importing data set from kaggle

```
In [1]:
```

```
# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read csv)
# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list all files u
nder the input directory
import os
for dirname, , filenames in os.walk('/kaggle/input'):
   for filename in filenames:
       print(os.path.join(dirname, filename))
# You can write up to 5GB to the current directory (/kaggle/working/) that gets preserved a
s output when you create a version using "Save & Run All"
# You can also write temporary files to /kaggle/temp/, but they won't be saved outside of t
he current session
```

/kaggle/input/titanic/gender_submission.csv
/kaggle/input/titanic/test.csv
/kaggle/input/titanic/train.csv

reading the data set to dataframe

```
In [2]:
```

```
df=pd.read_csv("../input/titanic/train.csv")
df
```

Out[2]:

	Passengerld	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	С
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	С
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.7500	NaN	Q

891 rows × 12 columns

checking for null values

```
In [3]:
Null=[]
for i in df:
  Null.append((i,df[i].isna().mean()*100))
Null=pd.DataFrame(Null,columns=['class','per'])
Null
```

Out[3]:

	class	per
0	Passengerld	0.000000
1	Survived	0.000000
2	Pclass	0.000000
3	Name	0.000000
4	Sex	0.000000
5	Age	19.865320
6	SibSp	0.000000
7	Parch	0.000000
8	Ticket	0.000000
9	Fare	0.000000
10	Cabin	77.104377
11	Embarked	0.224467

we can remove canbin as it has 77% of null values

Name and Ticke will not be useful in decison making so we can drop them too

```
In [4]:
```

```
df=df.drop(["Cabin","Name","Ticket"],axis=1)
df.dtypes
```

Out[4]:

PassengerId int64
Survived int64
Pclass int64
Sex object
Age float64 Pclass Sex Age SibSp int64 int64 Parch float64
Embarked objection

dtype: object

filling other na values with mode

```
In [5]:
```

```
df=df.fillna(df.mode)
df.isna().sum()
```

Out[5]:

```
0
PassengerId
Survived
            0
            0
Pclass
            0
Sex
```

```
0
Age
              0
SibSp
Parch
Fare
              0
Embarked
dtype: int64
```

Handling Object data type

label encoding the Sex column

```
In [6]:
df.Sex.unique()
Out[6]:
array(['male', 'female'], dtype=object)
In [7]:
df.Sex=df.Sex.replace("male",1)
df.Sex=df.Sex.replace("female",2)
df.Sex.unique()
Out[7]:
array([1, 2])
```

in Embarked column values are stored with unwanted values shown below

```
In [8]:
```

```
df.Embarked = df.Embarked.apply(str)
k=df.Embarked.unique()
k[-1]
```

Out[8]:

```
1 0 7.25
         2 1
3 female 26.0
                    1 lemare 55...
0 0 7.9250 \n3
3
    1
                                        4
1 female 35.0
              0 53.1000 \n4
                               5
                                          3
          1
                                            male 35.
   0 0 8.0500 \n..
                            ...
                    0 2
                                    0
       \n886
                             male 27.0
                                         0 13.0000
               887
             1 1 female 19.0 0 0 30.0000 \n888
n887
       888
     0
           3 female NaN 1 2 23.4500 \n889
                                          890
889
                                                 1
         0 0 30.0000 \n890
                            891
S \n1
  male 26.0
                                         3 male 32.
                                      0
1
     0 7.7500
                                         C \n2
0
               \n\n Embarked \n0
               S \n.. \n886 S \n887 S \n888
 \n3
       S \n4
S
        C \n890
 \n889
                 Q \n = 0 \n = 0 \n
S
```

label encoding the column and replacing unwanted values with most frequent value i.e. 'S'

```
In [9]:
```

```
df.Embarked=df.Embarked.replace('S',1)
df.Embarked=df.Embarked.replace('C',2)
df.Embarked=df.Embarked.replace('Q',3)
df.Embarked=df.Embarked.replace(k[-1],1)
```

similar problem with Age attribute, so replacing the unk value with 28 and converting into float

```
In [10]:
```

```
df.Age=df.Age.apply(str)
```

```
k=df.Age.unique()
df.Age=df.Age.replace(k[4],"28.0")
df.Age=df.Age.apply(float)
```

