Capstone Project - 2

Bike Sharing Demand Prediction

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Agenda

- Problem Statement
- Data Summary
- Feature Engineering
- Exploratory Data Analysis (EDA)
- Modelling Approach
- Predictive Modelling
    - ➔ Decision Tree
    - ➔ Random Forests
    - ➔ Gradient Boosting
    - ➔ XG Boost
- Model comparison
- Challenges faced and Conclusions

Problem Statement

- Currently Rental bikes are introduced in many urban cities for the enhancement of mobility comfort
- It is important to make the rental bike available and accessible to the public at the right time as it lessens the **waiting time**, eventually, providing the city with a **stable supply** of rental bikes
- The goal of this project is to build a ML model that is able to predict the demand of rental bikes in the city of Seoul.

Data Summary

- Date
- Rented Bike count
- Hour - Hour of the day
- Temperature - Celsius
- Humidity - %
- Windspeed - m/s
- Visibility - 10m
- Dew point temperature – Celsius
- Solar radiation - MJ/m2
- Rainfall - mm
- Snowfall - cm
- Seasons
- Holiday
- Functional Day
- **Day of week**
- **Month**
- **Weekend**

Feature Engineering

- **Td = T - ((100 - RH)/5)**

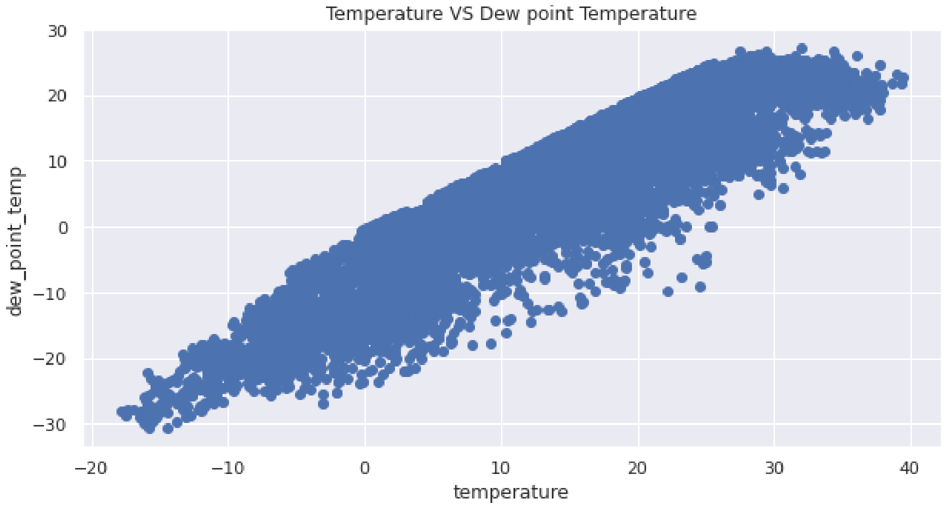
➔ Td = dew point temperature

➔ T = Temperature

➔ RH = Relative humidity (%)

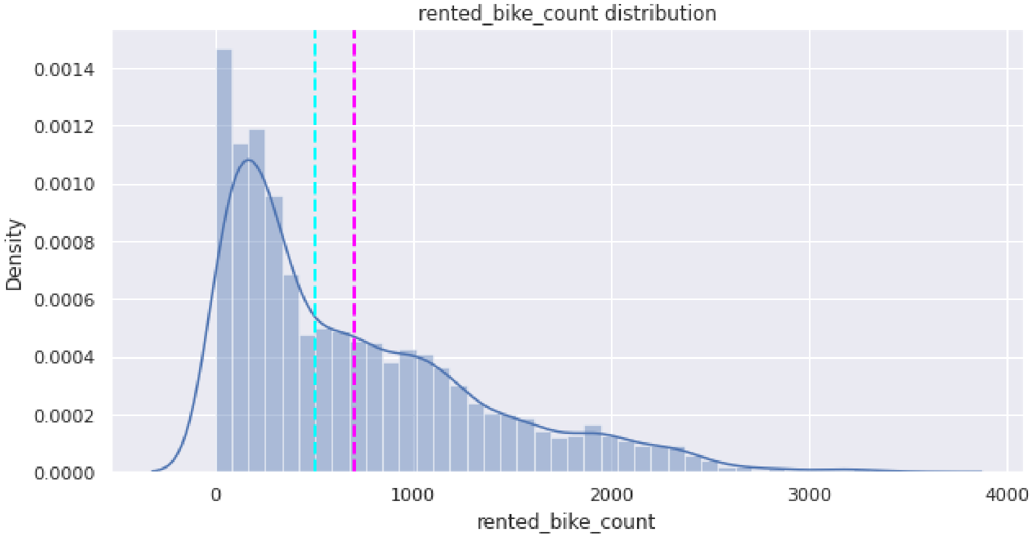
- Also these variables are **highly correlated** (0.912798)
- Hence we can drop dew point temperature

- There are **no missing values** in the dataset



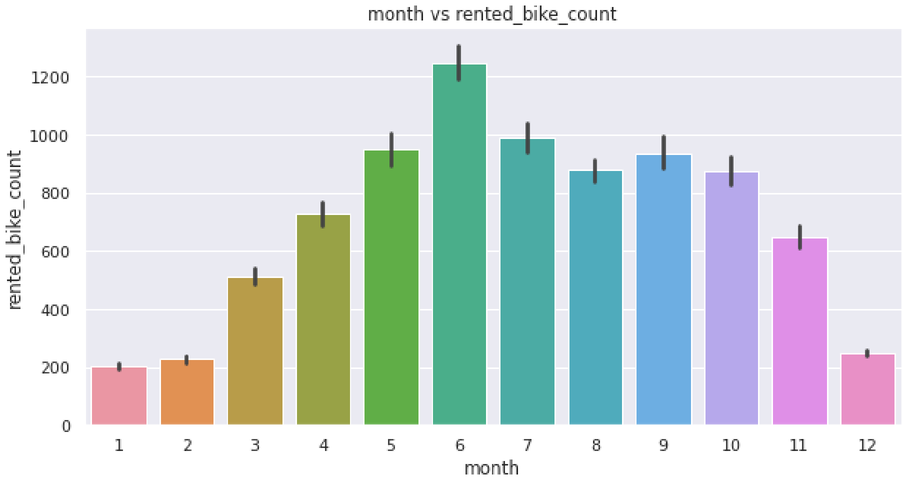
Exploratory Data Analysis (EDA)

