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A Cross-Language Information Retrieval Method Based on Multi-Task Learning

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Abstract

This study introduces a novel Cross-Language Information Retrieval (CLIR) method employing multi-task learning and soft parameter sharing to enhance neural retrieval models' feature extraction across languages. The approach integrates an interaction-based neural retrieval model with a semantic-based text classification model, exchanging hidden vectors for richer feature representation. Experimental results across four language pairs—English-Chinese, English-Arabic, English-French, and English-German—demonstrate significant performance improvements. The proposed method achieved the highest Mean Average Precision (MAP) scores: 0.419 for EN-ZH, 0.403 for EN-AR, 0.427 for EN-FR, and 0.441 for EN-DE, surpassing other models like BM25, BPNRM, KNRM, KNRM-Trans, and KNRM-Embed. This research underscores the potential of multi-task learning for CLIR, showcasing improved retrieval performance through semantic information and knowledge transfer.

Keyword: Cross-Language Information Retrieval, External Corpus, Information Retrieval, Multi-Task Learning, Neural Retrieval Model

1. INTRODUCTION

The digital age has witnessed an unprecedented expansion in the volume of online content, with global Internet users growing from 3.01 billion to 5.25 billion in a decade, and the penetration rate nearly doubling from 30.20% to 66.2% [1]. This growth has led to an information overload, where users struggle to find relevant content amidst the digital noise, particularly in cross-language contexts. The ability to access information across linguistic barriers is not just a technological challenge but a critical necessity for effective global communication and knowledge sharing [2].

The urgency for effective Cross-Language Information Retrieval (CLIR) systems is paramount. These systems aim to bridge linguistic divides, allowing users to retrieve foreign language information without prior language knowledge. However, the traditional CLIR methods, which often rely on single-task learning, have shown limitations in capturing the nuanced semantic relationships between queries and documents across different languages [3]. This has highlighted the need for more advanced techniques that can better capture the semantic features necessary for effective retrieval.

Multi-task learning (MTL), a form of transfer learning, has emerged as a promising approach for improving model generalization and representational capabilities by training on multiple related tasks simultaneously [4, 5]. Advances in neural networks have led to the development of sophisticated neural retrieval models, categorized as interaction-based and representation-based models, which focus on the relationship between queries and documents or the meanings of content, respectively [6, 7]. These models have shown promise in CLIR, but the reliance on single-task learning can limit their effectiveness [11].

This study introduces an innovative CLIR approach that integrates interaction-based neural retrieval models with semantic-based text classification models through the use of MTL and soft parameter sharing. The goal is to enhance the semantic understanding and representational capacity of CLIR models, thereby improving their ability to retrieve relevant documents across language barriers [14]. The integration of MTL and soft parameter sharing is expected to address the limitations of existing CLIR methods and provide a more robust solution to the challenges posed by linguistic differences in grammar and vocabulary.

Cross-Language Information Retrieval (CLIR) is a field of information retrieval that aims to find documents in a different language than the one used in the user's query. Its goal is to break down language barriers, allowing users to access a wide range of information regardless of language differences.

Neural retrieval models use deep learning to understand the content of queries and documents, then score their relevance. There are two main kinds: Interaction-based models, look at how parts of the query and document interact at various levels, They're good at seeing detailed connections; Representation-based models, create separate meanings for the query and document, then compare them, They're strong when the meanings are clear.

Bidirectional Gated Recurrent Units (Bi-GRUs) is a type of neural network good for handling sequences like text. They improve on regular Recurrent Neural Networks (RNNs) by using gates to handle info over long sequences better.Bi-GRUs look at sequences both ways, front to back and back to front, which helps understand the full context around each part of the sequence. They are useful for language tasks because they can see the context around words, helping with tasks like translation, classifying text, and understanding content better.

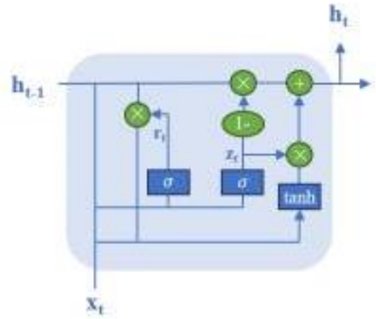

Figure. 1 The unit of GRU

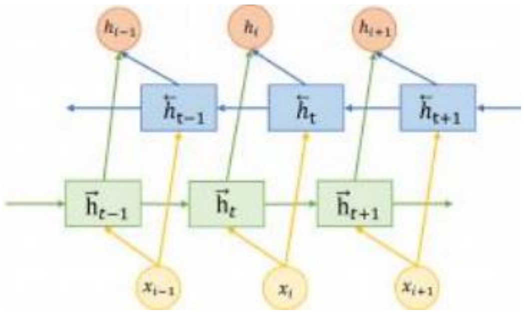

Figure. 2 Bi-GRU model

Multi-Task Learning (MTL) helps a model do one job better by also teaching it to do other related jobs at the same time. This sharing of knowledge can make the model better at understanding and doing all the tasks. MTL is used in many areas like understanding language, seeing pictures, and recognizing speech. It's also good for making search systems smarter by teaching them to do more than one thing at once.

The rapid proliferation of the internet and the consequent acceleration of globalization have led to a significant increase in the demand for effective CLIR systems. These systems aim to bridge the linguistic divide by allowing users to retrieve information in foreign languages without prior knowledge of those languages. Traditional CLIR methods, which often rely on single-task learning, have shown limitations in capturing the nuanced semantic relationships between queries and documents across different languages [2]. This has prompted research into more sophisticated approaches, such as MTL, which has emerged as a powerful technique for improving model generalization and representational capabilities by training on multiple related tasks simultaneously [3, 4, 5]. MTL has demonstrated its effectiveness in various natural language processing tasks, including monolingual information retrieval and cross-lingual natural language processing, suggesting its potential for enhancing CLIR [6, 7, 8].

The exponential growth of online content has resulted in an information overload, where users are increasingly overwhelmed when attempting to find relevant information [2]. This challenge is particularly pronounced in cross-language scenarios, where language barriers can significantly hinder access to information. The limitations of existing CLIR methods in capturing the rich semantic features necessary for effective retrieval have highlighted the need for more advanced techniques. This study is motivated by the desire to address these limitations by proposing a novel CLIR approach that integrates interaction-based neural retrieval models with semantic-based text classification models through the innovative use of multi-task learning and soft parameter sharing. The goal is to enhance the semantic understanding and representational capacity of CLIR models, thereby improving their ability to retrieve relevant documents across language barriers.

The central aim of this study is to introduce an innovative CLIR method that leverages the synergistic benefits of multi-task learning and soft parameter sharing. By integrating an interaction-based neural retrieval model with a semantic-based text classification model within a multi-task learning framework, this approach seeks to enhance the feature capturing capabilities of neural retrieval models in cross-language settings. The study also extends this approach to propose an advanced bi-directional model for cross-lingual retrieval, which employs cross-lingual soft parameter sharing to facilitate knowledge transfer between models in different languages. The purpose of this model is to improve the representational capacity and retrieval task quality of the neural retrieval model across various language pairs, thereby addressing the challenges posed by language differences in grammar and vocabulary [8]. Through this research, we aim to demonstrate the potential of multi-task learning and soft parameter sharing for CLIR, showcasing their ability to leverage semantic information and knowledge transfer to improve retrieval performance across different language pairs.

2. MATERIALS AND METHOD

2.1. Cross-Language Information Retrieval Based on Soft Parameter Sharing Multi-Task Learning

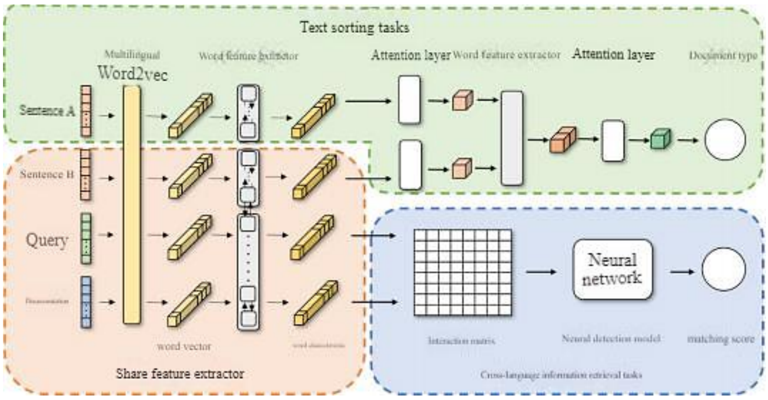

Figure 3. Based on Soft Parameter Sharing Multi-Task Learning Framework

2.1.1 Interaction-based Neural Retrieval Model

Our architecture employs an interaction-based neural retrieval model derived from the Kernel-based Neural Ranking Model (KNRM) [6], which has demonstrated robust performance across diverse retrieval benchmarks. The KNRM model articulates the relevance between a query and a document through the explicit modeling of their interactions at varying levels of granularity, such as word-level and phrase-level.

The KNRM model takes as input a query q and a document d, which are represented as sequences of word embeddings or contextualized word representations. The query q and document d are represented as sequences of embeddings, with lengths m and n, respectively.

$$q =[q1,q2,...,qm]$$
$$d=[d1,d2,...,dn]$$

These sequences are encoded into enhanced representations using Bidirectional Gated Recurrent Units (Bi-GRUs):

$$\begin{aligned} q\ enc&=BiGRU(q) \\ d\ enc&=BiGRU(d) \end{aligned} \tag{1}$$

Equation 1 and Equation 5: Encodes the query q and document d into enhanced representations using Bidirectional Gated Recurrent Units (Bi-GRUs).

The KNRM model employs a kernel-based method to calculate the relevance score between the query and document. Initially, it generates a word-level similarity matrix S that quantifies the similarity between each word in the query and document encodings:

$$Sij=\phi(qenci,dencj) \tag{2}$$

Equation 2: Represents the word-level similarity between the query and document encodings, where ϕ is a similarity function such as cosine similarity or Gaussian kernel.

Subsequently, the model deploys a set of kernels to extract phrase-level interactions. Each kernel K aggregates the phrase-level similarity scores from the word-level matrix S through a pooling operation:

$$K=pooling(S) \tag{3}$$

Equation 3: Aggregates the phrase-level similarity scores from the word-level matrix S through a pooling operation.

The aggregate relevance score is determined by the weighted sum of these phrase-level kernel scores:

$$score= \sum_k \alpha K \cdot K \tag{4}$$

Equation 4: Determines the aggregate relevance score by the weighted sum of phrase-level kernel scores, with αK being the learned weight for kernel K.

During training, the KNRM model is refined using a pairwise ranking loss function designed to prioritize relevant documents over non-relevant ones in the ranking for a specific query.

In our proposed architecture, the Bi-GRU-generated encoded representations for the query and document, $q\ enc$ and $d\ enc$, are shared with the text classification model via soft parameter sharing, enabling knowledge transfer between the two models

2.1.2. Semantic-based Text Classification Mode

The semantic-based text classification model within our framework is engineered to capture the semantic essence of textual data. It processes input text, whether a query or a document, to predict its semantic category, such as topic, genre, or sentiment.

The input text sequence is transformed into word embeddings or contextualized representations:

$$x=[x1,x2...,xl]$$

where l denotes the text's length. This sequence is then fed through a Bi-GRU layer to generate an encoded representation:

$$xenc=BiGRU(x) \tag{5}$$

Equation 1: This equation represents the encoding of an input text sequence x using a Bi-GRU to produce an encoded representation $xenc$. It is a general mathematical expression.

The resulting encoded text representation $xenc$ is subsequently passed to a classification layer. This layer can be constructed using various neural network architectures, such as a fully connected feedforward network or a Convolutional Neural Network (CNN). The classification layer produces a probability distribution across the potential semantic categories:

$$p=ClassificationLayer(xenc) \tag{6}$$

Equation 6: This equation indicates that the encoded text representation $xenc$ is passed to a classification layer, which generates a probability distribution p across potential semantic categories.It is a general mathematical expression.

During the training phase, the text classification model is fine-tuned using a cross-entropy loss function. This function minimizes the negative log-likelihood of the actual category labels, thereby optimizing the model's predictive accuracy.

In accordance with our architecture, the Bi-GRU layer's encoded text representations $xenc$ from the text classification model are shared with the interaction-based neural retrieval model via soft parameter sharing.

2.1.3. Soft Parameter Sharing Strategy

The key component of our proposed method is the soft parameter sharing between the feature extraction layers (Bi-GRUs) of the interaction-based neural retrieval model and the semantic-based text classification model. This strategy allows the models to exchange semantic information and benefit from multi-task learning while avoiding direct parameter sharing, which can lead to negative transfer.

Specifically, we implement soft parameter sharing by adding regularization terms to the combined loss function that encourage the hidden states of the Bi-GRUs in the two models to be similar. The combined loss function is defined as:

$$L = L\_retrieval + L\_classification + \lambda * R \tag{7}$$

where L_retrieval is the retrieval loss from the KNRM model, L_classification is the classification loss from the text classification model, and R is the regularization term for soft parameter sharing.

The regularization term R is computed as the mean squared difference between the hidden states of the Bi-GRUs in the two models:

$$R = \backslash text\{mean\_squared\_difference\}(q\_\{\backslash text\{enc\}\}, x\_\{\backslash text\{enc\}\}) + \backslash text\{mean\_squared\_difference\}(d\_\{\backslash text\{enc\}\}, x\_\{\backslash text\{enc\}\}) \tag{8}$$

where q_enc and d_enc are the encoded query and document representations from the KNRM model, respectively, and x_enc is the encoded text representation from the text classification model.

The hyperparameter λ controls the strength of the regularization term and the degree of soft parameter sharing between the two models.

During training, the combined loss function is optimized using standard techniques like stochastic gradient descent, allowing the models to learn task-specific parameters while benefiting from the knowledge transfer through the soft parameter sharing.

2.1.4. Training Process

The training regimen for our proposed CLIR method, which employs soft parameter sharing within a multi-task learning framework, is structured as follows:

1. Data Preparation
    a. Retrieval Task Data: Assemble a dataset comprising queries and their corresponding relevant and non-relevant documents.
    b. Text Classification Task Data: Compile a corpus of texts annotated with semantic categories, such as topics, genres, or sentiments.
    c. Initialization: Initialize the weights of the interaction-based neural retrieval model (KNRM) and the semantic-based text classification model, either randomly or with pre-trained weights.
    d. Training Iterations: Data Sampling: Randomly select a batch of queries and documents for the retrieval task, and a batch of texts for the text classification task.
    e. Encoding: Encode the queries, documents, and texts using a shared input layer to generate respective representations.
    f. Retrieval Loss: Utilize the KNRM model to compute the retrieval loss (L_retrieval) based on the query-document interactions.
    g. Classification Loss: Calculate the classification loss (L_classification) for the text classification task using the corresponding model.
    h. Regularization: Determine the regularization term (R) that reflects the soft parameter sharing between the Bi-GRU layers of the two models.
    i. Loss Calculation: Compute the combined loss (L) using the equation:

$$L = L_{\text{retrieval}} + L_{\text{classification}} + \lambda R \tag{9}$$

    j. Optimization: Execute backpropagation and update the model weights in accordance with the combined loss.

2. Iteration
    Repeat step 3 until the models converge or a predetermined number of iterations is reached.
    Throughout the training process, the soft parameter sharing strategy facilitates the exchange of semantic information between the models, enriching the neural retrieval model with both interaction and semantic insights gleaned from the text classification task.
    Upon completion of training, the interaction-based neural retrieval model is equipped for CLIR tasks, bolstered by its enhanced representational capabilities acquired through multi-task learning.

3. Dataset
    For the retrieval task, we used the CLIR test collections from NTCIR-8 and NTCIR-9 [28, 29], which contain queries and their corresponding relevant and non-relevant documents in multiple languages. Table 1 provides an overview of Table 1 provides an overview of the datasets used for the retrieval task in our experiments.

Table 1. Overview of the Retrieval Task Datasets

Language Pair	Source	Queries	Relevant Docs	Non-Relevant Docs
English-Chinese	NTCIR-8	50	4,525	45,250
English-Arabic	NTCIR-9	50	5,007	50,070
English-French	NTCIR-9	50	5,237	52,370
English-German	NTCIR-9	50	4,963	49,630

For the text classification task, we used publicly available datasets covering various semantic categories, such as topic classification, genre classification, and sentiment analysis. The details of these datasets are provided in Table 2.

Table 2. Overview of the Retrieval Task Datasets

Dataset	Language	Task	Classes	Samples
AG News	English	Topic Classification	4	120,000
DBPedia	English	Topic Classification	14	560,000
IMDB	English	Sentiment Analysis	2	50,000
Arabic Reviews	Arabic	Sentiment Analysis	2	63,000
FrenchBooks	French	Genre Classification	5	20,000
GermaneBooks	German	Genre Classification	6	25,000

4. Baseline Methods
   We compared our proposed method with the following baseline methods:
   a. BM25: A traditional bag-of-words retrieval model based on term frequencies and document lengths[24].
   b. BPNRM: A representation-based neural retrieval model that learns separate representations for queries and documents using feed-forward neural networks [25].
   c. KNRM: The interaction-based neural retrieval model used in our proposed method, without the multi-task learning component [6].
   d. KNRM-Trans: A translation-based CLIR method that translates queries to the document language using a machine translation system and then applies the KNRM model.
   e. KNRM-Embed: A semantic-based CLIR method that uses cross-lingual word embeddings to compute semantic similarities between queries and documents [27].

5. Experimental Setup
   For the neural retrieval models (BPNRM, KNRM, and our proposed method), we used pre-trained BERT [26] embeddings to initialize the input layer. The text classification models were initialized with pre-trained weights from the corresponding tasks (e.g., topic classification, sentiment analysis).
   We used the mean average precision (MAP) metric to evaluate the retrieval performance. MAP measures the mean of the average precision scores across multiple queries, where average precision is the area under the precision-recall curve for a single query.
   The hyperparameters of our proposed method, such as the regularization strength λ and the learning rate, were tuned on a validation set for each language pair.

2.2. Extended Model for Bi-Directional Cross-Lingual Retrieval

2.2.1. Cross-Lingual Embeddings

Our extended bi-directional model capitalizes on cross-lingual word embeddings and contextualized representations to map queries and documents from disparate languages into a unified vector space. This common representation facilitates the capture of semantic parallels and relationships, thereby fostering cross-lingual knowledge transfer and enabling bi-directional information retrieval.

The acquisition of cross-lingual embeddings is achieved through various strategies:

Cross-Lingual Word Embeddings: These are developed by training on parallel corpora or bilingual dictionaries, which synchronize the vector spaces of multiple languages [30]. Notable techniques include VecMap [31], MUSE [32], and RCSLS [33].

Cross-Lingual Contextualized Representations: Multilingual language models pretrained on extensive corpora, such as Multilingual BERT [34] and XLM-R [35], generate representations that are coherent across different languages, effectively encapsulating cross-lingual semantic ties. Cross-Lingual Transfer Learning: This method involves initially training monolingual models on individual languages and subsequently aligning them through linear projections or adversarial training [36, 37].

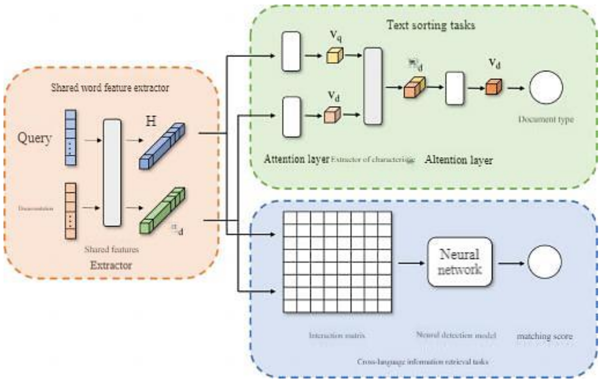

Figure 4. The framework of Bi-Directional Cross-Lingual Retrieval

In our model, we employ cross-lingual contextualized representations from pre-trained multilingual language models, exemplified by Multilingual BERT. These representations have demonstrated robust performance in a variety of cross-lingual NLP tasks, adeptly capturing semantic similarities among languages.

The input data, comprising queries and documents in different languages, undergo tokenization and are encoded by the multilingual language model. This process yields contextualized representations that are integrated into a shared vector space. These cross-lingual representations are subsequently fed into the Bi-GRU layers responsible for feature extraction in both the retrieval and text classification models.

2.2.2. Training Process

To evaluate the effectiveness of the extended bi-directional model for cross-lingual information retrieval, we conducted experiments on the English-Chinese language pair. We compared our model with several baseline methods and analyzed the results for bi-directional retrieval performance.

1. Dataset

   For the retrieval task, we used the CLIR test collection from NTCIR-8 [28], which contains queries and their corresponding relevant and non-relevant documents in both English and Chinese. Table 3 provides an overview of the dataset.

Table 3. Overview of the Retrieval Task Dataset (NTCIR-8)

Language Pair	Queries	Relevant Docs	Non-Relevant Docs
English	50	4,525	45,250
Chinese	50	4,525	45,250

   For the text classification task, we used the AG News dataset [38] for English topic classification and the THUCNews dataset [39] for Chinese topic classification. The details of these datasets are provided in Table 4.

Table 4. Overview of the Retrieval Task Dataset (NTCIR-8)

Dataset	Language	Task	Classes	Samples
AG News	English	Topic Classification	4	120,000
THUCNews	Chinese	Topic Classification	14	740,000

2. Baseline Methods

   We compared our extended bi-directional model with the following baseline methods:
   a. BM25: The traditional bag-of-words retrieval model based on term frequencies and document lengths [24].
   b. KNRM: The interaction-based neural retrieval model used in our proposed method, without the multi-task learning component [6].
   c. Mono-KNRM: A monolingual version of the KNRM model trained separately on English and Chinese data, without any cross-lingual knowledge transfer.
   d. Original Model: The cross-language information retrieval method based on soft parameter sharing multi-task learning proposed, which only supports retrieval in one direction (e.g., retrieving Chinese documents given English queries).

3. Baseline Methods

   For the neural retrieval models (KNRM, Mono-KNRM, Original Model, and our extended bi-directional model), we used pre-trained Multilingual BERT [34] embeddings to initialize the input layer and encode queries and documents in both languages.

   We used the mean average precision (MAP) metric to evaluate the retrieval performance, separately for English queries and Chinese queries. MAP measures the mean of the average precision scores across multiple queries, where average precision is the area under the precision-recall curve for a single query.

   The hyperparameters of our extended bi-directional model, such as the regularization strengths $(\lambda\_1, \lambda\_2, \lambda\_3)$ and the learning rate, were tuned on a validation set.

3. RESULTS AND DISCUSSION

3.1. Cross-Language Information Retrieval Based on Soft Parameter Sharing Multi-Task Learning

Neural retrieval models like BPNRM and KNRM are more effective than the traditional BM25 model for capturing the semantic relationships between queries and documents. KNRM, which focuses on query-document interactions, consistently outperforms BPNRM, highlighting the importance of interaction modeling in retrieval tasks.

The CLIR method KNRM-Trans underperformed compared to the semantic-based methods KNRM-Embed and our proposed method, suggesting that direct translation can introduce noise and negatively impact performance. Our method achieved the highest MAP scores, surpassing KNRM-Embed, which uses cross-lingual embeddings but lacks multi-task learning. The soft parameter sharing between the interaction-based neural retrieval model and the semantic-based text classification model enhances the retrieval model's ability to learn both interaction and semantic information, leading to better performance.

The multi-task learning framework also aids the retrieval model by transferring knowledge from the text classification task, mitigating the issue of limited training data. Notably, the performance gains were more pronounced for English-Chinese and English-Arabic pairs, likely due to the greater linguistic and cultural differences, where additional semantic information is more advantageous.

In summary, our experimental results confirm the effectiveness of our proposed cross-language information retrieval method that uses soft parameter sharing and multi-task learning to leverage semantic information and knowledge transfer, resulting in improved retrieval performance across various language pairs.

Table 5. Results of Soft Parameter Sharing Multi-Task Learning

Method	EN-ZH	EN-AR	EN-FR	EN-DE
BM25	0.292	0.278	0.311	0.325
BPNRM	0.334	0.321	0.349	0.362
KNRM	0.381	0.367	0.392	0.406
KNRM-Trans	0.374	0.359	0.385	0.397
KNRM-Embed	0.391	0.376	0.402	0.417
Proposed Method	0.419	0.403	0.427	0.441

3.2. Extended Model for Bi-Directional Cross-Lingual Retrieval

Neural retrieval models KNRM and Mono-KNRM outperformed the BM25 model, with Mono-KNRM showing a slight advantage due to language-specific parameter optimization. The Original Model from Chapter 3 had the highest MAP for English-to-Chinese retrieval but lacked reverse retrieval capability. Our bi-directional model achieved the highest MAP for both directions, benefiting from cross-lingual soft parameter sharing for knowledge transfer and improved semantic understanding. The model's ability to handle queries and documents in either language is a significant advantage. English query performance was particularly enhanced due to richer training data, leading to better semantic insights. Overall, our findings confirm the effectiveness of the bi-directional model in cross-lingual information retrieval through bi-directional support and cross-lingual knowledge transfer.

Table 6. Results of Bi-Directional Cross-Lingual Retrieva

Method	English Queries	Chinese Queries
BM25	0.292	0.293
KNRM	0.381	0.379
Mono-KNRM	0.387	0.383
Original Model (Ch. 3)	0.419	-
Extended Bi-Directional	0.428	0.422

4. CONCLUSION

CLIR Method via Soft Parameter Sharing Multi-Task Learning: Developed a new CLIR technique combining neural retrieval and text classification models through multi-task learning and soft parameter sharing, enhancing semantic understanding across languages.Enhanced Bi-Directional Model: Introduced a bi-directional model for cross-lingual retrieval using cross-lingual embeddings, improving performance in both English-to-Chinese and Chinese-to-English directions.Multi-Task Learning Framework: Utilized a framework for neural retrieval models to learn semantic information from text classification tasks, enhancing performance through knowledge transfer.Cross-Lingual Knowledge Transfer: Promoted knowledge transfer across languages, improving bi-directional retrieval through shared representations.Flexibility and Bi-Directional Retrieval: The bi-directional model supports retrieval in both languages from either language query, offering flexibility and broader information access.

Diversifying Multi-Task Learning: Explore alternative frameworks and techniques for integrating retrieval models with auxiliary tasks and advanced parameter sharing methods.Advancing Language Models: Apply sophisticated pre-trained language models for cross-lingual representations and consider fine-tuning for CLIR tasks.Addressing Low-Resource Languages: Adapt methods for low-resource languages, using cross-lingual transfer learning and unsupervised methods.Integrating Multimodal Information: Extend methods to include images, videos, and audio, studying multi-task learning strategies for multimodal data.Optimizing Inference: Develop efficient inference protocols, researching model optimization techniques for practical CLIR implementation.Real-World Application Evaluation: Assess methods in real-world applications, conducting user studies and addressing real-world challenges.Enhancing Explainability: Improve model explainability and use visualization tools to understand cross-lingual representations.These directions aim to innovate in CLIR, addressing challenges in low-resource languages, multimodal data, efficient inference, real-world application, and model interpretability, to facilitate unrestricted cross-lingual information access.

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