# Report02 - Titanic: Machine Learning from Disaster


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## 任务简介

1. 任务类型： 二元分类，预测灾难中那些人可能幸存下来；
2. 背景介绍： 泰坦尼克号的沉没是历史上最臭名昭着的沉船之一。 1912年4月15日，在她的处女航中，泰坦尼克号在与冰山相撞后沉没，在2224名乘客和机组人员中造成1502人死亡。 这场耸人听闻的悲剧震惊了国际社会，并导致了更好的船舶安全规定。造成海难失事的原因之一是乘客和机组人员没有足够的救生艇。 尽管幸存下沉有一些运气因素，但有些人比其他人更容易生存，比如妇女，儿童和上流社会。在这个挑战中，我们要求您完成对哪些人可能存活的分析。 特别是，我们要求您运用机器学习工具来预测哪些乘客幸免于悲剧。
3. 数据介绍：

- training set (train.csv)
  训练数据包含了891名乘客的信息，信息的格式如下：

| PassengerId | Survived | Pclass | Name | Sex | Age | SibSp | Parch | Ticket | Fare | Cabin | Embarked |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 乘客ID | 幸存与否 | 船票级别 | 姓名 | 性别 | 年龄 | 同行的兄弟姐妹或配偶总数 | 同行的父母或孩子总数 | 票号 | 票价 | 船舱号 | 登船港口 |

将数据读入并快速了解数据

In [1]:
```python
import pandas as pd
import os.path as path
from matplotlib.pyplot import *
def readCsvData(fname):
    fname = path.join('data', fname + '.csv')
    table = pd.read_csv(fname, sep=',')
    return table

train = readCsvData('train')
test = readCsvData('test')
titanic = pd.concat((train, test), sort=True)
print(titanic.info())
#train.head(25)
test.head(25)
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1309 entries, 0 to 417
Data columns (total 12 columns):
Age            1046 non-null float64
Cabin          295 non-null object
Embarked       1307 non-null object
Fare           1308 non-null float64
Name           1309 non-null object
Parch          1309 non-null int64
PassengerId    1309 non-null int64
Pclass         1309 non-null int64
Sex            1309 non-null object
SibSp          1309 non-null int64
Survived       891 non-null float64
Ticket         1309 non-null object
dtypes: float64(3), int64(4), object(5)
memory usage: 132.9+ KB
None
```

Out[1]:

| | PassengerId | Pclass | Name | Sex | Age | SibSp | Parch | Ticket | Fare | Ca |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 892 | 3 | Kelly, Mr. James | male | 34.5 | 0 | 0 | 330911 | 7.8292 | N |
| **1** | 893 | 3 | Wilkes, Mrs. James (Ellen Needs) | female | 47.0 | 1 | 0 | 363272 | 7.0000 | N |
| **2** | 894 | 2 | Myles, Mr. Thomas Francis | male | 62.0 | 0 | 0 | 240276 | 9.6875 | N |
| **3** | 895 | 3 | Wirz, Mr. Albert | male | 27.0 | 0 | 0 | 315154 | 8.6625 | N |
| **4** | 896 | 3 | Hirvonen, Mrs. Alexander (Helga E Lindqvist) | female | 22.0 | 1 | 1 | 3101298 | 12.2875 | N |
| **5** | 897 | 3 | Svensson, Mr. Johan Cervin | male | 14.0 | 0 | 0 | 7538 | 9.2250 | N |
| **6** | 898 | 3 | Connolly, Miss. Kate | female | 30.0 | 0 | 0 | 330972 | 7.6292 | N |
| **7** | 899 | 2 | Caldwell, Mr. Albert Francis | male | 26.0 | 1 | 1 | 248738 | 29.0000 | N |
| **8** | 900 | 3 | Abrahim, Mrs. Joseph (Sophie Halaut Easu) | female | 18.0 | 0 | 0 | 2657 | 7.2292 | N |
| **9** | 901 | 3 | Davies, Mr. John Samuel | male | 21.0 | 2 | 0 | A/4 48871 | 24.1500 | N |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **10** | 902 | 3 | Ilieff, Mr. Ylio | male | NaN | 0 | 0 | 349220 | 7.8958 | N |
| **11** | 903 | 1 | Jones, Mr. Charles Cresson | male | 46.0 | 0 | 0 | 694 | 26.0000 | N |
| **12** | 904 | 1 | Snyder, Mrs. John Pillsbury (Nelle Stevenson) | female | 23.0 | 1 | 0 | 21228 | 82.2667 | B |
| **13** | 905 | 2 | Howard, Mr. Benjamin | male | 63.0 | 1 | 0 | 24065 | 26.0000 | N |
| **14** | 906 | 1 | Chaffee, Mrs. Herbert Fuller (Carrie Constance... | female | 47.0 | 1 | 0 | W.E.P. 5734 | 61.1750 | E |
| **15** | 907 | 2 | del Carlo, Mrs. Sebastiano (Argenia Genovesi) | female | 24.0 | 1 | 0 | SC/PARIS 2167 | 27.7208 | N |
| **16** | 908 | 2 | Keane, Mr. Daniel | male | 35.0 | 0 | 0 | 233734 | 12.3500 | N |
| **17** | 909 | 3 | Assaf, Mr. Gerios | male | 21.0 | 0 | 0 | 2692 | 7.2250 | N |
| **18** | 910 | 3 | Ilmakangas, Miss. Ida Livija | female | 27.0 | 1 | 0 | STON/O2. 3101270 | 7.9250 | N |
| **19** | 911 | 3 | Assaf Khalil, Mrs. Mariana (Miriam")" | female | 45.0 | 0 | 0 | 2696 | 7.2250 | N |
| **20** | 912 | 1 | Rothschild, Mr. Martin | male | 55.0 | 1 | 0 | PC 17603 | 59.4000 | N |
| **21** | 913 | 3 | Olsen, Master. Artur Karl | male | 9.0 | 0 | 1 | C 17368 | 3.1708 | N |
| **22** | 914 | 1 | Flegenheim, Mrs. Alfred (Antoinette) | female | NaN | 0 | 0 | PC 17598 | 31.6833 | N |
| **23** | 915 | 1 | Williams, Mr. Richard Norris II | male | 21.0 | 0 | 1 | PC 17597 | 61.3792 | N |
| **24** | 916 | 1 | Ryerson, Mrs. Arthur Larned (Emily Maria Borie) | female | 48.0 | 1 | 3 | PC 17608 | 262.3750 | B B B B |

In [2]:
```
corr_matrix = train.corr()
corr_matrix["Survived"].sort_values(ascending=False) # ascending=Fa
lse 降序排列
```

Out[2]:
```
Survived       1.000000
Fare           0.257307
Parch          0.081629
PassengerId   -0.005007
SibSp         -0.035322
Age           -0.077221
Pclass        -0.338481
Name: Survived, dtype: float64
```

数据中 `Age` ， `Cabin` ， `Embarked` ， `Fare` 均存在缺失值。

# 解决途径

## 数据的预处理

原始数据中有一些缺失项和无用项； `PassengerId` 是乘客身份编号，与 `Survived` 相关性很小， `Cabin` 缺失太多， `Ticket` 杂乱无章，将这些信息丢弃

In [3]:
```
PsgIds = titanic.PassengerId
titanic.drop(['Cabin', 'Ticket', 'PassengerId'], axis=1, inplace=Tr
ue)
titanic.head()
```

Out[3]:

| | Age | Embarked | Fare | Name | Parch | Pclass | Sex | SibSp | Survived |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 22.0 | S | 7.2500 | Braund, Mr. Owen Harris | 0 | 3 | male | 1 | 0.0 |
| **1** | 38.0 | C | 71.2833 | Cumings, Mrs. John Bradley (Florence Briggs Th... | 0 | 1 | female | 1 | 1.0 |
| **2** | 26.0 | S | 7.9250 | Heikkinen, Miss. Laina | 0 | 3 | female | 0 | 1.0 |
| **3** | 35.0 | S | 53.1000 | Futrelle, Mrs. Jacques Heath (Lily May Peel) | 0 | 1 | female | 1 | 1.0 |
| **4** | 35.0 | S | 8.0500 | Allen, Mr. William Henry | 0 | 3 | male | 0 | 0.0 |

*数字化类别信息

In [4]:
```
titanic.describe(include=["O"])
```

Out[4]:

| | Embarked | Name | Sex |
|---|---|---|---|
| **count** | 1307 | 1309 | 1309 |
| **unique** | 3 | 1307 | 2 |
| **top** | S | Kelly, Mr. James | male |
| **freq** | 914 | 2 | 843 |

