In [1]:
```
! python --version
```

Python 3.9.10

SEER Breast Cancer Dataset: Feature Selection and Classification

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The purpose of this notebook is to select the top 5 features and fit a decision tree classifier so we may recreate it via a tableau dashboard.

The `SEER Breast Cancer Dataset` can be found at this link: https://ieee-dataport.org/open-access/seer-breast-cancer-data

In [2]:
```
%matplotlib inline
```

In [3]:
```
import numpy as np
import random as py_random
import numpy.random as np_random
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd
import scipy.stats as stats
import graphviz
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import f_classif
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn import tree
from sklearn.tree import export_graphviz
from IPython.display import Image
import pydotplus

import warnings
warnings.filterwarnings('ignore')

sns.set(style="whitegrid")
```

In [4]:
```
df = pd.read_csv('SEER Breast Cancer clean.csv')
df.head()
```

Out[4]:

	Age	Race	MaritalStatus	TStage	NStage	6thStage	Grade	AStage	TumorSize	EstrogenStatus	ProgesteroneStatus	RegionalNodeExamined	RegionalNodePositive	SurvivalMonths	Status
0	43	Other (American Indian/AK Native, Asian/Pacifi...	Married (including common law)	T2	N3	IIIC	Moderately differentiated; Grade II	Regional	40	Positive	Positive	19	11	1	Alive
1	47	Other (American Indian/AK Native, Asian/Pacifi...	Married (including common law)	T2	N2	IIIA	Moderately differentiated; Grade II	Regional	45	Positive	Positive	25	9	2	Alive
2	67	White	Married (including common law)	T2	N1	IIB	Poorly differentiated; Grade III	Regional	25	Positive	Positive	4	1	2	Dead
3	46	White	Divorced	T1	N1	IIA	Moderately differentiated; Grade II	Regional	19	Positive	Positive	26	1	2	Dead
4	63	White	Married (including common law)	T2	N2	IIIA	Moderately differentiated; Grade II	Regional	35	Positive	Positive	21	5	3	Dead

Feature Selection via ANOVA f-test

For feature selection, we need to convert all strings to integer values.

In [5]:
```
# Target Variable encoding

df['Status_str'] = df['Status']
status_map = {'Alive':1, 'Dead':0}
df['Status'] = df['Status'].map(status_map)


# all feature encodings

df['Race_str'] = df['Race']
race_map = {'Other (American Indian/AK Native, Asian/Pacific Islander)':3, 'Black':2, 'White':1}
df['Race'] = df['Race'].map(race_map)


df['MaritalStatus_str'] = df['MaritalStatus']
marital_map = {'Separated':5, 'Widowed':4, 'Divorced':3, 'Married (including common law)':2, 'Single (never married)':1}
df['MaritalStatus'] = df['MaritalStatus'].map(marital_map)

df['TStage_str'] = df['TStage']
tstage_map = {'T4':4, 'T3':3, 'T2':2, 'T1':1}
df['TStage'] = df['TStage'].map(tstage_map)


df['NStage_str'] = df['NStage']
nstage_map = {'N3':3, 'N2':2, 'N1':1}
df['NStage'] = df['NStage'].map(nstage_map)


df['6thStage_str'] = df['6thStage']
sixstage_map = {'IIIB':5, 'IIIC':4, 'IIIA':3, 'IIB':2, 'IIA':1}
df['6thStage'] = df['6thStage'].map(sixstage_map)


df['Grade_str'] = df['Grade']
grade_map = {'Undifferentiated; anaplastic; Grade IV':4, 'Poorly differentiated; Grade III':3,
             'Moderately differentiated; Grade II':2, 'Well differentiated; Grade I':1}
df['Grade'] = df['Grade'].map(grade_map)


df['AStage_str'] = df['AStage']
astage_map = {'Regional':2, 'Distant':1}
df['AStage'] = df['AStage'].map(astage_map)


df['EstrogenStatus_str'] = df['EstrogenStatus']
estrogen_map = {'Negative':2, 'Positive':1}
df['EstrogenStatus'] = df['EstrogenStatus'].map(estrogen_map)


df['ProgesteroneStatus_str'] = df['ProgesteroneStatus']
progesterone_map = {'Negative':2, 'Positive':1}
df['ProgesteroneStatus'] = df['ProgesteroneStatus'].map(progesterone_map)

df.to_csv('SEER Breast Cancer Encoded.csv', index=False)

df.head()
```

