Titanic Data Exploration Project

Hi, my name is Hernando Andrianto Willy Ren and I would like to perform data exploration on titanic passenger survival data

Titanic Data Contains demographics and passenger information from 891 of the 2224 passengers and crew on board the Titanic.

First, here's the data dictionary of the set

Data Dictionary

Variable Definition Key survival Survival 0 = No, 1 = Yes pclass Ticket class 1 = 1st, 2 = 2nd, 3 = 3rd sex Sex
Age Age in years
sibsp # of siblings / spouses aboard the Titanic
parch # of parents / children aboard the Titanic
ticket Ticket number
fare Passenger fare
cabin Cabin number
embarked Port of Embarkation C = Cherbourg, Q = Queenstown, S = Southampton

Variable Notes

pclass: A proxy for socio-economic status (SES) 1st = Upper 2nd = Middle 3rd = Lower

age: Age is fractional if less than 1. If the age is estimated, is it in the form of xx.5

sibsp: The dataset defines family relations in this way... Sibling = brother, sister, stepbrother, stepsister Spouse = husband, wife (mistresses and fiancés were ignored)

parch: The dataset defines family relations in this way... Parent = mother, father Child = daughter, son, stepdaughter, stepson Some children travelled only with a nanny, therefore parch=0 for them.

Research Question :

1. What factors made people more likely to survive?

Initial Analysis on Dataset using Data Dictionary

first, as we explore the data dictionary, there are numbers of interesting variable that may potentially affect survivability rate of a passenger. From my perspective, it can be :

1. Ticket Class - because it is a proxy of socioeconomic status, as the class higher, the survivability might get highe because first class may get better priority (but have to validify this hypothesis)
2. Sex- women might get better priority
3. number of siblings, spouses, parents or children aboard in titanic may also have effect on the survivability
4. Passenger fare may become a proxy of socioeconomic status, but this is a bit redundant with Ticket class variable, but we will check on it either way
5. Cabin number indicates the location of cabin, there's also might affect the survibality of the passenger

as for ticket number and port of embarkation, i don't think it will have any impact on the analysis of sruvivability , we will only take a look slighty on this variable

Okay! let's do this !

Step 1. IMPORTING DATA

In [ ]:

```
# pandas
import pandas as pd
from pandas import Series,DataFrame

# numpy, matplotlib, seaborn
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style('whitegrid')
%matplotlib inline

# machine learning
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC, LinearSVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB


import plotly.offline as py
py.init_notebook_mode(connected=True)
import plotly.graph_objs as go
import plotly.tools as tls

####
import warnings
warnings.filterwarnings('ignore')

# Going to use these 5 base models for the stacking
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier, Gradient
from sklearn.svm import SVC
from sklearn.cross_validation import KFold;
```

In [ ]:

```
gender_submission = pd.read_csv('gender_submission.csv')
ti_train_df = pd.read_csv('train.csv')
ti_test_df = pd.read_csv('test.csv')
```

Step 2. Data Exploration

2.1 INITIAL EXPLORATION

In [3]:

```
ti_test_df
```

Out[3]:

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	C
0	892	3	Kelly, Mr. James	male	34.5	0	0	330911	7.8292	
1	893	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.0000	
2	894	2	Myles, Mr. Thomas Francis	male	62.0	0	0	240276	9.6875	
3	895	3	Wirz, Mr. Albert	male	27.0	0	0	315154	8.6625	
4	896	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	female	22.0	1	1	3101298	12.2875	
5	897	3	Svensson, Mr. Johan Cervin	male	14.0	0	0	7538	9.2250	
6	898	3	Connolly, Miss. Kate	female	30.0	0	0	330972	7.6292	
7	899	2	Caldwell, Mr. Albert Francis	male	26.0	1	1	248738	29.0000	
8	900	3	Abrahim, Mrs. Joseph (Sophie Halaut Easu)	female	18.0	0	0	2657	7.2292	
9	901	3	Davies, Mr. John Samuel	male	21.0	2	0	A/4 48871	24.1500	
10	902	3	Ilieff, Mr. Ylio	male	NaN	0	0	349220	7.8958	
11	903	1	Jones, Mr. Charles Cresson	male	46.0	0	0	694	26.0000	

12	904	1	Snyder, Mrs. John Pillsbury (Nelle Stevenson)	female	23.0	1	0	21228	82.2667
13	905	2	Howard, Mr. Benjamin	male	63.0	1	0	24065	26.0000
14	906	1	Chaffee, Mrs. Herbert Fuller (Carrie Constance...	female	47.0	1	0	W.E.P. 5734	61.1750
15	907	2	del Carlo, Mrs. Sebastiano (Argenia Genovesi)	female	24.0	1	0	SC/PARIS 2167	27.7208
16	908	2	Keane, Mr. Daniel	male	35.0	0	0	233734	12.3500
17	909	3	Assaf, Mr. Gerios	male	21.0	0	0	2692	7.2250
18	910	3	Ilmakangas, Miss. Ida Livija	female	27.0	1	0	STON/O2. 3101270	7.9250
19	911	3	Assaf Khalil, Mrs. Mariana (Miriam")"	female	45.0	0	0	2696	7.2250
20	912	1	Rothschild, Mr. Martin	male	55.0	1	0	PC 17603	59.4000
21	913	3	Olsen, Master. Artur Karl	male	9.0	0	1	C 17368	3.1708
22	914	1	Flegenheim, Mrs. Alfred (Antoinette)	female	NaN	0	0	PC 17598	31.6833
23	915	1	Williams, Mr. Richard Norris II	male	21.0	0	1	PC 17597	61.3792
24	916	1	Ryerson, Mrs. Arthur Larned (Emily Maria Borie)	female	48.0	1	3	PC 17608	262.3750
25	917	3	Robins, Mr. Alexander A	male	50.0	1	0	A/5. 3337	14.5000
26	918	1	Ostby, Miss. Helene Ragnhild	female	22.0	0	1	113509	61.9792
27	919	3	Daher, Mr. Shedid	male	22.5	0	0	2698	7.2250
28	920	1	Brady, Mr. John Bertram	male	41.0	0	0	113054	30.5000
29	921	3	Samaan, Mr. Elias	male	NaN	2	0	2662	21.6792

...	...	...	...	...	...	...	...	...	...
388	1280	3	Canavan, Mr. Patrick	male	21.0	0	0	364858	7.7500
389	1281	3	Palsson, Master. Paul Folke	male	6.0	3	1	349909	21.0750
390	1282	1	Payne, Mr. Vivian Ponsonby	male	23.0	0	0	12749	93.5000
391	1283	1	Lines, Mrs. Ernest H (Elizabeth Lindsey James)	female	51.0	0	1	PC 17592	39.4000
392	1284	3	Abbott, Master. Eugene Joseph	male	13.0	0	2	C.A. 2673	20.2500
393	1285	2	Gilbert, Mr. William	male	47.0	0	0	C.A. 30769	10.5000
394	1286	3	Kink-Heilmann, Mr. Anton	male	29.0	3	1	315153	22.0250
395	1287	1	Smith, Mrs. Lucien Philip (Mary Eloise Hughes)	female	18.0	1	0	13695	60.0000
396	1288	3	Colbert, Mr. Patrick	male	24.0	0	0	371109	7.2500
397	1289	1	Frolicher-Stehli, Mrs. Maxmillian (Margaretha ...	female	48.0	1	1	13567	79.2000
398	1290	3	Larsson-Rondberg, Mr. Edvard A	male	22.0	0	0	347065	7.7750
399	1291	3	Conlon, Mr. Thomas Henry	male	31.0	0	0	21332	7.7333
400	1292	1	Bonnell, Miss. Caroline	female	30.0	0	0	36928	164.8667
401	1293	2	Gale, Mr. Harry	male	38.0	1	0	28664	21.0000
402	1294	1	Gibson, Miss. Dorothy Winifred	female	22.0	0	1	112378	59.4000
403	1295	1	Carrau, Mr. Jose Pedro	male	17.0	0	0	113059	47.1000
404	1296	1	Frauenthal, Mr. Isaac Gerald	male	43.0	1	0	17765	27.7208

405	1297	2	Nourney, Mr. Alfred (Baron von Drachstedt")"	male	20.0	0	0	SC/PARIS 2166	13.8625
406	1298	2	Ware, Mr. William Jeffery	male	23.0	1	0	28666	10.5000
407	1299	1	Widener, Mr. George Dunton	male	50.0	1	1	113503	211.5000
408	1300	3	Riordan, Miss. Johanna Hannah""	female	NaN	0	0	334915	7.7208
409	1301	3	Peacock, Miss. Treasteall	female	3.0	1	1	SOTON/O.Q. 3101315	13.7750
410	1302	3	Naughton, Miss. Hannah	female	NaN	0	0	365237	7.7500
411	1303	1	Minahan, Mrs. William Edward (Lillian E Thorpe)	female	37.0	1	0	19928	90.0000
412	1304	3	Henriksson, Miss. Jenny Lovisa	female	28.0	0	0	347086	7.7750
413	1305	3	Spector, Mr. Woolf	male	NaN	0	0	A.5. 3236	8.0500
414	1306	1	Oliva y Ocana, Dona. Fermina	female	39.0	0	0	PC 17758	108.9000
415	1307	3	Saether, Mr. Simon Sivertsen	male	38.5	0	0	SOTON/O.Q. 3101262	7.2500
416	1308	3	Ware, Mr. Frederick	male	NaN	0	0	359309	8.0500
417	1309	3	Peter, Master. Michael J	male	NaN	1	1	2668	22.3583

418 rows × 11 columns

In [4]:

```
ti_train_df
```

Out[4]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
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	C85
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN

In [5]:

```
gender_submission.head(10)
```

Out[5]:

	PassengerId	Survived
0	892	0
1	893	1
2	894	0
3	895	0
4	896	1
5	897	0
6	898	1
7	899	0
8	900	1
9	901	0

As we can see in this set we can see three dataset, which is ti_train_df, ti_test_df, and gender submission

Overview

training set (train.csv) test set (test.csv) The training set should be used to build our machine learning models. For the training set, we have the outcome (also known as the “ground truth”) for each passenger. our model will be based on “features” like passengers’ gender and class.

Test set (test.csv) The test set should be used to see how well our model performs on unseen data. For the test set, we do not provide the ground truth for each passenger. It is your job to predict these outcomes. For each passenger in the test set, use the model you trained to predict whether or not they survived the sinking of the Titanic.

basically for data exploration we are going to use the train set, which is ti_train_df

In [6]:

```
ti_train_df.shape
#it has 891 record, and 12 variables
```

Out[6]:

```
(891, 12)
```

In [7]:

```
ti_train_df.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
```

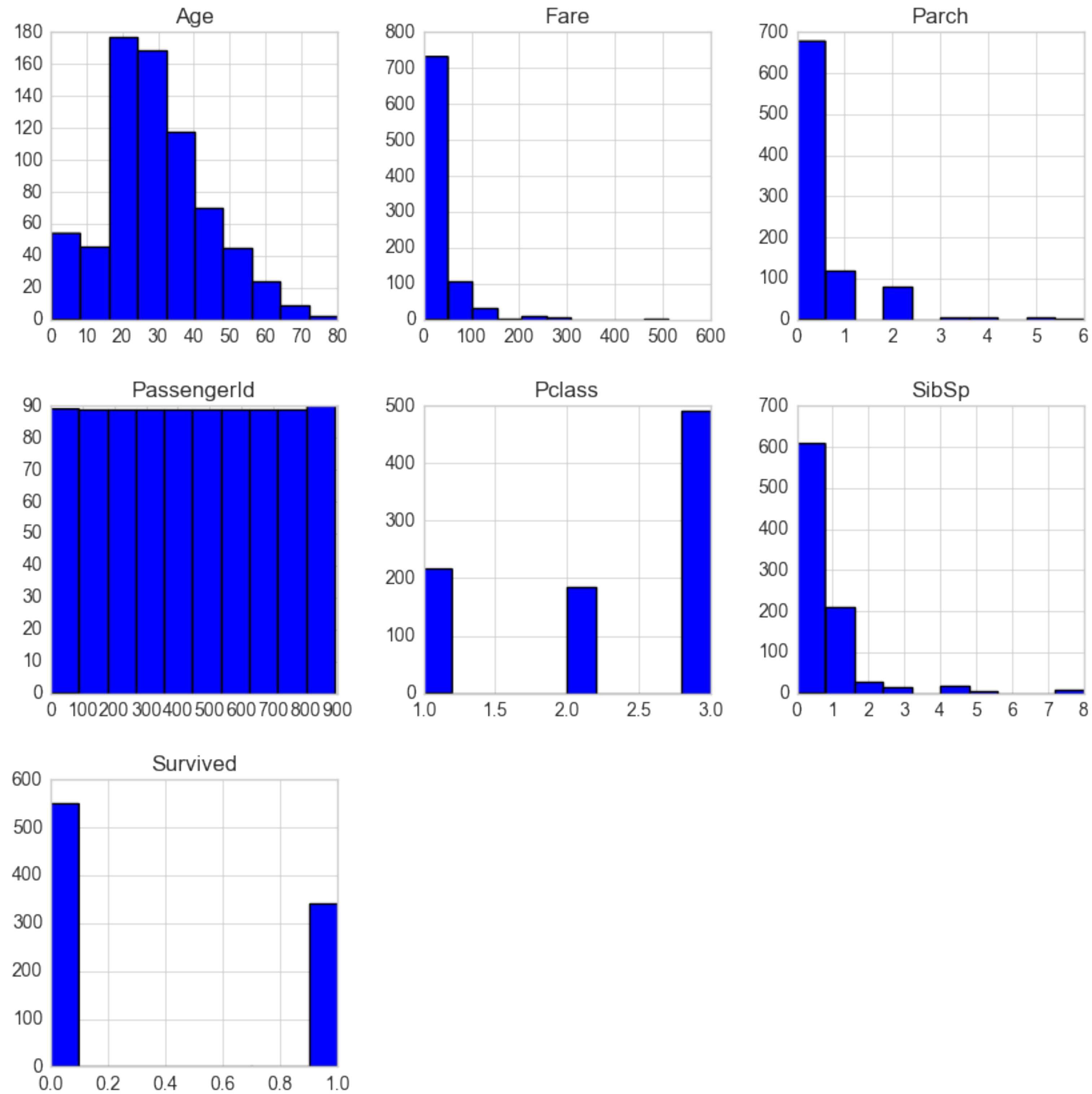
In [8]:

```
ti_train_df.hist(bins=10,figsize = (10,10))
```

Out[8]:

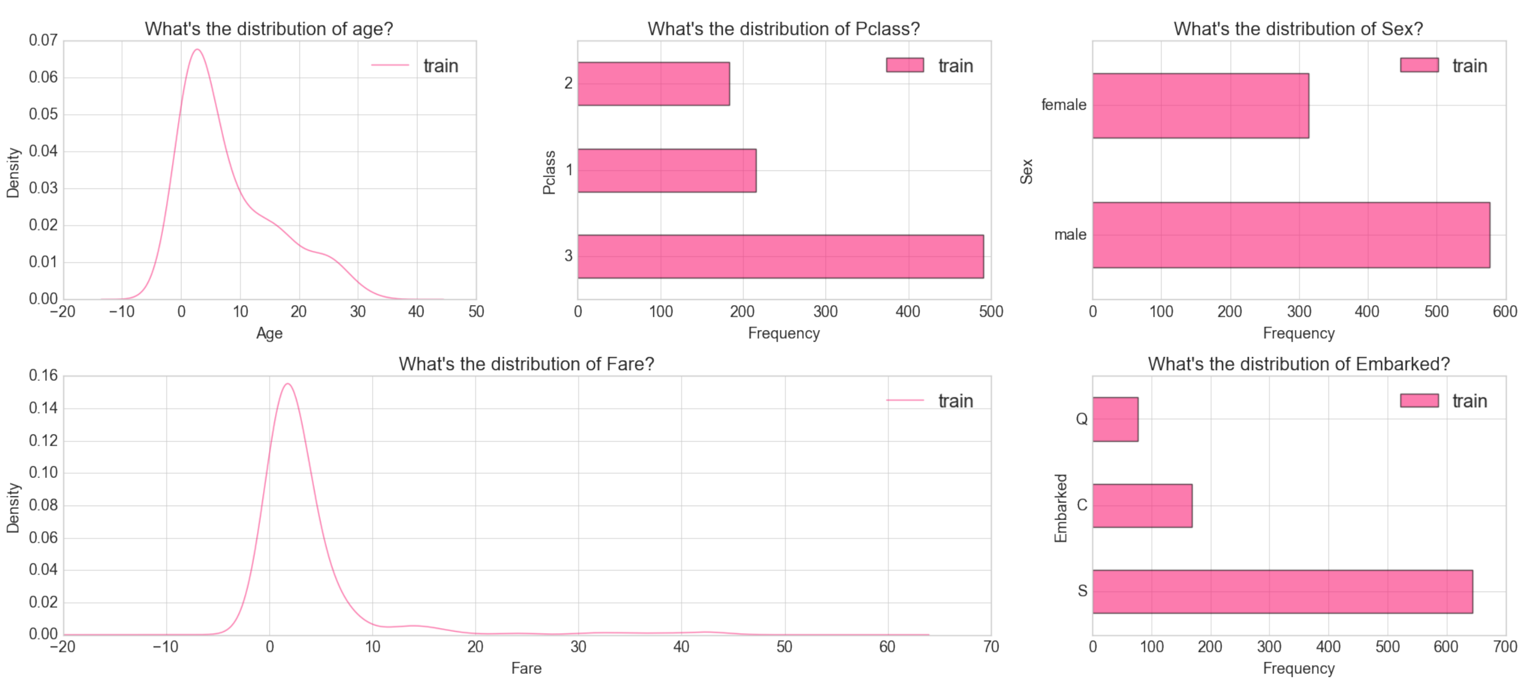
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x110f6b7f0
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x104a1fcf8
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x110ea7128
>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x110df4240
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x110e10278
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x110e78630
>],
```

```
       [<matplotlib.axes._subplots.AxesSubplot object at 0x110fa1e80
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1113041d0
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x11134f208
>]], dtype=object)
```



In [9]:

```
plt.rc('font', size=13)
fig = plt.figure(figsize=(18, 8))
alpha = 0.6

ax1 = plt.subplot2grid((2,3), (0,0))
ti_train_df.Age.value_counts().plot(kind='kde', color='#FA2379', label='train', a
ax1.set_xlabel('Age')
ax1.set_title("What's the distribution of age?" )
plt.legend(loc='best')

ax2 = plt.subplot2grid((2,3), (0,1))
ti_train_df.Pclass.value_counts().plot(kind='barh', color='#FA2379', label='train
ax2.set_ylabel('Pclass')
ax2.set_xlabel('Frequency')
ax2.set_title("What's the distribution of Pclass?" )
plt.legend(loc='best')

ax3 = plt.subplot2grid((2,3), (0,2))
ti_train_df.Sex.value_counts().plot(kind='barh', color='#FA2379', label='train',
ax3.set_ylabel('Sex')
ax3.set_xlabel('Frequency')
ax3.set_title("What's the distribution of Sex?" )
plt.legend(loc='best')

ax4 = plt.subplot2grid((2,3), (1,0), colspan=2)
ti_train_df.Fare.value_counts().plot(kind='kde', color='#FA2379', label='train',
ax4.set_xlabel('Fare')
ax4.set_title("What's the distribution of Fare?" )
plt.legend(loc='best')

ax5 = plt.subplot2grid((2,3), (1,2))
ti_train_df.Embarked.value_counts().plot(kind='barh', color='#FA2379', label='tra
ax5.set_ylabel('Embarked')
ax5.set_xlabel('Frequency')
ax5.set_title("What's the distribution of Embarked?" )
plt.legend(loc='best')
plt.tight_layout()
```



These charts the histogram for all Variables. This will give us the feeling and understanding on how vary the variables are. For example we can see the distribution of the data majority in class 3,male, and embarked from S, and . this will be used as reference for further analysis.

2.2. Exploring Missing Values

we can see from above that Age, Cabin & Embarked have missing values

In [10]:

```
ti_train_df.isnull().sum()
```

Out[10]:

```
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
```

In [11]:

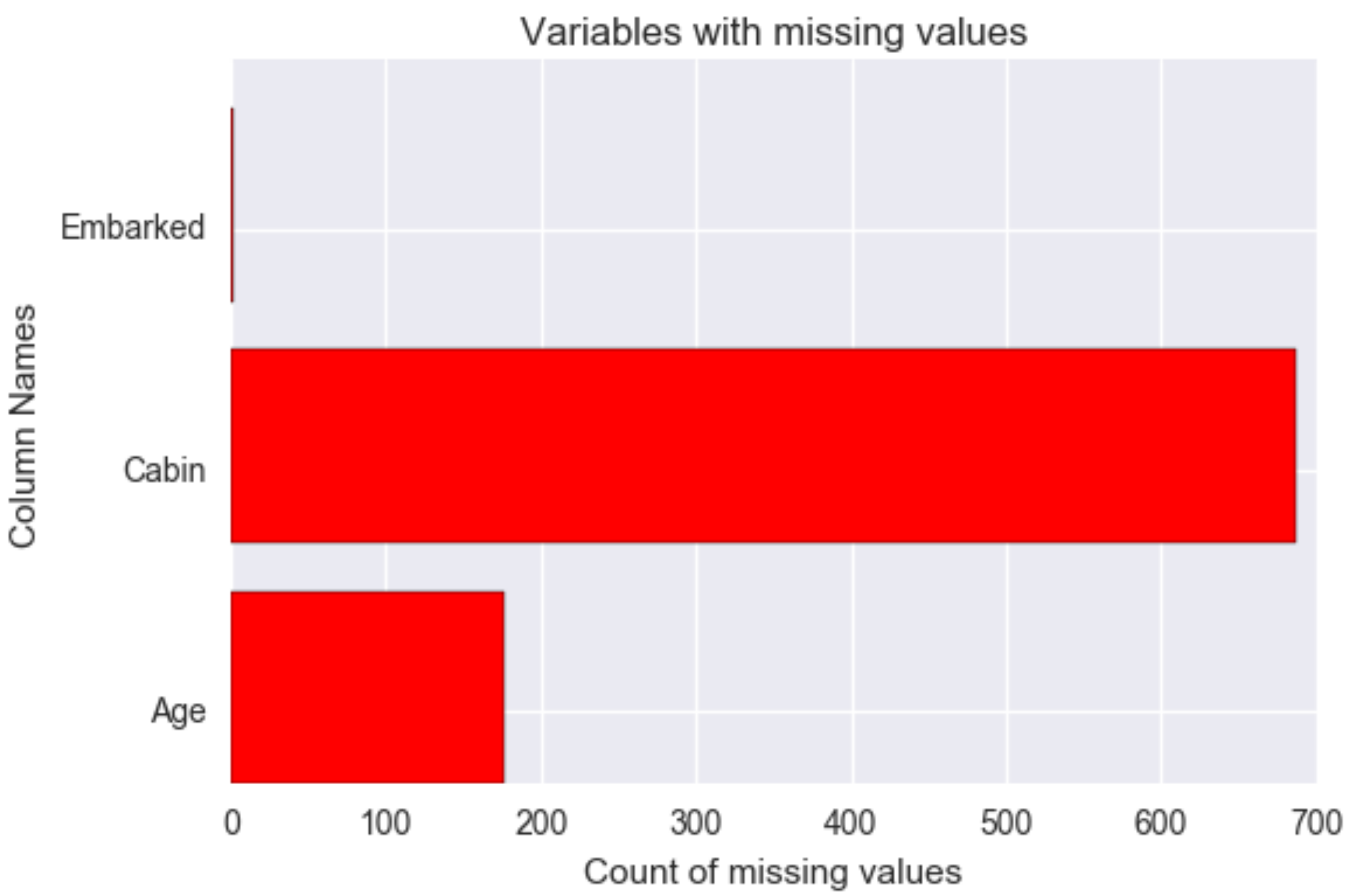
```
null_columns=ti_train_df.columns[ti_train_df.isnull().any()]
null_columns
```

Out[11]:

```
Index(['Age', 'Cabin', 'Embarked'], dtype='object')
```

In [12]:

```
sns.set(font_scale=1)
plt.style.use = 'default'
labels = []
values = []


for col in null_columns:
    labels.append(col)
    values.append(ti_train_df[col].isnull().sum())

ind = np.arange(len(labels))
width=0.6
fig, ax = plt.subplots(figsize=(6,4))
rects = ax.barh(ind, np.array(values), color='red')
ax.set_yticks(ind+((width)/2.))

ax.set_yticklabels(labels, rotation='horizontal')
ax.set_xlabel("Count of missing values")
ax.set_ylabel("Column Names")
ax.set_title("Variables with missing values");
```



The chart above shows the number of missing values in the dataset, we found that in training set we have missing values in column 'Embarked', 'Cabin', and 'Age' with amount of around 2, almost 700, and almost 200 missing values respectively.

we may want to check further on how much in percentage the missing values are.

In [13]:

```
ti_train_df.isnull().sum() /891
```

Out[13]:

```
PassengerId    0.000000
Survived       0.000000
Pclass         0.000000
Name           0.000000
Sex            0.000000
Age            0.198653
SibSp          0.000000
Parch          0.000000
Ticket         0.000000
Fare           0.000000
Cabin          0.771044
Embarked       0.002245
dtype: float64
```

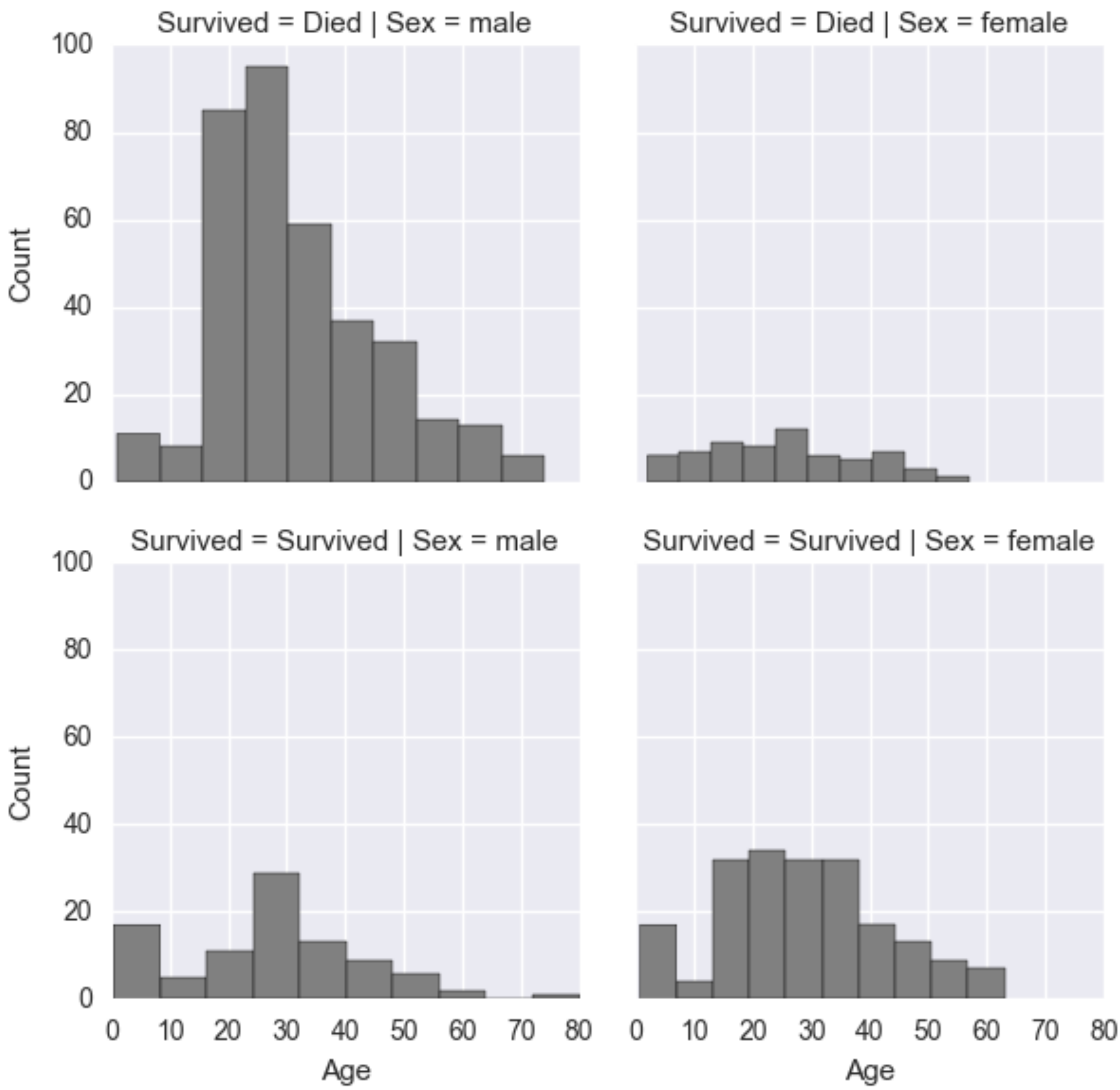
As we can see that the missing values for Age is 19.86%, Cabin 77% , and embarked 0.2%.

- For Age, we may want to do imputation process since the portion is substantial but i think might be one of the important factor on survivability, so its not good to drop the column. there are several ways to input the Age, which is using the most common age, the mean age, or we can also use machine learning to predict the age for the certain person. In this case I will perform Random Forest to predict missing ages
- For Cabin, majority of the records are missing values, so I want to drop the cabin later on. But I will keep it for a while to analyze was cabin location actually affect the survivability by analyzing only the passenger that have cabin records.
- For embarked it has only 2 missing values, we can fill this by imputing the common value of Embarked.

2.3 Survival By Sex

In [14]:

```
ti_train_df['Survived'].replace({0:'Died', 1:'Survived'}, inplace=True)
g = sns.FacetGrid(ti_train_df, col="Sex", row="Survived")
g.map(plt.hist, "Age",color="grey")
g.set_axis_labels("Age", "Count");
```



we can see here that actually female higher survival rate compared by men. The proportion of female who survived is larger that female who did not survive. We can also see age less than 10, then men age around 20-30, women 20-40 also have higher rate of survivability

2.4 Survival By Age

In [15]:

```
ax = sns.boxplot(x="Survived", y="Age",
                data=ti_train_df)
ax = sns.stripplot(x="Survived", y="Age",
                   data=ti_train_df, jitter=True,
                   edgecolor="gray")
plt.title("Survival by Age",fontsize=12);
```

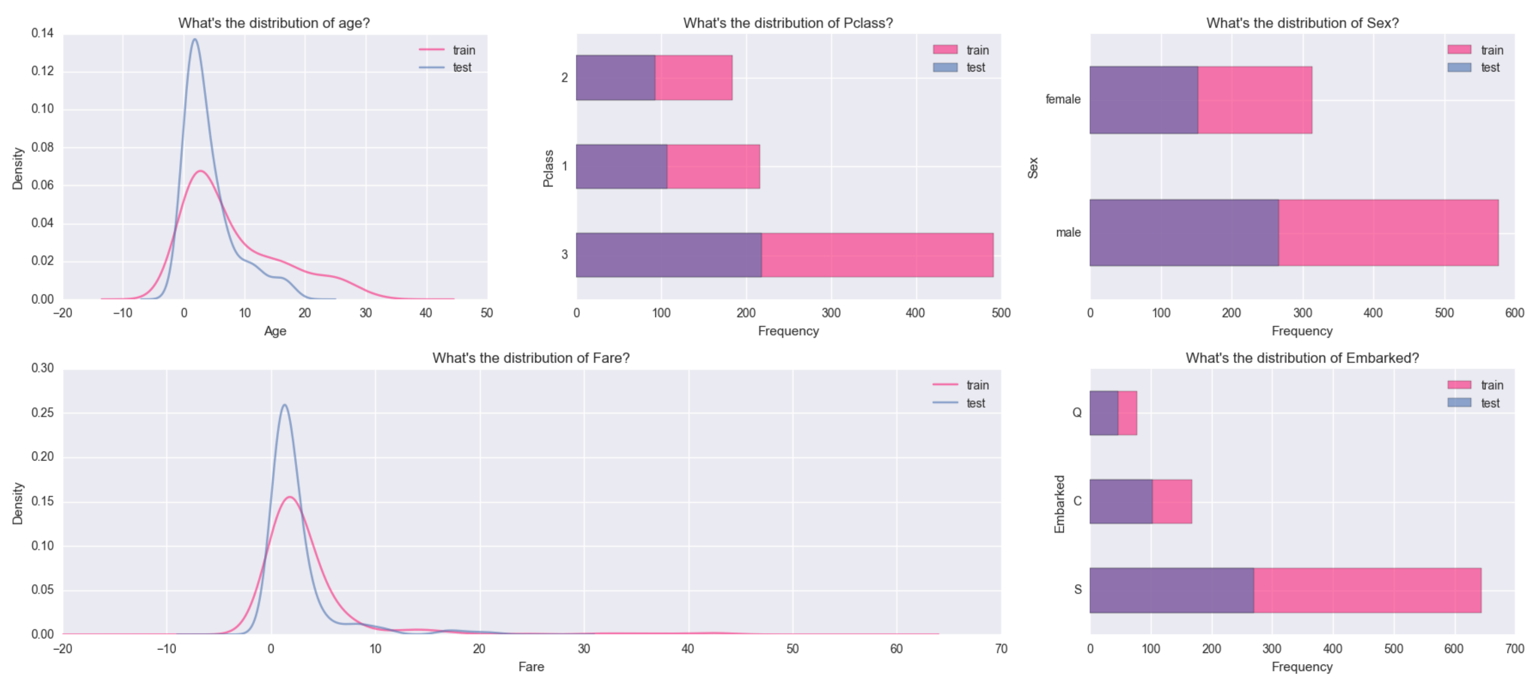
We can see here that females are more likely to survive compared by males, and most of the survived males are the one who are in productive age range 25-30 , and as for female the distribution arequite even deom 15 to 40, then the survival number drops after age 40, and below 20

2.5 Explore more...

In [16]:

```
plt.rc('font', size=13)
fig = plt.figure(figsize=(18, 8))
alpha = 0.6

ax1 = plt.subplot2grid((2,3), (0,0))
ti_train_df.Age.value_counts().plot(kind='kde', color='#FA2379', label='train', a
ti_test_df.Age.value_counts().plot(kind='kde', label='test', alpha=alpha)
ax1.set_xlabel('Age')
ax1.set_title("What's the distribution of age?" )
plt.legend(loc='best')

ax2 = plt.subplot2grid((2,3), (0,1))
ti_train_df.Pclass.value_counts().plot(kind='barh', color='#FA2379', label='train
ti_test_df.Pclass.value_counts().plot(kind='barh', label='test', alpha=alpha)
```

