泰坦尼克号生还者数据分析

数据集简介

数据表包含了近千条泰坦尼克号的乘客信息。罗列了各个乘客的性别、年龄、票面级别、船舱级别、登船位置和最后的生还情况等

接下来将利用这些数据，尝试从年龄、性别等方面去分析这些因素和生存率之间的联系

提出问题

1. 男女乘客之间生存率的差异如何?
2. 乘客的票面级别对生存率是否有影响?
3. 乘客的年龄分布如何？各年龄阶段的乘客的生存率是怎样的?

数据处理和分析过程

1. 检查数据的完整性，尤其是年龄、性别和票面级别，并对数据进行清理
    - 发现2条 Embarked 值缺失的记录，但是因为不影响相关问题的分析，所以不做处理
    - 有些乘客的年龄数据缺失，这在分析和年龄相关的问题的时候会有影响；所以建立数据集 valid_age_df 来移除整个数据集中年龄缺失的记录
2. 单一从性别和票面级别因素上了解对生存率的影响
3. 从票面级别和性别两个因素共同分析对生存率的影响
4. 各年龄段

结论

通过对乘客数据的简单探索，我有以下几个发现：

1. 7成以上的妇女得以逃生，而少于2成的男性得以逃身，总体来说，妇女幸存的概率要高于男性，这预示着性别和生存率的相关性较大
2. 头等舱的乘客逃生的几率达到6成，而三等舱的乘客逃生的几率只有2成，这可能由于头等舱乘客有优先权利乘坐逃生艇，但差别不算特别的大
3. 三等舱乘客中妇女逃生率远比不上一二等舱妇女，预示着船舱等级是和生存率大小相关的因素
4. 20-40岁的乘客占大多数；儿童(8岁以下)生存率高，年长者(50岁以上)生存率低，预示着年龄和生存率的相关性，年纪小的儿童比老人更可能幸存

参考文献

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3. https://stackoverflow.com/questions/10373660/converting-a-pandas-groupby-object-to-dataframe (https://stackoverflow.com/questions/10373660/converting-a-pandas-groupby-object-to-dataframe)
4. https://stackoverflow.com/questions/38174155/group-dataframe-and-get-sum-and-count (https://stackoverflow.com/questions/38174155/group-dataframe-and-get-sum-and-count)
5. https://stackoverflow.com/questions/18504967/pandas-dataframe-create-new-columns-and-fill-with-calculated-values-from-same-df (https://stackoverflow.com/questions/18504967/pandas-dataframe-create-new-columns-and-fill-with-calculated-values-from-same-df)

In [94]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from decimal import *
```

从 CSV 文件中读取数据，并检查数据行数 (即乘客数)

In [95]:
```
df = pd.read_csv('titanic-data.csv')

