# **Data Preparation**

\*Loading traning dataset

#### In [1]:

```
import pandas as pd
import numpy as np

data = pd.read_csv('LoansTrainingSet.csv')
data.head()
```

//anaconda/envs/python2/lib/python2.7/site-packages/IPython/core/inter activeshell.py:2717: DtypeWarning: Columns (16) have mixed types. Spec ify dtype option on import or set low\_memory=False.

interactivity=interactivity, compiler=compiler, result=result)

#### Out[1]:

	Loan ID	Customer ID	Loan Status	Current Loan Amount	Term	Credit Score	Years in current job	Home Ownership	Annı Inco
(	000025bb- 5694-4cff- b17d- 192b1a98ba44	5ebc8bb1- 5eb9-4404- b11b- a6eebc401a19	Fully Paid	11520	Short Term	741.0	10+ years	Home Mortgage	3369
1	00002c49- 3a29-4bd4- 8f67- c8f8fbc1048c	927b388d- 2e01-423f- a8dc- f7e42d668f46	Fully Paid	3441	Short Term	734.0	4 years	Home Mortgage	4226
2	00002d89- 27f3-409b- aa76- 90834f359a65	defce609- c631-447d- aad6- 1270615e89c4	Fully Paid	21029	Short Term	747.0	10+ years	Home Mortgage	9012
3	00005222- b4d8-45a4- ad8c- 186057e24233	070bcecb- aae7-4485- a26a- e0403e7bb6c5	Fully Paid	18743	Short Term	747.0	10+ years	Own Home	3807
4	0000757f- a121-41ed- b17b- 162e76647c1f	dde79588- 12f0-4811- bab0- e2b07f633fcd	Fully Paid	11731	Short Term	746.0	4 years	Rent	5002

```
data.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 256984 entries, 0 to 256983
Data columns (total 19 columns):
Loan ID
                                  256984 non-null object
Customer ID
                                  256984 non-null object
                                  256984 non-null object
Loan Status
Current Loan Amount
                                  256984 non-null int64
                                  256984 non-null object
Term
                                  195308 non-null float64
Credit Score
                                  256984 non-null object
Years in current job
Home Ownership
                                  256984 non-null object
                                  195308 non-null float64
Annual Income
                                  256984 non-null object
Purpose
                                  256984 non-null object
Monthly Debt
                                  256984 non-null float64
Years of Credit History
                                  116601 non-null float64
Months since last delinquent
Number of Open Accounts
                                  256984 non-null int64
Number of Credit Problems
                                  256984 non-null int64
Current Credit Balance
                                  256984 non-null int64
Maximum Open Credit
                                  256984 non-null object
Bankruptcies
                                  256455 non-null float64
                                  256961 non-null float64
Tax Liens
dtypes: float64(6), int64(4), object(9)
memory usage: 37.3+ MB
*As we can see from above, we have problems with some missing values & data types
*Let's take a look at "Current Loan Amount" Column
In [3]:
data['Current Loan Amount'].max(), data['Current Loan Amount'].min(),data['Current 1
Out[3]:
(99999999, 505, 13713306.260237992)
*Selecting the rows of "Current Loan Amount" is lesser than 99999999
In [4]:
data = data[(data['Current Loan Amount'] < 99999999)]</pre>
```

In [2]:

```
In [5]:
data['Current Loan Amount'].describe()
Out[5]:
         221774.000000
count
          13979.687389
mean
           8260.519207
std
min
            505.000000
25%
           7819.000000
50%
          12058.000000
          19438.750000
75%
          41000.000000
max
Name: Current Loan Amount, dtype: float64
*Now, in "Current Loan Amount" column, the mean value is 13979.69 and median value is 12058.00
*Looking at unique values of "Years in current job", "Home Ownership", and "Purpose" columns
In [6]:
data['Years in current job'].unique()
Out[6]:
array(['10+ years', '4 years', '6 years', '5 years', 'n/a', '2 years',
        '< 1 year', '3 years', '1 year', '7 years', '9 years', '8 years
'], dtype=object)
In [7]:
data['Home Ownership'].unique()
Out[7]:
array(['Home Mortgage', 'Own Home', 'Rent', 'HaveMortgage'], dtype=obj
ect)
In [8]:
data['Purpose'].unique()
Out[8]:
array(['Debt Consolidation', 'other', 'Business Loan', 'Home Improveme
nts',
        'Buy House', 'Other', 'Buy a Car', 'Medical Bills', 'Take a Tri
p',
        'Educational Expenses'], dtype=object)
```

## Data Problems

- 1. Missing values: credit score (has nan), Annual Income, Months since last delinquent (has nan), Bankruptcies (has nan), Tax Liens (has nan)
- Spelling differences & punctuation format Years in current job: delete years, 10+, <1, n/a;</li>
   Home Ownership: Home Mortgage == HaveMortgage; Purpose: Other == other; Monthly Debt: delete
   \$;

Maximum Open Credit: why is it Object?; Years of Credit History: decimal 1 place

- 3. Duplicates rows
- 4. Some of Credit scores are too high, have to devide by 10
- 5. Current Loan Amount: too high 9999999 compared to their annual income
- 6. Data types: convert Credit Score float64 to int64; convert Monthly Debt, Maximum Open Credit object to float64
- 1. missing values: credit score (has nan)

## In [9]:

```
credit_score_nan = data['Credit Score'].isnull()
data[credit_score_nan].head()
```

## Out[9]:

		Loan ID	Customer ID	Loan Status	Current Loan Amount	Term	Credit Score	Years in current job	Home Ownership	A
7		0000afa6- 8902-4f8f- b870- 25a8fdad0aeb	e49c1a82- a0f7-45e8- 9f46- 2f75c43f9fbc	Charged Off	24613	Long Term	NaN	6 years	Rent	N
8		00011dfc- 31c1-4178- 932a- fbeb3f341efb	ef6e098c- 6c83-4752- 8d00- ff793e476b8c	Fully Paid	10036	Short Term	NaN	5 years	Rent	N
1	2	00029f9f- 0cc5-4d4e- aabc- ea4a7fe74e12	afbc2fa3- 3bad-4d48- b691- 829aed78bad5	Charged Off	17980	Short Term	NaN	< 1 year	Own Home	N
2	0	00038a08- f058-4add- a8ed- 497b91672a9e	727bb429- dfa1-41c4- a347- 23230e23949f	Charged Off	16929	Long Term	NaN	3 years	Home Mortgage	N
2	2	0003b749- 307f-4830- 9fb4- 9db7ed1b1c48	998dc43c- f9ce-466e- bdaa- 7057b0bbb9cd	Fully Paid	7228	Short Term	NaN	3 years	Home Mortgage	N

<sup>\*</sup>Creating a new dataframe as df that has "Credit Score" values

### In [10]:

```
df = data[data['Credit Score'].notnull()]
```

```
df.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 160098 entries, 0 to 256983
Data columns (total 19 columns):
Loan ID
                                 160098 non-null object
Customer ID
                                 160098 non-null object
                                 160098 non-null object
Loan Status
Current Loan Amount
                                 160098 non-null int64
                                 160098 non-null object
Term
Credit Score
                                 160098 non-null float64
                                 160098 non-null object
Years in current job
                                 160098 non-null object
Home Ownership
Annual Income
                                 160098 non-null float64
                                 160098 non-null object
Purpose
Monthly Debt
                                 160098 non-null object
Years of Credit History
                                 160098 non-null float64
                                 72761 non-null float64
Months since last delinquent
Number of Open Accounts
                                 160098 non-null int64
Number of Credit Problems
                                 160098 non-null int64
Current Credit Balance
                                 160098 non-null int64
Maximum Open Credit
                                 160098 non-null object
Bankruptcies
                                 159756 non-null float64
Tax Liens
                                 160085 non-null float64
dtypes: float64(6), int64(4), object(9)
memory usage: 24.4+ MB
*convert Credit Score column from float to int type
In [12]:
df['Credit Score'] = df['Credit Score'].astype(np.int64)
/anaconda/envs/python2/lib/python2.7/site-packages/ipykernel/ main .
py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row indexer,col indexer] = value instead
See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
(http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-vi
ew-versus-copy)
  if name == ' main ':
```

