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]:

```python
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]:
```python
# 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]:
```python
# 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]:

```python
# 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
----------
```

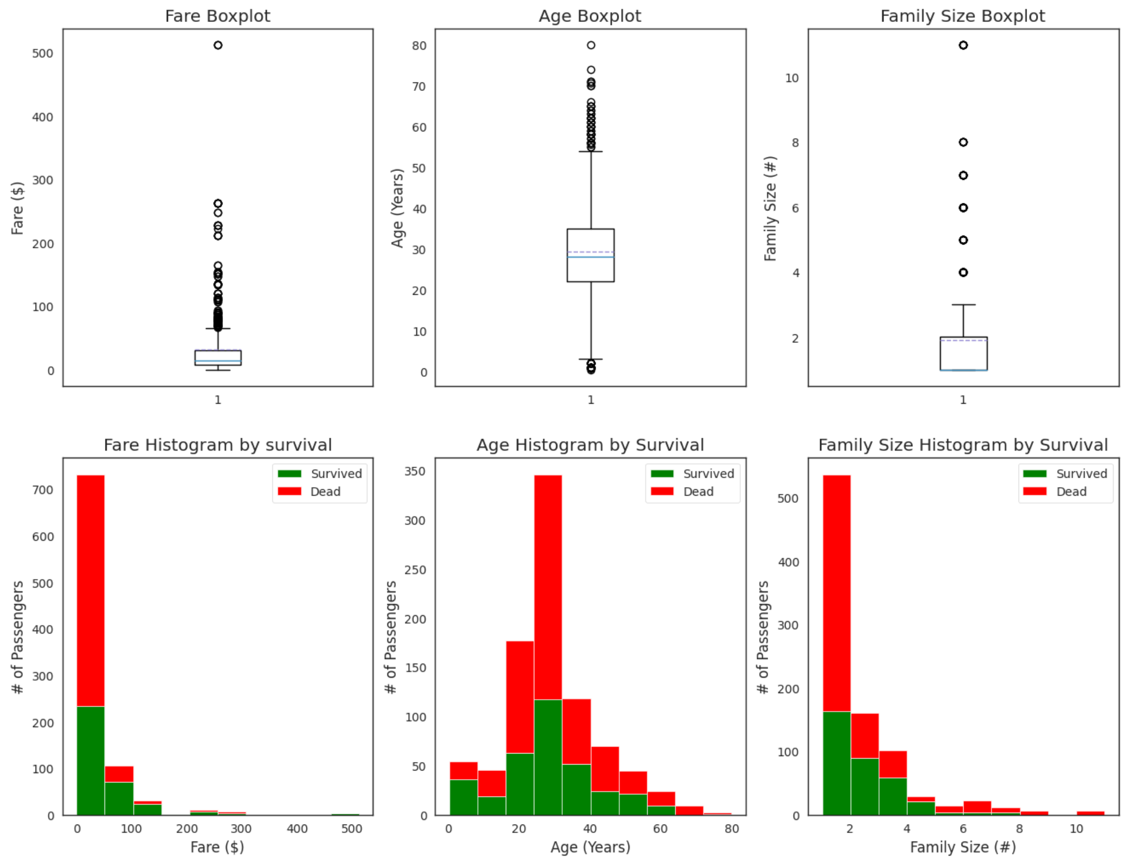
```
Survival Correlation by:  Parch
   Parch  Survived
0      0  0.343658
1      1  0.550847
2      2  0.500000
3      3  0.600000
4      4  0.000000
5      5  0.200000
6      6  0.000000
----------

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]:

```
# 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)
```

