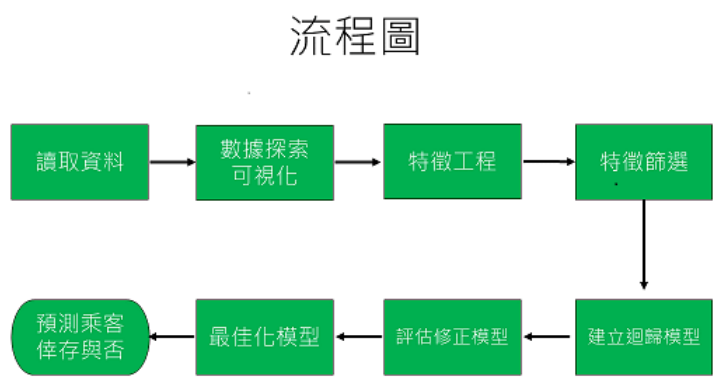
應數四 吳榮峻

目標:預測搭乘鐵達尼號的乘客倖存與否



●讀取資料

In [2]:
```
train.shape, test.shape
```

```
((891, 12), (418, 11))
```

In [3]:
```
train
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S
...	...	...	...	...	...	...	...	...	...	...	...	...
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.0000	NaN	S
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.0000	B42	S
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.4500	NaN	S
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.0000	C148	C
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.7500	NaN	Q

891 rows × 12 columns

變數說明

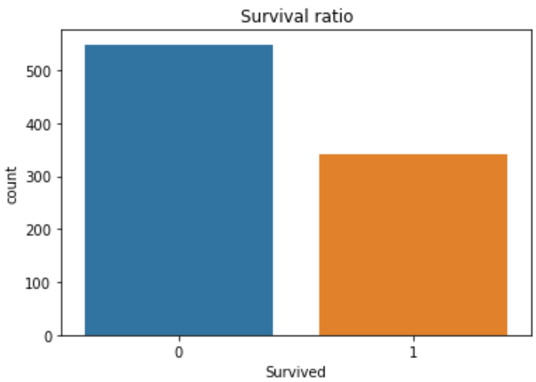
- PassengerId-旅客編號
- Survived-倖存與否(1:是，0:否)
- Pclass-票務艙等 (1 = 1st, 2 = 2nd, 3 = 3rd)
- Name-名子
- Sex-性別
- Age-年齡
- SibSp-船上的兄弟姐妹配偶人數
- Parch-船上的父母子女人數
- Ticket-票號
- Fare-乘客票價
- Cabin-艙
- Embarked-登船港口(C = Cherbourg(瑟堡), Q = Queenstown(皇后鎮), S = Southampton(修咸頓))

●數據探索

Survived

```
0    549
1    342
Name: Survived, dtype: int64
```

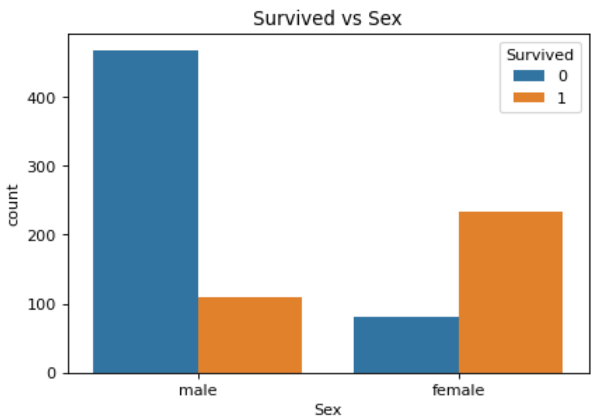
```
D:\ANACONDA\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```



Survived: 38%

Sex

```
<matplotlib.axes._subplots.AxesSubplot at 0x2e8b9d9b1c0>
```

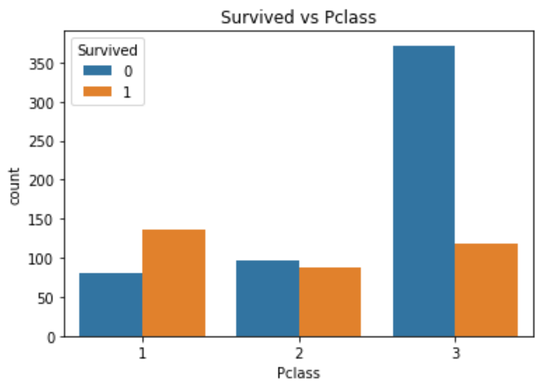



```
Sex     Survived
female  1           233
        0            81
male    0           468
        1           109
Name: Survived, dtype: int64
```

明顯得知，女性的存活率高許多(高達74%)

Pclass

```
<matplotlib.axes._subplots.AxesSubplot at 0x2e8c2aa30d0>
```

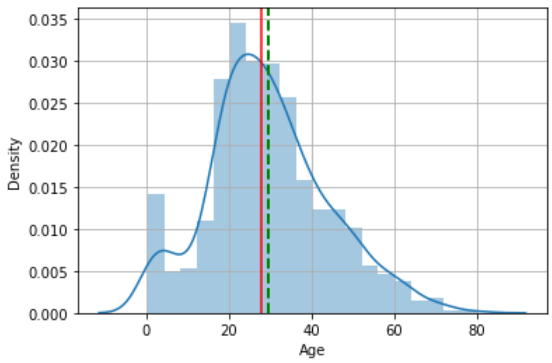



```
Pclass  Survived
1       1           136
        0            80
2       0            97
        1            87
3       0           372
        1           119
Name: Survived, dtype: int64
```

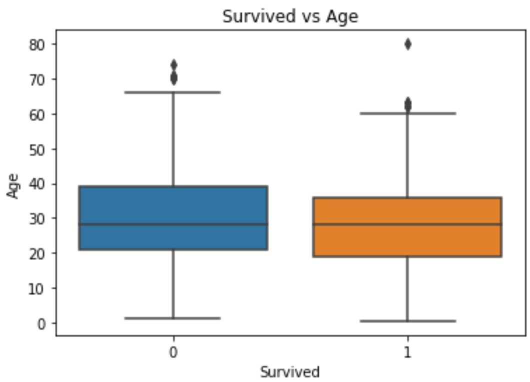
頭等艙的存活率最高(62%)

Age

```
D:\ANACONDA\lib\site-packages\seaborn\distributions.py:2551: FutureWarning: `distplot` is a deprecated function and wi
ll be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with simila
r flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



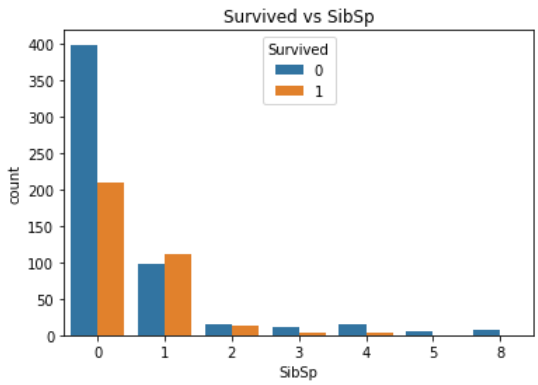
1. 年齡為右偏的分佈(mean > median)
2. 船上年輕人與中年人(20~40歲)占大多數比例
3. 平均年齡: 29.7 ，中位數:28，最大值:80，最小值:0.42



倖存者大多為年輕人(20~40歲)

SipSp

