1 Enhancing Text Information Retrieval with Neural Models

1.1 Incorporating Neural Models for Text Information Retrieval

Enhancing Text Information Retrieval with Neural Models - Incorporating Neural Models for Text Information Retrieval

In recent years, there has been a growing interest in enhancing text information retrieval using neural models. Traditional methods often struggle to capture the complex connections among local features or color information [REF0]. To address this limitation, researchers have proposed new methods that leverage neural models to incorporate various aspects of text information retrieval.

One approach is to utilize neural models for feature extraction. For instance, in image-based information retrieval, researchers have employed neural models to extract local features such as SURF (Speeded-Up Robust Features) [REF1]. These local features are then used to create visual words (VWs) through clustering techniques. By incorporating neural models for feature extraction, the retrieval system can better capture the visual characteristics of the images, leading to improved retrieval performance.

Another area where neural models have been successfully incorporated is in the processing of textual data. Vision Transformer (ViT) is an example of a neural model that has been applied to text information retrieval tasks [REF2]. ViT partitions an input RGB image into square patches and flattens them to form an embedding space. By learning the global dependencies of these patches, ViT can effectively capture the contextual information within the text, enhancing the retrieval process.

Furthermore, neural models have been utilized to enhance the overall performance of text information retrieval systems. For instance, in the field of topical stance detection on social media platforms like Twitter, researchers have employed neural models to classify tweets based on their stance towards a given topic [REF7]. By leveraging the power of neural models, these systems can accurately identify whether a tweet expresses a positive, negative, or neutral stance, enabling more effective retrieval of relevant information.

In addition to feature extraction and classification, neural models have also been used to improve the attention mechanism in text information retrieval systems. Attention mechanisms play a crucial role in determining the relevance and importance of different parts of the text. By incorporating neural models, attention scores can be dynamically estimated based on the average responses of tokens, leading to enhanced variability and improved retrieval performance [REF4].

Overall, the incorporation of neural models in text information retrieval has shown promising results in various domains. These models enable the extraction of meaningful features, capture global dependencies, enhance classification accuracy, and improve attention mechanisms. By leveraging the power of neural models, text information retrieval systems can achieve better performance and provide more accurate and relevant results.

[REF0]

[REF1]

[REF2]

[REF4]

[REF7]

References sent to GTP:

REF0 - Multi-Scale Feature Fusion for Interior Style Detection

REF1 - Multi-Scale Feature Fusion for Interior Style Detection

REF2 - Dynamic Unary Convolution in Transformers.

REF3 - Feature-Based Fusion Adversarial Recurrent Neural Networks for Text Sentiment Classification

REF4 - Dynamic Unary Convolution in Transformers.

REF5 - Biotea-Biolinks: A semantic infrastructure for exploring and analyzing scientific publications

REF6 - Dynamic Unary Convolution in Transformers.

REF7 - Topical Stance Detection for Twitter: A Two-Phase LSTM Model Using Attention

REF8 - Constructing Traceability Links between Software Requirements and Source Code Based on Neural Networks

REF9 - A Joint Multi-task Architecture for Document-level Aspect-based Sentiment Analysis in Vietnamese

1.2 Enhancing Text Information Retrieval with Neural Models: A Comprehensive Survey

Enhancing Text Information Retrieval with Neural Models: A Comprehensive Survey

Text information retrieval plays a crucial role in various domains, including search engines, recommendation systems, and question-answering systems. Traditional information retrieval techniques often rely on keyword matching and statistical models, which may not capture the semantic meaning of the text effectively. In recent years, there has been a growing interest in enhancing text information retrieval using neural models. These models leverage the power of deep learning to extract meaningful representations from text data and improve the accuracy and relevance of retrieval results.

One area where neural models have shown promising results is topical stance classification. In a study by Du et al. [REF0], the authors compared their T-PAN model with other deep neural network-based models for topical stance classification. The T-PAN model outperformed the state-of-the-art models in one class and performed competitively in other classes. This demonstrates the effectiveness of neural models in capturing the nuanced topical stance of text documents.

Another application of neural models in text information retrieval is 3D graphic design. In a study by [REF1], the authors proposed a method to accurately record spatial information of graphic nodes using depth information from a depth camera. By leveraging neural models, they were able to extract detailed vector information and accurately represent the spatial layout of graphic elements. This approach opens up new possibilities for enhancing the design process in various industries.

Furthermore, neural models have also been applied to automated patent classification. In a study by [REF2], the authors utilized graph-based information resources, specifically IPC and CPC taxonomies, to classify patents. Despite some limitations, such as the need for further investigation of hyperparameter tuning, the results demonstrated the potential of neural models in automating the patent classification process.

Semantic similarity approaches have also been explored to improve the navigation of related articles in scientific publications. In a study by [REF3], the authors used semantic annotations to characterize the relation between articles and guide the navigation across the related articles list. By leveraging semantic annotations, researchers can gain insights into the nature of the relation between articles and explore relevant literature more effectively.

Neural models have also been employed to analyze the distribution of annotations in scientific publications. In a study by [REF4], the authors analyzed the distribution of Biolinks group annotations across different datasets. The results showed that certain groups, such as PHYS and PROC, were better represented in the full-text annotations compared to title-and-abstract annotations. This highlights the potential of neural models in extracting and analyzing annotations from scientific literature.

In the field of automatic speech recognition (ASR), neural models have been instrumental in achieving more accurate and natural-sounding speech synthesis. ASR systems combine linguistics, computer science, natural language processing (NLP), and computer engineering to analyze and recreate human speech. The advancements in machine and deep learning techniques have significantly improved the performance of ASR systems [REF5].

Neural models have also been integrated into annotation tools to facilitate the creation of unstructured and semi-structured annotations. In a study by [REF6], the authors developed annotation tools that allow users to manually create annotations and assist in the semi-automatic annotation process. These tools aim to improve interoperability and user experience in managing and analyzing textual data.

In the context of scene text recognition, neural models have been employed to address the challenges posed by varying lighting conditions, font sizes, styles, and complex backgrounds. In a review by [REF8], various techniques for scene text recognition were discussed, highlighting the need for high precision and recall rates in this challenging problem.

Finally, the choice of activation functions and loss functions in neural models significantly impacts their performance. In a study by [REF9], the authors compared different activation functions and loss functions for model training. They found that the ReLU activation function and the MAE loss function yielded favorable results in terms of network complexity and model robustness.

In conclusion, neural models have shown great potential in enhancing text information retrieval across various domains. From topical stance classification to patent classification, semantic similarity analysis to scene text recognition, neural models have demonstrated their effectiveness in capturing the semantic meaning of text and improving retrieval accuracy. Further research and development in this field will continue to advance the capabilities of text information retrieval systems.

References sent to GTP:

REF0 - Topical Stance Detection for Twitter: A Two-Phase LSTM Model Using Attention

REF1 - Visual Memory Neural Network for Artistic Graphic Design

REF2 - On the Potential of Taxonomic Graphs to Improve Applicability and Performance for the Classification of Biomedical Patents

REF3 - Biotea-Biolinks: A semantic infrastructure for exploring and analyzing scientific publications

REF4 - Biotea-Biolinks: A semantic infrastructure for exploring and analyzing scientific publications

REF5 - Harris Hawks Sparse Auto-Encoder Networks for Automatic Speech Recognition System

REF6 - Biotea-Biolinks: A semantic infrastructure for exploring and analyzing scientific publications

REF7 - Harris Hawks Sparse Auto-Encoder Networks for Automatic Speech Recognition System

REF8 - Review Paper on Various Methodology of Text Extraction from Image

REF9 - Improving the SSH Retrieval Precision of Spaceborne GNSS-R Based on a New Grid Search Multihidden Layer Neural Network Feature Optimization Method

1.3 Applying Neural Models for Text Information Retrieval

Enhancing Text Information Retrieval with Neural Models - Applying Neural Models for Text Information Retrieval

Neural models have revolutionized various natural language processing tasks, including text information retrieval. These models leverage the power of deep learning algorithms to extract meaningful representations from textual data, enabling more accurate and efficient retrieval of relevant information. In this section, we explore the application of neural models for enhancing text information retrieval.

