Regularized Multiple Linear Regression

September 19, 2019

We have already implemented a simple linear regression model by manually implementing gradient descent. For that implementation of linear regression, refer to the notebook titled "Linear Regression with two variables and manual implementation of gradient descent 22.06.2019".

In this notebook we will solve a case study by using multiple linear regression, and regularised linear regression [Ridge and Lasso]. We will also look at hyperparameter tuning for regularised regression. Also, we will concentrate on feature engineering and data preperation.

This dataset comes from a loan aggregator who collects loan applications from different people and sends it to various financial institutions.

They have collected various information from the loan applicants and have also collected what percentage of interest the bank offered to each of them. Our task now is to predict interest rate for future customers.

The name of our output variable is "Interest.Rate" in the dataset

In [1]:
```
# In the class, train_test_split and KFold methods are downloaded from
#sklearn.cross_validationlibrary but, python packages have been updated,
#so now the correct package is sklearn.model_selection

import pandas as pd
import numpy as np
import math
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression, Lasso, Ridge
from sklearn.model_selection import KFold
%matplotlib inline
```

In [2]:
```
data_file=r'C:/Users/HP/Dropbox/Edvancer/CMLEP/Data/Data/loans data.csv'
loan_data = pd.read_csv(data_file)
```

In [3]:
```
loan_data.head()
```

Out[3]:
```
        ID Amount.Requested Amount.Funded.By.Investors Interest.Rate  \
0  81174.0            20000                      20000         8.90%
1  99592.0            19200                      19200        12.12%
2  80059.0            35000                      35000        21.98%
3  15825.0            10000                       9975         9.99%
4  33182.0            12000                      12000        11.71%

  Loan.Length        Loan.Purpose Debt.To.Income.Ratio State Home.Ownership  \
```

```
0   36 months  debt_consolidation              14.90%    SC        MORTGAGE
1   36 months  debt_consolidation              28.36%    TX        MORTGAGE
2   60 months  debt_consolidation              23.81%    CA        MORTGAGE
3   36 months  debt_consolidation              14.30%    KS        MORTGAGE
4   36 months         credit_card              18.78%    NJ            RENT

   Monthly.Income FICO.Range Open.CREDIT.Lines Revolving.CREDIT.Balance  \
0         6541.67    735-739                14                    14272
1         4583.33    715-719                12                    11140
2        11500.00    690-694                14                    21977
3         3833.33    695-699                10                     9346
4         3195.00    695-699                11                    14469

   Inquiries.in.the.Last.6.Months Employment.Length
0                             2.0          < 1 year
1                             1.0           2 years
2                             1.0           2 years
3                             0.0           5 years
4                             0.0           9 years
```

```
In [4]: loan_data.dtypes
```

```
Out[4]: ID                                float64
        Amount.Requested                   object
        Amount.Funded.By.Investors         object
        Interest.Rate                      object
        Loan.Length                        object
        Loan.Purpose                       object
        Debt.To.Income.Ratio               object
        State                              object
        Home.Ownership                     object
        Monthly.Income                    float64
        FICO.Range                         object
        Open.CREDIT.Lines                  object
        Revolving.CREDIT.Balance           object
        Inquiries.in.the.Last.6.Months    float64
        Employment.Length                  object
        dtype: object
```

Variables Interest.Rate and Debt.To.Income.Ratio contains "%" sign in their values and because of which they are a "character" column and not a "numeric" column.

Therefore those "%" signs should be removed first.

```
In [5]: col_with_percentage=['Interest.Rate','Debt.To.Income.Ratio']

        #first we convert the entire column into string so we can easily remove % sign using
        #string operation then we replace % with '' in each string using list comprehension
```

```
# and replace the column with this list

for col in col_with_percentage:
    loan_data[col]= loan_data[col].astype('str')
    loan_data[col]= [x.replace('%','') for x in loan_data[col]]
```

In [6]:
```
loan_data.dtypes
```

Out[6]:
```
ID                                float64
Amount.Requested                   object
Amount.Funded.By.Investors         object
Interest.Rate                      object
Loan.Length                        object
Loan.Purpose                       object
Debt.To.Income.Ratio               object
State                              object
Home.Ownership                     object
Monthly.Income                    float64
FICO.Range                         object
Open.CREDIT.Lines                  object
Revolving.CREDIT.Balance           object
Inquiries.in.the.Last.6.Months    float64
Employment.Length                  object
dtype: object
```

In [7]:
```
loan_data.head()
```

Out[7]:
```
        ID Amount.Requested Amount.Funded.By.Investors Interest.Rate  \
0  81174.0            20000                      20000          8.90
1  99592.0            19200                      19200         12.12
2  80059.0            35000                      35000         21.98
3  15825.0            10000                       9975          9.99
4  33182.0            12000                      12000         11.71

  Loan.Length        Loan.Purpose Debt.To.Income.Ratio State Home.Ownership  \
0   36 months  debt_consolidation                14.90    SC       MORTGAGE
1   36 months  debt_consolidation                28.36    TX       MORTGAGE
2   60 months  debt_consolidation                23.81    CA       MORTGAGE
3   36 months  debt_consolidation                14.30    KS       MORTGAGE
4   36 months         credit_card                18.78    NJ           RENT

   Monthly.Income FICO.Range Open.CREDIT.Lines Revolving.CREDIT.Balance  \
0         6541.67    735-739                14                    14272
1         4583.33    715-719                12                    11140
2        11500.00    690-694                14                    21977
3         3833.33    695-699                10                     9346
4         3195.00    695-699                11                    14469

   Inquiries.in.the.Last.6.Months Employment.Length
```

```
0                              2.0         < 1 year
1                              1.0          2 years
2                              1.0          2 years
3                              0.0          5 years
4                              0.0          9 years
```

Now the '%' symbol from 'Debt.To.Income.Ratio' and 'Interest.Rate' columns are gone. But still, they are not converted to integers, they are still string values.

```
In [8]: loan_data.dtypes
```

```
Out[8]: ID                                float64
        Amount.Requested                   object
        Amount.Funded.By.Investors         object
        Interest.Rate                      object
        Loan.Length                        object
        Loan.Purpose                       object
        Debt.To.Income.Ratio               object
        State                              object
        Home.Ownership                     object
        Monthly.Income                    float64
        FICO.Range                         object
        Open.CREDIT.Lines                  object
        Revolving.CREDIT.Balance           object
        Inquiries.in.the.Last.6.Months    float64
        Employment.Length                  object
        dtype: object
```