In [11]:

```
df.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 160098 entries, 0 to 256983
Data columns (total 19 columns):
Loan ID
                                 160098 non-null object
Customer ID
                                 160098 non-null object
                                 160098 non-null object
Loan Status
Current Loan Amount
                                 160098 non-null int64
                                 160098 non-null object
Term
Credit Score
                                 160098 non-null int64
                                 160098 non-null object
Years in current job
                                 160098 non-null object
Home Ownership
Annual Income
                                 160098 non-null float64
                                 160098 non-null object
Purpose
Monthly Debt
                                 160098 non-null object
Years of Credit History
                                 160098 non-null float64
                                 72761 non-null float64
Months since last delinquent
Number of Open Accounts
                                 160098 non-null int64
Number of Credit Problems
                                 160098 non-null int64
Current Credit Balance
                                 160098 non-null int64
Maximum Open Credit
                                 160098 non-null object
Bankruptcies
                                 159756 non-null float64
Tax Liens
                                 160085 non-null float64
dtypes: float64(5), int64(5), object(9)
memory usage: 24.4+ MB
*Dividing "Credit Score" by 10, for the values more than 800
In [14]:
df['Credit Score'] = df['Credit Score'].map(lambda x: x/10 if x > 800 else x)
/anaconda/envs/python2/lib/python2.7/site-packages/ipykernel/ main .
py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row indexer,col indexer] = value instead
See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
(http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-vi
ew-versus-copy)
  if name == ' main ':
```

In [13]:

```
In [15]:
df['Credit Score'][(df['Credit Score'] > 800)].count()
Out[15]:
0
*Now, we don't have credit score more than 800
*Convert Monthly Debt from object to float64, removing the $
In [16]:
df['Monthly Debt'] = df['Monthly Debt'].replace( '[\$, ]','', regex=True).astype(floor)
df['Monthly Debt'].head()
/anaconda/envs/python2/lib/python2.7/site-packages/ipykernel/__main__.
py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row indexer,col indexer] = value instead
See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
(http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-vi
ew-versus-copy)
  if __name__ == '__main__':
Out[16]:
0
      584.03
1
     1106.04
2
     1321.85
      751.92
3
```

Name: Monthly Debt, dtype: float64

4

355.18

<sup>\*</sup>Converting "Maximum Open Credit" from object to float64

```
df['Maximum Open Credit'] = df['Maximum Open Credit'].convert objects(convert numer:
df['Maximum Open Credit'].head()
/anaconda/envs/python2/lib/python2.7/site-packages/ipykernel/ main .
py:1: FutureWarning: convert objects is deprecated. Use the data-type
specific converters pd.to datetime, pd.to timedelta and pd.to numeric.
  if name == '__main__':
/anaconda/envs/python2/lib/python2.7/site-packages/ipykernel/ main .
py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row indexer,col indexer] = value instead
See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
(http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-vi
ew-versus-copy)
  if __name__ == '__main__':
Out[17]:
0
     16056.0
1
     19149.0
2
     28335.0
3
     43915.0
     37081.0
Name: Maximum Open Credit, dtype: float64
*Home Ownership: converting "HaveMortgage" to "Home Mortgage"
In [18]:
df['Home Ownership'] = df['Home Ownership'].map(lambda x: 'Home Mortgage' if x == 'H
/anaconda/envs/python2/lib/python2.7/site-packages/ipykernel/ main .
py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row indexer,col indexer] = value instead
See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
(http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-vi
ew-versus-copy)
  if name == ' main ':
*Purpose: converting "other" to "Other"
```

In [17]:

```
#Purpose: other == Other
df['Purpose'] = df['Purpose'].map(lambda x: 'Other' if x == 'other' else x)
/anaconda/envs/python2/lib/python2.7/site-packages/ipykernel/ main .
py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row indexer,col indexer] = value instead
See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
(http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-vi
ew-versus-copy)
  app.launch new instance()
*Checking the unique values of "Home Ownership" and "Purpose"
In [20]:
print "Home Ownership: ", df['Home Ownership'].unique()
print "Purpose: ", df['Purpose'].unique()
                 ['Home Mortgage' 'Own Home' 'Rent']
Home Ownership:
          ['Debt Consolidation' 'Other' 'Business Loan' 'Home Improvem
Purpose:
ents'
 'Buy House' 'Medical Bills' 'Take a Trip' 'Buy a Car'
 'Educational Expenses']
*We have missing values in "Month since last delinquent" column. Let's take a look at the relationship between
```

NA values in "Month since last delinquent" column and other "problem columns" such as "Purpose", "Number

of Credit Problems", "Bankruptcies", and "Tax Liens"

In [19]:

```
In [21]:
msld nan = df['Months since last delinquent'].isnull()
print df[msld_nan]['Purpose'].value_counts()
print df[msld nan]['Number of Credit Problems'].value counts()
print df[msld_nan]['Bankruptcies'].value_counts()
print df[msld_nan]['Tax Liens'].value_counts()
Debt Consolidation
                          69495
Other
                           8295
Home Improvements
                           4513
Business Loan
                           1728
                           1205
Buy a Car
Medical Bills
                            942
                            552
Take a Trip
Buy House
                            515
                             92
Educational Expenses
Name: Purpose, dtype: int64
0
     76539
1
      9711
       808
2
3
       179
4
        63
5
        21
6
        11
7
         3
9
         1
8
         1
Name: Number of Credit Problems, dtype: int64
       78011
0.0
        9016
1.0
         266
2.0
3.0
           35
            5
4.0
            2
5.0
Name: Bankruptcies, dtype: int64
0.0
       86179
1.0
         837
2.0
         220
3.0
           48
4.0
           28
5.0
           16
6.0
            5
9.0
            1
7.0
            1
```

Name: Tax Liens, dtype: int64

<sup>\*</sup>Most of NA values in "Month since last delinquent" column have: purpose of Debt Consolidation; 0 Number of Credit Problems; 0 Bankruptcies; 0 Tax Liens

\*Now, taking a look at correlations

In [22]:

df.corr()

Out[22]:

	Current Loan Amount	Credit Score	Annual Income	Monthly Debt	Years of Credit History	Months since last delinquent	Number of Open Account
Current Loan Amount	1.000000	-0.233733	0.335476	0.435983	0.152230	-0.044143	0.201689
Credit Score	-0.233733	1.000000	0.009421	-0.095841	0.087433	0.046790	-0.04668
Annual Income	0.335476	0.009421	1.000000	0.452869	0.146897	-0.063535	0.139885
Monthly Debt	0.435983	-0.095841	0.452869	1.000000	0.188655	-0.056744	0.409085
Years of Credit History	0.152230	0.087433	0.146897	0.188655	1.000000	-0.039912	0.130126
Months since last delinquent	-0.044143	0.046790	-0.063535	-0.056744	-0.039912	1.000000	-0.03558
Number of Open Accounts	0.201689	-0.046681	0.139885	0.409085	0.130126	-0.035585	1.000000
Number of Credit Problems	-0.072039	-0.055539	-0.010737	-0.049905	0.061586	0.088823	-0.01214
Current Credit Balance	0.331326	-0.015774	0.283434	0.476020	0.207288	-0.023838	0.231627
Maximum Open Credit	0.038276	0.017475	0.040757	0.037311	0.027981	0.001044	0.030191
Bankruptcies	-0.095954	-0.039888	-0.043599	-0.076680	0.062593	0.111428	-0.02095
Tax Liens	0.014140	-0.028144	0.041296	0.022576	0.020989	0.007285	0.005294

<sup>\*</sup>Let's take a look at "Months since last delinquent" column

```
In [23]:
df['Months since last delinquent'].max()
Out[23]:
176.0
*Let's fill in NA in 'Months since last delinquent' with 200 which is even more than max number of credit
problems (176), because we noticed above that most NA in 'Months since last delinquent' has "least" problems
In [24]:
df["Months since last delinquent"].fillna(value=200, inplace=True)
//anaconda/envs/python2/lib/python2.7/site-packages/pandas/core/generi
c.py:3191: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
(http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-vi
ew-versus-copy)
  self._update_inplace(new_data)
In [25]:
df['Months since last delinquent'].describe()
Out[25]:
```

```
160098.000000
count
             124.948338
mean
std
              83.539069
               0.00000
min
25%
              35.000000
50%
             200.000000
75%
             200.000000
             200.000000
max
```

