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Informationstechnik für Führungssysteme (ITF)

Sub-topic modeling and ranking analysis in document retrieval systems

Masterarbeit

zur Erlangung des Grades Master of Science (M.Sc.)
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vorgelegt von

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Ich versichere, dass ich die vorliegende Arbeit selbständig verfasst und keine anderen als die angegebenen Quellen und Hilfsmittel benutzt habe.

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Kurzfassung

Die Suche nach hochrelevanten Dokumenten in den Top-Ergebnissen für eine bestimmte Benutzeranfrage ist eine der schwierigsten Aufgaben im Information Retrieval (IR). Diese Herausforderung wird noch verstärkt, wenn der Benutzer eine bestimmte Absicht hat und der Suchanfrage der Kontext seiner Absicht fehlt. Zum Beispiel kann die Benutzeranfrage *"Robotik"* Dokumente zu vielen Bereichen wie Fertigung, Landwirtschaft, Militär usw. abrufen. Eine einfache Schlüsselwortsuche kann den Benutzer mit vielen falsch-positiven Ergebnissen überfordern, wenn der Benutzer die Innovationsdokumente nur in Bezug auf einen bestimmten Bereich, wie z.B. *"Military"*, untersuchen möchte. Um die abgerufenen Dokumente effizient darzustellen, wird in dieser Masterarbeit eine auf der Ähnlichkeit von Suchanfragen basierende Phrasenauswahltechnik vorgeschlagen und getestet. Die Dokumentrepräsentationen werden als Unterthemen bezeichnet, die als eindeutige Pfade für den Zugriff auf Dokumente im Retrieval Set. Der Selektionsansatz wird mit der Dokumentenrepräsentation ohne Selektion verglichen. Des Weiteren wird eine manuelle Auswertung der Ergebnisse mittels eines Fragebogens durchgeführt. Die Mehrheit der Teilnehmer war mit der vorgeschlagenen Methodik der Bildung von unterscheidbaren Clustern zu. Darüber hinaus wird eine explorative Analyse durchgeführt, um die Leistung der Retrievalsysteme zu testen, die aus den Rankings der Unterthemen generiert werden.

Abstract

Retrieving highly relevant documents in the top results for a given user query is one of the challenging tasks in Information Retrieval (IR). This challenge is amplified when the user has a specific intention, and the search query lacks the context of their intention. For example, the user query *"Robotics"* can retrieve documents related to many domains such as manufacturing, agriculture, military, etc. A simple keyword search can overwhelm the user with many false positives when the user wants to explore the innovation documents only related to a specific domain, such as *"Military"*. To efficiently represent the retrieved documents, a phrase selection technique based on query similarity is proposed and tested in this master thesis. The document representations are referred to as sub-topics which act as unique pathways to access documents in the retrieval set. The selection approach is compared against the document representation without selection. Furthermore, a manual evaluation of the results is carried out using a survey questionnaire. The majority of the participants agreed with the proposed methodology of creating distinctive clusters. In addition, an exploratory analysis is performed to test the performance of the retrieval systems generated from the rankings of sub-topics.

Contents

Chapter 1

Introduction

Information Seeking (IS) is a process of fulfilling the information need of individuals by obtaining appropriate information [68]. IS has become a crucial part of today's life. People interact daily with multiple web platforms, such as Google[1], Youtube[2], ChatGPT[3], etc., to obtain information from various sources according to their needs or requirements. The information source can be of different types, namely text, audio, video, etc., and the interacting human query can also be simple text input, image input, audio input, etc. In [3], authors refer to these methods of interaction by human beings to seek information as information behaviors. Some people want to gather insights to be informed about the latest news, social activities, entertainment, technology, etc.; others want to play an active seeker role by seeking precise information. This accurate information can be further used to make crucial decisions.

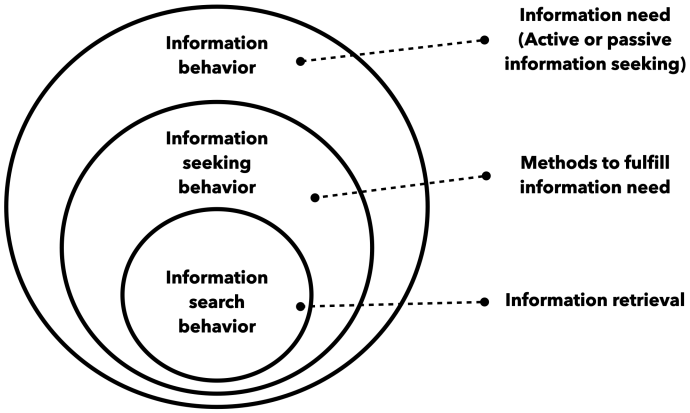


Figure 1.1: Nested model of information behavior

Irrespective of being active or passive information seekers, individuals need more information and want to seek information from external sources. Due to the lack of information, users interpret the information gap as a problem and try to manage or resolve this problem by interacting with information sources [10]. These user activities are characterized as information seeking behaviors [10] and are referred as information search behaviors when seeking the information through a search query. Figure 1.1 shows the nested relationship between the different information behaviors, as depicted by Wilson[53]. This shows that the information search behavior

[1] https://www.google.com/
[2] https://www.youtube.com/
[3] https://chat.openai.com/

is a subset of information seeking behavior and in turn, the information seeking behavior is a subset of information behavior.

In this master thesis, we consider the behaviors related to text interacting information seeking, as most information seeking happens in text search. Moreover, the thesis is explicitly targeted toward specific and exploratory information-seeking behaviors to understand and help the users in their information-seeking process effectively.

1.1 Motivation

Regardless of the search platform, the quality of the search results depends on the formulation of the information needed by the information seekers, and the same is described by the researchers as ***Quality-in quality-out*** *principle: "A query that more accurately reflects the user's information need will produce better results"* [22]. This principle not only implies the syntactic matching techniques but also to the semantic matching algorithms. Therefore, query formulation plays a crucial role in information seeking process, but the quality of the formulated query is hard to determine and is influenced by several factors, such as the user's knowledge of the information need, search experience, system experience (user interface), etc [46].

Query Completion (QC) is a popular technique to help users formulate their information needs better. QC leverages the actively indexed data on the web and query logs generated by millions of users and is observed in almost every modern browser with the facilities such as real-time auto-completion, spelling correction, etc [8, 30]. Researchers in [46] have shown that information seekers are more involved in their search when using QC and leading to higher user satisfaction. Once the query is formulated, there are some possible reasons for the poor web search results (low relevancy) [7].

- **Cross-domain queries:** User queries related to multiple domains or topics. This results in high false positives and can only be resolved with a well-formed query mapped to a certain topic according to the interest of the information seeker.
- **Short queries:** If the query length is too short, then the user's information need is not well expressed. The nature of providing short queries can also be seen as a habit. A recent analysis to understand the user search queries on 306 million keywords used in google search showed that user queries were comprised of a relatively small number of keywords and the mean keyword length is 1.9 words and 8.5 characters [25].
- **Poor information needs:** The user is only sure what they are looking for once they see the search results. The user should do an exploratory search on a topic and learn from the results.
- **Poor query formulation:** The user is sure of what they want but does not formulate the search query appropriately.

The length of the documents in the information source can also significantly influence the search results. Smaller text documents used in many NLP projects, such as IMDB reviews, tweets, requirements, etc., are generally mapped to a single class or a topic. On the other hand, longer documents, such as news articles, blogs, e-books, research papers, etc., contain several topics in it and can not be logically mapped to a single topic. Reading such long documents in top results can lead to poor user satisfaction when their relevancy is very low (due to the factors mentioned above).

The user should frame a well-written query specifying their intent to tackle this problem. For example, the query *"What are the technological advancements in Robotics related to Unmanned Weapon Systems?"* shows a well-formulated query specifying the information needed. Demanding users to provide such a query every time can be challenging, especially in the case of an exploratory task where the users are unsure what they are looking for. Furthermore, this can also lead to a poor search experience because only specific types of queries are allowed to the users. Figure 1.2 shared the distribution of search queries according to their length. It is evident that the short user queries with weaker intent are more prevalent than the long queries with strong intent and is depicted as "Long tail" search queries in the Figure 1.2. This signifies that the short keyword queries are part of the user search behavior.

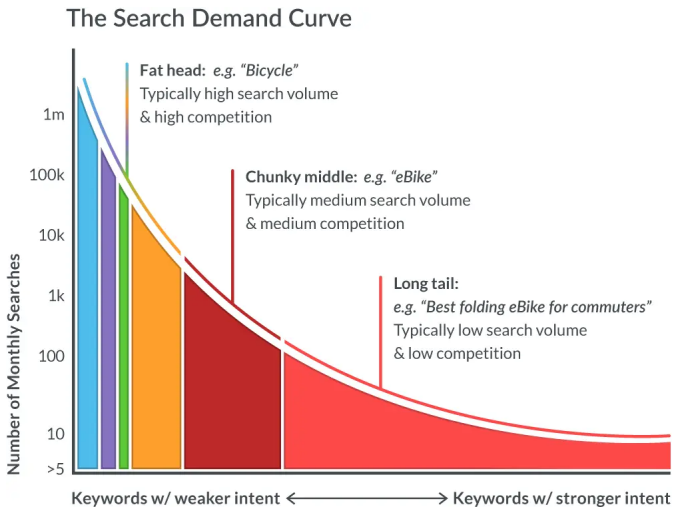


Figure 1.2: Distribution of search queries according to their length [74]

Instead of asking the users to formulate a proper query every time, they can be guided using the interactive relevance paths generated from a simple user query. These relevance paths are document representations that are extracted from the top retrieved documents for the original query. This approach assumes that the top documents are relevant to the query and are called *Content-driven information seeking* [46]. The outcome of one research suggests that content-driven relevance paths are beneficial in the case of exploratory searches and could be more useful in known-item searches [46]. Especially when seeking information from very long text documents, these content-driven interfaces can help the user narrow down the search space and reach the relevant documents easily. An efficient and unsupervised context extraction technique from the top 100 documents is proposed in this master thesis to help users with highly heterogeneous topics.

1.2 Research questions (RQ)

Information Extraction (IE) and Information Retrieval (IR) are two effective techniques in research to satisfy the user's information needs. IE is a technique for automatically extracting or mining pre-specified information from the data. On the other hand, IR is a technique for extracting relevant documents for a given user query. In [30], the authors characterize the complementary nature of these two techniques and the potential of building practical and powerful tools by combining them. For example, IE can be used to formulate the user's information need better, and IR can be used to retrieve high-quality search results.

In this master thesis, an interactive system with the combination of these two techniques is proposed and tested to fulfill the user's information needs. An unsupervised soft clustering approach is designed to model documents (from multiple languages) as a mixture of sub-topics, which are extracted using the deep inherent information from keywords. The testing of this approach is divided into 3 phases, not only evaluating the clustering with some evaluation metrics but also with a user satisfaction survey.Below are the research questions that address the proposed approach's evaluation.

RQ1: ***How effective is the sub-topic modeling approach in creating distinctive clusters from the news articles?***

Any clustering algorithm can generate topics (well-formed clusters) from a collection of documents. Still, these topics are highly significant to the users only if they are distinctive. Heterogeneous clusters help the user make a quick decision and retrieve documents related to the query and the sub-topic cluster. A candidate keyword selection approach is introduced and evaluated to generate such highly distinctive clusters. This research question aims to test the effectiveness of this keyword selection technique with normal clustering. Both intrinsic and extrinsic clustering evaluation techniques and a survey are chosen to evaluate the clustering output. The parameters of the clustering pipeline are tuned using the evaluation metrics and manual observation.

RQ2: ***Which IR system retrieves more relevant documents for a user query and a sub-topic?***

When a user chooses a particular sub-topic cluster, it is assumed that the retrieval results related to the query and the sub-topic are retrieved and shown to the user. Two different IR systems are proposed in this master thesis to retrieve documents relevant to the given user query and the chosen sub-topic. This research question targets comparing these two retrieval systems and determining the better one. A survey will be performed, and the collected data will be analyzed to answer the *RQ2*. Survey participants can read the retrieved documents from the two IR systems and answer five questions. A statistical t-test is conducted on the collected survey data to determine whether the two IR system results are the same or different. More details about the IR systems and survey questions are shared further in the report.

RQ3: ***What is the effect of sub-topic ranking in finding the positive documents from the candidate pool?***

Showing only the documents related to a specific sub-topic can restrict the user from reading the retrieved results for the given query. This research question addresses the impact of the sub-topic clustering output to find the positive documents against the baseline approach and is evaluated through an exploratory precision analysis. This research question also aims to extract inherent insights from the clusters and their rankings. For example: *Does any specific sub-topic cluster ranking produce better precision than the baseline?* A popular IR evaluation metric Mean Average Precision (MAP), is used to perform the ranking analysis and answer this research question.

1.3 Structure of the thesis

This master thesis is divided into six chapters, namely, from chapter 2 to chapter 8. Chapter 2 deals with the background and fundamentals needed to understand the thesis and highlights the problem statement. Chapter 3 describes the crucial technical information required for understanding the technologies chosen in implementing the proposed methodology. Consequently, chapter 4 details the literature work specifically related to the master thesis. Chapter 5 outlines the proposed methodology in this master thesis. Chapter 6 and 7 illustrates the experiment setup and experiment results, respectively. Finally, chapter 8 highlights the critical aspects of the thesis and also outlines the limitations.

Chapter 2

Background and Fundamentals

2.1 Fraunhofer FKIE

Fraunhofer FKIE (Fraunhofer-Institut für Kommunikation, Informationsverarbeitung und Ergonomie) is a research institute for providing innovative solutions in information and communications technology, and their main focus is on developing effective and efficient human-machine systems[1]. The users at FKIE are specially interested in reading news articles related to innovation and breakthroughs in *Technology and Military*. The below image, Figure 2.1, shows an example of areas of interest to the FKIE users, and this list is not bounded and can include more domains.

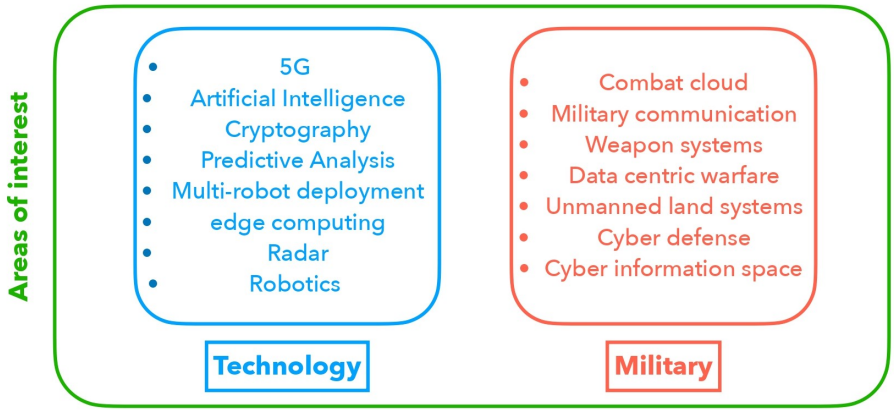


Figure 2.1: Areas of interest for the users at FKIE

2.2 Technical details

2.2.1 Abbreviations

1. **URL:** A URL is a short form for Uniform Resource Locator and is used to locate resources uniquely on the Internet [13]. Any resource on the Internet can be accessed with a unique URL. For example, the URL <https://www.linux.org/> represents a resource on the Internet.

[1] `https://www.fkie.fraunhofer.de/en/about-fkie.html`

2. **HTML:** HTML stands for HyperText Markup Language and is a markup language for representing documents on the World Wide Web (WWW) and links to other documents or information sources such as images, video, audio, etc [35].

3. **CSS:** CSS abbreviates to Cascading Style Sheets and is a rule-based language for styling websites[77]. The elements in a website can be placed appropriately using specific rules mentioned in CSS. Furthermore, many front-end visual features, such as text size, color, animations, etc., can be configured using CSS.

4. **UUID:** UUID stands for Universally Unique IDentifiers and is generally used to identify an entity universally uniquely. UUID4 creates a 36-character alphanumeric string that is based on random numbers and does not use any information regarding network address. In this master thesis, UUID4[2] from Python is used.

2.2.2 Machine Learning (ML)

1. **Ground-truth:** Ground-truth labels are the information that is more accurate, relevant, and true than the knowledge of the system we are testing [19]. This information is critical to evaluate and compare different systems.

2. **Supervised learning:** Supervised learning algorithms are ML approaches that use labeled data [23] for training the algorithm parameters using specific criteria or a loss function. *Classification* is a supervised technique to learn patterns from the labeled data and classify the unseen data automatically into several classes.

3. **Unsupervised learning:** Clustering is an example of these algorithms, and similar data points are clustered into groups according to the features in the data [44]. These groups are called *Clusters*. Document clustering is a technique to group documents into topics without ground-truth information [24].

4. **Soft clustering:** In *Soft clustering*, the data points are assigned to one or more clusters by the clustering algorithm [24]. This depends mainly on the structure of the data, and especially in news articles, documents are assigned to multiple topics rather than one.

5. **Support Vector Machine (SVM):** SVM is a supervised learning algorithm used for classification and regression. Using the labeled data information, *SVM* selects a maximum margin separating hyperplane(a decision boundary) between the data points. This hyperplane is used later for classifying new data points [55].

6. **Tensorflow Hub:** Tensorflow Hub[3] is a repository of pre-trained ML models from Tensorflow[4]. Tensorflow is an open-source platform for ML that provides an ecosystem of tools and libraries and allows developers to build and deploy ML-powered apps and researchers to push state-of-the-art models [26].

2.2.3 Natural Language Processing (NLP)

1. **Token:** In NLP, a token is a word or basic entity in a text document, and Tokenization is the process of splitting a text document into tokens [73]. Document token length is calculated as the number of tokens present in a document.

[2] `https://docs.python.org/3/library/uuid.html`
[3] `https://www.tensorflow.org/hub`
[4] `https://www.tensorflow.org/`

2. **Noun chunks:** Noun chunks or phrases are the nouns and all the words that depend on these nouns [54]. Consider the sentence, *"Army project may improve military communications by boosting 5G technology"* [1]. The possible noun chunks extracted from this sentence are *"Army project"*, *"Military communications"*, *"5G technology"*.

3. **Keywords:** Keywords are the noun chunks that are highly meaningful in a text document and can best describe or summarize a document [9]. An unsupervised multi-lingual keyword extraction approach is used in the proposed approach to extract the most significant keywords from each news article.

4. **Stopwords:** Stopwords often appear in a text document (or in a corpus) and carry very little information. Due to their low significance compared to other words, they are considered uninformative and removed during text processing[67]. Some examples of stopwords are 'der', 'das', 'and', 'of', etc.

5. **Lemmatization:** Lemmatization is extracting the base or normalized form from the original words. For example, 'worse' and 'worst' are lemmatized to their base form 'bad'. Lemmatization helps text processing techniques based on lexical matching and reduces computational and storage complexity. In this thesis, lemmatization is performed with the help of the spacy library.

6. **Lexical matching:** Lexical or syntactic matching is a technique to assign a relevance score between two text data (strings) based on the terms present in the data. This matching technique is not optimal for retrieval, as it does not consider the meaning of the query [39].

7. **Fuzzy string matching:** Fuzzy string matching is an approximate string matching technique that identifies how approximately two strings are similar. In lexical matching, the outcome of string matching follows a binary outcome of similar or not similar. In fuzzy matching, the individual parts of the text are considered to generate an approximate string similarity score. This approximate string matching is beneficial in information retrieval when certain words are misspelled in the user query[70].

8. **Levenshtein distance:** Levenshtein distance is a string-matching metric for measuring the difference between two strings at the character level. The distance is generally interpreted as the minimum number of changes to make the strings identical[70]. The higher the levenshtein distance signifies the strings are more dissimilar or nonidentical. For example, the strings 'Jan' and 'John'. The levenshtein distance is two between these strings, as it takes two changes to make the strings identical.

9. **Semantic matching:** Semantic matching assigns a relevance score between the two text data by considering the semantic information (meaning of the terms).

10. **Text embeddings:** The distributed vector representation of a text in the semantic space is generally referred as text embeddings. These embeddings are generally described in the research as word or sentence embeddings referring to the text being either a word or a sentence repectively. These embeddings can also be generated with short phrases and noun chunks [20, 80].

2.2.4 Information Retrieval (IR)

1. **Document retrieval system:** IR system specially developed to retrieve the document or text data for a given user query is generally referred to as a Document retrieval system.

2. **BM-25:** BM-25, Best Match 25, is a ranking function based on a probabilistic relevance framework that ranks documents based on the query terms occurring in each document [5]. BM-25 ranking is a lexical or syntactic matching approach and does not consider word semantics.

3. **Semantic search:** Unlike syntactic matching or calculating term frequencies, Semantic search engines try to understand the meaning of the search query and retrieve the matching documents close to the query in the semantic space [28].

2.2.5 Data storage

1. **Document index:** Document indexing or compression is a technique to store documents in an optimized way on the disk for efficient retrieval. This stored data on the disk is now referred to as *Document Index* [85].

