Chapter 3 - Regression Models

Segment 3 - Logistic regression

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

from pandas import Series, DataFrame
from pylab import rcParams
from sklearn import preprocessing
```

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_predict

from sklearn import metrics
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_score, recall_score
```

```
%matplotlib inline
rcParams['figure.figsize'] = 5, 4
sb.set_style('whitegrid')
```

Logistic regression on the titanic dataset

```
address = 'C:/Users/Lillian/Desktop/ExerciseFiles/Data/titanic-training-data.csv'
titanic_training = pd.read_csv(address)
titanic_training.columns = ['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp', 'Parch', 'Ticket', 'Fare', 'Cabin', 'E
print(titanic_training.head())
```

```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         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

   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
```

```
print(titanic_training.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: 83.6+ KB
None
```

VARIABLE DESCRIPTIONS

Survived - Survival (0 = No; 1 = Yes)

Pclass - Passenger Class (1 = 1st; 2 = 2nd; 3 = 3rd)

Name - Name

Sex - Sex

Age - Age

SibSp - Number of Siblings/Spouses Aboard

Parch - Number of Parents/Children Aboard

Ticket - Ticket Number

Fare - Passenger Fare (British pound)

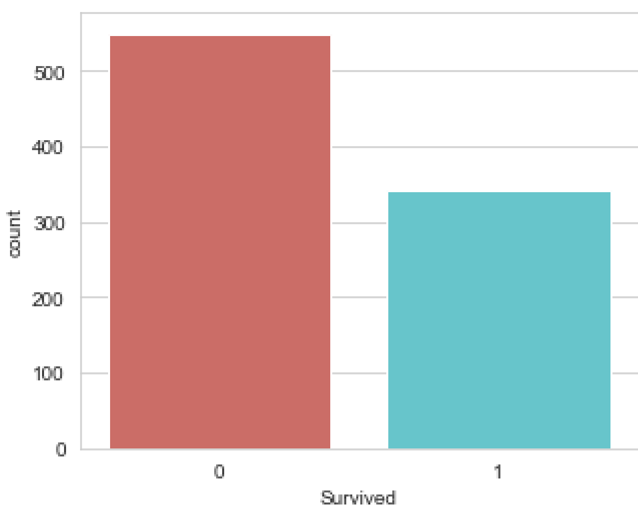
Cabin - Cabin

Embarked - Port of Embarkation (C = Cherbourg, France; Q = Queenstown, UK; S = Southampton - Cobh, Ireland)

Checking that your target variable is binary

```
sb.countplot(x='Survived', data=titanic_training, palette='hls')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x1c2bf493080>
```



Checking for missing values

```
titanic_training.isnull().sum()
```

```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

```
titanic_training.describe()
```

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

Taking care of missing values

Dropping missing values

So let's just go ahead and drop all the variables that aren't relevant for predicting survival. We should at least keep the following:

- Survived - This variable is obviously relevant.
- Pclass - Does a passenger's class on the boat affect their survivability?

- Sex - Could a passenger's gender impact their survival rate?
- Age - Does a person's age impact their survival rate?
- SibSp - Does the number of relatives on the boat (that are siblings or a spouse) affect a person survivability? Probability
- Parch - Does the number of relatives on the boat (that are children or parents) affect a person survivability? Probability
- Fare - Does the fare a person paid effect his survivability? Maybe - let's keep it.
- Embarked - Does a person's point of embarkation matter? It depends on how the boat was filled... Let's keep it.

What about a person's name, ticket number, and passenger ID number? They're irrelavant for predicting survivability. And as you recall, the cabin variable is almost all missing values, so we can just drop all of these.

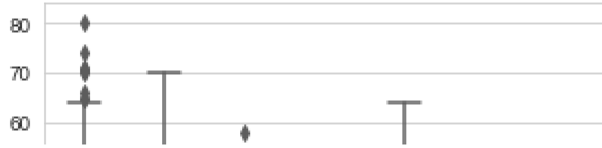
```
titanic_data = titanic_training.drop(['Name', 'Ticket', 'Cabin'], axis=1)
titanic_data.head()
```

	PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	1	0	3	male	22.0	1	0	7.2500	S
1	2	1	1	female	38.0	1	0	71.2833	C
2	3	1	3	female	26.0	0	0	7.9250	S
3	4	1	1	female	35.0	1	0	53.1000	S
4	5	0	3	male	35.0	0	0	8.0500	S

Imputing missing values

```
sb.boxplot(x='Parch', y='Age', data=titanic_data, palette='hls')
```

<matplotlib.axes._subplots.AxesSubplot at 0x1c2c021ad30>




```
Parch_groups = titanic_data.groupby(titanic_data['Parch'])
Parch_groups.mean()
```

Parch	PassengerId	Survived	Pclass	Age	SibSp	Fare
0	445.255162	0.343658	2.321534	32.178503	0.237463	25.586774
1	465.110169	0.550847	2.203390	24.422000	1.084746	46.778180
2	416.662500	0.500000	2.275000	17.216912	2.062500	64.337604
3	579.200000	0.600000	2.600000	33.200000	1.000000	25.951660
4	384.000000	0.000000	2.500000	44.500000	0.750000	84.968750
5	435.200000	0.200000	3.000000	39.200000	0.600000	32.550000
6	679.000000	0.000000	3.000000	43.000000	1.000000	46.900000

```
def age_approx(cols):
    Age = cols[0]
    Parch = cols[1]

    if pd.isnull(Age):
        if Parch == 0:
            return 32
        elif Parch == 1:
            return 24
        elif Parch == 2:
            return 17
        elif Parch == 3:
            return 33
        elif Parch == 4:
            return 45
        else:
            return 30
```

```
    else:
        return Age


titanic_data['Age']= titanic_data[['Age', 'Parch']].apply(age_approx, axis=1)
titanic_data.isnull().sum()
```

```
PassengerId    0
Survived       0
Pclass         0
Sex            0
Age            0
SibSp          0
Parch          0
Fare           0
Embarked       2
dtype: int64
```

```
titanic_data.dropna(inplace=True)
titanic_data.reset_index(inplace=True, drop=True)

print(titanic_data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 889 entries, 0 to 888
Data columns (total 9 columns):
PassengerId    889 non-null int64
Survived       889 non-null int64
Pclass         889 non-null int64
Sex            889 non-null object
Age            889 non-null float64
SibSp          889 non-null int64
Parch          889 non-null int64
Fare           889 non-null float64
Embarked       889 non-null object
dtypes: float64(2), int64(5), object(2)
memory usage: 62.6+ KB
None
```

Converting categorical variables to a dummy indicators

```
from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()
gender_cat = titanic_data['Sex']
gender_encoded = label_encoder.fit_transform(gender_cat)
gender_encoded[0:5]
```

```
array([1, 0, 0, 0, 1])
```

```
titanic_data.head()
```

	PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	1	0	3	male	22.0	1	0	7.2500	S
1	2	1	1	female	38.0	1	0	71.2833	C
2	3	1	3	female	26.0	0	0	7.9250	S
3	4	1	1	female	35.0	1	0	53.1000	S
4	5	0	3	male	35.0	0	0	8.0500	S

```
# 1 = male / 0 = female
gender_DF = pd.DataFrame(gender_encoded, columns=['male_gender'])
gender_DF.head()
```

	male_gender
0	1
1	0
2	0
3	0
4	1

```
embarked_cat = titanic_data['Embarked']
embarked_encoded = label_encoder.fit_transform(embarked_cat)
embarked_encoded[0:100]
```

```
array([2, 0, 2, 2, 2, 1, 2, 2, 2, 0, 2, 2, 2, 2, 2, 2, 1, 2, 2, 0, 2, 2,
```

```
       1, 2, 2, 2, 0, 2, 1, 2, 0, 0, 1, 2, 0, 2, 0, 2, 2, 0, 2, 2, 0, 0,
       1, 2, 1, 1, 0, 2, 2, 2, 0, 2, 0, 2, 2, 0, 2, 2, 0, 2, 2, 0, 0, 2,
       2, 2, 2, 2, 2, 2, 0, 2, 2, 2, 2, 2, 2, 2, 2, 1, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 0, 0, 2, 2, 2])
```

```
from sklearn.preprocessing import OneHotEncoder
binary_encoder = OneHotEncoder(categories='auto')
embarked_1hot = binary_encoder.fit_transform(embarked_encoded.reshape(-1,1))
embarked_1hot_mat = embarked_1hot.toarray()
embarked_DF = pd.DataFrame(embarked_1hot_mat, columns = ['C', 'Q', 'S'])
embarked_DF.head()
```

	C	Q	S
0	0.0	0.0	1.0
1	1.0	0.0	0.0
2	0.0	0.0	1.0
3	0.0	0.0	1.0
4	0.0	0.0	1.0

