实验目的

熟悉掌握数据预处理操作

并采用SVM，决策树和xgboost三种模型对数据进行分类，比较三种模型的分类效果。

In [ ]:
```
# 导入所需的包
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from xgboost import XGBClassifier
```

数据预处理

读取数据，展示数据信息

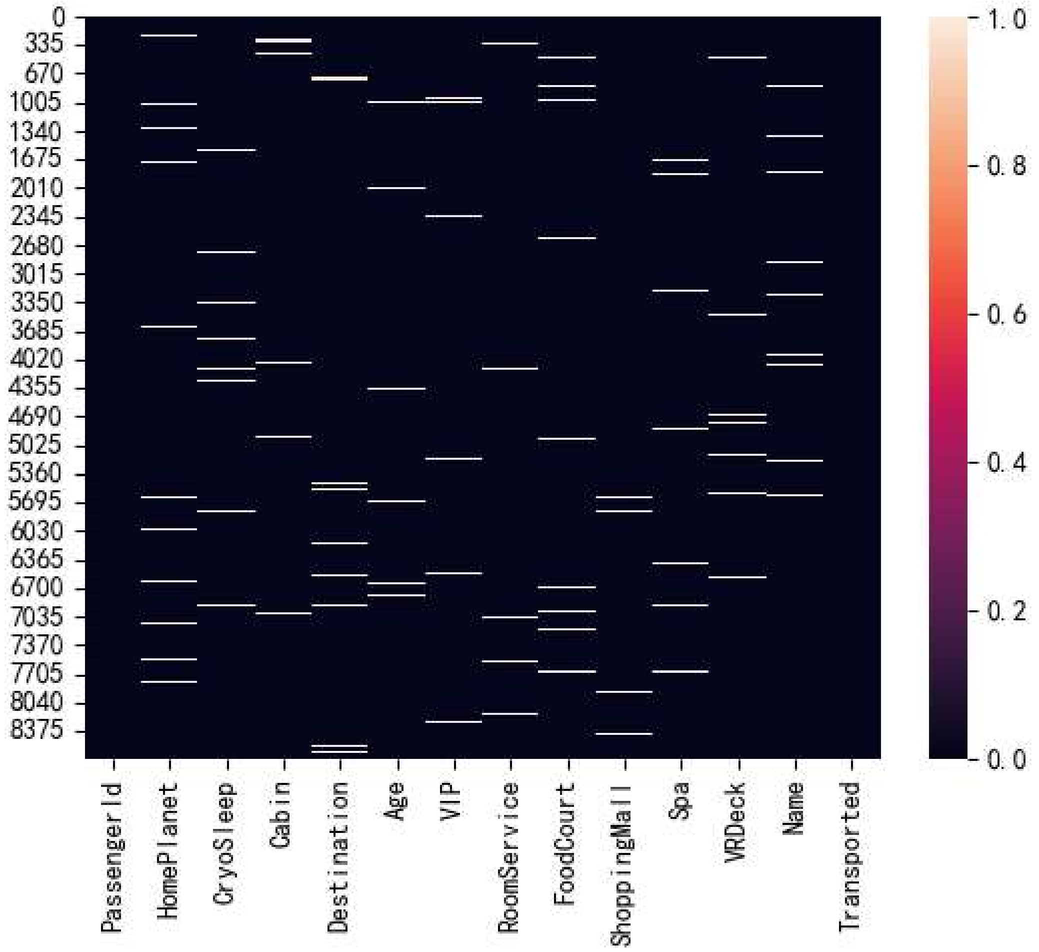
In [ ]:
```
# 读取数据
train = pd.read_csv('spaceship-titanic/train.csv')
test = pd.read_csv('spaceship-titanic/test.csv')

# 查看是否有缺失值和异常值
# 训练集
print('训练集信息:\n')
print(train.info())
print('缺失值数量:', train.isnull().sum())
sns.heatmap(train.isnull())
plt.show()

# 测试集
print('测试集信息:\n')
print(test.info())
print('缺失值数量:', test.isnull().sum())
sns.heatmap(test.isnull())
plt.show()
```

训练集信息:

