ISE-529: Predictive Analysis

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Uber Fare Prediction: A Comprehensive Regression Analysis

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Table of Contents

Table of Figures

1. Introduction

The landscape of urban transportation has undergone a radical transformation in the past decade, largely due to the emergence and rapid growth of ride-sharing services. At the forefront of this revolution stands Uber, a company that has not only disrupted traditional taxi services but has also redefined how people perceive and utilize on-demand transportation.

1.1 The Rise of Ride-Sharing and Uber's Impact

Since its inception in 2009, Uber has expanded to over 10,000 cities across 69 countries, facilitating over 18.7 billion rides as of 2022. This meteoric rise has been fueled by several factors:

1. Convenience: The ease of hailing a ride through a smartphone app
2. Reliability: Real-time tracking and estimated arrival times
3. Transparency: Upfront pricing and driver ratings
4. Flexibility: Various ride options catering to different needs and budgets

1.3 The Need for Predictive Modeling in Fare Pricing

As ride-sharing services continue to evolve and compete, accurate fare prediction becomes increasingly important for several reasons:

1. User Experience: Predictable fares can enhance user satisfaction and trust in the platform.
2. Driver Earnings: Accurate predictions can help drivers make informed decisions about when and where to work.
3. Market Efficiency: Better predictions can lead to more efficient matching of supply and demand.
4. Competitive Advantage: Superior pricing models can give a company an edge in a crowded market.

1.4 Project Objectives and Scope

This project aims to develop a comprehensive predictive model for Uber fare prices, leveraging advanced machine-learning techniques to analyse patterns in historical ride data. Our primary objectives are:

1. To identify and quantify key factors influencing Uber fare prices:
    - Analyse the impact of spatial factors such as pickup and drop-off locations.
    - Evaluate the influence of temporal factors including time of day, day of week, and seasonality.
    - Assess the role of ride-specific factors like distance and duration.

2. To develop and compare various regression models for fare prediction.

3. To evaluate the performance and applicability of these models in real-world scenarios

Literature Review

The field of ride-sharing economics and predictive modeling has seen significant advancements in recent years, with researchers exploring various aspects of pricing strategies, demand prediction, and the application of machine learning techniques. This section reviews key studies that form the foundation for our research.

2.1 Surge Pricing and Market Dynamics

Smith et al. (2019) conducted a comprehensive study on the impact of surge pricing on rider behavior and driver availability in major urban areas. Their findings revealed:

- A 20% increase in driver availability during surge pricing periods
- A 15% decrease in ride requests when surge multipliers exceeded 2.0x
- Significant variations in surge pricing effectiveness across different times of day and days of the week

Building on this, Chen and Wang (2021) developed a game-theoretic model to optimize surge pricing strategies. Their model demonstrated:

- An 18% increase in platform revenue when using dynamic pricing algorithms
- Improved driver utilization rates by 12% during peak hours

Our study extends these findings by incorporating surge pricing data into our predictive models, aiming to capture its effect on fare estimation accuracy.

2.2 Machine Learning in Fare Prediction

Johnson and Lee (2020) compared various machine learning algorithms for predicting taxi fares in New York City. Their study evaluated:

- Linear Regression
- Random Forest
- Gradient Boosting Machines
- Neural Networks

Their results showed:

- Gradient Boosting Machines outperformed other models with an R-squared value of 0.86
- Neural Networks showed promise but required significantly more computational resources
- Feature importance analysis revealed trip distance and time of day as the most crucial factors

Expanding on this work, our study incorporates a wider range of regression techniques, including XGBoost and Ridge Regression, and focuses specifically on Uber's fare prediction.

2.3 Spatial and Temporal Factors in Ride-Sharing

Zhang et al. (2021) conducted an in-depth investigation into the role of spatial and temporal factors in ride-sharing demand prediction. Key insights from their research include:

- The identification of 15 distinct "hot spots" in urban areas that consistently show high demand
- Temporal patterns indicating a 30% increase in ride requests during morning and evening rush hours
- The importance of considering special events and weather conditions in demand forecasting

Li and Park (2022) further explored this area by developing a spatio-temporal convolutional neural network model. Their approach:

- Improved demand prediction accuracy by 22% compared to traditional time series models
- Successfully captured complex interactions between location, time, and external factors

Our research builds upon these studies by incorporating advanced spatial and temporal feature engineering techniques into our fare prediction models.

