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[ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
from sklearn.feature_selection import SelectKBest
from sklearn.ensemble import RandomForestClassifier
from sklearn.pipeline import make_pipeline
from sklearn.model_selection import cross_validate
from collections import Counter
from xgboost import XGBClassifier
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier,␣
↪GradientBoostingClassifier, ExtraTreesClassifier, VotingClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV, cross_val_score,␣
↪StratifiedKFold, learning_curve
```

1 Introduction

- Aquiring Data and analyzing the dataset
- EDA - Exploratory data analysis

2 Aquiring Data

We'll first read the csv(comma separated values) files into a training and testing dataframes which we can manipulate for analysis and predictions

[ ]:
```
#Reading data in the .csv format (no special encoding schemes required)

df_train = pd.read_csv('/content/train.csv')
```

```
df_test = pd.read_csv('/content/test.csv')
id_t = df_test['PassengerId']
print(df_train.shape)
print(df_test.shape)
```

```
(891, 12)
(418, 11)
```

Outlier detection

```
[ ]: #Outlier detection using the Tukey method

def detect(dataframe,n,features):
    ind = []
    for column in features:
        q1 = np.percentile(dataframe[column],25)
        q3 = np.percentile(dataframe[column],75)
        res = q3 - q1
        new = 1.5 * res
        out = dataframe[(dataframe[column]<q1 - new) | (dataframe[column] >q3 +
 ↪new)].index
        ind.extend(out)
    ind = Counter(ind)
    val = list(s for s,i in ind.items() if i>n)
    return val

#Detecting outliers for the numerical features
ott = detect(df_train,2,["Age","SibSp","Parch","Fare"])
```

Outliers can have dramatic effects on our predictions and can also result in harming our final result. We find outliers for the numerical features in the given dataset and we outlined rows with atleast two outliers

```
[ ]: #Our final outliers - can have a harmful effect on regression tasks
df_train.loc[ott]
```

```
[ ]:      PassengerId  Survived  Pclass                               Name     Sex  \
27             28         0       1     Fortune, Mr. Charles Alexander    male
88             89         1       1         Fortune, Miss. Mabel Helen  female
159           160         0       3         Sage, Master. Thomas Henry    male
180           181         0       3       Sage, Miss. Constance Gladys  female
201           202         0       3                Sage, Mr. Frederick    male
324           325         0       3           Sage, Mr. George John Jr    male
341           342         1       1     Fortune, Miss. Alice Elizabeth  female
792           793         0       3            Sage, Miss. Stella Anna  female
846           847         0       3           Sage, Mr. Douglas Bullen    male
863           864         0       3  Sage, Miss. Dorothy Edith "Dolly"  female
```

```
     Age  SibSp  Parch    Ticket    Fare        Cabin Embarked
27   19.0      3      2     19950  263.00  C23 C25 C27        S
88   23.0      3      2     19950  263.00  C23 C25 C27        S
159   NaN      8      2  CA. 2343   69.55          NaN        S
180   NaN      8      2  CA. 2343   69.55          NaN        S
201   NaN      8      2  CA. 2343   69.55          NaN        S
324   NaN      8      2  CA. 2343   69.55          NaN        S
341  24.0      3      2     19950  263.00  C23 C25 C27        S
792   NaN      8      2  CA. 2343   69.55          NaN        S
846   NaN      8      2  CA. 2343   69.55          NaN        S
863   NaN      8      2  CA. 2343   69.55          NaN        S
```

These rows were identified as outliers according to our given function so we will proceed to drop them from our dataframe

[ ]:
```
df_train.drop(ott,axis=0,inplace=True) #dropping on the row axis
```

Create a final dataset (used while feature tuning and cleaning) by combining the training and testing dataframe

[ ]:
```
#Dataset combining both the training and testing datasets
t_len = len(df_train)
final = pd.concat([df_train,df_test],axis=0).reset_index(drop=True)
final.shape
```

[ ]:
```
(1299, 12)
```

3 Analyzing the dataset

Viewing the first 5 rows of the dataset

[ ]:
```
df_train.head()
```

[ ]:
```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0
```

```
   Parch            Ticket     Fare Cabin Embarked
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S
```

List of columns present in the dataset

[ ]:
```
df_train.columns
```

[ ]:
```
Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
      dtype='object')
```

[ ]:
```
df_test.head()
```

[ ]:
```
   PassengerId  Pclass                                          Name     Sex  \
0          892       3                              Kelly, Mr. James    male
1          893       3              Wilkes, Mrs. James (Ellen Needs)  female
2          894       2                     Myles, Mr. Thomas Francis    male
3          895       3                              Wirz, Mr. Albert    male
4          896       3  Hirvonen, Mrs. Alexander (Helga E Lindqvist)  female

    Age  SibSp  Parch   Ticket     Fare Cabin Embarked
0  34.5      0      0   330911   7.8292   NaN        Q
1  47.0      1      0   363272   7.0000   NaN        S
2  62.0      0      0   240276   9.6875   NaN        Q
3  27.0      0      0   315154   8.6625   NaN        S
4  22.0      1      1  3101298  12.2875   NaN        S
```

Checking for NULL values

Multiple NULL values present in Age and Cabin while only 2 in the Embarked column.

[ ]:
```
df_train.info()
df_train.isnull().sum()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 881 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  881 non-null    int64
 1   Survived     881 non-null    int64
 2   Pclass       881 non-null    int64
 3   Name         881 non-null    object
 4   Sex          881 non-null    object
 5   Age          711 non-null    float64
```

```
 6   SibSp        881 non-null    int64
 7   Parch        881 non-null    int64
 8   Ticket       881 non-null    object
 9   Fare         881 non-null    float64
 10  Cabin        201 non-null    object
 11  Embarked     879 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 89.5+ KB
```

[ ]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            170
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          680
Embarked         2
dtype: int64
```

[ ]:
```
df_test.info()
df_test.isnull().sum()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  418 non-null    int64
 1   Pclass       418 non-null    int64
 2   Name         418 non-null    object
 3   Sex          418 non-null    object
 4   Age          332 non-null    float64
 5   SibSp        418 non-null    int64
 6   Parch        418 non-null    int64
 7   Ticket       418 non-null    object
 8   Fare         417 non-null    float64
 9   Cabin        91 non-null     object
 10  Embarked     418 non-null    object
dtypes: float64(2), int64(4), object(5)
memory usage: 36.0+ KB
```

[ ]:
```
PassengerId      0
Pclass           0
Name             0
```

```
Sex            0
Age           86
SibSp          0
Parch          0
Ticket         0
Fare           1
Cabin        327
Embarked       0
dtype: int64
```

The describe method provides us a brief summary of basic statistical measures such as quartiles, mean, count etc.

