PREDICTION OF RAIN TOMORROW IN AUSTRALIA

We will predict whether or not it will rain tomorrow by training a binary classification model on target RainTomorrow

Input: We have 23 features except target.

- Date
- Location
- MinTemp
- MaxTemp
- Rainfall
- WindGust
- WindDir
- WinSpeed
- Humidity
- Pressure
- Cloud
- Temperature
- RainToday
- ...

Target Class: RainTomorrow Yes(1) - No(0)

- 1 - tomorrow is rainy
- 0 - tomorrow isn't rainy

How many datasets we have?:

- Number of Instances : 142.193
- Target Class (Rain Tomorrow): 110316 No - 31877 Yes

Data Source:

- [Rain in Australia]

Via kodluyoruz

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GROUP MEMBERS:

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- Eda AYDIN
- Enes KÖSER

```
import warnings
warnings.filterwarnings("ignore")
```

DATA DROPPING

```
import pandas as pd
import numpy as np
import seaborn as sns
data = pd.read_csv("weatherAUS.csv")

def SplittingDate(df):
    df['Year'] = pd.DatetimeIndex(df['Date']).year
    df['Month'] = pd.DatetimeIndex(df['Date']).month
    df['Day'] = pd.DatetimeIndex(df['Date']).day
SplittingDate(data)
data=data.drop(columns=['Date','RISK_MM'])
data['RainTomorrow'] = data['RainTomorrow'].str.lower().replace({"yes":1,"no":0})
data['RainToday'] = data['RainToday'].str.lower().replace({"yes":1,"no":0})
```

```
data.describe(include=['O'])
```

	Location	WindGustDir	WindDir9am	WindDir3pm
count	142193	132863	132180	138415
unique	49	16	16	16
top	Canberra	W	N	SE
freq	3418	9780	11393	10663

```
data.describe()
```

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGus
count	141556.000000	141871.000000	140787.000000	81350.000000	74377.000000	132923.
mean	12.186400	23.226784	2.349974	5.469824	7.624853	39.
std	6.403283	7.117618	8.465173	4.188537	3.781525	13.
min	-8.500000	-4.800000	0.000000	0.000000	0.000000	6.
25%	7.600000	17.900000	0.000000	2.600000	4.900000	31.
50%	12.000000	22.600000	0.000000	4.800000	8.500000	39.
75%	16.800000	28.200000	0.800000	7.400000	10.600000	48.
max	33.900000	48.100000	371.000000	145.000000	14.500000	135.

```
def MissingUniqueStatistics(df):
    import pandas as pd
    import time
    print("MissingUniqueStatistics process has began:\n")
    start_time = time.time()

    entry_lenght_list = []
    variable_name_list = []
    total_entry_list = []
    missing_value_number_list = []
    missing_value_ratio_list = []
    data_type_list = []
    unique_values_list = []
    number_of_unique_values_list = []

    for col in df.columns:

        entry_lenght = df.shape[0]
        variable_name = str(col)
        missing_value_number = df[col].isnull().sum()
        total_entry = entry_lenght - missing_value_number
        missing_value_ratio = round(float(missing_value_number/entry_lenght),4)
        data_type = df[col].dtype

        number_of_unique_values = len(df[col].unique())
        unique_values = df[col].unique()

        entry_lenght_list.append(entry_lenght)
        variable_name_list.append(variable_name)
        total_entry_list.append(total_entry)
        missing_value_number_list.append(missing_value_number)
        missing_value_ratio_list.append(missing_value_ratio)
        data_type_list.append(data_type)
        unique_values_list.append(unique_values)
        number_of_unique_values_list.append(number_of_unique_values)

    data_info_df = pd.DataFrame({'Variable': variable_name_list, '#_Total_Entry':total_ent
                                 '#_Missing_Value': missing_value_number_list,'%_Missing_V
                                 'Data_Type': data_type_list, 'Unique_Values': unique_valu
```

```
                                   '#_Unique_Values':number_of_unique_values_list})

    print('MissingUniqueStatistics process has been completed!')
    print("--- in %s minutes ---" % ((time.time() - start_time)/60))

    return data_info_df.sort_values(by='%_Missing_Value', ascending=False)


data_info = MissingUniqueStatistics(data)
data_info['Variable_Structure']=["Continuous","Continuous","Ordinal","Ordinal","Continuous
numerical_columns = list(data_info.loc[(data_info.loc[:,"Variable_Structure"]=="Continuous
categorical_columns = list(set(data_info.loc[(data_info.Variable_Structure=="Nominal") | (
```

```
MissingUniqueStatistics process has began:

MissingUniqueStatistics process has been completed!
--- in 0.0029558698336283337 minutes ---
```

```
data_info
```

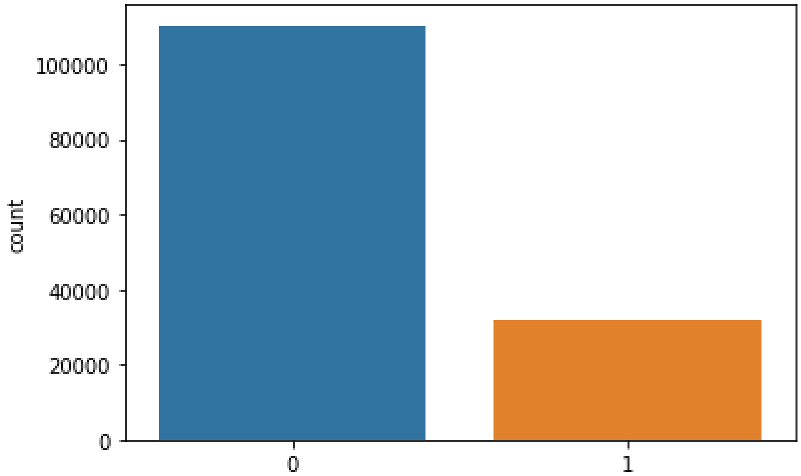
	Variable	#_Total_Entry	#_Missing_Value	%_Missing_Value	Data_Type	Uni
5	Sunshine	74377	67816	0.4769	float64	[n 1
4	Evaporation	81350	60843	0.4279	float64	[n 1
17	Cloud3pm	85099	57094	0.4015	float64	[na 1.
16	Cloud9am	88536	53657	0.3774	float64	[8.(0.
14	Pressure9am	128179	14014	0.0986	float64	[1 1 1
15	Pressure3pm	128212	13981	0.0983	float64	[1 1 1
8	WindDir9am	132180	10013	0.0704	object	EN
6	WindGustDir	132863	9330	0.0656	object	[V NE, SW
7	WindGustSpeed	132923	9270	0.0652	float64	[4 4
9	WindDir3pm	138415	3778	0.0266	object	[NV EN
13	Humidity3pm	138583	3610	0.0254	float64	[2 1
19	Temp3pm	139467	2726	0.0192	float64	[2 2
11	WindSpeed3pm	139563	2630	0.0185	float64	[2
12	Humidity9am	140419	1774	0.0125	float64	[7 4

3	Rainfall	140787	1406	0.0099	float64	[0. 1.4
20	RainToday	140787	1406	0.0099	float64	
10	WindSpeed9am	140845	1348	0.0095	float64	[
18	Temp9am	141289	904	0.0064	float64	[1 1
1	MinTemp	141556	637	0.0045	float64	[
2	MaxTemp	141871	322	0.0023	float64	[2 2
22	Year	142193	0	0.0000	int64	
23	Month	142193	0	0.0000	int64	[12
0	Location	142193	0	0.0000	object	B
21	RainTomorrow	142193	0	0.0000	int64	
24	Day	142193	0	0.0000	int64	[1

DATA SPLITTING (TRAIN & TEST)

```
import seaborn as sns
target = data['RainTomorrow']
sns.countplot(data['RainTomorrow'])
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f5b5e91fac8>




```
# Getting the count and percentage column by using target column

counts = data.RainTomorrow.value_counts()
percentage = data.RainTomorrow.value_counts(normalize=True).mul(100).round(1).astype(str)
pd.DataFrame({'Counts':counts,'Percentage': percentage})
```

	Counts	Percentage
0	110316	77.6%
1	31877	22.4%

```
from sklearn.model_selection import train_test_split
import pandas as pd
y = data.loc[:,'RainTomorrow']
y_dropped = data.drop('RainTomorrow', axis=1)
X = y_dropped.loc[:,:]

for c in X.columns:
    col_type= X[c].dtype
    if col_type == "object" or col_type.name=="category":
        X[c] = X[c].astype("category")

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, random_state=42)
print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
```

```
(99535, 24) (42658, 24) (99535,) (42658,)
```

FEATURE IMPORTANCE - LGBM

FEATURE IMPORTANCE WITHOUT GAIN

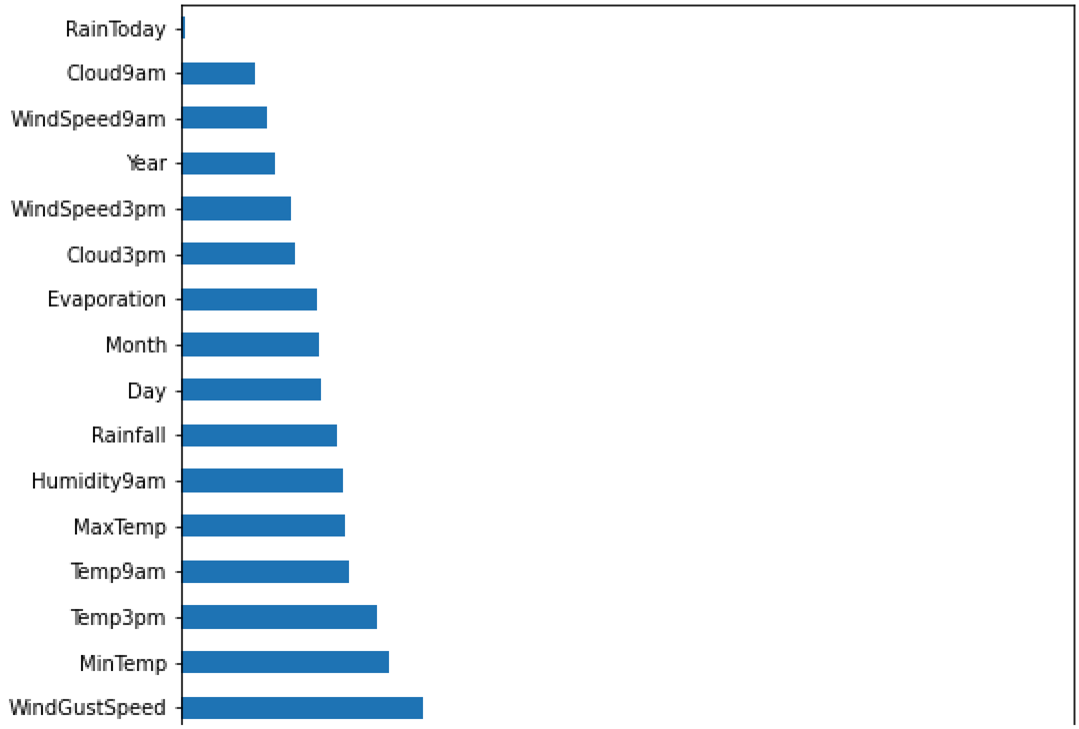
Without Gain refers the importance of the features according to the branching of the tree.

```
import lightgbm as lgb


fit_params={"early_stopping_rounds":10,
            "eval_metric" : 'auc',
            "eval_set" : [(X_test,y_test)],
            'eval_names': ['valid'],
            'verbose': 100,
            'feature_name': 'auto', # that's actually the default
            'categorical_feature': 'auto' # that's actually the default
           }

#n_estimators is set to a "large value". The actual number of trees build will depend on e
clf = lgb.LGBMClassifier(num_leaves= 15, max_depth=-1,
                         random_state=314,
                         silent=True,
                         metric='None',
                         n_jobs=4,
                         n_estimators=1000,
                         colsample_bytree=0.9,
                         subsample=0.9,
                         learning_rate=0.1)

#force larger number of max trees and smaller learning rate
clf.fit(X_train, y_train, **fit_params)
```

```
Training until validation scores don't improve for 10 rounds.
[100]   valid's auc: 0.892054
[200]   valid's auc: 0.89658
[300]   valid's auc: 0.898335
[400]   valid's auc: 0.899656
Early stopping, best iteration is:
[462]   valid's auc: 0.900184
LGBMClassifier(boosting_type='gbdt', class_weight=None, colsample_bytree=0.9,
               importance_type='split', learning_rate=0.1, max_depth=-1,
               metric='None', min_child_samples=20, min_child_weight=0.001,
               min_split_gain=0.0, n_estimators=1000, n_jobs=4, num_leaves=15,
               objective=None, random_state=314, reg_alpha=0.0, reg_lambda=0.0,
               silent=True, subsample=0.9, subsample_for_bin=200000,
               subsample_freq=0)
```

```
feat_imp = pd.Series(clf.feature_importances_, index=X.columns)
feat_imp.nlargest(30).plot(kind='barh', figsize=(8,10))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f5b3e1edac8>
```



FEATURE IMPORTANCE WITH GAIN

With Gain refers the importance of the features according to the gain in each branch

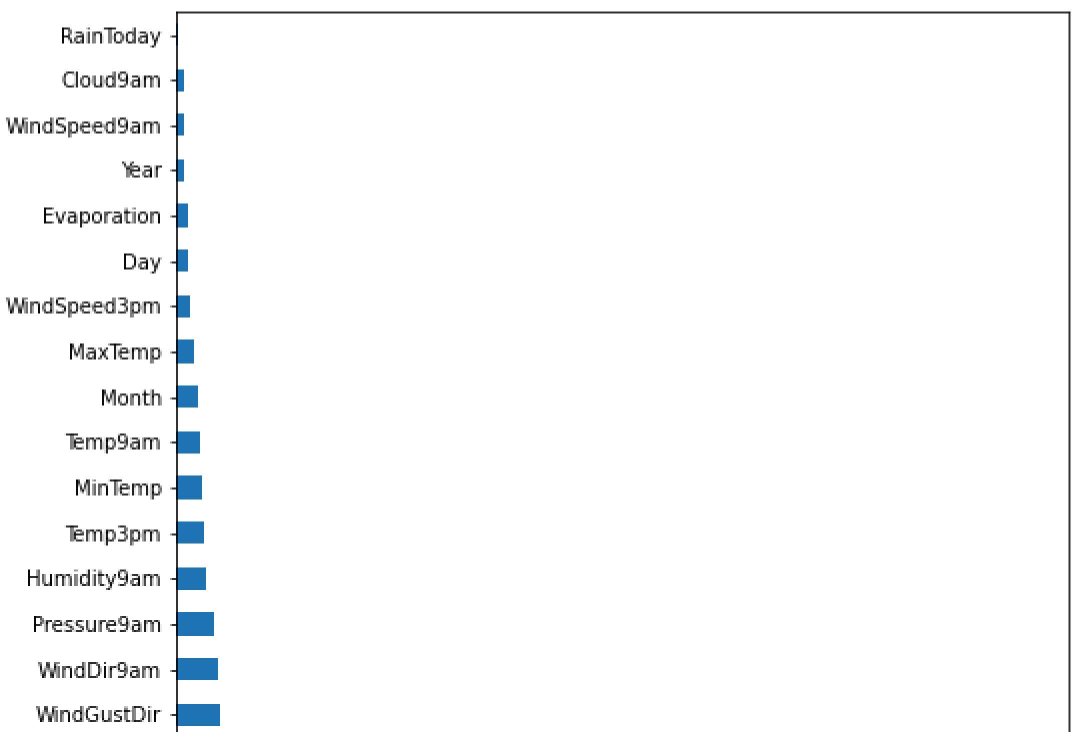
```
class LGBMClassifier_GainFE(lgb.LGBMClassifier):
    @property
    # We used @property decorator to give "special" functionality such as deleters to cert
    def feature_importances_(self):
        if self._n_features is None:
            raise LGBMNotFittedError('No feature_importances found. Need to call fit befor
        return self.booster_.feature_importance(importance_type='gain')

clf2 = LGBMClassifier_GainFE(num_leaves= 15, max_depth=-1,
                         random_state=314,
                         silent=True,
                         metric='None',
                         n_jobs=4,
                         n_estimators=1000,
                         colsample_bytree=0.9,
```

```
                             subsample=0.9,
                             learning_rate=0.1)

clf2.fit(X_train, y_train, **fit_params)
```

```
Training until validation scores don't improve for 10 rounds.
[100]   valid's auc: 0.892054
[200]   valid's auc: 0.89658
[300]   valid's auc: 0.898335
[400]   valid's auc: 0.899656
Early stopping, best iteration is:
[462]   valid's auc: 0.900184
LGBMClassifier_GainFE(boosting_type='gbdt', class_weight=None,
                      colsample_bytree=0.9, importance_type='split',
                      learning_rate=0.1, max_depth=-1, metric='None',
                      min_child_samples=20, min_child_weight=0.001,
                      min_split_gain=0.0, n_estimators=1000, n_jobs=4,
                      num_leaves=15, objective=None, random_state=314,
                      reg_alpha=0.0, reg_lambda=0.0, silent=True,
subsample=0.9,
                      subsample_for_bin=200000, subsample_freq=0)
```

```
feat_imp = pd.Series(clf2.feature_importances_, index=X.columns)
feat_imp.nlargest(30).plot(kind='barh', figsize=(8,10))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f5b3e0fc780>
```

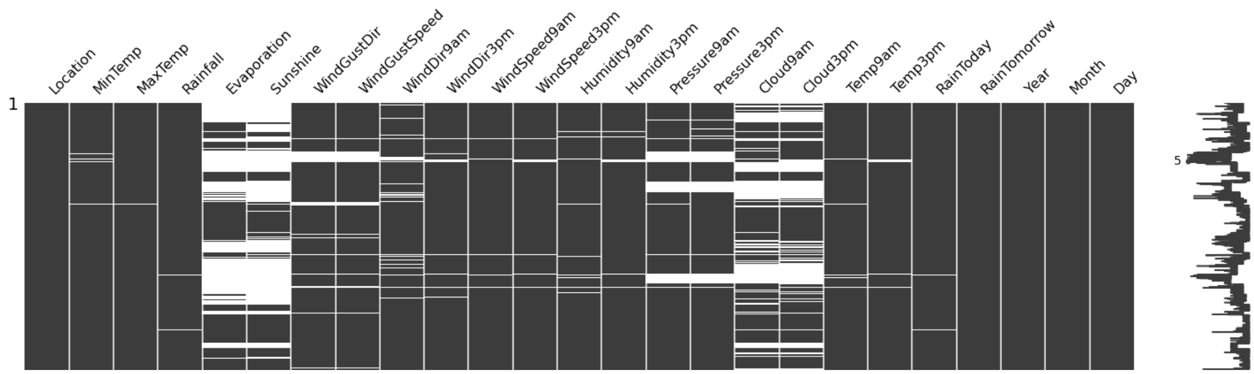


```
for c in X_train.columns:
    col_type= X_train[c].dtype
    if col_type.name=="category":
        X_train[c] = X_train[c].astype("object")
```

VISUALIZATION OF MISSING DATA

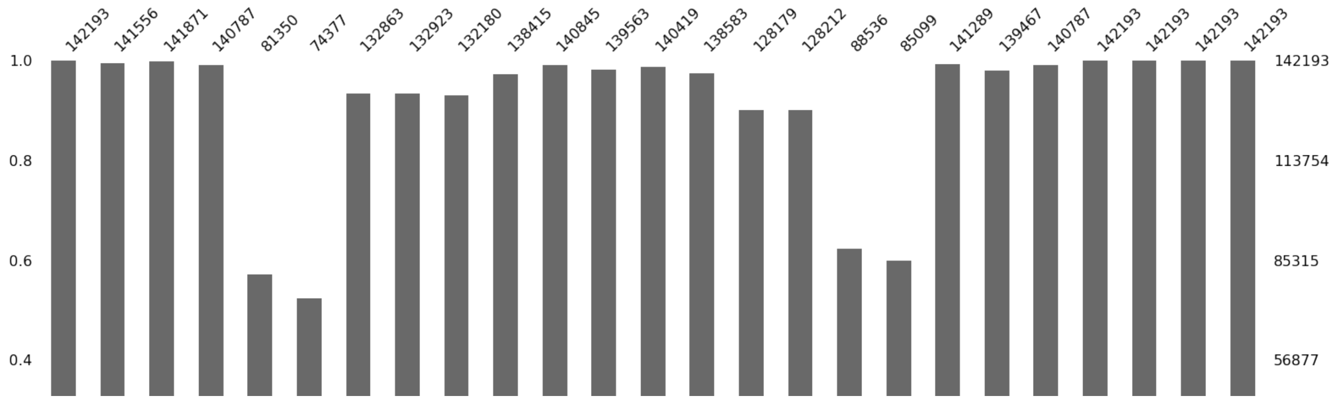
```
import missingno as msno
msno.matrix(data)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f5b3dfb9e48>
```




```
msno.bar(data)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f5b3d74c7b8>
```



OUTLIER DETECTION - DATA VISUALIZATION

DETERMINATION OF QUANTILE FOR EACH COLUMN

```
sparse_columns2=[]
for col in numerical_columns:
  if (X_train[col].mode()[0]==X_train[col].quantile(0.01)==X_train[col].quantile(0.25)):
    sparse_columns2.append(col)

sparse_columns=[]
for col in numerical_columns:
    if (X_train[col].mode()[0]==X_train[col].quantile(0.99)==X_train[col].quantile(0.75)):
        sparse_columns.append(col)
len(sparse_columns)
```

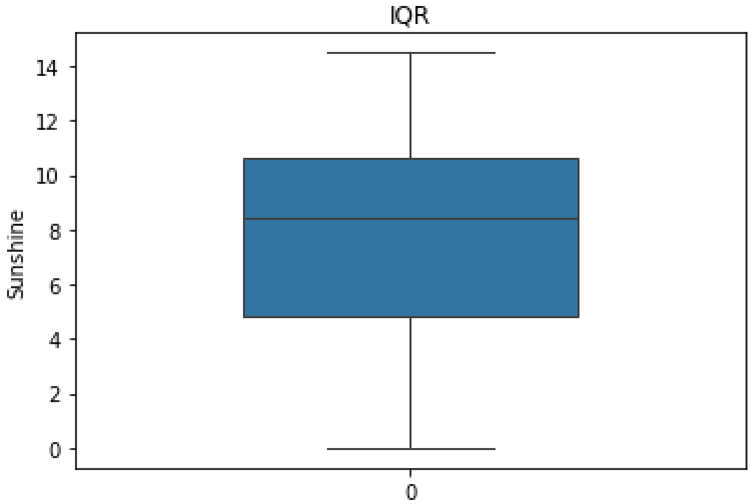
```
0
```

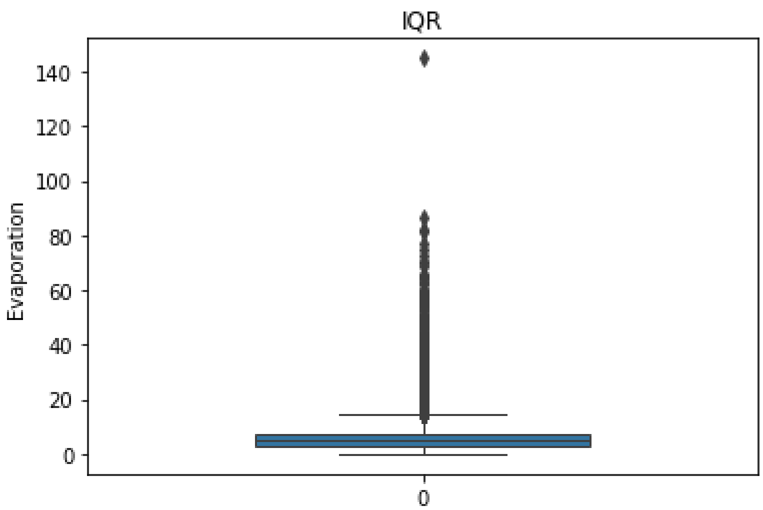
```
left_skewed_columns = []
for col in numerical_columns:
  if X_train.loc[X_train[col]!=X_train[col].mode()[0],col].median() < -1:
    left_skewed_columns.append(col)
left_skewed_columns
```

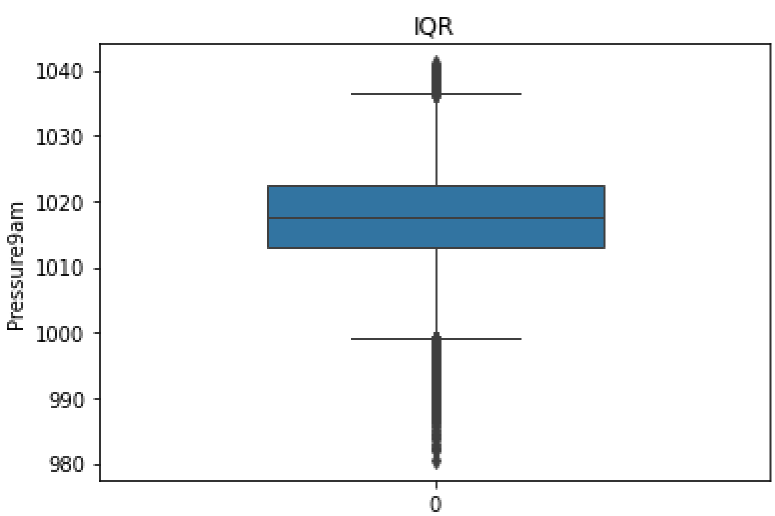
```
[]
```

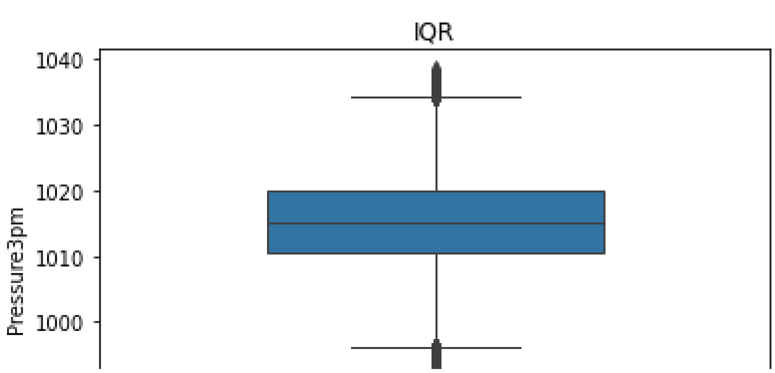
VISUALIZATION OF OUTLIERS FOR EACH COLUMN

```
import seaborn as sns
%matplotlib inline
for col in numerical_columns:
  sns.boxplot(data = [X_train[col]], linewidth = 1, width = 0.5)
  plt.ylabel(col)
  plt.title("IQR")
  plt.show()
```


IQR
Sunshine
0


IQR
Evaporation
0


IQR
Pressure9am
0

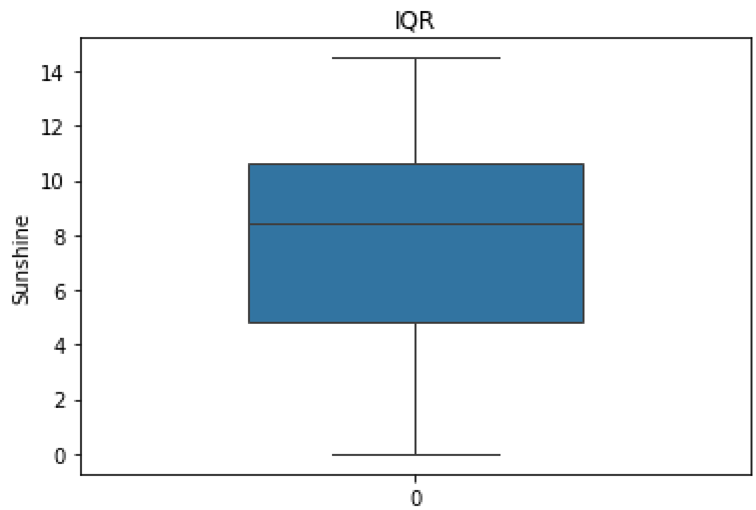

IQR
Pressure3pm

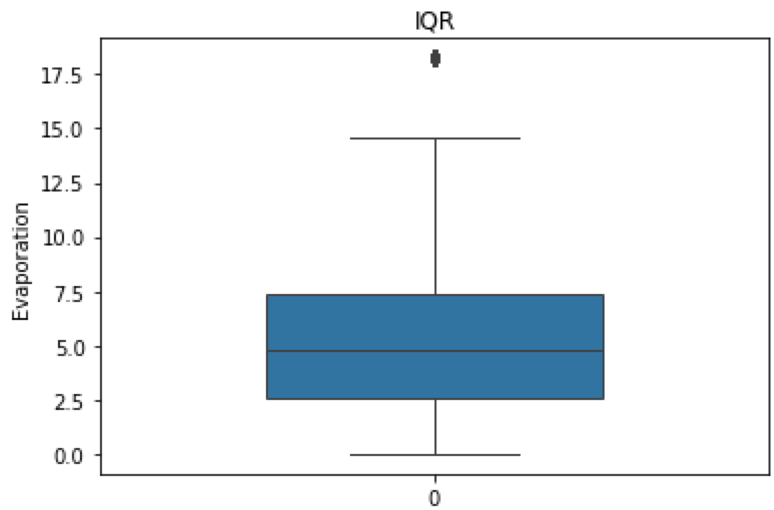
DETERMINATION LOWER AND UPPER BOUND FOR EACH COLUMN

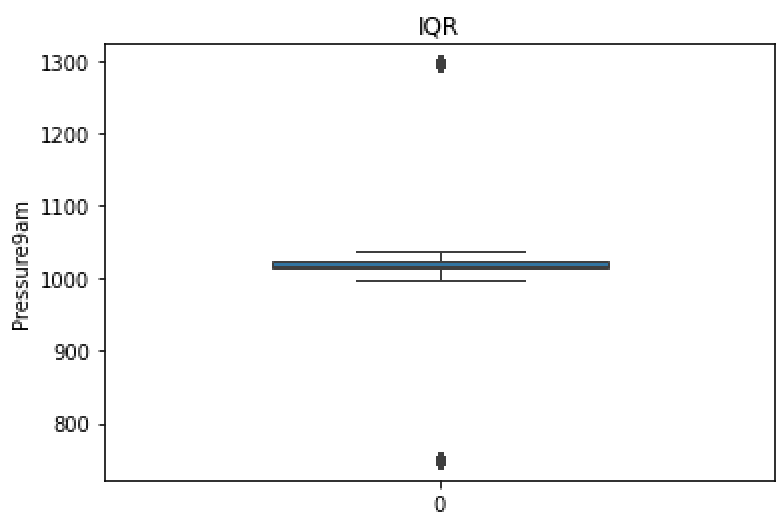
```
Q1 = X_train.quantile(0.25)
Q3 = X_train.quantile(0.75)
IQR = Q3 - Q1
```

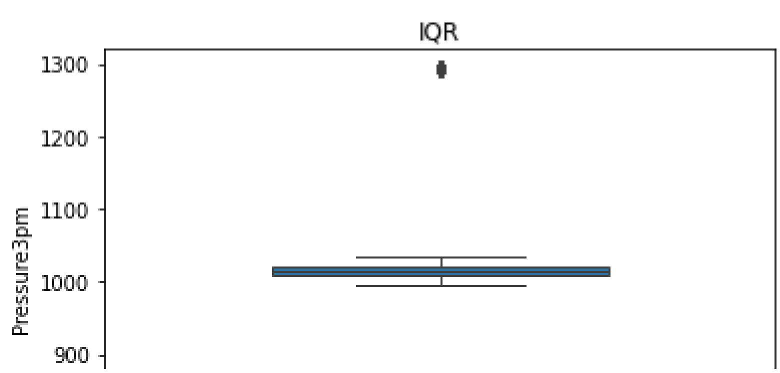
```
for col in numerical_columns:
  if col in sparse_columns:
    nonsparse_data = pd.DataFrame(X_train[X_train[col] !=X_train[col].mode()[0]][col])
    if nonsparse_data[col].quantile(0.25) < X_train[col].mode()[0]: #Unexpected case
      lower_bound_sparse = nonsparse_data[col].quantile(0.25)
    else:
      lower_bound_sparse = X_train[col].mode()[0]

    if nonsparse_data[col].quantile(0.75) < X_train[col].mode()[0]: #Unexpected case
      upper_bound_sparse = X_train[col].mode()[0]
    else:
      upper_bound_sparse = nonsparse_data[col].quantile(0.75)

    number_of_outliers = len(X_train[(X_train[col] < lower_bound_sparse) | (X_train[col] >

    if number_of_outliers > 0:

      X_train.loc[X_train[col] < lower_bound_sparse,col] = lower_bound_sparse*0.75 #--> MA

      X_train.loc[X_train[col] > upper_bound_sparse,col] = upper_bound_sparse*1.25 # --> M
  else:
    lower_bound = X_train[col].quantile(0.25) - 1.5*IQR[col]
    upper_bound = X_train[col].quantile(0.75) + 1.5*IQR[col]

    X_train[col] = np.where(X_train[col] > upper_bound, 1.25*upper_bound, X_train[col])
    X_train[col] = np.where(X_train[col] < lower_bound, 0.75*lower_bound, X_train[col])

    X_test[col] = np.where(X_test[col] > upper_bound, 1.25*upper_bound, X_test[col])
    X_test[col] = np.where(X_test[col] < lower_bound, 0.75*lower_bound, X_test[col])

X_train_outlier_cleaned = X_train.copy()
X_test_outlier_cleaned = X_test.copy()
```

```
for col in numerical_columns:
  sns.boxplot(data = [X_train_outlier_cleaned[col]], linewidth = 1, width = 0.5)
  plt.ylabel(col)
  plt.title("IQR")
  plt.show()
```


IQR
Sunshine
0
2
4
6
8
10
12
14
0

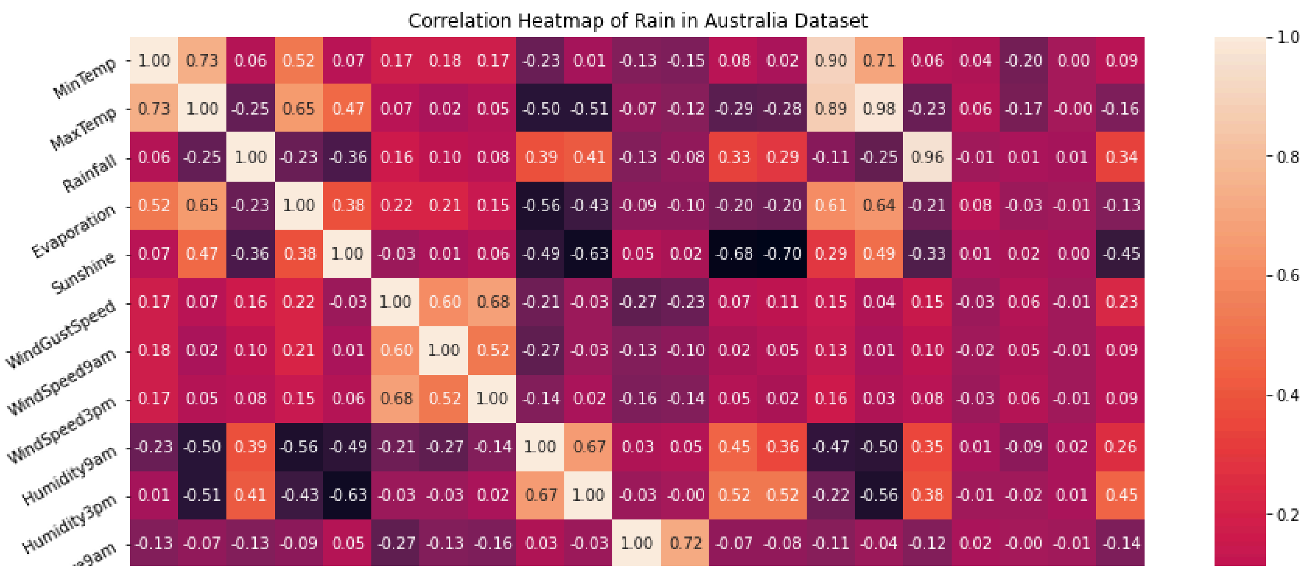

IQR
Evaporation
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
0


IQR
Pressure9am
800
900
1000
1100
1200
1300
0


IQR
Pressure3pm
900
1000
1100
1200
1300

CORRELATION HEATMAP

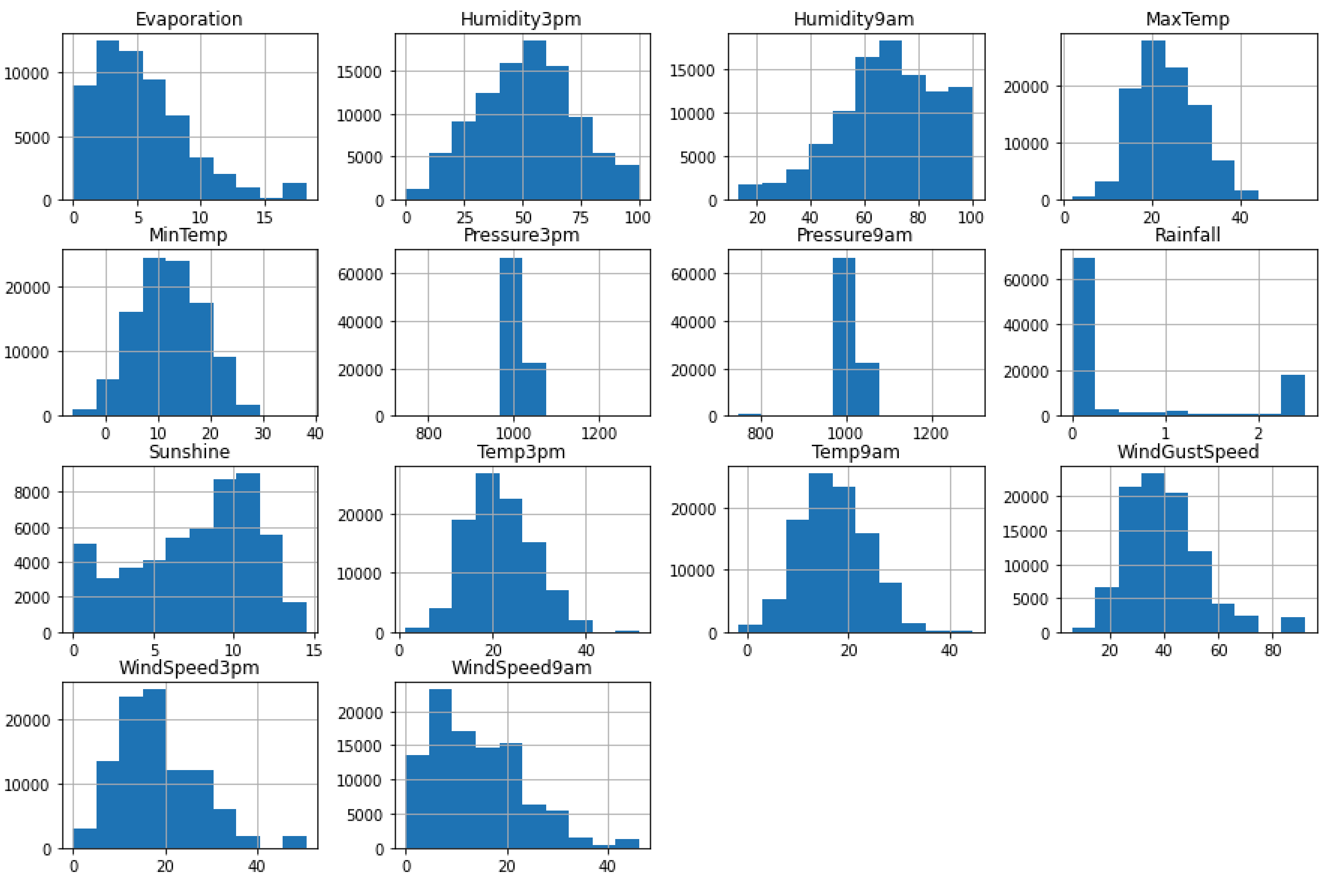
```
correlation = pd.concat([X_train_outlier_cleaned,y_train],axis=1).corr()
plt.figure(figsize=(16,12))
plt.title('Correlation Heatmap of Rain in Australia Dataset')
ax = sns.heatmap(correlation, square=True, annot=True, fmt='.2f', linecolor='white')
ax.set_xticklabels(ax.get_xticklabels(), rotation=90)
ax.set_yticklabels(ax.get_yticklabels(), rotation=30)
plt.show()
```



PLOTTING CATEGORICAL & NUMERICAL DATA

```
import matplotlib.pyplot as plt

#plot histogram to check distribution for numerical columns

X_train_outlier_cleaned[numerical_columns].hist(figsize=(15,10))
```

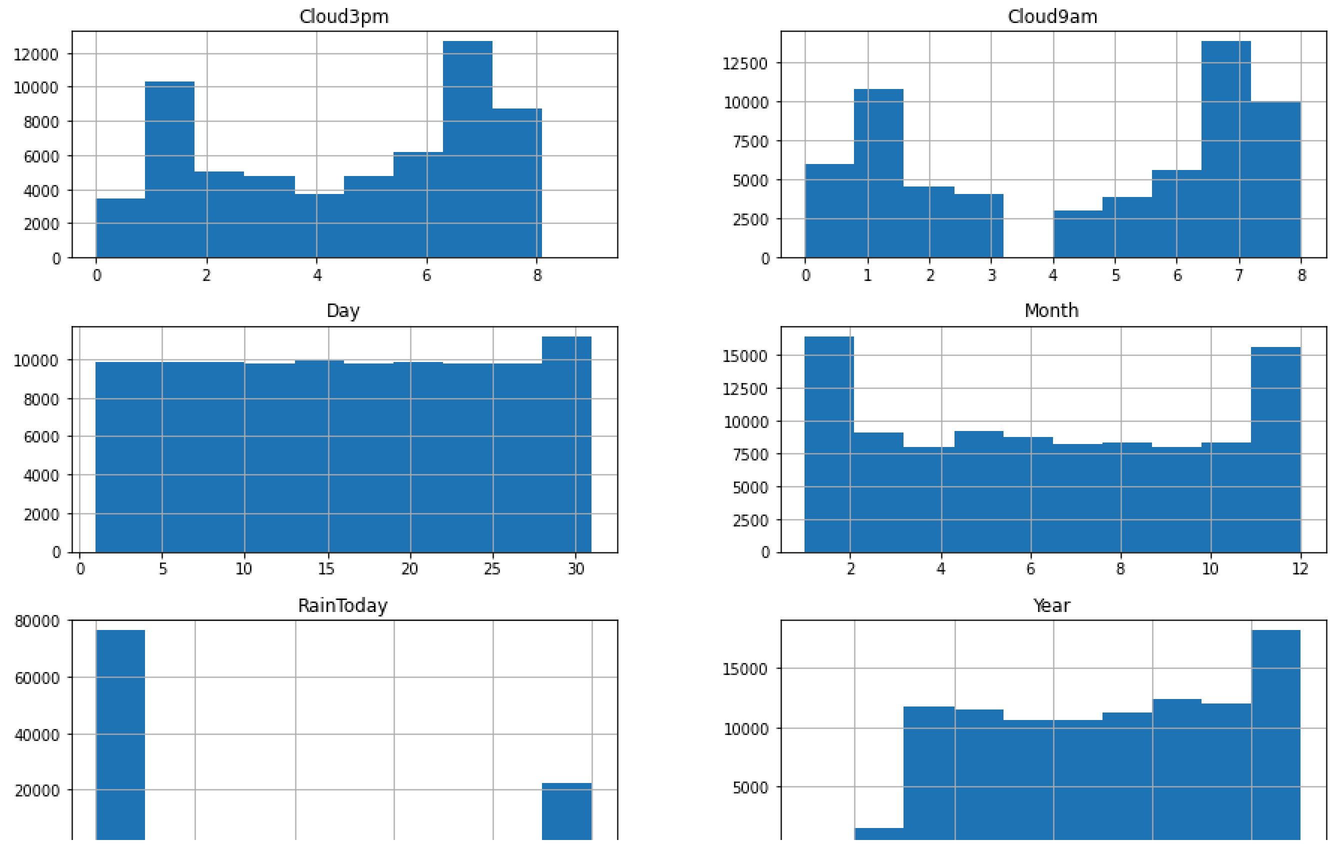
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f5b3d677c18>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f5b3ffbf7f0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f5b3d741ba8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f5b3d9bc908>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7f5b3dd68400>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f5b3e713128>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f5b3d59e4e0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f5b3d279710>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7f5b3d279780>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f5b3d8afc18>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f5b3de4ee80>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f5b3d6094e0>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7f5b3d9e2860>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f5b3dbebbe0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f5b3d511f60>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f5b3dd66320>]],
      dtype=object)
```




```
import matplotlib.pyplot as plt

#plot histogram to check distribution for categorical columns
```

```
X_train_outlier_cleaned[categorical_columns].hist(figsize=(15,10))
```

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f5b3de34940>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f5b3de2a668>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7f5b3ddc79e8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f5b3de82d68>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7f5b3d442128>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f5b3d4744a8>]],
      dtype=object)
```



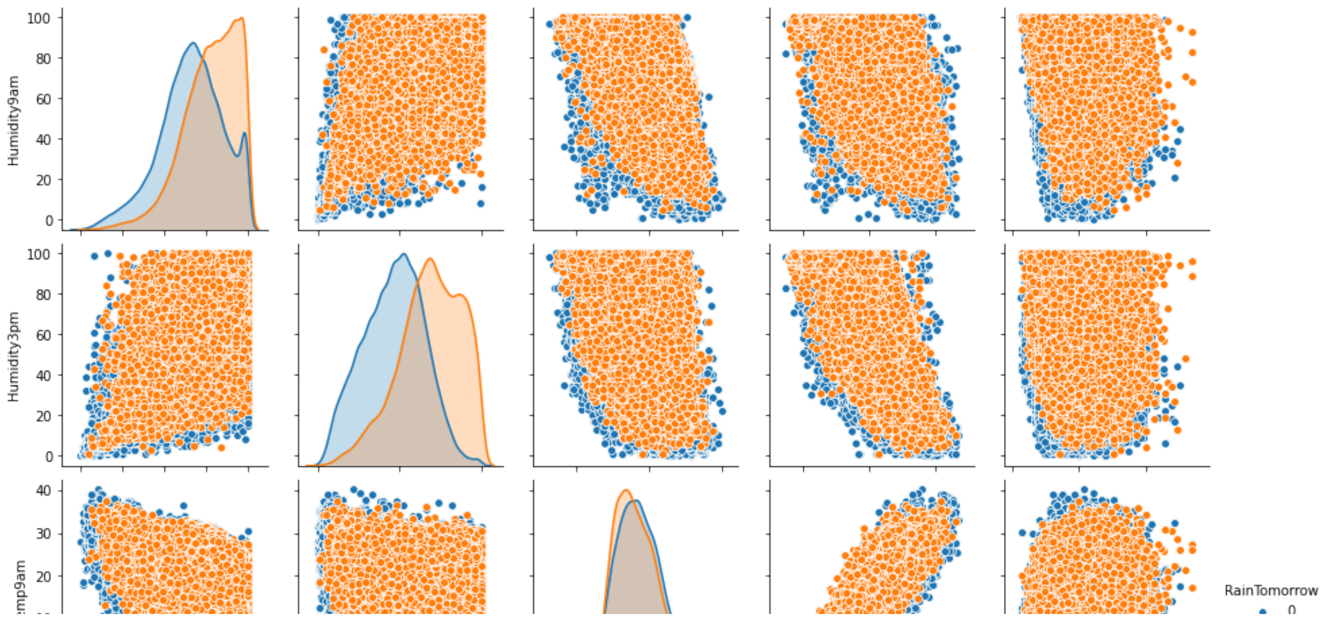
The blue points in here show that the weather isn't rainy for today.

The orange points in here show that the weather is rainy for today.

In terms of feature importance, we chose that these features affect the target too much.

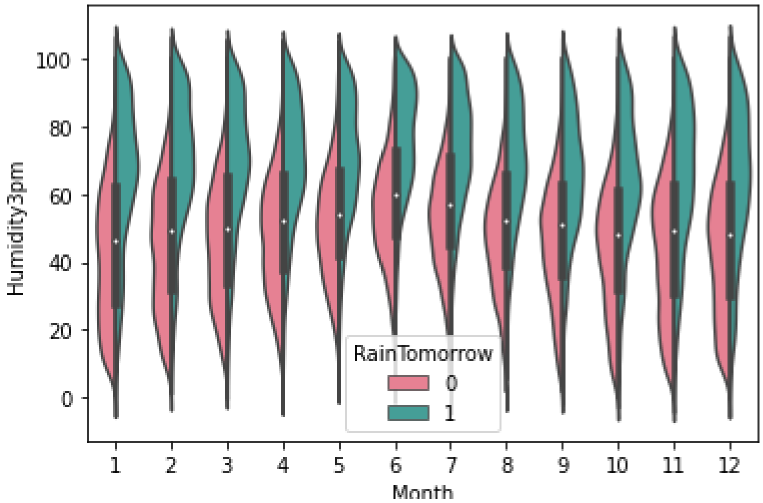
```
sns.pairplot(data,hue = "RainTomorrow", vars= ['Humidity9am', 'Humidity3pm','Temp9am', 'Te
```

```
<seaborn.axisgrid.PairGrid at 0x7f5b3dda84e0>
```



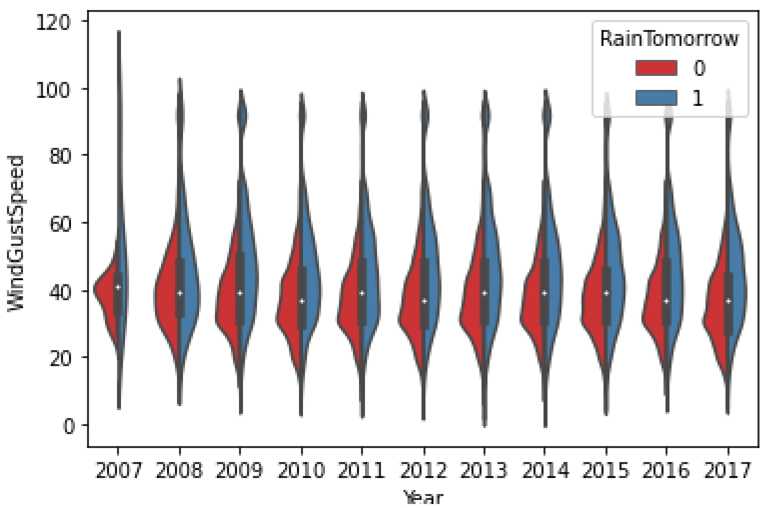
```
sns.violinplot(x="Month", y="Humidity3pm",hue = target, data = X_train_outlier_cleaned, pa
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f5b3c9dc7f0>



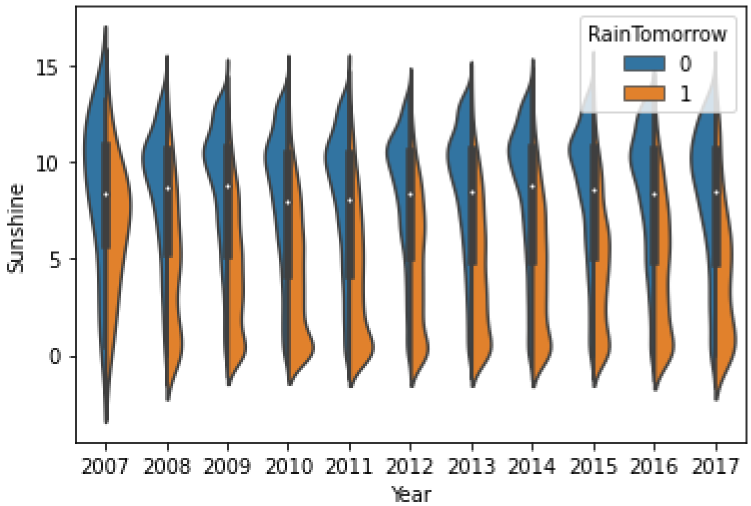

```
sns.violinplot(x="Year", y="WindGustSpeed",hue = target, data = X_train_outlier_cleaned, p
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f5b3c653be0>



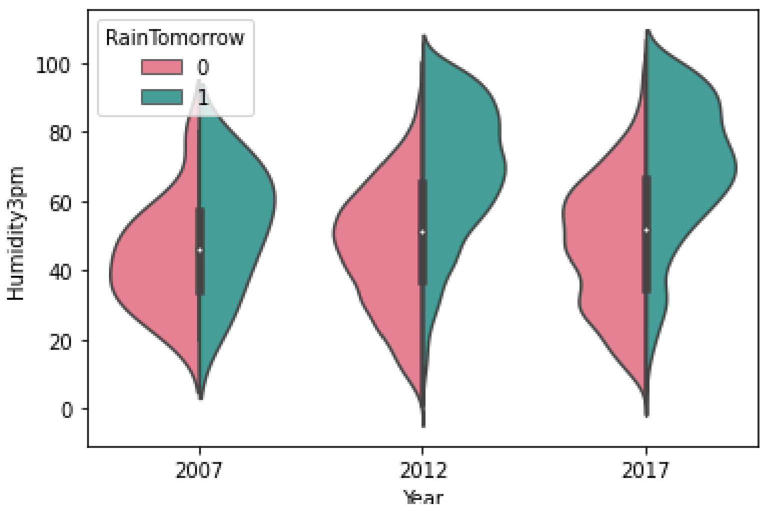

```
sns.violinplot(x="Year", y="Sunshine",hue = target, data = X_train_outlier_cleaned,split="
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f5b3c550128>



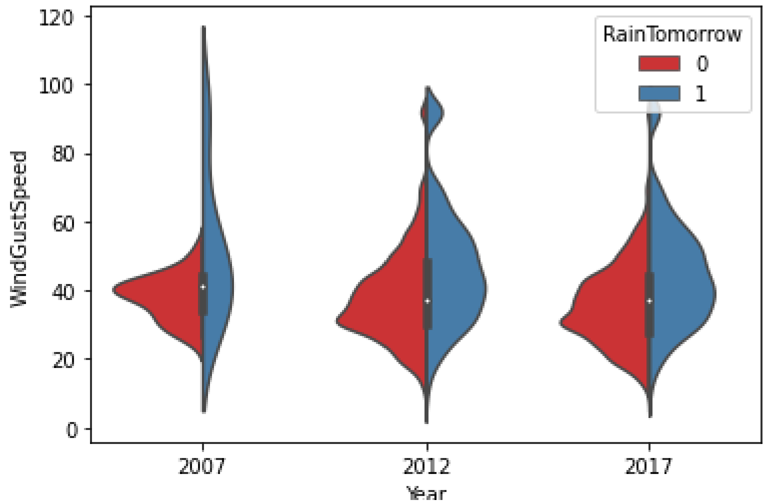

```
# Humidity3pm difference between 2007,2012, 2017
sns.violinplot(x="Year" , y="Humidity3pm", hue= target, data = X_train_outlier_cleaned, or
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f5b3c543278>



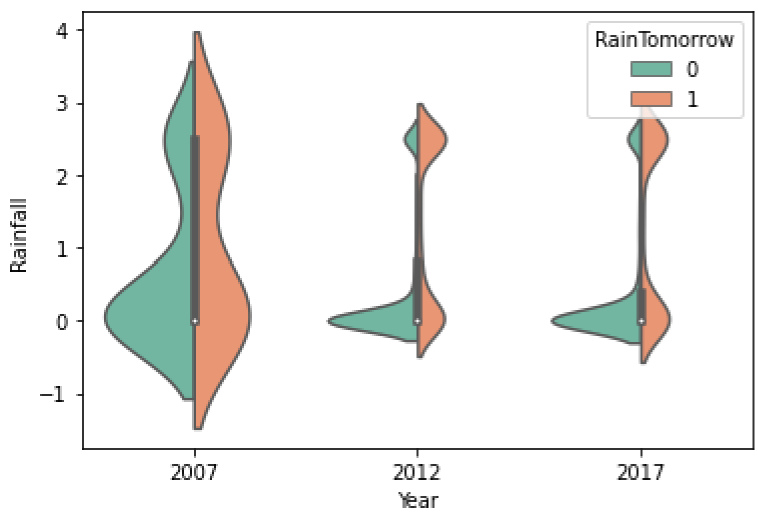

```
# WindGustSpeed difference between 2007,2012, 2017
sns.violinplot(x="Year" , y="WindGustSpeed", hue= target, data = X_train_outlier_cleaned, 
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f5b3c3c6860>



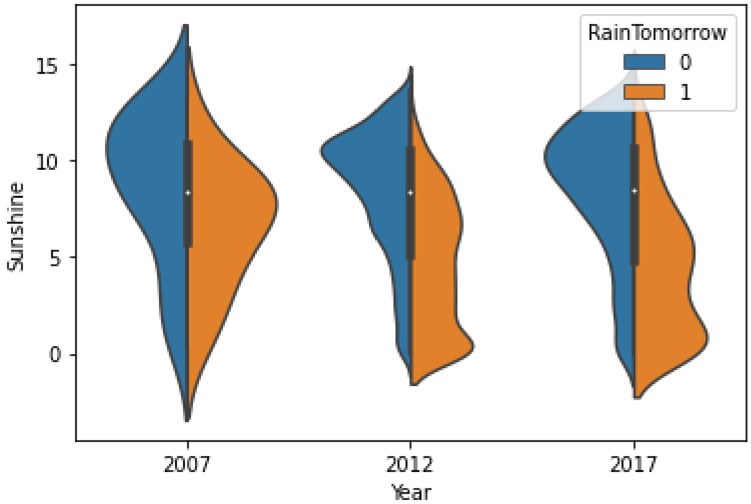

```
# Rainfall difference between 2007,2012, 2017
sns.violinplot(x="Year" , y="Rainfall", hue= target, data = X_train_outlier_cleaned, order
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f5b3c3e4518>




```
# Sunshine difference between 2007,2012, 2017
sns.violinplot(x="Year" , y="Sunshine", hue= target, data = X_train_outlier_cleaned, order
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f5b3c28e2e8>
```



COMPARISON ACCURACY OF DIFFERENT CLASSIFICATION ALGORITHMS WITH SIMPLE IMPUTATION

```
X_train1 = X_train_outlier_cleaned.copy()
X_test1 = X_test_outlier_cleaned.copy()


for col in numerical_columns:
  X_train1[col].fillna(value=(X_train[col].mean()),inplace=True)
  X_test1[col].fillna(value=(X_train[col].mean()),inplace=True)
for col in categorical_columns:
  X_train1[col].fillna(value=(X_train[col].value_counts().idxmax()),inplace=True)
  X_test1[col].fillna(value=(X_train[col].value_counts().idxmax()),inplace=True)


variable_list = ['Location','Month','WindGustDir','WindDir9am','WindDir3pm','Cloud9am','Cl
target_name = 'RainTomorrow'

from sklearn.model_selection import KFold
X_train1 = pd.concat([X_train1,y_train],axis=1).copy()
kf = KFold(n_splits=3, shuffle=False, random_state=2020)
encoded_name_dict = {}
for col in variable_list:
  col_mean_name = str(col) + '_' + 'Kfold_Mean_Enc'
  encoded_name_dict[col] = col_mean_name
  X_train1[col_mean_name] = np.nan
  X_test1[col_mean_name] = np.nan
  for tr_ind, val_ind in kf.split(X_train1):
    X_tr, X_val = X_train1.iloc[tr_ind], X_train1.iloc[val_ind]
    X_train1.loc[X_train1.index[val_ind], col_mean_name] = X_val[col].map(X_tr.groupby(col
X_train1['Cloud3pm_Kfold_Mean_Enc'].fillna(value=(X_train1['Cloud3pm_Kfold_Mean_Enc'].mean
# X_train.loc[:,col_mean_name] = X_train[col].map(X_train.groupby(col)[col_mean_name].mean

for i in encoded_name_dict:
```

```
  mean = 0
  mean =  X_train1[[i,encoded_name_dict[i]]].groupby(i).mean().reset_index()
  mean_dict = {}
  for index, row in mean.iterrows():
    mean_dict[row[i]] = row[encoded_name_dict[i]]
  X_test1[encoded_name_dict[i]] = X_test1[i]
  X_test1 = X_test1.replace({encoded_name_dict[i]:mean_dict})

X_train1 = X_train1.drop(columns=[target_name])
X_train1 = X_train1.drop(columns=variable_list)
X_test1 = X_test1.drop(columns=variable_list)


from sklearn.preprocessing import StandardScaler
for col in X_train1.columns:
  scaler_fitted = StandardScaler().fit(np.array(X_train1[col]).reshape(-1,1))
  X_train1[col] = scaler_fitted.transform(np.array(X_train1[col]).reshape(-1,1))
  X_test1[col] = scaler_fitted.transform(np.array(X_test1[col]).reshape(-1,1))


from sklearn.ensemble import RandomForestClassifier
from lightgbm import LGBMClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.neural_network import MLPClassifier
from xgboost import XGBClassifier
from sklearn.tree import DecisionTreeClassifier
!pip3 install catboost
from catboost import CatBoostClassifier

from sklearn.metrics import classification_report,confusion_matrix,accuracy_score
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt
```

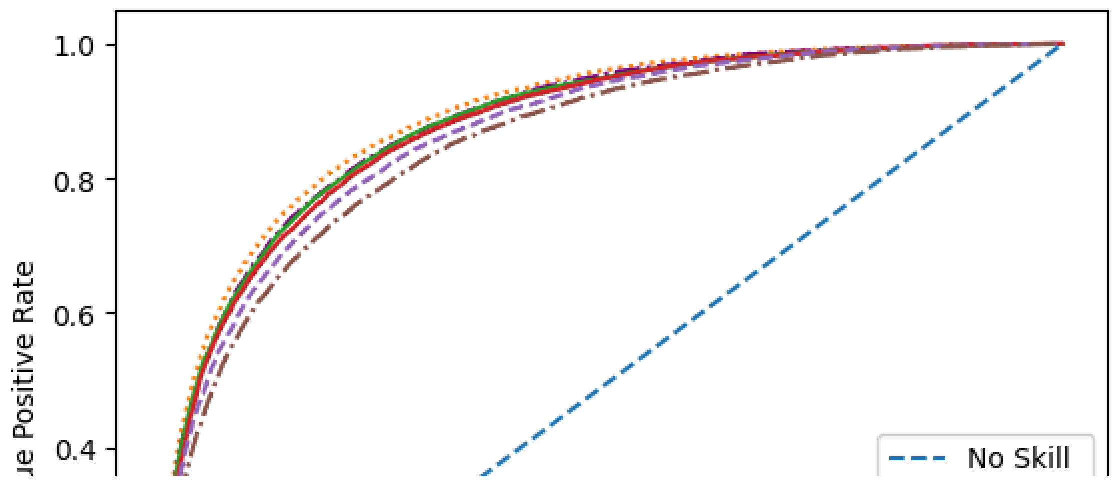
```
Collecting catboost
  Downloading https://files.pythonhosted.org/packages/94/ec/12b9a42b2ea7dfe5b60
     |████████████████████████████████| 64.4MB 64kB/s
Requirement already satisfied: six in /usr/local/lib/python3.6/dist-packages (f
Requirement already satisfied: scipy in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: matplotlib in /usr/local/lib/python3.6/dist-pack
Requirement already satisfied: pandas>=0.24.0 in /usr/local/lib/python3.6/dist-
Requirement already satisfied: graphviz in /usr/local/lib/python3.6/dist-packag
Requirement already satisfied: plotly in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: numpy>=1.16.0 in /usr/local/lib/python3.6/dist-p
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.6
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.6/di
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.6/dist-pa
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.6/dist-pa
Requirement already satisfied: retrying>=1.3.3 in /usr/local/lib/python3.6/dist
Installing collected packages: catboost
Successfully installed catboost-0.22
```

```
rfc1 = RandomForestClassifier()
rfc1.fit(X_train1,y_train)

lgbm1 = LGBMClassifier()
lgbm1.fit(X_train1,y_train)
```

```
catboost1 = CatBoostClassifier()
catboost1.fit(X_train1,y_train)

logreg1 = LogisticRegression()
logreg1.fit(X_train1,y_train)

mlp1 = MLPClassifier()
mlp1.fit(X_train1,y_train)

xgb1 = XGBClassifier()
xgb1.fit(X_train1,y_train)

dt1 = DecisionTreeClassifier()
dt1.fit(X_train1,y_train)


ns_probs = [0 for _ in range(len(y_test))]
ns_auc = roc_auc_score(y_test, ns_probs)
ns_fpr, ns_tpr, _ = roc_curve(y_test, ns_probs)

rfc1_probs = rfc1.predict_proba(X_test1)
rfc1_probs = rfc1_probs[:, 1]
rfc1_auc = roc_auc_score(y_test, rfc1_probs)
rfc1_fpr, rfc1_tpr, _ = roc_curve(y_test, rfc1_probs)

lgbm1_probs = lgbm1.predict_proba(X_test1)
lgbm1_probs = lgbm1_probs[:, 1]
lgbm1_auc = roc_auc_score(y_test, lgbm1_probs)
lgbm1_fpr, lgbm1_tpr, _ = roc_curve(y_test, lgbm1_probs)

catboost1_probs = catboost1.predict_proba(X_test1)
catboost1_probs = catboost1_probs[:, 1]
catboost1_auc = roc_auc_score(y_test, catboost1_probs)
catboost1_fpr, catboost1_tpr, _ = roc_curve(y_test, catboost1_probs)

logreg1_probs = logreg1.predict_proba(X_test1)
logreg1_probs = logreg1_probs[:, 1]
logreg1_auc = roc_auc_score(y_test, logreg1_probs)
logreg1_fpr, logreg1_tpr, _ = roc_curve(y_test, logreg1_probs)

mlp1_probs = mlp1.predict_proba(X_test1)
mlp1_probs = mlp1_probs[:, 1]
mlp1_auc = roc_auc_score(y_test, mlp1_probs)
mlp1_fpr, mlp1_tpr, _ = roc_curve(y_test, mlp1_probs)

xgb1_probs = xgb1.predict_proba(X_test1)
xgb1_probs = xgb1_probs[:, 1]
xgb1_auc = roc_auc_score(y_test, xgb1_probs)
xgb1_fpr, xgb1_tpr, _ = roc_curve(y_test, xgb1_probs)

dt1_probs = dt1.predict_proba(X_test1)
dt1_probs = dt1_probs[:, 1]
dt1_auc = roc_auc_score(y_test,dt1_probs)
dt1_fpr, dt1_tpr, _ = roc_curve(y_test, dt1_probs)

print('CATBOOST: ROC AUC = %{:.2f}'.format((catboost1_auc)*100))
print('LGBM: ROC AUC= % {:.2f}'.format((lgbm1_auc)*100))
print('RFC: ROC AUC= % {:.2f}'.format((rfc1_auc)*100))
print('MLP: ROC AUC= % {:.2f}'.format((mlp1_auc)*100))
print('XGB: ROC AUC= % {:.2f}'.format((xgb1_auc)*100))
```

```
print('LOGREG: ROC AUC= % {:.2f}'.format((logreg1_auc)*100))
print('DT: ROC AUC= % {:.2f}'.format((dt1_auc)*100))
print('No Skill: ROC AUC= % {:.2f}'.format((ns_auc)*100))

plt.plot(ns_fpr, ns_tpr, linestyle='--', label='No Skill')
plt.plot(catboost1_fpr,catboost1_tpr,linestyle=':',label='CAT')
plt.plot(lgbm1_fpr, lgbm1_tpr, linestyle='-.', color='purple', label='LGBM')
plt.plot(rfc1_fpr, rfc1_tpr, linestyle='-', label='RFC')
plt.plot(mlp1_fpr, mlp1_tpr, linestyle='-', label='MLP')
plt.plot(xgb1_fpr, xgb1_tpr, linestyle='--', label='XGB')
plt.plot(logreg1_fpr, logreg1_tpr, linestyle='-.', label='LOGREG')

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```

```
CATBOOST: ROC AUC = %89.46
LGBM: ROC AUC= % 88.62
RFC: ROC AUC= % 88.46
MLP: ROC AUC= % 88.03
XGB: ROC AUC= % 87.05
LOGREG: ROC AUC= % 85.62
DT: ROC AUC= % 70.31
No Skill: ROC AUC= % 50.00
```



MISSING VALUE IMPUTATION

We determined the variable lists according to "Missing Value Handling Mindmap.

```
Zero_MR_variables_list = list(data_info[data_info['%_Missing_Value']==0]['Variable'])
Low_MR_variables_list = list(data_info[(data_info['%_Missing_Value']>0)&
                                        (data_info['%_Missing_Value']<=0.05)]['Variable'])
Moderate_MR_variables_list = list(data_info[(data_info['%_Missing_Value']>0.05)&\
                                                       (data_info['%_Missing_Value']<=0.25)
High_MR_variables_list = list(data_info[(data_info['%_Missing_Value']>0.25)&\
                                                   (data_info['%_Missing_Value']<=0.37)]['V
Extreme_MR_variables_list = list(data_info[(data_info['%_Missing_Value']>0.37)&
                                            (data_info['%_Missing_Value']<=0.95)]['Variable
Drop_MR_variables_list = list(data_info[data_info['%_Missing_Value']>0.95]['Variable'])
```

MEAN ENCODING

We used Mean Encoding Imputation for Categorical Variables in our dataset.

The main point of this imputation is average of target column which is "RainTomorrow".

```
variable_list = ['Location','Month']
target_name = 'RainTomorrow'
X_train = X_train_outlier_cleaned.copy()
X_test = X_test_outlier_cleaned.copy()

from sklearn.model_selection import KFold
X_train = pd.concat([X_train,y_train],axis=1).copy()
kf = KFold(n_splits=3, shuffle=False, random_state=2020)
encoded_name_dict = {}
for col in variable_list:
  col_mean_name = str(col) + '_' + 'Kfold_Mean_Enc'
  encoded_name_dict[col] = col_mean_name
  X_train[col_mean_name] = np.nan
  X_test[col_mean_name] = np.nan
  for tr_ind, val_ind in kf.split(X_train):
    X_tr, X_val = X_train.iloc[tr_ind], X_train.iloc[val_ind]
    X_train.loc[X_train.index[val_ind], col_mean_name] = X_val[col].map(X_tr.groupby(col)[
# X_train.loc[:,col_mean_name] = X_train[col].map(X_train.groupby(col)[col_mean_name].mean

for i in encoded_name_dict:
  mean = 0
  mean =  X_train[[i,encoded_name_dict[i]]].groupby(i).mean().reset_index()
  mean_dict = {}
  for index, row in mean.iterrows():
    mean_dict[row[i]] = row[encoded_name_dict[i]]
  X_test[encoded_name_dict[i]] = X_test[i]
  X_test = X_test.replace({encoded_name_dict[i]:mean_dict})

X_train = X_train.drop(columns=[target_name])
X_train = X_train.drop(columns=variable_list)
X_test = X_test.drop(columns=variable_list)


numerical_columns.append('Location_Kfold_Mean_Enc')
numerical_columns.append('Month_Kfold_Mean_Enc')
categorical_columns = list(set(categorical_columns)-set(variable_list))
```

SIMPLE IMPUTATION

We used Simple Imputation for Numerical Variables in our dataset.

We determined the missing values in both train and test data according to the percentage distribution of unique values in the train data.

```
X_train_outlier_cleaned = X_train.copy()
X_test_outlier_cleaned = X_test.copy()


def SimpleImputers(df_train,df_test,data_info,variable_list):
  from sklearn.impute import SimpleImputer
  for col in variable_list:
    count_nan_train = 0
    count_nan_train = df_train[col].isnull().sum()

    count_nan_test = 0
    count_nan_test = df_test[col].isnull().sum()
    if col in numerical_columns:
      average_train = 0
      average_train = df_train[col].mean()

      std_train = 0
      std_train = df_train[col].std()

      rand_train = 0
      rand_train = np.random.normal(loc=average_train, scale=std_train, size=count_nan_tra

      rand_test = 0
      rand_test = np.random.normal(loc=average_train, scale=std_train, size=count_nan_test

      col_slice_train = 0
      col_slice_train = pd.Series(df_train[col].copy())

      col_slice_test = 0
      col_slice_test = pd.Series(df_test[col].copy())

      col_slice_train[pd.isnull(col_slice_train)] = rand_train
      col_slice_test[pd.isnull(col_slice_test)] = rand_test

      df_train[col] = col_slice_train
      df_test[col] = col_slice_test

    elif col in categorical_columns:
      df_train.loc[df_train.loc[:,col].isnull(),col] = np.random.choice(sorted(list(df_tra
                                                        size=int(df_train.loc[df_train
                                                        p=[pd.Series(df_train.groupby(
                                                           np.arange(0,len(df_train.lo

      df_test.loc[df_test.loc[:,col].isnull(),col] = np.random.choice(sorted(list(df_train
                                                        size=int(df_test.loc[df_tes
                                                        p=[pd.Series(df_test.groupb
                                                        np.arange(0,len(df_test.loc
```

```
  print("TRAİN DATADA Number of null values: \n", df_train[variable_list].isnull().sum())
  print("TEST DATADA Number of null values: \n", df_test[variable_list].isnull().sum())

SimpleImputers(X_train_outlier_cleaned,X_test_outlier_cleaned,data_info,Low_MR_variables_l
```

```
TRAİN DATADA Number of null values:
 WindDir3pm      0
Humidity3pm     0
Temp3pm         0
WindSpeed3pm    0
Humidity9am     0
Rainfall        0
RainToday       0
WindSpeed9am    0
Temp9am         0
MinTemp         0
MaxTemp         0
dtype: int64
TEST DATADA Number of null values:
 WindDir3pm      0
Humidity3pm     0
Temp3pm         0
WindSpeed3pm    0
Humidity9am     0
Rainfall        0
RainToday       0
WindSpeed9am    0
Temp9am         0
MinTemp         0
MaxTemp         0
dtype: int64
```

ENCODING IMPUTED CATEGORICAL FEATURES : WINDDIR3PM

```
categorical_columns = list(set(categorical_columns)-set(['WindDir3pm','Location','Month'])

X_train_outlier_cleaned = pd.concat([X_train_outlier_cleaned[numerical_columns],
                                     X_train_outlier_cleaned[categorical_columns],
                                     pd.get_dummies(X_train_outlier_cleaned.WindDir3pm)],

X_test_outlier_cleaned = pd.concat([X_test_outlier_cleaned[numerical_columns],
                                    X_test_outlier_cleaned[categorical_columns],
                                    pd.get_dummies(X_test_outlier_cleaned.WindDir3pm)], ax
```

STRING CONVERSION IMPUTATION

```
from sklearn import base
from sklearn.model_selection import KFold
class KFoldTargetEncoderTrain(base.BaseEstimator,
                              base.TransformerMixin):
    def __init__(self,colnames,targetName,
                 n_fold=5, verbosity=True,
```

```
                  discardOriginal_col=False):
        self.colnames = colnames
        self.targetName = targetName
        self.n_fold = n_fold
        self.verbosity = verbosity
        self.discardOriginal_col = discardOriginal_col

    def fit(self, X, y=None):
        return self

    def transform(self,X):
        assert(type(self.targetName) == str)
        assert(type(self.colnames) == str)
        assert(self.colnames in X.columns)
        assert(self.targetName in X.columns)

        mean_of_target = X[self.targetName].mean()
        kf = KFold(n_splits = self.n_fold,
                   shuffle = False, random_state=2020)
        col_mean_name = self.colnames + '_' + 'Kfold_Target_Enc'
        X[col_mean_name] = np.nan
        for tr_ind, val_ind in kf.split(X):
            X_tr, X_val = X.iloc[tr_ind], X.iloc[val_ind]
            X.loc[X.index[val_ind], col_mean_name] = \
            X_val[self.colnames].map(X_tr.groupby(self.colnames)
                                     [self.targetName].mean())
            X[col_mean_name].fillna(mean_of_target, inplace = True)
        if self.verbosity:
            encoded_feature = X[col_mean_name].values
            print('Correlation between the new feature, {} and, {} is {}.'\
                  .format(col_mean_name,self.targetName,
                          np.corrcoef(X[self.targetName].values,
                                      encoded_feature)[0][1]))
        if self.discardOriginal_col:
            X = X.drop(self.targetName, axis=1)
        return X


lst = ['WindDir9am','WindGustDir']
encoded_name_dict = {"WindDir9am":"WindDir9am_Kfold_Target_Enc","WindGustDir":"WindGustDir_

def StringConverter(df, target_name, variable_list):
  for col in variable_list:
    targetc = KFoldTargetEncoderTrain(col,target_name,n_fold=3)
    new_train = targetc.fit_transform(df)
  return new_train


df_deneme_train = pd.concat([X_train_outlier_cleaned,y_train],axis=1).copy()
df_output_train = StringConverter(df=df_deneme_train,target_name="RainTomorrow",variable_l
print(df_output_train.loc[:,["WindDir9am_Kfold_Target_Enc","WindGustDir_Kfold_Target_Enc"]
df_output_train.loc[:,["WindDir9am_Kfold_Target_Enc","WindGustDir_Kfold_Target_Enc"]]
```

```
Correlation between the new feature, WindDir9am_Kfold_Target_Enc and, RainTomor
Correlation between the new feature, WindGustDir_Kfold_Target_Enc and, RainTomo
WindDir9am_Kfold_Target_Enc     0
WindGustDir_Kfold_Target_Enc    0
dtype: int64
```

	WindDir9am_Kfold_Target_Enc	WindGustDir_Kfold_Target_Enc
118102	0.224564	0.222605
18630	0.264388	0.224802
127854	0.307141	0.203080
112595	0.144784	0.167707
108492	0.144784	0.224564
...	...	...
110268	0.270846	0.266538
119879	0.237986	0.197919
103694	0.216216	0.227137
131932	0.177179	0.167453
121958	0.211105	0.196643

99535 rows × 2 columns

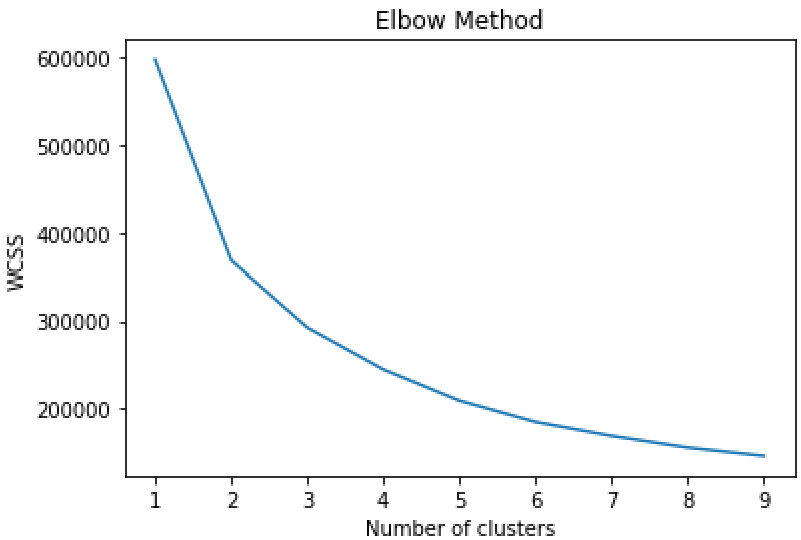
```
for i in encoded_name_dict:
  print(i)
  mean = 0
  mean =  df_output_train[[i,encoded_name_dict[i]]].groupby(i).mean().reset_index()
  mean_dict = {}

  for index, row in mean.iterrows():
    mean_dict[row[i]] = row[encoded_name_dict[i]]
  X_test_outlier_cleaned[encoded_name_dict[i]] = X_test_outlier_cleaned[i]
  X_test_outlier_cleaned = X_test_outlier_cleaned.replace({encoded_name_dict[i]:mean_dict}
  X_test_outlier_cleaned[encoded_name_dict[i]].fillna(df_output_train[encoded_name_dict[i]

df_output_test = X_test_outlier_cleaned.copy()
df_output_train=df_output_train.drop(columns=['WindDir9am','WindGustDir','RainTomorrow'])
df_output_test=df_output_test.drop(columns=['WindDir9am','WindGustDir'])
categorical_columns = list(set(categorical_columns) - set(['WindDir9am','WindGustDir']))
numerical_columns.append('WindDir9am_Kfold_Target_Enc')
numerical_columns.append('WindGustDir_Kfold_Target_Enc')
```

```
WindDir9am
WindGustDir
```

CLUSTERING BASED BINNING

```
import sklearn
from sklearn.cluster import KMeans, SpectralClustering
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans

df_output_train1=df_output_train[['Temp3pm','Rainfall','MaxTemp','Humidity9am','Humidity3p
df_output_train1_dropna=df_output_train1.dropna()
cluster = StandardScaler().fit_transform(df_output_train1_dropna)
wcss = []
for i in range(1, 10):
    kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=400, n_init=10, random_state=
    kmeans.fit(cluster)
    wcss.append(kmeans.inertia_)
plt.plot(range(1, 10), wcss)
plt.title('Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
km = KMeans(n_clusters=8, max_iter=100).fit(cluster)
pred_y = km.predict(cluster)
df_output_train1_dropna['cluster']=pred_y
clust=df_output_train1_dropna.cluster
clust=clust.reset_index()
data1=df_output_train.reset_index().merge(clust,on='index',how='outer')
df2=data1
col_list = ['Sunshine','Evaporation']
for col in col_list:
    e=data1.groupby('cluster')[col].mean().reset_index()

    for i in e.cluster:
        n=e[e.cluster==i][col]
        data1.loc[(data1.cluster==i)&(data1[col].isna()==True),col]=n[i]
    print(data1[col].isnull().sum())

col_list = ['Cloud3pm','Cloud9am']
for col in col_list:

    for i in data1.cluster.unique():
        data1.loc[(data1.cluster==i)&(data1[col].isna()==True),col]=data1[data1.cluster==i

    print(data1[col].isnull().sum())

#Imputation for test
df_output_test1=df_output_test[['Temp3pm','Rainfall','MaxTemp','Humidity9am','Humidity3pm'
df_output_test1_dropna=df_output_test1.dropna()
cluster_test = StandardScaler().fit_transform(df_output_test1_dropna)
pred_test = km.predict(cluster_test)
df_output_test1_dropna['cluster']=pred_test
clust_test=df_output_test1_dropna.cluster
clust_test=clust_test.reset_index()
data1_test=df_output_test.reset_index().merge(clust_test,on='index',how='outer')
col_list = ['Sunshine','Evaporation']
for col in col_list:
    e=df2.groupby('cluster')[col].mean().reset_index()
    for i in e.cluster:
        n=e[e.cluster==i][col]
        data1_test.loc[(data1_test.cluster==i)&(data1_test[col].isna()==True),col]=n[i]
    print(data1_test[col].isnull().sum())

col_list = ['Cloud3pm','Cloud9am']
```

```
for col in col_list:

    for i in data1_test.cluster.unique():
        data1_test.loc[(data1_test.cluster==i)&(data1_test[col].isna()==True),col]=df2[df2
    print(data1_test[col].isnull().sum())
```




```
0
0
0
0
0
```

```
data1.set_index("index",inplace=True)
data1 = data1.drop(columns=['cluster'])
data1_test.set_index("index", inplace=True)
data1_test = data1_test.drop(columns=['cluster'])
```

MODEL BASED IMPUTATION

```
df_train = data1.copy()
df_test = data1_test.copy()
lst = [item for item in Moderate_MR_variables_list if item in numerical_columns]

from sklearn.preprocessing import StandardScaler, LabelEncoder, OneHotEncoder, MinMaxScale
from sklearn.neural_network import MLPRegressor
!pip install category_encoders
from category_encoders import BinaryEncoder
for col in numerical_columns:
  scaler_fitted = StandardScaler().fit(np.array(df_train[col]).reshape(-1,1))
  df_train[col] = scaler_fitted.transform(np.array(df_train[col]).reshape(-1,1))
  df_test[col] = scaler_fitted.transform(np.array(df_test[col]).reshape(-1,1))

# MLP IMPUTER
import pandas as pd
import time
```

```
print("MLP IMPUTER process has began:\n")
start_time = time.time()

for col in lst:
  y_col_nan_train = df_train.loc[df_train.loc[:,col].isnull(),col]
  y_col_train = df_train.loc[df_train.loc[:,col].notnull(),col]
  X_col_nan_train = df_train.drop(columns=lst).loc[y_col_nan_train.index,:]
  X_col_train = df_train.drop(columns=lst,axis=1).loc[y_col_train.index,:]

  y_col_nan_test = df_test.loc[df_test.loc[:,col].isnull(),col]
  y_col_test = df_test.loc[df_test.loc[:,col].notnull(),col]
  X_col_nan_test = df_test.drop(columns=lst).loc[y_col_nan_test.index,:]
  X_col_test = df_test.drop(columns=lst,axis=1).loc[y_col_test.index,:]

  mlp = MLPRegressor(hidden_layer_sizes=(100,10,),
                     activation='tanh',
                     solver='adam',
                     learning_rate='adaptive',
                     max_iter=1000,
                     learning_rate_init=0.01,
                     alpha=0.01,
                     early_stopping = False)

  mlp_fitted = mlp.fit(X_col_train,y_col_train)
  y_col_pred_train = mlp_fitted.predict(X_col_nan_train)
  y_col_pred_test = mlp_fitted.predict(X_col_nan_test)

  df_train.loc[y_col_nan_train.index,col] = y_col_pred_train
  df_test.loc[y_col_nan_test.index,col] = y_col_pred_test

  print(col,"TRAİN null sayisi:",df_train[col].isnull().sum())
  print(col,"TEST null sayisi:",df_train[col].isnull().sum())

print('MLP IMPUTER process has been completed!')
print("--- in %s minutes ---" % ((time.time() - start_time)/60))
```

```
Collecting category_encoders
  Downloading https://files.pythonhosted.org/packages/a0/52/c54191ad3782de633ea
     |████████████████████████████████| 102kB 2.0MB/s
Requirement already satisfied: statsmodels>=0.6.1 in /usr/local/lib/python3.6/d
Requirement already satisfied: scipy>=0.19.0 in /usr/local/lib/python3.6/dist-p
Requirement already satisfied: numpy>=1.11.3 in /usr/local/lib/python3.6/dist-p
Requirement already satisfied: patsy>=0.4.1 in /usr/local/lib/python3.6/dist-pa
Requirement already satisfied: pandas>=0.21.1 in /usr/local/lib/python3.6/dist-
Requirement already satisfied: scikit-learn>=0.20.0 in /usr/local/lib/python3.6
Requirement already satisfied: six in /usr/local/lib/python3.6/dist-packages (f
Requirement already satisfied: python-dateutil>=2.6.1 in /usr/local/lib/python3
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.6/dist-pa
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.6/dist-pa
Installing collected packages: category-encoders
Successfully installed category-encoders-2.1.0
MLP IMPUTER process has began:

Pressure9am TRAİN null sayisi: 0
Pressure9am TEST null sayisi: 0
Pressure3pm TRAİN null sayisi: 0
Pressure3pm TEST null sayisi: 0
WindGustSpeed TRAİN null sayisi: 0
WindGustSpeed TEST null sayisi: 0
```

```
MLP IMPUTER process has been completed!
--- in 0.7832816163698832 minutes ---
```

MODELLING

ENSEMBLED CLASSIFIER

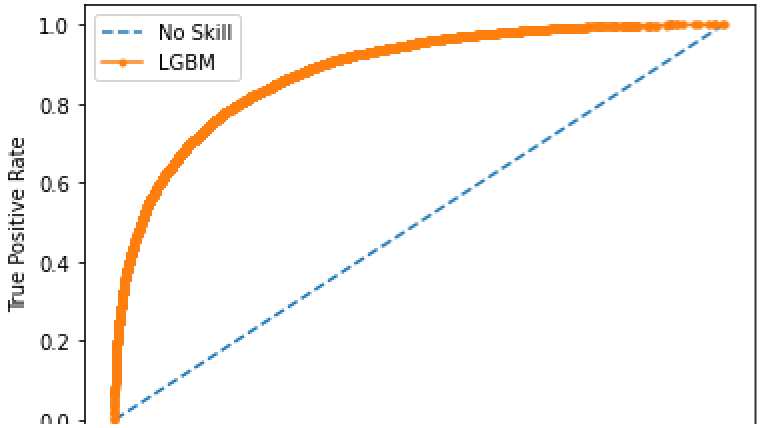
LIGHT-GBM MODEL

```
from lightgbm import LGBMClassifier
from sklearn.metrics import classification_report,confusion_matrix,accuracy_score
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt


lgbm = LGBMClassifier()
lgbm.fit(df_train,y_train)
```

```
LGBMClassifier(boosting_type='gbdt', class_weight=None, colsample_bytree=1.0,
               importance_type='split', learning_rate=0.1, max_depth=-1,
               min_child_samples=20, min_child_weight=0.001,
min_split_gain=0.0,
               n_estimators=100, n_jobs=-1, num_leaves=31, objective=None,
               random_state=None, reg_alpha=0.0, reg_lambda=0.0, silent=True,
               subsample=1.0, subsample_for_bin=200000, subsample_freq=0)
```

```
ns_probs = [0 for _ in range(len(y_test))]
ns_auc = roc_auc_score(y_test, ns_probs)
ns_fpr, ns_tpr, _ = roc_curve(y_test, ns_probs)

lgbm_probs = lgbm.predict_proba(df_test)
lgbm_probs = lgbm_probs[:, 1]
lgbm_auc = roc_auc_score(y_test, lgbm_probs)
lgbm_fpr, lgbm_tpr, _ = roc_curve(y_test, lgbm_probs)

print('No Skill: ROC AUC=%{:.3f}'.format((ns_auc)*100))
print('LGBM: ROC AUC=%{:.3f}'.format((lgbm_auc)*100))

plt.plot(ns_fpr, ns_tpr, linestyle='--', label='No Skill')
plt.plot(lgbm_fpr, lgbm_tpr, marker='.', label='LGBM')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```

```
No Skill: ROC AUC=%50.000
LGBM: ROC AUC=%88.340
```



HYPERPARAMETER TUNNING

```
from sklearn.model_selection import GridSearchCV
lgbm_tunned = LGBMClassifier()
lgbm_tunned_params = {"boosting_type":['gbdt', 'dart', 'goss', 'rf'],
                      "n_estimators ":[100,200,500],
                      "learning_rate":[0.01,0.1,0.5]}

lgbm_tunned_model = GridSearchCV(lgbm_tunned, lgbm_tunned_params, scoring='roc_auc', cv=3,
print(lgbm_tunned_model.best_params_)
```

