Group 5 - Bike Rental Project ADS 505

October 17, 2022

[867]:

```
# Import dependences

import pandas as pd
import numpy as np
import matplotlib as mpl
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn import preprocessing
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.model_selection import train_test_split, KFold, cross_val_score
import sklearn.metrics as metrics
from sklearn.metrics import accuracy_score, confusion_matrix, precision_score,␣
↪recall_score, f1_score
from sklearn.neural_network import MLPClassifier, MLPRegressor
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.neighbors import NearestNeighbors, KNeighborsClassifier,␣
↪KNeighborsRegressor
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression, LogisticRegressionCV
from sklearn.svm import SVR
import math
import operator
from prettytable import PrettyTable
warnings.filterwarnings("ignore")

# mpl.rc_file_defaults()
# plt.rcParams.update(plt.rcParamsDefault)
# plt.rcParams['axes.facecolor'] = 'black'

%matplotlib inline
```

[868]:
```
# parse_dates=[0]: We give the function a hint that data in the first column␣
↪contains dates that need to be parsed.
# This argument takes a list, so we provide it a list of one element, which is␣
↪the index of the first column

Seoul_Bike_df = pd.read_csv('/Users/JohnnyBlaze/Website Data Sets/SeoulBikeData.
↪csv', encoding='unicode_escape', parse_dates=[0])
```

[869]:
```
Seoul_Bike_df.head()
```

[869]:
```
        Date  Rented Bike Count  Hour  Temperature(°C)  Humidity(%)  \
0 2017-01-12                254     0             -5.2           37
1 2017-01-12                204     1             -5.5           38
2 2017-01-12                173     2             -6.0           39
3 2017-01-12                107     3             -6.2           40
4 2017-01-12                 78     4             -6.0           36

   Wind speed (m/s)  Visibility (10m)  Dew point temperature(°C)  \
0               2.2              2000                      -17.6
1               0.8              2000                      -17.6
2               1.0              2000                      -17.7
3               0.9              2000                      -17.6
4               2.3              2000                      -18.6

   Solar Radiation (MJ/m2)  Rainfall(mm)  Snowfall (cm) Seasons     Holiday  \
0                      0.0           0.0            0.0  Winter  No Holiday
1                      0.0           0.0            0.0  Winter  No Holiday
2                      0.0           0.0            0.0  Winter  No Holiday
3                      0.0           0.0            0.0  Winter  No Holiday
4                      0.0           0.0            0.0  Winter  No Holiday

  Functioning Day
0             Yes
1             Yes
2             Yes
3             Yes
4             Yes
```

[870]:
```
Seoul_Bike_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8760 entries, 0 to 8759
Data columns (total 14 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   Date                       8760 non-null   datetime64[ns]
 1   Rented Bike Count          8760 non-null   int64
 2   Hour                       8760 non-null   int64
```

```
 3   Temperature(°C)           8760 non-null   float64
 4   Humidity(%)               8760 non-null   int64
 5   Wind speed (m/s)          8760 non-null   float64
 6   Visibility (10m)          8760 non-null   int64
 7   Dew point temperature(°C) 8760 non-null   float64
 8   Solar Radiation (MJ/m2)   8760 non-null   float64
 9   Rainfall(mm)              8760 non-null   float64
 10  Snowfall (cm)             8760 non-null   float64
 11  Seasons                   8760 non-null   object
 12  Holiday                   8760 non-null   object
 13  Functioning Day           8760 non-null   object
dtypes: datetime64[ns](1), float64(6), int64(4), object(3)
memory usage: 958.2+ KB
```

[871]:
```
Seoul_Bike_df = Seoul_Bike_df.astype({'Rented Bike Count':'float','Hour':
 ↪'object'})
# Seoul_Bike_df.info()
```

[872]:
```
# Reformat Column Names
Seoul_Bike_df = Seoul_Bike_df.copy()

Seoul_Bike_df.columns = [d.replace(' ','_').replace('.','') for d in␣
 ↪Seoul_Bike_df.columns]

Seoul_Bike_df = Seoul_Bike_df.rename(columns={'Wind_speed_(m/s)':'Wind_speed(m/
 ↪s)','Visibility_(10m)':'Visibility(10m)',
                                              'Solar_Radiation_(MJ/m2)':
 ↪'Solar_Radiation(MJ/m2)','Snowfall_(cm)':'Snowfall(cm)'})

# Print Column Names
for col in Seoul_Bike_df.columns:
    print(col)
```

```
Date
Rented_Bike_Count
Hour
Temperature(°C)
Humidity(%)
Wind_speed(m/s)
Visibility(10m)
Dew_point_temperature(°C)
Solar_Radiation(MJ/m2)
Rainfall(mm)
Snowfall(cm)
Seasons
Holiday
Functioning_Day
```

[873]:
```python
# Check for Nulls
Seoul_Bike_df.isnull().sum()
```

[873]:
```
Date                          0
Rented_Bike_Count             0
Hour                          0
Temperature(°C)               0
Humidity(%)                   0
Wind_speed(m/s)               0
Visibility(10m)               0
Dew_point_temperature(°C)     0
Solar_Radiation(MJ/m2)        0
Rainfall(mm)                  0
Snowfall(cm)                  0
Seasons                       0
Holiday                       0
Functioning_Day               0
dtype: int64
```

[874]:
```python
Seoul_Bike_df.describe().transpose().style.
 ↪background_gradient(cmap='brg',axis=None)
```

[874]:
```
<pandas.io.formats.style.Styler at 0x7fb0f8429b50>
```

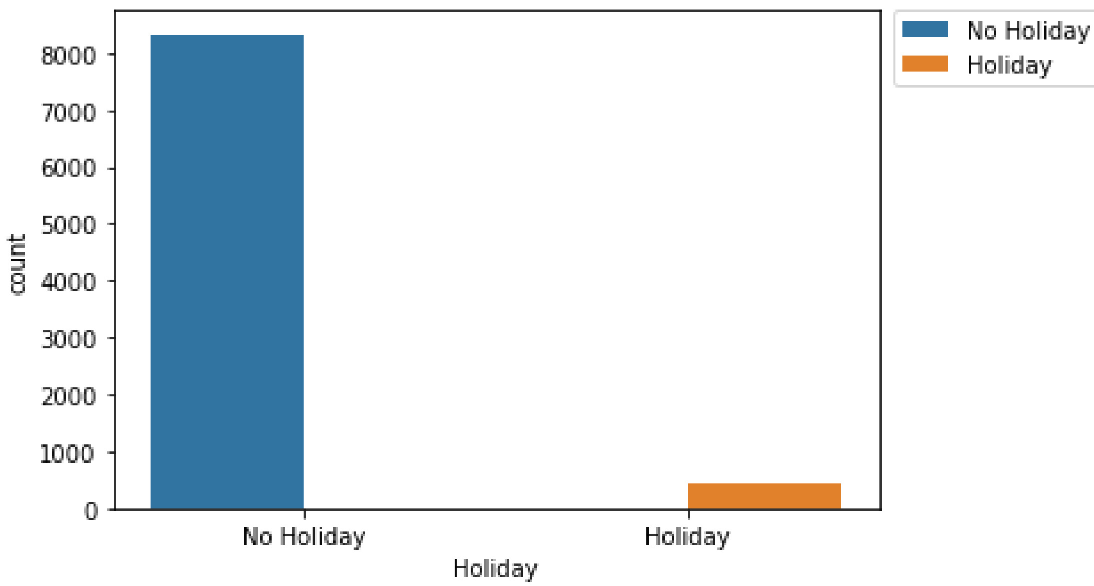
[875]:
```python
# Count of Unique Values

Seoul_Bike_df.nunique().sort_values(ascending=False)
```

