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# MODELING AND ANALYSIS OF ENGLISH INTERCULTURAL COMMUNICATION TEACHING EFFECT BASED ON DATA MINING

**Yang Peng*, Xu Zhuoyi**
School of Foreign Languages, Dalian Polytechnic University, Dalian, 116034, China
yangpeng5659@hotmail.com

**Abstract:** In order to master the teaching effect of English cross-cultural communication course, this paper designs a data mining based modeling and analysis method for the teaching effect of English cross-cultural communication course. Firstly, data mining technology is used to mine the teaching effect of English intercultural communication course, and Weka platform is used in the mining. Mining data can not be directly used for data analysis due to the problems of data redundancy, multiple data sources, and inconsistent with the requirements of the algorithm, so it needs to be preprocessed such as selection, cleaning, conversion and so on. The model is divided into several modules, including data management module, teaching evaluation mining module, user management module and database management module. The test results show that the design method can accurately analyze the students' performance and teachers' performance in English intercultural communication course, and provide strong data support for the improvement of teaching quality.

**Key words:** data mining; Weka platform; English intercultural communication course; teaching effect modeling;

## 0 Introduction

English teaching is not only to impart language knowledge, but also to cultivate students' ability to use English for cross-cultural communication. The research of English intercultural communication teaching aims to improve the overall level of English Teaching in our country under the unique national conditions, explore the English teaching ideas, methods and ways to achieve the ultimate goal of English teaching, and provide favorable theoretical basis and practical reference for modern English Teaching in our country[1].

The basic purpose of studying cross-cultural communication is to cultivate people's positive attitude towards different cultures, their adaptability to cross-cultural contact and their skills of cross-cultural communication. The fundamental goal of English Teaching in China is to help English learners achieve successful cross-cultural communication, so the study of cross-cultural communication has important practical significance and practical value for English Teaching in China [2].

Culture teaching has been studied for many years in the field of foreign languages. Language cannot exist without culture. Language teaching must include culture teaching. This is a consensus reached so far. American linguist Claire Kramsch said that "language expresses, carries and symbolizes cultural reality, and the two are inseparable" [3]. This interdependent relationship between language and culture determines the important position of culture in language teaching. English culture must be transferred in English teaching. English culture is an important basis for

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students to form communication ability. In English teaching, we are often aware of the interference of mother tongue on English learning, but often ignore the interference of cultural factors. In order to master a foreign language and communicate successfully, the speaker should not only have the necessary basic knowledge of language and the ability of listening and speaking, but also understand and master the cultural background of the other party in order to use the appropriate language for communication. Paying attention to the study of intercultural communication and English culture teaching, cultivating students' awareness and sensitivity of cultural differences between China and foreign countries, and their ability to use English for intercultural communication is one of the ways to effectively improve teaching efficiency and cultivate students' comprehensive ability to use foreign languages. We have long realized that effective English teaching is far beyond the limits of English language itself. It must combine social norms, language environment, cultural rules, pragmatic rules and many other factors closely with the language symbol system, so that English learners can complete a more complex cross-cultural communication process in the actual language application. Fundamentally speaking, language learning and culture learning is a process of mutual promotion and two in one learning practice. The process of language learning is also the process of culture learning [4]. Therefore, cross-cultural communication research plays an important role in English teaching. Ignoring the research in this field is bound to lead to time-consuming and inefficient English teaching, and English learners often encounter obstacles in practice.

The lack of cultural knowledge also directly affects the improvement of students' English listening, speaking and reading comprehension. Taking listening comprehension as an example, many students often complain that they spend a lot of time on listening training, but they still make slow progress. Students all have this experience. When they listen to some materials about familiar events and characters, they can easily understand and understand some new words even if they encounter some new words. When they encounter materials about unfamiliar fields, it sounds very difficult. Although there are some materials, there are not many new words, the grammar is not difficult, and the literal meaning is also understood. However, due to the lack of cultural background knowledge, we can not understand the real meaning behind the words [5]. The same problem often occurs in reading comprehension. Many students feel powerless, not because they encounter many difficult words in reading, not because the grammatical relationship is not clear, but because they are confused by the differences between Chinese and English cultural understanding. In fact, whether listening comprehension or reading comprehension, the key and difficult points are all focused on "understanding". As an embodiment of comprehensive quality, understanding ability not only needs certain language skills, but also needs considerable comprehensive cultural literacy.

