Tooling Seminar - Titanic

May 4, 2017

In [2]:
```
%matplotlib inline
# Scientific computing
import numpy as np

# Data frames (R-style)
import pandas as pd

# Visualisation
import matplotlib.pyplot as plt
import seaborn as sns

# Machine learning packages
from sklearn import tree
from sklearn.tree import export_graphviz
from sklearn.metrics import confusion_matrix, f1_score, roc_auc_score
from sklearn.ensemble import RandomForestClassifier
```

In [3]:
```
# Read data
train_data = pd.read_csv('./data/train.csv')
test_data = pd.read_csv('./data/test.csv')
test_y = pd.read_csv('./data/gender_submission.csv').Survived

train_data.head(10)
```

Out[3]:
```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3
5            6         0       3
6            7         0       1
7            8         0       3
8            9         1       3
9           10         1       2

                                                Name     Sex   Age  SibSp  \
```

```
0                            Braund, Mr. Owen Harris    male   22      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female   38      1
2                             Heikkinen, Miss. Laina  female   26      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female   35      1
4                           Allen, Mr. William Henry    male   35      0
5                                   Moran, Mr. James    male  NaN      0
6                            McCarthy, Mr. Timothy J    male   54      0
7                     Palsson, Master. Gosta Leonard    male    2      3
8  Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)  female   27      0
9                Nasser, Mrs. Nicholas (Adele Achem)  female   14      1

   Parch            Ticket     Fare Cabin Embarked
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S
5      0            330877   8.4583   NaN        Q
6      0             17463  51.8625   E46        S
7      1            349909  21.0750   NaN        S
8      2            347742  11.1333   NaN        S
9      0            237736  30.0708   NaN        C
```

In [4]:
```python
train_data.info()
print("--------------")
test_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 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: 90.5+ KB
--------------
<class 'pandas.core.frame.DataFrame'>
Int64Index: 418 entries, 0 to 417
Data columns (total 11 columns):
```

```
PassengerId    418 non-null int64
Pclass         418 non-null int64
Name           418 non-null object
Sex            418 non-null object
Age            332 non-null float64
SibSp          418 non-null int64
Parch          418 non-null int64
Ticket         418 non-null object
Fare           417 non-null float64
Cabin          91 non-null object
Embarked       418 non-null object
dtypes: float64(2), int64(4), object(5)
memory usage: 39.2+ KB
```

As shown we have 891 entries in the training data and 418 entries in the test data. However, the info also shows there are missing values in the age column. For test there is also a missing Fare value.

```
In [5]: grouped = train_data.groupby('Survived')
        grouped.count()
```

```
Out[5]:           PassengerId  Pclass  Name  Sex  Age  SibSp  Parch  Ticket  Fare  \
        Survived
        0                 549     549   549  549  424    549    549     549   549
        1                 342     342   342  342  290    342    342     342   342

                  Cabin  Embarked
        Survived
        0            68       549
        1           136       340
```

From the breakdown above we see the our target class (Survived) is relatively balanced over the training set. We also again see missing values.

There are some columns (Name, Ticket, Embarked) that probably are not as strong for our prediction. They are also fairly difficult to transform into something more useful. Lets discard these.

After we get rid of the columns specified above, we still have to deal with the NaN values we found.

```
In [6]: train_data.drop(['PassengerId','Name','Ticket','Cabin','Embarked'], axis=1, inplace=Tru
        train_data['Age'].fillna(train_data['Age'].mean(), inplace=True)
        train_data.Age = train_data.Age.round(decimals=0)
        train_data.head(10)
```

```
Out[6]:    Survived  Pclass     Sex  Age  SibSp  Parch     Fare
        0         0       3    male   22      1      0   7.2500
        1         1       1  female   38      1      0  71.2833
        2         1       3  female   26      0      0   7.9250
```

3	1	1	female	35	1	0	53.1000
4	0	3	male	35	0	0	8.0500
5	0	3	male	30	0	0	8.4583
6	0	1	male	54	0	0	51.8625
7	0	3	male	2	3	1	21.0750
8	1	3	female	27	0	2	11.1333
9	1	2	female	14	1	0	30.0708

In [7]:

```
test_data.drop(['PassengerId','Name','Ticket','Cabin','Embarked'], axis=1, inplace=Tru
test_data['Age'].fillna(test_data['Age'].mean(), inplace=True)
test_data.Age = test_data.Age.round(decimals=0)
test_data['Fare'].fillna(test_data['Fare'].median(), inplace=True)
test_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 418 entries, 0 to 417
Data columns (total 6 columns):
Pclass    418 non-null int64
Sex       418 non-null object
Age       418 non-null float64
SibSp     418 non-null int64
Parch     418 non-null int64
Fare      418 non-null float64
dtypes: float64(2), int64(3), object(1)
memory usage: 22.9+ KB
```

In our final preparation step we turn the 'Sex' column into a dummy column with 0 being male and 1 being female.

