# 7_titanic_machine_learning_from_disaster

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# 1 泰坦尼克：从灾难中生存

使用机器学习方法预测从泰坦尼克灾难中生存下来的概率

## 1.1 第一步：定义问题

根据船上人员的性别，年龄，职业等信息，设计一种算法来预测泰坦尼克号上的乘客的生存概率

## 1.2 第二步：获取数据

```
pip install --upgrade kaggle
```

如果本地没有数据，则从 Kaggle 上进行下载. 需要设置账号和 API 到 ~/.kaggle/kaggle.json

```
kaggle competitions download -c titanic
```

[1]:

```
import sys
import pandas as pd
import matplotlib
import numpy as np
import scipy as sp
import IPython
import sklearn

import random
import time

# ignore warnings
import warnings
warnings.filterwarnings('ignore')
print('-'*25)

# Input data files are available in the `../dataset/` directory
from subprocess import check_output
print(check_output(['ls', '../dataset']).decode('utf8'))
```

```
-------------------------
gender_submission.csv
test.csv
titanic.zip
```

train.csv

### 1.3 加载数据建模库

使用 scikit-learn 库来开发机器学习算法. 在 sklearn 中, 算法被叫做 Estimators, 实现在他们各自的类里. 对于数据可视化, 使用 matplotlib 和 seaborn 库.

[2]:
```
# common model algorithms
from sklearn import svm, tree, linear_model, neighbors, naive_bayes, ensemble,␣
↪discriminant_analysis, gaussian_process
from xgboost import XGBClassifier

# common model helpers
from sklearn.preprocessing import OneHotEncoder, LabelEncoder
from sklearn import feature_selection, model_selection, metrics

# visualization
import matplotlib as mpl
import matplotlib.pyplot as plt
import matplotlib.pylab as pylab
import seaborn as sns
from pandas.plotting import scatter_matrix

# configure visualization defaults
# show plots in jupyter notebook inplace
%matplotlib inline
mpl.style.use('ggplot')
sns.set_style('white')
pylab.rcParams['figure.figsize']=12,8
```

### 1.4 了解数据

了解数据的形状 (数据类型, 数据值) 等等

1. Survived 代表乘客是否存活
2. PassengerID 和 Ticket 被假设为随机独立标识符, 对输出没有影响, 因此会被从分析中移除
3. Pclass 代表票型, 并映射社会经济状态, 表示 1 = 上层阶级, 2 = 中层阶级, 3 = 下层阶级;
4. Name 是名字数据类型, 可能可以在特征工程中根据 title 判断性别, 从 surname 中家庭大小.
5. Sex 和 Embarked 变量是命名数据类型. 会被转为 dummy 变量来进行数学计算.
6. Age 和 Fare 变量是连续量化数据类型;
7. SibSp 表示同在船上的兄弟姐妹的数量, Parch 表示同在船上的父母孩子. 都是离散量化数据类型. 可以在特征工程中建立一个家庭大小, 是孤立的变量;
8. Cabin 变量是命名数据类型, 可以在特征工程中大致定位事故发生时在船上的位置, 以及根据等级判断接机. 然而, 犹豫有许多 Null 值, 该变量用处不大, 被排除在分析之外;

[3]:
```
# import data
data_raw = pd.read_csv("../dataset/train.csv")
```

```python
# break dataset into train, test and validation
# the test file provided is the validation file for competition submission
# split the train set into train and test data
data_val = pd.read_csv("../dataset/test.csv")

# to play with our data, create a copy
# python assignment or equal passes by reference vs vslues
data1 = data_raw.copy(deep=True)

# however passing by reference is convenient, because learn both datasets at
# once
data_cleaner = [data1, data_val]

# preview data
print(data_raw.info())
data_raw.sample(10)
```

```
<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
None
```

[3]:

```
     PassengerId  Survived  Pclass  \
882          883         0       3
134          135         0       2
875          876         1       3
323          324         1       2
280          281         0       3
148          149         0       2
218          219         1       1
```

```
177           178         0       1
877           878         0       3
840           841         0       3

                                                 Name     Sex   Age  SibSp  \
882                         Dahlberg, Miss. Gerda Ulrika  female  22.0      0
134                           Sobey, Mr. Samuel James Hayden    male  25.0      0
875                         Najib, Miss. Adele Kiamie "Jane"  female  15.0      0
323  Caldwell, Mrs. Albert Francis (Sylvia Mae Harb…  female  22.0      1
280                                    Duane, Mr. Frank    male  65.0      0
148          Navratil, Mr. Michel ("Louis M Hoffman")    male  36.5      0
218                                Bazzani, Miss. Albina  female  32.0      0
177                            Isham, Miss. Ann Elizabeth  female  50.0      0
877                                  Petroff, Mr. Nedelio    male  19.0      0
840                               Alhomaki, Mr. Ilmari Rudolf    male  20.0      0

     Parch            Ticket     Fare Cabin Embarked
882      0              7552  10.5167   NaN        S
134      0        C.A. 29178  13.0000   NaN        S
875      0              2667   7.2250   NaN        C
323      1            248738  29.0000   NaN        S
280      0            336439   7.7500   NaN        Q
148      2            230080  26.0000    F2        S
218      0             11813  76.2917   D15        C
177      0          PC 17595  28.7125   C49        C
877      0            349212   7.8958   NaN        S
840      0  SOTON/O2 3101287   7.9250   NaN        S
```

#### 1.4.1 数据清理：数据纠正，数据补全，数据创建和数据转换

在该阶段中，1) 修正不正常数据和离群数据，2) 完成丢失的信息，3) 为分析创建新的特征，4) 转换数据到正确的格式以用于计算和表示

[4]:
```python
print('Train columns with null values:\n', data1.isnull().sum())
print('-'*10)

print('Test/Validation columns with null values:\n', data_val.isnull().sum())
print('-'*10)

data_raw.describe(include='all')
```

```
Train columns with null values:
 PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
```

```
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
----------
Test/Validation columns with null values:
 PassengerId      0
Pclass           0
Name             0
Sex              0
Age             86
SibSp            0
Parch            0
Ticket           0
Fare             1
Cabin          327
Embarked         0
dtype: int64
----------
```

[4]:

```
        PassengerId    Survived      Pclass                     Name   Sex  \
count    891.000000  891.000000  891.000000                      891   891
unique          NaN         NaN         NaN                      891     2
top             NaN         NaN         NaN  Braund, Mr. Owen Harris  male
freq            NaN         NaN         NaN                        1   577
mean     446.000000    0.383838    2.308642                      NaN   NaN
std      257.353842    0.486592    0.836071                      NaN   NaN
min        1.000000    0.000000    1.000000                      NaN   NaN
25%      223.500000    0.000000    2.000000                      NaN   NaN
50%      446.000000    0.000000    3.000000                      NaN   NaN
75%      668.500000    1.000000    3.000000                      NaN   NaN
max      891.000000    1.000000    3.000000                      NaN   NaN

               Age       SibSp       Parch  Ticket        Fare    Cabin  \
count   714.000000  891.000000  891.000000     891  891.000000      204
unique         NaN         NaN         NaN     681         NaN      147
top            NaN         NaN         NaN  347082         NaN  B96 B98
freq           NaN         NaN         NaN       7         NaN        4
mean     29.699118    0.523008    0.381594     NaN   32.204208      NaN
std      14.526497    1.102743    0.806057     NaN   49.693429      NaN
min       0.420000    0.000000    0.000000     NaN    0.000000      NaN
25%      20.125000    0.000000    0.000000     NaN    7.910400      NaN
50%      28.000000    0.000000    0.000000     NaN   14.454200      NaN
75%      38.000000    1.000000    0.000000     NaN   31.000000      NaN
```

```
max      80.000000    8.000000    6.000000      NaN  512.329200       NaN

       Embarked
count       889
unique        3
top           S
freq        644
mean        NaN
std         NaN
min         NaN
25%         NaN
50%         NaN
75%         NaN
max         NaN
```

[5]:

```
# completing: complete or delete missing values in train and test/validation
# dataset
for dataset in data_cleaner:
    # complete missing age with median
    dataset['Age'].fillna(dataset['Age'].median(), inplace=True)

    # complete embarked with mode
    dataset['Embarked'].fillna(dataset['Embarked'].mode()[0], inplace=True)

    # complete missing fare with median
    dataset['Fare'].fillna(dataset['Fare'].median(), inplace=True)

# delete the cabin feature/column and others previously stated to exclude in
# train dataset
drop_column=['PassengerId','Cabin','Ticket']
data1.drop(drop_column,axis=1,inplace=True)

print(data1.isnull().sum())
print('-'*10)
print(data_val.isnull().sum())
```

```
Survived    0
Pclass      0
Name        0
Sex         0
Age         0
SibSp       0
Parch       0
Fare        0
Embarked    0
dtype: int64
----------
PassengerId      0
```

```
Pclass           0
Name             0
Sex              0
Age              0
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          327
Embarked         0
dtype: int64
```

[6]:
```
# create: feature engineering for train and test/validation dataset
for dataset in data_cleaner:
    # discrete variables
    dataset["FamilySize"] = dataset["SibSp"] + dataset["Parch"] + 1

    dataset["IsAlone"] = 1  # initialize to yes/1 is alone
    dataset["IsAlone"].loc[
        dataset["FamilySize"] > 1
    ] = 0  # now update to no/0 if family size is greater than 1

    # quick and dirty code split title from name
    dataset["Title"] = (
        dataset["Name"]
        .str.split(", ", expand=True)[1]
        .str.split(".", expand=True)[0]
    )

    # continuous variable bins using qcut, cut into bins with approximately
    # equal amount of elements
    dataset["FareBin"] = pd.qcut(dataset["Fare"], 4)

    # age bins/buckets using cut with the same interval of each bin
    dataset["AgeBin"] = pd.cut(dataset["Age"].astype(int), 5)

# cleanup rare title names
print(data1["Title"].value_counts())
stat_min = (
    10  # while small is arbitrary, we'll use the common minimum in statistics
)
title_names = (
    data1["Title"].value_counts() < stat_min
)  # this will create a true false series with title name as index

# apply and lambda functions are quick and dirty code to find and replace with
# fewer lines of code
```

```
data1["Title"] = data1["Title"].apply(
    lambda x: "Misc" if title_names.loc[x] == True else x
)
print(data1['Title'].value_counts())
print('-'*10)

# preview data again
data1.info()
data_val.info()
data1.sample(10)
```

```
Title
Mr              517
Miss            182
Mrs             125
Master           40
Dr                7
Rev               6
Mlle              2
Major             2
Col               2
the Countess      1
Capt              1
Ms                1
Sir               1
Lady              1
Mme               1
Don               1
Jonkheer          1
Name: count, dtype: int64
Title
Mr        517
Miss      182
Mrs       125
Master     40
Misc       27
Name: count, dtype: int64
----------
<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    float64
```

```
 5   SibSp       891 non-null    int64
 6   Parch       891 non-null    int64
 7   Fare        891 non-null    float64
 8   Embarked    891 non-null    object
 9   FamilySize  891 non-null    int64
 10  IsAlone     891 non-null    int64
 11  Title       891 non-null    object
 12  FareBin     891 non-null    category
 13  AgeBin      891 non-null    category
dtypes: category(2), float64(2), int64(6), object(4)
memory usage: 85.9+ KB
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 16 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          418 non-null    float64
 5   SibSp        418 non-null    int64
 6   Parch        418 non-null    int64
 7   Ticket       418 non-null    object
 8   Fare         418 non-null    float64
 9   Cabin        91 non-null     object
 10  Embarked     418 non-null    object
 11  FamilySize   418 non-null    int64
 12  IsAlone      418 non-null    int64
 13  Title        418 non-null    object
 14  FareBin      418 non-null    category
 15  AgeBin       418 non-null    category
dtypes: category(2), float64(2), int64(6), object(6)
memory usage: 47.1+ KB
```

[6]:

```
     Survived  Pclass                             Name     Sex    Age  SibSp  \
750         1       2                Wells, Miss. Joan  female   4.00      1
666         0       2      Butler, Mr. Reginald Fenton    male  25.00      0
233         1       3   Asplund, Miss. Lillian Gertrud  female   5.00      4
216         1       3          Honkanen, Miss. Eliina  female  27.00      0
633         0       1     Parr, Mr. William Henry Marsh    male  28.00      0
655         0       2       Hickman, Mr. Leonard Mark    male  24.00      2
803         1       3  Thomas, Master. Assad Alexander    male   0.42      0
611         0       3            Jardin, Mr. Jose Neto    male  28.00      0
580         1       2      Christy, Miss. Julie Rachel  female  25.00      1
257         1       1            Cherry, Miss. Gladys  female  30.00      0
```

```
     Parch     Fare Embarked  FamilySize  IsAlone   Title          FareBin  \
750      1  23.0000        S           3        0    Miss   (14.454, 31.0]
666      0  13.0000        S           1        1      Mr   (7.91, 14.454]
233      2  31.3875        S           7        0    Miss  (31.0, 512.329]
216      0   7.9250        S           1        1    Miss   (7.91, 14.454]
633      0   0.0000        S           1        1      Mr   (-0.001, 7.91]
655      0  73.5000        S           3        0      Mr  (31.0, 512.329]
803      1   8.5167        C           2        0  Master   (7.91, 14.454]
611      0   7.0500        S           1        1      Mr   (-0.001, 7.91]
580      1  30.0000        S           3        0    Miss   (14.454, 31.0]
257      0  86.5000        S           1        1    Miss  (31.0, 512.329]

             AgeBin
750  (-0.08, 16.0]
666   (16.0, 32.0]
233  (-0.08, 16.0]
216   (16.0, 32.0]
633   (16.0, 32.0]
655   (16.0, 32.0]
803  (-0.08, 16.0]
611   (16.0, 32.0]
580   (16.0, 32.0]
257   (16.0, 32.0]
```

### 1.4.2 转换格式

将类别数据转换成 dummy 变量, 用于数学分析.

