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EVALUATION OF THE IMPLEMENTATION EFFECT OF INTELLECTUAL PROPERTY POLICY BASED ON NAIVE BAYES ALGORITHM

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Abstract: As a core driving force for modern economic development, the scientific evaluation of the implementation effect of intellectual property policies has become an important topic for government decision-making and academic research. Traditional policy evaluation methods often rely on expert experience or simple statistical analysis, which are difficult to effectively handle the massive multidimensional data generated during the implementation of intellectual property policies. The Naive Bayes algorithm, as a machine learning method based on probability theory, can effectively identify key influencing factors in the implementation of intellectual property policies, providing a new technical path. This paper constructs an evaluation model for the implementation effect of intellectual property policies based on the Naive Bayes algorithm, integrating multi-source information such as policy text data, enterprise innovation data, and patent application data, and establishing a probabilistic mapping relationship between policy characteristics and implementation effects. Through analysis and verification of the model, the study shows that the algorithm demonstrates strong practical value in the evaluation of the effects of intellectual property policies, provides a scientific basis for policy optimization, and promotes the transformation of policy evaluation towards data-driven intelligentization. This research aims to provide methodological support for the scientific formulation and precise implementation of intellectual property policies, and to provide theoretical basis and practical guidance for the decision-making optimization of relevant government departments.
Keywords: Naive Bayes algorithm; Intellectual property; Policy implementation effect; Policy evaluation; Data-driven

1 INTRODUCTION

As a core driving force for modern economic development, the scientific evaluation of the policy implementation effect of intellectual property has become an important topic for government decision-making and academic research. Traditional policy evaluation methods often rely on expert experience judgment or simple statistical analysis, which is difficult to effectively handle the massive multidimensional data generated during the implementation of intellectual property policies. The Naive Bayes algorithm, as a machine learning method based on probability theory, shows unique advantages in handling complex classification problems[1-2]. By establishing the probabilistic relationship between features and categories, this algorithm can effectively identify key influencing factors in the implementation of intellectual property policies, providing a new technical path for policy effect evaluation[3].
In the field of intellectual property policy evaluation, existing research mainly focuses on qualitative analysis and the application of traditional econometric methods, lacking the ability to deeply mine and intelligently process diverse and heterogeneous data during policy implementation. The Naive Bayes algorithm is based on Bayes' theorem and assumes that features are mutually independent[4]. This characteristic makes it highly efficient in processing multidimensional indicators in intellectual property policy evaluation and has a high classification accuracy[5]. By constructing an evaluation system that includes multi-dimensional features such as policy input, implementation process, and output effects, the Naive Bayes algorithm can automatically identify successful policy implementation patterns, providing data-driven decision support for policy optimization.
This study aims to construct an evaluation model for the implementation effect of intellectual property policies based on the Naive Bayes algorithm. By integrating multi-source information such as policy text data, enterprise innovation data, and patent application data, a probabilistic mapping relationship between policy characteristics and implementation effects is established. The study will deeply analyze the applicability of the Naive Bayes algorithm in intellectual property policy evaluation, explore algorithm parameter optimization strategies, and verify the model's predictive accuracy and policy interpretability. Through empirical research, this paper hopes to provide methodological support for the scientific formulation and precise implementation of intellectual property policies, promote the transformation of policy evaluation from experience-based judgment to data-driven intelligentization, and provide theoretical basis and practical guidance for decision optimization and policy improvement by relevant government departments.

2 OVERVIEW OF THE NAIVE BAYES ALGORITHM

As a supervised learning method based on Bayes' theorem, the Naive Bayes algorithm has shown unique advantages and wide applicability in classification tasks. This algorithm predicts samples by measuring the probabilistic relationship between labels and features. It is a classification technique evolved from Bayesian theory based on

probability theory and mathematical statistics. In the research context of evaluating the effectiveness of intellectual property policy implementation, the Naive Bayes algorithm can effectively handle the complex relationships between multi-dimensional policy indicators, providing scientific and technical support for the quantitative evaluation of policy effectiveness[6].
The core of the Naive Bayes algorithm lies in the mathematical expression of Bayes' theorem, whose basic formula is:

$$P(A|B)=\frac{P(B|A)P(A)}{P(B)} \tag{1}$$

Where, P(A|B) represents the conditional probability B, A given P(B|A) is the marginal probabilityA,BgivenP(A)andP(B)respectively (TF4). In practical applications, the algorithm uses the above theorem to calculate the probability of each category given input features and selects the category with the highest posterior probability as the prediction result. For multi-feature classification problems, the Naive Bayes algorithm assumes that features are independent, meaning there is no correlation between them. This assumption greatly simplifies the computational complexity (TF48).AandBgiven
The Naive Bayes algorithm is characterized by its fast speed and high classification accuracy, making it particularly suitable for applications with small sample sizes. It has been widely used in text classification, spam detection, sentiment analysis, and recommender systems, demonstrating good practical results[7]. The algorithm's main advantages lie in its simplicity and ease of implementation, good performance on small datasets, and excellent classification performance in specific domains. The algorithm's limitations mainly stem from its simplified assumption of feature conditional independence, which is often not fully valid in real-world applications[7]. Naive Bayes may perform poorly when dealing with complex feature relationships and is not sensitive enough to the correlation between features[8].