```
<matplotlib.axes._subplots.AxesSubplot at 0x2e8c4c692b0>
```

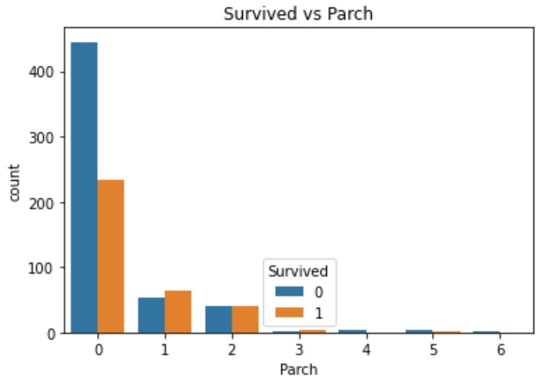



```
SibSp  Survived
0      0           398
       1           210
1      1           112
       0            97
2      0            15
       1            13
3      0            12
       1             4
4      0            15
       1             3
5      0             5
8      0             7
Name: Survived, dtype: int64
```

1. 船上的旅客，大多數有1位兄弟姊妹配偶
2. 有1位兄弟姊妹配偶的旅客存活率較高(54%)

Parch

```
<matplotlib.axes._subplots.AxesSubplot at 0x2e8c4cdb880>
```

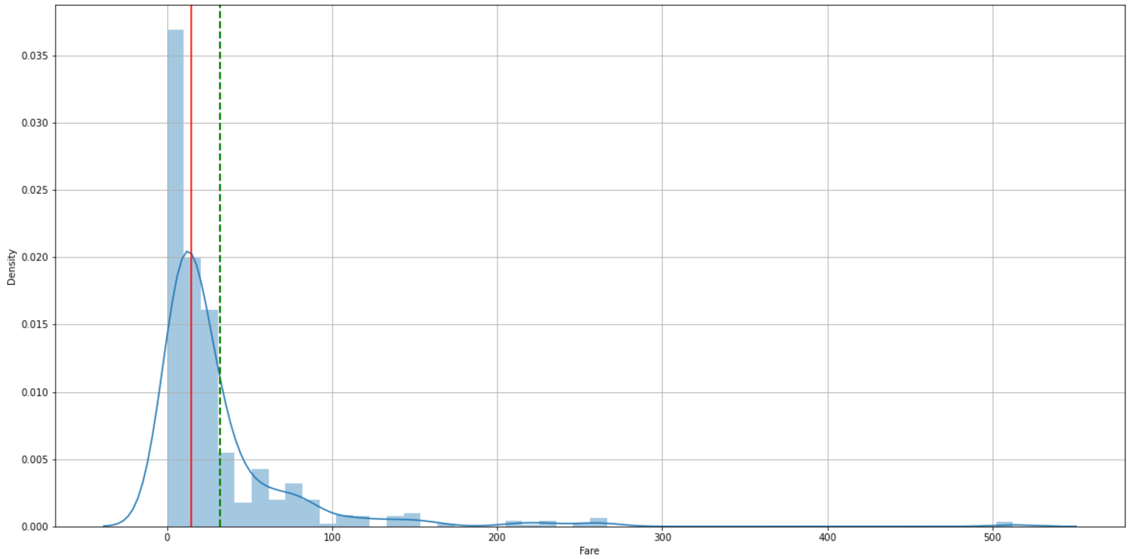



```
Parch  Survived
0      0           445
       1           233
1      1            65
       0            53
2      0            40
       1            40
3      1             3
       0             2
4      0             4
5      0             4
       1             1
6      0             1
Name: Survived, dtype: int64
```

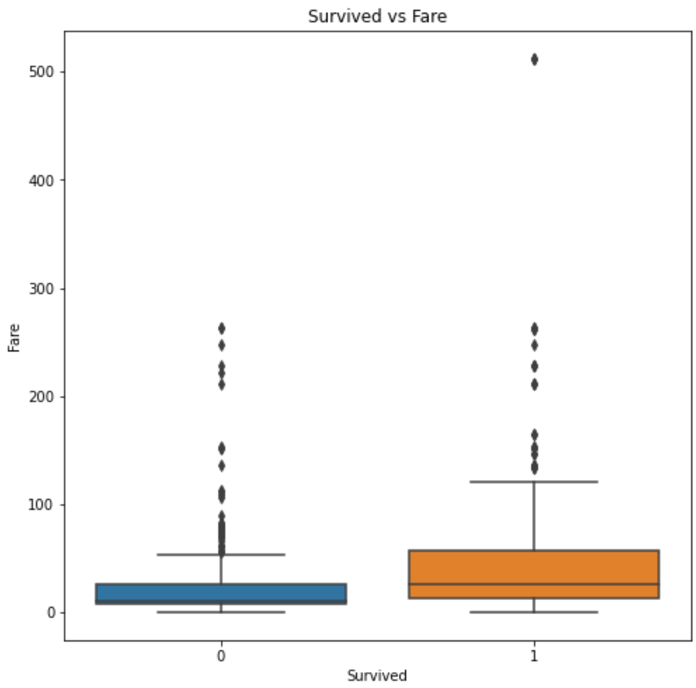
1. 船上的旅客，大多數有1~2位父母子女
2. 有1位父母子女的旅客存活率較高(55%)

Fare

```
D:\ANACONDA\lib\site-packages\seaborn\distributions.py:2551: FutureWarning: `distplot` is a deprecated function and wi
ll be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with simila
r flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



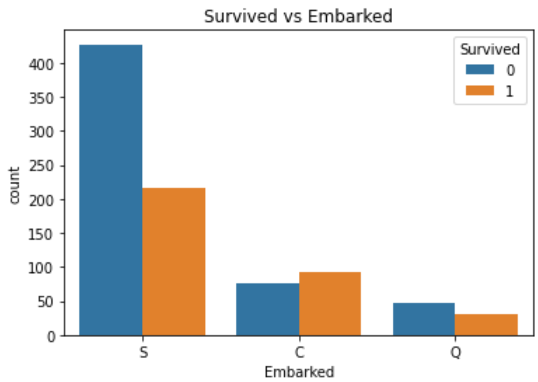
1. 票價的分布呈現右偏 (mean > median)
2. 票價平均:32.20，中位數:14.4542，最大值:512.3292，最小值:0



票價相對高的旅客存活率較高

Embarked

```
<matplotlib.axes._subplots.AxesSubplot at 0x2e8c55890d0>
```




```
Embarked  Survived
C         1            93
          0            75
Q         0            47
          1            30
S         0           427
          1           217
Name: Survived, dtype: int64
```

