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

from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model_selection import cross_val_score, train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix, classification_report

## The matplotlib and seaborn library for result visualization and analysis
import matplotlib.pyplot as plt
import seaborn as sns

sns.set_theme(style='darkgrid')
```

Loading the Dataset

First we load the dataset and find out the number of columns, rows, NULL values, etc.

In [2]:
```python
train = pd.read_csv('train.csv')
test = pd.read_csv('test.csv')
```

In [3]:
```python
train.shape, test.shape
```

Out[3]:
```
((891, 12), (418, 11))
```

In [4]:
```python
train.info()
```

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

In [5]:
```python
test.info()
```

```
<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
```

In [6]:
```python
train.head()
```

Out[6]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S

In [7]:

```
test.head()
```

Out[7]:

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	892	3	Kelly, Mr. James	male	34.5	0	0	330911	7.8292	NaN	Q
1	893	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.0000	NaN	S
2	894	2	Myles, Mr. Thomas Francis	male	62.0	0	0	240276	9.6875	NaN	Q
3	895	3	Wirz, Mr. Albert	male	27.0	0	0	315154	8.6625	NaN	S
4	896	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	female	22.0	1	1	3101298	12.2875	NaN	S

In [8]:

```
train.describe()
```

Out[8]:

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

In [9]:

```
test.describe()
```

Out[9]:

	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

In [10]:

```
train.nunique()
```

Out[10]:
```
PassengerId    891
Survived         2
Pclass           3
Name           891
Sex              2
Age             88
SibSp            7
Parch            7
Ticket         681
Fare           248
Cabin          147
Embarked         3
dtype: int64
```

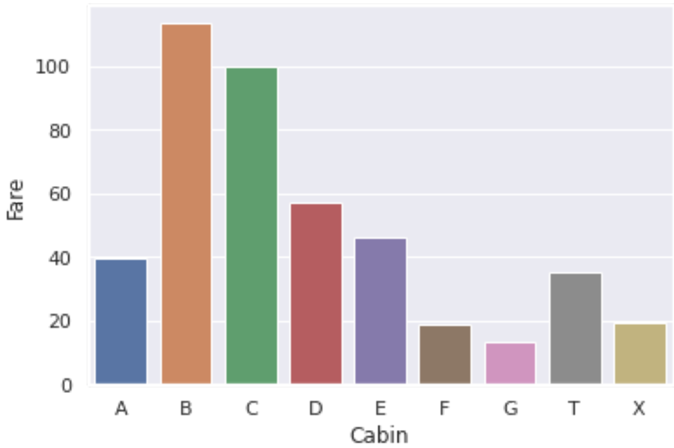
In [11]:
```
test.nunique()
```

Out[11]:
```
PassengerId    418
Pclass           3
Name           418
Sex              2
Age             79
SibSp            7
Parch            8
Ticket         363
Fare           169
Cabin           76
Embarked         3
dtype: int64
```

Handling Missing Values

Train Cabin and Fare

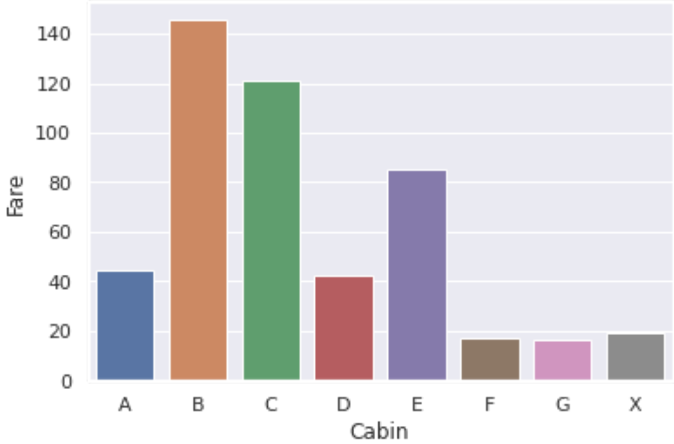
In [12]:
```
train['Cabin'].fillna(value='X', inplace=True)
train['Cabin'] = train['Cabin'].str[0]
df_tr = train[['Cabin', 'Fare']].groupby('Cabin').mean().reset_index()
a = sns.barplot(x=df_tr['Cabin'], y=df_tr['Fare'])
```



In [13]:
```
## Defining a function which reassigns the cabin according to the fare. After that, it is
## applied to the dataframe to fill all the cabin column's missing value.
def reasign_cabin_tr(cabin_fare):

    cabin = cabin_fare[0]
    fare = cabin_fare[1]

    if cabin == 'X':
        df_tr_copy = df_tr.copy()
        df_tr_copy['Fare'] = abs(df_tr_copy['Fare']-pd.Series([fare]*len(df_tr_copy)))
        minimum = df_tr_copy['Fare'].min()
        return list(df_tr_copy[df_tr_copy['Fare'] == minimum].Cabin)[0]
    return cabin

train['Cabin'] = train[['Cabin', 'Fare']].apply(reasign_cabin_tr, axis=1)
train['Cabin'] = train.Cabin.astype("category").cat.codes
```

Train Cabin and Fare

In [14]:
```
test['Fare'].fillna(value=test.Fare.mean(), inplace=True)
test['Cabin'].fillna(value='X', inplace=True)
test['Cabin'] = test['Cabin'].str[0]
df_te = test[['Cabin', 'Fare']].groupby('Cabin').mean().reset_index()
a = sns.barplot(x=df_te['Cabin'], y=df_te['Fare'])
```



In [15]:
```
def reasign_cabin_te(cabin_fare):

    cabin = cabin_fare[0]
    fare = cabin_fare[1]

    if cabin == 'X':
        df_te_copy = df_te.copy()
        df_te_copy['Fare'] = abs(df_te_copy['Fare']-pd.Series([fare]*len(df_te_copy)))
        minimum = df_te_copy['Fare'].min()
        return list(df_te_copy[df_te_copy['Fare'] == minimum].Cabin)[0]
    return cabin

test['Cabin'] = test[['Cabin', 'Fare']].apply(reasign_cabin_te, axis=1)
test['Cabin'] = test.Cabin.astype("category").cat.codes
```

Train Embarked

In [16]:
```
train['Embarked'] = train.Embarked.fillna(train.Embarked.dropna().max())
```

Train & Test Age from Pclass and Sex

In [17]:
```
# we will guess the age from Pclass and Sex:

guess_ages = np.zeros((2,3))
guess_ages
```

Out[17]:
```
array([[0., 0., 0.],
       [0., 0., 0.]])
```

Now we iterate over Sex (0 or 1) and Pclass (1, 2, 3) to calculate guessed values of Age for the six combinations.

In [18]:
```
combine = [train , test]

