Implementation of Sequential Estimator and Bayesian Linear Regression

Description:

1. Random Data Generator

- a. Univariate gaussian data generator
 - Input
 - Expectation value or mean: *m*
 - Variance: s
 - Output: A data point from N(m, s)
 - HINT
 - Generating values from normal distribution
 - You have to handcraft your geneartor based on one of the approaches given in the hyperlink.
 - You can use uniform distribution function (Numpy)
- b. Polynomial basis linear model data generator
 - $\circ \ y = W^T \phi(x) + e$
 - W is a $n \times 1$ vector
 - \bullet $e \sim N(0,a)$
 - Input: n (basis number), a, w

• e.g.
$$n=2 \to y=w_0 x^0 + w_1 x^1$$
,

- Output: *y* (a number)
- Internal constraint
 - -1.0 < x < 1.0
 - lacksquare x is uniformly distributed.

2. Sequential Estimator

- Sequential estimate the mean and variance
 - Data is given from the univariate gaussian data generator (1.a).
- Input: m, s as in (1.a)
- Function:
 - Call (1.a) to get a new data point from N(m, s)
 - \circ Use sequential estimation to find the current estimates to m and s

- Repeat steps above until the estimates converge.
- Output: Print the new data point and the current estimiates of m and s in each iteration.
- Notes
 - You should derive the recursive function of mean and variance based on the sequential esitmation.
 - Hint: Online algorithm
- Sample input & output (**for reference only 1**)

```
Data point source function: N(3.0, 5.0)
1
2
3
  Add data point: 3.234685454257290
  Mean = 3.408993960833291 Variance = 0.030383455464755956
  Add data point: 0.519242879651157
  Add data point: 1.347113997201991
  Add data point: 8.979491998496083
10
  11
  Add data point: 3.603448448693051
12 Mean = 3.544547540951477 Variance = 7.270131583917285
  Add data point: 4.127197937610908
13
   Mean = 3.627783311902824  Variance = 6.273110519038578
15 Add data point: 4.992735798186870
   Mean = 3.798402372688330 Variance = 5.692747751482052
16
17
18
19
  Add data point: 4.233592159021013
2.0
  Mean = 2.961576104513964 Variance = 5.045715437349161
21
22 Add data point: 3.529990930040463
23 Mean = 2.961883688294010 Variance = 5.043159812425648
24 Add data point: 1.125210345431449
25 Mean = 2.960890354955524 Variance = 5.042255747918937
```

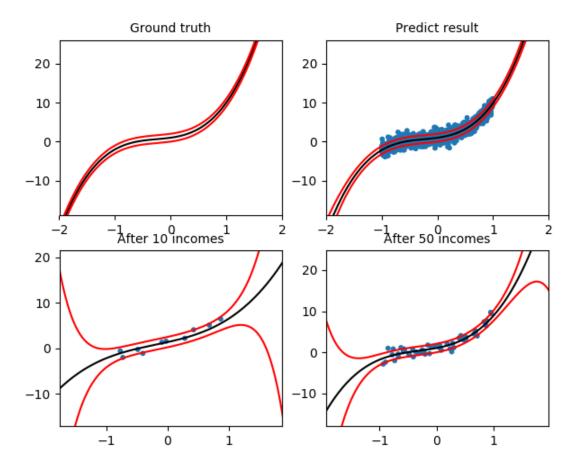
3. Baysian Linear regression

- Input
 - \circ The precision (i.e., b) for initial prior $w \sim N(0, b^{-1}I)$
 - All other required inputs for the polynomial basis linear model geneartor (1.b)
- Function
 - o Call (1.b) to generate one data point
 - Update the prior, and calculate the parameters of predictive distribution
 - Repeat steps above until the posterior probability converges.
- Output
 - Print the new data point and the current paramters for posterior and predictive distribution.