```
Fitting 3 folds for each of 36 candidates, totalling 108 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:   34.7s
[Parallel(n_jobs=-1)]: Done 108 out of 108 | elapsed:  1.5min finished
{'boosting_type': 'gbdt', 'learning_rate': 0.1, 'n_estimators ': 100}
```

```
lgbm_tunned_auc = lgbm_auc.copy()
```

```
#{'boosting_type': 'gbdt', 'learning_rate': 0.1, 'n_estimators ': 100}
```

XGBOOST MODEL

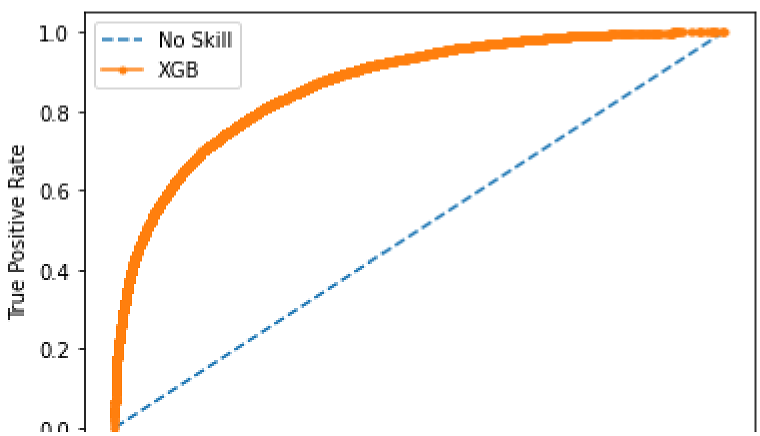
```
from xgboost import XGBClassifier
xgb = XGBClassifier()
xgb.fit(df_train,y_train)
```

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0,
              learning_rate=0.1, max_delta_step=0, max_depth=3,
              min_child_weight=1, missing=None, n_estimators=100, n_jobs=1,
```

```
              nthread=None, objective='binary:logistic', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=None, subsample=1, verbosity=1)
```

```
ns_probs = [0 for _ in range(len(y_test))]
ns_auc = roc_auc_score(y_test, ns_probs)
ns_fpr, ns_tpr, _ = roc_curve(y_test, ns_probs)

xgb_probs = xgb.predict_proba(df_test)
xgb_probs = xgb_probs[:, 1]
xgb_auc = roc_auc_score(y_test, xgb_probs)
xgb_fpr,xgb_tpr, _ = roc_curve(y_test, xgb_probs)

print('No Skill: ROC AUC=%{:.3f}'.format((ns_auc)*100))
print('XGB: ROC AUC=%{:.3f}'.format((xgb_auc)*100))

plt.plot(ns_fpr, ns_tpr, linestyle='--', label='No Skill')
plt.plot(xgb_fpr, xgb_tpr, marker='.', label='XGB')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```

```
No Skill: ROC AUC=%50.000
XGB: ROC AUC=%86.812
```



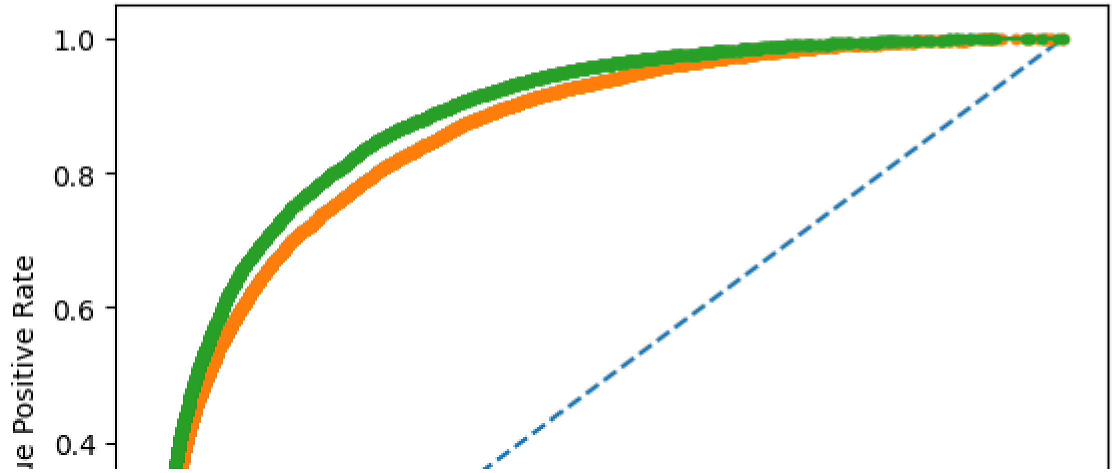
HYPERPARAMETER TUNNING

```
from sklearn.model_selection import GridSearchCV
xgb_tunned = XGBClassifier()
xgb_tunned_params = {"learning_rate"    : [0.01, 0.10, 0.25 ] ,
                     "max_depth"        : [ 3, 6, 10],
                     "min_child_weight" : [ 1, 3, 7 ],
                     "gamma"            : [ 0.0, 0.1 , 0.3],
                     "colsample_bytree" : [ 0.3, 0.5 , 0.7 ],
                     "booster"          : ['gbtree','gblinear','dart'],
                     "n-jobs"           : [-1]}

xgb_tunned_model = GridSearchCV(xgb_tunned, xgb_tunned_params, scoring='roc_auc', cv=3, n_
print(xgb_tunned_model.best_params_)
```

```
Fitting 3 folds for each of 729 candidates, totalling 2187 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:  1.8min
[Parallel(n_jobs=-1)]: Done 154 tasks      | elapsed:  8.7min
[Parallel(n_jobs=-1)]: Done 357 tasks      | elapsed: 22.3min
[Parallel(n_jobs=-1)]: Done 640 tasks      | elapsed: 46.8min
[Parallel(n_jobs=-1)]: Done 1005 tasks      | elapsed: 62.5min
[Parallel(n_jobs=-1)]: Done 1450 tasks      | elapsed: 73.9min
[Parallel(n_jobs=-1)]: Done 1977 tasks      | elapsed: 176.8min
[Parallel(n_jobs=-1)]: Done 2187 out of 2187 | elapsed: 224.8min finished
{'booster': 'dart', 'colsample_bytree': 0.7, 'gamma': 0.0, 'learning_rate': 0.1
```

```
#{'booster': 'dart', 'colsample_bytree': 0.7, 'gamma': 0.0, 'learning_rate': 0.1, 'max_dep


ns_probs = [0 for _ in range(len(y_test))]
ns_auc = roc_auc_score(y_test, ns_probs)
ns_fpr, ns_tpr, _ = roc_curve(y_test, ns_probs)

xgb_tunned_probs = xgb_tunned_model.predict_proba(df_test)
xgb_tunned_probs = xgb_tunned_probs[:, 1]
xgb_tunned_auc = roc_auc_score(y_test, xgb_tunned_probs)
xgb_tunned_fpr,xgb_tunned_tpr, _ = roc_curve(y_test, xgb_tunned_probs)

print('No Skill: ROC AUC=%{:.3f}'.format((ns_auc)*100))
print('XGB: ROC AUC=%{:.3f}'.format((xgb_auc)*100))
print('XGB-TUNNED: ROC AUC=%{:.3f}'.format((xgb_tunned_auc)*100))

plt.plot(ns_fpr, ns_tpr, linestyle='--', label='No Skill')
plt.plot(xgb_fpr, xgb_tpr, marker='.', label='XGB')
plt.plot(xgb_tunned_fpr, xgb_tunned_tpr, marker='.', label=('XGB-TUNNED'))
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```

```
No Skill: ROC AUC=%50.000
XGB: ROC AUC=%86.812
XGB-TUNNED: ROC AUC=%89.142
```



CATBOOST MODEL

```
from catboost import CatBoostClassifier
from sklearn.metrics import classification_report,confusion_matrix,accuracy_score
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt
```

```
catboost = CatBoostClassifier()
catboost.fit(df_train,y_train)
```

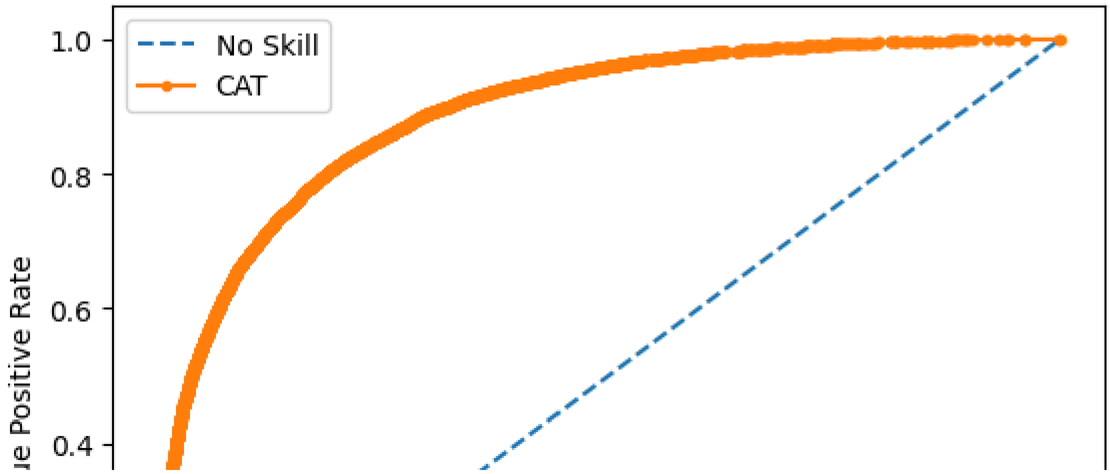
```
Learning rate set to 0.073463
0:      learn: 0.6412283        total: 33.9ms   remaining: 33.9s
1:      learn: 0.5998476        total: 59.6ms   remaining: 29.7s
2:      learn: 0.5643289        total: 84ms     remaining: 27.9s
3:      learn: 0.5343749        total: 111ms    remaining: 27.7s
4:      learn: 0.5083045        total: 139ms    remaining: 27.6s
5:      learn: 0.4869526        total: 166ms    remaining: 27.5s
6:      learn: 0.4699246        total: 196ms    remaining: 27.8s
7:      learn: 0.4562533        total: 223ms    remaining: 27.6s
8:      learn: 0.4442005        total: 250ms    remaining: 27.5s
9:      learn: 0.4343565        total: 277ms    remaining: 27.4s
10:     learn: 0.4251581        total: 305ms    remaining: 27.4s
11:     learn: 0.4172246        total: 333ms    remaining: 27.4s
```

```
12:     learn: 0.4103671        total: 358ms    remaining: 27.2s
13:     learn: 0.4041479        total: 386ms    remaining: 27.2s
14:     learn: 0.3994131        total: 416ms    remaining: 27.3s
15:     learn: 0.3951772        total: 443ms    remaining: 27.2s
16:     learn: 0.3917046        total: 468ms    remaining: 27.1s
17:     learn: 0.3888622        total: 494ms    remaining: 26.9s
18:     learn: 0.3859310        total: 525ms    remaining: 27.1s
19:     learn: 0.3828540        total: 551ms    remaining: 27s
20:     learn: 0.3805038        total: 579ms    remaining: 27s
21:     learn: 0.3782135        total: 607ms    remaining: 27s
22:     learn: 0.3761829        total: 636ms    remaining: 27s
23:     learn: 0.3743180        total: 663ms    remaining: 27s
24:     learn: 0.3730146        total: 691ms    remaining: 26.9s
25:     learn: 0.3719647        total: 717ms    remaining: 26.8s
26:     learn: 0.3708172        total: 743ms    remaining: 26.8s
27:     learn: 0.3697750        total: 769ms    remaining: 26.7s
28:     learn: 0.3688628        total: 796ms    remaining: 26.6s
29:     learn: 0.3679649        total: 826ms    remaining: 26.7s
30:     learn: 0.3671136        total: 856ms    remaining: 26.8s
31:     learn: 0.3662903        total: 885ms    remaining: 26.8s
32:     learn: 0.3654739        total: 911ms    remaining: 26.7s
33:     learn: 0.3648691        total: 943ms    remaining: 26.8s
34:     learn: 0.3641262        total: 970ms    remaining: 26.7s
35:     learn: 0.3634522        total: 997ms    remaining: 26.7s
36:     learn: 0.3628229        total: 1.02s    remaining: 26.6s
37:     learn: 0.3621904        total: 1.05s    remaining: 26.6s
38:     learn: 0.3615569        total: 1.08s    remaining: 26.6s
39:     learn: 0.3610826        total: 1.1s     remaining: 26.5s
40:     learn: 0.3605723        total: 1.13s    remaining: 26.5s
41:     learn: 0.3601281        total: 1.16s    remaining: 26.5s
42:     learn: 0.3595632        total: 1.19s    remaining: 26.5s
43:     learn: 0.3591351        total: 1.22s    remaining: 26.4s
44:     learn: 0.3586508        total: 1.24s    remaining: 26.4s
45:     learn: 0.3583314        total: 1.27s    remaining: 26.3s
46:     learn: 0.3578659        total: 1.3s     remaining: 26.3s
47:     learn: 0.3575114        total: 1.32s    remaining: 26.3s
48:     learn: 0.3570657        total: 1.35s    remaining: 26.2s
49:     learn: 0.3567213        total: 1.38s    remaining: 26.2s
50:     learn: 0.3564142        total: 1.4s     remaining: 26.1s
51:     learn: 0.3560522        total: 1.43s    remaining: 26.1s
52:     learn: 0.3556369        total: 1.46s    remaining: 26s
53:     learn: 0.3553226        total: 1.48s    remaining: 26s
54:     learn: 0.3550241        total: 1.51s    remaining: 26s
55:     learn: 0.3546615        total: 1.54s    remaining: 26s
56:     learn: 0.3543605        total: 1.57s    remaining: 26s
```

```
ns_probs = [0 for _ in range(len(y_test))]
ns_auc = roc_auc_score(y_test, ns_probs)
ns_fpr, ns_tpr, _ = roc_curve(y_test, ns_probs)

catboost_probs = catboost.predict_proba(df_test)
catboost_probs = catboost_probs[:, 1]
catboost_auc = roc_auc_score(y_test, catboost_probs)
catboost_fpr, catboost_tpr, _ = roc_curve(y_test, catboost_probs)

print('No Skill: ROC AUC=%{:.3f}'.format((ns_auc)*100))
print('CatBoost: ROC AUC=%{:.3f}'.format((catboost_auc)*100))
```

```
plt.plot(ns_fpr, ns_tpr, linestyle='--', label='No Skill')
plt.plot(catboost_fpr, catboost_tpr, marker='.', label='CAT')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```

```
No Skill: ROC AUC=%50.000
CatBoost: ROC AUC=%89.161
```



HYPERPARAMETER TUNNING

```
from sklearn.model_selection import GridSearchCV
catboost_tunned = CatBoostClassifier()
catboost_tunned_params = {'iterations':[10, 1000],
                          'depth': [1, 8],
                          'learning_rate': [0.01, 1.0, 'log-uniform']
}

catboost_tunned_model = GridSearchCV(catboost_tunned, catboost_tunned_params, scoring='roc
print(catboost_tunned_model.best_params_)
```

```
Fitting 3 folds for each of 12 candidates, totalling 36 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  36 out of  36 | elapsed:  4.3min finished
0:      learn: 0.6855441        total: 46.6ms   remaining: 46.5s
1:      learn: 0.6779530        total: 83.9ms   remaining: 41.8s
2:      learn: 0.6704841        total: 122ms    remaining: 40.6s
3:      learn: 0.6634350        total: 159ms    remaining: 39.6s
```

```
4:	learn: 0.6564261	total: 197ms	remaining: 39.2s
5:	learn: 0.6498557	total: 235ms	remaining: 38.9s
6:	learn: 0.6431476	total: 275ms	remaining: 39.1s
7:	learn: 0.6364220	total: 314ms	remaining: 38.9s
8:	learn: 0.6302520	total: 352ms	remaining: 38.8s
9:	learn: 0.6240024	total: 391ms	remaining: 38.7s
10:	learn: 0.6179713	total: 428ms	remaining: 38.5s
11:	learn: 0.6120018	total: 465ms	remaining: 38.3s
12:	learn: 0.6061735	total: 506ms	remaining: 38.4s
13:	learn: 0.6004133	total: 543ms	remaining: 38.3s
14:	learn: 0.5950831	total: 585ms	remaining: 38.4s
15:	learn: 0.5897518	total: 624ms	remaining: 38.4s
16:	learn: 0.5845590	total: 661ms	remaining: 38.2s
17:	learn: 0.5793634	total: 698ms	remaining: 38.1s
18:	learn: 0.5743563	total: 739ms	remaining: 38.1s
19:	learn: 0.5698286	total: 778ms	remaining: 38.1s
20:	learn: 0.5650998	total: 817ms	remaining: 38.1s
21:	learn: 0.5604498	total: 859ms	remaining: 38.2s
22:	learn: 0.5556564	total: 898ms	remaining: 38.2s
23:	learn: 0.5512043	total: 937ms	remaining: 38.1s
24:	learn: 0.5471408	total: 978ms	remaining: 38.2s
25:	learn: 0.5432180	total: 1.01s	remaining: 38s
26:	learn: 0.5390420	total: 1.05s	remaining: 37.9s
27:	learn: 0.5350197	total: 1.09s	remaining: 37.8s
28:	learn: 0.5311566	total: 1.13s	remaining: 37.7s
29:	learn: 0.5275579	total: 1.16s	remaining: 37.6s
30:	learn: 0.5238152	total: 1.2s	remaining: 37.6s
31:	learn: 0.5200652	total: 1.24s	remaining: 37.5s
32:	learn: 0.5165844	total: 1.28s	remaining: 37.4s
33:	learn: 0.5132341	total: 1.31s	remaining: 37.3s
34:	learn: 0.5098282	total: 1.35s	remaining: 37.3s
35:	learn: 0.5066325	total: 1.39s	remaining: 37.2s
36:	learn: 0.5034284	total: 1.43s	remaining: 37.2s
37:	learn: 0.5003898	total: 1.47s	remaining: 37.2s
38:	learn: 0.4975127	total: 1.5s	remaining: 37.1s
39:	learn: 0.4945876	total: 1.54s	remaining: 37.1s
40:	learn: 0.4918607	total: 1.58s	remaining: 37s
41:	learn: 0.4891481	total: 1.62s	remaining: 37s
42:	learn: 0.4864767	total: 1.66s	remaining: 37s
43:	learn: 0.4838329	total: 1.7s	remaining: 37s
44:	learn: 0.4813656	total: 1.74s	remaining: 37s
45:	learn: 0.4790192	total: 1.78s	remaining: 36.9s
46:	learn: 0.4765946	total: 1.82s	remaining: 36.9s
47:	learn: 0.4741240	total: 1.86s	remaining: 36.9s
48:	learn: 0.4718732	total: 1.9s	remaining: 36.9s
49:	learn: 0.4693800	total: 1.94s	remaining: 36.9s
50:	learn: 0.4670308	total: 1.98s	remaining: 36.8s
51:	learn: 0.4648012	total: 2.01s	remaining: 36.7s
52:	learn: 0.4625910	total: 2.05s	remaining: 36.7s
53:	learn: 0.4604832	total: 2.09s	remaining: 36.7s
54:	learn: 0.4583463	total: 2.13s	remaining: 36.7s
```

