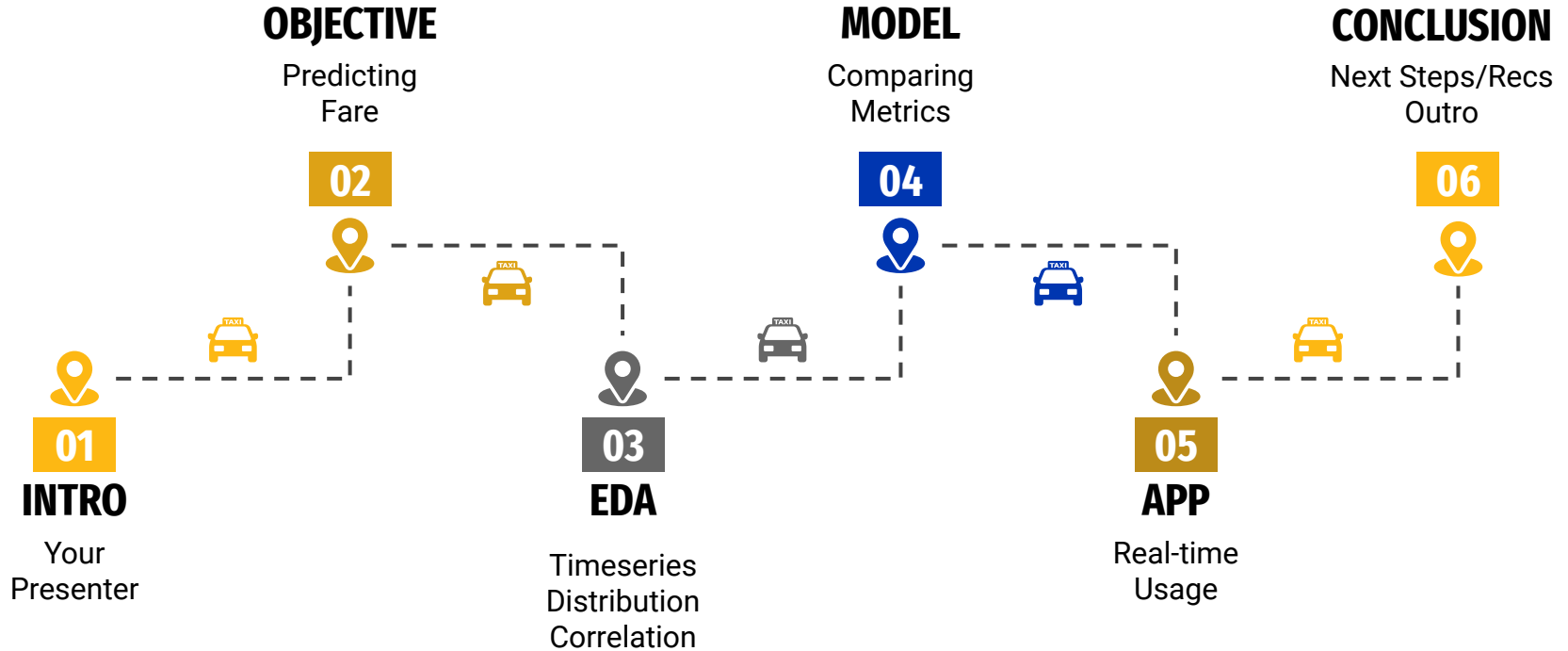


# Fare Forecaster

Save Time, Make Money



# CONTENTS



# INTRO

**Dillon Diatlo**

***Data Scientist***

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# INTRO

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## CREDENTIALS

4.90 Lyft Rating

4.78 Uber Rating

N/A Taxi Rating



**OBJECTIVE**



**A**



## CHALLENGE

Determine where in NYC for-hire vehicle drivers can make the most money per trip, at that moment.

## OBJECTIVE

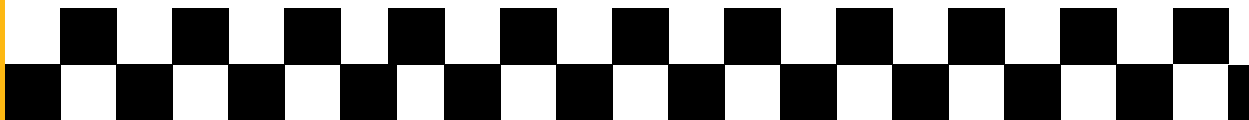


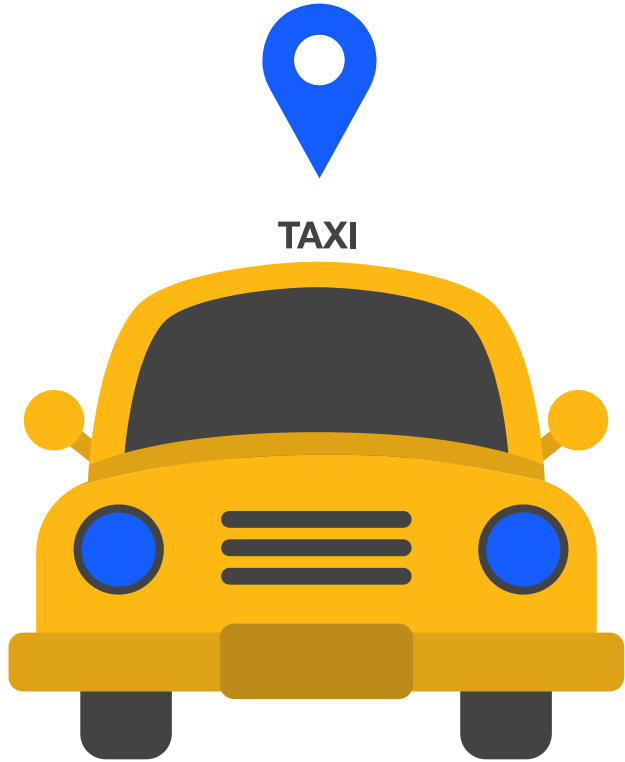
**B**

## OBJECTIVE

Sample 212M rows of 2022 NYC for-hire-vehicle trip data to predict total driver revenue by trip.

Deploy an app to help drivers determine which zone to go to for the highest average fare.





