



IA353A - Neural Networks EC1

Rafael Claro Ito
(R.A.: 118430)

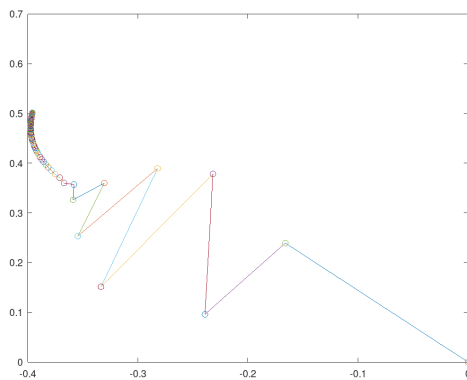
May 2020

Question 1

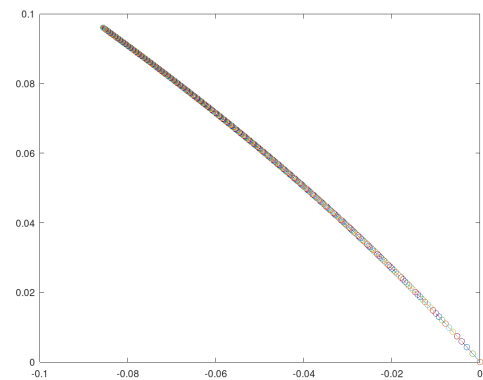
1.1 SGD

1.1.1 Underdetermined

```
1 % SGD para o caso de sistema linear subdeterminado
2 clear all;
3 randn('state',0);
4 N = 10;
5 Nit = 500;
6 X = randn(N,2*N);
7 S = sign(randn(N,1));
8 w = (X'/(X*X'))*S;
9 w1 = zeros(2*N,1);
10 %passo = 0.1;
11 passo = 0.001;
12 for it=2:Nit,
13     w1(:,it) = w1(:,it-1) - (passo/sqrt(it))*(X'*X*w1(:,it-1)-X'*S);
14 end
15 figure(1);
16 title('Stochastic Gradient Descent');
17 for it = 1:(Nit-1),
18     plot([w1(1,it);w1(1,it+1)],[w1(2,it);w1(2,it+1)]);hold on;
19     plot(w1(1,it),w1(2,it),'o');
20     plot(w1(1,it+1),w1(2,it+1),'o');
21 end
22 hold off;
23 disp('[Minimum Norm Solution Obtained solution]');
24 disp([w w1(:,Nit)]);
25 [S X*w X*w1(:,Nit)]
26 %-----
27 % save figure
28 path = strcat(' ../figures/Q1/sgd_under_step_', num2str(passo), '.png');
29 saveas(gcf, path);
```



(a) Progression of W using step of 0.1



(b) Progression of W using step of 0.001

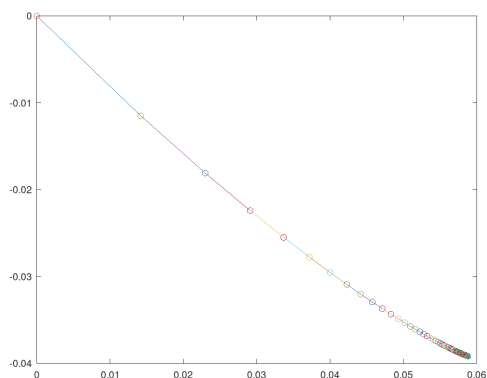
Figure 2: Progression of W for underdetermined system using SGD