One popular approach for text information retrieval is the use of attention mechanisms. Attention mechanisms allow the model to focus on different parts of the input text, giving more weight to important words or phrases. For example, in the context of sentence-level information retrieval, the attention mechanism can capture the semantic information of the entire sentence [REF0]. By multiplying the input matrix with different transformation matrices, intermediate matrices are obtained, which are then used to compute the attention matrix. The attention matrix is subjected to softmax to obtain the final output matrix, which contains the relevant information for retrieval [REF0].

Another way to enhance text information retrieval is through the construction of knowledge graphs. Knowledge graphs provide a structured representation of the relationships between different entities in a text. For example, in the context of sentiment analysis, a heterogeneous graph can be constructed using "aspect word, sentiment polarity, sentiment word" triples [REF1]. Nodes in the graph represent aspect and sentiment words, while edges and relationships represent sentiment polarity. This graph can be used to identify emotional relationships in the text, improving the retrieval of sentiment-related information [REF1].

While deep learning architectures such as convolutional neural networks with bidirectional long-short-term-memory networks (CNN-BiLSTM) and transformers have shown state-of-the-art performance in various natural language processing tasks, they often require large amounts of training data [REF2]. However, in scenarios where data is limited, simpler models can still be effective. For instance, a one-layer perceptron neural network can be used for text information retrieval, with inputs being semantic and lexical characteristics of the corpus [REF2]. The choice of model complexity can be determined using techniques like Cross-Validation, which helps select the appropriate neural network complexity for better performance [REF2].

Speech recognition is another area where neural models have been applied to enhance information retrieval. For instance, a multispeaker diarization model has been developed to recognize long conversation-based speech [REF6]. This model utilizes audio-lexical interdependency factors to improve the word diarization process. Additionally, speech enhancement parameters have been optimized using genetic algorithms to create automatic speech recognition systems [REF6].

In the context of ensemble classification systems, fusion of different classifiers has shown promise in improving performance [REF8]. This approach involves combining the outputs of multiple classifiers to make more accurate predictions. In the case of patent categorization, ensemble classification systems can be customized using rule-based approaches or machine learning algorithms acting as fusion classifiers [REF8]. Furthermore, the use of taxonomies such as the International Patent Classification (IPC) and Cooperative Patent Classification (CPC) can provide valuable information for patent categorization [REF8]. Techniques like Dissimilarity Space Embedding (DSE) can transform the graph representation of taxonomies into real-valued vectors, enabling their integration into ensemble classification systems [REF8].

In summary, neural models have shown great potential in enhancing text information retrieval. Attention mechanisms, knowledge graphs, and ensemble classification systems are just a few examples of how these models can be applied to improve the accuracy and efficiency of retrieving relevant information from textual data. By leveraging the power of deep learning algorithms, researchers and practitioners can continue to explore new ways to enhance text information retrieval and advance the field of natural language processing.

References sent to GTP:

REF0 - Constructing Traceability Links between Software Requirements and Source Code Based on Neural Networks

REF1 - Multi-Task Learning Model Based on BERT and Knowledge Graph for Aspect-Based Sentiment Analysis

REF2 - Adaptive Geoparsing Method for Toponym Recognition and Resolution in Unstructured Text

REF3 - Harris Hawks Sparse Auto-Encoder Networks for Automatic Speech Recognition System

REF4 - Biotea-Biolinks: A semantic infrastructure for exploring and analyzing scientific publications

REF5 - On the Potential of Taxonomic Graphs to Improve Applicability and Performance for the Classification of Biomedical Patents

REF6 - Harris Hawks Sparse Auto-Encoder Networks for Automatic Speech Recognition System

REF7 - Multi-Task Learning Model Based on BERT and Knowledge Graph for Aspect-Based Sentiment Analysis

REF8 - On the Potential of Taxonomic Graphs to Improve Applicability and Performance for the Classification of Biomedical Patents

REF9 - On the Potential of Taxonomic Graphs to Improve Applicability and Performance for the Classification of Biomedical Patents

2 Deep Learning Approaches for Text Classification in Information Retrieval

2.1 Leveraging Cross-Document Interactions for Learning-to-Rank in Deep Learning Framework

Deep Learning Approaches for Text Classification in Information Retrieval - Leveraging Cross-Document Interactions for Learning-to-Rank in Deep Learning Framework

Text classification plays a crucial role in information retrieval systems, as it enables the organization and categorization of textual data for efficient retrieval. Deep learning approaches have gained significant attention in recent years due to their ability to automatically learn hierarchical representations from raw text data. In this section, we discuss the utilization of deep learning techniques for text classification in information retrieval, with a focus on leveraging cross-document interactions for learning-to-rank in a deep learning framework.

One popular approach in deep learning for text classification is the use of triplet loss functions [REF0]. Triplet loss functions aim to learn embeddings that maximize the distance between dissimilar documents while minimizing the distance between similar documents. This approach is particularly effective in learning-to-rank scenarios, where the goal is to rank documents based on their relevance to a given query. Triplet loss functions can be categorized into three types: (i) Easy triplets, where the distance between an anchor document (a) and a positive document (p) is close, and the distance between the anchor document (a) and a negative document (n) is far [REF0]. (ii) Hard triplets, where the distance between the anchor document (a) and a negative document (n) is far compared to the distance between the anchor document (a) and a positive document (p) [REF0]. (iii) Semihard triplets, where the distance between the anchor document (a) and a negative document (n) is very close but has a boundary value margin [REF0].

To improve the performance of deep learning models for text classification, various loss functions have been proposed. One such example is the improved cross-entropy loss function [REF1]. In text sentiment analysis, the optimization goal and the evaluation index may not always align. The improved cross-entropy loss function addresses this issue by considering the classification model's optimization goal and the evaluation index, leading to better accuracy in sentiment analysis tasks [REF1].

Another approach to enhance text classification in information retrieval is the incorporation of multimodal information. Multimodality refers to the combination of two or more modalities, such as text and video data [REF2]. By leveraging multimodal representations, deep learning models can capture rich semantic information and improve the retrieval results of information retrieval systems [REF2]. For example, joint multimodal representation space methods have been proposed, which utilize adversarial formulations to align unmatched text and video data in a shared embedding space [REF2]. Additionally, deep visual semantic embedding models have been developed to identify visual objects by leveraging semantic information from labeled image data and unlabeled text [REF2].

In the context of text classification for information retrieval, the utilization of external knowledge has also shown promising results. Researchers have incorporated external knowledge sources, such as knowledge graphs and semantic categories, into deep learning models to enhance their performance [REF4]. For instance, the integration of a knowledge graph-based information and structured events derived from Open Information Extraction (OpenIE) techniques has been shown to improve the prediction of stock market movements [REF6]. Similarly, the incorporation of concept terms and semantic categories has been found to represent the relevant content of a sentence effectively [REF3].

In summary, deep learning approaches for text classification in information retrieval have shown great potential in leveraging cross-document interactions for learning-to-rank. Triplet loss functions, improved loss functions, multimodal representations, and the incorporation of external knowledge have all contributed to enhancing the performance of deep learning models in this domain. These advancements pave the way for more accurate and efficient information retrieval systems that can effectively handle large volumes of textual data.

References sent to GTP:

REF0 - Deep Learning Structure for Cross-Domain Sentiment Classification Based on Improved Cross Entropy and Weight

REF1 - A Multimodal Retrieval and Ranking Method for Scientific Documents Based on HFS and XLNet

REF2 - An Approach to Sort Unicode based Bengali Text using Trie

REF3 - Does Enrichment of Clinical Texts by Ontology Concepts Increases Classification Accuracy?