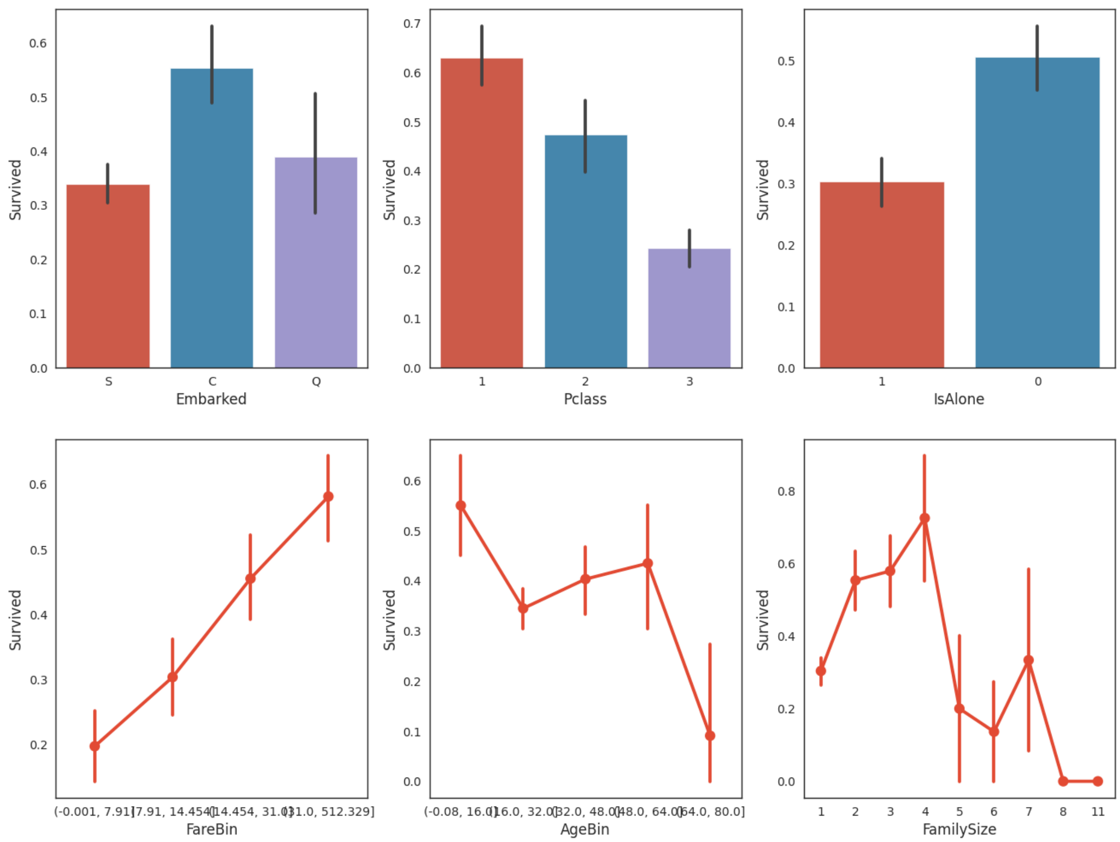
```
plt.boxplot(data1['Age'], showmeans=True,meanline=True)
plt.title('Age Boxplot')
plt.ylabel('Age (Years)')

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>



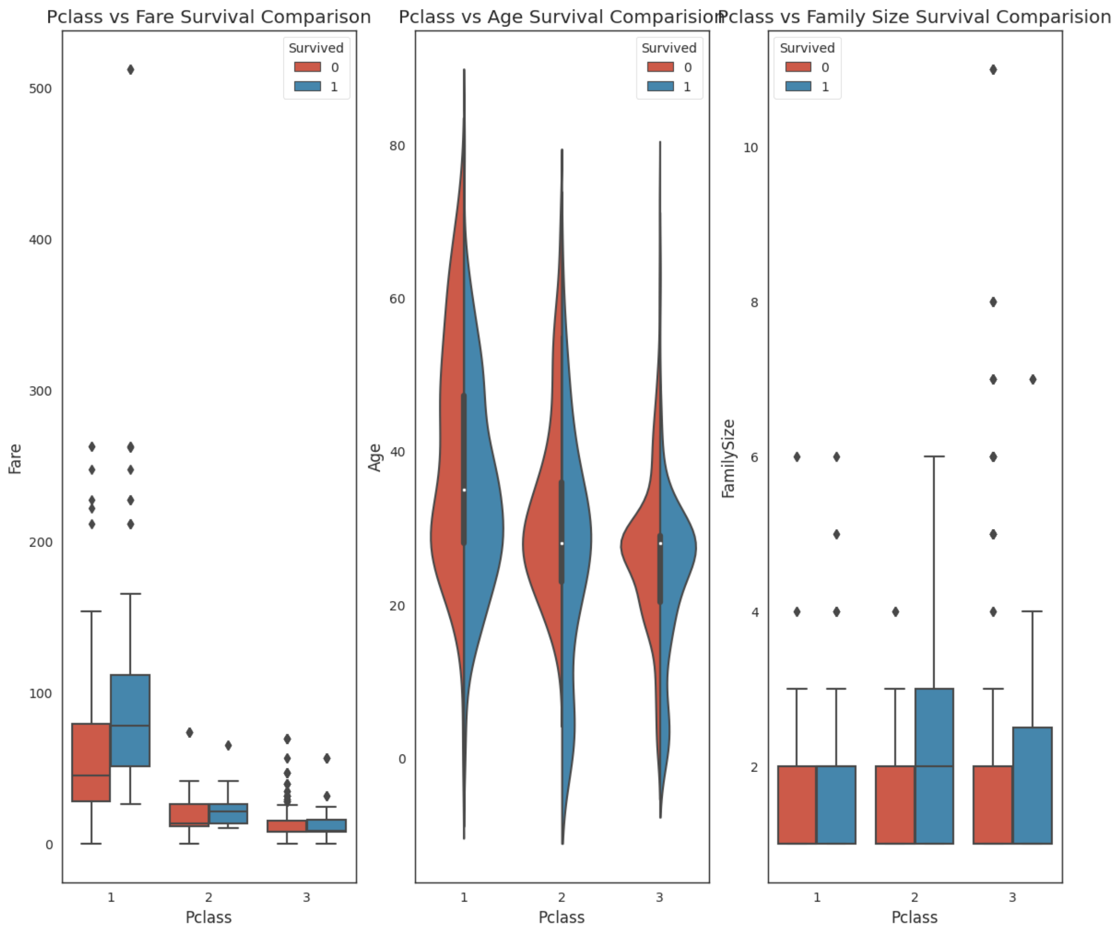

