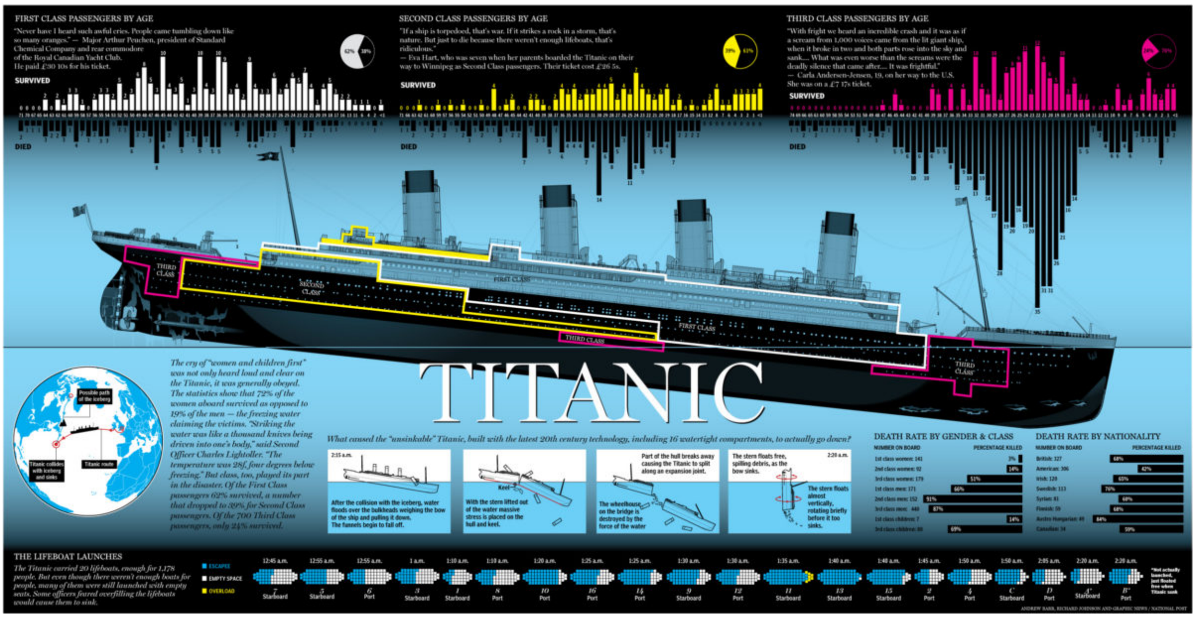
Titanic

In [1]:

```
from IPython.display import Image
from IPython.core.display import HTML
Image(url= 'https://bit.ly/2HCKyas')
```

Out[1]:



Introduction

Titanic was a British passenger liner that sank in the North Atlantic Ocean in 1912, after colliding with an iceberg during her maiden voyage from Southampton to New York City. Of the estimated 2,224 passengers and crew aboard, more than 1,500 died, making it one of modern history's deadliest commercial marine disasters during peacetime.

The dataset we are going to work with contains demographics and passenger information from 891 passengers and crew on board of the Titanic.

The Titanic dataset has the following attributes:

PassengerId: Unique identifier for passengers 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 Cabin: Cabin Embarked: Port of Embarkation (C = Cherbourg; Q = Queenstown; S = Southampton)

Import Libraries

In [2]:

```
# Importing pandas and Series + DataFrame:
import pandas as pd
from pandas import Series, DataFrame

# Importing numpy, matplotlib and seaborn:
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

Import the Data

The following code loads data from our csv file into jupyter notebook and sets it as a DataFrame:

In [3]:

```
titanic_df = pd.read_csv('titanic_train.csv')
```

Explore your dataset:

In [4]:

```
# A short preview of our data from Titanic file (displays first 5 rows):
titanic_df.head()
```

Out[4]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Ca
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	I
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	I
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	I

In [5]:

```
# To display basic stats for columns filled in with numerical values:
titanic_df.describe()
```

Out[5]:

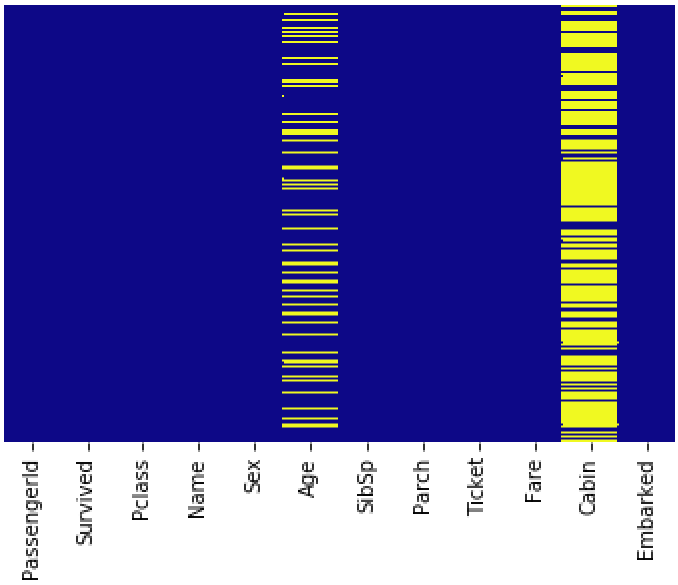
	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	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 [6]:

```
# Heatmap for visualising missing data:
sns.heatmap(titanic_df.isnull(), yticklabels = False, cbar = False, cmap = 'plasma')
```

Out[6]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x11a869400>
```



In our Titanic dataset we have missing data in Age and Cabin columns.

Data Cleaning

Looking at the visualisation above - heatmap, we can see that some values, such as age and cabin are missing. We will try to estimate those missing values and add them to our dataset.

Filling in Missing Age values

In [7]:

```
print('Number of rows where Age data is missing: ' + str(titanic_df.Age.isnull().sur
print('Percentage of Age data missing: ' + str(titanic_df.Age.isnull().sum()/len(tit
```

```
Number of rows where Age data is missing: 177
Percentage of Age data missing: 19.865319865319865
```

Our first data filling will be related to the passengers' age. We will use groupped data for Sex, Pclass and Title. This should give us more accurate ages, than just simply filling NaN values with the average age of known ages.

In the next step we will show that we have 17 different titles used in names and try to map them to 6 main categories: Mr, Miss, Mrs, Master, Officer and Royalty.

In [8]:

```
# What are different titles on the board of Titanic?
titanic_df.Name.apply(lambda name: name.split(',')[1].split('.')[0].strip()).unique(
```

Out[8]:

```
array(['Mr', 'Mrs', 'Miss', 'Master', 'Don', 'Rev', 'Dr', 'Mme', 'Ms',
       'Major', 'Lady', 'Sir', 'Mlle', 'Col', 'Capt', 'the Countess',
       'Jonkheer'], dtype=object)
```

In [9]:

```
# We create new feature 'Title' in our dataset, and we map our 17 titles to 6 main c
titanic_df['Title'] = titanic_df.Name.apply(lambda name: name.split(',')[1].split('.
```

In [10]:

```
# Normalise the titles:
normalised_titles = {'Mr':'Mr', 'Mrs':'Mrs', 'Miss':'Miss', 'Master':'Master', 'Don
                     'Dr':'Officer', 'Mme':'Mrs', 'Ms':'Mrs', 'Major':'Officer', 'La
                     'Mlle':'Miss', 'Col':'Officer', 'Capt':'Officer', 'the Countess
                     'Dona':'Royalty'}
```

In [11]:

```
# Map normalised titles to the current titles:
titanic_df['Title'] = titanic_df['Title'].map(normalised_titles)
```

In [12]:

```
# Check the new column 'Title' in titanic dataset:
titanic_df.head()
```

Out[12]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Ca
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	I
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	I
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	I

In [13]:

```
print(titanic_df['Title'].value_counts())
```

```
Mr         517
Miss       184
Mrs        127
Master      40
Officer     18
Royalty      5
Name: Title, dtype: int64
```

There are 177 NaN values for passengers' age. We will now try to estimate those missing values, by using groupped data and averages.

In [14]:

```
# Group by Sex, Pclass and title:
group = titanic_df.groupby(['Sex', 'Pclass', 'Title'])
```

In [15]:

```
# To display mediang age by the groupped features:
group['Age'].median()
```

Out[15]:

```
Sex     Pclass  Title
female  1       Miss        30.0
                Mrs         40.0
                Officer     49.0
                Royalty     40.5
        2       Miss        24.0
                Mrs         31.5
        3       Miss        18.0
                Mrs         31.0
male    1       Master       4.0
                Mr          40.0
                Officer     51.0
                Royalty     40.0
        2       Master       1.0
                Mr          31.0
                Officer     46.5
        3       Master       4.0
                Mr          26.0
Name: Age, dtype: float64
```

In [16]:

```
# Fill in the NaN age values by group median values:
titanic_df['Age'] = group['Age'].apply(lambda x: x.fillna(x.median()))
```

Setting Binary Values for Sex Column

KEY:
0 - male
1 - female

For data visualisation we will keep male/female description in the Sex column, but this can be set later.

