CMPE 257: Machine Learning

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Bike Sharing Demand Prediction

Importing all dataasets

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.colors import ListedColormap
import seaborn as sns
from warnings import filterwarnings
filterwarnings('ignore')

pd.options.display.max_columns = None

pd.options.display.max_rows = None
pd.options.display.float_format = '{:.6f}'.format

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_score
from sklearn.metrics import confusion_matrix, roc_auc_score, roc_curve, precision_recall_curve
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn import tree
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV, StratifiedKFold

import pydotplus
from IPython.display import Image
from sklearn import metrics
from sklearn.metrics import classification_report
from sklearn.metrics import cohen_kappa_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import roc_curve
from sklearn.metrics import accuracy_score

# import various functions from statsmodels
import statsmodels
import statsmodels.api as sm

from collections import Counter



plt.rcParams['figure.figsize'] = [15,8]


datasetUrl1 = 'https://drive.google.com/file/d/10wKdg9HnqQ_o9UZatlAsTMfiIpg8NtMq'
datasetUrl1 ='https://drive.google.com/uc?id=' + datasetUrl1.split('/')[-1]
data1 = pd.read_csv(datasetUrl1)
data1.head(5)
```

	instant	dteday	season	yr	mnth	hr	holiday	weekday	workingday	weathersit	temp	atemp	hum	windspeed	casua
0	1	2011-01-01	1	0	1	0	0	6	0	1	0.240000	0.287900	0.810000	0.000000	
1	2	2011-01-01	1	0	1	1	0	6	0	1	0.220000	0.272700	0.800000	0.000000	

```
datasetUrl2 = 'https://drive.google.com/file/d/1yVL1fUAfZ5ktpPbaAAF8zQrLlBAicgN7'
datasetUrl2 ='https://drive.google.com/uc?id=' + datasetUrl2.split('/')[-1]
data2 = pd.read_csv(datasetUrl2, encoding_errors='ignore')
data2.head(5)
```

	Date	Rented Bike Count	Hour	Temperature(C)	Humidity(%)	Wind speed (m/s)	Visibility (10m)	Dew point temperature(C)
0	01/12/2017	254	0	-5.200000	37	2.200000	2000	-17.60000(
1	01/12/2017	204	1	-5.500000	38	0.800000	2000	-17.60000(
2	01/12/2017	173	2	-6.000000	39	1.000000	2000	-17.70000(
3	01/12/2017	107	3	-6.200000	40	0.900000	2000	-17.60000(

```
data1.dtypes
```

```
instant         int64
dteday         object
season          int64
yr              int64
mnth            int64
hr              int64
holiday         int64
weekday         int64
workingday      int64
weathersit      int64
temp          float64
atemp         float64
hum           float64
windspeed     float64
casual          int64
registered      int64
cnt             int64
dtype: object
```

```
data2.dtypes
```

```
Date                          object
Rented Bike Count              int64
Hour                           int64
Temperature(C)               float64
Humidity(%)                    int64
Wind speed (m/s)             float64
Visibility (10m)               int64
Dew point temperature(C)     float64
Solar Radiation (MJ/m2)      float64
Rainfall(mm)                 float64
Snowfall (cm)                float64
Seasons                       object
Holiday                       object
Functioning Day               object
dtype: object
```

```
data2.rename(columns = {'Temperature(C)':'temp','Wind speed (m/s)':'windspeed','Humidity(%)':'hum', 'Rented Bike Count':'cnt','Hou
```

```
data2.head()
```

	dteday	cnt	hr	temp	hum	windspeed	Visibility (10m)	Dew point temperature(C)	solarRadiation	Rainfall(mm)	Snowfa
0	01/12/2017	254	0	-5.200000	37	2.200000	2000	-17.600000	0.000000	0.000000	
1	01/12/2017	204	1	-5.500000	38	0.800000	2000	-17.600000	0.000000	0.000000	
2	01/12/2017	173	2	-6.000000	39	1.000000	2000	-17.700000	0.000000	0.000000	
3	01/12/2017	107	3	-6.200000	40	0.900000	2000	-17.600000	0.000000	0.000000	

Data Preparation and wrangling

```
data1.workingday.replace( (1, 0),('Yes', 'No'), inplace=True)
```

```
data2.holiday.replace(('Holiday', 'No Holiday'), (1, 0), inplace=True)
```

```
data1.season.replace( (1,2,3,4),('Winter', 'Autumn','Summer','Spring'), inplace=True)
```

```
data2.head()
```

	dteday	cnt	hr	temp	hum	windspeed	Visibility (10m)	Dew point temperature(C)	solarRadiation	Rainfall(mm)	Snowfa
0	01/12/2017	254	0	-5.200000	37	2.200000	2000	-17.600000	0.000000	0.000000	
1	01/12/2017	204	1	-5.500000	38	0.800000	2000	-17.600000	0.000000	0.000000	
2	01/12/2017	173	2	-6.000000	39	1.000000	2000	-17.700000	0.000000	0.000000	
3	01/12/2017	107	3	-6.200000	40	0.900000	2000	-17.600000	0.000000	0.000000	

```
data1=data1.drop(['instant'],axis=1)
```

```
data1.head()
```

	dteday	season	yr	mnth	hr	holiday	weekday	workingday	weathersit	temp	atemp	hum	windspeed	casual	regist
0	2011-01-01	Winter	0	1	0	0	6	No	1	0.240000	0.287900	0.810000	0.000000	3	
1	2011-01-01	Winter	0	1	1	0	6	No	1	0.220000	0.272700	0.800000	0.000000	8	
2	2011-01-01	Winter	0	1	2	0	6	No	1	0.220000	0.272700	0.800000	0.000000	5	
3	2011-01-01	Winter	0	1	3	0	6	No	1	0.240000	0.287900	0.750000	0.000000	3	

```
data2.head()
```


	dteday	cnt	hr	temp	hum	windspeed	Visibility (10m)	Dew point temperature(C)	solarRadiation	Rainfall(mm)	Snowfa
0	01/12/2017	254	0	-5.200000	37	2.200000	2000	-17.600000	0.000000	0.000000	
1	01/12/2017	204	1	-5.500000	38	0.800000	2000	-17.600000	0.000000	0.000000	
2	01/12/2017	173	2	-6.000000	39	1.000000	2000	-17.700000	0.000000	0.000000	
3	01/12/2017	107	3	-6.200000	40	0.900000	2000	-17.600000	0.000000	0.000000	


```
data1.dteday.head()
```

```
0    2011-01-01
1    2011-01-01
2    2011-01-01
3    2011-01-01
4    2011-01-01
Name: dteday, dtype: object
```

```
pd.to_datetime(data1.dteday.head()).dt.month,
pd.to_datetime(data1.dteday.head()).dt.day,
pd.to_datetime(data1.dteday.head()).dt.year
```

```
0    2011
1    2011
2    2011
3    2011
4    2011
Name: dteday, dtype: int64
```

```
data2.head()
```

	dteday	cnt	hr	temp	hum	windspeed	Visibility (10m)	Dew point temperature(C)	solarRadiation	Rainfall(mm)	Snowfa
0	01/12/2017	254	0	-5.200000	37	2.200000	2000	-17.600000	0.000000	0.000000	
1	01/12/2017	204	1	-5.500000	38	0.800000	2000	-17.600000	0.000000	0.000000	
2	01/12/2017	173	2	-6.000000	39	1.000000	2000	-17.700000	0.000000	0.000000	
3	01/12/2017	107	3	-6.200000	40	0.900000	2000	-17.600000	0.000000	0.000000	

```
df = data1.merge(data2, on = ['cnt','hr','temp','hum','windspeed','dteday','holiday','workingday','season'], how = 'outer')
```

```
df.head()
```

	dteday	season	yr	mnth	hr	holiday	weekday	workingday	weathersit	temp	atemp	hum	windspeed	casual
0	2011-01-01	Winter	0.000000	1.000000	0	0	6.000000	No	1.000000	0.240000	0.287900	0.810000	0.000000	3.000000
1	2011-01-01	Winter	0.000000	1.000000	1	0	6.000000	No	1.000000	0.220000	0.272700	0.800000	0.000000	8.000000

```
df=df.drop(['registered','atemp','yr','mnth','weekday','Visibility (10m)','Dew point temperature(C)','solarRadiation','Snowfall (c
```

```
df.head()
```

	dteday	season	hr	holiday	workingday	temp	hum	windspeed	cnt
0	2011-01-01	Winter	0	0	No	0.240000	0.810000	0.000000	16
1	2011-01-01	Winter	1	0	No	0.220000	0.800000	0.000000	40
2	2011-01-01	Winter	2	0	No	0.220000	0.800000	0.000000	32
3	2011-01-01	Winter	3	0	No	0.240000	0.750000	0.000000	13