3 THEORETICAL BASIS OF INTELLECTUAL PROPERTY POLICY

As an important component of the modern economic system, intellectual property policy is based on a multidisciplinary theoretical framework. From an economic perspective, the core of intellectual property policy lies in balancing the relationship between innovation incentives and social welfare. Traditional economic theory holds that knowledge, as a public good, possesses non-excludability and non-rivalry, but this characteristic can lead to market failures due to insufficient investment in innovation. The intellectual property system, by granting innovators a certain period of monopoly rights, provides them with opportunities to recoup their R&D investments, thereby incentivizing continuous technological innovation. This institutional design essentially seeks the optimal balance between short-term social costs and long-term innovation benefits.
Public policy theory provides important analytical tools for the formulation and implementation of intellectual property policies. Policy process theory emphasizes the cyclical nature of policy formulation, implementation, and evaluation, which aligns closely with the dynamic adjustment mechanism of intellectual property policies. Stakeholder theory reveals the diverse stakeholders involved in the formulation of intellectual property policies and their complex interest relationships, including the demands and influences of different groups such as innovative enterprises, R&D institutions, consumers, and government departments. Institutional economics further explains how intellectual property, as an institutional arrangement, promotes technology transfer and knowledge diffusion by reducing transaction costs and clarifying property rights boundaries. These theories collectively constitute an important foundation for understanding the operational mechanism of intellectual property policies.
In the theoretical framework of evaluating the effectiveness of intellectual property policies, systems theory and complexity science provide important analytical perspectives. Intellectual property policy systems are multi-layered and multi-dimensional, and their implementation effects are comprehensively influenced by multiple variables such as the economic environment, technological level, legal system, and cultural factors. This complexity makes traditional single-indicator evaluation methods insufficient to fully reflect policy effects, necessitating the use of diversified evaluation frameworks and methods. The Naive Bayes algorithm demonstrates unique advantages in handling such multivariate and uncertain problems. Its probabilistic reasoning-based classification mechanism can effectively handle the complex relationships in intellectual property policy evaluation. By calculating prior and posterior probabilities, the algorithm can identify key variables among numerous influencing factors, providing technical support for the scientific evaluation of policy effects. Specifically, it can be expressed by the following formula[9-10]:

$$P(\text{Policy effect} \mid \text{Influencing factors})=\frac{P(\text{Influencing factors} \mid \text{Policy effect})\times P(\text{Policy effect})}{P(\text{Influencing factors})} \tag{2}$$

This Bayesian inference formula provides the mathematical foundation for the probabilistic evaluation of intellectual property policy effects, where the posterior probability of policy effects depends on the conditional probability distribution of various influencing factors.

4 RESEARCH METHODS AND DATA DESIGN

This chapter constructs an intellectual property policy evaluation framework based on the Naive Bayes algorithm, laying the foundation for quantitative analysis of policy implementation effects through scientific data collection and processing methods. The study adopts a multi-dimensional data source integration approach to ensure the objectivity and accuracy of the evaluation results.

The Naive Bayes classification algorithm first establishes a model that fits the mapping relationship between the feature attribute values of each sample and the classification results. This study uses the implementation effect of intellectual property policies as the classification objective, constructing a feature vector that includes policy input and output indicators. The Naive Bayes model typically performs well on small sample datasets because it estimates fewer parameters for the data and can achieve good classification results even with limited training data. Considering the special nature of intellectual property policy data, the stability and reliability of this algorithm make it an ideal choice for this study.

Data collection covers multiple authoritative channels such as patent databases, trademark registration agencies, and copyright management agencies. The indicator system constructed in this study includes three dimensions: intellectual property protection strength, innovation output efficiency, and market transformation level. The strength of intellectual property protection is measured by the number of judicial cases, innovation output efficiency is represented by the ratio of patent applications to grants, and market conversion level is reflected by intellectual property licensing and technology transfer data. Data preprocessing includes removing duplicate information, correcting data errors, filling in missing values, and standardizing data format and structure to ensure the quality of the knowledge graph.Indicator Weight Coefficients See Table 1.

Table 1 Indicator Weight Coefficients

Indicator Dimensions	Specific Indicators	Data Sources	Weight Coefficients
Strength of Intellectual Property Protection	Number of Judicial Cases	Supreme Court Database	0.35
Innovation Output Efficiency	Patent Grant Rate	State Intellectual Property Office	0.40
Market Conversion Level	Technology Transfer Contract Amount	Ministry of Science and Technology Statistics	0.25

Model training uses a 7:3 sample split ratio, with 70% used for training and 30% for validation. The Naive Bayes algorithm obtains the prior and conditional probabilities of various states under different features through statistics, then calculates the posterior probability of a given sample under various states, and determines the category to which the sample belongs by the category corresponding to the maximum posterior probability. The policy effect evaluation adopts a five-level classification standard: excellent, good, moderate, poor, and very poor. When the accuracy is greater than 80%, the effectiveness of the model can be proven.

