In [1]:
```
#pip install --upgrade pandas
```

In [2]:
```
#pip install plotting
```

In [3]:
```
#pip install ggplot
```

In [4]:
```
#pip install fancyimpute
```

In [5]:
```
import pandas as pd
bank=pd.read_csv('C:/Users/saigo/Desktop/s/bank-loan.csv')
print(bank.head(5))
bank.head(5).describe()
```

```
   age  ed  employ  address  income  debtinc   creddebt   othdebt  default
0   41   3      17       12     176      9.3  11.359392  5.008608      1.0
1   27   1      10        6      31     17.3   1.362202  4.000798      0.0
2   40   1      15       14      55      5.5   0.856075  2.168925      0.0
3   41   1      15       14     120      2.9   2.658720  0.821280      0.0
4   24   2       2        0      28     17.3   1.787436  3.056564      1.0
```

Out[5]:

	age	ed	employ	address	income	debtinc	creddebt	othdebt	default
count	5.00000	5.000000	5.000000	5.00000	5.000000	5.000000	5.000000	5.000000	5.000000
mean	34.60000	1.600000	11.800000	9.20000	82.000000	10.460000	3.604765	3.011235	0.400000
std	8.38451	0.894427	6.058052	6.09918	64.276745	6.645901	4.385097	1.618346	0.547723
min	24.00000	1.000000	2.000000	0.00000	28.000000	2.900000	0.856075	0.821280	0.000000
25%	27.00000	1.000000	10.000000	6.00000	31.000000	5.500000	1.362202	2.168925	0.000000
50%	40.00000	1.000000	15.000000	12.00000	55.000000	9.300000	1.787436	3.056564	0.000000
75%	41.00000	2.000000	15.000000	14.00000	120.000000	17.300000	2.658720	4.000798	1.000000
max	41.00000	3.000000	17.000000	14.00000	176.000000	17.300000	11.359392	5.008608	1.000000

In [6]:
```
bank.rename(columns = {'default':'result'}, inplace = True)
```

In [7]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
%matplotlib inline
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import make_pipeline
```

```
from sklearn import svm
from sklearn.preprocessing import scale
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import auc
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
from sklearn.decomposition import PCA
from sklearn.ensemble import GradientBoostingClassifier
from fancyimpute import KNN
```

In [8]:

```
columns=list (bank.columns)
columns
```

Out[8]:

```
['age',
 'ed',
 'employ',
 'address',
 'income',
 'debtinc',
 'creddebt',
 'othdebt',
 'result']
```

In [9]:

```
bank.tail(5)
```

Out[9]:

	age	ed	employ	address	income	debtinc	creddebt	othdebt	result
845	34	1	12	15	32	2.7	0.239328	0.624672	NaN
846	32	2	12	11	116	5.7	4.026708	2.585292	NaN
847	48	1	13	11	38	10.8	0.722304	3.381696	NaN
848	35	2	1	11	24	7.8	0.417456	1.454544	NaN
849	37	1	20	13	41	12.9	0.899130	4.389870	NaN

In [10]:

```
bank.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 850 entries, 0 to 849
Data columns (total 9 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   age       850 non-null    int64  
 1   ed        850 non-null    int64  
 2   employ    850 non-null    int64  
 3   address   850 non-null    int64  
 4   income    850 non-null    int64  
 5   debtinc   850 non-null    float64
 6   creddebt  850 non-null    float64
 7   othdebt   850 non-null    float64
 8   result    700 non-null    float64
dtypes: float64(4), int64(5)
memory usage: 59.9 KB
```

In [11]:
```
bank.shape
```

Out[11]: (850, 9)

In [12]:
```
bank.describe()
```

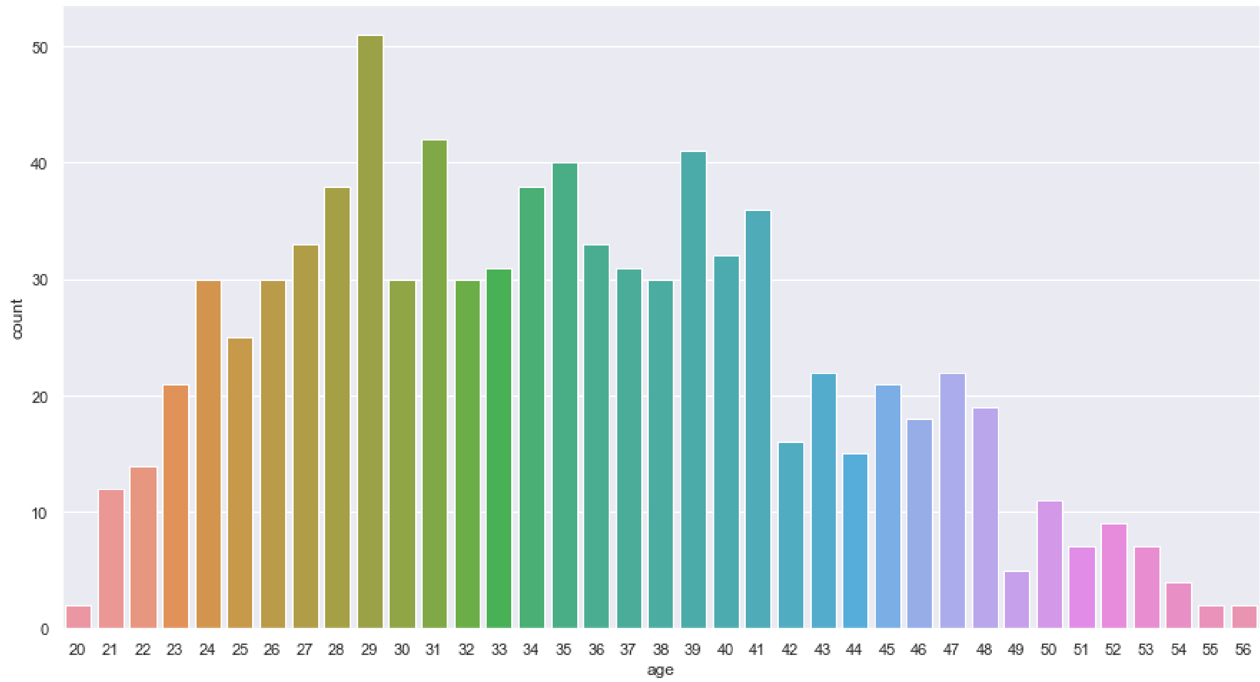
Out[12]:

	age	ed	employ	address	income	debtinc	creddebt	othdebt
count	850.000000	850.000000	850.000000	850.000000	850.000000	850.000000	850.000000	850.000000
mean	35.029412	1.710588	8.565882	8.371765	46.675294	10.171647	1.576805	3.078789
std	8.041432	0.927784	6.777884	6.895016	38.543054	6.719441	2.125840	3.398803
min	20.000000	1.000000	0.000000	0.000000	13.000000	0.100000	0.011696	0.045584
25%	29.000000	1.000000	3.000000	3.000000	24.000000	5.100000	0.382176	1.045942
50%	34.000000	1.000000	7.000000	7.000000	35.000000	8.700000	0.885091	2.003243
75%	41.000000	2.000000	13.000000	12.000000	55.750000	13.800000	1.898440	3.903001
max	56.000000	5.000000	33.000000	34.000000	446.000000	41.300000	20.561310	35.197500

In [13]:
```
############ univariate analysis and bivariate analysis ##########################

#Analysis for single variable in the dataset is Univariate Analysis and plotting relati
sns.set(rc = {'figure.figsize':(15,8)})
sns.countplot(bank["age"])
# age_20 = bank[bank["age"] == 20]
# print()
```

