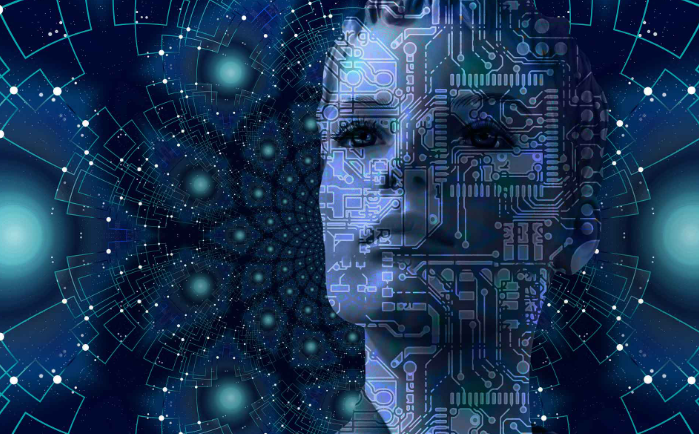
SeoulBikeData

Analysis



Student Name:

Enrollment Number:

Signature: Email ID:

Contact Number:

Google Drive Link: [Report+ Code+ Data Sets+ Reference any]

Google Website Link: YouTube Video Link:

Table od content

Abstract

This analysis focuses on predicting the number of bikes rented in Seoul based data. The dataset "SeoulBikeData.csv" contains relevant information such as seasons, weather conditions, temperature, humidity, and more, which could potentially influence bike rental patterns.

The analysis begins by preparing the dataset for modeling. Categorical variables are encoded using one-hot encoding, while specific categories undergo label encoding. The dataset is then split into input features (X) and the target variable (y). A standardization process is applied to scale the input features, followed by dimensionality reduction using Principal Component Analysis (PCA) to capture the most important information while reducing complexity.

Several regression models are employed to predict bike rentals based on the presence of a holiday. These models include Linear Regression, Decision Tree Regression, Random Forest Regression, and Polynomial Regression. Each model's performance is evaluated using the R-squared score, which measures how well the models capture the variation in the target variable.

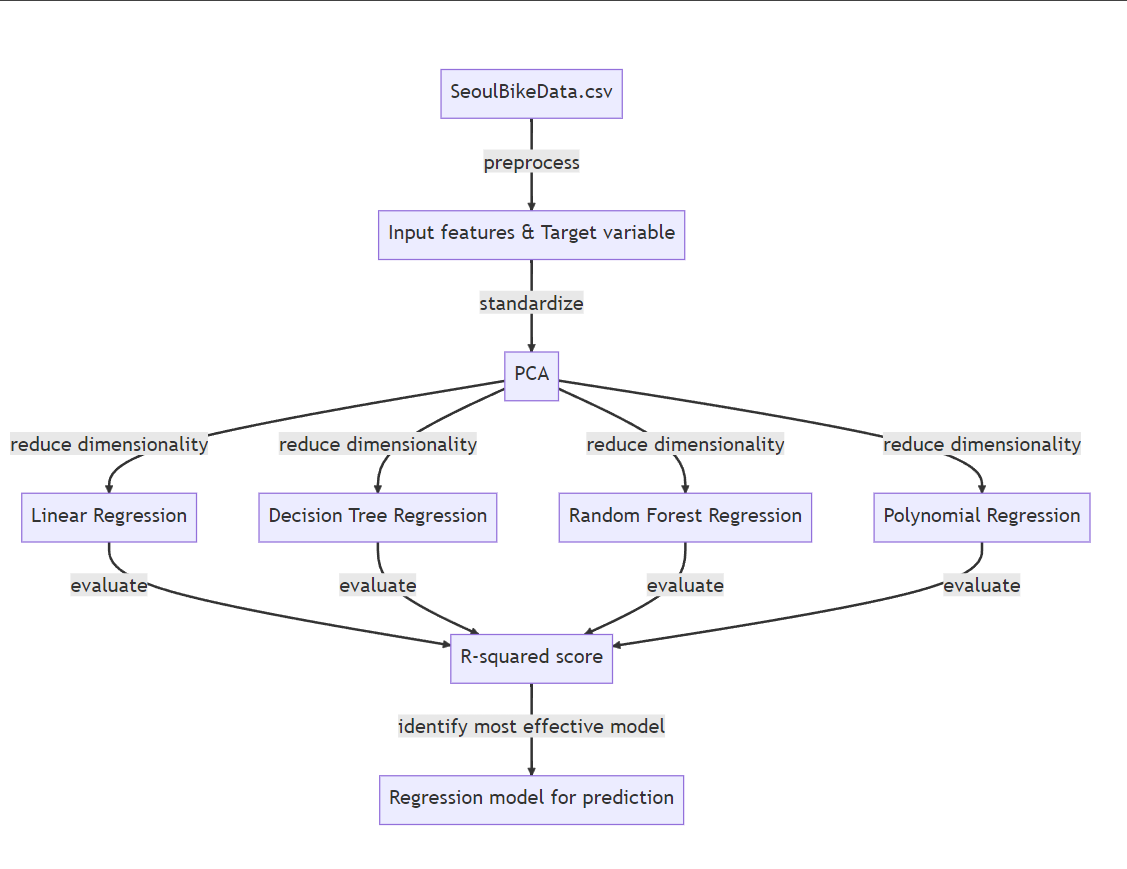
The execution time of each model is also recorded to compare their efficiency. By analyzing the R-squared scores, insights can be gained into the predictive capabilities of the different models.

