In [1]:
```
#Banking Loan Approval ratings
#Shaquiel Pashtunyar
#DSC630 Term Project
```

In [2]:
```
import pandas as pd
import numpy as np
```

In [3]:
```
#Import datasets
LoanDefault = pd.read_csv('application_data.csv')
```

In [4]:
```
LoanDefault.head()
```

Out[4]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALT
0	100002	1	Cash loans	M	N	
1	100003	0	Cash loans	F	N	
2	100004	0	Revolving loans	M	Y	
3	100006	0	Cash loans	F	N	
4	100007	0	Cash loans	M	N	

5 rows × 122 columns

In [5]:
```
LoanDefault.shape
```

Out[5]:
```
(307511, 122)
```

In [6]:
```
print('From my initial look at the data we see that the data has 307,511 entries with
```

```
From my initial look at the data we see that the data has 307,511 entries with 122 va
riables
```

In [7]:
```
#the data set came with a description as well
LoanDesc =  pd.read_csv('columns_description.csv')
```

In [8]:
```
LoanDesc
```

Out[8]:

	Unnamed: 0	Table	Row	Description	Special
0	1	application_data	SK_ID_CURR	ID of loan in our sample	NaN
1	2	application_data	TARGET	Target variable (1 - client with payment diffi...	NaN
2	5	application_data	NAME_CONTRACT_TYPE	Identification if loan is cash or revolving	NaN
3	6	application_data	CODE_GENDER	Gender of the client	NaN
4	7	application_data	FLAG_OWN_CAR	Flag if the client owns a car	NaN
...	...	...	...	...	...
155	209	previous_application.csv	DAYS_FIRST_DUE	Relative to application date of current applic...	time only relative to the application
156	210	previous_application.csv	DAYS_LAST_DUE_1ST_VERSION	Relative to application date of current applic...	time only relative to the application
157	211	previous_application.csv	DAYS_LAST_DUE	Relative to application date of current applic...	time only relative to the application
158	212	previous_application.csv	DAYS_TERMINATION	Relative to application date of current applic...	time only relative to the application
159	213	previous_application.csv	NFLAG_INSURED_ON_APPROVAL	Did the client requested insurance during the ...	NaN

160 rows × 5 columns

In [9]:

```
LoanDefault.isnull().values.sum()
```

Out[9]:

```
9152465
```

In [10]:

```
print('there are 9 million null values on the data set we have picked')
```

```
there are 9 million null values on the data set we have picked
```

In [11]:

```
LoanDefaultCount = LoanDefault["TARGET"].value_counts()
```

In [12]:
```
LoanDefaultCount
```

Out[12]:
```
0    282686
1     24825
Name: TARGET, dtype: int64
```

In [13]:
```
print('We can see that the loan default summary has 24825 targetted loan defaulters, t
```

```
We can see that the loan default summary has 24825 targetted loan defaulters, thats
8% of all loans
```

In [14]:
```
LoanDefault.describe()
```

Out[14]:

	SK_ID_CURR	TARGET	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNU
count	307511.000000	307511.000000	307511.000000	3.075110e+05	3.075110e+05	307499.00(
mean	278180.518577	0.080729	0.417052	1.687979e+05	5.990260e+05	27108.57
std	102790.175348	0.272419	0.722121	2.371231e+05	4.024908e+05	14493.73
min	100002.000000	0.000000	0.000000	2.565000e+04	4.500000e+04	1615.50(
25%	189145.500000	0.000000	0.000000	1.125000e+05	2.700000e+05	16524.00(
50%	278202.000000	0.000000	0.000000	1.471500e+05	5.135310e+05	24903.00(
75%	367142.500000	0.000000	1.000000	2.025000e+05	8.086500e+05	34596.00(
max	456255.000000	1.000000	19.000000	1.170000e+08	4.050000e+06	258025.50(

8 rows × 106 columns

In [15]:
```
print('What we know about the data, we can see that there are 300000 results, and 160
```

```
What we know about the data, we can see that there are 300000 results, and 160 variab
les to look at. Although that seems apealing, there are over 9 million null values, a
nd flags and variables that are buried in this dataset. Although there could be some
good information in this, it might be easier to start smaller with another data set a
nd come back at a more apporpriate time, as the data munging effort for this large of
the data set could go on for quite some time
```

