### **UBER FARE PREDICTION**

USING REGRESSION ANALYSIS

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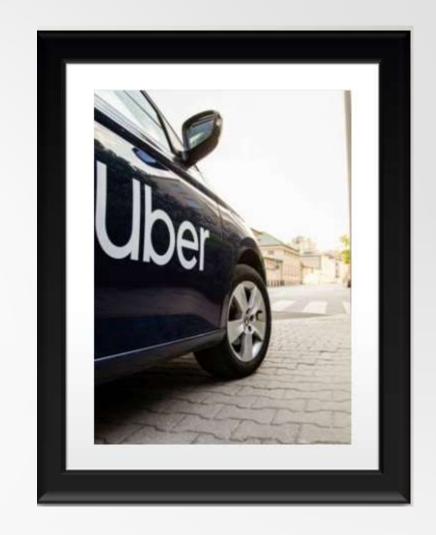
### **AGENDA**

- Introduction
- 2. Data Preprocessing and Exploration
- 3. Exploratory Data Analysis (EDA)
- 4. Regression Modeling
- 5. Model Evaluation and Insights
- 6. Recommendations

## INTRODUCTION

### **Project Objective**

The goal of this project is to predict Uber fare prices for future rides. Accurate fare prediction is crucial for enhancing customer satisfaction and operational efficiency.



### **Dataset Description**

The dataset contains 200,000 rows and 9 columns. Key fields include:

- •Key: A unique identifier for each trip.
- •Fare Amount: The cost of each trip in USD.
- •Pickup Datetime: Date and time when the meter was engaged.
- •Passenger Count: Number of passengers in the vehicle.
- •Pickup Longitude/Latitude: Geographic coordinates where the trip started.
- •Dropoff Longitude/Latitude: Geographic coordinates where the trip ended.

## **DATA PREPROCESSING**

#### **Libraries Used**

Libraries such as NumPy, Pandas, Matplotlib, and Seaborn were employed for data processing and visualization.

### **Data Loading**

The dataset was loaded into a Pandas DataFrame (df) from the uber.csv file.

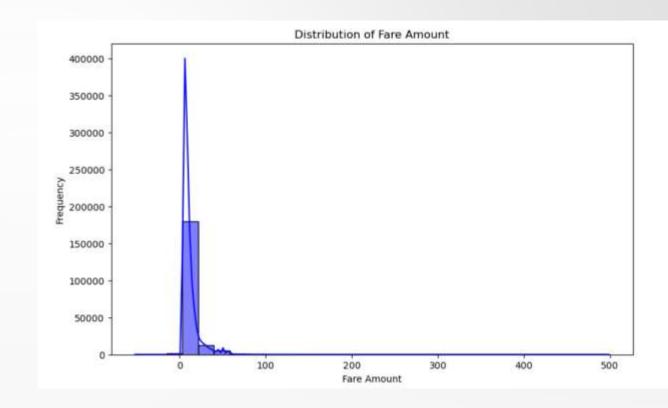
### **Steps Taken:**

- Initial Exploration: Checked column names, data types, and dataset shape.
- Handling Missing Data: Removed rows with null values to ensure data integrity.
- **Feature Engineering**: Added a distance column using the Haversine formula to calculate the distance between pickup and dropoff points.

### **EXPLORATORY DATA ANALYSIS**

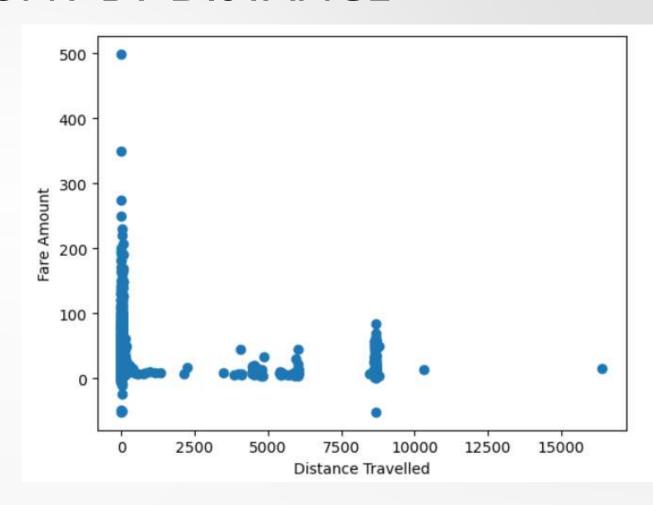
### DISTRIBUTION OF FARE AMOUNT

The histogram shows that the majority of fare amounts are concentrated between 0 and 20, indicating that most trips are short-distance or low-cost.