[ ]:
```
#Brief statistics
df_train.describe()
```

[ ]:

	PassengerId	Survived	Pclass	Age	SibSp
count	881.000000	881.000000	881.000000	711.000000	881.000000
mean	446.713961	0.385925	2.307605	29.731603	0.455165
std	256.617021	0.487090	0.835055	14.547835	0.871571
min	1.000000	0.000000	1.000000	0.420000	0.000000
25%	226.000000	0.000000	2.000000	20.250000	0.000000
50%	448.000000	0.000000	3.000000	28.000000	0.000000
75%	668.000000	1.000000	3.000000	38.000000	1.000000
max	891.000000	1.000000	3.000000	80.000000	5.000000

\

	Parch	Fare
count	881.000000	881.000000
mean	0.363224	31.121566
std	0.791839	47.996249
min	0.000000	0.000000
25%	0.000000	7.895800
50%	0.000000	14.454200
75%	0.000000	30.500000
max	6.000000	512.329200

[ ]:
```
df_test.describe()
```

[ ]:

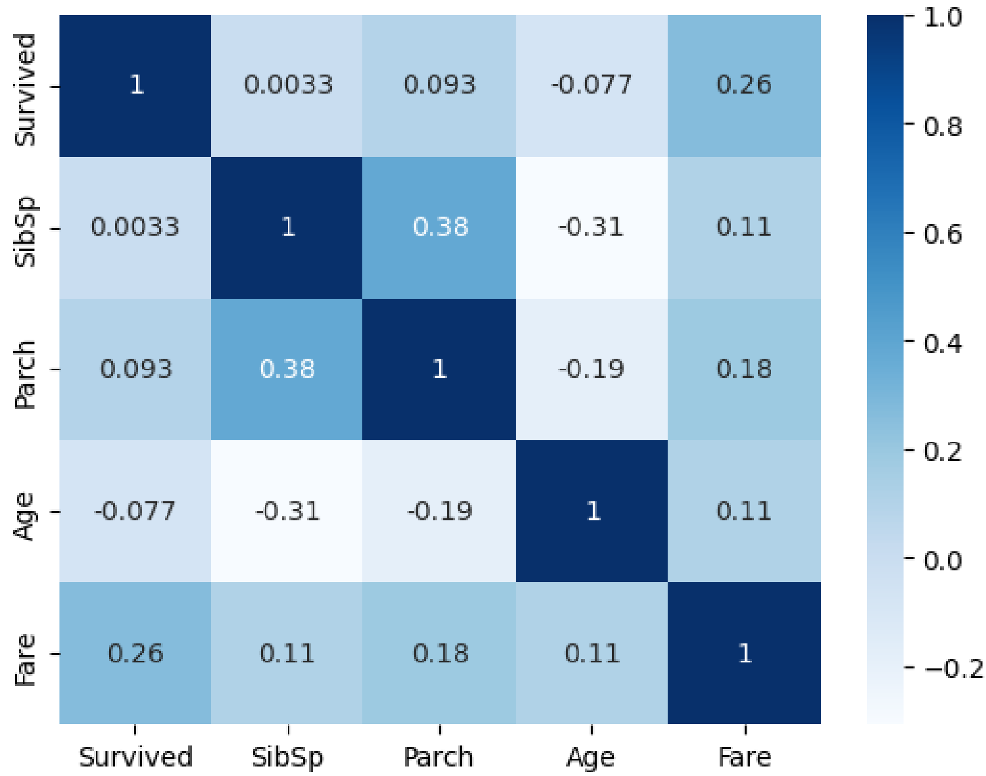
	PassengerId	Pclass	Age	SibSp	Parch	Fare
count	418.000000	418.000000	332.000000	418.000000	418.000000	417.000000
mean	1100.500000	2.265550	30.272590	0.447368	0.392344	35.627188
std	120.810458	0.841838	14.181209	0.896760	0.981429	55.907576
min	892.000000	1.000000	0.170000	0.000000	0.000000	0.000000
25%	996.250000	1.000000	21.000000	0.000000	0.000000	7.895800
50%	1100.500000	3.000000	27.000000	0.000000	0.000000	14.454200
75%	1204.750000	3.000000	39.000000	1.000000	0.000000	31.500000
max	1309.000000	3.000000	76.000000	8.000000	9.000000	512.329200

4 EDA (exploratory data analysis)

Checking the correlation among the numerical variables present in the dataset

[ ]:
```
#Correlation between numerical values

hm = sns.heatmap(df_train[['Survived','SibSp','Parch','Age','Fare']].
  ↪corr(),annot=True,cmap='Blues')
```



We see that there's high correlation only between fare and survival probabilities, this feature may turn out to be our main focus

[ ]:
```
df_train[['Sex','Survived']].groupby(['Sex'],as_index=False).mean().
  ↪sort_values(by='Survived',ascending=False)
```