Name: Months since last delinquent, dtype: float64

```
df.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 160098 entries, 0 to 256983
Data columns (total 19 columns):
Loan ID
                                 160098 non-null object
Customer ID
                                 160098 non-null object
                                 160098 non-null object
Loan Status
Current Loan Amount
                                 160098 non-null int64
                                 160098 non-null object
Term
                                 160098 non-null int64
Credit Score
Years in current job
                                 160098 non-null object
Home Ownership
                                 160098 non-null object
                                 160098 non-null float64
Annual Income
                                 160098 non-null object
Purpose
Monthly Debt
                                 160098 non-null float64
Years of Credit History
                                 160098 non-null float64
Months since last delinquent
                                 160098 non-null float64
Number of Open Accounts
                                 160098 non-null int64
Number of Credit Problems
                                 160098 non-null int64
Current Credit Balance
                                 160098 non-null int64
Maximum Open Credit
                                 160095 non-null float64
Bankruptcies
                                 159756 non-null float64
Tax Liens
                                 160085 non-null float64
```

dtypes: float64(7), int64(5), object(7)

memory usage: 24.4+ MB

\*Tax Liens is highly correlated with Number of credit problems = 0.59, so let's only include none missing values in Tax Liens for our new dataframe df

```
In [27]:
```

In [26]:

```
df = df[df['Tax Liens'].notnull()]
```

```
df.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 160085 entries, 0 to 256983
Data columns (total 19 columns):
Loan ID
                                 160085 non-null object
Customer ID
                                 160085 non-null object
                                 160085 non-null object
Loan Status
Current Loan Amount
                                 160085 non-null int64
                                 160085 non-null object
Term
                                 160085 non-null int64
Credit Score
Years in current job
                                 160085 non-null object
Home Ownership
                                 160085 non-null object
Annual Income
                                 160085 non-null float64
                                 160085 non-null object
Purpose
                                 160085 non-null float64
Monthly Debt
                                 160085 non-null float64
Years of Credit History
Months since last delinquent
                                 160085 non-null float64
Number of Open Accounts
                                 160085 non-null int64
Number of Credit Problems
                                 160085 non-null int64
Current Credit Balance
                                 160085 non-null int64
Maximum Open Credit
                                 160082 non-null float64
Bankruptcies
                                 159756 non-null float64
Tax Liens
                                 160085 non-null float64
dtypes: float64(7), int64(5), object(7)
```

\*Let's only include none missing values in Bankruptcies for our new dataframe df

#### In [29]:

memory usage: 24.4+ MB

In [28]:

```
df = df[df['Bankruptcies'].notnull()]
```

```
df.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 159756 entries, 0 to 256983
Data columns (total 19 columns):
Loan ID
                                  159756 non-null object
Customer ID
                                  159756 non-null object
                                  159756 non-null object
Loan Status
Current Loan Amount
                                  159756 non-null int64
                                  159756 non-null object
Term
                                  159756 non-null int64
Credit Score
Years in current job
                                  159756 non-null object
Home Ownership
                                 159756 non-null object
                                  159756 non-null float64
Annual Income
                                  159756 non-null object
Purpose
                                  159756 non-null float64
Monthly Debt
Years of Credit History
                                  159756 non-null float64
Months since last delinquent
                                  159756 non-null float64
Number of Open Accounts
                                  159756 non-null int64
Number of Credit Problems
                                 159756 non-null int64
Current Credit Balance
                                  159756 non-null int64
Maximum Open Credit
                                 159753 non-null float64
Bankruptcies
                                  159756 non-null float64
Tax Liens
                                  159756 non-null float64
dtypes: float64(7), int64(5), object(7)
memory usage: 24.4+ MB
*Taking a look at "Maximum Open Credit" column
In [31]:
moc nan = df['Maximum Open Credit'].isnull()
moc nan.value counts()
Out[31]:
False
         159753
True
Name: Maximum Open Credit, dtype: int64
*Selecting none missing values in Maximum Open Credit for our new dataframe df
In [32]:
df = df[df['Maximum Open Credit'].notnull()]
```

In [30]:

```
In [33]:
df.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 159753 entries, 0 to 256983
Data columns (total 19 columns):
Loan ID
                                 159753 non-null object
Customer ID
                                 159753 non-null object
                                 159753 non-null object
Loan Status
Current Loan Amount
                                 159753 non-null int64
                                 159753 non-null object
Term
                                 159753 non-null int64
Credit Score
Years in current job
                                 159753 non-null object
Home Ownership
                                 159753 non-null object
                                 159753 non-null float64
Annual Income
                                 159753 non-null object
Purpose
Monthly Debt
                                 159753 non-null float64
                                 159753 non-null float64
Years of Credit History
Months since last delinquent
                                 159753 non-null float64
Number of Open Accounts
                                 159753 non-null int64
Number of Credit Problems
                                 159753 non-null int64
Current Credit Balance
                                 159753 non-null int64
Maximum Open Credit
                                 159753 non-null float64
                                 159753 non-null float64
Bankruptcies
Tax Liens
                                 159753 non-null float64
dtypes: float64(7), int64(5), object(7)
memory usage: 24.4+ MB
*Now, we don't have any missing values
*Taking look at "Loan ID" and "Customer ID" columns
In [34]:
print "Total unique Loan IDs: ", df['Loan ID'].nunique()
print "Total unique Customer IDs: ", df['Customer ID'].nunique()
print "Total entries: ", len(df)
Total unique Loan IDs:
                         135696
Total unique Customer IDs:
                             135696
Total entries:
                159753
In [35]:
df['Loan ID'].value_counts()
Out[35]:
9d601e9f-2e11-42f6-868a-82ba3aa9e401
                                          4
bbf7a3d6-c415-417e-b6a1-5095a6a5fcca
                                          4
80bf6f56-b3f3-41d8-bb26-191ead5a8a4c
                                          4
```

