Research Article

Deep Neural Network-Based Business Data Classification in Intelligent Business Management

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The purpose of this paper is to explore how intelligent data mining technology can be used to improve the customer service capability of commercial companies. Based on extensive research on commercial business, this paper uses data mining and machine learning techniques to build an overall framework for applying intelligent technologies to business improvement, and uses multilayer perceptrons and integrated learning algorithms to build classifiers for customer segmentation; uses association rule mining to assist commercial companies in business decisions; uses clustering algorithms and visualization techniques to further analyze claims cases and assist in commercial fraud detection. The multilayer perceptron classification makes the classification of commercial customers more detailed and reasonable, and the company’s business staff can sell products in a more targeted manner; association rule mining greatly improves the quality and efficiency of the company’s management’s decision making.

1. Introduction

With the rapid development of China’s market economy, the competition among industries is becoming more and more intense. In order to gain a competitive advantage and win the initiative in the fierce market competition, enterprises need to use information technology tools, and business intelligence can effectively guide the business of enterprises and play a supporting role in specific business decisions [1]. In order to promote the further development of enterprises and seize the first opportunity in the market, it is necessary to adapt to the current market development requirements and make full use of advanced information technology for guidance, which is the application of data mining technology of business intelligence in enterprises. In the 1980s, the concept of data mining began to be put forward by the academic community, and in the subsequent practice, its theoretical value and real economic value began to be discovered, so it became popular in the market, and many enterprises began to apply this technology, at this time, the market for data mining has initially formed. In the following 10 years [2, 3], it was continuously practiced and further researched by various enterprises, and data mining technology in this period has formed a unique branch of research, which is formed on the basis of continuously absorbing excellent and new research results from other frontier disciplines. Although the data mining system has been developed for a long time and continuously optimized, it is not perfect and free of any problems, among which, there are still some problems that need to be studied and explored more deeply [4].

With the continuous development of IT technology, more and more business enterprises are realizing the importance of IT technology. When the construction of IT infrastructure system is maturing, the establishment and implementation of BI system will provide a unified view for the enterprise, which means that the application of BI can centralize and present the data from various systems, provide the management with various useful data needed, and improve the quality and efficiency of the management’s decision making [5, 6].

In this paper, the database design and establishment for commercial business, using data mining and machine learning technology to explore the auxiliary analysis of
commercial business, to a certain extent, has a wide range of implications [7]. The data warehouse establishes an exclusive information database for business customer groups, which can not only meet customer needs in a timely manner and ensure customer information security, but also improve customer service capability and creditworthiness, and help accumulate customer resources and business expansion.

2. Related Work

The first is to understand the retention patterns of customers by classifying policyholders into two categories: renewals and terminations [8]. The second is to better understand customer claims patterns and thus identify higher risk policyholder types, both of which can simultaneously affect decisions on pricing strategies for policyholders and thus directly impact the company’s profitability. Using a database of medical business companies, [9] investigates the characteristics of knowledge discovery and data mining algorithms to demonstrate how they can be used to predict health outcomes and inform the management of hypertension. Reference [10] applied data mining techniques to detect anomalous data in U.S. agricultural crop commerce to uncover commercial fraud, concluding that data mining methods to investigate individual instances are more effective than current random selection techniques. The focus of [11] is on the application of data mining techniques in commerce with data warehousing in the hope of addressing the problem of high mobility of commercial agents in Hong Kong. Reference [12] tries to construct a customer evaluation index system for commercial companies by analyzing the characteristics of commercial business and treating customers as evaluation variables in commercial business. Taking the customer data of a domestic commercial company as an example, a customer evaluation model is established using data mining theory. Through testing, it is shown that the BP neural network model can realize the correct evaluation and classification of commercial company’s customers, thus helping commercial companies to avoid reasonable operational risks. Reference [13] proposed a three-stage data mining method that detects and screens out customers who are more likely to buy a specific commercial at the expiration of a commercial contract and is able to identify a loyal customer base and plan appropriate commercial sales plans for them accordingly, which has considerable accuracy and has been practically applied to a commercial company in Iran. Reference [14] analyzed the risk of commercial business based on data mining techniques, and the database of commercial companies was the basis of their analysis, which contains information about policies and claims, based on which they discovered the different characteristics of the insured who had made claims, and in the process found the areas of greater risk and obtained the appropriate control methods. In [15], it is argued that “business intelligence” is important for companies to find effective data quickly and make optimal business decisions, and by analyzing the value chain of commercial companies and taking customer relationship management of commercial companies as an example, the application of business intelligence, data mining and other technologies in commercial business management is explained, and it is concluded that business intelligence can find best strategies and apply them in business, mainly in three areas: claims management, customer relationship management, and sales channel optimization, and the return on investment obtained in this way is relatively large and enables the company to develop a competitive advantage in the market. Reference [16] argued that with the development of the economy, competition among commercial enterprises is no longer purely price competition, and the concept of customer-centeredness is being promoted by more and more companies. Reference [17] studied the architecture of data mining and customer relationship management framework, and designed a data mining-based customer relationship mining algorithm with a commercial company’s customer relationship management system as an example.

