titanic_data

May 30, 2016

1 Titanic Passenger Data

This classic dataset about the information on passengers aboard the RMS Titanic which was travelling from Southampton to New York City in the year 1912. The dataset contains information on the passenger details like age, sex, cabin class, ticket fare and whether the passenger survived or not.

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

```
/Users/abkds/anaconda/lib/python2.7/site-packages/matplotlib/font_manager.py:273: UserWarning: Matplotli
  warnings.warn('Matplotlib is building the font cache using fc-list. This may take a moment.')
```

Let us check the total number of data points available in the data set.

```
In [2]: titanic_data = pd.read_csv('titanic_data.csv')
```

```
In [3]: print "Total data points: {}".format(len(titanic_data))

        # print some sample data points
        titanic_data.head()
```

```
Total data points: 891
```

```
Out[3]:    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
```

Before marching ahead, we will first check whether there are any missing values or cleaning that needs to be done.

```
In [4]: titanic_data.isnull().sum()
```

```
Out[4]: 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
```

Since we have so many missing values in the **Cabin** column, we will drop the column. Analysing the tickets also, would not be of much practical use either, so we will drop the columns.

```
In [5]: titanic_data.drop(['Cabin', 'Ticket'], axis=1, inplace=True)
```

We have removed the **Cabin** and **Ticket** axis but still we have so many NaN in the **Age** column. We will go ahead and remove those rows, which contain NaN values for age.

```
In [6]: titanic_data = titanic_data[pd.notnull(titanic_data['Age'])]
```

Let's have a look at the data remaining and analyze if any more cleaning needs to be done. Ofcourse we would return to more cleaning if we encounter problems during the explrolation phase.

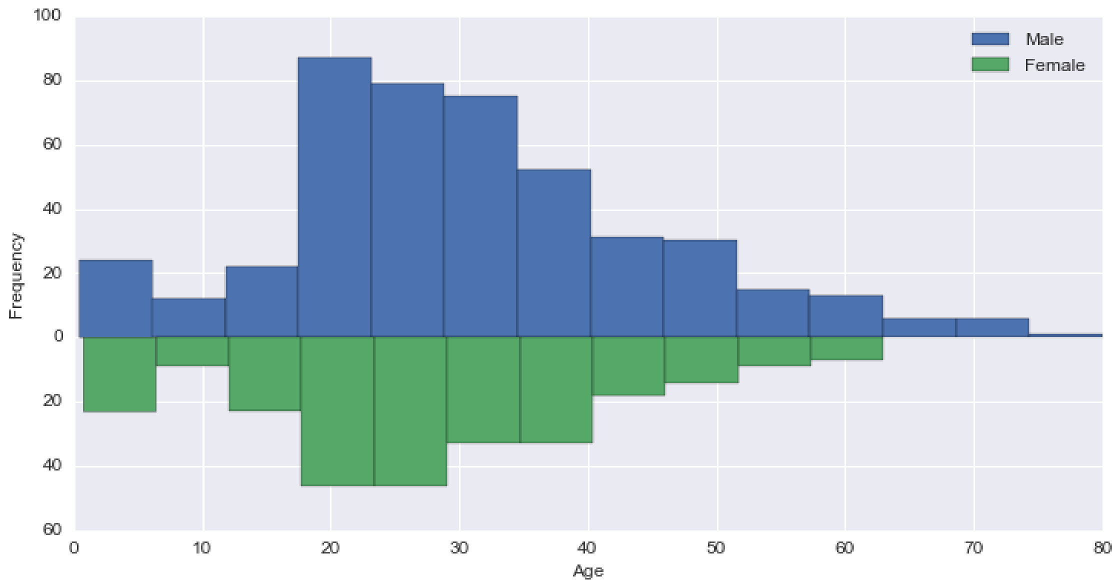
```
In [7]: print titanic_data.isnull().sum()
        print '\n'
        print 'Data points remaining after cleaning: {}'.format(len(titanic_data))
```

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


Data points remaining after cleaning: 714
```

1.0.1 Who all were travelling on the Titanic ?

A demographics of the people travelling on the Titanic would give us a good idea. A histogram depicting the demographics can be plotted.