Now, lets convert all the columns that has only numbers into numeric data types.

```
In [9]: columns_with_numbers_only = ['Amount.Requested','Amount.Funded.By.Investors',
                                     'Interest.Rate','Debt.To.Income.Ratio',
                                     'Monthly.Income','Open.CREDIT.Lines',
                                     'Revolving.CREDIT.Balance',
                                     'Inquiries.in.the.Last.6.Months']
        #Creating a list of column names that should be converted to integers
```

```
In [10]: for numeric_column_name in columns_with_numbers_only:
             loan_data[numeric_column_name]=pd.to_numeric(loan_data[numeric_column_name],
                                                          errors='coerce')

         #The 'errors=coerce' argument will replace all non-numeric values in the columns
         # with NaN values If this argument is missing then we will get an error and
         #execution will stop.
```

```
In [11]: loan_data.dtypes
```

```
Out[11]: ID                                float64
         Amount.Requested                  float64
```

```
Amount.Funded.By.Investors        float64
Interest.Rate                     float64
Loan.Length                        object
Loan.Purpose                       object
Debt.To.Income.Ratio              float64
State                              object
Home.Ownership                     object
Monthly.Income                    float64
FICO.Range                         object
Open.CREDIT.Lines                 float64
Revolving.CREDIT.Balance          float64
Inquiries.in.the.Last.6.Months    float64
Employment.Length                  object
dtype: object
```

In [12]:
```python
loan_data.head()
```

Out[12]:
```
        ID  Amount.Requested  Amount.Funded.By.Investors  Interest.Rate  \
0  81174.0           20000.0                     20000.0           8.90
1  99592.0           19200.0                     19200.0          12.12
2  80059.0           35000.0                     35000.0          21.98
3  15825.0           10000.0                      9975.0           9.99
4  33182.0           12000.0                     12000.0          11.71

  Loan.Length        Loan.Purpose  Debt.To.Income.Ratio State Home.Ownership  \
0   36 months  debt_consolidation                 14.90    SC       MORTGAGE
1   36 months  debt_consolidation                 28.36    TX       MORTGAGE
2   60 months  debt_consolidation                 23.81    CA       MORTGAGE
3   36 months  debt_consolidation                 14.30    KS       MORTGAGE
4   36 months         credit_card                 18.78    NJ           RENT

   Monthly.Income FICO.Range  Open.CREDIT.Lines  Revolving.CREDIT.Balance  \
0         6541.67    735-739               14.0                   14272.0
1         4583.33    715-719               12.0                   11140.0
2        11500.00    690-694               14.0                   21977.0
3         3833.33    695-699               10.0                    9346.0
4         3195.00    695-699               11.0                   14469.0

   Inquiries.in.the.Last.6.Months Employment.Length
0                             2.0          < 1 year
1                             1.0           2 years
2                             1.0           2 years
3                             0.0           5 years
4                             0.0           9 years
```

In [13]:
```python
(loan_data.dtypes=='object').sum(), (loan_data.dtypes=='float64').sum()
```

Out[13]:
```
(6, 9)
```

Now, we can see that we have only 6 columns as strings/object and the remaining 9 are integers. Let's also see what those object columns are

In [14]:
```
object_column_names = loan_data.columns[loan_data.dtypes=='object']
#creating a list of all columns which are of data type 'object'

loan_data[object_column_names].head()
#slicing the dataframe using those column names only
```

Out[14]:
```
  Loan.Length        Loan.Purpose State Home.Ownership FICO.Range  \
0   36 months  debt_consolidation    SC       MORTGAGE    735-739
1   36 months  debt_consolidation    TX       MORTGAGE    715-719
2   60 months  debt_consolidation    CA       MORTGAGE    690-694
3   36 months  debt_consolidation    KS       MORTGAGE    695-699
4   36 months         credit_card    NJ           RENT    695-699

  Employment.Length
0          < 1 year
1           2 years
2           2 years
3           5 years
4           9 years
```

We can see that all the 6 object type columns clearly have strings or some string value in them

Here the variable 'Loan.Lenght' seems to be clearly categorical, so let's convert that into dummy variable

In [15]:
```
loan_data['Loan.Length'].value_counts()
```

Out[15]:
```
36 months    1950
60 months     548
.               1
Name: Loan.Length, dtype: int64
```

As we can see, there are 3 categories in that variable.

The function 'get_dummies' from pandas creates dummy variables for all the categorical values we have. This function returns a dataframe. So, we can use that to create dummy variables, then drop the variables that we don't need.

In [16]:
```
loan_lenght_dummies = pd.get_dummies(loan_data['Loan.Length'])
```

In [17]:
```
loan_lenght_dummies.head()
```

Out[17]:
```
   .  36 months  60 months
0  0          1          0
1  0          1          0
2  0          0          1
3  0          1          0
4  0          1          0
```

since ‘60_months’ and the other value ‘.’ has very less number of values compared to the value ‘36_months’ we can drop them both altogether and add the dummy variable ‘36 months’ to our original dataframe.

```
In [18]: loan_data['Loan_lenght_36']= loan_lenght_dummies['36 months']
```

Now that we don’t need the variable ‘loan_length_dummies’ we can drop it altogether. Note:dropping variables from notebook environment is a permenant operation.

```
In [19]: %reset_selective loan_lenght_dummies
         #deleting the variable 'loan_lenght_dummies'
```

```
Once deleted, variables cannot be recovered. Proceed (y/[n])?  y
```

To know what all variables we have in our environment at present we can use the function ‘who’

```
In [20]: who
```

```
KFold         Lasso         LinearRegression         Ridge         col         col_with_percen
math         np         numeric_column_name         object_column_names         pd         tra
```

Now that we have created dummy variables for the variable Loan.Lenght we can drop that variable from our original dataset

```
In [21]: loan_data.drop(labels='Loan.Length', axis=1, inplace=True)
```

```
In [22]: loan_data.head()
```

```
Out[22]:          ID  Amount.Requested  Amount.Funded.By.Investors  Interest.Rate  \
         0  81174.0           20000.0                     20000.0           8.90
         1  99592.0           19200.0                     19200.0          12.12
         2  80059.0           35000.0                     35000.0          21.98
         3  15825.0           10000.0                      9975.0           9.99
         4  33182.0           12000.0                     12000.0          11.71

                  Loan.Purpose  Debt.To.Income.Ratio State Home.Ownership  \
         0  debt_consolidation                 14.90    SC       MORTGAGE
         1  debt_consolidation                 28.36    TX       MORTGAGE
         2  debt_consolidation                 23.81    CA       MORTGAGE
         3  debt_consolidation                 14.30    KS       MORTGAGE
         4         credit_card                 18.78    NJ           RENT

            Monthly.Income FICO.Range  Open.CREDIT.Lines  Revolving.CREDIT.Balance  \
         0         6541.67    735-739               14.0                   14272.0
         1         4583.33    715-719               12.0                   11140.0
         2        11500.00    690-694               14.0                   21977.0
         3         3833.33    695-699               10.0                    9346.0
```

```
4          3195.00    695-699               11.0                   14469.0

   Inquiries.in.the.Last.6.Months Employment.Length  Loan_lenght_36
0                             2.0          < 1 year               1
1                             1.0           2 years               1
2                             1.0           2 years               0
3                             0.0           5 years               1
4                             0.0           9 years               1
```

