M1 Project fall 2019: Financial data about vehicle loan default prediction.

Groupmembers:

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This notebook can be accessed here: https://colab.research.google.com/drive/1gTQ_F7BUl5kzPY4Jg9KfptAUtUjRqS8j (https://colab.research.google.com/drive/1gTQ_F7BUl5kzPY4Jg9KfptAUtUjRqS8j)

Github link here: https://github.com/mvonke15/SDS-M1---Group-assignment (https://github.com/mvonke15/SDS-M1---Group-assignment)

Origin of dataset.

This project is based on data from Kaggle.

https://www.kaggle.com/mamtadhaker/lt-vehicle-loan-default-prediction (https://www.kaggle.com/mamtadhaker/lt-vehicle-loan-default-prediction)

We have chosen data that gives us a chance to work with a problem that relate to the real world. In this case: How can we help financial institutions to prevent loses due to the default of vehicle loans.

The dataset has Loanee Information (Demographic data like age, Identity proof etc.) Loan Information (Disbursal details, loan to value ratio etc.) Bureau data & history (Bureau score, number of active accounts, the status of other loans, credit history etc.)

The data comes in three sets: test, train and a feature describtion.

In [0]:

```
# Import stuff

# Importing modules
import pandas as pd
import numpy as np
from sklearn import preprocessing
import matplotlib
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
matplotlib.style.use('ggplot')
from sklearn.cluster import KMeans


# Allow access to www.netfordig.dk
import ssl
ssl.match_hostname = lambda cert, hostname: True

dictionary = pd.read_csv('https://www.netfordig.dk/m1project/mod_data/data_dictionar
y.csv')
test = pd.read_csv('https://www.netfordig.dk/m1project/mod_data/test.csv')
train = pd.read_csv('https://www.netfordig.dk/m1project/mod_data/train.csv')
print("Datasets loaded")
```

```
Datasets loaded
```

In [0]:

```
# Initial overview of dataframe
test.head()
```

Out[0]:

	UniqueID	disbursed_amount	asset_cost	ltv	branch_id	supplier_id	manufacturer_id	Cu
0	655269	53478	63558	86.54	67	22807	45	
1	723482	55513	63163	89.45	67	22807	45	
2	758529	65282	84320	79.93	78	23135	86	
3	763449	46905	63896	76.58	78	17014	45	
4	708663	51428	63896	86.08	78	17014	45	

In [0]:

```
# Initial overview of dataframe
train.head()
```

Out[0]:

	UniqueID	disbursed_amount	asset_cost	ltv	branch_id	supplier_id	manufacturer_id
420825	50578	58400	89.55	67	22807	45	1441
537409	47145	65550	73.23	67	22807	45	1502
417566	53278	61360	89.63	67	22807	45	1497
624493	57513	66113	88.48	67	22807	45	1501
539055	52378	60300	88.39	67	22807	45	1495

PREPROCESING ON TEST AND TRAIN SET - MERGE DATESETS.

We observe that our test and train dataframes are not compatible, thus needs some preprocessing. The 'train' dataframe have columns which are shifted to the left as well as another index than 'test' dataframe.

This means that we aren't able to use them for classification in the state they are now. Likewise, we don't have knowledge about how the original split was undertaken. Was it done manually or using test/train split method which we will use later?

The safe method for us would be to preprocess the two dataframes, merge them and later complete our own and controlled test/train splits.

We will do that with the code below.

In [0]:

```
# reset index in traindata.
train.reset_index(inplace=True)

# We have one additional column in the 'train' dataframe now. Thus we drop the last
 one as this 'info' is not available in the 'test' dataframe.
train.drop(['NO_OF_INQUIRIES'], axis=1, inplace=True)
# Defining new column-names for the 'train' dataframe based on the 'test' dataframe
 names.
new_cols = test.columns

# Replacing old column names.
train.columns = new_cols

# Merging the dataframes
loans = pd.merge(test, train, how='outer')
loans.head()
```

Out[0]:

	UniqueID	disbursed_amount	asset_cost	ltv	branch_id	supplier_id	manufacturer_id	Ci
0	655269	53478	63558	86.54	67	22807	45	
1	723482	55513	63163	89.45	67	22807	45	
2	758529	65282	84320	79.93	78	23135	86	
3	763449	46905	63896	76.58	78	17014	45	
4	708663	51428	63896	86.08	78	17014	45	

PREPROCESSING ON MERGED DATASET

After merging test and train, we would like to convert all the objectbased columns to numerical values, so we can scale the data. Using head() and info() we observe, that we will have to work on the following columns:

1. CREDIT_HISTORY_LENGTH: Column is filled with objects (strings), that need to be number.
2. AVERAGE_ACCT_AGE: Column is filled with objects (strings), that need to be number.
3. Date_of_Birth: Column is filled with objects (strings), that need to be datetime.
4. DisbursalData: Column is filled with objects (strings), that need to be datetime.
5. Employment_Type: Column is filled with objects (strings), that need to be number.
6. PERFORM_CNS_SCORE_DESCRIPTION: This a description of another columns data. We dont need that.
7. We need DELINQUENT_ACCTS_IN_LAST_SIX_MONTHS turned into something more manageable eg. when is a loan default or not.

In [0]:

```
# The number of months without payment, before we consider a loan default eg 1 means that 0 and 1 months late is "OK".
# 2 month or above and we consider (for the purpose this project) that the loan is default.
# The n_default variable can be changed.
n_default = 1
```

In [0]:

```
# Define function for replacing X yrs and X mon in CREDIT_HISTORY_LENGTH and AVERAGE_ACCT_AGE:
def converter(text):
  # Splits at space
  substrings = text.split()
  sub1 = substrings[0].replace('yrs', '')
  sub2 = substrings[1].replace('mon', '')
  sub1 = int(sub1)
  sub2 = int(sub2)
  mon1 = sub1 *12
  mon=mon1 + sub2
  return mon

# Applying converter function
loans['CREDIT_HISTORY_LENGTH'] = loans.CREDIT_HISTORY_LENGTH.apply(converter)
loans['AVERAGE_ACCT_AGE'] = loans.AVERAGE_ACCT_AGE.apply(converter)
```

In [0]:

```
# Converting objects to datetime - SLOW.
loans['Date_of_Birth'] = pd.to_datetime(loans['Date_of_Birth'], errors='coerce')
loans['DisbursalDate'] = pd.to_datetime(loans['DisbursalDate'], errors='coerce')

# today = this is the day, to which we estimate age. It's the last date in the Disbursal columns => last recorded day of the dataframe.
today = loans['DisbursalDate'].max()
```

In [0]:

```
loans['AGE_IN_DAYS'] = ((today - loans['Date_of_Birth'])) # input in days, not in years. This doesn´t matters, because we scale later.
loans['AGE_IN_DAYS'] = loans['AGE_IN_DAYS'].dt.days
```

In [0]:

```
# Label encode objects specifying type of work/employment.
loans['Employment_Type'] = loans.Employment_Type.fillna('Unknown')
from sklearn import preprocessing
le = preprocessing.LabelEncoder()
loans['Employment_Type'] = le.fit_transform(loans['Employment_Type'])
```

In [0]:

```
# We drop columns that are no longer needed.
loans.drop(['PERFORM_CNS_SCORE_DESCRIPTION'], axis=1, inplace=True) # Not relevant f
or classification. Just at description of another column´s data.
loans.drop(['Date_of_Birth'], axis=1, inplace=True) # Not relevant for classificatio
n. We changes this into age in days.
```

In [0]:

```
loans["Default"] = np.nan

# Function for making booleans for default or not. Anything above 1 months delayed p
ayment is deafult in this case.
def defaultconverter(number):
  if number > n_default:
    value = 1
  else:
    value = 0
  return value

# Applying converter function
loans['Default'] = loans.DELINQUENT_ACCTS_IN_LAST_SIX_MONTHS.apply(defaultconverter)
```

In [0]:

```
# Our new dateframe - top 5
loans.head()
```

Out[0]:

	UniqueID	disbursed_amount	asset_cost	ltv	branch_id	supplier_id	manufacturer_id	Cı
0	655269	53478	63558	86.54	67	22807	45	
1	723482	55513	63163	89.45	67	22807	45	
2	758529	65282	84320	79.93	78	23135	86	
3	763449	46905	63896	76.58	78	17014	45	
4	708663	51428	63896	86.08	78	17014	45	

In [0]:

```
# Our new dataframe - bottom 5.
loans.tail()
```

Out[0]:

	UniqueID	disbursed_amount	asset_cost	ltv	branch_id	supplier_id	manufacturer_
345541	626432	63213	105405	60.72	34	20700	
345542	606141	73651	100600	74.95	34	23775	
345543	613658	33484	71212	48.45	77	22186	
345544	548084	34259	73286	49.10	77	22186	
345545	630213	75751	116009	66.81	77	22186	

In [0]:

```
# Ensuring that we have the required format.
loans.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 345546 entries, 0 to 345545
Data columns (total 40 columns):
UniqueID                               345546 non-null int64
disbursed_amount                       345546 non-null int64
asset_cost                             345546 non-null int64
ltv                                    345546 non-null float64
branch_id                              345546 non-null int64
supplier_id                            345546 non-null int64
manufacturer_id                        345546 non-null int64
Current_pincode_ID                     345546 non-null int64
Employment_Type                        345546 non-null int64
DisbursalDate                          345546 non-null datetime64[ns]
State_ID                               345546 non-null int64
Employee_code_ID                       345546 non-null int64
MobileNo_Avl_Flag                      345546 non-null int64
Aadhar_flag                            345546 non-null int64
PAN_flag                               345546 non-null int64
VoterID_flag                           345546 non-null int64
Driving_flag                           345546 non-null int64
Passport_flag                          345546 non-null int64
PERFORM_CNS_SCORE                      345546 non-null int64
PRI_NO_OF_ACCTS                        345546 non-null int64
PRI_ACTIVE_ACCTS                       345546 non-null int64
PRI_OVERDUE_ACCTS                      345546 non-null int64
PRI_CURRENT_BALANCE                    345546 non-null int64
PRI_SANCTIONED_AMOUNT                  345546 non-null int64
PRI_DISBURSED_AMOUNT                   345546 non-null int64
SEC_NO_OF_ACCTS                        345546 non-null int64
SEC_ACTIVE_ACCTS                       345546 non-null int64
SEC_OVERDUE_ACCTS                      345546 non-null int64
SEC_CURRENT_BALANCE                    345546 non-null int64
SEC_SANCTIONED_AMOUNT                  345546 non-null int64
SEC_DISBURSED_AMOUNT                   345546 non-null int64
PRIMARY_INSTAL_AMT                     345546 non-null int64
SEC_INSTAL_AMT                         345546 non-null int64
NEW_ACCTS_IN_LAST_SIX_MONTHS           345546 non-null int64
DELINQUENT_ACCTS_IN_LAST_SIX_MONTHS    345546 non-null int64
AVERAGE_ACCT_AGE                       345546 non-null int64
CREDIT_HISTORY_LENGTH                  345546 non-null int64
NO_OF_INQUIRIES                        345546 non-null int64
AGE_IN_DAYS                            345546 non-null int64
Default                                345546 non-null int64
dtypes: datetime64[ns](1), float64(1), int64(38)
memory usage: 108.1 MB
```

In [0]:

```
# Checking for missing values.
loans.isnull().sum()
```

Out[0]:

```
UniqueID                               0
disbursed_amount                       0
asset_cost                             0
ltv                                    0
branch_id                              0
supplier_id                            0
manufacturer_id                        0
Current_pincode_ID                     0
Employment_Type                        0
DisbursalDate                          0
State_ID                               0
Employee_code_ID                       0
MobileNo_Avl_Flag                      0
Aadhar_flag                            0
PAN_flag                               0
VoterID_flag                           0
Driving_flag                           0
Passport_flag                          0
PERFORM_CNS_SCORE                      0
PRI_NO_OF_ACCTS                        0
PRI_ACTIVE_ACCTS                       0
PRI_OVERDUE_ACCTS                      0
PRI_CURRENT_BALANCE                    0
PRI_SANCTIONED_AMOUNT                  0
PRI_DISBURSED_AMOUNT                   0
SEC_NO_OF_ACCTS                        0
SEC_ACTIVE_ACCTS                       0
SEC_OVERDUE_ACCTS                      0
SEC_CURRENT_BALANCE                    0
SEC_SANCTIONED_AMOUNT                  0
SEC_DISBURSED_AMOUNT                   0
PRIMARY_INSTAL_AMT                     0
SEC_INSTAL_AMT                         0
NEW_ACCTS_IN_LAST_SIX_MONTHS           0
DELINQUENT_ACCTS_IN_LAST_SIX_MONTHS    0
AVERAGE_ACCT_AGE                       0
CREDIT_HISTORY_LENGTH                  0
NO_OF_INQUIRIES                        0
AGE_IN_DAYS                            0
Default                                0
dtype: int64
```

In [0]:

```
# Ensuring that we have borrowers that pays in time and as well as delinquent ones.
loans.Default.unique()
```

Out[0]:

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

Conclusion of preproccesing.

We have removed selected features/columns and converted objecs to number. We can now do some descriptive statistics in the dataset and later scale it. We can also observe whether we have outliers or not.

GENERAL DESCRIPTION OF THE DATAFRAME.

Below we do some initial exploration of the dataframe. We find that the total amount of issued loans are 345.546 from which 4.718 to varying extend are delinquent. In total there have been issued loans worth 18.976.134.542 USD. This has occured in 82 branches split across 22 states with 3.398 employees in total. In regard to the borrower the mean age is 26,19 and the mean loan issued is 54.916 USD for a mean cost of a car at 76.294 USD.

