IMPORTING THE REQUIRED LIBRARIES

In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

IMPORTING THE DATASET

In [2]:

```
data = pd.read_csv(r'C:\Users\More\Downloads\1614238459_salarydata.csv')
```

EXPLORINGTHE DATASET

In [3]:

```
data
```

Out[3]:

	age	workclass	education	education-num	marital-status	occupation	relationship	
0	39	State-gov	Bachelors	13	Never-married	Adm-clerical	Not-in-family	\
1	50	Self-emp-not-inc	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	\
2	38	Private	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	\
3	53	Private	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	I
4	28	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	I
...	...	...	...	...	...	...	...	
32556	27	Private	Assoc-acdm	12	Married-civ-spouse	Tech-support	Wife	\
32557	40	Private	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	\
32558	58	Private	HS-grad	9	Widowed	Adm-clerical	Unmarried	\

32559	22	Private	HS-grad	9	Never-married	Adm-clerical	Own-child	\
32560	52	Self-emp-inc	HS-grad	9	Married-civ-spouse	Exec-managerial	Wife	\

32561 rows × 14 columns

In [4]:

```
data.head()
```

Out[4]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race
0	39	State-gov	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White
1	50	Self-emp-not-inc	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White
2	38	Private	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White
3	53	Private	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black
4	28	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black

In [5]:

```
data.tail()
```

Out[5]:

	age	workclass	education	education-num	marital-status	occupation	relationship	
32556	27	Private	Assoc-acdm	12	Married-civ-spouse	Tech-support	Wife	\
32557	40	Private	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	\
32558	58	Private	HS-grad	9	Widowed	Adm-clerical	Unmarried	\
32559	22	Private	HS-grad	9	Never-married	Adm-clerical	Own-child	\
32560	52	Self-emp-inc	HS-grad	9	Married-civ-spouse	Exec-managerial	Wife	\

In [6]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 14 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             32561 non-null  int64 
 1   workclass       32561 non-null  object
 2   education       32561 non-null  object
 3   education-num   32561 non-null  int64 
 4   marital-status  32561 non-null  object
 5   occupation      32561 non-null  object
 6   relationship    32561 non-null  object
 7   race            32561 non-null  object
 8   sex             32561 non-null  object
 9   capital-gain    32561 non-null  int64 
 10  capital-loss    32561 non-null  int64 
 11  hours-per-week  32561 non-null  int64 
 12  native-country  32561 non-null  object
 13  salary          32561 non-null  object
dtypes: int64(5), object(9)
memory usage: 3.5+ MB
```

CHECKING THE MISSING VALUES

In [7]:

```
data.isna().sum()
```

Out[7]:

```
age               0
workclass         0
education         0
education-num     0
marital-status    0
occupation        0
relationship      0
race              0
sex               0
capital-gain      0
capital-loss      0
hours-per-week    0
native-country    0
salary            0
dtype: int64
```

In [8]:

```
h = data[data['age']=='?']
h
```

```
C:\Users\More\anaconda3\lib\site-packages\pandas\core\ops\arr
ay_ops.py:253: FutureWarning: elementwise comparison failed;
returning scalar instead, but in the future will perform elem
entwise comparison
  res_values = method(rvalues)
```

Out[8]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race	s

In [9]:

```
h = data[data['workclass']=='?']
h
```

Out[9]:

	age	workclass	education	education-num	marital-status	occupation	relationship
27	54	?	Some-college	10	Married-civ-spouse	?	Husband
61	32	?	7th-8th	4	Married-spouse-absent	?	Not-in-family
69	25	?	Some-college	10	Never-married	?	Own-child
77	67	?	10th	6	Married-civ-spouse	?	Husband
106	17	?	10th	6	Never-married	?	Own-child
...	...	...	...	...	...	...	...
32530	35	?	Bachelors	13	Married-civ-spouse	?	Wife
32531	30	?	Bachelors	13	Never-married	?	Not-in-family
32539	71	?	Doctorate	16	Married-civ-spouse	?	Husband
32541	41	?	HS-grad	9	Separated	?	Not-in-family
32542	72	?	HS-grad	9	Married-civ-spouse	?	Husband

1836 rows × 14 columns

In [10]:

```
h = data[data['education']=='?']
h
```

Out[10]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race	s

In [11]:

```
h = data[data['education-num']=='?']
h
```

```
C:\Users\More\anaconda3\lib\site-packages\pandas\core\ops\arr
ay_ops.py:253: FutureWarning: elementwise comparison failed;
returning scalar instead, but in the future will perform elem
entwise comparison
  res_values = method(rvalues)
```

Out[11]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race	s

In [12]:

```
h = data[data['marital-status']=='?']
h
```

Out[12]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race	s

In [13]:

```
h = data[data['occupation']=='?']
h
```

Out[13]:

	age	workclass	education	education-num	marital-status	occupation	relationship
27	54	?	Some-college	10	Married-civ-spouse	?	Husband
61	32	?	7th-8th	4	Married-spouse-absent	?	Not-in-family
69	25	?	Some-college	10	Never-married	?	Own-child
77	67	?	10th	6	Married-civ-spouse	?	Husband
106	17	?	10th	6	Never-married	?	Own-child
...	...	...	...	...	...	...	...
32530	35	?	Bachelors	13	Married-civ-spouse	?	Wife

32531	30	?	Bachelors	13	Never-married	?	Not-in-family
32539	71	?	Doctorate	16	Married-civ-spouse	?	Husband
32541	41	?	HS-grad	9	Separated	?	Not-in-family
32542	72	?	HS-grad	9	Married-civ-spouse	?	Husband

1843 rows × 14 columns

In [14]:

```
h = data[data['relationship']=='?']
h
```

Out[14]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race	s

In [15]:

```
h = data[data['sex']=='?']
h
```

Out[15]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race	s

In [16]:

```
h = data[data['capital-gain']=='?']
h
```

```
C:\Users\More\anaconda3\lib\site-packages\pandas\core\ops\arr
ay_ops.py:253: FutureWarning: elementwise comparison failed;
returning scalar instead, but in the future will perform elem
entwise comparison
  res_values = method(rvalues)
```

Out[16]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race	s

In [17]:

```
h = data[data['capital-loss']=='?']
h
```

```
C:\Users\More\anaconda3\lib\site-packages\pandas\core\ops\arr
```

```
ay_ops.py:253: FutureWarning: elementwise comparison failed;
returning scalar instead, but in the future will perform elem
entwise comparison
  res_values = method(rvalues)
```

Out[17]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race	s

In [18]:

```
h = data[data['hours-per-week']=='?']
h
```

```
C:\Users\More\anaconda3\lib\site-packages\pandas\core\ops\arr
ay_ops.py:253: FutureWarning: elementwise comparison failed;
returning scalar instead, but in the future will perform elem
entwise comparison
  res_values = method(rvalues)
```

Out[18]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race	s

In [19]:

```
data['native-country'].loc[data['native-country']=='?']
```

Out[19]:

```
14       ?
38       ?
51       ?
61       ?
93       ?
        ..
32449    ?
32469    ?
32492    ?
32510    ?
32525    ?
Name: native-country, Length: 583, dtype: object
```

In [20]:

```
h = data[data['salary']=='?']
h
```

Out[20]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race	s

In [21]:

```
h = data[data['race']=='?']
h
```

Out[21]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race	s

In [22]:

```
data['education-num'].unique()
```

Out[22]:

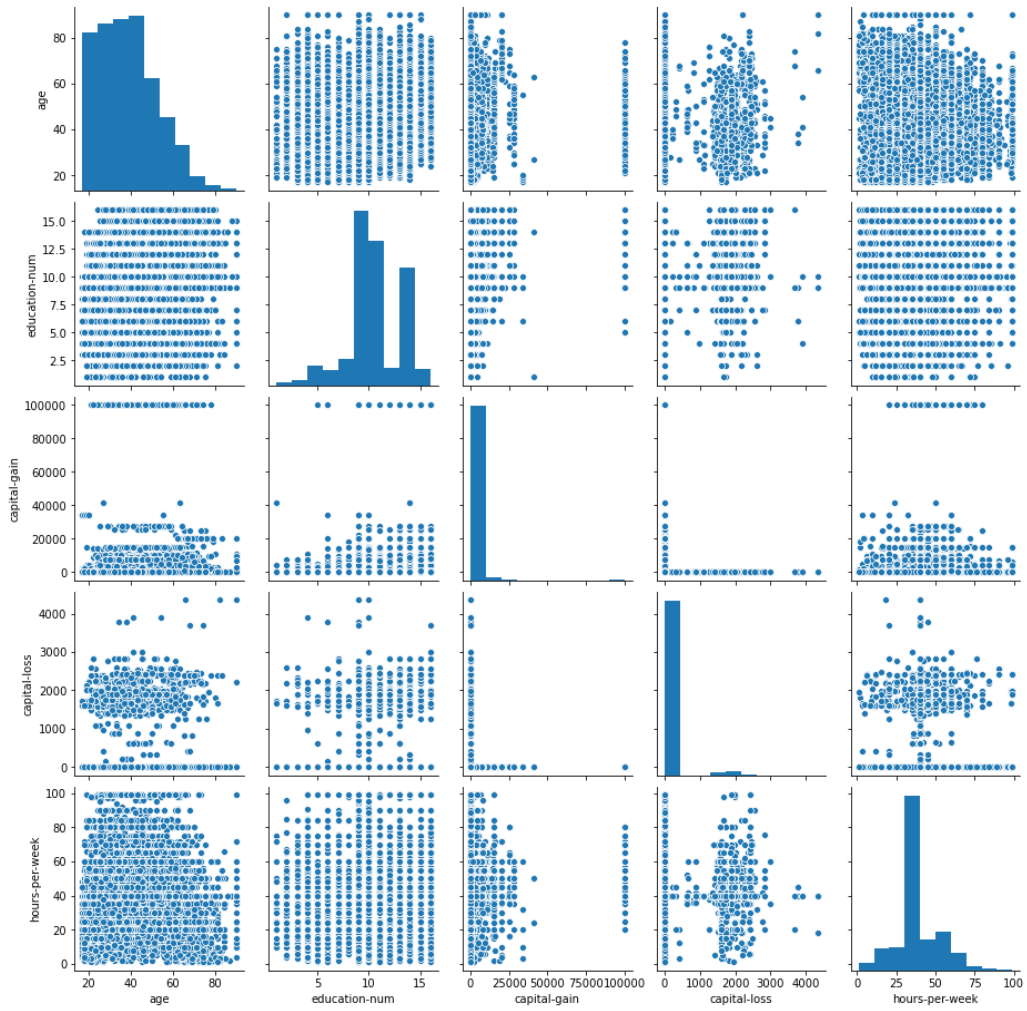
```
array([13,  9,  7, 14,  5, 10, 12, 11,  4, 16, 15,  3,  6,
2,  1,  8],
      dtype=int64)
```

In [23]:

```
sns.pairplot(data)
```

Out[23]:

```
<seaborn.axisgrid.PairGrid at 0x1babab65bb0>
```



In [24]:

```
corrmatrix = data.corr()
plt.subplots(figsize =(20,8))
sns.heatmap(corrmatrix, vmin =-.4,vmax=0.9,annot =True ,linewidth =.2)
```

Out[24]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1babd2285e0>
```

In [25]:

```
data['relationship'].mode()
```

Out[25]:

```
0    Husband
dtype: object
```

In [26]:

```
h1 = data[data['native-country'] != "?"]
f1 = h1.mode()
data['native-country'] = data['native-country'].replace("?",data['native-country'].mode())
```