```
In [8]: titanic_data_by_sex = titanic_data.groupby(['Sex'])

        titanic_data_male = titanic_data_by_sex.get_group('male')
        titanic_data_female = titanic_data_by_sex.get_group('female')

        plt.figure(figsize=(12, 6))
        plt.hist(titanic_data_male['Age'], bins=14, label='Male')
        plt.hist(titanic_data_female['Age'], weights=[-1 for _ in range(len(titanic_data_female))], bins
        ax = plt.gca()

        from matplotlib import ticker
        ax.yaxis.set_major_formatter(ticker.FuncFormatter(lambda x, pos: int(np.abs(x))))
        plt.xlim([0, 80])

        # labelling the axis
        plt.xlabel('Age', fontsize=12)
        plt.ylabel('Frequency', fontsize=12)

        # formatting the legend
        plt.legend(fontsize=12, loc=1)
        plt.tick_params(axis='both', which='major', labelsize=12)
```

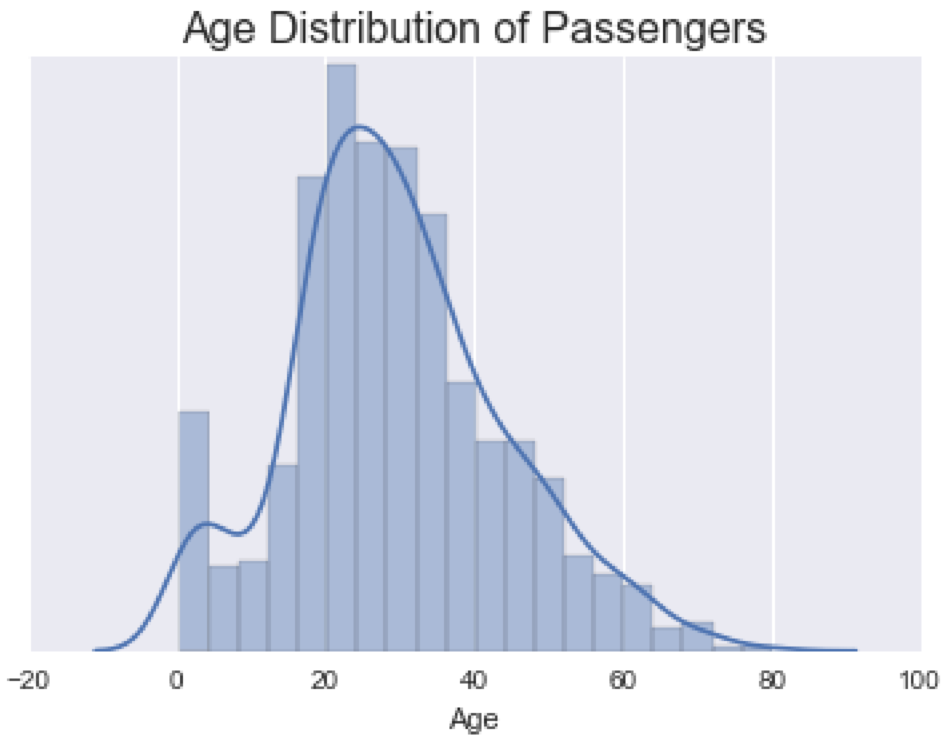


As seen from the plot, we can see that most of the males and females were from the age group 18-40. Let us find the percentage of people from that age group for the entire passenger list, male passengers and female passengers respectively.

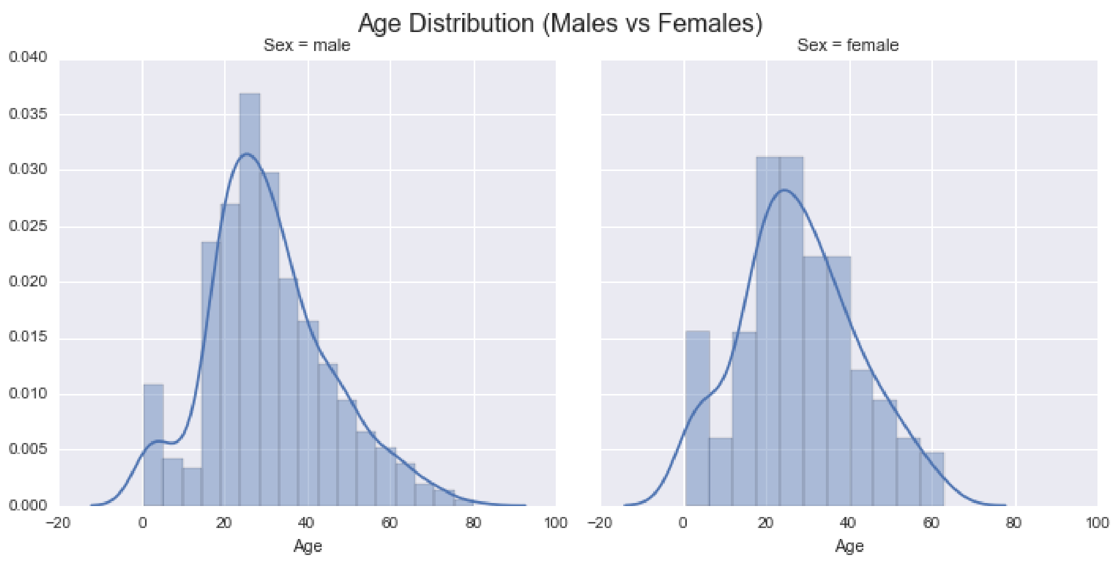
```
In [9]: def percent_in_18_to_40(data):
            age_in_18_to_40 = ((data['Age'] < 40) & (data['Age'] > 18)).sum()
            return age_in_18_to_40 * 100/len(data['Age'])

