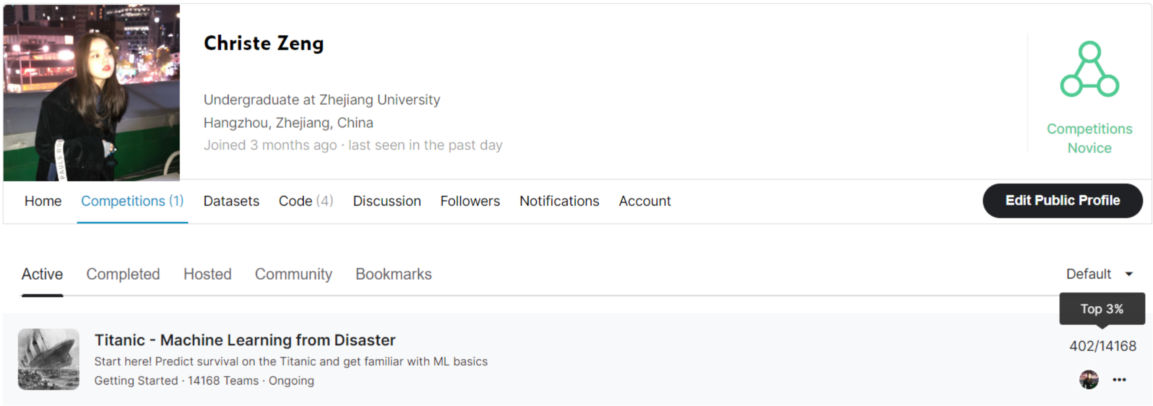
Project: Titanic生存预测竞赛

Introdution

项目介绍

本次项目是在Kaggle上的一个竞赛项目，项目名称为：Titanic: Machine Learning from Disaster。本次实验使用对Titanic上的乘客数据集进行了数据挖掘，并且使用多种预测模型对乘客的生存状态进行了预测。最终也取得了很好的效果，获得了Kaggle竞赛排名的Top3%。

在此实验中，我采用多种模型，多种参数和多种随机状态选择，在随机森林的最优调参上取得了最佳的结果，为方便起见我将预测文件一并提交并且描述了我的所有尝试过程。因为随机种子和交叉验证的分类集每次都会有比较大的差别，所以分数也会随着每次提交不断改变，在这里我附上了最佳结果的分数和预测文件my_best_submission.csv。



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Titanic - Machine Learning from Disaster
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项目流程

本次实验采用了数据挖掘的经典流程进行处理：数据集分析与可视化，数据清洗与特征提取和训练模型

- 数据分析与可视化：主要使用python可视化库对数据集重要部分做了分析
- 数据清洗：使用Pandas读取数据，并对数据进行清洗，包括数据清洗、缺失值填充、特征工程、数据分割等。
- 训练模型：尝试了大量模型，包括随机森林、决策树、支持向量机、KNN、SVM、逻辑回归、梯度提升树、神经网络等。

主要方法与尝试

本项目主要使用的方法与模型有：

- 决策模型使用：
  - GBDT：Gradient Boosting Decision Tree，梯度提升决策树。
  - XGBoost：深度学习决策框架。
  - Random Forest：随机森林。
  - SVMC：Support Vector Machine Classifier，支持向量机分类器。
- 组合预测模型的使用：使用投票树将上述决策模型进行ensemble。

数据集介绍

本此比赛的数据集为Titanic上的乘客信息，具体的属性介绍如下：

- PassengerId：乘客的编号。
- Pclass：乘客的船舱等级，1为经济舱，2为豪华舱，3为商务舱。
- Survived：乘客是否存活，0为死亡，1为生存。
- Name：乘客的姓名。
- Sex：乘客的性别
- Age：乘客的年龄
- SibSp：乘客的兄弟姐妹与配偶数量
- Parch：乘客的父母与子女数量
- Ticket：乘客的票的编号
- Fare：票价
- Cabin：乘客的座位号
- Embarked：乘客的登船港口

数据集分析与可视化

In [45…

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
```

加载数据集

加载训练数据集，并且通过descibe()方法和isnull()方法对数据集进行简单的初步分析

In [45…

```
test_data = pd.read_csv("kaggle/input/titanic/test.csv")
train_data = pd.read_csv("kaggle/input/titanic/train.csv")
```

数据集加载后的大致结构如下：

In [45…

```
train_data.head()
```

Out[459]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN

通过isnull()函数可以看到有大量缺失值需要处理

In [46…

```
train_data.isnull().sum()
```

Out[460]:

```
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
```

缺失值分析

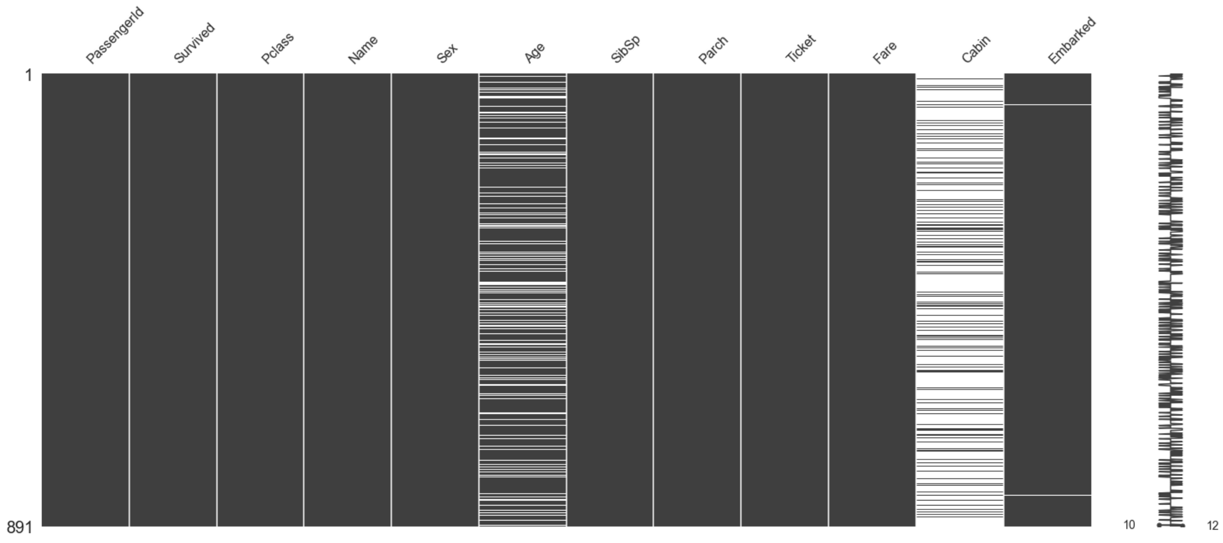
在这一部分我们可以简单的分析一下缺失值的分布和缺失值之间的关系，为后续数据清洗做准备。首先可以通过missingno库可视化的查看缺失的数据情况，可以看到乘客的年龄和Cabin信息缺失比较严重

In [46…

```
import missingno as msno
msno.matrix(train_data)
```

Out[461]:

```
<AxesSubplot:>
```



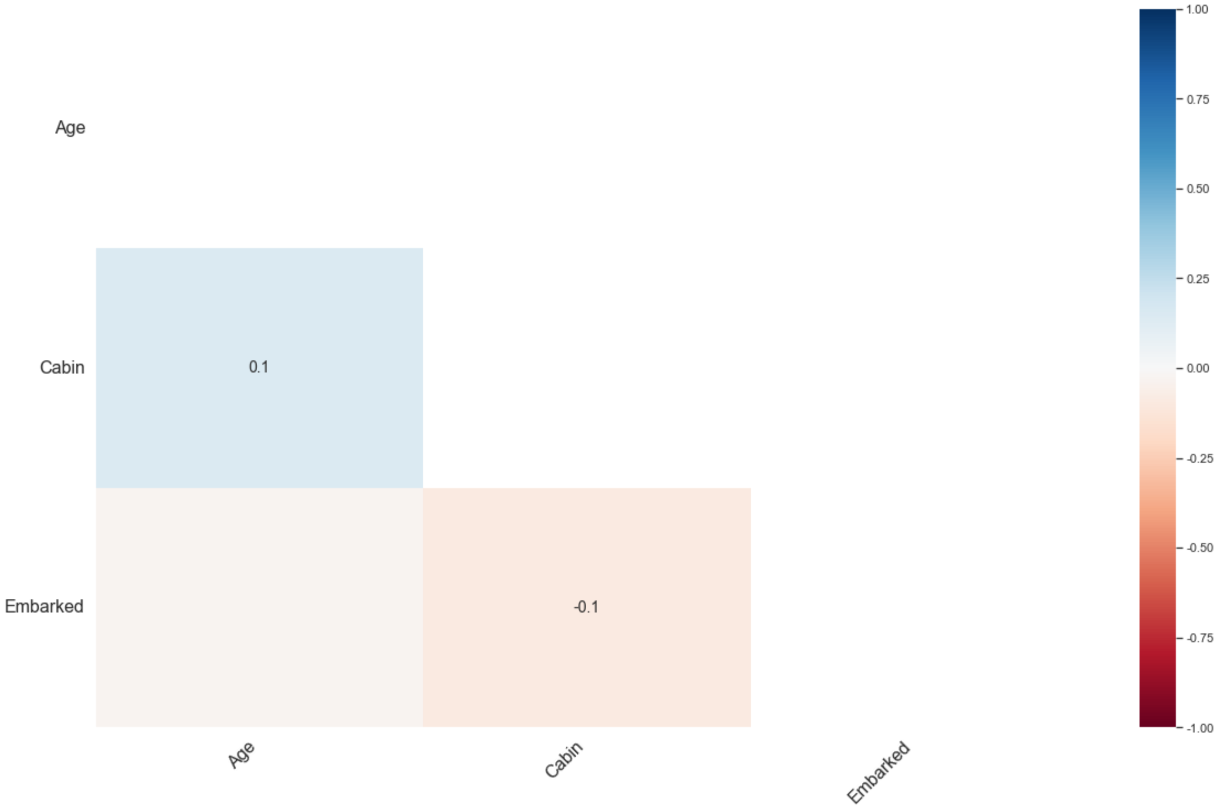
为了更好的对缺失的数据进行处理，我们先通过missingno库方法查看缺失数据的heatmap，以期找到缺失数据与其它数据的相关性，我们通过结果得知它们之间的联系不大，可以单独进行处理

In [46…

