

# Applied Data Science with R Capstone project

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# Outline

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- Executive Summary
- Introduction
- Methodology
- Results
- Conclusion
- Appendix

# Executive Summary

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- 4 selected big cities over the worldWeather forecast for next 5 days while using Regression Model
- Created an app to access forecast + prediction
- Make data based decision according peaks
- The demand of bikes have factors that can influence their demand within a city. For example season, renting price, temperature, and hour of the day.

# Introduction

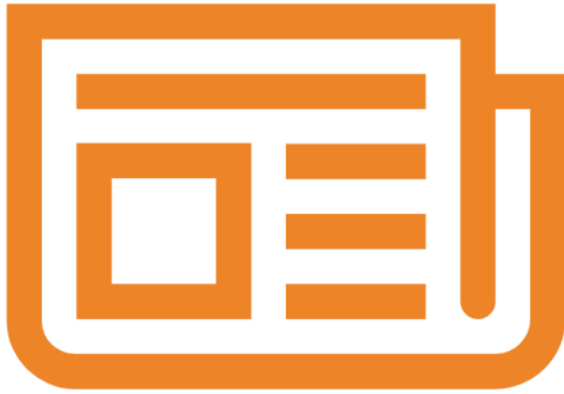
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- Problem: how to predict bike sharing demand in big cities?
- Requirement:
  - Use only few public available data sets
  - Apply regression model in programming language R
  - Predict number bikes rented each hour based on the weather
  - Use Data Collection and sources
  - Use Data exploration and analysis
  - Use Data Modeling
  - Create Dashboard
  - Derive Conclusion

# Methodology

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- Perform data collection
- Perform data wrangling
- Perform exploratory data analysis (EDA) using SQL and visualization
- Perform predictive analysis using regression models
  - How to build the baseline model
  - How to improve the baseline model
- Build a R Shiny dashboard app

# Methodology

- Used Web Scraping from Wikipedia
- Used Openweather API
- Did data Wrangling
- Performed Data Exploration
- Performed Data Visualization
- Predicted hourly bikes rented using linear regression
- Then refined the process of baseline regression models

# Data collection

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- The data was available on Wikipedia, I used the R Programming language to scrape the table.
- Extracted the Bike Sharing System HTML table from a wikipedia and converted it to a data frame.
- Used OpenWeatherAPI to get a 5-day weather forecast for a list of cities (Seoul, Washington D. C, Paris, Suzhou)

# Data wrangling

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- Data wrangling was performed using Regular Expressions
- Performed data wrangling using dplyr
- Standardize column names and processed the scraped data into its columns
- Removed all the undesired reference links using regular expressions
- Detected and handled missing values in the data using dplyr
- Normalized the data using dplyr



# EDA with SQL

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- Most bikes being rented during summer and the least during winter
- I established connection using RSQlite
- Seoul offers highest bike sharing per population compared to other big cities

# EDA with data visualization

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- Scatter plot was used to visualise correlation between Bike count and Temperature by Seasons
- Created histogram overlay where I deducted the following:
- We can see from the histogram that most of the time there are relatively few bikes rented. Indeed, the 'mode', or most frequent amount of bikes rented, is about 250.
  - Judging by the 'bumps' at about 700, 900, and 1900, and 3200 bikes, it looks like there may be other modes hiding within subgroups of the data.
  - Interestingly, judging from the tail of the distribution, on rare occasions there are many more bikes rented out than usual.
- Although the overall scale of bike rental counts changes with the seasons, key features remain very similar.

For example, peak demand times are the same across all seasons, at 8 am and 6

# Predictive analysis

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- Split the data into training and testing data
- Did a model evaluation and identification of important variables
- Used linear regression model to perform variable correlations

# Build a R Shiny dashboard

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## Plots

- Leaflet (world map and cities (incl. Barcelona))
- Temperature forecast
- Bikes rented prediction (cursor with additional info)
- Linear model bikes rented  $\sim$  humidity<sup>5</sup>

# Results

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- Exploratory data analysis results
- Predictive analysis results
- A dashboard demo in screenshots

# EDA with SQL

- Using SQL we found
- Maximum bike rental amount
- How the popularity of the rental is affected by the temperature
- The season ability of the bikes
- Found the total bike count in Seoul

# Busiest bike rental times

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- The busiest bike rental times are from the hour of 8 – 23 hour.

	DATE	RENTED_BIKE_COUNT	HOUR	TEMPERATURE	HUMIDITY	WI
0	2017-01-12T00:00:00+08...	254	0	-5.2000	37	
1	2017-01-12T00:00:00+08...	204	1	-5.5000	38	
2	2017-01-12T00:00:00+08...	173	2	-6	39	
3	2017-01-12T00:00:00+08...	107	3	-6.2000	40	
4	2017-01-12T00:00:00+08...	78	4	-6	36	

# Hourly popularity and temperature by seasons

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	SEASONS	HOUR	AVG_bikes_rented	AVG_temp
1	Summer	18	2135.141	29.41868
2	Autumn	18	1983.333	16.03185
3	Summer	19	1889.250	28.29231
4	Summer	20	1801.924	27.06630
5	Summer	21	1754.065	26.27826
6	Spring	18	1689.311	15.97222
7	Summer	22	1567.870	25.69891
8	Autumn	17	1562.877	17.27778
9	Summer	17	1526.293	30.15444
10	Autumn	19	1515.568	15.06346

- The hour of 18 recorded the highest across the season



# Rental Seasonality

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- Rental Seasonality

	SEASONS	AVG_Rented	Max_Rented	MIN_Rented	STD_deviation
1	Summer	1034.0734	3556	9	690.0884
2	Autumn	924.1105	3298	2	617.3885
3	Spring	746.2542	3251	2	618.5247
4	winter	225.5412	937	3	150.3374

- Summer has the most record of bike rented
- The least recorded bike rented is winter

# Weather Seasonality

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- Weather Seasonality

	SEASONS	AVG_Rented	AVG_TEMPERATURE	AVG_HUMIDITY	AVG_WIND_SPEED	AVG_VISIBILITY	AVG_DEW_POINT_TEMPERATURE
1	Summer	1034.0734	26.587711	64.98143	1.609420	1501.745	18.750136
2	Autumn	924.1105	13.821580	59.04491	1.492101	1558.174	5.150594
3	Spring	746.2542	13.021685	58.75833	1.857778	1240.912	4.091389
4	Winter	225.5412	-2.540463	49.74491	1.922685	1445.987	-12.416667
		AVG_SOLAR_RADIATION	AVG_RAINFALL	AVG_SNOWFALL			
1		0.7612545	0.25348732	0.00000000			
2		0.5227827	0.11765617	0.06350026			
3		0.6803009	0.18694444	0.00000000			
4		0.2981806	0.03282407	0.24750000			

- The more variation in temperature the more impact on the number of bike rented.

# Bike-sharing info in Seoul

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- Find the total Bike count and city info for Seoul

	Bike Count	Population
Seoul	20000	1540234

- Seoul offers 20000 bikes for a population of 15 millions

# Cities similar to Seoul

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- Find all city names and coordinates with comparable bike scale to Seoul's bike sharing system

	CITY	sum(s.BICYCLES)	LAT	LNG	POPULATION
1	Beijing	16000	39.9050	116.3914	19433000
2	Ningbo	15000	29.8750	121.5492	7639000
3	Shanghai	19165	31.1667	121.4667	22120000
4	Weifang	20000	36.7167	119.1000	9373000
5	Zhuzhou	20000	27.8407	113.1469	3855609

- SEOUL has biggest rental bike offer compared to similar big cities (37,500 vs 20,000 at most)
- While Shanghai with more population offers less bike rentals

