Bike Sharing Demand

Springboard Capstone Project - I

Project

- Bike Sharing Demand (Hourly)
  - Bike sharing systems automate obtaining bike riders membership, bike rental and return.
  - Data for capstone project is a historical log of rentals for year 2011, 2012.
  - Bike share data is aggregated on Hourly basis and combined with Weather data
  - This Project uses data from bike sharing systems in Washington D.C., USA.

- Outcome from this Project
  - Provide insights into demand patterns.
  - Predict the demand based on different environmental and seasonal conditions.

Clients

- Bike Rental Companies
  - Scale bike stations to be able to meet demand
  - Increase the demand of bike sharing in the City
  - Help convert casual riders to membership/registered riders
  - Retain existing registered riders

- City Transportation
  - Manage city transit services based on bike demand

- Society
  - Stress free Commute in City
  - Healthy Lifestyle

Data Acquisition

- ➢Retrieved dataset from https://www.kaggle.com/c/bike-sharing-demand
- ➢The core data set is from http://capitalbikeshare.com/system-data aggregated on hourly and daily basis combined with seasonal & weather information
- ➢This data is of Washington D.C area for year 2011 and 2012

Dataset Exploration

- ➢Dataset has 17379 rows with 17 columns
- ➢Record ID is the Index
- ➢Data Size of 2.3 MB

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17379 entries, 0 to 17378
Data columns (total 17 columns):
instant       17379 non-null int64
dteday        17379 non-null object
season        17379 non-null int64
yr            17379 non-null int64
mnth          17379 non-null int64
hr            17379 non-null int64
holiday       17379 non-null int64
weekday       17379 non-null int64
workingday    17379 non-null int64
weathersit    17379 non-null int64
temp          17379 non-null float64
atemp         17379 non-null float64
hum           17379 non-null float64
windspeed     17379 non-null float64
casual        17379 non-null int64
registered    17379 non-null int64
cnt           17379 non-null int64
dtypes: float64(4), int64(12), object(1)
memory usage: 2.3+ MB
```

Data Dictionary