3. Mining Algorithms and Corresponding Models

3.1. Association Rule Algorithm. In data mining, association rules are knowledge patterns that describe the rules of simultaneous occurrence between all possible events in an experiment. That is, association rules reveal implicit new relationships that are achieved by quantifying experiments. If we let \( T = \{ t_1, t_2, \ldots, t_m \} \) be a set of items and \( W \) be a set of transactions. Each transaction \( R \) in the set of \( W \) is a set of items, \( R \in T \). Here if there exists a set \( A \) of items and a set \( R \) of transactions, if \( A \in R \), then we say that the \( R \) transactions support the set of \( T \) items. The association rule is thus formalized as follows: if \( a \Rightarrow b \), here \( a \) and \( b \) are a set of items, \( a \subseteq T \), \( b \subseteq T \), and \( a \cap b = \emptyset \). To describe the properties of the association rule, four parameters are often used: credibility \( C \); support \( S \); expected credibility \( E \); usefulness \( L \) [18].

Among the four attributes of association rules, the attributes that provide a more intuitive picture of the nature of association rules are support and credibility. In real life, people are only concerned about these two attributes, so the two values obtained Both values must be within a certain threshold, i.e., the minimum value of each, and the association rule is specified, these two minimum values must be satisfied. In the case that these two conditions are satisfied, we call It is called a strong rule.

3.2. Clustering Algorithm. The concept of cluster analysis is that a dataset is partitioned into various classes (Classes) that are relatively similar to each other and individually distinct, subject to a specific criterion, which is often expressed as a certain distance. Intuitively, each of the final clusters formed is a dense region in space.

The operation of the classical K-Means clustering algorithm can be described by the following image in Figure 1. In the Figure 1(a), there are 5 samples of ABCDE. At the beginning, the 2 initial centroids on the right are selected, \( K = 2 \), and all of them have different colors, and there is no concept of class or distinction [19].
In Figure 1(b), the 5 samples calculate the distance to the 2 initial centroids, and choose the one with the closest distance, then the 5 samples are divided into 2 groups of red and black.

In Figure 1(c), after the calculation in Figure 2, the 2 initial centroids disappear, and 2 new centroids reappear at the center of each of the 2 classes, and the sum of the distances of these 2 new centroids from the samples in the class must be the smallest.

In Figure 1(d), the new centers and categories appear, and the categories are divided differently.

(Figure 1(d) in the above Figure 1(f)) The centers of the original two clusters disappear and the new centers (with the smallest sum of examples of each sample in the category) appear, at which point it is found that the divided categories do not change and converge.

3.3. Classification Algorithm. Decision tree algorithm is an algorithm to determine the category to which the data belongs in data mining, it is a relatively basic class of classification algorithm in data mining.

Figure 2 is one of the most basic decision tree models, as a tree-like decision structure, where circles represent internal nodes, identifying a feature or attribute, and squares represent leaf nodes, indicating a classification. A complete decision path is represented as an extension of the root node to each leaf node, where each branch node has a role in that they detect a specific feature in the sample and assign the sample to one of the child nodes, corresponding to their respective different special fetch values. Assuming that a predicted sample now exists, the complete process from the root of the tree to the corresponding subtree and then to the leaf nodes, each with different responsibilities, first detects the features of the sample and transmits them according to the fetched values, and then repeats the same operation in the second process, gradually extending down to the final node where the fetched values, or class markers, are formed as the final predicted result [20].

In the above description, it is clear that the merit of feature selection will directly determine the efficiency of the whole algorithm. That means with what criteria are the features selected? This explains that splitting attributes is a crucial step in decision trees. The concept of splitting attributes is to construct different branches to nodes based on different divisions of feature attributes, with the goal that each subset of the splits will be “pure”. The “pure” criterion is to create a collection of subsets that are classified in the same category as much as possible. The key to decision tree learning is the selection of the optimal division attributes, with the goal of increasing the “purity” of the branch nodes. The different measures of “purity” have led to two common algorithms, the ID3 algorithm and the C4.5 algorithm. So how to measure this “purity”? Three concepts are introduced here: information entropy, conditional entropy, and information gain.

Information entropy is the most common measure of uncertainty (purity) of a sample set. It is defined as follows:

\[
H(x) = -\sum_{k=1}^{n} p_k \ln(p_k). \tag{1}
\]

Where: \(n\) represents the type of all samples and the proportion of class \(k\) samples. It is agreed that when \(p_k = 0\), \(H(x) = 0\). Information entropy can be understood as uncertainty. The higher the information entropy of a system, the greater the uncertainty of the system. Corresponding to the space composed of all samples, the larger the information entropy, the more average the classification of samples, and the smaller the information entropy, the more inclined the samples are to a certain class.

