grebena_regresija

August 23, 2017

```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        from sklearn import linear_model
        from sklearn import metrics
        from sklearn import model_selection
        %matplotlib inline
```

```
In [2]: # radimo sa podacima koji se ticu bejzbol igraca
        # hteli bismo na osnovu svih statistika o performansama igraca da predvidi
        # podaci koji se koriste su preuzeti iz knjige Introduction to Statisctical
        # link do knjige je: http://www-bcf.usc.edu/~gareth/ISL/
        data = pd.read_csv('hitters.csv')
```

```
In [3]: # skup sadrzi 21 atribut (ukljucujuci i platu koju zelimo da predvidimo)
        # i 322 informacije koje se ticu pojedinacnih igraca
        data.shape
```

```
Out[3]: (322, 21)
```

```
In [4]: data.head(5)
```

```
Out[4]:               Player  AtBat  Hits  HmRun  Runs  RBI  Walks  Years  CAtBat
        0     -Andy Allanson    293    66      1    30   29     14      1     293
        1        -Alan Ashby    315    81      7    24   38     39     14    3449
        2       -Alvin Davis    479   130     18    66   72     76      3    1624
        3      -Andre Dawson    496   141     20    65   78     37     11    5628
        4  -Andres Galarraga    321    87     10    39   42     30      2     396

           CHits    ...      CRuns  CRBI  CWalks  League Division PutOuts  Assists
        0     66    ...         30    29      14       A        E     446       33
        1    835    ...        321   414     375       N        W     632       43
        2    457    ...        224   266     263       A        W     880       82
        3   1575    ...        828   838     354       N        E     200       11
        4    101    ...         48    46      33       N        E     805       40

           Errors  Salary  NewLeague
        0      20     NaN          A
        1      10   475.0          N
        2      14   480.0          A
        3       3   500.0          N
        4       4    91.5          N

        [5 rows x 21 columns]
```

```
In [5]: # ispitujemo prirodu podataka koji se nalaze u tabeli
        data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 322 entries, 0 to 321
Data columns (total 21 columns):
Player       322 non-null object
AtBat        322 non-null int64
Hits         322 non-null int64
HmRun        322 non-null int64
Runs         322 non-null int64
RBI          322 non-null int64
Walks        322 non-null int64
Years        322 non-null int64
CAtBat       322 non-null int64
CHits        322 non-null int64
CHmRun       322 non-null int64
CRuns        322 non-null int64
CRBI         322 non-null int64
CWalks       322 non-null int64
League       322 non-null object
Division     322 non-null object
PutOuts      322 non-null int64
Assists      322 non-null int64
Errors       322 non-null int64
Salary       263 non-null float64
NewLeague    322 non-null object
dtypes: float64(1), int64(16), object(4)
memory usage: 52.9+ KB
```

```
In [6]: # neke od vrsta zadrze nedostajuce vrednosti tako da nam nisu podesne u mo
        data = data.dropna()
```

```
In [7]: data.shape
```

```
Out[7]: (263, 21)
```

```
In [8]: # informacije o platama su nam potrebne za predvidjanje kao posebna velici
        Y = data['Salary']
```

```
In [10]: # neki atributi nam nisu informativni - kategorickog su tipa, a ne numeri
         # to su Player, League, Division, NewLeague
         # Salary takodje treba ukloniti
         X = data.drop(['Player', 'League', 'Division', 'NewLeague', 'Salary'], axi
         print(X)
```

```
     AtBat  Hits  HmRun  Runs  RBI  Walks  Years  CAtBat  CHits  CHmRun  \
1      315    81      7    24   38     39     14    3449    835      69   
2      479   130     18    66   72     76      3    1624    457      63   
3      496   141     20    65   78     37     11    5628   1575     225   
4      321    87     10    39   42     30      2     396    101      12   
5      594   169      4    74   51     35     11    4408   1133      19   
6      185    37      1    23    8     21      2     214     42       1   
7      298    73      0    24   24      7      3     509    108       0   
8      323    81      6    26   32      8      2     341     86       6   
9      401    92     17    49   66     65     13    5206   1332     253   
10     574   159     21   107   75     59     10    4631   1300      90   
11     202    53      4    31   26     27      9    1876    467      15   
12     418   113     13    48   61     47      4    1512    392      41   
13     239    60      0    30   11     22      6    1941    510       4   
14     196    43      7    29   27     30     13    3231    825      36   
16     568   158     20    89   75     73     15    8068   2273     177   
17     190    46      2    24    8     15      5     479    102       5   
19     127    32      8    16   22     14      8     727    180      24   
20     413    92     16    72   48     65      1     413     92      16   
21     426   109      3    55   43     62      1     426    109       3   
23     472   116     16    60   62     74      6    1924    489      67   
24     629   168     18    73  102     40     18    8424   2464     164   
25     587   163      4    92   51     70      6    2695    747      17   
26     324    73      4    32   18     22      7    1931    491      13   
27     474   129     10    50   56     40     10    2331    604      61   
28     550   152      6    92   37     81      5    2308    633      32   
29     513   137     20    90   95     90     14    5201   1382     166   
31     419   108      6    55   36     22      3     591    149       8   
33     583   168     17    83   80     56      5    1646    452      44   
34     204    49      6    23   25     12      7    1309    308      27   
35     379   106     10    38   60     30     14    6207   1906     146   
..     ...   ...    ...   ...  ...    ...    ...     ...    ...     ...   
