Contents

In this paper we look at the chances of surviving the Titanic using python. We predict the chances of an unseen set of data by using supervised machinelearning on the known dataset.

We use information from this site.

This is one of the first drafts to get to know the dataset and to experiment with the python and all the packages included.

1 Preparation

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

The adventure begins with importing the right packages. The dataset is downloaded from kaggle site as csv_file. Next the data is read into a dataframe by using pandas' pd.read_csv

```
data = pd.read_csv('titanic.csv')
```

Here we see the head of our dataframe. A couple of questions come to mind. Which variables play a role by determining the probability of surviving the Titanic. Sex and Cabin are not numeric values. How do we convert these to numeric values?

2 A first look at the dataset

```
data.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S

Here are the summary statistics of the dataframe. The mean, standard-deviation etc are given in this table.

```
data.describe()
```

	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
```

It is possible to search for particular passenger in the dataset. Such as passengers who were older than eighty years.

```
data[data.Age == 80]
```

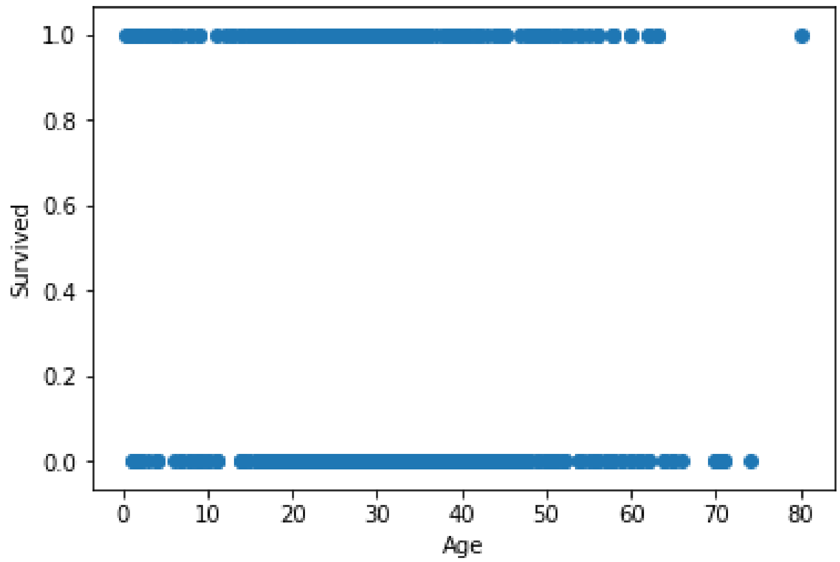
```
     PassengerId  Survived  Pclass                                  Name  \
630          631         1       1  Barkworth, Mr. Algernon Henry Wilson

      Sex   Age  SibSp  Parch Ticket  Fare Cabin Embarked
630  male  80.0      0      0  27042  30.0   A23        S
```

3 First figures

To get a good impression of the dataset and the influence of the variables, a couple of diagrams are made using `mathplotlib`.

```
plt.scatter(data.Age,data.Survived)
plt.xlabel('Age')
plt.ylabel('Survived')
```

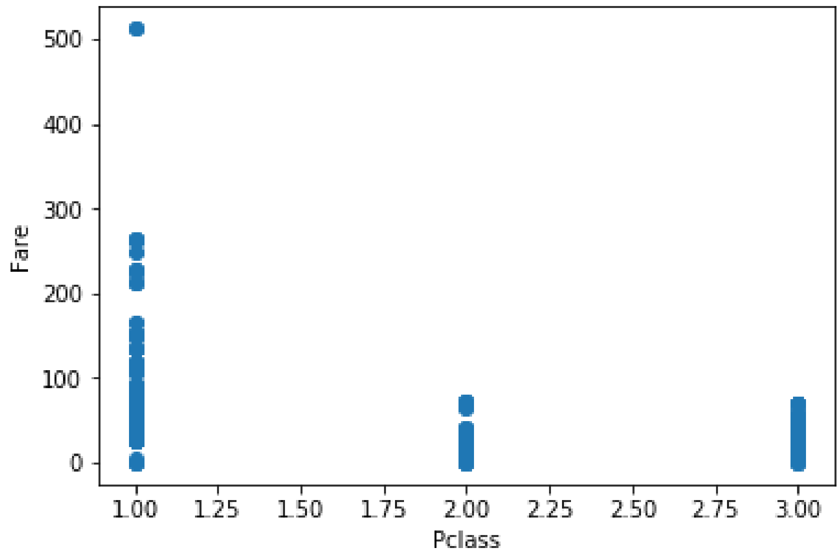
```
Text(0,0.5,'Survived')
```



Scatterplots are not always the best choice to illustrate some of the variables. There is not much to say about the variance because of the fact that a lot of points are close to eachother. A couple of values however stand out. We see that a passenger or more passengers travelling first class have paid more than 500 pounds for their ticketprice.

