dwjesr11i

September 11, 2023

[5]:

```python
# Linear algebra
import numpy as np

# Data manipulation and analysis
import pandas as pd

# Data visualization
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
from matplotlib import style

# Algorithms
from sklearn import linear_model
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import Perceptron
from sklearn.linear_model import SGDClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
```

[7]:

```python
train_df = pd.read_csv('taks_2 Train.csv')
test_df = pd.read_csv('taks_2 Test.csv')

train_df['train_test'] = 1
test_df['train_test'] = 0
# test_df['Survived'] = np.NaN
all_data = pd.concat([train_df,test_df])

%matplotlib inline
all_data.columns
```

[7]:

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

[8]:

```
train_df.head(10)
```

[8]:

```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3
5            6         0       3
6            7         0       1
7            8         0       3
8            9         1       3
9           10         1       2

                                                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
5                                   Moran, Mr. James    male   NaN      0
6                            McCarthy, Mr. Timothy J    male  54.0      0
7                     Palsson, Master. Gosta Leonard    male   2.0      3
8  Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)  female  27.0      0
9                Nasser, Mrs. Nicholas (Adele Achem)  female  14.0      1

   Parch            Ticket     Fare Cabin Embarked  train_test
0      0         A/5 21171   7.2500   NaN        S           1
1      0          PC 17599  71.2833   C85        C           1
2      0  STON/O2. 3101282   7.9250   NaN        S           1
3      0            113803  53.1000  C123        S           1
4      0            373450   8.0500   NaN        S           1
5      0            330877   8.4583   NaN        Q           1
6      0             17463  51.8625   E46        S           1
7      1            349909  21.0750   NaN        S           1
8      2            347742  11.1333   NaN        S           1
9      0            237736  30.0708   NaN        C           1
```

[9]:

```
test_df.head(10)
```

[9]:

```
   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
5          897       3                    Svensson, Mr. Johan Cervin    male
```

```
6          898       3                         Connolly, Miss. Kate  female
7          899       2                 Caldwell, Mr. Albert Francis    male
8          900       3    Abrahim, Mrs. Joseph (Sophie Halaut Easu)  female
9          901       3                      Davies, Mr. John Samuel    male

    Age  SibSp  Parch     Ticket     Fare Cabin Embarked  train_test
0  34.5      0      0     330911   7.8292   NaN        Q           0
1  47.0      1      0     363272   7.0000   NaN        S           0
2  62.0      0      0     240276   9.6875   NaN        Q           0
3  27.0      0      0     315154   8.6625   NaN        S           0
4  22.0      1      1    3101298  12.2875   NaN        S           0
5  14.0      0      0       7538   9.2250   NaN        S           0
6  30.0      0      0     330972   7.6292   NaN        Q           0
7  26.0      1      1     248738  29.0000   NaN        S           0
8  18.0      0      0       2657   7.2292   NaN        C           0
9  21.0      2      0  A/4 48871  24.1500   NaN        S           0
```

```
[10]: train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 13 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
 12  train_test   891 non-null    int64
dtypes: float64(2), int64(6), object(5)
memory usage: 90.6+ KB
```

```
[11]: train_df.describe()
```

```
[11]:        PassengerId    Survived      Pclass         Age       SibSp  \
       count   891.000000  891.000000  891.000000  714.000000  891.000000
       mean    446.000000    0.383838    2.308642   29.699118    0.523008
       std     257.353842    0.486592    0.836071   14.526497    1.102743
       min       1.000000    0.000000    1.000000    0.420000    0.000000
```

```
25%     223.500000    0.000000    2.000000   20.125000    0.000000
50%     446.000000    0.000000    3.000000   28.000000    0.000000
75%     668.500000    1.000000    3.000000   38.000000    1.000000
max     891.000000    1.000000    3.000000   80.000000    8.000000

            Parch        Fare  train_test
count  891.000000  891.000000       891.0
mean     0.381594   32.204208         1.0
std      0.806057   49.693429         0.0
min      0.000000    0.000000         1.0
25%      0.000000    7.910400         1.0
50%      0.000000   14.454200         1.0
75%      0.000000   31.000000         1.0
max      6.000000  512.329200         1.0
```

[12]:

```
total = train_df.isnull().sum().sort_values(ascending=False)
percent_1 = train_df.isnull().sum()/train_df.isnull().count()*100
percent_2 = (round(percent_1, 1)).sort_values(ascending=False)
missing_data = pd.concat([total, percent_2], axis=1, keys=['Total', '%'])
missing_data.head(13)
```

[12]:

```
             Total     %
Cabin          687  77.1
Age            177  19.9
Embarked         2   0.2
PassengerId      0   0.0
Survived         0   0.0
Pclass           0   0.0
Name             0   0.0
Sex              0   0.0
SibSp            0   0.0
Parch            0   0.0
Ticket           0   0.0
Fare             0   0.0
train_test       0   0.0
```

[13]:

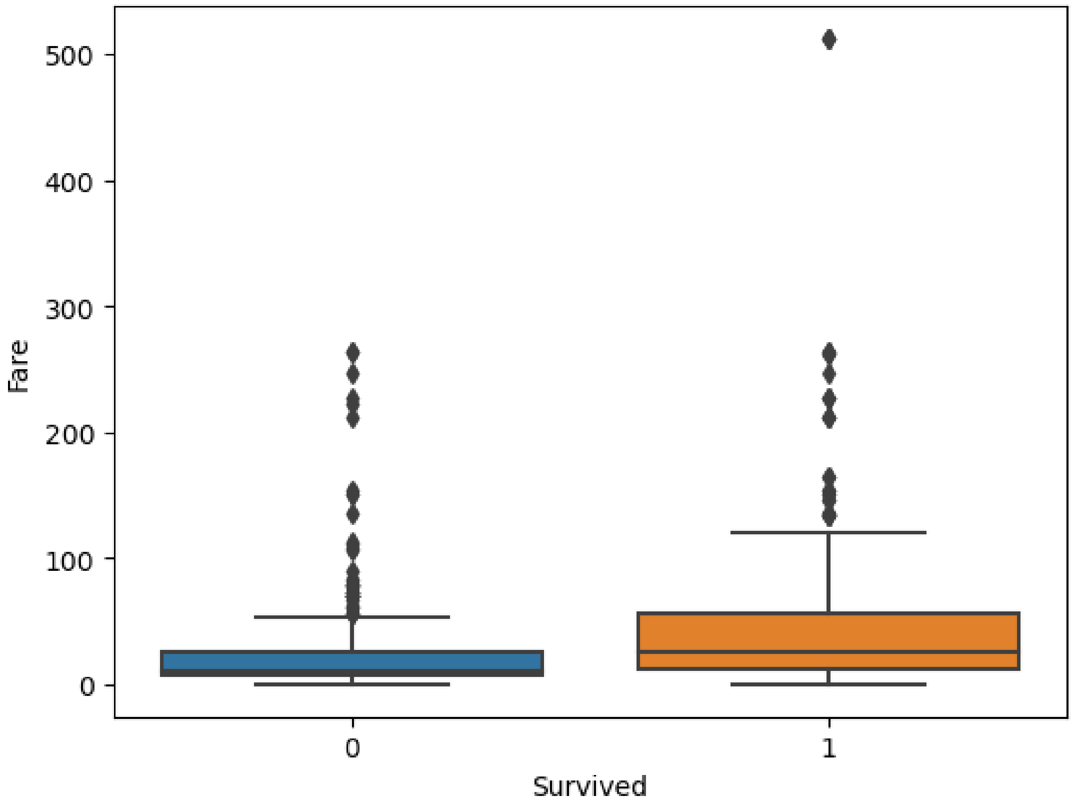
```
train_df.columns.values
```

[13]:

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

[14]:

```
sns.boxplot(x='Survived',y='Fare',data=train_df);
```



[15]:
```
train_df[train_df['Fare']>300]
```

[15]:
```
     PassengerId  Survived  Pclass                                Name  \
258          259         1       1                    Ward, Miss. Anna   
679          680         1       1  Cardeza, Mr. Thomas Drake Martinez   
737          738         1       1              Lesurer, Mr. Gustave J   

        Sex   Age  SibSp  Parch    Ticket      Fare        Cabin Embarked  \
258  female  35.0      0      0  PC 17755  512.3292          NaN        C   
679    male  36.0      0      1  PC 17755  512.3292  B51 B53 B55        C   
737    male  35.0      0      0  PC 17755  512.3292         B101        C   

     train_test  
258           1  
679           1  
737           1  
```

