



Decision Support System in Marketing Strategy Using Data Mining Techniques

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Abstract

The increasing complexity of market competition and the rapid growth of enterprise data have made traditional marketing decision-making approaches inadequate in addressing information asymmetry and dynamic market changes. Conventional decision support systems (DSS) are often limited to data-level reporting and lack advanced analytical capabilities to uncover hidden patterns and strategic insights. This study aims to design and evaluate an intelligent marketing Decision Support System by integrating data warehousing, Online Analytical Processing (OLAP), and data mining techniques to enhance the quality and effectiveness of marketing decisions. The proposed method adopts a data-driven DSS architecture that performs extract-transform-load (ETL) processes to build a unified subject-oriented data warehouse, followed by multidimensional analysis and knowledge discovery using decision tree classification and neural network models. Experimental validation was conducted using FoodMart 2000 sales data to assess the predictive performance and decision support capability of the system. The results demonstrate that the three-layer BP neural network model achieved a mean absolute percentage error of 15.13% in sales prediction, indicating satisfactory forecasting accuracy, while simulation and sensitivity analyses reveal a positive correlation between promotional investment and corporate profit growth. These findings confirm that the proposed marketing DSS can effectively reduce information asymmetry, improve forecasting reliability, and support strategic marketing decisions related to pricing, promotion, and market expansion. The study implies that integrating data mining with DSS provides a robust analytical foundation for data-driven marketing management and sustainable enterprise competitiveness in complex market environments.

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1. Introduction

With the gradual transformation of China's economic system from a planned economy to a market economy and the deepening of reform and opening-up, enterprises' business activities are in a rapidly evolving three-dimensional strategic space. Enterprises have been thrust into a complex and

fluctuating business environment [1]. There are many factors involved in the marketing system, including internal and external factors, and all of these factors are evolving and changing without exception. Therefore, the company's marketing strategy and combination must be able to make appropriate adjustments to changes in the company's internal and external environments. Finally, effective measures must be taken to ensure the implementation of the marketing plan [2].

Traditional management information systems are mainly aimed at daily structured problems, with the main goal of improving the operational efficiency of enterprises, and strengthening management by converting large amounts of data into valuable information [3]. Along with the progress of society and the development of technology, people are no longer just satisfied with obtaining various information and simply using it, but want to utilize the information to help companies make more in-depth decisions, by combining modern information technology with marketing concepts to help company leaders make scientific marketing decisions to meet the demands of market competition [4].

The development of data mining technology provides strong support for companies to improve their decision-making capabilities. Experts, data warehouses, data mining, online analytical processing, and other technologies can not only help users make structured quantitative decisions, but also can help users make semi-structured and unstructured qualitative decisions, which can greatly improve the effectiveness of decision-making by senior managers [5,6]. Data mining can automatically process large amounts of raw data in databases through pre-defined algorithms. Data mining uses various methods and means to extract necessary and meaningful patterns from large amounts of data, explore specific relationships between objects, find answers to required questions, and assist decision-making [7].

Data Mining is a specific step of knowledge discovery. Knowledge discovery refers to the overall process of discovering useful knowledge from data, while data mining is the process of extracting patterns from data with special algorithms [8,9]. The main methods and techniques used to obtain these results include statistics, cluster analysis and pattern recognition, decision number classification, artificial neural networks and genetic algorithms, rule induction, and visualization techniques [10]. Data mining can help decision makers make more scientific decisions by transforming original data into comprehensive data and providing analytical tools for multidimensional data analysis [11]. Data mining is based on utilizing new information about consumers and markets and their dominance [12,13].

The results of this study support a more scientific and rational marketing decision-making process, thereby improving the efficiency of market management. The overall structure of this paper consists of five sections. Section 1 introduces the background and significance of Marketing Decision Support Systems (DSS), and then introduces the main works of this paper. Section 2 mainly introduces related works on DSS. Section 3 analyzes the concepts and models of marketing DSS and designs a marketing DSS framework. Section 4 conducts simulation experiments and draws conclusions. Section 5 summarizes the full text. The innovation of this paper is that the marketing decision support system proposed in this paper can solve the problem of information asymmetry in the game with other companies and sales agents in sales. This system adopts a messaging mechanism that allows managers to obtain information on competing companies and pre-determined agent teams and know all sales in the next few days, thereby leading the entire sales game.

