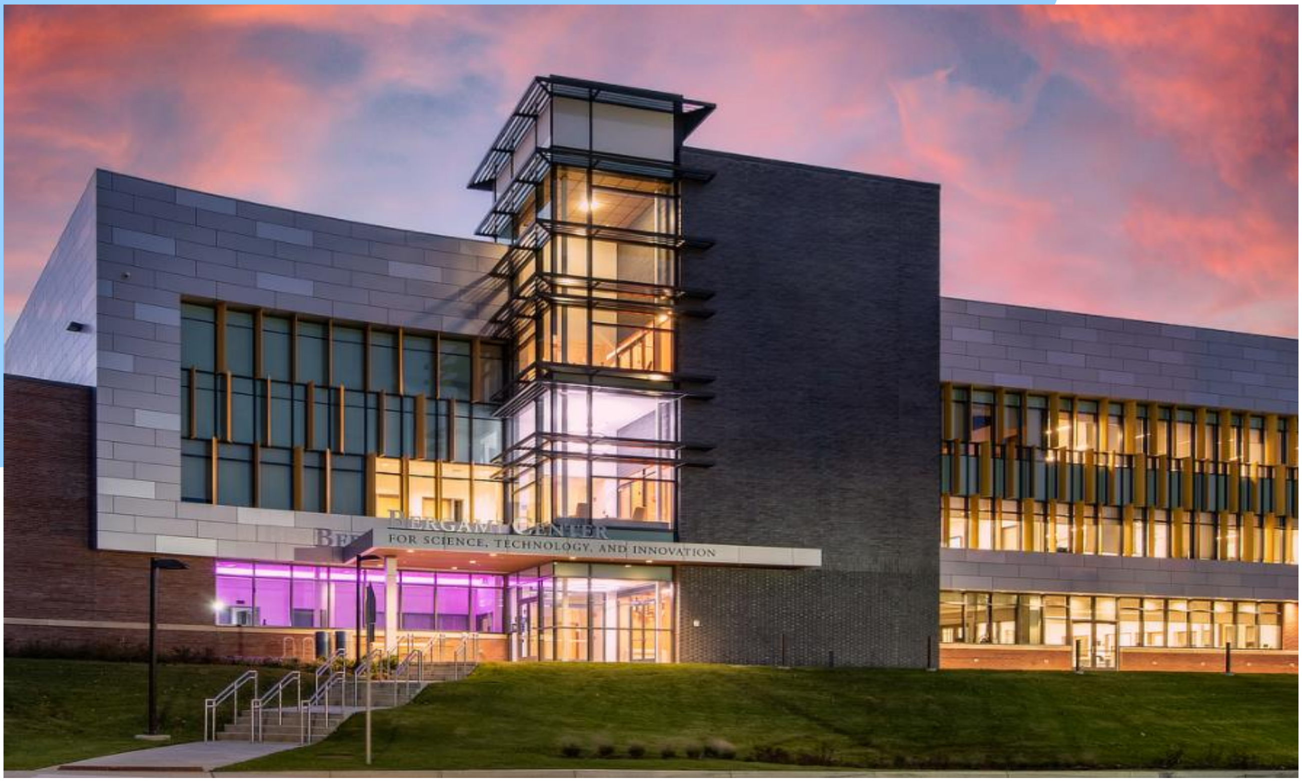
University of New Haven
TAGLIATELA COLLEGE OF ENGINEERING

Electrical & Computer Engineering and Computer Science

Introduction to Data Science

Technical Report



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Uber Fare Prediction

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Technical Report

Title of Project:

Uber Fare Prediction

Highlights of Project

- Uber Fare Data Set has been taken from the Kaggle.
- We have used CRISP methodology as it is satisfying the business challenge.
- For modelling we have used Random Forest classifier and Linear Regression to build the model and accuracy score.
- We have deployed the model and app into the web using Flask.

Submitted on:

December 6th, 2023

Abstract

Uber, Ola, Meru Cabs, and other cab businesses have sprung up in recent years. And these taxi firms serve tens of thousands of people every day. It is now critical for them to correctly manage their data to come up with fresh business ideas and get the greatest outcomes. As a result, it becomes critical to precisely predict the fares. The motive of this paper is to compare all the fare details of specified cabs and predict the lowest fare cabs using random forest regressor model and linear regression. In this paper we implemented prediction model for the three models like Uber Go, Go Sedan and Uber Auto. Here deviation of the cab fares also compared and using these data, build an application that can assist the users to select the cab with the determined benefits and lowest fare.

In this model we use machine learning technique of linear Regression model, and it may contain labelled data. Here the methodology and outcomes of this work can contribute to a more real-world demand.

