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_sc
from sklearn.metrics import confusion_matrix, roc_auc_score, roc_curve, precisio
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn import tree
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV, Stratified

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	weathe
0	1	2011-01-01	1	0	1	0	0	6	0	
1	2	2011-01-01	1	0	1	1	0	6	0	
2	3	2011-01-01	1	0	1	2	0	6	0	
3	4	2011-01-01	1	0	1	3	0	6	0	

```
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)
0	01/12/2017	254	0	-5.200000	37	2.200000	2000
1	01/12/2017	204	1	-5.500000	38	0.800000	2000
2	01/12/2017	173	2	-6.000000	39	1.000000	2000
3	01/12/2017	107	3	-6.200000	40	0.900000	2000
4	01/12/2017	78	4	-6.000000	36	2.300000	2000

```
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','
```

```
data2.head()
```

	dteday	cnt	hr	temp	hum	windspeed	Visibility (10m)	Dew point temperature(C)	sc
0	01/12/2017	254	0	-5.200000	37	2.200000	2000	-17.600000	
1	01/12/2017	204	1	-5.500000	38	0.800000	2000	-17.600000	
2	01/12/2017	173	2	-6.000000	39	1.000000	2000	-17.700000	

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=
```

```
data2.head()
```

	dteday	cnt	hr	temp	hum	windspeed	Visibility (10m)	Dew point temperature(C)	sc
0	01/12/2017	254	0	-5.200000	37	2.200000	2000	-17.600000	
1	01/12/2017	204	1	-5.500000	38	0.800000	2000	-17.600000	
2	01/12/2017	173	2	-6.000000	39	1.000000	2000	-17.700000	
3	01/12/2017	107	3	-6.200000	40	0.900000	2000	-17.600000	
4	01/12/2017	78	4	-6.000000	36	2.300000	2000	-18.600000	

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

```
data1.head()
```

	dteday	season	yr	mnth	hr	holiday	weekday	workingday	weathersit	
0	2011-01-01	Winter	0	1	0	0	6	No	1	0.24
1	2011-01-01	Winter	0	1	1	0	6	No	1	0.22
2	2011-01-01	Winter	0	1	2	0	6	No	1	0.22

```
data2.head()
```

	dteday	cnt	hr	temp	hum	windspeed	Visibility (10m)	Dew point temperature(C)	sc
0	01/12/2017	254	0	-5.200000	37	2.200000	2000	-17.600000	
1	01/12/2017	204	1	-5.500000	38	0.800000	2000	-17.600000	
2	01/12/2017	173	2	-6.000000	39	1.000000	2000	-17.700000	
3	01/12/2017	107	3	-6.200000	40	0.900000	2000	-17.600000	
4	01/12/2017	78	4	-6.000000	36	2.300000	2000	-18.600000	

```
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)	sc
0	01/12/2017	254	0	-5.200000	37	2.200000	2000	-17.600000	
1	01/12/2017	204	1	-5.500000	38	0.800000	2000	-17.600000	
2	01/12/2017	173	2	-6.000000	39	1.000000	2000	-17.700000	
3	01/12/2017	107	3	-6.200000	40	0.900000	2000	-17.600000	
4	01/12/2017	78	4	-6.000000	36	2.300000	2000	-18.600000	

```
df = data1.merge(data2, on = ['cnt','hr','temp','hum','windspeed','dteday','holi
```

```
df.head()
```

	dteday	season	yr	mnth	hr	holiday	weekday	workingday	weather
0	2011-01-01	Winter	0.000000	1.000000	0	0	6.000000	No	1.00
1	2011-01-01	Winter	0.000000	1.000000	1	0	6.000000	No	1.00
2	2011-01-01	Winter	0.000000	1.000000	2	0	6.000000	No	1.00
3	2011-01-01	Winter	0.000000	1.000000	3	0	6.000000	No	1.00
4	2011-01-01	Winter	0.000000	1.000000	4	0	6.000000	No	1.00

```
df=df.drop(['registered','atemp','yr','mnth','weekday','Visibility (10m)','Dew p
```

```
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
	2011-								

```
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
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

```
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

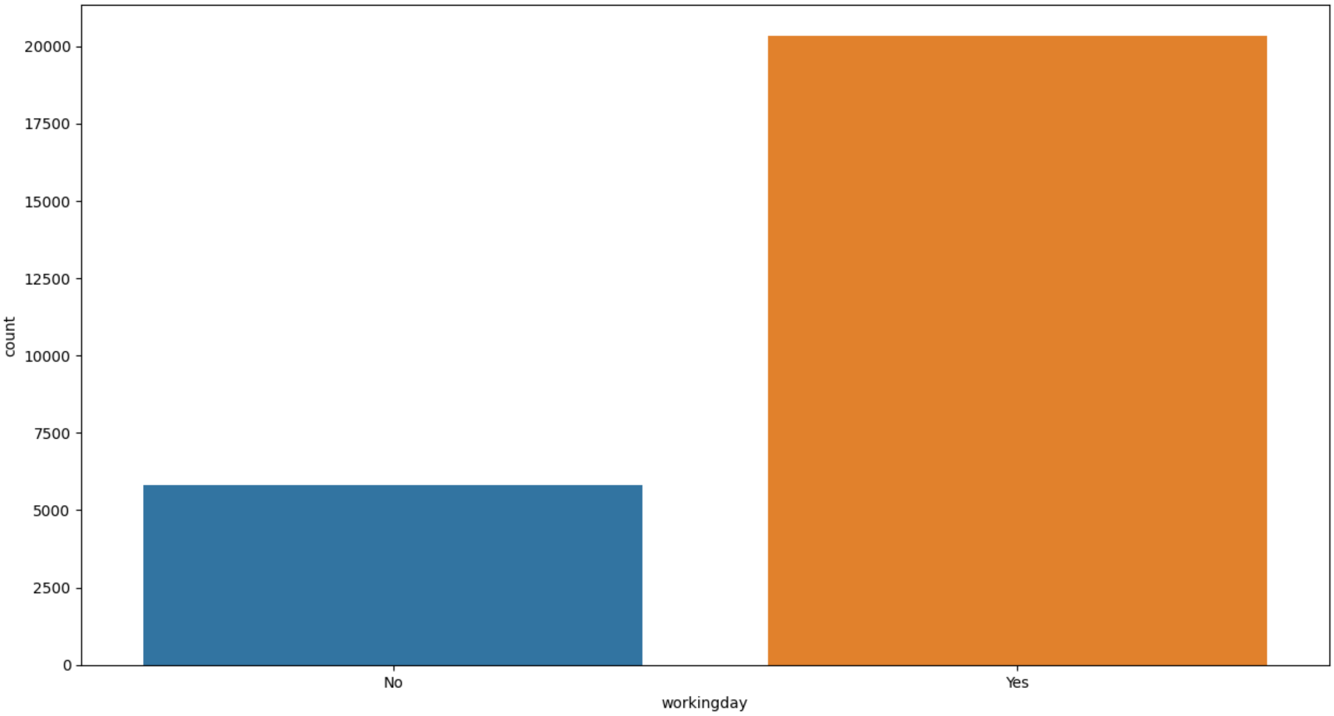
```
df_cat = df.select_dtypes(include=[np.object])
df_cat.head()
```

