In [1]: # Importing the libraries import pandas as pd import numpy as np from sklearn import metrics import matplotlib.pyplot as plt import seaborn as sns %matplotlib inline from sklearn import linear_model In [2]: # Importing the Boston Housing dataset df=pd.read_csv("housing.csv") 0.00632 18.00 2.310 0 0.5380 6.5750 65.20 4.0900 1 296.0 15.30 396.90 4.98 24.00 Out[2]: 0 0.02731 0.00 7.070 0 0.4690 6.4210 78... 1 0.02729 0.00 7.070 0 0.4690 7.1850 61... 2 0.03237 0.00 2.180 0 0.4580 6.9980 45... 3 0.06905 0.00 2.180 0 0.4580 7.1470 54... 4 0.02985 0.00 2.180 0 0.4580 6.4300 58... 500 0.06263 0.00 11.930 0 0.5730 6.5930 69... 501 0.04527 0.00 11.930 0 0.5730 6.1200 76... 0.06076 0.00 11.930 0 0.5730 6.9760 91... 502 503 0.10959 0.00 11.930 0 0.5730 6.7940 89... 0.04741 0.00 11.930 0 0.5730 6.0300 80... 504 505 rows × 1 columns In [3]: # See head of the dataset df.head() $0.00632\ 18.00\ 2.310\ 0\ 0.5380\ 6.5750\ 65.20\ 4.0900\ 1\ 296.0\ 15.30\ 396.90\ 4.98\ 24.00$ Out[3]: 0 0.02731 0.00 7.070 0 0.4690 6.4210 78... 1 0.02729 0.00 7.070 0 0.4690 7.1850 61... 2 0.03237 0.00 2.180 0 0.4580 6.9980 45... 0.06905 0.00 2.180 0 0.4580 7.1470 54... 0.02985 0.00 2.180 0 0.4580 6.4300 58... 4 In [6]: #Adding the feature names to the dataframe df=pd.read_csv("housing12.csv") df Out[6]: CRIM ZN INDUS CHAS NOX RM AGE DIS RAD TAX PTRATIO **B LSTAT MEDV** 65.2 4.0900 1 296.0 **0** 0.00632 18.0 2.31 0.0 0.538 6.575 15.3 396.90 24.0 4.98 **1** 0.02731 7.07 0.0 0.469 6.421 78.9 4.9671 2 242.0 17.8 396.90 21.6 0.0 9.14 0.0 0.469 7.185 **2** 0.02729 0.0 7.07 61.1 4.9671 2 242.0 17.8 392.83 4.03 34.7 0.0 0.458 6.998 3 222.0 18.7 394.63 33.4 **3** 0.03237 0.0 2.18 45.8 6.0622 2.94 54.2 6.0622 4 0.06905 0.0 2.18 0.0 0.458 7.147 3 222.0 18.7 396.90 5.33 36.2 69.1 2.4786 **501** 0.06263 11.93 1 273.0 21.0 391.99 9.67 22.4 0.0 0.0 0.573 6.593 502 0.04527 0.0 11.93 0.0 0.573 6.120 76.7 2.2875 273.0 21.0 396.90 9.08 20.6 21.0 396.90 11.93 91.0 2.1675 1 273.0 **503** 0.06076 0.0 0.0 0.573 6.976 5.64 23.9 0.10959 1 273.0 22.0 **505** 0.04741 0.0 11.93 0.0 0.573 6.030 80.8 2.5050 1 273.0 21.0 396.90 7.88 11.9 506 rows × 14 columns In [7]: df.head() Out[7]: ΖN INDUS CHAS NOX RMAGE DIS RAD TAX PTRATIO B LSTAT MEDV **0** 0.00632 18.0 2.31 0.0 0.538 6.575 65.2 4.0900 1 296.0 15.3 396.90 4.98 24.0 6.421 78.9 4.9671 **1** 0.02731 0.0 7.07 0.0 0.469 2 242.0 17.8 396.90 9.14 21.6 2 242.0 **2** 0.02729 0.0 7.07 0.0 0.469 7.185 