In [16]:
```
print('Before we begin the data munging experience lets take a look at a second, much
```

```
Before we begin the data munging experience lets take a look at a second, much smalle
r dataset on the same topic, maybe it will be easier to work with and have less data
to munge
```

In [17]:
```
LoanWork2 = pd.read_csv('Default_fin.csv')
```

In [18]:
```
LoanWork2.head()
```

Out[18]:

	Index	Employed	Bank Balance	Annual Salary	Defaulted?
0	1	1	8754.36	532339.56	0
1	2	0	9806.16	145273.56	0
2	3	1	12882.60	381205.68	0
3	4	1	6351.00	428453.88	0
4	5	1	9427.92	461562.00	0

In [19]:
```
LoanWork2.shape
```
Out[19]:
```
(10000, 5)
```

In [20]:
```
print('The second data set has only 10,000 rows and only looks at 4 variables, did the
```
```
The second data set has only 10,000 rows and only looks at 4 variables, did the invid
ual default on the loan, their salary, bank balance, and if they are employed
```

In [21]:
```
print('Lets take a look at this data and see what we can make of it')
```
```
Lets take a look at this data and see what we can make of it
```

In [22]:
```
LoanWork2.isnull().values.sum()
```
Out[22]:
```
0
```

In [23]:
```
print('Data has no null values making it good to work with')
```
```
Data has no null values making it good to work with
```

In [24]:
```
LoanWork2.describe()
```
Out[24]:

	Index	Employed	Bank Balance	Annual Salary	Defaulted?
count	10000.00000	10000.000000	10000.000000	10000.000000	10000.000000
mean	5000.50000	0.705600	10024.498524	402203.782224	0.033300
std	2886.89568	0.455795	5804.579486	160039.674988	0.179428
min	1.00000	0.000000	0.000000	9263.640000	0.000000
25%	2500.75000	0.000000	5780.790000	256085.520000	0.000000
50%	5000.50000	1.000000	9883.620000	414631.740000	0.000000
75%	7500.25000	1.000000	13995.660000	525692.760000	0.000000
max	10000.00000	1.000000	31851.840000	882650.760000	1.000000

In [25]:
```
print('Data does show some people defaulting on their loans so lets dig into that')
```
```
Data does show some people defaulting on their loans so lets dig into that
```

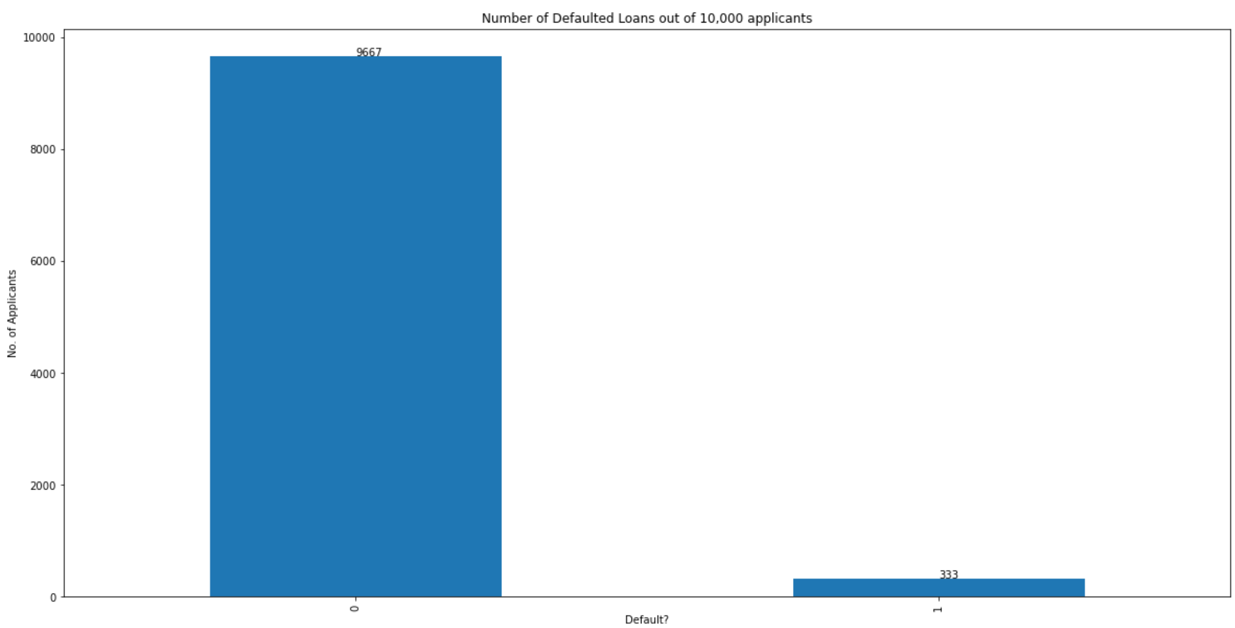
In [26]:
```
import matplotlib.pyplot as plt
print(' We can make a plot to visualize the number of defaulted loans')
```
```
 We can make a plot to visualize the number of defaulted loans
```