In fact, in the practical application of English, we are faced with cross-cultural challenges anytime and anywhere, which inevitably requires modern English teaching to take cross-cultural teaching as an important content. In order to make students understand the differences between Chinese and English cultural backgrounds and become more and more sensitive to cultural differences, this paper makes a systematic study of the relevant contents of cross-cultural

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communication and applies it throughout English daily teaching; At the same time, let students always feel the close relationship between language and culture, effectively avoid them in the use of English due to cultural conflicts and communication barriers or mistakes, and ultimately ensure that English teaching to achieve efficient, so that students can both high scores and high energy. In order to master the teaching effect of English cross-cultural communication course, this paper designs a data mining based modeling and analysis method for the teaching effect of English cross-cultural communication course.

## 1 Designing a data mining based modeling and analysis method for the teaching effect of English intercultural communication course

### 1.1 Data mining of teaching effect

Firstly, data mining technology is used to mine the teaching effect of English intercultural communication course. The tool used in the mining is Weka platform [6]. Weka is a free non-commercial data mining software developed in Java environment for open source machine learning. Its full name is Waikato intelligent analysis environment. The platform is developed by the University of Waikato in New Zealand and is one of the most complete data mining tools. The interface of the platform, as shown in Figure 1, is version 3.6.12. As an open source data mining platform, Weka integrates a large number of data mining algorithms and technologies, including data preprocessing, association rules, classification, clustering and so on [7]. Through Weka platform, users can use different data mining algorithms to get the corresponding results as Figure. 1 .

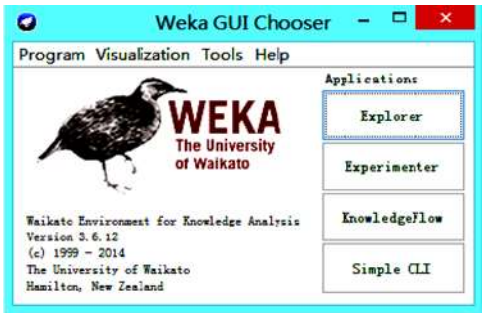


**Fig. 1 Platform Interface**

From the above Weka interface, we can see that there are four different application portals in Weka. The following describes the meaning of these application portals:

Explorer: Explorer provides all the functions of data mining algorithm, which is a common graphical user interface. In Weka, all mining functions can be completed through menu selection and form filling [8]. Explorer application mainly includes data preprocessing, classification, clustering, association rule mining, attribute analysis and other data processing and mining processes. Through the application of explorer, combined with the filtering power of the system algorithm, we can select the mining algorithm, configure the algorithm parameters, finally obtain the mining results, and use the visualization tools to visualize the data set. There are six processing tabs in the application environment of Explorer, namely Preprocess, Classify, Cluster, Associate, Select Attributes and Visualize.

Experimenter: Experimenter is a running algorithm experiment management tool, which provides a working environment for users to compare different learning methods [9]. It allows users to apply filters and classifiers set by different parameters to the same data set more easily, and provides users with a convenient test.

Knowledgeflow: Knowledgeflow is a "knowledge flow" graphical data mining interface, which is suitable for large data sets and a supplement to the explorer interface. It combines the processes by dragging the function modules in the toolbar, and finally forms the data mining knowledge flow design and implements the mining process.

SimpleCLI: SimpleCLI is a simple command line interface, which can operate all Java packages and classes in Weka, and allows users to complete almost all operations in Weka through commands.

In Weka platform, there are not only tools for data preprocessing, but also data mining algorithms such as association rules, classification analysis, clustering analysis and regression analysis [10]. Before mining the target data, the first thing to do is to preprocess the data, then select the appropriate data mining algorithm for analysis, and finally interpret and evaluate the results.

Through the Weka platform for data mining of English intercultural communication teaching effect, the main data mining algorithms are association rule analysis, cluster analysis and analysis method [11].

