Lab #3 - EDA - Exploration Data Analises

Understanding the Titanic Survival

Wellcome to the Titanic, the largest British ship at the time, that sank in the North Atlantic Ocean in the early hours of 15 April 1912.

In this notebook we will try to undestand the characteristics of the individuals that were at the Titanic, how many survived and who survived.

This dataset is a partial dataset used as the training set on Kaggle's Titanic challenge. [https://www.kaggle.com/c/titanic/data (https://www.kaggle.com/c/titanic/data)](https://www.kaggle.com/c/titanic/data)

Columns

Those the descriptions of the variables in this dataset:

PassengerId	type should be integers
Survived	Survived or Not
Pclass	Class of Travel
Name	Name of Passenger
Sex	Gender
Age	
SibSp	Number of Sibling/Spouse abord

Parch	Number of Parent/Child abord
Ticket	
Fare	
Cabin	
Embarked	The port in which a passenger has embarked. C - Cherbourg, S - Southampton, Q = Queenstown

In [393]:
```
# Import all required libraries

# data analysis and wrangling
import numpy as np
import pandas as pd

# data visualization
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

plt.rcParams['figure.figsize']= (16,8)

import warnings
warnings.filterwarnings("ignore")
```

In [394]:
```
# Load the training and testing data

data_train = pd.read_csv('train.csv')

data_test = pd.read_csv('test.csv')
# combin the train and test data to one df
combined_data =pd.concat([data_train, data_test])
```

In [395]:
```
# data_train head
# [
#     data_test.shape[0],
# data_train.shape[0],
# combined_data.shape[0]]

data_train.head()
```

Out[395]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	(
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 [396]:
```
data_test.head()
```

Out[396]:

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Emba
0	892	3	Kelly, Mr. James	male	34.5	0	0	330911	7.8292	NaN	
1	893	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.0000	NaN	
2	894	2	Myles, Mr. Thomas Francis	male	62.0	0	0	240276	9.6875	NaN	
3	895	3	Wirz, Mr. Albert	male	27.0	0	0	315154	8.6625	NaN	
4	896	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	female	22.0	1	1	3101298	12.2875	NaN	

In [397]:
```
plt.style.use('seaborn-whitegrid')
```

In [398]:
```
# shape of the data_train
data_train.shape
data_train.columns
```

Out[398]:
```
Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'S
ibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
      dtype='object')
```

In [399]:
```
# shape of the data_test
data_test.shape
```

Out[399]:
```
(418, 11)
```

Our response variable is **Survived** indicating who survived the Titanic. We will use four features: Pclass, Sex, Age and Fare.

Pclass is the Ticket class (1 = 1st, 2 = 2nd, 3 = 3rd)

For more information, please refer to https://www.kaggle.com/c/titanic/data (https://www.kaggle.com/c/titanic/data)

In [400]:
```
# colum in data_train values
data_train.columns.values
```

Out[400]:
```
array(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'S
ibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'], dtype=objec
t)
```

In [401]:
```
# colum in data_test values

data_test.columns.values
```

Out[401]:
```
array(['PassengerId', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp', 'Parc
h',
       'Ticket', 'Fare', 'Cabin', 'Embarked'], dtype=object)
```

In [402]:
```
# get the dtype object and category in data_train
data_train.select_dtypes(include=['object']).columns
```

Out[402]:
```
Index(['Name', 'Sex', 'Ticket', 'Cabin', 'Embarked'], dtype='objec
t')
```

In [403]:
```
# get the dtype object and category in data_test

data_test.select_dtypes(include=['int', 'float']).columns
```

Out[403]:
```
Index(['PassengerId', 'Pclass', 'Age', 'SibSp', 'Parch', 'Fare'], dt
ype='object')
```

Pre-processing

Check the missing values in the training and testing dataset

In [404]:
```
# summing up the missing values (column-wise) in data_train
data_train.isnull().sum().sort_values(ascending=False)
```

Out[404]:
```
Cabin          687
Age            177
Embarked         2
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
SibSp            0
Parch            0
Ticket           0
Fare             0
dtype: int64
```

In [405]:
```
# summing up the missing values (column-wise) in data_test
t = data_test.isnull().sum().sort_values(ascending=False)
# get the precent of the missing values in data_test
d = pd.DataFrame(t, columns=['Total'])
d['Precent'] = 100 * (d['Total'] / data_test.shape[0])
d
```

Out[405]:

	Total	Precent
Cabin	327	78.229665
Age	86	20.574163
Fare	1	0.239234
PassengerId	0	0.000000
Pclass	0	0.000000
Name	0	0.000000
Sex	0	0.000000
SibSp	0	0.000000
Parch	0	0.000000
Ticket	0	0.000000
Embarked	0	0.000000

In [406]:
```
# len(data_train.PassengerId.unique())
# data_train.Survived.sum()
```

In [407]:
```
def missing_percentage(df):
    '''
    exlain the function ...
    Passangers and Survival First, lets check how many passangers are
    '''
    total_null_series = df.isnull().sum().sort_values(ascending=False)
    table_of_total = pd.DataFrame(total_null_series, columns=['Total']
    table_of_total['Precent'] = round(100 * table_of_total['Total'] /
    return table_of_total
```

In [408]:
```
# Passangers and Survival - First, lets check how many passangers are
# train data
missing_percentage(data_train)
```

Out[408]:

	Total	Precent
Cabin	687	77.10
Age	177	19.87
Embarked	2	0.22
PassengerId	0	0.00
Survived	0	0.00
Pclass	0	0.00
Name	0	0.00
Sex	0	0.00
SibSp	0	0.00
Parch	0	0.00
Ticket	0	0.00
Fare	0	0.00

In [409]:
```
# Passangers and Survival - First, lets check how many passangers are
# test data
missing_percentage(data_test)
```

Out[409]:

	Total	Precent
Cabin	327	78.23
Age	86	20.57
Fare	1	0.24
PassengerId	0	0.00
Pclass	0	0.00
Name	0	0.00
Sex	0	0.00
SibSp	0	0.00
Parch	0	0.00
Ticket	0	0.00
Embarked	0	0.00

In [410]:
```
# get the infomation about the data_train
data_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  891 non-null    int64  
 1   Survived     891 non-null    int64  
 2   Pclass       891 non-null    int64  
 3   Name         891 non-null    object 
 4   Sex          891 non-null    object 
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64  
 7   Parch        891 non-null    int64  
 8   Ticket       891 non-null    object 
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object 
 11  Embarked     889 non-null    object 
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

In [411]:
```
# get the infomation about the data_test
data_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  418 non-null    int64  
 1   Pclass       418 non-null    int64  
 2   Name         418 non-null    object 
 3   Sex          418 non-null    object 
 4   Age          332 non-null    float64
 5   SibSp        418 non-null    int64  
 6   Parch        418 non-null    int64  
 7   Ticket       418 non-null    object 
 8   Fare         417 non-null    float64
 9   Cabin        91 non-null     object 
 10  Embarked     418 non-null    object 
dtypes: float64(2), int64(4), object(5)
memory usage: 36.0+ KB
```

In [412]:
```
# get the infomation about the type of values in the data_train

data_train.dtypes
```

Out[412]:
```
PassengerId      int64
Survived         int64
Pclass           int64
Name            object
Sex             object
Age            float64
SibSp            int64
Parch            int64
Ticket          object
Fare           float64
Cabin           object
Embarked        object
dtype: object
```

In [413]:
```
# get the infomation about the type of values in the data_test

data_test.dtypes
```

Out[413]:
```
PassengerId      int64
Pclass           int64
Name            object
Sex             object
Age            float64
SibSp            int64
Parch            int64
Ticket          object
Fare           float64
Cabin           object
Embarked        object
dtype: object
```

In [414]:
```
# Summary statistics of the training data_train
data_train.describe()
```

Out[414]:

	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

In [415]:
```
# Summary statistics of the testing data_test

