For this assigment I've chosen standard Titanic dataset. This dataset contains a flag 'survived' and some meaningful features like 'Sex', 'Age' etc. Firstly, we should import all needed dependencies.

```
In [1]: import pandas as pd

        import numpy as np
        import graphviz
        import itertools
        import pydotplus
        import pydot

        import sklearn as sk
        from sklearn.tree import export_graphviz
        from sklearn.model_selection import train_test_split
        from sklearn.tree import DecisionTreeClassifier
        from sklearn.metrics import accuracy_score
        from sklearn.metrics import confusion_matrix

        from IPython.display import Image
        import matplotlib.pyplot as plt
        %matplotlib inline
```

Loading and data transformation:

```
In [2]: data = pd.read_csv('titanic.csv')
        data.drop(data.columns[0],axis=1,inplace=True)
        replace_sex={'male':1,'female':0}
        data.replace(replace_sex,inplace=True)
        data.head(n=5)
```

```
Out[2]:    PassengerId  Survived  Pclass  \
        0            1         2       3
        1            2         1       1
        2            3         1       3
        3            4         1       1
        4            5         2       3

                                                        Name  Sex   Age  SibSp  Parch  \
        0                            Braund, Mr. Owen Harris    1  22.0      1      0
        1  Cumings, Mrs. John Bradley (Florence Briggs Th...    0  38.0      1      0
        2                             Heikkinen, Miss. Laina    0  26.0      0      0
        3       Futrelle, Mrs. Jacques Heath (Lily May Peel)    0  35.0      1      0
        4                           Allen, Mr. William Henry    1  35.0      0      0

                     Ticket     Fare Cabin Embarked
        0         A/5 21171   7.2500   NaN        S
        1          PC 17599  71.2833   C85        C
        2  STON/O2. 3101282   7.9250   NaN        S
        3           113803  53.1000  C123        S
        4           373450   8.0500   NaN        S
```

```
In [3]: data.dtypes
```

```
Out[3]: PassengerId      int64
        Survived         int64
        Pclass           int64
        Name            object
        Sex              int64
        Age            float64
        SibSp            int64
        Parch            int64
        Ticket          object
        Fare           float64
        Cabin           object
        Embarked        object
        dtype: object
```

```
In [4]: data.describe()
```

```
Out[4]:        PassengerId    Survived      Pclass         Sex         Age  \
        count   891.000000  891.000000  891.000000  891.000000  891.000000
        mean    446.000000    1.616162    2.308642    0.647587   29.758889
        std     257.353842    0.486592    0.836071    0.477990   13.002570
        min       1.000000    1.000000    1.000000    0.000000    0.420000
        25%     223.500000    1.000000    2.000000    0.000000   22.000000
        50%     446.000000    2.000000    3.000000    1.000000   30.000000
        75%     668.500000    2.000000    3.000000    1.000000   35.000000
        max     891.000000    2.000000    3.000000    1.000000   80.000000

                    SibSp       Parch        Fare
        count  891.000000  891.000000  891.000000
        mean     0.523008    0.381594   32.204208
        std      1.102743    0.806057   49.693429
        min      0.000000    0.000000    0.000000
        25%      0.000000    0.000000    7.910400
        50%      0.000000    0.000000   14.454200
        75%      1.000000    0.000000   31.000000
        max      8.000000    6.000000  512.329200
```

We only need these features:

```
In [5]: meaningful_columns=['Survived','Pclass','Sex','Age','SibSp','Parch','Fare']
        data=data[meaningful_columns]
        data.head(n=5)
```

```
Out[5]:    Survived  Pclass  Sex   Age  SibSp  Parch     Fare
        0         2       3    1  22.0      1      0   7.2500
```

```
1          1        1     0   38.0       1       0  71.2833
2          1        3     0   26.0       0       0   7.9250
3          1        1     0   35.0       1       0  53.1000
4          2        3     1   35.0       0       0   8.0500
```