1. 乘客大多數是Southampton(修咸頓)站上船的
2. 在Cherbourg(瑟堡)上船的旅客存活率相對較高(55%)

●特徵工程

Train資料的遺漏值

In [23]:
```
#檢查是否有遺漏值
train.isnull().sum()
```

```
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
```

將Train資料與Test資料合併,命名為data

In [24]:
```
#合併Data,以利做特徵工程,之後再分割
data= train.append(test)
data
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0.0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1.0	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1.0	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1.0	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0.0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S
...	...	...	...	...	...	...	...	...	...	...	...	...
413	1305	NaN	3	Spector, Mr. Woolf	male	NaN	0	0	A.5. 3236	8.0500	NaN	S
414	1306	NaN	1	Oliva y Ocana, Dona. Fermina	female	39.0	0	0	PC 17758	108.9000	C105	C
415	1307	NaN	3	Saether, Mr. Simon Sivertsen	male	38.5	0	0	SOTON/O.Q. 3101262	7.2500	NaN	S
416	1308	NaN	3	Ware, Mr. Frederick	male	NaN	0	0	359309	8.0500	NaN	S
417	1309	NaN	3	Peter, Master. Michael J	male	NaN	1	1	2668	22.3583	NaN	C

1309 rows × 12 columns

Data資料的遺漏值

In [25]:
```
data.isnull().sum()
```

```
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
```

由於變數Cabin(船艙)遺失值過多,很難衡量用什麼值去填入,故刪除此欄位(變數)

In [26]:
```
data=data.drop( ['Cabin'], axis=1 )
```

處理Fare 與 Embarked的遺失值

In [27]:

```
#Fare遺失值填入中位數
data['Fare'].fillna(data['Fare'].median(), inplace = True)
```

In [28]:

```
#Embarked遺失值填入眾數
data['Embarked'].fillna(data['Embarked'].mode()[0], inplace = True)
```

新的欄位title(姓名的姓氏)

In [29]:

```
import re
regex = re.compile( ' ([A-Za-z]+)\.' )
data['Title'] = data.Name.map( lambda x:regex.search(x)[0] )
# Dropping the first and the last words
data['Title'] = data.Title.map( lambda x:x[1:][:-1] )
data['Title'].unique()
```

```
array(['Mr', 'Mrs', 'Miss', 'Master', 'Don', 'Rev', 'Dr', 'Mme', 'Ms',
       'Major', 'Lady', 'Sir', 'Mlle', 'Col', 'Capt', 'Countess',
       'Jonkheer', 'Dona'], dtype=object)
```

In [30]:

```
data['Title'] = data.Title.replace( ['Ms','Mlle'], 'Miss' )
data['Title'] = data.Title.replace( 'Mme', 'Mrs' )
```

In [31]:

```
data['Title'].value_counts()
```

```
Mr          757
Miss        264
Mrs         198
Master       61
Rev           8
Dr            8
Col           4
Major         2
Dona          1
Sir           1
Jonkheer      1
Countess      1
Don           1
Lady          1
Capt          1
Name: Title, dtype: int64
```

In [32]:

```
#將Title裡的前六多變數抓出
imp_Title = data["Title"].value_counts()[:6].index.tolist()
imp_Title
```

```
['Mr', 'Miss', 'Mrs', 'Master', 'Rev', 'Dr']
```

In [33]:

```
data["Title"]=data["Title"].apply(lambda x: x if imp_Title else "Other")
```

處理Age的遺失值

In [34]:

```
#Age的遺失值透過Title分群，並將其分類的中位數填入
med_age = {}
for X in imp_Title:
    med_age[X]= data.loc[data.Title == X]["Age"].median()
med_age["Other"] = data.Age.median()
data.loc[data.Age.isnull(), "Age"]= data[data.Age.isnull()]["Title"].map(med_age)
```

將分類變數做編碼

In [35]:
```
# 對性別做標籤編碼
Sex_mapping = { 'male':0, 'female':1 }
data[ 'Sex' ] = data.Sex.map( Sex_mapping )
```

In [36]:
```
# 對Embarked(登船入口)做標籤編碼
Embarked_mapping ={"S":0, "C":1, "Q":2}
data["Embarked"]=data.Embarked.map(Embarked_mapping)
```

In [37]:
```
#對 Title 做編碼
from sklearn.preprocessing import LabelEncoder
data["Title"]=LabelEncoder().fit_transform(data.Title)
```

新欄位Age_level

In [38]:
```
# 新增欄位"Age_level"
train["Age_cut"]=pd.cut(train.Age,6)
train[['Age_cut', 'Survived']].groupby(['Age_cut'], as_index=False).mean().sort_values(by=
```

	Age_cut	Survived
0	(0.34, 13.683]	0.591549
1	(13.683, 26.947]	0.354839
2	(26.947, 40.21]	0.428571
3	(40.21, 53.473]	0.390000
4	(53.473, 66.737]	0.348837
5	(66.737, 80.0]	0.142857

In [39]:
```
data["Age_level"]= data["Age"]
data.loc[ data.Age <= 13.683, 'Age_level'] = 0
data.loc[(data.Age > 13.683) & (data.Age <= 26.947), 'Age_level'] = 1
data.loc[(data.Age > 26.947) & (data.Age <= 40.21), 'Age_level'] = 2
data.loc[(data.Age > 40.21) & (data.Age <= 53.473), 'Age_level'] = 3
data.loc[(data.Age > 53.473) & (data.Age <= 66.737), 'Age_level'] = 4
data.loc[data.Age > 66.737, 'Age_level'] =5
data.head(5)
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked	Title	Age_level
0	1	0.0	3	Braund, Mr. Owen Harris	0	22.0	1	0	A/5 21171	7.2500	0	11	1.0
1	2	1.0	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	1	38.0	1	0	PC 17599	71.2833	1	12	2.0
2	3	1.0	3	Heikkinen, Miss. Laina	1	26.0	0	0	STON/O2. 3101282	7.9250	0	10	1.0
3	4	1.0	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	1	35.0	1	0	113803	53.1000	0	12	2.0
4	5	0.0	3	Allen, Mr. William Henry	0	35.0	0	0	373450	8.0500	0	11	2.0

新欄位Fare_level

In [40]:
```
train["Fare_cut"]=pd.qcut(train.Fare,4)
train[['Fare_cut', 'Survived']].groupby(['Fare_cut'], as_index=False).mean().sort_values(t
```

	Fare_cut	Survived
0	(-0.001, 7.91]	0.197309
1	(7.91, 14.454]	0.303571
2	(14.454, 31.0]	0.454955
3	(31.0, 512.329]	0.581081