1.1.2 Overdetermined

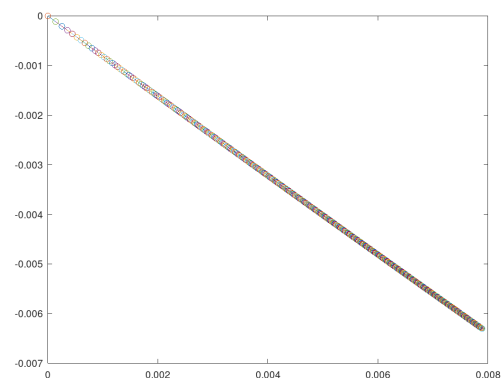
```

1 % SGD para o caso de sistema linear sobredeterminado
2 clear all;
3 randn('state',0);
4 N = 10;
5 Nit = 500;
6 X = randn(N,2);
7 S = sign(randn(N,1));
8 w = (X'*X)\X'*S;
9 disp('Optimal solution');
10 disp(w);
11 w1 = zeros(2,1);
12 %passo = 0.1;
13 passo = 0.001;
14 for it=2:Nit,
15     w1(:,it) = w1(:,it-1) - (passo/sqrt(it))*(X'*X*w1(:,it-1)-X'*S);
16 end
17 figure(1);
18 title('Stochastic Gradient Descent');
19 for it = 1:(Nit-1),
20     plot([w1(1,it);w1(1,it+1)],[w1(2,it);w1(2,it+1)]);hold on;
21     plot(w1(1,it),w1(2,it),'o');
22     plot(w1(1,it+1),w1(2,it+1),'o');
23 end
24 hold off;
25 disp('Obtained solution');
26 disp(w1(:,Nit));
27 [S X*w X*w1(:,Nit)]
28 %-----
29 % save figure
30 path = strcat(' ../figures/Q1/sgd_over_step_', num2str(passo), '.png');
31 saveas(gcf, path);

```



(a) Progression of W using step of 0.1



(b) Progression of W using step of 0.001

Figure 3: Progression of W for overdetermined system using SGD

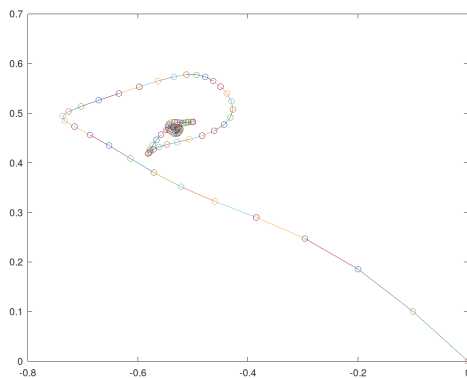
1.2 Adam

1.2.1 Underdetermined

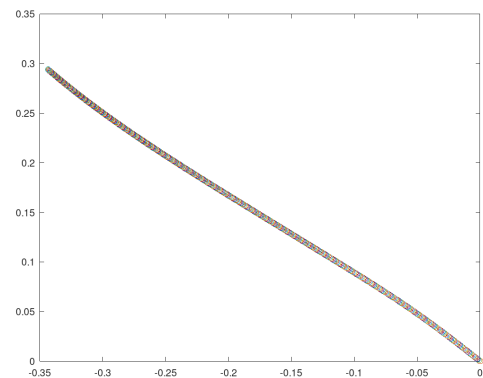
```

1 % Adam para o caso de sistema linear subdeterminado
2 clear all;
3 randn('state',0);
4 N = 10;
5 Nit = 500;
6 X = randn(N,2*N);
7 S = sign(randn(N,1));
8 w = (X'/(X*X'))*S;      % optimal solution
9 w1 = zeros(2*N,1);      % initial weights
10 passo = 0.1;
11 passo = 0.001
12 %-----
13 % parameters
14 beta_1 = 0.9;
15 beta_2 = 0.999;
16 e = 1e-8;
17 m = v = m_hat = v_hat = zeros(2*N,1);
18 %-----
19 % loop
20 for it=2:Nit,
21     g = X'*X*w1(:,it-1)-X'*S;
22     m = beta_1*m + (1-beta_1)*g;
23     v = beta_2*v + (1-beta_2)*g.^2;
24     m_hat = m / (1 - beta_1^(it-1));
25     v_hat = v / (1 - beta_2^(it-1));
26     w1(:,it) = w1(:,it-1) - passo./(sqrt(v_hat) + e) .* m_hat;
27     %w1(:,it) = w1(:,it-1) - (passo/sqrt(it))*(X'*X*w1(:,it-1)-X'*S);
28 end
29 %-----
30 % plot weights
31 figure(1);
32 title('Stochastic Gradient Descent');
33 for it = 1:(Nit-1),
34     plot([w1(1,it);w1(1,it+1)],[w1(2,it);w1(2,it+1)]);hold on;
35     plot(w1(1,it),w1(2,it),'o');
36     plot(w1(1,it+1),w1(2,it+1),'o');
37 end
38 hold off;
39 disp(' [Minimum Norm Solution Obtained solution] ');
40 disp([w w1(:,Nit)]);
41 [S X*w X*w1(:,Nit)]
42 %-----
43 % save figure
44 path = strcat(' ../figures/Q1/adam_under_step_', num2str(passo), '.png');
45 saveas(gcf, path);

