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Retraction

Retracted: A Data Mining-Based Method for Quality Assessment of Ideological and Political Education in Universities

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] M. Li, "A Data Mining-Based Method for Quality Assessment of Ideological and Political Education in Universities," *Mobile Information Systems*, vol. 2022, Article ID 2178385, 10 pages, 2022.

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Research Article

A Data Mining-Based Method for Quality Assessment of Ideological and Political Education in Universities

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The procedure of assisting learning, gathering of information, skills, values, morals, beliefs, habits, and personal growth, is referred to as education. Education should focus not only on developing students' professional abilities but also on developing and guiding students' ideological and political perspectives. The purpose of the ideological and political education is to promote Marxist and sociology theories with Chinese features, as well as to bring students together for learning about the development of Marxist theory in China and the path to Chinese political identification. Students will be able to understand the superiority and scientific nature of socialism theory with Chinese characteristics along with actively preserving the socialism development path with Chinese characteristics. However, there are multiple weaknesses in the current evaluation of ideology and political science quality of teaching, including a misaligned evaluation goal, one object, and one-way evaluation. In order to solve these weaknesses, this study proposes an Apriori improvement approach for mining statistics from college political science classes. The important elements affecting instructors' teaching quality are determined through a series of data collecting and data preprocessing procedures, which can assist teachers to improve and increase their teaching level as well as provide a strong foundation for teaching reform and management. During advanced stages, efficient monitoring and administration of teaching quality assessment can improve the scientific structure of teaching quality evaluation, give positive and constructive suggestions for political reform and development, and improve the college's overall education level.

1. Introduction

Education is the action of supporting learning, or the acquisition of knowledge, skills, values, morals, beliefs, habits, and personal growth. Education is the growth of learning and transformation in a rational, hopeful, and courteous manner, with the idea that everyone should be able to participate in life. Education should not only cultivate students' professional skills, but also focus on the cultivation and guidance of students' ideology and politics [1]. In social sciences, a political ideology is a system of ethical ideas, opinions, doctrines, mythology, or symbols of a social movement, institution, class, or large community that determines how society should run and offers a political and cultural pattern for a particular social order. A political ideology is largely concerned with how power must be apportioned and exercised. Some political parties adhere to a particular ideology, while others draw inspiration from a wide range of important concepts without embracing any of them. The influence of moral entrepreneurs, who occasionally act in their own interests, contributes to an idea's appeal. The goal of ideological and political education is to develop Marxist and sociological theories with Chinese characteristics, and to bring students together to study about the history of Marxist theory in China as well as the route to Chinese political identity. Students will be able to recognize the superiority and scientific nature of Chinese-style socialism theory, as well as actively defend the Chinese-style socialism growth path. High school is a crucial transitional time for students as they prepare to enter society and improving ideological and political education for students during this period is beneficial to growing excellent talents with strong will, high morals, and entrepreneurial abilities. However, it is becoming increasingly difficult to offer ideological and political courses at colleges and universities due to the following factors.

1.1. Deviation in the Orientation of Evaluation Purpose. In real teaching, the focus of ideological and political courses in colleges and universities is usually placed on theoretical concepts, resulting in the problem of putting horse before cart. The reason of this situation is that the ideology and politics course's evaluation is misplaced and mixed up with the evaluation of other discipline courses. Presently, grades are still used as the primary grading mechanism in college and university political science classes.

1.2. Neglecting the Special Characteristics of Evaluation Courses. The educational nature of ideological and political courses has a significant impact on the assessment of teaching quality in these courses. Many institutions neglect the ideological and political essence of courses and use the conventional duck-filling teaching style, which is incompatible with students' actual learning demands and politics literacy needs for talents [2]. As a result, many colleges and institutions ignore this distinctiveness when evaluating ideological and political courses, focusing instead on short-term teaching quality evaluations rather than long-term growth, rendering class teaching quality evaluations unscientific and inappropriate.