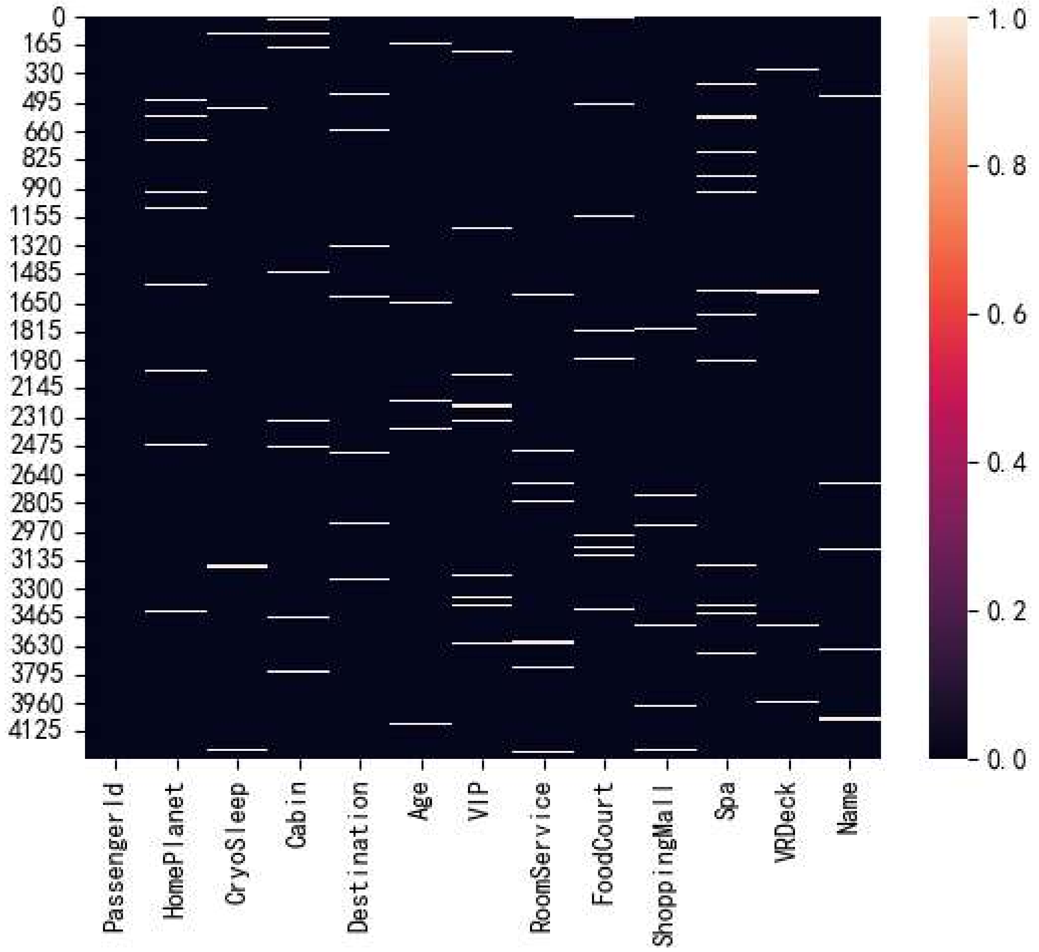
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8693 entries, 0 to 8692
Data columns (total 14 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   PassengerId   8693 non-null   object 
 1   HomePlanet    8492 non-null   object 
 2   CryoSleep     8476 non-null   object 
 3   Cabin         8494 non-null   object 
 4   Destination   8511 non-null   object 
 5   Age           8514 non-null   float64
 6   VIP           8490 non-null   object 
 7   RoomService   8512 non-null   float64
 8   FoodCourt     8510 non-null   float64
 9   ShoppingMall  8485 non-null   float64
 10  Spa           8510 non-null   float64
 11  VRDeck        8505 non-null   float64
 12  Name          8493 non-null   object 
 13  Transported   8693 non-null   bool   
dtypes: bool(1), float64(6), object(7)
memory usage: 891.5+ KB
None
缺失值数量: PassengerId       0
HomePlanet      201
CryoSleep       217
Cabin           199
Destination     182
Age             179
VIP             203
RoomService     181
FoodCourt       183
ShoppingMall    208
Spa             183
VRDeck          188
Name            200
Transported       0
dtype: int64
```



0
335
670
1005
1340
1675
2010
2345
2680
3015
3350
3685
4020
4355
4690
5025
5360
5695
6030
6365
6700
7035
7370
7705
8040
8375
PassengerId
HomePlanet
CryoSleep
Cabin
Destination
Age
VIP
RoomService
FoodCourt
ShoppingMall
Spa
VRDeck
Name
Transported
1.0
0.8
0.6
0.4
0.2
0.0

测试集信息:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4277 entries, 0 to 4276
Data columns (total 13 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   PassengerId   4277 non-null   object 
 1   HomePlanet    4190 non-null   object 
 2   CryoSleep     4184 non-null   object 
 3   Cabin         4177 non-null   object 
 4   Destination   4185 non-null   object 
 5   Age           4186 non-null   float64
 6   VIP           4184 non-null   object 
 7   RoomService   4195 non-null   float64
 8   FoodCourt     4171 non-null   float64
 9   ShoppingMall  4179 non-null   float64
 10  Spa           4176 non-null   float64
 11  VRDeck        4197 non-null   float64
 12  Name          4183 non-null   object 
dtypes: float64(6), object(7)
memory usage: 434.5+ KB
None
缺失值数量: PassengerId       0
HomePlanet       87
CryoSleep        93
Cabin           100
Destination      92
Age              91
VIP              93
RoomService      82
FoodCourt       106
ShoppingMall     98
Spa             101
VRDeck           80
Name             94
dtype: int64
```



