

Introduction to Machine Learning

HW 2

-Kaushal Vinay Nerkar

Collab Notebook link : - <https://colab.research.google.com/drive/1icy-VheLeebTezEmiEx4Y3cjM1yKiAi6?authuser=1#scrollTo=vnd3ezO-qHXw&uniqifier=1>

Question 2

Exercise 2.6

- a) Error bar on train_data for $N=400$, tolerance = 0.05, Hypothesis size = 1000 is 0.11509037065006825
Error bar on test_data for $N=200$, tolerance = 0.05 is 0.09603227913199208
- b) If we reserve more samples for testing, we will get less accurate target function, thus E_{test} will much off compared to E_{in} .

M	T	W	T	F	S	S
Page No.:					YOUVA	
Date:						

Problem 2.12

given $d_{vc} = 10$

confidence = 95% so $\delta = 0.05$

generalization error; $\epsilon = 0.05$

So sample size (N) will be

$$N \geq \frac{8}{\epsilon^2} \ln \left(\frac{4((2N)^{d_{vc}} + 1)}{\delta} \right)$$

So lets take $N = 10^{10}$ as initial in RHS
then we get

$$N \geq \frac{8}{(0.05)^2} \ln \left(\frac{4(2 \times 10^{10})^{10} + 4}{0.05} \right)$$

$$N \geq \frac{8}{(0.05)^2} (241.57)$$

$$N \approx 773,030$$

Now using this $N = 773,030$ we get

$$N \geq \frac{8}{(0.05)^2} \ln \left(\frac{4(2 \times 773030)^{10} + 4}{0.05} \right)$$

$$> \frac{8}{(0.05)^2} (146.89)$$

$$N \approx 470,062$$

Similarly in next iteration using $N = 470,062$

$$\text{we get } N \geq \frac{8}{(0.05)^2} \times (141)$$

$$N \approx 454,143$$

Now using $N \approx 454,143$

$$N \geq \frac{8}{(0.05)^2} (141.5)$$

$$N \approx 452,962$$

Now using $N = 452,962$

$$N \geq \frac{8}{(0.05)^2} (141.55)$$

$$N \approx 4,52,962$$

So here N converged to 452,962

so sample size = 452,962

Question 4

a,b)

M	T	W	T	F	S	S
Page No.:						YOUVA
Date:						

$$f(n) = n^2$$

$$h(n) = an + b$$

data set has 2 points $\{x_1, x_2\}$

thus full dataset is $\{(x_1, x_1^2), (x_2, x_2^2)\}$

$$E_{in}(h) = \sum_{i=1}^2 (h(x_i) - f(x_i))^2$$

$$E_{in}(h) = \sum_{i=1}^2 (ax_i + b - x_i^2)^2$$

$$\frac{\partial E_{in}(h)}{\partial a} = -2 \sum_{i=1}^2 x_i (ax_i + b - x_i^2) \quad \rightarrow (1)$$

$$\frac{\partial E_{in}(h)}{\partial b} = -2 \sum_{i=1}^2 (ax_i + b - x_i^2) \quad \rightarrow (2)$$

so for these 2 equation $\nabla = 0$

thus

from 1

$$x_1^2 - ax_1 - b = 0$$

from 2

$$x_2^2 - ax_2 - b = 0$$

$$a(x_2 - x_1) = x_2^2 - x_1^2$$

$$a = (x_2 + x_1) ; b = -x_1 x_2$$

So $h(n) = a \cdot n + b$

\therefore So $h(n) = (n_1 + n_2) \cdot n - n_1 n_2$

So now average function

is $\bar{g}(n) = E_D[h(n)]$

$$\bar{g}(n) = E_D[n_1 n + n_2 n - n_1 n_2]$$

$$\bar{g}(n) = E_D[n_1] n + E_D[n_2] n - E_D[n_1] E_D[n_2]$$

(b)

To calculate $\bar{g}(n)$

- Compute $h(n)$ for 2 points from $[1, 1]$
- then take average using the points chosen above

for variance

we know $\text{variance} = E_p \left[(h(n) - \bar{g}(n))^2 \right]$

So for the 2 points chosen from $[-1, 1]$

find ~~each~~ $(h(n) - \bar{g}(n))^2$ ~~at each~~ and then

~~sum~~ take average of this for 2 points.

ie
$$\frac{\sum_{i=1}^2 (h(n) - \bar{g}(n))^2}{(N=2)}$$

bias is $E_p \left[(\bar{g}(n) - f(n))^2 \right]$

so similarly as above find average.