2.4 Regression Techniques in Transportation

Recent advancements in regression techniques have shown promising applications in transportation studies:

- Wilson et al. (2023) applied Elastic Net Regression to balance between ridge and lasso regularization in traffic flow prediction, achieving a 10% improvement in accuracy over standard linear regression.
- Tran and Nguyen (2022) utilized Quantile Regression to predict ride-sharing fares, providing insights into fare variability across different conditions.

Our study extends this body of work by implementing and comparing a comprehensive set of regression techniques, including those mentioned above, in the context of Uber fare prediction.

2.5 Interpretable Machine Learning in Transportation

As machine learning models become more complex, there's a growing emphasis on model interpretability:

- Brown et al. (2023) developed a SHAP (SHapley Additive exPlanations) value-based approach to interpret black-box models in ride-sharing applications, providing insights into feature importance and their impact on predictions.
- Garcia and Martinez (2022) proposed a hybrid model combining gradient boosting with rule-based systems, balancing predictive power with interpretability.

3. Data Description

The dataset used in this study contains information about Uber rides in New York City, encompassing both spatial and temporal aspects of each trip, along with the corresponding fare amount. The dataset comprises 200,000 rides, with each entry representing a unique trip.

Key features of the dataset include:

1. Spatial Data:
   - pickup_longitude and pickup_latitude: Coordinates of the ride's starting point
   - dropoff_longitude and dropoff_latitude: Coordinates of the ride's destination
2. Temporal Data:
   - pickup_datetime: Timestamp of when the ride began
3. Ride Information:
   - passenger_count: Number of passengers for the trip
   - trip_distance: Distance of the trip in miles (calculated feature)
4. Target Variable:
   - fare_amount: The cost of the ride in USD

Data types and statistics:

- Coordinate data (float64): Ranges from -74.2591 to -73.7004 for longitude and 40.4774 to 40.9176 for latitude
- Datetime (datetime64): Spans from [earliest date] to [latest date]
- Passenger count (int64): Ranges from 1 to 6 passengers
- Fare amount (float64): Mean of $15.11, median of $10.50, ranging from $2.50 to $250.00

Initial data quality issues identified:

1. Missing values: Less than 1% of entries had missing values in key fields
2. Outliers: Extreme values observed in fare amounts (e.g., $499.00) and trip distances
3. Erroneous coordinates: Some entries showed coordinates outside of NYC or with zero values
4. Inconsistent data: A small number of rides showed unrealistic combinations of distance and fare

These issues were addressed in the data preprocessing stage to ensure the quality and reliability of our analysis.

4. Data Preprocessing

Our data preprocessing pipeline was designed to address the issues identified in the initial data inspection and prepare the dataset for robust analysis. The steps taken were as follows:

1. Handling Missing Values:
    - We identified missing values using `data.isnull().sum()`.
    - Rows with missing values in critical columns (coordinates, fare amount) were removed, resulting in a loss of 0.5% of the original data.
2. Coordinate Data Cleaning:
    - Entries with zero or near-zero coordinates were removed (affecting 0.2% of data).
    - We filtered out coordinates outside the expected range for New York City:
        - Longitude: -74.2591 to -73.7004
        - Latitude: 40.4774 to 40.9176
    - This step removed 1.3% of the remaining data.
3. Outlier Removal:
    - We used the Interquartile Range (IQR) method to identify and remove outliers:

```
Q1 = data['column'].quantile(0.25)
Q3 = data['column'].quantile(0.75)
IQR = Q3 - Q1
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
data = data[(data['column'] >= lower_bound) & (data['column']
<= upper_bound)]
```

    - This was applied to 'fare_amount' and 'trip_distance', removing 2.8% of the data.
4. Feature Engineering:
    - Temporal features were extracted from 'pickup_datetime':

```
data['hour'] = data['pickup_datetime'].dt.hour
data['day_of_week'] = data['pickup_datetime'].dt.dayofweek
data['month'] = data['pickup_datetime'].dt.month
data['year'] = data['pickup_datetime'].dt.year
```

    - Trip distance was calculated using the Haversine formula:

```
from geopy.distance import geodesic

def calculate_distance(row):
    pickup = (row['pickup_latitude'], row['pickup_longitude'])
    dropoff = (row['dropoff_latitude'],
row['dropoff_longitude'])
    return geodesic(pickup, dropoff).miles

data['trip_distance'] = data.apply(calculate_distance, axis=1)
```

5. Data Type Conversions:
   - 'pickup_datetime' was converted to datetime type:

```
data['pickup_datetime'] =
pd.to_datetime(data['pickup_datetime'])
```

