# Bike Sharing in Washington D.C.

## Statistical Programming - Python

MBD OCT 2018 - O17 - Group G

# Context

**2011**

1,500 bicycles

165 stations

18,000 members

**2012**

1,650 bicycles

175 stations

22,200 members

**Objectives**

1. Predict the amount of users on an hourly basis
2. Ensure high level of service and availability
3. Optimize Logistics and Maintenance Teams

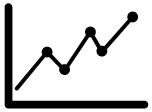
# 1.
# Project Structure

# Project Organization

### Model and Predictions

3

Using a Linear Regression algorithm, test the impact of the features on the model score ($R^2$)



### Data Preparation and Features Construction

2

Based on Exploratory Data Analysis and Machine Learning principles

### GitHub + GitKraken

1

Teamwork improved using collaborative developer tools

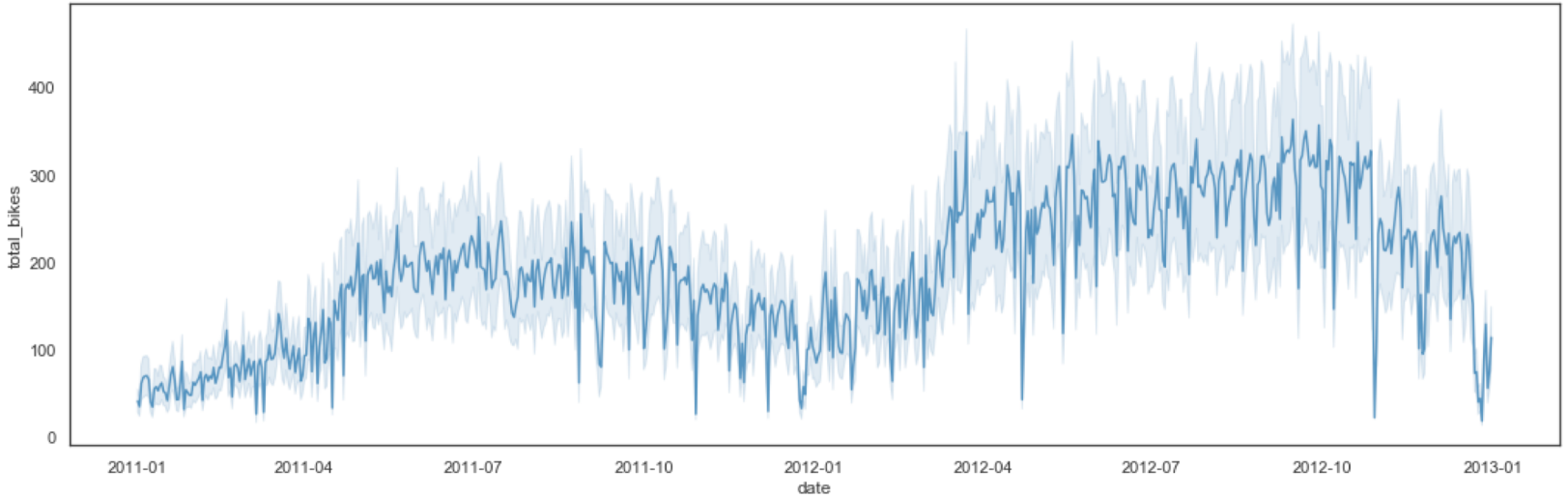
# Machine Learning Process

| | | |
|---|---|---|
| 01 | EDA and Data Preparation | • Remove *Casual*, *Registered*, *Holiday*, *Feeling Temperature*<br>• Scaling, Skewness, Encoding |
| 02 | Machine Learning Strategy | • Train set: Jan 2011 - Jul 2012<br>• Test set: Aug 2012 - Dec 2012<br>• Time Series Cross Validation (10 folds) |
| 03 | Feature Engineering | • Patterns on Dates and Hours<br>• Peak Detection<br>• Exceptional Weather Conditions<br>• Polynomials |
| 04 | Selection and Final Metric | • Recursive Feature Elimination<br>• Manual Selection<br>• Model Predictions vs Reality |

# 2.
# Data Exploration Key Insights

# 2011-2012 Utilization

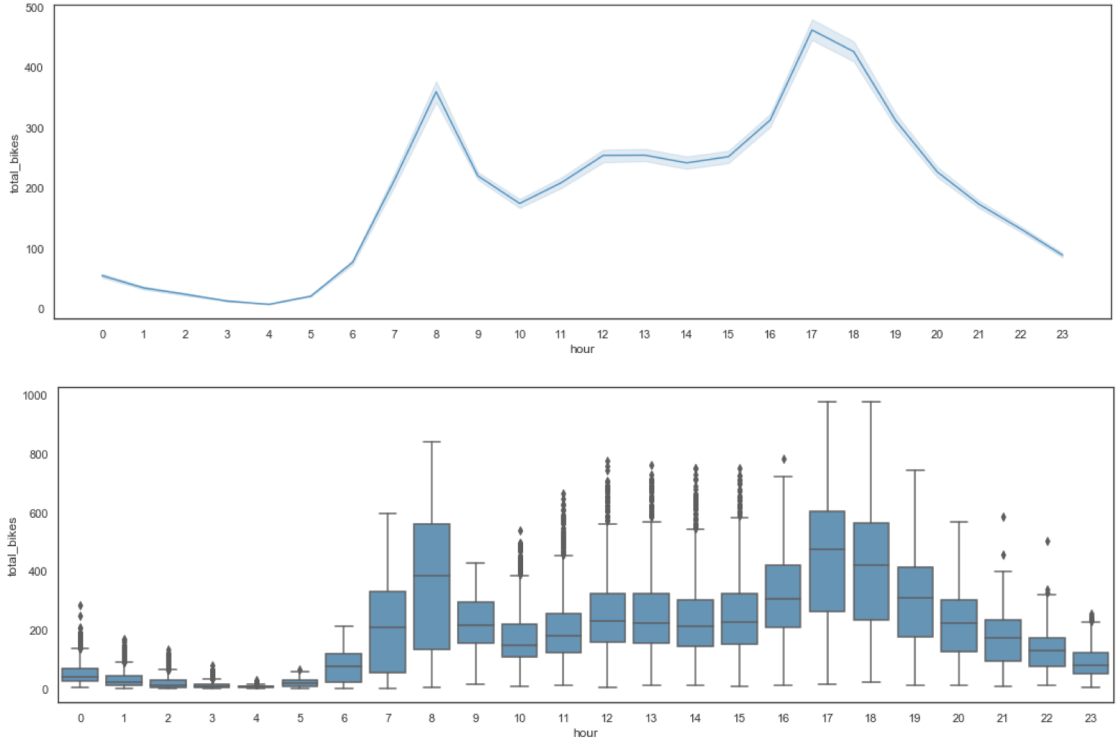
**Our bike sharing system gets more users every year.**