```
[12]: # use seaborn graphics for multi-variable comparision:

      # 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'>
```



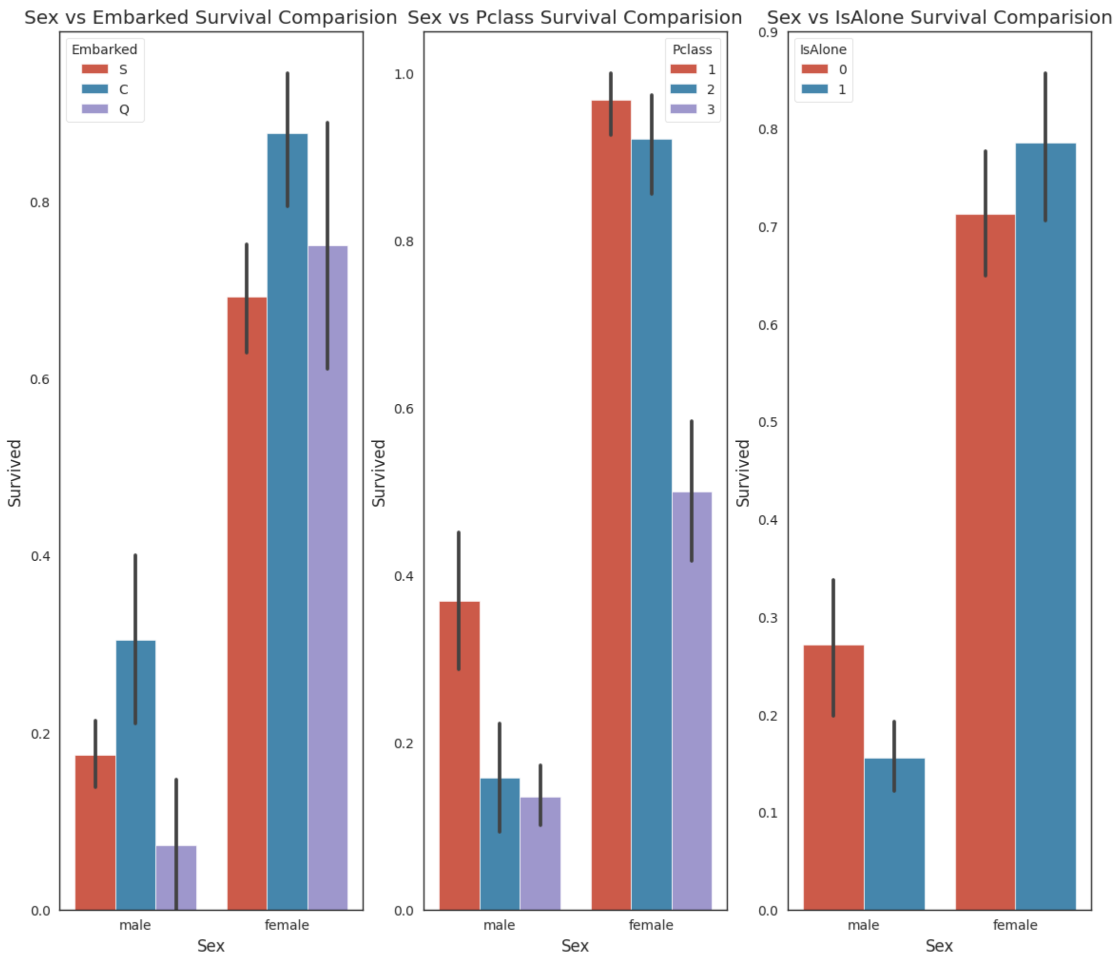
[13]:
```
# graph distribution of qualitative data: Pclass
# compare class and a 2nd feature
fig, (axis1, axis2, axis3)=plt.subplots(1,3,figsize=(14,12))