[875]:
```
Rented_Bike_Count             2166
Visibility(10m)               1789
Dew_point_temperature(°C)      556
Temperature(°C)                546
Date                           365
Solar_Radiation(MJ/m2)         345
Humidity(%)                     90
Wind_speed(m/s)                 65
Rainfall(mm)                    61
Snowfall(cm)                    51
Hour                            24
Seasons                          4
Holiday                          2
Functioning_Day                  2
dtype: int64
```

[876]:
```python
# Unique Object Dtype Values

print(Seoul_Bike_df.iloc[:, -3:].apply(lambda col: col.unique()))
```

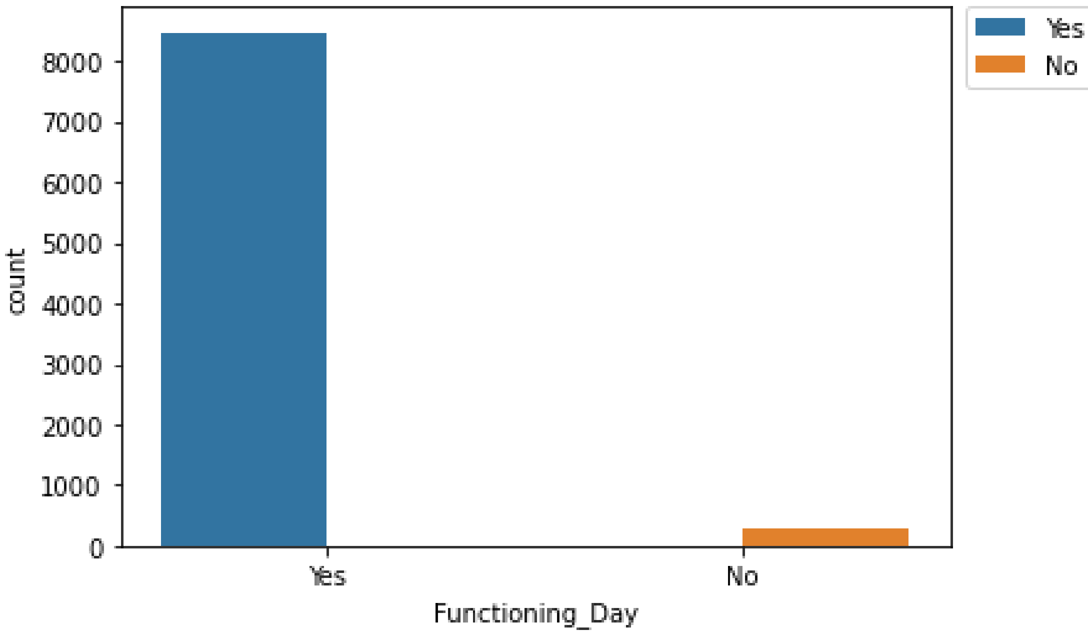
```
Seasons             [Winter, Spring, Summer, Autumn]
Holiday                        [No Holiday, Holiday]
Functioning_Day                            [Yes, No]
dtype: object
```

[877]:
```python
# Counts of Holiday

sns.countplot(data=Seoul_Bike_df, x='Holiday', hue='Holiday')
plt.legend(bbox_to_anchor=(1.02, 1), loc='upper left', borderaxespad=0)
plt.show()

print(Seoul_Bike_df['Holiday'].value_counts())
print()
```




```
No Holiday    8328
Holiday        432
Name: Holiday, dtype: int64
```

[878]:
```python
# Counts of Functioning Day

sns.countplot(data=Seoul_Bike_df, x='Functioning_Day', hue='Functioning_Day')
plt.legend(bbox_to_anchor=(1.02, 1), loc='upper left', borderaxespad=0)
plt.show()

print(Seoul_Bike_df['Functioning_Day'].value_counts())
print()
```

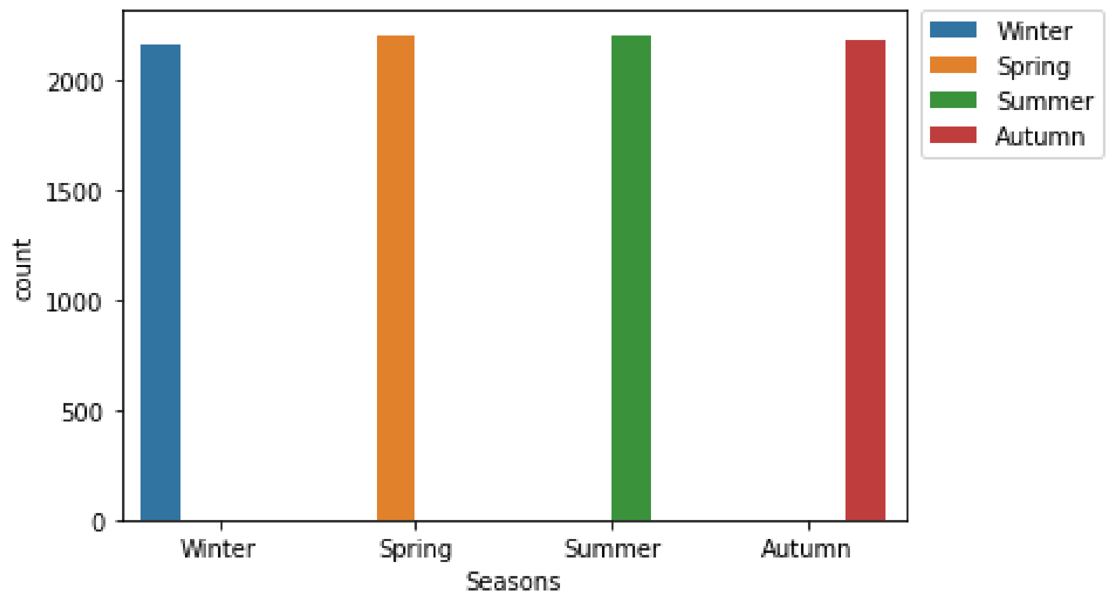



```
Yes    8465
No      295
Name: Functioning_Day, dtype: int64
```

[879]:

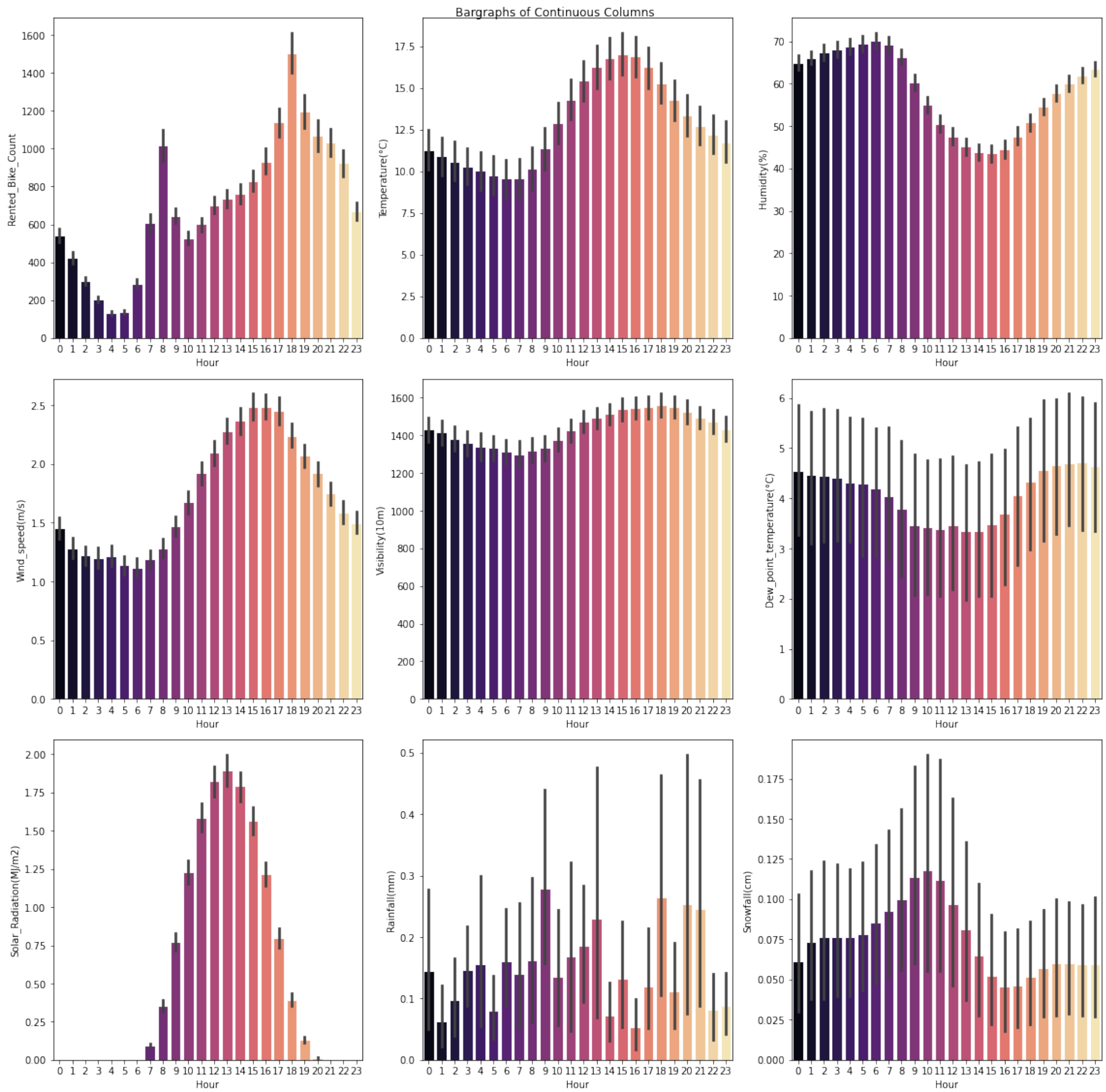
```
# Counts of Seasons

sns.countplot(data=Seoul_Bike_df, x='Seasons', hue='Seasons')
plt.legend(bbox_to_anchor=(1.02, 1), loc='upper left', borderaxespad=0)

print(Seoul_Bike_df['Seasons'].value_counts())
print()
plt.show()
```

```
Spring    2208
Summer    2208
Autumn    2184
Winter    2160
Name: Seasons, dtype: int64
```

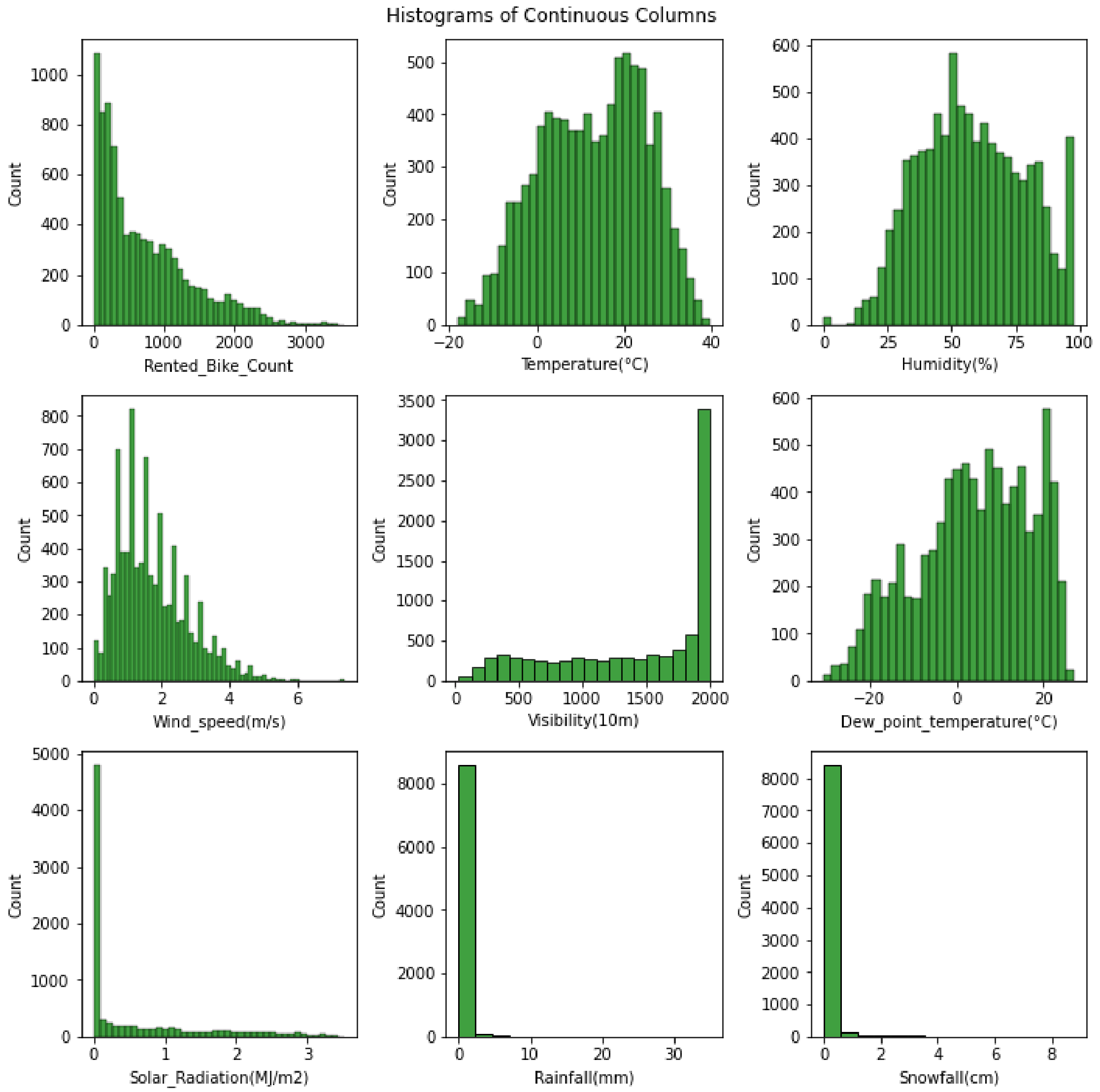


[880]:

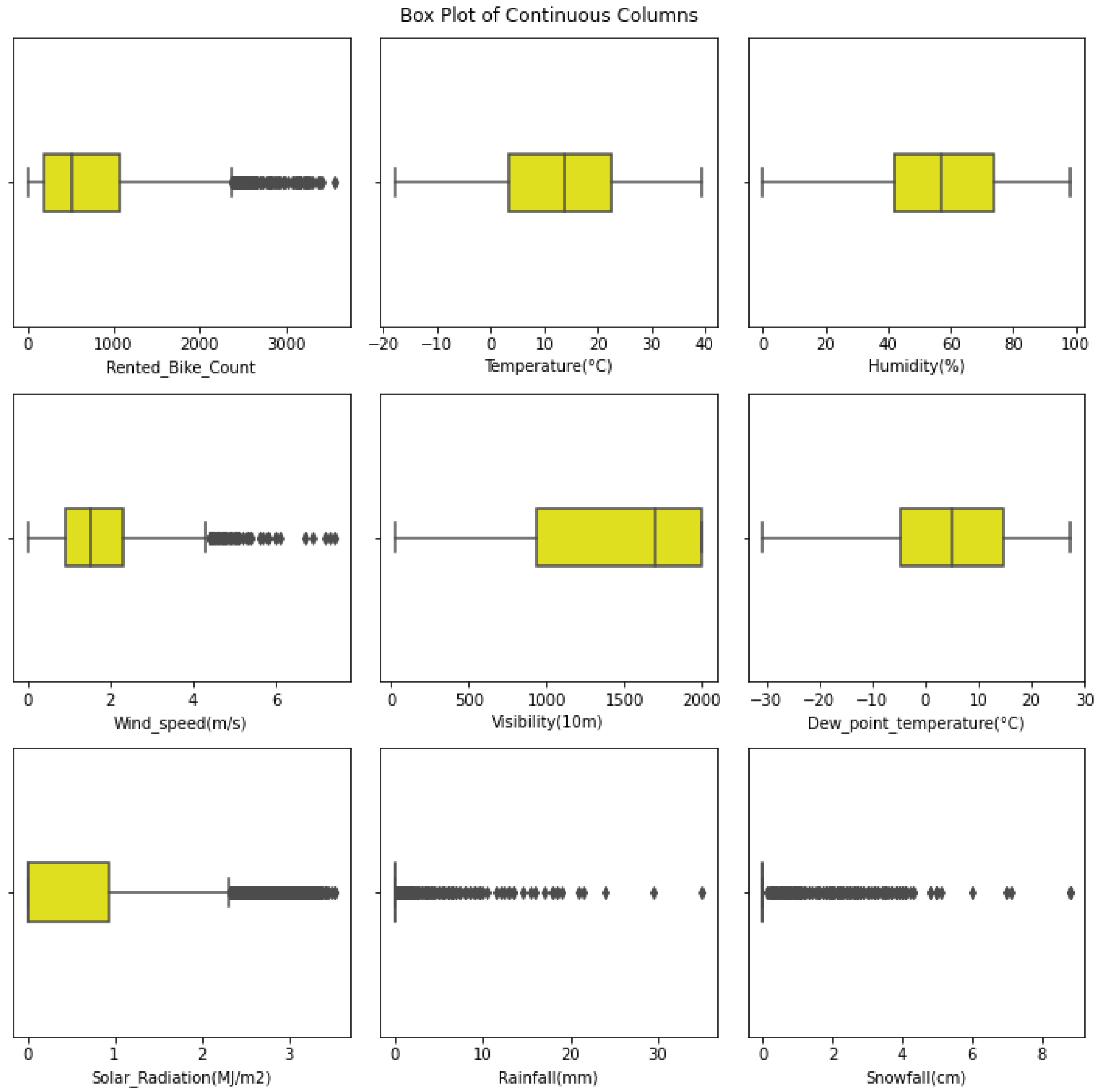
```
# Bargraphs

plt.figure(figsize=(16, 16))
for i, col in enumerate(Seoul_Bike_df.
 ↪select_dtypes(exclude=['datetime64[ns]','object']).columns):
    ax = plt.subplot(3,3, i+1)
    sns.barplot(data=Seoul_Bike_df, x='Hour', y=col, ax=ax, edgecolor='white',␣
 ↪palette='magma')
plt.suptitle('Bargraphs of Continuous Columns')
plt.tight_layout()
plt.show()
```



[881]:
```
# Histograms

plt.figure(figsize=(10, 10))
for i, col in enumerate(Seoul_Bike_df.select_dtypes(include=['float','int']).
    ↪columns):
    ax = plt.subplot(3,3, i+1)
    sns.histplot(data=Seoul_Bike_df, x=col, ax=ax, color='green')
plt.suptitle('Histograms of Continuous Columns')
plt.tight_layout()
plt.show()
```



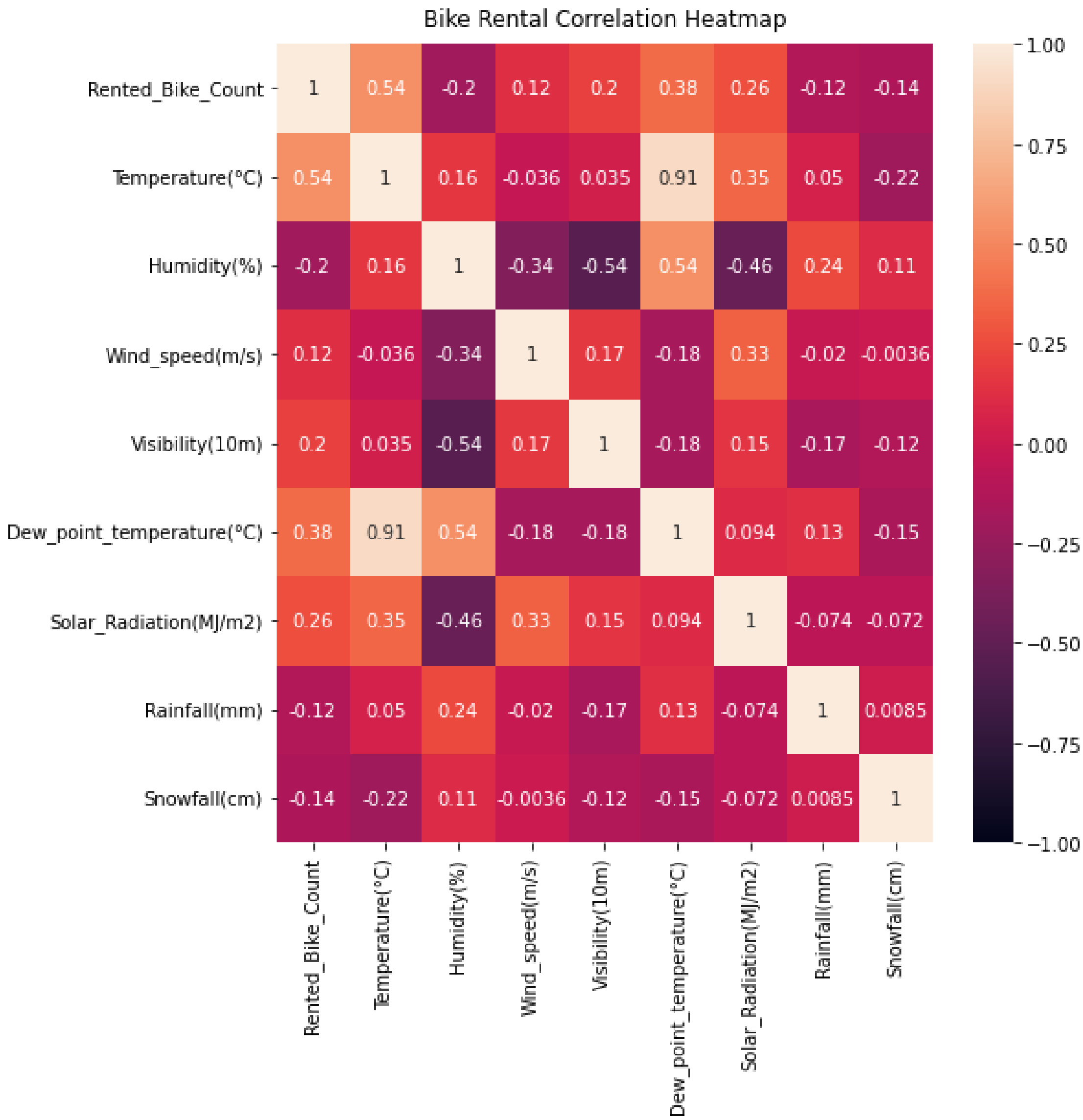
[882]:
```
# Box & Whisker

plt.figure(figsize=(10, 10))
for i, col in enumerate(Seoul_Bike_df.select_dtypes(include=['float','int']).
 ↪columns):
    ax = plt.subplot(3,3, i+1)
    sns.boxplot(data=Seoul_Bike_df, x=col, ax=ax, color='yellow', width=0.2)
plt.suptitle('Box Plot of Continuous Columns')
plt.tight_layout()
plt.show()
```



