An Analysis of Cyclist Bike Share Dataset

Term Paper for Business Intelligence II

Group 2 (Option 2)

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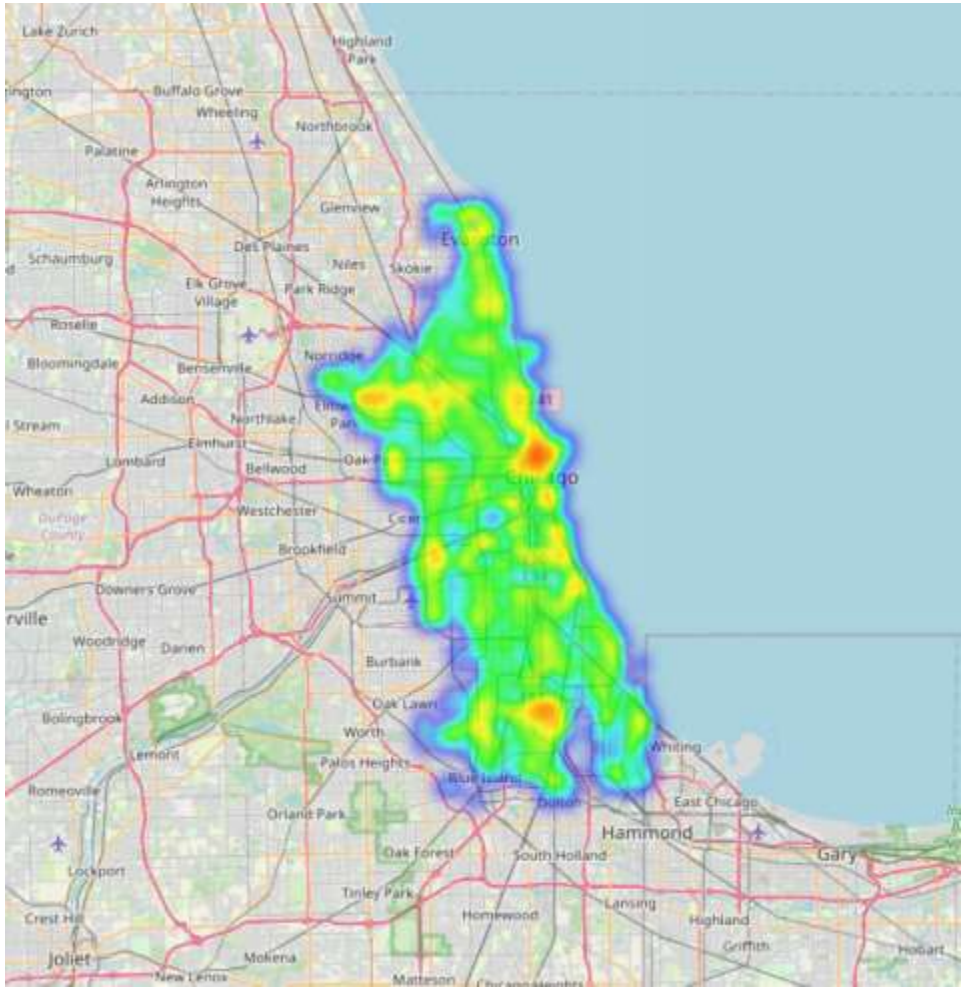
Member riders

Introduction

Dataset Description



12 months of public trip data from Divvy (Chicago's bike-share system)

5.7 Million individual rides analyzed

Key feature points:

— Ride start/end times and locations

— Bike type (Classic, Electric, Docked)

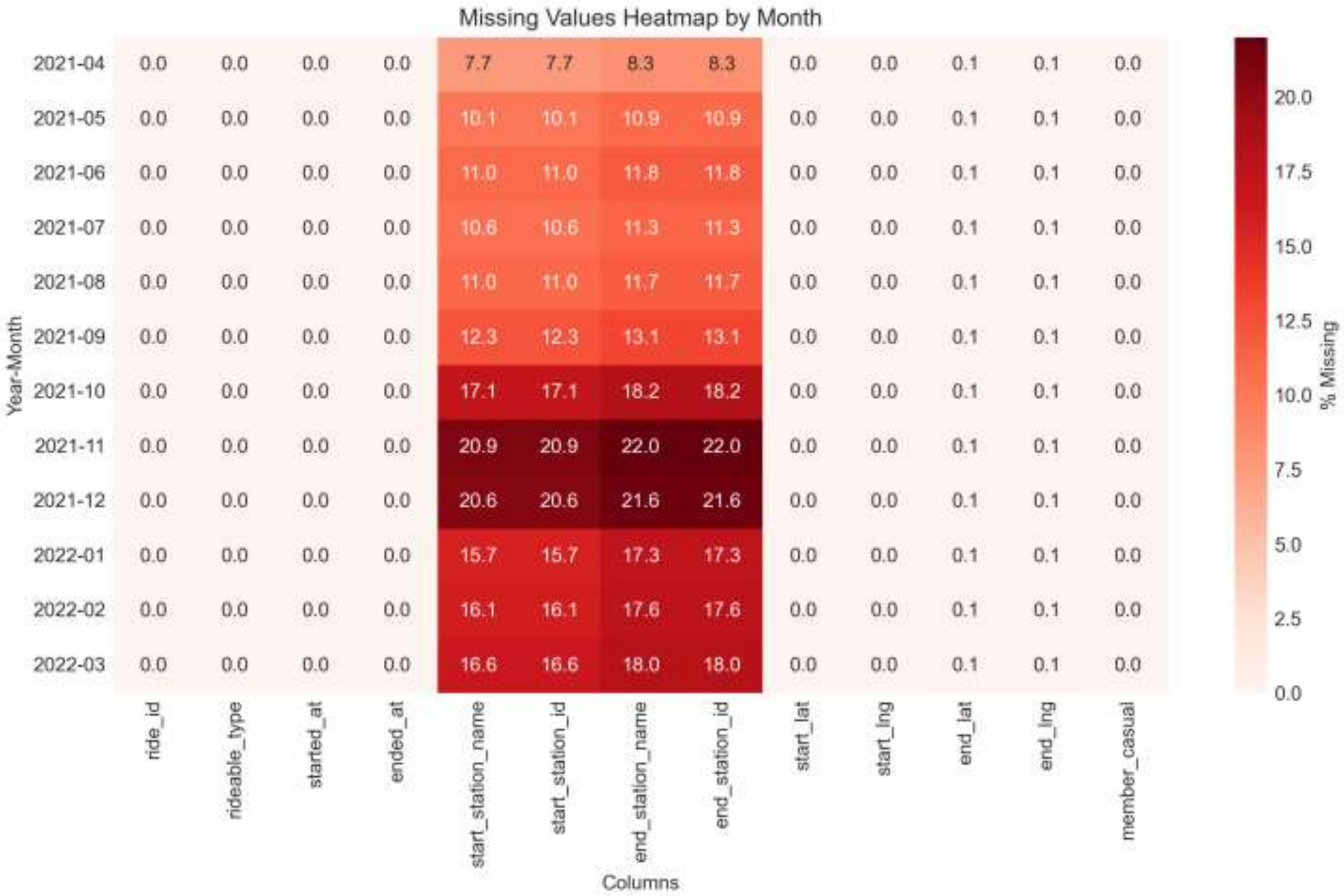
— Rider type (Casual vs. Member)