```



(a) Progression of W using step of 0.1



(b) Progression of W using step of 0.001

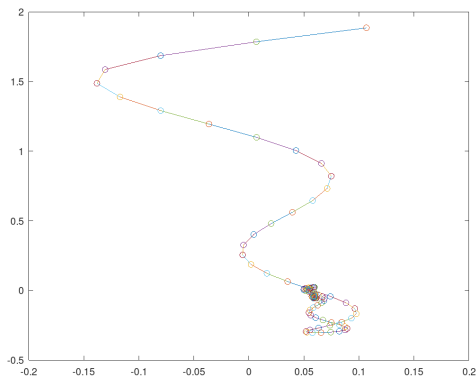
Figure 4: Progression of W for underdetermined system using Adam

1.2.2 Overdetermined

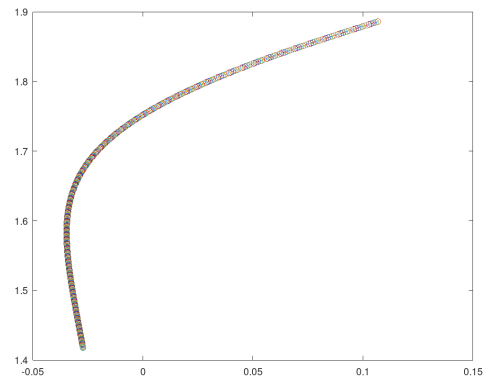
```

1 % Adam para o caso de sistema linear sobredeterminado
2 clear all;
3 randn('state',0);
4 N = 10;
5 Nit = 500;
6 X = randn(N,2);
7 S = sign(randn(N,1));
8 w = (X'*X)\X'*S; % optimal solution
9 disp('Optimal solution');
10 disp(w);
11 w1 = randn(2,1);
12 passo = 0.1;
13 %passo = 0.001
14 %-----
15 % parameters
16 beta_1 = 0.9;
17 beta_2 = 0.999;
18 e = 1e-8;
19 m = v = m_hat = v_hat = zeros(2,1);
20 %-----
21 % loop
22 for it=2:Nit,
23     g = X'*X*w1(:,it-1)-X'*S;
24     m = beta_1*m + (1-beta_1).*g;
25     v = beta_2*v + (1-beta_2).*g.^2;
26     m_hat = m / (1 - beta_1^(it-1));
27     v_hat = v / (1 - beta_2^(it-1));
28     w1(:,it) = w1(:,it-1) - passo./(sqrt(v_hat) + e) .* m_hat;
29     %w1(:,it) = w1(:,it-1) - (passo/sqrt(it))*(X'*X*w1(:,it-1)-X'*S);
30 end
31 %-----
32 % plot weights
33 figure(1);
34 title('Stochastic Gradient Descent');
35 for it = 1:(Nit-1),
36     plot([w1(1,it);w1(1,it+1)],[w1(2,it);w1(2,it+1)]);hold on;
37     plot(w1(1,it),w1(2,it),'o');
38     plot(w1(1,it+1),w1(2,it+1),'o');
39 end
40 hold off;
41 disp('Obtained solution');
42 disp(w1(:,Nit));
43 [S X*w X*w1(:,Nit)]
44 %-----
45 % save figure
46 path = strcat(' ../figures/Q1/adam_over_step_', num2str(passo), '.png');
47 saveas(gcf, path);