**EDA**

# PIT STOP: DOWNSIZING

**212,000,000**

- Slow to download
- Forever to analyze



**MONTH-A | MONTH-B**

- Split 'em up
- Chunksize param



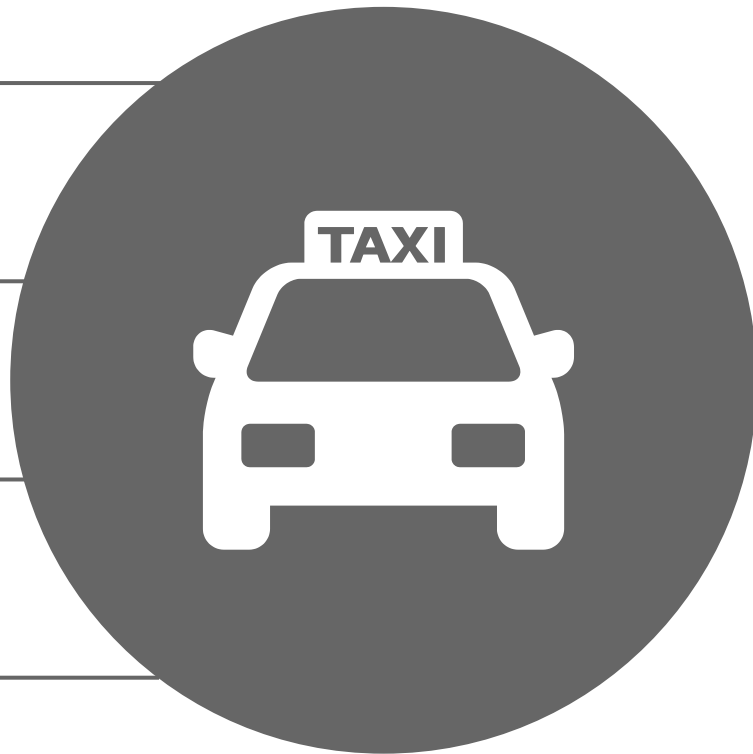
**CONCATENATE**

- Put 'em back together by month



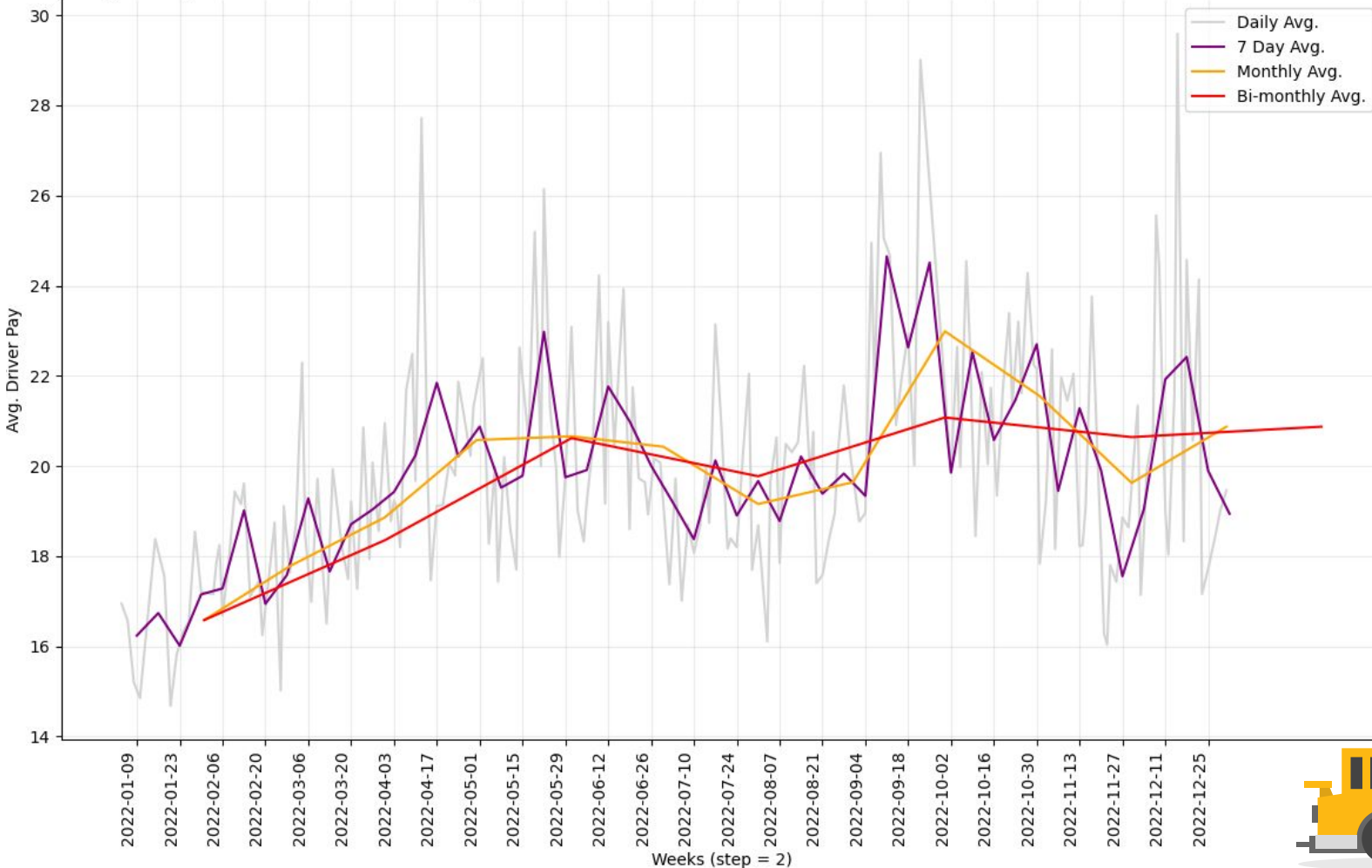
**READ | CREATE**

- One BIG beautiful df
- ~4M rows





# Avg. Pay Received Per Trip



## Outliers

- A few daily outliers can skew

## Plateau

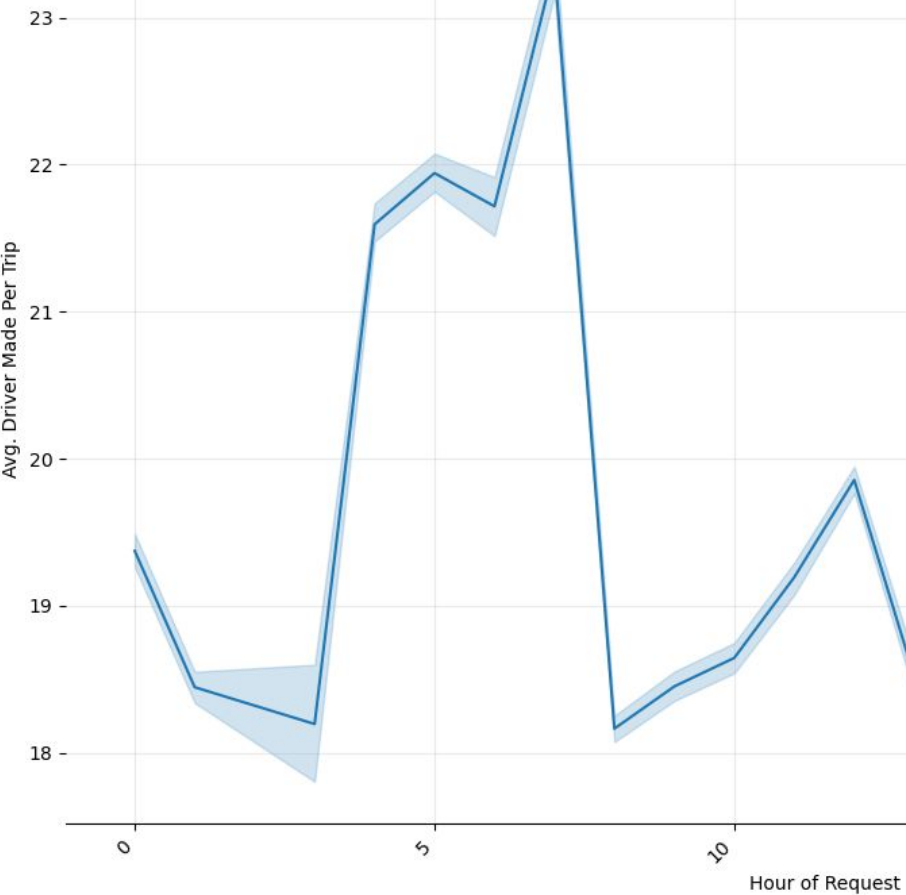
- Increase until May  
- Plateau could be holidays