# Converting Sex categories (male and female) to 0 and 1:
for dataset in combine:
    dataset['Sex'] = dataset['Sex'].map( {'female': 1, 'male': 0} ).astype(int)

# Filling missed age feature:
for dataset in combine:
    for i in range(0, 2):
        for j in range(0, 3):
            guess_df = dataset[(dataset['Sex'] == i) & \
                                  (dataset['Pclass'] == j+1)]['Age'].dropna()
            age_guess = guess_df.median()

            # Convert random age float to nearest .5 age
            guess_ages[i,j] = int( age_guess/0.5 + 0.5 ) * 0.5

    for i in range(0, 2):
        for j in range(0, 3):
            dataset.loc[ (dataset.Age.isnull()) & (dataset.Sex == i) & (dataset.Pclass == j+1),\
                    'Age'] = guess_ages[i,j]

    dataset['Age'] = dataset['Age'].astype(int)

train.head()
```

Out[18]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	0	22	1	0	A/5 21171	7.2500	6	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	1	38	1	0	PC 17599	71.2833	2	C
2	3	1	3	Heikkinen, Miss. Laina	1	26	0	0	STON/O2. 3101282	7.9250	6	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	1	35	1	0	113803	53.1000	2	S
4	5	0	3	Allen, Mr. William Henry	0	35	0	0	373450	8.0500	6	S

In [19]:
```
train.isna().sum()
```

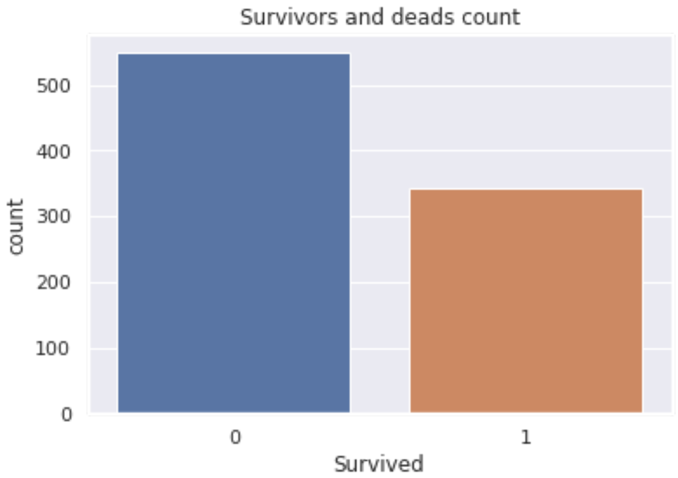
Out[19]:
```
PassengerId    0
Survived       0
Pclass         0
Name           0
Sex            0
Age            0
SibSp          0
Parch          0
Ticket         0
Fare           0
Cabin          0
Embarked       0
dtype: int64
```

In [20]:
```
test.isna().sum()
```

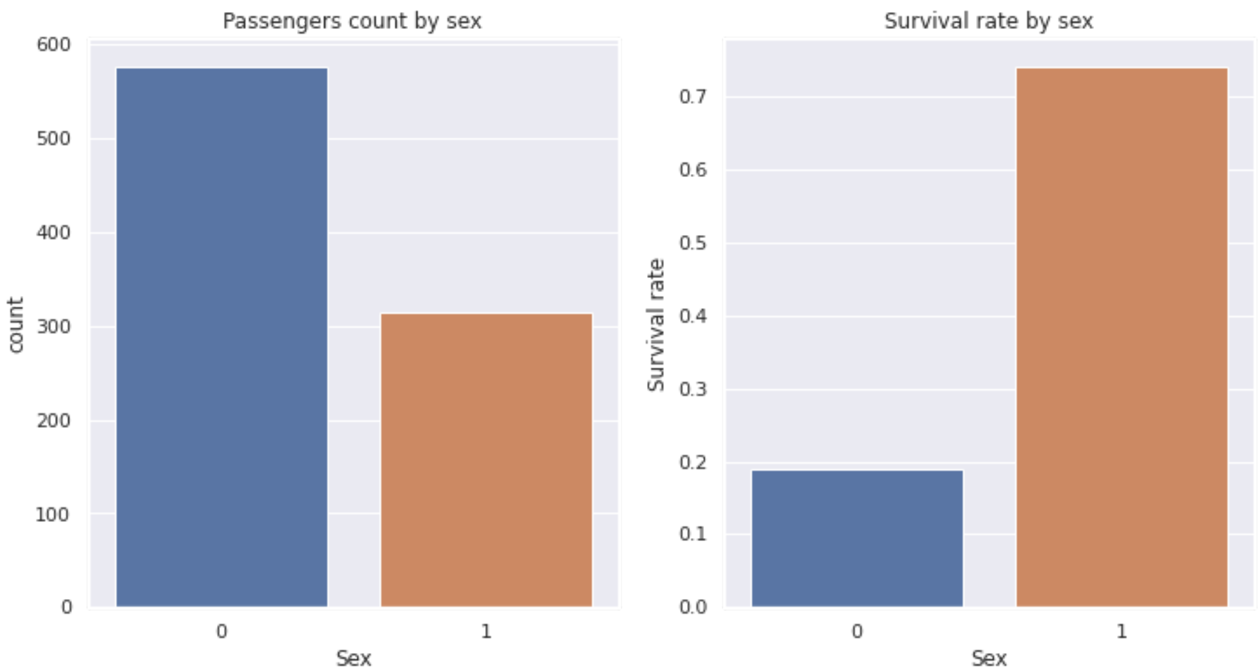
Out[20]:
```
PassengerId    0
Pclass         0
Name           0
Sex            0
Age            0
SibSp          0
Parch          0
Ticket         0
Fare           0
Cabin          0
Embarked       0
dtype: int64
```

Exploratory Data Analysis

In [21]:
```
g = sns.countplot(x=train['Survived']).set_title('Survivors and deads count')
```

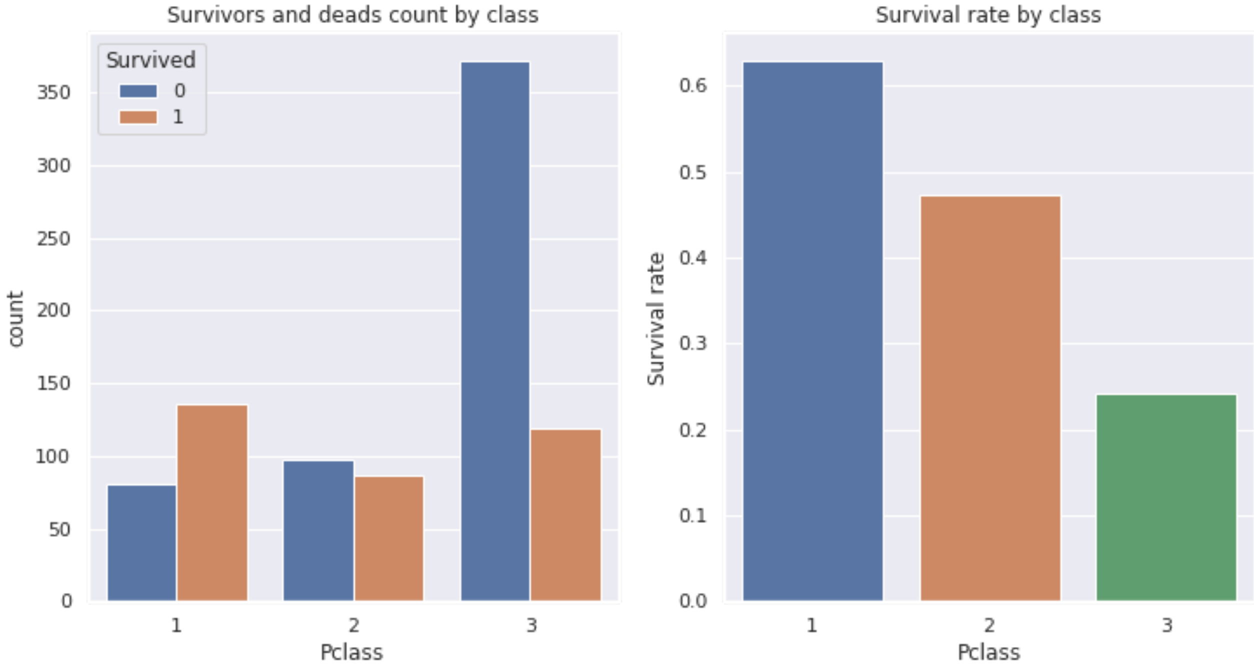


In [22]:
```
# Ladies first??
fig, axarr = plt.subplots(1, 2, figsize=(12,6))
a = sns.countplot(x=train['Sex'], ax=axarr[0]).set_title('Passengers count by sex')
axarr[1].set_title('Survival rate by sex')
b = sns.barplot(x='Sex', y='Survived', data=train, ax=axarr[1], ci=None).set_ylabel('Survival rate')
```



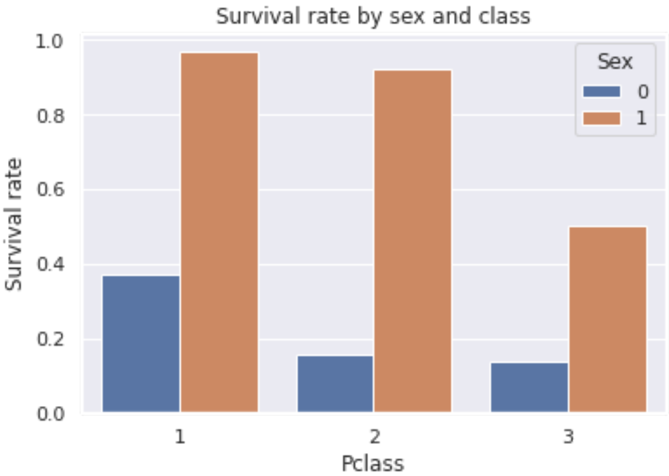
In [23]:

```
# Little dependent on pclass
fig, axarr = plt.subplots(1,2,figsize=(12,6))
a = sns.countplot(x='Pclass', hue='Survived', data=train, ax=axarr[0]).set_title('Survivors and deads count by
axarr[1].set_title('Survival rate by class')
b = sns.barplot(x='Pclass', y='Survived', data=train, ax=axarr[1], ci=None).set_ylabel('Survival rate')
```



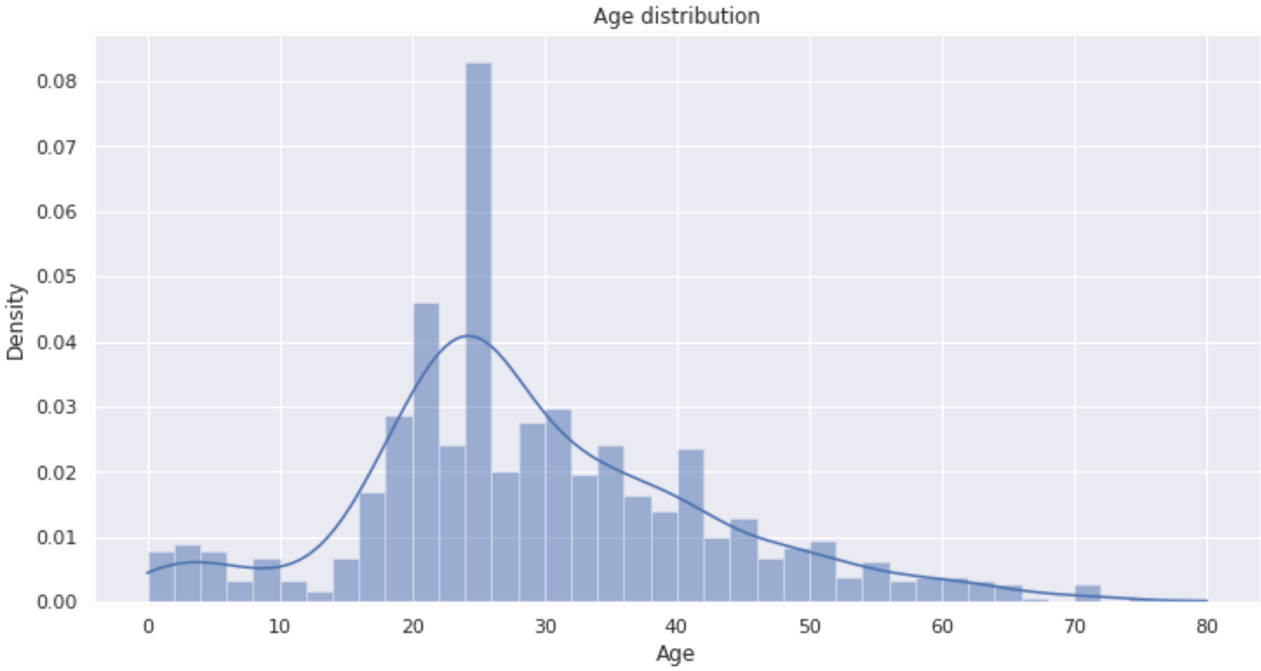
In [24]:

```
plt.title('Survival rate by sex and class')
g = sns.barplot(x='Pclass', y='Survived', hue='Sex', data=train, ci=None).set_ylabel('Survival rate')
```

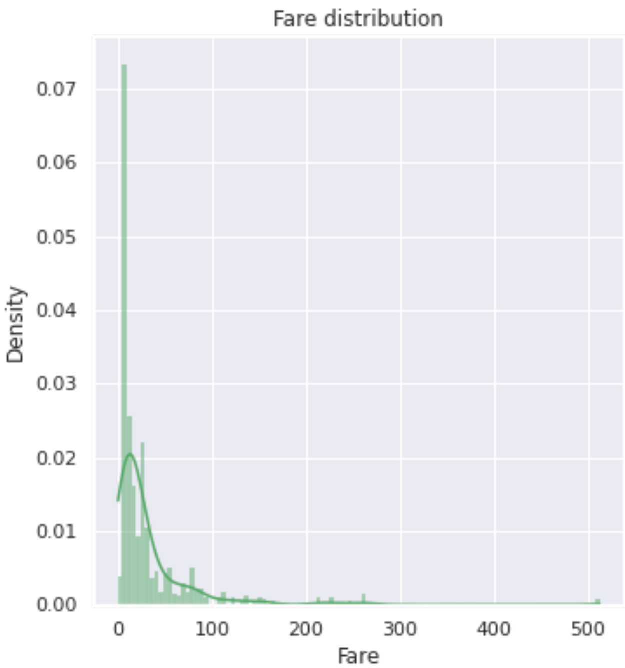


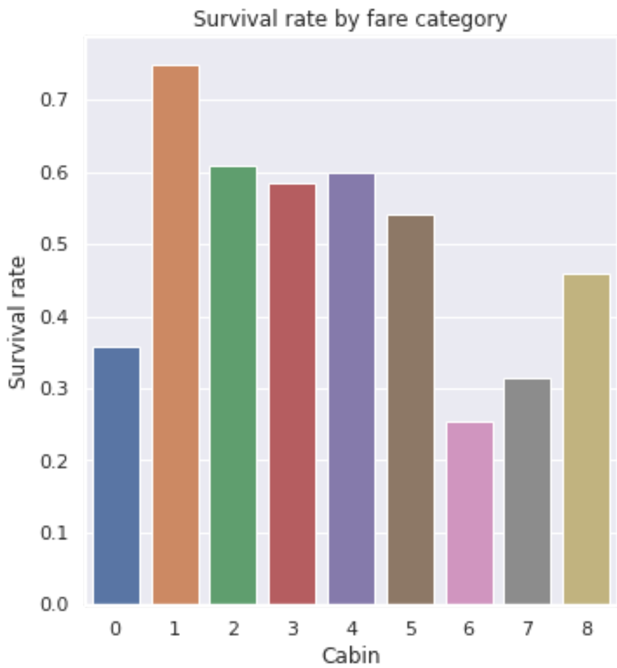
In [25]:

```
# Normal?
fig = plt.figure(figsize=(12,6))
sns.histplot(x=train['Age'], bins=40, kde=True, stat="density", edgecolor=(1,1,1,0.3)).set_title('Age distribu
plt.show()
```

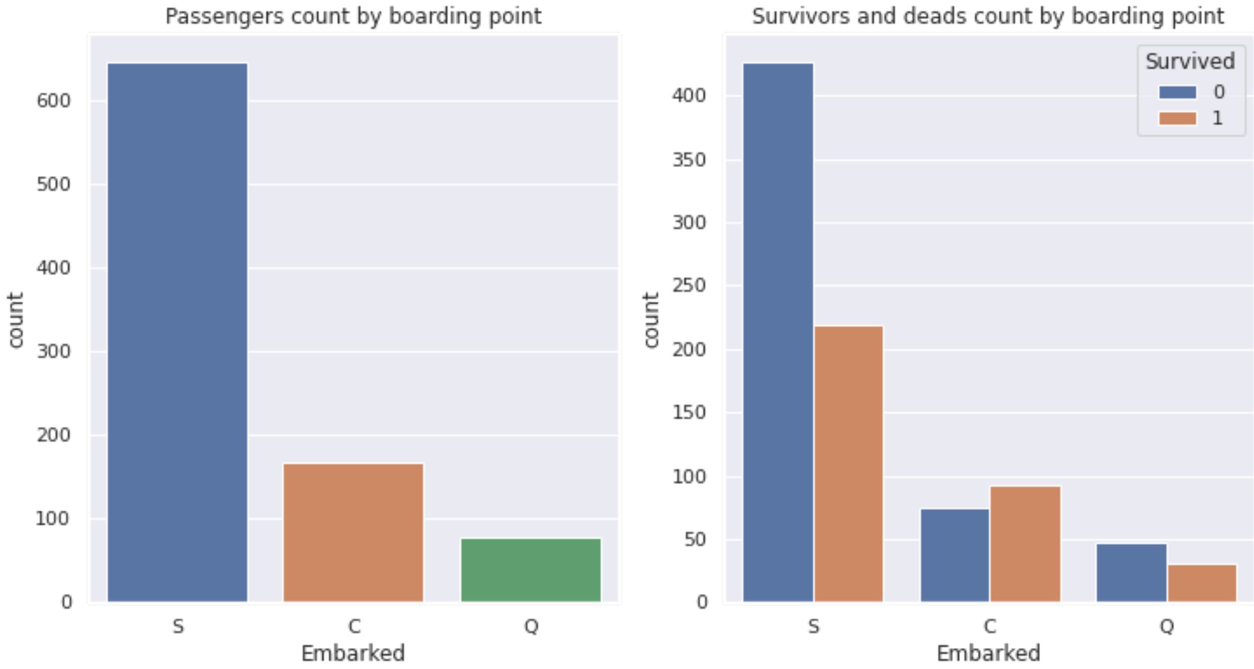


In [26]:
```
fig, axarr = plt.subplots(1,2,figsize=(12,6))
f = sns.histplot(x=train.Fare, color='g', ax=axarr[0], kde=True, stat="density", edgecolor=(1,1,1,0.3)).set_ti
fare_ranges = pd.qcut(train.Fare, 4, labels = ['Low', 'Mid', 'High', 'Very high'])
axarr[1].set_title('Survival rate by fare category')
g = sns.barplot(x=train['Cabin'], y=train.Survived, ci=None, ).set_ylabel('Survival rate')
```

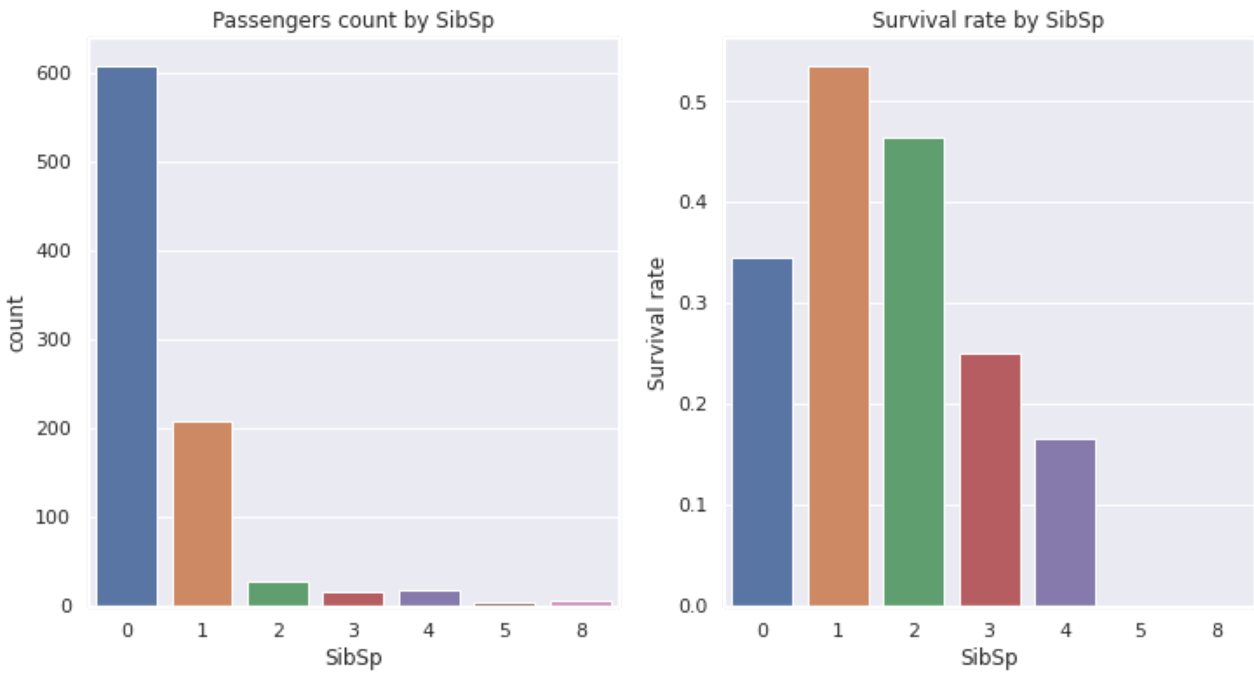




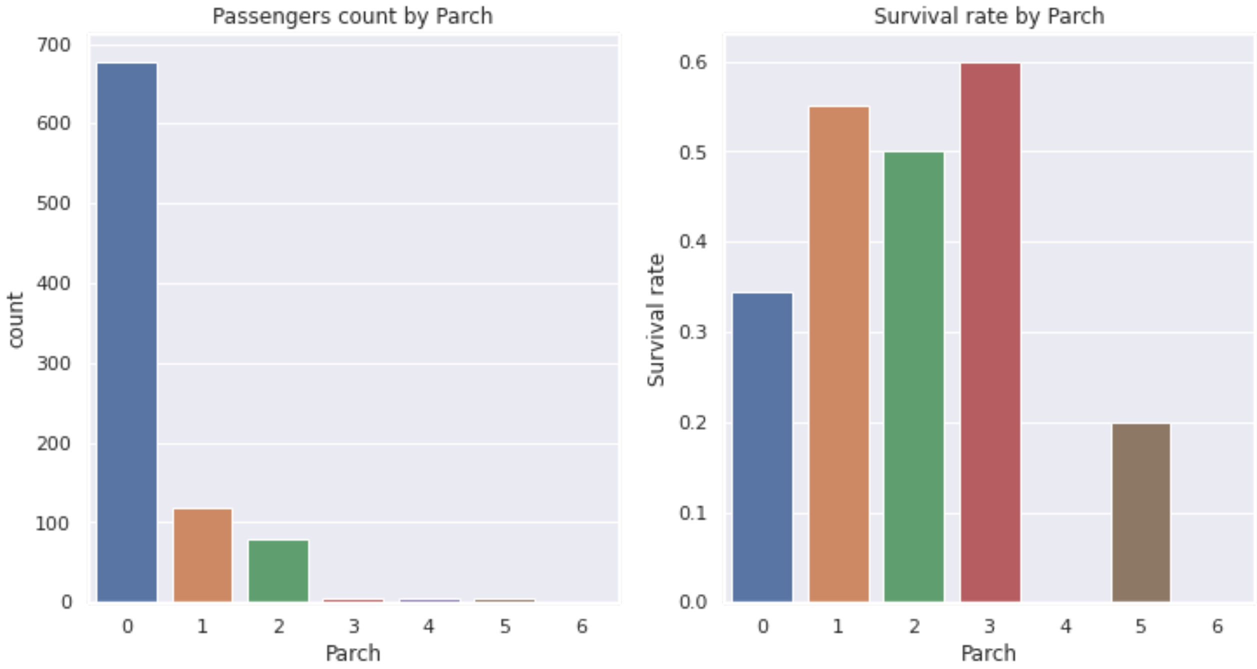
In [27]:
```
fig, axarr = plt.subplots(1,2,figsize=(12,6))
sns.countplot(x=train['Embarked'], ax=axarr[0]).set_title('Passengers count by boarding point')
p = sns.countplot(x = 'Embarked', hue = 'Survived', data = train,
                  ax=axarr[1]).set_title('Survivors and deads count by boarding point')
```



In [28]:
```
fig, axarr = plt.subplots(1,2,figsize=(12,6))
a = sns.countplot(x=train['SibSp'], ax=axarr[0]).set_title('Passengers count by SibSp')