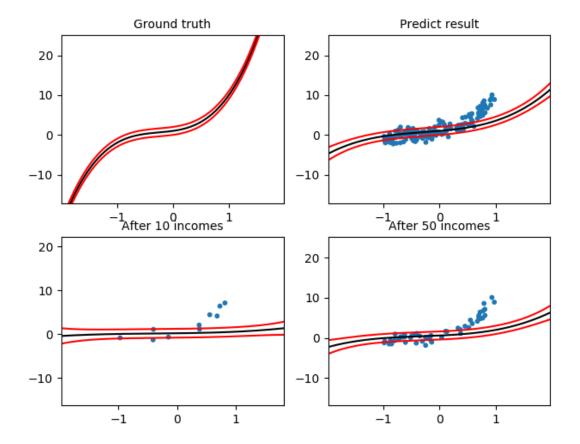
- After probability converged, do the visualization
 - Ground truth function (from linear model generator)
 - Final predict result
 - At the time that have seen 10 data points
 - At the time that have seen 50 data points
 - Note
 - Except ground truth, you have to draw those data points which you have seen before
 - Draw a black line to represent the mean of function at each point
 - Draw two red lines to represent the variance of function at each point
 - In other words, distance between red line and mean is **ONE** variance
- Hint: Online learning
- Sample input & output (for reference only)
- 1. b = 1, n = 4, a = 1, w = [1, 2, 3, 4]

```
Add data point (-0.64152, 0.19039):
2
3
   Postirior mean:
4
     0.0718294547
5
    -0.0460797888
6
     0.0295609502
7
     -0.0189638408
9
   Posterior variance:
     0.6227289276, 0.2420256620, -0.1552634839, 0.0996041049
10
     0.2420256620, 0.8447365161, 0.0996041049, -0.0638976884
11
     -0.1552634839, 0.0996041049, 0.9361023116, 0.0409914289
12
     0.0996041049, -0.0638976884, 0.0409914289, 0.9737033172
13
14
15
   Predictive distribution ~ N(0.00000, 2.65061)
16
   ______
17
   Add data point (0.07122, 1.63175):
18
19
   Postirior mean:
     0.6736864869
20
21
     0.2388980107
22
    -0.1054659080
23
     0.0710615952
24
25
   Posterior variance:
     0.3765992302, 0.1254838660, -0.1000441911, 0.0627881634
2.6
     0.1254838660, 0.7895542671, 0.1257503020, -0.0813299447
27
    -0.1000441911, 0.1257503020, 0.9237138418, 0.0492510997
28
     0.0627881634, -0.0813299447, 0.0492510997, 0.9681964094
29
```

```
30
31
    Predictive distribution ~ N(0.06869, 1.66008)
32
33
    Add data point (-0.19330, 0.24507):
34
   Postirior mean:
35
      0.5760972313
36
37
      0.2450231522
     -0.0801842453
38
39
      0.0504992402
40
   Posterior variance:
41
     0.2867129751, 0.1311255325, -0.0767580827, 0.0438488542
42
      0.1311255325, 0.7892001707, 0.1242887609, -0.0801412282
43
44
     -0.0767580827, 0.1242887609, 0.9176812972, 0.0541575540
      0.0438488542, -0.0801412282, 0.0541575540, 0.9642058389
45
46
47
    Predictive distribution ~ N(0.62305, 1.34848)
48
49
50
51
52
53
    Add data point (-0.76990, -0.34768):
54
55
   Postirior mean:
56
      0.9107496675
57
      1.9265499885
58
      3.1119297129
59
      4.1312375189
60
61 Posterior variance:
      0.0051883836, -0.0004416700, -0.0086000319, 0.0008247001
62
     -0.0004416700, 0.0401966605, 0.0012708906, -0.0554822477
63
     -0.0086000319, 0.0012708906, 0.0265353911, -0.0031205875
64
65
      0.0008247001, -0.0554822477, -0.0031205875, 0.0937197255
66
67
   Predictive distribution \sim N(-0.61566, 1.00921)
68
69
    Add data point (0.36500, 2.22705):
70
71 Postirior mean:
72
      0.9107404583
73
     1.9265225090
74
      3.1119408740
75
      4.1312734131
76
77 Posterior variance:
      0.0051731092, -0.0004872471, -0.0085815201, 0.0008842340
78
```



- 2. b = 100, n = 4, a = 1, w = [1, 2, 3, 4]
- 1 (Console output omitted)



- 3. b = 1, n = 3, a = 3, w = [1, 2, 3]
- 1 (Console output omitted)