In [8]:

```
#train_data.Pclass = train_data.Pclass.astype('category')
#train_data.Sex = train_data.Sex.astype('category')
train_data['Sex'] = np.where(train_data['Sex'] == 'female', 1, 0)

#test_data.Pclass = test_data.Pclass.astype('category')
#test_data.Sex = test_data.Sex.astype('category')
test_data['Sex'] = np.where(test_data['Sex'] == 'female', 1, 0)
test_data.head(10)
```

Out[8]:

	Pclass	Sex	Age	SibSp	Parch	Fare
0	3	0	34	0	0	7.8292
1	3	1	47	1	0	7.0000
2	2	0	62	0	0	9.6875
3	3	0	27	0	0	8.6625
4	3	1	22	1	1	12.2875
5	3	0	14	0	0	9.2250
6	3	1	30	0	0	7.6292
7	2	0	26	1	1	29.0000
8	3	1	18	0	0	7.2292
9	3	0	21	2	0	24.1500

Lets start looking at our data now we have cleaned it. Do we need any other steps to handle correlations before we train a model?

```
In [9]: correlations = train_data.corr()
        print(correlations['Survived'])

        plt.figure(figsize=(10,10))
        sns.heatmap(correlations,linewidths=0.25, square=True, cbar_kws={'shrink' : .6}, annot=
        plt.title("Heatmap over de correlaties tussen de variabelen")
```

```
Survived    1.000000
Pclass     -0.338481
Sex         0.543351
Age        -0.070324
SibSp      -0.035322
Parch       0.081629
Fare        0.257307
Name: Survived, dtype: float64
```

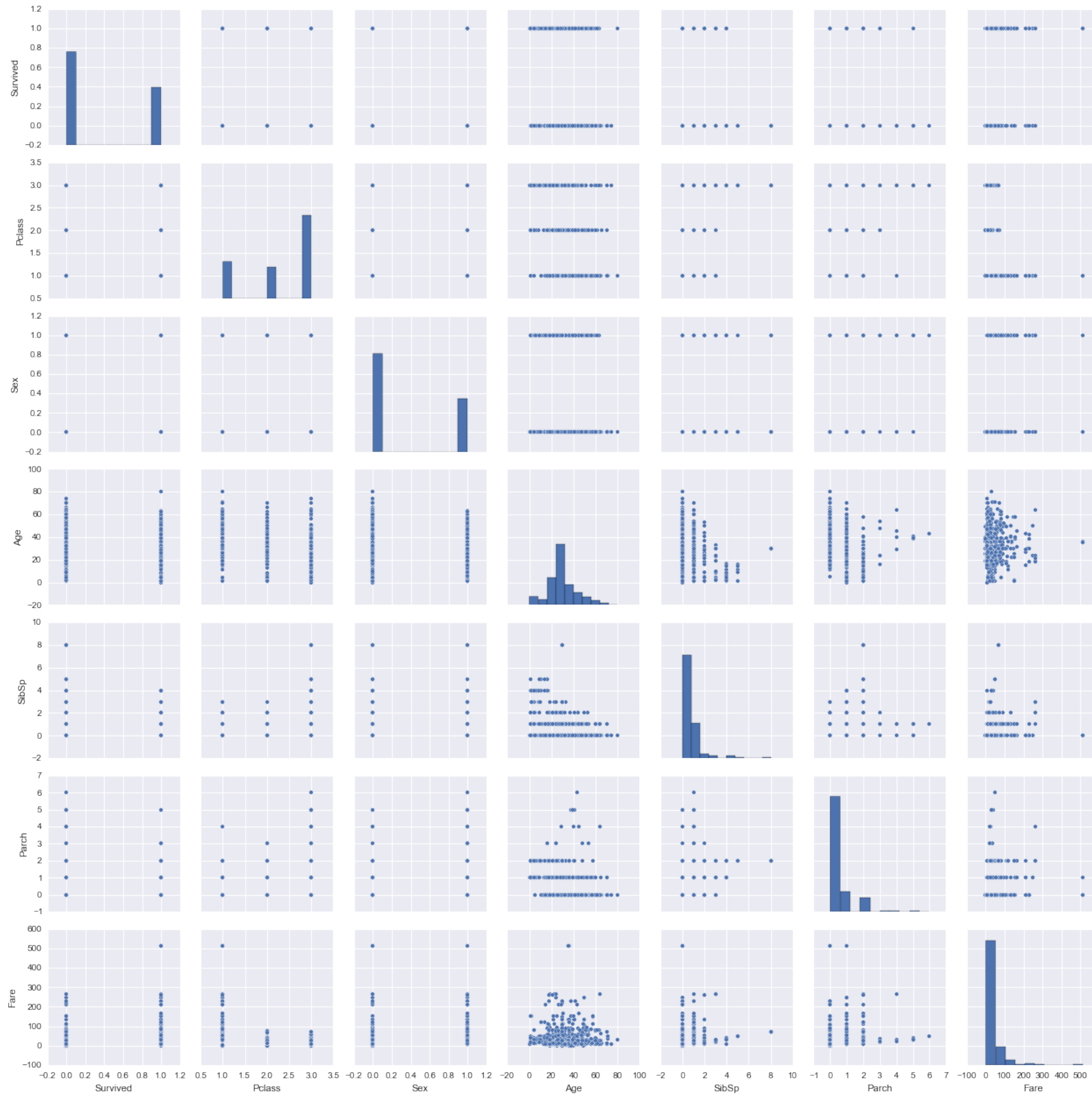
```
Out[9]: <matplotlib.text.Text at 0x938f550>
```

It appears are variables are not strongly correlated to each other. From the list of how the variables are correlated to the Survived label we can get the feeling a model might work quite well.