axarr[1].set_title('Survival rate by SibSp')
b = sns.barplot(x='SibSp', y='Survived', data=train, ax=axarr[1], ci=None).set_ylabel('Survival rate')
```

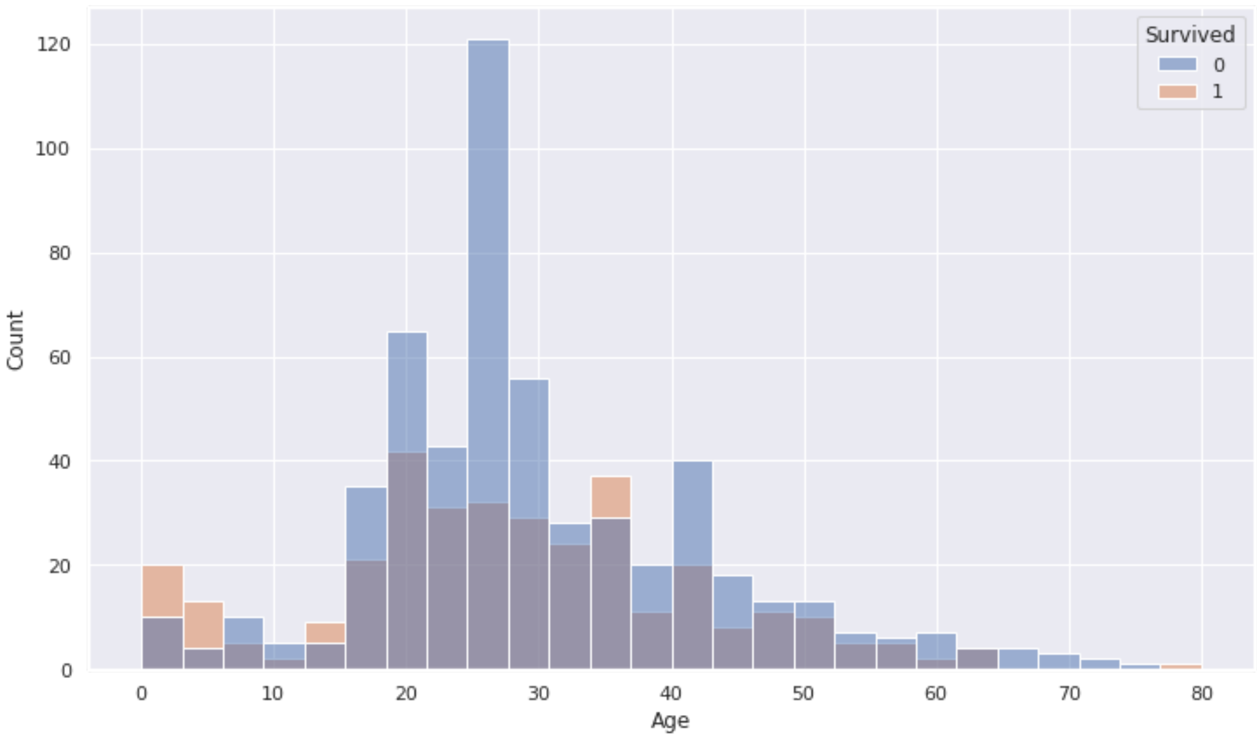


In [29]:
```
fig, axarr = plt.subplots(1,2,figsize=(12,6))
a = sns.countplot(x=train['Parch'], ax=axarr[0]).set_title('Passengers count by Parch')
axarr[1].set_title('Survival rate by Parch')
b = sns.barplot(x='Parch', y='Survived', data=train, ax=axarr[1], ci=None).set_ylabel('Survival rate')
```

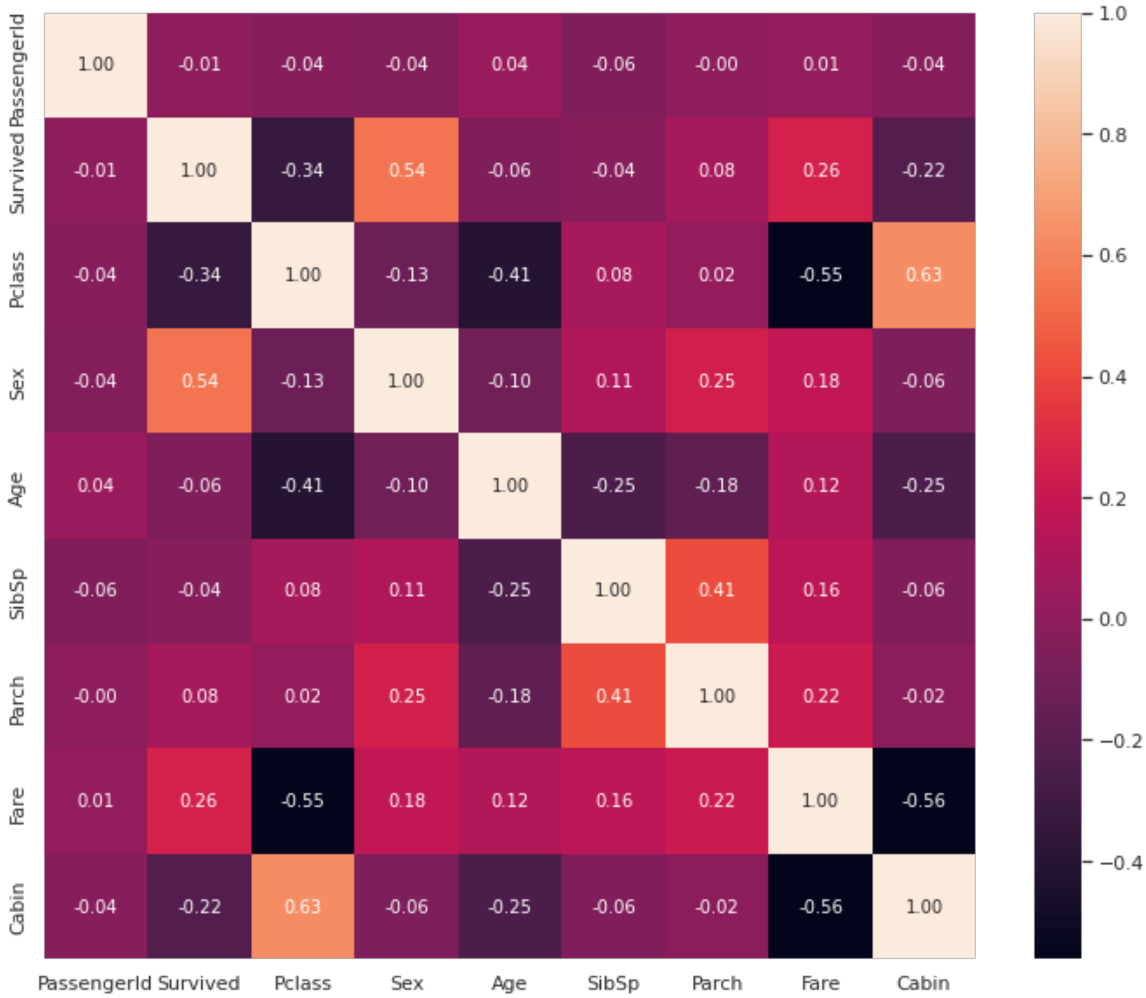


In [30]:
```
fig = plt.figure(figsize=(12,7))
sns.histplot(x=train['Age'], hue=train['Survived'])
```

Out[30]:
```
<AxesSubplot:xlabel='Age', ylabel='Count'>
```



In [31]:
```
fig = plt.figure(figsize=(12,10))
sns.heatmap(train.corr(), annot=True, fmt='.2f')
plt.show()
```



Splitting the Dataset

Training and Test Set

In [32]:
```
train.drop(['PassengerId', 'Name', 'Ticket', 'Parch','Age','SibSp', 'Embarked'], axis=1, inplace=True)
test.drop(['PassengerId', 'Name', 'Ticket', 'Parch','Age','SibSp', 'Embarked'], axis=1, inplace=True)
```