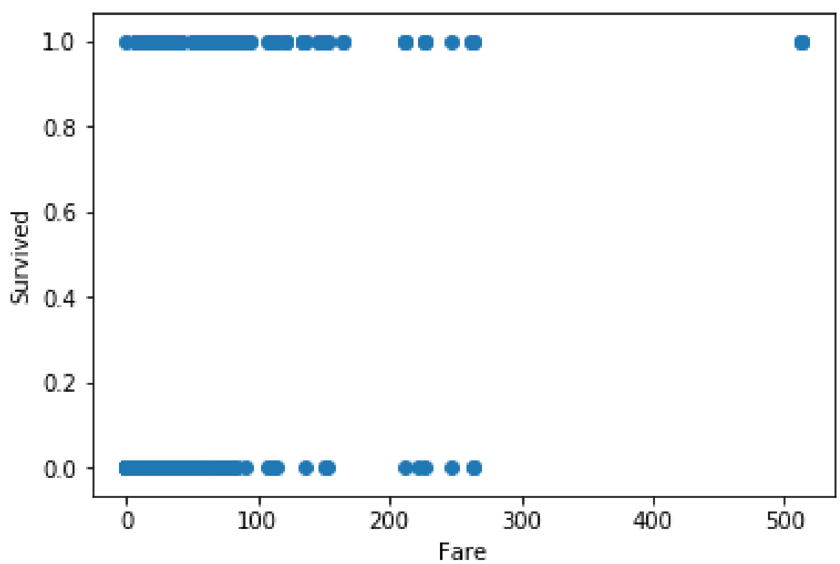
```
plt.scatter(data.Pclass,data.Fare)
plt.xlabel('Pclass')
plt.ylabel('Fare')
```

```
Text(0,0.5,'Fare')
```



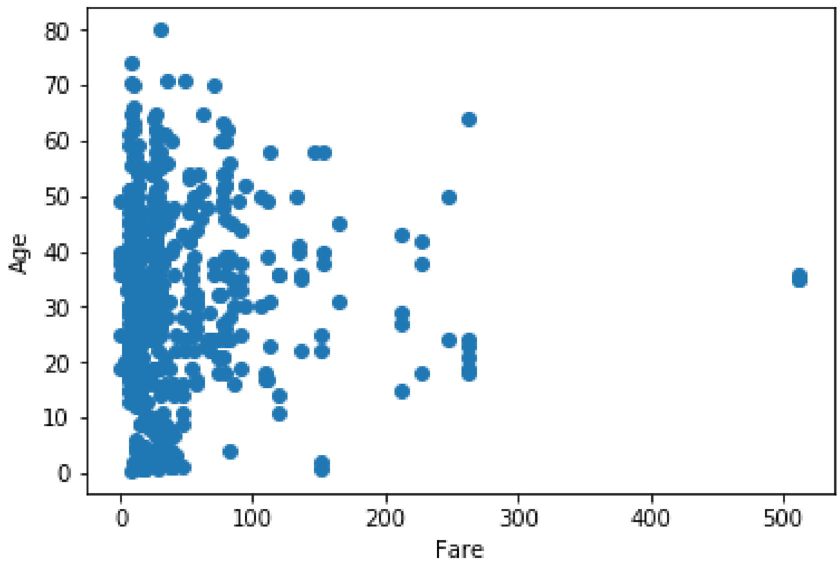

```
plt.scatter(data.Fare, data.Survived)
plt.xlabel('Fare')
plt.ylabel('Survived')
```

```
Text(0,0.5,'Survived')
```



```python
plt.scatter(data.Fare, data.Age)
plt.xlabel('Fare')
plt.ylabel('Age')
```

```
Text(0,0.5,'Age')
```