As a last step before we start training a model we will plot the pairwise distribution between the variables. Note: This only works because we only have a few columns. With more columns the figures look terrible.

```
In [10]: sns.pairplot(train_data)
```

```
Out[10]: <seaborn.axisgrid.PairGrid at 0x931aac8>
```




```
In [11]: # Train the model
         train_x = train_data.drop('Survived', axis=1, inplace=False)
         train_y = train_data.Survived

         classifier = tree.DecisionTreeClassifier()
         classifier.fit(train_x, train_y)
```

```
Out[11]: DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None,
                     max_features=None, max_leaf_nodes=None, min_samples_leaf=1,
                     min_samples_split=2, min_weight_fraction_leaf=0.0,
                     random_state=None, splitter='best')
```

```
In [26]: # Check score on training set
         cm_train = confusion_matrix(train_y, classifier.predict(train_x))
```

```
auc_train = roc_auc_score(train_y, classifier.predict(train_x))
f1_train = f1_score(train_y, classifier.predict(train_x))
print(cm_train)
print('------------------------------')
print('AUC      : {}'.format(auc_train))
print('F1 Score : {}'.format(f1_train))
```

```
[[546   3]
 [ 16 326]]
------------------------------
AUC      : 0.9738759466973445
F1 Score : 0.9716840536512668
```

In [15]:
```
# Create predictions on the test set
predictions = classifier.predict(test_data)
```

In [27]:
```
# Score on the test outcomes
cm_test = confusion_matrix(test_y, predictions)
f1_test = f1_score(test_y, predictions)
auc_test = roc_auc_score(test_y, predictions)
print(cm_test)
print('------------------------------')
print('AUC      : {}'.format(auc_test))
print('F1 Score : {}'.format(f1_test))
```

```
[[225  41]
 [ 35 117]]
------------------------------
AUC      : 0.8078007518796992
F1 Score : 0.7548387096774193
```

In [19]:
```
# Possibility to save the tree to file, load it, turn it into PNG and show it here. D
# Save decision tree to file, reload it and show in a plot
#with open("dt.dot", 'w') as f:
#    export_graphviz(classifier, out_file=f,
#                    feature_names=list(train_x))
#
#    pydot.graph_from_dot_data(dotfile.getvalue()).write_png(file_path)
#    i = misc.imread(file_path)
#    plt.imshow(i)
```

There seems to be a lot of overfitting. Perhaps we can tweak the model to have some more constraints.

In [20]:
```
# Look at our current tree
classifier.get_params
```

```
Out[20]: <bound method DecisionTreeClassifier.get_params of DecisionTreeClassifier(class_weigh
                     max_features=None, max_leaf_nodes=None, min_samples_leaf=1,
                     min_samples_split=2, min_weight_fraction_leaf=0.0,
                     random_state=None, splitter='best')>
```

```
In [21]: c2 = tree.DecisionTreeClassifier(max_depth = 15, max_leaf_nodes=10)
         c2.fit(train_x, train_y)

         f1_score(train_y, c2.predict(train_x))
```

```
Out[21]: 0.76609105180533754
```

We now have a highly constrained decision tree. A much lower score on the train set means we're not fitting to all our training examples anymore.

Lets see if this helps our test predictions any

```
In [28]: pred = c2.predict(test_data)
         print(confusion_matrix(test_y, pred))
         print("------------------------------")
         print("AUC Score = {}".format(roc_auc_score(test_y, pred)))
         print("F1 Score  = {}".format(f1_score(test_y, pred)))
```

```
[[260   6]
 [ 12 140]]
------------------------------
AUC Score = 0.9492481203007519
F1 Score  = 0.9395973154362416
```

We get a much better score with our constrained tree. Overfitting indeed was the problem.

Finally lets try a Random Forest to see if a whole set of (constrained) decision trees does better then a single tree.

```
In [29]: forest = RandomForestClassifier(n_estimators=100, max_leaf_nodes=10)
         forest.fit(train_x, train_y)
         y_pred = forest.predict(test_data)
         print("Accuracy score = {}".format(forest.score(test_data, test_y)))
         print("F1 score       = {}".format(f1_score(test_y, y_pred)))
         print("AUC score      = {}".format(roc_auc_score(test_y,y_pred)))
         print("---------")
         print(confusion_matrix(test_y, y_pred))
```

```
Accuracy score = 0.930622009569378
F1 score       = 0.9010238907849829
AUC score      = 0.9172932330827068
---------
[[257   9]
 [ 20 132]]
```