A decision support system (DSS) is a scientific tool to assist decision-making in a specific form. A DSS provides a work environment for decision-makers that combines knowledge, initiative, creativity, and information-processing capabilities, combining qualitative and quantitative methods through human-computer dialogue. A DSS helps decision-makers analyze problems, explore decision-making methods, and conduct evaluations, predictions, and optimizations.

Jamalian E. et al. suggested that the management decision-making process with decision-makers as the core subjects should be subject to information and intelligence, design and planning, and selection decisions. In this process, to better identify problems and ultimately handle decision-making results, it is necessary to complete the determination of factors influencing decision-making

and data collection, analysis, and processing in the information stage [14]. Wang Y. et al. proposed a three-part DSS structure, which defined the basic components of DSS and greatly promoted the development of DSS. In the late 1980s and early 1990s, DSS began to combine with expert systems to form intelligent DSS [15]. Miller J. et al. suggested that currently, most query systems used by corporate marketing management departments are based on OLTP technology, and the characteristics of OLTP indicate that OLTP is not suitable for the increasingly developing marketing DSS [16]. Othman S. B. et al. suggested that in the final decision-making process, we should re-evaluate these schemes, choose one with strong operability that is most conducive to achieving decision-making goals, and start implementing it. Because each link in the decision-making chain has its own emphasis, the process is complex, but at the same time, it cannot be denied that the three are inseparably interconnected, interdependent, and influential [17]. Pablo et al. pointed out that despite a late start, the application and development of DSS in China is relatively rapid. For example, the DSS developed by the Institute of Systems Engineering of Huazhong University of Science and Technology for resource allocation and distribution of freight cars supports strategic decisions on population and economic development and has achieved good results in practical applications [18]. Koowrocki K. et al. pointed out that existing marketing DSS can only provide existing information, lacks analysis and data mining functions, cannot discover business rules hidden behind the data, and also cannot realize real-time monitoring and risk prediction [19]. McCoy C. et al. pointed out that in China's telecommunications industry, research on DSS is on the rise. Zhejiang Telecom, Qingdao Telecom, Xiamen Telecom, Fujian Mobile Bureau, Guangdong Institute of Telecom Science and Technology, Zhongda Xintai High-tech Company, Neusoft Software Co., Ltd., and other telecommunications companies and software companies are all developing telecommunications DSS [20]. Zhang S. proposed that decision-making by decision-making managers is based on database analysis and calculation in many aspects, and OLTP can no longer meet the needs of decision-makers. In addition, OLTP is mainly used to complete transactional processing, which usually requires many update operations and high response time [21].

Although the application of DSS has achieved initial results, there are still not many successful examples, especially traditional DSS. Data shows that successful DSS applications abroad only account for about 30% of the total R&D, and the same is true in China [22]. There are many reasons for the failure of DSS development, but there are two main ones. First, traditional DSS can only provide data-level support in the incremental decision-making process. However, the data needed for practical decision-making is often distributed and heterogeneous, which limits the system's adaptability and does not meet the needs of the decision-making process. Second, traditional DSS requires decision-makers not only to have professional knowledge but also to have a higher level of knowledge of the DSS construction model, which makes it difficult for decision-makers to understand and accept it [23]. With the emergence of data warehouses, online analytical processing, and data mining technologies, a new generation of Decision Support Systems based on DW, OLAP, and Data Mining has been proposed. Due to the inherent interrelationship and complementarity between the three, combining them to design a new DSS architecture, namely a data warehouse-based solution and using data mining and OLAP tools as a means, can maximize the advantages of each. Leveraging the massive data available in a company to extract valuable knowledge and rules can provide more effective support for decision-making.