In [27]:
```python
Loan2DefaultCount = LoanWork2["Defaulted?"].value_counts()
```

In [28]:
```python
Loan2DefaultCount
```

Out[28]:
```
0    9667
1     333
Name: Defaulted?, dtype: int64
```

In [29]:
```python
plt.figure(figsize=(20,10))
ax = Loan2DefaultCount.plot(kind='bar')
plt.xlabel("Default?")
plt.ylabel("No. of Applicants")
ax.set_title("Number of Defaulted Loans out of 10,000 applicants")
x= ["Not Defaulted", "Defaulted"]
y= [9667,333]
def addlabels(x,y):
    for i in range(len(x)):
        plt.text(i,y[i],y[i])
addlabels(x, y)
```

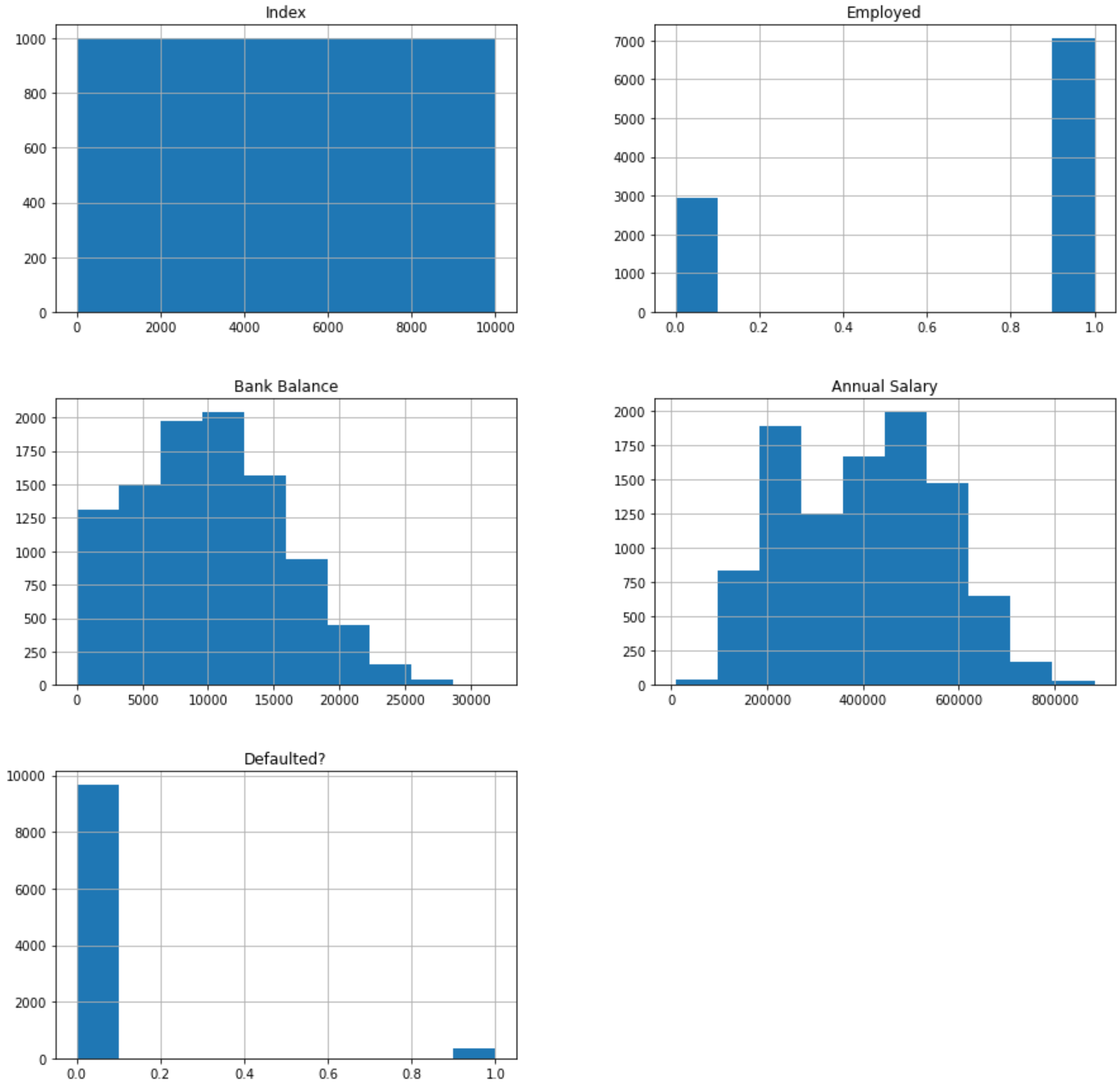


In [30]:
```python
print('From the above chart we can see that 333 applicants did default on the loan anc
```

```
From the above chart we can see that 333 applicants did default on the loan and we ha
ve something to work with, now we can start building a model to predict this
```

In [31]:
```python
#we can also get more histograms to dig into the data a little more using a basic hist
LoanWork2.hist(figsize=(15,15))
```

Out[31]:
```
array([[<AxesSubplot:title={'center':'Index'}>,
        <AxesSubplot:title={'center':'Employed'}>],
       [<AxesSubplot:title={'center':'Bank Balance'}>,
        <AxesSubplot:title={'center':'Annual Salary'}>],
       [<AxesSubplot:title={'center':'Defaulted?'}>, <AxesSubplot:>]],
      dtype=object)
```

