Titanic: Machine Learning from Disaster

November 30, 2018

1 Introduction

The sinking of the RMS Titanic is one of the most infamous shipwrecks in history. On April 15, 1912, during her maiden voyage, the Titanic sank after colliding with an iceberg, killing 1502 out of 2224 passengers and crew. This sensational tragedy shocked the international community and led to better safety regulations for ships.

One of the reasons that the shipwreck led to such loss of life was that there were not enough lifeboats for the passengers and crew. Although there was some element of luck involved in surviving the sinking, some groups of people were more likely to survive than others, such as women, children, and the upper-class.

In this project, we apply machine learning tools to predict which passengers survived the tragedy. In Section 2 and 3, we provide a brief summary of the data and also visulaize the features. In Section 4, we drop the features that we don't need, complete features with missing values, create and convert features as needed. We then consider different machine learning models to predict survival and compare their perfomances in Section 5. Finally, we conclude the project and make our suggestions in Section 6.

2 Summary of Data

The variables in the dataset are as follow:

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	

Variable	Definition	Key
ticket	Ticket number	
fare	Passenger fare	
cabin	Cabin number	
embarked	Port of Embarkation	C = Cherbourg, Q = Queenstown, S = Southampton

In [1]:
```
import pandas as pd
import numpy as np
import random as rnd

# visualization
import seaborn as sns
import matplotlib.pyplot as plt
%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
from sklearn.linear_model import Perceptron
from sklearn.tree import DecisionTreeClassifier
```

Note that in the original project, the test set 'test.scv' doesn't contain the dependent variable Survived. Thus in our analysis, we split the dataset 'train.csv' (the training set of the original project) into test and training sets, and evaluate the performance of different models.

Now let's observe the first few rows:

In [2]:
```
dataset = pd.read_csv('train.csv')
from sklearn.cross_validation import train_test_split
train_data, test_data = train_test_split(dataset, test_size = 0.25, random_state = 0)

train_data.head()
```

```
/Users/luwang/anaconda3/lib/python3.6/site-packages/sklearn/cross_validation.py:41: DeprecationW
  "This module will be removed in 0.20.", DeprecationWarning)
```

Out[2]:
```
     PassengerId  Survived  Pclass                    Name   Sex  \
105          106         0       3       Mionoff, Mr. Stoytcho  male
```

```
68            69         1        3  Andersson, Miss. Erna Alexandra  female
253          254         0        3         Lobb, Mr. William Arthur    male
320          321         0        3               Dennis, Mr. Samuel    male
706          707         1        2    Kelly, Mrs. Florence "Fannie"  female

      Age  SibSp  Parch     Ticket     Fare Cabin Embarked
105  28.0      0      0     349207   7.8958   NaN        S
68   17.0      4      2    3101281   7.9250   NaN        S
253  30.0      1      0  A/5. 3336  16.1000   NaN        S
320  22.0      0      0  A/5 21172   7.2500   NaN        S
706  45.0      0      0     223596  13.5000   NaN        S
```

In [3]:
```
train_data.info()
test_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 668 entries, 105 to 684
Data columns (total 12 columns):
PassengerId    668 non-null int64
Survived       668 non-null int64
Pclass         668 non-null int64
Name           668 non-null object
Sex            668 non-null object
Age            535 non-null float64
SibSp          668 non-null int64
Parch          668 non-null int64
Ticket         668 non-null object
Fare           668 non-null float64
Cabin          157 non-null object
Embarked       666 non-null object
dtypes: float64(2), int64(5), object(5)
memory usage: 67.8+ KB
<class 'pandas.core.frame.DataFrame'>
Int64Index: 223 entries, 495 to 10
Data columns (total 12 columns):
PassengerId    223 non-null int64
Survived       223 non-null int64
Pclass         223 non-null int64
Name           223 non-null object
Sex            223 non-null object
Age            179 non-null float64
SibSp          223 non-null int64
Parch          223 non-null int64
Ticket         223 non-null object
Fare           223 non-null float64
Cabin          47 non-null object
Embarked       223 non-null object
dtypes: float64(2), int64(5), object(5)
```

```
memory usage: 22.6+ KB
```

We can see that there are four categorical features: Survived, Sex, Embarked and Pclass, where Pclass is also an ordinal feature.

Numerical features are Age, SibSp, Parch and Fare, where Age and Fare are continuous, SibSp and Parch are discrete.

Ticket is a mix of numeric and alphanumeric data types. Cabin is alphanumeric.

In training set, there are missing values for features Age, Cabin and Embarked. In test set, features Age and Cabin have missing values.

2.1 Distribution of numerical features

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

Out[4]:
```
       PassengerId    Survived      Pclass         Age       SibSp  \
count   668.000000  668.000000  668.000000  535.000000  668.000000
mean    445.911677    0.386228    2.305389   29.900000    0.534431
std     259.966783    0.487249    0.837377   14.487993    1.161739
min       1.000000    0.000000    1.000000    0.670000    0.000000
25%     216.250000    0.000000    2.000000   21.000000    0.000000
50%     445.500000    0.000000    3.000000   29.000000    0.000000
75%     674.500000    1.000000    3.000000   38.000000    1.000000
max     890.000000    1.000000    3.000000   80.000000    8.000000

            Parch        Fare
count  668.000000  668.000000
mean     0.392216   32.373621
std      0.822509   50.632021
min      0.000000    0.000000
25%      0.000000    7.925000
50%      0.000000   14.500000
75%      0.000000   31.275000
max      6.000000  512.329200
```

Obeservations:

1. 38.6% passengers in the training set survived.
2. There are few old passengers (<25%), since the 75% quantile is 38.
3. Over 75% passengers didn't travel with their parents or children.
4. Fares varies a lot among passengers.

2.2 Distribution of categorical features

In [310]:
```
train_data.describe(include=['O'])
```

Out[310]:
```
                                      Name  Sex  Ticket  Cabin  \
count                                  668  668     668    157
unique                                 668    2     538    123
```

```
top     Goldenberg, Mrs. Samuel L (Edwiga Grabowska)  male  CA. 2343  B96 B98
freq                                               1   437         7        3

       Embarked
count       666
unique        3
top           S
freq        490
```

Obeservations:

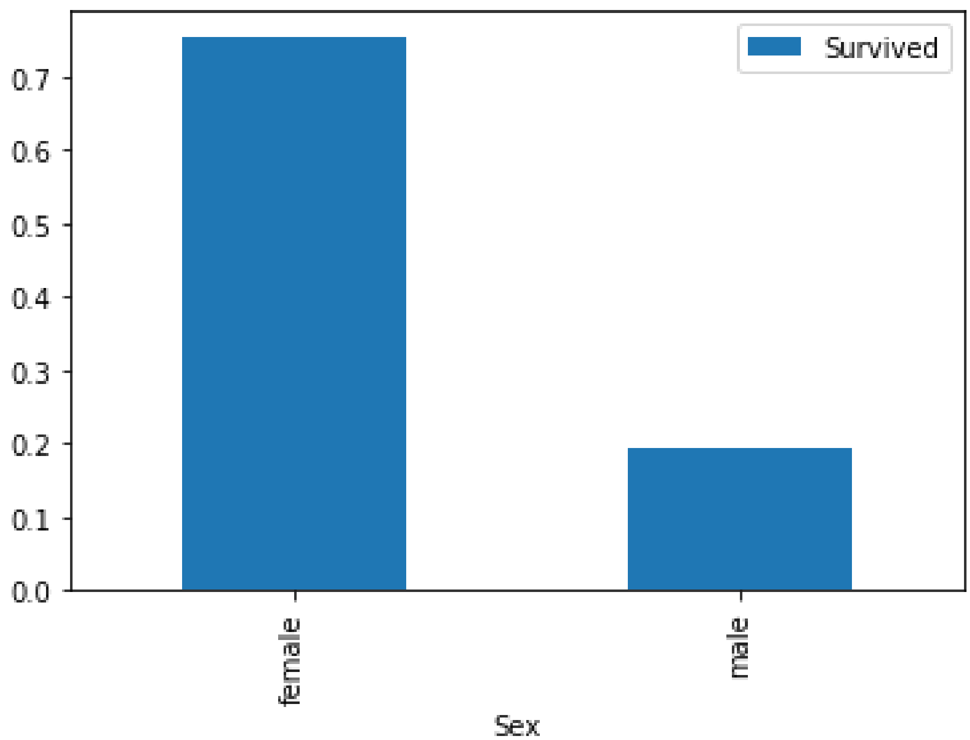
1. 65.4% passengers in the training set were male, 34.6% were female.
2. Embarked takes three values, the most frequent one is S.
3. Some passengers shared the cabins.

3 Visualizing data

3.1 Sex

In [5]:
```
# survival rates of male and female
train_data[['Sex','Survived']].groupby(['Sex']).mean().plot.bar()
```

Out[5]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x108e7e278>
```

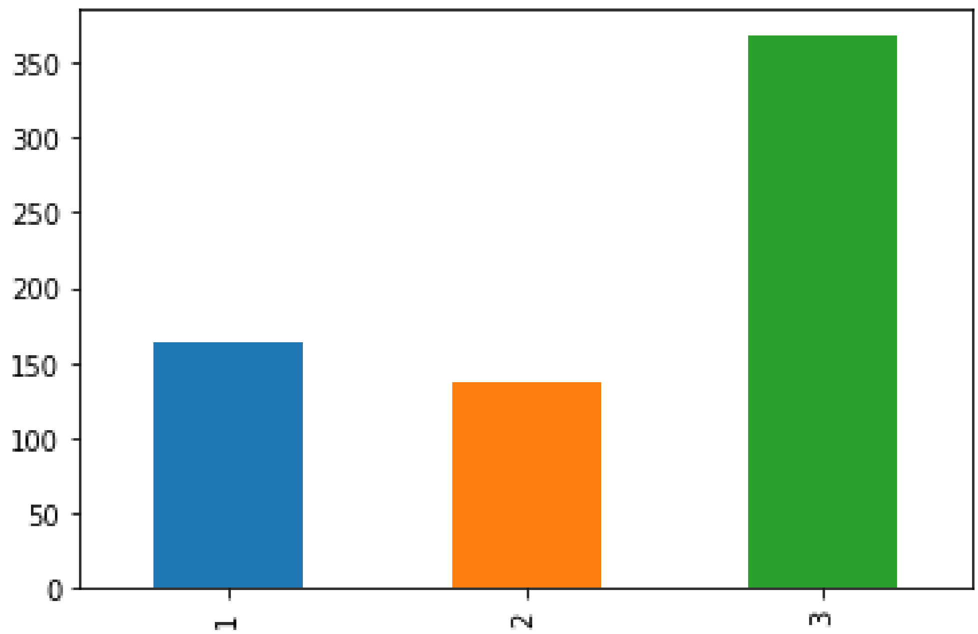


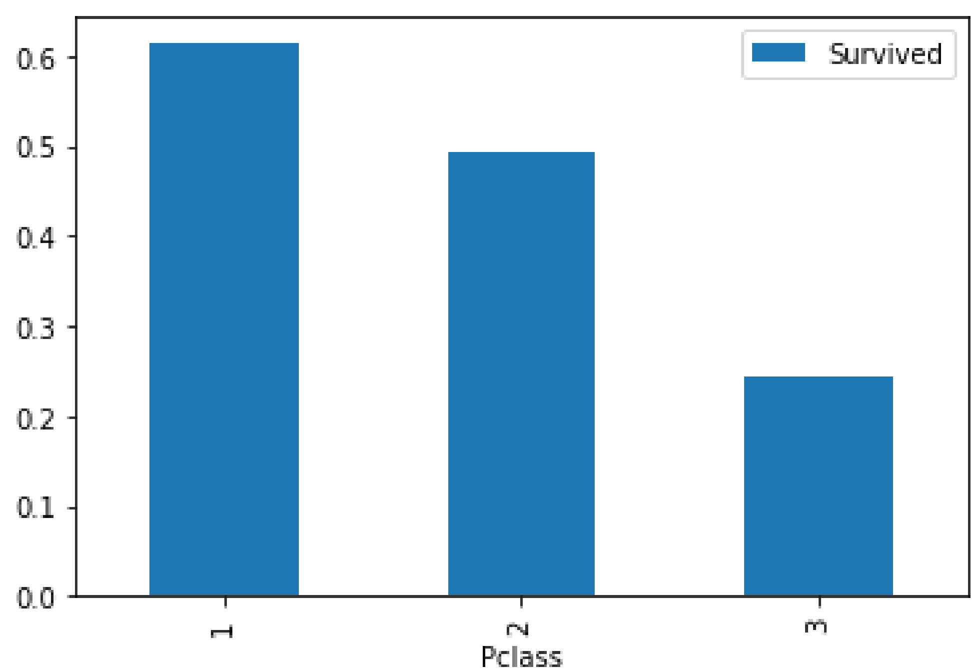
Sex correlates with Survived: Sex = female had much higher survival rate.

3.2 Pclass

In [6]:
```
# histogram of Pclass and the survival rates of each class
train_data['Pclass'].value_counts()[[1,2,3]].plot(kind='bar')
train_data[['Pclass','Survived']].groupby(['Pclass']).mean().plot.bar()
```

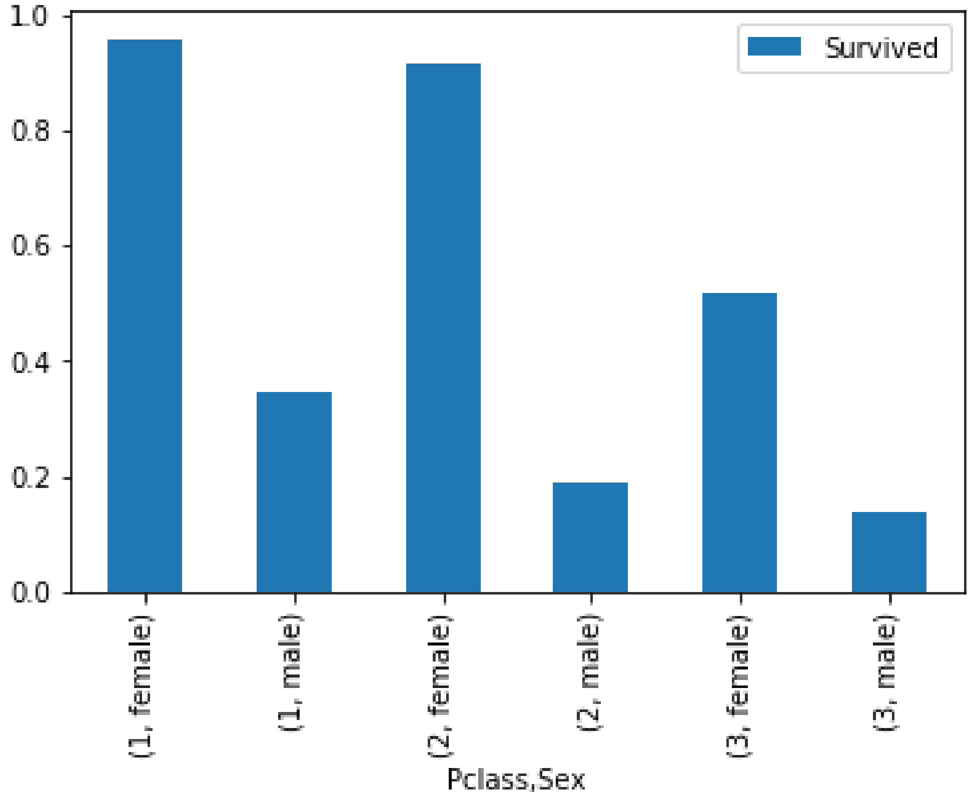
Out[6]: <matplotlib.axes._subplots.AxesSubplot at 0x108f615c0>





```
In [7]: train_data[['Sex','Pclass','Survived']].groupby(['Pclass','Sex']).mean().plot.bar()
```

```
Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x1a0fd629b0>
```

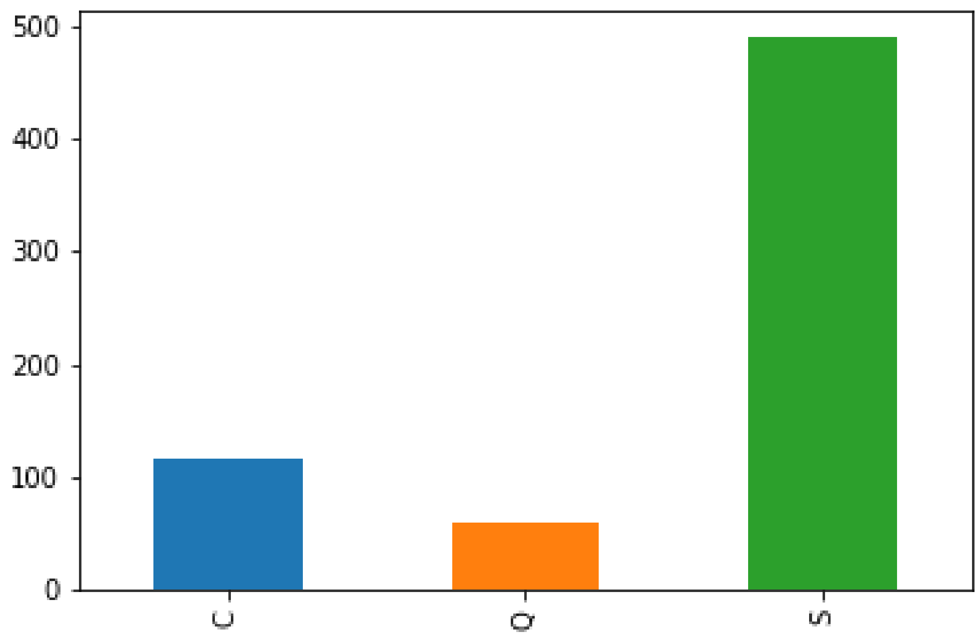


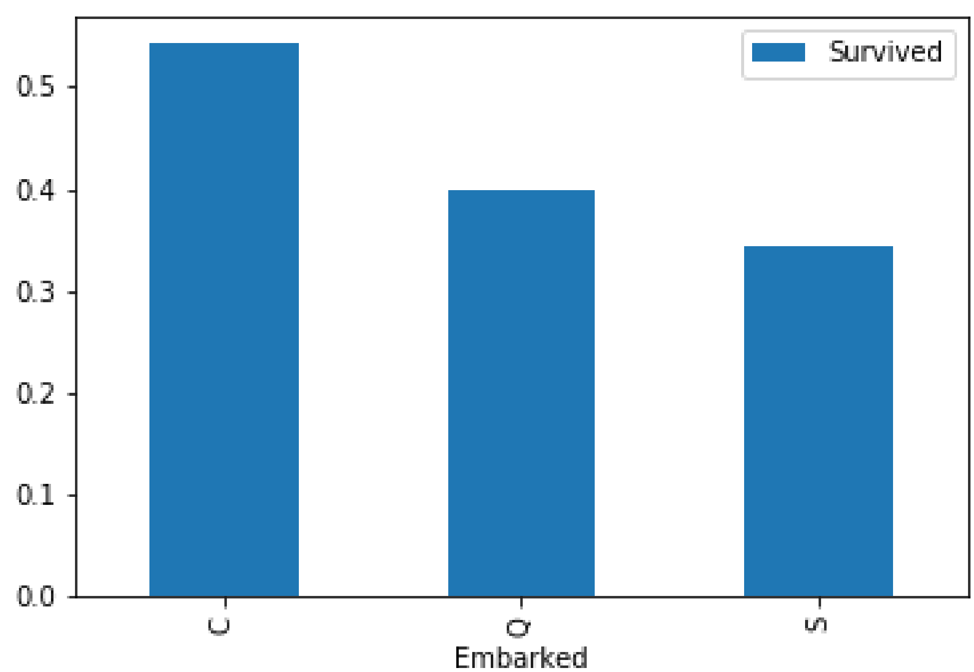
1. Pclass = 3 has most passengers but has lowest survival rate.
2. Pclass = 1 has the highest survival rate.
3. Pclass varies in terms of Sex distribution of passengers.

3.3 Embarked

```
In [8]: # histogram of Embarked and the survival rates of each class
        train_data['Embarked'].value_counts()[['C','Q','S']].plot(kind='bar')
        train_data[['Embarked','Survived']].groupby(['Embarked']).mean().plot.bar()
```

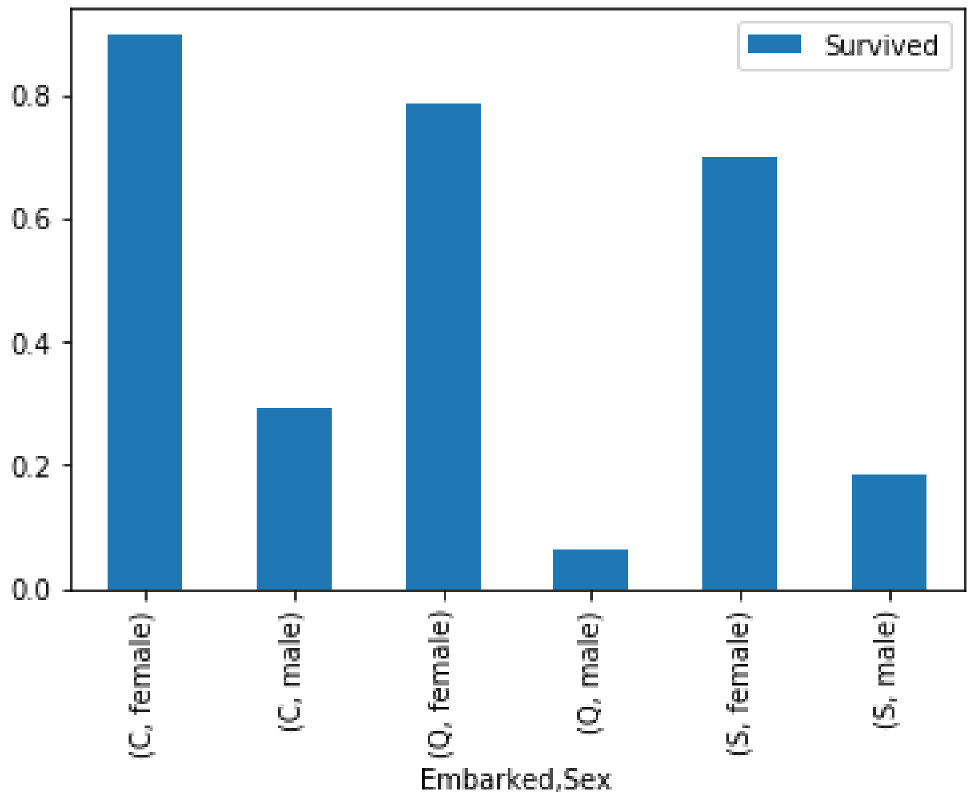
```
Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x1a18c3e6a0>
```






```
In [9]: train_data[['Sex','Embarked','Survived']].groupby(['Embarked','Sex']).mean().plot.bar()

Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x108eb7400>
```

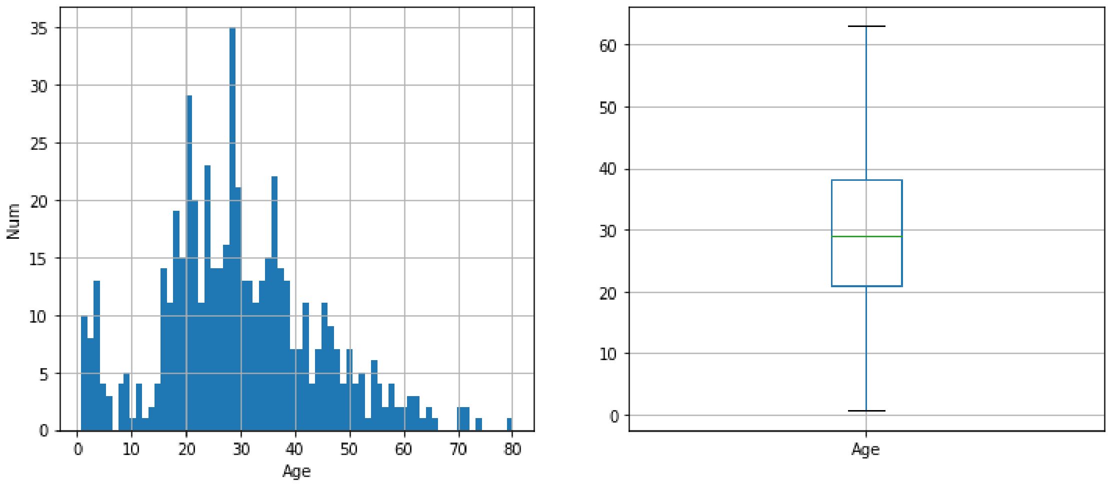


1. Embarked correlates with Survived, Embarked = S has most passengers but also has the lowest survival rate.
2. Embarked varies in terms of Sex distribution of passengers.
3. Survival rate of Embarked varies among male passengers, and Embarked = Q has the lowest survival rate.

3.4 Age

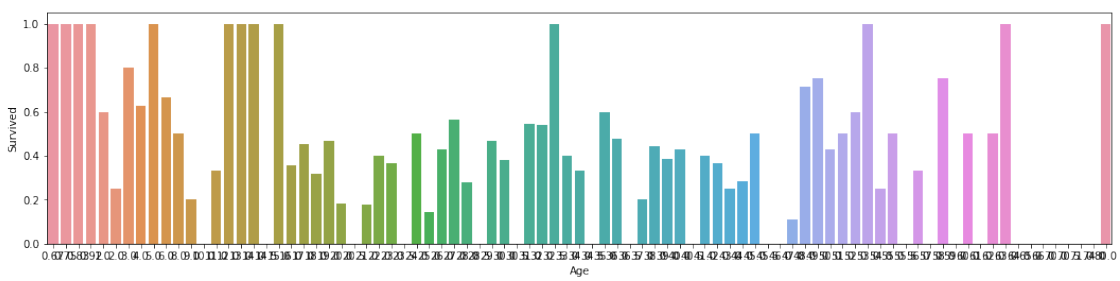
```
In [10]: # distribution of Age
         plt.figure(figsize=(12,5))
         plt.subplot(121)
         train_data['Age'].hist(bins=70)
         plt.xlabel('Age')
         plt.ylabel('Num')

         plt.subplot(122)
         train_data.boxplot(column='Age', showfliers=False)
         plt.show()
```




```
In [11]: # survival rate by age
         fig, axis1 = plt.subplots(1,1,figsize=(18,4))
         average_age = train_data[["Age", "Survived"]].groupby(['Age'],as_index=False).mean()
         sns.barplot(x='Age', y='Survived', data=average_age)
```

```
Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1905b5f8>
```



We divide the age into four groups: (0,12] = children, (12,18] = teenagers, (18,65] = adults, (65,100] = old people.

In this case, the survival rate by age group is:

```
In [12]: bins = [0, 12, 18, 65, 100]
         train_data['Age_group'] = pd.cut(train_data['Age'], bins)
         by_age = train_data.groupby('Age_group')['Survived'].mean()
         by_age
```

```
/Users/luwang/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:2: SettingWithCopyWarn
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
```

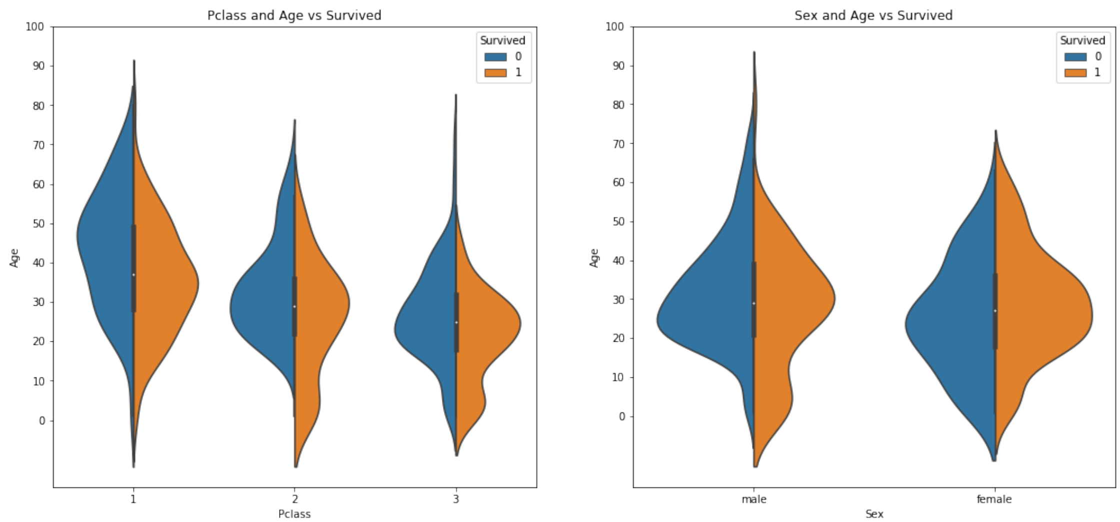
```
See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
```

```
Out[12]: Age_group
         (0, 12]      0.576923
         (12, 18]     0.431373
         (18, 65]     0.390588
         (65, 100]    0.142857
         Name: Survived, dtype: float64
```

```
In [13]: fig, ax = plt.subplots(1, 2, figsize = (18, 8))
         sns.violinplot("Pclass", "Age", hue="Survived", data=train_data, split=True, ax=ax[0])
         ax[0].set_title('Pclass and Age vs Survived')
         ax[0].set_yticks(range(0, 110, 10))

         sns.violinplot("Sex", "Age", hue="Survived", data=train_data, split=True, ax=ax[1])
         ax[1].set_title('Sex and Age vs Survived')
         ax[1].set_yticks(range(0, 110, 10))

         plt.show()
```



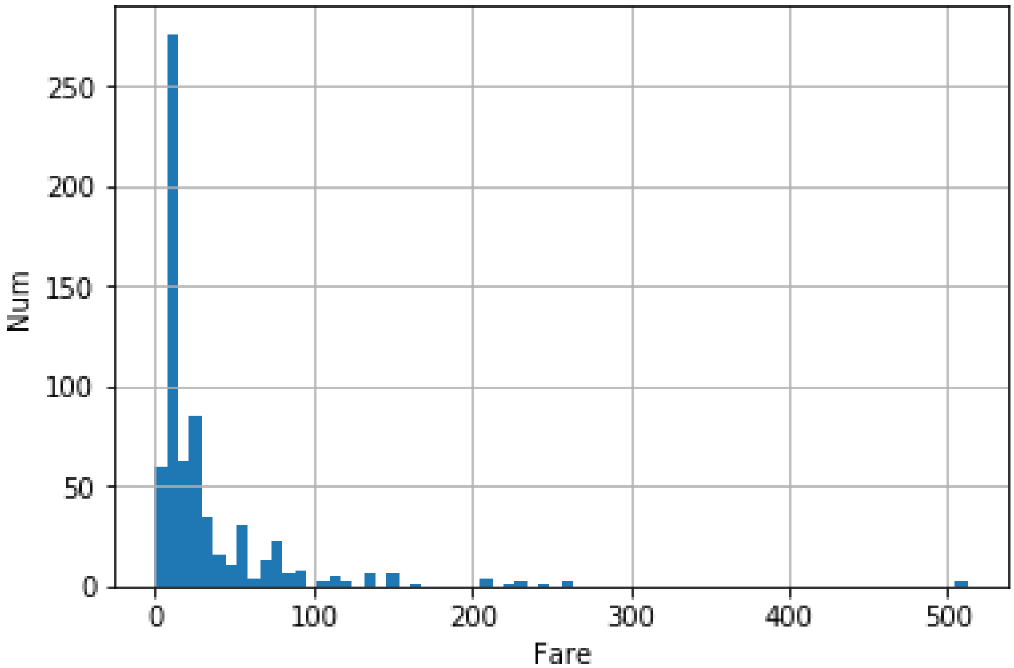
1. From the boxplot, we see that most passengers are between 20 and 40 years old.
2. Children and very old passengers have high survival rates.
3. Many passengers between 20 and 40 did not survive.
4. Age distribution varies with Pclass and Sex.

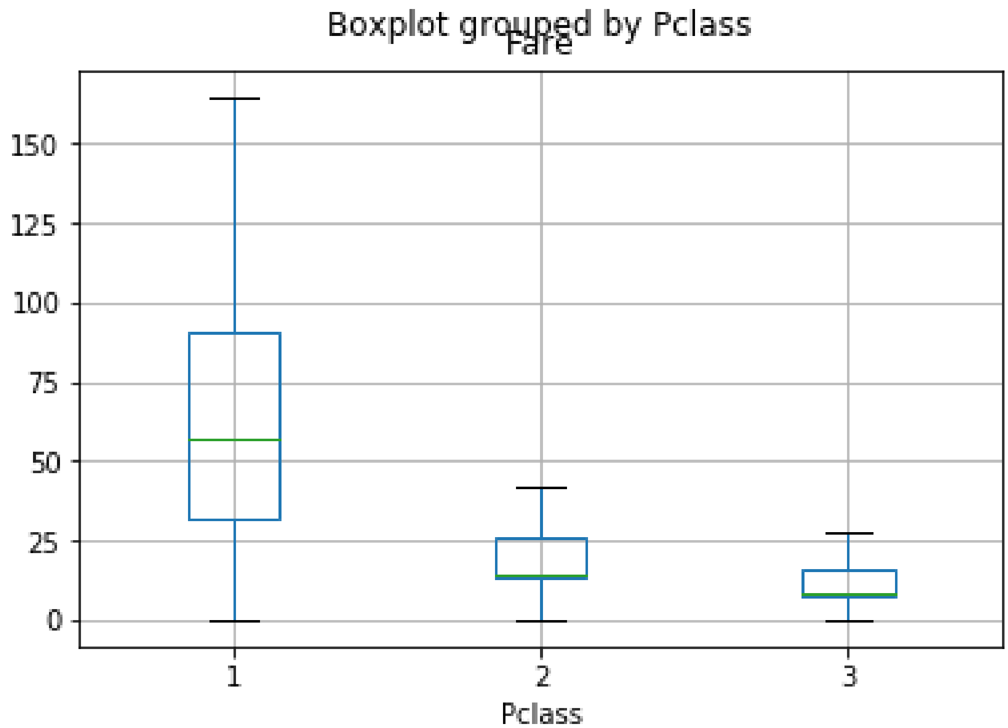
3.5 Fare

```
In [14]: # distribution of Fare
         train_data['Fare'].hist(bins=70)
```

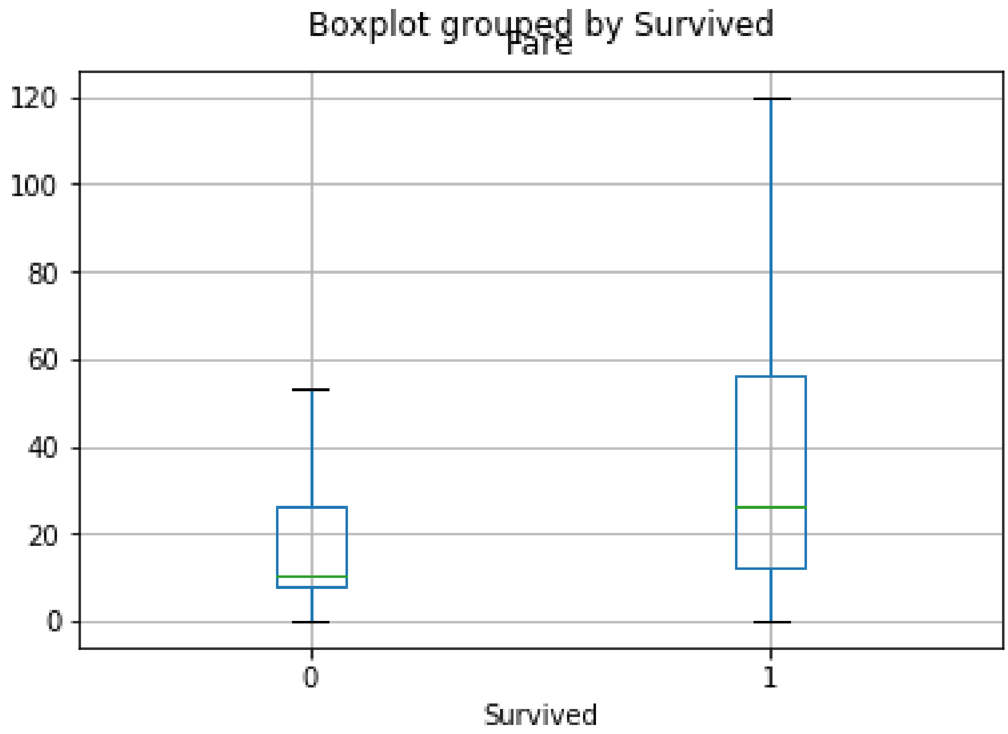
```
plt.xlabel('Fare')
plt.ylabel('Num')

# boxplot of Fare for different Pclass
train_data.boxplot(column='Fare', by = 'Pclass', showfliers=False)
plt.show()
```





In [15]:
```
# boxplot of Fare for passengers survived and not survived
train_data.boxplot(column='Fare', by = 'Survived', showfliers=False)
plt.show()
```



1. Survived passengers paid higher fares.
2. Fares are different for different Pclass: Pclass = 1 paid much higher fares compared to the other two classes.

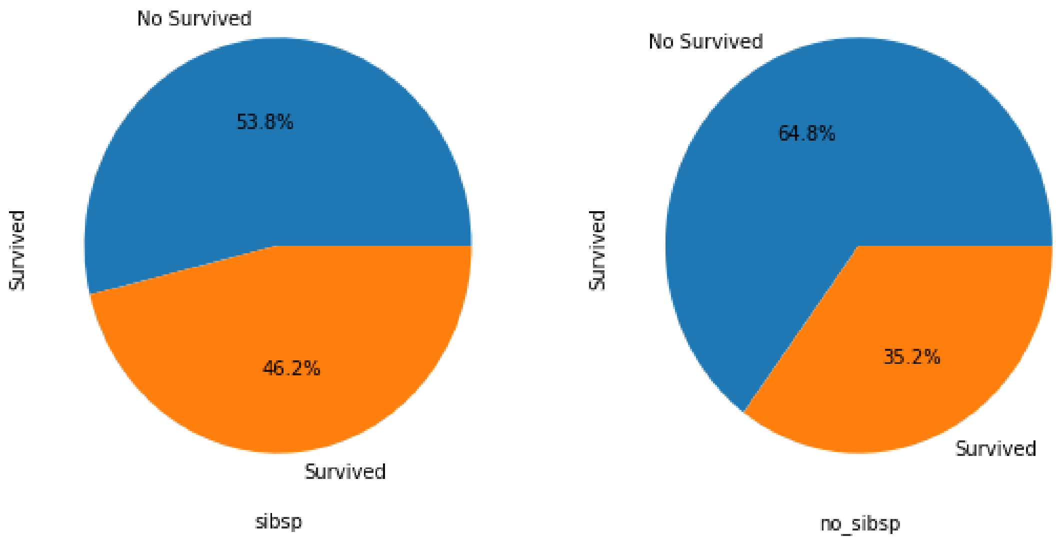
3.6 Sibsp

In [16]:
```
# survival rates of passengers with or without Sibsp.
sibsp_df = train_data[train_data['SibSp'] != 0]
no_sibsp_df = train_data[train_data['SibSp'] == 0]

plt.figure(figsize=(10,5))
plt.subplot(121)
sibsp_df['Survived'].value_counts().plot.pie(labels=['No Survived', 'Survived'], autopc
plt.xlabel('sibsp')

plt.subplot(122)
no_sibsp_df['Survived'].value_counts().plot.pie(labels=['No Survived', 'Survived'], aut
plt.xlabel('no_sibsp')

plt.show()
```



Passengers with siblings or spouses aboard are more likely to survive.

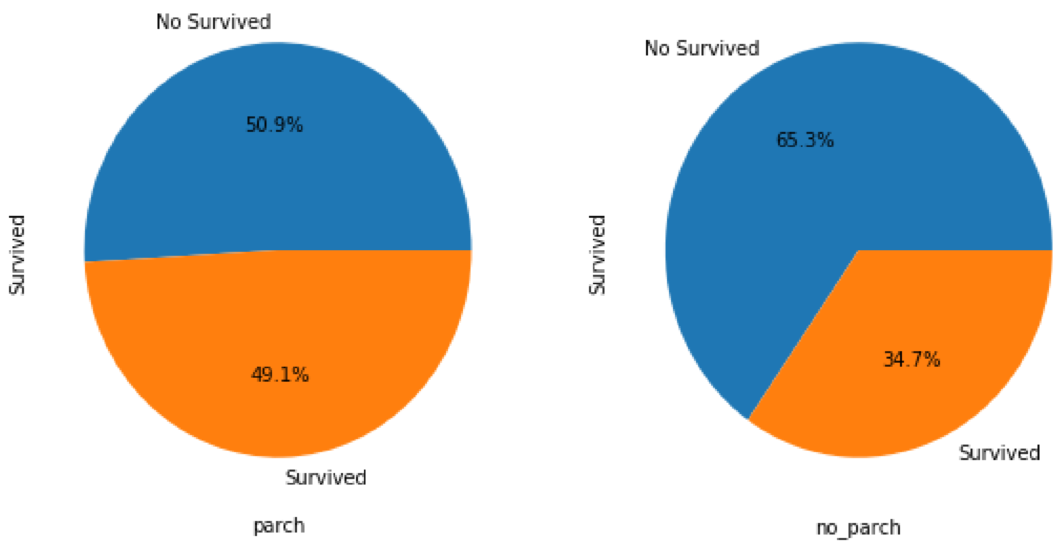
3.7 Parch

```
In [17]: # survival rates of passengers with or without Parch.
         parch_df = train_data[train_data['Parch'] != 0]
         no_parch_df = train_data[train_data['Parch'] == 0]

         plt.figure(figsize=(10,5))
         plt.subplot(121)
         parch_df['Survived'].value_counts().plot.pie(labels=['No Survived', 'Survived'], autopc
         plt.xlabel('parch')

         plt.subplot(122)
         no_parch_df['Survived'].value_counts().plot.pie(labels=['No Survived', 'Survived'], aut
         plt.xlabel('no_parch')

         plt.show()
```



Passengers who had parents or childern aboard had higher survival rate.

4 Dropping, creating, completing and converting features

4.1 PassengerId, Ticket and Cabin

In the analysis, we can drop the features PassengerId, Ticket and Cabin, since PassengerId and Ticket don't contribute to survival, and Cabin has too many missing values.

```
In [18]: train_data = train_data.drop(['Ticket', 'Cabin', 'PassengerId'], axis=1)
         test_data = test_data.drop(['Ticket', 'Cabin', 'PassengerId'], axis=1)
         combined_data = [train_data, test_data]
         train_data.shape, test_data.shape
```

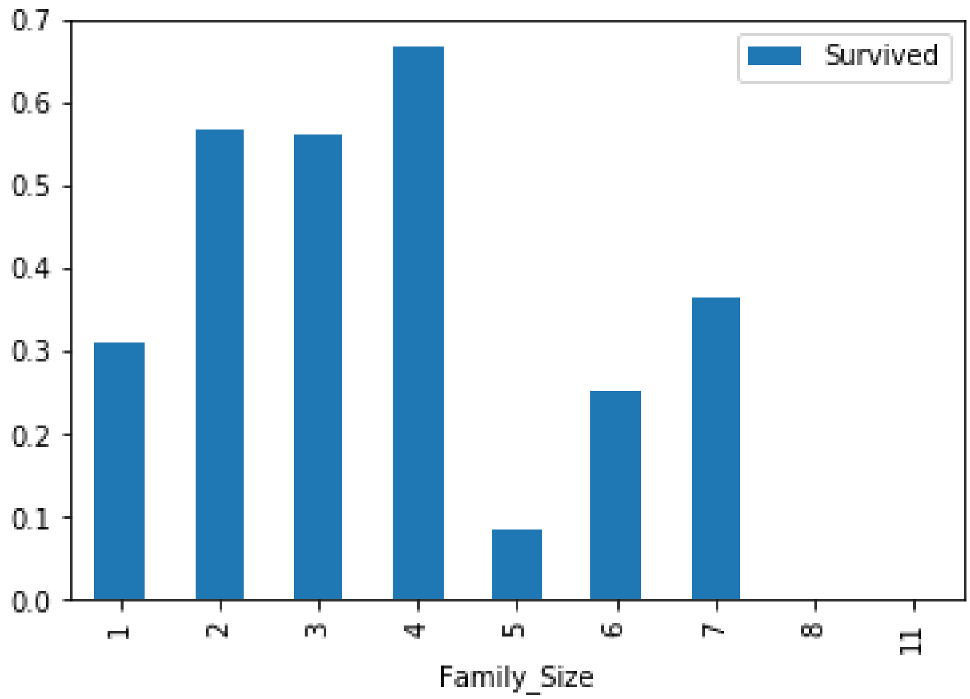
```
Out[18]: ((668, 10), (223, 9))
```

4.2 Parch and Sibsp

We can combine Parch and Sibsp to create a new feature Family_Size.

```
In [19]: # compute the family size of each passenger by adding Parch and Sibsp
         for data in combined_data:
             data['Family_Size'] = data['Parch'] + data['SibSp'] + 1
         train_data[['Family_Size','Survived']].groupby(['Family_Size']).mean().plot.bar()
```

```
Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1a003a58>
```



We can see that passengers with 2 - 4 family members were more likely to survive. Also, create a categorical variable Family_Size_Category and use label encoding.

In [20]:
```
def family_size_category(family_size):
    if family_size <= 1:
        return 'Single'
    elif family_size <= 4:
        return 'Small_Family'
    else:
        return 'Large_Family'
for data in combined_data:
    data['Family_Size_Category'] = data['Family_Size'].map(family_size_category)

# drop Parch, Sibsp
for data in combined_data:
    data.drop(['Parch', 'SibSp', 'Family_Size'],axis=1,inplace=True)

train_data.head()
```

Out[20]:

	Survived	Pclass	Name	Sex	Age	Fare \
105	0	3	Mionoff, Mr. Stoytcho	male	28.0	7.8958
68	1	3	Andersson, Miss. Erna Alexandra	female	17.0	7.9250
253	0	3	Lobb, Mr. William Arthur	male	30.0	16.1000
320	0	3	Dennis, Mr. Samuel	male	22.0	7.2500
706	1	2	Kelly, Mrs. Florence "Fannie"	female	45.0	13.5000

```
    Embarked Age_group Family_Size_Category
105        S  (18, 65]               Single
68         S  (12, 18]         Large_Family
253        S  (18, 65]         Small_Family
320        S  (18, 65]               Single
706        S  (18, 65]               Single
```

In [21]:
```
# convert Family_Size_Category into a numeric feature
for data in combined_data:
    data['Family_Size_Category'] = data['Family_Size_Category'].map( {'Single': 0, 'Sma

train_data.head()
```

Out[21]:
```
     Survived  Pclass                            Name     Sex   Age     Fare  \
105         0       3           Mionoff, Mr. Stoytcho    male  28.0   7.8958
68          1       3  Andersson, Miss. Erna Alexandra  female  17.0   7.9250
253         0       3        Lobb, Mr. William Arthur    male  30.0  16.1000
320         0       3              Dennis, Mr. Samuel    male  22.0   7.2500
706         1       2   Kelly, Mrs. Florence "Fannie"  female  45.0  13.5000

    Embarked Age_group  Family_Size_Category
105        S  (18, 65]                     0
68         S  (12, 18]                     2
253        S  (18, 65]                     1
320        S  (18, 65]                     0
706        S  (18, 65]                     0
```

4.3 Title

We can extract the feature Title from Name, and look at its correlation bewteen survival rate.

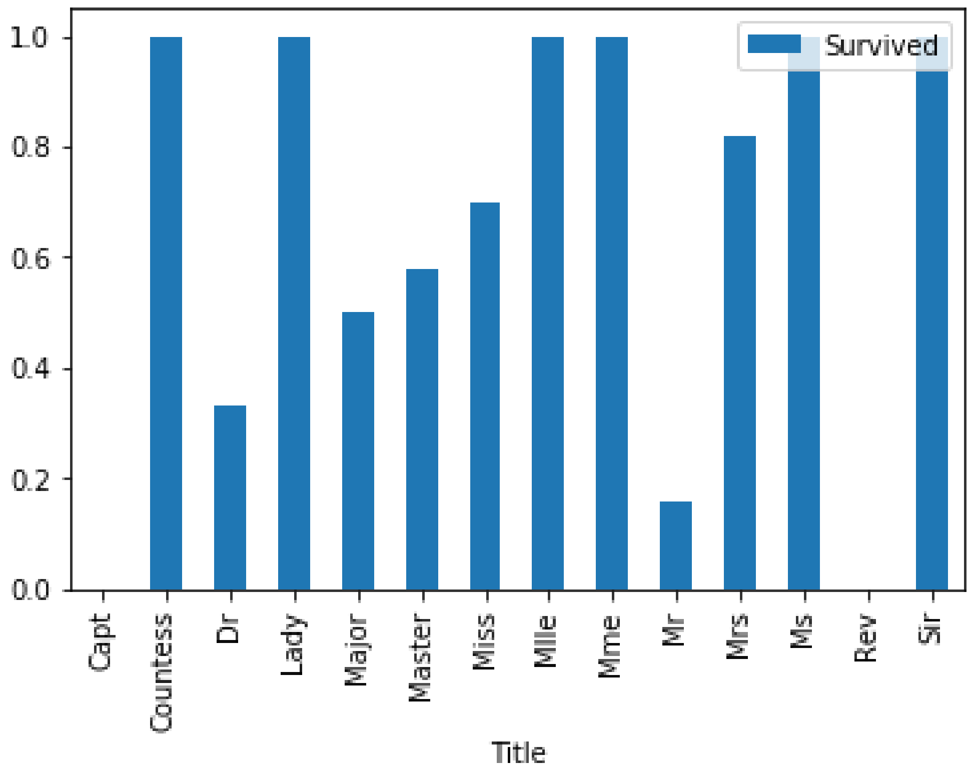
In [22]:
```
for data in combined_data:
    data['Title'] = data['Name'].str.extract(' ([A-Za-z]+)\.', expand=False)
pd.crosstab(train_data['Title'], train_data['Sex'])
```

Out[22]:
```
Sex       female  male
Title
Capt           0     1
Countess       1     0
Dr             0     3
Lady           1     0
Major          0     2
Master         0    33
Miss         132     0
Mlle           2     0
Mme            1     0
Mr             0   394
Mrs           93     0
```

```
Ms              1      0
Rev             0      3
Sir             0      1
```

In [23]:
```python
train_data[['Title','Survived']].groupby(['Title']).mean().plot.bar()
```

Out[23]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a1a0a62b0>
```



We can see that some titles such as Countess, Lady, Ms, Mlle have survival rate 1.
We then divide the titles into several title groups, and look at the survival rate by title group.

In [24]:
```python
for data in combined_data:
    data['Title'] = data['Title'].replace(['Capt', 'Col', 'Major', 'Dr', 'Rev', 'Don',
    data['Title'] = data['Title'].replace('Mme', 'Mrs')
    data['Title'] = data['Title'].replace(['Mlle', 'Ms'], 'Miss')

train_data[['Title', 'Survived']].groupby(['Title'], as_index=False).mean()
```

Out[24]:

	Title	Survived
0	Master	0.575758
1	Miss	0.703704
2	Mr	0.157360
3	Mrs	0.819149
4	Other	0.416667

In [25]:
```
# now we can drop the feature Name
for data in combined_data:
    data.drop(['Name'],axis=1,inplace=True)
train_data.head()
```

Out[25]:
```
     Survived  Pclass     Sex   Age     Fare Embarked Age_group  \
105         0       3    male  28.0   7.8958        S  (18, 65]
68          1       3  female  17.0   7.9250        S  (12, 18]
253         0       3    male  30.0  16.1000        S  (18, 65]
320         0       3    male  22.0   7.2500        S  (18, 65]
706         1       2  female  45.0  13.5000        S  (18, 65]

     Family_Size_Category Title
105                     0    Mr
68                      2  Miss
253                     1    Mr
320                     0    Mr
706                     0   Mrs
```

In [26]:
```
# label encoding
for data in combined_data:
    data['Title'] = data['Title'].map( {'Mr': 0, 'Other': 1, 'Master': 2, 'Miss': 3, 'M

train_data.head()
```

Out[26]:
```
     Survived  Pclass     Sex   Age     Fare Embarked Age_group  \
105         0       3    male  28.0   7.8958        S  (18, 65]
68          1       3  female  17.0   7.9250        S  (12, 18]
253         0       3    male  30.0  16.1000        S  (18, 65]
320         0       3    male  22.0   7.2500        S  (18, 65]
706         1       2  female  45.0  13.5000        S  (18, 65]

     Family_Size_Category  Title
105                     0      0
68                      2      3
253                     1      0
320                     0      0
706                     0      4
```

4.4 Embarked

Since there are only two missing values for Embarked in the training set, we can use the mode for missing values, and encode the feature.

In [27]:
```
train_data['Embarked'] = train_data['Embarked'].fillna(train_data.Embarked.dropna().mod

# convert it to a numeric feature
for data in combined_data:
    data['Embarked'] = data['Embarked'].map( {'S': 0, 'C': 1, 'Q': 2} ).astype(int)
```

```
train_data.head()
```

Out[27]:

```
     Survived  Pclass     Sex   Age     Fare  Embarked Age_group  \
105         0       3    male  28.0   7.8958         0  (18, 65]
68          1       3  female  17.0   7.9250         0  (12, 18]
253         0       3    male  30.0  16.1000         0  (18, 65]
320         0       3    male  22.0   7.2500         0  (18, 65]
706         1       2  female  45.0  13.5000         0  (18, 65]

     Family_Size_Category  Title
105                     0      0
68                      2      3
253                     1      0
320                     0      0
706                     0      4
```

4.5 Sex

We can also convert the feature Sex to a numeric feature: male = 0 and female = 1.

In [28]:

```
for data in combined_data:
    data['Sex'] = data['Sex'].map( {'male': 0, 'female': 1} ).astype(int)

train_data.head()
```

Out[28]:

```
     Survived  Pclass  Sex   Age     Fare  Embarked Age_group  \
105         0       3    0  28.0   7.8958         0  (18, 65]
68          1       3    1  17.0   7.9250         0  (12, 18]
253         0       3    0  30.0  16.1000         0  (18, 65]
320         0       3    0  22.0   7.2500         0  (18, 65]
706         1       2    1  45.0  13.5000         0  (18, 65]

     Family_Size_Category  Title
105                     0      0
68                      2      3
253                     1      0
320                     0      0
706                     0      4
```

4.6 Fare

For the feature Fare, we create a new feature Fare_Group and divide the Fare into 4 groups, and look at the survival rate by fare group.

In [29]:

```
train_data['Fare_Group'] = pd.qcut(train_data['Fare'], 4)
train_data.groupby('Fare_Group')['Survived'].mean()
```

Out[29]:
```
Fare_Group
(-0.001, 7.925]      0.234973
(7.925, 14.5]        0.300654
(14.5, 31.275]       0.433735
(31.275, 512.329]    0.584337
Name: Survived, dtype: float64
```

In [30]:
```
# label encoding
for data in combined_data:
    data['Fare_Category'] = 0
    data.loc[(data['Fare'] > 7.925) & (data['Fare'] <= 14.5), 'Fare_Category'] = 1
    data.loc[(data['Fare'] > 14.5) & (data['Fare'] <= 31.275), 'Fare_Category']   = 2
    data.loc[ data['Fare'] > 31.275, 'Fare_Category'] = 3
    data['Fare_Category'] = data['Fare_Category'].astype(int)

train_data = train_data.drop(['Fare_Group', 'Fare'], axis=1)
test_data = test_data.drop(['Fare'], axis=1)
train_data.head()
```

Out[30]:
```
     Survived  Pclass  Sex   Age  Embarked Age_group  Family_Size_Category  \
105         0       3    0  28.0         0  (18, 65]                     0
68          1       3    1  17.0         0  (12, 18]                     2
253         0       3    0  30.0         0  (18, 65]                     1
320         0       3    0  22.0         0  (18, 65]                     0
706         1       2    1  45.0         0  (18, 65]                     0

     Title  Fare_Category
105      0              0
68       3              0
253      0              2
320      0              0
706      4              1
```

4.7 Age

There are many missing values for Age, so we cannot use the mode. We can build a random forest model to predict Age using other features, where the traning set is the dataset with known Age, and the test set is the observations with missing values.

In [31]:
```
from sklearn import ensemble
from sklearn import model_selection
from sklearn.ensemble import RandomForestRegressor

def predict_age(data):
    data[data['Age'].isnull()]
    age_data = data[['Age', 'Embarked', 'Sex', 'Title', 'Family_Size_Category', 'Fare_C
    age_train = age_data[age_data['Age'].notnull()]
    age_test = age_data[age_data['Age'].isnull()]
    age_train_X = age_train.drop(['Age'], axis=1)
```

```python
    age_train_Y = age_train['Age']
    age_test_X = age_test.drop(['Age'], axis=1)

    rf = RandomForestRegressor()
    param_grid = {'n_estimators': [200], 'max_depth': [5], 'random_state': [0]}
    rf_grid = model_selection.GridSearchCV(rf, param_grid, cv=10, n_jobs=25, verbose=1,
    rf_grid.fit(age_train_X, age_train_Y)

    data.loc[(data.Age.isnull()), 'Age'] = rf_grid.predict(age_test_X)
    return data

train_data = predict_age(train_data)
test_data = predict_age(test_data)

train_data.info()
test_data.info()
```

```
Fitting 10 folds for each of 1 candidates, totalling 10 fits


[Parallel(n_jobs=25)]: Done   5 out of  10 | elapsed:    1.2s remaining:    1.2s
[Parallel(n_jobs=25)]: Done  10 out of  10 | elapsed:    1.2s finished


Fitting 10 folds for each of 1 candidates, totalling 10 fits


[Parallel(n_jobs=25)]: Done   5 out of  10 | elapsed:    0.8s remaining:    0.8s
[Parallel(n_jobs=25)]: Done  10 out of  10 | elapsed:    0.9s finished


<class 'pandas.core.frame.DataFrame'>
Int64Index: 668 entries, 105 to 684
Data columns (total 9 columns):
Survived                668 non-null int64
Pclass                  668 non-null int64
Sex                     668 non-null int64
Age                     668 non-null float64
Embarked                668 non-null int64
Age_group               535 non-null category
Family_Size_Category    668 non-null int64
Title                   668 non-null int64
Fare_Category           668 non-null int64
dtypes: category(1), float64(1), int64(7)
memory usage: 67.7 KB
<class 'pandas.core.frame.DataFrame'>
Int64Index: 223 entries, 495 to 10
Data columns (total 8 columns):
Survived                223 non-null int64
```

```
Pclass                  223 non-null int64
Sex                     223 non-null int64
Age                     223 non-null float64
Embarked                223 non-null int64
Family_Size_Category    223 non-null int64
Title                   223 non-null int64
Fare_Category           223 non-null int64
dtypes: float64(1), int64(7)
memory usage: 15.7 KB
```

As in Fare, we can now update the feature Age_group and encode it.

In [32]:
```
bins = [0, 12, 18, 65, 100]
train_data['Age_group'] = pd.cut(train_data['Age'], bins)
train_data.groupby('Age_group')['Survived'].mean()
```

Out[32]:
```
Age_group
(0, 12]      0.537313
(12, 18]     0.423077
(18, 65]     0.367159
(65, 100]    0.142857
Name: Survived, dtype: float64
```

In [33]:
```
def age_category(data):
    data['Age_Category'] = 0
    data.loc[(data['Age'] > 12) & (data['Age'] <= 18), 'Age_Category'] = 1
    data.loc[(data['Age'] > 18) & (data['Age'] <= 65), 'Age_Category']   = 2
    data.loc[ data['Age'] > 65, 'Age_Category'] = 3
    data['Age_Category'] = data['Age_Category'].astype(int)
    return data

train_data = age_category(train_data)
test_data = age_category(test_data)
train_data = train_data.drop(['Age_group', 'Age'], axis=1)
test_data = test_data.drop(['Age'], axis=1)
train_data.head()
```

Out[33]:
```
     Survived  Pclass  Sex  Embarked  Family_Size_Category  Title  \
105         0       3    0         0                     0      0
68          1       3    1         0                     2      3
253         0       3    0         0                     1      0
320         0       3    0         0                     0      0
706         1       2    1         0                     0      4

     Fare_Category  Age_Category
105              0             2
68               0             1
253              2             2
```

320	0	2
706	1	2

4.8 Correlation plot

At the end of the section, we create a correlation plot which gives the correlation of every pair of features.

```
In [34]: Correlation = pd.DataFrame(train_data[['Embarked', 'Sex', 'Title', 'Family_Size_Categor
         colormap = plt.cm.viridis
         plt.figure(figsize=(14,12))
         sns.heatmap(Correlation.astype(float).corr(),linewidths=0.1,vmax=1.0, square=True, cmap
```

```
Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1a0afa20>
```

5 Models

Now we can build models to predict Survival, the features we use are Pclass, Sex, Embarked, Family_Size_Category, Title, Fare_Category, Age_Category. We compare the performances of different models, including logistic regression, kNN, perceptron, SVM, decision tree, neural network, random forest, and gradient boosting.

5.1 Logistic Regression

The accuracy of logistic regression model is:

```
In [35]: from sklearn.metrics import accuracy_score
         train_data_X = train_data.drop(['Survived'],axis=1)
         train_data_Y = train_data['Survived']
         test_data_X = test_data.drop(['Survived'],axis=1)
         test_data_Y = test_data['Survived']
         lr = LogisticRegression(random_state = 0)
         lr.fit(train_data_X, train_data_Y)
         Y_pred = lr.predict(test_data_X)
         lr_acc = accuracy_score(test_data_Y, Y_pred)
         lr_acc

Out[35]: 0.8116591928251121
```

5.2 KNN

```
In [36]: knn = KNeighborsClassifier(n_neighbors = 5)
         knn.fit(train_data_X, train_data_Y)
         Y_pred = knn.predict(test_data_X)
         knn_acc = accuracy_score(test_data_Y, Y_pred)
         knn_acc

Out[36]: 0.8295964125560538
```

5.3 Naive Bayes

```
In [37]: nb = GaussianNB()
         nb.fit(train_data_X, train_data_Y)
         Y_pred = nb.predict(test_data_X)
         nb_acc = accuracy_score(test_data_Y, Y_pred)
         nb_acc

Out[37]: 0.7892376681614349
```

5.4 Perceptron

```
In [38]: pc = Perceptron(random_state = 0)
         pc.fit(train_data_X, train_data_Y)
         Y_pred = pc.predict(test_data_X)
```

```
pc_acc = accuracy_score(test_data_Y, Y_pred)
pc_acc
```

```
/Users/luwang/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/stochastic_gradient.py:
  "and default tol will be 1e-3." % type(self), FutureWarning)
```

Out[38]: 0.7802690582959642

5.5 SVM

In [39]:
```
svm = LinearSVC(random_state = 0)
svm.fit(train_data_X, train_data_Y)
Y_pred = svm.predict(test_data_X)
svm_acc = accuracy_score(test_data_Y, Y_pred)
svm_acc
```

Out[39]: 0.8161434977578476

5.6 Decision Tree

In [40]:
```
dt = DecisionTreeClassifier(random_state = 0)
dt.fit(train_data_X, train_data_Y)
Y_pred = dt.predict(test_data_X)
dt_acc = accuracy_score(test_data_Y, Y_pred)
dt_acc
```

Out[40]: 0.8430493273542601

5.7 Random Forest

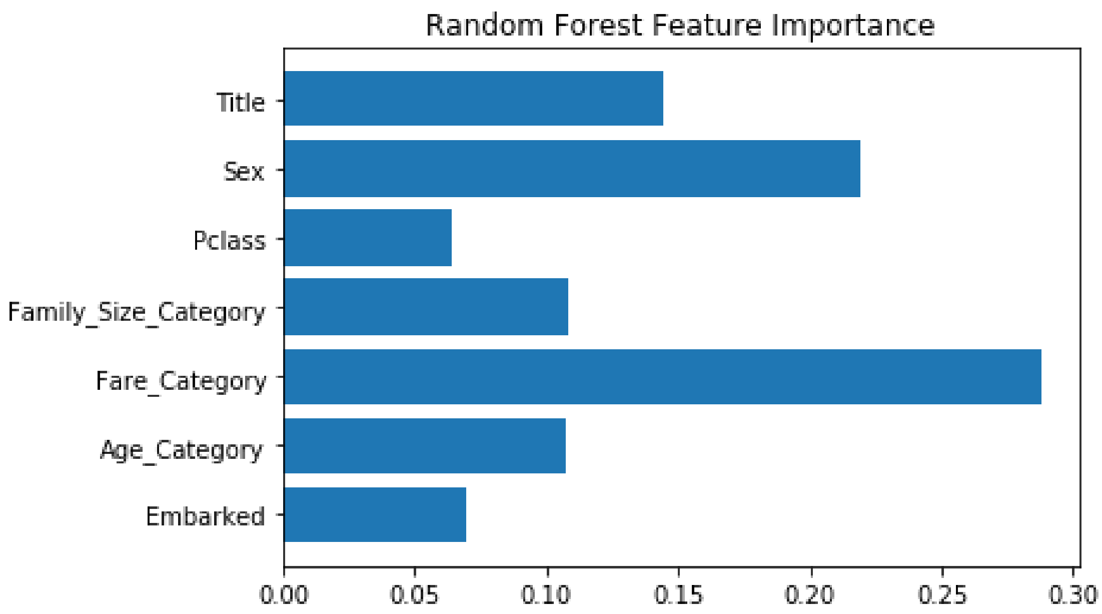
In [41]:
```
rf = RandomForestClassifier(n_estimators=500, random_state = 0)
rf.fit(train_data_X, train_data_Y)
Y_pred = rf.predict(test_data_X)
rf_acc = accuracy_score(test_data_Y, Y_pred)
rf_acc
```

Out[41]: 0.8430493273542601

For random forest model, we can create the featue importance plot.

In [42]:
```
rf_feature_imp = pd.DataFrame({'feature': list(train_data_X),'importance': rf.feature_i
rf_feature_importance = rf_feature_imp['importance']
rf_important_idx = np.where(rf_feature_importance)[0]
pos = np.arange(rf_important_idx.shape[0]) + .5
plt.barh(pos, rf_feature_importance[rf_important_idx][::-1])
plt.yticks(pos, rf_feature_imp['feature'][::-1])
plt.title('Random Forest Feature Importance')
```

Out[42]: Text(0.5,1,'Random Forest Feature Importance')



5.8 Gradient Boosting

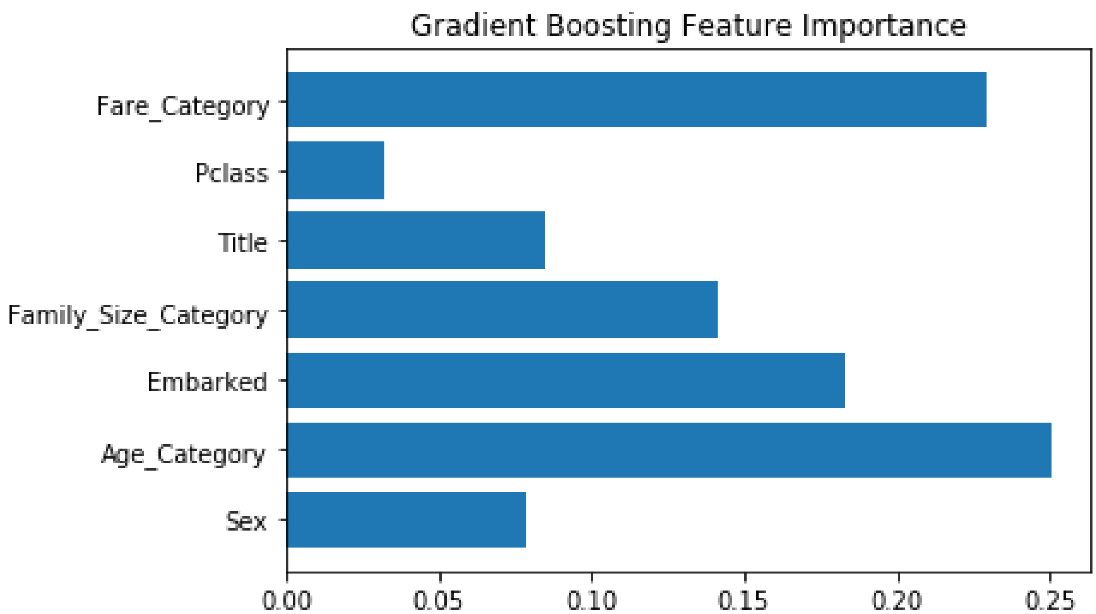
In [44]:
```
from sklearn.ensemble import GradientBoostingClassifier
gb = GradientBoostingClassifier(n_estimators=500, random_state = 0)
gb.fit(train_data_X, train_data_Y)
Y_pred = gb.predict(test_data_X)
gb_acc = accuracy_score(test_data_Y, Y_pred)
gb_acc
```

Out[44]: 0.8430493273542601

As for Radom Forest, we can also plot the feature importance for gradient boosting.

In [45]:
```
gb_feature_imp = pd.DataFrame({'feature': list(train_data_X),'importance': gb.feature_i
gb_feature_importance = gb_feature_imp['importance']
gb_important_idx = np.where(gb_feature_importance)[0]
pos = np.arange(gb_important_idx.shape[0]) + .5
plt.barh(pos, gb_feature_importance[gb_important_idx][::-1])
plt.yticks(pos, gb_feature_imp['feature'][::-1])
plt.title('Gradient Boosting Feature Importance')
```

Out[45]: Text(0.5,1,'Gradient Boosting Feature Importance')



We can see that this plot is quite different from the feature importance plot for random forest.

5.9 Summary

At last, we summarize the models and rank them according to their performance. We can see that decision tree, random forest and gradient boosting give the same highest accuracy. However, we prefer to use random forest and gradient boosting than decision tree since they are less likely to overfit.

```
In [46]: models = pd.DataFrame({
             'Model': ['Logistic Regression', 'KNN', 'Naive Bayes', 'Perceptron', 'SVM', 'Decisi
             'Accuracy Score': [lr_acc, knn_acc, nb_acc, pc_acc, svm_acc, dt_acc, rf_acc, gb_acc
         models.sort_values(by='Accuracy', ascending=False)
```

```
Out[46]:    Accuracy Score                Model
         5        0.843049        Decision Tree
         6        0.843049        Random Forest
         7        0.843049    Gradient Boosting
         1        0.829596                  KNN
         4        0.816143                  SVM
         0        0.811659  Logistic Regression
         2        0.789238          Naive Bayes
         3        0.780269           Perceptron
```

6 Conclusion

In this project, we use machine learning algorithms to predict survival for each passenger on Titanic, based on features like sex, age, fare, etc. We consider several models such as logistic regression, kNN, perceptron, SVM, decision tree, neural network, random forest, and gradient boosting. Among these models, decision trees, random forest and gradient boosting perform the best, achieving an accuracy of 84.3%. However, we would prefer random forest and gradient boosting than decision tree since the first two models are less likely to overfit.