*Number of bikes used over 2011-2012*

# Utilization by Hour

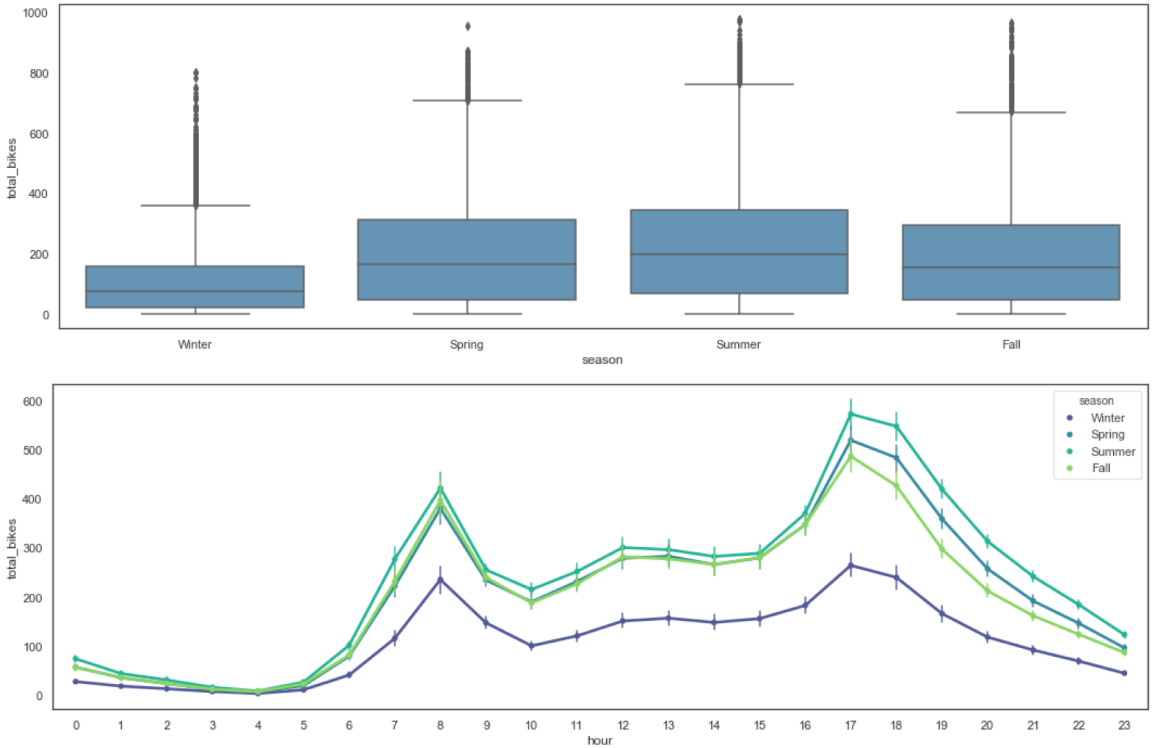
- **Day time usage**
- **One peak around 8am**
- **One peak between 5-6pm**
- **Up to 1000 bikes within an hour**




*Number of bikes used by Hour*

# Utilization by Season

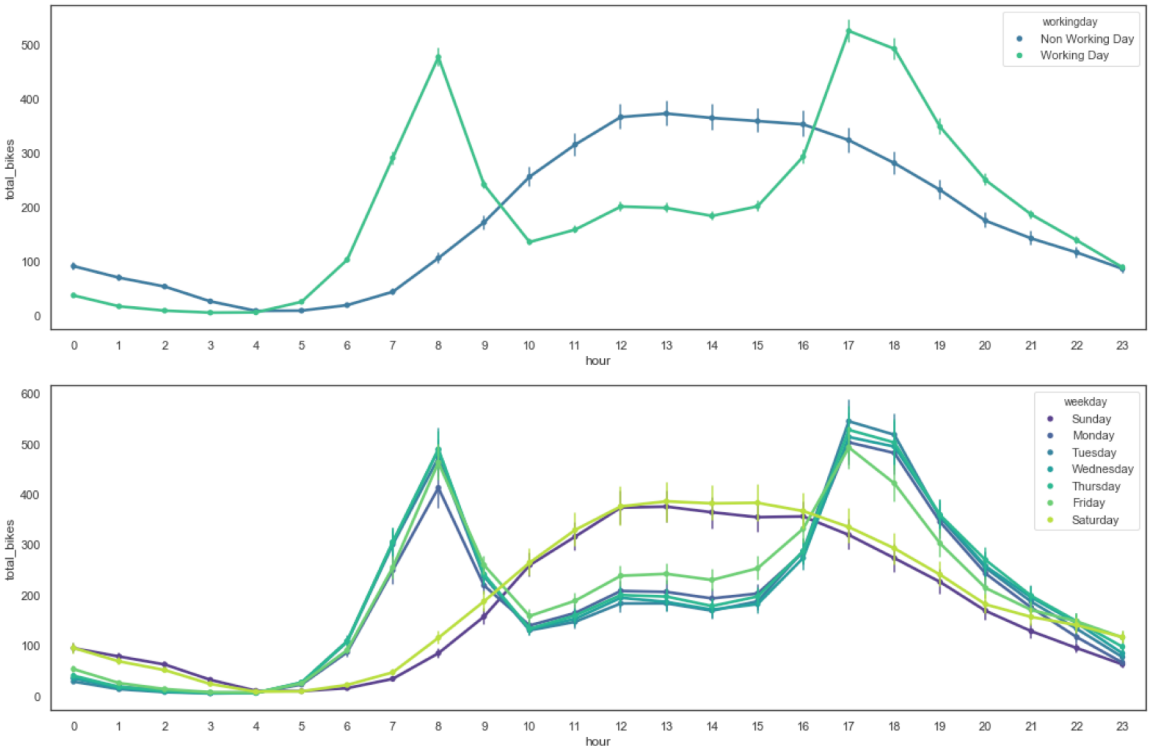
- **Summer is the high season**
- **Winter is the low season**
- **Spring and Fall have similar utilization shapes**




*Overall and Hourly Utilizations by Season*

# Working Days

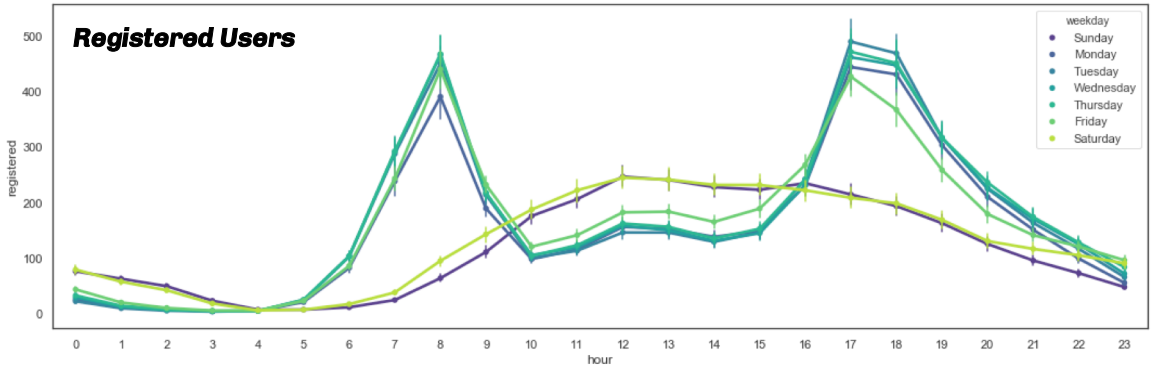
- **2 peaks on working days during commuting hours**
- **No peak during non working days, but higher overall utilization in the afternoon**
- **Slight change of shape on Fridays, maybe because people leave work earlier on that day**

