Tree Learning – implementation and application of decision trees

Introduction

This notebook gives you the opportunity to implement some key components of decision tree learning and run your algorithm on a benchmark dataset. So restrictions will be made to simplify the problem. The notebook concludes by asking you to run the decision tree learning (and tree-based method of "Random Forests") from scikit-learn for comparison.

Make sure you have the Titanic dataset (" `titanic.csv` ") in the directory from where you are running the notebook before you start.

In [3]:
```
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
%matplotlib inline
import seaborn as sns
```

In [4]:
```
ds = pd.read_csv('titanic.csv')
ds.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
PassengerId    891 non-null int64
Survived       891 non-null int64
Pclass         891 non-null int64
Name           891 non-null object
Sex            891 non-null object
Age            714 non-null float64
SibSp          891 non-null int64
Parch          891 non-null int64
Ticket         891 non-null object
Fare           891 non-null float64
Cabin          204 non-null object
Embarked       889 non-null object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

Data Preprocessing

To simplify things we will focus on the supplied dataset and start by doing some preprocessing, including feature selection, turning categorical data to numeric, and some other stuff. Spend about 10 minutes and go through this if you have any doubts. We start by inspecting the dataset.

In [5]:
```
ds.head()
```

Out[5]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Far
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.250
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.283
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.925
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.100
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.050

In [6]:
```
cols_to_drop = [
    'PassengerId',
    'Name',
    'Ticket',
    'Cabin',
    'Embarked',
]

df = ds.drop(cols_to_drop, axis=1)
df.head()
```

Out[6]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare
0	0	3	male	22.0	1	0	7.2500
1	1	1	female	38.0	1	0	71.2833
2	1	3	female	26.0	0	0	7.9250
3	1	1	female	35.0	1	0	53.1000
4	0	3	male	35.0	0	0	8.0500

Another simplification will be to treat all attributes as numeric. So we need to convert any that are not.

In [7]:
```
def convert_sex_to_num(s):
    if s=='male':
        return 0
    elif s=='female':
        return 1
    else:
        return s

df.Sex = df.Sex.map(convert_sex_to_num)
df.head()
```

Out[7]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare
0	0	3	0	22.0	1	0	7.2500
1	1	1	1	38.0	1	0	71.2833
2	1	3	1	26.0	0	0	7.9250
3	1	1	1	35.0	1	0	53.1000
4	0	3	0	35.0	0	0	8.0500

Let's overview the preprocessed dataset now with some standard commands.

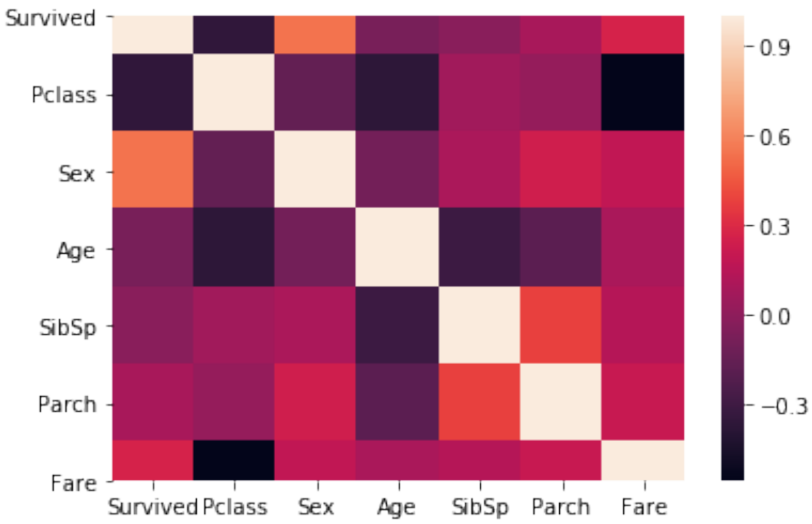
In [8]:
```
data = df.dropna()
data.describe()
```

Out[8]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare
count	714.000000	714.000000	714.000000	714.000000	714.000000	714.000000	714.000000
mean	0.406162	2.236695	0.365546	29.699118	0.512605	0.431373	34.694514
std	0.491460	0.838250	0.481921	14.526497	0.929783	0.853289	52.918930
min	0.000000	1.000000	0.000000	0.420000	0.000000	0.000000	0.000000
25%	0.000000	1.000000	0.000000	20.125000	0.000000	0.000000	8.050000
50%	0.000000	2.000000	0.000000	28.000000	0.000000	0.000000	15.741700
75%	1.000000	3.000000	1.000000	38.000000	1.000000	1.000000	33.375000
max	1.000000	3.000000	1.000000	80.000000	5.000000	6.000000	512.329200

In [9]:
```
plt.figure()
sns.heatmap(data.corr())
```

Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1957d828>



In [10]:
```
input_cols = ['Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Fare']
out_cols = ['Survived']

