Project 2: Titanic Dataset Analysis

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VARIABLE DESCRIPTIONS:

The dataset of study contains demographics and passenger information from 891 of the 2224 passengers and crew on board the Titanic. The variables included are:

```
survival        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)
```

SPECIAL NOTES: Pclass is a proxy for socio-economic status (SES) 1st ~ Upper; 2nd ~ Middle; 3rd ~ Lower

Age is in Years; Fractional if Age less than One (1) If the Age is Estimated, it is in the form xx.5

With respect to the family relation variables (i.e. sibsp and parch) some relations were ignored. The following are the definitions used for sibsp and parch.

Sibling: Brother, Sister, Stepbrother, or Stepsister of Passenger Aboard Titanic Spouse: Husband or Wife of Passenger Aboard Titanic (Mistresses and Fiances Ignored) Parent: Mother or Father of Passenger Aboard Titanic Child: Son, Daughter, Stepson, or Stepdaughter of Passenger Aboard Titanic

Other family relatives excluded from this study include cousins, nephews/nieces, aunts/uncles, and in-laws. Some children travelled only with a nanny, therefore parch=0 for them. As well, some travelled with very close friends or neighbors in a village, however, the definitions do not support such relations.

Data Analysis :

Questions :

In this analysis we will try to answer some questions related to Survival rate according to :

1. Fare category
2. A person being Male or Female
3. Age of the person i.e, Child , Adult , Senior Citizen
4. Male Child or Female Child
5. Socio-economic status Upper Class (1st), Middle Class(2nd) , Lower Class(3rd)
6. Comparision of survival with respect to embarkment station
7. Chances of survival of Men with child(Father) or spouse(Husband) or Single?
8. Age-group of people with higher probablity of survival

Investigating Data

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib

import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

titanic_data = pd.read_csv('titanic_data.csv')
```

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

Out[3]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.25
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.92
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.05

Data Wrangling

This dataset have some NaN values which will stop us doing proper analysis. In this phase we will detect those records and will clean our dataset.

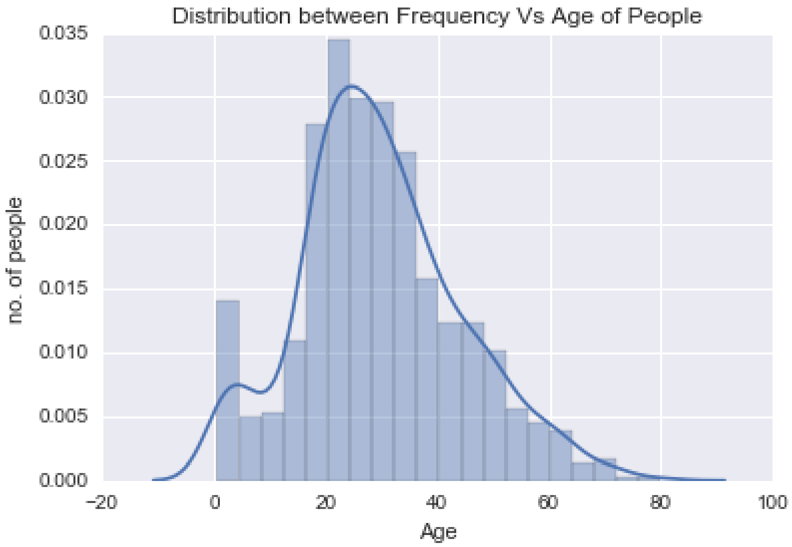
In [4]:
```
#Testing Presence of Null values in data set

total_null_values    = titanic_data.isnull().sum().sum()              #Total
 null values in titanic_dataset
null_values_survived = titanic_data.Survived.isnull().sum().sum()     #Total
 null values in Survived col titanic_dataset
null_values_pclass   = titanic_data.Pclass.isnull().sum().sum()       #Total
 null values in Pclass col titanic_dataset
null_values_name     = titanic_data.Name.isnull().sum().sum()         #Total
 null values in Name col titanic_dataset
null_values_sex      = titanic_data.Sex.isnull().sum().sum()          #Total
 null values in Sex col titanic_dataset
null_values_Age      = titanic_data.Age.isnull().sum().sum()          #Total
 null values in Age col titanic_dataset
null_values_SibSp    = titanic_data.SibSp.isnull().sum().sum()        #Total
 null values in SibSp col titanic_dataset
null_values_parch    = titanic_data.Parch.isnull().sum().sum()        #Total
 null values in Parch col titanic_dataset
null_values_ticket   = titanic_data.Ticket.isnull().sum().sum()       #Total
 null values in Ticket col titanic_dataset
null_values_fare     = titanic_data.Fare.isnull().sum().sum()         #Total
 null values in Fare col titanic_dataset
null_values_cabin    = titanic_data.Cabin.isnull().sum().sum()        #Total
 null values in Cabin col titanic_dataset
null_values_embarked = titanic_data.Embarked.isnull().sum().sum()     #Total
 null values in Embarked col titanic_dataset

print 'Total null values in titanic_dataset : {}'.format(total_null_values)
print 'Total null values in Survived col titanic_dataset : {}'.format(null_val
ues_survived)
print 'Total null values in Pclass col titanic_dataset : {}'.format(null_value
s_pclass)
print 'Total null values in Name col titanic_dataset : {}'.format(null_values_
name)
print 'Total null values in Sex col titanic_dataset : {}'.format(null_values_s
ex)
print 'Total null values in Age col titanic_dataset : {}'.format(null_values_A
ge)
print 'Total null values in Sibsp col titanic_dataset : {}'.format(null_values
_SibSp)
print 'Total null values in Parch col titanic_dataset : {}'.format(null_values
_parch)
print 'Total null values in Ticket col titanic_dataset : {}'.format(null_value
s_ticket)
print 'Total null values in Cabin col titanic_dataset : {}'.format(null_values
_cabin)
print 'Total null values in Embarked col titanic_dataset : {}'.format(null_val
ues_embarked)

float(2)/891*100
```

```
Total null values in titanic_dataset : 866
Total null values in Survived col titanic_dataset : 0
Total null values in Pclass col titanic_dataset : 0
Total null values in Name col titanic_dataset : 0
Total null values in Sex col titanic_dataset : 0
Total null values in Age col titanic_dataset : 177
Total null values in Sibsp col titanic_dataset : 0
Total null values in Parch col titanic_dataset : 0
Total null values in Ticket col titanic_dataset : 0
Total null values in Cabin col titanic_dataset : 687
Total null values in Embarked col titanic_dataset : 2
```