In [0]:

```
# Codes for description of dataframe
n_loans = loans.UniqueID.nunique()
n_default = loans.Default.sum()
p_default = n_default/n_loans
n_branches = loans.branch_id.nunique()
n_employees = loans.Employee_code_ID.nunique()
n_states = loans.State_ID.nunique()
m_age = (loans.AGE_IN_DAYS.mean()/365)
m_carcost = loans.asset_cost.mean()
max_date = pd.to_datetime(loans['DisbursalDate'].max()).date()
min_date = pd.to_datetime(loans['DisbursalDate'].min()).date()
n_total_loans = loans['disbursed_amount'].sum()
n_mean_loans = loans['disbursed_amount'].mean()
n_mean_loan_branch = loans['UniqueID'].nunique()/loans['branch_id'].nunique()

# We print the above
print("Date ranges from", "\t",  "\t" , min_date, "to ", max_date)
print("Number of loans", "\t","\t", n_loans)
print("Number of defaults", "\t","\t", n_default)
print("Percentages of default loans" , "\t", p_default)
print("Number of none-defaults", "\t",n_loans - n_default)
print("Total amount of Loans", "\t", "\t", n_total_loans)
print("Number of branches", "\t","\t", n_branches)
print("Mean loan by branches", "\t","\t", n_mean_loan_branch)
print("Number of employees", "\t", "\t", n_employees)
print("Number of states", "\t", "\t", n_states)
print("Mean Age", "\t", "\t", "\t", m_age)
print("Mean cost of car",  "\t", "\t", m_carcost)
print("Mean of disbursed","\t", "\t", n_mean_loans)
```

```
Date ranges from                 2018-01-08 to  2018-12-11
Number of loans                  345546
Number of defaults               4718
Percentages of default loans     0.013653753769396839
Number of none-defaults          340828
Total amount of Loans            18976134542
Number of branches               82
Mean loan by branches            4213.975609756098
Number of employees              3398
Number of states                 22
Mean Age                         26.1905007037106
Mean cost of car                 76294.83864955751
Mean of disbursed                54916.377391143295
```

In [0]:

HOW MANY LOANS ARE ISSUED AND HOW BIG OF A SHARE OF THE LOANS ARE DELIQUINT AFTER 2 MONTHS OR ABOVE?

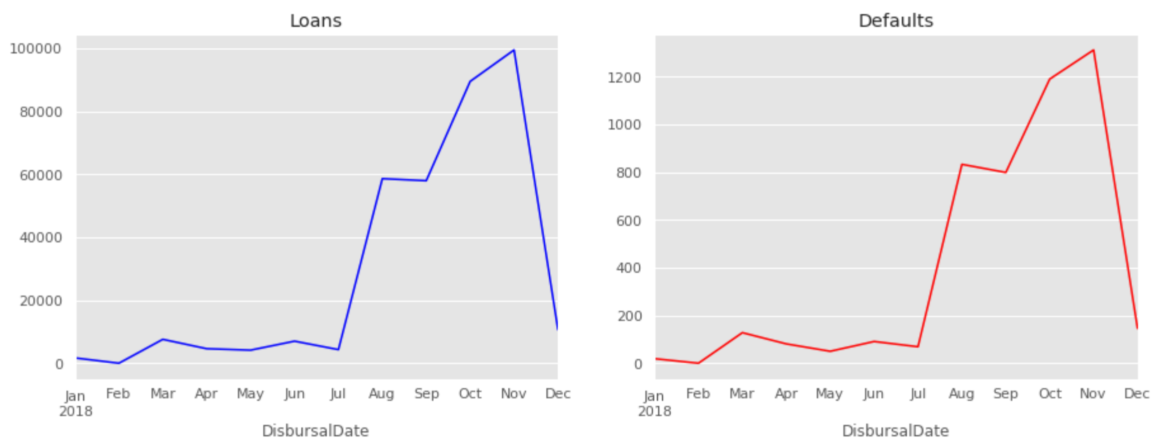
In [0]:

```
# Sets the size of the visual plot (widt x height).
plt.rcParams["figure.figsize"] =(10,10)

# Copy of loans dataframe for visualizing and reindexing.
resampled_loans = loans.copy()
resampled_loans.set_index(resampled_loans['DisbursalDate'], inplace=True)

# Resample loans
loans_month = resampled_loans.resample('M').UniqueID.count()
loans_month_def = resampled_loans.resample('M').Default.sum()


# Printing text.
print("Months", "\t", "\t", "Loans", "\t",  "Defaults", "\t", "Percentages defaults"
)
for i in range(len(loans_month)):
    print(pd.to_datetime(loans_month.index[i]).date(), "\t", loans_month[i], "\t", l
oans_month_def[i], "\t", "\t", (loans_month_def[i]/loans_month[i])*100 )

fig, ax = plt.subplots(ncols=2, figsize=(15,5))
loans_month.plot(ax=ax[0],c ='blue', title='Loans')
loans_month_def.plot(ax=ax[1], c='red', title='Defaults')
```

```
Months          Loans   Defaults        Percentages defaults
2018-01-31      1708    19              1.1241217798594886
2018-02-28      25      0               0.0
2018-03-31      7601    128             1.6839889488225235
2018-04-30      4627    81              1.7505943375837476
2018-05-31      4178    50              1.1967448539971277
2018-06-30      7024    91              1.2955580865603644
2018-07-31      4339    69              1.5902281631712378
2018-08-31      58586   833             1.4218413955552522
2018-09-30      57939   799             1.37903657294741
2018-10-31      89440   1190            1.3305008944543828
2018-11-30      99420   1312            1.31965399316033
2018-12-31      10659   146             1.369734496669481
```

Out[0]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb31f0f4ac8>
```



DESCRIPTION OF BORROWERS

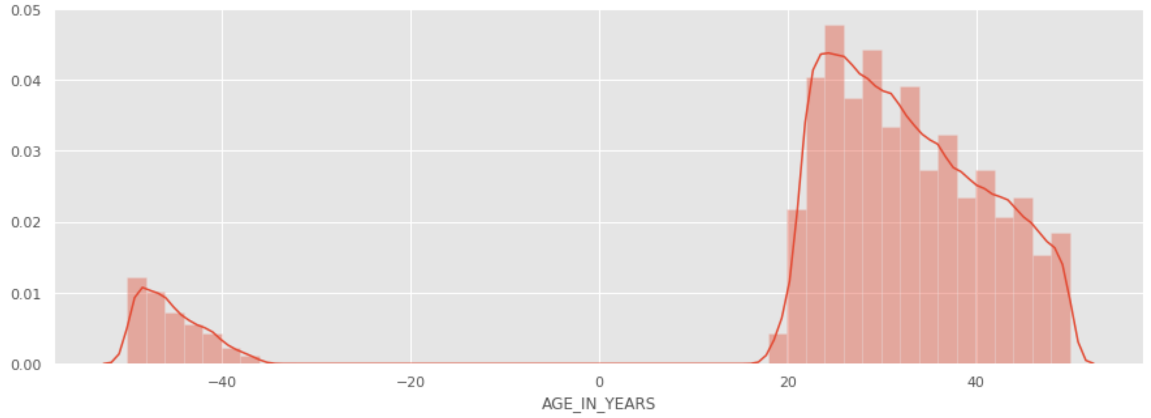
In [0]:

```
# Estimating max. and min. age of the borrower.
max_age = (loans['AGE_IN_DAYS'].max()/365)
min_age = (loans['AGE_IN_DAYS'].min()/365)

print ("Oldest customer:",max_age)
print ("Youngest customer:",min_age)
```

```
Oldest customer: 49.97534246575343
Youngest customer: -50.09041095890411
```

In [0]:

```
# Plotting graph of age distribution of borrowers.
plt.rcParams["figure.figsize"] =(15,5)
loans['AGE_IN_YEARS'] = ((loans['AGE_IN_DAYS'])/365)
#Displot på antal år på folk som låner.
sns.distplot((loans['AGE_IN_YEARS']))
plt.show()

# Clear the distplot
plt.clf()
```




```
<Figure size 1080x360 with 0 Axes>
```

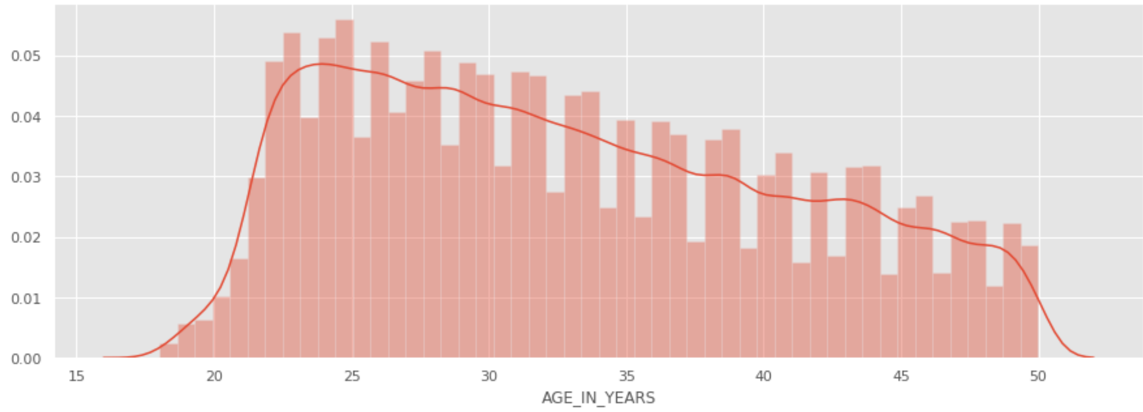
The graph above is odd as we have borrowers with a negative age. We drop these so we are left with a min. age of 18 as we consider this a 'legal' age to be issued a loan.

In [0]:

```
# Dropping borrowers below the age of 18.
loans = loans.drop(loans[loans.AGE_IN_DAYS < (18*365)].index)
```

In [0]:

```
# New plot.
plt.rcParams["figure.figsize"] =(15,5)
loans['AGE_IN_YEARS'] = ((loans['AGE_IN_DAYS'])/365)
#Displot på antal år på folk som låner.
sns.distplot((loans['AGE_IN_YEARS']))
plt.show()

# Clear the distplot
plt.clf()
```




```
<Figure size 1080x360 with 0 Axes>
```

DESCRIPTION OF THE ASSETS, COMMONALITIES AND MISC.

We want to do some further exploration. Which cars are most predominat in each state, which states has the biggest share of delinquent borrowers, how is the asset distribution (the cost of the car), and what is the disbursed amount.

In [0]:

```
# Exploring the most predominant car brand by state.
pd.crosstab(loans.State_ID, loans.manufacturer_id)
```

Out[0]:

manufacturer_id	45	48	49	51	67	86	120	145	152	153	155	156
State_ID												
1	4060	64	228	3724	19	4496	544	4	0	0	0	0
2	3106	219	57	669	48	2604	78	4	0	0	0	0
3	11666	3989	5237	8050	268	14548	1378	111	0	3	0	0
4	14530	2755	1450	5255	428	35955	3188	356	0	4	0	1
5	2965	976	1249	1717	186	5100	405	46	0	0	0	0
6	14630	2094	523	2112	265	22193	2436	2	0	0	0	0
7	2312	290	1270	2052	367	3374	127	43	0	0	0	0
8	2278	3676	904	2512	26	8073	536	16	0	0	0	0
9	1345	637	323	2104	163	13468	1773	7	8	0	0	0
10	1433	204	107	715	47	2496	80	47	0	0	0	0
11	4248	86	3	488	227	4945	65	0	0	0	0	0
12	1237	1351	319	588	16	1332	96	0	0	0	0	0
13	4911	3863	1791	2430	478	6237	1150	311	0	16	0	0
14	1722	830	77	692	17	8636	165	43	0	0	0	0
15	3256	20	108	2758	58	2648	150	0	0	0	0	0
16	1572	50	29	554	202	2227	57	0	0	0	1	0
17	866	211	71	216	31	3451	198	11	0	0	0	0
18	3695	97	89	676	250	3042	95	0	0	0	0	0
19	245	55	2	48	1	701	163	0	0	0	0	0
20	70	15	2	4	2	179	10	0	0	0	0	0
21	29	0	2	11	2	307	1	0	0	0	0	0
22	1	0	0	42	0	82	0	0	0	0	0	0

In [0]:

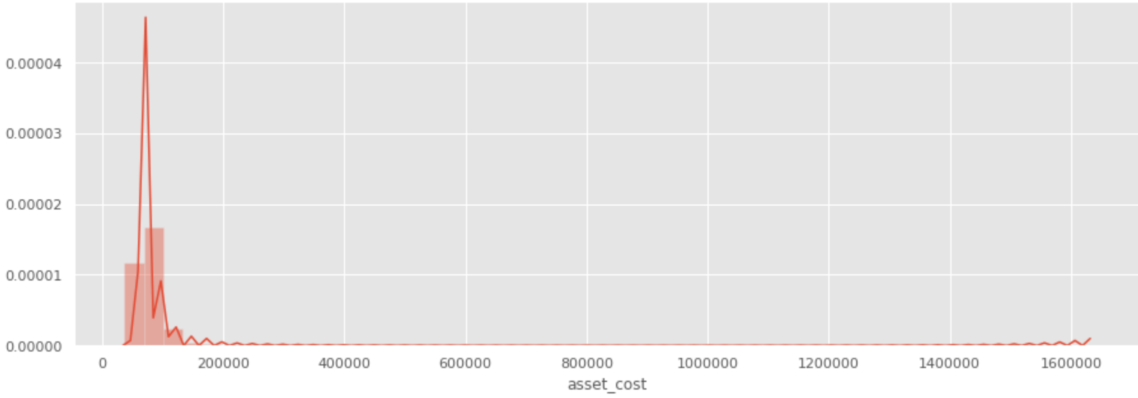
```
# Delinquent number of months by state
pd.crosstab(loans.State_ID, loans.DELINQUENT_ACCTS_IN_LAST_SIX_MONTHS)
```

Out[0]:

DELINQUENT_ACCTS_IN_LAST_SIX_MONTHS	0	1	2	3	4	5	6	7	8	9	10	1
State_ID												
1	11582	1236	239	63	10	5	2	0	1	0	0	
2	6267	424	73	15	6	0	0	0	0	0	0	
3	43457	1562	182	35	11	3	0	0	0	0	0	
4	58633	4368	697	144	47	17	3	5	2	3	1	
5	11812	710	96	14	10	1	0	0	0	0	0	
6	40905	2801	420	88	17	8	6	4	1	2	1	
7	9196	550	69	17	1	1	1	0	0	0	0	
8	16020	1529	339	83	29	12	3	2	3	0	0	
9	17698	1691	339	64	25	5	3	2	1	0	0	
10	4756	326	33	12	2	0	0	0	0	0	0	
11	9284	653	97	21	4	1	2	0	0	0	0	
12	4799	130	9	1	0	0	0	0	0	0	0	
13	20218	878	83	8	0	0	0	0	0	0	0	
14	11354	649	123	37	8	6	1	3	1	0	0	
15	8208	640	111	25	7	4	2	1	0	0	0	
16	4246	352	64	19	6	3	0	1	0	1	0	
17	4731	255	50	12	2	3	1	1	0	0	0	
18	7471	411	49	10	2	0	1	0	0	0	0	
19	1098	98	17	1	0	0	1	0	0	0	0	
20	274	6	2	0	0	0	0	0	0	0	0	
21	322	25	4	1	0	0	0	0	0	0	0	
22	120	5	0	0	0	0	0	0	0	0	0	

In [0]:

```
# Asset distribution in USD.

plt.rcParams["figure.figsize"] =(15,5)
# Plot of distribution.
sns.distplot(loans['asset_cost'])
plt.show()
# Clear the distplot.
plt.clf()
```




```
<Figure size 1080x360 with 0 Axes>
```

An odd plot - not a very normal distribution above. Let´s take a look at what is causing it.

In [0]:

```
# Estimating max., min., mean, and median of assets.
max_ass = loans['asset_cost'].max()
min_ass = loans['asset_cost'].min()
mean_ass = loans['asset_cost'].mean()
median_ass = loans['asset_cost'].median()
#print ("Most expensive car:",max_ass)
print ("Cheapest car:",min_ass)
print ("Mean car:",mean_ass)
print ("Median car:",median_ass)
print ("Top 10 most expensive cars")
mycars = loans.nlargest(10, ['asset_cost'])
print(mycars.asset_cost)
```

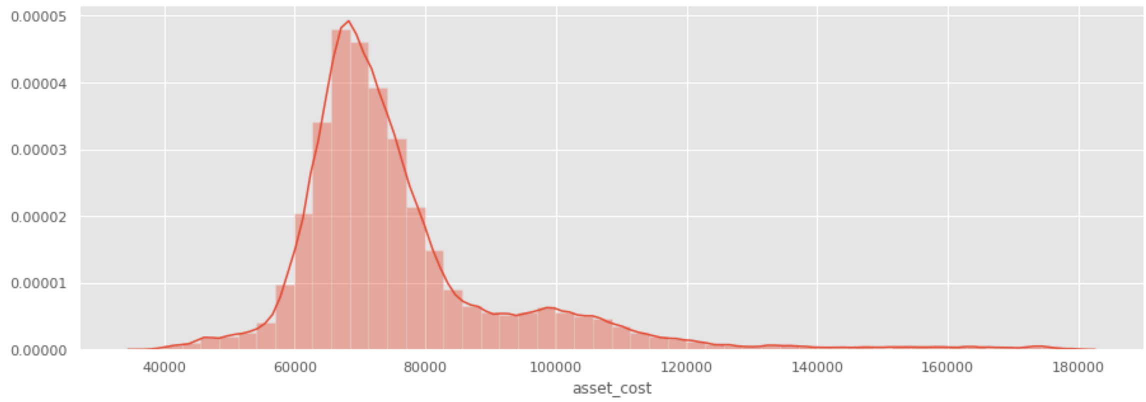
```
Cheapest car: 37000
Mean car: 76497.70291697404
Median car: 71647.0
Top 10 most expensive cars
322644    1628992
199067    1328954
91092     1271553
91094      720592
322647     715186
304998     459625
322645     388025
322646     383600
322642     378092
322643     378092
Name: asset_cost, dtype: int64
```

In [0]:

```
# We found some ridiculously priced cars - now we drop assets priced > 180.000 USD.
loans = loans.drop(loans[loans.asset_cost > 180000].index)
```

In [0]:

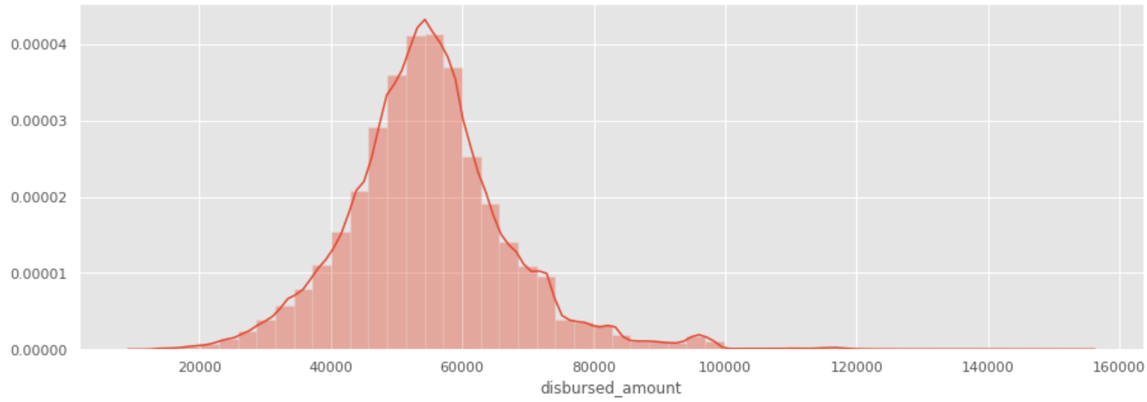
```
plt.rcParams["figure.figsize"] =(15,5)
# New plot of asset distribution.
sns.distplot(loans['asset_cost'])
plt.show()
# Clear the distplot.
plt.clf()
```



<Figure size 1080x360 with 0 Axes>

In [0]:

```
# Graphing distribution of disbursed amount (the distribution of loans issued).
plt.rcParams["figure.figsize"] =(15,5)
sns.distplot(loans['disbursed_amount'])
plt.show()
# Clear the distplot.
plt.clf()
```



<Figure size 1080x360 with 0 Axes>

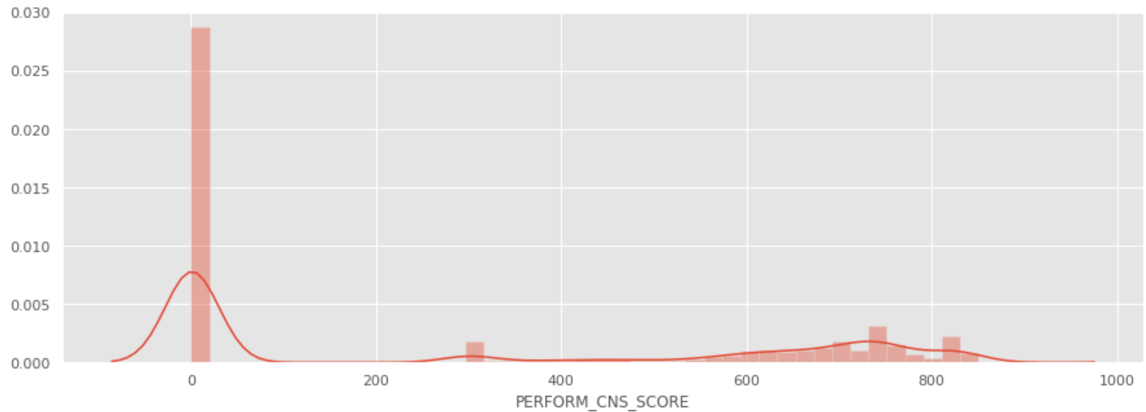
In [0]:

```
# We repeated the proces that we did for assets.
max_ass = loans['disbursed_amount'].max()
min_ass = loans['disbursed_amount'].min()
mean_ass = loans['disbursed_amount'].mean()
median_ass = loans['disbursed_amount'].median()
#print ("Most expensive car:",max_ass)
print ("Smallest loan:",min_ass)
print ("Mean loan:",mean_ass)
print ("Median loan:",median_ass)
print ("Top 10 loans")
toploans = loans.nlargest(10, ['disbursed_amount'])
print(toploans.asset_cost)
```

```
Smallest loan: 11613
Mean loan: 54836.65213804308
Median loan: 54303.0
Top 10 loans
260520    179158
304608    176523
15657     177791
61386     173018
332239    168409
258172    173918
150393    172309
313996    178714
229384    169726
304629    176523
Name: asset_cost, dtype: int64
```

In [0]:

```
# Disribution CNS Score. Max score is 900 in the real world. Do we have any outlier
s?
plt.rcParams["figure.figsize"] =(15,5)
#Displot på lånet størrelse.
sns.distplot(loans['PERFORM_CNS_SCORE'])
plt.show()
# Clear the distplot
plt.clf()
```




```
<Figure size 1080x360 with 0 Axes>
```

SCALING THE DATASET

Scaling means that we have to make a standardization of our loans dataset.

This is commonly required for many machine learning estimators implemented in scikit-learn.

If our individual features such as eg. geographical state, customers age and employment type does not look like standard normally distributed data we will get in trouble.

Our loans data are different in scale.

Just looking a loans.head() and loans.tail() show us that the feature 'Asset Cost' goes from 63558 to twice that amount (and this is a quick glance, the actual values could be lower and higher in each end of the scale).

States on the other hand, can naturally only go from 1 to 50 states. And there´s not even that many in the dataset, which means that we dont have data from all 50 US states.

So the two columns are very different in scale. We will need them in a common scale before we continue.

We can do this by scaling the data to mean of 0 and standard deviation of 1.

We will use the StandardScaler for this in the code below. But first we will print out at short describtive analysis of the dataset before scaling, so we have something to compare to the scaled date.

In [0]:

```
# Dropping columns not relevant for classification.
loans.drop(['DELINQUENT_ACCTS_IN_LAST_SIX_MONTHS'], axis=1, inplace=True) # not rele
vant for classification
loans.drop(['DisbursalDate'], axis=1, inplace=True) # not relevant for classificatio
n
loans.drop(['AGE_IN_YEARS'], axis=1, inplace=True) # not relevant for classification

# Describtive analysis of dataset before scaling
pd.DataFrame(loans, columns = loans.columns).describe()
```

Out[0]:

	UniqueID	disbursed_amount	asset_cost	ltv	branch_id	
count	315148.000000	315148.000000	315148.000000	315148.000000	315148.000000	315
mean	592916.290454	54836.652138	76216.488729	74.870799	74.876020	19
std	101502.815635	12319.584248	17451.604132	11.274966	70.535076	3
min	417429.000000	11613.000000	37000.000000	10.030000	1.000000	10
25%	505218.750000	47649.000000	66308.750000	69.240000	14.000000	16
50%	592586.000000	54303.000000	71616.000000	77.030000	64.000000	20
75%	680309.250000	60947.000000	79814.000000	83.580000	135.000000	23
max	769909.000000	153803.000000	180000.000000	95.000000	261.000000	24

In [0]:

```
# Installing Scaler.
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()

# Picking the columns, that we would like to work with.
loans_features = loans.loc[:,'disbursed_amount':'AGE_IN_DAYS']

# Scaling the data.
scaler = StandardScaler().fit(loans_features)
loans_scaled = scaler.transform(loans_features)

# Showing scaled data
pd.DataFrame(loans_scaled, columns=loans_features.columns).describe().round(3)
```

Out[0]:

	disbursed_amount	asset_cost	ltv	branch_id	supplier_id	manufacturer_id
count	315148.000	315148.000	315148.000	315148.000	315148.000	315148.000
mean	-0.000	0.000	0.000	-0.000	-0.000	-0.000
std	1.000	1.000	1.000	1.000	1.000	1.000
min	-3.509	-2.247	-5.751	-1.047	-2.617	-1.067
25%	-0.583	-0.568	-0.499	-0.863	-0.888	-1.067
50%	-0.043	-0.264	0.192	-0.154	0.216	0.786
75%	0.496	0.206	0.772	0.852	0.954	0.786
max	8.033	5.947	1.785	2.639	1.478	3.813

In [0]:

```
# New info
loans.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 315148 entries, 0 to 345545
Data columns (total 38 columns):
UniqueID                        315148 non-null int64
disbursed_amount                315148 non-null int64
asset_cost                      315148 non-null int64
ltv                             315148 non-null float64
branch_id                       315148 non-null int64
supplier_id                     315148 non-null int64
manufacturer_id                 315148 non-null int64
Current_pincode_ID              315148 non-null int64
Employment_Type                 315148 non-null int64
State_ID                        315148 non-null int64
Employee_code_ID                315148 non-null int64
MobileNo_Avl_Flag               315148 non-null int64
Aadhar_flag                     315148 non-null int64
PAN_flag                        315148 non-null int64
VoterID_flag                    315148 non-null int64
Driving_flag                    315148 non-null int64
Passport_flag                   315148 non-null int64
PERFORM_CNS_SCORE               315148 non-null int64
PRI_NO_OF_ACCTS                 315148 non-null int64
PRI_ACTIVE_ACCTS                315148 non-null int64
PRI_OVERDUE_ACCTS               315148 non-null int64
PRI_CURRENT_BALANCE             315148 non-null int64
PRI_SANCTIONED_AMOUNT           315148 non-null int64
PRI_DISBURSED_AMOUNT            315148 non-null int64
SEC_NO_OF_ACCTS                 315148 non-null int64
SEC_ACTIVE_ACCTS                315148 non-null int64
SEC_OVERDUE_ACCTS               315148 non-null int64
SEC_CURRENT_BALANCE             315148 non-null int64
SEC_SANCTIONED_AMOUNT           315148 non-null int64
SEC_DISBURSED_AMOUNT            315148 non-null int64
PRIMARY_INSTAL_AMT              315148 non-null int64
SEC_INSTAL_AMT                  315148 non-null int64
NEW_ACCTS_IN_LAST_SIX_MONTHS    315148 non-null int64
AVERAGE_ACCT_AGE                315148 non-null int64
CREDIT_HISTORY_LENGTH           315148 non-null int64
NO_OF_INQUIRIES                 315148 non-null int64
AGE_IN_DAYS                     315148 non-null int64
Default                         315148 non-null int64
dtypes: float64(1), int64(37)
memory usage: 93.8 MB
```

USML - A closer look at the patterns of the dataset.

After preproccesing, we have 36 features. While preprocessing we removed some features. There was some descriptions that we didn´t need, and we also added an 'AGE' column and removed an 'Data_of_birth" column. This is called feature selection (or in this case it´s more accurate to call it feature reduction).

36 features are still a lot to work with. We could expand on our features selection and remove more features. Do we really need to know which customer provided copy of drivers license, voters registration, passport etc. Would it not be enough to just register if the customer provided valid ID or not? Perhaps, but such a destinction would be subjective on our part, and we would not know the value of the information that we drop.

The alternative is dimensionality reduction. Both feature selection and dimensionality reduction can be used to reduce features, but while feature selection is simply selecting and excluding given features without changing them, dimensionality reduction transforms features into a lower dimension

We will show examples of how this proces work later, but for now we will start by looking at one method to reduce dimensions. This is called Principal Component Analysis (PCA)

Principal Component Analysis (PCA)

We start with a quick exploratory analysis and try to fit our 36 features into a PCA-model and explore what datavalue each feature has.

In [0]:

```
# Import the module and instantiate a PCA object
from sklearn.decomposition import PCA
pca = PCA(n_components=36) # We test with 36 component. 100% of our features.

loans_pca = pca.fit_transform(loans_scaled)
pca.components_.shape # This will show us the number of new dimensions compared to t
he previous number. Should be 36,36 in this case.
```

Out[0]:

```
(36, 36)
```

Measuring the effect of the dimensionality reduction.

We can measure the effect of the dimensionality reduction with the variance ratio. That will tell us, how much information each of the 36 components holds. See the code below. The cumulative ratio should be 100% since we add up all 36 dimension.

In [0]:

```
# PCA Explained variance ratio

# Ratio for each of the 36 components.
evr = pca.explained_variance_ratio_

print("Amount of information in each component\n")
print("This will show us that the first component give us 13% of the information in
 the dataset\n")
print("Second component gives us an additionel 10% of information. And so on.\n")
for x in evr:
  print(x)


print("\n\nThe culumative information in all 36 components\n")
sum(pca.explained_variance_ratio_)*100
```

```
Amount of information in each component

This will show us that the first component give us 13% of the informatio
n in the dataset

Second component gives us an additionel 10% of information. And so on.

