JJ Seoul Bike Rental Project ADS 505

October 16, 2022

[788]:
```python
# 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
```

[789]:
```
# 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])
```

[790]:
```
Seoul_Bike_df.head()
```

[790]:
```
        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
```

[791]:
```
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
```

[792]:

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

[793]:

```
# 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
```

[794]:
```
# Check for Nulls
Seoul_Bike_df.isnull().sum()
```

[794]:
```
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
```

[795]:
```
Seoul_Bike_df.describe().style.background_gradient(cmap='brg',axis=None)
```

[795]:
```
<pandas.io.formats.style.Styler at 0x7fb108abeac0>
```

[796]:
```
# Count of Unique Values

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

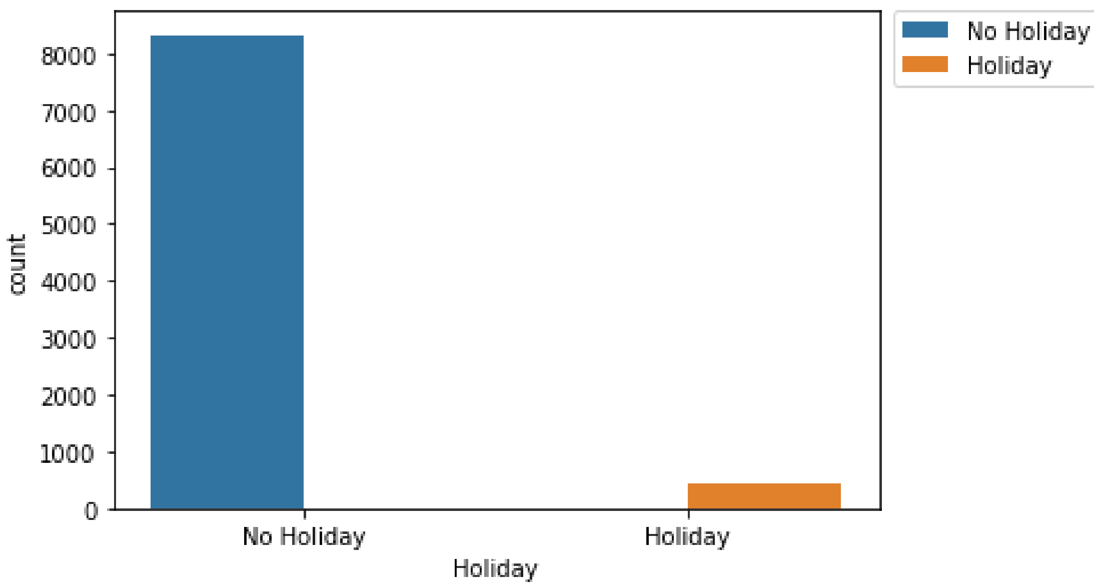
[796]:
```
Rented_Bike_Count            2166
Visibility(10m)              1789
Dew_point_temperature(°C)     556
Temperature(°C)               546
Date                          365
Solar_Radiation(MJ/m2)        345
Humidity(%)                    90
Wind_speed(m/s)                65
Rainfall(mm)                   61
Snowfall(cm)                   51
Hour                           24
Seasons                         4
Holiday                         2
Functioning_Day                 2
dtype: int64
```

[797]:
```
# Unique Object Dtype Values

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

```
Seasons            [Winter, Spring, Summer, Autumn]
```