Association rule mining is mainly aimed at transactional database, and relational database can also be used as the object of data mining. Apriori algorithm is mainly used. Association rules have two basic measures of interest: support and confidence. Support represents the availability of the existence of rules, and confidence represents the certainty of the existence of rules. Apriori algorithm is one of the most influential algorithms in association rules, which divides the discovery of association rules into the following two processes:

(1) Find all frequent itemsets: from a given dataset, find all frequent itemsets, that is, the support degree should be greater than or equal to the defined minimum support count [12].

(2) Strong association rules are generated from frequent itemsets: all rules are found according to the frequent itemsets obtained, and then the rules whose confidence is not less than the minimum confidence threshold are selected from these rules, which are called strong association rules.

Therefore, the core of Apriori algorithm is mining its frequent itemsets. In a transaction set, an itemset containing K items is called a K-itemset. The frequency of itemsets is the number of transactions containing itemsets, that is, the frequency and support calculation of itemsets. If the relative frequency of an itemset is greater than or equal to the predetermined minimum support threshold, it is called frequent itemset. Among them, the itemset with k data item elements is called k-frequent itemset, which is called K-frequency itemset for short. The specific process of Apriori algorithm: first, scan the whole data set, count each item set, and generate a candidate set C1 with the number of items of 1. Then, compared with the minimum support threshold, all the item sets whose support is greater than this threshold are frequent item sets, and generate 1-frequent item sets; Then, using the connection of Apriori algorithm, the candidate set C2 with 2 items is

generated. The whole data set is scanned and each item set is counted. Compared with the minimum support threshold, if the support is greater than this threshold, the 2-frequent item set is generated; By analogy, the candidate set CK is generated, and the k-frequent itemsets are obtained until the candidate set is empty and the algorithm ends, and then all frequent itemsets are obtained. That is to say, Apriori algorithm produces frequent itemsets by iterating layer by layer.

In the process of generating frequent itemsets from candidate item sets, according to Apriori property: all non empty subsets of frequent itemsets must also be frequent [13]. That is, if a non empty subset of this candidate set is not in frequent item set L (k-1), the candidate will not be compared with the minimum support threshold, but deleted directly.

Cluster analysis is an important analysis method. It can divide data into different classes or clusters, so that there is a lot of similarity between the objects in the same cluster, and there is a lot of difference between the objects in different clusters. In fact, cluster analysis is to group many different cases. The cases with similar characteristics are grouped into one group. The principle of grouping reflects the high degree of aggregation between the same group and the low degree of aggregation between different groups. In this way, the cases can be divided into a specific group. Clustering analysis is the main feature of "birds of a feather flock together", which requires the objects in the same classification to be as similar as possible. Before using clustering analysis, the rules of grouping are not specified, the number of clusters is unknown, and the data is divided and analyzed according to its own characteristics. Clustering analysis will train the data to form a series of classification, and the use of scattered points can intuitively describe the classification of the algorithm for cases [14]. The diagram of cluster analysis is shown in Figure 2.

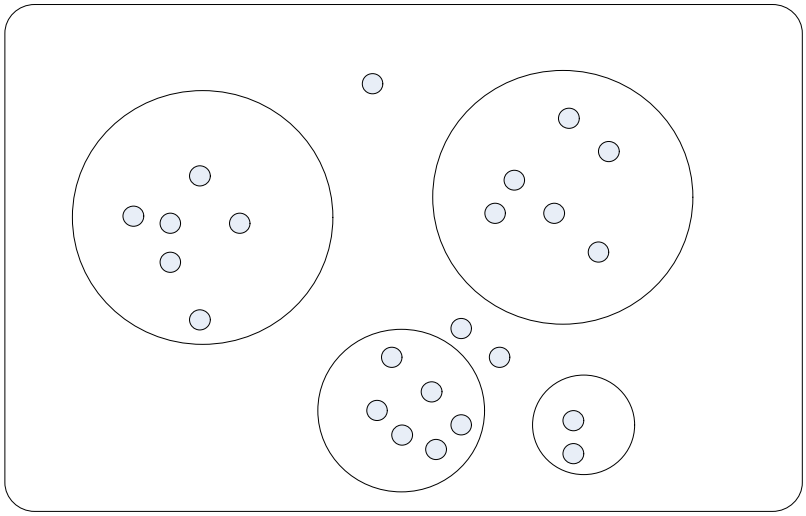

**Fig. 2 Schematic diagram of cluster analysis**

As can be seen from Figure 2, each point represents an instance, and different circles represent different groups. In this way, data points can be divided into different groups according to the degree of aggregation between them.