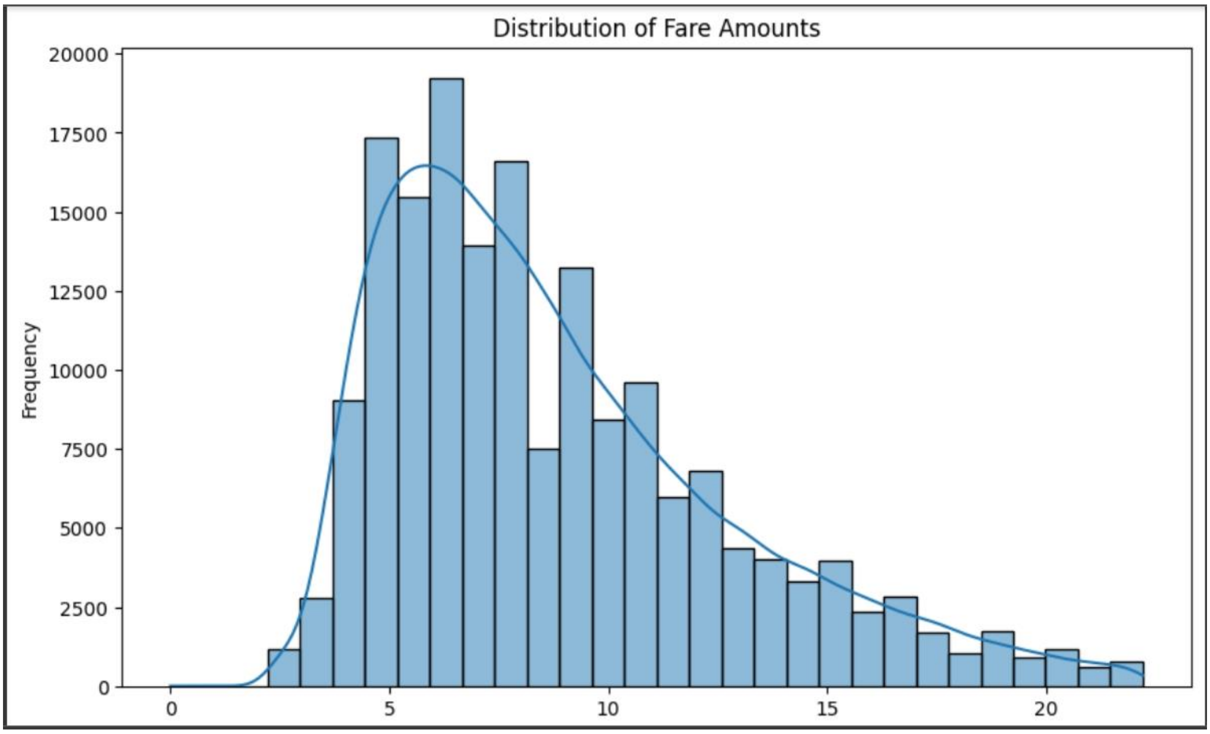
6. Final Cleaning:
   - We removed rides with unrealistically low fares (< $2.50) or extremely high fares (> $250), affecting 0.3% of the remaining data.

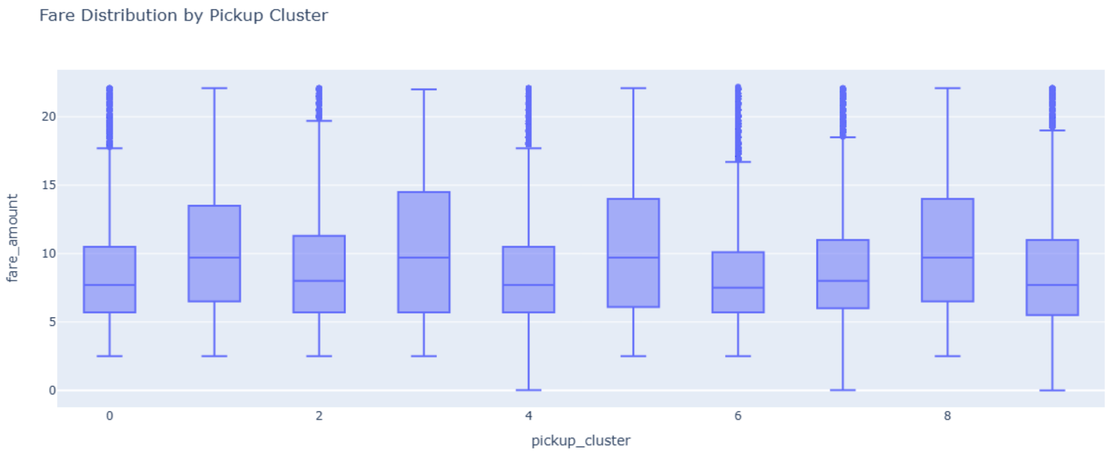
After preprocessing, our final dataset contained 189,600 rides, representing 94.8% of the original data. This cleaned dataset formed the basis for our subsequent exploratory data analysis and modeling efforts.