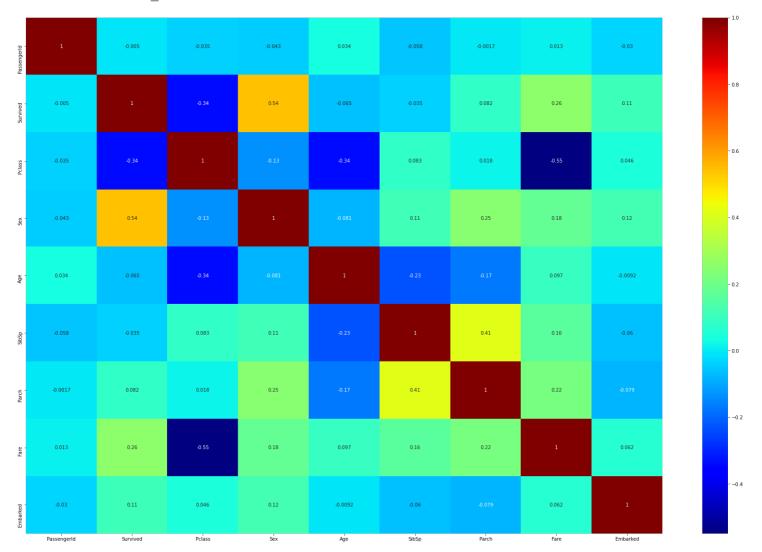
correlation heatmap

In [11]:

```
import seaborn as sns
import matplotlib.pyplot as plt
plt.figure(figsize=(30,20))
sns.heatmap(df.corr(),annot = True,cmap="jet")
```

Out[11]:

 ${\tt <matplotlib.axes._subplots.AxesSubplot}$ at ${\tt 0x7fcfacbc84d0>}$



seperating X and Y values

```
In [12]:
```

```
cols = [col for col in df.columns if col not in ["Survived"]]
X = df[cols]
y = df["Survived"]
```

stroring the feature used for training in I

```
In [13]:
```

l=list(X)

using Logirithmic Regression for fitting the model

```
In [14]:
from sklearn.linear model import LogisticRegression as LR
model = LR()
model.fit(X,y)
model.score(X,y)
/opt/conda/lib/python3.7/site-packages/sklearn/linear model/ logistic.py:764: ConvergenceWa
rning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
Increase the number of iterations (max iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear model.html#logistic-regression
  extra warning msg= LOGISTIC SOLVER CONVERGENCE MSG)
Out[14]:
0.8013468013468014
inputing the test data and selecting required features
In [15]:
df=pd.read csv("../input/titanic/test.csv")
df=df[1]
label encoding the Sex column
In [16]:
df.Sex=df.Sex.replace("male",1)
df.Sex=df.Sex.replace("female",2)
df.Sex.unique()
Out[16]:
array([1, 2])
In [17]:
df.Embarked = df.Embarked.apply(str)
k=df.Embarked.unique()
label encoding embarked column
In [18]:
df.Embarked=df.Embarked.replace('S',1)
df.Embarked=df.Embarked.replace('C',2)
df.Embarked=df.Embarked.replace('Q',3)
filling null values mode
```

```
In [19]:

df=df.fillna(df.mode)
df.isna().sum()

Out[19]:
PassengerId 0
```