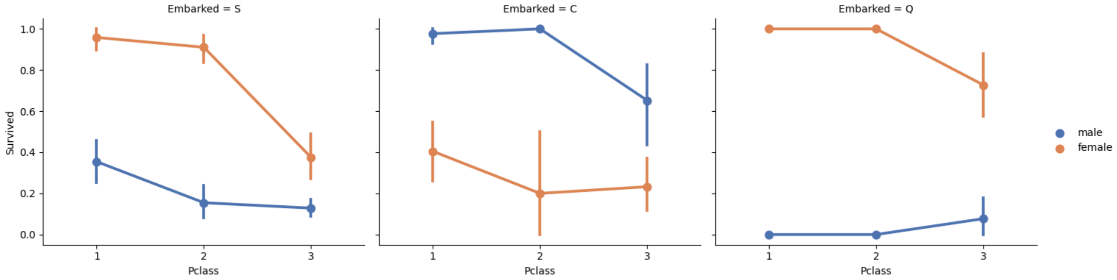
[16]:
```
train_df[train_df['Name'].str.contains("Capt")]
```

[16]:
```
     PassengerId  Survived  Pclass                          Name   Sex   Age  \
745          746         0       1  Crosby, Capt. Edward Gifford  male  70.0   
```

```
     SibSp  Parch     Ticket  Fare Cabin Embarked  train_test
745      1      1  WE/P 5735  71.0   B22        S           1
```

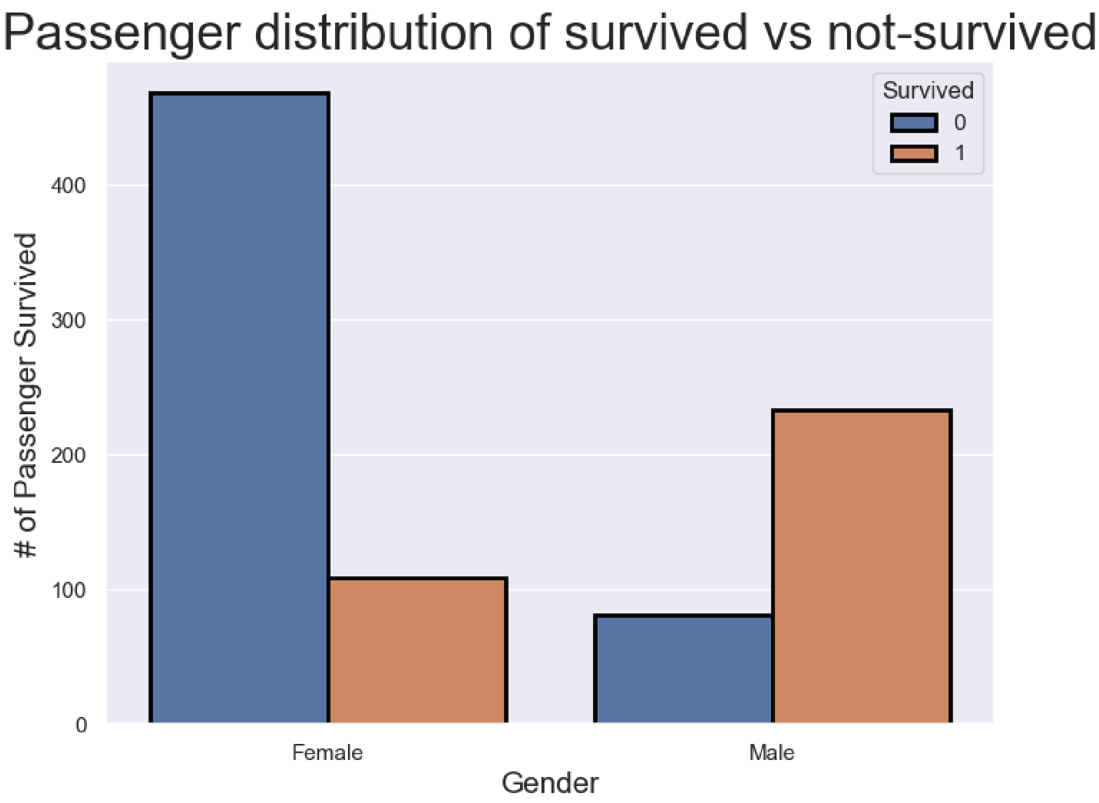
[17]:

```
FacetGrid = sns.FacetGrid(train_df, col='Embarked', height=4, aspect=1.2)
FacetGrid.map(sns.pointplot, 'Pclass', 'Survived', 'Sex', ci=95.0,␣
 ↪palette='deep', order=None, hue_order=None)
FacetGrid.add_legend();
```



[18]:

```
sns.set(style='darkgrid')
plt.subplots(figsize = (8,6))
ax=sns.countplot(x='Sex', data = train_df, hue='Survived', edgecolor=(0,0,0),␣
 ↪linewidth=2)

# Fixing title, xlabel and ylabel
plt.title('Passenger distribution of survived vs not-survived', fontsize=25)
plt.xlabel('Gender', fontsize=15)
plt.ylabel("# of Passenger Survived", fontsize = 15)
labels = ['Female', 'Male']

# Fixing xticks.
plt.xticks(sorted(train_df.Survived.unique()),labels);
```



```
[19]: train_df.groupby(['Sex']).mean()
```

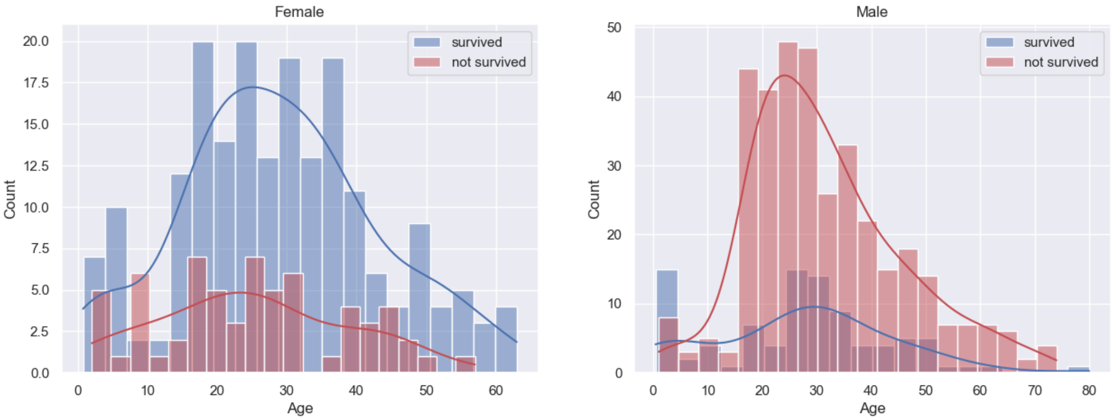
```
[19]:         PassengerId  Survived    Pclass        Age     SibSp     Parch  \
      Sex
      female   431.028662  0.742038  2.159236  27.915709  0.694268  0.649682
      male     454.147314  0.188908  2.389948  30.726645  0.429809  0.235702

                   Fare  train_test
      Sex
      female  44.479818         1.0
      male    25.523893         1.0
```

```
[20]: train_df.groupby(['Sex','Pclass']).mean()
```

```
[20]:                PassengerId  Survived        Age     SibSp     Parch  \
      Sex    Pclass
      female 1        469.212766  0.968085  34.611765  0.553191  0.457447
             2        443.105263  0.921053  28.722973  0.486842  0.605263
             3        399.729167  0.500000  21.750000  0.895833  0.798611
      male   1        455.729508  0.368852  41.281386  0.311475  0.278689
             2        447.962963  0.157407  30.740707  0.342593  0.222222
```

```
       3        455.515850  0.135447  26.507589  0.498559  0.224784

                          Fare  train_test
Sex    Pclass
female 1        106.125798         1.0
       2         21.970121         1.0
       3         16.118810         1.0
male   1         67.226127         1.0
       2         19.741782         1.0
       3         12.661633         1.0
```