```
msno.heatmap(train_data)
```

Out[462]:

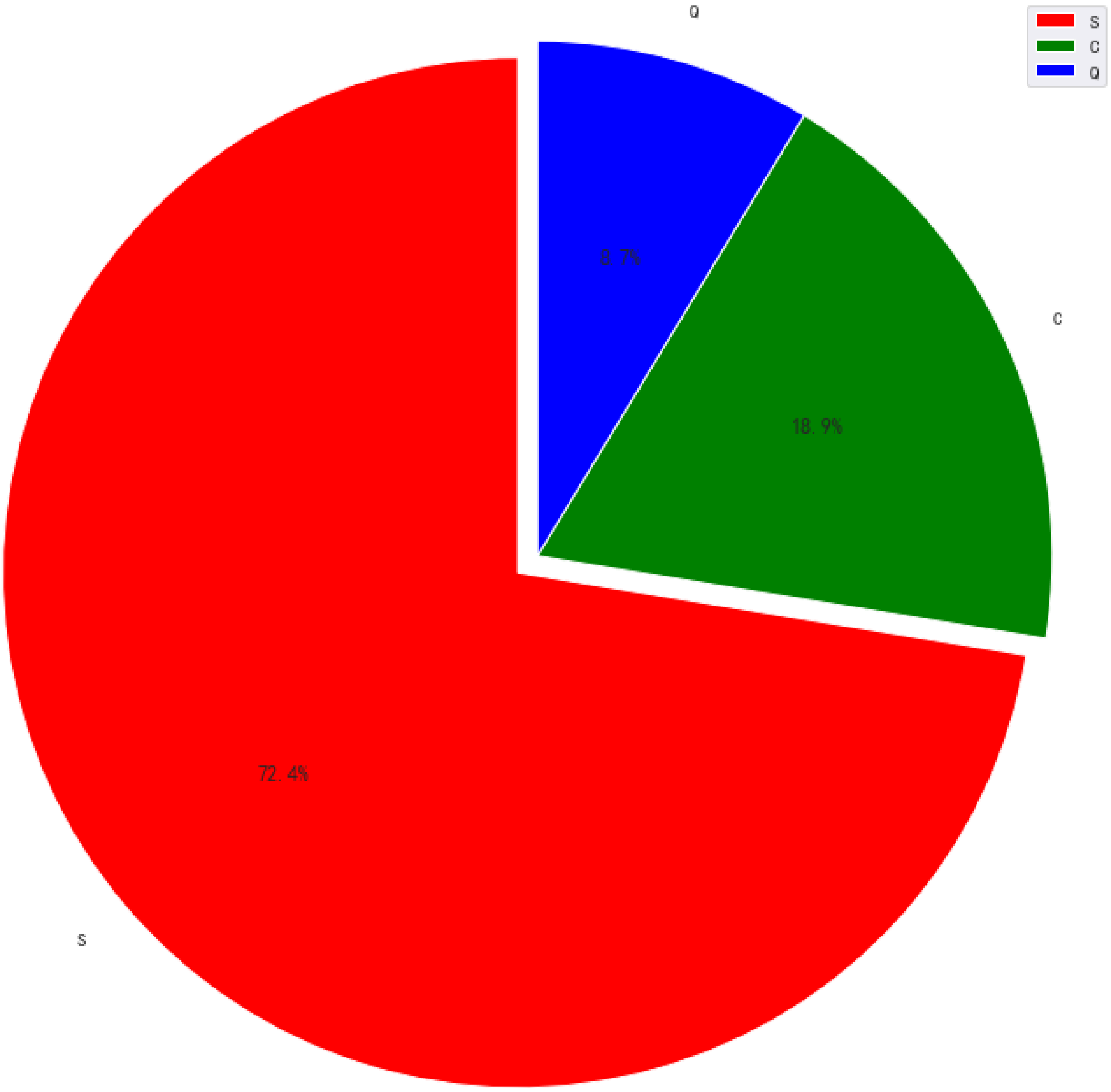
```
<AxesSubplot:>
```



为了填补缺失数较少的Embarked(登船港口)信息，我们可以先通过饼状图了解Embarked的分布，并且在以后选择分布最多的编号来进行填补。

In [46…

```
import matplotlib.pyplot as plt
import matplotlib

matplotlib.rcParams['font.sans-serif'] = ['SimHei']
matplotlib.rcParams['axes.unicode_minus'] = False

label_list = ["S", "C", "Q"]
size = [train_data['Embarked'].value_counts()[0], train_data['Embarked'].value_counts
color = ["red", "green", "blue"]
explode = [0.05, 0, 0]

patches, l_text, p_text = plt.pie(size, explode=explode, colors=color, labels=label_l
plt.axis("equal")
plt.legend()
plt.show()
```



从上图得知，大部分乘客的Embarked都是S，所以我们合理猜测缺失数据为'S'的可能性最大

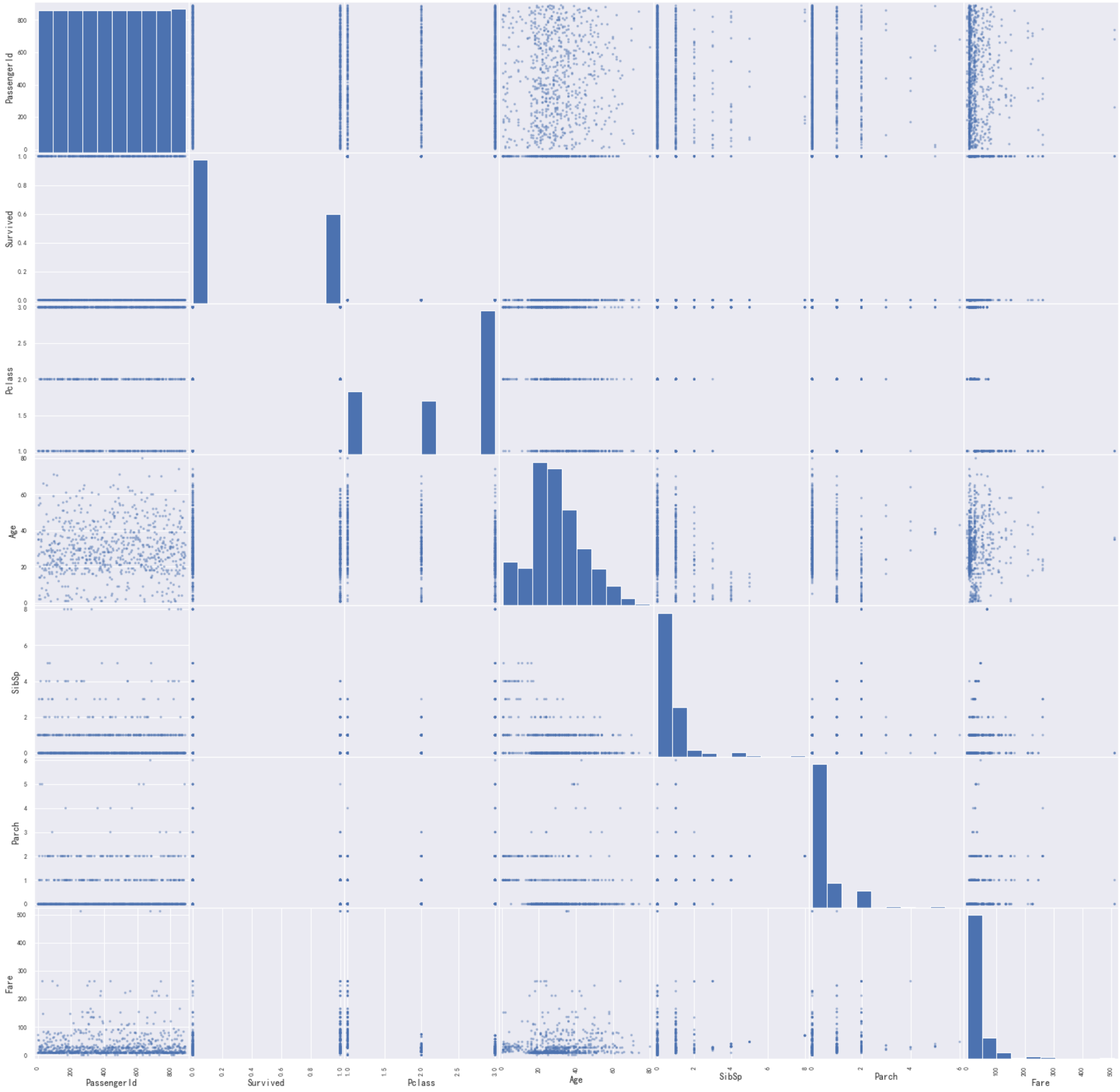
虽然Embarked属性的填充比较简单，但对于乘客年龄的填充是本次实验的非常棘手也是非常关键的一点，因为年龄数据可能需要使用随机森林依赖其他属性数据生成，所以我首先使用scatter matrix(矩阵散点图)来展示数据之间的相关性，并且给出heatmap。

In [46…

```
from pandas.plotting import scatter_matrix
scatter_matrix(train_data, figsize = (25, 25))
```

Out[464]:

```
array([[<AxesSubplot:xlabel=’PassengerId’, ylabel=’PassengerId’>,
        <AxesSubplot:xlabel=’Survived’, ylabel=’PassengerId’>,
        <AxesSubplot:xlabel=’Pclass’, ylabel=’PassengerId’>,
        <AxesSubplot:xlabel=’Age’, ylabel=’PassengerId’>,
        <AxesSubplot:xlabel=’SibSp’, ylabel=’PassengerId’>,
        <AxesSubplot:xlabel=’Parch’, ylabel=’PassengerId’>,
        <AxesSubplot:xlabel=’Fare’, ylabel=’PassengerId’>],
       [<AxesSubplot:xlabel=’PassengerId’, ylabel=’Survived’>,
        <AxesSubplot:xlabel=’Survived’, ylabel=’Survived’>,
        <AxesSubplot:xlabel=’Pclass’, ylabel=’Survived’>,
        <AxesSubplot:xlabel=’Age’, ylabel=’Survived’>,
        <AxesSubplot:xlabel=’SibSp’, ylabel=’Survived’>,
        <AxesSubplot:xlabel=’Parch’, ylabel=’Survived’>,
        <AxesSubplot:xlabel=’Fare’, ylabel=’Survived’>],
       [<AxesSubplot:xlabel=’PassengerId’, ylabel=’Pclass’>,
        <AxesSubplot:xlabel=’Survived’, ylabel=’Pclass’>,
        <AxesSubplot:xlabel=’Pclass’, ylabel=’Pclass’>,
 <AxesSubplot:xlabel='Age’, ylabel='Pclass’>,
 <AxesSubplot:xlabel='SibSp’, ylabel='Pclass’>,
 <AxesSubplot:xlabel='Parch’, ylabel='Pclass’>,
 <AxesSubplot:xlabel='Fare’, ylabel='Pclass’>],
[<AxesSubplot:xlabel='PassengerId’, ylabel='Age’>,
 <AxesSubplot:xlabel='Survived’, ylabel='Age’>,
 <AxesSubplot:xlabel='Pclass’, ylabel='Age’>,
 <AxesSubplot:xlabel='Age’, ylabel='Age’>,
 <AxesSubplot:xlabel='SibSp’, ylabel='Age’>,
 <AxesSubplot:xlabel='Parch’, ylabel='Age’>,
 <AxesSubplot:xlabel='Fare’, ylabel='Age’>],
[<AxesSubplot:xlabel='PassengerId’, ylabel='SibSp’>,
 <AxesSubplot:xlabel='Survived’, ylabel='SibSp’>,
 <AxesSubplot:xlabel='Pclass’, ylabel='SibSp’>,
 <AxesSubplot:xlabel='Age’, ylabel='SibSp’>,
 <AxesSubplot:xlabel='SibSp’, ylabel='SibSp’>,
 <AxesSubplot:xlabel='Parch’, ylabel='SibSp’>,
 <AxesSubplot:xlabel='Fare’, ylabel='SibSp’>],
[<AxesSubplot:xlabel='PassengerId’, ylabel='Parch’>,
 <AxesSubplot:xlabel='Survived’, ylabel='Parch’>,
 <AxesSubplot:xlabel='Pclass’, ylabel='Parch’>,
 <AxesSubplot:xlabel='Age’, ylabel='Parch’>,
 <AxesSubplot:xlabel='SibSp’, ylabel='Parch’>,
 <AxesSubplot:xlabel='Parch’, ylabel='Parch’>,
 <AxesSubplot:xlabel='Fare’, ylabel='Parch’>],
[<AxesSubplot:xlabel='PassengerId’, ylabel='Fare’>,
 <AxesSubplot:xlabel='Survived’, ylabel='Fare’>,
 <AxesSubplot:xlabel='Pclass’, ylabel='Fare’>,
 <AxesSubplot:xlabel='Age’, ylabel='Fare’>,
 <AxesSubplot:xlabel='SibSp’, ylabel='Fare’>,
 <AxesSubplot:xlabel='Parch’, ylabel='Fare’>,
 <AxesSubplot:xlabel='Fare’, ylabel='Fare’>]], dtype=object)
```

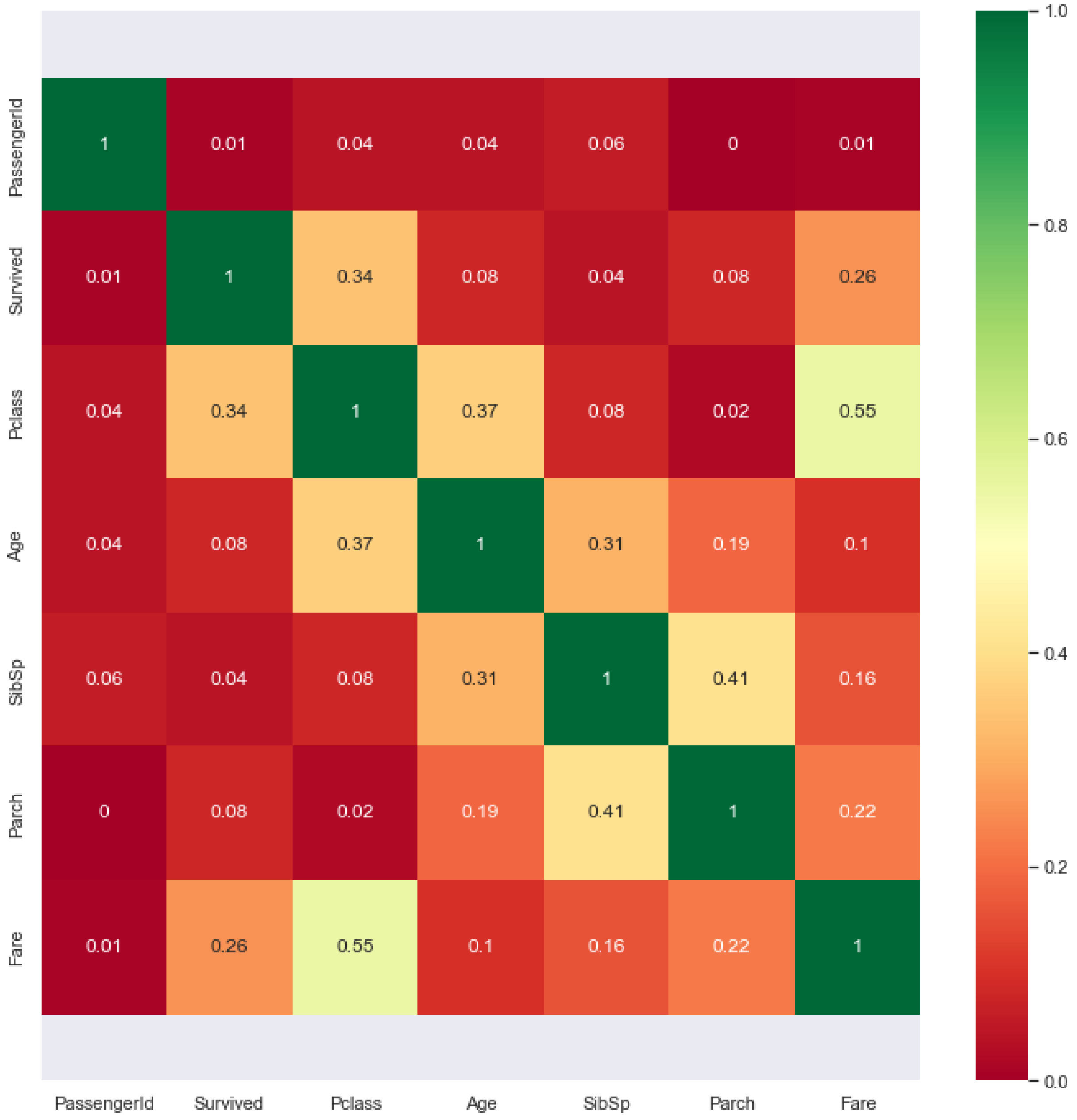


In [46…

```
import seaborn as sns
correlation_matrix = np.absolute(train_data.corr().round(2))
sns.set(rc={'figure.figsize':(12, 12)})
ax = sns.heatmap(correlation_matrix, annot=True, cmap='RdYlGn')
bottom, top = ax.get_ylim()
ax.set_ylim(bottom + 0.5, top - 0.5)
```

Out[465]:

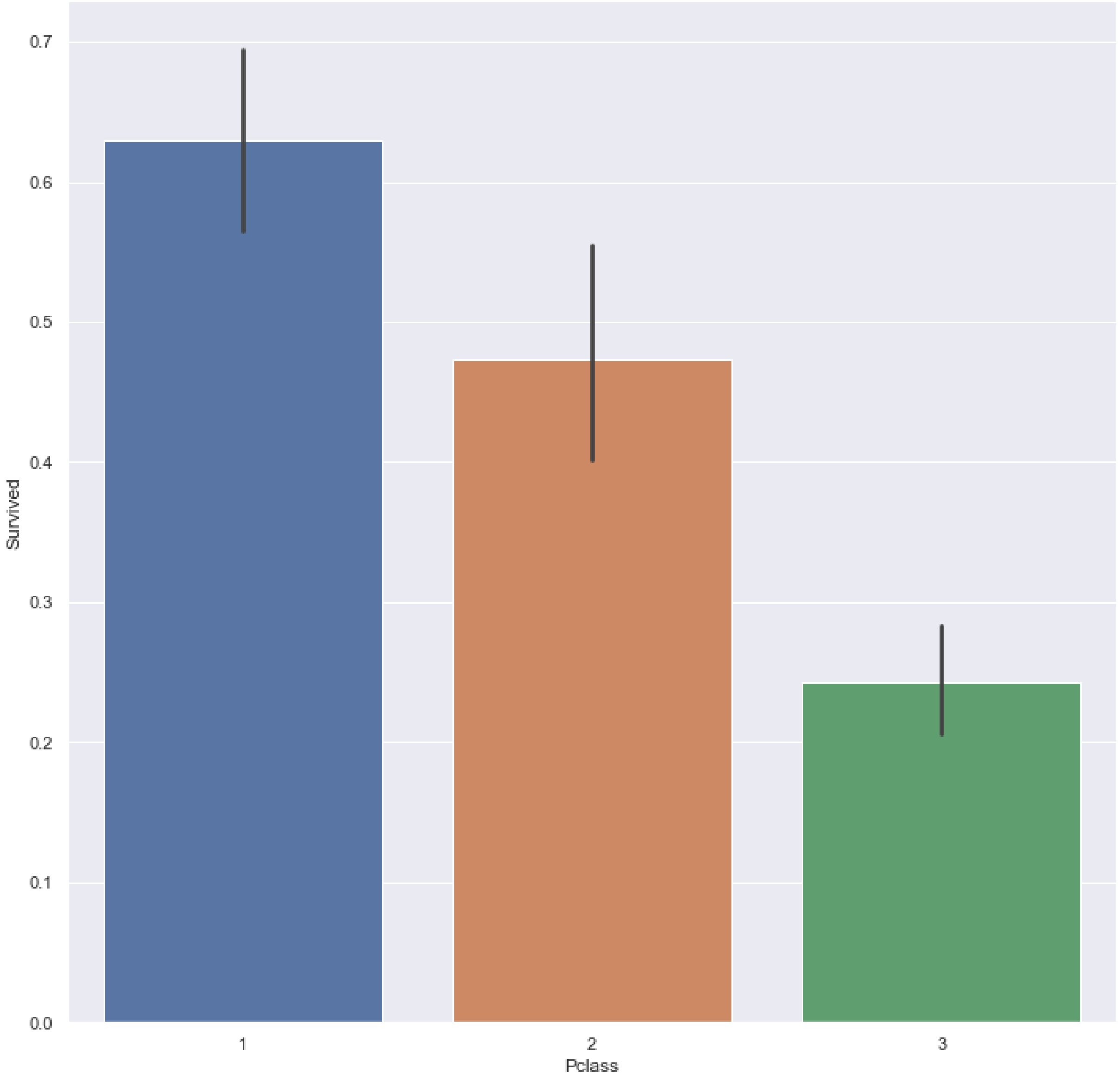
```
(7.5, -0.5)
```



从上面两张图我们可以直观地看到一些关系。比如生存率可能与PClass(舱位)，Fare(票价)联系比较紧密，后续操作可能会优先从这两个因素入手。同时从heatmap我们也可得知票价与舱位的相关性比较大，符合直觉。下面就要使用条形图和箱线图等对生存率与其他数据之间的联系进行进一步的分析。

