Building a Linear Regression Model to Predict Diabetes Progression

Import software libraries and load the dataset

In [1]:
```python
import sys                                                  # Read system parameters.
import numpy as np                                          # Work with multi-dimensional arrays and matrices.
import pandas as pd                                         # Manipulate and analyze data.
import matplotlib as mpl                                    # Create 2D charts.
import matplotlib.pyplot as plt
import matplotlib.cm as cm
import seaborn as sns                                       # Perform data visualization.
import sklearn                                              # Perform data mining and analysis.
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error

%matplotlib inline

# Summarize software libraries used.
print('Libraries used in this project:')
print('- Python {}'.format(sys.version))
print('- NumPy {}'.format(np.__version__))
print('- pandas {}'.format(pd.__version__))
print('- Matplotlib {}'.format(mpl.__version__))
print('- Seaborn {}'.format(sns.__version__))
print('- scikit-learn {}\n'.format(sklearn.__version__))

# Load the dataset.
diabetes = datasets.load_diabetes()
print('Loaded {} records.'.format(len(diabetes.data)))
```

```
Libraries used in this project:
- Python 3.8.5 (default, Sep  3 2020, 21:29:08) [MSC v.1916 64 bit (AMD64)]
- NumPy 1.19.2
- pandas 1.1.3
- Matplotlib 3.3.2
- Seaborn 0.11.0
- scikit-learn 0.23.2

Loaded 442 records.
```

Get acquainted with the dataset

In [2]:
```python
# Convert array to pandas DataFrame.

# View data types and see if there are missing entries.

# View first 10 records.
```