```
Out[4]: 0.22446689113355783
```

It means there are 3 columns with NaN values **Age(177) =19.8 %** , **Cabin(687) = 77.1%** ,**Embarked(2)=0.22%** of 891 values So, for analysis we can ignore *Embarked* for their NaN because it will not effect much. Let's consider the statistics of Age , Cabin column.

In [5]:
```
Age_data = titanic_data['Age']
no_NaN_Age = [x for x in Age_data if str(x) != 'nan']
ax = sns.distplot(no_NaN_Age)
ax.set(xlabel='Age', ylabel='no. of people',title="Distribution between Freque
ncy Vs Age of People")
sns.plt.show()
no_NaN_Age = np.array(no_NaN_Age)
print('Mean of Age data with No NaNs = {}').format(np.mean(no_NaN_Age))

Cabin_data = titanic_data['Cabin']
no_NaN_Cabin = [x for x in Cabin_data if str(x) != 'nan']
Cabin_set = set()
for x in no_NaN_Cabin:
    Cabin_set.add(x)

print '\n'
print('Number of distinct cabins are {}+').format(len(Cabin_set))
print 'List of all distinct cabins :'
for x in Cabin_set:
    print '"'+x+'"',
print '\n'
```




```
Mean of Age data with No NaNs = 29.6991176471


Number of distinct cabins are 147+
List of all distinct cabins :
"C78" "D17" "D50" "E77" "C30" "D56" "C32" "G6" "B50" "C62 C64" "D" "B102" "B1
01" "E68" "F33" "T" "F38" "A24" "E63" "E67" "B28" "B22" "B20" "B4" "B5" "B58
 B60" "B3" "F G73" "C54" "C52" "C50" "C46" "F E69" "E58" "E50" "D28" "B38" "B
39" "B35" "B37" "B30" "E121" "B71" "E8" "F G63" "C45" "E40" "C47" "E46" "E44"
 "B80" "E49" "C49" "B86" "B82 B84" "C23 C25 C27" "D48" "C104" "C106" "C101"
 "C103" "D15" "E34" "E33" "D11" "E31" "C70" "B94" "D19" "E38" "E36" "B18" "B1
9" "D37" "A32" "A31" "A36" "A34" "E101" "C118" "C2" "C7" "C111" "C110" "E24"
 "E25" "E12" "B57 B59 B63 B66" "C68" "D21" "D20" "C65" "D26" "E17" "A20" "F2"
 "A23" "F4" "A26" "B69" "B42" "C128" "C123" "C126" "C124" "C125" "B51 B53 B5
5" "D36" "E10" "D35" "D33" "D30" "B96 B98" "D10 D12" "C93" "A14" "C91" "B73"
 "A10" "C95" "B77" "B78" "B79" "C99" "A19" "C90" "A5" "A7" "A6" "C22 C26" "C9
2" "D49" "A16" "D47" "D46" "D45" "C82" "C83" "B41" "C85" "C86" "C87" "C148"
 "B49" "D9" "D6" "D7"
```

Age data with No NaNs is approximately normally distributed, so mean value will give better clarity about data's central tendancy. So, for analysis stuff we can clean the data by *replacing all NaNs with mean(29.699)* value of data.

Cabin data is having 147+ discrete string values,due to this we cann't calculate mean value for it. We cann't even use classification model to categorize data as there will be 147+ different categories on 891 samples.There are some values with "B51 B53 B55"which looks like including 3 cabin no.s . So, will ignore Cabin data for analysis.

*** Let's clean Age data and make it NaN free and remove Cabin data from titanic_data dataframe.**

In [6]:
```
titanic_data.Age.fillna(np.mean(no_NaN_Age),inplace=True)
del titanic_data['Cabin']
```

Q1. Analysis of Survival on the basis of Ship Fare

In [7]:
```
#No. of different fares in Titanic Ship
#Fare Variation

fare_list = titanic_data.Fare.unique()
fare_list = pd.DataFrame(fare_list)
#fare_list.describe()

no_survived = titanic_data['Survived'].value_counts()[1] #no of people survive
d

#print no_survived
no_died = len(titanic_data)  - no_survived  #no of people died
#print no_died
print('No of people Survived : {} , {:.2f}% of total'.format(no_survived, floa
t(no_survived*100 )/len(titanic_data)))
print('No of people Died : {} , {:.2f}% of total'.format(no_died, float(no_die
d*100 )/len(titanic_data)))
```

```
No of people Survived : 342 , 38.38% of total
No of people Died : 549 , 61.62% of total
```

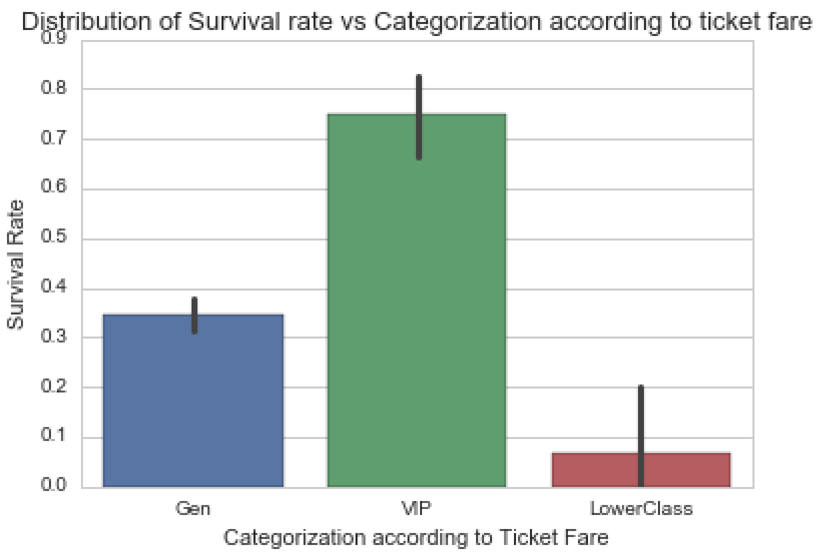
In [8]:
```
fare_list.sort_values([0],inplace =True)
fares = pd.DataFrame(titanic_data.Fare)
fares.sort_values(['Fare'],inplace =True)