[883]:
```
# Count of Outliers

ContCols = Seoul_Bike_df.select_dtypes(include=['float','int'])

#ContCols.head()

Q1 = ContCols.quantile(0.25)
Q3 = ContCols.quantile(0.75)
IQR = Q3 - Q1

((ContCols < (Q1 - 1.5 * IQR)) | (ContCols > (Q3 + 1.5 * IQR))).sum()
```

[883]:
```
Rented_Bike_Count            158
Temperature(°C)                0
Humidity(%)                    0
Wind_speed(m/s)              161
Visibility(10m)                0
Dew_point_temperature(°C)      0
Solar_Radiation(MJ/m2)       641
Rainfall(mm)                 528
Snowfall(cm)                 443
dtype: int64
```

[884]:
```python
# Correlation Heatmap

plt.figure(figsize=(8, 8))
heatmap = sns.heatmap(ContCols.corr(method='pearson'), vmin=-1, vmax=1,␣
 ↪annot=True)
heatmap.set_title('Bike Rental Correlation Heatmap', fontdict={'fontsize':12},␣
 ↪pad=10);
```



[885]:

```
# Sort Correlation Values

ContCols[ContCols.columns[:]].corr()['Rented_Bike_Count'][:].
 ↪sort_values(ascending=False)
```

[885]:

```
Rented_Bike_Count            1.000000
Temperature(°C)              0.538558
Dew_point_temperature(°C)    0.379788
Solar_Radiation(MJ/m2)       0.261837
Visibility(10m)              0.199280
Wind_speed(m/s)              0.121108
Rainfall(mm)                -0.123074
```

```
Snowfall(cm)                 -0.141804
Humidity(%)                  -0.199780
Name: Rented_Bike_Count, dtype: float64
```

[886]:
```
# Converting Categorical to Dummies

# Hour = pd.get_dummies(Seoul_Bike_df.index.hour, prefix='hour')
Seoul_Bike_df = pd.
 ↪get_dummies(Seoul_Bike_df,columns=['Holiday','Seasons','Functioning_Day'],drop_first=True)

# Seoul_Bike_df.head()
```

[887]:
```
X = Seoul_Bike_df[['Temperature(°C)', 'Humidity(%)', 'Wind_speed(m/
 ↪s)','Visibility(10m)','Dew_point_temperature(°C)',
    'Solar_Radiation(MJ/m2)','Rainfall(mm)','Snowfall(cm)']]
```

[888]:
```
# VIF Function

def _calc_vif(X):
    # Multicollinearity detection
    vif = pd.DataFrame()

    # point here suspicious variables or just all variables
    vif["VIF"] = [variance_inflation_factor(X.values, i) for i in range(X.
 ↪shape[1])]
    vif["variables"] = X.columns

    return(vif)
```

[889]:
```
# Run VIF

_calc_vif(X).sort_values(by=['VIF'], ascending=False) # High VIF from␣
 ↪temperature column and dew point
```

[889]:

	VIF	variables
0	29.075866	Temperature(°C)
4	15.201989	Dew_point_temperature(°C)
3	9.051931	Visibility(10m)
1	5.069743	Humidity(%)
2	4.517664	Wind_speed(m/s)
5	2.821604	Solar_Radiation(MJ/m2)
7	1.118903	Snowfall(cm)
6	1.079919	Rainfall(mm)

[890]:
```
# Remove Dew Point Column
```

```
X = Seoul_Bike_df[['Temperature(°C)', 'Humidity(%)', 'Wind_speed(m/
↪s)','Visibility(10m)',

                   'Solar_Radiation(MJ/m2)','Rainfall(mm)','Snowfall(cm)']]
```

[891]:
```
# VIF again

_calc_vif(X).sort_values(by=['VIF'], ascending=False)
```

[891]:

	VIF	variables
1	4.758651	Humidity(%)
3	4.409448	Visibility(10m)
2	4.079926	Wind_speed(m/s)
0	3.166007	Temperature(°C)
4	2.246238	Solar_Radiation(MJ/m2)
6	1.118901	Snowfall(cm)
5	1.078501	Rainfall(mm)

[892]:
```
# Define Predictor and Outcome

X = Seoul_Bike_df.iloc[:,2:]
y = Seoul_Bike_df['Rented_Bike_Count']

# X.head()
# X.shape
```

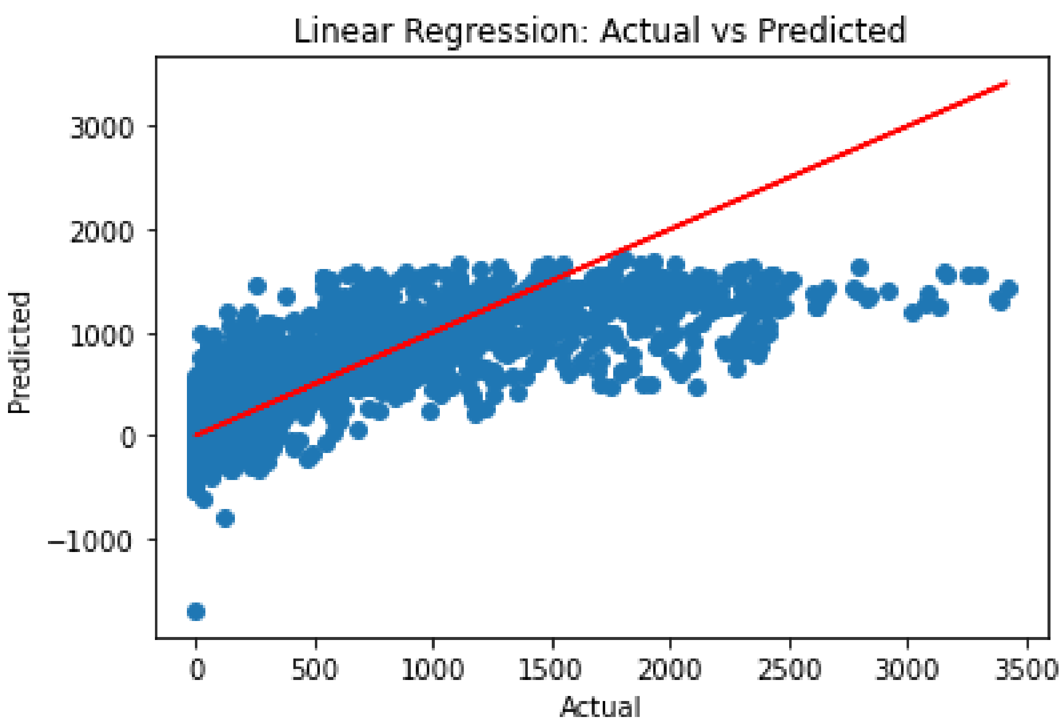
[893]:
```
# Split the Data - 75% train, 25% test

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,␣
↪random_state=12345)
```