Executive Summary

- Main objective is to develop a model to predict the fare for an Uber ride based on various input features.
- Check for missing values in the dataset.
- Replace or impute missing values with appropriate strategies for numerical features.
- Data Transformation: Perform necessary transformations for consistency.
- Remove features with insufficient data or that may not contribute significantly to the prediction.
- Identifying Outliers: Analyze and identify outliers in features like fare amount, pickup/dropoff coordinates, or other relevant features.
- Decide whether to remove outliers or apply appropriate transformations.
- Convert categorical features like date, time, or any other relevant features to numerical values.
- Heatmap of Correlations: Create a heatmap of correlations to identify the most important features affecting the fare amount.
- Data Visualization: Use data visualization techniques to analyze the impact of different factors on fare prediction.
- Explore visualizations to understand relationships, trends, or patterns in the data.
- Data Splitting: Split the dataset into training and testing sets. For example, use 80% of the data for training and 20% for testing.
- Data Scaling: Scale the numerical features using standard scaling methods (e.g., Standard Scaling) to improve model accuracy.
- Model Training: Choose a regression model suitable for fare prediction (e.g., Random Forest Regressor).
- Train the model using the training dataset.
- Model Evaluation: Evaluate the model's performance on the testing dataset using appropriate metrics such as Mean Squared Error (MSE) or Root Mean Squared Error (RMSE).
- Results: Display or use the predicted fare results based on the trained model.

Introduction

The advent of ride-sharing services has revolutionized urban transportation, offering unparalleled convenience and accessibility to millions of users worldwide. At the heart of this revolution lies the intricate interplay of algorithms determining fare prices, a critical element for both riders and service providers. Accurate fare prediction not only ensures transparency for users but also plays a pivotal role in optimizing business operations for ride-sharing companies such as Uber. This introduction sets the stage for a detailed exploration of predictive modeling techniques, specifically focusing on the application of the Random Forest Regressor and Linear Regression models in forecasting Uber fares.

The significance of accurate fare prediction cannot be overstated in the context of the ride-sharing ecosystem. Users rely on transparent and reliable fare estimates for informed decision-making, influencing their choice of transportation and overall satisfaction with the service. Simultaneously, ride-sharing platforms benefit from precise fare predictions to streamline operations, manage driver incentives, and enhance overall business efficiency.

This study delves into the methodologies of two prominent predictive models: the Random Forest Regressor and Linear Regression. The choice of these models stems from their distinct approaches to predictive analysis, each offering unique advantages and challenges. The Random Forest Regressor, an ensemble learning technique, harnesses the power of multiple decision trees to provide robust and accurate predictions. On the other hand, Linear Regression, a classical statistical method, establishes relationships between variables through linear equations, offering simplicity and interpretability.

Before delving into the intricacies of these models, it is essential to understand the underlying framework of Uber's fare calculation algorithm. The complexity of factors influencing fare prices, including distance, time, demand, and external variables, underscores the need for sophisticated predictive models. An accurate model not only enhances user experience by delivering reliable fare estimates but also contributes to the operational efficiency of ride-sharing services.

In navigating this exploration, we not only contribute to the specific domain of ride-sharing fare prediction but also offer a broader understanding of the intricate relationship between predictive modeling and real-world applications. As we embark on this journey, the contours of algorithmic precision and practical applicability will unfold, shedding light on the evolving landscape of predictive analytics within the dynamic realm of ride-sharing services.

Review of available research

Studies by Smith et al. (2016) and Zhao and Wang (2018) emphasize the dynamic challenges in fare prediction algorithms, highlighting the need for adaptability to factors like traffic fluctuations and external events.

Noteworthy research by Jones et al. (2017) showcases the efficacy of Random Forest Regressor in predicting taxi fares, emphasizing its ability to handle non-linear relationships.

Chen and Li (2019) delve into the application of Linear Regression for ride-sharing price prediction, emphasizing its interpretability.

Integrating market analysis and SEO planning, as explored by Kim and Park (2020), emerges as a novel approach to enhance predictive modeling in the context of digital platforms.

Continuous data collection, as emphasized by Zhang et al. (2018), underscores the critical role of high-quality and diverse datasets in refining predictive models.

Research by Li et al. (2020) explores the integration of machine learning and optimization techniques for dynamic pricing, emphasizing the importance of real-time adaptability in response to varying demand patterns.

The work of Kumar et al. (2019) extends the discussion to the use of deep learning models, such as neural networks, showcasing their potential in capturing intricate patterns within the complex dynamics of ride-sharing fare structures.