top_90_fare = fares[800:801]['Fare']  #Top 10% fare
top_90_fare
```

Out[8]:
```
102    77.2875
Name: Fare, dtype: float64
```

In [9]:
```
def isVIP(x):
    if x == 0:
        return "LowerClass" #Probably a Staff's relative/friend travelling wit
h passes
    elif x >= 77.2875:
        return "VIP" # One of Top 10% guys travelling in Ship
    else:
        return "Gen" #Normal People travelling in Ship

titanic_data["Is_VIP"] = pd.Series(titanic_data["Fare"].apply(isVIP), index=ti
tanic_data.index)
```

In [10]:
```
no_Gen = titanic_data['Is_VIP'].value_counts()['Gen']
no_Lower = titanic_data['Is_VIP'].value_counts()['LowerClass']
no_VIP = titanic_data['Is_VIP'].value_counts()['VIP']


no_Gen_survived =  titanic_data.groupby(['Is_VIP' , 'Survived']).size()['Gen']
[1]
no_Gen_died = no_Gen - no_Gen_survived

no_Lower_survived =  titanic_data.groupby(['Is_VIP' , 'Survived']).size()['Low
erClass'][1]
no_Lower_died = no_Lower - no_Lower_survived

no_VIP_survived =  titanic_data.groupby(['Is_VIP' , 'Survived']).size()['VIP']
[1]
no_VIP_died = no_VIP - no_VIP_survived

print('No. of General People with $0< fare < 77.28 : {}  , {:.2f}% of total'.f
ormat(no_Gen, float(no_Gen*100 )/len(titanic_data)))
print('No. of General People Survived : {} , {:.2f}%'.format(no_Gen_survived ,
 float(no_Gen_survived)*100/no_Gen))
print('No. of General People Died : {}, {:.2f}% '.format( no_Gen_died, float(n
o_Gen_died)*100/no_Gen))

print '\n'

print('No. of Lower Class People / Employees who were travelling for free : {}
  , {:.2f}% of total'.format(no_Lower, float(no_Lower*100
)/len(titanic_data)))
print('No. of Lower Class People/ Employees Survived : {} , {:.2f}%'.format(no
_Lower_survived , float(no_Lower_survived)*100/no_Lower))
print('No. of Lower Class People/ Employees Died : {}, {:.2f}% '.format( no_Lo
wer_died, float(no_Lower_died)*100/no_Lower))

print '\n'

print('No. of VIPs who were travelling : {}  , {:.2f}% of
total'.format(no_VIP, float(no_VIP*100 )/len(titanic_data)))
print('No. of VIPs Survived : {} , {:.2f}%'.format(no_VIP_survived , float(no_
VIP_survived)*100/no_VIP))
print('No. of VIPs Died : {}, {:.2f}% '.format( no_VIP_died,
float(no_VIP_died)*100/no_VIP))


sns.set_style("whitegrid")
sns.barplot(data = titanic_data , y = "Survived" , x ="Is_VIP")
plt.xlabel('Categorization according to Ticket Fare')
plt.ylabel('Survival Rate')
plt.title("Distribution of Survival rate vs Categorization according to ticket
 fare" , fontsize = 13)
sns.plt.show()
```

```
No. of General People with $0< fare < 77.28 : 784  , 87.99% of total
No. of General People Survived : 272 , 34.69%
No. of General People Died : 512, 65.31%


No. of Lower Class People / Employees who were travelling for free : 15  , 1.
68% of total
No. of Lower Class People/ Employees Survived : 1 , 6.67%
No. of Lower Class People/ Employees Died : 14, 93.33%


No. of VIPs who were travelling : 92  , 10.33% of total
No. of VIPs Survived : 69 , 75.00%
No. of VIPs Died : 23, 25.00%
```



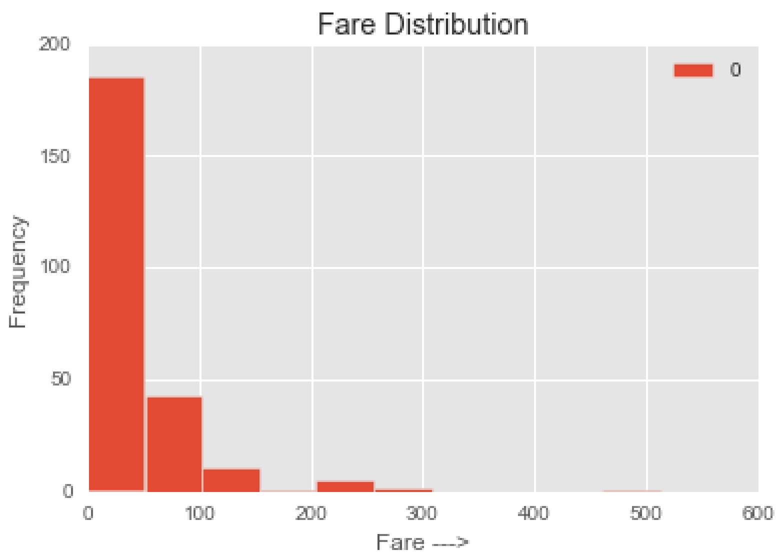
In [11]:

```
%pylab inline
#This graph shows the basic fare analysis
import matplotlib
matplotlib.style.use('ggplot')
ax = fare_list.plot(kind="hist")
ax.set_xlabel("Fare --->")
ax.set_title("Fare Distribution")
```

```
Populating the interactive namespace from numpy and matplotlib
```

Out[11]:

```
<matplotlib.text.Text at 0xba2c470>
```



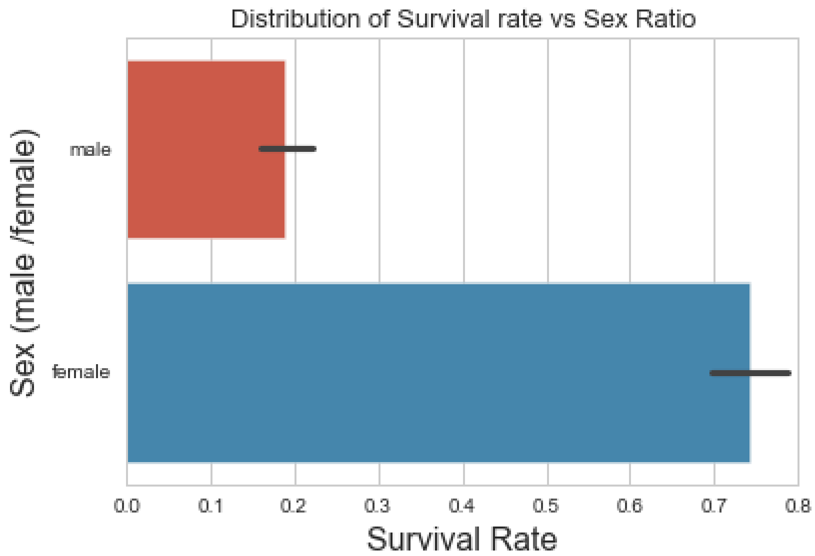
The above analysis shows that if a person is travelling with *high price ticket* i.e, **VIPs** then their survival rate is much higher then **General & Lower Class / Employees**.

Q2. Comparision of Survival for Male & Female ?

In [12]:

```
#No. of males
no_male = titanic_data['Sex'].value_counts()['male']

no_female = titanic_data['Sex'].value_counts()['female']

#Survived/Died Male guys who survived
no_male_survived =  titanic_data.groupby(['Sex' , 'Survived']).size()[3]
no_male_died = no_male - no_male_survived

#Survived/Died Female guys who survived
no_female_survived =  titanic_data.groupby(['Sex' , 'Survived']).size()[1]
no_female_died = no_female - no_female_survived

print('No. of Males : {}  , {:.2f}% of total'.format(no_male, float(no_male*10
0 )/len(titanic_data)))
print('No. of Male Survived : {} , {:.2f}%'.format(no_male_survived , float(no
_male_survived)*100/no_male))
print('No. of Male Died : {}, {:.2f}% '.format( no_male_died, float(no_male_di
ed)*100/no_male ))

print '\n'
print('No. of Females : {}  , {:.2f}% of total'.format(no_female, float(no_fem
ale)*100 /len(titanic_data)))
print('No. of Female Survived : {} , {:.2f}%'.format(no_female_survived , floa
t(no_female_survived)*100/no_female))
print('No. of Female Died : {}, {:.2f}% '.format( no_female_died, float(no_fem
ale_died)*100/no_female ))


sns.set_style("whitegrid")
sns.barplot(data = titanic_data , x = "Survived" , y ="Sex",capsize=14)
plt.ylabel('Sex (male /female)', fontsize=16)
plt.xlabel('Survival Rate', fontsize=16)
plt.title("Distribution of Survival rate vs Sex Ratio" , fontsize = 13)
sns.plt.show()
```

```
No. of Males : 577  , 64.76% of total
No. of Male Survived : 109 , 18.89%
No. of Male Died : 468, 81.11%


No. of Females : 314  , 35.24% of total
No. of Female Survived : 233 , 74.20%
No. of Female Died : 81, 25.80%
```



The above analysis gives an insight that Females were preferred to be saved i.e, their survival rate was high

---

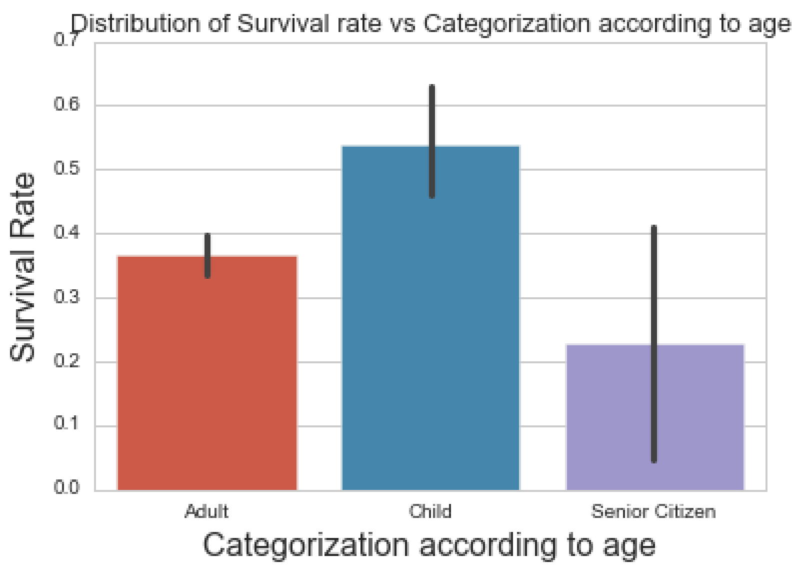
Q3. Analysis of Survival according to age , i.e, Children | Adults | Senior Citizens

In [13]:

```
def isAge(x):
    if x < 18.0:
        return "Child"
    elif x >60.0:
        return "Senior Citizen"
    else:
        return "Adult"

titanic_data["IsChild"] = pd.Series(titanic_data["Age"].apply(isAge), index=ti
tanic_data.index)
```

In [14]:
```
no_Child = titanic_data['IsChild'].value_counts()['Child']
no_SrCz = titanic_data['IsChild'].value_counts()['Senior Citizen']
no_Adult = titanic_data['IsChild'].value_counts()['Adult']

no_Child_survived =  titanic_data.groupby(['IsChild' , 'Survived']).size()['Ch
ild'][1]
no_Child_died = no_Child - no_Child_survived