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

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

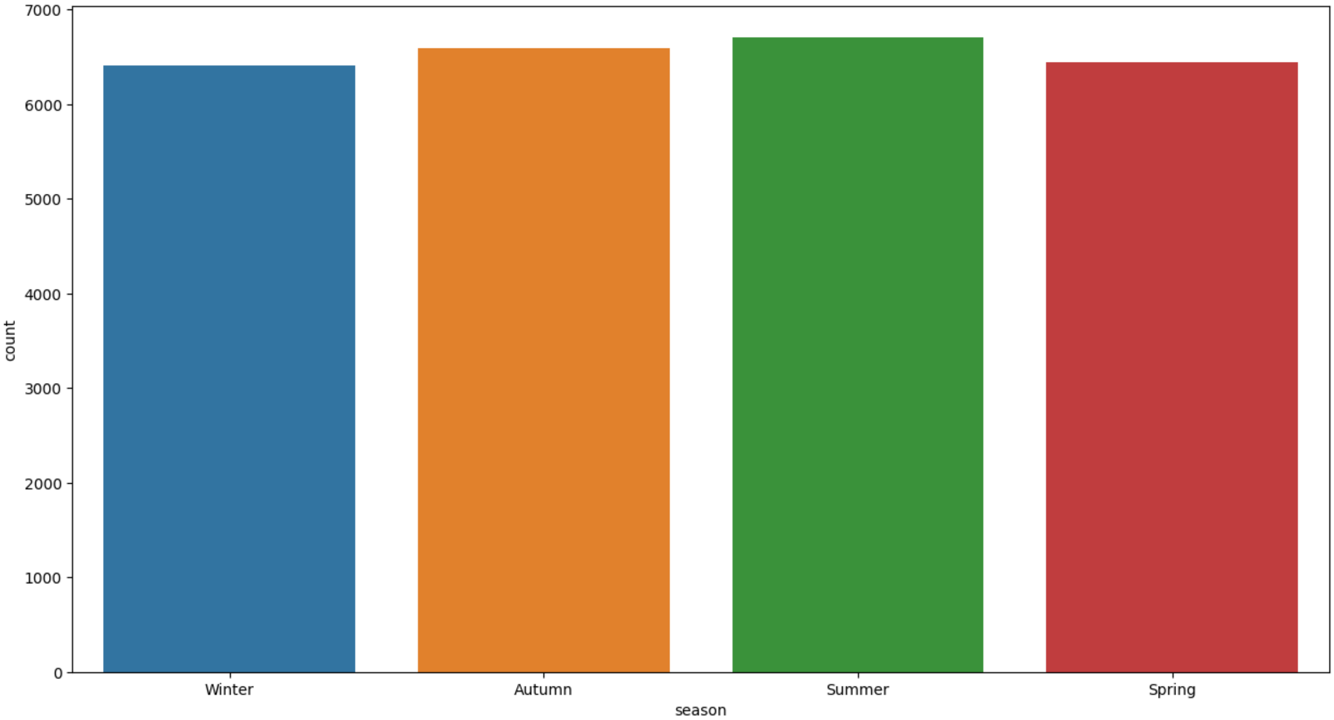
```
sns.countplot(x='workingday',data=df_cat)
```

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

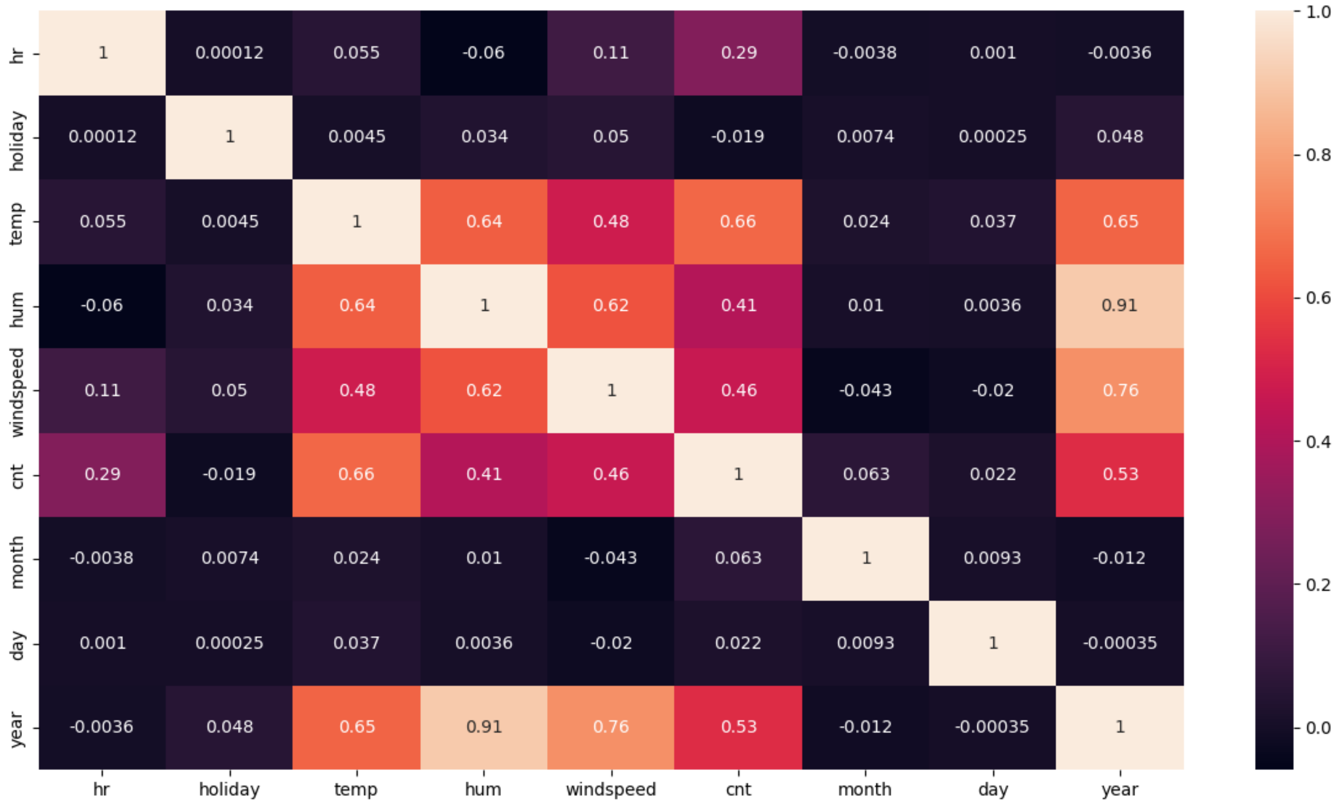


```
sns.countplot(x='season',data=df_cat)
```

