```python
import numpy as np
import pandas as pd
from scipy import stats

import matplotlib.pyplot as plt
import seaborn as sns

# Read Dataset
df = pd.read_csv('./income_evaluation.csv')
df.columns = list(map(lambda a: a.lstrip(), df.columns))
df.head()
```

```
   age         workclass  fnlwgt   education  education-num  \
0   39         State-gov   77516   Bachelors             13   
1   50  Self-emp-not-inc   83311   Bachelors             13   
2   38           Private  215646     HS-grad              9   
3   53           Private  234721        11th              7   
4   28           Private  338409   Bachelors             13   

       marital-status          occupation    relationship    race  
sex  \
0       Never-married        Adm-clerical   Not-in-family   White  
Male   
1  Married-civ-spouse     Exec-managerial         Husband   White  
Male   
2            Divorced   Handlers-cleaners   Not-in-family   White  
Male   
3  Married-civ-spouse   Handlers-cleaners         Husband   Black  
Male   
4  Married-civ-spouse      Prof-specialty            Wife   Black  
Female   

   capital-gain  capital-loss  hours-per-week  native-country  income
  
0          2174             0              40   United-States   <=50K
  
1             0             0              13   United-States   <=50K
  
2             0             0              40   United-States   <=50K
  
3             0             0              40   United-States   <=50K
  
4             0             0              40            Cuba   <=50K
```

Exploratory Data Analysis

Count Missing Values

```
missing_count = {}
for column in df.columns:
    df[column].replace(' ?', np.NaN, inplace=True)
    missing_count[column] = df[column].isna().sum()

for key in missing_count:
  print(f"{key}: {missing_count[key]}")
```

```
age: 0
workclass: 1836
fnlwgt: 0
education: 0
education-num: 0
marital-status: 0
occupation: 1843
relationship: 0
race: 0
sex: 0
capital-gain: 0
capital-loss: 0
hours-per-week: 0
native-country: 583
income: 0
```

```
df.isnull().sum()
```

```
age                  0
workclass         1836
fnlwgt               0
education            0
education-num        0
marital-status       0
occupation        1843
relationship         0
race                 0
sex                  0
capital-gain         0
capital-loss         0
hours-per-week       0
native-country     583
income               0
dtype: int64
```

Count Numerical & Categorical Features

```
numerical_features=[features for features in df.columns if
df[features].dtype!='O']
categorical_features = [features for features in df.columns if
```

```
df[features].dtype == 'O']

print("Numerical Features: ", ', '.join(numerical_features), "\
nCategorical Features: ", ', '.join(categorical_features))
```

```
Numerical Features:  age, fnlwgt, education-num, capital-gain,
capital-loss, hours-per-week
Categorical Features:  workclass, education, marital-status,
occupation, relationship, race, sex, native-country, income
```

Continuous and Discrete Features

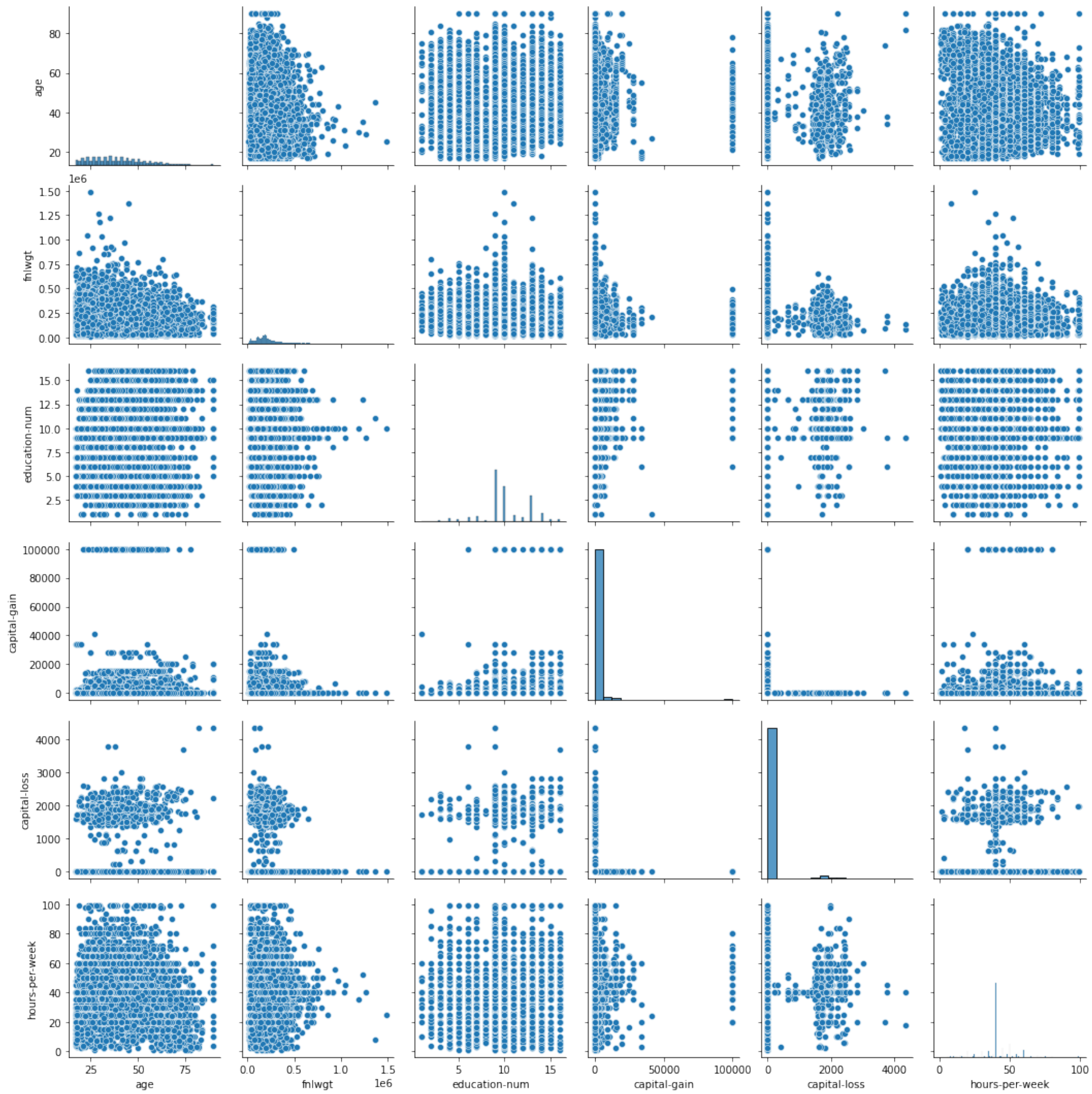
```
continuous_features=[features for features in numerical_features if
len(pd.unique(df[features]))>25]
discrete_features=[features for features in numerical_features if
len(pd.unique(df[features]))<=25]
print("Continuous Features: ", ', '.join(continuous_features), "\
nDiscrete Features: ", ', '.join(discrete_features))
```

```
Continuous Features:  age, fnlwgt, capital-gain, capital-loss, hours-
per-week
Discrete Features:  education-num
```

Pair Plots

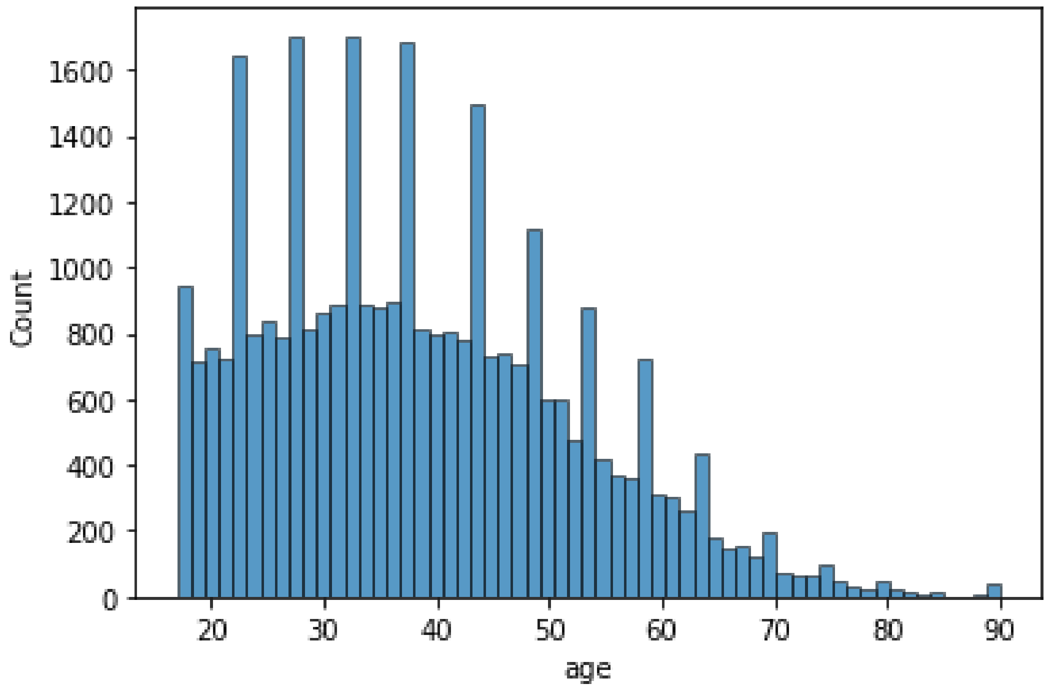
```
sns.pairplot(df,kind='scatter')
```

```
<seaborn.axisgrid.PairGrid at 0x7f2e790cdf90>
```

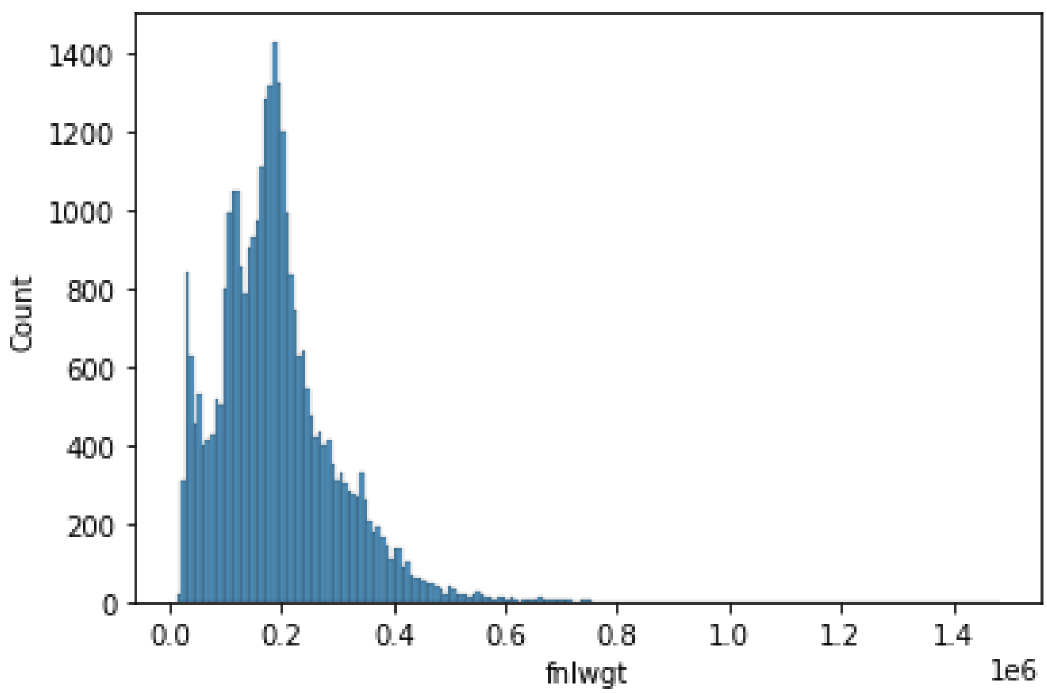


Histograms

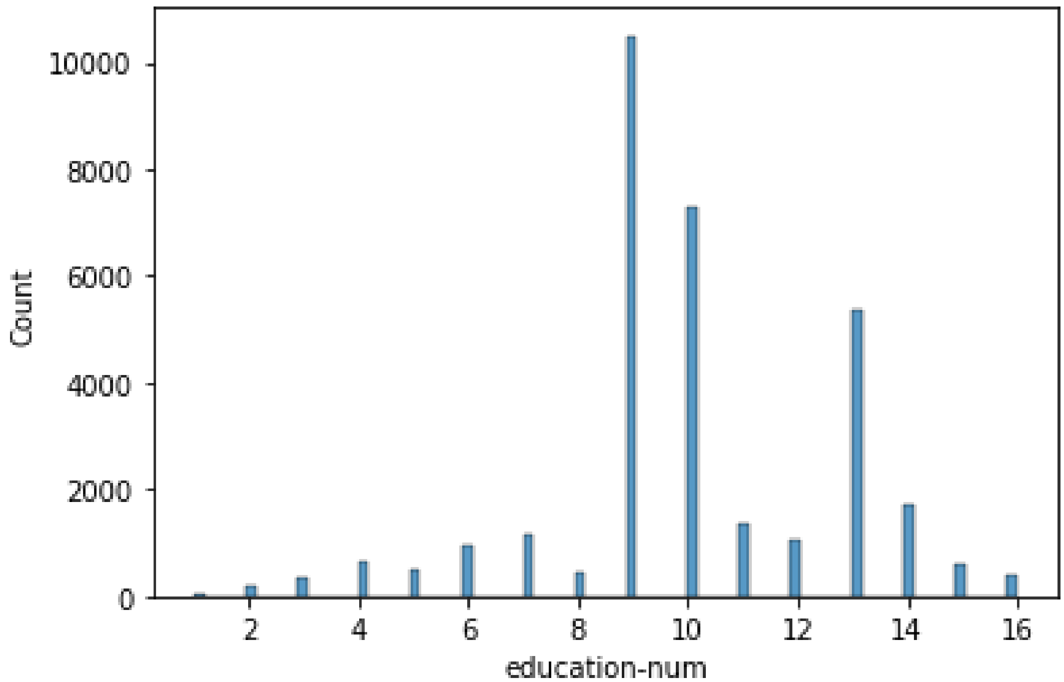
```
for col in numerical_features:
    sns.histplot(df[col])
    plt.show()
```