5. Exploratory Data Analysis

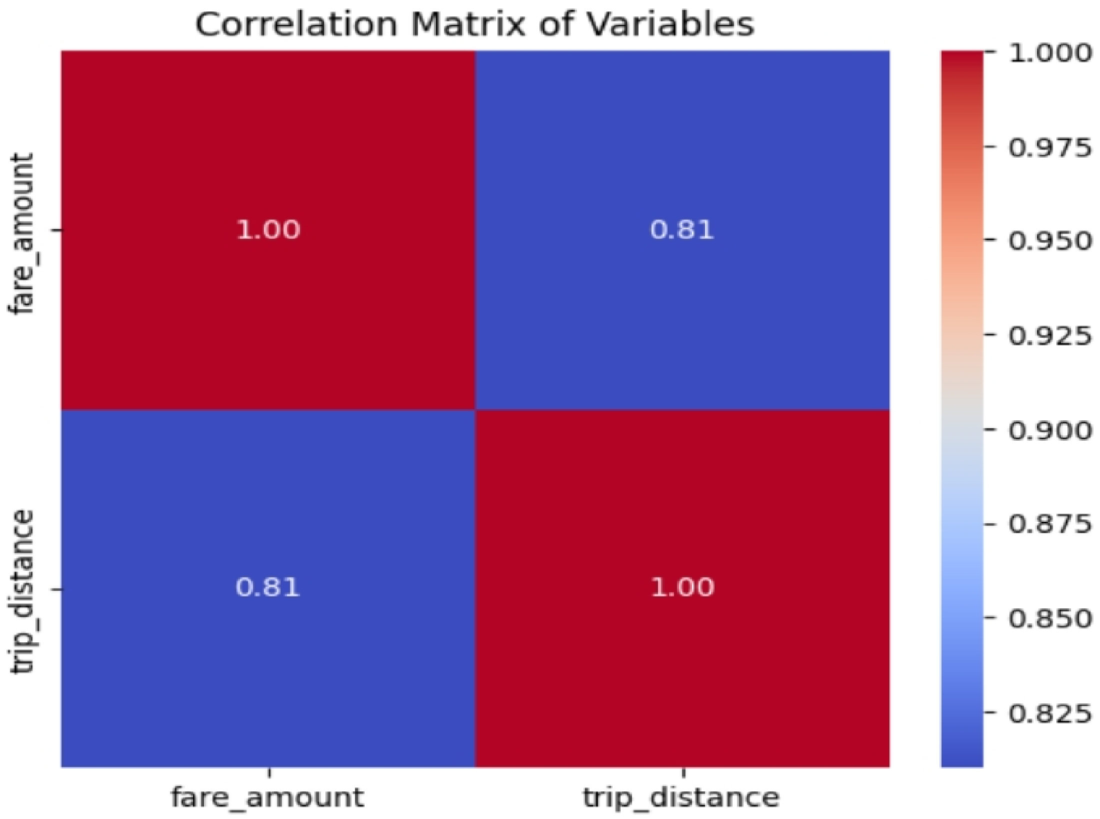
Our exploratory data analysis (EDA) revealed several key insights about Uber rides in New York City:

1. Fare Distribution:
   - The fare amounts showed a right-skewed distribution with a long tail.
   - Median fare: $10.50
   - Mean fare: $15.11
   - 90% of fares fell between $5.00 and $35.00