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



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



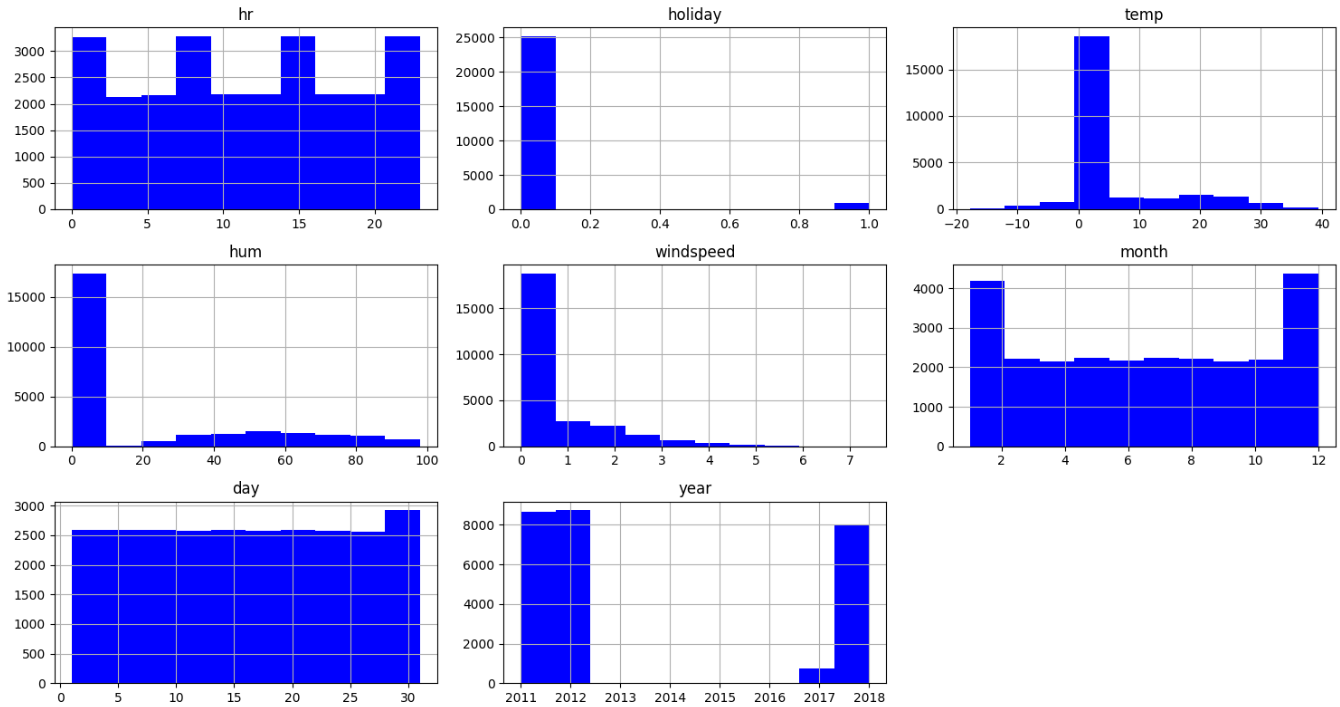
Variables Distribution

```
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()
```




```
Skewness:
hr          -0.007103
holiday      5.008592
temp         1.625359
hum          1.159319
windspeed    1.990985
month       -0.009671
day          0.010786
year         0.650560
dtype: float64
```

Missing Values

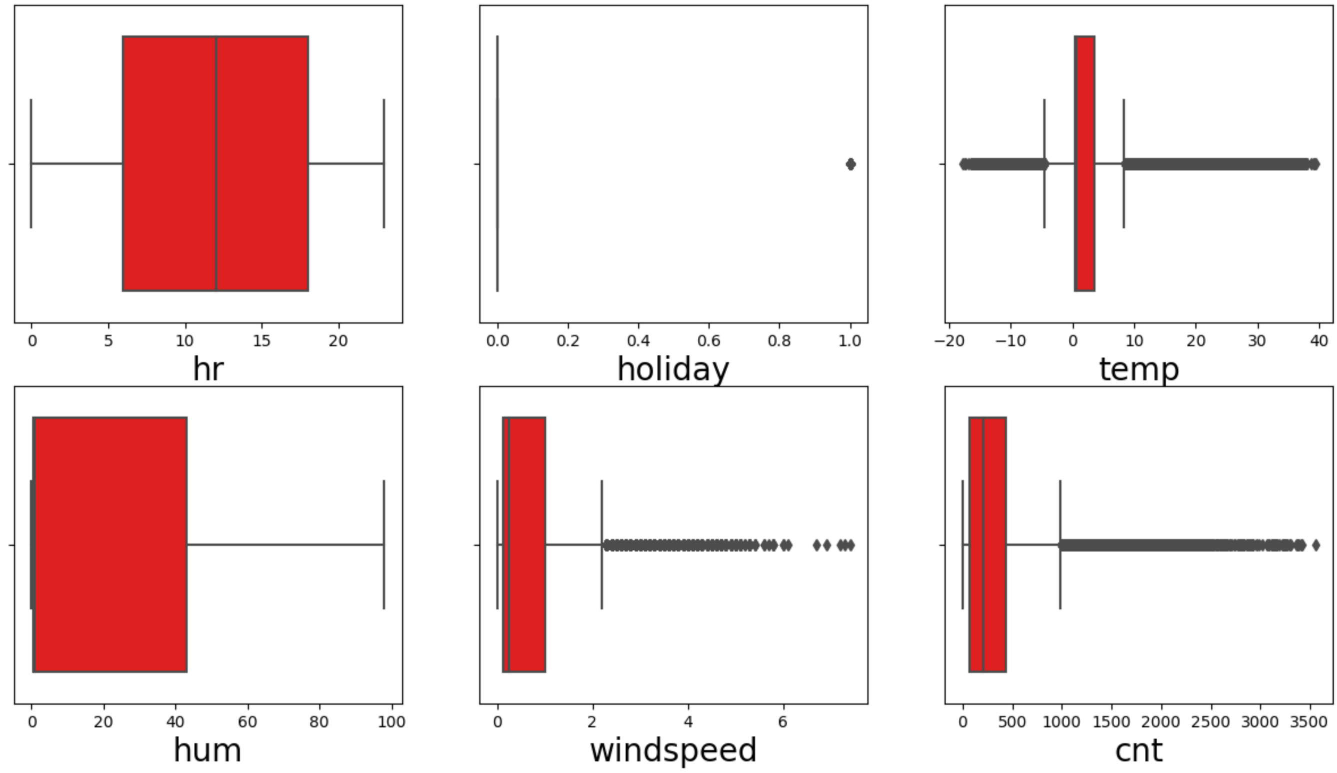
```
Total = df.isnull().sum().sort_values(ascending=False)
Percent = (df.isnull().sum()*100/df.isnull().count()).sort_values(ascending=Fals
missing_data = pd.concat([Total, Percent], axis = 1, keys = ['Total', 'Percentag
missing_data
```