data_test.describe()
```

Out[415]:

	PassengerId	Pclass	Age	SibSp	Parch	Fare
count	418.000000	418.000000	332.000000	418.000000	418.000000	417.000000
mean	1100.500000	2.265550	30.272590	0.447368	0.392344	35.627188
std	120.810458	0.841838	14.181209	0.896760	0.981429	55.907576
min	892.000000	1.000000	0.170000	0.000000	0.000000	0.000000
25%	996.250000	1.000000	21.000000	0.000000	0.000000	7.895800
50%	1100.500000	3.000000	27.000000	0.000000	0.000000	14.454200
75%	1204.750000	3.000000	39.000000	1.000000	0.000000	31.500000
max	1309.000000	3.000000	76.000000	8.000000	9.000000	512.329200

Distribution of categorical features

In [416]:
```
#  Summary statistics of the training data_train
data_train.describe(include=['object'])
```

Out[416]:

	Name	Sex	Ticket	Cabin	Embarked
count	891	891	891	204	889
unique	891	2	681	147	3
top	Kelly, Mr. James	male	347082	B96 B98	S
freq	1	577	7	4	644

In [417]:
```
#  distribution of categorical features in data_test
data_test.describe(include=['object'])
```

Out[417]:

	Name	Sex	Ticket	Cabin	Embarked
count	418	418	418	91	418
unique	418	2	363	76	3
top	Kelly, Mr. James	male	PC 17608	B57 B59 B63 B66	S
freq	1	266	5	3	270

Missing values

How many missing values are in the data_train?

In [418]:
```
# count the the null values in the data_train
data_train.isnull().sum()
```

Out[418]:
```
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
```

Answer :

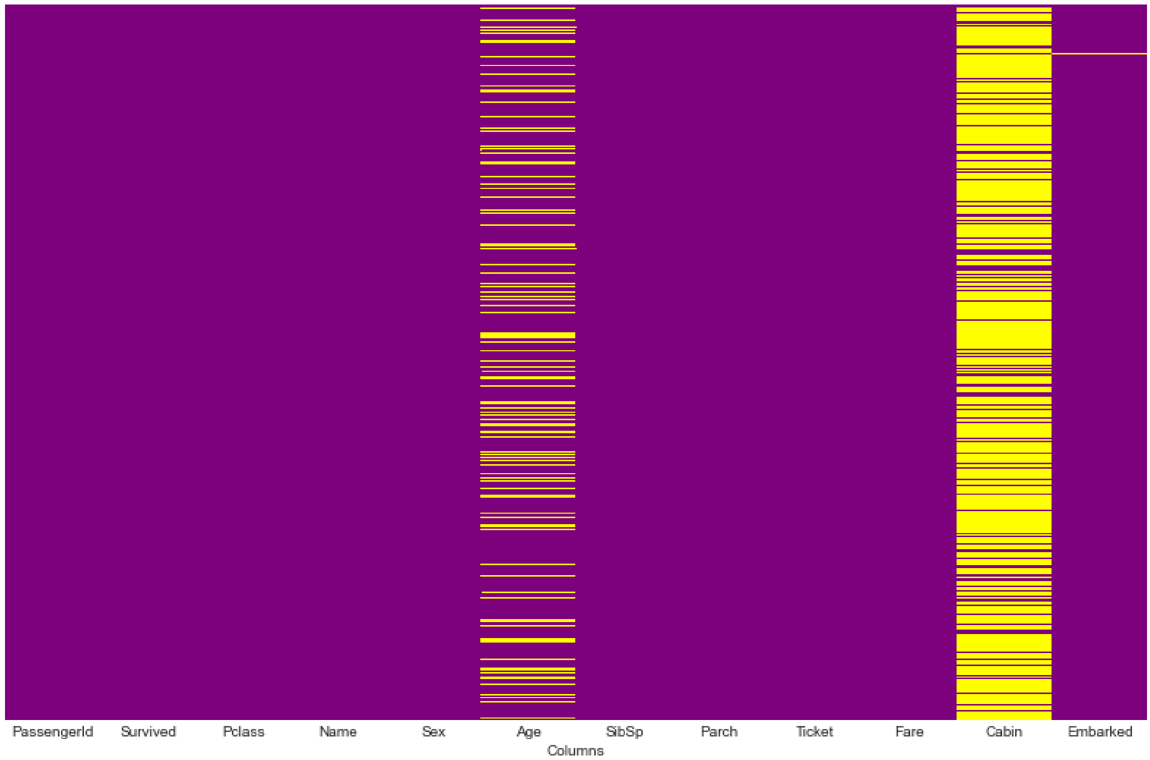
Exploratory Data Analysis

We'll start by checking out missing data!

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

In [419]:
```
# plot the mising values using seaborn
missing_data_train = data_train.isnull()
plt.figure(figsize=(14,9))
sns.heatmap(missing_data_train, cbar=False, cmap=['purple', 'yellow'],
plt.xlabel('Columns')
plt.ylabel('')
```

Out[419]:
```
Text(122.0, 0.5, '')
```

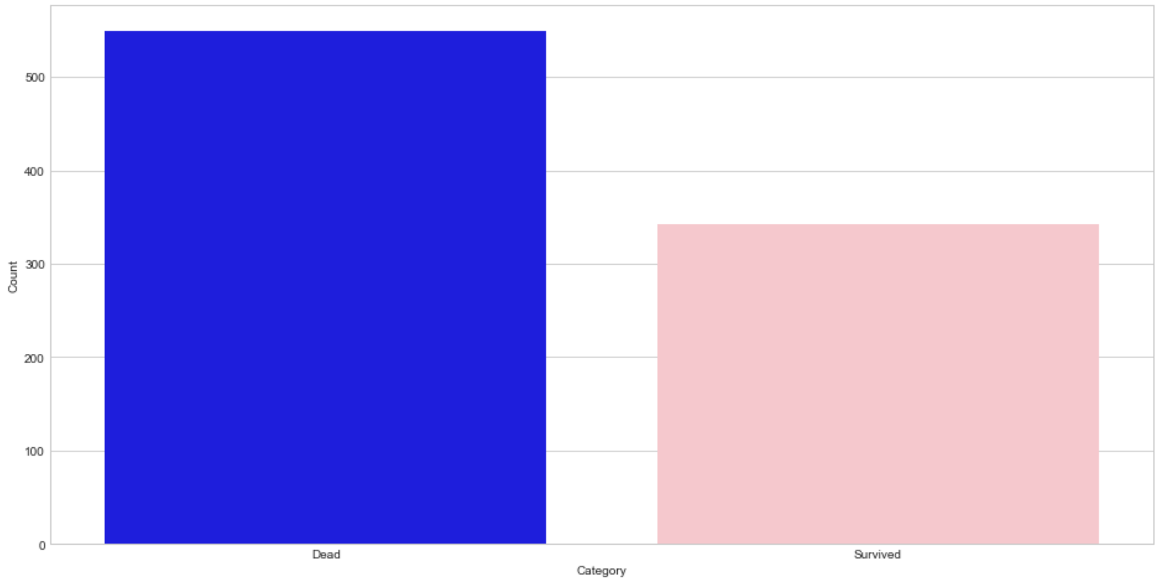


Where we have missing values?

Roughly 20 percent of the Age data is missing. The proportion of Age missing is likely small enough for reasonable replacement with some form of imputation. Looking at the Cabin column, it looks like we are just missing too much of that data to do something useful with at a basic level. We'll probably drop this later, or change it to another feature like "Cabin Known: 1 or 0"

In [420]:
```
# create the df to aggregate the data_train by the surrvied and dead
df_survvied = pd.DataFrame({
    'Category': ['Dead','Survived', ],
    "Count": [
        len(data_train.PassengerId) - data_train.Survived.sum()
        ,data_train.Survived.sum()