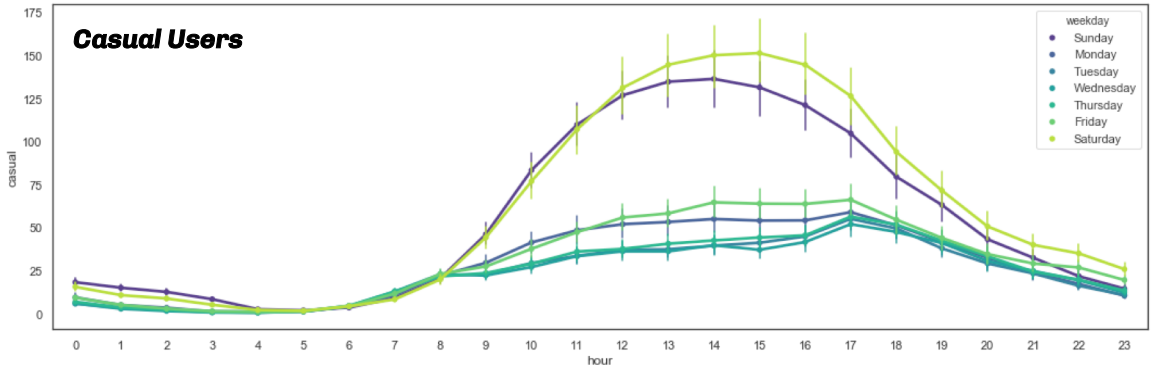



*Hourly Utilization on Working/Non Working Days*

# Working Days

- **Clear difference in behaviours between our registered users and the casual users**
- **Commuting and Leisure effects**



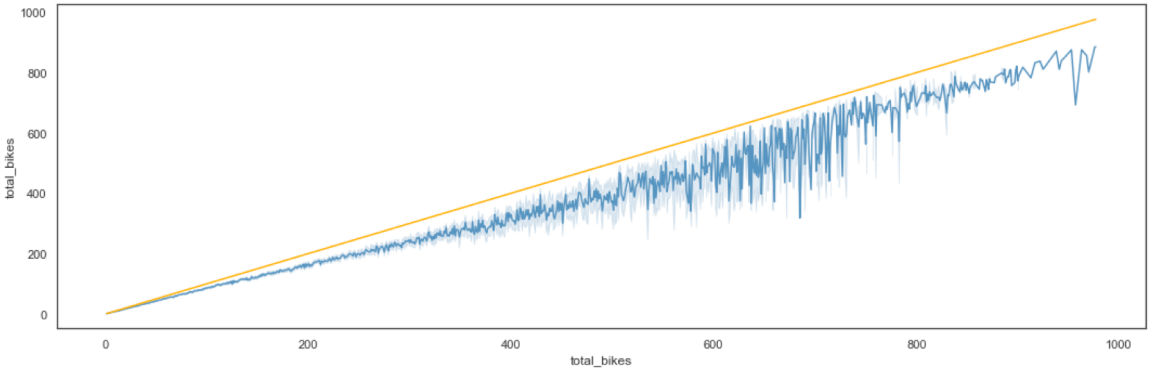



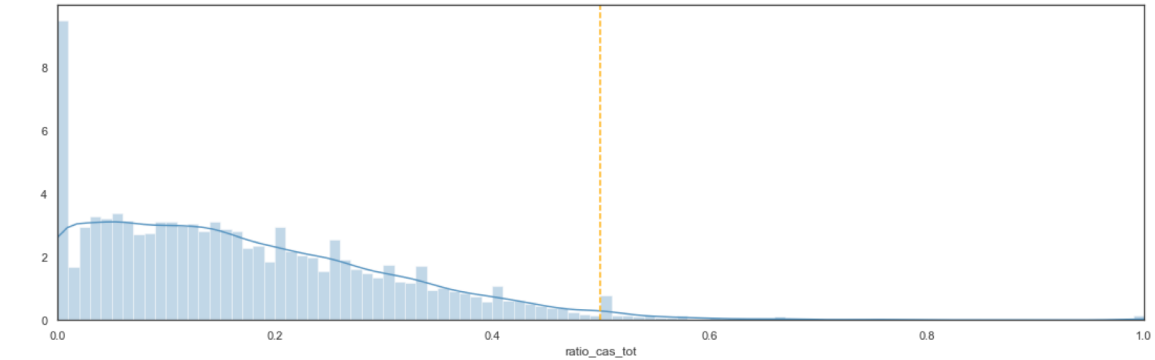

*Hourly Utilization on Working/Non Working Days*

# Utilization by User Type

- **Most users are registered**
- **High correlation with the Total number of bikes**

→ ***Casual*** **and** ***Registered*** **users information removed from the dataset**

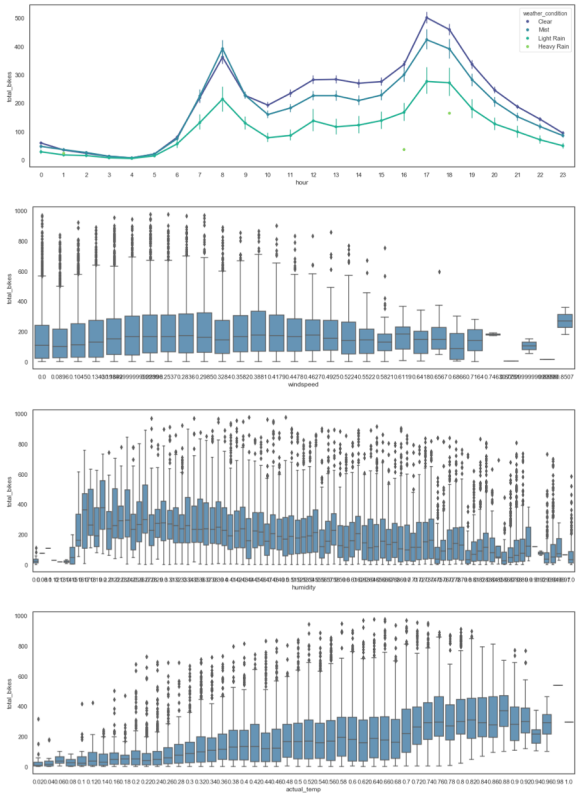



***Ratio of Registered Users***

# Weather Conditions

- **Weather conditions have a small impact on the service utilization**
- **Rain has the clearest effect**
- **Strong Wind discourages users**
- **Humidity and Temperature seem to have less influence**