#Survived/Died Female guys who survived
no_SrCz_survived =  titanic_data.groupby(['IsChild' , 'Survived']).size()['Sen
ior Citizen'][1]
no_SrCz_died = no_SrCz - no_SrCz_survived

no_Adult_survived =  titanic_data.groupby(['IsChild' , 'Survived']).size()['Ad
ult'][1]
no_Adult_died = no_Adult - no_Adult_survived


print('No. of Children : {}  , {:.2f}% of total'.format(no_Child, float(no_Chi
ld*100 )/len(titanic_data)))
print('No. of Child Survived : {} , {:.2f}%'.format(no_Child_survived ,
float(no_Child_survived)*100/no_Child))
print('No. of Child Died : {}, {:.2f}% '.format( no_Child_died, float(no_Child
_died)*100/no_Child ))

print '\n'

print('No. of Senior Citizen : {}  , {:.2f}% of total'.format(no_SrCz, float(n
o_SrCz*100 )/len(titanic_data)))
print('No. of Senior Citizen Survived : {} , {:.2f}%'.format(no_SrCz_survived
, float(no_SrCz_survived)*100/no_SrCz))
print('No. of Senior Citizen Died : {}, {:.2f}% '.format( no_SrCz_died,
float(no_SrCz_died)*100/no_SrCz ))

print '\n'

print('No. of Adults : {}  , {:.2f}% of total'.format(no_Adult,
float(no_Adult*100 )/len(titanic_data)))
print('No. of Adults Survived : {} , {:.2f}%'.format(no_Adult_survived ,
float(no_Adult_survived)*100/no_Adult))
print('No. of Adults  Died : {}, {:.2f}% '.format( no_Adult_died, float(no_Adu
lt_died)*100/no_Adult ))


sns.set_style("whitegrid")
sns.barplot(data = titanic_data , y = "Survived" , x ="IsChild")
plt.ylabel('Survival Rate', fontsize=16)
plt.xlabel('Categorization according to age', fontsize=16)
plt.title("Distribution of Survival rate vs Categorization according to age" ,
 fontsize = 13)
sns.plt.show()
```

```
No. of Children : 113  , 12.68% of total
No. of Child Survived : 61 , 53.98%
No. of Child Died : 52, 46.02%


No. of Senior Citizen : 22  , 2.47% of total
No. of Senior Citizen Survived : 5 , 22.73%
No. of Senior Citizen Died : 17, 77.27%


No. of Adults : 756  , 84.85% of total
No. of Adults Survived : 276 , 36.51%
No. of Adults  Died : 480, 63.49%
```



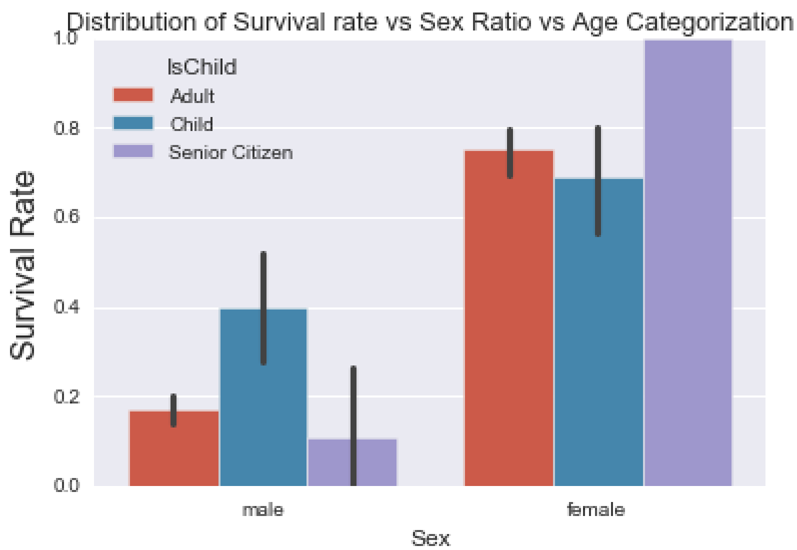
The Above Analysis shows that

> - **54% of Children** were saved. So, survival of children were **higher than Adults and Senior Citizens.**
> - Survival Rate of **Adults(36.5%)** is **higher** than **Senior Citizens(22.7%)**

Q4. Analysis of Survival in Male Child and Female Child

In [15]:
```
no_Female_Child = titanic_data.groupby(['IsChild' , 'Sex']).size()['Child']['f
emale']
no_male_Child =  titanic_data.groupby(['IsChild' , 'Sex']).size()['Child']['ma
le']

no_CFemale_Survived = titanic_data.groupby(['IsChild' ,'Survived', 'Sex']).siz
e()['Child'][1]['female']
no_CFemale_Died = no_Female_Child - no_CFemale_Survived
no_CMale_Survived = titanic_data.groupby(['IsChild' ,'Survived',
'Sex']).size()['Child'][1]['male']
no_CMale_Died = no_male_Child -no_CMale_Survived


print('No. of Female Child : {}  , {:.2f}% of total'.format(no_Female_Child, f
loat(no_Female_Child*100 )/len(titanic_data)))
print('No. of Female Child Survived : {} , {:.2f}%'.format(no_CFemale_Survived
 , float(no_CFemale_Survived)*100/no_Female_Child))
print('No. of Female Child Died : {}, {:.2f}% '.format( no_CFemale_Died,
float(no_CFemale_Died)*100/no_Female_Child ))

print '\n'

print('No. of Male Child : {}  , {:.2f}% of total'.format(no_male_Child,
float(no_male_Child*100 )/len(titanic_data)))
print('No. of Male Child Survived : {} , {:.2f}%'.format(no_CMale_Survived , f
loat(no_CMale_Survived)*100/no_male_Child))
print('No. of Male Child Died : {}, {:.2f}% '.format( no_CMale_Died, float(no_
CMale_Died)*100/no_male_Child ))

print '\n'
sns.set_style("darkgrid")
sns.barplot(data = titanic_data , y = "Survived" , x ="Sex"  , hue="IsChild")
plt.ylabel('Survival Rate', fontsize=16)
plt.title("Distribution of Survival rate vs Sex Ratio vs Age Categorization" ,
 fontsize = 13)
sns.plt.show()
```

```
No. of Female Child : 55  , 6.17% of total
No. of Female Child Survived : 38 , 69.09%
No. of Female Child Died : 17, 30.91%