In [3]:
```python
print(diabetes)
```

```
{'data': array([[ 0.03807591,  0.05068012,  0.06169621, ..., -0.00259226,
         0.01990842, -0.01764613],
       [-0.00188202, -0.04464164, -0.05147406, ..., -0.03949338,
        -0.06832974, -0.09220405],
       [ 0.08529891,  0.05068012,  0.04445121, ..., -0.00259226,
         0.00286377, -0.02593034],
       ...,
       [ 0.04170844,  0.05068012, -0.01590626, ..., -0.01107952,
        -0.04687948,  0.01549073],
       [-0.04547248, -0.04464164,  0.03906215, ...,  0.02655962,
         0.04452837, -0.02593034],
       [-0.04547248, -0.04464164, -0.0730303 , ..., -0.03949338,
        -0.00421986,  0.00306441]]), 'target': array([151.,  75., 141., 206., 135.,  97., 138.,  63., 110.,
310., 101.,
        69., 179., 185., 118., 171., 166., 144.,  97., 168.,  68.,  49.,
        68., 245., 184., 202., 137.,  85., 131., 283., 129.,  59., 341.,
        87.,  65., 102., 265., 276., 252.,  90., 100.,  55.,  61.,  92.,
       259.,  53., 190., 142.,  75., 142., 155., 225.,  59., 104., 182.,
       128.,  52.,  37., 170., 170.,  61., 144.,  52., 128.,  71., 163.,
       150.,  97., 160., 178.,  48., 270., 202., 111.,  85.,  42., 170.,
       200., 252., 113., 143.,  51.,  52., 210.,  65., 141.,  55., 134.,
        42., 111.,  98., 164.,  48.,  96.,  90., 162., 150., 279.,  92.,
        83., 128., 102., 302., 198.,  95.,  53., 134., 144., 232.,  81.,
       104.,  59., 246., 297., 258., 229., 275., 281., 179., 200., 200.,
       173., 180.,  84., 121., 161.,  99., 109., 115., 268., 274., 158.,
       107.,  83., 103., 272.,  85., 280., 336., 281., 118., 317., 235.,
        60., 174., 259., 178., 128.,  96., 126., 288.,  88., 292.,  71.,
       197., 186.,  25.,  84.,  96., 195.,  53., 217., 172., 131., 214.,
        59.,  70., 220., 268., 152.,  47.,  74., 295., 101., 151., 127.,
       237., 225.,  81., 151., 107.,  64., 138., 185., 265., 101., 137.,
       143., 141.,  79., 292., 178.,  91., 116.,  86., 122.,  72., 129.,
       142.,  90., 158.,  39., 196., 222., 277.,  99., 196., 202., 155.,
        77., 191.,  70.,  73.,  49.,  65., 263., 248., 296., 214., 185.,
        78.,  93., 252., 150.,  77., 208.,  77., 108., 160.,  53., 220.,
       154., 259.,  90., 246., 124.,  67.,  72., 257., 262., 275., 177.,
        71.,  47., 187., 125.,  78.,  51., 258., 215., 303., 243.,  91.,
       150., 310., 153., 346.,  63.,  89.,  50.,  39., 103., 308., 116.,
       145.,  74.,  45., 115., 264.,  87., 202., 127., 182., 241.,  66.,
        94., 283.,  64., 102., 200., 265.,  94., 230., 181., 156., 233.,
        60., 219.,  80.,  68., 332., 248.,  84., 200.,  55.,  85.,  89.,
        31., 129.,  83., 275.,  65., 198., 236., 253., 124.,  44., 172.,
       114., 142., 109., 180., 144., 163., 147.,  97., 220., 190., 109.,
       191., 122., 230., 242., 248., 249., 192., 131., 237.,  78., 135.,
       244., 199., 270., 164.,  72.,  96., 306.,  91., 214.,  95., 216.,
       263., 178., 113., 200., 139., 139.,  88., 148.,  88., 243.,  71.,
        77., 109., 272.,  60.,  54., 221.,  90., 311., 281., 182., 321.,
        58., 262., 206., 233., 242., 123., 167.,  63., 197.,  71., 168.,
       140., 217., 121., 235., 245.,  40.,  52., 104., 132.,  88.,  69.,
       219.,  72., 201., 110.,  51., 277.,  63., 118.,  69., 273., 258.,
        43., 198., 242., 232., 175.,  93., 168., 275., 293., 281.,  72.,
       140., 189., 181., 209., 136., 261., 113., 131., 174., 257.,  55.,
        84.,  42., 146., 212., 233.,  91., 111., 152., 120.,  67., 310.,
        94., 183.,  66., 173.,  72.,  49.,  64.,  48., 178., 104., 132.,
       220.,  57.]), 'frame': None, 'DESCR': '.. _diabetes_dataset:\n\nDiabetes dataset\n----------------\n
\nTen baseline variables, age, sex, body mass index, average blood\npressure, and six blood serum measuremen
ts were obtained for each of n =\n442 diabetes patients, as well as the response of interest, a\nquantitativ
e measure of disease progression one year after baseline.\n\n**Data Set Characteristics:**\n\n  :Number of I
nstances: 442\n\n  :Number of Attributes: First 10 columns are numeric predictive values\n\n  :Target: Colum
n 11 is a quantitative measure of disease progression one year after baseline\n\n  :Attribute Information:\n
      - age     age in years\n      - sex\n      - bmi     body mass index\n      - bp      average blood pr
essure\n      - s1      tc, T-Cells (a type of white blood cells)\n      - s2      ldl, low-density lipoprot
eins\n      - s3      hdl, high-density lipoproteins\n      - s4      tch, thyroid stimulating hormone\n
  - s5      ltg, lamotrigine\n      - s6      glu, blood sugar level\n\nNote: Each of these 10 feature varia
bles have been mean centered and scaled by the standard deviation times `n_samples` (i.e. the sum of squares
of each column totals 1).\n\nSource URL:\nhttps://www4.stat.ncsu.edu/~boos/var.select/diabetes.html\n\nFor m
ore information see:\nBradley Efron, Trevor Hastie, Iain Johnstone and Robert Tibshirani (2004) "Least Angle
Regression," Annals of Statistics (with discussion), 407-499.\n(https://web.stanford.edu/~hastie/Papers/LAR
S/LeastAngle_2002.pdf)', 'feature_names': ['age', 'sex', 'bmi', 'bp', 's1', 's2', 's3', 's4', 's5', 's6'],
'data_filename': 'C:\\ProgramData\\Anaconda3\\lib\\site-packages\\sklearn\\datasets\\data\\diabetes_data.cs
v.gz', 'target_filename': 'C:\\ProgramData\\Anaconda3\\lib\\site-packages\\sklearn\\datasets\\data\\diabetes
_target.csv.gz'}
```

