1 Text Representations for Ranking

1.1 BOW Encodings

Text Representations for Ranking - BOW Encodings

Bag-of-Words (BOW) encodings are widely used in information retrieval systems for representing text documents. In this approach, each document is represented as a vector of word frequencies, disregarding the order and structure of the words within the document. BOW encodings have been extensively studied and applied in the context of neural information retrieval [REF0].

One of the advantages of BOW encodings is their simplicity and efficiency in capturing the overall content of a document. By considering the frequency of each word, BOW encodings provide a compact representation that can be easily processed and compared. This makes them suitable for large-scale retrieval systems that deal with massive amounts of text data [REF1].

To construct BOW encodings, a vocabulary is first created by collecting all unique words from the document collection. Each word in the vocabulary is assigned a unique index. Then, for each document, a vector is formed where each element represents the frequency of the corresponding word in the document. This results in a high-dimensional vector space, where each dimension corresponds to a word in the vocabulary [REF2].

BOW encodings have been widely used in ranking algorithms for information retrieval. One common approach is to compute the similarity between a query and each document in the collection using a similarity measure such as cosine similarity. The documents are then ranked based on their similarity scores, with the most similar documents being ranked higher [REF3].

Despite their simplicity, BOW encodings have some limitations. One major limitation is the loss of word order and context information. Since BOW encodings only consider word frequencies, they cannot capture the semantic relationships between words or the syntactic structure of sentences. This can lead to suboptimal ranking results, especially for queries that require a more nuanced understanding of the document content [REF4].

To address this limitation, various extensions and modifications to BOW encodings have been proposed. For example, techniques such as term weighting, where the importance of each word is adjusted based on its frequency in the document collection, can improve the ranking performance [REF5]. Additionally, the use of n-grams, which consider sequences of adjacent words, can capture some level of word order information [REF6].

In conclusion, BOW encodings provide a simple and efficient representation for ranking documents in information retrieval systems. While they have limitations in capturing word order and context, they have been widely used and serve as a baseline for more advanced text representation techniques. Future research in neural information retrieval should focus on developing more sophisticated encodings that can better capture the semantic and syntactic aspects of text documents [REF7].

References sent to GTP:

REF0 - Scalability Challenges in Web Search Engines

REF1 - Scalability Challenges in Web Search Engines

REF2 - Scalability Challenges in Web Search Engines

REF3 - Scalability Challenges in Web Search Engines

REF4 - Scalability Challenges in Web Search Engines

REF5 - Scalability Challenges in Web Search Engines

REF6 - Scalability Challenges in Web Search Engines

REF7 - Scalability Challenges in Web Search Engines

REF8 - Scalability Challenges in Web Search Engines

REF9 - Scalability Challenges in Web Search Engines

1.2 LTR Features

Text Representations for Ranking - LTR Features

In the field of neural information retrieval, text representations play a crucial role in ranking documents for information retrieval tasks. Learning to Rank (LTR) techniques have been widely used to improve the effectiveness of retrieval systems by training models to rank documents based on their relevance to a given query. In this section, we discuss the use of LTR features for text representations in ranking documents.

One important aspect to consider when using LTR features is the choice of learning evaluation measures. Different measures, such as Precision (P), Normalized Discounted Cumulative Gain (NDCG), Mean Average Precision (MAP), and Expected Reciprocal Rank (ERR), have been proposed to evaluate the effectiveness of learned models [REF1]. It is crucial to select informative measures that can differentiate between relevant documents of different relevance grades and respond to changes in the document ranking during learning [REF2]. In particular, NDCG and MAP have been found to be effective learning evaluation measures, while ERR may not be as informative [REF3].

The sample size of documents used for training the LTR models is another important factor to consider. It has been observed that the impact of sample size can depend on the type of information need and the presence of anchor text in the document representation [REF5]. For navigational queries, the presence of anchor text is important for assuring the effectiveness of smaller sample sizes [REF5]. Anchor text helps in identifying homepages and improves retrieval effectiveness for smaller samples [REF9]. However, for mixed query sets, the effectiveness of learned models may depend on both the choice of the learning to rank technique and the sample size [REF5]. It has been found that deep samples are necessary for effective retrieval in large web corpora [REF3].

The choice of learning to rank technique also plays a significant role in the effectiveness of learned models. Different techniques, such as LambdaMART and Automatic Feature Selection (AFS), have been used for learning to rank [REF4]. The choice of technique can have an impact on the performance of the learned models, particularly for specific query sets [REF5]. It has been observed that some learning to rank techniques struggle to properly rank relevant documents when anchor text is deployed, leading to variations in performance [REF6].

In summary, the effectiveness of learned models in neural information retrieval depends on various factors related to text representations for ranking. The choice of learning evaluation measures, sample size, presence of anchor text, and the selection of learning to rank techniques all contribute to the overall performance of the models. Understanding these factors and their impact on retrieval effectiveness is crucial for developing effective neural information retrieval systems.

References sent to GTP:

REF0 - The Whens and Hows of Learning to Rank for Web Search

REF1 - The Whens and Hows of Learning to Rank for Web Search

REF2 - The Whens and Hows of Learning to Rank for Web Search

REF3 - The Whens and Hows of Learning to Rank for Web Search

REF4 - The Whens and Hows of Learning to Rank for Web Search

REF5 - The Whens and Hows of Learning to Rank for Web Search

REF6 - The Whens and Hows of Learning to Rank for Web Search

REF7 - The Whens and Hows of Learning to Rank for Web Search

REF8 - The Whens and Hows of Learning to Rank for Web Search

REF9 - The Whens and Hows of Learning to Rank for Web Search

1.3 Word Embeddings

Text Representations for Ranking - Word Embeddings

Word embeddings have emerged as a powerful technique for representing text in neural information retrieval systems. Word embeddings capture the semantic and syntactic relationships between words by mapping them to dense vector representations in a continuous space. These representations have been shown to improve the performance of various natural language processing tasks, including information retrieval and ranking.

One popular method for generating word embeddings is the Word2Vec model [REF9]. Word2Vec utilizes a neural network architecture to learn word embeddings from large corpora of text. The model learns to predict the context words surrounding a target word, or vice versa, by optimizing the objective function of maximizing the probability of observing the context words given the target word. The resulting word embeddings capture semantic similarities between words, as words that appear in similar contexts tend to have similar vector representations.

Another widely used word embedding model is GloVe (Global Vectors for Word Representation) [REF9]. GloVe combines global matrix factorization with local context window methods to learn word embeddings. It leverages the co-occurrence statistics of words in a corpus to capture both global and local word relationships. The resulting embeddings encode semantic and syntactic similarities between words, making them suitable for ranking and retrieval tasks.

Word embeddings have been successfully applied in various information retrieval scenarios. For instance, in named entity recognition tasks, word embeddings have been used to improve the identification of entities such as persons, locations, organizations, and miscellaneous categories [REF4]. By incorporating word embeddings into the models, the systems can capture the contextual information and improve the accuracy of entity recognition.

In the context of semantic memory retrieval, word embeddings have been utilized to model how concepts are organized and retrieved from memory [REF0]. Traditional computational accounts of semantic memory assumed context-free semantic representations. However, recent evidence suggests that retrieval from semantic memory is inherently contextual and influenced by linguistic and task-based contexts [REF0]. Word embeddings provide a way to capture these contextual influences and enhance the retrieval of concepts from semantic memory.

Furthermore, word embeddings have been employed in word games and interactive tasks to study how individuals modify their search processes based on semantically relevant interactions [REF1]. By incorporating word embeddings into models of pragmatic reasoning and theory-of-mind, researchers have gained insights into how individuals incorporate the perspectives of others and adapt their search strategies accordingly.

In summary, word embeddings have proven to be valuable representations for ranking and retrieval tasks in neural information retrieval systems. They capture semantic and syntactic relationships between words, enabling better understanding of text and improving the performance of various natural language processing tasks. By incorporating word embeddings into models, researchers have been able to enhance the retrieval of concepts from semantic memory, improve named entity recognition, and study how individuals adapt their search processes based on semantic interactions.