## Seasonality

- Difficult to track w/ 1 year of data



# Avg. Driver Pay by Request Hour

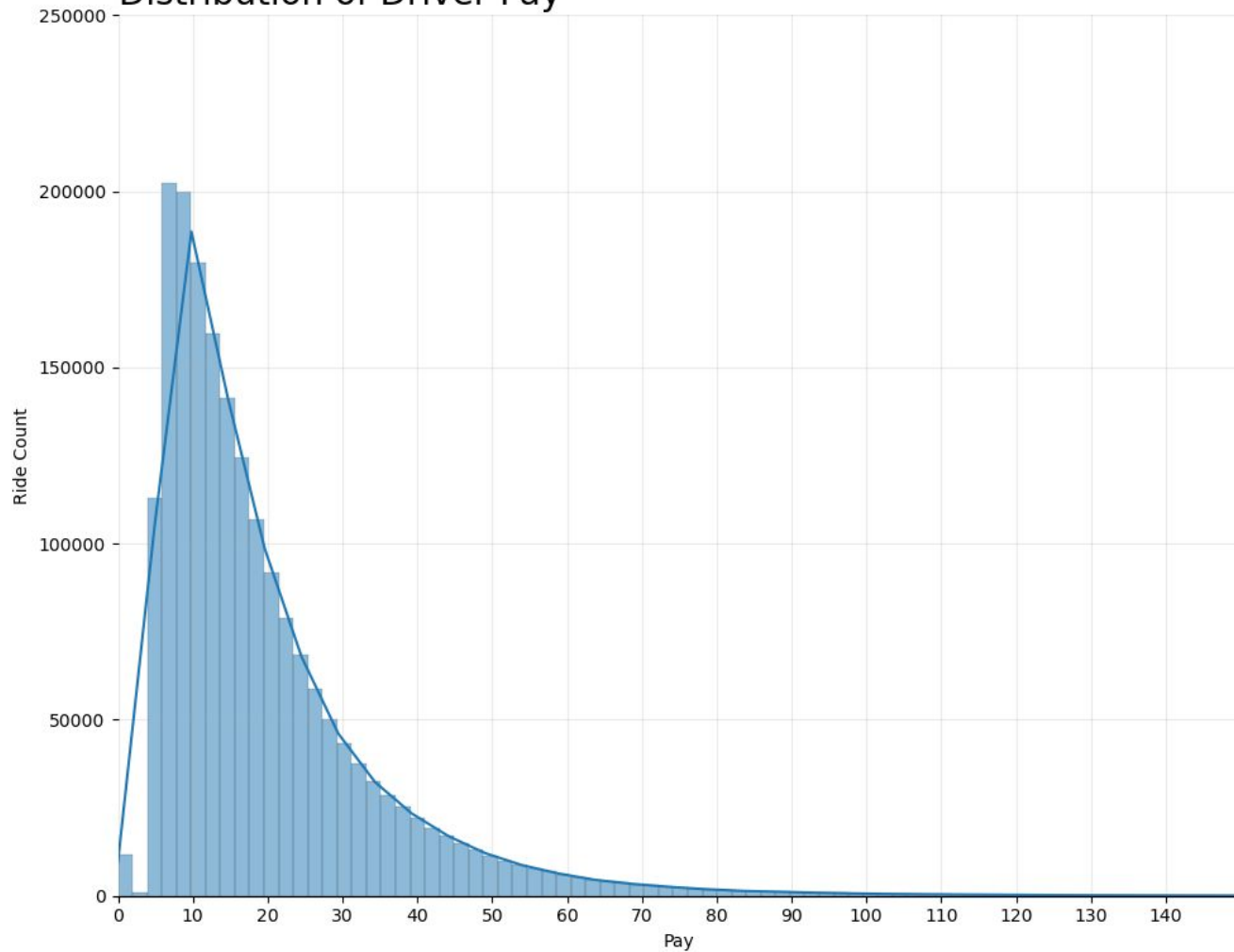


**Bi-modal**

- 7am & 5pm



# Distribution of Driver Pay

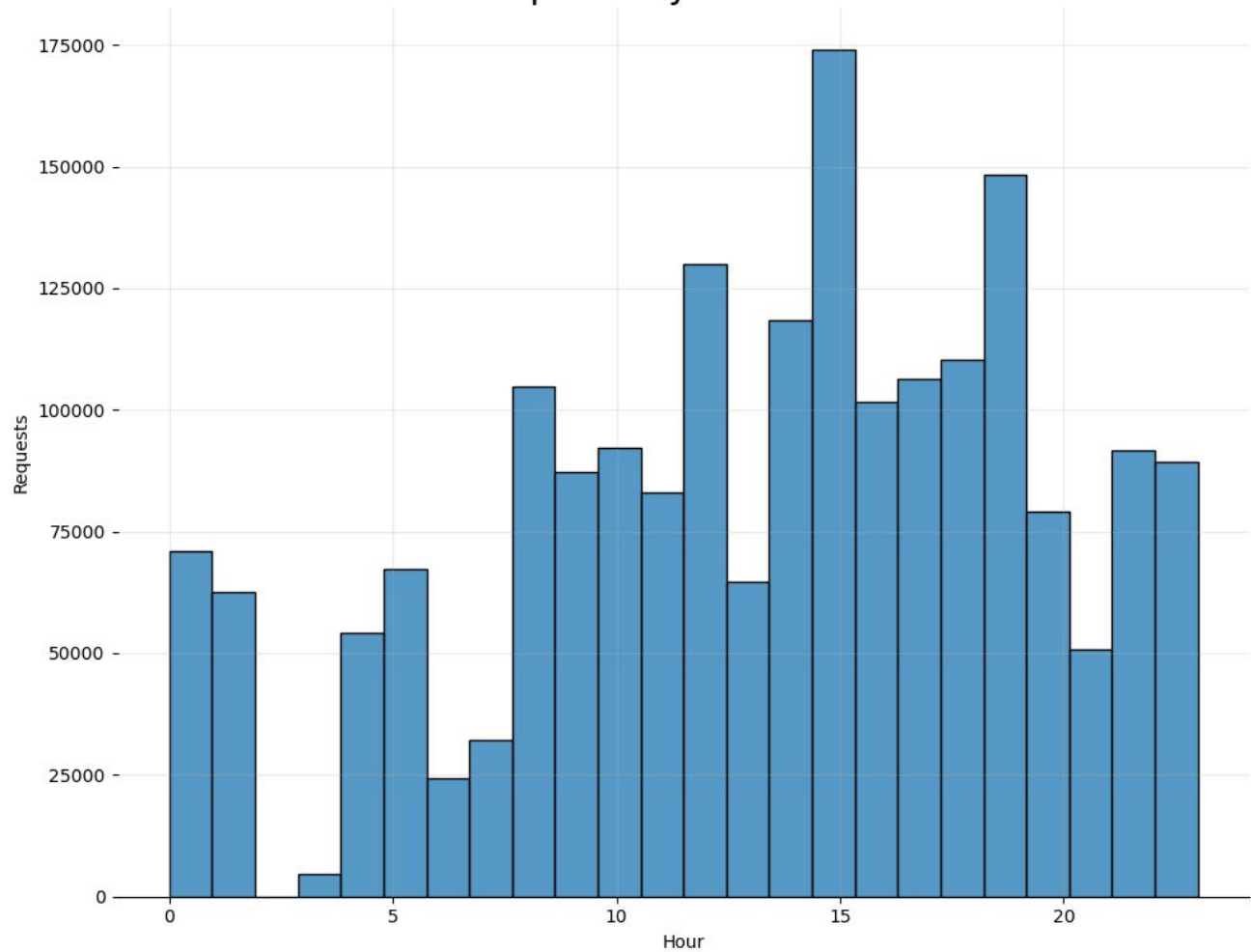


## Distribution

- Right skewed
- Most trips between \$5-20



# Distribution of Ride Requests by Hour

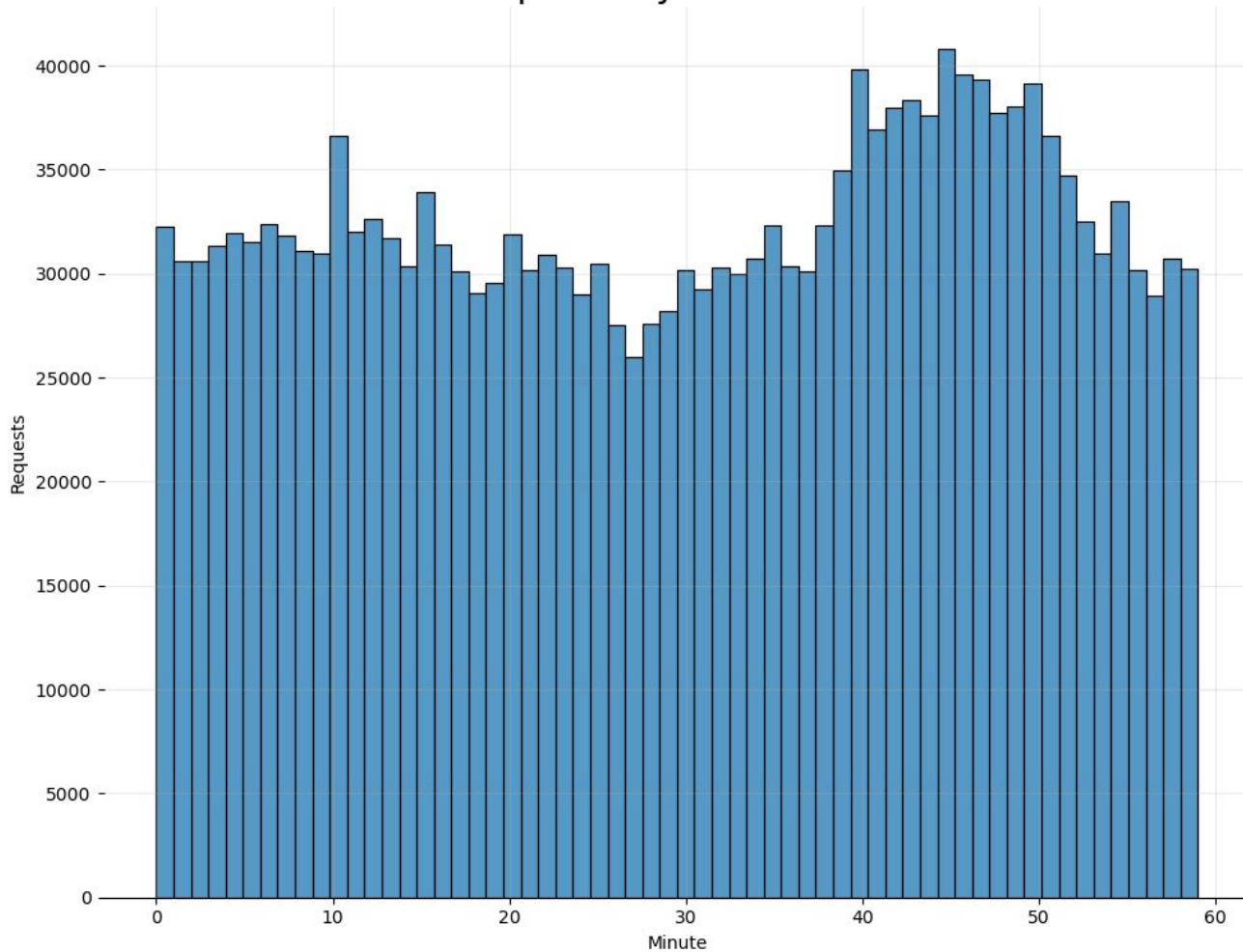


## Distribution

- Left skew
- Less trips in the AM