Out[5]:

	Age	Race	MaritalStatus	TStage	NStage	6thStage	Grade	AStage	TumorSize	EstrogenStatus	...	Status_str	Race_str	MaritalStatus_str	TStage_str	NStage_str	6thStage_str	Grade_str	AStage_str
0	43	3	2	2	3	4	2	2	40	1	...	Alive	Other (American Indian/AK Native, Asian/Pacifi...	Married (including common law)	T2	N3	IIIC	Moderately differentiated; Grade II	Regional
1	47	3	2	2	2	3	2	2	45	1	...	Alive	Other (American Indian/AK Native, Asian/Pacifi...	Married (including common law)	T2	N2	IIIA	Moderately differentiated; Grade II	Regional
2	67	1	2	2	1	2	3	2	25	1	...	Dead	White	Married (including common law)	T2	N1	IIB	Poorly differentiated; Grade III	Regional
3	46	1	3	1	1	1	2	2	19	1	...	Dead	White	Divorced	T1	N1	IIA	Moderately differentiated; Grade II	Regional
4	63	1	2	2	2	3	2	2	35	1	...	Dead	White	Married (including common law)	T2	N2	IIIA	Moderately differentiated; Grade II	Regional

5 rows × 25 columns

In [6]:
```
# extract row data for each patient; X is all potential features, Y is the target variable
array = df.values
X_0 = array[:,0:14]
Y_0 = array[:,14]

# feature extraction
test = SelectKBest(score_func=f_classif, k=5)
fit = test.fit(X_0, Y_0)

# summarize scores
np.set_printoptions(precision=3)
scores = pd.DataFrame(fit.scores_)
scores.sort_values(by=[0],inplace = True, ascending=False)
features = fit.transform(X_0)

feature_names = []
for index in scores.index:
    feature_names.append(df.columns[index])

scores['Feature'] = feature_names

scores #display scores for all features in descending order
```

Out[6]:

	0	Feature
13	1181.547984	SurvivalMonths
12	283.578806	RegionalNodePositive
4	281.534137	NStage
5	245.803278	6thStage
9	141.973835	EstrogenStatus
10	130.200888	ProgesteroneStatus
6	107.572314	Grade
3	98.614252	TStage
8	73.768949	TumorSize
7	37.872571	AStage
0	12.617026	Age
2	10.190984	MaritalStatus
11	4.868855	RegionalNodeExamined
1	0.070422	Race

Building the Decision Tree Classifier

In [7]:
```
top_features = feature_names[0:6] # the top 6 features gives us the best accuracy

X = df[top_features]
y = df.Status
```

First, we will create a decision tree of max depth = 3, before we find the ideal max depth that maximizes the bias/variance trade off.