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]:
```python
# 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')
```

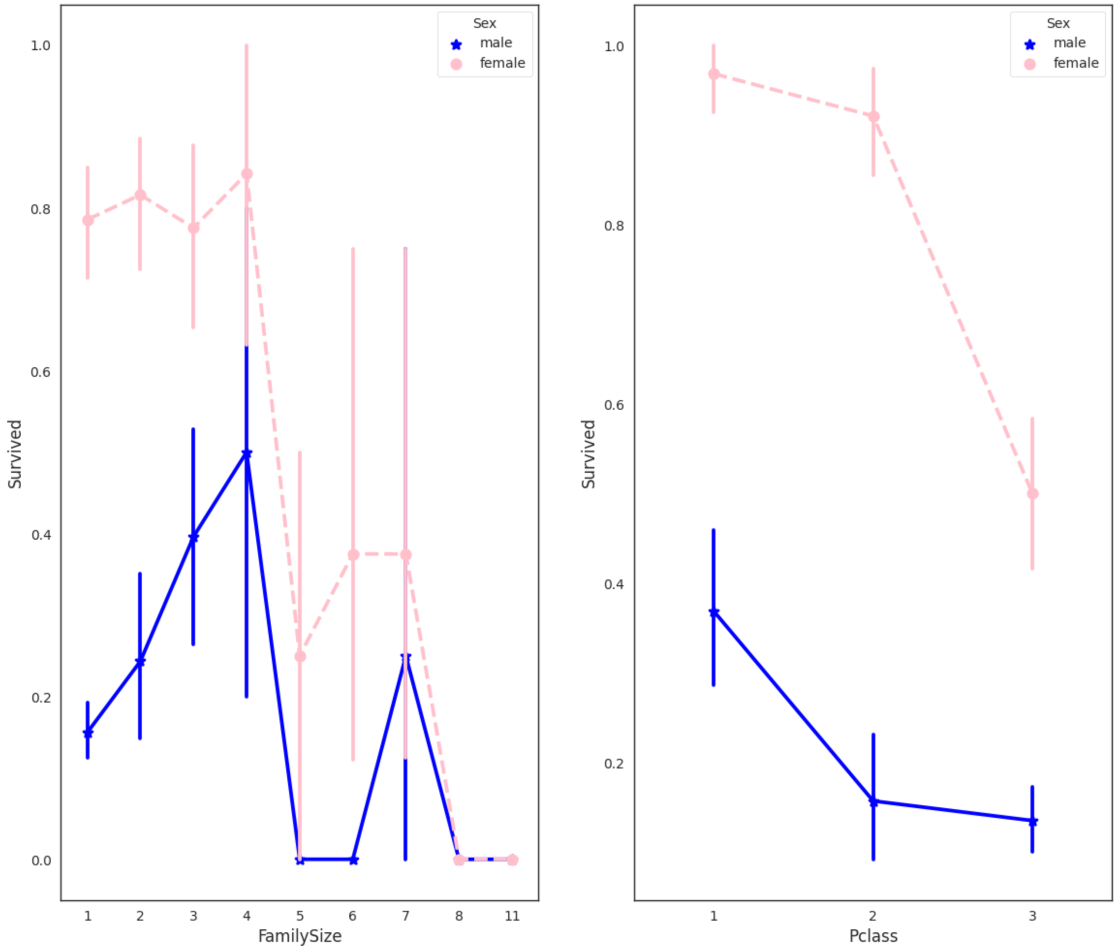


[15]:

```
# 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)
```

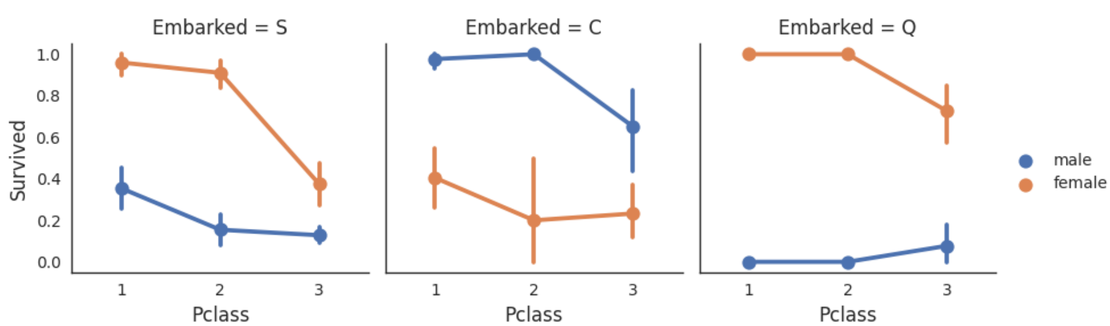
[15]:

```
<Axes: xlabel='Pclass', ylabel='Survived'>
```



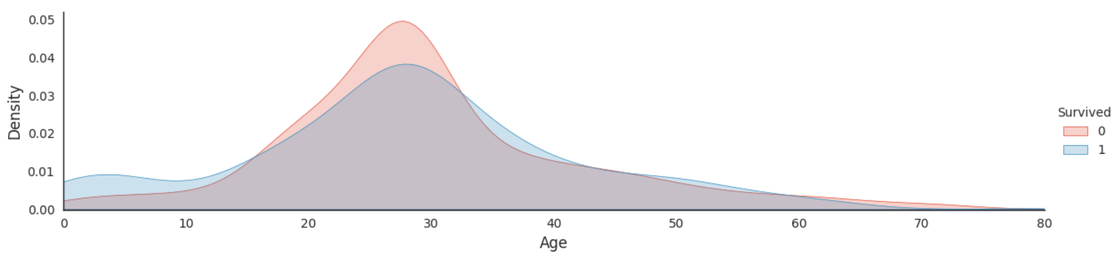
[16]:
```
# how does embark port factor with class, sex, and survival compare
e=sns.FacetGrid(data1,col='Embarked')