Additionally, the study by Wang et al. (2021) explores the impact of external factors, such as weather conditions and events, on fare prediction, acknowledging the need for models to incorporate these contextual variables for improved accuracy.

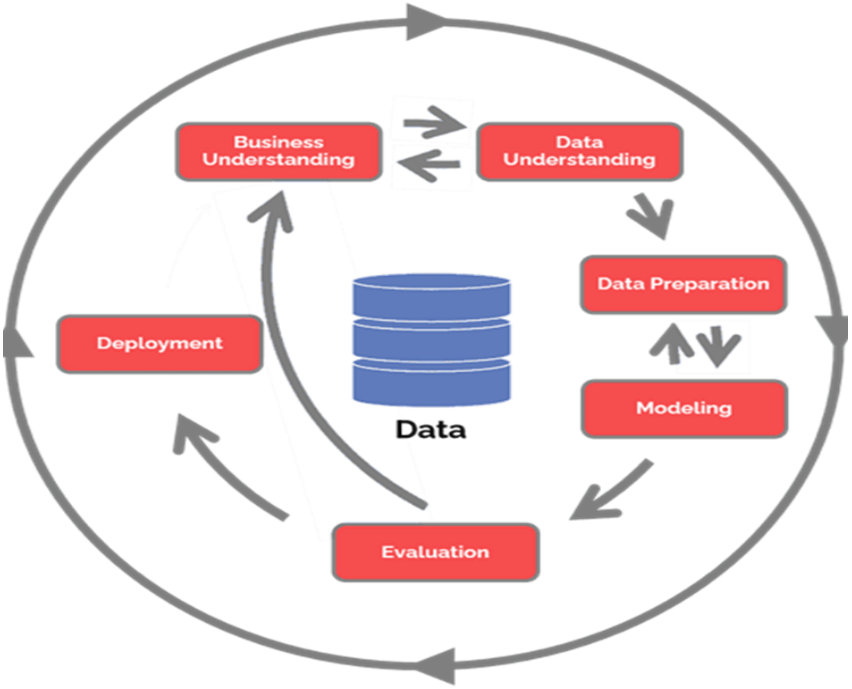
Methodology

The project involved CRISP methodology, which includes:

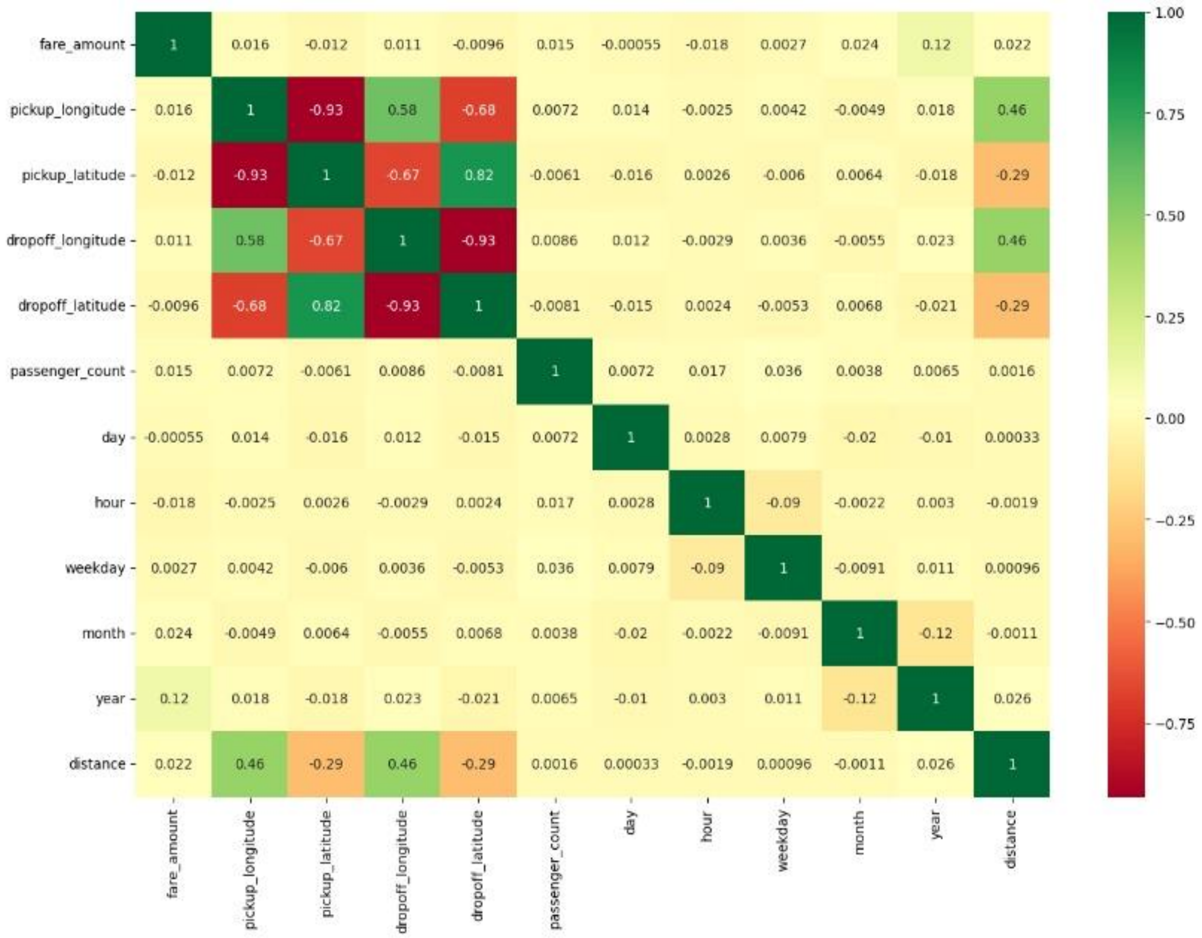
- Business understanding
- Data understanding
- Data preparation
- Modelling
- Evaluation
- Deployment