0.1346404888064898
0.10148927662573498
0.06803604806262596
0.05987971459915027
0.051233307517296545
0.04412768006965651
0.043245310043107166
0.040818351620501764
0.040157718865954185
0.030146299303479136
0.02924471882024796
0.028708255271356776
0.02817879420976068
0.027739468746107214
0.027467714497850758
0.026535283283440955
0.025680088570444435
0.024789374234658972
0.023920665009717824
0.02363738802305909
0.022173064923007416
0.020589642637735203
0.017494695009043795
0.015791741840524894
0.012644927832113162
0.01071680803961414
0.004927534385552019
0.004567992218540314
0.004220824316754977
0.003223330059561496
0.0018698436190545098
0.001602087651433787
0.0003634103940781528
0.00012901901252500084
9.131879820368208e-06
6.0629737117839655e-34


The culumative information in all 36 components
```

Out[0]:

```
100.00000000000003
```

Visualizing the components and their values.

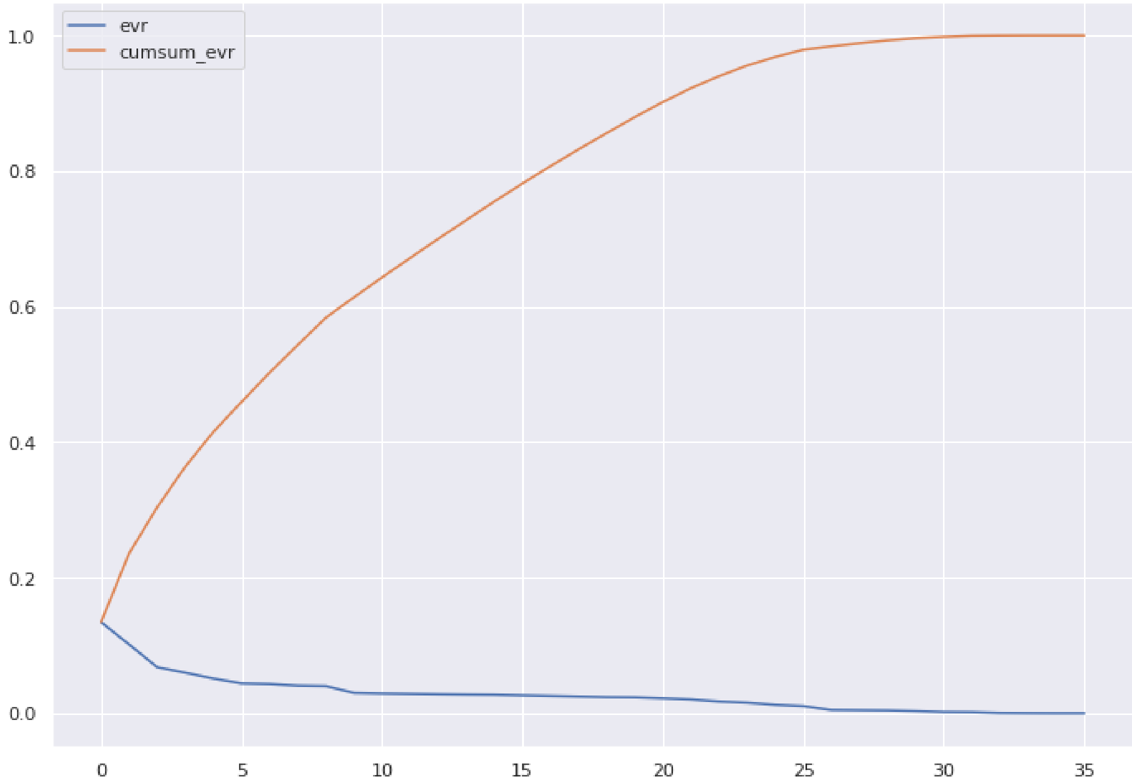
It can be hard to read the numbers. A 2D graph will make that easier.

In [0]:

```
# Plotting graph
plot_data = pd.DataFrame({'evr': pca.explained_variance_ratio_, 'cumsum_evr': np.cum
sum(pca.explained_variance_ratio_)}).stack()
sns.set(rc={'figure.figsize':(11.7,8.27)})
sns.lineplot(y = plot_data.values, x = plot_data.index.get_level_values(0), hue=plot
_data.index.get_level_values(1))
```

Out[0]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb31f3c74e0>
```



The result.

The graph above (red line) show that we dont need all 36 components in order to retain 100% of our information. In fact, we could reduce the dimensions to 30 and still retain 100% af value in the dataset.

On the other hand, if we reduce to 1 component, we will only have 13% of our data´s value.

What would be an acceptable amount of dataloss? As a rule of thumb 90% of the data´s value should be retained. Looking at the graph, we see that 20 component will get us a little less than 90%. We choose 23 components and continue.

In [0]:

```
# Running PCA again, now with 23 component.
pca = PCA(n_components=23)

loans_pca = pca.fit_transform(loans_scaled)
pca.components_.shape # This will show us the number of new dimensions compared to t
he previous number. Should be 23,36 in this case.
```

Out[0]:

```
(23, 36)
```

In [0]:

```
# PCA Explained variance ratio
evr = pca.explained_variance_ratio_

print("\n\nThe culumative information in 23 principal components\n")
sum(pca.explained_variance_ratio_)*100
```

```
The culumative information in 23 principal components
```

Out[0]:

```
93.9933348750427
```

After applying the PCA and compressing the data into the 23 component, we get a new dataframe.

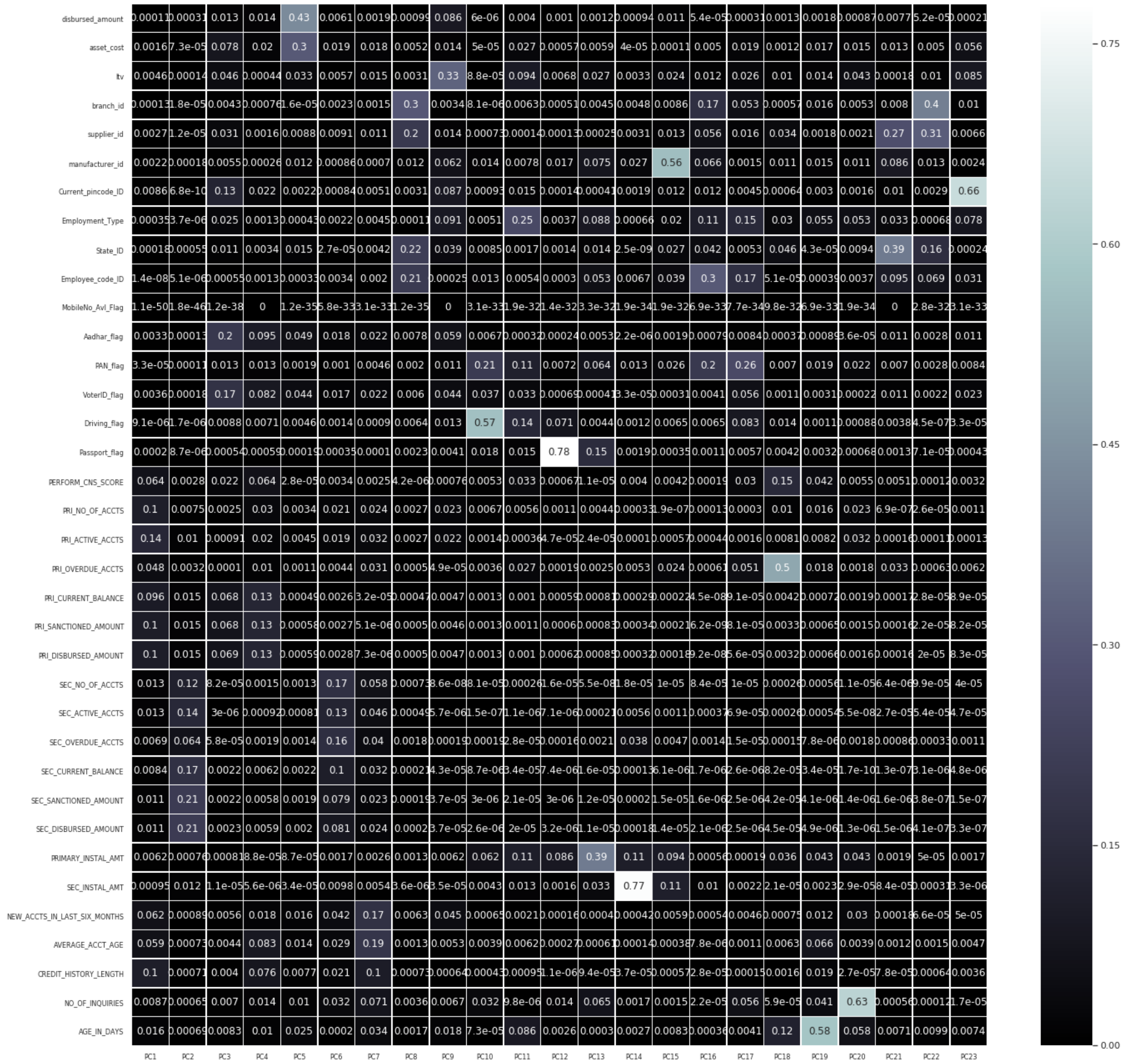
But which of the original 36 features affects the 23 principal component the most? Run the code below and you will get a visual answer to that question.

In [0]:

```
#Visualizing Loading of the PCA

from IPython.display import Javascript
display(Javascript('''google.colab.output.setIframeHeight(0, true, {maxHeight: 5000}
)'''))

cols = ['disbursed_amount', 'asset_cost', 'ltv', 'branch_id',
       'supplier_id', 'manufacturer_id', 'Current_pincode_ID',
       'Employment_Type', 'State_ID', 'Employee_code_ID', 'MobileNo_Avl_Flag',
       'Aadhar_flag', 'PAN_flag', 'VoterID_flag', 'Driving_flag',
       'Passport_flag', 'PERFORM_CNS_SCORE', 'PRI_NO_OF_ACCTS',
       'PRI_ACTIVE_ACCTS', 'PRI_OVERDUE_ACCTS', 'PRI_CURRENT_BALANCE',
       'PRI_SANCTIONED_AMOUNT', 'PRI_DISBURSED_AMOUNT', 'SEC_NO_OF_ACCTS',
       'SEC_ACTIVE_ACCTS', 'SEC_OVERDUE_ACCTS', 'SEC_CURRENT_BALANCE',
       'SEC_SANCTIONED_AMOUNT', 'SEC_DISBURSED_AMOUNT', 'PRIMARY_INSTAL_AMT',
       'SEC_INSTAL_AMT', 'NEW_ACCTS_IN_LAST_SIX_MONTHS', 'AVERAGE_ACCT_AGE',
       'CREDIT_HISTORY_LENGTH', 'NO_OF_INQUIRIES', 'AGE_IN_DAYS']

loans_principal_components = pca.fit_transform(loans_scaled)
loans_principal_data = pd.DataFrame(data = loans_principal_components, columns = ['P
C1', 'PC2','PC3','PC4','PC5', 'PC6','PC7','PC8','PC9', 'PC10','PC11','PC12','PC13',
'PC14','PC15','PC16','PC17', 'PC18','PC19','PC20','PC21', 'PC22','PC23'])

pca.fit(loans_scaled)
pcscores = pd.DataFrame(pca.transform(loans_scaled))
pcscores.columns = ['PC'+str(i+1) for i in range(len(pcscores.columns))]
loadings = pd.DataFrame(pca.components_, columns=cols)
loadings.index = ['PC'+str(i+1) for i in range(len(pcscores.columns))]

load_sqr = loadings**2
import matplotlib.pyplot as plt
import seaborn
fig, ax = plt.subplots(figsize=(23,23))
ax = sns.heatmap(load_sqr.transpose(), ax=ax, linewidths=0.5, cmap="bone", annot=Tru
e)
ax.set_xticklabels(ax.xaxis.get_majorticklabels(), rotation=0, fontsize=8)
ax.set_yticklabels(ax.yaxis.get_majorticklabels(), rotation=0, fontsize=8)
```