    ]
})
sns.barplot(x='Category', y='Count', data=df_survvied, palette=['blue'
```

Out[420]: `<AxesSubplot:xlabel='Category', ylabel='Count'>`



Gender distribution and survival

How distributed the survivors by gender?

In [421]:
```
# create the groupby to aggregate the data_train by the surrvied and d
data_train.groupby('Sex')['Survived'].agg(['count', 'sum', 'mean'])
```

Out[421]:

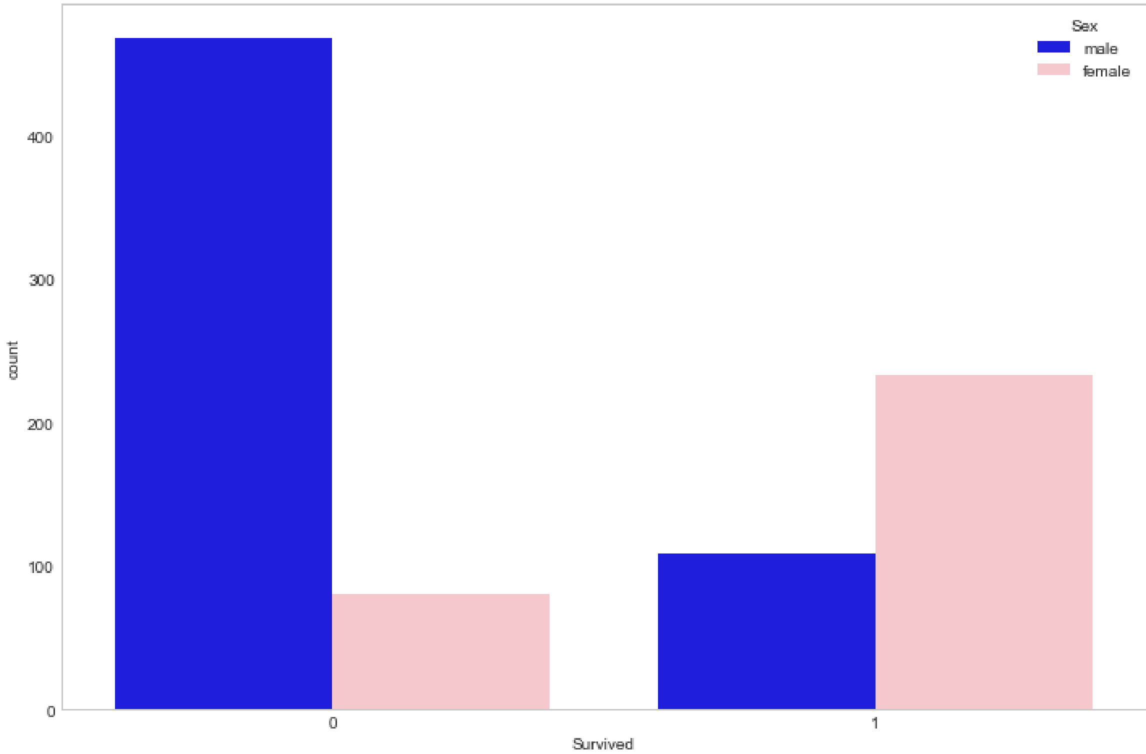
Sex	count	sum	mean
female	314	233	0.742038
male	577	109	0.188908

In [422]:
```
# use groupby() and agg() to get the table bellow
```

Answer:

In [423]:
```
# plot the count of the survived and dead by Sex
plt.figure(figsize=(12,8))
plt.grid()
sns.countplot(x='Survived', hue='Sex', data=data_train, palette=['blue
```

Out[423]: <AxesSubplot:xlabel='Survived', ylabel='count'>



Survived vs Class

In [424]:
```
# create the groupby to aggregate the data_train by the surrvied and c
g = data_train.groupby('Pclass')['Survived']
# reset the index to get the table bellow
t = g.agg(['mean']).reset_index()
# reset  the column name so that the column name will be the same as t
t['Survived'] = t['mean']
# show only the column that we need
t[['Pclass', 'Survived']]
```

Out[424]:

	Pclass	Survived
0	1	0.629630
1	2	0.472826
2	3	0.242363

In [425]:
```
# correlation (average survived ratio > 0.5) among the group of Pclass
# using groupby() and sord_values()
```

We can see that there is a significant correlation (average survived ratio > 0.5) among `Pclass=1` and `Survived` .

In [426]:
```
# create the groupby to aggregate the data_train by the surrvied and c
g = data_train.groupby('Sex')['Survived']
# reset the index to get the table bellow
t = g.agg(['mean']).reset_index()
# reset  the column name so that the column name will be the same as t
t['Survived'] = t['mean']
# show only the column that we need
t[['Sex', 'Survived']]
```

Out[426]:

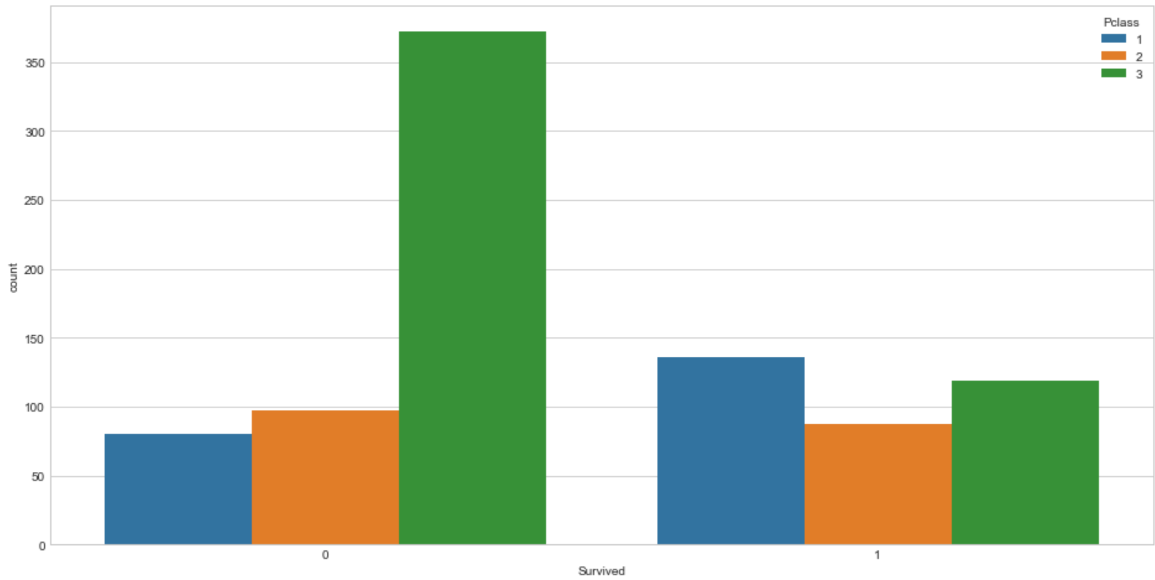
	Sex	Survived
0	female	0.742038
1	male	0.188908

In [427]:
```
# correlation between Sex and Survived
```

Who survival more male of female ?? explain

In [428]:
```
# count the survived and dead by the Pclass
sns.countplot(x='Survived', hue='Pclass', data=data_train)
```

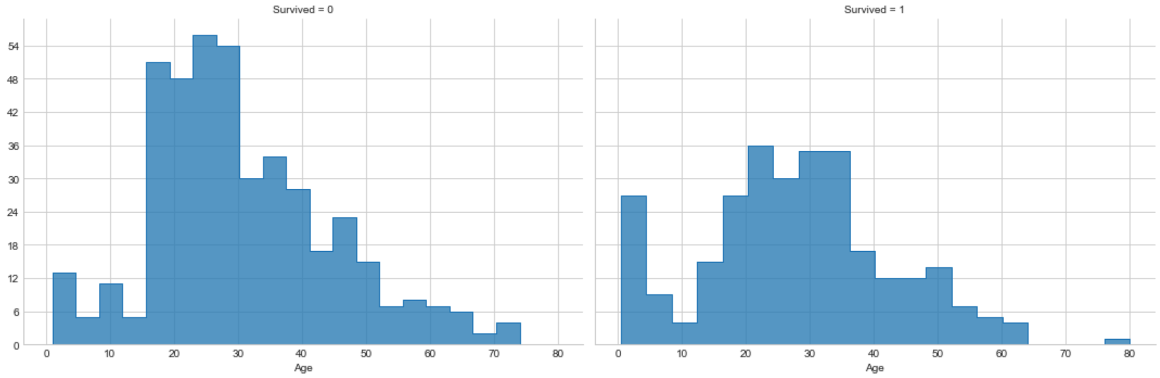
Out[428]: <AxesSubplot:xlabel='Survived', ylabel='count'>



Analyze by visualizing the Titanic data

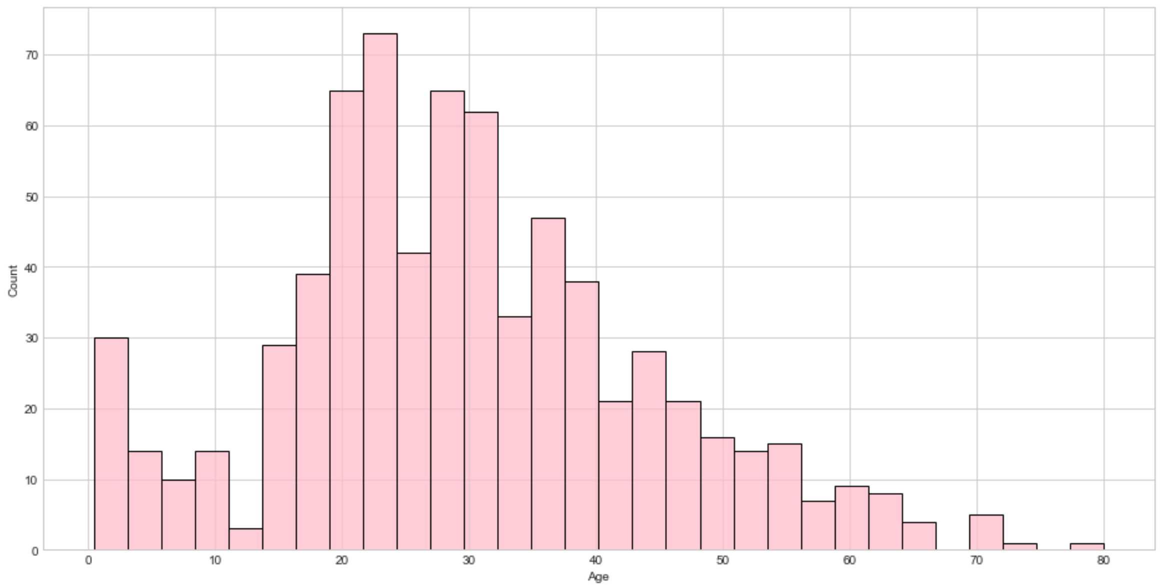
Correlations between a numeric feature (Age) and our predictive goal (Survived)

In [429]:
```
#sns.histplot(data=data_train, x='Age', hue='Survived')