```
C:\Users\saigo\anaconda3\lib\site-packages\seaborn\_decorators.py:43: FutureWarning: Pas
s the following variable as a keyword arg: x. From version 0.12, the only valid position
al argument will be `data`, and passing other arguments without an explicit keyword will
result in an error or misinterpretation.
  FutureWarning
```

Out[13]: <AxesSubplot:xlabel='age', ylabel='count'>



In [14]:
```
# it means there are missing values in var

bank['result'].unique()
```

Out[14]:
```
array([ 1.,  0., nan])
```

In [15]:
```
bank['result'].value_counts()
```

Out[15]:
```
0.0    517
1.0    183
Name: result, dtype: int64
```

In [16]:
```
(850-517-183) # nan values
```

Out[16]:
```
150
```

In [17]:
```
columns
```

Out[17]:
```
['age',
 'ed',
 'employ',
 'address',
 'income',
 'debtinc',
 'creddebt',
 'othdebt',
 'result']
```

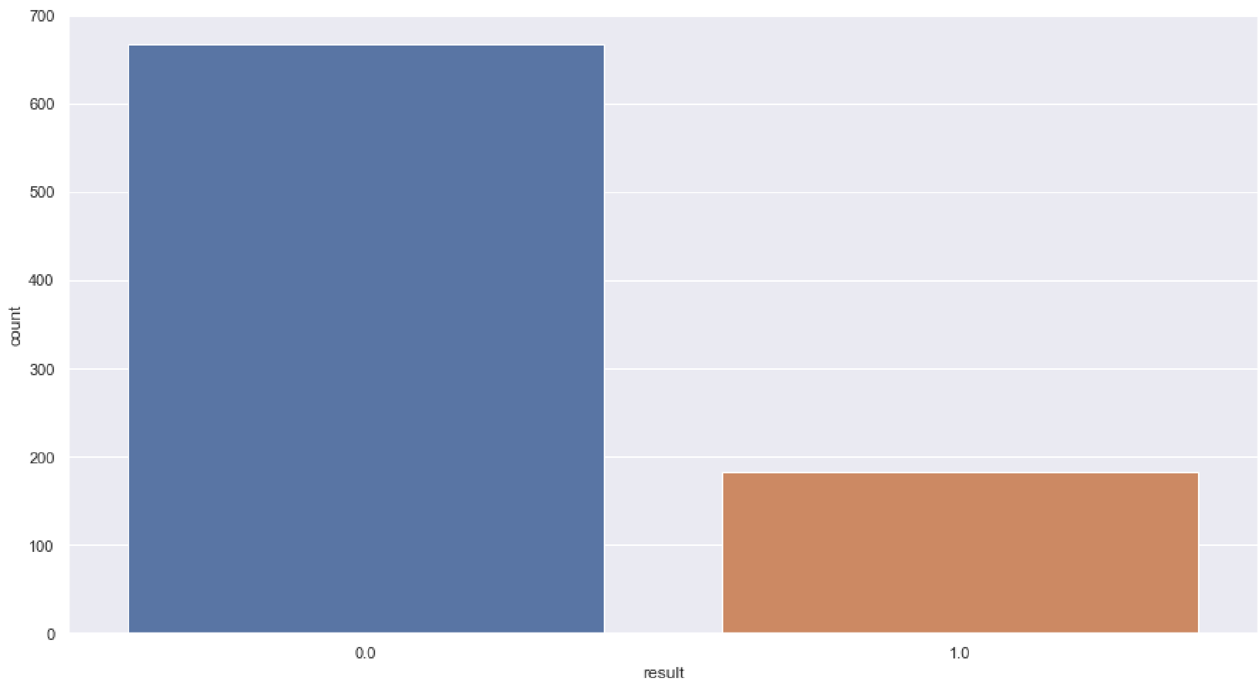
In [18]:
```
# replacing nan values with 0 in each and every column
for i in columns:
  bank[i] = bank[i].fillna(0)
```

In [19]:
```
columns[0]
```

Out[19]: 'age'

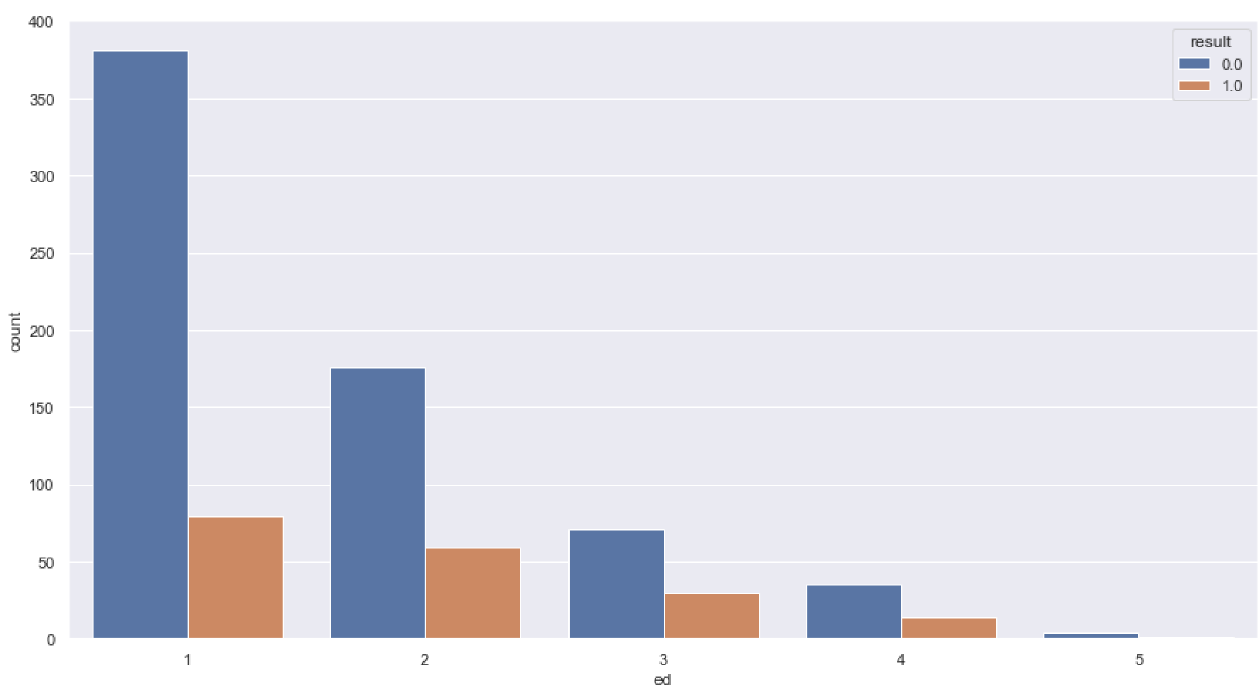
In [20]:
```
sns.countplot( x = "result" , data = bank,)
```

Out[20]: <AxesSubplot:xlabel='result', ylabel='count'>



In [21]:
```
sns.countplot( x = "ed" , data = bank, hue = "result")
```

Out[21]: <AxesSubplot:xlabel='ed', ylabel='count'>



Outliers Analysis and Synthesis

In [22]:

```
print(bank.head())
bank.describe()
```

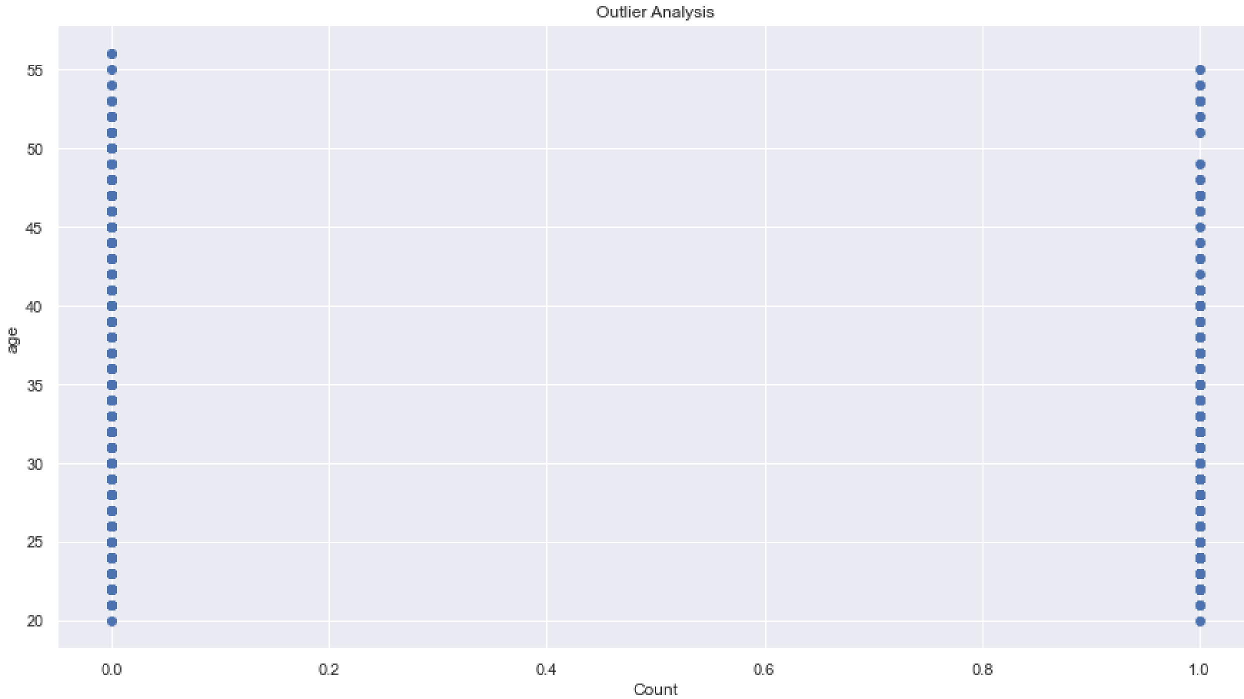
```
   age  ed  employ  address  income  debtinc   creddebt   othdebt  result
0   41   3      17       12     176      9.3  11.359392  5.008608     1.0
1   27   1      10        6      31     17.3   1.362202  4.000798     0.0
2   40   1      15       14      55      5.5   0.856075  2.168925     0.0
3   41   1      15       14     120      2.9   2.658720  0.821280     0.0
4   24   2       2        0      28     17.3   1.787436  3.056564     1.0
```

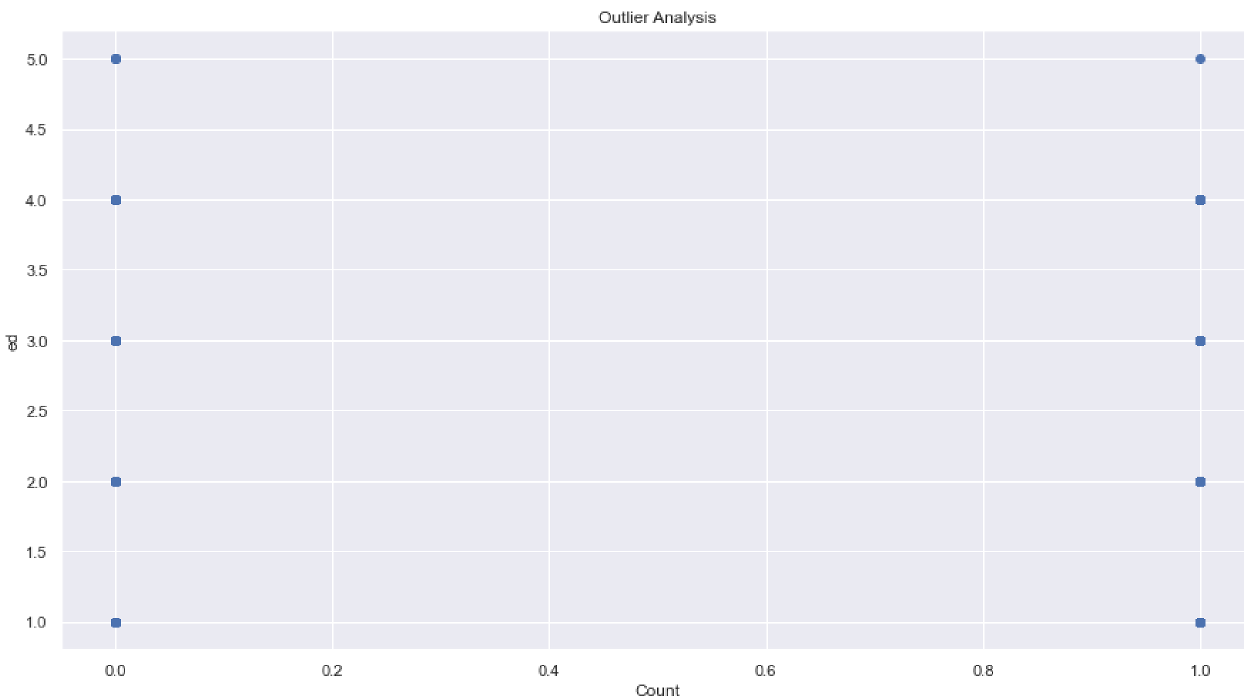
Out[22]:

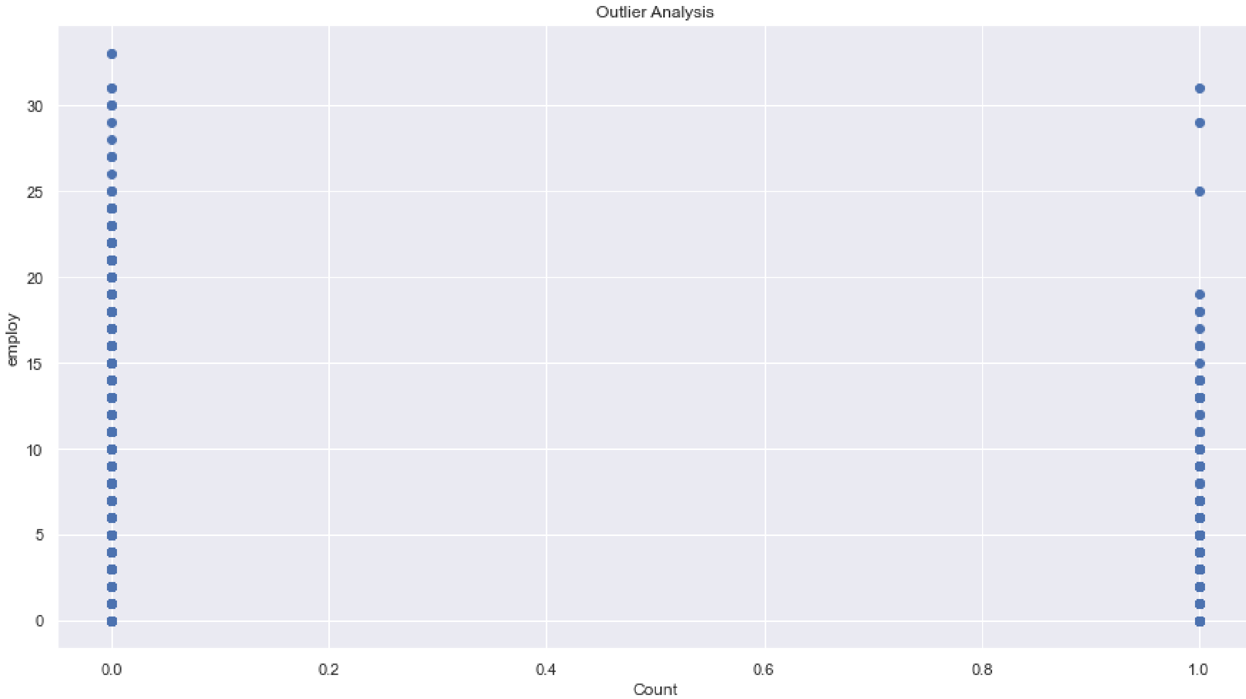
	age	ed	employ	address	income	debtinc	creddebt	othdebt
count	850.000000	850.000000	850.000000	850.000000	850.000000	850.000000	850.000000	850.000000
mean	35.029412	1.710588	8.565882	8.371765	46.675294	10.171647	1.576805	3.078789
std	8.041432	0.927784	6.777884	6.895016	38.543054	6.719441	2.125840	3.398803
min	20.000000	1.000000	0.000000	0.000000	13.000000	0.100000	0.011696	0.045584
25%	29.000000	1.000000	3.000000	3.000000	24.000000	5.100000	0.382176	1.045942
50%	34.000000	1.000000	7.000000	7.000000	35.000000	8.700000	0.885091	2.003243
75%	41.000000	2.000000	13.000000	12.000000	55.750000	13.800000	1.898440	3.903001
max	56.000000	5.000000	33.000000	34.000000	446.000000	41.300000	20.561310	35.197500

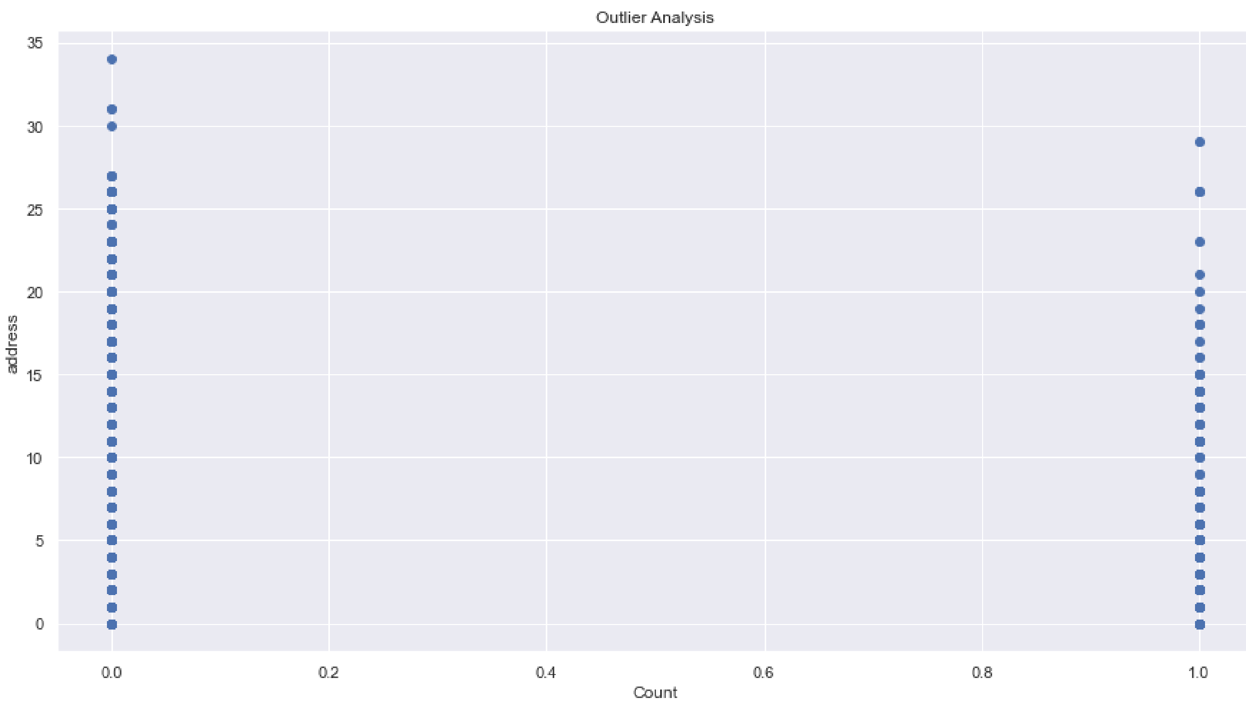
In [23]:

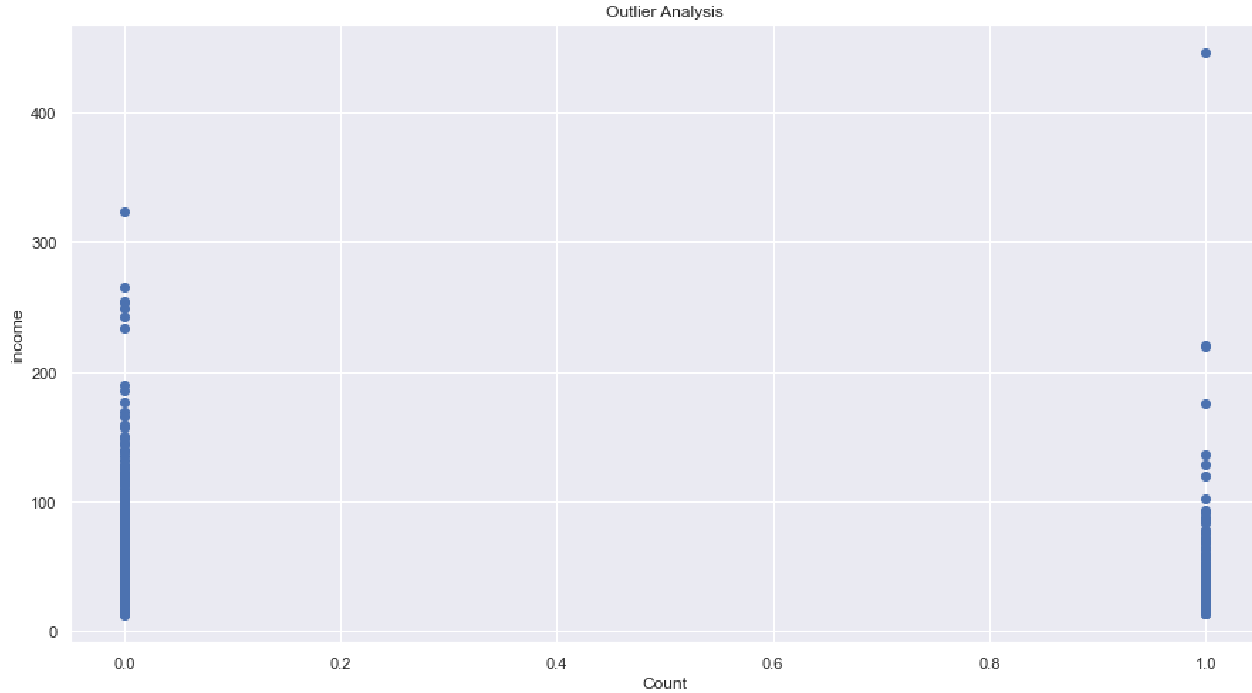
```
#scatter plot for outlier Analysis
for i in columns:
  if i!='result':
    plt.scatter(bank['result'],bank[i])
    plt.title('Outlier Analysis')
    plt.xlabel('Count')
    plt.ylabel(i)
    plt.show()
```

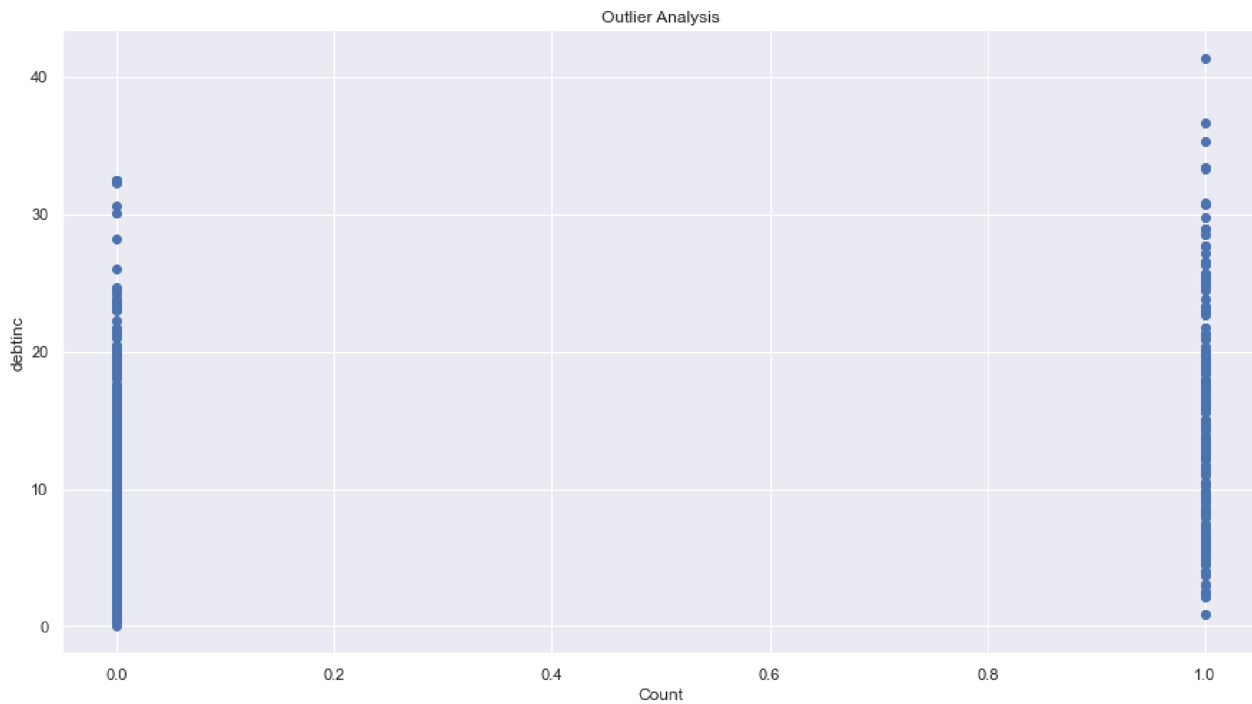

Outlier Analysis
age
Count

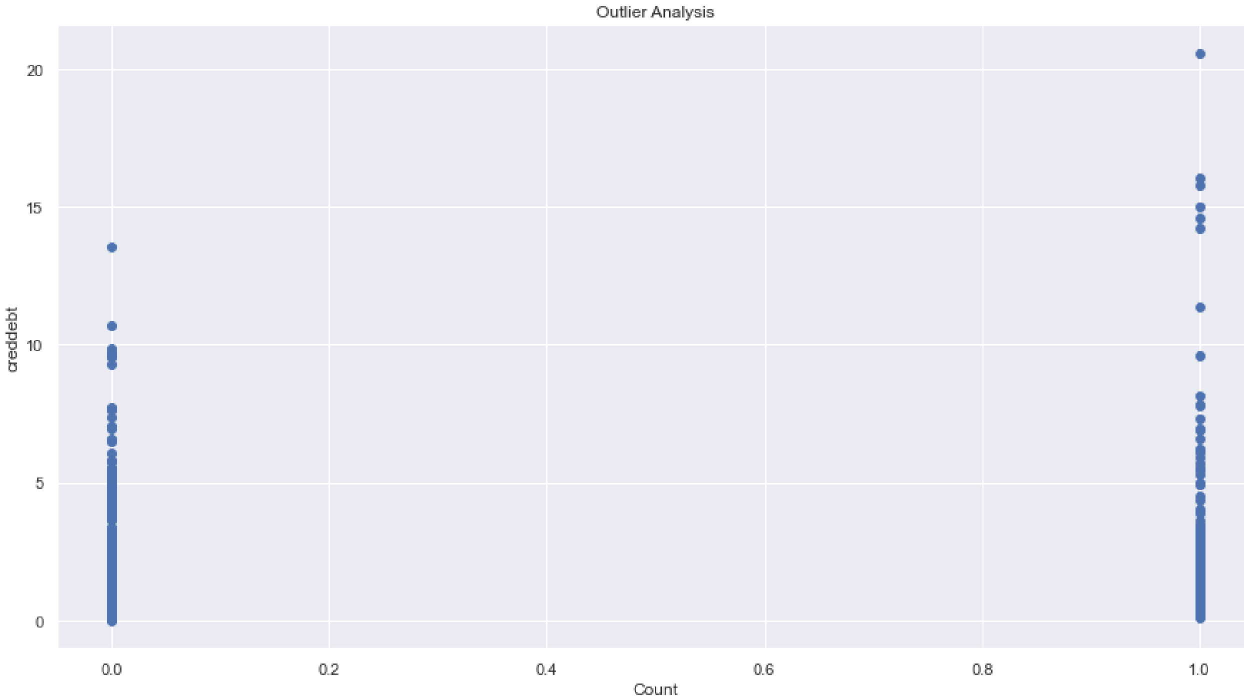

Outlier Analysis
ed
Count

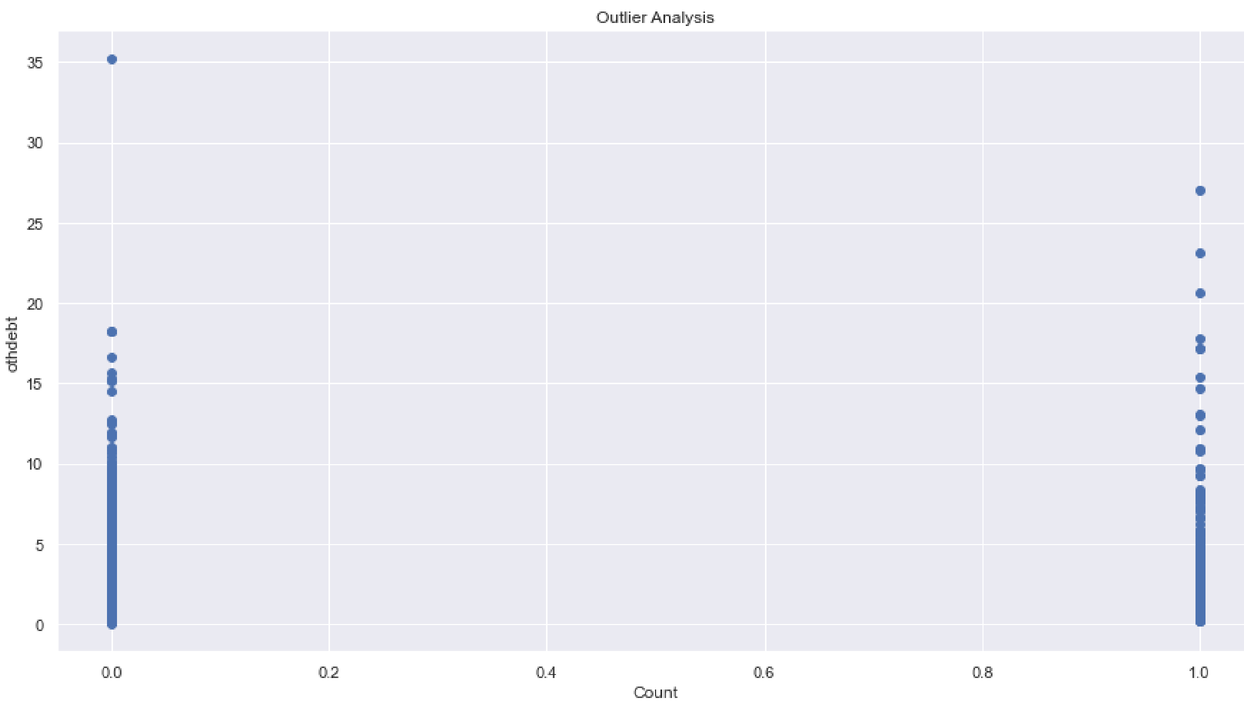

Outlier Analysis
employ
Count
0
5
10
15
20
25
30
0.0
0.2
0.4
0.6
0.8
1.0


Outlier Analysis
address
Count
0
5
10
15
20
25
30
35
0.0
0.2
0.4
0.6
0.8
1.0


Outlier Analysis
income
0
100
200
300
400
0.0
0.2
0.4
0.6
0.8
1.0
Count


Outlier Analysis
debtinc
0
10
20
30
40
0.0
0.2
0.4
0.6
0.8
1.0
Count





In [24]:
```
bank.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 850 entries, 0 to 849
Data columns (total 9 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       850 non-null    int64
 1   ed        850 non-null    int64
 2   employ    850 non-null    int64
 3   address   850 non-null    int64
 4   income    850 non-null    int64
 5   debtinc   850 non-null    float64
 6   creddebt  850 non-null    float64
 7   othdebt   850 non-null    float64
```