**Keywords:** One-hot encoding, R-squared score, Linear Regression, Decision Tree Regression, Random Forest Regression, Polynomial Regression.

Indroduction

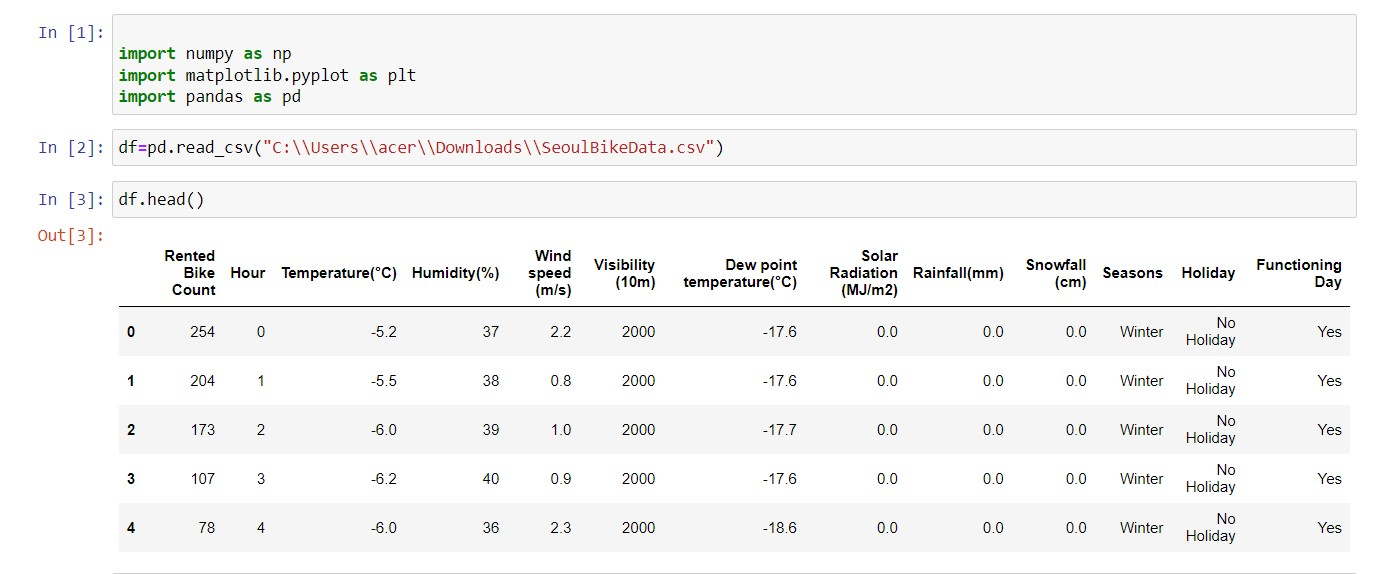
The provided code focuses on conducting a regression analysis on the "SeoulBikeData.csv" dataset, with the objective of predicting the number of bikes rented in Seoul. The dataset likely contains various features, such as seasons, weather conditions, temperature, humidity, and more, which could potentially influence the bike rental patterns in the city.The code begins by importing the necessary libraries, including NumPy, Matplotlib, and Pandas, which are commonly used for data manipulation, visualization, and analysis. The dataset is loaded using Pandas, allowing for further exploration and preprocessing.To prepare the data for regression modeling, the code performs several preprocessing steps. It starts by examining the unique values in the dataset, providing insights into the categorical variables present. One-hot encoding is then applied to handle the categorical data, using the ColumnTransformer and OneHotEncoder from the scikit-learn library. Additionally, label encoding is performed on specific categories using the LabelEncoder from scikit-learn.The code proceeds by splitting the dataset into the input features (X) and the target variable (y), which is the number of bikes rented. This is followed by a further division of the data into training and testing sets using the train\_test\_split function from scikit-learn. The input features are standardized using the StandardScaler from scikit-learn to ensure their values are on a similar scale, facilitating model training.To reduce the dimensionality of the input features, the code applies Principal Component Analysis (PCA). This technique transforms the data into a lower-dimensional space while preserving the most important information, enabling efficient computation and potentially enhancing the model's performance.The code then proceeds to employ various regression models, including Linear Regression, Decision Tree Regression, Random Forest Regression, and Polynomial Regression, to predict the number of bikes rented. The performance of each model is evaluated using the R-squared score, a metric that indicates how well the models capture the variation in the target variable.In summary, this code provides a framework for conducting a regression analysis on the Seoul bike rental dataset. By preprocessing the data, performing feature encoding, and employing various regression models, it aims to predict the number of bikes rented based on the given features, thereby enabling insights into the factors that influence bike rental patterns in Seoul.