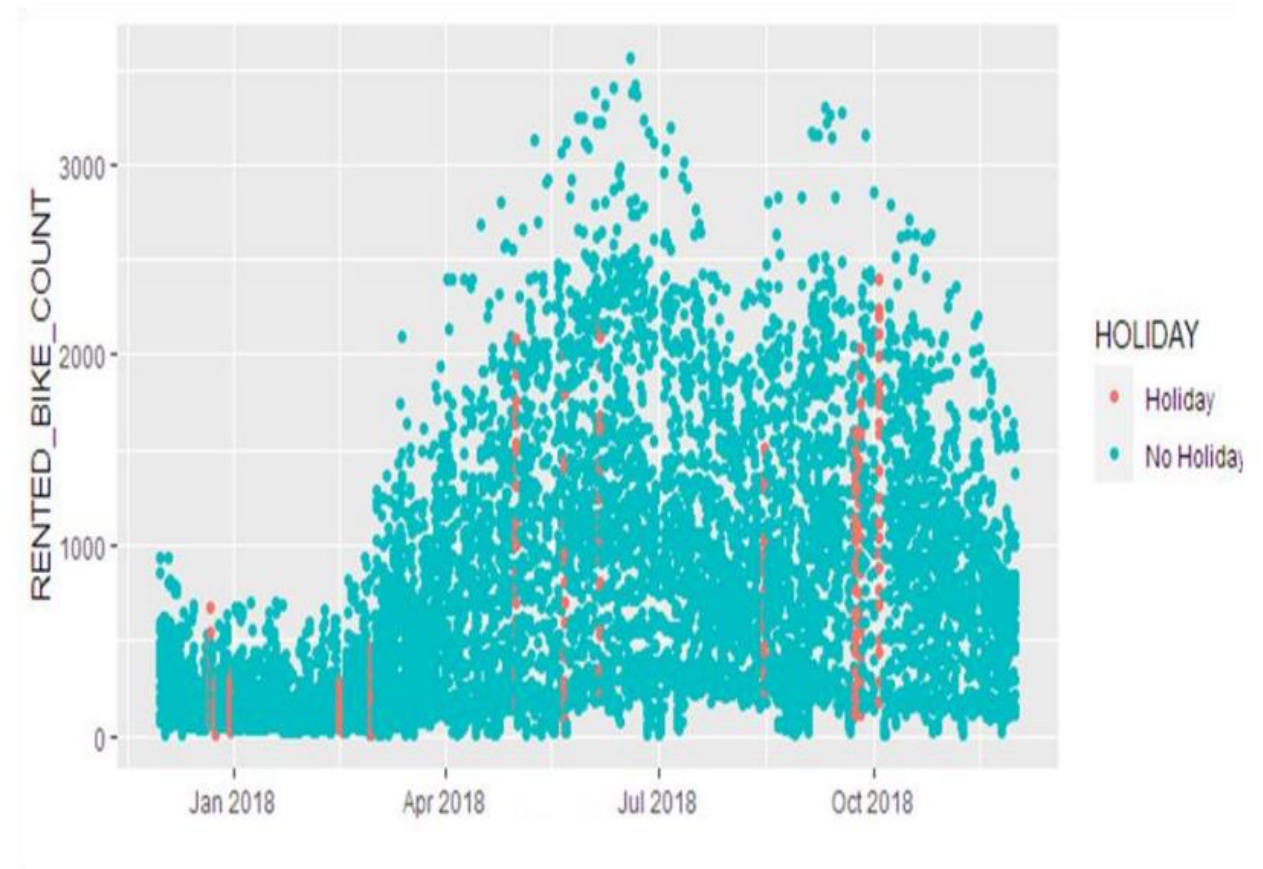
# EDA with Visualization

- Charts that were plotted were
- Weather forecast
- Temperature
- The demand for bikes compared to the population of the country

# Bike rental vs. Date

Rented bikes during 2018 (holidays highlighted)

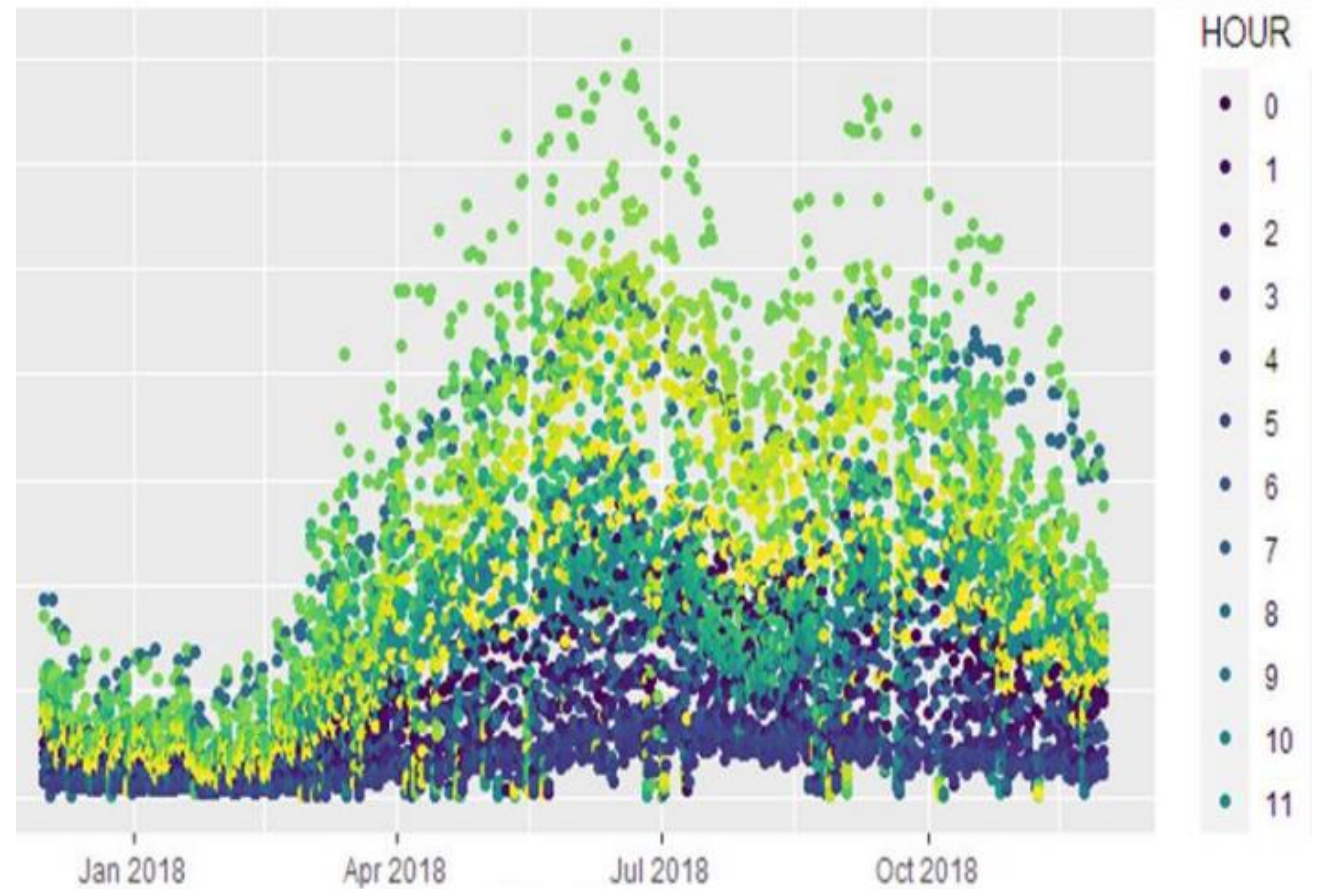
Fewest bike rented during winter, the most during at the peak of Summer



# Bike rental vs. Datetime

RENTED\_BIKE\_COUNT time  
series (different hours  
highlighted)

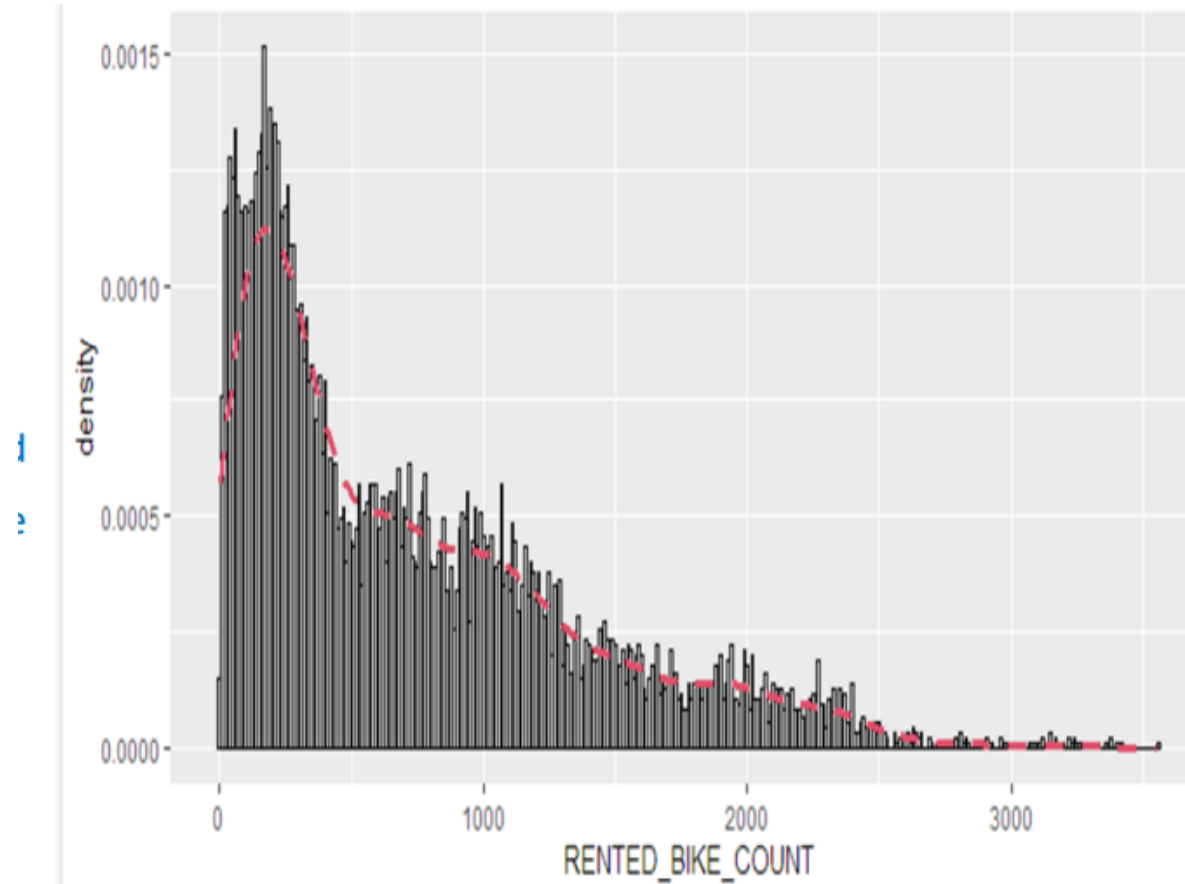
Most rentings during 18th  
hour, Fewest during night  
hours(0h-7h)