e.map(sns.pointplot,'Pclass','Survived','Sex',ci=95.0,palette='deep')
e.add_legend()
```

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



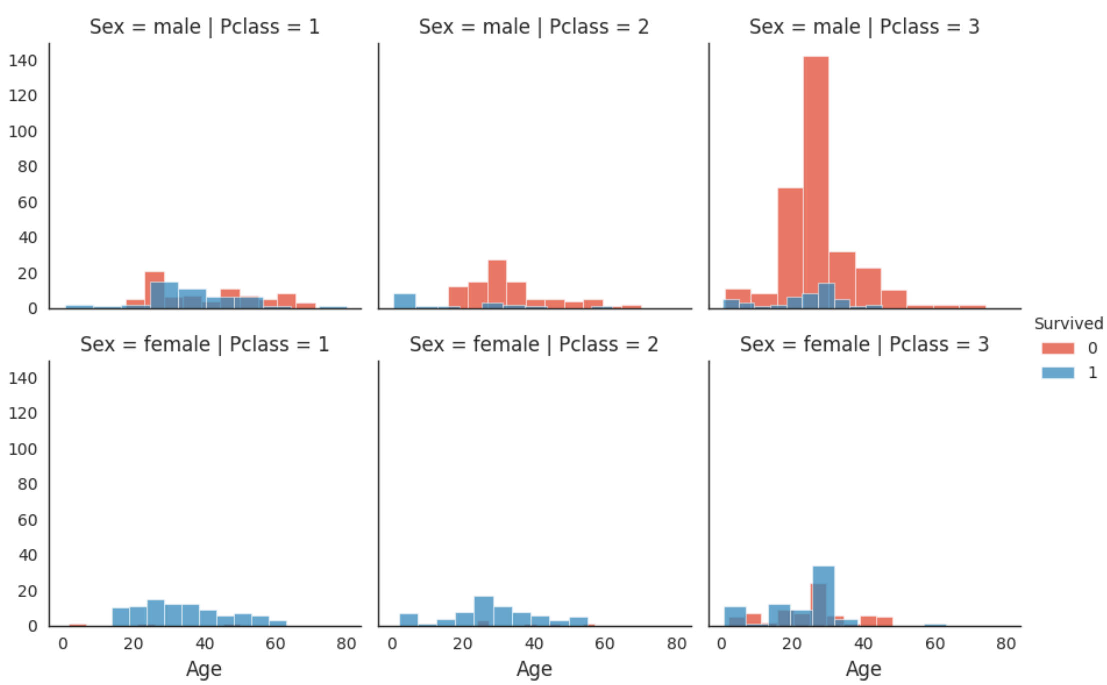
[17]:
```
# plot distributions of age of passengers who survived or did not survive
a=sns.FacetGrid(data1,hue='Survived',aspect=4)
a.map(sns.kdeplot,'Age',shade=True)
a.set(xlim=(0,data1['Age'].max()))
a.add_legend()
```

