Predict survival on the Titanic

In this Lab, we ask you to apply the tools of machine learning to predict which passengers survived the tragedy

Dataset

The dataset contains 891 observations of 12 variables:

- **PassengerId**: Unique ID for each passenger
- **Survived**: Survival (0 = No; 1 = Yes)
- **Pclass**: Passenger Class (1 = 1st; 2 = 2nd; 3 = 3rd)
- **Name**: Name
- **Sex**: Sex
- **Age**: Age
- **Sibsp**: Number of Siblings/Spouses Aboard
- **Parch**: Number of Parents/Children Aboard
- **Ticket**: Ticket Number
- **Fare**: Passenger Fare
- **Cabin**: Cabin
- **Embarked** Port of Embarkation (C = Cherbourg; Q = Queenstown; S = Southampton)

```
# imports
import warnings
warnings.filterwarnings('ignore')
import pandas as pd
import numpy as np
```

```
titanic = pd.read_csv("/content/titanic.csv" )
titanic.drop('Cabin', axis=1, inplace=True) # Drop this column because it contains a lot o
titanic["Age"].fillna(titanic["Age"].median(),inplace=True)
titanic["Embarked"].fillna("S", inplace = True)
print ('survival rate =', titanic.Survived.mean())
```

```
survival rate = 0.3838383838383838
```

Model training

```
# Some of the columns don't have predictive power, so let's specify which ones are include
predictors = ["Pclass", "Sex", "Age", 'SibSp' ,'Parch', "Fare", "Embarked"]
# We need now to convert text columns in predictors to numerical ones
for col in predictors: # Loop through all columns in predictors
    if titanic[col].dtype == 'object':  # check if column's type is object (text)
```

```
        titanic[col] = pd.Categorical(titanic[col]).codes  # convert text to numerical

titanic.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fa
0	1	0	3	Braund, Mr. Owen Harris	1	22.0	1	0	A/5 21171	7.25
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th	0	38.0	1	0	PC 17599	71.28

```
# Split the data into a training set and a testing set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(titanic[predictors], titanic['Survived

from sklearn.linear_model import LogisticRegression
clf = LogisticRegression(random_state=1)
clf.fit(X_train, y_train)
train_score = clf.score(X_train, y_train)
print ('train accuracy =', clf.score(X_train, y_train))

from sklearn.model_selection import cross_val_score
scores = cross_val_score(clf, titanic[predictors], titanic["Survived"], scoring='accuracy'
print('cross validation accuracy =', scores.mean())
```

```
train accuracy = 0.8073836276083467
cross validation accuracy = 0.7957428214731586
```

Decision Trees

Let's start with one single tree

```
from sklearn.tree import DecisionTreeClassifier

clf_dt = DecisionTreeClassifier(random_state=1)
clf_dt.fit(X_train, y_train)

print ('train accuracy =', clf_dt.score(X_train, y_train))
print ('test accuracy =', clf_dt.score(X_test, y_test))
```

```
train accuracy = 0.9887640449438202
test accuracy = 0.7574626865671642
```

Predictions are obtained in the same way of Logistic Regression

```
from sklearn.metrics import accuracy_score

y_pred = clf_dt.predict(X_test)
print (y_pred)
```

```
[1 0 1 1 1 0 0 1 0 1 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 1 1 0 1 0 0 1 0 0 0 1
 0 1 0 0 0 1 0 1 0 0 0 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0
 1 0 1 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 1 0 0 0 0 1 0 1 0 0 0 0 0 1
 1 0 0 0 0 0 0 1 0 1 1 0 0 1 1 1 1 0 0 0 0 1 0 1 1 1 0 0 1 1 0 1 0 0 0 1 0
 0 0 1 0 0 0 0 1 0 0 1 0 0 0 1 1 0 0 1 0 1 0 1 0 1 0 1 0 0 0 1 0 1 1 0 0 1
 0 0 1 0 1 0 1 1 1 0 1 0 1 0 0 0 1 0 1 0 0 1 0 0 0 1 0 0 1 0 0 0 1 1 0 0 0
 1 1 0 0 1 1 1 0 1 0 1 0 0 0 0 1 0 0 0 0 0 1 0 1 1 1 0 1 0 0 1 1 1 1 1 1 0
 0 1 0 1 0 0 0 0 1]
```