Embarked 有三个值，分配为(0,1,2)
Sex 有两个值，分配为(0,1)
Name 中有效的信息为人名的称呼，从称呼中可以提取到社会信息，我们将 Name 中的“Mr”,"Mrs","Master"等这些信息保留，然后分配类别信息

In [5]:
```
titanic["Sex"] = titanic["Sex"].map({"female": 1, "male": 0}).astype(int)
titanic["Embarked"] = titanic["Embarked"].map({"S": 0, "C": 1, "Q": 2})
import re
titles = set(re.findall(r', (.*?)\.', t)[0] for t in titanic.Name)
titleDict = dict(zip(titles, range(len(titles))))

# 将信息保存到 Name 列
titanic["Name"] = titanic.Name.str.extract(r', (.*?)\.')
#print(titanic["Name"])
titanic["Name"] = titanic["Name"].map(titleDict).astype(int)
```

In [ ]:
```

```

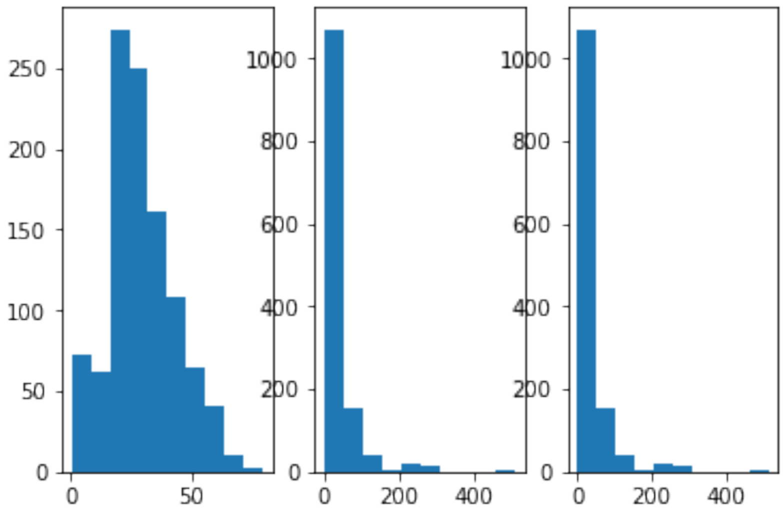
对 Age ， Embarked 和 Fare 的缺失项进行填充，首先查看每个数据的分布情况

In [6]:
```
# 查看缺失项的分布情况
print(titanic.Age.describe())
print(titanic.Embarked.describe())
print(titanic.Fare.describe())
subplot(131).hist(titanic.Age)
subplot(132).hist(titanic.Fare)
subplot(133).hist(titanic.Fare)
```

```
count    1046.000000
mean       29.881138
std        14.413493
min         0.170000
25%        21.000000
50%        28.000000
75%        39.000000
max        80.000000
Name: Age, dtype: float64
count    1307.000000
mean        0.394797
std         0.653817
min         0.000000
25%         0.000000
50%         0.000000
75%         1.000000
max         2.000000
Name: Embarked, dtype: float64
count    1308.000000
mean       33.295479
std        51.758668
min         0.000000
25%         7.895800
50%        14.454200
75%        31.275000
max       512.329200
Name: Fare, dtype: float64
```

```
/Users/lichen/anaconda3/lib/python3.6/site-packages/numpy/lib/hist
ograms.py:754: RuntimeWarning: invalid value encountered in greate
r_equal
  keep = (tmp_a >= first_edge)
/Users/lichen/anaconda3/lib/python3.6/site-packages/numpy/lib/hist
ograms.py:755: RuntimeWarning: invalid value encountered in less_e
qual
  keep &= (tmp_a <= last_edge)
```

Out[6]:
```
(array([1070.,  154.,   42.,    4.,   21.,   13.,    0.,    0.,
0.,
           4.]),
 array([  0.     ,  51.23292, 102.46584, 153.69876, 204.93168, 256
.1646 ,
        307.39752, 358.63044, 409.86336, 461.09628, 512.3292 ]),
 <a list of 10 Patch objects>)
```