```
pd.to_datetime(data1.dteday.head()).dt.month,
pd.to_datetime(data1.dteday.head()).dt.day,
pd.to_datetime(data1.dteday.head()).dt.year
```

```
0    2011
1    2011
2    2011
3    2011
4    2011
Name: dteday, dtype: int64
```

```
df["month"]=pd.to_datetime(df.dteday).dt.month
```

```
df["day"]=pd.to_datetime(df.dteday).dt.day
df["year"]=pd.to_datetime(df.dteday).dt.year
```

```
df.head()
```

	dteday	season	hr	holiday	workingday	temp	hum	windspeed	cnt	month	day	year
0	2011-01-01	Winter	0	0	No	0.240000	0.810000	0.000000	16	1	1	2011
1	2011-01-01	Winter	1	0	No	0.220000	0.800000	0.000000	40	1	1	2011
2	2011-01-01	Winter	2	0	No	0.220000	0.800000	0.000000	32	1	1	2011
3	2011-01-01	Winter	3	0	No	0.240000	0.750000	0.000000	13	1	1	2011

```
df=df.drop(['dteday'],axis=1)
```

```
df.dtypes
```

```
season         object
hr              int64
holiday         int64
workingday     object
temp          float64
hum           float64
windspeed     float64
cnt             int64
month           int64
day             int64
year            int64
dtype: object
```

```
df.to_csv("dataset3.csv",index=False)
```

Remove Insignificant variables

```
df_cat = df.select_dtypes(include=[np.object])
df_cat.head()
```

	season	workingday
0	Winter	No
1	Winter	No
2	Winter	No
3	Winter	No

```
cols = list(df.columns)
```

```
sns.countplot(x='workingday',data=df_cat, palette =['pink', 'teal'])
```

```
<Axes: xlabel='workingday', ylabel='count'>
```

```python
sns.countplot(x='season',data=df_cat)
```

```
<Axes: xlabel='season', ylabel='count'>
```


```python
sns.heatmap(df.corr(),annot = True,color = 'y')
plt.show()
```

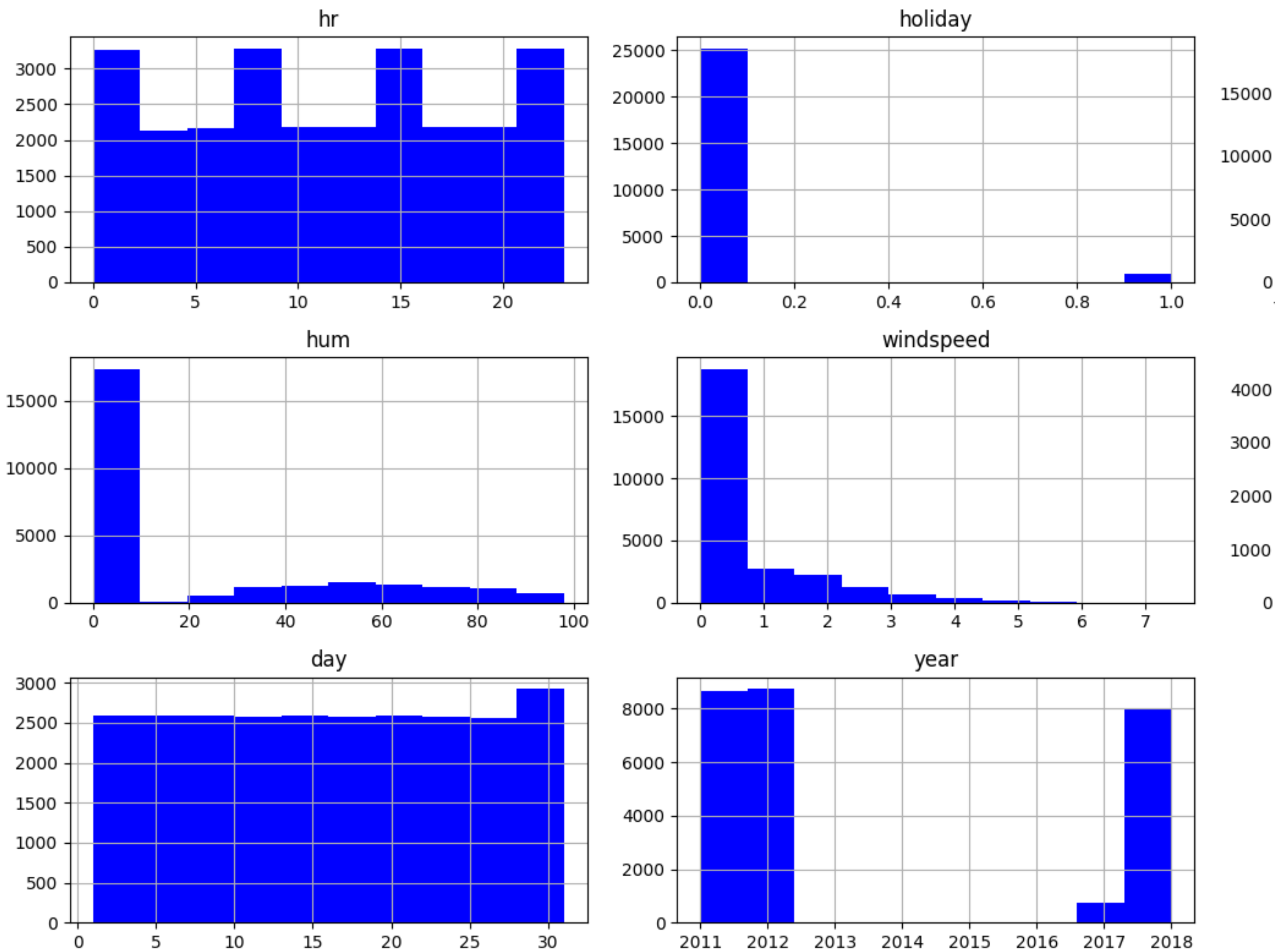
Variables Distribution

```
df.drop('cnt', axis = 1).hist(color = "b")

# adjust the subplots
plt.tight_layout()

# display the plot
plt.show()
print('Skewness:')

df.drop('cnt', axis = 1).skew()
```



Missing Values

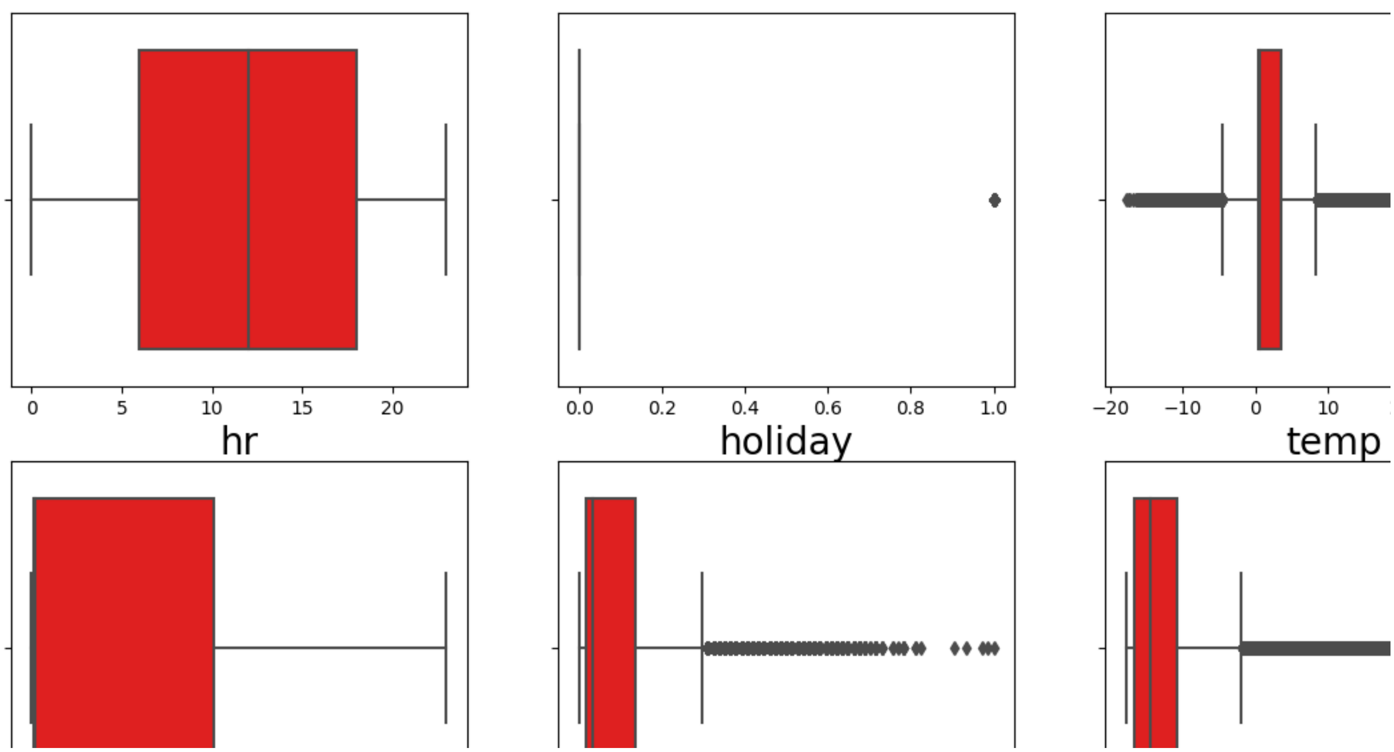
```
Total = df.isnull().sum().sort_values(ascending=False)
Percent = (df.isnull().sum()*100/df.isnull().count()).sort_values(ascending=False)
missing_data = pd.concat([Total, Percent], axis = 1, keys = ['Total', 'Percentage of Missing Values'])
missing_data
```

	Total	Percentage of Missing Values
season	0	0.000000
hr	0	0.000000
holiday	0	0.000000
workingday	0	0.000000
temp	0	0.000000
hum	0	0.000000
windspeed	0	0.000000
cnt	0	0.000000
month	0	0.000000

Ploting variable Based on boxplots