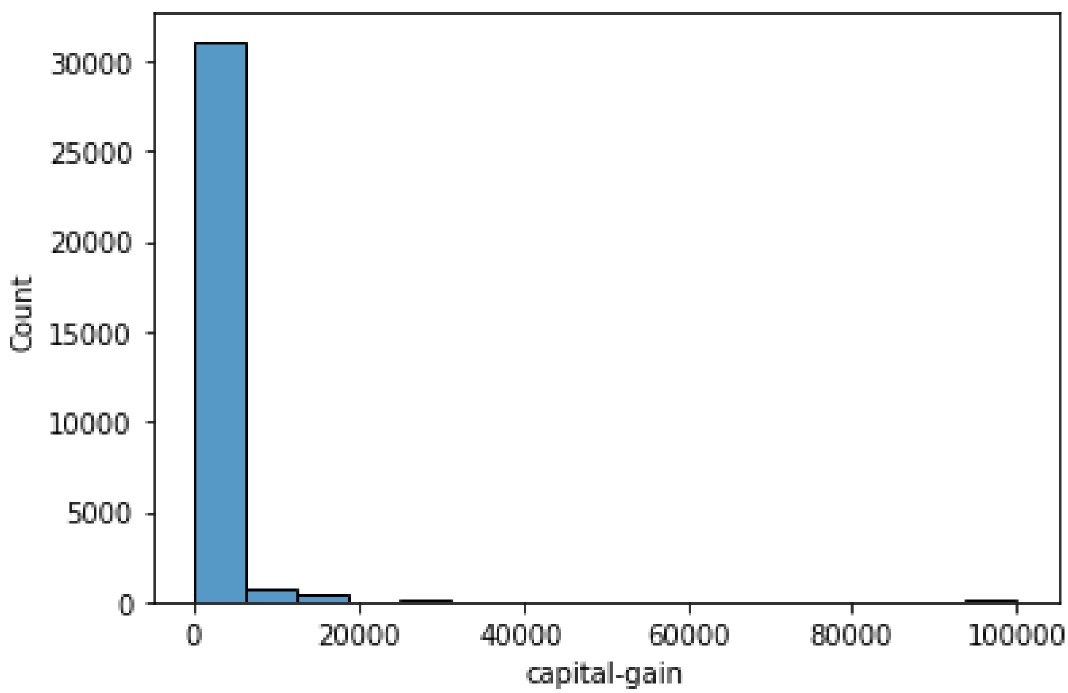
1600
1400
1200
1000
800
600
400
200
0
Count
20
30
40
50
60
70
80
90
age



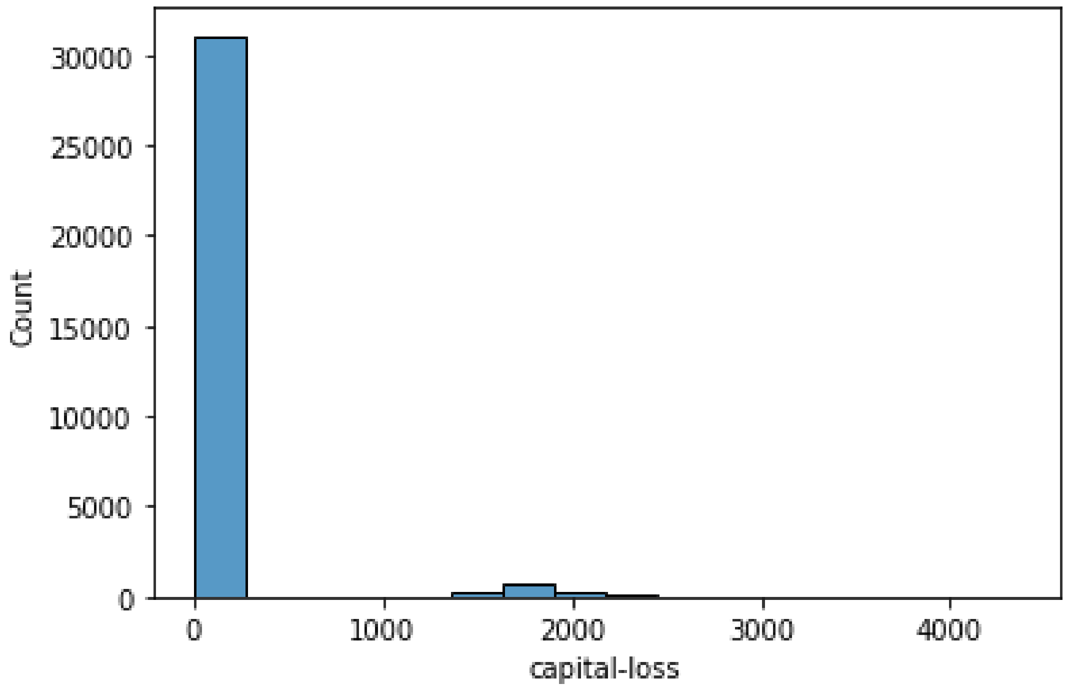
1400
1200
1000
800
600
400
200
0
Count
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1e6
fnlwgt

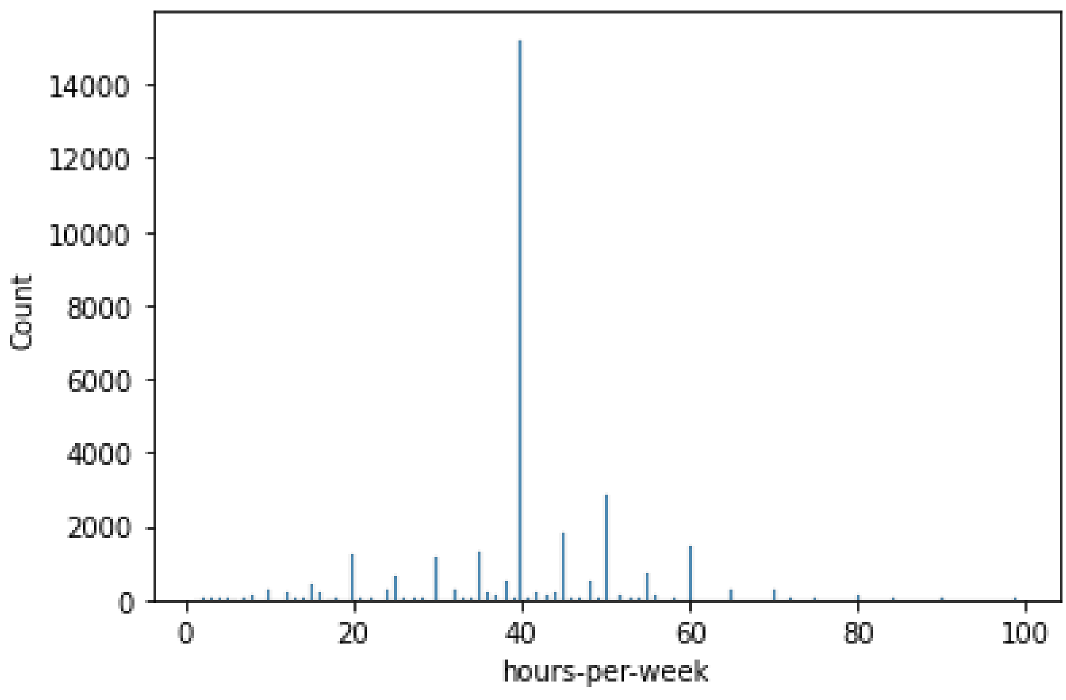


10000
8000
6000
4000
2000
0
Count
2
4
6
8
10
12
14
16
education-num



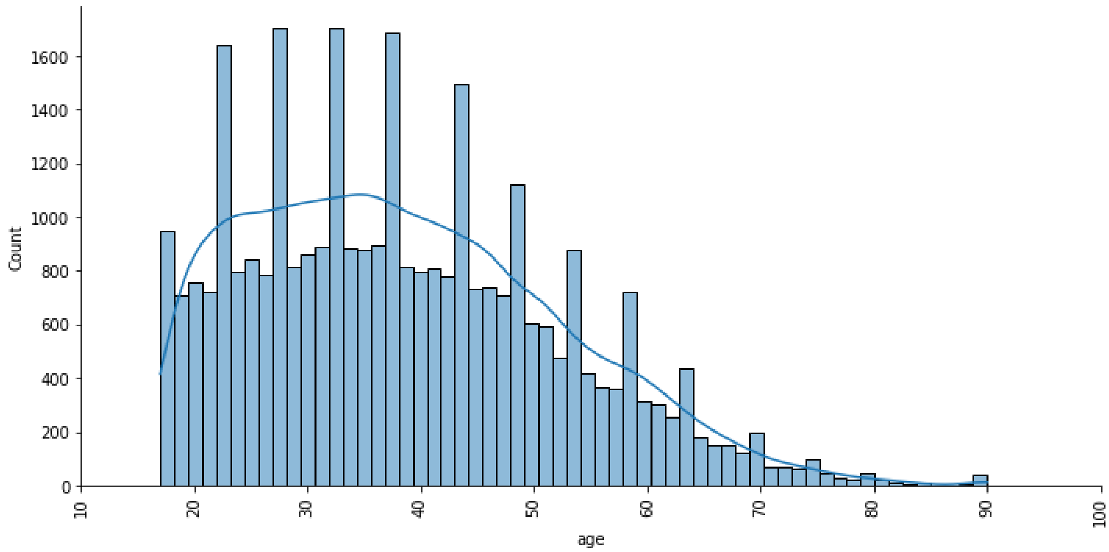
30000
25000
20000
15000
10000
5000
0
Count
0
20000
40000
60000
80000
100000
capital-gain



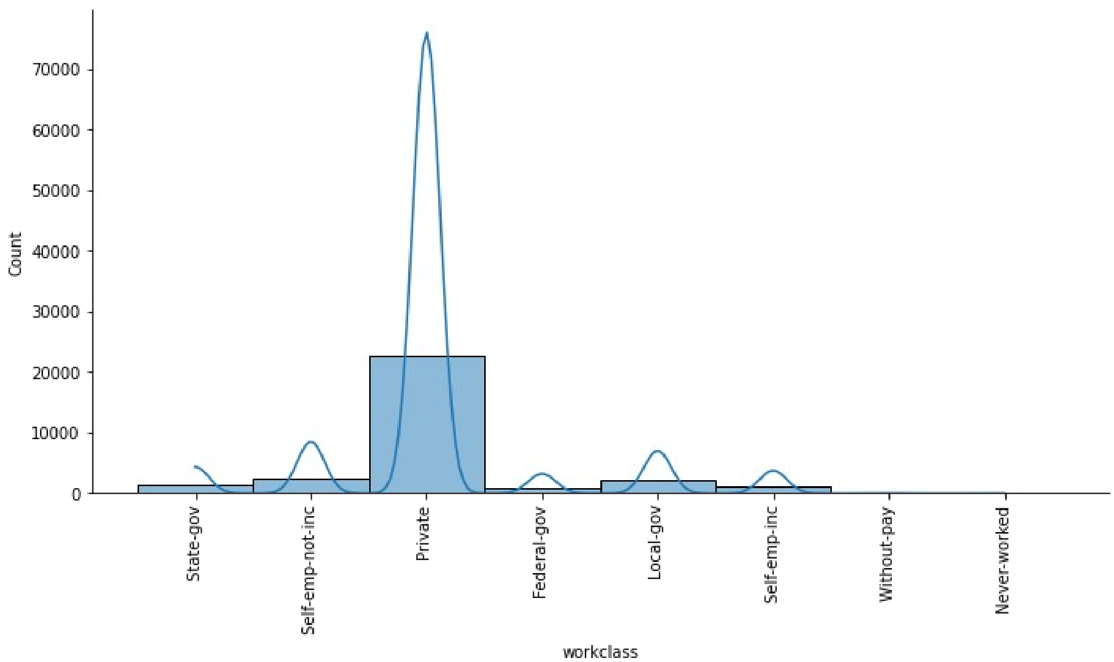


Displot

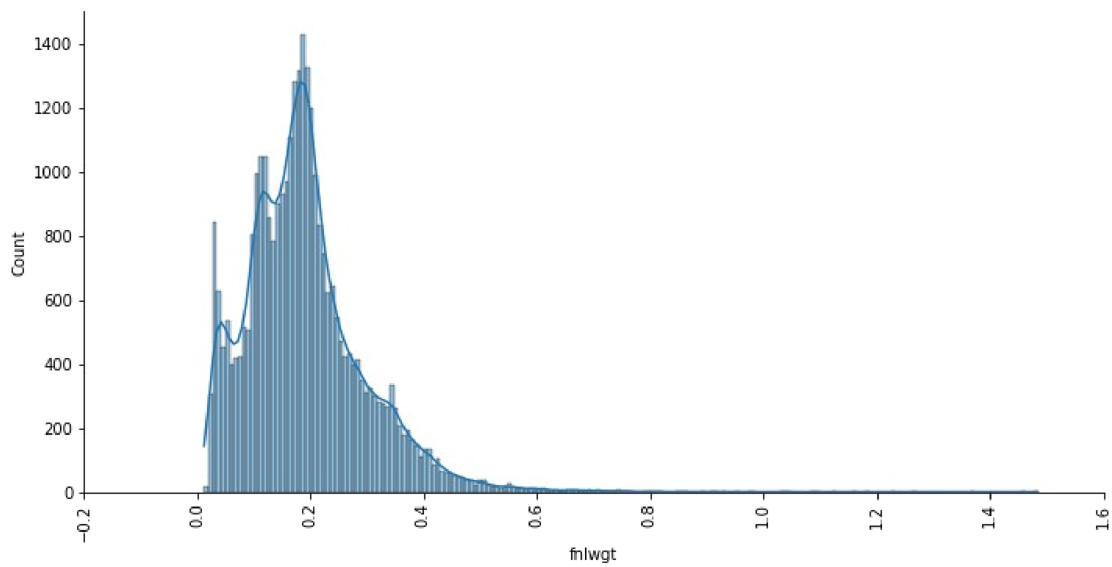
```
for col in df.columns:
    sns.displot(df[col], kde=True, legend=True,
aspect=2).set_xticklabels(rotation=90)
```



