Decision_Tree

June 2, 2021

0.0.1 Read the Data

[1]:
```
import pandas as pd
import numpy as np
import numpy as np
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
from matplotlib import pyplot as plt
from matplotlib import pyplot
%matplotlib inline

df1 =pd.read_csv("week1-5_24_to_5_31_/final_merged.csv")
sum_column = df1['PHQ+AF8-1']+df1['PHQ+AF8-2']+df1['PHQ+AF8-3']+\
                            df1['PHQ+AF8-4']+df1['PHQ+AF8-5']+ \
                            ␣
 ↪df1['PHQ+AF8-6']+df1['PHQ+AF8-7']+df1['PHQ+AF8-8']+df1['PHQ+AF8-9']
df1["PHQ"] = sum_column
df =df1.iloc[:,2:59]
df["PHQ"] =df1["PHQ"]
columns=df.columns
```

0.0.2 Detect existing (non-missing) values in our Dataset

[2]:
```
df.notnull().sum()
```

[2]:
```
BIRTH           6340
SEX             6337
HISPANIC        6229
RACE            6340
VET             5370
ACTIVE          1400
DEPLOY          1400
MILFAM           778
```

AUDIT	6340
DAST	6340
COSCREEN	6340
SCREEN	6340
BI	6340
BT	6340
RT	6340
ANYALC	803
BINGEDAYS	811
DRUGDAYS	804
ALCDRUGS	805
DAYSCOCAINE	805
MARYJDAYS	805
ANYOPIATEDAYS	804
METHADONE	805
HALLUC	805
METHDAYS	805
OTHERDRUGS	804
INJECT	808
WHERELIVE	118
PREGNANT	119
CHILDREN	119
JOBTRAIN	119
EDUC	119
EMPLOY	119
INCOME	118
ARRESTED	119
CRIMES	119
HEALTHSTAT	119
ANYSEX	119
SEXCONTACT	118
SEXUNPROTECT	118
EVERHIVT	117
HIVRESULT	90
DEPRESSDAYS	119
ANXIETYDAYS	119
HALLUCINATE	119
MEMORYBAD	119
SUICIDEATTEMPT	119
ATTENDAA	119
AATIMES	119
ATTENDRELIGION	119
RELIGIONTIMES	119
ATTENDOTHER	119
OTHERTIMES	119
FAMILYINT	119
SBIRTCONT	119

```
AGE                 6371
TOBMONTH            6294
PHQ                   83
dtype: int64
```

0.0.3 Preprocessing Dataset

[3]:
```
x=np.where( (df['AGE'].notnull()) & (df['BIRTH'].isnull()))[0]
for i in x:
        df.iloc[i,0]=2021-df.iloc[i,55]
```

[4]:
```
y=np.where( (df['AGE'].isnull()) & (df['BIRTH'].notnull()))[0]
for i in y:
    df.iloc[i,55]=2021-df.iloc[i,0]
```

[5]:
```
deploy=np.where( (df['DEPLOY'].isnull()) & (df['VET']==0))[0]
for i in deploy:
    df.iloc[i,6]=0
```

[6]:
```
active=np.where( (df['ACTIVE'].isnull()) & (df['VET']==0))[0]
for i in active:
    df.iloc[i,5]=0
```

[7]:
```
sex=np.where((df['SEX'].isnull()) & (df['PREGNANT'].notnull()))[0]
for i in sex: # if  PREGNANT =yes -----female
    df.iloc[i,1]=1
```

[8]:
```
sex=np.where((df['SEX']==0) & (df['PREGNANT'].isnull()))[0]
for i in sex:
    df.iloc[i,28]=0
```

[9]:
```
columns1=df1.columns
audit=np.where( (df1['Audit+AF8-1']==0) & (df['ANYALC'].isnull()))[0]
for i in audit:
    df.iloc[i,15]=0
```

[10]:
```
audit1=np.where( (df1['Audit+AF8-2']==0) & (df['ANYALC'].isnull()))[0]
for i in audit1:
    df.iloc[i,15]=0
```

[11]:
```
audit2=np.where( (df['AUDIT']==0) & (df['ANYALC'].isnull()))[0]
for i in audit2:
    df.iloc[i,15]=0
```

[12]:
```
x=np.where( (df1['Audit+AF8-1']==0) & (df['BINGEDAYS'].isnull()))[0]
for i in x:
    df.iloc[i,16]=0
```

[13]:
```
y=np.where( (df1['Audit+AF8-2']==0) & (df['BINGEDAYS'].isnull()))[0]
for i in y:
    df.iloc[i,16]=0
```

[14]:
```
z=np.where( (df['AUDIT']==0) & (df['BINGEDAYS'].isnull()))[0]
for i in z:
    df.iloc[i,16]=0
```

[15]:
```
z=np.where( (df1['Dast+AF8-1']==0) & (df['DRUGDAYS'].isnull()))[0]
for i in z:
    df.iloc[i,17]=0
```