```
df_num = df.select_dtypes(include=[np.number])
fig, ax = plt.subplots(2, 3, figsize=(15, 8))

for variable, subplot in zip(df_num.columns, ax.flatten()):
    z = sns.boxplot(x = df_num[variable], ax=subplot,color='red', orient = "h",whis=1.5) # plot the boxplot
    z.set_xlabel(variable, fontsize = 20)
```



```
lower = df_num.temp.quantile(0.25)
upper = df_num.temp.quantile(0.75)

IQR = upper - lower

# print the IQR
print(IQR)
df_num = df_num[~((df_num.temp < (lower - 1.5 * IQR)) |(df_num.temp > (upper + 1.5 * IQR)))]
```

```
3.24
```

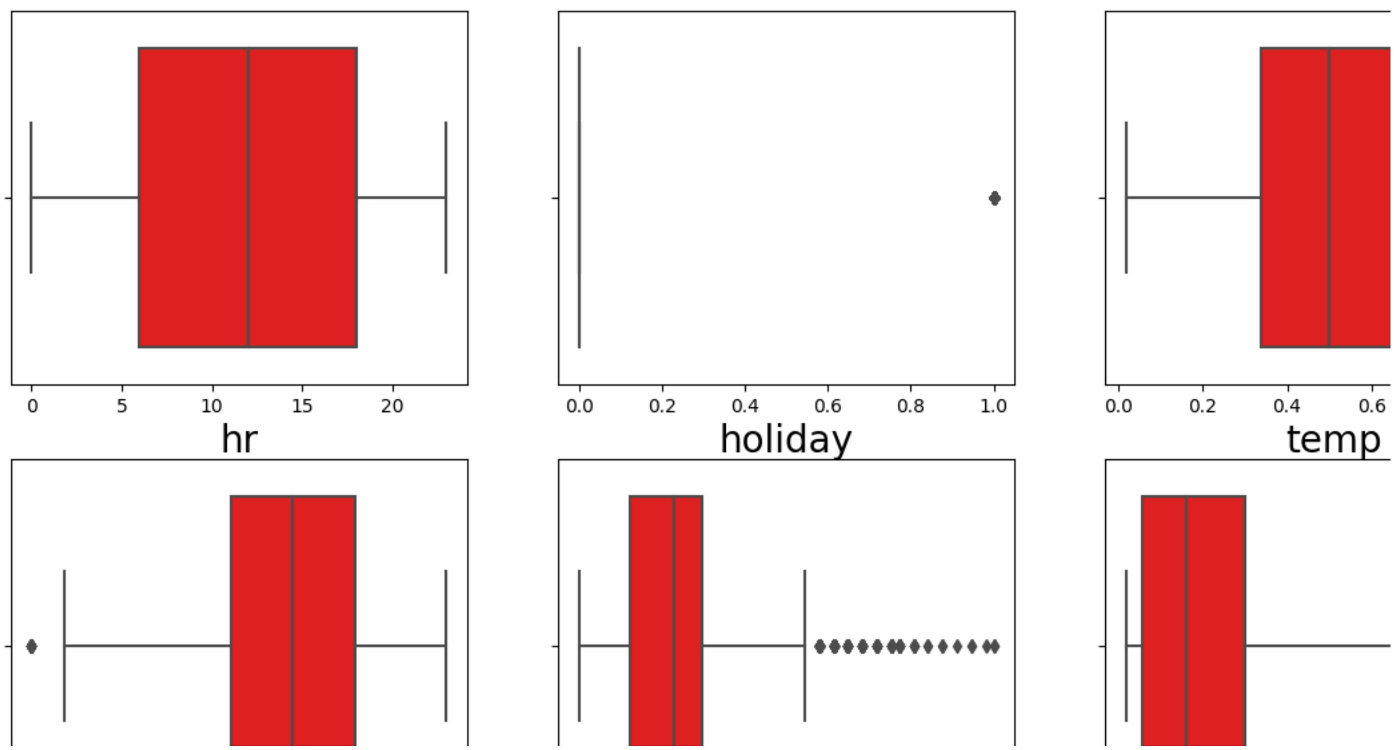
```
lower = df_num.hum.quantile(0.25)

upper = df_num.hum.quantile(0.75)
IQR = upper - lower

print(IQR)
df_num = df_num[~((df_num.hum < (lower - 1.5 * IQR)) |(df_num.hum > (upper + 1.5 * IQR)))]
```

```
0.37
```

```
fig, ax = plt.subplots(2, 3, figsize=(15, 8))
for variable, subplot in zip(df_num.columns, ax.flatten()):
    z = sns.boxplot(x = df_num[variable], ax=subplot,color='red', orient = "h",whis=1.5 )
    z.set_xlabel(variable, fontsize = 20)
```



Mock Encode

```
df_target = df['cnt']
df_feature = df.drop(['cnt','holiday'], axis = 1)
df_num = df_feature.select_dtypes(include = [np.number])
df_num.head()
```

	hr	temp	hum	windspeed	month	day	year
0	0	0.240000	0.810000	0.000000	1	1	2011
1	1	0.220000	0.800000	0.000000	1	1	2011
2	2	0.220000	0.800000	0.000000	1	1	2011
3	3	0.240000	0.750000	0.000000	1	1	2011

```
df_cat = df_feature.select_dtypes(include = [np.object])
df_cat.columns
dummy_var = pd.get_dummies(data = df_cat, drop_first = True)
```

Data Scaling And Train_Test Spliting

Before employing diverse classification methods to forecast student admission outcomes, let's divide the dataset into training and testing sets.

```
target = df['holiday']
X_scaler = StandardScaler()
num_scaled = X_scaler.fit_transform(df_num)

df_num_scaled = pd.DataFrame(num_scaled, columns = df_num.columns)
```

```
X = pd.concat([df_num, dummy_var], axis = 1)
#X.drop("Sold",axis = 1,inplace = True)
X.head()
```

	hr	temp	hum	windspeed	month	day	year	season_Spring	season_Summer	season_Winter	workingday_Yes
0	0	0.240000	0.810000	0.000000	1	1	2011	0	0	1	0
1	1	0.220000	0.800000	0.000000	1	1	2011	0	0	1	0
2	2	0.220000	0.800000	0.000000	1	1	2011	0	0	1	0
3	3	0.240000	0.750000	0.000000	1	1	2011	0	0	1	0

```
X = sm.add_constant(X)

X_train, X_test, y_train, y_test = train_test_split(X, target, random_state = 10, test_size = 0.2)

y_train = np.round(y_train).astype(int)
y_test = np.round(y_test).astype(int)

print('X_train', X_train.shape)
print('y_train', y_train.shape)
print('X_test', X_test.shape)
print('y_test', y_test.shape)
```

```
X_train (20911, 12)
y_train (20911,)
X_test (5228, 12)
y_test (5228,)
```

Decision Tree for Classification

```
decision_tree_classifier = DecisionTreeClassifier(criterion = 'gini', random_state = 10)
decision_tree = decision_tree_classifier.fit(X_train, y_train)
```

```
!pip install -q graphviz
```

Finding Gini Scores

Making a full decision tree model using 'entropy'.

