In [1]:
```
## CENSUS INCOME PROJECT
```

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

In [2]:
```
df=pd.read_csv('https://raw.githubusercontent.com/dsrscientist/dataset1/master/census_income.csv')
```

In [3]:
```
df.head(10)
```

Out[3]:

	Age	Workclass	Fnlwgt	Education	Education_num	Marital_status	Occupation	Relationship	Race	Sex	Capital_gain	Capital_loss	Hou
0	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	
1	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	
2	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	
3	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	
4	37	Private	284582	Masters	14	Married-civ-spouse	Exec-managerial	Wife	White	Female	0	0	
5	49	Private	160187	9th	5	Married-spouse-absent	Other-service	Not-in-family	Black	Female	0	0	
6	52	Self-emp-not-inc	209642	HS-grad	9	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	
7	31	Private	45781	Masters	14	Never-married	Prof-specialty	Not-in-family	White	Female	14084	0	
8	42	Private	159449	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	5178	0	
9	37	Private	280464	Some-college	10	Married-civ-spouse	Exec-managerial	Husband	Black	Male	0	0	

In [4]:
```
df.dtypes
```

Out[4]:
```
Age               int64
Workclass        object
Fnlwgt            int64
Education        object
Education_num     int64
Marital_status   object
Occupation       object
Relationship     object
Race             object
Sex              object
Capital_gain      int64
Capital_loss      int64
Hours_per_week    int64
Native_country   object
Income           object
dtype: object
```

In [5]:
```
df.isnull().sum() ## checking for null values
```

Out[5]:
```
Age               0
Workclass         0
Fnlwgt            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
```

```
Income            0
dtype: int64
```

In [6]:
```
## looks like there are no null values
```

In [7]:
```
df.describe()
```

Out[7]:

	Age	Fnlwgt	Education_num	Capital_gain	Capital_loss	Hours_per_week
count	32560.000000	3.256000e+04	32560.000000	32560.000000	32560.000000	32560.000000
mean	38.581634	1.897818e+05	10.080590	1077.615172	87.306511	40.437469
std	13.640642	1.055498e+05	2.572709	7385.402999	402.966116	12.347618
min	17.000000	1.228500e+04	1.000000	0.000000	0.000000	1.000000
25%	28.000000	1.178315e+05	9.000000	0.000000	0.000000	40.000000
50%	37.000000	1.783630e+05	10.000000	0.000000	0.000000	40.000000
75%	48.000000	2.370545e+05	12.000000	0.000000	0.000000	45.000000
max	90.000000	1.484705e+06	16.000000	99999.000000	4356.000000	99.000000

In [8]:
```
df.shape
```

Out[8]:
```
(32560, 15)
```

In [9]:
```
## dropping the unnecessary columns
```

In [10]:
```
df.drop(['Marital_status','Relationship','Race'],axis=1)
```

Out[10]:

	Age	Workclass	Fnlwgt	Education	Education_num	Occupation	Sex	Capital_gain	Capital_loss	Hours_per_week	Native_country	Ir
0	50	Self-emp-not-inc	83311	Bachelors	13	Exec-managerial	Male	0	0	13	United-States	
1	38	Private	215646	HS-grad	9	Handlers-cleaners	Male	0	0	40	United-States	
2	53	Private	234721	11th	7	Handlers-cleaners	Male	0	0	40	United-States	
3	28	Private	338409	Bachelors	13	Prof-specialty	Female	0	0	40	Cuba	
4	37	Private	284582	Masters	14	Exec-managerial	Female	0	0	40	United-States	
...	...	...	...	...	...	...	...	...	...	...	...	...
32555	27	Private	257302	Assoc-acdm	12	Tech-support	Female	0	0	38	United-States	
32556	40	Private	154374	HS-grad	9	Machine-op-inspct	Male	0	0	40	United-States	
32557	58	Private	151910	HS-grad	9	Adm-clerical	Female	0	0	40	United-States	
32558	22	Private	201490	HS-grad	9	Adm-clerical	Male	0	0	20	United-States	
32559	52	Self-emp-inc	287927	HS-grad	9	Exec-managerial	Female	15024	0	40	United-States	

32560 rows × 12 columns

In [11]:
```
## exploring the continuous variables
```

In [12]:
```
cont_data = df.select_dtypes(exclude = ['object'] )
cont_data
```

Out[12]:

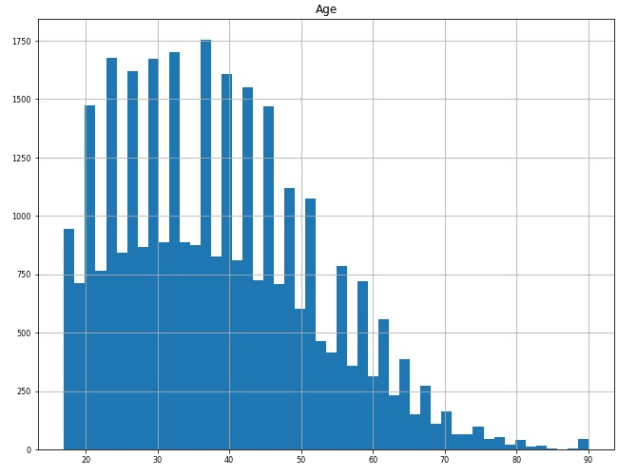
	Age	Fnlwgt	Education_num	Capital_gain	Capital_loss	Hours_per_week
0	50	83311	13	0	0	13
1	38	215646	9	0	0	40

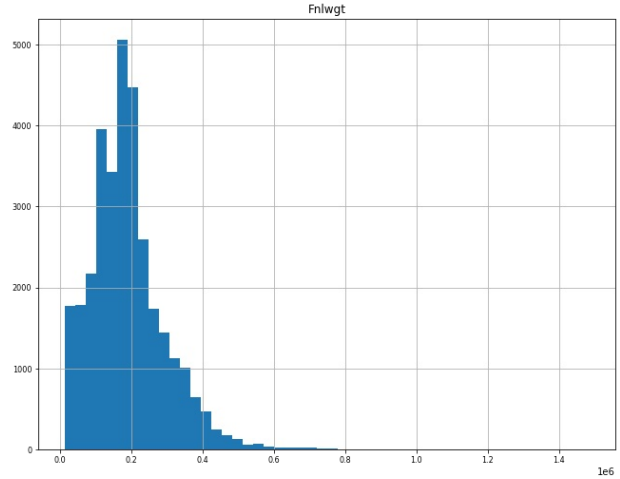
2	53	234721	7	0	0	40
3	28	338409	13	0	0	40
4	37	284582	14	0	0	40
...	...	...	...	...	...	...
32555	27	257302	12	0	0	38
32556	40	154374	9	0	0	40
32557	58	151910	9	0	0	40
32558	22	201490	9	0	0	20
32559	52	287927	9	15024	0	40

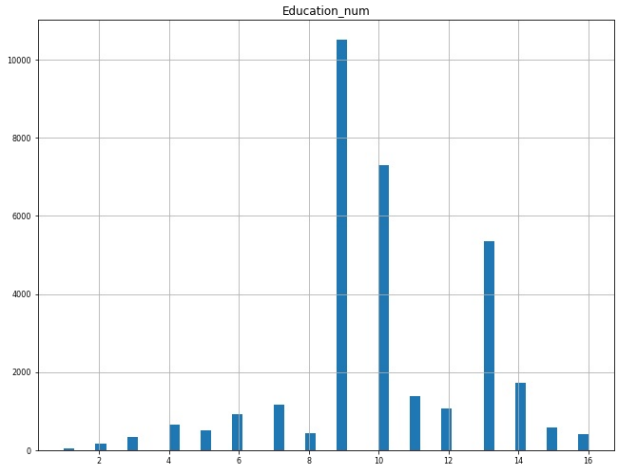
32560 rows × 6 columns

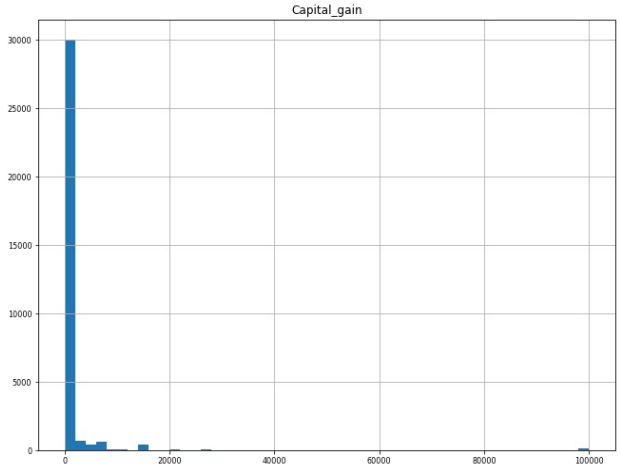
In [13]:
```
##data distribution
```

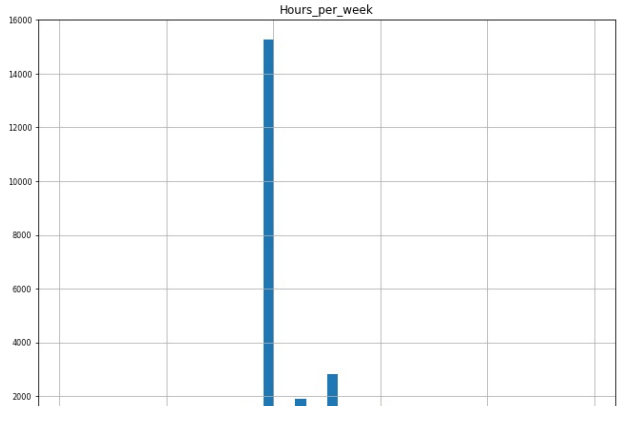
In [14]:
```
cont_data.hist(figsize = (25, 30), bins = 50, xlabelsize = 8, ylabelsize = 8)
plt.show()
```