Data Preprocessing - Feature Engineering

1. Unification and Cleaning
   a) Combined *12 monthly files into one master dataset.*
   b) Handled missing station data by creating an „**Unknown**" category, presenving over *800,000 rides from dockless bikes.*
2. Feature Engineering
   a) Created new metrics like **ride duration, distance,** and **speed**
   b) Added temporal context: **hour, day of week**, and **rush hour flags**

Preprocessing - Missing Values

Summary of Missing Values



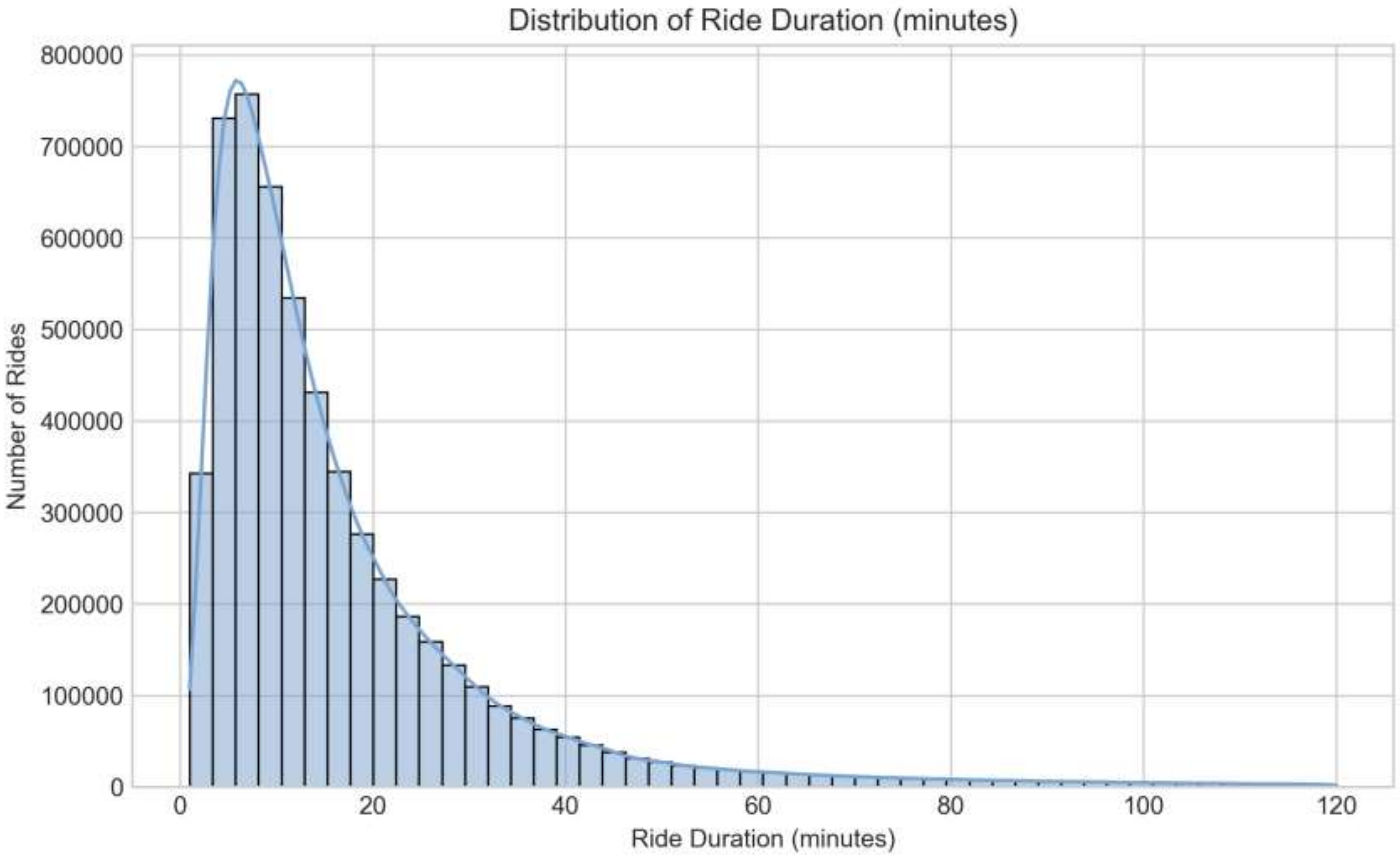
Classic Bikes – must be returned to a docking station.

