TITANIC PROBLEM

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

link to dataset : [https://www.kaggle.com/c/titanic/data (https://www.kaggle.com/c/titanic/data)](https://www.kaggle.com/c/titanic/data)

In [2]:
```
gender=pd.read_csv('gender_submission.csv')
gender.head()
```

Out[2]:

	PassengerId	Survived
0	892	0
1	893	1
2	894	0
3	895	0
4	896	1

In [3]:
```
data=pd.read_csv('train.csv')
data.head()
```

Out[3]:

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

In [4]:
```
data.describe()
```

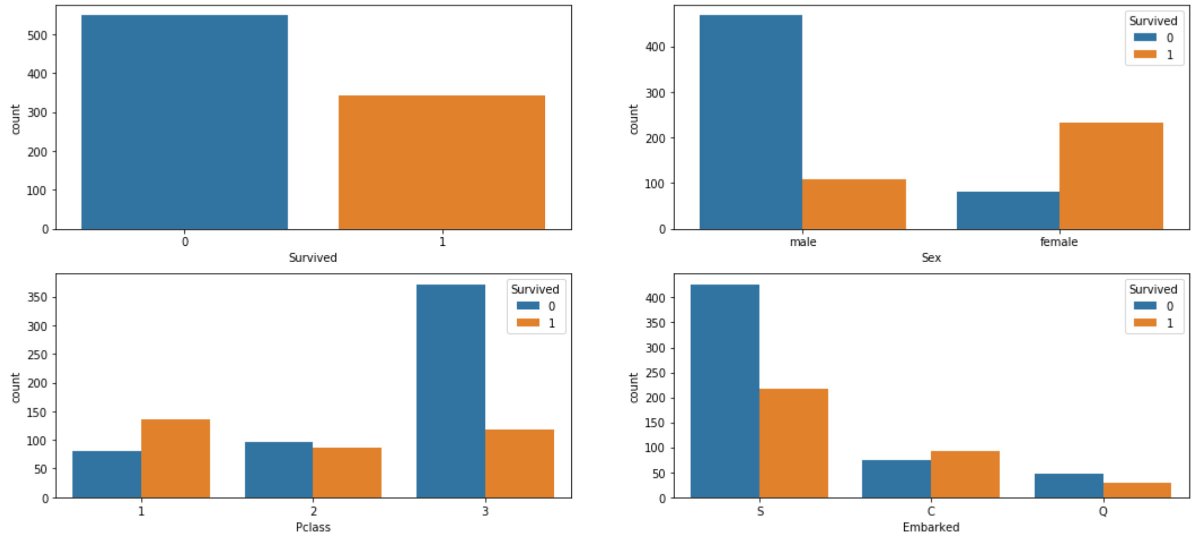
Out[4]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

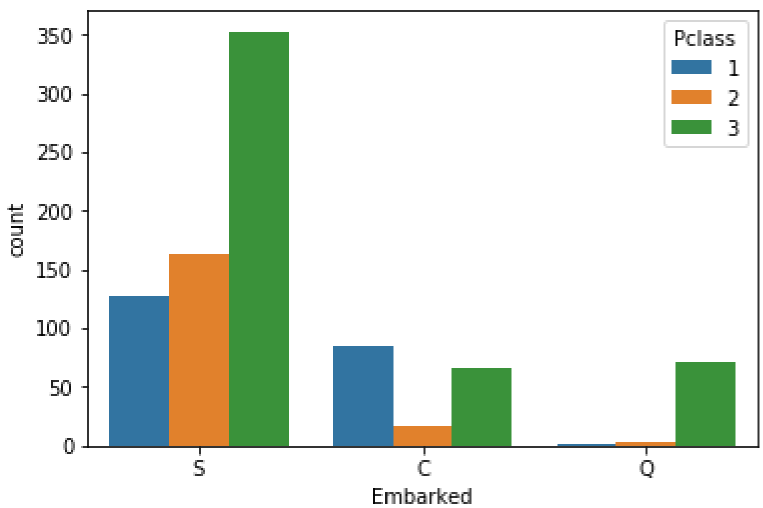
Assumptions

- 1.Female and children will survive more compared to male(age column changes)
- 2.sibsp and parch gives will give new features that passenger is alone or not and no.s doesnot matter
- 3.Rich people would have survived