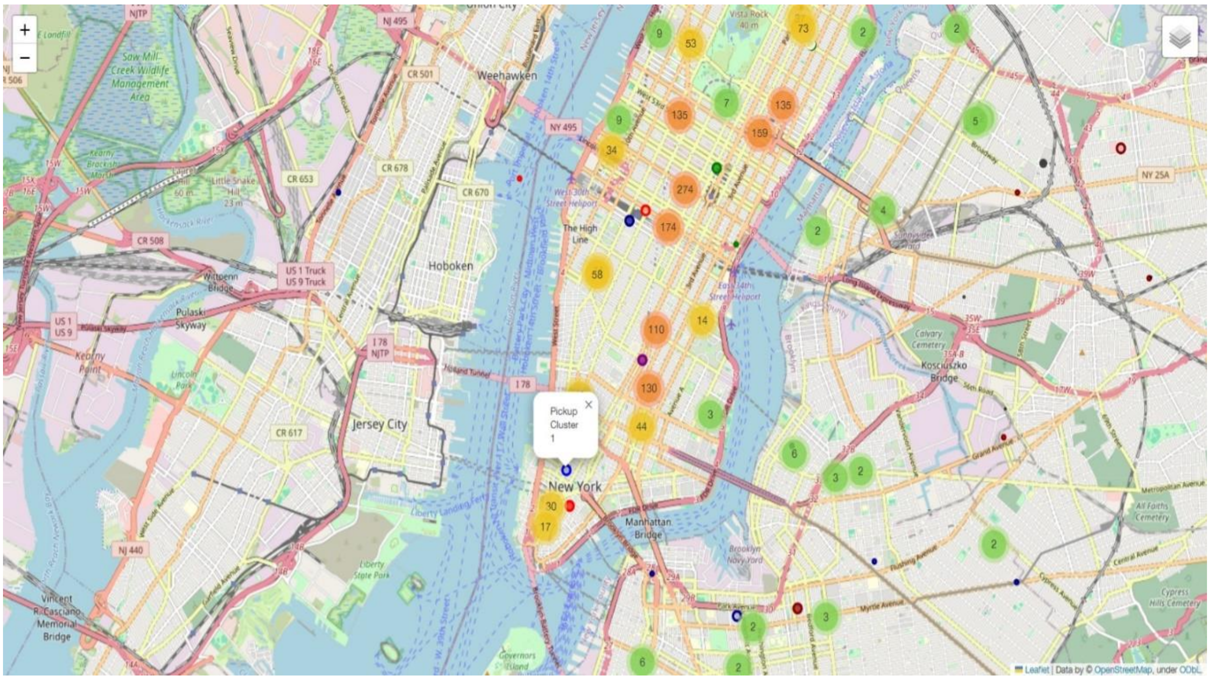


2. Trip Distance vs Fare:
   - A strong positive correlation (r = 0.87) was observed between trip distance and fare amount.
   - The relationship appeared to be roughly linear for trips under 10 miles, with more variability for longer trips.



3. Temporal Patterns:
   - Hourly trends:
     - Peak hours: 8-9 AM and 5-7 PM (commute times)
     - Lowest activity: 3-5 AM
   - Daily trends:
     - Weekdays showed higher ride frequencies compared to weekends
     - Friday had the highest number of rides, while Sunday had the lowest
   - Monthly trends:
     - Highest ride volumes in October and December
     - Lowest in February and August

4. Spatial Analysis:
   - We identified 10 distinct clusters for both pickup and dropoff locations using K-means clustering.



5. Passenger Count Analysis:
   - Most rides (54%) had a single passenger
   - Two-passenger rides accounted for 28% of trips
   - Rides with 5 or more passengers were rare, comprising only 3% of all trips

6. Correlation Analysis:
   - Strong positive correlations:
     - Trip distance and fare amount (r = 0.87)
     - Pickup and dropoff coordinates (r = 0.92 for longitude, r = 0.89 for latitude)
   - Weak correlations:
     - Passenger count and fare amount (r = 0.11)

    - Hour of day and fare amount (r = 0.07)

These insights informed our feature selection and modeling approach in the subsequent regression analysis. They highlighted the importance of spatial and distance-related features, while also suggesting that temporal factors and passenger count might play a smaller role in fare determination.