```
        - instant: record index
        - dteday : date
        - season : season (1:springer, 2:summer, 3:fall, 4:winter)
        - yr : year (0: 2011, 1:2012)
        - mnth : month ( 1 to 12)
        - hr : hour (0 to 23)
        - holiday : weather day is holiday or not (extracted from http://dchr.dc.gov/page/holiday-schedule)
        - weekday : day of the week
        - workingday : if day is neither weekend nor holiday is 1, otherwise is 0.
        + weathersit :
                - 1: Clear, Few clouds, Partly cloudy, Partly cloudy
                - 2: Mist + Cloudy, Mist + Broken clouds, Mist + Few clouds, Mist
                - 3: Light Snow, Light Rain + Thunderstorm + Scattered clouds, Light Rain + Scattered clouds
                - 4: Heavy Rain + Ice Pallets + Thunderstorm + Mist, Snow + Fog
        - temp : Normalized temperature in Celsius. The values are divided to 41 (max)
        - atemp: Normalized feeling temperature in Celsius. The values are divided to 50 (max)
        - hum: Normalized humidity. The values are divided to 100 (max)
        - windspeed: Normalized wind speed. The values are divided to 67 (max)
        - casual: count of casual users
        - registered: count of registered users
        - cnt: count of total rental bikes including both casual and registered
```

Data Wrangling

- Rename column names
- Combine Date and Hour columns as Index
- Delete instant column
- Create Part_Of_Day column

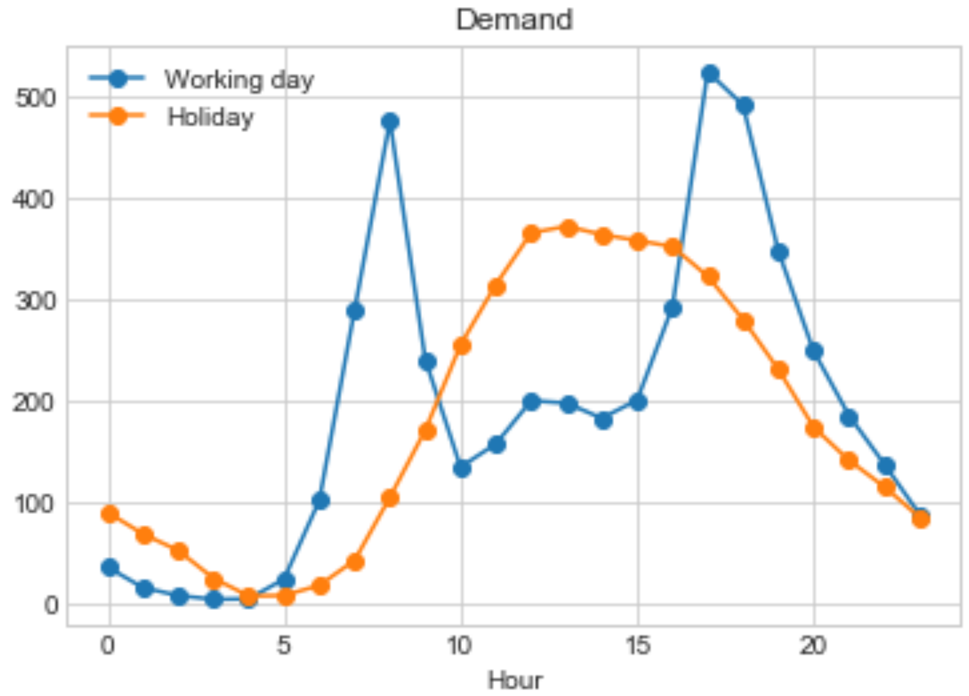
  (divides a day in 6 windows/periods)
  - 0-4 : 0
  - 4-8 : 1
  - 8-12 : 2
  - 12-16 : 3
  - 16-20 : 4
  - 20-23 : 5

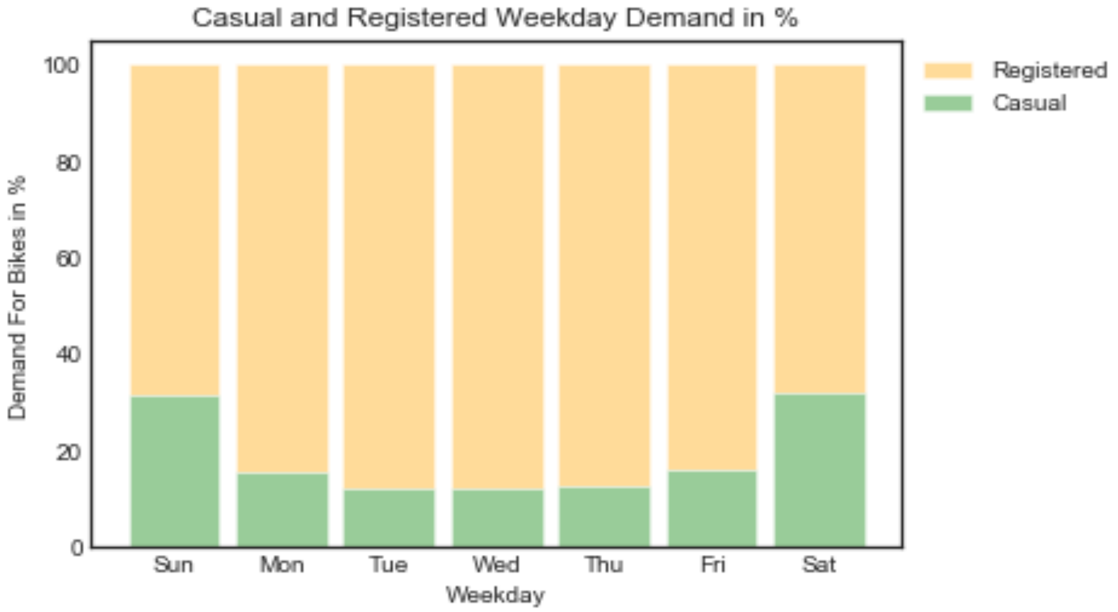
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17379 entries, 0 to 17378
Data columns (total 18 columns):
Instant                       17379 non-null int64
Date                          17379 non-null object
Season                        17379 non-null int64
Year                          17379 non-null int64
Month                         17379 non-null int64
Hour                          17379 non-null int64
Holiday                       17379 non-null int64
Weekday                       17379 non-null int64
Workingday                    17379 non-null int64
Weather_Condition             17379 non-null int64
Normalized_Temperature        17379 non-null float64
Normalized_Feels_Temperture   17379 non-null float64
Huumidity                     17379 non-null float64
Windspeed                     17379 non-null float64
Casual                        17379 non-null int64
Registered                    17379 non-null int64
Demand                        17379 non-null int64
Part_Of_Day                   17379 non-null category
dtypes: category(1), float64(4), int64(12), object(1)
memory usage: 2.3+ MB
```