2. **Inverted index:** The *Inverted index* is a data structure that contains every unique word that appears in the corpus and the separate list of documents where the word occurs [85]. This way of document storage provides an efficient document retrieval in real-time.

3. **Elasticsearch:** Elasticsearch[5] is a search engine mainly designed for textual data. Elasticsearch can be used as a document index and to retrieve documents for a given user query (which offers lexical matching). Elasticsearch uses an inverted index for document storage, which allows fast full-text searches.

4. **Semantic search index:** The *Semantic search index* stores the distributed embedding vectors of the documents on the disk and uses them later for retrieval. This index is generally also referred as vector database.

5. **FAISS:** FAISS is a library to save dense embeddings for an efficient similarity search. The semantic search developed in this thesis is built using FAISS. As a ranking function, FAISS uses L2 euclidean distance to calculate the similarity between the query and documents[31]. In this thesis, this distance function output is re-ordered using cosine similarities.

6. **SQLite DB:** SQLite is a lightweight serverless, self-contained, transactional database engine [14]. In this master thesis, labeled data are stored in *SQLite DB* using a library sqlite3[6].

7. **Redis DB:** Redis[7] is an open-source, in-memory data store used as a database, cache, etc. In this thesis, redis is used for caching sentence embeddings and has shown a huge improvement in the time taken for the clustering and document retrieval.

2.2.6 Evaluation

1. **Statistical testing:** A statistical test is a way to determine whether there is enough evidence to accept or reject a hypothesis about a process [36]. These tests are useful in making critical decisions about a process by determining whether two data samples significantly differ. There are two types of statistical tests, namely parametric and non-parametric. Parametric tests assume that the population follows a particular distribution

[5] https://www.elastic.co/what-is/elasticsearch
[6] https://docs.python.org/3/library/sqlite3.html
[7] https://redis.io/

and requires the sample data to follow the same distribution. A distribution here signifies parameters such as mean, standard deviation, and parametric testing. On the contrary, the non-parameter tests do not assume the population to follow any particular distribution. Wilcoxon signed-rank test is a non-parametric statistical hypothesis test that is used in this master thesis.

2. **Intrinsic evaluation:** In case of no labeled data or ground-truth, the clustering output is evaluated through the methods considering only the inherent representation of clustered data [24]. These methods of evaluation are referred to as *Intrinsic evaluation*.

3. **Extrinsic evaluation:** In *Extrinsic evaluation*, the clustering output is evaluated using the external knowledge such as ground-truth or the relevance judgments [24].

4. **Silhouette index:** Irrespective of the clustering algorithm, the output is more distinctive when the distance between the data points within the cluster is minimum and the distance between the clusters is maximum. Silhouette index [66] is an intrinsic clustering evaluation measure and is calculated by using the intra-cluster and inter-cluster distances for each sample.

5. **Precision:** In IR system evaluation, Precision is defined as the ratio of retrieved documents that are relevant to all the retrieved documents [86]. This measure can be used to compare different IR systems and be calculated at different retrieved indices. For example, $P@5, P@10, P@15$ measures precision scores at retrieved indices $5, 10, 15$ respectively.

6. **Cosine similarity:** Cosine similarity is a metric to measure the degree of similarity between two vectors [40]. In the case of IR systems, the similarity is calculated between the user query and document sentence embeddings, and can be further used to rank the documents.

2.2.7 Technology fundamentals

1. **Python:** Python[8] is an interpreted, object-oriented, and high-level programming language. Python is popular for its simple, easy-to-use syntax and data structures. Python uses dynamic typing that determines the type of the data dynamically during the runtime. The majority of the analysis and website backend development is developed using python.

2. **JavaScript (JS):** Javascript is a lightweight interpreted programming language popular as the scripting language for web pages[78]. JS helps to update the data on the websites dynamically and also handles user interaction. In this master thesis, the asynchronous data transfer between the survey website and the backend Python server is facilitated by JS.

3. **Bootstrap:** Bootstrap is an open-source CSS framework for developing responsive websites[76]. Responsive websites look alike when tested in different environments, such as device screen sizes and orientations (portrait/landscape). The website used in the survey questionnaire is developed using Bootstrap.

4. **Docker:** Docker is an open-source technology that allows developers to build, test and deploy their software applications efficiently. Docker uses container technology, software that packages the code and its dependencies to run the applications from one computing

[8] `https://www.python.org/doc/essays/blurb/`

environment to another [75]. Containers virtualize the operating system independent of the hardware, which creates better code reproducibility.

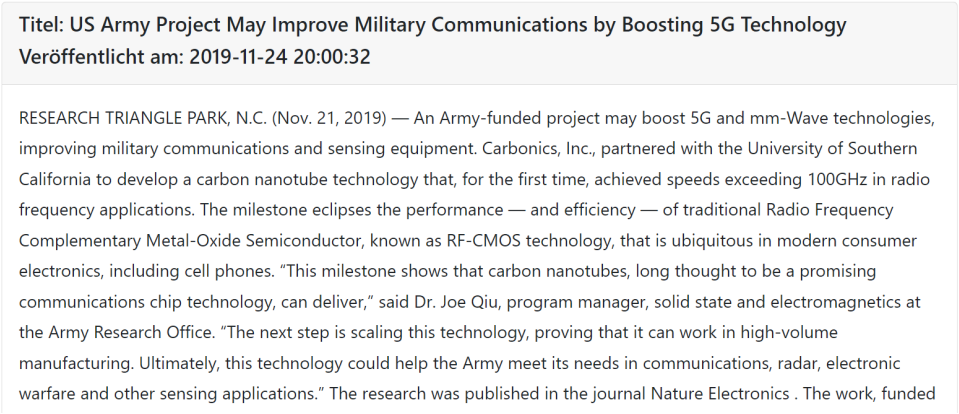
5. **FastAPI:** FastAPI[9] is a Python-based web framework for building APIs used as a backend or server-side technology. The survey questionnaire developed in this master is developed using FastAPI.

6. **Scrapy:** Scrapy[10] is an open-source framework to extract data from websites, i.e., web scraping. This framework also provides an efficient pipeline to save the scraped data in a database or a text file. Thousands of news websites are efficiently downloaded using the Scrapy framework and the data is saved in a SQLite-DB.

7. **FuzzyWuzzy:** FuzzyWuzzy[11] is an open-source library in python to calculate the syntactical text similarity between two strings. Internally the library uses Levenshtein distance. FuzzyWuzzy assigns a score between 0 to 100 according to the similarity between two strings.

2.2.8 Keywords specific to this master thesis

1. **News article:** A news article is a text document published by a news website. An example of a news article (this is only a part of the original article) is shown in Figure 2.2. The phrases 'news article' and a 'text document' are identical in this master thesis.



Titel: US Army Project May Improve Military Communications by Boosting 5G Technology
Veröffentlicht am: 2019-11-24 20:00:32

RESEARCH TRIANGLE PARK, N.C. (Nov. 21, 2019) — An Army-funded project may boost 5G and mm-Wave technologies, improving military communications and sensing equipment. Carbonics, Inc., partnered with the University of Southern California to develop a carbon nanotube technology that, for the first time, achieved speeds exceeding 100GHz in radio frequency applications. The milestone eclipses the performance — and efficiency — of traditional Radio Frequency Complementary Metal-Oxide Semiconductor, known as RF-CMOS technology, that is ubiquitous in modern consumer electronics, including cell phones. "This milestone shows that carbon nanotubes, long thought to be a promising communications chip technology, can deliver," said Dr. Joe Qiu, program manager, solid state and electromagnetics at the Army Research Office. "The next step is scaling this technology, proving that it can work in high-volume manufacturing. Ultimately, this technology could help the Army meet its needs in communications, radar, electronic warfare and other sensing applications." The research was published in the journal Nature Electronics . The work, funded

Figure 2.2: A sample news article from the document database [1]

2. **Web scraping:** Web scraping is a technique to automatically extraction of data from websites [37]. In the case of text data, most approaches download the structured HTML webpages and extract needed information. In this master thesis, news articles from different websites are scraped.

3. **Candidate pool:** A candidate or retrieval pool is a set of documents from lexical and semantic matching results for a given user query. These documents are very diverse, contain keywords present in the query (or semantically similar), and are further used for clustering.

4. **Sub-topic:** Sub-topics are second-level representations of a document. Generally, news articles are long text documents and can not be represented logically with a single topic

[9] https://fastapi.tiangolo.com/lo/
[10] https://scrapy.org/
[11] https://pypi.org/project/fuzzywuzzy/

or keyword. If the user query provided to the *Retriever* is considered the main topic, then the distinctive topics extracted from the candidate pool are sub-topics. The phrases 'sub-topic' and a 'cluster' are equivalent in this master thesis. The sub-topics are nothing but the outcome of the clustering pipeline.

5. **Context:** In this master thesis, we define a context as a particular domain or field in which the user is interested. For example, in the user query *Cloud*, the retrieved documents are related to different domains or contexts, such as cloud computing, combat cloud, and clouds in the sky. Even though there is some syntactic and semantic matching, the user intention is still unclear from the query.

6. **Labeler:** A person who assigns an appropriate label to the data according to the labeling criteria.

7. **Query type:** Input search queries from the user can be of any form. For example ., abbreviation, single word query, etc. In this master thesis, each form of a possible user query is referred to as a query type. All possible user queries can be categorized into two major query types, namely phrase (three words or less) and sentence queries.

2.3 IR system setup

A document retrieval system was developed to support users at FKIE in retrieving news articles related to technology and military topics. The retrieval setup contains three primary components: *Web scraper, Document filter*, and *Retriever*, as shown in Figure 2.3.

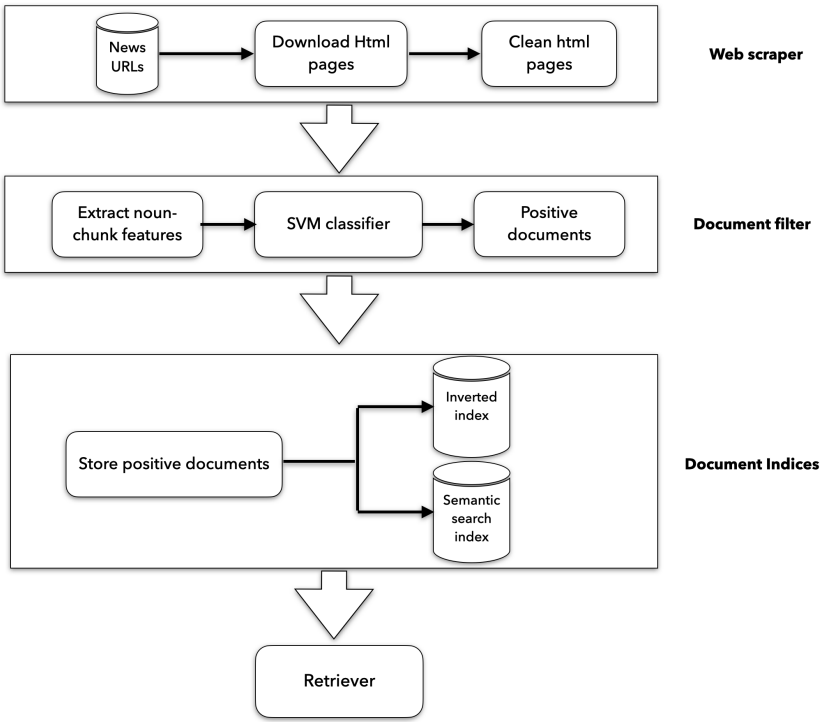


Figure 2.3: Document retrieval system designed at Fraunhofer FKIE

The first component, the *Web scraper*, downloads news articles (HTML pages) from a list of URLs and cleans the raw HTML data from advertisements and noise. Each cleaned news article is considered as a single entity, namely a *Document*. The majority of downloaded documents

are a mixture of topics such as military, technology, artificial intelligence, etc., and also contain a small number of typical news topics, namely politics, sports, advertisements, etc. The downloaded news articles are in *German* and *English*.

The second component, the *Document filter*, is based on Support Vector Machine (SVM) classifier that filters most of the irrelevant documents related to specific news topics. The documents are classified into two classes namely, *Positive* and *Negative*. *Positive* documents are documents related to technology and military, and *Negative* documents are related to everything else. After several tests at FKIE, it was found that features from noun-chunks in a document are performing better to differentiate *Positive* documents from the *Negative* documents. Noun chunk features based on the pre-trained multi-lingual Universal Sentence Encoder (USE) is used for the task of classification.

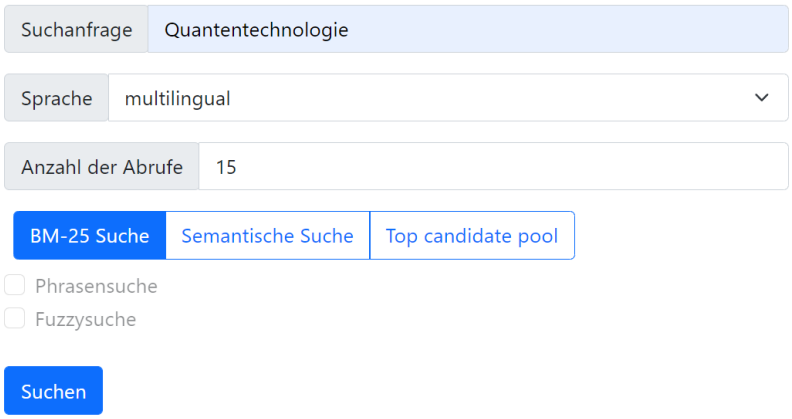


Figure 2.4: User interface to retrieve documents for FKIE users

In order to facilitate positive documents to the FKIE users, a *Retriever* component is designed to retrieve documents for a given user query using lexical and semantic matching techniques. Therefore, the positive documents from the *Document filter* stage are stored in two different document indices namely *Inverted index* and *Semantic search index*. Finally, the component *Retriever* uses both of the indices and retrieves documents according to the user request through a web user interface, as shown in Figure 2.4. Total number of news-articles scraped in this thesis is 327421 and the number of news-articles stored in the document indices after filtering is 26954.

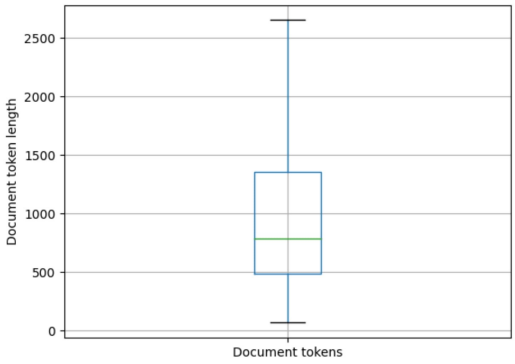
2.4 Problem description

Semantic matching of query and documents is better suited when the user query is a long sentence query due to the context embedded in the search query. For example, the user query *"What are the technological advancements in Robotics related to Unmanned Weapon Systems?"* provide high-quality results in the top results, as the information request is detailed in the query. Consequently, the search query *"Robotics"* results are mapped to multiple domains and lead to many false positives (according to the user's intention).In the case of keyword queries, it was observed that semantic and lexical matching are prone to high false positives and have no unique advantage. In [39], the authors observed a similar challenge in their research. On the one hand, lexical matching does not consider the inherent meaning of the word causing a vocabulary mismatch problem, and semantic matching fails to retrieve the relevant documents in the top results as it matches too many keywords semantically. A manual observation of retrieved results is carried out with a set of sample queries to evaluate the retrieval algorithms, and the results are shared in Table 2.1 on page 21.

Table 2.1: Retrieval algorithms comparison on different query types

S No.	Query type	Better retrieval technique	Reason	Queries used
1	No meaning queries	BM-25	Lexical matching	Person or object names[12]
2	Multi-lingual queries	Semantic search	Semantic matching	Artificial Intelligence vs Künstliche Intelligenz
3	German composite words	Semantic search	Semantic matching	Quantentech-nologie
4	Spelling mistakes	Semantic search	Semantic matching	Kryptografy, Rbot
5	Polysemy	Semantic search	Semantic matching	Combat Cloud, Cloud computing
6	Sentence/long phrase queries	Semantic search	Semantic matching	Schwachstell-enanalyse eigene Waffen-Systeme

The users at FKIE provide only one or two phrase queries, and his or her intention is to explore information to specific topics such as *"Technology"* and *"Military"*. Without labeled data, learning user intention from a single word or phrase query is a huge challenge. One further challenge is that a wide variety of sources can also result in high noise or false positives, and the user is less likely to find the relevant documents in the top results. Unlike tweets or requirements, news articles are long documents with the 50% (percentile) token length of 788 and consist of keywords from multiple domains. Document token length details is shown in Figure 2.5.



(a)

S No	Statistical parameter	Value
1	Minimum token length	69
2	Mean token length	1280.64
3	Maximum token length	122657
4	Token length at 25%	489
5	Token length at 50%	788
6	Token length at 75%	1355

(b)

Figure 2.5: (a) Boxplot showing the document token length distribution(after removing the outliers) (b) Important statistical details about the token length

Information related to innovation and technological breakthroughs is hard to find in the news articles. However, the probability is not zero, as positive news articles are gathered during data collection for classification. Nevertheless, their low distribution makes it challenging to create

[12]User query with no innate meaning of the word namely out of vocabulary words: for example John Dowe, Wester etc.

a dataset sufficient for supervised approaches. After considering the challenges with positive documents for the user intention, a supervised solution is hard to achieve, in order to match the performance of a full sentence query. Real-time user feedback and continuous reinforcement algorithms can fulfill the lack of labeled datasets, but they need feedback from diverse users regularly. Otherwise, the search results can be highly inclined to a particular user and lead to biased results.

Table 2.2: Clustering results to generate more document representations

Query	Clusters
Quantentechnologie	Technologie, Microsoft, Military, KI, Quantenteilchen, Quantum computing, Forschung, Bundesministerium, Quantencomputer, München, Industrie, Netzwerke, Algorithm, Quantencomputing, Ingenieuren Informatiker, Qubit, Programmierung, Marineschiff, Intelligence, China, Verteidigung, IBM, AI, Quantum physic, Wissenschaftler, Electronic, Prozessor, Deutschland, Future, Vorsprung, Robotic, Compute, Memory SSDs, USA, Entwicklung, Raumfahrt, Klima, Cybersicherheit, Stau, Rheinmetall Waffe, Laserstrahl
5G	5G, 5G network, Frequenzspektrum, 5G deployment, China, Defence intelligence, Nokia, Berlin, Mobilfunkmast, Telekom, Gigabit speed, 4G, WiFi, UMTS, Military, Fiberoptic broadband, 5G technology, Vodafone, Experimentation testing, Mobilfunknetzbetreiber, Technologie, Netzwerk, LTE, Smartphones, Netz, Aircraft, 5G service, Data cap, Deutsche Telekom, Telefónica, Apple, Gebiet, Netzausbau, Anbieter

A template-based search query is an option to improve the context of a search query. For example, we have a pre-defined template such as *Innovations in XXX related to the Military*. When the user provides a query: *Robotics*, we replace the *XXX* with the user query, and this results in the final query *Innovations in Robotics related to Military*. An option to update the template according to the user's interest from the user interface can provide tailored results without any extra training. This approach restricts the user to having only a few sets of templates and is also inefficient when a new template needs to be added, or an existing template needs to be updated.

Table 2.3: Keywords present in one retrieved document for the query Quantentechnologie

Keywords similar to the query	Keywords useful for clustering
Quantum Technology	Sciences
technological application	electronic warfare capability
quantum system	the Defense Science Board
quantum computer	nuclear material
quantum communication	military
Quantum application	encode information
quantum bit	military personnel
Quantum sensing	military sensing
quantum radar	Military Applications
quantum physics	Defense Primer
a quantum computer increase	enhanced military capability
a compute unit	the National Academy
	potential military application
	sea-base nuclear deterrent

The retrieved documents for some queries are clustered using the words present inside the documents to generate more clusters.The high cluster size is used to capture more patterns in the retrieved results. These clusters act as pathways to reach the retrieved documents. Table 2.2 on page 22 presents the clustering output where the parameters are selected to create more deep representations of the retrieved documents. Some of the clusters are repetitive and similar to the query. These clusters result in the same set of documents and can lead to poor user satisfaction.