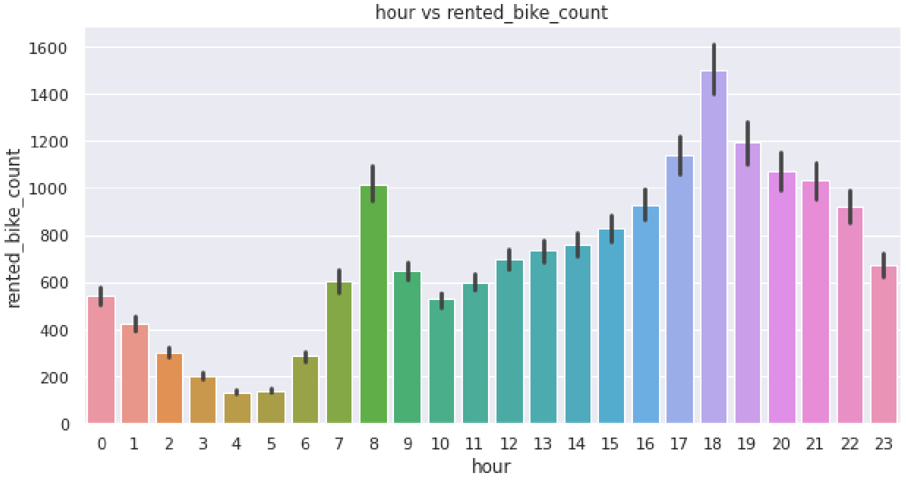
- The dependent variable - rented bike counts is **positively skewed**
- **Normally distributed attributes:** temperature, humidity.
- **Positively skewed attributes:** wind, solar radiation, snowfall, rainfall.
- **Negatively skewed attributes:** visibility.

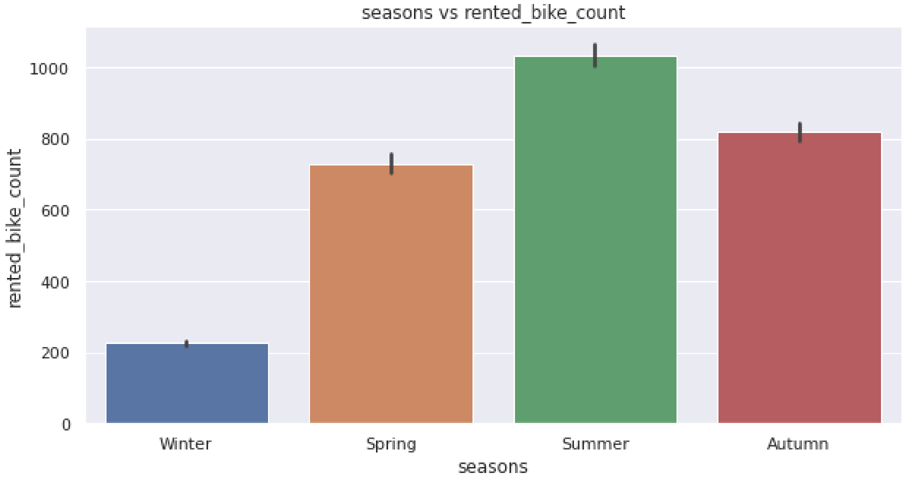


EDA (Contd.)

- Highest demand - **June**
- Lowest demand - **January**
- On a typical day, there is a **surge** in demand for rental bikes during the **rush hours**

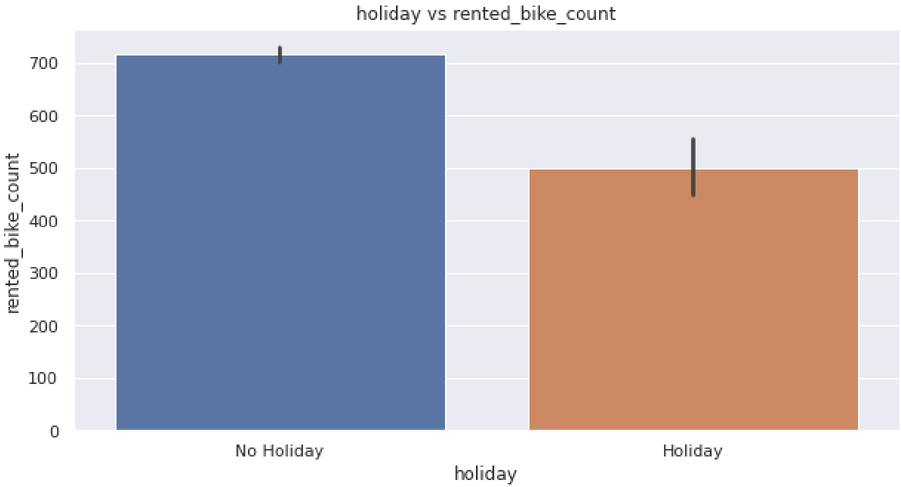


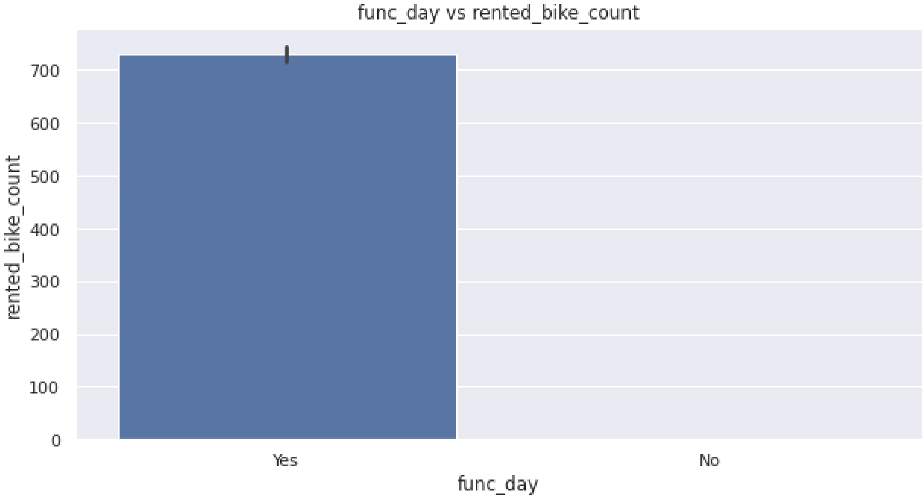


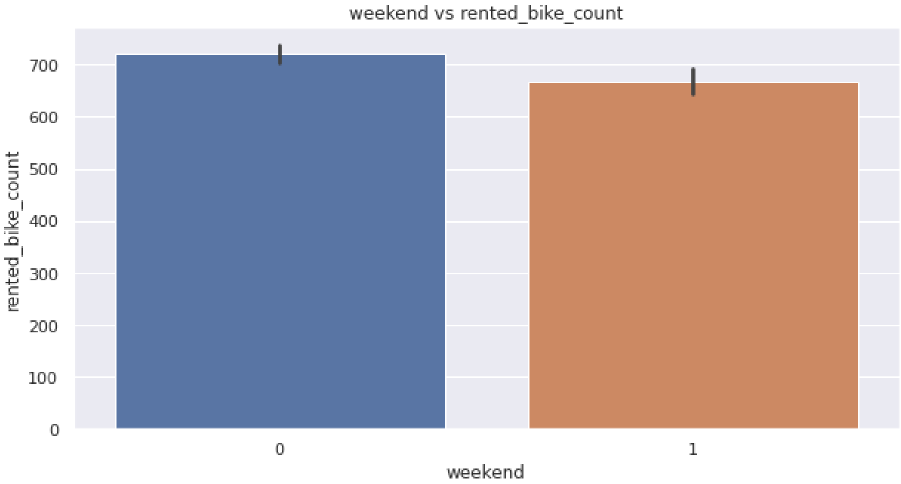


EDA (Contd.)

