

Intelligence-assisted college English teaching: The application of artificial intelligence technology in personalized learning path design

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Copyright © 2024 by author(s). *Molecular & Cellular Biomechanics* is published by Sin-Chn Scientific Press Pte. Ltd. This work is licensed under the Creative Commons Attribution (CC BY) license. https://creativecommons.org/licenses/ by/4.0/ **Abstract:** English learning is an integrated learning process in which listening, speaking, reading, writing and other parts are interrelated. Because of this feature of English learning, higher requirements are put forward for the design of English learning assistance systems. On the other hand, the wide application of advanced science and technology such as automation and cloud computing in all walks of life has promoted the development of society into the era of artificial intelligence. Under such a large development background, how to build a multifunctional integrated English learning system to realize the personalized learning of learners with different levels and different needs has become a focus of current English teaching research. With the increasing abundance of English learning materials, it has become very important to help users find suitable English learning resources from the massive materials, which directly affects the cost of learning time and interest of users. Based on this, this paper introduces a multi-similarity ranking model to achieve personalized design, and then uses artificial intelligence technology to design and implement a personalized intelligent assistant system for college English teaching.

Keywords: intelligent assistance; college English teaching; artificial intelligence; personalized learning; path design

1. Introduction

In recent years, the combination of artificial intelligence and education has become closer and closer, and the needs of students are no longer just basic resource learning and exercises, but also strengthening and consolidating their weak knowledge points. Since each student has different ability to accept knowledge points, which leads to different learning progress, it is especially important to provide differentiated learning for students with different circumstances.

Students' personalized learning cannot be separated from the participation of artificial intelligence, for this reason, experts and scholars at home and abroad have conducted in-depth research on the English personalized learning system based on artificial intelligence. Speretta used clustering technology to label each page with the corresponding user interest label, and modeled the user interest based on this. In the study, it was found that users' interests changed with time and could be divided into long-term interests and short-term interests. Short-term interests reflected current social hot events or public concerns, while long-term interests reflected their own unique interest points [1]. Liu used the user-based collaborative filtering technology and association rule mining technology to build a software system suitable for nursing students to learn relevant professional English textbooks [2]. Yong-Ming Huang designed and developed a ubiquitous learning system related to English vocabulary,

in which cut micro-videos are the main learning materials in the learning platform. By watching micro-videos and learning the knowledge explained in the micro-videos, learners can improve the efficiency of consolidating old vocabulary and learning new vocabulary [3]. Wu aimed at the problem of non-semantic consideration in collaborative filtering recommendation algorithm, embedded semantic data into lowdimensional semantic space by using knowledge graph, and made up for the semantic defects of collaborative filtering algorithm by calculating semantic similarity [4]. In order to solve the problem of eigenvalue fusion, Yang proposed a personalized recommendation algorithm for ranking learning based on knowledge graph by combining different features with deep learning methods. In order to solve the problem of students' knowledge stranding in the learning system [5]. Pan designed an intelligent English learning software for graduate students in Android version, and then developed an intelligent English learning platform for graduate students in Android version by using Java language in Android Studio environment, which realized the intelligent recommendation of learning materials in personalized learning [6]. Deng used ChatGPT to construct a personalized teaching mode based on ChatGPT from the path of "Understanding the function of ChatGPT-Setting teaching goals-Designing strategies and methods -Implementation, feedback and optimization" as the path to build a personalized teaching mode based on ChatGPT, realizing the present 'tailor-made teaching'. The personalized teaching model based on ChatGPT is built from the path of "understanding the function of ChatGPT-setting teaching objectivesdesigning strategies and methods-implementing, feedback and optimization", which realizes the "teaching according to the material", and provides the students with an independent and innovative learning mode through ChatGPT [7].

In the process of English teaching and learning, test-oriented thinking occupies a dominant position, which makes most English learners stay in the stage of mastering grammar, resulting in the awkward situation of easy reading and writing and difficult listening and speaking. However, English learning software can generally combine listening, speaking, reading, writing and other aspects to provide users with a variety of learning methods, which is convenient for users to learn from various aspects. The existing English assistant learning system lacks the dynamic adaptive ability based on user's personalization, and fails to systematically rearrange and sort the corresponding data according to a user's English level [8]. Based on this, this paper uses artificial intelligence technology to study the personalized intelligent assistant system in college English teaching.