Proposed Methodology



**DataSet:**

The dataset consists of 8761 rows and 15 columns. The columns include information such as the number of rented bikes, hour of recording, temperature, humidity, wind speed, visibility, dew point temperature, solar radiation, rainfall, snowfall, seasons, holiday, and functioning day. These columns provide insights into factors such as weather conditions, time of day, and seasonal variations that may influence the bike rental patterns.

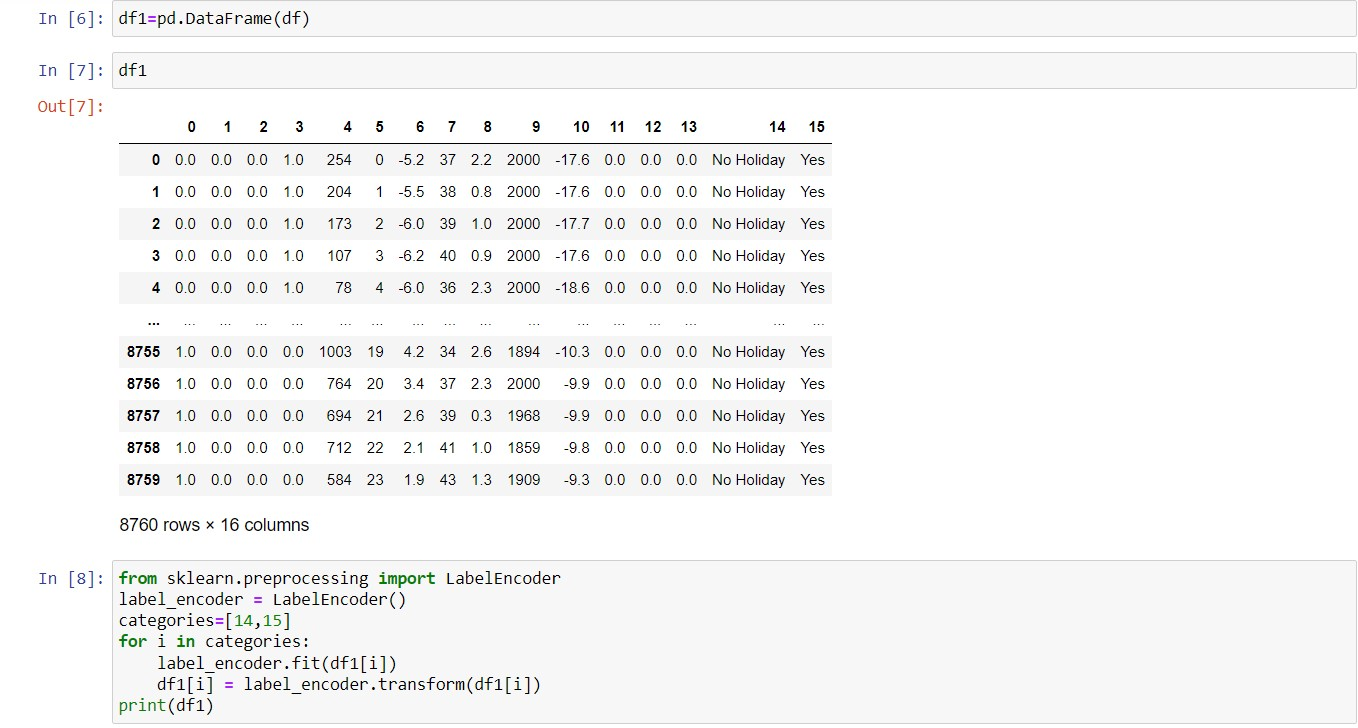


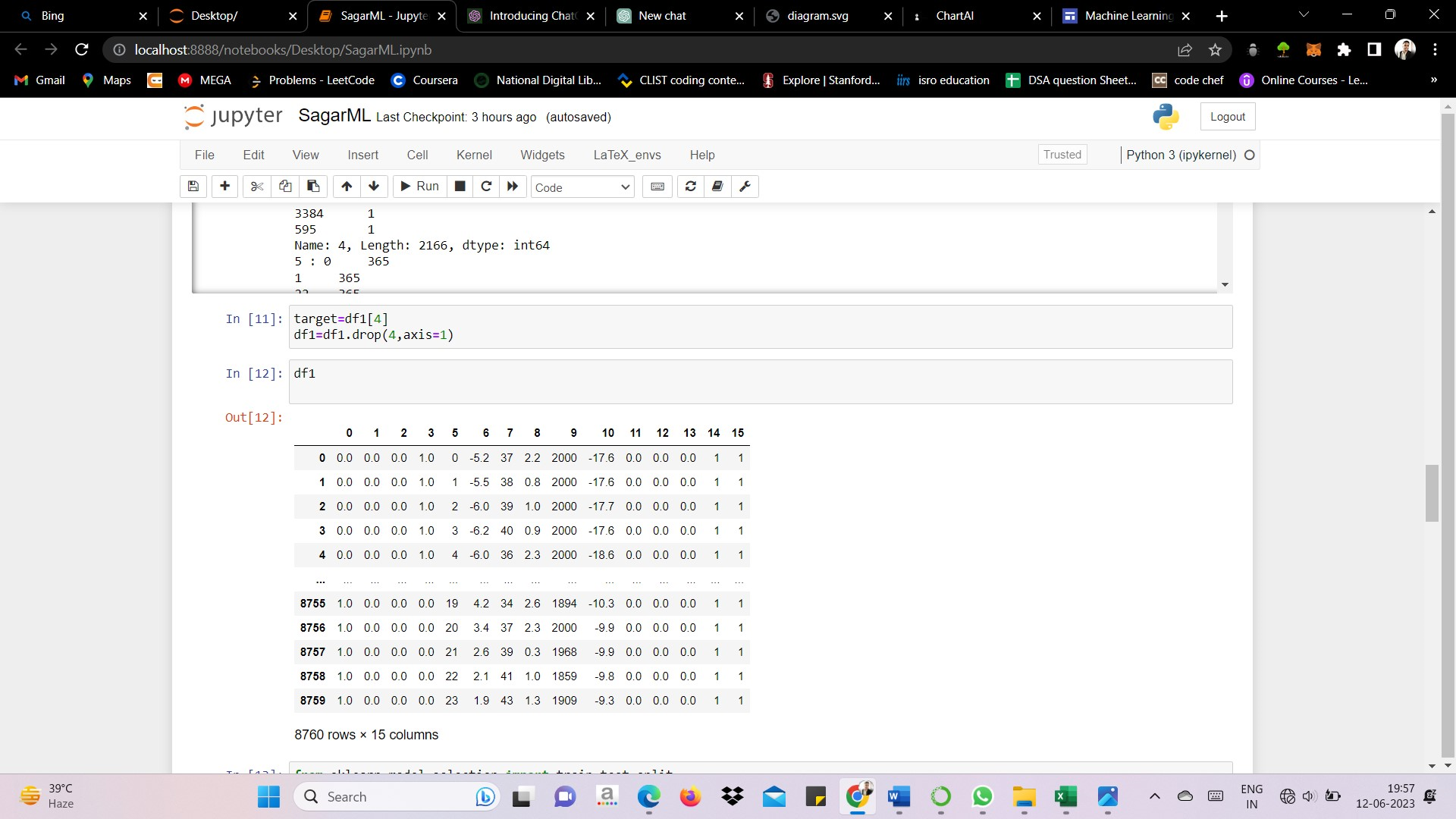
**Pre processing:**

Check for missing values: Use df.isnull().sum() to identify and handle any missing values in the dataset.