In [41]:

```
data["Fare_level"]= data["Fare"]
data.loc[ data.Fare <= 7.91, 'Fare_level'] = 0
data.loc[(data.Fare > 7.91) & (data.Fare <= 14.454), 'Fare_level'] = 1
data.loc[(data.Fare > 14.454) & (data.Fare <= 31.0), 'Fare_level'] = 2
data.loc[data.Fare > 31.0, 'Fare_level'] =3
data.head(5)
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked	Title	Age_level	Fare_level
0	1	0.0	3	Braund, Mr. Owen Harris	0	22.0	1	0	A/5 21171	7.2500	0	11	1.0	0.0
1	2	1.0	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	1	38.0	1	0	PC 17599	71.2833	1	12	2.0	3.0
2	3	1.0	3	Heikkinen, Miss. Laina	1	26.0	0	0	STON/O2. 3101282	7.9250	0	10	1.0	1.0
3	4	1.0	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	1	35.0	1	0	113803	53.1000	0	12	2.0	3.0
4	5	0.0	3	Allen, Mr. William Henry	0	35.0	0	0	373450	8.0500	0	11	2.0	1.0

In [42]:

```
data.columns
```

```
Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Embarked', 'Title', 'Age_level',
       'Fare_level'],
      dtype='object')
```

In [43]:

```
#再次檢查是否有遺漏值
data.isnull().sum()
```

```
PassengerId      0
Survived       418
Pclass           0
Name             0
Sex              0
Age              0
SibSp            0
Parch            0
Ticket           0
Fare             0
Embarked         0
Title            0
Age_level        0
Fare_level       0
dtype: int64
```

產生Train(訓練集)和Test(測試集)

In [44]:

```
# 產生訓練集和測試集
Train = data[ pd.notnull(data.Survived) ]
Test = data[ pd.isnull(data.Survived) ]
Train.shape, Test.shape
```

```
((891, 14), (418, 14))
```

In [45]:

```
Y_Train = Train.Survived
X_Train = Train.drop( ['Survived'], axis=1 )
X_Train.shape, Y_Train.shape
```

```
((891, 13), (891,))
```

特徵篩選

In [46]:
```
X_Train.columns, X_Train.dtypes
```

```
(Index(['PassengerId', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp', 'Parch',
        'Ticket', 'Fare', 'Embarked', 'Title', 'Age_level', 'Fare_level'],
       dtype='object'),
 PassengerId      int64
 Pclass           int64
 Name            object
 Sex              int64
 Age            float64
 SibSp            int64
 Parch            int64
 Ticket          object
 Fare           float64
 Embarked         int64
 Title            int32
 Age_level      float64
 Fare_level     float64
 dtype: object)
```

•KBest

用想要的檢驗方法算出每個特徵的得分,並依據這個特徵得分,移除得分前k名以外的所有特徵

In [47]:
```
X_Train
```

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked	Title	Age_level	Fare_level
0	1	3	Braund, Mr. Owen Harris	0	22.0	1	0	A/5 21171	7.2500	0	11	1.0	0.0
1	2	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	1	38.0	1	0	PC 17599	71.2833	1	12	2.0	3.0
2	3	3	Heikkinen, Miss. Laina	1	26.0	0	0	STON/O2. 3101282	7.9250	0	10	1.0	1.0
3	4	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	1	35.0	1	0	113803	53.1000	0	12	2.0	3.0
4	5	3	Allen, Mr. William Henry	0	35.0	0	0	373450	8.0500	0	11	2.0	1.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
886	887	2	Montvila, Rev. Juozas	0	27.0	0	0	211536	13.0000	0	13	2.0	1.0
887	888	1	Graham, Miss. Margaret Edith	1	19.0	0	0	112053	30.0000	0	10	1.0	2.0
888	889	3	Johnston, Miss. Catherine Helen "Carrie"	1	22.0	1	2	W./C. 6607	23.4500	0	10	1.0	2.0
889	890	1	Behr, Mr. Karl Howell	0	26.0	0	0	111369	30.0000	1	11	1.0	2.0
890	891	3	Dooley, Mr. Patrick	0	32.0	0	0	370376	7.7500	2	11	2.0	0.0

891 rows × 13 columns

In [48]:
```
from sklearn.model_selection import train_test_split
import numpy as np
y = Y_Train
cols = ["Pclass", 'Sex', 'SibSp', 'Parch', 'Embarked', 'Title', 'Age_level',
        'Fare_level']
X = X_Train[cols]
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size=0.3, random_state=1234)
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
((623, 8), (268, 8), (623,), (268,))
```

In [49]:
```
#chi2:卡方檢定
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
new_clf  = SelectKBest(chi2, k=7).fit(X_train, y_train)
```

In [50]:
```
new_clf.get_support(),cols
```

```
(array([ True,  True,  True,  True,  True, False,  True,  True]),
 ['Pclass',
  'Sex',
  'SibSp',
  'Parch',
  'Embarked',
  'Title',
  'Age_level',
  'Fare_level'])
```

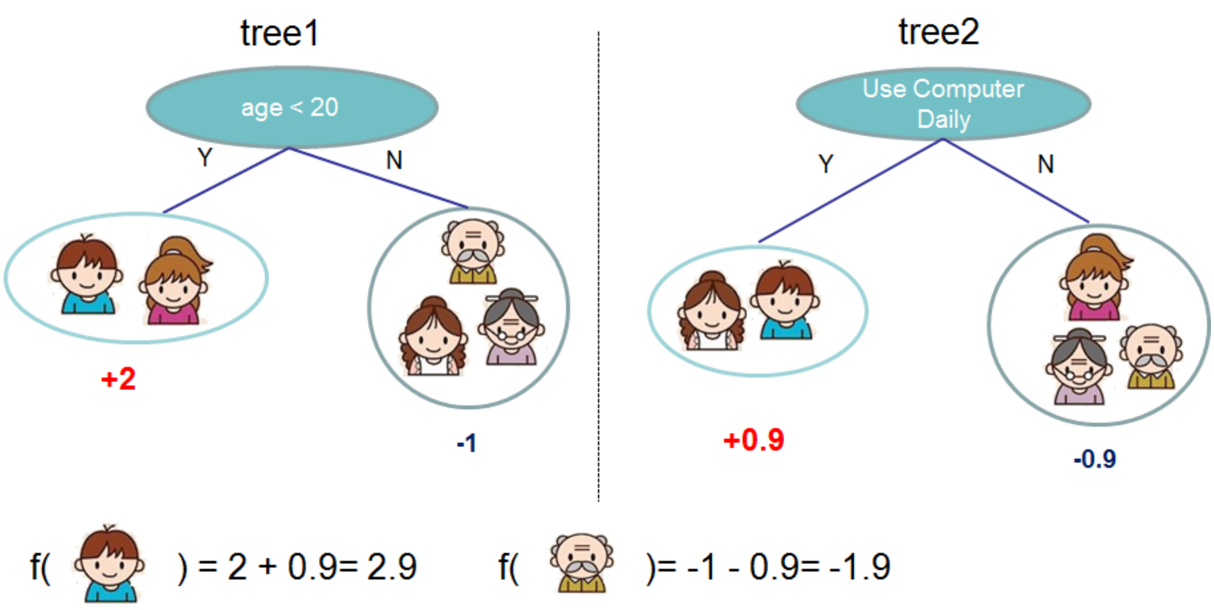
Choose "Pclass", 'Sex', 'SibSp','Parch', 'Embarked', 'Age_level','Fare_level'

建立模型與預測

方法一：XGBoost(極限梯度提升法)

*每一次保留原來的模型不變，並且加入一個新的函數至模型中，修正上一棵樹的錯誤，以提升整體的模型。故此方法為數個模型所組成的加法模型，即為一排樹的概念。

*預測一個樣本的分數，其實就是根據這個樣本的特徵，在每棵樹中會落到對應的一個葉子節點，每個葉子節點就對應一個分數，最後只需要將每棵樹對應的分數加起來就是該樣本的預測值



In [51]:
```
SelectedFeatures = ["Pclass", 'Sex', 'SibSp','Parch','Embarked','Age_level','Fare_level']
X=X_Train[SelectedFeatures]
y=Y_Train
X.shape, y.shape
```

```
((891, 7), (891,))
```

In [52]:
```
# 分割資料
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size=0.3, random_state=1234)
X_train.shape, X_test.shape, y_train.shape , y_test.shape, y_test.sum
X_train.shape, X_test.shape, y_train.shape , y_test.shape
```

```
((623, 7), (268, 7), (623,), (268,))
```

In [53]:
```
#導入套件
from xgboost import XGBClassifier
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import cross_val_score, KFold
#設定xgbc模型參數 #n_estimators:樹木的數量，max_depth:樹生長的深度
xgbc = XGBClassifier(n_estimators=5 ,max_depth=6)
xgbc.fit(X_train[SelectedFeatures], y_train)
#訓練資料評估 與 測試資料評估
xgbc.score(X_train[SelectedFeatures], y_train),xgbc.score(X_test[SelectedFeatures], y_test
```

```
(0.8571428571428571, 0.835820895522388)
```

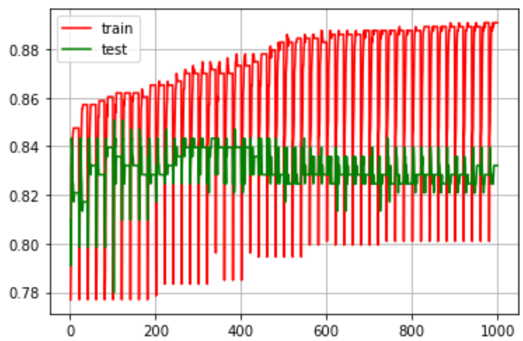
In [54]:
```
from xgboost import XGBClassifier
#加入n ，把 accuracy 設為一個空的list
accuracy = []
for i in range(1,51,1):
    for j in range(1,21,1):
        xgbc = XGBClassifier(n_estimators=i ,max_depth=j)
        xgbc.fit(X_train[SelectedFeatures], y_train)
        accuracy.append((xgbc.score(X_train[SelectedFeatures], y_train),
                         xgbc.score(X_test[SelectedFeatures], y_test)))
```

In [55]:
```
#accuracy
```

In [56]:
```
train_score = [t[0] for t in accuracy ]
test_score = [t[1] for t in accuracy ]
print(max(test_score))
print(test_score.index(max(test_score)))
#(102+1)/20= 5......3
#i = 6 , j=3
```

```
0.8507462686567164
102
```

In [57]:
```
#畫圖
import matplotlib.pyplot as plt
plt.grid()
plt.plot(range(1,1001,1),train_score, color='red',label='train')
plt.plot(range(1,1001,1),test_score, color='green',label='test')
plt.legend()
plt.savefig("n_neighbors&max_depth ")
plt.show()
```



In [58]:

```
#i = 6 , j=3
from xgboost import XGBClassifier
xgbc_new = XGBClassifier(n_estimators=6 ,max_depth=3)
xgbc_new.fit(X_train[SelectedFeatures], y_train)
xgbc_new.score(X_train[SelectedFeatures], y_train),xgbc_new.score(X_test[SelectedFeatures]
```

```
(0.8330658105939005, 0.8507462686567164)
```

In [59]:

```
# kfold- cross validataion
kfold =KFold(n_splits=5, shuffle=True)
Kf_cv_scores = cross_val_score(xgbc_new,X_train, y_train,cv=kfold)
print(Kf_cv_scores)
print('mean of K fold=',Kf_cv_scores.mean())
```

```
[0.8        0.816      0.744      0.87096774 0.81451613]
mean of K fold= 0.8090967741935484
```

In [60]:

```
# Confusion matrix :評估模型好壞
predicted_labels = xgbc_new.predict(X_test)
true_labels = y_test
from sklearn.metrics import confusion_matrix, classification_report
cm = confusion_matrix(true_labels, predicted_labels)
print(classification_report(true_labels, predicted_labels))
print("Confusion matrix")
print(cm)
```

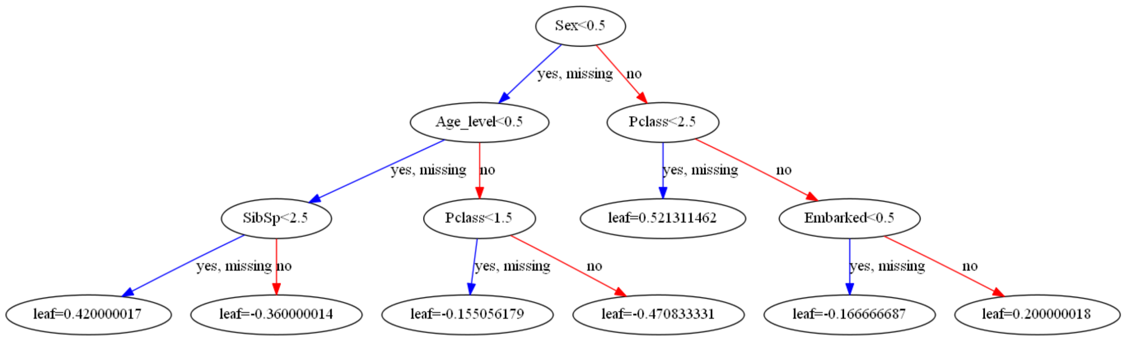
```
              precision    recall  f1-score   support

         0.0       0.83      0.96      0.89       166
         1.0       0.91      0.68      0.78       102

    accuracy                           0.85       268
   macro avg       0.87      0.82      0.83       268
weighted avg       0.86      0.85      0.85       268