- Demand for rental bikes is **lower** on **holidays** and **weekends**
- On a non functional day, no bikes were rented in **all** instances

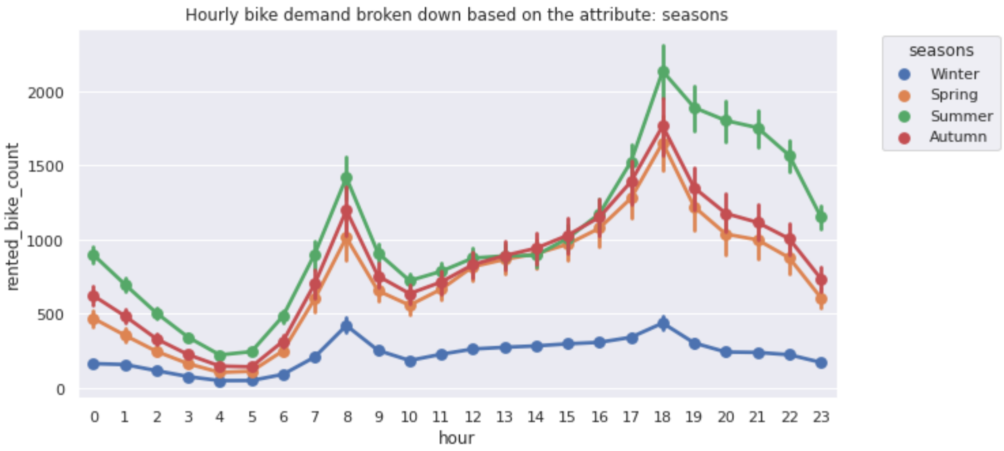


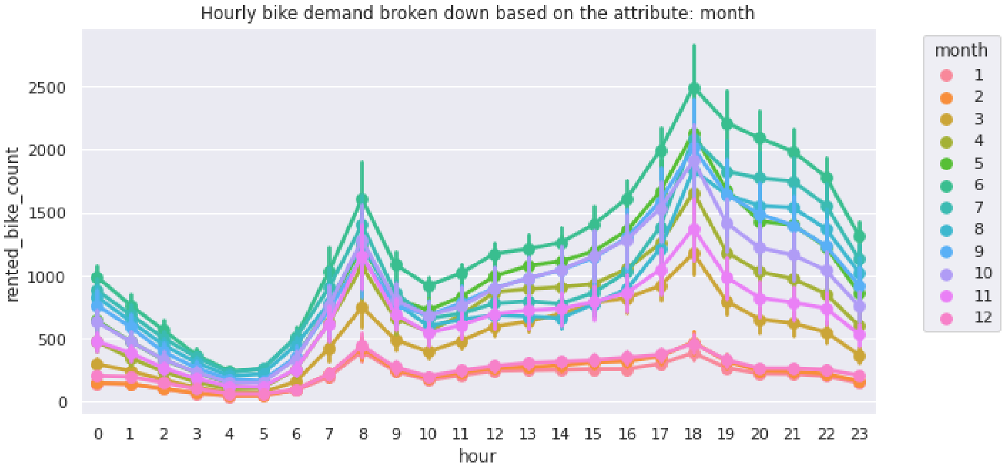




EDA (Contd.)

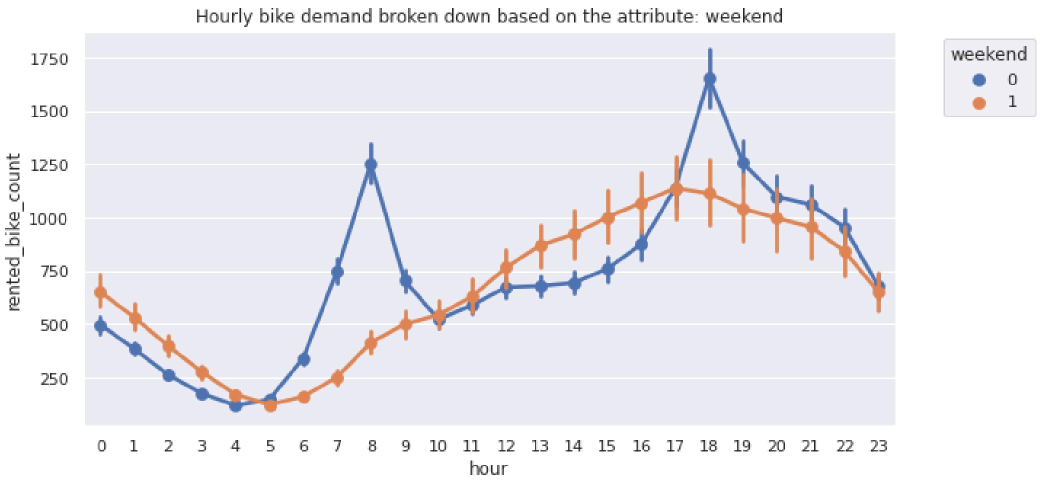
- Lowest demand - **Winter**
- Highest demand - **Summer**
- In autumn and spring, the demand on average is similar throughout the day

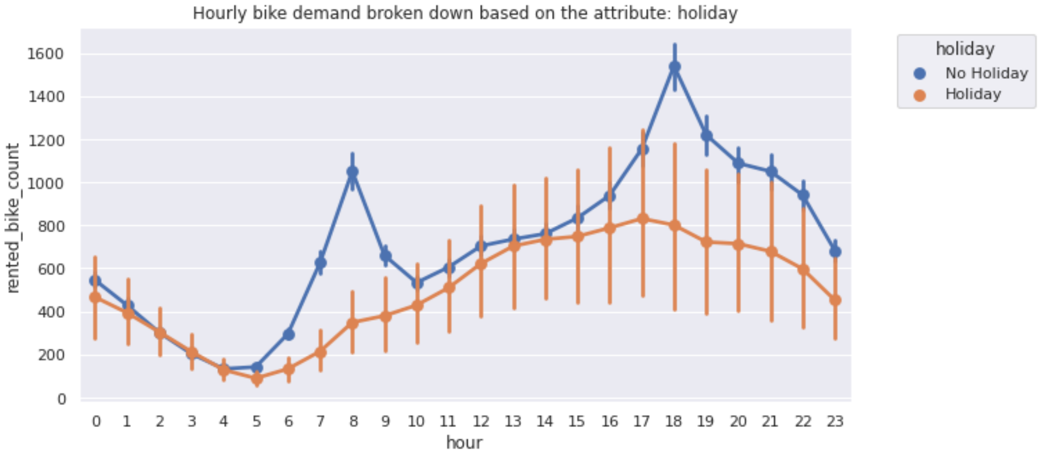




EDA (Contd.)