The evaluation of teaching quality in ideological and political science subjects is currently uncommon at institutions, for example limited number of questionnaires, student meetings, teacher meetings, experts listening to class ratings, and other forms of development. This evaluation method focuses on classroom teaching of teachers and satisfaction of students in classroom teaching; as a result, it has significant subjective qualities, despite the fact that it ignores the content of qualitative and quantitative evaluations, which makes it difficult to give scientific feedback on real teaching quality of teachers.

Currently, college and university political science course evaluations focus on instructor's classroom teaching objectives and students learning results, while disregarding a unified evaluation of the teaching process. As a result, some teaching quality evaluation results are distorted and fail to include the development of student's application skills, leading the students with strong theoretical knowledge but weak practical skills. This is incompatible with student's application of ideology and politics theory to real-life guidance, but it prevents students from fully comprehending the superiority and advancement of the idea of socialism with Chinese characteristics.

The teacher has been deliberately taught to preach, instruct, and solve problems for thousands of years. Students' overall "aversion to learning" and teachers' "helplessness" concerning classroom quality have become a vicious loop under the present academic division of labor. Teaching is not a one-way street, but establishing an assessment system helps teachers and students had better connect. Giving instructors low ratings is both a demand and a catharsis, but it also serves as a warning bell [3]. The fundamental problem is how to transform secondary teacher's evaluation, assessment, and incentive such that college instructors can focus on classroom instruction and professional development. The assessment mechanism is currently extensively employed across a wide range of businesses, and its evaluation style is maturing. In schools, the implementation of a teacher evaluation system coincides with the emergence of the service idea.

To enhance school administration and decision-making, a scientific teaching quality evaluation approach is needed. Because using data that is based on knowledge is a significant approach to improve educational management decision-making, the research and implementation of data mining technology in the secondary school teaching quality evaluation system are quite important.

As a result, a scientific teaching assessment system is required to measure the effectiveness and quality of teaching for instructors using a tight and standardized evaluation method. This paper uses association rules in data mining to evaluate teaching data in effort to encourage instructors ongoing learning, improvement in teaching quality and professionalism, and effectiveness of teachers, promote learning development of students, and find out the factors affecting the teaching as well as their relationships. The recommended method mines teaching evaluation data and employs association rules to associate instructor index data with student assessment data. Based on the findings of rule mining for association, teaching supervisors can audit instructors, evaluate teacher effectiveness, and encourage and develop teachers' teaching abilities.

The structure of the remaining paper is as follows: In Section 2, the related work about the proposed scheme is discussed. Section 3 is the method that is applied for the implementation of this paper. Section 4 is composed of the experimental results and its analysis of the proposed technique. Finally, the conclusion of the proposed work is present in Section 5.

2. Related Work

In the proposed work, the related work is divided into the following sections.

2.1. Data Mining in Education. The first section of the related work focuses on the various data mining application strategies in the education sector. It is further categorized into two parts, with the first emphasizing the technical meaning of data mining and the second emphasizing the educational meaning of data mining.

2.1.1. The Technical Meaning of Data Mining. Data mining is the process of searching large data sets for patterns and correlations that can be used to solve business problems through data analysis. Methods and techniques for data mining assist firms in forecasting future trends and optimizing business operations. Data mining can be used to reveal the laws contained in faculty data processing, and these laws can then be used to educational teaching management to assist in educational teaching reform and increase the quality of education and management. Therefore, it has been determined that "knowledge" is the crucial concept and that understanding the context of "knowledge" is essential to grasping the meaning of "data mining."

Alexander et al. categorize knowledge into declarative, procedural, and conditional [4]. Rather than knowledge in the traditional sense "concept/class descriptions," "frequent patterns, relationships, and correlations," "classification and prediction," "clustering," "outliers," and "evolution" are included. These data patterns correspond to data mining algorithms such as association and rule algorithms for "frequent patterns, associations, and correlations," Bayesian, decision tree, and neural network algorithms for "classification and prediction," and clustering and sequence clustering algorithms for "evolution." These correspondences form the research direction of data mining expansion, with these correspondences and the tools to implement these algorithms; data mining becomes a practical and operational method [5].

To employ data mining techniques to uncover relevant information, the data must be preprocessed, and the mined results must be thoroughly evaluated. A data mining project is a whole work process that includes data mining, preprocessing, and postanalysis activities [6]. The data mining project implementation process, as represented in Figure 1, is the process of executing a data mining project.