此外, 为数据建模定义 x(independent/features/explanatory/predictor/etc.) 和 y(dependent/target/outcome/response/etc.) 变量

[7]:
```python
# convert: convert objects to categoryusiing Label Encoder for train and
# test/validation dataset

# code categorical data
label = LabelEncoder()
for dataset in data_cleaner:
    dataset["Sex_Code"] = label.fit_transform(dataset["Sex"])
    dataset["Embarked_Code"] = label.fit_transform(dataset["Embarked"])
    dataset["Title_Code"] = label.fit_transform(dataset["Title"])
    dataset["FareBin_Code"] = label.fit_transform(dataset["FareBin"])
    dataset["AgeBin_Code"] = label.fit_transform(dataset["AgeBin"])

# define y variable aka target/outcome
Target = ["Survived"]

# define x variables for original features aka feature selection
data1_x = [
```

```
    "Sex",
    "Pclass",
    "Embarked",
    "Title",
    "SibSp",
    "Parch",
    "Age",
    "Fare",
    "FamilySize",
    "IsAlone",
]  # pretty name/values for charts
data1_x_calc = [
    "Sex_Code",
    "Pclass",
    "Embarked_Code",
    "Title_Code",
    "SibSp",
    "Parch",
    "Age",
    "Fare",
]  # code for algorithm calculation

# define x variables original w/bin features to remove continuous variables
data1_x_bin = [
    "Sex_Code",
    "Pclass",
    "Embarked_Code",
    "Title_Code",
    "FamilySize",
    "AgeBin_Code",
    "FareBin_Code",
]
data1_xy_bin = Target + data1_x_bin
print("Bin X Y: ", data1_xy_bin, "\n")

# define x and y variables for dummy features original
data1_dummy=pd.get_dummies(data1[data1_x])
data1_x_dummy=data1_dummy.columns.tolist()
data1_xy_dummy=Target+data1_x_dummy
print('Dummy X Y: ', data1_xy_dummy, '\n')

data1_dummy.head()
```

```
Bin X Y:  ['Survived', 'Sex_Code', 'Pclass', 'Embarked_Code', 'Title_Code',
'FamilySize', 'AgeBin_Code', 'FareBin_Code']

Dummy X Y:  ['Survived', 'Pclass', 'SibSp', 'Parch', 'Age', 'Fare',
'FamilySize', 'IsAlone', 'Sex_female', 'Sex_male', 'Embarked_C', 'Embarked_Q',
```

```
'Embarked_S', 'Title_Master', 'Title_Misc', 'Title_Miss', 'Title_Mr',
'Title_Mrs']
```

[7]:
```
   Pclass  SibSp  Parch   Age     Fare  FamilySize  IsAlone  Sex_female  \
0       3      1      0  22.0   7.2500           2        0       False
1       1      1      0  38.0  71.2833           2        0        True
2       3      0      0  26.0   7.9250           1        1        True
3       1      1      0  35.0  53.1000           2        0        True
4       3      0      0  35.0   8.0500           1        1       False

   Sex_male  Embarked_C  Embarked_Q  Embarked_S  Title_Master  Title_Misc  \
0      True       False       False        True         False       False
1     False        True       False       False         False       False
2     False       False       False        True         False       False
3     False       False       False        True         False       False
4      True       False       False        True         False       False

   Title_Miss  Title_Mr  Title_Mrs
0       False      True      False
1       False     False       True
2        True     False      False
3       False     False       True
4       False      True      False
```

### 1.4.3 Da-Double 检测清理后数据

清理数据后, 进行一次折扣 da-double 检测

[8]:
```python
print('Train columns with null values: \n', data1.isnull().sum())
print('-'*10)
print(data1.info())
print('-'*10)

print('Test/Validation columns with null values: \n', data_val.isnull().sum())
print('-'*10)
print(data_val.info())
print('-'*10)

data_raw.describe(include='all')
```

```
Train columns with null values:
 Survived      0
Pclass        0
Name          0
Sex           0
Age           0
SibSp         0
Parch         0
```

```
Fare             0
Embarked         0
FamilySize       0
IsAlone          0
Title            0
FareBin          0
AgeBin           0
Sex_Code         0
Embarked_Code    0
Title_Code       0
FareBin_Code     0
AgeBin_Code      0
dtype: int64
----------
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 19 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    float64
 5   SibSp          891 non-null    int64
 6   Parch          891 non-null    int64
 7   Fare           891 non-null    float64
 8   Embarked       891 non-null    object
 9   FamilySize     891 non-null    int64
 10  IsAlone        891 non-null    int64
 11  Title          891 non-null    object
 12  FareBin        891 non-null    category
 13  AgeBin         891 non-null    category
 14  Sex_Code       891 non-null    int64
 15  Embarked_Code  891 non-null    int64
 16  Title_Code     891 non-null    int64
 17  FareBin_Code   891 non-null    int64
 18  AgeBin_Code    891 non-null    int64
dtypes: category(2), float64(2), int64(11), object(4)
memory usage: 120.7+ KB
None
----------
Test/Validation columns with null values:
 PassengerId       0
Pclass            0
Name              0
Sex               0
Age               0
```

```
SibSp              0
Parch              0
Ticket             0
Fare               0
Cabin            327
Embarked           0
FamilySize         0
IsAlone            0
Title              0
FareBin            0
AgeBin             0
Sex_Code           0
Embarked_Code      0
Title_Code         0
FareBin_Code       0
AgeBin_Code        0
dtype: int64
----------
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 21 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            418 non-null    float64
 5   SibSp          418 non-null    int64
 6   Parch          418 non-null    int64
 7   Ticket         418 non-null    object
 8   Fare           418 non-null    float64
 9   Cabin          91 non-null     object
 10  Embarked       418 non-null    object
 11  FamilySize     418 non-null    int64
 12  IsAlone        418 non-null    int64
 13  Title          418 non-null    object
 14  FareBin        418 non-null    category
 15  AgeBin         418 non-null    category
 16  Sex_Code       418 non-null    int64
 17  Embarked_Code  418 non-null    int64
 18  Title_Code     418 non-null    int64
 19  FareBin_Code   418 non-null    int64
 20  AgeBin_Code    418 non-null    int64
dtypes: category(2), float64(2), int64(11), object(6)
memory usage: 63.5+ KB
None
----------
```

[8]:

|        | PassengerId | Survived | Pclass | Name | Sex |
|---|---|---|---|---|---|
| count | 891.000000 | 891.000000 | 891.000000 | 891 | 891 |
| unique | NaN | NaN | NaN | 891 | 2 |
| top | NaN | NaN | NaN | Braund, Mr. Owen Harris | male |
| freq | NaN | NaN | NaN | 1 | 577 |
| mean | 446.000000 | 0.383838 | 2.308642 | NaN | NaN |
| std | 257.353842 | 0.486592 | 0.836071 | NaN | NaN |
| min | 1.000000 | 0.000000 | 1.000000 | NaN | NaN |
| 25% | 223.500000 | 0.000000 | 2.000000 | NaN | NaN |
| 50% | 446.000000 | 0.000000 | 3.000000 | NaN | NaN |
| 75% | 668.500000 | 1.000000 | 3.000000 | NaN | NaN |
| max | 891.000000 | 1.000000 | 3.000000 | NaN | NaN |

|        | Age | SibSp | Parch | Ticket | Fare | Cabin |
|---|---|---|---|---|---|---|
| count | 714.000000 | 891.000000 | 891.000000 | 891 | 891.000000 | 204 |
| unique | NaN | NaN | NaN | 681 | NaN | 147 |
| top | NaN | NaN | NaN | 347082 | NaN | B96 B98 |
| freq | NaN | NaN | NaN | 7 | NaN | 4 |
| mean | 29.699118 | 0.523008 | 0.381594 | NaN | 32.204208 | NaN |
| std | 14.526497 | 1.102743 | 0.806057 | NaN | 49.693429 | NaN |
| min | 0.420000 | 0.000000 | 0.000000 | NaN | 0.000000 | NaN |
| 25% | 20.125000 | 0.000000 | 0.000000 | NaN | 7.910400 | NaN |
| 50% | 28.000000 | 0.000000 | 0.000000 | NaN | 14.454200 | NaN |
| 75% | 38.000000 | 1.000000 | 0.000000 | NaN | 31.000000 | NaN |
| max | 80.000000 | 8.000000 | 6.000000 | NaN | 512.329200 | NaN |

|        | Embarked |
|---|---|
| count | 889 |
| unique | 3 |
| top | S |
| freq | 644 |
| mean | NaN |
| std | NaN |
| min | NaN |
| 25% | NaN |
| 50% | NaN |
| 75% | NaN |
| max | NaN |

### 1.4.4 划分训练和测试数据

Kaggle 提供的测试文件实际上是验证数据，因此使用 `sklearn1` 的函数来将训练数据划分为两个数据集，75/25 划分. 这样做可以避免模型的过拟合.

[9]:
```
# split train and test data with function defaults
# random_state: seed of random number generator
train1_x, test1_x, train1_y, test1_y = model_selection.train_test_split(
    data1[data1_x_calc], data1[Target], random_state=42
)
```

```
)
(
    train1_x_bin,
    test1_x_bin,
    train_y_bin,
    test1_y_bin,
) = model_selection.train_test_split(
    data1[data1_x_bin], data1[Target], random_state=42
)
(
    train1_x_dummy,
    test1_x_dummy,
    train1_y_dummy,
    test1_y_dummy,
) = model_selection.train_test_split(
    data1_dummy[data1_x_dummy], data1[Target], random_state=42
)

print('Data1 shape[{}]'.format(data1.shape))
print('Train1 shape[{}]'.format(train1_x.shape))
print('Test1 shape[{}]'.format(test1_x.shape))

train1_x_bin.head()
```

```
Data1 shape[(891, 19)]
Train1 shape[(668, 8)]
Test1 shape[(223, 8)]
```

[9]:

```
     Sex_Code  Pclass  Embarked_Code  Title_Code  FamilySize  AgeBin_Code  \
298         1       1              2           3           1            1
884         1       3              2           3           1            1
247         0       2              2           4           3            1
478         1       3              2           3           1            1
305         1       1              2           0           4            0

     FareBin_Code
298             2
884             0
247             2
478             0
305             3
```

## 1.5 第四步：执行探索分析与统计

数据已经清理完成，可以使用描述性和图形性的统计来探索我们的数据，描述和总结我们的变量.