of these value at 2 points

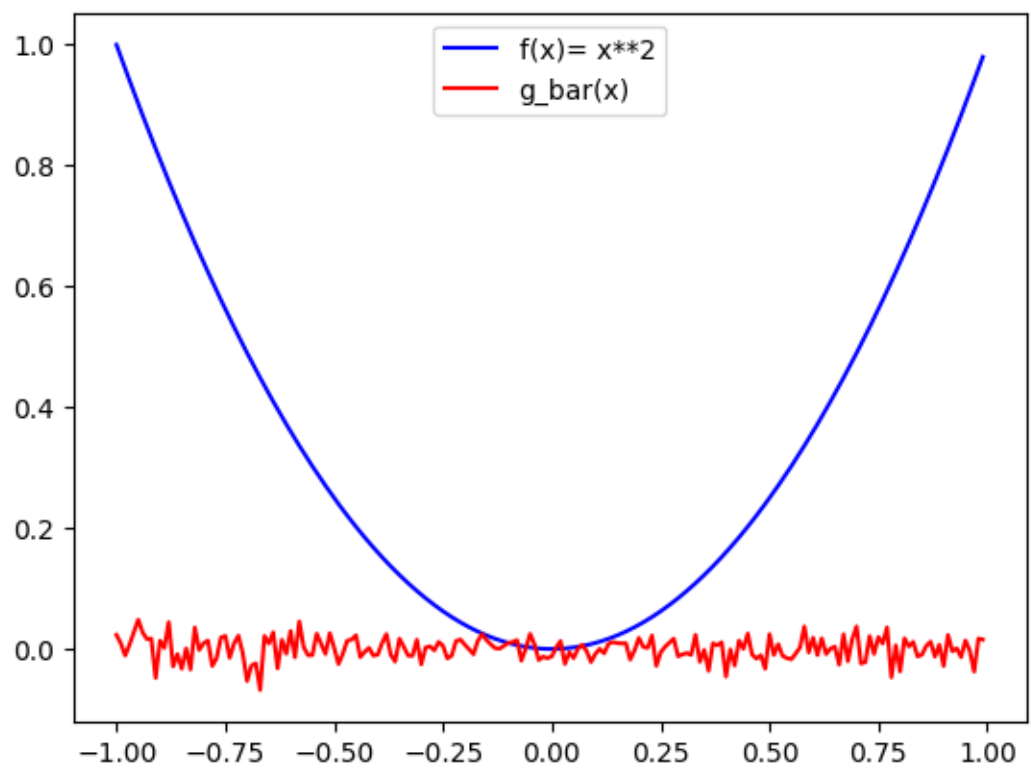
ie
$$\frac{\sum (\bar{g}(n) - f(n))^2}{(N=2)}$$

out of sample error is $E_p \left[(h(n) - f(n))^2 \right]$

so iteratively find average of 2 points

ie
$$\frac{\sum (h(n) - f(n))^2}{(N=2)}$$

c)



Variance = 0.33481

Bias = 0.20162

Eout = 0.5382

sum(variance, bias) = 0.5364

d)

d)

$$\text{Variance} = E_D [(n(x) - \bar{y}(x))^2]$$

$$= E_D [(n_1 + n_2)x - n_1 n_2]^2$$

$$= E_D (n_1^2 + n_2^2 + 2n_1 n_2) x^2$$

$$+ E_D (n_1^2 n_2^2) - 2x E_D (n_1^2 n_2^2 x)$$

$$\text{So } E_D [x^2] = \frac{1}{3}$$

$$E_D [x] = 0$$

$$\text{So } = x^2 \left(\frac{1}{3} + \frac{1}{3} \right) + \left(\frac{1}{3} \times \frac{1}{3} \right) - 2(0 + 0)$$

$$= x^2 \left(\frac{2}{3} \right) + \frac{1}{9}$$

$$= \frac{6x^2 + 1}{9}$$

$$\text{So } = \left(6 \times \frac{1}{3} + 1 \right) / 9 \quad E_D [x^2] = \frac{1}{3}$$