2.1.2. Meaning of Educational Data Mining. The educational data mining (EDM) 2008 conference pointed out the meaning of "educational data mining." Educational data mining is the activity of transforming historical data from various educational systems toward useful information for instructors, students and their parents, educational researchers, and developers of educational software systems [7]. Through the implications, it is understandable that mining methods developed by educational data mining are applied to educational management systems to mine effective information and give decision-makers and administrators with a more objective as well as compelling foundation [8].

2.2. Methods of Data Mining in Education. Romero and Ventura divided educational data mining approaches into four categories: prediction, clustering, relational mining, and visualization techniques [9]. Relationship mining approaches are popular among them. The above four categories of educational data mining methods are described below.

2.2.1. Prediction. Prediction is the process of using past data to determine the development pattern of things and then developing models to anticipate the features of data in the future. There are some common prediction methods: regression analysis, time series analysis, etc.

2.2.2. Clustering. Different data have different characteristics; a complete set of data can be divided into different subsets. For example, researchers divide learners into different groups according to their different learning ability levels, etc., and then provide appropriate learning resources as well as organize the appropriate learning activities for different groups [10].

2.2.3. Relationship Mining. The act of discovering meaningful relationships between large amounts of data in order to give the support for particular decisions is known as relationship mining. It is important and difficult to mine knowledge point that exists in databases and is widely used in opinion decision-making systems. For example, the analysis of students' course choices can be used to determine which components of the course they favor, impacting course improvement.

2.2.4. Visualization Technology. Visualization is a method of displaying difficult-to-understand data in an easy-to-understand format that other experts may examine and study the data's qualities. This method uses visual data analysis techniques.

2.3. Classification of Educational Data Mining. When using data mining to educational institution operations such as teaching, management, and research, the data mining demands and activities differ based on the business process and the target audience of concern. Therefore, educational data mining can be divided into three categories based on the educational software used: data mining for e-learning, e-management, and e-research [11].

2.3.1. Data Mining for e-Leaning. Various teaching and learning software systems will be employed to convert data into relevant information. The raw data acquired from numerous scientific databases are converted into meaningful knowledge. This procedure can boost research efficiency and increase research results.

2.3.2. e-Management Data Mining. The process of turning raw data is acquired through various educational management systems such as teacher management, enrollment management, school registration management, and academic affairs management, into valuable information. A better understanding of management objects (students, instructors) and numerous business processes can assist education managers and system developers in optimizing school teaching management.

2.3.3. Data Mining for e-Research. Academics in education can utilize the gathered data to better understand the present stage of growth in their field and forecast future trends. For example, raw data acquired in education are converted into knowledge and information [12].