Through the organic combination of Data Mining and DSS technologies, this paper designs a set of intelligent DSS, and applies it to marketing. Specifically, the Decision support system extracts, transforms, and loads various business data related to marketing decisions according to themes, and builds a unified, standardized, and highly accessible theme data center. On this basis, OLAP and data mining technologies are used to analyze data from multiple perspectives and extract potential knowledge from them, so as to build an efficient marketing decision support system [24]. This system provides assistant decision support for management and decision makers in new product development, product pricing, market maintenance and development, competitor analysis, customer relationship management (CRM), marketing goal formulation, product promotion, advertising

promotion, performance evaluation, employee management, and many other aspects related to marketing decisions, and lays a solid foundation for Enterprise development and market development.

2. Research Methodolgy

1. Data Mining concepts and models

Data Mining is the process of selecting interesting knowledge from a large amount of data stored in a database, data warehouse, or other information base. In other words, we extract the parts we need from a lot of data and ignore the useless parts. Data Mining is a good knowledge extraction method [25]. Data Mining allows valuable knowledge, rules, or high-level information to be extracted from relevant data sets in a database, so that the large-scale database serves as a rich and reliable resource for decision making. The core technologies of Data Mining are artificial intelligence, machine learning, statistics, etc. However, a Data Mining system is not a simple combination of several technologies, but a complete whole. This system also requires the support of other supporting technologies. The main methods and technologies used include statistics, cluster analysis and pattern recognition, decision tree classification, artificial neural networks and genetic algorithms, rule induction, and technology visualization. Common knowledge pattern extraction methods in data mining include classification, concept description deviation detection, and sequential pattern discovery and association rules. This method can complete a series of tasks such as data collection, pre-processing, data analysis, and result expression, and finally present the analysis results to users [26]. MDOLAP uses a multidimensional database as the core and displays data multidimensionally. MDOLAP can intuitively convey the "one-to-many" and "many-to-many" relationships in the real world, and its multidimensional concepts are clearly expressed. The comprehensive data organization mode ROLAP uses a relational database as the core and uses two-dimensional tables in the relational database to organize data and express multidimensional concepts. Its data organization adopts a star pattern. The data-oriented organization pattern of ROLAP with sales analysis in marketing analysis as the theme is shown in Figure 1.

Each topic in the data warehouse corresponds to a star schema structure, which consists of a fact table and several dimension tables. Each record in the fact table contains a pointer to each dimension table, through which multidimensional data can be linked. The data warehouse design of this system adopts a star pattern. Therefore, the OLAP design of this system adopts the ROLAP mode [27].

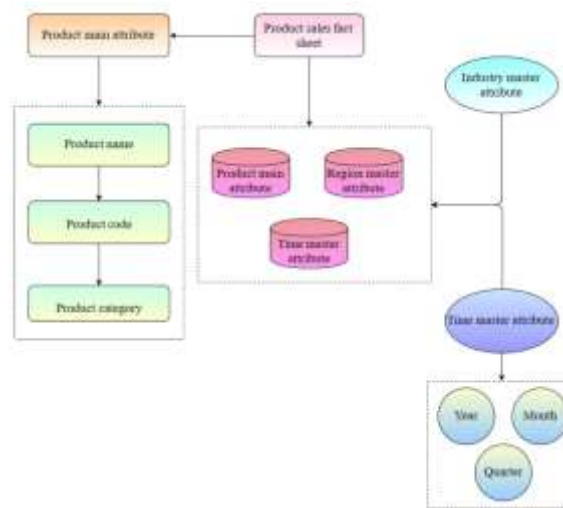


Figure 1. OLAP data organization model for Data Mining sales analysis.

Decision tree classification analysis primarily aims to train a decision tree or Bayesian neural network through transaction samples in a transaction database to form classification rules for sample points in the sample. This analysis can explain the primary and secondary attributes that form classification differences in samples and can classify and predict samples with predefined attributes according to the classification rules in the decision tree. This system uses the ID₃ algorithm, a representative algorithm based on information gain theory, to realize decision tree analysis.

