Prediction Of Criminal Sentence for Dangerous Driving Based on Probability Graph Model

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Abstract. In order to improve the accuracy and efficiency of predicting the sentence for the crime of dangerous driving, this article analyzes the application of probability graph models in judicial reasoning. By constructing an accurate model of complex evidence relationships and integrating uncertainty information in court evidence, the results show that the model can effectively support judgments and improve the transparency and fairness of judicial decision-making. In addition, the interpretability of the model provides legal professionals with a clear view of the decision-making process, enhancing the scientific and rational nature of legal judgments.

Keywords: probability graph model; Judicial reasoning; dangerous driving.

1. Introduction

With the increasing demand for technological tools in the judicial system, exploring the application of probability graph models in predicting the sentence of dangerous driving crimes has become an important task. This model provides scientific support for judgments by integrating uncertainty information and conditional dependencies, aiming to improve the accuracy and transparency of judgments through precise modeling and algorithmic interpretability, thereby promoting the modernization and efficiency of the legal judgment process.

2. The advantages of the probability graph model in judicial reasoning

The probability graph model has significant advantages in judicial reasoning, mainly reflected in its ability to accurately model and reason complex evidence relationships. By establishing conditional dependencies between variables, this model can effectively integrate and handle uncertainty information in court evidence, providing solid data support for judges and lawyers. In specific applications, the probability graph model connects different evidence items through a graph structure, evaluates the influence of each evidence using conditional probability tables and Bayesian inference algorithms, so that the inference process not only relies on a single evidence, but also comprehensively considers all relevant factors for comprehensive cooperation[1]. This method is particularly suitable for handling cases where there is complex interaction between evidence, such as criminal cases involving multiple motives and behaviors. In addition, the algorithm of the probability graph model has strong interpretability and can clearly show the calculation logic and evidence weight of each decision point to judges and lawyers. This not only increases the transparency of the judgment, but also enhances the public's trust in the judicial process. Therefore, using probability graph models for judicial reasoning can significantly improve the accuracy and efficiency of judgments while enhancing their rationality, thereby optimizing the allocation and use of judicial resources, and promoting the development of the judicial system towards higher efficiency and fairness[2].

3. A Model for Predicting the Sentence of Dangerous Driving Crimes

3.1. Sentencing elements

In the prediction model of the sentence for the crime of dangerous driving, the sentencing element is the key to determining the judgment result. The legal elements include whether the driver's behavior constitutes dangerous driving, such as speeding, drunk driving, etc., as well as the specific environment and consequences of the behavior, such as whether it causes traffic accidents or casualties[3]. The discretionary elements involve factors such as the driver's subjective malice, past driving records, and whether to take proactive measures to mitigate the consequences. Through the probability graph model, these statutory and discretionary elements can be used as nodes, and regular expression matching technology can be used to accurately capture and analyze relevant information in legal texts, thereby constructing a comprehensive sentencing reasoning framework, as shown in Figure 1:

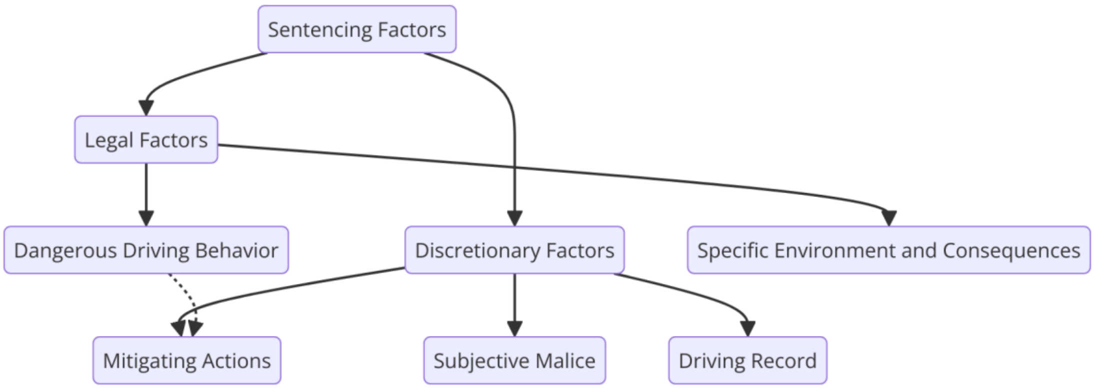

Figure 1: Framework diagram of sentencing for dangerous driving

This model provides judges with a data-driven, objective and reasonable judgment reference by assigning weights to different sentencing elements and calculating conditional probabilities, ensuring the fairness and appropriateness of sentencing.

3.2. Probability Graph Model Construction

When constructing a probability graph model for predicting the sentence of dangerous driving crimes, we first define the structure of the model, including clarifying the various sentencing elements and their probability relationships[4]. These elements are subdivided into observable nodes and hidden nodes, where hidden nodes are usually factors that are not easily observable but have a significant impact on decision-making, such as the driver's psychological state or intention. The use of Conditional Probability Table (CPT) to describe the dependency relationships between nodes is a key step in model construction. Define nodes X For driving behavior, nodes Y As a legal consequence, node Z We can set the following conditional probability expression for the driver's psychological state:

$$P(Y|X,Z) = \alpha P(Y|X) + (1-\alpha) P(Y|Z) \tag{1}$$

Among them, α It is an adjustment parameter used to balance the influence of different factors on the judgment result. Considering that the decision-making process for sentencing requires evaluating the sentencing elements at different stages, Table 1 provides a detailed description of the different stages and related elements of the crime of dangerous driving:

Table 1: Classification of sentencing elements for predicting the sentence of dangerous driving crimes

Category	Hidden Node	Sentencing Elements
During Crime	Dangerous Driving Condition	Drunk Driving (20-80mg/100mL)
		Drunk Driving (80-200mg/100mL)
		Drunk Driving (over 200mg/100mL)
	Accident Responsibility	Offender bears main responsibility
		Offender bears full responsibility
		Offender bears direct responsibility
Before Crime	Criminal Responsibility Capacity	Full criminal responsibility capacity
		Limited criminal responsibility capacity
		No criminal responsibility capacity
	Repeat Offense and Criminal Record	Prior convictions
		General repeat offender
		Special repeat offender
After Crime	Statutory Mitigating Circumstances	Confession
		Surrender
		Actively obtaining the victim's forgiveness

In the model inference stage, we use the hidden nodes and sentencing elements in the above table to perform probability inference through Bayesian networks. The posterior probability of a node is usually calculated using the Bayesian formula:

$$P(X|Y)=\frac{P(Y|X)P(X)}{P(Y)} \tag{2}$$

This structure enables the model to integrate various complex factors, provide reasonable sentencing recommendations, and ensure the accuracy and fairness of legal judgments.

3.3. Parameter learning and inference

In the probability graph model for predicting the sentence of dangerous driving crimes, parameter learning and inference are key steps to ensure the accuracy and practicality of the model. Parameter learning mainly involves estimating the parameters of conditional probability tables (CPTs) defined in the model structure from data[5]. It can be achieved through maximum likelihood estimation (MLE) or Bayesian estimation methods. Consider maximum likelihood estimation, assuming θ Represents a parameter in the model that represents the probability of a node's state occurring under a given parent node state. For simple discrete data, θ The maximum likelihood estimation of can be expressed as:

$$\hat{\theta}_{MLE}=\frac{N(x, pa(x))}{N(pa(x))} \tag{3}$$

Among them, $N(x, pa(x))$ It's a node x And its parent node $pa(x)$ The number of samples that occur simultaneously, $N(x, pa(x))$ It is the parent node $pa(x)$ The number of samples that appear.