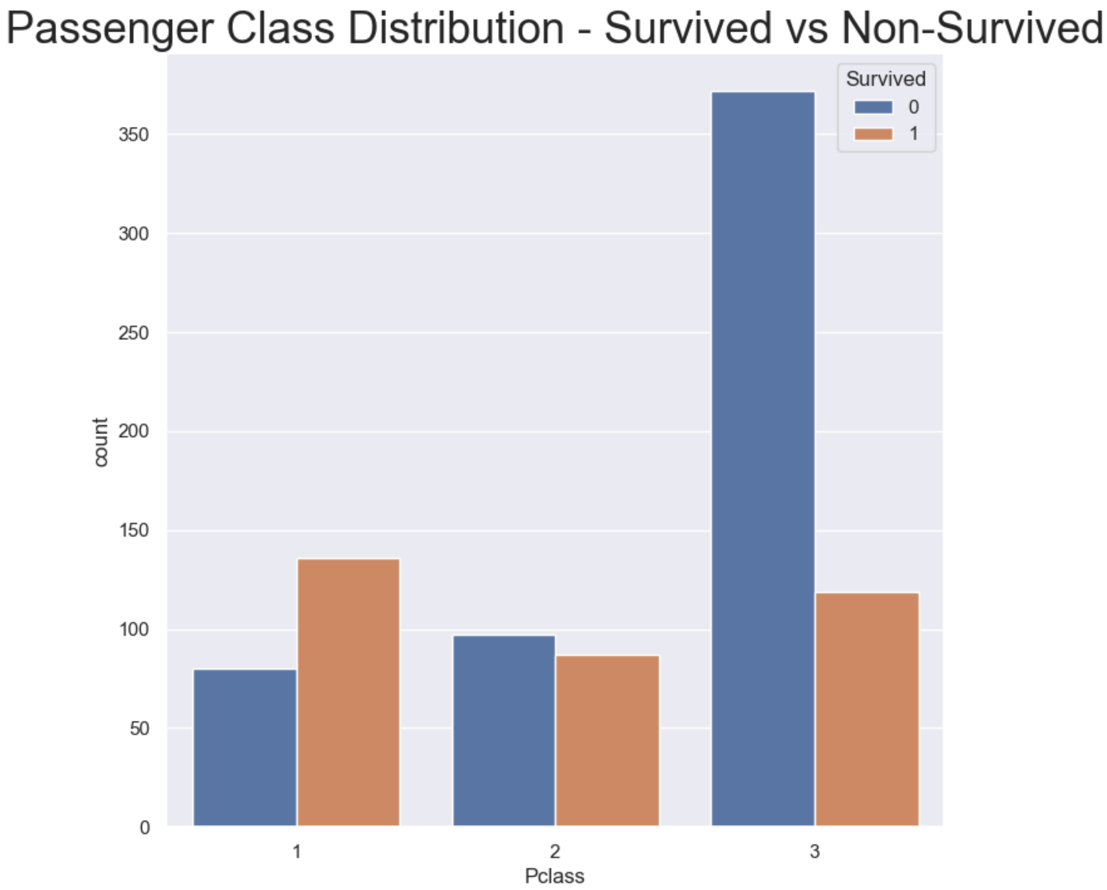
[21]:
```
survived = 'survived'
not_survived = 'not survived'

fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(15, 5))

women = train_df[train_df['Sex']=='female']
men = train_df[train_df['Sex']=='male']

# Plot Female Survived vs Not-Survived distribution
ax = sns.histplot(women[women['Survived']==1].Age.dropna(), bins=20, label =␣
 ↪survived, ax = axes[0],color='b', kde=True)
ax = sns.histplot(women[women['Survived']==0].Age.dropna(), bins=20, label =␣
 ↪not_survived, ax = axes[0],color='r', kde=True)
ax.legend()
ax.set_title('Female')

# Plot Male Survived vs Not-Survived distribution
ax = sns.histplot(men[men['Survived']==1].Age.dropna(), bins=20, label =␣
 ↪survived, ax = axes[1],color='b', kde=True)
ax = sns.histplot(men[men['Survived']==0].Age.dropna(), bins=20, label =␣
 ↪not_survived, ax = axes[1],color='r', kde=True)
ax.legend()
ax.set_title('Male');
```



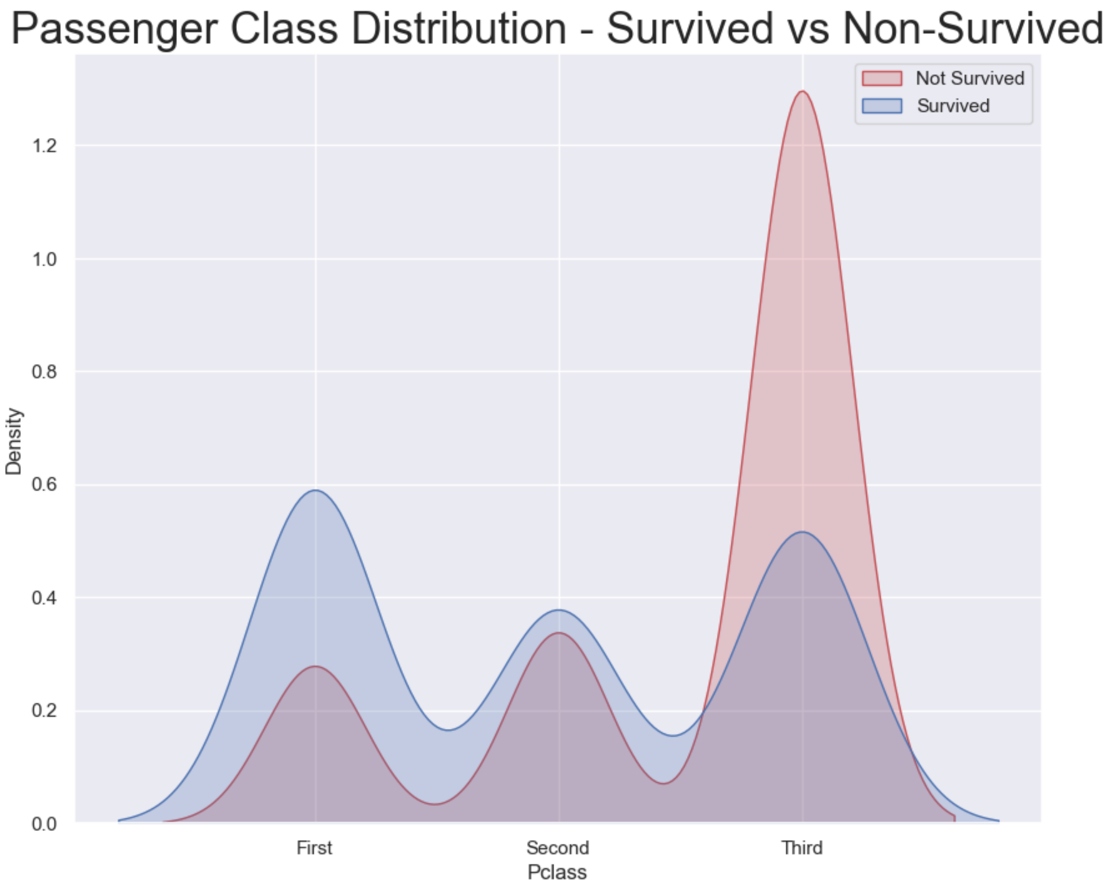
[22]:
```
train_df[train_df['Age']<18].groupby(['Sex','Pclass']).mean()
```

[22]:
```
               PassengerId  Survived        Age     SibSp     Parch  \
Sex    Pclass
female 1        525.375000  0.875000  14.125000  0.500000  0.875000
       2        369.250000  1.000000   8.333333  0.583333  1.083333
       3        374.942857  0.542857   8.428571  1.571429  1.057143
male   1        526.500000  1.000000   8.230000  0.500000  2.000000
       2        527.818182  0.818182   4.757273  0.727273  1.000000
       3        437.953488  0.232558   9.963256  2.069767  1.000000

                     Fare  train_test
Sex    Pclass
female 1       104.083337         1.0
       2        26.241667         1.0
       3        18.727977         1.0
male   1       116.072900         1.0
       2        25.659473         1.0
       3        22.752523         1.0
```

[23]:
```
plt.subplots(figsize = (8,8))
ax=sns.countplot(x='Pclass',hue='Survived',data=train_df)
plt.title("Passenger Class Distribution - Survived vs Non-Survived", fontsize =␣
 ↪25);
```