        print 'Percentage of passengers in age group 18-40: {}%'.format(percent_in_18_to_40(titanic_data
        print 'Percentage of male passengers in age group 18-40: {}%'.format(percent_in_18_to_40(titanic
        print 'Percentage of female passengers in age group 18-40: {}%'.format(percent_in_18_to_40(titan
Percentage of passengers in age group 18-40: 57%
Percentage of male passengers in age group 18-40: 60%
Percentage of female passengers in age group 18-40: 53%
```

As depicted by the histograms, the numbers also show that majority of the male and female passengers were in the age group of 18 to 40. Since we have already plotted the histogram, we will also plot the age distributions of the passengers travelling.

```
In [10]: # plotting the age
         sns.distplot(titanic_data['Age'])
         plt.gca().yaxis.set_major_locator(plt.NullLocator())
         plt.title('Age Distribution of Passengers', fontdict={'fontsize': 16})

Out[10]: <matplotlib.text.Text at 0x119c47fd0>
```

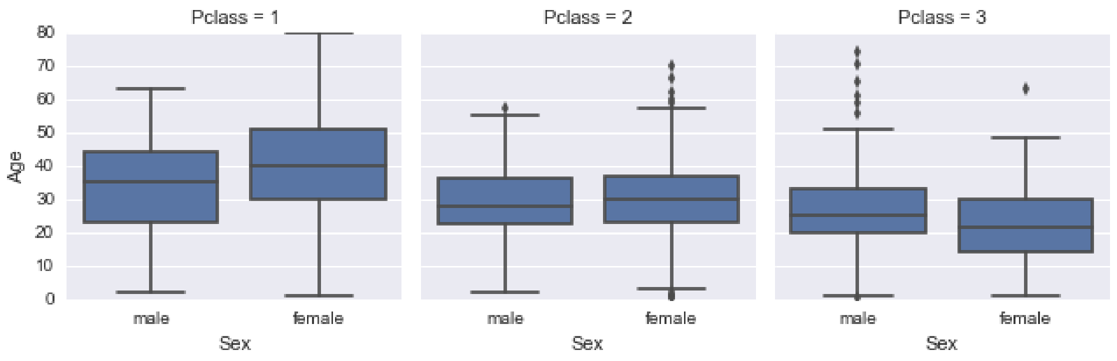


```
In [11]: facet_grid = sns.FacetGrid(titanic_data, col='Sex', size=5, aspect=1)
         facet_grid.map(sns.distplot, "Age")
         plt.subplots_adjust(top=0.9)
         facet_grid.fig.suptitle('Age Distribution (Males vs Females)', fontsize=16)

Out[11]: <matplotlib.text.Text at 0x119fb9f90>
```



We will just crackdown into age to find age details for all class (passenger class - 1st, 2nd or 3rd) and gender combinations.

```
In [12]: # use facet grid for a box plot of age distribution
         g = sns.FacetGrid(titanic_data, col="Pclass")
         g.map(sns.boxplot, "Sex", "Age")