No. of Male Child : 58  , 6.51% of total
No. of Male Child Survived : 23 , 39.66%
No. of Male Child Died : 35, 60.34%
```

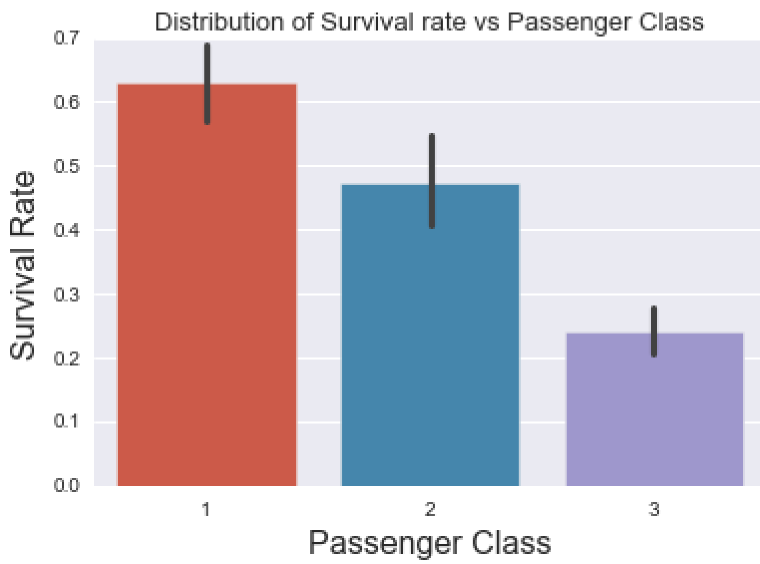


It shows that Survival Rate of **Female Children(69%) is more than Male Child(40%)**

Q5. Analysis of Survival according to Socio-economic status Upper Class (1st), Middle Class(2nd) , Lower Class(3rd)

In [16]:
```
no_class_1 = titanic_data['Pclass'].value_counts()[1]
no_class_2 = titanic_data['Pclass'].value_counts()[2]
no_class_3 = titanic_data['Pclass'].value_counts()[3]

#print titanic_data.groupby(['Pclass' , 'Survived']).size()

no_class_1_survived =  titanic_data.groupby(['Pclass' , 'Survived']).size()[1]
[1]
no_class_1_died = no_class_1 - no_class_1_survived

no_class_2_survived =  titanic_data.groupby(['Pclass' , 'Survived']).size()[2]
[1]
no_class_2_died = no_class_2 - no_class_2_survived

no_class_3_survived =  titanic_data.groupby(['Pclass' , 'Survived']).size()[3]
[1]
no_class_3_died = no_class_3 - no_class_3_survived

print('No. of Class 1 people : {}  , {:.2f}% of total'.format(no_class_1, floa
t(no_class_1*100 )/len(titanic_data)))
print('No. of Class 1 people Survived : {} , {:.2f}%'.format(no_class_1_surviv
ed , float(no_class_1_survived)*100/no_class_1))
print('No. of Class 1 people Died : {}, {:.2f}% '.format( no_class_1_died, flo
at(no_class_1_died)*100/no_class_1 ))

print '\n'
print('No. of Class 2 people : {}  , {:.2f}% of total'.format(no_class_2, floa
t(no_class_2)*100 /len(titanic_data)))
print('No. of Class 2 people Survived : {} , {:.2f}%'.format(no_class_2_surviv
ed , float(no_class_2_survived)*100/no_class_2))
print('No. of Class 2 people Died : {}, {:.2f}% '.format( no_class_2_died, flo
at(no_class_2_died)*100/no_class_2 ))

print '\n'
print('No. of Class 3 people : {}  , {:.2f}% of total'.format(no_class_3, floa
t(no_class_3)*100 /len(titanic_data)))
print('No. of Class 3 people Survived : {} , {:.2f}%'.format(no_class_3_surviv
ed , float(no_class_3_survived)*100/no_class_3))
print('No. of Class 3 people Died : {}, {:.2f}% '.format( no_class_3_died, flo
at(no_class_3_died)*100/no_class_3 ))


sns.set_style("darkgrid")
sns.barplot(data = titanic_data , y = "Survived" , x ="Pclass" )
plt.ylabel('Survival Rate', fontsize=16)
plt.xlabel('Passenger Class', fontsize=16)
plt.title("Distribution of Survival rate vs Passenger Class" , fontsize = 13)
sns.plt.show()
```

```
No. of Class 1 people : 216  , 24.24% of total
No. of Class 1 people Survived : 136 , 62.96%
No. of Class 1 people Died : 80, 37.04%


No. of Class 2 people : 184  , 20.65% of total
No. of Class 2 people Survived : 87 , 47.28%
No. of Class 2 people Died : 97, 52.72%


No. of Class 3 people : 491  , 55.11% of total
No. of Class 3 people Survived : 119 , 24.24%
No. of Class 3 people Died : 372, 75.76%
```



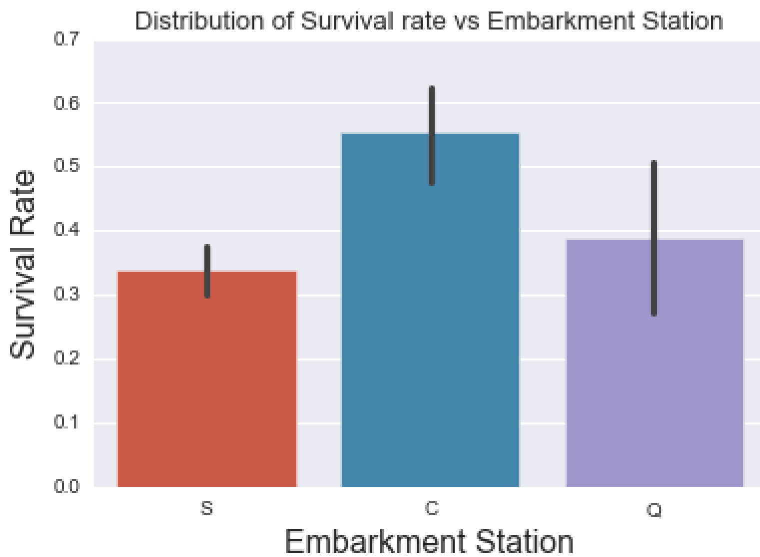
It shows that **Upper Class (63%)** were **preffered** over **Middle Class(47%) & Lower Class(24%)** people.

Q6. Chances of Survival According to Embarkment Station.

In [17]:

```
no_boarded_C = titanic_data['Embarked'].value_counts()['C']
no_boarded_Q = titanic_data['Embarked'].value_counts()['Q']
no_boarded_S = titanic_data['Embarked'].value_counts()['S']