## Distribution of Ride Requests by Minute



### High Passenger Time

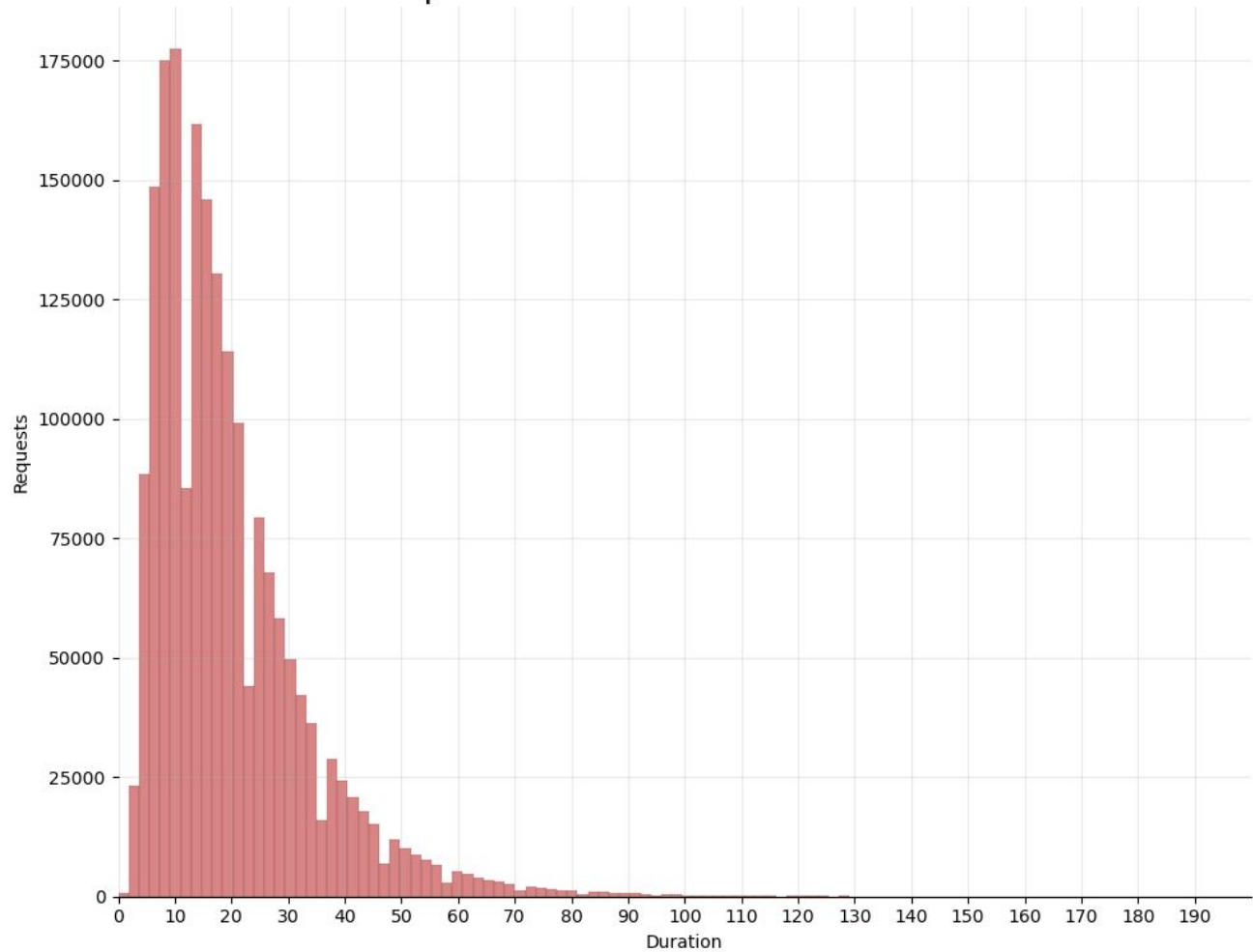
- 4:40pm - 4:55pm

### Distribution

- Almost bi-modal
- Mid-hour dip
- Most between 40min - 55min



## Distribution of Trip Duration

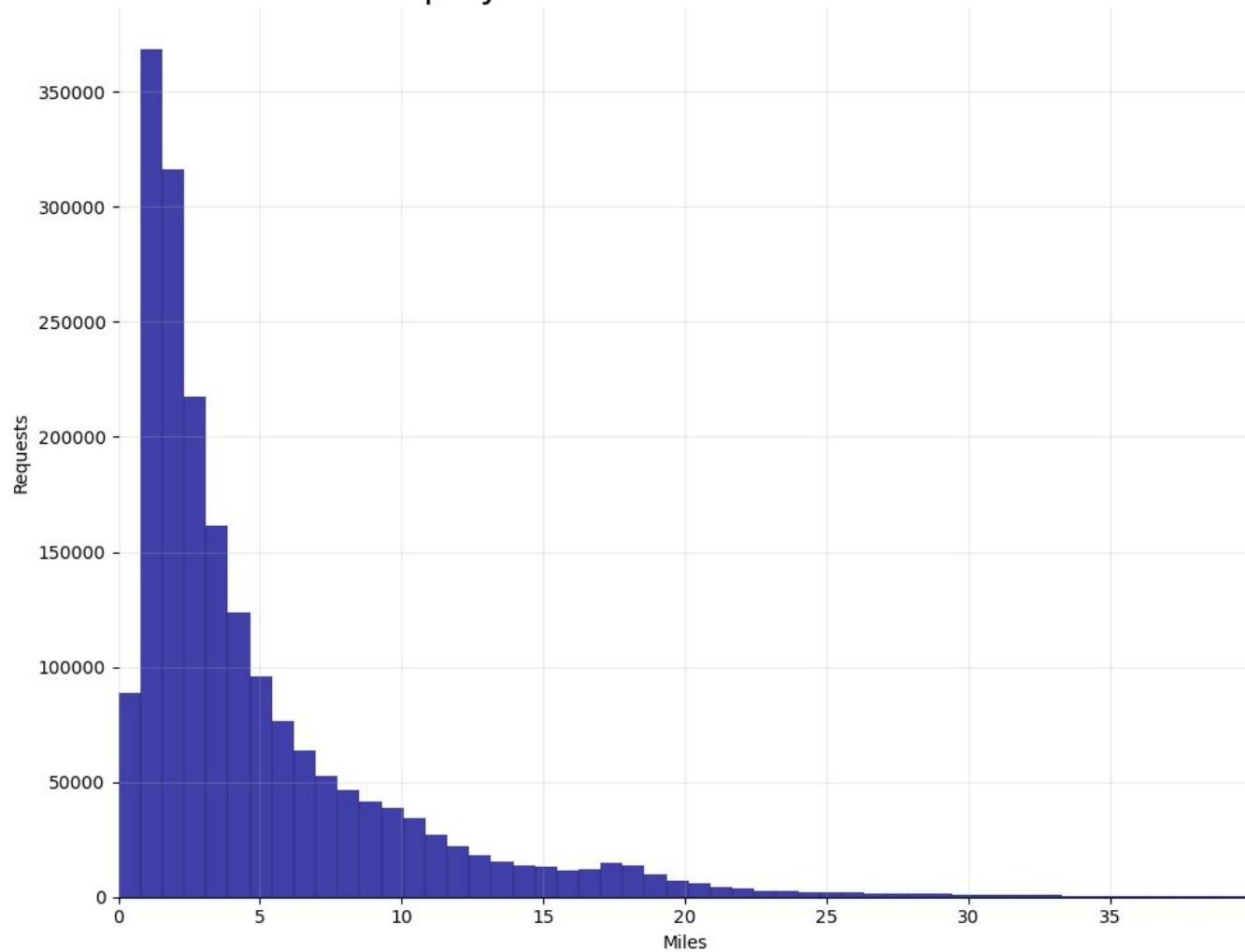


### Distribution

- Right skewed
- Pattern of dips and peaks every 10-15 minutes



# Distribution of Trip by Miles

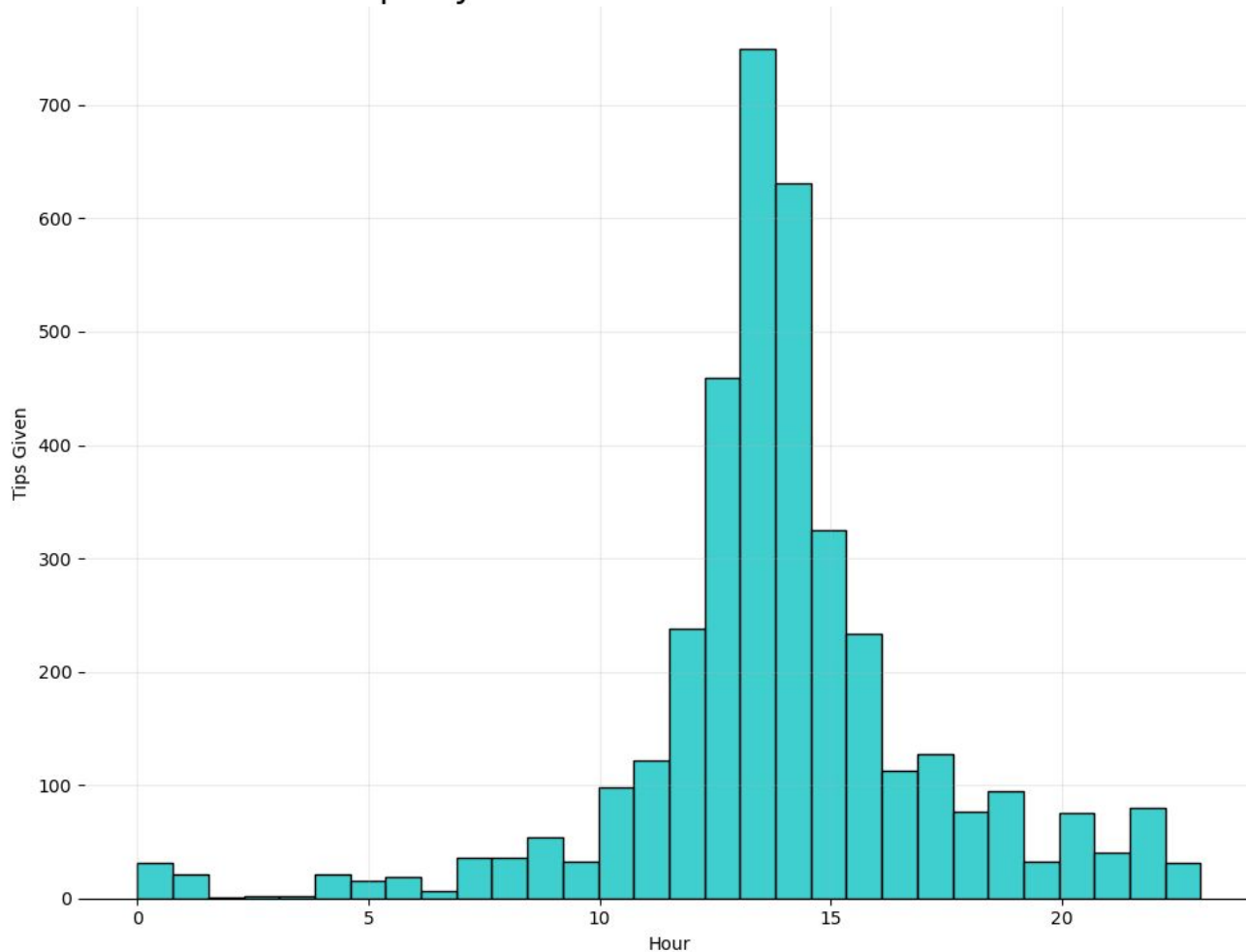


## Distribution

- Right skewed
- 2-10 miles