In [5]:
```
f,ax=plt.subplots(2,2,figsize=(18,8))
sns.countplot('Survived',data=data,ax=ax[0][0])
sns.countplot('Sex',hue='Survived',data=data,ax=ax[0][1])
sns.countplot('Pclass',hue='Survived',data=data,ax=ax[1][0])
sns.countplot('Embarked',hue='Survived',data=data,ax=ax[1][1])
plt.show()
```

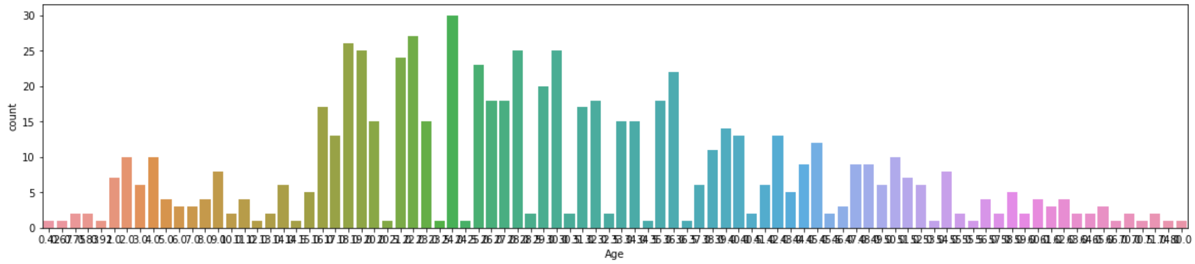


In [6]:
```
sns.countplot('Embarked',hue='Pclass',data=data)
plt.show()
print("From Q there were very less Pclass 3 people hence survival rate is les
s")
```




```
From Q there were very less Pclass 3 people hence survival rate is less
```

In [7]:
```
#age
plt.figure(figsize=(20,4))
sns.countplot('Age',data=data)
plt.show()
```



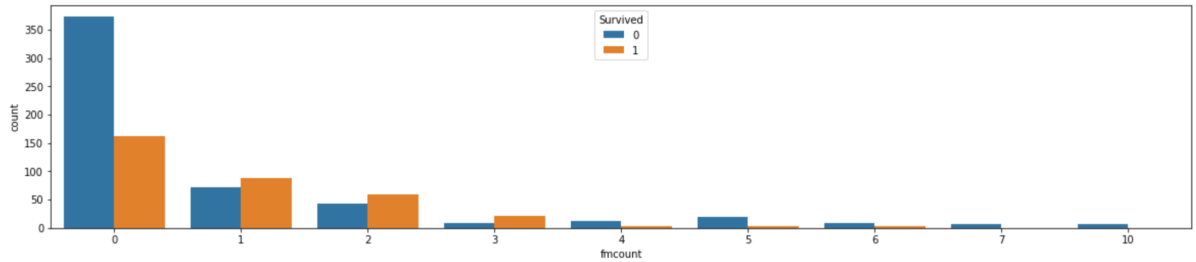
In [8]:
```
data[data['Age']<1]
```

Out[8]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
78	79	1	2	Caldwell, Master. Alden Gates	male	0.83	0	2	248738	29.0000
305	306	1	1	Allison, Master. Hudson Trevor	male	0.92	1	2	113781	151.5500
469	470	1	3	Baclini, Miss. Helene Barbara	female	0.75	2	1	2666	19.2583
644	645	1	3	Baclini, Miss. Eugenie	female	0.75	2	1	2666	19.2583
755	756	1	2	Hamalainen, Master. Viljo	male	0.67	1	1	250649	14.5000
803	804	1	3	Thomas, Master. Assad Alexander	male	0.42	0	1	2625	8.5167
831	832	1	2	Richards, Master. George Sibley	male	0.83	1	1	29106	18.7500