X = data[input_cols]
y = data[out_cols]

#X.head()
print (X.shape, y.shape)
```

```
(714, 6) (714, 1)
```

In [11]:
```
data = data.reset_index(drop=True)
```

Functions for your Decision Tree learning algorithm

Now is your chance to go ahead and implement some of the functionality needed for the decision tree learner. Remember that the *class* variable for which we need to learn a tree is `Survived` .

In [12]:
```
def divide_data(x_data, fkey, fval):
    x_right = pd.DataFrame([], columns=x_data.columns)
    x_left = pd.DataFrame([], columns=x_data.columns)


    for ix in range(x_data.shape[0]):
        # Retrieve the current value for the fkey column
        try:
            val = x_data[fkey].loc[ix]
        except:
            print (x_data[fkey])
            val = x_data[fkey].loc[ix]
        # print val

        # Check where the row needs to go
        if val > fval:
            # pass the row to right
            x_right = x_right.append(x_data.loc[ix])
        else:
            # pass the row to left
            x_left = x_left.append(x_data.loc[ix])

    # return the divided datasets
    return x_left, x_right


def entropy(col):
    p = []
    p.append(col.mean())
    p.append(1-p[0])

    ent = 0.0
    for px in p:
        ent += (-1.0 * px * np.log2(px))
    return ent

def information_gain(xdata, fkey, fval):
    left, right = divide_data(xdata, fkey, fval)

    if left.shape[0] == 0 or right.shape[0] == 0:
        return -10000

    return entropy(xdata.Survived) - (entropy(left.Survived)*float(
```

In [13]:
```
#Here X is your data without the Survived column. Run it after you
for fx in X.columns:
    print (fx)
    print (information_gain(data, fx, data[fx].mean()))
```

```
Pclass
0.0841581440715109
Sex
0.21601606075154267
Age
2.6666107433293007e-08
SibSp
0.006904127996153919
Parch
0.019278172321014697
Fare
0.053719589963652226
```

In [14]:
```
class DecisionTree:
    def __init__(self, depth=0, max_depth=5):
        self.left = None
        self.right = None
        self.fkey = None
        self.fval = None
        self.max_depth = max_depth
        self.depth = depth
        self.target = None

    def train(self, X_train):
        print (self.depth, '-'*10)
        # Get the best possible feature and division value
        features = ['Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Fare
        gains = []
        for fx in features:
            gains.append(information_gain(X_train, fx, X_train[fx].

        # store the best feature (using min information gain)
        self.fkey = features[np.argmax(gains)]
        self.fval = X_train[self.fkey].mean()

        # divide the dataset
        data_left, data_right = divide_data(X_train, self.fkey, sel
        data_left = data_left.reset_index(drop=True)
        data_right = data_right.reset_index(drop=True)

        # Check the shapes
        if data_left.shape[0] == 0 or data_right.shape[0] == 0:
            if X_train.Survived.mean() >= 0.5:
                self.target = 'Survived'
            else:
                self.target = 'Dead'
            return
```

```
        if self.depth >= self.max_depth:
            if X_train.Survived.mean() >= 0.5:
                self.target = 'Survived'
            else:
                self.target = 'Dead'
            return

