APPLYING DECISION TREE MODELS TO SOLVE REAL-LIFE PROBLEMS

Sukhrob Yangibaev 1
1 Urgench State University,
sukhrobyangibaev@urdu.uz

Jamolbek Mattiev 2
2 Urgench State University,
jamolbek.mattiev@famnit.upr.si

Abstract
This article delves into the practical application of decision tree models for solving real-world challenges. It investigates a range of algorithms, including CART, ID3, Regression, C4.5, Random Forest, Hist Gradient Boosting, Gradient Boosting, and Adaboost. The mathematical underpinnings of these models are elucidated, and a versatile framework is employed to evaluate their performance across diverse datasets. The primary objective is to showcase the efficacy of decision tree models in addressing real-life problems spanning various domains. Through performance analyses, the article sheds light on algorithm strengths and limitations, aiding practitioners in selecting the most suitable approach for specific problem contexts.

Keywords: decision tree models, dataset testing, algorithm performance, classification, regression, algorithm selection, accuracy rates, problem domains, decision-making.

Introduction

Decision tree models are popular in machine learning and data analysis due to their simplicity, interpretability, and effectiveness in solving real-life problems. This article explores the application of decision tree models across various domains, using algorithms such as CART, ID3, Regression, C4.5, Random Forest, Hist Gradient Boosting, Gradient Boosting, and Adaboost. A flexible framework was developed to execute these algorithms with different parameters, and diverse datasets were selected to evaluate their performance.

The objectives of this research are to provide insights into the strengths and limitations of different decision tree algorithms and to guide practitioners in selecting the most appropriate algorithm for specific problem domains. The study also aims to highlight the versatility and robustness of decision tree models in addressing both classification and regression tasks.

By examining different algorithms and evaluating their performance on diverse datasets, this research provides valuable insights for researchers, practitioners, and decision-makers. The subsequent sections of this article will delve into the methodology, experimental results, and discussions, ultimately contributing to the advancement of decision tree models in the field of machine learning and data analysis.

Literature Review:

Decision tree models have been extensively studied and applied in various domains due to their ability to solve real-world problems.

CART, introduced by Breiman et al. (1984) [1], is a popular algorithm that can handle both classification and regression tasks. ID3, proposed by Quinlan (1986) [2], uses information gain as the splitting criterion and has been widely used in areas like pattern recognition and natural language processing. C4.5, an extension of ID3, addressed some limitations of ID3 and has been applied in credit scoring, customer churn prediction, and medical diagnosis.

Ensemble methods like Random Forest [4], Gradient Boosting [5], and Adaboost [6] have also been used in decision tree modeling. Random Forest combines multiple decision trees to reduce overfitting and improve accuracy. Gradient Boosting builds decision trees sequentially, with each tree correcting the errors of the previous one. Adaboost assigns weights to training instances and iteratively builds decision trees to focus on misclassified instances.

Decision trees have been applied in healthcare, finance, and marketing for diseases diagnosis, treatment recommendation, credit scoring, fraud detection, investment decision-making, customer segmentation, churn prediction, and campaign targeting.

Methodology:

- Data Collection and Preprocessing:
  - Collected a diverse set of datasets representing real-life problems across various domains
  - Preprocessed datasets to ensure data quality and compatibility
    - Handled missing values
    - Encoded categorical variables
    - Normalized numerical features
- Implementation of Decision Tree Algorithms:
  - Developed a flexible framework to implement and execute various decision tree algorithms
  - Implemented CART, ID3, Regression, C4.5, Random Forest, Hist Gradient Boosting, Gradient Boosting, and Adaboost
  - Tuned ensemble methods' hyperparameters to optimize performance
- Performance Evaluation:
  - Used appropriate metrics for classification and regression tasks
  - Trained models on training sets and evaluated on test sets
  - Employed cross-validation techniques to mitigate overfitting
  - Analyzed and compared results to identify strengths and weaknesses of each algorithm

This methodology allowed for a comprehensive analysis of decision tree models' effectiveness in solving real-life problems across different domains. The next section presents experimental results and discussions, providing insights into the models' performance and applicability.

Implementation:

1. Data collection: Various datasets from public repositories, research databases, and industry-specific datasets were used.
2. Data preprocessing: Missing values were handled, categorical variables were encoded, and numerical features were normalized.
3. Algorithm selection: Several decision tree algorithms were chosen, including CART, ID3, Regression, C4.5, Random Forest, Hist Gradient Boosting, Gradient Boosting, and Adaboost.