Let's see how many string datatype columns we have now

```
In [23]: object_column_names = loan_data.columns[loan_data.dtypes=='object']
         #creating a list of all columns which are of data type 'object'

         loan_data[object_column_names].head()
         #slicing the dataframe using those column names only
```

```
Out[23]:          Loan.Purpose State Home.Ownership FICO.Range Employment.Length
         0  debt_consolidation    SC       MORTGAGE    735-739          < 1 year
         1  debt_consolidation    TX       MORTGAGE    715-719           2 years
         2  debt_consolidation    CA       MORTGAGE    690-694           2 years
         3  debt_consolidation    KS       MORTGAGE    695-699           5 years
         4         credit_card    NJ           RENT    695-699           9 years
```

Now, we have only 4. Let's start to examine the next variable 'Loan.Purpose'

```
In [24]: loan_data['Loan.Purpose'].value_counts()
```

```
Out[24]: debt_consolidation    1307
         credit_card            444
         other                  200
         home_improvement       152
         major_purchase         101
         small_business          87
         car                     50
         wedding                 39
         medical                 30
         moving                  29
         vacation                21
         house                   20
         educational             15
         renewable_energy         4
         Name: Loan.Purpose, dtype: int64
```

```
In [25]: print(len(loan_data['Loan.Purpose'].value_counts()))
```

```
14
```

We have 14 categories in the variable 'Loan.Purpose'.

We can either make 13 dummy variables or we can group some categories together to reduce the number of effective dummy variables needed.

One method we can use to find possibilities to group categories together is by performing group_by operation between this variable and the response variable 'Interest.Rate'.

```
In [26]: loan_data.groupby('Loan.Purpose')['Interest.Rate'].mean().round()
```

```
Out[26]: Loan.Purpose
         car                   11.0
         credit_card           13.0
         debt_consolidation    14.0
         educational           11.0
         home_improvement      12.0
         house                 13.0
         major_purchase        11.0
         medical               12.0
         moving                14.0
         other                 13.0
         renewable_energy      10.0
         small_business        13.0
         vacation              12.0
         wedding               12.0
         Name: Interest.Rate, dtype: float64
```

Let's see how many effective categories this grouping provides us

```
In [27]: loan_data.groupby('Loan.Purpose')['Interest.Rate'].mean().round().value_counts()
```

```
Out[27]: 12.0    4
         13.0    4
         11.0    3
         14.0    2
         10.0    1
         Name: Interest.Rate, dtype: int64
```

We can see there are 4 effective categories

```
In [28]: for i in range(len(loan_data)):
             # grouping all categories with mean value 11(received in line 25) together
             if loan_data.loc[i]['Loan.Purpose'] in ['car','educational','major_purchase']:
                 loan_data.loc[i,'Loan.Purpose']='cem'
             # grouping all categories with mean value 12(received in line 25) together
             if loan_data.loc[i]['Loan.Purpose'] in  ['home_improvement','medical','vacation',
                                                      'wedding']:
                 loan_data.loc[i,'Loan.Purpose']='hmvw'
             # grouping all categories with mean value 13(received in line 25) together
             if loan_data.loc[i]['Loan.Purpose'] in ['credit_card','house','other',
                                                     'small_business']:
```

```
            loan_data.loc[i,'Loan.Purpose'] = 'chos'
        # grouping all categories with mean value 14 (received in line 25) together
        if loan_data.loc[i]['Loan.Purpose'] in ['debt_consolidation','moving']:
            loan_data.loc[i,'Loan.Purpose']='dm'
```

```
In [29]: loan_data['Loan.Purpose'].head()
```

```
Out[29]: 0      dm
         1      dm
         2      dm
         3      dm
         4    chos
         Name: Loan.Purpose, dtype: object
```

As we can see, we have effectively combined the 13 out of 14 categories into 4 categories.

We have not included the category 'renewable_energy' in this grouping because it had only 4 occurences in the entire data frame.

Now, let's create dummies for the variable Loan.Purpose

```
In [30]: loan_data_dummies = pd.get_dummies(loan_data['Loan.Purpose'], prefix='lp')
```

```
In [31]: loan_data_dummies.head()
```

Out[31]:

	lp_cem	lp_chos	lp_dm	lp_hmvw	lp_renewable_energy
0	0	0	1	0	0
1	0	0	1	0	0
2	0	0	1	0	0
3	0	0	1	0	0
4	0	1	0	0	0

As we can see we have a dummy variable for 'renewable_energy'. Since we don't need it we can drop this variable and also the original variable 'Loan.Purpose'. But before that let's just concatanate the dummy variables to the original dataframe.

```
In [32]: loan_data = loan_data.join(loan_data_dummies)
```

Now, let's drop the variables 'Loan.Purpose' and 'lp_renewable_energy'

```
In [33]: loan_data.drop(['Loan.Purpose','lp_renewable_energy'], axis=1, inplace=True)
```

Now let's check tha variable 'state'

```
In [34]: loan_data['State'].value_counts()
```

```
Out[34]: CA    433
         NY    255
         TX    174
         FL    169
         IL    101
         GA     97
```

```
PA      96
NJ      94
VA      78
MA      73
OH      71
MD      68
NC      64
CO      61
WA      58
CT      50
AZ      46
MI      45
MN      38
AL      38
MO      33
NV      32
OR      30
SC      28
WI      26
KY      23
LA      22
OK      21
KS      21
UT      16
RI      15
NH      15
WV      14
AR      13
NM      13
HI      12
DC      11
AK      11
DE       8
MT       7
VT       5
SD       4
WY       4
IN       3
IA       1
.        1
MS       1
Name: State, dtype: int64
```

There are too many states. Let's check how many unique values this variable has.

```
In [35]: loan_data['State'].nunique()
```

```
Out[35]: 47
```

There are 47 unique values in this variable, so for now, let's decide to drop this variable altogether. Although we don't have a reason to drop this variable, we will just to do that to reduce the amount of data preperation needed for now. We can add this variable later if needed.

```
In [36]: loan_data.drop(labels='State',axis=1,inplace=True)
```

```
In [37]: loan_data.columns[loan_data.dtypes=='object']
```

```
Out[37]: Index(['Home.Ownership', 'FICO.Range', 'Employment.Length'], dtype='object')
```

We have effectively reduced 6 'object' variables to 3. Let's go further and work with the other 3 variables.