```
y_prob = accuracy_score(y_test,y_pred)
print (y_prob)
```

```
0.7574626865671642
```

Let's play around with some of the decision tree's parameters

```
# check the sklearn documentation and change the folowing parametrs: max_depth, min_sample
clf_dt = DecisionTreeClassifier(random_state=1, max_depth=3, min_samples_leaf=3,min_sample
clf_dt.fit(X_train,y_train)
print ('train accuracy =',clf_dt.score(X_train, y_train))

# Cross validation
scores_dt = cross_val_score(clf_dt, titanic[predictors], titanic["Survived"], scoring='acc
print('cross validation accuracy =', scores_dt)
```

```
train accuracy = 0.8571428571428571
cross validation accuracy = [0.82122905 0.81460674 0.81460674 0.78651685 0.82022472]
```

Plot the decision tree

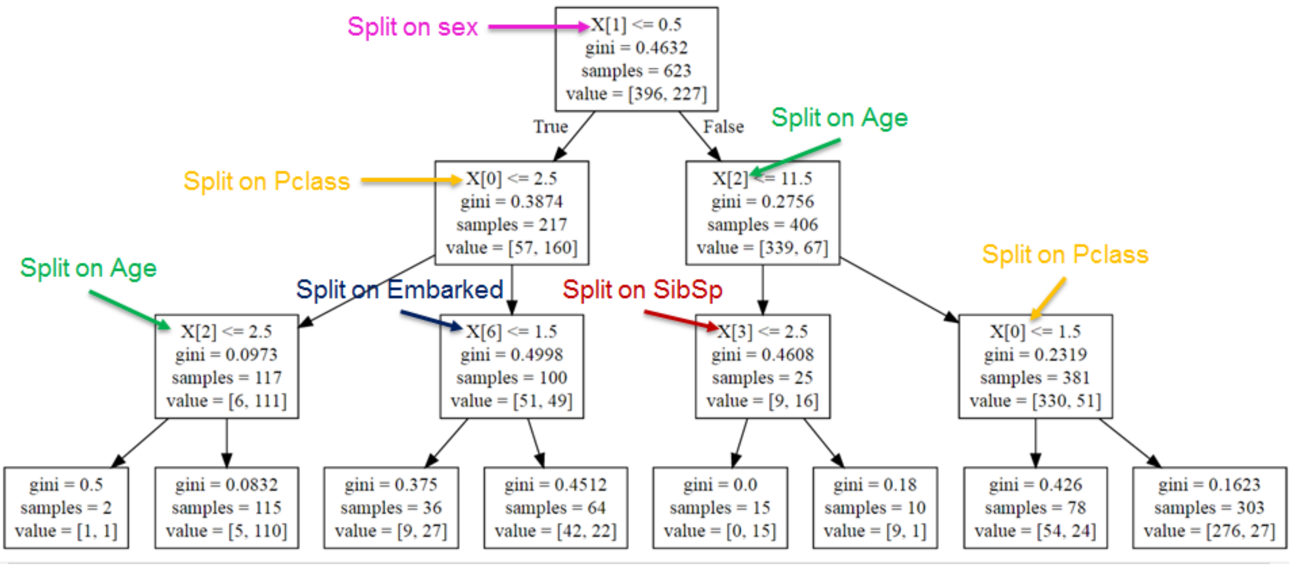
Set the max_depth parameter in the previous classifier to 3 and leave all the other ones to default values.