In [4]:
```python
type(diabetes)
```

Out[4]:
```
sklearn.utils.Bunch
```

In [5]:
```python
df = pd.DataFrame(pd.DataFrame(diabetes.data, columns=diabetes.feature_names))
```

In [6]:
```python
df["target"] = pd.Series(diabetes.target)
```

In [7]:
```python
df
```

Out[7]:

	age	sex	bmi	bp	s1	s2	s3	s4	s5	s6	target
0	0.038076	0.050680	0.061696	0.021872	-0.044223	-0.034821	-0.043401	-0.002592	0.019908	-0.017646	151.0
1	-0.001882	-0.044642	-0.051474	-0.026328	-0.008449	-0.019163	0.074412	-0.039493	-0.068330	-0.092204	75.0
2	0.085299	0.050680	0.044451	-0.005671	-0.045599	-0.034194	-0.032356	-0.002592	0.002864	-0.025930	141.0
3	-0.089063	-0.044642	-0.011595	-0.036656	0.012191	0.024991	-0.036038	0.034309	0.022692	-0.009362	206.0
4	0.005383	-0.044642	-0.036385	0.021872	0.003935	0.015596	0.008142	-0.002592	-0.031991	-0.046641	135.0
...	...	...	...	...	...	...	...	...	...	...	...
437	0.041708	0.050680	0.019662	0.059744	-0.005697	-0.002566	-0.028674	-0.002592	0.031193	0.007207	178.0
438	-0.005515	0.050680	-0.015906	-0.067642	0.049341	0.079165	-0.028674	0.034309	-0.018118	0.044485	104.0
439	0.041708	0.050680	-0.015906	0.017282	-0.037344	-0.013840	-0.024993	-0.011080	-0.046879	0.015491	132.0
440	-0.045472	-0.044642	0.039062	0.001215	0.016318	0.015283	-0.028674	0.026560	0.044528	-0.025930	220.0
441	-0.045472	-0.044642	-0.073030	-0.081414	0.083740	0.027809	0.173816	-0.039493	-0.004220	0.003064	57.0

442 rows × 11 columns

In [8]:
```python
#df.to_csv("diabetes.csv",index=False)
```

In [9]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 442 entries, 0 to 441
Data columns (total 11 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   age     442 non-null    float64
 1   sex     442 non-null    float64
 2   bmi     442 non-null    float64
 3   bp      442 non-null    float64
 4   s1      442 non-null    float64
 5   s2      442 non-null    float64
 6   s3      442 non-null    float64
 7   s4      442 non-null    float64
 8   s5      442 non-null    float64
 9   s6      442 non-null    float64
 10  target  442 non-null    float64
dtypes: float64(11)
memory usage: 38.1 KB
```

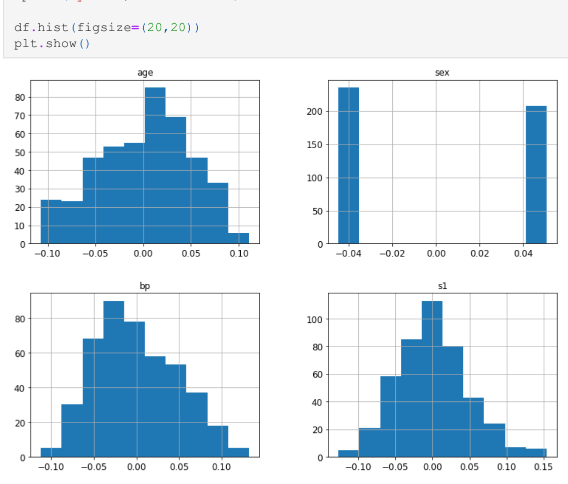
In [10]:
```python
df.head(10)
```

Out[10]:

	age	sex	bmi	bp	s1	s2	s3	s4	s5	s6	target
0	0.038076	0.050680	0.061696	0.021872	-0.044223	-0.034821	-0.043401	-0.002592	0.019908	-0.017646	151.0
1	-0.001882	-0.044642	-0.051474	-0.026328	-0.008449	-0.019163	0.074412	-0.039493	-0.068330	-0.092204	75.0
2	0.085299	0.050680	0.044451	-0.005671	-0.045599	-0.034194	-0.032356	-0.002592	0.002864	-0.025930	141.0
3	-0.089063	-0.044642	-0.011595	-0.036656	0.012191	0.024991	-0.036038	0.034309	0.022692	-0.009362	206.0
4	0.005383	-0.044642	-0.036385	0.021872	0.003935	0.015596	0.008142	-0.002592	-0.031991	-0.046641	135.0
5	-0.092695	-0.044642	-0.040696	-0.019442	-0.068991	-0.079288	0.041277	-0.076395	-0.041180	-0.096346	97.0
6	-0.045472	0.050680	-0.047163	-0.015999	-0.040096	-0.024800	0.000779	-0.039493	-0.062913	-0.038357	138.0
7	0.063504	0.050680	-0.001895	0.066630	0.090620	0.108914	0.022869	0.017703	-0.035817	0.003064	63.0
8	0.041708	0.050680	0.061696	-0.040099	-0.013953	0.006202	-0.028674	-0.002592	-0.014956	0.011349	110.0
9	-0.070900	-0.044642	0.039062	-0.033214	-0.012577	-0.034508	-0.024993	-0.002592	0.067736	-0.013504	310.0

Examine the distribution of various features

In [11]:
```python
# Use Matplotlib to plot distribution histograms for all features.