Out[0]:

```
[Text(0, 0.5, 'disbursed_amount'),
 Text(0, 1.5, 'asset_cost'),
 Text(0, 2.5, 'ltv'),
 Text(0, 3.5, 'branch_id'),
 Text(0, 4.5, 'supplier_id'),
 Text(0, 5.5, 'manufacturer_id'),
 Text(0, 6.5, 'Current_pincode_ID'),
 Text(0, 7.5, 'Employment_Type'),
 Text(0, 8.5, 'State_ID'),
 Text(0, 9.5, 'Employee_code_ID'),
 Text(0, 10.5, 'MobileNo_Avl_Flag'),
 Text(0, 11.5, 'Aadhar_flag'),
 Text(0, 12.5, 'PAN_flag'),
 Text(0, 13.5, 'VoterID_flag'),
 Text(0, 14.5, 'Driving_flag'),
 Text(0, 15.5, 'Passport_flag'),
 Text(0, 16.5, 'PERFORM_CNS_SCORE'),
 Text(0, 17.5, 'PRI_NO_OF_ACCTS'),
 Text(0, 18.5, 'PRI_ACTIVE_ACCTS'),
 Text(0, 19.5, 'PRI_OVERDUE_ACCTS'),
 Text(0, 20.5, 'PRI_CURRENT_BALANCE'),
 Text(0, 21.5, 'PRI_SANCTIONED_AMOUNT'),
 Text(0, 22.5, 'PRI_DISBURSED_AMOUNT'),
 Text(0, 23.5, 'SEC_NO_OF_ACCTS'),
 Text(0, 24.5, 'SEC_ACTIVE_ACCTS'),
 Text(0, 25.5, 'SEC_OVERDUE_ACCTS'),
 Text(0, 26.5, 'SEC_CURRENT_BALANCE'),
 Text(0, 27.5, 'SEC_SANCTIONED_AMOUNT'),
 Text(0, 28.5, 'SEC_DISBURSED_AMOUNT'),
 Text(0, 29.5, 'PRIMARY_INSTAL_AMT'),
 Text(0, 30.5, 'SEC_INSTAL_AMT'),
 Text(0, 31.5, 'NEW_ACCTS_IN_LAST_SIX_MONTHS'),
 Text(0, 32.5, 'AVERAGE_ACCT_AGE'),
 Text(0, 33.5, 'CREDIT_HISTORY_LENGTH'),
 Text(0, 34.5, 'NO_OF_INQUIRIES'),
 Text(0, 35.5, 'AGE_IN_DAYS')]
```


disbursed_amount
asset_cost
ltv
branch_id
supplier_id
manufacturer_id
Current_pincode_ID
Employment_Type
State_ID
Employee_code_ID
MobileNo_Avl_Flag
Aadhar_flag
PAN_flag
VoterID_flag
Driving_flag
Passport_flag
PERFORM_CNS_SCORE
PRI_NO_OF_ACCTS
PRI_ACTIVE_ACCTS
PRI_OVERDUE_ACCTS
PRI_CURRENT_BALANCE
PRI_SANCTIONED_AMOUNT
PRI_DISBURSED_AMOUNT
SEC_NO_OF_ACCTS
SEC_ACTIVE_ACCTS
SEC_OVERDUE_ACCTS
SEC_CURRENT_BALANCE
SEC_SANCTIONED_AMOUNT
SEC_DISBURSED_AMOUNT
PRIMARY_INSTAL_AMT
SEC_INSTAL_AMT
NEW_ACCTS_IN_LAST_SIX_MONTHS
AVERAGE_ACCT_AGE
CREDIT_HISTORY_LENGTH
NO_OF_INQUIRIES
AGE_IN_DAYS
PC1 PC2 PC3 PC4 PC5 PC6 PC7 PC8 PC9 PC10 PC11 PC12 PC13 PC14 PC15 PC16 PC17 PC18 PC19 PC20 PC21 PC22 PC23
0.75
0.60
0.45
0.30
0.15
0.00

PCA Loading Values.

PCA makes principal components that explain most of the variance or scatter of the original dataset.

Each component is a linear combination of all the variables and is perpendicular to every other component.

Each variable in each component is multiplied by set of factors, the loading factors, which transforms the original data into this new component space.

These loading factors are constrained so that the square of the sum is equal to 1, hence they can serve as weights to see which parameters are most important for a particular principal component.

In the heatmap above, the darkest shades indicate which parameters are the most important. For example, **the loading factors for PC12 show that Passport_Flag is the most dominant parameter.**

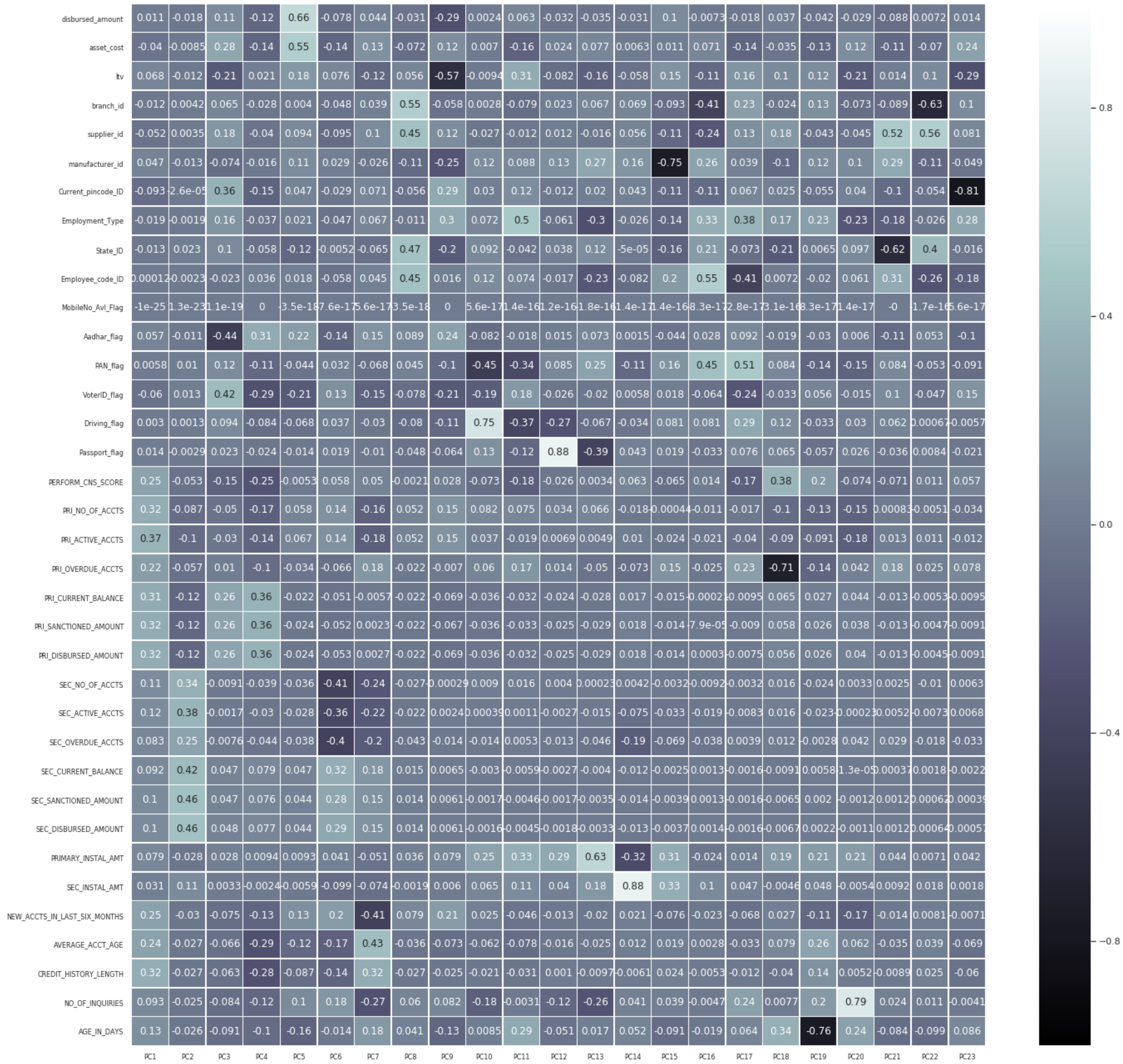
But these are only loading values. Run the code below to see the actual values.

In [0]:

```
# Visualizing actual values

from IPython.display import Javascript
display(Javascript('''google.colab.output.setIframeHeight(0, true, {maxHeight: 5000}
)'''))

fig, ax = plt.subplots(figsize=(23,23))
ax = sns.heatmap(loadings.transpose(), center=0, linewidths=0.5,
                 cmap="bone", vmin=-1, vmax=1, annot=True)
ax.set_xticklabels(ax.xaxis.get_majorticklabels(), rotation=0, fontsize=8)
ax.set_yticklabels(ax.yaxis.get_majorticklabels(), rotation=0, fontsize=8)
```

Out[0]:

```
[Text(0, 0.5, 'disbursed_amount'),
 Text(0, 1.5, 'asset_cost'),
 Text(0, 2.5, 'ltv'),
 Text(0, 3.5, 'branch_id'),
 Text(0, 4.5, 'supplier_id'),
 Text(0, 5.5, 'manufacturer_id'),
 Text(0, 6.5, 'Current_pincode_ID'),
 Text(0, 7.5, 'Employment_Type'),
 Text(0, 8.5, 'State_ID'),
 Text(0, 9.5, 'Employee_code_ID'),
 Text(0, 10.5, 'MobileNo_Avl_Flag'),
 Text(0, 11.5, 'Aadhar_flag'),
 Text(0, 12.5, 'PAN_flag'),
 Text(0, 13.5, 'VoterID_flag'),
 Text(0, 14.5, 'Driving_flag'),
 Text(0, 15.5, 'Passport_flag'),
 Text(0, 16.5, 'PERFORM_CNS_SCORE'),
 Text(0, 17.5, 'PRI_NO_OF_ACCTS'),
 Text(0, 18.5, 'PRI_ACTIVE_ACCTS'),
 Text(0, 19.5, 'PRI_OVERDUE_ACCTS'),
 Text(0, 20.5, 'PRI_CURRENT_BALANCE'),
 Text(0, 21.5, 'PRI_SANCTIONED_AMOUNT'),
 Text(0, 22.5, 'PRI_DISBURSED_AMOUNT'),
 Text(0, 23.5, 'SEC_NO_OF_ACCTS'),
 Text(0, 24.5, 'SEC_ACTIVE_ACCTS'),
 Text(0, 25.5, 'SEC_OVERDUE_ACCTS'),
 Text(0, 26.5, 'SEC_CURRENT_BALANCE'),
 Text(0, 27.5, 'SEC_SANCTIONED_AMOUNT'),
 Text(0, 28.5, 'SEC_DISBURSED_AMOUNT'),
 Text(0, 29.5, 'PRIMARY_INSTAL_AMT'),
 Text(0, 30.5, 'SEC_INSTAL_AMT'),
 Text(0, 31.5, 'NEW_ACCTS_IN_LAST_SIX_MONTHS'),
 Text(0, 32.5, 'AVERAGE_ACCT_AGE'),
 Text(0, 33.5, 'CREDIT_HISTORY_LENGTH'),
 Text(0, 34.5, 'NO_OF_INQUIRIES'),
 Text(0, 35.5, 'AGE_IN_DAYS')]
```


disbursed_amount
asset_cost
ltv
branch_id
supplier_id
manufacturer_id
Current_pincode_ID
Employment_Type
State_ID
Employee_code_ID
MobileNo_Avl_Flag
Aadhar_flag
PAN_flag
VoterID_flag
Driving_flag
Passport_flag
PERFORM_CNS_SCORE
PRI_NO_OF_ACCTS
PRI_ACTIVE_ACCTS
PRI_OVERDUE_ACCTS
PRI_CURRENT_BALANCE
PRI_SANCTIONED_AMOUNT
PRI_DISBURSED_AMOUNT
SEC_NO_OF_ACCTS
SEC_ACTIVE_ACCTS
SEC_OVERDUE_ACCTS
SEC_CURRENT_BALANCE
SEC_SANCTIONED_AMOUNT
SEC_DISBURSED_AMOUNT
PRIMARY_INSTAL_AMT
SEC_INSTAL_AMT
NEW_ACCTS_IN_LAST_SIX_MONTHS
AVERAGE_ACCT_AGE
CREDIT_HISTORY_LENGTH
NO_OF_INQUIRIES
AGE_IN_DAYS
PC1 PC2 PC3 PC4 PC5 PC6 PC7 PC8 PC9 PC10 PC11 PC12 PC13 PC14 PC15 PC16 PC17 PC18 PC19 PC20 PC21 PC22 PC23
0.8
0.4
0.0
−0.4
−0.8

Result of PCA.

We have reduced our 36 features to 23 components, and we still have 93% of our information. We have also visualized how the original features affects our primary component.

Cluster Analysis. Elbow method. How many clusters do we need?

The cluster analysis is done based on data, that has been scaled, but not reduced in dimensions by using PCA.