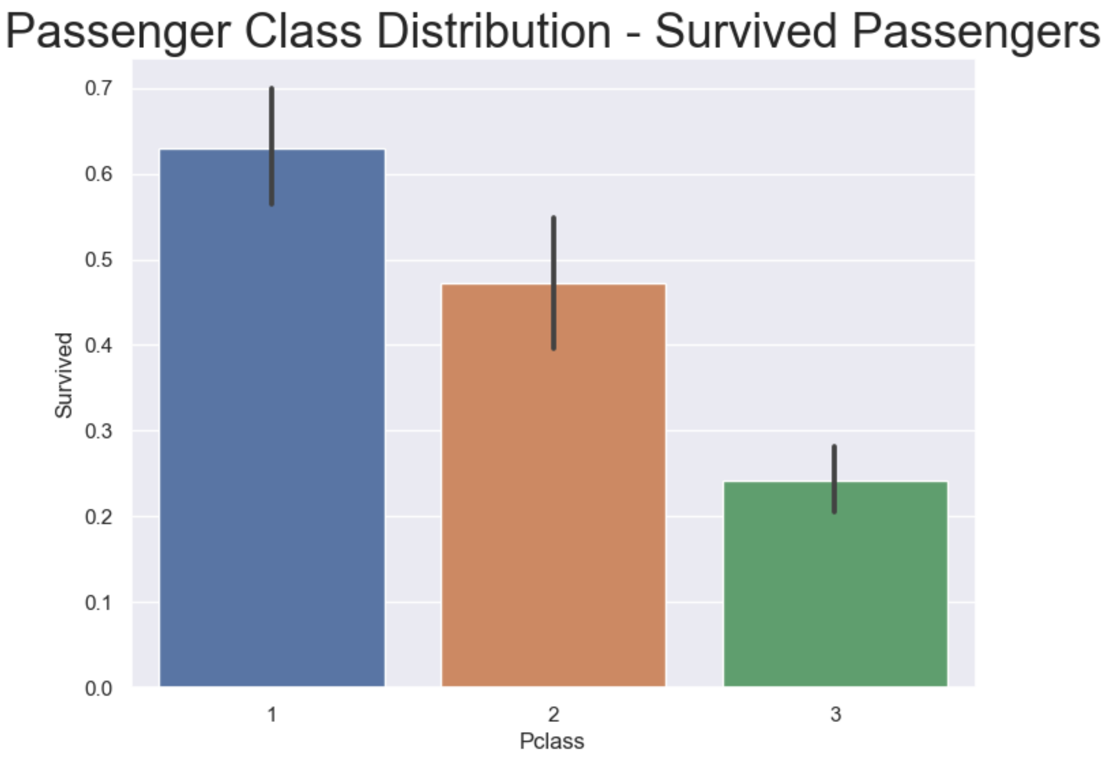


[24]:
```
plt.subplots(figsize=(10,8))
ax=sns.kdeplot(train_df.loc[(train_df['Survived'] ==␣
 ↪0),'Pclass'],shade=True,color='r',label='Not Survived')
ax.legend()
ax=sns.kdeplot(train_df.loc[(train_df['Survived'] ==␣
 ↪1),'Pclass'],shade=True,color='b',label='Survived')
ax.legend()

plt.title("Passenger Class Distribution - Survived vs Non-Survived", fontsize =␣
 ↪25)
labels = ['First', 'Second', 'Third']
plt.xticks(sorted(train_df.Pclass.unique()),labels);
```



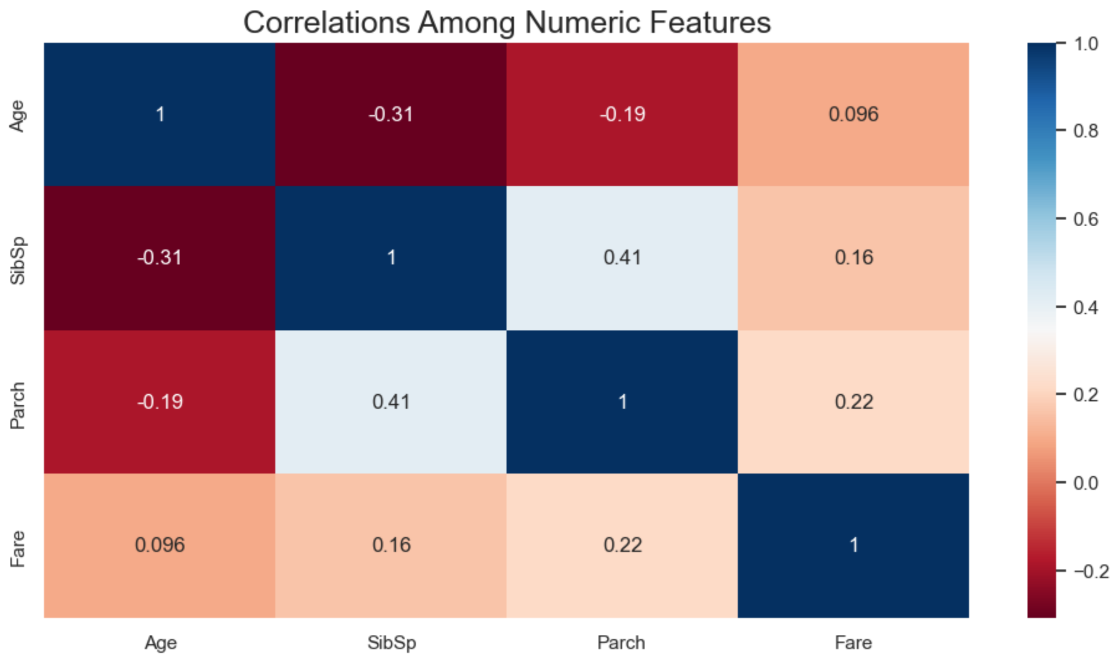
[25]:

```
plt.subplots(figsize = (8,6))
sns.barplot(x='Pclass', y='Survived', data=train_df);
plt.title("Passenger Class Distribution - Survived Passengers", fontsize = 25);
```



[26]:
```
# Look at numeric and categorical values separately
df_num = train_df[['Age','SibSp','Parch','Fare']]
df_cat = train_df[['Survived','Pclass','Sex','Ticket','Cabin','Embarked']]
```

[27]:
```
plt.subplots(figsize = (12,6))
sns.heatmap(df_num.corr(), annot=True,cmap="RdBu")
plt.title("Correlations Among Numeric Features", fontsize = 18);
```



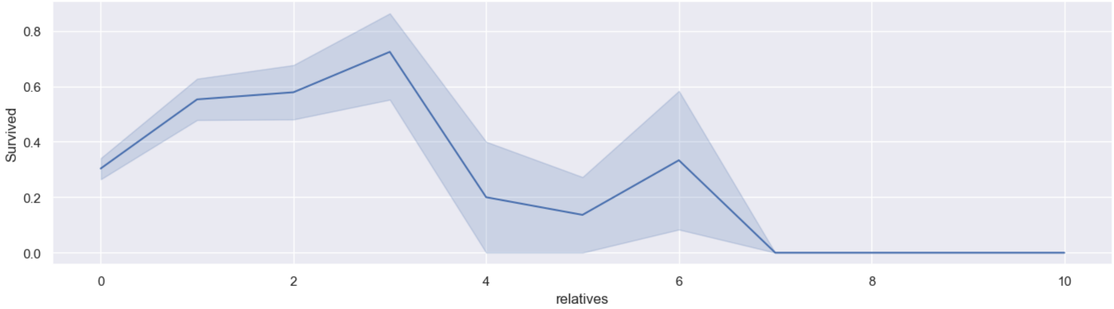
[28]:
```
train_df = train_df.drop(['PassengerId'], axis=1)
train_df.head()
```