$$\text{Variance} = \frac{1}{3}$$

$$\text{bias} = E_D [(g(n) - f(n))^2]$$

$$= E_D [(0 - n^2)^2]$$

$$= E_D [n^4]$$

$$\because E_D [n^4] = \frac{1}{5}$$

$$= \frac{1}{5}$$

$$E_{out} = E_D [(h(n) - f(n))^2]$$

$$= E_D [((n_1 + n_2)x - n^2)^2]$$

$$= (n_1 + n_2)^2 x^2 + n^4 - 2(n_1 + n_2)x^3$$

$$= n_1^2 x^2 + n_2^2 x^2 + 2n_1 n_2 x^2 + n^4 - 2n_1 x^3 - 2n_2 x^3$$

$$= \frac{1}{9} + \frac{1}{9} + \frac{1}{9} + \frac{1}{5} - 0 - 0$$

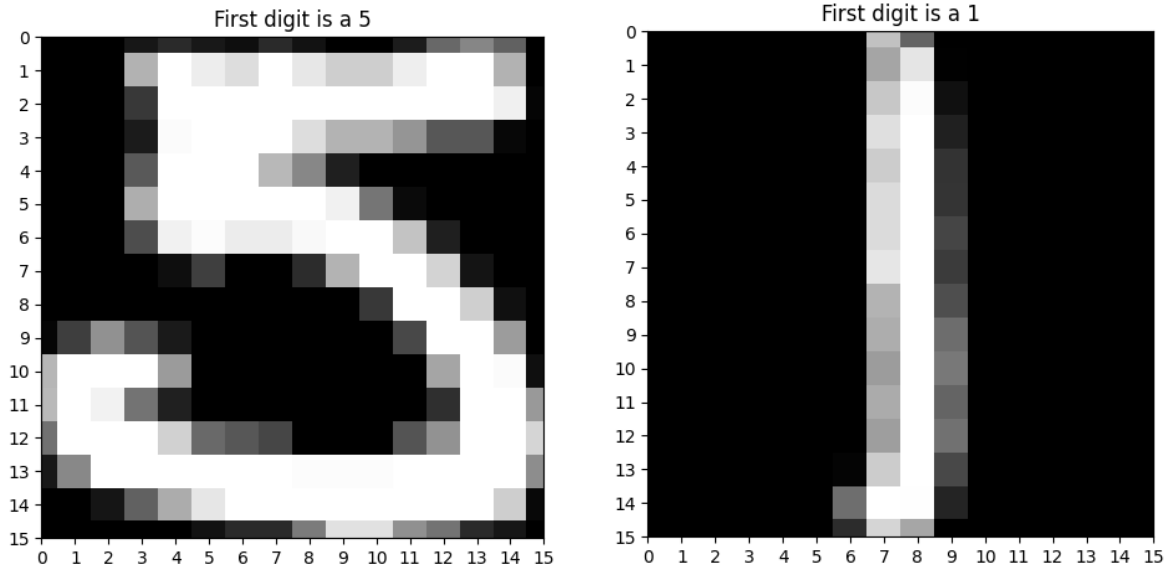
$$= \frac{1}{3} + \frac{1}{5}$$

$$= \frac{8}{15}$$

$$\text{also } E_{out} = \text{variance} + \text{bias}$$

Question 5

a)



b) Average intensity : For a 16 * 16 image with each element between [-1,1] showing intensity. Average intensity is the sum of all pixel intensity over total pixels .

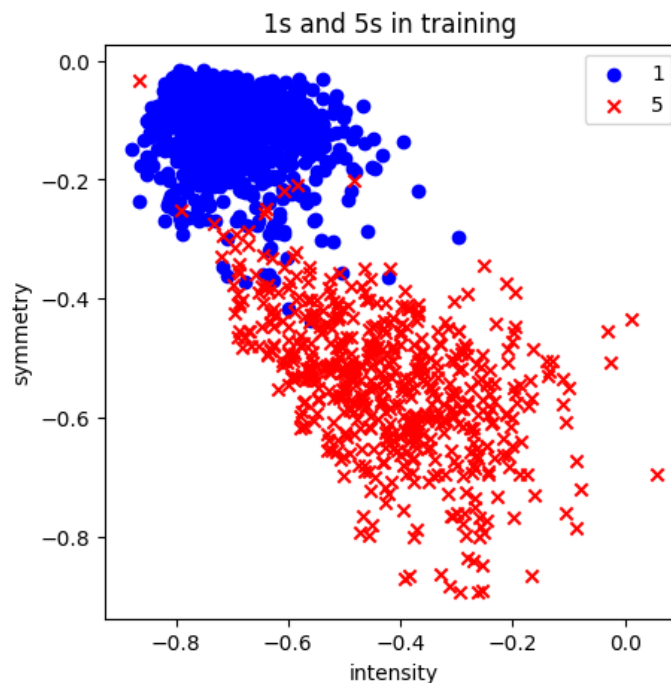
$$\text{Average Intensity} = \frac{\sum_0^{256} \text{pixelIntensity}(i)}{\text{totalpixels}}$$

Symmetry:

Asymmetry is average absolute difference between an image and its flipped versions, and symmetry is then negation of asymmetry. So let X be image and X_flipped be flipped image.