```
 8   result    850 non-null    float64
dtypes: float64(4), int64(5)
memory usage: 59.9 KB
```

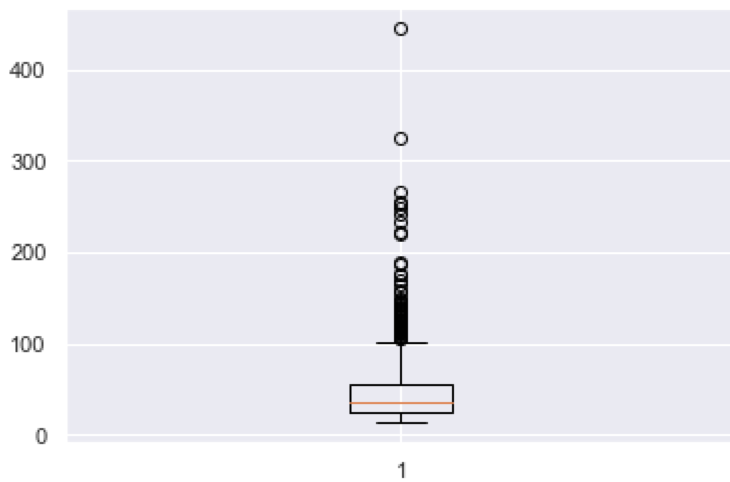
Now detect and replace Outliers

In [25]:

```
%matplotlib inline

plt.boxplot(bank['income'])
```

Out[25]:

```
{'whiskers': [<matplotlib.lines.Line2D at 0x1bdfca0c588>,
  <matplotlib.lines.Line2D at 0x1bdfc9ee708>],
 'caps': [<matplotlib.lines.Line2D at 0x1bdfca20fc8>,
  <matplotlib.lines.Line2D at 0x1bdfca20f48>],
 'boxes': [<matplotlib.lines.Line2D at 0x1bdfc9eeac8>],
 'medians': [<matplotlib.lines.Line2D at 0x1bdfc9ae8c8>],
 'fliers': [<matplotlib.lines.Line2D at 0x1bdfc9ae688>],
 'means': []}
```



In [26]:

```
# 2.Detect outliers and replace  NAn later impute by KNN imputation

#Extract quartiles
q75, q25 = np.percentile(bank['income'], [75 ,25])

#Calculate IQR
iqr = q75 - q25

#Calculate inner and outer fence
minimum = q25 - (iqr*1.5)
maximum = q75 + (iqr*1.5)

#Replace with NA
bank.loc[bank['income']  < minimum,:'income'] = np.nan

bank.loc[bank['income'] > maximum,:'income'] = np.nan

#Calculate missing value
bank.income.isnull().sum()

# missing_val = pd.DataFrame(bank.isnull().sum())
```

Out[26]: 53

In [27]:
```
#replacing NaNs with Knn imputation
bank = pd.DataFrame(KNN(k = 3).fit_transform(bank), columns = bank.columns)
```

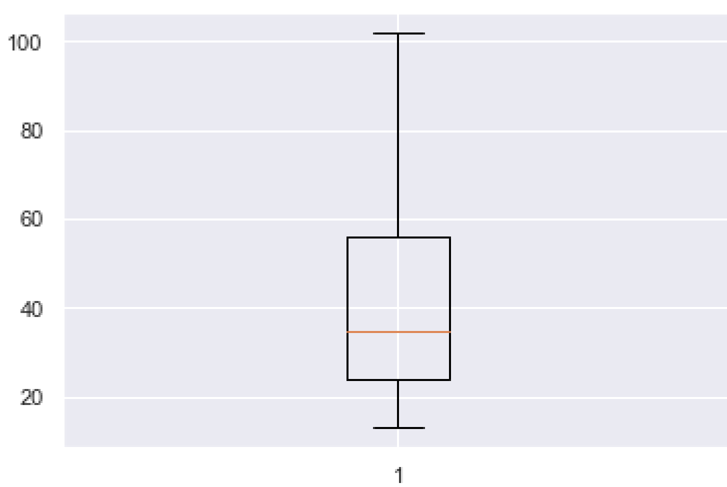
```
Imputing row 1/850 with 5 missing, elapsed time: 0.293
Imputing row 101/850 with 5 missing, elapsed time: 0.293
Imputing row 201/850 with 0 missing, elapsed time: 0.299
Imputing row 301/850 with 5 missing, elapsed time: 0.301
Imputing row 401/850 with 0 missing, elapsed time: 0.301
Imputing row 501/850 with 0 missing, elapsed time: 0.301
Imputing row 601/850 with 0 missing, elapsed time: 0.310
Imputing row 701/850 with 0 missing, elapsed time: 0.314
Imputing row 801/850 with 0 missing, elapsed time: 0.314
```

In [28]:
```
bank.result.isnull().sum()
```

Out[28]: 0

In [29]:
```
    ## Now check outliers got imputed or not
%matplotlib inline

plt.boxplot(bank['income'])
```

Out[29]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x1bdfc03b0c8>,
  <matplotlib.lines.Line2D at 0x1bdfbf73748>],
 'caps': [<matplotlib.lines.Line2D at 0x1bdfbf70808>,
  <matplotlib.lines.Line2D at 0x1bdfbf70d48>],
 'boxes': [<matplotlib.lines.Line2D at 0x1bdfbf73348>],
 'medians': [<matplotlib.lines.Line2D at 0x1bdfbf70ec8>],
 'fliers': [<matplotlib.lines.Line2D at 0x1bdfbf70bc8>],
 'means': []}
```