[10]:

```
# discrete variable correlation by survival using group by pivot table
for x in data1_x:
```

```python
    if data1[x].dtype != 'float64':
        print('Survival Correlation by: ', x)
        print(data1[[x, Target[0]]].groupby(x, as_index=False).mean())
        print('-'*10, '\n')

# using crosstabs
print(pd.crosstab(data1['Title'], data1[Target[0]]))
```

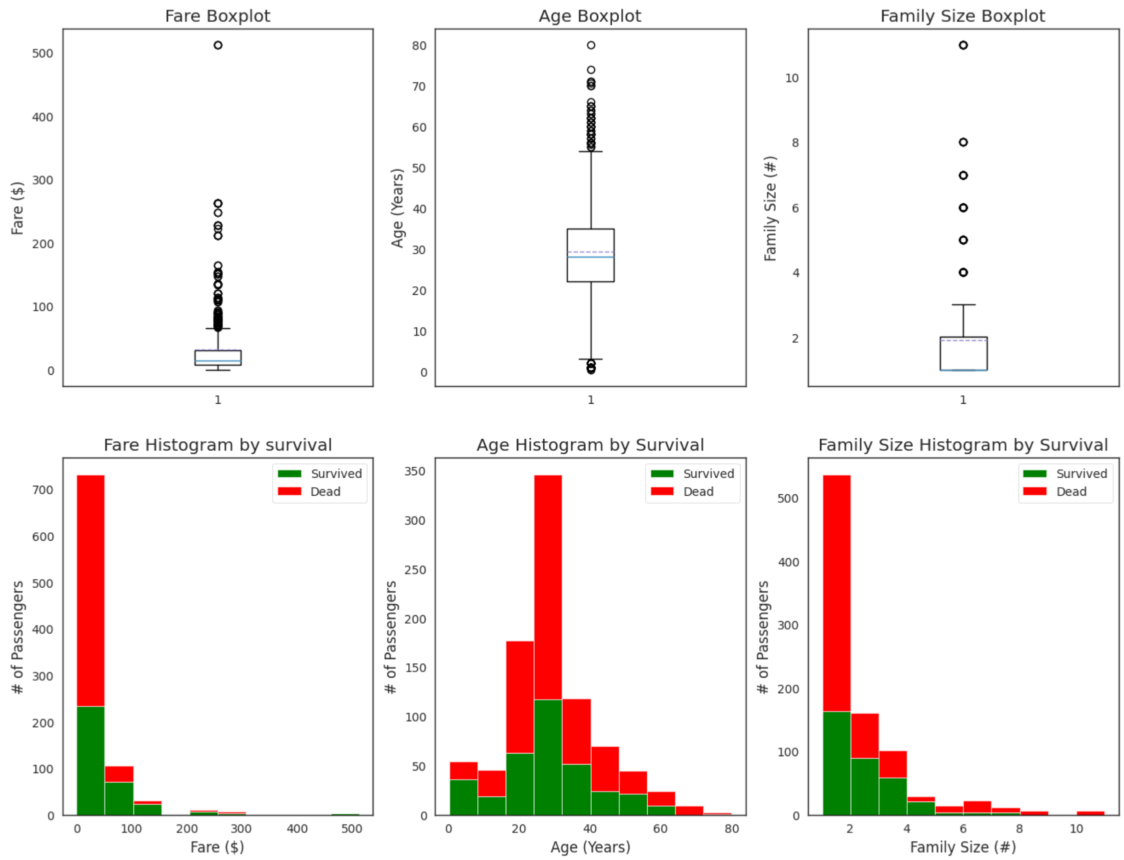
```
Survival Correlation by:  Sex
      Sex  Survived
0  female  0.742038
1    male  0.188908
----------

Survival Correlation by:  Pclass
   Pclass  Survived
0       1  0.629630
1       2  0.472826
2       3  0.242363
----------

Survival Correlation by:  Embarked
  Embarked  Survived
0        C  0.553571
1        Q  0.389610
2        S  0.339009
----------

Survival Correlation by:  Title
    Title  Survived
0  Master  0.575000
1    Misc  0.444444
2    Miss  0.697802
3      Mr  0.156673
4     Mrs  0.792000
----------

Survival Correlation by:  SibSp
   SibSp  Survived
0      0  0.345395
1      1  0.535885
2      2  0.464286
3      3  0.250000
4      4  0.166667
5      5  0.000000
6      8  0.000000
----------
```

```
Survival Correlation by:  Parch
   Parch  Survived
0      0  0.343658
1      1  0.550847
2      2  0.500000
3      3  0.600000
4      4  0.000000
5      5  0.200000
6      6  0.000000
----------

Survival Correlation by:  FamilySize
   FamilySize  Survived
0           1  0.303538
1           2  0.552795
2           3  0.578431
3           4  0.724138
4           5  0.200000
5           6  0.136364
6           7  0.333333
7           8  0.000000
8          11  0.000000
----------

Survival Correlation by:  IsAlone
   IsAlone  Survived
0        0  0.505650
1        1  0.303538
----------

Survived    0    1
Title
Master     17   23
Misc       15   12
Miss       55  127
Mr        436   81
Mrs        26   99
```

[11]:
```python
# graph distribution of quantative data
plt.figure(figsize=[16,12])

plt.subplot(231)
plt.boxplot(x=data1['Fare'], showmeans=True, meanline=True)
plt.title('Fare Boxplot')
plt.ylabel('Fare ($)')

plt.subplot(232)
```

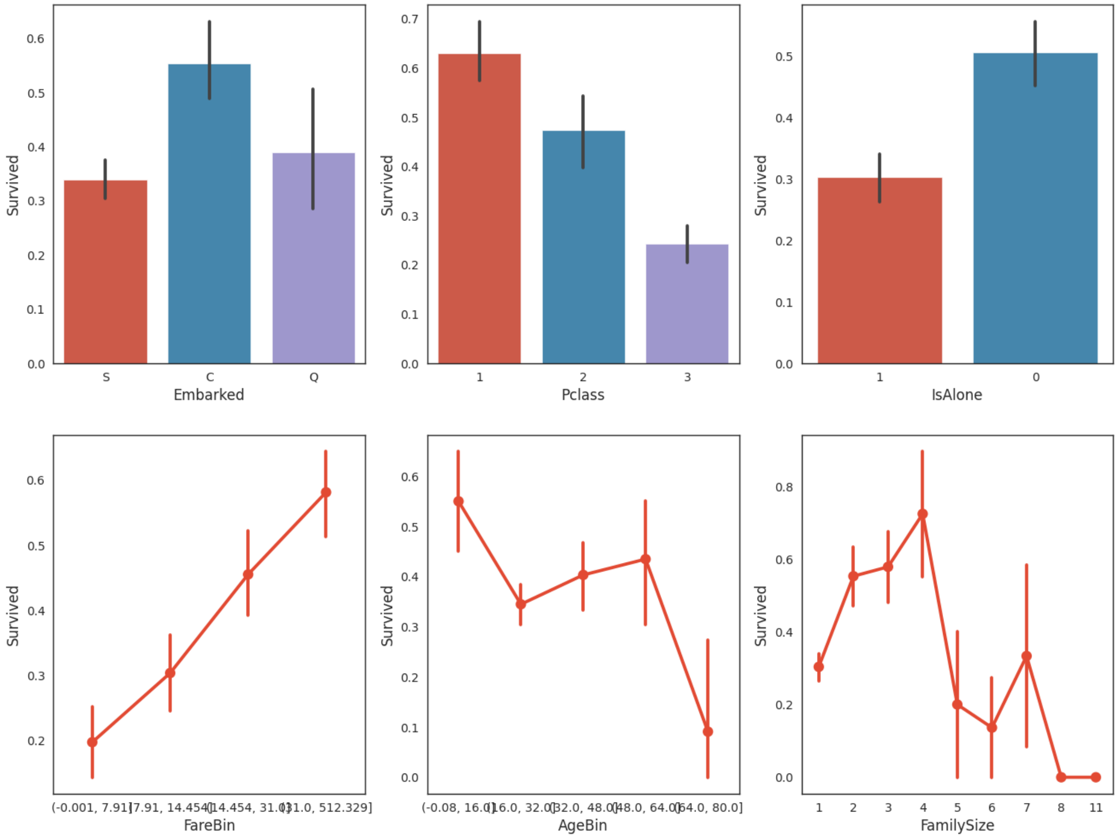
```
plt.boxplot(data1['Age'], showmeans=True,meanline=True)
plt.title('Age Boxplot')
plt.ylabel('Age (Years)')

plt.subplot(233)
plt.boxplot(data1['FamilySize'], showmeans=True,meanline=True)
plt.title('Family Size Boxplot')
plt.ylabel('Family Size (#)')

plt.subplot(234)
plt.hist(x=[data1[data1['Survived']==1]['Fare'],␣
 ↪data1[data1['Survived']==0]['Fare']],stacked=True,color=['g','r'],label=['Survived','Dead']
plt.title('Fare Histogram by survival')
plt.xlabel('Fare ($)')
plt.ylabel('# of Passengers')
plt.legend()

plt.subplot(235)
plt.hist(x=[data1[data1['Survived']==1]['Age'],␣
 ↪data1[data1['Survived']==0]['Age']], stacked=True,␣
 ↪color=['g','r'],label=['Survived','Dead'])
plt.title('Age Histogram by Survival')
plt.xlabel('Age (Years)')
plt.ylabel('# of Passengers')
plt.legend()

plt.subplot(236)
plt.
 ↪hist(x=[data1[data1['Survived']==1]['FamilySize'],data1[data1['Survived']==0]['FamilySize']]
plt.title('Family Size Histogram by Survival')
plt.xlabel('Family Size (#)')
plt.ylabel('# of Passengers')
plt.legend()
```

[11]:
```
<matplotlib.legend.Legend at 0x7ff2800f1990>
```



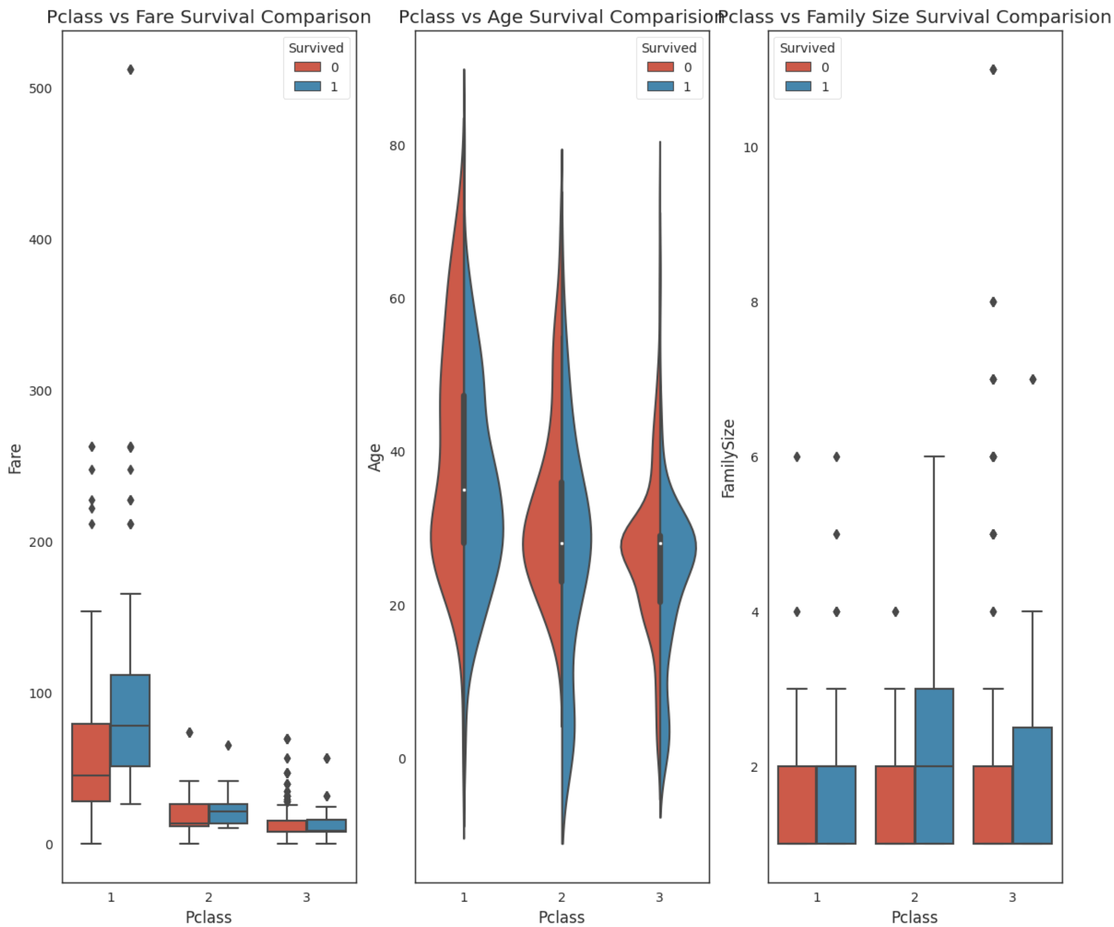

[12]:
```python
# use seaborn graphics for multi-variable comparision:

# graph individual features by survival
fig, saxis = plt.subplots(2,3,figsize=(16,12))

sns.barplot(x='Embarked',y='Survived',data=data1,ax=saxis[0,0])
sns.barplot(x='Pclass',y='Survived',order=[1,2,3],data=data1,ax=saxis[0,1])
sns.barplot(x='IsAlone',y='Survived',order=[1,0],data=data1,ax=saxis[0,2])

sns.pointplot(x='FareBin',y='Survived',data=data1,ax=saxis[1,0])
sns.pointplot(x='AgeBin',y='Survived',data=data1,ax=saxis[1,1])
sns.pointplot(x='FamilySize',y='Survived',data=data1,ax=saxis[1,2])
```

