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

%matplotlib inline
plt.style.use('bmh')
```

In [3]:
```
df=pd.read_csv("train.csv")
df
```

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	7.2500
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500
...	...	...	...	...	...	...	...	...	...	...
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.0000
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.0000
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.4500
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.0000
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.7500

891 rows × 12 columns

DATA DESCRIPTION

1. Survival: Survival (0 = No; 1 = Yes)
2. pclass: Passenger Class (1 = 1st; 2 = 2nd; 3 = 3rd)
3. name: Name
4. sex: Sex
5. age: Age
6. sibsp: Number of Siblings/Spouses Aboard
7. parch: Number of Parents/Children Aboard
8. ticket: Ticket Number
9. fare: Passenger Fare
10. cabin: Cabin
11. embarked: Port of Embarkation (C = Cherbourg; Q = Queenstown; S = Southampton)

VARIABLE NOTES

1. pclass: A proxy for socio-economic status (SES) 1st = Upper 2nd = Middle 3rd = Lower
2. age: Age is fractional if less than 1. If the age is estimated, is it in the form of xx.5
3. sibsp: The dataset defines family relations in this way… Sibling = brother, sister, stepbrother, stepsister Spouse = husband, wife (mistresses and fiancés were ignored)
4. 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.
5. Now let's see some statistical summary of the imported dataset using pandas.describe() method.

In [4]:
```
df.describe()
```

Out[4]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

In [5]:
```
df.info()
```

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

In [11]:
```
train = df.drop(['PassengerId', 'Name', 'Ticket', 'Cabin'], axis=1)
train.head()
```

Out[11]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	male	22.0	1	0	7.2500	S
1	1	1	female	38.0	1	0	71.2833	C
2	1	3	female	26.0	0	0	7.9250	S
3	1	1	female	35.0	1	0	53.1000	S
4	0	3	male	35.0	0	0	8.0500	S

In [13]:
```
train.describe()
```

Out[13]:

	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

In [15]:
```
train.isnull().sum()
```

Out[15]:
```
Survived      0
Pclass        0
Sex           0
Age         177
SibSp         0
Parch         0
Fare          0
Embarked      2
dtype: int64
```

Data exploration:

I will be exploring the following questions on the dataframe

1. How Survival is correlated to other attributes of the dataset ? Findout Pearson’s r.
2. Did Sex play a role in Survival ?
3. Did class played role in survival ?
4. How fare is related to Age, Class and Port of Embarkation ?
5. How Embarkation varied across different ports ?

Q1;How Survival is correlated to other attributes of the dataset ? Findout Pearson’s r.

In [17]:
```
#How Survival is correlated to other attributes of the dataset ? Findout Pears
on’s r
train.corr(method='pearson')
```

Out[17]:

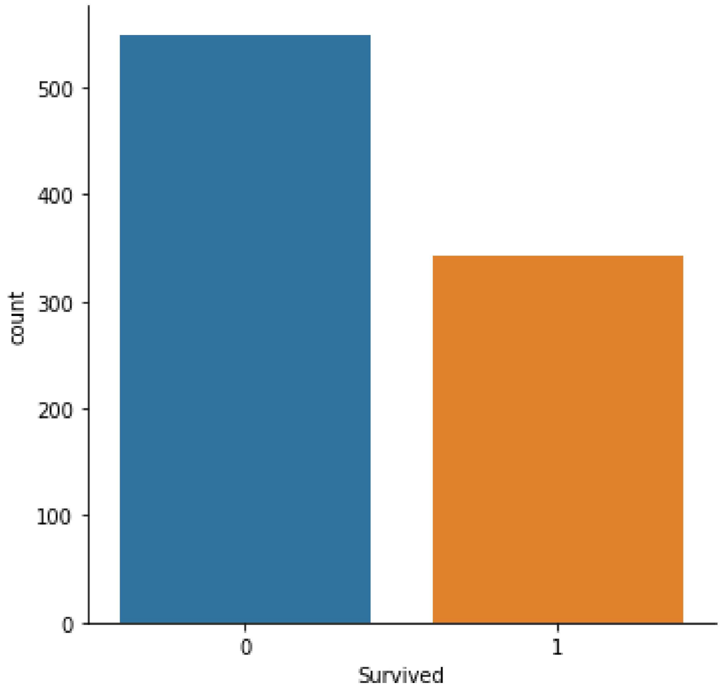
	Survived	Pclass	Age	SibSp	Parch	Fare
Survived	1.000000	-0.338481	-0.077221	-0.035322	0.081629	0.257307
Pclass	-0.338481	1.000000	-0.369226	0.083081	0.018443	-0.549500
Age	-0.077221	-0.369226	1.000000	-0.308247	-0.189119	0.096067
SibSp	-0.035322	0.083081	-0.308247	1.000000	0.414838	0.159651
Parch	0.081629	0.018443	-0.189119	0.414838	1.000000	0.216225
Fare	0.257307	-0.549500	0.096067	0.159651	0.216225	1.000000

From above correlation table we can see that Survival is inversly correlated to Pclass value. In our case since Class 1 has lower numerical value, it had better survival rate compared to other classes. We also see that Age and Survival are slighltly correlated.