287    687   213     10    91   65     27      4    1518    448      15   
288    368   103      3    48   28     54      8    1897    493       9   
289    263    70      1    26   23     30      4     888    220       9   
290    642   211     14   107   59     52      5    2364    770      27   
291    265    68      8    26   30     29      7    1337    339      32   
293    559   141      2    48   61     73      8    3162    874      16   
294    520   120     17    53   44     21      4     927    227      22   
295     19     4      1     2    3      1      1      19      4       1   
296    205    43      2    24   17     20      7     854    219      12   
297    193    47     10    21   29     24      6    1136    256      42   
299    213    61      4    17   22      3     17    4061   1145      83   
300    510   147     10    56   52     53      7    2872    821      63   
```

```
301    578   138      1    56   59     34      3    1399    357       7
303    441   113      5    76   52     76      5    1546    397      17
304    172    42      3    17   14     15     10    4086   1150      57
306    127    32      4    14   25     12     19    8396   2402     242
307    279    69      4    35   31     32      4    1359    355      31
308    480   112     18    50   71     44      7    3031    771     110
309    600   139      0    94   29     60      2    1236    309       1
310    610   186     19   107   98     74      6    2728    753      69
311    360    81      5    37   44     37      7    2268    566      41
312    387   124      1    67   27     36      7    1775    506       6
313    580   207      8   107   71    105      5    2778    978      32
314    408   117     11    66   41     34      1     408    117      11
315    593   172     22    82  100     57      1     593    172      22
317    497   127      7    65   48     37      5    2703    806      32
318    492   136      5    76   50     94     12    5511   1511      39
319    475   126      3    61   43     52      6    1700    433       7
320    573   144      9    85   60     78      8    3198    857      97
321    631   170      9    77   44     31     11    4908   1457      30

     CRuns  CRBI  CWalks  PutOuts  Assists  Errors
1      321   414     375      632       43      10
2      224   266     263      880       82      14
3      828   838     354      200       11       3
4       48    46      33      805       40       4
5      501   336     194      282      421      25
6       30     9      24       76      127       7
7       41    37      12      121      283       9
8       32    34       8      143      290      19
9      784   890     866        0        0       0
10     702   504     488      238      445      22
11     192   186     161      304       45      11
12     205   204     203      211       11       7
13     309   103     207      121      151       6
14     376   290     238       80       45       8
16    1045   993     732      105      290      10
17      65    23      39      102      177      16
19      67    82      56      202       22       2
20      72    48      65      280        9       5
21      55    43      62      361       22       2
23     242   251     240      518       55       3
24    1008  1072     402     1067      157      14
25     442   198     317      434        9       3
26     291   108     180      222        3       3
27     246   327     166      732       83      13
28     349   182     308      262      329      16
29     763   734     784      267        5       3
31      80    46      31      226        7       4
33     219   208     136      109      292      25
```

```
34     126   132      66      419       46        5
35     859   803     571       72      170       24
..     ...   ...     ...      ...      ...      ...