```
import pydotplus
from sklearn import tree
```

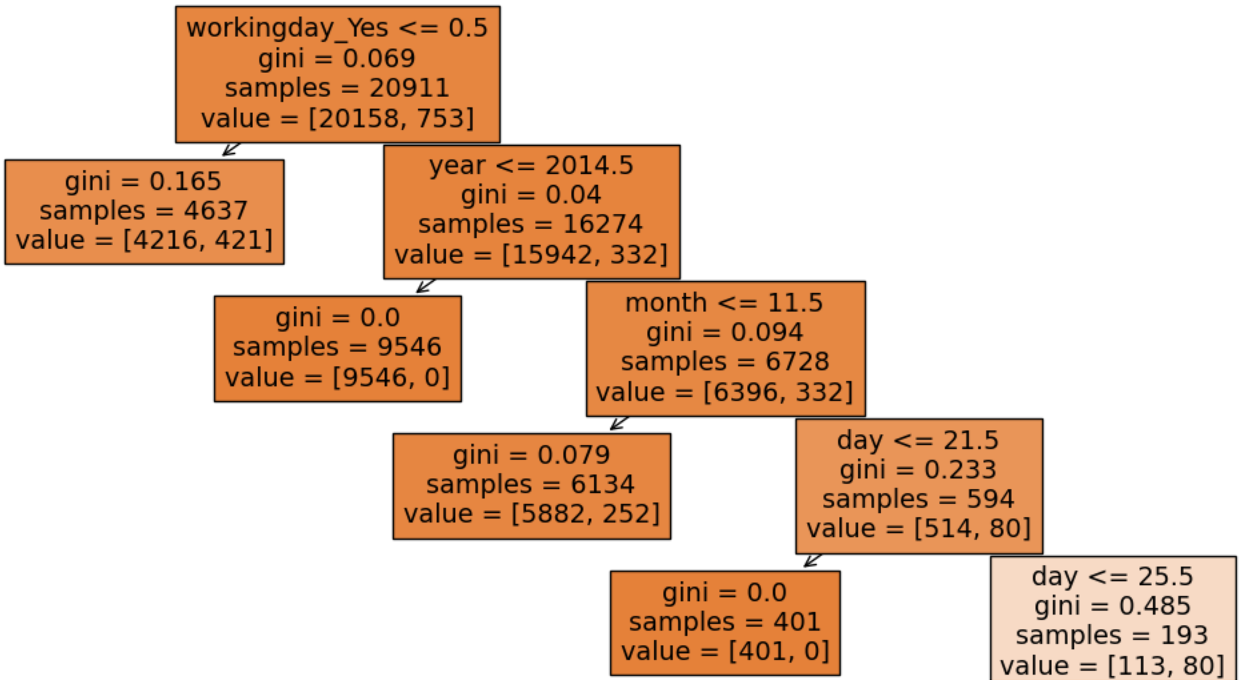
```
from IPython.display import Image
from sklearn.tree import export_graphviz


decision_tree = DecisionTreeClassifier(max_leaf_nodes=6,criterion='gini')

decision_tree = decision_tree.fit(X_train,y_train.astype(int))

labels = X_train.columns

dot_data = tree.plot_tree(decision_tree,filled = True,feature_names=X_train.columns)
```



Train Set Performance Evaluation:

Obtaining performance metrics on the training set using a decision tree model.

```
def get_train_report(model):
    train_pred = model.predict(X_train)

    return(classification_report(y_train, train_pred))


train_report = get_train_report(decision_tree)
print(train_report)
```

```
              precision    recall  f1-score   support

           0       0.97      1.00      0.98     20158
           1       0.75      0.08      0.14       753

    accuracy                           0.97     20911
   macro avg       0.86      0.54      0.56     20911
weighted avg       0.96      0.97      0.95     20911
```

```
def get_test_report(model):

    test_pred = model.predict(X_test)
    report = classification_report(y_test, test_pred)
```

```
    #print(report)
    return(report, test_pred)
```

```
test_report_dt, y_pred_dt= get_test_report(decision_tree)
```

```
print('y_pred:',  y_pred_dt)
```

```
    y_pred: [0 0 0 ... 0 0 0]
```

```
print(test_report_dt)
```

```
                  precision    recall  f1-score   support

               0       0.97      1.00      0.98      5049
               1       0.74      0.08      0.14       179

        accuracy                           0.97      5228
       macro avg       0.85      0.54      0.56      5228
    weighted avg       0.96      0.97      0.95      5228
```

Hyperparameter Tuning to Mitigate Overfitting:

1. **Hyperparameter Grid and Model Initialization:**

Defining hyperparameters for decision tree tuning to address overfitting. Initializing a decision tree model with specified hyperparameters.

2. **Model Training and Performance Evaluation:**

Training the decision tree model on the training data. Assessing model performance on both the training and test datasets.

```
tree_param_grid = {'criterion' :'gini',
'max_depth' :5,
'min_samples_split' : 4,
'max_leaf_nodes' : 6,
'random_state' : 10}
```

```
dt_model = DecisionTreeClassifier(criterion = 'gini',
                                  max_depth = 5,
                                  min_samples_split = 4,
                                  max_leaf_nodes = 6,
                                  random_state = 10)

decision_tree = dt_model.fit(X_train, y_train)

train_report = get_train_report(decision_tree)
print('Train data:\n', train_report)

test_report_dt = get_test_report(decision_tree)
print('Test data:\n', test_report_dt)
```

```
    Train data:
                   precision    recall  f1-score   support

               0       0.97      1.00      0.98     20158
               1       0.75      0.08      0.14       753

        accuracy                           0.97     20911
       macro avg       0.86      0.54      0.56     20911
    weighted avg       0.96      0.97      0.95     20911

    Test data:
     ('              precision    recall  f1-score   support\n\n           0       0.97      1.00      0.98      5049\n
```

Features Importance

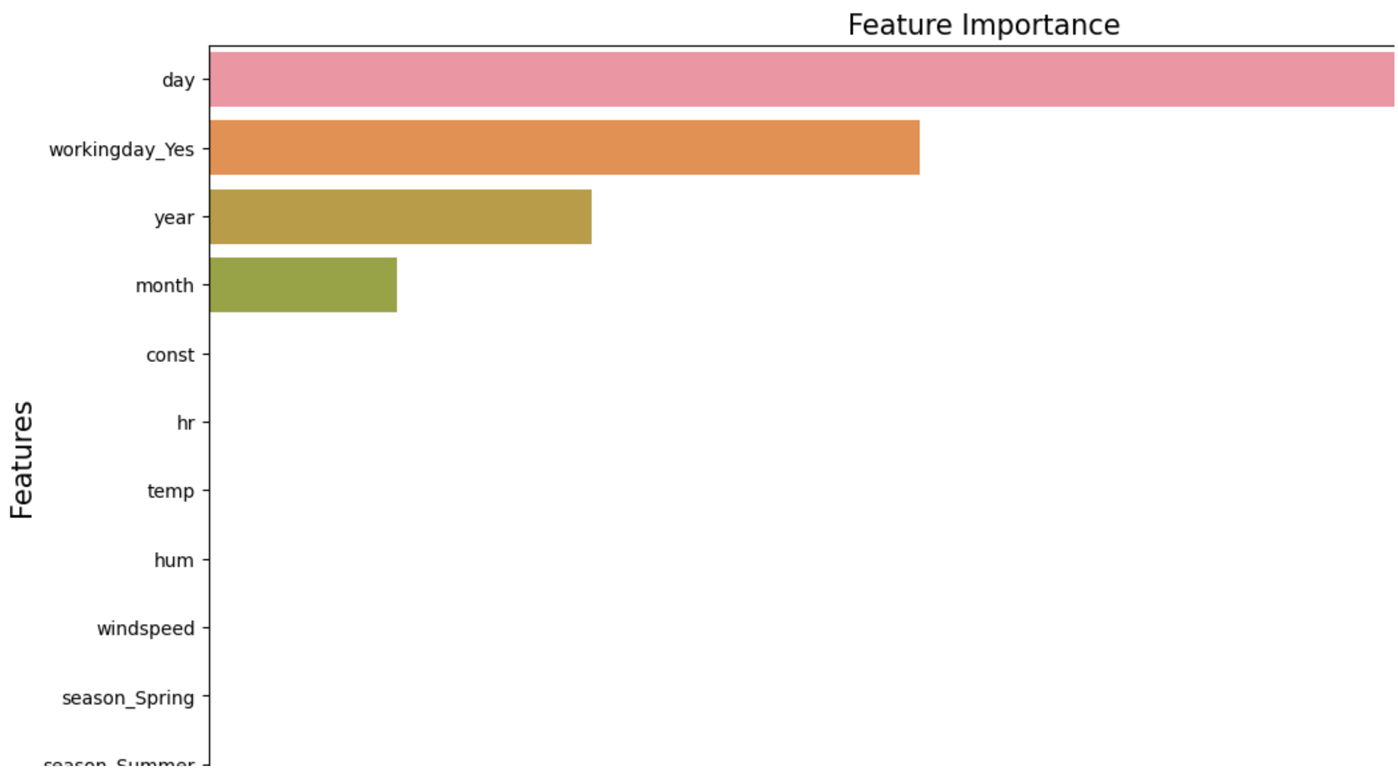
```
def FeatureImp(model):
  imp_features = pd.DataFrame({'Features': X_train.columns,
                                    'Importance': dt_model.feature_importances_})
```

```
  imp_features = imp_features.sort_values('Importance', ascending = False)
  sns.barplot(x = 'Importance', y = 'Features', data = imp_features)

  plt.title('Feature Importance', fontsize = 15)
  plt.xlabel('Importance', fontsize = 15)
  plt.ylabel('Features', fontsize = 15)

  plt.show()
```

```
FeatureImp(dt_model)
```



4. Random Forest for Classification Model

Initializing and training a Random Forest classifier with 10 estimators and a random state of 10.