255cc82a-2733-48bd-a784-aa61a494833b	4
21d50a6a-0e3d-49d9-843d-e4c9e2959e11	4
2f7500e8-695a-4d4d-b91c-bdfaedb06745	4
536c1d67-0e1a-4060-909b-b23b7d6eff50	4
4e800cb9-955b-45f9-85d5-196c3054f2f1	4
f1dc64e8-b329-480a-b289-e793e954fd3c	4
a4bd5c89-275a-4539-9e27-5c256845bd2c	4
943b437f-b6aa-4581-9ca7-611a5ffffc4a	4
16a5ca88-8f09-4a8e-a40c-9e9bc394abc7	4
6e766ede-75e9-4b26-b781-e268faf258f0	4
e6559d6b-42fa-4285-a565-200b693fb976	4
91037789-b0a2-4d49-89dc-78c27b5e5297	4
9f20c0be-fac2-4400-8c2a-fa6063a123a0	4
b1e4e451-4a27-4a35-9d48-3fc55702992b	4
66bb3e99-6468-4193-a7d3-4d0134581e30	4
b8dbe5c6-6c6d-4b26-850f-8f52c4303383	4
55931e3a-d5d2-4be5-94c6-d4c8bb9d4844	4
	_
c7f0e509-28b8-4349-99db-f863fb067237	4
16be66d9-607a-43a4-8fbf-5327a16708c1	4
889bb6f2-91f1-46c6-ba21-92f37ea2e662	4
93663d95-1686-4fb7-8d4f-b06c237d5689	4
8a036c7c-9836-4763-8f69-980b23e3f381	4
14c5fb07-d3bd-4fc8-aad0-54d21f491daf	4
f57c84b6-cf4d-4023-ab5d-8ae55a708524	4
e94aceda-a038-4444-bb52-a481f2ac5472	4
2e03e705-c9eb-474c-9e45-6e898d75dbd8	4
cadb86e8-b6da-420f-95ce-a477f5cb3040	4
cadb86e8-b6da-420f-95ce-a477f5cb3040	4
cadb86e8-b6da-420f-95ce-a477f5cb3040 ea9580a3-53e8-4ae8-b986-b2ceb009a613	
	• •
ea9580a3-53e8-4ae8-b986-b2ceb009a613	1
ea9580a3-53e8-4ae8-b986-b2ceb009a613 838674cc-5d8a-487b-99db-34ed9a417d87	1 1
ea9580a3-53e8-4ae8-b986-b2ceb009a613 838674cc-5d8a-487b-99db-34ed9a417d87 0a9c74d7-35f3-4f5c-ae7f-d4963fe25c74	1 1 1
ea9580a3-53e8-4ae8-b986-b2ceb009a613 838674cc-5d8a-487b-99db-34ed9a417d87 0a9c74d7-35f3-4f5c-ae7f-d4963fe25c74 81cf9604-580e-4360-a39e-ad42f3bfe840	1 1 1 1
ea9580a3-53e8-4ae8-b986-b2ceb009a613 838674cc-5d8a-487b-99db-34ed9a417d87 0a9c74d7-35f3-4f5c-ae7f-d4963fe25c74 81cf9604-580e-4360-a39e-ad42f3bfe840 9aa79939-a953-4472-aa07-2b35f04a7100	1 1 1 1 1
ea9580a3-53e8-4ae8-b986-b2ceb009a613 838674cc-5d8a-487b-99db-34ed9a417d87 0a9c74d7-35f3-4f5c-ae7f-d4963fe25c74 81cf9604-580e-4360-a39e-ad42f3bfe840 9aa79939-a953-4472-aa07-2b35f04a7100 8fedaaf8-f844-4d8d-8b35-4aeae3862844	1 1 1 1 1 1
ea9580a3-53e8-4ae8-b986-b2ceb009a613 838674cc-5d8a-487b-99db-34ed9a417d87 0a9c74d7-35f3-4f5c-ae7f-d4963fe25c74 81cf9604-580e-4360-a39e-ad42f3bfe840 9aa79939-a953-4472-aa07-2b35f04a7100 8fedaaf8-f844-4d8d-8b35-4aeae3862844 3d8ab1c0-42eb-4495-9aa8-1afb4fa72b1b	1 1 1 1 1 1 1
ea9580a3-53e8-4ae8-b986-b2ceb009a613 838674cc-5d8a-487b-99db-34ed9a417d87 0a9c74d7-35f3-4f5c-ae7f-d4963fe25c74 81cf9604-580e-4360-a39e-ad42f3bfe840 9aa79939-a953-4472-aa07-2b35f04a7100 8fedaaf8-f844-4d8d-8b35-4aeae3862844 3d8ab1c0-42eb-4495-9aa8-1afb4fa72b1b 0fd0dd72-a6e7-4971-8f19-d7b820b6c84e	1 1 1 1 1 1 1
ea9580a3-53e8-4ae8-b986-b2ceb009a613 838674cc-5d8a-487b-99db-34ed9a417d87 0a9c74d7-35f3-4f5c-ae7f-d4963fe25c74 81cf9604-580e-4360-a39e-ad42f3bfe840 9aa79939-a953-4472-aa07-2b35f04a7100 8fedaaf8-f844-4d8d-8b35-4aeae3862844 3d8ab1c0-42eb-4495-9aa8-1afb4fa72b1b 0fd0dd72-a6e7-4971-8f19-d7b820b6c84e 14ba0515-b8a8-4bce-873b-d6143df45b13 fbd4aade-5491-48cd-b87c-fdcbb615a771	1 1 1 1 1 1 1 1 1
ea9580a3-53e8-4ae8-b986-b2ceb009a613 838674cc-5d8a-487b-99db-34ed9a417d87 0a9c74d7-35f3-4f5c-ae7f-d4963fe25c74 81cf9604-580e-4360-a39e-ad42f3bfe840 9aa79939-a953-4472-aa07-2b35f04a7100 8fedaaf8-f844-4d8d-8b35-4aeae3862844 3d8ab1c0-42eb-4495-9aa8-1afb4fa72b1b 0fd0dd72-a6e7-4971-8f19-d7b820b6c84e 14ba0515-b8a8-4bce-873b-d6143df45b13 fbd4aade-5491-48cd-b87c-fdcbb615a771 97a385bc-b849-4fc0-997e-bfa9db1878af	1 1 1 1 1 1 1 1 1
ea9580a3-53e8-4ae8-b986-b2ceb009a613 838674cc-5d8a-487b-99db-34ed9a417d87 0a9c74d7-35f3-4f5c-ae7f-d4963fe25c74 81cf9604-580e-4360-a39e-ad42f3bfe840 9aa79939-a953-4472-aa07-2b35f04a7100 8fedaaf8-f844-4d8d-8b35-4aeae3862844 3d8ab1c0-42eb-4495-9aa8-1afb4fa72b1b 0fd0dd72-a6e7-4971-8f19-d7b820b6c84e 14ba0515-b8a8-4bce-873b-d6143df45b13 fbd4aade-5491-48cd-b87c-fdcbb615a771 97a385bc-b849-4fc0-997e-bfa9db1878af a7933509-e00c-402c-8211-819d7bcdac06	1 1 1 1 1 1 1 1 1 1
ea9580a3-53e8-4ae8-b986-b2ceb009a613 838674cc-5d8a-487b-99db-34ed9a417d87 0a9c74d7-35f3-4f5c-ae7f-d4963fe25c74 81cf9604-580e-4360-a39e-ad42f3bfe840 9aa79939-a953-4472-aa07-2b35f04a7100 8fedaaf8-f844-4d8d-8b35-4aeae3862844 3d8ab1c0-42eb-4495-9aa8-1afb4fa72b1b 0fd0dd72-a6e7-4971-8f19-d7b820b6c84e 14ba0515-b8a8-4bce-873b-d6143df45b13 fbd4aade-5491-48cd-b87c-fdcbb615a771 97a385bc-b849-4fc0-997e-bfa9db1878af a7933509-e00c-402c-8211-819d7bcdac06 ee215047-6034-484e-b98b-8659c9d6ab50	1 1 1 1 1 1 1 1 1 1 1
ea9580a3-53e8-4ae8-b986-b2ceb009a613 838674cc-5d8a-487b-99db-34ed9a417d87 0a9c74d7-35f3-4f5c-ae7f-d4963fe25c74 81cf9604-580e-4360-a39e-ad42f3bfe840 9aa79939-a953-4472-aa07-2b35f04a7100 8fedaaf8-f844-4d8d-8b35-4aeae3862844 3d8ab1c0-42eb-4495-9aa8-1afb4fa72b1b 0fd0dd72-a6e7-4971-8f19-d7b820b6c84e 14ba0515-b8a8-4bce-873b-d6143df45b13 fbd4aade-5491-48cd-b87c-fdcbb615a771 97a385bc-b849-4fc0-997e-bfa9db1878af a7933509-e00c-402c-8211-819d7bcdac06 ee215047-6034-484e-b98b-8659c9d6ab50 f6a9f7a0-e6ce-4bba-a489-ce54096fdd9c	1 1 1 1 1 1 1 1 1 1 1 1
ea9580a3-53e8-4ae8-b986-b2ceb009a613 838674cc-5d8a-487b-99db-34ed9a417d87 0a9c74d7-35f3-4f5c-ae7f-d4963fe25c74 81cf9604-580e-4360-a39e-ad42f3bfe840 9aa79939-a953-4472-aa07-2b35f04a7100 8fedaaf8-f844-4d8d-8b35-4aeae3862844 3d8ab1c0-42eb-4495-9aa8-lafb4fa72b1b 0fd0dd72-a6e7-4971-8f19-d7b820b6c84e 14ba0515-b8a8-4bce-873b-d6143df45b13 fbd4aade-5491-48cd-b87c-fdcbb615a771 97a385bc-b849-4fc0-997e-bfa9db1878af a7933509-e00c-402c-8211-819d7bcdac06 ee215047-6034-484e-b98b-8659c9d6ab50 f6a9f7a0-e6ce-4bba-a489-ce54096fdd9c d4f2074f-e816-4724-a984-732a8844b7e9	1 1 1 1 1 1 1 1 1 1 1 1
ea9580a3-53e8-4ae8-b986-b2ceb009a613 838674cc-5d8a-487b-99db-34ed9a417d87 0a9c74d7-35f3-4f5c-ae7f-d4963fe25c74 81cf9604-580e-4360-a39e-ad42f3bfe840 9aa79939-a953-4472-aa07-2b35f04a7100 8fedaaf8-f844-4d8d-8b35-4aeae3862844 3d8ab1c0-42eb-4495-9aa8-1afb4fa72b1b 0fd0dd72-a6e7-4971-8f19-d7b820b6c84e 14ba0515-b8a8-4bce-873b-d6143df45b13 fbd4aade-5491-48cd-b87c-fdcbb615a771 97a385bc-b849-4fc0-997e-bfa9db1878af a7933509-e00c-402c-8211-819d7bcdac06 ee215047-6034-484e-b98b-8659c9d6ab50 f6a9f7a0-e6ce-4bba-a489-ce54096fdd9c d4f2074f-e816-4724-a984-732a8844b7e9 6fb2fadc-92b3-4704-9aae-78236b924fa4	1 1 1 1 1 1 1 1 1 1 1 1 1
ea9580a3-53e8-4ae8-b986-b2ceb009a613 838674cc-5d8a-487b-99db-34ed9a417d87 0a9c74d7-35f3-4f5c-ae7f-d4963fe25c74 81cf9604-580e-4360-a39e-ad42f3bfe840 9aa79939-a953-4472-aa07-2b35f04a7100 8fedaaf8-f844-4d8d-8b35-4aeae3862844 3d8ab1c0-42eb-4495-9aa8-1afb4fa72b1b 0fd0dd72-a6e7-4971-8f19-d7b820b6c84e 14ba0515-b8a8-4bce-873b-d6143df45b13 fbd4aade-5491-48cd-b87c-fdcbb615a771 97a385bc-b849-4fc0-997e-bfa9db1878af a7933509-e00c-402c-8211-819d7bcdac06 ee215047-6034-484e-b98b-8659c9d6ab50 f6a9f7a0-e6ce-4bba-a489-ce54096fdd9c d4f2074f-e816-4724-a984-732a8844b7e9 6fb2fadc-92b3-4704-9aae-78236b924fa4 17e3da6f-2161-4864-b7b3-682cca6430d2	1 1 1 1 1 1 1 1 1 1 1 1 1 1
ea9580a3-53e8-4ae8-b986-b2ceb009a613 838674cc-5d8a-487b-99db-34ed9a417d87 0a9c74d7-35f3-4f5c-ae7f-d4963fe25c74 81cf9604-580e-4360-a39e-ad42f3bfe840 9aa79939-a953-4472-aa07-2b35f04a7100 8fedaaf8-f844-4d8d-8b35-4aeae3862844 3d8ab1c0-42eb-4495-9aa8-lafb4fa72b1b 0fd0dd72-a6e7-4971-8f19-d7b820b6c84e 14ba0515-b8a8-4bce-873b-d6143df45b13 fbd4aade-5491-48cd-b87c-fdcbb615a771 97a385bc-b849-4fc0-997e-bfa9db1878af a7933509-e00c-402c-8211-819d7bcdac06 ee215047-6034-484e-b98b-8659c9d6ab50 f6a9f7a0-e6ce-4bba-a489-ce54096fdd9c d4f2074f-e816-4724-a984-732a8844b7e9 6fb2fadc-92b3-4704-9aae-78236b924fa4 17e3da6f-2161-4864-b7b3-682cca6430d2 36b424f8-a6b8-443b-a46e-b08b1818ff60	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