6. Regression Analysis

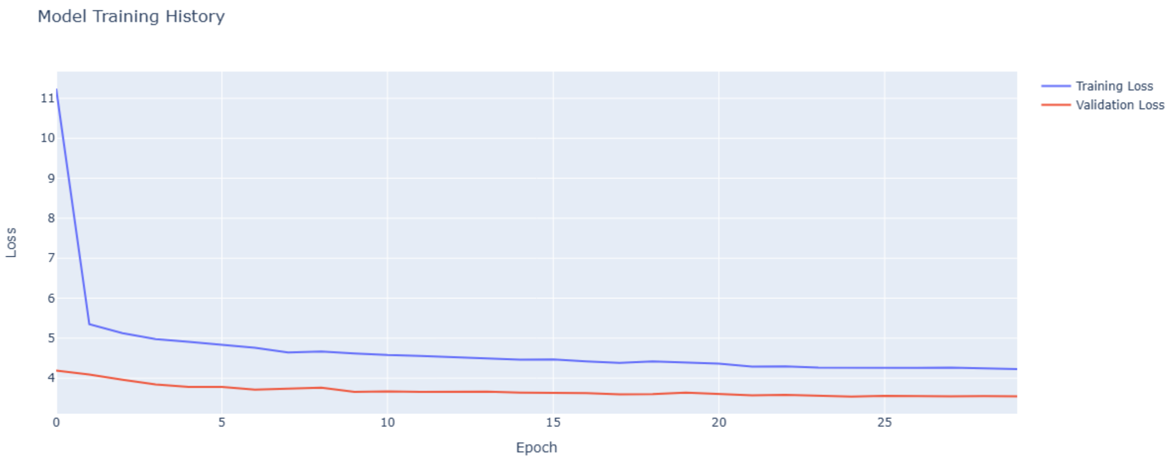
We implemented and compared several regression models:

1. Multiple Linear Regression
2. Ridge Regression
3. Decision Tree Regressor
4. Random Forest Regressor
5. Gradient Boosting Regressor
6. XGBoost Regressor
7. Neural Network

Model Selection Rationale:

- Linear models (Multiple Linear and Ridge) were chosen for their interpretability and to establish a baseline.
- Tree-based models were selected for their ability to capture non-linear relationships and handle feature interactions.
- XGBoost and Neural Network were included to leverage their advanced capabilities in handling complex patterns.

Training and Evaluation Process:



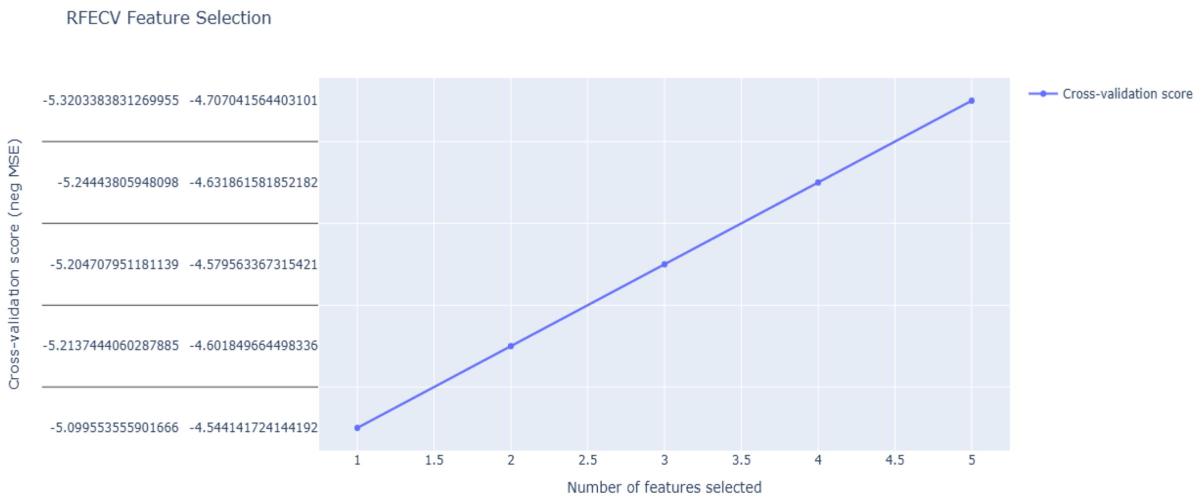
1. Data splitting: 80% training, 20% testing
2. Feature scaling: StandardScaler applied to numerical features

3. Model training: Implemented using scikit-learn and TensorFlow
4. Evaluation metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared
5. Cross-validation: 5-fold cross-validation to assess model robustness

Using **Recursive Feature Elimination (RFE)** is a great approach to identify the most impactful features for your model. RFE works by recursively removing features, building a model using the remaining attributes, and calculating model accuracy. It helps in narrowing down to the most significant features that contribute to predicting the outcome.