[894]:
```
# Scaling

sc = StandardScaler()
X_train_scaled = sc.fit_transform(X_train)
X_test_scaled = sc.transform(X_test)
```

[895]:
```
# Linear Regression

lin_reg = LinearRegression()
lin_reg.fit(X_train_scaled,y_train)

# Prediction
y_pred_lin = lin_reg.predict(X_test_scaled)
R2_lin = metrics.r2_score(y_test, y_pred_lin).round(4)
mae_lin = metrics.mean_absolute_error(y_test, y_pred_lin).round(4)
mse_lin = metrics.mean_squared_error(y_test, y_pred_lin).round(4)
```

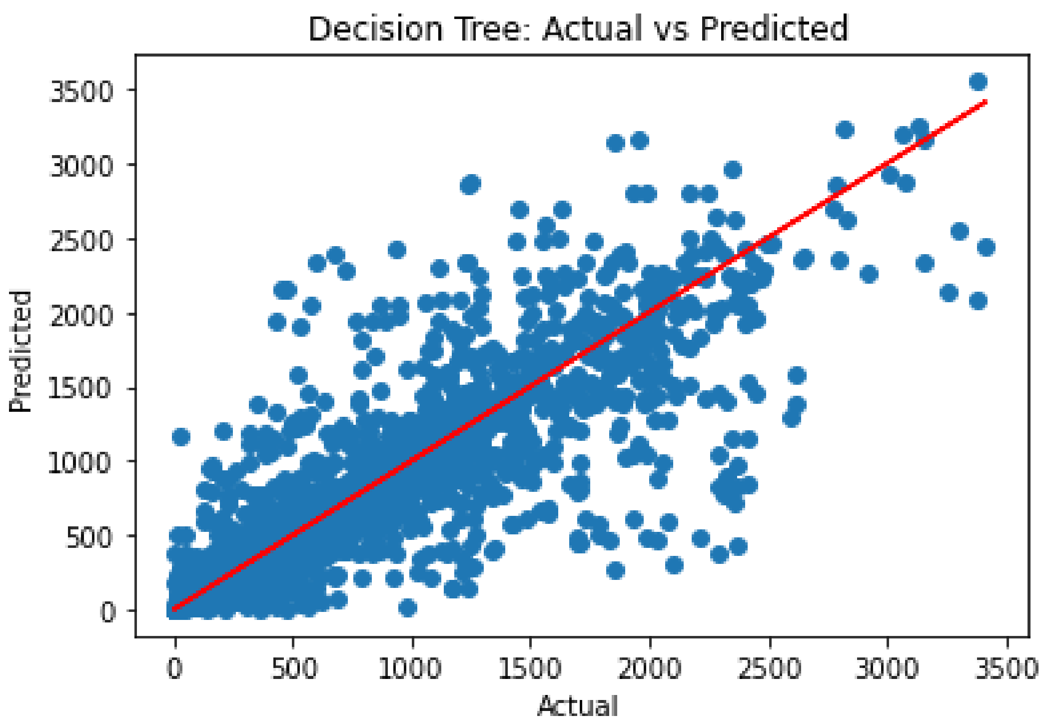
```python
rmse_lin = np.sqrt(mse_lin).round(4)

# Printing the metrics
print('Linear Regression Accuracy: ', lin_reg.score(X_test_scaled, y_test).
 ↪round(4))
print('R2 square:', R2_lin)
print('MAE: ', mae_lin)
print('MSE: ', mse_lin)
print('RMSE: ', rmse_lin)

# Scatterplot
plt.scatter(y_test, y_pred_lin)
plt.plot(y_test, y_test, color = 'red')
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.title('Linear Regression: Actual vs Predicted')
plt.show()
```

```
Linear Regression Accuracy:  0.5397
R2 square: 0.5397
MAE:  326.7375
MSE:  195443.5773
RMSE:  442.09
```



[896]:
```python
# Decision Tree

dt_regressor = DecisionTreeRegressor(random_state = 12345)
dt_regressor.fit(X_train_scaled, y_train)

# Prediction
y_pred_dt = dt_regressor.predict(X_test_scaled)
R2_dt = metrics.r2_score(y_test, y_pred_dt).round(4)
mae_dt = metrics.mean_absolute_error(y_test, y_pred_dt).round(4)
mse_dt = metrics.mean_squared_error(y_test, y_pred_dt).round(4)
rmse_dt = np.sqrt(mse_dt).round(4)

# Printing the metrics
print('Decision Tree Regression Accuracy: ', dt_regressor.score(X_test_scaled,␣
↪y_test).round(4))
print('R2 square:', R2_dt)
print('MAE: ', mae_dt)
print('MSE: ', mse_dt)
print('RMSE: ', rmse_dt)

# Scatterplot
plt.scatter(y_test, y_pred_dt)
plt.plot(y_test, y_test, color = 'red')
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.title('Decision Tree: Actual vs Predicted')
plt.show()
```

```
Decision Tree Regression Accuracy:  0.7192
R2 square: 0.7192
MAE:  198.4635
MSE:  119256.1356
RMSE:  345.3348
```