ea9580a3-53e8-4ae8-b986-b2ceb009a613 838674cc-5d8a-487b-99db-34ed9a417d87 0a9c74d7-35f3-4f5c-ae7f-d4963fe25c74 81cf9604-580e-4360-a39e-ad42f3bfe840 9aa79939-a953-4472-aa07-2b35f04a7100 8fedaaf8-f844-4d8d-8b35-4aeae3862844 3d8ab1c0-42eb-4495-9aa8-1afb4fa72b1b 0fd0dd72-a6e7-4971-8f19-d7b820b6c84e 14ba0515-b8a8-4bce-873b-d6143df45b13 fbd4aade-5491-48cd-b87c-fdcbb615a771 97a385bc-b849-4fc0-997e-bfa9db1878af a7933509-e00c-402c-8211-819d7bcdac06 ee215047-6034-484e-b98b-8659c9d6ab50 f6a9f7a0-e6ce-4bba-a489-ce54096fdd9c d4f2074f-e816-4724-a984-732a8844b7e9 6fb2fadc-92b3-4704-9aae-78236b924fa4 17e3da6f-2161-4864-b7b3-682cca6430d2 36b424f8-a6b8-443b-a46e-b08b1818ff60 b480f024-aeb7-4a1c-96be-fb58f99b2301	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
ea9580a3-53e8-4ae8-b986-b2ceb009a613 838674cc-5d8a-487b-99db-34ed9a417d87 0a9c74d7-35f3-4f5c-ae7f-d4963fe25c74 81cf9604-580e-4360-a39e-ad42f3bfe840 9aa79939-a953-4472-aa07-2b35f04a7100 8fedaaf8-f844-4d8d-8b35-4aeae3862844 3d8ab1c0-42eb-4495-9aa8-1afb4fa72b1b 0fd0dd72-a6e7-4971-8f19-d7b820b6c84e 14ba0515-b8a8-4bce-873b-d6143df45b13 fbd4aade-5491-48cd-b87c-fdcbb615a771 97a385bc-b849-4fc0-997e-bfa9db1878af a7933509-e00c-402c-8211-819d7bcdac06 ee215047-6034-484e-b98b-8659c9d6ab50 f6a9f7a0-e6ce-4bba-a489-ce54096fdd9c d4f2074f-e816-4724-a984-732a8844b7e9 6fb2fadc-92b3-4704-9aae-78236b924fa4 17e3da6f-2161-4864-b7b3-682cca6430d2 36b424f8-a6b8-443b-a46e-b08b1818ff60 b480f024-aeb7-4a1c-96be-fb58f99b2301 a28ca379-87b6-4332-a0f5-acdfc2c75701	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
ea9580a3-53e8-4ae8-b986-b2ceb009a613 838674cc-5d8a-487b-99db-34ed9a417d87 0a9c74d7-35f3-4f5c-ae7f-d4963fe25c74 81cf9604-580e-4360-a39e-ad42f3bfe840 9aa79939-a953-4472-aa07-2b35f04a7100 8fedaaf8-f844-4d8d-8b35-4aeae3862844 3d8ab1c0-42eb-4495-9aa8-1afb4fa72b1b 0fd0dd72-a6e7-4971-8f19-d7b820b6c84e 14ba0515-b8a8-4bce-873b-d6143df45b13 fbd4aade-5491-48cd-b87c-fdcbb615a771 97a385bc-b849-4fc0-997e-bfa9db1878af a7933509-e00c-402c-8211-819d7bcdac06 ee215047-6034-484e-b98b-8659c9d6ab50 f6a9f7a0-e6ce-4bba-a489-ce54096fdd9c d4f2074f-e816-4724-a984-732a8844b7e9 6fb2fadc-92b3-4704-9aae-78236b924fa4 17e3da6f-2161-4864-b7b3-682cca6430d2 36b424f8-a6b8-443b-a46e-b08b1818ff60 b480f024-aeb7-4a1c-96be-fb58f99b2301 a28ca379-87b6-4332-a0f5-acdfc2c75701 e8b0b33a-ad7c-4dc5-91e8-8df5deb35735	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
ea9580a3-53e8-4ae8-b986-b2ceb009a613 838674cc-5d8a-487b-99db-34ed9a417d87 0a9c74d7-35f3-4f5c-ae7f-d4963fe25c74 81cf9604-580e-4360-a39e-ad42f3bfe840 9aa79939-a953-4472-aa07-2b35f04a7100 8fedaaf8-f844-4d8d-8b35-4aeae3862844 3d8ab1c0-42eb-4495-9aa8-1afb4fa72b1b 0fd0dd72-a6e7-4971-8f19-d7b820b6c84e 14ba0515-b8a8-4bce-873b-d6143df45b13 fbd4aade-5491-48cd-b87c-fdcbb615a771 97a385bc-b849-4fc0-997e-bfa9db1878af a7933509-e00c-402c-8211-819d7bcdac06 ee215047-6034-484e-b98b-8659c9d6ab50 f6a9f7a0-e6ce-4bba-a489-ce54096fdd9c d4f2074f-e816-4724-a984-732a8844b7e9 6fb2fadc-92b3-4704-9aae-78236b924fa4 17e3da6f-2161-4864-b7b3-682cca6430d2 36b424f8-a6b8-443b-a46e-b08b1818ff60 b480f024-aeb7-4a1c-96be-fb58f99b2301 a28ca379-87b6-4332-a0f5-acdfc2c75701 e8b0b33a-ad7c-4dc5-91e8-8df5deb35735 f4cf3374-4203-4cb1-8fe6-45108ccebda1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
ea9580a3-53e8-4ae8-b986-b2ceb009a613 838674cc-5d8a-487b-99db-34ed9a417d87 0a9c74d7-35f3-4f5c-ae7f-d4963fe25c74 81cf9604-580e-4360-a39e-ad42f3bfe840 9aa79939-a953-4472-aa07-2b35f04a7100 8fedaaf8-f844-4d8d-8b35-4aeae3862844 3d8ab1c0-42eb-4495-9aa8-1afb4fa72b1b 0fd0dd72-a6e7-4971-8f19-d7b820b6c84e 14ba0515-b8a8-4bce-873b-d6143df45b13 fbd4aade-5491-48cd-b87c-fdcbb615a771 97a385bc-b849-4fc0-997e-bfa9db1878af a7933509-e00c-402c-8211-819d7bcdac06 ee215047-6034-484e-b98b-8659c9d6ab50 f6a9f7a0-e6ce-4bba-a489-ce54096fdd9c d4f2074f-e816-4724-a984-732a8844b7e9 6fb2fadc-92b3-4704-9aae-78236b924fa4 17e3da6f-2161-4864-b7b3-682cca6430d2 36b424f8-a6b8-443b-a46e-b08b1818ff60 b480f024-aeb7-4a1c-96be-fb58f99b2301 a28ca379-87b6-4332-a0f5-acdfc2c75701 e8b0b33a-ad7c-4dc5-91e8-8df5deb35735 f4cf3374-4203-4cb1-8fe6-45108ccebda1 d7360a03-c7a9-4574-8ac7-a7fc0cd636a1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
ea9580a3-53e8-4ae8-b986-b2ceb009a613 838674cc-5d8a-487b-99db-34ed9a417d87 0a9c74d7-35f3-4f5c-ae7f-d4963fe25c74 81cf9604-580e-4360-a39e-ad42f3bfe840 9aa79939-a953-4472-aa07-2b35f04a7100 8fedaaf8-f844-4d8d-8b35-4aeae3862844 3d8ab1c0-42eb-4495-9aa8-1afb4fa72b1b 0fd0dd72-a6e7-4971-8f19-d7b820b6c84e 14ba0515-b8a8-4bce-873b-d6143df45b13 fbd4aade-5491-48cd-b87c-fdcbb615a771 97a385bc-b849-4fc0-997e-bfa9db1878af a7933509-e00c-402c-8211-819d7bcdac06 ee215047-6034-484e-b98b-8659c9d6ab50 f6a9f7a0-e6ce-4bba-a489-ce54096fdd9c d4f2074f-e816-4724-a984-732a8844b7e9 6fb2fadc-92b3-4704-9aae-78236b924fa4 17e3da6f-2161-4864-b7b3-682cca6430d2 36b424f8-a6b8-443b-a46e-b08b1818ff60 b480f024-aeb7-4a1c-96be-fb58f99b2301 a28ca379-87b6-4332-a0f5-acdfc2c75701 e8b0b33a-ad7c-4dc5-91e8-8df5deb35735 f4cf3374-4203-4cb1-8fe6-45108ccebda1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

```
d070b35b-cb35-474c-9e72-f26ef01c3bbd
                                          1
2f282acf-636a-456f-9b13-aec30d35b817
                                          1
efc6e397-4743-4843-9477-2a0269abae8a
                                          1
5b11b29a-700e-42fa-9992-14067457ec62
                                          1
Name: Loan ID, dtype: int64
*Let's drop the duplicate Loan ID values & keep first row, and set new dataframe df
In [36]:
df = df.drop duplicates(['Loan ID'], keep ='first')
In [37]:
print "Total unique Loan IDs: ", df['Loan ID'].nunique()
print "Total unique Customer IDs: ", df['Customer ID'].nunique()
print "Total entries: ", len(df)
Total unique Loan IDs:
Total unique Customer IDs:
                             135696
Total entries: 135696
In [38]:
df.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 135696 entries, 0 to 256983
Data columns (total 19 columns):
Loan ID
                                 135696 non-null object
Customer ID
                                 135696 non-null object
                                 135696 non-null object
Loan Status
Current Loan Amount
                                 135696 non-null int64
                                 135696 non-null object
Term
                                 135696 non-null int64
Credit Score
                                 135696 non-null object
Years in current job
                                 135696 non-null object
Home Ownership
Annual Income
                                 135696 non-null float64
Purpose
                                 135696 non-null object
                                 135696 non-null float64
Monthly Debt
                                 135696 non-null float64
Years of Credit History
Months since last delinquent
                                 135696 non-null float64
Number of Open Accounts
                                 135696 non-null int64
Number of Credit Problems
                                 135696 non-null int64
Current Credit Balance
                                 135696 non-null int64
Maximum Open Credit
                                 135696 non-null float64
Bankruptcies
                                 135696 non-null float64
Tax Liens
                                 135696 non-null float64
dtypes: float64(7), int64(5), object(7)
memory usage: 20.7+ MB
```