g = sns.FacetGrid(data_train, col="Survived", height=5, aspect=1.5)
g.map(sns.histplot, "Age", element="step", bins=20 )

# Customize the ticks and grid lines
for ax in g.axes.flat:
    ax.grid(True)  # Enable grid lines
    ax.xaxis.set_major_locator(plt.MaxNLocator(integer=True))  # Set x
    ax.yaxis.set_major_locator(plt.MaxNLocator(integer=True))  # Set y

# Display the plots
plt.show()
```



In [430]:
```
# correlations between a numeric feature (Age) and our predictive goal
sns.histplot(data=data_train, x='Age', bins=30, color='pink')
```

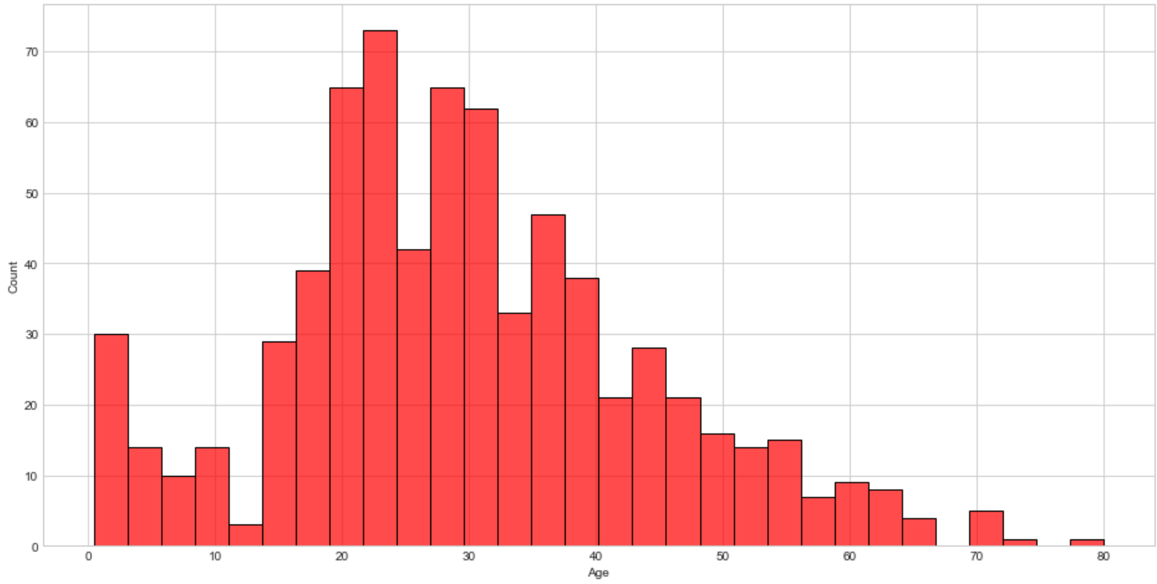
Out[430]: <AxesSubplot:xlabel='Age', ylabel='Count'>



In [431]:
```
# plot the all surviver not using subplot, number of  bins = 30 ,  wit
```

In [432]:
```
sns.histplot(x='Age', data=data_train,alpha=0.7, bins=30, color='red')
```

Out[432]: <AxesSubplot:xlabel='Age', ylabel='Count'>

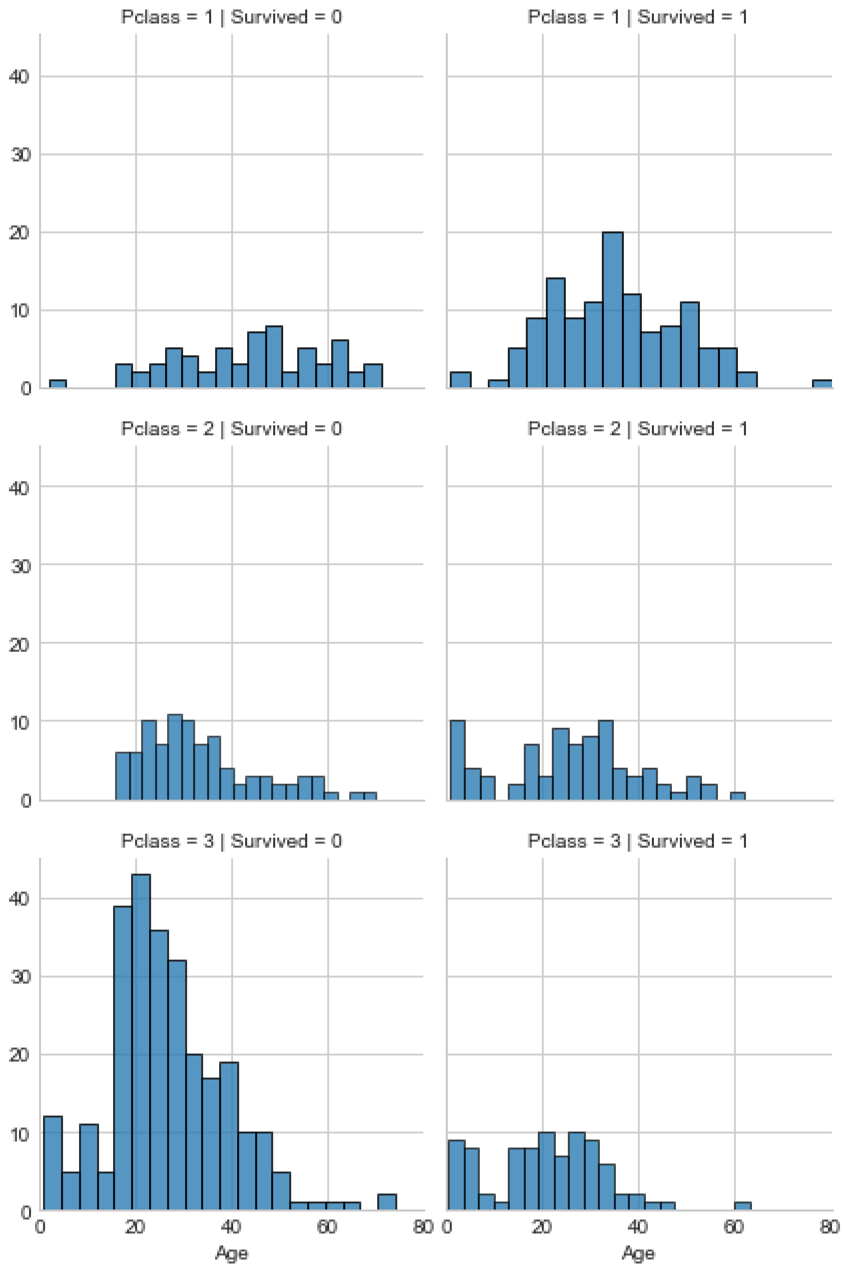


In [433]:
```
# using hist function with bins =3- and alpha =0.7
```

Combine three features (age, Pclass, and survived) for identifying correlations

In [434]:
```
g = sns.FacetGrid(data=data_train, col='Survived', row='Pclass')
g.map(sns.histplot, 'Age', bins=20)
g.set(xlim=(0, 80))

