Code walkthrough - scratch implementation for threshold

Loading data

```
[ ] import pandas as pd
    import numpy as np
```

```
[ ] !gdown 176WcJFfaSz3Yk01TiGEg_EqWgJ4YQEwO
```

```
Downloading...
From: https://drive.google.com/uc?id=176WcJFfaSz3Yk01TiGEg_EqWgJ4YQEwO
To: /content/regData.csv
100% 13.4k/13.4k [00:00<00:00, 15.3MB/s]
```

```
[ ] regression_data = pd.read_csv('regData.csv')
```

```
[ ] regression_data.head()
```

	X	Y
0	1	1.018138
1	2	0.813685
2	3	0.795484
3	4	0.860005
4	5	0.990648

```
[ ] regression_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 600 entries, 0 to 599
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   X       600 non-null    int64
 1   Y       600 non-null    float64
dtypes: float64(1), int64(1)
memory usage: 9.5 KB
```

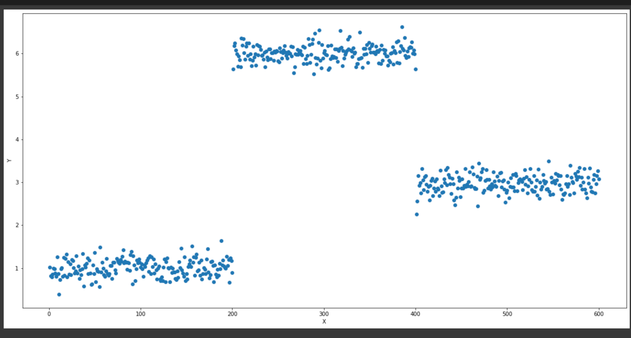
Ther are total of 600 datapoints

```
[ ] X = regression_data['X']
    y = regression_data['Y']
```

Plotting data

```
[ ] from matplotlib import pyplot as plt
```

```
[ ] plt.figure(figsize = (20,10))
    plt.scatter(X,y)
    plt.xlabel('X')
    plt.ylabel('Y')
    plt.show()
```



Splitting data

```
[ ] from sklearn.model_selection import train_test_split
    X_train, X_test, y_train, y_test = train_test_split(X,
                                                        y,
                                                        test_size=0.25,
                                                        random_state=43,
                                                        shuffle = True)
```

Sorting feature to calculate threshold

```
[ ] thresholds = X_train.sort_values().unique()
```

```
[ ] thresholds
```

```
array([  1,   2,   4,   5,   6,   7,   8,   9,  10,  11,  14,  15,  17,
        19,  20,  21,  22,  23,  24,  26,  27,  28,  29,  30,  31,  32,
        33,  34,  35,  37,  38,  39,  40,  41,  42,  43,  44,  45,  46,
        47,  50,  51,  52,  53,  54,  55,  56,  57,  59,  60,  61,  63,
        65,  66,  67,  71,  73,  74,  75,  76,  77,  78,  79,  80,  81,
        82,  84,  85,  86,  87,  88,  89,  90,  92,  93,  94,  95,  96,
        98,  99, 100, 101, 102, 103, 105, 107, 108, 109, 110, 111, 112,
       113, 114, 115, 116, 117, 119, 121, 123, 125, 126, 127, 129, 130,
       132, 133, 134, 135, 136, 137, 138, 141, 147, 148, 149, 150, 152,
       153, 154, 155, 156, 157, 158, 159, 160, 161, 162, 163, 164, 165,
       168, 169, 170, 171, 172, 173, 174, 176, 178, 180, 182, 183, 185,
       188, 189, 190, 194, 195, 198, 199, 200, 201, 202, 203, 205, 208,
       209, 210, 212, 213, 214, 216, 217, 219, 220, 221, 223, 225, 226,
       227, 228, 230, 231, 233, 235, 237, 238, 240, 241, 242, 243, 244,
       245, 246, 247, 249, 253, 254, 255, 256, 258, 259, 260, 263, 264,
       266, 267, 268, 269, 270, 273, 274, 275, 276, 277, 278, 279, 280,
       281, 282, 283, 284, 288, 290, 291, 293, 296, 297, 299, 300, 301,
       302, 304, 305, 306, 307, 308, 310, 313, 314, 315, 317, 318, 320,
       321, 322, 323, 324, 325, 326, 328, 330, 331, 332, 333, 334, 337,
       339, 341, 342, 344, 345, 346, 347, 349, 350, 351, 352, 353, 355,
       356, 357, 358, 360, 361, 363, 365, 366, 368, 369, 371, 374, 375,
       377, 379, 380, 382, 383, 384, 385, 386, 388, 389, 390, 391, 392,
       396, 397, 399, 400, 401, 402, 404, 405, 406, 407, 408, 409, 410,
       411, 412, 413, 414, 415, 416, 417, 418, 419, 420, 421, 422, 423,
       424, 425, 427, 428, 430, 431, 432, 433, 434, 435, 436, 437, 438,
       439, 441, 444, 445, 446, 448, 449, 450, 451, 452, 453, 454, 455,
       456, 457, 458, 459, 460, 461, 464, 465, 466, 467, 468, 469, 470,
       473, 474, 475, 476, 477, 479, 481, 483, 485, 487, 488, 489, 490,
       491, 492, 493, 495, 497, 498, 499, 500, 501, 502, 503, 504, 505,
       507, 509, 510, 511, 512, 513, 514, 515, 516, 517, 518, 519, 520,
       523, 524, 525, 527, 528, 532, 533, 534, 535, 536, 537, 539, 541,
       542, 543, 544, 545, 546, 547, 548, 549, 551, 552, 553, 554, 555,
       558, 561, 562, 563, 564, 568, 569, 570, 571, 572, 573, 575, 576,
       577, 578, 579, 580, 581, 582, 583, 584, 586, 587, 588, 589, 590,
       591, 592, 594, 595, 596, 597, 599, 600])
```

Calculating MSE

```
[ ] def calculate_MSE(y):
        if(y.shape[0] == 0):
            return 0

        y_pred = np.mean(y)

        n = y.shape[0]

        mse = np.sum((y - np.mean(y))**2)
        mse /= n

        return mse
```

Calculating delta MSE

```
[ ] def calulate_deltaMSE(y,mask):
        left_node_count = sum(mask)
        total = mask.shape[0]
        right_node_count = total - left_node_count

        parent_MSE = calculate_MSE(y)

        child_MSE = left_node_count/total*calculate_MSE(y[mask]) + right_node_count/total*calculate_MSE(y[~mask])

        deltaMSE = parent_MSE - child_MSE

        return deltaMSE
```

Calculating best threshold for split

```
[ ] delta_mse_train = []

    for thr in thresholds:
        mask = X_train <= thr

        delta_MSE = calulate_deltaMSE(y_train, mask)

        delta_mse_train.append(delta_MSE)
```

```
[ ] delta_mse_train = np.array(delta_mse_train)

    print(f'Best reduction in MSE is {delta_mse_train.max()} is for threshold: {thresholds[delta_mse_train.argmax()]}')
```

```
Best reduction in MSE is 2.539507086209006 is for threshold: 200
```

Note

sklearn implementation creates thresholds by taking average of two values.

Let's see an example:

- Say, we have feature X_1 as $[1, 2, 3, 4, 5]$.
- So, thresholds here will be $[1.5, 2.5, 3.5, 4.5]$
- i.e. First threshold will be $\frac{1+2}{2} = 1.5$
- Similarly, second threshold will be $\frac{2+3}{2} = 2.5$

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