```
from sklearn import tree
tree.export_graphviz(clf_dt, out_file='tree.dot')
# As a reminder, these are the predicting features in order
print (dict(zip(range(len(predictors)),predictors)))
```

```
{0: 'Pclass', 1: 'Sex', 2: 'Age', 3: 'SibSp', 4: 'Parch', 5: 'Fare', 6: 'Embarked'}
```

The image should look like the following

```
from IPython.display import Image
Image("/content/DT.png")
```



Predict the survival of a female, Pclass 1 or 2, above age 2.5

```
passenger1=np.array([1,0,2.5,0,0,0,0]).reshape(1, -1)

print ('proba =', clf_dt.predict_proba(passenger1))
print ('class =', clf_dt.predict(passenger1))
```

```
    proba = [[0.11363636 0.88636364]]
    class = [1]
```

Predict the survival of a male, above age 11.5, Pclass 2 or 3

```
passenger2=np.array([1,1,11.5,0,0,0,0]).reshape(1, -1)
print ('proba =', clf_dt.predict_proba(passenger2))
print ('class =', clf_dt.predict(passenger2))
```

```
    proba = [[0. 1.]]
    class = [1]
```

By looking at this decision tree, you can get a sense the relative importance between features. let's see which are the most important ones using the attribute: **feature_importances_**

```
feat_imp = pd.DataFrame(clf_dt.feature_importances_, predictors, columns=['Importance'])
feat_imp.sort_values('Importance', ascending=False)
```

	Importance
Sex	0.612883
Pclass	0.189340
Age	0.079526
SibSp	0.064308
Embarked	0.050315
Fare	0.003628
Parch	0.000000

As expected, **Parch** and **Fare** are the least important ones because they were not used for splitting, while **Sex** is the most important one since it was used first for splitting.

Random Forest

A [Random Forest](http://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html#sklearn.ensemble.RandomForestClassifier from sklearn.ensemble import RandomForestClassifier) is an ensemble of decision trees

```
from sklearn.ensemble import RandomForestClassifier
clf_rf = RandomForestClassifier(random_state=1)

clf_rf.fit(X_train,y_train)
print ('train accuracy =',clf_rf.score(X_train, y_train))

# Cross validation
scores_rf = accuracy_score(y_test,y_pred)
print('cross validation accuracy =', scores_rf)
```

```
train accuracy = 0.9887640449438202
cross validation accuracy = 0.7574626865671642
```

In the same way, you can print the feature importance of all the trees

```
feat_impr = pd.DataFrame(clf_rf.feature_importances_, predictors, columns=['Importance'])
feat_impr.sort_values('Importance', ascending=False)
```

	Importance
Fare	0.260215
Sex	0.260039
Age	0.252220
Pclass	0.088561
SibSp	0.053251
Parch	0.045476

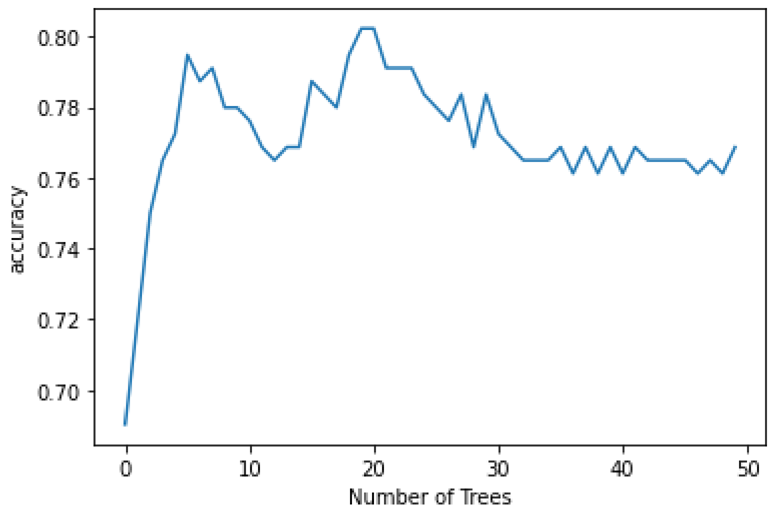
Random forest, like decision trees have a lot of parameters to tune. Usually, performance does not change linearly with parameters. Let's take as an example, the accuracy as a function of number of trees (**n_estimators**)