References sent to GTP:

REF0 - Semantic Memory Search and Retrieval in a Novel Cooperative Word Game: A Comparison of Associative and Distributional Semantic Models

REF1 - Semantic Memory Search and Retrieval in a Novel Cooperative Word Game: A Comparison of Associative and Distributional Semantic Models

REF2 - Bag of Tricks for Efficient Text Classification

REF3 - Semantic Memory Search and Retrieval in a Novel Cooperative Word Game: A Comparison of Associative and Distributional Semantic Models

REF4 - GloVe: Global Vectors for Word Representation

REF5 - Semantic Memory Search and Retrieval in a Novel Cooperative Word Game: A Comparison of Associative and Distributional Semantic Models

REF6 - Semantic Memory Search and Retrieval in a Novel Cooperative Word Game: A Comparison of Associative and Distributional Semantic Models

REF7 - Semantic Memory Search and Retrieval in a Novel Cooperative Word Game: A Comparison of Associative and Distributional Semantic Models

REF8 - Semantic Memory Search and Retrieval in a Novel Cooperative Word Game: A Comparison of Associative and Distributional Semantic Models

REF9 - Semantic Memory Search and Retrieval in a Novel Cooperative Word Game: A Comparison of Associative and Distributional Semantic Models

2 Interaction-focused Systems

2.1 Convolutional Neural Networks

Interaction-focused Systems - Convolutional Neural Networks

Convolutional Neural Networks (CNNs) have gained significant attention in the field of neural information retrieval due to their ability to capture hierarchical matching patterns from different levels of interaction signals. Unlike traditional CNNs that treat exact matching and similarity matching signals equally, interaction-focused models, such as the deep relevance matching model, aim to extract position-free and strength-focused patterns from diverse matching requirements in ad-hoc retrieval [REF0].

One approach employed by interaction-focused models is the use of special pooling strategies to convert position-aware interactions into strength-based fixed-length representations. For instance, the MV-LSTM model utilizes the K-max pooling strategy to select the top K strongest interaction signals from the matching matrix as input for a Multi-Layer Perceptron (MLP) [REF0]. This pooling strategy allows the model to focus on the most relevant and informative signals, enhancing its performance in capturing important matching patterns.

CNNs also leverage the concept of shared weights and subsampling to ensure shift and distortion invariance, which is crucial for handling images, speech, and time-series data [REF3]. By restricting the receptive fields of hidden units to be local, CNNs force the extraction of local features, taking advantage of the strong 2D local structure in images and the strong 1D structure in time-series data [REF3]. This property enables CNNs to effectively recognize spatial or temporal objects by extracting and combining local features before making predictions [REF6].

Moreover, the replication of convolutional networks allows for efficient scanning or replication over large, variable-size input fields. This replication can be achieved by increasing the size of the field over which convolutions are performed and replicating the output layer, effectively making it a convolutional layer [REF2]. This approach enables the network to produce outputs centered on different positions of the input field, providing evidence for the categories of objects present in the input [REF4].

The ease of implementation in hardware is another advantage of CNNs, making them suitable for real-time applications. Specialized analog/digital chips have been designed and utilized for character recognition and image preprocessing tasks, achieving high speeds with a relatively small number of connections [REF9]. Additionally, the concept of subsampling can be reversed to construct networks similar to Time-Delay Neural Networks (TDNNs), which can generate sequences from labels. These networks, known as reverse-TDNNs, employ oversampling and convolution layers to increase temporal resolution from input to output [REF9].

In summary, interaction-focused systems based on Convolutional Neural Networks have shown promising results in neural information retrieval tasks. By extracting hierarchical matching patterns, utilizing pooling strategies, and leveraging shared weights and subsampling, these models can effectively handle diverse matching requirements and capture important interaction signals. The ease of implementation in hardware further enhances their applicability in real-time scenarios.

References sent to GTP:

REF0 - A Deep Relevance Matching Model for Ad-hoc Retrieval

REF1 - Convolutional Networks for Images, Speech, and Time-Series

REF2 - Convolutional Networks for Images, Speech, and Time-Series

REF3 - Convolutional Networks for Images, Speech, and Time-Series

REF4 - Convolutional Networks for Images, Speech, and Time-Series

REF5 - Convolutional Networks for Images, Speech, and Time-Series

REF6 - Convolutional Networks for Images, Speech, and Time-Series

REF7 - Convolutional Networks for Images, Speech, and Time-Series

REF8 - Convolutional Networks for Images, Speech, and Time-Series

REF9 - Convolutional Networks for Images, Speech, and Time-Series

2.2 Pre-trained Language Models

Interaction-focused Systems - Pre-trained Language Models

Pre-trained language models have gained significant attention in the field of neural information retrieval due to their ability to capture contextual information and generate high-quality representations of text. One particular area of interest is the use of pre-trained language models in interaction-focused systems. These systems aim to enhance the interaction between users and information retrieval systems by leveraging the power of pre-trained language models. In this section, we discuss the application of pre-trained language models in interaction-focused systems and highlight some key approaches and techniques.

One approach that has been explored is the use of pre-trained language models with a focus on fine-tuning for specific tasks. Fine-tuning allows the model to adapt to a particular task by updating its parameters based on task-specific data. This approach has been shown to improve performance in various tasks, such as question answering and machine translation [REF1]. For example, BERT (Bidirectional Encoder Representations from Transformers) is a pre-trained language model that has been successfully fine-tuned for a wide range of tasks, including sentence-level and token-level tasks [REF1]. By incorporating context from both directions, BERT overcomes the limitations of unidirectional language models and improves the performance of fine-tuning approaches [REF1].

Another approach in interaction-focused systems is the use of pre-trained language models for information retrieval tasks. These models can be used to generate representations of queries and documents, which can then be used for ranking and retrieval purposes. For instance, pre-trained language models have been used to improve the performance of question answering systems by generating more accurate answers based on the context of the query and the document [REF2]. By leveraging the contextual information captured by pre-trained language models, these systems can provide more relevant and accurate responses to user queries.

Furthermore, pre-trained language models have been used in interaction-focused systems to enhance the user experience and improve the efficiency of information retrieval. For example, the use of pre-trained language models with a masking objective has been explored to reconstruct the original uncorrupted sequence and improve the efficiency of the encoder-decoder text-to-text setup [REF0]. By replacing corrupted tokens with mask tokens or unique mask tokens, these models can avoid predicting the entire uncorrupted text span, reducing the computational cost of self-attention over long sequences in the decoder [REF0].

Ensembling models that were pre-trained together but fine-tuned separately has also shown promise in improving the performance of interaction-focused systems [REF4]. By combining the predictions of multiple models, ensembling can lead to substantial performance gains, providing a cost-effective means of improving system performance [REF4]. However, the choice of scaling methods and the consideration of the eventual use of the model are important factors to consider when employing ensembling techniques [REF4].

In conclusion, pre-trained language models have emerged as a powerful tool in interaction-focused systems for neural information retrieval. By fine-tuning these models for specific tasks, generating representations for information retrieval, and enhancing the user experience, these systems can provide more accurate and relevant responses to user queries. The use of pre-trained language models in interaction-focused systems opens up new possibilities for improving the efficiency and effectiveness of information retrieval processes.

References sent to GTP:

REF0 - Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer

REF1 - BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

REF2 - Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer

REF3 - Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer

REF4 - Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer

REF5 - BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

REF6 - Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer

REF7 - Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer

REF8 - Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer

REF9 - Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer

2.3 Ranking with Encoder-only Models

Interaction-focused Systems - Ranking with Encoder-only Models

Encoder-only models have gained significant attention in the field of neural information retrieval due to their ability to capture complex semantic relationships between queries and documents. In this section, we explore the use of encoder-only models in interaction-focused systems, specifically focusing on ranking.

One notable approach in this context is the use of monoBERT, a model that leverages the power of BERT (Bidirectional Encoder Representations from Transformers) for ranking tasks [REF1]. MonoBERT demonstrates impressive improvements over traditional baselines such as BM25, achieving substantial gains in Mean Average Precision (MAP) on datasets like MS MARCO and TREC CAR [REF1] [REF5]. By learning to assign high matching scores to n-grams, monoBERT surpasses the limitations of BM25, which often neglects n-grams in favor of unigram matches [REF0].

To further enhance the ranking performance, duoBERT is introduced as an extension to monoBERT [REF1]. DuoBERT focuses on capturing semantic relationships between query terms and document passages, enabling it to match synonyms and distinguish between similar terms [REF0]. The duoBERT model, when combined with monoBERT, provides additional improvements in MAP, demonstrating its effectiveness in capturing more nuanced semantic information [REF1].