## Distribution of Tips by Hour



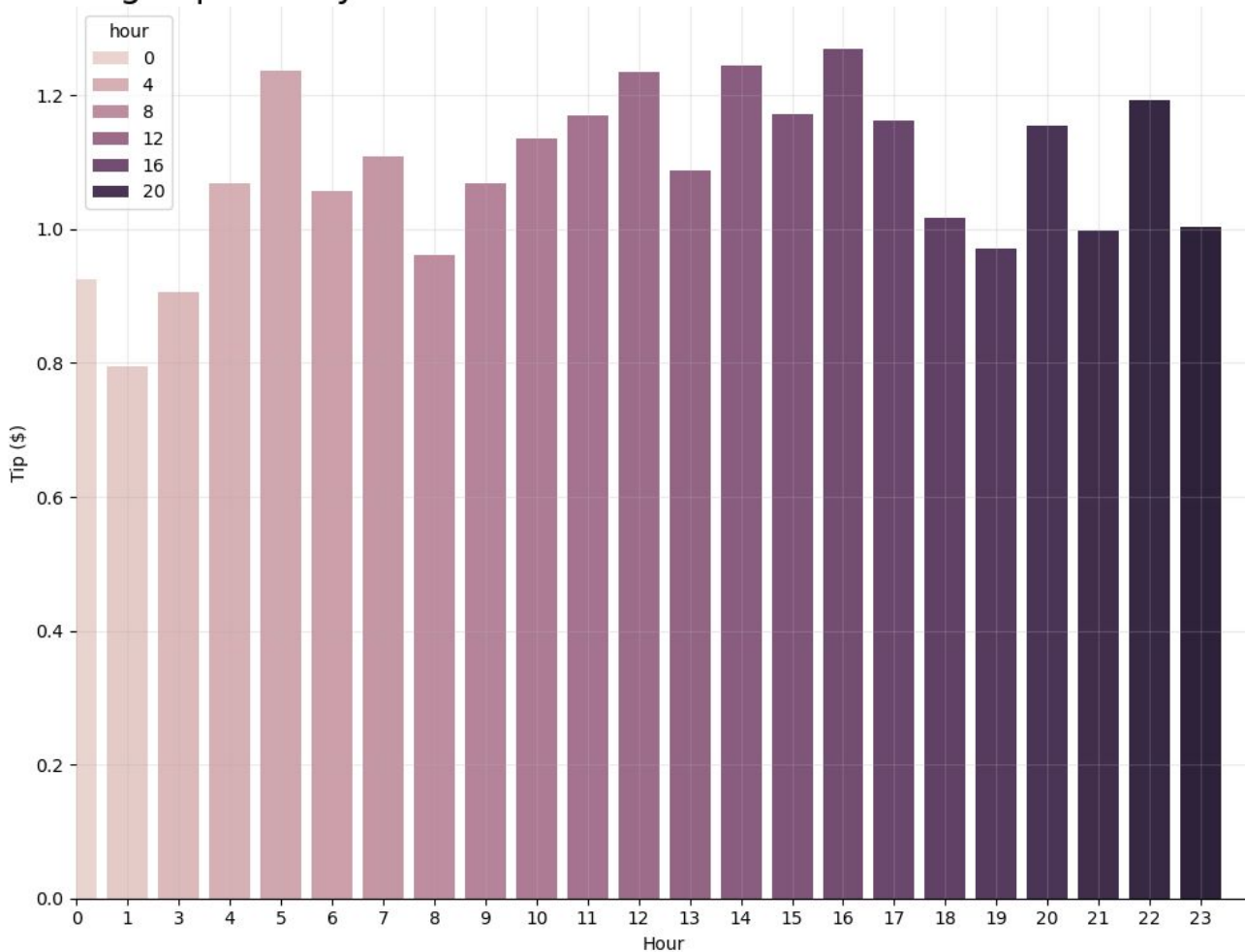
### Distribution

- Closer to normal distribution, though a bit left skewed
- Follows similar distribution of trips per hour





## Avg. Tip Size by Hour

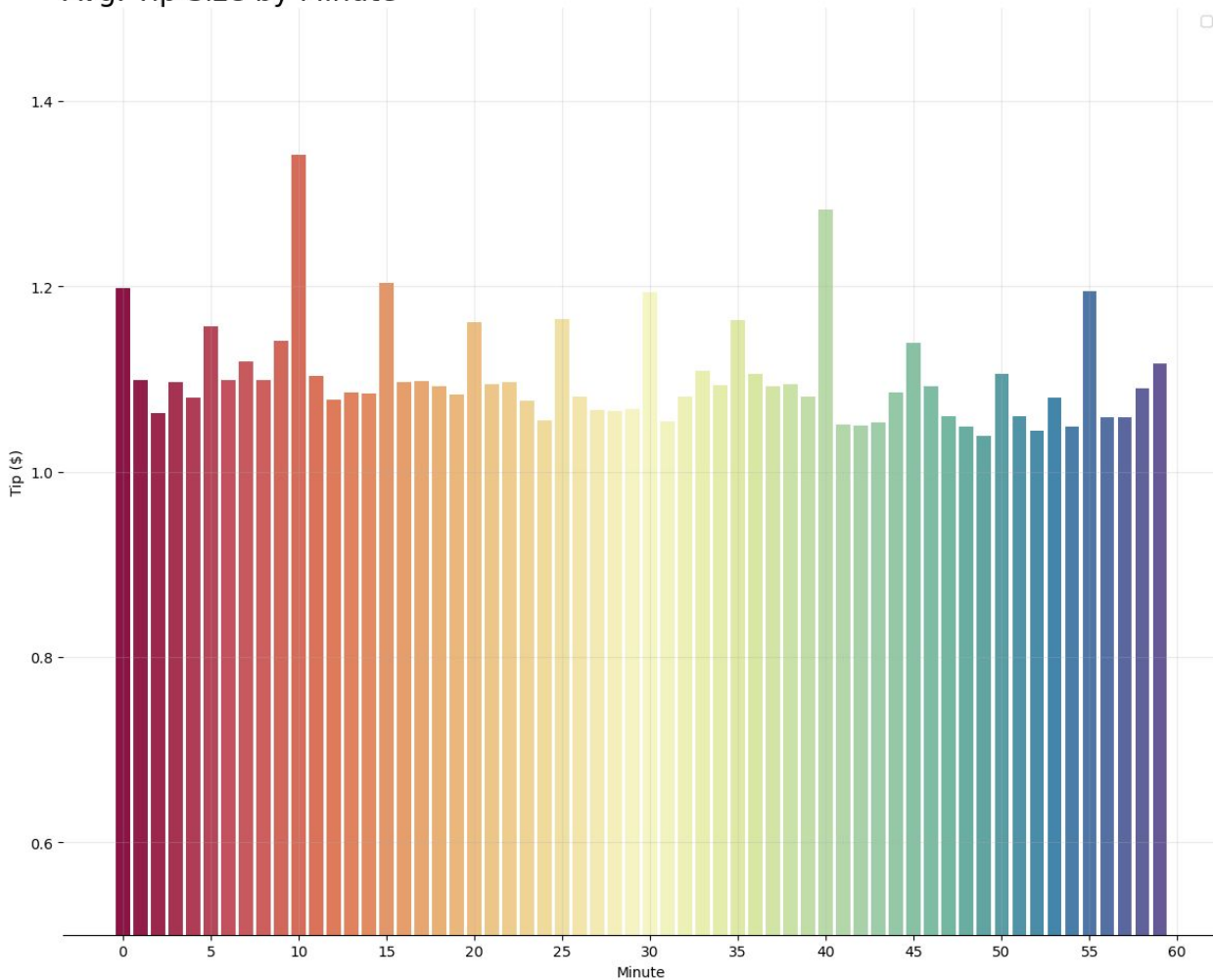


**Best Times for  
Bigger Tips**

- 5am, 5pm



Avg. Tip Size by Minute



## Biggest Tips Happen

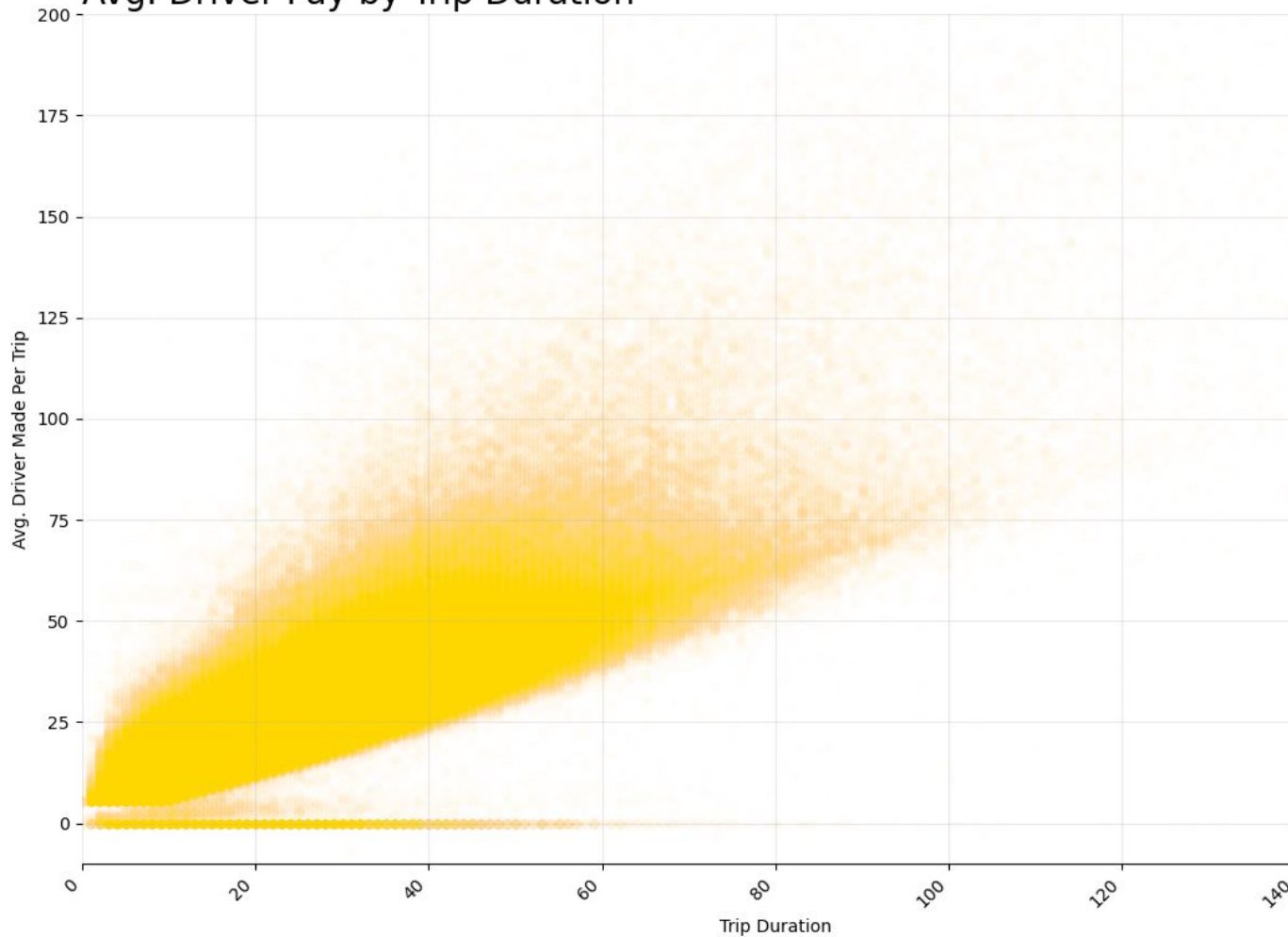
- 10 minutes past the hour
- 40 minutes past the hour