Let's process the variable 'Home.Ownership'

```
In [38]: loan_data['Home.Ownership'].value_counts()
```

```
Out[38]: MORTGAGE    1147
         RENT        1146
         OWN          200
         OTHER          5
         NONE           1
         Name: Home.Ownership, dtype: int64
```

Here we can simply ignore the categories 'OTHER' and 'NONE' and create dummy variables for the remaing 3 categories

```
In [39]: loan_data['ho_mortgage'] = np.where(loan_data['Home.Ownership']=='MORTGAGE',1,0)
         loan_data['ho_rent'] = np.where(loan_data['Home.Ownership']== 'RENT',1,0)
```

```
In [40]: loan_data.head()
```

```
Out[40]:         ID  Amount.Requested  Amount.Funded.By.Investors  Interest.Rate  \
         0  81174.0           20000.0                     20000.0           8.90
         1  99592.0           19200.0                     19200.0          12.12
         2  80059.0           35000.0                     35000.0          21.98
         3  15825.0           10000.0                      9975.0           9.99
         4  33182.0           12000.0                     12000.0          11.71

            Debt.To.Income.Ratio Home.Ownership  Monthly.Income FICO.Range  \
         0                 14.90       MORTGAGE         6541.67    735-739
         1                 28.36       MORTGAGE         4583.33    715-719
         2                 23.81       MORTGAGE        11500.00    690-694
         3                 14.30       MORTGAGE         3833.33    695-699
         4                 18.78           RENT         3195.00    695-699

            Open.CREDIT.Lines  Revolving.CREDIT.Balance  \
         0               14.0                   14272.0
         1               12.0                   11140.0
         2               14.0                   21977.0
```

```
3               10.0                         9346.0
4               11.0                        14469.0

   Inquiries.in.the.Last.6.Months Employment.Length  Loan_lenght_36  lp_cem  \
0                             2.0          < 1 year               1       0
1                             1.0           2 years               1       0
2                             1.0           2 years               0       0
3                             0.0           5 years               1       0
4                             0.0           9 years               1       0

   lp_chos  lp_dm  lp_hmvw  ho_mortgage  ho_rent
0        0      1        0            1        0
1        0      1        0            1        0
2        0      1        0            1        0
3        0      1        0            1        0
4        1      0        0            0        1
```

Now that we have created dummy variables for 'Home.Ownership' we can go ahead and drop that variable.

```
In [41]: loan_data.drop(labels='Home.Ownership',axis=1, inplace=True)

In [42]: loan_data.columns[loan_data.dtypes=='object']

Out[42]: Index(['FICO.Range', 'Employment.Length'], dtype='object')
```

Let's deal with the variable 'FICO.Range' next

```
In [43]: loan_data['FICO.Range'].head()

Out[43]: 0    735-739
         1    715-719
         2    690-694
         3    695-699
         4    695-699
         Name: FICO.Range, dtype: object
```

Since this variable has a range, one easy way is to replace each value with the average of the range.

In order to do that, 1. first let's split each value in the variable 'FICO.Range' on the hyphen('-') in the middle of the value. 2. Then let's put the first part of the split result (which will be the lower limit) in a list called 'lower_limit' and the second part of the split result (which will be the upper limit) in a list called 'upper_limit'. 3. Finally let's slice the lower and upper limit values from each list then find the average of these and insert them in a new variable called 'fico' in the original dataframe 'loan_data'

```
In [44]: lower_limit=[]
         upper_limit=[]
         for i in range(len(loan_data)):
```

```
        lower_limit.append(int(loan_data['FICO.Range'][i].split('-')[0]))
        upper_limit.append(int(loan_data['FICO.Range'][i].split('-')[1]))
    #splitting the column on '-' and appending the results to two columns
    # called lower_limit and upper_limit

    for i in range(len(loan_data)):
        loan_data.loc[i,'fico']= ((lower_limit[i]+upper_limit[i])/2)

    # on a for loop we slice the values from the two lists, find their average and insert
    # them in a new column called 'fico' in the original dataframe 'loan_data'
```

Now that we have created a new variable for the original variable ‘FICO.Range’ containing the average value of the range, we can drop the original variable ‘FICO.Range’ and the temproary lists ‘lower_limit’ and ‘upper_limit’.

```
In [45]: loan_data.drop(labels='FICO.Range', axis=1, inplace=True)
         %reset_selective lower_limit, upper_limit
```

```
Once deleted, variables cannot be recovered. Proceed (y/[n])?  y
```

```
In [46]: loan_data.head()
```

```
Out[46]:        ID  Amount.Requested  Amount.Funded.By.Investors  Interest.Rate  \
         0  81174.0           20000.0                     20000.0           8.90
         1  99592.0           19200.0                     19200.0          12.12
         2  80059.0           35000.0                     35000.0          21.98
         3  15825.0           10000.0                      9975.0           9.99
         4  33182.0           12000.0                     12000.0          11.71

            Debt.To.Income.Ratio  Monthly.Income  Open.CREDIT.Lines  \
         0                 14.90         6541.67               14.0
         1                 28.36         4583.33               12.0
         2                 23.81        11500.00               14.0
         3                 14.30         3833.33               10.0
         4                 18.78         3195.00               11.0

            Revolving.CREDIT.Balance  Inquiries.in.the.Last.6.Months Employment.Length  \
         0                   14272.0                             2.0          < 1 year
         1                   11140.0                             1.0           2 years
         2                   21977.0                             1.0           2 years
         3                    9346.0                             0.0           5 years
         4                   14469.0                             0.0           9 years

            Loan_lenght_36  lp_cem  lp_chos  lp_dm  lp_hmvw  ho_mortgage  ho_rent  \
         0               1       0        0      1        0            1        0
         1               1       0        0      1        0            1        0
         2               0       0        0      1        0            1        0
         3               1       0        0      1        0            1        0
```

```
4                1       0        1       0        0              0        1

    fico
0  737.0
1  717.0
2  692.0
3  697.0
4  697.0
```

```
In [47]: loan_data.columns[loan_data.dtypes=='object']

Out[47]: Index(['Employment.Length'], dtype='object')
```

The only remaining 'object' column is 'Employment.Length'. Let's deal with that now.

```
In [48]: loan_data['Employment.Length'].value_counts()

Out[48]: 10+ years    653
         < 1 year     249
         2 years      243
         3 years      235
         5 years      202
         4 years      191
         1 year       177
         6 years      163
         7 years      127
         8 years      108
         9 years       72
         .              2
         Name: Employment.Length, dtype: int64
```

Let's first fix remove the words 'years' and 'year' from the variable.

```
In [49]: loan_data['Employment.Length'] = loan_data['Employment.Length'].astype('str')
             # first let's convert the variable to string datatype so that removing words and
             # be easy

         loan_data['Employment.Length'] = [x.replace('years','') for x in
                                           loan_data['Employment.Length']]
         loan_data['Employment.Length'] = [x.replace('year', '') for x in
                                           loan_data['Employment.Length']]

In [50]: loan_data['Employment.Length'].value_counts()

Out[50]: 10+     653
         < 1     249
         2       243
         3       235
         5       202
```

```
4        191
1        177
6        163
7        127
8        108
nan       78
9         72
.          2
Name: Employment.Length, dtype: int64
```

Now let's group this variable with the response variable 'Interest.Rate' so we can combine categories togther

```
In [51]: loan_data.groupby('Employment.Length')['Interest.Rate'].mean().round(2)
```

```
Out[51]: Employment.Length
         .       11.34
         1       12.49
         10+     13.34
         2       12.87
         3       12.77
         4       13.14
         5       13.40
         6       13.29
         7       13.10
         8       13.01
         9       13.15
         < 1     12.86
         nan     12.78
         Name: Interest.Rate, dtype: float64
```