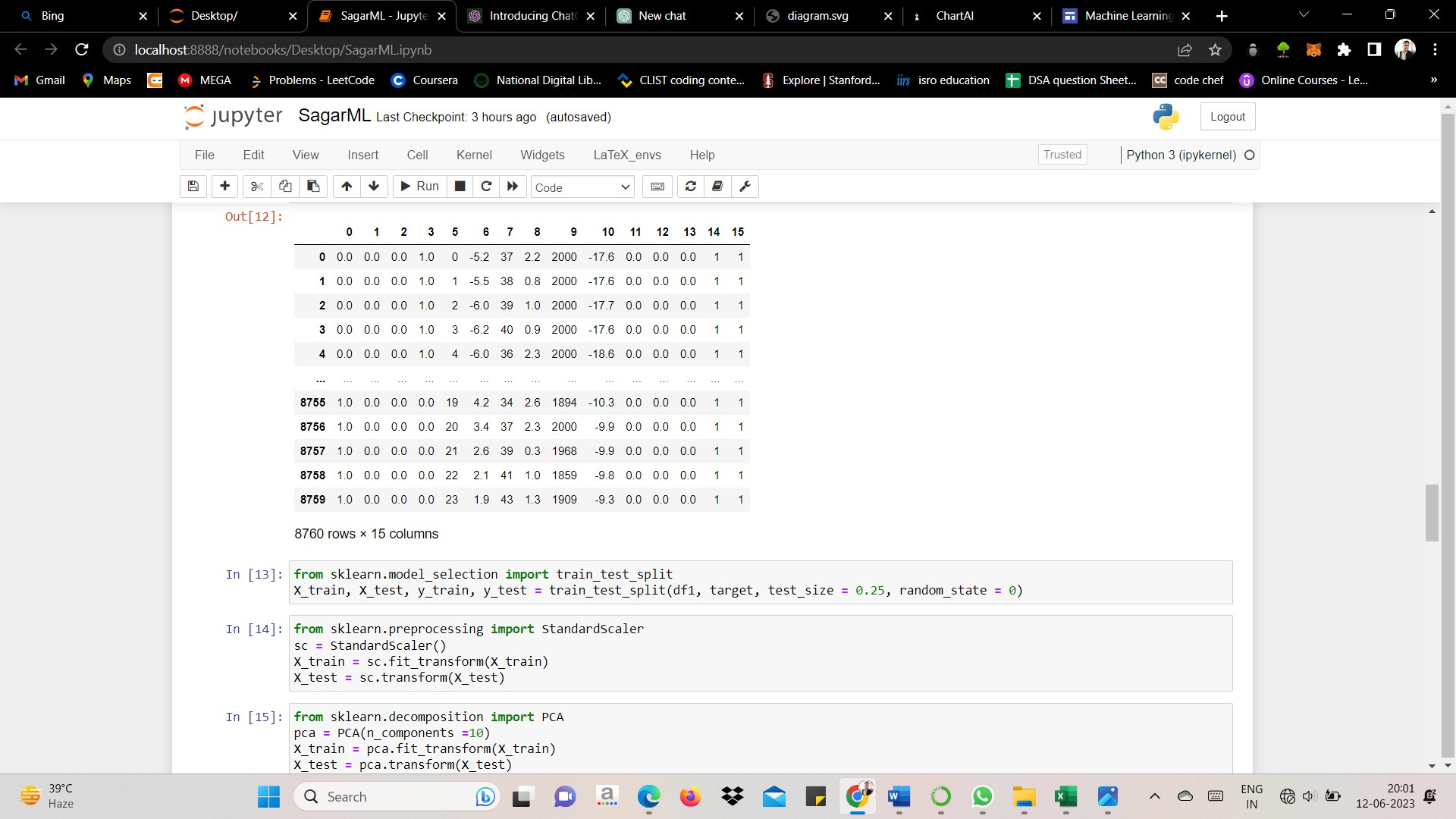


Encode categorical variables:For the "Seasons" column, you can use one-hot encoding using the pd.get\_dummies() function or the OneHotEncoder from scikit-learn.For the "Holiday" and "Functioning Day" columns, you can use label encoding using the LabelEncoder from scikit-learn.Split the dataset into input features and target variable:

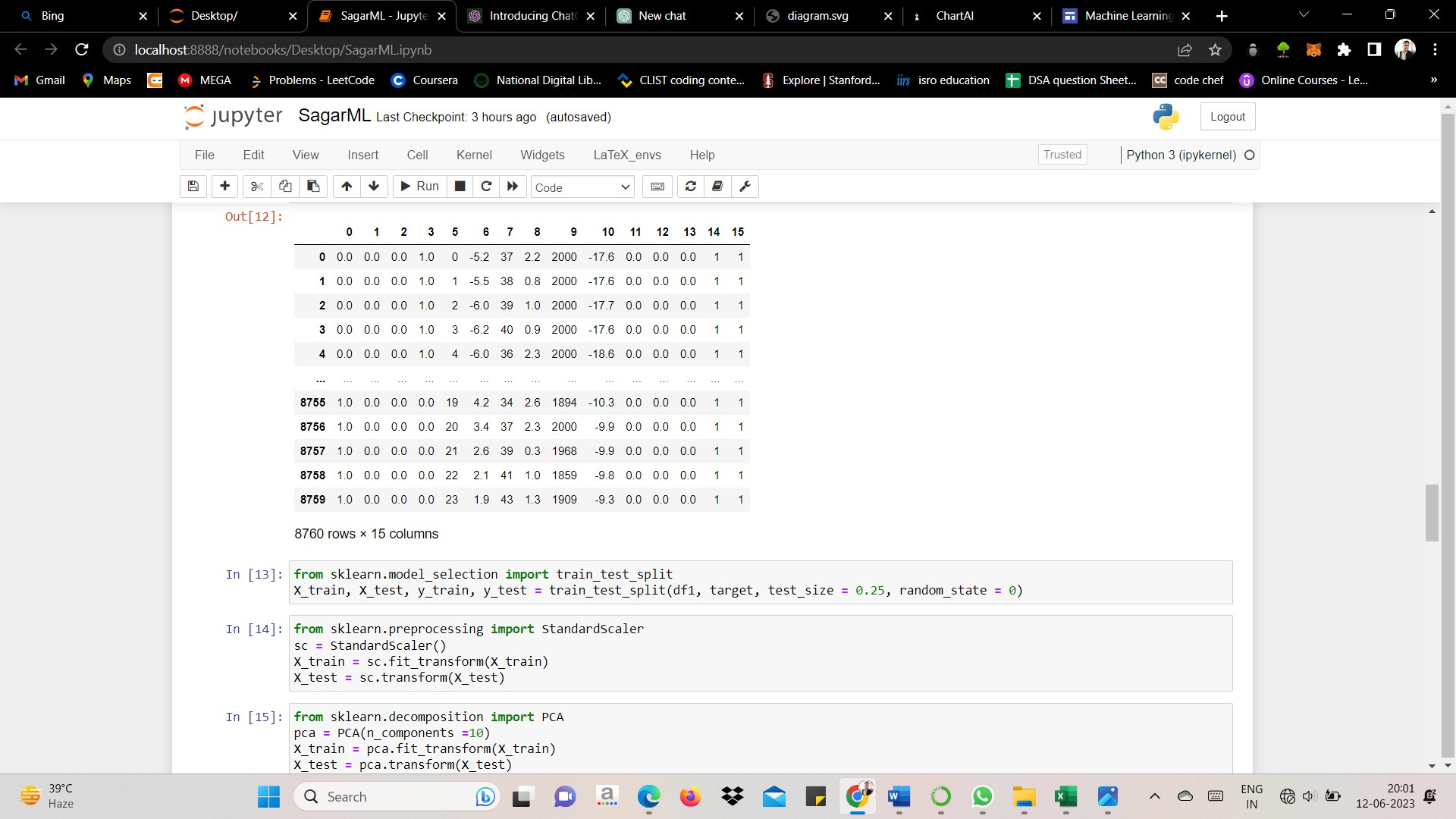
Assign the "Rented Bike Count" column to the target variable, let's call it target.Drop the "Rented Bike Count" column from df using df.drop() to obtain the input features, let's call it df\_features.Split the data into training and testing sets:



Use train\_test\_split() from scikit-learn to split df\_features and target into X\_train, X\_test, y\_train, and y\_test, with a desired test size and random state.