	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
day	0	0.000000
year	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",w
    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
```

```
3.24
```

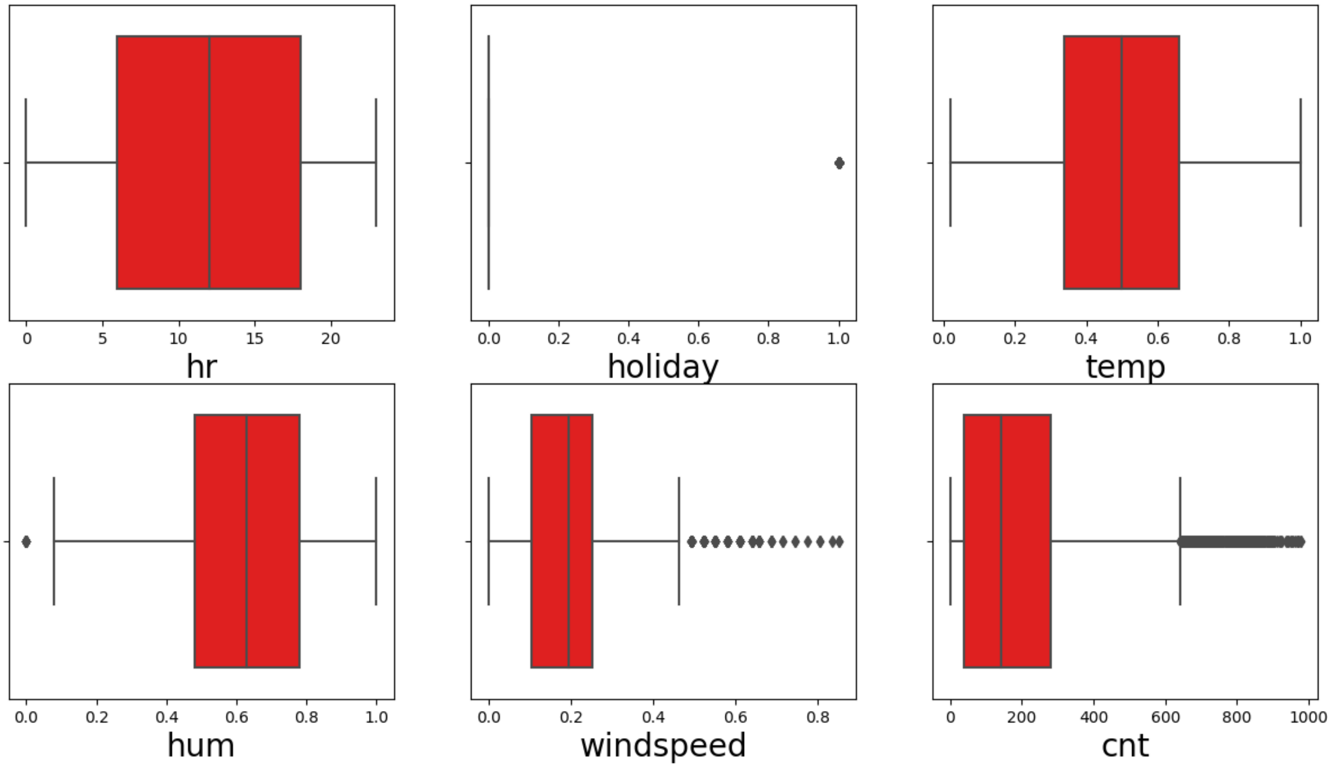
```
lower = df_num.hum.quantile(0.25)