1. As we can see, 'nan' and '<1' are similar to each other in mean. so we can compare them together.
2. '<1' means 0, so we can replace that with 0.
3. '10+' can be replaced by 10.

```
In [52]: loan_data['Employment.Length']=[x.replace('nan','< 1') for x in
                                          loan_data['Employment.Length']]
         loan_data['Employment.Length']=[x.replace('10+','10') for x in
                                          loan_data['Employment.Length']]
         loan_data['Employment.Length']=[x.replace('< 1','0') for x in
                                          loan_data['Employment.Length']]
         loan_data['Employment.Length']=pd.to_numeric(loan_data['Employment.Length'],
                                                      errors='coerce')
```

```
In [53]: loan_data['Employment.Length'].head()
```

```
Out[53]: 0    0.0
         1    2.0
```

```
2    2.0
3    5.0
4    9.0
Name: Employment.Length, dtype: float64
```

In [54]:
```
loan_data.dtypes
```

Out[54]:
```
ID                                 float64
Amount.Requested                   float64
Amount.Funded.By.Investors         float64
Interest.Rate                      float64
Debt.To.Income.Ratio               float64
Monthly.Income                     float64
Open.CREDIT.Lines                  float64
Revolving.CREDIT.Balance           float64
Inquiries.in.the.Last.6.Months     float64
Employment.Length                  float64
Loan_lenght_36                       uint8
lp_cem                               uint8
lp_chos                              uint8
lp_dm                                uint8
lp_hmvw                              uint8
ho_mortgage                          int32
ho_rent                              int32
fico                               float64
dtype: object
```

Now, all our variables are numeric. We can also drop the variable 'ID' because it's the identity number for every person and doesn't solve any real purpose.

In [55]:
```
loan_data.drop(labels='ID',axis=1,inplace=True)
```

In [56]:
```
loan_data.head()
```

Out[56]:
```
   Amount.Requested  Amount.Funded.By.Investors  Interest.Rate  \
0           20000.0                     20000.0           8.90
1           19200.0                     19200.0          12.12
2           35000.0                     35000.0          21.98
3           10000.0                      9975.0           9.99
4           12000.0                     12000.0          11.71

   Debt.To.Income.Ratio  Monthly.Income  Open.CREDIT.Lines  \
0                 14.90         6541.67               14.0
1                 28.36         4583.33               12.0
2                 23.81        11500.00               14.0
3                 14.30         3833.33               10.0
4                 18.78         3195.00               11.0

   Revolving.CREDIT.Balance  Inquiries.in.the.Last.6.Months  \
```

```
0              14272.0                       2.0
1              11140.0                       1.0
2              21977.0                       1.0
3               9346.0                       0.0
4              14469.0                       0.0

   Employment.Length  Loan_lenght_36  lp_cem  lp_chos  lp_dm  lp_hmvw  \
0                0.0               1       0        0      1        0
1                2.0               1       0        0      1        0
2                2.0               0       0        0      1        0
3                5.0               1       0        0      1        0
4                9.0               1       0        1      0        0

   ho_mortgage  ho_rent   fico
0            1        0  737.0
1            1        0  717.0
2            1        0  692.0
3            1        0  697.0
4            0        1  697.0
```

```
In [57]: loan_data.isna().sum().sum()

Out[57]: 33

In [58]: loan_data.shape

Out[58]: (2500, 17)

In [59]: loan_data.dropna(axis=0,inplace=True)

In [60]: loan_data.shape

Out[60]: (2473, 17)
```

Now, let's split the data into train and test data to proceed with modelling.

```
In [61]: train_loan_data, test_loan_data = train_test_split(loan_data, test_size=0.2,
                                                             random_state=2)

In [62]: train_loan_data.shape, test_loan_data.shape

Out[62]: ((1978, 17), (495, 17))
```

'Interest.Rate' variable is the one we are going to predict, so let's make that the 'Y' variable in both training and test data and drop it from the X variable in both training and test data.

Also the variable 'Amount.Funded.By.Investors' won't be available to us at this point in real life. So, let's drop this also from the training and test data.

```
In [63]: x_train=train_loan_data.drop(labels=['Interest.Rate','Amount.Funded.By.Investors'],
                                       axis=1)
         y_train=train_loan_data['Interest.Rate']
         x_test=test_loan_data.drop(labels=['Interest.Rate','Amount.Funded.By.Investors'],
                                     axis=1)
         y_test=test_loan_data['Interest.Rate']

In [64]: linreg=LinearRegression()
         #Initializing a linear regression object

In [65]: linreg.fit(X=x_train, y=y_train)
         #fitting the linear model on train data

Out[65]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
                  normalize=False)

In [66]: predictions=linreg.predict(X=x_test)
         #Making predictions on test data

In [67]: error=predictions-y_test
         #calculating the errors in prediction by fiding the difference in actual 'y' and
         # predicted 'y'

In [68]: %%latex
         $rmse = 1/m*\sum_{i=0}^{m-1}\sqrt{(predictions(i)-ytest(i))^2}$
```

$rmse = 1/m * \sum_{i=0}^{m-1} \sqrt{(predictions(i) - ytest(i))^2}$

```
In [69]: rmse=np.sqrt((np.sum(error**2))/len(x_test))

In [70]: rmse

Out[70]: 2.0225656998568877
```

RMSE can be used to compare our linear regression model with other techniques and eventually pick the model with the least error.

Next, let's see how to extract coefficients from the model.

```
In [71]: coefs=linreg.coef_
         #these are the beta or theta values(beta_1 to beta_n) that our model is predicting

In [72]: linreg.intercept_
         # this is the intercept value

Out[72]: 75.24596218863286

In [73]: features = x_train.columns

In [74]: list(zip(features,coefs))
```

```
Out[74]: [('Amount.Requested', 0.00016318429645184338),
          ('Debt.To.Income.Ratio', 0.0005724866425414895),
          ('Monthly.Income', -4.108884860357515 6e-05),
          ('Open.CREDIT.Lines', -0.0393078462756966),
          ('Revolving.CREDIT.Balance', -2.472474215323584e-06),
          ('Inquiries.in.the.Last.6.Months', 0.3870776386826336),
          ('Employment.Length', 0.004939976256298612),
          ('Loan_lenght_36', -3.082420573668312),
          ('lp_cem', -0.33812455519896284),
          ('lp_chos', -0.37631807997293887),
          ('lp_dm', -0.513743744137324),
          ('lp_hmvw', -0.640702578936149),
          ('ho_mortgage', -0.3785684674068913),
          ('ho_rent', -0.13052594354375308),
          ('fico', -0.08592703966767974)]
```

0.1 Regularization

As we can see, linear regression gives the coefficient value for each feature. Ideally, the feature which does not contribute much in predicting our output variable should have a coefficient value of 0. But it is not the case. So, we use regularization to penalize and minimize the coefficients of variables that don't contribute much to our model.