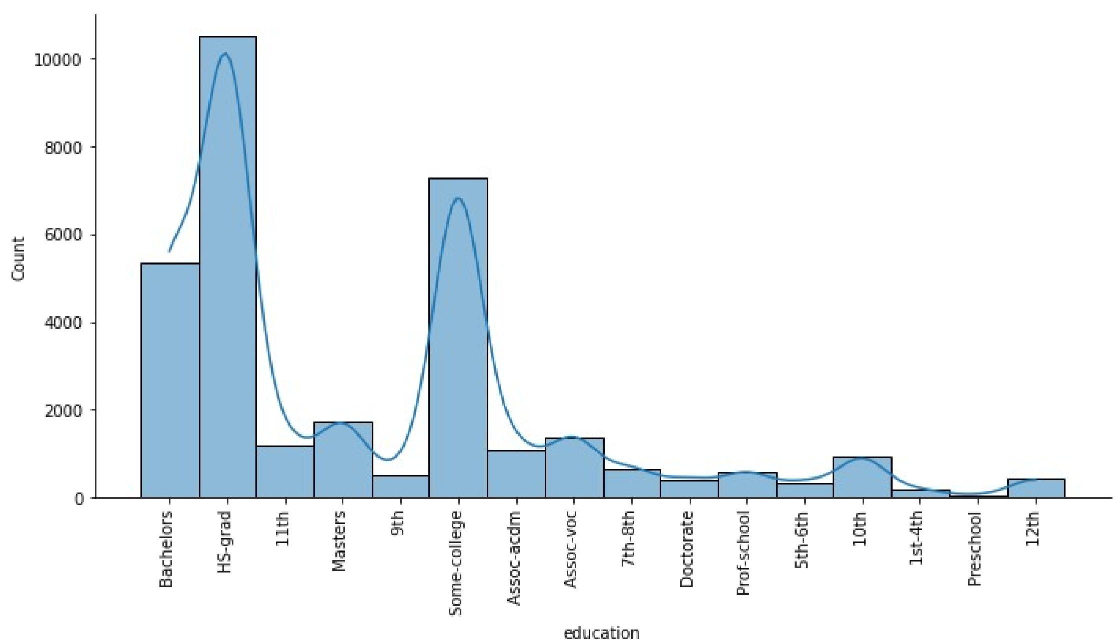
Count
age
0
200
400
600
800
1000
1200
1400
1600
10
20
30
40
50
60
70
80
90
100



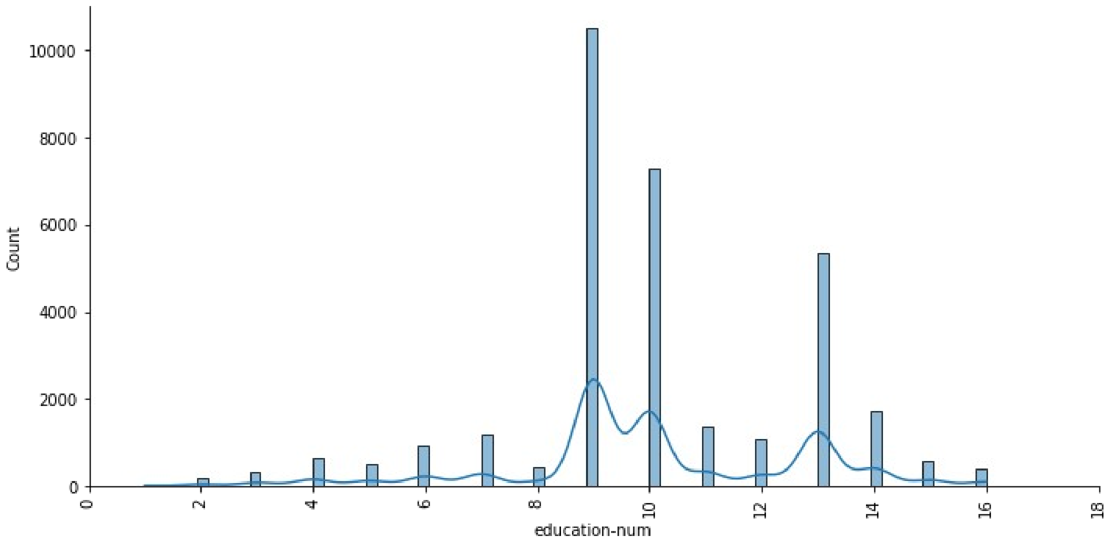
Count
workclass
0
10000
20000
30000
40000
50000
60000
70000
State-gov
Self-emp-not-inc
Private
Federal-gov
Local-gov
Self-emp-inc
Without-pay
Never-worked

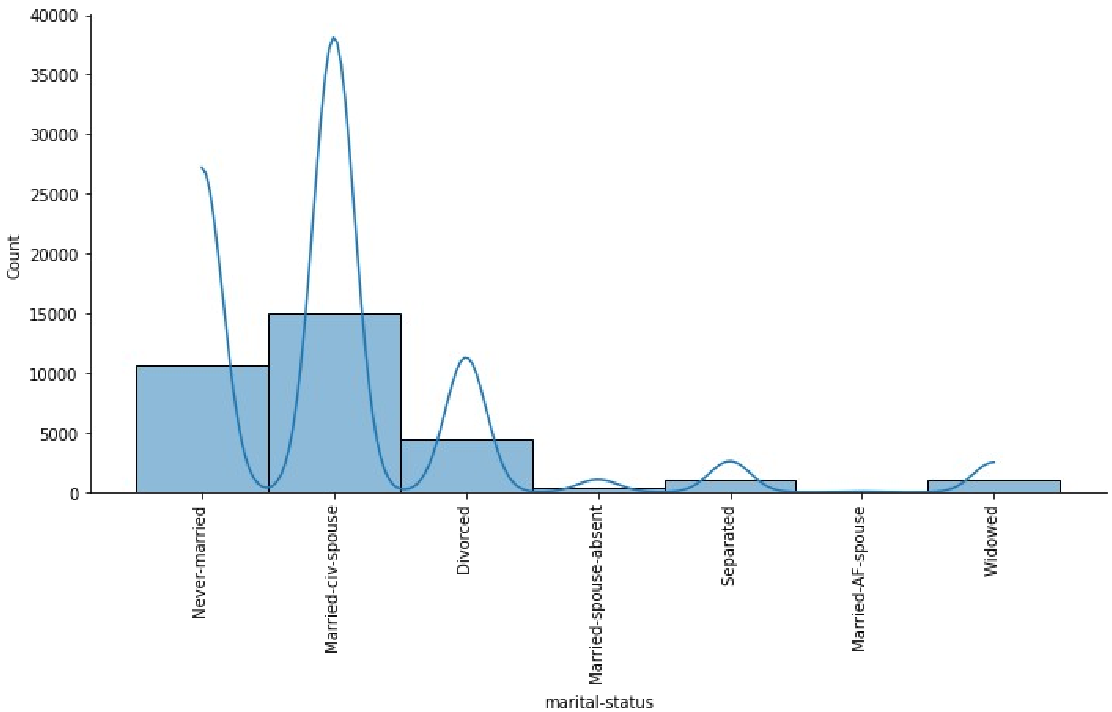


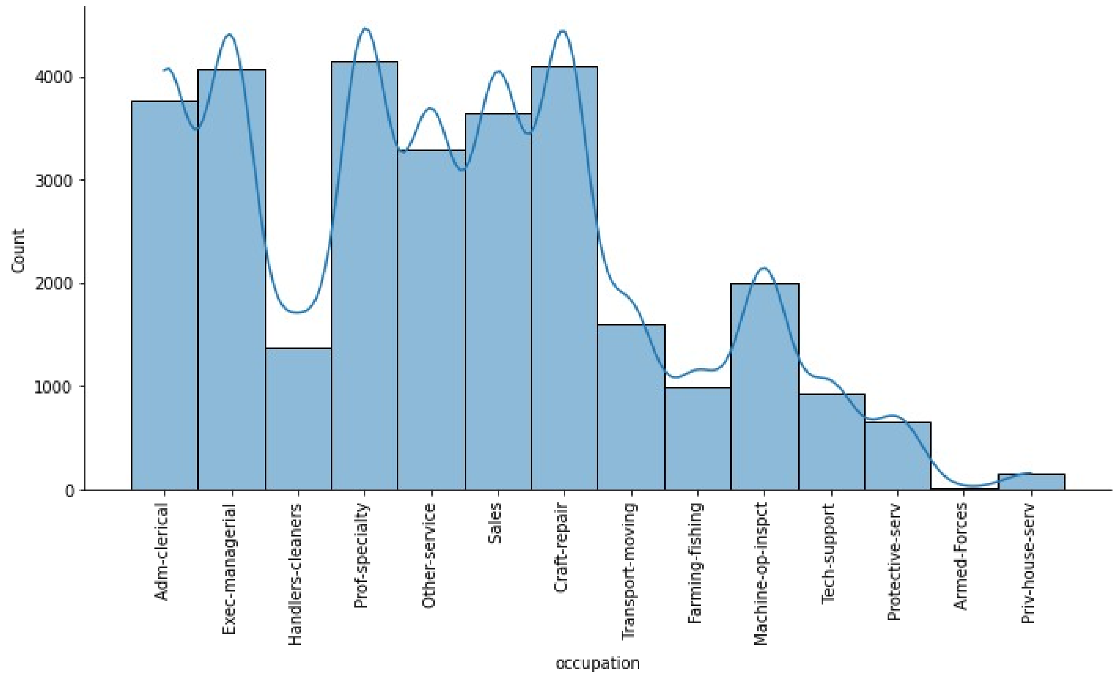
1400
1200
1000
800
600
400
200
0
Count
−0.2
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6
fnlwgt



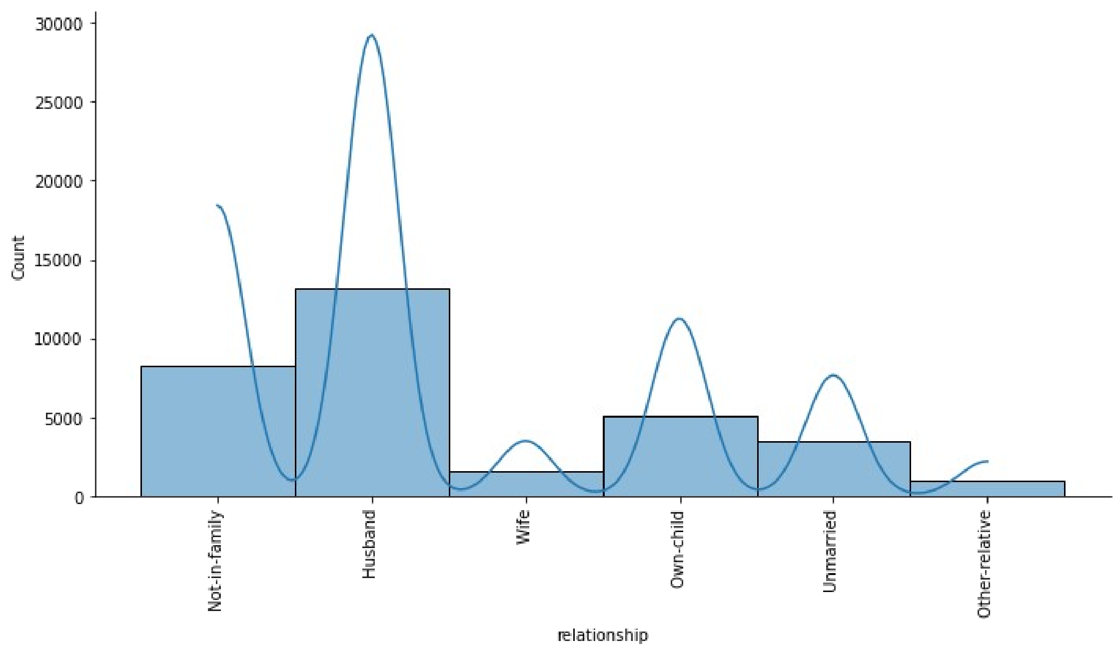
10000
8000
6000
4000
2000
0
Count
Bachelors
HS-grad
11th
Masters
9th
Some-college
Assoc-acdm
Assoc-voc
7th-8th
Doctorate
Prof-school
5th-6th
10th
1st-4th
Preschool
12th
education