Docked Bikes – picked up and returned at specific docking stations.

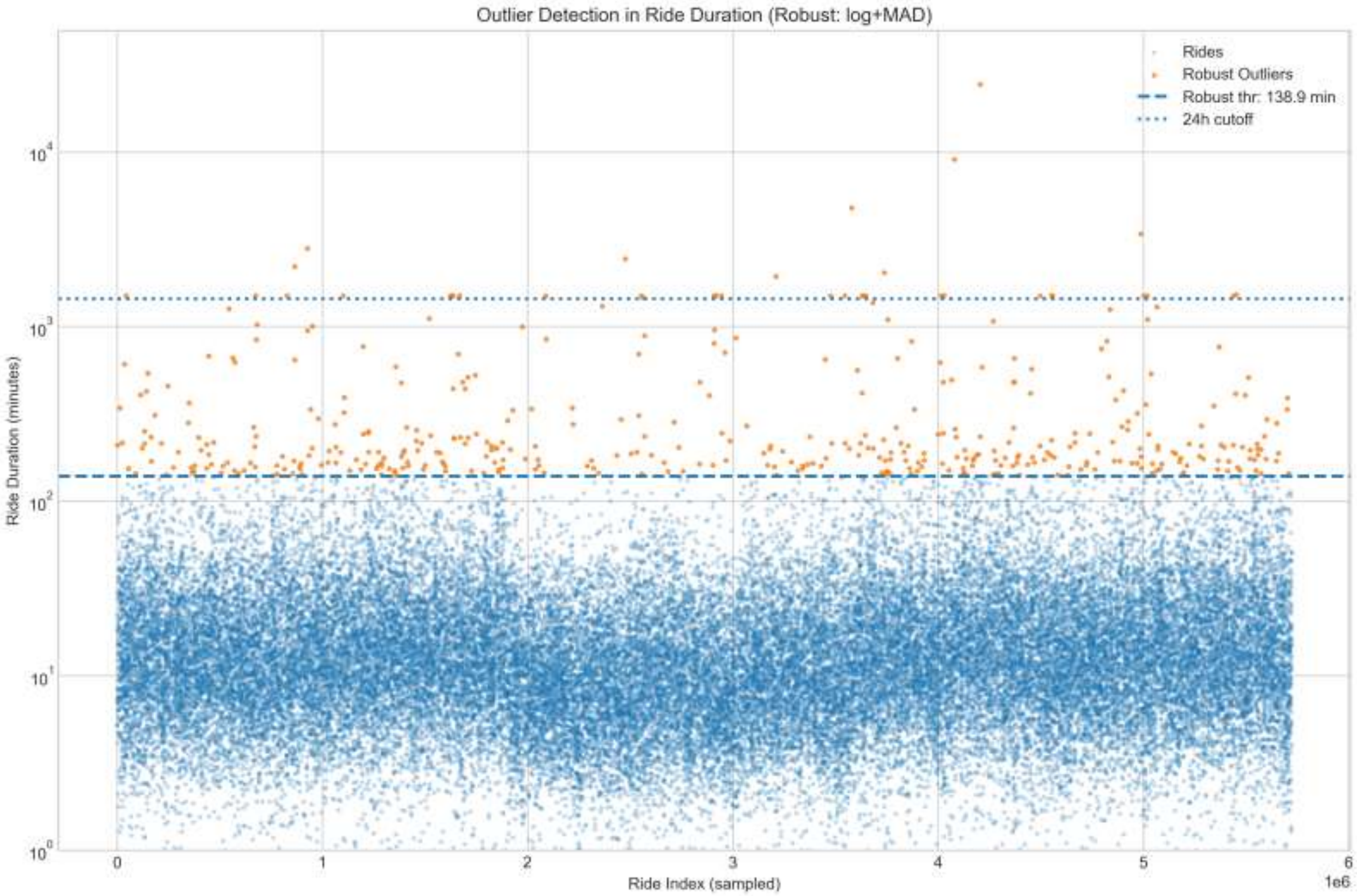
Electric Bikes – can be parked anywhere within the service area.

