UNIVERSIDAD NACIONAL DE INGENIERÍA

FACULTAD DE CIENCIAS

INTELIGENCIA ARTIFICIAL



Informe 1 : REDES NEURONALES

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1. Redes Neuronales

En el presente informe se analiza los algoritmos de aprendizaje Batch y Patron. La red neuronal presenta una sola capa oculta.

Las variaciones se realizan en las funciones de sigmoidea y gaussiana, variando el parametro de aprendizaje (eta) y el número de neuronas en la única capa oculta (nm).

Todas las pruebas con con bias.

1.1. Entrenamiento Batch

```
% Entrenamiento Batch con bias
clear;
clc;
close all;
a = 3;
b = 4;
x = -4:0.1:4;
x = x';
N = length(x);
yb = a*x + b;
yb = yb + 0.75*randn(N,1);
ne = 1;
nm = 5;
bias = input('Bias: \_SI = 1: ');
if(bias == 1)
ne = ne +1;
x = [x ones(N,1)];
end
v = 0.15*randn(ne,nm);
w = 0.15*randn(nm, 1);
eta = input('eta_:_')
for iter = 1:2000
         dJdv = 0;
         dJdw = 0;
         for k = 1:N
                 in = (x(k,:))';
                 m = v' * in;
                 n = 2.0./(1 + exp(-m)) - 1;
                                                   % Sigmoidea 2
                  \% n = exp(-m.^2);
                                                      % Gaussiana
                  out = w'*n;
                 y(k,1) = out;
                  er = out - yb(k,1);
                 \mathbf{error}(\mathbf{k}, 1) = \mathbf{er};
                 dndm = (1 - n.*n)/2;
                  \% \ dndm = -2.0*(n.*m);
```

```
\begin{array}{c} {\rm d} J{\rm d} w \,=\, {\rm d} J{\rm d} w \,+\, {\rm er\,.*n\,;} \\ {\rm d} J{\rm d} v \,=\, {\rm d} J{\rm d} v \,+\, {\rm er\,.*in\,*}(w.**{\rm d} n{\rm d} m)\,\,{\rm ';} \\ {\it \%}\,\,w \,=\, w \,-\, et\, a*\, dJ{\rm d} w/nx\,; \\ {\it \%}\,\,v \,=\, v \,-\, et\, a*\, dJ{\rm d} v/nx\,; \\ {\it end} \\ {\it w} \,=\, w \,-\, et\, a*\, dJ{\rm d} v/N\,; \\ {\it v} \,=\, v \,-\, et\, a*\, dJ{\rm d} v/N\,; \\ {\it J} J \,=\, 0.5*{\it sum}({\it error\,.*error\,}) \\ {\it J}(\,iter\,\,,1) \,=\, JJ\,; \\ {\it end} \\ {\it figure}\,\,(1)\,; \\ {\it plot}\,\,(x\,(:\,,1)\,\,,y\,,x\,(:\,,1)\,\,,yb\,,\,\,'*\,\,')\,; \\ {\it figure}\,\,(2)\,; \\ {\it plot}\,\,(J)\,; \end{array}
```