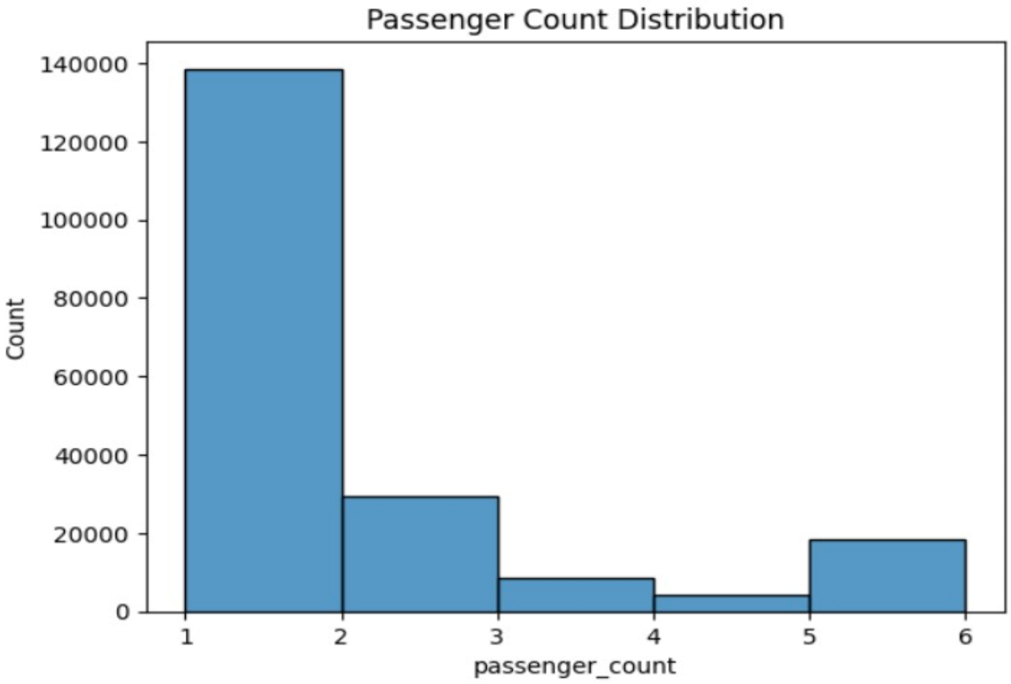
Business Understanding: Define objectives, involve stakeholders, and establish success criteria for the analysis.