Preprocessing - Outlier Detection

Data Spread



Preprocessing - Outlier Detection



Preprocessing - Outlier Identification

Noise in the Data

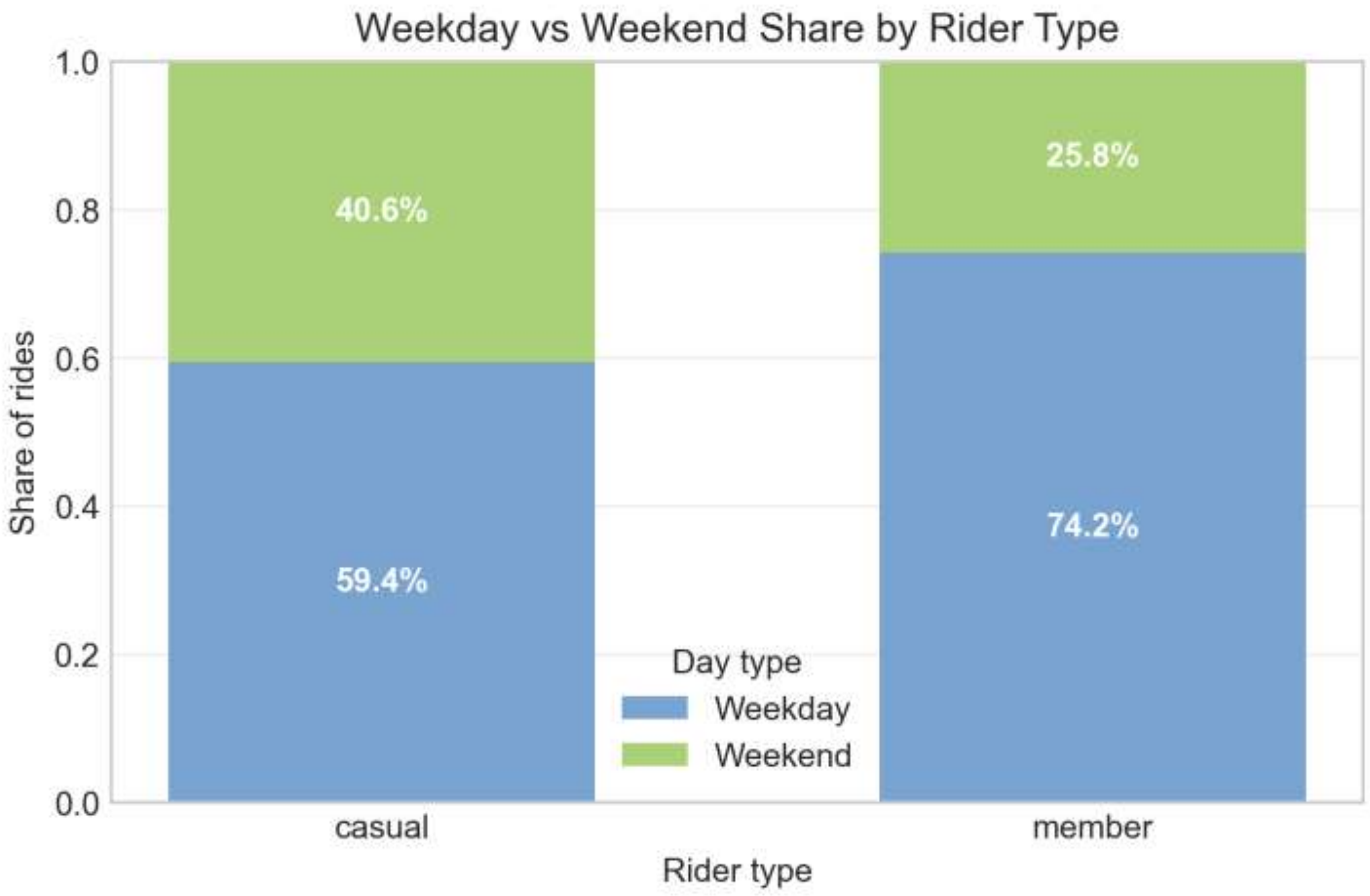
- 145 negative duration rides
- 514 zero-minute rides
- 4,138 rides longer than 24 hours