I was curious to see who had paid more than 400 pounds for their ticket. We see that it is easy to make a selection in our dataset using the > sign

```python
data[data.Fare > 400]
```

```
     PassengerId  Survived  Pclass                                Name  \
258          259         1       1                    Ward, Miss. Anna
679          680         1       1  Cardeza, Mr. Thomas Drake Martinez
737          738         1       1              Lesurer, Mr. Gustave J

        Sex   Age  SibSp  Parch    Ticket      Fare        Cabin Embarked
258  female  35.0      0      0  PC 17755  512.3292          NaN        C
679    male  36.0      0      1  PC 17755  512.3292  B51 B53 B55        C
737    male  35.0      0      0  PC 17755  512.3292         B101        C
```

```python
df_cleaned = data.dropna()
df_cleaned['male_dummy'] = (df_cleaned.Sex == 'male') #nieuwe kolom definiëren om male te veranderen in een boo
```

```
X = df_cleaned[['Age','male_dummy', 'Pclass', 'SibSp', 'Fare']]
y = df_cleaned[['Survived']]
```

```
/Users/myrthe/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:2: SettingW
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/ind
```

Here we see that we clean our dataset for the first time to make it more suitable for the packages we will be using. All rows with missing values (these are called NaNs, short for Not a Number) are deleted for scikit_-learn can't work with NaNs by using `.dropna()`. There are other ways than deleting rows to handle this problem. Replace the NaNs with the mean or to interpolate for example. However the choice was made to delete these rows. Furthermore we see that the problem of the `Sex` column not being a numeric value is handled. The values in the `Sex` column are changed into a boolean. Males are given a `True` and the females are given a `False`. Next a couple of variables have added to `X`. `Age`,=male_dummy=, `Pclass`, `SibSp`, `Fare` are all numeric values and therefore easy to use.

Here we see the cleaned dataframe with the new added column `male_dummy`

```
df_cleaned.head()
```

```
    PassengerId  Survived  Pclass  \
1             2         1       1
3             4         1       1
6             7         0       1
10           11         1       3
11           12         1       1

                                                 Name     Sex   Age  SibSp  \
1   Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0      1
3        Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
6                             McCarthy, Mr. Timothy J    male  54.0      0
10                    Sandstrom, Miss. Marguerite Rut  female   4.0      1
11                           Bonnell, Miss. Elizabeth  female  58.0      0
```

```
    Parch    Ticket     Fare Cabin Embarked  male_dummy
1       0  PC 17599  71.2833   C85        C       False
3       0    113803  53.1000  C123        S       False
6       0     17463  51.8625   E46        S        True
10      1   PP 9549  16.7000    G6        S       False
11      0    113783  26.5500  C103        S       False
```

```python
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression()
logreg.fit(X, y)
y_pred = logreg.predict(X)
```

```
/Users/myrthe/anaconda3/lib/python3.6/site-packages/sklearn/utils/validation.py:578:
  y = column_or_1d(y, warn=True)
```

Here we initialize the first regression called logistic regression. We don't split our dataframe in test and training set yet. For a general indication we only use the regressor and fit it on the cleaned dataset. After that we predict on the same dataset.

```python
logreg.coef_
```

```
array([[-0.01636209, -2.08109476,  0.01318695,  0.2035389 ,  0.00296447]])
```

Here we see the outcome of our first try with the logistic regression.

To interpret these coefficients, let's look at the order of the columns in `X`:

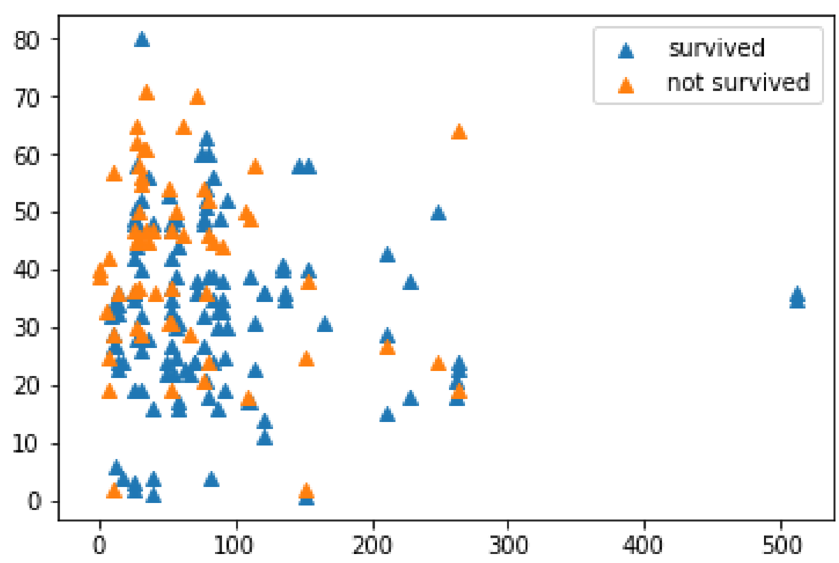
```python
X.head()
```

```
     Age  male_dummy  Pclass  SibSp     Fare
1   38.0       False       1      1  71.2833
3   35.0       False       1      1  53.1000
6   54.0        True       1      0  51.8625
10   4.0       False       3      1  16.7000
11  58.0       False       1      0  26.5500
```