mpl.rc('axes', labelsize=14)
mpl.rc('xtick', labelsize=12)
mpl.rc('ytick', labelsize=12)

df.hist(figsize=(20,20))
plt.show()
```



Examine a general summary of statistics

In [12]:
```python
# View summary statistics (mean, standard deviation, min, max, etc.) for each feature.
df.describe()
```

Out[12]:

	age	sex	bmi	bp	s1	s2	s3	s4	s5
count	4.420000e+02	4.420000e+02	4.420000e+02	4.420000e+02	4.420000e+02	4.420000e+02	4.420000e+02	4.420000e+02	4.420000e+02
mean	-3.634285e-16	1.308343e-16	-8.045349e-16	1.281655e-16	-8.835316e-17	1.327024e-16	-4.574646e-16	3.777301e-16	-3.830854e-16
std	4.761905e-02	4.761905e-02	4.761905e-02	4.761905e-02	4.761905e-02	4.761905e-02	4.761905e-02	4.761905e-02	4.761905e-02
min	-1.072256e-01	-4.464164e-02	-9.027530e-02	-1.123996e-01	-1.267807e-01	-1.156131e-01	-1.023071e-01	-7.639450e-02	-1.260974e-01
25%	-3.729927e-02	-4.464164e-02	-3.422907e-02	-3.665645e-02	-3.424784e-02	-3.035840e-02	-3.511716e-02	-3.949338e-02	-3.324879e-02
50%	5.383060e-03	-4.464164e-02	-7.283766e-03	-5.670611e-03	-4.320866e-03	-3.819065e-03	-6.584468e-03	-2.592262e-03	-1.947634e-03
75%	3.807591e-02	5.068012e-02	3.124802e-02	3.564384e-02	2.835801e-02	2.984439e-02	2.931150e-02	3.430886e-02	3.243323e-02
max	1.107267e-01	5.068012e-02	1.705552e-01	1.320442e-01	1.539137e-01	1.987880e-01	1.811791e-01	1.852344e-01	1.335990e-01

Look for columns that correlate with `target` (disease progression)

In [13]:
```python
# View the correlation values for each feature compared to the label.