```



(a) Progression of W using step of 0.1



(b) Progression of W using step of 0.001

Figure 5: Progression of W for overdetermined system using Adam

1.3 Comparison

	λ optimum	
	MSE	Accuracy
coarse search	64	1024
fine search	51.5	1091.8

Table 1: Values of regularization coefficient found in coarse and fine searches

Question 2

$$\|Ax - b\|_P^2 + \|x - x_0\|_Q^2$$

Since we are searching for x that minimizes the previous expression, we will calculate the derivative with relation to x and set it equal to zero:

$$\frac{d}{dx}(\|Ax - b\|_P^2 + \|x - x_0\|_Q^2) = 0$$

Property used: $\|x\|_Q^2 = x^T Q x$

$$\frac{d}{dx} \left[\overbrace{(Ax - b)^T P (Ax - b)}^{\|Ax - b\|_P^2} + \overbrace{(x - x_0)^T Q (x - x_0)}^{\|x - x_0\|_Q^2} \right] = 0$$

Property used: $(M + N)^T = M^T + N^T$

$$\frac{d}{dx} \{ [(Ax)^T - b^T] P (Ax - b) + (x^T - x_0^T) Q (x - x_0) \} = 0$$

Property used: $(MN)^T = N^T M^T$

$$\frac{d}{dx} \{ [x^T A^T - b^T] P (Ax - b) + (x^T - x_0^T) Q (x - x_0) \} = 0$$

$$\frac{d}{dx} [(x^T A^T P A x - x^T A^T P b - b^T P A x + b^T P b) + (x^T Q x - x^T Q x_0 - x_0^T Q x + x_0^T Q x_0)] = 0$$

Properties used:

- $\frac{d}{dy}(y^T M y) = M^T y + M y$.
- $\frac{d}{dy}(y^T M y) = 2M y$, if $M = M^T$ (i.e. M is symmetric)
- $\frac{d(Ax)}{dx} = A$
- $\frac{d(x^T A)}{dx} = A^T$
- obs.: $A^T P A$ is symmetric, since $(A^T P A)^T = (P A)^T (A^T)^T = A^T P^T A$, but $P^T = P$, since P is symmetric. Then $A^T P A = (A^T P A)^T$

Using the previous properties, we have:

$$\frac{d}{dx} [(x^T A^T P A x - x^T A^T P b - b^T P A x + b^T P b) + (x^T Q x - x^T Q x_0 - x_0^T Q x + x_0^T Q x_0)] = 0$$

$$[2A^T P A x - (A^T P b)^T - b^T P A + 0] + [2Q x - (Q x_0)^T - x_0^T Q + 0] = 0$$

$$2A^T P A x - (P b)^T (A^T)^T - b^T P A + 2Q x - x_0^T Q^T - x_0^T Q = 0$$

$$2A^T P A x - b^T P^T A - b^T P A + 2Q x - x_0^T Q - x_0^T Q = 0$$

$$2A^T P A x - b^T P A - b^T P A + 2Q x - x_0^T Q - x_0^T Q = 0$$

$$2A^T P A x - 2b^T P A + 2Q x - 2x_0^T Q = 0$$

$$2A^T P A x + 2Q x = 2b^T P A + 2x_0^T Q$$

$$A^T P A x + Q x = b^T P A + x_0^T Q$$

$$(A^T P A + Q)^{-1} (A^T P A + Q) x = (A^T P A + Q)^{-1} (b^T P A + x_0^T Q)$$

$$x = (A^T P A + Q)^{-1} (b^T P A + x_0^T Q)$$

$$x = (A^T P A + Q)^{-1} (b^T P^T A + x_0^T Q^T)$$

$$x = (A^T P A + Q)^{-1} [(P b)^T A + (Q x_0)^T]$$

$$x = (A^T P A + Q)^{-1} [(A^T P b)^T + (Q x_0)^T]$$

$$\boxed{x = (A^T P A + Q)^{-1} (A^T P b + Q x_0)^T}$$

Question 3

a)

b)

c)

We want to prove that N may not be unique in $M = N^T N$. For this, let's consider the orthogonal matrix Q and the new matrix that is the result by its multiplication with N , i.e., QN :

$$M = (QN)^T(QN) = (N^T Q^T)(QN) = N^T(Q^T Q)N$$

Since Q is orthogonal, $Q^T Q$ is equal to the identity matrix I . Hence:

$$M = N^T(Q^T Q)N = N^T I N = N^T N$$

So if M can be decomposed in $N^T N$, it can also be decomposed by $(QN)^T(QN)$, with Q being an orthogonal matrix.