Tradeoffs between latency and quality are crucial considerations in interaction-focused systems. By varying the hyperparameter k1, which controls the number of documents considered for ranking, the latency-quality tradeoff can be controlled [REF2]. The experiments show that a good operating point is k1 = 20 with binary aggregation on MS MARCO and sum aggregation on TREC CAR, achieving close to the maximum achievable score with a reasonable increase in latency compared to monoBERT alone [REF6].

Qualitative analyses further highlight the strengths of encoder-only models in interaction-focused systems. By sampling retrieved passages from different methods, such as BM25, monoBERT, and duoBERTSUM, it becomes evident that monoBERT and duoBERT are capable of capturing more nuanced semantic relationships between queries and documents [REF0]. For example, duoBERT successfully matches synonyms between query terms and document passages, while monoBERT fails to distinguish between similar terms [REF0].

In conclusion, encoder-only models, such as monoBERT and duoBERT, have shown significant promise in interaction-focused systems for ranking tasks. These models effectively capture complex semantic relationships, surpassing traditional baselines like BM25. By controlling the tradeoff between latency and quality, encoder-only models can be optimized for specific use cases. Further research in this area aims to explore the joint building of stages in the pipeline and the development of models capable of handling longer documents without truncation [REF7] [REF8].

References sent to GTP:

REF0 - Multi-Stage Document Ranking with BERT

REF1 - Multi-Stage Document Ranking with BERT

REF2 - Multi-Stage Document Ranking with BERT

REF3 - Multi-Stage Document Ranking with BERT

REF4 - Multi-Stage Document Ranking with BERT

REF5 - Multi-Stage Document Ranking with BERT

REF6 - Multi-Stage Document Ranking with BERT

REF7 - Multi-Stage Document Ranking with BERT

REF8 - Multi-Stage Document Ranking with BERT

REF9 - Multi-Stage Document Ranking with BERT

2.4 Ranking with Encoder-decoder Models

Interaction-focused Systems - Ranking with Encoder-decoder Models

Encoder-decoder models have gained significant attention in the field of neural information retrieval due to their ability to capture the interaction between queries and documents. These models utilize a two-step process, where the encoder encodes the query and document representations, and the decoder generates a relevance score based on the encoded representations [REF2].

One popular approach in encoder-decoder models is the use of sequence-to-sequence models, such as T5, which have been adapted for document reranking [REF2]. This approach involves training a pretrained sequence-to-sequence model on a large dataset and fine-tuning it for the task of document ranking. The pretrained model captures the semantic information of the documents, allowing for better ranking performance [REF2].

In the encoder-decoder framework, the encoder takes the query and document as input and encodes them into fixed-length representations. This encoding process captures the semantic meaning of the query and document, enabling the model to understand the relevance between them [REF2]. The decoder then generates a relevance score based on the encoded representations, which can be used for ranking the documents [REF2].

To train the encoder-decoder models, a large amount of training data is required. However, in data-poor regimes, where limited training examples are available, encoder-decoder models have shown superior performance compared to other approaches, such as classification-based encoder-only models [REF2]. This highlights the effectiveness of encoder-decoder models in capturing the interaction between queries and documents, even with limited training data.

Several baselines have been used to compare the performance of encoder-decoder models. For instance, the BM25 baseline, which utilizes a bag-of-words retrieval approach, has been widely used for comparison [REF1]. Another baseline, BM25+RM3, incorporates query expansion to improve retrieval performance [REF1]. These baselines provide a benchmark for evaluating the effectiveness of encoder-decoder models in ranking documents [REF1].

In conclusion, encoder-decoder models, particularly those based on sequence-to-sequence models like T5, have shown promise in the field of neural information retrieval. These models capture the interaction between queries and documents, allowing for better ranking performance. While encoder-decoder models require a large amount of training data, they have demonstrated superior performance even in data-poor regimes. Baseline models, such as BM25 and BM25+RM3, provide a basis for comparison and evaluation of encoder-decoder models.

References sent to GTP:

REF0 - Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer

REF1 - Document Ranking with a Pretrained Sequence-to-Sequence Model

REF2 - Document Ranking with a Pretrained Sequence-to-Sequence Model

REF3 - Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer

REF4 - Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer

REF5 - Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer

REF6 - Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer

REF7 - Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer

REF8 - Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer

REF9 - Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer

2.5 Fine-tuning Interaction-focused Systems

Interaction-focused Systems - Fine-tuning Interaction-focused Systems

In the context of neural information retrieval, interaction-focused systems play a crucial role in improving the effectiveness of information retrieval by incorporating user interactions into the retrieval process. These systems aim to capture user preferences and intents through various forms of interactions, such as query reformulation, relevance feedback, and click-through data. One important aspect of interaction-focused systems is the fine-tuning of these systems to optimize their performance based on user feedback and interactions.

Fine-tuning interaction-focused systems involves leveraging the user interactions to improve the retrieval models and algorithms. This process typically involves two main steps: learning a distance metric that respects the relationships between similar pairs of points and using this metric to enhance the clustering performance.

Several studies have demonstrated the effectiveness of fine-tuning interaction-focused systems. For instance, in [REF0], the authors presented an algorithm that learns a distance metric based on examples of similar pairs of points. They showed that this approach can improve clustering performance, particularly when using a learned diagonal or full metric. Similarly, in [REF1], the authors applied their methods to various datasets and observed significant improvements in clustering performance when using a learned metric compared to traditional K-means algorithms.

To evaluate the performance of fine-tuned interaction-focused systems, various metrics can be used. Accuracy scores, as shown in [REF1], can measure how well the clustering results match the true clusters based on similarity information. Additionally, the amount of side-information provided can also impact the performance of these systems. As demonstrated in [REF5], having more side-information typically leads to better clusterings.

It is worth noting that the effectiveness of fine-tuning interaction-focused systems may vary depending on the problem domain. In some cases, such as wine datasets, the algorithm can quickly learn good diagonal and full metrics with only a small amount of side-information [REF5]. However, for more complex problems like protein datasets, learning the full metric may be more challenging and provide less benefit over constrained K-means [REF5].

In summary, fine-tuning interaction-focused systems is a crucial step in optimizing their performance. By leveraging user interactions and learning distance metrics that respect the relationships between similar pairs of points, these systems can significantly improve clustering performance. However, the effectiveness of fine-tuning may vary depending on the problem domain and the amount of side-information available.

References sent to GTP:

REF0 - Distance metric learning, with application to clustering with side-information

REF1 - Distance metric learning, with application to clustering with side-information

REF2 - Distance metric learning, with application to clustering with side-information

REF3 - Distance metric learning, with application to clustering with side-information

REF4 - Distance metric learning, with application to clustering with side-information

REF5 - Distance metric learning, with application to clustering with side-information

REF6 - Distance metric learning, with application to clustering with side-information

REF7 - Distance metric learning, with application to clustering with side-information

REF8 - Distance metric learning, with application to clustering with side-information

REF9 - Distance metric learning, with application to clustering with side-information

2.6 Dealing with long texts

Interaction-focused Systems - Dealing with long texts

In the context of neural information retrieval, interaction-focused systems play a crucial role in effectively dealing with long texts. These systems aim to capture the interactions between queries and documents to improve retrieval performance. One challenge in dealing with long texts is the need to effectively model the interactions between different parts of the text, such as queries and passages. In this section, we discuss various approaches that have been proposed to address this challenge.

One approach to modeling interactions in long texts is through representation aggregation. PARADE models, for example, have shown effectiveness in capturing query-document interactions by aggregating passage representations [REF0]. By training on more passages than will be used at inference time, PARADE models can improve their effectiveness, resulting in a small increase in normalized discounted cumulative gain (nDCG) [REF0]. The PARADE–Transformer variant, in particular, has been found to be generally the most effective, although there are cases where PARADE–Max outperforms it, such as in the TREC DL and TREC Genomics collections [REF0]. This difference in effectiveness is hypothesized to be due to the focused nature of queries in these collections [REF0].

Another approach to modeling interactions in long texts is through score aggregation. PARADE variants, such as PARADE–Max, PARADE–Avg, and PARADE–Sum, have been compared on the Robust04 and GOV2 collections, with PARADE–Max generally being more effective [REF1]. However, the effectiveness of these variants can vary depending on the collection, with PARADE–Attn sometimes outperforming PARADE–Max on GOV2 [REF1]. Additionally, PARADE variants that use passage representations in a hierarchical manner, such as PARADE–CNN and PARADE–Transformer, consistently outperform other variants, highlighting the effectiveness of passage representation aggregation approaches [REF1].

BERT, a popular pre-trained language model, has also been utilized in interaction-focused systems for dealing with long texts. BERT has been used as a relevance classifier in a cross-encoder configuration, taking both queries and documents as input [REF2]. Different approaches have explored using BERT's outputs for document reranking, such as using BERT's [CLS] vector, sentence-level relevance scores, and passage-level relevance scores [REF2]. CEDR, for instance, combines BERT's outputs with existing neural IR models and handles passage aggregation through representation aggregation techniques, such as averaging [REF2].

Transformers, a key component in many neural IR models, have been employed to capture interactions between queries and documents in long texts. These models utilize multiple layers of transformers to generate contextualized embeddings for each token, considering query-document interactions through attention mechanisms [REF3]. The attention matrices in transformers capture different types of word relations, such as exact match and synonyms, enabling a comprehensive understanding of the query-document pair [REF3]. By using the output embedding of the first token as a representation for the entire query-document pair, transformers effectively model the interactions in long texts [REF3].

In addition to the aforementioned approaches, T5-3B, a pre-trained model, has been used for text ranking in a sequence-to-sequence generation context [REF4]. Similar to BERT-MaxP, T5-3B utilizes score max-pooling techniques for document reranking [REF4]. However, due to its large size and expensive training, the reported values are often from zero-shot settings [REF4]. Furthermore, the effectiveness of different models can vary across benchmarks, with PARADE–Max outperforming PARADE–Transformer in some cases, such as TREC Genomics [REF9].

In conclusion, interaction-focused systems have been developed to effectively deal with long texts in neural information retrieval. These systems employ various approaches, including representation aggregation, score aggregation, and the utilization of pre-trained models like BERT and T5-3B. By capturing the interactions between queries and documents, these approaches enhance retrieval performance and contribute to the advancement of neural information retrieval techniques.

References sent to GTP:

REF0 - PARADE: Passage Representation Aggregation for Document Reranking

REF1 - PARADE: Passage Representation Aggregation for Document Reranking

REF2 - PARADE: Passage Representation Aggregation for Document Reranking

REF3 - Deeper Text Understanding for IR with Contextual Neural Language Modeling

REF4 - PARADE: Passage Representation Aggregation for Document Reranking

REF5 - PARADE: Passage Representation Aggregation for Document Reranking

REF6 - PARADE: Passage Representation Aggregation for Document Reranking

REF7 - PARADE: Passage Representation Aggregation for Document Reranking

REF8 - PARADE: Passage Representation Aggregation for Document Reranking

REF9 - PARADE: Passage Representation Aggregation for Document Reranking

3 Representation-focused Systems

3.1 Single Representations

Representation-focused Systems - Single Representations

In neural information retrieval, representation-focused systems play a crucial role in improving the retrieval performance by leveraging single representations of documents. These systems aim to optimize the ranking performance by training efficient and effective models. In this section, we discuss several approaches that focus on single representations and their impact on retrieval performance.

One approach is the use of document embeddings generated by BM25 Neg, combined with product quantization (PQ) for index compression [REF0]. This approach not only reduces memory consumption but also maintains search quality. The performance loss is minimal, as demonstrated by the MRR@10 results on the MARCO Dev Passage dataset [REF0]. By compressing the index, the system can run efficiently on a single GPU, significantly reducing computational resources [REF0].

End-to-end training is another technique that optimizes the ranking performance for compressed indexes [REF1]. This approach has shown promising results in improving the performance of compressed indexes [REF1]. The training efficiency of these methods is evaluated in terms of training time and computational resources [REF1]. The results demonstrate significant efficiency gains compared to the baseline method [REF1].

Dynamic hard negatives have been shown to improve the ranking performance in representation-focused systems [REF2]. The use of dynamic hard negatives enhances the retrieval performance by mapping queries closer to relevant documents [REF2]. ADORE, a query-side training algorithm, utilizes the document encoder trained by BM25 Neg and further trains the query encoder to improve retrieval performance [REF2]. This approach has been validated through empirical analysis and t-SNE visualization [REF2].

Training efficiency is a crucial aspect of representation-focused systems. The training speed and computational resources required are important factors to consider [REF3]. Efficient training methods, such as those proposed in this context, offer significant speedup and resource savings compared to baseline methods [REF3]. These improvements contribute to the overall efficiency of the system.

The use of importance sampling techniques, such as sampling proportionally to per instance gradient norm, has been explored in representation-focused systems [REF4]. This approach leverages the correlation between gradient norm and training convergence to improve the training process [REF4]. By focusing on informative negatives and diminishing gradients of uninformative negatives, the training loss can be reduced and convergence can be achieved more efficiently [REF4].

In summary, representation-focused systems that leverage single representations have shown promising results in improving the retrieval performance. Techniques such as index compression, end-to-end training, dynamic hard negatives, and efficient training methods contribute to the overall effectiveness and efficiency of these systems. These approaches optimize the ranking performance and reduce computational resources, making them valuable in the field of neural information retrieval.

References sent to GTP:

REF0 - Optimizing Dense Retrieval Model Training with Hard Negatives

REF1 - Optimizing Dense Retrieval Model Training with Hard Negatives

REF2 - Optimizing Dense Retrieval Model Training with Hard Negatives

REF3 - Optimizing Dense Retrieval Model Training with Hard Negatives

REF4 - Approximate Nearest Neighbor Negative Contrastive Learning for Dense Text Retrieval

REF5 - Signature Verification using a "Siamese" Time Delay Neural Network

REF6 - Approximate Nearest Neighbor Negative Contrastive Learning for Dense Text Retrieval

REF7 - Optimizing Dense Retrieval Model Training with Hard Negatives

REF8 - Optimizing Dense Retrieval Model Training with Hard Negatives

REF9 - Optimizing Dense Retrieval Model Training with Hard Negatives

3.2 Multiple Representations

Representation-focused Systems - Multiple Representations

In neural information retrieval, representation-focused systems aim to enhance the effectiveness of information retrieval models by leveraging multiple representations of the input data. These systems go beyond traditional lexical matching approaches and incorporate additional contextual and semantic information to improve the retrieval performance [REF1].

One approach to incorporating multiple representations is through the use of contextualized exact match models. COIL (Contextualized Exact match with Intermediate Lexical) is an example of such a system that combines lexical signals with dense CLS match [REF0]. By considering both vocabulary and semantic mismatch, COIL is able to effectively handle different contexts and provide semantic-aware token match signals. Experimental results have shown that reducing the dimensionality of the CLS representation in COIL has minimal impact on performance, suggesting that a full-dimensional representation may not be necessary [REF0].

Another aspect of representation-focused systems is the ability to differentiate tokens in different contexts. COIL, for example, can differentiate between the same token used in different contexts and assign higher scores to matches that align with the query context [REF1]. This capability allows COIL to introduce rich context information and estimate matching beyond surface token forms. By incorporating contextual information, COIL systems demonstrate improved performance compared to traditional lexical systems [REF1].

In addition to COIL, other representation-focused systems have been proposed. Deep LM based Lexical Index Models like DeepCT and DocT5Query alter the term frequency component of retrieval models using deep language models such as BERT or T5 [REF6]. These models leverage the contextual information provided by the language models to enhance the matching signals and improve retrieval effectiveness.

The use of multiple representations in representation-focused systems offers several advantages. By incorporating contextual and semantic information, these systems can overcome the limitations of traditional lexical matching approaches and provide more accurate and relevant retrieval results. Furthermore, the ability to differentiate tokens in different contexts allows for a more nuanced understanding of the query and document content, leading to improved matching accuracy [REF1].

In conclusion, representation-focused systems that leverage multiple representations have shown promising results in improving the effectiveness of neural information retrieval models. By incorporating contextual and semantic information, these systems can overcome the limitations of traditional lexical matching approaches and provide more accurate and relevant retrieval results. Future research in this area could explore novel ways of combining and leveraging multiple representations to further enhance retrieval performance.

References sent to GTP:

REF0 - COIL: Revisit Exact Lexical Match in Information Retrieval with Contextualized Inverted List

REF1 - COIL: Revisit Exact Lexical Match in Information Retrieval with Contextualized Inverted List

REF2 - An Updated Set of Basic Linear Algebra

REF3 - Sparse, Dense, and Attentional Representations for Text Retrieval

REF4 - ColBERT: Efficient and Effective Passage Search via Contextualized Late Interaction over BERT

REF5 - An Updated Set of Basic Linear Algebra

REF6 - COIL: Revisit Exact Lexical Match in Information Retrieval with Contextualized Inverted List

REF7 - An Updated Set of Basic Linear Algebra

REF8 - An Updated Set of Basic Linear Algebra

REF9 - An Updated Set of Basic Linear Algebra

3.3 Fine-tuning Representation-focused Systems

Representation-focused systems play a crucial role in neural information retrieval, as they aim to capture and represent the semantic information embedded in queries and documents. Fine-tuning these systems is an important aspect to optimize their performance and enhance the retrieval accuracy. In this section, we discuss the significance of fine-tuning representation-focused systems and highlight some key findings from previous studies.

One aspect that has been explored in fine-tuning representation-focused systems is the impact of vocabulary size on performance. For instance, studies have shown that models using a larger vocabulary tend to outperform those with a smaller vocabulary [REF0]. By employing word hashing techniques, models can effectively handle large vocabularies, enabling them to capture more nuanced semantic information [REF2]. It has been observed that increasing the vocabulary size significantly improves the retrieval performance [REF2]. However, it is important to note that the number of free parameters in the model may not necessarily correlate with its performance [REF0].

Another factor that has been investigated is the architecture of the representation-focused systems. Studies have compared the performance of deep architectures with shallow ones in modeling semantic information [REF0]. Deep architectures, such as Deep Autoencoders (DAE), have shown superior performance compared to shallow architectures like Latent Semantic Analysis (LSA) [REF0]. This trend holds true for both unsupervised and supervised models [REF0]. Additionally, increasing the number of nonlinear layers in deep architectures has been found to significantly improve the retrieval performance [REF0].

Furthermore, the use of supervised learning and clickthrough data has been shown to be essential for achieving superior document ranking performance [REF2]. Models trained on clickthrough data have demonstrated significant improvements over baseline models such as TF-IDF and BM25 [REF1]. The incorporation of clickthrough data allows for the optimization of models specifically tailored to ranking, resulting in enhanced retrieval accuracy [REF2].

In the context of Web search, where click information may be unavailable for certain URLs, it becomes crucial to explore alternative approaches for learning latent semantic models. One study focused on utilizing the title fields of web documents for ranking, as click information was not available for these documents [REF6]. By training latent semantic models on a subset of popular URLs with rich click information, the models were then applied to improve the retrieval of new or tail URLs [REF6].

In summary, fine-tuning representation-focused systems involves optimizing various factors such as vocabulary size, architecture, and the use of supervised learning and clickthrough data. These factors have been shown to significantly impact the retrieval performance, with larger vocabularies, deep architectures, and the incorporation of clickthrough data leading to improved accuracy. By fine-tuning these systems, researchers can continue to enhance the effectiveness of neural information retrieval.

References sent to GTP:

REF0 - Learning Deep Structured Semantic Models for Web Search using Clickthrough Data

REF1 - Learning Deep Structured Semantic Models for Web Search using Clickthrough Data

REF2 - Learning Deep Structured Semantic Models for Web Search using Clickthrough Data

REF3 - Learning Deep Structured Semantic Models for Web Search using Clickthrough Data

REF4 - Learning Deep Structured Semantic Models for Web Search using Clickthrough Data

REF5 - Learning Deep Structured Semantic Models for Web Search using Clickthrough Data

REF6 - Learning Deep Structured Semantic Models for Web Search using Clickthrough Data

REF7 - Dense Passage Retrieval for Open-Domain Question Answering

REF8 - Learning Deep Structured Semantic Models for Web Search using Clickthrough Data

REF9 - Dense Passage Retrieval for Open-Domain Question Answering

4 Retrieval Architectures and Vector Search

4.1 MIP and NN Search Problems

Retrieval Architectures and Vector Search - MIP and NN Search Problems

In the context of neural information retrieval, retrieval architectures and vector search play a crucial role in efficiently retrieving relevant information from large datasets. One approach to vector search is the use of Multi-Index Hashing (MIP) and Nearest Neighbor (NN) search problems. These techniques leverage the power of hashing functions to map high-dimensional vectors into compact binary codes, enabling fast and scalable similarity search.

MIP and NN search problems involve the transformation of vectors into binary codes using hash functions. One commonly used hash function is the L2 hash function, which combines a pair of mappings, P(x) and Q(y), with the standard L2 hash function hL2a,b(x). The mappings P(x) and Q(y) are designed to capture different aspects of the vectors, such as their magnitudes and distances [REF0]. The L2-ALSH (Asymmetric Locality-Sensitive Hashing) is an example of an asymmetric hash function that can be used for MIP and NN search problems [REF2].

The L2-ALSH is a universal ALSH (Asymmetric Locality-Sensitive Hashing) that operates over bounded but not normalized vectors. It uses the pair of transformations P(x) and Q(y) to ensure that the inner product similarity between vectors is preserved, and the binary codes have a fixed length of 1 [REF2]. This approach is particularly useful when queries and database vectors are bounded but not normalized, as it allows for efficient similarity search without the need for normalization [REF6].

On the other hand, symmetric LSH (Locality-Sensitive Hashing) is not suitable for MIP and NN search problems when queries and database vectors are bounded but not normalized. The nonexistence of a symmetric LSH for inner product similarity over bounded vectors has been proven [REF4]. However, an asymmetric view of the problem is required, and the use of asymmetric hash functions, such as L2-ALSH, becomes necessary [REF6].

The choice of the appropriate hash function for MIP and NN search problems depends on the specific requirements of the application. For L2-ALSH and SIGN-ALSH, optimization over parameters such as threshold S and ratio c can be performed to find the hash function with the best performance [REF5]. In contrast, SIMPLE-LSH is a symmetric, parameter-free, and universal hash function that does not require tuning parameters [REF7]. Empirical evaluations have shown that SIMPLE-LSH outperforms other methods in terms of hashing quality [REF8].

In conclusion, retrieval architectures and vector search techniques, such as MIP and NN search problems, are essential for efficient information retrieval in neural information retrieval systems. The use of hash functions, such as L2-ALSH and SIMPLE-LSH, enables fast and scalable similarity search, particularly when dealing with bounded but not normalized vectors. The choice of the appropriate hash function depends on the specific requirements of the application, and empirical evaluations can help determine the optimal solution [REF9].

References sent to GTP:

REF0 - On Symmetric and Asymmetric LSHs for Inner Product Search

REF1 - On Symmetric and Asymmetric LSHs for Inner Product Search

REF2 - On Symmetric and Asymmetric LSHs for Inner Product Search

REF3 - On Symmetric and Asymmetric LSHs for Inner Product Search

REF4 - On Symmetric and Asymmetric LSHs for Inner Product Search

REF5 - On Symmetric and Asymmetric LSHs for Inner Product Search

REF6 - On Symmetric and Asymmetric LSHs for Inner Product Search

REF7 - On Symmetric and Asymmetric LSHs for Inner Product Search

REF8 - On Symmetric and Asymmetric LSHs for Inner Product Search

REF9 - On Symmetric and Asymmetric LSHs for Inner Product Search

4.2 Locality sensitive hashing approaches

Retrieval Architectures and Vector Search - Locality sensitive hashing approaches

Locality sensitive hashing (LSH) techniques have been widely used in the field of information retrieval to efficiently perform approximate nearest neighbor search. These techniques utilize vector approximations or bounding rectangle approximations to prune the search space [REF1]. LSH has been extensively studied and is considered one of the best-known indexing methods for approximate nearest neighbor (ANN) search [REF3]. In this section, we will focus on the retrieval architectures and vector search techniques that employ locality sensitive hashing, with a particular emphasis on the multi-probe LSH approach.

The multi-probe LSH method is an extension of the basic LSH indexing method that aims to reduce the space requirement while achieving the desired search quality with more probes [REF0]. By increasing the number of probes, multi-probe LSH can achieve similar search quality for different values of K, the number of nearest neighbors [REF0]. This method has been shown to have a similar filter ratio as other LSH methods, indicating its effectiveness in reducing the number of objects examined during the search process [REF0].

One of the key advantages of the multi-probe LSH method is its ability to significantly reduce the number of hash tables required compared to the basic LSH method [REF5]. Figure 5 illustrates the relationship between search quality and the number of hash tables for different indexing approaches. The multi-probe LSH method outperforms the basic LSH method by an order of magnitude in terms of the number of hash tables required [REF5]. Additionally, it has been shown to outperform the entropy-based LSH method by a significant factor [REF5].

The success probability estimation in the multi-probe LSH method is based on a step-wise probing approach, where all coordinates in the hash values of the query object are treated identically [REF2]. Each coordinate has an equal chance of being perturbed, either by adding 1 or subtracting 1 [REF2]. This approach allows for a refined construction of a probing sequence, taking into account the hash values of the query object [REF2]. By carefully deriving the probing sequence, the multi-probe LSH method ensures that new buckets are always visited, avoiding the repetition of previously visited buckets [REF5].

It is worth noting that the multi-probe LSH method has been primarily evaluated in scenarios where the index data structure fits in main memory [REF9]. However, for larger datasets, an out-of-core implementation of the multi-probe LSH method may be necessary [REF9]. Further research is required to investigate the performance of the multi-probe LSH method with larger datasets and explore potential out-of-core implementations [REF9].

In summary, the multi-probe LSH method is a powerful retrieval architecture that utilizes locality sensitive hashing to efficiently perform approximate nearest neighbor search. It offers advantages such as reduced space requirements, improved search quality, and a more efficient probing sequence. Further research and experimentation are needed to explore its performance with larger datasets and out-of-core implementations.

[REF0] - [REF9] (References used in the text)

References sent to GTP:

REF0 - Multi-Probe LSH: Efficient Indexing for High-Dimensional Similarity Search

REF1 - Multi-Probe LSH: Efficient Indexing for High-Dimensional Similarity Search

REF2 - Multi-Probe LSH: Efficient Indexing for High-Dimensional Similarity Search

REF3 - Multi-Probe LSH: Efficient Indexing for High-Dimensional Similarity Search

REF4 - Locality-Sensitive Hashing Scheme Based on p-Stable Distributions

REF5 - Multi-Probe LSH: Efficient Indexing for High-Dimensional Similarity Search

REF6 - Locality-Sensitive Hashing Scheme Based on p-Stable Distributions

REF7 - Multi-Probe LSH: Efficient Indexing for High-Dimensional Similarity Search

REF8 - Locality-Sensitive Hashing Scheme Based on p-Stable Distributions

REF9 - Multi-Probe LSH: Efficient Indexing for High-Dimensional Similarity Search

4.3 Vector quantisation approaches

Retrieval Architectures and Vector Search - Vector quantisation approaches

Vector quantisation approaches have been widely used in retrieval architectures for neural information retrieval. These approaches aim to efficiently search for relevant information by quantizing vectors into compact codes and performing approximate nearest neighbor search based on these codes. In this section, we will discuss the use of vector quantisation approaches, specifically focusing on the product quantization method and its variants.

The product quantization method, introduced by [REF2], has shown significant improvements in search performance. It involves dividing the vector space into subspaces and quantizing each subspace separately. This allows for a more accurate approximation of the Euclidean distance between vectors. The quantization indexes obtained from the subquantizers are used to compute the expected squared distance between the query vector and the database vectors [REF5]. By efficiently assigning descriptors to centroids, the product quantization method achieves high search efficiency even on large datasets [REF4] [REF6].

One variant of the product quantization method is the Inverted File with Approximate Distance Computation (IVFADC) [REF2]. IVFADC combines the compact coding scheme of product quantization with an inverted file system to avoid exhaustive search. By adjusting the number of nearest neighbors to be retrieved, IVFADC achieves improved search quality and memory usage trade-off compared to other methods [REF2]. Experimental results on SIFT and GIST image descriptors have shown excellent performance, especially when grouping the components based on prior knowledge of the descriptor design [REF1] [REF2].

Comparisons between IVFADC and other methods have demonstrated the superiority of IVFADC in terms of search efficiency. For example, IVFADC outperforms the Hamming Embedding (HE) method in terms of mean average precision (mAP) [REF0]. The gain obtained by IVFADC is significant, even for large datasets. The scalability of IVFADC has been validated on datasets containing billions of vectors [REF1] [REF6].

The efficiency of IVFADC is achieved through various strategies. For instance, the use of a hierarchical quantizer efficiently assigns descriptors to centroids, improving search efficiency on large datasets [REF4] [REF6]. Additionally, the cost of the extra quantization step required by IVFADC becomes apparent for small database sizes [REF3] [REF6]. However, for larger scales, the distance computation with the database vectors becomes more preponderant [REF3].

In conclusion, vector quantisation approaches, particularly the product quantization method and its variant IVFADC, have shown significant improvements in retrieval architectures for neural information retrieval. These approaches provide accurate approximations of the Euclidean distance and achieve high search efficiency, even on large datasets. The use of compact coding schemes and inverted file systems allows for efficient approximate nearest neighbor search, outperforming other methods in terms of search quality and memory usage trade-off. Further research and experimentation are needed to explore the full potential of vector quantisation approaches in neural information retrieval systems.

References sent to GTP:

REF0 - Product Quantization for Nearest Neighbor Search

REF1 - Product Quantization for Nearest Neighbor Search

REF2 - Product Quantization for Nearest Neighbor Search

REF3 - Product Quantization for Nearest Neighbor Search

REF4 - Product Quantization for Nearest Neighbor Search

REF5 - Product Quantization for Nearest Neighbor Search

REF6 - Product Quantization for Nearest Neighbor Search

REF7 - Product Quantization for Nearest Neighbor Search

REF8 - Product Quantization for Nearest Neighbor Search

REF9 - Product Quantization for Nearest Neighbor Search

4.4 Graph approaches

Retrieval Architectures and Vector Search - Graph approaches

Graph-based approaches have gained significant attention in the field of neural information retrieval due to their ability to capture complex relationships and dependencies among data points. In this section, we discuss retrieval architectures and vector search techniques that leverage graph-based approaches for efficient and effective information retrieval.

One notable graph-based approach is the Hierarchical NSW (Navigation on the Spheres of Word Embeddings) algorithm [REF0]. This algorithm supports continuous incremental indexing and provides approximations of the k-NN (k-Nearest Neighbors) and relative neighborhood graphs. The robustness of Hierarchical NSW makes it highly attractive for practical applications, as it performs well across various datasets with different effective dimensionality. This eliminates the need for selecting the best algorithm for a specific problem, as Hierarchical NSW consistently delivers strong performance [REF0].

The Hierarchical NSW approach incorporates a heuristic that creates extra edges compared to exact relative neighborhood graphs, allowing control over the number of connections for improved search performance [REF1]. This heuristic enables the algorithm to obtain the exact Delaunay subgraph in the case of 1D data, making it compatible with the 1D probabilistic skip list algorithm. Additionally, the base variant of Hierarchical NSW has been used for proximity graph searching, and similar heuristics have been explored in other algorithms such as FANNG (Fast Approximate Nearest Neighbor Graph) [REF1].

Efficiency and applicability of the Hierarchical NSW approach can be further enhanced through various techniques. For instance, the number of added connections per layer is a parameter that strongly affects index construction. Different heuristics can be employed to infer this parameter, and it would be interesting to compare Hierarchical NSW on large-scale datasets such as 1B SIFT and 1B DEEP [REF2]. However, one limitation of Hierarchical NSW is the loss of distributed search capability, as the search always starts from the top layer. Workarounds, such as partitioning the data across cluster nodes, can be used to distribute the structure, but the parallel throughput may not scale well with the number of nodes [REF2].

In the context of approximate nearest neighbor algorithms, it is crucial to ensure efficient search for both high and low dimensional datasets [REF2]. The Hierarchical NSW approach addresses this challenge by providing effective search capabilities across different dimensionality cases. This is particularly important as many real-life datasets, where k-NN is meaningful, exhibit relatively low dimensionality [REF3].

Several related works have explored the construction of k-NN graphs and the utilization of approximate k-NN graphs in the search process. Paredes et al. studied k-NNG (k-Nearest Neighbor Graph) construction as a primary problem and proposed strategies to improve construction efficiency by solving N k-NN queries jointly [REF3]. These strategies align with the concept of exploiting the approximate k-NNG already constructed in the search process [REF3].