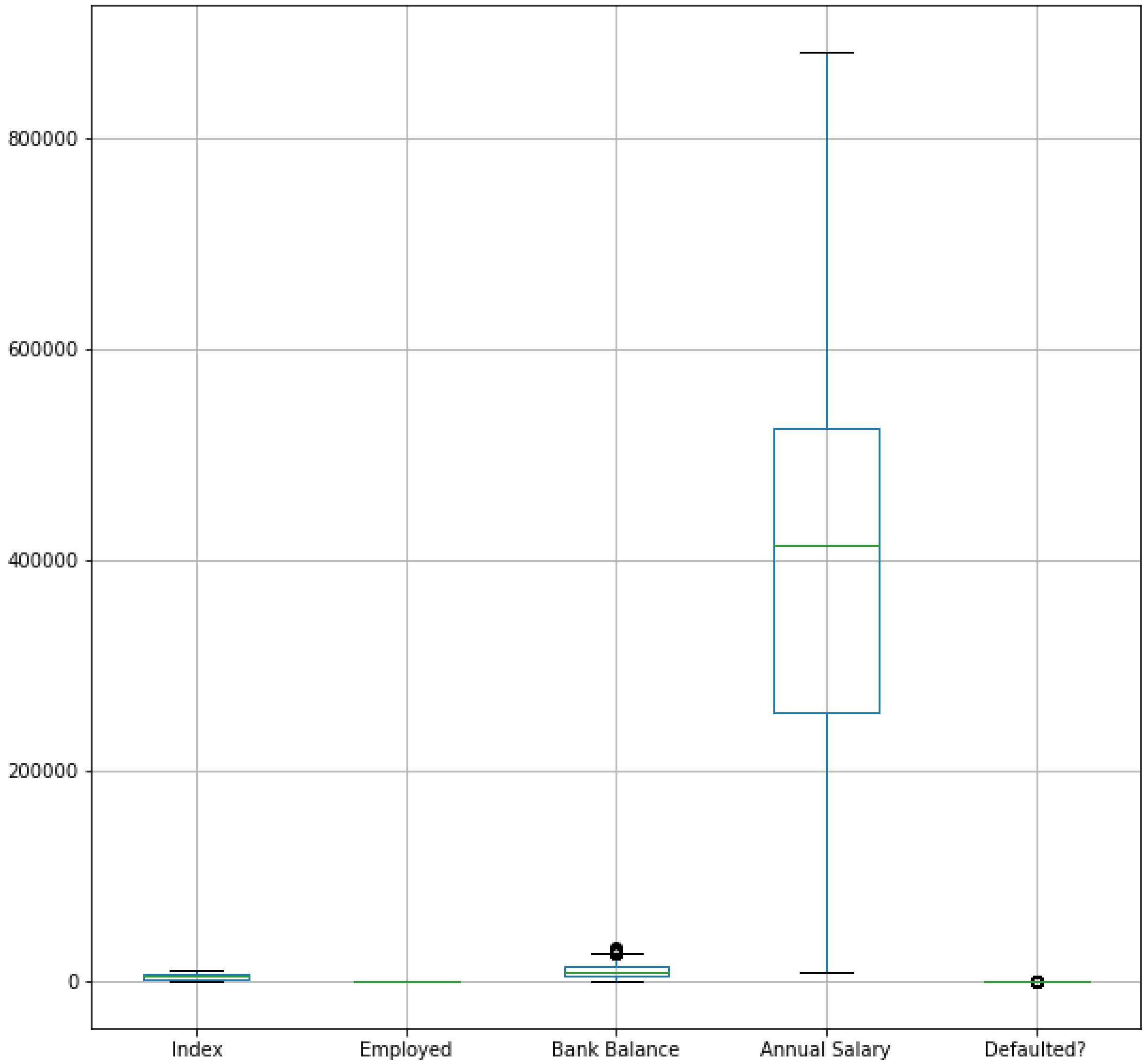


In [32]:

```
#We can also look at the basic boxplot function to see the spread in salary and bank b
LoanWork2.boxplot(figsize=(10,10))
```

Out[32]:

```
<AxesSubplot:>
```



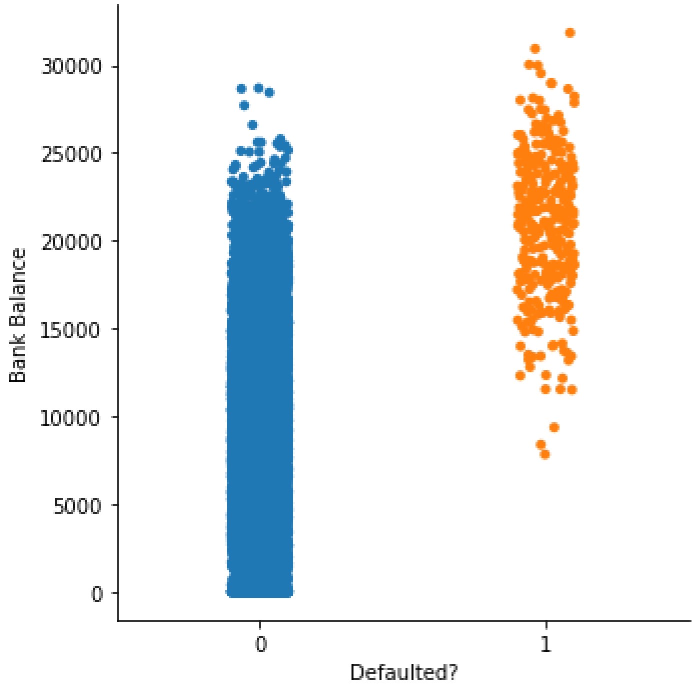
In [33]:
```
print('Interesting finding here is that the salary range is quite big, but the bank ba
```

```
Interesting finding here is that the salary range is quite big, but the bank balance
of most people is usuallyt less than 10,000. So most people arent hoarding cash in th
eir bank accounts
```