The innovation points and research organization of this paper are as follows: In order to realize the personalized design, this paper proposes the sorting model integrating multiple similarity, presents the similarity calculation method based on the spatial vector model and the realization path of the full-text retrieval sorting method adding user-defined information. In the design of intelligent assisted English learning system, the English clause algorithm based on SVM and the multi-layer HASH algorithm realize the extraction and denoising of text, and the text quality evaluation algorithm is designed to select high-quality text resources. Then, the retrieval system is established to realize the rapid detection of English words and sentences. Finally, the realization path of the system is given.

2. The ranking model of multiple similarity is integrated

For the specific task of resource retrieval in English learning, the research on sorting algorithm is a key component. A good sorting algorithm should be consistent with the user's English level. In this paper, the linear fusion method is used to design a personalized sorting algorithm that can adapt to dynamic changes.

2.1. Similarity calculation method based on spatial vector model

The text is represented as a point on the word space, and each text can be replaced by a word feature vector. It is assumed that each word feature is unrelated to each other and independent. After the representation as a spatial vector model, we use the cosine similarity method to calculate the text similarity. The specific algorithm is shown in **Table 1**.

Table 1. Cosine similarity algorithm based on spatial vector model.

Output: Similarity between document and query

Algorithm steps:

Calculate the weight of each dimension feature, here TFIDF of each word is used to form two features The vector:

The query vector is $Vq = \langle w(t1,q), w(t2,q), ..., w(tn,q) \rangle$

The document vector is Vd= \leq w (t1,d),w (t2,d),...,w (tn,d) >

Calculate the similarity based on two vectors using cosine similarity:

$$Score(q,d) = cos(\theta) = \frac{\bar{v}_q \times \bar{v}_d}{|\bar{v}_q| \times |\bar{v}_d|}$$
(1)

Return the similarity calculation score, the smaller the Angle indicates that the two vectors are more similar, the higher the score.

Consider that if the cosine similarity is completely used to calculate, there will be a short text priority situation. However, this situation sometimes does not fit the specific needs [9]. Therefore, the document weight vector is specially processed and designed as a function of the document length. The expression of the scoring function is:

$$Score(q,d) = \frac{1}{\sqrt{\sum_{tinq} idf(t,d)^2}} \times \sum_{tinq} \left(tf(t,d) \times idf(t,d)^2 \times \frac{1}{(length-6.5)^2} \right)$$
(2)

2.2. Add the sorting method for full-text search of user-defined information

On the basis of the previous section, it is also necessary to add user-defined information to realize the personalized recommendation of the system to the user. When evaluating the two similarity, our default goal is that the text with English query items should be sorted before the text with Chinese query items [10]. In order to solve

Input: Document vector={term1, term2,...,term N}

Query vector={term1, term2,, term N}

Parameter description: term indicates the word feature.

this problem, the domain weight is introduced into the basic formula in the previous section. The expression is as follows:

$$Score(q,d) = \frac{1}{\sqrt{\sum_{\text{ting}} \text{idf}(t,d)^2}} \times \sum_{\text{ting}} \left(\text{tf}(t,d) \times \text{idf}(t,d)^2 \times \frac{1}{(\text{length} - 6.5)^2} \times \text{tboost}() \right) (3)$$

In order to solve the problem of mixed search in Chinese and English, the Boolean model is introduced. In the Boolean model, multiple query items can be added and different options are set for each query item. In view of this situation, the number of multiple query items contained in the document needs to be considered.

$$Score(q,d) = coord(q,d) \times \frac{1}{\sqrt{\sum_{tinq} idf(t,d)^2}} \times \sum_{tinq} \left(tf(t,d) \times idf(t,d)^2 \times \frac{1}{(length - 6.5)^2} \times tboost() \right)$$
(4)

In the formula, coord (q, d) indicates that when a document contains more search terms, the higher the score of this document.

The final formula above, with a special note here, applies mainly to Boolean queries where the option is set to SHOULD, and if there is aMUST query [10]. It SHOULD be taken as the priority of the criterion, after containing such a query item, if it also contains the query item should, the corresponding bonus is added. The sorting algorithm of the final full-text search is shown in **Table 2**.