***Rain***

***Wind***

***Humidity***

***Temperature***

*Utilization based on Weather Conditions*

# Correlations

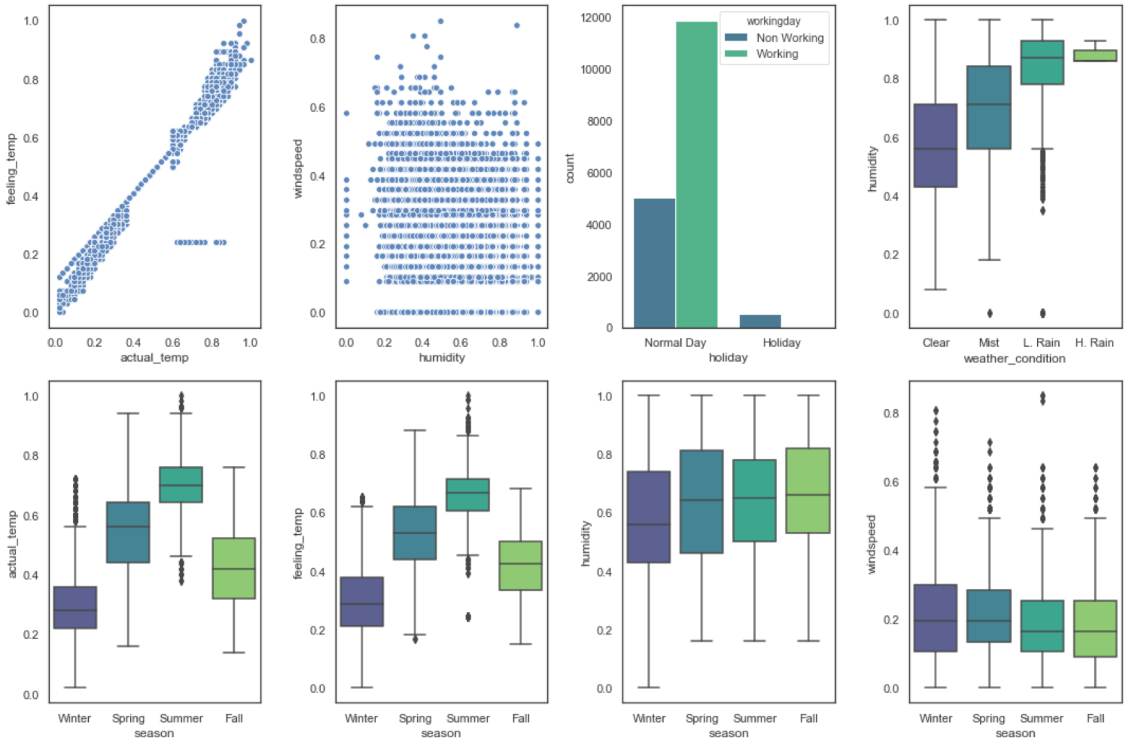
- **Correlation between Actual and Feeling Temperatures is clear**
- **No other strong correlation between other variables**


*Correlation Matrix*

# Correlations

- **Actual and Feeling Temperatures plot is clear**
- **Every Holiday is a Non-Working Day**

→ ***Feeling Temperature*** **and** ***Holiday*** **information removed from the dataset**