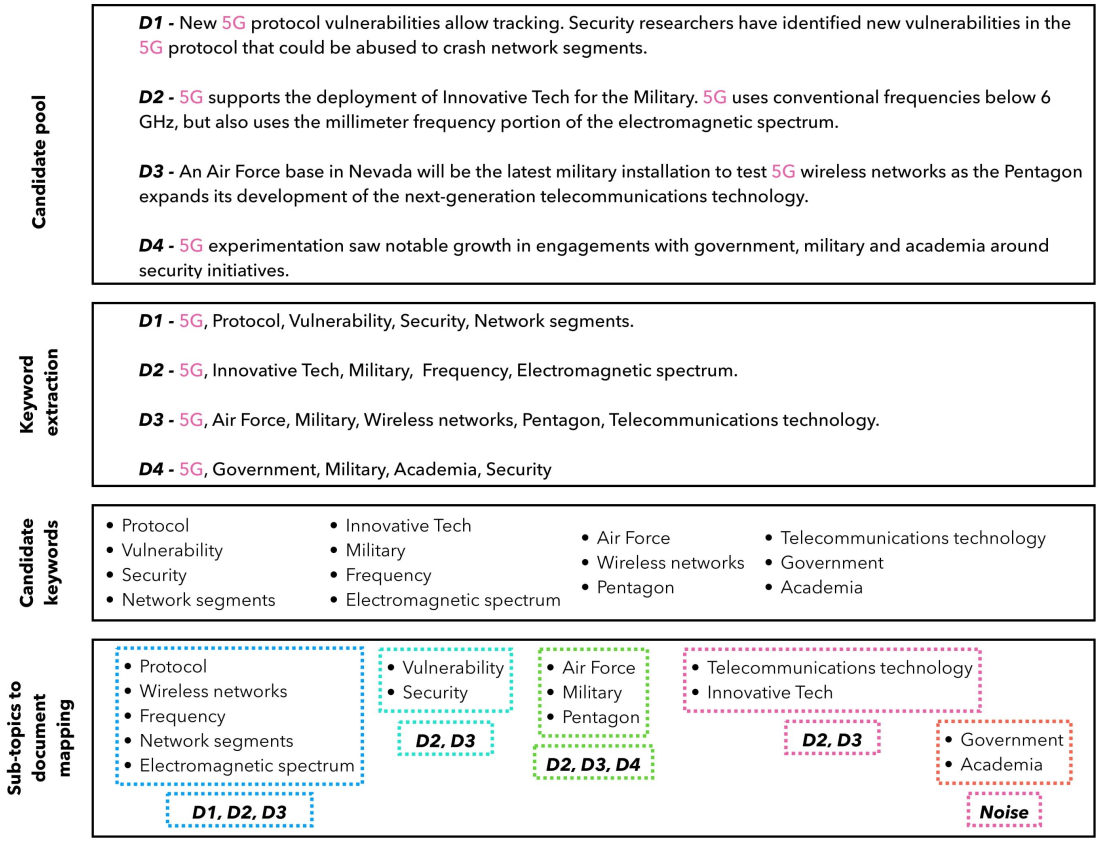


Figure 2.6: Expected sub-topic extraction for the query: 5G

On the other hand, when the parameters are selected to generate fewer representations, the individual cluster size increases and results in clusters containing more documents, and leads to the repetition of documents in the clusters. One crucial observation has shown that some keywords from the documents can be omitted during the clustering to improve the clustering output by creating diverse clusters and maintaining deep representations. Table 2.3 on page 22 details the keywords similar and dissimilar to the query. This query similarity can play an essential role in creating unique clusters, and it is evaluated extensively in this thesis.

After considering various approaches to fulfill the missing context, we believe that extracting the unique contexts from top results to the user query in an unsupervised way is more efficient, more explainable and can be better reproducible compared to supervised approaches. This would not only help the user to have deep insights into the results pool but also reduce the efforts to reach the highly relevant documents. A sample expected sub-topic extraction pipeline output is shown in Figure 2.6. These contexts are described as *sub-topics*. The proposed approach in this master thesis is aimed at handling the challenges mentioned above. News articles from diverse sources are considered, and the results can be easily transferred to other data sources in the future.

Chapter 3

Technical background

3.1 Sentence encoders

In most of the NLP techniques, text documents are represented in the form of distributed vectors. These vectors are dependent on the word or phrase level representations and are used for exploratory analysis, text classification, clustering, text retrieval etc.. In addition to the phrases, the meta information such as parts-of-speech and entities can further help to improve the performance of these tasks. The advancement of the phrase representations in the last decade have made a huge impact in NLP research. In this section, different phrase representations from the literature are reviewed and the representations that are used in this master thesis are highlighted.

3.1.1 Document representations from word embeddings

Word embeddings are vector representations of words or phrases. Let us consider a text corpus C which contains N documents with an vocabulary of size M. Documents and terms are represented with D and t respectively.

$$C = \{D_1, D_2, D_3, \ldots, D_N\}$$
$$V = \{t_1, t_2, t_3, \ldots, t_M\}$$

One of the earliest approaches namely "Bag of Words" (BoW) method represents a text document as a feature vector denoting the frequency of words in that document [83, 62]. BoW is a simple technique of representing the text in a high dimensional space and every word represents a dimension in this space. This representation of text in continuous space is referred as Vector Space Model (VSM) [2]. In matrix notation, this can be interpreted as Term-Document matrix and is presented in the Figure 3.1. Words are represented as one-hot vectors i.e vectors containing one in only one dimension and zeros in rest of the dimensions. The frequency of a term t_i in a document D is represented with $(tf_{t_i})_D$ and document vectors with $\hat{D}$. One of the main disadvantage of this method is computation when the vocabulary size M of the corpus is high.

$$\hat{D} = (tf_{t_1}, tf_{t_2}, tf_{t_3}, \ldots, tf_{t_M})_D$$

Considering only the word frequency can dominate the words which appear very often in a document and also does not consider the relation between documents in the corpus. To overcome this, an effective BoW approach namely Term frequency-Inverse document frequency (Tf-Idf) is proposed. In this modeling technique, how often a word appears in all documents

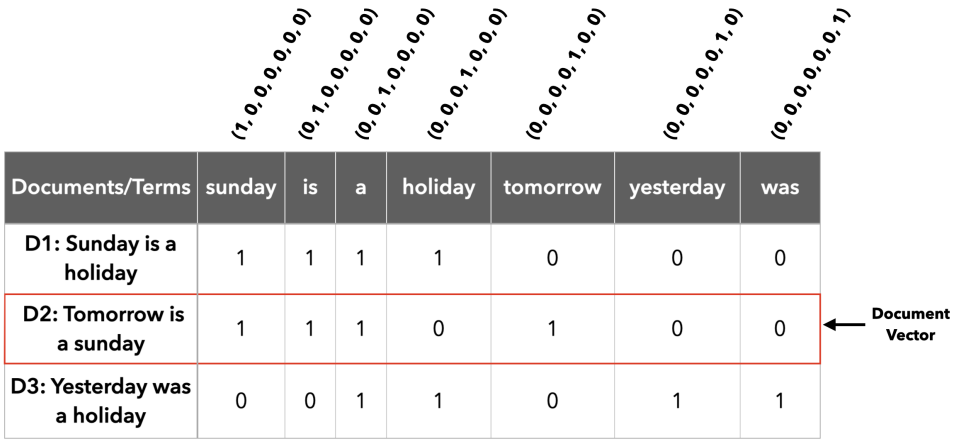


Figure 3.1: Term-Document matrix representing word and document vectors

in the corpus is considered along with term frequencies (or normalized) [41]. The terms which occur very often in many documents are now penalized and results in a better weighting score.

The above two approaches of BoW ignore the word order and meanings completely and also depend on the vocabulary of the corpus. This can lead also to computational issues when the size of vocabulary is in the range of millions. With the advancement of deep learning techniques, the documents representations are significantly improved and overcame the limitations of the above approaches. This is possible with the help of better semantic word representations which considered word meanings and embed vectors in continuous vector space rather than a discrete vector denoting a single dimension [51, 59].

In [51], the researchers proposed an unsuperived training approach with two model architectures to generate high quality semantic word vectors. These two architectures are namely Continuous Bag-of-Words (CBOW) model and continuous skip-gram model and consider a text document as continuous series of words (as a window of words). These architectures are generally referred as *Word2vec* Moreover, these words are referred to either context words or a current word at a given time. These architectures also consider a window which spans the length of the context words. The CBOW architecture predicts the probability of the current word given the surrounding context words and the skip-gram architecture predicts the probability of context words given the current word [51]. Accordingly, the words sharing the same context in the corpus are represented close to one another in the continuous vector space. Both these architectures utilizes a 2-layer feedforward neural network to generate the distributed representations for all words in the corpus. While training the neural network, instead of a non-linear hidden layer a projection layer is used, which is shared for all words.

The above architectures have shown a great results representing the semantics of the words. For example, the vector equation *"king - man + woman = queen"* signifies the advancement of word representations in the vector space. However, only the local context is given importance and global context (at corpus level) is ignored in creating these word representations in both CBOW and skipgram architectures [59]. Local context here indicates the relationship between the words that exist at a time in a document or word co-occurrences. In [59], researchers have tested an approach namely *GloVe:* Global Vectors for word representation, an unsupervised algorithm to generate distributed word representations using local and global word-word co-occurrences. Glove uses a global log-bilinear regression model combining global matrix factorization and local context window techniques [59]. Glove embeddings have outperformed CBOW and other models in tasks such as Named Entity Recognition (NER) and word similarity [59].

Polysemy is a concept of word or sign having multiple meanings. For example, the word *bank*, which represents multiple things such as river bank or the bank where we keep money. Polysemy is one of the main drawback in both *Word2vec* and *Glove* approaches, as it ignores the possibility of word having different semantics. *ELMo:* Embeddings from Language Models is one of the earliest approaches to address this problem and generates contextual word embeddings [61]. ELMo word representations are a functions of the complete sentence rather than context created by a fixed window length. Furthermore, word embeddings are generated from the internal states of a bi-directional Language Model (biLM) [61]. ELMo also uses character convolutions (taking character-level tokens as input for the biLM) which allows the model to handle the word representations of words that out of vocabulary. In [27], researchers have claimed that the ELMo token representations which are computed by combining the left-to-right and right-to-left representations from biLM are not deeply bidirectional.

To generate deeply bidirectional word representations, an approach named *BERT:* Bidirectional Encoder Representations is proposed [27]. BERT utilizes the transformer architecture with multi-head attention to compute the efficient embeddings in the vector space. Transformer architecture uses self-attention mechanism with encoder-decoder structure to generate input and output representations [72]. BERT uses "masked language model" (MLM) and "next sentence prediction" (NSP) techniques in its pre-training. MLM randomly masks token from the input sequence and predicts the probability of the missed token based only on its context. This random masking has enabled BERT to produce truely deep bidirectional representations [27]. Moreover, the NSP technique creates sentence pairs and jointly pre-trains the text-pair representations by predicting the next sentence given a particular sentence.

3.1.2 Sentence embeddings

Sentence embeddings are numerical representations of a text document namely a sentence or a paragraph and they play a crucial role in IR specially in semantic search. As a naive approach, one can generate sentence representations as the mean of vector representation of words in a sentence or paragraph (after removing the stop-words). This approach clears lacks the semantic coherence between the words and represents the context poorly in the continuous space. In the recent years, a lot of sentence encoding approaches were proposed, but only two popular techniques are discussed below.

1. **Sentence BERT (SBERT):** BERT encoder provides the input representations for a sequence of input tokens, which can be single sentence or two sentences combined together [27]. BERT uses some special tokens for recognizing certain features in the input sequence. For example, $[SEP]$ token is used to separate two contiguous sentences. BERT works on token level embeddings as a input rather than a single sentence. Therefore, in order to perform semantic similarity tasks, all sentence combinations shall be provided to the BERT network, which creates a massive computational overhead [64]. Authors in [64] have highlighted the disadvantage of BERT to generate independent sentence embeddings.

   A modification to BERT pre-training stage is proposed namely SBERT to generate sentence representations directly for a given sentence. SBERT uses a siamese and triplet networks for updating the network weights to generate sentence embeddings that are semantically similar [64]. Furthermore, pre-training of SBERT model is sufficient and does not need any further inference networks to generate the sentence representations. SBERT

sentence embeddings can be directly used in many NLP tasks such as semantic text similarity (STS), text classification, text clustering, etc and the models built on SBERT's architecture are accessed with the help of the python library sentence-transformers[1] .

2. **Universal Sentence Encoder (USE):** USE is a pre-trained DL model from tensorflow that encodes text data such as sentences, phrases, or paragraphs into a distributed semantic vector [20]. Two variants of USE models were proposed depending up on the performance. One model makes use of the transformer architecture and the other uses the deep averaging network (DAN). Similar to the SBERT, USE also enables the transfer learning using the sentence embeddings and no further inference is required. Transfer learning tasks performed using both these architectures have revealed that transformer has performed better than DAN in different transfer learning tasks but requires high computational resources.

   One year later, two new multi-lingual USE (M-USE) models were proposed from tensowflow and the model embeds text from sixteen different languages into a single semantic space [80]. One model uses the transformer architecture and the other uses convolutional neural network (CNN) architecture. M-USE uses a multi-task dual encoder training framework which enables the DL model to train multiple languages simultaneously [80]. In this master thesis, a USE model with transformer architecture from Tensorflow Hub[2] is used. Tensorflow-hub specifies that this USE model is optimized for mutli-word text elements, such as sentences, phrases or short paragraphs and there is no need to explicitly mention the language of the text.

3.2 Dimensionality reduction

Sentence or word embeddings are very high dimensional distributed vectors, specially M-USE embeddings which have a dimension size of 512. Data processing tasks such as visualization, data analysis, feature extraction, clustering etc., on data having high dimensions can be computationally expensive. Therefore, the dimensions of the data are reduced for all the data points in the dataset without losing the crucial patterns or information. This technique is generally referred as dimensionality reduction. Many dimensionality reduction techniques were proposed in the recent years and they can be categorized into two types. Algorithms that preserve the pairwise distance structure among all the data points in the dataset [49]. One example in this category is Principal Component Analysis (PCA). PCA assumes that the data is linear and does not perform well in case of data having non-linear relationships. The other type of algorithms consider the non-linear relationships in the data and preserves local or global structures in the data. One example in this non-linear algorithms is Uniform Manifold Approximation and Projection (UMAP).

In [4], researchers observed an increase in performance of clustering methods after the dimensionality reduction on the data using UMAP and is shown at Figure 3.2. They have tested few popular clustering techniques such as k-means, Gaussian Mixture Models (GMM), Agglomerative hierarchical clustering, HDBSCAN and observed an increase in accuracy after UMAP dimensionality reduction. Moreover, the time taken for clustering is drastically reduced. UMAP works based on the Riemannian geometry and algebraic topology and preserves the global structure in the data [49]. One of the main reasons for acceptance of UMAP in ML is its computational efficiency. However, UMAP algorithm is slower than PCA [60], but given the quality of reduced representations and handling the non-linear relationship in the data, UMAP is clearly

[1] `https://pypi.org/project/sentence-transformers/`
[2] `https://tfhub.dev/google/universal-sentence-encoder-multilingual-large/3`

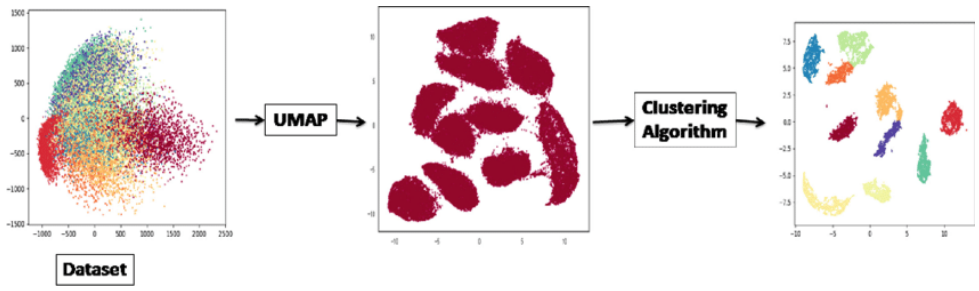


Figure 3.2: Improved clustering pipeline after reducing the data dimensions [4]

a viable dimensionality reduction technique in ML. In this master thesis, UMAP is used to reduce the data dimensionality.

3.3 Document clustering

Document clustering (DC) is the task of separating documents into meaningful groups where the documents with similar characteristics belong to a similar groups. In addition to DC, the task of topic modeling is also referred to achieve the same outcome. DC play a crucial role in the field of big data and data mining. Generally, clustering is performed on numerical data points in the continuous space. Text documents however are in alphanumeric (also some special characters) format. One of the earliest approaches to represent text documents is BoW method and tf-idf weighting, which is described in the section 3.1.1. Two main disadvantages of these methods is lack of semantic representation and high dimensional representation. As the dimensions depend on the number of words in the corpus, this can lead to a computational overhead. Semantic (contextual) text representations with the help of word or sentence embeddings, etc. encodes the text in a fixed length vectors. There are several clustering techniques tested on text document clustering such as partitioning, hierarchical, density based [2], etc. Below are few clustering algorithms discussed on an abstract level and their advantages and disadvantages are highlighted.

1. **Partitioning clustering:** This type of clustering deals with creating a fixed number of clusters of similar data based on a particular criteria. K-means clustering is one of the popular and simple clustering technique based on distance measurement in ML. K-means algorithm partitions the data of n samples into k clusters using a centroid-based iterative approach [2]. Being a parametric clustering approach, the number of clusters k needs to be well designed according to the data. One major drawback is the cluster shape, as the algorithm expects a spherical or circular shape output due to the centroid approach. K-means also does not assume any inherent noise in the data and assigns all data points to a cluster.

2. **Hierarchical clustering:** These clustering algorithms create a hierarchical structure from the data samples. There are two types of hierarchical clustering methods namely top-bottom/divisive approach and bottom-top/agglomerative approach [2]. In top-bottom approach, all data samples are considered to be a single cluster and this cluster is further decomposed into smaller cluster until a certain criteria is achieved. Adversely in bottom-top approach, each data sample is considered as a single cluster and the clusters are merged to form larger clusters until a certain criteria is met [84].

   Agglomerative hierarchical clustering is one of the popular hierarchical algorithms in ML and unlike k-means, there is no need to specify the number of clusters before clustering.

However, an extensive experiments on comparing both the clustering algorithms shows that partitioning clustering performs always better than agglomerative clustering [84]. The authors also suggested partitional clustering for large document collections.

3. **Density based clustering:** Similar to hierarchical clustering, density based clusters are non-parametric and moreover separates data samples into clusters which have a high density areas until a certain criteria is met. Density can be interpreted as the number of points located within a certain region. Density-based spatial clustering of applications with noise (DBSCAN) is one of the popular density clustering algorithm. DBSCAN characterizes every data point as either a core point or a border point or a noise point [18]. Two crucial parameters in the DBSCAN algorithm are ϵ (epsilon) and $minPts$ (minimum number of points). A data point is defined as a core point when it contains neighbouring datapoints higher than $minPts$ within a circle of radius eps.

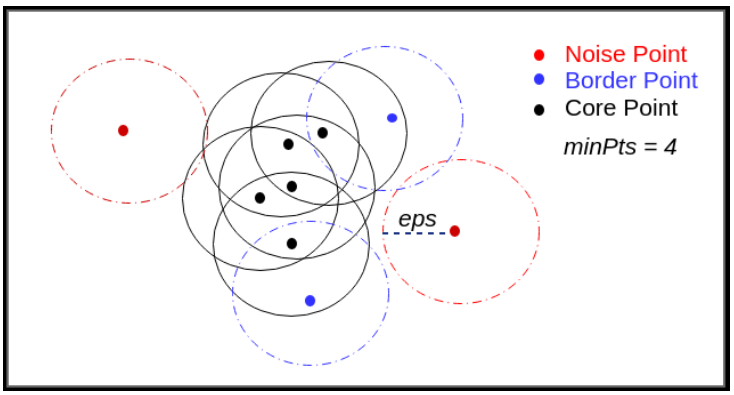


Figure 3.3: DBSCAN classification of data points [71]

A density-based cluster is expressed as a maximally connected component of the data points that lie within a distance less than eps from a core point (as described above) [18]. Border points are data points inside a cluster which do not follow the core point property. Data points that are not part of a cluster and does not follow the core point criteria are noise points. Different data points are presnted visually in the Figure 3.3 There are more parameters in this algorithm which define the final clustering output but the number of clusters is not a parameter. This helps the algorithm to assign number of clusters according to the given data.

Density based clustering clearly have many advantages compared to other clustering algorithms with efficient noise handling, non-parametric, flexible clusters (no specific shape and size). However, DBSCAN has limitations such as difficulty of parameter selection and varying density clusters [47]. To overcome this limitation, an algorithm namely Hierarchical DBSCAN (HDBSCAN) was proposed. This clustering algorithm extends DBSCAN by removing the concept of border points and varying different values of eps. A hierarchy of different DBSCAN clusterings are generated through different values of eps [47]. The hierarchy is condensed and used to find clustering output which provides stability of eps. To achieve a new parameter named "minimum cluster size" is introduced. In this way, HDBSCAN overcomes the limitation of handling varying densities and there is no need to explicitly select the parameter eps. In the Figure 3.4, the results from three clustering algorithms is presented and it can be observed that the HDBSCAN handles both low density noise points and high density clusters very well. However, HDBSCAN is computationally slower compared to DBSCAN.