df.corr()
```

Out[13]:

	age	sex	bmi	bp	s1	s2	s3	s4	s5	s6	target
age	1.000000	0.173737	0.185085	0.335427	0.260061	0.219243	-0.075181	0.203841	0.270777	0.301731	0.187889
sex	0.173737	1.000000	0.088161	0.241013	0.035277	0.142637	-0.379090	0.332115	0.149918	0.208133	0.043062
bmi	0.185085	0.088161	1.000000	0.395415	0.249777	0.261170	-0.366811	0.413807	0.446159	0.388680	0.586450
bp	0.335427	0.241013	0.395415	1.000000	0.242470	0.185558	-0.178761	0.257653	0.393478	0.390429	0.441484
s1	0.260061	0.035277	0.249777	0.242470	1.000000	0.896663	0.051519	0.542207	0.515501	0.325717	0.212022
s2	0.219243	0.142637	0.261170	0.185558	0.896663	1.000000	-0.196455	0.659817	0.318353	0.290600	0.174054
s3	-0.075181	-0.379090	-0.366811	-0.178761	0.051519	-0.196455	1.000000	-0.738493	-0.398577	-0.273697	-0.394789
s4	0.203841	0.332115	0.413807	0.257653	0.542207	0.659817	-0.738493	1.000000	0.617857	0.417212	0.430453
s5	0.270777	0.149918	0.446159	0.393478	0.515501	0.318353	-0.398577	0.617857	1.000000	0.464670	0.565883
s6	0.301731	0.208133	0.388680	0.390429	0.325717	0.290600	-0.273697	0.417212	0.464670	1.000000	0.382483
target	0.187889	0.043062	0.586450	0.441484	0.212022	0.174054	-0.394789	0.430453	0.565883	0.382483	1.000000

In [14]:
```python
df.corr()["target"].sort_values()
```

Out[14]:
```
s3       -0.394789
sex       0.043062
s2        0.174054
age       0.187889
s1        0.212022
s6        0.382483
s4        0.430453
bp        0.441484
s5        0.565883
bmi       0.586450
target    1.000000
Name: target, dtype: float64
```

Split the label from the dataset

In [15]:
```python
df = pd.read_csv("diabetes.csv")
```

In [16]:
```python
# Split the training and test datasets and their labels.