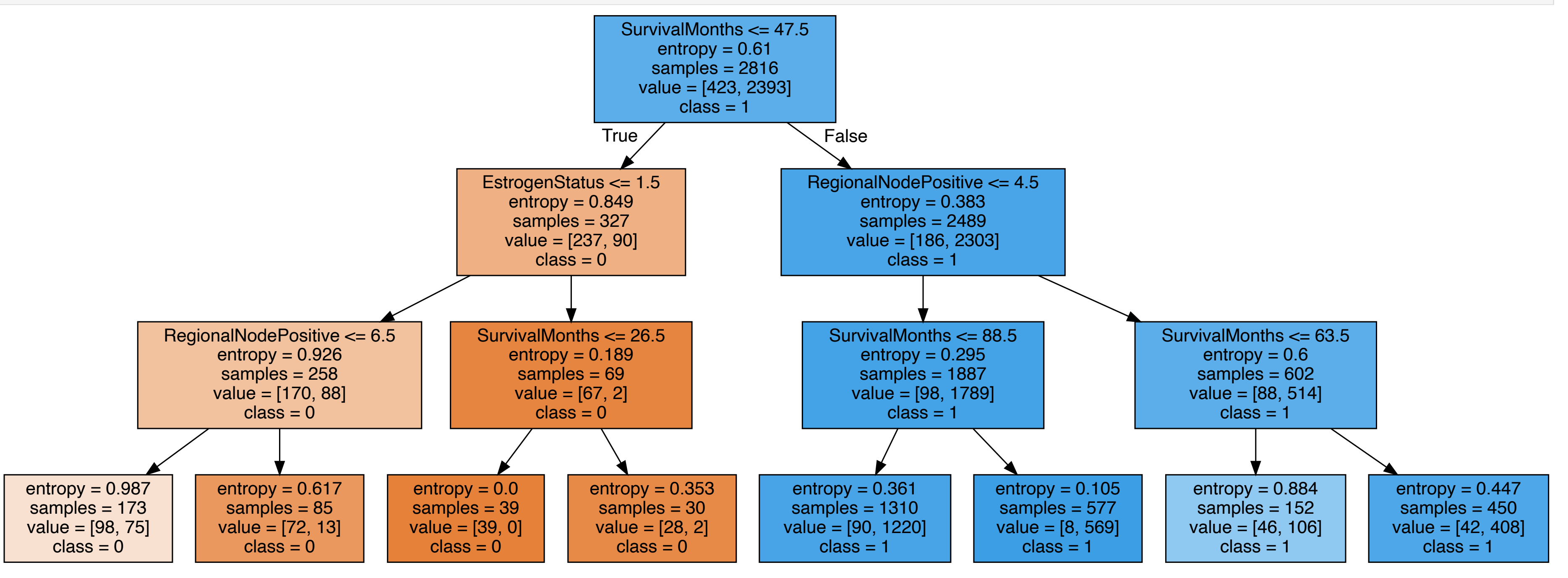
In [8]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1)
```

In [9]:
```
# Create Decision Tree classifer object
clf = DecisionTreeClassifier(criterion="entropy", max_depth=3, random_state = 1)

# Train Decision Tree Classifer
clf = clf.fit(X_train,y_train)

#Predict the response for test dataset
y_pred = clf.predict(X_test)

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

Accuracy: 0.8932119205298014

In [10]:
```
# DOT data
dot_data = export_graphviz(clf, out_file=None,
                           feature_names=top_features,
                           class_names=['0', '1'],
                           filled=True)

# Draw graph
graph = graphviz.Source(dot_data, format="png")
graph.render('BreastCancerDecisionTree_depth3',format='png', view=False)

graph
```

Out[10]:

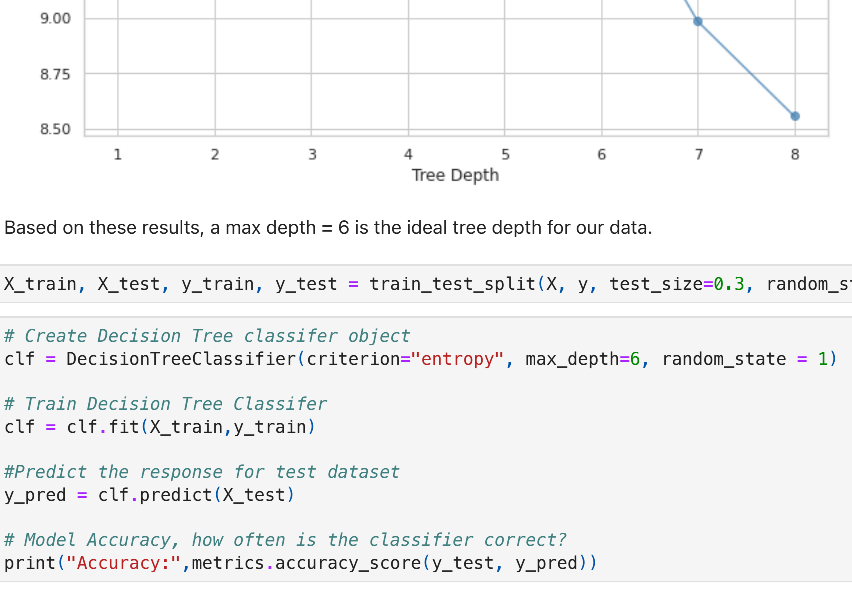


Now, we can try generating a validation curve to test depths 1 through 8, to find the optimal max depth for our data.