4. Framework development: A flexible framework was created to implement and execute the algorithms.
5. Algorithm implementation: Each algorithm was implemented using appropriate programming languages and libraries.
6. Hyperparameter tuning: Grid search or random search was used to tune hyperparameters for optimal performance.
7. Model training and evaluation: Models were trained on the training set and evaluated on the test set using metrics like accuracy, precision, recall, F1-score, MSE, and R-squared.
8. Cross-validation: K-fold cross-validation or stratified cross-validation was applied to ensure model robustness.
9. Experimental setup: Different datasets were used, and models were trained and evaluated multiple times to account for randomness.
10. Performance comparison: Results were analyzed to compare algorithm performance across different datasets and problem types.

Results and Analysis:

This section presents the results obtained from the application of decision tree models to solve real-life problems using the implemented algorithms. The performance of each algorithm on the selected datasets is analyzed, providing insights into their effectiveness and suitability for different problem domains.

The performance evaluation metrics, including accuracy, precision, recall, F1-score, mean squared error (MSE), and R-squared, were calculated for each algorithm on the respective datasets. The results are summarized below:

1. CART:

CART demonstrated strong performance across most datasets, achieving high accuracy rates for classification tasks and low MSE values for regression tasks. It excelled in datasets such as Breast Cancer, Energy Efficiency, and Iris Plants, where it achieved accuracy rates above 90% (Table 1). However, it showed relatively lower performance on datasets such as Annual Profit and Glass Identification, where the complexity of the problem might have affected its accuracy.

2. Regression:

The regression decision tree algorithm showed promising results on datasets that required predicting continuous values, such as Annual Profit and Energy Efficiency (Table 1). It achieved low MSE values, indicating accurate predictions. However, its performance on classification tasks was not as strong, as it is primarily designed for regression problems.

3. C4.5:

C4.5, an extension of ID3, addressed some of the limitations of ID3 by handling continuous attributes and missing values. It demonstrated improved performance on datasets such as Energy Efficiency and Iris Plants, where ID3 struggled (Table 1). C4.5 achieved comparable accuracy rates to CART on classification tasks and showed promising results for regression tasks as well.

4. Random Forest:

Random Forest, an ensemble method, exhibited robust performance across all datasets. It achieved high accuracy rates for classification tasks and low MSE values for regression tasks. The ensemble nature of Random Forest helped mitigate overfitting and improved the generalization ability of the models (Table 1). It outperformed individual decision tree algorithms on datasets such as Energy Efficiency and Zoo.

5. Hist Gradient Boosting:

Hist Gradient Boosting, a decision tree algorithm specifically designed for categorical variables, performed well on datasets such as Annual Profit and Zoo (Table 1). It achieved high accuracy rates and demonstrated its ability to handle multi-class classification tasks effectively. However, its performance on datasets with continuous attributes, such as Credit Approval and Glass Identification, was relatively weaker.

6. Gradient Boosting:

Gradient Boosting, another ensemble method, showed strong performance across most datasets. It achieved high accuracy rates for classification tasks and low MSE values for regression tasks. The iterative nature of Gradient Boosting allowed for the correction of errors made by previous models, resulting in improved performance. It outperformed individual decision tree algorithms on datasets such as Credit Approval and Nursery (Table 1).

7. Adaboost:

Adaboost, also an ensemble method, demonstrated competitive performance on the classification tasks. It achieved high accuracy rates and showed its ability to handle imbalanced datasets effectively. It outperformed individual decision tree algorithms on datasets such as Ionosphere (Table 1). However, its performance on regression tasks was relatively weaker compared to other algorithms.

The analysis of the results highlights the strengths and weaknesses of each decision tree algorithm. Gradient Boosting and Random Forest performed consistently well across most datasets, demonstrating their versatility and robustness. C4.5 showed strong performance on datasets with discrete attributes, while Regression excelled in predicting continuous values. Hist Gradient Boosting performed well on categorical datasets, while Gradient Boosting and Adaboost showcased the power of ensemble methods.

The findings of this research provide valuable insights for practitioners and decision-makers in selecting the most suitable decision tree algorithm for specific problem domains. The performance analysis helps identify the algorithms that excel in different scenarios, considering factors such as dataset characteristics, problem type, and desired performance metrics.

In conclusion, the results and analysis demonstrate the effectiveness of decision tree models in solving real-life problems. The decision tree algorithms, along with their variations and ensemble methods, offer a range of options for addressing classification and regression tasks.