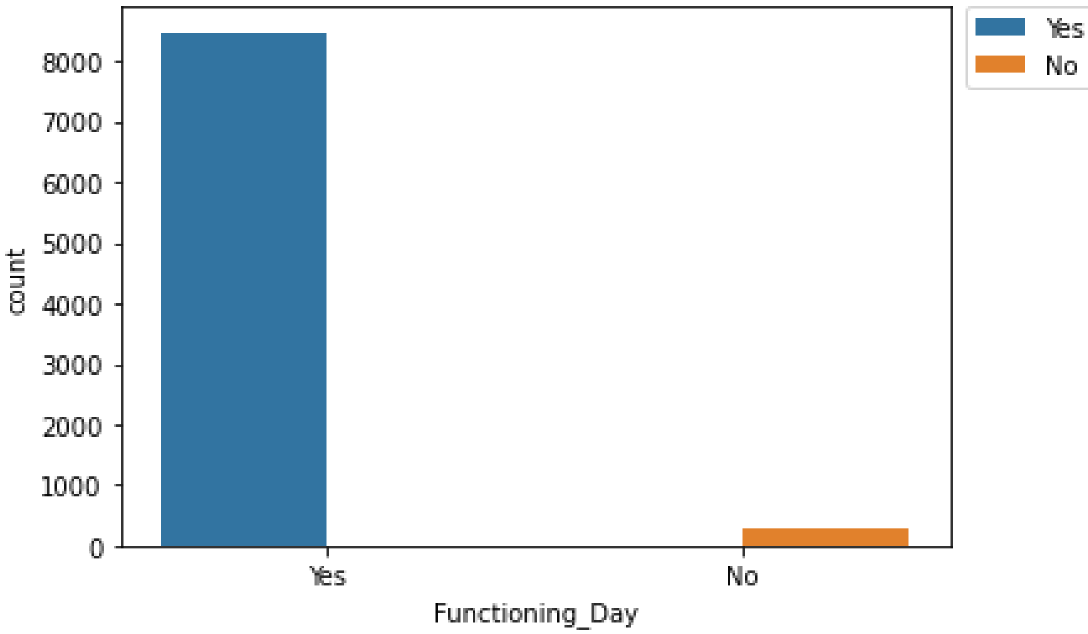
```
Holiday                              [No Holiday, Holiday]
Functioning_Day                                  [Yes, No]
dtype: object
```

[798]:
```
# 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
```

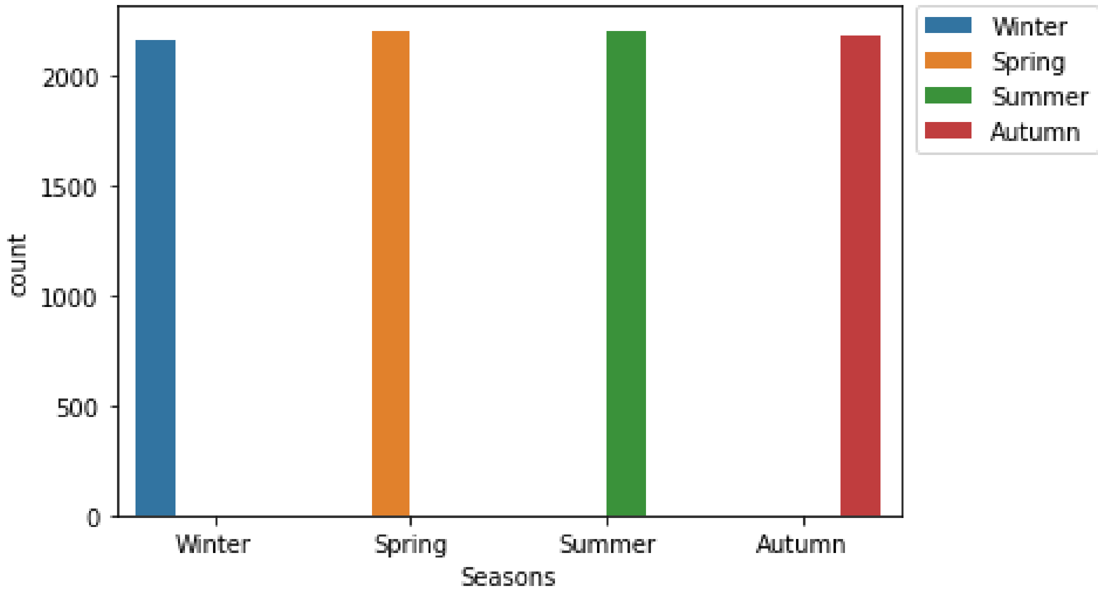
[799]:
```
# Counts of Functioning Day

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()
```