$$\text{symmetryMeasure} = -\frac{\sum_0^{256} |X(i) - X_{\text{flipped}(i)}|}{\text{totalpixels}}$$

c)

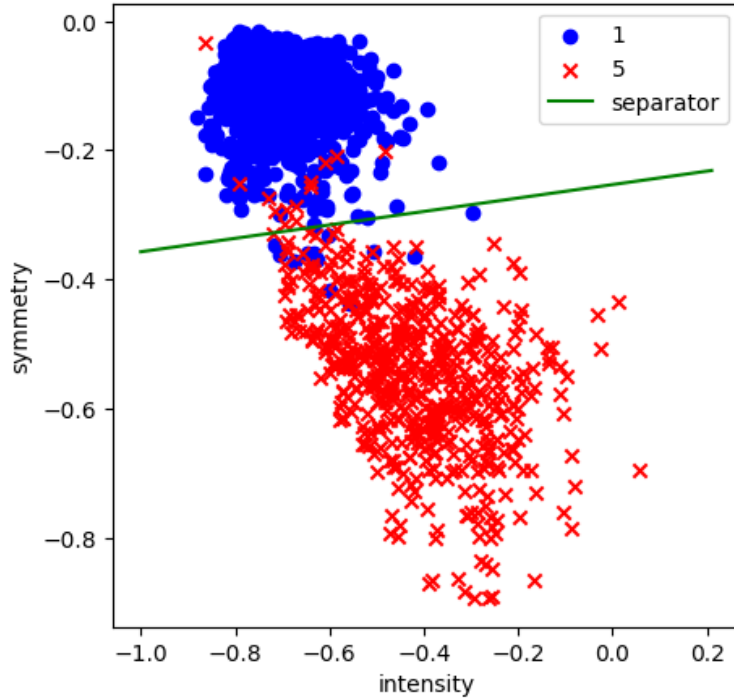


Question 6

Using Linear Regression

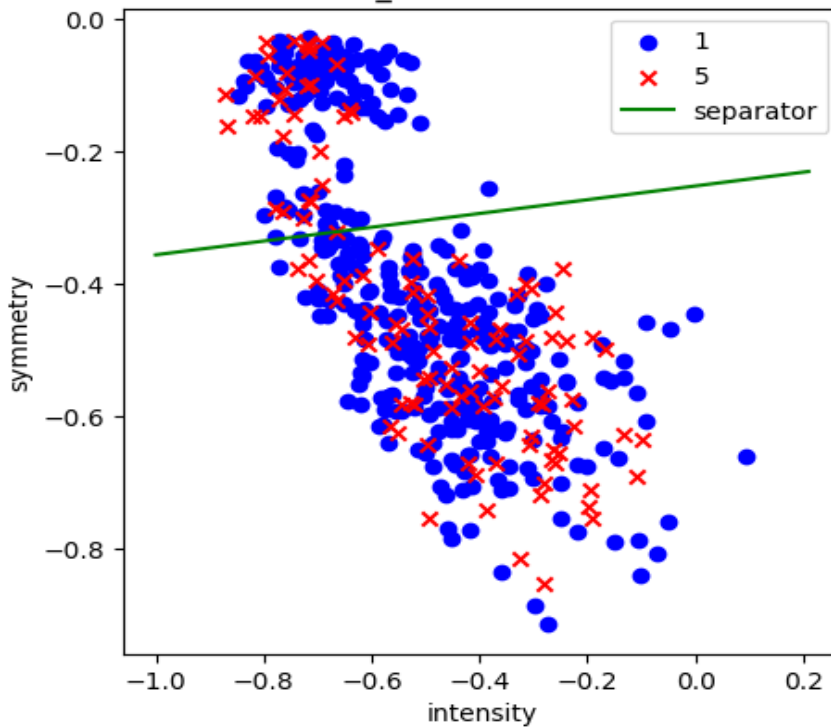
a) From training Data

Pocket algorithm after Linear Regression with 1000 iterations;
 $E_{in}=0.01666$



Below is from Testing Data

On test data;
 $E_{Test}=0.58734$



b) Ein on train data

Ein_best = 0.0166

w_best = [[3.0012006], [-1.23252726], [11.8526552]