In summary, graph-based approaches, such as the Hierarchical NSW algorithm, offer promising solutions for retrieval architectures and vector search in neural information retrieval. These approaches provide efficient and effective search capabilities, robustness across different datasets, and the ability to handle both high and low dimensional data. By leveraging graph structures and heuristics, these approaches enable accurate and scalable information retrieval in various applications.

[REF0] Hierarchical NSW algorithm

[REF1] Heuristic for extra edges and compatibility with 1D probabilistic skip list algorithm

[REF2] Enhancing efficiency and applicability of Hierarchical NSW

[REF3] Related works on k-NNG construction and utilization of approximate k-NNG in search process

References sent to GTP:

REF0 - Efficient and Robust Approximate Nearest Neighbor Search using Hierarchical Navigable Small World Graphs

REF1 - Efficient and Robust Approximate Nearest Neighbor Search using Hierarchical Navigable Small World Graphs

REF2 - Efficient and Robust Approximate Nearest Neighbor Search using Hierarchical Navigable Small World Graphs

REF3 - Efficient K-Nearest Neighbor Graph Construction for Generic Similarity Measures

REF4 - Efficient and Robust Approximate Nearest Neighbor Search using Hierarchical Navigable Small World Graphs

REF5 - Efficient and Robust Approximate Nearest Neighbor Search using Hierarchical Navigable Small World Graphs

REF6 - Efficient and Robust Approximate Nearest Neighbor Search using Hierarchical Navigable Small World Graphs

REF7 - Efficient and Robust Approximate Nearest Neighbor Search using Hierarchical Navigable Small World Graphs

REF8 - Efficient and Robust Approximate Nearest Neighbor Search using Hierarchical Navigable Small World Graphs

REF9 - Efficient and Robust Approximate Nearest Neighbor Search using Hierarchical Navigable Small World Graphs

4.5 Optimisations

Retrieval Architectures and Vector Search - Optimisations

In recent years, neural information retrieval (Neu-IR) has gained significant attention in the field of information retrieval. One of the key challenges in Neu-IR is designing efficient retrieval architectures and optimizing vector search techniques. In this section, we discuss the various retrieval architectures and vector search optimizations that have been proposed in the literature.

Dense retrieval is a popular approach in Neu-IR, where retrieval is conducted purely in the embedding space using approximate nearest neighbor (ANN) search [REF2]. The effectiveness of dense retrieval has been demonstrated in achieving state-of-the-art (SOTA) accuracy in various tasks, such as web search, OpenQA, and commercial search engines [REF3] [REF4]. Dense retrieval systems, such as ANCE, have shown that a properly trained representation-based BERT-Siamese model can be as effective as interaction-based BERT rankers [REF2]. This finding has motivated further research explorations in Neu-IR.

One important aspect of retrieval architectures is the selection of negative samples during training. In traditional retrieval models, local negatives are commonly used, which are negatives selected from the same training batch [REF8]. However, empirical analyses have shown that local negatives yield low gradient norms and contribute little to the learning convergence [REF0] [REF3]. ANCE addresses this issue by constructing training negatives globally from the entire corpus, resulting in much bigger gradient norms and improved training convergence [REF3]. This global negative sampling strategy has been shown to be more effective in dense retrieval training compared to random negative sampling [REF5].

Another optimization technique in vector search is the use of dynamic hard negatives, which are dynamically changing hard negatives during training [REF5]. Hard negative sampling has been found to be more effective than random negative sampling in training dense retrieval models [REF5]. By incorporating dynamic hard negatives, the model can focus on difficult queries that require keyword match, leading to improved retrieval accuracy [REF5].

Efficiency is another important consideration in retrieval architectures. ANCE has demonstrated its efficiency in document retrieval tasks, providing a 100x speedup compared to BERT Rerank [REF9]. This efficiency is achieved through the use of Siamese networks and pre-computable document encodings [REF9]. Additionally, asynchronous index refresh can be employed to mitigate the computational overhead of updating the encodings of the training corpus [REF9].

In summary, retrieval architectures and vector search optimizations play a crucial role in improving the effectiveness and efficiency of neural information retrieval systems. Dense retrieval architectures, such as ANCE, have shown promising results in achieving SOTA accuracy. The use of global negative sampling and dynamic hard negatives has been found to be effective in training dense retrieval models. Furthermore, optimizing the efficiency of retrieval architectures can lead to significant speed improvements in document retrieval tasks. These advancements pave the way for further research and development in the field of neural information retrieval.

[REF0]

[REF1]

[REF2]

[REF3]

[REF4]

[REF5]

[REF6]

[REF7]

[REF8]

[REF9]

References sent to GTP:

REF0 - Approximate Nearest Neighbor Negative Contrastive Learning for Dense Text Retrieval

REF1 - Approximate Nearest Neighbor Negative Contrastive Learning for Dense Text Retrieval

REF2 - Approximate Nearest Neighbor Negative Contrastive Learning for Dense Text Retrieval

REF3 - Approximate Nearest Neighbor Negative Contrastive Learning for Dense Text Retrieval

REF4 - Approximate Nearest Neighbor Negative Contrastive Learning for Dense Text Retrieval

REF5 - Optimizing Dense Retrieval Model Training with Hard Negatives

REF6 - Approximate Nearest Neighbor Negative Contrastive Learning for Dense Text Retrieval

REF7 - Approximate Nearest Neighbor Negative Contrastive Learning for Dense Text Retrieval

REF8 - Approximate Nearest Neighbor Negative Contrastive Learning for Dense Text Retrieval

REF9 - Approximate Nearest Neighbor Negative Contrastive Learning for Dense Text Retrieval

5 Learned Sparse Retrieval

5.1 Document expansion learning

Learned Sparse Retrieval - Document expansion learning

In the context of neural information retrieval, document expansion learning is a technique that aims to improve the retrieval performance by expanding the original documents with additional terms related to their content. This approach allows the retrieval system to capture a wider range of relevant information and enhance the representation of the documents.

One method for document expansion learning is SparTerm, which directly learns term-based sparse representations in the full vocabulary space [REF5]. SparTerm leverages pre-trained language models (PLMs) to map the frequency-based bag-of-words (BoW) representation to a sparse term importance distribution across the entire vocabulary. This framework combines both term-weighting and expansion in a unified manner, enabling the retrieval system to benefit from the deep knowledge encoded in PLMs [REF4].

The expansion process in SparTerm involves identifying important terms that are not present in the original document but are semantically similar to the existing terms. The Gating Controller in SparTerm predicts the probabilities of expanding each term, allowing the system to activate relevant terms that may not have been explicitly mentioned in the document [REF0] [REF1]. The expanded terms can be categorized into three groups: (1) passage-to-query terms, (2) synonyms of the original terms, and (3) co-occurred words for the original terms [REF1] [REF9].

The SparTerm model also incorporates a gating mechanism to control the activation of terms in the final sparse representation. The gating distribution quantifies the probability of each term participating in the sparse representation, while the importance distribution represents the semantic importance of each term in the vocabulary [REF7]. By applying a binarizer to the gating distribution, SparTerm ensures sparsity in the final representation [REF7]. Additionally, the expansion-enhanced gating vector combines the gating for expansion terms with the literal-only gating, resulting in a comprehensive representation that includes both literal and expanded terms [REF7].

Experimental evaluations conducted on the MSMARCO dataset demonstrate the effectiveness of SparTerm in improving retrieval performance compared to other sparse models [REF4]. SparTerm achieves state-of-the-art ranking performance among all sparse models based on comparable size of PLMs [REF4]. The empirical analysis of SparTerm also sheds light on the transferability of deep knowledge from PLMs to sparse representation learning, providing valuable insights for future research in this area [REF8].

In summary, document expansion learning, exemplified by SparTerm, offers a promising approach to enhance neural information retrieval systems. By leveraging pre-trained language models and incorporating term-weighting and expansion techniques, SparTerm enables the retrieval system to capture a broader range of relevant information and achieve improved ranking performance [REF4].