```
In  [46⋯

sns.barplot(x='Pclass',y='Survived',data=train_data)
```

```
Out[466]:  <AxesSubplot:xlabel='Pclass', ylabel='Survived'>
```



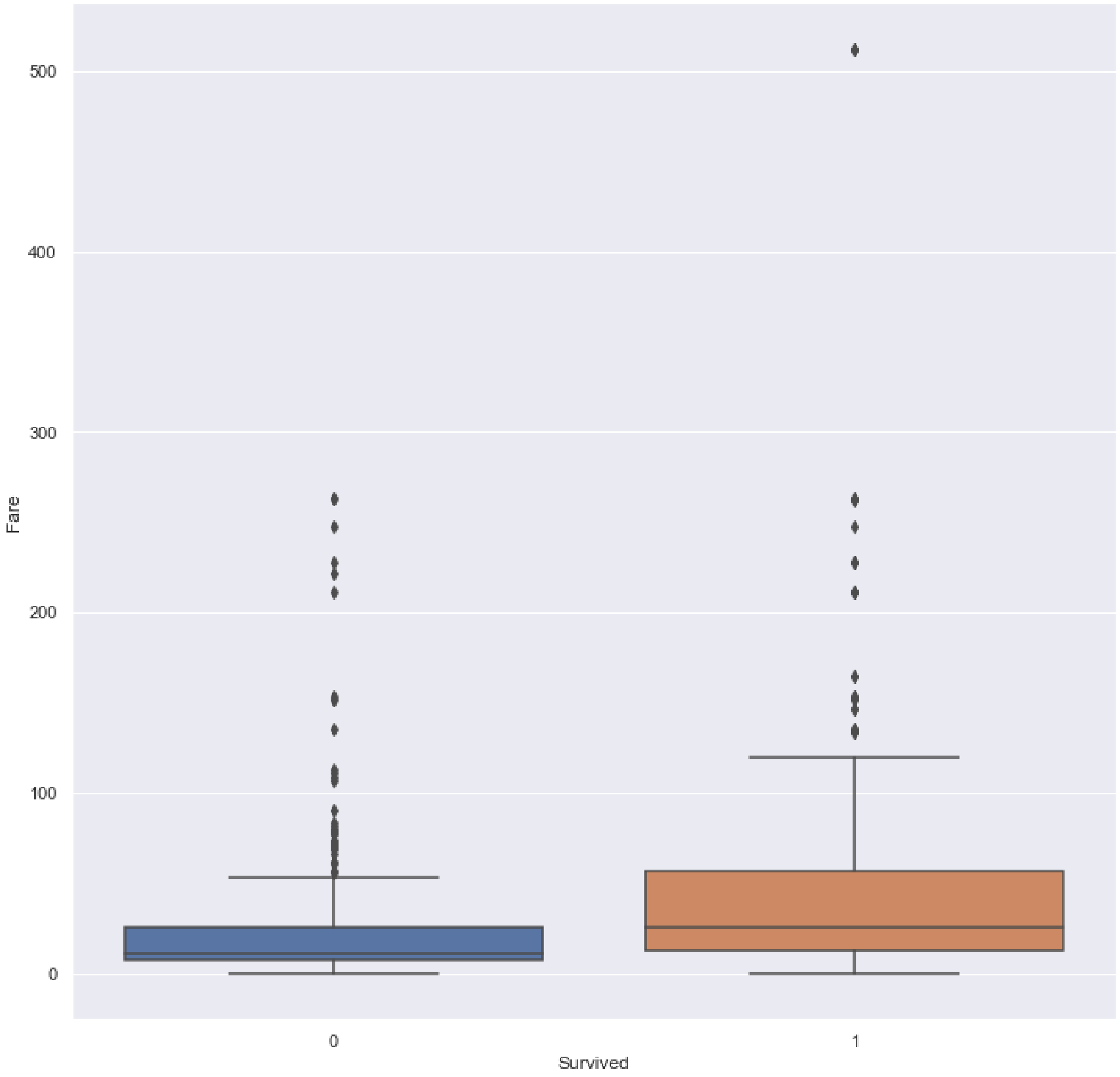
从上条形可以看到生存率与舱位之间的关系，舱位1的生存率明显高于其他两个舱位，达到了62%左右的生存率。

In [46…

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

Out[467]:

```
<AxesSubplot:xlabel='Survived', ylabel='Fare'>
```

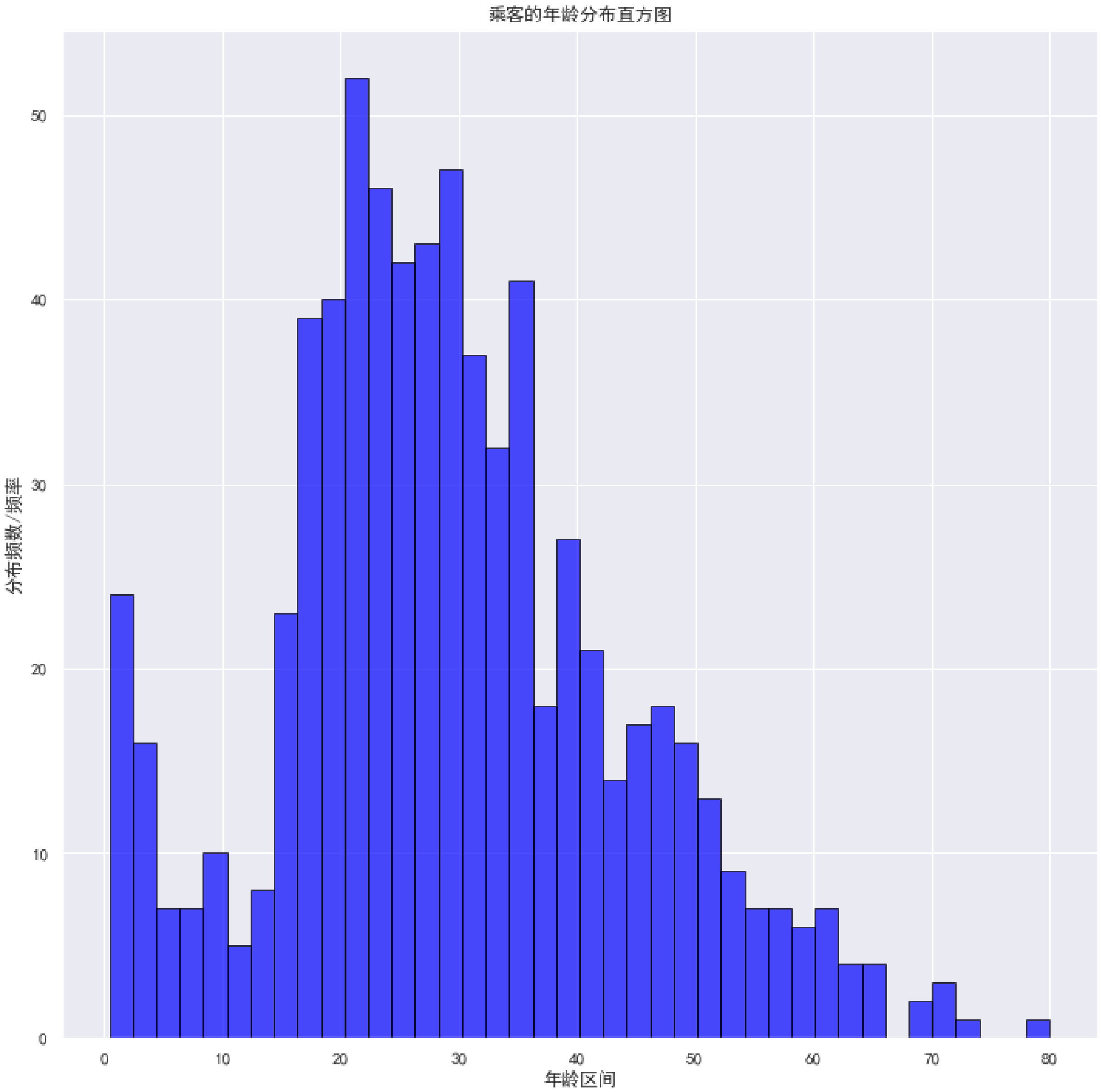


前面我们提到过票价与舱位联系比较紧密，所以我们就可以推测生存率与票价也有一定的联系，在这里我们通过箱线图来可视化两者之间的关系。从上图可以看到，生存下来的乘客购买的票价明显高于死亡乘客。除了舱位与票价之外，我们不难通过经验推测出性别和年龄也与生存率有一定的关系。下面我们就借助几个常用的可视化工具来进行分析。

首先可以对乘客的年龄分布做一个简单分析，获取大概的认知。通过直方图可以得知年龄分布主要集中在20-40岁之间。并且我还使用Q-Q图去分析年龄分布是否符合正态分析，但从结果来看年龄的正态分布趋势不明显。

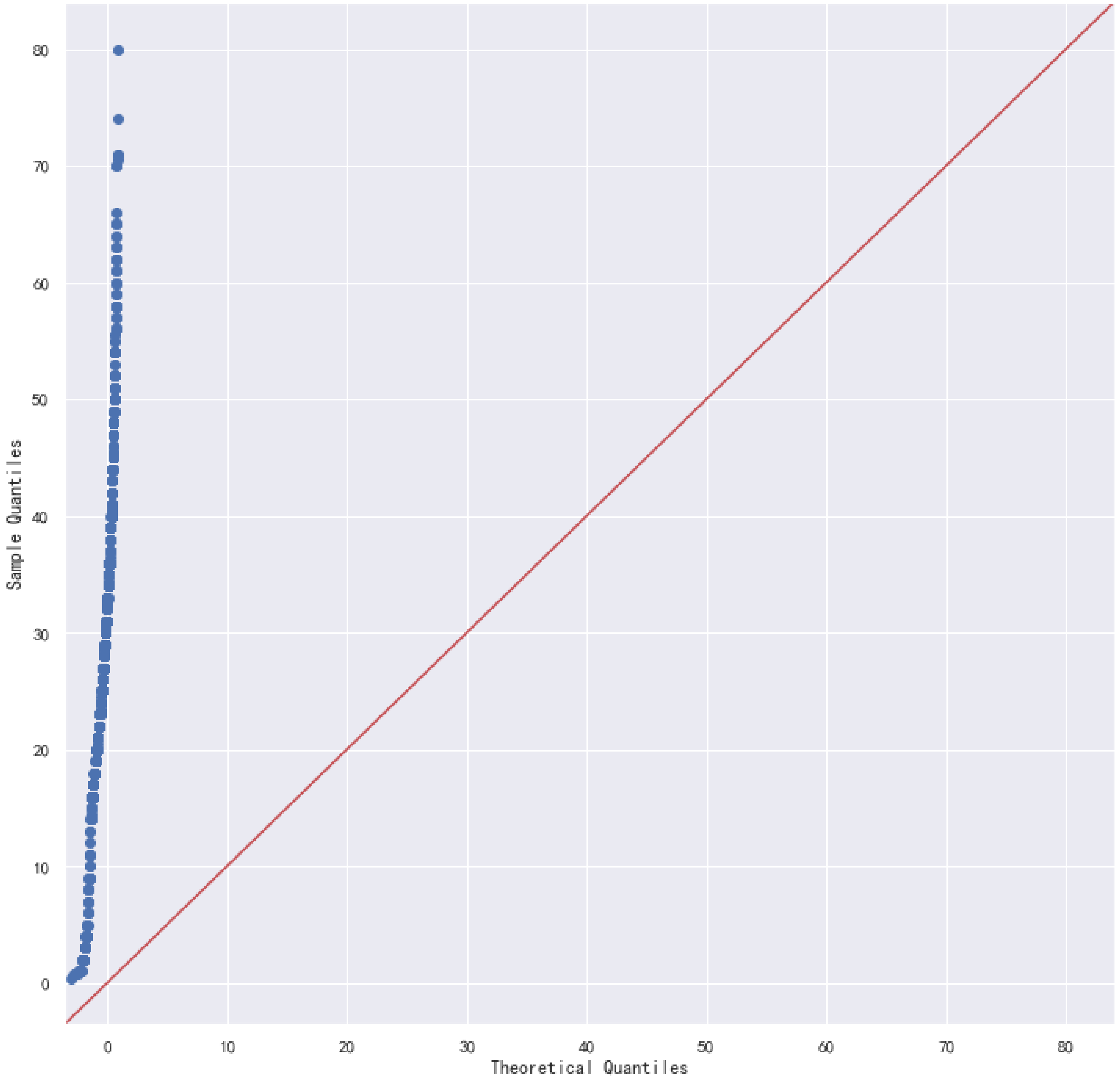
In [46…