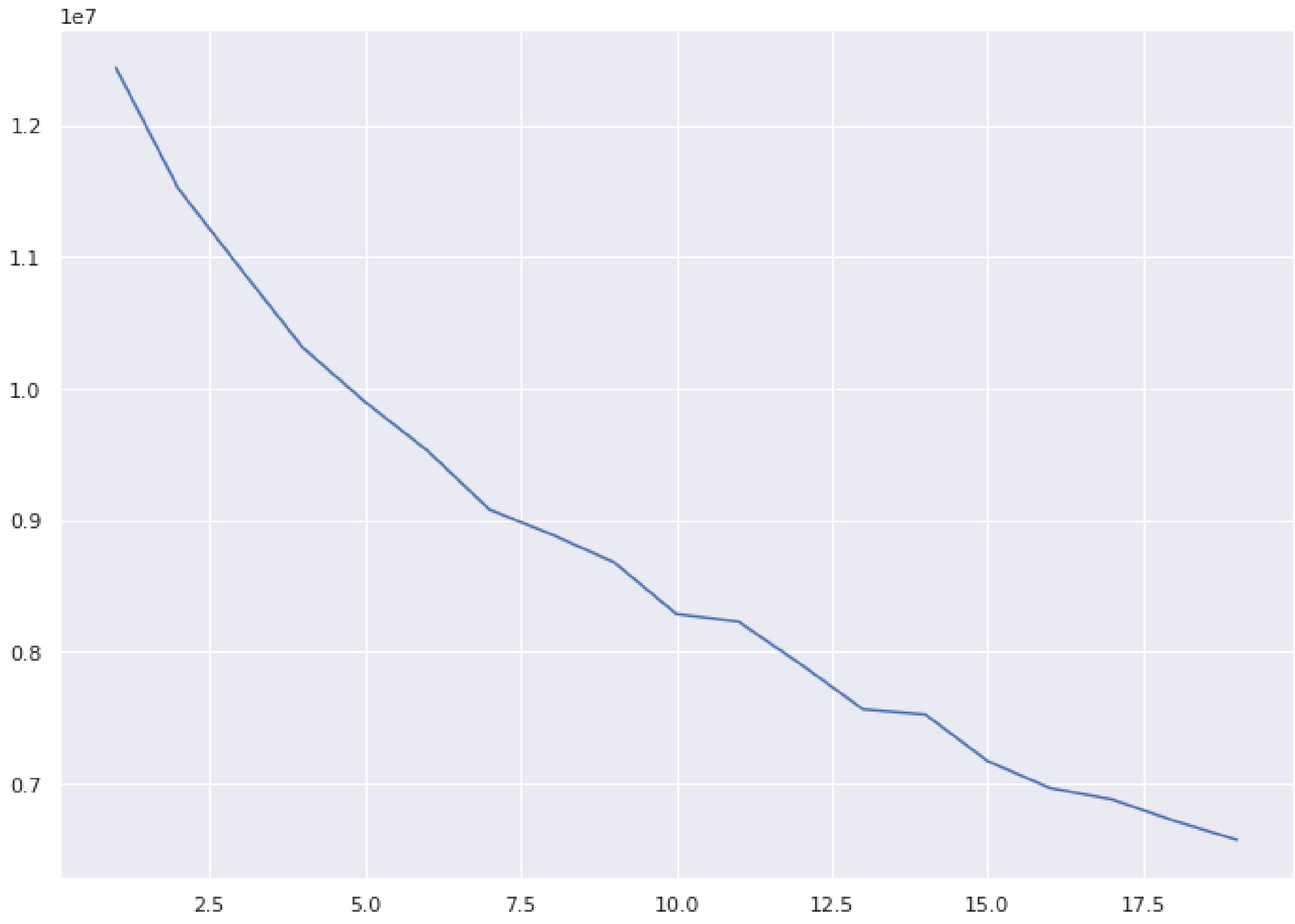
When we cluster by KMeans we will need to define the number of clusters that we would like to use. We can pick that number arbitrarely (probably not a good idea) or we can run the code below.

In [0]:

```
# This code takes a long time to run (345.000 rows)
# Therefore the output has been saved after the first runthrough and is displayed as an image.
# If you want to run this code, then change run = yes in the line below.
# %time

run = "no"

if run == "yes":
  # Installing KMeans
  from sklearn.cluster import KMeans
  # Number of cluster that we want to visualize.
  testnumber = 20
  inertia = []
  for i in range(1,testnumber):
    k_means = KMeans(n_clusters=i)
    inertia.append(k_means.fit(loans_scaled).inertia_)
  sns.lineplot(y = inertia, x = range(1,testnumber))

else:
  print("No plot shown here. Se image from previously below. If you want to run code, change run = \"no\" to yes.")
  print("Warning: It takes a long time with 345.000 rows.")

# A plot will be made.
```

```
No plot shown here. Se image from previously below. If you want to run c
ode, change run = "no" to yes.
Warning: It takes a long time with 345.000 rows.
```

Saved output from first run of loop.



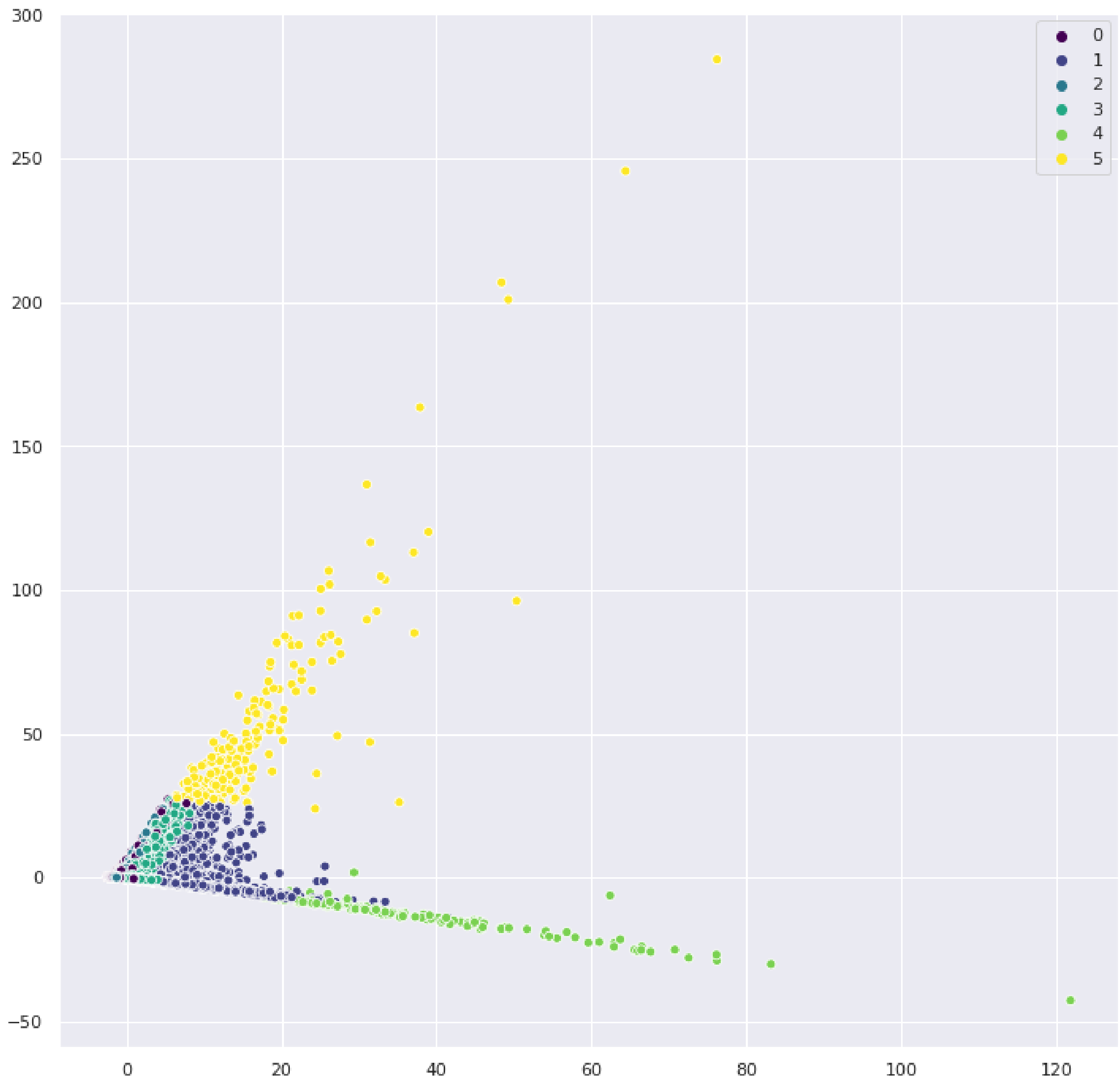
Conclusion in number of clusters.

There is no real break in the elbow. More like a straight line. We will assume that 6 clusters is an optimal number.

Visualizing of the first 2 Principal Components.

In [0]:

```
# Javascript in order to avoid have two scrollbars.
from IPython.display import Javascript
display(Javascript('''google.colab.output.setIframeHeight(0, true, {maxHeight: 5000}
)'''))

clusterer = KMeans(n_clusters=6)
clusterer.fit(loans_principal_components)

# Now we can plot in our points with some coloring.
plt.figure(figsize=(12,12))
g = sns.scatterplot(loans_principal_components[:,0], loans_principal_components[:,1
], hue=clusterer.labels_, legend='full', palette='viridis')

legend = g.get_legend()
```

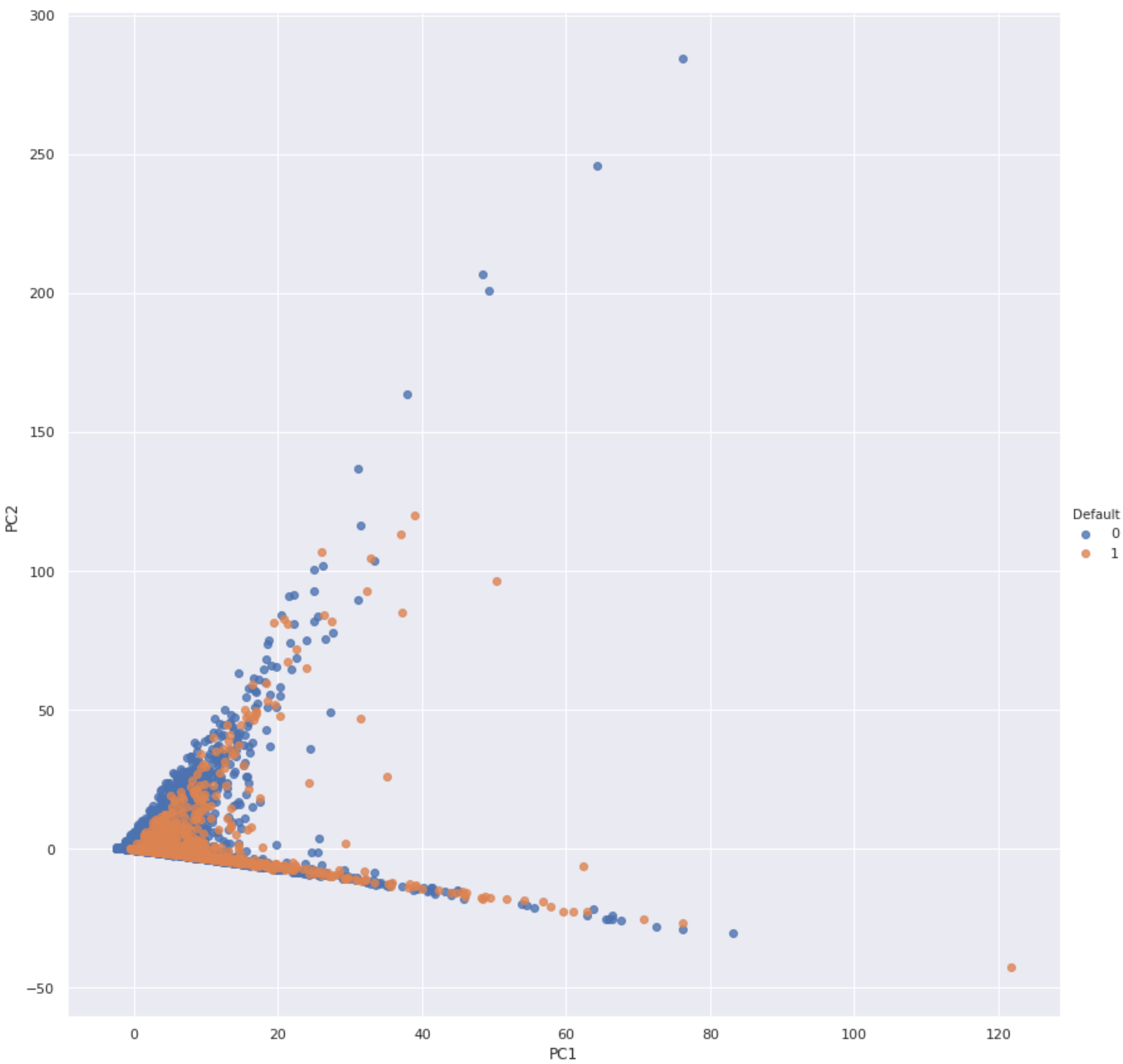


The plot above has been colored based on the labels in the KMeans cluster fit.

Below is another visualization, based on the default-facor (1 or 0).

In [0]:

```
from IPython.display import Javascript
display(Javascript('''google.colab.output.setIframeHeight(0, true, {maxHeight: 5000}
)'''))

from sklearn.decomposition import PCA
model = PCA(n_components=23)

# Fit model with our scaled data.
model.fit(loans_scaled)

# Making a two dimensional visualisation.
X_2D = model.transform(loans_scaled)

loans['PC1'] = X_2D[:, 0]
loans['PC2'] = X_2D[:, 1]

# Plot by delinquent account.
sns.lmplot("PC1", "PC2",hue='Default', data=loans, fit_reg=False, height=12, aspect=
1.0);
```



Inspection of the distribution of geographical states across the clusters.

This (and other combinations) is possible with the Bokeh Crosshair, but it takes a lot af RAM and freezes the page often. It is not recommended to run it. If you want to run it anyway, change run = "yes" below.

In [0]:

```
run = "no"

if run == "yes":
  # Load the needed bokeh modules.
  from bokeh.models import ColumnDataSource
  from bokeh.plotting import figure, show, output_notebook
  from bokeh.palettes import Spectral6
  from bokeh.transform import factor_cmap

  clusterer = KMeans(n_clusters=6) # number of clusters based on where the elbow bre
aks.
  clusterer.fit(loans_principal_components) # We now plt the clusters based on the d
ata that has been PCAéd.


  # Define the data that we are going to use as a dictionary.

  d = {'y':loans_principal_components[:,1],'x':loans_principal_components[:,0], 'Sta
te': loans.State_ID,
       'cluster': pd.Series(clusterer.labels_).map({0:'a',1:'b',2:'c',3:'d',4:'e',5:
'f'}),
      }

  # Define and transform a color-palette.

  colors = factor_cmap('cluster', palette=Spectral6, factors=d['cluster'].unique())

  # Transform the data to Bokeh format.
  d = ColumnDataSource(d)

  # Define interactive tooling and plot for notebook output.

  output_notebook()

  TOOLS="hover,crosshair,pan,wheel_zoom,zoom_in,zoom_out,box_zoom,undo,redo,reset,ta
p,save,box_select,poly_select,lasso_select"
  p = figure(tools=TOOLS)
  p.hover.tooltips = [('State', "@State")]
  p.scatter(x='x', y='y',fill_alpha=0.8,
            color = colors,
            line_color = None,
            radius = 0.1,
            source=d)
  show(p)
else:
  print("We are not running crosshairs. Freezes the system with 345K rows.")
```

```
We are not running crosshairs. Freezes the system with 345K rows.
```

Another way to inspect the clusters is to use crosstabs. In this case with 345K rows it is probably the most effective way. Se below.