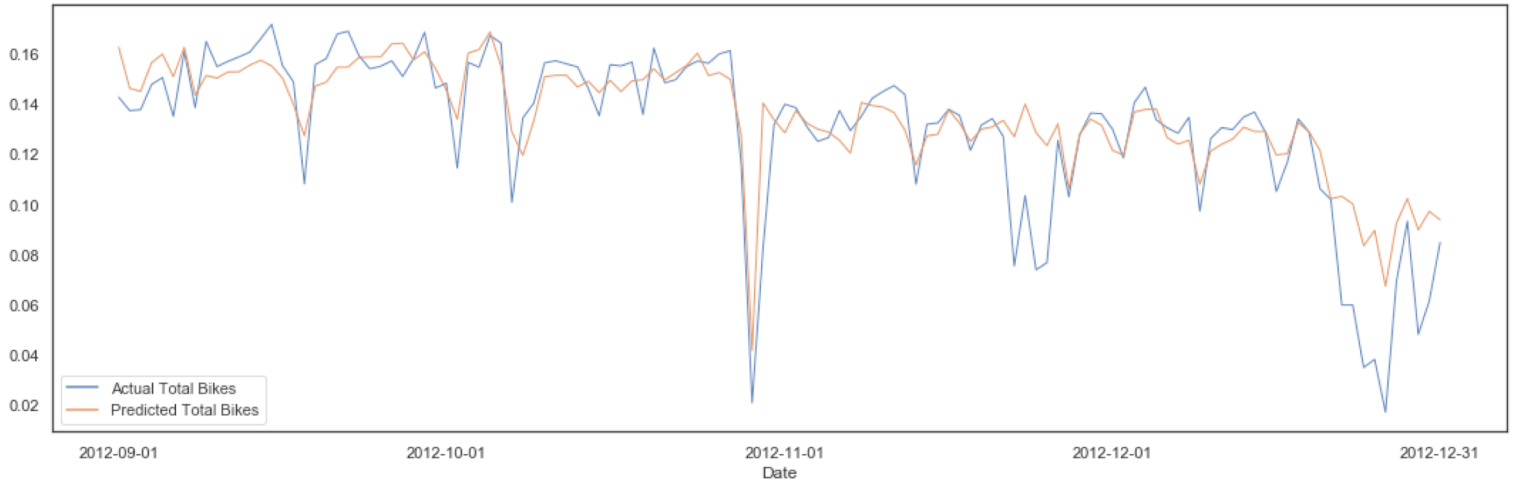

***Pair Plots***

# 3.
# Features Construction

# Baseline

***Features:*** ***57***

***$R^2$:*** ***0.76***




***Baseline Predictions vs Reality***

*Reminder - Features removed from dataset:*

*Casual, Registered, Holiday, Feeling Temperature*

# Calendar Features

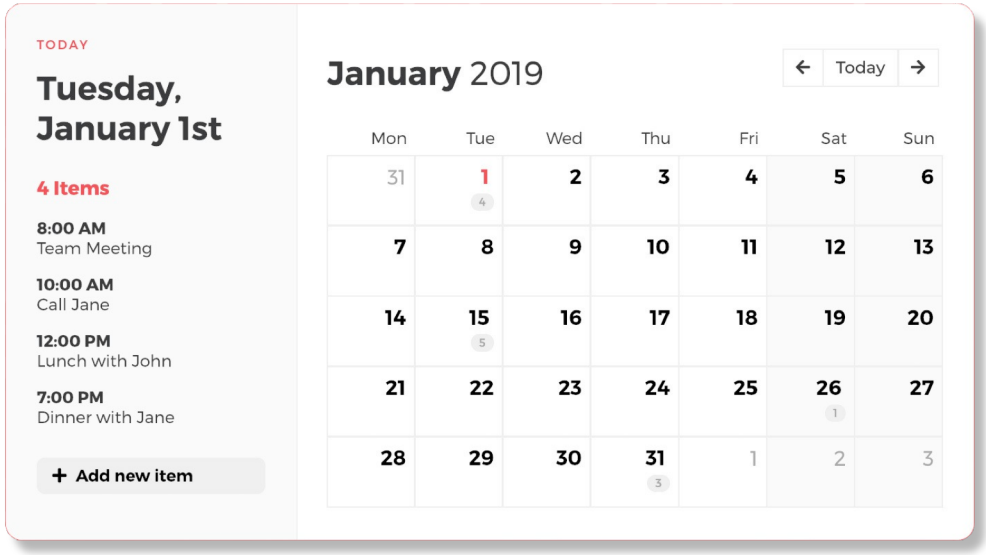
$R^2$ 0.76 — 0.75

**BASELINE**

Without
Casual, Registered,
Holiday, Feeling
Temperature

**DAY AND MONTH-DAY**

Add Day and Month-Day
to identify patterns
specific to special dates



# Peaks


**BASELINE**

Without Casual, Registered, Holiday, Feeling Temperature

**DAY AND MONTH-DAY**

Add Day and Month-Day to identify patterns specific to special dates

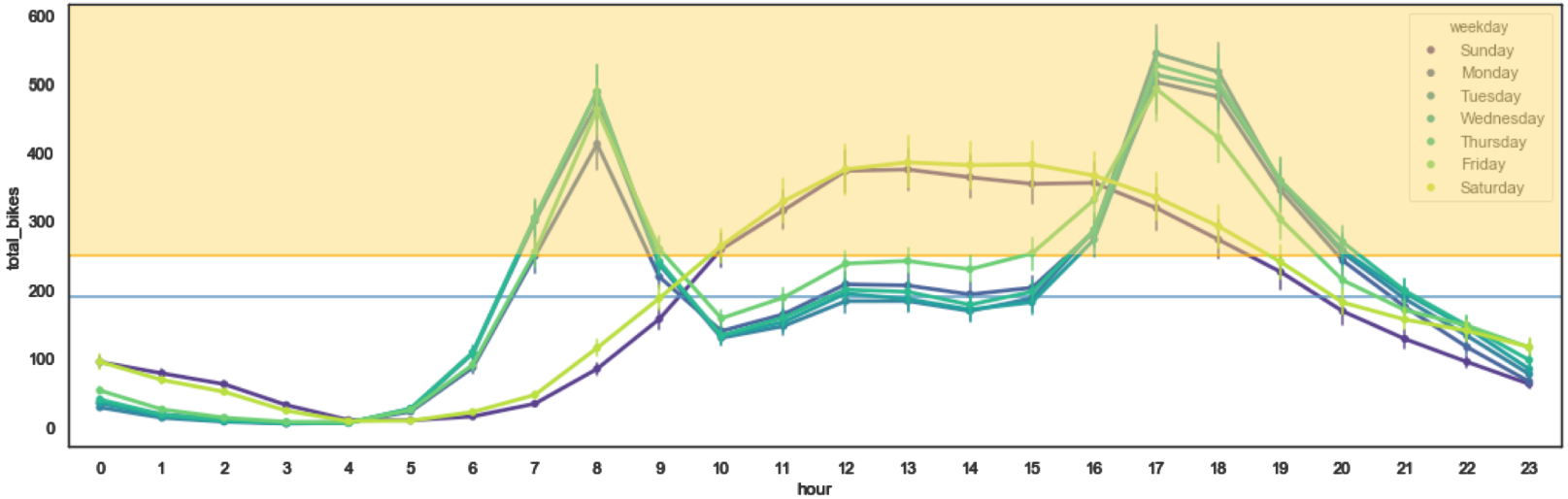
**PEAKS DETECTION**

Flag hours with utilization higher than a dynamic threshold

# Peaks

(1+ x%)