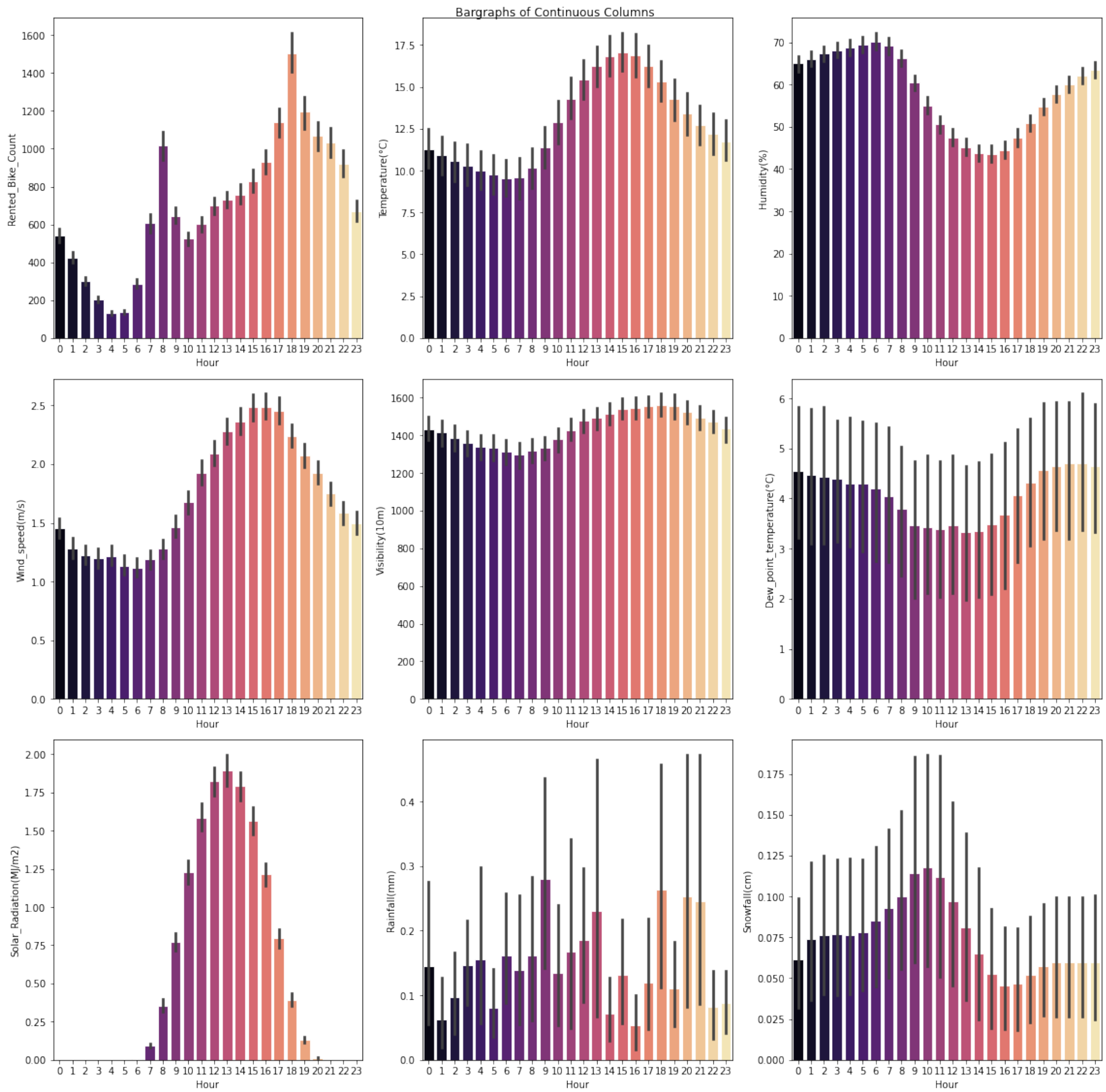

```
Yes    8465
No      295
Name: Functioning_Day, dtype: int64
```