# Compare the number of rows and columns in the original data to the training and test sets.

df.shape
```

Out[16]:
```
(442, 11)
```

In [17]:
```python
X = df.iloc[:,0:10]
y = df.iloc[:,10]
```

In [18]:
```python
X.values, y.values
```

Out[18]:
```
(array([[ 0.03807591,  0.05068012,  0.06169621, ..., -0.00259226,
          0.01990842, -0.01764613],
        [-0.00188202, -0.04464164, -0.05147406, ..., -0.03949338,
         -0.06832974, -0.09220405],
        [ 0.08529891,  0.05068012,  0.04445121, ..., -0.00259226,
          0.00286377, -0.02593034],
        ...,
        [ 0.04170844,  0.05068012, -0.01590626, ..., -0.01107952,
         -0.04687948,  0.01549073],
        [-0.04547248, -0.04464164,  0.03906215, ...,  0.02655962,
          0.04452837, -0.02593034],
        [-0.04547248, -0.04464164, -0.0730303 , ..., -0.03949338,
         -0.00421986,  0.00306441]]),
 array([151.,  75., 141., 206., 135.,  97., 138.,  63., 110., 310., 101.,
         69., 179., 185., 118., 171., 166., 144.,  97., 168.,  68.,  49.,
         68., 245., 184., 202., 137.,  85., 131., 283., 129.,  59., 341.,
         87.,  65., 102., 265., 276., 252.,  90., 100.,  55.,  61.,  92.,
        259.,  53., 190., 142.,  75., 142., 155., 225.,  59., 104., 182.,
        128.,  52.,  37., 170., 170.,  61., 144.,  52., 128.,  71., 163.,
        150.,  97., 160., 178.,  48., 270., 202., 111.,  85.,  42., 170.,
        200., 252., 113., 143.,  51.,  52., 210.,  65., 141.,  55., 134.,
         42., 111.,  98., 164.,  48.,  96.,  90., 162., 150., 279.,  92.,
         83., 128., 102., 302., 198.,  95.,  53., 134., 144., 232.,  81.,
        104.,  59., 246., 297., 258., 229., 275., 281., 179., 200., 200.,
        173., 180.,  84., 121., 161.,  99., 109., 115., 268., 274., 158.,
        107.,  83., 103., 272.,  85., 280., 336., 281., 118., 317., 235.,
         60., 174., 259., 178., 128.,  96., 126., 288.,  88., 292.,  71.,
        197., 186.,  25.,  84.,  96., 195.,  53., 217., 172., 131., 214.,
         59.,  70., 220., 268., 152.,  47.,  74., 295., 101., 151., 127.,
        237., 225.,  81., 151., 107.,  64., 138., 185., 265., 101., 137.,
        143., 141.,  79., 292., 178.,  91., 116.,  86., 122.,  72., 129.,
        142.,  90., 158.,  39., 196., 222., 277.,  99., 196., 202., 155.,
         77., 191.,  70.,  73.,  49.,  65., 263., 248., 296., 214., 185.,
         78.,  93., 252., 150.,  77., 208.,  77., 108., 160.,  53., 220.,
        154., 259.,  90., 246., 124.,  67.,  72., 257., 262., 275., 177.,
         71.,  47., 187., 125.,  78.,  51., 258., 215., 303., 243.,  91.,
        150., 310., 153., 346.,  63.,  89.,  50.,  39., 103., 308., 116.,
        145.,  74.,  45., 115., 264.,  87., 202., 127., 182., 241.,  66.,
         94., 283.,  64., 102., 200., 265.,  94., 230., 181., 156., 233.,
         60., 219.,  80.,  68., 332., 248.,  84., 200.,  55.,  85.,  89.,
         31., 129.,  83., 275.,  65., 198., 236., 253., 124.,  44., 172.,
        114., 142., 109., 180., 144., 163., 147.,  97., 220., 190., 109.,
        191., 122., 230., 242., 248., 249., 192., 131., 237.,  78., 135.,
        244., 199., 270., 164.,  72.,  96., 306.,  91., 214.,  95., 216.,
        263., 178., 113., 200., 139., 139.,  88., 148.,  88., 243.,  71.,
         77., 109., 272.,  60.,  54., 221.,  90., 311., 281., 182., 321.,
         58., 262., 206., 233., 242., 123., 167.,  63., 197.,  71., 168.,
        140., 217., 121., 235., 245.,  40.,  52., 104., 132.,  88.,  69.,
        219.,  72., 201., 110.,  51., 277.,  63., 118.,  69., 273., 258.,
         43., 198., 242., 232., 175.,  93., 168., 275., 293., 281.,  72.,
        140., 189., 181., 209., 136., 261., 113., 131., 174., 257.,  55.,
         84.,  42., 146., 212., 233.,  91., 111., 152., 120.,  67., 310.,
         94., 183.,  66., 173.,  72.,  49.,  64.,  48., 178., 104., 132.,
        220.,  57.]))
```

Drop columns that won't be used for training

In [19]:
```python
# Drop the three features that have the least correlation with the label.
X = X.drop(['s3','sex','s2'],axis=1)
```

In [20]:
```python
X
```

Out[20]:

	age	bmi	bp	s1	s4	s5	s6
0	0.038076	0.061696	0.021872	-0.044223	-0.002592	0.019908	-0.017646
1	-0.001882	-0.051474	-0.026328	-0.008449	-0.039493	-0.068330	-0.092204
2	0.085299	0.044451	-0.005671	-0.045599	-0.002592	0.002864	-0.025930
3	-0.089063	-0.011595	-0.036656	0.012191	0.034309	0.022692	-0.009362
4	0.005383	-0.036385	0.021872	0.003935	-0.002592	-0.031991	-0.046641
...	...	...	...	...	...	...	...
437	0.041708	0.019662	0.059744	-0.005697	-0.002592	0.031193	0.007207
438	-0.005515	-0.015906	-0.067642	0.049341	0.034309	-0.018118	0.044485
439	0.041708	-0.015906	0.017282	-0.037344	-0.011080	-0.046879	0.015491
440	-0.045472	0.039062	0.001215	0.016318	0.026560	0.044528	-0.025930
441	-0.045472	-0.073030	-0.081414	0.083740	-0.039493	-0.004220	0.003064

442 rows × 7 columns

In [21]:
```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)
```

In [22]:
```python
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[22]:
```
((353, 7), (89, 7), (353,), (89,))
```

Create a linear regression model

In [23]:
```python
# Construct a basic linear regression class object.

# Fit the training data to the regression object.

lr = LinearRegression()
```