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
```

```
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",w
    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
4	4	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_Su
0	0	0.240000	0.810000	0.000000	1	1	2011	0	
1	1	0.220000	0.800000	0.000000	1	1	2011	0	
2	2	0.220000	0.800000	0.000000	1	1	2011	0	
3	3	0.240000	0.750000	0.000000	1	1	2011	0	
4	4	0.240000	0.750000	0.000000	1	1	2011	0	

```
X = sm.add_constant(X)

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

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_sta
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'.

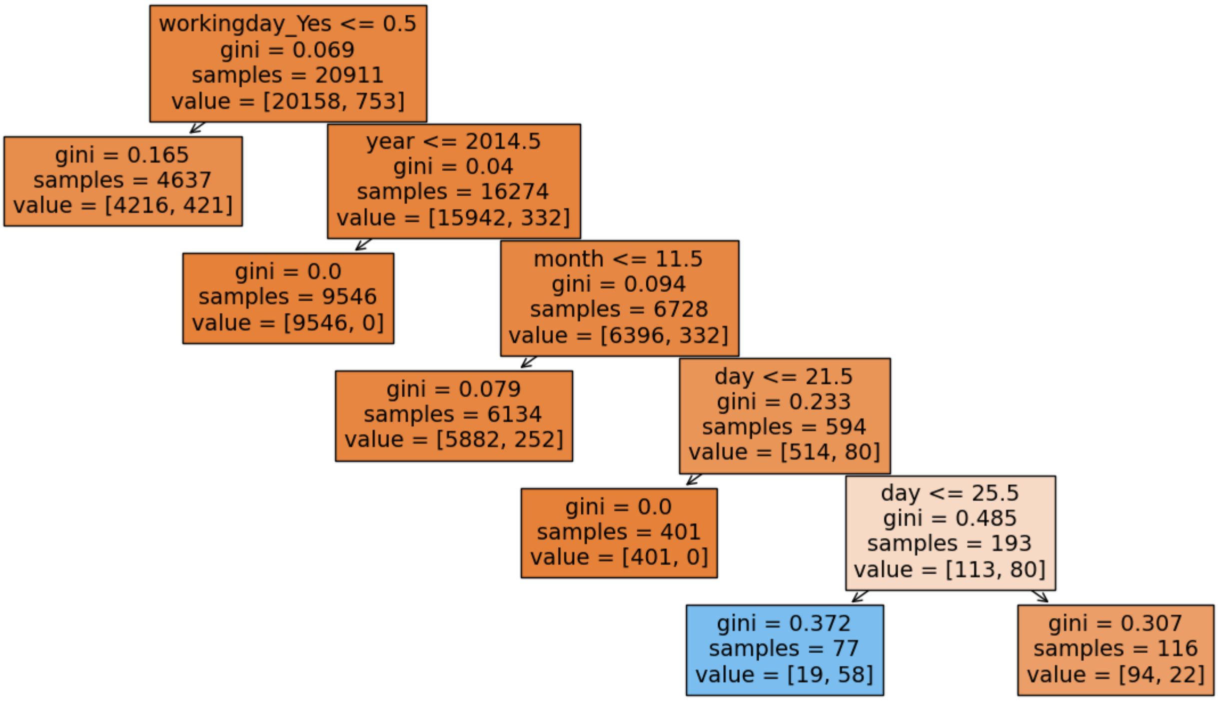
```
import pydotplus
from sklearn import tree
from IPython.display import Image
from sklearn.tree import export_graphviz
```

```
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.colu
```



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
```

Features Importance

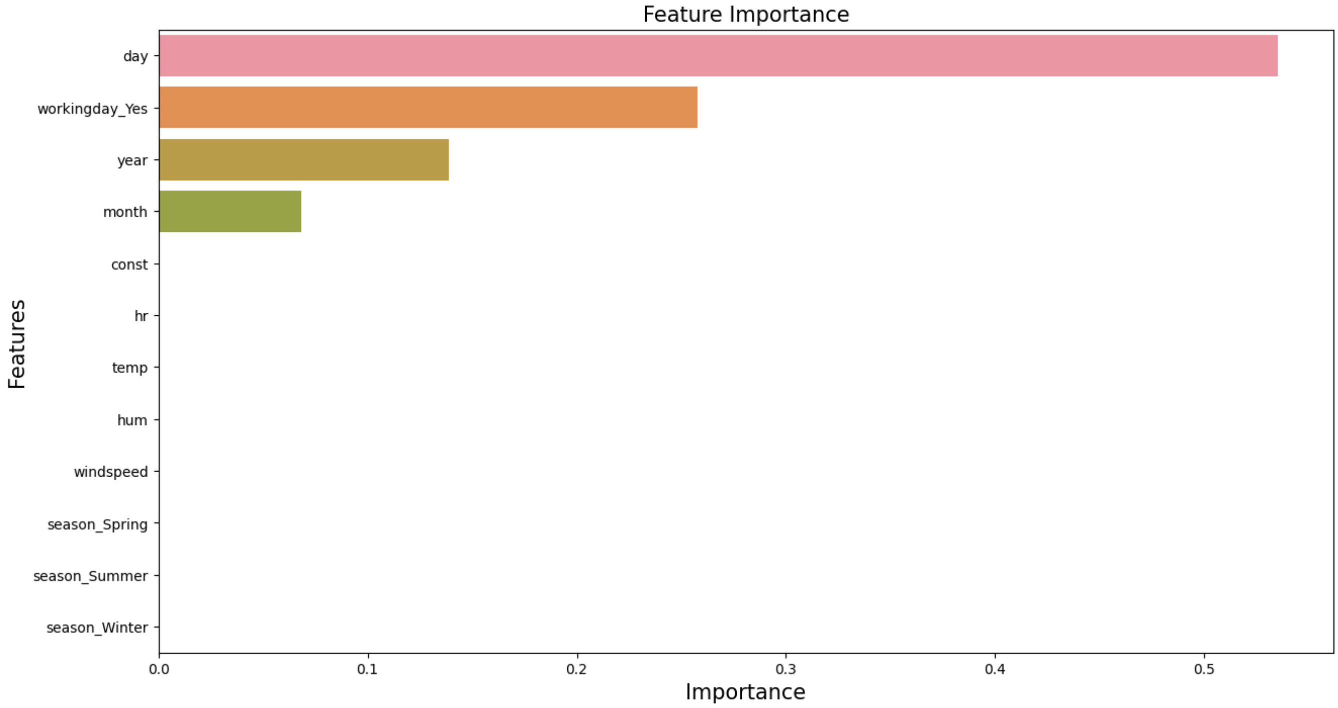
```
def FeatureImp(model):
  imp_features = pd.DataFrame({'Features': X_train.columns,
                               'Importance': dt_model.feature_importances_}

  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_
```

```
Best parameters for random forest classifier:  {'criterion': 'gini', 'max_d
```