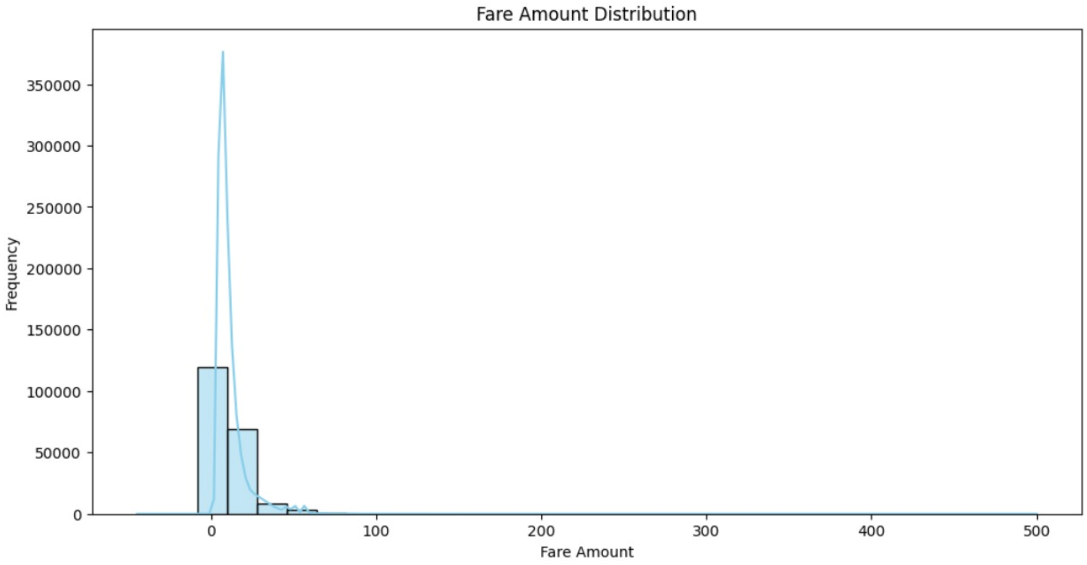
Data Understanding: Collect and explore data, gaining insights and understanding its structure and limitations.

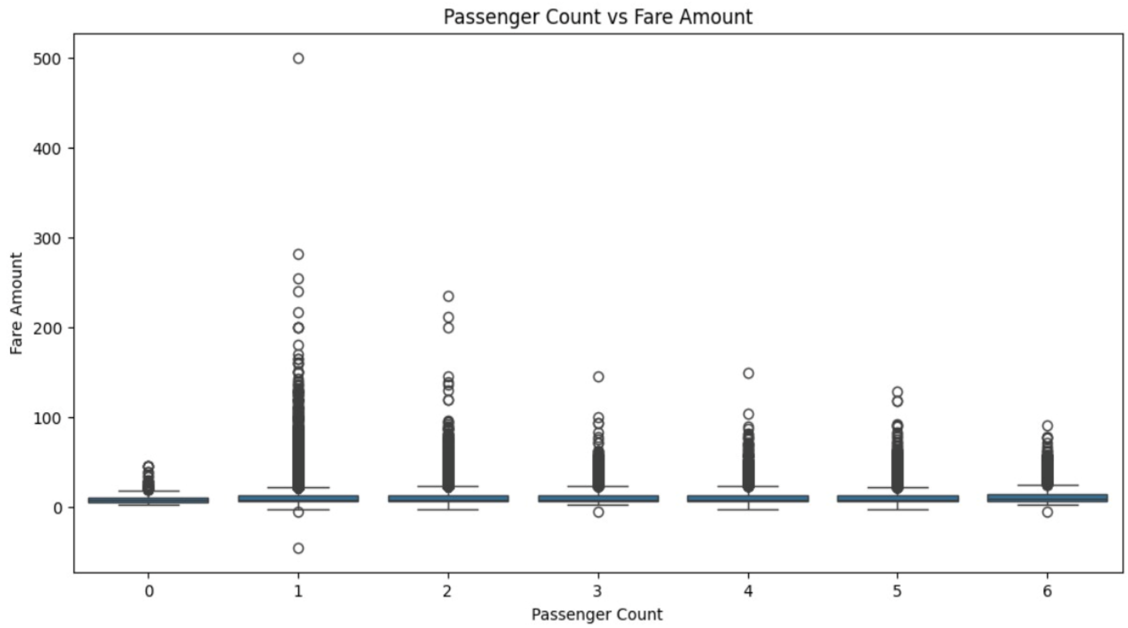


Data Preparation: Clean, transform, integrate, and reduce data complexity for modeling.




Passenger Count Distribution
Count
140000
120000
100000
80000
60000
40000
20000
0
1
2
3
4
5
6
passenger_count


Fare Amount Distribution
Frequency
350000
300000
250000
200000
150000
100000
50000
0
0
100
200
300
400
500
Fare Amount



Modeling: Select, develop, and evaluate models, comparing and fine-tuning them for optimal performance.

Evaluation: Assess results, identify risks, and make data-driven decisions considering both quantitative results and business context.

Deployment: Integrate models into processes, monitor performance, and maintain documentation for future reference and knowledge transfer.