[28]:
```
   Survived  Pclass                                               Name  \
0         0       3                            Braund, Mr. Owen Harris
1         1       1  Cumings, Mrs. John Bradley (Florence Briggs Th…
2         1       3                             Heikkinen, Miss. Laina
3         1       1       Futrelle, Mrs. Jacques Heath (Lily May Peel)
4         0       3                           Allen, Mr. William Henry

      Sex   Age  SibSp  Parch            Ticket     Fare Cabin Embarked  \
0    male  22.0      1      0         A/5 21171   7.2500   NaN        S
1  female  38.0      1      0          PC 17599  71.2833   C85        C
2  female  26.0      0      0  STON/O2. 3101282   7.9250   NaN        S
3  female  35.0      1      0            113803  53.1000  C123        S
4    male  35.0      0      0            373450   8.0500   NaN        S

   train_test
0           1
1           1
2           1
3           1
4           1
```

```
[29]: data = [train_df, test_df]
      for dataset in data:
          dataset['relatives'] = dataset['SibSp'] + dataset['Parch']
          dataset.loc[dataset['relatives'] > 0, 'not_alone'] = 0
          dataset.loc[dataset['relatives'] == 0, 'not_alone'] = 1
          dataset['not_alone'] = dataset['not_alone'].astype(int)
      train_df['not_alone'].value_counts()
```

```
[29]: 1    537
      0    354
      Name: not_alone, dtype: int64
```

```
[30]: plt.subplots(figsize = (16,4))
      ax = sns.lineplot(x='relatives',y='Survived', data=train_df)
```



```
[31]: import re
      deck = {"A": 1, "B": 2, "C": 3, "D": 4, "E": 5, "F": 6, "G": 7, "U": 8}
      data = [train_df, test_df]

      for dataset in data:
          dataset['Cabin'] = dataset['Cabin'].fillna("U0")
          dataset['Deck'] = dataset['Cabin'].map(lambda x: re.compile("([a-zA-Z]+)").
       ↪search(x).group())
          dataset['Deck'] = dataset['Deck'].map(deck)
          dataset['Deck'] = dataset['Deck'].fillna(0)
          dataset['Deck'] = dataset['Deck'].astype(int)
```

```
[32]: # We can now drop the Cabin feature
      train_df = train_df.drop(['Cabin'], axis=1)
      test_df = test_df.drop(['Cabin'], axis=1)
```

```
[33]: data = [train_df, test_df]

      for dataset in data:
          mean = train_df["Age"].mean()
```

```
    std = test_df["Age"].std()
    is_null = dataset["Age"].isnull().sum()

    # Compute random numbers between the mean, std and is_null
    rand_age = np.random.randint(mean - std, mean + std, size = is_null)

    # Fill NaN values in Age column with random values generated
    age_slice = dataset["Age"].copy()
    age_slice[np.isnan(age_slice)] = rand_age
    dataset["Age"] = age_slice
    dataset["Age"] = train_df["Age"].astype(int)
```

[34]:
```
train_df["Age"].isnull().sum()
```

[34]:
```
0
```

[35]:
```
train_df['Embarked'].describe()
```

[35]:
```
count     889
unique      3
top         S
freq      644
Name: Embarked, dtype: object
```

[36]:
```
common_value = 'S'
data = [train_df, test_df]

for dataset in data:
    dataset['Embarked'] = dataset['Embarked'].fillna(common_value)
```

[37]:
```
train_df['Embarked'].isnull().sum()
```

[37]:
```
0
```

[38]:
```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 14 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Survived    891 non-null    int64
 1   Pclass      891 non-null    int64
 2   Name        891 non-null    object
 3   Sex         891 non-null    object
 4   Age         891 non-null    int32
 5   SibSp       891 non-null    int64
 6   Parch       891 non-null    int64  
 7   Ticket      891 non-null    object 
 8   Fare        891 non-null    float64
 9   Embarked    891 non-null    object 
 10  train_test  891 non-null    int64  
 11  relatives   891 non-null    int64  
 12  not_alone   891 non-null    int32  
 13  Deck        891 non-null    int32  
dtypes: float64(1), int32(3), int64(6), object(4)
memory usage: 87.1+ KB
```

[39]:

```python
data = [train_df, test_df]

for dataset in data:
    dataset['Fare'] = dataset['Fare'].fillna(0)
    dataset['Fare'] = dataset['Fare'].astype(int)
```

[40]:

```python
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 14 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   Survived    891 non-null    int64 
 1   Pclass      891 non-null    int64 
 2   Name        891 non-null    object
 3   Sex         891 non-null    object
 4   Age         891 non-null    int32 
 5   SibSp       891 non-null    int64 
 6   Parch       891 non-null    int64 
 7   Ticket      891 non-null    object
 8   Fare        891 non-null    int32 
 9   Embarked    891 non-null    object
 10  train_test  891 non-null    int64 
 11  relatives   891 non-null    int64 
 12  not_alone   891 non-null    int32 
 13  Deck        891 non-null    int32 
dtypes: int32(4), int64(6), object(4)
memory usage: 83.7+ KB
```

[41]:

```python
data = [train_df, test_df]
titles = {"Mr": 1, "Miss": 2, "Mrs": 3, "Master": 4, "Other": 5}

for dataset in data:
    # Extract titles
    dataset['Title'] = dataset.Name.str.extract('([A-Za-z]+)\.', expand=False)
    # Replace titles with a more common title or as Other
    dataset['Title'] = dataset['Title'].replace(['Lady', 'Countess','Capt',␣
↪'Col','Don', 'Dr','Major', 'Rev', 'Sir', 'Jonkheer', 'Dona'], 'Other')
    dataset['Title'] = dataset['Title'].replace('Mlle', 'Miss')
    dataset['Title'] = dataset['Title'].replace('Ms', 'Miss')
    dataset['Title'] = dataset['Title'].replace('Mme', 'Mrs')

    # Convert titles into numbers
    dataset['Title'] = dataset['Title'].map(titles)

    # Filling NaN with 0 just to be safe
    dataset['Title'] = dataset['Title'].fillna(0)
```

[42]:
```
train_df = train_df.drop(['Name'], axis=1)
test_df = test_df.drop(['Name'], axis=1)
```

[43]:
```
# Checking results
train_df.head()
```

[43]:
```
   Survived  Pclass     Sex  Age  SibSp  Parch            Ticket  Fare  \
0         0       3    male   22      1      0         A/5 21171     7
1         1       1  female   38      1      0          PC 17599    71
2         1       3  female   26      0      0  STON/O2. 3101282     7
3         1       1  female   35      1      0            113803    53
4         0       3    male   35      0      0            373450     8

  Embarked  train_test  relatives  not_alone  Deck  Title
0        S           1          1          0     8      1
1        C           1          1          0     3      3
2        S           1          0          1     8      2
3        S           1          1          0     3      3
4        S           1          0          1     8      1
```

[44]:
```
genders = {"male": 0, "female": 1}
data = [train_df, test_df]

for dataset in data:
    dataset['Sex'] = dataset['Sex'].map(genders)
```

[45]:
```
train_df['Ticket'].describe()
```

[45]:
```
count         891
unique        681
top        347082
freq            7
Name: Ticket, dtype: object
```

[46]:

```
train_df = train_df.drop(['Ticket'], axis=1)
test_df = test_df.drop(['Ticket'], axis=1)
```

[47]:

```
ports = {"S": 0, "C": 1, "Q": 2}
data = [train_df, test_df]

for dataset in data:
    dataset['Embarked'] = dataset['Embarked'].map(ports)
```

[48]:

```
train_df.head()
```

[48]:

```
   Survived  Pclass  Sex  Age  SibSp  Parch  Fare  Embarked  train_test  \
0         0       3    0   22      1      0     7         0           1
1         1       1    1   38      1      0    71         1           1
2         1       3    1   26      0      0     7         0           1
3         1       1    1   35      1      0    53         0           1
4         0       3    0   35      0      0     8         0           1

   relatives  not_alone  Deck  Title
0          1          0     8      1
1          1          0     3      3
2          0          1     8      2
3          1          0     3      3
4          0          1     8      1
```

[49]:

```
data = [train_df, test_df]
for dataset in data:
    dataset['Age'] = dataset['Age'].astype(int)
    dataset.loc[ dataset['Age'] <= 11, 'Age'] = 0
    dataset.loc[(dataset['Age'] > 11) & (dataset['Age'] <= 18), 'Age'] = 1
    dataset.loc[(dataset['Age'] > 18) & (dataset['Age'] <= 22), 'Age'] = 2
    dataset.loc[(dataset['Age'] > 22) & (dataset['Age'] <= 27), 'Age'] = 3
    dataset.loc[(dataset['Age'] > 27) & (dataset['Age'] <= 33), 'Age'] = 4
    dataset.loc[(dataset['Age'] > 33) & (dataset['Age'] <= 40), 'Age'] = 5
    dataset.loc[(dataset['Age'] > 40) & (dataset['Age'] <= 66), 'Age'] = 6
    dataset.loc[ dataset['Age'] > 66, 'Age'] = 6
```