Decision tree analysis can obtain the levels and categories of various influencing factors and the resulting sales levels. The tuple data from the training set is marked as class D, assuming that class D is marked with M distinct values, and those M distinct values represent M distinct classes, which are marked as C_i ($i = 1, 2, \dots, m$). A set of tuples in class C_i is denoted by C_i, d . $|D|$ represents the number of data in a tuple. The expected information in C_i is Formula (1):

$$Info(D) = - \sum_{i=1}^m \log_2(P_i) \quad (1)$$

Info(D) is the entropy of D. P_i represents the probability of data being in each tuple, and p_i is calculated as $|C_i, D| / |D|$. The data tuple should be divided by A, and A will obtain V different results after dividing the tuple, each division of which has the value a_j ; thus, the information of A can be obtained, as shown in Formula (2):

$$Info_A(D) = - \sum_{j=1}^V Info(D_j) \quad (2)$$

The information gain metric is used to select the test attribute at each node of the tree. This metric is called the attribute selection metric or the goodness of split metric. Select the attribute with the highest information gain or maximum entropy compression as the test attribute of the current node. This attribute minimizes the information and quantity required for sample classification in the result split and reflects the minimum randomness of the split.

Assuming that the initial information request is $\text{Info}(D)$ and the new information request is $\text{Info}_A(D)$, the information gain is the difference between the two, as shown in formula (3):

$$\text{Gain}(A) = \text{Info}(D) - \text{Info}_A(D) \quad (3)$$

The information acquisition rate normalizes the information acquisition using the k value of the shared information. The information classification is similar to $\text{Info}(D)$, and is defined as Formula (4):

$$\text{SplitInfo}_A(D) = - \sum_{j=1}^v \log_2 \frac{D_j}{D} \quad (4)$$

This value represents the information generated by dividing the training data set D into v divisions corresponding to v test outputs of attribute A .

Select the attribute with the maximum reinforcement level as the split attribute, as shown in Formula (5):

$$\text{GainRatio}(A) = (\text{Gain}(A)) / (\text{SplitInfo}(A)) \quad (5)$$

As mentioned above, the decision tree obtained through training the data set can continuously segment the sales market based on the impact of various factors on sales at different market levels.

2. Marketing Decision Support System Architecture Design

The marketing decision support system designed in this paper can address the problem of information asymmetry in competition with other companies and sales agents. The system adopts a messaging mechanism, allowing managers to obtain information about competitors and pre-determined agent teams, as well as information about all sales in the next few days, thereby gaining a lead in the overall sales competition. The business involved in the sales management system is relatively confidential. If deployed directly on a public network, security is obviously inadequate. Users on the public network using a VPN to connect to the company intranet to access the sales management database and applications is a better choice. The operating environment of the Marketing Decision Support System is shown in Figure 2.

After a decision maker issues a decision request, the data mining tool utilizes the data warehouse, model base, and knowledge base to complete the data mining process. The data warehouse management system is triggered by the data mining tool to retrieve task-related data from the data warehouse and generate additional patterns and relationships. After these patterns and relationships are analyzed and evaluated, some of the data deemed interesting is provided to the decision maker through a human-computer interaction system, and some findings are added to the knowledge base for new knowledge discovery and evaluation.

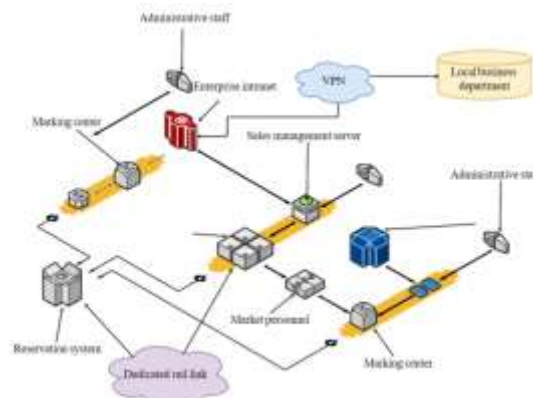


Figure 2. Marketing Decision Support System Operating Environment

Based on the system design objectives, the marketing Decision Support System (DSS) can be divided into six levels based on its function: basic data, data extraction, data warehouse, information extraction, information presentation, and system management.