处理缺失值，并进行预处理

对于PassengerId，分离前面的gggg建立新一列room_id，无缺失值

对于HomePlanet，缺失值用最频繁的值填充

对于CryoSleep，当CryoSleep为True时，代表假死状态，不会有后序RoomService&FoodCourt&ShoppingMall&Spa&VRDeck的额外花费，所以将这些值设为0，缺失值用最频繁的值填充

对于cabin，分离为cabin_deck,cabin_num,cabin_side，若cabin为空，则cabin_deck设为空，cabin_num设为空，cabin_side设为空

对于Destination，缺失值用最频繁的值填充

对于Age，缺失值用平均值填充

对于VIP，缺失值用最频繁的值填充

对于RoomService&FoodCourt&ShoppingMall&Spa&VRDeck这几个属性，若为空用平均值填充加起来作为为新的spend属性

对于Name，若Name为空，去除该行

对于cabin_deck，cabin_side这几个属性，缺失值用最频繁的值填充

对于cabin_num，缺失值用平均值填充

为HomePlanet, CryoSleep, Destination, VIP, cabin_deck, cabin_num, cabin_side, Name, room_id这几个属性进行one-hot编码转化

将Transported标签转换为0,1

In [ ]:
```
def data_process(data):
    # 对于PassengerId, 分离前面的gggg建立新一列room_id, 无缺失值
    data['room_id'] = data['PassengerId'].apply(lambda x: x[:4])
    # 对于HomePlanet, 缺失值用最频繁的值填充
    data['HomePlanet'] = data['HomePlanet'].fillna(data['HomePlanet'].mode()[0])
    # 对于CryoSleep, 当CryoSleep为True时, 代表假死状态, 不会有后序RoomService&FoodC
    data.loc[data['CryoSleep'] == True, ['RoomService', 'FoodCourt', 'ShoppingMall
    data['CryoSleep'] = data['CryoSleep'].fillna(data['CryoSleep'].mode()[0])
    # 对于cabin, 分离为cabin_deck,cabin_num,cabin_side(使用'/'分离), 若cabin为空, 贝
    for i in range(len(data)):
        if data.loc[i, 'Cabin'] == data.loc[i, 'Cabin']:
            data.loc[i, 'cabin_deck'] = data.loc[i, 'Cabin'].split('/')[0]
            data.loc[i, 'cabin_num'] = data.loc[i, 'Cabin'].split('/')[1]
            data.loc[i, 'cabin_side'] = data.loc[i, 'Cabin'].split('/')[2]
        else:
            data.loc[i, 'cabin_deck'] = np.nan
            data.loc[i, 'cabin_num'] = np.nan
            data.loc[i, 'cabin_side'] = np.nan
    # 对于Destination, 缺失值用最频繁的值填充
    data['Destination'] = data['Destination'].fillna(data['Destination'].mode()[0]
    # 对于Age, 缺失值用平均值填充
    data['Age'] = data['Age'].fillna(data['Age'].mean())
    # 对于VIP, 缺失值用最频繁的值填充
    data['VIP'] = data['VIP'].fillna(data['VIP'].mode()[0])
    # 对于RoomService&FoodCourt&ShoppingMall&Spa&VRDeck这几个属性, 若为空用平均值填
    data['RoomService'] = data['RoomService'].fillna(data['RoomService'].mean())
    data['FoodCourt'] = data['FoodCourt'].fillna(data['FoodCourt'].mean())
    data['ShoppingMall'] = data['ShoppingMall'].fillna(data['ShoppingMall'].mean()
    data['Spa'] = data['Spa'].fillna(data['Spa'].mean())
    data['VRDeck'] = data['VRDeck'].fillna(data['VRDeck'].mean())
    data['spend'] = data['RoomService'] + data['FoodCourt'] + data['ShoppingMall']
    # 对于Name, 若Name为空, 设为unknown
    data['Name'] = data['Name'].fillna('unknown')
    # 对于cabin_deck, cabin_side这几个属性, 缺失值用最频繁的值填充
    data['cabin_deck'] = data['cabin_deck'].fillna(data['cabin_deck'].mode()[0])
    data['cabin_side'] = data['cabin_side'].fillna(data['cabin_side'].mode()[0])
    # 为HomePlanet, CryoSleep, Destination, VIP, cabin_deck, cabin_num, cabin_side,
    data['HomePlanet'] = data['HomePlanet'].astype('category')
    data['CryoSleep'] = data['CryoSleep'].astype('category')
    data['Destination'] = data['Destination'].astype('category')
    data['VIP'] = data['VIP'].astype('category')
    data['cabin_deck'] = data['cabin_deck'].astype('category')
    data['cabin_num'] = data['cabin_num'].astype('category')
    data['cabin_side'] = data['cabin_side'].astype('category')
    data['Name'] = data['Name'].astype('category')
    data['room_id'] = data['room_id'].astype('category')

    data['HomePlanet'] = data['HomePlanet'].cat.codes
    data['CryoSleep'] = data['CryoSleep'].cat.codes
    data['Destination'] = data['Destination'].cat.codes
    data['VIP'] = data['VIP'].cat.codes
    data['cabin_deck'] = data['cabin_deck'].cat.codes
    data['cabin_num'] = data['cabin_num'].cat.codes
    data['cabin_side'] = data['cabin_side'].cat.codes
    data['Name'] = data['Name'].cat.codes
```