As of now we got data having zero missing values and Outliers

Next step = Feature Selection

Selection of categorical vars -- Chi_Sqr Test of Independance

Selection of Numerical vars i.e. (cnames) -- Correlation analysis

In [30]:
```
cnames=['age',  'employ'       ,'address',     'income'       ,'debtinc'      ,'credd
```

In [31]:
```
df_corr = bank.loc[:,cnames]
df_corr
```

Out[31]:

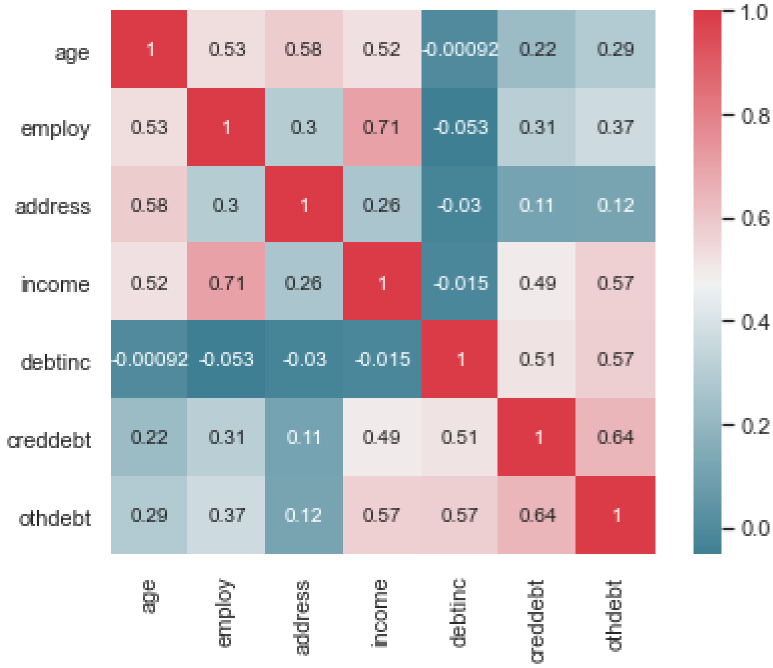
	age	employ	address	income	debtinc	creddebt	othdebt
0	32.356193	7.236156	2.601503	89.801565	9.3	11.359392	5.008608
1	27.000000	10.000000	6.000000	31.000000	17.3	1.362202	4.000798
2	40.000000	15.000000	14.000000	55.000000	5.5	0.856075	2.168925
3	45.812528	17.114644	16.862865	82.601082	2.9	2.658720	0.821280
4	24.000000	2.000000	0.000000	28.000000	17.3	1.787436	3.056564
...	...	...	...	...	...	...	...
845	34.000000	12.000000	15.000000	32.000000	2.7	0.239328	0.624672
846	40.556120	17.662846	7.265821	89.968082	5.7	4.026708	2.585292
847	48.000000	13.000000	11.000000	38.000000	10.8	0.722304	3.381696
848	35.000000	1.000000	11.000000	24.000000	7.8	0.417456	1.454544
849	37.000000	20.000000	13.000000	41.000000	12.9	0.899130	4.389870

850 rows × 7 columns

In [32]:
```
#Set the width and hieght of the correlation plot

f, ax = plt.subplots(figsize = (7, 5))

#Generate correlation matrix
corr = df_corr.corr()

#Plot using seaborn library
sns.heatmap(corr, mask=np.zeros_like(corr, dtype=np.bool), cmap=sns.diverging_palette(2
            square=True, ax=ax , annot = True )
```

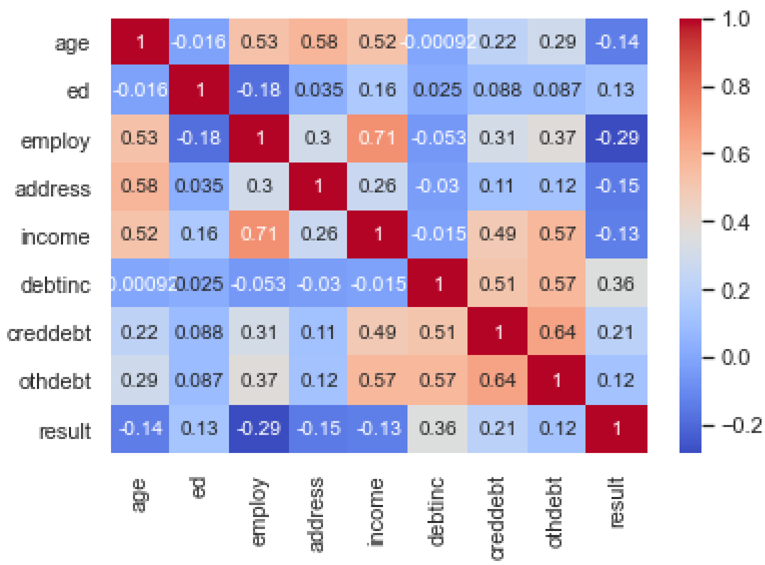
```
C:\Users\saigo\anaconda3\lib\site-packages\ipykernel_launcher.py:9: DeprecationWarning:
`np.bool` is a deprecated alias for the builtin `bool`. To silence this warning, use `bo
ol` by itself. Doing this will not modify any behavior and is safe. If you specifically
wanted the numpy scalar type, use `np.bool_` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/relea
se/1.20.0-notes.html#deprecations
  if __name__ == '__main__':
```

Out[32]: <AxesSubplot:>



In [33]:
```
df_1 = bank.corr()
sns.heatmap(df_1 , annot = True , cmap = "coolwarm")
```

Out[33]: <AxesSubplot:>



As u can see above in plot, no any variable is identical to other var, it means these vars are no hiighly correlated variables, so we have to carry all variables and we will put all of them in model developement as all vars are imp right now.

In [34]:
```
bank['ed'].unique()
```

Out[34]:
```
array([2.96064072, 1.        , 2.24554266, 2.        , 3.        ,
       4.        , 2.79827474, 1.97645001, 2.25922096, 2.38215714,
       1.72680475, 1.8126923 , 1.9645205 , 2.27977579, 1.32411487,
       3.10697651, 1.39366539, 1.75318272, 1.32647735, 1.97201906,
       2.6976684 , 5.        , 1.81890805, 2.35655901, 1.27382004,
       2.01090174, 1.94521205, 2.0093577 , 2.62380155, 1.53298316,
       1.28018361, 1.31112169, 1.32483921, 1.62666983, 1.86209418,
```

```
1.32740931, 1.85469455, 1.90879037, 1.26029512, 1.76154984,
2.33544809, 1.97650496, 1.60802394, 2.37331826, 1.59472773,
1.2113529 , 2.1230242 , 1.32070963, 1.56469926, 2.09702113,
1.32444713, 2.34431695, 1.24268178, 1.37444458, 1.78899958,
1.86508575, 1.28881365, 1.5819134 ])
```

In [35]:

```
bank['result'].unique()
```

Out[35]:

```
array([1., 0.])
```

In [36]:

```
bank['ed'] = pd.Categorical(bank['ed'])
print(bank.ed.dtype)

bank['result'] = pd.Categorical(bank['result'])
print(bank.result.dtype)
```

```
category
category
```

As we can see here both ed and result columns are categorical so we perform chi 2 statistics to see the relation between them

In [37]:

```
cat_names = ["ed"]
from scipy.stats import chi2_contingency  # for chi-sqr test and comtingency table
for i in cat_names:
    print(i)
    chi2, p, dof, ex = chi2_contingency(pd.crosstab(bank['result'], bank[i]))
    print(p)
```

```
ed
0.586723187105507
```

As we can, see , p Value of cat var (ed) is > 0.05 , It means We Accept Null Hhypothesis saying that these two variables are , not imp to each other, n we can drop any one of them instead of carrying both same vars.