In [24]:
```python
lr.fit(X_train,y_train)
```

Out[24]:
```
LinearRegression()
```

Compare the first ten predictions to actual values

In [25]:
```python
# Make predictions on the test set.

# View examples of the predictions compared to actual disease progression.
```

In [26]:
```python
lr_pred = lr.predict(X_test)
```

In [27]:
```python
lr_pred[:10]
```

Out[27]:
```
array([246.52152298, 237.49962928, 168.15189429, 108.45065349,
       181.207177  , 251.03066105, 105.76063771, 194.56077313,
       144.43387399, 229.1423256 ])
```

In [28]:
```python
y_test[:10]
```

Out[28]:
```
362    321.0
249    215.0
271    127.0
435     64.0
400    175.0
403    275.0
12     179.0
399    232.0
198    142.0
205     99.0
Name: target, dtype: float64
```

In [29]:
```python
X_test
```

Out[29]:

	age	bmi	bp	s1	s4	s5	s6
362	0.019913	0.104809	0.070073	-0.035968	-0.002592	0.003712	0.040343
249	-0.012780	0.060618	0.052858	0.047965	0.034309	0.070211	0.007207
271	0.038076	0.008883	0.042530	-0.042848	-0.002592	-0.018118	0.007207
435	-0.012780	-0.023451	-0.040099	-0.016704	-0.002592	-0.038459	-0.038357
400	-0.023677	0.045529	0.090730	-0.018080	-0.039493	-0.034524	-0.009362
...	...	...	...	...	...	...	...
381	-0.070900	-0.089197	-0.074528	-0.042848	-0.002592	-0.012908	-0.054925
213	0.001751	-0.070875	-0.022885	-0.001569	-0.039493	-0.022512	0.007207
134	-0.074533	0.043373	-0.033214	0.012191	-0.039493	-0.027129	-0.046641
49	-0.041840	0.014272	-0.005671	-0.012577	0.071210	0.035462	-0.013504
52	-0.052738	-0.009439	-0.005671	0.039710	-0.002592	-0.018118	-0.013504

89 rows × 7 columns

In [30]:
```python
table = X_test.copy()
```

In [31]:
```python
table.shape
```

Out[31]:
```
(89, 7)
```

In [32]:
```python
table["True Value"] = y_test.copy()
```

In [33]:
```python
table
```

Out[33]:

	age	bmi	bp	s1	s4	s5	s6	True Value
362	0.019913	0.104809	0.070073	-0.035968	-0.002592	0.003712	0.040343	321.0
249	-0.012780	0.060618	0.052858	0.047965	0.034309	0.070211	0.007207	215.0
271	0.038076	0.008883	0.042530	-0.042848	-0.002592	-0.018118	0.007207	127.0
435	-0.012780	-0.023451	-0.040099	-0.016704	-0.002592	-0.038459	-0.038357	64.0
400	-0.023677	0.045529	0.090730	-0.018080	-0.039493	-0.034524	-0.009362	175.0
...	...	...	...	...	...	...	...	...
381	-0.070900	-0.089197	-0.074528	-0.042848	-0.002592	-0.012908	-0.054925	104.0
213	0.001751	-0.070875	-0.022885	-0.001569	-0.039493	-0.022512	0.007207	49.0
134	-0.074533	0.043373	-0.033214	0.012191	-0.039493	-0.027129	-0.046641	103.0
49	-0.041840	0.014272	-0.005671	-0.012577	0.071210	0.035462	-0.013504	142.0
52	-0.052738	-0.009439	-0.005671	0.039710	-0.002592	-0.018118	-0.013504	59.0