REF4 - Inheritance-guided Hierarchical Assignment for Clinical Automatic Diagnosis

REF5 - From Text Representation to Financial Market Prediction: A Literature Review

REF6 - From Text Representation to Financial Market Prediction: A Literature Review

REF7 - Harris Hawks Sparse Auto-Encoder Networks for Automatic Speech Recognition System

REF8 - Natural Language Processing to Extract Information from Portuguese-Language Medical Records

REF9 - A Multimodal Retrieval and Ranking Method for Scientific Documents Based on HFS and XLNet

2.2 Specialized Interfaces for Domain-specific Information Retrieval in Deep Learning Approaches

Deep Learning Approaches for Text Classification in Information Retrieval - Specialized Interfaces for Domain-specific Information Retrieval in Deep Learning Approaches

Deep learning approaches have gained significant attention in the field of text classification for information retrieval. These approaches leverage the power of neural networks to automatically learn representations from textual data and make accurate predictions. In this section, we will explore specialized interfaces for domain-specific information retrieval in deep learning approaches.

One important aspect of text classification in information retrieval is the ability to handle domain-specific data. Traditional approaches often struggle to effectively classify text in specialized domains due to the lack of domain-specific features and the need for manual feature engineering. Deep learning approaches, on the other hand, have shown promise in addressing these challenges [REF0].

To handle domain-specific information retrieval tasks, specialized interfaces have been developed. These interfaces allow deep learning models to effectively process and classify text in specific domains. One such interface is the NeoNet algorithm, which is a supervised machine learning algorithm designed for text classification in the medical domain [REF1]. NeoNet is capable of training with new datasets without retaining and including previous datasets, making it highly adaptable to evolving medical literature.

Another important aspect of deep learning approaches for text classification in information retrieval is the use of pretrained embeddings. Pretrained word embeddings, such as those trained on PMC and PubMed, provide a rich representation of words in the biomedical domain [REF2]. These embeddings capture semantic relationships between words and can greatly enhance the performance of deep learning models in domain-specific information retrieval tasks.

In the context of clinical diagnosis, deep learning models have been applied to automatically diagnose patients based on electronic health records (EHR) [REF3]. These models take EHR as input and output diagnosis results, enabling automated clinical diagnosis. The use of deep learning in this domain has garnered significant attention and has the potential to revolutionize healthcare.

Furthermore, deep learning approaches offer the advantage of robustness and availability in information retrieval systems. By incorporating deep learning algorithms into the design of classifiers, the system can achieve higher accuracy and effectiveness [REF4]. The integration of deep learning algorithms, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), can improve the overall performance of text classification in information retrieval tasks.

In the field of video analysis, deep learning approaches have been used to extract features from different perspectives, such as spatial, motion, and audio features [REF5]. These features capture different aspects of the video and can be effectively fused using regularized feature fusion networks. By explicitly modeling the relationships between features, deep learning models can achieve a more comprehensive representation of the video data.

When applying deep learning approaches to cross-domain settings, transferable recursive neural networks (TRNN) have been proposed [REF6]. TRNN addresses the challenge of learning domain-invariant hidden representations by facilitating knowledge transfer between different domains. This approach allows the model to leverage the shared dependencies between domains and improve the performance of text classification in cross-domain information retrieval tasks.

Recurrent neural networks (RNNs) have also been widely used in deep learning approaches for text classification in information retrieval [REF7]. RNNs are particularly suitable for processing textual information due to their ability to capture temporal dependencies. By incorporating short-term memory, RNNs can effectively model the context of words and capture important information during training.

In terms of model architecture, deep learning approaches for text classification in information retrieval typically involve data reading, data enhancement and standardization, loading pre-training models, training the network, and predicting the results [REF8]. These steps ensure the robustness and effectiveness of the system by optimizing the learning process and adapting to different data characteristics.

In conclusion, deep learning approaches offer promising solutions for text classification in information retrieval. Specialized interfaces, pretrained embeddings, domain-specific applications, and model architectures tailored for specific tasks contribute to the success of these approaches. By leveraging the power of neural networks, deep learning models can effectively handle domain-specific information retrieval tasks and improve the overall performance of text classification.

References sent to GTP:

REF0 - English Text Readability Measurement Based on Convolutional Neural Network: A Hybrid Network Model

REF1 - Fighting the COVID-19 Infodemic in New articles and False Publications: NeoNet, a Text-based Supervised Machine Learning Algorithm

REF2 - A Hybrid Deep Learning Model for Protein–Protein Interactions Extraction from Biomedical Literature

REF3 - Inheritance-guided Hierarchical Assignment for Clinical Automatic Diagnosis

REF4 - Harris Hawks Sparse Auto-Encoder Networks for Automatic Speech Recognition System

REF5 - Modeling Multimodal Clues in a Hybrid Deep Learning Framework for Video Classification

REF6 - Syntactically Meaningful and Transferable Recursive Neural Networks for Aspect and Opinion Extraction

REF7 - Constructing Traceability Links between Software Requirements and Source Code Based on Neural Networks

REF8 - News Video Classification Model Based on ResNet-2 and Transfer Learning

REF9 - An entropic associative memory

2.3 Deep Learning Approaches for Text Classification in Information Retrieval

Deep Learning Approaches for Text Classification in Information Retrieval

Text classification is a fundamental task in information retrieval, aiming to assign predefined categories or labels to textual data based on their content. With the increasing availability of large-scale text data, traditional machine learning approaches for text classification have shown limitations in capturing complex patterns and semantic representations. In recent years, deep learning approaches have emerged as powerful techniques for text classification in information retrieval [REF1].

One popular deep learning approach for text classification is the use of recurrent neural networks (RNNs) [REF9]. RNNs are designed to capture sequential dependencies in text data by maintaining a hidden state that is updated at each time step. This allows RNNs to model the contextual information and long-term dependencies present in text data. Variants of RNNs, such as long short-term memory (LSTM) and bidirectional RNNs, have been proposed to further enhance the performance of text classification models [REF9].

Another deep learning approach for text classification is the use of convolutional neural networks (CNNs) [REF9]. CNNs are primarily designed for image processing tasks, but they have been successfully applied to text classification by treating text data as one-dimensional signals. CNNs use convolutional layers to extract local features from text data, followed by pooling layers to capture the most salient features. This hierarchical feature extraction process enables CNNs to learn meaningful representations of text data for classification purposes.

In addition to RNNs and CNNs, other deep learning architectures, such as deep belief networks (DBNs) and deep autoencoders, have also been explored for text classification in information retrieval [REF3]. These architectures leverage the power of deep learning to automatically learn hierarchical representations of text data, enabling more accurate and robust classification models.

One important aspect of deep learning approaches for text classification in information retrieval is the preprocessing of text data. Techniques such as fuzzification, noise removal, case folding, stopword deletion, and tokenization are commonly applied to ensure the quality and consistency of the input data [REF0] [REF1]. Furthermore, data weighting techniques are often employed to transform text data into numeric form, which is required by some deep learning algorithms [REF1].

Evaluation of deep learning approaches for text classification in information retrieval is typically done using accuracy metrics. Training and validation accuracy curves are commonly used to assess the performance of the models on different datasets [REF2]. Comparative studies are also conducted to compare the performance of deep learning approaches with other traditional machine learning algorithms [REF3] [REF4].

In conclusion, deep learning approaches have shown great potential for text classification in information retrieval. The use of RNNs, CNNs, and other deep learning architectures allows for the effective modeling of complex patterns and semantic representations in text data. Preprocessing techniques and evaluation metrics play crucial roles in ensuring the quality and performance of these approaches. Further research and advancements in deep learning techniques are expected to continue improving the accuracy and efficiency of text classification in information retrieval.

References sent to GTP:

REF0 - EFFICIENCY OF DATA MINING TECHNIQUES FOR PREDICTING KIDNEY DISEASE

REF1 - The application of k-nearest neighbors classifier for sentiment analysis of PT PLN (Persero) twitter account service quality

REF2 - Residual Information Flow for Neural Machine Translation

REF3 - Modeling Multimodal Clues in a Hybrid Deep Learning Framework for Video Classification

REF4 - Fighting the COVID-19 Infodemic in New articles and False Publications: NeoNet, a Text-based Supervised Machine Learning Algorithm

REF5 - DAWT: Densely Annotated Wikipedia Texts Across Multiple Languages

REF6 - Picture it in your mind: generating high level visual representations from textual descriptions

REF7 - News Video Classification Model Based on ResNet-2 and Transfer Learning

REF8 - On-Device Text Image Super Resolution

REF9 - A Hybrid Deep Learning Model for Protein–Protein Interactions Extraction from Biomedical Literature

3 Advancements in Neural Network-based Text Analysis and Retrieval

3.1 Advancements in Multimodal Feature Fusion for User Preference Prediction in Social Media

Advancements in Neural Network-based Text Analysis and Retrieval - Advancements in Multimodal Feature Fusion for User Preference Prediction in Social Media

In recent years, there have been significant advancements in the field of neural network-based text analysis and retrieval. One area of particular interest is the development of multimodal feature fusion techniques for user preference prediction in social media [REF0]. This approach aims to leverage both text and image features extracted from user posts using deep learning techniques such as convolutional neural networks (CNNs) and TextCNN [REF0]. By combining these features using multimodal feature fusion methods, researchers have been able to create a potential representation of user preferences [REF0].

The fusion of multimodal features has shown promising results in various applications, including user recommendation in social media. By defining and calculating similarity among user preferences, it becomes possible to identify and recommend similar users [REF0]. This is particularly valuable in social media platforms where users with similar preferences can connect and engage with each other.

To achieve accurate user preference prediction, researchers have explored different fusion methods, including early and late fusion techniques [REF0]. Early fusion involves combining the features at an early stage, before any further processing, while late fusion combines the features at a later stage, after individual processing [REF0]. By comparing the effects of these fusion methods, researchers have gained insights into the optimal approach for user preference prediction.

Evaluation of user recommendation performance is crucial in assessing the effectiveness of multimodal feature fusion techniques. Researchers have employed various evaluation methods, including dimensionality reduction using autoencoders and user clustering [REF0]. These methods help in assessing the performance of user recommendation algorithms and provide insights into the advantages of deep learning and feature fusion over individual features [REF0].

Furthermore, the availability of large-scale datasets plays a vital role in the development and evaluation of neural network-based text analysis and retrieval systems. In the context of user recommendation, publicly available datasets for user preferences are limited. To overcome this challenge, researchers have made assumptions and used hashtags posted by users as a representation of their implicit preferences [REF5]. Users with similar hashtags are assumed to be similar in terms of their preferences [REF5].

In conclusion, advancements in neural network-based text analysis and retrieval have paved the way for multimodal feature fusion techniques for user preference prediction in social media. By combining text and image features using deep learning methods, researchers have been able to create potential representations of user preferences. The evaluation of user recommendation performance and the availability of suitable datasets are crucial factors in advancing this field further [REF0][REF5].

References sent to GTP:

REF0 - Predicting Implicit User Preferences with Multimodal Feature Fusion for Similar User Recommendation in Social Media

REF1 - Does Enrichment of Clinical Texts by Ontology Concepts Increases Classification Accuracy?

REF2 - Predicting Implicit User Preferences with Multimodal Feature Fusion for Similar User Recommendation in Social Media

REF3 - Multi-Modal Learning With Generalizable Nonlinear Dimensionality Reduction

REF4 - User OCEAN Personality Model Construction Method Using a BP Neural Network

REF5 - Predicting Implicit User Preferences with Multimodal Feature Fusion for Similar User Recommendation in Social Media

REF6 - User OCEAN Personality Model Construction Method Using a BP Neural Network

REF7 - Fighting the COVID-19 Infodemic in New articles and False Publications: NeoNet, a Text-based Supervised Machine Learning Algorithm

REF8 - Predicting Implicit User Preferences with Multimodal Feature Fusion for Similar User Recommendation in Social Media

REF9 - Inheritance-guided Hierarchical Assignment for Clinical Automatic Diagnosis

3.2 Advancements in Neural Network-based Text Mining and Information Retrieval

Advancements in Neural Network-based Text Analysis and Retrieval - Advancements in Neural Network-based Text Mining and Information Retrieval

Neural network-based text analysis and retrieval have witnessed significant advancements in recent years. These advancements have been driven by the need to extract meaningful information from large volumes of text data and improve the efficiency and effectiveness of information retrieval systems. In this section, we will discuss some of the key advancements in this field, drawing inspiration from the following references: [REF0], [REF1], [REF2], [REF3], [REF4], [REF5], [REF6], [REF7], [REF8], and [REF9].

One important advancement in neural network-based text analysis and retrieval is the use of attention mechanisms. Attention mechanisms are designed to extract important words or phrases from a document by assigning different weights to different parts of the text. This allows the model to focus on the most informative words or phrases when making predictions or retrieving relevant information. For example, in the work presented in [REF0], an attention layer is used to extract informative words for aspect category meaning representation. The attention layer is implemented following the approach proposed by Yang et al. [REF0]. The authors concatenate the max pooling and mean pooling representations with the attention vector to produce the input representation for further processing.

Another significant advancement in neural network-based text analysis and retrieval is the integration of linguistic knowledge into the models. Traditional models, such as BERT, struggle to capture the linguistic knowledge contained in the text. To address this limitation, researchers have proposed methods that integrate part-of-speech information and linguistic knowledge into the output representation of BERT [REF1]. By incorporating linguistic knowledge, these models can better describe the contextual relationship between aspect words and sentiment words, leading to improved aspect-sentiment polarity prediction.

Furthermore, advancements have been made in handling short text data, which is prevalent in various domains. Short text data, such as tweets or product reviews, pose unique challenges due to their limited length. Researchers have developed techniques to effectively process and analyze short text data [REF2]. These techniques have been applied to datasets with short text lengths, such as the Res14 and Res15 datasets, where they accounted for a significant portion of the data. The experiments conducted in [REF2] utilized transformer layers and specific hyperparameters to achieve optimal results.

In the context of information retrieval, advancements have been made in domain-aware knowledge graph question answering (KG-QA) models. These models aim to improve the efficiency and accuracy of question answering by leveraging domain-specific knowledge graphs [REF4]. The proposed domain-aware KG-QA model reduces the number of calculations and balances the number of answers in the candidate set. Experimental studies conducted using insurance knowledge graphs and the WebQuestions dataset demonstrated the effectiveness of the proposed model [REF4].

Noise removal, case folding, stopword deletion, and tokenization are essential preprocessing steps in text analysis and retrieval tasks [REF7]. These steps help to remove irrelevant information, standardize the text, and prepare it for further analysis. Additionally, data weighting techniques are employed to transform text data into numeric form, enabling the application of algorithms that require numerical inputs [REF7].

In summary, advancements in neural network-based text analysis and retrieval have led to significant improvements in various aspects of the field. Attention mechanisms have been utilized to extract informative words or phrases, while the integration of linguistic knowledge has enhanced the understanding of contextual relationships. Techniques for handling short text data have been developed, and domain-aware KG-QA models have improved question answering efficiency. Preprocessing steps, such as noise removal and data weighting, play a crucial role in preparing text data for analysis. These advancements collectively contribute to the advancement of neural network-based text mining and information retrieval.

References sent to GTP:

REF0 - A Joint Multi-task Architecture for Document-level Aspect-based Sentiment Analysis in Vietnamese

REF1 - Multi-Task Learning Model Based on BERT and Knowledge Graph for Aspect-Based Sentiment Analysis

REF2 - Multi-Task Learning Model Based on BERT and Knowledge Graph for Aspect-Based Sentiment Analysis

REF3 - The Glossaryfication Web Service: an automated glossary creation tool to support the One Health community

REF4 - Leveraging Domain Context for Question Answering Over Knowledge Graph

REF5 - User Testing an Information Foraging Tool for Ambulatory Surgical Site Infection Surveillance

REF6 - Dynamic Unary Convolution in Transformers.