```
import matplotlib.pyplot as plt
import numpy as np
import matplotlib

matplotlib.rcParams['font.sans-serif'] = ['SimHei']
matplotlib.rcParams['axes.unicode_minus'] = False

plt.hist(train_data['Age'], bins = 40, facecolor = "blue", edgecolor = "black", alpha
plt.xlabel("年龄区间")
plt.ylabel("分布频数/频率")
plt.title("乘客的年龄分布直方图")
plt.show()
```



In [46…

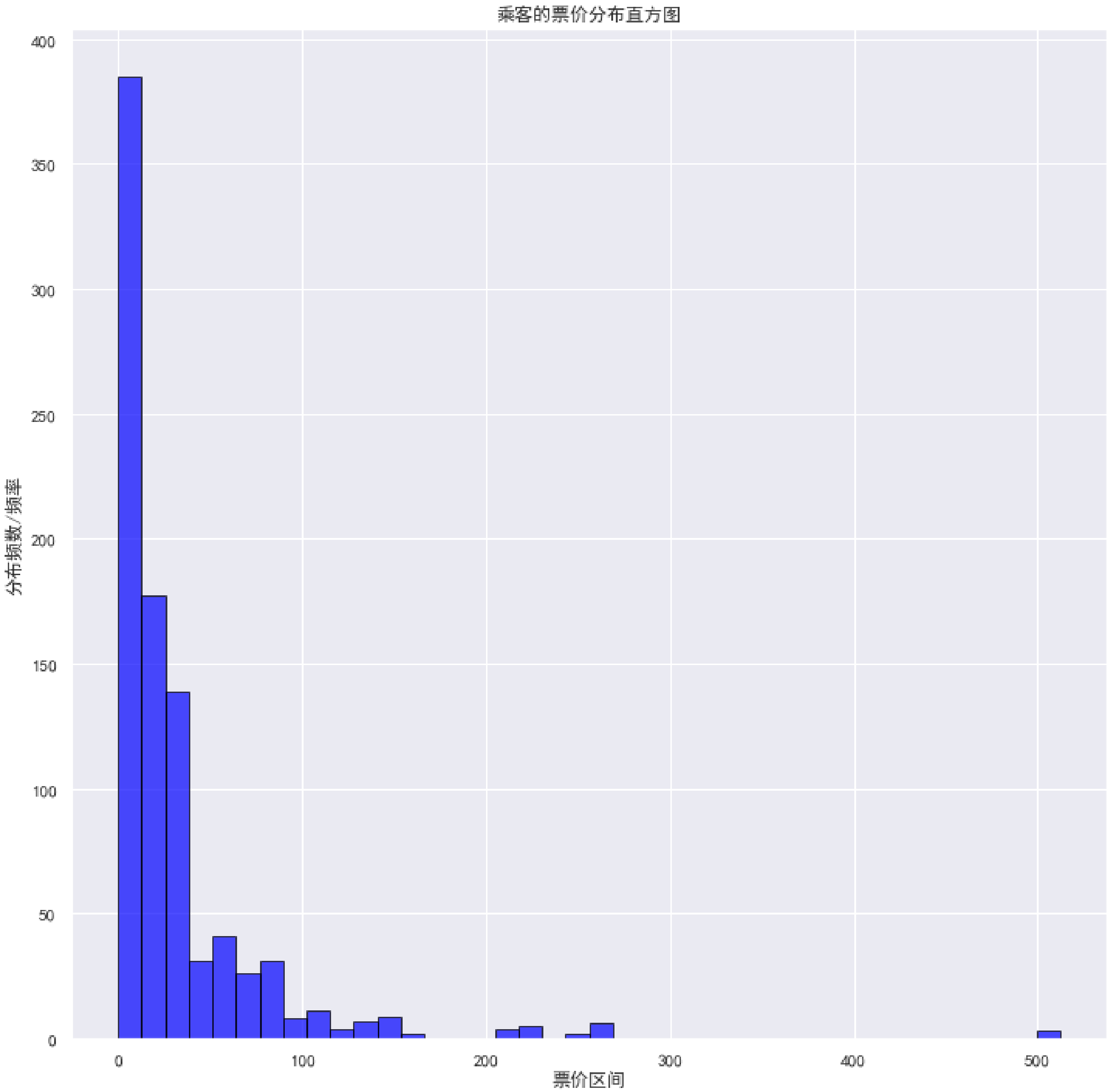
```
import scipy.stats as stats
import statsmodels.api as sm
import pylab as py

sm.qqplot(train_data['Age'], line ='45')
py.show()
```



前面提到票价与生存率有紧密的联系，那么票价分布与年龄分布是否有某种联系呢？我们可以通过直方图来统计票价的分布，并且将其与年龄分步进行对比。可以看到票价大部分分布在低价区间。

In [47…

```
import matplotlib.pyplot as plt
import numpy as np
import matplotlib

matplotlib.rcParams['font.sans-serif'] = ['SimHei']
matplotlib.rcParams['axes.unicode_minus'] = False

plt.hist(train_data['Fare'], bins = 40, facecolor = "blue", edgecolor = "black", alph
plt.xlabel("票价区间")
plt.ylabel("分布频数/频率")
plt.title("乘客的票价分布直方图")
plt.show()
```



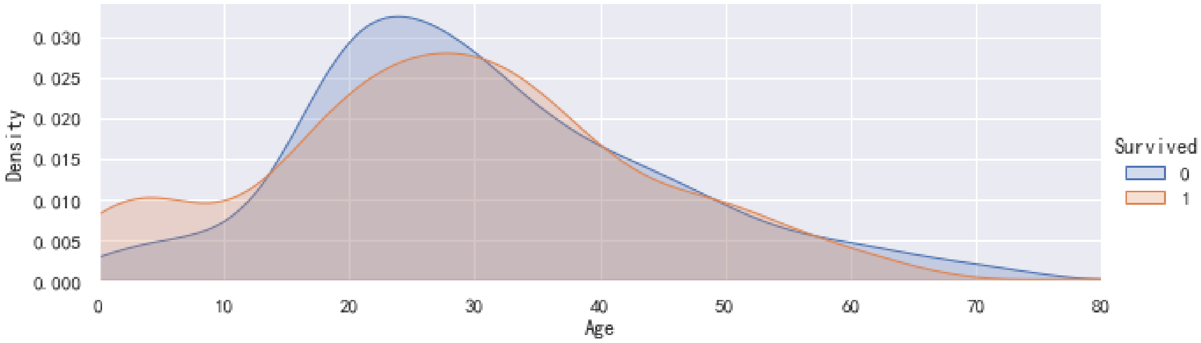
知道了年龄分布之后，我们就可以分析年龄与生存率之间的关系，这里使用FacetGrid来对数据进行统计，可以清楚地看出年龄与生存率的分布，从图中可以明显看出0-10岁的乘客生存率最高

In [47…

```
ageFacet = sns.FacetGrid(train_data,hue='Survived',aspect=3)
ageFacet.map(sns.kdeplot,'Age',shade=True)
ageFacet.set(xlim=(0,train_data['Age'].max()))
ageFacet.add_legend()
```

Out[471]:

```
<seaborn.axisgrid.FacetGrid at 0x2ac85ad1160>
```



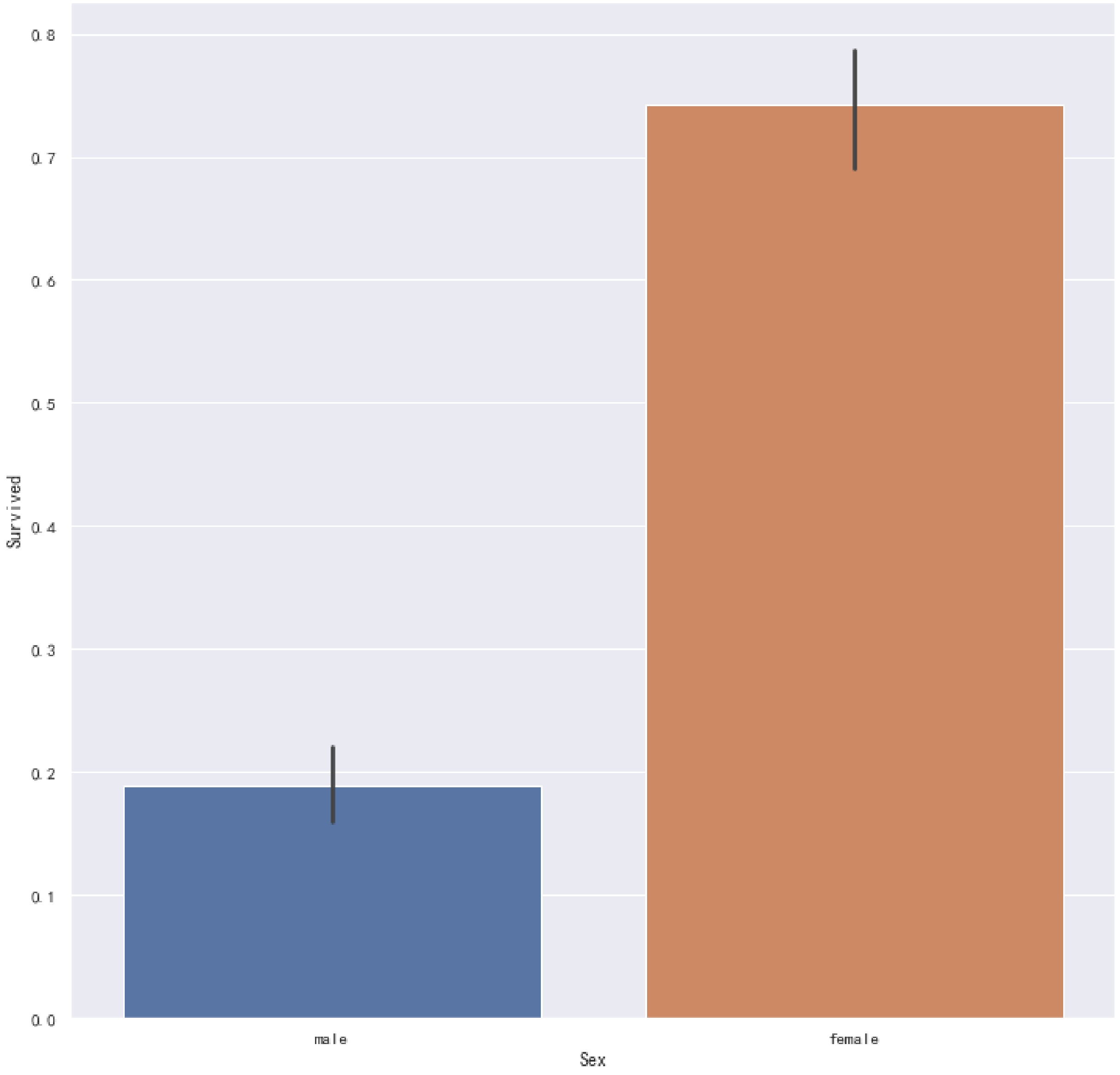
性别的统计分析使用条形图就可以轻松完成，从下图来看，女性的生存率远高于男性，后续在统计时需要将女性这一因素纳入重点考虑范围。

In [47…