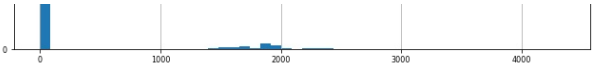






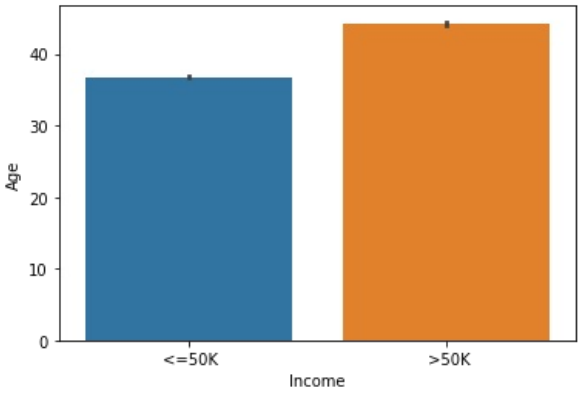


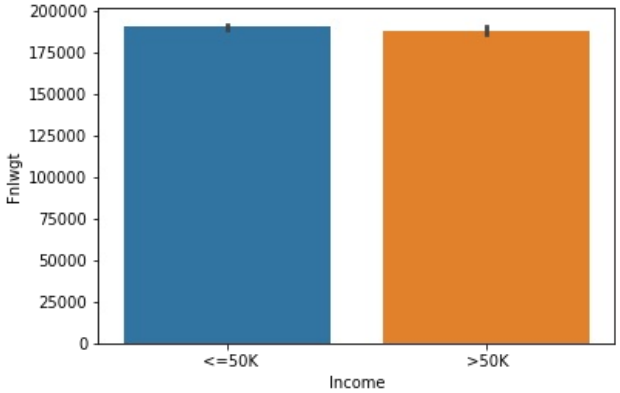


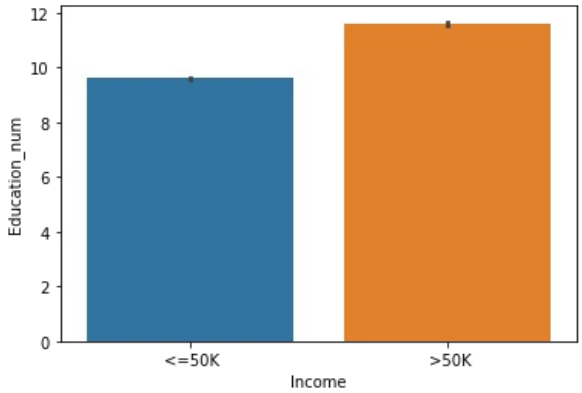


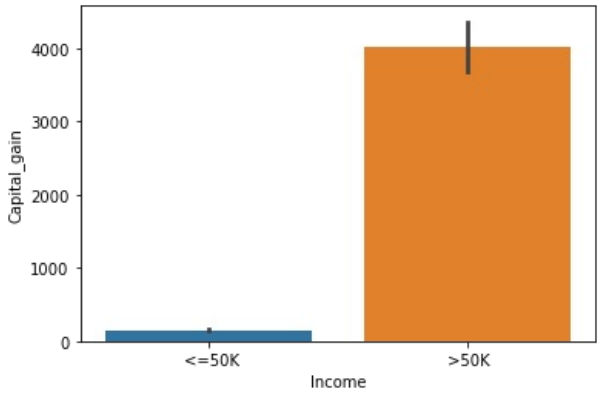
In [15]:

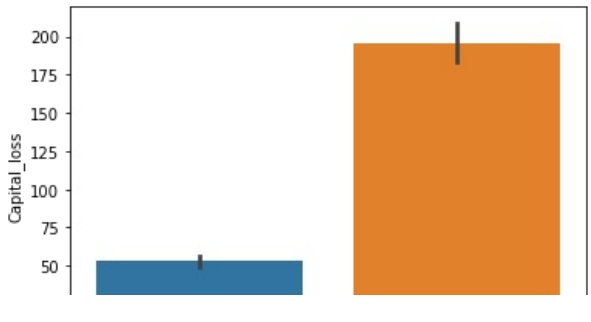
```
for i in cont_data:
    sns.barplot(y = cont_data[i], x = df['Income'])
    plt.show()
```

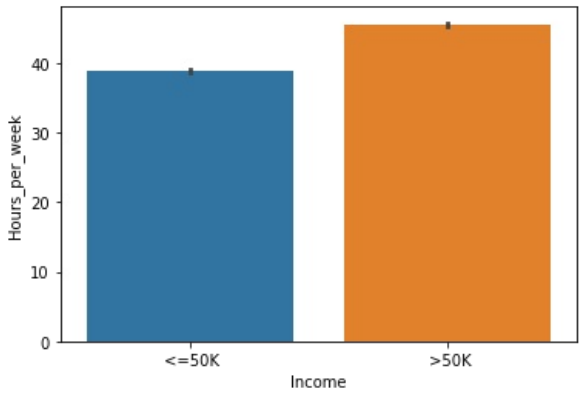






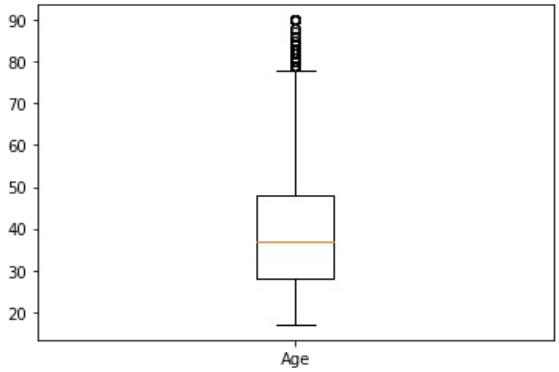


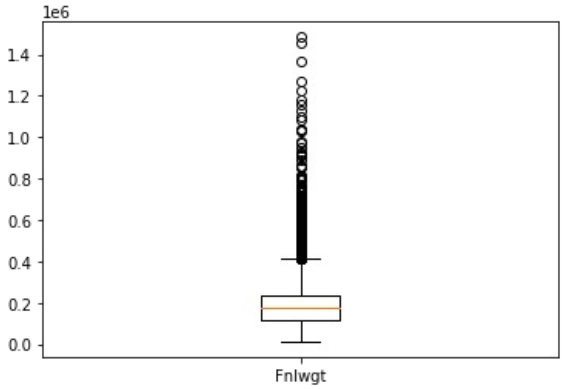


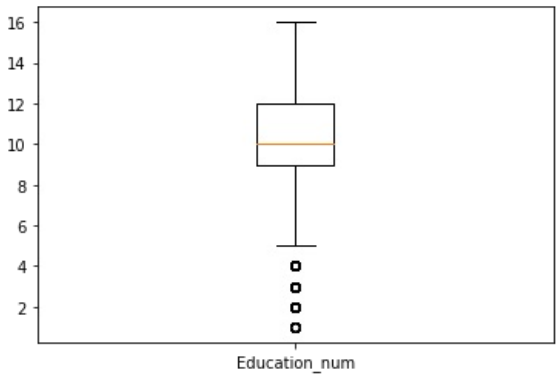


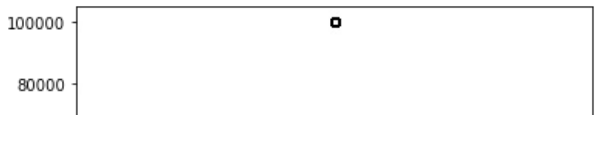
In [16]:
```
## Checking for outliers
```

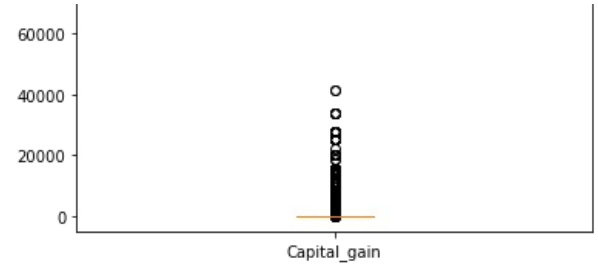
In [17]:
```
for i in cont_data:
    plt.boxplot(cont_data[i], labels = [i])
    plt.show()
```