#print titanic_data.groupby(['Embarked' , 'Survived']).size()

no_boarded_C_survived =  titanic_data.groupby(['Embarked' ,
'Survived']).size()['C'][1]
no_boarded_C_died = no_boarded_C - no_boarded_C_survived

no_boarded_Q_survived =  titanic_data.groupby(['Embarked' ,
'Survived']).size()['Q'][1]
no_boarded_Q_died = no_boarded_Q - no_boarded_Q_survived

no_boarded_S_survived =  titanic_data.groupby(['Embarked' ,
'Survived']).size()['S'][1]
no_boarded_S_died = no_boarded_S - no_boarded_S_survived

print('No. of People boarded from Cherbourg : {}  , {:.2f}% of total'.format(n
o_boarded_C, float(no_boarded_C*100 )/len(titanic_data)))
print('No. of People boarded from Cherbourg  who Survived: {} , {:.2f}%'.forma
t(no_boarded_C_survived , float(no_boarded_C_survived)*100/no_boarded_C))
print('No. of People boarded from Cherbourg  who Died : {}, {:.2f}% '.format(
no_boarded_C_died, float(no_boarded_C_died)*100/no_boarded_C ))

print '\n'
print('No. of People boarded from Queenstown : {}  , {:.2f}% of
total'.format(no_boarded_Q, float(no_class_2)*100 /len(titanic_data)))
print('No. of People boarded from Queenstown  who Survived : {} , {:.2f}%'.for
mat(no_boarded_Q_survived , float(no_boarded_Q_survived)*100/no_boarded_Q))
print('No. of People boarded from Queenstown  who Died : {}, {:.2f}% '.format(
 no_boarded_Q_died, float(no_boarded_Q_died)*100/no_boarded_Q ))

print '\n'
print('No. of People boarded from Southampton : {}  , {:.2f}% of
total'.format(no_boarded_S, float(no_boarded_S)*100 /len(titanic_data)))
print('No. of People boarded from Southampton  who Survived : {} , {:.2f}%'.fo
rmat(no_boarded_S_survived , float(no_boarded_S_survived)*100/no_boarded_S))
print('No. of People boarded from Southampton  who Died : {}, {:.2f}%
'.format( no_boarded_S_died, float(no_boarded_S_died)*100/no_boarded_S ))

sns.set_style("darkgrid")
sns.barplot(data = titanic_data , y = "Survived" , x ="Embarked" )
plt.ylabel('Survival Rate', fontsize=16)
plt.xlabel('Embarkment Station', fontsize=16)
plt.title("Distribution of Survival rate vs Embarkment Station" , fontsize = 1
3)
sns.plt.show()
```

```
No. of People boarded from Cherbourg : 168  , 18.86% of total
No. of People boarded from Cherbourg  who Survived: 93 , 55.36%
No. of People boarded from Cherbourg  who Died : 75, 44.64%


No. of People boarded from Queenstown : 77  , 20.65% of total
No. of People boarded from Queenstown  who Survived : 30 , 38.96%
No. of People boarded from Queenstown  who Died : 47, 61.04%


No. of People boarded from Southampton : 644  , 72.28% of total
No. of People boarded from Southampton  who Survived : 217 , 33.70%
No. of People boarded from Southampton  who Died : 427, 66.30%
```



It shows that people who boarded from :

> - **Cherbourg** had higher probablity of survival**(55.36%)**
> - **Southampton** had lowest probablity of survival**(33.7%)**

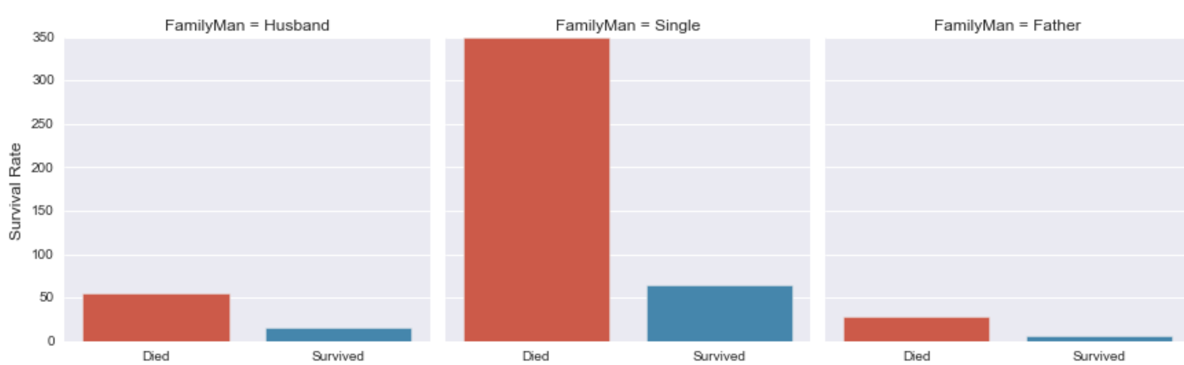
Q7. Chances of survival of Men with child(Father) or spouse(Husband) or Single

In [18]:

```
def isAdultMan(x):
    return (x["IsChild"] =="Senior Citizen" or x["IsChild"] =="Adult")  and 
x["Sex"] == "male"

adult_man_titanic_data = titanic_data[titanic_data.apply(isAdultMan, axis=1)]


def isFamilyMan(x):
    if x["SibSp"] > 0:
        if x["Parch"] > 0:
            return "Father"
        else:
            return "Husband"
    else:
        return "Single"
adult_man_titanic_data["FamilyMan"] = pd.Series(adult_man_titanic_data.apply(i
sFamilyMan, axis=1), index=adult_man_titanic_data.index)
# print adult_man_titanic_data["FamilyMan"].value_counts()

no_Adult_Fathers_survived =  adult_man_titanic_data.groupby(['FamilyMan' , 'Su
rvived']).size()['Father'][1]
no_Adult_Fathers_died = adult_man_titanic_data.groupby(['FamilyMan' , 'Survive
d']).size()['Father'][0]

no_Fathers = adult_man_titanic_data["FamilyMan"].value_counts()["Father"]