Clustering algorithms can be further characterized into two types namely hard clustering and soft clustering depending upon the clustering output [24]. When the clustering algorithm

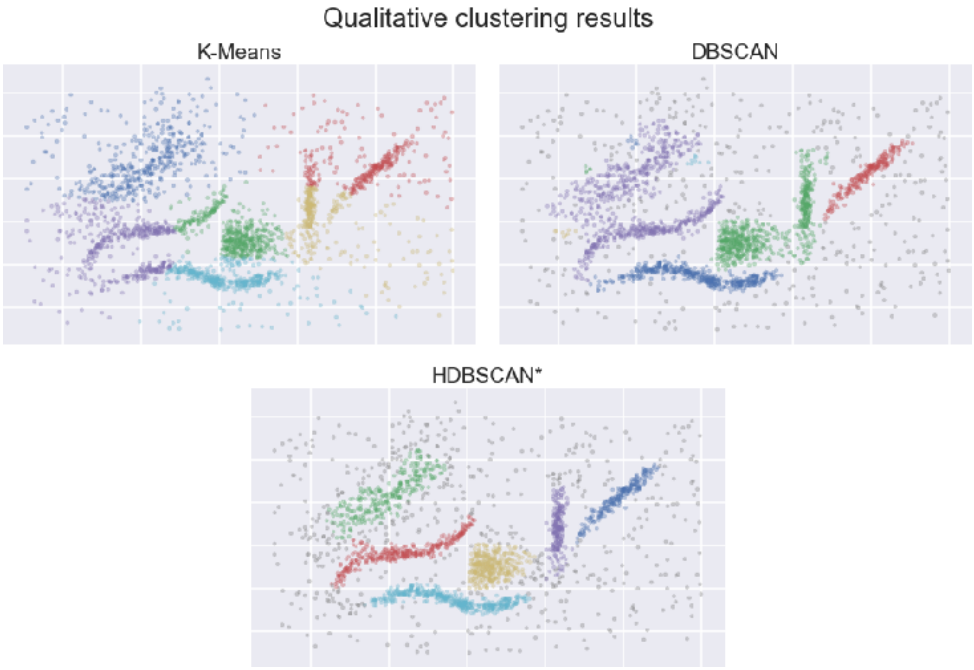


Figure 3.4: Comparision of clustering results from three algorithms namely k-means, DBSCAN, HDBSCAN [47]

strictly assign each data point to a single cluster, it is referred to as Hard clustering. In DC, one document assigned to one cluster is an example of hard clustering output. When the clustering output assigns a data point to several clusters, then it is referred as Soft clustering. For example, when a document is assigned to several clusters, then it is soft clustering.

3.4 Topic modeling

Topic modeling (TM) is a technique of extracting inherent patterns or structures from a large collection of text documents [6]. TM is an unsupervised ML approach to express a text document as a mixture of topics. For example, a topic is general theme such as sports, politics, business, movies, health et,. Latent Dirichlet Allocation (LDA) is one of the popular TM algorithms which generates a soft-clustering output. LDA is a generative probabilistic model which represents each document as a finite mixture of topics and each topic as finite mixture of words [16, 6]. LDA uses BoW representation where a document is a finite set of words. One major limitation of LDA method is the lack of semantic representation.

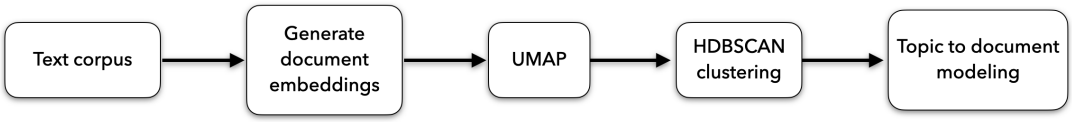


Figure 3.5: Top2vec methodology to generate semantic topic-modeling

To overcome this limitation a new approach namely top2vec is proposed. With the help of the distributed semantic representation of words and sentences, a text document can be represented in the continuous space. This gives an advantage to learn topics in the continuous vector space [6]. top2vec encodes the text documents into the vector space using sentence embeddings. These high dimensional embeddings are reduced to low dimensions using UMAP

technique and further clustered using HDBSCAN clustering. The pipeline used in top2vc is presented in the Figure 3.5. During clustering, the high dense areas in the semantic space are grouped. This results in expressing a topic as a cluster centroid. In [6], the results show that top2vec finds topics that are more informative and representative than traditional topic modeling algorithm LDA.

Chapter 4

Related work

Many researchers have considered different techniques from Machine Learning (ML) to improve the retrieval results based on the availability of labeled data. The research can be categorized into two types: supervised and unsupervised.

4.1 Supervised approaches

Many researchers used ML algorithms with special loss functions based on relevance between the query, and documents and some of the popular pairwise ranking methods are RankBoost [29], RankNet [17], Rank-SVM [33] (using click-through data). Recent state-of-the-art supervised approaches are neural re-ranking methods and are based on complex Deep Learning (DL) architectures. Distributed word embeddings combined with the performance of non-linear neural networks have shown remarkable results in improving the performance of retrieval systems by considering semantics [52, 32, 56].

4.2 Unsupervised approaches

These approaches use no-labeled data and re-rank the retrieved results based on the user query and top retrieved documents [65, 7]. One common challenge in these approaches is the user query, which is mostly comprised of only a few keywords [7, 34]. To tackle this problem, many researchers have tested Query Expansion (QE) approaches that partially fill the missing meaning and context in the query. QE techniques include clustering search results, query filtering, word sense disambiguation, and relevance feedback, etc., [7]. Relevance Feedback is a method of retrieving search results using the original query given by the user and then using the top-k documents for query expansion [7]. Researchers have clustered search results in many different ways, such as at the document level, keyphrases, query-specific clustering, etc. [12, 38, 82, 57, 42, 43]. Typical distance-based clustering algorithms such as k-means are used in some research and also hierarchical clustering is also tested [12, 50, 81], as it is flexible to change the threshold level for cutting the clustering dendrogram in a bottom-up approach. A common drawback in most clustering approaches is mapping a document to a single cluster, which is not logically valid, as a document can contain keywords from different domains.

4.3 Thesis contribution

The approaches based on clustering at the word level [12, 50] consider only a single language of retrieval results or corpus and hence cannot be directly implemented on a multi-lingual corpus and does not have any special keyword selection stage. With the advantage of contextual embeddings from sentence encoders, the authors in [6] made a breakthrough in document clustering with an efficient and explainable topic-modeling approach.

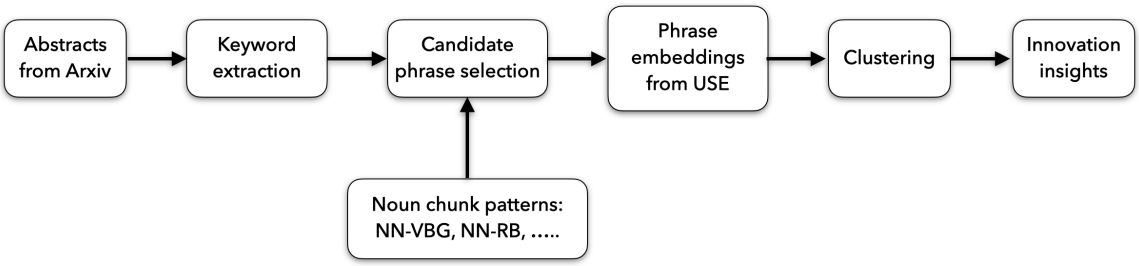


Figure 4.1: Pipeline to extract innovation insights using candidate selection

In [45], authors have used a particular candidate selection approach to filter some phrases from the keyword extraction and a specific noun chunks selection. The pipeline used in this research is shown in the Figure 4.1. This pipeline is explicitly used to extract innovation insights from research projects. Authors have detailed specific noun-chunk patterns in order to restrict the keywords used in the clustering. This directly impacts on the outcome of the clustering. One drawback of this approach is the lack of semantics during selection which can lead to elimination of crucial keywords. As the user intention is related to *Innovation* at FKIE, a unique query-specific candidate keyword selection is proposed. Moreover, the documents are semantically mapped to a specific topic, and multiple languages are modeled using a single multilingual pre-trained sentence encoder. News articles from multiple languages can be easily integrated into the document indices, and no changes are needed in the clustering pipeline. The proposed approach can be further extended to analyze any corpus containing long text documents for a given phrase or keyword.

Chapter 5

Thesis Methodology

5.1 Proposed methodology

One way to extract different contexts from the candidate pool is to perform any clustering algorithm. This results in very generic clusters closely related to a given query and not provide new insights to the user. To generate diverse and distinctive clusters, we need to use the latent information at the word or phrase level rather than at the document level [16]. As the documents contain multiple occurrences of the query and are also highly similar in semantic space, we need to reduce the impact of the given user query to generate a clear distinction between the documents. Suppose we ignore the query-related keywords while clustering. In that case, it leads to a high number of clusters that are similar to each other (repetitive clusters) and can impact user satisfaction. Figure 5.1 illustrates the proposed approach on an abstract level to tackle the above issue and generate highly heterogeneous clusters.

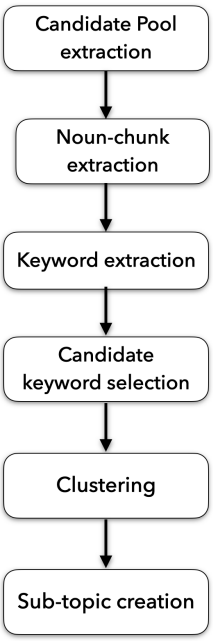


Figure 5.1: Proposed approach on an abstract level

The proposed approach, shown in Figure 5.1, does not assume fixed templates or specific user intentions. Major components in the pipeline are: *Candidate pool selection, Noun-chunk extraction,*

Keyword extraction, Candidate keyword selection, Clustering, and Sub-topic creation. This pipeline's first step is retrieving a candidate or retrieval pool for the given query. Subsequently, to extract keywords with high diversity and low noise (stopwords), a candidate selection module is proposed. his component consists of three significant steps, namely *Noun-chunk extraction, Keyword extraction and Candidate keyword selection*. Keyword extraction is extracting the most meaningful noun phrases in a text document. Specific keywords are selected and used for clustering using a percentile selection. This process is referred to as candidate keyword selection, and the resulting phrases after this stage are called candidate keywords. Below sections detail the above in-depth and with appropriate examples.

5.2 Candidate pool selection

Sub-topics related to the user query are extracted from the top retrieved results to extract A large set of retrieved documents for the query is required for a wide variety of these sub-topics. This set is referred to as the Candidate pool and is comprised of retrieved results from both semantic and lexical matching. A diverse and large candidate pool is crucial for generating a wide variety of query-related sub-topics. The length of a candidate pool directly influences the sub-topics output, and two candidate pools of lengths around 30 and 100 are considered in this approach. These document pools are constructed from an equal mixture of documents retrieved from lexical and semantic matching.

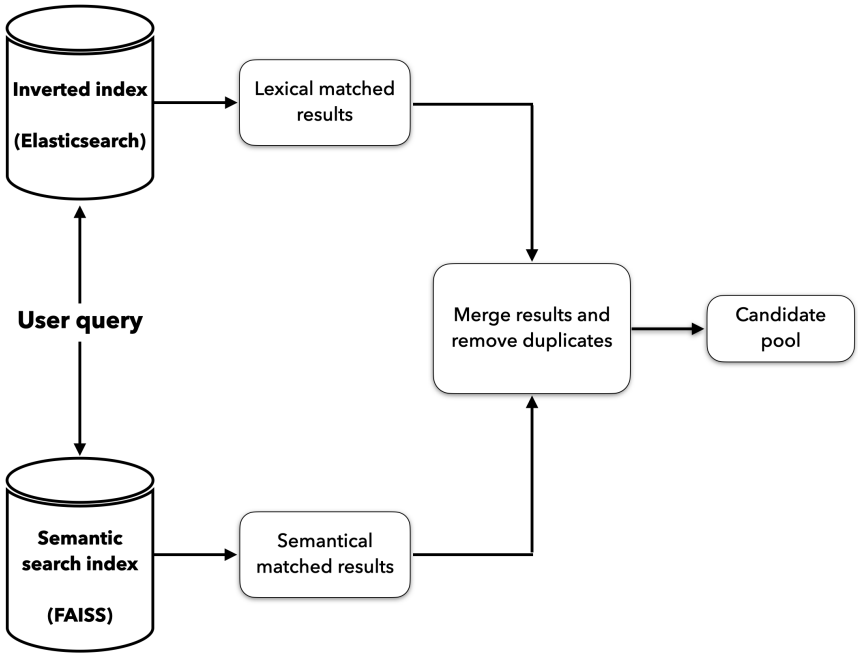


Figure 5.2: Steps to generate a diverse candidate document pool

It is assumed that the top retrieved documents are relevant to the query and the user, and thus, these retrieved documents are used for sub-topic extraction. This assumption can lead to poor sub-topics when the retrieved documents are entirely not related to the query, especially in the case of semantic matching. In lexical matching, the retrieved documents contain the query keywords and ensure that the documents are at least partially relevant. However, only cosine similarity is used as the selection criteria in semantic matching. For example, to create a candidate pool of 30 (CP-30), the top-15 documents from lexical matching results and the top-15 documents from semantic matching results are combined. There is a clear possibility that the

top semantically matched results are not entirely related to the user-given query. Consequently, the cosine similarity of these top semantically matched results needs to be evaluated before creating the candidate pool.

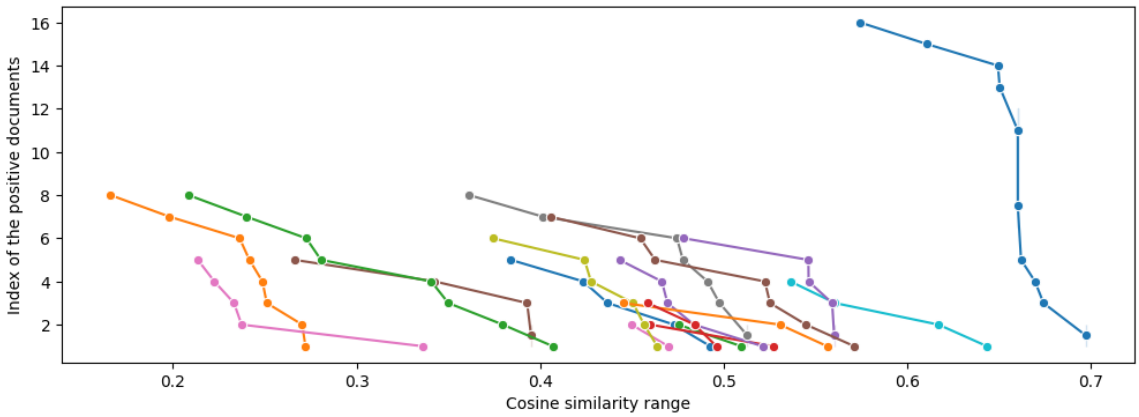


Figure 5.3: Cosine similarity between the query and retrieved documents

The cosine similarities between the query and retrieved documents are observed to perform this analysis. In retrieved documents, only relevant documents and the document which has the highest cosine similarity are considered. In Figure 5.3, each query is shown in a unique colored plot, and it is clear that the spread of cosine similarity differs from query to query. Queries have high cosine similarities with the retrieved results ranging at 0.5, and some queries even at a range up to 0.7. On the other hand, there are some queries with a cosine similarity range below 0.3. Considering the maximum cosine similarity in the retrieved documents (CS_{max}) as the reference, an appropriate lower similarity threshold (CS_{min}) needs to be determined. So that only an optimal set of retrieved documents are selected for the candidate pool. This information is represented in the below equation with the help of a cut-off parameter cp.

$$CS_{\text{min}} = (cp * CS_{\text{max}})$$

From the above equation, the value of cp can be determined in multiple ways. One approach tested in this master thesis is the average min-max similarity ratio. The ratio is calculated from the mean of the minimum to maximum cosine similarities over multiple queries. Let us consider the maximum cosine similarity in the retrieved results set of query q is max_{q}, and the minimum cosine similarity of the relevant document is min_{q}. Now the approximation of the value cp over N queries is described as:

$$cp = (\sum_{q=1}^{N} min_{\text{q}}/max_{\text{q}})/N$$

Applying the above approximation to the data from Figure 5.3 resulted in the value of cp as 0.78. However, a slightly lower value of 0.75 is chosen at the end, as there is an expected human bias during data labeling. This approximation can even be modified further by a multiplying factor according to the human bias in the dataset. This optimal threshold selection is designed to prevent selecting irrelevant documents for a given user query. This selection technique can be used in any semantic matching retrieval method.

Algorithm 1: Algorithm to retrieve semantically similar documents with optimal selection

Input: query - string, pool_size - integer

Output: top_docs_semantic - list $[top\_docs\_semantic\_i]$, $i = 1, 2, \cdots, n$, where each element is a string

```
Function Get_semantic_matching_results(query, pool_size):

    MIN_THRESHOLD_SEMANTIC = 0.27
    CP = 0.75

    /* top_docs_semantic_search - contains semantically similar documents,
       doc_sim_list - contains respective cosine similarity score          */
    top_docs_semantic_search, doc_sim_list = get_semantic_search_results (query,
     pool_size)

    max_cosine_sim = max (doc_sim_list)
    min_cosine_sim = min (doc_sim_list)
    max_diff_cosine_sim = get_max_diff_sim (doc_sim_list)

    /* Optimal cutoff similarity selection from three individual cutoffs   */
    final_cutoff_sim = min (MIN_THRESHOLD_SEMANTIC, (CP * max_cosine_sim),
     max_diff_cosine_sim)

    top_docs_semantic = []
    for idx ← 0 to pool_size do

        doc = top_docs_semantic_search[idx]
        sim = doc_sim_list[idx]
        // Selecting documents that have high cosine similarty than the optimal
           cutoff similarity.
        if sim > final_cutoff_sim then
            top_document_semantic.append(doc)

    if len (top_docs_semantic) < 10 then
        /* Selecting only top 10 in case of poor similarity distribution between
           the query and documents                                          */
        top_docs_semantic = top_docs_semantic_search[:10]

    return top_docs_semantic
```

Furthermore, it is also observed that only some queries to document similarities are highly abnormal. For example, cosine similarity distributions below 0.3 are in Figure 5.3. An optimal candidate pool selection approach is proposed to handle these exceptional cases. This proposed selection technique extends the existing threshold by two more considerations. These two criteria are chosen in case of an unexpected or poor query to document distributions. One criterion is to have some fixed threshold for cosine similarity, and the other is to capture the max difference in cosine similarity between the top two similar documents. Algorithms 1 and 2 detail these criteria clearly. In case of no results at the end of the selection, the top 10 semantically matched documents are selected. After the successful selection of documents from the semantic matching, the documents from lexical matching are combined, and duplicates are

removed. Without any redundancy, this final set of documents is referred to as the candidate pool.

Algorithm 2: Algorithm to calculate similarity at the maximum difference

Input: sim_list - list $[sim\_list\_i]$, $i = 1, 2, \cdots, n$, where each element is a float
Output: max_diff_sim - float

```
Function Get_max_diff_sim(sim_list):

    diff_list = []
    sim_list_len = len(sim_list)

    for idx ← 1 to sim_list_len do
        // store the difference in similarities at recurrent indices.
        diff_list.append(sim_list [idx] - sim_list [idx - 1])

    max_diff = max(diff_list)
    // Get the index where the similarity difference is maximum.
    max_diff_index = diff_list.index(max_diff)

    max_diff_sim = sim_list[max_diff_index]

    return max_diff_sim
```

5.3 Candidate keyword selection

This section details the steps involved in selecting specific keywords and their criteria involved in selection. The main objective of this stage is to choose very diverse noun chunks from each text document. Candidate selection is the most crucial step in the whole pipeline, and the quality of the clustering output is directly dependent on the outcome of this step.

5.3.1 Noun chunk extraction

News articles are very long text documents, and most of the crucial information in a document lies in nouns. A noun is one of the parts of speech element which identifies a person, place, or thing, and a noun-chunk is a noun that is a phrase (group of words). To extract the noun chunks automatically from each document, a library named spacy[1] is used. The noun-chunks from spacy are closely analyzed, and some inconsistencies are identified that need further cleaning. A unique pipeline to clean these noun chunks is proposed to target the noise elements: *stopwords, punctuation, determiners, duplicates, and long noun chunks*.

- **Remove longer Noun-chunks:** It is observed in the output of spacy noun chunks that there are some longer noun phrases of length more than three words and mostly consist of no significant information. Consequently, these noun chunks are removed from the spacy output. For example, *"standort- und zeitunabhängigen Zusammenarbeit"*, *"Every successive cellular generation"*. There might be useful information in these long noun phrases, but extracting that information is very challenging. The ratio of occurrences of these phrases is

[1] https://spacy.io/

relatively smaller than phrases with a length below 3. Therefore, these long noun phrases are filtered from the noun chunks set.

- **Remove stopwords:** Stopwords are words that carry no significant information and thus are omitted from the noun chunks. There is no universal set of stopwords in any language, and also, there are numerous types of stopwords observed in news articles in both English and German languages. Therefore, a robust set of stopwords from various sources[2] is collected in both languages. Stopwords can appear either as a complete noun chunk or as a part of a noun chunk and are removed in any case. Stopwords generally consist of determiners, adjectives, articles, prepositions, etc.

- **Remove numeric noun-chunks:** Some noun chunks have numeric values which contain no useful information, and furthermore, it is observed that the complete noun-chunk does not convey have any significance either. Thus the numeric noun chunks are removed from the noun-chunks set. For example: *"mehr als 50 Ländern"*, *"1,95 m Länge"*, *"1,5 Milliarden"* etc,. However, the noun chunks where the numeric value is attached to an alphabet are ignored, i.e., *"4G Technology"*, *"2D-Zeichnungen,"* etc.

- **Remove punctuation:** This step is designed to remove all sorts of punctuation elements and keep the noun chunks clean and more readable to the user. For example, the original noun chunk *"Bündnis- und Landesverteidigung"* is transformed to *"Bündnis Landesverteidigung"* after removing the hyphen (-) and stopword (und).

- **Lemmatization:** To lemmatize the noun chunks spacy module is used again. Both the English and German noun chunks are lemmatized using spacy. For example: *"Ansätze"* is lemmatized to *"Ansatz"*.

- **Fuzzy redundancy removal:** It is observed that there are a lot of noun chunks that are syntactically similar to each other. These similar noun chunks can be categorized into two types, namely exact duplicates and close duplicates. Exact duplicate noun-chunks can be easily filtered in Python, but identifying the close duplicates and filtering is a challenge. For example, the noun chunks *"5G network"* and *" 5G 4G network"*. Only one of the noun-chunk that is longer is retained, and the other is removed. Algorithm 3 details the steps used to achieve the cleaned noun chunks. The main objective of this step is to reduce the similar phrases and increase diversity in the data. This can lead to a loss of information to a certain extent. Accordingly, a fuzzy string matching-based noun chunk removal approach is designed to tackle the above problem, and close duplicates are removed to a certain extent using the FuzzyWuzzy library.

[2] `https://gist.github.com/sebleier/554280`, `https://countwordsfree.com/stopwords`, `https://solariz.de/de/downloads/6/german-enhanced-stopwords.htm`

Algorithm 3: Algorithm to remove close duplicates

Input: noun_chunk_list - list $[noun\_chunk\_list\_i]$, $i = 1, 2, \cdots, n$, where each element is a string

Output: cleaned_noun_chunk_list - list $[cleaned\_noun\_chunk\_list\_i]$, $i = 1, 2, \cdots, n$, where each element is a string

```
Function Remove_close_duplicates(noun_chunk_list):

    // Removing exact duplicates using set in python
    noun_chunk_list = list(set(noun_chunk_list))

    close_duplicates = []
    noun_chunk_list_len = len(noun_chunk_list)

    for i ← 1 to noun_chunk_list_len do
        phrase_1 = noun_chunk_list [i]

        for j ← i + 1 to noun_chunk_list_len do
            phrase_2 = noun_chunk_list [j]

            // fuzzy gives the syntactical text similarity score
            if fuzzy (phrase_1, phrase_2) > 85 then
                // When the score is high, the smaller phrase is recorded
                close_duplicates.append(get_shorter_text(phrase_1, phrase_2))

    // Removing the close duplicates using recorded close_duplicates
    cleaned_noun_chunk_list = list(set(noun_chunk_list) - set(close_duplicates))

    return cleaned_noun_chunk_list
```

5.3.2 Keyword extraction (KE)

The cleaned noun chunks describe a text document very well. However, not all noun-chunks are of great significance in representing a document, especially in the case of a news article. As the length of the news article is large, the size of extracted noun-chunks set can also be large. This large set of noun chunks is well-processed syntactically. It needs to be processed now semantically to select only noun chunks that can significantly influence the meaning of a text document (a news article). These crucial noun chunks in a text document are referred to as Keywords. In [9], authors describe keyword extraction as automatically identifying the terms that best represent the most relevant information in the document.

Keyword extraction techniques are majorly classified into either unsupervised or supervised approaches[11].Supervised KE approaches require many labeled datasets of both documents and keywords from each document. Annotating keywords manually from each document is a very expensive and tedious task [9], depending on the length of the documents.On the other hand, unsupervised approaches do not require any labeled information but often have poor accuracy[11].

In this master thesis, an approach to select keywords based on contextual embeddings is chosen. This approach is inspired by the recent research related to using contextualized sentence embeddings for keyphrase extraction, namely EmbedRank [11]. In this research, it is shown that the EmbedRank approach has performed better than the state-of-the-art graph-based KE approaches. The cleaned noun chunks generated from the earlier stage are used to generate keywords. To generate phrase embeddings of the noun chunks and the original news article, a multi-lingual pre-trained Universal Sentence Encoder (USE) from TensorFlow is used. USE used in the thesis is a transformer-based architecture that can embed text input from sixteen different languages into a single semantic space [80]. The target languages in our dataset, namely English and German, are included.

Transformer architectures compute context-aware embeddings of tokens in a sentence considering the order and identity of the tokens, and these token-level representations are further averaged to calculate sentence embeddings. There is a possibility that sentence-level embeddings as a means of token embedding can result in poor representations of long text documents. It is observed in the news articles that the length of the text documents is longer, and different contexts are discussed in different paragraphs. Therefore, a document is divided into multiple paragraphs, and the mean of all paragraph embeddings is considered as a *Document representation vector*. A paragraph length of 500 tokens is considered in this approach. For example, a text document with a token length of 1600 is divided into four paragraphs of length 500, 500, 500, 100, and the final representation vector is the mean representation vector of these paragraph vectors. The best possible parameter for the paragraph length is not explicitly tested in this master thesis and can be considered as future work.

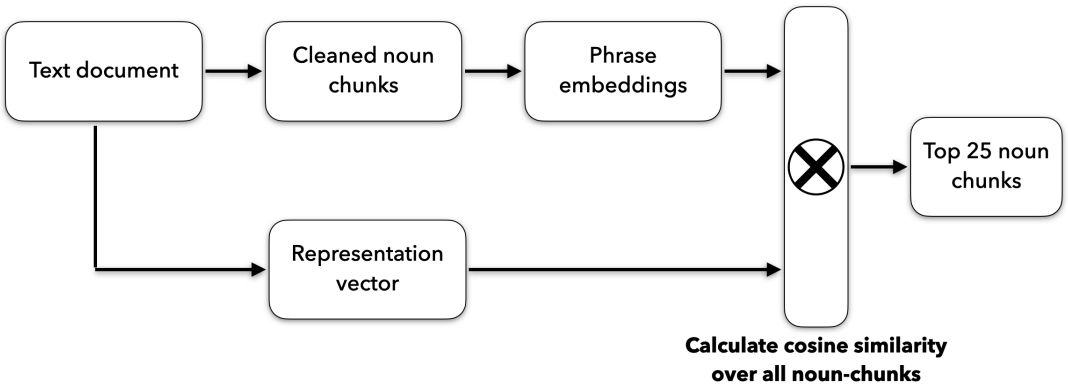


Figure 5.4: Automatic keyword extraction using phrase embeddings

Phrase embeddings for each cleaned noun-chunks are computed using the same USE model. With the help of noun-chunk embeddings and the document representation vector, the relevance of a noun-chunk in a document is expressed as the cosine similarity between the vectors in the semantic space. The higher the similarity, the better the relevance of the noun chunk in a document. Consequently, all noun chunks are ranked according to their similarity of relevance with the document. Top-25 noun chunks with the highest relevance similarity are considered *Keywords*. The pipeline to extract these keywords is shown in Figure 5.4.

5.3.3 Candidate keyword selection

Keywords extracted from a document from the earlier stage are syntactically diverse as they are derived from the noun chunks generated by removing the close duplicates. Let us consider

the case of using these keywords to distinguish documents in an IR setup where the user provides a search query and expects relevant documents. Given the user query and the retrieved candidate pool, a preliminary manual analysis has shown that there are certain keywords that are not similar to the user query and carry a significant value in improving the information search behavior. Therefore, the task of removing the query-related keywords and retaining the highly distinctive keywords is referred to as *Candidate keyword selection*.

Let us consider a text corpus C that contains n documents where each document D is a news article. These documents are saved inside two indices, namely inverted index and semantic search indices, to retrieve documents for a given search query.

$$C = \{D_1, D_2, D_3, \ldots, D_n\}$$

Once the user provides the IR system a search query q and a candidate pool CP of size m is generated, which is a document set.

$$CP_q = \{D_i, D_j, D_k, \ldots\}$$

Taking one document D_i into account, a keywords (k) set is extracted using the above steps, namely noun-chunk and automatic keyword extraction. A news article is now transformed to a group of key phrases that can be expressed below.

$$D_i = \{k_1, k_2, k_3, \ldots\}$$

The objective of this step is to select certain keywords that are similar to the query efficiently. This similarity selection must also consider the close semantic and multi-lingual nature of the keywords. Accordingly, cosine similarity is considered, and the multi-lingual USE model is used to encode the query and the keywords into semantic embeddings. The similarity between the query and document keywords is a function of distance in semantic space. The keywords with high cosine similarity must be selected to have highly diverse keywords to the query. A parameter, namely Candidate keyword selection cks, is proposed to remove the query similar keywords.

The selection parameter must consider the distribution of similarity between query and keywords in a document. Moreover, it should be independent of a document. A percentile selection is adopted as a selection criterion in order to avoid a static similarity threshold. For example, the parameter cks takes the value 30, which signifies that the keywords with similarity under the similarity of 30 percentile are retained, and the keywords above the 30 percentile are removed. To the best of my knowledge, the testing of this selective approach to improve clustering and IR performance is one of the earliest attempts in IR system research. Further criteria and parameters for better keyword selection other than query similarity shall be explored.

5.4 Clustering

Candidate keywords from each document in the candidate pool are combined, and duplicates are removed to create a final set of candidate keywords. These keywords are further clustered using the HDBSCAN algorithm to generate distinctive sub-topics. This stage has three main steps, namely *Phrase embeddings extraction, Dimensionality reduction, and Hierarchical clustering*. To achieve semantic clustering, multi-lingual pre-trained sentence encoders are used to generate phrase embeddings for each candidate keyword. These densely distributed embeddings are usually highly dimensional (512), and clustering in high dimension space is complex to capture patterns and can be resource intensive. Therefore, the embeddings are compressed with the help of a dimensionality reduction technique, namely UMAP. The dimensionality of the embeddings is reduced without losing underlying information in the data using the UMAP algorithm [49] from the umap-learn library.

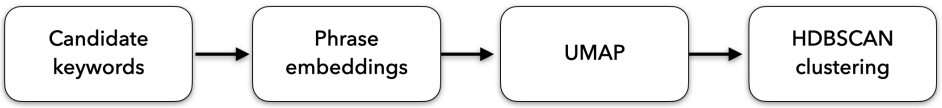


Figure 5.5: Clustering to generate sub-topics

These embeddings are further clustered in low dimensions using a hierarchical clustering algorithm. Noise is expected in the candidate keyword extraction phrase, and all the keywords are not crucial for modeling. So, clustering algorithms such as k-means, Gaussian Mixture Models are not suggested in this case, as they assign all data points to a cluster during clustering. Furthermore, these algorithms follow a particular cluster shape, either spherical or elliptical. Consequently, HDBSCAN and DBSCAN clustering algorithms are preferred as they innately consider the noise in the data and avoid assigning a cluster for every data point. One significant advantage of these algorithms is that the number of clusters is not a parameter, and the algorithm creates clusters effectively based on the data. HDBSCAN algorithm [48] with its varying epsilon and merging clusters, it has shown robust clustering results by finding varying density clusters. The same algorithm is considered in this master thesis. Figure 5.5 presents steps taken to perform clustering after extracting the candidate keywords. This clustering pipeline is already tested and shown excellent results with documents in recent research [6]. However, in this approach, keywords are clustered rather than the documents, and later the keywords and documents are connected using the clusters.

5.5 Sub-topic creation

5.5.1 Sub-topic labeling

After clustering, sub-topics are extracted using a centroid approach. A mean phrase vector (centroid vector) is calculated from all the keywords inside a cluster, and the closest keyword vector to the centroid vector is considered a cluster label. This process is named *Cluster labeling*, and the cluster labels are considered sub-topics. After clustering, the individual clusters are considered sub-topics. Sub-topics and documents inside a sub-topic can be further ranked before showing to the user. The pipeline ends with this last component, *Sub-topic creation*.

Thereafter the keyword set M_q is clustered into r groups (s) and is defined as a sub-topic set S_q.

$$S_q = \{s_i, s_j, s_k, \ldots, s_r\}$$

Each sub-topic (s) is again expressed as a set of keywords (k). The number of keywords in a sub-topic cluster can vary from cluster to cluster.

$$s_i = \{k_x, k_y, k_z, \ldots\}$$

The mapping between the document and keywords is already known from above. Now, we can express each document as a set of sub-topics, and each sub-topic is described as a set of documents.

$$D = \{s_i, s_j, s_k, \ldots\}$$
$$s_i = \{D_x, D_y, D_z, \ldots\}$$

Chapter 6

Experiment setup

6.1 System specifications

The experiment is carried out in two different systems according to the time taken to execute specific tasks. All the code development, exploratory analysis, and statistical testing are performed on an HP ELITEBOOK system with an AMD Ryzen 5 PRO 4650U processor, 16 GB of RAM, and 500 GB of disk space. Web scraping, IR system hosting, data storage, clustering, and further benchmark testing are performed on a large virtual machine (VM) hosted at Fraunhofer FKIE. The technical specifications of the VM are four processors CPU (Intel(R) Xeon(R) Gold 6136 CPU @ 3.00GHz), 48 GB RAM, and 370 GB disk space.

6.2 Testset description

For two main reasons, a dataset specific to this research problem is hard to find in the current IR data repositories. Foremost, the search query needs to be a phrase rather than a sentence. Furthermore, the documents need to be labeled with a specific intention rather than just coherence with the query. The interest at Fraunhofer FKIE is to retrieve the documents related to "Innovation and Technology", and a new testset is collected for this purpose. Below are a few specific areas of interest in news articles that describe the user intention: *Innovation, Technology breakthroughs, Future products, Applied research, New procurement strategies, and Artificial Intelligence*. These topics are also described as positive document characteristics because a document is considered positive when it is strongly related to any of the abovementioned characteristics.

The strategy for the testset collection is to consider documents from lexical and semantic matching. The results from both algorithms help find the diverse contexts related to the user query. Therefore, a candidate pool with a maximum length of 30 documents is considered. Fifteen lexical and semantic matching documents are combined into a merged set where duplicate documents are removed. Relevance labeling is assigning an appropriate label to the retrieval results inside the candidate pool. Every labeler has to assign a label coherent to the query and consider the FKIE user's intention, i.e., coherence with the positive document characteristics mentioned above. Once the labeler gives a particular label to a document, labeled information is stored in an SQLite DB.

Table 6.1: Relevance labels definition and document distribution

Label-id	Label name	Document count	Label definition
1	Perfect	78	A document that strongly matches one of the positive document characteristics.
2	Partially relevant	147	A document that contains keywords and seems to be relevant, but still lacks innovation or novelty.
3	Irrelevant	306	A document containing the given user keyword still lacks innovation and coherent discussion about the query. Eg: click-baits, advertisements, etc,.
4	Wrong	98	These are false documents and have nothing to do with the user query.

A total of 22 queries are labeled from 5 different labelers. After analyzing the label distribution of the queries, it is observed that the perfect and partially relevant document distributions are very low compared to the other labels, shown in Table 6.1 on page 45. Five queries are removed from this testset due to either no perfect documents or very low perfect and partially relevant documents. The rest of the 17 queries are considered for evaluation. Below table Table 6.2 on page 45 shows the queries and respective label details.

Table 6.2: Testset queries used for the evaluation

S No.	Query	Perfect	Partially relevant	Irrelevant	Wrong
1	Architekturanalyse	4	6	15	4
2	Big Data, KI für Analyse	7	11	10	2
3	Edge computing	1	5	11	11
4	IT-Standards	1	7	9	11
5	Kommunikationsnetze	4	5	18	1
6	Methode Architektur	4	8	15	2
7	Militärische Kommunikation	7	5	18	0
8	Mixed Reality	5	10	8	6
9	Quantentechnologie	3	4	16	1
10	Robotik	15	8	6	0
11	Satellitenkommunikation	2	6	21	1
12	Schutz von unbemannten Systemen	7	11	12	0
13	Visualisierung	5	4	10	11
14	Waffen Systeme	6	15	8	0
15	Wellenformen und -ausbreitung	4	13	8	5
16	militärische Entscheidungsfindung	1	6	20	3
17	unbemannte Landsysteme	2	10	1	17

6.3 Preprocessing

As described in section 2.3, the IR system setup consists of web scraping of news articles, filtering articles not related to technology and the military, and storing the articles in two different document indices to facilitate information retrieval. Sub-topic modeling works on this IR setup to extract a candidate pool and to select candidate keywords which are very crucial steps to generate good diverse sub-topics. In both steps, a USE model is used to encode the documents and keywords to distributed semantic embeddings.

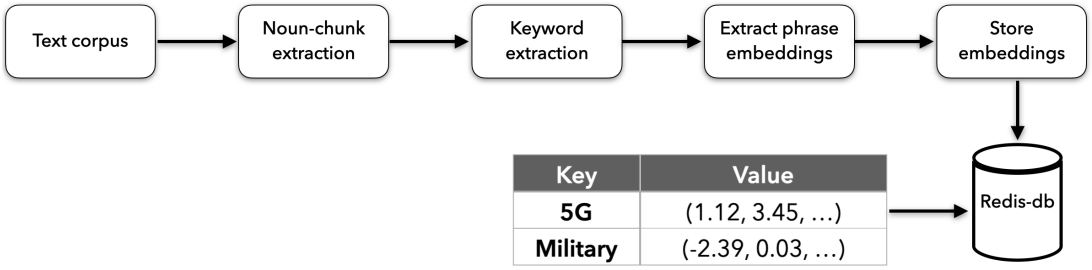


Figure 6.1: Preprocessing pipeline for efficient sub-topic modeling

It is observed in the manual analysis of sub-topic modeling that the time taken for encoding a text using a USE model is high. Due to this high encoding time, users shall wait for a while to get the response from the IR system. In order to overcome this, a cache system is developed to store the embeddings from the USE model in a Redis-DB. Figure 6.1 shows the pipeline to improve the time the sub-topic modeling takes to perform clustering.

6.4 Clustering evaluation

The main objective of this evaluation is to find parameters of the sub-topic modeling that create clusters which best represent the candidate pool and also heterogeneous (diverse). Due to the lack of cluster labels for the query in the testset, an alternative approach is adopted to evaluate the quality of clusters generated.

6.4.1 Intrinsic evaluation:

In case of no labeled data, the clustering output is generally evaluated using an intrinsic evaluation approach. Silhouette index is a metric used for evaluating the clustering performance and is calculated by using the intra-cluster and inter-cluster distances for each sample [66, 69]. Let us consider the testset T as a set of data points where each data point is denoted as x_i.

$$T = \{x_1, x_2, x_2, \dots\}$$

The testset T is clustered using a clustering algorithm resulting the data points segregated into groups. Let us consider the cluster set C where each cluster is denoted as c_i.

$$C = \{c_1, c_2, c_2, \dots\}$$

The silhouette index $s(x_i)$ for a data point x_i which is an element of cluster c_k is expressed as below.

$$s(x_i) = \frac{b(x_i) - a(x_i)}{max(b(x_i), a(x_i))}$$

$a(x_i)$ is the mean distance between the data point x_i and all other data points inside the cluster c_k. $b(x_i)$ is the mean distance between the data point x_i and all other data points in the nearest cluster c_l [69]. $a(x_i)$ and $b(x_i)$ represent the intra and inter cluster distances respectively. The silhouette score $s(x_i)$ is calculated over all the data points in the testset and the final mean is considered as the silhouette score S of the clustering. Silhouette score ranges from -1 to 1 and higher the score represents better clustering performance.

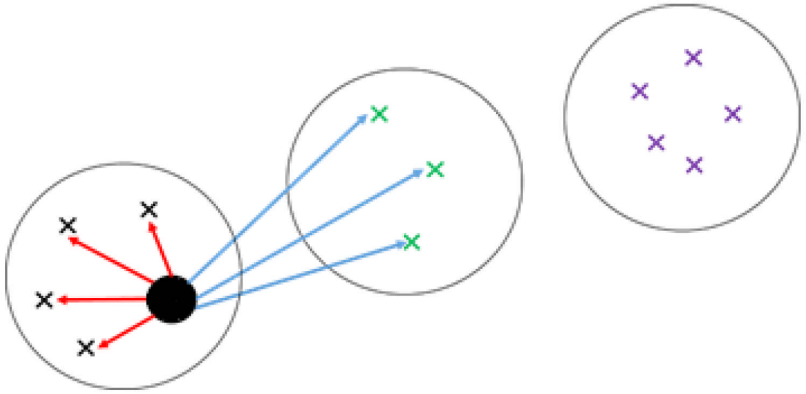


Figure 6.2: Visualization of silhouette index calculation [69].

Silhouette index formula is represented for the data point x_i (highlighted in dark) in the figure Figure 6.2 where red lines represent the intra-cluster distances $a(x_i)$ and the blue lines represent the inter-cluster distances to the nearest cluster$b(x_i)$. In the best case scenario, the value of $a(x_i)$ is very low in comparison to the value $b(x_i)$ which leads to very well-formed clusters. Therefore, the goal of achieving heterogeneous can be measured using the silhouette score.