d)

Question 4

The Taylor series expansion of a function $f(x, y)$ in a neighborhood around (x_0, y_0) is as follows:

$$f(x, y) \approx f(x_0, y_0) + \underbrace{f_x(x_0, y_0)(x - x_0) + f_y(x_0, y_0)(y - y_0)}_{\text{first order term}} + \dots$$

Ignoring terms from second order and higher, and considering the linearized function given $f_L(x, y) = 2x + py - 8$, we have:

$$f_L(x, y) = f(x_0, y_0) + f_x(x_0, y_0)(x - x_0) + f_y(x_0, y_0)(y - y_0)$$

Taking $f(x, y) = x\sqrt{y}$, we have:

- $f_x(x, y) = \sqrt{y}$
- $f_y(x, y) = \frac{x}{2\sqrt{y}}$

$$2x + py - 8 = \underbrace{x_0\sqrt{y_0}}_{f(x_0, y_0)} + \underbrace{\sqrt{y_0}}_{f_x(x_0, y_0)}(x - x_0) + \underbrace{\frac{x_0}{2\sqrt{y_0}}}_{f_y(x_0, y_0)}(y - y_0)$$

$$2x + py - 8 = x_0\sqrt{y_0} + x\sqrt{y_0} - x_0\sqrt{y_0} + \frac{x_0 y}{2\sqrt{y_0}} - \frac{x_0 y_0}{2\sqrt{y_0}}$$

$$2x + py - 8 = \sqrt{y_0}x + \left(\frac{x_0}{2\sqrt{y_0}}\right)y - \left(\frac{x_0 y_0}{2\sqrt{y_0}}\right)$$

Now, if we compare the terms that only depend on x , that only depend on y and the independent terms (that only depend on x_0 and y_0), we have:

- (i) $2 = \sqrt{y_0} \implies \boxed{y_0 = 4}$
- (ii) $p = \left(\frac{x_0}{2\sqrt{y_0}}\right)$
- (iii) $8 = \left(\frac{x_0 y_0}{2\sqrt{y_0}}\right)$

Substituting in (i) in (iii):

$$\frac{x_0 y_0}{2\sqrt{y_0}} = 8$$

$$\frac{4x_0}{2 \cdot 2} = 8$$

$$\boxed{x_0 = 8}$$

Substituting in (ii):

$$p = \frac{x_0}{2\sqrt{y_0}}$$

$$p = \frac{8}{2 \cdot 2}$$

$$\boxed{p = 2}$$

So the point from where the function was linearized is $(x_0, y_0) = (8, 4)$ and the coefficient $p = 2$, then $f_L(x, y) = 2x + 2y - 8$.

Question 5

Question 6

O primeiro paper selecionado é de 2002 com 2173 citações. Esse paper foi publicado no JAMA (The Journal of the American Medical Association) que é um jornal da área médica com 48 publicações por ano pela AMA (American Medical Association).

title: Effects of Cognitive Training Interventions With Older Adults - A Randomized Controlled Trial
year: 2002 cited by: 2173 publication: JAMA reference:

Ball K, Berch DB, Helmers KF, et al. Effects of Cognitive Training Interventions With Older Adults: A Randomized Controlled Trial. JAMA. 2002;288(18):2271–2281. doi:10.1001/jama.288.18.2271

O segundo paper selecionado é de 2009 e conta com 315 citações. Esse paper foi publicado no jornal acadêmico Alzheimer's & Dementia, que conta com publicações mensais da associação sem fins lucrativos Journal of the Alzheimer's Association.

title: Immediate and delayed effects of cognitive interventions in healthy elderly: A review of current literature and future directions year: 2009 cited by: 315 publication: Alzheimer's & Dementia (Volume 5, Issue 1, January 2009, Pages 50-60) reference:

Papp K V, Walsh S J, Snyder P J. Immediate and delayed effects of cognitive interventions in healthy elderly: a review of current literature and future directions. Alzheimer's and Dementia 2009; 5(1): 50-60. [PubMed]