```
Problem Statement:

Banks wants to know, whether credit facility will extend to the customer based on the
customer data, for this analysis bank is using individual customer geography details,
gender, income, industry employement and experience.

Using Chi2_square_test and ANNOVA test and different ML algo, we are trying to suggest
the bank
```

In [34]:

```python
#import the required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import chi2_contingency
import stat
from scipy.stats import iqr
```

In [35]:

```python
#read the data sets with display the data
df=pd.read_csv(r"D:\clean_dataset.csv")
df
```

Out[35]:

	Gender	Age	Debt	Married	BankCustomer	Industry	Ethnicity	YearsEmployed
0	1	30.83	0.000	1	1	Industrials	White	1.25
1	0	58.67	4.460	1	1	Materials	Black	3.04
2	0	24.50	0.500	1	1	Materials	Black	1.50
3	1	27.83	1.540	1	1	Industrials	White	3.75
4	1	20.17	5.625	1	1	Industrials	White	1.71
...	...	...	...	...	...	...	...	..
685	1	21.08	10.085	0	0	Education	Black	1.25
686	0	22.67	0.750	1	1	Energy	White	2.00
687	0	25.25	13.500	0	0	Healthcare	Latino	2.00
688	1	17.92	0.205	1	1	ConsumerStaples	White	0.04
689	1	35.00	3.375	1	1	Energy	Black	8.29

690 rows × 16 columns

In [36]:

```
#check the datasets information
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 690 entries, 0 to 689
Data columns (total 16 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Gender          690 non-null    int64
 1   Age             690 non-null    float64
 2   Debt            690 non-null    float64
 3   Married         690 non-null    int64
 4   BankCustomer    690 non-null    int64
 5   Industry        690 non-null    object
 6   Ethnicity       690 non-null    object
 7   YearsEmployed   690 non-null    float64
 8   PriorDefault    690 non-null    int64
 9   Employed        690 non-null    int64
 10  CreditScore     690 non-null    int64
 11  DriversLicense  690 non-null    int64
 12  Citizen         690 non-null    object
 13  ZipCode         690 non-null    int64
 14  Income          690 non-null    int64
 15  Approved        690 non-null    int64
dtypes: float64(3), int64(10), object(3)
memory usage: 86.4+ KB
```

In [37]:

```
#check the any null values in the datasets
df.isnull().sum()
```

Out[37]:

```
Gender            0
Age               0
Debt              0
Married           0
BankCustomer      0
Industry          0
Ethnicity         0
YearsEmployed     0
PriorDefault      0
Employed          0
CreditScore       0
DriversLicense    0
Citizen           0
ZipCode           0
Income            0
Approved          0
dtype: int64
```

In [38]:

```
#check the mean,mode details
df.describe()
```

Out[38]:

	Gender	Age	Debt	Married	BankCustomer	YearsEmployed	PriorDe
count	690.000000	690.000000	690.000000	690.000000	690.000000	690.000000	690.00
mean	0.695652	31.514116	4.758725	0.760870	0.763768	2.223406	0.52
std	0.460464	11.860245	4.978163	0.426862	0.425074	3.346513	0.49
min	0.000000	13.750000	0.000000	0.000000	0.000000	0.000000	0.00
25%	0.000000	22.670000	1.000000	1.000000	1.000000	0.165000	0.00
50%	1.000000	28.460000	2.750000	1.000000	1.000000	1.000000	1.00
75%	1.000000	37.707500	7.207500	1.000000	1.000000	2.625000	1.00
max	1.000000	80.250000	28.000000	1.000000	1.000000	28.500000	1.00

In [39]:

```
#check the value counts for each parameters
for i in df:
    print(df[i].value_counts())
```

```
CommunicationServices     38
Utilities                 38
Real Estate               30
Education                 25
Research                  10
Transport                  3
Name: Industry, dtype: int64
White     408
Black     138
Asian      59
Latino     57
Other      28
Name: Ethnicity, dtype: int64
0.000    70
0.250    35
0.040    33
1.000    31
0.125    30
         ..
4.165     1
```

First will select the categorical type data for chi2_suare_test,here categorical type means "object type", "yes/no" lets check the categorical data and create the seperate list.

In [40]:

```
#create the list of categorical type variables
category=['Gender','Married','BankCustomer','Industry','Ethnicity','PriorDefault','Employed
          'DriversLicense','Citizen','ZipCode','Approved']
```

In [41]:

```
df.loc[:,category]
```

Out[41]:

	Gender	Married	BankCustomer	Industry	Ethnicity	PriorDefault	Employed	Drive
0	1	1	1	Industrials	White	1	1	
1	0	1	1	Materials	Black	1	1	
2	0	1	1	Materials	Black	1	0	
3	1	1	1	Industrials	White	1	1	
4	1	1	1	Industrials	White	1	0	
...	...	...	...	...	...	...	...	
685	1	0	0	Education	Black	0	0	
686	0	1	1	Energy	White	0	1	
687	0	0	0	Healthcare	Latino	0	1	
688	1	1	1	ConsumerStaples	White	0	0	
689	1	1	1	Energy	Black	0	0	

690 rows × 11 columns

Statistical Testing using Chisquare:

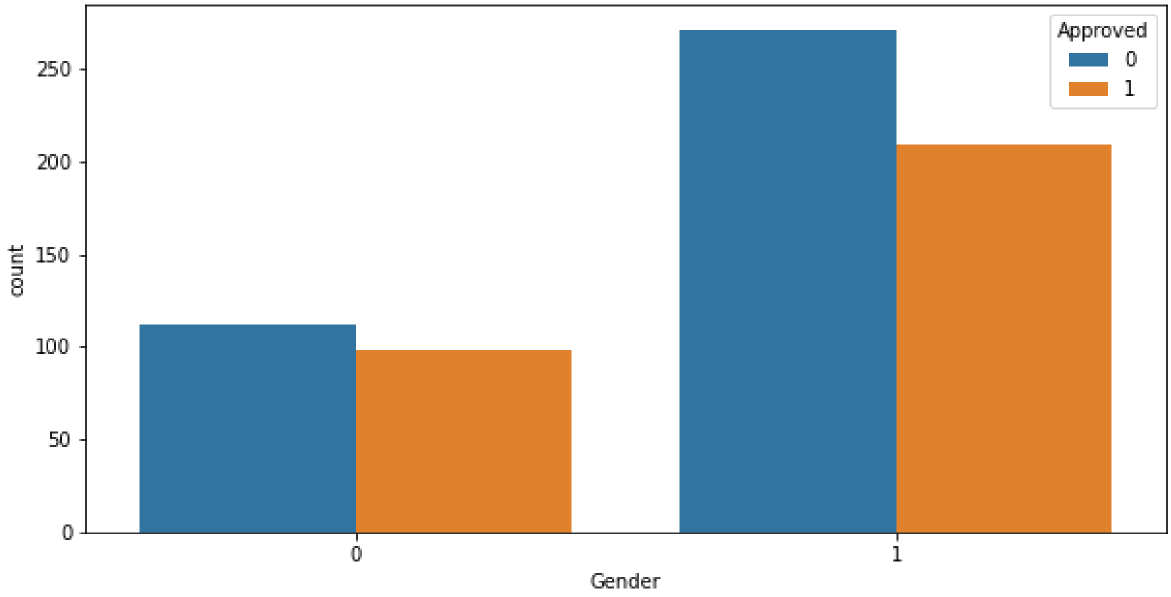
In [42]:

```
import colorama
from colorama import Fore
```

In [43]:

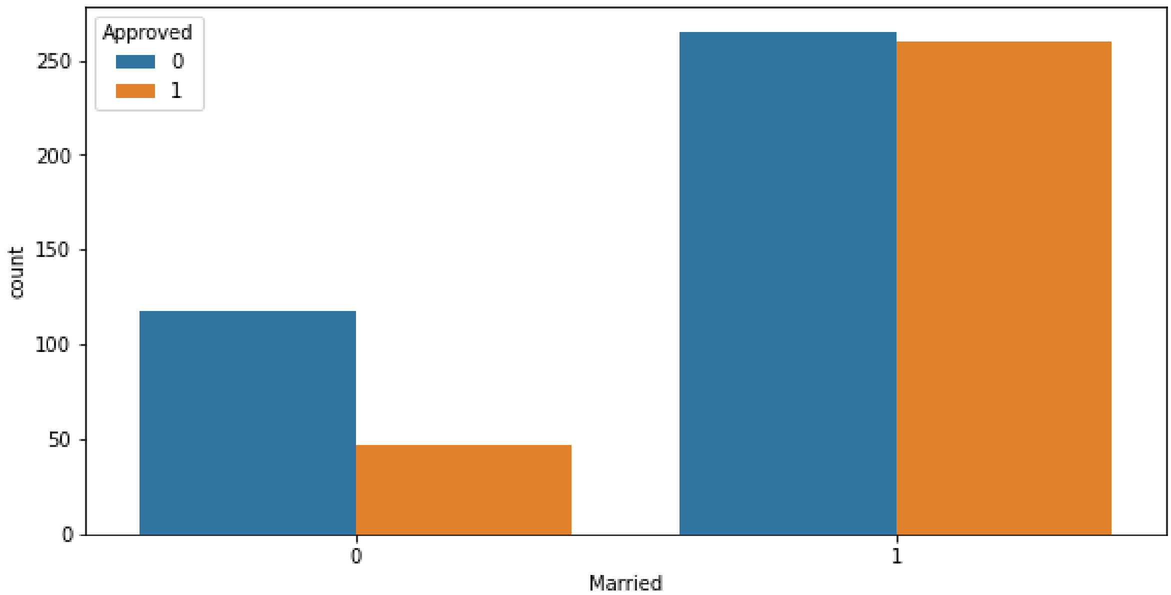
```
for i in category:
    print(i+":")
    plt.figure(figsize=(10,5))
    sns.countplot(x=i,data=df,hue="Approved")
    plt.show()
    a=np.array(pd.crosstab(df.Approved,df[i]))
    (stats,p,dof,_)=chi2_contingency(a,correction=False)
    if p>0.05:
        print(Fore.RED + "'{}'is a 'bad Predictor'".format(i))
        print('p_val={}\n'.format(p))
    else:
        print(Fore.GREEN + "'{}' is a Good Predictor".format(i))
        print('p_val={}\n'.format(p))
```

Gender:

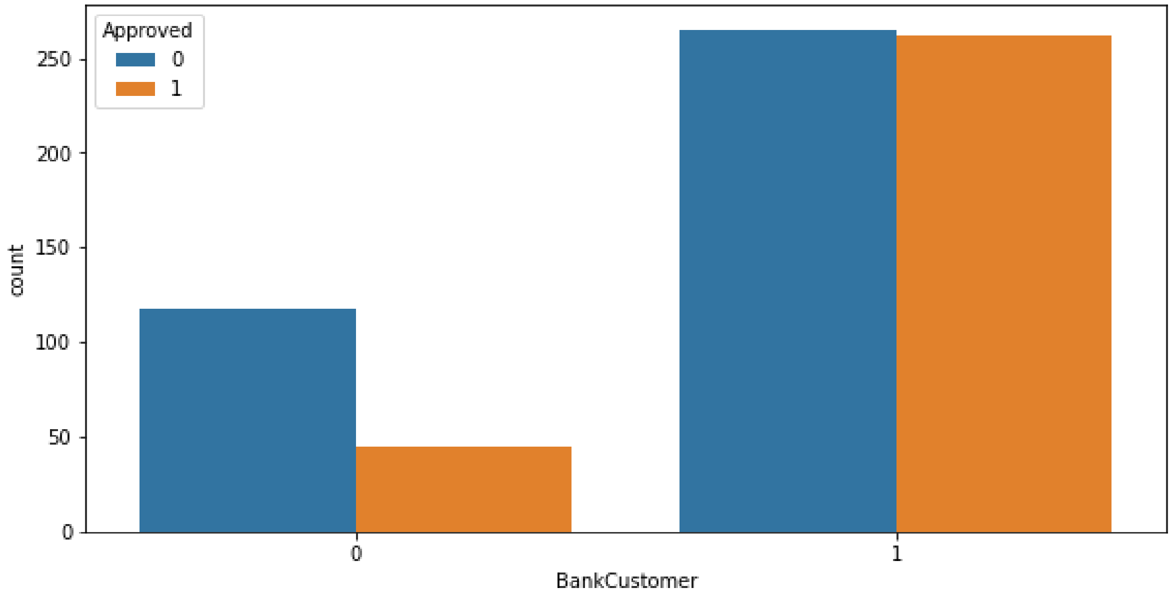


'Gender'is a 'bad Predictor'
p_val=0.44723087514133186

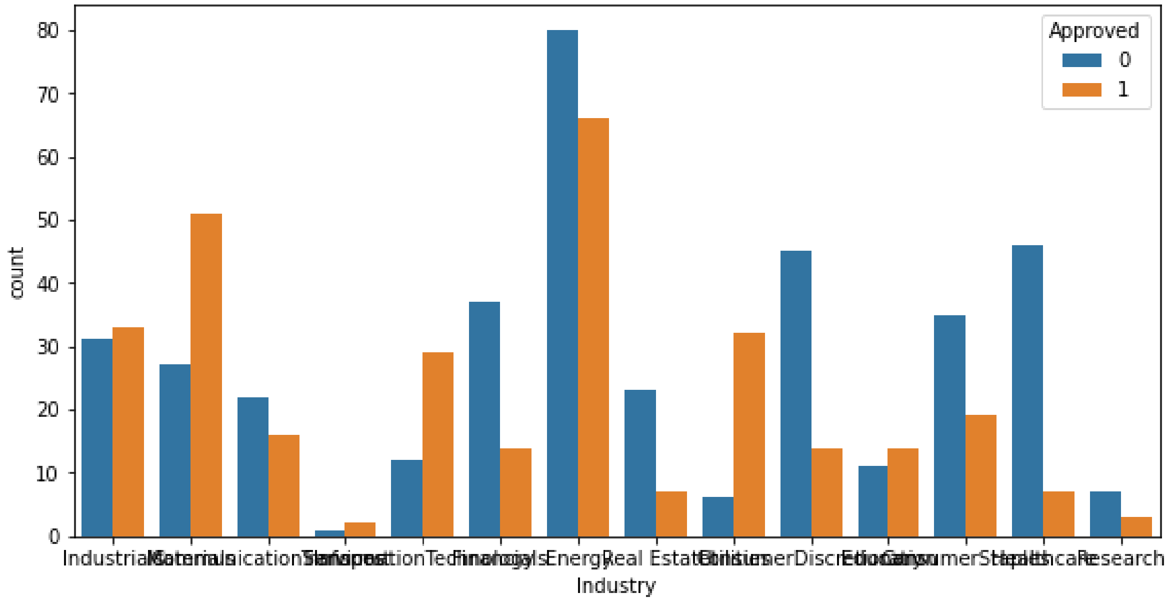
Married:



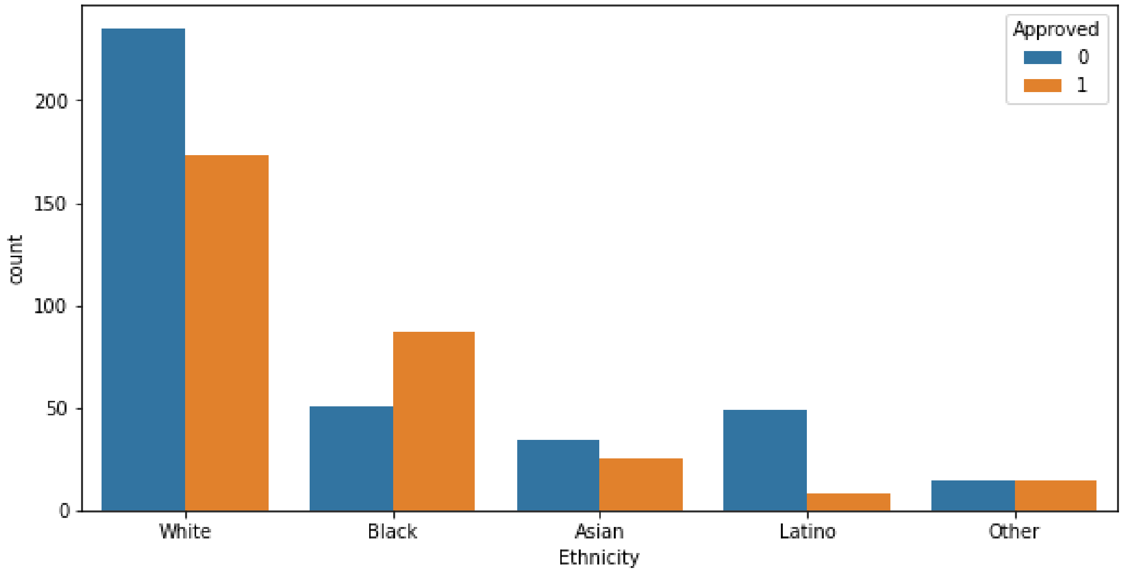
```
'Married' is a Good Predictor
p_val=2.100231920165588e-06

BankCustomer:
```



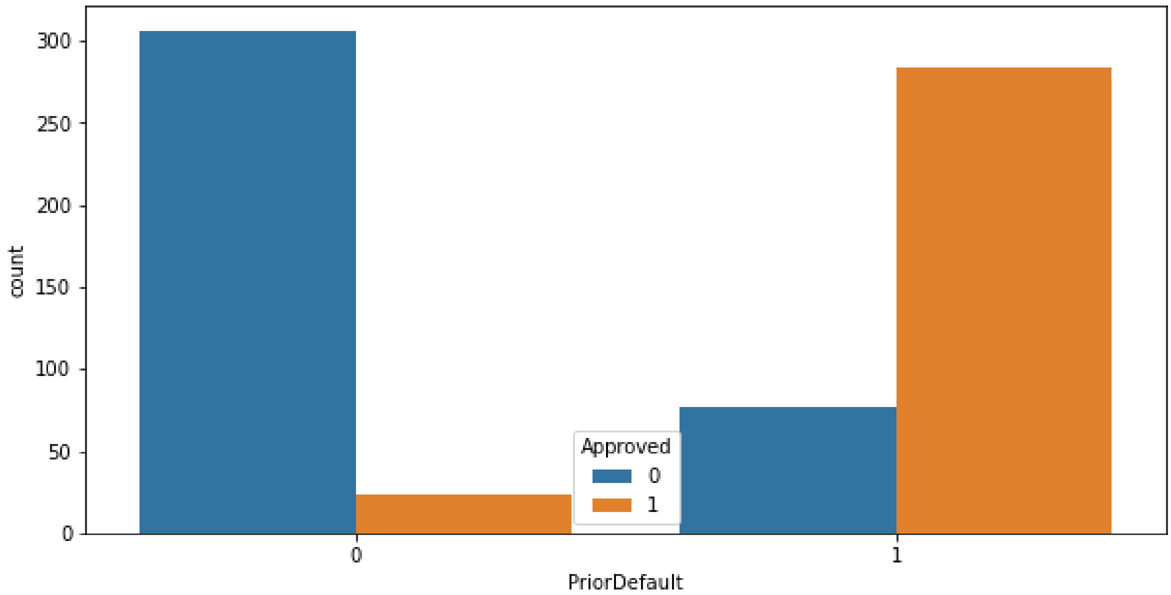

```
'BankCustomer' is a Good Predictor
p_val=6.916613205418033e-07

Industry:
```




```
'Industry' is a Good Predictor
p_val=3.502987066102042e-15

Ethnicity:
```



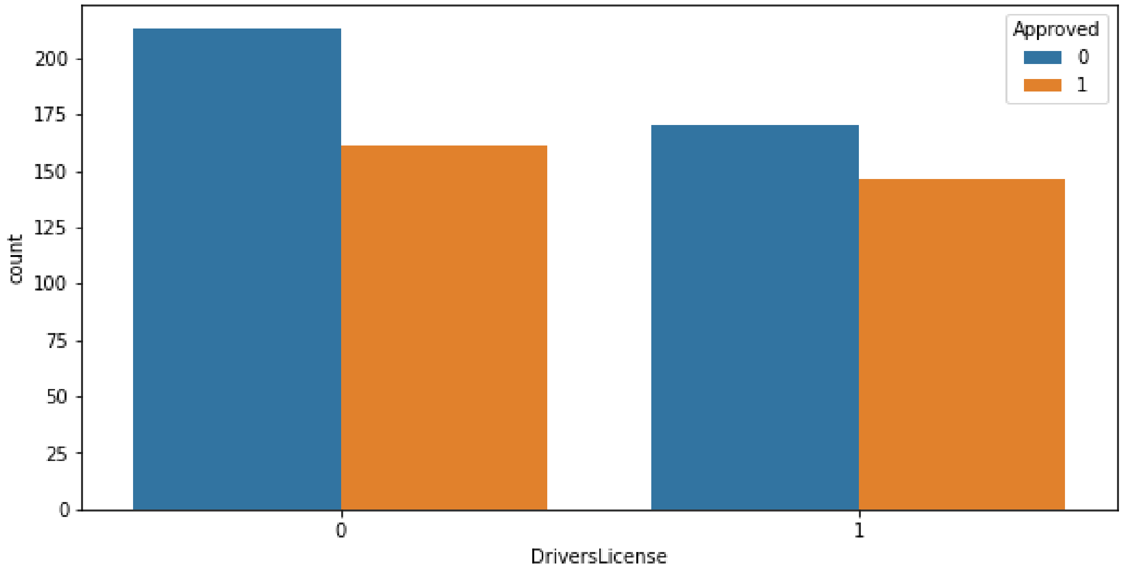

```
'Ethnicity' is a Good Predictor
p_val=1.823665654934685e-08

PriorDefault:
```




```
'PriorDefault' is a Good Predictor
p_val=7.298530125411298e-80

Employed:
```

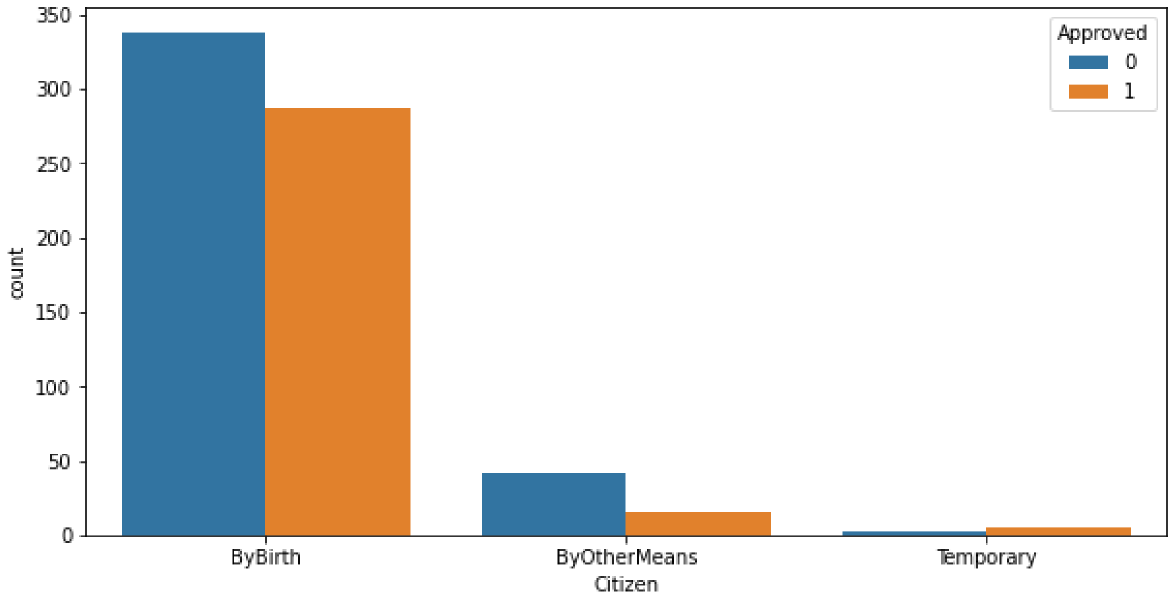
'Employed' is a Good Predictor
p_val=2.227269345312281e-33

DriversLicense:



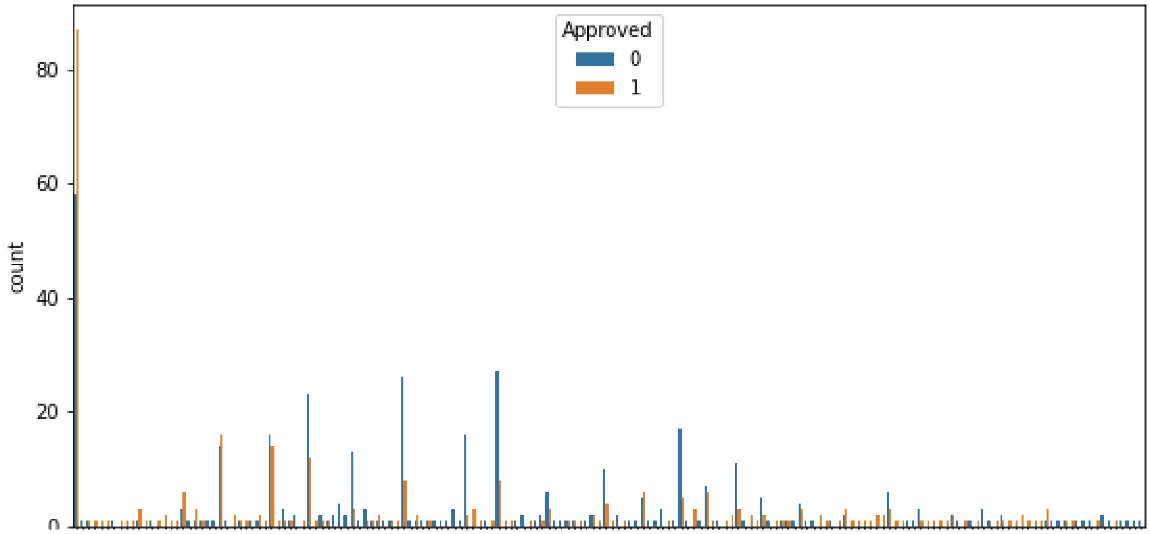
'DriversLicense'is a 'bad Predictor'
p_val=0.4061341323141693

Citizen:

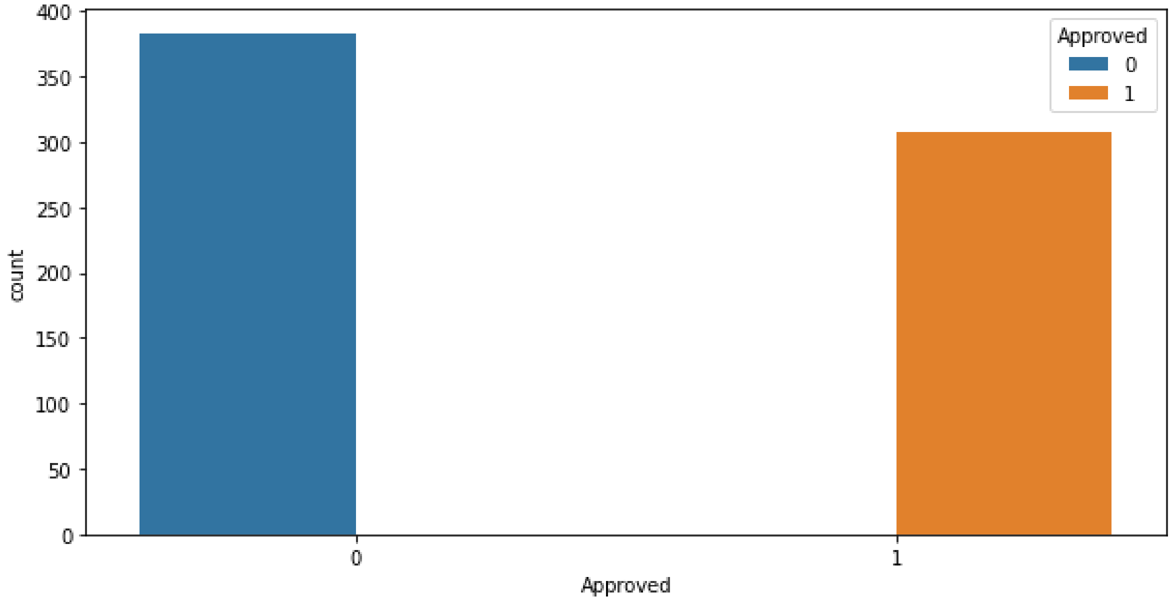


'Citizen' is a Good Predictor
p_val=0.010094291370456362

ZipCode:




```
'ZipCode' is a Good Predictor
p_val=0.006354824252183887

Approved:
```




```
'Approved' is a Good Predictor
p_val=4.469841378183071e-152
```

Gender:

"we see that majority of credit card holders are males " "since Gender is a bad predictor towards Approval we drop the attribute"

In [44]:

```
df.drop(['Gender'],1,inplace=True)
```

```
C:\Users\SMFL-20531\AppData\Local\Temp\ipykernel_14400\2126209942.py:1: Futu
reWarning: In a future version of pandas all arguments of DataFrame.drop exc
ept for the argument 'labels' will be keyword-only.
  df.drop(['Gender'],1,inplace=True)
```

Married:

"we see that majority of credit card holders are Married "

BankCustomer:

"we see that majority of credit card holders are BankCustomers only " "we see that BankCustomers have equal probability of getting approval to not getting approval of credit card " "If the Applicant is not BankCustomers then he/she has higher probability of getting approval of credit card "

Industry:

"we see that majority of credit card holders are people working in Energy sector " "There is Heigh Probability of credit card approval if he/she working in HealthCare sector"

Ethnicity:

"we see that people belonging to White ethnicity use credit card majorly "

PriorDefault:

"we see that people with no defaults have high probability of creditcard approval " "we see that people with payment defaults have less probability of creditcard approval "

DriversLicense:

"we see that majority of credit card holders have DrivingLicense" "since DriversLicense is a bad predictor towards Approval we drop the attribute"

In [45]:

```
df.drop(['DriversLicense'],1,inplace=True)
```

```
C:\Users\SMFL-20531\AppData\Local\Temp\ipykernel_14400\2114335881.py:1: Futu
reWarning: In a future version of pandas all arguments of DataFrame.drop exc
ept for the argument 'labels' will be keyword-only.
  df.drop(['DriversLicense'],1,inplace=True)
```

Citizen:

"we see that majority of credit card holders have Citizenship bybirth"

Continious type of variable:

In [46]:

```
column_names=df.columns.tolist()
continious=list(set(column_names)-set(category))
```

In [47]:

```
continious
```

Out[47]:

```
['Income', 'Age', 'YearsEmployed', 'CreditScore', 'Debt']
```

In [48]:

```
df.loc[:,continious]
```

Out[48]:

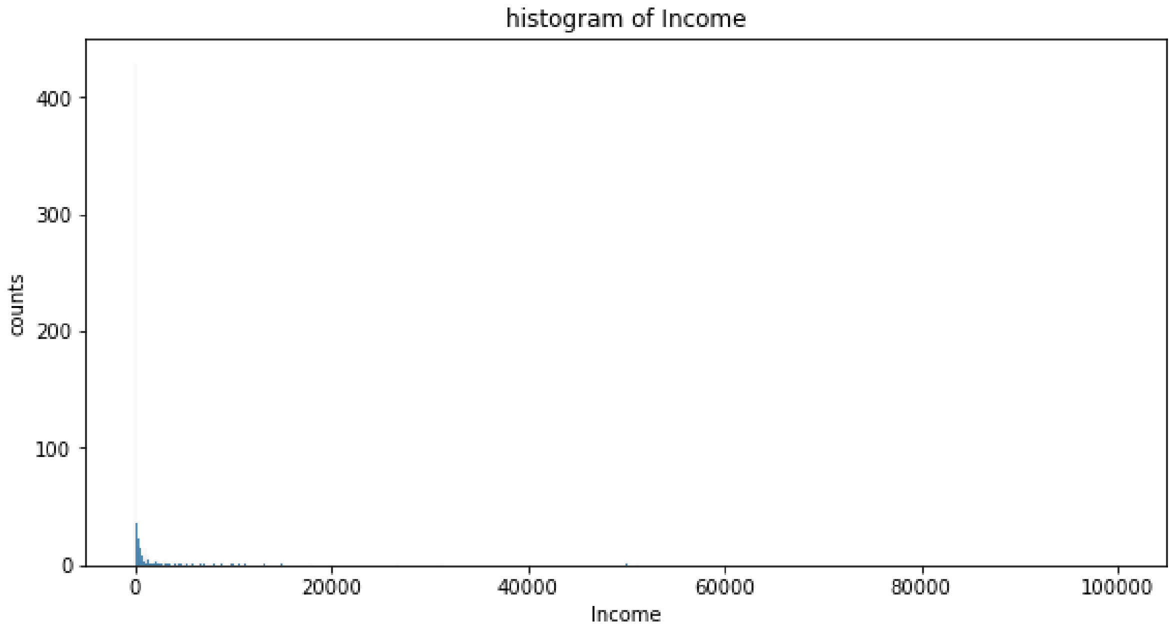
	Income	Age	YearsEmployed	CreditScore	Debt
0	0	30.83	1.25	1	0.000
1	560	58.67	3.04	6	4.460
2	824	24.50	1.50	0	0.500
3	3	27.83	3.75	5	1.540
4	0	20.17	1.71	0	5.625
...	...	...	...	...	...
685	0	21.08	1.25	0	10.085
686	394	22.67	2.00	2	0.750
687	1	25.25	2.00	1	13.500
688	750	17.92	0.04	0	0.205
689	0	35.00	8.29	0	3.375

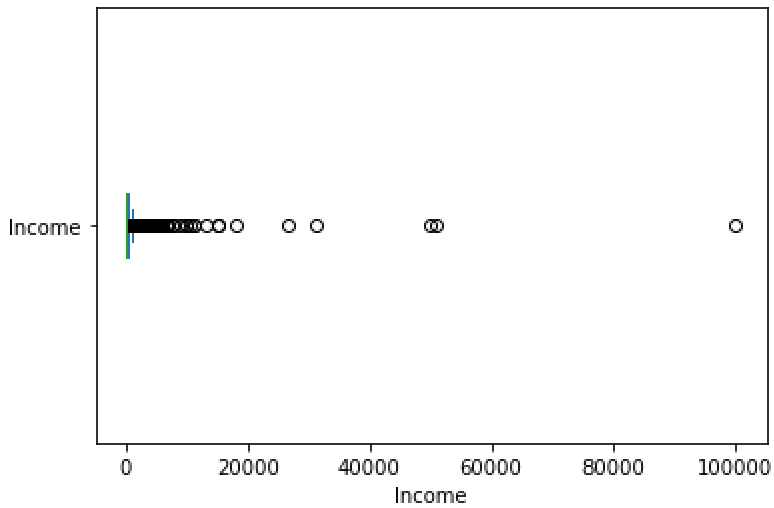
690 rows × 5 columns

In [49]:

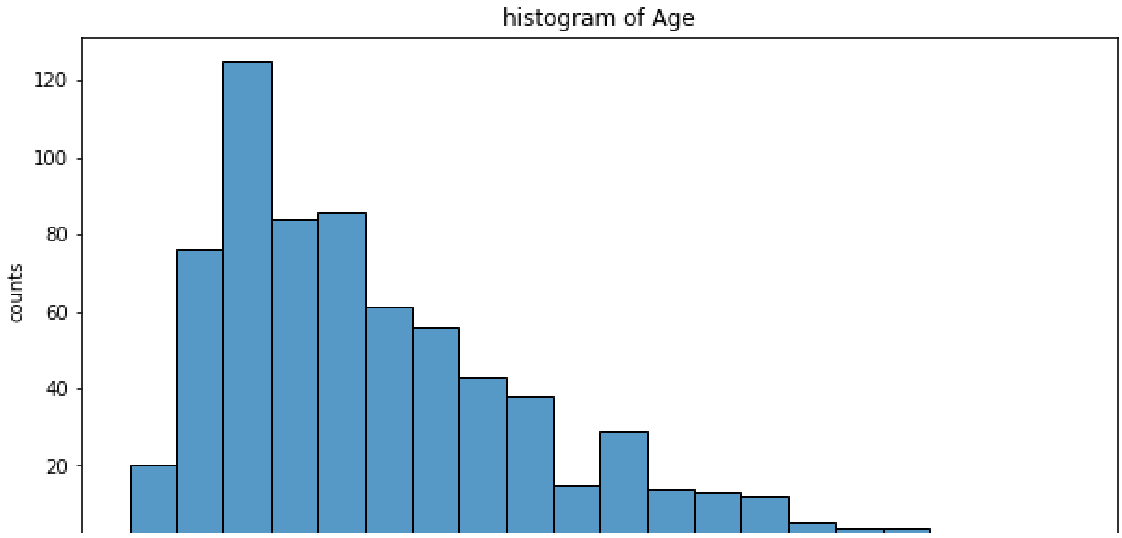
```
for i in continious:
    print(i+':')
    plt.figure(figsize=(10,5))
    sns.histplot(df[i])
    plt.xlabel(i)
    plt.ylabel('counts')
    plt.title('histogram of ' + i)
    plt.show()
    df[i].plot.box(vert=False,patch_artist=True)
    plt.xlabel(i)
    plt.show()
```

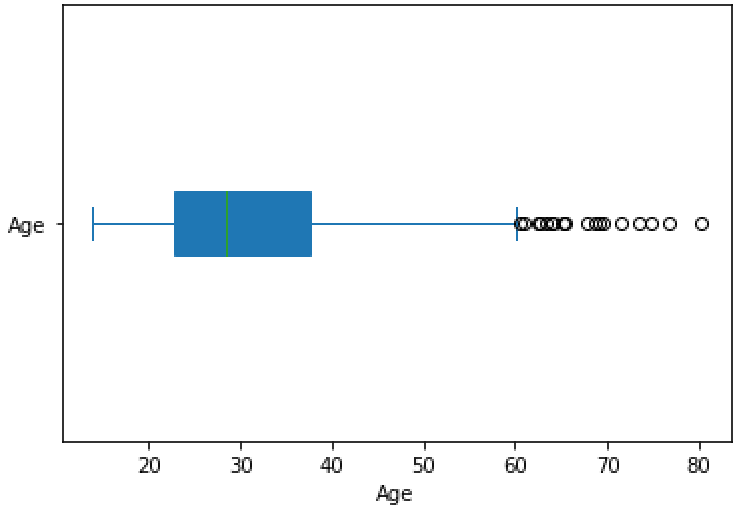
Income:



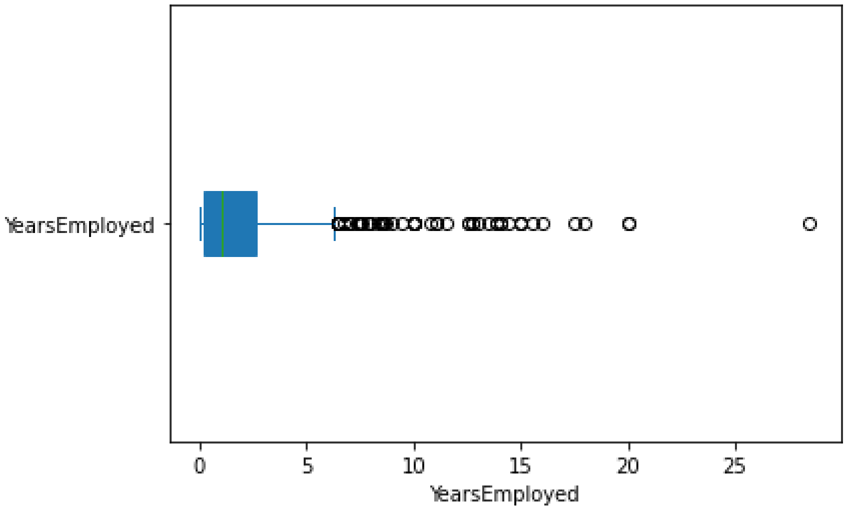


Age:

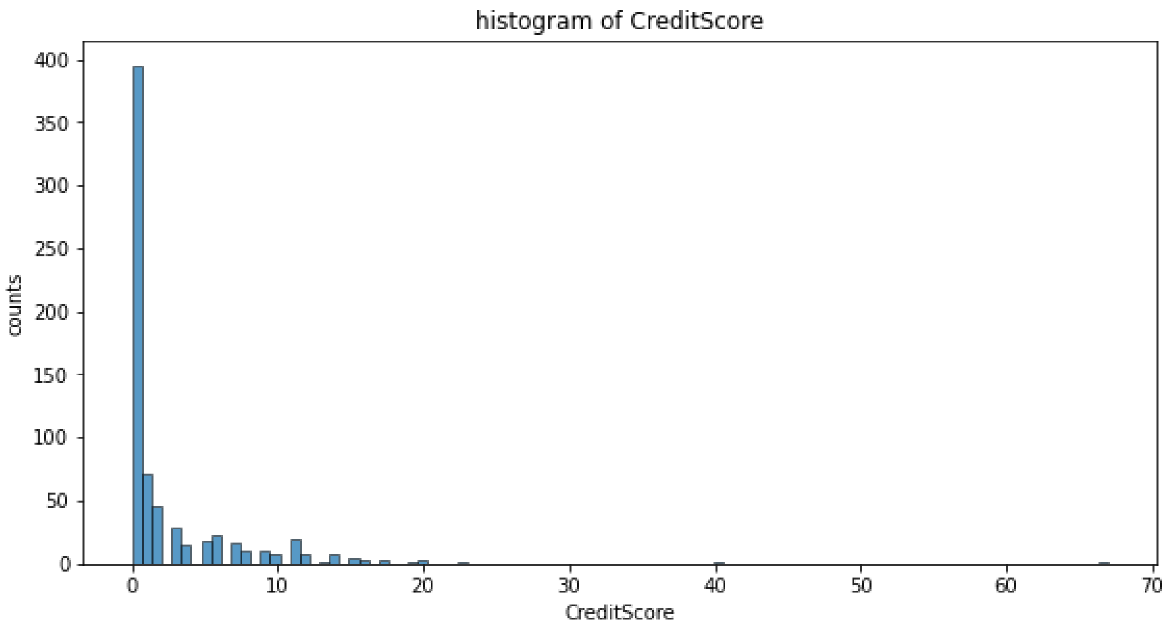


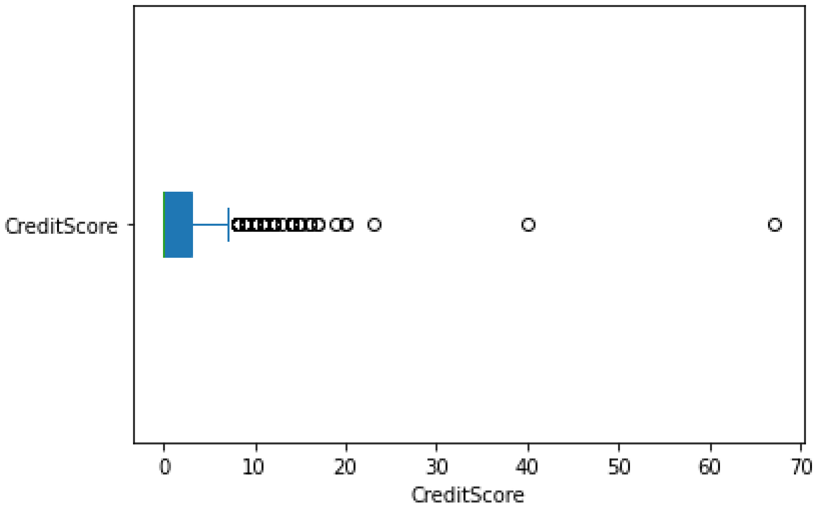


YearsEmployed:

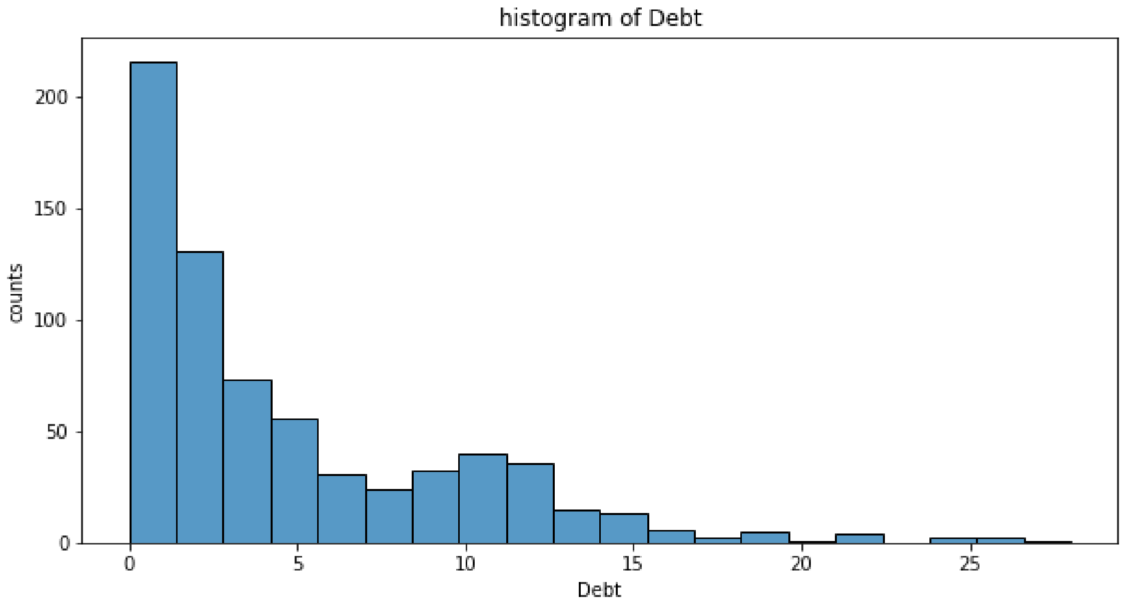


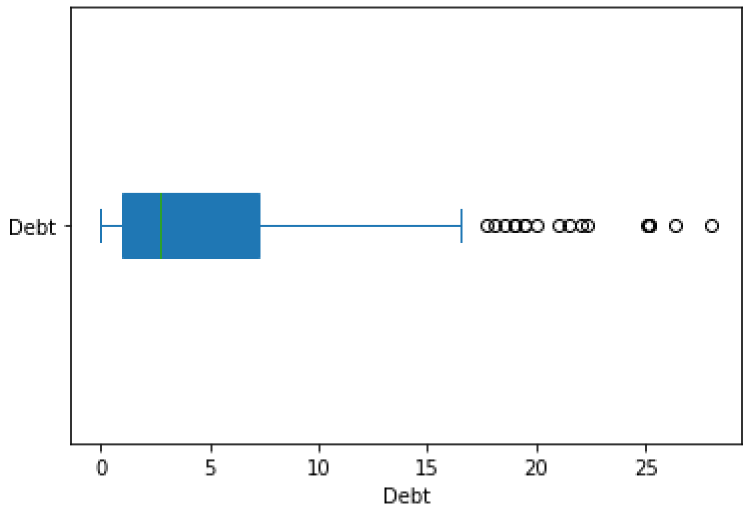
CreditScore:





Debt:





Treating Outliers:

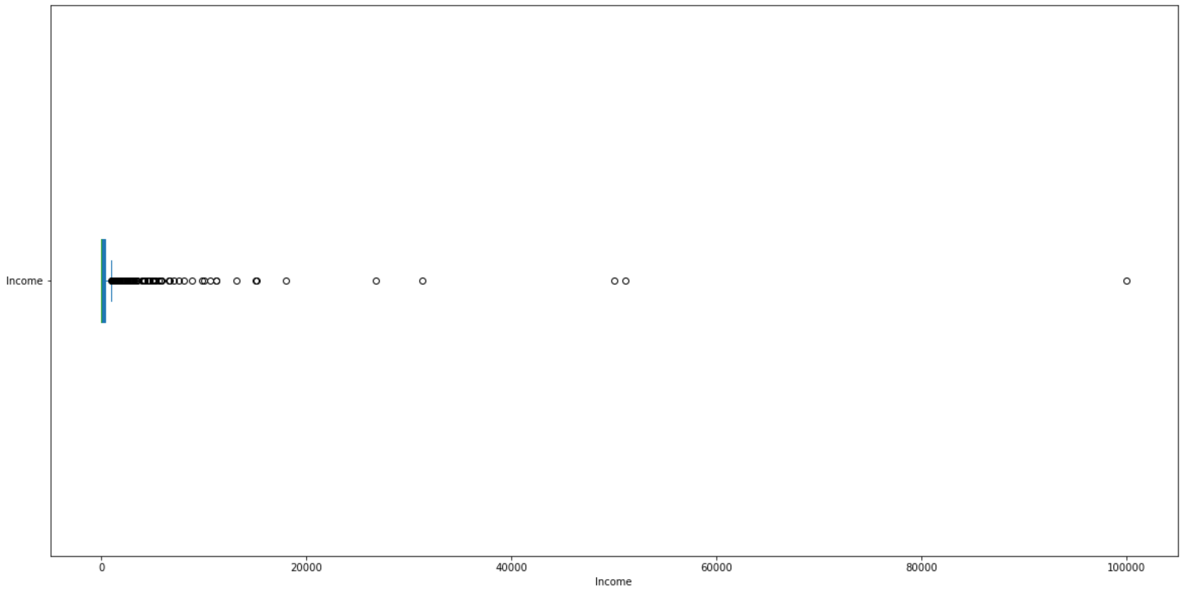
In [50]:

```
iqr=iqr
```

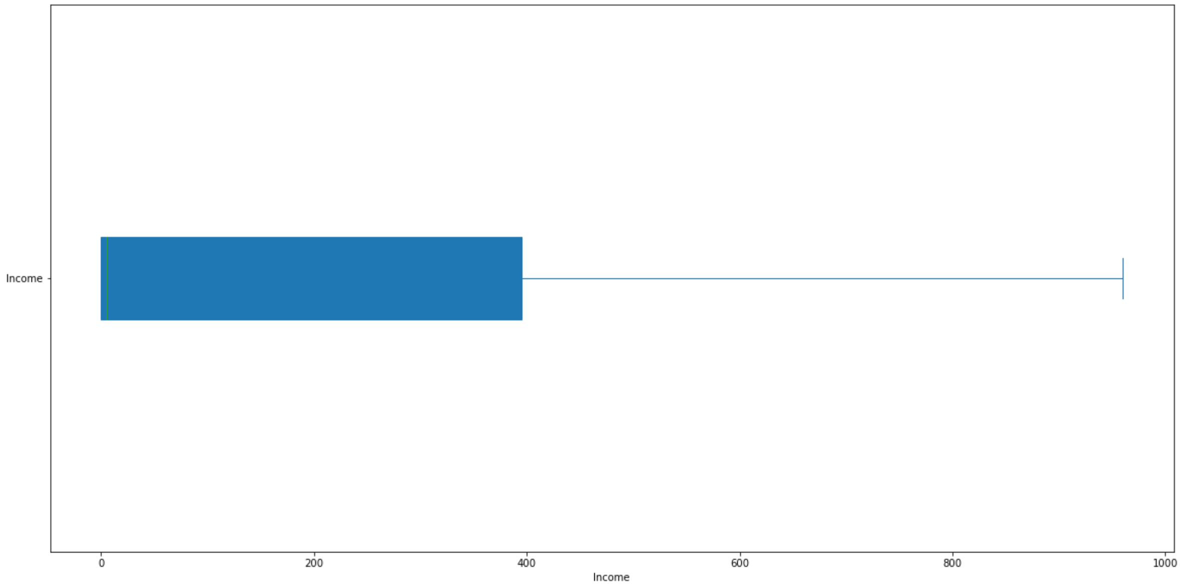
In [51]:

```
for i in continious:
    print(i+":")
    plt.figure(figsize=(20,10))
    df[i].plot.box(vert=False,patch_artist=True)
    plt.xlabel(i)
    plt.show()

    iqr=df[i].describe()['75%']-df[i].describe()['25%']
    right_lim=df[i].quantile(0.75)+1.5*iqr
    left_lim=df[i].quantile(0.25)-1.5*iqr
    print('Left Limit:{}'.format(left_lim))
    print('Right Limit:{}'.format(right_lim))
    print('iqr:{}'.format(iqr))

    a=input("if left outlier type 'left' else 'right' else 'both' if no outliers then type
    a=a.lower()
    if a=='left':
        lo=float(input('by what number do you want to replace'))
        df[i]=[lo if val<left_lim else val for val in df[i]]
    elif a=='right':
        ro=float(input('by what number do you want to replace'))
        df[i]=[ro if val>right_lim else val for val in df[i]]
    elif a=='both':
        lo=float(input('by what number do you want to replace'))
        ro=float(input('by what number do you want to replace'))
        df[i]=[ro if val>right_lim else val for val in df[i]]
        df[i]=[lo if val<left_lim else val for val in df[i]]
    elif a=='no':
        pass
    plt.figure(figsize=(20,10))
    df[i].plot.box(vert=False,patch_artist=True)
    plt.xlabel(i)
    plt.show()
```