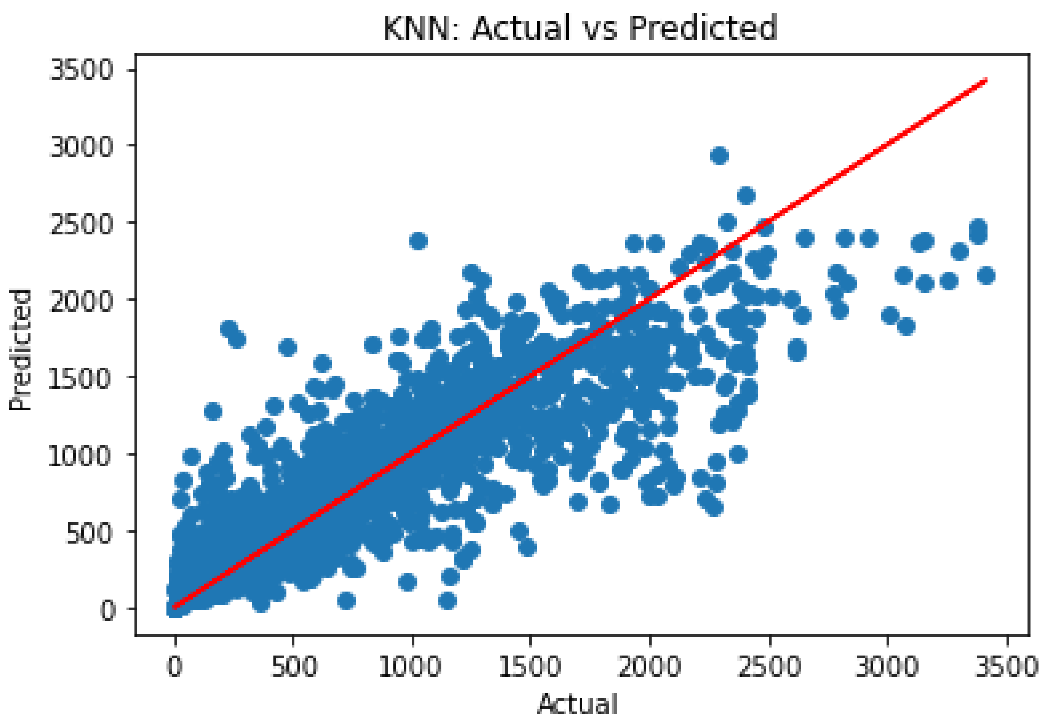


[897]:

```
# KNN

knn_9 = KNeighborsRegressor(n_neighbors=9)
KNeighborsRegressor(algorithm='auto', leaf_size=40, metric='minkowski',
                    metric_params=None, n_jobs=-1, n_neighbors=9, p=2,␣
 ↪weights='uniform')
knn_9.fit(X_train_scaled, y_train)
# print(knn_9)

# Prediction
y_pred_knn = knn_9.predict(X_test_scaled)
R2_knn = metrics.r2_score(y_test, y_pred_knn).round(4)
mae_knn = metrics.mean_absolute_error(y_test, y_pred_knn).round(4)
mse_knn = metrics.mean_squared_error(y_test, y_pred_knn).round(4)
rmse_knn = np.sqrt(mse_knn).round(4)

# Printing the metrics
print('KNN Regression Accuracy: ', knn_9.score(X_test_scaled, y_test).round(4))
print('R2 square:', R2_knn)
print('MAE: ', mae_knn)
print('MSE: ', mse_knn)
print('RMSE: ', rmse_knn)
```

```
# Scatterplot
plt.scatter(y_test, y_pred_knn)
plt.plot(y_test, y_test, color = 'red')
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.title('KNN: Actual vs Predicted')
plt.show()
```

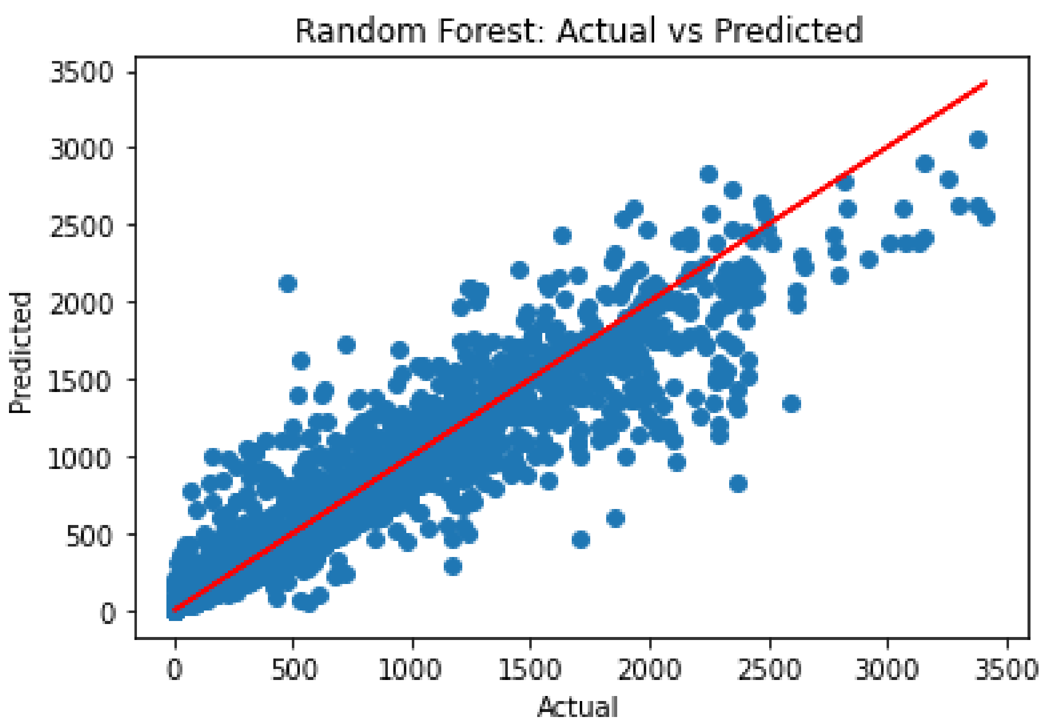
```
KNN Regression Accuracy:  0.7747
R2 square: 0.7747
MAE:  201.818
MSE:  95671.1062
RMSE:  309.3075
```



[898]:
```
# Random Forest Regression

rf_regressor = RandomForestRegressor(n_estimators = 300 ,  random_state = 12345)
rf_regressor.fit(X_train_scaled, y_train)

# Prediction
y_pred_rf = rf_regressor.predict(X_test_scaled)
R2_rf = metrics.r2_score(y_test, y_pred_rf).round(4)
mae_rf = metrics.mean_absolute_error(y_test, y_pred_rf).round(4)
mse_rf = metrics.mean_squared_error(y_test, y_pred_rf).round(4)
```

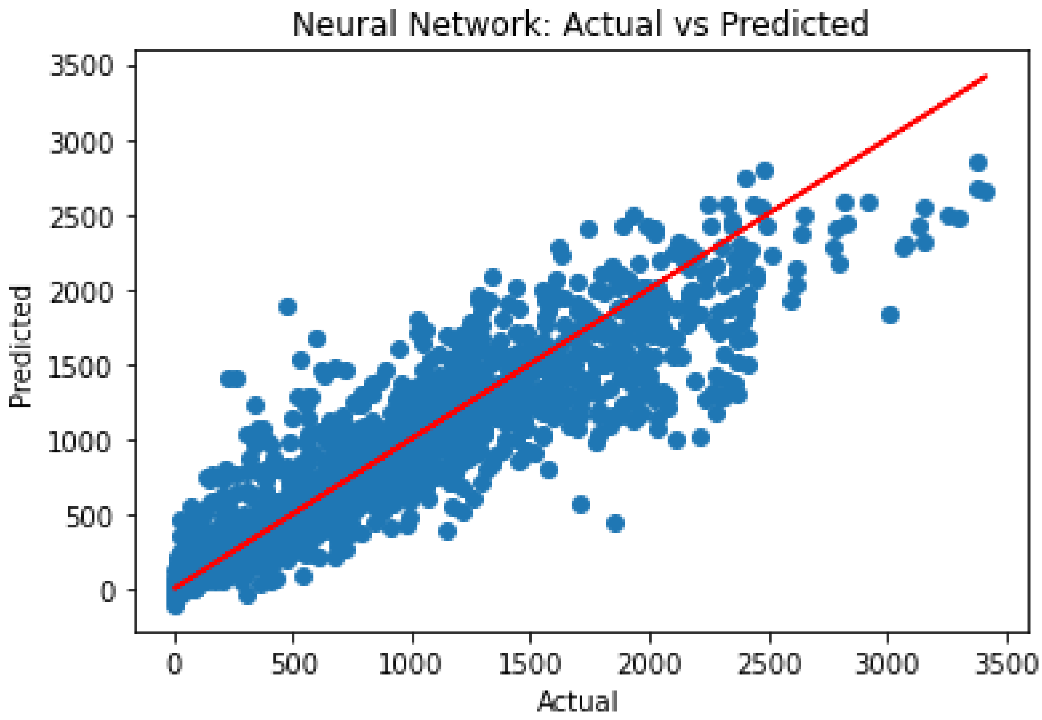
```
rmse_rf = np.sqrt(mse_rf).round(4)

# Printing the metrics
print('Random Forest Regression Accuracy: ', rf_regressor.score(X_test_scaled,␣
↪y_test).round(4))
print('R2 square:', R2_rf)
print('MAE: ', mae_rf)
print('MSE: ', mse_rf)
print('RMSE: ', rmse_rf)

# Scatterplot
plt.scatter(y_test, y_pred_rf)
plt.plot(y_test, y_test, color = 'red')
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.title('Random Forest: Actual vs Predicted')
plt.show()
```

```
Random Forest Regression Accuracy:  0.8642
R2 square: 0.8642
MAE:  147.5391
MSE:  57655.2637
RMSE:  240.1151
```