```
ti_test_df.Pclass.value_counts().plot(kind='barh', label='test', alpha=alpha)
ax2.set_ylabel('Pclass')
ax2.set_xlabel('Frequency')
ax2.set_title("What's the distribution of Pclass?" )
plt.legend(loc='best')

ax3 = plt.subplot2grid((2,3), (0,2))
ti_train_df.Sex.value_counts().plot(kind='barh', color='#FA2379', label='train',
ti_test_df.Sex.value_counts().plot(kind='barh', label='test', alpha=alpha)
ax3.set_ylabel('Sex')
ax3.set_xlabel('Frequency')
ax3.set_title("What's the distribution of Sex?" )
plt.legend(loc='best')

ax4 = plt.subplot2grid((2,3), (1,0), colspan=2)
ti_train_df.Fare.value_counts().plot(kind='kde', color='#FA2379', label='train',
ti_test_df.Fare.value_counts().plot(kind='kde', label='test', alpha=alpha)
ax4.set_xlabel('Fare')
ax4.set_title("What's the distribution of Fare?" )
plt.legend(loc='best')

ax5 = plt.subplot2grid((2,3), (1,2))
ti_train_df.Embarked.value_counts().plot(kind='barh', color='#FA2379', label='tra
ti_test_df.Embarked.value_counts().plot(kind='barh', label='test', alpha=alpha)
ax5.set_ylabel('Embarked')
ax5.set_xlabel('Frequency')
ax5.set_title("What's the distribution of Embarked?" )
plt.legend(loc='best')
plt.tight_layout()
```



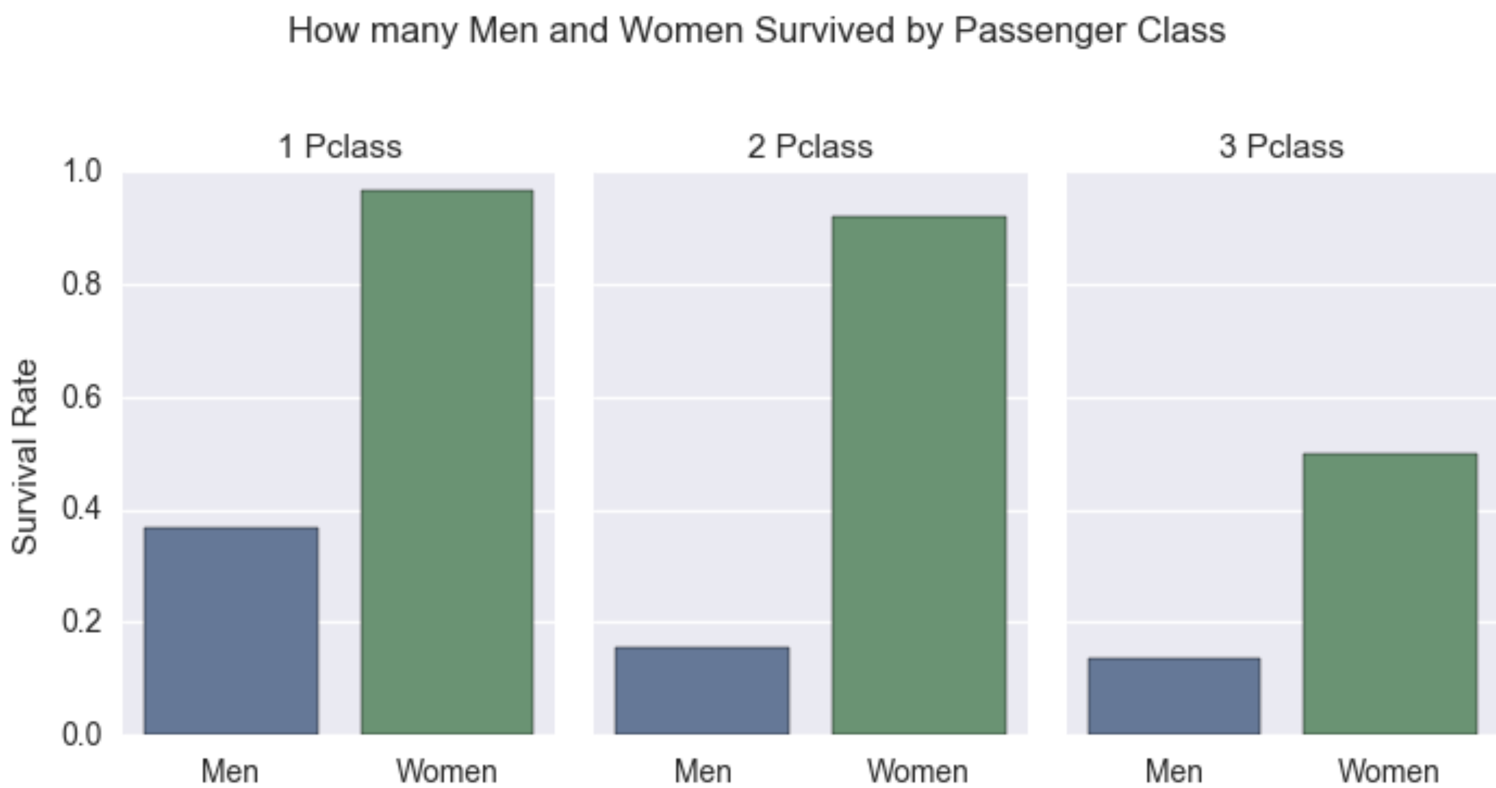
This shows the distribution of the test set and train set, as we can see there's not much difference from train set and test set distribution.

In [17]:

```
ti_train_df['Survived'].replace({'Died':0,'Survived':1}, inplace=True)
```

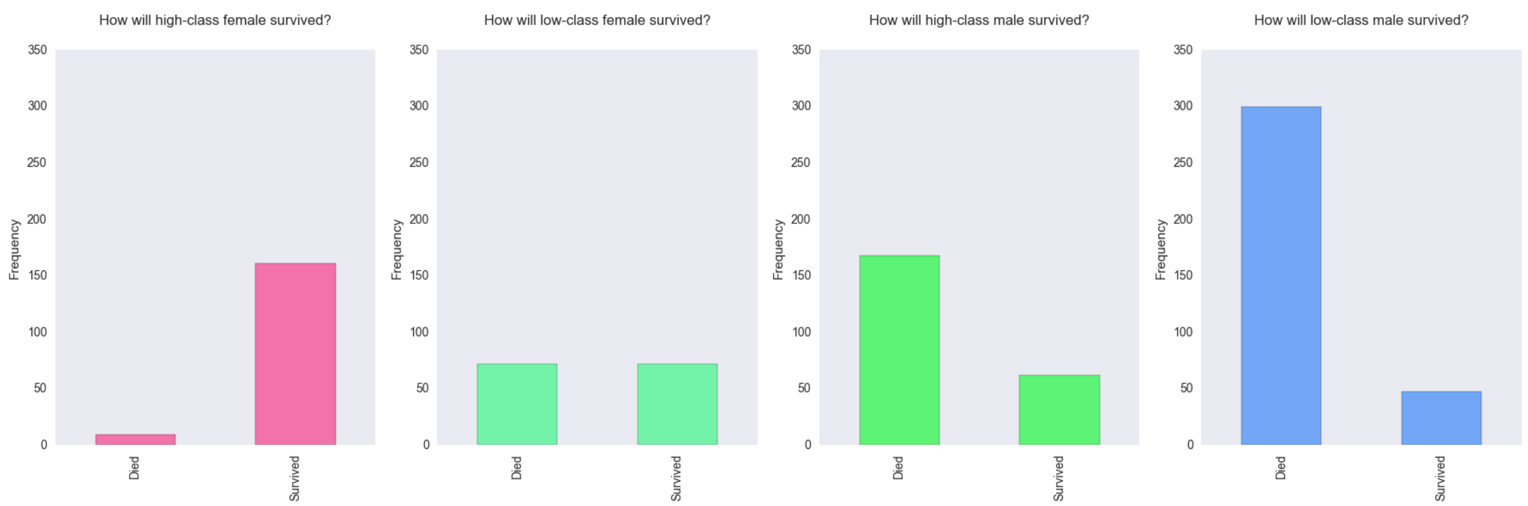
In [18]:

```
sns.set(font_scale=1)
g = sns.factorplot(x="Sex", y="Survived", col="Pclass",
                    data=ti_train_df, saturation=.5,
                    kind="bar", ci=None, aspect=.6)
(g.set_axis_labels("", "Survival Rate")
    .set_xticklabels(["Men", "Women"])
    .set_titles("{col_name} {col_var}")
    .set(ylim=(0, 1))
    .despine(left=True))
plt.subplots_adjust(top=0.8)
g.fig.suptitle('How many Men and Women Survived by Passenger Class');
```



In [19]:

```
df_male = ti_train_df[ti_train_df.Sex=='male']
df_female = ti_train_df[ti_train_df.Sex=='female']
fig = plt.figure(figsize=(18, 6))

ax1 = plt.subplot2grid((1,4), (0,0))
df_female[df_female.Pclass<3].Survived.value_counts().sort_index().plot(kind='bar
ax1.set_ylabel('Frequency')
ax1.set_ylim((0,350))
ax1.set_xticklabels(['Died', 'Survived'])
ax1.set_title("How will high-class female survived?", y=1.05)
plt.grid()

ax2 = plt.subplot2grid((1,4), (0,1))
df_female[df_female.Pclass==3].Survived.value_counts().sort_index().plot(kind='ba
ax2.set_ylabel('Frequency')
ax2.set_ylim((0,350))
ax2.set_xticklabels(['Died', 'Survived'])
ax2.set_title("How will low-class female survived?", y=1.05)
plt.grid()

ax3 = plt.subplot2grid((1,4), (0,2))
df_male[df_male.Pclass<3].Survived.value_counts().sort_index().plot(kind='bar', c
ax3.set_ylabel('Frequency')
ax3.set_ylim((0,350))
ax3.set_xticklabels(['Died', 'Survived'])
ax3.set_title("How will high-class male survived?", y=1.05)
plt.grid()

ax4 = plt.subplot2grid((1,4), (0,3))
df_male[df_male.Pclass==3].Survived.value_counts().sort_index().plot(kind='bar',
ax4.set_ylabel('Frequency')
ax4.set_ylim((0,350))
ax4.set_xticklabels(['Died', 'Survived'])
ax4.set_title("How will low-class male survived?", y=1.05)
plt.grid()
plt.tight_layout()
```



Here we can see good insight that actually High Class female has the highest survivability among all, and most of the low class male did not survive.

This gives stronger lead that age and class might be a good predictor for survivability.

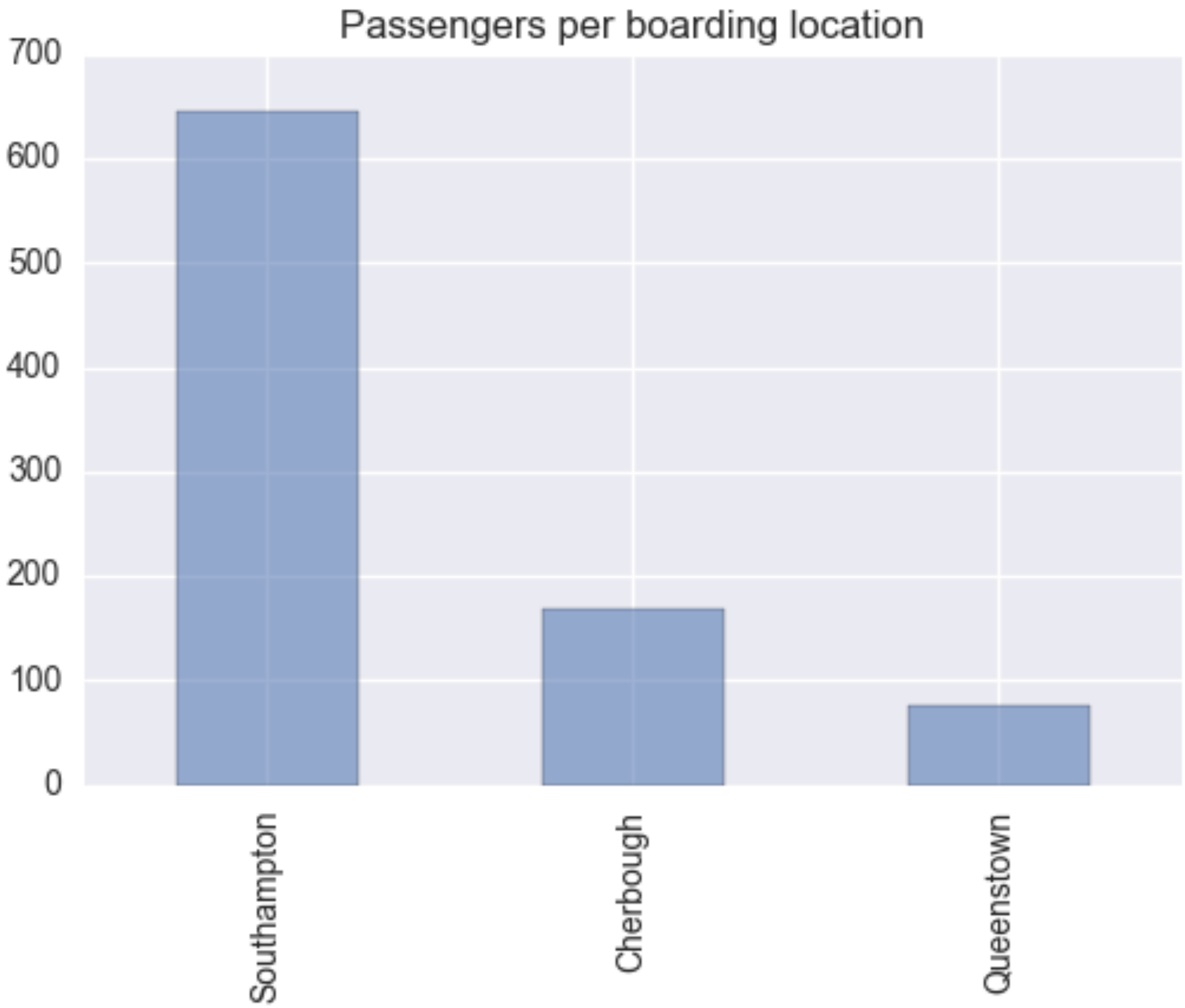
2.6 Embarked

In [20]:

```
ti_train_df['Embarked'].replace({'S' : 'Southampton','Q':'Queenstown', 'C':'Cherb
```

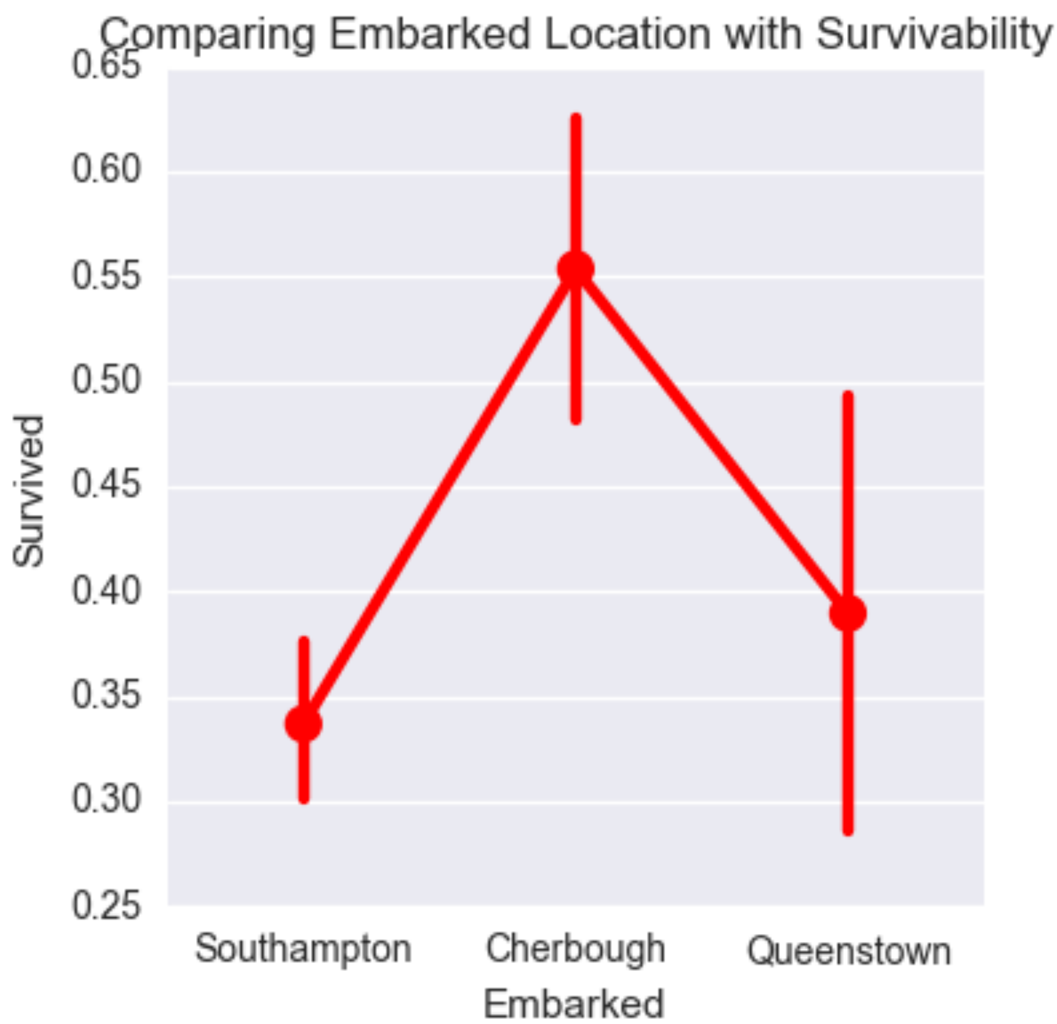
In [21]:

```
ti_train_df.Embarked.value_counts().plot(kind='bar', alpha=0.55)
plt.title("Passengers per boarding location");
```



In [22]:

```
sns.factorplot(x = 'Embarked',y="Survived", data = ti_train_df,color="r")
plt.title('Comparing Embarked Location with Survivability');
```



Suprisingly, we found that most passenger came embarked from Southampton, but apparently they have low rate of survivability. In contrast, passengers who embarked from Cherbough have higher survivability rate.

2.7 Fare

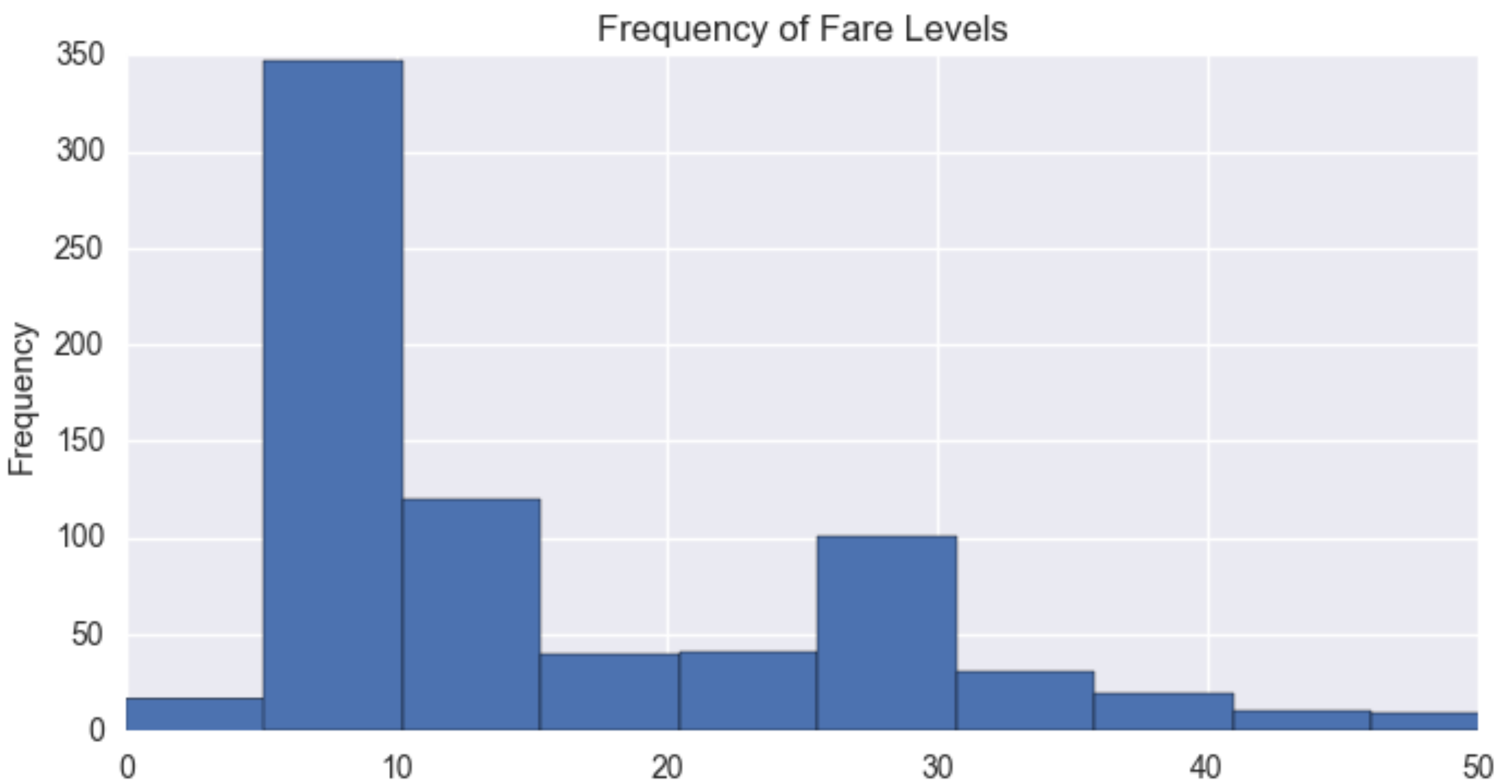
In [23]:

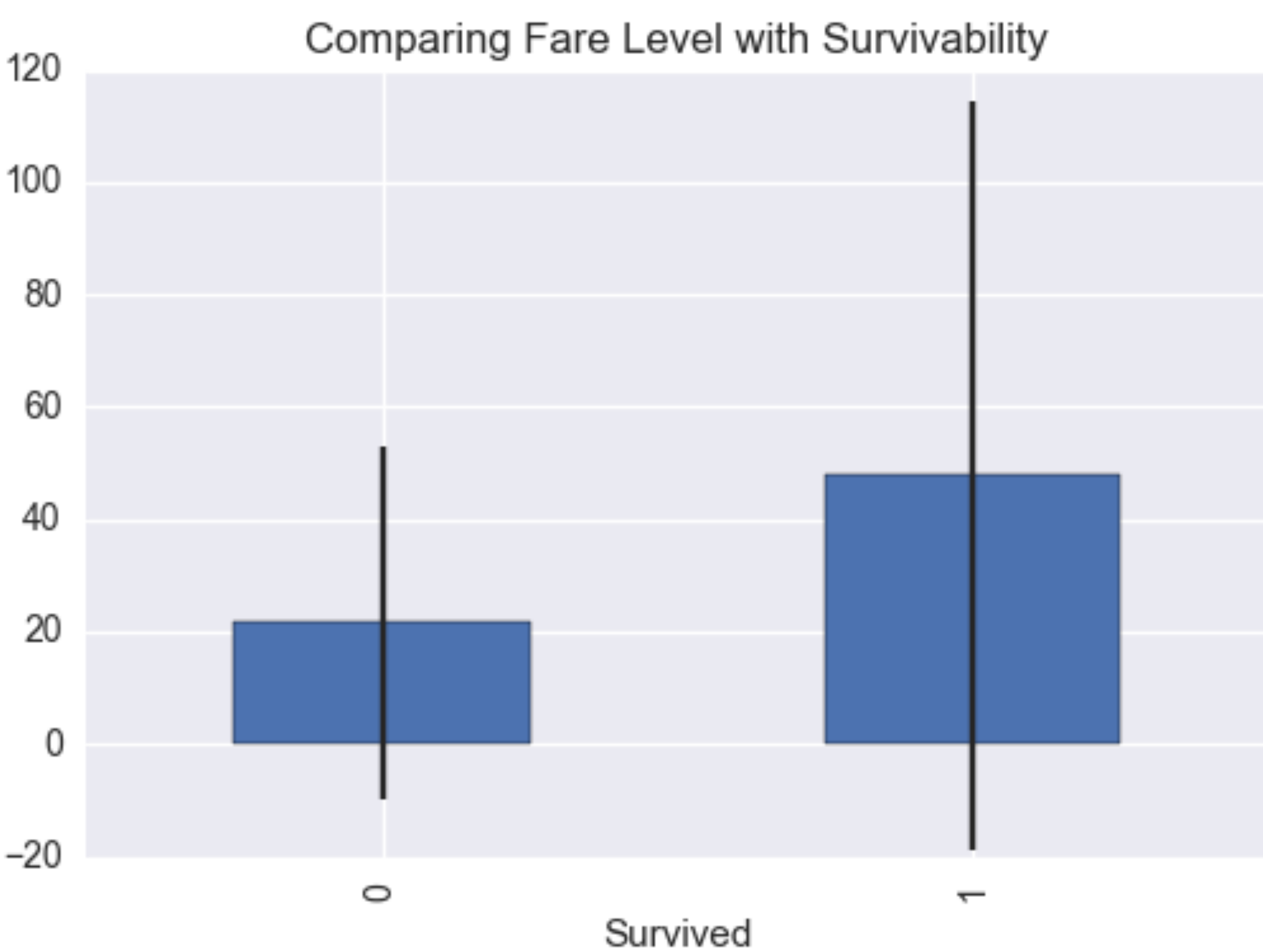
```
# Fare

# only for test_df, since there is a missing "Fare" values
ti_test_df["Fare"].fillna(ti_test_df["Fare"].median(), inplace=True)

# convert from float to int
ti_train_df['Fare'] = ti_train_df['Fare'].astype(int)
ti_test_df['Fare']    =ti_test_df['Fare'].astype(int)

# get fare for survived & didn't survive passengers
fare_not_survived = ti_train_df["Fare"][ti_train_df["Survived"] == 0]
fare_survived     = ti_train_df["Fare"][ti_train_df["Survived"] == 1]

# get average and std for fare of survived/not survived passengers
avgerage_fare = DataFrame([fare_not_survived.mean(), fare_survived.mean()])
std_fare      = DataFrame([fare_not_survived.std(), fare_survived.std()])
```

```
# plot
ti_train_df['Fare'].plot(kind='hist', figsize=(8,4),bins=100, xlim=(0,50))
plt.title('Frequency of Fare Levels')
avgerage_fare.index.names = std_fare.index.names = ["Survived"]



avgerage_fare.plot(yerr=std_fare,kind='bar',legend=False)
plt.title('Comparing Fare Level with Survivability')
```

Out[23]:

<matplotlib.text.Text at 0x114351c18>





We can't see much differences between fare and survivability. while mostly non-survivor have low fare. The degree of survivor itself have ranging fare between 0-50. This means higher fare passenger have more degree of survivor itself have ranging fare between 0-50. This means higher fare passenger have more likelihood to survive (0 means not survived, 1 means survived)

2.8 Age

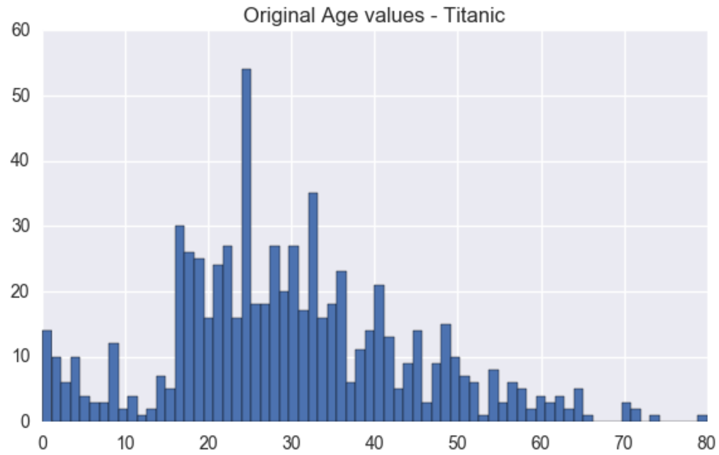
First we will conduct imputation

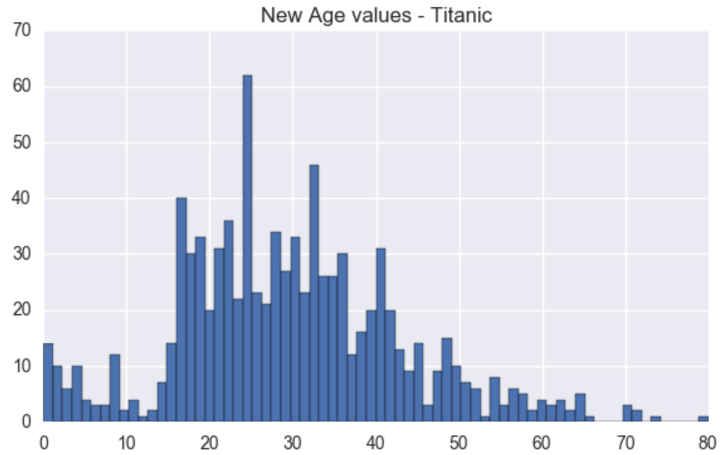
In [24]:

```
# Age

fig, (axis1,axis2) = plt.subplots(1,2,figsize=(15,4))
axis1.set_title('Original Age values - Titanic')
axis2.set_title('New Age values - Titanic')

# axis3.set_title('Original Age values - Test')
# axis4.set_title('New Age values - Test')

# get average, std, and number of NaN values in titanic_df
average_age_titanic   = ti_train_df["Age"].mean()
std_age_titanic       = ti_train_df["Age"].std()
count_nan_age_titanic = ti_train_df["Age"].isnull().sum()

# get average, std, and number of NaN values in test_df
average_age_test   = ti_test_df["Age"].mean()
std_age_test       = ti_test_df["Age"].std()
count_nan_age_test = ti_test_df["Age"].isnull().sum()

# generate random numbers between (mean - std) & (mean + std)
rand_1 = np.random.randint(average_age_titanic - std_age_titanic, average_age_tit
rand_2 = np.random.randint(average_age_test - std_age_test, average_age_test + st

# plot original Age values
# NOTE: drop all null values, and convert to int
ti_train_df['Age'].dropna().astype(int).hist(bins=70, ax=axis1)
# test_df['Age'].dropna().astype(int).hist(bins=70, ax=axis1)

# fill NaN values in Age column with random values generated
ti_train_df["Age"][np.isnan(ti_train_df["Age"])] = rand_1
ti_test_df["Age"][np.isnan(ti_test_df["Age"])] = rand_2

# convert from float to int
ti_train_df['Age'] = ti_train_df['Age'].astype(int)
ti_test_df['Age']    = ti_test_df['Age'].astype(int)

# plot new Age Values
ti_train_df['Age'].hist(bins=70, ax=axis2)
ti_test_df['Age'].hist(bins=70, ax=axis4)
```

```
---------------------------------------------------------------------
-------
NameError                                 Traceback (most recent cal
l last)
<ipython-input-24-8ec1598b981b> in <module>()
     37 # plot new Age Values
     38 ti_train_df['Age'].hist(bins=70, ax=axis2)
```

```
---> 39 ti_test_df['Age'].hist(bins=70, ax=axis4)

NameError: name 'axis4' is not defined
```





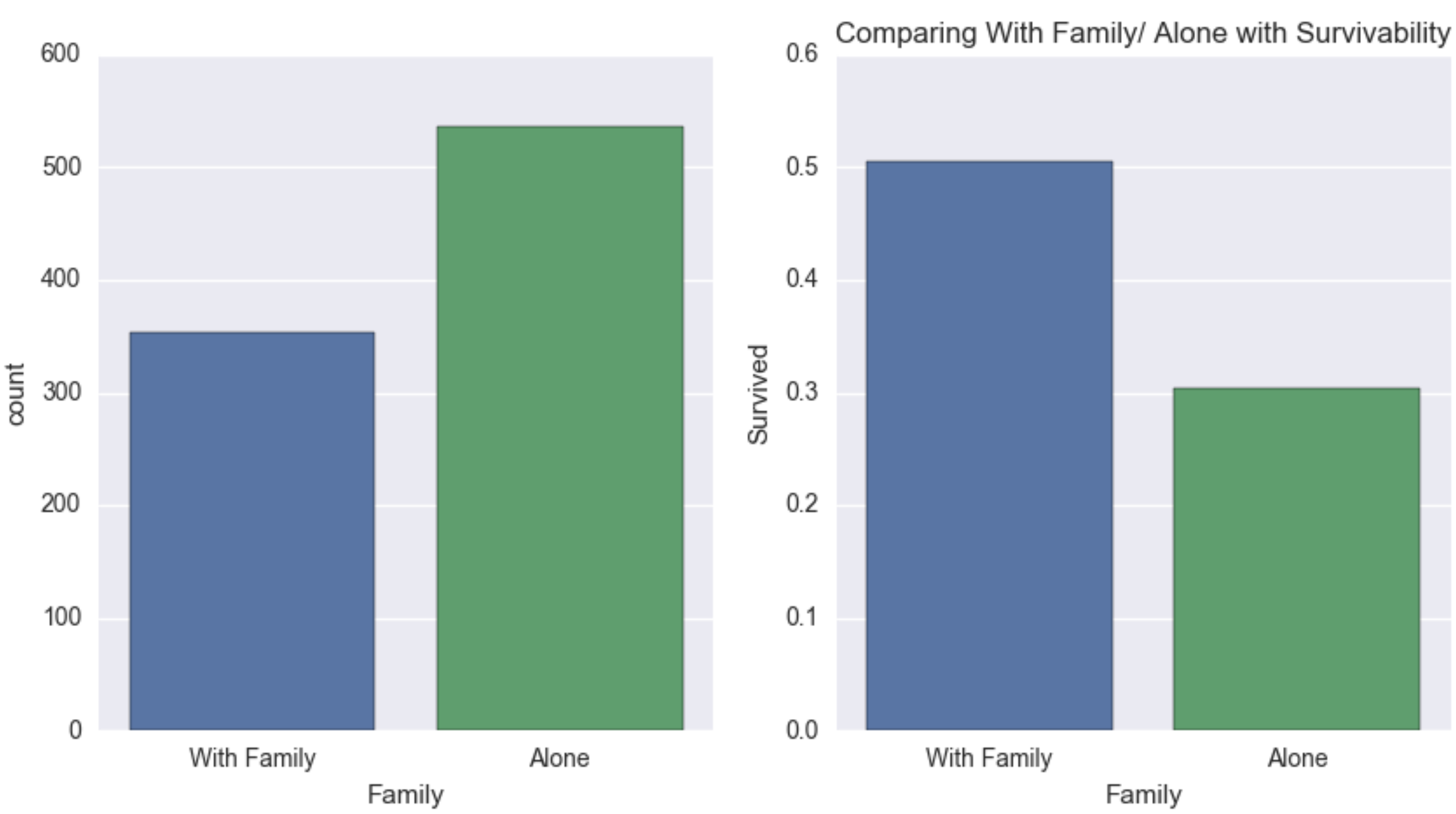
2.9 Family

In [25]:

```
# Family

# Instead of having two columns Parch & SibSp,
# we can have only one column represent if the passenger had any family member ab
# Meaning, if having any family member(whether parent, brother, ...etc) will incr
ti_train_df['Family'] =  ti_train_df["Parch"] + ti_train_df["SibSp"]
ti_train_df['Family'].loc[ti_train_df['Family'] > 0] = 1
ti_train_df['Family'].loc[ti_train_df['Family'] == 0] = 0

ti_test_df['Family'] =  ti_test_df["Parch"] + ti_test_df["SibSp"]
ti_test_df['Family'].loc[ti_test_df['Family'] > 0] = 1
ti_test_df['Family'].loc[ti_test_df['Family'] == 0] = 0

# plot
fig, (axis1,axis2) = plt.subplots(1,2,sharex=True,figsize=(10,5))

# sns.factorplot('Family',data=ti_train_df,kind='count',ax=axis1)
sns.countplot(x='Family', data=ti_train_df, order=[1,0], ax=axis1)


# average of survived for those who had/didn't have any family member
family_perc = ti_train_df[["Family", "Survived"]].groupby(['Family'],as_index=Fal
sns.barplot(x='Family', y='Survived', data=family_perc, order=[1,0], ax=axis2)
plt.title('Comparing With Family/ Alone with Survivability')
axis1.set_xticklabels(["With Family","Alone"], rotation=0)
```

Out[25]:

```
[<matplotlib.text.Text at 0x1143c2278>, <matplotlib.text.Text at 0x1
152486d8>]
```



if you want to drop family sibs and parch columns, use this:

drop Parch & SibSp

ti_train_df = ti_train_df.drop(['SibSp','Parch'], axis=1) test_df = test_df.drop(['SibSp','Parch'], axis=1)

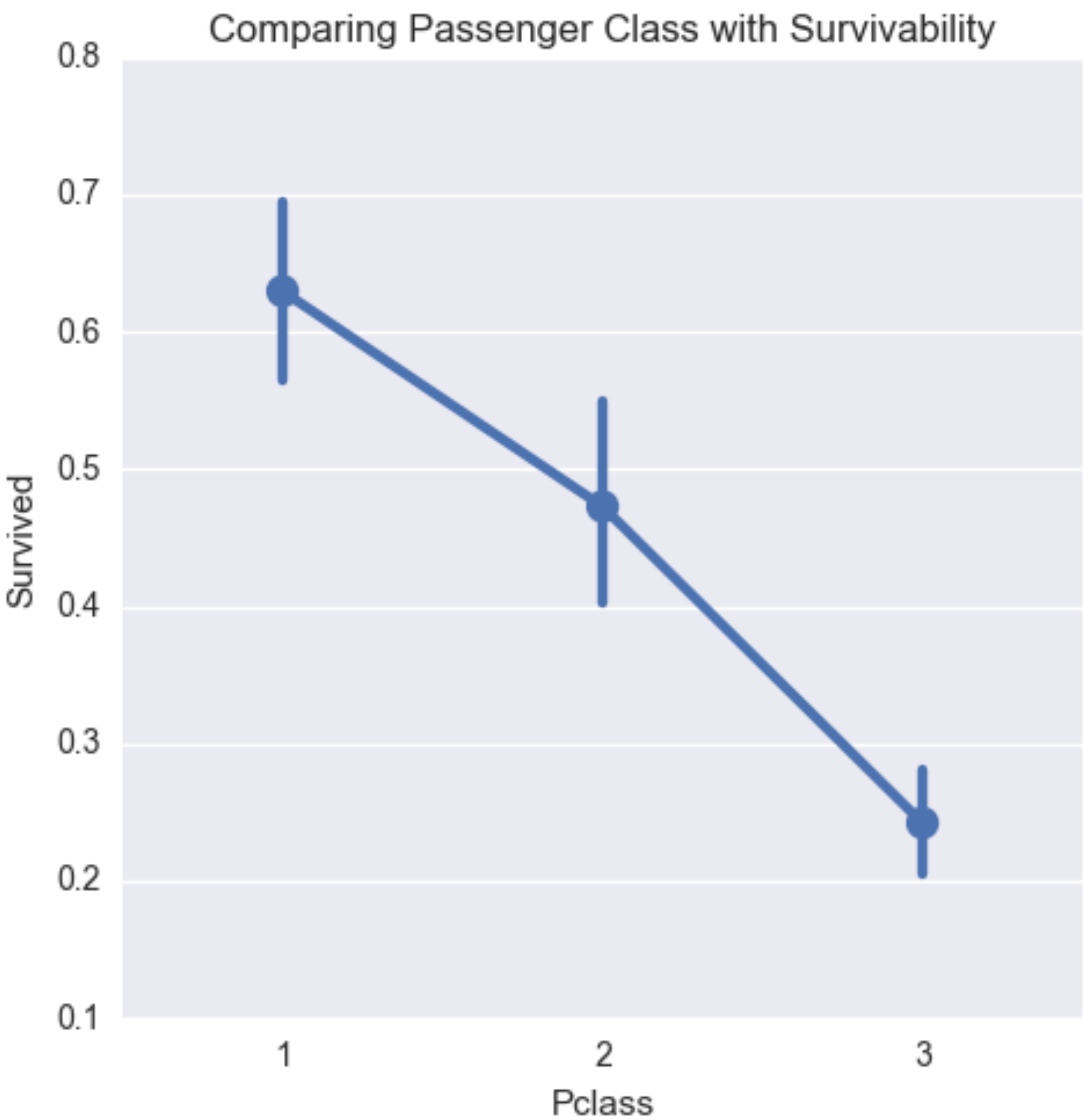
2.1 PClass

In [26]:

```
# Pclass

# sns.factorplot('Pclass',data=titanic_df,kind='count',order=[1,2,3])
sns.factorplot('Pclass','Survived',order=[1,2,3], data=ti_train_df,size=5)
plt.title('Comparing Passenger Class with Survivability')
```

Out[26]:

```
<matplotlib.text.Text at 0x116ab9470>
```



We can see that level 1 passenger class have higher survivability rate compared the other 2 pclass. The asumption is the higher the passenger class, they will get better treatment and more priority of safety.

In [27]:

```
#correlation of features with target variable
ti_train_df.corr()["Survived"]
```

Out[27]:

```
PassengerId   -0.005007
Survived       1.000000
Pclass        -0.338481
Age           -0.074070
SibSp         -0.035322
Parch          0.081629
Fare           0.257482
Family         0.203367
Name: Survived, dtype: float64
```

Step 3 Data CLEANING

Examine how many values missing in BOTH Dataset

In [28]:

```
ti_train_df.isnull().sum()
```

Out[28]:

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

In [29]:

```
ti_test_df.isnull().sum()
```

Out[29]:

```
PassengerId      0
Pclass           0
Name             0
Sex              0
Age              0
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          327
Embarked         0
Family           0
dtype: int64
```

Missing Values on Embarked

In [30]:

```
#Lets check which rows have null Embarked column
ti_train_df[ti_train_df['Embarked'].isnull()]
```

Out[30]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
61	62	1	1	Icard, Miss. Amelie	female	38	0	0	113572	80	B28
829	830	1	1	Stone, Mrs. George Nelson (Martha Evelyn)	female	62	0	0	113572	80	B28

In [31]:

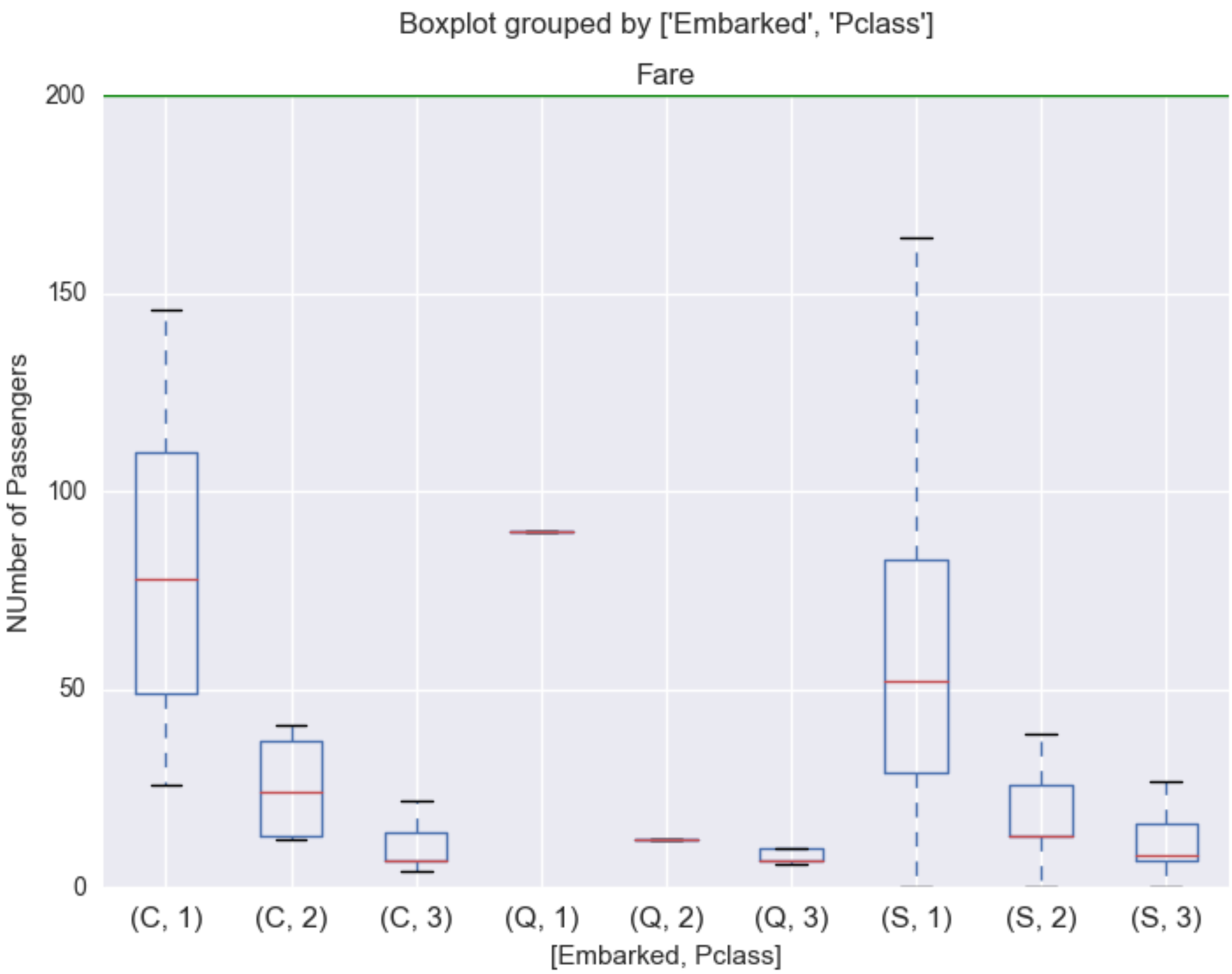
```
ti_train_df['Embarked'].replace({'Southampton':'S','Queenstown':'Q', 'Cherbough':
```

In [32]:

```
fig = plt.figure(figsize=(8, 6))
ax = fig.add_subplot(111)
ax = ti_train_df.boxplot(column='Fare', by=['Embarked','Pclass'], ax=ax)
plt.ylim(0,200)
plt.axhline(y=200, color='green')
plt.ylabel('NUmber of Passengers')
ti_train_df[ti_train_df.Embarked.isnull()][['Fare', 'Pclass', 'Embarked']]
```

Out[32]:

	Fare	Pclass	Embarked
61	80	1	NaN
829	80	1	NaN



From the above boxplot, we should replace NA with C because most people who had Pclass 1 and Fare 80 would be Embarked C

In [33]:

```
_ = ti_train_df.set_value(ti_train_df.Embarked.isnull(), 'Embarked', 'C')
```

Missing Values on Fare

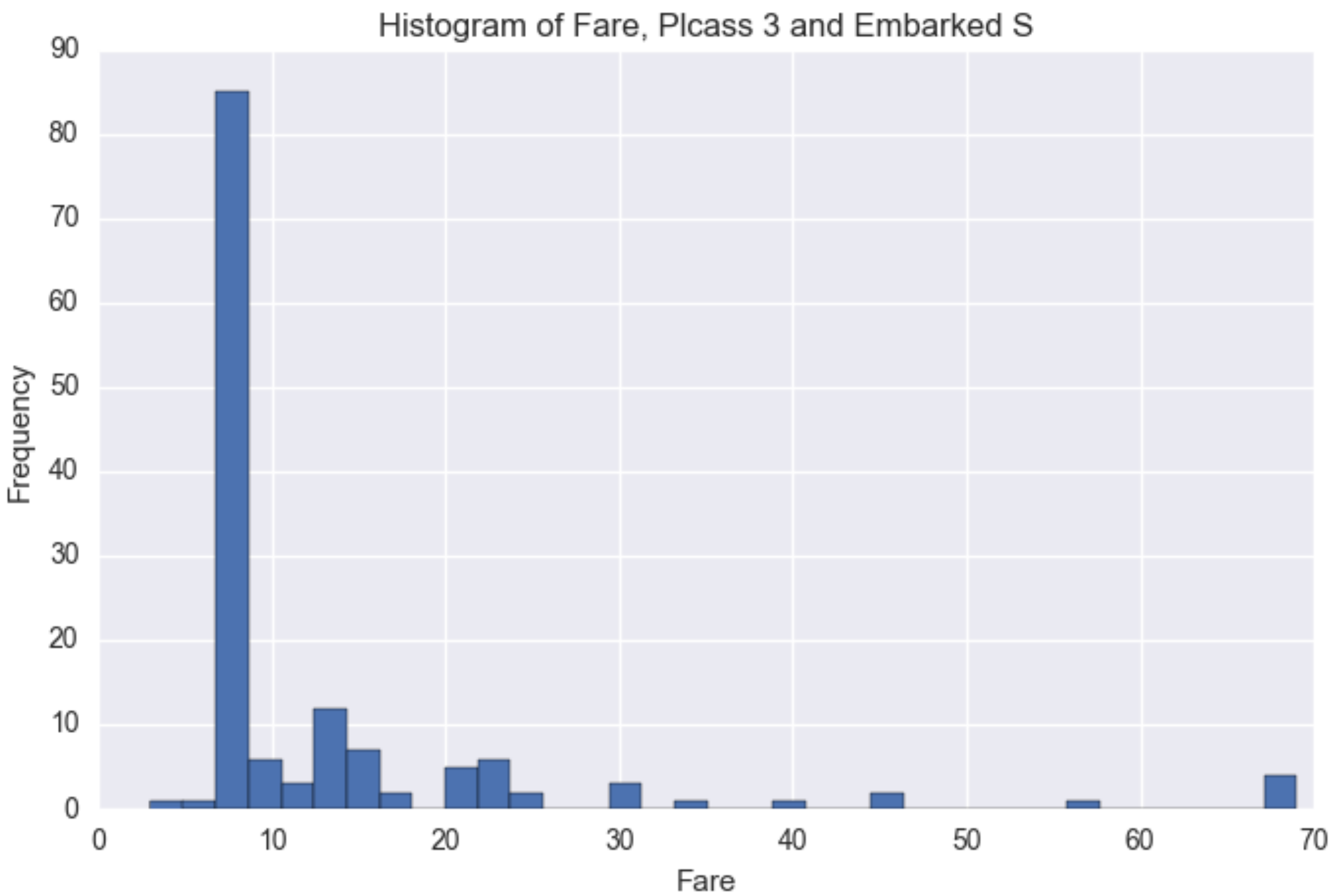
By fixing the values of Embarked and Pclass, we could plot histogram of Fare. And we should use the most common value to replace the NA value of Fare.

In [34]:

```
fig = plt.figure(figsize=(8, 5))
ax = fig.add_subplot(111)
ti_test_df[(ti_test_df.Pclass==3)&(ti_test_df.Embarked=='S')].Fare.hist(bins=35,
ti_test_df[ti_test_df.Fare.isnull()][['Pclass', 'Fare', 'Embarked']]
plt.xlabel('Fare')
plt.ylabel('Frequency')
plt.title('Histogram of Fare, Plcass 3 and Embarked S')

ti_test_df[ti_test_df.Fare.isnull()][['Pclass', 'Fare', 'Embarked']]
```

Out[34]:

Pclass	Fare	Embarked



In [35]:

```
print ("The top 5 most common value of Fare")
ti_test_df[(ti_test_df.Pclass==3)&(ti_test_df.Embarked=='S')].Fare.value_counts()
```

```
The top 5 most common value of Fare
```

Out[35]:

```
7     57
8     28
14     7
9      6
13     5
Name: Fare, dtype: int64
```

In [36]:

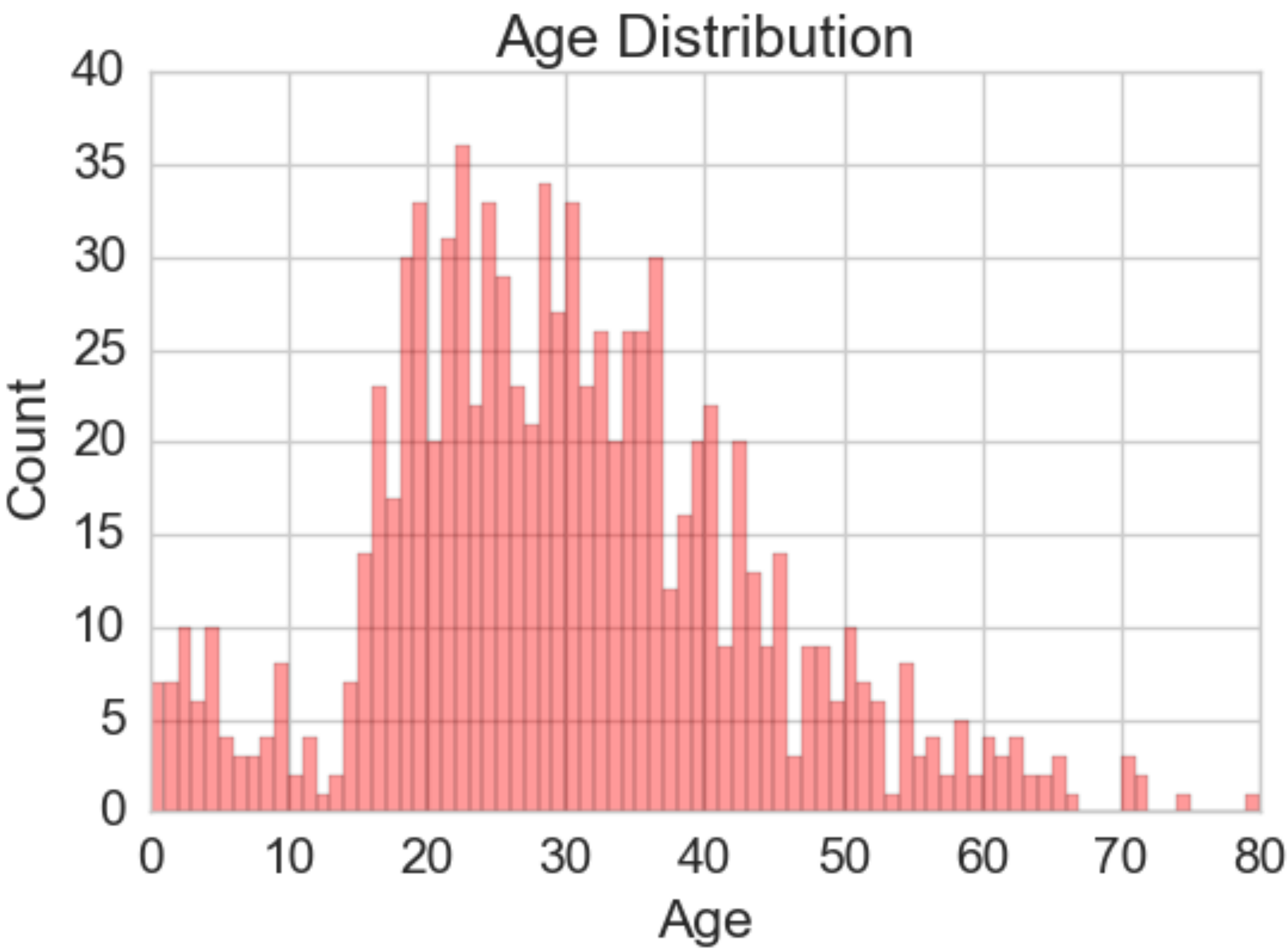
```
_ = ti_test_df.set_value(ti_test_df.Fare.isnull(), 'Fare', 8.05)
```

Age Column

Age seems to be promising feature. So it doesnt make sense to simply fill null values out with median/mean/mode. We will use Random Forest algorithm to predict ages.

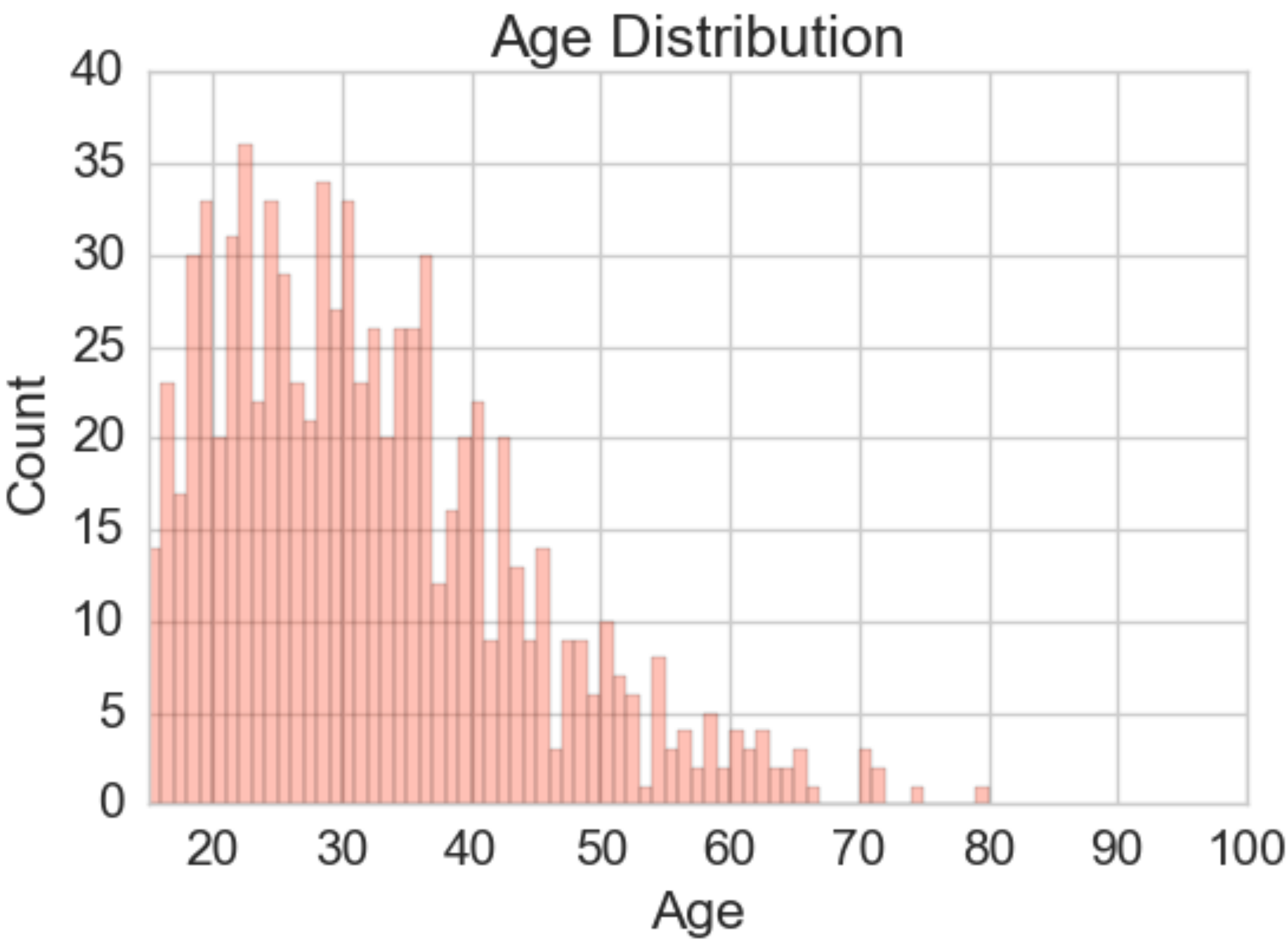
In [37]:

```
titanic = ti_train_df
titanic_test = ti_test_df

with sns.plotting_context("notebook",font_scale=1.5):
    sns.set_style("whitegrid")
    sns.distplot(titanic["Age"].dropna(),
                 bins=80,
                 kde=False,
                 color="red")
    plt.title("Age Distribution")
    plt.ylabel("Count");
```



In [38]:

```
with sns.plotting_context("notebook",font_scale=1.5):
    sns.set_style("whitegrid")
    sns.distplot(titanic["Age"].dropna(),
                 bins=80,
                 kde=False,
                 color="tomato")
    plt.title("Age Distribution")
    plt.ylabel("Count")
    plt.xlim((15,100));
```



Missing Values on Cabin

In [39]:

```
ti_train_df['Cabin'].describe()
```

Out[39]:

```
count           204
unique          147
top       C23 C25 C27
freq              4
Name: Cabin, dtype: object
```

In [40]:

```
ti_train_df['Cabin'].dropna()
```

Out[40]:

```
1              C85
3             C123
6              E46
10              G6
11            C103
21             D56
23              A6
27     C23 C25 C27
31             B78
52             D33
54             B30
55             C52
61             B28
62             C83
66             F33
75           F G73
88     C23 C25 C27
92             E31
96              A5
97         D10 D12
102            D26
110           C110
118        B58 B60
123           E101
124            D26
128          F E69
136            D47
137           C123
139            B86
148             F2
          ...
751           E121
759            B77
763        B96 B98
765            D11
772            E77
776            F38
779             B3
781            B20
782             D6
789        B82 B84
796            D17
802        B96 B98
806            A36
809             E8
815           B102
820            B69
823           E121
829            B28
835            E49
839            C47
849            C92
853            D28
857            E17
862            D17
867            A24
```

```
871              D35
872     B51 B53 B55
879              C50
887              B42
889             C148
Name: Cabin, dtype: object
```

In [41]:

```
ti_train_df[ti_train_df['Cabin']!= ' ']
```

Out[41]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Emb
0	1	0	3	Braund, Mr. Owen Harris	male	22	1	0	A/5 21171	7	NaN	
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38	1	0	PC 17599	71	C85	
2	3	1	3	Heikkinen, Miss. Laina	female	26	0	0	STON/O2. 3101282	7	NaN	
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35	1	0	113803	53	C123	
4	5	0	3	Allen, Mr. William Henry	male	35	0	0	373450	8	NaN	

We will have to deal with Cabin information n feature engineering, but most probably I'll have to drop off the Cabin information later

Step 4. FEATURE ENGINEERING

Step 4.1 FE for Exploration Purposes

4.1.1. Deck - where is the cabin located?

In [42]:

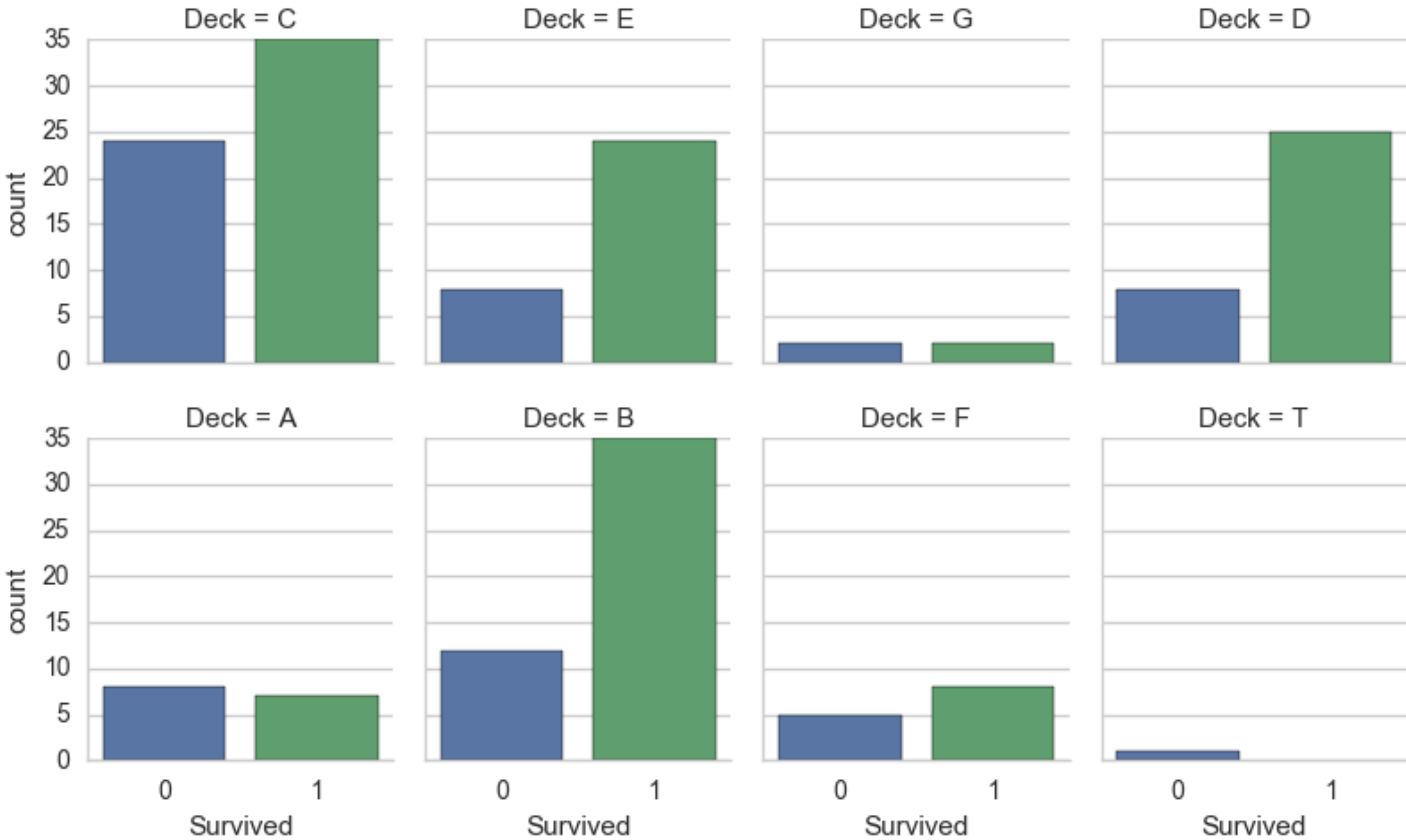
```
#taking out Cabin first letter as Deck, create a column 'Deck'
ti_train_df["Deck"]=ti_train_df.Cabin.str[0]
ti_test_df["Deck"]=ti_test_df.Cabin.str[0]
ti_train_df["Deck"].unique() # 0 is for null values
```

Out[42]:

```
array([nan, 'C', 'E', 'G', 'D', 'A', 'B', 'F', 'T'], dtype=object)
```

In [43]:

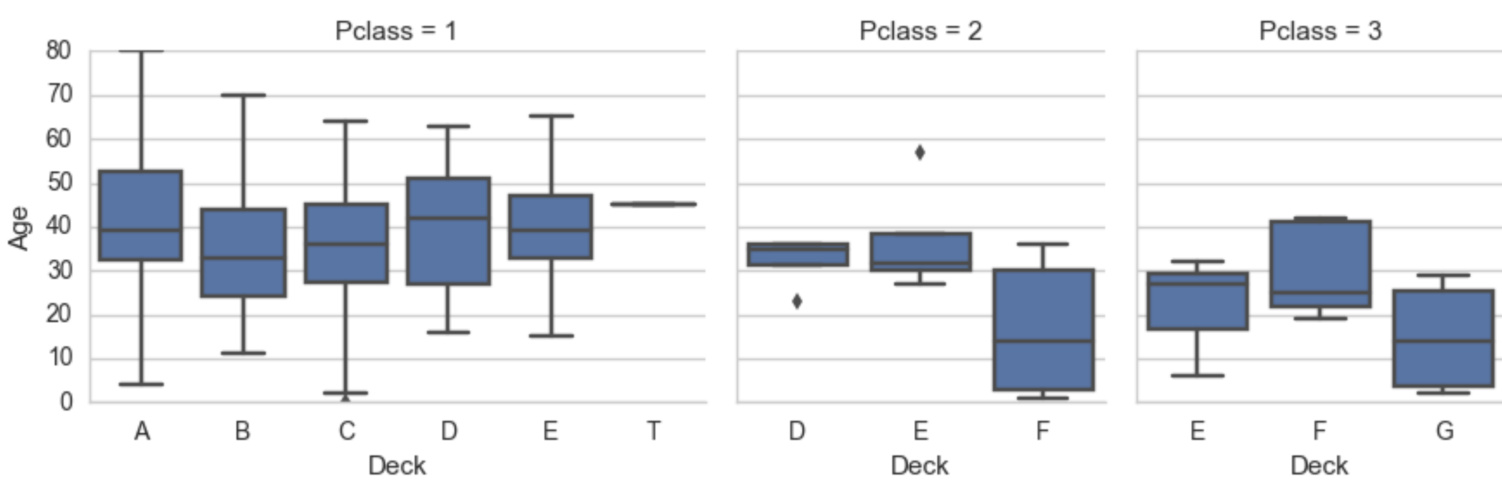
```
g = sns.factorplot("Survived", col="Deck", col_wrap=4,
                    data=ti_train_df[ti_train_df.Deck.notnull()],
                    kind="count", size=2.5, aspect=.8);
```



These charts more exploration data that actually passenger who has their deck/ cabin record have averagely more than 50% chance of survived, except of deck T. We can also see high survivarl rate from deck B, C,E& D.

In [44]:

```
titanic = ti_train_df.assign(Deck=ti_train_df.Deck.astype(object)).sort("Deck")
g = sns.FacetGrid(titanic, col="Pclass", sharex=False,
                  gridspec_kws={"width_ratios": [5, 3, 3]})
g.map(sns.boxplot, "Deck", "Age");
```



In [45]:

```
ti_train_df.Deck.fillna('Z', inplace=True)
ti_test_df.Deck.fillna('Z', inplace=True)
ti_train_df["Deck"].unique() # Z is for null values
```

Out[45]:

```
array(['Z', 'C', 'E', 'G', 'D', 'A', 'B', 'F', 'T'], dtype=object)
```

4.1.2 How Big is your family

In [46]:

```
ti_train_df.head()
```

Out[46]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Ca
0	1	0	3	Braund, Mr. Owen Harris	male	22	1	0	A/5 21171	7	N
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38	1	0	PC 17599	71	(
2	3	1	3	Heikkinen, Miss. Laina	female	26	0	0	STON/O2. 3101282	7	N
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35	1	0	113803	53	C
4	5	0	3	Allen, Mr. William Henry	male	35	0	0	373450	8	N

In [47]:

```
# Create a family size variable including the passenger themselves
ti_train_df["FamilySize"] = ti_train_df["SibSp"] + ti_train_df["Parch"]+1
ti_test_df["FamilySize"] = ti_test_df["SibSp"] +ti_test_df["Parch"]+1
print(ti_train_df["FamilySize"].value_counts())
```

```
1     537
2     161
3     102
4      29
6      22
5      15
7      12
11      7
8       6
Name: FamilySize, dtype: int64
```

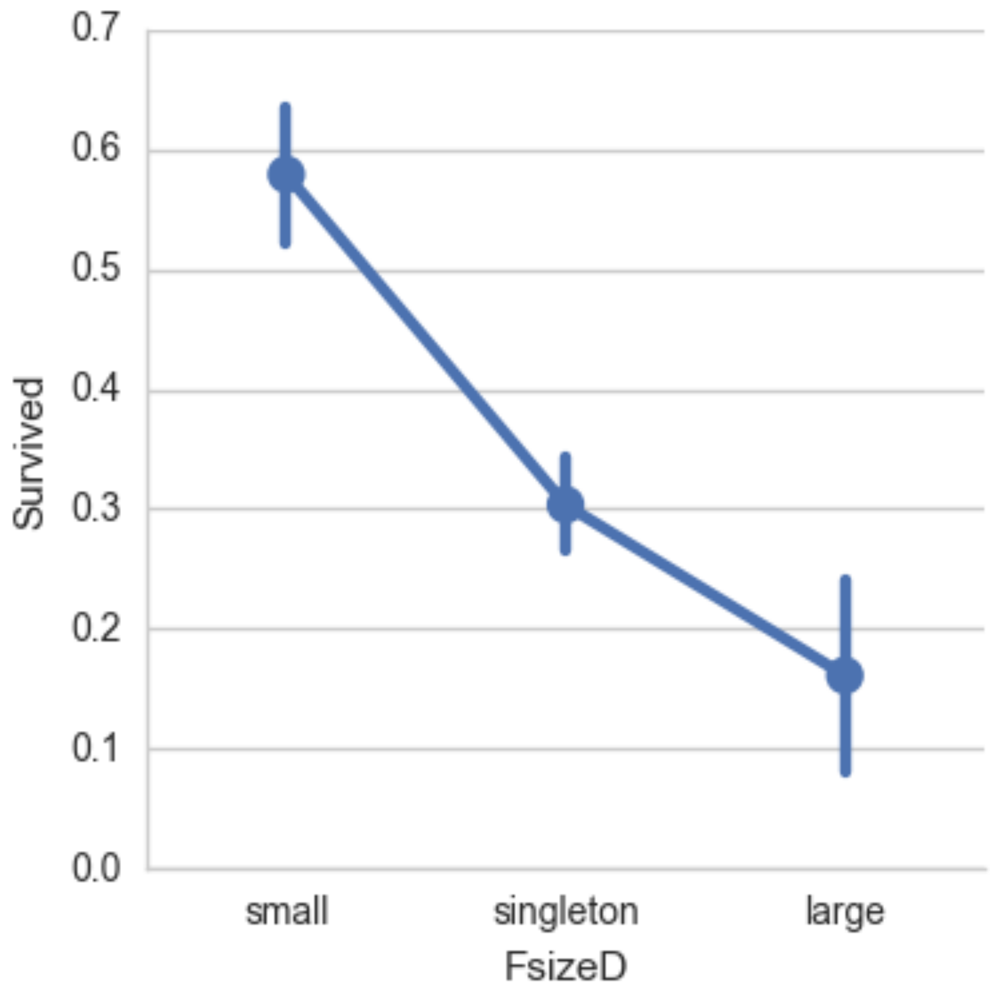
In [48]:

```
# Discretize family size
ti_train_df.loc[ti_train_df["FamilySize"] == 1, "FsizeD"] = 'singleton'
ti_train_df.loc[(ti_train_df["FamilySize"] > 1)  &  (ti_train_df["FamilySize"] <
ti_train_df.loc[ti_train_df["FamilySize"] >4, "FsizeD"] = 'large'

ti_test_df.loc[ti_test_df["FamilySize"] == 1, "FsizeD"] = 'singleton'
ti_test_df.loc[(ti_test_df["FamilySize"] >1) & (ti_test_df["FamilySize"] <5) , "F
ti_test_df.loc[ti_test_df["FamilySize"] >4, "FsizeD"] = 'large'
print(ti_train_df["FsizeD"].unique())
print(ti_train_df["FsizeD"].value_counts())
```

```
['small' 'singleton' 'large']
singleton    537
small        292
large         62
Name: FsizeD, dtype: int64
```

In [49]:

```
sns.factorplot(x="FsizeD", y="Survived", data=ti_train_df);
```



This chart shows more further that actually passenger with small family have the highest rate of survivability compared by single or have large number of family joined the trip.

4.1.3 Names- Do you have longer names?

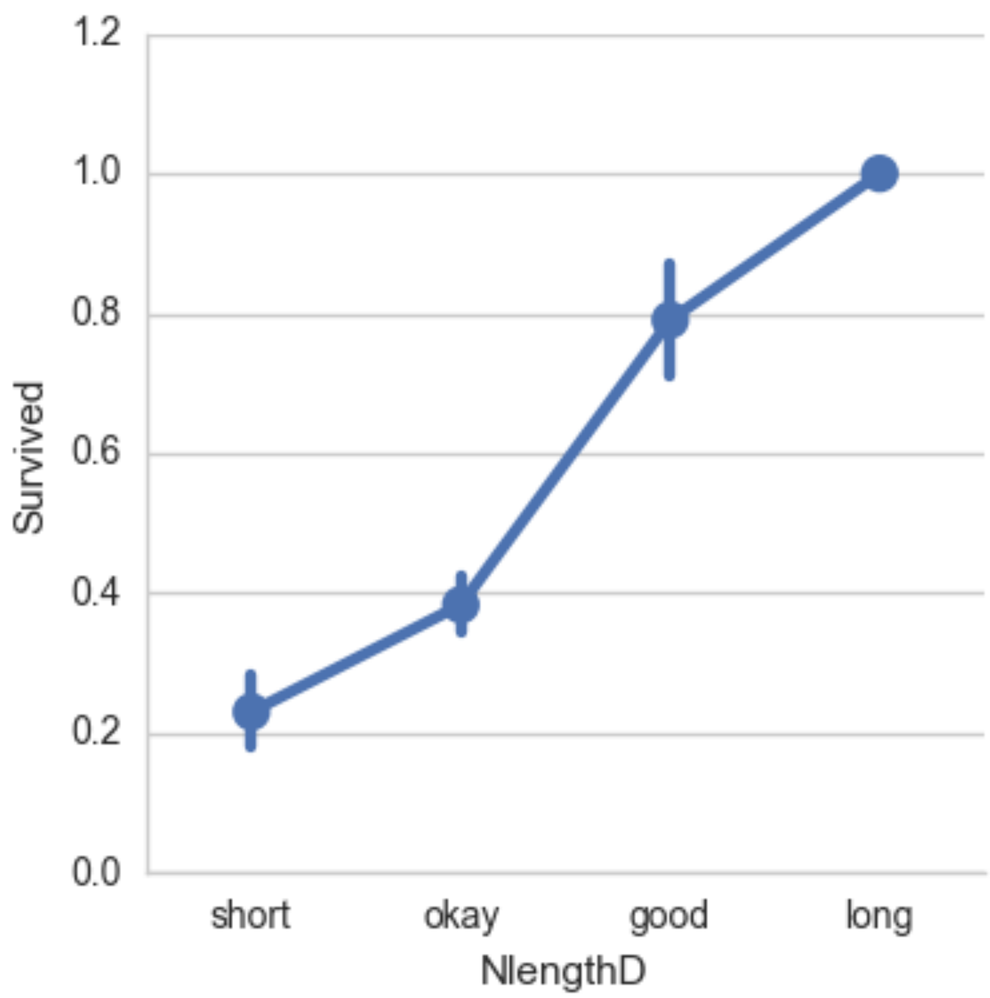
In [50]:

```
titanic = ti_train_df
titanic_test = ti_test_df
```

In [51]:

```
#Create feture for length of name
# The .apply method generates a new series
titanic["NameLength"] = titanic["Name"].apply(lambda x: len(x))

titanic_test["NameLength"] = titanic_test["Name"].apply(lambda x: len(x))
#print(titanic["NameLength"].value_counts())

bins = [0, 20, 40, 57, 85]
group_names = ['short', 'okay', 'good', 'long']
titanic['NlengthD'] = pd.cut(titanic['NameLength'], bins, labels=group_names)
titanic_test['NlengthD'] = pd.cut(titanic_test['NameLength'], bins, labels=group_

sns.factorplot(x="NlengthD", y="Survived", data=titanic)
print(titanic["NlengthD"].unique())
```

```
[okay, good, short, long]
Categories (4, object): [short < okay < good < long]
```



Surprisingly the longer the name means higher survuvability. This be true that the royalty tend to have more titles and family names, which whom might get priority over regular passenger.

4.1.4 Names- Titles

4.1.5 Ticket

In [52]:

```
titanic["Ticket"].tail()
```

Out[52]:

```
886        211536
887        112053
888    W./C. 6607
889        111369
890        370376
Name: Ticket, dtype: object
```

In [53]:

```
titanic["TicketNumber"] = titanic["Ticket"].str.extract('(\d{2,})', expand=True)
titanic["TicketNumber"] = titanic["TicketNumber"].apply(pd.to_numeric)


titanic_test["TicketNumber"] = titanic_test["Ticket"].str.extract('(\d{2,})', exp
titanic_test["TicketNumber"] = titanic_test["TicketNumber"].apply(pd.to_numeric)
```

In [54]:

```
#some rows in ticket column dont have numeric value so we got NaN there
titanic[titanic["TicketNumber"].isnull()]
```

Out[54]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Ca
179	180	0	3	Leonard, Mr. Lionel	male	36	0	0	LINE	0	N
271	272	1	3	Tornquist, Mr. William Henry	male	25	0	0	LINE	0	N
302	303	0	3	Johnson, Mr. William Cahoone Jr	male	19	0	0	LINE	0	N
597	598	0	3	Johnson, Mr. Alfred	male	49	0	0	LINE	0	N
772	773	0	2	Mack, Mrs. (Mary)	female	57	0	0	S.O./P.P. 3	10	I
841	842	0	2	Mudd, Mr. Thomas Charles	male	16	0	0	S.O./P.P. 3	10	N

4.2 RE Convert Categorical variables into Numerical ones

In [55]:

```
titanic.head(8)
```

Out[55]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Ca
0	1	0	3	Braund, Mr. Owen Harris	male	22	1	0	A/5 21171	7	N
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38	1	0	PC 17599	71	(
2	3	1	3	Heikkinen, Miss. Laina	female	26	0	0	STON/O2. 3101282	7	N
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35	1	0	113803	53	C
4	5	0	3	Allen, Mr. William Henry	male	35	0	0	373450	8	N
5	6	0	3	Moran, Mr. James	male	19	0	0	330877	8	N
6	7	0	1	McCarthy, Mr. Timothy J	male	54	0	0	17463	51	I
7	8	0	3	Palsson, Master. Gosta Leonard	male	2	3	1	349909	21	N

In [56]:

```
ti_train_df['Embarked'].replace({'Southampton':'S','Queenstown':'Q', 'Cherbough':
```

In [57]:

```
from sklearn.preprocessing import LabelEncoder,OneHotEncoder

labelEnc=LabelEncoder()

cat_vars=['Sex',"FsizeD","NlengthD",'Deck',]
for col in cat_vars:
    titanic[col]=labelEnc.fit_transform(titanic[col])
    titanic_test[col]=labelEnc.fit_transform(titanic_test[col])

titanic.head(8)
```

Out[57]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabi
0	1	0	3	Braund, Mr. Owen Harris	1	22	1	0	A/5 21171	7	Nal
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	0	38	1	0	PC 17599	71	C8
2	3	1	3	Heikkinen, Miss. Laina	0	26	0	0	STON/O2. 3101282	7	Nal
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	0	35	1	0	113803	53	C12
4	5	0	3	Allen, Mr. William Henry	1	35	0	0	373450	8	Nal
5	6	0	3	Moran, Mr. James	1	19	0	0	330877	8	Nal
6	7	0	1	McCarthy, Mr. Timothy J	1	54	0	0	17463	51	E4
7	8	0	3	Palsson, Master. Gosta Leonard	1	2	3	1	349909	21	Nal

Feature Scaling

We can see that Age, Fare are measured on different scales, so we need to do Feature Scaling first before we proceed with predictions.

In [58]:

```
from sklearn import preprocessing

std_scale = preprocessing.StandardScaler().fit(titanic[['Age', 'Fare']])
titanic[['Age', 'Fare']] = std_scale.transform(titanic[['Age', 'Fare']])


std_scale = preprocessing.StandardScaler().fit(titanic_test[['Age', 'Fare']])
titanic_test[['Age', 'Fare']] = std_scale.transform(titanic_test[['Age', 'Fare']]
```

Correlation Analysis

In [59]:

```
titanic.head(5)
```

Out[59]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	F
0	1	0	3	Braund, Mr. Owen Harris	1	-0.560628	1	0	A/5 21171	-0.498
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	0	0.620793	1	0	PC 17599	0.789
2	3	1	3	Heikkinen, Miss. Laina	0	-0.265273	0	0	STON/O2. 3101282	-0.498
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	0	0.399277	1	0	113803	0.427
4	5	0	3	Allen, Mr. William Henry	1	0.399277	0	0	373450	-0.478

In [60]:

```
titanic.corr()["Survived"]
```

Out[60]:

```
PassengerId    -0.005007
Survived        1.000000
Pclass         -0.338481
Sex            -0.543351
Age            -0.074070
SibSp          -0.035322
Parch           0.081629
Fare            0.257482
Family          0.203367
Deck           -0.301116
FamilySize      0.016639
FsizeD          0.283810
NameLength      0.332350
NlengthD       -0.312234
TicketNumber   -0.097302
Name: Survived, dtype: float64
```

In [61]:

```
titanic_drop = titanic.drop(['PassengerId','SibSp','Parch', 'Cabin','Name','Famil
test_drop = titanic_test.drop(['PassengerId','SibSp','Parch', 'Cabin','Name','Fam
```

In [62]:

```
colormap = plt.cm.viridis
plt.figure(figsize=(12,12))
plt.title('Pearson Correlation of Features', y=1.05, size=15)
sns.heatmap(titanic_drop.astype(float).corr(),linewidths=0.1,vmax=1.0, square=Tru
```

Out[62]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1162c2518>
```

	Survived	Pclass	Sex	Age	Fare	Family	Deck	FsizeD	NameLength	NlengthD
Survived	1	-0.34	-0.54	-0.074	0.26	0.2	-0.3	0.28	0.33	-0.31
Pclass	-0.34	1	0.13	-0.33	-0.55	-0.14	0.75	-0.25	-0.22	0.25
Sex	-0.54	0.13	1	0.081	-0.18	-0.3	0.12	-0.17	-0.45	0.38
Age	-0.074	-0.33	0.081	1	0.094	-0.18	-0.26	0.016	0.039	-0.074
Fare	0.26	-0.55	-0.18	0.094	1	0.27	-0.52	0.1	0.16	-0.16
Family	0.2	-0.14	-0.3	-0.18	0.27	1	-0.14	0.55	0.41	-0.36
Deck	-0.3	0.75	0.12	-0.26	-0.52	-0.14	1	-0.19	-0.19	0.22
FsizeD	0.28	-0.25	-0.17	0.016	0.1	0.55	-0.19	1	0.27	-0.28
NameLength	0.33	-0.22	-0.45	0.039	0.16	0.41	-0.19	0.27	1	-0.87
NlengthD	-0.31	0.25	0.38	-0.074	-0.16	-0.36	0.22	-0.28	-0.87	1

In [63]:

```
titanic_drop.head()
```

Out[63]:

	Survived	Pclass	Sex	Age	Fare	Family	Deck	FsizeD	NameLength	NlengthD
0	0	3	1	-0.560628	-0.498948	1	8	2	23	2
1	1	1	0	0.620793	0.789405	1	2	2	51	0
2	1	3	0	-0.265273	-0.498948	0	8	1	22	2
3	1	1	0	0.399277	0.427056	1	2	2	44	0
4	0	3	1	0.399277	-0.478817	0	8	1	24	2

Takeaway from the Plots One thing that that the Pearson Correlation plot can tell us is that there are not too many features strongly correlated with one another. This is good from a point of view of feeding these features into your learning model because this means that there isn't much redundant or superfluous data in our training set and we are happy that each feature carries with it some unique information. Here are two most correlated features are that Deck and Pclass. (0.75)

this show actually passenger class and deck code is strongly correlated. another one is name length & namelength D so we can just use one of the variables for each pair

We will conduct preliminary decision tree analysis using Pclass, Age,Fare, Embarked, Deck, Family size , Name length, Title and ticket number

Predict Survival

Ensembling and Stacking Models

Finally after that brief whirlwind detour with regards to feature engineering and formatting, we finally arrive at the meat and gist of the this notebook. Creating a Stacking ensemble

Helpers via Python Classes

Here we invoke the use of Python's classes to help make it more convenient for us. For any newcomers to programming, one normally hears Classes being used in conjunction with Object-Oriented Programming (OOP). In short, a class helps to extend some code/program for creating objects (variables for old-school peeps) as well as to implement functions and methods specific to that class. In the section of code below, we essentially write a class SklearnHelper that allows one to extend the inbuilt methods (such as train, predict and fit) common to all the Sklearn classifiers. Therefore this cuts out redundancy as won't need to write the same methods five times if we wanted to invoke five different classifiers.

In [64]:

```
# Some useful parameters which will come in handy later on
ntrain = titanic_drop.shape[0]
ntest = test_drop.shape[0]
SEED = 0 # for reproducibility
NFOLDS = 5 # set folds for out-of-fold prediction
kf = KFold(ntrain, n_folds= NFOLDS, random_state=SEED)

# Class to extend the Sklearn classifier
class SklearnHelper(object):
    def __init__(self, clf, seed=0, params=None):
        params['random_state'] = seed
        self.clf = clf(**params)

    def train(self, x_train, y_train):
        self.clf.fit(x_train, y_train)

    def predict(self, x):
        return self.clf.predict(x)

    def fit(self,x,y):
        return self.clf.fit(x,y)

    def feature_importances(self,x,y):
        print(self.clf.fit(x,y).feature_importances_)

# Class to extend XGboost classifer
```

Bear with me for those who already know this but for people who have not created classes or objects in Python before, let me explain what the code given above does. In creating my base classifiers, I will only use the models already present in the Sklearn library and therefore only extend the class for that. def init : Python standard for invoking the default constructor for the class. This means that when you want to create an object (classifier), you have to give it the parameters of clf (what sklearn classifier you want), seed (random seed) and params (parameters for the classifiers). The rest of the code are simply methods of the class which simply call the corresponding methods already existing within the sklearn classifiers.

Out of fold predictions

Now as alluded to above in the introductory section, stacking uses predictions of base classifiers as input for training to a second-level model. However one cannot simply train the base models on the full training data, generate predictions on the full test set and then output these for the second-level training. This runs the risk of your base model predictions already having "seen" the test set and therefore overfitting when feeding these predictions.

In [65]:

```
def get_oof(clf, x_train, y_train, x_test):
    oof_train = np.zeros((ntrain,))
    oof_test = np.zeros((ntest,))
    oof_test_skf = np.empty((NFOLDS, ntest))

    for i, (train_index, test_index) in enumerate(kf):
        x_tr = x_train[train_index]
        y_tr = y_train[train_index]
        x_te = x_train[test_index]

        clf.train(x_tr, y_tr)

        oof_train[test_index] = clf.predict(x_te)
        oof_test_skf[i, :] = clf.predict(x_test)

    oof_test[:] = oof_test_skf.mean(axis=0)
    return oof_train.reshape(-1, 1), oof_test.reshape(-1, 1)
```

Generating our Base First-Level Models

So now let us prepare five learning models as our first level classification. These models can all be conveniently invoked via the Sklearn library and are listed as follows:

Random Forest classifier

Extra Trees classifier

AdaBoost classifer

Gradient Boosting classifer

Support Vector Machine

Parameters

Just a quick summary of the parameters that we will be listing here for completeness,

n_jobs : Number of cores used for the training process. If set to -1, all cores are used.

n_estimators : Number of classification trees in your learning model (set to 10 per default)

max_depth : Maximum depth of tree, or how much a node should be expanded. Beware if set to too high a number

would run the risk of overfitting as one would be growing the tree too deep

verbose : Controls whether you want to output any text during the learning process. A value of 0 suppresses all text while a value of 3 outputs the tree learning process at every iteration. Please check out the full description via the official Sklearn website. There you will find that there are a whole host of other useful parameters that you can play around with.

In [66]:

```
# Put in our parameters for said classifiers
# Random Forest parameters
rf_params = {
    'n_jobs': -1,
    'n_estimators': 500,
     'warm_start': True,
     #'max_features': 0.2,
    'max_depth': 6,
    'min_samples_leaf': 2,
    'max_features' : 'sqrt',
    'verbose': 0
}

# Extra Trees Parameters
et_params = {
    'n_jobs': -1,
    'n_estimators':500,
    #'max_features': 0.5,
    'max_depth': 8,
    'min_samples_leaf': 2,
    'verbose': 0
}

# AdaBoost parameters
ada_params = {
    'n_estimators': 500,
    'learning_rate' : 0.75
}

# Gradient Boosting parameters
gb_params = {
    'n_estimators': 500,
     #'max_features': 0.2,
    'max_depth': 5,
    'min_samples_leaf': 2,
    'verbose': 0
}

# Support Vector Classifier parameters
svc_params = {
    'kernel' : 'linear',
    'C' : 0.025
}
```

Furthermore, since having mentioned about Objects and classes within the OOP framework, let us now create 5 objects that represent our 5 learning models via our Helper Sklearn Class we defined earlier.