```
rf_classification = RandomForestClassifier(n_estimators = 10, random_state = 10)

rf_model = rf_classification.fit(X_train, y_train)
```

Calculate performance for train set.

```
train_report = get_train_report(rf_model)

print(train_report)
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     20158
           1       1.00      0.99      0.99       753

    accuracy                           1.00     20911
   macro avg       1.00      0.99      1.00     20911
weighted avg       1.00      1.00      1.00     20911
```

4.1 Tune the Hyperparameters using GridSearchCV (Random Forest)

```
tuned_paramaters = [{'criterion': ['entropy', 'gini'],
                     'n_estimators': [10, 20, 25],
                     'max_depth': [10, 15, 20],
                     'max_features': ['sqrt', 'log2'],
                     'min_samples_split': [8, 11],
                     'min_samples_leaf': [1, 5, 9],
                     'max_leaf_nodes': [2, 5, 8, 11]}]

random_forest_classification = RandomForestClassifier(random_state = 10)
rf_grid = GridSearchCV(estimator = random_forest_classification,
                       param_grid = tuned_paramaters,
                       cv = 5)
rf_grid_model = rf_grid.fit(X_train, y_train)

print('Random forest classifier top paramters list: ', rf_grid_model.best_params_,)
```

```
Random forest classifier top paramters list:  {'criterion': 'gini', 'max_depth': 10, 'max_features': 'sqrt', 'max_leaf_nodes
```

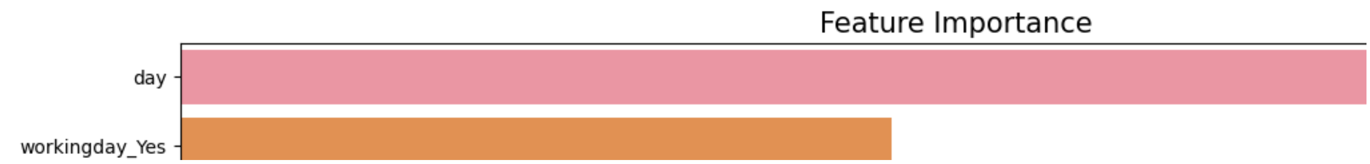
```
rf_model = RandomForestClassifier(criterion = rf_grid_model.best_params_.get('criterion'),
                                  n_estimators = rf_grid_model.best_params_.get('n_estimators'),
                                  max_depth = rf_grid_model.best_params_.get('max_depth'),
                                  max_features = rf_grid_model.best_params_.get('max_features'),
                                  max_leaf_nodes = rf_grid_model.best_params_.get('max_leaf_nodes'),
                                  min_samples_leaf = rf_grid_model.best_params_.get('min_samples_leaf'),
                                  min_samples_split = rf_grid_model.best_params_.get('min_samples_split'),
                                  random_state = 10)

rf_model = rf_model.fit(X_train, y_train)
print('Classification Report for test set:\n', get_test_report(rf_model))
```

```
Classification Report for test set:
 ('              precision    recall  f1-score   support\n\n           0       0.97      1.00      0.98      5049\n
```

Features Importance RF Model

```
FeatureImp(rf_model)
```




```
train_report = get_train_report(rf_model)

print(train_report)

              precision    recall  f1-score   support

           0       0.96      1.00      0.98     20158
           1       0.00      0.00      0.00       753

    accuracy                           0.96     20911
   macro avg       0.48      0.50      0.49     20911
weighted avg       0.93      0.96      0.95     20911
```

Muller Classifier

Setting up a comparison of various machine learning classifiers, including k-Nearest Neighbors, Support Vector Machines with linear and RBF kernels, Decision Tree, Random Forest, Neural Network, AdaBoost, and Naive Bayes.

```
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.colors import ListedColormap
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.datasets import make_moons, make_circles, make_classification
from sklearn.neural_network import MLPClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.gaussian_process import GaussianProcessClassifier
from sklearn.gaussian_process.kernels import RBF
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis

names = [
    "Nearest Neighbors", "Linear SVM", "RBF SVM","Decision Tree", "Random Forest", #"GridSearchCV",
    "Neural Net", "AdaBoost", "Naive Bayes"
         ]

classifiers = [
    KNeighborsClassifier(2),
    SVC(kernel="linear", C=0.025),
    SVC(gamma=2, C=1),
    DecisionTreeClassifier(max_depth=5),
    RandomForestClassifier(criterion = rf_grid_model.best_params_.get('criterion'),
                              n_estimators = rf_grid_model.best_params_.get('n_estimators'),
                              max_depth = rf_grid_model.best_params_.get('max_depth'),
                              max_features = rf_grid_model.best_params_.get('max_features'),
                              max_leaf_nodes = rf_grid_model.best_params_.get('max_leaf_nodes'),
                              min_samples_leaf = rf_grid_model.best_params_.get('min_samples_leaf'),
                              min_samples_split = rf_grid_model.best_params_.get('min_samples_split'),
                              random_state = 10),
    MLPClassifier(alpha=1, max_iter=1000),
    AdaBoostClassifier(),
    GaussianNB()]


from sklearn import metrics

def muller_classification(X_train, X_test, y_train, y_test):
  max_score = 0.0
  max_class = ''
  # iterate over classifiers
  metrics_df = pd.DataFrame({
      'Classifier': [],
```

```
        'MSE' : [],
        'MAE': [],
        'RSquared': [],
        'Test Accuracy': [],
        'Recall':[],
        'Precision': []
        })
    global m_pred
    m_pred = {}

    for name, clf in zip(names, classifiers):
      print(name)
      clf.fit(X_train, y_train)
      y_pred = clf.predict(X_test)
      score = 100.0 * clf.score(X_test, y_test)
      mean_absolute_error = np.round(metrics.mean_absolute_error(y_test, y_pred), 2)
      mean_squared_error = np.round(metrics.mean_squared_error(y_test, y_pred), 2)
      r_squared = np.round(metrics.r2_score(y_test, y_pred), 2)
      test_acc = metrics.accuracy_score(y_test, y_pred) * 100
      recall = metrics.recall_score(y_test, y_pred, average = 'weighted')
      precision = metrics.precision_score(y_test, y_pred, average = 'weighted')
      new_row = pd.DataFrame({
      'Classifier': name,
      'MSE' : mean_absolute_error,
      'MAE': mean_squared_error,
      'RSquared': r_squared,
      'Test Accuracy': test_acc,
      'Recall': recall,
      'Precision': precision}, index=[0])

      m_pred[name] = {
          'y_pred' : y_pred,
          'y_test': y_test
      }

      metrics_df = pd.concat([new_row,metrics_df.loc[:]]).reset_index(drop=True)

      print('Classifier = %s, Score (test, accuracy) = %.2f,' %(name, score))
      if score > max_score:
          clf_best = clf
          max_score = score
          max_class = name

    print('Best Classifier = %s, Score (test, accuracy) = %.2f' %(max_class, max_score))

    return metrics_df


metrics_df = muller_classification(X_train, X_test, y_train, y_test)
metrics_df.head(10)
```

```
Nearest Neighbors
Classifier = Nearest Neighbors, Score (test, accuracy) = 98.16,
Linear SVM
Classifier = Linear SVM, Score (test, accuracy) = 96.58,
RBF SVM
```

Muller Loop Regressor