        # branch to right
        self.right = DecisionTree(depth=self.depth+1, max_depth=sel
        self.right.train(data_right)
        # branch to left
        self.left = DecisionTree(depth=self.depth+1, max_depth=self
        self.left.train(data_left)

        if X_train.Survived.mean() >= 0.5:
            self.target = 'Survived'
        else:
            self.target = 'Dead'

        return

    def predict(self, test):
        if test[self.fkey] > self.fval:
            # go right
            if self.right is None:
                return self.target
            return self.right.predict(test)
        else:
            # go left
            if self.left is None:
                return self.target
            return self.left.predict(test)
```

Divide your data: separate Training and Test sets

In [15]:
```
split = int(0.8 * data.shape[0])

training_data = data[:split]
testing_data = data[split:]
```

Train your own decision tree

In [16]:
```
dt = DecisionTree()
dt.train(training_data)
```

```
0 ----------
1 ----------
2 ----------
3 ----------
4 ----------
5 ----------
5 ----------
4 ----------
5 ----------

/anaconda3/envs/python35/lib/python3.6/site-packages/ipykernel_lau
ncher.py:34: RuntimeWarning: divide by zero encountered in log2
/anaconda3/envs/python35/lib/python3.6/site-packages/ipykernel_lau
ncher.py:34: RuntimeWarning: invalid value encountered in double_s
calars

5 ----------
3 ----------
4 ----------
5 ----------
```

In [17]:
```
print (dt.fkey, dt.fval)
print (dt.right.fkey, dt.right.fval)
print (dt.left.fkey, dt.left.fval)

print (dt.right.right.fkey, dt.right.right.fval)
print (dt.right.left.fkey, dt.right.left.fval)


print (dt.left.right.fkey, dt.left.right.fval)
print (dt.left.left.fkey, dt.left.left.fval)
```

```
Sex 0.36777583187390545
Pclass 2.080952380952381
Fare 28.257881994459833
SibSp 0.9036144578313253
Age 30.830708661417322
SibSp 1.0721649484536082
Fare 12.418069696969695
```

Make predictions for the first 10 and see if they are correct.

In [18]:
```
for ix in testing_data.index[:10]:
    print (dt.predict(testing_data.loc[ix]))
```

```
Dead
Survived
Dead
Dead
Dead
Survived
Dead
Survived
Dead
Dead
```

In [19]:
```
testing_data.head(10)
```

Out[19]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare
571	0	3	0	33.0	0	0	7.7750
572	1	2	1	6.0	0	1	33.0000
573	0	3	0	17.0	1	0	7.0542
574	0	2	0	34.0	0	0	13.0000
575	0	2	0	50.0	0	0	13.0000
576	1	1	0	27.0	1	0	53.1000
577	0	3	0	20.0	0	0	8.6625
578	1	2	1	30.0	3	0	21.0000
579	0	2	0	25.0	1	0	26.0000
580	0	3	1	25.0	1	0	7.9250

Now check for the entire test set how many you get correct: aim to get at least 75 percent accuracy !

In [20]:
```
correct = 0
for ix in testing_data.index:
    a = dt.predict(testing_data.loc[ix])
    if testing_data.loc[ix].Survived == 0 :
        if a == 'Dead' :
            correct += 1
    if testing_data.loc[ix].Survived == 1 :
        if a == 'Survived' :
            correct += 1
print (correct)
print (testing_data.shape[0])
print (float(correct/testing_data.shape[0]))
```

```
120
143
0.8391608391608392
```

Now use SKLEARN: Decision tree and Random Forests

In [21]:
```
import sklearn
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
```

In [22]:
```
DT = DecisionTreeClassifier()
DT.fit(X[:split], y[:split])
```

Out[22]:
```
DecisionTreeClassifier(class_weight=None, criterion='gini', max_de
pth=None,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_spl
it=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort=False
,
                       random_state=None, splitter='best')
```

In [23]:
```
DT.score(X[split:], y[split:])
```

Out[23]:
```
0.7972027972027972
```

In [24]:
```
rf = RandomForestClassifier(n_estimators=100)
rf.fit(X[:split], y[:split])

rf.score(X[split:], y[split:])
```

```
/anaconda3/envs/python35/lib/python3.6/site-packages/ipykernel_lau
ncher.py:2: DataConversionWarning: A column-vector y was passed wh
en a 1d array was expected. Please change the shape of y to (n_sam
ples,), for example using ravel().
```

Out[24]:
```
0.8531468531468531
```

In [ ]:
```
```