6.4.2 Extrinsic evaluation:

To evaluate the quality of clustering with the help of document labels in the testset, a custom target function F is designed. Target function F tests the quality of clusters against the relevance labels from the dataset. The objective is to test whether the relevant documents are clustered into a similar cluster and the same case with irrelevant documents. Without any relation between clustering and relevance labeling, it can not be assumed that the positive and negative documents are clustered automatically because they cover a wide range of keywords in different domains. Therefore, it is more meaningful to evaluate the clustering for negative documents, i.e., Irrelevant and Wrong labeled documents. A target function is designed to address the number of negative documents isolated through sub-topic modeling.

The sub-topic modeling pipeline's output is distinctive clusters with a unique context, independent of relevance to user intention. However, the clusters can be divided into relevant and irrelevant clusters according to the relevance labels in the dataset. Let us consider that N_1, N_2, N_3, N_4 represent functions to get the number of documents in a single cluster with label-ids $1, 2, 3, 4$ respectively, as shown in Table 6.1 on page 45, and C represents the cluster set.

$$C = \{c_1, c_2, c_2, \dots\}$$

Relevant clusters C_r are clusters, that contain at least one document with label-id 1 or documents with majority of label-id 2. This can be determined using the below expression.

$$C_r = \{c_i \in C | (N_1(c_i) > 0) \vee (2 * N_2(c_i) >= (N_3(c_i) + N_4(c_i)))\}$$

With this expression, relevant clusters are differentiated from others and the focus is only on labels 1 and 2. The clusters that do not satisfy the above condition are logically considered irrelevant clusters.

$$C_i = \{c_j \in C \setminus C_r\}$$

The target function assesses the clustering with a ratio of documents in irrelevant documents to the documents in the candidate pool CP_q to a given user query q. Given N queries, the target function maps the score using the below equation. The function F ranges from 0 to 100 and higher score represents better separation of negative documents from positive documents. Therefore, indirectly representing the diversity of clustering results.

$$F = \sum_{i=1}^{N} (|C_i|/|CP_i|) * 100$$

6.4.3 Objective function:

Both the target functions *Silhouette index* and F are used to tune the parameters of the sub-topic modeling pipeline. *Silhouette index* evaluates the clustering output and the custom target function F evaluates the distribution of relevant labels. In order to perform an automatic parameter selection, an objective function O is proposed, which takes the harmonic mean of silhouette and target function scores. As the scores are on different scales, both are normalized to a range [0-1] using min-max normalization. Therefore, the O ranges from [0-1], and the clustering parameters which generate a higher score are considered as the final sub-topic pipeline parameters. Table 6.3 on page 48 shows the parameters which will be tested during clustering evaluation.

$$O = \frac{(2*S*F)}{(S+F)}$$

6.4.4 Hyperparameter selection:

Three main components in the sub-topic modeling pipeline are candidate keyword selection, dimensionality reduction with UMAP, and clustering using HDBSCAN. Candidate keyword selection has only one parameter ranging from 10 to 100, signifying the percentile selection according to the query similarity. UMAP dimensionality reduction has many parameters, but only the output data's reduced dimensions are considered for parameter selection. The other parameters are taken after some preliminary tests. Two main parameters used in HDBSCAN clustering are minimum cluster size and minimum samples. Minimum cluster size is a very crucial parameter that determines the final cluster size of the clusters and is used by the HDBSCAN to merge clusters until the specified clustering size is achieved. Minimum samples signify the minimum number of neighbors to a core point. The larger the value of this parameter, the resulting clusters are dense, and also more data points are made noise points[58]. Table 6.3 on page 48 shows the parameters which will be tested during clustering evaluation.

Table 6.3: Parameters used in the pipeline for testing

S No.	Hyperparameters	Range
1	Candidate keyword selection parameter	[10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 90, 95, 100]
2	Reduced dimensions (UMAP)	[5, 10]
3	Min cluster size (HDBSCAN)	[20, 25, 30, 35, 40, 45, 50, 55, 60]
4	Min samples (HDBSCAN)	[1, 3, 5, 7, 10]

6.5 Survey evaluation

The sub-topics are assumed to help the user by retrieving the documents that are related to the query and sub-topics. This can be referred to as the assumption of user satisfaction. Precision analysis can evaluate this assumption when we have a dataset with two inputs rather than one input. Two inputs here denote the original query and an additional sub-topic. As Fraunhofer FKIE is keenly interested in specific topics of technology and the military and the user intention is also restricted to the innovation-related theme, a manual evaluation with the help of a survey is chosen.

Two IR systems, namely *System A* and *System B*, are designed to represent the documents during retrieval when a query and sub-topic are provided. This survey evaluates the performance of these two IR systems. Template queries are used to retrieve and rank the text documents semantically. A template *"Innovation in **Query** and **Sub-topic**"* is used in the retrieval. The "Query" and "Sub-topic" are used as placeholders in the template and are dynamically replaced by actual values the user gives. In addition to evaluating the system, the sub-topic modeling output is also tested by taking the user's feedback on sub-topics' quality. Below are the two IR systems developed and tested in the survey.

1. **System A** is an IR system that retrieves documents from the sub-topic cluster chosen by the user and re-ranks the retrieved documents using the template similarity. Cosine similarity is used as ranking function. Figure 6.3 shows the pipeline to extract documents extracted with system A.

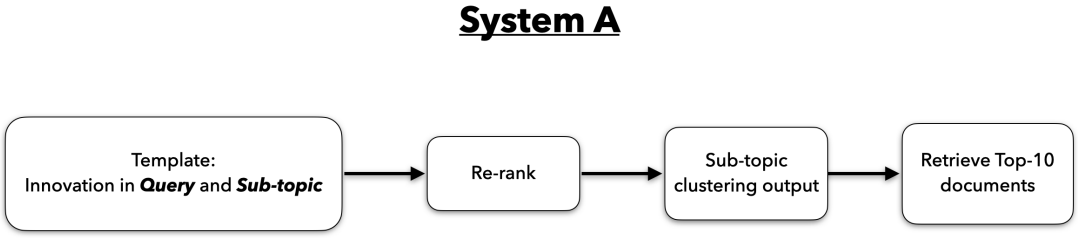


Figure 6.3: Steps to retrieve system A results

2. **System B** is an IR system that retrieves documents semantically using a new search query generated by the template. As the documents are retrieved semantically there is no need to re-rank the documents again. Figure 6.4 shows the pipeline to extract documents extracted with system B.

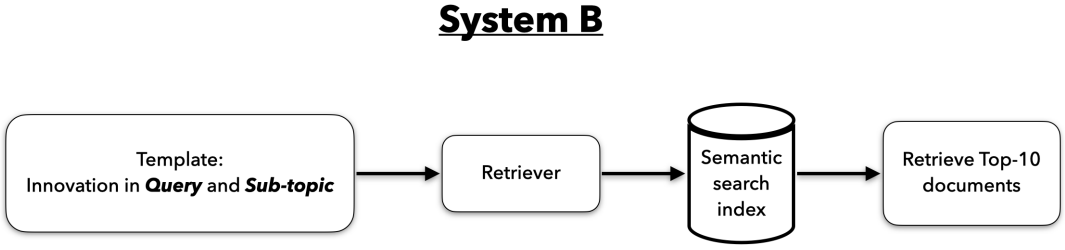


Figure 6.4: Steps to retrieve system B results

6.5.1 Survey questionnaire

A website is developed to conduct the survey and collect participant data. The feedback collected is stored in an SQLite DB. The participants of this survey are employees at Fraunhofer FKIE. The participants are invited through an email (not chosen by any particular means) and no personal user information is collected during the survey. Only a UUID is used to differentiate users when filling out the survey concurrently. The user interface is developed in Python, fastAPI, bootstrap, HTML, and javascript and deployed using docker on the VM.

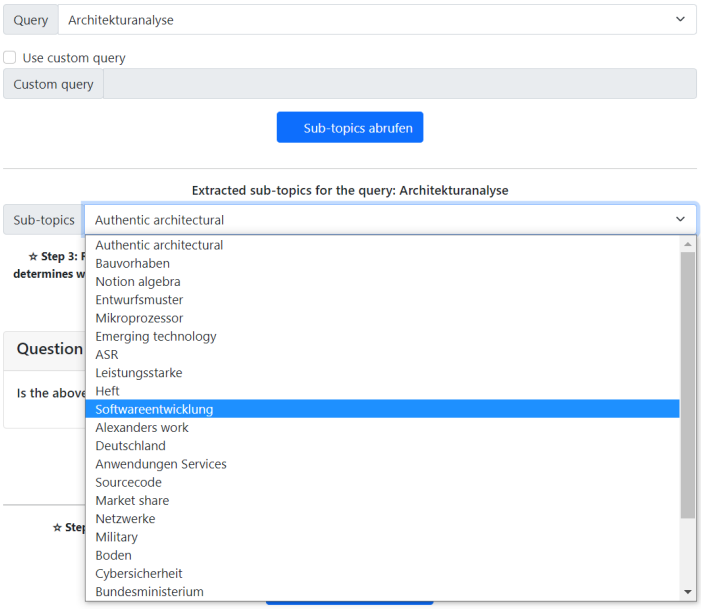


Figure 6.5: Extracted sub-topic list for a given user query

Five questions are developed to evaluate user satisfaction with the retrieved results and sub-topic modeling output. Survey participants are requested to provide a query from a drop-down list or an input text box. Subsequently, the sub-topics are retrieved during the runtime and displayed to the user as a list. Figure 6.5 shows the extracted sub-topic list for the query "Architekturanalyse". Participants are now asked to share feedback on the quality of this sub-topic list.

Following the feedback, participants are requested to select a sub-topic and retrieve documents relevant to the query and the sub-topic. Figure 6.6 shows the retrieved IR system results for the query "Architekturanalyse" and the sub-topic "Military". Once again, the participants are asked to share feedback on the system results by rating the systems quantitatively. Lastly, the participants are given an optional question regarding the significance of the whole sub-topic approach. The questionnaire used in the survey is briefly described below.

1. **Is the above sub-topic clustering output distinctive and well-labeled?**

   This question aims to evaluate the effectiveness of the methodology tested in the master thesis, i.e., well-formed heterogeneous clusters. Participants are requested to share feedback on the clustering output based on two characteristics, namely the distinctiveness and readability of the sub-topics. Distinctiveness describes the diversity of sub-topics, and readability depicts the ease of understanding the sub-topic by its name or label. Below are the options provided to the survey participants, and only one option must be selected.

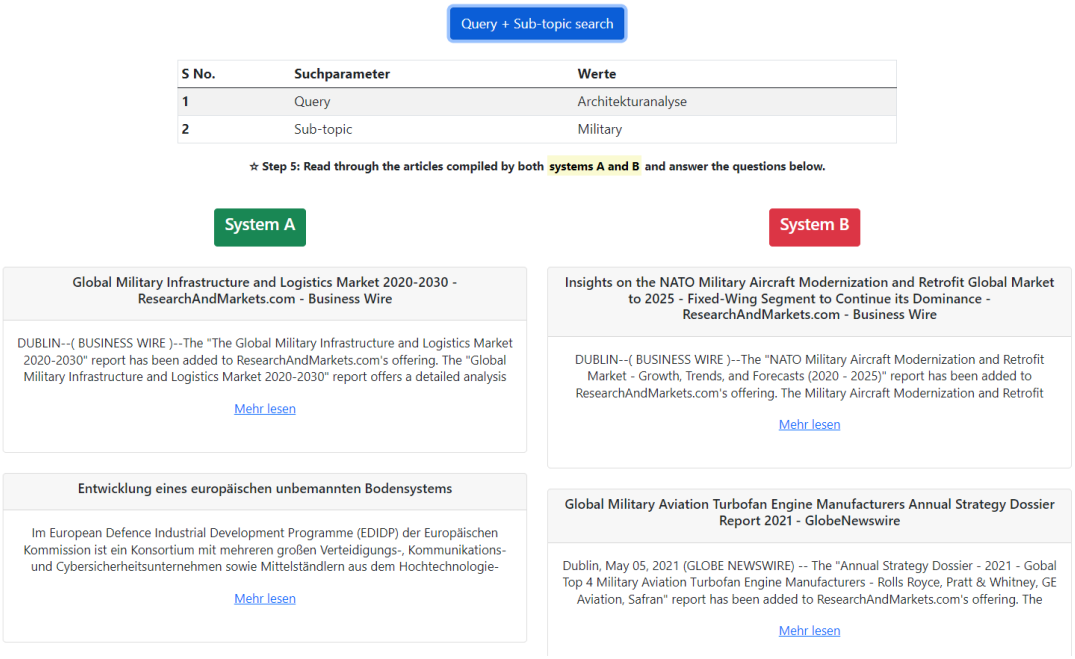


Figure 6.6: Extracted IR system results for a given user query and sub-topic

(a) Distinctive and well-labeled
(b) Distinctive and not well-labeled
(c) Not distinctive and well-labeled
(d) Not distinctive and not well-labeled

2. **Which system results better represent the relevant news articles according to the given query and sub-topic?**

   Relevant news articles are retrieved text documents that have positive document characteristics (mentioned in section 6.2). Participants are asked to read the retrieved results from IR systems A and B and then share the feedback accordingly. Below are the options provided to the survey participants, and only one option must be selected.

   (a) System A
   (b) System B
   (c) Neither System A nor System B

3. **Rate the retrieval system A results for the given query and sub-topic (0-10).**

   Participants are requested to share quantitative feedback by rating the system A results between 0 to 10. Ratings can take fractional values up to 1 decimal place. For example, a user can provide a 3.4 rating but not a 4.65. The user ratings directly signify the user satisfaction corresponding to the retrieved results.

4. **Rate the retrieval system B results for the given query and sub-topic (0-10).**

   Participants are requested to share a quantitative feedback by rating the system B results between 0 to 10.

5. **Were the sub-topics helpful for you to find the relevant documents?**

   This question aims to evaluate the usefulness of the sub-topic modeling in IR. This answers the practicality of using the proposed methodology in this master thesis in a real environment to find innovation-related documents. Participants are requested to provide a boolean response of either Yes or No corresponding to fulfilling their expectations.

   (a) Yes

   (b) No

6.6 Precision evaluation

Assuming that the cluster labels could be more helpful to the user, the next evaluation technique shows that the clustering output does not deteriorate the performance of the retrieval results. The clustering output is hard to examine with the baseline IR systems because the order of documents needs to be included, and the performance metrics related to false positives need to be addressed. For this purpose, we are extending the sub-topic creation with sub-topic ranking and document ranking. These two rankings help the existing pipeline to create a sequential order of documents and facilitate the evaluation of precision against the baselines. Therefore, this evaluation approach proposes eight different retrieval systems and evaluates the ranked results.

Table 6.4: Proposed IR systems for evaluation

IR system name	Sub-topic ranking	Document ranking
IR0	NA	Uniform distribution
IR1	NA	Query similarity
IR2	Query similarity	Query similarity
IR3	Template similarity	Template similarity
IR4	Document cardinality	Query similarity
IR5	(IR4, IR2)	Query similarity
IR6	(IR4, IR2, IR3)	Query similarity
IR7	Random combinations	Query similarity

The first system, *IR0*, is an arbitrary system where the positive documents are distributed uniformly on the ranking order. *IR1* system is simple query re-ranked results based on cosine similarity between the query and documents. The systems *IR2, IR3, IR4* are results of sub-topic pipeline clustering, where the clusters are first ranked, and later the documents are re-ranked with certain criteria. These three systems simulate the user reading the results linearly or in a sequence. In *IR2*, the sub-topic clusters are ranked by the cosine similarity between the query and centroid vector of the cluster and similarly for document ranking.

The system *IR3* uses a template similarity criteria, where the similarity is calculated between a template and centroid vector rather than the query. For example, the template string can be "Innovation and Technology". In the same way, *IR4* clusters are ranked using the number of documents in the cluster. The last system, *IR7*, is an unreal system just like the *IR0*, but multiple combinations of random ranking of clusters are considered to simulate the random selection of a sub-topic by the user and reading the documents in different sub-topics.

6.6.1 Combinational IR systems

The systems *IR5* and *IR6* are produced by combining sub-topic rankings of other IR systems. The sub-topics are combined in such a way that the top-ranking sub-topics are clustered together. This approach adopts the benefits of two ranking criteria into a ranking. As a part of the exploratory analysis, the potential of sub-topic ranking is explored with these combinations. Algorithm 4 details the steps to generate a unique combined ranking output in case of two individual rankings.

Algorithm 4: Algorithm to genreate combinational IR system

Input: ranking_lists - list $[ranking\_lists\_i]$, $i = 1, 2, \cdots, n$, where each element is an individual ranking list

Output: combined_ranking_list - list $[combined\_ranking\_list\_i]$, $i = 1, 2, \cdots, n$, where each element is a string

```
Function Combine_individual_ranking(ranking_list):

    combined_ranking_list = []
    ranking_list_1 = ranking_list[0]
    ranking_list_2 = ranking_list[1]
    ranking_list_len = len(ranking_list_1)

    for i ← 1 to ranking_list_len do
        // rank_1 and rank_2 signifies the ranking id of the sub-topics
        rank_1 = ranking_list_1 [i]
        rank_2 = ranking_list_2 [i]

        // Append only if the rank id is not added to the combined ranking list
        if rank_1 not in combined_ranking_list then
            combined_ranking_list.append(rank_1))

        if rank_2 not in combined_ranking_list then
            combined_ranking_list.append(rank_2))


    return combined_ranking_list
```

The idea of ranking combinations is influenced from ensemble techniques in machine learning. Ensemble methods improve performance and create robust models by combining the strength from multiple weak-performing models[15]. This technique eliminates the individual model bias and consolidates the unique benefits of individual models. The output of combined IR systems pose the opportunity to test a unique ranking of sub-topics. This unique ranking of sub-topics creates a unique sequential order of documents. Following the Algorithm 4, an example of the combined ranking output, is presented in Table 6.5 on page 53.

Table 6.5: Combined IR5 system results

IR system	Sub-topic ranking type	Ranking list of sub-topics
IR4	Document cardinality	[4, 3, 1, 2, 0]
IR2	Query cardinality	[1, 3, 0, 4, 2]
IR5	(IR4, IR2)	[4, 1, 3, 0, 2]

6.6.2 IR systems evaluation

In [50], a new evaluation measure for IR systems named expectation score is introduced. The expectation score (E) is similar to Precision (P) but does not consider false positives. E_k represents the number of positive documents at the index k, whereas P_k represents the ratio of positive documents at the index k to k. Similarly, the mean expectation score (ME) is proposed to analyze the mean number of positive documents for N queries. This metric is especially useful to compare IR systems that retrieve relevant documents best at a given index k.

$$ME@k = (\sum_{i=1}^{N} E_i@k)/N$$

Furthermore, Mean Average Precision (MAP) [21] is used to evaluate the ranking performance. MAP is calculated through the Average Precision (AP) metric, which is an average of precision scores only at the positive document indices. Let us consider that G is a set of all positive document index with size g, the average precision and mean average precision is formulated as below. MAP is alone sufficient to compare different IR systems, and the system with the highest MAP value is considered the best IR system.

$$AP = (\sum_{i=1}^{G} P_i)/g$$

$$MAP = (\sum_{i=1}^{N} AP_i)/N$$

6.7 Evaluation summarization

The table Table 6.6 on page 54 shares the evaluation techniques chosen in this master thesis and the respective research questions answered.

Table 6.6: Proposed evaluation techniques

S No.	Evaluation type	Research questions addressed
1	Clustering analysis	**RQ1**
2	Survey Questionnaire	**RQ1, RQ2**
3	Precision analysis	**RQ3**

Chapter 7

Experiment results

7.1 Clustering results

As the testset contains 17 user queries and the clustering analysis is performed on each query, and the output is analyzed on the mean values of clustering output. Two candidate pools are generated for each query with sizes 30 and 100, respectively. The small candidate pool *CP-30*, and the large candidate pool *CP-100* represents the retrieved results of the original query from both syntactic and semantic matching. *CP-30* contains a maximum of 30 documents each document is labeled. *CP-100* contains around 100 documents, and only a few documents that are present in the testset are labeled. Therefore, more than half of the *CP-100* documents are unlabeled. The unlabeled documents are removed from the clustering output during the analysis, and only the labeled documents are used for evaluation. This assumes that the more documents present in the *CP-100* helps to provide better clusters compared to *CP-30*. This assumes that more documents in the *CP-100* help provide better clusters than in *CP-30*. Furthermore, it is expected to extract better sub-topics from the large collections to get deep insights into the data.

7.1.1 Clustering output analysis

Sub-topic modeling pipeline is tested on all the hyper-parameters of clustering that are mentioned in section 6.4.3. Ideally, there should be 1710 cases to test the clustering output for small and large candidate pools. However, few test cases have produced very low clustering (only one cluster) and are not to be considered in the parameter selection. Ultimately 1588 and 1009 possible hyper-parameter combinations are evaluated for large and small candidate pools, respectively. The clustering output consisting of the evaluation metrics is expressed as the mean overall 17 queries. Furthermore, the analysis is shared separately for the small and large candidate pools. In the below analysis, "silhouette score" denotes the intrinsic evaluation metric, and "targeted negative document ratio" signifies the extrinsic evaluation metric denoting the quality of separation between the relevant and irrelevant clusters.