0.2 Ridge Regression

alpha or regularisation parameter is a hyperparameter and we'd look at multiple values of it and choose the best one through 10 fold cross validation. Note: In class notes, regularisation parameter is called lambda

```
In [75]: #finding the best value of regularisation parameter with cross validation for ridge
         # regression.
         alphas=np.linspace(0.0001,10,100)
         # We need to reset index for cross validation to work without hitch.
         x_train.reset_index(drop=True, inplace=True)
         y_train.reset_index(drop=True, inplace=True)
```

```
In [76]: """
         We have 100 values of alpha between 0.001 and 10.
         We use these 100 values and 10 fold CV for each value
         to see which value has the least rmse value, that value
         will give the best alpha value.

             In the for-loop below:

             1. For each value of alpha:

                 1.1 We initiate a KFold object for 10 fold
                 cross-validation.
```

```
        We have initiated 10 fold cross validation object so
        cross validation loop will run for 10 iterations and each time
        our training data X_train will be split into 10 buckets.
        Likewise if we use 20 fold cross validation our cross validation
        loop will run for 20 times and the training data will be split
        into 20 buckets.

        1.2. We initiate an object called xval_err as 0.

        1.3. For each alpha and first iteration of the KFold validation:

            1.3.1. The k-fold will split our training data [x_train] into
            9 buckets of training data and 1 bucket of validation data.
            It will use 9 buckets of the training data [X_train] to train
            the Ridge model and 1 bucket of the training data [X_train] to
            preidct the output [Y_cap].

            1.3.2. This predicted 'y_cap' is subtracted from the actual
            y values from the training data [X_train] corresponding to the
            10th set (validation set) to calculate the validation
            error.

            1.3.3. The validation error for this iteration is squared and
            added to the variable xval_err for the next 10 iterations.

        1.4. The total validation error for the past 10 iterations
        are squared, divided by the length of the
        training dataset(x_train) and a squared root is taken on the
        quotient.
        This is the RMSE for this value of alpha using 10 fold CV.

        1.5. This RMSE value is stored in the rmse_list object.
        Once we have completed iterating through all the alpha values,
        the rmse_list object will have a length of 100, since we
        use 100 different alpha values.

        1.6. Finally the alpha value which corresponds to the minimum
        rmse value is returned as the optimal alpha value.
    """
rmse_list=[]

for a in alphas:
    ridge=Ridge(fit_intercept=True, alpha=a)
    # ridge is a linear regression model with L2 regularization.

    kf = KFold(n_splits=10)
    xval_err=0
```

```python
    i =0
    for train_index, validation_index in kf.split(x_train):
        #print(len(train_index), len(validation_index))
        ridge.fit(x_train.iloc[train_index,:], y_train[train_index])
        p=ridge.predict(x_train.iloc[validation_index,:])
        err = p-y_train[validation_index] #iloc doesn't work here for some reason
        xval_err = xval_err+np.dot(err, err)
    rmse_10cv = np.sqrt(xval_err/len(x_train))
    rmse_list.append(rmse_10cv)
    print('{:.3f}\t {:.6f}\t'.format(a, rmse_10cv))
best_alpha= alphas[rmse_list==min(rmse_list)]
print('Alpha with minimum 10CV error is {} and the corresponding RMSE is {}: '.
      format(best_alpha[0], min(rmse_list)))
```

```
0.000        2.070131
0.101        2.070081
0.202        2.070040
0.303        2.070008
0.404        2.069980
0.505        2.069957
0.606        2.069938
0.707        2.069921
0.808        2.069906
0.909        2.069892
1.010        2.069881
1.111        2.069870
1.212        2.069861
1.313        2.069853
1.414        2.069845
1.515        2.069838
1.616        2.069832
1.717        2.069827
1.818        2.069821
1.919        2.069817
2.020        2.069813
2.121        2.069809
2.222        2.069806
2.323        2.069803
2.424        2.069800
2.525        2.069797
2.626        2.069795
2.727        2.069793
2.828        2.069792
2.929        2.069790
3.030        2.069789
3.131        2.069788
3.232        2.069788
3.333        2.069787
```

3.434	2.069787
3.535	2.069787
3.636	2.069787
3.737	2.069787
3.838	2.069787
3.939	2.069788
4.040	2.069789
4.141	2.069790
4.242	2.069791
4.343	2.069792
4.444	2.069793
4.546	2.069795
4.647	2.069796
4.748	2.069798
4.849	2.069800
4.950	2.069802
5.051	2.069804
5.152	2.069807
5.253	2.069809
5.354	2.069812
5.455	2.069815
5.556	2.069817
5.657	2.069820
5.758	2.069824
5.859	2.069827
5.960	2.069830
6.061	2.069834
6.162	2.069837
6.263	2.069841
6.364	2.069845
6.465	2.069849
6.566	2.069853
6.667	2.069857
6.768	2.069861
6.869	2.069866
6.970	2.069870
7.071	2.069875
7.172	2.069880
7.273	2.069884
7.374	2.069889
7.475	2.069894
7.576	2.069900
7.677	2.069905
7.778	2.069910
7.879	2.069916
7.980	2.069921
8.081	2.069927
8.182	2.069933

```
8.283         2.069939
8.384         2.069945
8.485         2.069951
8.586         2.069957
8.687         2.069964
8.788         2.069970
8.889         2.069977
8.990         2.069983
9.091         2.069990
9.192         2.069997
9.293         2.070004
9.394         2.070011
9.495         2.070018
9.596         2.070025
9.697         2.070032
9.798         2.070040
9.899         2.070047
10.000        2.070055
Alpha with minimum 10CV error is 3.5354181818181822 and the corresponding RMSE is 2.0697866245
```

Now we will use the best alpha value that we just determined to fit a ridge regression object on the entire dataset and predict the rmse value for the entire dataset.

```
In [77]: ridge=Ridge(fit_intercept=True, alpha=best_alpha)
         ridge.fit(x_train, y_train)
         predictionsOnTestData = ridge.predict(x_test)
         predictionErrorOnTestData = predictionsOnTestData - y_test
         rmse_ridge = np.sqrt(np.dot(predictionErrorOnTestData,
                                     predictionErrorOnTestData)/len(predictionsOnTestData))
         rmse_ridge
```

```
Out[77]: 2.0236668696412723
```

```
In [78]: list(zip(x_train.columns,ridge.coef_))
```

```
Out[78]: [('Amount.Requested', 0.00016417991900803233),
          ('Debt.To.Income.Ratio', 0.0006487949921075561),
          ('Monthly.Income', -4.169344863753166e-05),
          ('Open.CREDIT.Lines', -0.039616383599302744),
          ('Revolving.CREDIT.Balance', -2.5209565104184987e-06),
          ('Inquiries.in.the.Last.6.Months', 0.3870049295626152),
          ('Employment.Length', 0.004888838204666946),
          ('Loan_lenght_36', -3.041894854788477),
          ('lp_cem', 0.011310143101232472),
          ('lp_chos', -0.0321514576874333),
          ('lp_dm', -0.1690620008874746),
          ('lp_hmvw', -0.2882910897632634),
          ('ho_mortgage', -0.3626507937625516),
```

```
('ho_rent', -0.11681552700277421),
('fico', -0.08593974410496531)]
```

0.2.1 Results of Ridge Regression:

We can see that ridge even though regression shrinks the coefficient value for each variable, it never really makes them 0. Which means it never shrinks the size of our model.