[800]:
```
# 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()
```

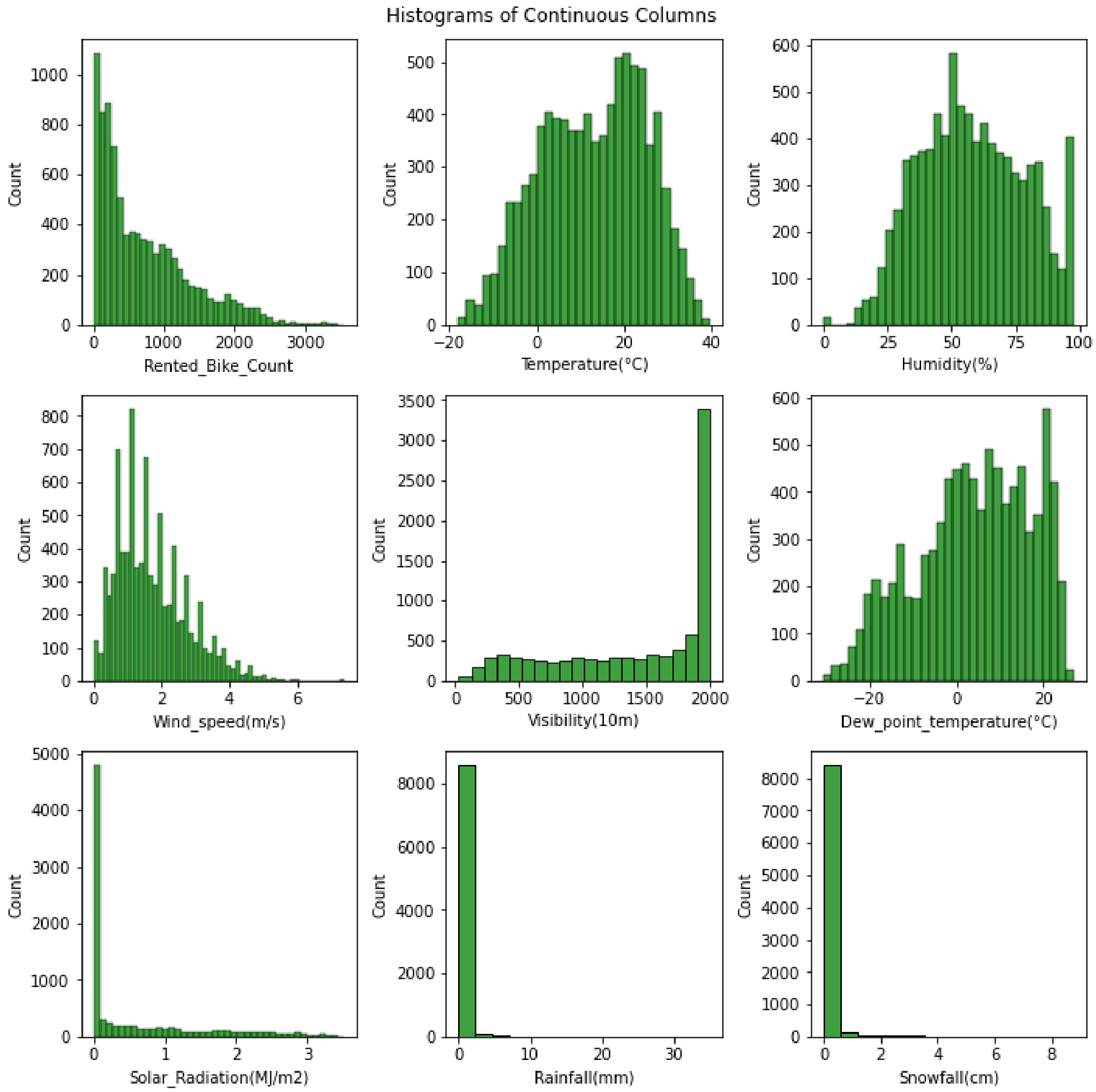
```
Spring    2208
Summer    2208
Autumn    2184
Winter    2160
Name: Seasons, dtype: int64
```



