Construction of an Academic Query Intent Classifier Based on Deep Learning Algorithms (Postprint)

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Abstract

[Purpose/Significance] To achieve automatic recognition of academic query intent and improve the efficiency of academic search engines. [Method/Process] By combining existing query intent features with the characteristics of academic search, features were constructed for query expressions from four dimensions: basic information, specific keywords, entities, and occurrence frequency. Four classification algorithms—Naive Bayes, Logistic regression, SVM, and Random Forest—were employed for preliminary experiments on automatic query intent recognition, calculating accuracy, recall, and F-value for different methods. A method was proposed to extend the recognition results predicted by the Logistic regression algorithm to large-scale datasets and extract "keyword category" features to construct a deep learning two-layer classifier for academic query intent recognition. [Result/Conclusion] The macro-average F1 value of the two-layer classifier is 0.651, which outperforms other algorithms and can effectively balance the category accuracy and recall performance across different academic query intents. The two-layer classifier performs best on the academic exploration category, with an F1 value of 0.783.

Full Text

Constructing an Academic Query Intent Classifier Based on Deep Learning Algorithms[1]

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Abstract

[**Purpose/Significance**] This study aims to achieve automatic identification of academic query intent and improve the efficiency of academic search engines. [**Method/Process**] Combining existing query intent features with the characteristics of academic search, we constructed features for query expressions from four dimensions: basic information, specific keywords, entity information, and frequency statistics. We conducted preliminary experiments on automatic query intent recognition using four classification algorithms—Naive Bayes, Logistic Regression, SVM, and Random Forest—calculating the precision, recall, and F-measure for each method. We propose a method that extends the prediction results from the Logistic Regression algorithm to a large-scale dataset to extract "keyword-type" features for constructing a deep learning-based two-layer classifier for academic query intent recognition. [**Result/Conclusion**] The two-layer classifier achieved a macro-averaged F1-score of 0.651, outperforming other algorithms, and effectively balancing the precision and recall across different academic query intent categories. The classifier performed best on academic exploration queries, with an F1-score of 0.783.

Keywords: academic query intent; automatic identification; two-layer classifier
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1. Introduction

With the explosive growth of academic resources such as scientific literature [1], professional academic search engines have evolved from serving a small number of specialized users to accommodating large numbers of diverse user types, and from addressing single research needs to meeting complex, varied demands [2]. Meanwhile, due to the specialized nature of academic database retrieval systems (Web of Science, CNKI, etc.) and their lack of interoperability, "one-stop" academic search engines such as Baidu Scholar and Google Scholar have become the preferred choice for academic queries [3-4]. Users' academic backgrounds and capabilities vary considerably, leading to different information needs when conducting academic searches. For researchers using academic search engines, their need for diverse academic information—to understand research progress and track cutting-edge developments—cannot be accurately expressed through short query expressions. For novice researchers or non-academic users, their limited understanding of relevant academic fields results in inaccurate keywords and imprecise search results.

Academic query intent refers to the user's information needs expressed through query expressions during academic searches. Existing academic search engines predominantly rely on keyword-matching technology that cannot recognize the underlying intent of academic queries. Identifying academic query intent can optimize search results, improve retrieval efficiency, save user time, enhance the academic search experience, and enable access to more precise academic information.

Automatic query intent identification typically employs text classification algorithms, where researchers test different feature combinations for a given classification algorithm. The foundation of such experiments is a query intent taxonomy. However, most taxonomies for academic query intent are derived from general query intent frameworks, lacking a specialized system for academic contexts. To address this, our previous foundational research constructed a dedicated academic query intent taxonomy with five categories:

(1) **Academic Literature Category**: Queries aimed at retrieving specific academic publications, such as constructing queries from academic paper titles.

(2) **Academic Entity Category**: Queries seeking information about academic entities, such as research institutions (e.g., "Shandong Academy of Agricultural Sciences Crop Research Institute").

(3) **Academic Exploration Category**: Exploratory queries in a particular domain requiring multiple interactions to obtain needed academic resources, such as queries for academic concept terms like "neural network algorithm."