```
titanic_data.drop(['Sex', 'Embarked'], axis=1, inplace=True)
titanic_data.head()
```

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
0	1	0	3	22.0	1	0	7.2500
1	2	1	1	38.0	1	0	71.2833
2	3	1	3	26.0	0	0	7.9250
3	4	1	1	35.0	1	0	53.1000
4	5	0	3	35.0	0	0	8.0500

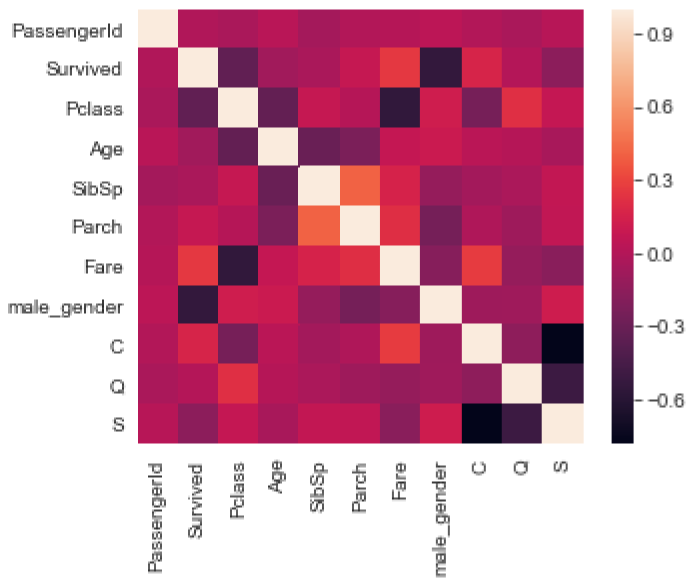
```
titanic_dmy = pd.concat([titanic_data, gender_DF, embarked_DF], axis=1, verify_integrity=True).astype(float)
titanic_dmy[0:5]
```

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare	male_gender	C	Q	S
0	1.0	0.0	3.0	22.0	1.0	0.0	7.2500	1.0	0.0	0.0	1.0
1	2.0	1.0	1.0	38.0	1.0	0.0	71.2833	0.0	1.0	0.0	0.0
2	3.0	1.0	3.0	26.0	0.0	0.0	7.9250	0.0	0.0	0.0	1.0
3	4.0	1.0	1.0	35.0	1.0	0.0	53.1000	0.0	0.0	0.0	1.0
4	5.0	0.0	3.0	35.0	0.0	0.0	8.0500	1.0	0.0	0.0	1.0

Checking for independence between features

```
sb.heatmap(titanic_dmy.corr())
```

<matplotlib.axes._subplots.AxesSubplot at 0x1c2c0cb5dd8>




```
titanic_dmy.drop(['Fare','Pclass'], axis=1, inplace=True)
titanic_dmy.head()
```

	PassengerId	Survived	Age	SibSp	Parch	male_gender	C	Q	S
0	1.0	0.0	22.0	1.0	0.0	1.0	0.0	0.0	1.0
1	2.0	1.0	38.0	1.0	0.0	0.0	1.0	0.0	0.0

Checking that your dataset size is sufficient

```
titanic_dmy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 889 entries, 0 to 888
Data columns (total 9 columns):
PassengerId    889 non-null float64
Survived       889 non-null float64
Age            889 non-null float64
SibSp          889 non-null float64
Parch          889 non-null float64
male_gender    889 non-null float64
C              889 non-null float64
Q              889 non-null float64
S              889 non-null float64
dtypes: float64(9)
memory usage: 62.6 KB
```

```
X_train, X_test, y_train, y_test = train_test_split(titanic_dmy.drop('Survived', axis=1),
                                                    titanic_dmy['Survived'], test_size=0.2,
                                                    random_state=200)
```

```
print(X_train.shape)
print(y_train.shape)
```

```
(711, 8)
(711,)
```

```
X_train[0:5]
```

	PassengerId	Age	SibSp	Parch	male_gender	C	Q	S
719	721.0	6.0	0.0	1.0	0.0	0.0	0.0	1.0
165	167.0	24.0	0.0	1.0	0.0	0.0	0.0	1.0
879	882.0	33.0	0.0	0.0	1.0	0.0	0.0	1.0

Deploying and evaluating the model

```
LogReg = LogisticRegression(solver='liblinear')
LogReg.fit(X_train, y_train)
```

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=None, solver='liblinear', tol=0.0001, verbose=0,
                   warm_start=False)
```

```
y_pred = LogReg.predict(X_test)
```

Model Evaluation

Classification report without cross-validation

```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

         0.0       0.83      0.88      0.85       109
         1.0       0.79      0.71      0.75        69

    accuracy                           0.81       178
   macro avg       0.81      0.80      0.80       178
weighted avg       0.81      0.81      0.81       178
```

K-fold cross-validation & confusion matrices

```
y_train_pred = cross_val_predict(LogReg, X_train, y_train, cv=5)
confusion_matrix(y_train, y_train_pred)
```

```
array([[377,  63],
       [ 91, 180]], dtype=int64)
```

```
precision_score(y_train, y_train_pred)
```

```
0.7407407407407407
```

Make a test prediction

```
titanic_dmy[863:864]
```

	PassengerId	Survived	Age	SibSp	Parch	male_gender	C	Q	S
863	866.0	1.0	42.0	0.0	0.0	0.0	0.0	0.0	1.0

```
test_passenger = np.array([866, 40, 0, 0, 0, 0, 0, 1]).reshape(1,-1)

print(LogReg.predict(test_passenger))
print(LogReg.predict_proba(test_passenger))
```

```
[1.]
[[0.26351831 0.73648169]]
```