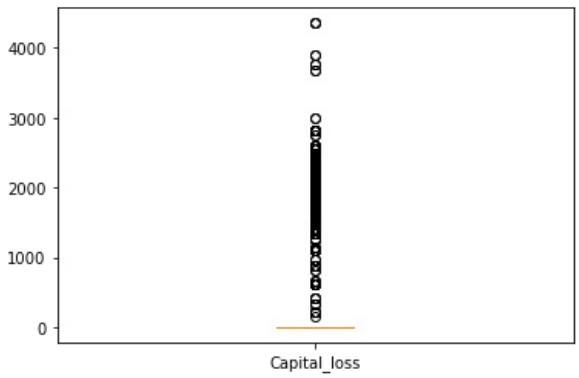


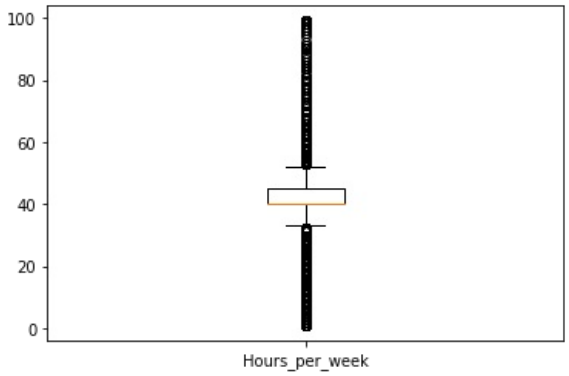








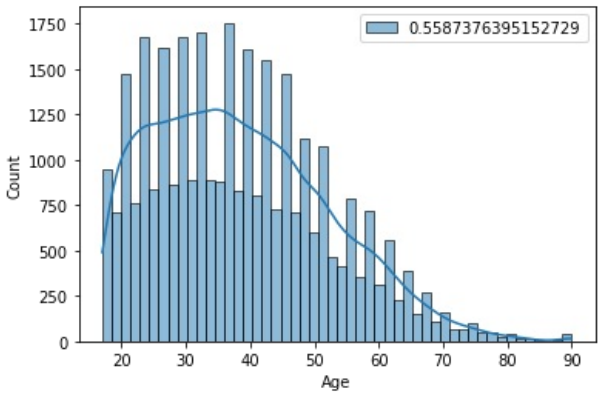


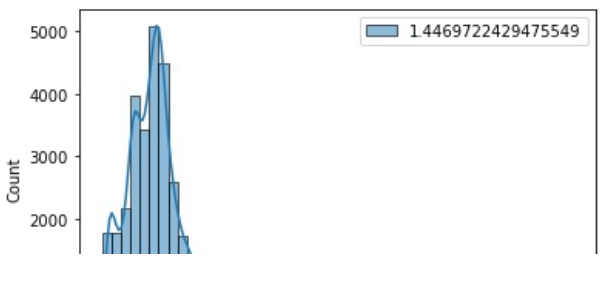


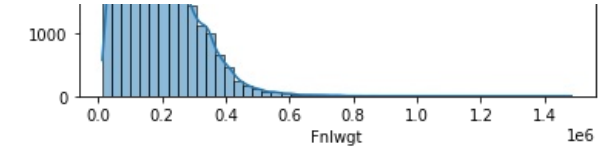
In [18]:
```
## looks like we are having the outliers
```

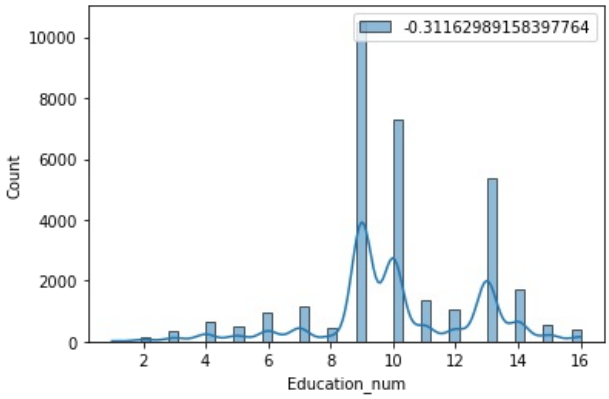
In [19]:
```
a=['Age','Fnlwgt','Education_num','Capital_gain','Capital_loss','Hours_per_week']
```

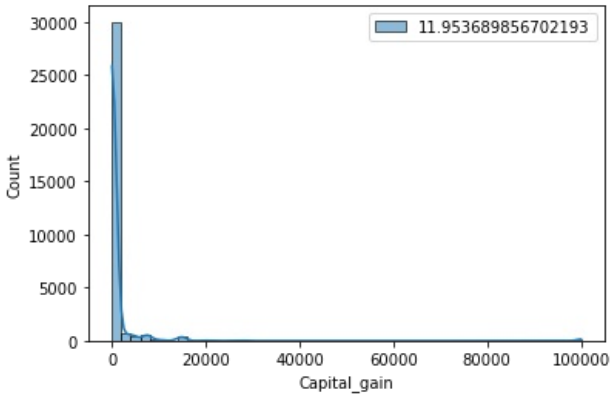
In [20]:
```
for i in a:
    sns.histplot(cont_data[i], kde = True, bins = 50, label = cont_data[i].skew())
    plt.legend(loc = 'upper right')
    plt.show()
```

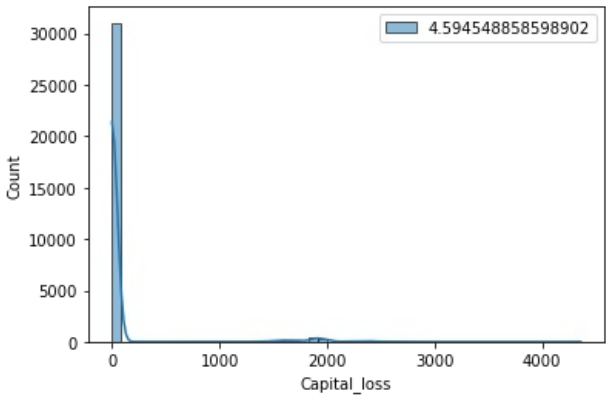


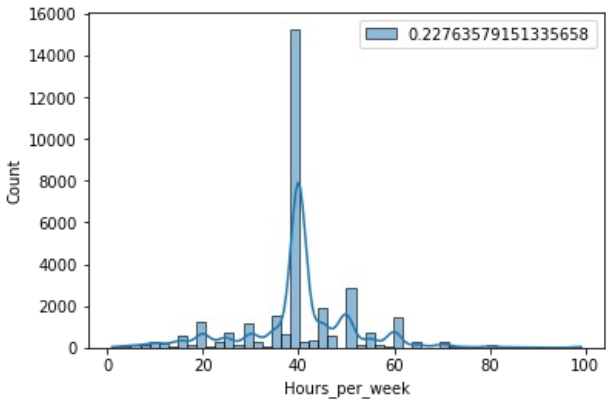












In [21]:
```
out_vars=['Age','Fnlwgt','Education_num','Capital_gain','Capital_loss','Hours_per_week']
```

In [22]:
```
def outlierTreat(x):
    upper = x.quantile(.75) + 1.5 * (x.quantile(.75) - x.quantile(.25))
    lower = x.quantile(.25) - 1.5 * (x.quantile(.75) - x.quantile(.25))
    return x.clip(lower, upper)
```

In [23]:
```
cont_data.loc[:, out_vars] = cont_data.loc[:, out_vars].apply(outlierTreat)
cont_data.loc[:, out_vars]
```

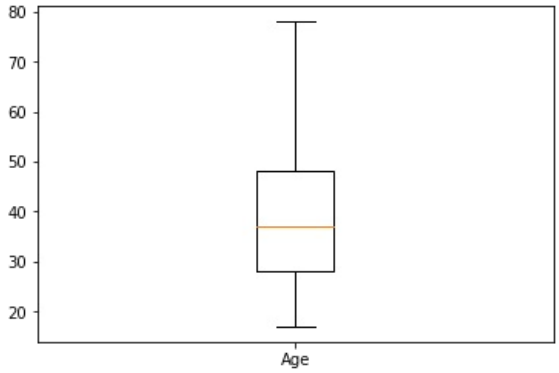
```
C:\Users\Rakesh Lodem\anaconda3\lib\site-packages\pandas\core\indexing.py:1787: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  self._setitem_single_column(loc, val, pi)
```

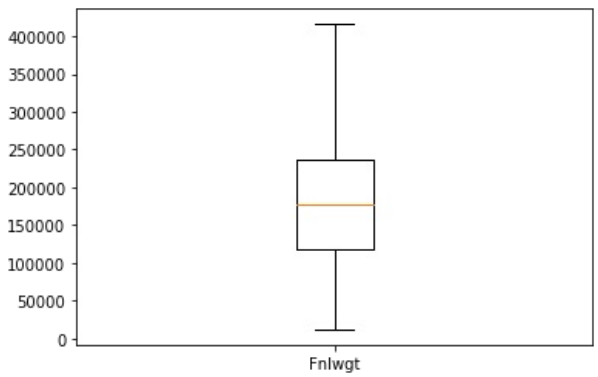
Out[23]:

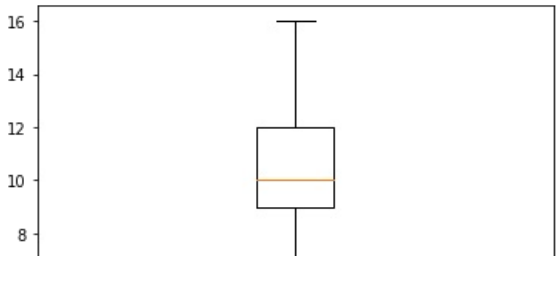
	Age	Fnlwgt	Education_num	Capital_gain	Capital_loss	Hours_per_week
0	50	83311	13.0	0	0	32.5
1	38	215646	9.0	0	0	40.0
2	53	234721	7.0	0	0	40.0
3	28	338409	13.0	0	0	40.0
4	37	284582	14.0	0	0	40.0
...	...	...	...	...	...	...
32555	27	257302	12.0	0	0	38.0
32556	40	154374	9.0	0	0	40.0
32557	58	151910	9.0	0	0	40.0
32558	22	201490	9.0	0	0	32.5
32559	52	287927	9.0	0	0	40.0

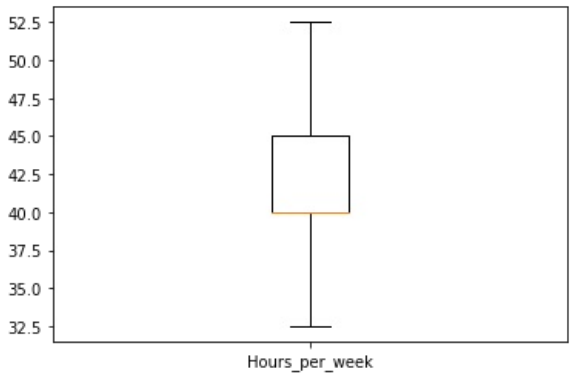
32560 rows × 6 columns

In [24]:
```
# Using box plot for checking the presence of outliers.
for i in cont_data:
    plt.boxplot(cont_data[i], labels = [i])
    plt.show()
```