In [33]:
```
train.shape, test.shape
```

Out[33]:
```
((891, 5), (418, 4))
```

Separating Label and Features

In [34]:
```
X = train.iloc[:,1:]
y = train.iloc[:,0]
```

In [35]:
```
X_train, X_val, Y_train, Y_val = train_test_split(X, y, test_size=0.2 ,random_state=42)
```

In [36]:
```
ss = StandardScaler()
X_train = ss.fit_transform(X_train)
X_val = ss.transform(X_val)
test = ss.transform(test)
```

Machine Learning model

In [37]:
```
def print_scores(model, X_train, Y_train, predictions, cv_splites=10):
    print("The mean accuracy score of the train data is %.5f" % model.score(X_train, Y_train))
    CV_scores = cross_val_score(model, X_train, Y_train, cv=cv_splites)
    print("The individual cross-validation scores are: \n",CV_scores)
    print("The minimum cross-validation score is %.3f" % min(CV_scores))
    print("The maximum cross-validation score is %.3f" % max(CV_scores))
    print("The  mean   cross-validation score is %.5f ± %0.2f" % (CV_scores.mean(), CV_scores.std() * 2))
```

In [38]:
```
depth_range = range(1, 30, 1)
acc_vs_depth = {
    "depth": [],
    "train_acc": [],
    "valid_acc": []
}