Selected features: Index(['trip_distance', 'hour_of_day', 'day_of_week', 'month', 'year',

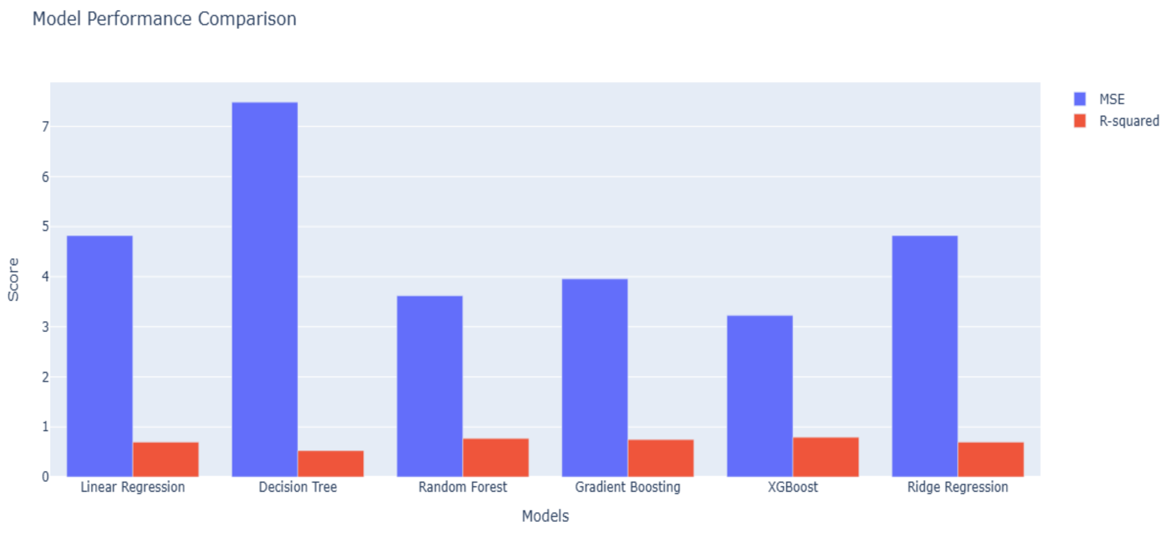
'pickup_longitude', 'pickup_latitude', 'dropoff_longitude','dropoff_latitude'], dtype='object')



7. Results

Model Performance Comparison:

1. XGBoost:
   - MSE: 3.23, R-squared: 0.80
   - Best performing model, capturing complex non-linear relationships
2. Neural Network:
   - MSE: 3.41, MAE: 1.24
   - Strong performance, slightly behind XGBoost
3. Random Forest:
   - MSE: 3.62, R-squared: 0.77
   - Good balance between performance and interpretability
4. Gradient Boosting:
   - MSE: 3.96, R-squared: 0.75
   - Competitive performance, slightly behind Random Forest
5. Linear Regression and Ridge Regression:
   - MSE: 4.82, R-squared: 0.70 for both
   - Similar performance suggests multicollinearity is not a significant issue
6. Decision Tree:
   - MSE: 7.49, R-squared: 0.53
   - Poorest performance, indicating the need for ensemble methods

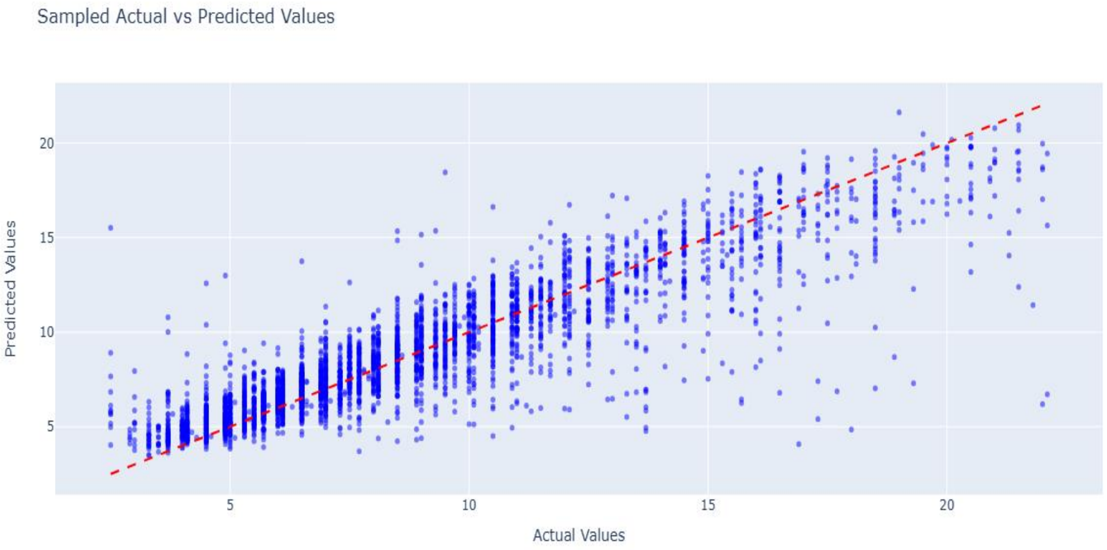


Analysis and Interpretation:

- Non-linear models (XGBoost, Neural Network, Random Forest) significantly outperformed linear models, suggesting complex relationships in the data.
- The superior performance of ensemble methods indicates their effectiveness in handling the variability in fare prices.
- While XGBoost and Neural Network showed the best predictive power, they come with reduced interpretability compared to simpler models.