# check how many passengers are there

passenger_count = len(df.index)
print(passenger_count)
```

```
891
```

对数据的完整性进行检查

In [96]:
```
# check if some columns has empty data

df.count()
```

Out[96]:
```
PassengerId    891
Survived       891
Pclass         891
Name           891
Sex            891
Age            714
SibSp          891
Parch          891
Ticket         891
Fare           891
Cabin          204
Embarked       889
dtype: int64
```

In [97]:
```
df.loc[~df['Embarked'].isin(['S','C','Q'])]
```

Out[97]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Emb
61	62	1	1	Icard, Miss. Amelie	female	38.0	0	0	113572	80.0	B28	NaN
829	830	1	1	Stone, Mrs. George Nelson (Martha Evelyn)	female	62.0	0	0	113572	80.0	B28	NaN

In [98]:
```
df.loc[pd.isnull(df['Age'])].head()
```

Out[98]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabi
5	6	0	3	Moran, Mr. James	male	NaN	0	0	330877	8.4583	NaN
17	18	1	2	Williams, Mr. Charles Eugene	male	NaN	0	0	244373	13.0000	NaN
19	20	1	3	Masselmani, Mrs. Fatima	female	NaN	0	0	2649	7.2250	NaN
26	27	0	3	Emir, Mr. Farred Chehab	male	NaN	0	0	2631	7.2250	NaN
28	29	1	3	O'Dwyer, Miss. Ellen "Nellie"	female	NaN	0	0	330959	7.8792	NaN

检查下来的结果

1. 有两条记录缺少乘船地点，但不影响到所提出来的问题的分析，将其保留并不做处理
2. 有些年龄数据丢失，在分析和年龄相关的数据的时候，剔除这部分的数据。因为无法了解到这部分数据中的年龄分布情况，可能对年龄相关问题的分析造成一定的影响

将剔除异常年龄数据后的数据点保存到新的 DataFrame 当中

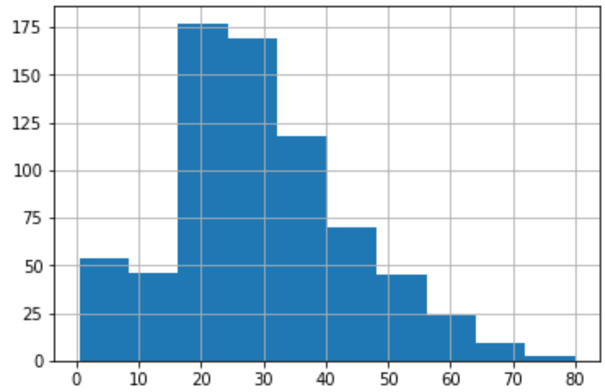
In [99]:
```
df2 = df.loc[pd.notnull(df['Age'])].copy()
```

分析年龄因素和生存率的相关性

In [100]:
```
df2['Age'].describe()
```

Out[100]:
```
count    714.000000
mean      29.699118
std       14.526497
min        0.420000
25%       20.125000
50%       28.000000
75%       38.000000
max       80.000000
Name: Age, dtype: float64
```

In [106]:
```
df2['Age'].hist()
plt.show()
```



In [102]:
```
bins = np.arange(0, 90, 10)
df2['age_range'] = pd.cut(df['Age'], bins)

df2.groupby('age_range')['Survived'].mean()
```

Out[102]:
```
age_range
(0, 10]      0.593750
(10, 20]     0.382609
(20, 30]     0.365217
(30, 40]     0.445161
(40, 50]     0.383721
(50, 60]     0.404762
(60, 70]     0.235294
(70, 80]     0.200000
Name: Survived, dtype: float64
```

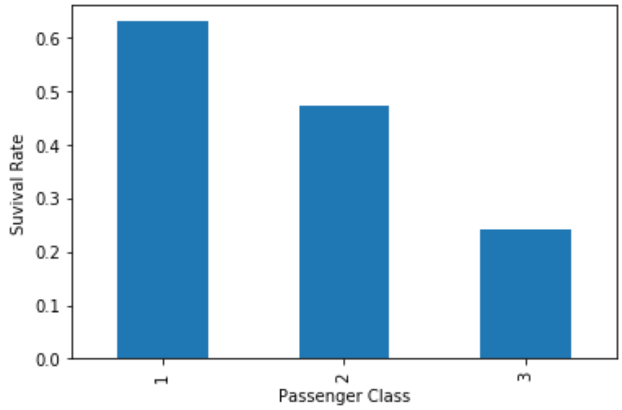
得到的结论

1. 乘客年龄在20-40岁之间是最多的
2. 年龄在0-10岁范围内的乘客的生存率最高，有将近6成的生还率
3. 年龄在70-80岁范围内的乘客的生存率最低，只有2成左右的生还率

In [103]:
```
pclass_serial = df.groupby(['Pclass'])['Survived'].mean()
pclass_serial
```

Out[103]:
```
Pclass
1    0.629630
2    0.472826
3    0.242363
Name: Survived, dtype: float64
```

In [104]:
```
pclass_serial_plt = pclass_serial.plot(kind='bar')
pclass_serial_plt.set_xlabel('Passenger Class')
pclass_serial_plt.set_ylabel('Suvival Rate')
plt.show()
```



the above bar chart shows that the 3rd class passengers had a less chance to survive compared to those in 1st class and 2nd class

In [105]:
```
df.groupby(['Pclass', 'Sex'])['Survived'].mean()
```

Out[105]:
```
Pclass  Sex
1       female    0.968085
        male      0.368852
2       female    0.921053
        male      0.157407
3       female    0.500000
        male      0.135447
Name: Survived, dtype: float64
```

得到的结论

1. 一等舱乘客的生存率远高于三等舱的乘客
2. 女性的生存率要高于男性，尤其在一、二等舱的乘客中更是如此