In [9]:
```
data['fmcount']=data['Parch']+data['SibSp']
```

In [10]:
```
plt.figure(figsize=(20,4))
sns.countplot('fmcount',hue="Survived",data=data)
plt.show()
print("Less the family size more the survival rate")
```




```
Less the family size more the survival rate
```

In [11]:
```
data['Embarked'].fillna('S',inplace=True)
data['Age'].fillna(data['Age'].median(),inplace=True)
data[data['Age']<1]=data['Age'].median()
data.head()
```

Out[11]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	C
0	1.0	0.0	3.0	Braund, Mr. Owen Harris	male	22.0	1.0	0.0	A/5 21171	7.2500	
1	2.0	1.0	1.0	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1.0	0.0	PC 17599	71.2833	
2	3.0	1.0	3.0	Heikkinen, Miss. Laina	female	26.0	0.0	0.0	STON/O2. 3101282	7.9250	
3	4.0	1.0	1.0	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1.0	0.0	113803	53.1000	C
4	5.0	0.0	3.0	Allen, Mr. William Henry	male	35.0	0.0	0.0	373450	8.0500	

Proved assumptions

1.rich passengers with pclass-3 survived

2.women survived more wrt to men

New conclusions

1.Less family size more survival rate

2.Age range of 14-24 has more survival rate

3.people boarding in southhampton has more survival rate

In [12]:
```
#binning age and fare
data['Fare_Bin']=pd.qcut(data['Fare'],6)
data.groupby(['Fare_Bin'])['Survived'].mean().to_frame()

data['Fare_cat']=0
data.loc[data['Fare']<=7.775,'Fare_cat']=0
data.loc[(data['Fare']>7.775)&(data['Fare']<=8.662),'Fare_cat']=1
data.loc[(data['Fare']>8.662)&(data['Fare']<=14.454),'Fare_cat']=2
data.loc[(data['Fare']>14.454)&(data['Fare']<=26.0),'Fare_cat']=3
data.loc[(data['Fare']>26.0)&(data['Fare']<=52.369),'Fare_cat']=4
data.loc[data['Fare']>52.369,'Fare_cat']=5

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

data[['Age_cat','Fare_cat']].head()
```

Out[12]:

	Age_cat	Fare_cat
0	1	0
1	2	5
2	1	1
3	2	5
4	2	1

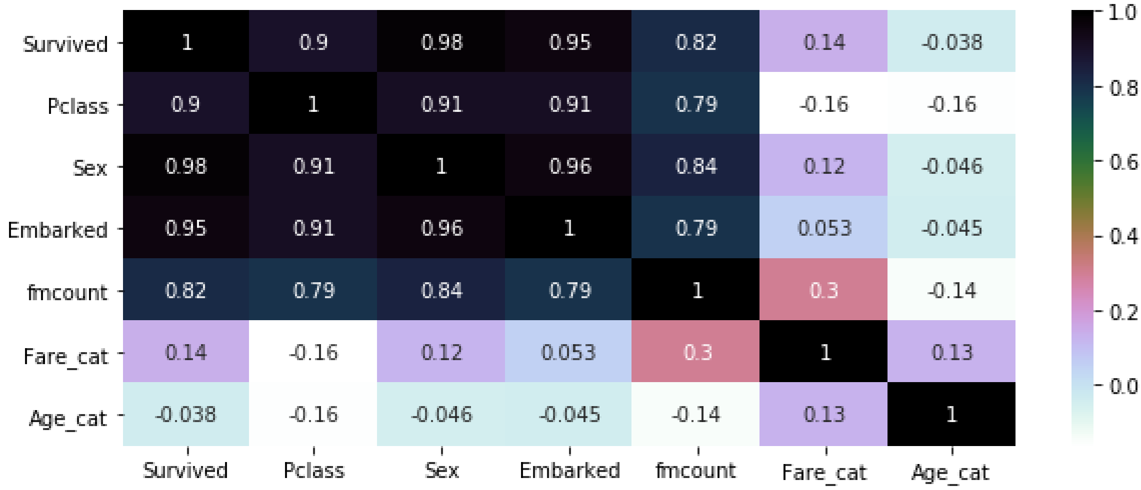
In [13]:
```
data['Sex'].replace(['male','female'],[0,1],inplace=True)
data['Embarked'].replace(['S','C','Q'],[0,1,2],inplace=True)
```

In [14]:
```
#dropping
data=data.drop(columns=['PassengerId', 'Name', 'SibSp','Parch', 'Ticket', 'Cab
in','Age','Fare','Fare_Bin'])
data.head()
```

Out[14]:

	Survived	Pclass	Sex	Embarked	fmcount	Fare_cat	Age_cat
0	0.0	3.0	0.0	0.0	1.0	0	1
1	1.0	1.0	1.0	1.0	1.0	5	2
2	1.0	3.0	1.0	0.0	0.0	1	1
3	1.0	1.0	1.0	0.0	1.0	5	2
4	0.0	3.0	0.0	0.0	0.0	1	2

In [15]:
```
plt.figure(figsize=(10,4))
sns.heatmap(data.corr(),annot=True,cmap='cubehelix_r')
plt.show()
```



In [16]:
```
data.columns
```

Out[16]:
```
Index(['Survived', 'Pclass', 'Sex', 'Embarked', 'fmcount', 'Fare_cat',
       'Age_cat'],
      dtype='object')
```

In [17]:
```
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import cross_val_score

x=data[['Pclass', 'Sex', 'fmcount', 'Fare_cat', 'Age_cat','Embarked']]
y=data['Survived']

x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.33,random_state
=44)
print("training data set:",x_train.shape)
print("testing data set:",x_test.shape)
```

```
training data set: (596, 6)
testing data set: (295, 6)
```

In [18]:
```
data['Embarked'].isnull().value_counts()
```

Out[18]:
```
False    891
Name: Embarked, dtype: int64
```

In [19]:
```
results=pd.DataFrame(columns=['Classifier','MSE'])
results.head()
```

Out[19]:

Classifier	MSE

In [20]:
```
from sklearn.linear_model import LinearRegression

lm=LinearRegression()
lm.fit(x_train,y_train)
yhat=lm.predict(x_test)
mse=mean_squared_error(yhat,y_test)
print('Mean squared error:',mse)
results=results.append(pd.Series(['Regression',mse],index=results.columns ),ig
nore_index=True)
```

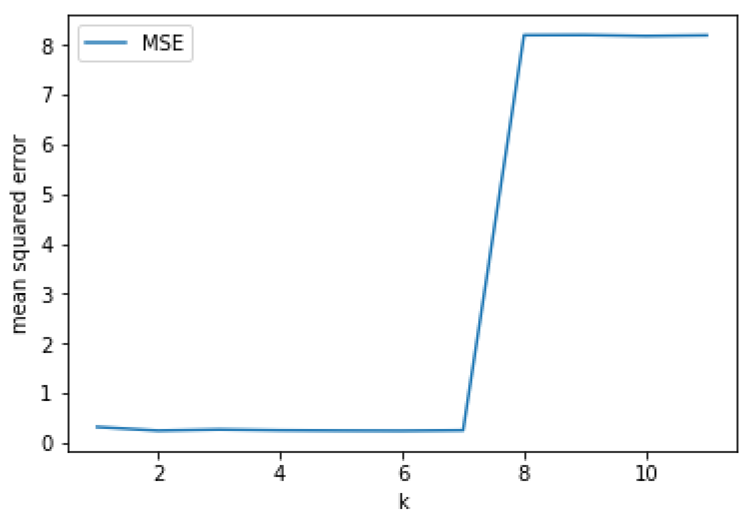
```
Mean squared error: 0.191275579175187
```