```
Random Forest
```

```
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.colors import ListedColormap
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.neural_network import MLPRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn import metrics
names = [
    "Linear Regression",
    "MLP Regressor",
    "RandomForest Regressor",
    "Gradient Boosting Regressor",
    "KNeighbors Regressor"
         ]

regressors = [
    LinearRegression(),
    MLPRegressor(random_state=1, max_iter=500),
    RandomForestRegressor(max_depth=4, random_state=1),
    GradientBoostingRegressor(random_state=1),
    KNeighborsRegressor(n_neighbors=2)
    ]


def muller_loop(x_train, x_test, y_train, y_test):
  max_score = 0.0
  max_class = ''
  metrics_df = pd.DataFrame({
      'Regressor': [],
      'MSE' : [],
      'MAE': [],
      'RSquared': [],
      'Test Accuracy': []
      })
  for name, reg in zip(names, regressors):
      reg.fit(x_train, y_train)
      y_pred = reg.predict(x_test)
      score = 100.0 * reg.score(x_test, y_test)
      mean_absolute_error = np.round(metrics.mean_absolute_error(y_test, y_pred), 2)
      mean_squared_error = np.round(metrics.mean_squared_error(y_test, y_pred), 2)
      r_squared = np.round(metrics.r2_score(y_test, y_pred), 2)
      new_row = pd.DataFrame({
      'Regressor': name,
      'MSE' : mean_absolute_error,
      'MAE': mean_squared_error,
      'RSquared': r_squared,
      'Test Accuracy': score}, index=[0])
      metrics_df = pd.concat([new_row,metrics_df.loc[:]]).reset_index(drop=True)


      print('Regressor = %s, Score (test, accuracy) = %.2f,' %(name, score))
      if score > max_score:
          reg_best = reg
          max_score = score
          max_class = name

  print('***** Best Regressor = %s, Score (test, accuracy) = %.2f' %(max_class, max_score))


muller_loop(X_train, X_test, y_train, y_test )
```

```
Regressor = Linear Regression, Score (test, accuracy) = 3.75,
Regressor = MLP Regressor, Score (test, accuracy) = -82.29,
Regressor = RandomForest Regressor, Score (test, accuracy) = 14.01,
Regressor = Gradient Boosting Regressor, Score (test, accuracy) = 23.51,
```

```
Regressor = KNeighbors Regressor, Score (test, accuracy) = 63.12,
***** Best Regressor = KNeighbors Regressor, Score (test, accuracy) = 63.12
```

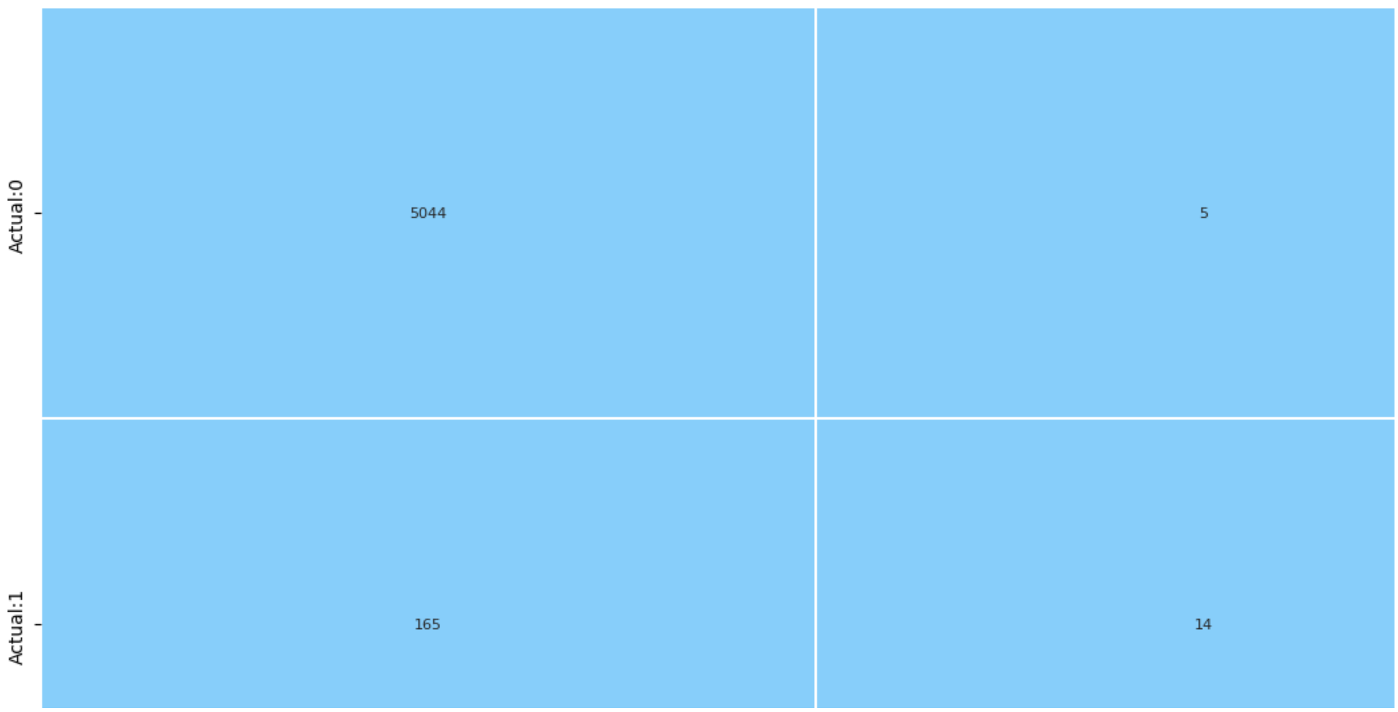
Confusion matrix nd metrics

```
def confMatrix(y_test, y_pred):
  cm = confusion_matrix(y_test, y_pred)
  conf_matrix = pd.DataFrame(data = cm,columns = [f'Predicted:{i}' for i in range(2)], index = [f'Actual:{i}' for i in range(2)])
  return (cm, conf_matrix)

def plot_cm(conf_matrix):
  sns.heatmap(conf_matrix, annot = True, fmt = 'd', cmap = ListedColormap(['lightskyblue']), cbar = False,
              linewidths = 0.1, annot_kws = {'size':8})
  plt.xticks(fontsize = 10)
  plt.yticks(fontsize = 10)
  plt.show()
```

```
cm_dt, conf_matrix_dt = confMatrix(y_test, y_pred_dt)
```

```
plot_cm(conf_matrix_dt)
```




```
def calculateMetrics(cm, y_test, y_pred):
  # True Negatives are denoted by 'TN'
  # Actual 'O' values which are classified correctly
  TN = cm[0,0]

  # True Positives are denoted by 'TP'
  # Actual '1' values which are classified correctly
  TP = cm[1,1]

  # False Positives are denoted by 'FP'
  # it is the type 1 error
  # Actual 'O' values which are classified wrongly as '1'
  FP = cm[0,1]

  # False Negatives are denoted by 'FN'
  # it is the type 2 error
  # Actual '1' values which are classified wrongly as '0'
```

```
  FN = cm[1,0]

  precision = TP / (TP+FP)
  recall = TP / (TP+FN)
  specificity = TN / (TN+FP)
  f1_score = 2*((precision*recall)/(precision+recall))
  accuracy = (TN+TP) / (TN+FP+FN+TP)
  acc_table = classification_report(y_test, y_pred)
  print(acc_table)
```

```
metrics_dt = calculateMetrics(cm_dt, y_test, y_pred_dt)
```

```
                  precision    recall  f1-score   support

               0       0.97      1.00      0.98      5049
               1       0.74      0.08      0.14       179

        accuracy                           0.97      5228
       macro avg       0.85      0.54      0.56      5228
    weighted avg       0.96      0.97      0.95      5228
```

```
def ROC(y_test, y_pred):
  fpr, tpr, thresholds = roc_curve(y_test, y_pred)

  plt.plot(fpr, tpr)

  plt.xlim([0.0, 1.0])
  plt.ylim([0.0, 1.0])
  plt.plot([0, 1], [0, 1],'r--')
  plt.title('ROC', fontsize = 15)
  plt.xlabel('False rate 1-Specificity', fontsize = 15)
  plt.ylabel('True rate Sensitivity', fontsize = 15)

  plt.text(x = 0.02, y = 0.9, s = ('AUC Score:', round(metrics.roc_auc_score(y_test, y_pred),4)))
  plt.grid(True)

ROC(y_test,y_pred_dt)
```

Class Imbalance Handling and Evaluation

class imbalance by using SMOTE for oversampling and RandomUnderSampler for undersampling, followed by storing evaluation metrics (precision, recall, F1 score, and AUC-ROC) for various models.