Count
0
2000
4000
6000
8000
10000
0
2
4
6
8
10
12
14
16
18
education-num

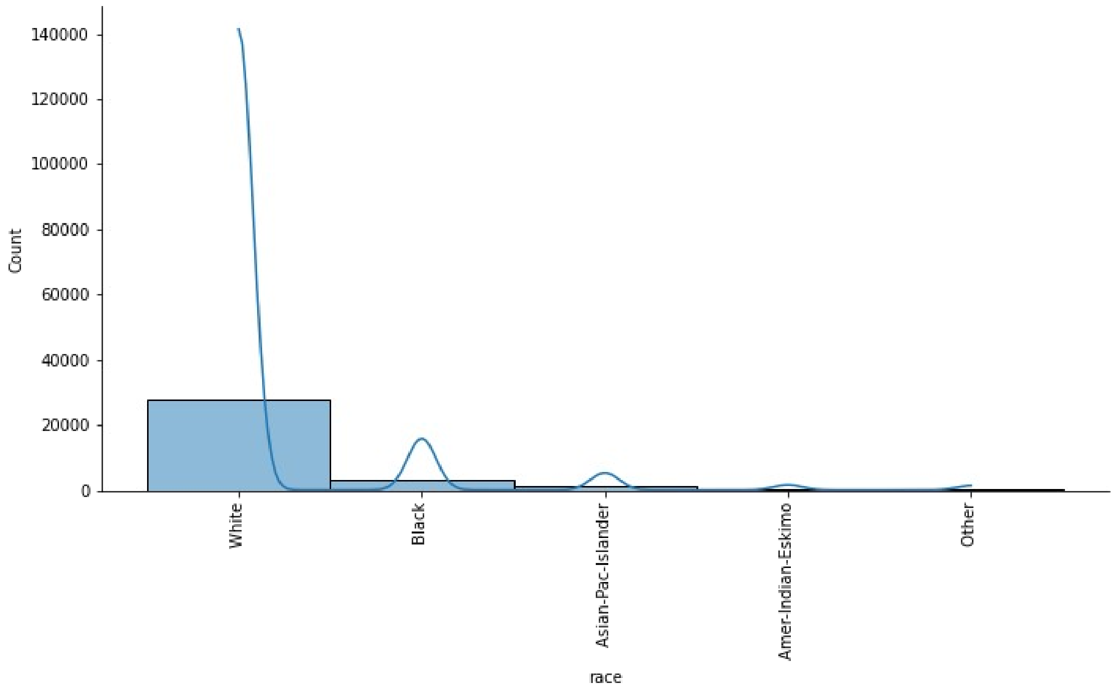

Count
0
5000
10000
15000
20000
25000
30000
35000
40000
Never-married
Married-civ-spouse
Divorced
Married-spouse-absent
Separated
Married-AF-spouse
Widowed
marital-status



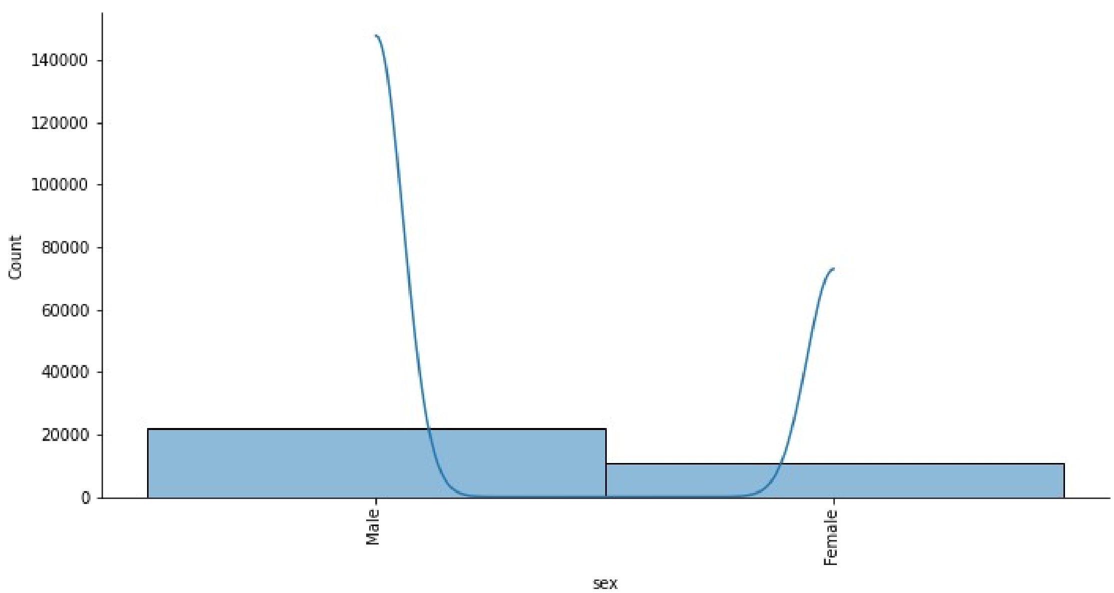
Count
4000
3000
2000
1000
0
Adm-clerical
Exec-managerial
Handlers-cleaners
Prof-specialty
Other-service
Sales
Craft-repair
Transport-moving
Farming-fishing
Machine-op-inspct
Tech-support
Protective-serv
Armed-Forces
Priv-house-serv
occupation



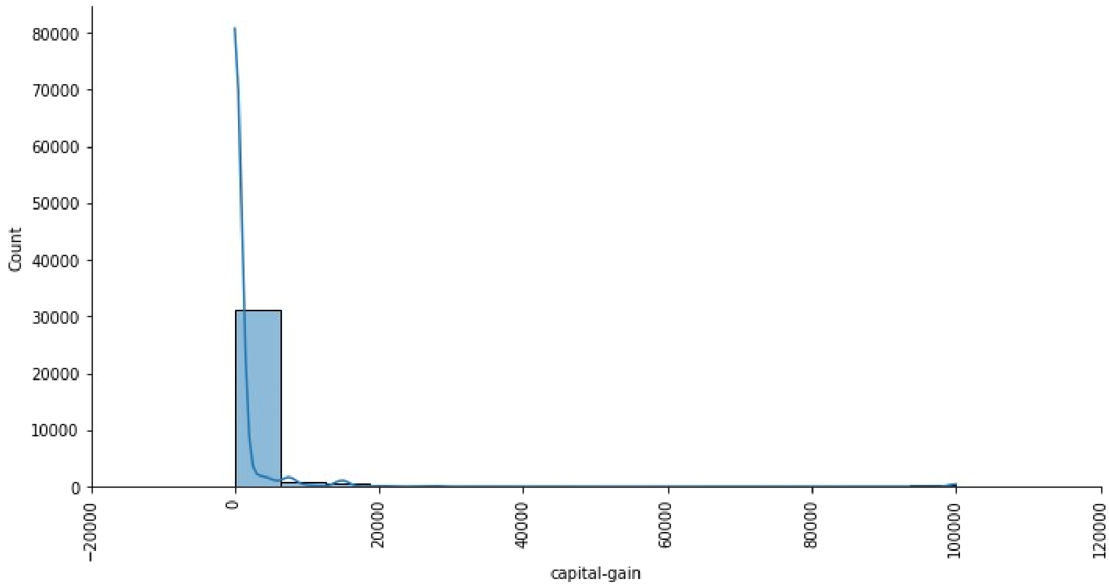
Count
30000
25000
20000
15000
10000
5000
0
Not-in-family
Husband
Wife
Own-child
Unmarried
Other-relative
relationship



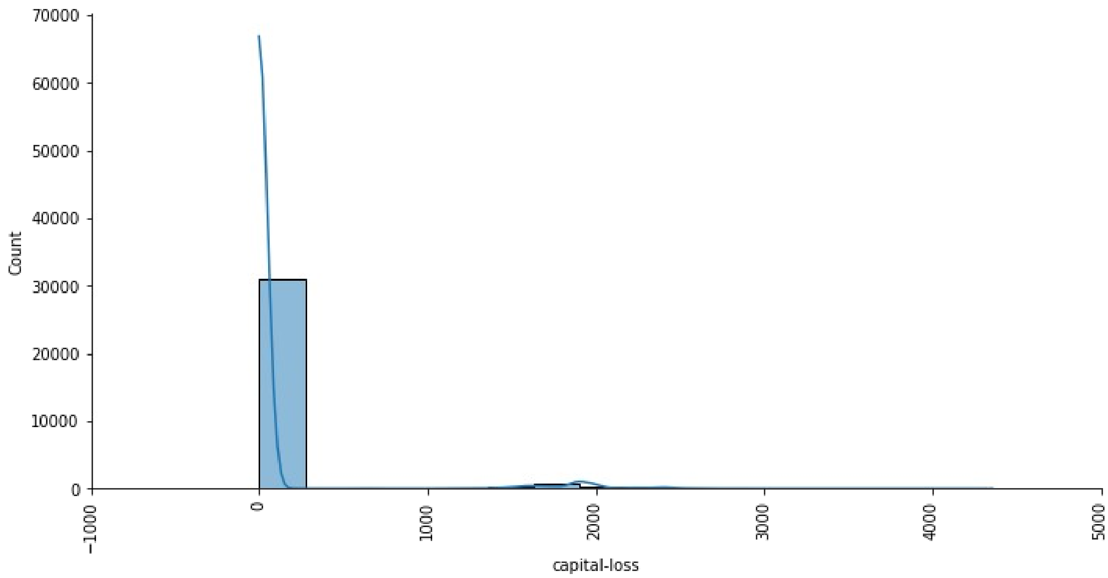
Count
140000
120000
100000
80000
60000
40000
20000
0
White
Black
Asian-Pac-Islander
Amer-Indian-Eskimo
Other
race



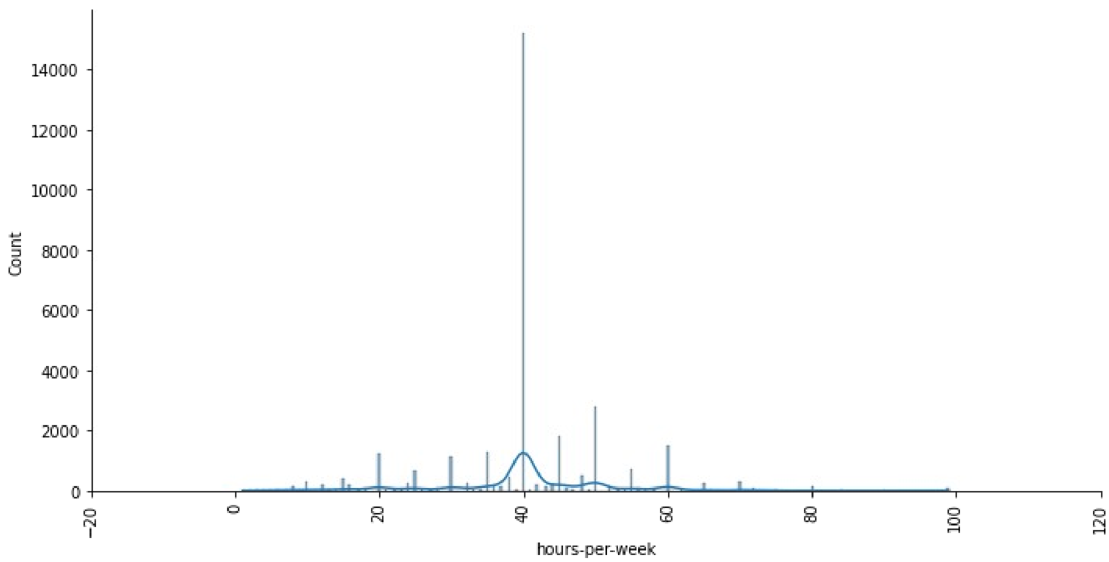
Count
140000
120000
100000
80000
60000
40000
20000
0
Male
Female
sex