#sns.histplot(x='Age', data=data_train, hue='Pclass', multiple="" ).ma
```

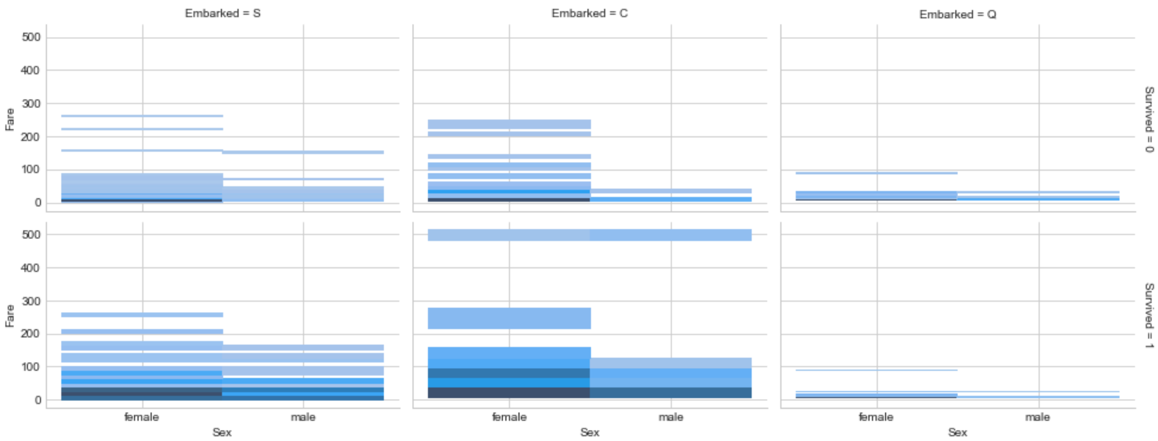
Out[434]:
```
<seaborn.axisgrid.FacetGrid at 0x7fb5a2691eb0>
```



In [435]:
```
# combine three features (age, Pclass, and survived) for identifying c
```

Correlations among Embarked, Sex, Fare, and Survived

In [436]:
```
# we are plotting the
g = sns.FacetGrid(data_train, col="Embarked", row="Survived", margin_t
g.map_dataframe(sns.histplot, x="Sex", y="Fare")

g.set_axis_labels("Sex", "Fare")
g.set_titles(col_template="Embarked = {col_name}", row_template="Survi
plt.subplots_adjust(top=0.8)

g.savefig('corr-embarked-sex-fare-survived.png')
```



In [437]:
```
# correlations of Embarked, Sex, Fare, and Survived
# make plot not using subplot
# save plot "corr-embarked-sex-fare-survived.png"
```

Converting `Sex` feature to a new feature called Gender where `female=1`, and `male=0`

In [438]:
```
# converting Sex feature to a new feature called Gender where female=1
# on the combined_data


data_train['Gender'] = data_train.Sex.map({'male': 0, 'female': 1})
```

In [439]:
```
# see the data_train head  after the convertion of male=0 famle =1
data_train.head()
```

Out[439]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
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

Missing values in the `Cabin` features of training dataset

In [440]:
```
train_missing_cabin = data_train.Cabin.isnull().sum()
print(train_missing_cabin)
print(data_test.Cabin.isnull().sum())
```

```
687
327
```

In [441]:
```
# Null values in the Cabin feature of the combine dataset of training
# troing the number of missing values in the data_train and data_test
```

In [442]:
```
# Null values in the Cabin feature of the training dataset

print(f'The null values in the Cabin feature of the training dataset {
```

```
The null values in the Cabin feature of the training dataset 687
```

The null values in the Cabin feature of the training dataset :

Rate of duplication for the Ticket feature

In [443]:
```
# count the number of duplication the the data_train one line code


# print the number of the duplication
#len(data_train.Ticket.unique())

duplication_rate = round(1- len(data_train.Ticket.unique()) / len(data
print(f'Rate of duplication for the Ticket feature : {duplication_rate
```

```
Rate of duplication for the Ticket feature : 0.24
```

Rate of duplication for the Ticket feature :

Correlation between the Ticket feature and survival

In [444]:
```
ticket_to_freq_series = data_train.groupby('Ticket')['Ticket'].count()

# ticket_to_freq_series.to_dict()
# we are adding the Ticket_frequency feature to the data_train
data_train['Ticket_frequency'] = data_train.Ticket.map(ticket_to_freq_

data_train.head()