[50]:

```
# Checking the distribution
train_df['Age'].value_counts()
```

[50]:

```
4    162
6    158
5    147
3    146
2    119
1     91
0     68
```

```
Name: Age, dtype: int64
```

[51]:
```
train_df.head()
```

[51]:
```
   Survived  Pclass  Sex  Age  SibSp  Parch  Fare  Embarked  train_test  \
0         0       3    0    2      1      0     7         0           1
1         1       1    1    5      1      0    71         1           1
2         1       3    1    3      0      0     7         0           1
3         1       1    1    5      1      0    53         0           1
4         0       3    0    5      0      0     8         0           1

   relatives  not_alone  Deck  Title
0          1          0     8      1
1          1          0     3      3
2          0          1     8      2
3          1          0     3      3
4          0          1     8      1
```

[52]:
```
pd.qcut(train_df['Fare'], q=6)
```

[52]:
```
0      (-0.001, 7.0]
1      (52.0, 512.0]
2      (-0.001, 7.0]
3      (52.0, 512.0]
4         (7.0, 8.0]
            …
886      (8.0, 14.0]
887     (26.0, 52.0]
888     (14.0, 26.0]
889     (26.0, 52.0]
890    (-0.001, 7.0]
Name: Fare, Length: 891, dtype: category
Categories (6, interval[float64, right]): [(-0.001, 7.0] < (7.0, 8.0] < (8.0,
14.0] < (14.0, 26.0] < (26.0, 52.0] < (52.0, 512.0]]
```

[53]:
```
data = [train_df, test_df]

for dataset in data:
    dataset.loc[ dataset['Fare'] <= 7, 'Fare'] = 0
    dataset.loc[(dataset['Fare'] > 7) & (dataset['Fare'] <= 8), 'Fare'] = 1
    dataset.loc[(dataset['Fare'] > 8) & (dataset['Fare'] <= 14), 'Fare']   = 2
    dataset.loc[(dataset['Fare'] > 14) & (dataset['Fare'] <= 26), 'Fare']   = 3
    dataset.loc[(dataset['Fare'] > 26) & (dataset['Fare'] <= 52), 'Fare']   = 4
    dataset.loc[dataset['Fare'] > 52, 'Fare'] = 5
    dataset['Fare'] = dataset['Fare'].astype(int)
```

[54]:
```
# Checking the dataset
train_df.head(10)
```

[54]:
```
   Survived  Pclass  Sex  Age  SibSp  Parch  Fare  Embarked  train_test  \
0         0       3    0    2      1      0     0         0           1
1         1       1    1    5      1      0     5         1           1
2         1       3    1    3      0      0     0         0           1
3         1       1    1    5      1      0     5         0           1
4         0       3    0    5      0      0     1         0           1
5         0       3    0    4      0      0     1         2           1
6         0       1    0    6      0      0     4         0           1
7         0       3    0    0      3      1     3         0           1
8         1       3    1    3      0      2     2         0           1
9         1       2    1    1      1      0     4         1           1

   relatives  not_alone  Deck  Title
0          1          0     8      1
1          1          0     3      3
2          0          1     8      2
3          1          0     3      3
4          0          1     8      1
5          0          1     8      1
6          0          1     5      1
7          4          0     8      4
8          2          0     8      3
9          1          0     8      3
```

[55]:
```
X_train = train_df.drop("Survived", axis=1)
Y_train = train_df["Survived"]
X_test  = test_df.drop("PassengerId", axis=1).copy()
```

[56]:
```
sgd = linear_model.SGDClassifier(max_iter=5, tol=None)
sgd.fit(X_train, Y_train)

Y_pred = sgd.predict(X_test)

sgd.score(X_train, Y_train)
acc_sgd = round(sgd.score(X_train, Y_train) * 100, 2)

# Print score
print(round(acc_sgd,2,), "%")
```

```
58.14 %
```

[57]:
```
decision_tree = DecisionTreeClassifier()
decision_tree.fit(X_train, Y_train)
```

```
Y_pred = decision_tree.predict(X_test)

acc_decision_tree = round(decision_tree.score(X_train, Y_train) * 100, 2)

# Print score
print(round(acc_decision_tree,2,), "%")
```

```
92.59 %
```

[58]:

```
random_forest = RandomForestClassifier(n_estimators=100)
random_forest.fit(X_train, Y_train)

Y_prediction = random_forest.predict(X_test)

random_forest.score(X_train, Y_train)
acc_random_forest = round(random_forest.score(X_train, Y_train) * 100, 2)

# Print score
print(round(acc_random_forest,2,), "%")
```

```
92.59 %
```

[59]:

```
logreg = LogisticRegression()
logreg.fit(X_train, Y_train)

Y_pred = logreg.predict(X_test)

acc_log = round(logreg.score(X_train, Y_train) * 100, 2)

# Print score
print(round(acc_log,2,), "%")
```

```
81.48 %
```

[60]:

```
knn = KNeighborsClassifier(n_neighbors = 3)
knn.fit(X_train, Y_train)

Y_pred = knn.predict(X_test)

acc_knn = round(knn.score(X_train, Y_train) * 100, 2)

# Print score
print(round(acc_knn,2,), "%")
```

```
85.52 %
```

```
C:\ProgramData\Anaconda3\lib\site-
packages\sklearn\neighbors\_classification.py:228: FutureWarning: Unlike other
```

```
reduction functions (e.g. `skew`, `kurtosis`), the default behavior of `mode`
typically preserves the axis it acts along. In SciPy 1.11.0, this behavior will
change: the default value of `keepdims` will become False, the `axis` over which
the statistic is taken will be eliminated, and the value None will no longer be
accepted. Set `keepdims` to True or False to avoid this warning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
C:\ProgramData\Anaconda3\lib\site-
packages\sklearn\neighbors\_classification.py:228: FutureWarning: Unlike other
reduction functions (e.g. `skew`, `kurtosis`), the default behavior of `mode`
typically preserves the axis it acts along. In SciPy 1.11.0, this behavior will
change: the default value of `keepdims` will become False, the `axis` over which
the statistic is taken will be eliminated, and the value None will no longer be
accepted. Set `keepdims` to True or False to avoid this warning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
```

[61]:

```python
gaussian = GaussianNB()
gaussian.fit(X_train, Y_train)

Y_pred = gaussian.predict(X_test)

acc_gaussian = round(gaussian.score(X_train, Y_train) * 100, 2)

# Print score
print(round(acc_gaussian,2,), "%")
```

```
78.68 %
```

[62]:

```python
perceptron = Perceptron(max_iter=1000)
perceptron.fit(X_train, Y_train)

Y_pred = perceptron.predict(X_test)

acc_perceptron = round(perceptron.score(X_train, Y_train) * 100, 2)

# Print score
print(round(acc_perceptron,2,), "%")
```

```
75.76 %
```

[63]:

```python
results = pd.DataFrame({
    'Model': ['KNN', 'Logistic Regression',
              'Random Forest', 'Naive Bayes', 'Perceptron',
              'Stochastic Gradient Decent',
              'Decision Tree'],
    'Score': [acc_knn, acc_log,
              acc_random_forest, acc_gaussian, acc_perceptron,
              acc_sgd, acc_decision_tree]})
```

```
result_df = results.sort_values(by='Score', ascending=False)
result_df = result_df.set_index('Score')
result_df.head(9)
```

[63]:

```
                            Model
Score
92.59               Random Forest
92.59               Decision Tree
85.52                         KNN
81.48         Logistic Regression
78.68                 Naive Bayes
75.76                  Perceptron
58.14  Stochastic Gradient Decent
```

[64]:

```
from sklearn.model_selection import cross_val_score

rf = RandomForestClassifier(n_estimators=100)
scores = cross_val_score(rf, X_train, Y_train, cv=10, scoring = "accuracy")
```

[65]:

```
print("Scores:", scores)
print("Mean:", scores.mean())
print("Standard Deviation:", scores.std())
```

```
Scores: [0.81111111 0.82022472 0.73033708 0.83146067 0.87640449 0.83146067
 0.79775281 0.7752809  0.85393258 0.82022472]
Mean: 0.8148189762796505
Standard Deviation: 0.03865286486020869
```