[12]:
```
<Axes: xlabel='FamilySize', ylabel='Survived'>
```



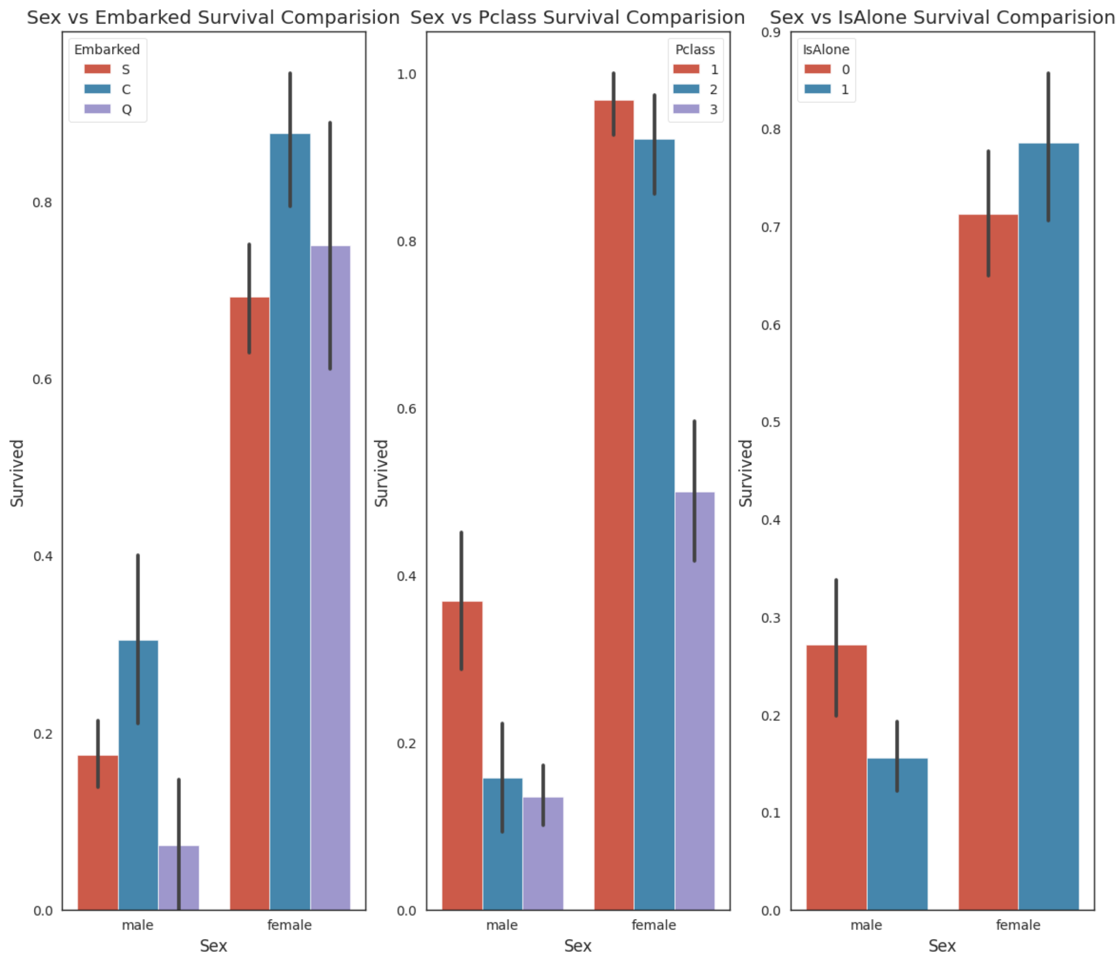

[13]:
```
# graph distribution of qualitative data: Pclass
# compare class and a 2nd feature
fig, (axis1, axis2, axis3)=plt.subplots(1,3,figsize=(14,12))

sns.boxplot(x='Pclass',y='Fare',hue='Survived',data=data1,ax=axis1)
axis1.set_title('Pclass vs Fare Survival Comparison')

sns.violinplot(x='Pclass',y='Age',hue='Survived',data=data1,split=True,ax=axis2)
axis2.set_title('Pclass vs Age Survival Comparision')

sns.boxplot(x='Pclass',y='FamilySize',hue='Survived',data=data1,ax=axis3)
axis3.set_title('Pclass vs Family Size Survival Comparision')
```

[13]:
```
Text(0.5, 1.0, 'Pclass vs Family Size Survival Comparision')
```



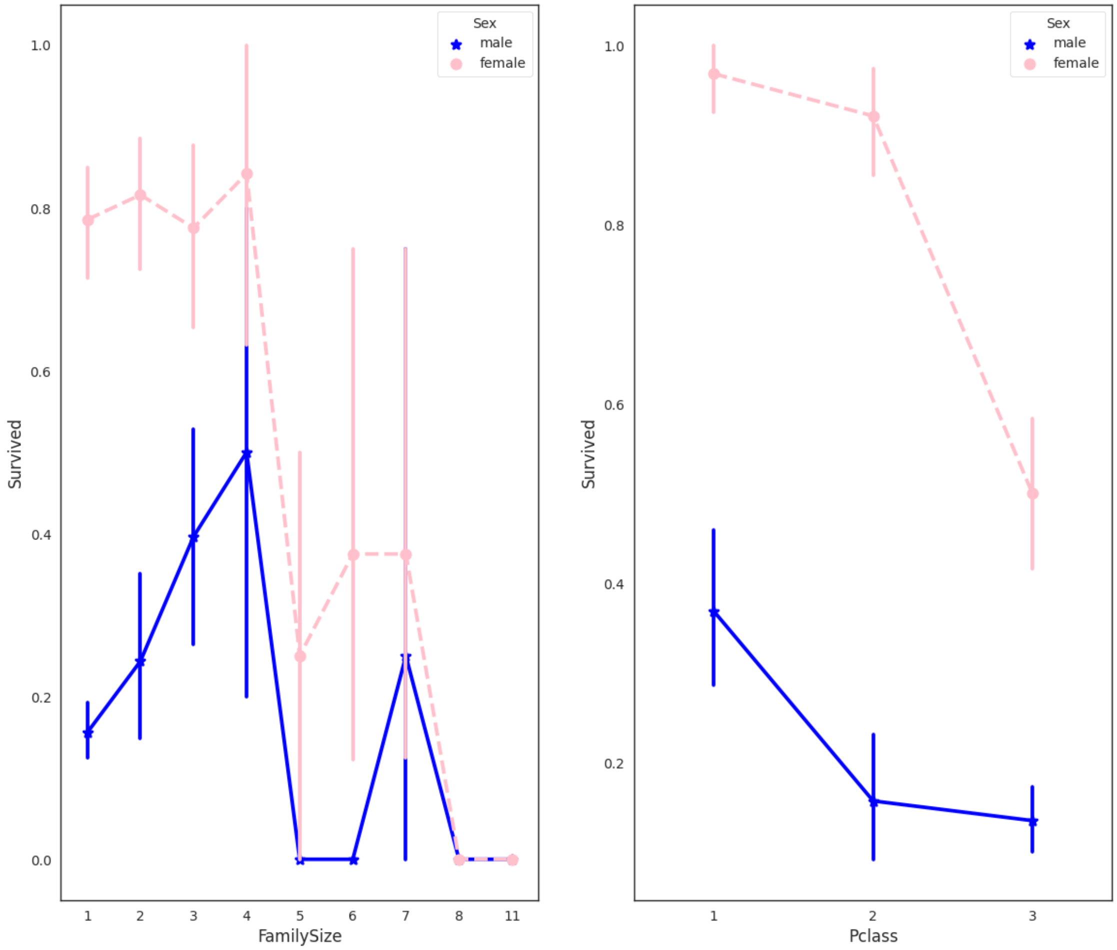

[14]:
```
# graph distribution of qualitative data: Sex
# compare sex and a 2nd feature
fig, qaxis=plt.subplots(1,3,figsize=(14,12))

sns.barplot(x='Sex',y='Survived',hue='Embarked',data=data1,ax=qaxis[0])
qaxis[0].set_title('Sex vs Embarked Survival Comparision')

sns.barplot(x='Sex',y='Survived',hue='Pclass',data=data1,ax=qaxis[1])
qaxis[1].set_title('Sex vs Pclass Survival Comparision')

sns.barplot(x='Sex',y='Survived',hue='IsAlone',data=data1,ax=qaxis[2])
qaxis[2].set_title('Sex vs IsAlone Survival Comparision')
```

[14]: Text(0.5, 1.0, 'Sex vs IsAlone Survival Comparision')



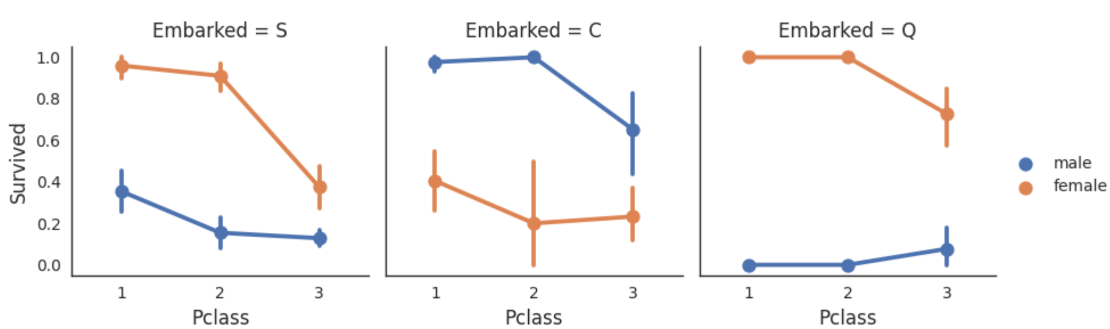

[15]:
```
# more side-by-side comparisions
fig, (maxis1,maxis2)=plt.subplots(1,2,figsize=(14,12))

# how does family size factor with sex and sirvival compare
sns.pointplot(x='FamilySize',y='Survived',hue='Sex',data=data1,palette={'male':
 ↪'blue','female':'pink'},markers=['*','o'],linestyles=['-','--'],ax=maxis1)

# how does class factor with sex and survival compare
sns.pointplot(x='Pclass',y='Survived',hue='Sex',data=data1,palette={'male':
 ↪'blue','female':'pink'},markers=['*','o'],linestyles=['-','--'],ax=maxis2)
```

[15]: <Axes: xlabel='Pclass', ylabel='Survived'>



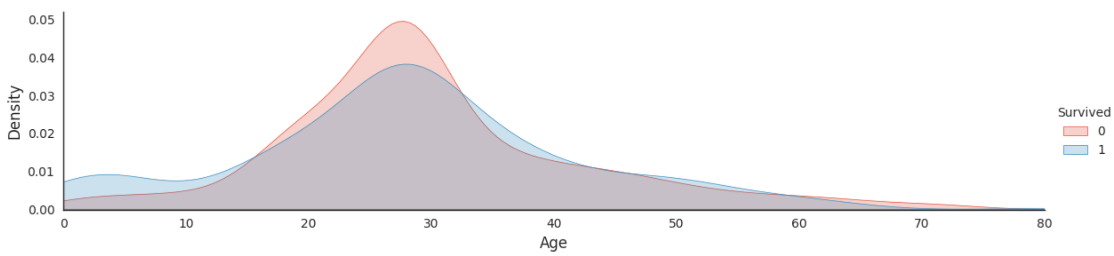

[16]:
```
# how does embark port factor with class, sex, and survival compare
e=sns.FacetGrid(data1,col='Embarked')
e.map(sns.pointplot,'Pclass','Survived','Sex',ci=95.0,palette='deep')
e.add_legend()
```