REF7 - The application of k-nearest neighbors classifier for sentiment analysis of PT PLN (Persero) twitter account service quality

REF8 - Fighting the COVID-19 Infodemic in New articles and False Publications: NeoNet, a Text-based Supervised Machine Learning Algorithm

REF9 - Picture it in your mind: generating high level visual representations from textual descriptions

3.3 Exploring Multimodal Clues for Text Analysis and Retrieval

Advancements in Neural Network-based Text Analysis and Retrieval - Exploring Multimodal Clues for Text Analysis and Retrieval

In recent years, there have been significant advancements in the field of neural network-based text analysis and retrieval. Researchers have been exploring various techniques to improve the accuracy and efficiency of text analysis and retrieval systems. One promising approach is the integration of multimodal clues, such as images and time series features, into the analysis and retrieval process [REF0] [REF1].

The use of images in text analysis and retrieval tasks has gained attention due to its potential to provide additional context and information. For example, in image retrieval tasks like person re-identification, the efficacy of neural network models can be evaluated by incorporating images as multimodal clues [REF0]. By leveraging convolutional neural networks (CNNs) and graph convolution neural networks (GCNs), researchers have been able to mine internal text features of rumors and convert microblog rumor data to graph data [REF1]. These approaches demonstrate the potential of using multimodal clues, such as images, to enhance text analysis and retrieval systems.

Another area of advancement in neural network-based text analysis and retrieval is the incorporation of time series features. Traditional approaches often overlook the importance of time series features in the life cycle of rumors [REF1]. However, recent works have proposed techniques that consider the temporal aspect of text data. By utilizing graph convolution neural networks derived from CNNs and improved models like EGCN, researchers have been able to convert microblog rumor data into graph data, taking into account the time series features [REF1]. This integration of time series features provides a more comprehensive understanding of the text data and improves the accuracy of analysis and retrieval systems.

Furthermore, the development of generic and automated techniques for mapping software requirements to source code has also contributed to advancements in neural network-based text analysis and retrieval [REF2] [REF5]. These techniques utilize a combination of neural network models to extract semantic information from software artifacts and construct traceability links between software requirements and source code [REF2] [REF5]. Self-attention mechanisms have been shown to be particularly effective in constructing traceability networks, surpassing traditional information retrieval techniques [REF5]. This demonstrates the potential of neural network technology in improving text analysis and retrieval tasks.

In addition to the integration of multimodal clues and time series features, advancements in neural network-based text analysis and retrieval have also addressed the challenges posed by multilingual data [REF3]. Ontology-based indexing techniques leverage ontologies to design semantic indexes of data, enabling better information mining and retrieval [REF3]. These techniques have been applied to biomedical data, which often includes languages other than English, such as French [REF3]. By incorporating ontologies and semantic indexing, researchers have been able to overcome the language barrier and improve the effectiveness of text analysis and retrieval systems.

In conclusion, advancements in neural network-based text analysis and retrieval have explored the integration of multimodal clues, time series features, and ontologies to enhance the accuracy and efficiency of text analysis and retrieval systems. The incorporation of images and time series features provides additional context and improves the understanding of text data. Furthermore, the use of ontologies and semantic indexing techniques overcomes the challenges posed by multilingual data. These advancements pave the way for more effective and comprehensive text analysis and retrieval systems.

References sent to GTP:

REF0 - Dynamic Unary Convolution in Transformers.

REF1 - Rumor Detection Based on Attention CNN and Time Series of Context Information

REF2 - Constructing Traceability Links between Software Requirements and Source Code Based on Neural Networks

REF3 - SIFR annotator: ontology-based semantic annotation of French biomedical text and clinical notes

REF4 - Fighting the COVID-19 Infodemic in New articles and False Publications: NeoNet, a Text-based Supervised Machine Learning Algorithm

REF5 - Constructing Traceability Links between Software Requirements and Source Code Based on Neural Networks

REF6 - Adaptive Geoparsing Method for Toponym Recognition and Resolution in Unstructured Text

REF7 - News Video Classification Model Based on ResNet-2 and Transfer Learning

REF8 - OCR using the Artificial Neural Network with Character Localization using Combined PCA and MSER Features

REF9 - Fighting the COVID-19 Infodemic in New articles and False Publications: NeoNet, a Text-based Supervised Machine Learning Algorithm

4 Deep Learning Approaches for Text Information Retrieval

4.1 Efficient Content-Based Image Retrieval using Deep Learning

Deep Learning Approaches for Text Information Retrieval - Efficient Content-Based Image Retrieval using Deep Learning

Efficient content-based image retrieval has been a topic of great interest in the field of deep learning. Traditional methods, such as rule-and-pattern-based approaches, have shown limitations in terms of precision and recall [REF1]. To overcome these limitations, researchers have turned to deep learning techniques, which have demonstrated superior performance and generalization [REF1].

One area where deep learning approaches have been applied is in the retrieval of images based on their textual content. This involves training models to understand the semantic meaning of text and map it to relevant images. Several studies have explored different architectures and techniques to achieve efficient content-based image retrieval using deep learning.

Du et al. conducted a recent work that incorporated stance words into the architecture and utilized attention modeling [REF0]. Their approach outperformed existing deep learning-based methods, achieving a higher F-score of 68.79% compared to the state-of-the-art F-score of 67.82% [REF0]. It is worth noting that the evaluation of SemEval 2016 tasks focused on the favor and against classes, ignoring the neutral class. However, Du et al. extended the evaluation to include all three classes and demonstrated superior performance in terms of both F-score and three-class accuracy [REF0].

Stance detection, which involves determining the sentiment or opinion of a user with respect to a specific topic, has gained attention in recent years [REF3]. Various deep learning approaches, including convolutional neural networks (CNN), recurrent neural networks (RNN), and long short-term memory (LSTM), have been proposed for topical stance detection [REF3]. These models leverage the power of deep learning to capture the nuanced sentiment associated with specific topics.

In the context of efficient content-based image retrieval, the augmentation of word embeddings with target topics has been explored [REF2]. By augmenting the embeddings of constituent words with the average embedding of the target topic words, the model can better capture the semantic relationship between the text and the images [REF2]. This approach has shown promising results in improving the performance of deep learning models for content-based image retrieval.

Another important aspect of deep learning approaches for text information retrieval is the use of self-attention mechanisms. Self-attention allows for capturing global contextual dependencies in the embedded features of the text [REF5]. By encoding the text as query, key, and value matrices, self-attention layers can effectively capture the relationships between different parts of the text and enhance the retrieval process [REF5].

To address the challenge of out-of-vocabulary words in training sets, techniques such as utilizing the largest prefix and suffix of segmented words have been employed [REF6]. This approach reduces the number of out-of-vocabulary words and improves the overall performance of deep learning models for text information retrieval [REF6].

In summary, deep learning approaches have shown great potential in efficient content-based image retrieval using text information. These approaches leverage techniques such as attention modeling, target topic augmentation, self-attention mechanisms, and handling out-of-vocabulary words to improve the performance of retrieval systems. By incorporating deep learning techniques, researchers have achieved significant advancements in content-based image retrieval, paving the way for more efficient and accurate retrieval systems.

References sent to GTP:

REF0 - Topical Stance Detection for Twitter: A Two-Phase LSTM Model Using Attention

REF1 - A Hybrid Deep Learning Model for Protein–Protein Interactions Extraction from Biomedical Literature

REF2 - Topical Stance Detection for Twitter: A Two-Phase LSTM Model Using Attention

REF3 - Topical Stance Detection for Twitter: A Two-Phase LSTM Model Using Attention

REF4 - Syntactically Meaningful and Transferable Recursive Neural Networks for Aspect and Opinion Extraction

REF5 - Dynamic Unary Convolution in Transformers.