E_test on test data

E_test_best = 0.58734

c) Bounds

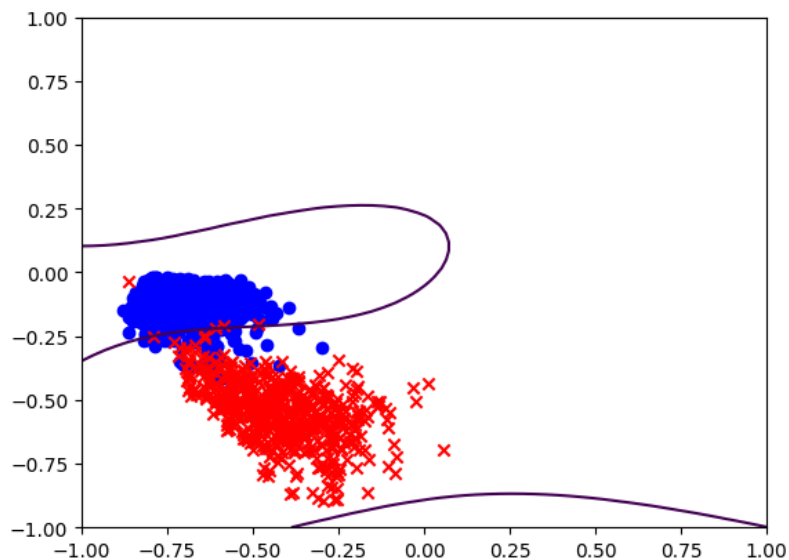
Bound on Eout in train : 0.07490960460609433

Bound on Eout in test : 0.6948963969719182

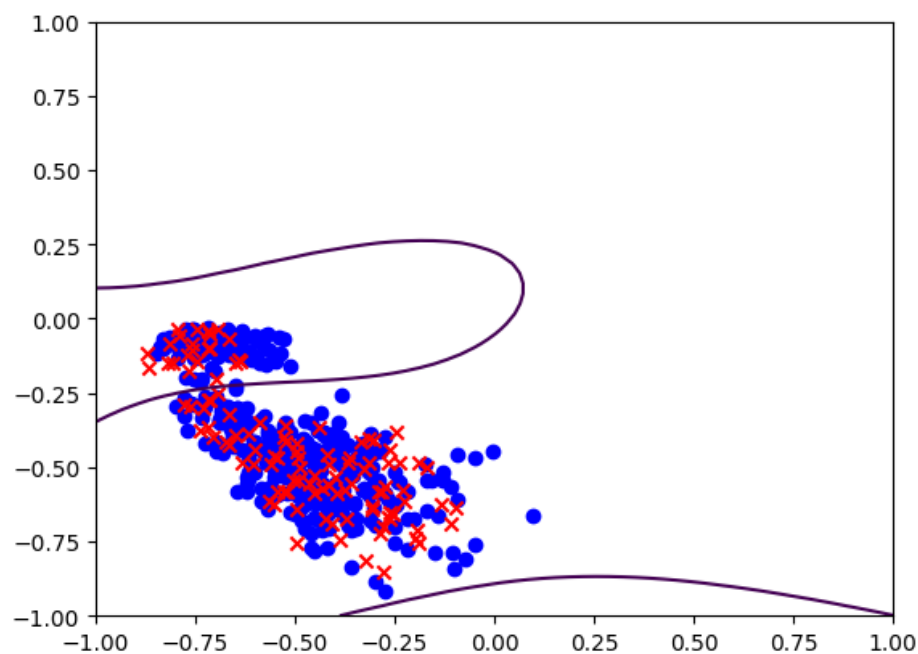
Eout on train data is better than Eout on test as hypothesis(target function) can classify train data much better than test data.

d) After 3rd degree Polynomial transform

On train data



On test data



On train data

$E_{in_best} = 0.016015374759769378$,

$w_{best} = [[2.65603268], [-4.14485003], [6.26405377], [-6.78598422], [-0.92928893], [-13.14130524], [-3.09777974], [-2.89000424], [10.72310204], [-12.93772741]]$