In [21]:
```
from sklearn.neighbors import KNeighborsClassifier
import matplotlib.pyplot as plt

x1axes,x2axes=[],[]

for i in range(1,12):
    neigh = KNeighborsClassifier(n_neighbors=i)
    neigh.fit(x_train,y_train)
    yhat=neigh.predict(x_test)
    x2axes.append(mean_squared_error(yhat,y_test))

plt.plot(list(range(1,12)),x2axes,label="MSE")
plt.xlabel('k')
plt.ylabel('mean squared error')
plt.legend()
plt.show()
```



In [22]:
```
results=results.append(pd.Series(['K nearest neighbours',min(x2axes)],index=re
sults.columns ),ignore_index=True)
```

In [23]:
```
from sklearn.tree import DecisionTreeClassifier

clf = DecisionTreeClassifier(random_state=0)
clf.fit(x_train,y_train)
yhat=clf.predict(x_test)
mse=mean_squared_error(yhat,y_test)
print('Mean squared error:',mse)
print("cross val score:",cross_val_score(clf, x_train, y_train, cv=10).mean())
results=results.append(pd.Series(['Decision Tree',mse],index=results.columns
),ignore_index=True)
```

```
Mean squared error: 0.2542372881355932
cross val score: 0.7786624796798599

C:\Users\vivek\AppData\Local\Continuum\anaconda3\lib\site-packages\sklearn\mo
del_selection\_split.py:652: Warning: The least populated class in y has only
4 members, which is too few. The minimum number of members in any class canno
t be less than n_splits=10.
  % (min_groups, self.n_splits)), Warning)
```

In [24]:
```
from sklearn.linear_model import LogisticRegression

lr = LogisticRegression(random_state=0,C=1.0, solver='lbfgs',multi_class='mult
inomial')
lr.fit(x_train, y_train)
yhat=lr.predict(x_test)
mse=mean_squared_error(yhat,y_test)
print('Mean squared error:',mse)
results=results.append(pd.Series(['Logistic Regression',mse],index=results.col
umns ),ignore_index=True)
print("score:",lr.score(x_train, y_train))
```

```
Mean squared error: 0.2440677966101695
score: 0.8104026845637584

C:\Users\vivek\AppData\Local\Continuum\anaconda3\lib\site-packages\sklearn\li
near_model\logistic.py:758: ConvergenceWarning: lbfgs failed to converge. Inc
rease the number of iterations.
  "of iterations.", ConvergenceWarning)
```

In [25]:
```
from sklearn.svm import SVC

svc = SVC(gamma='auto')
svc.fit(x_train, y_train)
yhat=svc.predict(x_test)
mse=mean_squared_error(yhat,y_test)
results=results.append(pd.Series(['SVC',mse],index=results.columns),ignore_ind
ex=True)
print('Mean squared error:',mse)
```

```
Mean squared error: 0.2
```

In [26]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.datasets import make_classification

rnd = RandomForestClassifier(n_estimators=100, max_depth=3,
                             random_state=0)
rnd.fit(x_train, y_train)
yhat=rnd.predict(x_test)
mse=mean_squared_error(yhat,y_test)
results=results.append(pd.Series(['Random forest',mse],index=results.columns),
ignore_index=True)
print('Mean squared error:',mse)
```

```
Mean squared error: 0.19661016949152543
```

In [27]:
```
results
```

Out[27]:

	Classifier	MSE
0	Regression	0.191276
1	K nearest neighbours	0.244068
2	Decision Tree	0.254237
3	Logistic Regression	0.244068
4	SVC	0.200000
5	Random forest	0.196610

In [28]:
```
test_data=pd.read_csv('test.csv')
test_data.head()
print(test_data.shape)
```