对缺失项的分布进行分析，对**Age**的缺失项取均值进行填充，对**Embarked**和**Fare**取众数进行填充

In [7]:
```
# 取众数填充
FareMode = titanic['Fare'].mode().iloc[0]
titanic.fillna({ "Fare": FareMode}, inplace=True)
EmbMode = titanic['Embarked'].mode().iloc[0]
titanic.fillna({ "Embarked": EmbMode}, inplace=True)
AgeMean = titanic['Age'].mean()
titanic.fillna({ "Age": AgeMean}, inplace=True)
# print(titanic.info())
```

In [8]:
```
print(titanic.Embarked.describe())
```

```
count    1309.000000
mean        0.394194
std         0.653499
min         0.000000
25%         0.000000
50%         0.000000
75%         1.000000
max         2.000000
Name: Embarked, dtype: float64
```

## 构建模型

此时处理过的信息与 `Report01` 中的信息有些类似，同时这个问题也是二分类问题，使用KNN模型和随机森林模型进行预测。

1. 数据预处理

In [9]:
```
from sklearn.utils import shuffle
# 训练数据与测试数据分离
trainData = titanic[:len(train)]
# 将训练数据打乱
trainData = shuffle(trainData)
#分离标签
y_train = trainData.pop('Survived')
#trainData.drop('Survived', axis=1, inplace = True)
# 划分数据为2:8, 20%的数据用于测试
slash = int(trainData.shape[0] * 0.8)
trainTrain, y_trainTrain = trainData[:slash], y_train[:slash]
testTrain, y_testTrain = trainData[slash: ], y_train[slash: ]
```

1. KNN模型

In [10]:
```
#训练KNN模型
from sklearn import neighbors
from sklearn.metrics import average_precision_score
from sklearn.metrics import accuracy_score
import sklearn

testCaseNum = testTrain.shape[0]
# 对于给定的近邻 K 值, 计算其在分配的测试集上的效果
def testNeighborNum(neighborNum):
    start = time.time()
    knn = neighbors.KNeighborsClassifier(n_neighbors=neighborNum, n_jobs=-1)
    knn.fit(trainTrain, y_trainTrain)

    output = knn.predict(testTrain)
    testTime = time.time() - start
    #print(output)
    # 定义判定标准为平均的正确率
    accuracy = accuracy_score(y_testTrain, output)
    TrainTime = time.time() - start
    avpr = average_precision_score(y_testTrain, output)
    print(f'KNN Train time = {TrainTime:.2f}s')
    return [neighborNum,avpr,accuracy]
```

选取不同的K值进行实验，并画出K值与预测准确率的关系

In [11]:
```
total, step = 50, 1
result=[]
for k in range(1, total+1,step):
    result.append(testNeighborNum(k))
#result = np.array(result)
```

```
KNN Train time = 0.11s
KNN Train time = 0.11s
KNN Train time = 0.11s
KNN Train time = 0.11s
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KNN Train time = 0.11s
KNN Train time = 0.11s
KNN Train time = 0.11s
KNN Train time = 0.11s
```
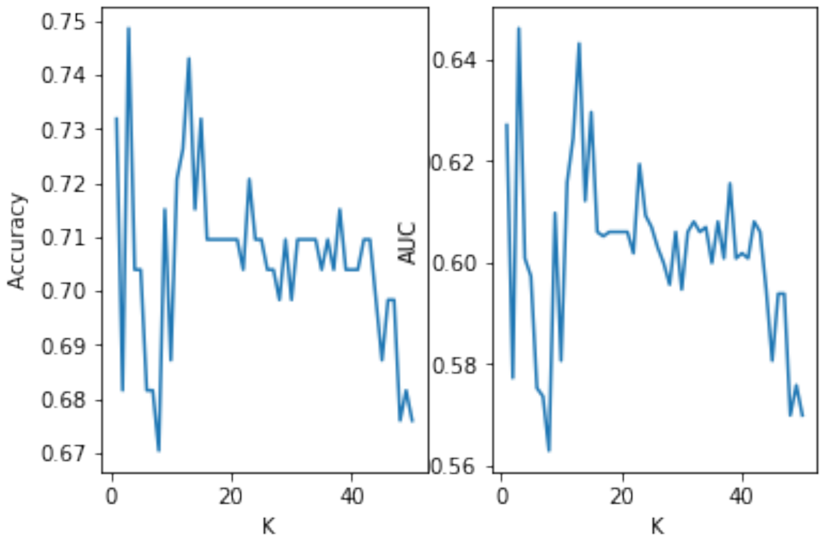

In [12]:
```
from matplotlib.pyplot import *
result = np.array(result)
figure(1)
ax1 = subplot(121)
plot(result[:,0],result[:,2])
#title(r"$sin^2(x - 2) e^{-x^2}$")
xlabel(' K')
ylabel(' Accuracy ')
ax2 = subplot(122)
plot(result[:,0],result[:,1])
xlabel(' K')
ylabel('AUC')
```

Out[12]: Text(0, 0.5, 'AUC')




在之后的测试环节，选择 $K = 13$ 进行测试

1. 随机森林算法
   随机森林是一个包含多个决策树的分类器，输出的类型由输出的类别的众数而定。

In [13]:
```
#trainData.head(15)
```

In [14]:
```
#titanic.head(15)
```

In [15]:
```
testData = titanic[len(train):]
#分离标签
testData.pop('Survived')
testData.head(15)
#trainData.drop('Survived', axis=1, inplace = True)
# 划分数据为2:8, 20%的数据用于测试
```

Out[15]:

| | Age | Embarked | Fare | Name | Parch | Pclass | Sex | SibSp |
|---|---|---|---|---|---|---|---|---|
| **0** | 34.500000 | 2.0 | 7.8292 | 3 | 0 | 3 | 0 | 0 |
| **1** | 47.000000 | 0.0 | 7.0000 | 12 | 0 | 3 | 1 | 1 |
| **2** | 62.000000 | 2.0 | 9.6875 | 3 | 0 | 2 | 0 | 0 |
| **3** | 27.000000 | 0.0 | 8.6625 | 3 | 0 | 3 | 0 | 0 |
| **4** | 22.000000 | 0.0 | 12.2875 | 12 | 1 | 3 | 1 | 1 |
| **5** | 14.000000 | 0.0 | 9.2250 | 3 | 0 | 3 | 0 | 0 |
| **6** | 30.000000 | 2.0 | 7.6292 | 0 | 0 | 3 | 1 | 0 |
| **7** | 26.000000 | 0.0 | 29.0000 | 3 | 1 | 2 | 0 | 1 |
| **8** | 18.000000 | 1.0 | 7.2292 | 12 | 0 | 3 | 1 | 0 |
| **9** | 21.000000 | 0.0 | 24.1500 | 3 | 0 | 3 | 0 | 2 |
| **10** | 29.881138 | 0.0 | 7.8958 | 3 | 0 | 3 | 0 | 0 |
| **11** | 46.000000 | 0.0 | 26.0000 | 3 | 0 | 1 | 0 | 0 |
| **12** | 23.000000 | 0.0 | 82.2667 | 12 | 0 | 1 | 1 | 1 |
| **13** | 63.000000 | 0.0 | 26.0000 | 3 | 0 | 2 | 0 | 1 |
| **14** | 47.000000 | 0.0 | 61.1750 | 12 | 0 | 1 | 1 | 1 |

In [16]:
```
# FareMode = titanic['Fare'].mode().iloc
# titanic.fillna({ "Fare": FareMode}, inplace=True)
# print(testData.Fare.describe())
```

In [17]:
```
#testData.info()
```

In [18]:
```
from sklearn.ensemble import RandomForestClassifier
# 建立随机森林模型
clf = RandomForestClassifier(n_estimators=500, random_state=0)
clf.fit(trainData, y_train)
# 预测
y_preds = clf.predict(testData)
```

In [19]:
```
testPsgIds = PsgIds[len(train):].values
submitFile = path.join('data', 'submit_probRf.csv')
with open(submitFile, 'w+') as f:
    print('PassengerId', 'Survived', sep=',', file=f)
    for testPsgId, y_pred in zip(testPsgIds, y_preds):
        print(testPsgId, int(y_pred), sep=',', file=f)
```

随机森林准确率76.555%

# 总结

这次报告任务是实现对灾难中幸存人员预测，也是一个二分类问题。报告中我们使用了KNN近邻算法以及随机森林算法。这次报告的主要工作是对数据进行处理，我们将有很多缺失值的和部分无用的数据进行了舍弃，对部分缺失值进行简单的数据分析并进行补全，对所有的数据进行了数字化。 在分类任务中，使用有效的分类算法很重要，对数据进行预处理分析也是十分重要的。