On test data

$E_{test} = 0.58515$

Bound on E_{out} in 3rd degree Poly train : 0.07619660460609433

Bound on E_{out} in 3rd degree Poly test : 0.6927063969719182

e) So Standard Error on Linear Regression = 2.34934498

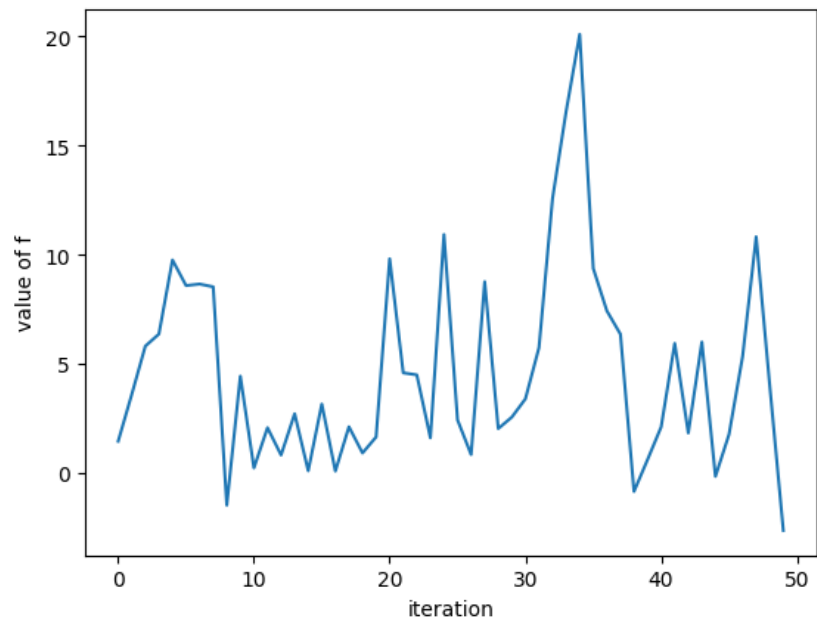
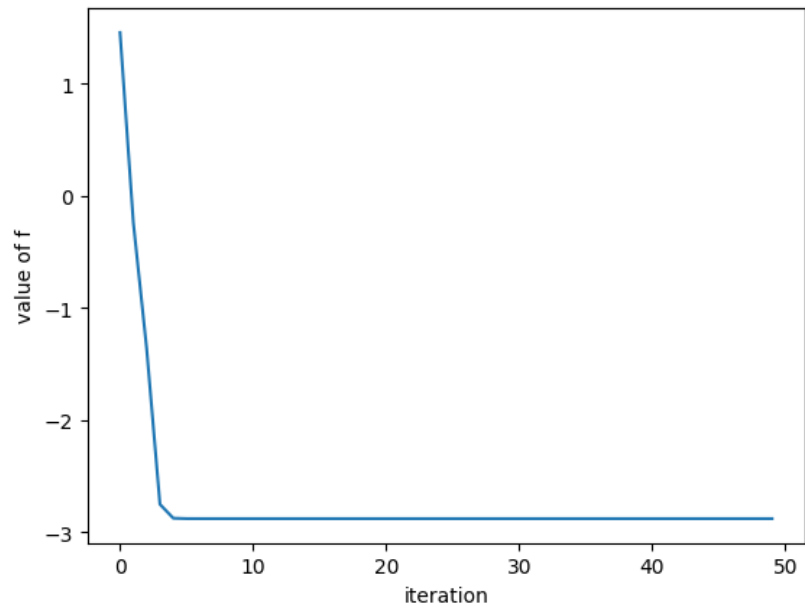
and Standard Error on Linear Regression with polynomial transform = 2.34061135

So, both are comparatively similar thus we will use one without polynomial transform as it will give a simpler target function.

Question 7

$f(x, y) = 2x^2 + y^2 + 3 \sin(2 \pi x) \cos(2 \pi y)$

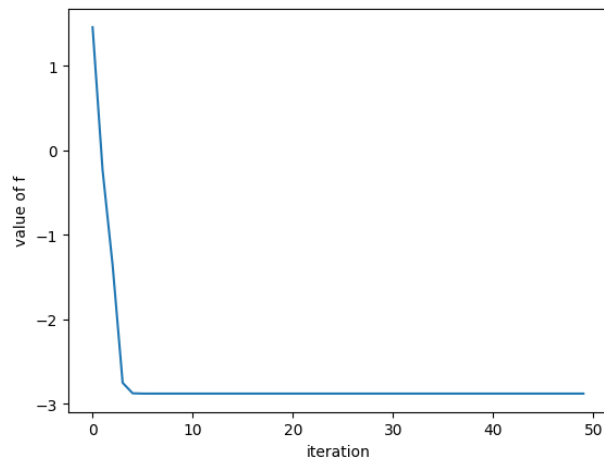
a)



With the increase in Learning Rate, we observe abrupt increase in f values in iterations thus finding global minimum of function becomes difficult.