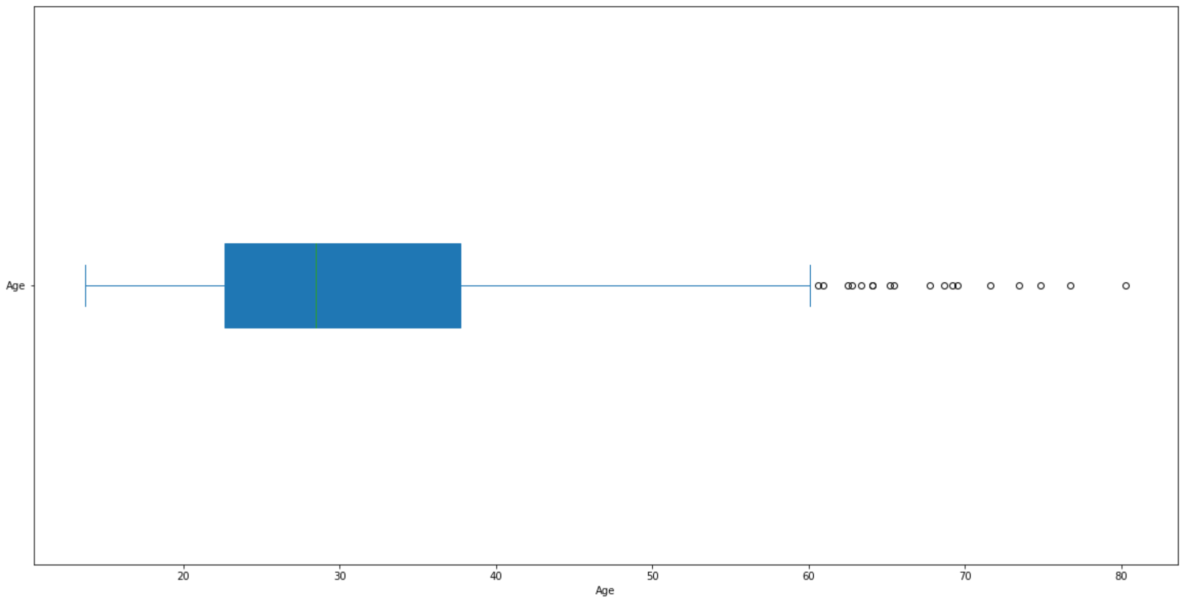
Income:



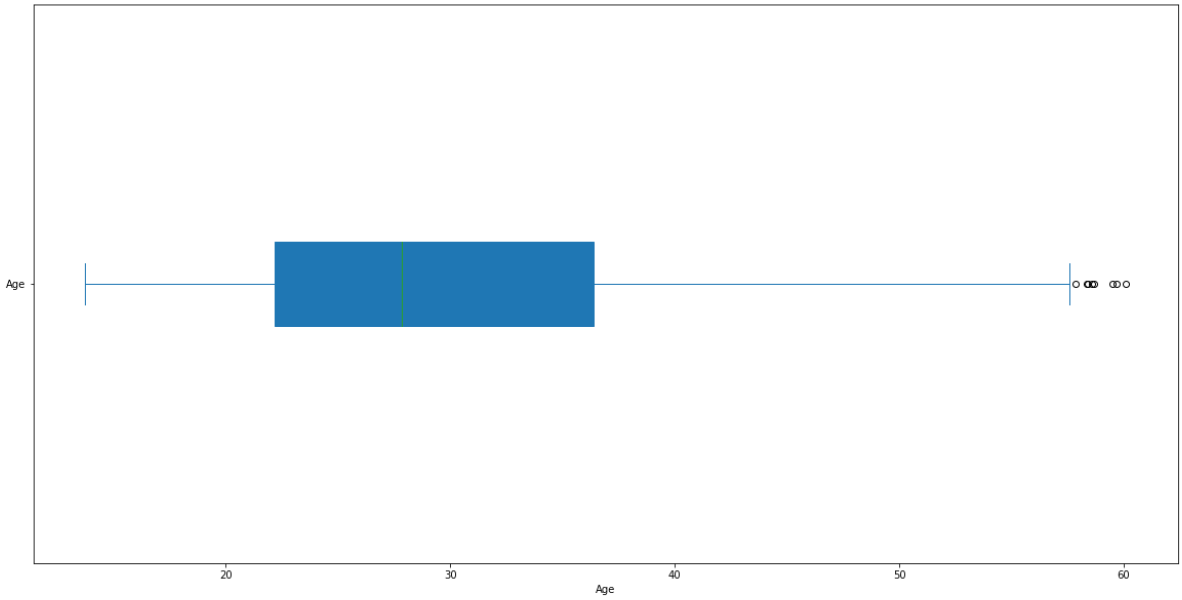
Left Limit:-593.25
Right Limit:988.75
iqr:395.5
if left outlier type 'left' else 'right' else 'both' if no outliers then typ
e 'no'right
by what number do you want to replace395.5



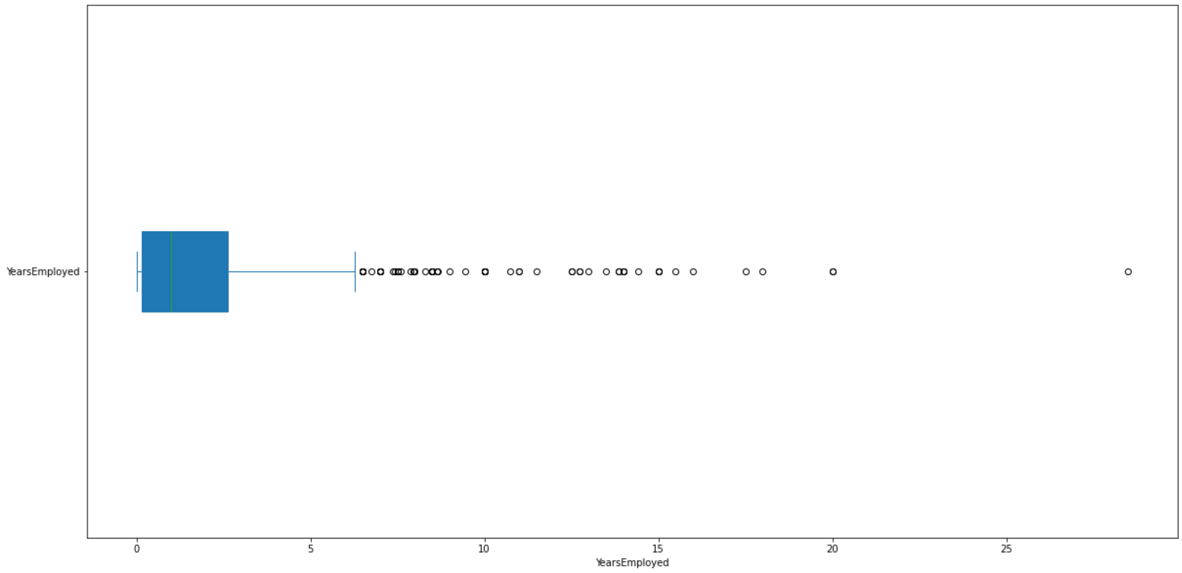
Age:



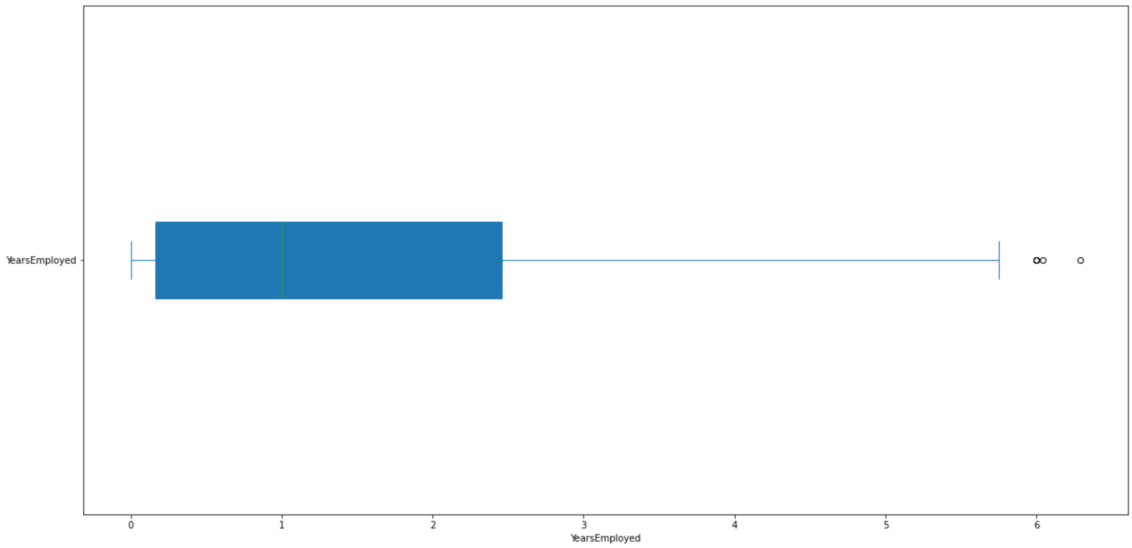
Left Limit:0.11375000000001023
Right Limit:60.26374999999999
iqr:15.037499999999994
if left outlier type 'left' else 'right' else 'both' if no outliers then typ
e 'no'right
by what number do you want to replace15.03



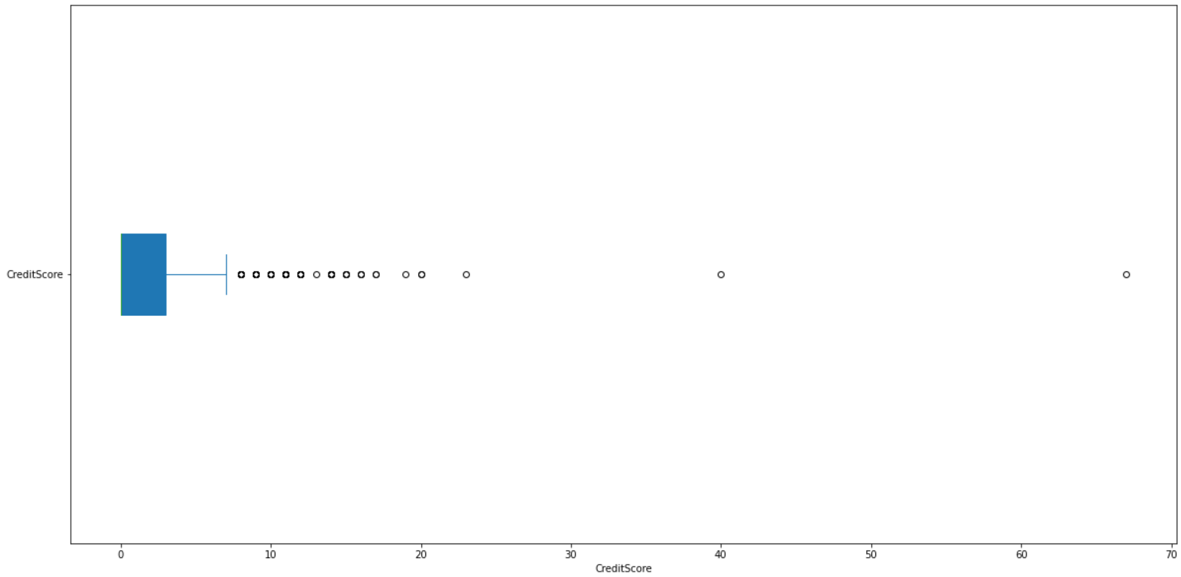
YearsEmployed:



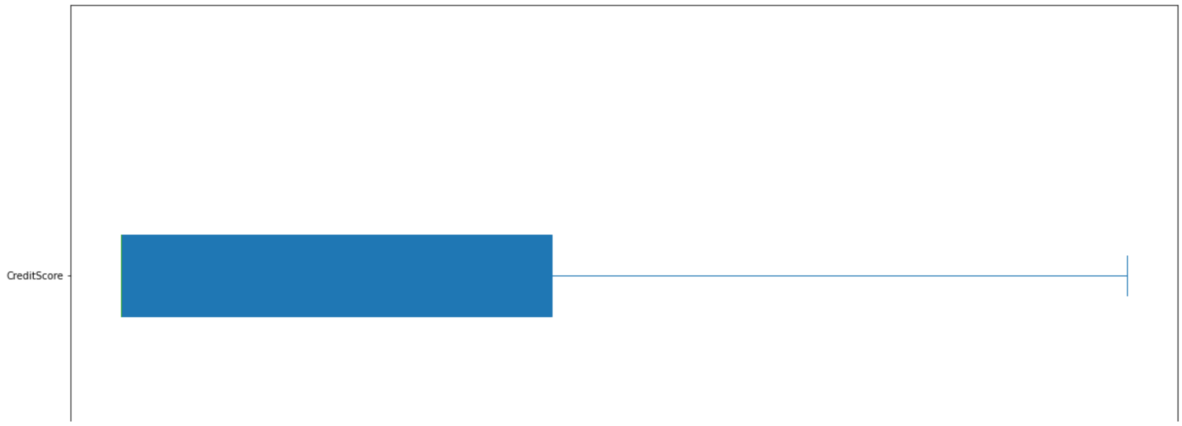

```
Left Limit:-3.525
Right Limit:6.3149999999999995
iqr:2.46
if left outlier type 'left' else 'right' else 'both' if no outliers then typ
e 'no'right
by what number do you want to replace2.46
```



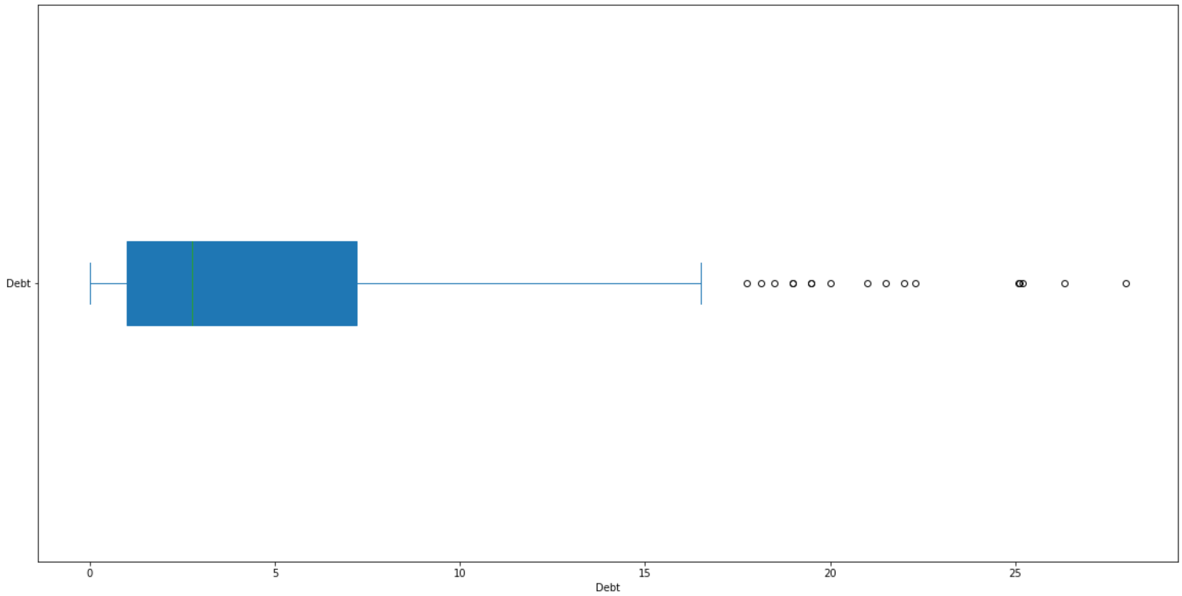
CreditScore:



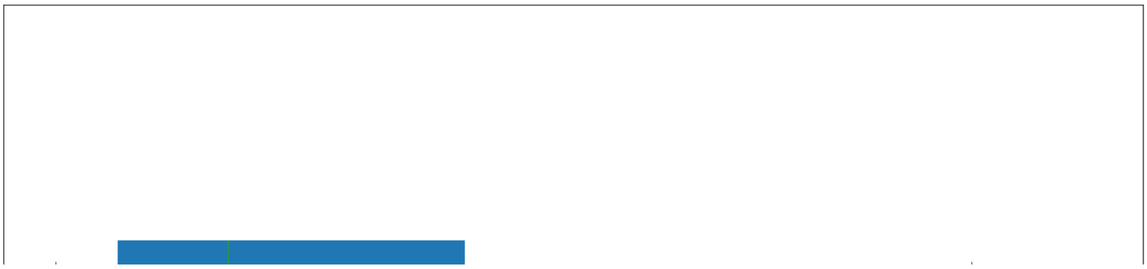

```
Left Limit:-4.5
Right Limit:7.5
iqr:3.0
if left outlier type 'left' else 'right' else 'both' if no outliers then typ
e 'no'right
by what number do you want to replace3.0
```



Debt:



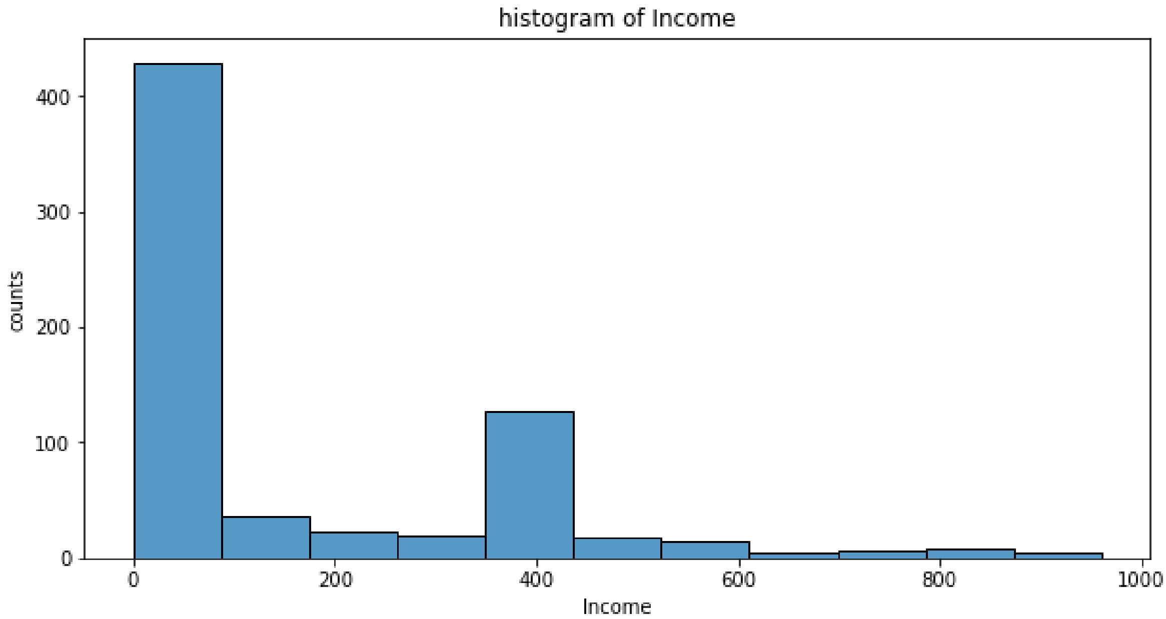

```
Left Limit:-8.31125
Right Limit:16.518749999999997
iqr:6.2075
if left outlier type 'left' else 'right' else 'both' if no outliers then typ
e 'no'right
by what number do you want to replace6.2075
```

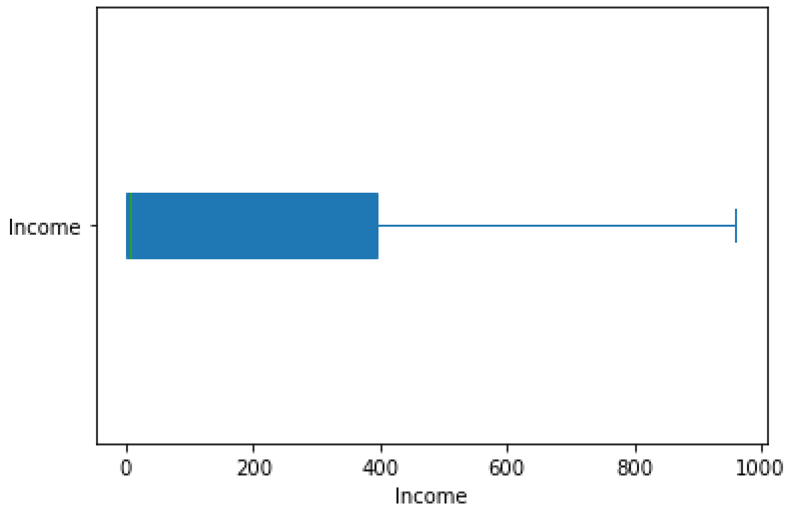


In [53]:

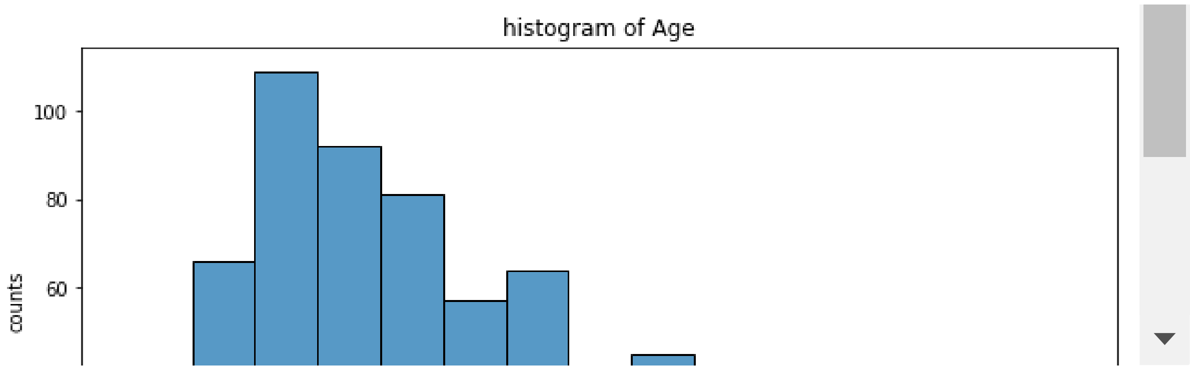
```
for i in continious:
    print(i+":")
    plt.figure(figsize=(10,5))
    sns.histplot(df[i])
    plt.xlabel(i)
    plt.ylabel('counts')
    plt.title('histogram of '+i)
    plt.show()
    df[i].plot.box(vert=False,patch_artist=True)
    plt.xlabel(i)
    plt.show()
```

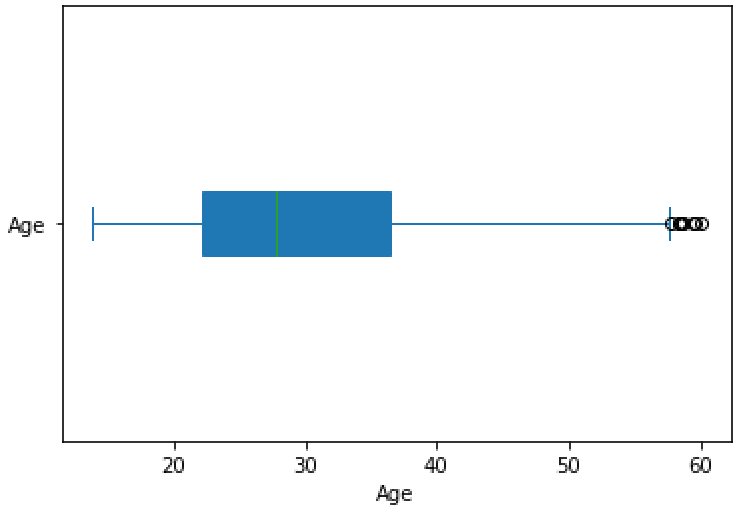
Income:



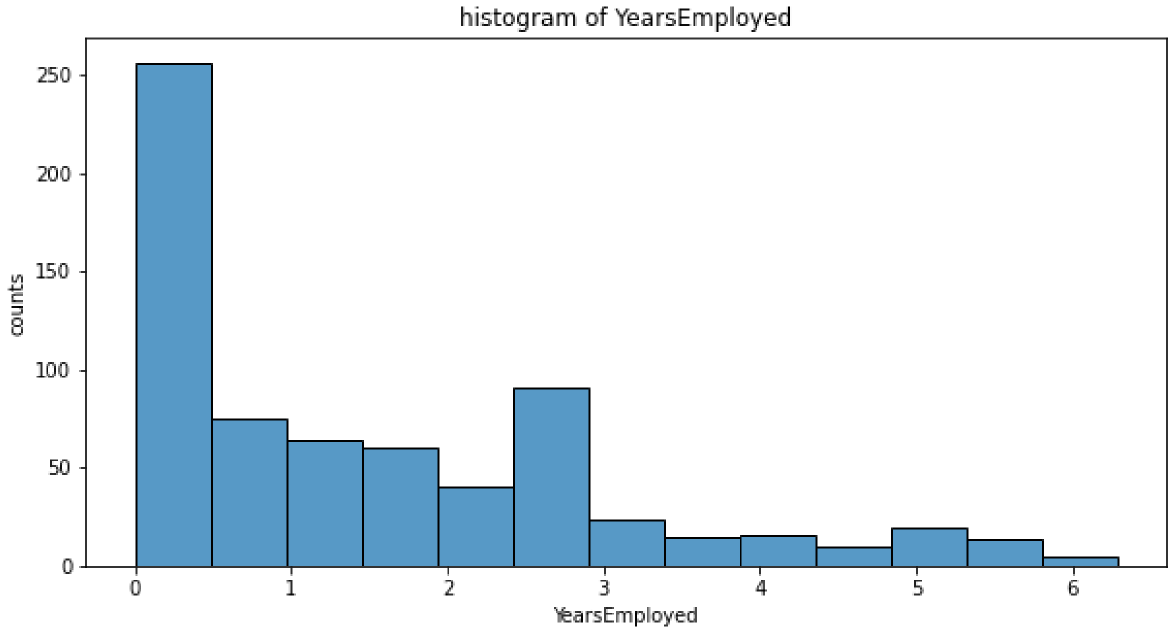


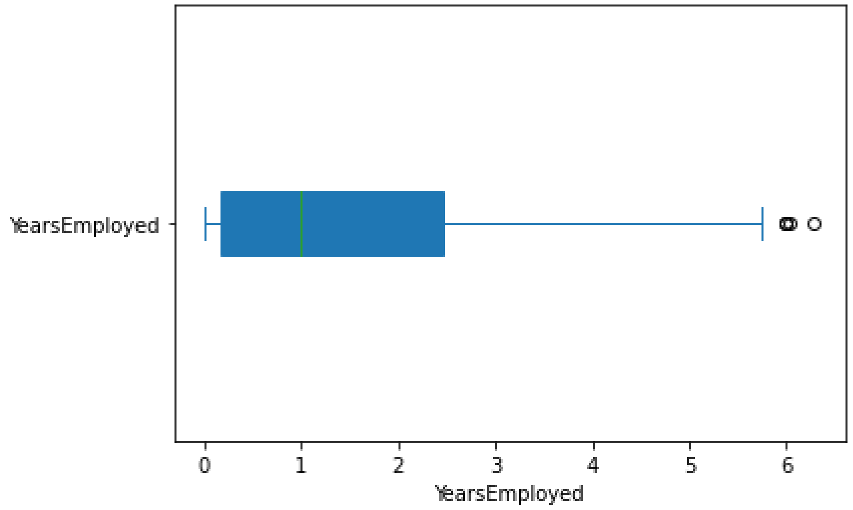
Age:



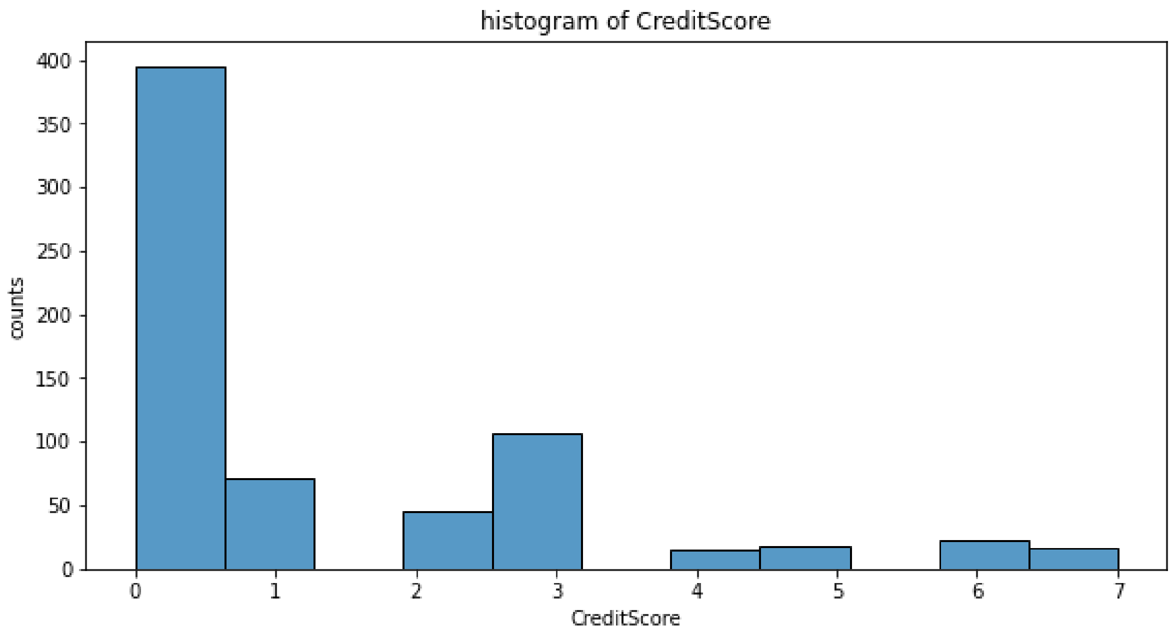


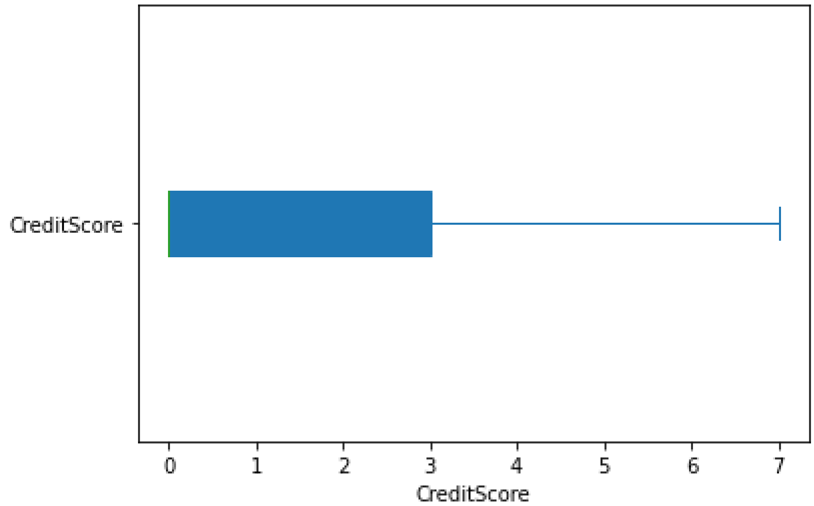
YearsEmployed:





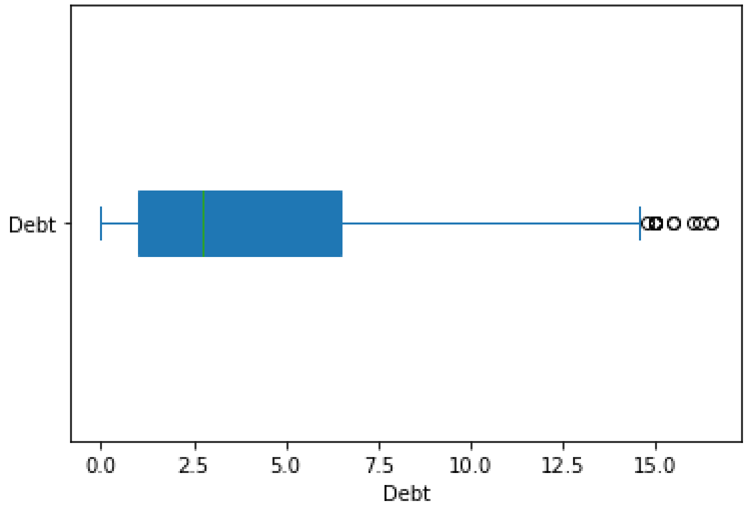
CreditScore:





Debt:

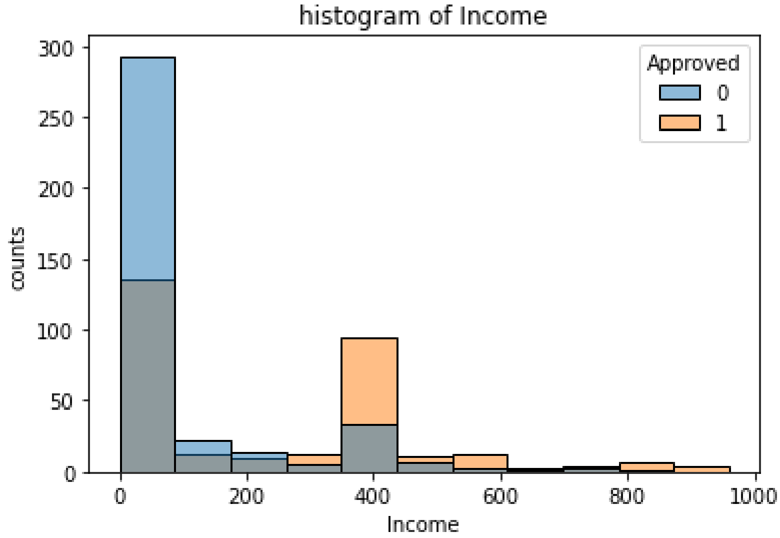

histogram of Debt
counts
200
175
150
125
100
75
50

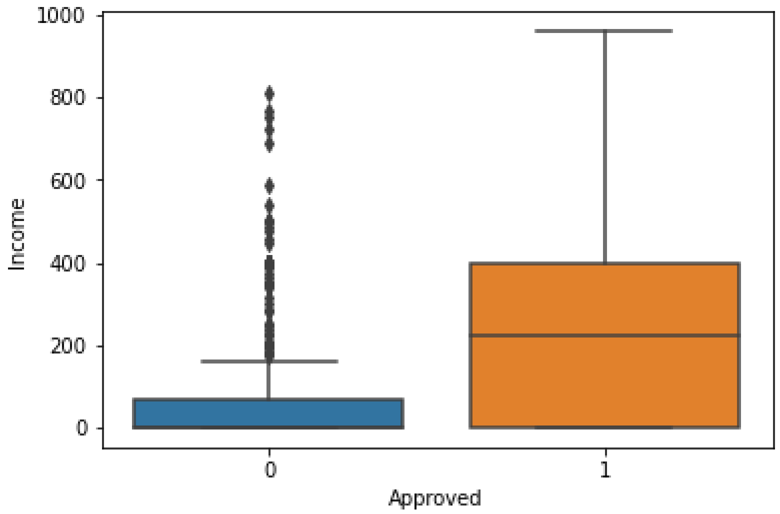

Debt
0.0
2.5
5.0
7.5
10.0
12.5
15.0
Debt

In [54]:

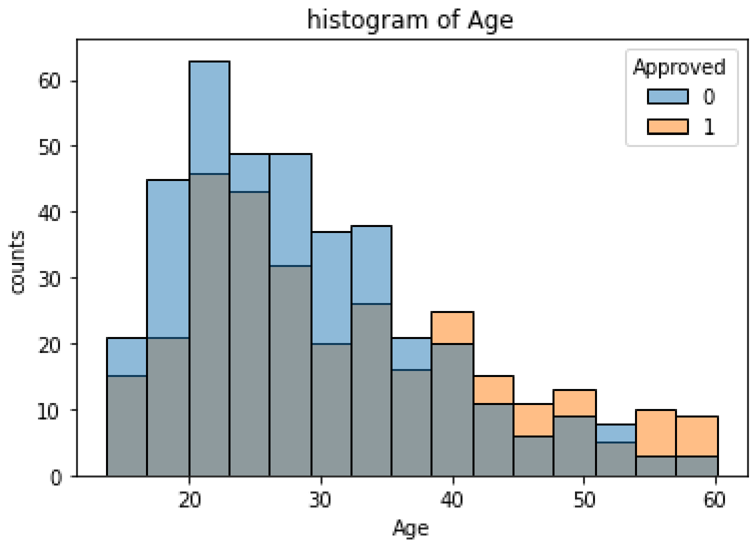
```
for i in continious:
    print(i+":")
    sns.histplot(x=df[i],hue=df.Approved)
    plt.xlabel(i)
    plt.ylabel('counts')
    plt.title('histogram of '+ i)
    plt.show()
    sns.boxplot(y=df[i],x=df.Approved)
    plt.show()
```

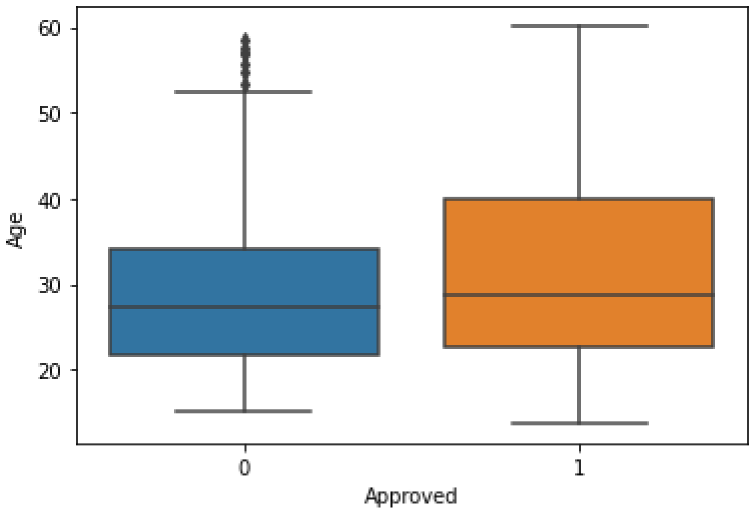
Income:



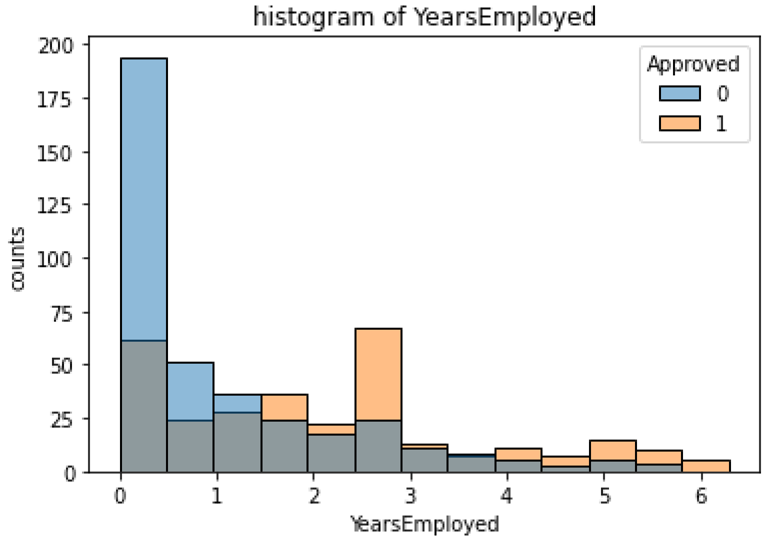


Age:

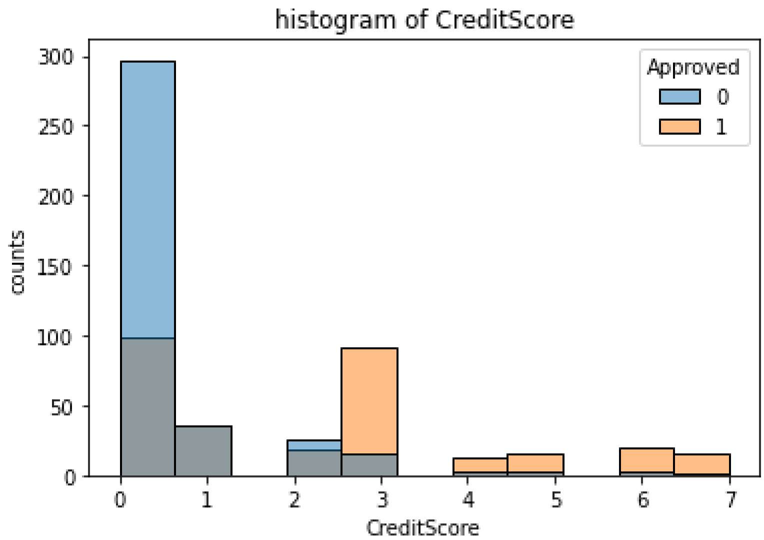


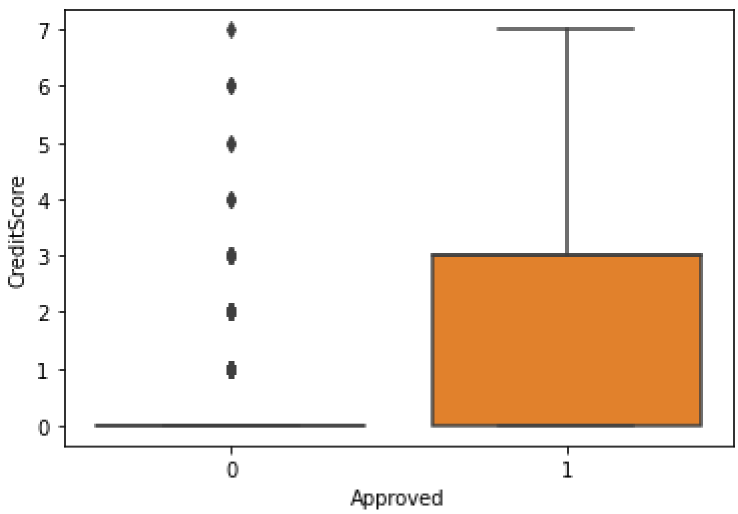


YearsEmployed:

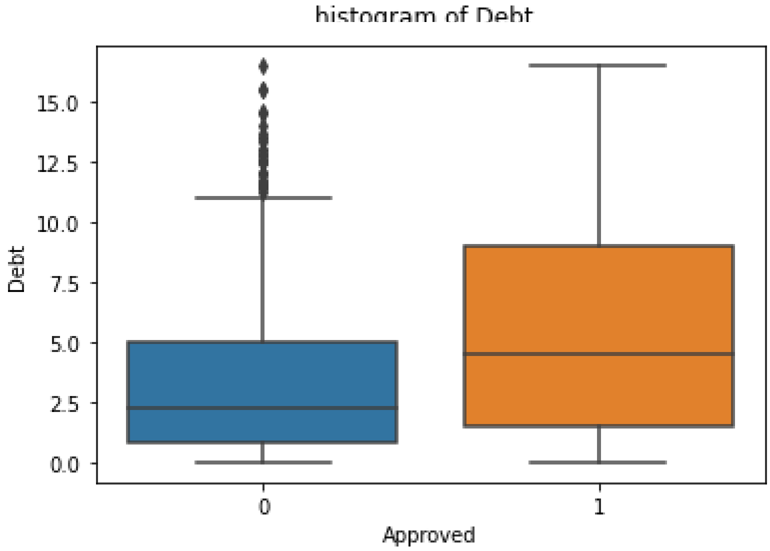


CreditScore:





Debt:



Statistical Testing using Anova:

In [57]:

```
from statsmodels.stats.multicomp import pairwise_tukeyhsd
from statsmodels.formula.api import ols
import statsmodels.api as smf
```

In [58]:

```
for i in continious:
    print("-----------------------------------------------------------------------------------
    print(i+":\n")
    print('ANOVA:\n')
    mod=ols(i+'~Approved',data=df).fit()
    aov_table=smf.stats.anova_lm(mod,type = 2)
    print(aov_table,'\n')
    print('Pvalue={}\n'.format(aov_table['PR(>F)'][0]))
    p=aov_table['PR(>F)'][0]

    if p>0.05:
        print(Fore.RED +"'{}' is a 'bad Predictor'\n".format(i))
        print('Avg of this feature is same for both card approved group and not approved gr
        print("p_val = {}\n".format(p))
    else:
        print('TUKEY:\n')
        print(Fore.RED +"'{}' is a 'good Predictor'\n".format(i))
        print('Avg of this feature is not same for both card approved group and not approve
        print('we need to perform Tuckey as atleast one category is different\n')
        print(Fore.GREEN +"'{}' is a 'good Predictor'\n".format(i))
        tukey=pairwise_tukeyhsd(df[i],df.Approved,alpha=0.05)
        print(tukey,'\n')
```

```
----------------------------------------------------------------------------
---------------------------------------
Income:

ANOVA:

             df        sum_sq       mean_sq           F        PR(>F)
Approved    1.0  4.161531e+06  4.161531e+06  104.814081  5.417547e-23
Residual  688.0  2.731631e+07  3.970393e+04         NaN           NaN

Pvalue=5.4175472814508e-23

TUKEY:

'Income' is a 'good Predictor'

Avg of this feature is not same for both card approved group and not approve
d group

we need to perform Tuckey as atleast one category is different

'Income' is a 'good Predictor'

 Multiple Comparison of Means - Tukey HSD, FWER=0.05
=====================================================
group1 group2 meandiff p-adj  lower    upper   reject
-----------------------------------------------------
     0      1 156.2725  -0.0 126.3026 186.2424   True
-----------------------------------------------------


----------------------------------------------------------------------------
---------------------------------------
Age:

ANOVA:
```

```
              df        sum_sq      mean_sq          F    PR(>F)
Approved    1.0   1565.625577  1565.625577  14.427262  0.000159
Residual  688.0  74660.762713   108.518550        NaN       NaN

Pvalue=0.00015856086530408587

TUKEY:

'Age' is a 'good Predictor'

Avg of this feature is not same for both card approved group and not approve
d group

we need to perform Tuckey as atleast one category is different

'Age' is a 'good Predictor'

Multiple Comparison of Means - Tukey HSD, FWER=0.05
==================================================
group1 group2 meandiff p-adj  lower  upper  reject
--------------------------------------------------
     0      1   3.0311 0.0002 1.4643 4.5979   True
--------------------------------------------------

-----------------------------------------------------------------------------
---------------------------------------
YearsEmployed:

ANOVA:

              df      sum_sq     mean_sq           F        PR(>F)
Approved    1.0   200.03432  200.034320  100.012285  4.467613e-22
Residual  688.0  1376.06708    2.000098         NaN           NaN

Pvalue=4.467613399885831e-22

TUKEY:

'YearsEmployed' is a 'good Predictor'

Avg of this feature is not same for both card approved group and not approve
d group

we need to perform Tuckey as atleast one category is different

'YearsEmployed' is a 'good Predictor'

Multiple Comparison of Means - Tukey HSD, FWER=0.05
=================================================
group1 group2 meandiff p-adj lower  upper  reject
-------------------------------------------------
     0      1   1.0834  -0.0 0.8707 1.2962   True
-------------------------------------------------

-----------------------------------------------------------------------------
---------------------------------------
CreditScore:

ANOVA:
```

```
              df       sum_sq     mean_sq           F        PR(>F)
Approved     1.0   562.393969  562.393969  211.877834  4.856202e-42
Residual   688.0  1826.179944    2.654331         NaN           NaN

Pvalue=4.856202409405879e-42

TUKEY:

'CreditScore' is a 'good Predictor'

Avg of this feature is not same for both card approved group and not approve
d group

we need to perform Tuckey as atleast one category is different

'CreditScore' is a 'good Predictor'

Multiple Comparison of Means - Tukey HSD, FWER=0.05
=================================================
group1 group2 meandiff p-adj lower  upper  reject
-------------------------------------------------
     0      1   1.8167  -0.0 1.5716 2.0617   True
-------------------------------------------------

----------------------------------------------------------------------------
---------------------------------------
Debt:

ANOVA:

              df        sum_sq     mean_sq        F        PR(>F)
Approved     1.0    469.578045  469.578045  28.0154  1.620321e-07
Residual   688.0  11531.860794   16.761426      NaN           NaN

Pvalue=1.6203209859251425e-07

TUKEY:

'Debt' is a 'good Predictor'

Avg of this feature is not same for both card approved group and not approve
d group

we need to perform Tuckey as atleast one category is different

'Debt' is a 'good Predictor'

Multiple Comparison of Means - Tukey HSD, FWER=0.05
=================================================
group1 group2 meandiff p-adj lower  upper  reject
-------------------------------------------------
     0      1     1.66   0.0 1.0442 2.2758   True
-------------------------------------------------
```

In [59]:

```
df_industry = pd.get_dummies(df['Industry'], drop_first=True, prefix = "Industry")
```

In [61]:

```
df=pd.concat([df,df_industry],axis=1)
```

In [63]:

```
del df['Industry']
```

In [65]:

```
df_ethnicity = pd.get_dummies(df['Ethnicity'], drop_first=True, prefix = "Ethnicity")
```

In [67]:

```
df=pd.concat([df,df_ethnicity],axis=1)
```

In [68]:

```
del df['Ethnicity']
```

In [69]:

```
df_citizen = pd.get_dummies(df['Citizen'], drop_first=True, prefix = "Citizen")
```

In [71]:

```
df=pd.concat([df,df_citizen],axis=1)
```

In [74]:

```
del df['Citizen']
```

In [75]:

```
df.head()
```

Out[75]:

	Age	Debt	Married	BankCustomer	YearsEmployed	PriorDefault	Employed	CreditScore
0	30.83	0.000	1	1	1.25	1	1	1.0
1	58.67	4.460	1	1	3.04	1	1	6.0
2	24.50	0.500	1	1	1.50	1	0	0.0
3	27.83	1.540	1	1	3.75	1	1	5.0
4	20.17	5.625	1	1	1.71	1	0	0.0

5 rows × 30 columns

VIF Calculation

In [76]:

```
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [77]:

```
x = df[['Age','Debt','YearsEmployed','CreditScore','Income']]
```

In [78]:

```
x
```

Out[78]:

	Age	Debt	YearsEmployed	CreditScore	Income
0	30.83	0.000	1.25	1.0	0.0
1	58.67	4.460	3.04	6.0	560.0
2	24.50	0.500	1.50	0.0	824.0
3	27.83	1.540	3.75	5.0	3.0
4	20.17	5.625	1.71	0.0	0.0
...	...	...	...	...	...
685	21.08	10.085	1.25	0.0	0.0
686	22.67	0.750	2.00	2.0	394.0
687	25.25	13.500	2.00	1.0	1.0
688	17.92	0.205	0.04	0.0	750.0
689	35.00	3.375	2.46	0.0	0.0

690 rows × 5 columns

In [79]:

```
vif_data=pd.DataFrame()
```

In [81]:

```
vif_data['features']=x.columns
```

In [84]:

```
vif_data['VIF']=[variance_inflation_factor(x.values,i) for i in range (len(x.columns))]
```

In [85]:

```
vif_data
```

Out[85]:

	features	VIF
0	Age	2.828930
1	Debt	2.054744
2	YearsEmployed	2.298794
3	CreditScore	1.817621
4	Income	1.680393

Creating model

In [86]:

```
x=df.iloc[:,df.columns != 'Approved']
```

In [88]:

```
y=df.iloc[:,df.columns == 'Approved']
```

In [90]:

```
from sklearn.model_selection import train_test_split
```

In [91]:

```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3,random_state=123)
```

In [92]:

```
from sklearn.linear_model import LogisticRegression
```

In [93]:

```
model=LogisticRegression(solver='liblinear',random_state=123)
```

In [94]:

```
clf=model.fit(x_train,y_train)
```

```
C:\Conda dist\lib\site-packages\sklearn\utils\validation.py:993: DataConvers
ionWarning: A column-vector y was passed when a 1d array was expected. Pleas
e change the shape of y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
```

In [95]:

```
y_pred=clf.predict(x_test)
```

In [96]:

```
clf.score(x_test,y_test)
```

Out[96]:

```
0.8599033816425121
```

In [97]:

```
clf.intercept_
```

Out[97]:

```
array([-2.08619225])
```

In [98]:

```
clf.coef_
```

Out[98]:

```
array([[-0.01793299, -0.02983195,  0.01303626,  0.58230414,  0.27553144,
         2.93605989,  0.28787561,  0.19055028, -0.00326723,  0.00294504,
        -1.30864209, -0.51328852,  0.38796879, -0.13284517, -0.64602139,
        -0.99670274,  0.05582364,  1.29475446, -0.05681709, -0.69727162,
        -0.25373214,  0.06279072,  0.89018486,  0.08004152, -0.22185161,
        -0.14085112, -0.37031655,  0.56010133,  1.01904202]])
```

Creating confusion matrix

In [99]:

```
from sklearn import metrics
```

In [103]:

```
cm=metrics.confusion_matrix(y_test,y_pred)
print(cm)
```

```
[[98 11]
 [18 80]]
```

In [104]:

```
cr=metrics.classification_report(y_test,y_pred)
print(cr)
```

```
              precision    recall  f1-score   support

           0       0.84      0.90      0.87       109
           1       0.88      0.82      0.85        98

    accuracy                           0.86       207
   macro avg       0.86      0.86      0.86       207
weighted avg       0.86      0.86      0.86       207
```

ROC curve

In [107]:

```
from sklearn.metrics import roc_curve, roc_auc_score
```

In [110]:

```
y_pred_prob=clf.predict_proba(x_test)
print(y_pred_prob)
```

```
 [0.98187248 0.01812752]
 [0.21990199 0.78009801]
 [0.83120417 0.16879583]
 [0.59049407 0.40950593]
 [0.27374389 0.72625611]
 [0.13169043 0.86830957]
 [0.23676165 0.76323835]
 [0.05772132 0.94227868]
 [0.06839222 0.93160778]
 [0.91463342 0.08536658]
 [0.05748357 0.94251643]
 [0.14994097 0.85005903]
 [0.2397884  0.7602116 ]
 [0.82759593 0.17240407]
 [0.44878724 0.55121276]
 [0.06514231 0.93485769]
 [0.23688485 0.76311515]
 [0.49059855 0.50940145]
 [0.15915356 0.84084644]
 [0.62689163 0.37310837]
```

In [117]:

```
fpr,tpr,threshold = roc_curve(y_test,y_pred_prob[:,1])
```

In [112]:

```
roc_auc=roc_auc_score(y_test,y_pred_prob[:,1])
```

In [113]:

```
from sklearn.metrics import log_loss
```

In [114]:

```
log_loss(y_test,y_pred)
```

Out[114]:

```
4.838808265817111
```

In [119]:

```
plt.title('ROC curve for logloss:liblinear')
plt.xlabel('fpr')
plt.ylabel('tpr')
plt.plot([0,1],[0,1],"r--")
plt.xlim([0,1])
plt.ylim([0,1])
plt.plot(fpr,tpr,label='AUC ='+str(roc_auc))
plt.legend(loc='best')
plt.show()
```