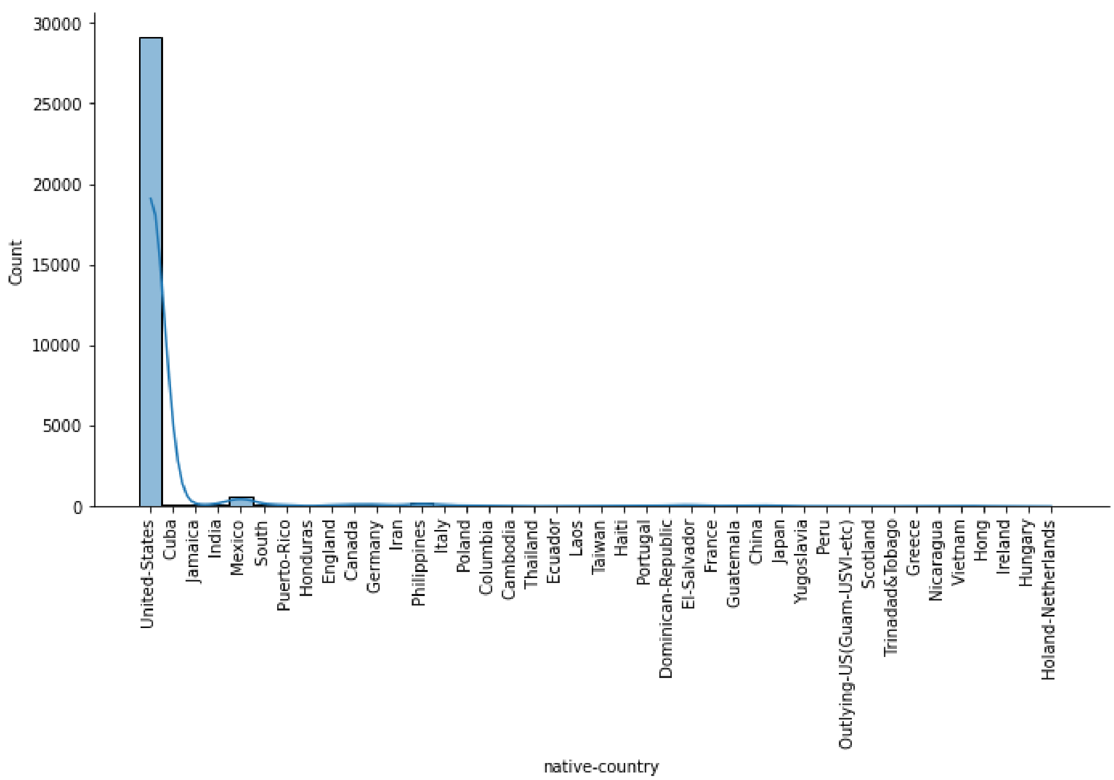


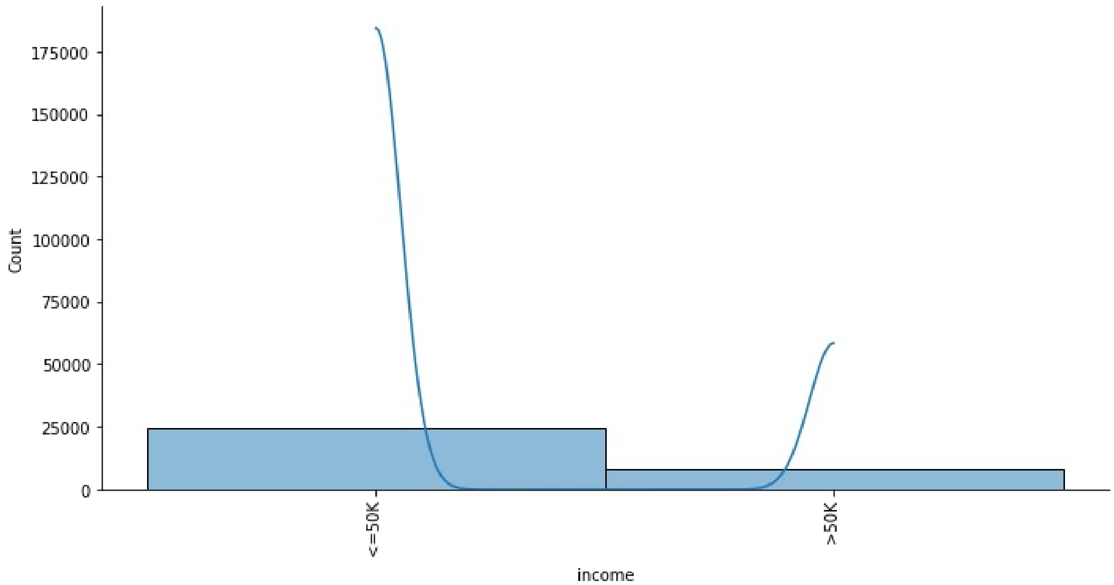
80000
70000
60000
50000
40000
30000
20000
10000
0
Count
−20000
0
20000
40000
60000
80000
100000
120000
capital-gain



70000
60000
50000
40000
30000
20000
10000
0
Count
−1000
0
1000
2000
3000
4000
5000
capital-loss

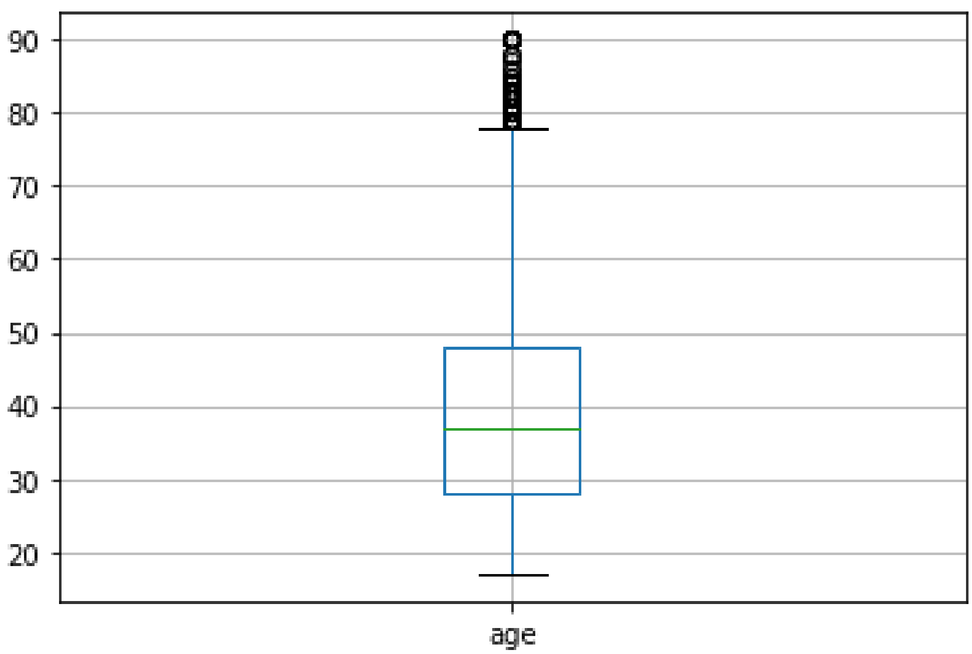

Count
14000
12000
10000
8000
6000
4000
2000
0
−20
0
20
40
60
80
100
120
hours-per-week

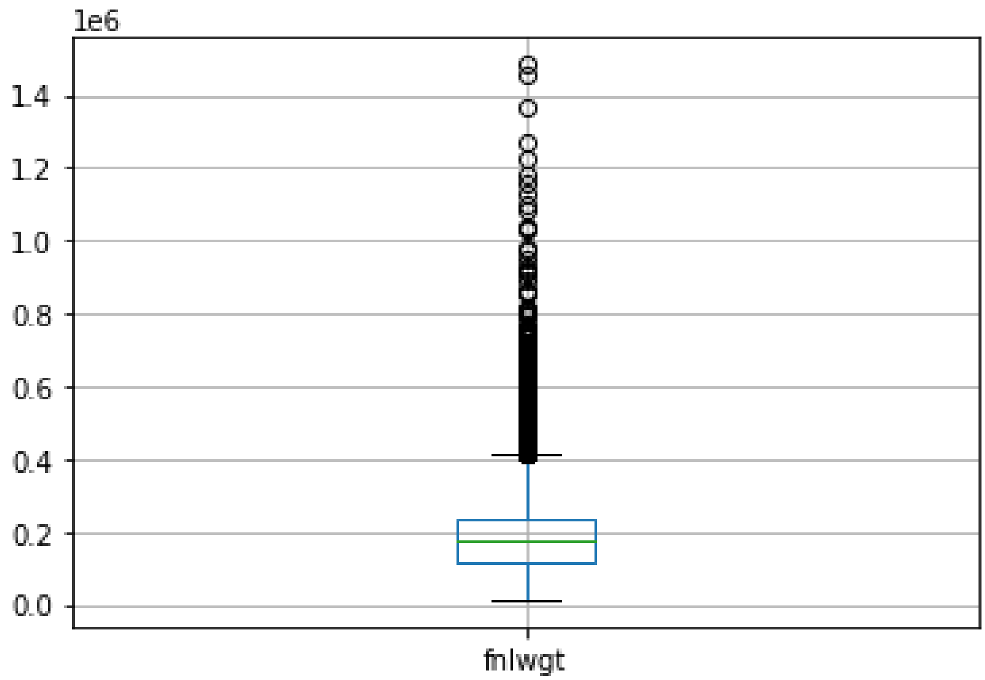

Count
30000
25000
20000
15000
10000
5000
0
United-States
Cuba
Jamaica
India
Mexico
South
Puerto-Rico
Honduras
England
Canada
Germany
Iran
Philippines
Italy
Poland
Columbia
Cambodia
Thailand
Ecuador
Laos
Taiwan
Haiti
Portugal
Dominican-Republic
El-Salvador
France
Guatemala
China
Japan
Yugoslavia
Peru
Outlying-US(Guam-USVI-etc)
Scotland
Trinadad&Tobago
Greece
Nicaragua
Vietnam
Hong
Ireland
Hungary
Holland-Netherlands
native-country

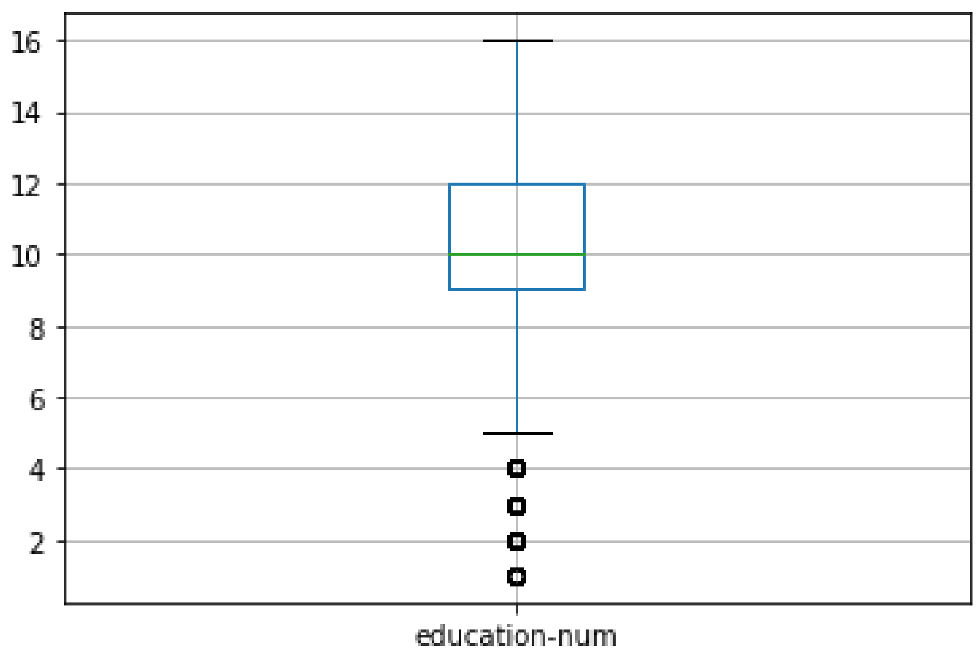


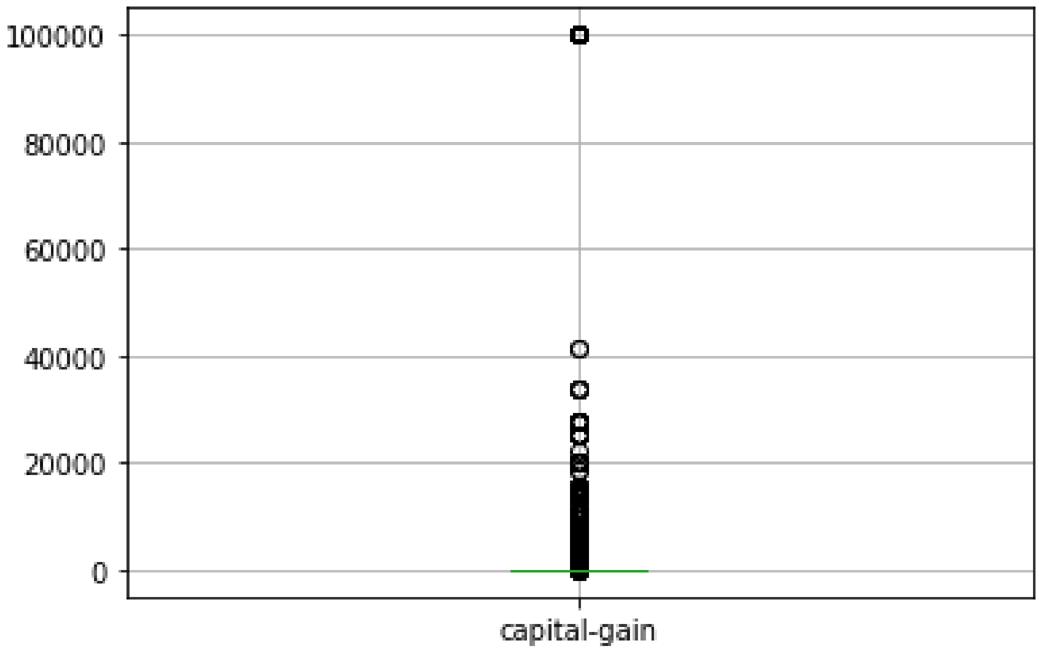
Are there any outliers present?