## Patterns

- Avg size of tips seem to peak every 5 minutes



Avg. Driver Pay by Trip Duration

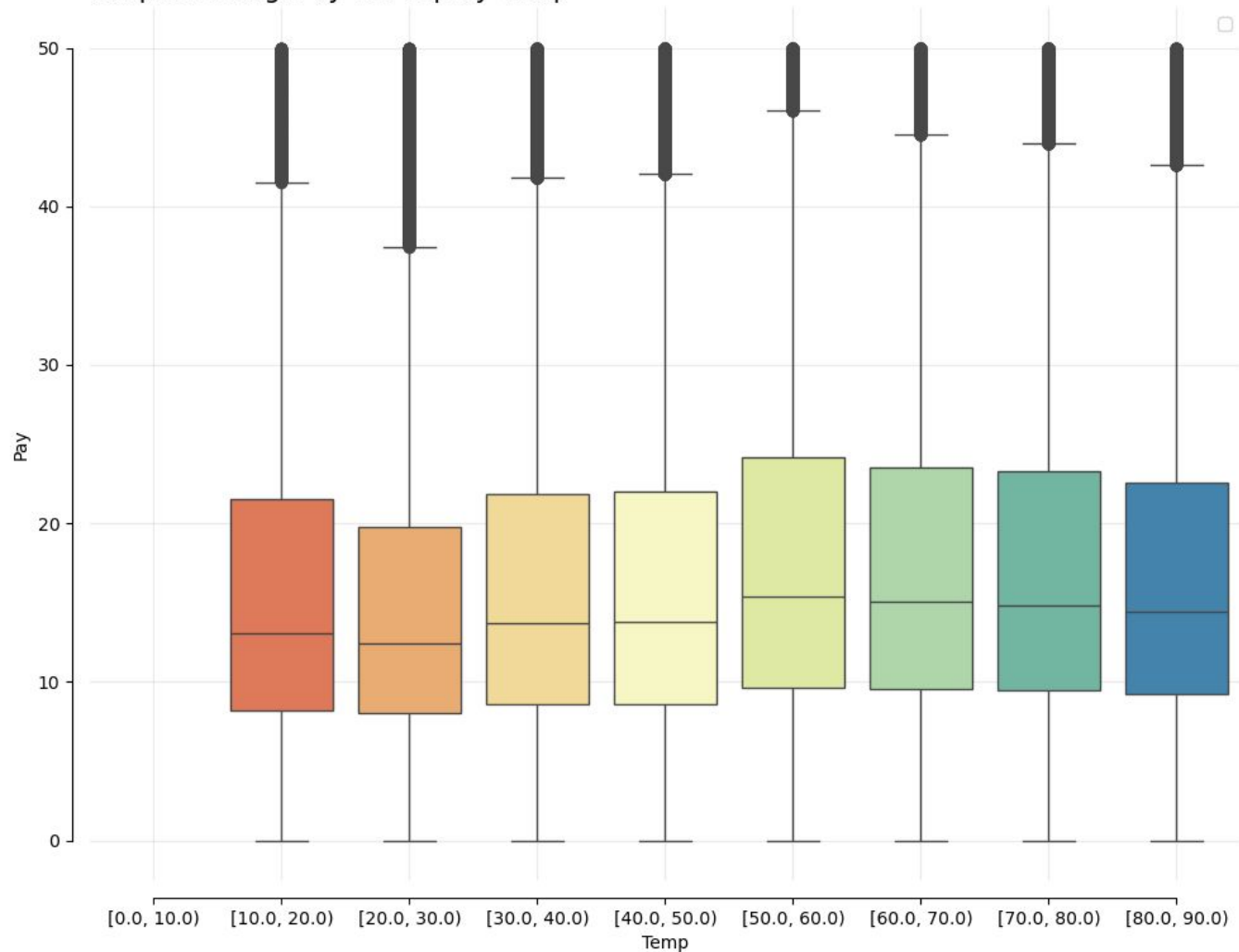


### Patterns

- Affirms expectations of positive correlation
- Discover of negative pay, which then went back to fix



Boxplot of Avg. Pay Per Trip by Temp



## Biggest Tips Happen

- 50-60 degrees
- could be more trips at this time
- excited to get out after winter