[16]: <seaborn.axisgrid.FacetGrid at 0x7ff27dc144d0>



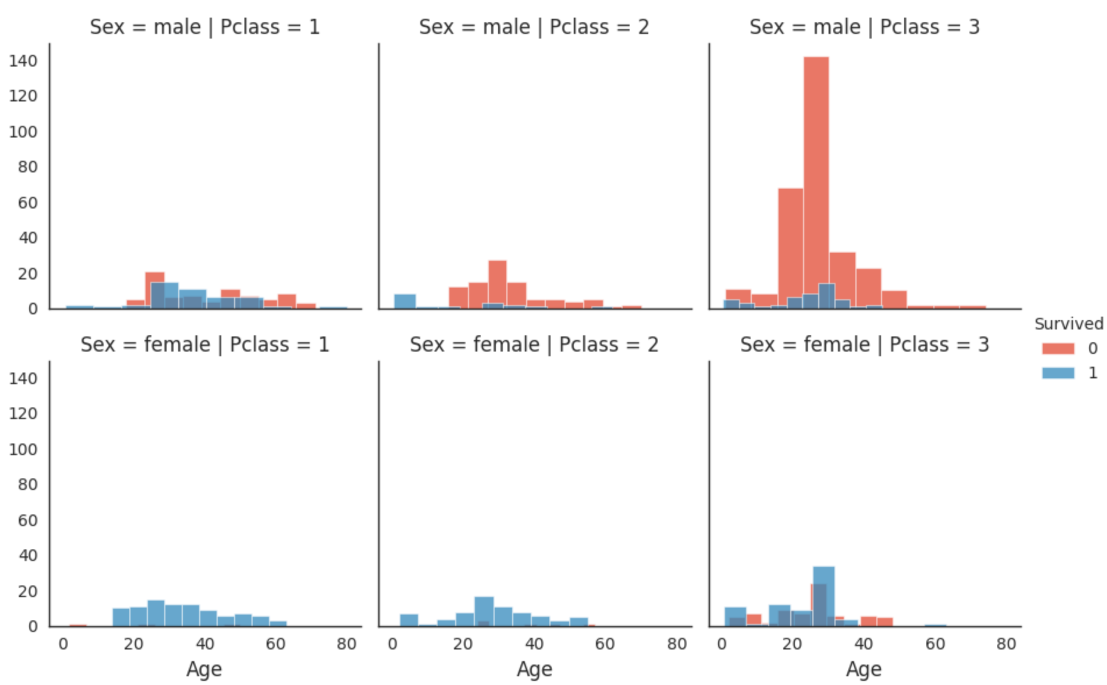
[17]:
```
# plot distributions of age of passengers who survived or did not survive
a=sns.FacetGrid(data1,hue='Survived',aspect=4)
a.map(sns.kdeplot,'Age',shade=True)
a.set(xlim=(0,data1['Age'].max()))
a.add_legend()
```

[17]:
```
<seaborn.axisgrid.FacetGrid at 0x7ff27de68dd0>
```



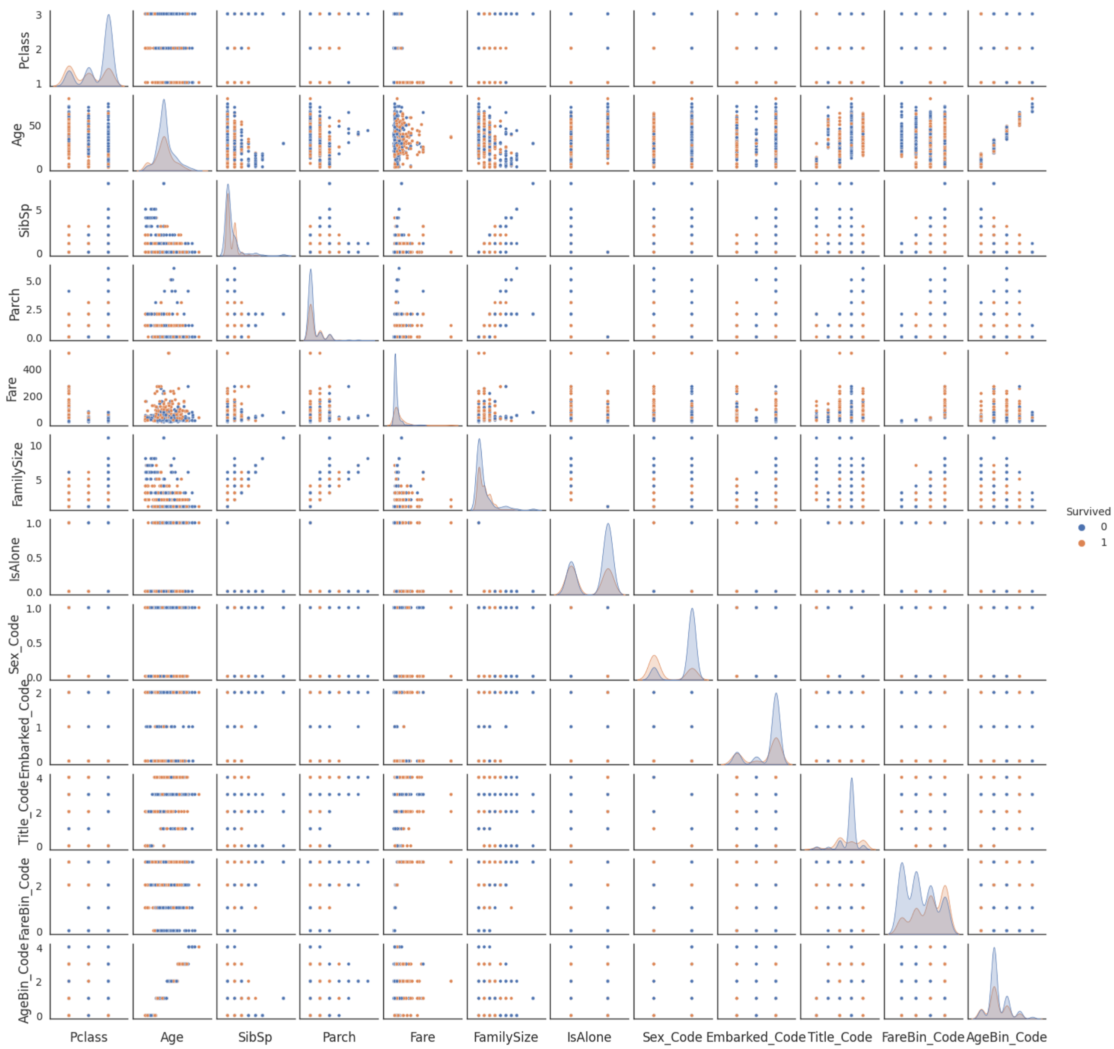

[18]:
```
# historical comparision of sex, class and age by survival
h=sns.FacetGrid(data1,row='Sex',col='Pclass',hue='Survived')
h.map(plt.hist,'Age',alpha=.75)
h.add_legend()
```

[18]:
```
<seaborn.axisgrid.FacetGrid at 0x7ff27c1a0a10>
```



[19]:
```
# pair plots of entire dataset
pp=sns.pairplot(data1,hue='Survived',palette='deep',size=1.
↪2,diag_kind='kde',diag_kws=dict(shade=True),plot_kws=dict(s=10))
pp.set(xticklabels=[])
```

[19]: <seaborn.axisgrid.PairGrid at 0x7ff27c118b10>

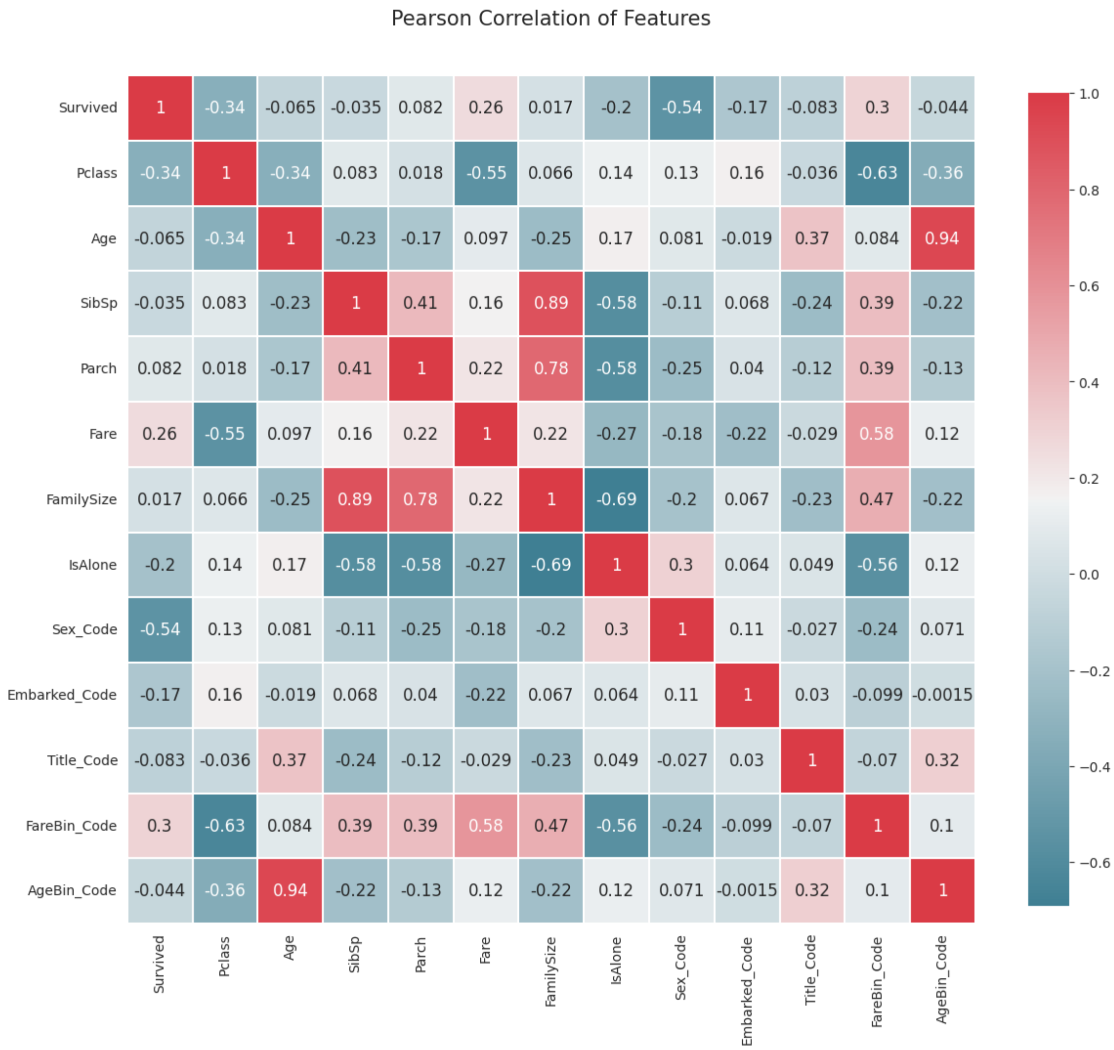



相关系数以 Pearson 相关性公式计算

$$\mathrm{corr}(X,Y)=\frac{\sum_{x=1}^{n}(x_i-\mathrm{mean}(X))*(y_i-\mathrm{mean}(Y))}{(n-1)*\mathrm{std}(X)*\mathrm{std}(Y)}$$

[20]:

```
# correlation heatmap of dataset
# ignore not-number columns, because they cannot be converted to float type
def correlation_heatmap(df):
    _, ax = plt.subplots(figsize=(14, 12))
    colormap = sns.diverging_palette(220, 10, as_cmap=True)
    numeric_cols = df.select_dtypes(
        include=[np.number]
    )  # only select numeric columns

    _ = sns.heatmap(
        numeric_cols.corr(),
        cmap=colormap,
        square=True,
        cbar_kws={"shrink": 0.9},
        ax=ax,
        annot=True,
        linewidths=0.1,
        vmax=1.0,
        linecolor="white",
        annot_kws={"fontsize": 12},
    )

    plt.title("Pearson Correlation of Features", y=1.05, size=15)


correlation_heatmap(data1)
```




## 1.6 第五步：数据建模

使用监督机器学习. 对于机器学习算法的选择, 机器学习算法有四中类别: 分类, 回归, 成簇, 降维. 对于本次的任务, 生存与否是离散的目标变量, 因此使用分类算法来进行分析. 使用交叉验证和评分矩阵来排序和比较几种不同算法的表现.