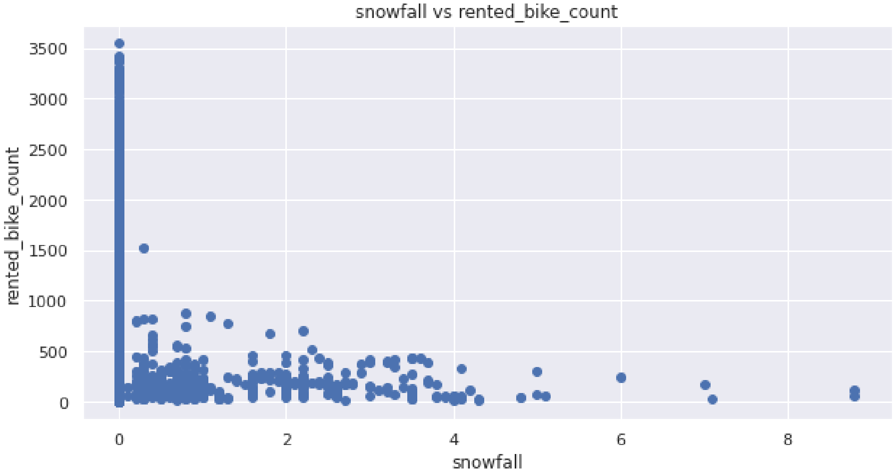
- On a regular day, there is a **surge** in demand for rental bikes during **rush** hours
- On holidays and weekends, the demand for rental bikes **increases** gradually throughout the day

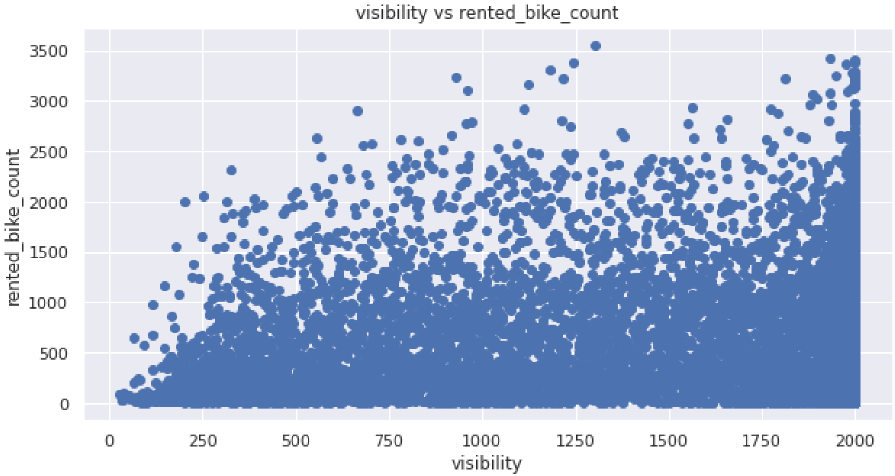


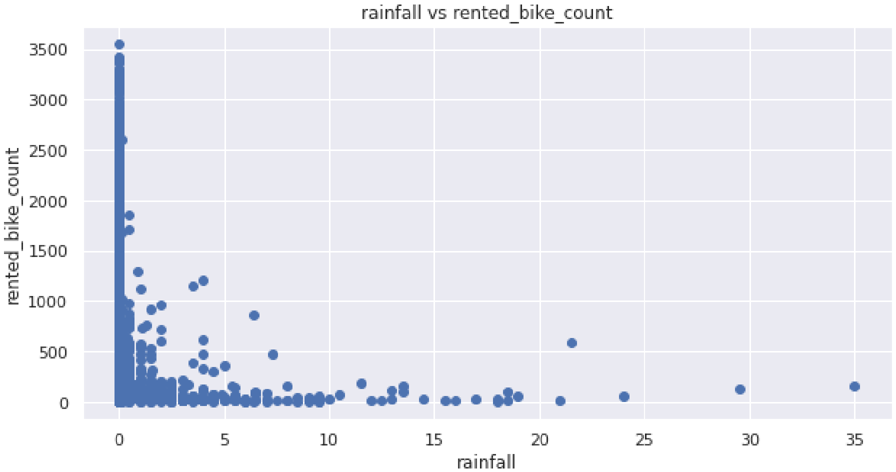


EDA (Contd.)

- The demand for rental bikes is typically **lower** when there is **rainfall / snowfall**, and on days with **low visibility**