# Bike rental histogram

histogram + density curve of rentings

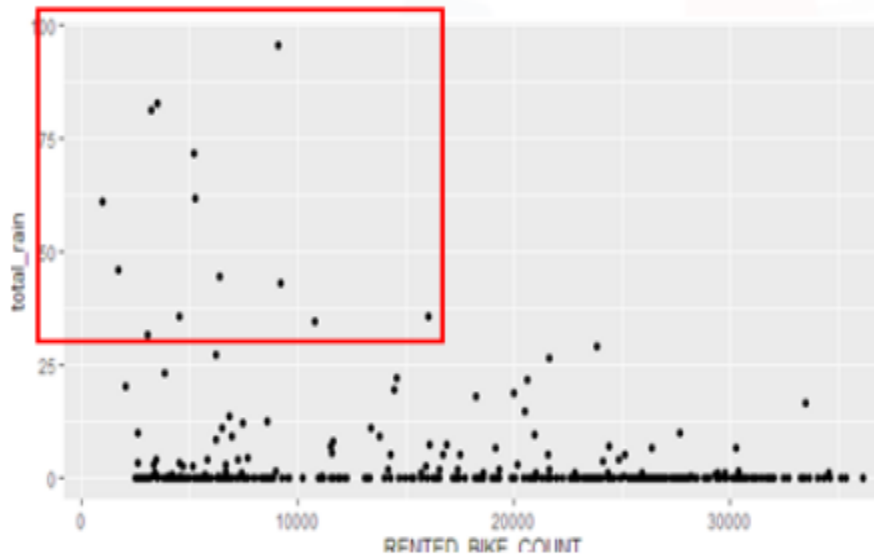
- Renting more than 2500 bikes
- Conclusion
- High peaks occur seldom, and basic demand exists



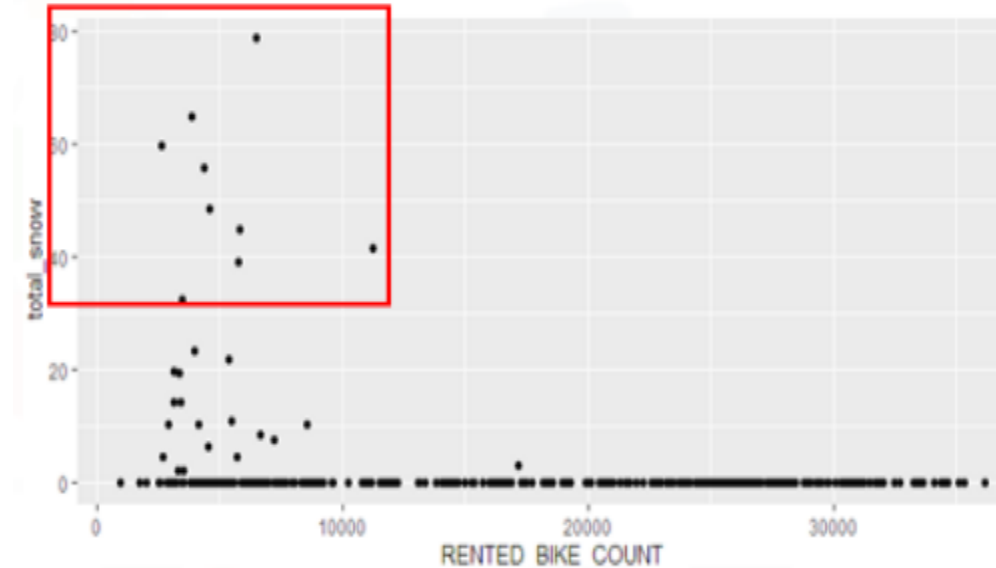


# Daily total rainfall and snowfall

Few hours raining (rain level 0-100) when raining, then fewer bikes rented (pattern left upper corner)



snow similar to rain pattern (left upper corner)