```
import imblearn
from imblearn.over_sampling import RandomOverSampler, SMOTE
from imblearn.under_sampling import RandomUnderSampler, EditedNearestNeighbours
```

```
counter = Counter(y_train)
print('Before',counter)
smt = SMOTE()

X_train_sm, y_train_sm = smt.fit_resample(X_train, y_train)

counter = Counter(y_train_sm)
print('After',counter)
```

```
Before Counter({0: 20158, 1: 753})
After Counter({0: 20158, 1: 20158})
```

```
counter1 = Counter(y_train)
print('Before',counter1)

rus = RandomUnderSampler()

X_train_rus, y_train_rus = rus.fit_resample(X_train, y_train)
counter1 = Counter(y_train_rus)
print('After',counter1)
```

```
Before Counter({0: 20158, 1: 753})
After Counter({0: 753, 1: 753})
```

```
model = list()
resample = list()
precision = list()
recall = list()
F1score = list()
AUCROC = list()

def test_eval(clf_model, X_test, y_test, algo=None, sampling=None):
    y_prob=clf_model.predict_proba(X_test)
    y_pred=clf_model.predict(X_test)

    print('Confusion Matrix')
    print('='*60)
    print(confusion_matrix(y_test,y_pred),"\n")
    print('Classification Report')
    print('='*60)
    print(classification_report(y_test,y_pred),"\n")
    print('AUC-ROC')
    print('='*60)
    print(roc_auc_score(y_test, y_prob[:,1]))

    model.append(algo)
    precision.append(precision_score(y_test,y_pred))
    recall.append(recall_score(y_test,y_pred))
    F1score.append(f1_score(y_test,y_pred))
    AUCROC.append(roc_auc_score(y_test, y_prob[:,1]))
    resample.append(sampling)
```

Original Data

```
estimators = [2,10,30,50,100]
max_depth = [i for i in range(5,16,2)]
min_samples_split = [2, 5, 10, 15, 20, 50, 100]
min_samples_leaf = [1, 2, 5]
```

```
tree_param_grid = {
'max_depth' :max_depth,
'min_samples_split' : min_samples_split,
'min_samples_leaf' : min_samples_leaf
}
cv = StratifiedKFold(n_splits=5, random_state=100, shuffle=True)


clf_DT = RandomizedSearchCV(dt_model, tree_param_grid, cv=cv, scoring='roc_auc', n_jobs=-1, verbose=2)
clf_DT.fit(X_train, y_train)
clf_DT.best_estimator_
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
▾                     DecisionTreeClassifier
DecisionTreeClassifier(max_depth=15, max_leaf_nodes=6, min_samples_split=100,
                       random_state=10)
```

Evaluate Decision Tree Classifier on Test Data

```
test_eval(clf_DT, X_test, y_test, 'Decision Tree', 'actual')
```

```
Confusion Matrix
============================================================
[[5044    5]
 [ 165   14]]

Classification Report
============================================================
              precision    recall  f1-score   support

           0       0.97      1.00      0.98      5049
           1       0.74      0.08      0.14       179

    accuracy                           0.97      5228
   macro avg       0.85      0.54      0.56      5228
weighted avg       0.96      0.97      0.95      5228


AUC-ROC
============================================================
0.8117581776799654
```

```
clf_DT.fit(X_train_sm, y_train_sm)
clf_DT.best_estimator_
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
▾                     DecisionTreeClassifier
DecisionTreeClassifier(max_depth=15, max_leaf_nodes=6, min_samples_split=15,
                       random_state=10)
```

```
test_eval(clf_DT, X_test, y_test, 'Decision Tree', 'smote')
```

```
Confusion Matrix
============================================================
[[3586 1463]
 [  20  159]]

Classification Report
============================================================
              precision    recall  f1-score   support

           0       0.99      0.71      0.83      5049
           1       0.10      0.89      0.18       179

    accuracy                           0.72      5228
   macro avg       0.55      0.80      0.50      5228
weighted avg       0.96      0.72      0.81      5228


AUC-ROC
============================================================
0.8315148417021567
```

Random Under Sampling

```
clf_DT.fit(X_train_rus, y_train_rus)
clf_DT.best_estimator_
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
                        DecisionTreeClassifier
DecisionTreeClassifier(max_depth=5, max_leaf_nodes=6, min_samples_leaf=5,
                       min_samples_split=15, random_state=10)
```

```
test_eval(clf_DT, X_test, y_test, 'Decision Tree', 'RandomUnderSampler')
```

```
Confusion Matrix
============================================================
[[2728 2321]
 [   1  178]]

Classification Report
============================================================
              precision    recall  f1-score   support

           0       1.00      0.54      0.70      5049
           1       0.07      0.99      0.13       179

    accuracy                           0.56      5228
   macro avg       0.54      0.77      0.42      5228
weighted avg       0.97      0.56      0.68      5228


AUC-ROC
============================================================
0.7813356480789934
```

Random Forest

```
rf_model = RandomForestClassifier()

rf_params={'n_estimators':estimators,
           'max_depth':max_depth,
           'min_samples_split':min_samples_split}

clf_RF = RandomizedSearchCV(rf_model, rf_params, cv=cv, scoring='roc_auc', n_jobs=-1, n_iter=20, verbose=2)
clf_RF.fit(X_train, y_train)
clf_RF.best_estimator_
test_eval(clf_RF, X_test, y_test, 'Random Forest', 'actual')
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
Confusion Matrix
============================================================
[[5049    0]
 [  56  123]]

Classification Report
============================================================
              precision    recall  f1-score   support

           0       0.99      1.00      0.99      5049
           1       1.00      0.69      0.81       179

    accuracy                           0.99      5228
   macro avg       0.99      0.84      0.90      5228
weighted avg       0.99      0.99      0.99      5228


AUC-ROC
============================================================
0.999361563935997
```

SMOTE Resampling and Evaluation

Random Forest Model

```
clf_RF.fit(X_train_sm, y_train_sm)
clf_RF.best_estimator_
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
▾                          RandomForestClassifier
RandomForestClassifier(max_depth=15, min_samples_split=5, n_estimators=50)
```

```
test_eval(clf_RF, X_test, y_test, 'Random Forest', 'smote')
```

```
Confusion Matrix
============================================================
[[4987   62]
 [  11  168]]

Classification Report
============================================================
              precision    recall  f1-score   support

           0       1.00      0.99      0.99      5049
           1       0.73      0.94      0.82       179

    accuracy                           0.99      5228
   macro avg       0.86      0.96      0.91      5228
weighted avg       0.99      0.99      0.99      5228


AUC-ROC
============================================================
0.9966495937577107
```

Random Under Sampling

```
clf_RF.fit(X_train_rus, y_train_rus)
clf_RF.best_estimator_
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
▾       RandomForestClassifier
RandomForestClassifier(max_depth=13)
```

```
test_eval(clf_RF, X_test, y_test, 'Decision Tree', 'RandomUnderSampler')
```

```
Confusion Matrix
============================================================
[[4641  408]
 [   1  178]]

Classification Report
============================================================
              precision    recall  f1-score   support

           0       1.00      0.92      0.96      5049
           1       0.30      0.99      0.47       179

    accuracy                           0.92      5228
   macro avg       0.65      0.96      0.71      5228
weighted avg       0.98      0.92      0.94      5228


AUC-ROC
============================================================
0.9922225873589658
```

Model Comparison

```
clf_compare = pd.DataFrame({'model':model,
                            'resample':resample,
                            'precision':precision,
                            'recall':recall,
                            'f1-score':F1score,
                            'AUC-ROC':AUCROC})
clf_compare
```

	model	resample	precision	recall	f1-score	AUC-ROC
0	Decision Tree	actual	0.736842	0.078212	0.141414	0.811758
1	Decision Tree	smote	0.098027	0.888268	0.176569	0.831515
2	Decision Tree	RandomUnderSampler	0.071228	0.994413	0.132935	0.781336
3	Random Forest	actual	1.000000	0.687151	0.814570	0.999362
4	Random Forest	smote	0.730435	0.938547	0.821516	0.996650

HoloViews Data distribution

```
!pip install -q hvplot
```

```
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 3.2/3.2 MB 28.0 MB/s eta 0:00:00
```

```
import holoviews as hv
hv.extension('bokeh')
import hvplot.pandas
import panel as pn
from sklearn.metrics import confusion_matrix, roc_curve
```

HoloViews Data Distribution Visualization with Interactive Controls:

Utilization HoloViews and Panel to create an interactive data distribution visualization with widgets for selecting **season, working day, and temperature**.

