Lecture 8-Part2

Logistic Regression

In [1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

The Data

Import the Dataset.

In [2]:
```python
data = pd.read_csv('Downloads/titanic-dataset.csv')
data.head(5)
```

Out[2]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabi
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	Na
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C8
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	Na
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C12
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	Na

In [3]:
```
data.head()
```

Out[3]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabi
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	Na
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C8
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	Na
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C12
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	Na

Missing Data

We can use seaborn to create a simple heatmap to see where we are missing data!

In [4]:
```
data.isnull()
```

Out[4]:

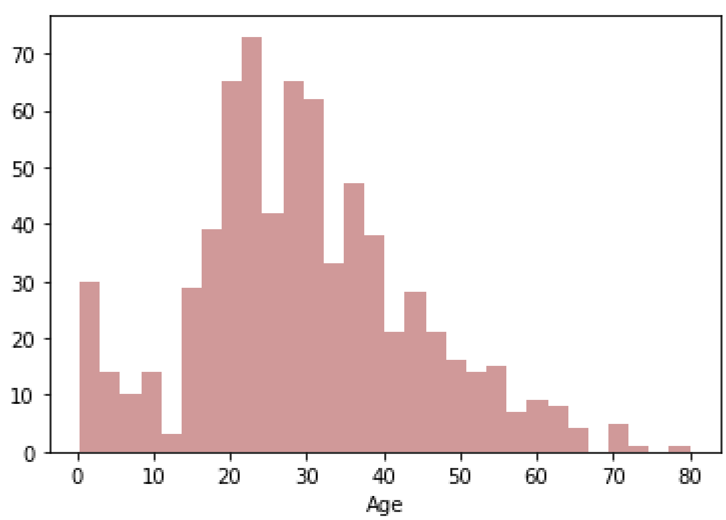
	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Emb
0	False	False	False	False	False	False	False	False	False	False	True	
1	False	False	False	False	False	False	False	False	False	False	False	
2	False	False	False	False	False	False	False	False	False	False	True	
3	False	False	False	False	False	False	False	False	False	False	False	
4	False	False	False	False	False	False	False	False	False	False	True	
...	...	...	...	...	...	...	...	...	...	...	...	
886	False	False	False	False	False	False	False	False	False	False	True	
887	False	False	False	False	False	False	False	False	False	False	False	
888	False	False	False	False	False	True	False	False	False	False	True	
889	False	False	False	False	False	False	False	False	False	False	False	
890	False	False	False	False	False	False	False	False	False	False	True	

891 rows × 12 columns

In [5]:
```
sns.distplot(data['Age'].dropna(),kde=False,color='darkred',bins=30)
```