[66]:

```
importances = pd.DataFrame({'feature':X_train.columns,'importance':np.
 ↪round(random_forest.feature_importances_,3)})
importances = importances.sort_values('importance',ascending=False).
 ↪set_index('feature')
```

[67]:

```
importances.head(12)
```

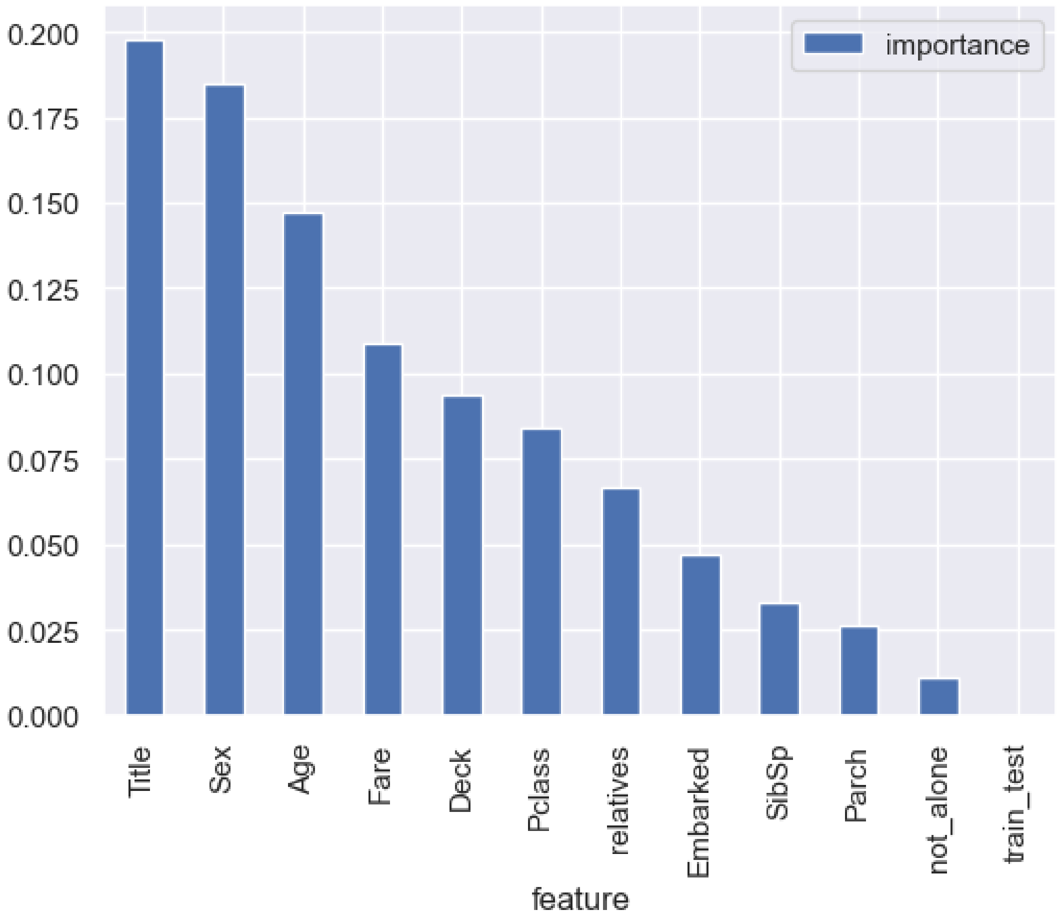
[67]:

```
            importance
feature
Title            0.198
Sex              0.185
Age              0.147
Fare             0.109
Deck             0.094
Pclass           0.084
relatives        0.067
Embarked         0.047
SibSp            0.033
Parch            0.026
```

```
not_alone       0.011
train_test      0.000
```

[68]:

```
importances.plot.bar();
```



[69]:

```
# Dropping not_alone
train_df  = train_df.drop("not_alone", axis=1)
test_df  = test_df.drop("not_alone", axis=1)

# Dropping Parch
train_df  = train_df.drop("Parch", axis=1)
test_df  = test_df.drop("Parch", axis=1)
```

[70]:

```
# # Reassigning features
X_train = train_df.drop("Survived", axis=1)
Y_train = train_df["Survived"]
X_test  = test_df.drop("PassengerId", axis=1).copy()
```

[71]:

```python
random_forest = RandomForestClassifier(n_estimators=100, oob_score = True)
random_forest.fit(X_train, Y_train)

Y_prediction = random_forest.predict(X_test)

random_forest.score(X_train, Y_train)
acc_random_forest = round(random_forest.score(X_train, Y_train) * 100, 2)

# Print scores
print(round(acc_random_forest,2,), "%")
```

```
92.59 %
```

[72]:

```python
importances = pd.DataFrame({'feature':X_train.columns,'importance':np.
 ↪round(random_forest.feature_importances_,3)})
importances = importances.sort_values('importance',ascending=False).
 ↪set_index('feature')
```

[73]:

```python
importances.head(12)
```

[73]:

```
            importance
feature
Title            0.234
Sex              0.154
Age              0.145
Fare             0.107
Deck             0.094
Pclass           0.090
relatives        0.084
SibSp            0.047
Embarked         0.046
train_test       0.000
```

[74]:

```python
print("oob score:", round(random_forest.oob_score_, 4)*100, "%")
```

```
oob score: 81.47999999999999 %
```

[75]:

```python
# Simple performance reporting function
def clf_performance(classifier, model_name):
    print(model_name)
    print('Best Score: ' + str(classifier.best_score_))
    print('Best Parameters: ' + str(classifier.best_params_))
```

[76]:

```python
from sklearn.model_selection import GridSearchCV

rf = RandomForestClassifier(random_state = 1)
param_grid =  {'n_estimators': [400,450,500,550],
               'criterion':['gini','entropy'],
               'bootstrap': [True],
               'max_depth': [15, 20, 25],
               'max_features': ['auto','sqrt', 10],
               'min_samples_leaf': [2,3],
               'min_samples_split': [2,3]}

clf_rf = GridSearchCV(rf, param_grid = param_grid, cv = 5, verbose = True,␣
 ↪n_jobs = -1)
best_clf_rf = clf_rf.fit(X_train,Y_train)

# Print score
clf_performance(best_clf_rf,'Random Forest')
```

```
Fitting 5 folds for each of 288 candidates, totalling 1440 fits
Random Forest
Best Score: 0.8338836231247255
Best Parameters: {'bootstrap': True, 'criterion': 'entropy', 'max_depth': 15,
'max_features': 10, 'min_samples_leaf': 3, 'min_samples_split': 2,
'n_estimators': 400}
```

[77]:

```
random_forest = RandomForestClassifier(criterion = "gini",
                                       max_depth = 20,
                                       max_features='auto',
                                       min_samples_leaf = 3,
                                       min_samples_split = 2,
                                       n_estimators=450,
                                       oob_score=True,
                                       random_state=1,
                                       n_jobs=-1)

random_forest.fit(X_train, Y_train)
Y_prediction = random_forest.predict(X_test)

random_forest.score(X_train, Y_train)

print("oob score:", round(random_forest.oob_score_, 4)*100, "%")
```

```
oob score: 82.72 %
```

[78]:

```
from sklearn.model_selection import cross_val_predict
from sklearn.metrics import confusion_matrix

predictions = cross_val_predict(random_forest, X_train, Y_train, cv=3)
confusion_matrix(Y_train, predictions)
```