Out[12]: <seaborn.axisgrid.FacetGrid at 0x116ef2110>
```



Looks interesting, plots depict that passengers travelling in the 1st class were older compared to passengers travelling in the 2nd and 3rd class. Let us quickly print the statistics for the above generated plot.

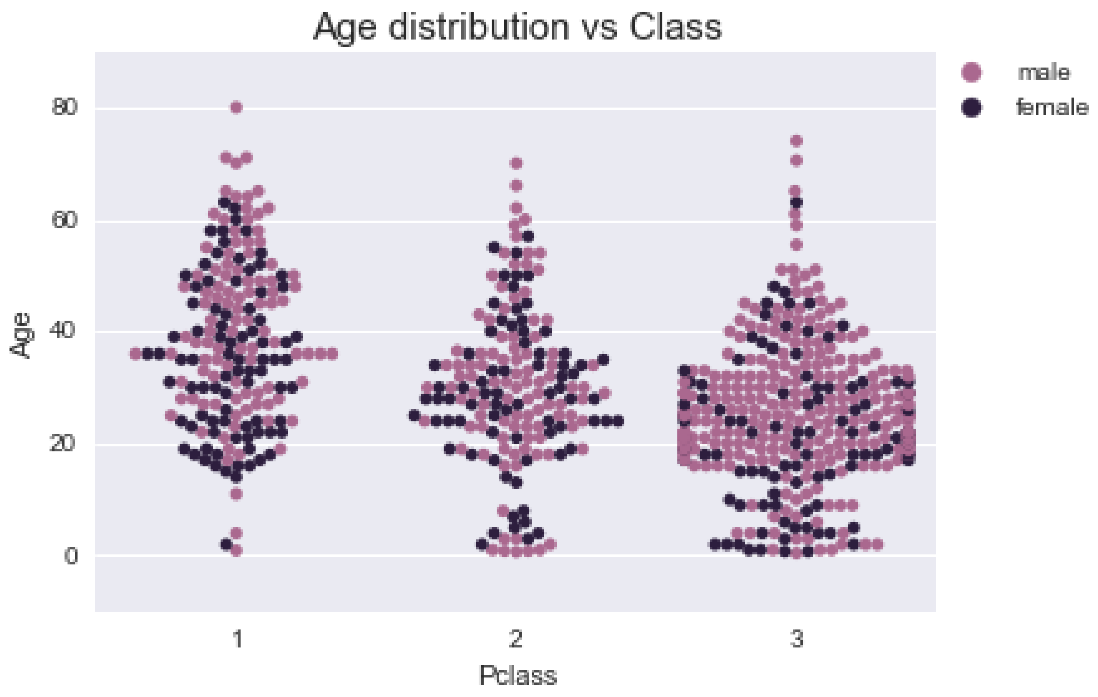
```
In [13]: groups = titanic_data.groupby(["Pclass", "Sex"])

In [14]: groups["Age"].describe()

Out[14]: Pclass  Sex
         1       female  count     85.000000
                         mean      34.611765
                         std       13.612052
```

```
                    min        2.000000
                    25%       23.000000
                    50%       35.000000
                    75%       44.000000
                    max       63.000000
            male    count    101.000000
                    mean      41.281386
                    std       15.139570
                    min        0.920000
                    25%       30.000000
                    50%       40.000000
                    75%       51.000000
                    max       80.000000
2       female  count     74.000000
                    mean      28.722973
                    std       12.872702
                    min        2.000000
                    25%       22.250000
                    50%       28.000000
                    75%       36.000000
                    max       57.000000
            male    count     99.000000
                    mean      30.740707
                    std       14.793894
                    min        0.670000
                    25%       23.000000
                    50%       30.000000
                    75%       36.750000
                    max       70.000000
3       female  count    102.000000
                    mean      21.750000
                    std       12.729964
                    min        0.750000
                    25%       14.125000
                    50%       21.500000
                    75%       29.750000
                    max       63.000000
            male    count    253.000000
                    mean      26.507589
                    std       12.159514
                    min        0.420000
                    25%       20.000000
                    50%       25.000000
                    75%       33.000000
                    max       74.000000
dtype: float64
```

These are the same descriptive statistics for the generated box plots, now we get the exact numbers for the 25, 50 and 75 percentile of the various passenger class, gender combinations. Seaborn provides something even more interesting called a swarm plot, if we do a simple scatterplot with categorical variables then many points will overlap, this can be avoided by adding some random jittering, but swarm plots have an algorithm built-in to avoid overlapping of the points which looks better than random jittering. Same plot but this time, Swarm !