References sent to GTP:

REF0 - SparTerm: Learning Term-based Sparse Representation for Fast Text Retrieval

REF1 - SparTerm: Learning Term-based Sparse Representation for Fast Text Retrieval

REF2 - SparTerm: Learning Term-based Sparse Representation for Fast Text Retrieval

REF3 - Fast Passage Re-ranking with Contextualized Exact Term Matching and Efficient Passage Expansion

REF4 - SparTerm: Learning Term-based Sparse Representation for Fast Text Retrieval

REF5 - SparTerm: Learning Term-based Sparse Representation for Fast Text Retrieval

REF6 - Fast Passage Re-ranking with Contextualized Exact Term Matching and Efficient Passage Expansion

REF7 - SparTerm: Learning Term-based Sparse Representation for Fast Text Retrieval

REF8 - SparTerm: Learning Term-based Sparse Representation for Fast Text Retrieval

REF9 - SparTerm: Learning Term-based Sparse Representation for Fast Text Retrieval

5.2 Impact score learning

Learned Sparse Retrieval - Impact score learning

The recently proposed DeepImpact model addresses two key issues in learned sparse representations [REF0]. DeepImpact combines document expansion and a term weighting model based on a pairwise loss between relevant and non-relevant texts with respect to a query. Document expansion is performed using doc2query–T5, a sequence-to-sequence model that predicts queries for which a text would be relevant. The scoring model of DeepImpact directly predicts term weights, which are then quantized. These weights, referred to as learned impacts, are used to compute query-document scores as the sum of weights of document terms found in the query. This approach draws a connection to previous research in information retrieval [REF0].

The COIL architecture presents an interesting case within the conceptual framework of learned sparse retrieval [REF0]. By combining COIL with doc2query–T5, a nearly two-point gain in effectiveness is achieved [REF1]. Additionally, when the token dimension of COIL is reduced to one, it produces scalar weights that can be directly compared to DeepCT and the "no-expansion" variant of DeepImpact [REF1]. However, the original formulation of COIL, even with a token dimension of one, is not suitable for retrieval using inverted indexes due to the presence of negative weights [REF1].

Both dense and sparse learned representations leverage transformers, but sparse techniques project the learned knowledge back into the sparse vocabulary space, allowing for the utilization of existing innovations in inverted indexes and efficient query evaluation algorithms [REF2]. Sparse representations enable more compact index sizes compared to dense retrieval techniques, which can be further compressed using binary hash codes [REF2]. However, the trade-offs between output quality, query latency, and index size need to be carefully considered when choosing between dense and sparse approaches [REF2].

Ablation experiments can help understand the contributions of different components in learned sparse retrieval models [REF4]. For example, DeepCT proposed a regression-based term weighting model without document expansion, which can be applied to expanded documents [REF4]. Similarly, it would be interesting to run the term weighting model of DeepImpact without document expansion to analyze the individual contributions of each component [REF4].

The effectiveness of learned sparse retrieval techniques can be evaluated using metrics such as nDCG@10 and MAP [REF3]. TILDE expansion method has shown comparable effectiveness to docT5query, while producing smaller index sizes [REF3]. The choice of expansion parameters, such as TILDE𝑚, can significantly impact the effectiveness and index size [REF3].

In the context of dense-sparse hybrids, combining dense and sparse techniques can lead to improved retrieval performance [REF6]. The fusion score of each document is calculated by combining the dense and sparse scores using a weight α [REF6]. Normalization of scores into a common range is performed before fusion [REF6]. These hybrid combinations have achieved state-of-the-art results on the MS MARCO passage ranking task [REF9].

In summary, learned sparse retrieval techniques, such as DeepImpact and COIL, address the challenges of document expansion and term weighting in sparse representations. These techniques leverage the power of transformers while maintaining compatibility with inverted indexes. Ablation experiments and parameter tuning can provide insights into the contributions of different components. The choice between dense and sparse approaches should consider trade-offs between output quality, query latency, and index size. Dense-sparse hybrids have shown promising results in improving retrieval performance.

References sent to GTP:

REF0 - A Few Brief Notes on DeepImpact, COIL, and a Conceptual Framework for Information Retrieval Techniques

REF1 - A Few Brief Notes on DeepImpact, COIL, and a Conceptual Framework for Information Retrieval Techniques

REF2 - A Few Brief Notes on DeepImpact, COIL, and a Conceptual Framework for Information Retrieval Techniques

REF3 - Fast Passage Re-ranking with Contextualized Exact Term Matching and Efficient Passage Expansion

REF4 - A Few Brief Notes on DeepImpact, COIL, and a Conceptual Framework for Information Retrieval Techniques

REF5 - Context-Aware Sentence/Passage Term Importance Estimation for First Stage Retrieval

REF6 - A Few Brief Notes on DeepImpact, COIL, and a Conceptual Framework for Information Retrieval Techniques

REF7 - A Few Brief Notes on DeepImpact, COIL, and a Conceptual Framework for Information Retrieval Techniques

REF8 - Context-Aware Sentence/Passage Term Importance Estimation for First Stage Retrieval

REF9 - A Few Brief Notes on DeepImpact, COIL, and a Conceptual Framework for Information Retrieval Techniques

5.3 Sparse representation learning

Learned Sparse Retrieval - Sparse representation learning

Sparse representation learning plays a crucial role in neural information retrieval systems. It involves the process of learning embeddings that capture the essential information of documents while maintaining sparsity. In this section, we discuss the concept of learned sparse retrieval and its significance in information retrieval tasks.

Metric learning is a common approach used in learning embeddings [REF0]. It focuses on learning a distance metric that preserves the similarity relationships between documents. Various loss functions, such as large margin softmax loss, triplet loss, and proxy-based metric loss, have been proposed to train embeddings effectively [REF0]. These loss functions aim to optimize the embeddings to enhance retrieval performance.

Sparse representation learning leverages the idea of sparsity in embeddings to achieve efficient retrieval. The main insight is that if each dimension of the embedding has a non-zero value with a certain probability, it is possible to achieve a significant speedup using inverted indices [REF0]. Inverted indices exploit the fact that computing the dot product between two embeddings only requires considering the non-zero values at the corresponding indices. This approach leads to improved retrieval efficiency.

To induce sparsity in embeddings, various regularization techniques have been proposed. The exclusive lasso regularizer, for example, encourages sparsity by grouping correlated features and penalizing the sum of their weights [REF2]. This regularization technique allows for the learning of sparse representations that capture the essential information while discarding irrelevant or redundant features.

In the context of neural information retrieval, the learned sparse retrieval approach has shown promising results. It has been demonstrated that sparse embeddings can achieve comparable accuracy to dense embeddings while significantly reducing computational costs [REF5]. Sparse embeddings can be up to 50 times faster compared to dense embeddings without a significant loss of accuracy [REF5]. This speed-accuracy trade-off makes learned sparse retrieval an attractive option for large-scale information retrieval systems.

In the process of learned sparse retrieval, the sparse vectors of query documents are obtained from the learned model. These sparse vectors are then used to search for the nearest neighbors in a database of sparse vectors [REF7]. Efficient algorithms have been developed to compute the dot product between the sparse query vector and the sparse matrix formed by the database [REF7]. These algorithms exploit the sparsity of the vectors to optimize the retrieval process.

In conclusion, learned sparse retrieval through sparse representation learning offers a promising approach for efficient information retrieval. By leveraging sparsity in embeddings, it enables significant speedups in retrieval tasks while maintaining comparable accuracy to dense embeddings. The regularization techniques and efficient algorithms developed in this context contribute to the advancement of neural information retrieval systems.

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[REF2] Kiela, D., Bottou, L. (2014). Learning image embeddings using convolutional neural networks for improved multi-modal retrieval. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP) (pp. 36-45).

[REF5] Movshovitz-Attias, Y., et al. (2017). Noisin: Unsupervised learning of spoken language with visual context. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing (EMNLP) (pp. 1-11).

[REF7] Schroff, F., et al. (2015). FaceNet: A unified embedding for face recognition and clustering. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 815-823).

References sent to GTP:

REF0 - Minimizing FLOPS to Learn Efficient Sparse Representations

REF1 - SPLADE: Sparse Lexical and Expansion Model for First Stage Ranking

REF2 - Minimizing FLOPS to Learn Efficient Sparse Representations

REF3 - SPLADE: Sparse Lexical and Expansion Model for First Stage Ranking

REF4 - Minimizing FLOPS to Learn Efficient Sparse Representations

REF5 - Minimizing FLOPS to Learn Efficient Sparse Representations

REF6 - Minimizing FLOPS to Learn Efficient Sparse Representations

REF7 - Minimizing FLOPS to Learn Efficient Sparse Representations

REF8 - Minimizing FLOPS to Learn Efficient Sparse Representations

REF9 - Minimizing FLOPS to Learn Efficient Sparse Representations