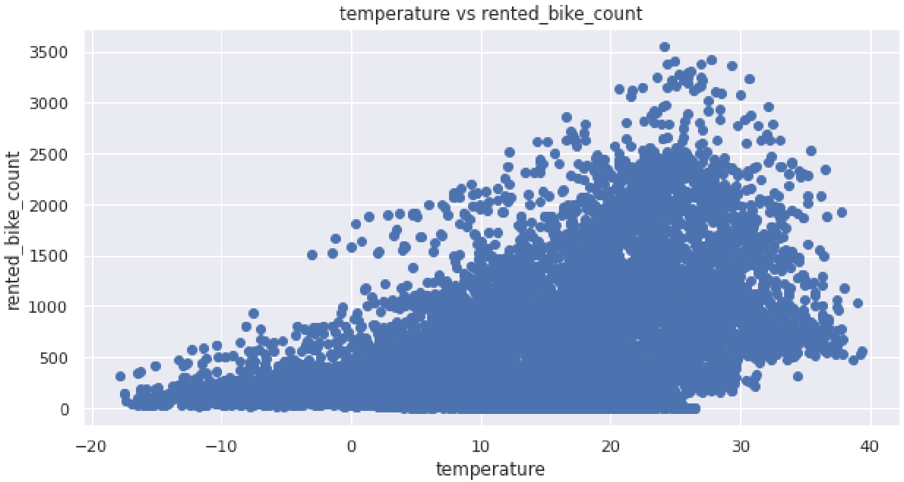


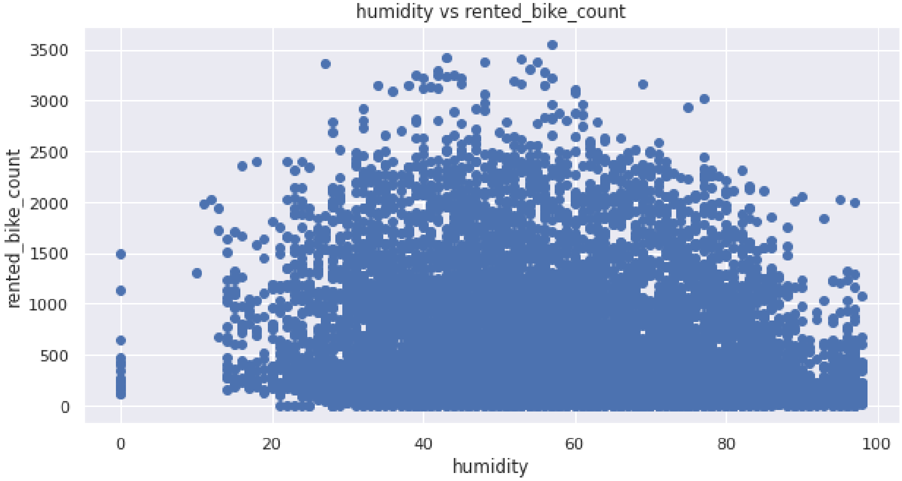


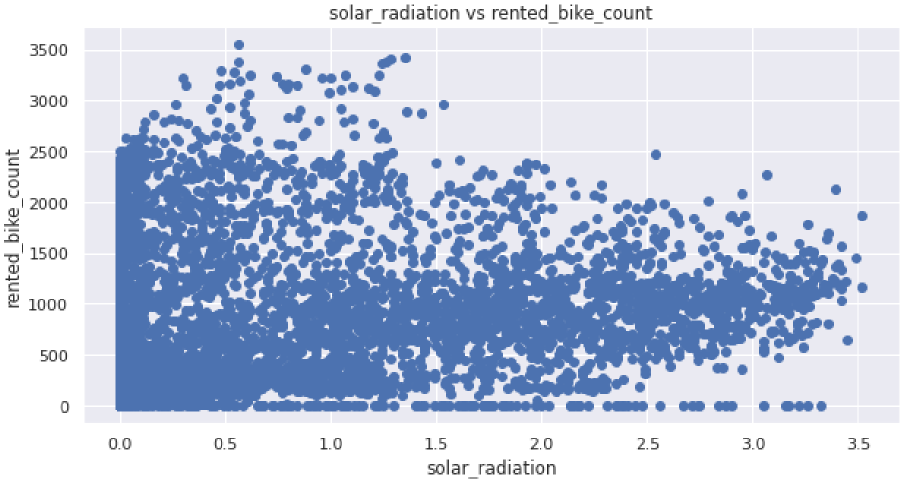


EDA (Contd.)

- The demand for rental bikes remains **low** for days with very **low temperatures**, and on days with high intensity of **solar radiation**

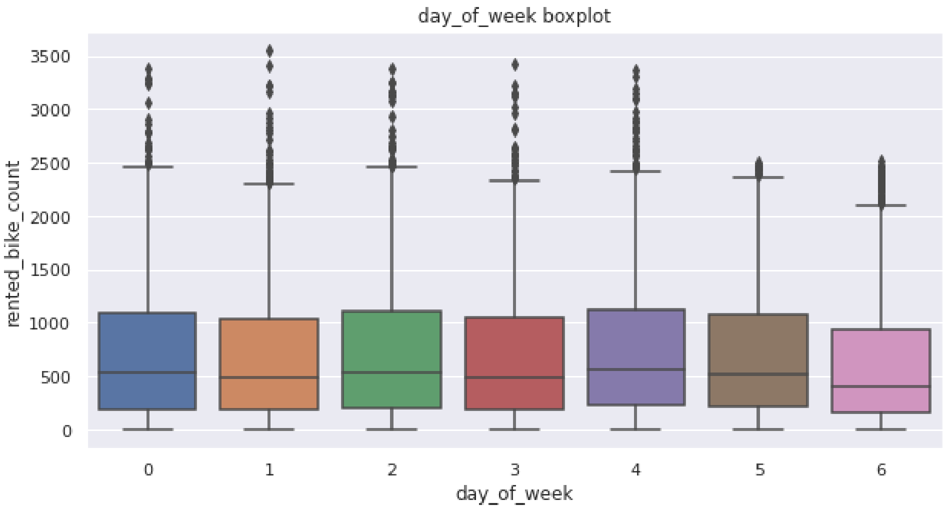


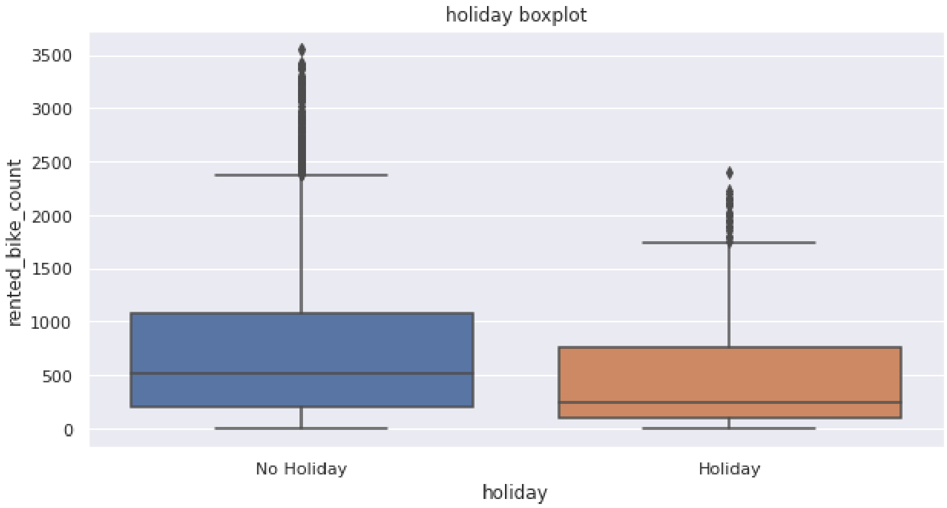


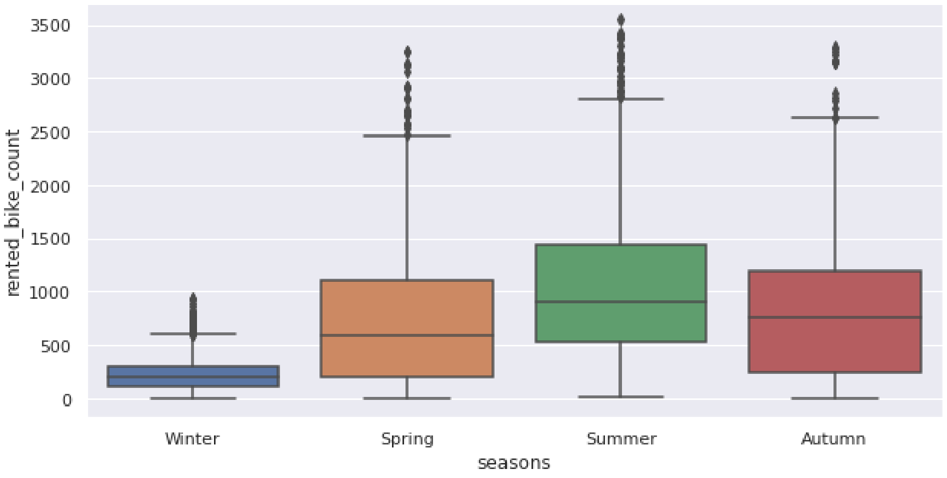


EDA (Contd.)