Mean Total Bikes



# Peaks


**BASELINE**

Without Casual, Registered, Holiday, Feeling Temperature

**DAY AND MONTH-DAY**

Add Day and Month-Day to identify patterns specific to special dates

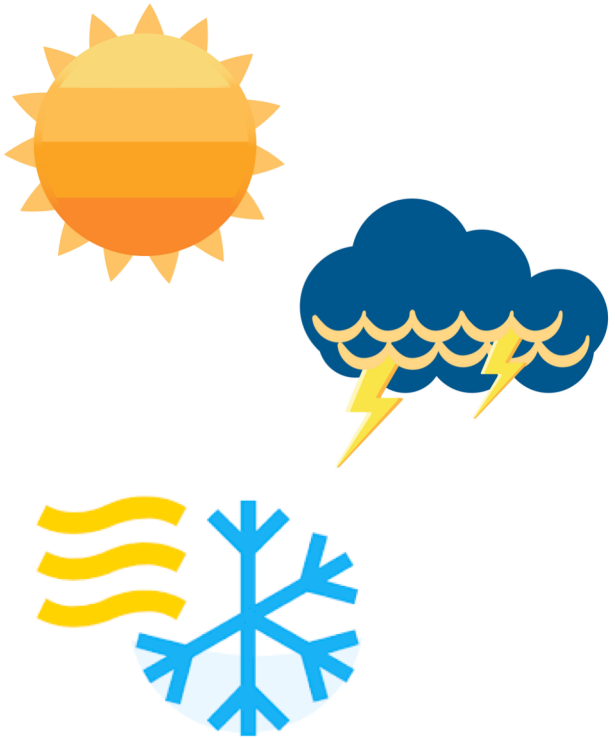
**PEAKS DETECTION**

Flag hours with utilization higher than a dynamic threshold

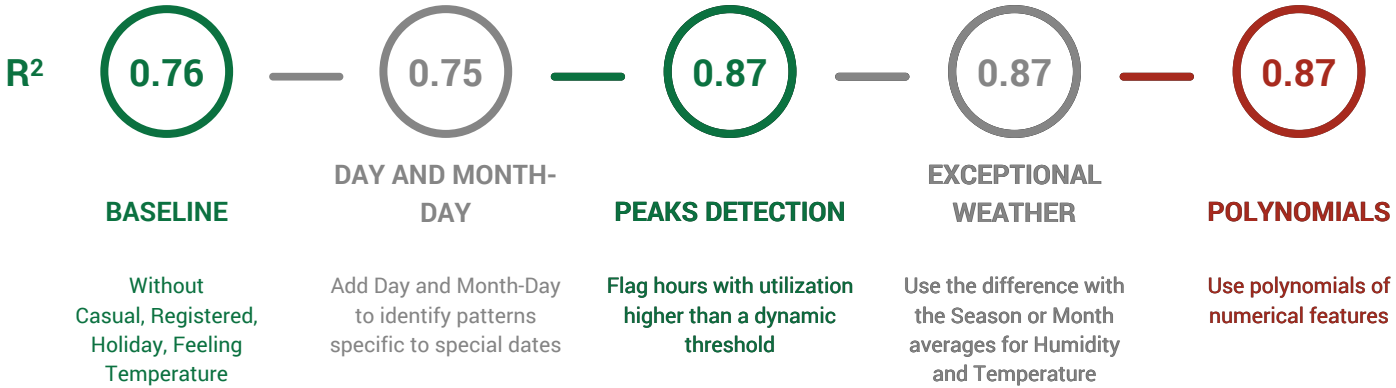
# Weather

$R^2$

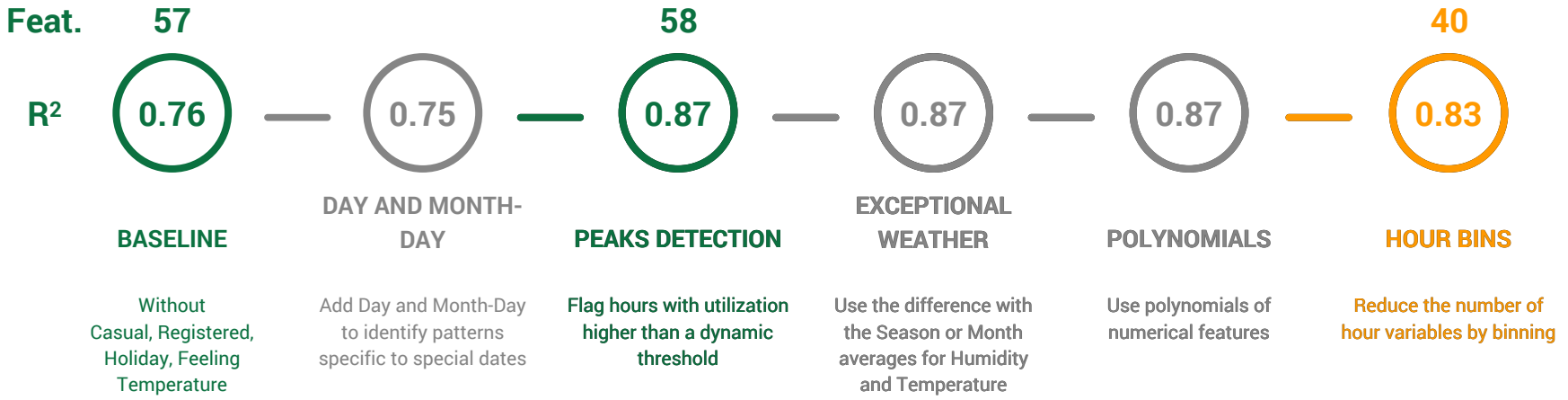
| 0.76 | 0.75 | 0.87 | 0.87 |
|---|---|---|---|
| **BASELINE** | **DAY AND MONTH-DAY** | **PEAKS DETECTION** | **EXCEPTIONAL WEATHER** |
| Without Casual, Registered, Holiday, Feeling Temperature | Add Day and Month-Day to identify patterns specific to special dates | Flag hours with utilization higher than a dynamic threshold | Use the difference with the Season or Month averages for Humidity and Temperature |



# Polynomials

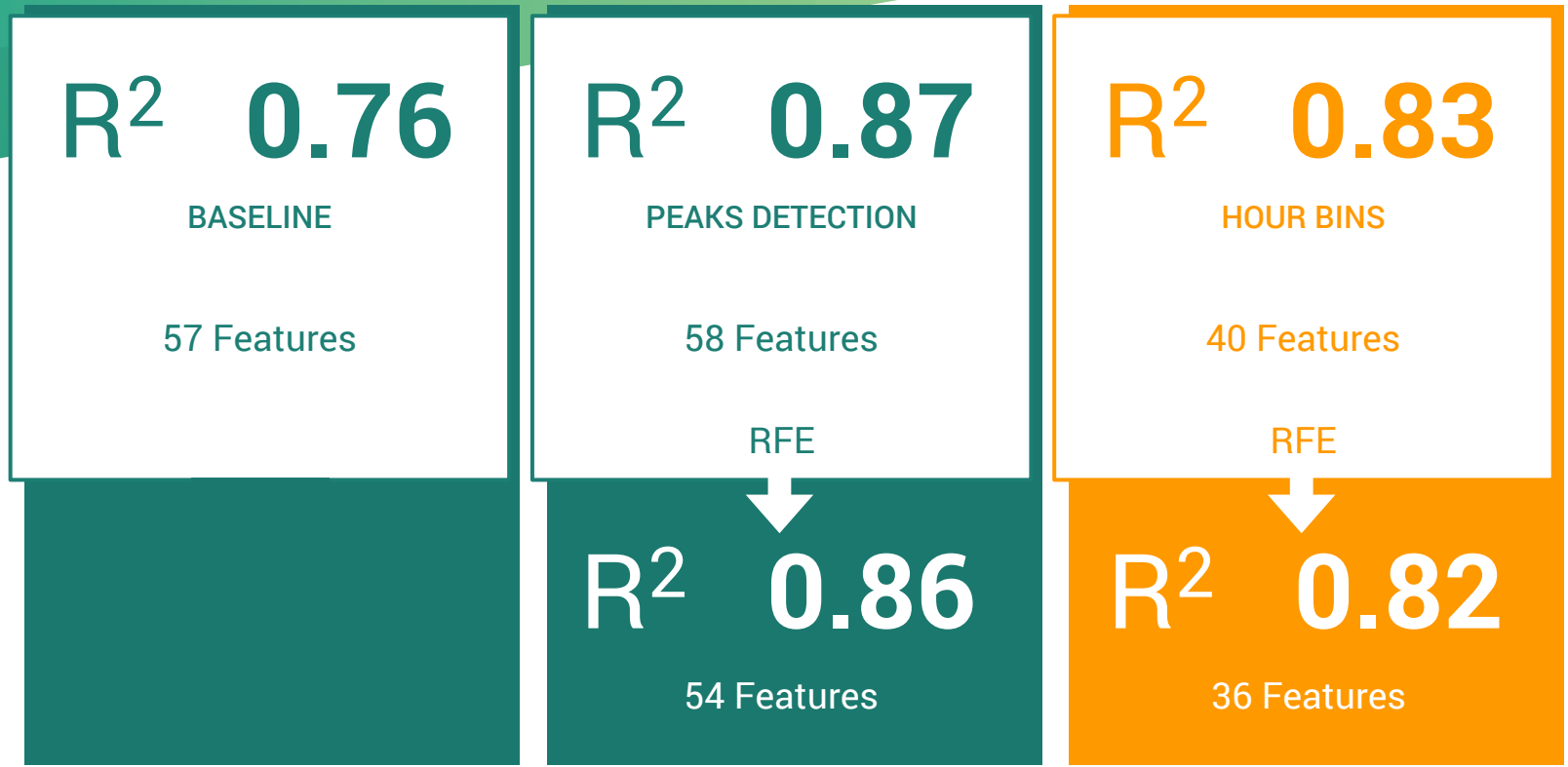


# Hour Bins


Feat.
57
58
40
R²
0.76
0.75
0.87
0.87
0.87
0.83
BASELINE
DAY AND MONTH-DAY
PEAKS DETECTION
EXCEPTIONAL WEATHER
POLYNOMIALS
HOUR BINS
Without Casual, Registered, Holiday, Feeling Temperature
Add Day and Month-Day to identify patterns specific to special dates
Flag hours with utilization higher than a dynamic threshold
Use the difference with the Season or Month averages for Humidity and Temperature
Use polynomials of numerical features
Reduce the number of hour variables by binning