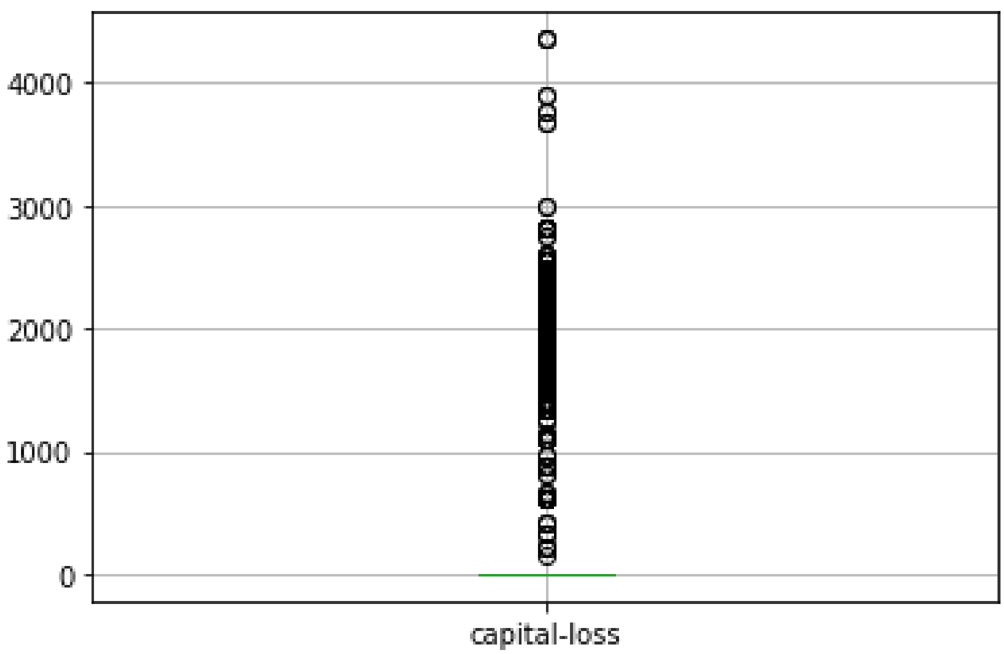
```
for col in numerical_features:
  df.boxplot(col)
  plt.show()
```

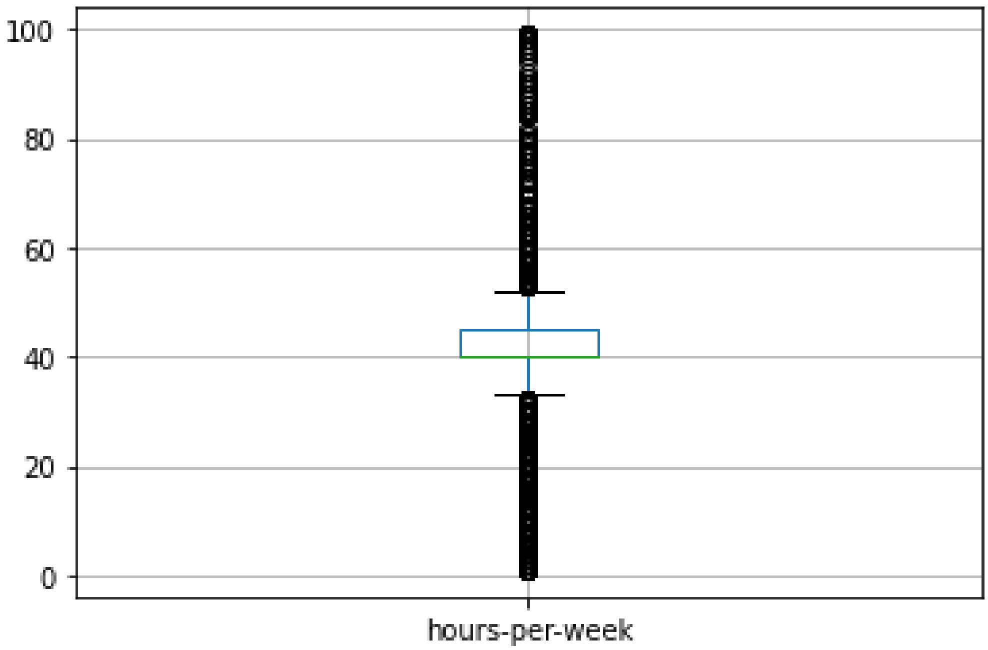



1e6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
fnlwgt


16
14
12
10
8
6
4
2
education-num


100000
80000
60000
40000
20000
0
capital-gain


4000
3000
2000
1000
0
capital-loss



Feature Engineering

Replace none values

```
df_modified=df
for col in numerical_features:
  df_modified[col].replace( np.NaN, df.median(axis=0,skipna=True)
[col],inplace=True)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:3:
FutureWarning: Dropping of nuisance columns in DataFrame reductions
(with 'numeric_only=None') is deprecated; in a future version this
will raise TypeError.  Select only valid columns before calling the
reduction.
  This is separate from the ipykernel package so we can avoid doing
imports until
```

```
for col in categorical_features:
  df_modified[col].replace( np.NaN, df.mode()[col][0],inplace=True)
```

Replace categorical features with numerical values

```
df_cat_to_num=pd.get_dummies(df_modified)

df_cat_to_num.head()
```

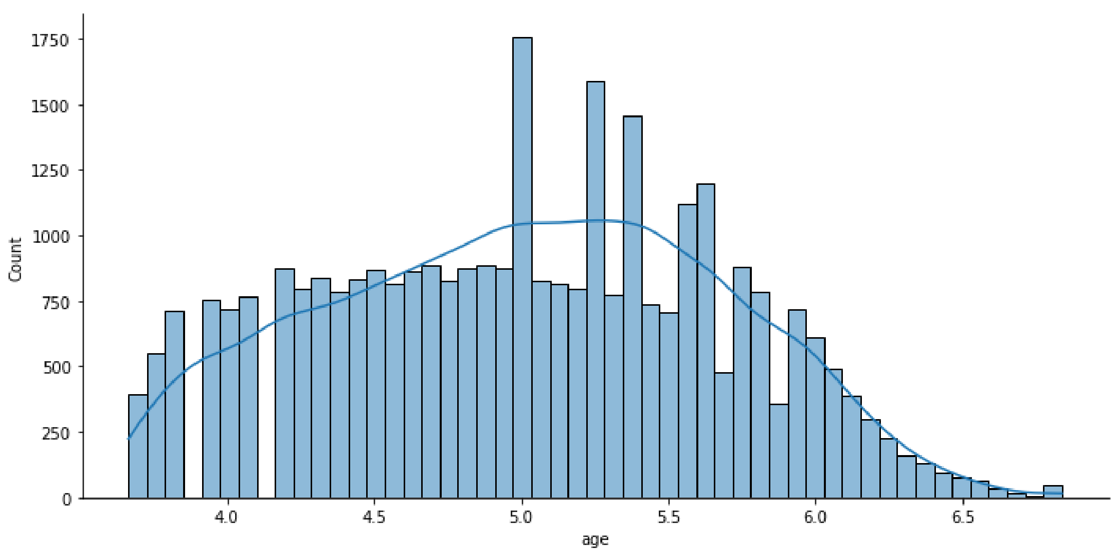
```
        age      fnlwgt  education-num  capital-gain  capital-loss  \
0  5.130679  266.098568             13      0.559558      0.274534
```

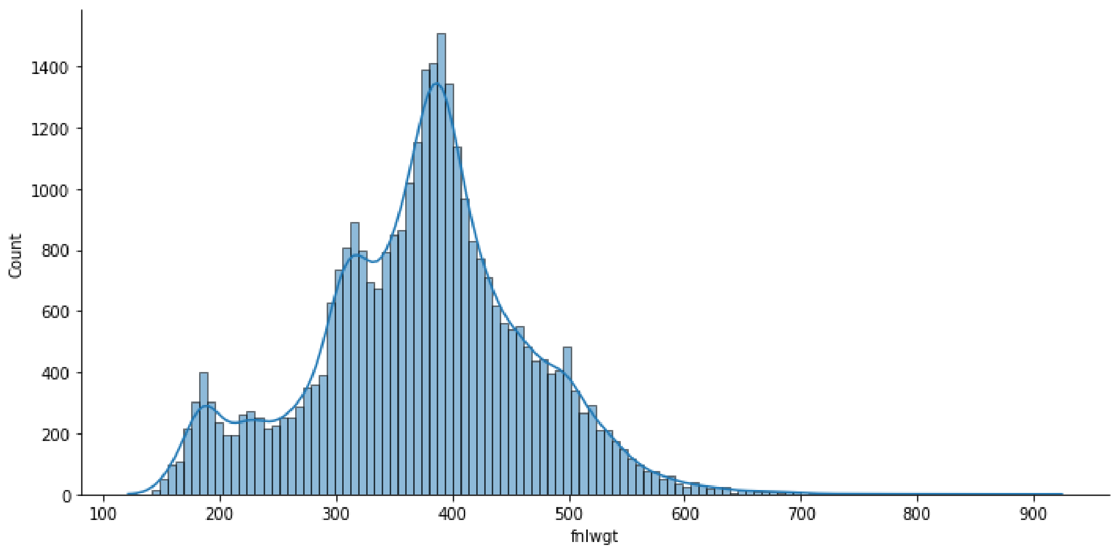
```
1  5.612071  274.345493            13      0.559558      0.274534
2  5.081547  410.077483             9      0.559558      0.274534
3  5.728022  425.012149             7      0.559558      0.274534
4  4.520327  495.934871            13      0.559558      0.274534

   hours-per-week  workclass_ Federal-gov  workclass_ Local-gov  \
0       39.163404                       0                     0
1       31.621057                       0                     0
2       39.163404                       0                     0
3       39.163404                       0                     0
4       39.163404                       0                     0

   workclass_ Never-worked  workclass_ Private  ...  native-country_ 
Scotland  \
0                        0                   0  ...
0
1                        0                   0  ...
0
2                        0                   1  ...
0
3                        0                   1  ...
0
4                        0                   1  ...
0

   native-country_ South  native-country_ Taiwan  native-country_ 
Thailand  \
0                      0                       0
0
1                      0                       0
0
2                      0                       0
0
3                      0                       0
0
4                      0                       0
0

   native-country_ Trinadad&Tobago  native-country_ United-States  \
0                                0                              1
1                                0                              1
2                                0                              1
3                                0                              1
4                                0                              0

   native-country_ Vietnam  native-country_ Yugoslavia  income_ <=50K 
\
0                        0                           0              1

1                        0                           0              1
```

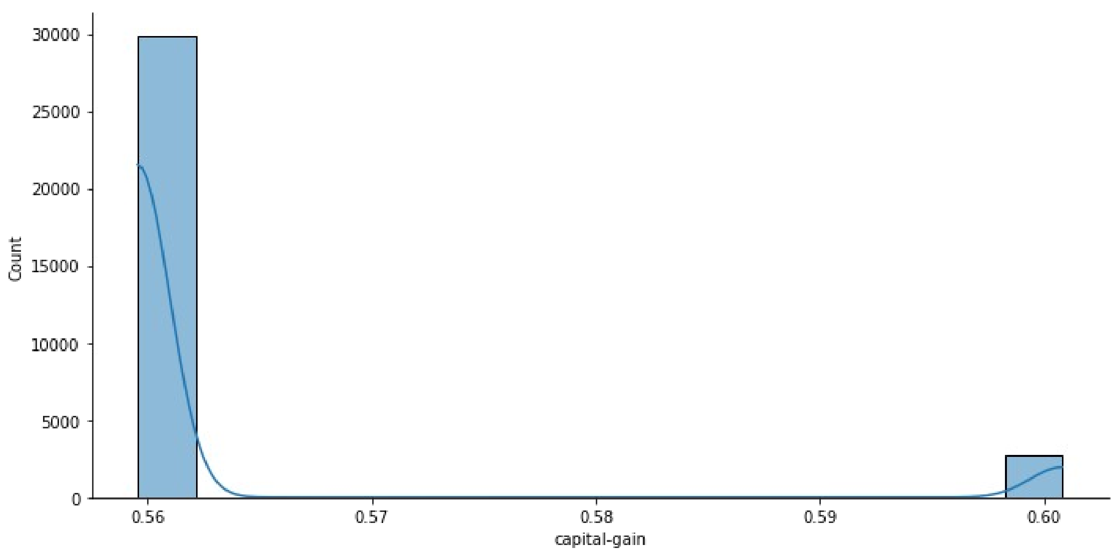
```
2                        0                           0              1

3                        0                           0              1

4                        0                           0              1


   income_ >50K
0              0
1              0
2              0
3              0
4              0

[5 rows x 107 columns]
```