```
hv.extension('bokeh')
season_text = pn.widgets.StaticText(name='season', value='')

select_season = pn.widgets.RadioBoxGroup(
    name='season', options=['Winter', 'Summer', 'Autumn', 'Spring'],
    inline=True)

workingday_text = pn.widgets.StaticText(name='workingday', value='')
select_workingday = pn.widgets.RadioBoxGroup(
    name='workingday', options=['Yes','No'],
    inline=True)

select_temp = pn.widgets.IntSlider(name='temp', start= int(min(df['temp'])), end= int(max(df['temp'])), step = 1)
@pn.depends(select_season, select_workingday, select_temp)

def exp_plot(select_season, select_workingday, select_temp):
  return df[(df.season==select_season) &(df.workingday==select_workingday) & (df.temp <= select_temp)].sort_values(by='cnt').hvplo

pn.Column(season_text, select_season, workingday_text, select_workingday, select_temp, exp_plot).embed()
```

season:

(•) Winter ( ) Summer ( ) Autumn ( ) Spring

```
def hv_confusion_matrix(y_pred,
                        y_test,
                        title='Confusion matrix'):
    tn, fp, fn, tp = confusion_matrix(y_test,  y_pred).ravel()
    pdf = pd.DataFrame(zip(y_pred, y_train), columns=['Prediction', 'Actual'])

    graph = pdf.groupby(['Prediction', 'Actual']).size().to_frame().reset_index()
    confusion = graph.rename(columns={0: 'Count'})
    conf_values = map(lambda l: [str(l[0]), str(l[1]), l[2]], [a.tolist() for a in confusion.values])
    return hv.HeatMap(conf_values, label='Confusion Matrix', kdims=['Predicted', 'Actual'], vdims=['Count']).sort().options(
        xrotation=45, width=500, height=500, cmap='viridis', tools=['hover'], invert_yaxis=True, zlim=(0,1))
```

```
def hv_roc_curve(y_pred, y_test):
  fpr, tpr, _ = roc_curve(y_test,  y_pred)
  roc_df = pd.DataFrame(zip(fpr, tpr), columns=['Specificity', 'Sensitivity'])
  return roc_df.hvplot(x='Specificity', y = 'Sensitivity')
def upsample(df, n):
  df = resample(df, n_samples=n, replace=True)
  return df
def downsample(df, n):
  df = resample(df, n_samples=n, replace=False)
  return df


from sklearn.utils import resample


random = pd.concat( [X, df['holiday']], axis = 1)
random = resample(random)
random_tar = random['holiday'].fillna(0)
random.drop(['holiday'], inplace=True, axis=1)
X_train, X_test, y_train, y_test = train_test_split(random, random_tar, random_state = 10, test_size = 0.2)
muller_classification(X_train, X_test, y_train, y_test)
```

```
Linear Regression
Classifier = Linear Regression, Score (test, accuracy) = 98.91,
MLP Regressor
Classifier = MLP Regressor, Score (test, accuracy) = 96.60,
RandomForest Regressor
Classifier = RandomForest Regressor, Score (test, accuracy) = 98.57,
Gradient Boosting Regressor
Classifier = Gradient Boosting Regressor, Score (test, accuracy) = 96.58,
KNeighbors Regressor
Classifier = KNeighbors Regressor, Score (test, accuracy) = 96.60,
Best Classifier = Linear Regression, Score (test, accuracy) = 98.91
```

	Classifier	MSE	MAE	RSquared	Test Accuracy	Recall	Precision
0	KNeighbors Regressor	0.030000	0.030000	-0.040000	96.595256	0.965953	0.933064
1	Gradient Boosting Regressor	0.030000	0.030000	-0.040000	96.576129	0.965761	0.951919
2	RandomForest Regressor	0.010000	0.010000	0.560000	98.565417	0.985654	0.985864

```
from sklearn.utils import resample

def exp_plot(event):
  temp_df = pd.concat( [X, df['holiday']], axis = 1)
  temp_df = resample(temp_df)
  temp_target = temp_df['holiday'].fillna(0)
  temp_train_df = temp_df.drop(['holiday'], axis=1)
  X_train_temp, X_test_temp, y_train_temp, y_test_temp = train_test_split(temp_train_df, temp_target, random_state = 10, test_size
  muller_classification(X_train_temp, X_test_temp, y_train_temp, y_test_temp)


hv.extension('bokeh')

samples_text = pn.widgets.StaticText(name='Select Number of Samples', value='')
select_sample_size = pn.widgets.IntSlider(name='SampleSize', start= 100, end= 506, step = 10)

button = pn.widgets.Button(name='Run Muller Loop', button_type='primary')
```

```
button.on_click(exp_plot)
pn.Column(samples_text, select_sample_size, button)
```

Select Number of Samples:

SampleSize: **100**

Run Muller Loop

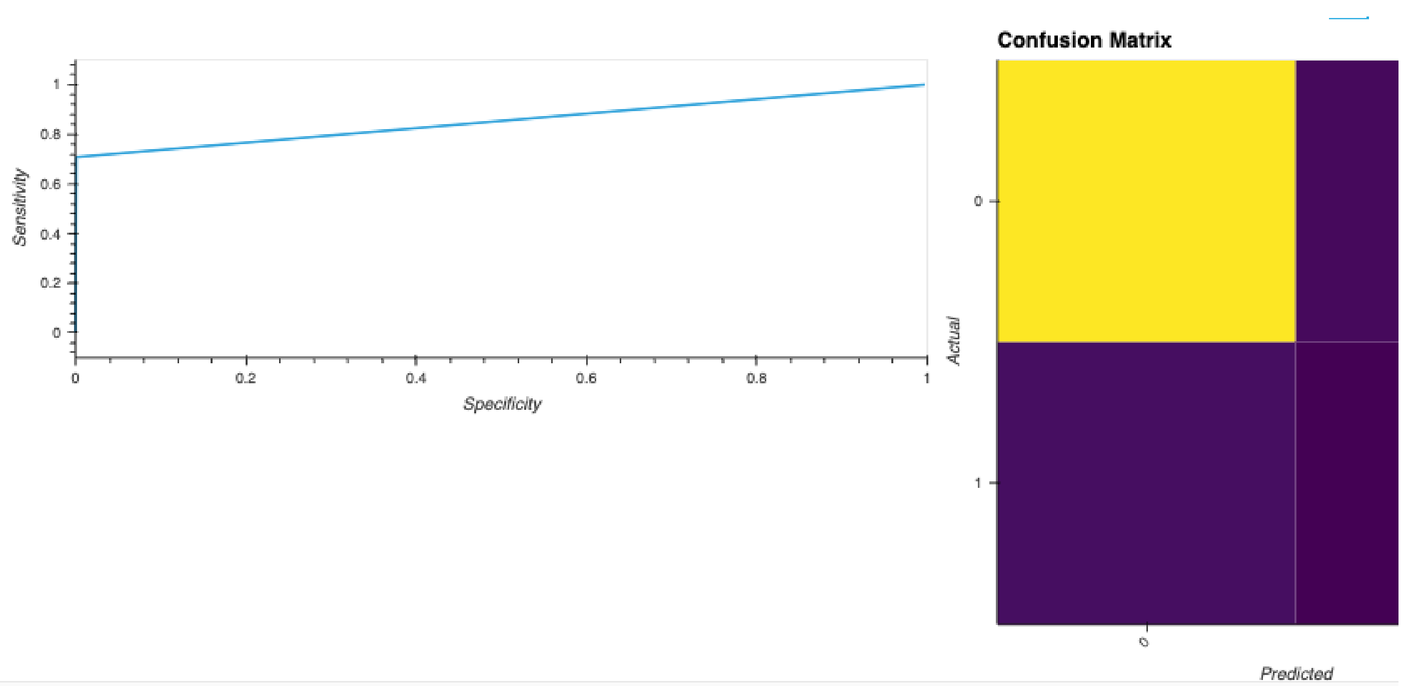
```
hv.extension('bokeh')
model_text = pn.widgets.StaticText(name='Model', value='',styles=dict(background='red'))
select_model = pn.widgets.RadioBoxGroup( name='model', options=["Linear Regression", "MLP Regressor", "RandomForest Regressor", "(

@pn.depends(select_model)
def plot_conf_roc(select_model):
  y_test = m_pred[select_model]['y_test']
  y_pred = m_pred[select_model]['y_pred']

  return hv_roc_curve(y_pred,y_test) + hv_confusion_matrix(y_pred,y_test)
pn.Column(model_text, select_model, plot_conf_roc).embed()
```

Model:

(•) Linear Regression ( ) MLP Regressor ( ) RandomForest Regressor ( ) Gradient Boosting Regressor ( ) KNeighbors Regressor



confusion matrices for bike rental prediction models, specifically for binary classification tasks with class labels "0" and "1." Users can select different regression models and evaluate their performance using these confusion matrices along with other visualizations