In [11]:
```
def error_rate(y, y_hat):
    return np.sum(np.abs(y - y_hat))/len(y)*100
```

In [12]:
```
def validation_curve(seed, X, y, min_depth, max_depth, test_size=0.30):
    train_scores = []
    test_scores = []

    for i in range(min_depth, max_depth + 1):
        from sklearn.model_selection import train_test_split
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=test_size, random_state=101)

        clf = DecisionTreeClassifier(criterion="entropy", random_state=101, max_depth=i)

        clf = clf.fit(X_train,y_train)

        y_pred = clf.predict(X_train)
        train_scores.append(error_rate(y_train, y_pred))

        y_pred = clf.predict(X_test)
        test_scores.append(error_rate(y_test, y_pred))

    return train_scores, test_scores
```

In [13]:
```
seed = 101
min_depth = 1
max_depth = 8
param_range = range(min_depth, max_depth + 1)
x_label = 'Tree Depth'
y_label = 'Error Rate'
title = "Validation Curves for {0} to {1} tree depth".format(min_depth, max_depth)

train_scores, test_scores = validation_curve(seed, X, y, min_depth, max_depth)

figure = plt.figure(figsize=(10,6))
axes = figure.add_subplot(1, 1, 1)
axes.plot(param_range, train_scores, 'o-', color="steelblue", alpha=0.75, label="Training score")
axes.plot(param_range, test_scores, "o-", color="firebrick", alpha=0.75, label="Test score")
axes.set_xlabel(x_label)
axes.set_ylabel(y_label)
axes.set_title(title)
plt.legend(loc="best")
plt.show()
plt.close()
```



Based on these results, a max depth = 6 is the ideal tree depth for our data.

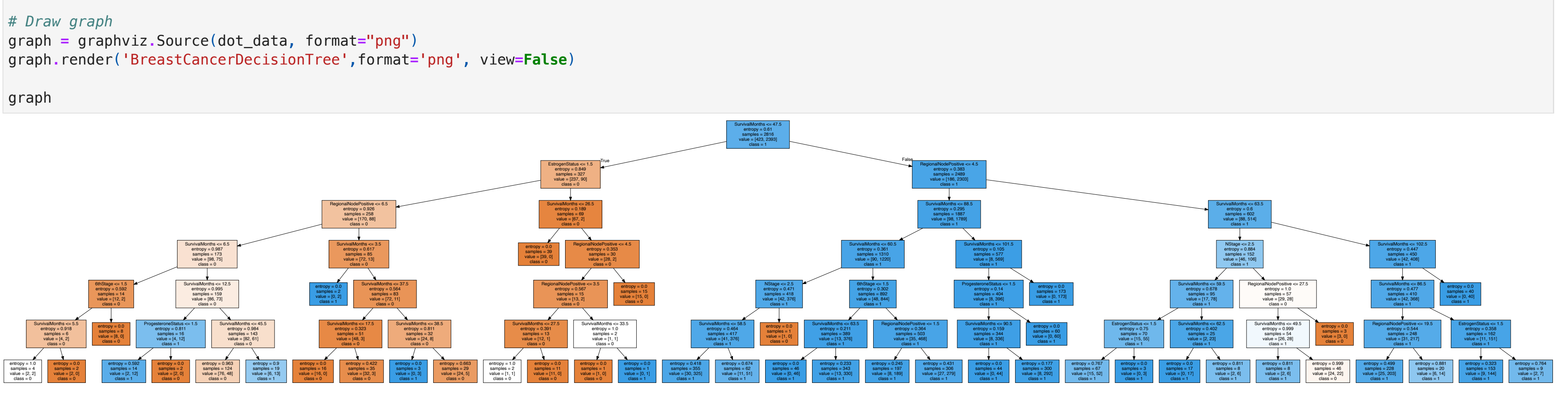
In [14]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1)
```

In [15]:
```
# Create Decision Tree classifer object
clf = DecisionTreeClassifier(criterion="entropy", max_depth=6, random_state = 1)

# Train Decision Tree Classifer
clf = clf.fit(X_train,y_train)

#Predict the response for test dataset
y_pred = clf.predict(X_test)

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

Accuracy: 0.8774834437086093

In [16]:
```
# DOT data
dot_data = export_graphviz(clf, out_file=None,
                           feature_names=top_features,
                           class_names=['0', '1'],
                           filled=True)

# Draw graph
graph = graphviz.Source(dot_data, format="png")
graph.render('BreastCancerDecisionTree',format='png', view=False)

graph
```

Out[16]:



References

[1] https://machinelearningmastery.com/feature-selection-machine-learning-python/

[2] https://www.datacamp.com/community/tutorials/decision-tree-classification-python