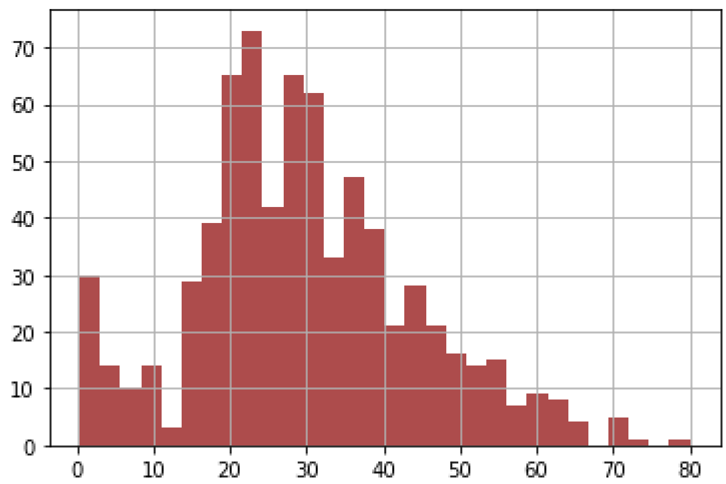
```
C:\Users\prpou\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[5]: <AxesSubplot:xlabel='Age'>



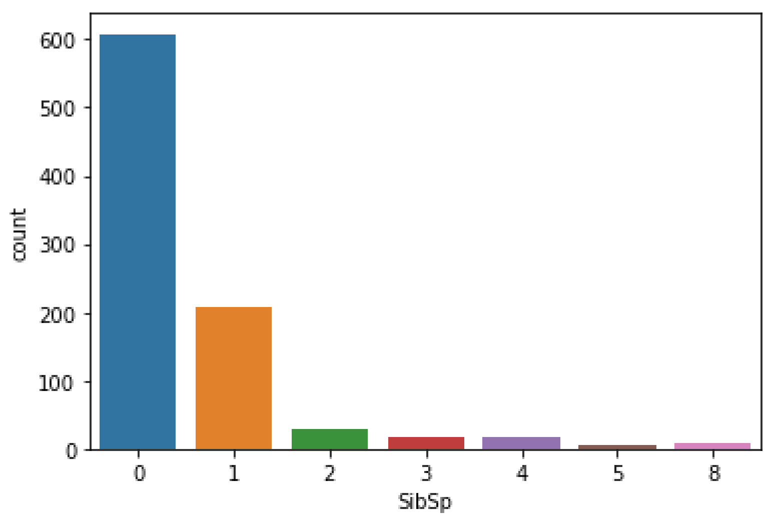
In [6]:
```
data['Age'].hist(bins=30,color='darkred',alpha=0.7)
```

Out[6]: <AxesSubplot:>



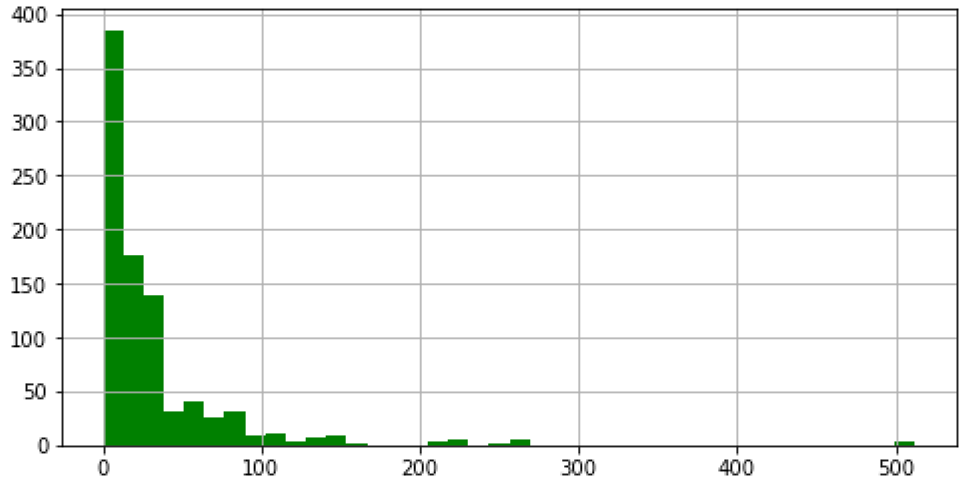
In [7]:
```
sns.countplot(x='SibSp',data=data)
```

Out[7]: <AxesSubplot:xlabel='SibSp', ylabel='count'>



In [8]:
```
data['Fare'].hist(color='green',bins=40,figsize=(8,4))
```

Out[8]: <AxesSubplot:>

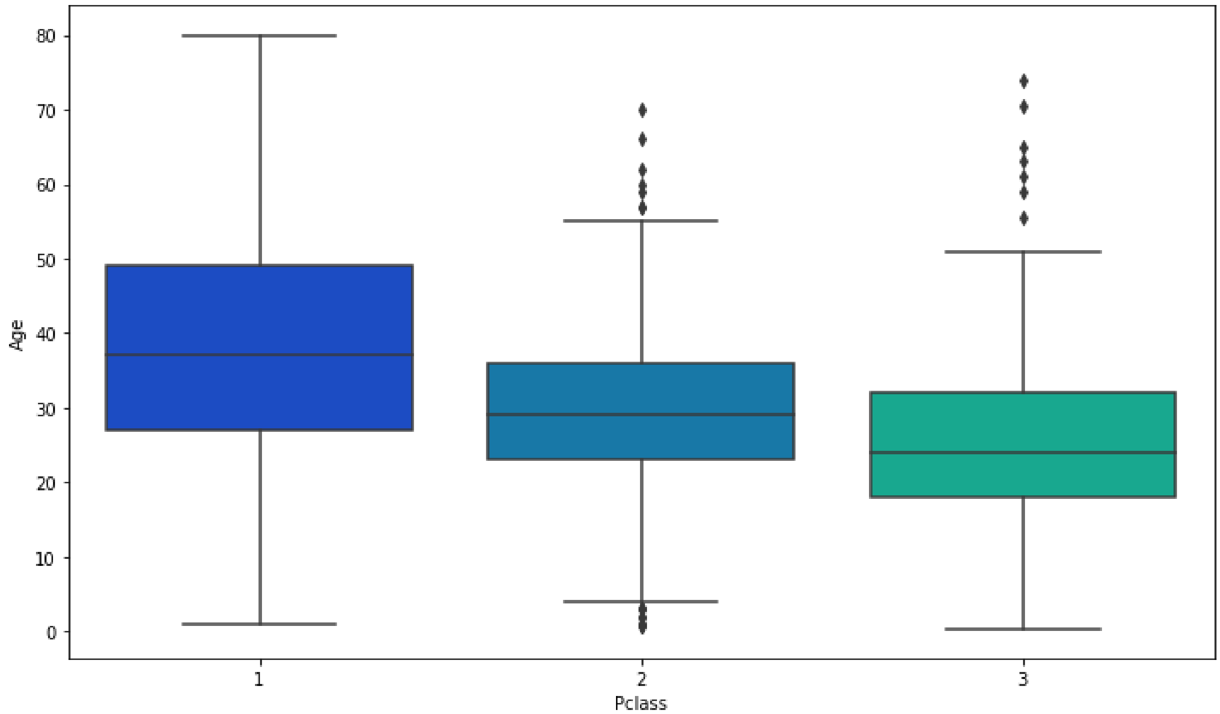


Data Cleaning

We want to fill in missing age data instead of just dropping the missing age data rows. One way to do this is by filling in the mean age of all the passengers (imputation). However we can be smarter about this and check the average age by passenger class. For example:

In [9]:
```
plt.figure(figsize=(12, 7))
sns.boxplot(x='Pclass',y='Age',data=data,palette='winter')
```

Out[9]: <AxesSubplot:xlabel='Pclass', ylabel='Age'>



We can see the wealthier passengers in the higher classes tend to be older, which makes sense. We'll use these average age values to impute based on Pclass for Age.

In [10]:
```python
def impute_age(cols):
    Age = cols[0]
    Pclass = cols[1]