```
In [15]: sns.swarmplot(x="Pclass", y="Age", hue="Sex", data=titanic_data,
                    palette=sns.cubehelix_palette(2, light=0.5))
        plt.legend(bbox_to_anchor=(1, 1), loc=2, borderaxespad=0.)
        plt.title("Age distribution vs Class", fontsize=15)
```

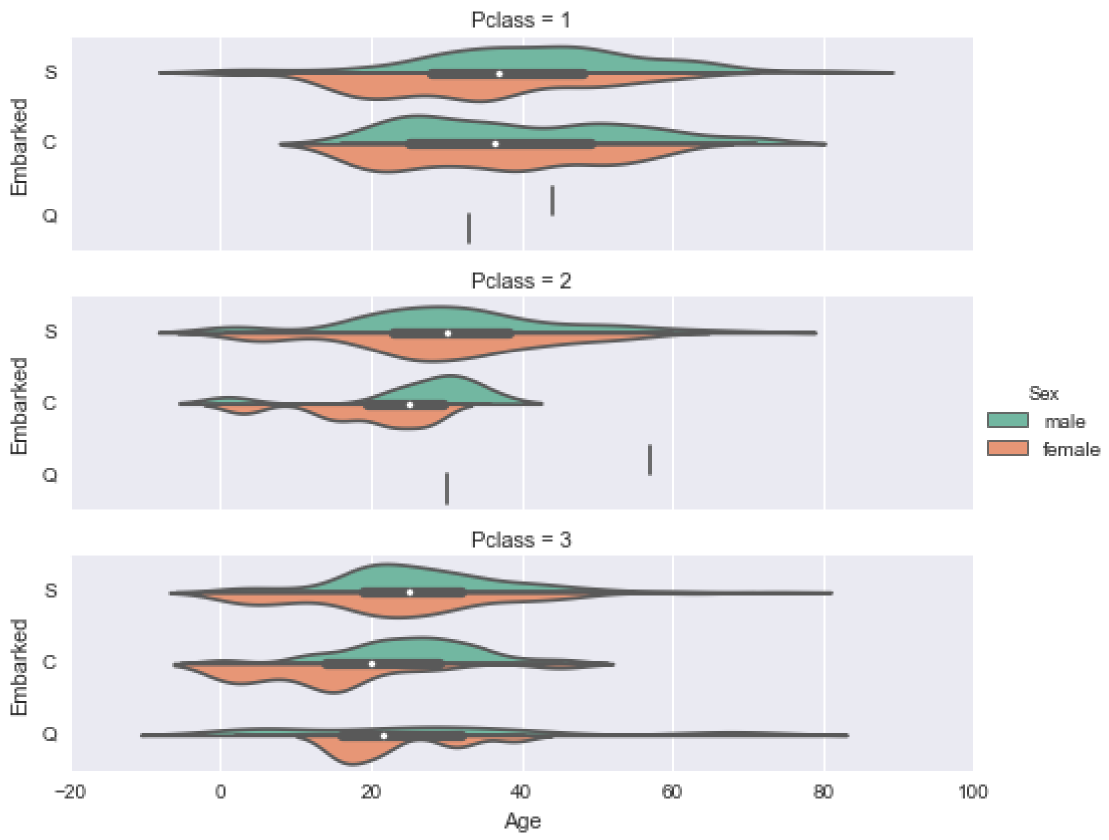
```
Out[15]: <matplotlib.text.Text at 0x11a6e86d0>
```



Plotting the age against all possible combinations of embarked location and passenger class

```
In [16]: # violin plot
         sns.factorplot(x="Age", y="Embarked", hue="Sex", row="Pclass",
                        data=titanic_data, orient="h", size=2, aspect=3.5,
                        palette="Set2", kind="violin", split=True, bw=0.3)
```

```
Out[16]: <seaborn.axisgrid.FacetGrid at 0x11a6d5390>
```

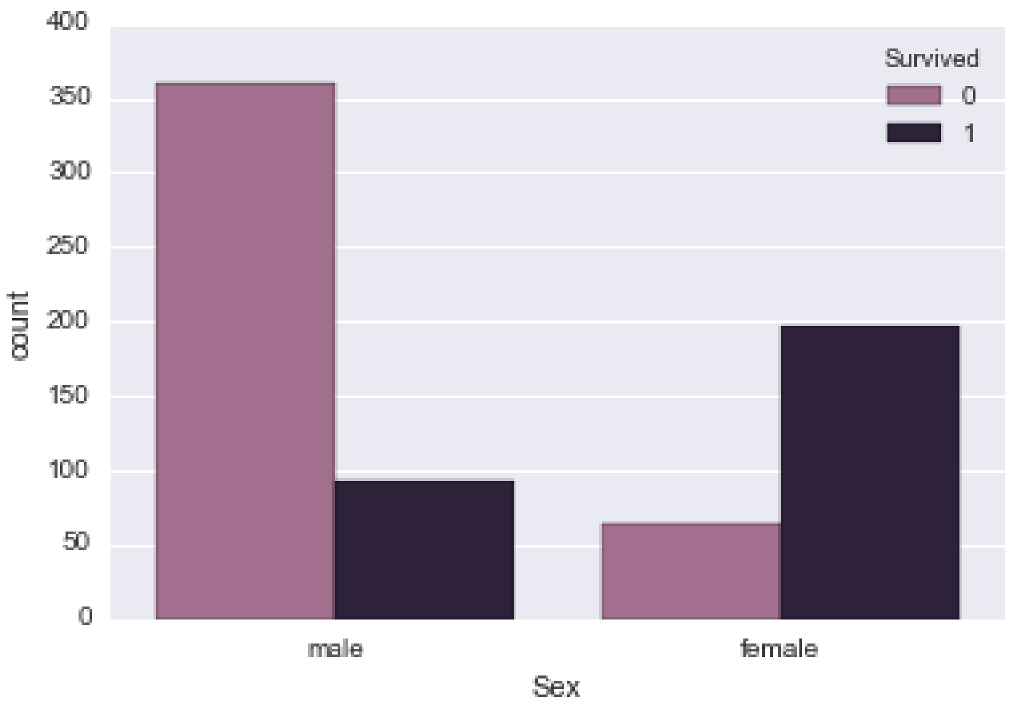


1.0.2 Enter "Survival"

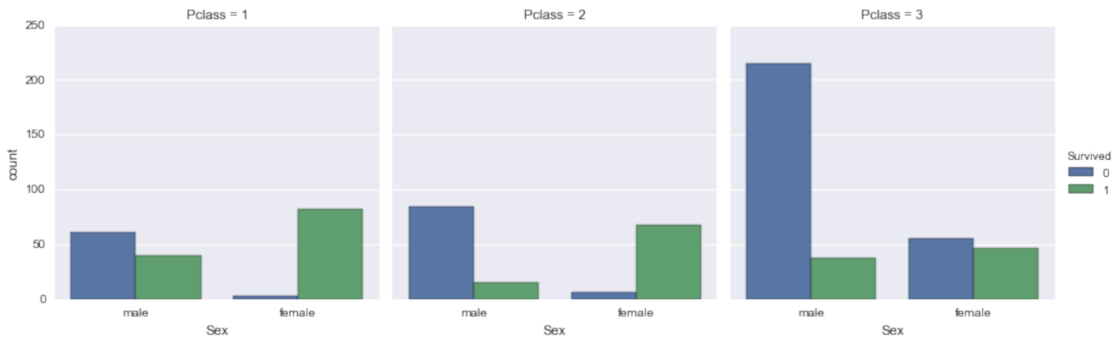
Till now we have toying around with ages of the passengers on board the titanic. I know, it started becoming boring. Enter "survival", lets take into account the "survived" column. This would give us insights on characteristics of the passengers who survived. Take a deep breath, because a lot of plots are coming !!

Let us have a look at some pure numbers on survivals. We will be plotting survival against various factors. Plotting survival against gender.

```
In [17]: # count plot for exact numbers
         sns.countplot(x="Sex", hue="Survived", data=titanic_data,
                       palette=sns.cubehelix_palette(2, light=0.5));
```



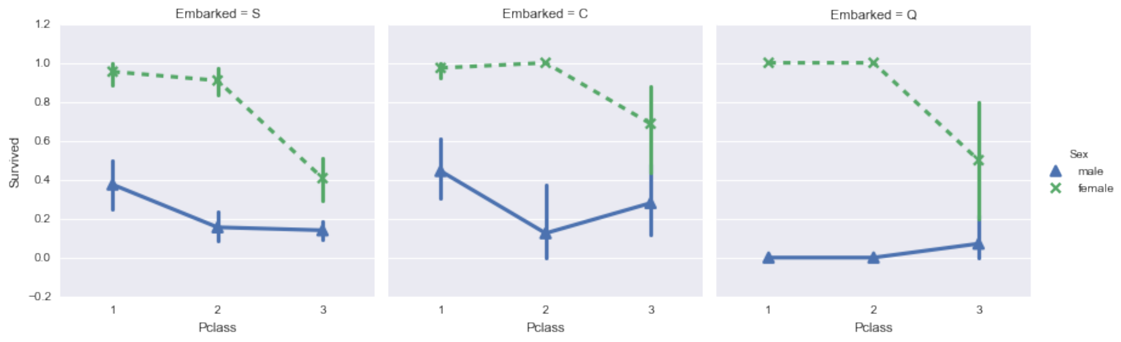
```
In [18]: # using pandas to find count
         # use group by pandas
         groupby_gender_survival = titanic_data.groupby(["Sex", "Survived"])
         groupby_gender_survival.apply(len)

Out[18]: Sex     Survived
         female  0            64
                 1           197
         male    0           360
                 1            93
         dtype: int64

In [19]: # Passenger class wise distribution of counts of survival statistics for men and women
         g = sns.factorplot("Sex", col="Pclass", data=titanic_data, kind="count", hue="Survived")
```



```
In [20]: # print exact count using groupby pandas
         grouped = titanic_data.groupby(["Sex", "Pclass", "Survived"])
         grouped.apply(len)