Sex 0
Age 0
SibSp 0
Parch 0

0

Pclass

```
Embarked
dtype: int64
In [20]:
df.dtvpes
Out[20]:
PassengerId
                      int64
Pclass
                      int64
Sex
                       int64
Age
                      object
SibSp
                      int64
                       int64
Parch
                      object
Embarked
                       int64
dtype: object
handling unkown or garbage values in Fare
In [21]:
df.Fare=df.Fare.apply(str)
df.Fare.unique()
Out[21]:
array(['7.8292', '7.0', '9.6875', '8.6625', '12.2875', '9.225', '7.6292', '29.0', '7.2292', '24.15', '7.8958', '26.0', '82.2667', '61.175', '27.7208', '12.35', '7.225', '7.925', '59.4', '3.1708', '31.6833',
           '61.3792', '262.375', '14.5', '61.9792', '30.5', '21.6792', '31.5',
          '20.575', '23.45', '57.75', '8.05', '9.5', '56.4958', '13.4167', '26.55', '7.85', '13.0', '52.5542', '29.7', '7.75', '76.2917', '15.9', '60.0', '15.0333', '23.0', '263.0', '15.5792', '29.125', '7.65', '16.1', '13.5', '7.725', '21.0', '7.8792', '42.4',
          '28.5375', '211.5', '25.7', '15.2458', '221.7792', '10.7083', '14.4542', '13.9', '7.775', '52.0', '7.7958', '78.85', '7.8542',
          '55.4417', '8.5167', '22.525', '7.8208', '8.7125', '15.0458', '7.7792', '31.6792', '7.2833', '6.4375', '16.7', '75.2417',
           '15.75', '7.25', '23.25', '28.5', '25.4667', '46.9', '151.55',
           '18.0', '51.8625', '83.1583',
Fare Embarked\n0 892 3 1 34.5 0 0 7.8292
893 3 2 47.0 1 0 7.0000 1\n2 894
62.0 0 0 9.6875 3\n3 895 3 1 27.0
8.6625 1\n4
                                                                 PassengerId Pclass Sex Age SibSp Parch
                                                                                                                            3\n1
                                                                                                                               1
                                                                                                                                Ω
                                    896 3 2 22.0 1 1 12.2875
... ... ... ... ... ... ... \n413
0 8.0500 1\n414 1306 1 2
2\n415 1307 3 1 38.5 0
3 1 NaN 0 0 0 0 0 0 0 0
                                                                                                                               1 n.
                 0 0 8.0500
                                                            2 39.0
           NaN
          0 108.9000
          1308 3 1 NaN 0 0 8.0500
3 1 NaN 1 1 22.3583 2\n\n[418 rows
'12.1833', '31.3875', '7.55', '13.775', '7.7333', '22.025',
1\n416
           '50.4958', '34.375', '8.9625', '39.0', '36.75', '53.1', '247.5208',
           '16.0', '69.55', '32.5', '134.5', '10.5', '8.1125', '15.5', '14.4',
           '227.525', '25.7417', '7.05', '73.5', '42.5', '164.8667',
          '13.8583', '27.4458', '15.1', '65.0', '6.4958', '71.2833', '75.25', '106.425', '30.0', '7.8875', '27.75', '136.7792', '9.325', '17.4', '12.7375', '0.0', '20.2125', '39.6', '6.95', '81.8583', '41.5792', '45.5', '9.35', '14.1083', '7.575', '135.6333', '146.5208',
           '211.3375', '79.2', '15.7417', '7.5792', '512.3292', '63.3583',
           '51.4792', '15.55', '37.0042', '14.4583', '39.6875', '11.5',
           '50.0', '12.875', '21.075', '39.4', '20.25', '47.1', '13.8625',
           '7.7208', '90.0', '108.9', '22.3583'], dtype=object)
```

In [22]:

Fare

s='<bound method DataFrame.mode of FassengerId Pclass Sex Age SibSp Parch
Fare Embarked\n0 892 3 1 34.5 0 0 7.8292 3\n1
893 3 2 47.0 1 0 7.0000 1\n2 895 3 1 27.0 0 0</pre>

```
896
                                   1 1 12.2875
8.6625
         1\n4
                            2 22.0
                                                      1\n
                                   ... 1306 ...\n413
               0 8.0500 1\n414
2\n415 1307
                                                    1305
  1 NaN 0
                   . . .
                                           1 2 39.0
0 0 7.2500
3
               0 0 108.9000
1\n416
       1308
                                                     130
       1 NaN
```

replacing it with most frequent value 7.75

```
In [23]:

df.Fare=df.Fare.replace(s,'7.75')
```

converting fare to float datatye

```
In [24]:

df.Fare=df.Fare.apply(float)
```

replacing garbage value in age with 34.5

```
In [25]:

df.Age=df.Age.apply(str)
k=df.Age.unique()[10]
df.Age=df.Age.replace(k,"34.5")
df.Age=df.Age.apply(float)
```

predicting the test values

In [26]:

```
pred=model.predict(df)

In [27]:

Id=df PassengerId values
```

```
Id=df.PassengerId.values
l=[]
for i ,j in zip(Id,pred):
    l.append([i,j])
```

converting them to a dataframe

```
In [28]:
sub=pd.DataFrame(1,columns=["PassengerId","Survived"])
```

```
In [29]:
sub
```

Out[29]:

413

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

1305

0

414	Passengle 1966	Survived
415	1307	O
416	1308	C
417	1309	C

418 rows × 2 columns

storing as a dataframe

```
In [30]:
filename = 'Titanic Predictions 1.csv'
sub.to_csv(filename,index=False)
print('Saved file: ' + filename)
Saved file: Titanic Predictions 1.csv
In []:
```