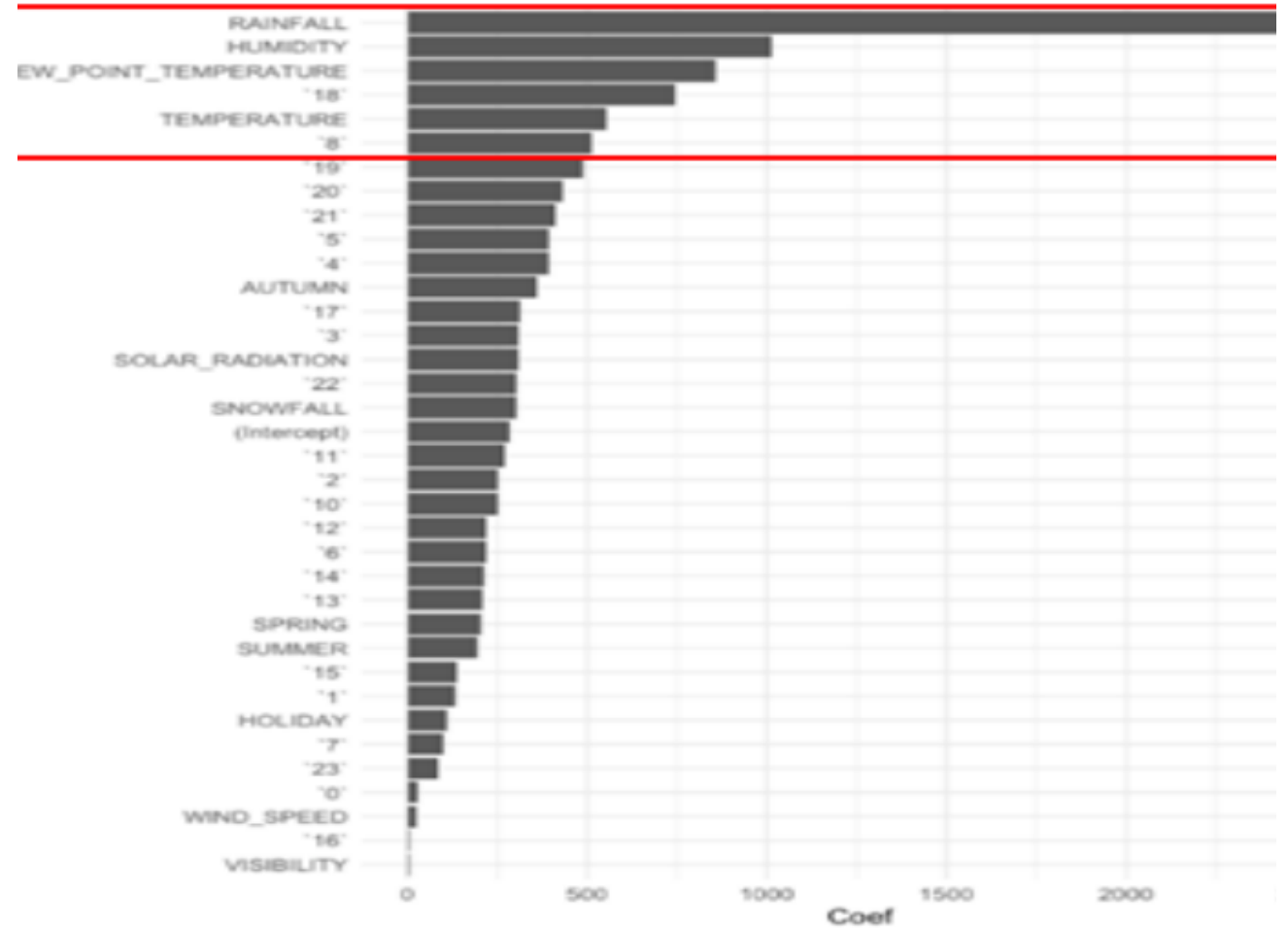


# Predictive analysis

# Ranked coefficients

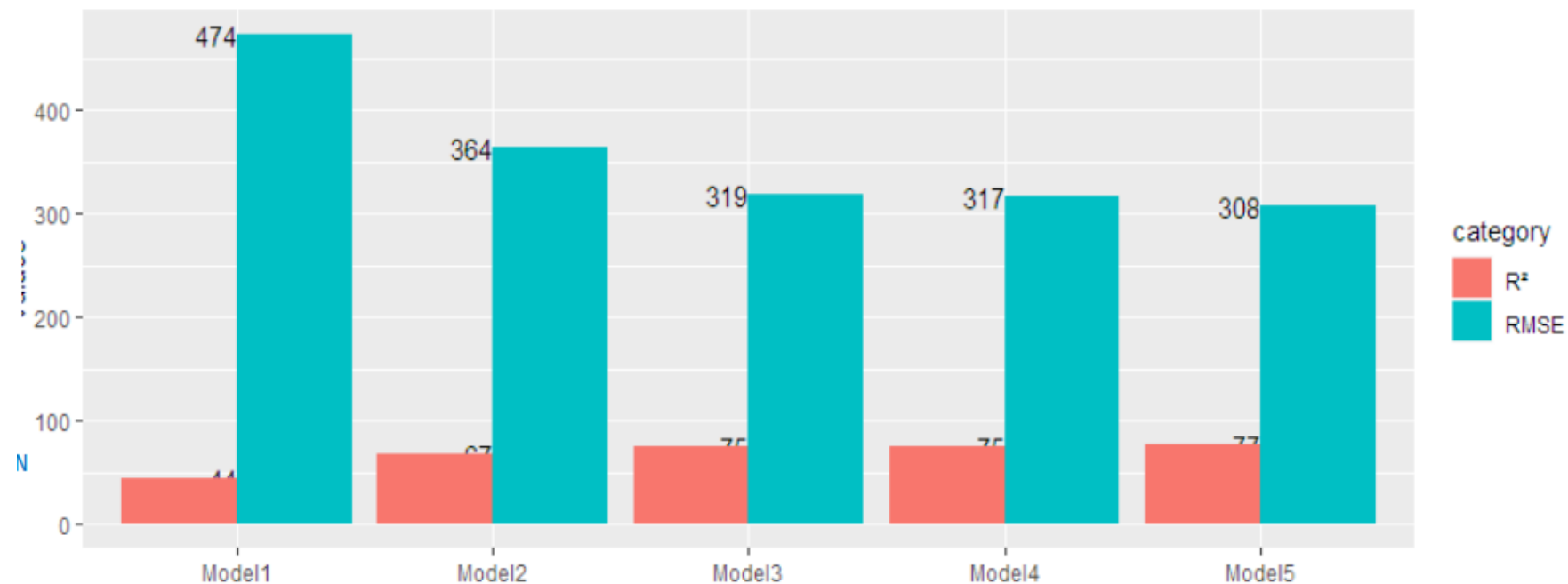
From the chart it shows that Rainfall has the most significant impact on the bike rent while humidity,

Try to tell a story why some variables are important while some are not for predicting bike-sharing demand



# Model evaluation

Model1= initial model “weather” (RENTED\_BIKE\_COUNT ~ TEMPERATURE + HUMIDITY + WIND\_SPEED + VISIBILITY + DEW\_POINT\_TEMPERATURE + SOLAR\_RADIATION + RAINFALL + SNOWFALL)



Models from 1 to 5 improving: RMSE down, while R<sup>2</sup> up

# Find the best performing model

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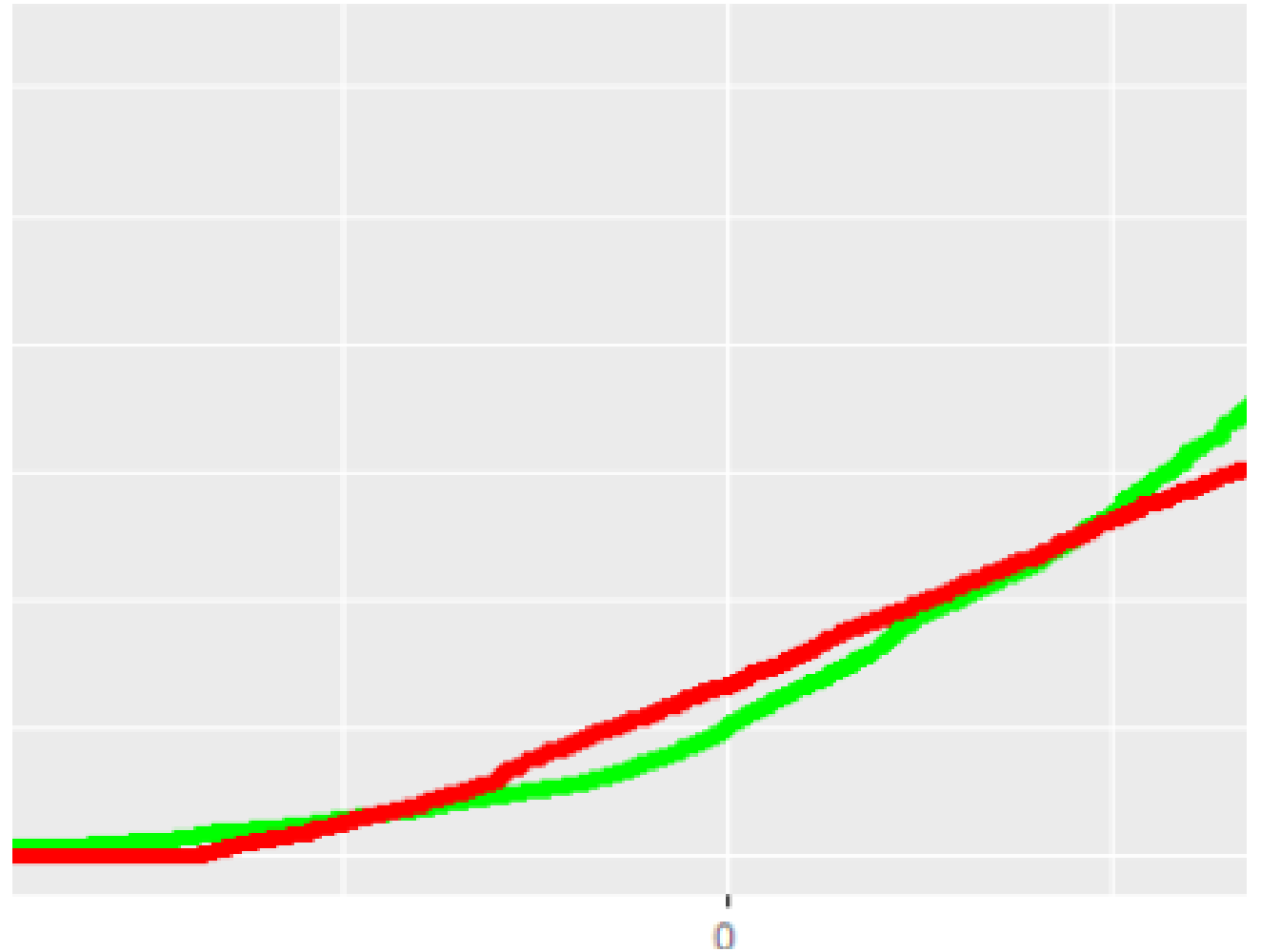
- Model5 with RMSE 308,  $R^2$  76.5% :

	$R^2$	RMSE	model type
Model1	0.4388245	474.1718	"Basic M"
Model2	0.6697276	363.7369	"All variables"
Model3	0.7476018	318.715	"Ridge"
Model4	0.7497703	316.5961	"ElasticNet"
Model5	0.7651839	308.3724	"Best Model Lasso"

# Q-Q plot of the best model

Test results (**predicted**) vs truths;

- “truths” values like a curve (tail with 0s at start).
- Conclusion: model is similar to the reality. This means that the prediction can be used since it is not expected to be 100% accurate