In [34]:
```
#importing seaborn for more chart options
import seaborn as sns
```

In [35]:
```
#plotting bank balance to the default rate
sns.catplot(data=LoanWork2,x="Defaulted?",y="Bank Balance")
```

Out[35]:
```
<seaborn.axisgrid.FacetGrid at 0x19b266dad90>
```

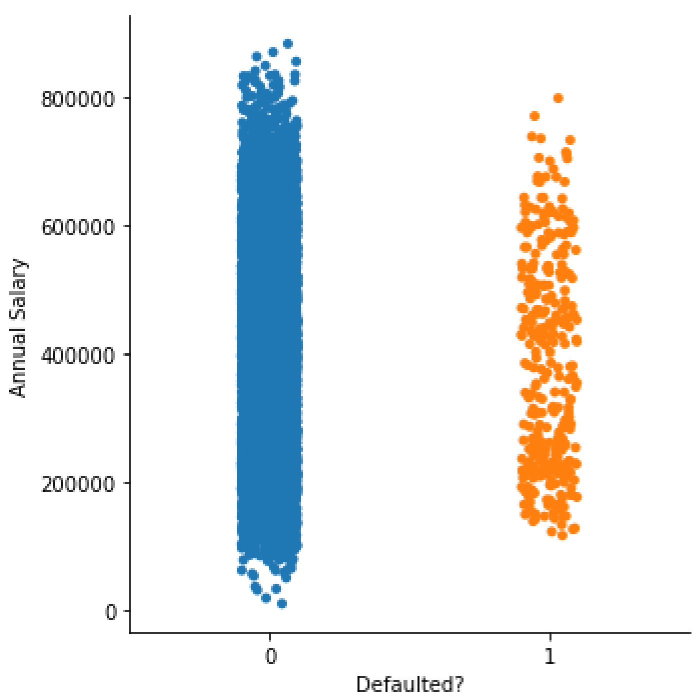


In [36]:
```
print('Interestingly enough, those who defaulted on their loans had more money in thei
```

```
Interestingly enough, those who defaulted on their loans had more money in their bank
balancethan others, this makes sense as the loan is smaller, you likely would not def
ault
```

In [37]:
```
#plotting salary to the default rate
sns.catplot(data=LoanWork2,x="Defaulted?",y="Annual Salary")
```

Out[37]: <seaborn.axisgrid.FacetGrid at 0x19b26b8d220>



In [38]:
```
print('Unlike the bank balance chart, the salary of an indiviudal seems to have little
```

```
Unlike the bank balance chart, the salary of an indiviudal seems to have little effec
t on their deault rate.
```

In [39]:
```
#Running correlation analysis after all the plotting
LoanWork2.corr()
```

Out[39]:

	Index	Employed	Bank Balance	Annual Salary	Defaulted?
Index	1.000000	-0.002597	0.010342	-0.001427	-0.005135
Employed	-0.002597	1.000000	-0.203578	0.753985	-0.035420
Bank Balance	0.010342	-0.203578	1.000000	-0.152243	0.350119
Annual Salary	-0.001427	0.753985	-0.152243	1.000000	-0.019871
Defaulted?	-0.005135	-0.035420	0.350119	-0.019871	1.000000

In [40]:
```
print('It would appear that most things are not too correlated but the bank balance ha
```

```
It would appear that most things are not too correlated but the bank balance has a 3
5% correlation to defaulting
```

In [41]:
```
print(' Current learnings from just visualizations and data exploration, there are no
```

```
 Current learnings from just visualizations and data exploration, there are no null v
alues and everything is accounted for in this data set. It is much cleaner and has a
clear target variable. From the charts and the describe funciton, we have learned tha
t the mean income is 400000, about 1/3 of all individuals surveyed were unemployed, m
ost people do not save much case even with a variable salary, the default loan rate i
s sitting at 3.3% and the data is mostly ready to go, with all of this, lets start wo
rking towards a logistic regression for our model
```

In [42]:
```
#Start with dropping some of my columns like the index column and the defaulted so I c
CleanerX = LoanWork2.drop(columns=["Defaulted?","Index"])
CleanerY = LoanWork2["Defaulted?"]
```

In [43]:
```
CleanerX.columns
```

Out[43]:
```
Index(['Employed', 'Bank Balance', 'Annual Salary'], dtype='object')
```