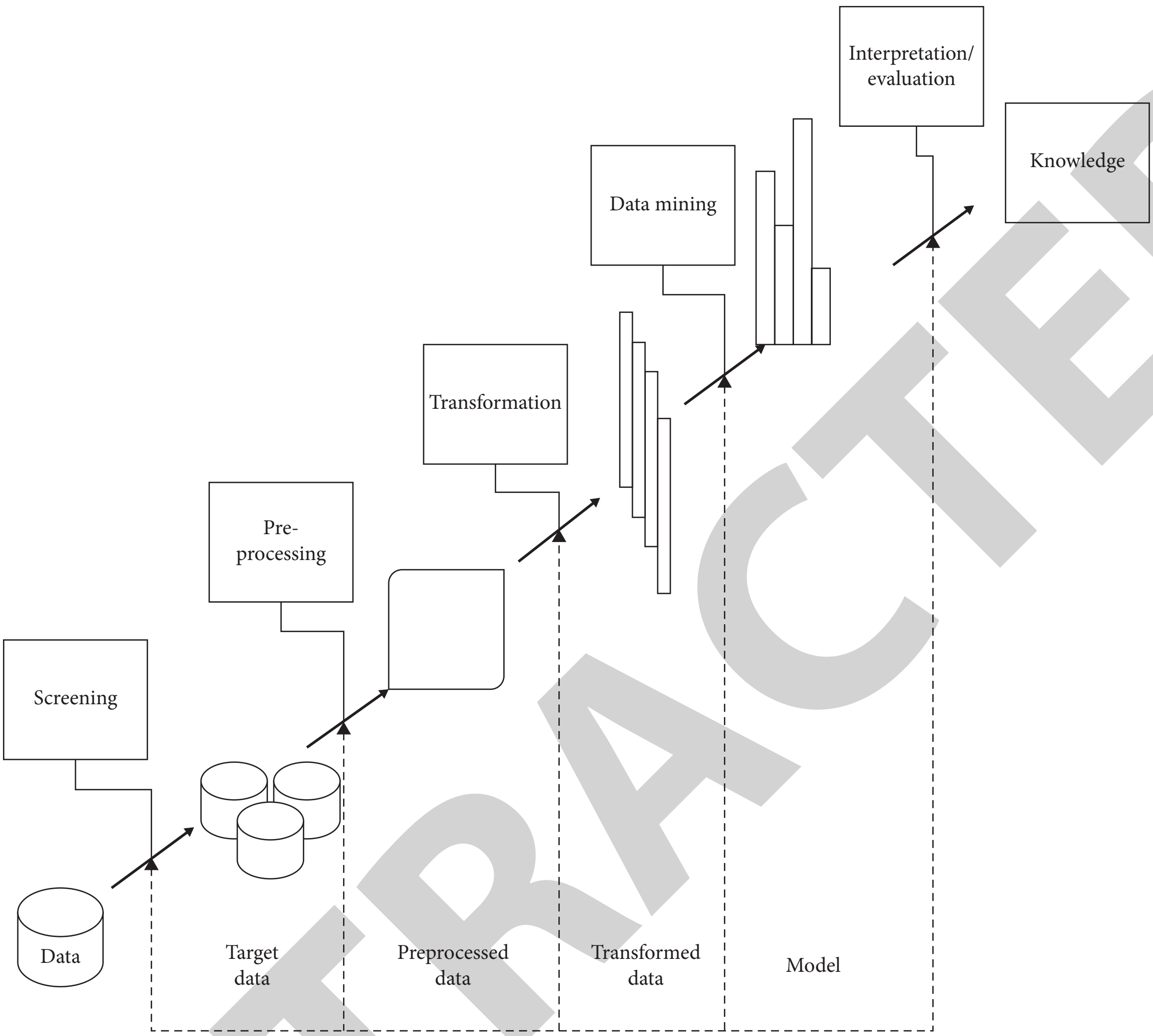

Figure 1: Data mining project process.

2.4. Apriori Algorithm. The Apriori algorithm employs an iterative way of searching layer by layer, which is simple and straightforward, but it is only suited to small data sets [13]. Moreover, during its execution, the database needs to be scanned several times with each scan yielding a candidate set until the longest candidate set is obtained. Since the length of the final longest frequent set determines the number of times, the Apriori algorithm scans the database, it has high input and output (I/O) overhead, high computational effort, and high time cost, and the cost of this approach will increase exponentially as the database data grow.

2.4.1. Improvements in Apriori Algorithm. Many researchers have developed better methods based on the Apriori algorithm to minimize I/O cost or eliminate the problem of candidate set inflation [14]. For example, AprioriTID algorithm is designed to calculate the support of frequent set simultaneously when first scanning the database and then combining the candidate sets generated from the first scan. AprioriHybird algorithm is the product of combining Apriori algorithm and AprioriTID algorithm. The algorithm scans the database using the Apriori algorithm, then calculates the pruned database size, and uses AprioriTID when its memory permits it to locate all frequent sets. The current improvements of the algorithm are based on the following techniques [15].

2.4.2. Hash Table-Based Item Set Counting Technique. The hash function is used to map each corresponding item set to a different column of the hash table, compare the column number with the supmin size, and eliminate the item set with fewer columns than the supmin size. Applying the hash technique can effectively reduce the number of candidate sets that need to be retrieved.