The conditional entropy represents the complexity (uncertainty) of a random variable under a given condition [21].

The information gain is the information entropy minus the conditional entropy, which defines the information gain of partitioning the sample set \(D\) using the attribute \(a\):

\[
G(D, a) = H(x) - \sum_{v=1}^{V} \frac{|D_v|}{|D|} H(D_v). \tag{2}
\]

\(V\) is all possible values of attribute \(a\), \(|D_v|/|D|\) represents the ratio of the number of samples to the overall number of samples when attribute \(a\) is taken as \(v\). Here, it represents the weight of information entropy. This weight measures the importance of these samples in the calculation. A higher information gain means that the samples are more discriminated when they are divided by \(a\).
In the ID3 algorithm, the quantity used for the measure of purity is the information gain, for which the selection is made so that its features are most evident by performing the splitting. The information gain is a measure of the effectiveness of the selected division feature. To make the information gain greater, it is necessary to make the features most evident by performing the splitting.

The information gain rate \( \frac{G(D,a)}{IV(a)} \) smaller. Ignoring the previous weights first when considering, it can be seen that the smaller the number of attributes is needed. According to the definition of information entropy, the samples are more unbalanced, and at the extreme, all of them are in the same category (positive or negative samples), so that the purpose of classification is achieved.

In C4.5 algorithm, instead of using information gain, information gain rate is used. C4.5 algorithm can be seen as an improvement of ID3 algorithm. If a feature has so many categories in the total sample that it is unique to each sample (e.g., a person’s ID number), ID3 will give priority to such a feature because each sample is divided into a separate node with maximum information gain, but this will have a negative impact on our decision tree [22, 23]. Because we want the decision tree to focus more on the attributes that the samples have in common, so that the new samples can be classified by our trained decision tree (with generalization ability). To balance the information gain and the number of attributes, the information gain rate is introduced:

\[
G_r = \frac{G(D,a)}{IV(a)},
\]

where \(IV(a) = \frac{|D^a|}{|D|}\log_2 \frac{|D^a|}{|D|}\).

The formula for the information gain rate suggests that features with a small number of samples are preferred when the information gain is the same. However, another problem arises at this point, the C4.5 algorithm will have a preference for features with a small number of attributes. In order to balance the relationship between information gain and the number of attributes again, we can give priority to a few attributes with high information gain when considering features, and then consider the features with the highest information gain rate [24].

3.4. Models Induced by Algorithms. The cross-selling model based on the association rule algorithm is mainly analyzed from the perspective of products. Through the analysis, potential patterns in customers’ purchasing behavior and those product combinations that are purchased at high frequencies are discovered, and commercial companies can conduct targeted marketing planning based on this implied information, or redevelop products with product combination characteristics to achieve the purpose of cross-selling [25].

The overall cross-selling model can be divided into four parts, as shown in Figure 3.

The first is customer classification, which differentiates customer groups according to the type of commercial products purchased and the amount of premiums; the second is to determine the input data relevant to the consumption set of insurance products. It mainly includes product items and parameters.

The third is association rule analysis, selecting the appropriate association rule algorithm for product set fact association mining. Finally is the analysis of mining results, a comprehensive and in-depth analysis of the algorithm output to identify cross-selling opportunities and select the optimal product set.

Here is the application of decision tree ID3 algorithm in commercial individual customer data analysis to illustrate how decision tree algorithm plays a very important role in facilitating customer relationship management [26].

A commercial company is planning to introduce a certain critical illness insurance product to the market this year. The information is basic information about gender, age, income, credit and other attributes, and whether or not to buy critical illness insurance is the category attribute of this group, i.e., customers are divided into two types, either they have already bought other critical illness insurance products of the company, or they have never bought this product.

4. Case Study

In business companies, the research of their customers and their segmentation according to group characteristics is not done by subjective In the current buyer’s market conditions, because each consumer has different business needs. Although commercial companies have a wide range of products, they cannot develop products that meet all the different individual needs. Therefore, it is necessary for business enterprises to segment their customers. Here, customer segmentation can be defined as a typical classification problem, and in this paper, decision trees and deep neural networks (multilayer perceptron) are used to train the classifiers respectively. The classifiers are trained separately using decision trees and deep neural networks (multilayer perceptron), and then integrated together using integrated learning to obtain better performance.

4.1. Classification Using Decision Tree Algorithm. An example of the use of decision trees is given below. A decision tree represents a knowledge, which is based on whether or
not a customer will take out a policy, and based on this knowledge can effectively predict the purchase intention of a particular customer. This knowledge is used to predict the purchase intention of a customer. Table 1 shows a simplified training set for a commercial company to analyze whether a customer is insured or not.