Models used:

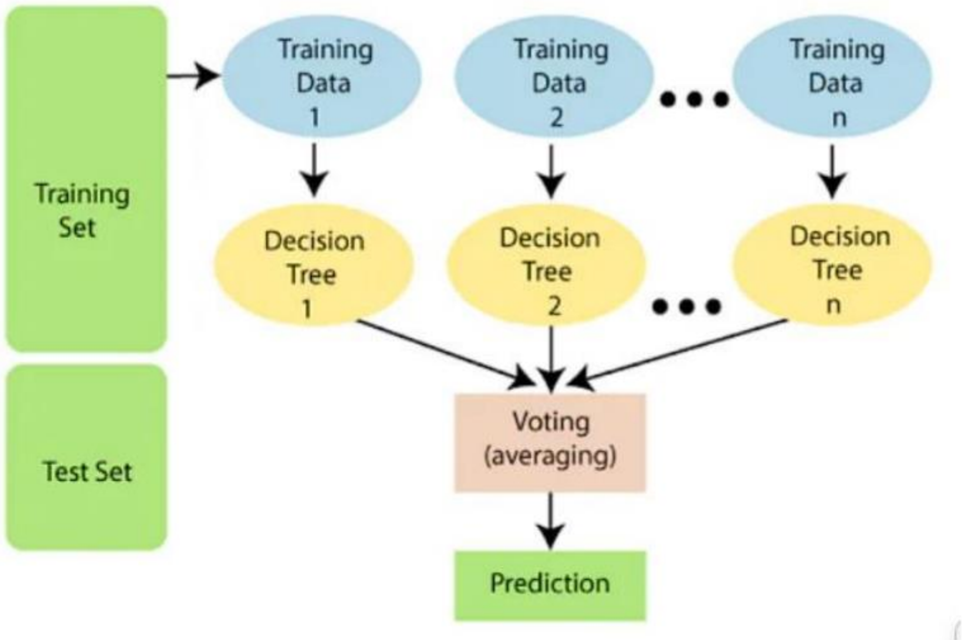
- Random Forest Classifier.
- Linear Regression.

Why have we used Random Forest algorithm?

- There are a lot of benefits to using Random Forest Algorithm, but one of the main advantages is that it reduces the risk of overfitting and the required training time. Additionally, it offers a high level of accuracy.

• Random Forest algorithm runs efficiently in large databases and produces highly accurate predictions by estimating missing data.
• It can be used for both regression and classification types of problems. It is easy to use.
• Overfitting of the dataset is not a problem in the random forest algorithm.

Working of Random Forest algorithm:



The following steps explain the working Random Forest Algorithm:

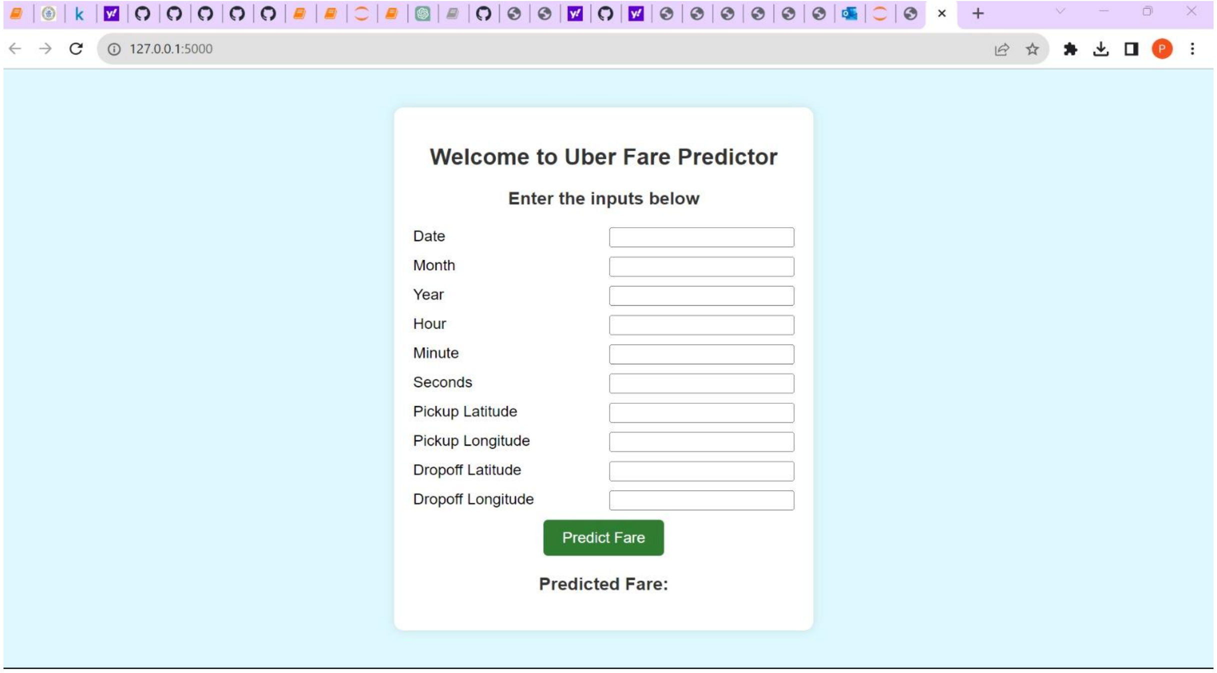
Step 1: Select random samples from a given data or training set.