- a. Basic data
- b. Data extraction
- c. Data warehouse
- d. Information extraction (OLAP analysis, data mining)
- e. Information Display
- f. System Management

A DSS is a comprehensive and integrated system that utilizes databases and human-computer interaction to organically combine various models and assist decision-makers in making scientific decisions. This system is developed based on management information systems and operational research. DSS requires not only relevant data from all departments across the company but also relevant data from external companies and competitors. To automatically discover potentially important relationships between various elements, DM is needed. By measuring the distance of attribute characteristics that affect sales costs, each point in the data set is allocated to a cluster. Here, the allocation principle is the proximity principle, that is, data points are allocated to the cluster when the distance from the center point is small.

DM technology provides advanced tools such as neural networks and genetic algorithms, which can detect and classify deviations in a timely manner. If these deviations are identified as abnormal reactions, marketers can take effective steps to prevent them. If changes are detected, further research is required. Competition lies not only in price but also in quality, timeliness, product customization, and customer support. Organizations must quickly and frequently change their operating modes, reorganize their processes and structures, empower employees, and innovate. Decision support technologies, such as expert systems, enable less knowledgeable individuals to make sound decisions.

Currently, most enterprise data is distributed and unintegrated. Decision Support Systems (DSS) need to integrate this scattered data, which is a very complex task and results in low data processing efficiency. Furthermore, DSS generally do not analyze detailed data, and decision analysis is mainly performed on various summary data. After extracting, converting, and loading various business data related to marketing decisions by subject, a

comprehensive subject data center that is unified, standardized, and widely accessible is built. On this basis, OLAP and DM technologies are used to analyze data from various perspectives and extract potential knowledge, thereby building an efficient marketing DSS. The DSS system architecture formed by the combination of data warehousing and data mining eliminates the problem of data inconsistency within the system. Thanks to its inherent unity, this new structure solves the problem of mutual connection. Data mining aims to use a series of data mining methods and models to mine and analyze data in data warehouses and OLAP, discover potential laws and knowledge within the data, and use these laws and knowledge to make predictions. DSS with this architecture can fully explore information, truly show the essence of information, and demonstrate the transformation of DSS design concepts from model-based to data-based, with a low level of development difficulty.

3. Results and Discussion

A data mining-based marketing decision support system was tested using FoodMart's 2000 sales data. Simulation results showed that the three-layer BP neural network model produced a mean absolute error rate of 15.13%, indicating a high level of accuracy in predicting product sales. Furthermore, a sensitivity analysis revealed a positive correlation between increased promotional investment and company profits.

Table 1. Results of Training and Testing of Difference Models.

Model Structure (Input Layer-Hidden Layer-Output Layer)	Learning Time	MAPE Sample
27-10-24	345	17.41%
54-10-24	356	16.52%
81-10-24	332	15.13%

Based on 2015 data, this paper simulates the number of franchise outlets and direct sales profits of this company from 2016 to 2021, then compares them with historical data to test the validity of the model. The specific results are shown in Tables 2 and 3, respectively.

Table 2. Franchise Store Quantity Model Inspection.

Certain Years	2016	2017	2018	2019	2020	2021
Actual value (number)	405	415	451	491	582	612
Predicted value (number)	401	412	425	464	572	874
Relative error (%)	+0.97%	+0.97%	+0.97%	+0.97%	+0.97%	+0.97%

Table 3. Company Profit Model Test.

Certain Years	2016	2017	2018	2019	2020	2021
Actual value (number)	6.6	10.34	13.55	20.3	28.11	41.7
Predicted value (number)	6.8	10.0787	14.1791	20.0744	29.0744	43.525
Relative error (%)	+2.98%	+2.98%	+2.98%	+2.98%	+2.98%	+2.98%

In this experiment, the promotion investment is changed in steps of 0.01 within the range of [0.21, 0.24], and the change of enterprise profit is shown in Figure 3.