In [38]:

```
#  Now remove less important features  / Diamension reduction
from copy import deepcopy
bank = bank.drop(['ed'], axis=1)
bank.head(2)
bank_1=deepcopy(bank)
```

In [39]:

```
bank_1.head()
```

Out[39]:

	age	employ	address	income	debtinc	creddebt	othdebt	result
0	32.356193	7.236156	2.601503	89.801565	9.3	11.359392	5.008608	1.0
1	27.000000	10.000000	6.000000	31.000000	17.3	1.362202	4.000798	0.0
2	40.000000	15.000000	14.000000	55.000000	5.5	0.856075	2.168925	0.0
3	45.812528	17.114644	16.862865	82.601082	2.9	2.658720	0.821280	0.0
4	24.000000	2.000000	0.000000	28.000000	17.3	1.787436	3.056564	1.0

Feature Scaling

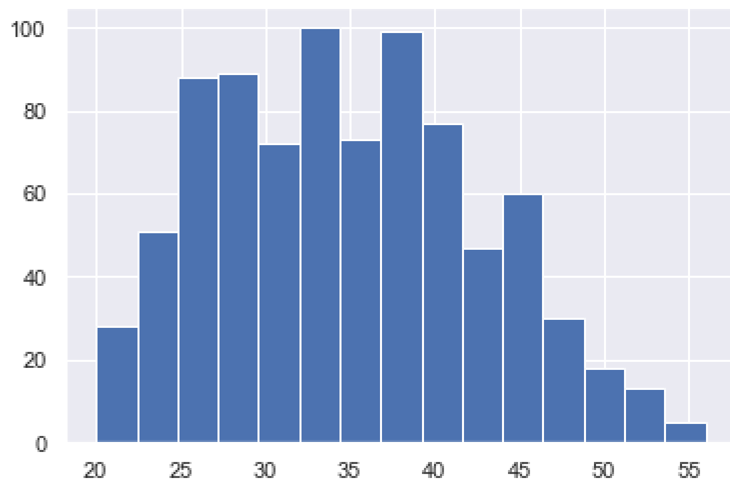
scale tht imp features in measurable units

___1) Scaling by Normalization

__or_2) Scaling by Standardization

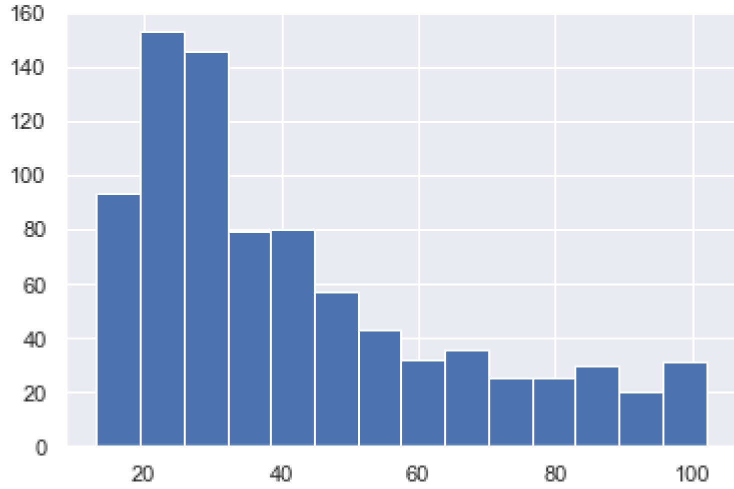
In [40]:
```
#check Normality by Histogram Before Normalization / Standerdization

%matplotlib inline
plt.hist(bank['age'], bins='auto')
```

Out[40]:
```
(array([ 28.,  51.,  88.,  89.,  72., 100.,  73.,  99.,  77.,  47.,  60.,
         30.,  18.,  13.,   5.]),
 array([20. , 22.4, 24.8, 27.2, 29.6, 32. , 34.4, 36.8, 39.2, 41.6, 44. ,
        46.4, 48.8, 51.2, 53.6, 56. ]),
 <BarContainer object of 15 artists>)
```



In [41]:
```
    # Again verify it

%matplotlib inline
plt.hist(bank['income'], bins='auto')
```

Out[41]:
```
(array([ 93., 153., 146.,  79.,  80.,  57.,  43.,  32.,  36.,  25.,  25.,
         30.,  20.,  31.]),
 array([ 13.        ,  19.35714286,  25.71428571,  32.07142857,
         38.42857143,  44.78571429,  51.14285714,  57.5       ,
         63.85714286,  70.21428571,  76.57142857,  82.92857143,
         89.28571429,  95.64285714, 102.        ]),
 <BarContainer object of 14 artists>)
```



Since we can see that , data is not normallaly distributed , Hence go for **Normalization** 1st instead of Stdn

In [42]:
```
cnames
```

Out[42]: ['age', 'employ', 'address', 'income', 'debtinc', 'creddebt', 'othdebt']

In [43]:
```
#Nomalisation

for i in cnames:
    print(i)
    bank[i] = (bank[i] - min(bank[i]))/(max(bank[i]) - min(bank[i]))
```

```
age
employ
address
income
debtinc
creddebt
othdebt
```

Machine Learning Algorithms

In [44]:
```
from sklearn.metrics import accuracy_score
```

In [45]:
```
from sklearn.model_selection import train_test_split
```

In [46]:
```
bank['result'] = bank['result'].astype('int64')#chaning dtype for result from float to
```

In [47]:
```
bank.head(2)
print(bank.age)
```

```
0      0.343228
1      0.194444
2      0.555556
```

```
3      0.717015
4      0.111111
         ...
845    0.388889
846    0.571003
847    0.777778
848    0.416667
849    0.472222
Name: age, Length: 850, dtype: float64
```

In [48]:

```
#Now divide the data into train and test

X= bank.values[:,0:7]     #saving all   var's in X
Y= bank.values[:,7]        #saving 1 dep var in Y
```

In [49]:

```
pd.DataFrame(X).head(2)
```

Out[49]:

	0	1	2	3	4	5	6
0	0.343228	0.241205	0.083919	0.862939	0.223301	0.552210	0.141188
1	0.194444	0.333333	0.193548	0.202247	0.417476	0.065719	0.112518

In [50]:

```
#Now split the data into train and test
   #devided 80% and 20% of ALL var's obs (except 'default' var) in X_train and into X_t
   #devided 80% and 20% of Dep.Var's obs ( default var's) into y_train and into y_test

X_train, X_test, y_train, y_test = train_test_split(X,Y,test_size=0.2,random_state=12)
```

In [51]:

```
import warnings
warnings.filterwarnings("ignore")
```

In [52]:

```
models=[]


from sklearn.linear_model import LogisticRegression
logre = LogisticRegression()
models.append(logre)

from sklearn.svm._classes import LinearSVC
lsvc=LinearSVC()
models.append(lsvc)

from sklearn.linear_model import LogisticRegressionCV
logrecv=LogisticRegressionCV()
models.append(logrecv)

from sklearn.svm import SVC
svc=SVC()
models.append(svc)

from sklearn.linear_model import SGDClassifier
sgd=SGDClassifier()
models.append(sgd)
```

```
from sklearn.naive_bayes import GaussianNB
nb=GaussianNB()
models.append(nb)

from sklearn.tree import  DecisionTreeClassifier
dt=DecisionTreeClassifier()
models.append(dt)

from sklearn.ensemble import RandomForestClassifier
rf=RandomForestClassifier()
models.append(rf)

from sklearn.neighbors import KNeighborsClassifier
knn=KNeighborsClassifier()
models.append(knn)
```

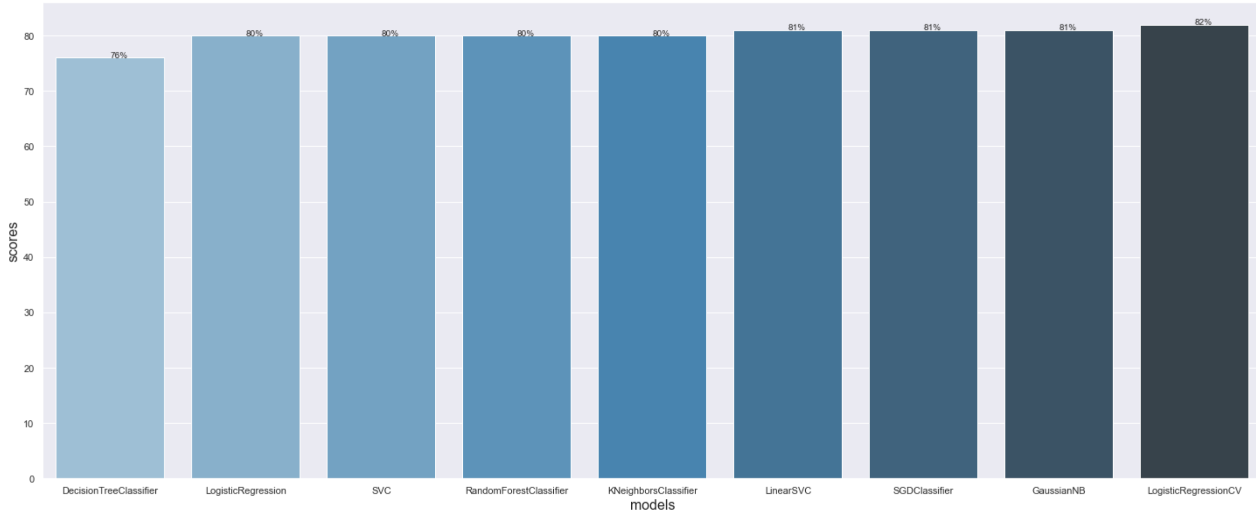
In [53]:

```
from sklearn.model_selection import KFold,cross_val_score
cv=KFold(10)
mls=[]
scores=[]

for model in models:
  score=cross_val_score(model,X_train,y_train,cv=cv)
  print(str(model).split('(')[0]+' :- ',np.mean(score))
  mls.append(str(model).split('(')[0])
  scores.append(int(np.mean(score)*100))
```

```
LogisticRegression :-  0.8044117647058824
LinearSVC :-  0.8161764705882353
LogisticRegressionCV :-  0.8264705882352941
SVC :-  0.801470588235294
SGDClassifier :-  0.8147058823529412
GaussianNB :-  0.8117647058823529
DecisionTreeClassifier :-  0.7602941176470589
RandomForestClassifier :-  0.8088235294117647
KNeighborsClassifier :-  0.8014705882352942
```