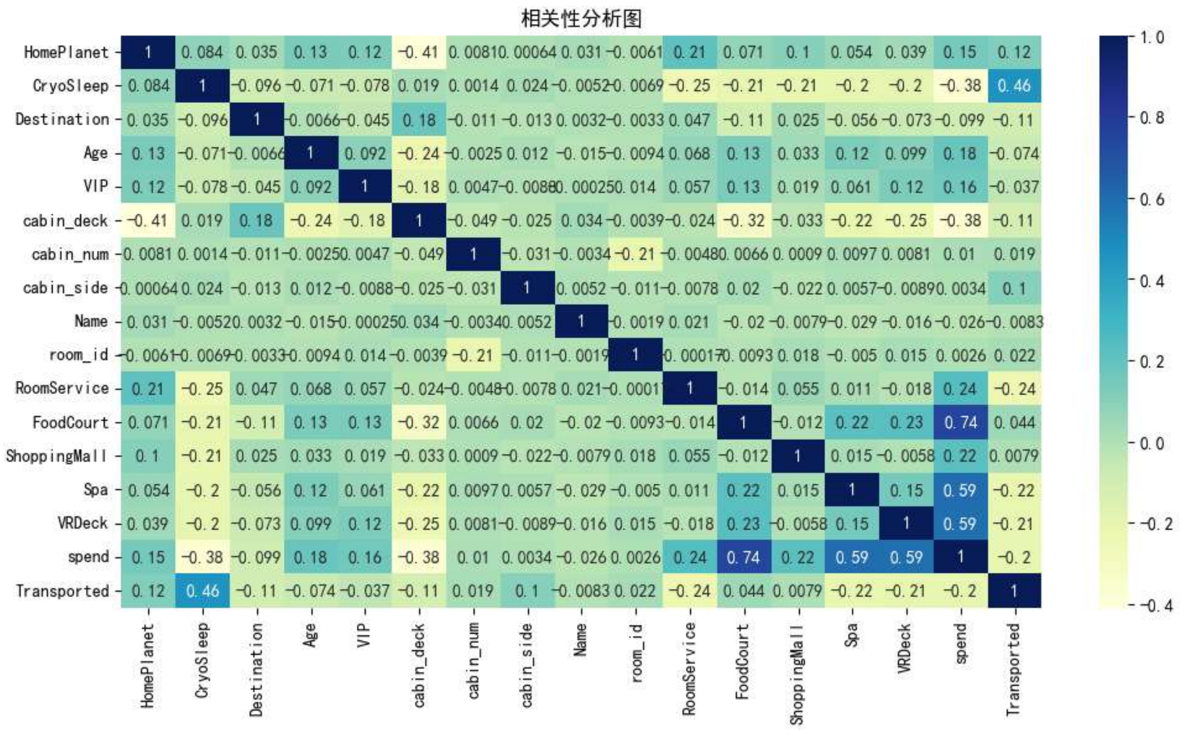
```
    data['room_id'] = data['room_id'].cat.codes

    # 若存在Transported标签
    if 'Transported' in data.columns:
        # 将Transported标签转换
        data['Transported'] = data['Transported'].astype('category')
        data['Transported'] = data['Transported'].cat.codes
    return data
train = data_process(train)
test = data_process(test)
```