In [25]:
```
## we are clear now
```

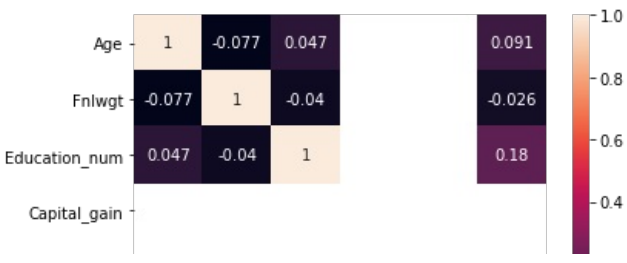
In [26]:
```
corr=cont_data.corr()
plt.figure(figsize=(20,25))
```

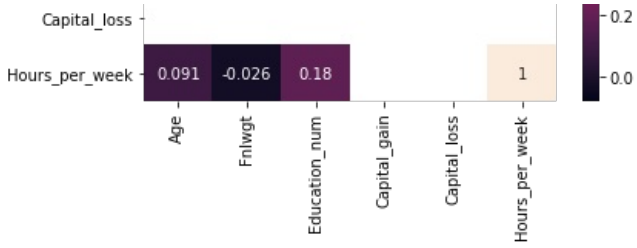
Out[26]: <Figure size 1440x1800 with 0 Axes>

<Figure size 1440x1800 with 0 Axes>

In [27]:
```
sns.heatmap(corr,annot=True)
```

Out[27]: <AxesSubplot:>





In [28]:
```
## no correlation found
```

In [29]:
```
## exploring the categorical variables
```

In [30]:
```
cat_vars = df.select_dtypes(include = ['object'])
cat_vars
```

Out[30]:

	Workclass	Education	Marital_status	Occupation	Relationship	Race	Sex	Native_country	Income
0	Self-emp-not-inc	Bachelors	Married-civ-spouse	Exec-managerial	Husband	White	Male	United-States	<=50K
1	Private	HS-grad	Divorced	Handlers-cleaners	Not-in-family	White	Male	United-States	<=50K
2	Private	11th	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	United-States	<=50K
3	Private	Bachelors	Married-civ-spouse	Prof-specialty	Wife	Black	Female	Cuba	<=50K
4	Private	Masters	Married-civ-spouse	Exec-managerial	Wife	White	Female	United-States	<=50K
...	...	...	...	...	...	...	...	...	...
32555	Private	Assoc-acdm	Married-civ-spouse	Tech-support	Wife	White	Female	United-States	<=50K
32556	Private	HS-grad	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	United-States	>50K
32557	Private	HS-grad	Widowed	Adm-clerical	Unmarried	White	Female	United-States	<=50K
32558	Private	HS-grad	Never-married	Adm-clerical	Own-child	White	Male	United-States	<=50K
32559	Self-emp-inc	HS-grad	Married-civ-spouse	Exec-managerial	Wife	White	Female	United-States	>50K

32560 rows × 9 columns

In [31]:
```
cat_vars.drop(['Marital_status','Relationship','Race'],axis=1)
```

Out[31]:

	Workclass	Education	Occupation	Sex	Native_country	Income
0	Self-emp-not-inc	Bachelors	Exec-managerial	Male	United-States	<=50K
1	Private	HS-grad	Handlers-cleaners	Male	United-States	<=50K
2	Private	11th	Handlers-cleaners	Male	United-States	<=50K
3	Private	Bachelors	Prof-specialty	Female	Cuba	<=50K
4	Private	Masters	Exec-managerial	Female	United-States	<=50K
...	...	...	...	...	...	...
32555	Private	Assoc-acdm	Tech-support	Female	United-States	<=50K
32556	Private	HS-grad	Machine-op-inspct	Male	United-States	>50K
32557	Private	HS-grad	Adm-clerical	Female	United-States	<=50K
32558	Private	HS-grad	Adm-clerical	Male	United-States	<=50K
32559	Self-emp-inc	HS-grad	Exec-managerial	Female	United-States	>50K

32560 rows × 6 columns

In [32]:
```
cat_vars
```

Out[32]:

	Workclass	Education	Marital_status	Occupation	Relationship	Race	Sex	Native_country	Income
0	Self-emp-not-inc	Bachelors	Married-civ-spouse	Exec-managerial	Husband	White	Male	United-States	<=50K
1	Private	HS-grad	Divorced	Handlers-cleaners	Not-in-family	White	Male	United-States	<=50K
2	Private	11th	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	United-States	<=50K
3	Private	Bachelors	Married-civ-spouse	Prof-specialty	Wife	Black	Female	Cuba	<=50K
4	Private	Masters	Married-civ-spouse	Exec-managerial	Wife	White	Female	United-States	<=50K

...	...	...	...	...	...	...	...	...	...
32555	Private	Assoc-acdm	Married-civ-spouse	Tech-support	Wife	White	Female	United-States	<=50K
32556	Private	HS-grad	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	United-States	>50K
32557	Private	HS-grad	Widowed	Adm-clerical	Unmarried	White	Female	United-States	<=50K
32558	Private	HS-grad	Never-married	Adm-clerical	Own-child	White	Male	United-States	<=50K
32559	Self-emp-inc	HS-grad	Married-civ-spouse	Exec-managerial	Wife	White	Female	United-States	>50K

32560 rows × 9 columns

In [33]:
```
cat_vars_new=cat_vars.drop(['Marital_status','Relationship','Race'],axis=1)
cat_vars_new
```

Out[33]:

	Workclass	Education	Occupation	Sex	Native_country	Income
0	Self-emp-not-inc	Bachelors	Exec-managerial	Male	United-States	<=50K
1	Private	HS-grad	Handlers-cleaners	Male	United-States	<=50K
2	Private	11th	Handlers-cleaners	Male	United-States	<=50K
3	Private	Bachelors	Prof-specialty	Female	Cuba	<=50K
4	Private	Masters	Exec-managerial	Female	United-States	<=50K
...	...	...	...	...	...	...
32555	Private	Assoc-acdm	Tech-support	Female	United-States	<=50K
32556	Private	HS-grad	Machine-op-inspct	Male	United-States	>50K
32557	Private	HS-grad	Adm-clerical	Female	United-States	<=50K
32558	Private	HS-grad	Adm-clerical	Male	United-States	<=50K
32559	Self-emp-inc	HS-grad	Exec-managerial	Female	United-States	>50K

32560 rows × 6 columns

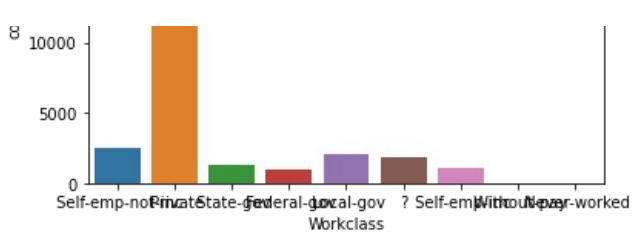
In [34]:
```
# Count values of different values for each variables.
for i in cat_vars_new:
    print(cat_vars_new[i].value_counts(), end = '\n---------\n\n')
```

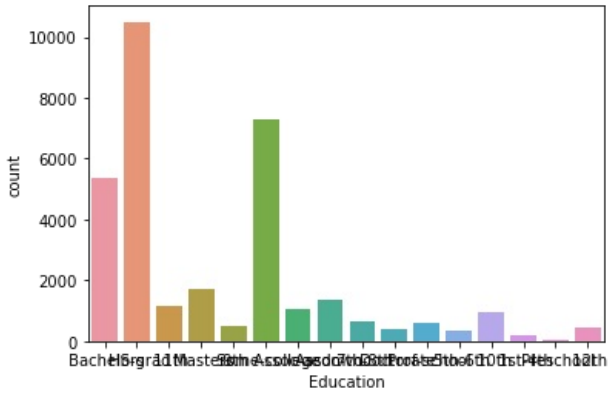
```
 Private             22696
 Self-emp-not-inc     2541
 Local-gov            2093
 ?                    1836
 State-gov            1297
 Self-emp-inc         1116
 Federal-gov           960
 Without-pay            14
 Never-worked            7
Name: Workclass, dtype: int64
---------

 HS-grad         10501
 Some-college     7291
 Bachelors        5354
 Masters          1723
 Assoc-voc        1382
 11th             1175
 Assoc-acdm       1067
 10th              933
 7th-8th           646
 Prof-school       576
 9th               514
 12th              433
 Doctorate         413
 5th-6th           333
 1st-4th           168
 Preschool          51
Name: Education, dtype: int64
---------

 Prof-specialty       4140
 Craft-repair         4099
 Exec-managerial      4066
 Adm-clerical         3769
 Sales                3650
 Other-service        3295
```

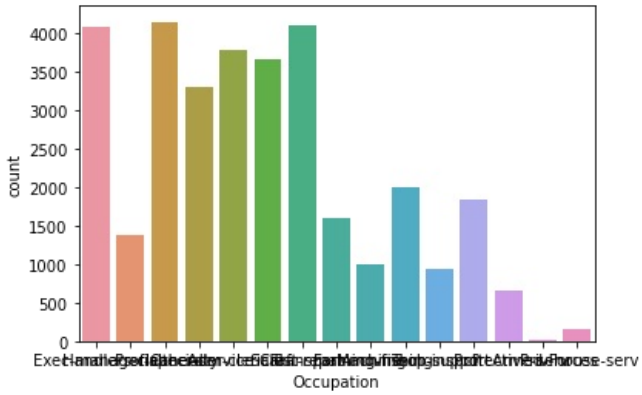
```
 Machine-op-inspct    2002
 ?                    1843
 Transport-moving     1597
 Handlers-cleaners    1370
 Farming-fishing       994
 Tech-support          928
 Protective-serv       649
 Priv-house-serv       149
 Armed-Forces            9
Name: Occupation, dtype: int64
---------

 Male      21789
 Female    10771
Name: Sex, dtype: int64
---------

 United-States                 29169
 Mexico                          643
 ?                               583
 Philippines                     198
 Germany                         137
 Canada                          121
 Puerto-Rico                     114
 El-Salvador                     106
 India                           100
 Cuba                             95
 England                          90
 Jamaica                          81
 South                            80
 China                            75
 Italy                            73
 Dominican-Republic               70
 Vietnam                          67
 Guatemala                        64
 Japan                            62
 Poland                           60
 Columbia                         59
 Taiwan                           51
 Haiti                            44
 Iran                             43
 Portugal                         37
 Nicaragua                        34
 Peru                             31
 France                           29
 Greece                           29
 Ecuador                          28
 Ireland                          24
 Hong                             20
 Trinadad&Tobago                  19
 Cambodia                         19
 Thailand                         18
 Laos                             18
 Yugoslavia                       16
 Outlying-US(Guam-USVI-etc)       14
 Hungary                          13
 Honduras                         13
 Scotland                         12
 Holand-Netherlands                1
Name: Native_country, dtype: int64
---------

 <=50K    24719
 >50K      7841
Name: Income, dtype: int64
---------
```

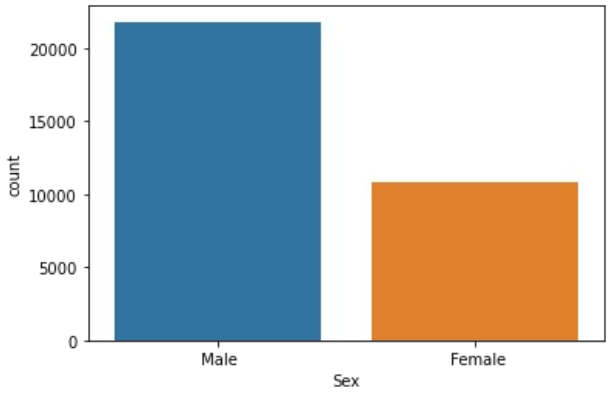
In [35]:

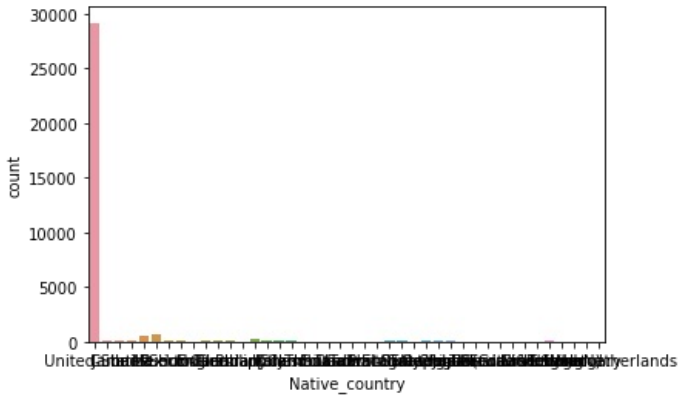
```
# Looking at the data distribution for different values.
plt.rcParams['figure.figsize'] = (6, 4)
for i in cat_vars_new:
    sns.countplot(x = cat_vars_new[i])
    plt.show()
```

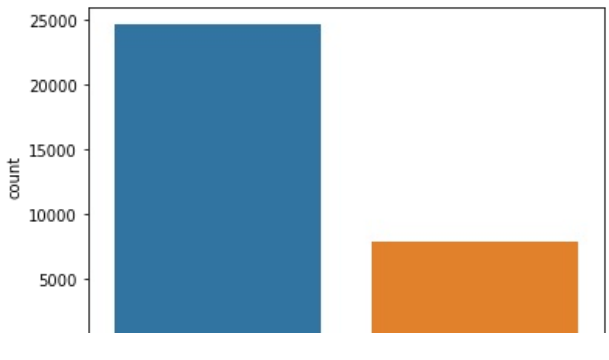

10000
5000
0
Workclass


count
10000
8000
6000
4000
2000
0
Education


count
4000
3500
3000
2500
2000
1500
1000
500
0
Occupation


count
20000
15000
10000
5000
0
Male
Female
Sex


count
30000
25000
20000
15000
10000
5000
0
Native_country


count
25000
20000
15000
10000
5000

In [36]:

```
cat_vars_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32560 entries, 0 to 32559
Data columns (total 6 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Workclass       32560 non-null  object
 1   Education       32560 non-null  object
 2   Occupation      32560 non-null  object
 3   Sex             32560 non-null  object
 4   Native_country  32560 non-null  object
 5   Income          32560 non-null  object
dtypes: object(6)
memory usage: 1.5+ MB
```

In [37]:

```
cat_data = cat_vars_new.copy()
cat_data = pd.get_dummies(cat_data, drop_first = True) ## numerical features to continuos features
cat_data
```

Out[37]:

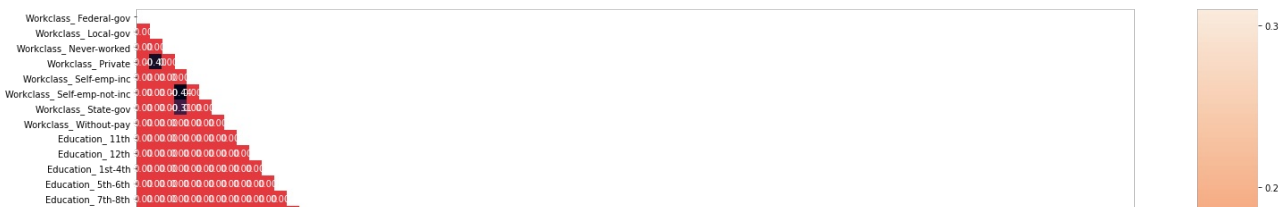
	Workclass_ Federal-gov	Workclass_ Local-gov	Workclass_ Never-worked	Workclass_ Private	Workclass_ Self-emp-inc	Workclass_ Self-emp-not-inc	Workclass_ State-gov	Workclass_ Without-pay	Education_ 11th	Education_ 12th	...	Native Pu
0	0	0	0	0	0	1	0	0	0	0	...	
1	0	0	0	1	0	0	0	0	0	0	...	
2	0	0	0	1	0	0	0	0	1	0	...	
3	0	0	0	1	0	0	0	0	0	0	...	
4	0	0	0	1	0	0	0	0	0	0	...	
...	...	...	...	...	...	...	...	...	...	...	...	
32555	0	0	0	1	0	0	0	0	0	0	...	
32556	0	0	0	1	0	0	0	0	0	0	...	
32557	0	0	0	1	0	0	0	0	0	0	...	
32558	0	0	0	1	0	0	0	0	0	0	...	
32559	0	0	0	0	1	0	0	0	0	0	...	