```
sns.barplot(x='Sex',y='Survived',data=train_data)
```

Out[472]:

```
<AxesSubplot:xlabel='Sex', ylabel='Survived'>
```



数据清洗

加载数据集

重新加载训练数据集，以防止前面数据分析部分对变量进行了修改

In [47…

```
test_data = pd.read_csv("kaggle/input/titanic/test.csv")
train_data = pd.read_csv("kaggle/input/titanic/train.csv")
```

为方便后续数据的清洗，现将测试集与训练集进行合并

In [47…

```
# join the two datasets
titanic = pd.concat([train_data, test_data])
```

合并后的数据集变为：

In [47…

```
titanic.head()
```

Out[475]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
0	1	0.0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN
1	2	1.0	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85
2	3	1.0	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN
3	4	1.0	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123
4	5	0.0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN

缺失值处理

从新合并的数据集来看，在Age, Fare, Cabin, Embarked这四个属性上有缺失值需要进行处理。

In [47…

```
titanic.isnull().sum()
```

Out[476]:

```
PassengerId       0
Survived        418
Pclass            0
Name              0
Sex               0
Age             263
SibSp             0
Parch             0
Ticket            0
Fare              1
Cabin          1014
Embarked          2
dtype: int64
```

Embarked和Cabin都是类型数据，并且在数据分析中没有看出与别的属性有明显的区别，首先考虑以下处理方式：

- Embarked属性缺失较少，所以我选择直接使用最多的类来进行缺失值的填补
- 对于Cabin，将缺失值标志位U (Unknown)，并且仅取第一个字母作为有效值

In [47…

```
titanic['Embarked'].fillna('S', inplace = True)
titanic['Cabin'].fillna('U', inplace = True)
titanic['Cabin'] = titanic['Cabin'].map(lambda x: x[0])
```

Fare缺失值虽然是数值属性，但缺失值只有一个并且再数据分析部分已经得出结论：Fare与Pclass高度相关，所以直接使用同一Pclass的票价均值来填补缺失。

In [47…

```
titanic['Fare'].fillna(titanic.groupby('Pclass')['Fare'].transform('median'), inplace
```

经过上述简单处理之后暂时只有Age数据需要填补缺失值

In [47…

```
print(titanic.isnull().sum())
```

```
PassengerId      0
Survived       418
Pclass           0
Name             0
Sex              0
Age            263
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin            0
Embarked         0
dtype: int64
```

特征提取

在数据分析部分我们提到，Age缺失值的填补依赖于其他属性，所以想要尽量有效地填补缺失的年龄，我们首先需要对尽可能地挖掘其他属性的特征。所以接下来需要做的事情就是分析各个非数字属性，并且将其转化为有效数值属性。

首先需要处理的是Name属性，通过直接观察，我们发现Name中会带有职位或者性别信息，所以通过分割进行处理。

In [48…

```
titanic['Title'] = titanic['Name'].map(lambda x: x.split(',')[1].split('.')[0].strip
titanic.drop('Name', axis=1, inplace=True)
titanic['Title'].value_counts()
```

Out[480]:

```
Mr              757
Miss            260
Mrs             197
Master           61
Rev               8
Dr                8
Col               4
Mlle              2
Major             2
Ms                2
Lady              1
Sir               1
Mme               1
Don               1
Capt              1
the Countess      1
Jonkheer          1
Dona              1
Name: Title, dtype: int64
```

In [48…

```
print(titanic.isnull().sum())
```

```
PassengerId      0
Survived       418
Pclass           0
Sex              0
Age            263
SibSp            0
```

```
Parch          0
Ticket         0
Fare           0
Cabin          0
Embarked       0
Title          0
dtype: int64
```

In [48…

```
titanic['Title'] = titanic['Title'].replace(['Rev', 'Dr', 'Col', 'Lady', 'Sir', 'Don',
titanic['Title'] = titanic['Title'].replace('Mlle', 'Miss')
titanic['Title'] = titanic['Title'].replace('Ms', 'Miss')
titanic['Title'] = titanic['Title'].replace('Mme', 'Mrs')
titanic['Title'].value_counts()
```

Out[482]:

```
Mr        757
Miss      264
Mrs       198
Master     61
Rare       29
Name: Title, dtype: int64
```

接下来分析SibSp与Parch这一属性，这一属性反映的是家庭成员数量，在决策树模型，连续的数值是不必要甚至影响正确判断的，所以需要根据家庭成员数量的大小将乘客分类为两种类型：独自和非独自。

In [48…

```
titanic['FamilySize'] = titanic['SibSp'] + titanic['Parch'] + 1
# titanic['Family'] = pd.cut(titanic['FamilySize'], [0, 1, 4, 7, 11], labels=['Single'
# titanic['Family'].value_counts()

titanic['Alone'] = titanic['FamilySize'].map(lambda x: 1 if x == 1 else 0)
titanic.drop(['SibSp', 'Parch', 'FamilySize'], axis=1, inplace=True)
titanic['Alone'].value_counts()
```

Out[483]:

```
1    790
0    519
Name: Alone, dtype: int64
```

暂时无法从Ticket中发掘出有用的信息，所以在此实验中我将Ticket忽略

In [48…

```
titanic.drop(['Ticket'], axis=1, inplace=True)
```

经过上述一系列处理，最终得到了以下特征：

In [48…

```
titanic.head()
```

Out[485]:

	PassengerId	Survived	Pclass	Sex	Age	Fare	Cabin	Embarked	Title	Alone
0	1	0.0	3	male	22.0	7.2500	U	S	Mr	0
1	2	1.0	1	female	38.0	71.2833	C	C	Mrs	0
2	3	1.0	3	female	26.0	7.9250	U	S	Miss	1
3	4	1.0	1	female	35.0	53.1000	C	S	Mrs	0
4	5	0.0	3	male	35.0	8.0500	U	S	Mr	1

接下来便是对Cabin与Embarked的分析处理，由于需要使用随机森林对Age进行预测，在此过程中此类型属性最好被转化为数值属性。

In [48…

```
titanic['Cabin'].value_counts()
titanic['Embarked'].value_counts()
```

Out[486]:

```
S    916
C    270
Q    123
Name: Embarked, dtype: int64
```

In [48…

```
# map categorical features to numerical values
titanic['Cabin'] = titanic['Cabin'].map({'A' : 0, 'B' : 1, 'C' : 2, 'D' : 3, 'E' : 4,
titanic['Sex'] = titanic['Sex'].map({'male' : 0, 'female' : 1})
titanic['Embarked'] = titanic['Embarked'].map({'S' : 0, 'C' : 1, 'Q' : 2})
titanic['Title'] = titanic['Title'].map({'Mr' : 0, 'Miss' : 1, 'Mrs' : 2, 'Master' :
```

一切都转化完毕后可以查看现在的数据集如下：

In [48…

```
titanic.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1309 entries, 0 to 417
Data columns (total 10 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  1309 non-null   int64  
 1   Survived     891 non-null    float64
 2   Pclass       1309 non-null   int64  
 3   Sex          1309 non-null   int64  
 4   Age          1046 non-null   float64
 5   Fare         1309 non-null   float64
 6   Cabin        1309 non-null   int64  
 7   Embarked     1309 non-null   int64  
 8   Title        1309 non-null   int64  
 9   Alone        1309 non-null   int64  
dtypes: float64(3), int64(7)
memory usage: 112.5 KB
```

In [48…

```
titanic.head()
```

Out[489]:

	PassengerId	Survived	Pclass	Sex	Age	Fare	Cabin	Embarked	Title	Alone
0	1	0.0	3	0	22.0	7.2500	8	0	0	0
1	2	1.0	1	1	38.0	71.2833	2	1	2	0
2	3	1.0	3	1	26.0	7.9250	8	0	1	1
3	4	1.0	1	1	35.0	53.1000	2	0	2	0
4	5	0.0	3	0	35.0	8.0500	8	0	0	1

In [49…