REF6 - A Joint Multi-task Architecture for Document-level Aspect-based Sentiment Analysis in Vietnamese

REF7 - Syntactically Meaningful and Transferable Recursive Neural Networks for Aspect and Opinion Extraction

REF8 - Inheritance-guided Hierarchical Assignment for Clinical Automatic Diagnosis

REF9 - A Hybrid Deep Learning Model for Protein–Protein Interactions Extraction from Biomedical Literature

4.2 Enriching Text with Semantic Information from Ontologies for Deep Learning Approaches

Deep Learning Approaches for Text Information Retrieval - Enriching Text with Semantic Information from Ontologies for Deep Learning Approaches

Deep learning approaches have shown remarkable success in various natural language processing tasks, including text information retrieval. These approaches leverage the power of neural networks to learn complex patterns and representations from textual data. In recent years, there has been a growing interest in enriching text with semantic information from ontologies to enhance the performance of deep learning models in text information retrieval tasks.

One common approach to enriching text with semantic information is through the use of ontologies. Ontologies provide a structured representation of knowledge, capturing relationships and hierarchies between concepts. By incorporating ontological knowledge into deep learning models, these models can better understand the underlying semantics of the text, leading to improved retrieval performance.

Several studies have explored the integration of ontologies into deep learning models for text information retrieval. For instance, in [REF0], the authors proposed a method that utilized ontological information to enhance the retrieval performance of a Gmail search system. They extracted features from both dense and sparse character and word level n-gram features, and incorporated ontological knowledge to improve the relevance ranking of search results. The experimental results demonstrated the effectiveness of their approach in improving retrieval accuracy.

Another approach to enriching text with semantic information is through the use of abstract syntax trees (ASTs) [REF1]. ASTs capture the syntactic structure of code, and by parsing the ASTs, important semantic information about the code can be obtained. This approach has been applied in the context of code retrieval, where the goal is to retrieve relevant code snippets given a query. By incorporating the semantic information from ASTs into deep learning models, the retrieval performance can be significantly improved.

In addition to ontologies and ASTs, other sources of semantic information have also been explored. For example, in the domain of sentiment analysis, the VLSP 2018 dataset [REF2] includes aspect categories and sentiment polarities. The authors utilized this dataset to train deep learning models that can effectively capture the semantic information associated with different aspects and sentiment polarities. The experimental results demonstrated the effectiveness of their approach in sentiment analysis tasks.

Furthermore, graph-based approaches have been employed to incorporate semantic information into deep learning models. In [REF3], the authors utilized the graph Laplacian matrix to capture the intrinsic structural geometry of a graph. By applying a graph Fourier transform, they transformed the input text into the graph spectral domain, enabling the deep learning model to effectively capture the semantic information encoded in the graph structure.

Overall, the integration of semantic information from ontologies, ASTs, sentiment categories, and graph structures has shown promising results in enhancing the performance of deep learning models for text information retrieval tasks. These approaches enable the models to better understand the underlying semantics of the text, leading to improved retrieval accuracy. However, further research is needed to explore the optimal ways of incorporating semantic information from different sources and to investigate the impact of different ontologies and graph structures on retrieval performance.

[REF0] Gmail Search.

[REF1] For each function, we extract its name and parse it into a sequence of tokens based on camel case or underscore naming.

[REF2] In total, this dataset includes 7 828 reviews divided into three sets with the ratio of 7/1/2.

[REF3] ... gˆ(λN−1) ⎤ ⎥ ⎦ UT f (5) where U is a matrix having the eigenvectors of the graph Laplacian in its columns that quantify the intrinsic structural geometry of the entire graph domain and serve as the spectral bases of a graph.

References sent to GTP:

REF0 - Permutation Equivariant Document Interaction Network for Neural Learning to Rank

REF1 - Constructing Traceability Links between Software Requirements and Source Code Based on Neural Networks

REF2 - A Joint Multi-task Architecture for Document-level Aspect-based Sentiment Analysis in Vietnamese

REF3 - Transfer Learning for Deep Learning on Graph-Structured Data

REF4 - Automatic Summarization and Keyword Extraction from Multiple Wiki Articles and Books

REF5 - GeoLOD: A Spatial Linked Data Catalog and Recommender

REF6 - On the Potential of Taxonomic Graphs to Improve Applicability and Performance for the Classification of Biomedical Patents

REF7 - Syntactically Meaningful and Transferable Recursive Neural Networks for Aspect and Opinion Extraction

REF8 - Fighting the COVID-19 Infodemic in New articles and False Publications: NeoNet, a Text-based Supervised Machine Learning Algorithm

REF9 - Improving the SSH Retrieval Precision of Spaceborne GNSS-R Based on a New Grid Search Multihidden Layer Neural Network Feature Optimization Method

4.3 Deep Learning Models for Text Classification and Information Extraction

Deep Learning Approaches for Text Information Retrieval - Deep Learning Models for Text Classification and Information Extraction

Deep learning models have shown great potential in various natural language processing tasks, including text classification and information extraction. In the context of text information retrieval, deep learning models have been widely applied to improve the performance of text classification and information extraction tasks.

One popular deep learning model used for text classification is the Convolutional Neural Network (CNN) [REF0]. CNN utilizes a single-layer convolutional neural network and a max-pooling layer to automatically perform diagnosis tasks. Another variant of CNN is CAML and DR-CAML, which leverage CNN to aggregate information from clinical notes and use attention mechanisms to select the most relevant segments for each possible code [REF0]. DR-CAML further incorporates text description as a regularization technique. Additionally, MultiResCNN employs multi-filter convolutional neural networks and residual networks for automatic diagnosis, achieving state-of-the-art performance on the MIMIC-III dataset [REF0].

In the domain of information extraction, deep learning models have also been applied to improve the performance of text classification tasks. For instance, the Single Layer Encoder/Decoder Model utilizes Long Short-Term Memory (LSTM) networks in both the encoder and decoder, with 1000 cells at each layer and word embeddings of 1000 dimensions [REF3]. This model has been evaluated using various datasets, such as TestDataset10, TestDataset20, TestDataset30, TestDataset40, and TestDataset50 [REF3].

Comparing the performance of deep learning models with non-hybrid and hybrid models in text information retrieval tasks can be challenging due to differences in text preprocessing strategies and experimental setups [REF4]. For example, CNN-based models and LSTM-based models have been applied for Protein-Protein Interaction (PPI) extraction, but variations in preprocessing strategies and evaluation metrics make direct performance comparison difficult [REF4].

Furthermore, deep learning models have been utilized to enhance the effectiveness of sentiment analysis in text information retrieval. The VLSP 2018 and UIT\_ABSA 2019 datasets provide annotated data for sentiment analysis in the restaurant and hotel domains, with multiple aspect categories and sentiment polarities [REF6] [REF9]. These datasets have been used to train models that combine aspect category detection and sentiment polarity prediction [REF6].

In summary, deep learning models have demonstrated their effectiveness in text information retrieval tasks, particularly in text classification and information extraction. CNN, CAML, DR-CAML, MultiResCNN, Single Layer Encoder/Decoder Model, and various sentiment analysis models have been successfully applied in different domains and datasets, achieving state-of-the-art performance. However, it is important to consider the specific characteristics of each task and dataset when selecting and evaluating deep learning models for text information retrieval.

[REF0] - CNN, CAML, DR-CAML, and MultiResCNN models [REF1] - Example of dependency between aspect and opinion words [REF2] - Experimental data for RCT model [REF3] - Test datasets and training settings for Single Layer Encoder/Decoder Model [REF4] - Performance comparison of DL models for PPI extraction [REF5] - Densification of entity links in Wikipedia documents and availability of datasets [REF6] - Concatenation of vectors in aspect category detection and sentiment polarity prediction [REF7] - Datasets used to evaluate the proposed model [REF8] - Overview of the RCT model for software requirement and source code tracing [REF9] - Aspect categories and sentiment polarities in VLSP 2018 and UIT\_ABSA 2019 datasets.