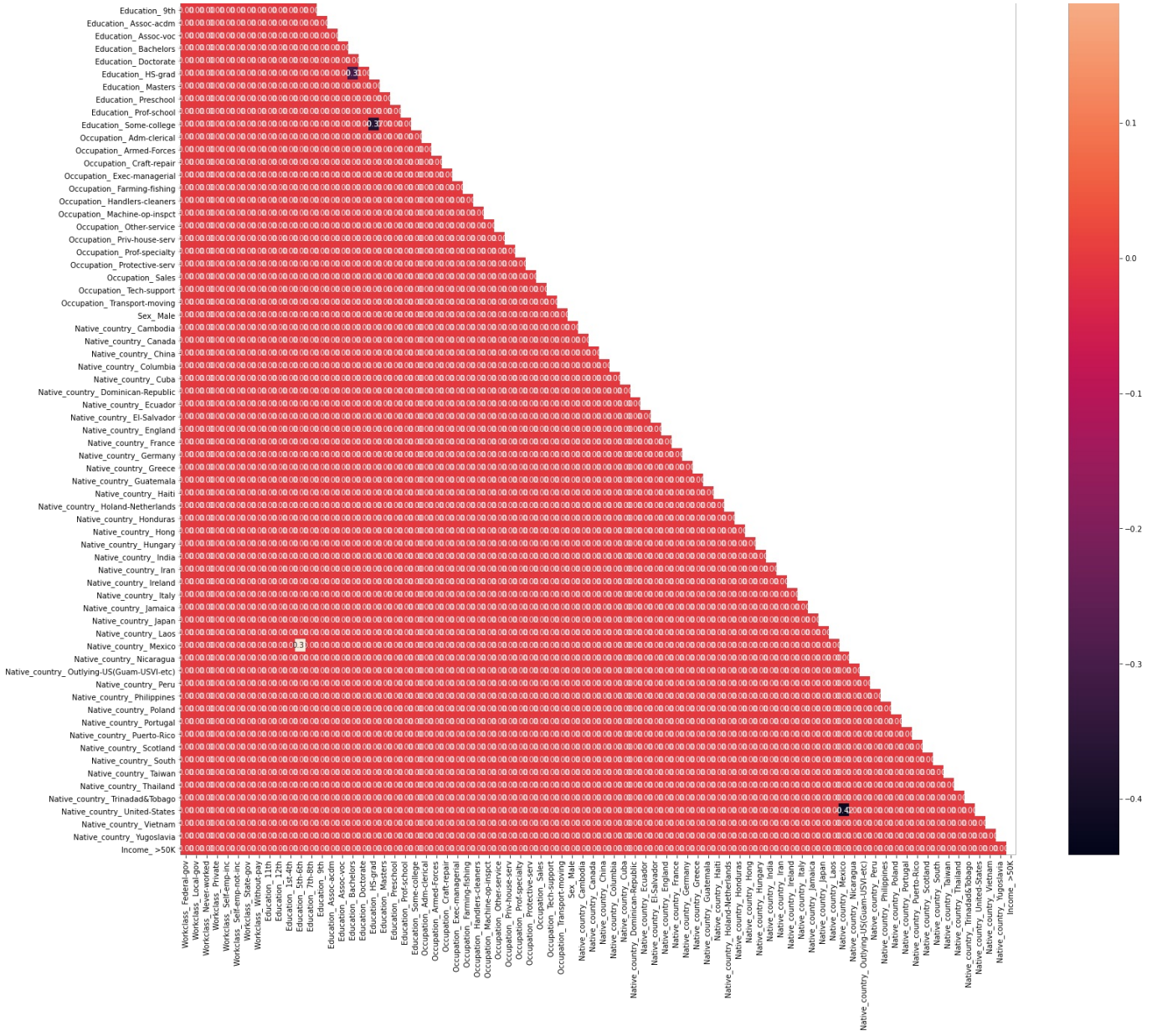
32560 rows × 80 columns

In [38]:

```
# Finding the correlation.
corr = cat_data.corr()

# Setting the size of figure.
plt.rcParams['figure.figsize'] = (25, 25)

# Argument Trimming out the values above the main diagonal.
mask = np.triu(corr)

# Setting low correlation value to 0.
corr[(corr.values < 0.3) & (corr.values > -0.3)] = 0

# Plotting the heatmap.
sns.heatmap(corr, annot = True, fmt = '.2f', mask = mask)
```

Out[38]: <AxesSubplot:>





In [43]:

```
# Combining Numerical and Categorical data.
final_data = pd.concat([cont_data, cat_data], axis = 1)
final_data
```

Out[43]:

	Age	Fnlwgt	Education_num	Capital_gain	Capital_loss	Hours_per_week	Workclass_ Federal-gov	Workclass_ Local-gov	Workclass_ Never-worked	Workclass_ Private	...	Native_ Pu
0	50	83311	13.0	0	0	32.5	0	0	0	0	...	
1	38	215646	9.0	0	0	40.0	0	0	0	1	...	
2	53	234721	7.0	0	0	40.0	0	0	0	1	...	
3	28	338409	13.0	0	0	40.0	0	0	0	1	...	
4	37	284582	14.0	0	0	40.0	0	0	0	1	...	
...	...	...	...	...	...	...	...	...	...	...	...	
32555	27	257302	12.0	0	0	38.0	0	0	0	1	...	
32556	40	154374	9.0	0	0	40.0	0	0	0	1	...	
32557	58	151910	9.0	0	0	40.0	0	0	0	1	...	
32558	22	201490	9.0	0	0	32.5	0	0	0	1	...	
32559	52	287927	9.0	0	0	40.0	0	0	0	0	...	

32560 rows × 86 columns

In [44]:

```
final_data
```

Out[44]:

							Workclass_		Workclass_			

	Age	Fnlwgt	Education_num	Capital_gain	Capital_loss	Hours_per_week	Federal-gov	Workclass_ Local-gov	Never-worked	Workclass_ Private	...	Native_ Pu
0	50	83311	13.0	0	0	32.5	0	0	0	0	...	
1	38	215646	9.0	0	0	40.0	0	0	0	1	...	
2	53	234721	7.0	0	0	40.0	0	0	0	1	...	
3	28	338409	13.0	0	0	40.0	0	0	0	1	...	
4	37	284582	14.0	0	0	40.0	0	0	0	1	...	
...	...	...	...	...	...	...	...	...	...	...	...	
32555	27	257302	12.0	0	0	38.0	0	0	0	1	...	
32556	40	154374	9.0	0	0	40.0	0	0	0	1	...	
32557	58	151910	9.0	0	0	40.0	0	0	0	1	...	
32558	22	201490	9.0	0	0	32.5	0	0	0	1	...	
32559	52	287927	9.0	0	0	40.0	0	0	0	0	...	

32560 rows × 86 columns

In [45]:
```
final_data.describe()
```

Out[45]:

	Age	Fnlwgt	Education_num	Capital_gain	Capital_loss	Hours_per_week	Workclass_ Federal-gov	Workclass_ Local-gov	Workclass_ Never-worked	W
count	32560.000000	32560.000000	32560.000000	32560.0	32560.0	32560.000000	32560.000000	32560.000000	32560.000000	32
mean	38.555590	186832.497451	10.124232	0.0	0.0	41.202488	0.029484	0.064281	0.000215	
std	13.556338	95129.303699	2.459756	0.0	0.0	6.187097	0.169161	0.245257	0.014661	
min	17.000000	12285.000000	4.500000	0.0	0.0	32.500000	0.000000	0.000000	0.000000	
25%	28.000000	117831.500000	9.000000	0.0	0.0	40.000000	0.000000	0.000000	0.000000	
50%	37.000000	178363.000000	10.000000	0.0	0.0	40.000000	0.000000	0.000000	0.000000	
75%	48.000000	237054.500000	12.000000	0.0	0.0	45.000000	0.000000	0.000000	0.000000	
max	78.000000	415889.000000	16.000000	0.0	0.0	52.500000	1.000000	1.000000	1.000000	

8 rows × 86 columns

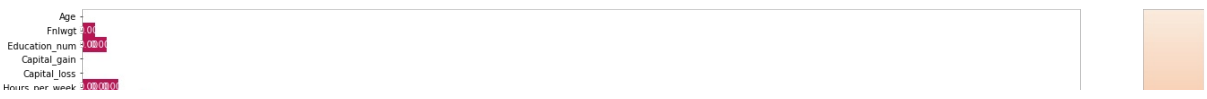
In [46]:
```
cont_data.skew()
```

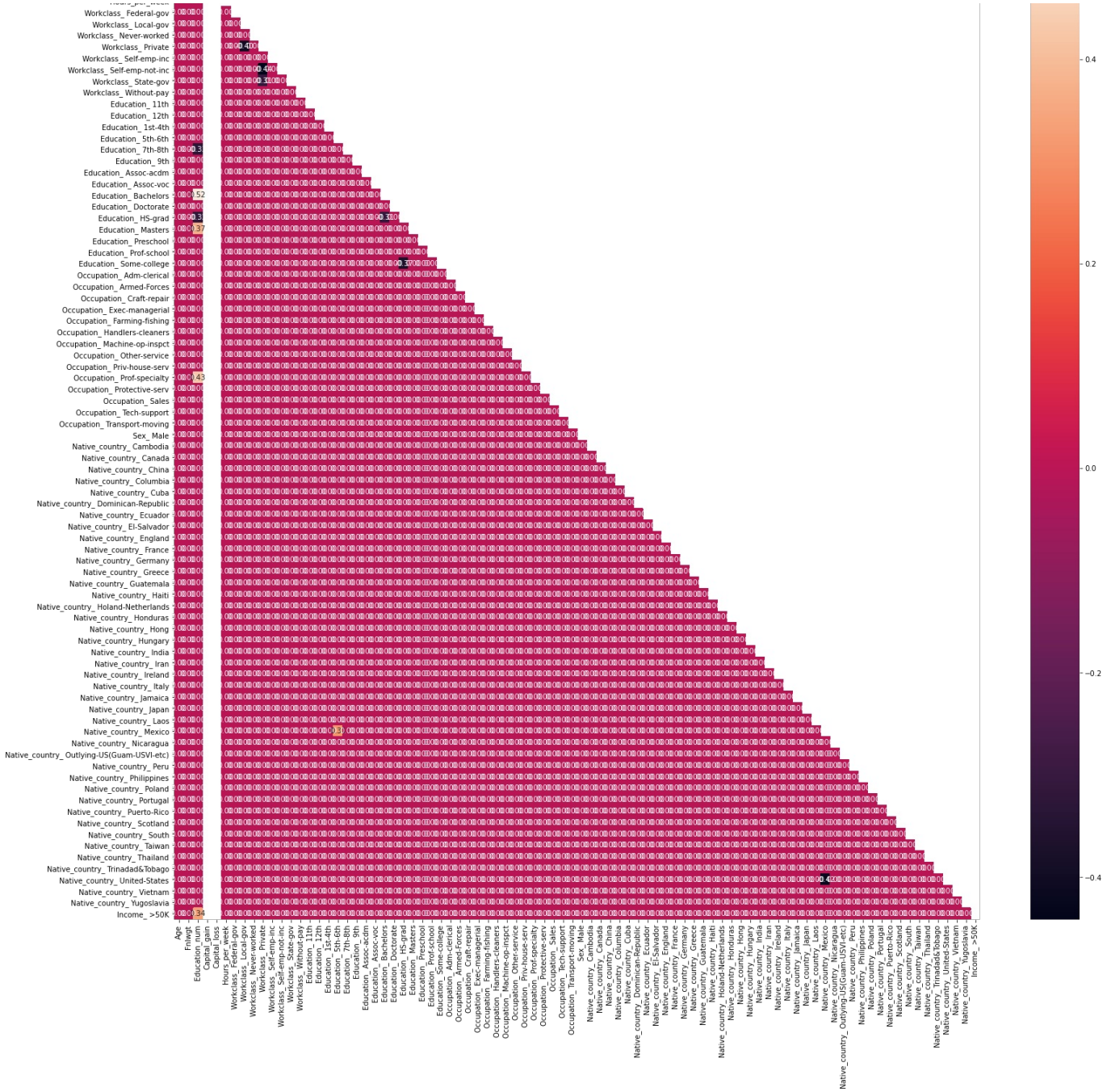
Out[46]:
```
Age              0.513883
Fnlwgt           0.548285
Education_num   -0.034043
Capital_gain     0.000000
Capital_loss     0.000000
Hours_per_week   0.438274
dtype: float64
```