89 rows × 8 columns

In [34]:
```python
table["Predicted"] = np.round(lr_pred,2)
```

In [35]:
```python
table
```

Out[35]:

	age	bmi	bp	s1	s4	s5	s6	True Value	Predicted
362	0.019913	0.104809	0.070073	-0.035968	-0.002592	0.003712	0.040343	321.0	246.52
249	-0.012780	0.060618	0.052858	0.047965	0.034309	0.070211	0.007207	215.0	237.50
271	0.038076	0.008883	0.042530	-0.042848	-0.002592	-0.018118	0.007207	127.0	168.15
435	-0.012780	-0.023451	-0.040099	-0.016704	-0.002592	-0.038459	-0.038357	64.0	108.45
400	-0.023677	0.045529	0.090730	-0.018080	-0.039493	-0.034524	-0.009362	175.0	181.21
...	...	...	...	...	...	...	...	...	...
381	-0.070900	-0.089197	-0.074528	-0.042848	-0.002592	-0.012908	-0.054925	104.0	86.30
213	0.001751	-0.070875	-0.022885	-0.001569	-0.039493	-0.022512	0.007207	49.0	82.69
134	-0.074533	0.043373	-0.033214	0.012191	-0.039493	-0.027129	-0.046641	103.0	145.36
49	-0.041840	0.014272	-0.005671	-0.012577	0.071210	0.035462	-0.013504	142.0	199.57
52	-0.052738	-0.009439	-0.005671	0.039710	-0.002592	-0.018118	-0.013504	59.0	123.23

89 rows × 9 columns

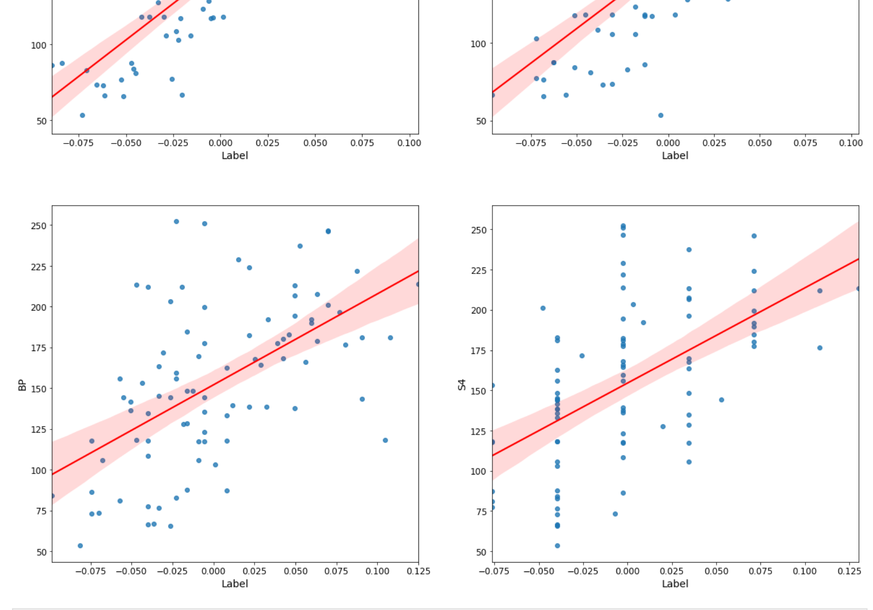
Calculate the error between predicted and actual values

In [36]:
```python
# Print the mean squared error (MSE) for the model's predictions on the test set.
mean_squared_error(y_test,lr_pred)
```

Out[36]:
```
3531.2250809792145
```

Plot lines of best fit for four features

In [37]:
```python
# Use Seaborn to create subplots for the four features that have the strongest correlation with the label.
# Also plot a line of best fit for each feature.

line_color = {'color': 'red'}
fig , ax = plt.subplots(2,2, figsize=(20,20))

#BMI

ax1 = sns.regplot(x=X_test.bmi, y=lr_pred, line_kws=line_color, ax=ax[0,0])
ax1.set_xlabel("Label")
ax1.set_ylabel("BMI")


#s5

ax2 = sns.regplot(x=X_test.s5, y=lr_pred, line_kws=line_color, ax=ax[0,1])
ax2.set_xlabel("Label")
ax2.set_ylabel("S5")


#bp

ax3 = sns.regplot(x=X_test.bp, y=lr_pred, line_kws=line_color, ax=ax[1,0])
ax3.set_xlabel("Label")
ax3.set_ylabel("BP")

#s4

ax4 = sns.regplot(x=X_test.s4, y=lr_pred, line_kws=line_color, ax=ax[1,1])
ax4.set_xlabel("Label")
ax4.set_ylabel("S4")

plt.show()
```



In [ ]: