# Titanic

November 4, 2016

## 1 Titanic Project

Udacity
Data Science Nano Degree
Project 2
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October 2016

In [1]:
```
# Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

### 1.1 Exploration

In [2]:
```
# Data import
path = r'/Users/philipp/Desktop/DS/Projects/Titanic/titanic-data.csv'

dataFrame = pd.read_csv(path)
dataFrame
```

Out[2]:

| | 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 | |
| 10 | 11 | 1 | 3 | |
| 11 | 12 | 1 | 1 | |
| 12 | 13 | 0 | 3 | |
| 13 | 14 | 0 | 3 | |
| 14 | 15 | 0 | 3 | |
| 15 | 16 | 1 | 2 | |
| 16 | 17 | 0 | 3 | |
| 17 | 18 | 1 | 2 | |
| 18 | 19 | 0 | 3 | |
| 19 | 20 | 1 | 3 | |
| 20 | 21 | 0 | 2 | |

| | | | |
|---|---|---|---|
| 21 | 22 | 1 | 2 |
| 22 | 23 | 1 | 3 |
| 23 | 24 | 1 | 1 |
| 24 | 25 | 0 | 3 |
| 25 | 26 | 1 | 3 |
| 26 | 27 | 0 | 3 |
| 27 | 28 | 0 | 1 |
| 28 | 29 | 1 | 3 |
| 29 | 30 | 0 | 3 |
| .. | ... | ... | ... |
| 861 | 862 | 0 | 2 |
| 862 | 863 | 1 | 1 |
| 863 | 864 | 0 | 3 |
| 864 | 865 | 0 | 2 |
| 865 | 866 | 1 | 2 |
| 866 | 867 | 1 | 2 |
| 867 | 868 | 0 | 1 |
| 868 | 869 | 0 | 3 |
| 869 | 870 | 1 | 3 |
| 870 | 871 | 0 | 3 |
| 871 | 872 | 1 | 1 |
| 872 | 873 | 0 | 1 |
| 873 | 874 | 0 | 3 |
| 874 | 875 | 1 | 2 |
| 875 | 876 | 1 | 3 |
| 876 | 877 | 0 | 3 |
| 877 | 878 | 0 | 3 |
| 878 | 879 | 0 | 3 |
| 879 | 880 | 1 | 1 |
| 880 | 881 | 1 | 2 |
| 881 | 882 | 0 | 3 |
| 882 | 883 | 0 | 3 |
| 883 | 884 | 0 | 2 |
| 884 | 885 | 0 | 3 |
| 885 | 886 | 0 | 3 |
| 886 | 887 | 0 | 2 |
| 887 | 888 | 1 | 1 |
| 888 | 889 | 0 | 3 |
| 889 | 890 | 1 | 1 |
| 890 | 891 | 0 | 3 |

| | Name | Sex | Age | SibSp | \ |
|---|---|---|---|---|---|
| 0 | Braund, Mr. Owen Harris | male | 22.0 | 1 | |
| 1 | Cumings, Mrs. John Bradley (Florence Briggs Th... | female | 38.0 | 1 | |
| 2 | Heikkinen, Miss. Laina | female | 26.0 | 0 | |
| 3 | Futrelle, Mrs. Jacques Heath (Lily May Peel) | female | 35.0 | 1 | |
| 4 | Allen, Mr. William Henry | male | 35.0 | 0 | |
| 5 | Moran, Mr. James | male | NaN | 0 | |
| 6 | McCarthy, Mr. Timothy J | male | 54.0 | 0 | |
| 7 | Palsson, Master. Gosta Leonard | male | 2.0 | 3 | |
| 8 | Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg) | female | 27.0 | 0 | |
| 9 | Nasser, Mrs. Nicholas (Adele Achem) | female | 14.0 | 1 | |
| 10 | Sandstrom, Miss. Marguerite Rut | female | 4.0 | 1 | |
| 11 | Bonnell, Miss. Elizabeth | female | 58.0 | 0 | |

| | | | | | |
|---|---|---|---|---|---|
| 12 | Saundercock, Mr. William Henry | male | 20.0 | 0 | |
| 13 | Andersson, Mr. Anders Johan | male | 39.0 | 1 | |
| 14 | Vestrom, Miss. Hulda Amanda Adolfina | female | 14.0 | 0 | |
| 15 | Hewlett, Mrs. (Mary D Kingcome) | female | 55.0 | 0 | |
| 16 | Rice, Master. Eugene | male | 2.0 | 4 | |
| 17 | Williams, Mr. Charles Eugene | male | NaN | 0 | |
| 18 | Vander Planke, Mrs. Julius (Emelia Maria Vande... | female | 31.0 | 1 | |
| 19 | Masselmani, Mrs. Fatima | female | NaN | 0 | |
| 20 | Fynney, Mr. Joseph J | male | 35.0 | 0 | |
| 21 | Beesley, Mr. Lawrence | male | 34.0 | 0 | |
| 22 | McGowan, Miss. Anna "Annie" | female | 15.0 | 0 | |
| 23 | Sloper, Mr. William Thompson | male | 28.0 | 0 | |
| 24 | Palsson, Miss. Torborg Danira | female | 8.0 | 3 | |
| 25 | Asplund, Mrs. Carl Oscar (Selma Augusta Emilia... | female | 38.0 | 1 | |
| 26 | Emir, Mr. Farred Chehab | male | NaN | 0 | |
| 27 | Fortune, Mr. Charles Alexander | male | 19.0 | 3 | |
| 28 | O'Dwyer, Miss. Ellen "Nellie" | female | NaN | 0 | |
| 29 | Todoroff, Mr. Lalio | male | NaN | 0 | |
| .. | ... | ... | ... | ... | |
| 861 | Giles, Mr. Frederick Edward | male | 21.0 | 1 | |
| 862 | Swift, Mrs. Frederick Joel (Margaret Welles Ba... | female | 48.0 | 0 | |
| 863 | Sage, Miss. Dorothy Edith "Dolly" | female | NaN | 8 | |
| 864 | Gill, Mr. John William | male | 24.0 | 0 | |
| 865 | Bystrom, Mrs. (Karolina) | female | 42.0 | 0 | |
| 866 | Duran y More, Miss. Asuncion | female | 27.0 | 1 | |
| 867 | Roebling, Mr. Washington Augustus II | male | 31.0 | 0 | |
| 868 | van Melkebeke, Mr. Philemon | male | NaN | 0 | |
| 869 | Johnson, Master. Harold Theodor | male | 4.0 | 1 | |
| 870 | Balkic, Mr. Cerin | male | 26.0 | 0 | |
| 871 | Beckwith, Mrs. Richard Leonard (Sallie Monypeny) | female | 47.0 | 1 | |
| 872 | Carlsson, Mr. Frans Olof | male | 33.0 | 0 | |
| 873 | Vander Cruyssen, Mr. Victor | male | 47.0 | 0 | |
| 874 | Abelson, Mrs. Samuel (Hannah Wizosky) | female | 28.0 | 1 | |
| 875 | Najib, Miss. Adele Kiamie "Jane" | female | 15.0 | 0 | |
| 876 | Gustafsson, Mr. Alfred Ossian | male | 20.0 | 0 | |
| 877 | Petroff, Mr. Nedelio | male | 19.0 | 0 | |
| 878 | Laleff, Mr. Kristo | male | NaN | 0 | |
| 879 | Potter, Mrs. Thomas Jr (Lily Alexenia Wilson) | female | 56.0 | 0 | |
| 880 | Shelley, Mrs. William (Imanita Parrish Hall) | female | 25.0 | 0 | |
| 881 | Markun, Mr. Johann | male | 33.0 | 0 | |
| 882 | Dahlberg, Miss. Gerda Ulrika | female | 22.0 | 0 | |
| 883 | Banfield, Mr. Frederick James | male | 28.0 | 0 | |
| 884 | Sutehall, Mr. Henry Jr | male | 25.0 | 0 | |
| 885 | Rice, Mrs. William (Margaret Norton) | female | 39.0 | 0 | |
| 886 | Montvila, Rev. Juozas | male | 27.0 | 0 | |
| 887 | Graham, Miss. Margaret Edith | female | 19.0 | 0 | |
| 888 | Johnston, Miss. Catherine Helen "Carrie" | female | NaN | 1 | |
| 889 | Behr, Mr. Karl Howell | male | 26.0 | 0 | |
| 890 | Dooley, Mr. Patrick | male | 32.0 | 0 | |

| | 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 |
| 10 | 1 | PP 9549 | 16.7000 | G6 | S |
| 11 | 0 | 113783 | 26.5500 | C103 | S |
| 12 | 0 | A/5. 2151 | 8.0500 | NaN | S |
| 13 | 5 | 347082 | 31.2750 | NaN | S |
| 14 | 0 | 350406 | 7.8542 | NaN | S |
| 15 | 0 | 248706 | 16.0000 | NaN | S |
| 16 | 1 | 382652 | 29.1250 | NaN | Q |
| 17 | 0 | 244373 | 13.0000 | NaN | S |
| 18 | 0 | 345763 | 18.0000 | NaN | S |
| 19 | 0 | 2649 | 7.2250 | NaN | C |
| 20 | 0 | 239865 | 26.0000 | NaN | S |
| 21 | 0 | 248698 | 13.0000 | D56 | S |
| 22 | 0 | 330923 | 8.0292 | NaN | Q |
| 23 | 0 | 113788 | 35.5000 | A6 | S |
| 24 | 1 | 349909 | 21.0750 | NaN | S |
| 25 | 5 | 347077 | 31.3875 | NaN | S |
| 26 | 0 | 2631 | 7.2250 | NaN | C |
| 27 | 2 | 19950 | 263.0000 | C23 C25 C27 | S |
| 28 | 0 | 330959 | 7.8792 | NaN | Q |
| 29 | 0 | 349216 | 7.8958 | NaN | S |
| .. | ... | ... | ... | ... | ... |
| 861 | 0 | 28134 | 11.5000 | NaN | S |
| 862 | 0 | 17466 | 25.9292 | D17 | S |
| 863 | 2 | CA. 2343 | 69.5500 | NaN | S |
| 864 | 0 | 233866 | 13.0000 | NaN | S |
| 865 | 0 | 236852 | 13.0000 | NaN | S |
| 866 | 0 | SC/PARIS 2149 | 13.8583 | NaN | C |
| 867 | 0 | PC 17590 | 50.4958 | A24 | S |
| 868 | 0 | 345777 | 9.5000 | NaN | S |
| 869 | 1 | 347742 | 11.1333 | NaN | S |
| 870 | 0 | 349248 | 7.8958 | NaN | S |
| 871 | 1 | 11751 | 52.5542 | D35 | S |
| 872 | 0 | 695 | 5.0000 | B51 B53 B55 | S |
| 873 | 0 | 345765 | 9.0000 | NaN | S |
| 874 | 0 | P/PP 3381 | 24.0000 | NaN | C |
| 875 | 0 | 2667 | 7.2250 | NaN | C |
| 876 | 0 | 7534 | 9.8458 | NaN | S |
| 877 | 0 | 349212 | 7.8958 | NaN | S |
| 878 | 0 | 349217 | 7.8958 | NaN | S |
| 879 | 1 | 11767 | 83.1583 | C50 | C |
| 880 | 1 | 230433 | 26.0000 | NaN | S |
| 881 | 0 | 349257 | 7.8958 | NaN | S |
| 882 | 0 | 7552 | 10.5167 | NaN | S |
| 883 | 0 | C.A./SOTON 34068 | 10.5000 | NaN | S |
| 884 | 0 | SOTON/OQ 392076 | 7.0500 | NaN | S |
| 885 | 5 | 382652 | 29.1250 | NaN | Q |
| 886 | 0 | 211536 | 13.0000 | NaN | S |

```
887      0            112053   30.0000          B42        S
888      2        W./C. 6607   23.4500          NaN        S
889      0            111369   30.0000         C148        C
890      0            370376    7.7500          NaN        Q

[891 rows x 12 columns]
```

From a sample of the RMS Titanic data, we can see the various features present for each passenger on the ship: - **Survived**: Outcome of survival (0 = No; 1 = Yes) - **Pclass**: Socio-economic class (1 = Upper class; 2 = Middle class; 3 = Lower class) - **Name**: Name of passenger - **Sex**: Sex of the passenger - **Age**: Age of the passenger (Some entries contain `NaN`) - **SibSp**: Number of siblings and spouses of the passenger aboard - **Parch**: Number of parents and children of the passenger aboard - **Ticket**: Ticket number of the passenger - **Fare**: Fare paid by the passenger - **Cabin** Cabin number of the passenger (Some entries contain `NaN`) - **Embarked**: Port of embarkation of the passenger (C = Cherbourg; Q = Queenstown; S = Southampton)

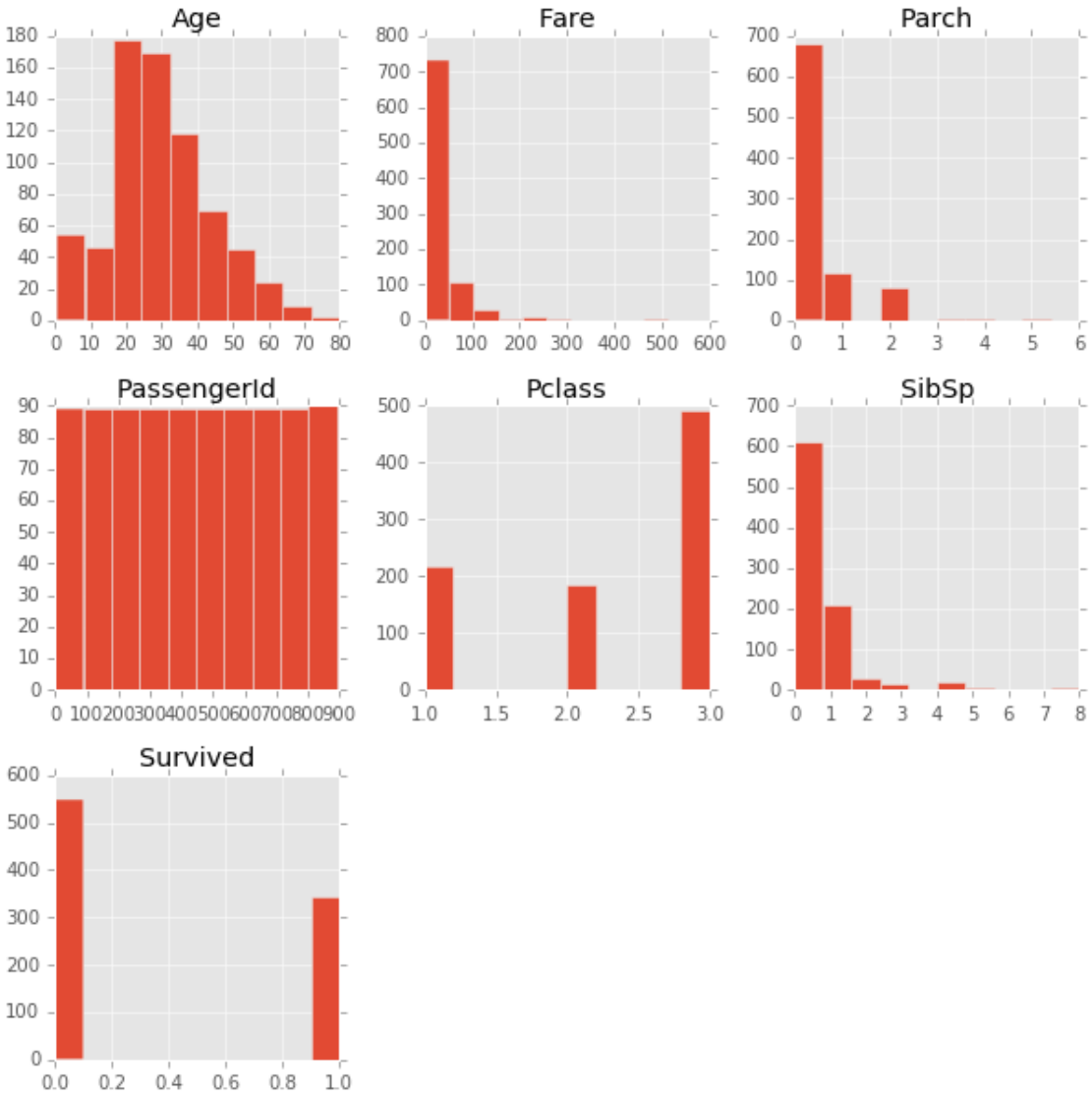
In [3]:
```
# Despriptive statistics
dataFrame.describe()
```

Out[3]:
```
       PassengerId    Survived      Pclass         Age       SibSp  \
count   891.000000  891.000000  891.000000  714.000000  891.000000
mean    446.000000    0.383838    2.308642   29.699118    0.523008
std     257.353842    0.486592    0.836071   14.526497    1.102743
min       1.000000    0.000000    1.000000    0.420000    0.000000
25%     223.500000    0.000000    2.000000   20.125000    0.000000
50%     446.000000    0.000000    3.000000   28.000000    0.000000
75%     668.500000    1.000000    3.000000   38.000000    1.000000
max     891.000000    1.000000    3.000000   80.000000    8.000000

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

In [4]:
```
# Initial Plot
%pylab inline

plt.style.use('ggplot')

dataFrame.hist(figsize=(10,10))
```

```
Populating the interactive namespace from numpy and matplotlib
```

Out[4]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x1144cd190>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1143cd8d0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x11457ce50>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x114705650>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x117b4f5d0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x117bb2490>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x117c35510>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x117c60bd0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x117d25410>]], dtype=object)
```




## 1.2 Research Question: ML Problem

Predicting the chance to survive from the the rest of the data is a clasification problem with lables. With less than 100k samples sci-kit learn suggests a support vector classifier with linear kernel. So that is what I am going to try. For simplicity I select only features which are numerice already.

## 1.3 Data wrangling

In [5]:
```
# Data Pre-Processing

feature_cols = dataFrame.drop(['PassengerId', 'Survived', 'Name', 'Sex', 'Ticket', 'Cabin', 'Eml
target_col = dataFrame.iloc[:,1] # target/label column

print "Feature column(s):-\n{}".format(feature_cols)
print "Target column: {}".format(target_col)
```

```
        # Imputation of missing values
        from sklearn.preprocessing import Imputer

        # Training Test Set
        from sklearn.cross_validation import train_test_split

        x_train, x_test, y_train, y_test = train_test_split(feature_cols, target_col) # test size is se

        print "Training set: {} samples".format(x_train.shape[0])
        print "Test set: {} samples".format(x_test.shape[0])
```

```
Feature column(s):-
     Pclass  SibSp  Parch      Fare
0         3      1      0    7.2500
1         1      1      0   71.2833
2         3      0      0    7.9250
3         1      1      0   53.1000
4         3      0      0    8.0500
5         3      0      0    8.4583
6         1      0      0   51.8625
7         3      3      1   21.0750
8         3      0      2   11.1333
9         2      1      0   30.0708
10        3      1      1   16.7000
11        1      0      0   26.5500
12        3      0      0    8.0500
13        3      1      5   31.2750
14        3      0      0    7.8542
15        2      0      0   16.0000
16        3      4      1   29.1250
17        2      0      0   13.0000
18        3      1      0   18.0000
19        3      0      0    7.2250
20        2      0      0   26.0000
21        2      0      0   13.0000
22        3      0      0    8.0292
23        1      0      0   35.5000
24        3      3      1   21.0750
25        3      1      5   31.3875
26        3      0      0    7.2250
27        1      3      2  263.0000
28        3      0      0    7.8792
29        3      0      0    7.8958
..      ...    ...    ...       ...
861       2      1      0   11.5000
862       1      0      0   25.9292
863       3      8      2   69.5500
864       2      0      0   13.0000
865       2      0      0   13.0000
866       2      1      0   13.8583
867       1      0      0   50.4958
868       3      0      0    9.5000
869       3      1      1   11.1333
```

```
870       3      0      0    7.8958
871       1      1      1   52.5542
872       1      0      0    5.0000
873       3      0      0    9.0000
874       2      1      0   24.0000
875       3      0      0    7.2250
876       3      0      0    9.8458
877       3      0      0    7.8958
878       3      0      0    7.8958
879       1      0      1   83.1583
880       2      0      1   26.0000
881       3      0      0    7.8958
882       3      0      0   10.5167
883       2      0      0   10.5000
884       3      0      0    7.0500
885       3      0      5   29.1250
886       2      0      0   13.0000
887       1      0      0   30.0000
888       3      1      2   23.4500
889       1      0      0   30.0000
890       3      0      0    7.7500

[891 rows x 4 columns]
Target column: 0      0
1      1
2      1
3      1
4      0
5      0
6      0
7      0
8      1
9      1
10     1
11     1
12     0
13     0
14     0
15     1
16     0
17     1
18     0
19     1
20     0
21     1
22     1
23     1
24     0
25     1
26     0
27     0
28     1
29     0
      ..
```

```
861    0
862    1
863    0
864    0
865    1
866    1
867    0
868    0
869    1
870    0
871    1
872    0
873    0
874    1
875    1
876    0
877    0
878    0
879    1
880    1
881    0
882    0
883    0
884    0
885    0
886    0
887    1
888    0
889    1
890    0
Name: Survived, dtype: int64
Training set: 668 samples
Test set: 223 samples
```

### 1.4 Training the Classifier

```
In [9]: # Classifier
        from sklearn.svm import LinearSVC #sklearn.svm.LinearSVC(penalty='l2', loss='squared_hinge', du
        from sklearn.grid_search import GridSearchCV

        # Set the parameters by cross-validation with linear SVC
        tuned_parameters = [{'C': [0.0001, 0.001, 0.01, 0.1, 1]}]

        # CV with grid search of C
        clf = GridSearchCV(LinearSVC (C = 1, random_state = 123), param_grid = tuned_parameters, cv = 5

        # Fit
        clf.fit(x_train, y_train)

        print clf
        print ('\n' "Best parameter from grid search: " + str(clf.best_params_) +'\n')
```

```
GridSearchCV(cv=5, error_score='raise',
       estimator=LinearSVC(C=1, class_weight=None, dual=True, fit_intercept=True,
     intercept_scaling=1, loss='squared_hinge', max_iter=1000,
```

```
     multi_class='ovr', penalty='l2', random_state=123, tol=0.0001,
     verbose=0),
       fit_params={}, iid=True, n_jobs=1,
       param_grid=[{'C': [0.0001, 0.001, 0.01, 0.1, 1]}],
       pre_dispatch='2*n_jobs', refit=True, scoring=None, verbose=0)

Best parameter from grid search: {'C': 0.001}
```

## 1.5 Validation

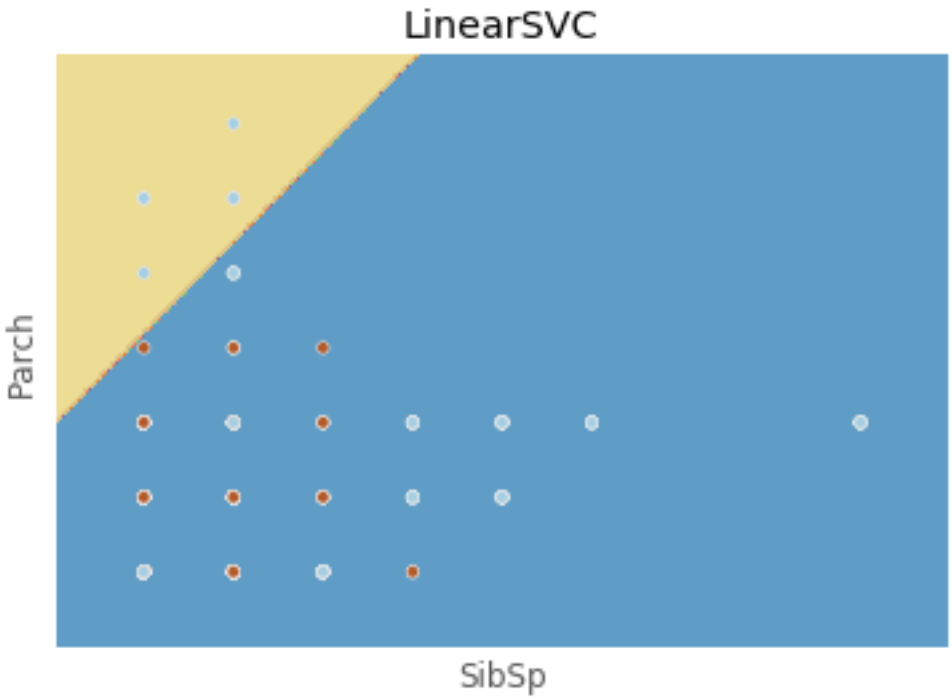
```
In [10]: # Predict
         y_pred = clf.predict(x_test)

         # Validation
         from sklearn.metrics import classification_report

         c_report = classification_report(y_test, y_pred)
         print "\n Classification report: \n {}".format(c_report)
```

```
Classification report:
             precision    recall  f1-score   support

          0       0.61      0.96      0.75       123
          1       0.84      0.26      0.40       100

avg / total       0.72      0.65      0.59       223
```

These scores are not overwhelming. But for a simple prediction model that utilizes only about half of the available data, it is not that bad.

```
In [35]: # Plotting one decision boundary of the Minear SVC

         import matplotlib.pyplot as plt

         X = feature_cols.values[:, 1:3]
         y = target_col

         h = 0.02  # step size in the mesh

         clf = svm.LinearSVC(C=0.001).fit(X, y)

         # create a mesh to plot in
         x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
         y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1
         xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))

         plt.subplot(1, 1, 1)
         plt.subplots_adjust(wspace=0.4, hspace=0.4)

         Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])

         # Put the result into a color plot
         Z = Z.reshape(xx.shape)
         plt.contourf(xx, yy, Z, cmap=plt.cm.Paired, alpha=0.8)
```

```
# Plot also the training points
plt.scatter(X[:, 0], X[:, 1], c=y, cmap=plt.cm.Paired)
plt.xlabel('SibSp')
plt.ylabel('Parch')
plt.xlim(xx.min(), xx.max())
plt.ylim(yy.min(), yy.max())
plt.xticks(())
plt.yticks(())
plt.title('LinearSVC')

plt.show()
```




The decision boundary for the features "Parch" and "SibSp" shows that the linear kernel of the classifier might not be the best fit. Feature engineering might help also.

## 1.6 Sources

- Kaggle
- Pandas Documentation
- Matplotlib Documentation
- sci-kit learn: Classification
- MLE Nanao Dergee Project 0
- sci-kit learn:Plot different SVM classifiers in the iris dataset