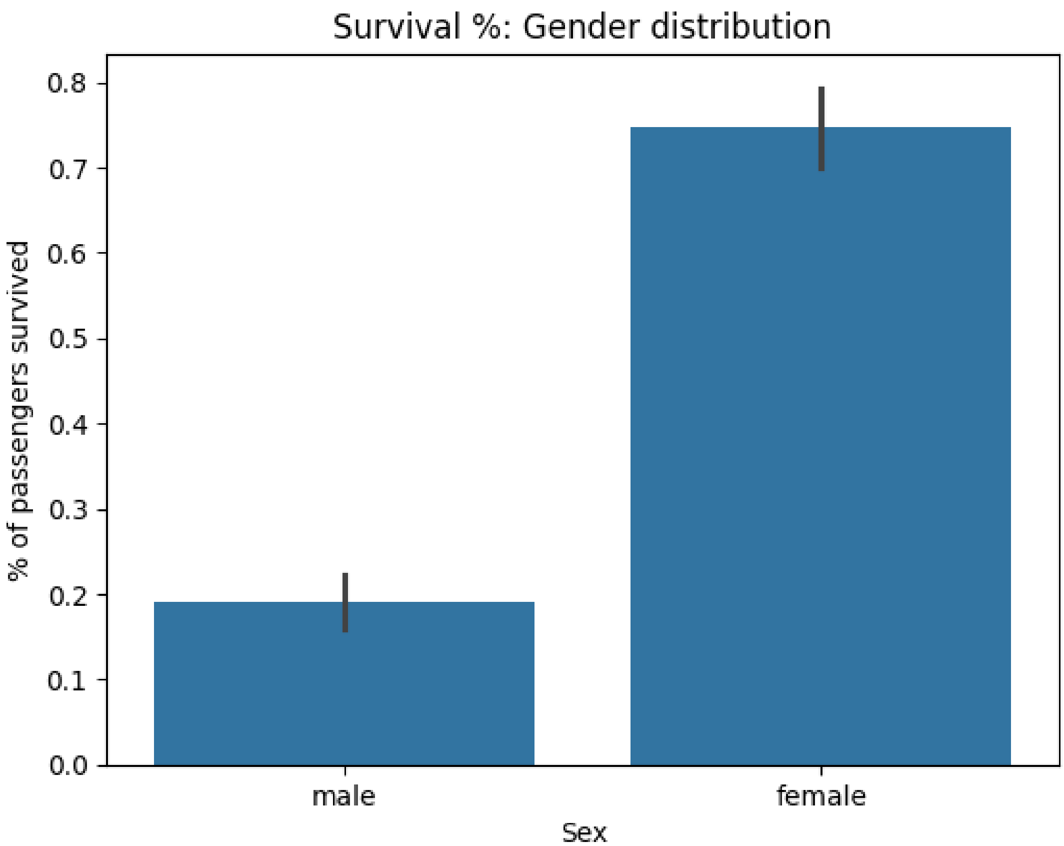
[ ]:

	Sex	Survived
0	female	0.747573
1	male	0.190559

There is a much higher probability of females surviving on the Titanic than men, Let us now proceed to visualize it.

[ ]:
```
#Plot for gender distribibtion of survival rate
sns.barplot(x='Sex',y='Survived',data=df_train)
plt.title('Survival %: Gender distribution')
plt.ylabel('% of passengers survived')
plt.xlabel('Sex')
```

[ ]: Text(0.5, 0, 'Sex')

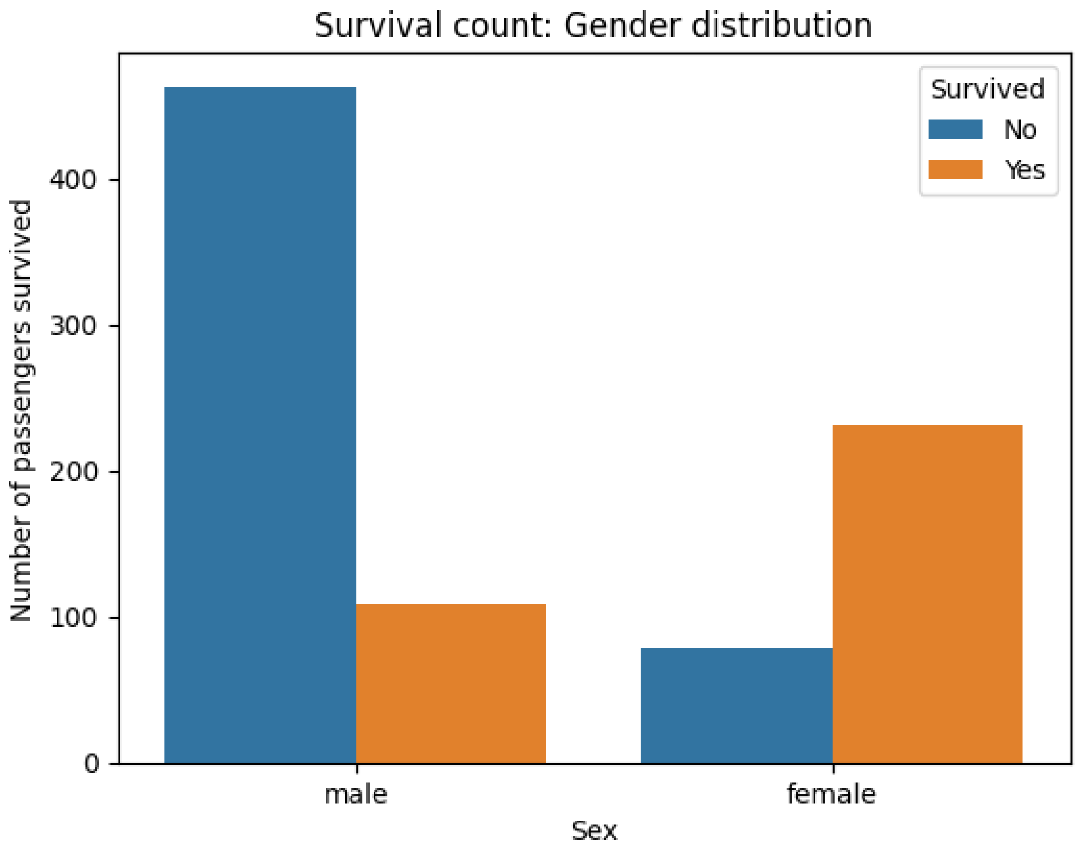


We can clearly see that gender plays a huge role in calculating the survival probability for a passenger. This is a crucial feature that would help to improve upon our predictions.