[16]:
```
z=np.where( (df1['Dast+AF8-3']==0) & (df['DRUGDAYS'].isnull()))[0]
for i in z:
    df.iloc[i,17]=0
```

[17]:
```
z=np.where( (df1['Dast+AF8-5']==0) & (df['DRUGDAYS'].isnull()))[0]
for i in z:
    df.iloc[i,17]=0
```

[18]:
```
z=np.where( (df1['Dast+AF8-1']==0) &(df1['Audit+AF8-1']==0) &(df['ALCDRUGS'].
 ↪isnull()))[0]
for i in z:
    df.iloc[i,18]=0
```

[19]:
```
z=np.where( (df1['Dast+AF8-3']==0) &(df1['Audit+AF8-1']==0) &(df['ALCDRUGS'].
 ↪isnull()))[0]
for i in z:
    df.iloc[i,18]=0
```

[20]:
```
z=np.where( (df1['Dast+AF8-5']==0) &(df1['Audit+AF8-1']==0) &(df['ALCDRUGS'].
 ↪isnull()))[0]
for i in z:
    df.iloc[i,18]=0
```

[21]:
```
z=np.where( (df1['Dast+AF8-1']==0) &(df1['Audit+AF8-2']==0) &(df['ALCDRUGS'].
 ↪isnull()))[0]
for i in z:
    df.iloc[i,18]=0
```

[22]:
```
z=np.where( (df1['Dast+AF8-3']==0) &(df1['Audit+AF8-2']==0) &(df['ALCDRUGS'].
 ↪isnull()))[0]
```

```
for i in z:
    df.iloc[i,18]=0
```

[23]:
```
z=np.where( (df1['Dast+AF8-5']==0) &(df1['Audit+AF8-2']==0) &(df['ALCDRUGS'].
↪isnull()))[0]
for i in z:
    df.iloc[i,18]=0
```

[24]:
```
z=np.where( (df1['Dast+AF8-1']==0) &(df['AUDIT']==0) &(df['ALCDRUGS'].
↪isnull()))[0]
for i in z:
    df.iloc[i,18]=0
```

[25]:
```
z=np.where( (df1['Dast+AF8-3']==0) &(df['AUDIT']==0) &(df['ALCDRUGS'].
↪isnull()))[0]
for i in z:
    df.iloc[i,18]=0
```

[26]:
```
z=np.where( (df1['Dast+AF8-5']==0) &(df['AUDIT']==0) &(df['ALCDRUGS'].
↪isnull()))[0]
for i in z:
    df.iloc[i,18]=0
```

[27]:
```
y=np.where( (df1['Dast+AF8-1']==0) & (df['DAYSCOCAINE'].isnull()))[0]
for i in y:
    df.iloc[i,19]=0
```

[28]:
```
y=np.where( (df1['Dast+AF8-1']==0) & (df['MARYJDAYS'].isnull()))[0]
for i in y:
    df.iloc[i,20]=0
```

[29]:
```
y=np.where( (df1['Dast+AF8-1']==0) & (df['ANYOPIATEDAYS'].isnull()))[0]
for i in y:
    df.iloc[i,21]=0
```

[30]:
```
y=np.where( (df1['Dast+AF8-1']==0) & (df['METHADONE'].isnull()))[0]
for i in y:
    df.iloc[i,22]=0
```

[31]:
```
y=np.where( (df1['Dast+AF8-1']==0) & (df['HALLUC'].isnull()))[0]
for i in y:
    df.iloc[i,23]=0
```

[32]:
```
y=np.where( (df1['Dast+AF8-1']==0) & (df['METHDAYS'].isnull()))[0]
for i in y:
    df.iloc[i,24]=0
```

[33]:
```
y=np.where( (df1['Dast+AF8-1']==0) & (df['OTHERDRUGS'].isnull()))[0]
for i in y:
    df.iloc[i,25]=0
```

[34]:
```
y=np.where( (df1['Dast+AF8-1']==0) & (df['INJECT'].isnull()))[0]
for i in y:
    df.iloc[i,26]=0
```

[35]:
```
y=np.where( (df1['Audit+AF8-8']>2) & (df['ARRESTED'].isnull()))[0]
for i in y:
    df.iloc[i,34]=1
```

[36]:
```
y=np.where( (df1['Dast+AF8-9']==1) & (df['ARRESTED'].isnull()))[0]
for i in y:
    df.iloc[i,34]=1
```