- There are outliers in the data
- We cannot handle them since we may **eliminate patterns** we had discovered earlier

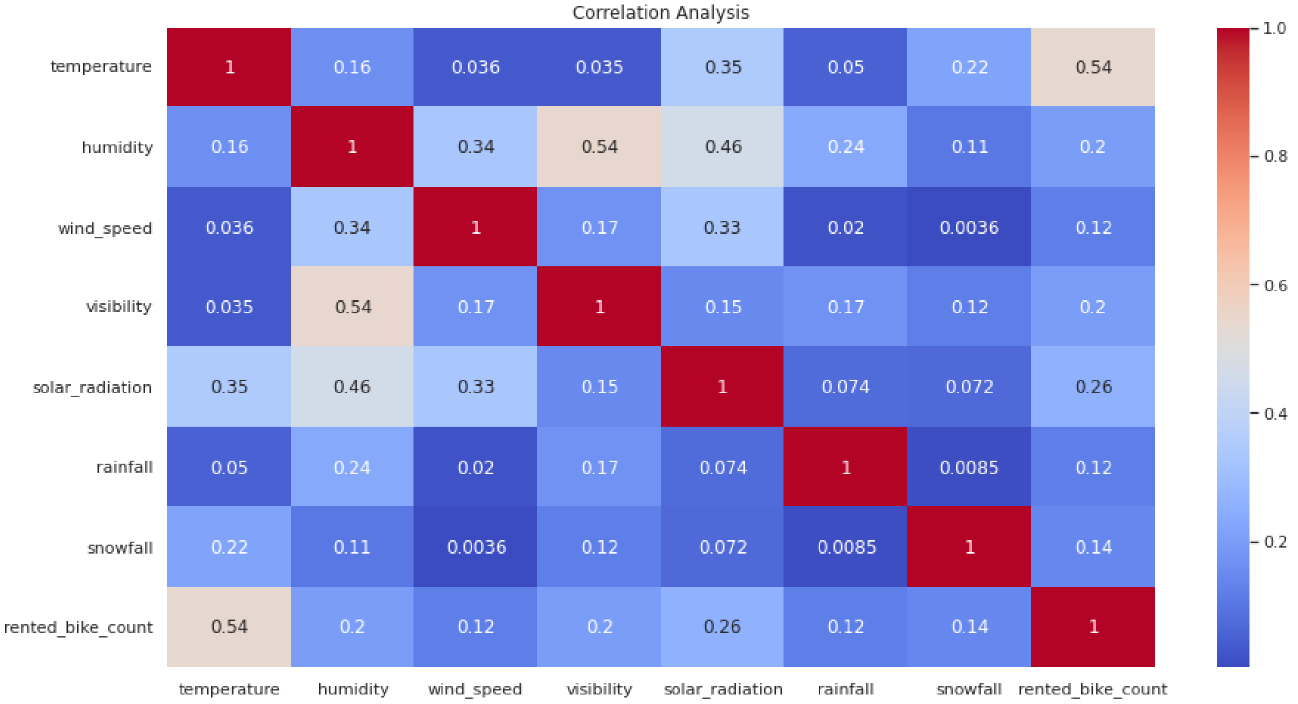






EDA (Contd.)

- Correlation magnitude
- There is no **multicollinearity** in the attributes
- Temperature has the **highest** correlation with the dependent variable



EDA Summary

- The dependent variable - rented bike counts is **positively skewed**
- Demand for rental bikes is lowest in the winters; highest in summers
- On regular days, there is a **surge** in demand for rental bikes during **rush** hours, this was absent during **holidays** and **weekends**
- The demand for rental bikes remains **low** when there is **snowfall / rainfall**, and on days with **low visibility**
- The demand for rental bikes remains **low** for days with very **low temperatures**, and on days with high intensity of **solar radiation**
- The data contains **outliers**, but we didn't handle them since by doing so, we may eliminate the patterns in the data we discovered
- Temperature has the highest correlation with dependent variable

Modelling Approach

- Since the data contains **outliers**, and many **categorical** attributes, It won’t be wise to fit linear models, as they will give high errors.
- We can use **tree** models instead, since they can handle outliers and categorical attributes better than linear models.
- We can use **decision tree** as a baseline model.
- Subsequently, to get better predictions, we can use **ensemble models**: Random forests, GBM, XG Boost.
- Final choice of model will depend on whether interpretability or accuracy is important to the stakeholders.

Modelling Approach

- Choice of split is taken as **K-fold cross validation**, with k=6, because of the computational power available and to reduce overfitting
- Evaluation metrics is **RMSE** to punish outliers, and choose a model that is able to generalize the results for all points including outliers.

$$\textbf{RMSE} = \sqrt{\frac{\sum(Y-\hat{Y})^2}{N}}$$

- Hyperparameter tuning is done to prevent overfitting, and the best parameters are chosen using **GridsearchCV**

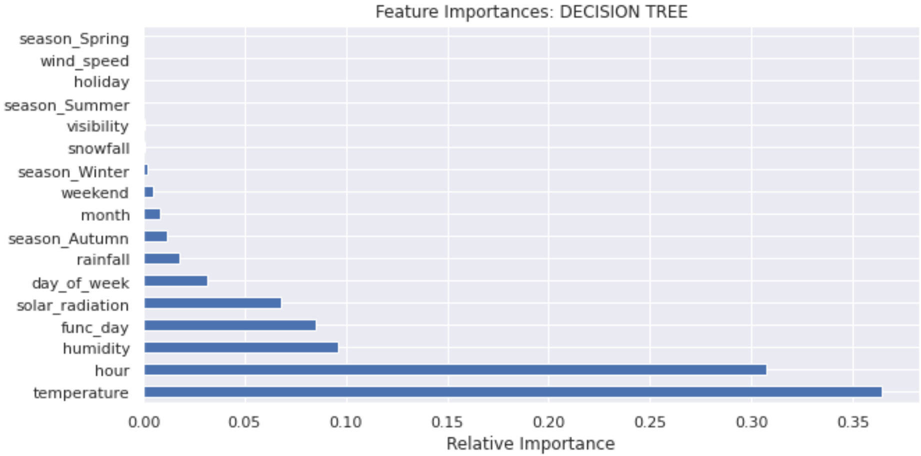
Decision Tree

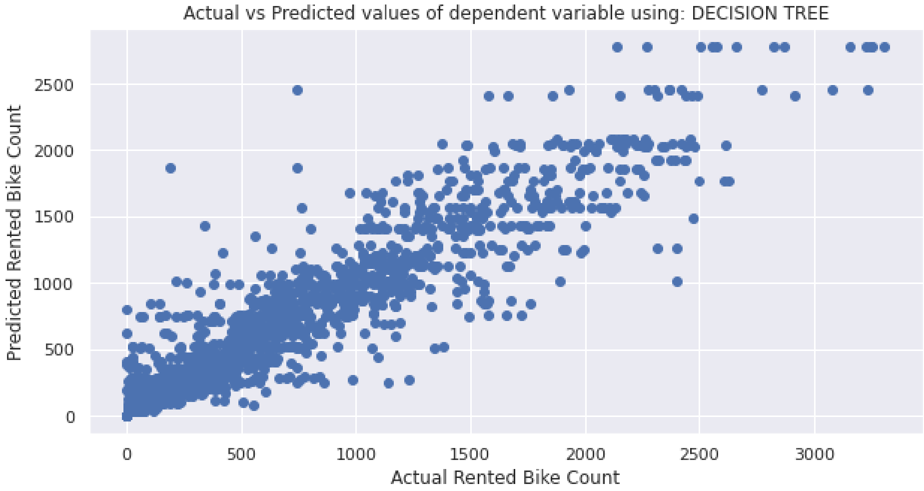
Parameters:

- Max_depth = 20
- Min_samples_leaf = 30

Evaluation metrics:

- Train RMSE = 224.90
- Test RMSE = 240.64





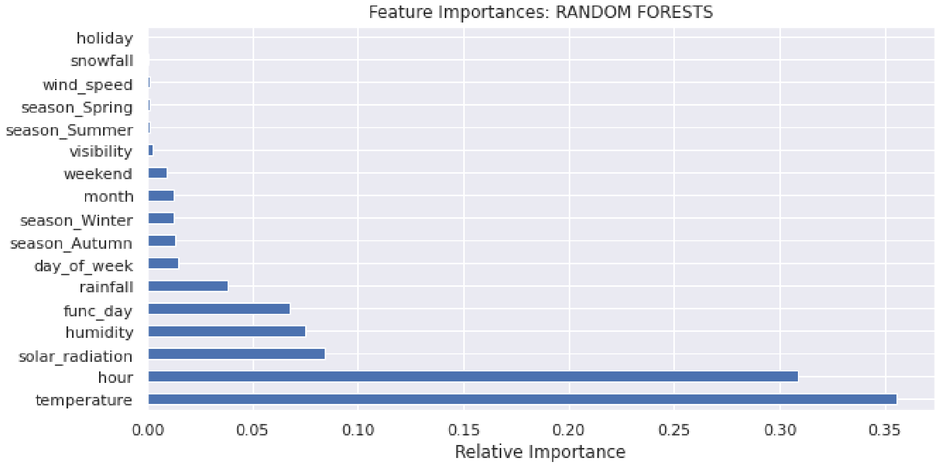
Random Forests

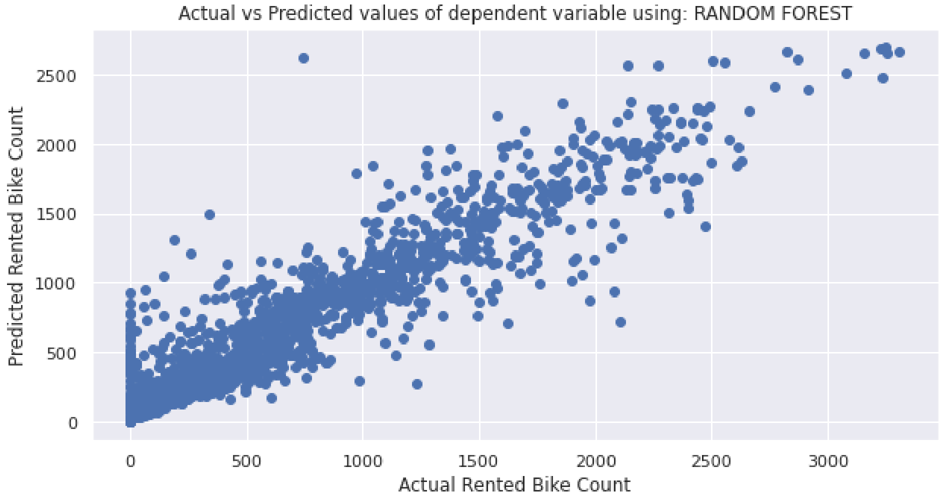
Parameters:

- N_estimators = 500
- Min_samples_leaf = 25

Evaluation metrics:

- Train RMSE = 210.61
- Test RMSE = 238.19





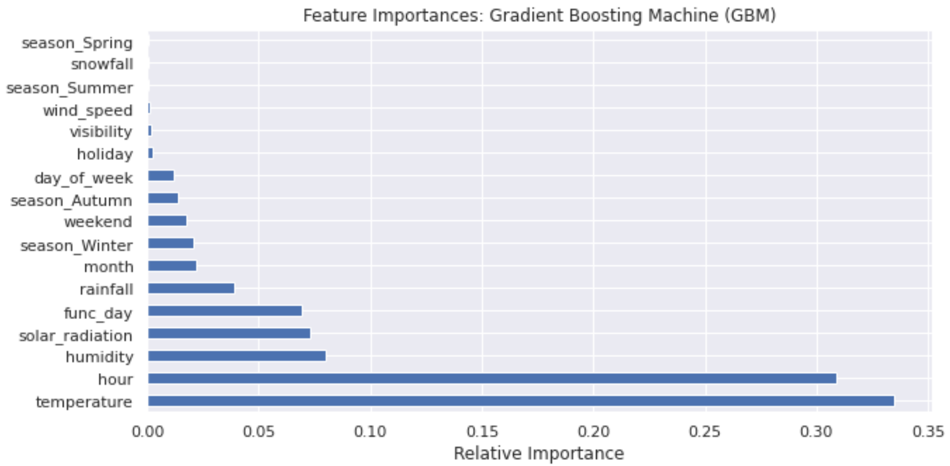
Gradient Boost

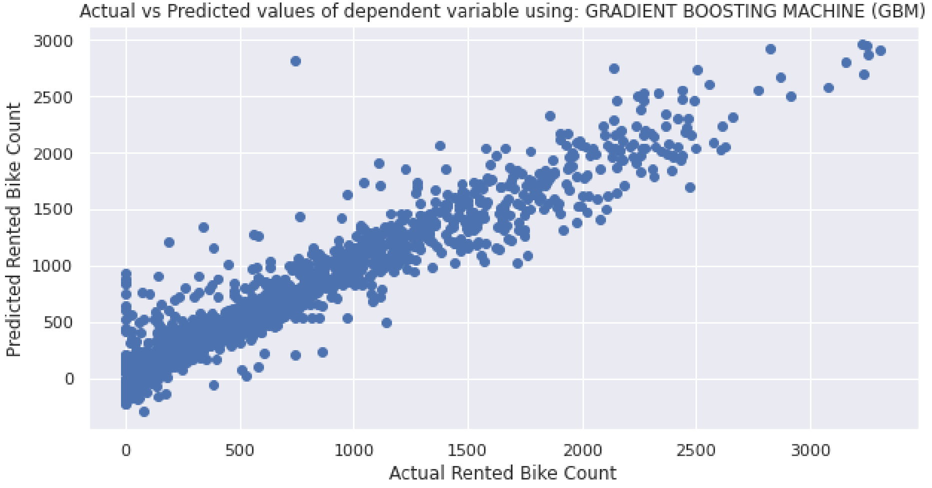
Parameters:

- N_estimators = 500
- Min_samples_leaf = 26

Evaluation metrics:

- Train RMSE = 160.93
- Test RMSE = 189.36





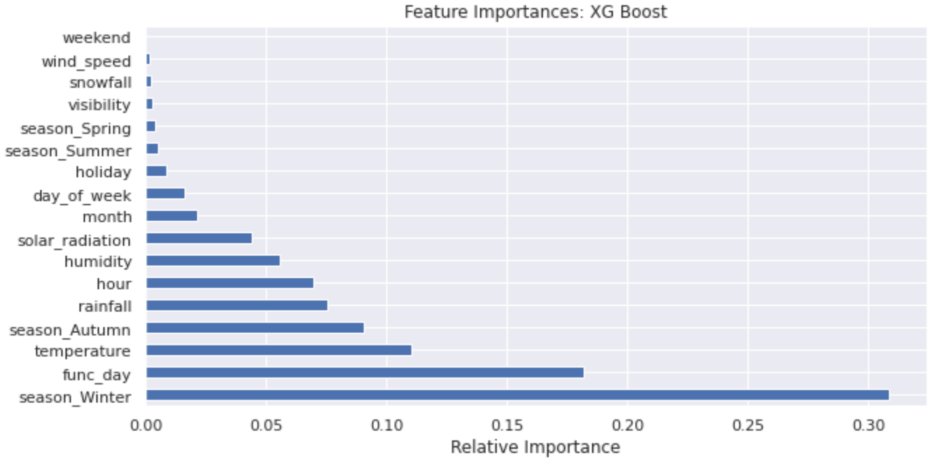
XG Boost

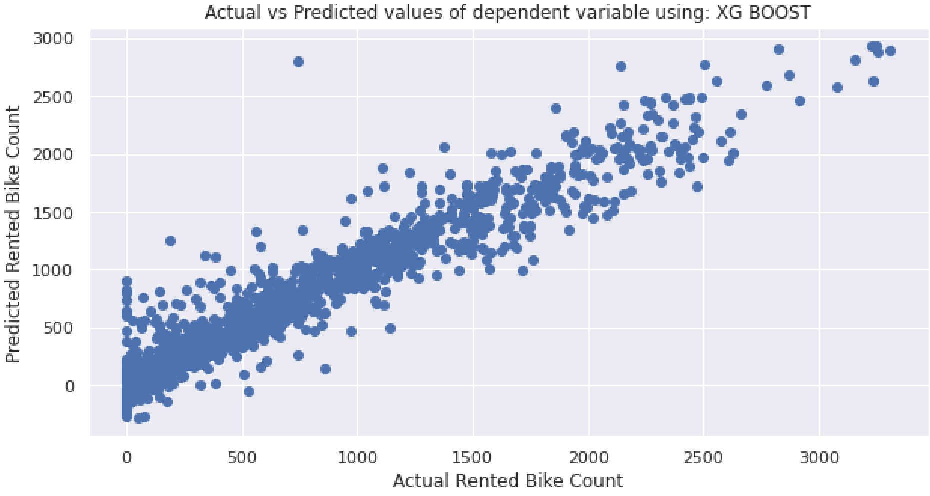
Parameters:

- N_estimators = 500
- Min_samples_leaf = 25

Evaluation metrics:

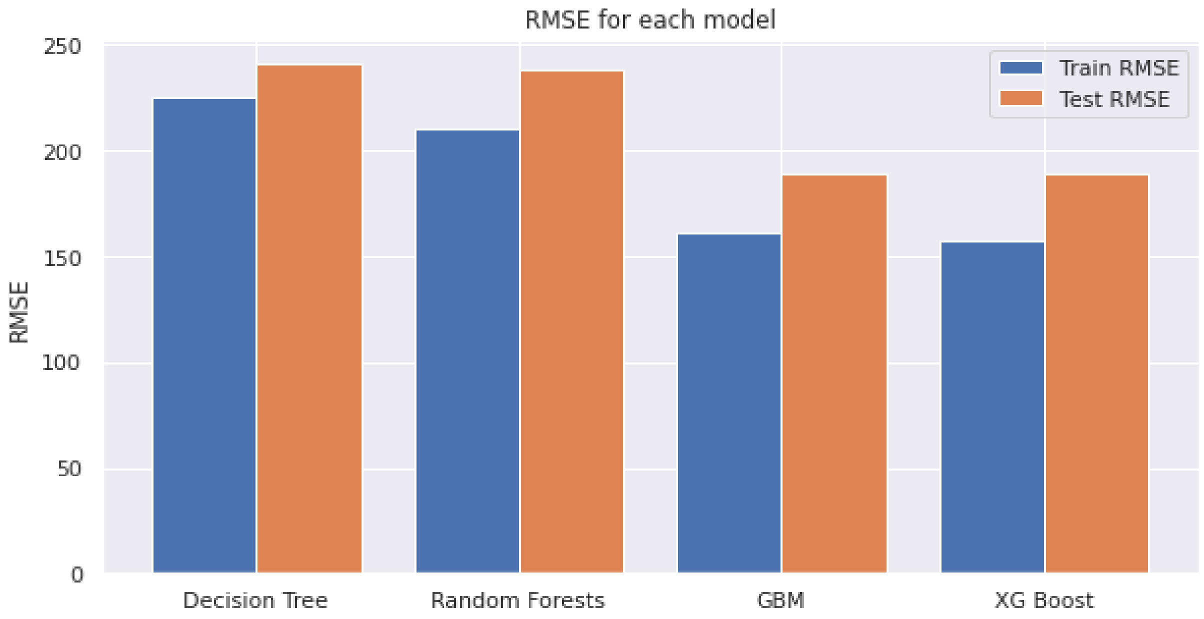
- Train RMSE = 157.58
- Test RMSE = 188.85





Model Comparison

- The test RMSE is slightly **higher** than train RMSE for all models
- The **XG Boost** model has the **lowest** train and test RMSE compared to others



Challenges Faced

- Comprehending the problem statement, and understanding the business implications
- Feature engineering – deciding on which features to be dropped / kept / transformed
- Choosing the best visualization to show the trends among different features clearly in the EDA phase
- Deciding on how to handle outliers
- Choosing the ML models to make predictions
- Deciding the evaluation metric to evaluate the models
- Choosing the best hyperparameters, which prevents overfitting

Conclusion

- We have successfully built predictive models that can predict the demand for rental bikes based on different weather conditions and other factors and, they were evaluated using RMSE
- The XG Boost prediction model had the lowest RMSE
- The final choice of model for deployment depends on the business need; if high accuracy in results is necessary, we can deploy XG Boost model
- If the model interpretability is important to the stakeholders, we can choose deploy the decision tree model.

Thank You!