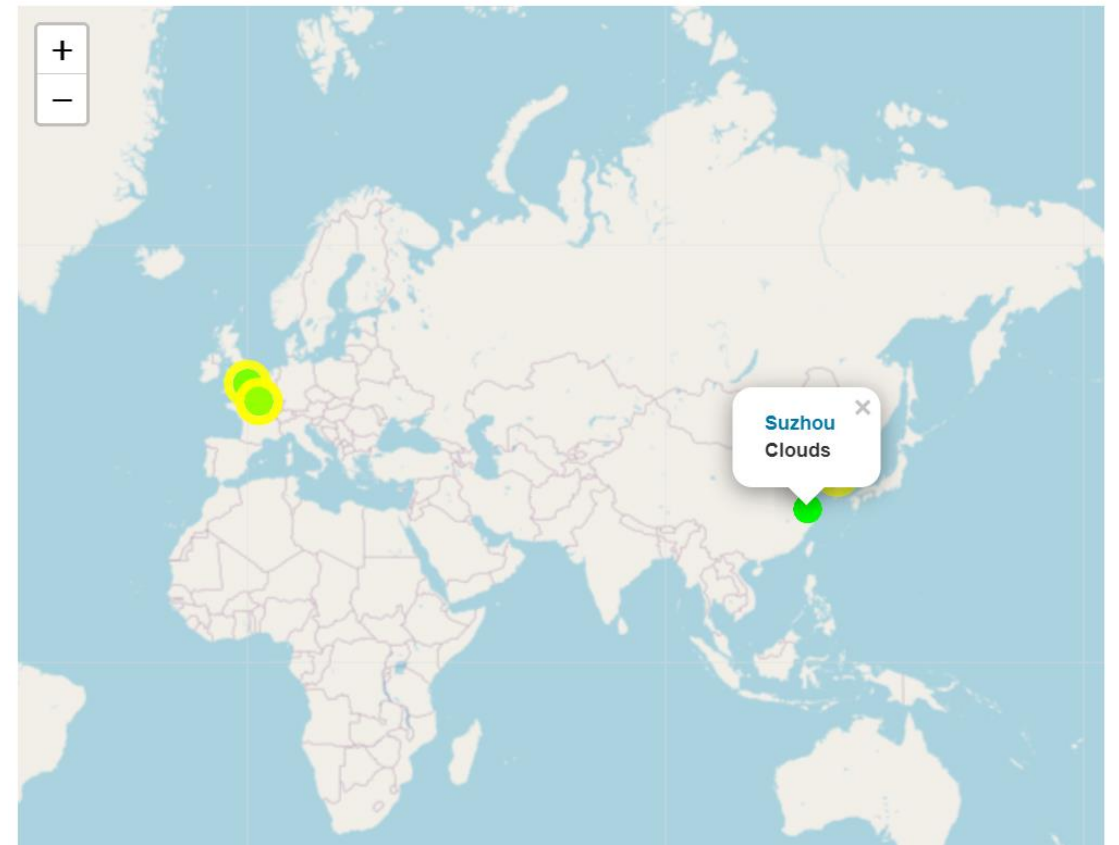
# Dashboard

@ <https://posit.cloud/content/7667416>

\*Desktop browser recommended

# Worldmap: forecast bike renting(cities)

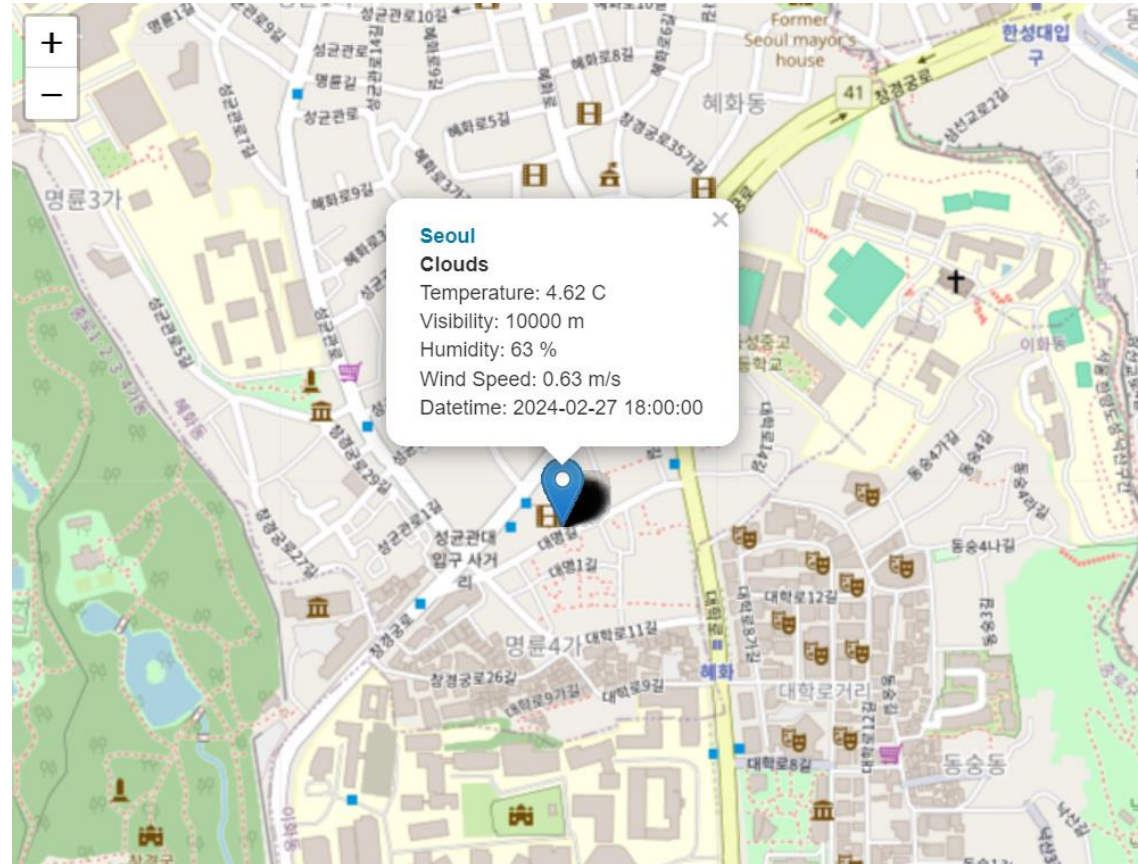
Map showing Suzhou with the least demand bike sharing (green) and other cities with high demand (yellow + green)





# Seoul City Selected

- Seoul City selected during low temperature



# CONCLUSION

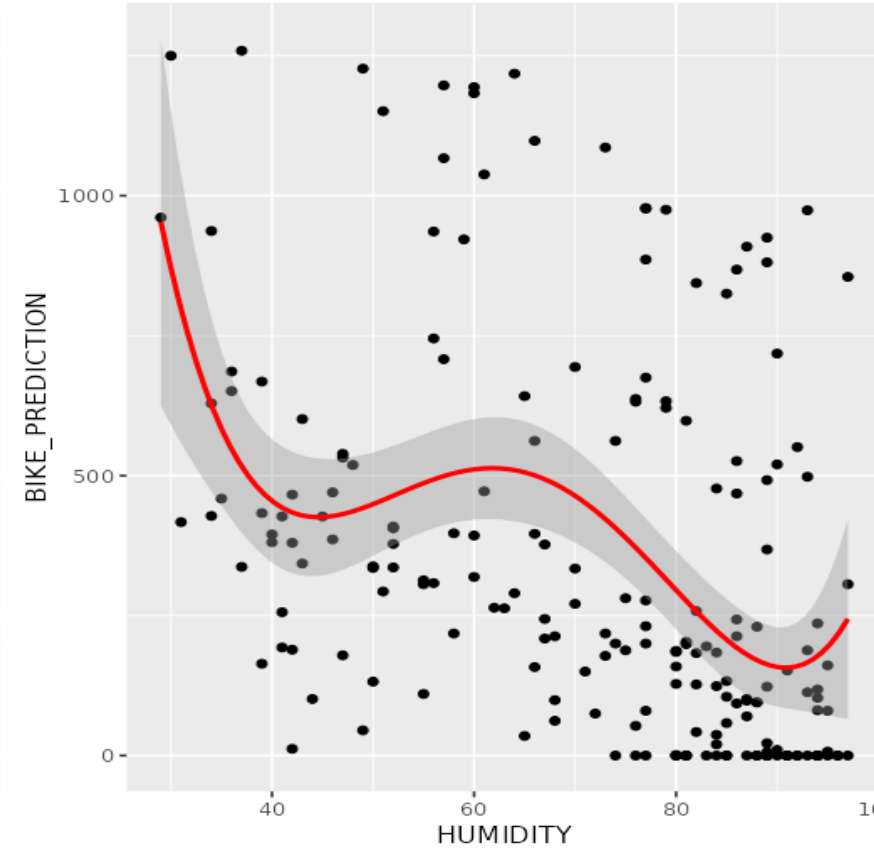
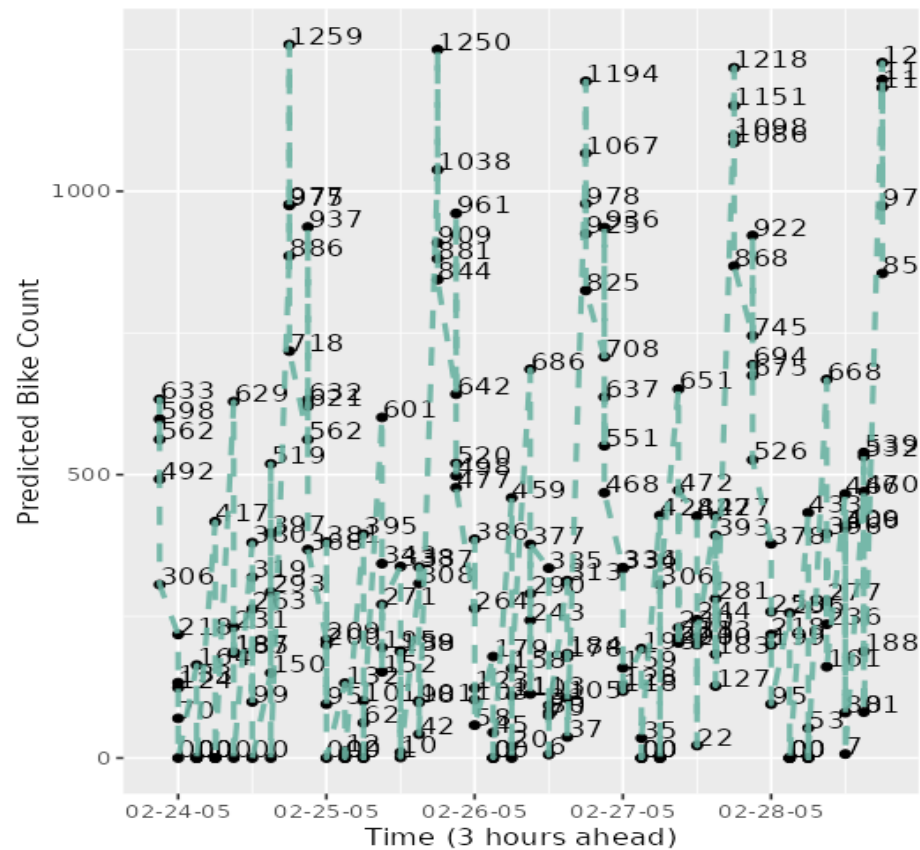
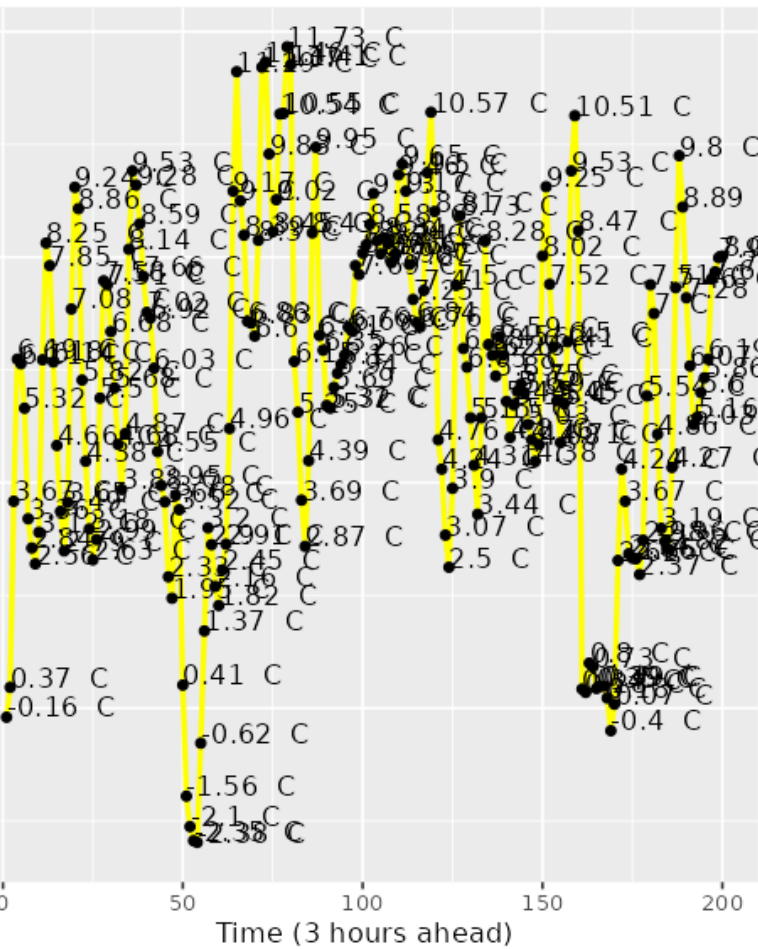
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- Demand for bikes are influenced by cities, availability of renting bikes, seasons, temperature, hour of the day and holidays
- Linear regression model is recommend to predict the demand of bikes
- Feasible to combine files, API, web scraping