HDBSCAN clustering does not need any parameter to specify the number of clusters created from the data. On the other hand, other parameters need to be well chosen to generate better clusters. Before evaluating the parameters which significantly affect the clustering output, the relation between the evaluation metrics and the number of clusters is analyzed. Figure 7.1

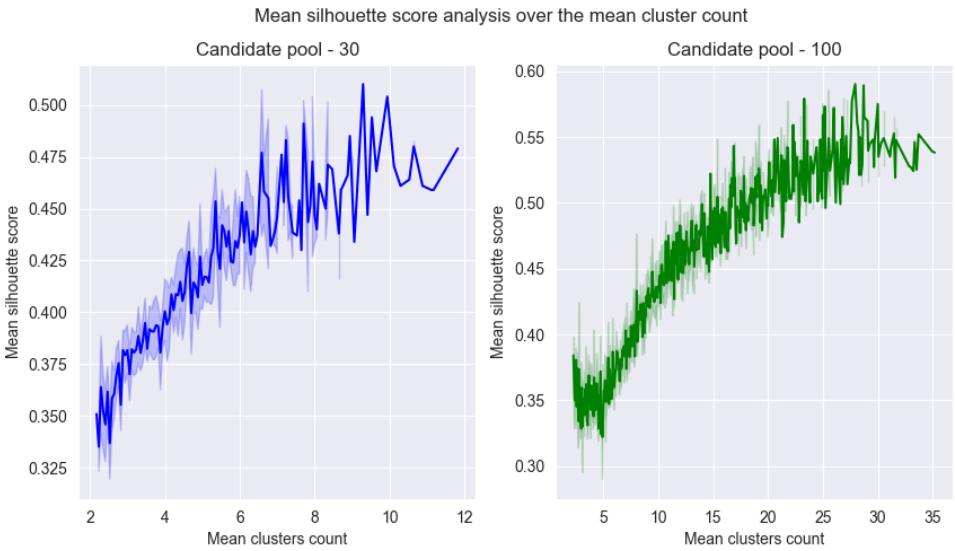


Figure 7.1: Silhouette score analysis over clusters count.

shows the relation between the silhouette score and the number of clusters. The data is generated when all the hyper-parameters possibilities of the clustering pipeline are tested over the testset queries.

The objective of this analysis is to observe whether the number of clusters has an impact on the silhouette score globally. This means the overall effect of cluster counts is not specific to a particular query or a hyper-parameter set. It is clear from Figure Figure 7.1 that a relatively high number of clusters are generating higher silhouette scores implying better cluster quality. However, many clusters in both small and large candidate pools (30 and 100) show lower silhouette scores than the highest value. This signifies that the high number of clusters can lead to many clusters with very few data points such that the quality of clustering is reduced, as the silhouette score is built on the intra- and inter-cluster distances. The possible better clustering can be achieved when the intra-cluster distance is minimum and inter-cluster distances are maximum. Therefore, a small number of clusters leads to overlapping clusters (very close) and is not a good choice for clustering parameter selection.

It is assumed to derive the heterogeneity or diversity of clusters from the cluster quality and to have a wide variety of clusters, the parameters which create a high number of clusters must be selected. One major drawback in this analysis is to combine all the clustering outputs for all 17 queries in the testset. Some queries generate a low number of clusters, and some generate a high number of clusters. Combining all queries into one analysis may mislead the analysis in some scenarios. As it is in the interest to observe the overall impact of the number of clusters, the analysis can be further considered for the parameter selection without any issue. Table 7.1 on page 56 on page 57 shows the Pearson correlation over all the hyperparameters tested, and there is a positive correlation between the cluster count and evaluation metrics chosen.

Table 7.1: Pearson correlation between the clustering observations

Parameter	CP-30	CP-100
Mean silhouette score and mean clusters count	0.71	0.89
Mean targeted negative document ratio and mean clusters count	0.76	0.94

Figure 7.2 shows the relationship between the targeted negative document score and the number of clusters. Similar to the silhouette score, a high cluster count positively correlates with the

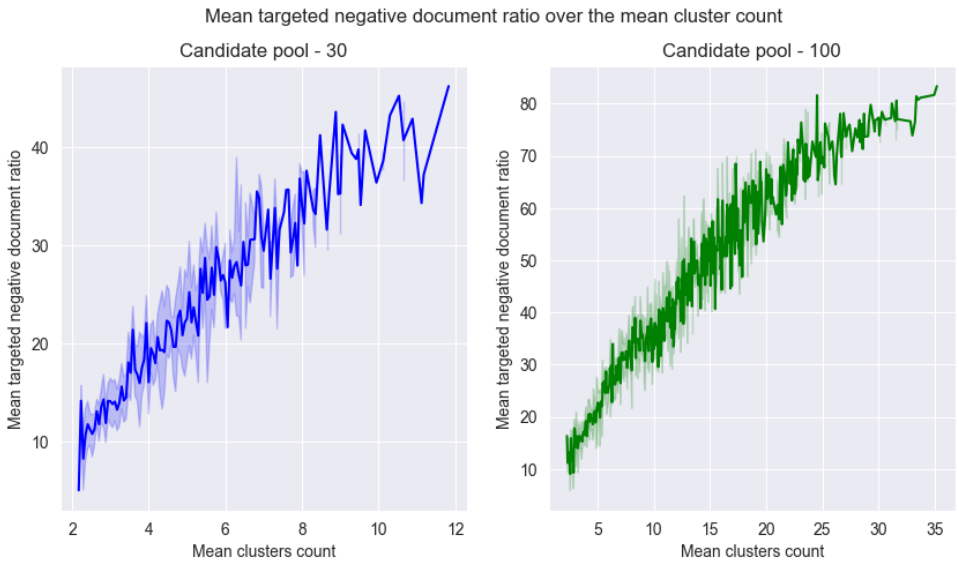


Figure 7.2: Targeted negative document ratio analysis over cluster count.

targeted document ratio. The design of this evaluation metric has a slight inclination to support the clustering output with a high cluster count, as it creates many clusters with low data points and leads to a greater separation between clusters. Consequently, fewer clusters signify poor cluster quality due to more inadequate separation between the documents. Therefore, this metric has to be relatively higher to create a diverse set of clusters with good separation. The large candidate pool has a better silhouette score and targeted negative document ratio than the smaller one. As the labels for all the documents in the large candidate pool are unknown, the actual scores could be even higher than those presented.

7.1.2 Candidate keyword selection (cks) analysis

This section explores the impact of the cks parameter for keywords selection on the clustering output. This analysis is also very crucial to finalize the parameter selection at the end. The parameter cks ranges from 10 to 100 with values incrementing by 5. These values signify the percentile selection based on the query similarity. For example, a value of 40 denotes the selection of keywords below the 40 percentile similarity and the removal of the rest of the keywords. Similarly, a value of 100 represents the selection of all keywords without any removal. The keywords selected using the cks parameter are further clustered using HDBSCAN. One of the main objectives of this master thesis is to test the effectiveness of clustering with keyword selection against no selection. The data used in this analysis is generated from the clustering result for all the possible parameter combinations in the hyper-parameter set over the testset queries. The x-axis represents the candidate keyword selection, and the y-axis represents the mean of respective evaluation metrics.

Figure 7.3 presents the relation between the mean silhouette score and the cks parameter. Results from the large candidate pool clearly show that a higher cks parameter generates a better mean silhouette score. This signifies that a lower selection of keywords is better, and the best clustering outcome is achieved with no keyword selection (cks = 100). Small candidate pool results partly agree with this outcome, as the highest silhouette score is achieved when no keywords are selected. However, it is observed that the mean silhouette score is decreased at around a selection of 30 and 55. This denotes a change in the structure of the clustering output

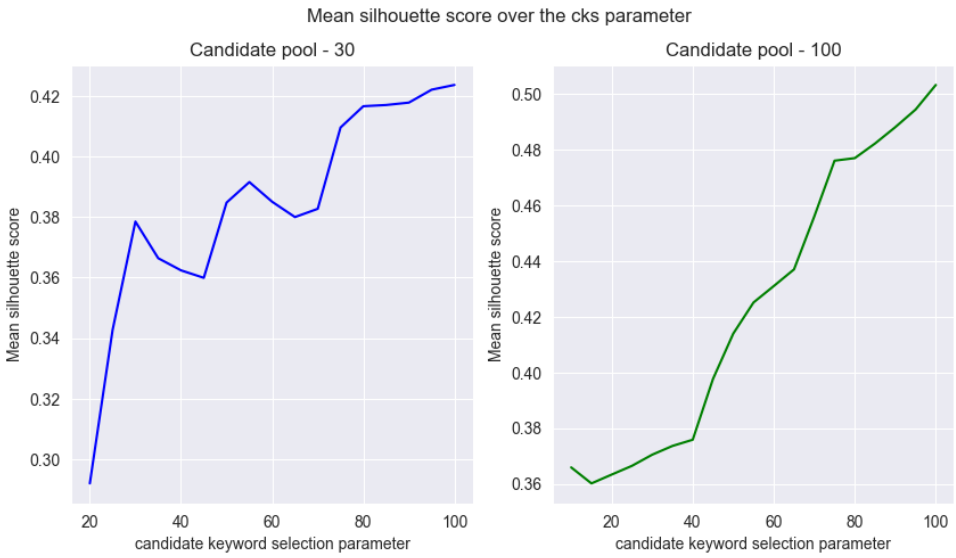


Figure 7.3: Silhouette score analysis over candidate selection parameter.

when specific keywords are selected. However, no downtrend in the data implies that keyword selection does not generate better clusters, and only an overall upward trend is observed.

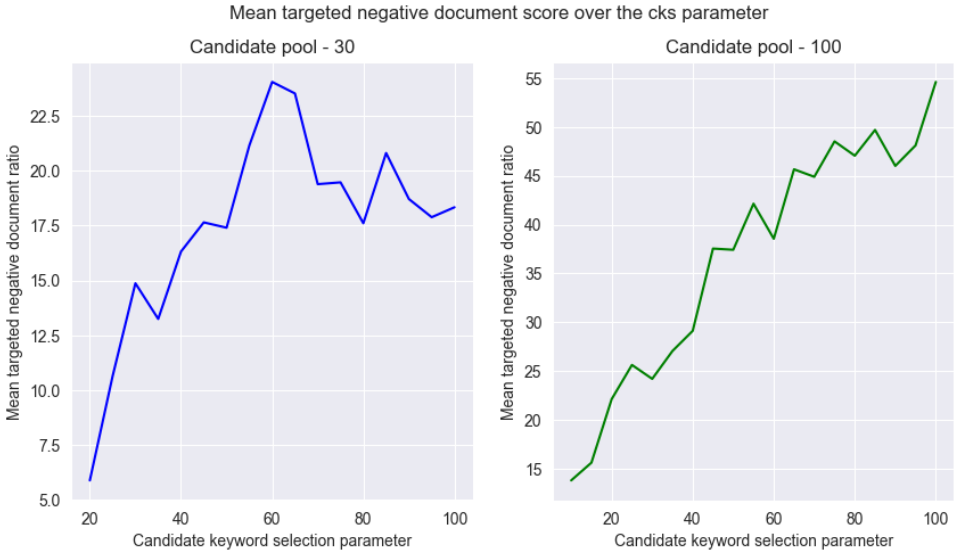


Figure 7.4: Targeted negative document ratio over candidate selection parameter.

Figure 7.4 presents the relation between the mean targeted negative document ratio and cks parameter. The metric here denotes the separation of clusters according to their similarities. The results from the small candidate pool show a highest separation of negative documents at cks = 60 and a downward trend for the values of cks higher than 60. This signifies that the keyword selection has positive impact on clustering achieving better separation. Large candidate pool results have a contrary outcome when compared to the earlier results. There is a clear upward trend implying that no keyword selection i.e cks = 100 has generated better separation of clusters. The results from the large candidate pool does not truly represent the nature of this evaluation metric as it ignores the unlabeled documents after clustering. When the labels of all 100 documents are considered, the results can be different.

Table 7.2: Mean of evaluation metrics over the cks parameter for the small candidate pool (30)

Cks parameter	Mean silhouette score	Mean targeted negative document ratio	Objective function score
85	0.42	20.81	0.48
75	0.41	19.48	0.46
60	0.39	24.06	0.45
100	0.42	18.34	0.45
95	0.42	17.89	0.45

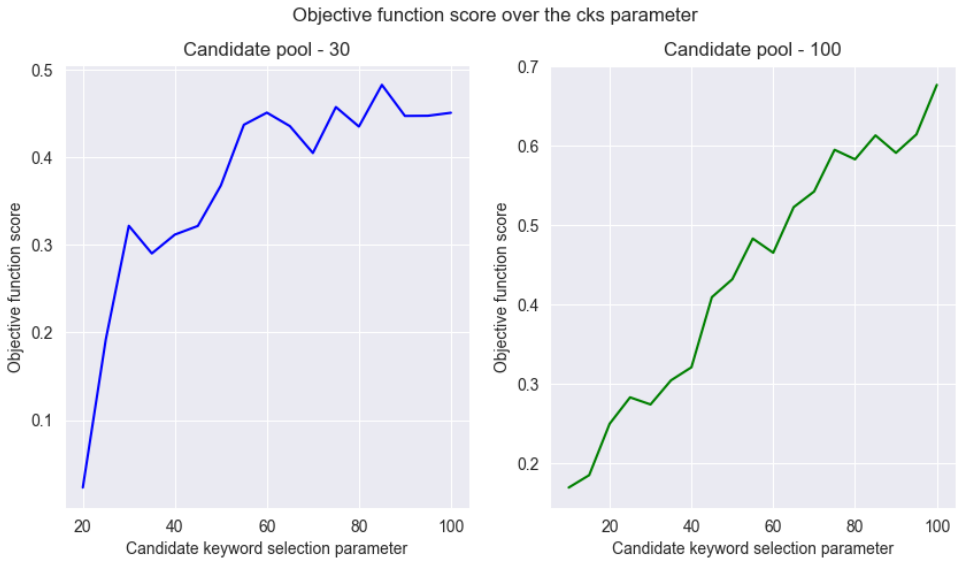


Figure 7.5: Objective function score analysis over candidate selection parameter.

The analysis results from intrinsic and extrinsic measures have shown a different pattern for a small candidate pool and similar patterns for a large candidate pool. Combining these two measures, a final objective function score, the harmonic mean of normalized intrinsic and extrinsic measures, is calculated. Figure 7.5 presents the relation between the objective function score and the cks parameter. The objective function for the small candidate pool has achieved the highest score when the keywords selection is 85. This shows that selecting keywords below the 85 percentile similarity generates better clustering.

However, the top 15 percentile keywords may contain around 3 to 4 keywords or even less. Therefore the significance of clustering improvement between the cks values 85 and 100 is very minimal. Moreover, the keywords selection at 60 and 75 also generate very close results compared to the highest score at 85. Table 7.2 on page 59 shares the top-5 cks parameter results ordered by the objective function score for the small candidate pool. Although 85 percentile selection has the highest objective function score, there is no significant difference in the scores when compared with other percentile selections.

However, the top 15 percentile keywords may contain around 3 to 4 keywords or even fewer. Therefore the significance of clustering improvement between the cks values 85 and 100 is minimal. Moreover, the keywords selection at 60 and 75 also generated very close results compared to the highest score at 85. Table 7.2 on page 59 on page 58 shares the top-5 cks parameter results ordered by the objective function score for the small candidate pool. Although the 85 percentile selection has the highest objective function score, there is no significant difference in the scores compared to other percentile selections.

Table 7.3: Mean of evaluation metrics over the cks parameter for the large candidate pool (100)

Cks parameter	Mean silhouette score	Mean targeted negative document ratio	Objective function score
100	0.50	54.62	0.68
95	0.49	48.12	0.61
85	0.48	49.70	0.61
75	0.48	48.53	0.59
90	0.49	46.02	0.59

On the other hand, a large candidate pool shows an increase in the objective function score with the large candidate keyword selection. Table 7.3 on page 60 on page 59 shares the top-5 cks parameter results ordered by the accurate function score for the large candidate pool. These results certainly convey no benefit of keyword selection as the cks parameter = 100 has the highest evaluation scores.

7.1.3 Missed document analysis

The proposed methodology clusters keywords in a document rather than the document itself. Documents are modeled as a set of clustered keywords. This leads to a soft-clustering output where a document is mapped to multiple clusters, as it can contain keywords from multiple clusters. The clustering algorithm HDBSCAN considers inherent noise in the data and does not assign all keywords to a specific cluster. This results in creating noise keywords that do not belong to any cluster. Suppose a document contains only keywords that are part of noise keywords. In that case, the document is missed (removed) during the modeling process. It is very crucial to analyze the missed documents because if more documents are removed then the document modeling has no significance.

Table 7.4: Mean missed document values over the cks parameter

Candidate pool - 30

Cks parameter	Mean missed documents
20	0.94
40	0.75
60	0.40
80	0.18
100	0.09

Candidate pool - 100

Cks parameter	Mean missed documents
20	1.07
40	0.59
60	0.34
80	0.11
100	0.01

Table 7.4 on page 60 on page 60 shows the average mean missed documents over the candidate selection parameter. This includes all possible combinations of the hyper-parameter set and the queries from the tesetset. In the case of a small candidate pool, only one document is missed on the average for lower values of the cks parameter. The missed documents for certain queries might be higher than the average scores, as only the mean is considered here. For large cks values, the mean missed documents are very small, and no significant leak of documents during the subtopic modeling. A similar pattern is observed in the large candidate pool where low values of the cks parameter have a high loss in documents. This data signifies avoiding taking a candidate selection less than the 40 percentile, which can lead to possible loss of documents during modeling.

7.1.4 Parameter selection analysis

This section details the clustering performance for top-5 parameters when considered individually. In the earlier analysis, the results are grouped over the candidate keyword selection (cks) parameter. Table 7.5 on page 61 details the small candidate pool's hyper-parameters and respective objective function scores. There is a huge variation in the parameter "minimum samples" in top-5 results. This parameter implies the minimum number of data points in a cluster. A value of 1 signifies that a minimum of one data point can create a cluster. This would create many clusters, such that clusters have very few data points. This leads to poor clustering even though the evaluation metrics show better performance. The change in the cks parameter between the values 90, 95, and 100 will not have a significant impact of the clustering output, as the number of keywords lies between 5 percentile selection can be very low.

Table 7.5: Objective score analysis over the parameters for the small candidate pool (30)

Cks parameter	Reduced dimensions	Minimum cluster size	Minimum samples	Objective function score
100.0	10.0	20.0	1.0	0.896
95.0	5.0	20.0	7.0	0.896
100.0	10.0	20.0	3.0	0.878
90.0	5.0	20.0	1.0	0.848
95.0	5.0	20.0	5.0	0.848

Table 7.6: Objective score analysis over the parameters for the large candidate pool (100)

Cks parameter	Reduced dimensions	Minimum cluster size	Minimum samples	Objective function score
100.0	5.0	20.0	10.0	0.964
100.0	10.0	20.0	10.0	0.946
100.0	10.0	20.0	5.0	0.941
100.0	10.0	20.0	7.0	0.939
100.0	5.0	20.0	7.0	0.935

Comparatively, the parameters such as reduced dimensions and minimum cluster size have very less variation. Table 7.5 on page 61 shares similar data for the large candidate pool. From this data, a higher minimum sample of 10 shows better clustering results, contrary to the small candidate pool. To generate a diverse clustering output, the cluster size should be relatively larger rather than very small clusters. Small clusters are generated when minimum samples of one or three data points can be considered as noise clusters and not desired. From both the candidate pools, a minimum cluster size of 20 and a reduced dimension of 5 can be chosen for the final parameter selection. The final parameters selected after this analysis is shown in Table 7.7 on page 61.

Table 7.7: Parameters selected after parameter selection analysis

Parameter	Value
Cks parameter	100
Reduced dimensions	5
Minimum cluster size	20
Minimum samples	10

7.1.5 Manual interpretation of results

After the parameters are selected from observing the clustering performance for both the small and candidate pool, a manual evaluation is performed on the large candidate pool. The clustering results provide deep insights into the candidate pool. However, it is also observed that the selected parameters' effectiveness in generating heterogeneous clusters still needs to be achieved (not achieved from automatic parameter selection). The main reason for the poor clustering results in diversity is the no keyword selection, i.e., cks = 100. Generating deep clusters and also maintaining cluster uniqueness is a challenging task. Evaluation metrics need to be more successful to capture this problem. Manual analysis is carried out on multiple clustering outputs with the parameters mentioned in Table 7.7 on page 61 and different values of the cks parameter.