本次实验中选择的算法列表: - Ensemble Methods, 集成算法 - Generalized Linear Models, 广义线性模型 - Naive Bayes, 朴素贝叶斯 - Nearest Neighbors, 最近邻居 - Support Vector Machines, 支持向量机 - Decision Trees, 决策树 - Discriminant Analysis, 判别分析法

[21]:
```
# machine learning algorithms (MLA) selection and Initialization
MLA = [
    # ensemble methods
    ensemble.AdaBoostClassifier(),
    ensemble.BaggingClassifier(),
```

```python
    ensemble.ExtraTreesClassifier(),
    ensemble.GradientBoostingClassifier(),
    ensemble.RandomForestClassifier(),
    # Gaussian Processes
    gaussian_process.GaussianProcessClassifier(),
    # GLM
    linear_model.LogisticRegressionCV(),
    linear_model.PassiveAggressiveClassifier(),
    linear_model.RidgeClassifierCV(),
    linear_model.SGDClassifier(),
    linear_model.Perceptron(),
    # Naive Bayes
    naive_bayes.BernoulliNB(),
    naive_bayes.GaussianNB(),
    # Nearest Neighbor
    neighbors.KNeighborsClassifier(),
    # SVM
    svm.SVC(probability=True),
    svm.NuSVC(probability=True),
    svm.LinearSVC(),
    # Trees
    tree.DecisionTreeClassifier(),
    tree.ExtraTreeClassifier(),
    # Discriminant Analysis
    discriminant_analysis.LinearDiscriminantAnalysis(),
    discriminant_analysis.QuadraticDiscriminantAnalysis(),
    # XGBoost
    XGBClassifier(),
]

# split dataset in cross-validation
# this is a alternative to train_test_split
cv_split = model_selection.ShuffleSplit(
    n_splits=10, test_size=0.3, train_size=0.6, random_state=0
)

# create table to compare MLA metrics
MLA_columns = [
    "MLA Name",
    "MLA Paramaters",
    "MLA Train Accuracy Mean",
    "MLA Test Accuracy Mean",
    "MLA Test Accuracy 3*STD",
    "MLA Time",
]
MLA_compare = pd.DataFrame(columns=MLA_columns)
```

```python
# create table to compare MLA predictions
MLA_predict = data1[Target]

# index through MLA and save performance to table
row_index = 0
for alg in MLA:
    # set name and parameters
    MLA_name = alg.__class__.__name__
    MLA_compare.loc[row_index, "MLA Name"] = MLA_name
    MLA_compare.loc[row_index, "MLA Parameters"] = str(alg.get_params())

    # score model with cross validation
    cv_results = model_selection.cross_validate(
        alg,
        data1[data1_x_bin],
        data1[Target],
        cv=cv_split,
        return_train_score=True,
    )

    MLA_compare.loc[row_index, "MLA Time"] = cv_results["fit_time"].mean()
    MLA_compare.loc[row_index, "MLA Train Accuracy Mean"] = cv_results[
        "train_score"
    ].mean()
    MLA_compare.loc[row_index, "MLA Test Accuracy Mean"] = cv_results[
        "test_score"
    ].mean()
    # if this is a non-bias random sample, then +/-3 standard deviations(std)
    # from the mean, should statistically capture 99.7% of the subsets
    MLA_compare.loc[row_index, "MLA Test Accuracy 3*STD"] = (
        cv_results["test_score"].std() * 3
    )  # the worst that can happen

    # save MLA predictions
    alg.fit(data1[data1_x_bin], data1[Target])
    MLA_predict[MLA_name] = alg.predict(data1[data1_x_bin])

    row_index += 1

# print and sort table
MLA_compare.sort_values(
    by=["MLA Test Accuracy Mean"], ascending=False, inplace=True
)
MLA_compare
# MLA_predict
```

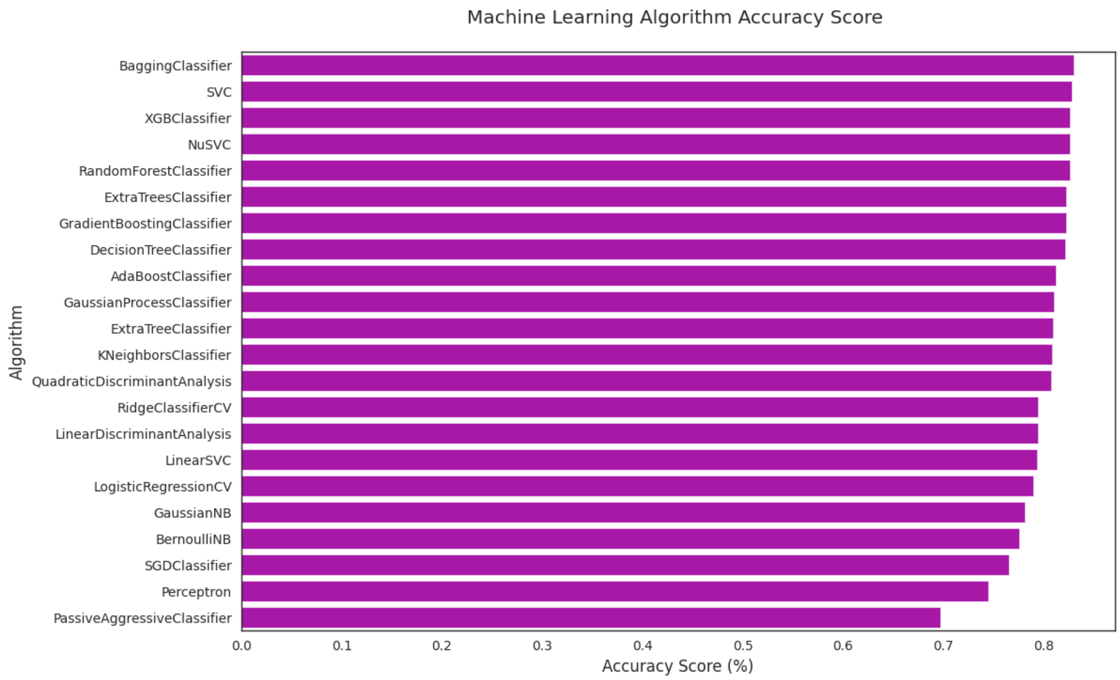
[21]:

```
                           MLA Name MLA Paramaters MLA Train Accuracy Mean  \
1                 BaggingClassifier            NaN                0.890449
14                              SVC            NaN                0.835206
21                    XGBClassifier            NaN                0.890449
15                            NuSVC            NaN                0.834082
4            RandomForestClassifier            NaN                0.895131
2              ExtraTreesClassifier            NaN                0.895131
3        GradientBoostingClassifier            NaN                0.866667
17           DecisionTreeClassifier            NaN                0.895131
0                AdaBoostClassifier            NaN                0.820412
5         GaussianProcessClassifier            NaN                0.871723
18              ExtraTreeClassifier            NaN                0.895131
13             KNeighborsClassifier            NaN                0.849813
20    QuadraticDiscriminantAnalysis            NaN                0.821536
8                 RidgeClassifierCV            NaN                0.796629
19       LinearDiscriminantAnalysis            NaN                0.796816
16                        LinearSVC            NaN                0.797378
6              LogisticRegressionCV            NaN                0.797004
12                       GaussianNB            NaN                0.794757
11                      BernoulliNB            NaN                0.785768
9                     SGDClassifier            NaN                 0.75824
10                       Perceptron            NaN                0.754494
7      PassiveAggressiveClassifier            NaN                0.699813

   MLA Test Accuracy Mean MLA Test Accuracy 3*STD  MLA Time  \
1                0.829478                0.055532  0.012231
14               0.827612                0.040916  0.022228
21               0.826493                 0.06177  0.045392
15               0.826119                0.045663  0.026037
4                0.825746                0.059665  0.070808
2                0.822761                 0.06177  0.053459
3                0.822761                0.049873  0.048777
17               0.821269                0.050174  0.001828
0                 0.81194                0.049861  0.043829
5                0.810448                0.049254  0.153705
18               0.809328                0.061811  0.001781
13               0.808209                0.083047   0.00188
20                0.80709                0.081039  0.001663
8                 0.79403                 0.03603  0.002492
19                0.79403                 0.03603  0.001943
16                0.79291                0.041053  0.013775
6                0.789179                0.061973  0.071602
12               0.781343                0.087457   0.00179
11               0.775373                0.057035  0.001927
9                0.765299                 0.11681  0.002637
10               0.744403                0.123667   0.00203
7                0.697015                0.331721  0.001996
```

```
                                       MLA Parameters
1   {'base_estimator': 'deprecated', 'bootstrap': …
14  {'C': 1.0, 'break_ties': False, 'cache_size': …
21  {'objective': 'binary:logistic', 'use_label_en…
15  {'break_ties': False, 'cache_size': 200, 'clas…
4   {'bootstrap': True, 'ccp_alpha': 0.0, 'class_w…
2   {'bootstrap': False, 'ccp_alpha': 0.0, 'class_…
3   {'ccp_alpha': 0.0, 'criterion': 'friedman_mse'…
17  {'ccp_alpha': 0.0, 'class_weight': None, 'crit…
0   {'algorithm': 'SAMME.R', 'base_estimator': 'de…
5   {'copy_X_train': True, 'kernel': None, 'max_it…
18  {'ccp_alpha': 0.0, 'class_weight': None, 'crit…
13  {'algorithm': 'auto', 'leaf_size': 30, 'metric…
20  {'priors': None, 'reg_param': 0.0, 'store_cova…
8   {'alphas': (0.1, 1.0, 10.0), 'class_weight': N…
19  {'covariance_estimator': None, 'n_components':…
16  {'C': 1.0, 'class_weight': None, 'dual': 'warn…
6   {'Cs': 10, 'class_weight': None, 'cv': None, '…
12           {'priors': None, 'var_smoothing': 1e-09}
11  {'alpha': 1.0, 'binarize': 0.0, 'class_prior':…
9   {'alpha': 0.0001, 'average': False, 'class_wei…
10  {'alpha': 0.0001, 'class_weight': None, 'early…
7   {'C': 1.0, 'average': False, 'class_weight': N…
```

[22]:
```python
# barplot
sns.barplot(x='MLA Test Accuracy Mean', y='MLA Name', data=MLA_compare,␣
↪color='m')

# prettify using pyplot
plt.title('Machine Learning Algorithm Accuracy Score \n')
plt.xlabel('Accuracy Score (%)')
plt.ylabel('Algorithm')
```

[22]:
```
Text(0, 0.5, 'Algorithm')
```




## 1.7 评价模型表现

借助前面的数据清理, 分析和选择的机器学习算法, 几行代码就获得了 82% 左右的准确率. 但是是不是可以做的更好, 或者获取更高的投资回报比?

### 1.7.1 设立合理的基线 (baseline)

在泰坦尼克号上 1502/2224, 即 67.5% 的人死掉了. 如果我们仅仅假设所有人都死掉了, 也可以获得 67.5% 的准确率. 因此, 基线需要设置在至少 67.5%, 即模型的最坏表现应该高于 67.5% 才有意义.

## 1.8 借助超参数调节模型

在使用决策树分类器的时候, 使用了所有的默认设置. 这给了我们查看不同超参数设置对模型精确度影响的机会.

然而, 为了调节一个模型, 需要弄懂他. 为了调节决策树模型, 我们需要了解一下这个模型.

**决策树的一些优点** - 简单易懂, 树可以被可视化; - 需要很少的数据准备. 另外的技巧一般需要数据规范化, dummy 变量需要被创建, 空值需要被删除. 注意这个模块不支持缺失值; - 使用决策树 (预测数据) 的开销相对于用来训练树的数据点是对数级的; - 可以处理数字和类别数据. 其他的技巧通常只能用于分析只具有一种类型变量的数据集; - 可以处理多输出问题; - 使用白盒模型. 如果一个给定的情况在一个模型中可以被看到, 对该情况的解释可以很容易的用布尔逻辑进行解释. 相反的, 一个黑盒模型 (例如一个人工神经网络), 结果会更难推测; - 可以使用统计测试来验证一个模型. 这使得承诺模型的可靠性成为可能; - 即便与数据生成的真是模型的假设有些出入, 表现仍旧很好; **决策树的一些缺点:** - 决策树学习者可以创建过于复杂的树, 因此不能再数据上泛化良好. 这被叫做**过拟合** . 例如剪枝 (目前没有支持), 设置在一个叶子节点需要的最少数量样本, 或者设置树的最大深度等等机制都是避免这一问题的必要方法; - 由于数据中的很小的偏差可能导致生成完全不同的树,

因此决策树可能十分不稳定. 这个问题可以借助多个决策树一起决策来缓解; - 学习一个最优决策树被认为是 NP 完备的, 在几个优化角度下, 即便对于简单的概念. 因此, 可行的决策树学习算法都基于启发算法的, 例如贪心算法. 在这种情况下在每个节点得到的都是局部最优决策. 这样的算法不能保证返回全局最优的决策树. 但使用一个集成学习器可以减小, 其中特征和样本被随机取样. - 有些概念难以被学习到, 因为决策树不显式的容易的表达他们, 例如异或, 偏序或者倍乘问题. - 决策树学习器创建有偏见的树, 如果一些类占统治地位. 因此推荐对数据集进行平衡来让他适合决策树.