# 4.
# Model Selection

# RFE




4 Features Eliminated:

Humidity | Actual Temperature | Wind Speed | Working Day

# Manual Feat. Selection

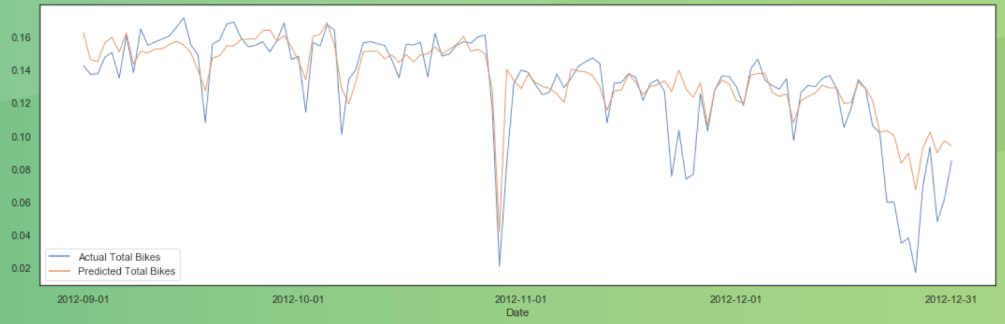
| Features Kept | Features Removed |
|---|---|
| Year | Actual Temperature |
| Month | Humidity |
| Days of the Week | Windspeed |
| Hours | Weather Condition |
| Peak Detection | Working Day Flag |
| | Seasons |

***Features: 46*** ***$R^2$: 0.85***

## BASELINE

**Features: 57** **$R^2$: 0.76**

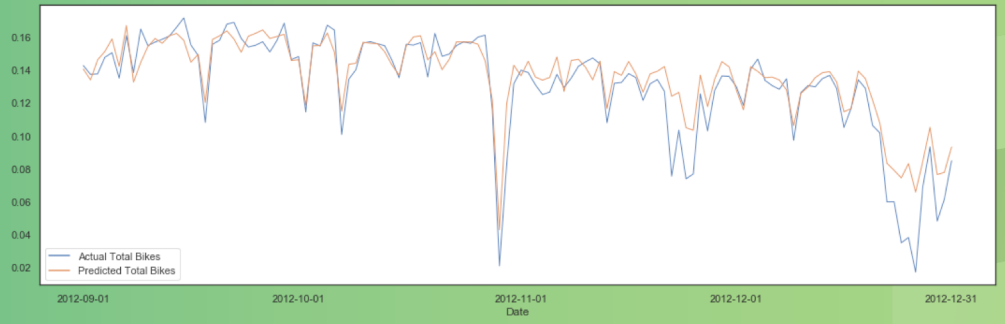
**Risk of shortage during peaks**




## PEAKS DETECTION

**Features: 54** **$R^2$: 0.86**

**Better peaks anticipation**




## MANUAL SELECTION

**Features: 46** **$R^2$: 0.85**

**Better general fit**

# 5.
# Business Conclusions

# Optimization Using Data

**Maintenance & Repair:**

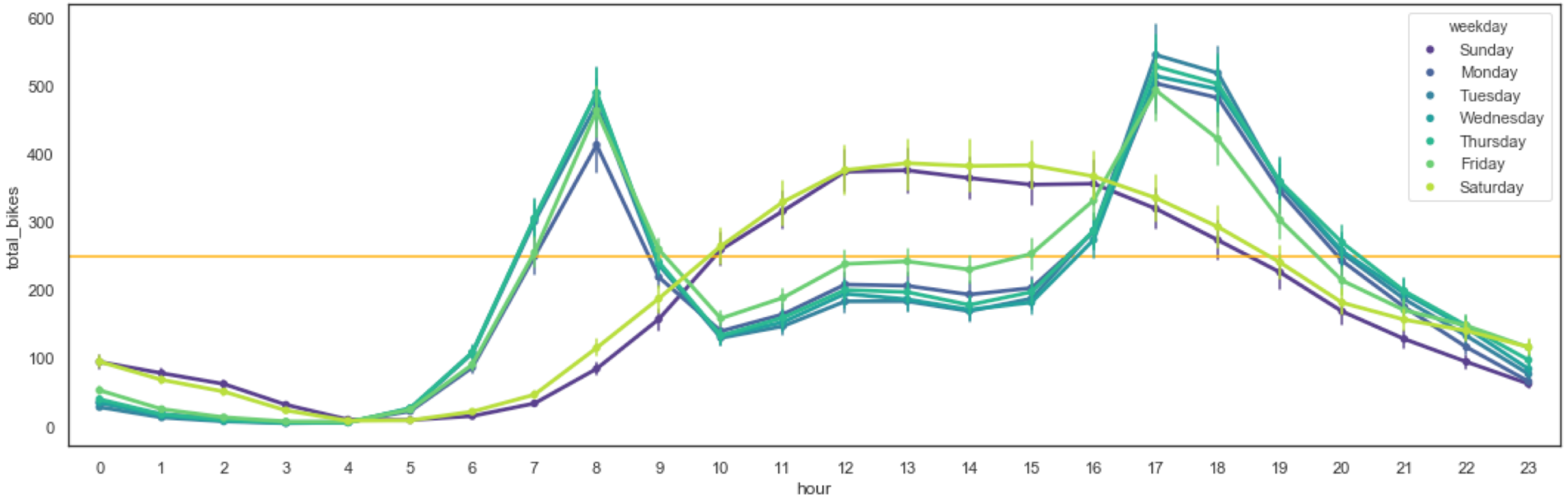
Data driven approach to optimize processes to keep bikes and docks in good repair, safe, and available.

**Adapting Technologies for Future Usage:**

Optimizing current operations, and the “bike valet service.”