287    196   137      89      294      445       13
288    207   162     198      209      246        3
289     83    82      86       81      147        4
290    352   230     193      337       19        4
291    135   163     128       92        5        3
293    421   349     359      352      414        9
294    106    80      52       70      144       11
295      2     3       1      692       70        8
296    105    99      71      131        6        1
297    129   139     106      299       13        5
299    488   491     244      178       45        4
300    307   340     174      810       99       18
301    149   161      87      133      371       20
303    226   149     191      160      290       11
304    579   363     406       65        0        0
306   1048  1348     819      167       18        6
307    180   148     158      133      173        9
308    338   406     239       94      270       16
309    201    69     110      300       12        9
310    399   366     286     1182       96       13
311    279   257     246      170      284        3
312    272   125     194      186      290       17
313    474   322     417      121      267       19
314     66    41      34      942       72       11
315     82   100      57     1222      139       15
317    379   311     138      325        9        3
318    897   451     875      313      381       20
319    217    93     146       37      113        7
320    470   420     332     1314      131       12
321    775   357     249      408        4        3

[263 rows x 16 columns]
```

```
In [13]: X.shape
```

```
Out[13]: (263, 16)
```

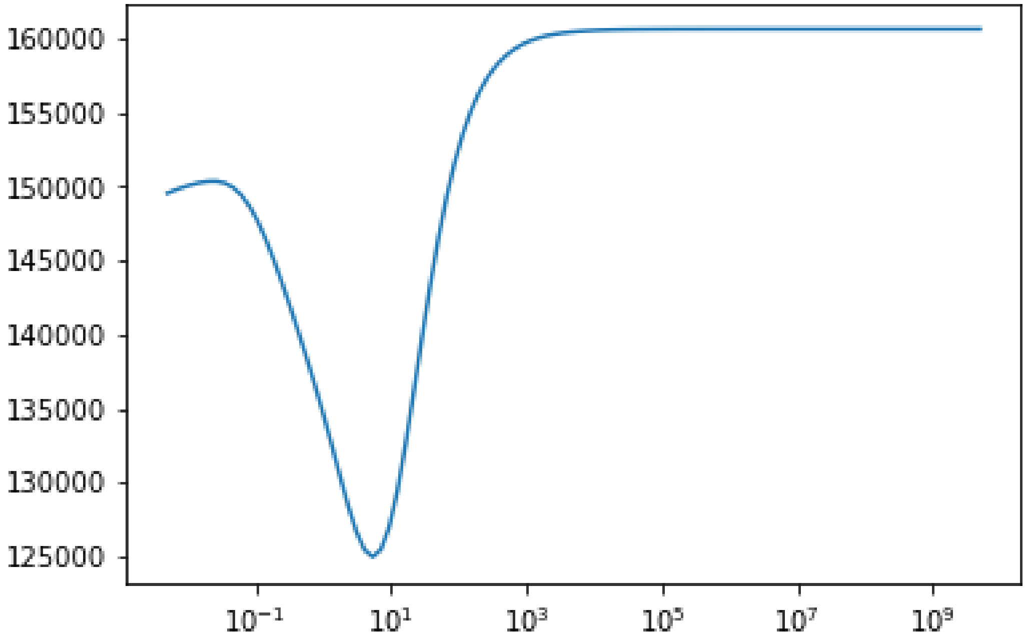
```
In [11]: # posto su skale vrednosti podataka neujednacene, ima smisla raditi normal
```

```
In [12]: # delimo skup podataka na:
         # trening skup
         # validacioni skup koji koristimo za ucenje metaparametara
         # test skup na kojem ocenjujemo uspesnost modela
         X_train_validation, X_test, Y_train_validation, Y_test = model_selection.t
         X_train, X_validation, Y_train, Y_validation = model_selection.train_test_

In [13]: # baseline - linearna regresija
         linreg = linear_model.LinearRegression(normalize=True)
         linreg.fit(X_train_validation, Y_train_validation)
         Y_predicted = linreg.predict(X_test)
         linreg_score = metrics.mean_squared_error(Y_test, Y_predicted)
         linreg_score

Out[13]: 138551.12033732756

In [14]: # grebena regresija sa metaparametrom 4
         reg_1= linear_model.Ridge(alpha=4, normalize=True)
         reg_1.fit(X_train_validation, Y_train_validation)
         Y_predicted = reg_1.predict(X_test)
         reg_score_1 = metrics.mean_squared_error(Y_test, Y_predicted)
         reg_score_1
         # na osnovu ovog rezultata zakljucujemo da ima smisla raditi regularizaci

Out[14]: 126928.00669545057

In [15]: # grebena regresija sa metaparametrom 10^10
         reg_2= linear_model.Ridge(alpha=10**10, normalize=True)
         reg_2.fit(X_train_validation, Y_train_validation)
         Y_predicted = reg_2.predict(X_test)
         reg_score_2 = metrics.mean_squared_error(Y_test, Y_predicted)
         reg_score_2
         # na osnovu ovog rezultata zakljucujemo da ima smisla odrediti i precizno
         # jer ocigledno nisu sve regularizacije dobre

Out[15]: 194839.49321934962

In [45]: # skup vrednosti iz kojeg trazimo najbolju vrednost za parametar alfa
         # imamo i male i velike vrednosti u skupu
         alphas = 10**np.linspace(10, -2, 100)*0.5

In [46]: alphas

Out[46]: array([  5.00000000e+09,   3.78231664e+09,   2.86118383e+09,