```
print(titanic.isnull().sum())
```

```
PassengerId      0
Survived       418
Pclass           0
Sex              0
Age            263
Fare             0
Cabin            0
Embarked         0
Title            0
Alone            0
dtype: int64
```

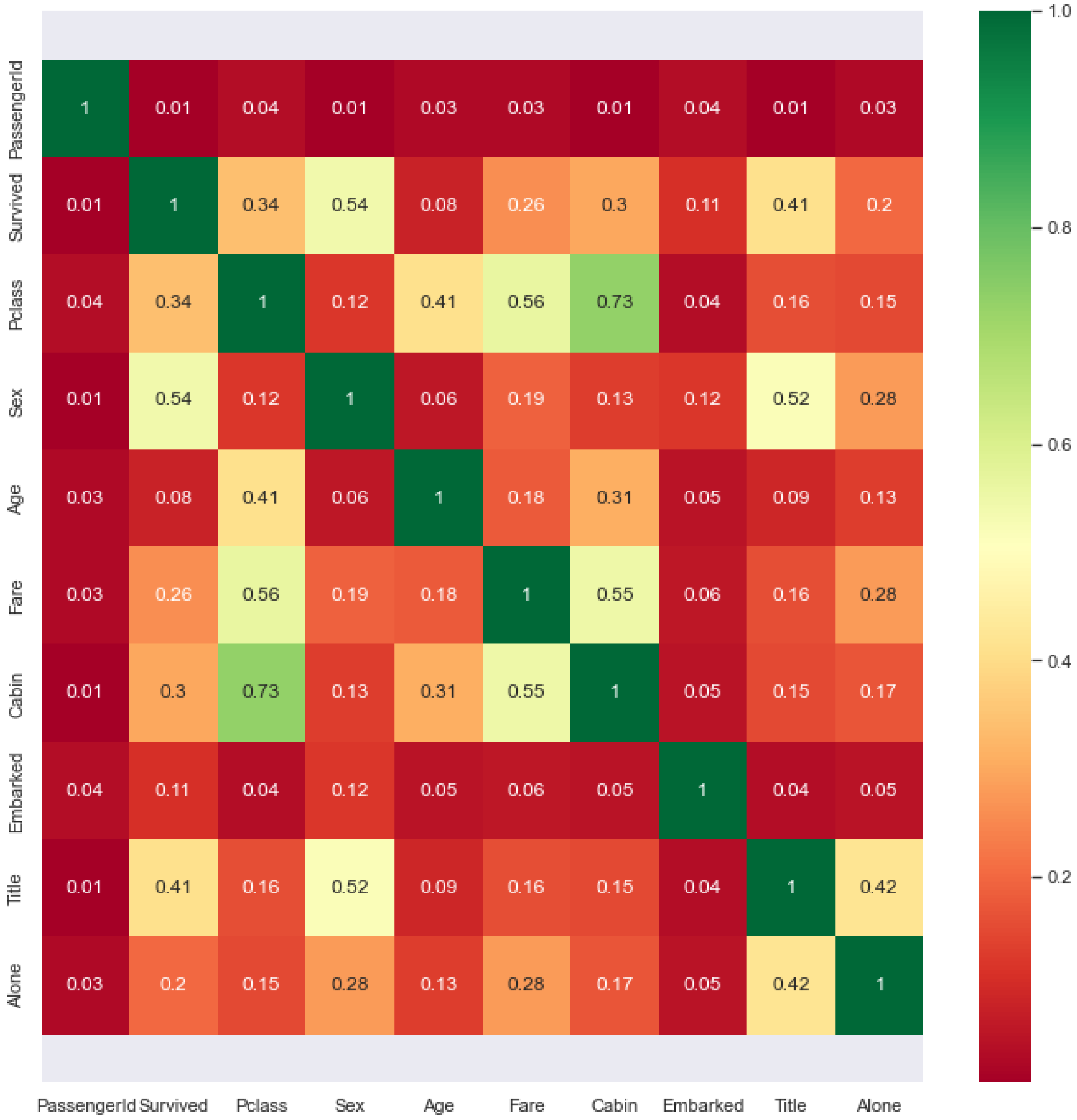
至此，除Age之外的属性都已处理完毕，接下来需要对Age进行处理，其中我们需要分析Age的分布情况，并且将其转化为数值属性。在此之前需要大致的决定哪些属性与Age最密切，使用heatmap来直观的查看相关系数。

In [49…

```python
import seaborn as sns
correlation_matrix = np.absolute(titanic.corr().round(2))
sns.set(rc={'figure.figsize':(12, 12)})
ax = sns.heatmap(correlation_matrix, annot=True, cmap='RdYlGn')
bottom, top = ax.get_ylim()
ax.set_ylim(bottom + 0.5, top - 0.5)
```

Out[491]:

```
(10.5, -0.5)
```



In [49…

```python
variables = ['Pclass', 'Sex', 'Age', 'Fare', 'Cabin', 'Embarked', 'Title', 'Alone']
titanicAge = titanic[variables]

ageTrain = titanicAge[titanicAge['Age'].notnull()]
agePredict = titanicAge[titanicAge['Age'].isnull()]

Train_X = ageTrain.drop(['Age'],axis=1)
Train_y = ageTrain['Age']
```

```
Predict_X = agePredict.drop([’Age’],axis=1)
#利用随机森林构建模型
from sklearn.ensemble import RandomForestRegressor
model = RandomForestRegressor(random_state=None, n_estimators=500, n_jobs=-1)
model.fit(Train_X, Train_y)
```

Out[492]:

```
RandomForestRegressor(n_estimators=500, n_jobs=-1)
```

In [49…

```
# 预测并填充
Predict_y = model.predict(Predict_X)
titanic.loc[titanic[’Age’].isnull(), [’Age’]] = Predict_y
# 预测模型得分
model.score(Train_X, Train_y)
```

Out[493]:

```
0.73970855212351
```

经过上述处理，数据集中的缺失值已经被全部填补完毕

In [49…

```
titanic.isnull().sum()
```

Out[494]:

```
PassengerId      0
Survived       418
Pclass           0
Sex              0
Age              0
Fare             0
Cabin            0
Embarked         0
Title            0
Alone            0
dtype: int64
```

由于决策树算法限制，为达到最佳效果，我们还需要把连续属性进行归类。

In [49…

```
titanic.loc[titanic[’Fare’] <= 7.91, ’Fare’] = 0
titanic.loc[(titanic[’Fare’] > 7.91) & (titanic[’Fare’] <= 14.454), ’Fare’] = 1
titanic.loc[(titanic[’Fare’] > 14.454) & (titanic[’Fare’] <= 31), ’Fare’] = 2
titanic.loc[titanic[’Fare’] > 31, ’Fare’] = 3

titanic.loc[titanic[’Age’] <= 16, ’Age’] = 0
titanic.loc[(titanic[’Age’] > 16) & (titanic[’Age’] <= 32), ’Age’] = 1
titanic.loc[(titanic[’Age’] > 32) & (titanic[’Age’] <= 48), ’Age’] = 2
titanic.loc[(titanic[’Age’] > 48) & (titanic[’Age’] <= 64), ’Age’] = 3
titanic.loc[titanic[’Age’] > 64, ’Age’] = 4

titanic[’Age’] = titanic[’Age’].astype(int)
titanic[’Fare’] = titanic[’Fare’].astype(int)
```

In [49…

```
titanic.head()
```

Out[496]:

	PassengerId	Survived	Pclass	Sex	Age	Fare	Cabin	Embarked	Title	Alone
0	1	0.0	3	0	1	0	8	0	0	0
1	2	1.0	1	1	2	3	2	1	2	0
2	3	1.0	3	1	1	1	8	0	1	1
3	4	1.0	1	1	2	3	2	0	2	0

	PassengerId	Survived	Pclass	Sex	Age	Fare	Cabin	Embarked	Title	Alone
4	5	0.0	3	0	2	1	8	0	0	1

模型预测

数据清洗和特征提取完毕之后就可以使用模型进行学习和预测了，首先恢复测试集与训练集

In [49…

```python
traindata = titanic[titanic['Survived'].notnull()]
testdata = titanic[titanic['Survived'].isnull()]
```

In [49…

```python
# 将Survived类转为int类型
traindata['Survived'] = traindata['Survived'].astype(int)
traindata
```

```
C:\Users\chris\AppData\Local\Temp\ipykernel_19632\948573567.py:2: SettingWithCopyWarni
ng:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/use
r_guide/indexing.html#returning-a-view-versus-a-copy
  traindata['Survived'] = traindata['Survived'].astype(int)
```

Out[498]:

	PassengerId	Survived	Pclass	Sex	Age	Fare	Cabin	Embarked	Title	Alone
0	1	0	3	0	1	0	8	0	0	0
1	2	1	1	1	2	3	2	1	2	0
2	3	1	3	1	1	1	8	0	1	1
3	4	1	1	1	2	3	2	0	2	0
4	5	0	3	0	2	1	8	0	0	1
...	...	...	...	...	...	...	...	...	...	...
886	887	0	2	0	1	1	8	0	4	1
887	888	1	1	1	1	2	1	0	1	1
888	889	0	3	1	0	2	8	0	1	0
889	890	1	1	0	1	2	2	1	0	1
890	891	0	3	0	1	0	8	2	0	1

891 rows × 10 columns

In [49…

```python
testdata
```

Out[499]:

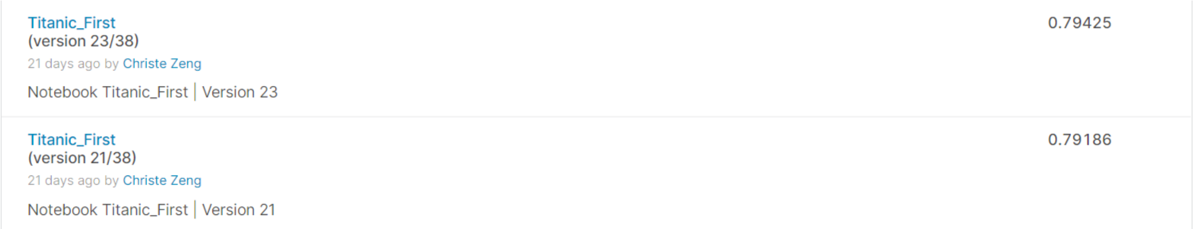
	PassengerId	Survived	Pclass	Sex	Age	Fare	Cabin	Embarked	Title	Alone
0	892	NaN	3	0	2	0	8	2	0	1
1	893	NaN	3	1	2	0	8	0	2	0
2	894	NaN	2	0	3	1	8	2	0	1
3	895	NaN	3	0	1	1	8	0	0	1

	PassengerId	Survived	Pclass	Sex	Age	Fare	Cabin	Embarked	Title	Alone
4	896	NaN	3	1	1	1	8	0	2	0
...	...	...	...	...	...	...	...	...	...	...
413	1305	NaN	3	0	1	1	8	0	0	1
414	1306	NaN	1	1	2	3	2	1	4	1
415	1307	NaN	3	0	2	0	8	0	0	1
416	1308	NaN	3	0	1	1	8	0	0	1
417	1309	NaN	3	0	0	2	8	1	3	0

418 rows × 10 columns

随机森林

使用随机森林进行预测，并且使用交叉验证，选择最优的参数。首先使用简单的随机森林执行一次预测得到的得分应该为0.79186-0.79425之间（由随机状态决定），无法满足我们的需求。



Titanic_First
(version 23/38)
21 days ago by Christe Zeng
Notebook Titanic_First | Version 23
0.79425

Titanic_First
(version 21/38)
21 days ago by Christe Zeng
Notebook Titanic_First | Version 21
0.79186

In [50…

```
y = traindata['Survived']
X = traindata.drop(['Survived', 'PassengerId'], axis=1)
X_test = testdata.drop(['Survived', 'PassengerId'], axis=1)

model = RandomForestClassifier(n_estimators=100, max_depth=5, random_state=1)
model.fit(X, y)
predictions = model.predict(X_test)

output = pd.DataFrame({'PassengerId': testdata.PassengerId, 'Survived': predictions})
output.to_csv('submission1.csv', index=False)
print("Your submission1 was successfully saved!")
```

```
Your submission1 was successfully saved!
```

使用GridSearchCV对随机森林进行参数调优，选择最优的参数。

In [40…

```
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import StratifiedKFold
kfold = StratifiedKFold(n_splits=10)
```

In [40…

