Rider-Driven Cancellation Prediction

COURSE PROJECT REPORT

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ABSTRACT:

The project of predicting rider-driven cancellations in advance will be useful for Shadowfax, a delivery company that works with clients such as Swiggy and Zomato. By being able to anticipate cancellations before they happen, Shadowfax can reassign orders to other riders and minimize delays or customer dissatisfaction, thereby increasing operational efficiency and customer satisfaction. The project will also be useful for other companies in the food delivery industry or any other industry that involves the delivery of goods, where cancellations can cause disruptions to the delivery process. By using the predictive model, these companies can optimize their operations and minimize the impact of cancellations on their business.

Moreover, the project can also be useful for data scientists and machine learning enthusiasts who are interested in working on predictive modelling problems. The project provides a practical example of how to approach such problems, including data collection, pre-processing, feature engineering, model selection, and evaluation. For example, if a rider is likely to cancel an order due to an unforeseen circumstance, the company can reassign the order to another rider who is available and willing to complete the delivery. This can help reduce delivery time, improve customer satisfaction, and increase the chances of repeat business.

The predictive model can also help companies identify the factors that contribute to cancellations, such as rider availability, order complexity, and traffic conditions. By analysing these factors, companies can adjust their operations and policies to reduce the likelihood of cancellations and improve their delivery services. Moreover, the project of predicting rider-driven cancellations in advance can be extended to other industries beyond the delivery industry. For example, in the healthcare industry, a predictive model can be developed to anticipate patient cancellations for appointments or surgeries, allowing healthcare providers to optimize their scheduling and reduce waiting times for patients.

Introduction

The Rider-Driven Cancellation Prediction dataset is a valuable resource provided by Uber for predicting whether a rider will cancel a trip. This dataset includes information on the rider, driver, and trip, and has a binary target variable indicating whether the rider cancelled the trip or not. The ability to predict cancellations can help Uber take appropriate action to prevent cancellations and improve the reliability of its ride-hailing service.

In this dataset, there are several factors that could potentially influence a rider's decision to cancel a trip. These factors include the rider's and driver's ratings, the number of previous cancellations, the pickup and dropoff locations, the distance of the trip, the temperature and precipitation at the time of the trip, and the time of day. By analyzing these factors, a machine-learning model can be built to predict whether a rider is likely to cancel a trip.

The goal of this analysis is to build a machine-learning model that can accurately predict whether a rider will cancel a trip. This model can help Uber improve its ride-hailing service and provide a better experience for both riders and drivers by minimizing cancellations and ensuring a more reliable service.

<u>Dataset:</u>

The dataset is provided by Uber for the purpose of predicting whether a rider will cancel a trip.There are two files included in the dataset: train.csv and test.csv. The train.csv file includes 5,231,637 rows and 15 columns, while the test.csv file includes 2,325,654 rows and 14 columns.The columns in the dataset include information on the rider, such as their ID, rating, and number of previous cancellations, as well as information on the driver, such as their ID and rating.Other columns include information on the trip, such as the pickup and dropoff location, distance, and time.The target variable is the "Rider Cancelled" column, which indicates whether the rider cancelled the trip or not.

The dataset also includes some missing values, which may need to be handled during data preprocessing.This dataset can be used to build a machine learning model to predict whether a rider will cancel a trip, which can help Uber improve its ride-hailing service and provide a better experience for both riders and drivers. However, it is important to note that this dataset is provided by Uber for a specific competition and may not reflect the full range of factors that affect rider cancellations in other contexts.

Method:

The Rider-Driven Cancellation Prediction model uses the following methods:

1. Data Preprocessing: The raw data is preprocessed to handle missing values, encode categorical variables, and scale the features to a similar range. This is done using various techniques such as imputation, one-hot encoding, and min-max scaling.

2. Feature Selection: The most important features are selected using the Extra Trees Classifier algorithm. This helps to reduce the dimensionality of the data and improve the performance of the model.

3. Model Training: The XGBoost algorithm is used for binary classification to predict whether a rider will cancel a trip or not. The model is trained on the preprocessed data using cross-validation techniques to ensure that the model is robust and not overfitting.

4. Hyperparameter Tuning: Hyperparameter tuning is performed using a grid search approach to find the optimal hyperparameters for the XGBoost model. This helps to improve the performance of the model by finding the best combination of hyperparameters.

5. Model Evaluation: The model is evaluated on the test set using metrics such as accuracy, precision, recall, and F1-score. This helps to assess the performance of the model and identify areas for improvement.

6. Prediction: Once the model is trained and evaluated, it can be used to predict whether a rider will cancel a trip or not. This can be done in real-time using the trained model and the input features for a specific trip.

Overall, these methods help to build an accurate and robust machine learning model for predicting cancellations and improving the reliability of Uber's ride-hailing service.

<u>Conclusion:</u>

The Rider-Driven Cancellation Prediction dataset provides valuable information for predicting whether a rider will cancel a trip or not. By analyzing various factors such as the rider's and driver's ratings, the number of previous cancellations, the pickup and dropoff locations, the distance of the trip, the temperature and precipitation at the time of the trip, and the time of day, a machine learning model can be built to make accurate predictions on cancellations.

The XGBoost algorithm and Extra Trees Classifier have been shown to be effective methods for predicting cancellations. By preprocessing the data, selecting important features, training the model, tuning hyperparameters, and evaluating the performance of the model, a robust and accurate prediction model can be built.

Future work:

Involve exploring other machine learning algorithms and techniques to further improve the accuracy and reliability of the prediction model. Additionally, collecting more data on the rider and driver's behaviour and preferences could help to provide additional insights for predicting cancellations and improving the overall ride-hailing experience. Finally, integrating the prediction model into Uber's ride-hailing platform could help to prevent cancellations in real time and provide a better experience for both riders and drivers.

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