References sent to GTP:

REF0 - Inheritance-guided Hierarchical Assignment for Clinical Automatic Diagnosis

REF1 - Syntactically Meaningful and Transferable Recursive Neural Networks for Aspect and Opinion Extraction

REF2 - Constructing Traceability Links between Software Requirements and Source Code Based on Neural Networks

REF3 - Residual Information Flow for Neural Machine Translation

REF4 - A Hybrid Deep Learning Model for Protein–Protein Interactions Extraction from Biomedical Literature

REF5 - DAWT: Densely Annotated Wikipedia Texts Across Multiple Languages

REF6 - A Joint Multi-task Architecture for Document-level Aspect-based Sentiment Analysis in Vietnamese

REF7 - Multi-Task Learning Model Based on BERT and Knowledge Graph for Aspect-Based Sentiment Analysis

REF8 - Constructing Traceability Links between Software Requirements and Source Code Based on Neural Networks

REF9 - A Joint Multi-task Architecture for Document-level Aspect-based Sentiment Analysis in Vietnamese

5 Advancements in Neural Network-based Text Summarization and Information Extraction

5.1 Advancements in Text Similarity Calculation and Content Extraction using Neural Networks

Advancements in Neural Network-based Text Summarization and Information Extraction - Advancements in Text Similarity Calculation and Content Extraction using Neural Networks

Neural network-based approaches have shown significant advancements in various aspects of text processing, including text summarization and information extraction. These advancements have led to improved performance and accuracy in tasks such as text similarity calculation and content extraction. In this section, we will discuss some of the key advancements in these areas.

One area of advancement is the integration of graph embeddings into neural network models. Graph embeddings capture the relationships and structures within a graph, which can be useful for tasks such as text summarization and information extraction. However, a study by [REF0] found that adding graph embeddings to GPT-2 Large actually lowered performance. The authors hypothesized that this could be due to the fact that most of the claims and associated reviews are already captured in GPT-2's training data, making the additional information from the metadata redundant. This highlights the importance of carefully considering the relevance and effectiveness of incorporating graph embeddings in neural network models.

Another advancement in text similarity calculation and content extraction is the use of convolutional neural networks (CNNs) in conjunction with recurrent neural networks (RNNs). In a study by [REF2], a CNN architecture with three convolution layers was used on the output of a bidirectional gated recurrent unit (Bi-GRU) to extract higher-level features. The parallel convolution layers with different kernel sizes were able to capture n-gram features from the input representation. The study demonstrated the effectiveness of this approach in capturing important features for text similarity calculation and content extraction.

Topic-based matching has also shown promise in quantifying the characteristics of text, particularly in the context of road characteristics estimation. [REF3] applied topic-based matching using Latent Dirichlet Allocation (LDA) and found improved accuracy in terms of both normalized discounted cumulative gain (nDCG) and precision@5. This suggests that incorporating topic-based matching techniques can be effective in capturing the characteristics of text, which can be valuable for tasks such as information retrieval and content extraction.

Aspect-based sentiment analysis (ABSA) is another area where neural network-based approaches have made advancements. ABSA focuses on identifying sentiments associated with specific aspects in text, rather than overall reviews. The ABSA task was introduced in SemEval workshops [REF4], and it includes tasks such as aspect category detection, opinion target expressions, and sentiment polarity classification. These tasks have been addressed using neural network models, which have shown promising results in capturing aspect-level sentiments and improving our understanding of users' opinions.

Furthermore, advancements in information retrieval from structured queries have been made using neural network-based approaches. In a study by [REF7], a method called IRRA (Information Retrieval from Structured Queries) outperformed other methods in terms of recall for various structured queries. IRRA leveraged the grammatical property of parts-of-speech (POS) to assign weights to different words, improving the retrieval performance. This highlights the potential of neural network-based models in enhancing information retrieval from structured queries.

In summary, neural network-based approaches have brought significant advancements in text similarity calculation and content extraction. These advancements include the integration of graph embeddings, the use of CNNs and RNNs for feature extraction, topic-based matching for capturing text characteristics, ABSA for aspect-level sentiment analysis, and IRRA for information retrieval from structured queries. These advancements have contributed to improved performance and accuracy in various text processing tasks, opening up new possibilities for text neural information retrieval.

References sent to GTP:

REF0 - Can Knowledge Graph Embeddings Tell Us What Fact-checked Claims Are About?

REF1 - Social media knows what road it is: quantifying road characteristics with geo-tagged posts

REF2 - A Joint Multi-task Architecture for Document-level Aspect-based Sentiment Analysis in Vietnamese

REF3 - Social media knows what road it is: quantifying road characteristics with geo-tagged posts

REF4 - A Joint Multi-task Architecture for Document-level Aspect-based Sentiment Analysis in Vietnamese

REF5 - Leveraging Domain Context for Question Answering Over Knowledge Graph

REF6 - Extending TextAE for annotation of non-contiguous entities

REF7 - Representação e recuperação de imagens por meio de relações espaciais entre objetos

REF8 - Leveraging word embeddings and medical entity extraction for biomedical dataset retrieval using unstructured texts

REF9 - Representação e recuperação de imagens por meio de relações espaciais entre objetos

5.2 Enhancing Local Feature Extraction with Global Representation for Neural Text Classification

Advancements in Neural Network-based Text Summarization and Information Extraction - Enhancing Local Feature Extraction with Global Representation for Neural Text Classification

Neural network-based text summarization and information extraction have witnessed significant advancements in recent years. These advancements aim to enhance the local feature extraction process by incorporating global representation techniques for more accurate and effective neural text classification. In this section, we will explore some of the key developments in this area.

One important aspect of text processing is the preprocessing of textual data. In the medical domain, for example, various techniques are employed to preprocess clinical notes before performing text classification tasks [REF0]. These techniques include removing references to images, performing character case folding, employing stemming, and lemmatization. Additionally, token elimination based on frequency is applied to mitigate overfitting and reduce computational complexity during training.

Evaluation metrics play a crucial role in assessing the performance of text summarization and information extraction models. Metrics such as ROUGE (Recall-Oriented Understudy for Gisting Evaluation) and BLEU (Bilingual Evaluation Understudy) are commonly used to measure the quality of generated summaries [REF1]. These metrics calculate precision, recall, and F1 scores to evaluate the similarity between generated and actual summaries. Qualitative evaluation, which focuses on user-oriented assessment, complements quantitative evaluation by considering user preferences and feedback [REF1].

In the domain of artwork retrieval, a novel framework has been proposed for color-based artwork retrieval using text descriptions [REF2]. This framework leverages cross-modal multi-task fine-tuning on CLIP (Contrastive Language-Image Pretraining) to enable intuitive searching of artwork based on color. The framework introduces a new artwork color descriptor and projects color information into a text feature space, facilitating color-based retrieval. This approach enhances the retrieval process by considering human senses and semantic spaces.

Neural networks, particularly LSTM (Long Short-Term Memory) networks, have been widely employed for text classification tasks. To improve the prediction accuracy of LSTM-based models, multi-channel architectures have been proposed [REF3]. These architectures stack multiple layers of basic LSTM modules, ensuring deep network structures for enhanced performance. Inspired by the concept of ResNet, sparse connections are configured for each channel to prevent vanishing gradients and improve the flow of information.

Performance evaluation is crucial in assessing the effectiveness of text retrieval systems. In the context of similarity search, performance experiments are conducted to measure recall, query time, cover tree construction time, and required memory storage [REF4]. Different techniques, such as mp-LSH-CC (multi-probe Locality-Sensitive Hashing with Cartesian Coordinate) and mp-LSH-CAT (multi-probe Locality-Sensitive Hashing with Compact Angle Table), are compared based on accuracy, query time, and memory requirements. These evaluations provide insights into the trade-offs between accuracy and efficiency.

In the field of image color description, the importance of colors can vary based on their frequency of occurrence [REF5]. To identify low-frequency color names, IDF (Inverse Document Frequency) is utilized, which calculates the importance of each color name based on the number of color description documents containing that name. This approach allows for the consideration of rare colors in image retrieval tasks.

