Application of Classification Models

Dataset Link

https://archive.ics.uci.edu/ml/machine-learning-databases/adult/ (https://archive.ics.uci.edu/ml/machine-learning-databases/adult/)

Problem 1: Prediction task is to determine whether a person makes over 50K a year.

Problem 2: Which factors are important

Problem 3: Which algorithms are best for this dataset

Solution

Importing the required libraries...

In [237]:

```
import numpy as np
import pandas as pd
import xgboost as xgb
import matplotlib.pyplot as plt
import seaborn as sns
from xgboost.sklearn import XGBClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier

from sklearn.preprocessing import StandardScaler
from sklearn.feature_selection import SelectFromModel
from sklearn.model_selection import train_test_split
from xgboost import plot_tree , plot_importance
from sklearn.metrics import accuracy_score , classification_report , confusion_matrix , pre
```

Reading Dataset...

In [239]:

```
# Loading Dataset
df_AdultData_trainSet = pd.read_csv('http://archive.ics.uci.edu/ml/machine-learning-databas
df_AdultData_testSet = pd.read_csv('http://archive.ics.uci.edu/ml/machine-learning-database
```

Data Preprocessing Steps

In [240]:

```
print(df_AdultData_trainSet.shape, df_AdultData_testSet.shape)
```

```
(32561, 15) (16281, 15)
```

In [241]:

```
df_AdultData_trainSet.head()
```

Out[241]:

	0	1	2	3	4	5	6	7	8	9	10	11
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0

In [242]:

```
df_AdultData_testSet.head()
```

Out[242]:

	0	1	2	3	4	5	6	7	8	9	10	11	12
0	25	Private	226802	11th	7	Never-married	Machine-op-inspct	Own-child	Black	Male	0	0	40
1	38	Private	89814	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband	White	Male	0	0	50
2	28	Local-gov	336951	Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband	White	Male	0	0	40
3	44	Private	160323	Some-college	10	Married-civ-spouse	Machine-op-inspct	Husband	Black	Male	7688	0	40
4	18	?	103497	Some-college	10	Never-married	?	Own-child	White	Female	0	0	30

In [243]:

```
# checking whether null values exist or not in training set
df_AdultData_trainSet.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
0     32561 non-null int64
1     32561 non-null object
2     32561 non-null int64
3     32561 non-null object
4     32561 non-null int64
5     32561 non-null object
6     32561 non-null object
7     32561 non-null object
8     32561 non-null object
9     32561 non-null object
10    32561 non-null int64
11    32561 non-null int64
12    32561 non-null int64
13    32561 non-null object
14    32561 non-null object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

In [244]:

```
# checking whether null values exist or not in test set
df_AdultData_testSet.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16281 entries, 0 to 16280
Data columns (total 15 columns):
0     16281 non-null int64
1     16281 non-null object
2     16281 non-null int64
3     16281 non-null object
4     16281 non-null int64
5     16281 non-null object
6     16281 non-null object
7     16281 non-null object
8     16281 non-null object
9     16281 non-null object
10    16281 non-null int64
11    16281 non-null int64
12    16281 non-null int64
13    16281 non-null object
14    16281 non-null object
dtypes: int64(6), object(9)
memory usage: 1.9+ MB
```

we can see that there is no null values present in the given datasets but we have values in form of '?'. we need to address them and need to add column headings as well.

In [245]:

```
# Adding column names...
col_labels = ['age', 'workclass', 'fnlwgt', 'education', 'education_num', 'marital_status',
              'occupation','relationship','race', 'sex', 'capital_gain', 'capital_loss',
              'hours_per_week','native_country', 'wage_class']
df_AdultData_trainSet.columns = col_labels
df_AdultData_testSet.columns = col_labels
```

In [246]:

```
df_AdultData_trainSet.head(1)
```

Out[246]:

	age	workclass	fnlwgt	education	education_num	marital_status	occupation	relationship
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family

In [247]:

```
df_AdultData_testSet.head(1)
```

Out[247]:

	age	workclass	fnlwgt	education	education_num	marital_status	occupation	relationship
0	25	Private	226802	11th	7	Never-married	Machine-op-inspct	Own-child

In [248]:

```
# trimming white spaces across the datasets
df_AdultData_trainSet=df_AdultData_trainSet.apply(lambda x: x.str.strip() if x.dtype == "ob
df_AdultData_testSet=df_AdultData_testSet.apply(lambda x: x.str.strip() if x.dtype == "obje
```

In [249]:

```
# check duplicates and remove the same
if(df_AdultData_trainSet.duplicated().any()):
    df_AdultData_trainSet=df_AdultData_trainSet.drop_duplicates(keep='first')
if(df_AdultData_testSet.duplicated().any()):
    df_AdultData_testSet=df_AdultData_testSet.drop_duplicates(keep='first')
```

In [250]:

```
# finding unique values present in each categorical features
for col in df_AdultData_trainSet.columns:
    if df_AdultData_trainSet[col].dtypes == 'object':
        unique_cat = len(df_AdultData_trainSet[col].unique())
        cat_names = df_AdultData_trainSet[col].unique()
        print("{col} has {unique_cat} unique categories - {cat_names}"
              .format(col=col,unique_cat=unique_cat, cat_names= cat_names))
```

```
workclass has 9 unique categories - ['State-gov' 'Self-emp-not-inc' 'Privat
e' 'Federal-gov' 'Local-gov' '?'
 'Self-emp-inc' 'Without-pay' 'Never-worked']
education has 16 unique categories - ['Bachelors' 'HS-grad' '11th' 'Masters'
'9th' 'Some-college' 'Assoc-acdm'
 'Assoc-voc' '7th-8th' 'Doctorate' 'Prof-school' '5th-6th' '10th'
 '1st-4th' 'Preschool' '12th']
marital_status has 7 unique categories - ['Never-married' 'Married-civ-spous
e' 'Divorced' 'Married-spouse-absent'
 'Separated' 'Married-AF-spouse' 'Widowed']
occupation has 15 unique categories - ['Adm-clerical' 'Exec-managerial' 'Han
dlers-cleaners' 'Prof-specialty'
 'Other-service' 'Sales' 'Craft-repair' 'Transport-moving'
 'Farming-fishing' 'Machine-op-inspct' 'Tech-support' '?'
 'Protective-serv' 'Armed-Forces' 'Priv-house-serv']
relationship has 6 unique categories - ['Not-in-family' 'Husband' 'Wife' 'Ow
n-child' 'Unmarried' 'Other-relative']
race has 5 unique categories - ['White' 'Black' 'Asian-Pac-Islander' 'Amer-I
ndian-Eskimo' 'Other']
sex has 2 unique categories - ['Male' 'Female']
native_country has 42 unique categories - ['United-States' 'Cuba' 'Jamaica'
'India' '?' 'Mexico' 'South'
 'Puerto-Rico' 'Honduras' 'England' 'Canada' 'Germany' 'Iran'
 'Philippines' 'Italy' 'Poland' 'Columbia' 'Cambodia' 'Thailand' 'Ecuador'
 'Laos' 'Taiwan' 'Haiti' 'Portugal' 'Dominican-Republic' 'El-Salvador'
 'France' 'Guatemala' 'China' 'Japan' 'Yugoslavia' 'Peru'
 'Outlying-US(Guam-USVI-etc)' 'Scotland' 'Trinadad&Tobago' 'Greece'
 'Nicaragua' 'Vietnam' 'Hong' 'Ireland' 'Hungary' 'Holand-Netherlands']
wage_class has 2 unique categories - ['<=50K' '>50K']
```

In [251]:

```
# Replacing '?' with 'unknown'
df_AdultData_trainSet = df_AdultData_trainSet.replace('?', 'unknown')
df_AdultData_testSet = df_AdultData_testSet.replace('?', 'unknown')
```

In [252]:

```
# Removing .symbol; in the test set for wage class column
df_AdultData_testSet['wage_class']=df_AdultData_testSet['wage_class'].replace({'<=50K.': '<
```

In [253]:

```
df_AdultData_testSet.tail()
```

Out[253]:

'gt	education	education_num	marital_status	occupation	relationship	race	sex	capital_(
19	Bachelors	13	Divorced	Prof-specialty	Not-in-family	White	Female	
03	HS-grad	9	Widowed	unknown	Other-relative	Black	Male	
83	Bachelors	13	Married-civ-spouse	Prof-specialty	Husband	White	Male	
91	Bachelors	13	Divorced	Adm-clerical	Own-child	Asian-Pac-Islander	Male	5
48	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	

Exploring Data - Analysis

In [254]:

```
df_AdultData_trainSet.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 32537 entries, 0 to 32560
Data columns (total 15 columns):
age               32537 non-null int64
workclass         32537 non-null object
fnlwgt            32537 non-null int64
education         32537 non-null object
education_num     32537 non-null int64
marital_status    32537 non-null object
occupation        32537 non-null object
relationship      32537 non-null object
race              32537 non-null object
sex               32537 non-null object
capital_gain      32537 non-null int64
capital_loss      32537 non-null int64
hours_per_week    32537 non-null int64
native_country    32537 non-null object
wage_class        32537 non-null object
dtypes: int64(6), object(9)
memory usage: 4.0+ MB
```

In [255]:

```
df_AdultData_testSet.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 16276 entries, 0 to 16280
Data columns (total 15 columns):
age               16276 non-null int64
workclass         16276 non-null object
fnlwgt            16276 non-null int64
education         16276 non-null object
education_num     16276 non-null int64
marital_status    16276 non-null object
occupation        16276 non-null object
relationship      16276 non-null object
race              16276 non-null object
sex               16276 non-null object
capital_gain      16276 non-null int64
capital_loss      16276 non-null int64
hours_per_week    16276 non-null int64
native_country    16276 non-null object
wage_class        16276 non-null object
dtypes: int64(6), object(9)
memory usage: 2.0+ MB
```

In [256]:

```
df_AdultData_trainSet.describe()
```

Out[256]:

	age	fnlwgt	education_num	capital_gain	capital_loss	hours_per_wee
count	32537.000000	3.253700e+04	32537.000000	32537.000000	32537.000000	32537.00000
mean	38.585549	1.897808e+05	10.081815	1078.443741	87.368227	40.44032
std	13.637984	1.055565e+05	2.571633	7387.957424	403.101833	12.34688
min	17.000000	1.228500e+04	1.000000	0.000000	0.000000	1.00000
25%	28.000000	1.178270e+05	9.000000	0.000000	0.000000	40.00000
50%	37.000000	1.783560e+05	10.000000	0.000000	0.000000	40.00000
75%	48.000000	2.369930e+05	12.000000	0.000000	0.000000	45.00000
max	90.000000	1.484705e+06	16.000000	99999.000000	4356.000000	99.00000

In [257]:

```
values_dict= {'<=50K':0, '>50K':1} # mapping string string values with numericalclass value
colname='wage_class'
if df_AdultData_trainSet[colname].dtype==np.object:
    df_AdultData_trainSet[colname]=df_AdultData_trainSet[colname].map(values_dict)
else:
    df_AdultData_trainSet

if df_AdultData_testSet[colname].dtype==np.object:
    df_AdultData_testSet[colname]=df_AdultData_testSet[colname].map(values_dict)
else:
    df_AdultData_testSet
print("Unique values of wage_class after replacing")
df_AdultData_trainSet['wage_class'].unique()
```

```
Unique values of wage_class after replacing
```

Out[257]:

```
array([0, 1], dtype=int64)
```

In [258]:

```
df_AdultData_testSet['wage_class'].unique()
```

Out[258]:

```
array([0, 1], dtype=int64)
```

In [259]:

```
# One Hot Encoding
object_cols = df_AdultData_trainSet.dtypes[df_AdultData_trainSet.dtypes == 'object'].index
object_cols
```

Out[259]:

```
Index(['workclass', 'education', 'marital_status', 'occupation',
       'relationship', 'race', 'sex', 'native_country'],
      dtype='object')
```

In [260]:

```
# One Hot Encoding
object_cols_test = df_AdultData_testSet.dtypes[df_AdultData_testSet.dtypes == 'object'].inc
object_cols_test
```

Out[260]:

```
Index(['workclass', 'education', 'marital_status', 'occupation',
       'relationship', 'race', 'sex', 'native_country'],
      dtype='object')
```

In [261]:

```
# Training Set
if any(x in object_cols for x in df_AdultData_trainSet.columns): # List comprehension for c
        for cols in object_cols:
            df_AdultData_trainSet = df_AdultData_trainSet.join(pd.get_dummies(df_AdultData_
        df_AdultData_trainSet=df_AdultData_trainSet.drop(object_cols, axis=1)

# Test set
if any(x in object_cols_test for x in df_AdultData_testSet.columns): # List comprehension f
        for cols in object_cols_test:
            df_AdultData_testSet = df_AdultData_testSet.join(pd.get_dummies(df_AdultData_te
        df_AdultData_testSet=df_AdultData_testSet.drop(object_cols_test, axis=1)
```

In [265]:

```
df_AdultData_trainSet.head(1)
```

Out[265]:

	age	fnlwgt	education_num	capital_gain	capital_loss	hours_per_week	wage_class	workcla
0	39	77516	13	2174	0	40	0	

1 rows × 101 columns

In [266]:

```
df_AdultData_testSet.head(1)
```

Out[266]:

	age	fnlwgt	education_num	capital_gain	capital_loss	hours_per_week	wage_class	workcl
0	25	226802	7	0	0	40	0	

1 rows × 100 columns

Seperating the target variable from rest of the dataset.

In [309]:

```
dep_feature=[x for x in df_AdultData_trainSet.columns.tolist() if x== 'wage_class' ]
indep_feature=[x for x in df_AdultData_trainSet.columns.tolist() if x!= 'wage_class' ]
df_target= df_AdultData_trainSet[dep_feature]
df_feature=df_AdultData_trainSet[indep_feature]
```

In [310]:

```
df_target.shape, df_feature.shape
```

Out[310]:

```
((32537, 1), (32537, 100))
```

In [311]:

```
df_target.tail(1)
```

Out[311]:

	wage_class
32560	1

In [312]:

```
df_feature.tail(1)
```

Out[312]:

	age	fnlwgt	education_num	capital_gain	capital_loss	hours_per_week	workclass_Fed
32560	52	287927	9	15024	0	40	

1 rows × 100 columns

Feature Selection and Modeling -XGBoost

In [326]:

```
# Define parameter for XGBoost model
params = {'objective':'binary:logistic' , 'max_depth':7, 'learning_rate':1.0,'silent':True
         'n_estimators':400,  'random_state':42 ,'subsample':0.6,'gamma':0.9 , 'n_jobs':-1}
XGB_model_clf= XGBClassifier(**params)
xgb_model =XGB_model_clf.fit(X=df_feature, y=np.ravel(df_target))
xgb_model
```

Out[326]:

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=1, gamma=0.9, learning_rate=1.0, max_delta_step=0,
       max_depth=7, min_child_weight=1, missing=None, n_estimators=400,
       n_jobs=-1, nthread=None, objective='binary:logistic',
       random_state=42, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
       seed=None, silent=True, subsample=0.6)
```

In [327]:

```
# From XGBoost model , Select important features
xgb_model.feature_importances_
```