Did Sex play a role in Survival ?

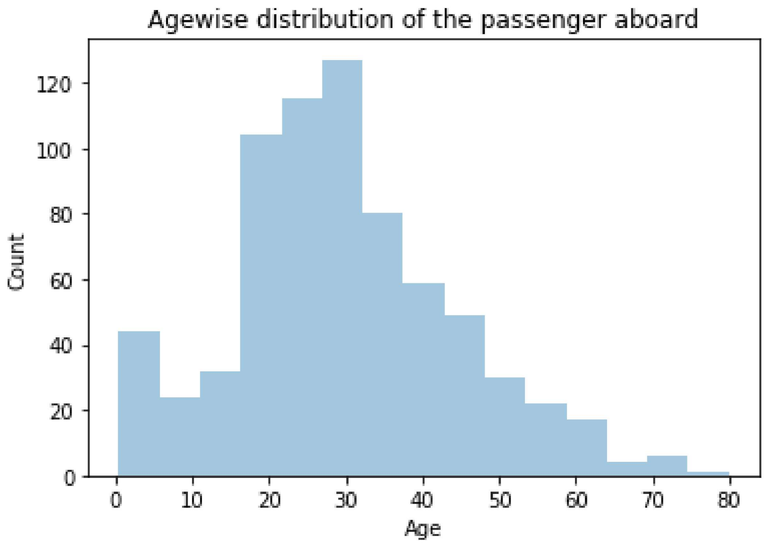
In [63]:
```
#train.groupby(['Survived']).hist()

sns.factorplot('Survived', data=df, kind='count')
```

Out[63]: <seaborn.axisgrid.FacetGrid at 0x1f86cb9e248>



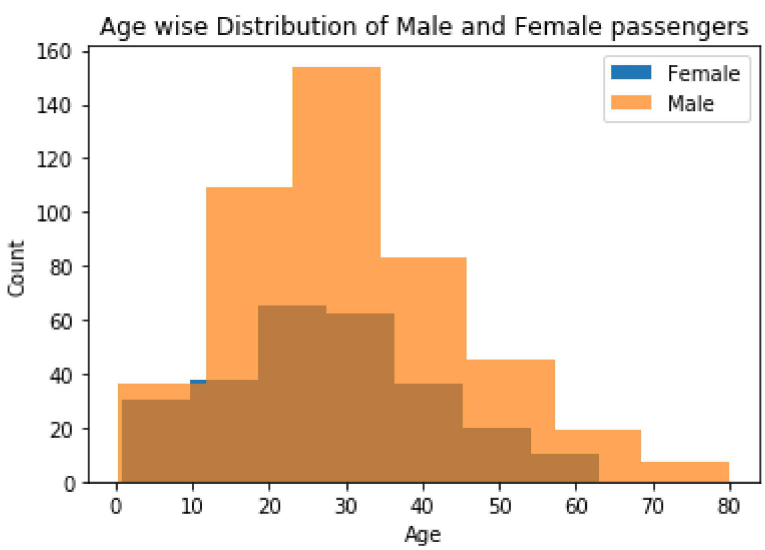
In [57]:
```
#agewise distribution of the passenger
#Histogram of Age of the given data set(sample)
#plt.hist(train['Age'].dropna())
sns.distplot(train['Age'].dropna(), bins=15, kde=False)
plt.ylabel('Count')
plt.title('Agewise distribution of the passenger')
```

Out[57]: Text(0.5, 1.0, 'Agewise distribution of the passenger aboard')



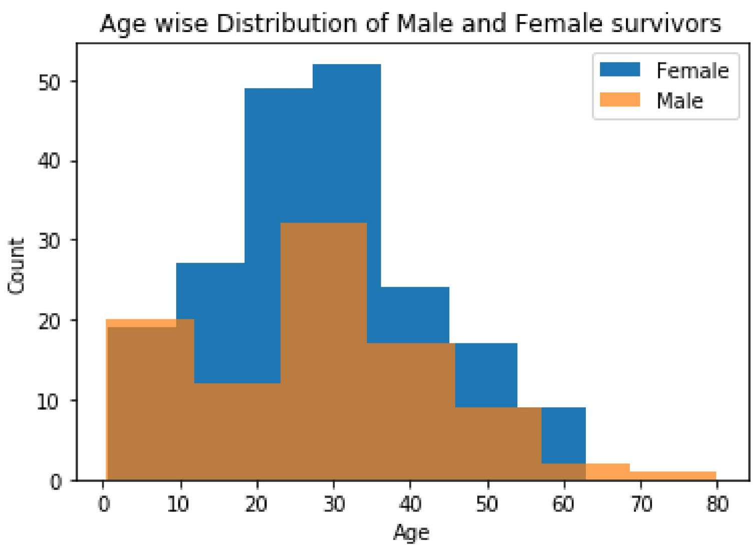
In [31]:
```
#Age wise Distribution of Male and Female passengers
plt.hist(train['Age'][(train['Sex'] == 'female')].dropna(), bins=7, label='Fem
ale', histtype='stepfilled')
plt.hist(train['Age'][(train['Sex'] == 'male')].dropna(), bins=7, label='Male'
, alpha=.7, histtype='stepfilled')
plt.xlabel('Age')
plt.ylabel('Count')
plt.title('Age wise Distribution of Male and Female passengers')
plt.legend()
```

Out[31]: <matplotlib.legend.Legend at 0x1f86c63cd88>



In [34]:
```
#passenges who Survived across both Genders
#Age wise Distribution of Male and Female survivors