(4) **Knowledge Q&A Category**: Queries seeking answers to specific questions, such as "Will subacute thyroiditis recur after being cured?"

(5) **Non-Academic Literature Category**: Queries aiming to obtain non-academic documents such as policies or industry reports, e.g., "automobile 下乡 policy."

2. Related Research

Research on academic query intent identification is relatively limited, with most studies focusing on library catalog query intent recognition or applications. For instance, Hu Lingxia [5] categorized library retrieval query intents into single and multiple intents, using dictionaries to classify search terms. Li Bing [6] adapted and improved Hu's library retrieval query intent taxonomy to enhance faceted book retrieval. Given the scarcity of research specifically on academic query intent recognition and its current focus on library queries, we draw upon user query intent identification studies from general search engines, considering that academic search is a specific vertical subdomain of search.

Query intent identification methods for general search engines can be divided into manual identification approaches [7-8] and automatic identification methods [9]. Due to the high cost of manual identification, most research employs automatic methods. The classification features and algorithms involved can be summarized as follows:

2.1 Sources of Classification Features for Automatic Query Intent Recognition

Sources of classification features for automatic query intent recognition include "user click behavior on search engine results" and "user query expressions." Brene et al. [10] identified user click behavior as the most effective feature for query intent classification. However, click behavior data involves privacy concerns and access restrictions, with only Liu et al. [11] utilizing click distribution as a feature for query intent identification in their experiments. Most researchers obtain classification features for general search by analyzing query expressions, which can be summarized into three categories: basic information, word-level information, and entity information.

(3) Entity Information: This refers to entity information contained in query expressions. For example, Zhang Xiaojuan [15] mapped entities to query intent categories, concluding that entities in navigational queries are primarily person names, place names, and organization names, while entities in resource queries are often game titles, song titles, etc. Chang et al. [17] used natural language processing (NLP) analysis results of entities as classification features.

2.2 Automatic Query Intent Recognition Algorithms

Automatic query intent recognition algorithms essentially employ text classification methods based on query expression features. When selecting classifiers, researchers typically choose different algorithms—such as SVM, decision trees, or PLSA—based on the experimental dataset, data characteristics, and specific classification tasks. For example, Liu et al. [11] used a typical decision tree algorithm combining nCS, nRS, and click distribution features for identification tasks. Mendoza [18] utilized SVM and PLSA to categorize query intents. Chang et al. [17] proposed using NLP analysis results as features for query intent classification, achieving favorable outcomes. Most features and methods for automatic query intent recognition target general search engines, with limited attention to the vertical domain of academic search. Due to the specialized nature and unique characteristics of academic search, these features and methods cannot be directly applied to academic query intent identification and require further extension.

3. Feature Selection and Classifier Construction

3.1 Feature Extraction for Academic Query Intent

In general search, query intent features can be obtained from query terms [13] and can be divided into three categories: basic information [12], word-level information [13-16], and entity information [15,17]. Combining these with the characteristics of academic search, we expanded the classification features for academic query intent into four aspects: basic information, word-level information, entity information, and statistical features of word frequency. Since approximately 30% of query expressions in Baidu Scholar are in English, we considered both Chinese and English languages in our feature design.

3.1.1 Basic Information Features Basic information features refer to information that can be directly extracted from query expressions, such as query length, term count, and term length. These features can be divided into two dimensions: character-level features and term-level features.

Character-level features include the absolute number and proportion of different character types in a query expression. The former refers to the absolute count of different character categories; the latter refers to their relative proportion. Query expression characters are divided into four categories: Chinese characters, English characters, punctuation marks, and other characters (characters other than Chinese/English/punctuation). Each character is counted as 1 when calculating absolute values.

Term-level features include the absolute number and proportion of different term types. The former refers to the absolute count of different term categories; the latter refers to their relative proportion. Due to differences between Chinese and English, we pre-processed Chinese query expressions with word segmentation and calculated Chinese term counts based on segmentation results, while counting each individual English word as one term.

The four categories of basic information features are shown in Table 1 .