In Bayesian estimation, introducing prior knowledge to adjust parameter estimation is particularly suitable for situations with limited data. Using the Dirichlet prior, the posterior distribution of parameters can be described as:

$$P(\theta|D)\propto P(D|\theta)P(\theta) \tag{4}$$

Among $P(\theta|D)$ It's data D In the parameters θ Lower likelihood, $P(\theta)$ yes θ The prior distribution of. When using the Dirichlet distribution as a prior, the updated posterior distribution is also the Dirichlet distribution, and its parameter update rule is:

$$\alpha' = \alpha + N(x, pa(x)) \tag{5}$$

Among them, α It is a prior parameter, α' It is a posterior parameter, and the inference process usually uses Bayesian network belief propagation or Markov Chain Monte Carlo (MCMC) methods. In belief propagation, each node updates its probability estimate of state based on the information of its parent and child nodes. A basic update formula can be expressed as:

$$P(X_i | pa(X_i)) = \frac{\Pi_{k \in children(X_i)} P(X_k | X_i) \Pi_{j \in pa(X_i)} P(X_j | pa(X_j))}{P(X_i)} \tag{6}$$

By iteratively applying these formulas, probability inference can be effectively performed in the network, providing theoretical support for decision-making. This method, which combines parameter learning and probability inference, enables the probability graph model to not only accurately describe and process sentencing elements in dangerous driving crimes, but also provide a dynamically adjusted and self improving intelligent judgment system[6].

4. Experimental Results and Analysis

4.1. Datasets and evaluation indicators

A probability graph model for predicting the sentence of dangerous driving crimes was constructed in the study, and its performance was tested through a series of experiments. Considering the potential impact of regional and ethnic differences on the judgment results, 4969 cases were specifically collected, of which 4000 cases were used as training sets to establish and optimize the model, and the remaining 696 cases were used as testing sets to verify the model's generalization ability and prediction accuracy[7]. In order to comprehensively evaluate the performance of the probability graph model and compare it with other machine learning methods, decision trees, random forests, support vector machines (SVM), and neural networks were selected as the comparison models. These models have a wide range of applications in the field of legal judgment prediction, each with its unique advantages and limitations[8]. To ensure fairness in comparison, all models are trained and tested using the same dataset.

In terms of evaluation indicators, several key statistical indicators were used to measure the predictive performance of the model. Accuracy is the basic indicator for measuring the accuracy of model predictions, and its calculation formula is:

$$Accuracy = \frac{NumberofCorrect\Pr edicitions}{TotalNumberof\Pr edicitions} \tag{7}$$

However, as sentence prediction is a regression problem, we also need to consider continuous output evaluation indicators, such as mean squared error (MSE) and mean absolute error (MAE), which respectively describe the average level of the square and absolute values of the difference between the predicted and actual values. The calculation formula for these indicators is:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{8}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{9}$$

Among y_i It's the number i The actual sentence of each sample, $\hat{y}_i$ It's predicting the sentence, n It is the total number of samples. These indicators can provide intuitive information about the size and distribution of model prediction errors. During the process of model training and testing, all experiments were conducted under the same hardware and software configurations, ensuring the reproducibility of experimental results[9].

4.2. Comparison of experimental results

In the process of conducting comparative experiments, we carefully analyzed the performance of probability graph models and several other machine learning methods (decision trees, random forests, support vector machines, and neural networks) in predicting the sentence for dangerous driving crimes[10]. The experimental results are presented through several key evaluation indicators, including accuracy, mean square error (MSE), and mean absolute error (MAE), ensuring the comprehensiveness and depth of the evaluation. Figure 2 shows the accuracy comparison of each model on the test set:

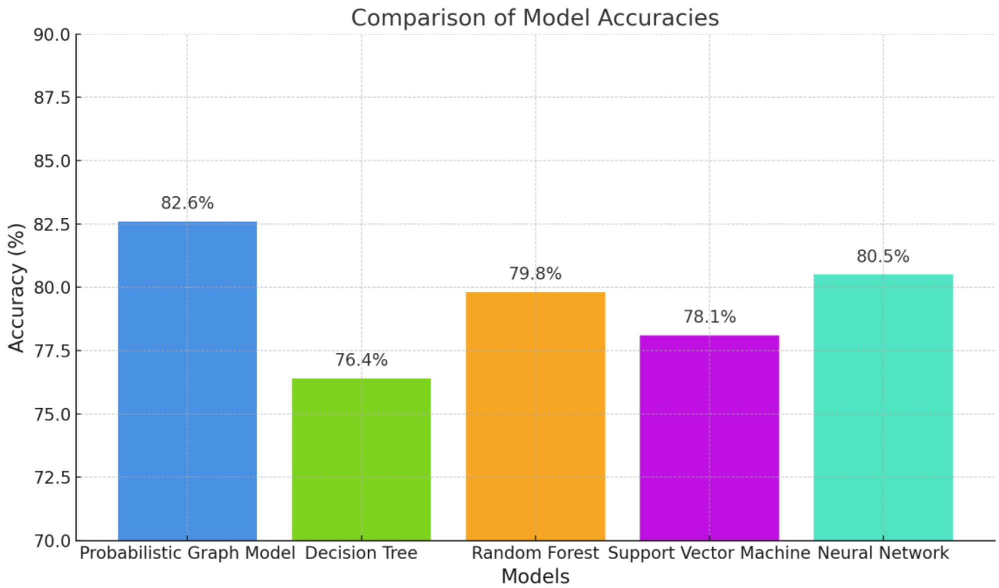

Figure 2: Comparison of model accuracy

Next, analyze the performance of each model in predicting sentence errors, measured by mean square error (MSE). Mean squared error reflects the average square of the difference between predicted and actual values, and is a commonly used indicator for evaluating the performance of regression models. Figure 3 shows the comparison results of different models on this indicator:

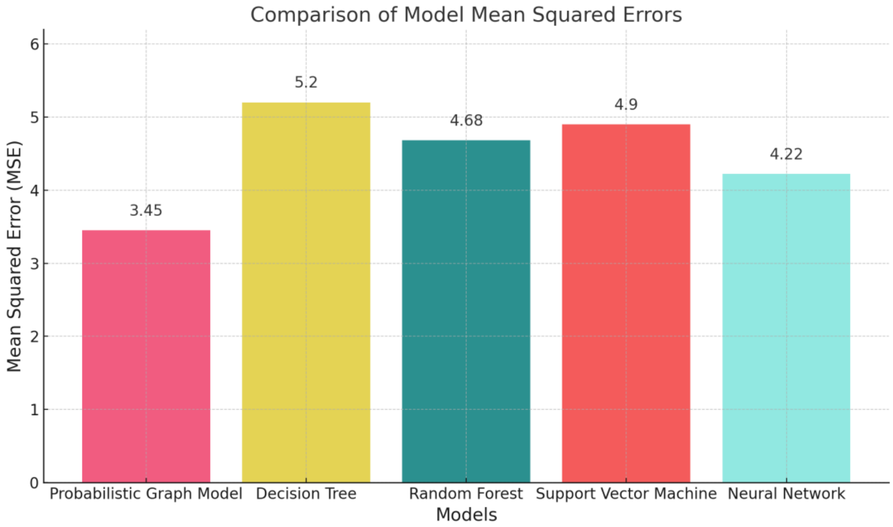

Figure 3: Comparison of Mean Square Error (MSE) of Models

To further understand the performance of each model, Mean Absolute Error (MAE) was also considered. The average absolute error provides the average level of difference between predicted and actual values, and is another key indicator for evaluating regression models. Figure 4 provides a detailed explanation of the performance of each model on this metric:

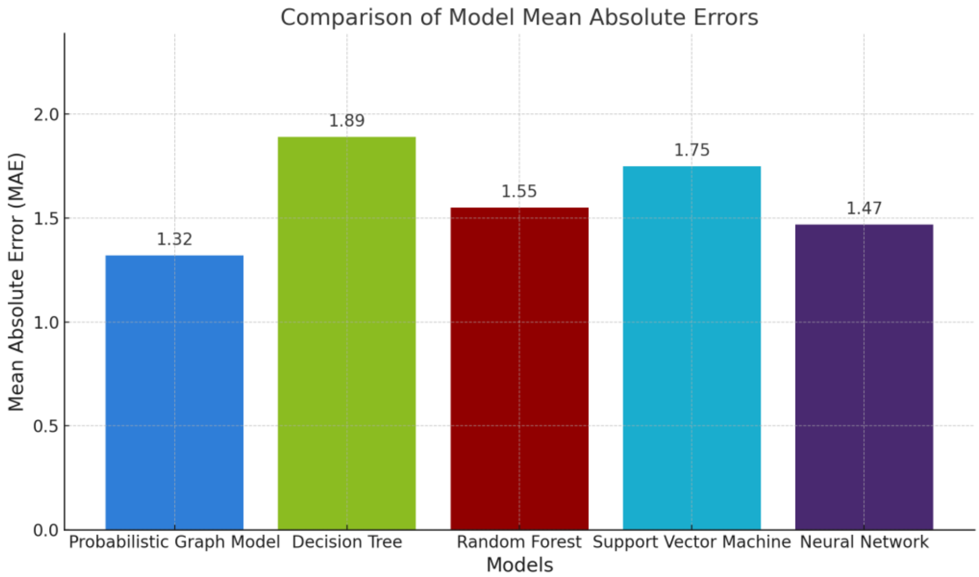

Figure 4: Comparison of Model Mean Absolute Error (MAE)

These experimental results not only validate the potential application of probability graph models in the legal field, but also demonstrate their effectiveness and reliability as auxiliary tools in practical judicial judgments.

4.3. Analysis of experimental results

When studying the performance of the prediction model for dangerous driving crimes, it was found that the probability graph model led the way with 82.6% accuracy compared to other models, which significantly demonstrated its efficient ability in grasping the complex sentencing element relationships. Relatively speaking, the decision tree model has an accuracy of only 76.4%, mainly due to its limitations in handling multidimensional data and complex data relationships. At the same time, the accuracy of random forest and support vector machine were 79.8% and 78.1%, respectively, and the performance was acceptable, but there was still a gap compared to the probability graph model. Although neural networks achieve an accuracy of 80.5%, their big data training requirements and interpretability are insufficient in legal judgment prediction applications. In terms of mean square error (MSE), the probability graph model demonstrates excellent prediction accuracy with a low score error of 3.45, while the decision tree shows the maximum prediction bias with a MSE of 5.20. The MSE of random forest and support vector machine are 4.68 and 4.90, respectively, indicating that although they have certain predictive ability, there is still room for further optimization. The MSE of the neural network is 4.22, although relatively low, it still cannot match the probability graph model.

In the mean absolute error (MAE) analysis, the probability graph model highlights its high-precision prediction ability with a result of 1.32, while the decision tree's 1.89 MAE reveals its significant shortcomings in precise prediction. The MAE of random forest and support vector machine are 1.55 and 1.75, respectively, while the MAE of neural network is 1.47, indicating that they have shown some performance in accuracy, but still have not reached the level of probability graph models. The excellent performance of the probability graph model in various key indicators proves its significant advantage in solving the complexity and uncertainty issues in legal judgments. This model not only provides accurate prediction results, but is also particularly valuable in legal professional applications due to its strong reasoning ability and good interpretability. In contrast, although other models have their own advantages, they still lack the ability to handle high-dimensional and complex data.

5. Conclusion

In the field of legal judgments, the probability graph model significantly improves the accuracy and efficiency of sentence prediction by accurately handling complex sentencing elements and their relationships. Its excellent interpretability further ensures the fairness and transparency of judgments. Future research can explore more refined model parameter learning methods and inference techniques to adapt to the constantly changing legal environment and increasing data volume, thereby optimizing model performance and enhancing its application value in judicial practice.

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