    if pd.isnull(Age):

        if Pclass == 1:
            return 37

        elif Pclass == 2:
            return 29

        else:
            return 24

    else:
        return Age
```

Now apply that function!

In [11]:
```python
data['Age'] = data[['Age','Pclass']].apply(impute_age,axis=1)
```

Let's go ahead and drop the Cabin column and the row in Embarked that is NaN.

In [14]:
```python
data.drop('Cabin',axis = 1,inplace=True)
```

In [15]:
```python
data.head()
```

Out[15]:

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

In [16]:
```
data.dropna(inplace=True)
```

Converting Categorical Features

In [17]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 889 entries, 0 to 890
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  889 non-null    int64  
 1   Survived     889 non-null    int64  
 2   Pclass       889 non-null    int64  
 3   Name         889 non-null    object 
 4   Sex          889 non-null    object 
 5   Age          889 non-null    float64
 6   SibSp        889 non-null    int64  
 7   Parch        889 non-null    int64  
 8   Ticket       889 non-null    object 
 9   Fare         889 non-null    float64
 10  Embarked     889 non-null    object 
dtypes: float64(2), int64(5), object(4)
memory usage: 83.3+ KB
```

In [18]:
```
sex = pd.get_dummies(data['Sex'],drop_first=True)
embark = pd.get_dummies(data['Embarked'],drop_first=True)
```

In [19]:
```
data.drop(['Sex','Embarked','Name','Ticket'],axis=1,inplace=True)
```

In [20]:
```
data = pd.concat([data,sex,embark],axis=1)
```

In [21]:
```
data.head()
```

Out[21]:

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

Logistic Regression model

Train Test Split

In [22]:
```
from sklearn.model_selection import train_test_split
```

In [23]:
```
X_train, X_test, y_train, y_test = train_test_split(data.drop('Survived',axi
                                                    data['Survived'], test_s
                                                    random_state=101)
```

Training and Predicting

In [24]:
```
from sklearn.linear_model import LogisticRegression
```

In [25]:
```
logmodel = LogisticRegression()
logmodel.fit(X_train,y_train)
```

```
C:\Users\prpou\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:81
8: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-
learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regressi
on (https://scikit-learn.org/stable/modules/linear_model.html#logistic-regressi
on)
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,
```

Out[25]:
```
LogisticRegression()
```

In [26]:
```
predictions = logmodel.predict(X_test)
```

Let's move on to evaluate our model!

Evaluation

We can check precision,recall,f1-score using classification report.

In [27]:
```
from sklearn.metrics import classification_report
```

In [28]:
```
print(classification_report(y_test,predictions))
```

```
              precision    recall  f1-score   support

           0       0.79      0.91      0.85       163
           1       0.81      0.62      0.71       104

    accuracy                           0.80       267
   macro avg       0.80      0.77      0.78       267
weighted avg       0.80      0.80      0.79       267
```

In [ ]:
```

```

In [ ]:
```

```