```
(418, 11)
```

In [29]:
```
test_data['fmcount']=test_data['Parch']+test_data['SibSp']

test_data['Embarked'].fillna('S')
test_data['Age'].fillna(test_data['Age'].median())
test_data['Fare_Bin']=pd.qcut(test_data['Fare'],6)


test_data['Fare_cat']=0
test_data.loc[test_data['Fare']<=7.775,'Fare_cat']=0
test_data.loc[(test_data['Fare']>7.775)&(test_data['Fare']<=8.662),'Fare_cat']
=1
test_data.loc[(test_data['Fare']>8.662)&(test_data['Fare']<=14.454),'Fare_cat'
]=2
test_data.loc[(test_data['Fare']>14.454)&(test_data['Fare']<=26.0),'Fare_cat']
=3
test_data.loc[(test_data['Fare']>26.0)&(test_data['Fare']<=52.369),'Fare_cat']
=4
test_data.loc[test_data['Fare']>52.369,'Fare_cat']=5


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

test_data['Sex'].replace(['male','female'],[0,1],inplace=True)
test_data['Embarked'].replace(['S','C','Q'],[0,1,2],inplace=True)
```

In [30]:
```
#dropping
test_data=test_data.drop(columns=['PassengerId', 'Name', 'SibSp','Parch', 'Tic
ket', 'Cabin','Fare','Age'])
test_data.head()
print(test_data.columns)
```

```
Index(['Pclass', 'Sex', 'Embarked', 'fmcount', 'Fare_Bin', 'Fare_cat',
       'Age_cat'],
      dtype='object')
```

In [31]:
```
x=test_data[['Pclass', 'Sex', 'fmcount', 'Fare_cat', 'Age_cat','Embarked']]
lm_score=lm.predict(x)
svc_predict=svc.predict(x)
lr_predict=lr.predict(x)
clf_predict=clf.predict(x)
rnd_predict=rnd.predict(x)
print(svc_predict)
```

```
[0. 0. 0. 0. 1. 0. 1. 0. 1. 0. 0. 0. 1. 0. 1. 1. 0. 0. 1. 1. 0. 0. 1. 0.
 1. 0. 1. 0. 0. 1. 0. 0. 0. 1. 0. 0. 1. 1. 0. 0. 0. 0. 0. 1. 1. 0. 0. 0.
 1. 1. 0. 0. 1. 1. 0. 0. 0. 0. 0. 1. 0. 0. 0. 1. 1. 1. 1. 0. 0. 1. 1. 0.
 1. 0. 1. 0. 0. 1. 0. 1. 1. 0. 0. 0. 0. 1. 1. 1. 1. 1. 1. 0. 1. 0. 0. 0.
 1. 0. 1. 0. 1. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 1. 1. 1. 1. 0. 0. 1. 0. 1.
 1. 0. 1. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 1. 1. 0.
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 0. 0. 0. 0. 1. 0. 0. 0. 1. 1. 0. 1. 0. 0. 0. 0. 1. 1. 1. 1. 1. 0. 0. 0.
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 0. 1. 1. 1. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 1. 0. 0. 1. 0. 0.
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 0. 1. 1. 0. 1. 0. 1. 1. 1. 0. 0. 1. 0. 0. 1. 1. 1. 0. 0. 0. 0. 0. 1. 1.
 0. 1. 0. 0. 0. 0. 0. 1. 1. 0. 0. 1. 0. 1. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0.
 1. 1. 1. 1. 1. 0. 1. 0. 0. 1.]
```

In [32]:
```
test_data=pd.read_csv('test.csv')
li=[]
li1=[]
for cnt,pass_id in enumerate(test_data['PassengerId']):
    li1.append(pass_id)
    li1.append(int(svc_predict[cnt]))
    li.append(li1)
    li1=[]


# importing the csv module
import csv

# data rows of csv file
rows =li
fields = ['PassengerId','Survived']

filename = "lr.csv"

# writing to csv file
with open(filename, 'w') as csvfile:
    csvwriter = csv.writer(csvfile)

    csvwriter.writerow(fields)
    csvwriter.writerows(rows)

print("sucessfully saved csv file")
```

```
sucessfully saved csv file
```