 Table 2. Sorting algorithms for full-text search.

Enter: Collection D of documents to be sorted

Output: Document collection DS in order of similarity from greatest to least

Algorithm steps:

Find the document collection that contains the query item that must be included, referred to as document collection M.

The other document collections are D-M and labeled S.

Use the Score function to calculate the score for each document in the document collection M.

Use the Score function to calculate the score for each document in document collection S.

Sort the documents in M by score from largest to smallest, and the sorted collection is MS.

Sort the documents in S by score from largest to smallest, and the collection after sorting is SS. Add the collection MS to DS, keeping the order of MS.

Add the set SS to DS, after the elements of the MS set, keeping the size of the SS set in relative order. Return the DS set.

2.3. Multi-similarity fusion algorithm

In the design of fusion algorithm, the idea of linear fusion is adopted, and two similarity modes are considered comprehensively. Then a new similarity score is obtained. The specific description of the algorithm is shown in **Table 3** below.

Table 3. Multi-similarity pattern fusion weight estimation.

Output: Weights of two similarity patterns Algorithm steps: Target a collection of user click records. The documents for this query item are sorted by two different similarity modes: F_S={document_1_F,document_2_F,,document_n_F} D_S={document_1_D,document_2_D,,document_n_D} (F_S is the document set sorted by full text search, D_S is the document set sorted by difficulty information) For each (location_i, document_id_i) in a click record: Find the location of document_id_i in F_S and D_S location_f_i,location_d_i Calculate the distance between location_i and location_f_i,location_d_i dis_f=location_f_i-location_i Calculate temporary weights temp_w_f,temp_w_d Add up the temporary weights: w_f+=temp_w_f	Input: User click Record
Algorithm steps: Target a collection of user click records. The documents for this query item are sorted by two different similarity modes: F_S={document_1_F,document_2_F,,document_n_F} D_S={document_1_D,document_2_D,,document_n_D} (F_S is the document set sorted by full text search, D_S is the document set sorted by difficulty information) For each (location_i, document_id_i) in a click record: Find the location of document_id_i in F_S and D_S location_f_i,location_d_i Calculate the distance between location_i and location_f_i,location_d_i dis_f=location_f_i-location_i Calculate temporary weights temp_w_f,temp_w_d Add up the temporary weights: w_f+=temp_w_f	Output: Weights of two similarity patterns
Target a collection of user click records. The documents for this query item are sorted by two different similarity modes: F_S={document_1_F,document_2_F,,document_n_F} D_S={document_1_D,document_2_D,,document_n_D} (F_S is the document set sorted by full text search, D_S is the document set sorted by difficulty information) For each (location_i, document_id_i) in a click record: Find the location of document_id_i in F_S and D_S location_f_i,location_d_i Calculate the distance between location_i and location_f_i,location_d_i dis_f=location_f_i-location_i Calculate temporary weights temp_w_f,temp_w_d Add up the temporary weights: w_f+=temp_w_f	Algorithm steps:
The documents for this query item are sorted by two different similarity modes: F_S={document_1_F,document_2_F,,document_n_F} D_S={document_1_D,document_2_D,,document_n_D} (F_S is the document set sorted by full text search, D_S is the document set sorted by difficulty information) For each (location_i, document_id_i) in a click record: Find the location of document_id_i in F_S and D_S location_f_i,location_d_i Calculate the distance between location_i and location_f_i,location_d_i dis_f=location_f_i-location_i Calculate temporary weights temp_w_f,temp_w_d Add up the temporary weights: w_f+=temp_w_f	Target a collection of user click records.
F_S={document_1_F,document_2_F,,document_n_F} D_S={document_1_D,document_2_D,,document_n_D} (F_S is the document set sorted by full text search, D_S is the document set sorted by difficulty information) For each (location_i, document_id_i) in a click record: Find the location of document_id_i in F_S and D_S location_f_i,location_d_i Calculate the distance between location_i and location_f_i,location_d_i dis_f=location_f_i-location_i dis_d=location_d_i-location_i Calculate temporary weights temp_w_f,temp_w_d Add up the temporary weights: w_f+=temp_w_f	The documents for this query item are sorted by two different similarity modes:
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Calculate the distance between location_i and location_f_i,location_d_i dis_f=location_f_i-location_i dis_d=location_d_i-location_i Calculate temporary weights temp_w_f,temp_w_d Add up the temporary weights: w_f+=temp_w_f	Find the location of document_id_i in F_S and D_S location_f_i,location_d_i
dis_f=location_f_i-location_i dis_d=location_d_i-location_i Calculate temporary weights temp_w_f,temp_w_d Add up the temporary weights: w_f+=temp_w_f	Calculate the distance between location_i and location_f_i,location_d_i
dis_d=location_d_i-location_i Calculate temporary weights temp_w_f,temp_w_d Add up the temporary weights: w_f+=temp_w_f	dis_f=location_f_i-location_i
Calculate temporary weights temp_w_f,temp_w_d Add up the temporary weights: w_f+=temp_w_f	dis_d=location_d_i-location_i
Add up the temporary weights: w_f+=temp_w_f	Calculate temporary weights temp_w_f,temp_w_d
w_f+=temp_w_f	Add up the temporary weights:
	w_f+=temp_w_f
w_d+=temp_w_d	w_d+=temp_w_d
Repeat steps 1,2, and 3 for each user record in the collection.	Repeat steps 1,2, and 3 for each user record in the collection.
	The average of all the final values.
	The average of all the final values.