Impossible data entries

System errors

Unclosed trips

EDA – Weekday vs. Weekend usage

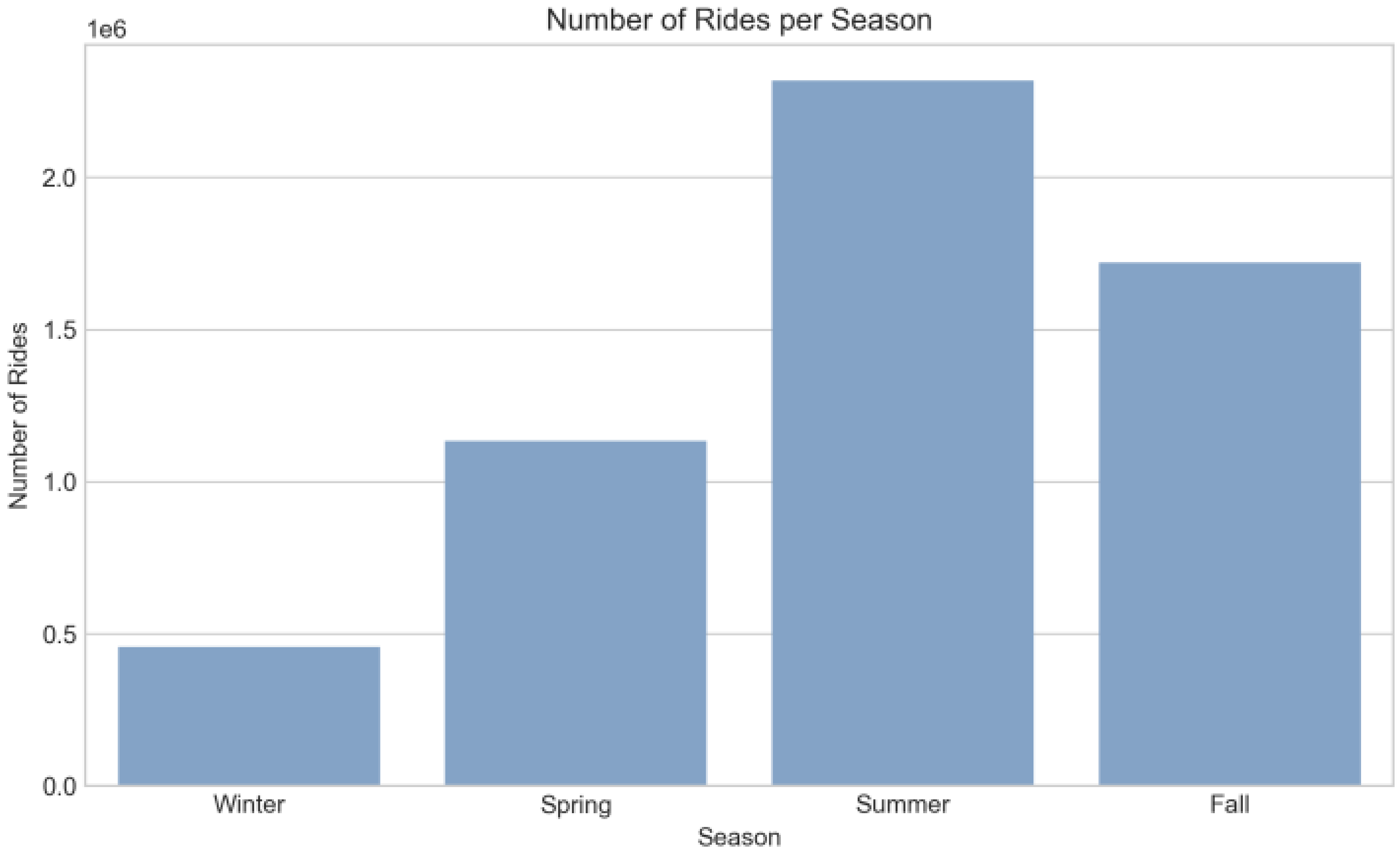


— Casual riders are weekend-focused

— Members are weekday commuters

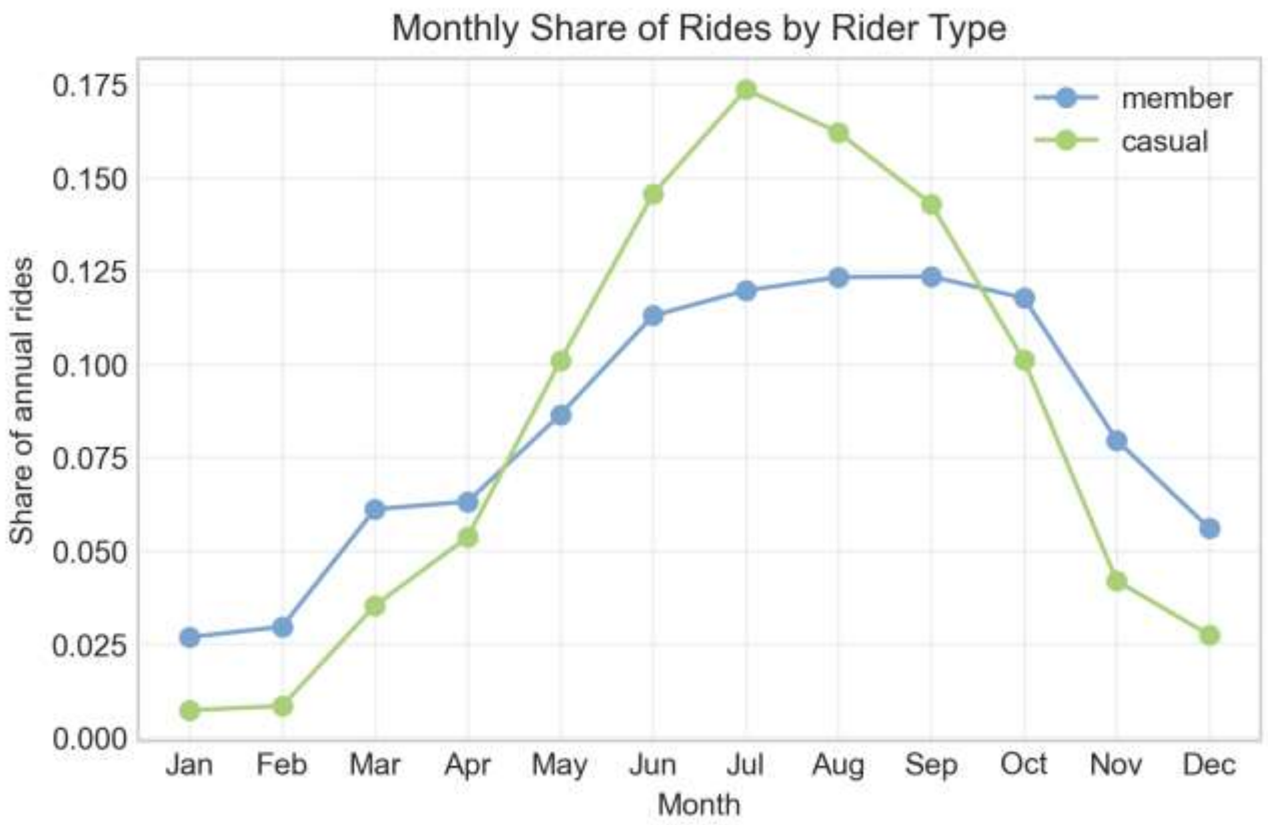
EDA

Impact of Seasonality



- Strong Seasonality

EDA – Impact of Seasonality



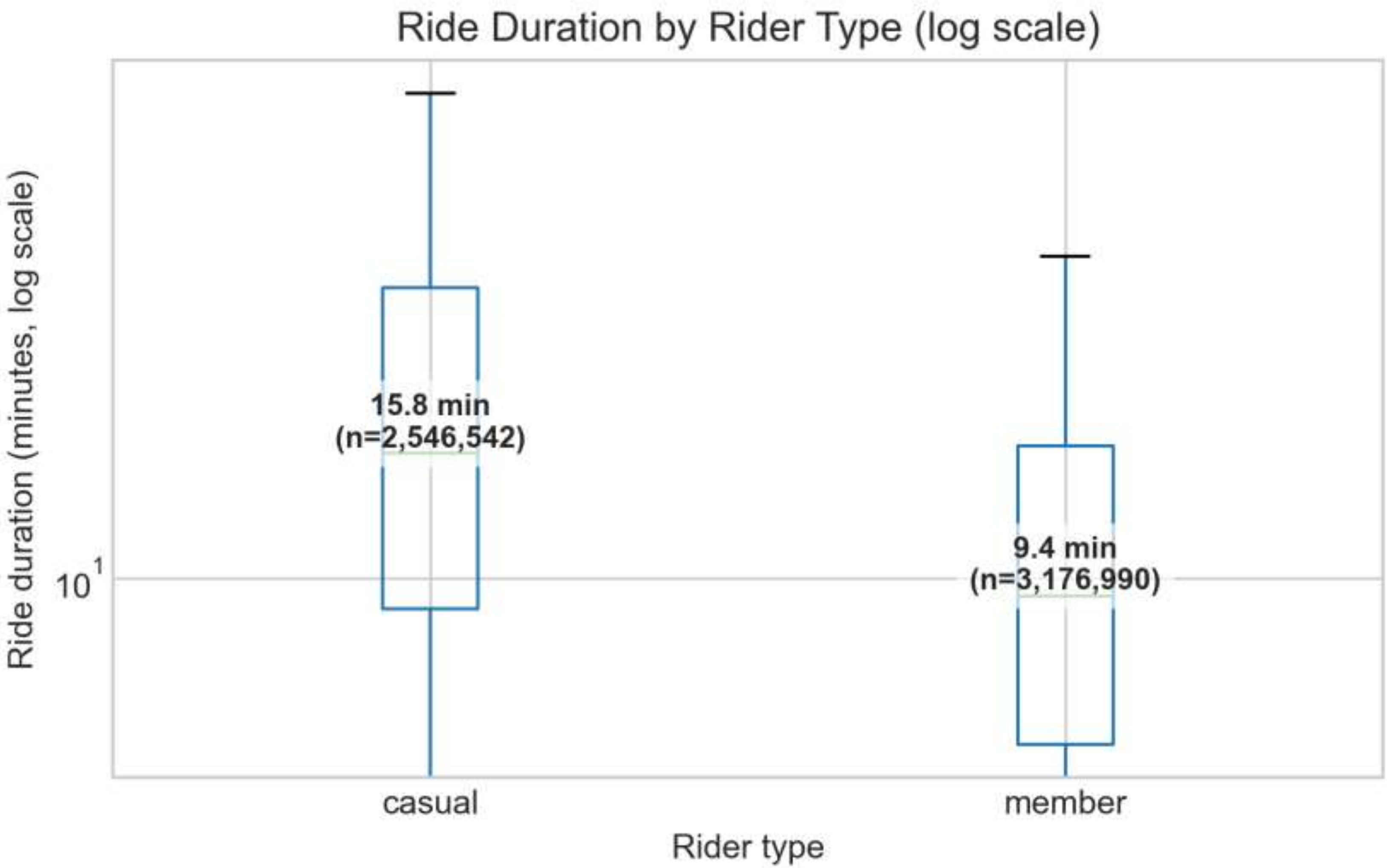
Casual Riders

- Strong summer peak: June–August
- Sharp winter decline: Jan–Feb
- Highly sensitive to weather/season

Annual Members

- Flatter seasonal trend
- Stable usage even in winter
- Less influenced by season

EDA – Casuals Take Longer Rides



External Data Integration

Temperature Data | **Population Density** | **Public Holidays & Events** | **COVID-19 Regulation Data**