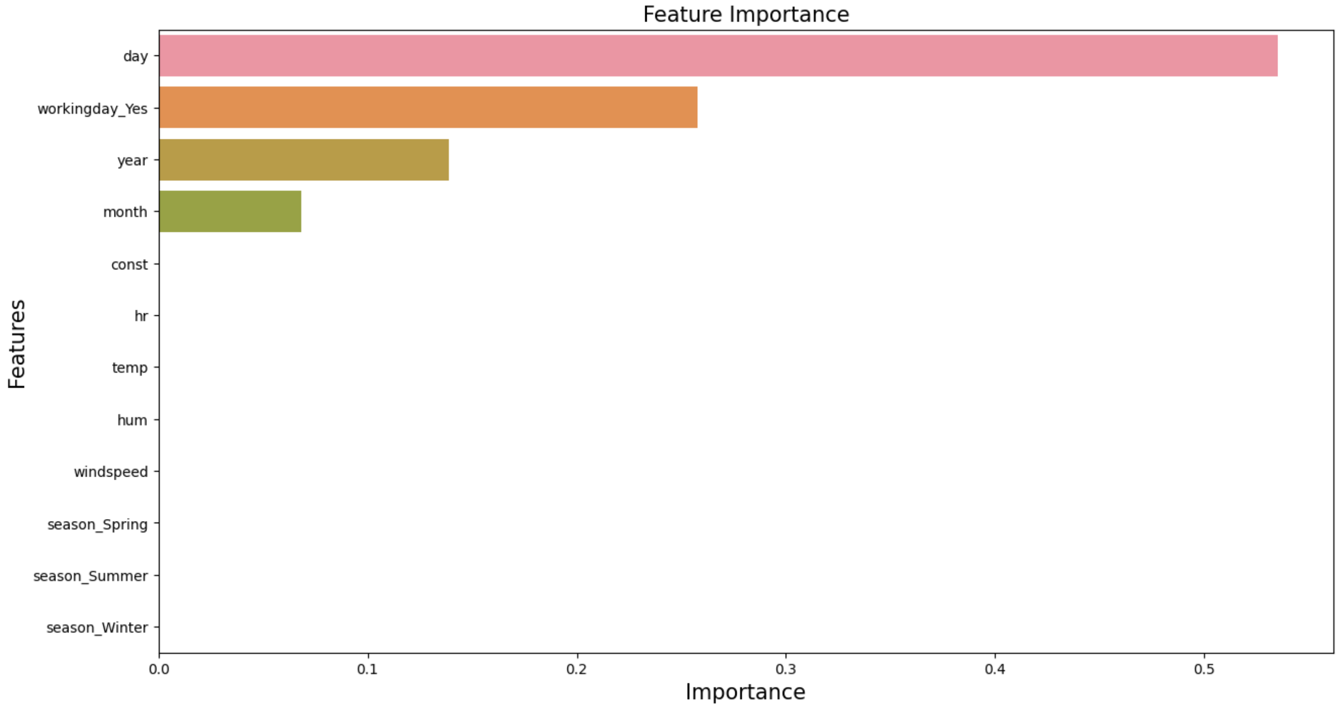
```
rf_model = RandomForestClassifier(criterion = rf_grid_model.best_params_.get('cr
                                  n_estimators = rf_grid_model.best_params_.get(
                                  max_depth = rf_grid_model.best_params_.get('ma
                                  max_features = rf_grid_model.best_params_.get(
                                  max_leaf_nodes = rf_grid_model.best_params_.ge
                                  min_samples_leaf = rf_grid_model.best_params_.
                                  min_samples_split = rf_grid_model.best_params_
                                  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
```

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
    "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(
                                  max_depth = rf_grid_model.best_params_.get('ma
                                  max_features = rf_grid_model.best_params_.get(
                                  max_leaf_nodes = rf_grid_model.best_params_.ge
                                  min_samples_leaf = rf_grid_model.best_params_.
                                  min_samples_split = rf_grid_model.best_params_
                                  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),
  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_s

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
Classifier = RBF SVM, Score (test, accuracy) = 96.58,
Decision Tree
Classifier = Decision Tree, Score (test, accuracy) = 96.77,
Random Forest
Classifier = Random Forest, Score (test, accuracy) = 96.58,
Neural Net
Classifier = Neural Net, Score (test, accuracy) = 96.58,
AdaBoost
Classifier = AdaBoost, Score (test, accuracy) = 96.08,
Naive Bayes
Classifier = Naive Bayes, Score (test, accuracy) = 95.70,
Best --> Classifier = Nearest Neighbors, Score (test, accuracy) = 98.16
```

	Classifier	MSE	MAE	RSquared	Test Accuracy	Recall	Precision
0	Naive Bayes	0.040000	0.040000	-0.300000	95.696251	0.956963	0.934118
1	AdaBoost	0.040000	0.040000	-0.190000	96.078806	0.960788	0.933925
2	Neural Net	0.030000	0.030000	-0.040000	96.576129	0.965761	0.932695
3	Random Forest	0.030000	0.030000	-0.040000	96.576129	0.965761	0.932695
4	Decision Tree	0.030000	0.030000	0.020000	96.767406	0.967674	0.961028
5	RBF SVM	0.030000	0.030000	-0.040000	96.576129	0.965761	0.932695
6	Linear SVM	0.030000	0.030000	-0.040000	96.576129	0.965761	0.932695
7	Nearest	0.020000	0.020000	0.440000	98.163734	0.981637	0.980389

Muller Loop Regressor

```
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)
      mean_squared_error = np.round(metrics.mean_squared_error(y_test, y_pred),
      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,
```

```
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
```

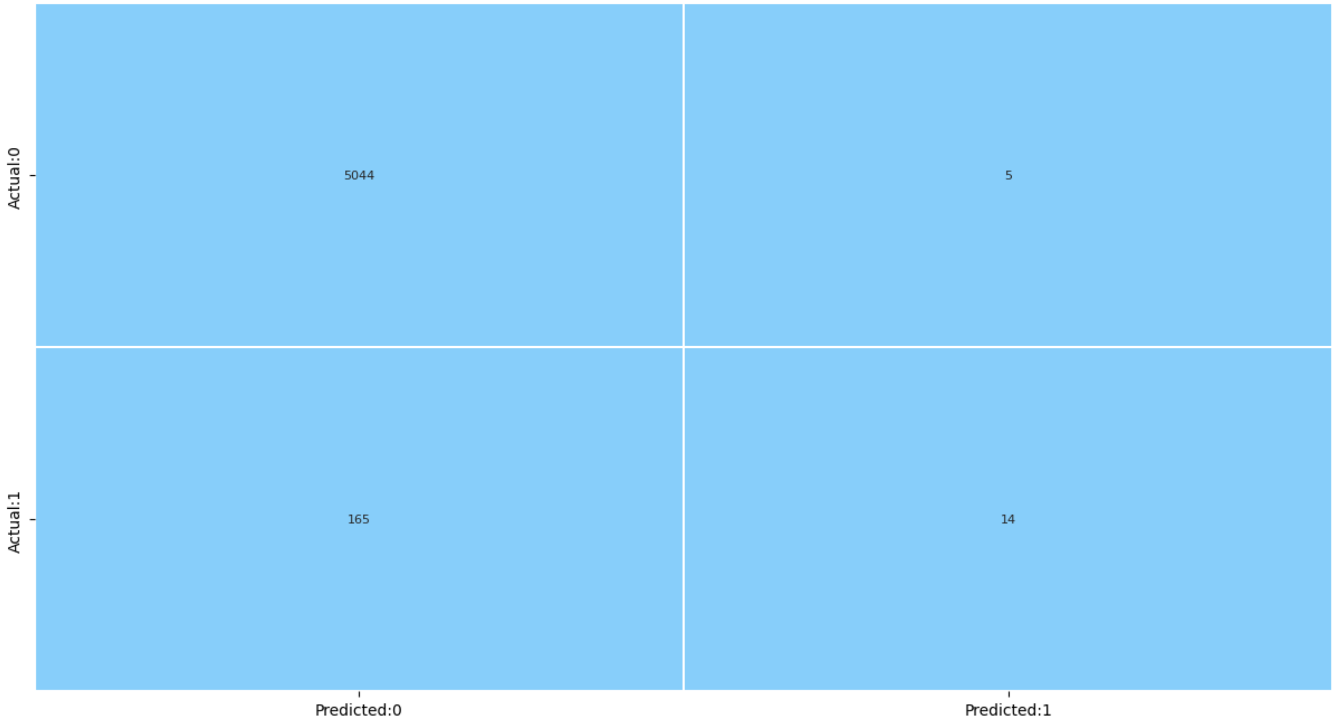
Confusion matrix nd metrics