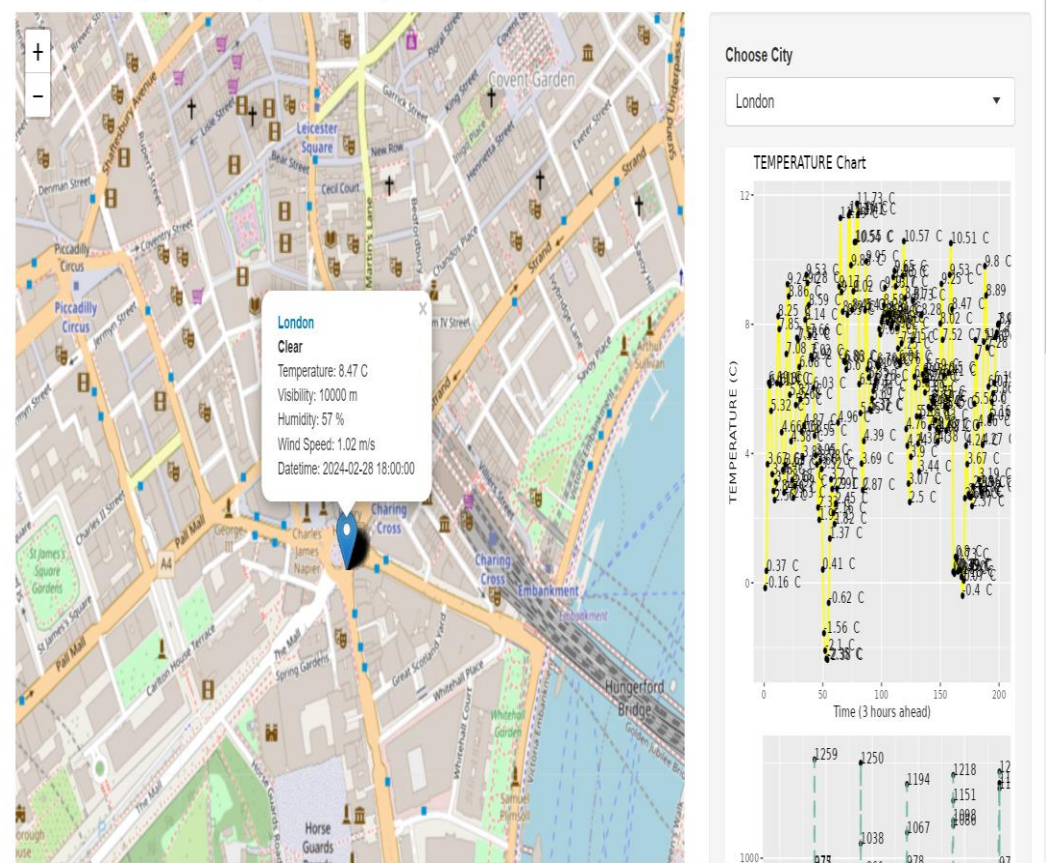
# APPENDIX

TEMPERATURE Chart



# APPENDIX

Bike-sharing demand prediction app

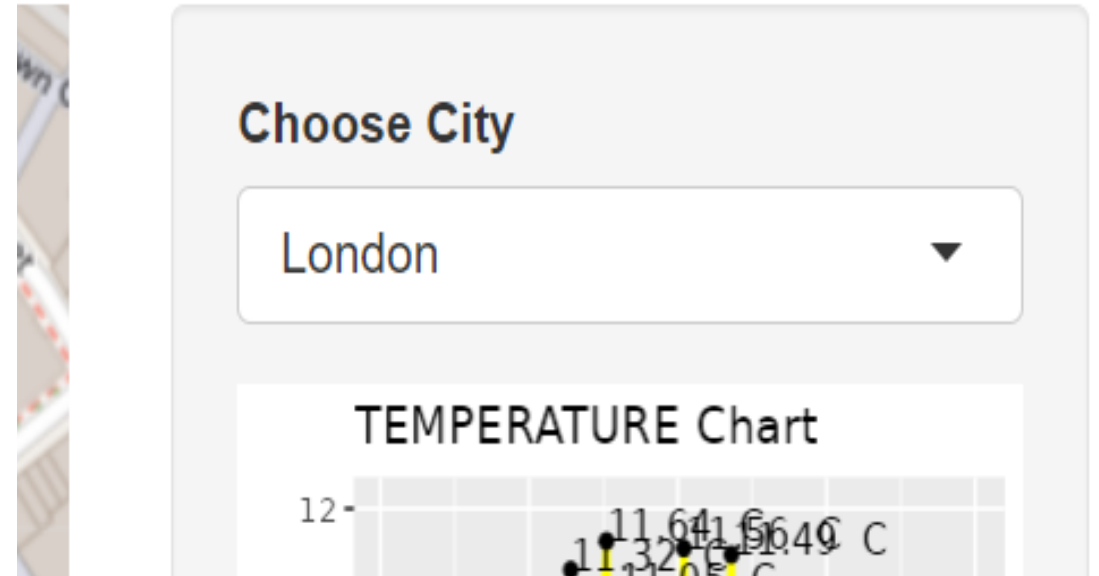
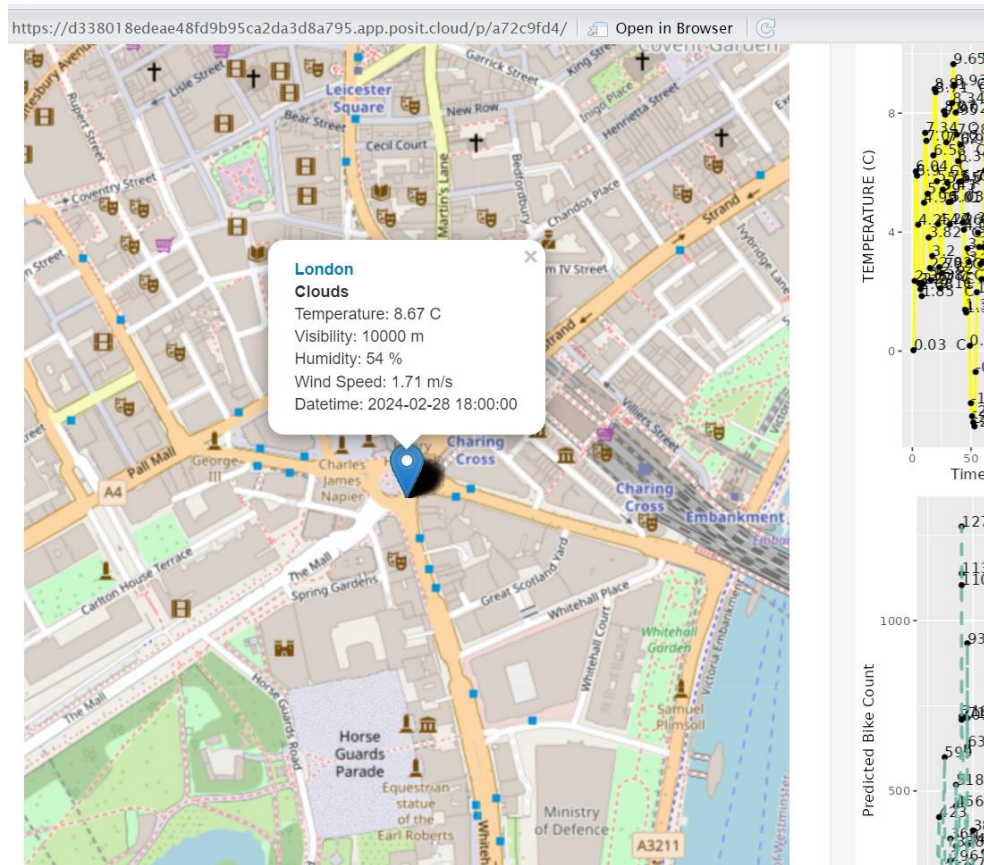


```
5 SELECT RENTED_BIKE_COUNT, HOUR FROM seoul_bike_sharing WHERE HOUR > '0'
6
```