1

201c3791-b28e-4605-a130-313fe0a2069e

```
*Double check that we don't have duplicated rows
In [39]:
print "Total unique Customer IDs: ", df['Customer ID'].nunique()
print "Total entries: ", len(df)
Total unique Customer IDs:
                               135696
Total entries: 135696
*Let's take a look at "Years in current job" column - removing the strings by deleting "years and +"; converting
it to int; converting n/a and <1 to 0
In [40]:
df['Years in current job'] = df['Years in current job'].map(lambda x: '0' if x == '1')
df['Years in current job'] = df['Years in current job'].map(lambda x: '0' if x == '
df['Years in current job'] = df['Years in current job'].replace( '[\+ years]','', ref
In [41]:
df['Years in current job'].unique()
Out[41]:
array([10, 4, 6, 0, 2, 5, 3, 1, 7, 9, 8])
*Now, we we have integers only for "Years in current job" column
*Converting "Loan Status" to binary output for easy modeling: Fully paid = 1
In [42]:
df['Loan Status'] = df['Loan Status'].map(lambda x: 1 if x == 'Fully Paid' else 0)
In [43]:
df['Loan Status'].unique()
Out[43]:
array([1, 0])
*Converting "Term" to binary output for easy modeling: Long Term = 1
In [44]:
df['Term'] = df['Term'].map(lambda x: 1 if x == 'Long Term' else 0)
```

```
df['Term'].unique()
Out[45]:
array([0, 1])
In [46]:
df.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 135696 entries, 0 to 256983
Data columns (total 19 columns):
                                 135696 non-null object
Loan ID
                                 135696 non-null object
Customer ID
                                 135696 non-null int64
Loan Status
Current Loan Amount
                                 135696 non-null int64
                                 135696 non-null int64
Term
Credit Score
                                 135696 non-null int64
                                 135696 non-null int64
Years in current job
Home Ownership
                                 135696 non-null object
                                 135696 non-null float64
Annual Income
                                 135696 non-null object
Purpose
                                 135696 non-null float64
Monthly Debt
Years of Credit History
                                 135696 non-null float64
Months since last delinquent
                                 135696 non-null float64
                                 135696 non-null int64
Number of Open Accounts
Number of Credit Problems
                                 135696 non-null int64
Current Credit Balance
                                 135696 non-null int64
Maximum Open Credit
                                 135696 non-null float64
                                 135696 non-null float64
Bankruptcies
Tax Liens
                                 135696 non-null float64
dtypes: float64(7), int64(8), object(4)
memory usage: 20.7+ MB
```

Feature engineering 1: Credit Utilization Rate = sum of outstanding balance / credit card's limit; In our case, Credit Utilization Rate = Current Credit Balance / Maximum Open Credit

```
In [47]:
```

In [45]:

df['Credit Utilization'] = df['Current Credit Balance'].div(df['Maximum Open Credit

```
df['Credit Utilization'].describe()
Out[48]:
          135696.000000
count
              29.092050
mean
std
            1536.194716
min
               0.00000
25%
               0.369991
50%
               0.562006
75%
               0.741875
         236458.000000
max
Name: Credit Utilization, dtype: float64
Feature engineering 2: Payment Rate = (Monthly Debt * 12) / Annual Income = Annual Payment / Annual
Income; Add 1 to this value
In [49]:
df['Annual Payment'] = df['Monthly Debt']*12
In [50]:
df['Payment Rate'] = df['Annual Payment'].div(df['Annual Income'] + 1, axis='index'
In [51]:
df['Payment Rate'].describe()
Out[51]:
          135696.000000
count
               0.170673
mean
std
               0.079576
min
               0.00000
25%
               0.110999
50%
               0.166998
75%
               0.225999
max
               0.591982
Name: Payment Rate, dtype: float64
```

In [48]:

\*Renaming all the columns to make it simple

```
In [52]:
```

### Out[52]:

	Loan ID	Customer ID	у	а	b	С	d	е	f	g	 Mo sir de
0	000025bb- 5694-4cff- b17d- 192b1a98ba44	5ebc8bb1- 5eb9-4404- b11b- a6eebc401a19	1	11520	0	741	10	Home Mortgage	33694.0	Debt Consolidation	 41
1	00002c49- 3a29-4bd4- 8f67- c8f8fbc1048c	927b388d- 2e01-423f- a8dc- f7e42d668f46	1	3441	0	734	4	Home Mortgage	42269.0	Other	 20
	00002d89-	defce609-									