Out[20]: Sex     Pclass  Survived
         female  1       0             3
                         1            82
                 2       0             6
                         1            68
                 3       0            55
                         1            47
         male    1       0            61
                         1            40
                 2       0            84
                         1            15
                 3       0           215
                         1            38
         dtype: int64
```

So we have the counts. But it's more interesting to study the survival in terms of ratios or percentages. So, to plot the survival ratio for various classes in terms of histograms , we will also plot the confidence intervals. This is provided by `seaborn` out of the box. Since we are taking only around 700 data points which is of course not the compltete data, so it's like a sample from an underlying observation, whose mean and standard deviation we don't know. In such cases there is technique called **bootstrapping** used to have confidence intervals for the data. Not going into the details here, if one wants to read about the technique, you can read about it here.

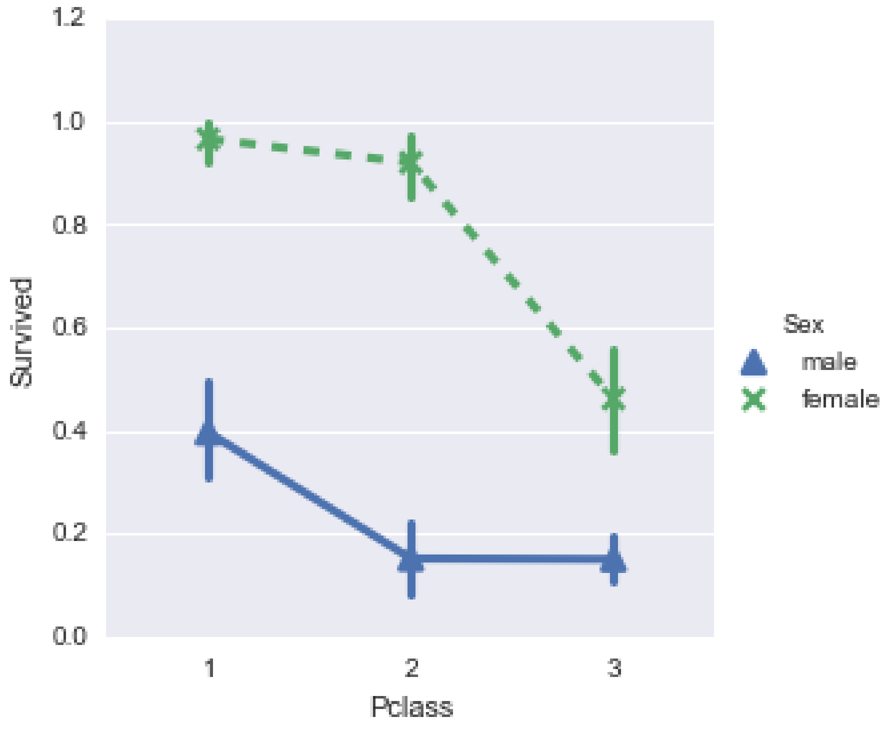
```
In [21]: sns.factorplot(x="Pclass", y="Survived", kind="point",
                        hue="Sex", col="Embarked", data=titanic_data,
                        markers=["^", "x"], linestyles=["-", "--"])

Out[21]: <seaborn.axisgrid.FacetGrid at 0x11b03a450>
```



The above plot shows survival ratios (with confidence intervals, 95% default) of male and females of various classes and also the places from where they embarked. In general we can see that females had a higher survival ratio than that of males. One more interesting trend is that people travelling in upper class (basically rich people) also had a higher survival ratio than those in lower classes. A similar plot for the entire dataset (not grouped by embarked location) would look like this.

```
In [22]: sns.factorplot(x="Pclass", y="Survived", kind="point",
                        hue="Sex", data=titanic_data,
                        markers=["^", "x"], linestyles=["-", "--"])
```

```
Out[22]: <seaborn.axisgrid.FacetGrid at 0x11b4ce550>
```



Again we will use Pandas to get the exact numbers in the plot.

```
In [23]: # survival ratios based on class and emabarked location
         grouped = titanic_data.groupby(["Sex", "Pclass", "Embarked"])
         grouped["Survived"].mean()
```

```
Out[23]: Sex     Pclass  Embarked
         female  1       C           0.973684
                         Q           1.000000
                         S           0.954545
                 2       C           1.000000
                         Q           1.000000
                         S           0.909091
                 3       C           0.687500
                         Q           0.500000
                         S           0.407895
         male    1       C           0.444444
                         Q           0.000000
                         S           0.375000
                 2       C           0.125000
                         Q           0.000000
                         S           0.155556
                 3       C           0.280000
                         Q           0.071429
                         S           0.140187
         Name: Survived, dtype: float64
```

```
In [24]: # overall survival ratio based on class and gender
         grouped = titanic_data.groupby(["Sex", "Pclass"])
         survival_ratio = grouped["Survived"].mean()

         # print all survival ratios
         gender = ["male", "female"]
         Pclass = [1, 2, 3]

         for i in range(len(gender)):
             for j in range(len(Pclass)):
                 print "Class {}, {} survival ratio: {:.2f}".format(Pclass[j],
                     gender[i].title(), survival_ratio[gender[i], Pclass[j]])
```