In [44]:
```
print('I now have my X variables in comparison to my target or y, which is the Default
```

```
I now have my X variables in comparison to my target or y, which is the Defaulted que
stion
```

In [45]:
```
CleanerX
```

Out[45]:

	Employed	Bank Balance	Annual Salary
0	1	8754.36	532339.56
1	0	9806.16	145273.56
2	1	12882.60	381205.68
3	1	6351.00	428453.88
4	1	9427.92	461562.00
...	...	...	...
9995	1	8538.72	635908.56
9996	1	9095.52	235928.64
9997	1	10144.92	703633.92
9998	1	18828.12	440029.32
9999	0	2411.04	202355.40

10000 rows × 3 columns

In [46]:

```
#emploted will need to get dummies so its a boolean variable
CleanerX = pd.get_dummies(CleanerX,columns=['Employed'])
```

In [47]:

```
CleanerX
```

Out[47]:

	Bank Balance	Annual Salary	Employed_0	Employed_1
0	8754.36	532339.56	0	1
1	9806.16	145273.56	1	0
2	12882.60	381205.68	0	1
3	6351.00	428453.88	0	1
4	9427.92	461562.00	0	1
...	...	...	...	...
9995	8538.72	635908.56	0	1
9996	9095.52	235928.64	0	1
9997	10144.92	703633.92	0	1
9998	18828.12	440029.32	0	1
9999	2411.04	202355.40	1	0

10000 rows × 4 columns

In [48]:

```
#Getting my model imported
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
from sklearn import linear_model
```

In [49]:
```
#splitting the data in both testing and training sets, picking a random state number c
X_train,X_test,Y_train,Y_test = train_test_split(CleanerX,CleanerY,random_state=2)
```

In [50]:
```
Y_train.value_counts()
```

Out[50]:
```
0    7234
1     266
Name: Defaulted?, dtype: int64
```

In [51]:
```
print(' We have a target train that has a good number of variables to target')
```

```
 We have a target train that has a good number of variables to target
```

In [52]:
```
X_train.shape
```

Out[52]:
```
(7500, 4)
```

In [53]:
```
Y_train.shape
```

Out[53]:
```
(7500,)
```

In [54]:
```
#will need smote for normaliztion and stats for scoring my results
from imblearn.over_sampling import SMOTE
from scipy import stats
```

In [55]:
```
#To rebalance the sample size I will use the smote function which normalizes the datas
X_train,Y_train = SMOTE(random_state=1).fit_resample(X_train,Y_train)
```

In [56]:
```
#Creating my logisitic regression fit
model=linear_model.LogisticRegression(random_state=2)
```

In [57]:
```
model.fit(X_train,Y_train)
pred=model.predict(X_test)
cm = confusion_matrix(Y_test,pred)
#took the confusion matrix formula from geeksforgeeks
print("accuracy is : ",(cm[0,0]+cm[1,1])/sum(sum(cm)))
```

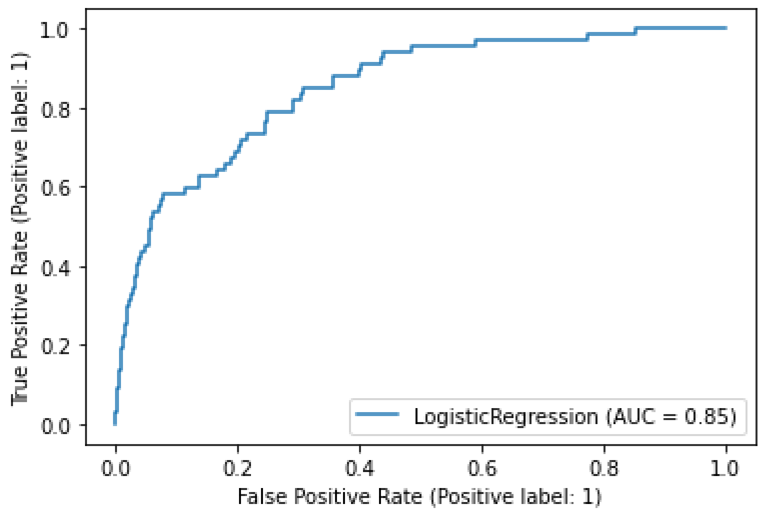
```
accuracy is :  0.6772
```

In [58]:
```
#additional charting functions
from sklearn.metrics import plot_precision_recall_curve,plot_roc_curve
```