Weekdays Data Analysis

- ➢Workday
  - ▪Demand peaks at Morning and Evening Hours
- ➢Holiday
  - ▪Demand peaks in afternoon

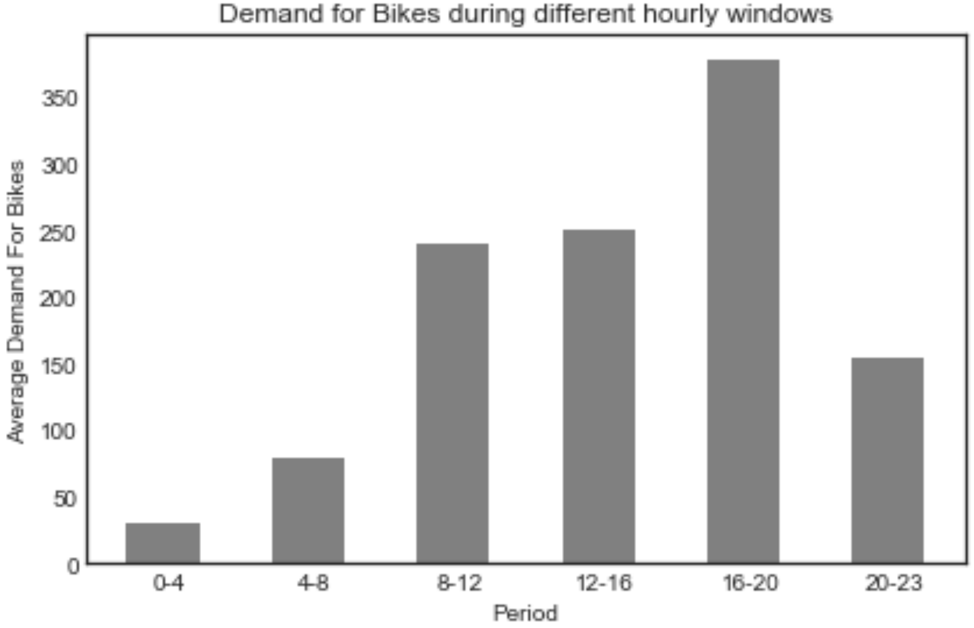


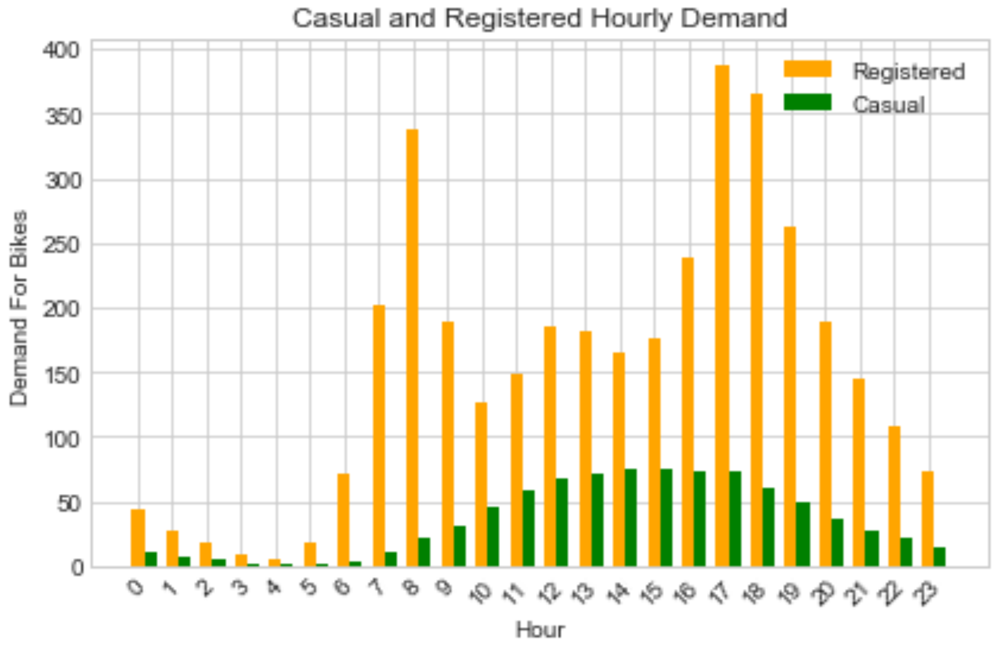


➢Registered riders contribute higher percentage demand

Hourly Data Analysis

➢ Evening Hours have higher demand than Mornings