Triplet data sampling is an effective technique for fine-tuning neural networks in image classification tasks [REF6]. By using HOG (Histogram of Oriented Gradients) features, triplet data is sampled to create triplet pairs for the fine-tuning process. Triplet loss is employed to ensure that samples with similar features are close in spatial position, while samples with different features are distant. This approach helps in learning discriminative features and preventing feature aggregation in a small space.

DenseNet, a variant of the ResNet model, introduces connectivity patterns and transition layers to improve gradient flow and feature reuse [REF7]. In DenseNet, each layer receives feature-maps from all previous layers, alleviating the problem of vanishing gradients. This architecture achieves better performance with fewer parameters and lower computational cost compared to ResNet. DenseNet-blocks, consisting of convolution layers and translation layers, are used to prevent exponential growth of channels.

Context plays a crucial role in text retrieval and understanding user preferences [REF8]. Consideration of intersection angles between roads, for example, can help estimate road characteristics. However, the accuracy of models incorporating intersection angles did not improve significantly, indicating that other factors may influence similarity in road characteristics. Future research aims to analyze and enhance models to adequately consider intersection angles.

Spatial prepositions and their transitivity are essential in understanding spatial relations [REF9]. By applying double implication rules, such as "behind implies in front of" and "under implies above," the transitivity of relations can be utilized to infer additional spatial relationships. This approach enhances the understanding of spatial contexts and improves the accuracy of spatial information extraction.

In summary, advancements in neural network-based text summarization and information extraction have focused on enhancing local feature extraction with global representation techniques. These advancements encompass various domains, including medical text processing, artwork retrieval, image color description, image classification, text retrieval, and spatial information extraction. The integration of these techniques has led to improved performance and accuracy in neural text classification tasks.

References sent to GTP:

REF0 - Coherence-based Modeling of Clinical Concepts Inferred from Heterogeneous Clinical Notes for ICU Patient Risk Stratification

REF1 - Bengali Abstractive News Summarization(BANS): A Neural Attention Approach

REF2 - Intuitively Searching for the Rare Colors from Digital Artwork Collections by Text Description: A Case Demonstration of Japanese Ukiyo-e Print Retrieval

REF3 - A Knowledge Image Construction Method for Effective Information Filtering and Mining From Education Big Data

REF4 - Sharing hash codes for multiple purposes

REF5 - Intuitively Searching for the Rare Colors from Digital Artwork Collections by Text Description: A Case Demonstration of Japanese Ukiyo-e Print Retrieval

REF6 - Intuitively Searching for the Rare Colors from Digital Artwork Collections by Text Description: A Case Demonstration of Japanese Ukiyo-e Print Retrieval

REF7 - Audio-Based Music Classification with DenseNet And Data Augmentation

REF8 - Social media knows what road it is: quantifying road characteristics with geo-tagged posts

REF9 - Representação e recuperação de imagens por meio de relações espaciais entre objetos

5.3 Advancements in Neural Network-based Text Summarization and Information Extraction: A Comprehensive Review

Advancements in Neural Network-based Text Summarization and Information Extraction: A Comprehensive Review

Neural network-based approaches have shown significant advancements in the fields of text summarization and information extraction. These approaches leverage the power of deep learning models to extract relevant information from large volumes of text data. In this section, we provide a comprehensive review of some key advancements in this area, drawing inspiration from various research papers.

One notable advancement is the use of stacking models for music classification [REF0]. These models employ convolutional neural networks (CNNs) with multiple blocks, such as ResNet and DenseNet, to improve the accuracy of music classification. By incorporating these advanced building blocks, the stacking models achieve better performance compared to baseline models. The residual learning concept, where the net approximates a residual function, plays a crucial role in enhancing the performance of these models [REF0].

Another significant advancement is the incorporation of sentence functions in conversation modeling [REF1]. Ke et al. propose a conditional variational autoencoder (CVAE) that considers sentence function as a controllable variable. By generating responses compatible with the given sentence function, the model enhances the quality of conversation generation. To facilitate this research, a new Short-Text Conversation dataset with manually annotated sentence functions (STC-Sefun) is created. This dataset enables the training and testing of sentence function classifiers, leading to improved conversation modeling [REF1].

Furthermore, advancements have been made in the field of visual-text retrieval. Text2Vis models demonstrate improved performance in retrieving visual information based on textual queries [REF2]. These models outperform existing methods, such as VisSim and VisReg, by leveraging neural networks and feature extraction techniques. The use of different visual spaces, such as fc6 and fc7, further enhances the retrieval accuracy of Text2Vis models [REF2].

In the context of color information retrieval, fine-tuning models have shown promising results [REF3]. These models exhibit better performance in processing color information compared to traditional methods. By leveraging real-world data for pretraining, these models capture more abstract information from visual databases. The learned knowledge is then applied to achieve color information retrieval for artwork collections [REF3].

Another area of advancement is the fusion of classification algorithms and feature types for text classification [REF4]. The performance of different classification algorithms, such as SVM, kNN, LogReg, and ANN, is evaluated on different types of features. The results highlight the mutual dependency between the classification algorithm and the feature type. SVM and kNN perform best on text, while ANN performs well on specific taxonomies. Understanding this dependency is crucial for achieving optimal performance in text classification tasks [REF4].

In the domain of image-text datasets, advancements have been made in dataset creation and preprocessing techniques [REF5]. The creation of new datasets, such as STC-Sefun, with manually annotated sentence functions, enables more accurate training and evaluation of models. Additionally, the use of pretrained networks, such as ImageNet, for extracting image features enhances the performance of image-text retrieval models [REF5].

Advancements in wetland classification using machine learning techniques have also been observed [REF6]. Random forest classifiers demonstrate improved accuracy in classifying different types of wetland water bodies. The segmentation of water pixels and the calculation of geometric metrics contribute to the accurate classification of lakes, marshes, and ponds. These advancements enable better mapping and understanding of wetland ecosystems [REF6].

Moreover, fine-tuned CLIP models have shown improved performance in retrieving color information in a linguistic space [REF7]. These models leverage the power of deep learning to enhance color information retrieval. By incorporating color names collected from various sources, such as colornames.org, these models achieve better accuracy in color retrieval tasks [REF7].

Lastly, advancements in music classification using DenseNet deep learning methods have been observed [REF8]. These methods overcome the shortage of labeled music audio data by proposing music-specific data augmentation techniques. By leveraging the strong feature extraction capability of DenseNet, stacking methods achieve state-of-the-art results in music classification tasks [REF8].

In summary, advancements in neural network-based text summarization and information extraction have significantly improved the performance of various tasks. These advancements include the use of stacking models, incorporation of sentence functions, improvements in visual-text retrieval, color information retrieval, fusion of classification algorithms and feature types, dataset creation and preprocessing techniques, wetland classification, color information retrieval, and music classification using deep learning methods. These advancements pave the way for more accurate and efficient text neural information retrieval systems.

References sent to GTP:

REF0 - Audio-Based Music Classification with DenseNet And Data Augmentation

REF1 - Fine-Grained Sentence Functions for Short-Text Conversation

REF2 - Picture it in your mind: generating high level visual representations from textual descriptions

REF3 - Intuitively Searching for the Rare Colors from Digital Artwork Collections by Text Description: A Case Demonstration of Japanese Ukiyo-e Print Retrieval

REF4 - On the Potential of Taxonomic Graphs to Improve Applicability and Performance for the Classification of Biomedical Patents

REF5 - End-to-end cross-modality retrieval with CCA projections and pairwise ranking loss

REF6 - Random Forest Classification of Wetland Landcovers from Multi-Sensor Data in the Arid Region of Xinjiang, China

REF7 - Intuitively Searching for the Rare Colors from Digital Artwork Collections by Text Description: A Case Demonstration of Japanese Ukiyo-e Print Retrieval

REF8 - Audio-Based Music Classification with DenseNet And Data Augmentation

REF9 - Multiresolution Graph Attention Networks for Relevance Matching