Replacing missing values in each feature by its mean.

```
In [6]: data.fillna(np.round(data.mean()),inplace=True)
```

```
Out[6]:      Survived  Pclass  Sex   Age  SibSp  Parch      Fare
        0           2       3    1  22.0      1      0    7.2500
        1           1       1    0  38.0      1      0   71.2833
        2           1       3    0  26.0      0      0    7.9250
        3           1       1    0  35.0      1      0   53.1000
        4           2       3    1  35.0      0      0    8.0500
        5           2       3    1  30.0      0      0    8.4583
        6           2       1    1  54.0      0      0   51.8625
        7           2       3    1   2.0      3      1   21.0750
        8           1       3    0  27.0      0      2   11.1333
        9           1       2    0  14.0      1      0   30.0708
        10          1       3    0   4.0      1      1   16.7000
        11          1       1    0  58.0      0      0   26.5500
        12          2       3    1  20.0      0      0    8.0500
        13          2       3    1  39.0      1      5   31.2750
        14          2       3    0  14.0      0      0    7.8542
        15          1       2    0  55.0      0      0   16.0000
        16          2       3    1   2.0      4      1   29.1250
        17          1       2    1  30.0      0      0   13.0000
        18          2       3    0  31.0      1      0   18.0000
        19          1       3    0  30.0      0      0    7.2250
        20          2       2    1  35.0      0      0   26.0000
        21          1       2    1  34.0      0      0   13.0000
        22          1       3    0  15.0      0      0    8.0292
        23          1       1    1  28.0      0      0   35.5000
        24          2       3    0   8.0      3      1   21.0750
        25          1       3    0  38.0      1      5   31.3875
        26          2       3    1  30.0      0      0    7.2250
        27          2       1    1  19.0      3      2  263.0000
        28          1       3    0  30.0      0      0    7.8792
        29          2       3    1  30.0      0      0    7.8958
        ..        ...     ...  ...   ...    ...    ...       ...
        861         2       2    1  21.0      1      0   11.5000
        862         1       1    0  48.0      0      0   25.9292
        863         2       3    0  30.0      8      2   69.5500
        864         2       2    1  24.0      0      0   13.0000
        865         1       2    0  42.0      0      0   13.0000
        866         1       2    0  27.0      1      0   13.8583
        867         2       1    1  31.0      0      0   50.4958
```

```
868         2       3    1  30.0      0      0    9.5000
869         1       3    1   4.0      1      1   11.1333
870         2       3    1  26.0      0      0    7.8958
871         1       1    0  47.0      1      1   52.5542
872         2       1    1  33.0      0      0    5.0000
873         2       3    1  47.0      0      0    9.0000
874         1       2    0  28.0      1      0   24.0000
875         1       3    0  15.0      0      0    7.2250
876         2       3    1  20.0      0      0    9.8458
877         2       3    1  19.0      0      0    7.8958
878         2       3    1  30.0      0      0    7.8958
879         1       1    0  56.0      0      1   83.1583
880         1       2    0  25.0      0      1   26.0000
881         2       3    1  33.0      0      0    7.8958
882         2       3    0  22.0      0      0   10.5167
883         2       2    1  28.0      0      0   10.5000
884         2       3    1  25.0      0      0    7.0500
885         2       3    0  39.0      0      5   29.1250
886         2       2    1  27.0      0      0   13.0000
887         1       1    0  19.0      0      0   30.0000
888         2       3    0  30.0      1      2   23.4500
889         1       1    1  26.0      0      0   30.0000
890         2       3    1  32.0      0      0    7.7500

[891 rows x 7 columns]
```

Splitting all dataset into train and test parts as relation 3 to 1.

```
In [7]: X_train, X_test, y_train, y_test = train_test_split(data[meaningful_columns[1:]], data[m
```

Tree building:

```
In [8]: clf = DecisionTreeClassifier(max_leaf_nodes = 10)
        clf.fit(X_train, y_train)
```

```
Out[8]: DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None,
                    max_features=None, max_leaf_nodes=10,
                    min_impurity_decrease=0.0, min_impurity_split=None,
                    min_samples_leaf=1, min_samples_split=2,
                    min_weight_fraction_leaf=0.0, presort=False, random_state=None,
                    splitter='best')
```

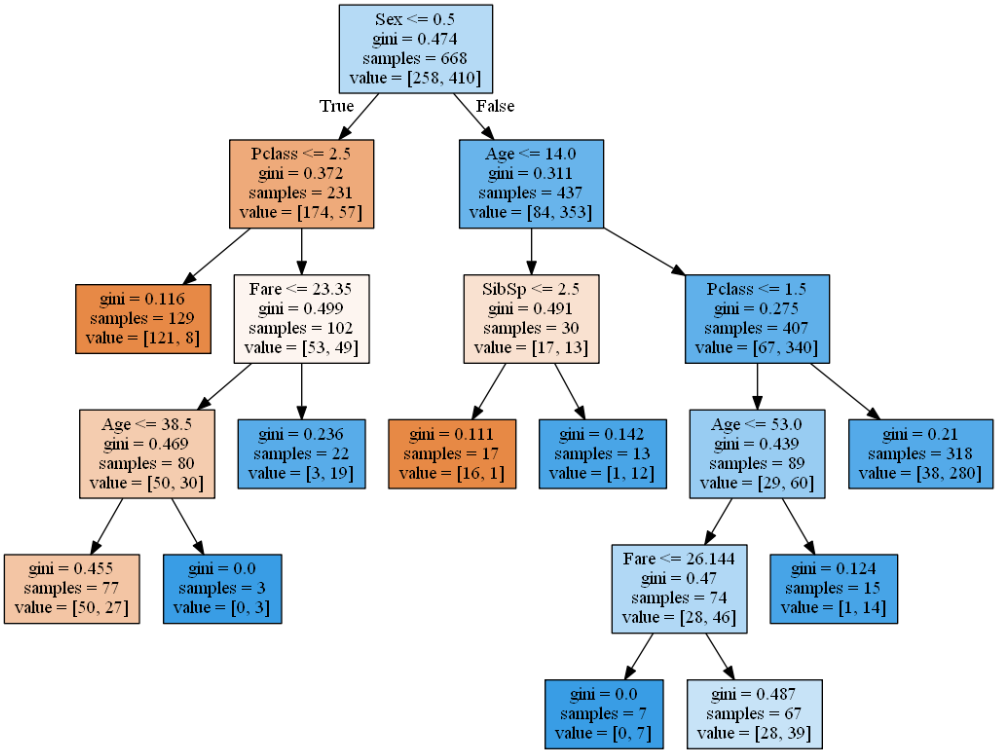
Test for our model:

```
In [9]: accuracy_score(clf.predict(X_test),y_test)
```

```
Out[9]: 0.82511210762331844
```

Plotting our tree:

```
In [10]: export_graphviz(clf, feature_names=data[meaningful_columns[1:]].columns, out_file='smal
```



According to tree above the most important predictor is sex of passenger. For female the second predictor is class and for male it is age.

Confusion matrix:

```
In [11]: cnf_matrix = confusion_matrix(y_test,clf.predict(X_test))
         print(cnf_matrix)
```

```
[[ 62  22]
 [ 17 122]]
```

We can see that total number of uncorrected classification is 22+17 = 39, while 62+122 = 184 observations are right.