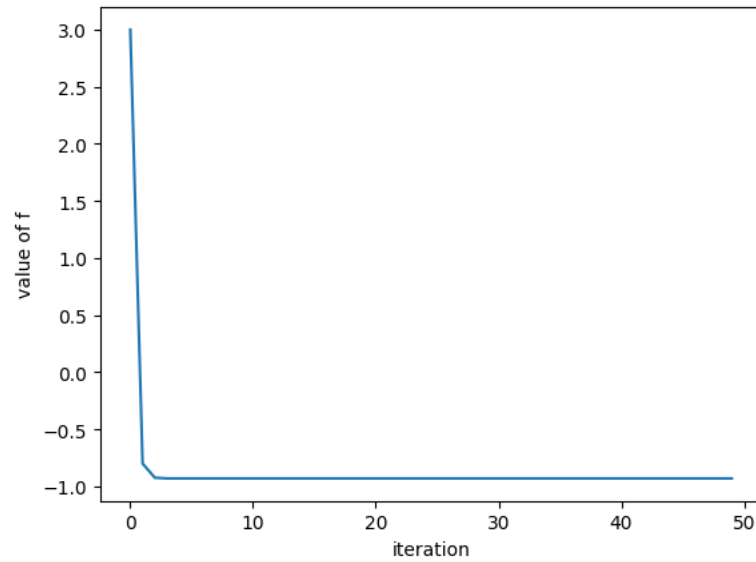
b) Starting points

a. (0.1, 0.1)



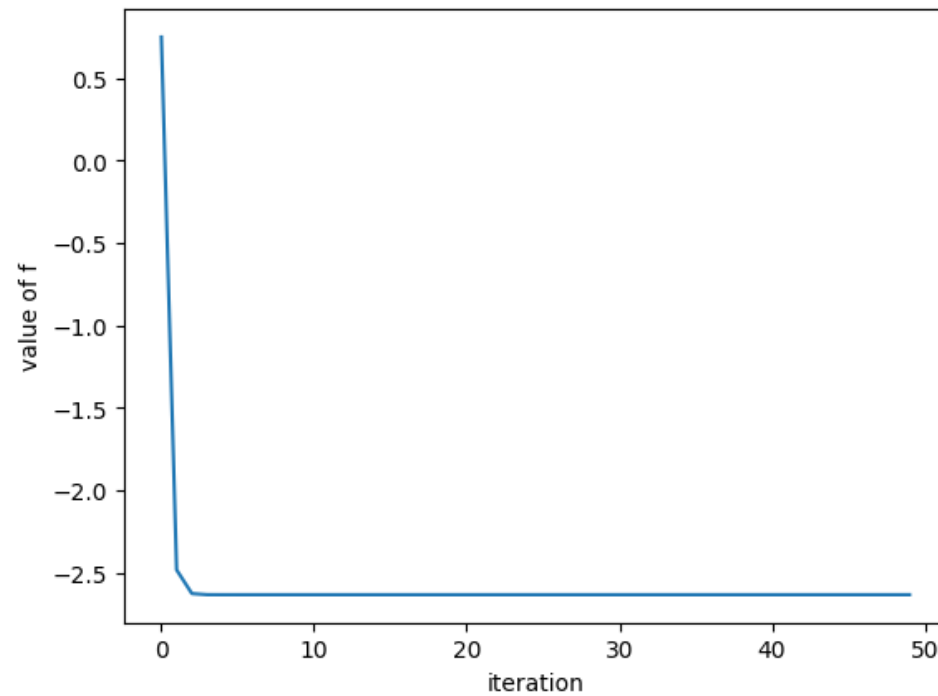
Min Value of f -2.8790846587644263 minX = -0.241828945494765 minY= 1.2269903410060357e-10

b. (1,1)



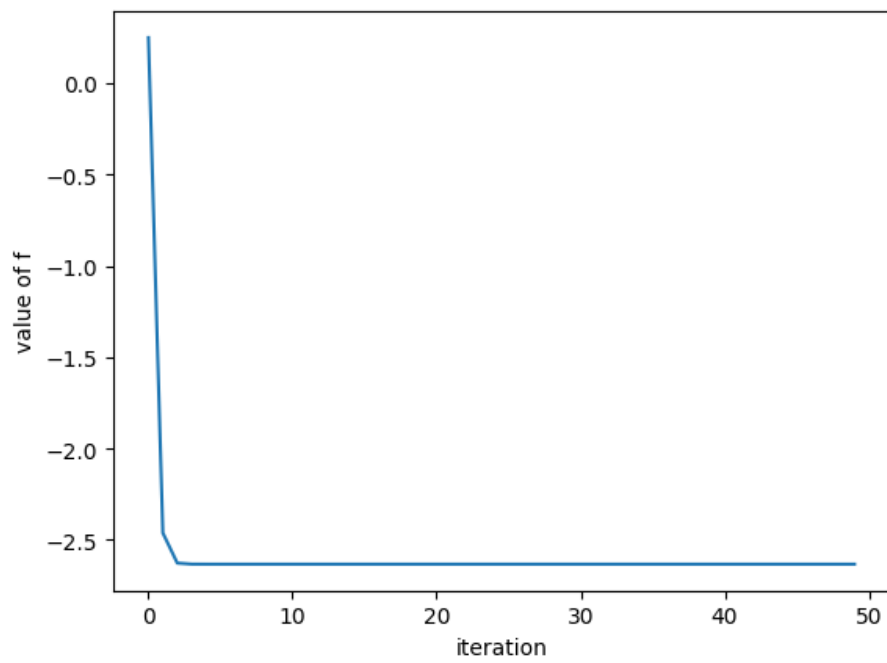
Min Value of f -0.9286447086312597 minX = 0.7252678803578847 minY= 0.9831635693235358

c. (0.5,0.5)