plt.hist(train['Age'][(train['Sex'] == 'female') & (train['Survived'] == 1)].d
ropna(), bins=7, label='Female', histtype='stepfilled')
plt.hist(train['Age'][(train['Sex'] == 'male') & (train['Survived'] == 1)].dro
pna(), bins=7, label='Male', alpha=.7, histtype='stepfilled')
plt.xlabel('Age')
plt.ylabel('Count')
plt.title('Age wise Distribution of Male and Female survivors')
plt.legend()
```

Out[34]:
```
<matplotlib.legend.Legend at 0x1f86c6101c8>
```



In [40]:
```
#From above visualization, it is evident that Women had better survival chanc
e. One can do an Hypothesis test to verify this.
#Lets take a look for youngest and oldest passenger to survive.
yougest_survive = train['Age'][(train['Survived'] == 1)].min()
youngest_die = train['Age'][(train['Survived'] == 0)].min()
oldest_survive = train['Age'][(train['Survived'] == 1)].max()
oldest_die = train['Age'][(train['Survived'] == 0)].max()

print ("Yougest to survive: {} \nYoungest to die: {} \nOldest to survive: {}
\nOldest to die: {}".format(yougest_survive, youngest_die, oldest_survive, old
est_die))
```

```
Yougest to survive: 0.42
Youngest to die: 1.0
Oldest to survive: 80.0
Oldest to die: 74.0
```

Q3;Did class played role in survival ?