```
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 rang
  return (cm, conf_matrix)

def plot_cm(conf_matrix):
  sns.heatmap(conf_matrix, annot = True, fmt = 'd', cmap = ListedColormap(['ligh
              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
```

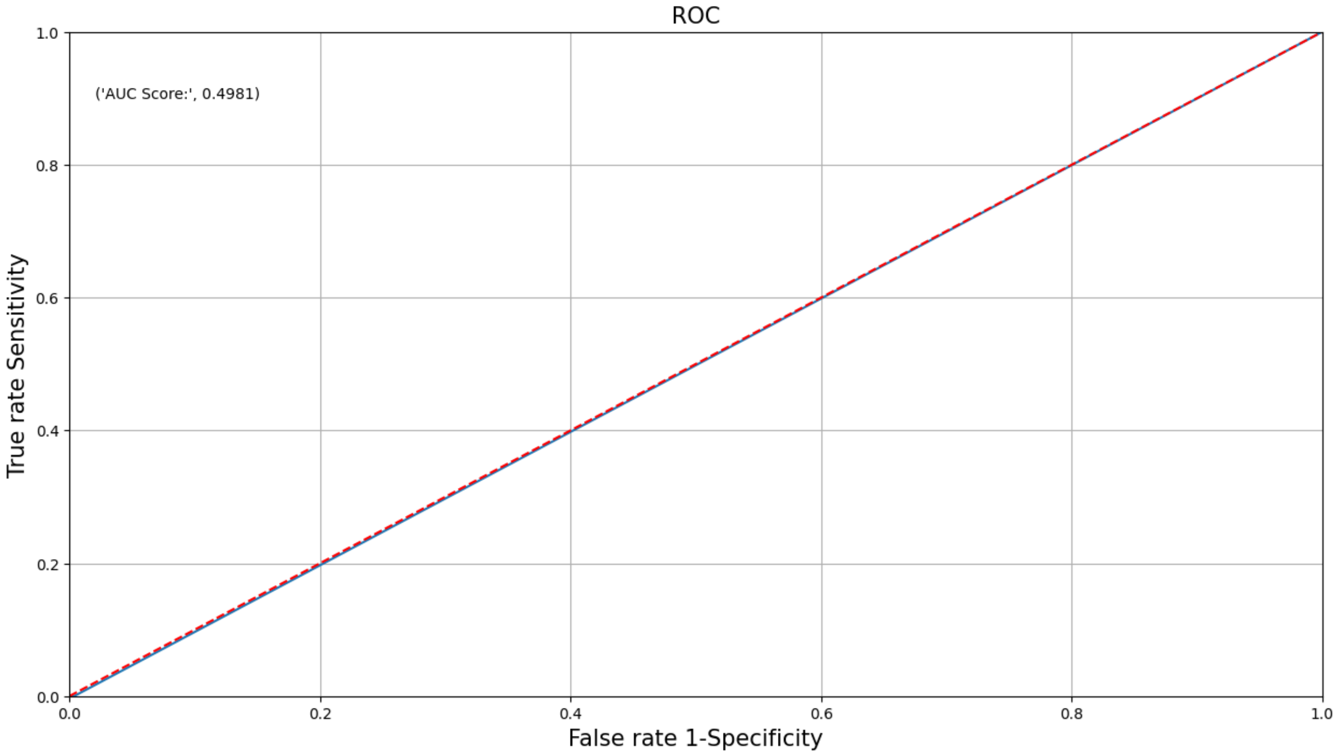
```
def ROC(y_test, y_pred):
  fpr, tpr, thresholds = roc_curve(y_test, y_pred)

  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_t
  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',
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=13, max_leaf_nodes=6, min_samples_split=10
                       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=13, max_leaf_nodes=6, min_samples_leaf=5,
                       min_samples_split=100, 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=13, max_leaf_nodes=6, random_state=10)
```

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

```
Confusion Matrix
============================================================
[[2757 2292]
 [   0  179]]

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

           0       1.00      0.55      0.71      5049
           1       0.07      1.00      0.14       179

    accuracy                           0.56      5228
   macro avg       0.54      0.77      0.42      5228
weighted avg       0.97      0.56      0.69      5228


AUC-ROC
============================================================
0.8188650664825492
```

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_job
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
============================================================
[[5024    0]
 [  54  150]]

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

           0       0.99      1.00      0.99      5024
           1       1.00      0.74      0.85       204

    accuracy                           0.99      5228
   macro avg       0.99      0.87      0.92      5228
weighted avg       0.99      0.99      0.99      5228


AUC-ROC
============================================================
0.9993599350568253
```

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, n_estimators=30)
```

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

```
Confusion Matrix
============================================================
[[4985   64]
 [  14  165]]

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

           0       1.00      0.99      0.99      5049
           1       0.72      0.92      0.81       179

    accuracy                           0.99      5228
   macro avg       0.86      0.95      0.90      5228
weighted avg       0.99      0.99      0.99      5228


AUC-ROC
============================================================
0.9964526412111033
```

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=11, min_samples_split=5)
```

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

```
Confusion Matrix
============================================================
[[4579  470]
 [   0  179]]

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

           0       1.00      0.91      0.95      5049
           1       0.28      1.00      0.43       179

    accuracy                           0.91      5228
   macro avg       0.64      0.95      0.69      5228
weighted avg       0.98      0.91      0.93      5228


AUC-ROC
============================================================
0.9900859841707689
```