1.1.1. Función Sigmoidea 2

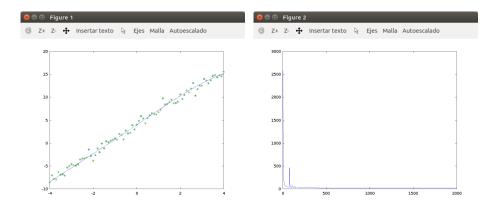


Figura 1: Usando nm 5, eta 0.1

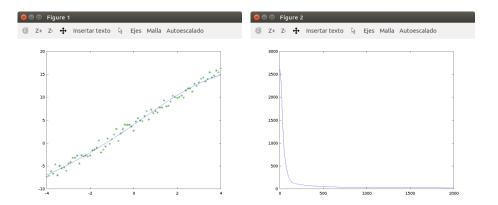


Figura 2: Usando nm 5, eta $0.01\,$

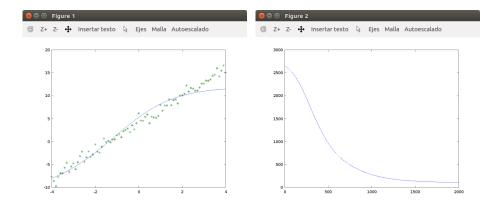


Figura 3: Usando nm 5, eta 0.001

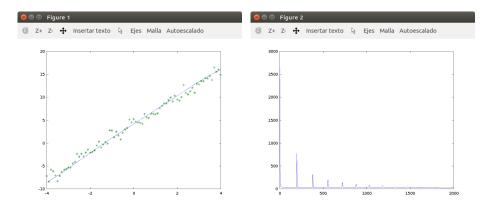


Figura 4: Usando nm 25, eta $0.1\,$

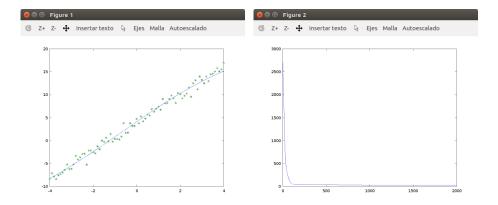


Figura 5: Usando nm 25, eta 0.01

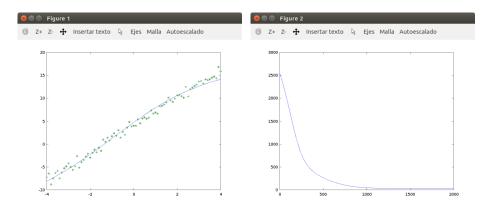


Figura 6: Usando nm 25, eta 0.001

1.1.2. Función Gaussiana

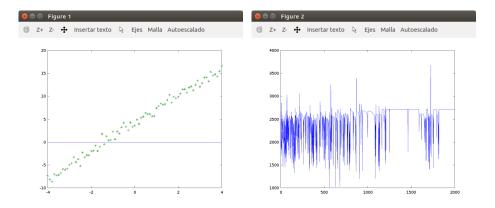


Figura 7: Usando nm 5, eta 0.1

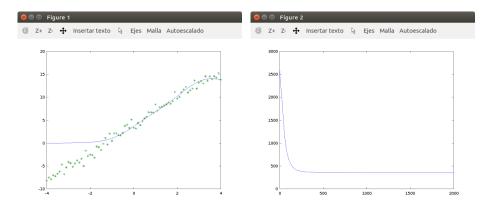


Figura 8: Usando nm 5, eta $0.01\,$

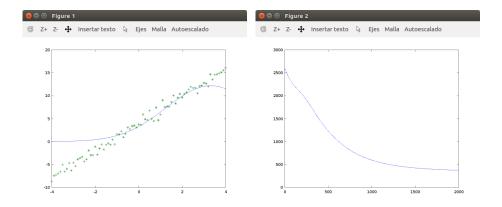


Figura 9: Usando nm 5, eta 0.001

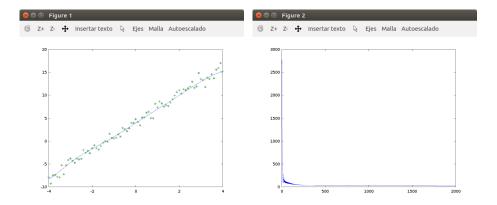


Figura 10: Usando nm25,eta $0.1\,$

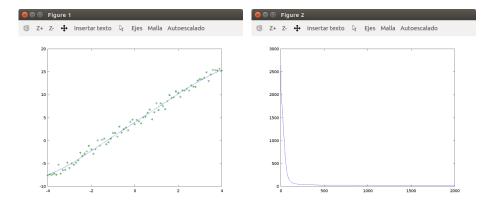


Figura 11: Usando nm 25, eta 0.01

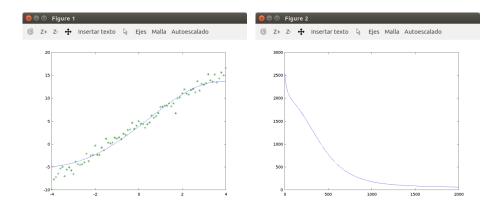


Figura 12: Usando nm25,eta 0.001

1.2. Entrenamiento Patron

% Entrenamiento Patron con bias

```
clear;
clc;
close all;
disp('Hello');
a = 1;
b = 2;
x = -2:0.05:3;
x = x';
N = length(x);
yb = a*x + b + 0.2*randn(N,1);
ne = 1;
nm = 5;
bias = input('Bias:__SI_=_1_:_');
if (bias == 1)
ne = ne +1;
x = [x ones(N,1)];
end
   = 0.25*randn(ne,nm);
w = 0.25*randn(nm, 1);
Jold = 1e15;
eta = input('eta_:_');
\mathbf{for} \quad \mathtt{iter} \ = \ 1\!:\!5000
```

```
w11(iter, 1) = w(1, 1);
         dJdv = 0;
                         dJdw = 0;