The clustering analysis used is K-means algorithm, and its division criterion is that the objects in the same cluster are relatively "close" or related, while the objects in different clusters are relatively "far away" or different [15]. Given a data set with n tuples, we need to complete K groups

randomly, each group represents a cluster, K < N. And the K groups should also meet the following requirements: each group should contain at least one data; Each data belongs to and only belongs to one group. Then repeat the following steps:

(1) The instance is assigned to the cluster center which is close to it, and K clusters are obtained;

(2) The average value of all instances in each cluster is calculated, and they are regarded as the new cluster centers of each cluster until the positions of K cluster centers are relatively fixed, that is, the instance allocation of the cluster is completed. In a word, through the above iteration to change the grouping, each grouping scheme is improved than before, but the so-called good standard is: the closer the records of the same group, the better, but the farther the records of different groups, the better [16].

In data mining, classification method is an effective KDD analysis method. Its function is to extract and describe the model of important data, and to judge the future development trend of data in advance. Classification algorithm is usually described as input data, also known as training set, which is composed of many database records. In each record in the input data set, there is a specific classification label corresponding [17]. As the input of the system, this specific tag is usually based on the previous experience data.

The definition of classification is given as follows: if the database of formula (1) and a group of classes of formula (2), the core of classification method is to find the mapping *f (x)* from database *D* to class *C*, and the tuple *ti* in the database can find a class partition. All tuples mapped to this class are included in class *Cj*, as shown in equation (3).

$$D = \{t_1, t_2, ...t_n\} \quad (1)$$

In formula (1), $t_n$ represents the $n$ th sub database.

$$C = \{C_1, C_2, ..., C_n\} \quad (2)$$

In formula (2), $C_n$ represents the $n$ th class.

$$\begin{cases} Cj = \{t_i \mid f(x) = Cj\} \\ 1 \le i \le n \\ 1 \le j \le n \\ t_i = D \end{cases} \quad (3)$$

The data classification techniques used in Weka platform mainly include decision tree induction, neural network method, Bayesian classification and so on.

There are three types of information in the data: (1) students' basic information: student number, name, grade, college, major and class （2) The related attributes of English intercultural communication course are: the code, name and semester of the college; Course category code and name; Course source, code, name and credits; The name and class number of the staff（3) Students' learning status: learning status (make-up examination, re study, postponed examination), achievement, credit and grade point.

**1.2 Data preprocessing**

Mining data can not be directly used for data analysis due to the problems of data redundancy, multiple data sources, and inconsistent with the requirements of the algorithm, so it needs to be preprocessed such as selection, cleaning, conversion and so on.

Data selection: the obtained data source cannot be directly used for analysis, and some irrelevant redundant data should be deleted. In order to ensure the consistency of the data, we should delete the data of make-up examination and re study students, and retain the data of the first examination. In all the performance data sources, not all the attributes are used in data mining, so we need to delete some irrelevant attributes, such as the opening college code, the opening college name, the opening code and so on. After the data selection process, the problem of data redundancy and clutter is solved [18].

Data cleaning: the main purpose of data cleaning is to fill in the missing data that may be caused by human or other reasons in the process of obtaining data. The main cleaning methods used are: (1) neglect: for those sample data whose course scores are missing too much, the method of directly ignoring or deleting relevant data is adopted. Because even machine generation can not reflect the real situation, it will also affect the mining results. In the correlation analysis of SPSS, the method of excluding cases by pairs can also be used （2) Fill in the vacancy value: for some students due to absence or other human reasons leading to individual courses without results, directly use the linear trend method of the nearest point in SPSS to fill in the individual missing value.