History		Results	
Result set 1		Details	
Filter table		Total:8113	
RENTED_BIKE_COUNT		HOUR	
204		1	
173		2	
107		3	
78		4	
Items per page: 50		1-50 of 8113 items	
		1 1 of 163 pages	



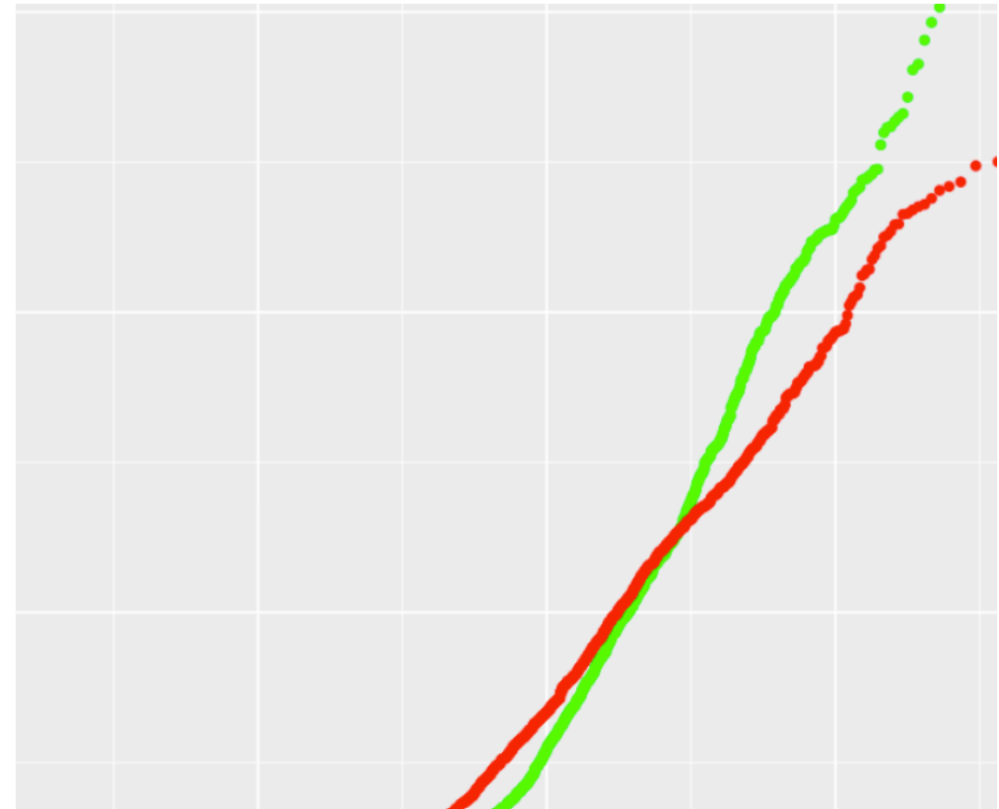
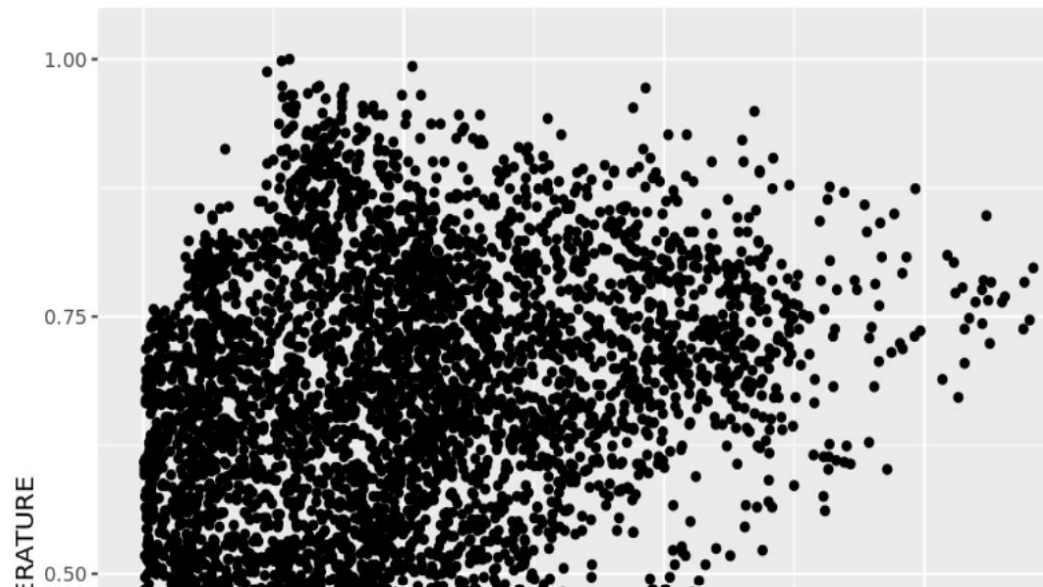
# APPENDIX



# APPENDIX

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```
[6]: ggplot(data = train_data, aes(RENTED_BIKE_COUNT, TEMPERATURE)) +  
      geom_point()
```



# C

```
5 SELECT RENTED_BIKE_COUNT, HOUR FROM seoul_bike_sharing WHERE HOUR > '0'
```

6

History	Results
---------	---------

Result set 1 Details

Filter table

Total:8113



RENTED\_BIKE\_COUNT

HOUR

204

1

173

2

107

3

78

4

Items per page: 50



1–50 of 8113 items

1



1 of 163 pages

< Week 5 > Peer Review: Submit your Work and Review your Peers

< Previous Next >

## Web Scrapping

```
] # Call the get_wiki_covid19_page function and print the response
get_wiki_covid19_page()
```

Response [https://en.wikipedia.org/w/index.php?Title=Template%3ACOVID-19\_testing\_by\_country]

Date: 2023-11-30 07:13

Status: 200

Content-Type: text/html; charset=UTF-8

Size: 100 kB

<!DOCTYPE html>

<html class="client-nojs vector-feature-language-in-header-enabled vector-fea...

<head>

<meta charset="UTF-8">

<title>Wikipedia, the free encyclopedia</title>

<script>(function(){var className="client-js vector-feature-language-in-heade...

"wgDefaultDateFormat":"dmy","wgMonthNames":["","January","February","March",...



# APPENDIX

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| DATE       | HOUR | max (RENTED_BIKE_COUNT) |
|------------|------|-------------------------|
| 19/06/2018 | 18   | 3556                    |

|    | DATE       | HOUR | RENTED_BIKE_COUNT |
|----|------------|------|-------------------|
| 1  | 19/06/2018 | 18   | 3556              |
| 2  | 21/06/2018 | 18   | 3418              |
| 3  | 12/06/2018 | 18   | 3404              |
| 4  | 20/06/2018 | 18   | 3384              |
| 5  | 04/06/2018 | 18   | 3380              |
| 6  | 22/06/2018 | 18   | 3365              |
| 7  | 08/06/2018 | 18   | 3309              |
| 8  | 10/09/2018 | 18   | 3298              |
| 9  | 17/09/2018 | 18   | 3277              |
| 10 | 12/09/2018 | 18   | 3256              |

```
ui <- fluidPage(  
  titlePanel("Trends in Demographics and Income"),  
  fluidRow(  
    column(width = 12,  
      wellPanel(  
        selectInput("country", "filter by country",  
                    choices = c("United-States", "Canada", "Mexico", "Germany", "Phillipines")  
        )  
      )  
    ),  
    fluidRow(  
      column(width = 4,  
        radioButtons(inputId = "continous_variables",  
                     choices = c("age", "hours_per_week")),  
        radioButtons(inputId = "graph_type",  
                     choices = c("histogram", "boxplot")  
        )  
      )  
    )  
  )  
)
```



# APPENDIX: DATA COLLECTION WEB SCRAPING

---