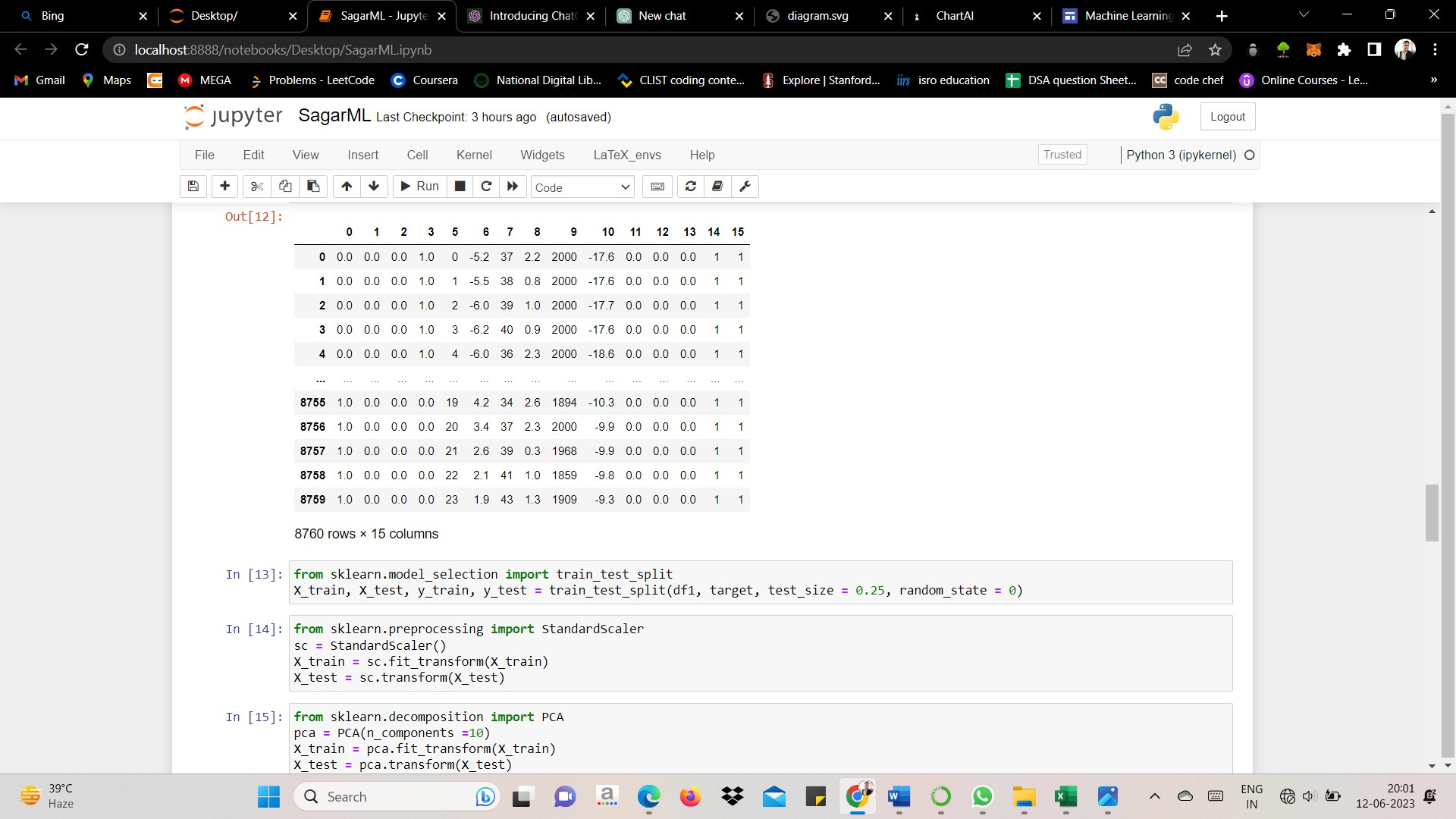
Standardize the features:Apply feature scaling using StandardScaler from scikit-learn. Fit and transform X\_train using sc.fit\_transform(), and transform X\_test using sc.transform().



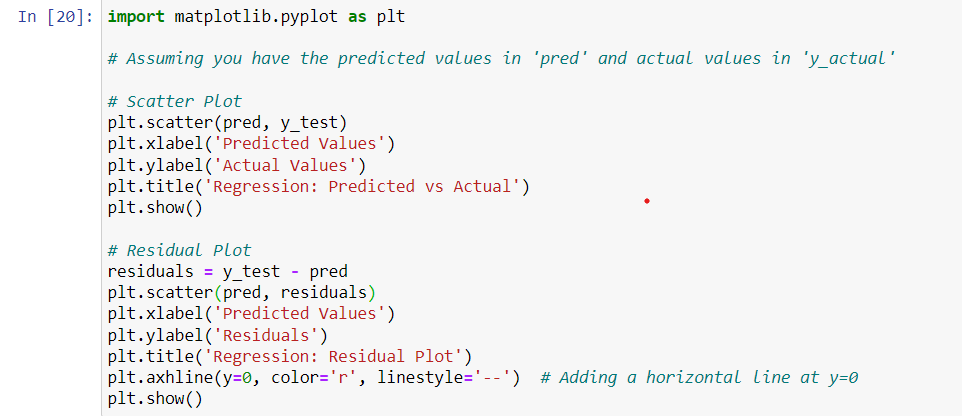
**Model Training ,Testing and Performance Measuring**