[801]:
```
# 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()
```

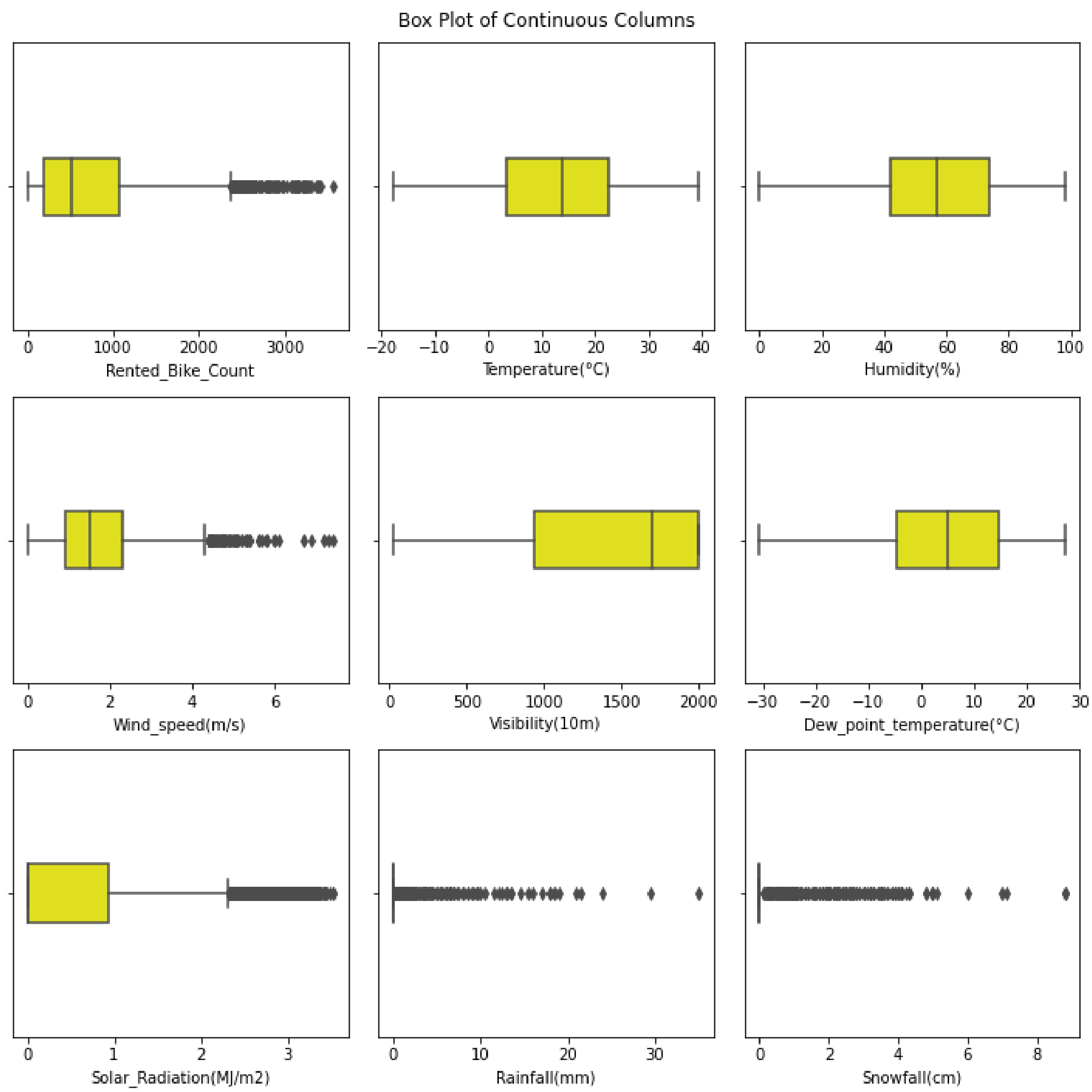


[802]:
```python
# Histograms

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()
```



[803]:

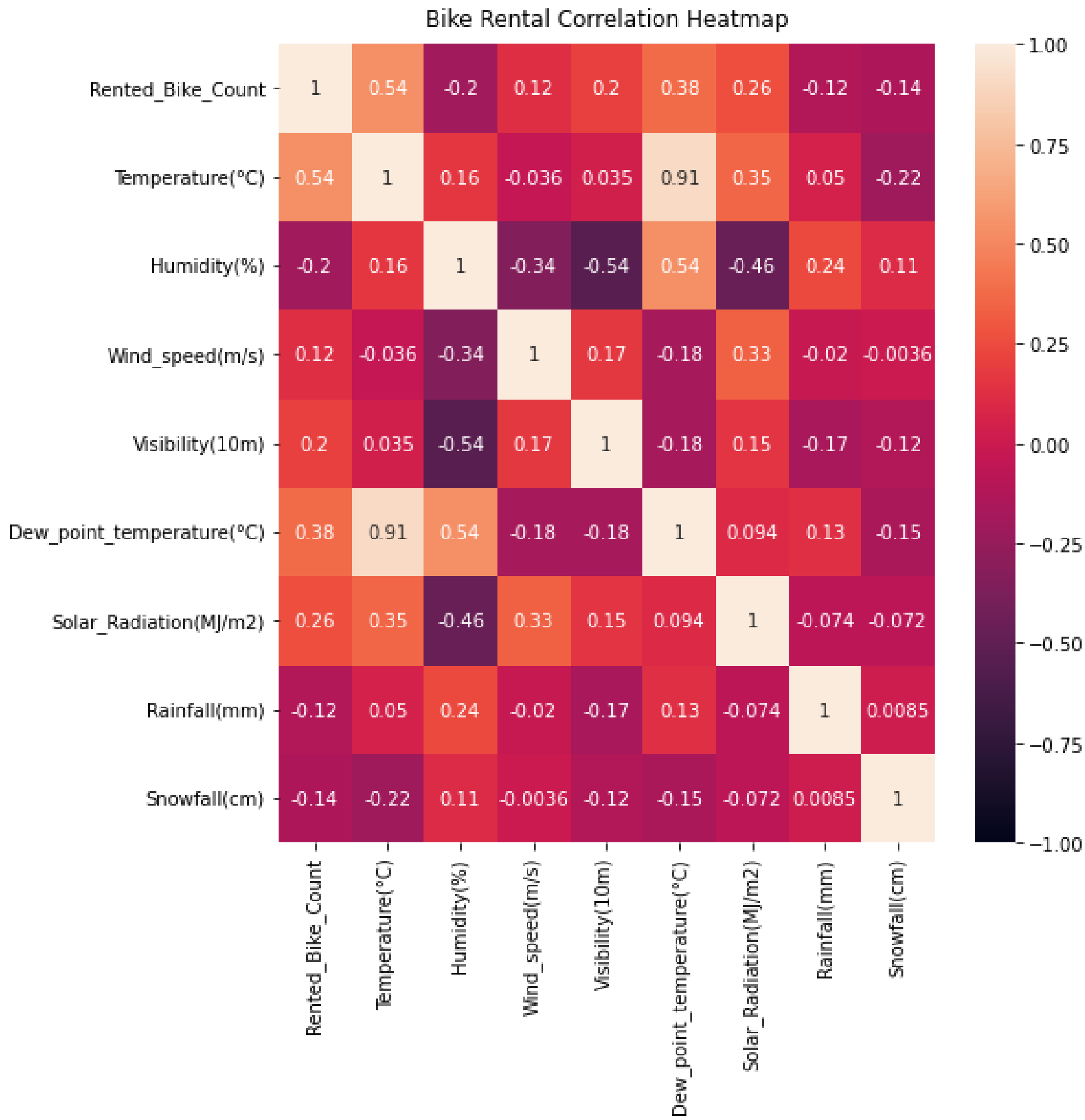
```
# Box & Whisker

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()
```



[804]:
```
# 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()
```

[804]:
```
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
```

[805]:
```
# 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);
```



[806]:

```python
# Sort Correlation Values

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

[806]:

```
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
```

[807]:
```python
# 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()
```

[808]:
```python
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)']]
```

[809]:
```python
# 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)
```

[810]:
```python
# Run VIF

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

[810]:

	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)

[811]:
```python
# 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)']]
```

[812]:
```
# VIF again

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

[812]:

	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)

[813]:
```
# Define Predictor and Outcome

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

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

[814]:
```
# 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)
```

[815]:
```
# Scaling

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

[816]:
```
# 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)
```

```
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)
```

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

[817]:

```
# 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)
```

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

[818]:

```
# 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)
```

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

[819]:

```
# 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).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)
```

```
Random Forest Regression Accuracy:  0.8642
R2 square: 0.8642
MAE:  147.5391
MSE:  57655.2637
RMSE:  530.4602
```

[820]:
```
# 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).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)
```

```
Neural Network Regression Accuracy:  0.8548
R2 square: 0.8548
MAE:  158.2314
MSE:  61641.2817
RMSE:  530.4602
```

[821]:
```
# 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).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)
```

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

[822]:
```python
# 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 | 530.4602 |
|   Random Forest   |   0.8642  | 147.5391 |  57655.2637 | 530.4602 |
+-------------------+-----------+----------+-------------+----------+
```