotations, independent of the linking system, is proposed. Following this specification, we make the annotations created by the REL system publicly available. We also publish data created by the BLINK entity linking system for the MS MARCO v1 passage collection. Using the annotations by REL, we show on the MS MARCO v1 collection that query expansion with entity annotations significantly improves recall for complicated queries. Although this is just a simple experiment, we show that these annotations contain valuable information for finding relevant documents, and they could be beneficial for more sophisticated methods. Also, through a demonstration that combines entity annotations with geographical information, we show that entity annotations benefit interactive search applications—considering research question 3: *When does information retrieval research benefit from graph data?*. We demonstrate that information retrieval can benefit from graph data, such as an entity graph. Employing it for retrieval techniques leads to an increase in retrieval effectiveness. Also, the graph model is ideal for interactive search systems.

Finally, to address the main research question; **How can information retrieval benefit from graph databases and graph query languages?**. This thesis demonstrates the usefulness of graph databases for information retrieval by creating a prototype system, GeeseDB, that is directly useful for information retrieval. With GeeseDB, it is possible to set up retrieval experiments using the graph model quickly. It inherits all benefits of using relational databases for information retrieval. We show that we can increase retrieval effectiveness by using a graph of entities. Moreover, this graph of entities can improve interactive search applications as well.

7.2 Future Work

Following the work presented in this thesis, interesting research opportunities can follow from this work. In particular, I would like to highlight three of them:

1. Firstly, an obvious follow-up on the work presented in this thesis is a study that combines the work of Chapters 4 and 6. In Chapter 4, we introduced GeeseDB, a graph-based system for information retrieval. In Chapter 6, we use graph data produced by the REL system. It would be interesting to see if we can reproduce the results of Chapter 6 using GeeseDB. We used an RDF engine for the demonstration in Chapter 6. Although this was a suited system for our demonstration, using our software would have demonstrated the additional benefits of using GeeseDB.

2. Then, the examples shown in Chapter 4 are relatively simple. Additional studies should be carried out that consider more complex graph structures. For example, can we employ a graph structure and utilize paths in the graph? These paths can, perhaps, propagate probabilities used to calculate relevancy scores, a strategy that is probably hard to express without using graphs.

3. Lastly, it would be interesting to see if the concepts of graph databases for information retrieval and deep learning for information retrieval can be married together. In the last couple of years, deep learning for information retrieval has become more prominent, especially with the rise of large language models. The representations found by these models can be expressed in graph databases, and both techniques can benefit from each other. Additional studies need to be conducted to determine how this can be done well.

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Summary

Samenvatting

Acknowlegements

Research Data Management

This thesis research has been carried out under the research data management policy of the Institute for Computing and Information Science of the Radboud University, the Netherlands.[1]

The following research datasets have been produced during this PhD research:

- Resources for Chapter 3
  - Code for OldDog [Kamphuis and de Vries, 2019b]: chriskamphuis/olddog: (v1.0.0). Zenodo. 10.5281/zenodo.3255060
  - Code for the OldDog docker [Kamphuis and de Vries, 2019b]: osirrc/olddog-docker: (v1.0.0). Zenodo. 10.5281/zenodo.3255060
- Resources for Chapter 4
  - Code for GeeseDB [Kamphuis and de Vries, 2021]: informagi/GeeseDB: (v0.0.2). Zenodo. 10.5281/zenodo.7892326
- Resources for Chapter 5
  - Code for REBL [Kamphuis et al., 2022]: informagi/REBL: (v0.0.1). Zenodo. 10.5281/zenodo.7892359
- Resources for Chapter 6
  - Code for MMEAD [Kamphuis et al., 2023]: informagi/mmead: (v0.1.0). Zenodo. 10.5281/zenodo.7897027
  - Data for MMEAD [Kamphuis et al., 2023]: informagi/mmead: (v0.1.0). Zenodo. 10.5281/zenodo.7896782

[1] `https://www.ru.nl/icis/research-data-management/`

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