Table 7.8: Manual clustering output analysis for the Query "5G" with different cks parameters

Cks parameter	Number of cluster	Sub-topics (clusters)
100	34	5G, 5G network, Frequenzspektrum, 5G deployment, China, Defence intelligence, Nokia, Berlin, Mobilfunkmast, Telekom, Gigabit speed, 4G, WiFi, UMTS, Military, Fiberoptic broadband, 5G technology, Vodafone, Experimentation testing, Mobilfunknetzbetreiber, Technologie, Netzwerk, LTE, Smartphones, Netz, Aircraft, 5G service, Data cap, Deutsche Telekom, Telefónica, Apple, Gebiet, Netzausbau, Anbieter
75	23	Anstieg, TelekomKunden, Netzausbau, ATT, Mobilfunkmast, Military, Frequenzspektrum, Defense cybersecurity, Berlin, Nokia Ericsson, Experimentation testing, USA, Fiberoptic broadband, Smartphones, Technologie, 4G network, Carrier, Military aviation, ISP, WiFis reach, Upload speed, Apple, 5G telecommunication
50	14	Deutschland, Fortschritt, Telecom, Mobilfunkantenn, Wireless ISPs, Frequenzspektrum, 4G network, Military, Defense cybersecurity, Technologie, Netzausbau, Nokia Ericsson, Experimentation testing, Military aviation
25	10	Ausbau, Military aviation, Testing experimentation, Trump administration, Verizon wireless, SmartphoneNutzer, Telekommunikationsdienstleister, Berliner Hauptbahnhof, Frequenzspektrum, Technologieführerschaft

The results of one query, namely "5G" is presented in the Table 7.8 on page 62. The subtopics generated when no keywords are selected are highly redundant and might not be useful to the

users, which have less significance. For example, the sub-topics "5G" and "5G network" are very similar and might lead to the same set of documents. The objective of creating unique pathways from the user query to retrieved documents is not achieved. The 75 percentile similarity selection shows similar clustering output. The practicality of sub-topics in the real world is successful only when the clusters are unique and diverse. On the other hand, the clustering outputs for the cks parameter of 25 and 50 are unique, as we have removed a significant amount of keywords similar to the query are removed. However, there is a high chance of missing documents in this scenario.

Table 7.9: Results from manual cks parameter selection 0f 65 for different queries

Query	Number of cluster	Sub-topics (clusters)
5G	18	5G telecommunication, 4G network, Broadband, ATT Verizon, WiFis reach, Smartphone, Frequenzspektrum, Netzausbau, Fortschritt, Mobilfunkmast, Deutschland, Carrier, Telekommunikationskonzer, Experimentation testing, Technologie, Defense cybersecurity, Aircraft, Military
Quantentechnologie	23	Industriebetrieb, Quantum physic, DAQC, SuperRechner, Vorsprung, Datennetzwerk, Luft Raumfahrt, Forscher, Simulation, AI, Qubit, IBM, Datum, Department defense, AmazonGründer, Deutschland, Entwicklung, Military, Congress, Marineschiffbau, Forschung, Bundesministerium, China

Figure 7.4 shows a downward trend in the targeted negative document ratio at cks = 60 for the small candidate pool. This signifies that there is better separation between the clusters at cks = 60, and then it decreases for higher cks values. However, only the larger candidate pool results are analyzed manually rather than the small candidate pool. Despite this difference, the information from the small candidate pool can be partly helpful, as it uses the labeled information. Therefore, a 65-percentile similarity selection is chosen after a manual analysis of several queries. The results of the manual parameter selection of cks = 60 are shared in the Table 7.9 on page 63. There are still some redundant clusters at this selection, but the results are better than the higher selection values. The choice of this particular 65 percentile selection is not only due to the heterogeneity of clusters but also to have a minimum loss of documents during clustering. Similarly, an 85-percentile selection is chosen for the smaller candidate pool. The final parameters through the manual selection are presented in Table 7.10 on page 63. Furthermore, the results from the 65 percentile selection are evaluated during the survey feedback and shared in upcoming sections.

Table 7.10: Final parameters selected after manual analysis

Parameter	CP-30	CP-100
Cks parameter	85	65
Reduced dimensions	5	5
Minimum cluster size	20	20
Minimum samples	10	10

7.1.6 Key statistics from clustering

After finalizing the parameters from Table 7.10 on page 63 with 65 percentile selection for the large candidate pool and 85 percentile selection for the small candidate pool, an analysis is carried out on the cluster metadata. Three clustering observations are collected from the sub-topic modeling and presented in Table 7.11 on page 64. All the data presented below are calculated over 17 queries in the testset.

1. **Mean number of clusters** gives the average number of clusters/sub-topics after sub-topic modeling.
2. **Mean keywords size** gives the average number of keywords used during the sub-topic modeling.
3. **Mean cluster size** gives the average number of keywords per cluster.

Table 7.11: Keyword observations during clustering over 17 queries

Parameter	CP-30	CP-100
Mean number of clusters	7.06	19.41
Mean keywords size	423.59	1057.47
Mean cluster size	70.12	78.96

It is evident from the above table that the large candidate pool considers more data points for clustering and generates around three times more sub-topics compared to the small candidate pool. This signifies that the user has the opportunity to view more diverse sub-topics and can access more documents. However, the average cluster size remains almost the same in both candidate pools.

7.2 Survey results

The survey aims to evaluate the clustering output and the effectiveness of subtopics to find relevant documents. A survey questionnaire with five questions is developed. The survey is tested by taking feedback from real users. The results from the survey directly answer the practicality of the proposed approach in this master thesis. Participants must answer the questions according to their inputs provided through the user interface. The survey can be partly answered depending on the user's interest, and this results in an unequal number of participants for each question. For example, questions 1 and 5 are independent questions where the participants can submit their feedback independently. However, the questions 2, 3, and 4 should be answered together.

Table 7.12: Pariticpant counts in the survey

Question id	Participant count
Question 1	12
Question 2, 3, 4	8
Question 5	8

The number of participants in each question is calculated by the unique UUID recorded during the session. One drawback of this approach is the need to recognize the same user performing in a different session. Due to privacy reasons, it is obliged not to record the user details, and therefore a session-based approach is adopted here. Furthermore, multiple answers are expected from each participant. Accordingly, the number of user feedback inputs is higher than the participant count. The participant's count score is shared in the Table 7.12 on page 64. Only a large candidate pool of around 100 documents is considered in the survey. In this section, only the survey results are shared, and the detailed survey questionnaire is accessible at 6.5.1.

7.2.1 Question 1

The participants are asked to share feedback on the clustering results in this question. The quality of clusters is evaluated using the distinctiveness and readability of clusters. The results from the survey for this question are shared in Table 7.13 on page 65. 14 survey inputs agree with the distinctiveness of the sub-topics, and four inputs share contrary feedback, i.e., non-distinctive. Similarly, 11 user inputs show that the cluster labels or sub-topic names need to be better labeled, and seven inputs show the opposite pattern.

Table 7.13: Question 1 results

Label	Count
Distinctive and well-labeled	6
Distinctive and not well-labeled	8
Not distinctive and well-labeled	1
Not distinctive and not well-labeled	3

It is evident from the above table that most of the survey participants agree with the distinctiveness of the sub-topics. Therefore, the candidate keyword selection positively impacts the clustering by creating distinctive clusters. However, the sub-topic labeling approach that uses the clusters' centroid needs to generate better results. After analyzing the sub-topic labels from Table 7.9 on page 63 and Table 7.8 on page 62, it can be observed that some of the sub-topics have abbreviations as labels. For example, DAQC, ATT, UMTS, etc., are some labels that might not be familiar to many participants and can lead to poor interpretation of the cluster and its documents.

7.2.2 Questions 2, 3, 4

These questions are targeted to evaluate the two IR systems developed to represent the retrieved documents. System A retrieves news articles using the sub-topic modeling output and re-ranks using a dynamic template, and System B, on the other hand, retrieves news articles with a new query request to the semantic index using the same template. Participants are requested to answer a qualitative comparison between the two systems, and the results are shared in Table 7.14 on page 66. Furthermore, quantitative ratings ranging from 0 to 10 are collected for both systems. Some participants have provided false inputs, and these inputs are considered anomalies. For example, a participant has chosen 'System B' for question 2 and provided eight and Five as ratings for systems A and B. The individual ratings do not agree with the system chosen initially. Such anomalies in the survey data are removed.

Table 7.14: Question 2, 3, and 4 results

Question 2

Label	Count
System A	18
System B	0
Neither System A nor System B	4

Questions 3 and 4

System	Mean	Standard deviation	Variance
A	5.46	2.92	8.54
B	3.28	2.77	7.7

After removing the anomalies, it is evident from Table 7.14 on page 66 that most participants have agreed that 'System A' retrieves documents better than 'System B'. This result is derived from the qualitative inputs of the survey. However, it is crucial to know the significance of this result through the quantitative inputs, i.e., system ratings. Table 7.14 on page 66 shows that the 'System A' has a better mean than the 'System B', and there is no huge difference in the standard deviation. Individual system ratings are plotted in a histogram and presented in Figure 7.6. These distributions clearly show that 'System B' ratings are more concentrated towards lower values and follow a right-skewed distribution. On the other hand, the 'System A' ratings are not concentrated at a certain level but indeed follow a positive trend with some high ratings.

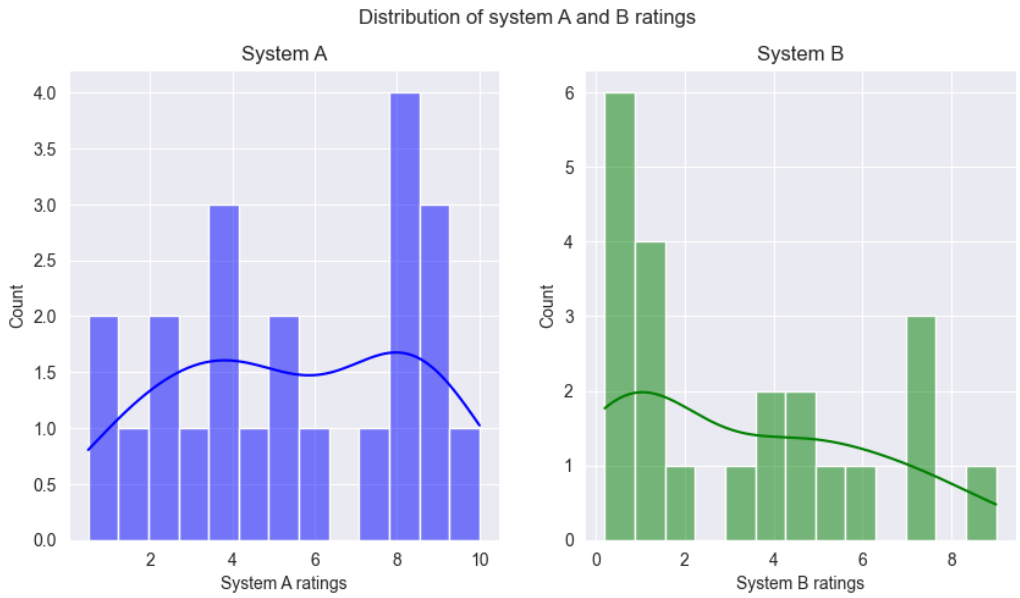


Figure 7.6: Histograms showing the distribution of system ratings

The significance of a system performing better than the other can be evaluated with the help of statistical testing. The system ratings are collected for two systems for a given query and sub-topic. Therefore the sample data can be considered as paired data as they are relative to each other and not with other queries or sub-topics. This relation between the data is also referred to as the dependent data samples. Figure 7.6 shows that the system ratings do not follow any specific distributions, and therefore, parametric statistical tests are not feasible. A non-parametric hypothesis test, namely Wilcoxon signed-rank test, is chosen in this master thesis. This statistical test considers the signs of the difference scores between the dependent data along with the magnitude of the differences[79]. In Wilcoxon Signed Rank Test, the hypothesis is built on the median of the difference scores, and the median is identical to the mean[79, 36].

1. **Null Hypothesis (H_0)**: The median difference between the samples, namely "System A"

and "System B" ratings is zero.

2. **Alternate Hypothesis (H_1)**: The median difference between the samples, namely "System A" and "System B" ratings is not zero.

The hypothesis is based on the median difference equal to zero or not rather compared to a particular value. Thus, this is referred to as a two-tailed test. Before performing the statistical testing, choosing the confidence level and the test statistic is crucial. A confidence level of 95 is chosen, i.e., a significance level (α) of 0.05, and for the test statistic, z-score is selected. Figure 7.7 shows the acceptance and rejection regions for the significance level $\alpha = 0.05$. Suppose the test score is lower than -1.96 or greater than 1.96. In that case, the null hypothesis should be rejected, and the alternate hypothesis shall be accepted. In any other case, the null hypothesis must be accepted.

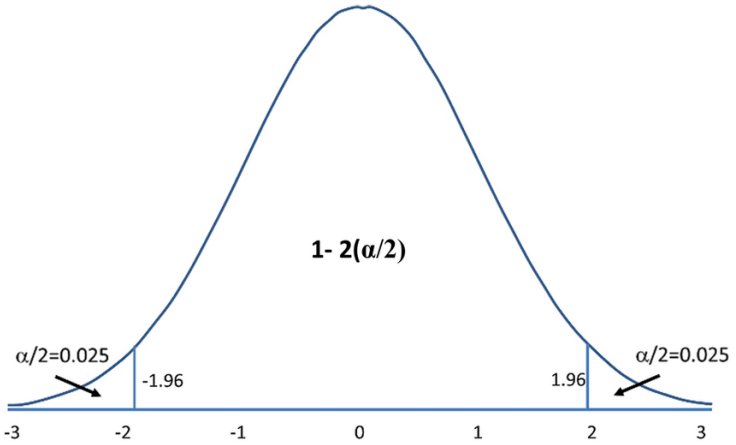


Figure 7.7: Rejection regions for a significance level of 0.05 and z test-statistic [63]

The test statistic is calculated with the help of a python library *researchpy*[1]. The calculated z-score is 4.06, and the test score is larger than the critical value of 1.96. Therefore, the null hypothesis is rejected, and the alternative hypothesis is accepted, i.e., the system ratings are significantly different, and system A retrieves better news articles related to the user query and the sub-topic. This ends the system by suggesting that the retrieval using sub-topic modeling output has performed better than a new query request.

7.2.3 Question 5

Participants are requested to share feedback on finding the relevant documents using the proposed methodology. This answers directly to the usability of the approach in real-life scenarios. The question is "Were the sub-topics helpful for you to find the relevant documents?". There is only one option to select, i.e.,'Yes' or 'No'. The results show that around half of the participants found the approach to retrieve documents using sub-topics does not help find news articles related to innovation. One drawback of this question is that it does not specify the particular IR system. This can lead the users to provide biased input during the survey. To overcome this, two questions specific to two systems (A and B) should have been asked to the participants.

Table 7.15: Question 5 results

[1] `https://researchpy.readthedocs.io/en/latest/index.html`

Label	Count
Yes	6
No	5

One reason for this can be the lack of relevant documents in the database for a particular query and sub-topic. Another reason could be the need for assessing the relevant documents by the participants, as the retrieved results are expected to have a low number of relevant documents. Assuming these are different from the cases here, the proposed approach did not successfully help the users provide the relevant documents. On the other hand, the participants who found it helpful pose the possibility of using this approach to find relevant documents.

7.3 Precision analysis results

This section details the exploratory analysis results from the ranking of sub-topics and the documents present inside the sub-topic. These rankings aim to generate a unique series of retrieved documents that simulate the user's traversal in real-time. The description of the IR systems developed in this master thesis is shared in section 6.6 and presented again briefly in Table 7.16 on page 68. Query similarity and Template similarity are represented as QS and TS, respectively. Two evaluation metrics, such as mean expectation score and mean average precision, are used to evaluate ranking output. Only a small candidate pool (CP- 30) is used for this analysis, as labeled data is required for calculating the mean expectation and precision scores.

Table 7.16: Brief IR system introduction

IR system name	(Sub-topic ranking, document ranking)
IR0	(NA, Uniform distribution)
IR1	(NA, QS)
IR2	(QS, QS)
IR3	(TS, TS)
IR4	(Document cardinality, QS)
IR5	((IR4, IR2), QS)
IR6	((IR4, IR2, IR3), QS)
IR7	(Random combinations, QS)

7.3.1 Mean expectation score analysis

Expectation scores are calculated at a specific index, depicting the number of relevant documents. This analysis uses mean expectation score, i.e., over the 17 queries in the testset. For example, a mean expectation score (ME_5) of 2 at index 5 signifies that, on average, there are two relevant documents from the top 20 retrieved documents. The higher the mean expectation score of an IR system, the better the retrieval. This analysis can be crucial for users who are interested in reading documents at a particular index. Accordingly, the best IR system at a specific index is chosen.

Figure 7.8 presents the mean expectation score of 6 IR systems over five retrieval indices. Combinational IR systems, namely IR5 and TR6, are excluded from this plot, as the results were similar to IR4 and redundant. One precise observation from Figure 7.8 is the IR4 system that uses template similarity performs poorly compared to the other IR systems. The same retrieval

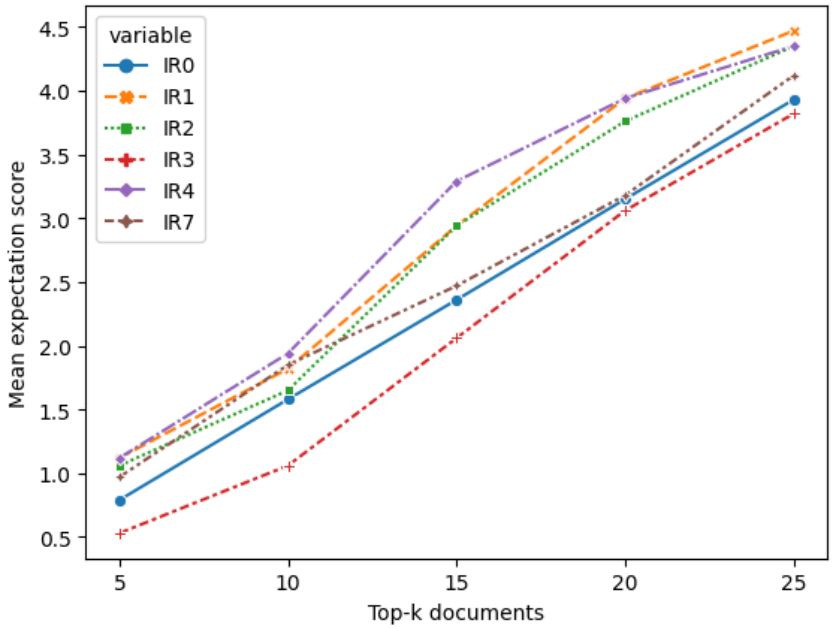


Figure 7.8: Mean expectation score plot

technique is being used in the survey. The other IR systems have shown almost similar patterns and are closely related. At 15, the IR4 system that uses document cardinality performs relatively better than the other retrieval system

Table 7.17: Mean expectation score results

IR system name	ME@5	ME@10	ME@15	ME@20	ME@25
IR0	0.79	1.58	2.36	3.15	3.93
IR1	1.12	1.82	2.94	3.94	4.47
IR2	1.06	1.65	2.94	3.76	4.35
IR3	0.53	1.06	2.06	3.06	3.82
IR4	1.12	1.94	3.29	3.94	4.35
IR5	1.12	1.94	3.29	3.94	4.41
IR6	1.12	1.94	3.29	3.88	4.41
IR7	0.97	1.85	2.47	3.18	4.12

Table 7.17 on page 69 shows the detailed expectation scores of the IR systems. One of the baseline IR1 system, which does not use clustering, has performed best at 25 retrieval index. However, the other IR systems, including the IR7 system, which uses random combinations, have performed very well compared to the baseline systems IR0 and IR1. This clearly signifies that the sub-topic clustering does not deteriorate the order of relevant documents when the user iterates through the sub-topics. Moreover, the user has the advantage of selecting a particular sub-topic and reading the documents directly, which makes the retrieval more efficient.

7.3.2 Mean average precision analysis

Mean average precision (MAP) provides a concrete score to compare different IR systems based on the retrieved documents. Without any particular index analysis, the IR system with the

highest MAP can be concluded as the best IR system.Table 7.18 on page 70 presents the MAP scores of IR systems. Similar to mean expectation scores, the IR3 system, which uses template similarity, performs poorly compared to other systems. Despite having the highest MAP score, the combination systems IR5 and IR6 do not show any improvement in retrieval performance. Combining multiple sub-topic rankings to generate a unique document ranking could be more successful, and one main reason is the need for a more relevant documents count.

Table 7.18: Mean average precision results

IR system name	MAP
IR0	0.185
IR1	0.3
IR2	0.303
IR3	0.198
IR4	0.316
IR5	0.316
IR6	0.315
IR7	0.292

The IR7 system, which uses random combinations of sub-topic clusters, achieves a significant score and performs better than the baseline IR0. A simple document ranking over the query similarity without sub-topics, i.e., IR1, has performed similarly to the IR2 system, which uses sub-topic ranking. This signifies that the retrieval performance is still the same with introducing sub-topics. Moreover, the IR4 system, which uses document cardinality as the ranking criteria, performed the best. Although the difference is not significantly higher than other systems, IR4 has the inherent advantage over the baselines IR0 and IR1 to access the documents in a particular sub-topic.

7.4 Results summary

Chapter 8

Conclusion

8.1 Conclusion

8.2 Limitations

8.3 Future work

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