2.4.3. Technique Based on Transaction Compression. If the transaction is unlikely to contain any $k+1$-item sets, such transactions can be immediately removed or noted during statistics, lowering the number of transactions, i.e., the transaction compression approach.

2.4.4. Techniques Based on Dividing Data. This technique requires two scans of the database. The first scan divides the data into multiple parts and finds the local frequent set of each part. A frequent set in the data set that appears in at least one section of the divided data is a local frequent set. The second scan evaluates each candidate set, solves for its support in database, and finds the global frequent set.

(1) Sampling-Based Technique. The Apriori algorithm is used to mine the frequent sets in a nonempty subset of the provided data. The supmin can be reduced moderately to avoid missing frequent sets.

(2) Dynamic Item Counting. This technique is proposed when the database is divided into chunks for mining. Divide the database into data blocks that can be mined individually and then add new candidate sets to any of the data blocks. It is a dynamic approach because it must count the support of all sets of items up to the current time.

3. Proposed Methodology

The method section of the proposed technique is divided into three parts, which are as follows.

3.1. Analysis of the Apriori Algorithm. Apriori algorithm presents numerous benefits including simple to learn and wide range of application, which are considered unique in the field of data mining. However, as the study progresses, its flaws become increasingly apparent to the public. There are certain flaws within the implementation procedure that can be noticed:

(1) Quick database scanning can produce heavy load pressure on I/O [16]. For each k-cycle, to establish if it is required to add L_k, each entry in the temporarily existent C_k must be visited in the database. When an item has ten sub-items in this large set of frequent items, at least 10 scans of the transactional database are required, when faced with a large amount of data; this should raise the system overhead and take more time.

(2) A large candidate set can appear during the runtime. The candidate set corresponding to k created from $L_k - 1$, i.e., C_k, grows exponentially in magnitude. For example, using the Apriori technique, a common item collection of order 104 level 1 may generate a level 2 candidate set of order 107 [17]. The developed candidate frequent item sets will be significantly larger in today's big data era. Therefore, a number of scholars, including Agrawal, have made very significant improvements to the algorithm.

(3) The operation of generating association rules is cumbersome. For each frequent item set L, it is necessary to first derive the true subset X of L and verify the confidence of the association rule "$X \longrightarrow L - X$" one by one, which is relatively complicated and time-consuming.

Based on the above three reasons, it is observed that the bottleneck of Apriori algorithm occurs in the act of candidate set generation. To directly enhance data mining efficiency and reduce mining time, an improved method is needed that can scan the database minimum as possible during the process of generating candidate sets. To address problems of Apriori algorithm, this paper will improve the performance of Apriori algorithm.

3.2. Optimization Techniques for Mining Algorithms. Many Apriori optimization techniques use many improvement algorithms to increase the performance of the algorithm. People aim to develop a more efficient and trustworthy improvement algorithm, and the most common improvement algorithms are as follows:

(1) Hash-based improvement algorithm can be used to compress the size of the set C_k $(k \geq 2)$ of marquee K items. If the candidate 1-item set in $C1$ is regularly created, 1-item sets $L1$ can be made for each transaction, and the appropriate bucket count is increased, as illustrated in Table 1. The hash table and mini support can be used to remove worthless candidate item sets from the upcoming generation. This hash-based approach can greatly condense the candidate k item set to be investigated.

(1) Improved Algorithm Based on Transaction Compression. If a transaction lacks frequent item set k and frequent item set $(k+1)$ because the database scan that yields $j(j > k)$ item sets is no longer required for that transaction, it may be tagged or removed [18].

(2) Improved Algorithm Based on Division. To mine frequent item sets, a division technique that requires only two database scans can be used as shown in Figure 2. It consists of two phases. In phase 1, the algorithm divides D. All frequent item sets in each division are found. These are called local frequent item set. Each stage requires one scan of the database to find all the local frequent item sets. To ensure algorithm correctness, every feasible frequent item set is a frequent set in at least one partition.

(3) Improved Algorithm Based on Sampling. When it comes to efficiency, the sampling approach is the best option. The idea of the sampling method is random sample S selected for a given data D, and the frequent item sets are searched in S. The rest of the database then computes the actual frequency of each item set in S.