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



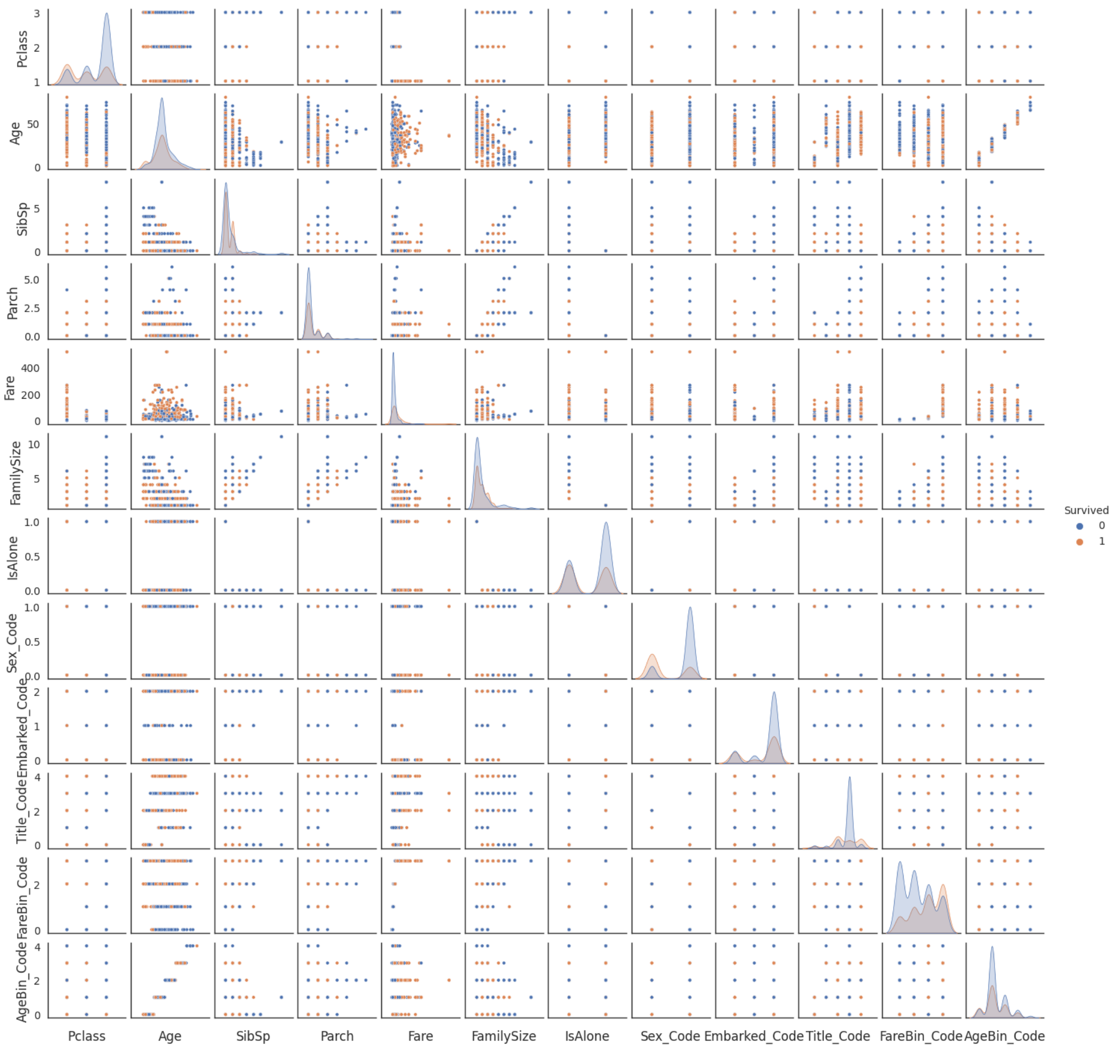
[18]:
```
# historical comparision of sex, class and age by survival
h=sns.FacetGrid(data1,row='Sex',col='Pclass',hue='Survived')
h.map(plt.hist,'Age',alpha=.75)
h.add_legend()
```