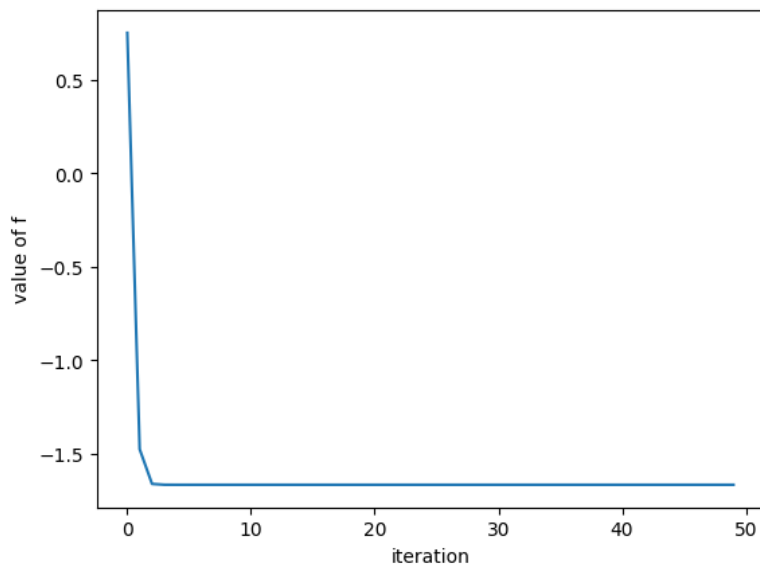
Min Value of f -2.6332425909756374 minX = 0.24181813075115313 minY= 0.4916822590684799

d. (0,0.5)



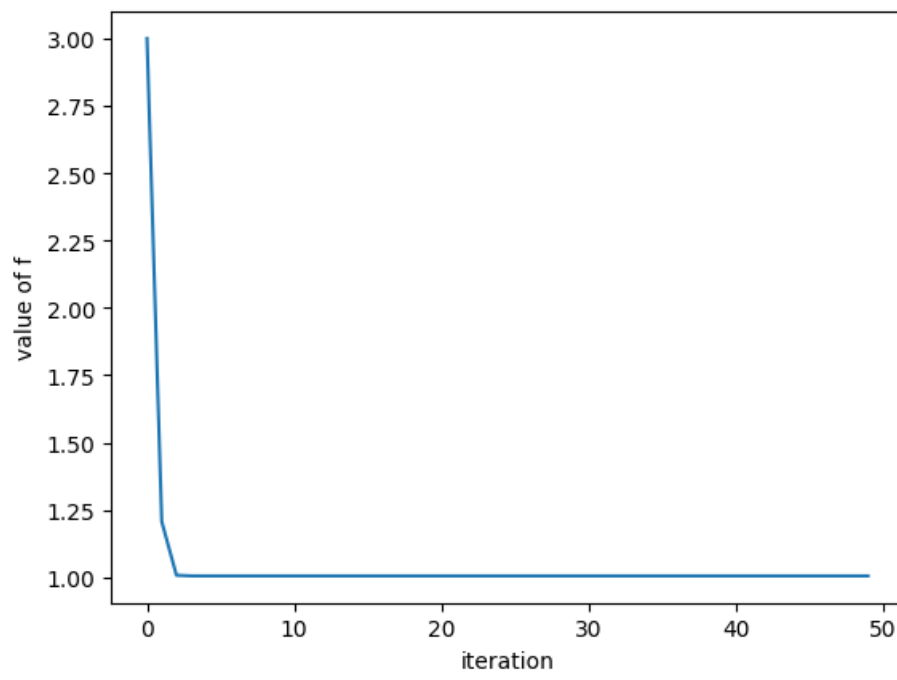
Min Value of f -2.6332425909756374 minX = 0.2418181308911715 minY= 0.49168225905153434

e. (-0.5,-0.5)



Min Value of f -1.6660267055389744 minX = -0.7253691676027778 minY= -0.49159419340047744

f. (-1,1)



Min Value of f 1.0051615759793306 minX = -1.2084759495263497 minY= 0.9827889176426049