In [59]:
```
#ROC Curve to look at the flase positive rate
plot_roc_curve(model,X_test,Y_test)
```

```
C:\Users\spashtunyar\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:87: FutureWarning: Function plot_roc_curve is deprecated; Function :func:`plot_roc_curve` is deprecated in 1.0 and will be removed in 1.2. Use one of the class methods: :meth:`sklearn.metric.RocCurveDisplay.from_predictions` or :meth:`sklearn.metric.RocCurveDisplay.from_estimator`.
  warnings.warn(msg, category=FutureWarning)
```

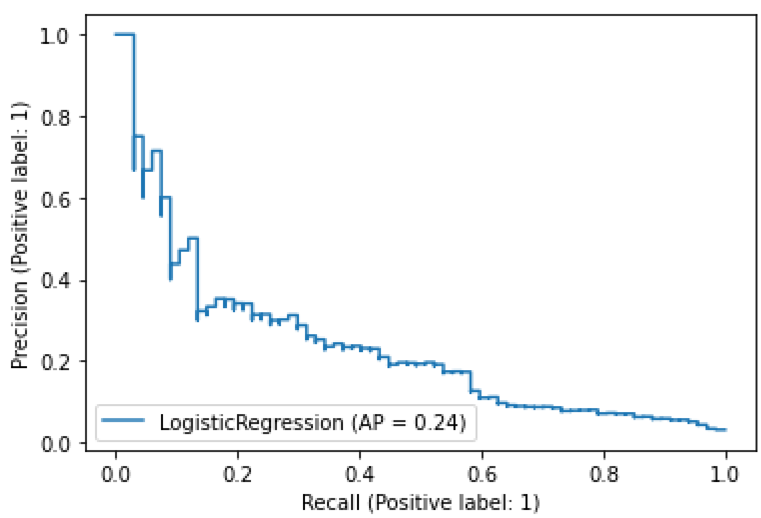
Out[59]:
```
<sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x19b22a084f0>
```



In [60]:
```
#Precision recall curve to look at preciseness
plot_precision_recall_curve(model,X_test,Y_test)
```

```
C:\Users\spashtunyar\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:87: Fut
ureWarning: Function plot_precision_recall_curve is deprecated; Function `plot_precis
ion_recall_curve` is deprecated in 1.0 and will be removed in 1.2. Use one of the cla
ss methods: PrecisionRecallDisplay.from_predictions or PrecisionRecallDisplay.from_es
timator.
  warnings.warn(msg, category=FutureWarning)
```

Out[60]:
```
<sklearn.metrics._plot.precision_recall_curve.PrecisionRecallDisplay at 0x19b3a64c130
>
```



In [61]:
```
#Time to score my analysis
from sklearn.metrics import mean_absolute_error, mean_squared_error
```

In [62]:
```
mae = mean_absolute_error(Y_test, pred)
mse = mean_squared_error(Y_test, pred)
rmse = np.sqrt(mse)
```

In [63]:
```
print(f'Mean absolute error: {mae:.2f}')
print(f'Mean squared error: {mse:.2f}')
print(f'Root mean squared error: {rmse:.2f}')
```

```
Mean absolute error: 0.32
Mean squared error: 0.32
Root mean squared error: 0.57
```

In [64]:

```python
print("R2 for the Log Regression is :",model.score(X_test,Y_test))
```

```
R2 for the Log Regression is : 0.6772
```

In [65]:

```python
print("With the analysis coming to an initial conclusion, we see that we are getting a
```

```
With the analysis coming to an initial conclusion, we see that we are getting about 6
5-70% accuracy, correctly predicting 2/3rds of the predictions made. This is not the
best result and there are a number of reasons. We may need more variables to create a
better model, this would be the route of using the other data set. Another option is
creating a second model using another method. Some contendors are decision tree or Nu
ral network to see their results.
```

In [ ]:

```python

```