print('No. of Adult Fathers : {}  , {:.2f}% of total'.format(no_Fathers , floa
t(no_Fathers *100 )/len(titanic_data)))
print('No. of Adult Fathers Survived : {} , {:.2f}%'.format(no_Adult_Fathers_s
urvived , float(no_Adult_Fathers_survived)*100/no_Fathers))
print('No. of Adult Fathers Died : {}, {:.2f}% '.format(
no_Adult_Fathers_died, float(no_Adult_Fathers_died)*100/no_Fathers ))

print '\n'

no_Husband_survived =  adult_man_titanic_data.groupby(['FamilyMan' , 'Survive
d']).size()['Husband'][1]
no_Husband_died = adult_man_titanic_data.groupby(['FamilyMan' , 'Survived']).s
ize()['Husband'][0]


no_Husband = adult_man_titanic_data["FamilyMan"].value_counts()["Husband"]

print('No. of Adult Husband : {}  , {:.2f}% of total'.format(no_Husband , floa
t(no_Husband *100 )/len(titanic_data)))
print('No. of Adult Husband Survived : {} , {:.2f}%'.format(no_Husband_survive
d , float(no_Husband_survived)*100/no_Husband))
print('No. of Adult Husband Died : {}, {:.2f}% '.format( no_Husband_died, floa
t(no_Husband_died)*100/no_Husband ))

print '\n'

no_Single_survived =  adult_man_titanic_data.groupby(['FamilyMan' , 
'Survived']).size()['Single'][1]
no_Single_died = adult_man_titanic_data.groupby(['FamilyMan' , 'Survived']).si
ze()['Single'][0]
```

```
no_Single = adult_man_titanic_data["FamilyMan"].value_counts()["Single"]

print('No. of Adult Single : {}  , {:.2f}% of total'.format(no_Single ,
float(no_Single *100 )/len(titanic_data)))
print('No. of Adult Single Survived : {} , {:.2f}%'.format(no_Single_survived
, float(no_Single_survived)*100/no_Single))
print('No. of Adult Single Died : {}, {:.2f}% '.format( no_Single_died,
float(no_Single_died)*100/no_Single ))

print '\n'



sns.set_style("darkgrid")
g= sns.factorplot(data=adult_man_titanic_data,x="Survived", col="FamilyMan", k
ind="count" )
g.set_axis_labels("", "Survival Rate").set_xticklabels(["Died", "Survived"])
sns.plt.show()
```

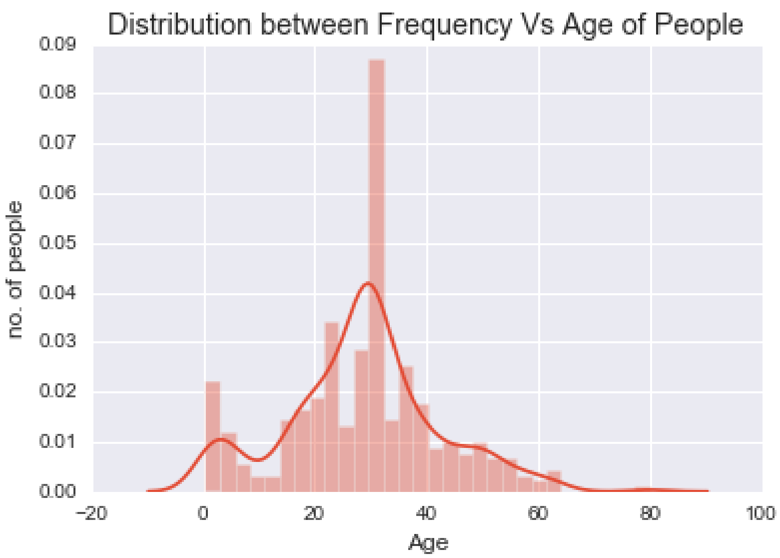
```
C:\Users\RAHUL\Anaconda2\lib\site-packages\ipykernel\__main__.py:15: SettingW
ithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/st
able/indexing.html#indexing-view-versus-copy

No. of Adult Fathers : 34  , 3.82% of total
No. of Adult Fathers Survived : 6 , 17.65%
No. of Adult Fathers Died : 28, 82.35%


No. of Adult Husband : 70  , 7.86% of total
No. of Adult Husband Survived : 15 , 21.43%
No. of Adult Husband Died : 55, 78.57%


No. of Adult Single : 415  , 46.58% of total
No. of Adult Single Survived : 65 , 15.66%
No. of Adult Single Died : 350, 84.34%
```



It shows that Suvival rate of Men travelling with their Wife is Higher that Men travelling with their kids

Q8. Best Age-group which had highest probablity of survival

In [19]:
```
Best_Age = titanic_data[titanic_data['Survived']==1]['Age']
ax = sns.distplot(Best_Age,bins=30)
ax.set(xlabel='Age', ylabel='no. of people',title="Distribution between Freque
ncy Vs Age of People")
sns.plt.show()
```



It shows that **(29 - 32) age group** people survived more

Conclusion :

Limitations :

While using the Titanic dataset I found several limitations that made making deeper analysis more difficult and in some cases unreliable. The dataset is filled with missing values. In Age , Cabin column there are many NaN values.

- The missing age values are imputed using mean(age). These values are just estimated on the basis of dataset. After replacing missing values with mean , it gives a totally different estimate in graph. This is a limitation because this estimate may be wrong upto some extent.
- We have ignored Cabin data from analysis part, it can be a useful for finding some correlations but due to large no. of missing values and string data(which can not be plotted on quantitative basis) it made the analysis of that column unreliable and probably useless.

References

The list of sources used to complete this investigation is:

- Titanic dataset (Data Analyst Nanodegree Project 2)
- Video lectures udacity
- Pandas documentation link (http://pandas.pydata.org/pandas-docs/stable/#)
- Numpy Documentation link (http://docs.scipy.org/doc/numpy/reference/)
- Seaborn statistical data visualization reference page link (http://stanford.edu/~mwaskom/software/seaborn/)
- Tutorials pandas (www.gregreda.com/2013/10/26/working-with-pandas-dataframes/) , latex (http://stackoverflow.com/questions/13208286/how-to-write-latex-in-ipython-notebook)
- nbconvert for conversion of ipynb to html link (https://github.com/jupyter/nbconvert)