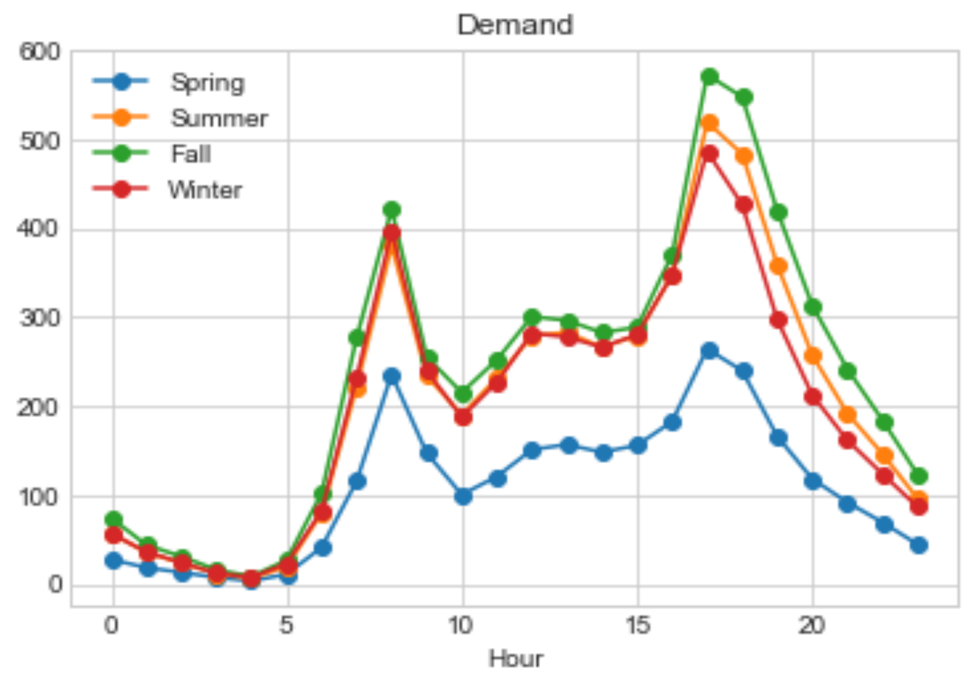


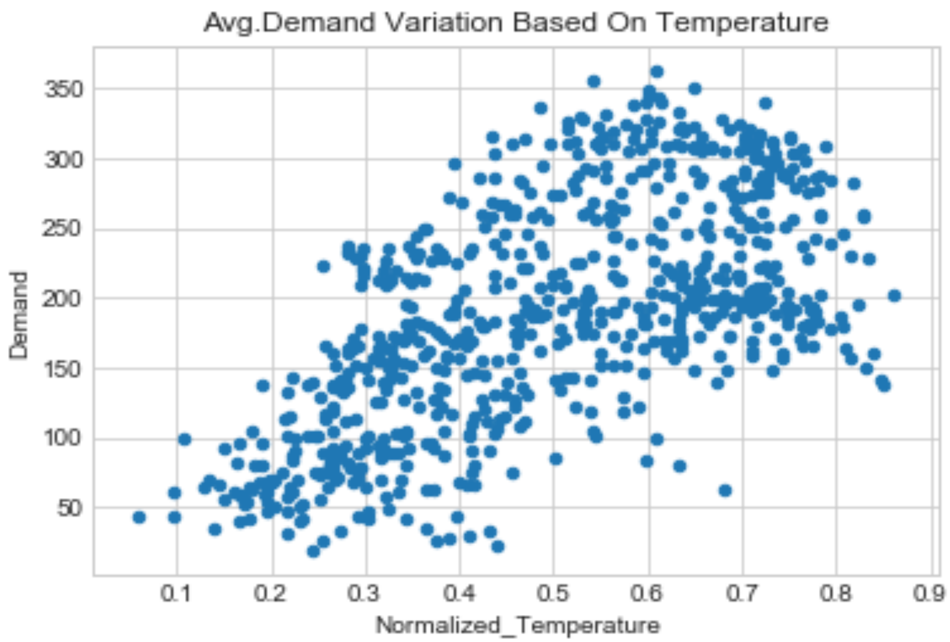


➢ Demand Peaks between 4 and 8 PM

Seasonal Data Analysis

➢ Demand is highest in Fall Season and lowest in Spring Season



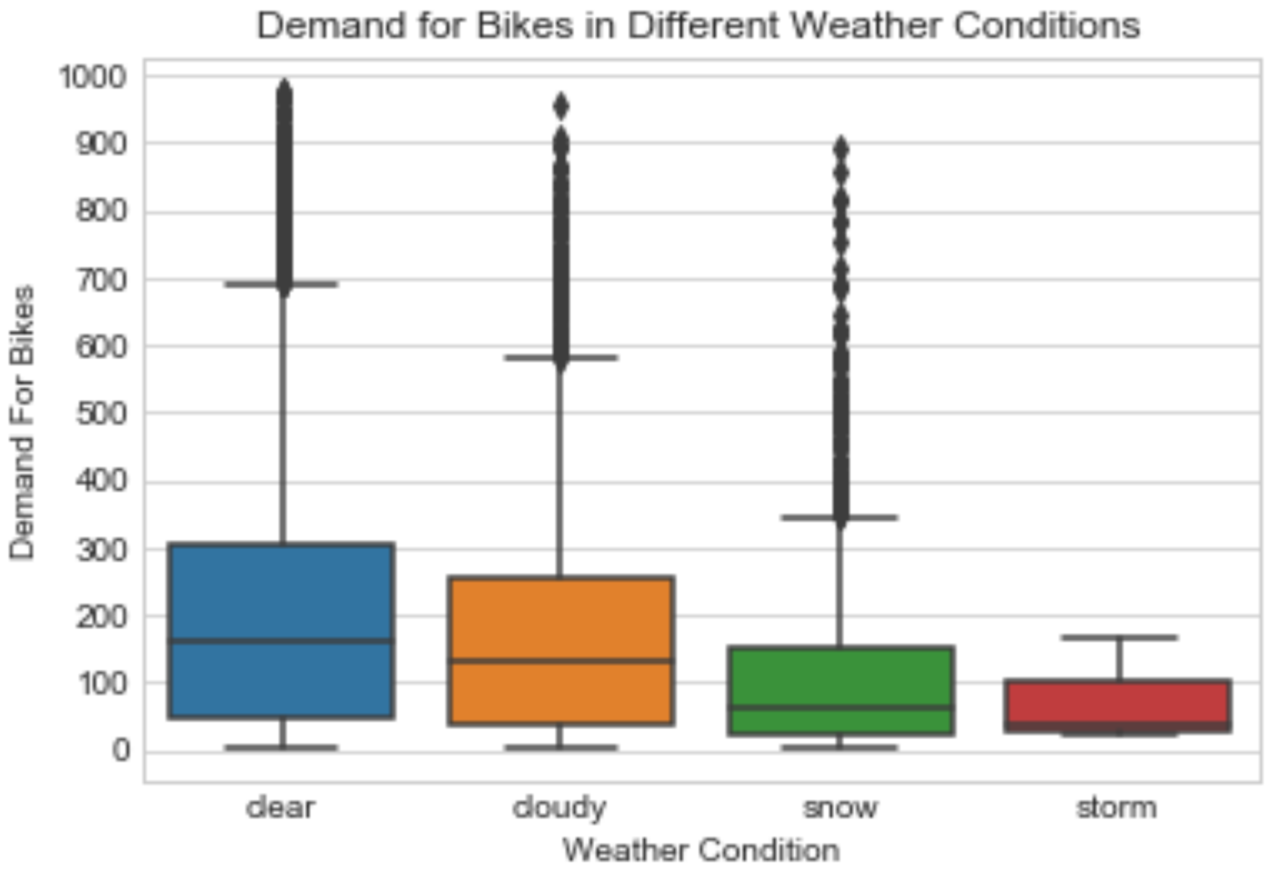


➢ Demand increases with temperature and it starts declining at very high temperature.

Weather Data Analysis

- ➢ Average Demand is highest in Clear Weather

- ➢ Demand is lowest in Stormy Weather



Model Evaluation & Selection

- Evaluated below 3 Linear Regression Models

	Linear Regression	Ridge Regression	Lasso Regression
R ^ 2	0.40	0.40	0.38
RMSE	139.97	140.23	139.85

- Its evident from above metrics, that linear regression is not the best model for this project