### LINE PLOT: FARE AMOUNT BY DISTANCE

- We can get rid of the trips with very large distance that are outliers as well as trips with 0 distance.
- Removed row with non-plausible fare\_amount and distance travelled.
- Final dataset contains 193,481 rows and 10 columns.



### CORRELATION MATRIX

- Strong Positive Correlation Between fare\_amount and distance (0.89).
- This indicates that as the distance increases, the fare amount also increases, which is logical for ride fare prediction.



## **REGRESSION MODEL**

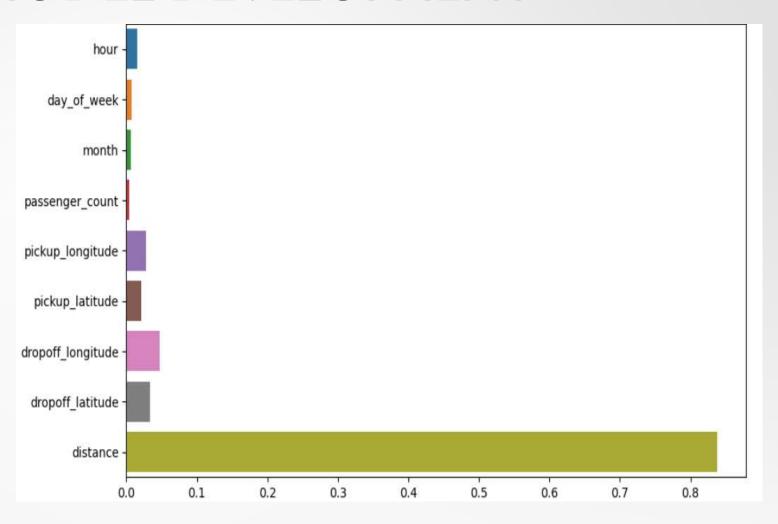
### REGRESSION MODEL DEVELOPMENT

#### **Feature Selection:**

 The derived distance feature showed a strong correlation with fare\_amount, making it a key predictor.

#### Model selection:

Random Forest Regression:
 Selected for its ability to handle both
 linear and non-linear relationships,
 making it well-suited for this dataset.



### **Model Evaluation Metrics**

**Mean Absolute Error (MAE)**: 2.32 (indicates low average error in predictions).

**Mean Squared Error (MSE)**: 18.50 (shows minimal large prediction errors).

R<sup>2</sup> Score: 0.794 (explains 79.4% of variance in fare\_amount).

### Recommendations

#### **Pricing Strategies**

- Dynamic Pricing: Implement a tiered system where longer rides offer discounted per-mile rates to attract more customers.
- **Short-Trip Discounts**: Offer loyalty points or discounts for frequent short-distance riders to encourage repeat usage.

#### **Operational Improvements**

- **Surge Pricing**: Introduce higher driver payouts and surge pricing during peak hours to ensure availability and meet demand.
- Outlier Detection: Deploy automated systems to flag and review outliers in real-time, improving fare
  accuracy.

#### **Customer Experience Enhancements**

- Fare Transparency: Display predicted fare ranges before trip confirmation to build customer trust.
- Shared Ride Incentives: Offer pricing incentives for shared rides, benefiting customers and maximizing driver earnings.

### Conclusion

- The project demonstrates high accuracy in predicting Uber fares, highlighting its potential to support real-world ride-hailing platforms.
- Practical recommendations are provided to enhance both customer satisfaction and operational efficiency.
- Future work could integrate additional contextual features, such as weather and traffic data, to make the model even more robust and adaptable across diverse scenarios.

# THANKYOU