We will now visualize the total passenger count according to gender and survivability.

[ ]:
```
#Survivor count for each gender
m = sns.countplot(x='Sex',hue='Survived',data=df_train)
plt.title('Survival count: Gender distribution')
plt.xlabel('Sex')
plt.ylabel('Number of passengers survived')
a = m.get_legend()
b = a.texts
b[0].set_text('No')
```

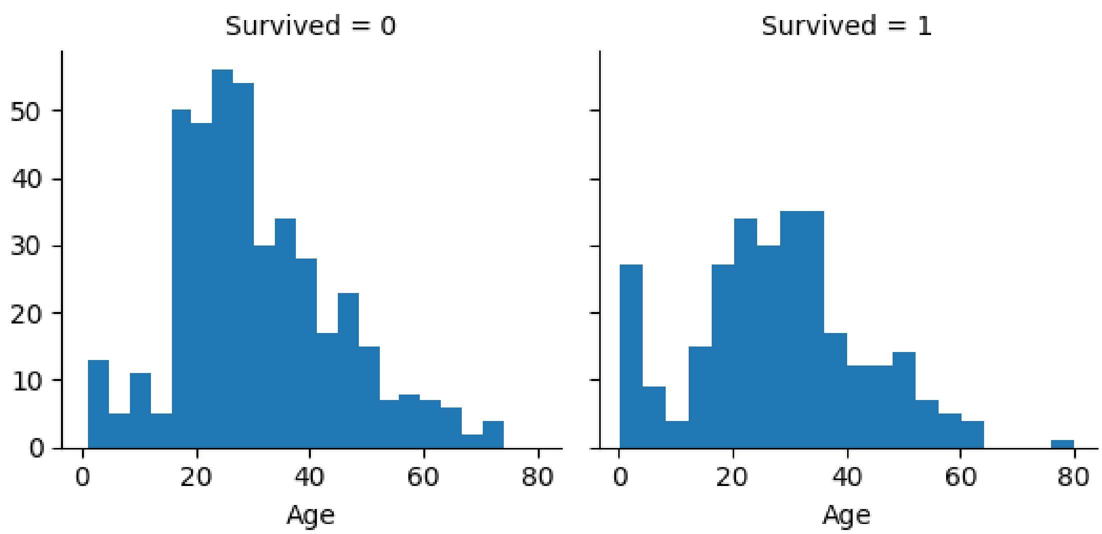
```
b[1].set_text('Yes')
```



Again, we see that there is a large difference between the number of survivors between both of the genders.

[ ]:
```
#Age survival ratio
s = sns.FacetGrid(df_train,col='Survived')
s.map(plt.hist,'Age',bins=20)
```

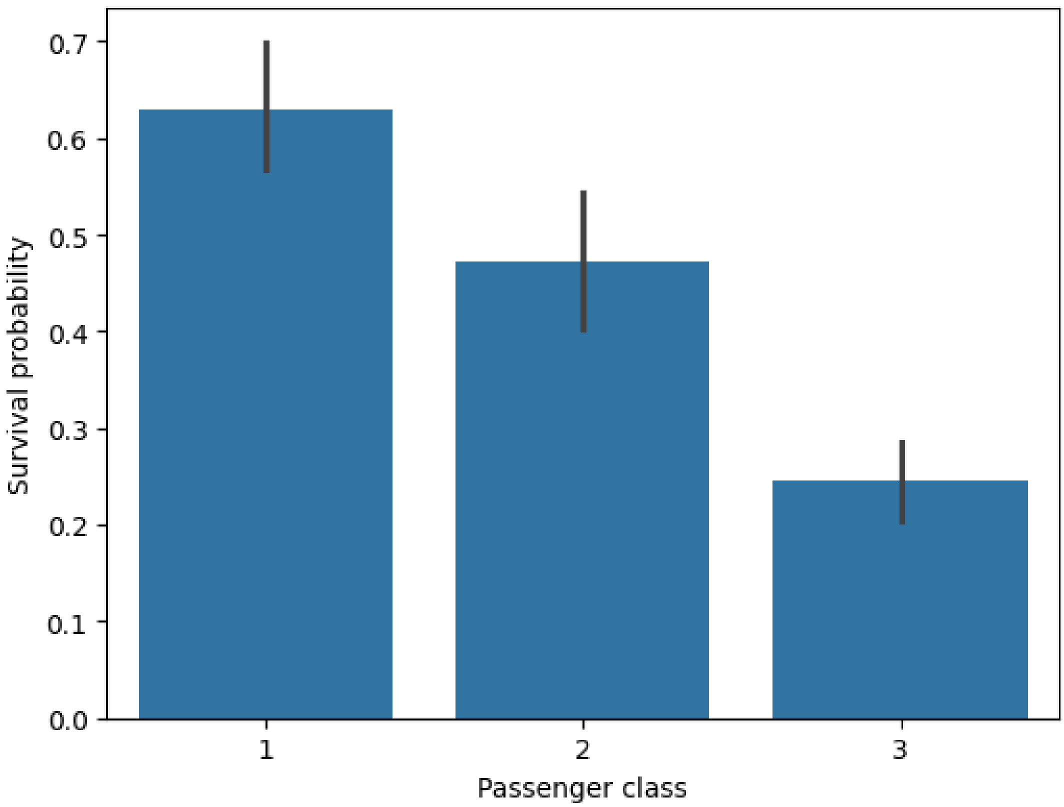
[ ]: <seaborn.axisgrid.FacetGrid at 0x7bd1d187b3a0>



It seems that the middle-aged and old people had a very low survival probability as compared to infants, childrens and young adults. Age plays an important role in saving yourself during a time of crisis.

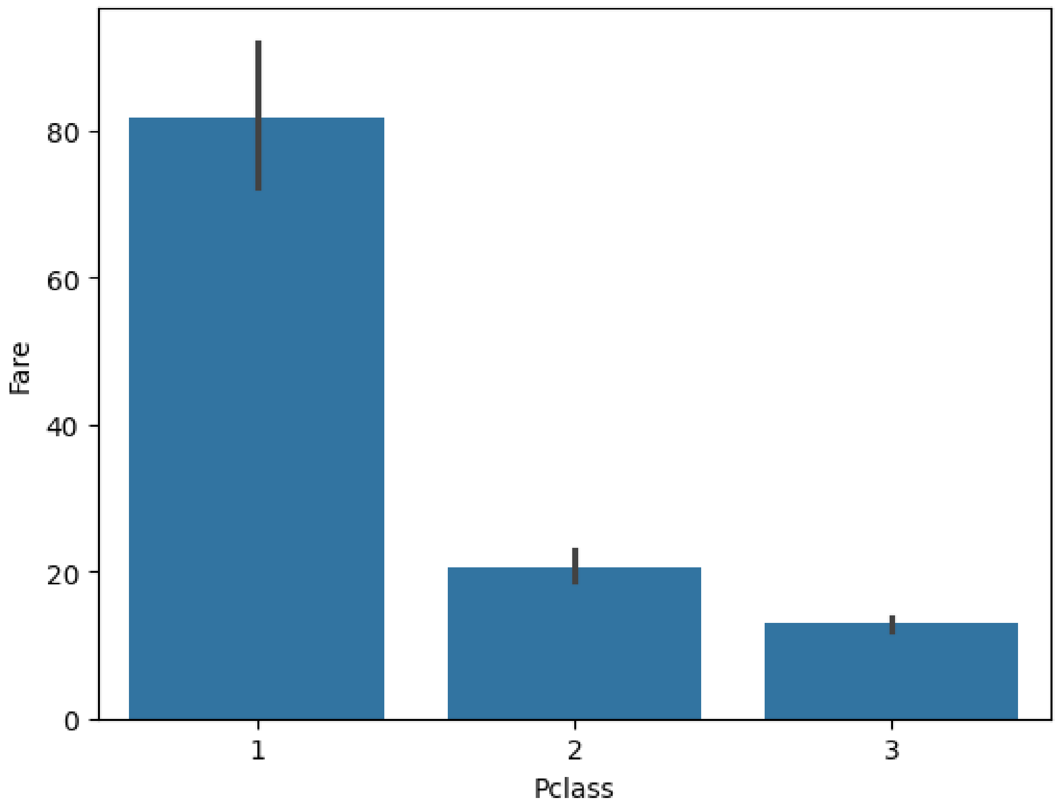
[ ]:
```
#Survival probability vs Class
b = sns.barplot(x='Pclass',y='Survived',data=df_train)
b.set_ylabel('Survival probability')
b.set_xlabel('Passenger class')
```

[ ]:
```
Text(0.5, 0, 'Passenger class')
```



[ ]:
```
c = sns.barplot(x='Pclass',y='Fare',data=df_train)
c.set_ylabel('Fare')
c.set_xlabel('Pclass')
```

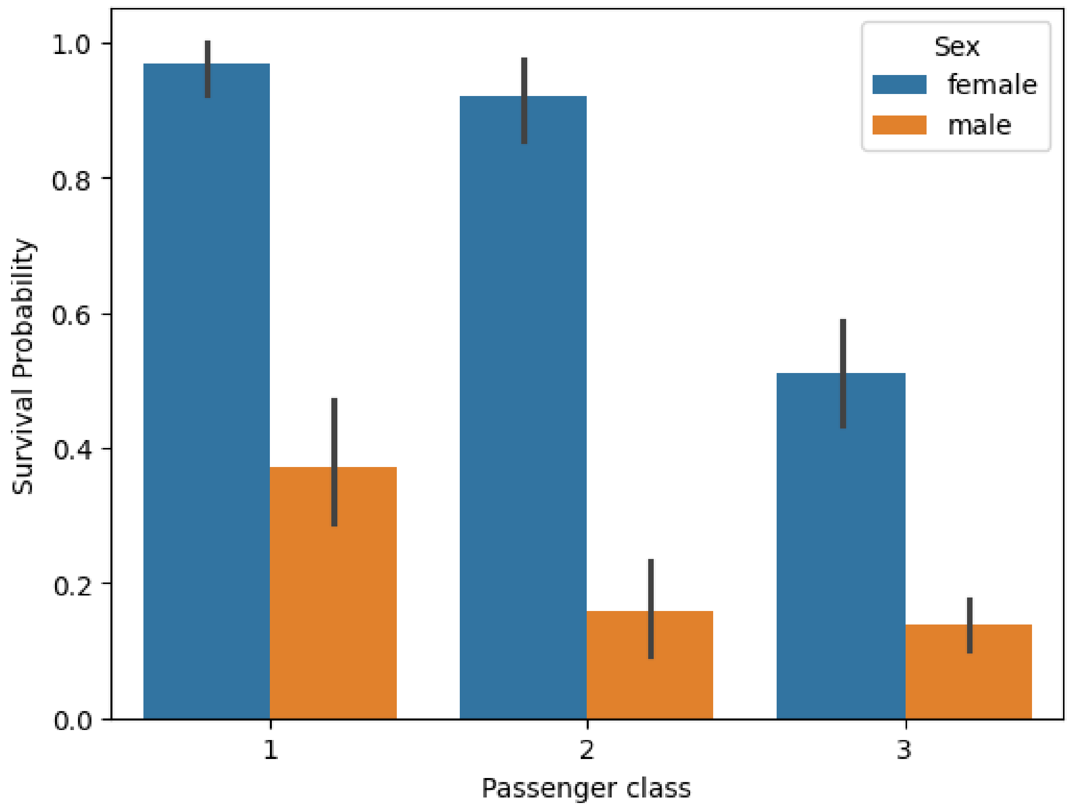
[ ]:
```
Text(0.5, 0, 'Pclass')
```



It seems that the rich people present in Passenger Class 1 had a much higher probability of survival in comparison to the other passenger classes. The fare is proportional to the survivability result.