## **Data Visualization**

```
In [53]:
```

```
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

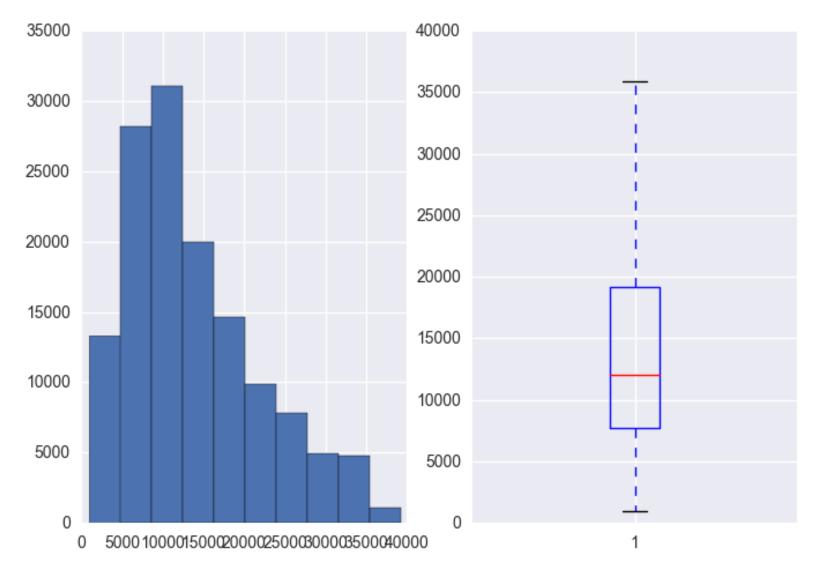
<sup>\*</sup>Plotting "Current Loan Amount" for histogram and boxplot

```
In [54]:
```

```
fig = plt.figure()
ax1 = fig.add_subplot(121)
ax2 = fig.add_subplot(122)

ax1.hist(df.a)
ax2.boxplot(df.a)
```

#### Out[54]:



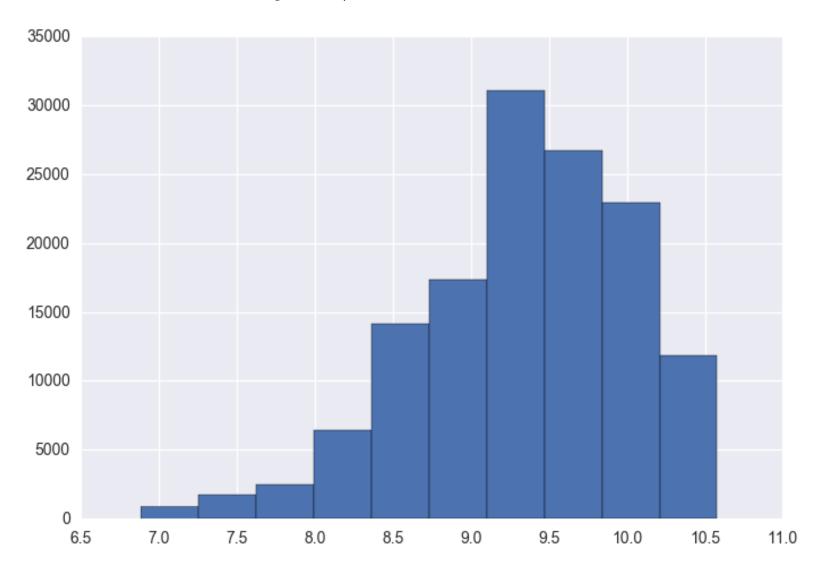
<sup>\*</sup>Normalizing it by applying log into "Current Loan Amount"

```
In [55]:
```

Out[55]:

```
plt.hist(np.log(df.a))
```

```
880.,
                 1740., 2525.,
                                  6426., 14170., 17367., 31075.,
(array([
        26720., 22926., 11867.]),
         6.88243747,
                     7.25210188,
                                   7.62176629, 7.9914307,
array([
         8.36109511,
                      8.73075952,
                                  9.10042393,
                                                9.47008834,
         9.83975275, 10.20941716,
                                  10.57908157]),
<a list of 10 Patch objects>)
```



\*Now we have the histogram that is skewed to the left

\*Now we want to plot x as "Credit Utilization" & y as "Loan Status"

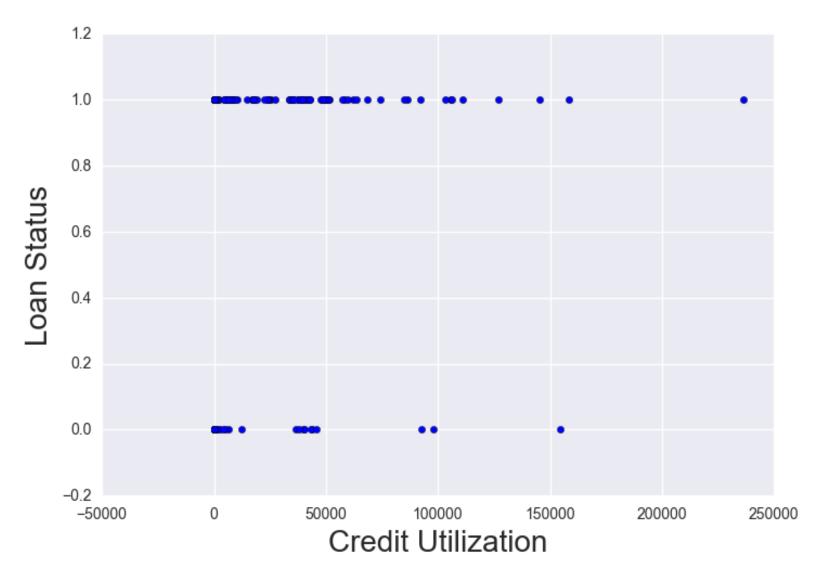
```
In [56]:
```

```
x = df['p']
y = df['y']

# make the plot
fig = plt.figure()
ax = fig.add_subplot(111)
ax.scatter(x, y)
ax.set_ylabel('Loan Status', fontsize=20)
ax.set_xlabel('Credit Utilization', fontsize=20)
```

#### Out[56]:

<matplotlib.text.Text at 0x10e7c0290>



\*Note that Loan Status = 1 is Fully Paid and it's more dense on the left; We can conclude that customers who have Loan Status of Fully Paid tend to have lower credit utilization rate

\*Now we want to create the dummy variables for categorical values using dmatrices

#### In [57]:

```
from patsy import dmatrices
y, X = dmatrices('y ~ a + b + c + d + C(e) + f + C(g) + h + i + j + k + l + m + n +
```

```
In [58]:
X.head()
```

Out[58]:

	Intercept	C(e) [T.Own Home]	C(e) [T.Rent]	C(g) [T.Buy House]	C(g) [T.Buy a Car]	C(g)[T.Debt Consolidation]	C(g) [T.Educational Expenses]	C(g)[T.Home
0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0
1	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	1.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0
3	1.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0
4	1.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0

5 rows × 26 columns

```
In [59]:
```

y.head()

Out[59]:

	У
0	1.0
1	1.0
2	1.0
3	1.0
4	1.0

In [60]:

```
X.shape, y.shape
```

```
Out[60]:
((135696, 26), (135696, 1))
```

## Modeling

```
In [61]:

from sklearn.cross_validation import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7, random_standardenvs/python2/lib/python2.7/site-packages/sklearn/cross_validation.py:44: DeprecationWarning: This module was deprecated in version 0.18 in favor of the model_selection module into which all the refactored classes and functions are moved. Also note that the interface of the new CV iterators are different from that of this module. This module will be removed in 0.20.