Confusion matrix
[[159   7]
 [ 33  69]]
```

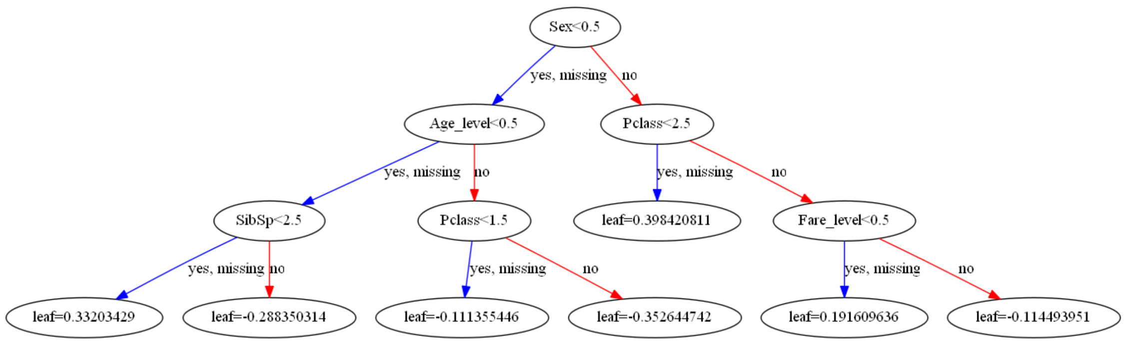
名稱說明

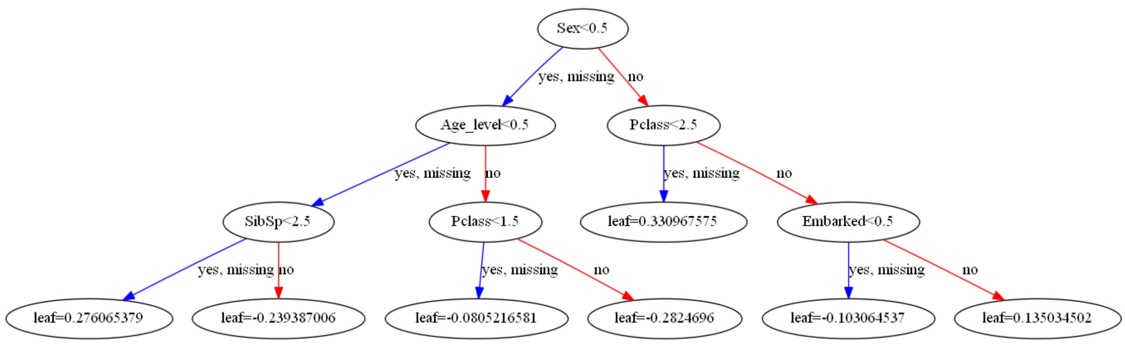
- Precision(精確率) ex: 這邊以倖存者來說，在預測倖存者為76人的情況，但實際上僅有69人倖存(91%)
- recall(召回率) ex: 以此例的倖存者來說，實際上有102人倖存，但在此模型中，僅預測倖存者人數為69人(68%)
- f1-score :precision 與 recall的調和平均
- accuracy(準確率): TP和TN把它加總起來除上所有情形個數 ex: (159+69)/268=0.85
- macro avg(巨集平均):所有類別的統計指標加總除以類別數 ex: precision's macro avg=(0.83+0.91)/2 = 0.87
- weighted avg(加權平均)

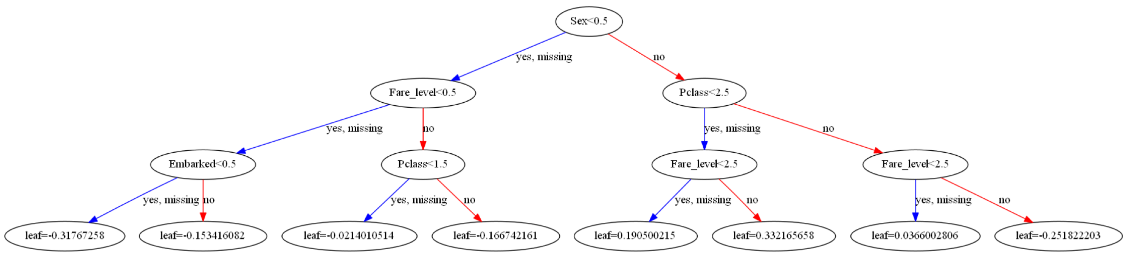
In [61]:

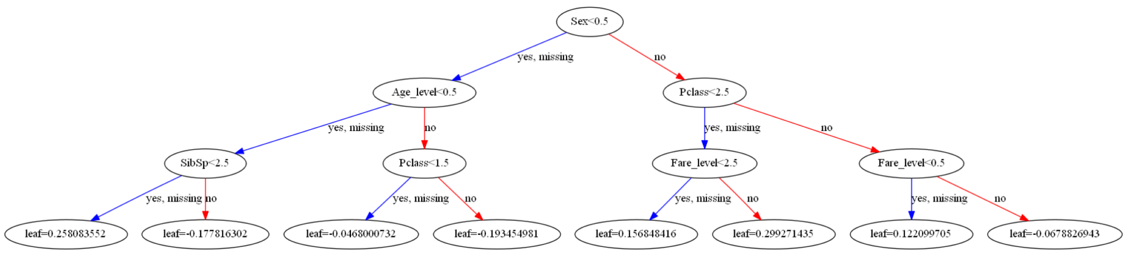
```
import graphviz
#設置Graphviz路徑
import os
os.environ["PATH"] += os.pathsep + 'C:/Program Files (x86)/Graphviz2.38/bin/'
import matplotlib.pyplot as plt
plt.rcParams["figure.figsize"] = (40, 40) #設定之後所有圖片大小
#XGB樹模型輸出
from xgboost import plot_tree
# plot_tree(xgbc,num_trees=0)
# plot_tree(xgbc,num_trees=1)
# plt.show()
for i in range(0,6):
    plot_tree(xgbc_new,num_trees=i)
    plt.show()
```

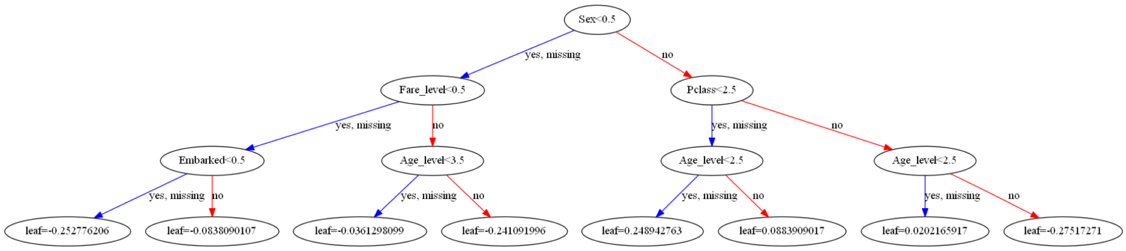












In [62]:

```
test_result = pd.Series(xgbc_new.predict(Test[SelectedFeatures]),
                        name = "Survived").astype(int)
results = pd.concat([test["PassengerId"], test_result],axis = 1)
results.to_csv("titanic_submissionXGBoost.csv", index = False)
results
```

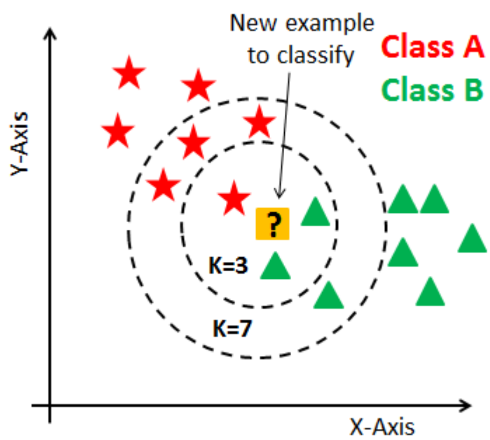
	PassengerId	Survived
0	892	0
1	893	0
2	894	0
3	895	0
4	896	0
...	...	...
413	1305	0
414	1306	1
415	1307	0
416	1308	0
417	1309	1

418 rows × 2 columns

Public Score = 0.77751

方法二: KNN(最近鄰居法)

選擇K個最近的數據點，並將此數據點分配給大多數K個數據點所屬的種類



In [63]:
```
SelectedFeatures =["Pclass", 'Sex', 'SibSp','Parch', 'Embarked','Age_level','Fare_level']
X=X_Train[SelectedFeatures]
y=Y_Train
X.shape, y.shape
```

```
((891, 7), (891,))
```

In [64]:
```
# 分割資料
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size=0.3, random_state=1234)
X_train.shape, X_test.shape, y_train.shape , y_test.shape, y_test.sum
X_train.shape, X_test.shape, y_train.shape , y_test.shape
```

```
((623, 7), (268, 7), (623,), (268,))
```

In [65]:
```
from sklearn.neighbors import KNeighborsClassifier
KNN = KNeighborsClassifier(n_neighbors=2)
KNN.fit(X_train, y_train)
KNN.score(X_train, y_train), KNN.score(X_test, y_test)
```

```
(0.8603531300160514, 0.7798507462686567)
```

In [66]:
```
from sklearn.neighbors import KNeighborsClassifier
#加入n ,把 accuracy 設為一個空的list
accuracy = []
for n in range(1,101,1):
    KNN = KNeighborsClassifier(n_neighbors=n)
    KNN.fit(X_train, y_train)
    accuracy.append((KNN.score(X_train, y_train), KNN.score(X_test, y_test)))
```

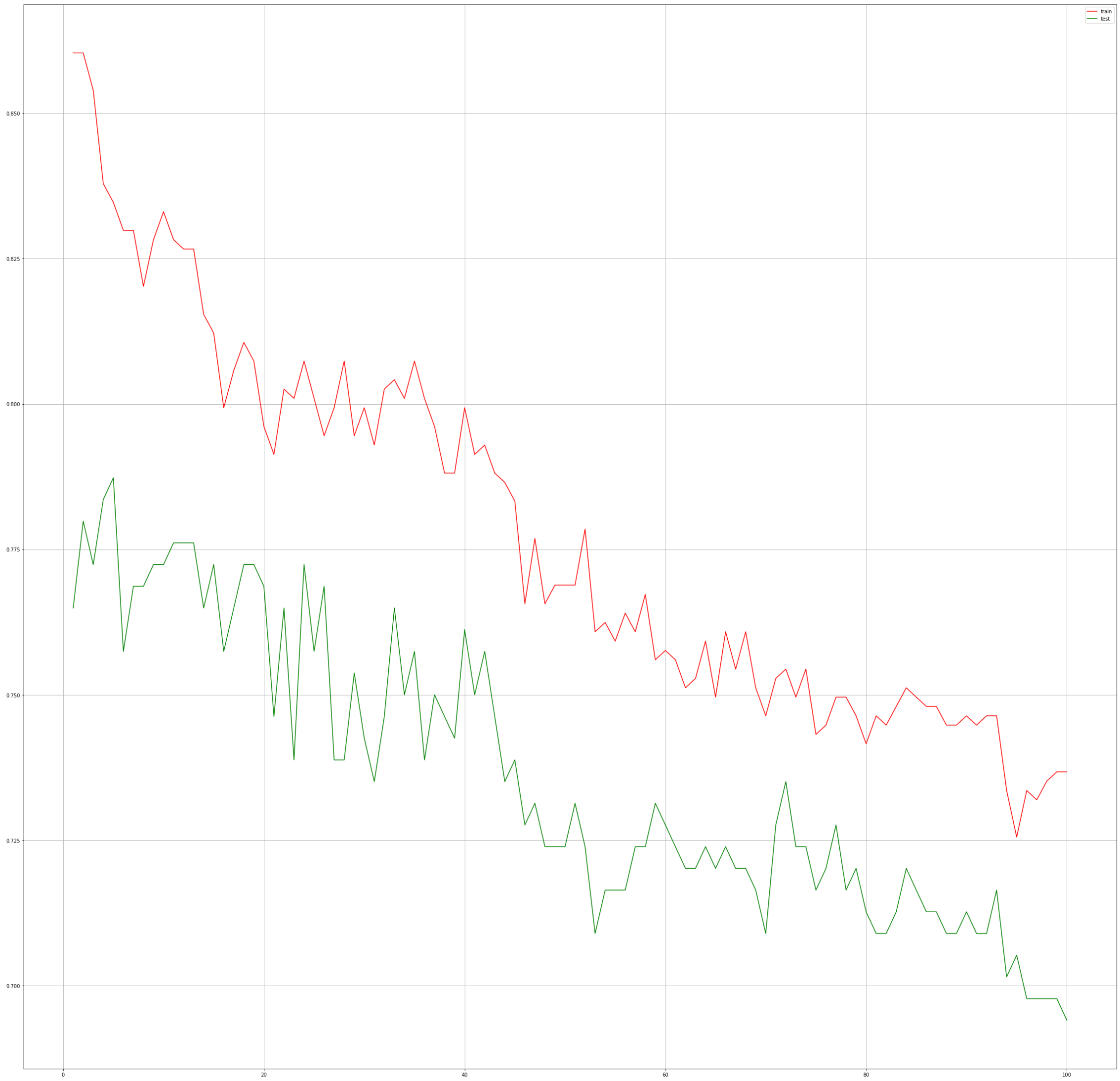
In [67]:
```
#accuracy
```

In [68]:
```
train_score = [t[0] for t in accuracy ]
test_score = [t[1] for t in accuracy ]
print(max(test_score))
print(test_score.index(max(test_score)))
```

```
0.7873134328358209
4
```

In [69]:

```
#畫圖
import matplotlib.pyplot as plt
plt.grid()
plt.plot(range(1,101,1),train_score, color='red',label='train')
plt.plot(range(1,101,1),test_score, color='green',label='test')
plt.legend()
plt.savefig("n_neighbors")
plt.show()
```



In [70]:

```
# n_neighbors=5
from sklearn.neighbors import KNeighborsClassifier
KNN_new = KNeighborsClassifier(n_neighbors=5)
KNN_new.fit(X_train, y_train)
KNN_new.score(X_train, y_train), KNN_new.score(X_test, y_test)
```

```
(0.8346709470304976, 0.7873134328358209)
```

In [71]:

```
from sklearn.model_selection import cross_val_score, KFold
# kfold- cross validataion
kfold =KFold(n_splits=5, shuffle=True)
Kf_cv_scores = cross_val_score(KNN_new,X_train, y_train,cv=kfold)
print(Kf_cv_scores)
print('mean of K fold=',Kf_cv_scores.mean())
```