In [67]:

```
# Create 5 objects that represent our 4 models
rf = SklearnHelper(clf=RandomForestClassifier, seed=SEED, params=rf_params)
et = SklearnHelper(clf=ExtraTreesClassifier, seed=SEED, params=et_params)
ada = SklearnHelper(clf=AdaBoostClassifier, seed=SEED, params=ada_params)
gb = SklearnHelper(clf=GradientBoostingClassifier, seed=SEED, params=gb_params)
svc = SklearnHelper(clf=SVC, seed=SEED, params=svc_params)
```

Creating NumPy arrays out of our train and test sets

Great. Having prepared our first layer base models as such, we can now ready the training and test test data for input into our classifiers by generating NumPy arrays out of their original dataframes as follows:

In [68]:

```
# Create Numpy arrays of train, test and target ( Survived) dataframes to feed ir
train = titanic_drop
test = test_drop



y_train = train['Survived'].ravel()
train = train.drop(['Survived'], axis=1)
x_train = train.values # Creates an array of the train data
x_test = test.values # Creats an array of the test data
```

Output of the Predictions

We now feed the training and test data into our 5 base classifiers and use the Out-of-Fold prediction function we defined earlier to generate our first level predictions. Allow a handful of minutes for the chunk of code below to run.

In [69]:

```
# Create our OOF train and test predictions. These base results will be used as r
et_oof_train, et_oof_test = get_oof(et, x_train, y_train, x_test) # Extra Trees
rf_oof_train, rf_oof_test = get_oof(rf,x_train, y_train, x_test) # Random Forest
ada_oof_train, ada_oof_test = get_oof(ada, x_train, y_train, x_test) # AdaBoost
gb_oof_train, gb_oof_test = get_oof(gb,x_train, y_train, x_test) # Gradient Boost
svc_oof_train, svc_oof_test = get_oof(svc,x_train, y_train, x_test) # Support Vec

print("Training is complete")
```

```
Training is complete
```

Feature importances generated from the different classifiers

Now having learned our the first-level classifiers, we can utilise a very nifty feature of the Sklearn models and that is to output the importances of the various features in the training and test sets with one very simple line of code.

As per the Sklearn documentation, most of the classifiers are built in with an attribute which returns feature importances by simply typing in .featureimportances. Therefore we will invoke this very useful attribute via our function earliand plot the feature importances as such

In [70]:

```
rf_feature = rf.feature_importances(x_train,y_train)
et_feature = et.feature_importances(x_train, y_train)
ada_feature = ada.feature_importances(x_train, y_train)
gb_feature = gb.feature_importances(x_train,y_train)
```

```
[ 0.10432983  0.34308605  0.11860145  0.14943221  0.01008972  0.0804
0772
  0.06840347  0.10018358  0.02546598]
[ 0.13593652  0.4956888   0.05886558  0.04257616  0.02720106  0.0767
7011
  0.06970418  0.04620357  0.04705401]
[ 0.01   0.016  0.35   0.318  0.008  0.042  0.016  0.232  0.008]
[ 0.03918464  0.03629812  0.34573924  0.22353935  0.01242343  0.0309
5704
  0.02344784  0.27975366  0.00865668]
```

So I have not yet figured out how to assign and store the feature importances outright. Therefore I'll print out the values from the code above and then simply copy and paste into Python lists as below (sorry for the lousy hack)

In [73]:

```
rf_features = [ 0.10432983 , 0.34308605 , 0.11860145 , 0.14943221 , 0.01008972 ,
                  ,0.06840347 , 0.10018358 , 0.02546598]
et_features = [ 0.13593652 , 0.4956888  , 0.05886558 , 0.04257616 , 0.02720106 ,
                  ,0.06970418 , 0.04620357 , 0.04705401]
ada_features= [ 0.01 ,  0.016 , 0.35  , 0.318 , 0.008 , 0.042 , 0.016 , 0.232 , 0
gb_features =[ 0.03918464 , 0.03629812 , 0.34573924 , 0.22353935 , 0.01242343 , 0
                  ,0.02344784 , 0.27975366 , 0.00865668]
```

In [74]:

```
cols = train.columns.values
# Create a dataframe with features
feature_dataframe = pd.DataFrame( {'features': cols,
     'Random Forest feature importances': rf_features,
     'Extra Trees  feature importances': et_features,
      'AdaBoost feature importances': ada_features,
    'Gradient Boost feature importances': gb_features
    })
```

Create a dataframe from the lists containing the feature importance data for easy plotting via the Plotly package.

Interactive feature importances via Plotly scatterplots

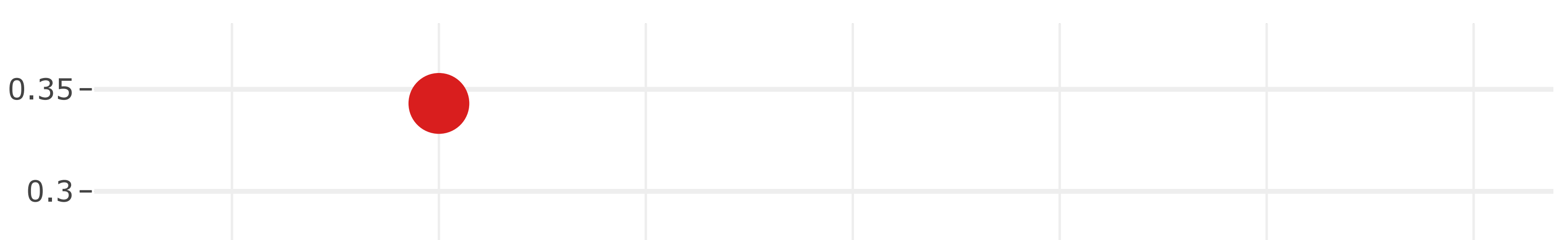
I'll use the interactive Plotly package at this juncture to visualise the feature importances values of the different classifiers

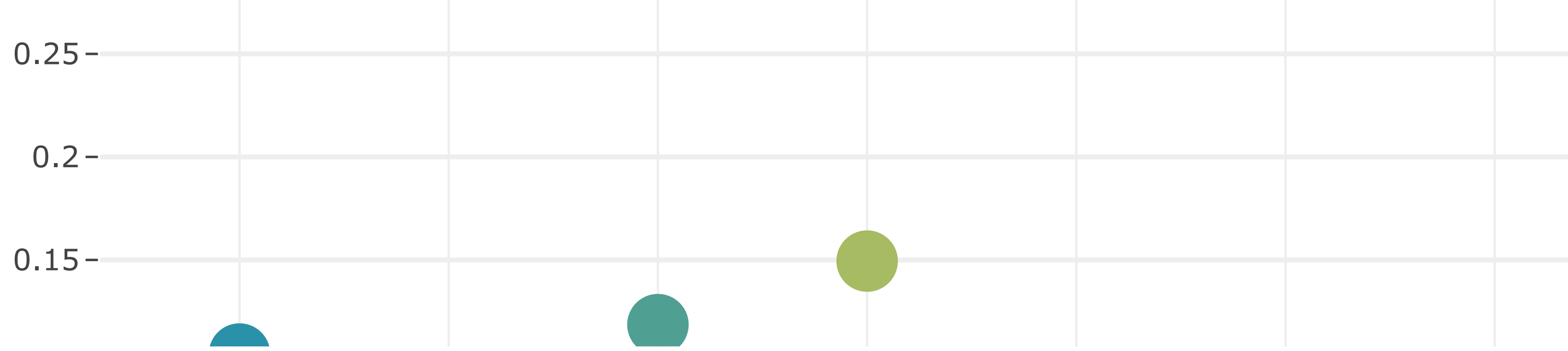
In [75]:

```
# Scatter plot
trace = go.Scatter(
    y = feature_dataframe['Random Forest feature importances'].values,
    x = feature_dataframe['features'].values,
    mode='markers',
    marker=dict(
        sizemode = 'diameter',
        sizeref = 1,
        size = 25,
#       size= feature_dataframe['AdaBoost feature importances'].values,
        #color = np.random.randn(500), #set color equal to a variable
        color = feature_dataframe['Random Forest feature importances'].values,
        colorscale='Portland',
        showscale=True
    ),
    text = feature_dataframe['features'].values
)
data = [trace]

layout= go.Layout(
    autosize= True,
    title= 'Random Forest Feature Importance',
    hovermode= 'closest',
#     xaxis= dict(
#         title= 'Pop',
#         ticklen= 5,
#         zeroline= False,
#         gridwidth= 2,
#     ),
    yaxis=dict(
        title= 'Feature Importance',
        ticklen= 5,
        gridwidth= 2
    ),
    showlegend= False
)
fig = go.Figure(data=data, layout=layout)
py.iplot(fig,filename='scatter2010')

# Scatter plot
trace = go.Scatter(
    y = feature_dataframe['Extra Trees  feature importances'].values,
    x = feature_dataframe['features'].values,
    mode='markers',
    marker=dict(
        sizemode = 'diameter',
        sizeref = 1,
        size = 25,
#       size= feature_dataframe['AdaBoost feature importances'].values,
        #color = np.random.randn(500), #set color equal to a variable
        color = feature_dataframe['Extra Trees  feature importances'].values,
        colorscale='Portland',
```

```
        showscale=True
    ),
    text = feature_dataframe['features'].values
)
data = [trace]

layout= go.Layout(
    autosize= True,
    title= 'Extra Trees Feature Importance',
    hovermode= 'closest',
#     xaxis= dict(
#         title= 'Pop',
#         ticklen= 5,
#         zeroline= False,
#         gridwidth= 2,
#     ),
    yaxis=dict(
        title= 'Feature Importance',
        ticklen= 5,
        gridwidth= 2
    ),
    showlegend= False
)
fig = go.Figure(data=data, layout=layout)
py.iplot(fig,filename='scatter2010')

# Scatter plot
trace = go.Scatter(
    y = feature_dataframe['AdaBoost feature importances'].values,
    x = feature_dataframe['features'].values,
    mode='markers',
    marker=dict(
        sizemode = 'diameter',
        sizeref = 1,
        size = 25,
#       size= feature_dataframe['AdaBoost feature importances'].values,
        #color = np.random.randn(500), #set color equal to a variable
        color = feature_dataframe['AdaBoost feature importances'].values,
        colorscale='Portland',
        showscale=True
    ),
    text = feature_dataframe['features'].values
)
data = [trace]

layout= go.Layout(
    autosize= True,
    title= 'AdaBoost Feature Importance',
    hovermode= 'closest',
#     xaxis= dict(
#         title= 'Pop',
#         ticklen= 5,
#         zeroline= False,
#         gridwidth= 2,
#     ),
    yaxis=dict(
        title= 'Feature Importance',
```

```
        ticklen= 5,
        gridwidth= 2
    ),
    showlegend= False
)
fig = go.Figure(data=data, layout=layout)
py.iplot(fig,filename='scatter2010')

# Scatter plot
trace = go.Scatter(
    y = feature_dataframe['Gradient Boost feature importances'].values,
    x = feature_dataframe['features'].values,
    mode='markers',
    marker=dict(
        sizemode = 'diameter',
        sizeref = 1,
        size = 25,
#       size= feature_dataframe['AdaBoost feature importances'].values,
        #color = np.random.randn(500), #set color equal to a variable
        color = feature_dataframe['Gradient Boost feature importances'].values,
        colorscale='Portland',
        showscale=True
    ),
    text = feature_dataframe['features'].values
)
data = [trace]

layout= go.Layout(
    autosize= True,
    title= 'Gradient Boosting Feature Importance',
    hovermode= 'closest',
#     xaxis= dict(
#         title= 'Pop',
#         ticklen= 5,
#         zeroline= False,
#         gridwidth= 2,
#     ),
    yaxis=dict(
        title= 'Feature Importance',
        ticklen= 5,
        gridwidth= 2
    ),
    showlegend= False
)
fig = go.Figure(data=data, layout=layout)
py.iplot(fig,filename='scatter2010')
```





Now let us calculate the mean of all the feature importances and store it as a new column in the feature importance dataframe

In [76]:

```
# Create the new column containing the average of values

feature_dataframe['mean'] = feature_dataframe.mean(axis= 1) # axis = 1 computes t
feature_dataframe.head(3)
```

Out[76]:

	AdaBoost feature importances	Extra Trees feature importances	Gradient Boost feature importances	Random Forest feature importances	features	mean
0	0.010	0.135937	0.039185	0.104330	Pclass	0.072363
1	0.016	0.495689	0.036298	0.343086	Sex	0.222768
2	0.350	0.058866	0.345739	0.118601	Age	0.218302

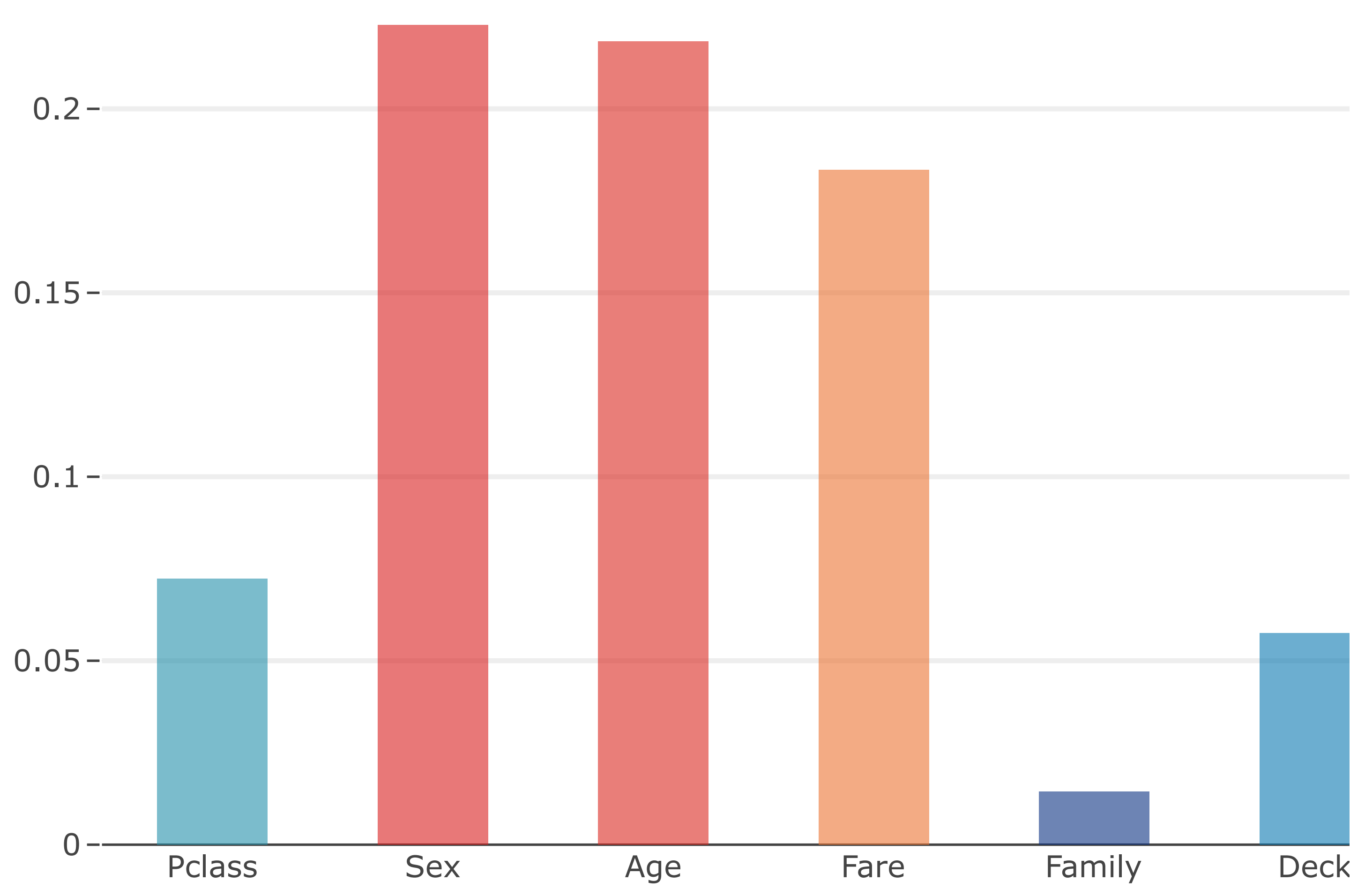
Plotly Barplot of Average Feature Importances

Having obtained the mean feature importance across all our classifiers, we can plot them into a Plotly bar plot as follows:

In [77]:

```
y = feature_dataframe['mean'].values
x = feature_dataframe['features'].values
data = [go.Bar(
            x= x,
             y= y,
            width = 0.5,
            marker=dict(
               color = feature_dataframe['mean'].values,
            colorscale='Portland',
            showscale=True,
            reversescale = False
            ),
            opacity=0.6
        )]

layout= go.Layout(
    autosize= True,
    title= 'Barplots of Mean Feature Importance',
```

```
    hovermode= 'closest',
#     xaxis= dict(
#         title= 'Pop',
#         ticklen= 5,
#         zeroline= False,
#         gridwidth= 2,
#     ),
    yaxis=dict(
        title= 'Feature Importance',
        ticklen= 5,
        gridwidth= 2
    ),
    showlegend= False
)
fig = go.Figure(data=data, layout=layout)
py.iplot(fig, filename='bar-direct-labels')
```



CONCLUSION

To Answer the main problem question:

What factors made people more likely to survive?

All the analysis above gives summary that the survivability of the passenger of titanic was affected strongly by these following factors:

1. Sex
2. Age
3. Fare
4. Name Length

1.Sex :

We can see that women have higher rate of survivability

2.Age :

We can see that children age less than 10, men age 20-30, and women age 20-40 have higher survival rate than the rest of age bracket in each gender

3.Fare :

We can see that passenger with higher fare have more survivability rate

4.Name Length :

We can see that name with more length have higher survivability rate. This may referred to fact that noble person have longer name due to their titles.

LIMITATION

In this research, we are faced with limitations such as missing values and other resources limitations. In order to proceed with analysis proses , we conducted value imputation to variable Embarked with using common variable, we imputed Age variables, which were in substantial amount (around 20%), using random forest technique, and also dropping several variables, for example : Cabin & Deck due to the large amount of missing Data (more than 70% missing data)

Potential improvement can be seen in visualization process and the comprehensiveness of the analysis. We can also be able to predict the survivability in the test set in the future

The other limitation was the time & resource limitation to preform more professional analysis regarding Titanic Passenger Survivability

Finally, the conclusion can also be improved by predicting the passenger survivability using the test set after making the model in the training set in the future.

Many Thanks!

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Data Analyst

In [ ]:

```

```