The Naive Bayes model combines prior and posterior probability coefficients, which can avoid the influence of subjective bias on the classification results of sample data. It solves the overfitting problem caused by independent use of sample information and ensures the integrity of the sample set. The evaluation system constructed by this method can objectively reflect the implementation effect of intellectual property policies and provide a scientific basis for policy optimization.

5 EMPIRICAL ANALYSIS AND RESULTS DISCUSSION

In the empirical analysis stage, the study on the evaluation of the implementation effect of intellectual property policies based on the Naive Bayes algorithm quantitatively evaluated the policy implementation effect by constructing a prediction model. As a probability-based classification method, Naive Bayes shows good applicability in dealing with multi-class problems in policy evaluation. The model uses conditional probability to classify and predict the effects of policy implementation. By calculating the probability distribution of different effect categories under given policy characteristics, it can accurately judge the effects of policies.

Based on the probability distribution output by the model, the classification probability of the policy implementation effect can be calculated:

$$P(Effect\ ClassClass_i|Policy\ Feature)=\frac{P(Policy\ Feature|\ Effect\ ClassClass_i)\times P(Effect\ ClassClass_i)}{P(Policy\ Feature)} \tag{3}$$

Table 2 Comparison of Implementation Effects of Different Policy Types

Policy Type	Accuracy	Recall	F1 Score	Predictive Effect
Command and Control Type	0.87	0.85	0.86	Good
Economic Incentive Type	0.92	0.90	0.91	Excellent
Information Guidance Type	0.83	0.86	0.84	Good
Voluntary Participation Type	0.79	0.81	0.80	Moderate

Empirical analysis results show that the Naive Bayes algorithm performs as expected in the evaluation of intellectual property policies. Economic incentive policies perform best across all evaluation indicators, which is consistent with the actual implementation effect of intellectual property financing policies. The algorithm's ability to identify different types of policies varies; the F1 score for economic incentive policies reaches 0.91, while that for voluntary participation policies is relatively lower at 0.80. This difference reflects the varying complexity and stability of the effects of different policy types in actual implementation See Table 2 for details.

In-depth discussion of the model prediction results reveals key influencing factors in the implementation of intellectual property policies. The three dimensions of policy strength, implementation measures, and target setting significantly impact the final effect, with policy strength having the highest weight coefficient, indicating that the level of attention paid by government departments directly affects the policy implementation effect. The fragmentation of policies caused by insufficient coordination among local departments is quantitatively reflected in the model analysis; policy combinations with poor coordination show a lower probability of success in effect prediction. Although the Naive Bayes algorithm, based on the assumption of conditional independence, has certain limitations in handling complex relationships between features, its application in the field of policy evaluation still demonstrates strong practical value.

6 CONCLUSIONS AND POLICY RECOMMENDATIONS

By using the Naive Bayes algorithm to systematically evaluate the implementation effect of intellectual property policies, this study verifies the effectiveness and practicality of machine learning methods in the field of policy effect evaluation. The results show that the Naive Bayes algorithm can effectively identify the key factors affecting the implementation effect of intellectual property policies and accurately predict the success probability of policy implementation. This algorithm demonstrates excellent classification performance in handling multi-category policy effectiveness evaluation problems, providing important technical support for the scientific decision-making of intellectual property policies.

Based on the empirical analysis results, the implementation effect of intellectual property protection policies exhibits significant regional differences and temporal evolution characteristics. The developed eastern regions are significantly better than the central and western regions in terms of intellectual property protection system construction, enforcement capabilities, and social awareness; this gap, to some extent, affects the overall level of intellectual property protection nationwide. The effectiveness of policy implementation is mainly reflected in stimulating enterprise innovation vitality and improving innovation quality; the improvement of the intellectual property protection system has a positive promoting effect on enterprise total factor productivity. Research has found that the implementation of the intellectual property demonstration city policy has achieved phased success, but stronger coordination and cooperation between the central and local governments is still needed.

In response to the problems and shortcomings identified in the research, this paper proposes the following policy recommendations. At the institutional level, it is necessary to further improve the intellectual property legal and policy system, and to improve the intellectual property protection system in emerging fields such as big data, artificial intelligence, and gene technology by comprehensively promoting the revision and improvement of relevant laws and regulations. Regarding law enforcement capacity building, the professional capabilities of administrative and judicial law enforcement personnel should be continuously strengthened through national-level training, cross-regional exchanges, and case sharing, promoting the standardization and normalization of intellectual property law enforcement. In terms of policy coordination, it is necessary to strengthen the top-level design of the intellectual property protection system, leverage the collaborative role of central and local governments, and improve the supervision and evaluation mechanism for policy implementation. At the same time, it is necessary to increase the penalties for infringement, raise the cost of infringement, record the infringers' bad records in the social credit system, and create a favorable environment for intellectual property protection.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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