                  2.16438064e+09,   1.63727458e+09,   1.23853818e+09,
                  9.36908711e+08,   7.08737081e+08,   5.36133611e+08,
                  4.05565415e+08,   3.06795364e+08,   2.32079442e+08,
                  1.75559587e+08,   1.32804389e+08,   1.00461650e+08,
                  7.59955541e+07,   5.74878498e+07,   4.34874501e+07,
                  3.28966612e+07,   2.48851178e+07,   1.88246790e+07,
                  1.42401793e+07,   1.07721735e+07,   8.14875417e+06,
                  6.16423370e+06,   4.66301673e+06,   3.52740116e+06,
                  2.66834962e+06,   2.01850863e+06,   1.52692775e+06,
                  1.15506485e+06,   8.73764200e+05,   6.60970574e+05,
                  5.00000000e+05,   3.78231664e+05,   2.86118383e+05,
                  2.16438064e+05,   1.63727458e+05,   1.23853818e+05,
                  9.36908711e+04,   7.08737081e+04,   5.36133611e+04,
                  4.05565415e+04,   3.06795364e+04,   2.32079442e+04,
                  1.75559587e+04,   1.32804389e+04,   1.00461650e+04,
                  7.59955541e+03,   5.74878498e+03,   4.34874501e+03,
                  3.28966612e+03,   2.48851178e+03,   1.88246790e+03,
                  1.42401793e+03,   1.07721735e+03,   8.14875417e+02,
                  6.16423370e+02,   4.66301673e+02,   3.52740116e+02,
                  2.66834962e+02,   2.01850863e+02,   1.52692775e+02,
                  1.15506485e+02,   8.73764200e+01,   6.60970574e+01,
                  5.00000000e+01,   3.78231664e+01,   2.86118383e+01,
                  2.16438064e+01,   1.63727458e+01,   1.23853818e+01,
                  9.36908711e+00,   7.08737081e+00,   5.36133611e+00,
                  4.05565415e+00,   3.06795364e+00,   2.32079442e+00,
                  1.75559587e+00,   1.32804389e+00,   1.00461650e+00,
                  7.59955541e-01,   5.74878498e-01,   4.34874501e-01,
                  3.28966612e-01,   2.48851178e-01,   1.88246790e-01,
                  1.42401793e-01,   1.07721735e-01,   8.14875417e-02,
                  6.16423370e-02,   4.66301673e-02,   3.52740116e-02,
                  2.66834962e-02,   2.01850863e-02,   1.52692775e-02,
                  1.15506485e-02,   8.73764200e-03,   6.60970574e-03,
                  5.00000000e-03])
```

```
In [47]: # niz gresaka nasih modela
         errors = []
```

```
In [48]: # izracunavamo gresku za skvaku vrednost metaparametra alfa
         for a in alphas:
             reg = linear_model.Ridge(normalize=True,  alpha=a)
             reg.fit(X_train, Y_train)
             Y_predicted = reg.predict(X_validation)
             error = metrics.mean_squared_error(Y_predicted, Y_validation)
             errors.append(error)
```

```
In [49]: # iscrtavamo zavisnost greske od vrednosti metaparametra alfa
         plt.plot(alphas, errors)
         plt.xscale('log')
```



```
In [50]: # trazimo koja je to vrednost

In [51]: type(errors)

Out[51]: list

In [52]: erros = np.array(errors)

In [53]: erros.argmin()

Out[53]: 74

In [54]: alpha = alphas[74]
         alpha

Out[54]: 5.3613361100516048

In [55]: # greska modela
         errors[74]

Out[55]: 124988.0740587797

In [56]: # sada kada znamo najbolju vrednost metaparametra alfa mozemo da naucimo i
         # da damo konacnu procenu greske
         # ne zaboraviti da se u ovom koraku koriste i trening i validacioni skup

         regfin = linear_model.Ridge(alpha=5.361, normalize=True)
```

```
          regfin.fit(X_train_validation, Y_train_validation)
          Y_predicted = regfin.predict(X_test)
          regfin_score = metrics.mean_squared_error(Y_test, Y_predicted)
          regfin_score
```

```
Out[56]: 131350.87475923024
```

```
In [ ]:
```