(4) Improved Algorithm Based on Dynamic Item Sets. The dynamic item set counting technique uses the start point as a marker to divide the database into blocks. Unlike Apriori, which determines new candidates before each complete database scan, it adds candidate item sets at various points of the scan, so that if a candidate item set already meets

Table 1: A hash table.

Barrel address	0	1	2	3	4	5	6
Bucket count	2	2	4	2	2	4	4
Bucket contents	$\{I_1, I_4\}$ $\{I_3, I_5\}$	$\{I_1, I_5\}$ $\{I_1, I_5\}$	$\{I_2, I_3\}$ $\{I_2, I_3\}$ $\{I_2, I_3\}$ $\{I_2, I_3\}$	$\{I_2, I_4\}$ $\{I_2, I_4\}$	$\{I_2, I_5\}$ $\{I_2, I_5\}$	$\{I_1, I_2\}$ $\{I_1, I_2\}$ $\{I_1, I_2\}$ $\{I_1, I_2\}$	$\{I_1, I_3\}$ $\{I_1, I_3\}$ $\{I_1, I_3\}$ $\{I_1, I_3\}$

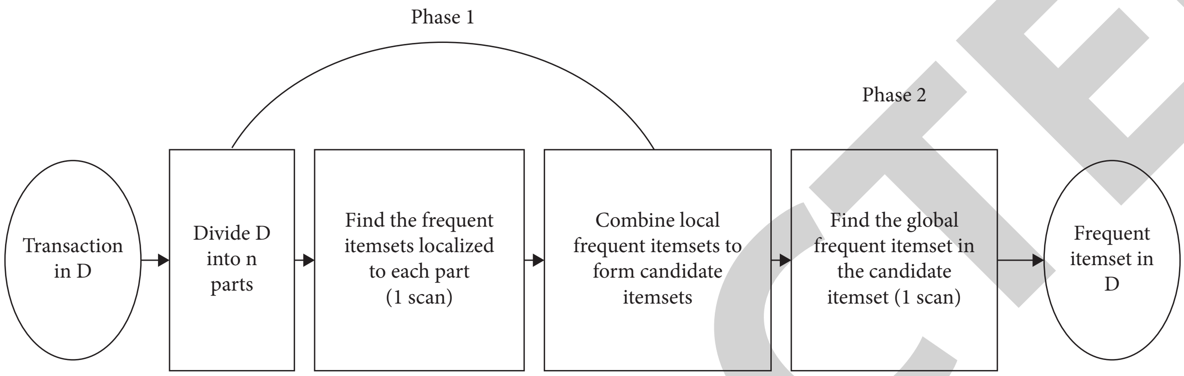

Figure 2: Mining by partitioning data.

minimum support, it can be added directly to the frequent item set without having to be calculated by comparison after this scan [19].

3.3. Division-Based Apriori Promotion Improvement Algorithm. The Apriori promotion algorithm divides the transaction database into N nonoverlapping blocks, processes each block using the Apriori algorithms to discover all local frequent item sets in a block, and merges them into a global candidate set [20]. The database is scanned again to find the global frequent item set, and mini support is evaluated by statistics for each candidate item, since the Apriori promotion technique takes two scanning to verify the mined data. Before analyzing the frequent events in the data block, the mining data set needs to be divided into blocks. As a result, as shown in Figure 3, the Apriori promotion method significantly improves the algorithm's execution efficiency [21].

3.3.1. Description of the Apriori Promotion Algorithm. The Apriori promotion algorithm is divided into four steps:

(1) Divide the transaction database D into N nonoverlapping chunks

(2) Each chunk is processed to produce a local set of frequent items

(3) Merge all the local frequent item sets in these N chunks into a global candidate set

(4) The actual support of each candidate frequent item is estimated for the entire database, which frequent item sets are helpful to mine are identified

The pseudo-code of the improved Apriori algorithm based on division is shown in Algorithm 1 as follows.

3.3.2. Advantages of the Apriori Promotion Algorithm. The improved Apriori algorithm based on partitioning is as follows:

(1) The improved algorithm based on division will scan the database twice, which makes the input and output faster and time efficient and effectively improves the efficiency, thus saving the space for data mining.