0.3 Lasso Regression

```
In [79]: """
         We have 100 values of alpha between 0.001 and 1.
         We use these 100 values and 10 fold CV for each value
         to see which value has the least rmse, that value
         will be the best alpha.

             In the for-loop below:

             1. For each value of alpha:

                 1.1 We initiate a KFold object for 10 fold
                 cross-validation.

                 We have initiated 10 fold cross validation object so
                 cross validation loop will run for 10 iterations and each time
                 our training data X_train will be split into 10 buckets.
                 Likewise if we use 20 fold cross validation our cross validation
                 loop will run for 20 times and the training data will be split
                 into 20 buckets.

                 1.2. We initiate an object called xval_err which is equal to 0.

                 1.3. For each alpha and first iteration of the KFold validation:

                     1.3.1. The k-fold will split our training data [x_train] into
                     9 buckets of training data and 1 bucket of validation data.
                     It will use 9 buckets of the training data [X_train] to train
                     the Lasso model and 1 bucket of the training data [X_train] to
                     preidct the output [Y_cap].

                     1.3.2. This predicted 'y_cap' is subtracted from the actual
                     y values from the training data [X_train] corresponding to the
                     10th set (validation set) to calculate the validation
                     error.

                     1.3.3. The validation error for this iteration is squared and
                     added to the variable xval_err for the next 10 iterations.
```

```
            1.4. The total validation error for the past 10 iterations
            are squared, divided by the length of the
            training dataset(x_train) and a squared root is taken on the
            quotient.
            This is the RMSE for this value of alpha using 10 fold CV.

            1.5. This RMSE value is stored in the rmse_list object.
            Once we have completed iterating through all the alpha values,
            the rmse_list object will have a length of 100, since we
            use 100 different alpha values.

            1.6. Finally the alpha value which corresponds to the minimum
            rmse value is returned as the optimal alpha value."""

    alphas=np.linspace(0.0001,1,100)
    rmse_list=[]

    for a in alphas:
        lasso=Lasso(fit_intercept=True, alpha=a, max_iter=10000)
        # Lasso is a linear regression model with L1 regularization.

        kf = KFold(n_splits=10)
        xval_err=0
        for train_index, validation_index in kf.split(x_train):
            lasso.fit(x_train.iloc[train_index,:], y_train[train_index])
            p=lasso.predict(x_train.iloc[validation_index,:])
            err = p-y_train[validation_index] #iloc doesn't work here for some reason
            xval_err = xval_err+np.dot(err, err)
        rmse_10cv = np.sqrt(xval_err/len(x_train))
        rmse_list.append(rmse_10cv)
        print('{:.3f}\t {:.6f}\t'.format(a, rmse_10cv))
    best_alpha= alphas[rmse_list==min(rmse_list)]
    print('Alpha with minimum 10CV error is {} and the corresponding RMSE is {}: '.
          format(best_alpha[0], min(rmse_list)))
```

```
0.000         2.070110
0.010         2.069490
0.020         2.069924
0.030         2.071233
0.041         2.073187
0.051         2.075622
0.061         2.077515
0.071         2.079609
0.081         2.082291
0.091         2.085403
0.101         2.088892
0.111         2.092756
0.121         2.096993
```

0.131	2.101651
0.141	2.106692
0.152	2.112098
0.162	2.117865
0.172	2.123991
0.182	2.130519
0.192	2.137403
0.202	2.144636
0.212	2.152212
0.222	2.160129
0.232	2.168383
0.242	2.176970
0.253	2.185886
0.263	2.195126
0.273	2.204688
0.283	2.214567
0.293	2.224758
0.303	2.235257
0.313	2.246061
0.323	2.257168
0.333	2.268569
0.343	2.280261
0.354	2.292239
0.364	2.304500
0.374	2.317037
0.384	2.329848
0.394	2.342926
0.404	2.356269
0.414	2.369871
0.424	2.382382
0.434	2.391821
0.444	2.397942
0.455	2.399453
0.465	2.400998
0.475	2.402576
0.485	2.404186
0.495	2.405833
0.505	2.407512
0.515	2.409228
0.525	2.410977
0.535	2.412759
0.545	2.414465
0.556	2.415905
0.566	2.417304
0.576	2.418402
0.586	2.419524
0.596	2.420670
0.606	2.421792

```
0.616         2.422704
0.626         2.423412
0.636         2.423918
0.646         2.424262
0.657         2.424449
0.667         2.424487
0.677         2.424484
0.687         2.424482
0.697         2.424464
0.707         2.424446
0.717         2.424429
0.727         2.424410
0.737         2.424384
0.747         2.424358
0.758         2.424331
0.768         2.424302
0.778         2.424273
0.788         2.424244
0.798         2.424217
0.808         2.424189
0.818         2.424163
0.828         2.424136
0.838         2.424113
0.848         2.424115
0.859         2.424118
0.869         2.424120
0.879         2.424123
0.889         2.424125
0.899         2.424128
0.909         2.424130
0.919         2.424133
0.929         2.424136
0.939         2.424138
0.949         2.424141
0.960         2.424144
0.970         2.424147
0.980         2.424149
0.990         2.424152
1.000         2.424155
Alpha with minimum 10CV error is 0.010199999999999999 and the corresponding RMSE is 2.06949040
```

The best alpha value we got throuh lasso regression is 0.010199. We will use this value to train our final Lasso model and calculate the rmse.

In [80]:
```
lasso=Lasso(fit_intercept=True, alpha=best_alpha)
lasso.fit(x_train, y_train)
predictionsOnTestData_lasso = lasso.predict(x_test)
```

```
predictionErrorOnTestData_lasso = predictionsOnTestData_lasso - y_test
rmse_lasso = np.sqrt(np.dot(predictionErrorOnTestData_lasso,
                            predictionErrorOnTestData_lasso)/len(predictionsOnTestDat
rmse_lasso
```

Out[80]: 2.023276788895483

In [81]:
```
list(zip(x_train.columns,lasso.coef_))
```

Out[81]:
```
[('Amount.Requested', 0.00016395821531931226),
 ('Debt.To.Income.Ratio', 0.00032219108556223947),
 ('Monthly.Income', -4.2720916538871394e-05),
 ('Open.CREDIT.Lines', -0.039075516991599986),
 ('Revolving.CREDIT.Balance', -2.5527196166969956e-06),
 ('Inquiries.in.the.Last.6.Months', 0.37860640070117296),
 ('Employment.Length', 0.0028101667417416 78),
 ('Loan_lenght_36', -3.0073811789972993),
 ('lp_cem', 0.0),
 ('lp_chos', 0.057359802778081066),
 ('lp_dm', -0.027293745553160276),
 ('lp_hmvw', -0.0562011482052836),
 ('ho_mortgage', -0.22708727621821279),
 ('ho_rent', -0.0),
 ('fico', -0.08593321837314784)]
```