[ ]:
```
#Survival Probability vs Class and Sex
b = sns.barplot(x='Pclass',y='Survived',hue='Sex',data=df_train)
b.set_ylabel('Survival Probability')
b.set_xlabel('Passenger class')
```

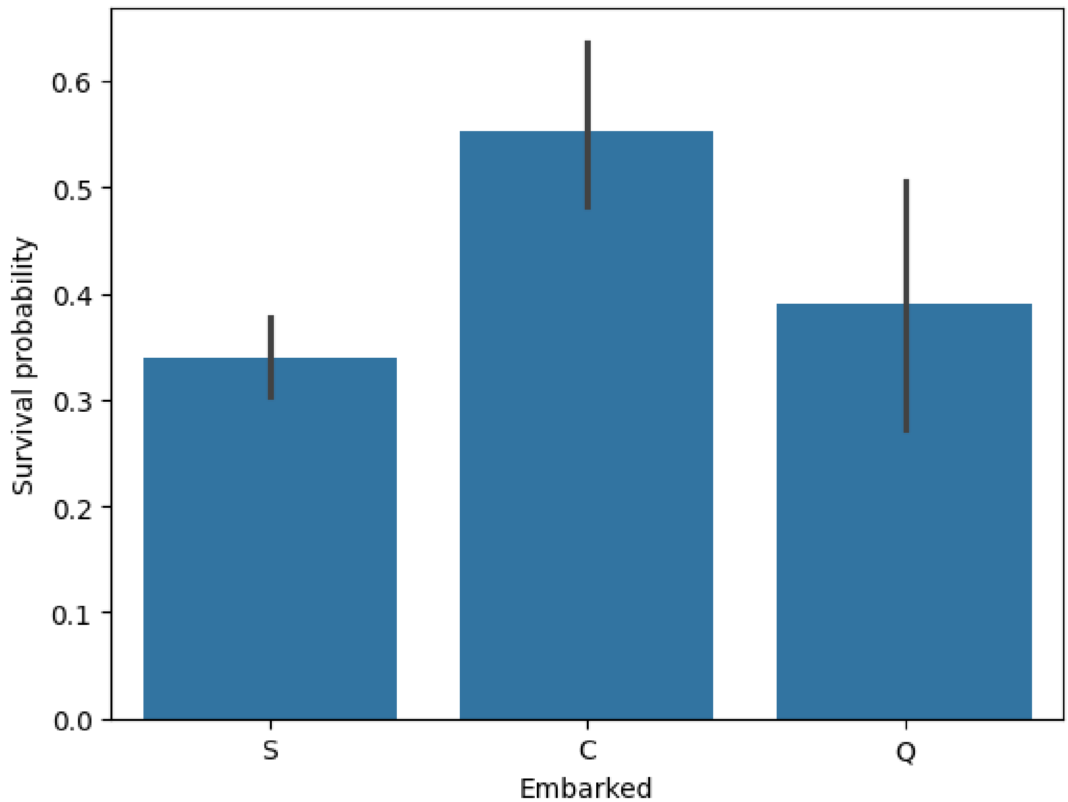
[ ]:
```
Text(0.5, 0, 'Passenger class')
```



We observe a similar trend here where the survival probability is in direct correlation with the gender as well as the Passenger class. Higher the passenger class equalled low fare which results in low survival chance.