[899]:
```python
# Neural Network

mlp_reg = MLPRegressor(hidden_layer_sizes =(150,100,50), max_iter = 300,␣
 ↪activation = 'relu',
                       solver = 'adam', random_state = 12345)
mlp_reg.fit(X_train_scaled, y_train)

# Prediction
y_pred_nn = mlp_reg.predict(X_test_scaled)
R2_nn = metrics.r2_score(y_test, y_pred_nn).round(4)
mae_nn = metrics.mean_absolute_error(y_test, y_pred_nn).round(4)
mse_nn = metrics.mean_squared_error(y_test, y_pred_nn).round(4)
rmse_nn = np.sqrt(mse_nn).round(4)

# Printing the metrics
print('Neural Network Regression Accuracy: ', mlp_reg.score(X_test_scaled,␣
 ↪y_test).round(4))
print('R2 square:', R2_nn)
print('MAE: ', mae_nn)
print('MSE: ', mse_nn)
print('RMSE: ', rmse_nn)

# Scatterplot
plt.scatter(y_test, y_pred_nn)
plt.plot(y_test, y_test, color = 'red')
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.title('Neural Network: Actual vs Predicted')
plt.show()
```

```
Neural Network Regression Accuracy:  0.8548
R2 square: 0.8548
MAE:  158.2314
MSE:  61641.2817
RMSE:  248.2766
```

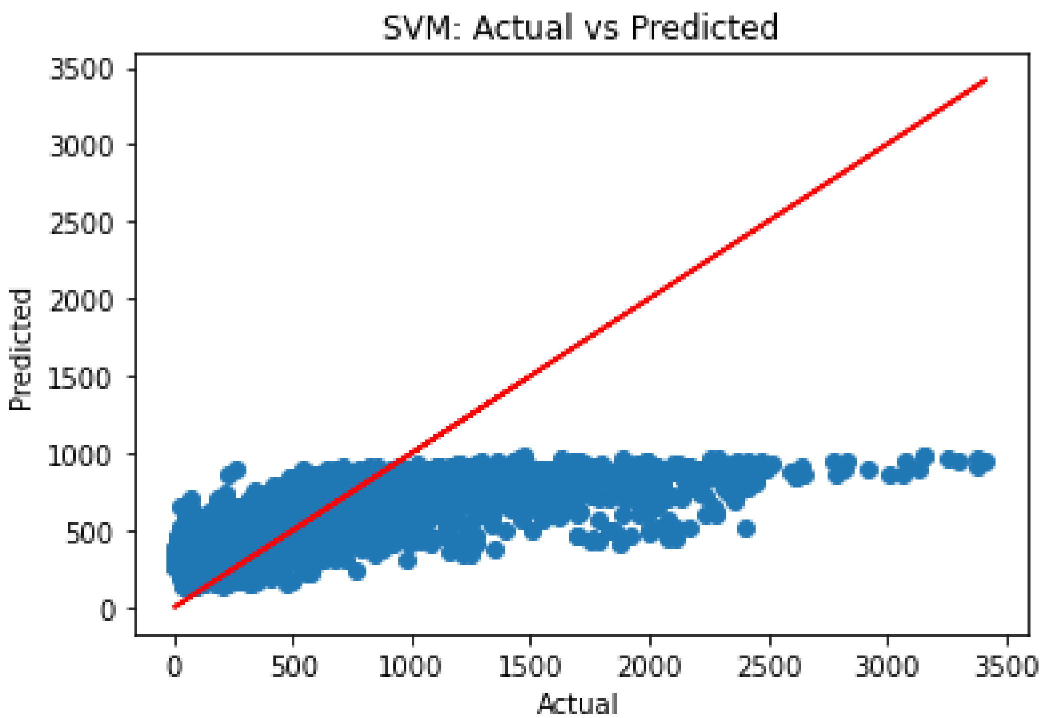


[900]:

```
# SVM

regressor = SVR(kernel='rbf')
regressor.fit(X_train_scaled,y_train)

# Prediction
y_pred_svm = regressor.predict(X_test_scaled)
R2_svm = metrics.r2_score(y_test, y_pred_svm).round(4)
mae_svm = metrics.mean_absolute_error(y_test, y_pred_svm).round(4)
mse_svm = metrics.mean_squared_error(y_test, y_pred_svm).round(4)
rmse_svm = np.sqrt(mse_svm).round(4)

# Printing the metrics
print('Suppport Vector Regression Accuracy: ', regressor.score(X_test_scaled,␣
↪y_test).round(4))
print('R2 square:', R2_svm)
print('MAE: ', mae_svm)
print('MSE: ', mse_svm)
print('RMSE: ', rmse_svm)

# Scatterplot
plt.scatter(y_test, y_pred_svm)
plt.plot(y_test, y_test, color = 'red')
```

```
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.title('SVM: Actual vs Predicted')
plt.show()
```

```
Suppport Vector Regression Accuracy:  0.3373
R2 square: 0.3373
MAE:  353.3543
MSE:  281388.0445
RMSE:  530.4602
```



[901]:

```
# Table Results

Table = PrettyTable(["Model","R-Squared","MAE","MSE","RMSE"])
Table.add_row(["Linear Regression", R2_lin, mae_lin, mse_lin, rmse_lin])
Table.add_row(["Decision Tree", R2_dt, mae_dt, mse_dt, rmse_dt])
Table.add_row(["KNN", R2_knn, mae_knn, mse_knn, rmse_knn])
Table.add_row(["Random Forest", R2_rf, mae_rf, mse_rf, rmse_rf])
Table.add_row(["Neural Network", R2_nn, mae_nn, mse_nn, rmse_nn])
Table.add_row(["SVM", R2_svm, mae_svm, mse_svm, rmse_svm])
print("Models Performance Sorted by R-Squared Values")
Table.sortby = "R-Squared"
print(Table)
```

Models Performance Sorted by R-Squared Values

Model	R-Squared	MAE	MSE	RMSE
SVM	0.3373	353.3543	281388.0445	530.4602
Linear Regression	0.5397	326.7375	195443.5773	442.09
Decision Tree	0.7192	198.4635	119256.1356	345.3348
KNN	0.7747	201.818	95671.1062	309.3075
Neural Network	0.8548	158.2314	61641.2817	248.2766
Random Forest	0.8642	147.5391	57655.2637	240.1151