3.1.2 Word-Level Information Specific words contained in query expressions are often used as important features for identifying user query intent [16]. Based on analysis of Baidu Scholar user query logs, we found that academic literature and knowledge Q&A categories exhibit distinct word-level information features. For academic literature queries, we observed frequent use of citation format information (e.g., using Chinese citation standards like [J], [C] to denote journal and conference papers). For knowledge Q&A queries, we found frequent use of interrogative words. Specific features are shown in Table 2 .

3.1.3 Entity Features Named entities frequently appear in general search queries. Guo [19] found that 70% of English queries in general search contain named entities. Additionally, since our previous research's academic query intent taxonomy includes an academic entity category, we incorporated entity information as a feature, primarily for identifying academic entity queries. Specifically, the named entities used as features include four types: person names, place names, organization names, and academic entities (e.g., journals, universities, research institutes, centers, laboratories).

3.1.4 Statistical Features of Word Frequency During our manual annotation experiments, we observed that academic terminology (e.g., amino acids, benzene) appears frequently in academic exploration queries, while everyday vocabulary appears more frequently in knowledge Q&A queries. To characterize this feature, we borrowed the concept of Inverse Document Frequency (IDF) and proposed a frequency indicator S(W) to quantify word frequency characteristics. For any word W:

$$S(W) = \log\left(\frac{n}{N(W)}\right) \quad \text{(Formula 1)}$$

where n is the total number of query expressions Q in the dataset, and N(W) represents the frequency of word W appearing in query expressions in the dataset, with a value range of [1, n]. If a word appears in all query expressions, its frequency S(W) equals 0; if a word appears in only one query expression, its frequency S(W) reaches the maximum value of log(n).

We calculate the frequency S(W) for each word W in all query expressions in the dataset. For each query expression Q, we compute three features: maximum frequency SMAX(Q), minimum frequency SMIN(Q), and average frequency SAVE(Q). The calculation formulas are:

$$SMAX(Q) = \max_{W \in Q} S(W) \quad \text{(Formula 2)}$$

$$SMIN(Q) = \min_{W \in Q} S(W) \quad \text{(Formula 3)}$$

$$SAVE(Q) = \frac{\sum_{W \in Q} S(W)}{\text{Count}(W)}$$

where Count(W) represents the number of distinct words W in Q.

3.2 Construction of Two-Layer Classifier

Given the small training set size in our experiments, we employed binary classification for each of the five academic query intent categories to improve accuracy. For each category, we constructed a supervised learning algorithm that represents query expressions as a series of features X and finds an optimal function F in the target space that can predict whether a query expression belongs to intent category y based on features X. This process can be simply expressed as:

$$y = F(x) \quad \text{(Formula 4)}$$

The feature extraction and training set scale for query expressions affect the performance of supervised learning algorithms. Since our available training dataset for supervised learning is small, we improved performance through two aspects: (1) extracting appropriate features that can characterize the training data, and (2) obtaining a sufficiently large training dataset. Based on this, we propose a two-layer classifier for automatic academic query intent identification, as shown in Figure 1 [Figure 1: see original paper].

In the first layer, experimenters used the Logistic Regression algorithm to train a classifier based on four types of data features from 4,000 annotated data instances. Due to the low recall rate of classification results, this stage is called the weak classifier. The binomial Logistic Regression model performs binary classification sequentially for each input query expression to determine whether it belongs to each of the five categories: academic literature, academic entity, academic exploration, knowledge Q&A, or non-academic literature. The classifier is trained on the annotated dataset to obtain the weak classifier.

The second layer is a deep learning classifier using a DNN model for training and classification. First, the weak classifier from the first layer is used to annotate and pre-classify large-scale unlabeled data for academic query intent categories. Second, these pre-classified annotated data serve as input for the second-layer classifier to train and classify using the DNN model. With large-scale datasets, the second-layer classifier can learn new data features not mentioned in the first-layer weak classifier. We collectively refer to these new features learned from large-scale datasets as "keyword-type" features to improve the performance of this layer. For example, for two query expressions "关于春天的谚语有哪些" (What are the proverbs about spring?) and "关于秋天的谚语有哪些" (What are the proverbs about autumn?), since both contain the word-level information feature "哪些" (what/which), the weak classifier would categorize them as knowledge Q&A. As the frequency of such query expressions increases in the large-scale dataset, the deep learning classifier learns that "关于 XX 的谚语" (proverbs about XX) is an important keyword pattern. When encountering a query like "关于龙的谚语" (proverbs about dragons), the deep learning classifier will categorize it as knowledge Q&A based on the newly extracted "keyword-type" feature. This experiment was implemented in Python using the TensorFlow open-source library.

4. Experiments

4.1 Experimental Data

We obtained query logs from Baidu Scholar as our experimental data. The logs record all user interactions in the Baidu Scholar search bar, with each data entry containing a unique user identifier (UID), query time (Time), query expression (Query), and query IP address (IP), as shown in Figure 2 [Figure 2: see original paper]. The total dataset contains 5,414,886 entries. After removing garbled and duplicate data, the total is 3,449,591 entries, of which 1,000 have been annotated by the original paper authors according to the academic query intent taxonomy from our previous research. We use these 1,000 entries as our test set.

From the cleaned dataset, we randomly sampled 4,000 entries (different from the test set) as our training set. We recruited six first-year graduate students majoring in information science with relevant annotation experience. The 4,000 academic query entries were annotated into five categories: "academic literature," "academic entity," "academic exploration," "knowledge Q&A," and "non-academic literature." The process was as follows:

(1) We introduced the annotation task background, experimental logic, and the usage context of the annotated dataset to the annotators.

(2) We compiled the "Academic Search Query Intent Manual Annotation Guidelines," introducing the academic query intent taxonomy and using examples from the 1,000-entry test set to illustrate the boundaries between the five intent categories, providing annotators with a general perception of the classification.

(3) The annotators were divided into three pairs, each independently annotating the assigned data according to the guidelines. The first two pairs were each assigned 1,340 entries, and the third pair was assigned 1,320 entries, totaling 4,000 entries. Annotators were allowed to refer to Baidu's search results pages when uncertain.

After completing the manual annotation task, we used the Kappa coefficient to measure inter-annotator consistency. The Kappa values for the three groups were 0.776, 0.759, and 0.806, respectively. All Kappa values exceed 0.75, indicating high consistency among annotators. For entries with different annotation results, we subsequently convened all annotators for discussion and determined the final category based on majority rule.

The annotation results for the 4,000 query expressions are shown in Table 3 . Among the 4,000 annotated entries, 34 contained completely meaningless text or pure punctuation symbols that did not constitute valid academic query expressions and could not be classified into the five categories; these were removed. The remaining 3,966 entries were statistically analyzed, revealing that "academic exploration" queries represented the highest proportion.

Figure 3 [Figure 3: see original paper] compares the category proportions between the manually annotated training set (3,966 entries) and test set (1,000 entries). The proportions for "academic literature," "academic entity," and "knowledge Q&A" are largely consistent between the two datasets, while "academic exploration" and "non-academic literature" show approximately 2% differences. Variations in datasets and annotators' understanding of the guidelines can cause some discrepancies, but the average proportion error is 1.13%, indicating similar category distributions between the training and test sets, which rules out model bias.

4.2 Experimental Results

Table 4 presents the statistical results of four preliminary experiments and one formal experiment using different algorithms. The data shows that SVM achieved the best macro-averaged precision at 0.789, while Naive Bayes achieved the best macro-averaged recall at 0.755. However, single-layer classifiers generally cannot balance precision and recall well, with most algorithms exhibiting low recall values. In contrast, our proposed two-layer classifier improves recall while maintaining precision, achieving a macro-averaged precision of 0.767, macro-averaged recall of 0.586, and macro-averaged F1-score of 0.651. This demonstrates that our two-layer classifier outperforms the other four single-layer algorithms.

Table 5 shows the classification performance of our two-layer classifier across academic query intent categories. The analysis reveals that the two-layer classifier performs well on academic literature and academic exploration categories, and moderately on academic entity and knowledge Q&A categories, though still better than other single-layer classifiers.