# data_train.join()
```

Out[444]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
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 [445]:
```
# use group by to create  Ticket_frequency col (check the result befor
```

In [446]:
```
d = data_train.groupby('Ticket_frequency')['Survived'].agg('mean')
d.reset_index()
```

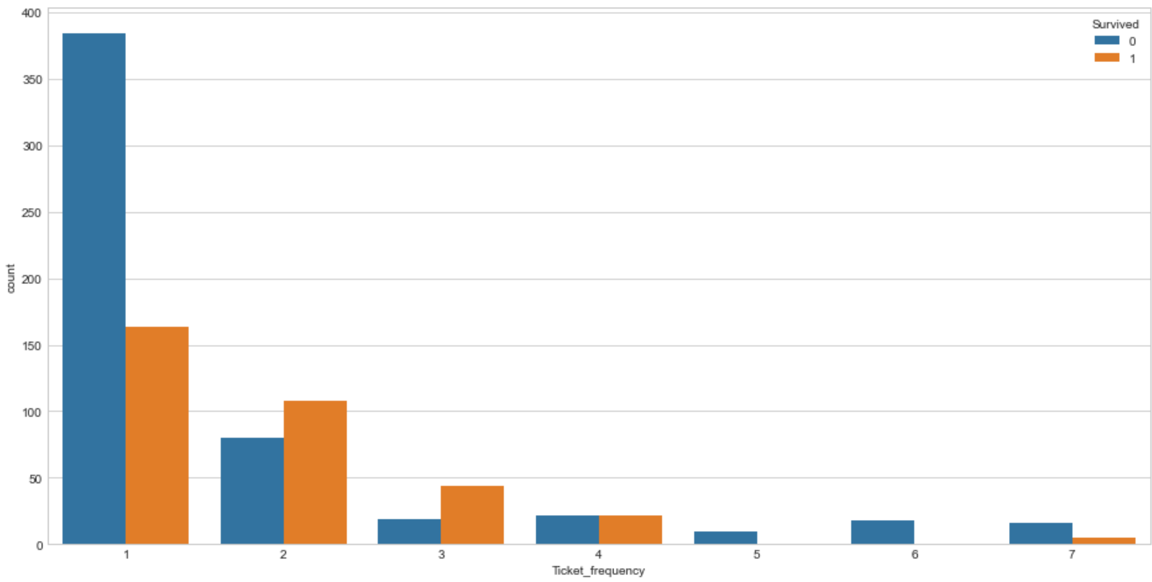
Out[446]:

	Ticket_frequency	Survived
0	1	0.297989
1	2	0.574468
2	3	0.698413
3	4	0.500000
4	5	0.000000
5	6	0.000000
6	7	0.238095

In [447]:
```
# calculate the mean for each Ticket_frequency values
```

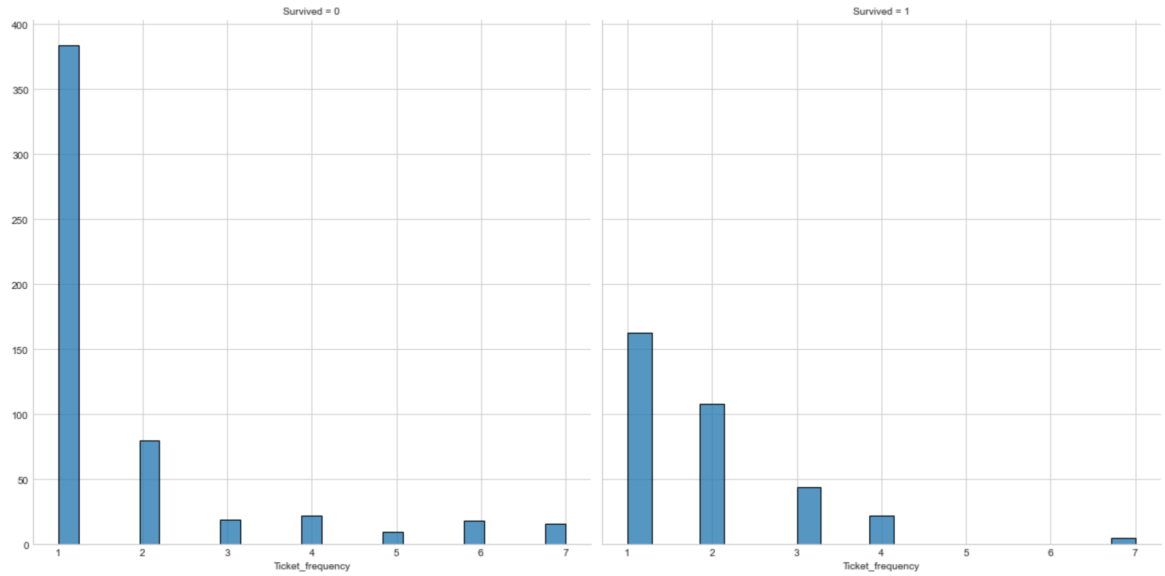
In [448]:
```
sns.countplot(
    x='Ticket_frequency',
    #y='',
    data=data_train,
    hue='Survived'
)
```

Out[448]: <AxesSubplot:xlabel='Ticket_frequency', ylabel='count'>



In [449]:
```
# plot using seabornd
#fig, axs = plt.subplots(figsize=(12, 9))
```

In [450]:
```
g = sns.FacetGrid(data=data_train, col='Survived', height=8)

g.map(sns.histplot,'Ticket_frequency')

# save the plot
plt.savefig('Ticket_frequency.png')

# for ax in g.axes.flat:
#     ax.set_xticks([1, 2, 3 , 4 , 5 , 6 , 7 ,])
#     ax.set_xticklabels(['1' , '2', '3', '4', '5', '6', '7',])


# data_train[(data_train.Ticket_frequency == 6) & (data_train.Survived
```



In [451]:
```
# make a plot using seabon and save it as png
```

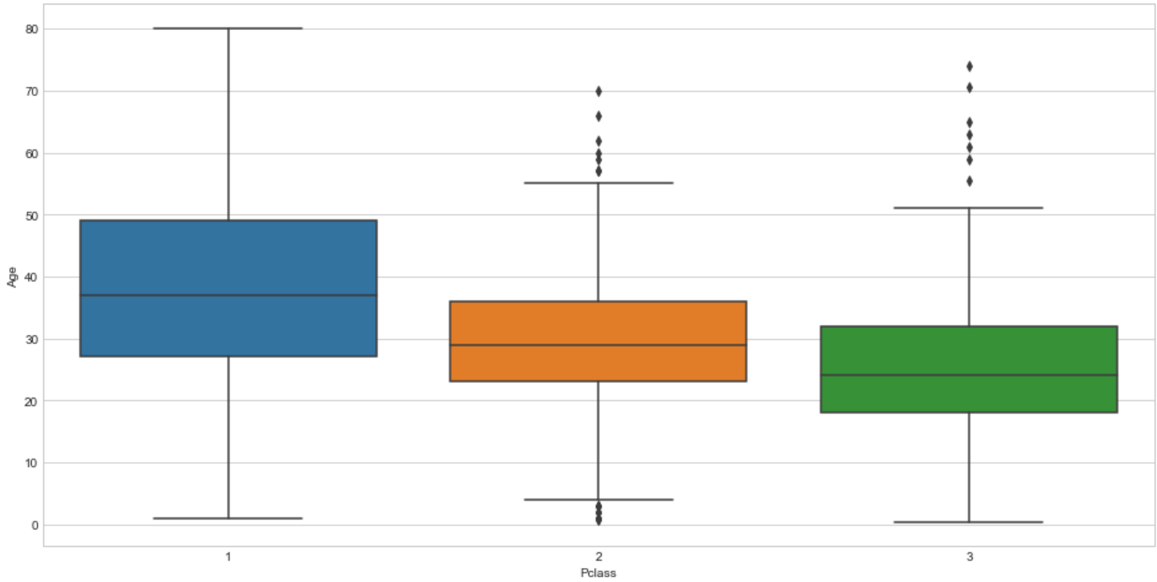
Data Cleaning

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.

In [452]:
```
sns.boxplot(data=data_train, x='Pclass', y='Age')
```

Out[452]:
```
<AxesSubplot:xlabel='Pclass', ylabel='Age'>
```



In [453]:
```
# plot using seaborn
```

Conclution

Type *Markdown* and LaTeX: α^2

Completing features with missing/null values

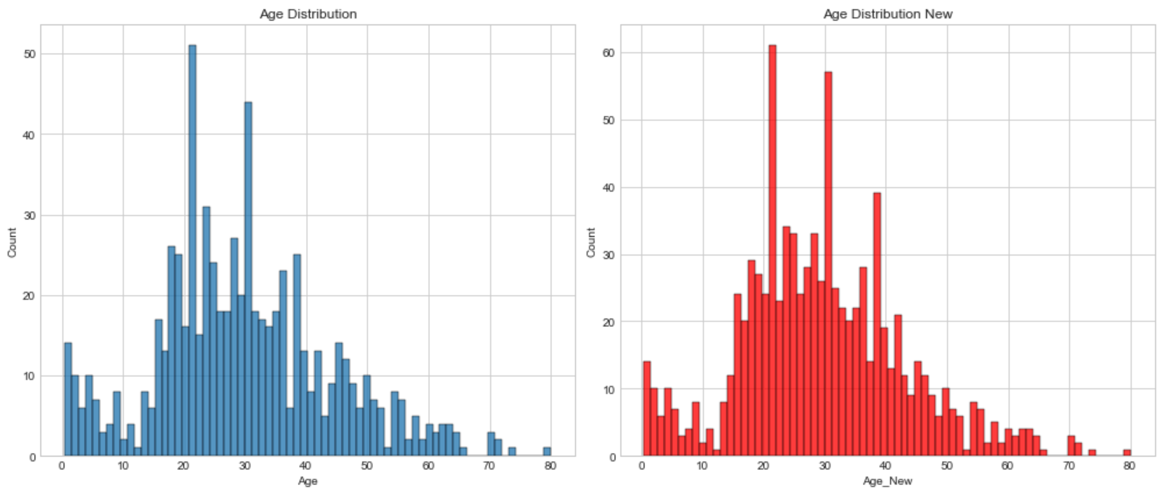
First way:

In [ ]:
```

```

CHECK !

In [454]:

```
avg_age = data_train['Age'].mean()
std_age = data_train.Age.std()
avg_age, std_age

def generateAge(avg_age, std_age , age):
    if (pd.isna(age)):
        return np.random.randint(avg_age - std_age, avg_age + std_age)
    return age

data_train['Age_New'] = data_train.Age.apply(lambda x: generateAge(avg

fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(14 , 6), )

# Plot the first plot on the first subplot
sns.histplot(data=data_train, x='Age', ax=axes[0], bins=70)
axes[0].set_title('Age Distribution')
# axes[0].set_xticks(np.arange(int(data_train['Age'].min()), int(data_

# Plot the second plot on the second subplot
sns.histplot(x='Age_New', data=data_train, ax=axes[1], bins=70, color=
axes[1].set_title('Age Distribution New')

# Adjust the layout
plt.tight_layout()

# Display the plots
plt.show()
```



In [455]:
```
# Filling the misisng/null values for Age feature in the training data


# get average, std, and number of null values in the training data


# generate random numbers between (mean - std) & (mean + std)



# plot original Age values
# NOTE: drop all null values, and convert to int


# fill null values in Age column with random values generated

# convert from float to int

# plot new Age Values
```

In [456]:
```
# sum the null values
data_train.Age_New.isna().sum()
```

Out[456]:
```
0
```

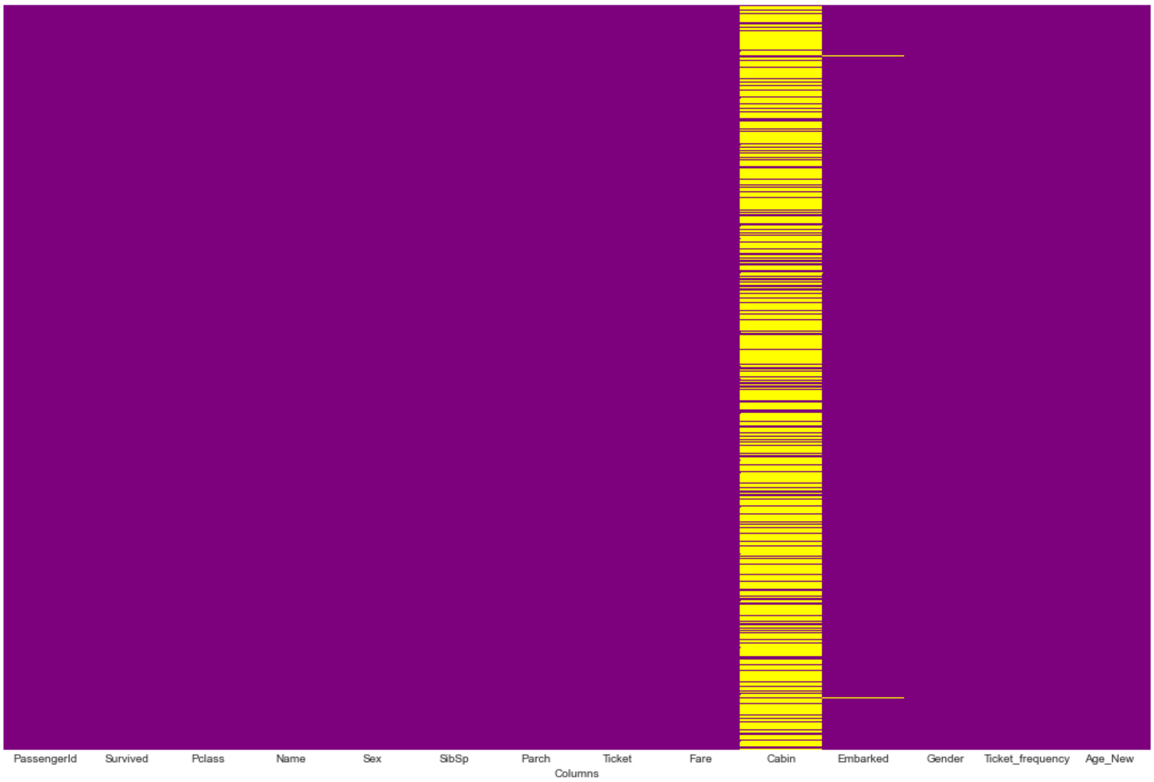
In [457]:
```
data_train.Embarked.isnull
```

Out[457]:
```
<bound method Series.isnull of 0      S
1      C
2      S
3      S
4      S
      ..
886    S
887    S
888    S
889    C
890    Q
Name: Embarked, Length: 891, dtype: object>
```

In [ ]:

In [458]:
```
missing_data_train = data_train.isnull()
plt.figure(figsize=(18,12))
sns.heatmap(missing_data_train.drop(columns=['Age',]), cbar=False, cma
plt.xlabel('Columns')
plt.ylabel('')
```

Out[458]: Text(158.0, 0.5, '')



In [459]:
```
# plot missing values after imputation
```

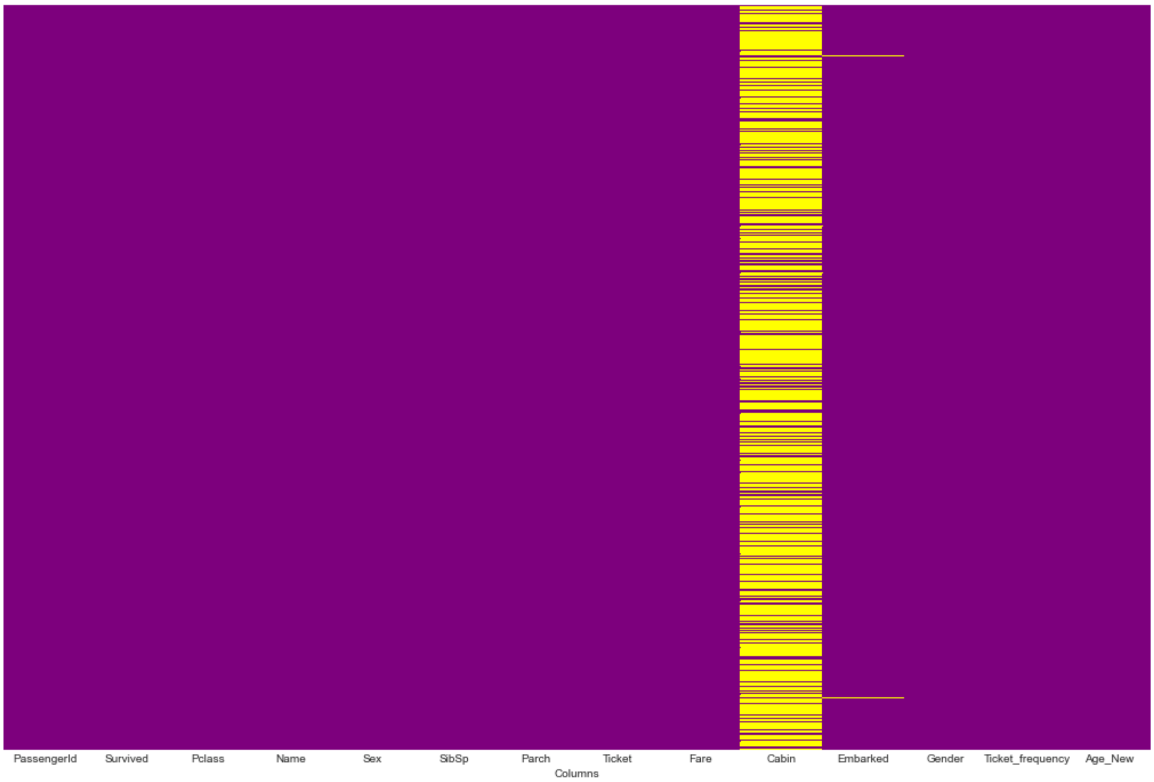
Second way

In [460]:
```
# get data_train from combine
data_train_tmp= combined_data
```

In [461]:
```
# def  Pclass 1-> 37, Pclass 2 -> 29, else 24, if not nul age
def impute_age(cols):
    '''Transform P class to age'''
    pclass_to_age = {1: 37, 2: 29, 3: 24}
    if pd.isna(cols['Age']):
        return pclass_to_age[cols['Pclass']]
    return cols['Age']
    # code
```

In [462]:
```
# plot the umputation
missing_data_train = data_train.isnull()
plt.figure(figsize=(18,12))
sns.heatmap(missing_data_train.drop(columns=['Age',]), cbar=False, cma
plt.xlabel('Columns')
plt.ylabel('')
```

Out[462]: Text(158.0, 0.5, '')



Drop the Cabin column and the row.****

In [463]:
```
# data_train.drop('Cabin', axis=1, inplace=True)
data_train.shape
# drop all the rows when the cabin is null
no_cabin  = data_train.dropna(subset=['Cabin'], )