         for k = 1:N
                  in = (x(k,:))';
                  m = v' * in;
                  \% = 1.0./(1+exp(-m));
                                                   % Sigmoidea 1
                  n = 2.0./(1 + \exp(-m)) - 1; % Sigmoidea 2
                  \% n = exp(-m.^2);
                                                   % Gaussiana
                  out = w'*n;
                  y(k,1) = out;
                  er = out - yb(k,1);
                  \mathbf{error}(\mathbf{k}, 1) = \mathbf{er};
                  % ndm = n.*(1-n);
                                            \% Sigmoidea 1
                  dndm = (1 - n.*n)/2;
                                             % Sigmoidea 2
                  \% \ dndm = -2.0*(n.*m);
                                                % Gaussiana
                  dJdw = 0*dJdw + er.*n;
                  dJdv = 0*dJdv + er.*in*(w.*dndm)';
                  w = w - eta*dJdw;
                  v = v - eta*dJdv;
         end
         \% w = w - eta*dJdw/N;
         \% v = v - eta*dJdv/N;
         JJ = 0.5*sum(error.*error)
         dJ = \mathbf{abs}(JJ - Jold);
         dJpor = sqrt(dJ/JJ)*100;
         if(dJpor < 0.75)
                             \% Porcentual
                  break;
         end
         J(iter, 1) = JJ;
         Jold = JJ;
end
figure (1);
plot(x(:,1),y,x(:,1),yb,'*');
figure (2);
subplot (2,1,1);
                  plot(J);
\mathbf{subplot}(2,1,2); \quad \mathbf{plot}(w11);
```