61.1 4.9671 17.8 392.83 4.03 34.7 45.8 6.0622 3 0.03237 0.0 2.18 0.0 0.458 6.998 3 222.0 18.7 394.63 2.94 33.4 4 0.06905 0.0 0.458 0.0 2.18 7.147 54.2 6.0622 3 222.0 18.7 396.90 5.33 36.2 In [8]: df.tail() CRIM ZN INDUS CHAS NOX RMAGE DIS RAD TAX PTRATIO B LSTAT **MEDV** Out[8]: **501** 0.06263 0.0 11.93 0.0 0.573 6.593 69.1 2.4786 1 273.0 21.0 391.99 9.67 22.4 **502** 0.04527 0.0 11.93 0.0 0.573 6.120 76.7 2.2875 1 273.0 21.0 396.90 9.08 20.6 503 0.06076 0.0 11.93 0.0 0.573 6.976 91.0 2.1675 1 273.0 21.0 396.90 5.64 23.9 **504** 0.10959 0.0 11.93 0.0 0.573 6.794 89.3 2.3889 1 273.0 21.0 393.45 22.0 6.48 **505** 0.04741 0.0 11.93 0.0 0.573 6.030 80.8 2.5050 1 273.0 21.0 396.90 7.88 11.9 In [9]: df.shape (506, 14)Out[9]: In [10]: df.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 506 entries, 0 to 505 Data columns (total 14 columns): Non-Null Count Dtype Column 0 CRIM 506 non-null float64 ZN 506 non-null 1 float64 2 INDUS 506 non-null float64 506 non-null 3 CHAS float64 float64 4 NOX 506 non-null 5 RM506 non-null float64 506 non-null 6 AGE float64 506 non-null DIS float64 506 non-null 8 RAD int64 9 TAX 506 non-null float64 506 non-null float64 10 PTRATIO 506 non-null float64 11 В 12 LSTAT 506 non-null float64 13 MEDV float64 452 non-null dtypes: float64(13), int64(1) memory usage: 55.5 KB In [11]: df.describe() Out[11]: **CRIM** ΖN **INDUS CHAS** NOX RM**AGE** DIS **RAD TAX PTRATIO LSTAT MEDV** count 506.000000 506.000000 506.000000 506.000000 506.000000 506.000000 506.000000 506.000000 506.000000 506.000000 506.000000 506.000000 506.000000 452.000000 mean 1.269195 13.295257 9.205158 0.140765 15.679800 58.744660 6.173308 78.063241 11.537806 87.585243 125.322456 6.064932 8.808602 2.399207 23.048697 7.169630 0.312765 1.646991 27.220206 33.104049 6.476435 203.542157 180.670077 std 0.000000 0.000000 0.000000 0.000000 0.385000 3.561000 1.137000 1.129600 1.000000 20.200000 2.600000 0.320000 1.730000 6.300000 min **25**% 0.049443 0.000000 3.440000 0.000000 0.449000 5.961500 32.000000 2.430575 4.000000 254.000000 17.000000 364.995000 6.877500 18.500000 **50**% 6.960000 0.000000 3.925850 0.144655 0.000000 0.538000 6.322500 65.250000 5.000000 307.000000 18.900000 390.660000 10.380000 21.950000 403.000000 20.200000 395.615000 **75**% 0.819623 18.100000 18.100000 0.000000 0.647000 6.949000 89.975000 6.332075 24.000000 15.015000 26.600000 9.966540 100.000000 27.740000 1.000000 7.313000 100.000000 100.000000 24.000000 666.000000 711.000000 396.900000 396.900000 34.410000 50.000000 max In [12] df.isnull() **CRIM** ΖN **INDUS** CHAS NOX RM**AGE** DIS RAD TAX PTRATIO B LSTAT **MEDV** Out[12]: **0** False 1 False False False False False False False False **2** False **3** False **4** False **501** False **502** False **503** False **504** False **505** False 506 rows × 14 columns In [14]: df.dtypes float64 CRIM Out[14]: ZN float64 INDUS float64 CHAS float64 NOX float64 RMfloat64 AGE float64 DIS float64 RAD int64 TAX float64 PTRATIO float64 float64 **LSTAT** float64 MEDV float64 dtype: object In [15]: # Identifying the unique number of values in the dataset df.nunique() CRIM 452 Out[15]: 27 ZN**INDUS** 77 CHAS 16 NOX 132 437 RMAGE 399 DIS 361 RAD 10 TAX 67 PTRATIO 85 374 LSTAT 445 210 dtype: int64 In [16]: # Check for missing values df.isnull().sum() CRIM 0 Out[16]: ZN0 **INDUS** 0 CHAS 0 NOX 0 RM0 AGE 0 DIS 0 RAD 0 TAX 0 PTRATIO 0 0 LSTAT 0 MEDV 54 dtype: int64 In [17]: # See rows with missing values df[df.isnull().any(axis=1)] CRIM ZN INDUS CHAS NOX RMAGE DIS RAD TAX PTRATIO **B LSTAT MEDV** Out[17]: 367 0.0 18.1 0.0 0.631 3.863 100.0 1.5106 24.0 666 20.2 131.42 13.33 23.1 NaN 373 0.0 18.1 0.0 0.668 4.906 100.0 1.1742 24.0 666 20.2 396.90 34.77 13.8 NaN 374 0.0 18.1 0.0 0.668 4.138 100.0 1.1370 24.0 666 20.2 396.90 37.97 13.8 NaN 375 0.0 18.1 0.0 0.671 7.313 97.9 1.3163 24.0 666 20.2 396.90 13.44 15.0 NaN 376 0.0 18.1 0.671 6.649 93.3 1.3449 24.0 666 20.2 363.02 23.24 13.9 0.0 NaN 0.0 18.1 378 0.0 0.671 6.380 96.2 1.3861 24.0 666 20.2 396.90 23.69 13.1 NaN 379 0.0 18.1 0.0 0.671 6.223 100.0 1.3861 24.0 666 20.2 393.74 21.78 10.2 NaN 380 0.0 18.1 0.0 0.671 6.968 91.9 1.4165 24.0 666 20.2 396.90 17.21 10.4 NaN 381 0.0 18.1 0.0 0.671 6.545 99.1 1.5192 24.0 666 20.2 396.90 21.08 10.9 NaN 384 0.0 18.1 0.0 0.700 4.368 91.2 1.4395 24.0 666 20.2 285.83 30.63 8.8 NaN 385 0.0 18.1 0.0 0.700 5.277 98.1 1.4261 24.0 666 20.2 396.90 30.81 7.2 NaN 386 0.0 18.1 0.0 0.700 4.652 100.0 1.4672 24.0 666 20.2 396.90 28.28 10.5 NaN 387 0.0 18.1 0.700 5.000 89.5 1.5184 24.0 666 20.2 396.90 31.99 0.0 7.4 NaN 388 0.0 18.1 0.0 0.700 4.880 100.0 1.5895 24.0 666 20.2 372.92 30.62 10.2 NaN 392 0.0 18.1 0.0 0.700 5.036 97.0 1.7700 24.0 666 20.2 396.90 25.68 9.7 NaN 394 0.0 18.1 0.0 0.693 5.887 94.7 1.7821 24.0 666 20.2 396.90 16.35 12.7 NaN 398 0.0 18.1 0.0 0.693 5.453 100.0 1.4896 24.0 666 20.2 396.90 30.59 5.0 NaN 400 0.0 18.1 0.0 0.693 5.987 100.0 1.5888 24.0 666 20.2 396.90 26.77 5.6 NaN 401 0.0 18.1 0.0 0.693 6.343 100.0 1.5741 24.0 666 20.2 396.90 20.32 7.2 NaN 403 0.0 18.1 0.0 0.693 5.349 96.0 1.7028 24.0 666 20.2 396.90 19.77 8.3 NaN 404 0.0 18.1 0.693 5.531 85.4 1.6074 24.0 666 20.2 329.46 27.38 0.0 8.5 NaN 100.0 1.4254 24.0 405 0.0 18.1 0.0 0.693 5.683 666 20.2 384.97 22.98 5.0 NaN 100.0 1.1781 24.0 406 0.0 18.1 0.0 0.659 4.138 666 20.2 370.22 23.34 11.9 NaN 407 0.0 18.1 0.0 0.659 5.608 100.0 1.2852 24.0 666 20.2 332.09 12.13 27.9 NaN 409 0.0 18.1 0.0 0.597 6.852 100.0 1.4655 24.0 666 20.2 179.36 19.78 27.5 NaN 410 0.0 18.1 0.0 0.597 5.757 100.0 1.4130 24.0 666 20.2 2.60 10.11 15.0 NaN 411 0.0 18.1 0.0 0.597 6.657 100.0 1.5275 24.0 666 20.2 35.05 21.22 17.2 NaN 0.0 18.1 0.597 4.628 100.0 1.5539 24.0 412 0.0 666 20.2 28.79 34.37 17.9 NaN 413 0.0 18.1 0.0 0.597 5.155 100.0 1.5894 24.0 666 20.2 210.97 20.08 16.3 NaN 414 0.0 18.1 0.0 0.693 4.519 100.0 1.6582 24.0 666 20.2 88.27 36.98 7.0 NaN 100.0 1.8347 24.0 415 0.0 18.1 0.0 0.679 6.434 666 20.2 27.25 29.05 7.2 NaN 416 0.0 18.1 0.0 0.679 6.782 90.8 1.8195 24.0 666 20.2 21.57 25.79 7.5 NaN 0.0 18.1 417 0.0 0.679 5.304 89.1 1.6475 24.0 666 20.2 127.36 26.64 10.4 NaN 418 0.0 18.1 0.0 0.679 5.957 100.0 1.8026 24.0 666 20.2 16.45 20.62 8.8 NaN 419 0.0 18.1 0.0 0.718 6.824 76.5 1.7940 24.0 666 20.2 48.45 22.74 8.4 NaN 0.0 18.1 0.718 6.411 100.0 1.8589 24.0 420 0.0 666 20.2 318.75 15.02 16.7 NaN 422 0.0 18.1 0.0 0.614 5.648 87.6 1.9512 24.0 666 20.2 291.55 14.10 20.8 NaN 0.0 18.1 7.68 24.39 425 0.0 0.679 5.896 95.4 1.9096 24.0 666 20.2 8.3 NaN 426 0.0 18.1 0.0 0.584 5.837 59.7 1.9976 24.0 666 20.2 24.65 15.69 10.2 NaN 427 0.0 18.1 0.0 0.679 6.202 78.7 1.8629 24.0 666 20.2 18.82 14.52 10.9 NaN 431 0.0 18.1 0.0 0.584 6.833 94.3 2.0882 24.0 666 20.2 81.33 19.69 14.1 NaN 434 0.0 18.1 0.0 0.713 6.208 95.0 2.2222 24.0 666 20.2 100.63 15.17 11.7 NaN 94.6 2.1247 24.0 435 0.0 18.1 0.0 0.740 6.629 666 20.2 109.85 23.27 13.4 NaN 436 0.0 18.1 0.0 0.740 6.461 93.3 2.0026 24.0 666 20.2 27.49 18.05 9.6 NaN 437 0.0 18.1 0.740 6.152 100.0 1.9142 24.0 666 20.2 9.32 26.45 0.0 8.7 NaN 438 0.0 18.1 0.0 0.740 5.935 87.9 1.8206 24.0 666 20.2 68.95 34.02 8.4 NaN 440 0.0 18.1 0.0 0.740 5.818 92.4 1.8662 24.0 666 20.2 391.45 22.11 10.5 NaN 444 0.0 18.1 0.0 0.740 5.854 96.6 1.8956 24.0 666 20.2 240.52 23.79 10.8 NaN 445 0.0 18.1 0.0 0.740 6.459 94.8 1.9879 24.0 666 20.2 43.06 23.98 11.8 NaN 468 0.0 18.1 0.0 0.580 5.926 71.0 2.9084 24.0 666 20.2 368.74 18.13 19.1 NaN 469 0.0 18.1 0.0 0.580 5.713 56.7 2.8237 24.0 666 20.2 396.90 14.76 20.1 NaN 477 0.0 18.1 0.0 0.614 5.304 97.3 2.1007 24.0 666 20.2 349.48 24.91 12.0 NaN 0.0 18.1 96.7 2.1705 24.0 20.2 379.70 18.03 478 0.0 0.614 6.185 666 14.6 NaN 479 0.0 18.1 0.0 0.614 6.229 88.0 1.9512 24.0 666 20.2 383.32 13.11 21.4 NaN In [18]: # Finding out the correlation between the features corr = df.corr() corr.shape (14, 14)Out[18]: In [19]: # Plotting the heatmap of correlation between features plt.figure(figsize=(20,20)) sns.heatmap(corr, cbar=True, square= True, fmt='.1f', annot=True, annot_kws={'size':15}, cmap='Greens') <AxesSubplot:> Out[19]: 1.00 0.5 8.0 1.0 -0.3 0.6 -0.1-0.1-0.2-0.3-0.2-0.1-0.10.4 -0.3 - 0.75 1.0 -0.5 -0.0 0.0 0.1 -0.50.3 0.1 -0.3 0.0 0.0 0.3 ĸ -0.3 -0.4 INDUS -0.51.0 -0.20.7 0.7 0.5 0.6 -0.4-0.4-0.6 -0.4-0.40.2 -0.4 - 0.50 -0.1-0.0 -0.2 1.0 0.6 0.6 -0.3 0.5 0.6 -0.30.5 -0.50.0 0.2 Š 0.0 0.6 1.0 1.0 0.9 1.0 -0.68.0 -0.9-0.1-0.4-0.6 0.1 -0.3 - 0.25 0.7 0.6 0.9 1.0 -0.68.0 -0.2 0.1 -0.41.0 1.0 -0.6 -0.8 0.0 RΜ AGE 0.5 -0.5 0.7 -0.3 1.0 0.6 -0.5 0.4 -0.6 -0.6 -0.7-0.60.4 -0.3 -0.3 0.3 -0.6 0.5 0.9 0.9 -0.71.0 0.9 -0.78.0 -0.8 -0.10.1 DIS - 0.00 RAD -0.40.6 1.0 0.9 1.0 -0.6 8.0 -0.9 -0.20.1 1.0 -0.6 0.1 -0.2 ΤΑΧ 0.8 -0.3 0.7 -0.3 1.0 -0.5 0.3 -0.6 -0.6 0.6 -0.7 -0.60.4 -0.3 - -0.25 PTRATIO 0.5 8.0 8.0 8.0 8.0 1.0 -0.7-0.5 -0.10.0 -0.4 -0.5 -0.5 0.0 -0.10.0 0.2 -0.5 -0.9 -0.8 0.4 -0.8 -0.90.4 -0.71.0 -0.2 0.3 В - -0.50 STAT 0.5 0.4 -0.40.0 0.1 0.0 0.4 -0.10.1 0.3 0.0 -0.21.0 -0.7 MEDV 1.0 -0.3 0.3 -0.40.2 -0.3 0.7 -0.30.1 -0.2-0.3-0.50.3 -0.7ΖŃ RМ PTRATIO в LSTAT MEDV INDUS CHAS NOX AGE DİS RÁD CRIM TAX - -0.75 In [21]: **#Correlation** coefficients df.corr() **INDUS CHAS AGE RAD** TAX PTRATIO **LSTAT** Out[21]: CRIM ΖN NOX RMDIS В **MEDV CRIM** 1.000000 -0.288969 0.586719 -0.067536 -0.139448 -0.185045 0.462470 -0.312843 -0.151996 0.754362 -0.140015 -0.053260 0.392225 -0.286245 **ZN** -0.288969 1.000000 -0.491587 -0.005843 0.038450 0.078721 -0.488006 0.268317 0.062767 -0.256799 0.049491 0.015810 -0.390092 0.331570 **INDUS** 0.586719 -0.491587 1.000000 -0.448809 0.700699 -0.605973 -0.427834 0.233471 0.465583 -0.185873 -0.394483 0.748951 -0.351166 -0.411915 CHAS -0.067536 -0.005843 -0.185873 1.000000 0.585243 0.585447 -0.269616 0.523772 0.587673 -0.347552 0.470870 -0.495956 0.011260 0.154409 0.975767 -0.550065 0.923503 0.079688 **NOX** -0.139448 0.038450 -0.394483 0.585243 1.000000 0.985957 -0.570346 0.775302 -0.856608 -0.332778 **RM** -0.185045 0.078721 -0.448809 0.585447 0.975767 1.000000 -0.595786 0.946946 0.992620 -0.610962 0.806522 -0.848289 0.029450 0.740181 **AGE** 0.462470 -0.488006 0.700699 -0.269616 -0.550065 -0.595786 1.000000 -0.744068 -0.585574 0.635697 -0.477048 0.417216 0.414354 -0.299893 **DIS** -0.312843 0.268317 -0.605973 0.523772 0.923503 0.946946 -0.744068 1.000000 0.947606 -0.689224 0.766224 -0.778075 -0.080368 0.138798 **RAD** -0.151996 0.062767 -0.427834 0.587673 0.985957 0.992620 -0.585574 0.947606 1.000000 -0.586540 0.805556 -0.861694 0.056185 -0.217902 0.754362 -0.256799 0.748951 -0.347552 -0.570346 -0.610962 0.635697 -0.689224 -0.586540 1.000000 -0.485166 0.372806 0.284030 -0.345898 **PTRATIO** -0.140015 0.049491 -0.351166 0.470870 0.775302 0.806522 -0.477048 0.049208 -0.461214 **B** -0.053260 0.015810 0.233471 -0.495956 -0.856608 -0.848289 0.417216 -0.778075 -0.861694 0.372806 -0.690245 1.000000 -0.186021 0.264797 LSTAT -0.706255 0.392225 -0.390092 0.465583 0.011260 0.079688 0.029450 0.414354 -0.080368 0.056185 0.284030 0.049208 -0.1860211.000000 **MEDV** -0.286245 0.331570 -0.411915 0.154409 -0.332778 0.740181 -0.299893 0.138798 -0.217902 -0.345898 -0.461214 0.264797 -0.706255 In [22]: from sklearn.linear_model import LinearRegression In [29]: df1 = pd.read_csv("https://raw.githubusercontent.com/akshaykhadse/ml-linear-regression/master/data/test.csv") In [30]: df1 ID **CRIM** ΖN INDUS CHAS NOX RM AGE DIS RAD TAX PTRATIO **B** LSTAT Out[30]: 30.0 0 0.10612 4.93 0 0.428 6.095 65.1 6.3361 6 300.0 16.6 394.62 12.40 0 0.34109 0.0 7.38 0 0.493 6.415 40.1 4.7211 5 287.0 19.6 396.90 6.12 2 12.24720 2 0.0 18.10 0 0.584 5.837 59.7 1.9976 24.65 15.69 24 666.0 20.2 0.22489 12.5 7.87 0 0.524 6.377 94.3 6.3467 5 311.0 15.2 392.52 20.45 1.80028 0.0 19.58 0 0.605 5.877 79.2 2.4259 5 403.0 14.7 227.61 12.14 **100** 100 0.19073 22.0 5.86 0 0.431 6.718 17.5 7.8265 7 330.0 19.1 393.74 6.56 **101** 101 6.96215 0.0 18.10 0 0.700 5.713 97.0 1.9265 24 666.0 20.2 394.43 17.11 **102** 102 0.05360 21.0 5.64 0 0.439 6.511 21.1 6.8147 4 243.0 16.8 396.90 5.28 **103** 103 0.10469 40.0 6.41 1 0.447 7.267 49.0 4.7872 4 254.0 17.6 389.25 6.05 **104** 104 4.55587 0.0 18.10 0 0.718 3.561 87.9 1.6132 20.2 354.70 24 666.0 7.12 105 rows × 14 columns In [31]: df1.head() ID CRIM ZN INDUS CHAS NOX RM AGE DIS RAD TAX PTRATIO **B** LSTAT Out[31]: 0.10612 30.0 65.1 6.3361 300.0 16.6 394.62 12.40 0 4.93 0 0.428 6.095 6 0.34109 0.0 7.38 0 0.493 6.415 40.1 4.7211 5 287.0 19.6 396.90 6.12 12.24720 0.0 18.10 0 0.584 5.837 59.7 1.9976 24 666.0 20.2 24.65 15.69 0.22489 12.5 7.87 0 0.524 6.377 94.3 6.3467 311.0 392.52 20.45 4 1.80028 0.0 19.58 0 0.605 5.877 79.2 2.4259 5 403.0 14.7 227.61 12.14 In [32]: df2 = pd.read_csv("https://raw.githubusercontent.com/akshaykhadse/ml-linear-regression/master/data/train.csv") In [33]: df2 **CRIM** ZN INDUS CHAS NOX RMAGE DIS RAD TAX PTRATIO B LSTAT **MEDV** ID Out[33]: 88.8 4.4534 0 0.95577 0.0 8.14 0 0.538 6.047 4 307.0 21.0 306.38 17.28 14.8 28.9 3.6659 1 0.02875 28.0 15.04 0 0.464 6.211 4 270.0 18.2 396.33 6.21 25.0 2 1.22358 0 0.605 6.943 5 403.0 0.0 19.58 97.4 1.8773 14.7 363.43 4.59 41.3 3 5.66637 0 0.740 6.219 100.0 2.0048 0.0 18.10 24 666.0 20.2 395.69 16.59 18.4 16.9 368.57 4 0.04544 0.0 3.24 0 0.460 6.144 32.2 5.8736 4 430.0 9.09 19.8 **395** 395 0.03615 23.4 5.1167 19.2 396.90 80.0 4.95 0 0.411 6.630 4 245.0 4.70 27.9 **396** 396 0.17505 5.96 0 0.499 5.966 30.2 3.8473 5 279.0 19.2 393.43 10.13 0.0 24.7 18.10 83.0 2.7344 24 666.0 20.2 396.90 19.5 **397** 397 6.65492 0.0 0 0.713 6.317 13.99 0 0.520 6.127 85.2 2.1224 **398** 398 0.13117 0.0 8.56 5 384.0 20.9 387.69 14.09 20.4 **399** 399 0.06466 70.0 2.24 0 0.400 6.345 20.1 7.8278 5 358.0 14.8 368.24 4.97 22.5 400 rows × 15 columns In [34]: df2.head() **B LSTAT MEDV** Out[34]: CRIM ZN INDUS CHAS NOX RM**AGE** DIS RAD TAX PTRATIO ID 0 0.95577 0.0 8.14 0 0.538 6.047 88.8 4.4534 4 307.0 21.0 306.38 17.28 14.8 **1** 1 0.02875 28.0 15.04 0 0.464 6.211 28.9 3.6659 4 270.0 18.2 396.33 25.0 6.21 5 403.0 2 1.22358 0.0 19.58 0 0.605 6.943 97.4 1.8773 14.7 363.43 4.59 41.3 3 5.66637 0.0 18.10 0 0.740 6.219 100.0 2.0048 24 666.0 20.2 395.69 16.59 18.4 **4** 4 0.04544 0.0 3.24 0 0.460 6.144 32.2 5.8736 4 430.0 16.9 368.57 9.09 19.8 In [57]: # Import phi from train data set phi = np.loadtxt('https://raw.githubusercontent.com/akshaykhadse/ml-linear-regression/master/data/train.csv', dtype='float', delimiter=',', skiprow usecols=tuple(range(1, 14))) In [37]: # Import y from train data set y = np.loadtxt('https://raw.githubusercontent.com/akshaykhadse/ml-linear-regression/master/data/train.csv', dtype='float', delimiter=',', skiprows= usecols=14, ndmin=2) In [38]: # Import phi_test from test data set phi_test = np.loadtxt('https://raw.githubusercontent.com/akshaykhadse/ml-linear-regression/master/data/test.csv', dtype='float', delimiter=',', skiprows=1, usecols=tuple(range(1, 14))) In [58]: # Add a cloloumn of 1s to right of phi and phi_test phi_test = np.concatenate((phi_test, np.ones((105, 1))), axis=1) phi = np.concatenate((phi, np.ones((400, 1))), axis=1) In [65]: # Min Max scaling for phi and phi_test (Feature Engineering) **for** i **in** range(0, 13): $col_max = max(phi[:, i])$ col_min = min(phi[:, i]) phi[:, i] = (phi[:, i] - col_min) / (col_max - col_min) phi_test[:, i] = (phi_test[:, i] - col_min) / (col_max - col_min) In [43]: # Log scaling on y y = np.log(y)In [44]: # Function to calculate change in error function def delta_w(p, phi, w): **if** p == 2: deltaw = (2 * (np.dot(np.transpose(phi), phi), w) np.dot(np.transpose(phi), y)) + lambd * p * np.power(np.absolute(w), (p - 1))) **if** p < 2 **and** p > 1: deltaw = (2 * (np.dot(np.dot(np.transpose(phi), phi), w) np.dot(np.transpose(phi), y)) + lambd * p * np.power(np.absolute(w), (p - 1)) * np.sign(w)) return deltaw In [45]: # Dictionary containing filenames as keys and p as values filenames = {'output.csv': 2.0, 'output_p1.csv': 1.75, 'output_p2.csv': 1.5, 'output_p3.csv': 1.3 In [48]: # For each item in this dictionary for (fname, p) in filenames.items(): # Set initial w to zeros w = np.zeros((14, 1))In [66]: # For each item in this dictionary for (fname, p) in filenames.items(): # Set initial w to zeros w = np.zeros((14, 1))# Hyperparameter lambda value lambd = 0.2# Maximum step size t = 0.00012# Calculate new value of w $w_new = w - t * delta_w(p, phi, w)$ # Repeat steps until error between consecutive w is less than threshold while(np.linalg.norm(w_new-w) > 10 ** -10): w = w_new $w_new = w - t * delta_w(p, phi, w)$ i = i + 1# Load values of id id_test = np.loadtxt('https://raw.githubusercontent.com/akshaykhadse/ml-linear-regression/master/data/test.csv', dtype='int', delimiter=',', skiprows=1, usecols=0, ndmin=2) In [72]: reg = linear_model.LinearRegression() reg.fit(df1[['CRIM','ZN','INDUS','CHAS','NOX','RM','AGE','DIS','RAD','TAX','PTRATIO','B']],df1.LSTAT) LinearRegression() Out[72]: In [73]: reg.coef_ array([0.417071 , -0.01975573, -0.01743688, -0.09044361, 0.19915205, Out[73]: -1.99662069, 0.12803679, 0.79823561, -0.39557847, 0.01229235, 0.50622051, -0.01484531]) In [74]: reg.intercept_ 6.721193193645522