Machine Learning - Introduction

Algorithms

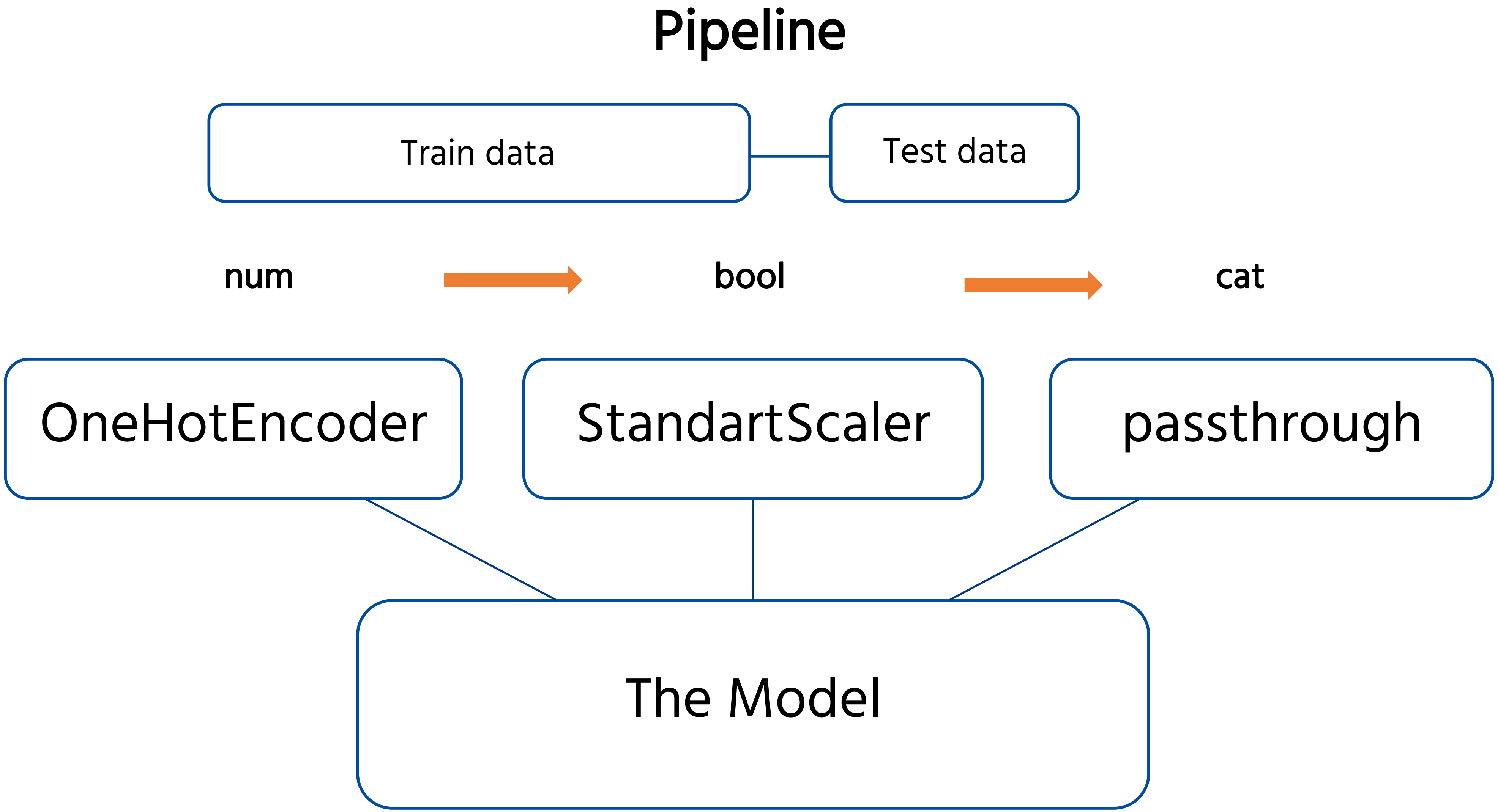
- Logistic Regression – Simple Benchmark
- Random Forest – Strong and Interpretable
- XGBoost – Efficient and High Accuracy

Features Used in Data Modeling

Type	Features
Numeric (scaled)	ride_distance_km, ride_duration_min, speed_kmh, start_hour, start_month, temp_c, precip_mm, wind_kmh, rh_pct, cloud_pct
Boolean (binary)	is_weekend, is_rush_hour
Categorical (one-hot encoded)	rideable_type, season, duration_category, temp_bin, precip_bin, wind_bin