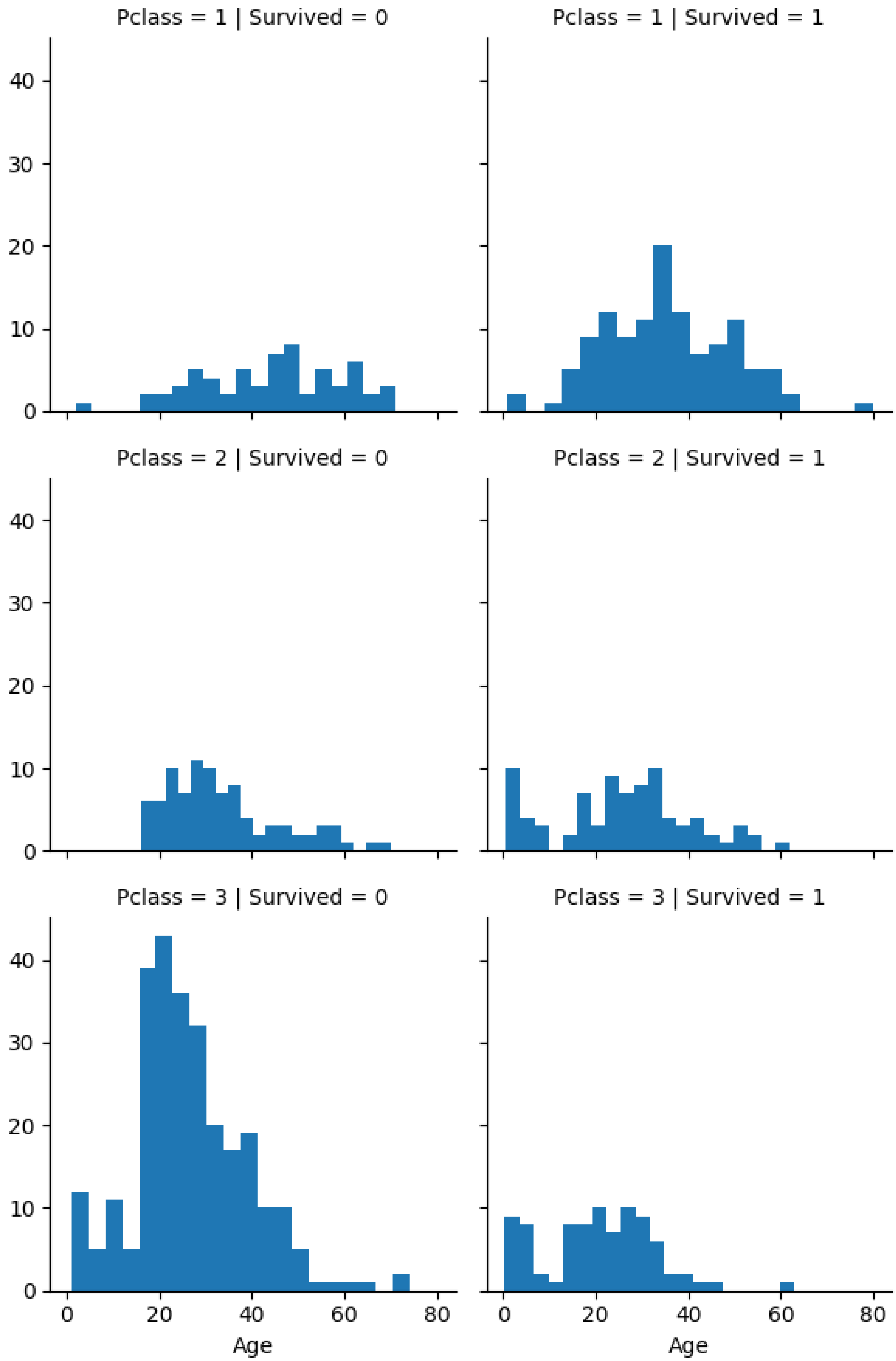
[ ]:
```
#Exploring Embarked vs Survival probability
ax = sns.barplot(x='Embarked',y='Survived',data=df_train)
ax.set_ylabel('Survival probability')
ax.set_xlabel('Embarked')
```

[ ]:
```
Text(0.5, 0, 'Embarked')
```



[ ]:
```
g1 = sns.FacetGrid(df_train,col='Survived',row='Pclass')
g1.map(plt.hist,'Age',bins=20)
```