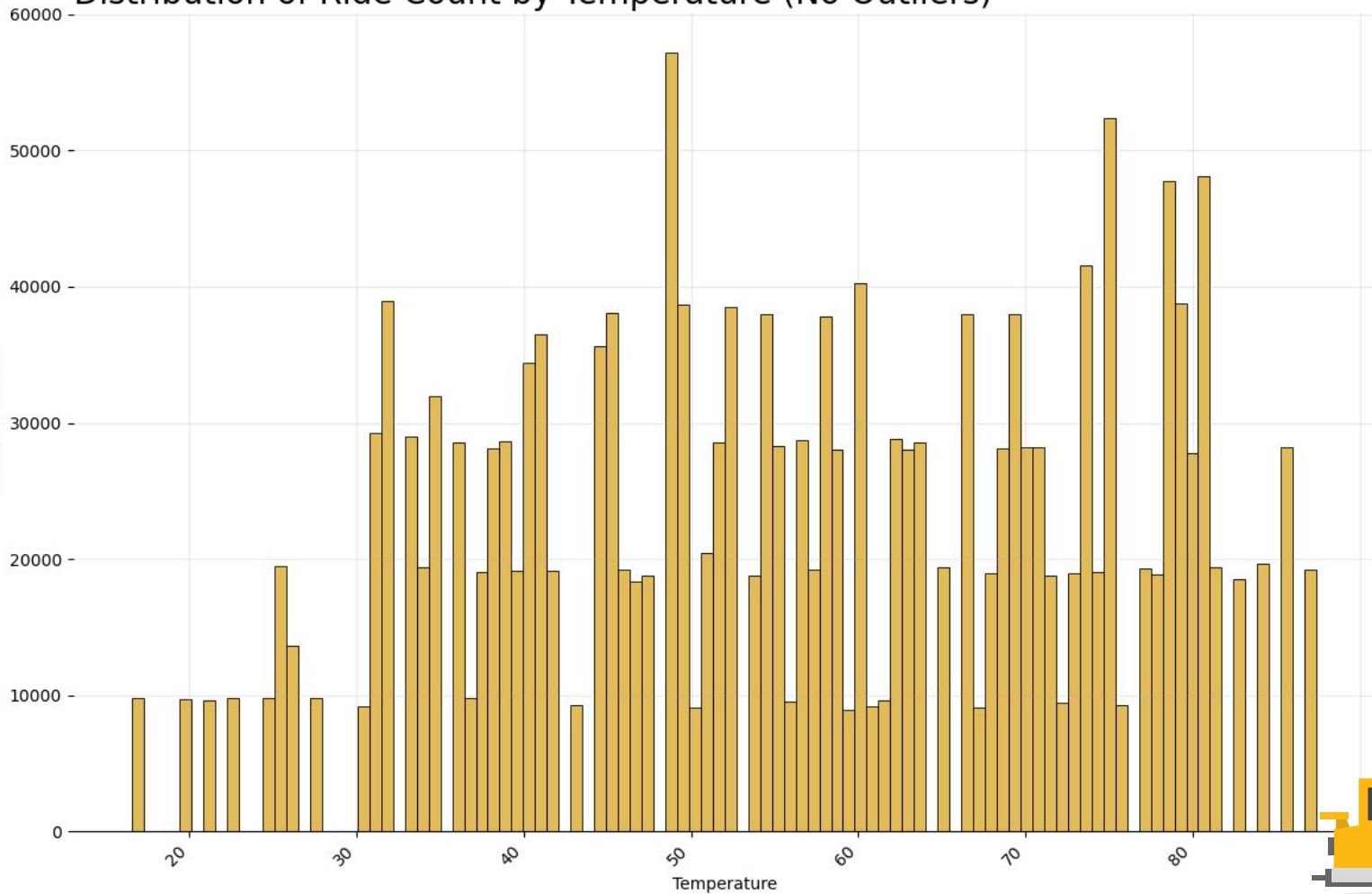
## Patterns

- Almost uniform distribution
- Ever so slight positive correlation



# Distribution of Ride Count by Temperature (No Outliers)

Number of Rides

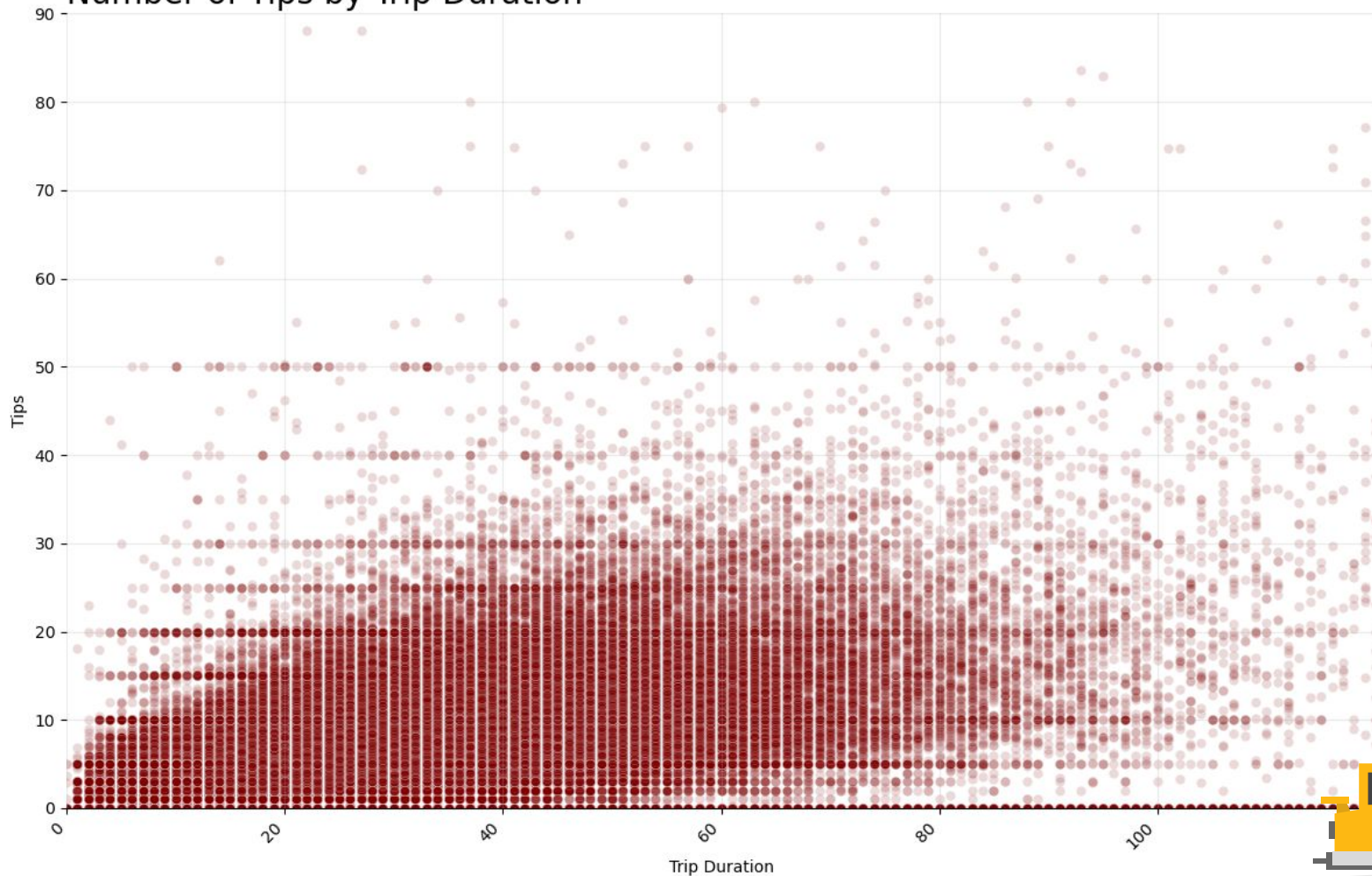


## Patterns

- Slight left skew
- bi-modal
- peak at 48/49 and 75



# Number of Tips by Trip Duration



## Biggest Tips Happen

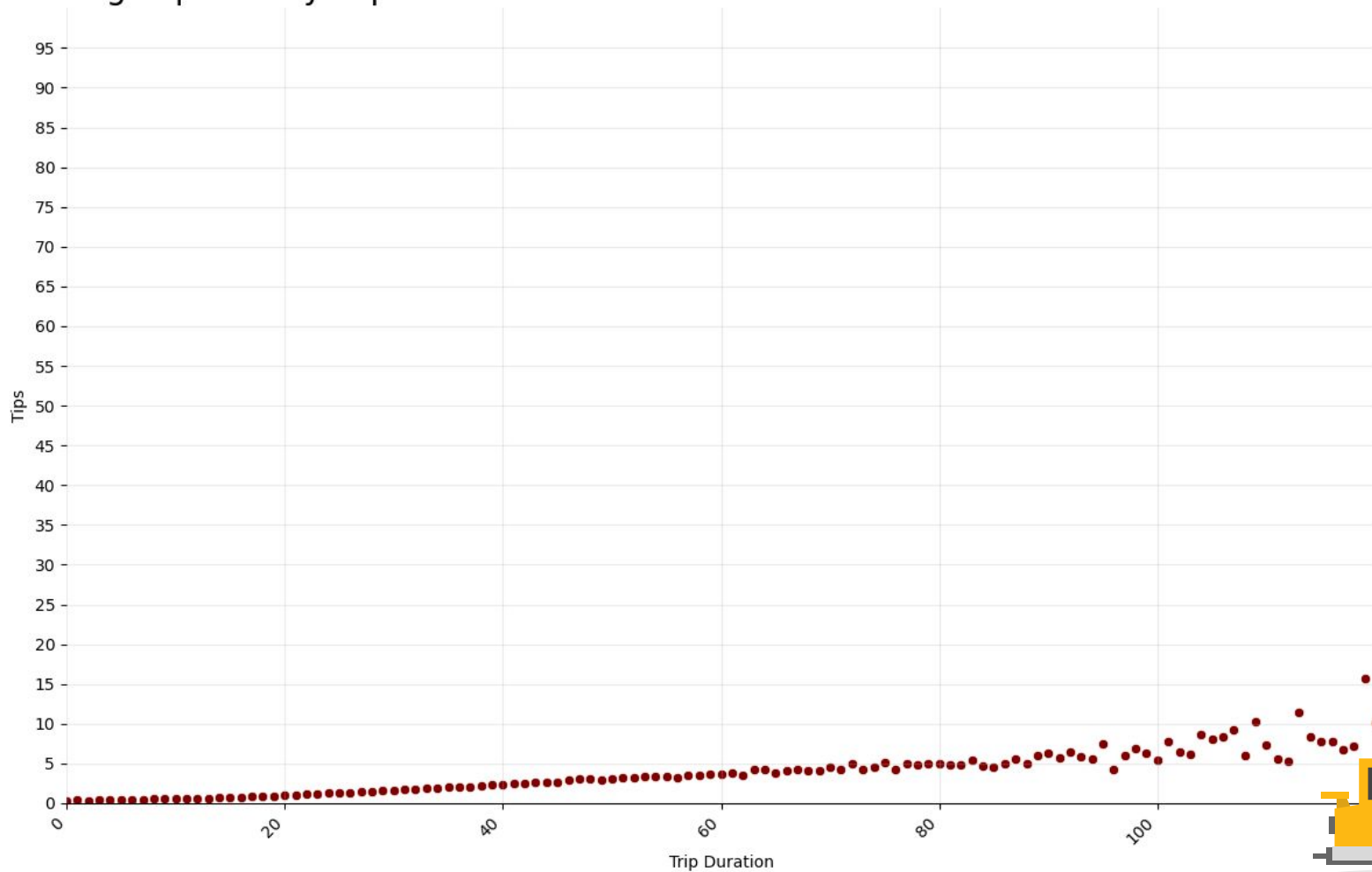
- As duration goes up number of tips goes up
- Majority of tips shrink after about 60-70 minutes

## Patterns

- Horizontal lines cutting across



## Avg. Tip Size by Trip Duration



### Patterns

- Tip size increases by trip duration
- plateaus a bit at 60, similar to before
- Tip size begins to flatten out rarely above \$15 avg





**MODELS**



	TYPE	Preprocessor	Params	Metric SCORE
MODEL 1	GradientBoosting-Regressor	ColumnTransformer OneHotEncoder	random_state=2024	Train $r^2$ : 86.8% Test $r^2$ : 87.4%  Train RMSE: \$5.90 Test RMSE: \$6.00
MODEL 2	RandomForest-Regressor	ColumnTransformer OneHotEncoder StandardScaler	n_estimators=250 max_depth=30 min_samples_split=300 max_features='sqrt' n_jobs=4)	Train $r^2$ : 81.2% Test $r^2$ : 78.6%
MODEL 3	LassoCV	StandardScaler	alphas= np.logspace(-3, 0, 100) cv=5 max_iter=10	Train $r^2$ : 86% Test $r^2$ : 86%
MODEL 4	XGBoostRegressor	ColumnTransformer OneHotEncoder	n_estimators=500 max_depth=10 min_samples_split=200 min_child_weight=1 max_features=TKTKTKTKT enable_categorical=True	Test $r^2$ : 12%  Test RMSE: \$15.95

# WINNER

## GradientBoostingRegressor

LinearRegression  
Baseline

-6%

Train RMSE: \$5.90  
Test RMSE: \$6.00

# 87.4%

*Of the variability of average driver  
revenue per trip can be explained by  
the features in this model*