In [42]:
```
#sns.plt.hist(train.groupby(['Pclass', 'Survived', 'Sex']).size())
grouped_by_pclass = train.groupby(['Pclass', 'Survived', 'Sex'])
grouped_by_pclass.size()
```

Out[42]:
```
Pclass  Survived  Sex
1       0         female      3
                  male       77
        1         female     91
                  male       45
2       0         female      6
                  male       91
        1         female     70
                  male       17
3       0         female     72
                  male      300
        1         female     72
                  male       47
dtype: int64
```

In [43]:
```
train.groupby(['Pclass', 'Sex']).describe()
```

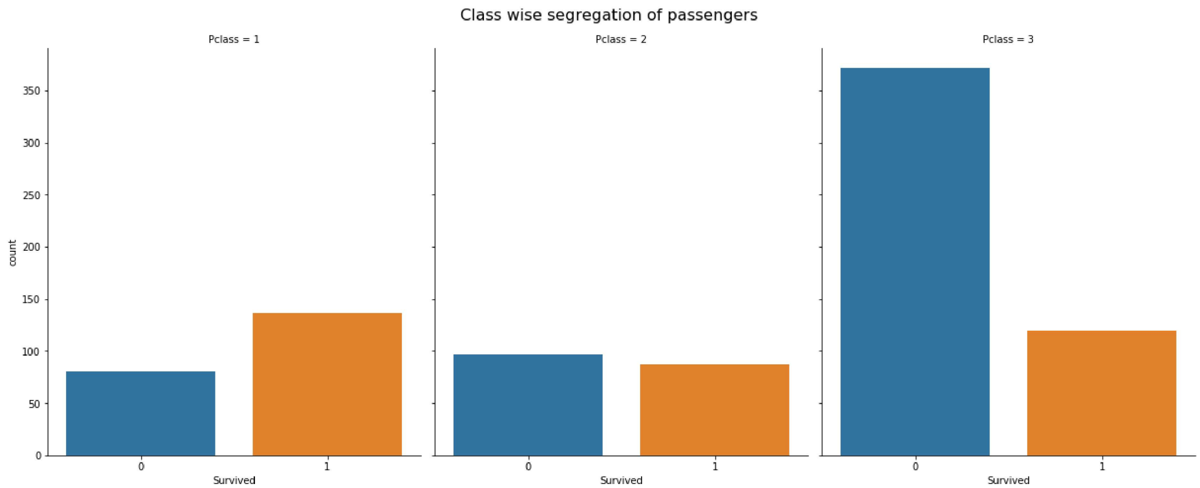
Out[43]:

		Survived								Age		...	P
		count	mean	std	min	25%	50%	75%	max	count	mean	...	7
Pclass	Sex												
1	female	94.0	0.968085	0.176716	0.0	1.0	1.0	1.0	1.0	85.0	34.611765	...	
	male	122.0	0.368852	0.484484	0.0	0.0	0.0	1.0	1.0	101.0	41.281386	...	
2	female	76.0	0.921053	0.271448	0.0	1.0	1.0	1.0	1.0	74.0	28.722973	...	
	male	108.0	0.157407	0.365882	0.0	0.0	0.0	0.0	1.0	99.0	30.740707	...	
3	female	144.0	0.500000	0.501745	0.0	0.0	0.5	1.0	1.0	102.0	21.750000	...	
	male	347.0	0.135447	0.342694	0.0	0.0	0.0	0.0	1.0	253.0	26.507589	...	