for depth in depth_range:
    model = RandomForestClassifier(n_estimators=200, max_depth=depth, max_features=8, min_samples_split=2, ranc
    model.fit(X_train, Y_train)
    X_train_pred = model.predict(X_train)
    X_val_pred = model.predict(X_val)
    acc_vs_depth["depth"].append(depth)
    acc_vs_depth["train_acc"].append((Y_train.to_numpy() == X_train_pred).mean())
    acc_vs_depth["valid_acc"].append((Y_val.to_numpy() == X_val_pred).mean())
```

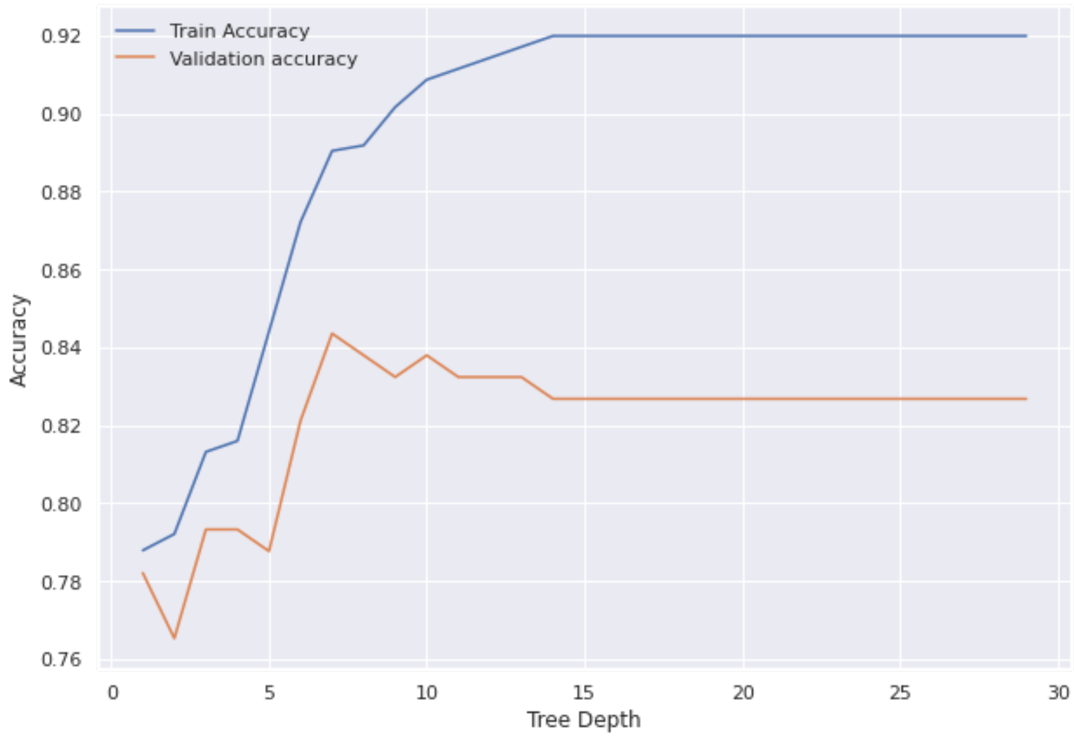
In [39]:
```
acc_vs_depth_df = pd.DataFrame(acc_vs_depth)
acc_vs_depth_df.sample(5)
```

Out[39]:

	depth	train_acc	valid_acc
24	25	0.919944	0.826816
22	23	0.919944	0.826816
1	2	0.792135	0.765363
0	1	0.787921	0.782123
7	8	0.891854	0.837989

Plotting results

In [40]:
```
fig = plt.figure(figsize=(10, 7))
plt.plot(acc_vs_depth_df.depth, acc_vs_depth_df.train_acc, label="Train Accuracy")
plt.plot(acc_vs_depth_df.depth, acc_vs_depth_df.valid_acc, label="Validation accuracy")
plt.legend(loc='upper left', frameon=False)
plt.xlabel('Tree Depth')
plt.ylabel('Accuracy')
plt.show()
```



In [41]:
```
model = RandomForestClassifier(n_estimators=200, max_depth=15, max_features=8, min_samples_split=2, random_stat
model.fit(X_train, Y_train)
predictions = model.predict(X_val)
```

In [42]:
```
confusion_matrix(Y_val, predictions)
```

Out[42]:
```
array([[92, 13],
       [18, 56]])
```

In [43]:
```
print(classification_report(Y_val, predictions))
```

```
              precision    recall  f1-score   support

           0       0.84      0.88      0.86       105
           1       0.81      0.76      0.78        74

    accuracy                           0.83       179
   macro avg       0.82      0.82      0.82       179
weighted avg       0.83      0.83      0.83       179
```

In [44]:
```
print_scores(model, X_train, Y_train, predictions)
```

```
The mean accuracy score of the train data is 0.91994
The individual cross-validation scores are:
 [0.83333333 0.75       0.74647887 0.90140845 0.84507042 0.78873239
 0.8028169  0.8028169  0.74647887 0.88732394]
The minimum cross-validation score is 0.746
The maximum cross-validation score is 0.901
The  mean   cross-validation score is 0.81045 ± 0.11
```

In [45]:
```
model.predict(test)
```