Machine Learning

Pipeline Structure



Machine Learning

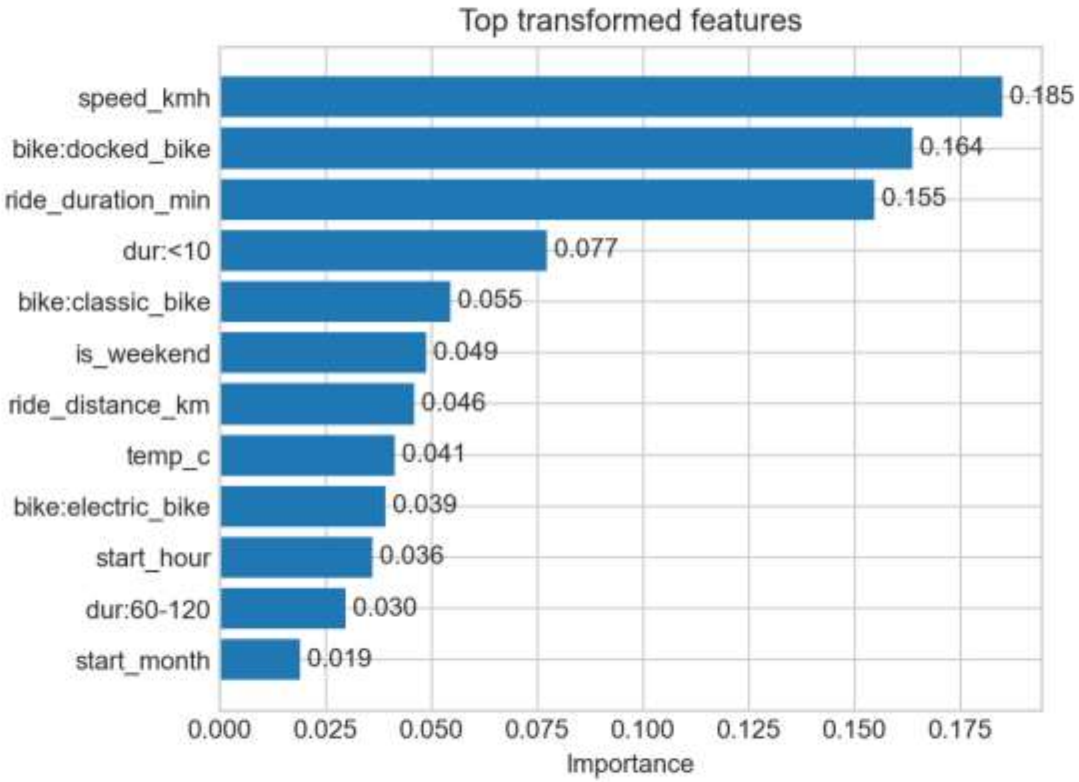
Random Forest Classification Report

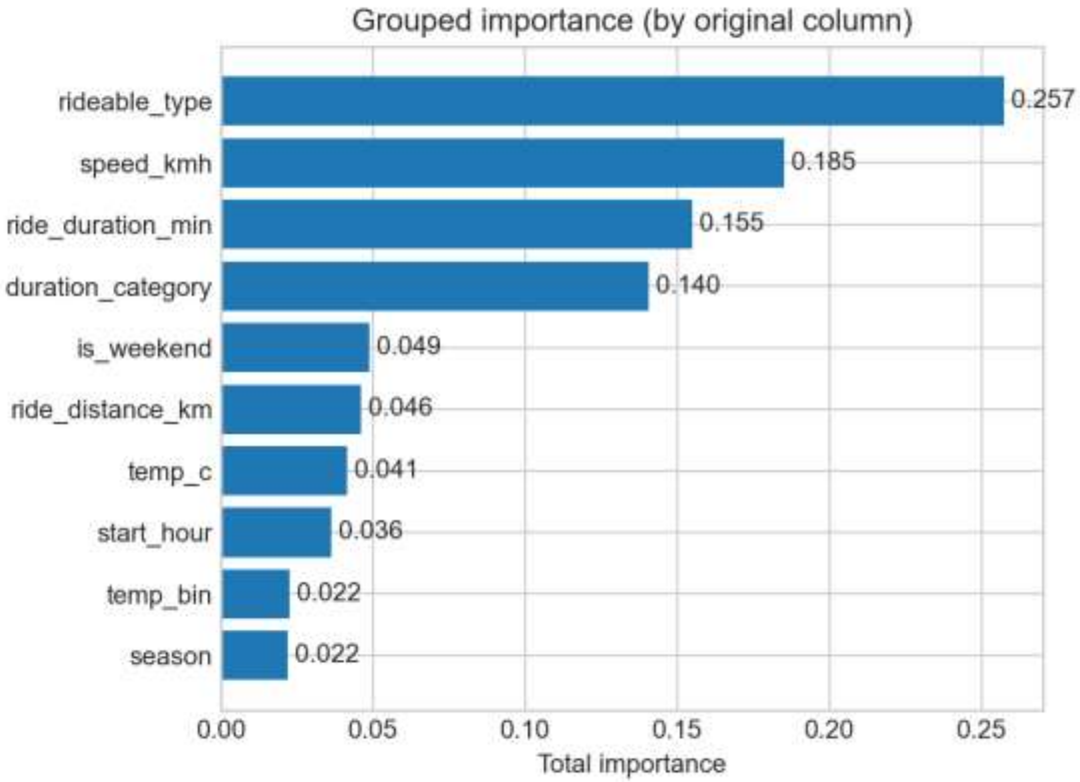
	Predicted Casual	Predicted Member
Actual Casual	37%	63%
Actual Member	7%	93%

	Precision	Recall	F1-score	Num(#)
Casual	0.67	0.37	0.48	109k
Member	0.79	0.93	0.86	282k
Macro avg.	0.73	0.65	0.67	391k
Weighted avg.	0.76	0.77	0.75	391k

Machine Learning – Random Forest

Key Drivers





Model Performance & Feature Importance

Confusion Matrix

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.76	0.71	0.64	0.65
Random Forest	0.77	0.73	0.65	0.67
XGBoost	0.77	0.77	0.72	0.74

Outlook and Future Steps

- Weekdays vs. Weekend ride patterns, action point, positioning of the bikes
- Seasonality
  - Summer - Casual rider campaigns
  - Winter - Member rider campaings
- Docked Bike Stations

References

Source of Data and Algorithms

1. Karahan, F., Hossin, R., & Tahirova, F. (2025). *An Analysis of Cyclist Bike Share Dataset Code*. GitHub. https://github.com/Fatih0234/bike-share-bi2-project

2. Gower, E. (2023). Cyclistic bike-share dataset [Data set]. Kaggle. https://www.kaggle.com/datasets/evangower/cyclistic-bike-share

3. Cox, D. R. (1958). *The regression analysis of binary sequences*. Journal of the Royal Statistical Society: Series B, 20(2), 215–242.

4. Breiman, L. (2001). *Random forests*. Machine Learning, 45(1), 5–32.

5. Chen, T., & Guestrin, C. (2016). *XGBoost: A scalable tree boosting system*. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 785–794). ACM.

6. Open-Meteo. (2025). *Free weather forecast API for non-commercial use*. Retrieved from https://open-meteo.com/

Thank you for your attention!

Are there any questions?