[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x7bd1d16d6da0>
```

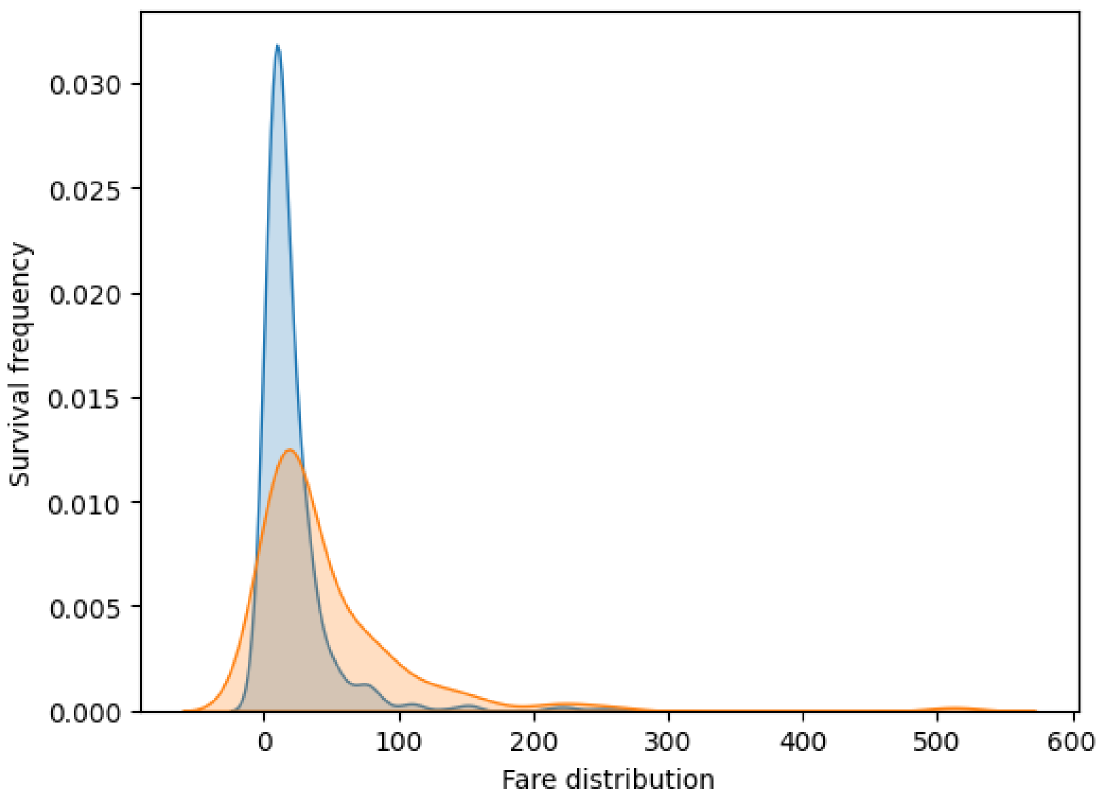

Pclass = 1 | Survived = 0
Pclass = 1 | Survived = 1
Pclass = 2 | Survived = 0
Pclass = 2 | Survived = 1
Pclass = 3 | Survived = 0
Pclass = 3 | Survived = 1
0
10
20
30
40
0
20
40
60
80
Age
Age

We see that Pclass 1 consists of more middle-aged and old men while P-class 2 and 3 consist of infants, children and the like. It is a similar occurence in real-life where usually old and rich people travel in First-Class with the presenece of children being very rare.

We also see that the survived histogram dwindles down in height as we move lower down the graph. The histogram still rises up pretty well for the lower age group which is what we saw above as well. Children, teenagers and young adults have a higher survival rate than the middle-aged and old people.

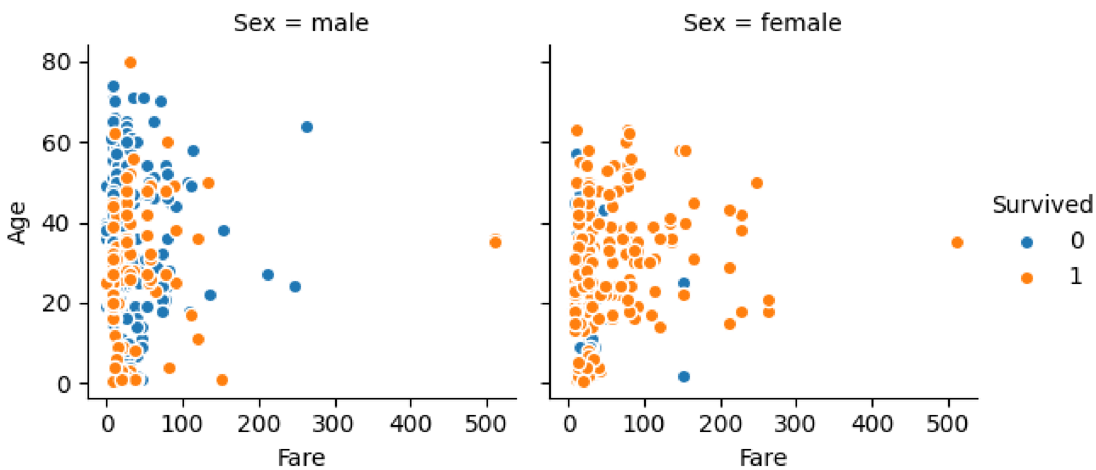
[ ]:
```
#Fare distribution
a1 = sns.kdeplot(df_train.
  ↪loc[(df_train['Survived']==0),'Fare'],shade=True,label='Not Survived')
a1 = sns.kdeplot(df_train.
  ↪loc[(df_train['Survived']==1),'Fare'],shade=True,label='Survived')
plt.ylabel('Survival frequency')
plt.xlabel('Fare distribution')
```

[ ]:
```
Text(0.5, 0, 'Fare distribution')
```

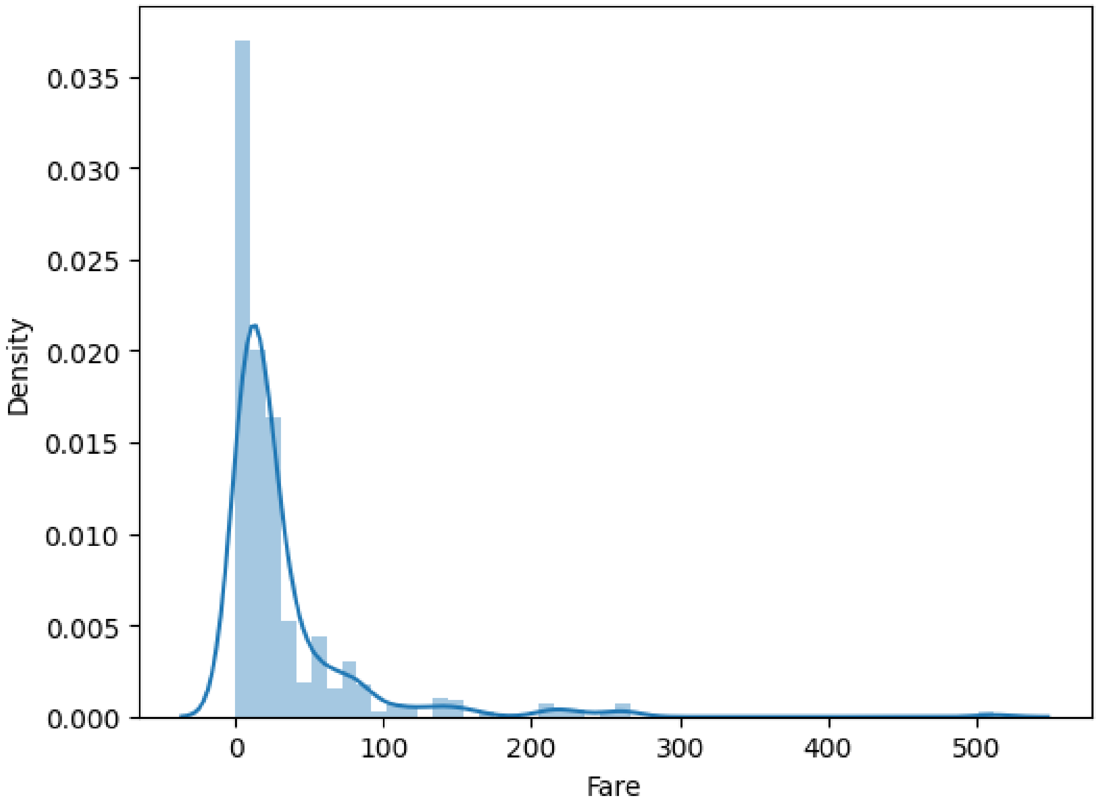


[ ]:
```
#Survival by Fare,Age and Sex
s = sns.FacetGrid(df_train,hue='Survived',col='Sex')
s.map(plt.scatter,'Fare','Age',edgecolor='w').add_legend()
```

[ ]: <seaborn.axisgrid.FacetGrid at 0x7bd1cef73970>



[ ]:
```
#Plotting fare in the combined dataset
s = sns.distplot(final['Fare'])
```


0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
Density
0
100
200
300
400
500
Fare