Out[327]:

```
array([1.86756238e-01, 3.56493920e-01, 5.72616756e-02, 7.67754298e-03,
       9.02111363e-03, 9.84644890e-02, 4.86244401e-03, 7.16570718e-03,
       0.00000000e+00, 2.02175304e-02, 5.88611653e-03, 8.63723643e-03,
       3.90275102e-03, 0.00000000e+00, 1.91938574e-03, 1.59948820e-03,
       1.02367240e-03, 6.39795253e-05, 6.39795253e-05, 7.67754333e-04,
       2.55918101e-04, 4.60652588e-03, 5.43825980e-03, 1.14523349e-02,
       0.00000000e+00, 1.26679465e-02, 4.54254635e-03, 0.00000000e+00,
       2.11132434e-03, 7.10172765e-03, 1.91938583e-04, 9.46896989e-03,
       1.15163147e-03, 7.35764578e-03, 8.31733865e-04, 1.03007033e-02,
       0.00000000e+00, 1.51631478e-02, 1.31797828e-02, 3.07101733e-03,
       3.26295593e-03, 6.90978905e-03, 4.54254635e-03, 0.00000000e+00,
       1.14523349e-02, 3.58285359e-03, 1.33717209e-02, 4.35060775e-03,
       6.71785045e-03, 1.27959056e-02, 7.74152251e-03, 5.11836202e-04,
       1.79142680e-03, 4.79846448e-03, 7.67754333e-04, 2.87907873e-03,
       6.58989139e-03, 6.39795253e-05, 1.35636600e-02, 0.00000000e+00,
       1.91938583e-04, 2.55918101e-04, 1.27959051e-04, 5.11836202e-04,
       6.39795253e-05, 0.00000000e+00, 0.00000000e+00, 2.55918101e-04,
       6.39795253e-05, 5.11836202e-04, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 1.91938583e-04, 1.91938583e-04, 0.00000000e+00,
       2.55918101e-04, 1.27959051e-04, 1.27959051e-04, 0.00000000e+00,
       1.47152913e-03, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       5.75815735e-04, 1.27959051e-04, 0.00000000e+00, 1.91938583e-04,
       0.00000000e+00, 1.27959051e-04, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 8.18937924e-03, 6.39795253e-05, 0.00000000e+00],
      dtype=float32)
```

In [328]:

```
df_feature_importances = pd.DataFrame({'feature':df_feature.columns,'importance':np.round(x
df_feature_importances = df_feature_importances.sort_values('importance',ascending=False)
df_feature_importances.head(25)
```

Out[328]:

	feature	importance
1	fnlwgt	0.3565
0	age	0.1868
5	hours_per_week	0.0985
2	education_num	0.0573
9	workclass_Private	0.0202
37	occupation_Craft-repair	0.0152
58	sex_Female	0.0136
46	occupation_Sales	0.0134
38	occupation_Exec-managerial	0.0132
49	relationship_Husband	0.0128
25	education_HS-grad	0.0127
23	education_Bachelors	0.0115
44	occupation_Prof-specialty	0.0115
35	occupation_Adm-clerical	0.0103
31	marital_status_Married-civ-spouse	0.0095
4	capital_loss	0.0090
11	workclass_Self-emp-not-inc	0.0086
97	native_country_United-States	0.0082
50	relationship_Not-in-family	0.0077
3	capital_gain	0.0077
33	marital_status_Never-married	0.0074
7	workclass_Local-gov	0.0072
29	marital_status_Divorced	0.0071
41	occupation_Machine-op-inspct	0.0069
48	occupation_Transport-moving	0.0067

In [329]:

```
df_important_features=df_feature_importances[df_feature_importances.importance>=0.01]
df_important_features
```

Out[329]:

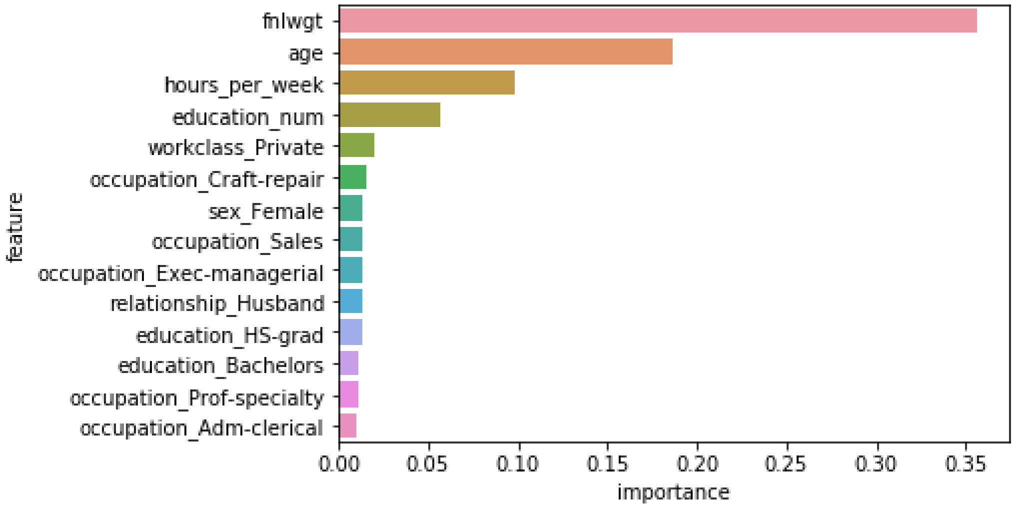
	feature	importance
1	fnlwgt	0.3565
0	age	0.1868
5	hours_per_week	0.0985
2	education_num	0.0573
9	workclass_Private	0.0202
37	occupation_Craft-repair	0.0152
58	sex_Female	0.0136
46	occupation_Sales	0.0134
38	occupation_Exec-managerial	0.0132
49	relationship_Husband	0.0128
25	education_HS-grad	0.0127
23	education_Bachelors	0.0115
44	occupation_Prof-specialty	0.0115
35	occupation_Adm-clerical	0.0103

In [330]:

```
sns.barplot(x=df_important_features.importance , y=df_important_features.feature)
plt.figure(figsize=(15,10))
```

Out[330]:

```
<Figure size 1080x720 with 0 Axes>
```




```
<Figure size 1080x720 with 0 Axes>
```

In [331]:

```
important_cols = df_important_features.feature.values
print(" Important features(columns) returned by model")
important_cols
```

```
 Important features(columns) returned by model
```

Out[331]:

```
array(['fnlwgt', 'age', 'hours_per_week', 'education_num',
       'workclass_Private', 'occupation_Craft-repair', 'sex_Female',
       'occupation_Sales', 'occupation_Exec-managerial',
       'relationship_Husband', 'education_HS-grad', 'education_Bachelors',
       'occupation_Prof-specialty', 'occupation_Adm-clerical'],
      dtype=object)
```

Re-fitting the Model with important features

In [332]:

```
XGB_model_clf= XGBClassifier(**params)
xgb_model =XGB_model_clf.fit(X=df_feature[important_cols], y=np.ravel(df_target))
xgb_model
```

Out[332]:

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=1, gamma=0.9, learning_rate=1.0, max_delta_step=0,
       max_depth=7, min_child_weight=1, missing=None, n_estimators=400,
       n_jobs=-1, nthread=None, objective='binary:logistic',
       random_state=42, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
       seed=None, silent=True, subsample=0.6)
```

Model Evaluation on Test Dataset

In [333]:

```
dep_feature=[x for x in df_AdultData_testSet.columns.tolist() if x== 'wage_class' ]
indep_feature=[x for x in df_AdultData_testSet.columns.tolist() if x!= 'wage_class' ]
df_target_test= df_AdultData_testSet[dep_feature]
df_feature_test=df_AdultData_testSet[indep_feature]

y_pred=xgb_model.predict(df_feature_test[important_cols])
y_pred_proba=xgb_model.predict_proba(df_feature_test[important_cols])
```

```
C:\Users\mkarthikeyan\AppData\Local\Continuum\anaconda3\lib\site-packages\sk
learn\preprocessing\label.py:151: DeprecationWarning: The truth value of an
empty array is ambiguous. Returning False, but in future this will result in
an error. Use `array.size > 0` to check that an array is not empty.
  if diff:
```

In [334]:

```
print("Predicted target variable (first 5 values):",y_pred[0:5])
print("Predicted target variable probabilities (first 5 values):\n",y_pred_prob[0:5])
```

```
Predicted target variable (first 5 values): [0 1 1 1 0]
Predicted target variable probabilities (first 5 values):
 [[1.0618925e-02 9.8938107e-01]
 [9.9997932e-01 2.0655802e-05]
 [9.9920726e-01 7.9273549e-04]
 [9.9999803e-01 1.9444028e-06]
 [6.8748909e-01 3.1251091e-01]]
```

Model Evaluation Metrics

```
- Confusion_matrix , Classification report , accuracy score, f-1 score , recall sc
ore, precision score ,
  roc_auc curve, auc , precision_recall_curve
```

In [335]:

```
actual_target_variable= df_target_test
predicted_target_variable=y_pred

# confusion matrix
confusion_matrix(y_true=actual_target_variable , y_pred=predicted_target_variable)
```

Out[335]:

```
array([[10738,  1692],
       [ 1914,  1932]], dtype=int64)
```

In [336]:

```
# Classification report
classification_report(y_true=actual_target_variable , y_pred=predicted_target_variable , ta
```

Out[336]:

```
'             precision    recall  f1-score   support\n\n      <=50K
0.85      0.86      0.86     12430\n       >50K       0.53      0.50      0.
52      3846\n\navg / total       0.77      0.78      0.78     16276\n'
```

In [338]:

```
acc_score= accuracy_score(y_true=actual_target_variable , y_pred=predicted_target_variable)
prec_score=precision_score(y_true=actual_target_variable , y_pred=predicted_target_variable
recl_score= recall_score(y_true=actual_target_variable, y_pred=predicted_target_variable)
f1score= f1_score(y_true= actual_target_variable, y_pred=predicted_target_variable)
```

In [325]:

```
print("Model Accuracy score (on Test set) :", acc_score )
print("Model Precision score (on Test set) :", prec_score )
print("Model Recall score (on Test set) :", recl_score)
print("Model F-1 score (on Test set) :", f1score)
```

```
Model Accuracy score (on Test set) : 0.7861882526419267
Model Precision score (on Test set) : 0.5513180033651149
Model Recall score (on Test set) : 0.5111804472178887
Model F-1 score (on Test set) : 0.5304910955207771
```

Problem 1:

    Prediction task is to determine whether a person makes over 50K a year.

Solution:

Yes, we can predict whether a person makes over 50k a year or not using XGBoost Classifier with important features and the accuracy is around 78.5 %

Problem 2:

    Which factors are important

Solution:

Following are some of the important features observed by the Model:

In [339]:

```
important_cols = df_important_features.feature.values
print(" Important features(columns) returned by model")
important_cols
```

```
 Important features(columns) returned by model
```

Out[339]:

```
array(['fnlwgt', 'age', 'hours_per_week', 'education_num',
       'workclass_Private', 'occupation_Craft-repair', 'sex_Female',
       'occupation_Sales', 'occupation_Exec-managerial',
       'relationship_Husband', 'education_HS-grad', 'education_Bachelors',
       'occupation_Prof-specialty', 'occupation_Adm-clerical'],
      dtype=object)
```

Problem 3:

    Which algorithms are best for this dataset

Solution:

In [341]:

```
# Let's try Logistics, decision tree, random forest , Xgboost models
# Parameter for XGboost model
model_params = {'objective':'binary:logistic' , 'max_depth':7, 'learning_rate':1.0,'silent'
         'n_estimators':400,  'random_state':15 ,'subsample':0.6,'gamma':0.9 , 'n_jobs':10}
# Model names for Classification model comparison
model_names=["Decision Tree", "Random Forest", "XGBoost", "Logistics Regression"]
# Apply model to some variables
dec_tree_clf = DecisionTreeClassifier(max_depth=5)
xgboost_clf = XGBClassifier(**model_params)
random_forest_clf = RandomForestClassifier(n_estimators=100)
logistics_clf = LogisticRegression()

model_classifiers=[dec_tree_clf, random_forest_clf,xgboost_clf, logistics_clf]
```

In [343]:

```
# Fit the Models into classifiers
for clf in zip(model_names, model_classifiers):
    clf[1].fit(df_feature_test, df_target_test)
```