In [27]:

```
h = data[data['native-country']=='?']
h
```

Out[27]:

	age	workclass	education	education-num	marital-status	occupation	relationship	
14	40	Private	Assoc-voc	11	Married-civ-spouse	Craft-repair	Husband	Is
38	31	Private	Some-college	10	Married-civ-spouse	Sales	Husband	
51	18	Private	HS-grad	9	Never-married	Other-service	Own-child	
					Married-			

61	32	?	7th-8th	4	spouse-absent	?	Not-in-family
93	30	Private	HS-grad	9	Married-civ-spouse	Sales	Wife
...	...	...	...	...	...	...	...
32449	44	Self-emp-inc	Masters	14	Married-civ-spouse	Sales	Husband
32469	58	Self-emp-inc	Doctorate	16	Never-married	Prof-specialty	Not-in-family
32492	42	Self-emp-not-inc	HS-grad	9	Divorced	Sales	Own-child
32510	39	Private	HS-grad	9	Married-civ-spouse	Prof-specialty	Husband
32525	81	?	Assoc-voc	11	Divorced	?	Unmarried

583 rows × 14 columns

CLEANING THE DATA SET (REPLACING THE "?")

In [28]:

```
data['native-country'].mode()
```

Out[28]:

```
0    United-States
dtype: object
```

In [29]:

```
data['native-country'] = data['native-country'].replace('?','United-States')
```

In [30]:

```
h = data[data['native-country']=='?']
h
```

Out[30]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race	s

In [31]:

```
data['occupation'].mode()
```

Out[31]:

```
0    Prof-specialty
```

```
dtype: object
```

In [32]:

```
data['occupation'] = data['occupation'].replace('?','Prof-specialty')
```

In [33]:

```
h = data[data['occupation']=='?']
h
```

Out[33]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race	s

In [34]:

```
data['workclass'].mode()
```

Out[34]:

```
0    Private
dtype: object
```

In [35]:

```
data['workclass'] = data['workclass'].replace('?','Private')
```

In [36]:

```
h = data[data['workclass']=='?']
h
```

Out[36]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race	s

FINDING OUTLIERS

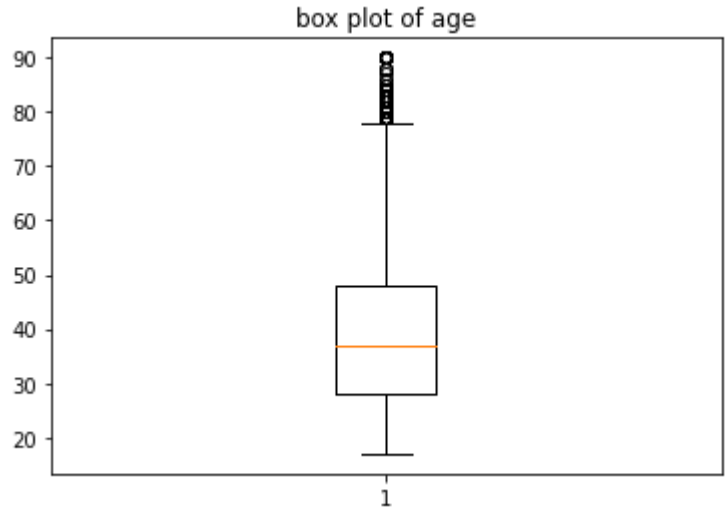
AGE

In [37]:

```
plt.boxplot(data['age'])
plt.title('box plot of age')
```

Out[37]:

```
Text(0.5, 1.0, 'box plot of age')
```



In [38]:

```
Q1 = np.percentile(data['age'],25,interpolation = 'midpoint')
Q2 =np.percentile(data['age'],50,interpolation = 'midpoint')
Q3 = np.percentile(data['age'],75,interpolation = 'midpoint')
```

In [39]:

```
print(Q1)
print(Q2)
print(Q3)
```

```
28.0
37.0
48.0
```

In [40]:

```
IQR = Q3-Q1
low_limit = Q1-1.5*IQR
up_limit = Q3+1.5*IQR
```

In [41]:

```
print(up_limit)
print(low_limit)
```

```
78.0
-2.0
```

In [42]:

```
Outliers = []
for x in data['age']:
```

```
    if((x>up_limit) or (x<low_limit)):
        Outliers.append(x)
```

In [43]:

```
Outliers
```

Out[43]:

```
[79,
 90,
 80,
 81,
 90,
 88,
 90,
 90,
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 82,
 81]
```

In [44]:

```
ind1 = data['age']>up_limit
f =data.loc[ind1].index
```

In [45]:

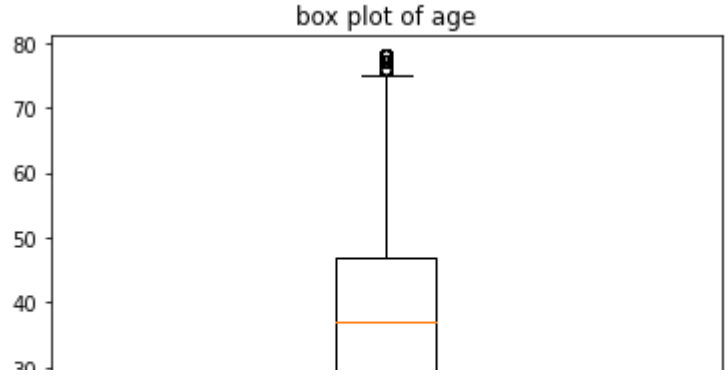
```
data.drop(f,inplace = True)
```

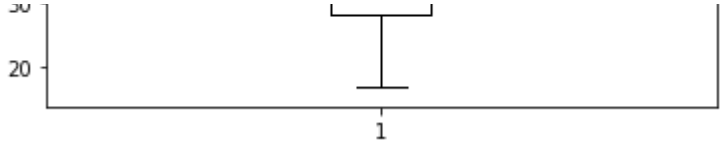
In [46]:

```
plt.boxplot(data['age'])
plt.title('box plot of age')
```