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	Random Forest	actual	1.000000	0.735294	0.847458	0.999360

HoloViews Data distribution

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

```
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 3.2/3.2 MB 29.3 MB/s eta 0:00
```

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

```
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
@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

pn.Column(season_text, select_season, workingday_text, select_workingday, select
```

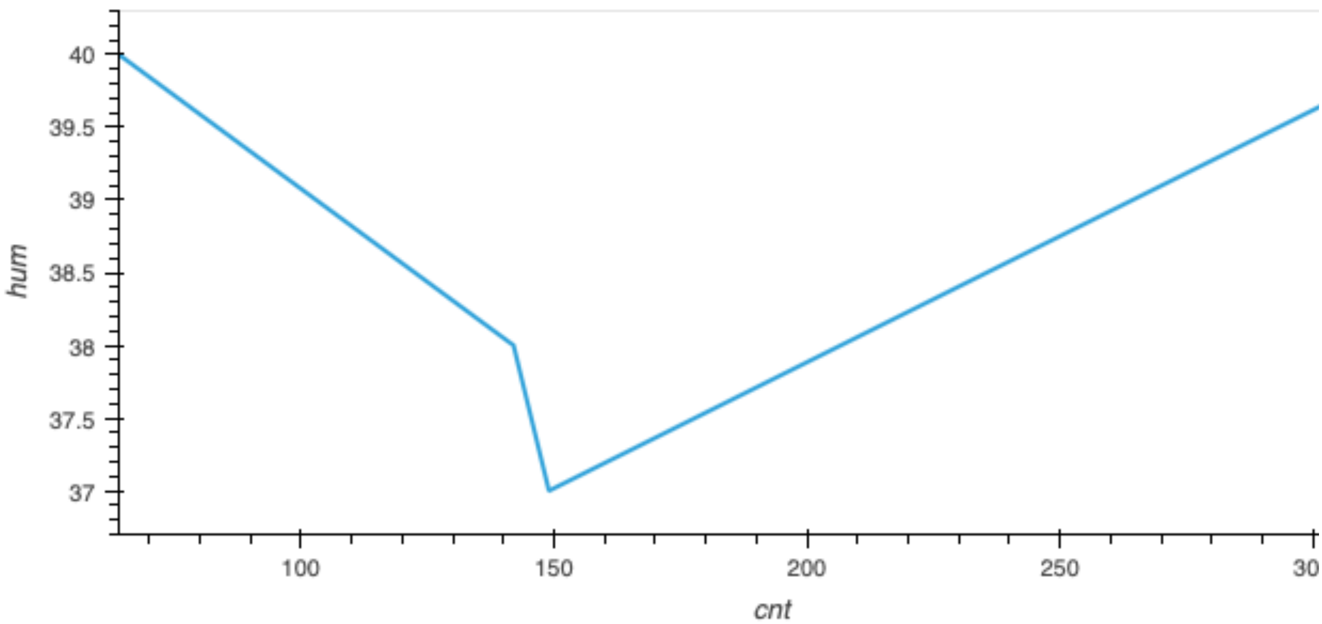
season:

Winter Summer Autumn Spring

workingday:

Yes No

temp: **-17**



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**.

```
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 
    return hv.HeatMap(conf_values, label='Confusion Matrix', kdims=['Predicted',
        xrotation=45, width=500, height=500, cmap='blues', tools=['hover'], inve
```

```
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_s
muller_classification(X_train, X_test, y_train, y_test)
```

```
Linear Regression
Classifier = Linear Regression, Score (test, accuracy) = 98.43,
MLP Regressor
Classifier = MLP Regressor, Score (test, accuracy) = 96.58,
RandomForest Regressor
Classifier = RandomForest Regressor, Score (test, accuracy) = 98.43,
Gradient Boosting Regressor
Classifier = Gradient Boosting Regressor, Score (test, accuracy) = 96.79,
KNeighbors Regressor
Classifier = KNeighbors Regressor, Score (test, accuracy) = 96.58,
Best --> Classifier = Linear Regression, Score (test, accuracy) = 98.43
```

	Classifier	MSE	MAE	RSquared	Test Accuracy	Recall	Precision
0	KNeighbors Regressor	0.030000	0.030000	-0.040000	96.576129	0.965761	0.932695
1	Gradient Boosting Regressor	0.030000	0.030000	0.030000	96.786534	0.967865	0.959400
2	RandomForest Regressor	0.020000	0.020000	0.530000	98.431523	0.984315	0.984566

```
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_t
  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= 50

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

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

Linear Regression
Classifier = Linear Regression, Score (test, accuracy) = 98.32,
MLP Regressor
Classifier = MLP Regressor, Score (test, accuracy) = 95.94,
RandomForest Regressor
Classifier = RandomForest Regressor, Score (test, accuracy) = 98.05,
Gradient Boosting Regressor
Classifier = Gradient Boosting Regressor, Score (test, accuracy) = 96.08,
KNeighbors Regressor
Classifier = KNeighbors Regressor, Score (test, accuracy) = 95.94,
Best --> Classifier = Linear Regression, Score (test, accuracy) = 98.32
Linear Regression
Classifier = Linear Regression, Score (test, accuracy) = 98.37,
MLP Regressor
Classifier = MLP Regressor, Score (test, accuracy) = 95.91,
RandomForest Regressor
Classifier = RandomForest Regressor, Score (test, accuracy) = 98.14,
Gradient Boosting Regressor
Classifier = Gradient Boosting Regressor, Score (test, accuracy) = 96.02,
KNeighbors Regressor
Classifier = KNeighbors Regressor, Score (test, accuracy) = 95.91,
Best --> Classifier = Linear Regression, Score (test, accuracy) = 98.37
Linear Regression
Classifier = Linear Regression, Score (test, accuracy) = 98.57,
MLP Regressor
Classifier = MLP Regressor, Score (test, accuracy) = 96.58,
RandomForest Regressor
Classifier = RandomForest Regressor, Score (test, accuracy) = 98.30,
Gradient Boosting Regressor
Classifier = Gradient Boosting Regressor, Score (test, accuracy) = 96.61,
KNeighbors Regressor
Classifier = KNeighbors Regressor, Score (test, accuracy) = 96.58,
Best --> Classifier = Linear Regression, Score (test, accuracy) = 98.57

Select Number of Samples:

SampleSize: **160**

Run Muller Loop

```
hv.extension('bokeh')
model_text = pn.widgets.StaticText(name='Model', value='')
select_model = pn.widgets.RadioBoxGroup( name='model', options=["Linear Regressi

@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 KN