[78]:
```
array([[493,  56],
       [ 97, 245]], dtype=int64)
```

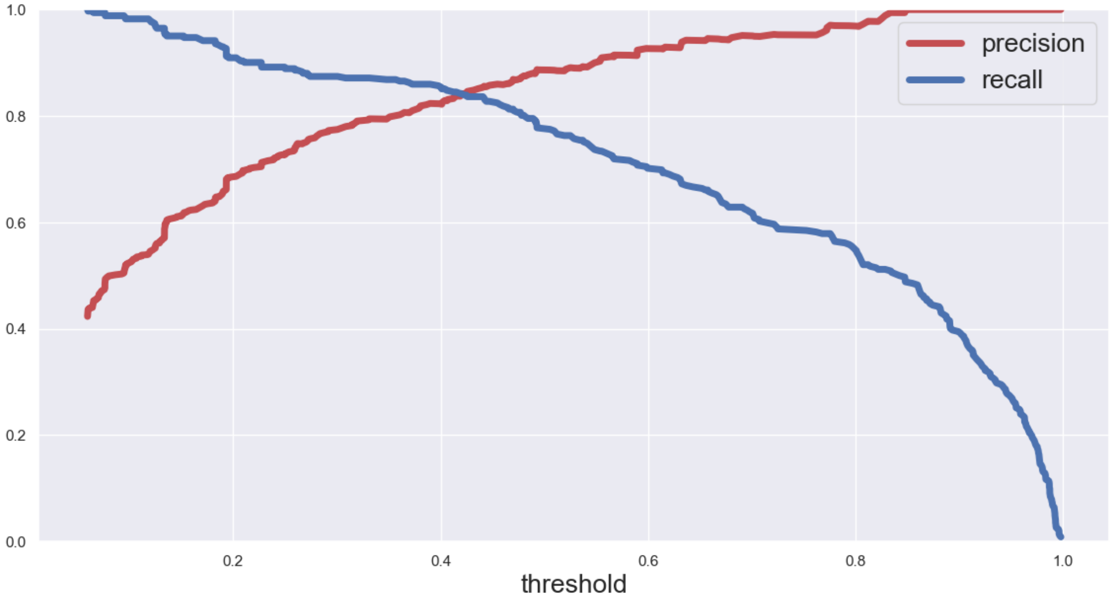
[79]:
```
from sklearn.metrics import precision_score, recall_score

print("Precision:", precision_score(Y_train, predictions))
print("Recall:",recall_score(Y_train, predictions))
```

```
Precision: 0.813953488372093
Recall: 0.716374269005848
```

[80]:
```
from sklearn.metrics import f1_score
f1_score(Y_train, predictions)
```

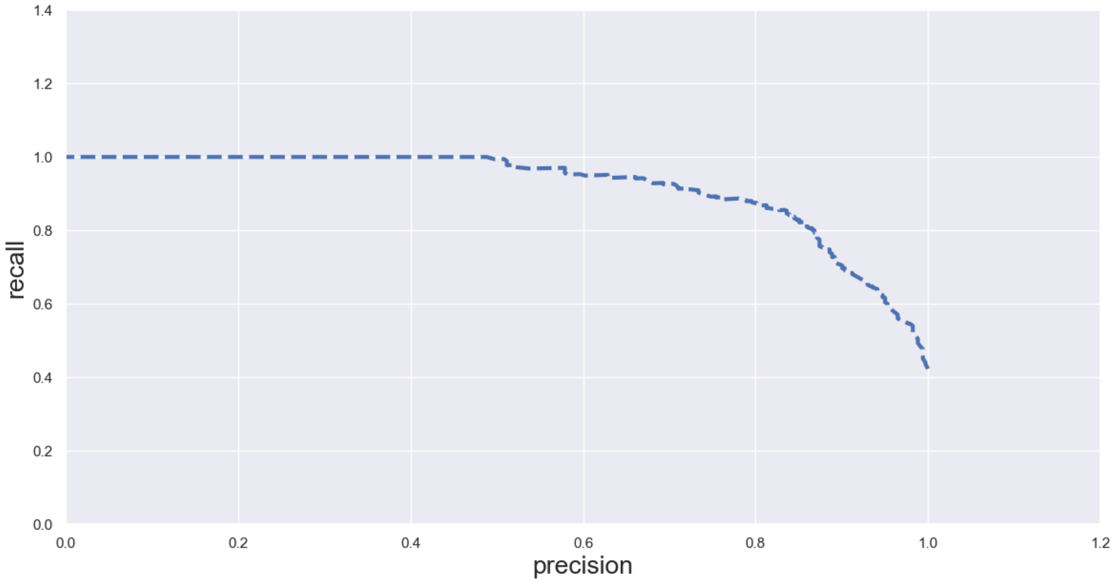
[80]:
```
0.7620528771384137
```

[82]:
```
from sklearn.metrics import precision_recall_curve

# Getting the probabilities of our predictions
y_scores = random_forest.predict_proba(X_train)
y_scores = y_scores[:,1]

precision, recall, threshold = precision_recall_curve(Y_train, y_scores)
def plot_precision_and_recall(precision, recall, threshold):
    plt.plot(threshold, precision[:-1], "r", label="precision", linewidth=5)
    plt.plot(threshold, recall[:-1], "b", label="recall", linewidth=5)
    plt.xlabel("threshold", fontsize=19)
    plt.legend(loc="upper right", fontsize=19)
    plt.ylim([0, 1])

plt.figure(figsize=(14, 7))
plot_precision_and_recall(precision, recall, threshold)
plt.show()
```



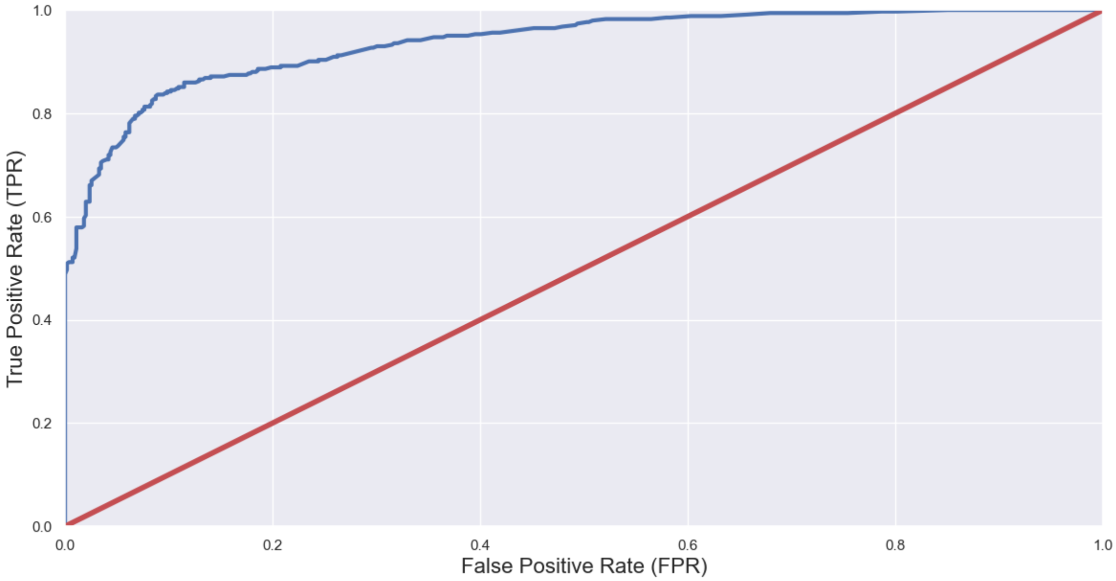
[83]:

```python
def plot_precision_vs_recall(precision, recall):
    plt.plot(recall, precision, "b--", linewidth=3)
    plt.xlabel("precision", fontsize=19)
    plt.ylabel("recall", fontsize=19)
    plt.axis([0, 1.2, 0, 1.4])

plt.figure(figsize=(14, 7))
plot_precision_vs_recall(precision, recall)
plt.show()
```



[84]:

```
from sklearn.metrics import roc_curve

# Compute true positive rate and false positive rate
false_positive_rate, true_positive_rate, thresholds = roc_curve(Y_train,␣
 ↪y_scores)

# Plotting them against each other
def plot_roc_curve(false_positive_rate, true_positive_rate, label=None):
    plt.plot(false_positive_rate, true_positive_rate, linewidth=3, label=label)
    plt.plot([0, 1], [0, 1], 'r', linewidth=4)
    plt.axis([0, 1, 0, 1])
    plt.xlabel('False Positive Rate (FPR)', fontsize=16)
    plt.ylabel('True Positive Rate (TPR)', fontsize=16)

plt.figure(figsize=(14, 7))
plot_roc_curve(false_positive_rate, true_positive_rate)
plt.show()
```



[85]:

```
from sklearn.metrics import roc_auc_score
r_a_score = roc_auc_score(Y_train, y_scores)
print("ROC-AUC-Score:", r_a_score)
```

```
ROC-AUC-Score: 0.9366604885011558
```

1 ROC AUC SCORE = 93%

[ ]:

```
```

[ ]:

```
```