Out[46]:

```
Text(0.5, 1.0, 'box plot of age')
```





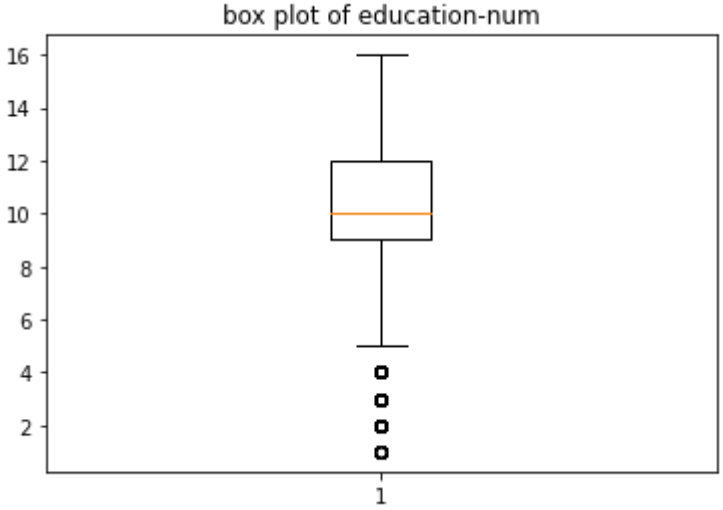
education-num

In [47]:

```
plt.boxplot(data['education-num'])
plt.title('box plot of education-num')
```

Out[47]:

```
Text(0.5, 1.0, 'box plot of education-num')
```



In [48]:

```
Q1 = np.percentile(data['education-num'],25,interpolation = 'midpoint')
Q2 =np.percentile(data['education-num'],50,interpolation = 'midpoint')
Q3 = np.percentile(data['education-num'],75,interpolation = 'midpoint')
```

In [49]:

```
print(Q1)
print(Q2)
print(Q3)
```

```
9.0
10.0
12.0
```

In [50]:

```
IQR = Q3-Q1
low_limit = Q1-1.5*IQR
up_limit = Q3+1.5*IQR
```

In [51]:

```
print(up_limit)
print(low_limit)
```

```
16.5
4.5
```

In [52]:

```
Outliers = []
for x in data['education-num']:
    if((x>up_limit) or (x<low_limit)):
        Outliers.append(x)
```

In [53]:

```
Outliers
```

Out[53]:

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In [54]:

```
ind1 = data['education-num']<low_limit
data.loc[ind1].index
```

Out[54]:

```
Int64Index([   15,    56,    61,    79,   160,   183,   195,
214,   221,
              224,
             ...
             32401, 32403, 32413, 32425, 32430, 32431, 32432,
32448, 32479,
             32517],
            dtype='int64', length=1177)
```

In [55]:

```
data = data.drop(columns="education-num")
```

In [56]:

```
data.columns
```

Out[56]:

```
Index(['age', 'workclass', 'education', 'marital-status', 'oc
cupation',
       'relationship', 'race', 'sex', 'capital-gain', 'capita
l-loss',
       'hours-per-week', 'native-country', 'salary'],
      dtype='object')
```

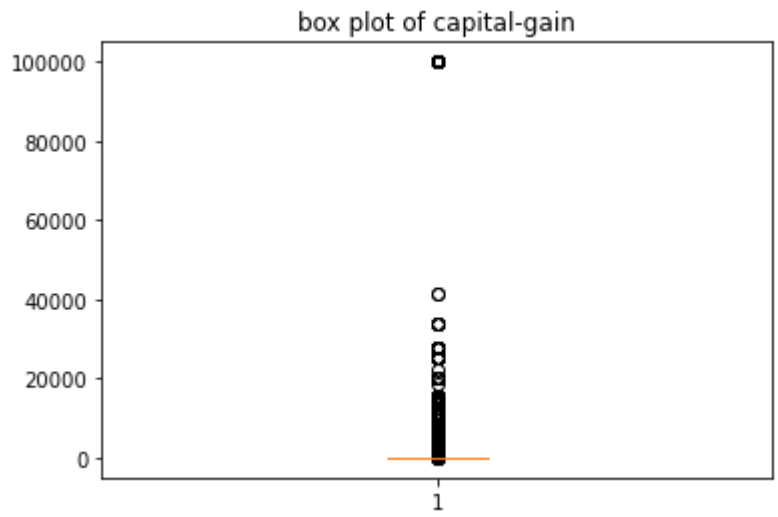
capital-gain

In [57]:

```
plt.boxplot(data['capital-gain'])
plt.title('box plot of capital-gain')
```

Out[57]:

```
Text(0.5, 1.0, 'box plot of capital-gain')
```



In [58]:

```
Q1 = np.percentile(data['capital-gain'],25,interpolation = 'midpoint')
Q2 =np.percentile(data['capital-gain'],50,interpolation = 'midpoint')
Q3 = np.percentile(data['capital-gain'],75,interpolation = 'midpoint')
```

In [59]:

```
print(Q1)
print(Q2)
print(Q3)
```

```
0.0
0.0
0.0
```

In [60]:

```
IQR = Q3-Q1
low_limit = Q1-1.5*IQR
up_limit = Q3+1.5*IQR
```

In [61]:

```
print(up_limit)
print(low_limit)
```

```
0.0
0.0
```

In [62]:

```
Outliers = []
for x in data['capital-gain']:
    if((x>up_limit) or (x<low_limit)):
        Outliers.append(x)
```

In [63]:

```
Outliers
```

Out[63]:

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5178,

5178,
20051,
4787,
14084,
2936,
10566,
7298,
6849,
4386,
7688,
3818,
27828,
8614,
7298,
2202,
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7298,
4650,
1151,
4508,
2993,
99999,
2829,
7688,
7688,
7688,
7298,
14344,
5178,
5013,
3103,
5178,
4064,
3411,
15024,
2174,
3325,
3464,
3887,
15831,
7688,
7688,
7298,
20051,
7688,
1086,
2174,
7298,
4386,
5455,
25236,
7298,
3325,
5721,
7298,
7443,
2036,
3137,
7688,
7298,
8614,

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 7688,
 99999,
 2176,
 7298,
 7688,
 7688,
 5178,
 99999,
 4386,
 99999,
 5178,
 4064,
 6360,
 1848,
 99999,
 3103,
 4386,
 5178,
 15024,
 2174,
 7688,
 15024,
 ...]
```

In [64]:

```
ind1 = data['capital-gain']>up_limit
data.loc[ind1].index
```

Out[64]:

```
Int64Index([    0,     8,     9,    59,    60,    84,   101,
105,   106,
              113,
            ...
            32399, 32434, 32462, 32466, 32473, 32515, 32518,
32538, 32548,
            32560],
           dtype='int64', length=2692)
```

In [65]:

```
data = data.drop(columns="capital-gain")
```

In [66]:

```
data.columns
```

Out[66]:

```
Index(['age', 'workclass', 'education', 'marital-status', 'oc
cupation',
       'relationship', 'race', 'sex', 'capital-loss', 'hours-
per-week',
       'native-country', 'salary'],
      dtype='object')
```

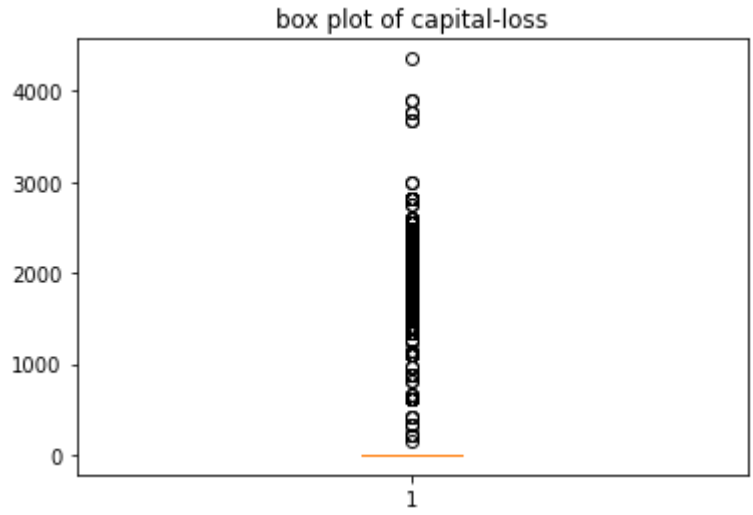
capital-loss

In [67]:

```
plt.boxplot(data['capital-loss'])
plt.title('box plot of capital-loss')
```

Out[67]:

```
Text(0.5, 1.0, 'box plot of capital-loss')
```



In [68]:

```
Q1 = np.percentile(data['capital-loss'],25,interpolation = 'midpoint')
Q2 =np.percentile(data['capital-loss'],50,interpolation = 'midpoint')
Q3 = np.percentile(data['capital-loss'],75,interpolation = 'midpoint')
```

In [69]:

```
print(Q1)
print(Q2)
print(Q3)
```

```
0.0
0.0
0.0
```

In [70]:

```
IQR = Q3-Q1
low_limit = Q1-1.5*IQR
up_limit = Q3+1.5*IQR
```

In [71]:

```
print(up_limit)
print(low_limit)
```

```
0.0
0.0
```

In [72]:

```
Outliers = []
for x in data['capital-loss']:
```

```
    if((x>up_limit) or (x<low_limit)):
        Outliers.append(x)
```

In [73]:

```
Outliers
```

Out[73]:

```
[2042,
 1408,
 1902,
 1573,
 1902,
 1887,
 1719,
 1762,
 1564,
 2179,
 1816,
 1980,
 1977,
 1876,
 1340,
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 1485,
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 2339,
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 2179,
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 1408,
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 1380,
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 1902,
 1762,
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 2051,
 2377,
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 2352,
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 1672,
 653,
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1579,
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2174,
2206,
2415,
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1980,
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1977,
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1602,
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1977,
2205,
1977,
1726,
1485,
2444,
2392,
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323,
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1590,
1628,
1719,
1974,
2001,
2559,
1887,
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213,
2179,
1138,
1504,
1594,
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2246,
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1876,
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2267,
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1672,
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1977,
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1902,
1669,
2001,
2205,
1564,
1602,
2603,
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2339,
1669,
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1902,
1602,
1887,
1617,
1980,
1573,
1902,
1887,
653,
1902,
1617,
1902,
1902,
1848,
625,
1887,
1602,
1485,
1672,
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1902,
1628,
1651,
1408,
2001,
2246,
1977,
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1977,
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1977,
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2824,
1590,
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2377

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2559,
1762,
1741,
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1564,
1887,
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2377,
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2258,
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1876,
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2205,
1876,
419,
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2444,
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2179,
1887,
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2179,
1887,
2179,
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2206,
2179,
1977,
1887,
1602,
1485,
1485,
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1902,
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 2174,
 155,
 1902,
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 625,
 3900,
 2201,
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 1902,
 1721,
 1887,
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 2415,
 1876,
 1902,
 1977,
 2051,
 2246,
 1902,
 2042,
 2002,
 1977,
 1902,
 1485,
 1876,
 1672,
 2415,
 1977,
 1340,
 1977,
 2547,
 2042,
 1944,
 2258,
 1887,
 1504,
 1887,
 1876,
 1902,
 2205,
 2001,
 1902,
 2258,
 1980,
 1258,
 2415,
 1669,
 1887,
 ...]
```

In [74]:

```
ind1 = data['capital-loss']>up_limit
data.loc[ind1].index
```

Out[74]:

```
Int64Index([   23,    32,    52,    93,    96,   112,   126,
```

```
131,   143,
             148,
            ...
            32307, 32311, 32393, 32400, 32416, 32441, 32443,
32445, 32458,
            32500],
           dtype='int64', length=1512)
```

In [75]:

```
data = data.drop(columns="capital-loss")
```

In [76]:

```
data.columns
```

Out[76]:

```
Index(['age', 'workclass', 'education', 'marital-status', 'oc
cupation',
       'relationship', 'race', 'sex', 'hours-per-week', 'nati
ve-country',
       'salary'],
      dtype='object')
```

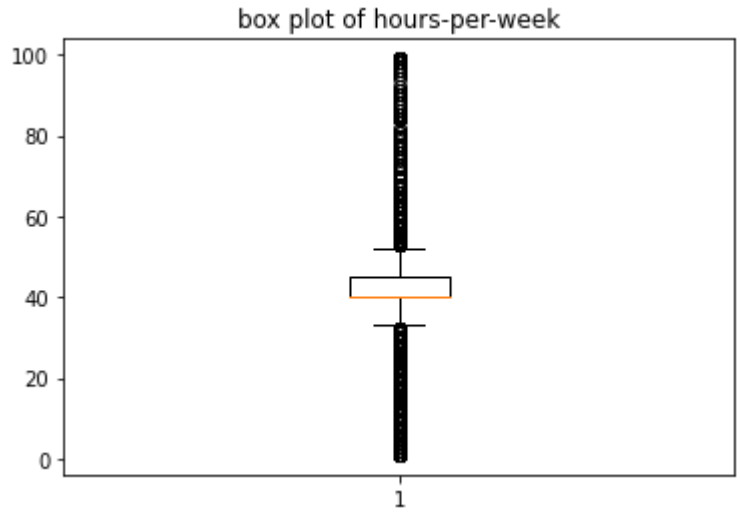
hours-per-week

In [77]:

```
plt.boxplot(data['hours-per-week'])
plt.title('box plot of hours-per-week')
```

Out[77]:

```
Text(0.5, 1.0, 'box plot of hours-per-week')
```



In [78]:

```
Q1 = np.percentile(data['hours-per-week'],25,interpolation = 'midpoint')
Q2 =np.percentile(data['hours-per-week'],50,interpolation = 'midpoint')
Q3 = np.percentile(data['hours-per-week'],75,interpolation = 'midpoint')
```

In [79]:

```
print(Q1)
print(Q2)
print(Q3)
```

```
40.0
40.0
45.0
```

In [80]:

```
IQR = Q3-Q1
low_limit = Q1-1.5*IQR
up_limit = Q3+1.5*IQR
```

In [81]:

```
print(up_limit)
print(low_limit)
```

```
52.5
32.5
```

In [82]:

```
Outliers = []
for x in data['hours-per-week']:
    if((x>up_limit) or (x<low_limit)):
        Outliers.append(x)
```

In [83]:

```
Outliers
```

Out[83]:

```
[13,
 16,
 80,
 30,
 60,
 20,
 60,
 80,
 15,
 25,
 30,
 60,
 55,
 60,
 58,
 32,
 70,
 2,
 22,
 30,
 25,
 60,
 60,
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32,
25,
56,
60,
28,
60,
60,
20,
30,
30,
24,
24,
2,
60,
20,
16,
20,
25,
12,
65,
1,
28,
24,
55,
60,
12,
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20,
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20,
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70,
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60,
30,
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60,
12,
75,
24,
24,
98,
15,
60,
56,
16,
60,
80,
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32,
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```

In [84]:

```
ind1 = data['hours-per-week']>up_limit
data.loc[ind1].index
```

Out[84]:

```
Int64Index([   10,    20,    27,    28,    52,    53,    54,
64,    72,
               96,
            ...
            32495, 32500, 32506, 32520, 32523, 32530, 32531,
32532, 32536,
            32548],
           dtype='int64', length=3483)
```

In [85]:

```
data = data.drop(columns ='hours-per-week')
```

In [86]:

```
data.columns
```

Out[86]:

```
Index(['age', 'workclass', 'education', 'marital-status', 'oc
cupation',
       'relationship', 'race', 'sex', 'native-country', 'sala
ry'],
      dtype='object')
```

In [87]:

```
data.describe(include ='object')
```

Out[87]:

	workclass	education	marital-status	occupation	relationship	race	sex	na co
count	32418	32418	32418	32418	32418	32418	32418	3

count	32418	32418	32418	32418	32418	32418	32418	3
unique	8	16	7	14	6	5	2	
top	Private	HS-grad	Married-civ-spouse	Prof-specialty	Husband	White	Male	U S
freq	24435	10452	14908	5928	13130	27687	21690	2

In [88]:

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
a=['workclass','education','marital-status','occupation','relationship','race','sex','native-country','salary']
for i in np.arange(len(a)):
    data[a[i]]=le.fit_transform(data[a[i]])
```

train the data set

In [89]:

```
Y = data['salary']
X = data.drop(['salary'],axis =1)
```

In [90]:

```
from sklearn.model_selection import train_test_split
X_train,X_test,Y_train,Y_test = train_test_split(X,Y,test_size = 0.25,random_state =0)
```

RANDOM FOREST CLASSIFIER

In [91]:

```
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier()
rf.fit(X_train,Y_train)
Y_pred = rf.predict(X_test)
```

In [92]:

```
from sklearn.metrics import confusion_matrix,accuracy_score,recall_score,f1_score,precision_score
print('accuracy:',accuracy_score(Y_test,Y_pred))
print('precision:',precision_score(Y_test,Y_pred))
print('recall:',recall_score(Y_test,Y_pred))
print("f1_score:",f1_score(Y_test,Y_pred))
print(confusion_matrix(Y_test,Y_pred))
```