4.2.1 Performance by Category **(1) Academic Literature Category**: Table 6 presents the experimental results for four preliminary classifiers and the two-layer classifier on the academic literature category. In terms of F1-score, the Random Forest single-layer classifier performed best (0.697), followed by our two-layer classifier (0.672). Overall, all five classifiers demonstrate good performance in automatically identifying academic literature queries.

In previous research, Khasba et al. [17] conducted query intent analysis on the academic search engine CiteSeerX, focusing on navigational queries (accounting for 12.5% of their data). In their framework, navigational queries in academic search were defined as "queries where users intend to find specific publications," consistent with our "academic literature" category. For this category, Khasba used the GBT algorithm with 579 manually annotated training instances, achieving precision of 0.68, recall of 0.68, and F1-score of 0.677. Our results for the academic literature category are comparable, with a slight improvement in F1-score.

(2) Academic Entity Category: Table 7 shows the experimental results for the academic entity category. Our two-layer classifier outperforms the preliminary classifiers in precision and F1-score. However, overall performance for academic entity query intent identification is the weakest among the four categories for two reasons: (1) our entity recognition tool (Stanford NER) performs poorly on Chinese text, and Chinese queries account for 70% of the total data; (2) our classification rule stipulates that queries containing only one scholar's name are classified as academic entity, while those with multiple scholar names are classified as "academic full-text," making academic entity identification not just a simple entity recognition problem but also requiring judgment of the number of scholars in the query expression, thus resulting in lower performance.

(3) Academic Exploration Category: Table 8 presents the experimental results for the academic exploration category. The two-layer classifier achieved the highest F1-score, with high precision and recall, indicating good performance in identifying academic exploration queries. This category represents the largest proportion of query expressions, approximately 46%.

(4) Knowledge Q&A Category: Table 9 shows the experimental results for the knowledge Q&A category. Except for Naive Bayes, recall rates are generally low. Overall, our two-layer classifier still slightly outperforms other methods in terms of F1-score.

5. Conclusion and Future Work

This study focuses on academic query intent classification. By analyzing academic query expressions, we constructed basic feature descriptions from four aspects—basic information, word-level information, entity information, and statistical features of word frequency—based on existing research. We developed a two-layer classifier for automatic academic query intent recognition and extracted "keyword-type" features from large-scale data classification. Compared to single-layer classifiers, our two-layer classifier achieved better results in macro-averaged F1-score and effectively balanced precision and recall across different query intent categories.

The limitation of this study lies in the relative scarcity of research on academic query intent, resulting in the lack of a unified, large-scale evaluation dataset. Consequently, it is difficult to conduct horizontal comparisons between our two-layer classifier's performance and other experimental results. Future work will focus on promoting relevant datasets for academic query intent automatic identification to facilitate horizontal comparisons among different methods.

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Author Contributions

Wang Ruixue: Experimental design, data cleaning, and paper drafting
Fang Jing: Data cleaning, experimental operation, and paper drafting
Gui Sisi: Experimental design and paper revision
Lu Wei: Experimental design and paper revision
Zhang Xian: Data cleaning and experimental design

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Based on Deep Learning Algorithm to Construct the Classifier of Academic Query Intent

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Abstract: [Purpose/significance] To find the solutions of automatically identifying search query intent and improve the efficiency of academic search engines. [Method/process] Combining the features of query intent and academic search, we constructed the feature from four aspects, which are the basic descriptive statistics, the special keywords, entity information and the frequency. For the experiments, we examined four types of classifiers which are the Naive Bayes, Logistic regression, SVM, Random Forest and calculated precision, recall and F-measure. A method which is extending the recognition result of academic query intent predicted by Logistic regression algorithm to large-scaled datasets and extracting "keyword type" features is proposed to construct a two-layer classifier based on deep learning algorithm for academic query intent recognition. [Result/conclusion] The macro-average F1 value of the two-layer classifier is 0.651, which is superior to other algorithms. This method can effectively balance the precision and recall rate of different academic query intentions. The final second-layer prediction model receives the best classification performance, the score of F1 is 0.783.

Keywords: academic query intent; automatic identification; two-layer classification

Note: Figure translations are in progress. See original paper for figures.