```
from sklearn.model_selection import GridSearchCV
catboost_tunned = CatBoostClassifier()
catboost_tunned_params = {'random_strength': [1e-9, 10, 'log-uniform'],
                          'bagging_temperature': [0.0, 1.0],
```

```
                    'border_count': [1, 255],
                    'l2_leaf_reg': [2, 30],
                    'scale_pos_weight':[0.01, 1.0, 'uniform']}

catboost_tunned_model = GridSearchCV(catboost_tunned, catboost_tunned_params, scoring='roc
print(catboost_tunned_model.best_params_)
```

```
Fitting 3 folds for each of 72 candidates, totalling 216 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:  5.1min
[Parallel(n_jobs=-1)]: Done 154 tasks      | elapsed: 24.0min
[Parallel(n_jobs=-1)]: Done 216 out of 216 | elapsed: 32.8min finished
0:      learn: 0.6709138        total: 35.5ms   remaining: 35.5s
1:      learn: 0.6501440        total: 65.2ms   remaining: 32.5s
2:      learn: 0.6306209        total: 91.7ms   remaining: 30.5s
3:      learn: 0.6122764        total: 121ms    remaining: 30.2s
4:      learn: 0.5953822        total: 156ms    remaining: 31s
5:      learn: 0.5796960        total: 185ms    remaining: 30.6s
6:      learn: 0.5660739        total: 213ms    remaining: 30.2s
7:      learn: 0.5525169        total: 245ms    remaining: 30.4s
8:      learn: 0.5403989        total: 275ms    remaining: 30.2s
9:      learn: 0.5288557        total: 304ms    remaining: 30.1s
10:     learn: 0.5184826        total: 334ms    remaining: 30s
11:     learn: 0.5087118        total: 364ms    remaining: 29.9s
12:     learn: 0.4992180        total: 394ms    remaining: 29.9s
13:     learn: 0.4906099        total: 427ms    remaining: 30.1s
14:     learn: 0.4828154        total: 461ms    remaining: 30.3s
15:     learn: 0.4756143        total: 492ms    remaining: 30.2s
16:     learn: 0.4687632        total: 520ms    remaining: 30s
17:     learn: 0.4621417        total: 548ms    remaining: 29.9s
18:     learn: 0.4562634        total: 578ms    remaining: 29.8s
19:     learn: 0.4502578        total: 607ms    remaining: 29.7s
20:     learn: 0.4452802        total: 636ms    remaining: 29.6s
21:     learn: 0.4400997        total: 668ms    remaining: 29.7s
22:     learn: 0.4359162        total: 697ms    remaining: 29.6s
23:     learn: 0.4315724        total: 728ms    remaining: 29.6s
24:     learn: 0.4276665        total: 756ms    remaining: 29.5s
25:     learn: 0.4238518        total: 784ms    remaining: 29.4s
26:     learn: 0.4205346        total: 814ms    remaining: 29.3s
27:     learn: 0.4171673        total: 843ms    remaining: 29.3s
28:     learn: 0.4142999        total: 875ms    remaining: 29.3s
29:     learn: 0.4115600        total: 904ms    remaining: 29.2s
30:     learn: 0.4090888        total: 934ms    remaining: 29.2s
31:     learn: 0.4065390        total: 963ms    remaining: 29.1s
32:     learn: 0.4043893        total: 991ms    remaining: 29s
33:     learn: 0.4021605        total: 1.02s    remaining: 29.1s
34:     learn: 0.4001999        total: 1.05s    remaining: 29s
35:     learn: 0.3984495        total: 1.08s    remaining: 29s
36:     learn: 0.3966045        total: 1.11s    remaining: 29s
37:     learn: 0.3947567        total: 1.14s    remaining: 28.9s
38:     learn: 0.3931162        total: 1.17s    remaining: 28.9s
39:     learn: 0.3916881        total: 1.2s     remaining: 28.9s
40:     learn: 0.3900536        total: 1.23s    remaining: 28.8s
41:     learn: 0.3887748        total: 1.26s    remaining: 28.8s
42:     learn: 0.3874549        total: 1.3s     remaining: 28.9s
43:     learn: 0.3860696        total: 1.33s    remaining: 28.8s
44:     learn: 0.3847879        total: 1.35s    remaining: 28.8s
```

```
45:     learn: 0.3837268        total: 1.38s    remaining: 28.7s
46:     learn: 0.3826428        total: 1.41s    remaining: 28.6s
47:     learn: 0.3815101        total: 1.44s    remaining: 28.6s
48:     learn: 0.3806213        total: 1.47s    remaining: 28.5s
49:     learn: 0.3795939        total: 1.5s     remaining: 28.5s
50:     learn: 0.3787244        total: 1.53s    remaining: 28.5s
51:     learn: 0.3777990        total: 1.56s    remaining: 28.4s
52:     learn: 0.3770935        total: 1.59s    remaining: 28.4s
```

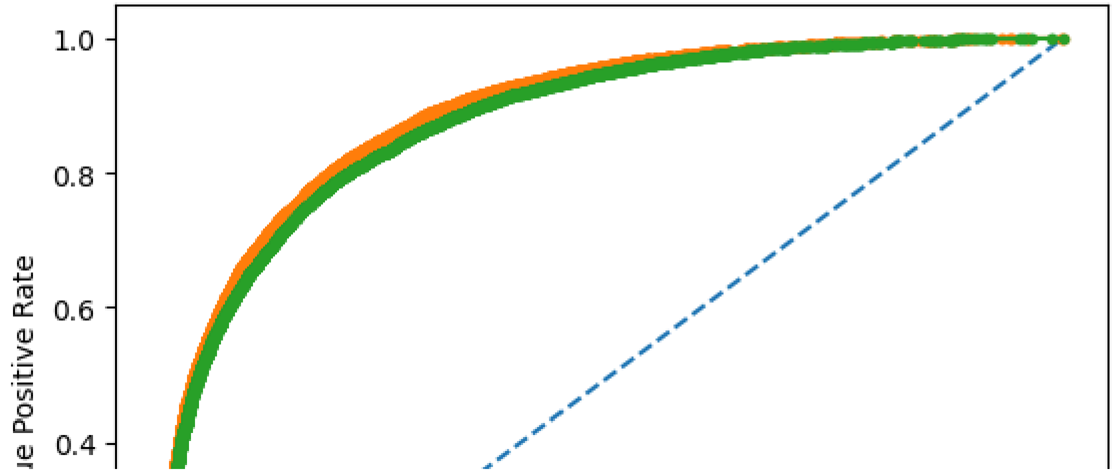
```
catboost_tunned = CatBoostClassifier(depth= 8,
                                     iterations= 1000,
                                     learning_rate= 0.01,
                                     random_strength=1e-09,
                                     bagging_temperature=0.0,
                                     border_count=255,
                                     l2_leaf_reg=30,
                                     scale_pos_weight=1.0).fit(df_train,y_train)
```

```
0:      learn: 0.6851486        total: 43.6ms   remaining: 43.5s
1:      learn: 0.6773256        total: 81.6ms   remaining: 40.7s
2:      learn: 0.6697072        total: 120ms    remaining: 39.9s
3:      learn: 0.6622749        total: 159ms    remaining: 39.6s
4:      learn: 0.6550273        total: 201ms    remaining: 40s
5:      learn: 0.6479901        total: 240ms    remaining: 39.8s
6:      learn: 0.6410155        total: 279ms    remaining: 39.6s
7:      learn: 0.6343781        total: 317ms    remaining: 39.3s
8:      learn: 0.6277637        total: 354ms    remaining: 39s
9:      learn: 0.6214048        total: 396ms    remaining: 39.2s
10:     learn: 0.6151937        total: 437ms    remaining: 39.3s
11:     learn: 0.6092443        total: 474ms    remaining: 39.1s
12:     learn: 0.6033920        total: 514ms    remaining: 39s
13:     learn: 0.5977120        total: 551ms    remaining: 38.8s
14:     learn: 0.5921261        total: 589ms    remaining: 38.7s
15:     learn: 0.5866563        total: 627ms    remaining: 38.6s
16:     learn: 0.5813706        total: 666ms    remaining: 38.5s
17:     learn: 0.5761395        total: 708ms    remaining: 38.6s
18:     learn: 0.5711631        total: 748ms    remaining: 38.6s
19:     learn: 0.5663004        total: 786ms    remaining: 38.5s
20:     learn: 0.5615448        total: 825ms    remaining: 38.5s
21:     learn: 0.5568882        total: 863ms    remaining: 38.3s
22:     learn: 0.5523086        total: 901ms    remaining: 38.3s
23:     learn: 0.5477463        total: 942ms    remaining: 38.3s
24:     learn: 0.5433710        total: 984ms    remaining: 38.4s
25:     learn: 0.5391548        total: 1.02s    remaining: 38.4s
26:     learn: 0.5350618        total: 1.06s    remaining: 38.3s
27:     learn: 0.5311784        total: 1.1s     remaining: 38.3s
28:     learn: 0.5274059        total: 1.14s    remaining: 38.2s
29:     learn: 0.5236868        total: 1.19s    remaining: 38.3s
30:     learn: 0.5199420        total: 1.22s    remaining: 38.3s
31:     learn: 0.5162664        total: 1.26s    remaining: 38.2s
32:     learn: 0.5127948        total: 1.3s     remaining: 38.2s
33:     learn: 0.5093509        total: 1.34s    remaining: 38.1s
34:     learn: 0.5059740        total: 1.38s    remaining: 38s
35:     learn: 0.5026115        total: 1.42s    remaining: 38s
36:     learn: 0.4995686        total: 1.46s    remaining: 38s
37:     learn: 0.4964663        total: 1.5s     remaining: 38s
```

```
38:	learn: 0.4933482	total: 1.54s	remaining: 37.9s
39:	learn: 0.4904247	total: 1.58s	remaining: 37.9s
40:	learn: 0.4876077	total: 1.62s	remaining: 37.9s
41:	learn: 0.4848719	total: 1.66s	remaining: 37.9s
42:	learn: 0.4822303	total: 1.7s	remaining: 37.9s
43:	learn: 0.4795438	total: 1.74s	remaining: 37.9s
44:	learn: 0.4770156	total: 1.78s	remaining: 37.9s
45:	learn: 0.4743869	total: 1.83s	remaining: 37.9s
46:	learn: 0.4718770	total: 1.87s	remaining: 37.9s
47:	learn: 0.4694638	total: 1.91s	remaining: 37.8s
48:	learn: 0.4671635	total: 1.95s	remaining: 37.8s
49:	learn: 0.4648115	total: 1.99s	remaining: 37.7s
50:	learn: 0.4626032	total: 2.03s	remaining: 37.7s
51:	learn: 0.4603734	total: 2.07s	remaining: 37.7s
52:	learn: 0.4582848	total: 2.11s	remaining: 37.7s
53:	learn: 0.4561956	total: 2.15s	remaining: 37.7s
54:	learn: 0.4541061	total: 2.19s	remaining: 37.7s
55:	learn: 0.4521616	total: 2.24s	remaining: 37.7s
56:	learn: 0.4501444	total: 2.27s	remaining: 37.6s
57:	learn: 0.4483568	total: 2.31s	remaining: 37.6s
```

```python
ns_probs = [0 for _ in range(len(y_test))]
ns_auc = roc_auc_score(y_test, ns_probs)
ns_fpr, ns_tpr, _ = roc_curve(y_test, ns_probs)

catboost_tunned_probs = catboost_tunned.predict_proba(df_test)
catboost_tunned_probs = catboost_tunned_probs[:, 1]
catboost_tunned_auc = roc_auc_score(y_test, catboost_tunned_probs)
catboost_tunned_fpr,catboost_tunned_tpr, _ = roc_curve(y_test, catboost_tunned_probs)

print('No Skill: ROC AUC=%{:.3f}'.format((ns_auc)*100))
print('CatBoost: ROC AUC=%{:.3f}'.format((catboost_auc)*100))
print('CAT-TUNNED: ROC AUC=%{:.3f}'.format((catboost_tunned_auc)*100))

plt.plot(ns_fpr, ns_tpr, linestyle='--', label='No Skill')
plt.plot(catboost_fpr, catboost_tpr, marker='.', label='CAT')
plt.plot(catboost_tunned_fpr, catboost_tunned_tpr, marker='.', label=('CAT-TUNNED'))
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```

```
No Skill: ROC AUC=%50.000
CatBoost: ROC AUC=%89.161
CAT-TUNNED: ROC AUC=%88.086
```



RANDOM FOREST CLASSIFIER(BAGGING)

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report,confusion_matrix,accuracy_score
```

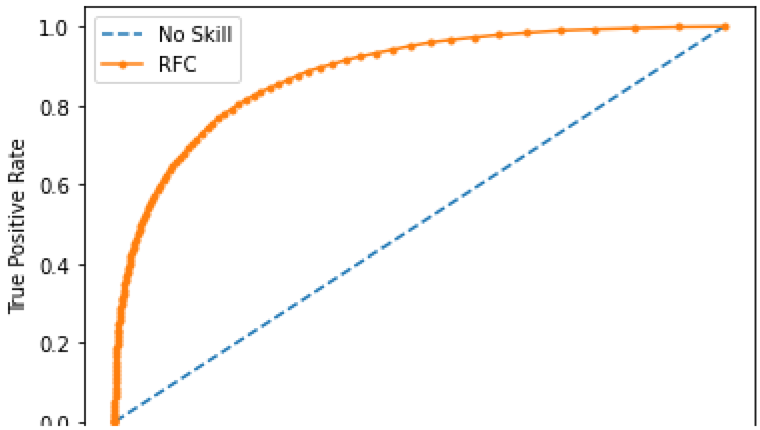
```
rfc = RandomForestClassifier()
rfc.fit(df_train,y_train)
```

```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=None, max_features='auto',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=100,
                       n_jobs=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)
```

```
ns_probs = [0 for _ in range(len(y_test))]
ns_auc = roc_auc_score(y_test, ns_probs)
ns_fpr, ns_tpr, _ = roc_curve(y_test, ns_probs)

rfc_probs = rfc.predict_proba(df_test)
rfc_probs = rfc_probs[:, 1]
```

```
rfc_auc = roc_auc_score(y_test, rfc_probs)
rfc_fpr, rfc_tpr, _ = roc_curve(y_test, rfc_probs)

print('No Skill: ROC AUC=%{:.3f}'.format((ns_auc)*100))
print('RFC: ROC AUC= % {:.3f}'.format((rfc_auc)*100))

plt.plot(ns_fpr, ns_tpr, linestyle='--', label='No Skill')
plt.plot(rfc_fpr, rfc_tpr, marker='.', label='RFC')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```

```
No Skill: ROC AUC=%50.000
RFC: ROC AUC= % 88.326
```



HYPERPARAMETER TUNNING

```
from sklearn.model_selection import GridSearchCV
rfc_tunned = RandomForestClassifier()
rfc_tunned_params = {'max_depth': [2,10,20],
                     'n_estimators': [100,200],
                     'max_features': [4,10,30],
                     'min_samples_leaf': [2,10]}

rfc_tunned_model = GridSearchCV(rfc_tunned, rfc_tunned_params, scoring='roc_auc', cv=3, n_
print(rfc_tunned_model.best_params_)
```

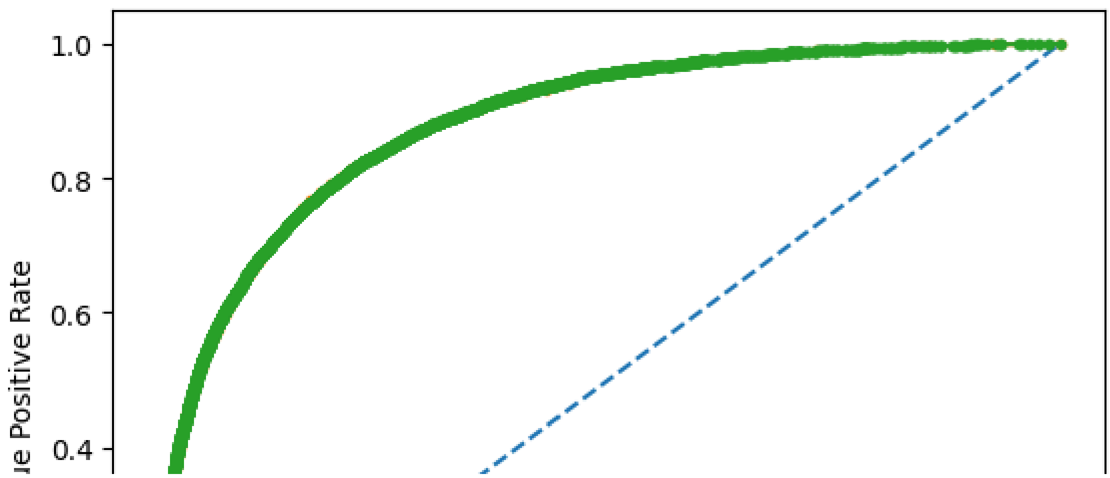
```
Fitting 3 folds for each of 36 candidates, totalling 108 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:  1.4min
[Parallel(n_jobs=-1)]: Done 108 out of 108 | elapsed: 20.3min finished
{'max_depth': 20, 'max_features': 10, 'min_samples_leaf': 2, 'n_estimators': 20
```

```
#{'max_depth': 20, 'max_features': 10, 'min_samples_leaf': 2, 'n_estimators': 200}
```

```
ns_probs = [0 for _ in range(len(y_test))]
ns_auc = roc_auc_score(y_test, ns_probs)
ns_fpr, ns_tpr, _ = roc_curve(y_test, ns_probs)
```

```
rfc_tunned_probs = rfc_tunned_model.predict_proba(df_test)
rfc_tunned_probs = rfc_tunned_probs[:, 1]
rfc_tunned_auc = roc_auc_score(y_test, rfc_tunned_probs)
rfc_tunned_fpr,rfc_tunned_tpr, _ = roc_curve(y_test, rfc_tunned_probs)

print('No Skill: ROC AUC=%{:.3f}'.format((ns_auc)*100))
print('RFC: ROC AUC=%{:.3f}'.format((rfc_auc)*100))
print('RFC-TUNNED: ROC AUC=%{:.3f}'.format((rfc_tunned_auc)*100))

plt.plot(ns_fpr, ns_tpr, linestyle='--', label='No Skill')
plt.plot(rfc_fpr, rfc_tpr, marker='.', label='RFC')
plt.plot(rfc_tunned_fpr, rfc_tunned_tpr, marker='.', label=('RFC-TUNNED'))
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```