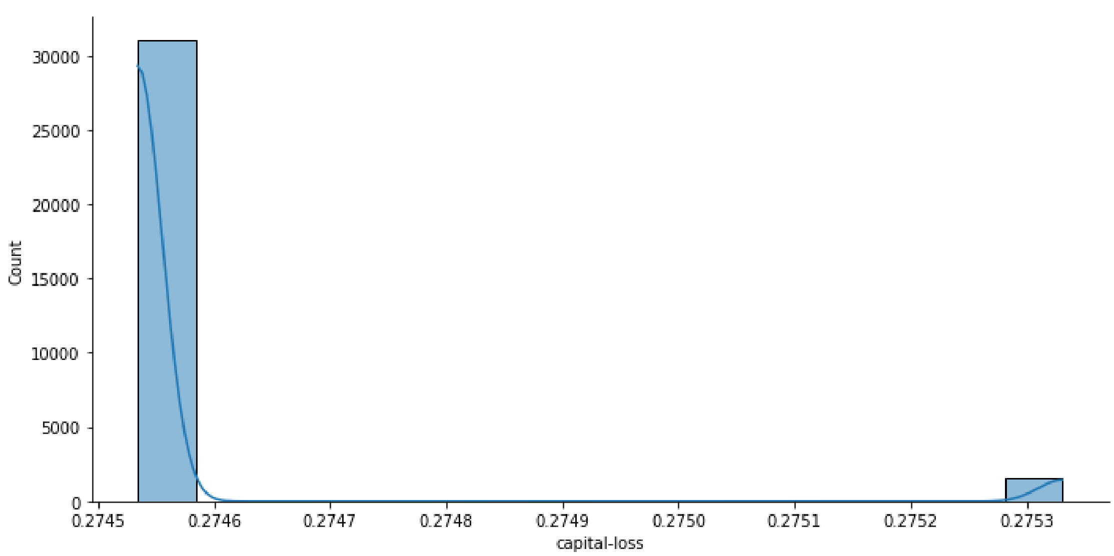
Using boxcox to normalise data

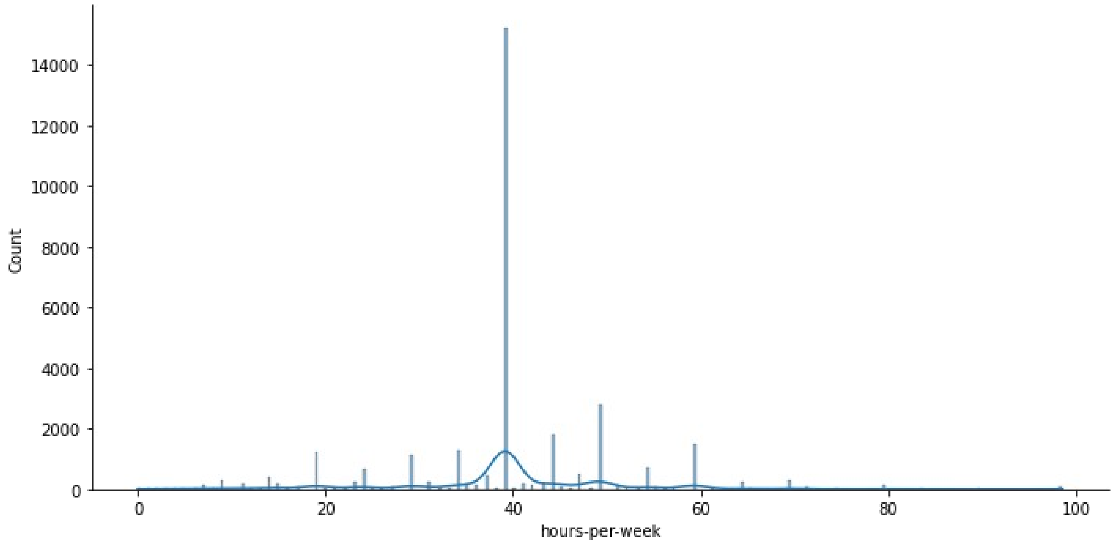
```
df_normalized=df_cat_to_num
df_normalized['capital-gain']=df_normalized['capital-gain']+5
df_normalized['capital-loss']=df_normalized['capital-loss']+5
for feature in continuous_features:
    df_normalized[feature] =
pd.DataFrame(stats.boxcox(df_normalized[feature])[0])
#     print(df[feature])
    sns.displot(df_normalized[feature], kde=True, legend=True,
height=5, aspect=2)
```




Count
fnlwgt
0
200
400
600
800
1000
1200
1400
100
200
300
400
500
600
700
800
900


Count
capital-gain
0
5000
10000
15000
20000
25000
30000
0.56
0.57
0.58
0.59
0.60


Count
capital-loss
0
5000
10000
15000
20000
25000
30000
0.2745
0.2746
0.2747
0.2748
0.2749
0.2750
0.2751
0.2752
0.2753



Removing outliers

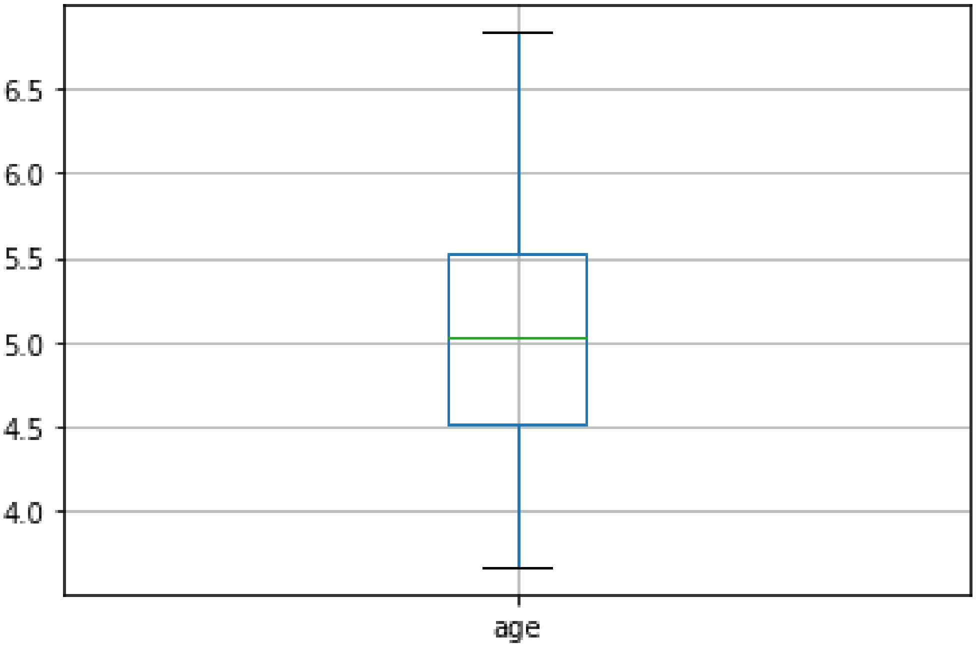
```
for feature in numerical_features:
    q75,q25 = np.percentile(df_normalized.loc[:,feature],[75,25])
    intr_qr = q75-q25

    max_range= q75+(1.5*intr_qr)
    min_range = q25-(1.5*intr_qr)

    df_normalized[feature].values[df_normalized[feature].values < 
min_range] = min_range
    df_normalized[feature].values[df_normalized[feature].values > 
max_range] = max_range

df_normalized.head()
```

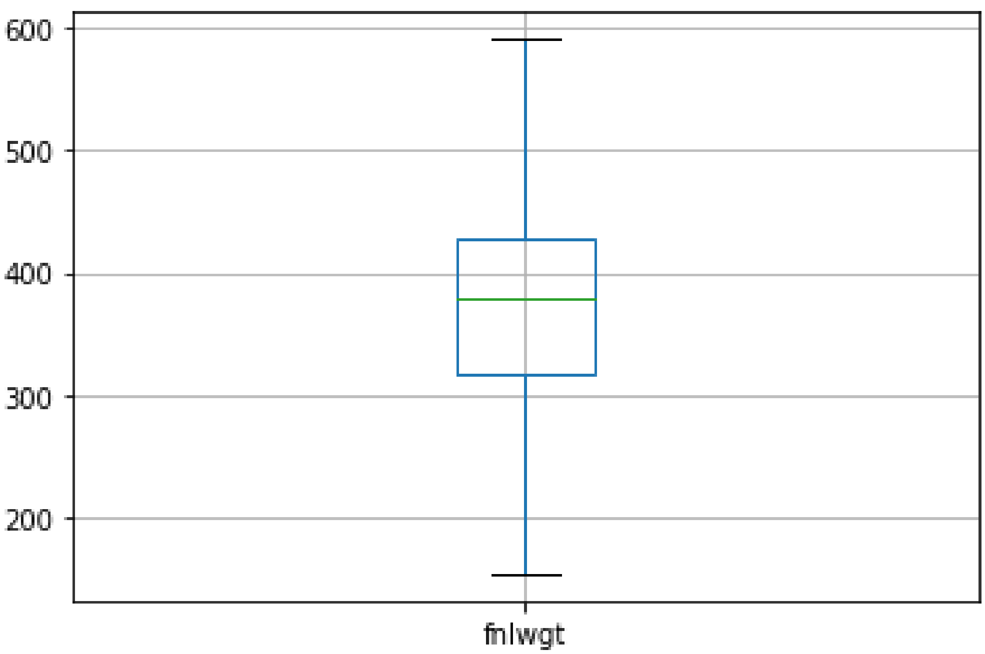
```
        age      fnlwgt  education-num  capital-gain  capital-loss  \
0  5.130679  266.098568             13      0.559558      0.274534   
1  5.612071  274.345493             13      0.559558      0.274534   
2  5.081547  410.077483              9      0.559558      0.274534   
3  5.728022  425.012149              7      0.559558      0.274534   
4  4.520327  495.934871             13      0.559558      0.274534   

   hours-per-week  workclass_ Federal-gov  workclass_ Local-gov  \
0       39.163404                       0                     0   
1       31.621057                       0                     0   
2       39.163404                       0                     0   
3       39.163404                       0                     0   
4       39.163404                       0                     0   

   workclass_ Never-worked  workclass_ Private  ...  native-country_ 
Scotland  \
0                        0                   0  ...                         
0
```

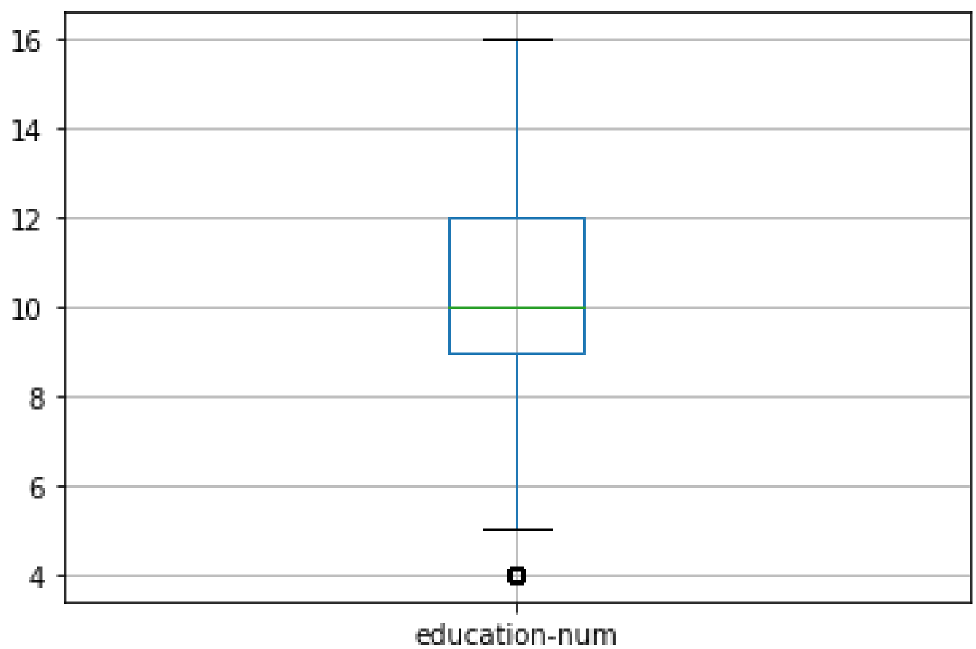
```
1                        0                   0  ...
0
2                        0                   1  ...
0
3                        0                   1  ...
0
4                        0                   1  ...
0

   native-country_ South  native-country_ Taiwan  native-country_
Thailand  \
0                      0                       0
0
1                      0                       0
0
2                      0                       0
0
3                      0                       0
0
4                      0                       0
0

   native-country_ Trinadad&Tobago  native-country_ United-States  \
0                                0                              1
1                                0                              1
2                                0                              1
3                                0                              1
4                                0                              0

   native-country_ Vietnam  native-country_ Yugoslavia  income_ <=50K
\
0                        0                           0              1

1                        0                           0              1

2                        0                           0              1

3                        0                           0              1

4                        0                           0              1


   income_ >50K
0             0
1             0
2             0
3             0
4             0
```

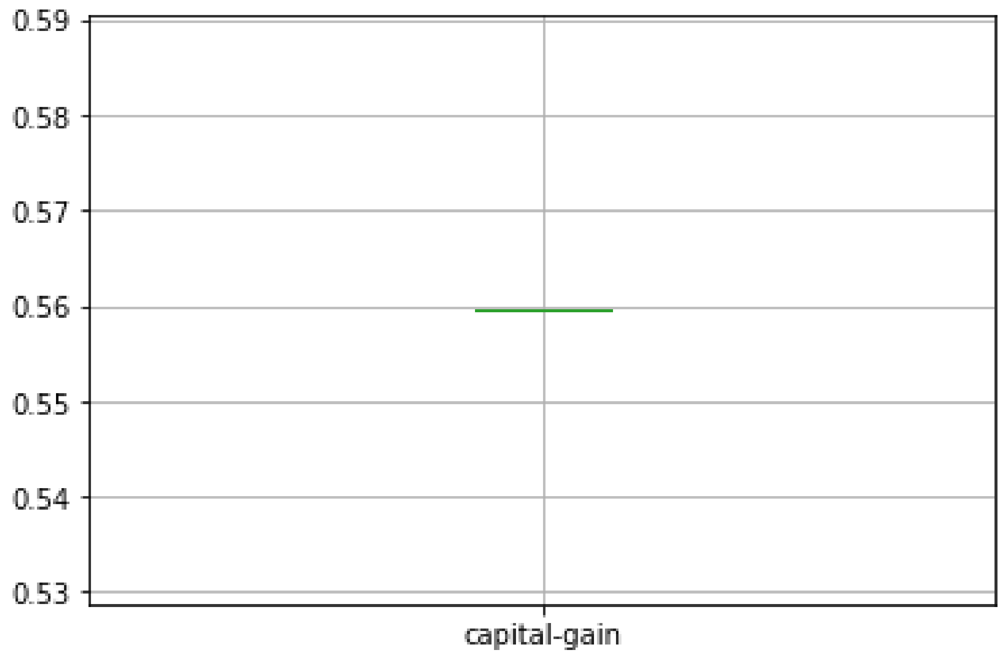
[5 rows x 107 columns]