(2) Based on the specific operation of this division-based algorithm, it automatically generates a series of frequent item sets during the first database scan, ensuring that the second scan contains the required mining rules and analyzes the extent to which these frequent item sets support database operation as early as possible. It aids in obtaining and confirming the final set of frequent items, promoting the most complete set of association rules to be mined, i.e., ensuring that all association rules are mined to the greatest extent feasible and constructing a solid bastion for the beneficial rules to be mined.

(3) This Apriori technique is based on division, and the fundamental task of mining is to split the database into groups of the same size, typically n. Initially, each database division will generate a set of frequent items corresponding to it and once all processes are performed, each final set is unified into a candidate frequent item set based on specific criteria. Following the completion of all procedures, each final set is unified into a candidate frequent item set based on certain criteria. This mining method operates on the principle of "small by large, parallel by small," which has the advantage of rapid growth of data volume, whereas the relevant data mining efficiency is not significantly impacted. If this approach is used for

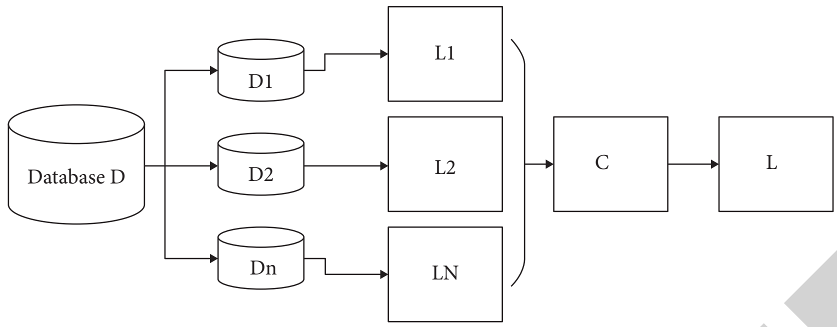

Figure 3: Apriori promotion algorithm.

```
Input: transaction database D.
Output: frequent item set L of D
Start
Scan D
For each transaction T ∈ D {
Find all subitem of T subItemSet
  For i = 1; i < max_t; i++ {
    If length of subitem = i {
      If i_hashTable not contain the subitem {
        Subitem.count = 1
        Add subitem to i_hashTable
      } else {
        Subitem.count+ = 1
        Value = subitem.count
        Update value of key subitem in i_hashTable
        }
      }
    }
}
If there is an update to the database data, cache the updated data
Cache the updated data to the data set db_delete, db_add, db_update, db_noupdate, respectively
If db_update not null {
  Add db_update to db_add
  Add db_noupdate to db_delete
}
If db_delete not null {
For each transaction T ∈ db_delete {
  Find all subitem of T subItemSet
    For each subitem ∈ subItemSet {
      Find the subitem key-value
      Subitem.count− = 1
      Update value of key subitem in i_hashTable
      }
    }
}
Produce has_infrequent_subset (c, L_k − 1)
  For all (k − 1) subset s of c
    If s in L_k − 1 return true;
    Else return false
End
```

Algorithm 1: Apriori promotion algorithm.

Table 2: Teaching evaluation data.

No.	Attitude	Content	Method	Effect	Total evaluation score	Evaluation result
1	28	24	29	15	96	Excellent
2	19	22	24	12	77	Excellent
3	25	22	25	15	87	Excellent
4	22	24	26	13	85	Excellent
5	23	22	21	14	80	Excellent
6	26	23	28	12	89	Excellent
7	27	23	28	12	90	Excellent
8	22	24	28	12	86	Excellent
9	23	22	27	13	85	Excellent
10	18	16	24	10	68	Medium

Table 3: Transaction table data.

Field	Field	Code
Gender	Male	S1
	Female	S2
Age	22–30	A1
	31–35	A2
	36–49	A3
	50–60	A4
Title	Assistant professor	J1
	Lecturer	J2
	Associate professor	J3
	Professor	J4
Academic qualification	Undergraduate	E1
	Master's degree	E2
	PhD	E3
Teaching attitude	25–30	T1
	20–25	T2
	10–20	T3
	0–10	T4
Teaching content	20–25	C1
	15–20	C2
	10–15	C3
	0–10	C4

the designed system, the mining efficiency could be unaffected by the accumulation of a large amount of data.