4 Graphic illustration of a prediction

One of the first graphic illustrations of the relation between fare, age and survival. The relation is not very clear but we see that the higher the fare the more people survived and the higher the age the less people survived. However, this figure is not very accurate, because of the fact that only three variables were used.

```
survived = df_cleaned[df_cleaned.Survived == 1]
not_survived = df_cleaned[df_cleaned.Survived == 0]

plt.scatter(survived.Fare, survived.Age, marker='^', label = 'survived')
plt.scatter(not_survived.Fare, not_survived.Age, marker='^', label = 'not survived')
plt.legend()
```




```
P = df_cleaned[['Pclass', 'Fare','Age','male_dummy']]
```

We select from our df_cleaned only the columns with numeric values. This is convenient for the splitting into train and testsets, for scikit_learn can only work with numbers. Difference between P and X here is that X also has the column siblings, whereas P only has four columns

```
P.head()
```

```
    Pclass     Fare   Age  male_dummy
1        1  71.2833  38.0       False
3        1  53.1000  35.0       False
6        1  51.8625  54.0        True
10       3  16.7000   4.0       False
11       1  26.5500  58.0       False
```

<div> <style scoped> .dataframe tbody tr th:only-of-type { vertical-align: middle; }

.dataframe tbody tr th { vertical-align: top; }

.dataframe thead th { text-align: right; } </style> <table border="1" class="dataframe"> <thead> <tr style="text-align: right;"> <th></th> <th>Pclass</th> <th>Fare</th> <th>Age</th> <th>male_dummy</th> </tr> </thead> <tbody> <tr> <th>1</th> <td>1</td> <td>71.2833</td> <td>38.0</td> <td>False</td> </tr> <tr> <th>3</th> <td>1</td> <td>53.1000</td> <td>35.0</td> <td>False</td> </tr> <tr> <th>6</th> <td>1</td> <td>51.8625</td> <td>54.0</td> <td>True</td> </tr> <tr> <th>10</th> <td>3</td> <td>16.7000</td> <td>4.0</td> <td>False</td> </tr> <tr> <th>11</th> <td>1</td> <td>26.5500</td> <td>58.0</td> <td>False</td> </tr> </tbody> </table> </div>

```python
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression(fit_intercept=True)
logreg.fit(P, y)
y_pred = logreg.predict(P)
```

```
/Users/myrthe/anaconda3/lib/python3.6/site-packages/sklearn/utils/validation.py:578:
  y = column_or_1d(y, warn=True)
```

We fit our regressor on our dataset and predict on that same dataset. Once again without splitting into train and testset. Just to get a general idea about the values of the coeffecients.

```python
logreg.coef_
```

```
array([[ 0.00917324,  0.00337838, -0.01693475, -2.07643966]])
```

One could interpret the found coeffecients as follows: The coeffecients for class and fare are positive, which may indicate that the higher the class and price paid for a ticket, the higher the chance of surviving the Titanic. When we look at age and sex we see the exact opposite for the coeffecients are negative. The higher the age the lower your chances and if you were a man on board of the titanic your chances of surviving were lower.

```python
from sklearn.neighbors import KNeighborsClassifier
```

Another regression is used in the following lines. (explanation K nearest neighbours)

```python
knn = KNeighborsClassifier(n_neighbors=6)
```

```python
knn.fit(P,y)
```

```
/Users/myrthe/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:1: DataConv
  """Entry point for launching an IPython kernel.
```

```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=6, p=2,
           weights='uniform')
```

```python
prediction = knn.predict(P)
```

```python
P.shape
```

```
(183, 4)
```

```python
print('Prediction{}'.format(prediction))
```

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

Here we see one of our first predictions. 1 indicates the passenger has survived and 0 indicates that the passenger has died

Elke persoon heeft andere karakteristieken, dus dit zijn voorspellingen per persoon. Dus er komt een kans uit en dan kijkt de regressor, boven of onder 0.5

```
knn.score(P,y)
```

```
0.7486338797814208
```

This score gives a number between 0 and 1 and gives an impression of the accuracy of our model. However, this accuracy is not an indication of how well our model performs (explanation spam mail etc.)

```
P.head()
```

	Pclass	Fare	Age	male_dummy
1	1	71.2833	38.0	False
3	1	53.1000	35.0	False
6	1	51.8625	54.0	True
10	3	16.7000	4.0	False
11	1	26.5500	58.0	False

```
q = df_cleaned.Survived
```

```
q.head()
```

```
1     1
3     1
6     0
10    1
11    1
Name: Survived, dtype: int64
```

```
from sklearn.linear_model import LogisticRegression
```

```
from sklearn.model_selection import train_test_split
```

```python
logreg = LogisticRegression()
P_train, P_test, q_train, q_test = train_test_split(P,q, test_size=0.2, random_state=42)
logreg.fit(P_train, q_train)
q_pred = logreg.predict(P_test)
```

Here we see the dataset being split into a test and a training set. The arguments give us information about how much of our data we use as a test_set and how much of our data we use as a training_set. This and the parameters will be varied to see which parameter gives the best prediction. We fit our regressor on the training_set and predict on the test_set.

```python
print('Prediction {}'.format(q_pred))
```

```
Prediction [1 1 1 0 0 0 1 1 1 0 0 1 0 1 0 0 1 0 0 1 1 1 0 1 0 1 1 0 1 1 1 1 0 1 1 1 1
```

```python
P_train.head()
```

	Pclass	Fare	Age	male_dummy
331	1	28.5000	45.5	True
336	1	66.6000	29.0	True
193	2	26.0000	3.0	True
75	3	7.6500	25.0	True
248	1	52.5542	37.0	True

```python
from sklearn.metrics import roc_auc_score
q_pred_prob = logreg.predict_proba(P_test)[:,1]
roc_auc_score(q_test, q_pred_prob)
```

```
0.8416149068322981
```

When the test_size is changed from 0.4 to 0.2 , the score increases with more than 10%. This makes sense because a smaller test_set gives a higher accuracy score.

```python
from sklearn.model_selection import cross_val_score
cv_scores = cross_val_score(logreg, P, q, cv=5, scoring='roc_auc')
print(cv_scores)
```

```
[0.86666667 0.80333333 0.74666667 0.73263889 0.92361111]
```

```
len(P)
```

183

```
len(prediction)
```

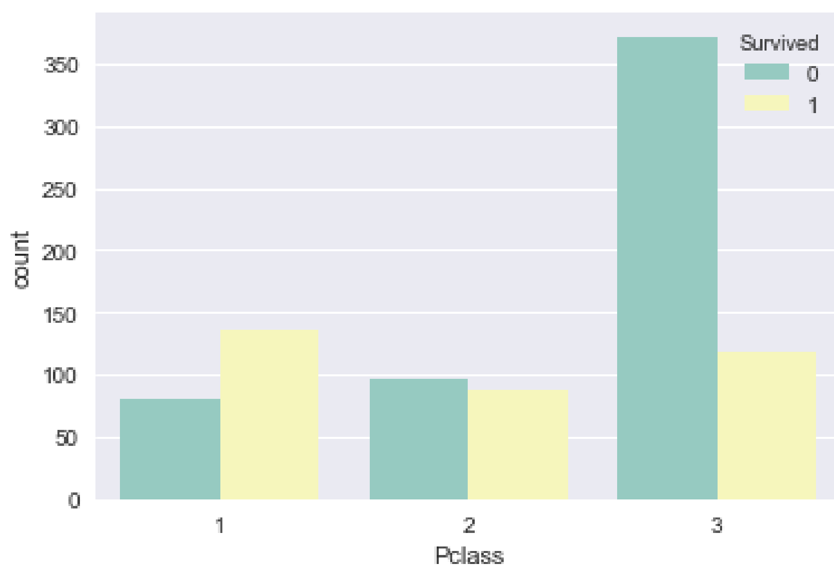
183

Seaborn countplot option? plt.figure()
sns.countplot(x='education', hue='party', data=df, palette='RdBu')
plt.xticks([0,1], ['No', 'Yes']) plt.show()

Given all the variables (age, gender, place of boarding etc.), you make a linear function (a1x1+a2x2+anxn+b). Computer puts this in the logistic function for x. For a particular x, you get a value between zero and one. This is your chance of survival. Boundary is 0,5. X < 0,5 passenger didn't survive. Computer tries to plot a logistic function where R2 is as small as possible. This is called the fitting process. The logistic function has to be as close to the datapoints as possible.

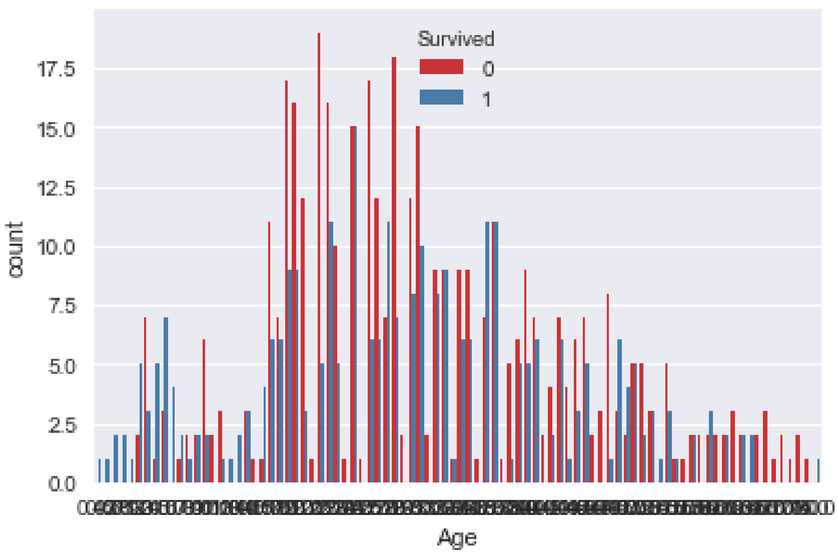
```
sns.countplot?
```

```
sns.set(style="darkgrid")
ax = sns.countplot(x="Pclass",hue="Survived", data=data, palette="Set3")
```

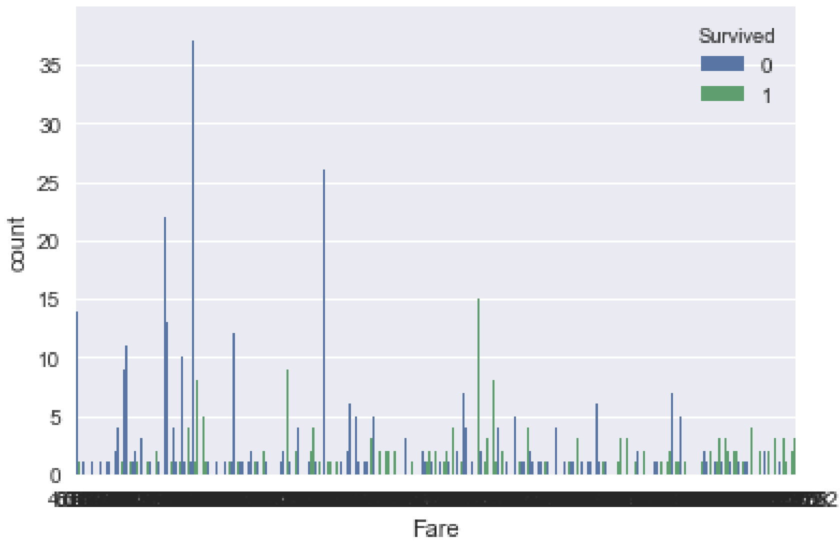


More people in class 3 than in class 1, makes it difficult to compare and draw a conclusion. Percentage? In general, we cannot draw a conclusion regarding survival probabilities because there were more people in class 3 than in one 1. In the third class, more passengers died than survived. In the first class, more people survived than perished. We cannot compare the results from the first class to the third class. The plot only shows us one variable. This is another reason why we cannot be sure about the influence of class on the chance of survival. *Simpson paradox*

```
sns.set(style="darkgrid")
ax = sns.countplot(x="Age",hue="Survived", data=data, palette="Set1")
```




```
sns.set(style="darkgrid")
ax = sns.countplot(x="Fare",hue="Survived", data=data)
```




```
sns.set(style="darkgrid")
ax = sns.countplot(x="male_dummy",hue="Survived", data=df_cleaned, palette="Set2")
```