In [47]:
```
## not much of skewness is found
```

In [48]:
```
# Finding the correlation.
corr = final_data.corr()

# Setting the size of figure.
plt.rcParams['figure.figsize'] = (25, 25)

# Argument Trimming out the values above the main diagonal.
mask = np.triu(corr)

# Setting low correlation value to 0.
corr[(corr.values < 0.3) & (corr.values > -0.3)] = 0

# Plotting the heatmap.
sns.heatmap(corr, annot = True, fmt = '.2f', mask = mask)
```

Out[48]: <AxesSubplot:>





In [49]:
```
x=final_data.drop(['Income_ >50K'],axis=1) ## independent features
```

In [50]:
```
x
```

Out[50]:

	Age	Fnlwgt	Education_num	Capital_gain	Capital_loss	Hours_per_week	Workclass_ Federal-gov	Workclass_ Local-gov	Workclass_ Never-worked	Workclass_ Private	...	Native_
0	50	83311	13.0	0	0	32.5	0	0	0	0	...	
1	38	215646	9.0	0	0	40.0	0	0	0	1	...	
2	53	234721	7.0	0	0	40.0	0	0	0	1	...	
3	28	338409	13.0	0	0	40.0	0	0	0	1	...	
4	37	284582	14.0	0	0	40.0	0	0	0	1	...	
...	...	...	...	...	...	...	...	...	...	...	...	...
32555	27	257302	12.0	0	0	38.0	0	0	0	1	...	
32556	40	154374	9.0	0	0	40.0	0	0	0	1	...	
32557	58	151910	9.0	0	0	40.0	0	0	0	1	...	
32558	22	201490	9.0	0	0	32.5	0	0	0	1	...	
32559	52	287927	9.0	0	0	40.0	0	0	0	0	...	

32560 rows × 85 columns

In [52]:
```
y=final_data['Income_ >50K'] ## dependent features
y
```

Out[52]:
```
0        0
1        0
2        0
3        0
4        0
        ..
32555    0
32556    1
32557    0
32558    0
32559    1
Name: Income_ >50K, Length: 32560, dtype: uint8
```

In [53]:
```
## STANDARD SCALING
```

In [54]:
```
from sklearn.preprocessing import StandardScaler
```

In [55]:
```
st=StandardScaler()
```

In [56]:
```
st.fit_transform(x)
```

Out[56]:
```
array([[ 0.84422402, -1.08823552,  1.16914516, ...,  0.34095976,
        -0.04540906, -0.022173  ],
       [-0.04098439,  0.30289242, -0.45705728, ...,  0.34095976,
        -0.04540906, -0.022173  ],
       [ 1.06552612,  0.50341205, -1.2701585 , ...,  0.34095976,
        -0.04540906, -0.022173  ],
       ...,
       [ 1.43436295, -0.36711121, -0.45705728, ...,  0.34095976,
        -0.04540906, -0.022173  ],
       [-1.22126226,  0.15408215, -0.45705728, ...,  0.34095976,
        -0.04540906, -0.022173  ],
       [ 0.99175875,  1.06272254, -0.45705728, ...,  0.34095976,
        -0.04540906, -0.022173  ]])
```

In [57]:
```
x.shape
```

Out[57]:
```
(32560, 85)
```

In [58]:
```
## feature selection
```

In [59]:
```
y.shape
```

Out[59]:
```
(32560,)
```

In [60]:
```
from sklearn.model_selection import train_test_split,cross_val_score
#importing models
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier,AdaBoostClassifier,GradientBoostingClassifier
```

In [61]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.30,random_state=41)
```

In [62]:
```
kn=KNeighborsClassifier()
```

In [63]:
```
kn.fit(x_train,y_train)
```

```
kn.fit(x_train,y_train)
```

Out[63]:
```
KNeighborsClassifier()
```

In [64]:
```
y_pred=kn.predict(x_test)
```

In [65]:
```
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report
```

In [66]:
```
accuracy_score(y_pred,y_test)
```

Out[66]:
```
0.7271703521703522
```

In [67]:
```
confusion_matrix(y_test,y_pred)
```

Out[67]:
```
array([[6627,  799],
       [1866,  476]], dtype=int64)
```

In [68]:
```
classification_report(y_test,y_pred)
```

Out[68]:
```
'              precision    recall  f1-score   support\n\n           0       0.78      0.89      0.83      7426\n
1       0.37      0.20      0.26      2342\n\n    accuracy                           0.73      9768\n   macro avg
0.58      0.55      0.55      9768\nweighted avg       0.68      0.73      0.70      9768\n'
```

In [ ]:
```

```

In [69]:
```
## svc
```

In [70]:
```
sv=SVC()
```

In [71]:
```
sv.fit(x_train,y_train)
```

Out[71]:
```
SVC()
```

In [72]:
```
y_pred=sv.predict(x_test)
```

In [73]:
```
accuracy_score(y_test,y_pred)
```

Out[73]:
```
0.7602375102375102
```

In [74]:
```
confusion_matrix(y_test,y_pred)
```

Out[74]:
```
array([[7426,    0],
       [2342,    0]], dtype=int64)
```

In [75]:
```
classification_report(y_test,y_pred)
```

```
C:\Users\Rakesh Lodem\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1245: UndefinedMetricWarning
: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_divis
ion` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\Rakesh Lodem\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1245: UndefinedMetricWarning
: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_divis
ion` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

```
C:\Users\Rakesh Lodem\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1245: UndefinedMetricWarning
: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_divis
ion` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

Out[75]:
```
'              precision    recall  f1-score   support\n\n           0       0.76      1.00      0.86      7426\n
1       0.00      0.00      0.00      2342\n\n    accuracy                           0.76      9768\n   macro avg
0.38      0.50      0.43      9768\nweighted avg       0.58      0.76      0.66      9768\n'
```

In [76]:
```
##decision tree classifier
```

In [77]:
```
dt=DecisionTreeClassifier()
```

In [78]:
```
dt.fit(x_train,y_train)
```

Out[78]:
```
DecisionTreeClassifier()
```

In [79]:
```
y_pred=dt.predict(x_test)
```

In [80]:
```
accuracy_score(y_test,y_pred)
```

Out[80]:
```
0.7480548730548731
```

In [81]:
```
confusion_matrix(y_test,y_pred)
```

Out[81]:
```
array([[6174, 1252],
       [1209, 1133]], dtype=int64)
```

In [82]:
```
classification_report(y_test,y_pred)
```

Out[82]:
```
'              precision    recall  f1-score   support\n\n           0       0.84      0.83      0.83      7426\n
1       0.48      0.48      0.48      2342\n\n    accuracy                           0.75      9768\n   macro avg
0.66      0.66      0.66      9768\nweighted avg       0.75      0.75      0.75      9768\n'
```

In [83]:
```
## RandomForestClassifier
```

In [84]:
```
rf=RandomForestClassifier()
```

In [85]:
```
rf.fit(x_train,y_train)
```

Out[85]:
```
RandomForestClassifier()
```

In [86]:
```
y_pred=rf.predict(x_test)
```

In [87]:
```
accuracy_score(y_test,y_pred)
```

Out[87]:
```
0.799037674037674
```

In [88]:
```
confusion_matrix(y_test,y_pred)
```

Out[88]:
```
array([[6734,  692],
       [1271, 1071]], dtype=int64)
```

In [89]:
```
classification_report(y_test,y_pred)
```

Out[89]:
```
'              precision    recall  f1-score   support\n\n           0       0.84      0.91      0.87      7426\n
1       0.61      0.46      0.52      2342\n\n    accuracy                           0.80      9768\n   macro avg
0.72      0.68      0.70      9768\nweighted avg       0.79      0.80      0.79      9768\n'
```

In [90]:
```
##GradientBoostingClassifier
```

In [91]:
```
gb=GradientBoostingClassifier()
```

In [92]:
```
gb.fit(x_train,y_train)
```

Out[92]:
```
GradientBoostingClassifier()
```

In [93]:
```
y_pred=gb.predict(x_test)
```

In [94]:
```
accuracy_score(y_test,y_pred)
```

Out[94]:
```
0.8211506961506961
```

In [95]:
```
confusion_matrix(y_test,y_pred)
```

Out[95]:
```
array([[6931,  495],
       [1252, 1090]], dtype=int64)
```

In [96]:
```
classification_report(y_test,y_pred)
```

Out[96]:
```
'              precision    recall  f1-score   support\n\n           0       0.85      0.93      0.89      7426\n
1       0.69      0.47      0.56      2342\n\n    accuracy                           0.82      9768\n   macro avg
0.77      0.70      0.72      9768\nweighted avg       0.81      0.82      0.81      9768\n'
```

In [97]:
```
## ADA BOOST CLASSIFIER
```

In [98]:
```
ad=AdaBoostClassifier()
```

In [99]:
```
ad.fit(x_train,y_train)
```

Out[99]:
```
AdaBoostClassifier()
```

In [100…
```
y_pred=ad.predict(x_test)
```

In [101…
```
accuracy_score(y_test,y_pred)
```

Out[101…
```
0.8198198198198198
```

In [102…
```
confusion_matrix(y_test,y_pred)
```

Out[102…
```
array([[6907,  519],
       [1241, 1101]], dtype=int64)
```

In [103…
```
classification_report(y_test,y_pred)
```

Out[103…
```
'              precision    recall  f1-score   support\n\n           0       0.85      0.93      0.89      7426\n
1       0.68      0.47      0.56      2342\n\n    accuracy                           0.82      9768\n   macro avg
0.76      0.70      0.72      9768\nweighted avg       0.81      0.82      0.81      9768\n'
```

In [104…
```
## looks like gradientBoosting and ada boosting works better
```

In [105…
```
##hyper parameter tuning for both these classifiers
```

In [111…
```
from sklearn.model_selection import RandomizedSearchCV
```

In [112…
```
gb=GradientBoostingClassifier()
parameters = {
    "n_estimators":[5,50,250,500],
    "max_depth":[1,3,5,7,9],
    "learning_rate":[0.01,0.1,1,10,100]}
```

In [109…
```
r=RandomizedSearchCV(gb,parameters)
```

In [ ]:
```
##
```

In [ ]:
```
##
```

In [110…
```
r.fit(x_train,y_train)
```

Out[110…
```
RandomizedSearchCV(estimator=GradientBoostingClassifier(),
                   param_distributions={'learning_rate': [0.01, 0.1, 1, 10,
                                                          100],
                                        'max_depth': [1, 3, 5, 7, 9],
                                        'n_estimators': [5, 50, 250, 500]})
```

In [114…
```
print(r.best_params_)
```