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



[19]:
```python
# 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>

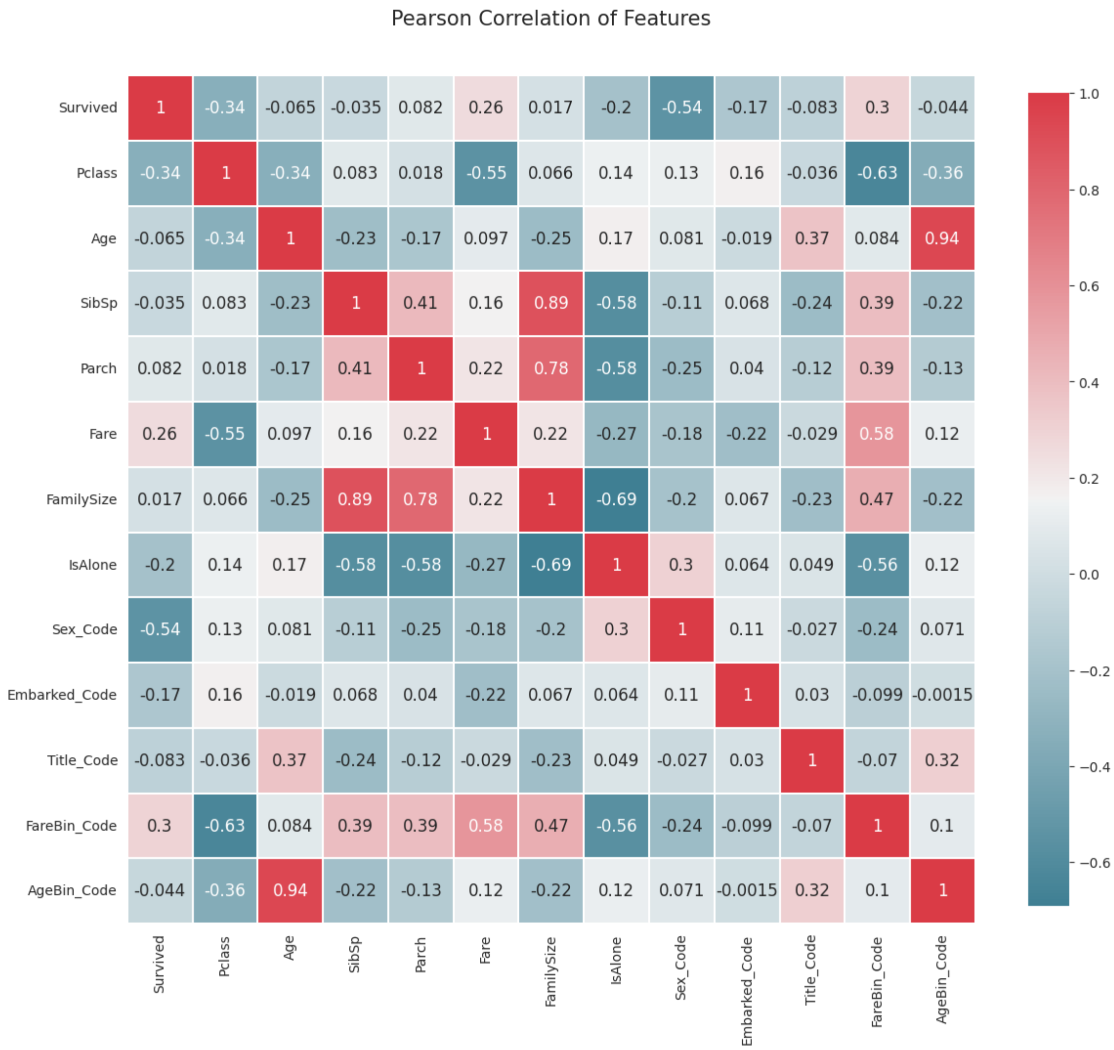


相关系数以 Pearson 相关性公式计算

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

[20]:

```python
# 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	

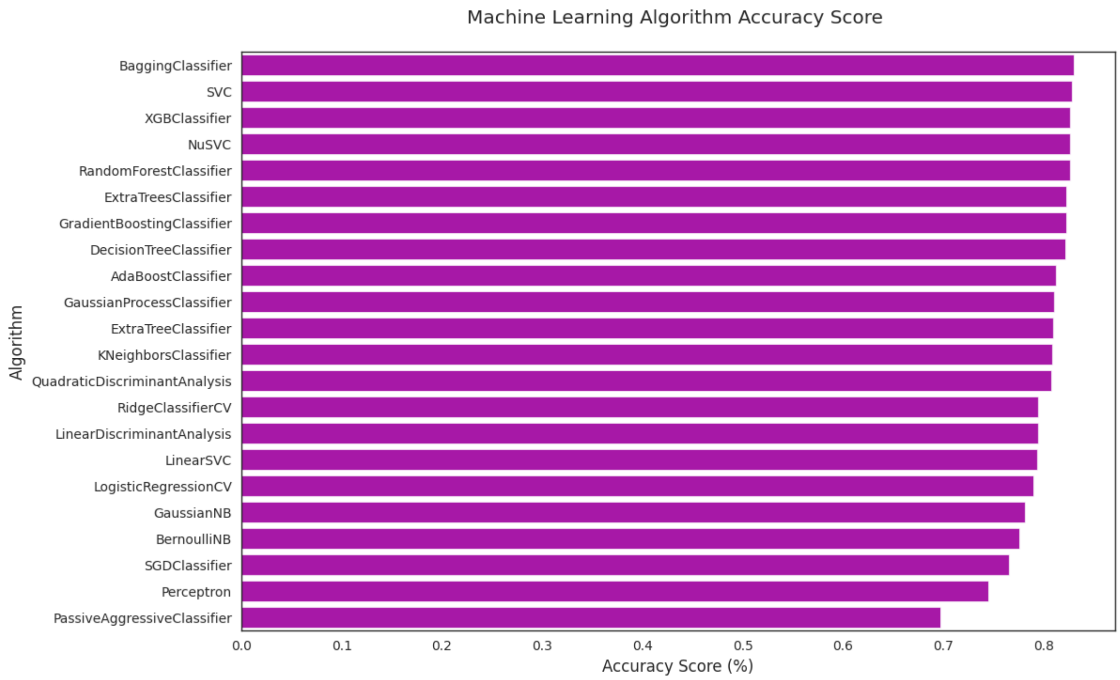
	MLA Test Accuracy Mean	MLA Test Accuracy 3*STD	MLA Time	\
1	0.829478	0.055532	0.012231	
14	0.827612	0.040916	0.022228	
21	0.826493	0.06177	0.045392	
15	0.826119	0.045663	0.026037	
4	0.825746	0.059665	0.070808	
2	0.822761	0.06177	0.053459	
3	0.822761	0.049873	0.048777	
17	0.821269	0.050174	0.001828	
0	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]:

```
# 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)
```

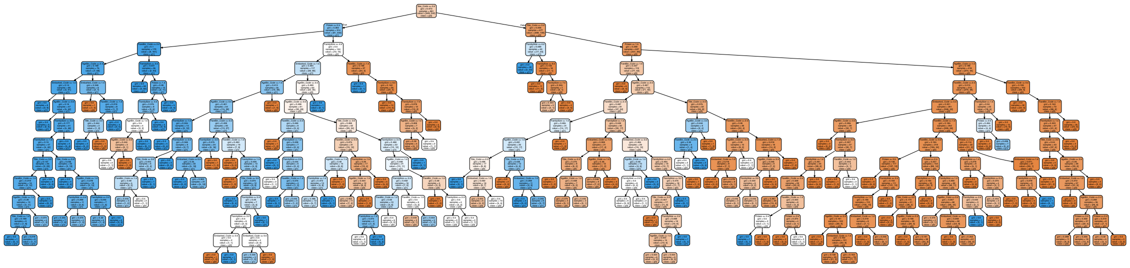
```
print(
    "AFTER DT RFE Training w/bin score mean: {:.2f}".format(
        rfe_results["train_score"].mean() * 100
    )
)
print(
    "AFTER DT RFE Test w/bin score mean: {:.2f}".format(
        rfe_results["test_score"].mean() * 100
    )
)
print(
    "AFTER DT RFE Test w/bin score 3*std: +/- {:.2f}".format(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

```
    "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]:
```
# 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
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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
----------
```