```
#web scraping:
url <- "https://en.wikipedia.org/wiki/List_of_bicycle-sharing_systems"

root_node <- read_html(url)
table_nodes <- html_nodes(root_node, "table")
table_node <- html_node(root_node, "table")

length_table <- length(table_nodes)
for (i in 1:length_table) { print (table_nodes[[i]]) } #seen 1st table is relevant

table_node <- table_nodes[[1]] #1st table
df <- as.data.frame(html_table(table_node))
summary(df)
write.csv(df, file="c:/Users/M/Desktop/Studieren 2013/R complete/IBM R Capstone/wiki_bicycle.csv", row.names=FALSE)
#end web scraping
```

```
> summary(df)
```

| Country          | City             | Name             | System           | Operator         | Launched         | Discontinued     |
|------------------|------------------|------------------|------------------|------------------|------------------|------------------|
| Length:564       | Length:564       | Length:564       | Length:564       | Length:564       | Length:564       | Length:564       |
| Class :character | Class :character | Class :character | Class :character | Class :character | Class :character | Class :character |
| Mode :character  | Mode :character  | Mode :character  | Mode :character  | Mode :character  | Mode :character  | Mode :character  |
| Stations         | Bicycles         | Daily ridership  |                  |                  |                  |                  |
| Length:564       | Length:564       | Length:564       |                  |                  |                  |                  |
| Class :character | Class :character | Class :character |                  |                  |                  |                  |
| Mode :character  | Mode :character  | Mode :character  |                  |                  |                  |                  |

# APPENDIX: DATA COLLECTION CSV FILE

---

```
# Download some general city information such as name and locations
url <- "https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBMDeveloperSkillsNetwork-RP0321EN-SkillsNetwork/labs/datasets/raw_worldcities.csv"
# download the file
download.file(url, destfile = "C:/Users/M/Desktop/Studieren 2013/R complete/IBM R Capstone/raw_worldcities.csv")

# Download a specific hourly Seoul bike sharing demand dataset
url <- "https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBMDeveloperSkillsNetwork-RP0321EN-SkillsNetwork/labs/datasets/raw_seoul_bike_sharing.csv"
# download the file
download.file(url, destfile = "C:/Users/M/Desktop/Studieren 2013/R complete/IBM R Capstone/raw_seoul_bike_sharing.csv")
```

D collection results: 4 files handled in next steps

```
(dataset_list <- c('wiki_bicycle.csv',
  'raw_seoul_bike_sharing.csv', 'cities_weather_forecast.csv',
  'raw_worldcities.csv'))
```

# APPENDIX: DATA WRANGLING

---

1. Standardize Uppercases, no white spaces
2. Regular Expressions to trim results

## 3. Handle missing values (NA)

4. Generate indicator columns (seasons, holiday)
5. Normalization (weather parameters)

```
#RENTED_BIKE_COUNT only has about 3% missing values (295 / 8760)
# Drop rows with `RENTED_BIKE_COUNT` column == NA
bike_sharing_df <- bike_sharing_df %>% drop_na(RENTED_BIKE_COUNT)
```

```
#missing values for TEMPERATURE are found in SEASONS == Summer, so
#reasonable to impute those missing values with the summer average temperature.
AVG_summer_temp <- bike_sharing_df %>%
  filter(SEASONS=="Summer") %>%
  group_by(SEASONS) %>%
  summarize(mean= mean(TEMPERATURE, na.rm=TRUE)) #AVG_summer_temp$mean

bike_sharing_df<-bike_sharing_df %>%
mutate(TEMPERATURE = ifelse(is.na(TEMPERATURE),AVG_summer_temp$mean,TEMPERATURE))
```

# APPENDIX: DATA WRANGLING

---

## 1. Standardize Uppercases, no white spaces

2. Regular Expressions to trim results
3. Handle missing values (NA)
4. Generate indicator columns (seasons,holiday)
5. Normalization (weather parameters)

```
for (dataset_name in dataset_list){  
  # Read dataset  
  dataset <- read_csv(dataset_name)  
  # Standardized its columns:  
  
  # Convert all column names to uppercase  
  names(dataset)<-toupper(names(dataset))  
  
  # Replace any white space separators by underscores, using the str_replace_all function  
  names(dataset)<-str_replace_all(names(dataset)," ","_")  
  
  # save the dataset  
  write_csv(dataset, dataset_name, row.names=FALSE)  
}
```

# APPENDIX: DATA WRANGLING

---

1. Standardize Uppercases, no white spaces

## 2. Regular Expressions to trim results

3. Handle missing values (NA)

4. Generate indicator columns (seasons,holiday)

5. Normalization (weather parameters)

```
# remove reference link
remove_ref <- function(strings) {
  #ref_pattern <- "Define a pattern matching a reference link such as [1]"
  ref_pattern <- "\\[[0-9]+\\]"

  # Replace all matched substrings with a white space using str_replace_all()
  #result<-str_replace_all(strings,ref_pattern," ") #official default
  result<-str_replace_all(strings,ref_pattern," ") #my preference

  # Trim the result if you want
  result<-str_trim(result, side= c("right"))

  return(result)
}
```

```
sub_bike_sharing_df<-sub_bike_sharing_df %>%
  #select(SYSTEM) %>%
  mutate(SYSTEM=remove_ref(SYSTEM),CITY=remove_ref(CITY))
```

```
# Extract the first number
extract_num <- function(columns){
  # Define a digital pattern
  digitals_pattern <- "[0-9]+" #Define a pattern matching a digital substring

  # Find the first match using str_extract
  first_match<- str_extract(columns,digitals_pattern)

  # Convert the result to numeric using the as.numeric() function
  result <- as.numeric(first_match)
  return (result)
}
```

```
sub_bike_sharing_df<-sub_bike_sharing_df %>%
  mutate(BICYCLES=extract_num(BICYCLES))
```

# APPENDIX: DATA WRANGLING WITH SQL

---

- `dbGetQuery(conn, 'SELECT COUNT(Date) FROM SEOUL_BIKE_SHARING_table')`
- `dbGetQuery(conn, 'SELECT COUNT(HOUR) FROM SEOUL_BIKE_SHARING_table WHERE RENTED_BIKE_COUNT <>0 ')`
- `dbGetQuery(conn, 'SELECT * FROM CITIES_WEATHER_FORECAST_table limit 1 ')`
- `dbGetQuery(conn, 'SELECT distinct(SEASONS) FROM SEOUL_BIKE_SHARING_table ')`
- `dbGetQuery(conn, 'SELECT (Date) FROM SEOUL_BIKE_SHARING_table limit 1 ')`
- `dbGetQuery(conn, 'SELECT DISTINCT(Date) FROM SEOUL_BIKE_SHARING_table WHERE Date=(SELECT MIN(Date) FROM SEOUL_BIKE_SHARING_table) OR Date=(SELECT MAX(Date) FROM SEOUL_BIKE_SHARING_table) ')`
- `dbGetQuery(conn, 'SELECT Date,HOUR,max (RENTED_BIKE_COUNT)FROM SEOUL_BIKE_SHARING_table ')`
- `dbGetQuery(conn, 'SELECT SEASONS, HOUR,AVG (RENTED_BIKE_COUNT)as AVG_bikes_rented, AVG(TEMPERATURE)as AVG_tempFROM SEOUL_BIKE_SHARING_table group by SEASONS, HOUR order by AVG_bikes_rented desc LIMIT 10 ')`
- `dbGetQuery(conn, 'SELECT SEASONS, AVG (RENTED_BIKE_COUNT) as AVG_Rented, MAX (RENTED_BIKE_COUNT)Max_Rented, MIN (RENTED_BIKE_COUNT) as MIN_Rented ,SQRT(AVG(RENTED_BIKE_COUNT*RENTED_BIKE_COUNT) - AVG(RENTED_BIKE_COUNT)*AVG(RENTED_BIKE_COUNT)) as STD_deviationFROM SEOUL_BIKE_SHARING_table group by SEASONS order by AVG_Rented DESC ')`
- `dbGetQuery(conn, 'SELECT SEASONS, AVG (RENTED_BIKE_COUNT) as AVG_Rented,AVG (TEMPERATURE) as AVG TEMPERATURE, AVG (HUMIDITY) as AVG HUMIDITY, AVG (WIND SPEED) as AVG WIND SPEED, AVG (VISIBILITY) as AVG VISIBILITY, AVG (DEW POINT TEMPERATURE) as AVG_DEW POINT TEMPERATURE, AVG (SOLAR RADIATION) as AVG SOLAR RADIATION, AVG (RAINFALL) as AVG_RAINFALL, AVG (SNOWFALL) as AVG_SNOWFALL FROM SEOUL_BIKE_SHARING_table group by SEASONS order by AVG_Rented desc ')`
- `dbGetQuery(conn, 'SELECT S.BICYCLES, S.CITY, S.COUNTRY, W.LAT, W.LNG, W.POPULATIONFROM BIKE_SHARING_SYSTEMS_table S, WORLD_CITIES_table W WHERE S.CITY="Seoul" AND S.CITY=W.CITY ')`
- `dbGetQuery(conn, 'SELECT S.CITY, sum(s.BICYCLES),W.LAT, W.LNG, W.POPULATION FROM BIKE_SHARING_SYSTEMS_table S, WORLD_CITIES_table W WHERE S.CITY=W.CITY group by S.CITY Having S.BICYCLES between 15000 AND 20000 ')`