```
%matplotlib inline
import matplotlib.pyplot as plt

trees=range(50)
accuracy=np.zeros(50)
for idx in range(len(trees)):
    clf_rf=RandomForestClassifier(random_state=1, n_estimators=idx + 1)
    clf_rf.fit(X_train,y_train)
    accuracy[idx]=clf_rf.score(X_test, y_test)

plt.plot(trees, accuracy)
plt.ylabel('accuracy')
plt.xlabel('Number of Trees')
```

```
Text(0.5, 0, 'Number of Trees')
```



In the following, try to tune manually the following parameters: **min_samples_leaf, min_samples_split, max_depth, n_estimators** in order to increase cross validation accuracy.

```
clf_rf = RandomForestClassifier(random_state=1,max_depth=3, min_samples_leaf=3,min_samples_
```

```
clf_rf.fit(X_train, y_train)
print ('train accuracy =', clf_rf.score(X_train, y_train))

# Cross validation
scores_rf = cross_val_score(clf_rf, titanic[predictors], titanic["Survived"], scoring='acc
print('cross validation accuracy =', scores_rf.mean())
```

```
train accuracy = 0.85553772070626
cross validation accuracy = 0.8014060636494884
```

This might be a difficult job to do manually. In other way is to search automatically the best combination of different ranges for these parameters. This is done using **Grid Search**

Grid Search

```
from sklearn.model_selection import GridSearchCV

params = {'min_samples_leaf':list(range(1,5)),'min_samples_split':list(range(2,10,2)),
          'n_estimators':list(range(10,50,10))}
clf_rf2=RandomForestClassifier(random_state=1)
clf_gs=GridSearchCV(clf_rf2, params, scoring = 'accuracy',cv=5)
clf_gs.fit(titanic[predictors], titanic["Survived"])
```

```
GridSearchCV(cv=5, estimator=RandomForestClassifier(random_state=1),
             param_grid={'min_samples_leaf': [1, 2, 3, 4],
                         'min_samples_split': [2, 4, 6, 8],
                         'n_estimators': [10, 20, 30, 40]},
             scoring='accuracy')
```

Print the best score

```
print(clf_gs.best_score_)
```

```
0.8327976900382902
```

Print the best parameters

```
print(clf_gs.best_params_)
```

```
{'min_samples_leaf': 3, 'min_samples_split': 8, 'n_estimators': 30}
```

Let's use these best parameters and check whether they achieve really the above cv accuracy

```
clf_rf3 = RandomForestClassifier(random_state=1,min_samples_leaf=3,min_samples_split=8,n_e
clf_rf3.fit(X_train, y_train)
print ('train accuracy =', clf_rf3.score(X_train, y_train))

scores_rf3 = cross_val_score(clf_rf3, titanic[predictors], titanic["Survived"], scoring='a
```

```
scores_rf3 = cross_val_score(clf_rf3,·titanic[predictors],·titanic['Survived'],·scoring='a
print('cross validation accuracy =',scores_rf3.mean())
```

```
train accuracy = 0.9036918138041734
cross validation accuracy = 0.8327976900382902
```

As you can see, grid search allows you to find the best model parameters to improve your accuracy. Now, we can see the most important features of this last classifier

```
feat_imp = pd.DataFrame(clf_rf3.feature_importances_, predictors, columns=['Importance'])
feat_imp.sort_values('Importance', ascending=False)
```

	Importance
Sex	0.464300
Fare	0.168838
Pclass	0.154466
Age	0.068293
SibSp	0.055289
Parch	0.047531
Embarked	0.041283