```
accuracy: 0.815916101172116
precision: 0.6221574344023324
recall: 0.5583464154892727
f1_score: 0.5885273028130171
[[5546  648]
 [ 844 1067]]
```

In [ ]:

```
```

KNN

In [93]:

```
from sklearn.neighbors import KNeighborsClassifier
acc_values = []
neighbors = np.arange(3,15)
for k in neighbors:
    Classifier = KNeighborsClassifier(n_neighbors = k,metric = 'minkowski'
)
    Classifier.fit(X_train,Y_train)
    Y_pred = Classifier.predict(X_test)
    acc = accuracy_score(Y_test,Y_pred)
    acc_values.append(acc)
```

In [94]:

```
acc_values
```

Out[94]:

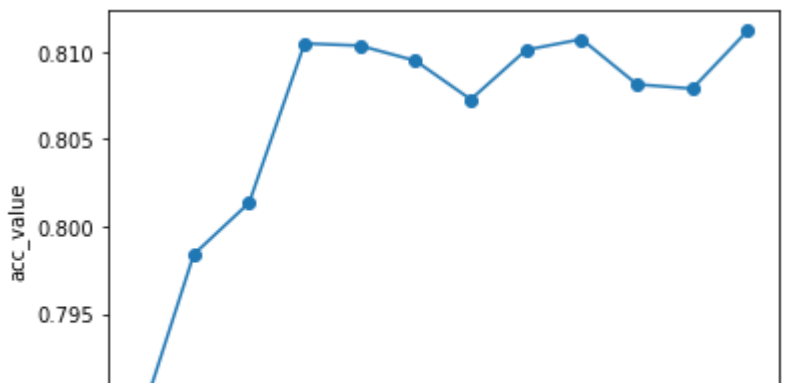
```
[0.7885256014805676,
 0.7983960518198643,
 0.8013571869216533,
 0.8104873534855028,
 0.8103639728562616,
 0.8095003084515731,
 0.8072794571252313,
 0.8101172115977792,
 0.8107341147439852,
 0.8081431215299199,
 0.8078963602714374,
 0.81122763726095]
```

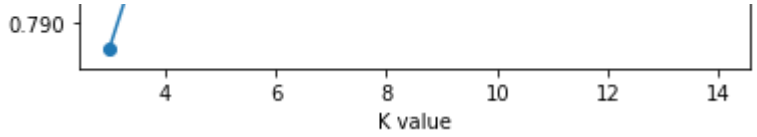
In [95]:

```
plt.plot(neighbors,acc_values,'o-')
plt.xlabel('K value')
plt.ylabel('acc_value')
```

Out[95]:

```
Text(0, 0.5, 'acc_value')
```





In [96]:

```
Classifier = KNeighborsClassifier(n_neighbors = 14,metric = 'minkowski')
Classifier.fit(X_train,Y_train)
Y_pred = Classifier.predict(X_test)
print('accuracy:',accuracy_score(Y_test,Y_pred))
print('precision:',precision_score(Y_test,Y_pred))
print('recall:',recall_score(Y_test,Y_pred))
print("f1_score:",f1_score(Y_test,Y_pred))
print(confusion_matrix(Y_test,Y_pred))
```

```
accuracy: 0.81122763726095
precision: 0.636168691922802
recall: 0.46572475143903713
f1_score: 0.5377643504531721
[[5685  509]
 [1021  890]]
```

svm

(LINEAR SVM)

In [ ]:

```
from sklearn.svm import SVC
svm_linear = SVC(kernel = 'linear')
svm_linear.fit(X_train,Y_train)
print('accuracy:',accuracy_score(Y_test,Y_pred))
print('precision:',precision_score(Y_test,Y_pred))
print('recall:',recall_score(Y_test,Y_pred))
print("f1_score:",f1_score(Y_test,Y_pred))
print(confusion_matrix(Y_test,Y_pred))
```

polynomial SVM

In [ ]:

```
svm_polinomial = SVC(kernel = 'poly', degree = 3)
svm_polinomial.fit(X_train,Y_train)
Y_pred = svm_polinomial.predict(X_test)
print('accuracy:',accuracy_score(Y_test,Y_pred))
print('precision:',precision_score(Y_test,Y_pred))
print('recall:',recall_score(Y_test,Y_pred))
print("f1_score:",f1_score(Y_test,Y_pred))
print(confusion_matrix(Y_test,Y_pred))
```

RADIAL SVM

In [ ]:

```
svm_radial = SVC(kernel = 'rbf')
svm_radial.fit(X_train,Y_train)
Y_pred = svm_radial.predict(X_test)
print('accuracy:',accuracy_score(Y_test,Y_pred))
print('precision:',precision_score(Y_test,Y_pred))
print('recall:',recall_score(Y_test,Y_pred))
print("f1_score:",f1_score(Y_test,Y_pred))
print(confusion_matrix(Y_test,Y_pred))
```

LOGISTIC REGRESSION

In [ ]:

```
from sklearn.linear_model import LogisticRegression
logit_model = LogisticRegression()
logit_model.fit(X_train,Y_train)
Y_pred = logit_model.predict(X_test)
print('accuracy:',accuracy_score(Y_test,Y_pred))
print('precision:',precision_score(Y_test,Y_pred))
print('recall:',recall_score(Y_test,Y_pred))
print("f1_score:",f1_score(Y_test,Y_pred))
print(confusion_matrix(Y_test,Y_pred))
```

DECISION TREE CLASSIFIER

In [ ]:

```
from sklearn.tree import DecisionTreeClassifier
dt = DecisionTreeClassifier()
dt.fit(X_train,Y_train)
Y_pred = dt.predict(X_test)
print('accuracy:',accuracy_score(Y_test,Y_pred))
print('precision:',precision_score(Y_test,Y_pred))
print('recall:',recall_score(Y_test,Y_pred))
print("f1_score:",f1_score(Y_test,Y_pred))
print(confusion_matrix(Y_test,Y_pred))
```

GRADIENT BOOST CLASSIFIER

In [ ]:

```
from sklearn.ensemble import GradientBoostingClassifier
gb = GradientBoostingClassifier()
gb.fit(X_train,Y_train)
Y_pred = gb.predict(X_test)
print('accuracy:',accuracy_score(Y_test,Y_pred))
print('precision:',precision_score(Y_test,Y_pred))
print('recall:',recall_score(Y_test,Y_pred))
print("f1_score:",f1_score(Y_test,Y_pred))
print(confusion_matrix(Y_test,Y_pred))
```

In [99]:

```
from sklearn.linear_model import LinearRegression
lr = LinearRegression()
lr.fit(X_train,Y_train)
Y_pred = lr.predict(X_test)
from sklearn.metrics import mean_squared_error,r2_score
print('MSE is :',mean_squared_error(Y_test,Y_pred))
print('R Squared Error is:',r2_score(Y_test,Y_pred))
```

```
MSE is : 0.15792998405241473
R Squared Error is: 0.12352659689431444
```

STANDARD SCALING

In [ ]:

```
from sklearn import preprocessing
from sklearn.preprocessing import StandardScaler
ss = StandardScaler()
X_train = ss.fit_transform(X_train)
X_test = ss.fit_transform(X_test)
```

In [ ]:

```
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier()
rf.fit(X_train,Y_train)
Y_pred = rf.predict(X_test)
print('accuracy:',accuracy_score(Y_test,Y_pred))
print('precision:',precision_score(Y_test,Y_pred))
print('recall:',recall_score(Y_test,Y_pred))
print("f1_score:",f1_score(Y_test,Y_pred))
print(confusion_matrix(Y_test,Y_pred))
```

In [ ]:

```
from sklearn.neighbors import KNeighborsClassifier
acc_values = []
neighbors = np.arange(3,15)
for k in neighbors:
    Classifier = KNeighborsClassifier(n_neighbors = k,metric = 'minkowski'
)
    Classifier.fit(X_train,Y_train)
    Y_pred = Classifier.predict(X_test)
    acc = accuracy_score(Y_test,Y_pred)
    acc_values.append(acc)
```

In [ ]:

```
acc_values
```

In [ ]:

```
plt.plot(neighbors,acc_values,'o-')
plt.xlabel('K value')
```

```
plt.ylabel('acc_value')
```

In [ ]:

```
Classifier = KNeighborsClassifier(n_neighbors = 10,metric = 'minkowski')
Classifier.fit(X_train,Y_train)
Y_pred = Classifier.predict(X_test)
print('accuracy:',accuracy_score(Y_test,Y_pred))
print('precision:',precision_score(Y_test,Y_pred))
print('recall:',recall_score(Y_test,Y_pred))
print("f1_score:",f1_score(Y_test,Y_pred))
print(confusion_matrix(Y_test,Y_pred))
```

In [ ]:

```
from sklearn.svm import SVC
svm_linear = SVC(kernel = 'linear')
svm_linear.fit(X_train,Y_train)
print('accuracy:',accuracy_score(Y_test,Y_pred))
print('precision:',precision_score(Y_test,Y_pred))
print('recall:',recall_score(Y_test,Y_pred))
print("f1_score:",f1_score(Y_test,Y_pred))
print(confusion_matrix(Y_test,Y_pred))
```

In [ ]:

```
svm_polinomial = SVC(kernel = 'poly', degree = 3)
svm_polinomial.fit(X_train,Y_train)
Y_pred = svm_polinomial.predict(X_test)
print('accuracy:',accuracy_score(Y_test,Y_pred))
print('precision:',precision_score(Y_test,Y_pred))
print('recall:',recall_score(Y_test,Y_pred))
print("f1_score:",f1_score(Y_test,Y_pred))
print(confusion_matrix(Y_test,Y_pred))
```

In [ ]:

```
svm_radial = SVC(kernel = 'rbf')
svm_radial.fit(X_train,Y_train)
Y_pred = svm_radial.predict(X_test)
print('accuracy:',accuracy_score(Y_test,Y_pred))
print('precision:',precision_score(Y_test,Y_pred))
print('recall:',recall_score(Y_test,Y_pred))
print("f1_score:",f1_score(Y_test,Y_pred))
print(confusion_matrix(Y_test,Y_pred))
```

In [ ]:

```
from sklearn.linear_model import LogisticRegression
logit_model = LogisticRegression()
logit_model.fit(X_train,Y_train)
Y_pred = logit_model.predict(X_test)
print('accuracy:',accuracy_score(Y_test,Y_pred))
print('precision:',precision_score(Y_test,Y_pred))
print('recall:',recall_score(Y_test,Y_pred))
print("f1_score:",f1_score(Y_test,Y_pred))
print(confusion_matrix(Y_test,Y_pred))
```

In [ ]:

```
from sklearn.tree import DecisionTreeClassifier
dt = DecisionTreeClassifier()
dt.fit(X_train,Y_train)
Y_pred = dt.predict(X_test)
print('accuracy:',accuracy_score(Y_test,Y_pred))
print('precision:',precision_score(Y_test,Y_pred))
print('recall:',recall_score(Y_test,Y_pred))
print("f1_score:",f1_score(Y_test,Y_pred))
print(confusion_matrix(Y_test,Y_pred))
```

In [ ]:

```
from sklearn.ensemble import GradientBoostingClassifier
gb = GradientBoostingClassifier()
gb.fit(X_train,Y_train)
Y_pred = gb.predict(X_test)
print('accuracy:',accuracy_score(Y_test,Y_pred))
print('precision:',precision_score(Y_test,Y_pred))
print('recall:',recall_score(Y_test,Y_pred))
print("f1_score:",f1_score(Y_test,Y_pred))
print(confusion_matrix(Y_test,Y_pred))
```

In [ ]:

```

```