Model Evaluation & Selection

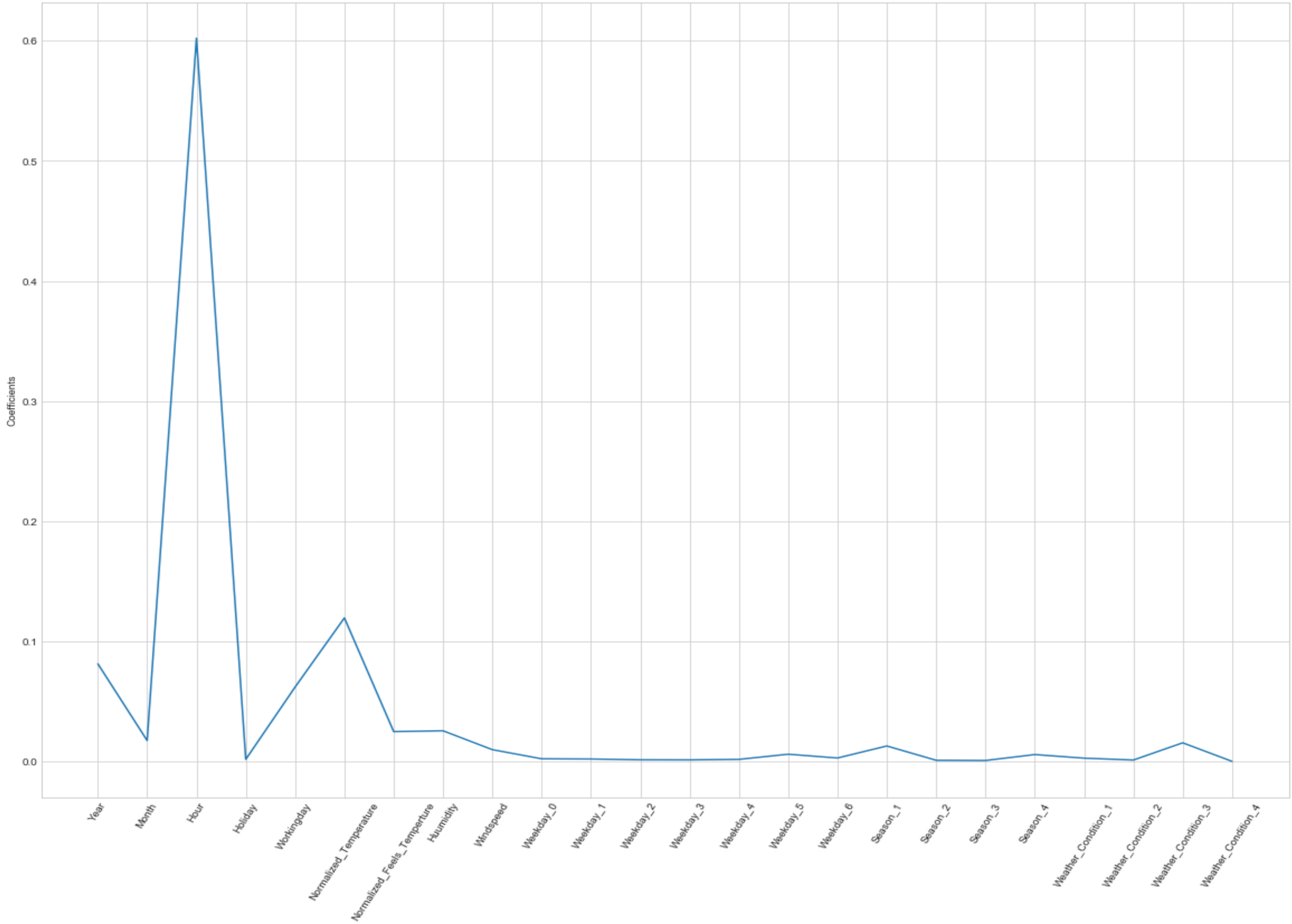
- Random Forest with One Hot Encoding
- Determine important parameters to build a final model with RandomizedSearchCV
  - max_depth=25
  - min_samples_leaf= 1
  - min_samples_split= 2
  - n_estimators = 100

	Decision Tree Regression	Random Forest Regression
R ^ 2	0.90	0.937
RMSE	57.12	46.05

- Random Forest regression with R^2 score of 0.937 is a better fit for this dataset

Model Evaluation

- Feature Importance
  - Hour seems to be the most important



Recommendations to Clients

- Factors Influencing increase in demand for bike sharing in city
  - Registered Ridership
  - Working Day
  - Evening Commute Hours (4 and 8 PM)
  - Clear Weather Conditions
  - Season
  - Moderate Temperatures
- Recommendations to Bike Rental Companies
  - Convert Casual Riders to Registered
  - Adapt bike stations to meet evening demand
- City Transportation
  - Increase services during bad weather conditions as bike rental demand decreases

Thank You.