```
No Skill: ROC AUC=%50.000
RFC: ROC AUC=%88.326
RFC-TUNNED: ROC AUC=%88.387
```



LOGISTIC REGRESSION CLASSIFIER

```
import statsmodels.api as sm
logm1 = sm.GLM(y_train,(sm.add_constant(df_train)), family=sm.families.Binomial())
logm1.fit().summary()
```

Generalized Linear Model Regression Results

Dep. Variable:	RainTomorrow	**No. Observations:**	99535
Model:	GLM	**Df Residuals:**	99496
Model Family:	Binomial	**Df Model:**	38
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-36811.
Date:	Fri, 10 Apr 2020	**Deviance:**	73622.
Time:	14:44:46	**Pearson chi2:**	1.00e+05
No. Iterations:	100		
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	5.8572	6.972	0.840	0.401	-7.809	19.523
Sunshine	-0.4547	0.014	-31.640	0.000	-0.483	-0.427
Evaporation	0.0137	0.016	0.885	0.376	-0.017	0.044
Pressure9am	-0.0229	0.014	-1.657	0.097	-0.050	0.004
Pressure3pm	-0.1619	0.016	-10.376	0.000	-0.192	-0.131
WindGustSpeed	0.6979	0.014	51.518	0.000	0.671	0.724
Humidity3pm	1.0284	0.019	54.715	0.000	0.992	1.065
Temp3pm	0.0728	0.033	2.184	0.029	0.007	0.138
WindSpeed3pm	-0.1693	0.012	-13.946	0.000	-0.193	-0.145
Humidity9am	0.0314	0.018	1.785	0.074	-0.003	0.066
Rainfall	0.3186	0.028	11.407	0.000	0.264	0.373
WindSpeed9am	-0.0976	0.012	-7.990	0.000	-0.121	-0.074
Temp9am	0.1678	0.038	4.387	0.000	0.093	0.243
MinTemp	0.1115	0.028	4.017	0.000	0.057	0.166
MaxTemp	0.0342	0.038	0.905	0.365	-0.040	0.108
Location_Kfold_Mean_Enc	-0.0576	0.011	-5.148	0.000	-0.080	-0.036
Month_Kfold_Mean_Enc	0.0579	0.011	5.060	0.000	0.035	0.080
Cloud9am	-0.0237	0.005	-4.477	0.000	-0.034	-0.013
Year	-0.0041	0.004	-1.107	0.268	-0.011	0.003
RainToday	-0.1935	0.065	-2.974	0.003	-0.321	-0.066
Day	-0.0006	0.001	-0.609	0.543	-0.003	0.001
Cloud3pm	0.0755	0.005	14.032	0.000	0.065	0.086
E	0.2718	0.437	0.622	0.534	-0.585	1.129
ENE	0.3148	0.437	0.720	0.472	-0.542	1.172
ESE	0.2140	0.438	0.489	0.625	-0.644	1.072
N	0.7054	0.437	1.613	0.107	-0.152	1.562
NE	0.1740	0.437	0.398	0.691	-0.683	1.031
NNE	0.5883	0.437	1.345	0.179	-0.269	1.445
NNW	0.8052	0.438	1.839	0.066	-0.053	1.663
NW	0.7250	0.437	1.658	0.097	-0.132	1.582
S	0.1139	0.437	0.260	0.795	-0.744	0.971
SE	0.1914	0.436	0.439	0.661	-0.664	1.047
SSE	0.1385	0.437	0.317	0.752	-0.719	0.996
SSW	0.1676	0.438	0.383	0.702	-0.691	1.026
SW	0.2113	0.437	0.483	0.629	-0.646	1.069

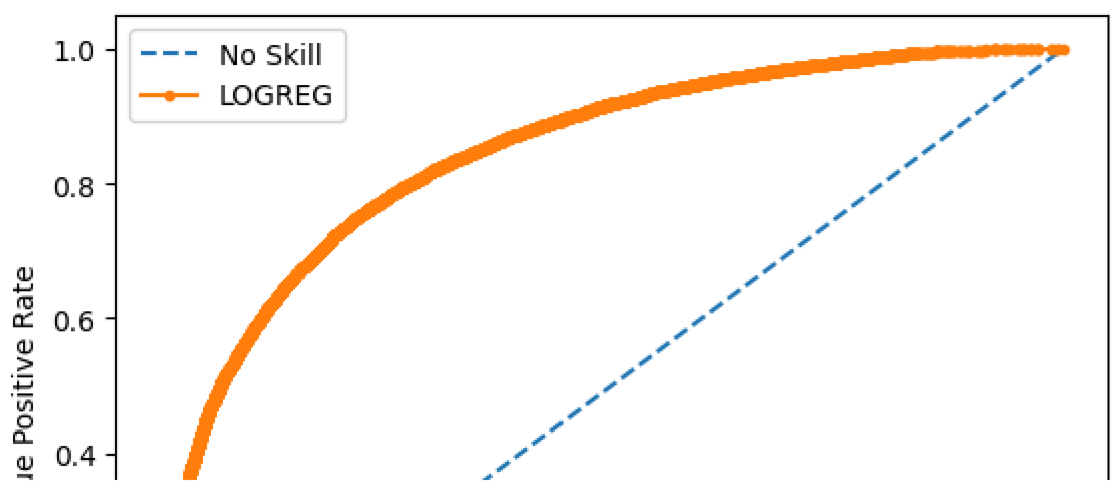
W	0.3796	0.438	0.867	0.386	-0.479	1.238

```
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
import matplotlib.pyplot as plt
logreg = LogisticRegression()
logreg.fit(df_train, y_train)
```

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

```
ns_probs = [0 for _ in range(len(y_test))]
ns_auc = roc_auc_score(y_test, ns_probs)
ns_fpr, ns_tpr, _ = roc_curve(y_test, ns_probs)

logreg_probs = logreg.predict_proba(df_test)
logreg_probs = logreg_probs[:, 1]
logreg_auc = roc_auc_score(y_test, logreg_probs)
logreg_fpr, logreg_tpr, _ = roc_curve(y_test, logreg_probs)


print('No Skill: ROC AUC= %{:.3f}'.format((ns_auc)*100))
print('LOGREG: ROC AUC= %{:.3f}'.format((logreg_auc)*100))

plt.plot(ns_fpr, ns_tpr, linestyle='--', label='No Skill')
plt.plot(logreg_fpr, logreg_tpr, marker='.', label='LOGREG')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```

```
No Skill: ROC AUC= %50.000
LOGREG: ROC AUC= %84.593
```



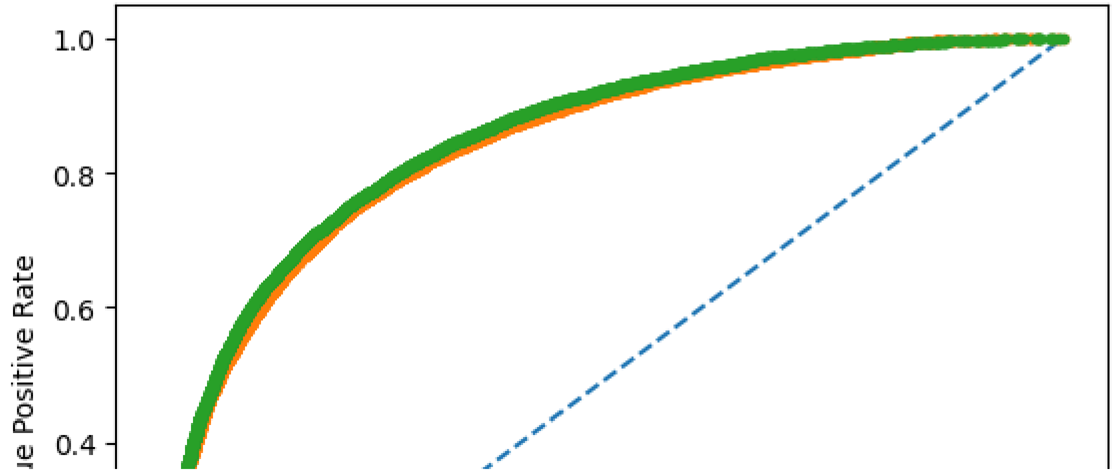
HYPERPARAMETER TUNNING

```
from sklearn.model_selection import GridSearchCV
logreg_tunned = LogisticRegression()
logreg_tunned_params = {"penalty": ['l1', 'l2', 'elasticnet'],
                        "solver":['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga'],
                        "max_iter": [50,100,200],
                        "n_jobs" : [-1],
                        "C": [0.1,1,10]}

logreg_tunned_model = GridSearchCV(logreg_tunned, logreg_tunned_params, scoring='roc_auc',
print(logreg_tunned_model.best_params_)
```

```
Fitting 3 folds for each of 135 candidates, totalling 405 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  40 tasks      | elapsed:   24.5s
[Parallel(n_jobs=-1)]: Done 162 tasks      | elapsed:  2.6min
[Parallel(n_jobs=-1)]: Done 365 tasks      | elapsed:  5.5min
[Parallel(n_jobs=-1)]: Done 405 out of 405 | elapsed:  6.4min finished
{'C': 10, 'max_iter': 100, 'n_jobs': -1, 'penalty': 'l1', 'solver': 'liblinear'
```

```
#{'C': 10, 'max_iter': 50, 'n_jobs': -1, 'penalty': 'l1', 'solver': 'liblinear'}


ns_probs = [0 for _ in range(len(y_test))]
ns_auc = roc_auc_score(y_test, ns_probs)
ns_fpr, ns_tpr, _ = roc_curve(y_test, ns_probs)

logreg_tunned_probs = logreg_tunned_model.predict_proba(df_test)
logreg_tunned_probs = logreg_tunned_probs[:, 1]
logreg_tunned_auc = roc_auc_score(y_test, logreg_tunned_probs)
logreg_tunned_fpr, logreg_tunned_tpr, _ = roc_curve(y_test, logreg_tunned_probs)


print('No Skill: ROC AUC= %{:.3f}'.format((ns_auc)*100))
print('LOGREG: ROC AUC= %{:.3f}'.format((logreg_auc)*100))
print('LOGREG-TUNNED: ROC AUC= %{:.3f}'.format((logreg_tunned_auc)*100))

plt.plot(ns_fpr, ns_tpr, linestyle='--', label='No Skill')
plt.plot(logreg_fpr, logreg_tpr, marker='.', label='LOGREG')
plt.plot(logreg_tunned_fpr, logreg_tunned_tpr, marker='.', label='LOGREG-TUNNED')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```

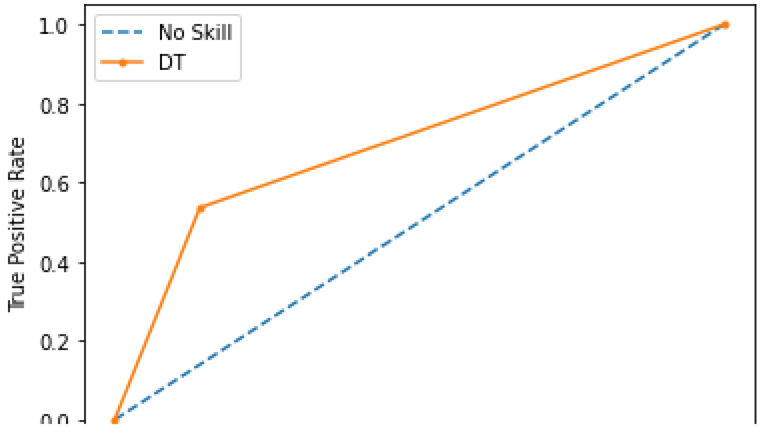
```
No Skill: ROC AUC= %50.000
LOGREG: ROC AUC= %84.593
LOGREG-TUNNED: ROC AUC= %85.319
```



DECISION TREE CLASSIFIER

```
from sklearn.tree import DecisionTreeClassifier
dt = DecisionTreeClassifier().fit(df_train,y_train)


ns_probs = [0 for _ in range(len(y_test))]
ns_auc = roc_auc_score(y_test, ns_probs)
ns_fpr, ns_tpr, _ = roc_curve(y_test, ns_probs)

dt_probs = dt.predict_proba(df_test)
dt_probs = dt_probs[:, 1]
dt_auc = roc_auc_score(y_test, dt_probs)
dt_fpr, dt_tpr, _ = roc_curve(y_test, dt_probs)

print('No Skill: ROC AUC= % {:.2f}'.format((ns_auc)*100))
print('DT: ROC AUC= % {:.2f}'.format((dt_auc)*100))

plt.plot(ns_fpr, ns_tpr, linestyle='--', label='No Skill')
plt.plot(dt_fpr, dt_tpr, marker='.', label='DT')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```

```
No Skill: ROC AUC= % 50.00
DT: ROC AUC= % 69.80
```



HYPERPARAMETER TUNNING

```
from sklearn.model_selection import GridSearchCV
dt_tunned = DecisionTreeClassifier()
dt_tunned_params = {"criterion" :['gini', 'entropy'],
                    "max_features": ['auto', 'sqrt', 'log2',None]}

dt_tunned_model = GridSearchCV(dt_tunned, dt_tunned_params, scoring='roc_auc', cv=3, n_job
print(dt_tunned_model.best_params_)
```

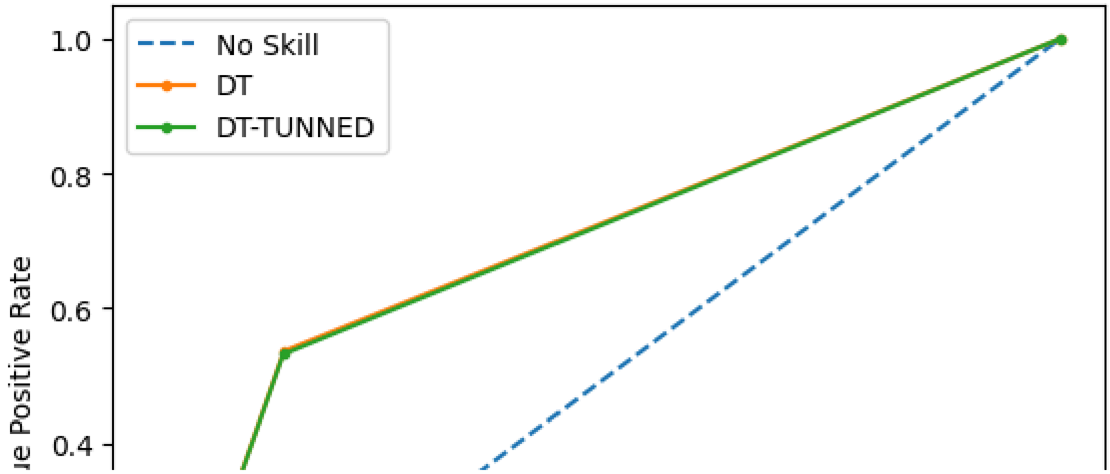
```
Fitting 3 folds for each of 8 candidates, totalling 24 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  24 out of  24 | elapsed:    7.6s finished
{'criterion': 'entropy', 'max_features': None}
```

```
#{'criterion': 'entropy', 'max_features': None}
```

```
ns_probs = [0 for _ in range(len(y_test))]
ns_auc = roc_auc_score(y_test, ns_probs)
ns_fpr, ns_tpr, _ = roc_curve(y_test, ns_probs)

dt_tunned_probs = dt_tunned_model.predict_proba(df_test)
dt_tunned_probs = dt_tunned_probs[:, 1]
dt_tunned_auc = roc_auc_score(y_test, dt_tunned_probs)
dt_tunned_fpr, dt_tunned_tpr, _ = roc_curve(y_test, dt_tunned_probs)

print('No Skill: ROC AUC= % {:.2f}'.format((ns_auc)*100))
print('DT: ROC AUC= % {:.2f}'.format((dt_auc)*100))
print('DT-TUNNED: ROC AUC= % {:.2f}'.format((dt_tunned_auc)*100))

plt.plot(ns_fpr, ns_tpr, linestyle='--', label='No Skill')
plt.plot(dt_fpr, dt_tpr, marker='.', label='DT')
plt.plot(dt_tunned_fpr, dt_tunned_tpr, marker='.', label='DT-TUNNED')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
```

```
plt.legend()
plt.show()
```

```
No Skill: ROC AUC= % 50.00
DT: ROC AUC= % 69.80
DT-TUNNED: ROC AUC= % 69.60
```



NEURAL NETWORKS CLASSIFIERS

MULTI-LAYER PERCEPTRON (MLP)

```
from sklearn.neural_network import MLPClassifier
mlp = MLPClassifier().fit(df_train,y_train)
```

```
ns_probs = [0 for _ in range(len(y_test))]
ns_auc = roc_auc_score(y_test, ns_probs)
ns_fpr, ns_tpr, _ = roc_curve(y_test, ns_probs)

mlp_probs = mlp.predict_proba(df_test)
mlp_probs = mlp_probs[:, 1]
mlp_auc = roc_auc_score(y_test, mlp_probs)
mlp_fpr, mlp_tpr, _ = roc_curve(y_test, mlp_probs)

print('No Skill: ROC AUC= % {:.2f}'.format((ns_auc)*100))
print('MLP: ROC AUC= % {:.2f}'.format((mlp_auc)*100))

plt.plot(ns_fpr, ns_tpr, linestyle='--', label='No Skill')
```