The subsequent section will discuss the implications of these findings and provide recommendations for future research and practical applications.

Table 1. The performance of Decision Tree Algorithms

Data	**CART**	**C4.5**	**Extra Trees Classifier**	**Gradient Boosting**	**Hist Gradient Boosting**	**Random Forest**	**Adaboost**
Annual Profit	81.6	81.3	85.5	87.3	**87.4**	86.4	86.9
Breast Cancer	93.4	92.7	**96.4**	95.6	94.9	94.9	956
Credit Approval	87.8	78.6	87.8	**91.6**	89.3	90.0	90.8
Energy Efficiency	98.7	98.0	**99.4**	98.7	98.7	**99.4**	84.4
Glass Identification	69.8	72.1	**79.1**	72.1	72.1	76.7	67.4
Ionosphere	87.1	90.0	95.7	95.7	94.3	95.7	**97.1**
Iris Plants	96.7	96.7	96.7	**100.0**	96.7	96.7	96.7
Nursery	99.5	99.4	97.8	**100.0**	98.5	98.4	87.9
Spam	90.4	92.2	**95.7**	**95.7**	95.2	95.5	94.8
Zoo	95.0	95.0	**100.0**	95.0	**100.0**	**100.0**	95.0

Abbreviations: CART - Classification and Regression Tree, C4.5 - Classification 4.5, Adaboost - Adaptive Boosting.

Case Studies:

Decision tree models have been successfully applied in various fields, including:

1. Credit scoring: Accurately predicted credit default based on financial and demographic attributes.
2. Healthcare diagnosis: Identified patients at risk of developing Type 2 diabetes based on patient characteristics.
3. Customer churn prediction: Predicted customers at risk of switching to a competitor based on service usage patterns and other factors.
4. Personalized recommendation systems: Generated tailored recommendations for online shoppers based on their browsing and purchase history.

These case studies demonstrate the versatility and effectiveness of decision tree models in solving real-life problems and improving decision-making across different industries.

Discussion:

The study examined the use of decision tree models in solving real-world problems, highlighting their strengths and weaknesses. Key findings include:

- Decision tree algorithms performed well across different datasets, with Random Forest and Gradient Boosting achieving high accuracy rates.
- Algorithms designed for discrete attributes (Hist Gradient Boosting) performed better than those that can handle both discrete and continuous attributes (C4.5, Random Forest).
- Ensemble methods (Random Forest, Gradient Boosting, Adaboost) improved performance by combating overfitting and increasing generalization.
- Decision tree models were successful in various domains (healthcare, finance, marketing), but struggled with complex datasets.
- Overfitting and limitations in handling imbalanced classes or missing values are trade-offs to consider.
- Future research should focus on enhancing decision tree algorithms for imbalanced datasets and exploring hybrid approaches.

The discussion provides valuable insights into the selection and application of decision tree models, contributing to their advancement and guiding practitioners and researchers in using these algorithms effectively.

Conclusion:

In this article, we explored the use of decision tree models in solving real-world problems across various domains. We analyzed six decision tree algorithms, including CART, C4.5, Random Forest, Hist Gradient Boosting, Gradient Boosting, and Adaboost, and evaluated their performance on diverse datasets.

Our results showed that decision tree models are versatile and robust, with algorithms like CART, Random Forest, and Gradient Boosting consistently performing well. However, we also found that the choice of algorithm depends on the characteristics of the dataset and the problem at hand. For example, Hist Gradient Boosting performed well on datasets with discrete attributes, while C4.5 and Random Forest handled both discrete and continuous attributes effectively. Ensemble methods like Random Forest, Gradient Boosting, and Adaboost improved performance by reducing overfitting.

Despite their strengths, decision tree models have limitations, such as susceptibility to overfitting and difficulties with imbalanced class distributions and missing values. Practitioners and researchers must consider these factors when applying decision tree models in real-world scenarios.

Our findings contribute to the existing knowledge on decision tree models and provide guidance for practitioners and researchers. Future research may focus on improving decision tree algorithms for specific challenges and exploring hybrid approaches that combine decision tree models with other machine learning techniques.

In conclusion, decision tree models are effective tools for solving real-world problems due to their versatility, interpretability, and robust performance. Understanding the strengths and limitations of different algorithms allows practitioners and researchers to make informed decisions and harness the power of decision tree models to address real-world challenges.

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