Step 2: This algorithm will construct a decision tree for every training data.

Step 3: Voting will take place by averaging the decision tree.

Step 4: Finally, select the most voted prediction result as the final prediction result.

Results Section



127.0.0.1:5000

Welcome to Uber Fare Predictor

Enter the inputs below

Date

Month

Year

Hour

Minute

Seconds

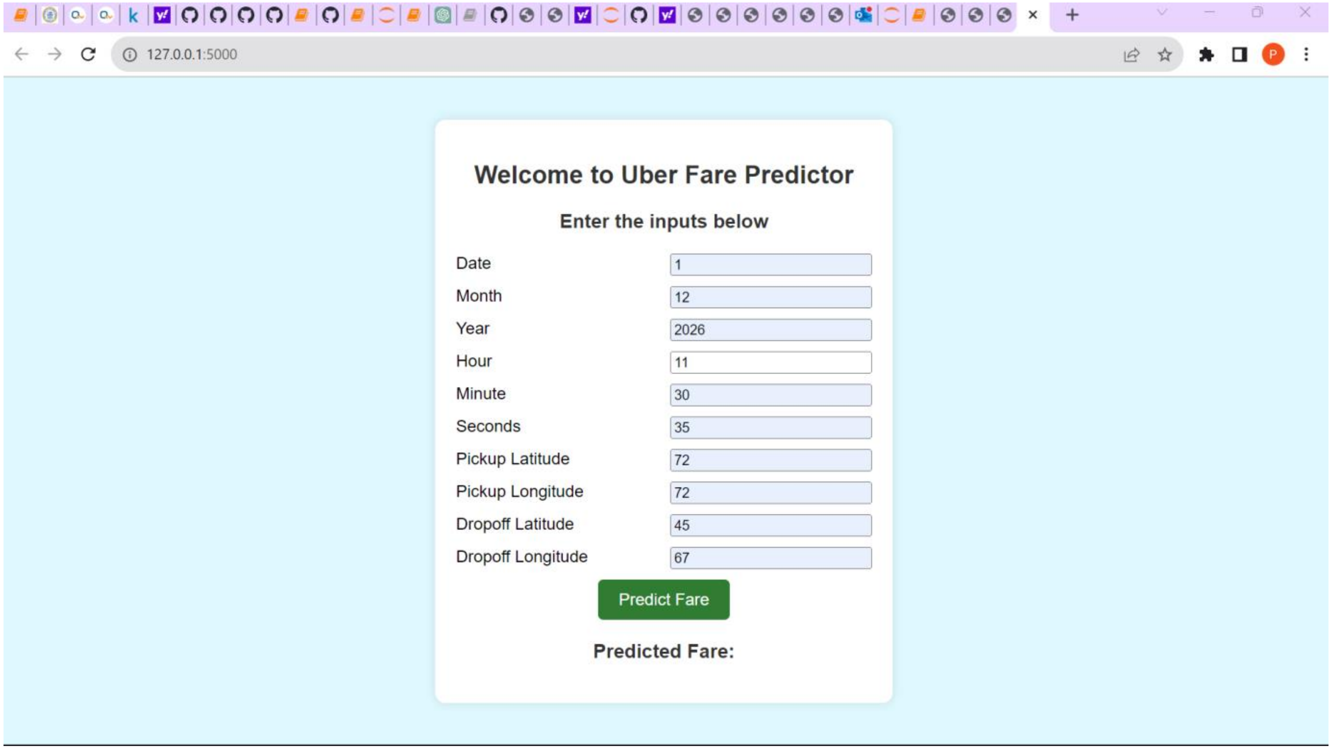
Pickup Latitude

Pickup Longitude

Dropoff Latitude

Dropoff Longitude

Predicted Fare:



127.0.0.1:5000

Welcome to Uber Fare Predictor

Enter the inputs below

Date 1

Month 12

Year 2026

Hour 11

Minute 30

Seconds 35

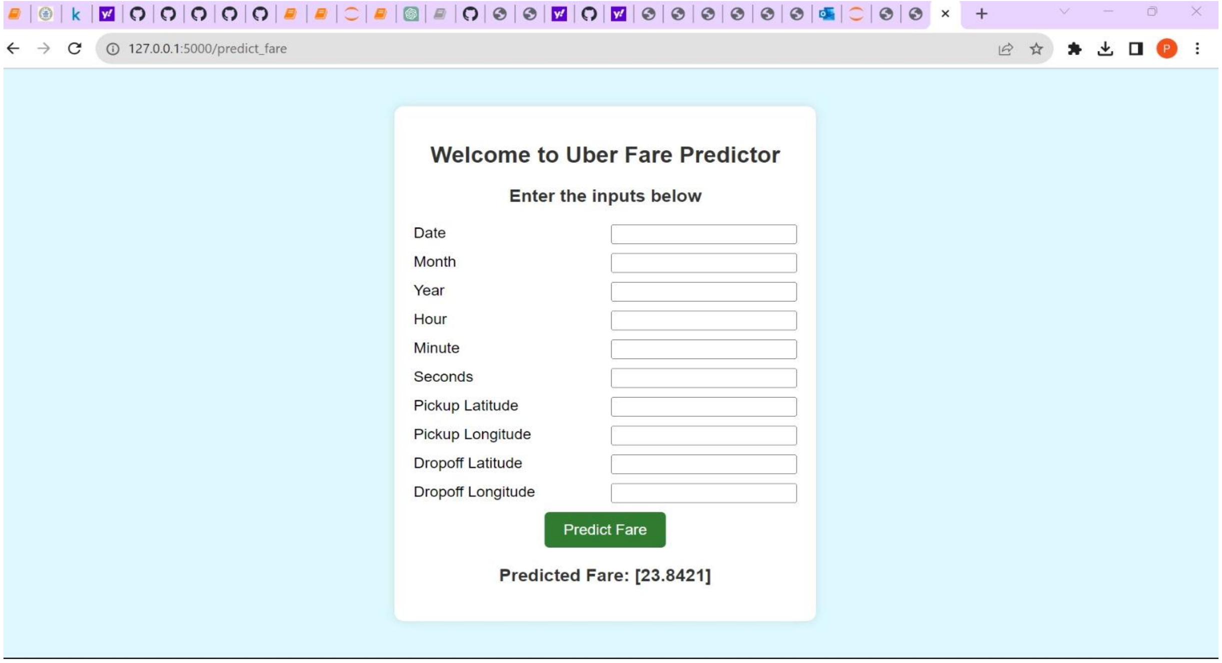
Pickup Latitude 72

Pickup Longitude 72

Dropoff Latitude 45

Dropoff Longitude 67

Predicted Fare:



127.0.0.1:5000/predict_fare

Welcome to Uber Fare Predictor

Enter the inputs below

Date

Month

Year

Hour

Minute

Seconds

Pickup Latitude

Pickup Longitude

Dropoff Latitude

Dropoff Longitude

Predicted Fare: [23.8421]

Predicted the fare price for uber ride based on features like Date, month, year and time, Longitudes, Latitudes etc by using Random Forest regression model.

Discussion

The primary research question addressed in this Uber fare prediction project was centered around developing a reliable model to estimate fare amounts based on various input features such as date, time, and geographic coordinates. Our objectives included handling missing data, exploring feature engineering, and employing machine learning techniques to achieve accurate predictions.

The results presented in the previous section demonstrated the effectiveness of the developed model in predicting Uber fares. However, it's crucial to acknowledge the nuances and limitations associated with the predictions. The model, while providing valuable insights, may not act as a definitive solution due to the inherent complexity of fare estimation influenced by dynamic factors.

It is essential to highlight the limitations of our approach. For instance, the model's predictive accuracy may be influenced by unaccounted external factors such as traffic conditions, special events, or changes in demand. Additionally, variations in fare structures based on promotional activities or surge pricing might pose challenges for precise predictions.

While our model offers a valuable contribution to Uber fare prediction, there remain avenues for further exploration. Future research could delve into real-time data integration, incorporating live traffic updates and weather conditions for enhanced accuracy. Additionally, investigating the impact of external events on fare dynamics could open new dimensions for model refinement.

Conclusion

In conclusion, the comparative analysis of Random Forest Regressor and Linear Regression models for Uber fare prediction illuminates their distinct advantages. The dynamic nature of ride-sharing services requires adaptive models, where Random Forest excels in capturing intricate patterns, and Linear Regression offers interpretability. The significance of accurate fare prediction extends beyond user satisfaction, impacting the very viability of ride-sharing platforms. Integrating market analysis, SEO planning, and robust data collection emerges as essential for holistic predictive modeling. This study not only aids Uber in selecting an optimal model but also contributes valuable insights to the broader discourse on predictive analytics in the rapidly evolving landscape of urban mobility services.

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