0.0.4 Detect existing (non-missing) values in our Dataset after Preprocessing

[37]:
```
df.notnull().sum()
```

[37]:
```
BIRTH            6947
SEX              6375
HISPANIC         6229
RACE             6340
VET              5370
ACTIVE           5370
DEPLOY           5370
MILFAM            778
AUDIT            6340
DAST             6340
COSCREEN         6340
SCREEN           6340
BI               6340
BT               6340
RT               6340
ANYALC           5451
BINGEDAYS        5457
DRUGDAYS         6424
ALCDRUGS         5214
DAYSCOCAINE      6368
MARYJDAYS        6368
ANYOPIATEDAYS    6368
METHADONE        6368
HALLUC           6368
METHDAYS         6368
OTHERDRUGS       6367
```

```
INJECT              6372
WHERELIVE            118
PREGNANT            2808
CHILDREN             119
JOBTRAIN             119
EDUC                 119
EMPLOY               119
INCOME               118
ARRESTED             143
CRIMES               119
HEALTHSTAT           119
ANYSEX               119
SEXCONTACT           118
SEXUNPROTECT         118
EVERHIVT             117
HIVRESULT             90
DEPRESSDAYS          119
ANXIETYDAYS          119
HALLUCINATE          119
MEMORYBAD            119
SUICIDEATTEMPT       119
ATTENDAA             119
AATIMES              119
ATTENDRELIGION       119
RELIGIONTIMES        119
ATTENDOTHER          119
OTHERTIMES           119
FAMILYINT            119
SBIRTCONT            119
AGE                 6947
TOBMONTH            6294
PHQ                   83
dtype: int64
```

0.0.5 Scoring the AUDIT

0.0.6 1) 1 to 7 —> 0 low-risk

0.0.7 2) 8 to 14 —> 1 meduim-risk

0.0.8 3) more than 15 -> 2 high-risk

[38]:
```
y=np.where( (df["AUDIT"]>=0) & (df["AUDIT"]<7))[0]
for i in y:
    df.iloc[i,8]=0
```

```
y=np.where( (df["AUDIT"]>=7) & (df["AUDIT"]<15))[0]
for i in y:
    df.iloc[i,8]=1

y=np.where( (df["AUDIT"]>=15))[0]
for i in y:
    df.iloc[i,8]=2
```

0.1 The GOAL in this experment is to find the class of DAST-10 to give Suggested Action

0.1.1 DAST-10 Score: / Degree of Problem: / Suggested Action:

0.1.2 0: —> CLASS 0 / No problems reported / None at this time

0.1.3 1-2: —> CLASS 1 / Low level Monitor / reassess at a later date

0.1.4 3-6: —> CLASS 2 / Moderate level / Further investigation

0.1.5 6–8: —> CLASS 3 / Substantial level / Intensive assessment

0.1.6 9–10: —> CLASS 4 / Severe level / Intensive assessment

[39]:
```
y1=np.where( (df["DAST"]==0))[0]
for i in y1:
    df.iloc[i,9]=0


y2=np.where( (df["DAST"]<3)  & (df["DAST"]>=1))[0]
for i in y2:
    df.iloc[i,9]=1

y3=np.where((df["DAST"]<6) & (df["DAST"]>=3))[0]
for i in y3:
    df.iloc[i,9]=2

y4=np.where((df["DAST"]<9) & (df["DAST"]>=6))[0]
for i in y4:
    df.iloc[i,9]=3

y5=np.where((df["DAST"]<=10) & (df["DAST"]>=9))[0]
for i in y5:
    df.iloc[i,9]=4
```

0.1.7 Choose the columns covered more than 70% from the Dataset

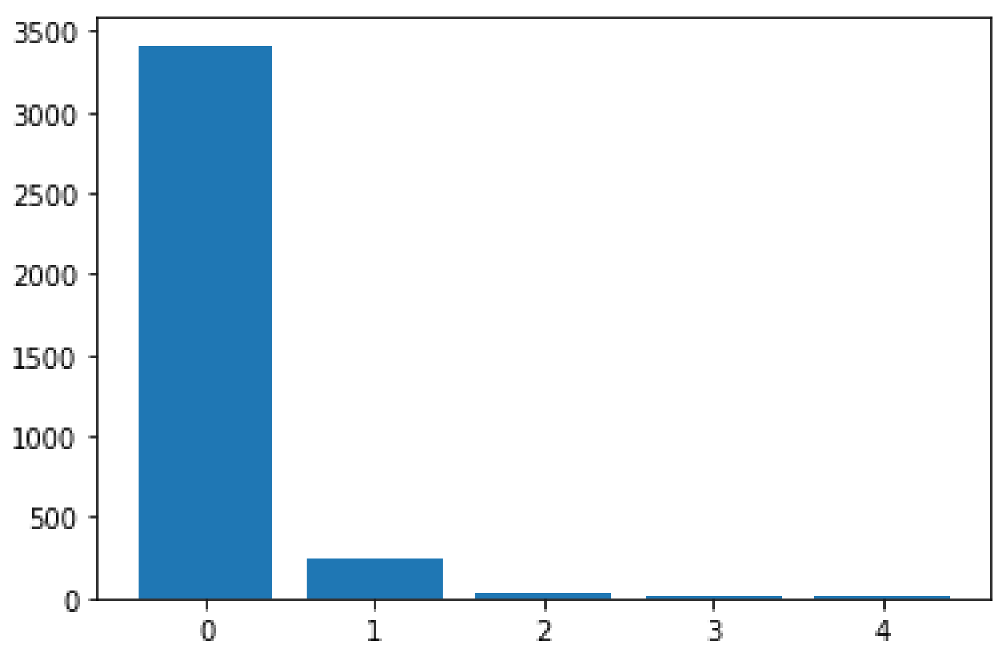
[40]:
```
df=df[['DAST','BIRTH','SEX','HISPANIC', 'RACE','VET','ACTIVE','DEPLOY','AUDIT',
       'COSCREEN','SCREEN','BI','BT','RT','ANYALC','BINGEDAYS',
       'DRUGDAYS','ALCDRUGS',
       'DAYSCOCAINE','MARYJDAYS','ANYOPIATEDAYS',
       'METHADONE','HALLUC','METHDAYS','OTHERDRUGS','INJECT','AGE','TOBMONTH']]
df=  df.dropna()
df1=df[['DAST']]
```