In [54]:

```
import matplotlib.pyplot as plt
ml_scores= pd.DataFrame({"models": mls,"scores": scores})
import seaborn as sns
ml_scores.sort_values('scores')

plt.figure(figsize=(25,10))
sns.barplot(x='models',y="scores",data=ml_scores,palette="Blues_d",order=ml_scores.sort


def addtext(x,y):
    for i in range(len(x)):
        plt.text(i,y[i],str(y[i])+'%')
addtext(models,sorted(scores))
plt.xlabel("models",size=16)
plt.ylabel("scores", size=16)
plt.show()
```



In [55]:

```
for model in models:
  model.fit(X_train,y_train)
  print(model)
  print('Train Accuracy:-',accuracy_score(y_train,model.predict(X_train)))
  print('Test Accuracy:-',accuracy_score(y_test,model.predict(X_test)))
  print()
```

```
LogisticRegression()
Train Accuracy:- 0.8088235294117647
Test Accuracy:- 0.7705882352941177

LinearSVC()
Train Accuracy:- 0.8264705882352941
Test Accuracy:- 0.7647058823529411

LogisticRegressionCV()
Train Accuracy:- 0.8352941176470589
Test Accuracy:- 0.7529411764705882

SVC()
Train Accuracy:- 0.825
Test Accuracy:- 0.7823529411764706

SGDClassifier()
Train Accuracy:- 0.7588235294117647
Test Accuracy:- 0.7294117647058823

GaussianNB()
Train Accuracy:- 0.8132352941176471
Test Accuracy:- 0.7647058823529411

DecisionTreeClassifier()
Train Accuracy:- 1.0
Test Accuracy:- 0.7705882352941177

RandomForestClassifier()
Train Accuracy:- 1.0
Test Accuracy:- 0.7764705882352941

KNeighborsClassifier()
Train Accuracy:- 0.8529411764705882
Test Accuracy:- 0.7823529411764706
```

among all these alogirthms we choose Logistic Regression because of its train and test scores which is best fit

In [56]:
```
X_train[0]
```

Out[56]:
```
array([0.38888889, 0.46666667, 0.25806452, 0.16853933, 0.41019417,
       0.05479149, 0.10175195])
```

In [57]:
```
cnames
```

Out[57]:
```
['age', 'employ', 'address', 'income', 'debtinc', 'creddebt', 'othdebt']
```

In [59]:
```
import pickle
logre_model=pickle.load(open('C:/Users/saigo/Desktop/s/logre_model','rb'))
```

In [60]:
```
X_train[0]
```

Out[60]:
```
array([0.38888889, 0.46666667, 0.25806452, 0.16853933, 0.41019417,
       0.05479149, 0.10175195])
```

In [61]:
```
user_input=np.array(X_train[0])
```

In [62]:
```
user_input=user_input.reshape(1,-1)
```

In [63]:
```
logre_model.predict(user_input)[0]
```

Out[63]:
```
0.0
```

In [ ]:
```
y_train[0]
```

In [ ]:
```
pip install pywebio
```

In [ ]:
```
#import pickle
#saving ml model
#pickle.dump(logre,open('C:/Users/saigo/Desktop/s/logre_model','wb'))
#loading ml model
#logre_model=pickle.load(open('C:/Users/saigo/Desktop/s/logre_model','rb'))
```

In [ ]:
```
app=Flask(__name__)
logre_model=pickle.load(open('C:/Users/saigo/Desktop/s/logre_model','rb'))
#sample inputs
#[0.11111111, 0.1       , 0.16129032, 0.02247191, 0.27184466,0.00297762, 0.04484908] - 
def predict():
    user_input=[]
    ss_user_input=[]
    for i in cnames:
        x=input(i+' :- ',type=FLOAT)
```

```
        user_input.append(x)

    for i in range(len(user_input)):
        ss = (user_input[i] - min(user_input))/(max(user_input) - min(user_input))
        ss_user_input.append(ss)

    ss_user_input=np.array(ss_user_input)
    ss_user_input=ss_user_input.reshape(1,-1)

    prediction=logre_model.predict(ss_user_input)[0]
    if prediction==1.0:
        prediction='Yes'
    else:
        prediction='No'
    put_text('prediction = %r' % prediction)



app.add_url_rule('/','webio_view',webio_view(predict),methods=['GET','POST','OPTIONS'])
app.run(host='localhost',port=88)
```

```
 * Serving Flask app "__main__" (lazy loading)
 * Environment: production
   WARNING: This is a development server. Do not use it in a production deployment.
   Use a production WSGI server instead.
 * Debug mode: off
 * Running on http://localhost:88/ (Press CTRL+C to quit)
127.0.0.1 - - [20/Jun/2022 10:24:14] "GET / HTTP/1.1" 200 -
127.0.0.1 - - [20/Jun/2022 10:24:14] "GET /?app=index HTTP/1.1" 200 -
127.0.0.1 - - [20/Jun/2022 10:24:15] "GET /?app=index HTTP/1.1" 200 -
127.0.0.1 - - [20/Jun/2022 10:24:17] "GET /?app=index HTTP/1.1" 200 -
127.0.0.1 - - [20/Jun/2022 10:24:17] "POST /?app=index HTTP/1.1" 200 -
127.0.0.1 - - [20/Jun/2022 10:24:18] "GET /?app=index HTTP/1.1" 200 -
127.0.0.1 - - [20/Jun/2022 10:24:18] "POST /?app=index HTTP/1.1" 200 -
127.0.0.1 - - [20/Jun/2022 10:24:19] "GET /?app=index HTTP/1.1" 200 -
127.0.0.1 - - [20/Jun/2022 10:24:19] "GET /?app=index HTTP/1.1" 200 -
127.0.0.1 - - [20/Jun/2022 10:24:20] "POST /?app=index HTTP/1.1" 200 -
127.0.0.1 - - [20/Jun/2022 10:24:20] "GET /?app=index HTTP/1.1" 200 -
127.0.0.1 - - [20/Jun/2022 10:24:22] "GET /?app=index HTTP/1.1" 200 -
127.0.0.1 - - [20/Jun/2022 10:24:22] "POST /?app=index HTTP/1.1" 200 -
127.0.0.1 - - [20/Jun/2022 10:24:22] "GET /?app=index HTTP/1.1" 200 -
127.0.0.1 - - [20/Jun/2022 10:24:24] "POST /?app=index HTTP/1.1" 200 -
127.0.0.1 - - [20/Jun/2022 10:24:24] "GET /?app=index HTTP/1.1" 200 -
127.0.0.1 - - [20/Jun/2022 10:24:24] "GET /?app=index HTTP/1.1" 200 -
127.0.0.1 - - [20/Jun/2022 10:24:25] "POST /?app=index HTTP/1.1" 200 -
127.0.0.1 - - [20/Jun/2022 10:24:26] "GET /?app=index HTTP/1.1" 200 -
127.0.0.1 - - [20/Jun/2022 10:24:26] "GET /?app=index HTTP/1.1" 200 -
127.0.0.1 - - [20/Jun/2022 10:24:28] "GET /?app=index HTTP/1.1" 200 -
127.0.0.1 - - [20/Jun/2022 10:24:28] "POST /?app=index HTTP/1.1" 200 -
```

In [ ]:

```
X_train[1]
```

In [ ]:

```
y_train[0]
```

In [ ]:

```
sampleList = np.array(bank_1[:2])
sampleList
```

In [ ]:
```
bank_1.head()
```

In [ ]:
```
#[32.35619303,  7.23615625,  2.60150296, 89.80156532,  9.3       ,11.359392  ,  5.00860
#[27.        , 10.        ,  6.        , 31.        , 17.3       ,1.362202  ,  4.000798
```