"This module will be removed in 0.20.", DeprecationWarning)
1. Logistic Regression
```

```
In [62]:
```

```
from sklearn.linear_model import LogisticRegression

logreg = LogisticRegression()
logreg.fit(X_train, y_train)
logreg.score(X_test, y_test)

//anaconda/envs/python2/lib/python2.7/site-packages/sklearn/utils/vali
dation.py:526: DataConversionWarning: A column-vector y was passed whe
n a 1d array was expected. Please change the shape of y to (n samples,
```

```
n a 1d array was expected. Please chan
), for example using ravel().
   y = column_or_1d(y, warn=True)
Out[62]:
```

0.73177921344174501

```
In [63]:

y_pred_loanstatus = logreg.predict(X_test)
```

```
In [64]:
```

```
from sklearn import metrics
print metrics.accuracy_score(y_pred_loanstatus, y_test)
```

0.731779213442

```
In [65]:
```

```
report = metrics.classification_report(y_pred_loanstatus, y_test)
print report
```

support	f1-score	recall	precision	
140	0.01	0.51	0.01	0.0
40569	0.84	0.73	1.00	1.0
40709	0.84	0.73	0.99	avg / total

\*Logistic Regression: accuracy score = 0.73; f1 score = 0.84

\*Drop Intercept column to fit different models

```
In [66]:
```

```
X = X.drop(['Intercept'], axis = 1)
```

#### In [67]:

```
from sklearn.cross_validation import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size = 0.7, random_s
```

#### 2.. Random Forest Classifier

\*Let's take a look at shapes of X, y, X\_train, y\_train, X\_test, y\_test

#### In [68]:

```
X.shape, y.shape
```

```
Out[68]:
```

```
((135696, 25), (135696, 1))
```

#### In [69]:

```
X_train.shape, y_train.shape
```

```
Out[69]:
((94987, 25), (94987, 1))
```

```
In [70]:
X_test.shape, y_test.shape
Out[70]:
((40709, 25), (40709, 1))
*1st method: GridSearchCV
*Converting y_train to array
In [71]:
y_train = np.ravel(y_train)
In [72]:
y_train.shape
Out[72]:
(94987,)
```

```
In [73]:
from sklearn.grid search import GridSearchCV
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier()
param grid = {"n estimators": [100, 200, 300],
              "max_features": [3, 5],
               "max depth": [10, 20],
               "min samples split": [2, 4]}
grid search = GridSearchCV(estimator=rfc, param grid=param grid, n jobs=-1, cv=2)
grid search.fit(X train, y train)
print grid search.best params
print grid search.best score
print grid search.best estimator
//anaconda/envs/python2/lib/python2.7/site-packages/sklearn/grid searc
h.py:43: DeprecationWarning: This module was deprecated in version 0.1
8 in favor of the model selection module into which all the refactored
classes and functions are moved. This module will be removed in 0.20.
  DeprecationWarning)
{'max features': 5, 'min samples split': 2, 'n estimators': 200, 'max
depth': 10}
0.735269036816
RandomForestClassifier(bootstrap=True, class weight=None, criterion='g
ini',
            max depth=10, max features=5, max leaf nodes=None,
            min impurity split=1e-07, min samples leaf=1,
            min samples split=2, min weight fraction leaf=0.0,
            n estimators=200, n jobs=1, oob score=False, random state=
None,
            verbose=0, warm start=False)
Now, we can put "best" parameters into random forest classifier; Fitting in training, scoring in testing
In [74]:
rfc = RandomForestClassifier(max_features= 5, min_samples_split= 2, n_estimators= 1(
rfc.fit(X train, y train)
rfc.score(X test, y test)
Out[74]:
0.73988552899850157
```

\*Prediting in X\_test

```
In [75]:
```

y\_pred\_loanstatus= rfc.predict(X\_test)

#### In [76]:

from sklearn import metrics
print metrics.accuracy\_score(y\_pred\_loanstatus, y\_test)

0.739885528999

#### In [77]:

report = metrics.classification\_report(y\_pred\_loanstatus, y\_test)
print report

support	f1-score	recall	precision	
2480	0.21	0.57	0.13	0.0
38229	0.84	0.75	0.96	1.0
40709	0.81	0.74	0.91	avg / total

<sup>\*</sup>Logistic Regression (1st method): accuracy score = 0.74; f1 score = 0.81

<sup>\*2</sup>nd method: GridSearchCV using make\_classification; use n\_samples = total rows from df (135696), #n\_features as number of total columns (26)

```
In [96]:
from sklearn.grid search import GridSearchCV
from sklearn.datasets import make classification
from sklearn.ensemble import RandomForestClassifier
# Build a classification task using 3 informative features
X, y = make classification(n samples=135696,
                            #n_features=26,
                            #n informative=3,
                            #n redundant=0,
                            #n_repeated=0,
                            #n classes=2,
                            random_state=0,
                            shuffle=False)
rfc = RandomForestClassifier(n_jobs=-1,max_features= 'sqrt' ,n_estimators=500, oob_s
param grid = {'n estimators': [100, 200, 300],
               'max_features': ['auto', 'sqrt', 'log2']}
grid = GridSearchCV(estimator=rfc, param_grid=param_grid, cv= 2)
grid.fit(X_train, y_train)
print grid.best params
print grid.best_score_
print grid.best_estimator_
{'max features': 'log2', 'n estimators': 300}
0.733237179825
RandomForestClassifier(bootstrap=True, class weight=None, criterion='g
ini',
            max depth=None, max features='log2', max leaf nodes=None,
            min impurity split=1e-07, min samples leaf=1,
            min_samples_split=2, min_weight_fraction_leaf=0.0,
            n estimators=300, n jobs=-1, oob score=True, random state=
None,
            verbose=0, warm start=False)
*Now, we can put "best" parameters into random forest classifier; Fitting in training, scoring in testing
```

rfc = RandomForestClassifier(max\_features= 'log2', n\_estimators= 300)

In [98]:

```
In [100]:
rfc.fit(X train, y train)
rfc.score(X test, y test)
Out[100]:
0.73887838070205603
*Prediting in X_test
In [101]:
y_pred_loanstatus = rfc.predict(X_test)
In [102]:
from sklearn import metrics
print metrics.accuracy_score(y_pred_loanstatus, y_test)
0.738878380702
In [103]:
report = metrics.classification_report(y_pred_loanstatus, y_test)
print report
              precision
                            recall
                                     f1-score
                                                 support
        0.0
                   0.18
                              0.54
                                         0.27
                                                     3699
        1.0
                   0.94
                              0.76
                                         0.84
                                                   37010
avg / total
                   0.87
                              0.74
                                         0.79
                                                   40709
*Logistic Regression (2nd method): accuracy score = 0.74; f1 score = 0.79
3.. Gradient boosting - 1st method
In [90]:
y_train.shape
```

\*We only need to run GridSearchCV once, so we don't have to re-run here, but we can add "learning rate" parameter for Gradient boosting

Out[90]:

(94987,)

```
In [91]:
from sklearn.ensemble import GradientBoostingClassifier
gbc = GradientBoostingClassifier()
param grid = {"learning rate": [0.1, 0.5]}
grid_search = GridSearchCV(estimator=gbc, param_grid=param_grid, n_jobs=-1, cv=2)
grid search.fit(X train, y train)
print grid search.best params
print grid_search.best_score_
print grid search.best estimator
{'learning rate': 0.1}
0.736279701433
GradientBoostingClassifier(criterion='friedman mse', init=None,
               learning rate=0.1, loss='deviance', max depth=3,
              max features=None, max leaf nodes=None,
              min impurity split=1e-07, min samples leaf=1,
              min samples split=2, min weight fraction leaf=0.0,
              n estimators=100, presort='auto', random state=None,
               subsample=1.0, verbose=0, warm start=False)
*Now, we can put "best" parameters(from previous modeling part) & adding learning rate parameter into
gradient boosting classifier; Fitting in training, scoring in testing
In [92]:
gbc = GradientBoostingClassifier(max features= 5, min samples split= 2, n estimators
gbc.fit(X_train, y_train)
gbc.score(X test, y test)
Out[92]:
0.73826426588715022
*Prediting in X_test
In [93]:
y_pred_loanstatus= gbc.predict(X_test)
```

```
In [94]:
from sklearn import metrics
print metrics.accuracy score(y pred loanstatus, y test)
0.738264265887
In [95]:
report = metrics.classification_report(y_pred_loanstatus, y_test)
print report
                           recall f1-score
             precision
                                                support
        0.0
                   0.21
                              0.53
                                         0.30
                                                   4374
                   0.93
                              0.76
                                        0.84
        1.0
                                                  36335
avg / total
                   0.85
                              0.74
                                        0.78
                                                  40709
*Gradient Boosting(1st method): accuracy score = 0.74; f1 score = 0.78
Gradient boosting - 2nd method:
In [104]:
gbc = GradientBoostingClassifier(max_features= 'log2', n_estimators= 300, learning_1
In [105]:
gbc.fit(X_train, y_train)
gbc.score(X test, y test)
Out[105]:
0.74212090692475863
In [106]:
y_pred_loanstatus= gbc.predict(X_test)
In [107]:
```

from sklearn import metrics

0.742120906925

print metrics.accuracy\_score(y\_pred\_loanstatus, y\_test)

## In [108]:

report = metrics.classification\_report(y\_pred\_loanstatus, y\_test)
print report

support	f1-score	recall	precision	
3727 36982	0.28 0.84	0.56 0.76	0.19 0.94	0.0 1.0
40709	0.79	0.74	0.88	avg / total

<sup>\*</sup>Gradient Boosting(2nd method): accuracy score = 0.74; f1 score = 0.79