**Features**

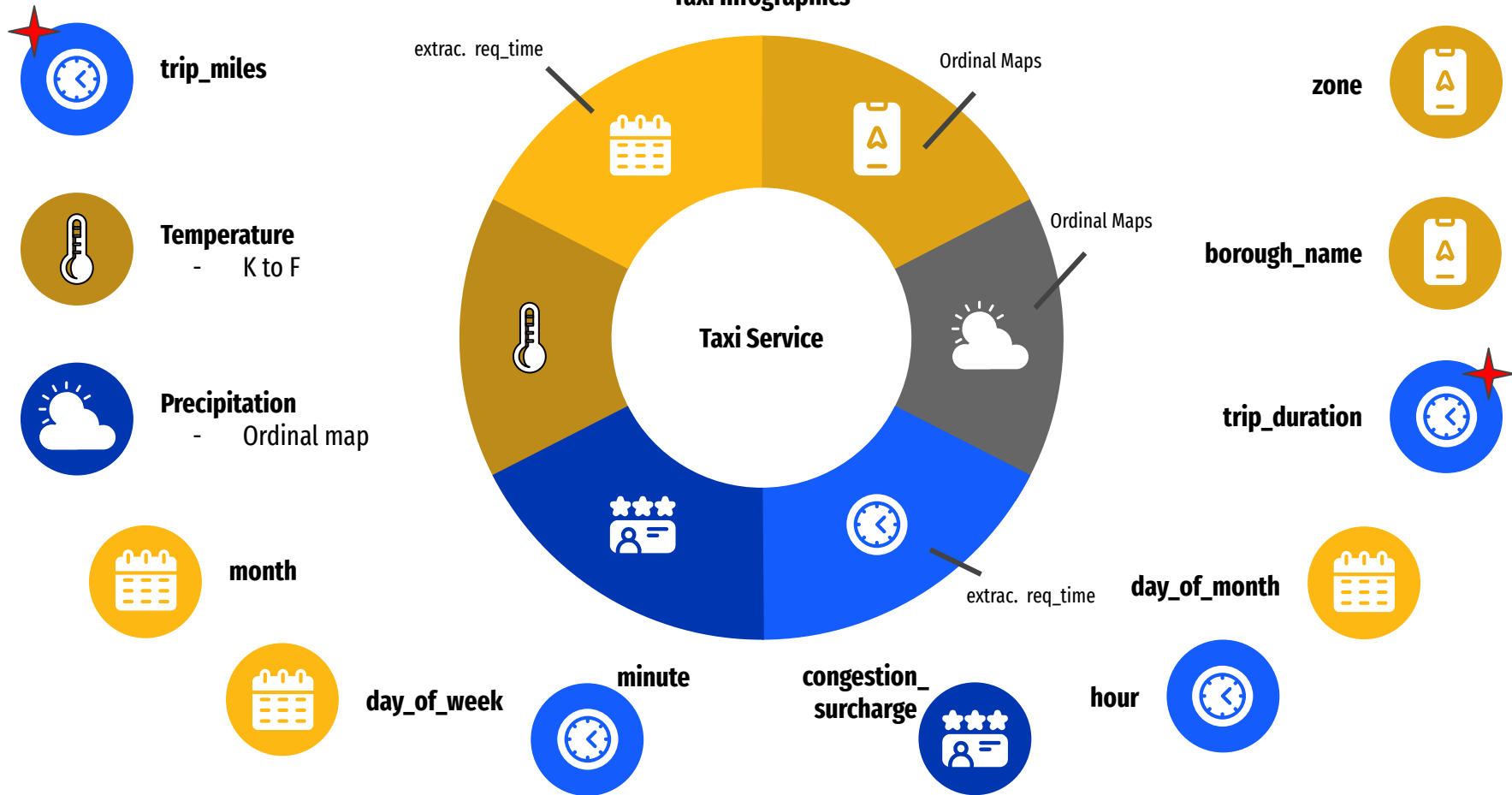
1. trip\_miles
2. temp
3. precip\_type
4. zone
5. borough\_name
6. trip\_duration
7. month
8. day\_of\_month
9. day\_of\_week
10. hour
11. minute
12. congestion\_surcharge





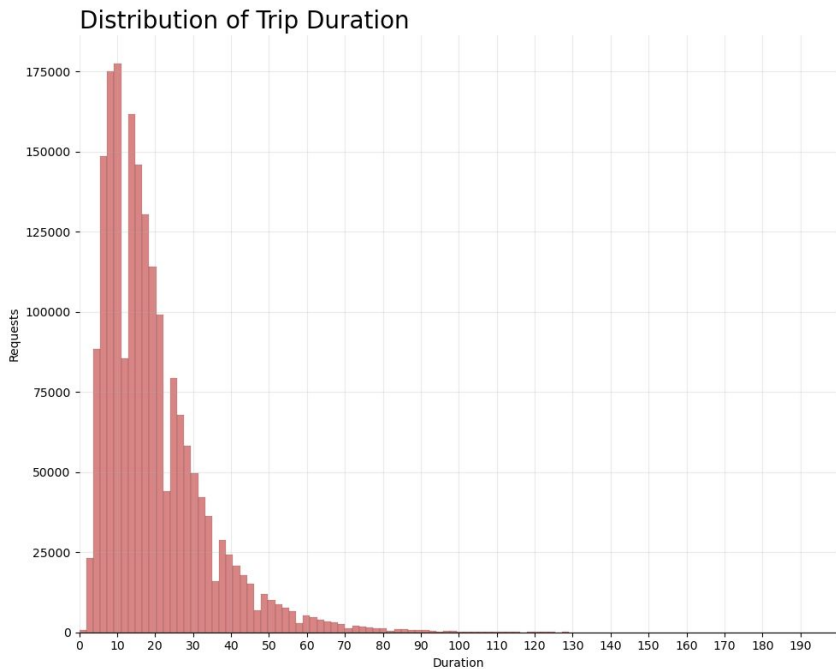
**APP**

## Taxi Infographics

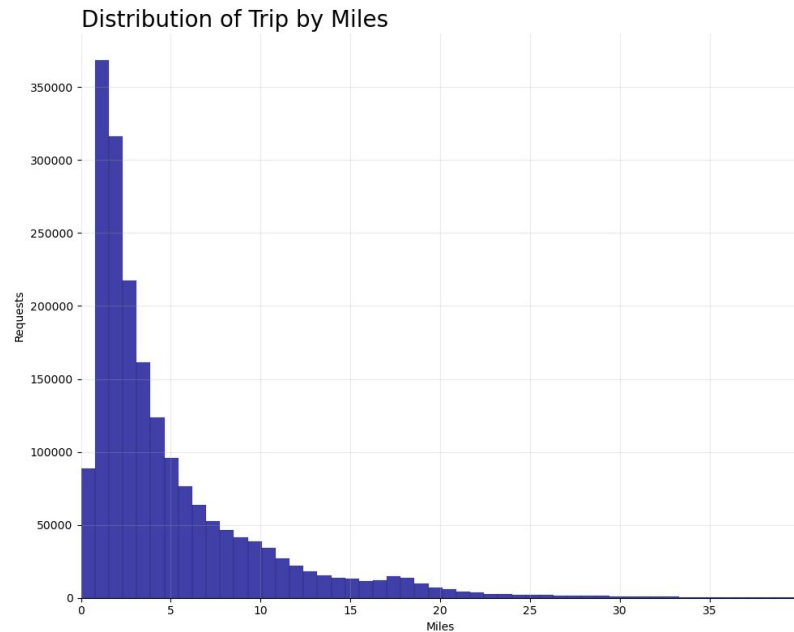


# FEATURES

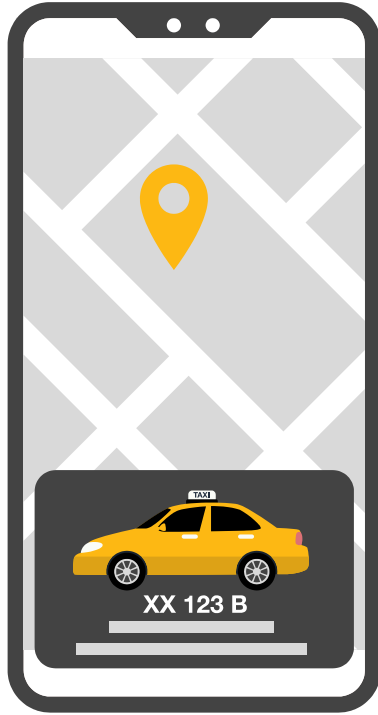
5-15 minutes



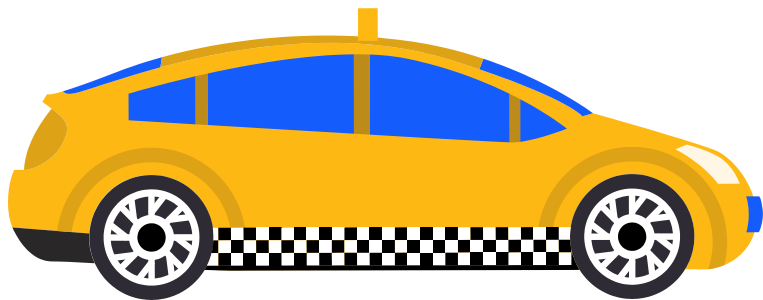
2-10 miles



# DEMONSTRATION

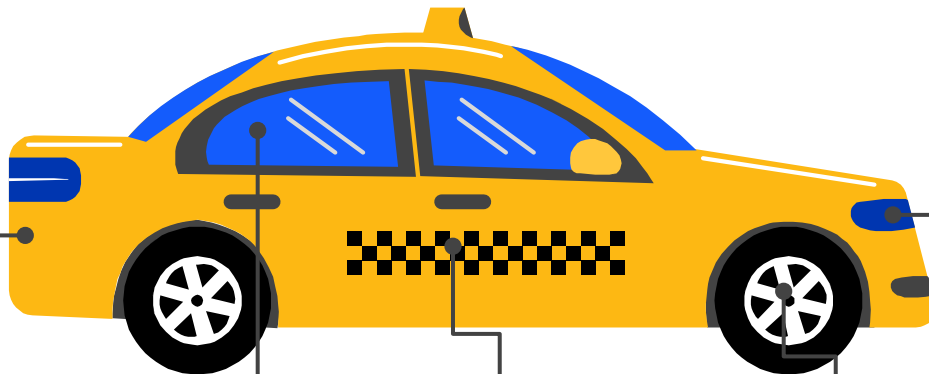


[Click Here to Try](#)



**CONCLUSION**

# NEXT STEPS/RECS



1

## TOOLS

Run experiment again w/ Spark, BigQuery, etc.

2

## GEO-GRANULAR

Mapped by taxi zone, can probably do by block

3

## TIME FRAME

Get data from multiple years

4

## BIASIS

Initially not, but downsizing made it more bias

5

## DEMAND

In future versions, include demand data



# THANK YOU!

*Questions?*

## Dillon Diatlo

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[Portfolio](#)