分析属性与标签的关联程度

In [ ]:
```
# 去除train中的PassengerId
train.drop(['PassengerId'], axis=1, inplace=True)

df_tmp1 = train[
    ['HomePlanet', 'CryoSleep', 'Destination', 'Age', 'VIP', 'cabin_deck', 'cabin_r
plt.rcParams['font.sans-serif'] = ['SimHei']  # 指定默认字体
plt.rcParams['axes.unicode_minus'] = False  # 解决保存图像是负号'-'显示为方块的问题
# 图片放大
plt.figure(figsize=(12, 6))
sns.heatmap(df_tmp1.corr(), cmap="YlGnBu", annot=True)
plt.title("相关性分析图")
plt.show()
```



模型设计与选择

使用sklearn中的SVM,决策树和xgBoost

In [ ]:
```
# SVM
def SVM(x_train, y_train, x_test):
    # 建立模型
    clf = SVC()
```

```
    clf.fit(x_train, y_train)
    # 预测
    y_pred = clf.predict(x_test)
    return y_pred

# 决策树
def DecisionTree(x_train, y_train, x_test):
    # 建立模型
    clf = DecisionTreeClassifier()
    clf.fit(x_train, y_train)
    # 预测
    y_pred = clf.predict(x_test)
    return y_pred

# xgBoost
def EI(x_train, y_train, x_test):
    # 建立模型
    clf = XGBClassifier()
    clf.fit(x_train, y_train)
    # 预测
    y_pred = clf.predict(x_test)
    return y_pred
```

预测结果

将预测的True和flase对应乘客id保存到csv文件

In [ ]:

```
# 根据相关性分析图，选择相关性较高的属性

x_train = train[['HomePlanet', 'CryoSleep', 'Destination', 'Age', 'cabin_deck', 'ca
y_train = train['Transported']
x_test = test[['HomePlanet', 'CryoSleep', 'Destination', 'Age', 'cabin_deck', 'cabi
# SVM预测
y_pred = SVM(x_train, y_train, x_test)
# 将y_pred变为编码前的值,变为布尔类型
y_pred = pd.DataFrame(y_pred)
y_pred = y_pred.replace(0, 'False')
y_pred = y_pred.replace(1, 'True')
# 将test['PassengerId']和y_pred合并, 列标题为PassengerId和Transported
result = pd.concat([test['PassengerId'], y_pred], axis=1)
result.columns = ['PassengerId', 'Transported']
# 保存结果
result.to_csv('result_svm.csv', index=False)

# 决策树预测
y_pred = DecisionTree(x_train, y_train, x_test)
# 将y_pred变为编码前的值
y_pred = pd.DataFrame(y_pred)
y_pred = y_pred.replace(0, 'False')
y_pred = y_pred.replace(1, 'True')
# 将test['PassengerId']和y_pred合并, 列标题为PassengerId和Transported
result = pd.concat([test['PassengerId'], y_pred], axis=1)
result.columns = ['PassengerId', 'Transported']
# 保存结果
result.to_csv('result_dt.csv', index=False)

# xgBoost预测
y_pred = EI(x_train, y_train, x_test)
```

```python
# 将y_pred变为编码前的值
y_pred = pd.DataFrame(y_pred)
y_pred = y_pred.replace(0, 'False')
y_pred = y_pred.replace(1, 'True')
# 将test['PassengerId']和y_pred合并, 列标题为PassengerId和Transported
result = pd.concat([test['PassengerId'], y_pred], axis=1)
result.columns = ['PassengerId', 'Transported']
# 保存结果
result.to_csv('result_el.csv', index=False)
```

Submissions

All | Successful | Errors | Recent

Submission and Description	Public Score
result_svm.csv Complete · now	0.79448
result_dt.csv Complete · 1s ago	0.72924
result_el.csv Complete · 4m ago	0.79448