6 rows × 40 columns

In [49]:
```
sns.catplot('Survived', col='Pclass', data=train, kind='count', height=7, aspe
ct=.8)
plt.subplots_adjust(top=0.9)
plt.suptitle('Class wise segregation of passengers', fontsize=16)
```

Out[49]: `Text(0.5, 0.98, 'Class wise segregation of passengers')`

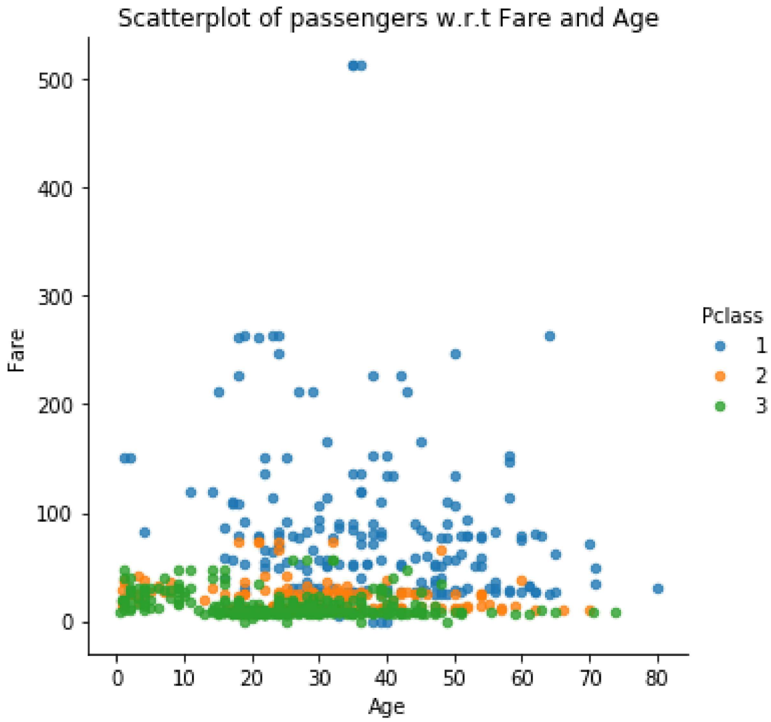


Q4; How fare is related to Age, Class and Port of Embarkation?

Q5; How Embarkation varied across different ports?

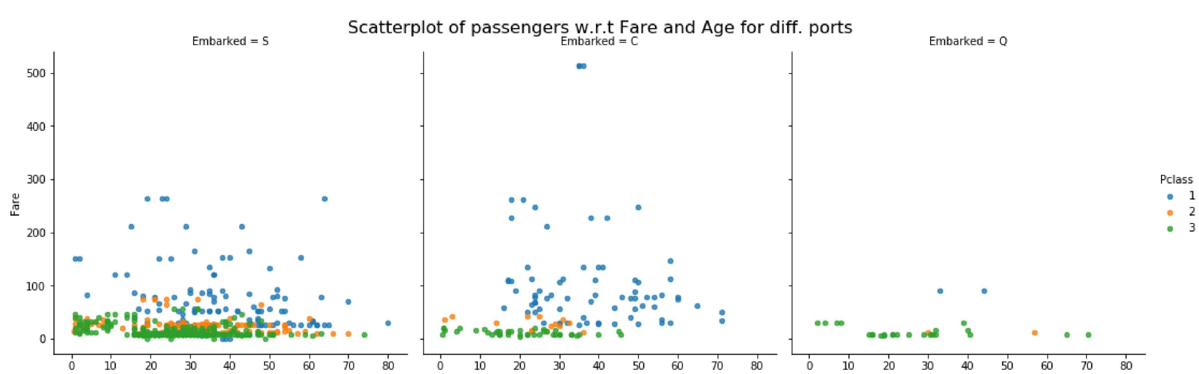
In [53]:
```
sns.lmplot('Age', 'Fare', data=train, fit_reg=False, hue="Pclass", scatter_kws
={"marker": ".", "s": 20})
plt.title('Scatterplot of passengers w.r.t Fare and Age')
```

Out[53]: Text(0.5, 1, 'Scatterplot of passengers w.r.t Fare and Age')



In [56]:
```
sns.lmplot('Age', 'Fare', data=train, fit_reg=False, hue="Pclass", col="Embark
ed", scatter_kws={"marker": ".", "s": 20})
plt.subplots_adjust(top=0.9)
plt.suptitle('Scatterplot of passengers w.r.t Fare and Age for diff. ports', f
ontsize=16)
```

Out[56]: Text(0.5, 0.98, 'Scatterplot of passengers w.r.t Fare and Age for diff. port
s')



IN CONCLUSION

From my exploratory analysis of the train dataset, we can conclude that Females younger than 40 had a high chance of survival and females older than 40 have a minimal chance of survival.I also see that Class(Socio-Economic status) of the passengers had played a role in their survival. There were some limitation for this dataset such as missing values for some attributes of passesngers.