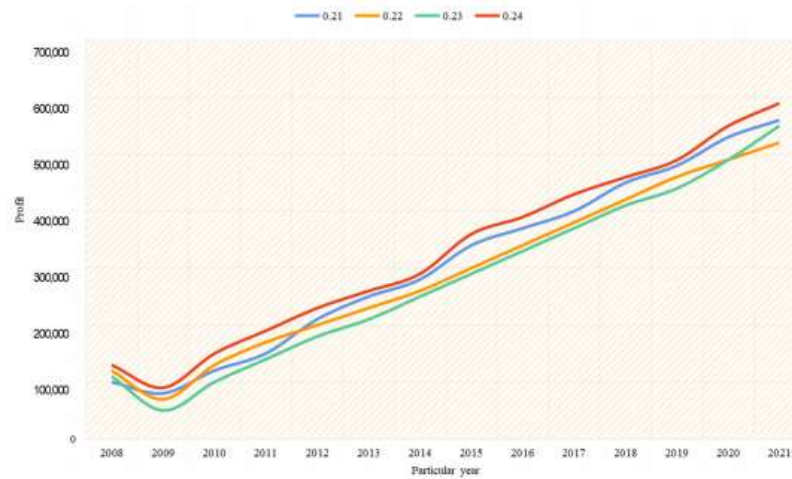


Figure 3. Curve of Changes in the Company's Promotion Investment Coefficient.

As can be seen from Figure 4, vertically, each curve shows that in the 14-year simulation, except for a slight decrease in corporate profits in the first year, corporate profits in subsequent years increased year by year, and the increase curve is close to the index curve. For horizontal comparison, the five curves represent the proportion values of products in different puts. It can be seen from the five curves that the product input coefficient is positively correlated with corporate profits. With the increase in product input, corporate profits increase. In the simulation year 2008–2017, with the increase in the product input coefficient from 0.21 to 0.24, corporate profits also increased, but not significantly, from 1.87 billion to 4.45 billion; in the forecast year 2018–2021, the input coefficient will increase from 0.23 to 0.26, and corporate profits will increase from 4.968 billion to 7.12 billion. With the increase in the product input coefficient, Corporate profits also maintain a corresponding growth, but the growth rate is not significant.

4. Conclusion

This study demonstrates that the integration of data warehousing, OLAP, and data mining techniques into a marketing Decision Support System (DSS) can substantially enhance the quality and effectiveness of managerial decision-making in complex and competitive market environments. The experimental results using FoodMart 2000 sales data confirm that the proposed data mining-based DSS is capable of generating reliable predictive insights, as evidenced by a relatively low mean absolute percentage error (MAPE) of 15.13% in sales forecasting and stable prediction accuracy in franchise expansion and profit modeling. Furthermore, the sensitivity analysis indicates a consistent positive relationship between promotional investment and corporate profit growth, supporting the system's ability to reveal meaningful patterns and strategic relationships hidden within large-scale marketing data. Overall, the findings validate that a data-driven, intelligent DSS can effectively reduce information asymmetry, improve market responsiveness, and provide robust analytical support for strategic marketing decisions. Based on these findings, future research is recommended to extend the proposed DSS framework by incorporating real-time data streams, advanced machine learning algorithms, and adaptive learning mechanisms to further improve predictive accuracy and system responsiveness. In addition, integrating external data sources such as social media analytics, customer sentiment data, and macroeconomic indicators could enhance the system's capability to capture dynamic market changes. From a practical perspective, enterprises should prioritize data integration and governance to ensure data quality, security, and consistency, particularly when deploying DSS in competitive and information-sensitive environments. By continuously refining analytical models and aligning DSS outputs with strategic objectives, organizations can strengthen their competitive advantage and support sustainable, evidence-based marketing decision-making.

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