[41]:
```
df=df[['BIRTH','SEX','HISPANIC', 'RACE','VET','ACTIVE','DEPLOY','AUDIT',
       'COSCREEN','SCREEN','BI','BT','RT','ANYALC','BINGEDAYS',
      'DRUGDAYS','ALCDRUGS','DAYSCOCAINE','MARYJDAYS','ANYOPIATEDAYS',
       'METHADONE','HALLUC','METHDAYS','OTHERDRUGS','INJECT','AGE','TOBMONTH']]
```

0.1.8 Splitting the Dataset

[42]:
```
X = df
y = df1
```

[43]:
```
class_=y.value_counts()
pyplot.bar([0,1,2,3,4], [class_[0],class_[1],class_[2],class_[3],class_[4]])
pyplot.show()
```



0.1.9 How to deal with Multi-Class Imbalanced Classification?

0.1.10 ** SMOTE Oversampling for Multi-Class Classification

0.1.11 Oversampling refers to copying or synthesizing new examples of the minority classes so that the number of examples in the minority class better resembles or matches the number of examples in the majority classes.

[44]:
```
import pandas as pd
from sklearn.tree import DecisionTreeClassifier # Import Decision Tree␣
↪Classifier
from sklearn.model_selection import train_test_split # Import train_test_split␣
↪function
from sklearn import metrics #Import scikit-learn metrics module for accuracy␣
↪calculation
import imblearn
from collections import Counter
from imblearn.over_sampling import SMOTE
from collections import Counter
from matplotlib import pyplot
from sklearn.preprocessing import LabelEncoder
from sklearn.tree import export_graphviz
from six import StringIO
from IPython.display import Image
import pydotplus
from numpy import mean
from numpy import std
from pandas import read_csv
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import RepeatedStratifiedKFold
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier,␣
↪GradientBoostingClassifier

X,y=df,df1
# label encode the target variable
```

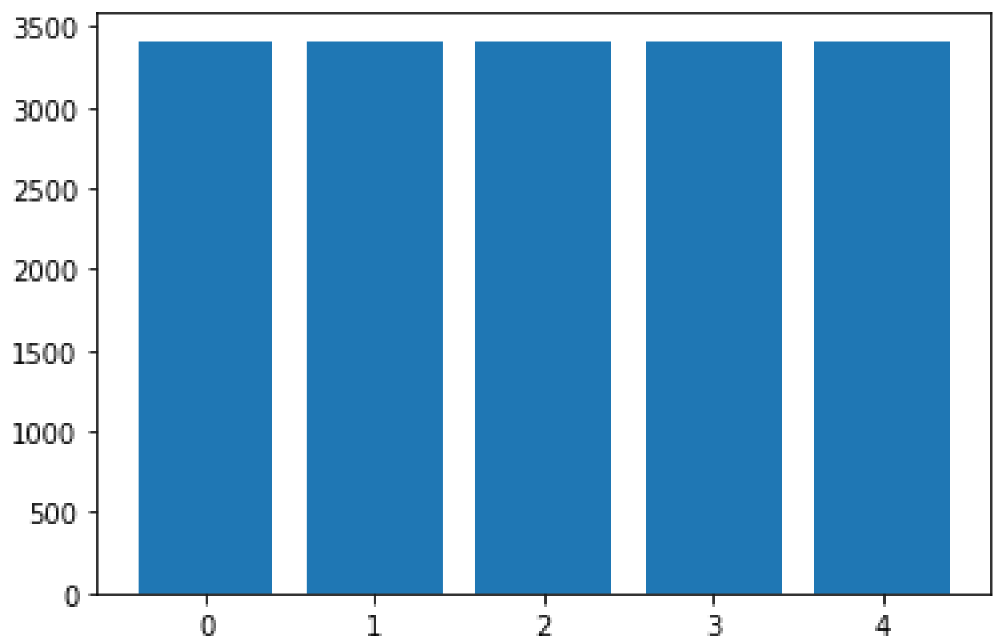
0.1.12 A bar chart of the class distribution will be created, providing a strong visual indication that all classes now have the same number of examples.

[45]:
```
y = LabelEncoder().fit_transform(y)
# transform the dataset
oversample = SMOTE()
X, y = oversample.fit_resample(X, y)
# summarize distribution
```

```
counter = Counter(y)
for k,v in counter.items():
        per = v / len(y) * 100
        print('Class=%d, n=%d (%.3f%%)' % (k, v, per))
# plot the distribution
pyplot.bar(counter.keys(), counter.values())
pyplot.show()
```

```
Class=1, n=3413 (20.000%)
Class=0, n=3413 (20.000%)
Class=2, n=3413 (20.000%)
Class=4, n=3413 (20.000%)
Class=3, n=3413 (20.000%)
```

```
/home/sameerahtalafha/anaconda3/envs/py3.8/lib/python3.8/site-
packages/sklearn/utils/validation.py:63: DataConversionWarning: A column-vector
y was passed when a 1d array was expected. Please change the shape of y to
(n_samples, ), for example using ravel().
  return f(*args, **kwargs)
```



[46]:
```
#efault weighting for classes 0 and 1.0 that have many examples and a double␣
 ↪class weighting of 2.0 for the other classes.
X,y=df,df1

strategy = {0:6813, 1:6813, 2:6813, 3:6813, 4:6813}
oversample = SMOTE(sampling_strategy=strategy)
```

```
X, y = oversample.fit_resample(X, y)
y = LabelEncoder().fit_transform(y)
weights = 'balanced'
X.shape
```

```
/home/sameerahtalafha/anaconda3/envs/py3.8/lib/python3.8/site-
packages/imblearn/utils/_validation.py:299: UserWarning: After over-sampling,
the number of samples (6813) in class 0 will be larger than the number of
samples in the majority class (class #0.0 -> 3413)
  warnings.warn(
/home/sameerahtalafha/anaconda3/envs/py3.8/lib/python3.8/site-
packages/imblearn/utils/_validation.py:299: UserWarning: After over-sampling,
the number of samples (6813) in class 1 will be larger than the number of
samples in the majority class (class #0.0 -> 3413)
  warnings.warn(
/home/sameerahtalafha/anaconda3/envs/py3.8/lib/python3.8/site-
packages/imblearn/utils/_validation.py:299: UserWarning: After over-sampling,
the number of samples (6813) in class 2 will be larger than the number of
samples in the majority class (class #0.0 -> 3413)
  warnings.warn(
/home/sameerahtalafha/anaconda3/envs/py3.8/lib/python3.8/site-
packages/imblearn/utils/_validation.py:299: UserWarning: After over-sampling,
the number of samples (6813) in class 3 will be larger than the number of
samples in the majority class (class #0.0 -> 3413)
  warnings.warn(
/home/sameerahtalafha/anaconda3/envs/py3.8/lib/python3.8/site-
packages/imblearn/utils/_validation.py:299: UserWarning: After over-sampling,
the number of samples (6813) in class 4 will be larger than the number of
samples in the majority class (class #0.0 -> 3413)
  warnings.warn(
/home/sameerahtalafha/anaconda3/envs/py3.8/lib/python3.8/site-
packages/sklearn/utils/validation.py:63: DataConversionWarning: A column-vector
y was passed when a 1d array was expected. Please change the shape of y to
(n_samples, ), for example using ravel().
  return f(*args, **kwargs)
```

[46]: (34065, 27)

0.2 First Model : Decision Tree

[47]:
```
clf = DecisionTreeClassifier(criterion="entropy", max_depth=6,␣
 ↪class_weight=weights)
# Splitting the dataset into train and test
X_train, X_test, y_train, y_test = train_test_split( X, y, test_size = 0.1,␣
 ↪random_state = 1)
```

```
# evaluate a model
def evaluate_model(X, y, model):
        # define evaluation procedure
        cv = RepeatedStratifiedKFold(n_splits=5, n_repeats=3, random_state=1)
        # evaluate model
        scores = cross_val_score(model, X, y, scoring='accuracy', cv=cv,␣
 ↪n_jobs=-1)
        return scores

clf.fit(X_train,y_train)
scores = evaluate_model(X_train, y_train,clf)
# summarize performance
print('Cross_validation_Mean Accuracy: %.3f (%.3f)' % (mean(scores),␣
 ↪std(scores)))
```

```
Cross_validation_Mean Accuracy: 0.997 (0.001)
```

[48]:
```
y_pred = clf.predict(X_test)

# Model Accuracy, how often is the classifier correct?
print("Test_Accuracy:",metrics.accuracy_score(y_test, y_pred))
```

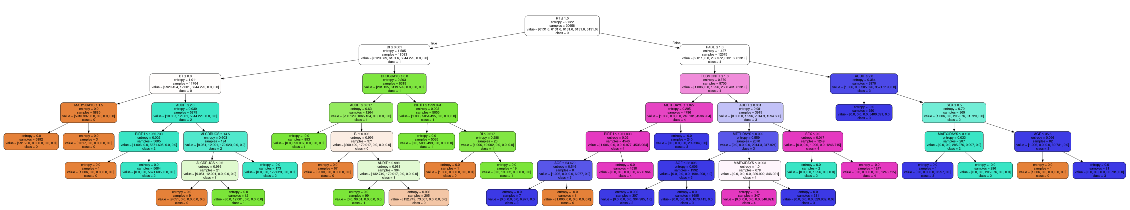
```
Test_Accuracy: 0.9991194599354271
```

[49]:
```
feature_cols=['BIRTH','SEX','HISPANIC', 'RACE','VET','ACTIVE','DEPLOY','AUDIT',
       'COSCREEN','SCREEN','BI','BT','RT','ANYALC','BINGEDAYS',
      'DRUGDAYS','ALCDRUGS','DAYSCOCAINE','MARYJDAYS','ANYOPIATEDAYS',
             ␣
 ↪'METHADONE','HALLUC','METHDAYS','OTHERDRUGS','INJECT','AGE','TOBMONTH']



dot_data = StringIO()
export_graphviz(clf, out_file=dot_data,
                filled=True, rounded=True,
                special_characters=True,feature_names =␣
 ↪feature_cols,class_names=['0','1','2','3','4'])
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
graph.write_png('DT.png')
Image(graph.create_png())
```

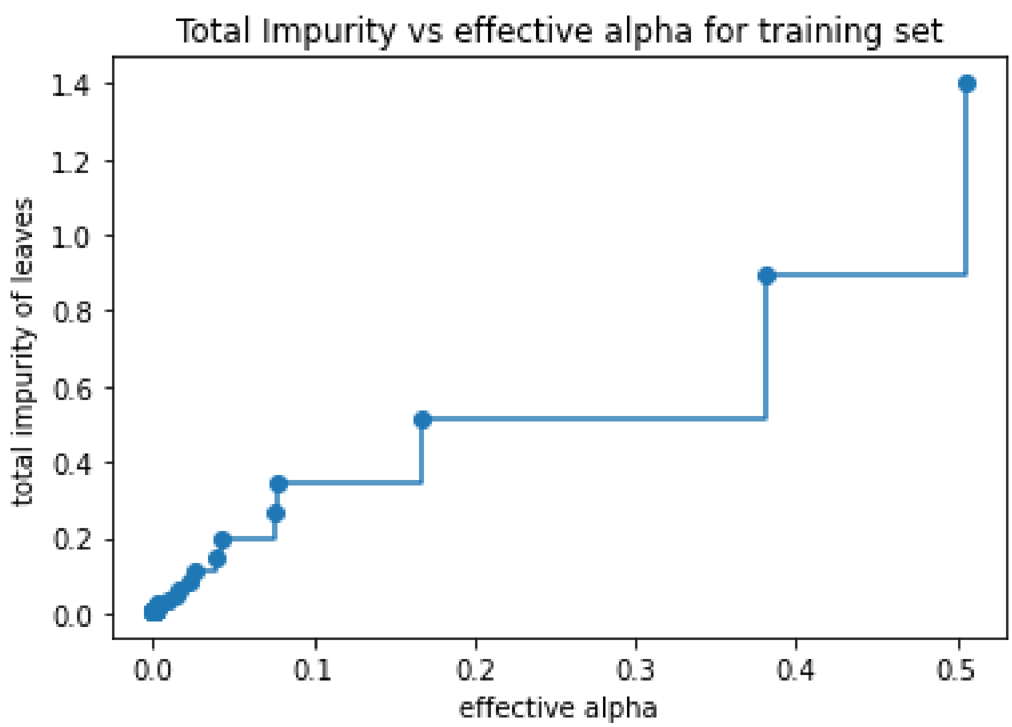
[49]:



0.3 Puning decision trees with cost complexity pruning

[50]:
```
path = clf.cost_complexity_pruning_path(X_train, y_train)
ccp_alphas, impurities = path.ccp_alphas, path.impurities
fig, ax = plt.subplots()
ax.plot(ccp_alphas[:-1], impurities[:-1], marker='o', drawstyle="steps-post")
ax.set_xlabel("effective alpha")
ax.set_ylabel("total impurity of leaves")
ax.set_title("Total Impurity vs effective alpha for training set")
```

[50]:
```
Text(0.5, 1.0, 'Total Impurity vs effective alpha for training set')
```



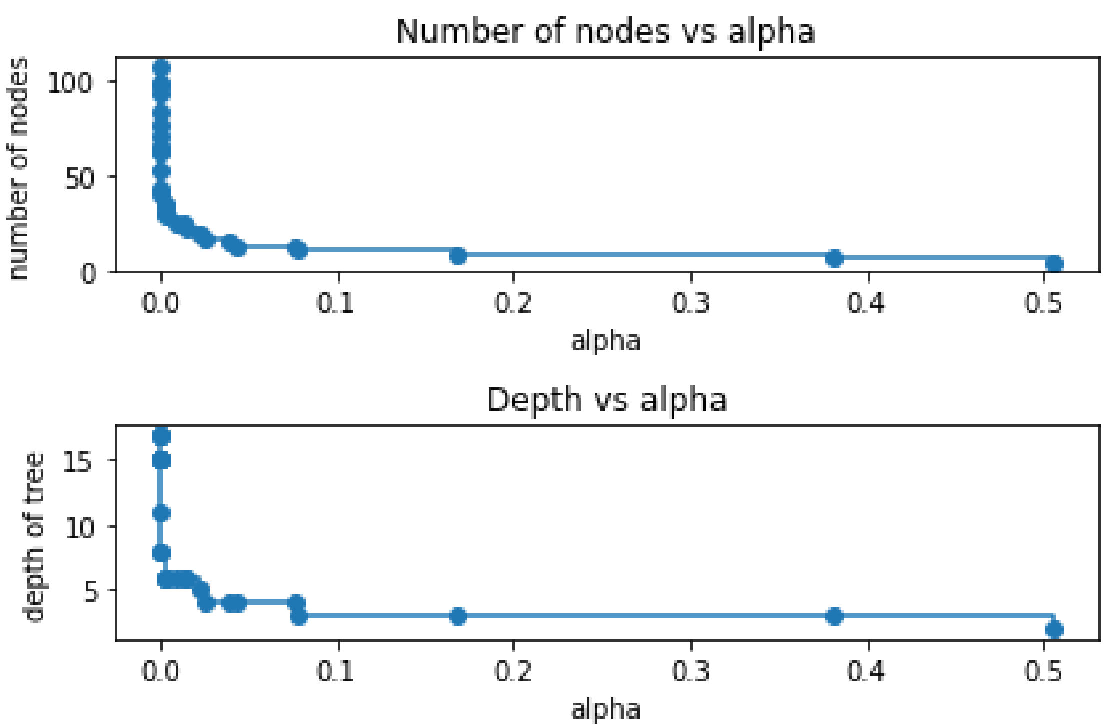
[51]:
```
clfs = []
for ccp_alpha in ccp_alphas:
    clf = DecisionTreeClassifier(random_state=0, criterion="entropy",␣
 ↪class_weight=weights,ccp_alpha=ccp_alpha)
    clf.fit(X_train, y_train)
    clfs.append(clf)
print("Number of nodes in the last tree is: {} with ccp_alpha: {}".format(
      clfs[-1].tree_.node_count, ccp_alphas[-1]))
```

```
Number of nodes in the last tree is: 1 with ccp_alpha: 0.9207635045786655
```

[52]:

```
clfs = clfs[:-1]
ccp_alphas = ccp_alphas[:-1]

node_counts = [clf.tree_.node_count for clf in clfs]
depth = [clf.tree_.max_depth for clf in clfs]
fig, ax = plt.subplots(2, 1)
ax[0].plot(ccp_alphas, node_counts, marker='o', drawstyle="steps-post")
ax[0].set_xlabel("alpha")
ax[0].set_ylabel("number of nodes")
ax[0].set_title("Number of nodes vs alpha")
ax[1].plot(ccp_alphas, depth, marker='o', drawstyle="steps-post")
ax[1].set_xlabel("alpha")
ax[1].set_ylabel("depth of tree")
ax[1].set_title("Depth vs alpha")
fig.tight_layout()
```

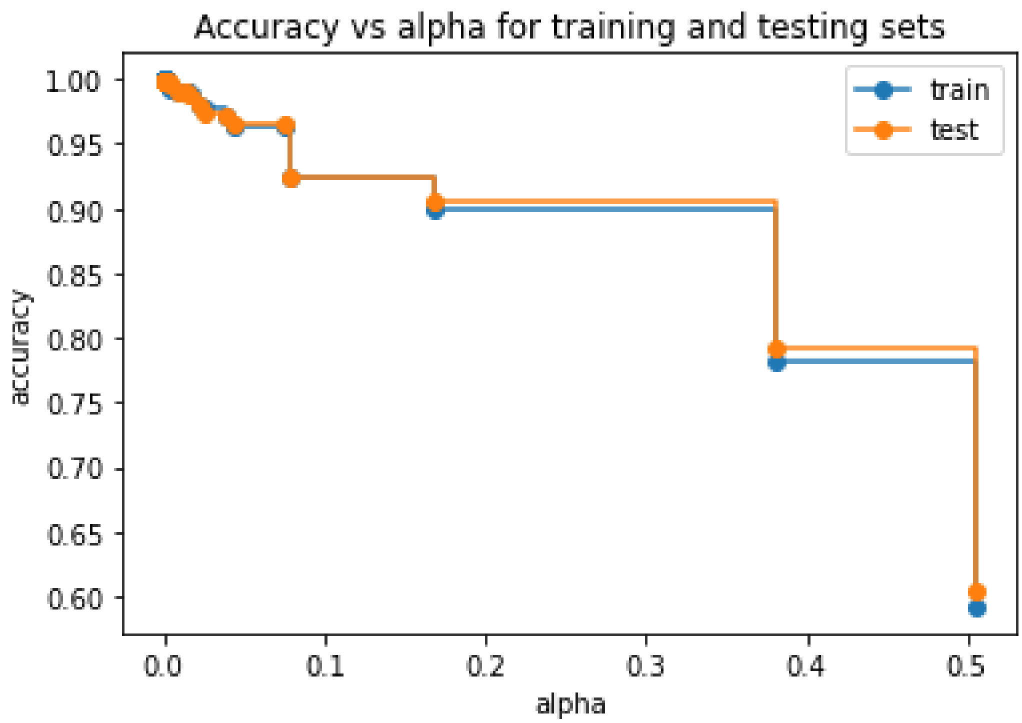


[53]:

```
train_scores = [clf.score(X_train, y_train) for clf in clfs]
test_scores = [clf.score(X_test, y_test) for clf in clfs]

fig, ax = plt.subplots()
ax.set_xlabel("alpha")
ax.set_ylabel("accuracy")
```

```
ax.set_title("Accuracy vs alpha for training and testing sets")
ax.plot(ccp_alphas, train_scores, marker='o', label="train",
        drawstyle="steps-post")
ax.plot(ccp_alphas, test_scores, marker='o', label="test",
        drawstyle="steps-post")
ax.legend()
plt.show()
```



0.3.1 Second Model : Random Forest

[54]:
```
# instantiate random forest classifier object

rft = RandomForestClassifier(n_estimators=1000,criterion="entropy", \
                             class_weight=weights, max_depth= 5)# fit the model␣
 ↪to the training data:
rft.fit(X_train, y_train)
scores = evaluate_model(X_train, y_train,rft)
# summarize performance
print('Cross_validation_Mean Accuracy: %.3f (%.3f)' % (mean(scores),␣
 ↪std(scores)))
```

```
Cross_validation_Mean Accuracy: 0.992 (0.002)
```

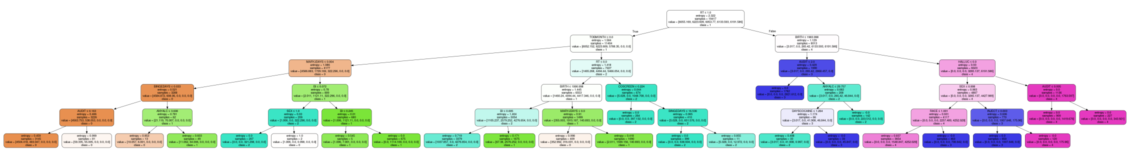
[55]:
```python
y_pred = rft.predict(X_test)

# Model Accuracy, how often is the classifier correct?
print("Test_Accuracy:",metrics.accuracy_score(y_test, y_pred))
```

```
Test_Accuracy: 0.9932491928382742
```

[56]:
```python
# Extract single tree
estimator = rft.estimators_[5]
dot_data = StringIO()
export_graphviz(estimator, out_file=dot_data,
                filled=True, rounded=True,
                special_characters=True,feature_names =␣
 ↪feature_cols,class_names=['0','1','2','3','4'])
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
graph.write_png('RandomForest.png')
Image(graph.create_png())
```

[56]:



0.3.2 Third Model: Gradient Boosting

[57]:
```python
# instantiate gradient boost classifier object
gbc = GradientBoostingClassifier(random_state = 15, max_depth= 5)# fit the␣
 ↪model to the training data:
gbc.fit(X_train, y_train)
scores = evaluate_model(X_train, y_train,gbc)
# summarize performance
print('Cross_validation_Mean Accuracy: %.3f (%.3f)' % (mean(scores),␣
 ↪std(scores)))
```

```
Cross_validation_Mean Accuracy: 0.999 (0.000)
```

[58]:
```python
y_pred = rft.predict(X_test)

# Model Accuracy, how often is the classifier correct?
print("Test_Accuracy:",metrics.accuracy_score(y_test, y_pred))
```

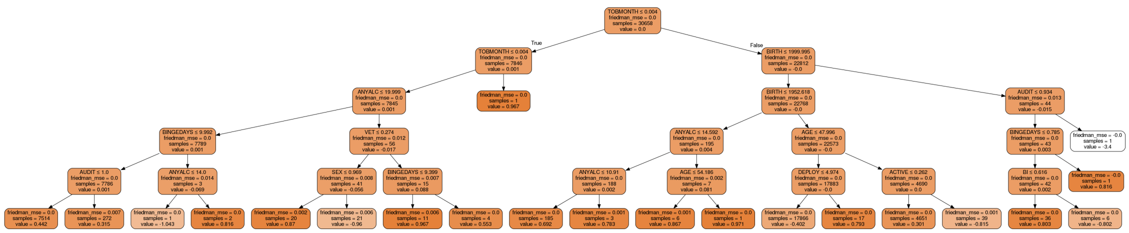
```
Test_Accuracy: 0.9932491928382742
```

[59]:

```
# Extract single tree
estimator = gbc.estimators_[42, 0]

dot_data = StringIO()
export_graphviz(estimator, out_file=dot_data,
                filled=True, rounded=True,
                special_characters=True,feature_names =␣
 ↪feature_cols,class_names=['0','1','2','3','4'])
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
graph.write_png('GradientBoosting.png')
Image(graph.create_png())
```

[59]:



[ ]:

```

```