Data integration: data integration is usually the integration of scattered data sources for data analysis. Since students' grades are based on different grades and semesters, data sources should be merged after data cleaning. In the process of score data integration, it mainly solves the problems of course name attribute conflict and course order inconsistency. Due to the inconsistency of teaching plans, the naming of individual courses in different grades may be inconsistent. Secondly, the order of courses is inconsistent. When merging data sources, we should pay attention to the order of courses. Finally, the data sources are integrated to analyze the course effect.

Data conversion: whether the integrated data source can be directly used for data analysis depends on the data requirements of relevant algorithms. If not, the data type and data format need to be further converted [19].

1. Conversion of correlation analysis data

The integrated data source can be directly used for course correlation analysis, and the data source of. Xlsx can be directly opened through SPSS software.

2. Conversion of association analysis data

Because the data type supported by Weka based association rule analysis among courses is nominal data, and the data source format is required to be CSV or ARFF, while the integrated data source is still digital and xlsx format file, it is necessary to further transform the data type and format.

By comparing the commonly used results discretization methods, the data discretization methods used in the study are obtained. See Table 1 for details.

**Table 1 Comparison of discretization methods**

| Serial number | method | result |
|---|---|---|
| 1 | Fixed interval method | A=≥85, B=≥75, C=≥65, D<60 |
| 2 | Equal width interval method | （Highest - lowest）/*n*, For example, if the highest score is 80 and the lowest score is 60, then, A=[60,65] , B=[65,70] , C=[70,75] , D=[75,80] |
| 3 | Equal frequency interval method | All the numerical values are sorted and divided into *n* parts averagely, and the number of people in each part is equal |
| 4 | Ranking quantification method | Rank the grades, for example, A = top 10%, B = next 40%, C = next 40%, D = last 10% |
| summary | Methods 1, 2 and 3 are only simple discretization of scores. Although they overcome some shortcomings of the percentile score analysis, if the test scores are generally high or low, it will cause distortion of grading. Method 4 solves the problem of generally high or low scores to a certain extent, but these four methods do not take into account the difficulty of different questions and the scoring habits of teachers, resulting in the different meanings of the same score. Therefore, on the basis of previous studies, according to the normal distribution of "small at both ends, big in the middle" similar to the "bell shaped" characteristics, first of all, we standardize the score data, and then discretize the scores of each course according to the following proportion: A: 10%, B: 40%, C: 40%, D: 10%. Methods 1, 2 and 3 are only simple discretization of scores. Although they overcome some shortcomings of the percentile score analysis, if the test scores are generally high or low, it will cause distortion of grading. Method 4 solves the problem of generally high or low scores to a certain extent, but these four methods do not take into account the difficulty of different questions and the scoring habits of teachers, resulting in the different meanings of the same score. Therefore, on the basis of previous studies, according to the normal distribution of "small at both ends, big in the middle" similar to the "bell shaped" characteristics, first of all, we standardize the score data, and then discretize the scores of each course according to the following proportion: A: 10%, B: 40%, C: 40%, D: 10%. | |

Before the discretization of scores, considering that the same course in different grades may be taught by different teachers or the difficulty of different test questions and the scoring habits of teachers, the meaning of the same score is different, so after a simple analysis of all the data, the first step is to standardize the course score data of each grade, and then use the ranking quantitative method, The converted data makes the results of different courses comparable. The data after

standardized processing obeys the standard normal distribution. No matter whether the examinee's score is generally high or low, this processing method will ensure that the division of each grade is reasonable.

Select the data preprocessing method provided in Weka. After importing the transformed ARFF data file, the unsupervised numerical standardization method is selected according to the characteristics of no classification of score data, that is, "Weka > Filters > Unsupervised > Attribute > Standardizes".

### 1.3 Teaching effect modeling

The model is divided into several modules, including data management module, teaching evaluation mining module, user management module and database management module.

The main function of data management module is to display data, and the main function of the module is to display data. The data stored in the Microsot SQL Server 2000 database is displayed in the form. If necessary, the data in the database can be modified directly by modifying the data in the form grid. Because of the implementation of synchronous operation, what users see is the data in the database. In addition, the module also provides the modification function - through this interface, users can add data to the database, modify data and delete data.

Teaching evaluation mining module has four functions. Establish decision tree function: used to display the results of users after classifying a large number of data in the mining database. Pruning decision tree function: pruning the decision tree to improve the accuracy of mining results. Rule extraction function: according to the different paths of each leaf node of the pruned decision tree, the corresponding rules are extracted respectively. Rule validation function: after rule extraction, test the validity of each rule in the test data set.

The user management module can easily modify and protect the password [20-21]. In the module, the user's information is stored in the database of Microsoft SQL Server 2000, which increases the security of the model and data.

The function of the database management module is to back up and restore the database, so as to prevent the user from operating the database incorrectly and making the database unusable.

In the model, the database connected is Microsoft SQL Server 2000 system, because the data is saved in Excel data table, after preprocessing, the data is still in Excel table, so it is necessary to import the processed data saved in Excel table into SQL Server 2000 system. By using the data import function provided by Microsoft SQL Server 2000 system, the processed data of Excel table is imported into the mining library, so the data import work is completed.

## 2 Experimental test

### 2.1 Experimental method

For the design of data mining based English intercultural communication course teaching effect modeling analysis method, test it. The test is carried out in a university, and Weka platform is needed in the test.

The data in the experiment comes from the data of English majors and their teachers' intercultural communication course in a university from 2012 to 2018, and the data source is the database of the Academic Affairs Office of the University. In the experiment, Apriori algorithm is

used to explore association rules mining. The algorithm parameters are set, the support is set to 0.1, and the confidence is between 0.6 and 1. 20 association rules are found, that is, numRules is set to 20, other values are the default.

Due to the large amount of data obtained from the database of the educational administration office, there are many attributes. In order to avoid the impact of redundant data in data set on the results, data preprocessing is needed before data analysis. In the process of data preparation, due to the imperfection of real data, data preprocessing is a necessary process. For the absence or cheating, the student's score is zero, which can be deleted, and then classified.

After the preliminary data preprocessing, the processed data can be imported into Weka platform for data analysis. However, it should be noted that the default data storage format of Weka platform is ARFF file, and it also supports data in CSV format. Therefore, before importing the data set in Excel format into Weka, it must be converted into the data format that Weka can support. In Excel, you can directly save the file as a data table in CSV format, and then import it into Weka to convert it into a file in ARFF format. The specific conversion steps are as follows: in the Weka platform interface, click the "ARFF viewer" tool under the "tools" menu, open the data to be converted, and then save it as a data file in ARFF format. In addition, through the ARFF viewer tool, you can delete, edit and query data files. The conversion of data files can also be realized by inputting a command in the "Simple CLI" module: Java Weka. Core. Converters. Csvloader file name. CSV > file name. ARFF.

This paper uses the data mining based modeling analysis method to analyze the students' performance and teachers' performance, obtains the confidence data of the analysis results as the experimental data, and makes an in-depth analysis of the experimental data.

**2.2 Experimental result**

In the analysis of students' performance and teachers' performance, the experimental data of confidence obtained are shown in Table 2.

**Table 2 Experimental data of confidence**

| Number of grades | degree of confidence（0.00-1.00） | |
|---|---|---|
| | Student performance analysis results | Results of teacher performance analysis |
| 2012 grade | 0.86 | 0.96 |
| 2013grade | 0.89 | 0.84 |
| 2014grade | 0.78 | 0.87 |
| 2015grade | 0.85 | 0.69 |
| 2016grade | 0.82 | 0.92 |
| 2017grade | 0.69 | 0.97 |
| 2018grade | 0.87 | 0.93 |

The experimental data in Table 2 show that the teaching effect modeling analysis method based on data mining can accurately analyze the students' performance and teachers' performance in English intercultural communication course, so as to improve the classroom teaching of English

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intercultural communication course, promote students' interest in learning, and give full play to students' main role, Improve course performance.

## 3 Conclusion

Based on the Weka platform, this paper uses data mining technology to model and analyze the teaching effect of English intercultural communication course, and realizes the application of data mining technology in teaching data analysis of colleges and universities.

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