下面将使用 PrameterGrid, GridSearchCV, 自定义的 sklearn scoring 来调节模型. 借助 graphviz 来可视化决策树.

[23]:
```
# base model
dtree = tree.DecisionTreeClassifier(random_state=0)
base_results = model_selection.cross_validate(
    dtree,
    data1[data1_x_bin],
    data1[Target],
    cv=cv_split,
    return_train_score=True,
)
dtree.fit(data1[data1_x_bin], data1[Target])

print("BEFORE DT Parameters: ", dtree.get_params())
print(
    "BEFORE DT Training w/bin score mean: {:.2f}".format(
        base_results["train_score"].mean() * 100
    )
)
print(
    "BEFORE DT Test w/bin score mean: {:.2f}".format(
        base_results["test_score"].mean() * 100
    )
)
print(
    "BEFORE DT Test w/bin score 3*std: +/- {:.2f}".format(
        base_results["test_score"].std() * 100 * 3
    )
)
print("-" * 10)

# tune hyper-parameters:
param_grid = {
    "criterion": [
        "gini",
        "entropy",
    ],  # scoring methodology; two supported formulas for calcularing␣
↪information gain. default is gini
    "max_depth": [
```

```
        2,
        4,
        6,
        7,
        10,
        None,
    ],  # max depth tree can grow; defualt is None
    "random_state": [0],
}


# choose best model with grid_search
tune_model = model_selection.GridSearchCV(
    tree.DecisionTreeClassifier(),
    param_grid=param_grid,
    scoring="roc_auc",
    cv=cv_split,
    return_train_score=True
)
tune_model.fit(data1[data1_x_bin], data1[Target])

print("AFTER DT Parameters: ", tune_model.best_params_)
print(
    "AFTER DT Training w/bin socre mean: {:.2f}".format(
        tune_model.cv_results_["mean_train_score"][tune_model.best_index_] * 100
    )
)
print(
    "AFTER DT Test w/bin score mean: {:.2f}".format(
        tune_model.cv_results_["mean_test_score"][tune_model.best_index_] * 100
    )
)
print(
    "AFTER DT Test w/bin score 3*std: +/- {:.2f}".format(
        tune_model.cv_results_["std_test_score"][tune_model.best_index_]
        * 100
        * 3
    )
)
print("-" * 10)
```

```
BEFORE DT Parameters:  {'ccp_alpha': 0.0, 'class_weight': None, 'criterion':
'gini', 'max_depth': None, 'max_features': None, 'max_leaf_nodes': None,
'min_impurity_decrease': 0.0, 'min_samples_leaf': 1, 'min_samples_split': 2,
'min_weight_fraction_leaf': 0.0, 'random_state': 0, 'splitter': 'best'}
BEFORE DT Training w/bin score mean: 89.51
BEFORE DT Test w/bin score mean: 82.09
BEFORE DT Test w/bin score 3*std: +/- 5.57
```

```
----------
AFTER DT Parameters:  {'criterion': 'gini', 'max_depth': 4, 'random_state': 0}
AFTER DT Training w/bin socre mean: 89.35
AFTER DT Test w/bin score mean: 87.40
AFTER DT Test w/bin score 3*std: +/- 5.00
----------
```

### 1.9 借助特征选择来微调模型

和在开头说过的一样, 更多的预测器变量并不能获得一个更好的模型, 但是正确的预测器可以. 因此在数据建模中的另一步是特征选择. Sklearn 中有多个选项, 其中这里使用递归特征消除 (Recursive feature elimination, RFE) 和交叉验证 (Cross validation, CV)

[24]:
```python
# base model
print("BEFORE DT RFE Training Shape Old: ", data1[data1_x_bin].shape)
print("BEFORE DT RFE Training Columns Old: ", data1[data1_x_bin].columns.values)

print(
    "BEFORE DT RFE Training w/bin score mean: {:.2f}".format(
        base_results["train_score"].mean() * 100
    )
)
print(
    "BEFORE DT RFE Test w/bin score mean: {:.2f}".format(
        base_results["test_score"].mean() * 100
    )
)
print(
    "BEFORE DT RFE Test w/bin score 3*std: {:.2f}".format(
        base_results["test_score"].std() * 100 * 3
    )
)
print("-" * 10)

# feature selection
dtree_rfe = feature_selection.RFECV(
    dtree, step=1, scoring="accuracy", cv=cv_split
)
dtree_rfe.fit(data1[data1_x_bin], data1[Target])

# transform x&y to reduced features and fit new model
X_rfe = data1[data1_x_bin].columns.values[dtree_rfe.get_support()]
rfe_results = model_selection.cross_validate(
    dtree, data1[X_rfe], data1[Target], cv=cv_split, return_train_score=True
)

print("AFTER DT RFE Training Shape New: ", data1[X_rfe].shape)
print("AFTER DT RFE Training Columns New: ", X_rfe)
```

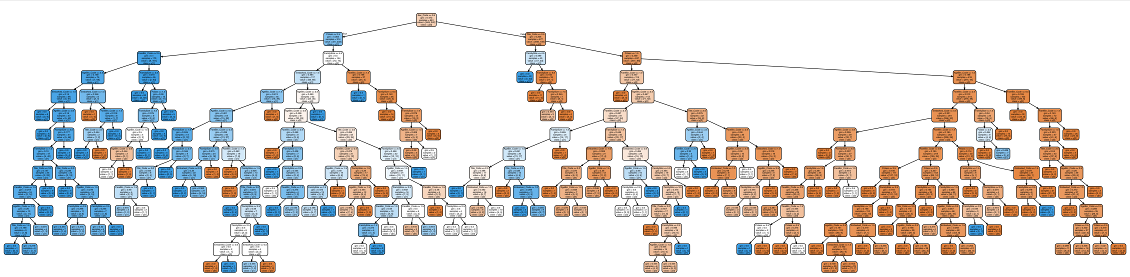
```python
print(
    "AFTER DT RFE Training w/bin score mean: {:.2f}".format(
        rfe_results["train_score"].mean() * 100
    )
)
print(
    "AFTER DT RFE Test w/bin score mean: {:.2f}".format(
        rfe_results["test_score"].mean() * 100
    )
)
print(
    "AFTER DT RFE Test w/bin score 3*std: +/- {:.2f}".format(
        rfe_results["test_score"].std() * 100 * 3
    )
)
print("-" * 10)

# ture rfe model
rfe_tune_model = model_selection.GridSearchCV(
    tree.DecisionTreeClassifier(),
    param_grid=param_grid,
    scoring="roc_auc",
    cv=cv_split,
    return_train_score=True,
)
rfe_tune_model.fit(data1[X_rfe], data1[Target])

print("AFTER DT RFE Tuned Parameters: ", rfe_tune_model.best_params_)
print(
    "AFTER DT RFE Tuned Training w/bin score mean: {:.2f}".format(
        rfe_tune_model.cv_results_["mean_train_score"][tune_model.best_index_]
        * 100
    )
)
print(
    "AFTER DT RFE Tuned Test w/bin score mean: {:.2f}".format(
        rfe_tune_model.cv_results_["mean_test_score"][tune_model.best_index_]
        * 100
    )
)
print(
    "AFTER DT RFE Tuned Test w/bin score 3*std: +/- {:.2f}".format(
        rfe_tune_model.cv_results_["std_test_score"][tune_model.best_index_]
        * 100
        * 3
    )
```

```
)
print("-" * 10)
```

```
BEFORE DT RFE Training Shape Old:  (891, 7)
BEFORE DT RFE Training Columns Old:  ['Sex_Code' 'Pclass' 'Embarked_Code'
'Title_Code' 'FamilySize'
 'AgeBin_Code' 'FareBin_Code']
BEFORE DT RFE Training w/bin score mean: 89.51
BEFORE DT RFE Test w/bin score mean: 82.09
BEFORE DT RFE Test w/bin score 3*std: 5.57
----------
AFTER DT RFE Training Shape New:  (891, 6)
AFTER DT RFE Training Columns New:  ['Sex_Code' 'Pclass' 'Title_Code'
'FamilySize' 'AgeBin_Code'
 'FareBin_Code']
AFTER DT RFE Training w/bin score mean: 88.16
AFTER DT RFE Test w/bin score mean: 83.06
AFTER DT RFE Test w/bin score 3*std: +/- 6.22
----------
AFTER DT RFE Tuned Parameters:  {'criterion': 'gini', 'max_depth': 4,
'random_state': 0}
AFTER DT RFE Tuned Training w/bin score mean: 89.39
AFTER DT RFE Tuned Test w/bin score mean: 87.34
AFTER DT RFE Tuned Test w/bin score 3*std: +/- 6.21
----------
```

[25]:
```
# graph MLA version of Decision Tree
import graphviz

dot_data = tree.export_graphviz(
    dtree,
    out_file=None,
    feature_names=data1_x_bin,
    class_names=True,
    filled=True,
    rounded=True,
)
graph = graphviz.Source(dot_data)
graph
```

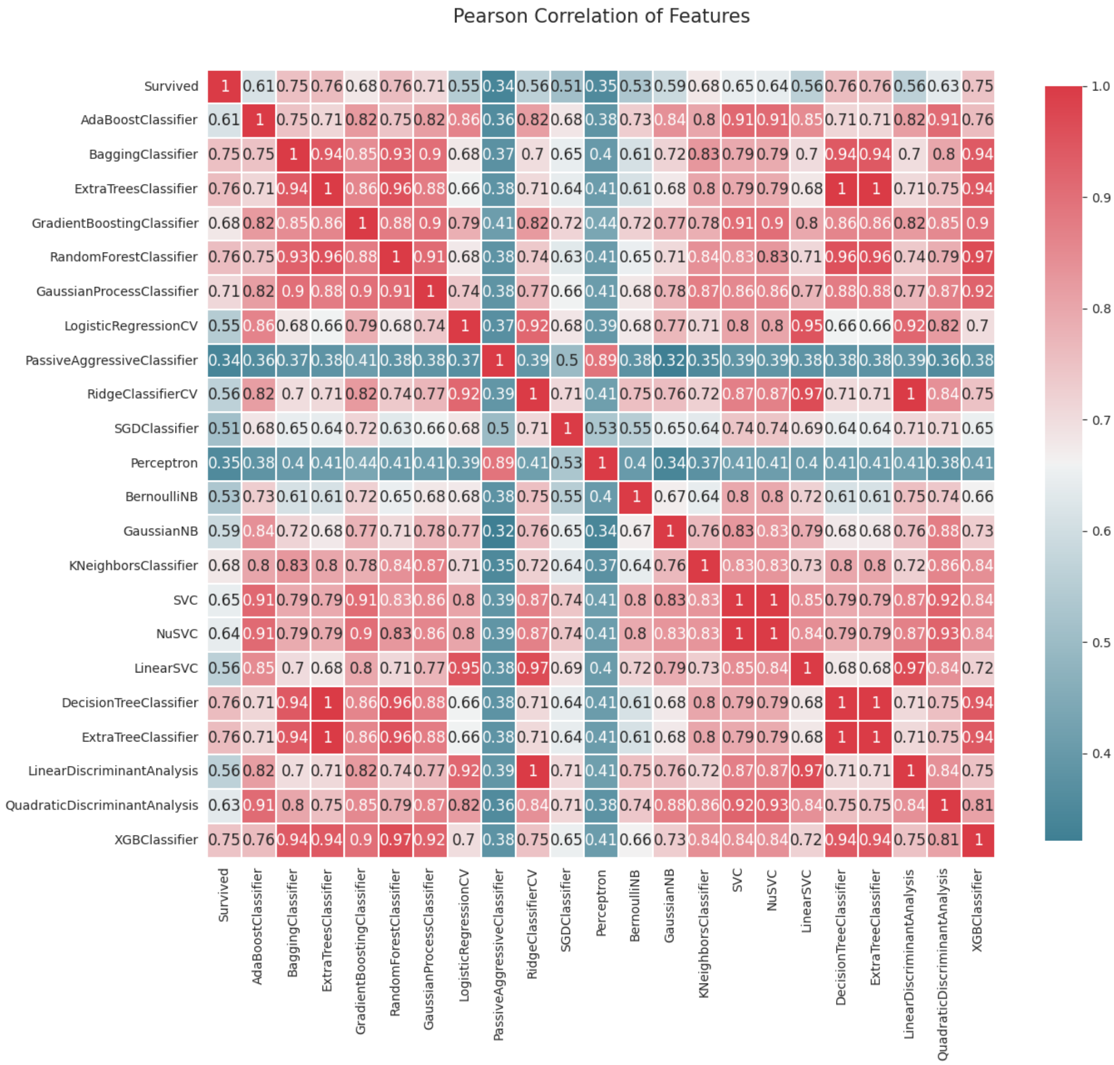
[25]:



# 2 第六步：验证和实现

使用模型对验证数据进行预测

[26]:
```
# compare algorithm predictions with each other, where 1 = exactly similar and 0
# = exactly opposite
# there are some 1's, but enough blues and light reds to create a 'super
# algorithm' by combining them
correlation_heatmap(MLA_predict)
```



[27]:

```python
# why choose one model, when you can pick them all with voting classifier
# removed models w/o attribute 'predict_proba' required for vote classifier and
# models with a 1.0 correlation to another model
vote_est = [
    # Ensemble Methods
    ("ada", ensemble.AdaBoostClassifier()),
    ("bc", ensemble.BaggingClassifier()),
    ("etc", ensemble.ExtraTreesClassifier()),
    ("gbc", ensemble.GradientBoostingClassifier()),
    ("rfc", ensemble.RandomForestClassifier()),
    # Gaussian Processes
    ("gpc", gaussian_process.GaussianProcessClassifier()),
    # GLM
    ("lr", linear_model.LogisticRegressionCV()),
    # Naive Bayes
    ("bnb", naive_bayes.BernoulliNB()),
    ("gnb", naive_bayes.GaussianNB()),
    # Nearest Neighbor
    ("knn", neighbors.KNeighborsClassifier()),
    # svm
    ("svc", svm.SVC(probability=True)),
    # xgboost
    ("xgb", XGBClassifier()),
]

# Hard Vote or majority rules
vote_hard = ensemble.VotingClassifier(estimators=vote_est, voting="hard")
vote_hard_cv = model_selection.cross_validate(
    vote_hard,
    data1[data1_x_bin],
    data1[Target],
    cv=cv_split,
    return_train_score=True,
)
vote_hard.fit(data1[data1_x_bin], data1[Target])

print(
    "Hard Voting Training w/bin score mean: {:.2f}".format(
        vote_hard_cv["train_score"].mean() * 100
    )
)
print(
    "Hard Voting Test w/bin score mean: {:.2f}".format(
        vote_hard_cv["test_score"].mean() * 100
    )
)
print(
```

```python
        "Hard Vote. Test w/bin score 3*std: +/- {:.2f}".format(
            vote_hard_cv["test_score"].std() * 3 * 100
        )
)
print("-" * 10)

# Soft Vote or weighted probabilitied
vote_soft = ensemble.VotingClassifier(estimators=vote_est, voting="soft")
vote_soft_cv = model_selection.cross_validate(
    vote_soft,
    data1[data1_x_bin],
    data1[Target],
    cv=cv_split,
    return_train_score=True,
)
vote_soft.fit(data1[data1_x_bin], data1[Target])

print(
    "Soft Voting Training w/bin score mean: {:.2f}".format(
        vote_soft_cv["train_score"].mean() * 100
    )
)
print(
    "Soft Voting Test w/bin socre mean: {:.2f}".format(
        vote_soft_cv["test_score"].mean() * 100
    )
)
print(
    "Soft Voting Test w/bin score 3*std: +/- {:.2f}".format(
        vote_soft_cv["test_score"].std() * 100 * 3
    )
)
print("-" * 10)
```

```
Hard Voting Training w/bin score mean: 87.28
Hard Voting Test w/bin score mean: 82.09
Hard Vote. Test w/bin score 3*std: +/- 4.00
----------
Soft Voting Training w/bin score mean: 87.77
Soft Voting Test w/bin socre mean: 82.35
Soft Voting Test w/bin score 3*std: +/- 3.85
----------
```

[28]:
```python
# WARNING: Running is very computational intensitive and time expensive

# Hyperparameter Tune with GridSearchCV
grid_n_estimator = [10, 50, 100, 300]
```

```python
grid_ratio = [0.1, 0.25, 0.5, 0.75, 1.0]
grid_learn = [0.01, 0.03, 0.05, 0.1, 0.25]
grid_max_depth = [2, 4, 6, 8, 10, None]
grid_min_samples = [5, 10, 0.03, 0.05, 0.10]
grid_critetion = ["gini", "entropy"]
grid_bool = [True, False]
grid_seed = [0]

grid_param = [
    [
        {
            "n_estimators": grid_n_estimator,  # default=50
            "learning_rate": grid_learn,  # default=1
            "random_state": grid_seed,
        }
    ],
    [
        {
            # BaggingClassifier
            "n_estimators": grid_n_estimator,  # default=10
            "max_samples": grid_ratio,  # default=1.0
            "random_state": grid_seed,
        }
    ],
    [
        {
            # ExtraTreesClassifier
            "n_estimators": grid_n_estimator,  # default=10
            "criterion": grid_critetion,  # default='gini'
            "max_depth": grid_max_depth,  # default=None
            "random_state": grid_seed,
        }
    ],
    [
        {
            # GradientBoostingClassifier
            "learning_rate": [
                0.05
            ],  # default=0.1, set to reduce runtime. The best parameter for␣
↪GradientBoostClassifier is {'learning_rate': 0.05, 'max_depth': 2,␣
↪'n_estimators': 300, 'random_state': 0}
            "n_estimators": [300],  # default=100
            "max_depth": grid_max_depth,  # default=3
            "random_state": grid_seed,
        }
    ],
    [
```

```
        {
            # random forest classifier
            "n_estimators": grid_n_estimator,  # default=10
            "criterion": grid_critetion,  # default=None
            "max_depth": grid_max_depth,  # default=None
            "oob_score": [True],  # default=False
            "random_state": grid_seed,
        }
    ],
    [
        {  # gaussian process classifier
            "max_iter_predict": grid_n_estimator,  # default:100
            "random_state": grid_seed,
        }
    ],
    [
        {
            # logistic regression cv
            "fit_intercept": grid_bool,  # default: True
            "solver": [
                "newton-cg",
                "lbfgs",
                "liblinear",
                "sag",
                "sage",
            ],  # default:lbfgs
            "random_state": grid_seed,
        }
    ],
    [
        {
            # BernoulliNB
            "alpha": grid_ratio,  # default: 1.0
        }
    ],
    [{}],  # GaussianNB
    [
        {
            # KNeighborsClassifier
            "n_neighbors": [1, 2, 3, 4, 5, 6, 7],  # default:5
            "weights": ["uniform", "distance"],  # default='uniform'
            "algorithm": ["auto", "ball_tree", "kd_tree", "brute"],
        }
    ],
    [
        {  # SVC
            "C": [1, 2, 3, 4, 5],  # default=1.0
```

```
            "gamma": grid_ratio,  # default:auto
            "decision_function_shape": ["ovo", "ovr"],  # default:ovr
            "probability": [True],
            "random_state": grid_seed,
        }
    ],
    [
        {
            # XGBClassifier
            "learning_rate": grid_learn,  # default:.3
            "max_depth": [1, 2, 4, 6, 8, 10],  # default:2
            "n_estimators": grid_n_estimator,
            "seed": grid_seed,
        }
    ],
]

start_total = time.perf_counter()
for clf, param in zip(vote_est, grid_param):
    start = time.perf_counter()
    best_search = model_selection.GridSearchCV(
        estimator=clf[1],
        param_grid=param,
        cv=cv_split,
        scoring="roc_auc",
        return_train_score=True,
    )
    best_search.fit(data1[data1_x_bin], data1[Target])
    run = time.perf_counter() - start

    best_param=best_search.best_params_
    print('The best parameter for {} is {} with a running time of {:.2f}␣
 ↪seconds.'.format(clf[1].__class__.__name__, best_param, run))
    clf[1].set_params(**best_param)

run_total=time.perf_counter()-start_total
print('Total optimization time was {:.2f} minutes.'.format(run_total/60))

print('-'*10)
```

```
The best parameter for AdaBoostClassifier is {'learning_rate': 0.1,
'n_estimators': 300, 'random_state': 0} with a running time of 26.63 seconds.
The best parameter for BaggingClassifier is {'max_samples': 0.25,
'n_estimators': 300, 'random_state': 0} with a running time of 28.41 seconds.
The best parameter for ExtraTreesClassifier is {'criterion': 'entropy',
'max_depth': 6, 'n_estimators': 100, 'random_state': 0} with a running time of
37.34 seconds.
The best parameter for GradientBoostingClassifier is {'learning_rate': 0.05,
```

```
'max_depth': 2, 'n_estimators': 300, 'random_state': 0} with a running time of
24.04 seconds.
The best parameter for RandomForestClassifier is {'criterion': 'entropy',
'max_depth': 6, 'n_estimators': 100, 'oob_score': True, 'random_state': 0} with
a running time of 57.25 seconds.
The best parameter for GaussianProcessClassifier is {'max_iter_predict': 10,
'random_state': 0} with a running time of 18.31 seconds.
The best parameter for LogisticRegressionCV is {'fit_intercept': True,
'random_state': 0, 'solver': 'newton-cg'} with a running time of 5.48 seconds.
The best parameter for BernoulliNB is {'alpha': 0.1} with a running time of 0.48
seconds.
The best parameter for GaussianNB is {} with a running time of 0.09 seconds.
The best parameter for KNeighborsClassifier is {'algorithm': 'ball_tree',
'n_neighbors': 6, 'weights': 'uniform'} with a running time of 6.60 seconds.
The best parameter for SVC is {'C': 2, 'decision_function_shape': 'ovo',
'gamma': 0.1, 'probability': True, 'random_state': 0} with a running time of
18.91 seconds.
The best parameter for XGBClassifier is {'learning_rate': 0.01, 'max_depth': 4,
'n_estimators': 300, 'seed': 0} with a running time of 95.83 seconds.
Total optimization time was 5.32 minutes.
----------
```

[30]:
```python
# Hard vote or majority rules w/Tuned Hyperparameters
grid_hard = ensemble.VotingClassifier(estimators=vote_est, voting="hard")
grid_hard_cv = model_selection.cross_validate(
    grid_hard,
    data1[data1_x_bin],
    data1[Target],
    cv=cv_split,
    return_train_score=True,
)
grid_hard.fit(data1[data1_x_bin], data1[Target])
print(
    "Hard Voting w/Tuned Hyperparameters Training w/bin score mean: {:.2f}".
 ↪format(
        grid_hard_cv["train_score"].mean() * 100
    )
)
print(
    "Hard Voting w/Tuned Hyperparameters Test w/bin score mean: {:.2f}".format(
        grid_hard_cv["test_score"].mean() * 100
    )
)
print(
    "Hard Voting w/Tuned Hyperparameters Test w/bin score 3*std: +/- {:.2f}".
 ↪format(
        grid_hard_cv["test_score"].std() * 100 * 3
```

```
    )
)
print("-" * 10)

# Soft vote or weighted probabilities w/Tuned Hyperparameters
grid_soft = ensemble.VotingClassifier(estimators=vote_est, voting="soft")
grid_soft_cv = model_selection.cross_validate(
    grid_soft,
    data1[data1_x_bin],
    data1[Target],
    cv=cv_split,
    return_train_score=True,
)
grid_soft.fit(data1[data1_x_bin], data1[Target])

print('Soft Voting w/Tuned Hyperparameters Training w/bin score mean: {:.2f}'.
 ↪format(grid_soft_cv['train_score'].mean()*100))
print('Soft Voting w/Tuned Hyperparameters Test w/bin score mean: {:.2f}'.
 ↪format(grid_soft_cv['test_score'].mean()*100))
    """_summary_
    """print('Soft Voting w/Tuned Hyperparameters Test w/bin 3*std: +/- {:.2f}'.
 ↪format(grid_soft_cv['test_score'].std()*100*3))
print('-'*10)
```

```
Hard Voting w/Tuned Hyperparameters Training w/bin score mean: 85.28
Hard Voting w/Tuned Hyperparameters Test w/bin score mean: 82.57
Hard Voting w/Tuned Hyperparameters Test w/bin score 3*std: +/- 5.28
----------
Soft Voting w/Tuned Hyperparameters Training w/bin score mean: 84.72
Soft Voting w/Tuned Hyperparameters Test w/bin score mean: 82.57
Soft Voting w/Tuned Hyperparameters Test w/bin 3*std: +/- 5.51
----------
```