According to the above analysis, the improved Apriori algorithm based on division has obvious advantages over the Apriori algorithm and the performance of the improved algorithm becomes more prominent when the support is smaller and the advantages become more obvious.

4. Experimental Results and Analysis

The experimental results and analysis section of the proposed technique are divided into four parts, which are as follows:

4.1. Data Preparation. Firstly, the public data of classes, students, and ideological and political courses were collected and the corresponding data in the system were synchronized. Furthermore, the system imported the basic information of 112 instructors in the institution as well as the teaching evaluation data of 2186 students on teachers and the system used the Apriori-P method to mine the association rules on the evaluation data. As shown in Table 2, it is some of the evaluation data of teachers.

4.2. Data Preprocessing. One of the important preparatory works before data mining is to preprocess the data. The data preprocessed can effectively improve the quality of data mining results and make the mining process more effective and accurate. Data preprocessing should be done in the following aspects [22].

4.2.1. Data Cleaning. Abnormal data might interrupt the mining process and produce incorrect results. Therefore, data cleaning is performed to supplement vacant data and correct inconsistent data.

4.2.2. Data Transformation. The Apriori promotion algorithm is applicable to transactional databases. Therefore, the mined data need to be converted to transactional tables to provide valid mining objects. As shown in Table 3, the data

Table 4: Mining results.

ID	Teaching attitude	Teaching content	Teaching method	Teaching effectiveness	Support (%)	Confidence (%)
1	A1	T1	C1	M1	31	37
2	A2	T2	C1	M2	32	43
3	A3	T3	C1	M2	12	43.5
4	A4	T4	C1	M1	41	34.5

Table 5: Comparison test results of feature selection algorithm.

Algorithm	Train time (s)	Test time (s)
Apriori	7.8	5.1
Apriori promotion	10.3	2.9

are discrete, group the attributes such as age, gender, title, education, attitude of teaching, content of teaching, method of teaching, effectiveness of teaching, and score of total evaluation into hierarchical groups, and then convert the field values into transactional tables.

4.3. Association Rule Mining. The user selects the data source, sets the mining settings, and then mines the association rules from the selected data source. The frequent item set is constructed initially, followed by association rules to uncover influencing factors with exceptional or decent teacher attributes. First, filter the database to find 64 records with a total score of at least 85 and 29 records with a score between 70 and 84. The Apriori promotion technique is used to improve the database's frequent item collection with a minimum support of 10% and a confidence of 5%. Once the frequent K item sets are formed, the corresponding candidate set is derived as a prerequisite for the association rule, and then the confidence level related to it is determined. Table 4 shows the partial results of mining teaching evaluation data.

4.4. Comparison and Validation of Results. In order to verify the superiority of the intelligent evaluation method proposed in this paper, other methods are compared as shown in Table 5.

From the table, it can be seen that the proposed algorithm consumes more time in the mining training process but the actual computational test is considerably smaller than the original Apriori algorithm.

5. Conclusion

Education should focus not just on improving students' professional skills, but also upon developing and directing students' political and ideological ideas. Curriculum thinking and politics refer to the integration of ideological and political material in colleges and universities with professional courses. The existing evaluation of ideology and political science quality of education has several problems, such as a misaligned evaluation purpose, one object, and one-way evaluation. This research presented an Apriori improvement algorithm for mining evaluation data for political and ideological courses at universities. Following a series of data collecting and preprocessing procedures, it is discovered that the important elements influence instructors' teaching quality, which can assist to improve and increase the teaching level of the teachers and create a strong foundation for teaching reform and management. Furthermore, the efficient monitoring and administration of teaching quality assessment can increase the scientific nature of the evaluation and give positive and valuable opinions for the reform and growth of ideology and politics courses.

Data Availability

The data used to support the findings of this study are available from the author upon request.

Conflicts of Interest

The author declares that he has no conflicts of interest.

Acknowledgments

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