```
[0.848      0.848      0.768      0.79032258 0.78225806]
mean of K fold= 0.8073161290322581
```

In [72]:

```
# Confusion matrix
predicted_labels = KNN_new.predict(X_test)
true_labels = y_test
from sklearn.metrics import confusion_matrix, classification_report
cm = confusion_matrix(true_labels, predicted_labels)
print(classification_report(true_labels, predicted_labels))
print("Confusion matrix")
print(cm)
```

```
              precision    recall  f1-score   support

         0.0       0.81      0.86      0.83       166
         1.0       0.74      0.68      0.71       102

    accuracy                           0.79       268
   macro avg       0.78      0.77      0.77       268
weighted avg       0.78      0.79      0.79       268

Confusion matrix
[[142  24]
 [ 33  69]]
```

In [73]:
```
test_result1 = pd.Series(KNN_new.predict(Test[SelectedFeatures]),
                         name = "Survived").astype(int)
results1 = pd.concat([test["PassengerId"], test_result1],axis = 1)
results1.to_csv("titanic_submission(KNN).csv", index = False)
results1
```

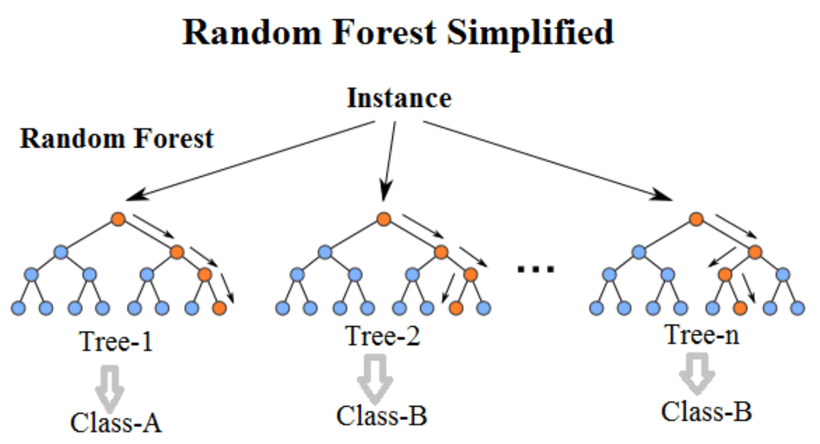
	PassengerId	Survived
0	892	0
1	893	0
2	894	0
3	895	0
4	896	0
...	...	...
413	1305	0
414	1306	1
415	1307	0
416	1308	0
417	1309	1

418 rows × 2 columns

Public Score = 0.71291

方法三: RandomForest(隨機森林)

* 隨機森林，是用隨機的方式建立一個森林，森林裡面由很多的決策樹組成，而決策樹彼此是沒有關聯的。
* 每一棵樹都會產生一個分類選擇，而再由多數決的方式，決定該樣本的預測值(分類選擇)



In [74]:
```
SelectedFeatures = ["Pclass", 'Sex', 'SibSp','Parch', 'Embarked',  'Age_level','Fare_level
X=X_Train[SelectedFeatures]
y=Y_Train
X.shape, y.shape
```

((891, 7), (891,))

In [75]:
```
# 分割資料
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size=0.3, random_state=1234)
X_train.shape, X_test.shape, y_train.shape , y_test.shape, y_test.sum
X_train.shape, X_test.shape, y_train.shape , y_test.shape
```

((623, 7), (268, 7), (623,), (268,))

In [76]:
```
from sklearn.ensemble import RandomForestClassifier
RFC=RandomForestClassifier(n_estimators=5 ,max_depth=6)
RFC.fit(X_train[SelectedFeatures], y_train)
```

```
RandomForestClassifier(max_depth=6, n_estimators=5)
```

In [77]:
```
#訓練資料評估 與 測試資料評估
RFC.score(X_train[SelectedFeatures], y_train),RFC.score(X_test[SelectedFeatures], y_test)
```

```
(0.85553772070626, 0.8171641791044776)
```

GridSearch

為一種調整參數的方法

In [91]:
```
#調整'n_estimators'and 'max_depth'
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
import numpy as np
import pandas as pd
clf = RandomForestClassifier()
param_dist = {'n_estimators':[5,10,20,30,40],
              'max_depth':range(1,11,1) }
grid=GridSearchCV(estimator = clf,
                  param_grid = param_dist,
                  scoring='accuracy',
                  cv=5
                  )
grid.fit(X_train, y_train) # 用訓練資料集來找最佳參數
print("Best parameters found: ",grid.best_params_)
print("Best Accuracy  found: ", grid.best_score_)
```

```
Best parameters found:  {'max_depth': 4, 'n_estimators': 40}
Best Accuracy  found:  0.8201290322580645
```

In [92]:
```
#'max_depth': 4, 'n_estimators': 40
from sklearn.ensemble import RandomForestClassifier
RFC1=RandomForestClassifier(n_estimators=40, max_depth=4)
RFC1.fit(X_train[SelectedFeatures], y_train)
#訓練資料評估 與 測試資料評估
RFC1.score(X_train[SelectedFeatures], y_train),RFC1.score(X_test[SelectedFeatures], y_test
```

```
(0.8443017656500803, 0.835820895522388)
```

In [93]:
```
# kfold- cross validataion
kfold =KFold(n_splits=5, shuffle=True)
Kf_cv_scores = cross_val_score(RFC1,X_train, y_train,cv=kfold)
print(Kf_cv_scores)
print('mean of K fold=',Kf_cv_scores.mean())
```

```
[0.888      0.8        0.824      0.80645161 0.80645161]
mean of K fold= 0.8249806451612903
```

In [94]:

```
# Confusion matrix
predicted_labels = RFC1.predict(X_test)
true_labels = y_test
from sklearn.metrics import confusion_matrix, classification_report
cm = confusion_matrix(true_labels, predicted_labels)
print(classification_report(true_labels, predicted_labels))
print("Confusion matrix")
print(cm)
```

```
              precision    recall  f1-score   support

         0.0       0.82      0.95      0.88       166
         1.0       0.88      0.66      0.75       102

    accuracy                           0.84       268
   macro avg       0.85      0.80      0.81       268
weighted avg       0.84      0.84      0.83       268

Confusion matrix
[[157   9]
 [ 35  67]]
```

In [95]:

```
test_result1 = pd.Series(RFC1.predict(Test[SelectedFeatures]),
                         name = "Survived").astype(int)
results1 = pd.concat([test["PassengerId"], test_result1],axis = 1)
results1.to_csv("titanic_submissionRFC.csv", index = False)
results1
```

	PassengerId	Survived
0	892	0
1	893	0
2	894	0
3	895	0
4	896	0
...	...	...
413	1305	0
414	1306	1
415	1307	0
416	1308	0
417	1309	1

418 rows × 2 columns

Public Score = 0.78229

Public Score: RandomForest > XGBoost > KNN

●討論:為何Public Score無法超過0.8?

●心得與未來