A serial number is a customer, that is, a specific example, and the other information in the table are the respective attributes of the specific customer. The objective of this analysis and prediction is set as whether the customer is insured or not, then the column of the table is the prediction attribute or the mining attribute, and the column where the insurance is located is the prediction column, and the prediction of this attribute has two results, either YES or NO. An example of the decision tree for processing the classification model of Table 1 is Figure 4.

In Figure 4, we train the first 10 steps and predict after 11 steps, so we do not show the first 10 steps in Figure 4. We usually design algorithms with a two-tier structure, which is the only way to make the class data table of nodes to be classified more open and efficient to build. The data mining middleware, a link between the data warehouse and the tree-building algorithm, is set up. The data mining client makes a request to it, which is about the class count table; secondly, the middleware extracts the relevant data from the data warehouse, then builds the class count table and sends them to the data mining client. These two queues make a connection between the middleware and the data mining client.

4.2. Construction of Classifiers Using Integrated Learning Algorithms and Analysis of Results. Assemble-learning accomplishes a learning task by building and combining multiple learners, also known as a multi-classifier system. It is a technical framework that allows the combination of underlying models according to different ideas and purposes.

Using a scalable decision tree classification algorithm combined with a deep neural network classifier, the resulting customer segmentation model is a relatively accurate one, which automatically classifies customers based on their intrinsic characteristics. The model is analyzed for all situations of the business customer during the business period and thus understands the characteristics that each customer has. This enables commercial companies to better understand the characteristics of different types of customers and to differentiate the use of marketing methods according to their situation. The customer records of a branch in 2007-2008 are shown in Table 2, where we can find the proportion and characteristics of each type of customer. This is shown in Figure 5.

From the information in the table above, it is found that business companies have to rely on the differentiation of a huge number of customer groups data mining techniques, in which there are four types of customers, which are divided according to their value, the higher the grade customers, the smaller the number, but their contribution to the business is the largest, in terms of the overall insurance. The higher the class, the smaller the number of customers, but they contribute the most to the business and account for a larger share of the overall sales of the entire insurance.

Using the input information such as gender, marital status, education level, occupation and age of the insured and the insured as the input of the above classifier, the output information predicting the type of insurance purchased by the customer can be relatively accurate, and 85% of the output entries are accurate, i.e. the accuracy rate reaches 85%. And the percentage of the retrieved accurate entries to the total entries reaches 79%, i.e., the recall rate reaches 79%. This result has considerable reference value in
Table 1: Training set for analyzing whether a customer buys a policy or not.

| Serial number | Gender | Age     | Education | Income | Insure |
|---------------|--------|---------|-----------|--------|--------|
| 1             | Male   | <35     | Research  | High   | Yes    |
| 2             | Male   | <35     | Junior college | Low   | Yes    |
| 3             | Female | 35–45   | University | Centre | Yes    |
| 4             | Male   | >45     | High school | Low   | No     |
| 5             | Male   | >45     | Junior high school | High  | No     |
| 6             | Female | 35–45   | Primary school | Centre | No     |
| 7             | Male   | <35     | High school | Low   | Yes    |

Figure 4: Decision tree prediction processing.

Table 2: Classification mining results.

| Customer type     | Proportion (%) | Characteristic information                                                                 |
|-------------------|----------------|---------------------------------------------------------------------------------------------|
| VIP customers     | 0.99           | Occupational category = 6 and annual income $\geq$ 50000 and population influence $= a$   |
| Quality customer  | 4.03           | Occupation category = 5 or 6 and 100000 $\leq$ annual income $\leq$ 50000                  |
| Ordinary customers| 22.4           | Occupation type = 304 and age $\leq$ 38 and 60000 annual income $\leq$ 10000              |
| Small customers   | 72.5           | Occupational category = 2 or other and 25000 $\leq$ annual income $\leq$ 400              |

Figure 5: Boosting.
practical use. In the later practical use, it enables the renewal management of the company to predict the secondary product purchase tendency of the insured customers more accurately, and provides a reference direction for the formulation of the company’s product policy and business policy. The effect of commercial classification is shown in Figure 6.

5. Conclusions

Based on extensive research on commercial business, this paper uses data mining and machine learning techniques to build an overall framework for applying intelligent technologies to business improvement, and uses multilayer perceptrons and integrated learning algorithms to build classifiers for customer segmentation; uses association rule mining to assist commercial companies in business decisions; uses clustering algorithms and visualization techniques to further analyze claims cases and assist in commercial fraud detection. The use of clustering algorithms and visualization techniques to further analyze claims and assist in commercial fraud detection. Association rule mining has greatly improved the quality and efficiency of decision making by company managers.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

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