In [0]:

```
# Looking at clusters across geopgraphical states.
model = KMeans(n_clusters=6)
model.fit(loans_scaled)
loans['cluster'] = model.labels_
pd.crosstab(loans['State_ID'], loans['cluster'], normalize='columns')
```

Out[0]:

cluster	0	1	2	3	4	5
State_ID						
1	0.007687	0.051948	0.064467	0.032599	0.065821	0.142132
2	0.008791	0.019481	0.024608	0.023385	0.021095	0.000000
3	0.222014	0.058442	0.085111	0.171619	0.060512	0.015228
4	0.034746	0.233766	0.256370	0.212111	0.231196	0.081218
5	0.027964	0.038961	0.035513	0.048611	0.030115	0.005076
6	0.127827	0.207792	0.162381	0.127992	0.145689	0.035533
7	0.007687	0.000000	0.029561	0.041252	0.017947	0.015228
8	0.012966	0.116883	0.070761	0.049822	0.135213	0.081218
9	0.071722	0.084416	0.065984	0.050144	0.110171	0.106599
10	0.003998	0.012987	0.020301	0.018018	0.011088	0.010152
11	0.010868	0.051948	0.041141	0.031065	0.037303	0.121827
12	0.008637	0.000000	0.008888	0.024603	0.002020	0.000000
13	0.415687	0.000000	0.005276	0.010665	0.010383	0.010152
14	0.009940	0.012987	0.031587	0.052745	0.036317	0.086294
15	0.002606	0.019481	0.034064	0.032879	0.025746	0.197970
16	0.003623	0.064935	0.018451	0.015067	0.019168	0.055838
17	0.002982	0.012987	0.014360	0.021139	0.016537	0.010152
18	0.017472	0.006494	0.024706	0.029169	0.016866	0.025381
19	0.001568	0.000000	0.004415	0.004155	0.004040	0.000000
20	0.000552	0.000000	0.000519	0.001335	0.000423	0.000000
21	0.000530	0.006494	0.001194	0.001095	0.002020	0.000000
22	0.000133	0.000000	0.000343	0.000527	0.000329	0.000000

SML CLASSIFYING DELIQUENT LOANS.

Overall the assigment is to make predictions between states (default or not) => classification. Is something one thing or another thing? Is this case: Based on a range of independent variables, will a customer default or not?

Split data into training and test datasets. 75%/25%

We train models using data. After training and fitting the model, we would like to test it, and see how well it performs.

But if we test the model on the same data, that we trained it on, we would get a perfect testscore. But that would be useless. We need to know, how well the model does when predicting or classifying on NEW data.

So how do we test the model? The answer is, to test it on data, that it has not seen before. That means splitting our data in 2 parts, a training set and a testing set.

We could do it by hand and just take the first part of a set for training and the second half for testing. But if our data eg. is a timeserie over a year, we would probably not get data that really represents what we are looking for.

Imagine that our trainingdata is the first 9 months of the year, and the test data is the last 3 months of the year. If we are looking to predict how many lawnmovers are sold based on a independent variable, we would proably get a somewhat precise result. If we then test the model on our test data, we would proably get a low testscore, as the data is not representative for what we are looking for (eg. not many people buy lawnmovers in december, regardless of the independent variable) The same thing could be said viceversa about christmas shopping. This is offcourse a very exaggerated example. but it goes to show, that we should rather not divide the data into train and test manually.

A better way would be to use the train_test_split utility function below.

In [0]:

```
# Defining the dependent variable. What are we looking for? Will the customer defaul
t?
y = loans.Default

# Importing the train-test split function.
from sklearn.model_selection import train_test_split

# Making the split. We keep 75% for training and 25% for test.
X_train, X_test, y_train, y_test = train_test_split(loans_scaled, y, test_size = 0.2
5, random_state=42)
```

In [0]:

```
# Take a look at the train and test set
print( X_train.shape, y_train.shape)
print( X_test.shape, y_test.shape)
```

```
(236361, 36) (236361,)
(78787, 36) (78787,)
```

In [0]:

```
# Some things we are going to need for later.

# Disabling FutureWarnings beacuse they are annoying to look at.
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)

# Import Classification Report for later evaluatoion of performance
from sklearn.metrics import classification_report

# Import CrossValidation
from sklearn.model_selection import cross_val_score
```

LOGISTIC REGRESSION

In [0]:

```
# Choosing model class. This is where we decide, which model to use. In this case lo
gistic regression.
# Installing log.res-model.
from sklearn.linear_model import LogisticRegression


# instantiating the model.
model = LogisticRegression()


# Getting our crossvalidation testscore.
# Please note that this is done on training data.
# Scores gives us a list of scores on each of the 5 subset, that is used in the tran
ing
scores = cross_val_score(model, X_train, y_train, cv = 5) # WHY 5? See my text and e
xplanation below the code.


# Fitting the model on the training data.
model.fit(X_train, y_train)

# Printing out the result of the training.
print("Scores for crossvalidation on each trainingdatafold. cv=5")
print(scores)
print("-------\n")
print("Mean score and std on the trainingset")
print("Accuracy: %0.5f (+/- %0.5f)" % (scores.mean(), scores.std() * 2))
print("-------\n")

# Prediction on the models succes, based on the testdata.
y_model = model.predict(X_test)

# Model score
print("Testscores for fittet model")
print(model.score(X_test, y_test))
print("-------\n")

# Classification report => Se explation below the code.
print("Classification report")
print(classification_report(y_test,y_model))
```

```
Scores for crossvalidation on each trainingdatafold. cv=5
[0.98677892 0.98680008 0.98665172 0.98694788 0.98654566]
-------

Mean score and std on the trainingset
Accuracy: 0.98674 (+/- 0.00027)
-------

Testscores for fittet model
0.9859113813192532
-------

Classification report
              precision    recall  f1-score   support

           0       0.99      1.00      0.99     77716
           1       0.43      0.11      0.18      1071

    accuracy                           0.99     78787
   macro avg       0.71      0.55      0.59     78787
weighted avg       0.98      0.99      0.98     78787
```

A few words about cross validation.

By splitting data into train and test sets, we reduce the number of rows that we can train on.

We had 315.148 loans (after removing outliers), but now we only train on 236.361. It makes sense to keep 78.787 for later to do the test, but our training will suffer because of it. Also our model is only as good as the way the data Is split. Even though we didn´t do a manual split, our data might not be representative for our models ability to generalize.

We can compensate for the loss of training data by using crossvalidation. The same way as we split our data into training and test, we now split the training data into parts called folds (k folds), eg. 5 folds. We then train on 4 folds and test on 1 fold. We repeat the process 5 times until all combinations have been done. We will get at score for each test and can calculate a mean based on these scores.

As to the number of folds that should be used, the general rules seems to be about 4 or 5 on most datasets. Very large sets can be done in 10 folds, but more folds require more computational power. We have not be able to find a way to calculate the optimal number of folds.

Classification report. What does the numbers mean?

Precision tells us how precise our model is. Eg. if False is 98%, it means that everytime the model classified a loan as being 'Default' the model was right 98% of the time.

Recall tells us the models ability to find all actual positives (or negatives). Eg. if False is 96%, it means all instances of loans classified as being default, we only found 96% of them

The F1 best score is 1.0 and the worst is 0.0. As a rule of thumb, the weighted average of F1 should be used to compare classifier models. That means that we can use this value to compare our model, in this case a logistic regression, to the other two models, that we are going to use.

Support tells us something about the testset being used. We can see, that of the 78787 loans, 77716 of them are not default and 1071 of the are default.

Confusion Matrix. Let´s see a confusion matrix.

Upper left shows us the True Negatives. eg. How many loans were classified as not default and how many were in fact not default.

Lower right shows us the True Positive. eg. How many loans were classified as default and how many were in fact default.

It´s in the upper left and the lower right, where we want as many observations as possible. These are where we do things right.

Upper right and Lower left shows us, where thing are not right. We would want a model, that minimizes the observations in the boxes.

In [0]:

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_model)
print(cm)

# This gives us a CM.
```

```
[[77557   159]
 [  951   120]]
```

In [0]:

```
# For that we need to install an updated version of the MLxtend library (it will mak
e plotting of the confusion matrix easy)
!pip install -U mlxtend
# Import the confusion matrix plotter module
from mlxtend.plotting import plot_confusion_matrix

# We will also import sklearns confusion matrix module that will make it easy to pro
duce a confusion matrix
# It's actually just a cross-tab of predicted vs. real values
from sklearn.metrics import confusion_matrix
```

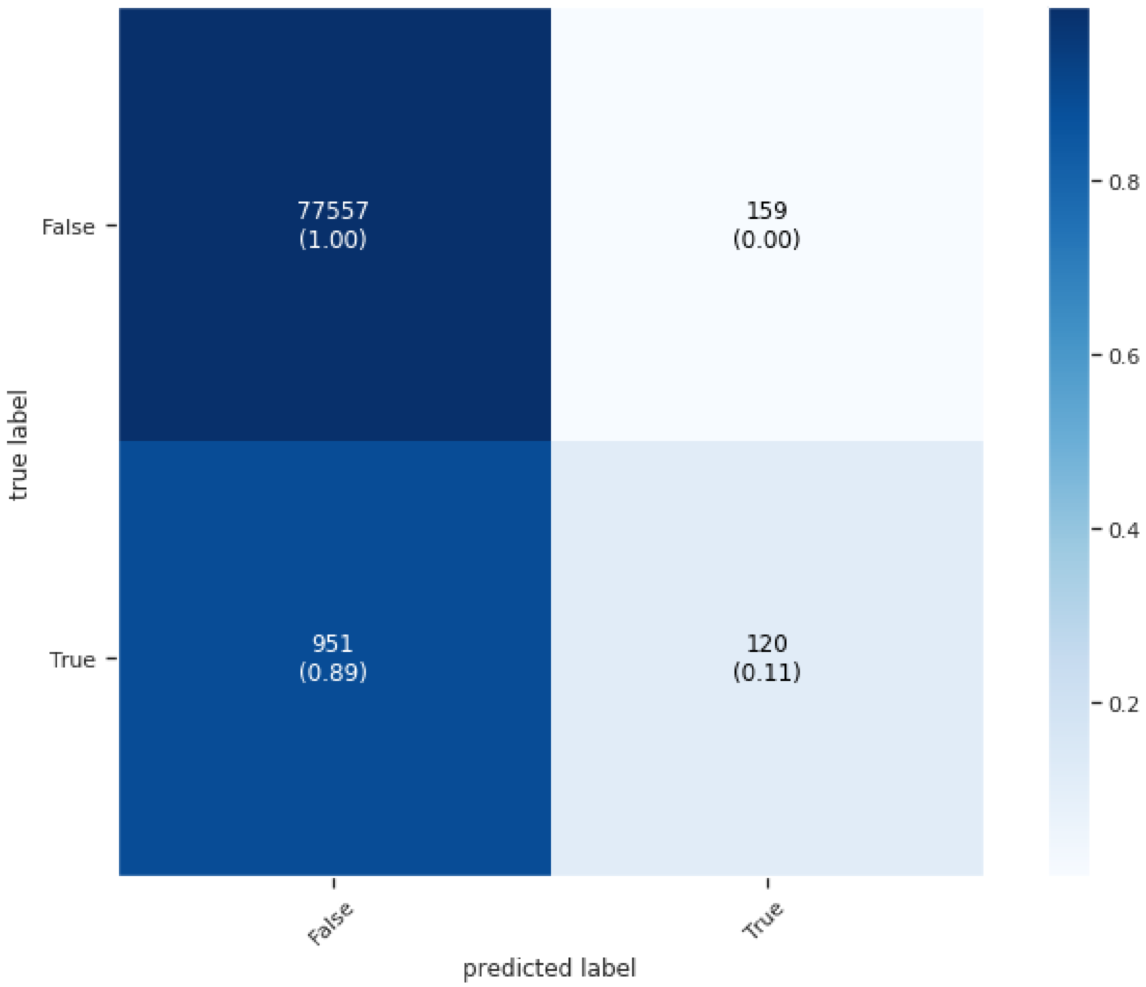
```
Requirement already up-to-date: mlxtend in /usr/local/lib/python3.6/dist
-packages (0.17.0)
Requirement already satisfied, skipping upgrade: numpy>=1.16.2 in /usr/l
ocal/lib/python3.6/dist-packages (from mlxtend) (1.16.5)
Requirement already satisfied, skipping upgrade: scipy>=1.2.1 in /usr/lo
cal/lib/python3.6/dist-packages (from mlxtend) (1.3.1)
Requirement already satisfied, skipping upgrade: matplotlib>=3.0.0 in /u
sr/local/lib/python3.6/dist-packages (from mlxtend) (3.0.3)
Requirement already satisfied, skipping upgrade: scikit-learn>=0.20.3 in
/usr/local/lib/python3.6/dist-packages (from mlxtend) (0.21.3)
Requirement already satisfied, skipping upgrade: pandas>=0.24.2 in /usr/
local/lib/python3.6/dist-packages (from mlxtend) (0.24.2)
Requirement already satisfied, skipping upgrade: joblib>=0.13.2 in /usr/
local/lib/python3.6/dist-packages (from mlxtend) (0.13.2)
Requirement already satisfied, skipping upgrade: setuptools in /usr/loca
l/lib/python3.6/dist-packages (from mlxtend) (41.2.0)
Requirement already satisfied, skipping upgrade: python-dateutil>=2.1 in
/usr/local/lib/python3.6/dist-packages (from matplotlib>=3.0.0->mlxtend)
(2.5.3)
Requirement already satisfied, skipping upgrade: kiwisolver>=1.0.1 in /u
sr/local/lib/python3.6/dist-packages (from matplotlib>=3.0.0->mlxtend)
(1.1.0)
Requirement already satisfied, skipping upgrade: pyparsing!=2.0.4,!=2.1.
2,!=2.1.6,>=2.0.1 in /usr/local/lib/python3.6/dist-packages (from matplo
tlib>=3.0.0->mlxtend) (2.4.2)
Requirement already satisfied, skipping upgrade: cycler>=0.10 in /usr/lo
cal/lib/python3.6/dist-packages (from matplotlib>=3.0.0->mlxtend) (0.10.
0)
Requirement already satisfied, skipping upgrade: pytz>=2011k in /usr/loc
al/lib/python3.6/dist-packages (from pandas>=0.24.2->mlxtend) (2018.9)
Requirement already satisfied, skipping upgrade: six>=1.5 in /usr/local/
lib/python3.6/dist-packages (from python-dateutil>=2.1->matplotlib>=3.0.
0->mlxtend) (1.12.0)
```

In [0]:

```
# Plotting CM
#plt.ylabel('somestring')
#plt.ylabel('true label')
#plt.ylabel = 'somestriddng'
#plt.xlabel = 'somestr333ing'

classNames = ['False','True']
plot_confusion_matrix(conf_mat=cm,
                                colorbar=True,
                                show_absolute=True,
                                show_normed=True,
                                class_names = classNames)
```

Out[0]:

```
(<Figure size 842.4x595.44 with 2 Axes>,
 <matplotlib.axes._subplots.AxesSubplot at 0x7fb32ba44d30>)
```



DECISION TREE

In [0]:

```
# Choosing model class. This is where we decide, which model to use. In this case De
cisionTreeClassifier.
# Installing Decision tree-model.
from sklearn.tree import DecisionTreeClassifier


# instantiating the model.
model = DecisionTreeClassifier()


# Getting our crossvalidation testscore.
# Please note that this is done on training data.
# Scores gives us a list of scores on each of the 5 subset, that is used in the tran
ing
scores = cross_val_score(model, X_train, y_train, cv = 5)


# Fitting the model on the training data.
model.fit(X_train, y_train)

# Printing out the result of the training.
print("Scores for crossvalidation on each trainingdata. cv=5")
print(scores)
print("-------\n")
print("Mean score and std on the trainingset")
print("Accuracy: %0.5f (+/- %0.5f)" % (scores.mean(), scores.std() * 2))
print("-------\n")

# Prediction on the models succes, based on the testdata.
y_model = model.predict(X_test)

# Model score
print("Testscores for fittet model")
print(model.score(X_test, y_test))
print("-------\n")

# Classification report => Se explation below the code.
print("Classification report")
print(classification_report(y_test,y_model))
```

```
Scores for crossvalidation on each trainingdata. cv=5
[0.97992512 0.9792905  0.97852852 0.97897275 0.97998773]
-------

Mean score and std on the trainingset
Accuracy: 0.97934 (+/- 0.00112)
-------

Testscores for fittet model
0.978422836254712
-------

Classification report
              precision    recall  f1-score   support

           0       0.99      0.99      0.99     77716
           1       0.24      0.27      0.25      1071

    accuracy                           0.98     78787
   macro avg       0.61      0.63      0.62     78787
weighted avg       0.98      0.98      0.98     78787
```

In [0]:

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_model)
print(cm)
```

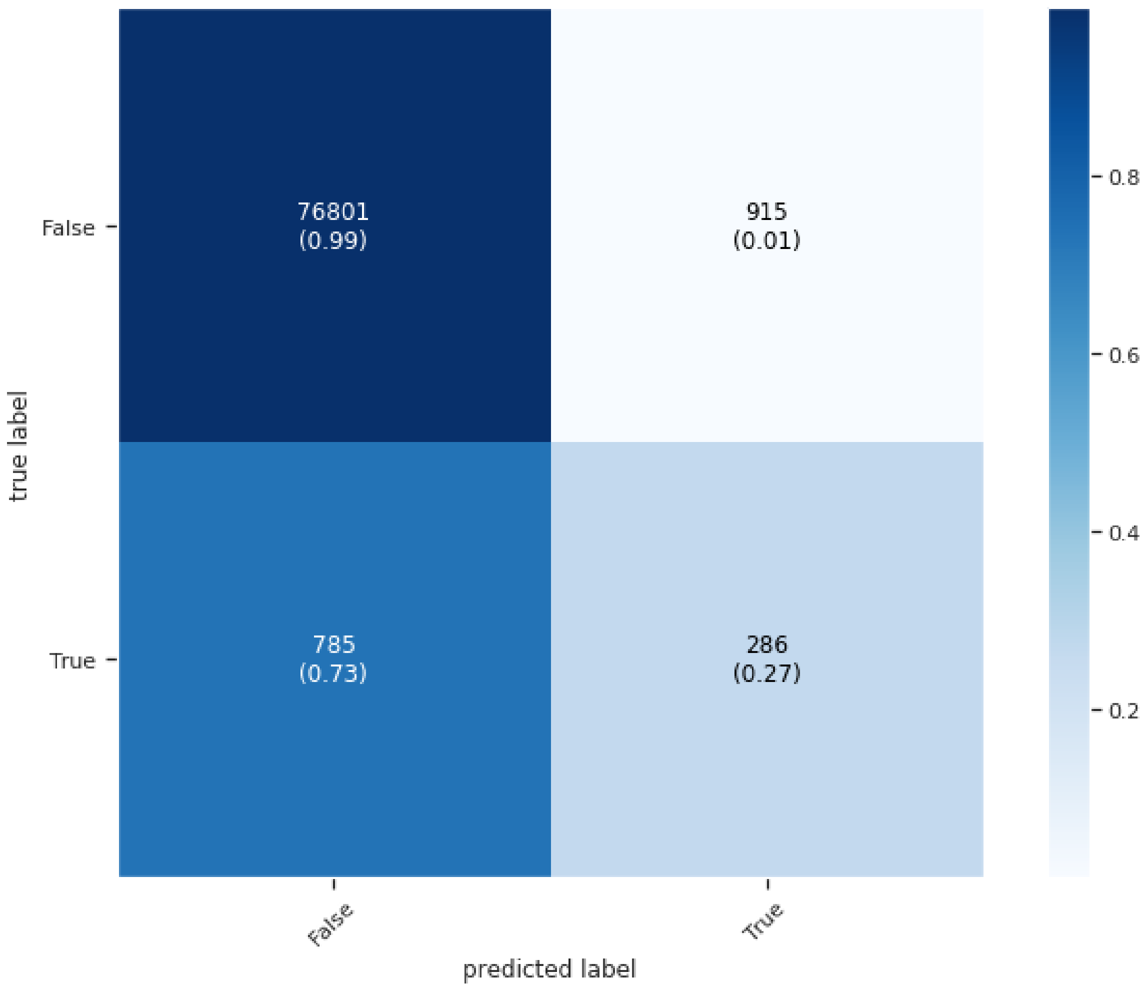
```
[[76801   915]
 [  785   286]]
```

In [0]:

```
# Plotting CM
classNames = ['False','True']
plot_confusion_matrix(conf_mat=cm,
                                colorbar=True,
                                show_absolute=True,
                                show_normed=True,
                                class_names = classNames)
```

Out[0]:

```
(<Figure size 842.4x595.44 with 2 Axes>,
 <matplotlib.axes._subplots.AxesSubplot at 0x7fb31ecfa940>)
```



XG BOOST

In [0]:

```
# Choosing model class. This is where we decide, which model to use. In this case XG
Boost.
# Installing XG BOOST.
import xgboost as xgb

# instantiating the model.
model = xgb.XGBClassifier()

# Getting our crossvalidation testscore.
# Please note that this is done on training data.
# Scores gives us a list of scores on each of the 5 subset, that is used in the tran
ing
scores = cross_val_score(model, X_train, y_train, cv = 5)


# Fitting the model on the training data.
model.fit(X_train, y_train)

# Printing out the result of the training.
print("Scores for crossvalidation on each trainingdata. cv=5")
print(scores)
print("-------\n")
print("Mean score and std on the trainingset")
print("Accuracy: %0.5f (+/- %0.5f)" % (scores.mean(), scores.std() * 2))
print("-------\n")

# Prediction on the models succes, based on the testdata.
y_model = model.predict(X_test)

# Model score
print("Testscores for fittet model")
print(model.score(X_test, y_test))
print("-------\n")

# Classification report => Se explation below the code.
print("Classification report")
print(classification_report(y_test,y_model))
```

```
Scores for crossvalidation on each trainingdata. cv=5
[0.98787892 0.98777315 0.98794212 0.98830174 0.98722261]
-------

Mean score and std on the trainingset
Accuracy: 0.98782 (+/- 0.00070)
-------

Testscores for fittet model
0.9873202431873278
-------

Classification report
              precision    recall  f1-score   support

           0       0.99      1.00      0.99     77716
           1       0.65      0.15      0.24      1071

    accuracy                           0.99     78787
   macro avg       0.82      0.57      0.62     78787
weighted avg       0.98      0.99      0.98     78787
```

In [0]:

```python
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_model)
print(cm)
```

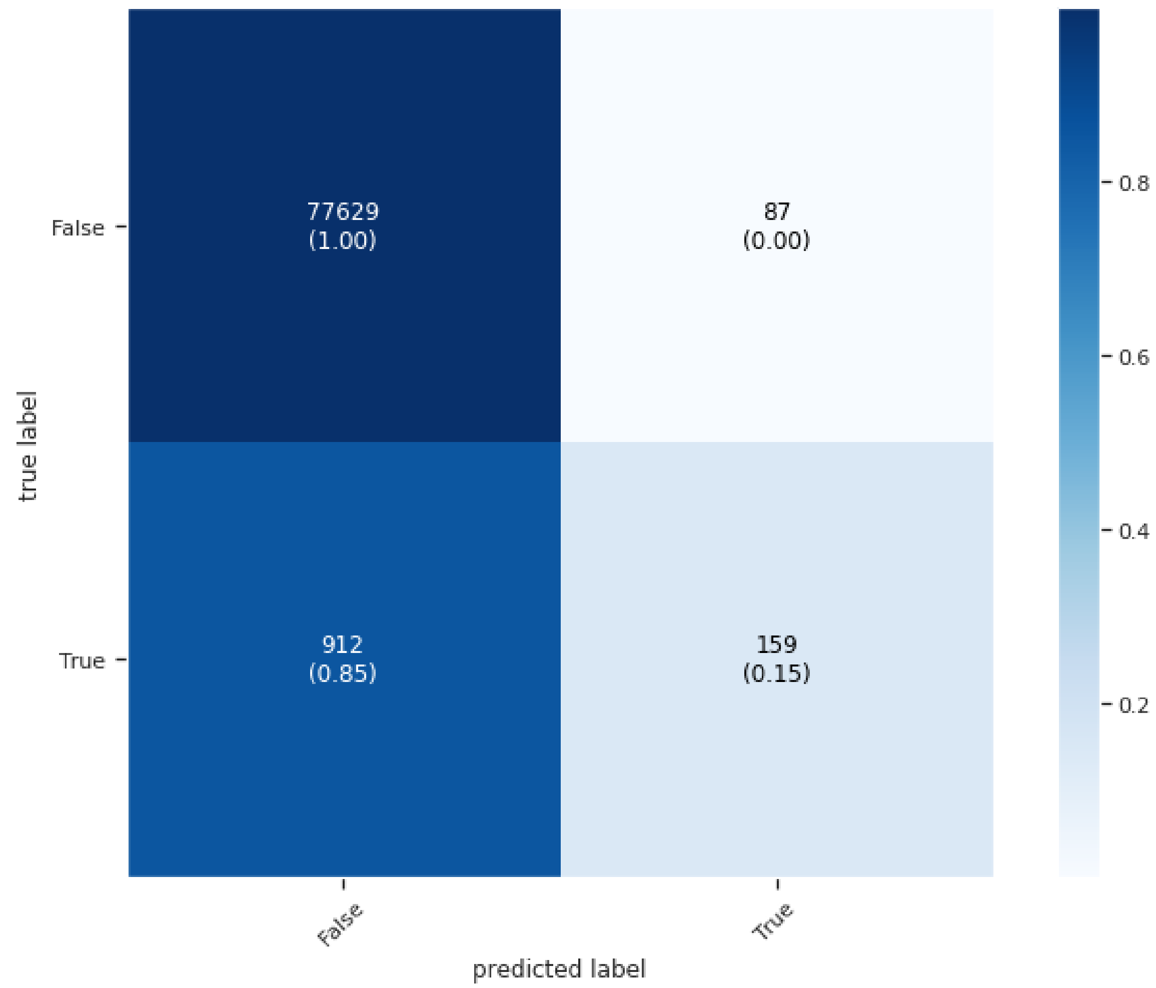
```
[[77629    87]
 [  912   159]]
```

In [0]:

```
# Plotting CM
classNames = ['False','True']
plot_confusion_matrix(conf_mat=cm,
                                colorbar=True,
                                show_absolute=True,
                                show_normed=True,
                                class_names = classNames)
```

Out[0]:

```
(<Figure size 842.4x595.44 with 2 Axes>,
 <matplotlib.axes._subplots.AxesSubplot at 0x7fb31ec6f0b8>)
```



CONCLUSION

The overall target of this assignment was to create a model which purpose was to predict whether a disbursement of a car loan would end up as a default or not. Before this could be done we had to do some preprocessing on our data. In the overall preprocessing the two dataset ‘train’ and ‘test’ was merged and alligned to a new dataset called ‘loans’. Next we explored the ‘loans’ dataset through visualisation and corrected it for outliers.

In order to do some unsupervised and supervised machine learning we then scaled the ‘loans’ dataset. In the unsupervised machine learning our data was compressed from 36 to 23 components through a PCA with an explained variance of 94% and clusters were visualized.

Finally we performed some supervised ML by creating three different models to predict default or not default loans. Overall the three models performed reasonable similar with a slightly advantage to the XGBoost model. This model was capable of predicting the target outcome with a 98.7% accuracy in the test set.