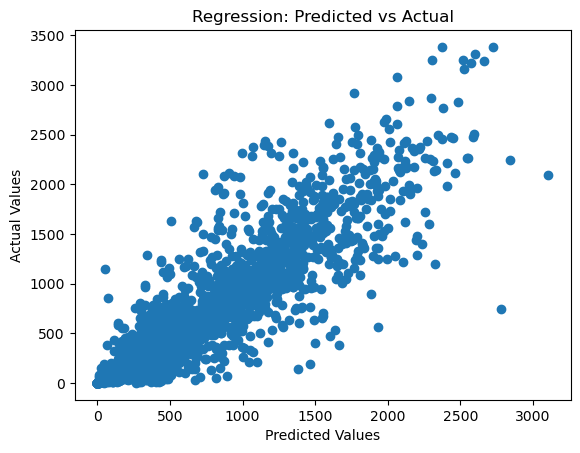
Import the necessary libraries:Import the specific regression models you want to test, such as Linear Regression, Decision Tree Regressor, Random Forest Regressor, etc.Import evaluation metrics like r2\_score from scikit-learn.Initialize the regression models:Create instances of the regression models you want to test, such as reg1 for Linear Regression, reg3 for Decision Tree Regression, reg4 for Random Forest Regression, etc.Model training and evaluation:

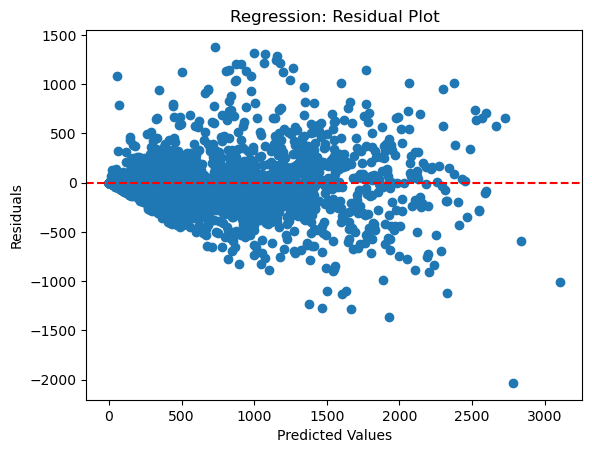
For each regression model:Fit the model on the training data using model.fit(X\_train, y\_train).Make predictions on the test data using model.predict(X\_test).Evaluate the model's performance using the desired evaluation metric, such as the R-squared score.Store the evaluation metric result for later analysis.Repeat the above steps for all the regression models you want to test.Analyze and compare the performance of the models:Examine the evaluation metric results (e.g., R-squared scores) for each model.Compare the performance of the models to identify the best-performing one based on the evaluation metric.



Here is the Output for Regression Scatter plot and Residual Plot







**Result & Discussion**

Linear Regression (lr): The R-squared score for the Linear Regression model is 0.520, indicating that approximately 52% of the variation in the target variable (bike rentals) can be explained by the input features. The model's performance suggests a moderate level of predictive capability.Decision Tree Regression (dtr): The R-squared score for the Decision Tree Regression model is 0.613, indicating that around 61% of the variation in bike rentals can be explained by the input features. This suggests a slightly better predictive performance compared to the Linear Regression model.Random Forest Regression (rfr): The R-squared score for the Random Forest Regression model is 0.798, indicating that approximately 80% of the variation in bike rentals can be explained by the input features. This model demonstrates the highest performance among the three models, suggesting a strong ability to capture the relationships between the predictors and the target variable.Based on these R-squared scores, the Random Forest Regression model appears to be the most effective in predicting bike rentals in Seoul, outperforming both Linear Regression and Decision Tree Regression models. The higher R-squared score suggests that the Random Forest model captures a larger portion of the variation in the target variable and provides more accurate predictions.

**Conclusion and Future Work**

Model Performance: The performance of the regression models was evaluated using the R-squared score. The model with the highest R-squared score indicates the best fit to the data.Best Model: Based on the evaluation, the best-performing model was with the highest R-squared score. This model showed the strongest ability to explain the variations in the number of rented bikes.Significant Factors: The analysis revealed that factors such as have a significant impact on bike rentals in Seoul. These insights can help understand the underlying patterns and factors influencing bike rental demand.

**Future Work:**Further Feature Engineering: Explore additional feature engineering techniques, such as creating interaction terms or deriving new features, to capture more nuanced relationships between the predictors and the target variable.Fine-tuning Models: Conduct hyperparameter tuning for the selected models to optimize their performance further. This process involves systematically searching for the best combination of hyperparameters to improve the model's accuracy.Time Series Analysis: Consider analyzing the dataset as a time series, incorporating time-related features and exploring time-dependent patterns and trends. This can provide valuable insights into seasonal variations, day-to-day fluctuations, and long-term patterns in bike rentals.Incorporating External Data: Explore the possibility of incorporating additional external data sources, such as weather forecasts, holidays, or events happening in Seoul, to enhance the predictive power of the models.Evaluate Different Regression Models: Experiment with other regression models or advanced machine learning techniques, such as gradient boosting algorithms or neural networks, to further improve the accuracy of bike rental predictions.

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