In [17]:

```
# Convert male and female groups to integer form:
# titanic_df['Sex'] = titanic_df['Sex'].map({'male':0, 'female':1})
```

Filling in Missing Cabin Values

In [18]:

```
print('Number of rows where Cabin data is missing: ' + str(titanic_df.Cabin.isnull(
print('Percentage of Cabin data missing: ' + str(titanic_df.Cabin.isnull().sum()/len
```

```
Number of rows where Cabin data is missing: 687
Percentage of Cabin data missing: 77.10437710437711
```

Because the percentage of mising Cabin data is quite high, we can drop the column from our dataframe titanic_df instead of filling it in.

In [19]:

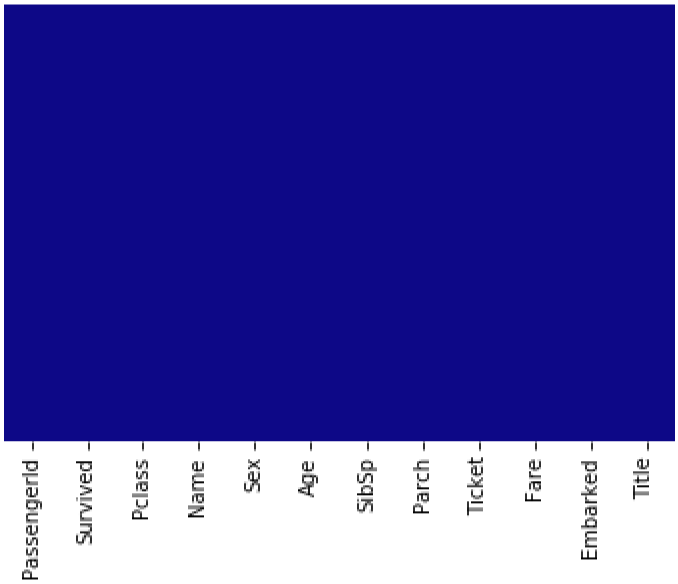
```
titanic_df = titanic_df.drop(['Cabin'], axis = 1)
```

In [20]:

```
# Visualising missing data with heatmap:
sns.heatmap(titanic_df.isnull(), yticklabels = False, cbar = False, cmap = 'plasma')
```

Out[20]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x11aae5a20>
```



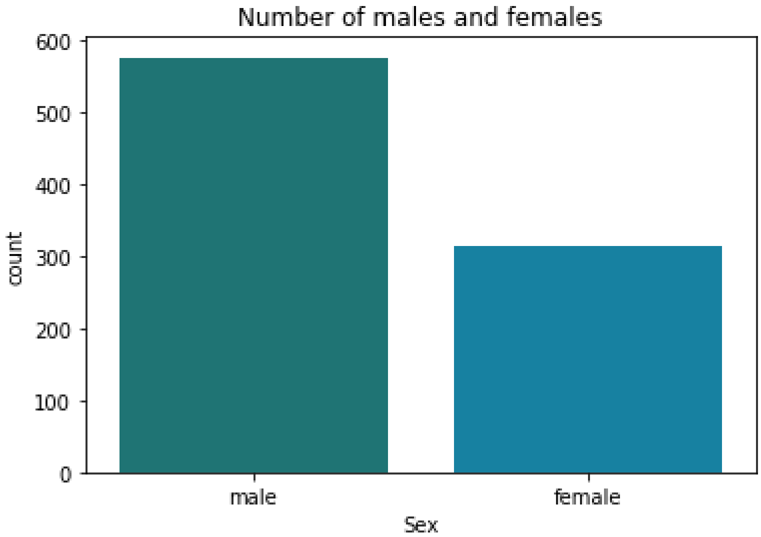
We now have no data missing and can go to explore our dataset further.

Exploratory Data Analysis (EDA)

Who were the passengers on the Titanic?

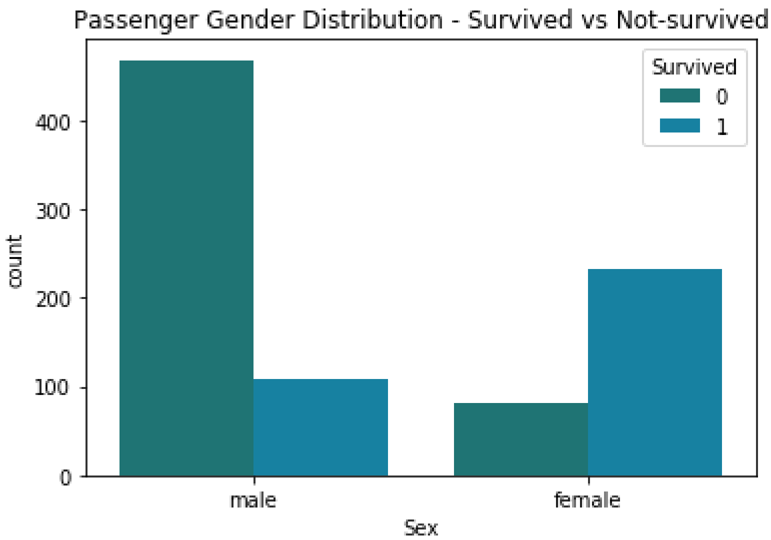
In [21]:

```
# Bar chart of total male and female passengers on the board:
plt.figure(figsize=(6,4))
sns.countplot(x = 'Sex', data=titanic_df,  palette = 'winter_d')
plt.title('Number of males and females')
plt.show()
```



In [22]:

```
# Bar chart of male and female, split into survived/not survived:
plt.figure(figsize=(6,4))
sns.countplot(x = 'Sex', hue = 'Survived', data=titanic_df, palette = 'winter_d')
plt.title('Passenger Gender Distribution - Survived vs Not-survived')
plt.show()
```

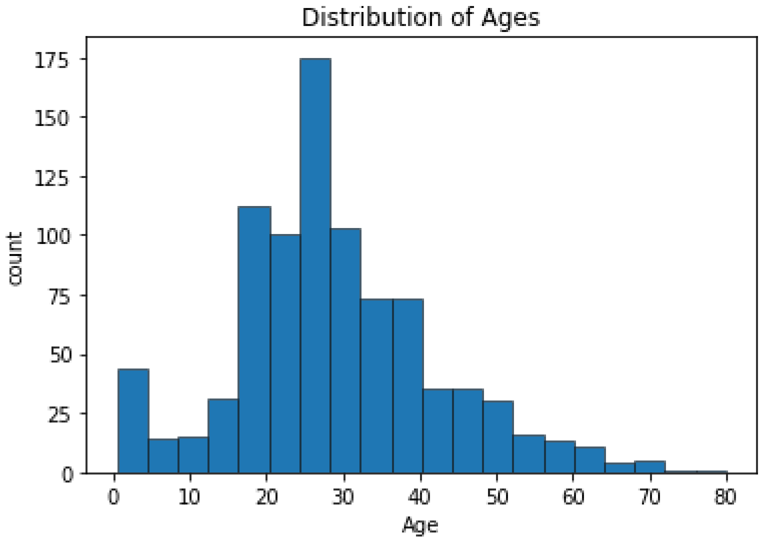


The bar charts above show that there are almost twice as many males on board as females. However, females have a better chance of survival.

Age Feature

In [23]:

```
# Distribution of ages (we will drop rows with no data in Age column):
plt.figure(figsize=(6,4))
plt.hist(titanic_df['Age'].dropna(), bins=20, edgecolor = 'black', linewidth = 0.5)
plt.title('Distribution of Ages')
plt.xlabel('Age')
plt.ylabel('count')
plt.show()
```



In [24]:

```
# Returns the average age of Titanic passenger:
mean = titanic_df['Age'].mean()
print('The average age of a passenger on Titanic was: ', mean)
```

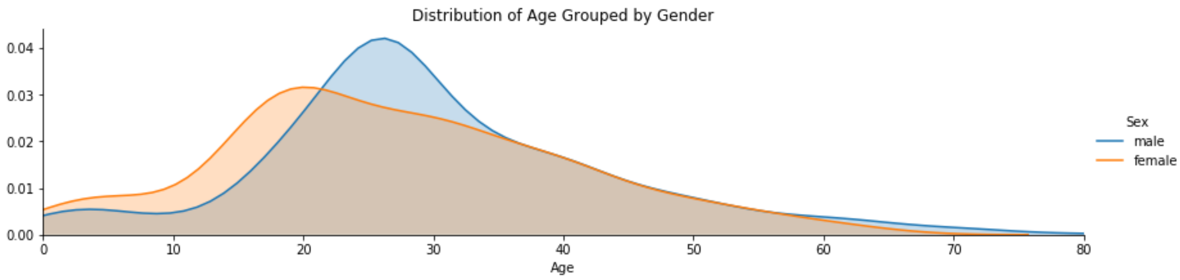
```
The average age of a passenger on Titanic was:  29.1382379349046
```

In [25]:

```
# Distribution of ages grouped by gender
fig = sns.FacetGrid(titanic_df, hue='Sex', aspect=4)
fig.map(sns.kdeplot, 'Age', shade=True)
oldest = titanic_df['Age'].max()
fig.set(xlim=(0,oldest))
fig.set(title='Distribution of Age Grouped by Gender')
fig.add_legend()
```

Out[25]:

```
<seaborn.axisgrid.FacetGrid at 0x11af4c588>
```



In [26]:

```
# Adding a new column 'Age Group':
def age_group(passenger):
    Age, Sex = passenger

    if Age < 5:
        return '0-4'
    elif Age < 10:
        return '5-9'
    elif Age < 20:
        return '10-19'
    elif Age < 30:
        return '20-29'
    elif Age < 40:
        return '30-39'
    elif Age < 50:
        return '40-49'
    elif Age < 60:
        return '50-50'
    elif Age < 70:
        return '60-69'
    else:
        return '70+'
```

In [27]:

```
# Add new column Age Groups into titanic dataset:
titanic_df['Age Groups'] = titanic_df[['Age', 'Sex']].apply(age_group, axis = 1)
```

In [28]:

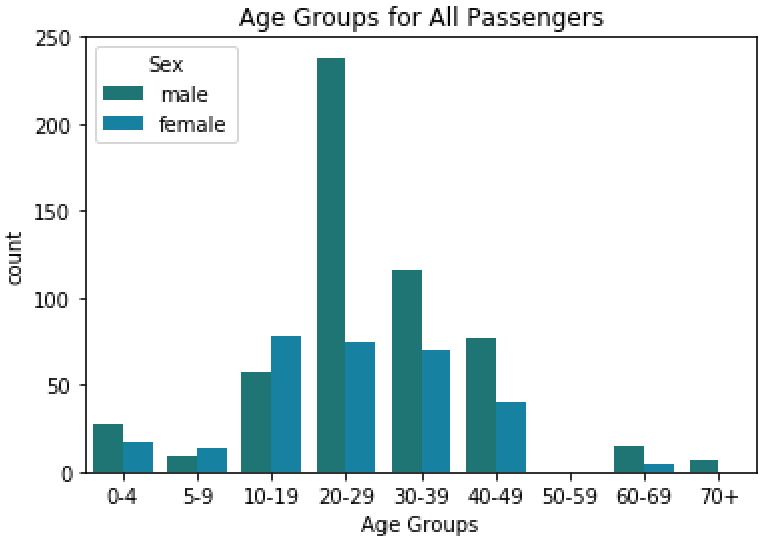
```
# Check the changes by displaying first 5 rows of the dataset:
titanic_df.head()
```

Out[28]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Er
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 [29]:

```
# Bar chart of 'Age Groups' and 'Sex':
plt.figure(figsize=(6,4))
sns.countplot(x = 'Age Groups', hue = 'Sex', data=titanic_df,  palette = 'winter_d',
              order = ['0-4','5-9','10-19','20-29','30-39','40-49','50-59','60-69',
plt.title('Age Groups for All Passengers')
plt.show()
```



In [30]:

```
# Returns counts of 'age groups' split into defined categories:
titanic_df['Age Groups'].value_counts()
```

Out[30]:

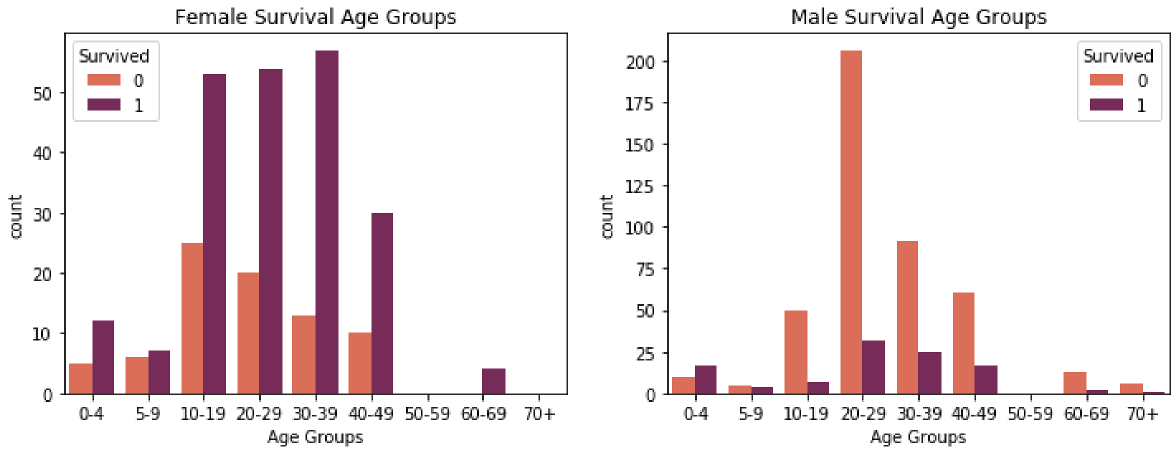
```
20-29    312
30-39    186
10-19    135
40-49    117
50-50     49
0-4       44
5-9       22
60-69     19
70+        7
Name: Age Groups, dtype: int64
```

In [31]:

```
# Bar chart of 'Age Groups' and 'Sex' for both males and females:
plt.figure(figsize=(12,4))
plt.subplot(121)
sns.countplot(x = 'Age Groups', hue = 'Survived', data = titanic_df[titanic_df.Sex =
              palette = 'rocket_r',
              order = ['0-4','5-9','10-19','20-29','30-39','40-49','50-59','60-69',
plt.title('Female Survival Age Groups')

plt.subplot(122)
sns.countplot(x = 'Age Groups', hue = 'Survived', data = titanic_df[titanic_df.Sex =
              order = ['0-4','5-9','10-19','20-29','30-39','40-49','50-59','60-69',
plt.title('Male Survival Age Groups')

plt.show()
```



Exploring the age feature shows us that females on the board of Titanic had a higher chance of survival than males.

Embarked Feature

Embark = port of embarkation (C = Cherbourg, Q = Queenstown, S = Southampton)

In [32]:

```
# How many people embarked in each of the ports?
titanic_df['Embarked'].value_counts()
```

Out[32]:

```
S    644
C    168
Q     77
Name: Embarked, dtype: int64
```

In [33]:

```
# How many passengers of each class embarked in C, Q, and S port?
emb = titanic_df.groupby(['Embarked', 'Pclass'])
emb.Pclass.sum()
```

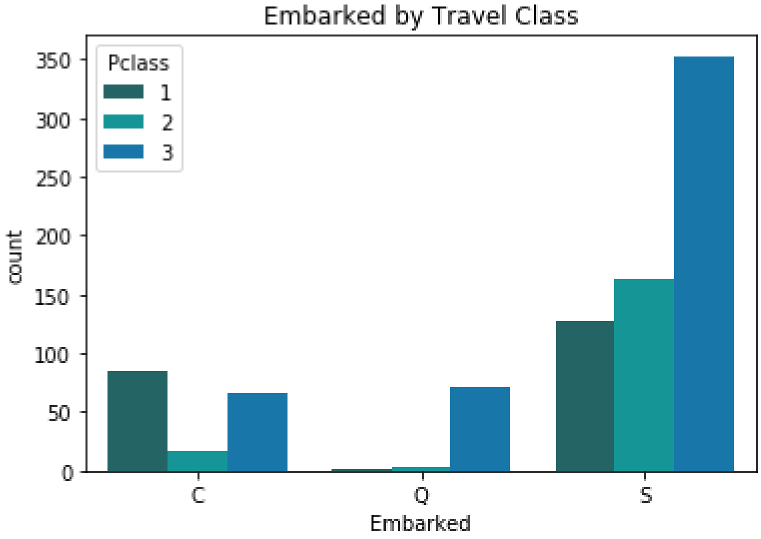
Out[33]:

```
Embarked  Pclass
C         1           85
          2           34
          3          198
Q         1            2
          2            6
          3          216
S         1          127
          2          328
          3         1059
Name: Pclass, dtype: int64
```

In [34]:

```
# Embarked split into travel class:

plt.figure(figsize = (6,4))
sns.countplot('Embarked', data=titanic_df, hue='Pclass', palette = 'winter_d', order
plt.title('Embarked by Travel Class')
plt.show()
```

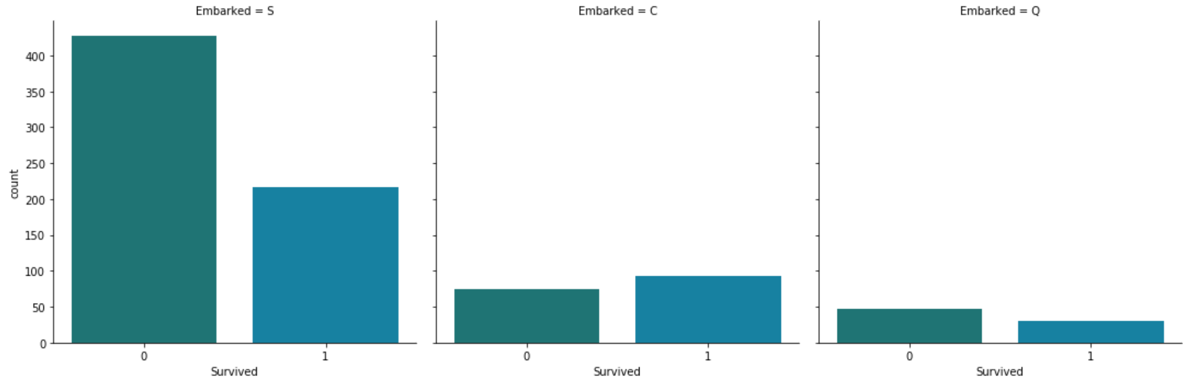


In [35]:

```
# Is there any relationship between embarked and survival?
sns.catplot(data = titanic_df, x = 'Survived', col = 'Embarked', kind = 'count', pal
```

Out[35]:

```
<seaborn.axisgrid.FacetGrid at 0x11da6dc88>
```

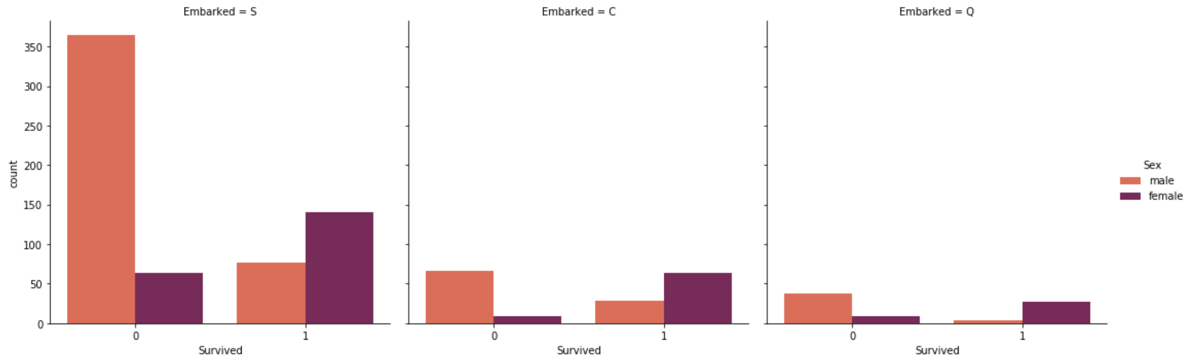


In [36]:

```
sns.catplot(data = titanic_df, x = 'Survived', hue = 'Sex',  col = 'Embarked', kind
```

Out[36]:

```
<seaborn.axisgrid.FacetGrid at 0x11e07f128>
```

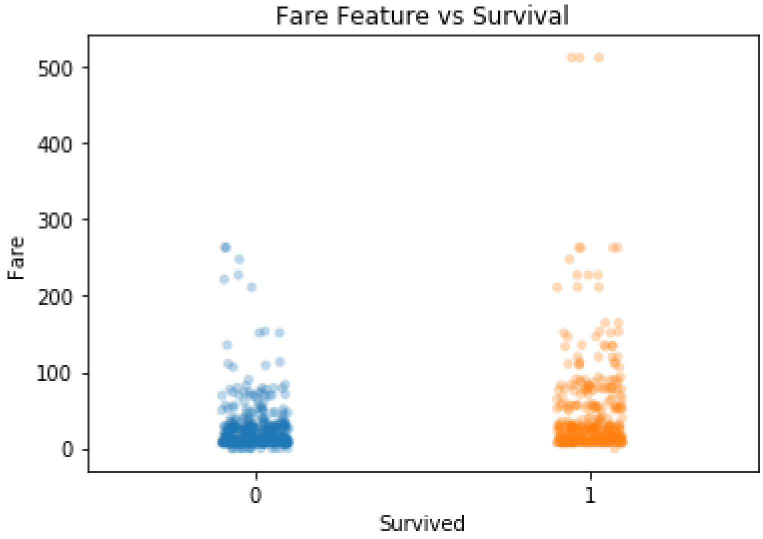


It seems like people who embarked in Southampton had higher survival rate than those who embarked in other two ports.

Fare Feature

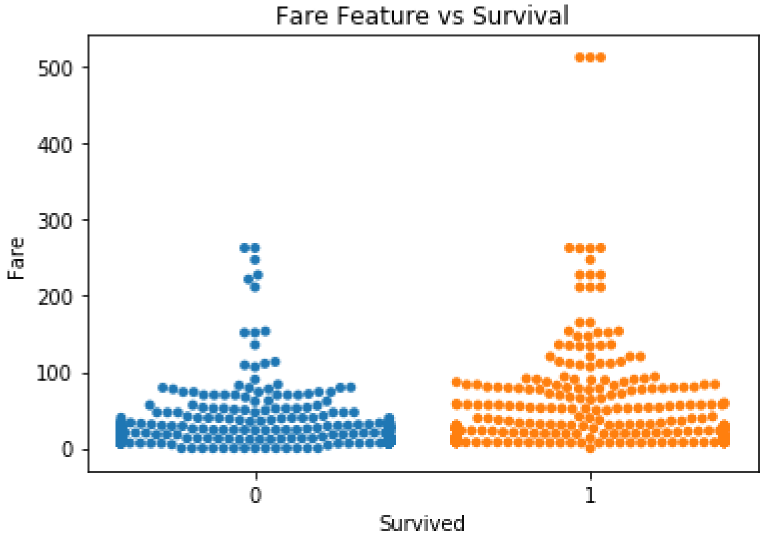
In [37]:

```
plt.figure(figsize = (6,4))
sns.stripplot(data = titanic_df, x='Survived', y='Fare', alpha=0.3, jitter=True)
plt.title('Fare Feature vs Survival')
plt.show()
```



In [38]:

```
plt.figure(figsize = (6,4))
sns.swarmplot(data = titanic_df, x = 'Survived', y = 'Fare')
plt.title('Fare Feature vs Survival')
plt.show()
```



There is a weak correlation between fare and survival.

What is the chance that a woman in her 30's with a 2nd class ticket survives?

In [39]:

```
# Create a crosstab with Age Groups, Pclass, Sex and Survived categories:
pd.crosstab([titanic_df.Sex, titanic_df.Survived],
            [titanic_df['Age Groups'], titanic_df.Pclass],
             margins=True).style.background_gradient(cmap='autumn_r')
```

Out[39]:

	Age Groups	0-4			10-19			20-29			30-39			40-49			5-9		50-5	
	Pclass	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	2	3	1	2
Sex	Survived																			
female	0	1	0	4	0	0	25	1	3	16	0	1	12	0	1	9	0	6	1	1
	1	0	4	8	13	8	32	15	24	15	28	16	13	21	9	0	4	3	11	5
male	0	0	0	10	3	9	38	9	28	169	11	35	45	30	7	23	0	5	12	9
	1	2	8	7	2	1	4	9	0	23	12	5	8	14	1	2	1	3	4	0
All		3	12	29	18	18	99	34	55	223	51	57	78	65	18	34	5	17	28	15

In [40]:

```
chance = round(16/17*100, 2)
print(print("The chance that a woman in her 30's with a 2nd class ticket survies is:
```

```
The chance that a woman in her 30's with a 2nd class ticket survies i
s:  94.12 %
None
```

Which variable has the highest impact when considering the likelihood of survival?

We can obtain this information from correlation. We will create a heatmap to show correlation between our variables/features:

In [41]:

```
# We can drop PassengerId, as this is only for ML purpose created feature.
titanic = titanic_df.drop(['PassengerId'], axis = 1)
```

In [42]:

```
# Change sex column to binary values 0 and 1:
titanic['Sex'] = titanic['Sex'].map({'male':0, 'female':1})
```

In [43]:

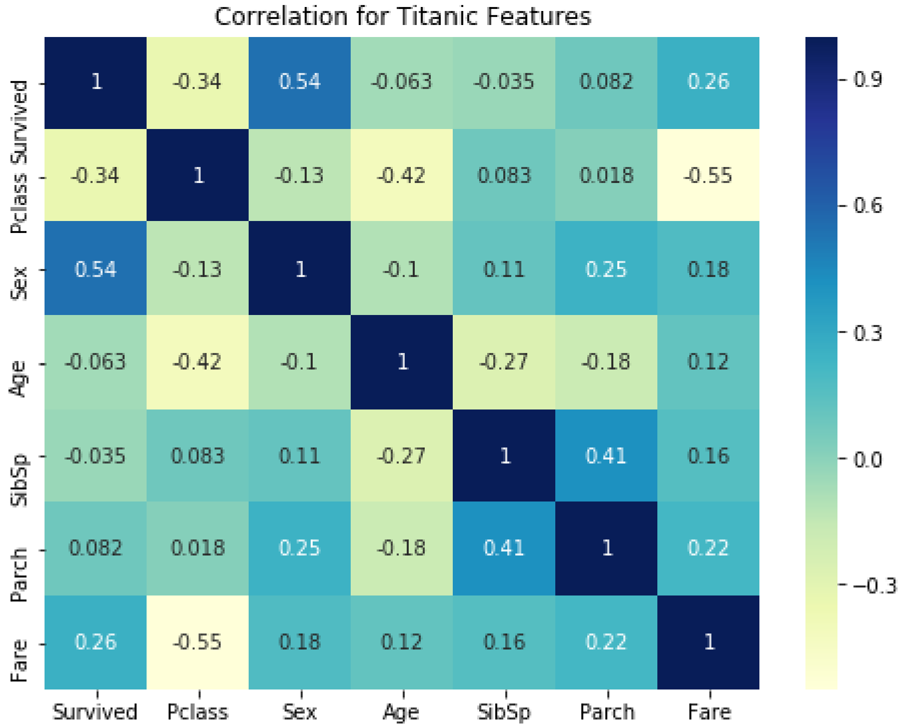
```
# Correlation between all features:

plt.figure(figsize = (8,6))
sns.heatmap(titanic.corr(), annot=True, cmap='YlGnBu', linecolor="white")

# Adding title to the heatmap:
plt.title('Correlation for Titanic Features')
```

Out[43]:

```
Text(0.5, 1.0, 'Correlation for Titanic Features')
```



The variable that has the highest impact on a likelihood of survival is 'Sex', followed by 'Pclass' and 'Fare'.