no_cabin.drop('Cabin', axis=1, inplace=True)
```

In [464]:
```
# data_train.groupby('Embarked')['Survived'].agg(['mean',])
```

In [465]:
```
# code  - Drop the Cabin column and the row.
data_train['Age_New_1'] = data_train.apply(lambda x: impute_age(x), ax

data_train.head()
```

Out[465]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
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 [ ]:

Completing a categorical feature and fill the missing values in `Embarked` feature with the most common occurrences

`Embarked` feature takes S, Q, C values based on port of embarkation. Our training dataset has some missing values. We simply fill these with the most common occurance.

In [466]:
```
# impute the missing values in the Embarked column with the mode value
data_train['Embarked'].fillna(data_train['Embarked'].mode()[0], inplac
# print(data_train['Embarked'].mode()[0])
```

In [467]:
```
# fill na on combined_Data of Embarked values
combined_data['Embarked'].fillna(combined_data['Embarked'].mode()[0],

# on data_train  group by the 'Embarked', 'Survived' column and caclul

data_train.groupby('Embarked')['Survived'].agg('mean')
```

Out[467]:
```
Embarked
C    0.553571
Q    0.389610
S    0.339009
Name: Survived, dtype: float64
```

In [468]:
```
# check if we have an null in the data_train on 'Embarked' values
data_train.Embarked.isnull().sum()
```

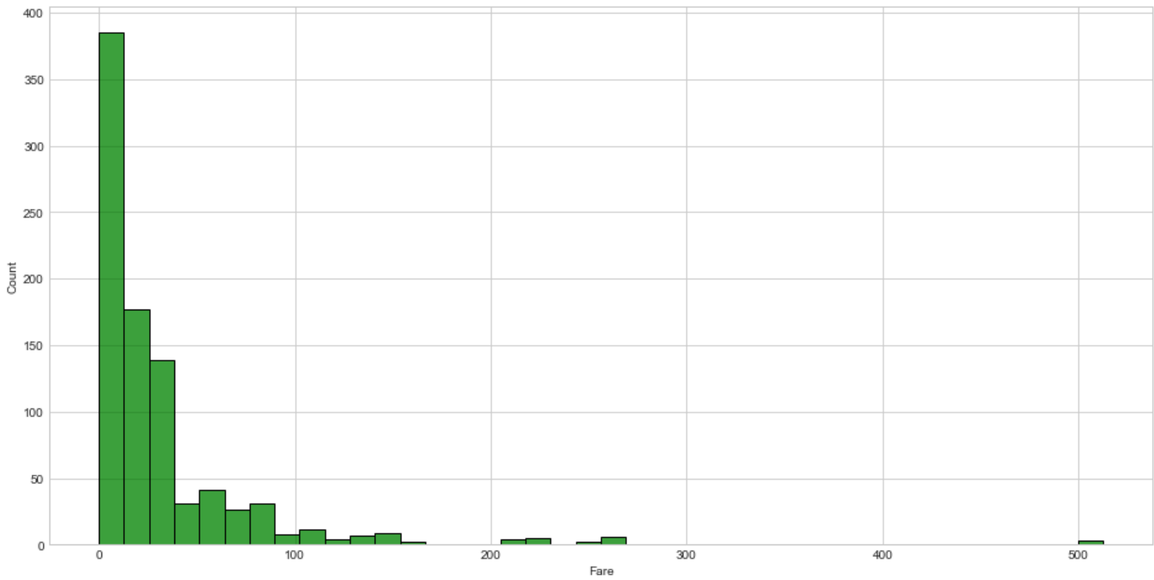
Out[468]:
```
0
```

Completing and converting a numeric feature

Please complete the `Fare` feature for single missing value in test dataset using mode to get the value that occurs most frequently for this feature.

In [469]:
```
sns.histplot(data=data_train, x='Fare', bins=40, color='green')
```

Out[469]:
```
<AxesSubplot:xlabel='Fare', ylabel='Count'>
```



In [470]:
```
# plot the Fare distribution, in bins - 40 using the mode
```

In [471]:
```
data_train['Fare'].median()
```

Out[471]:
```
14.4542
```

In [472]:
```
data_train['Fare'].fillna(data_train['Fare'].median(), inplace=True)

data_train.head()
```

Out[472]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
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 [473]:
```
# on one line code replace the missing values on Fare column by mediar
```

In [474]:
```
# code  that count number of missing values
data_train.isnull().sum()
```

Out[474]:
```
PassengerId          0
Survived             0
Pclass               0
Name                 0
Sex                  0
Age                177
SibSp                0
Parch                0
Ticket               0
Fare                 0
Cabin              687
Embarked             0
Gender               0
Ticket_frequency     0
Age_New              0
Age_New_1            0
dtype: int64
```

Convert the `Fare` feature to ordinal values based on the FareBand

In [475]:
```
# FireBand
# split the data to 4 equel pars one line code
data_train['FareBand'] = pd.qcut(data_train['Fare'], 4)




# ggroup by and calculate the each part mean sort by pars
data_train.groupby('FareBand')['Survived'].agg('mean').sort_values()
```

Out[475]:
```
FareBand
(-0.001, 7.91]     0.197309
(7.91, 14.454]     0.303571
(14.454, 31.0]     0.454955
(31.0, 512.329]    0.581081
Name: Survived, dtype: float64
```

In [476]:
```
data_train.loc[[0, 1]]
```

Out[476]:

	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	NaN
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C8

In [477]:
```
# Convert the Fare feature to ordinal values based on the FareBand  ir


def changeFare(row):
    if row['Fare'] <= 7.91:
        return 0
    elif row['Fare'] <= 14.454:
        return 1
    elif row['Fare'] <= 31:
        return 2
    else:
        return 3

data_train['Fare'] = data_train.apply(lambda x: changeFare(x), axis=1)

# drop FareBand column
data_train = data_train.drop(['FareBand'], axis=1)



data_train.head(15)
```

Out[477]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	0
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	3
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	1
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	3
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	1
5	6	0	3	Moran, Mr. James	male	NaN	0	0	330877	1
6	7	0	1	McCarthy, Mr. Timothy J	male	54.0	0	0	17463	3
7	8	0	3	Palsson, Master. Gosta Leonard	male	2.0	3	1	349909	2
8	9	1	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27.0	0	2	347742	1
9	10	1	2	Nasser, Mrs. Nicholas (Adele Achem)	female	14.0	1	0	237736	2
10	11	1	3	Sandstrom, Miss. Marguerite Rut	female	4.0	1	1	PP 9549	2
11	12	1	1	Bonnell, Miss. Elizabeth	female	58.0	0	0	113783	2
12	13	0	3	Saundercock, Mr. William Henry	male	20.0	0	0	A/5. 2151	1
13	14	0	3	Andersson, Mr. Anders Johan	male	39.0	1	5	347082	3
14	15	0	3	Vestrom, Miss. Hulda Amanda Adolfina	female	14.0	0	0	350406	0

In [478]:
```
#  using groupby calculate the mean of each new Fare data
data_train.groupby('Fare')['Survived'].agg('mean')
```

Out[478]:
```
Fare
0    0.197309
1    0.308756
2    0.445415
3    0.581081
Name: Survived, dtype: float64
```

GOOD JOB :)