3. Personalized college English learning system design

3.1. Resource acquisition and processing

The main starting point of building the whole system is that users can query example sentences and read the corresponding difficulty words through this system, which requires the construction of a rich English text resource library, and the requirements for resources are to build corresponding vocabularies and audio resource libraries for new concepts, levels 4, 6 and other difficulty levels [11]. The flow of resource acquisition and processing is shown in **Figure 1** below.



Figure 1. Acquisition and processing of resources.

In order to meet the above requirements, the construction of resources is divided into two levels: the words that guarantee to cover the vocabularies and the texts that guarantee to cover various difficulty levels and types. Among them, for the word construction of the covered vocabulary, vertical search engine is used to obtain the example sentence of the word as the query item, and the corresponding English is extracted by web page parsing technology [12]. For the text construction covering various difficulty levels and types, the strategy of directional crawling is adopted, which is to view the corresponding webpage updates for the predefined website resources, so as to form a collection of web pages to be parsed, and then carry out related operations such as webpage parsing under the unified call of the control module. Finally, after obtaining the whole audio clip, The audio segmentation module is used to cut the audio into the form of single sentences. The process of resource acquisition is shown in **Figure 2** below.



Figure 2. Progress of resource acquisition.

In resource processing, the de-noising of the resource needs to be considered. Denoising here mainly refers to the removal of text weight and the evaluation of text quality. Text de-noise is mainly aimed at the situation that the same text may appear several times during the construction of resource sets [13]. This process is solved by multi-layer HASH coding. The detailed description of the multi-layer HASH coding based deduplication algorithm is shown in **Table 4**.

Table 4. Text deduplication based on multi-layer HASH algorithm.

For a text D in d, parse the words in the text to get the number of words L contained in this text. Using L as the key is worth going to the HASH cluster C to which d belongs.

Input: Text set D that may contain duplicate English text, string HASH encoding Output: Text set D 'with no duplicate text Algorithm steps:

In cluster C, create a string of length L*len_unit based on the length L of the text d and the HASH encoded length of the string len_unit. Generate a HASH code for each word in the order from left to right in the text d, and copy the resulting HASH code into the newly created string in order to get the final HASH code H_d based on the text d.

In cluster C, find whether there is a key value containing H_d, if there is, ignore this text, if not, H_d as the key value, the text as the corresponding value, forming a key-value pair to join this set. Perform steps 1, 2, 3, 4 for each text in D.

Traverse the key-value pairs in each cluster to form the text set D'.

Another process of denoising is to evaluate the text quality of English sentences with some misspellings of words. In this process, the first step is to identify whether the word is misspelled or not, which is the way of dictionary and word drying. In this paper, the dictionary in NLTK is adopted. To judge whether a word is misspelled or not, we first need to convert it to lowercase format, and then query it in the machine-readable dictionary. If it is in the dictionary, it is determined that there is no spelling error [14–16]. If not, there may be a real spelling error or the correct word does not appear in the dictionary. Porter's stemming algorithm is used to make the judgment. If the word is still not in the dictionary after stemming, the word is judged to be a spelling error. The text quality evaluation process is shown in **Figure 3** below.



Figure 3. Text quality evaluation.

Finally, the above methods are used to establish example sentence audio resources for level 4 and 6 words, and related learning resources for new concepts.

3.2. Retrieval system

3.2.1. Building index files

The index method adopted in the system development process of this paper is inverted index, each word will save a linked list structure, save the number of its occurrence in the document and the corresponding location information. The words are arranged in lexicographical order here. For the data types that need to be saved, methods such as prefix suffix method and difference method are used respectively to optimize the space occupancy of different data types. The words are arranged in lexicographical order, so there will be the phenomenon that the prefix of the latter word overlaps with the previous word, so that only the suffix of the word that is different from the previous word can be stored, while marking the position of the same prefix in the previous word.

3.2.2. Difference rule

In the inverted index need to record the document number (ID number), the storage document ID number uses a variable length integer type, now briefly introduce this data type: indefinite length integer type, when it represents an integer will dynamically adjust the number of bytes occupied according to the size of the number, the specific rules are as follows: The highest bit of each byte represents whether there are the rest of the bytes, the last seven bits represent the numerical value, an indefinite

long integer type of bytes from left to right respectively represented by the numerical digit increments. Using this data type can save storage space [17]. However, even with this data type of indefinite length, there is a space waste problem, so we introduce the storage method based on the difference rule. The storage based on the difference rule mainly means that when storing consecutive numbers, the first number in the sequence saves the original value, and then the last number in the two adjacent numbers only saves the difference with the previous number. For example, save the following number 149, 148, 150, 151. If the previous variable length method is used, the space is 8 bytes, and if the difference method is used, it is only 5 bytes.

3.3. Fast query algorithm

The query process is mainly to find a document containing the query item, so in the retrieval process, on the one hand, is to optimize the efficiency of the query, on the other hand, is to optimize the efficiency of the merging in multiple queries. First of all, from the first aspect of the needs to start solving, first of all, for each query to find a document containing this query, and then find the location of the inverted index of this query, for the index word to establish a data structure suitable for querying, to be able to quickly find each word of the document chain table [18]. Therefore, the key lies in the word index lookup. To this end, the jump table is introduced as a data structure, which is similar to a binary tree, which is also built on the collection of words that have been sorted.

Jump table is an efficient query data structure, efficiency and red-black tree similar to its multi-layer chained table based on the addition of "fast track" to improve search efficiency. The time complexity is mainly reflected in its lookup, insertion and deletion operations. Because the jump table uses a multi-level index structure, these operations can be in the average and the worst case O (logn) time complexity. The space complexity of a jump table is O(n), and the number of elements in the index levels is a subset of n, except for the underlying linked table, which contains all n elements. However, since the number of index levels and the number of elements in each index level are dynamic, the actual space occupancy may vary depending on the implementation and operation history.

The operation of this data structure is as follows: the jump table is built on top of an already sorted set, and when building a data structure, elements are selected to build a layer of the index structure according to the previously set jump intervals, after which the next layer is built on top of this layer of indexes until the specified number of layers is reached. The jump table is shown in **Figure 4** below.



Figure 4. Skip table.

As shown in the figure, to find 83 in the table, first find the part that is greater than 50 according to the first layer, and then search from the node 50 in the zeroth layer, and find that it is between 50 and 94. Therefore, search in this interval in the original linked list until 72 is found, three comparison operations are needed. After finding the inverted table of the corresponding item, another work is to find the intersection or union and difference set of several queries in the inverted table. This operation is also a factor that affects the efficiency of retrieval. Therefore, some optimization measures are taken here, and the implementation method of open source software Lucene is used for reference. This paper introduces how to combine the document collection. In a merge operation, the optimization based on the particular structure of the data can be linear in time complexity.

4. Personalized college English learning system implementation

In this system includes English example sentence retrieval, audio example sentence audiovisual, thesaurus reading, personalized sorting and selection modules. According to the requirements and corresponding algorithms proposed before, the program is implemented, and the overall system architecture is shown in **Figure 5**.



Figure 5. Structure of system.