1.2.1. Función Sigmoidea 2

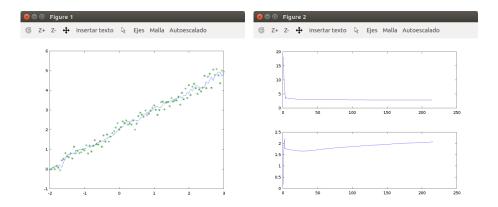


Figura 13: Usando n
m5,eta $0.1\,$

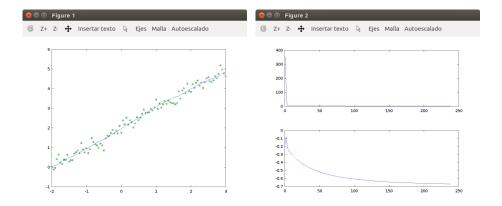


Figura 14: Usando nm 5, eta $0.01\,$

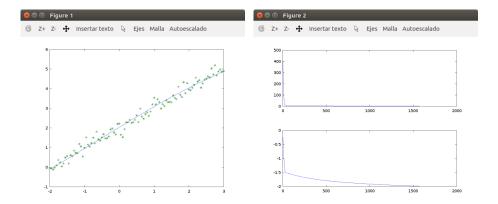


Figura 15: Usando nm 5, eta 0.001

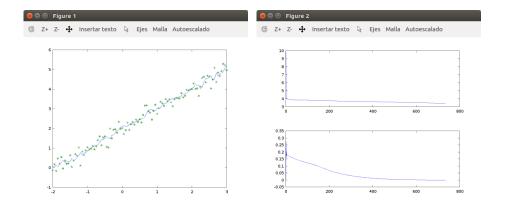


Figura 16: Usando nm 25, eta 0.1

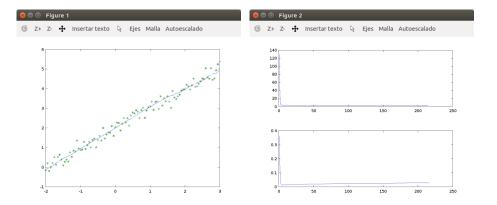


Figura 17: Usando nm 25, eta 0.01

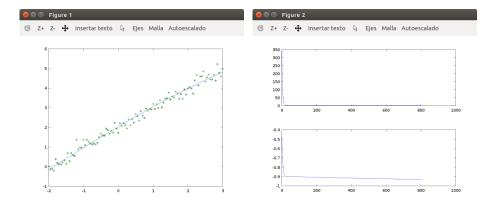


Figura 18: Usando nm 25, eta 0.001

1.2.2. Función Gaussiana

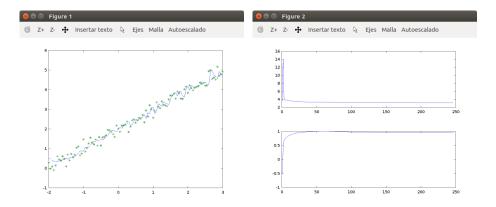


Figura 19: Usando nm 5, eta 0.1

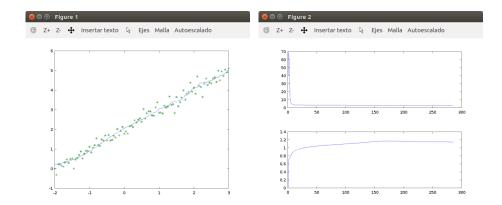


Figura 20: Usando nm 5, eta 0.01

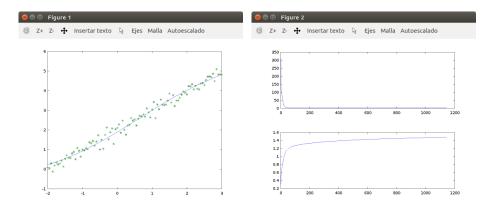


Figura 21: Usando nm 5, eta 0.001

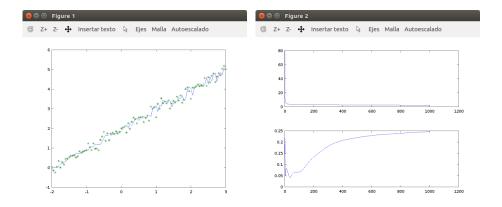


Figura 22: Usando nm 25, eta 0.1

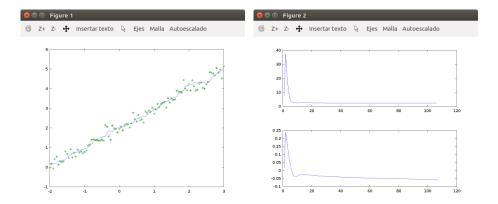


Figura 23: Usando nm 25, eta 0.01

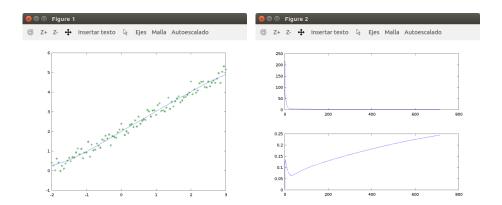


Figura 24: Usando nm 25, eta 0.001