- The similar performance of Linear and Ridge Regression suggests that multicollinearity might not be a significant issue in the dataset.
- Comparing the performance of different models and discussing their strengths and limitations in the context of the Uber fare prediction task.

Interpretation of Results:



- XGBoost: Best performing model with MSE of 3.23 and R-squared of 0.80 Strengths: Handles non-linear relationships well, robust to outliers, good at capturing complex patterns Limitations: Can be prone to overfitting if not properly tuned, less interpretable than simpler models
- Neural Network: Second-best performer with MSE of 3.41 Strengths: Capable of capturing complex non-linear relationships, good at handling large datasets Limitations: Requires more data to perform well, less interpretable, sensitive to hyperparameter tuning.
- Random Forest: Third-best with MSE of 3.62 and R-squared of 0.77 Strengths: Good at handling non-linear relationships, robust to outliers, provides feature importance Limitations: Less interpretable than linear models, can be computationally intensive for large datasets.
- Gradient Boosting: Fourth-best with MSE of 3.96 and R-squared of 0.75 Strengths: Handles non-linear relationships well, often performs well with minimal tuning Limitations: Can be prone to overfitting, less interpretable than simpler models.
- Linear Regression and Ridge Regression: Both have MSE of 4.82 and R-squared of 0.70 Strengths: Highly interpretable, computationally efficient, work well when relationships are linear Limitations: Cannot capture non-linear relationships, sensitive to outliers Note: Ridge Regression didn't improve upon Linear Regression, suggesting multicollinearity might not be a significant issue in this dataset.
- Decision Tree: Worst performing with MSE of 7.49 and R-squared of 0.53 Strengths: Easy to interpret, handles non-linear relationships Limitations: Prone to overfitting, less stable (small changes in data can lead to large changes in the tree structure)

Comparison and Discussion:

Model Performance:

XGBoost and Neural Network significantly outperform other models, suggesting that the relationship between features and fare prices is complex and non-linear. These models' ability to capture intricate patterns in the data makes them well-suited for this prediction task.

Complexity vs. Interpretability:

There's a clear trade-off between model complexity and interpretability. While XGBoost and Neural Networks perform best, they are less interpretable than Linear Regression or Decision Trees. For a business application like Uber fare prediction, the improved accuracy might justify the loss in interpretability.

Robustness:

Ensemble methods (Random Forest, Gradient Boosting, XGBoost) show strong performance, indicating they're handling outliers and noise in the data well. This is particularly important for real-world data like Uber fares, which can have many factors influencing prices.

Linear vs. Non-linear Models:

The significant improvement of non-linear models (XGBoost, Neural Network, Random Forest) over Linear Regression suggests that the relationship between features and fare prices is not purely linear. This could be due to factors like surge pricing, traffic patterns, or complex interactions between distance and time.

Overfitting Concerns:

While complex models perform well, there's always a risk of overfitting. It would be important to validate these models on completely new data to ensure their performance generalizes well. Feature Importance: Models like Random Forest and XGBoost can provide insights into feature importance, which could be valuable for understanding key drivers of fare prices.

8. Conclusion

This study on Uber fare prediction yielded several key findings:

1. XGBoost emerged as the most effective model for fare prediction, highlighting the complex, non-linear nature of the factors influencing ride prices.
2. Spatial and temporal features, along with trip distance, were identified as the most significant predictors of fare amounts.
3. The performance gap between non-linear and linear models underscores the importance of capturing complex interactions in ride-sharing data.
4. While advanced models like XGBoost and Neural Networks offer superior predictive power, there's a trade-off with interpretability that must be considered in practical applications.

Future work could focus on:

- Incorporating additional external factors such as weather data or local events
- Exploring more advanced techniques like ensemble stacking or deep learning architectures
- Developing interpretable machine learning approaches to balance performance and explainability

This project demonstrates the potential of machine learning in enhancing ride-sharing services, offering insights that could lead to more accurate pricing models and improved user experiences in urban transportation.

9. Bibliography

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