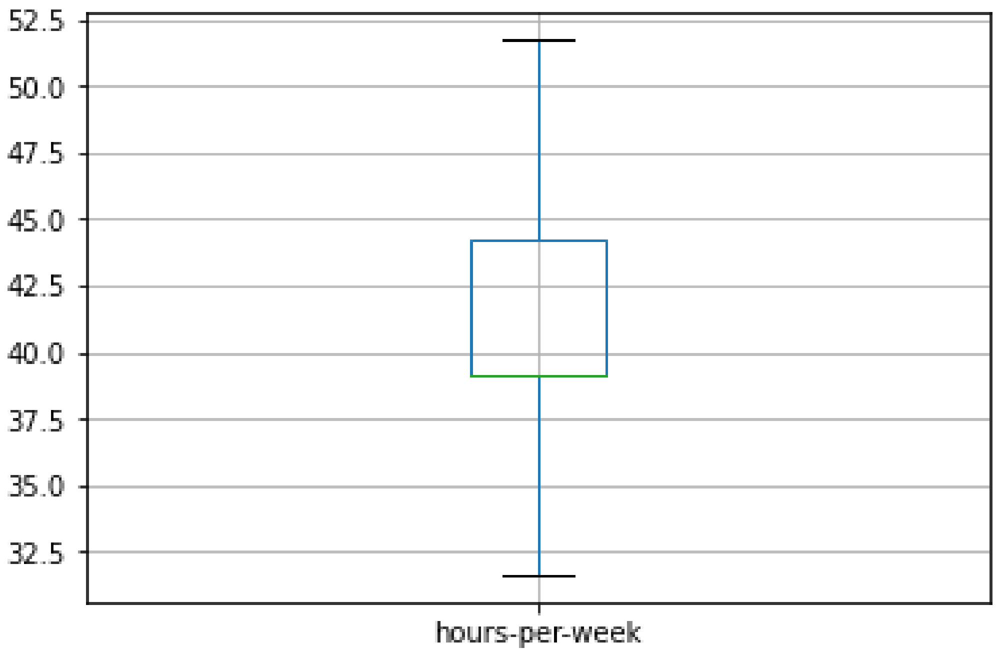
```
for col in numerical_features:
  df_normalized.boxplot(col)
  plt.show()
```






16
14
12
10
8
6
4
education-num


0.59
0.58
0.57
0.56
0.55
0.54
0.53
capital-gain



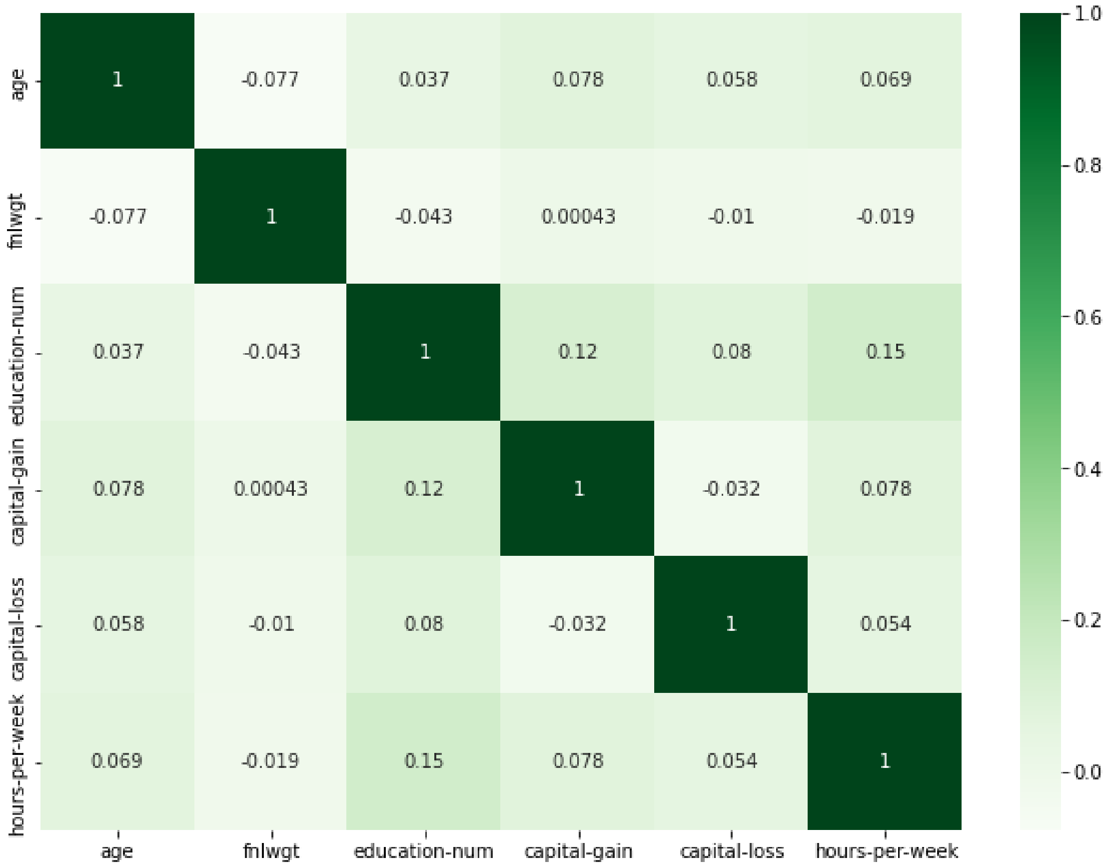
Correlation

```
corr=df_normalized.corr()['income_ <=50K'][:]
corr
```

```
age                              -0.264097
fnlwgt                            0.004985
education-num                    -0.339579
capital-gain                           NaN
capital-loss                           NaN
```

```
                                    ...
native-country_ United-States   -0.038942
native-country_ Vietnam          0.017649
native-country_ Yugoslavia      -0.006959
income_ <=50K                    1.000000
income_ >50K                    -1.000000
Name: income_ <=50K, Length: 107, dtype: float64
```

```
plt.figure(figsize=(11,8))
sns.heatmap(df_modified.corr(), cmap="Greens",annot=True)
plt.show()
```



##Modelling

```
X = df_normalized.drop(columns=['income_ >50K', 'income_ <=50K'])
y = df_normalized['income_ >50K']
```

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3)
```

Logistic regression tuning

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
```

```
score_list = []
solvers={'newton-cg':['l2','none'],'lbfgs': ['l2',
'none'],'liblinear':['l1', 'l2'],'sag':['l2', 'none'],'saga':
['elasticnet', 'l1', 'l2', 'none']}
for solver,penalty in solvers.items():
  for p in penalty:
    try:
      logistic_regression = LogisticRegression(penalty=p,
solver=solver)

      logistic_regression.fit(X_train, y_train)
      y_predict = logistic_regression.predict(X_test)
      accuracy = accuracy_score(y_test,y_predict)
      score_list.append([p,solver, accuracy])
    except:
      print("an error has occured")

df_LR = pd.DataFrame(score_list,
columns=['penalty','solver','accuracy'])
print(df_LR)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/optimize.py:212:
ConvergenceWarning: newton-cg failed to converge. Increase the number
of iterations.
  ConvergenceWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_logistic.
py:818: ConvergenceWarning: 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,
/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_logistic.
py:818: ConvergenceWarning: 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,
/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_sag.py:35
```

```
4: ConvergenceWarning: The max_iter was reached which means the coef_
did not converge
  ConvergenceWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_sag.py:35
4: ConvergenceWarning: The max_iter was reached which means the coef_
did not converge
  ConvergenceWarning,

an error has occured

/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/
_sag.py:354: ConvergenceWarning: The max_iter was reached which means
the coef_ did not converge
  ConvergenceWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_sag.py:35
4: ConvergenceWarning: The max_iter was reached which means the coef_
did not converge
  ConvergenceWarning,

   penalty     solver  accuracy
0       l2  newton-cg  0.834579
1     none  newton-cg  0.833965
2       l2      lbfgs  0.827413
3     none      lbfgs  0.826697
4       l1  liblinear  0.834783
5       l2  liblinear  0.834579
6       l2        sag  0.814515
7     none        sag  0.814515
8       l1       saga  0.806428
9       l2       saga  0.807043
10    none       saga  0.806428

/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/
_sag.py:354: ConvergenceWarning: The max_iter was reached which means
the coef_ did not converge
  ConvergenceWarning,
```

```
score_list_c=[]
for c in [100, 10, 1.0, 0.1, 0.01]:
   logistic_regression = LogisticRegression(solver='liblinear',
penalty='l1', C=c)
   logistic_regression.fit(X_train, y_train)
   y_predict = logistic_regression.predict(X_test)
   accuracy = accuracy_score(y_test,y_predict)
   score_list_c.append([c, accuracy])
df_LR_1 = pd.DataFrame(score_list_c, columns=['c','accuracy'])
print(df_LR_1)
```

```
        c  accuracy
0  100.00  0.834374
1   10.00  0.834272
```

```
2    1.00  0.835091
3    0.10  0.832736
4    0.01  0.820555
```

```
final_lr_model=LogisticRegression(solver='liblinear', penalty='l1',
C=1.0)
final_lr_model.fit(X_train, y_train)
y_predict = final_lr_model.predict(X_test)
accuracy = accuracy_score(y_test,y_predict)
accuracy
```

```
0.8350905926911659
```

Random forest classifier tuning

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.datasets import make_classification
score_list_rfc=[]
for depth in range(1,40):
  rfc= RandomForestClassifier(random_state=0,max_depth=depth)
  rfc.fit(X_train,y_train)
  y_predict = rfc.predict(X_test)
  accuracy = accuracy_score(y_test,y_predict)
  score_list_rfc.append([depth,accuracy])
```

```
score_list_rfc
```

```
[[1, 0.7648684614597195],
 [2, 0.7648684614597195],
 [3, 0.7968062237690654],
 [4, 0.8125703756781656],
 [5, 0.8257754120176067],
 [6, 0.8264919643771113],
 [7, 0.8291534445695568],
 [8, 0.8288463507011977],
 [9, 0.8302794554202068],
 [10, 0.8327362063670796],
 [11, 0.8338622172177296],
 [12, 0.8365236974101751],
 [13, 0.8386733544886887],
 [14, 0.8393899068481933],
 [15, 0.8399017299621251],
 [16, 0.8384686252431159],
 [17, 0.8421537516634251],
 [18, 0.8404135530760569],
 [19, 0.8376497082608251],
 [20, 0.8391851776026206],
 [21, 0.8376497082608251],
 [22, 0.8376497082608251],
 [23, 0.8383662606203296],
 [24, 0.8353976865595251],
 [25, 0.8353976865595251],
```

```
 [26, 0.8355000511823114],
 [27, 0.8328385709898659],
 [28, 0.8340669464633023],
 [29, 0.8334527587265841],
 [30, 0.8314054662708568],
 [31, 0.8309960077797113],
 [32, 0.8299723615518477],
 [33, 0.8282321629644794],
 [34, 0.8289487153239841],
 [35, 0.8265943289998976],
 [36, 0.8280274337189067],
 [37, 0.8276179752277613],
 [38, 0.8300747261746341],
 [39, 0.8284368922100522]]
```

```
accuracy
```

```
0.8421537516634251
```

```
score_list_rfc_1=[]
for trees in range(100,1001,100):
  rfc=
RandomForestClassifier(random_state=0,max_depth=17,n_estimators=trees)
  rfc.fit(X_train,y_train)
  y_predict = rfc.predict(X_test)
  accuracy = accuracy_score(y_test,y_predict)
  score_list_rfc_1.append([trees,accuracy])
```

```
score_list_rfc_1
```

```
[[100, 0.8421537516634251],
 [200, 0.8417442931722796],
 [300, 0.8422561162862114],
 [400, 0.8424608455317842],
 [500, 0.8420513870406388],
 [600, 0.8414371993039206],
 [700, 0.8418466577950661],
 [800, 0.8414371993039206],
 [900, 0.8415395639267069],
 [1000, 0.8414371993039206]]
```

```
score_list_rfc_2=[]
for max_feature in ['auto','sqrt']:
  rfc=
RandomForestClassifier(random_state=0,max_depth=17,n_estimators=400,ma
x_features=max_feature)
  rfc.fit(X_train,y_train)
  y_predict = rfc.predict(X_test)
  accuracy = accuracy_score(y_test,y_predict)
  score_list_rfc_2.append([max_feature,accuracy])
```

```
score_list_rfc_2
```

```
[['auto', 0.8424608455317842], ['sqrt', 0.8424608455317842]]
```

```
final_rfc_model=
RandomForestClassifier(random_state=0,max_depth=17,n_estimators=400,)
final_rfc_model.fit(X_train,y_train)
y_predict = final_rfc_model.predict(X_test)
accuracy = accuracy_score(y_test,y_predict)
```

```
accuracy
```

```
0.8424608455317842
```

```
columns=['age', 'workclass', 'fnlwgt', 'education', 'education-num',
'marital-status', 'occupation', 'relationship', 'race', 'sex',
'capital-gain', 'capital-loss', 'hours-per-week', 'native-country']
inp=[76, ' Private',124191, ' Masters',14, ' Married-civ-spouse', '
Exec-managerial', ' Husband', ' White', ' Male',0,0,40, ' United-
States']

inp_data={}
i=0

for col in columns:
  inp_data[col]=[inp[i]]
  i=i+1
inp_data=pd.DataFrame(inp_data)
inp_data=pd.get_dummies(inp_data)
print(type(inp_data))
df_modified_inp=pd.DataFrame()
for col in df_normalized.columns:
  df_modified_inp[col]=[0]
for col in inp_data:
  df_modified_inp[col]=inp_data[col]
df_modified_inp['capital-gain']=df_modified_inp['capital-gain']+5
df_modified_inp['capital-loss']=df_modified_inp['capital-loss']+5

df_modified_inp.drop(columns=['income_ >50K', 'income_
<=50K'],inplace=True)

y_predict = final_rfc_model.predict(df_modified_inp)
print(y_predict)
```

```
<class 'pandas.core.frame.DataFrame'>
[1]
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:15:
PerformanceWarning: DataFrame is highly fragmented.  This is usually
the result of calling `frame.insert` many times, which has poor
performance.  Consider joining all columns at once using
pd.concat(axis=1) instead.  To get a de-fragmented frame, use
```

```
`newframe = frame.copy()`
  from ipykernel import kernelapp as app
```