```
{'n_estimators': 250, 'max_depth': 9, 'learning_rate': 1}
```

In [116…
```
m=GradientBoostingClassifier(n_estimators=250,max_depth=9,learning_rate=1)
```

In [117…
```
m.fit(x_train,y_train)
```

Out[117…
```
GradientBoostingClassifier(learning_rate=1, max_depth=9, n_estimators=250)
```

In [118…
```
y_pred=m.predict(x_test)
```

In [120…
```
accuracy_score(y_test,y_pred)
```

Out[120…
```
0.7845004095004094
```

In [ ]:
```
 ## looks like ada boost is the best algorithm
```

In [ ]:
```
##finalzing the ada boost algoritm
```

In [121…
```
ad=AdaBoostClassifier()
```

In [122…
```
ad.fit(x_train,y_train)
```

Out[122… AdaBoostClassifier()

In [123…
```
y_pred=ad.predict(x_test)
```

In [125…
```
accuracy_score(y_test,y_pred)
```

Out[125… 0.8198198198198198

In [126…
```
confusion_matrix(y_test,y_pred)
```

Out[126…
```
array([[6907,  519],
       [1241, 1101]], dtype=int64)
```

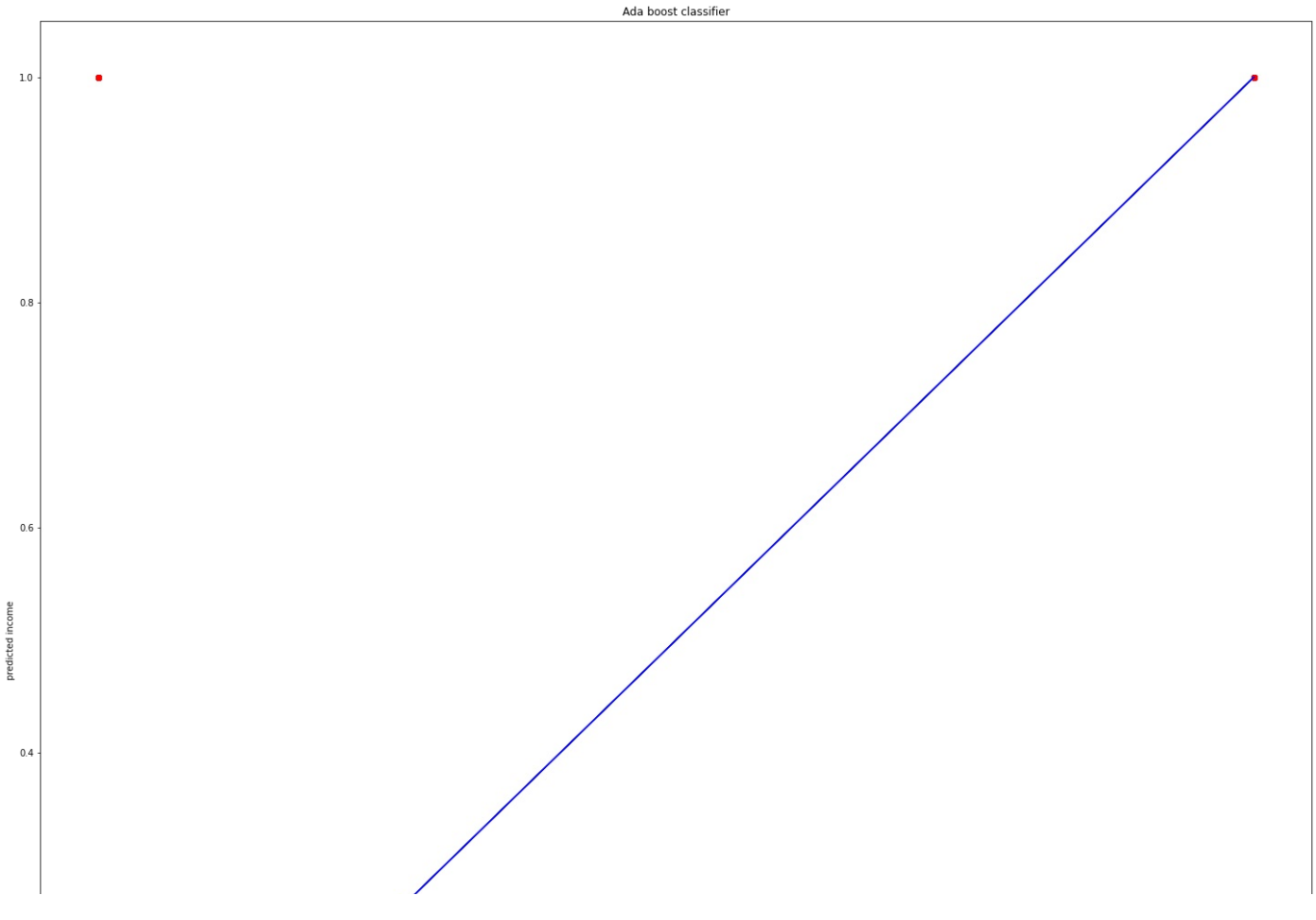
In [127…
```
classification_report(y_test,y_pred)
```

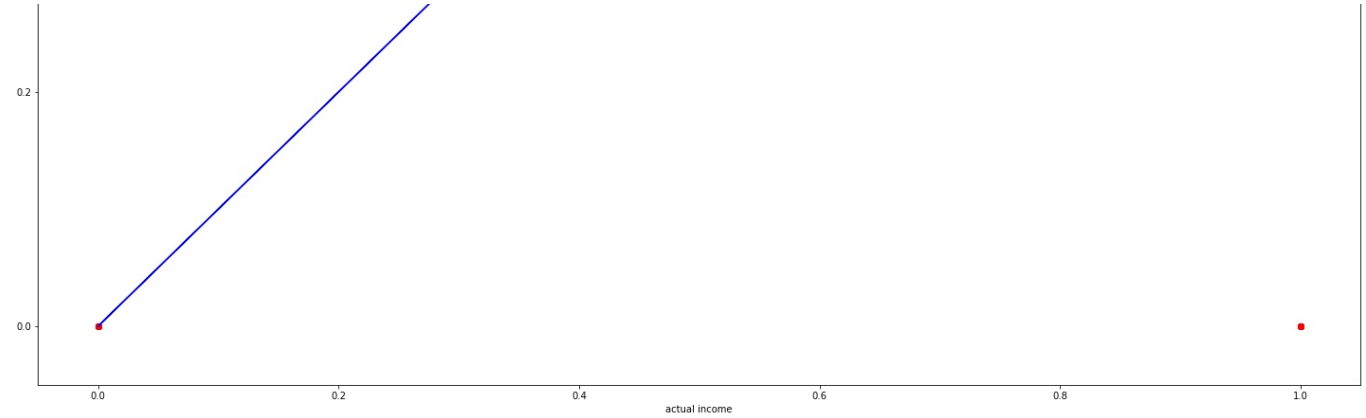
Out[127…
```
'              precision    recall  f1-score   support\n\n           0       0.85      0.93      0.89      7426\n
1       0.68      0.47      0.56      2342\n\n    accuracy                           0.82      9768\n   macro avg
0.76      0.70      0.72      9768\nweighted avg       0.81      0.82      0.81      9768\n'
```

In [128…
```
## evaluation metrics
```

In [129…
```
plt.scatter(x=y_test,y=y_pred,color='r')
plt.plot(y_test,y_test,color='b')
plt.xlabel('actual income')
plt.ylabel('predicted income')
plt.title('Ada boost classifier')
```

Out[129… Text(0.5, 1.0, 'Ada boost classifier')





In [130…
```
import numpy as np
```

In [131…
```
a=np.array(y_test)
```

In [132…
```
pred=np.array(ad.predict(x_test))
```

In [133…
```
df_com=pd.DataFrame({'predicted':pred,'actual':a},index=range(len(a)))
```

In [134…
```
df_com
```

Out[134…

	predicted	actual
0	0	1
1	0	0
2	0	0
3	0	1
4	0	0
...	...	...
9763	0	0
9764	0	0
9765	0	0
9766	1	1
9767	0	1

9768 rows × 2 columns

In [135…
```
## saving the model
```

In [136…
```
import pickle
```

In [137…
```
filename='CENSUS_INCOME_PROJECT.pkl'
```

In [140…
```
pickle.dump(ad,open(filename,'wb'))
```

In [ ]:
```

```