```
from sklearn.ensemble import RandomForestClassifier

# 选择参数范围
modelRFC = RandomForestClassifier()
n_estimators = [200, 500, 800, 1100, 1400]
max_depth = [1, 5, 10, 15, 20]
max_depth.append(None)
min_samples_split = [1, 5, 10]
min_samples_leaf = [1, 2, 4]
```

```python
params = {
            "max_depth": max_depth,
            "min_samples_split": min_samples_split,
            "min_samples_leaf": min_samples_leaf,
            "n_estimators" :n_estimators,
            "criterion": ["gini"]
        }

modelRFC_GCCV = GridSearchCV(modelRFC, param_grid = params, cv=kfold, scoring="accura
modelRFC_GCCV.fit(X, y)

modelRFCBest = modelRFC_GCCV.best_estimator_
```

```
Fitting 10 folds for each of 270 candidates, totalling 2700 fits
d:\Anaconda3\envs\data\lib\site-packages\sklearn\model_selection\_validation.py:372: F
itFailedWarning:
900 fits failed out of a total of 2700.
The score on these train-test partitions for these parameters will be set to nan.
If these failures are not expected, you can try to debug them by setting error_score
='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
900 fits failed with the following error:
Traceback (most recent call last):
  File "d:\Anaconda3\envs\data\lib\site-packages\sklearn\model_selection\_validation.p
y", line 680, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "d:\Anaconda3\envs\data\lib\site-packages\sklearn\ensemble\_forest.py", line 45
0, in fit
    trees = Parallel(
  File "d:\Anaconda3\envs\data\lib\site-packages\joblib\parallel.py", line 1043, in __
call__
    if self.dispatch_one_batch(iterator):
  File "d:\Anaconda3\envs\data\lib\site-packages\joblib\parallel.py", line 861, in dis
patch_one_batch
    self._dispatch(tasks)
  File "d:\Anaconda3\envs\data\lib\site-packages\joblib\parallel.py", line 779, in _di
spatch
    job = self._backend.apply_async(batch, callback=cb)
  File "d:\Anaconda3\envs\data\lib\site-packages\joblib\_parallel_backends.py", line 2
08, in apply_async
    result = ImmediateResult(func)
  File "d:\Anaconda3\envs\data\lib\site-packages\joblib\_parallel_backends.py", line 5
72, in __init__
    self.results = batch()
  File "d:\Anaconda3\envs\data\lib\site-packages\joblib\parallel.py", line 262, in __c
all__
    return [func(*args, **kwargs)
  File "d:\Anaconda3\envs\data\lib\site-packages\joblib\parallel.py", line 262, in <li
stcomp>
    return [func(*args, **kwargs)
  File "d:\Anaconda3\envs\data\lib\site-packages\sklearn\utils\fixes.py", line 216, in
__call__
    return self.function(*args, **kwargs)
  File "d:\Anaconda3\envs\data\lib\site-packages\sklearn\ensemble\_forest.py", line 18
5, in _parallel_build_trees
    tree.fit(X, y, sample_weight=curr_sample_weight, check_input=False)
  File "d:\Anaconda3\envs\data\lib\site-packages\sklearn\tree\_classes.py", line 937,
in fit
    super().fit(
  File "d:\Anaconda3\envs\data\lib\site-packages\sklearn\tree\_classes.py", line 250,
in fit
    raise ValueError(
ValueError: min_samples_split must be an integer greater than 1 or a float in (0.0, 1.
0]; got the integer 1
```

```
  warnings.warn(some_fits_failed_message, FitFailedWarning)
d:\Anaconda3\envs\data\lib\site-packages\sklearn\model_selection\_search.py:969: UserW
arning: One or more of the test scores are non-finite: [        nan         nan         n
an         nan         nan 0.77782772
 0.77444444 0.77558052 0.77220974 0.77334582 0.78233458 0.77444444
 0.77334582 0.77444444 0.77558052        nan        nan        nan
        nan        nan 0.77111111 0.7778402  0.76886392 0.78009988
 0.76883895 0.76661673 0.76774032 0.77109863 0.77446941 0.77558052
        nan        nan        nan        nan        nan 0.77560549
 0.7744819  0.77670412 0.77111111 0.77220974 0.77559301 0.77446941
 0.7778402  0.77222222 0.77445693        nan        nan        nan
        nan        nan 0.83389513 0.83277154 0.82830212 0.82942572
 0.83164794 0.83164794 0.83052434 0.83277154 0.82830212 0.82830212
        nan        nan        nan        nan        nan 0.82942572
 0.82942572 0.83277154 0.83164794 0.83389513 0.83054931 0.83389513
 0.83054931 0.83054931 0.83054931        nan        nan        nan
        nan        nan 0.82942572 0.83389513 0.83501873 0.83389513
 0.83167291 0.83501873 0.83389513 0.8327965  0.83167291 0.83501873
        nan        nan        nan        nan        nan 0.8294382
 0.83054931 0.82717853 0.82830212 0.82606742 0.82941323 0.82716604
 0.82268414 0.82379526 0.82491885        nan        nan        nan
        nan        nan 0.83052434 0.82827715 0.82940075 0.82715356
 0.82827715 0.83166042 0.82828964 0.82828964 0.83053683 0.82716604
        nan        nan        nan        nan        nan 0.83053683
 0.83167291 0.83615481 0.8327965  0.83726592 0.83615481 0.838402
 0.83615481 0.83615481 0.83389513        nan        nan        nan
        nan        nan 0.82942572 0.82606742 0.82719101 0.82606742
 0.82830212 0.82715356 0.82715356 0.82602996 0.82491885 0.82602996
        nan        nan        nan        nan        nan 0.83164794
 0.83052434 0.82827715 0.82715356 0.82940075 0.82716604 0.82828964
 0.82941323 0.82828964 0.82941323        nan        nan        nan
        nan        nan 0.83053683 0.83390762 0.83390762 0.8339201
 0.83501873 0.83390762 0.83389513 0.83501873 0.83614232 0.83390762
        nan        nan        nan        nan        nan 0.82941323
 0.82831461 0.82830212 0.82719101 0.82831461 0.82604245 0.82715356
 0.82490637 0.82604245 0.82602996        nan        nan        nan
        nan        nan 0.82604245 0.82715356 0.82715356 0.82940075
 0.82940075 0.83053683 0.82828964 0.83053683 0.83053683 0.83053683
        nan        nan        nan        nan        nan 0.83390762
 0.83503121 0.83615481 0.83503121 0.83726592 0.83390762 0.83501873
 0.83615481 0.83501873 0.83501873        nan        nan        nan
        nan        nan 0.83054931 0.82942572 0.82831461 0.82831461
 0.82719101 0.82602996 0.82378277 0.82378277 0.82491885 0.82490637
        nan        nan        nan        nan        nan 0.83052434
 0.82716604 0.82827715 0.82827715 0.83052434 0.83053683 0.82828964
 0.82716604 0.83053683 0.82941323        nan        nan        nan
        nan        nan 0.83614232 0.83951311 0.83389513 0.83616729
 0.83614232 0.83501873 0.83166042 0.83277154 0.83726592 0.83503121]
  warnings.warn(
```

GBC

In [40…

```
from sklearn.ensemble import GradientBoostingClassifier

learning_rate = [1, 0.25, 0.1, 0.05, 0.01]
n_estimators = [1, 2, 4, 32, 100, 150, 200,  300]
max_depth = np.linspace(1, 32, 8, endpoint=True)
min_samples_leaf = np.linspace(0.1, 0.5, 4, endpoint=True)
max_features = [0.5, 0.3, 0.1]

modelGBC = GradientBoostingClassifier()
params = {
            'loss' : ["deviance"],
            'n_estimators' : n_estimators,
            'learning_rate': learning_rate,
            'max_depth': max_depth,
            'min_samples_leaf': min_samples_leaf,
                'max_features': max_features
        }

modelGBC_GCCV = GridSearchCV(modelGBC, param_grid = params, cv=kfold, scoring="accura
modelGBC_GCCV.fit(X, y)

modelGBCBest = modelGBC_GCCV.best_estimator_
```

```
Fitting 10 folds for each of 3840 candidates, totalling 38400 fits
```

SVMC

In [40…

```
from sklearn.svm import SVC

SVMC = SVC(probability=True)

C = [0.001, 0.01, 0.1, 1, 10, 50, 100,200,300, 1000, 3000]
gamma = [0.00001, 0.0001, 0.001, 0.01, 0.1, 1 ]

params = {
            'kernel': ['rbf'],
            'gamma': gamma,
            'C': C,
        }

modelSVMC_GCCV = GridSearchCV(SVMC, param_grid = params, cv=kfold, scoring="accuracy"
modelSVMC_GCCV.fit(X, y)
modelSVMCBest = modelSVMC_GCCV.best_estimator_
```

```
Fitting 10 folds for each of 66 candidates, totalling 660 fits
```

XGBoost

In [40…

```
from xgboost import XGBClassifier

XGB = XGBClassifier()

max_depth = [1,2,4,8,10]
min_child_weight = np.linspace(1, 10, 5, endpoint=True)
gamma = np.linspace(0.5, 5, 5, endpoint=True)
subsample = np.linspace(0.5, 1, 5, endpoint=True)
colsample_bytree = np.linspace(0.5, 1, 5, endpoint=True)

params = {
        'min_child_weight': min_child_weight,
        'gamma': gamma,
        'subsample': subsample,
        'colsample_bytree': colsample_bytree,
        'max_depth': max_depth
}


modelXGB_GCCV = GridSearchCV(estimator = XGB, param_grid = params, cv=kfold, scoring=
modelXGB_GCCV.fit(X, y)

modelXGBBest = modelXGB_GCCV.best_estimator_
```

```
Fitting 10 folds for each of 3125 candidates, totalling 31250 fits
```

组合模型(Ensemble)

组合模型就是将上述决策模型组合到一起，以期获得最好的效果。在此次实验中，我选择的组合方式是使用决策树。首先可以将四种模型在交叉验证上的得分展示出来：

In [41…

```
print('RFC Score: ', modelRFC_GCCV.best_score_)
print('GBC Score: ',modelGBC_GCCV.best_score_)
print('SVMC Score: ', modelSVMC_GCCV.best_score_)
print('XGB Score: ', modelXGB_GCCV.best_score_)
```

```
RFC Score:  0.8395131086142322
GBC Score:  0.8282771535580524
SVMC Score:  0.8305243445692885
XGB Score:  0.839538077403246
```

使用VotingClassifier组合模型

In [41…

```
from sklearn.ensemble import VotingClassifier

votingTree = VotingClassifier(estimators=[('GBC', modelGBCBest), ('SVM', modelSVMCBes
votingTree = votingTree.fit(X, y)
```

使用组合模型进行预测，并且将预测结果写入文件

In [41…

```
predictions = votingTree.predict(X_test)

output = pd.DataFrame({'PassengerId': testdata.PassengerId, 'Survived': predictions})
output.to_csv('submission2.csv', index=False)
```