```
C:\Users\mkarthikeyan\AppData\Local\Continuum\anaconda3\lib\site-packages\ip
ykernel_launcher.py:3: DataConversionWarning: A column-vector y was passed w
hen a 1d array was expected. Please change the shape of y to (n_samples,), f
or example using ravel().
  This is separate from the ipykernel package so we can avoid doing imports
until
C:\Users\mkarthikeyan\AppData\Local\Continuum\anaconda3\lib\site-packages\sk
learn\preprocessing\label.py:95: DataConversionWarning: A column-vector y wa
s passed when a 1d array was expected. Please change the shape of y to (n_sa
mples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
C:\Users\mkarthikeyan\AppData\Local\Continuum\anaconda3\lib\site-packages\sk
learn\preprocessing\label.py:128: DataConversionWarning: A column-vector y w
as passed when a 1d array was expected. Please change the shape of y to (n_s
amples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
C:\Users\mkarthikeyan\AppData\Local\Continuum\anaconda3\lib\site-packages\sk
learn\utils\validation.py:578: DataConversionWarning: A column-vector y was
passed when a 1d array was expected. Please change the shape of y to (n_samp
les, ), for example using ravel().
  y = column_or_1d(y, warn=True)
```

In [350]:

```
# Model Comparison
classification_models = pd.DataFrame(index=['accuracy_score','precision_score','recall_scor
                      columns=['logistic_regression','decision_tree','random_forest','xgboc
```

In [352]:

```
classification_models.loc['accuracy_score','logistic_regression'] = accuracy_score(y_true=
classification_models.loc['precision_score','logistic_regression'] = precision_score(y_true
classification_models.loc['recall_score','logistic_regression'] = recall_score(y_true= df_t
classification_models.loc['f1-score','logistic_regression'] = f1_score(y_true= df_target_te

classification_models.loc['accuracy_score','decision_tree'] = accuracy_score(y_true= df_tar
classification_models.loc['precision_score','decision_tree'] = precision_score(y_true= df_t
classification_models.loc['recall_score','decision_tree'] = recall_score(y_true= df_target_
classification_models.loc['f1-score','decision_tree'] = f1_score(y_true= df_target_test, y_

classification_models.loc['accuracy_score','random_forest'] = accuracy_score(y_true= df_tar
classification_models.loc['precision_score','random_forest'] = precision_score(y_true= df_t
classification_models.loc['recall_score','random_forest'] = recall_score(y_true= df_target_
classification_models.loc['f1-score','random_forest'] = f1_score(y_true= df_target_test, y_

classification_models.loc['accuracy_score','xgboost'] = accuracy_score(y_true= df_target_te
classification_models.loc['precision_score','xgboost'] = precision_score(y_true= df_target_
classification_models.loc['recall_score','xgboost'] = recall_score(y_true= df_target_test ,
classification_models.loc['f1-score','xgboost'] = f1_score(y_true= df_target_test, y_pred=
```

```
C:\Users\mkarthikeyan\AppData\Local\Continuum\anaconda3\lib\site-packages\sk
learn\preprocessing\label.py:151: DeprecationWarning: The truth value of an
empty array is ambiguous. Returning False, but in future this will result in
an error. Use `array.size > 0` to check that an array is not empty.
  if diff:
C:\Users\mkarthikeyan\AppData\Local\Continuum\anaconda3\lib\site-packages\sk
learn\preprocessing\label.py:151: DeprecationWarning: The truth value of an
empty array is ambiguous. Returning False, but in future this will result in
an error. Use `array.size > 0` to check that an array is not empty.
  if diff:
C:\Users\mkarthikeyan\AppData\Local\Continuum\anaconda3\lib\site-packages\sk
learn\preprocessing\label.py:151: DeprecationWarning: The truth value of an
empty array is ambiguous. Returning False, but in future this will result in
an error. Use `array.size > 0` to check that an array is not empty.
  if diff:
C:\Users\mkarthikeyan\AppData\Local\Continuum\anaconda3\lib\site-packages\sk
learn\preprocessing\label.py:151: DeprecationWarning: The truth value of an
empty array is ambiguous. Returning False, but in future this will result in
an error. Use `array.size > 0` to check that an array is not empty.
  if diff:
```

In [353]:

```
print("Results of the classification models:")
classification_models
```

```
Results of the classification models:
```

Out[353]:

	logistic_regression	decision_tree	random_forest	xgboost
accuracy_score	0.798538	0.854264	0.999877	0.999078
precision_score	0.709225	0.785217	1	0.999218
recall_score	0.24987	0.527561	0.99948	0.99688
f1-score	0.369544	0.631104	0.99974	0.998048

Looks like, Random Forest, XG Boost algorithms works best for the given dataset