4.1. Text retrieval module

The text retrieval module analyzes the query item, uses the query parser, cuts the query into the basic units that can be searched, and then combines different basic units of search on the basis of the Boolean search model. In terms of index construction, the inverted index is used (which can speed up the search time on the basis of a given keyword). In the search, the inverted list is loaded first, and then the corresponding Token (in the inverted index, the smallest unit of the index) is searched, and the document collection containing this Token is found and merged [19]. After the collection of documents is obtained, the algorithm introduced in Chapter 3 is used to calculate the degree of similarity of the documents, and the similarity is sorted from the largest to the smallest. Finally, the sorted results are returned. In order to enhance the user experience, the keyword highlighting function is introduced, which uses different text colors for the query keywords in the document, so that users can distinguish the keywords from the ordinary text content.

4.2. Audio playback module

In the construction of audio playback function, it is necessary to take into account some practical needs of users, such as the function of repeatedly playing listening, the function of arbitrarily defining the starting point of audio playback, the function of freely controlling the volume, etc. [20]. At the same time, in addition to these actual needs, because the system is based on the mobile platform, taking into account the capacity problem, so the audio is not directly deployed to the local, but stored in the server side, after the user clicks, the audio file needs to be downloaded to the machine. Moreover, compared with the text file, the audio file is generally much larger, so in the specific implementation process, the multithreaded download mode is used. The audio remote acquisition is shown in **Figure 6**.



Figure 6. Progress of audio obtaining.

4.3. Thesaurus reading module

Word reading and memory is the focus of English learning, reciting words is often to take a variety of tests, such as CET-4, CET-6, TOEFL and so on. Based on this actual demand, the function of word list reading is introduced into this system. The existing system includes four books of CET-4, CET-6, and new concepts. And in the arrangement of each small part of the vocabulary, users can choose different sorting ways according to their preferences, including the following two kinds, one is arranged by letter, which is also a general way. The other is arranged according to the relevance, the context collocation relationship of similar words into the same unit. List an example sentence for each word to facilitate the user to understand the meaning and usage of the word, at the same time, the word list reading function and the text retrieval module are linked together, the user can jump to the text retrieval module when the word reading, to achieve the dynamic organization of resources and horizontal sorting process.

4.4. Automatic prompt module

In the daily use of the retrieval system, when several words are entered, it is hoped that the system can automatically give hints to make up the rest. This function is introduced in the implementation of the system, in order to facilitate the use of users, at the same time, in order to correct the spelling of the user's input, according to the user's input in the database to find the matching candidate words, so as to show the user. Concrete implementation of the introduction of Trie tree, first of all, the construction of this module needs to build a candidate word library, the method is to establish the inverted index at the same time will analyze the words out of the extraction to establish this candidate library. After that, it is also necessary to search the candidate word set according to the user input words, taking into account the characteristics of English and user input habits, take the same prefix to search, find the candidate with the input query item as the prefix.

5. Conclusion

The process of English learning is an extremely personalized one, and English learners at different levels may face different learning tasks and have different choices of resources. In order to realize the personalized design, this paper proposes a sorting model incorporating multiple similarities. In the design of the intelligent assisted English learning system, the SVM-based English clause segmentation algorithm and the multi-layer HASH-based algorithm realize the extraction and denoising of text, and the text quality evaluation algorithm is designed to select high-quality text resources. On this basis, a personalized intelligent auxiliary system design and implementation path for university English learning is completed. Compared with the existing English auxiliary learning system, it lacks the dynamic adaptive ability based on the personalization of the user, and does not systematically rearrange and sort the corresponding materials according to the level of a user's English. The English assisted learning system based on artificial intelligence technology given in this paper can provide learners with more accurate and personalized learning solutions to enhance their learning efficiency.

On the whole, although this paper gives a personalized university English learning assistance system based on artificial intelligence, it still faces the problem of verifying the effectiveness of the personalization algorithm in the research process due to the lack of user's usage data, which does not allow us to draw very definite conclusions. In view of this problem, it is necessary to analyze the users from multiple dimensions in the future research process, so as to form a more three-dimensional user information, and then adopt the research method of recommender system to explore how to recommend corresponding and more appropriate English resources to the users, so as to further enhance the personalization of the intelligent English assistive system, and provide more help for the users to learn English.

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