```
Class 1, Male survival ratio: 0.40
Class 2, Male survival ratio: 0.15
Class 3, Male survival ratio: 0.15
Class 1, Female survival ratio: 0.96
Class 2, Female survival ratio: 0.92
Class 3, Female survival ratio: 0.46
```

Although we didn't plot the overall survival ratios for both genders (we plotted their counts), we will also find the overal survival ration based on gender.

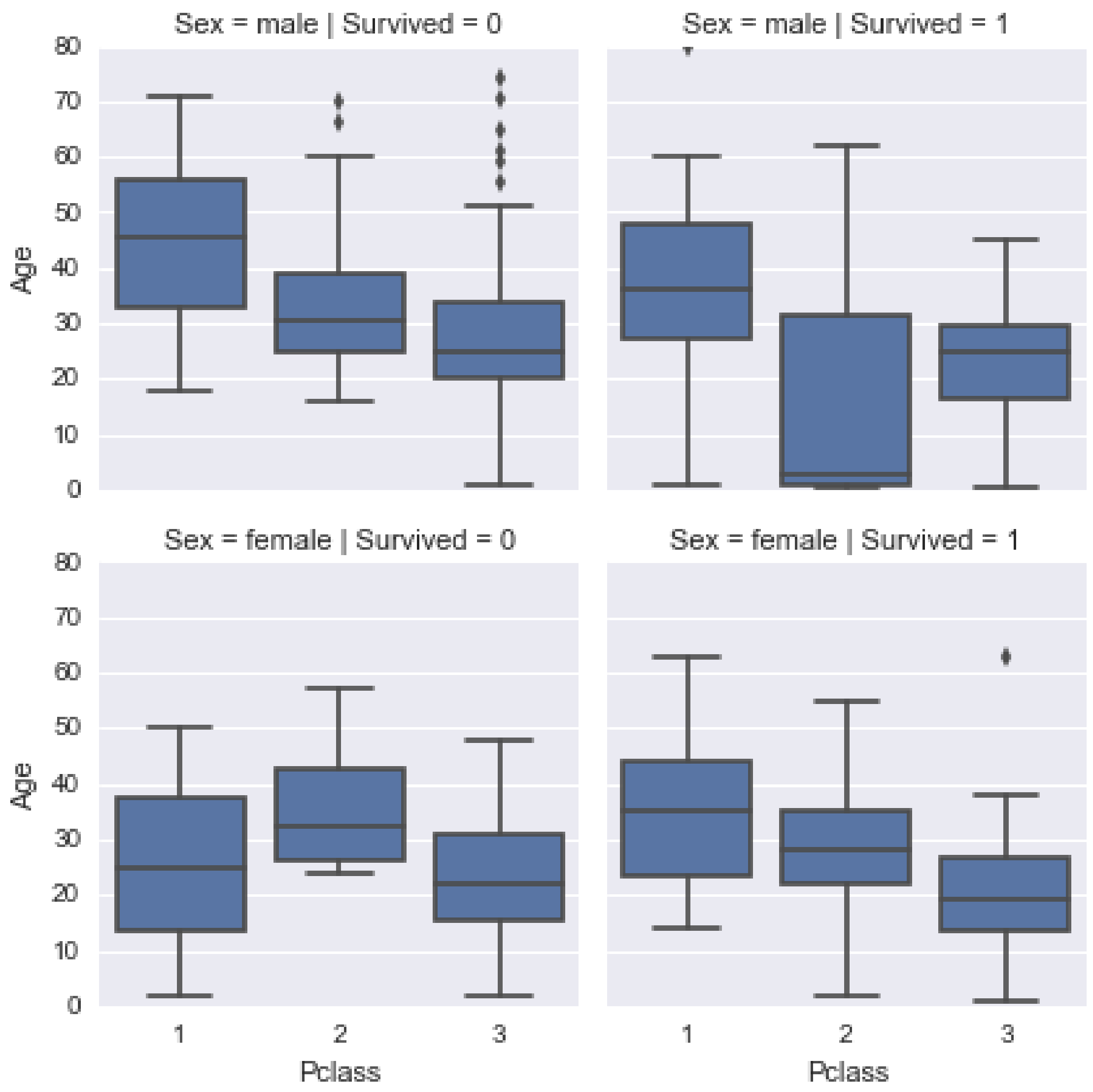
```
In [25]: # survival ratio based on gender
         grouped = titanic_data.groupby(["Sex"])
         survival_ratio = grouped["Survived"].mean()
         print "Female survival ratio: {:.2f}".format(survival_ratio['female'])
         print "Male survival ratio: {:.2f}".format(survival_ratio['male'])
```

```
Female survival ratio: 0.75
Male survival ratio: 0.21
```

That was all about counts and ratios of the overall passengers who survived, but we haven't yet analyzed the "ages" of passengers and how age relates with survival statistics.

```
In [26]: facet_grid = sns.FacetGrid(titanic_data, col='Survived', row='Sex')
         facet_grid.map(sns.boxplot, "Pclass", "Age")
```

```
Out[26]: <seaborn.axisgrid.FacetGrid at 0x11c6d0dd0>
```



From the plots we can observe that, age of the passengers surviving tends to be on the younger side on average, but still there are exceptions like in case of passenger class 1 females. The mean age for passenger class 1 females, who survived is more than that of who died.