0.3.1 Results of Lasso Regression

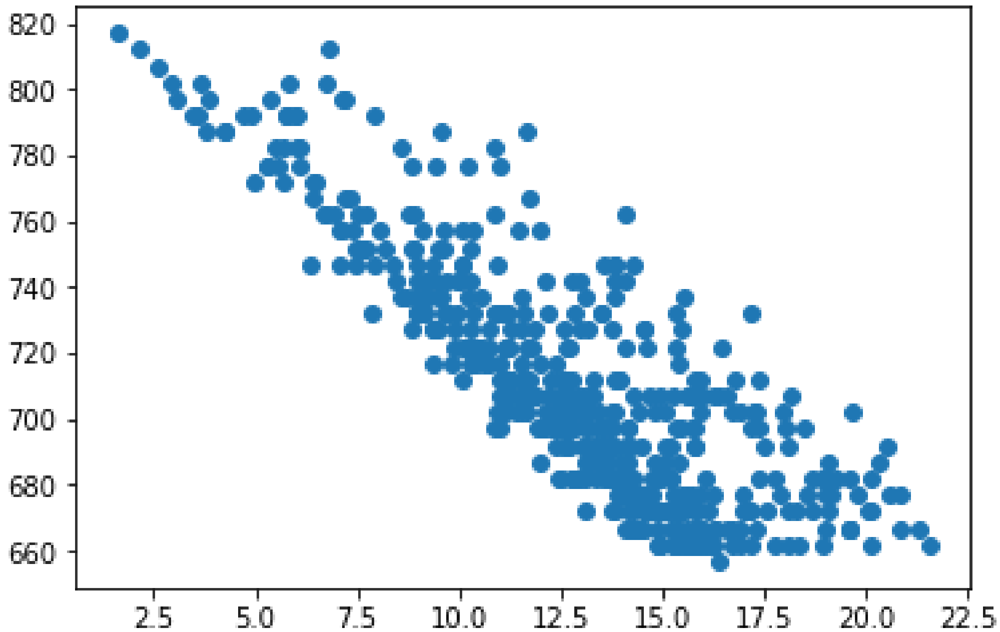
As, we can see Lasso regression not only reduces our RMSE value a little, it also reduces the size of our model by making the coefficients of some variables as zero.

0.4 Analysing the trend between the FICO score in our test data and the response variables from the Linear Regression model without regularisation and Lasso and Ridge regression models and the.

In [92]:
```
""" Trend between LR model without regularization and FICO score in the data set"""

plt.scatter(x=predictions, y=x_test.fico)
```

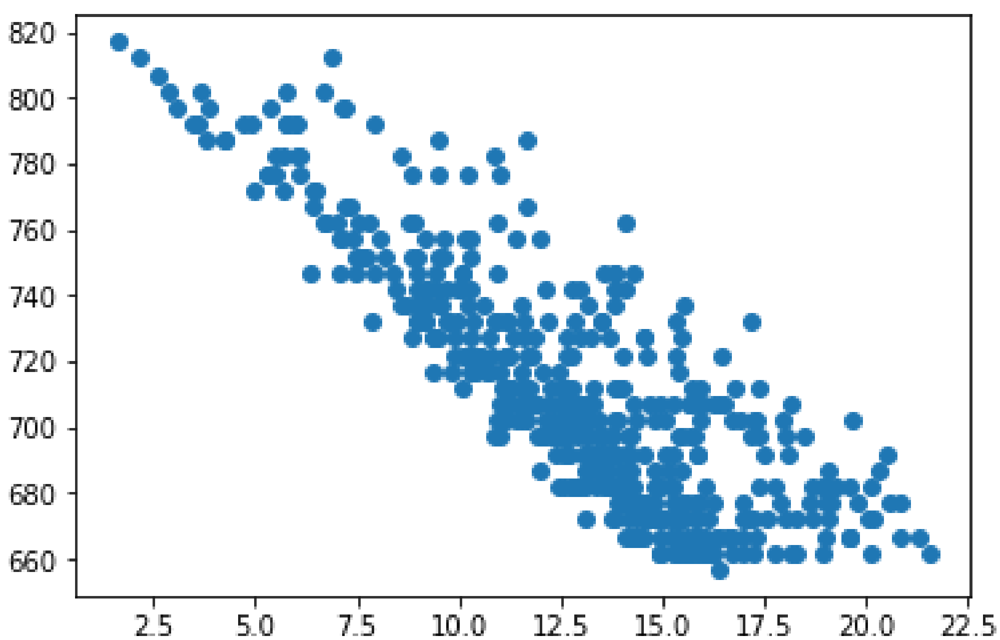
Out[92]: <matplotlib.collections.PathCollection at 0x19f4d8b16d8>



In [93]:
```
""" Trend between LR model with Ridge regularization and FICO score in the data set""

plt.scatter(x=predictionsOnTestData, y=x_test.fico)
```

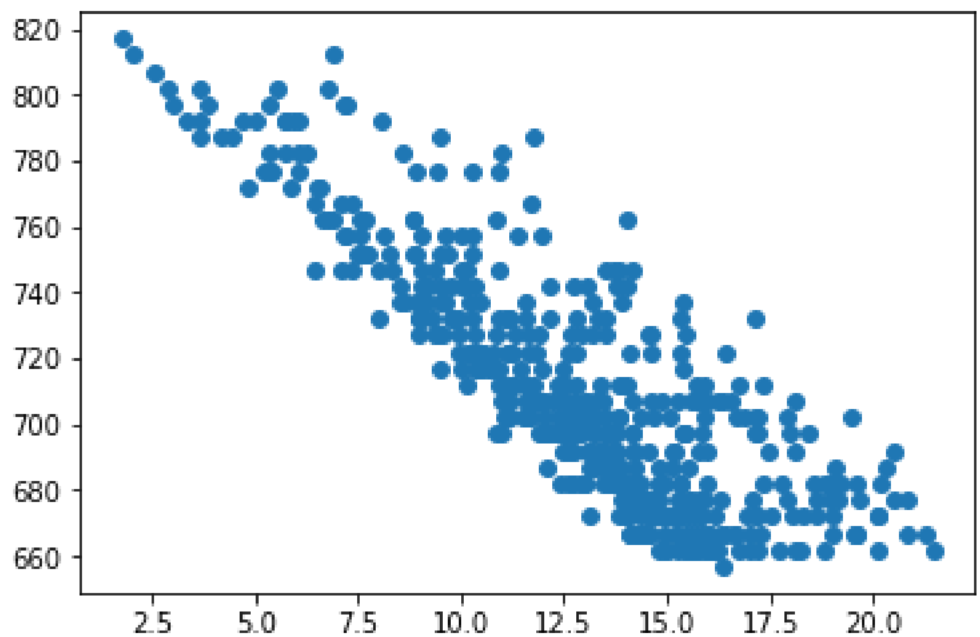
Out[93]: <matplotlib.collections.PathCollection at 0x19f4cbde518>



```
In [94]: """ Trend between LR model with Lasso regularization and FICO score in the data set""

         plt.scatter(x=predictionsOnTestData_lasso, y=x_test.fico)

Out[94]: <matplotlib.collections.PathCollection at 0x19f4d332048>
```



0.4.1 The trend between our response variables and FICO score is linear as we assumed in the beggining. This linearity assumption is what made us choose Linear Regression model.