# Determining Peak Times

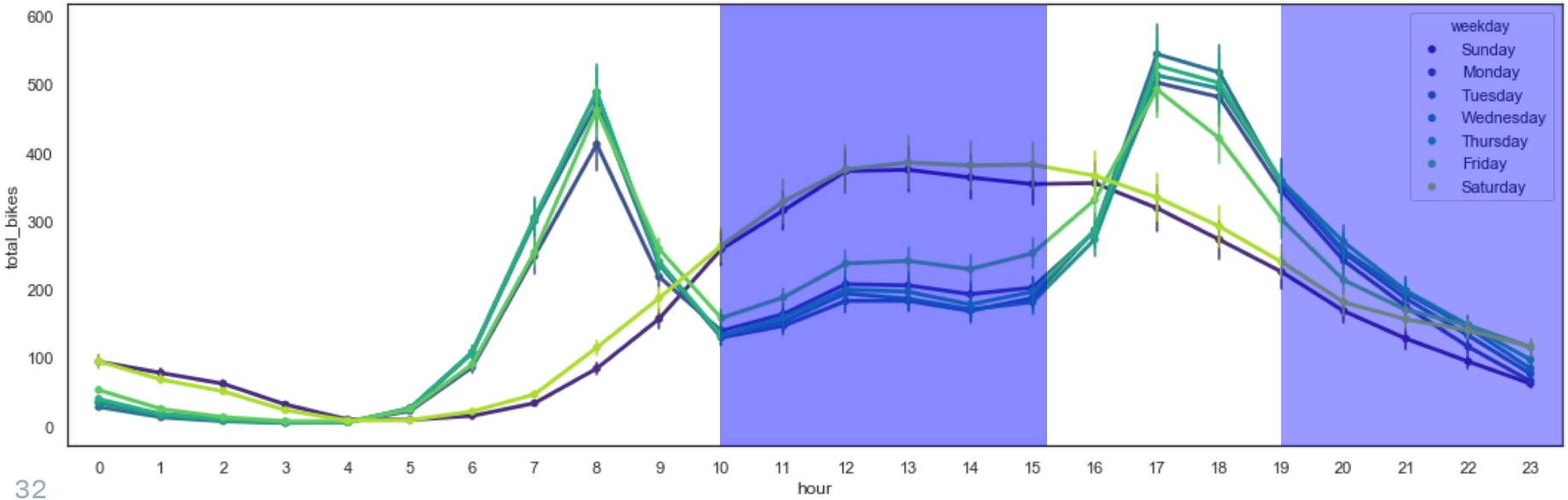
- Peak times based on mean + 31.5%
- Process allows model flexibility
- Additional data will adapt to model




Total_Bikes by Hour with Weekday Hue

# Peak Times + Maintenance Weekdays

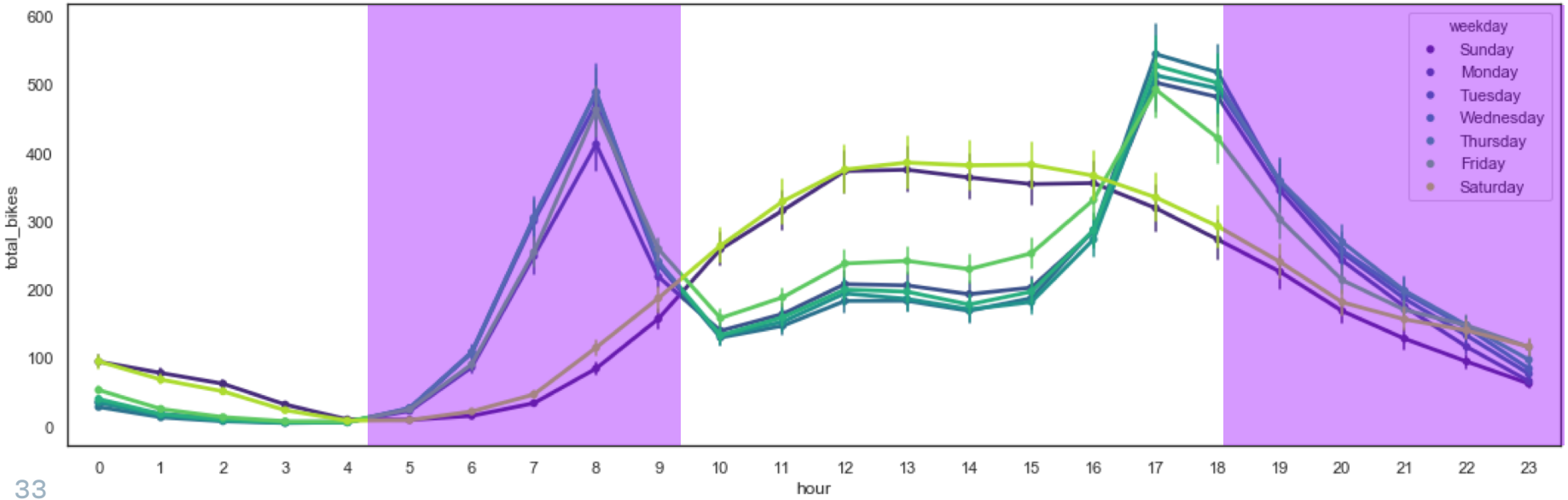
- Weekdays/Commuting-highest usage
- Peak hours for determining maintenance time
- Goal: Least disturbance to business




Total_Bikes by Hour with Weekday Hue

# Peak Times + Maintenance Weekends

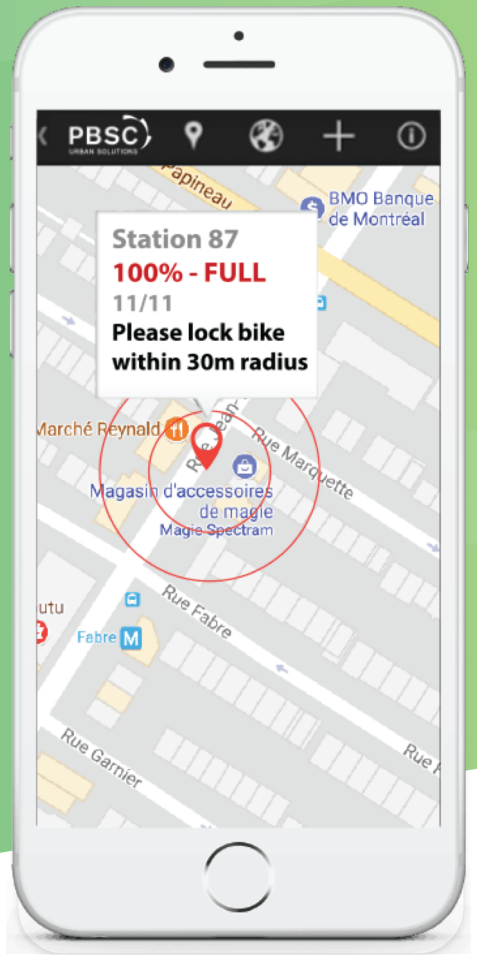
- Weekend-lower usage
- Peak hours different from weekday
- Goal: Least disturbance to business




Total_Bikes by Hour with Weekday Hue

# Optimizing Operations

- Rebalancing
- Bike Valet Service
- Geofencing/Station Availability



# Peak Times and Growth Optimization

- Use models in conjunction with other departments
- Avg. time increases can provide insight on inventory
- Optimize inventory based on trends

**Thank you!!**

**Who Has The First Question?**