

ADALINES

The Adaline (Adaptive Linear Neuron or “Adaptive Linear Element”) is a model similar to the Perceptron. There are several variations:

- One has the **threshold** function similar to a perceptron.
- Another uses a **pure linear** function with no threshold.
- We can devise more.

Adaline Training

With or without the threshold, the Adaline is **trained** based on the output of the linear function rather than the final output.

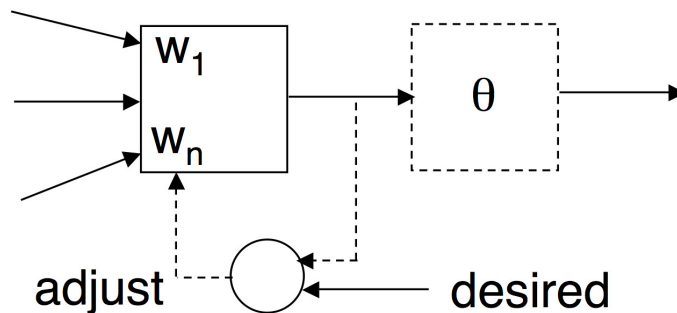


Fig. 24: Adaline training

The catch here is that we have to state the **desired** value in terms of the output of the linear part, rather than the output after the threshold.

What is this for a classifier?

A reasonable approach is to use any nominal target value such as -1 as desired for a “no” classification and a +1 for a “yes” classification.

The formula for Adaline weight updating is very similar to the Perceptron:

Add to the weights Δw where;

$$\Delta \omega = \epsilon \eta \left[-1, X_1, X_2, \dots, X_n \right]$$

only now the **error is not limited to 1, -1, 0 as before**; it can have a fractional value, since it is based on the output of the linear part of the device.

One major difference from this vs. the Perceptron is that a learning rate of 1 won’t generally be acceptable. It will need to be smaller, say 0.01. There is a theory that tells us how large we can make it.

Adaline Convergence

The Adaline admits a more refined stopping criterion:

The **Mean-Squared Error (MSE)** is the average of the squares of the error taken over all samples. Squaring makes the measure insensitive to the sign of the error. It also provides certain analytic properties.

This quantity ideally converges toward a specific minimum (which might never be exactly attained). The algorithm can be set to stop when the MSE reaches a desired value.

Adaline Example

We'll use the same example as before. But now we'll train on the output of the linear portion and target for +1 for a "yes" answer and -1 for a "no" answer.

(4, 5)	+1
(6, 1)	+1
(4, 1)	-1
(1, 2)	-1

Try a learning rate of 0.01.

- Start with initial weights all 0.
- (In general, can use random weights.)
- Progress:
 - trying sample desired: 1, inputs: -1 4 5 output: -1
 - diff is 2
 - error is 1
 - new weights: -0.01 0.04 0.05

- weights: -0.01 0.04 0.05
- trying sample desired: 1, inputs: -1 6 1 output: 1
- diff is 0
- error is 0.7
- new weights: -0.017 0.082 0.057

- trying sample desired: -1, inputs: -1 4 1 output: 1
- diff is -2
- error is -1.402
- new weights: -0.00298 0.02592 0.04298

- trying sample desired: -1, inputs: -1 4 1 output: 1
- diff is -2
- error is -1.402
- new weights: -0.00298 0.02592 0.04298

- trying sample desired: -1, inputs: -1 1 2 output: 1
- diff is -2
- error is -1.11486
- new weights: 0.0081686 0.0147714 0.0206828

- **epoch 1: wrong = 3, mse = 1.17463**

- epoch 1: wrong = 3, mse = 1.17463
- epoch 2: wrong = 2, mse = 1.11176
- epoch 3: wrong = 2, mse = 1.08817
- epoch 4: wrong = 2, mse = 1.07521
- epoch 5: wrong = 2, mse = 1.06563

...

- epoch 30: wrong = 2, mse = 0.888344
- epoch 31: wrong = 1, mse = 0.881999

...

- epoch 197: wrong = 1, mse = 0.363726
- epoch 198: wrong = 0, mse = 0.362493

- **Final weights: 1.54436 0.273645 0.252003**

- **Final weights: 1.54436 0.273645 0.252003**

● input	desired	weighted sum	actual
● (4, 5)	+1	0.810235	1
● (6, 1)	+1	0.359513	1
● (4, 1)	-1	-0.197777	-1
● (1, 2)	-1	-0.766709	-1

Alternate Rule Names

Because the Adaline rule minimizes MSE, it is sometimes called the “**LMS rule**” [LMS = “least mean square”].

The term “**Delta rule**” is also sometimes used, although this will be seen to be a rule for a more general class of networks.

The “**Widrow-Hoff**” rule is also used.

Minimizing Error Iteratively

Consider the task of finding the minimum of a function of one variable. Could try to extend this to functions of multiple variables.

One standard method for doing this, if the derivative of the function is known, is **Newton’s method**, which entails constructing a tangent line from a current estimate, then using the intersection of the line with the origin for the next.

What function is minimized?

- Think of the inputs as being **constants**.
- The weights are the variables.
- We want to find the weights that minimize the **MSE** as a function of the weights.
- The fact that the MSE is defined analytically is a big help.

Gradient Descent

Gradient descent is another method for finding the minimum.

It consists of computing the **gradient** of the function, then taking a small **step** in the **direction of negative gradient**, which hopefully corresponds to decreased function value, then repeating for the new value of the dependent variable.

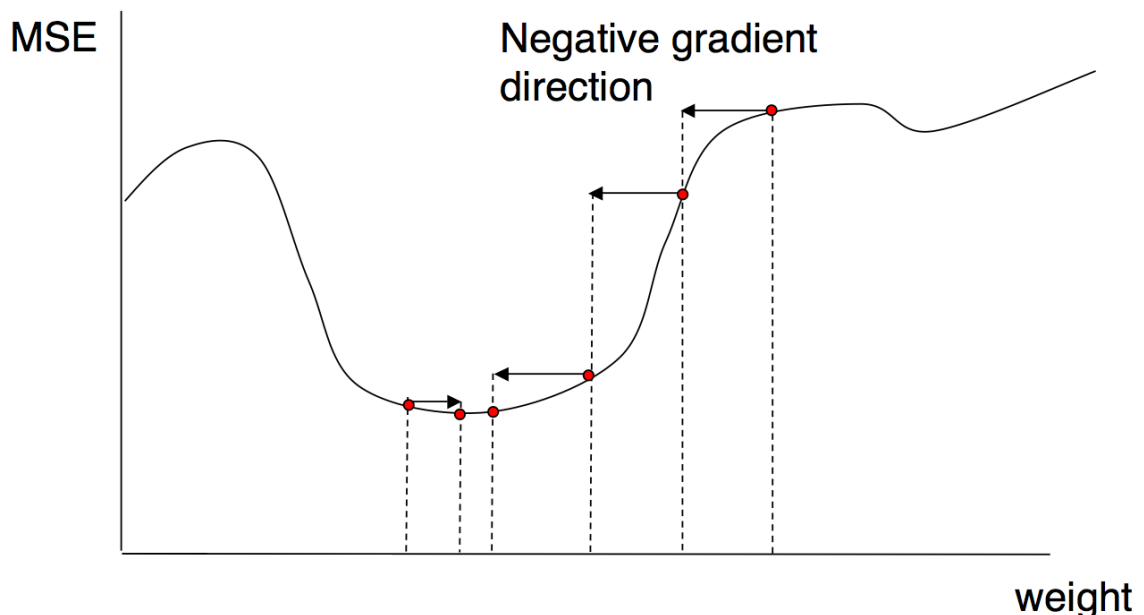


Fig. 26: Gradient Descent

- The previous diagram is mainly to enhance our intuition.
- A single dimension for weights (including bias) is atypical.
- For the general case, the gradient is a **vector** of gradient components, one for each weight (including bias).

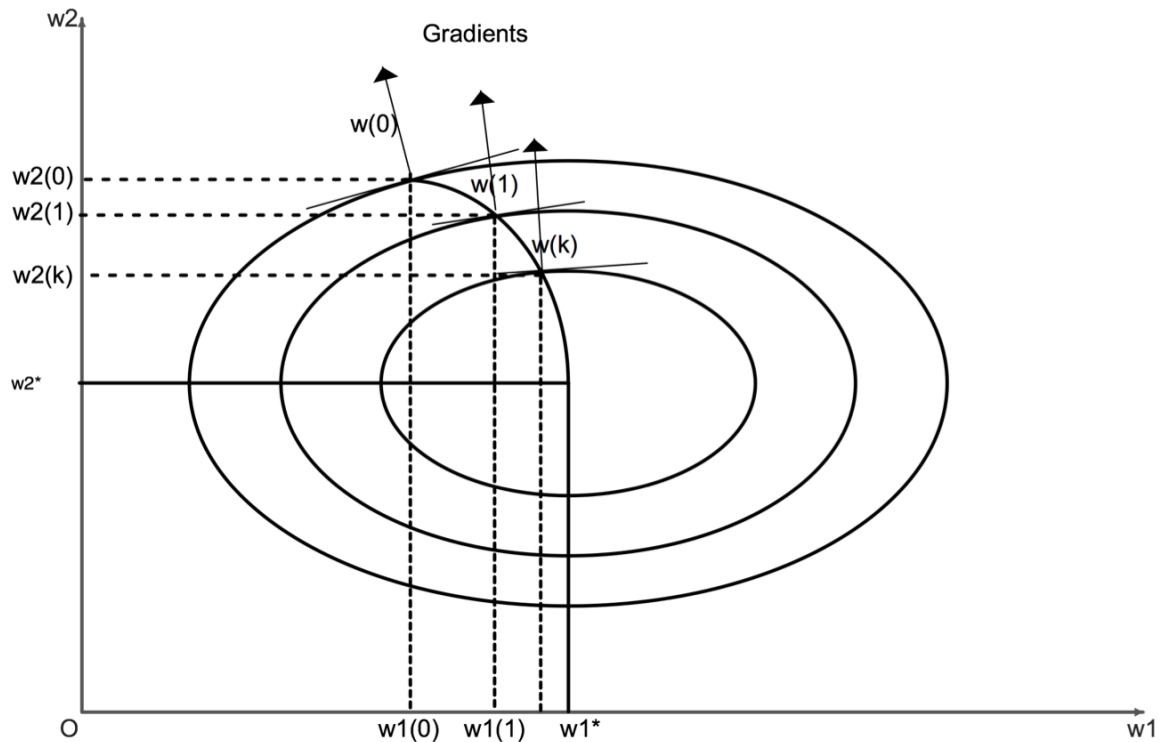


Fig. 27: 2D Gradient descent

Computing Gradients

- $MSE = J(w) = \Sigma(\text{desired} - \text{actual})^2 / n$
where Σ is over n samples.
- desired is a fixed constant for each sample.
- $\text{actual} = \Sigma w_j \cdot x_j$ (Σ over input lines)
- So $J(w) = \Sigma(\text{desired} - \Sigma w_j \cdot x_j)^2 / n$

On-Line Approximation to Gradient

“On-line” means based on a **single sample**, vs. “batch”, which means using all samples

$$J \approx (d - \Sigma w_j x_j)^2 \quad \leftarrow \begin{array}{l} \text{(note: no outer sum)} \\ \text{(d = desired)} \end{array}$$

$$i^{\text{th}} \text{ gradient component} = \partial J / \partial w_i$$

$$= \partial / \partial w_i (d - \Sigma w_j x_j)^2$$

$$= 2 \underbrace{(d - \Sigma w_j x_j)}_{= \text{error, } \epsilon} \underbrace{\partial / \partial w_i (d - \Sigma w_j x_j)}_{-x_i} = -2\epsilon x_i$$

Computing Gradients (contd...)

- $i^{\text{th}} \text{ gradient component} = -2 \epsilon x_i$
- However we want to move in the direction of **negative** gradient, tempered by the **learning rate** η , so:

Amount to add to weight is

$$\Delta \mathbf{w}_i = 2 \varepsilon \eta \mathbf{x}_i \quad (2 \text{ can be folded into } \eta)$$

which we recognize as the LMS (Adaline) rule.

Vector Version of the Analysis of Gradient Descent for Adaline

- $\text{MSE} = J(\mathbf{w}) = E[(d - \mathbf{w}^T \mathbf{x})^2]$ ($E = \mathbf{expectation}$ or mean averaged over samples)
 - $= E[d^2 - 2d\mathbf{w}^T \mathbf{x} + \mathbf{w}^T \mathbf{x} \mathbf{x}^T \mathbf{w}]$
 - $= E[d^2] - E[2d\mathbf{w}^T \mathbf{x}] + E[\mathbf{w}^T \mathbf{x} \mathbf{x}^T \mathbf{w}]$
 - $= E[d^2] - 2\mathbf{w}^T E[d\mathbf{x}] + \mathbf{w}^T E[\mathbf{x} \mathbf{x}^T] \mathbf{w}$
 - $= c - 2\mathbf{w}^T \mathbf{h} + \mathbf{w}^T \mathbf{R} \mathbf{w}$, for appropriate const. $c, \mathbf{h}, \mathbf{R}$
- $J(\mathbf{w}) = c - 2\mathbf{w}^T \mathbf{h} + \mathbf{w}^T \mathbf{R} \mathbf{w}$
 where $c = E[d^2]$, $\mathbf{h} = E[d \mathbf{x}]$, $\mathbf{R} = E[\mathbf{x} \mathbf{x}^T]$
- This is a **quadratic form** in \mathbf{w} with coefficients derived from the data vectors \mathbf{x} .
- \mathbf{R} is called the (auto-) **correlation matrix**

Example

$$\text{Sample 1 } \left\{ \mathbf{x}_1 = \begin{bmatrix} -1 \\ 1 \\ -1 \end{bmatrix}, \mathbf{d}_1 = [-1] \right\} \quad \text{Sample 2 } \left\{ \mathbf{x}_2 = \begin{bmatrix} 1 \\ 1 \\ -1 \end{bmatrix}, \mathbf{d}_2 = [1] \right\}$$

$$\mathbf{R} = E[\mathbf{x} \mathbf{x}^T] = \frac{1}{2} \mathbf{x}_1 \mathbf{x}_1^T + \frac{1}{2} \mathbf{x}_2 \mathbf{x}_2^T$$

$$\mathbf{R} = \frac{1}{2} \begin{bmatrix} -1 \\ 1 \\ -1 \end{bmatrix} \begin{bmatrix} -1 & 1 & -1 \end{bmatrix} + \frac{1}{2} \begin{bmatrix} 1 \\ 1 \\ -1 \end{bmatrix} \begin{bmatrix} 1 & 1 & -1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & -1 \\ 0 & -1 & 1 \end{bmatrix}$$

$$\lambda_1 = 1.0, \quad \lambda_2 = 0.0, \quad \lambda_3 = 2.0$$

$$\eta < \frac{1}{\lambda_{\max}} = \frac{1}{2.0} = 0.5$$

The training – First epoch

$$\text{Sample 1} \quad a(0) = \mathbf{W}(0)\mathbf{p}(0) = \mathbf{W}(0)\mathbf{x}_1 = \begin{bmatrix} 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} -1 \\ 1 \\ -1 \end{bmatrix} = 0$$

$$\varepsilon(0) = d(0) - a(0) = d_1 - a(0) = -1 - 0 = -1$$

$$\mathbf{W}(1) = \mathbf{W}(0) + 2\eta\varepsilon(0)\mathbf{x}^T(0)$$

$$\mathbf{W}(1) = \begin{bmatrix} 0 & 0 & 0 \end{bmatrix} + 2(0.2)(-1) \begin{bmatrix} -1 \\ 1 \\ -1 \end{bmatrix}^T = \begin{bmatrix} 0.4 & -0.4 & 0.4 \end{bmatrix}$$

Second epoch

$$\text{Sample 2} \quad a(1) = \mathbf{W}(1)\mathbf{p}(1) = \mathbf{W}(1)\mathbf{p}_2 = \begin{bmatrix} 0.4 & -0.4 & 0.4 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ -1 \end{bmatrix} = -0.4$$

$$\varepsilon(1) = d(1) - a(1) = d_2 - a(1) = 1 - (-0.4) = 1.4$$

$$\mathbf{W}(2) = \begin{bmatrix} 0.4 & -0.4 & 0.4 \end{bmatrix} + 2(0.2)(1.4) \begin{bmatrix} 1 \\ 1 \\ -1 \end{bmatrix}^T = \begin{bmatrix} 0.96 & 0.16 & -0.16 \end{bmatrix}$$

Third epoch

$$a(2) = \mathbf{W}(2)\mathbf{p}(2) = \mathbf{W}(2)\mathbf{p}_1 = \begin{bmatrix} 0.96 & 0.16 & -0.16 \end{bmatrix} \begin{bmatrix} -1 \\ 1 \\ -1 \end{bmatrix} = -0.64$$

$$\varepsilon(2) = d(2) - a(2) = d_1 - a(2) = -1 - (-0.64) = -0.36$$

$$\mathbf{W}(3) = \mathbf{W}(2) + 2\eta\varepsilon(2)\mathbf{x}^T(2) = \begin{bmatrix} 1.1040 & 0.0160 & -0.0160 \end{bmatrix}$$

$$\mathbf{W}(\infty) = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix}$$

Rattling

If learning rate too high, minimum solution won't be achieved, even if there is no divergence.

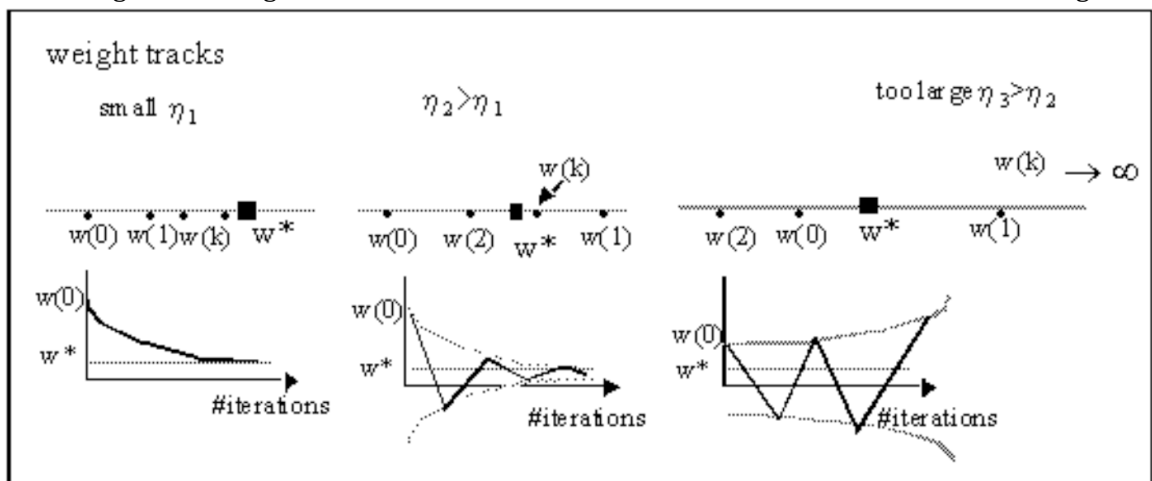


Fig. 30: Rattling

Solutions to Rattling

- Rule of thumb: Use a learning rate 0.1 times the theoretical maximum, **or**
- Gradually decrease the learning rate, e.g. according to a pre-set schedule, **or**
- Adaptively set the learning rate:
 - If the MSE is taking big steps, make it smaller.
 - If the MSE is taking small steps, make it larger.

Generalizing the Adaline

Suppose that we replace the threshold stage with a general analytic function f and revert to expressing desired in terms of its output:

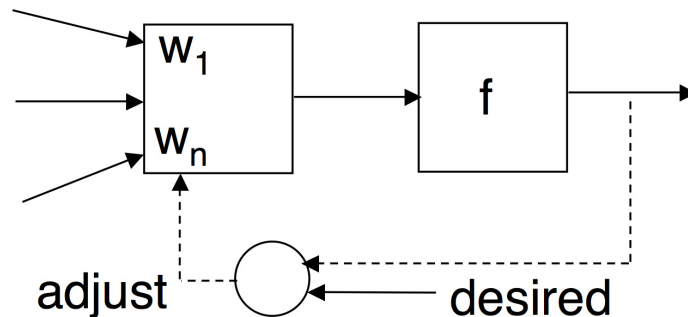


Fig. 31: Generalized adaline

- Consider again the derivation of the LMS rule:
 $J(w) = \frac{1}{n} \sum (desired - f(\sum w_j x_j))^2$
- $J \approx (d - f(\sum w_j x_j))^2$ ($d = desired$)
- i^{th} gradient component $= \partial J / \partial w_i$
 $= \partial / \partial w_i (d - f(\sum w_j x_j))^2$
 $= 2 (d - f(\sum w_j x_j)) \partial / \partial w_i (d - f(\sum w_j x_j))$
 $= -2 \epsilon \partial / \partial w_i f(\sum w_j x_j)$
 $= -2 \epsilon f'(\sum w_j x_j) \partial / \partial w_i \sum w_j x_j = -2 \epsilon x_i f'(\sum w_j x_j)$

Generalized LMS Rule (or Delta Rule)

- $\Delta w = 2 \epsilon \eta f'(\sum w_j x_j) x_i$
 assuming that f has a derivative f' .
- $\sum w_j x_j$ is often called the “**net**” value or “**activation**” value, and f the **activation function**.
- For the special case of f being the **identity** function, this reduces to the LMS rule we had before.

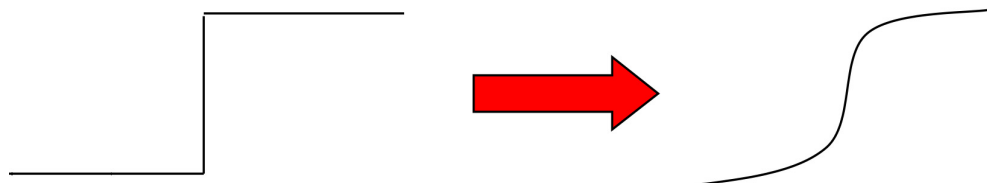
Why worry about this generalization?

$$\Delta w = 2 \epsilon \eta f'(\sum w_j x_j) x_i$$

It will have a number important uses.

Use #1

- In the Adaline with **threshold**, we can't very well treat the model analytically, due to the fact that we have a noncontinuous function at the output.
- But we can approximate the noncontinuous function with a continuous one:



Sigmoids

- The “S” shape on the right of the previous figure is called a sigmoid curve.
- This is a generic term and there are several different analytic functions that behave this way.

Logistic Sigmoid

- Logistic function (“logsig”–Matlab):

$$f(x) = 1/(1+\exp(-ax))$$

- $f'(x) = f(x)(1-f(x))$

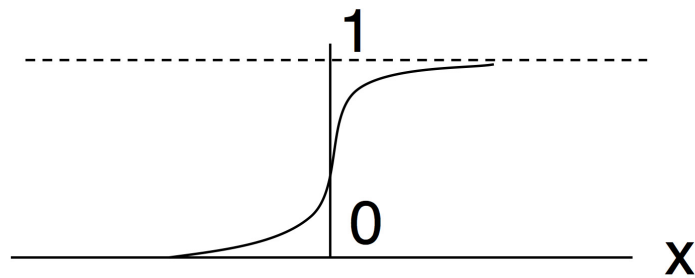


Fig. 33: Logistic Sigmoid

Hyperbolic Sigmoid

- Hyperbolic tangent function (“tansig”):

$$\begin{aligned} f(x) &= \tanh(x) \\ &= (\exp(x) - \exp(-x)) / (\exp(x) + \exp(-x)) \end{aligned}$$

- $f'(x) = 1 - f^2(x)$

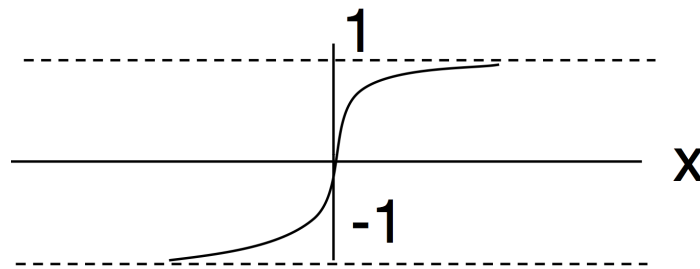


Fig. 34: Hyperbolic sigmoid

Squashing Functions

- Sigmoids, step functions, and other functions that force their results to be in a limited range are called “squashing functions”.
- It is generally accepted that biological neural system is based on such functions, since there are physical limits to the response level.

Applications - Medicine

(Refer to :)

References

- Rojas, R., *Neural Networks – A Systematic Introduction*
- Anderson, J.A., *An Introduction to Neural Networks*
- Haykin, S., *Neural Networks – A Comprehensive Foundation*
- Keller, B., *Neural Networks, CS-152*

PRACTICAL # 3

Perceptrons classification
(June 13, 2009)

Objectives

To implement error-corrective learning for classification using threshold activation function.

Description

Implement a perceptron and train it for classification using error-correction and threshold activation function. The perceptron will be trained for 4 different train set.

Platform

Any platform with any language of choice.

Model

- Use a set of **training samples**:
 - Input vectors, each paired with desired output
- Initialize the weights and threshold arbitrarily. (the input X_0 is the threshold)
- Repeat:
 - Choose a sample
 - Test the network against the sample
 - If answer is incorrect, **adjust** weights
- until all samples test correctly. We'

(Refer to page 8 – 14 of Unit 3)

Here's my program.

```

/*-----
Program name: error corrective learning for classification (program # 3)
Description : This program demonstrates error corrective learning to establish
              association between inputs and logical output and classifies the
              inputs into two classes.

              Uses threshold activation function.

By           : Pramod Parajuli
Date          : June 13, 2009
-----*/

#include <stdio.h>
#include <stdlib.h>
#include <string.h>

#define INPUTS          3
#define TRAIN_SAMPLES    4

#define THRESHOLD        0

/* let's define a structure to represent the perceptron */
typedef struct perceptron
{
    long inp[INPUTS];           // inputs to the perceptron
    long weights[INPUTS];       // weights of the inputs
    long threshold;             // threshold of the neuron
    long function_out;          // functional output of the neuron
    long outp;                  // threshold driven output of the perceptron
    long error;                 // error of the perceptron
    long target;
}PERCEPTRON;

/* let's create a classifier instance of PERCEPTRON*/
PERCEPTRON classifier;

/* this structure defines template for one training set
   - 1 input vector
   - one expected output */
typedef struct {
    long inputs[INPUTS];
    long expected_out;
} TRAIN_ELEMENT;

/* for logical classifiers with two inputs, let's define 4 training sets */
TRAIN_ELEMENT training_set[TRAIN_SAMPLES] = {
    {{-1, 4, 5}, 1},
    {{-1, 6, 1}, 1},
    {{-1, 4, 1}, 0},
    {{-1, 1, 2}, 0}
};

long counter;                // general purpose counter

long LEARNING_RATE;          // learning rate of the perceptron
long EPOCH;                  // defines no. of iterations

void menu(void);              // displays a user help menu
void randomize(void);          // assigns random weights to the weight vector
void print(void);              // print the weight vector
void train(void);              // train the perceptron for adaptation
void feedforward(void);        // feedforward function (inputs * weights)
void backpropaclassifier(void); // backpropagate (weight += error * input * learning rate)
void test(void);               // test the perceptron by using feedforward

int main (int argc, char * argv[]){
    int exit;                  // status variable for flow control
    char user_input[10];       // user input - string

    menu();                    // display menu

    exit = 0;

    classifier.threshold = THRESHOLD;

    do{

```

```

        printf("\ncommand $ ");
        gets(user_input);

        if(strcmp(user_input, "SHUFFLE") == 0){
            randomize();
            print();
        }
        else if(strcmp(user_input, "TRAIN") == 0){
            printf("\nEnter the learning rate : ");
            scanf("%ld", &LEARNING_RATE);
            train();
        }
        else if(strcmp(user_input, "TEST") == 0){
            test();
        }
        else if(strcmp(user_input, "PRINT") == 0){
            print();
        }
        else if(strcmp(user_input, "EXIT") == 0){
            exit = 1;
        }
        else{
            menu();
        }

    }while(exit == 0);

    printf("\npress any key to exit...");
    getc(stdin);

    return 0;
}

/*-----
Function name : menu
Description : Displays menu
-----*/
void menu(void){
    printf("\n\n\t\t\tPerceptron training for classification (PROGRAM# 3.0)");
    printf("\n\t\tUse only integer inputs for data entry");
    printf("\nPlease use following commands");
    printf("\n-----");
    printf("\nSHUFFLE : to randomize weights | TRAIN : to train the perceptron");
    printf("\nTEST : to test the perceptron | PRINT : to print the weights");
    printf("\nHELP : to display this menu | EXIT : to exit the program");
    printf("\n-----\n");
}

/*-----
Function name : randomize weights
Description : randomizes the weights to new values
-----*/
void randomize(void){
    for(counter = 0; counter < INPUTS; counter++){
        printf("\nEnter a random weight[%ld]: ", counter);
        scanf("%ld", &classifier.weights[counter]);
    }
}

/*-----
Function name : print
Description : prints the weights
-----*/
void print(void){
    for(counter = 0; counter < INPUTS; counter++){
        printf("\nWeight [%ld] : %ld", counter, classifier.weights[counter]);
    }
}

/*-----
Function name : feedforward
Description : feedforward the inputs by multiplying input vector and weight
vector
-----*/
void feedforward(void){
    long sum = 0;

```

```

        for(counter = 0; counter < INPUTS; counter++){
            sum += classifier.inp[counter] * classifier.weights[counter];
        }

        classifier.function_out = sum;

        if(sum > THRESHOLD){
            classifier.outp = 1;
        }
        else{
            classifier.outp = 0;
        }

        printf("\nFunctional output: %ld, threshold output: %ld", classifier.function_out,
classifier.outp);
    }

    /*-----
    Function name : backpropaclassifier
    Description : backpropaclassifier by finding the error and update the weight
                vector
    -----*/
    void backpropagate(void){

        if(classifier.target - classifier.outp > 0){
            printf("\nTarget > functional output,");
            classifier.error = 1;
        }
        else if(classifier.target - classifier.outp < 0){
            printf("\nTarget < functional output,");
            classifier.error = -1;
        }
        else{
            printf("\nTarget = functional output,");
            classifier.error = 0;
        }

        printf("\terror: %ld", classifier.error);

        for(counter = 0; counter < INPUTS; counter++){
            classifier.weights[counter] += classifier.error * LEARNING_RATE *
classifier.inp[counter];
            printf("\tweights[%ld]: %ld", counter, classifier.weights[counter]);
        }
        printf("\n");
    }

    /*-----
    Function name : train
    Description : trains the perceptron using following algo.
                1. Select the first train set
                2. Feed-forward the inputs
                3. Back-propagate
                4. Select next train set
                5. Repeat till good level of convergence is achieved
    -----*/
    void train(void){
        int samples; // keeps track of training sample
        int iterations=0;
        long current_sample_error = RAND_MAX;

        while(current_sample_error > 0){ // train till errors in all the samples become 0

            current_sample_error = 0;

            for(samples = 0; samples < TRAIN_SAMPLES; samples++){

                /* set the input of perceptron to be inputs of current train set */
                for(counter = 0; counter < INPUTS; counter++){
                    classifier.inp[counter] = training_set[samples].inputs[counter];
                }
                /* set the target of perceptron to be target of current train set */
                classifier.target = training_set[samples].expected_out;

                /* just for debugging */
                printf("\nCurrent inputs: ");
            }
        }
    }

```

```
        for(counter = 0; counter < INPUTS; counter++){
            printf("%ld, ", classifier.inp[counter]);
        }
        printf("\ttarget: %ld", classifier.target);

        feedforward();           // feed forward
        backpropagate();         // backpropagate

        if(abs(classifier.error)){
            current_sample_error += abs(classifier.error);
        }
        //current_sample_error += classifier.error;
    }
    iterations++;
}

printf("\nTraining finished in %ld no. of iterations", iterations);
}

/*-----
Function name : test
Description : test the perceptron by using feedforward
-----*/
void test(void){
    long input;

    /* take user values for inputs */
    for(counter = 0; counter < INPUTS; counter++){
        printf("\nEnter input (%ld) : ", counter);
        scanf("%ld", &input);
        classifier.inp[counter] = input;
    }

    feedforward();

    printf("\nThe functional output of the perceptron : %ld, classifier output : %ld",
        classifier.function_out, classifier.outp);
}
```

PRACTICAL # 4

Adaline classification
(June 14, 2009)

Objectives

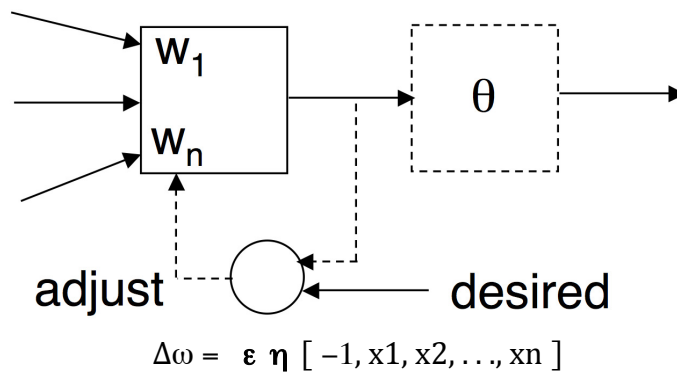
To implement error-corrective learning for classification using threshold activation function for adaline.

Description

Implement an adaline and train it for classification using error-correction and threshold activation function. The adaline will be trained for 4 different train set.

Platform

Any platform with any language of choice.

Model

(Refer to page 23 – 25 of Unit 3)

Here's my program.


```

/*-----
Program name: error corrective learning for classification using adaline
              (program # 4)
Description : This program demonstrates implementation of adaline for
              error corrective learning to establish association between inputs
              and logical output and classifies the inputs into two classes.

              Uses threshold activation function.

By            : Pramod Parajuli
Date          : June 13, 2009
-----*/

#include <stdio.h>
#include <stdlib.h>
#include <string.h>

#define INPUTS      3
#define TRAIN_SAMPLES  4

#define THRESHOLD    0

/* let's define a structure to represent the adaline */
typedef struct
{
    double inp[INPUTS];           // inputs to the adaline
    double weights[INPUTS];       // weights of the inputs
    double threshold;             // threshold of the neuron
    double function_out;          // functional output of the neuron
    double outp;                  // threshold driven output of the
    double error;                 // error of the adaline
    double target;                // target of adaline
}ADALINE;

/* let's create a classifier instance of ADALINE*/
ADALINE classifier;

/* this structure defines template for one training set
   - 1 input vector
   - one expected output */
typedef struct {
    double inputs[INPUTS];
    double expected_out;
} TRAIN_ELEMENT;

/* for logical classifiers with two inputs, let's define 4 training sets */
TRAIN_ELEMENT training_set[TRAIN_SAMPLES] = {
    {{-1, 4, 5}, 1},
    {{-1, 6, 1}, 1},
    {{-1, 4, 1}, -1},
    {{-1, 1, 2}, -1}
};

long counter;                // general purpose counter

double LEARNING_RATE;        // learning rate of the perceptron
long EPOCH;                   // defines no. of iterations

void menu(void);              // displays a user help menu
void randomize(void);         // assigns random weights to the weight vector
void print(void);             // print the weight vector
void train(void);             // train the perceptron for adaptation
void feedforward(void);       // feedforward function (inputs * weights)
void backpropaclassifier(void); // backpropagate (weight += error * input * learning rate)
void test(void);              // test the perceptron by using feedforward

int main (int argc, char * argv[]){
    int exit;                  // status variable for flow control
    char user_input[10];       // user input - string

    menu();                    // display menu

    exit = 0;

    classifier.threshold = THRESHOLD;

```

```

do{
    printf("\ncommand $ ");
    gets(user_input);

    if(strcmp(user_input, "SHUFFLE") == 0){
        randomize();
        print();
    }
    else if(strcmp(user_input, "TRAIN") == 0){
        printf("\nEnter the learning rate : "); // learning rate
        scanf("%lf", &LEARNING_RATE);
        train();
    }
    else if(strcmp(user_input, "TEST") == 0){
        test();
    }
    else if(strcmp(user_input, "PRINT") == 0){
        print();
    }
    else if(strcmp(user_input, "EXIT") == 0){
        exit = 1;
    }
    else{
        menu();
    }

}while(exit == 0);

printf("\npress any key to exit...");
getc(stdin);

return 0;
}

/*-----
Function name : menu
Description : Displays menu
-----*/
void menu(void){
    printf("\n\n\t\t\t\t\tPerceptron training for classification (PROGRAM# 3.0)");
    printf("\n\t\t\t\t\tUse float value inputs for data entry");
    printf("\nPlease use following commands");
    printf("\n-----");
    printf("\nSHUFFLE : to randomize weights | TRAIN : to train the perceptron");
    printf("\nTEST : to test the perceptron | PRINT : to print the weights");
    printf("\nHELP : to display this menu | EXIT : to exit the program");
    printf("\n-----\n");
}

/*-----
Function name : randomize weights
Description : randomizes the weights to new values
-----*/
void randomize(void){
    for(counter = 0; counter < INPUTS; counter++){
        printf("\nEnter a random weight[%ld]: ", counter);
        scanf("%lf", &classifier.weights[counter]);
    }
}

/*-----
Function name : print
Description : prints the weights
-----*/
void print(void){
    for(counter = 0; counter < INPUTS; counter++){
        printf("\nWeight [%ld] : %lf", counter, classifier.weights[counter]);
    }
}

/*-----
Function name : feedforward
Description : feedforward the inputs by multiplying input vector and weight
vector
-----*/

```

```

void feedforward(void){
    double sum = 0.0;
    for(counter = 0; counter < INPUTS; counter++){
        sum += classifier.inp[counter] * classifier.weights[counter];
    }

    classifier.function_out = sum;

    if(sum > THRESHOLD){
        classifier.outp = 1;
    }
    else{
        classifier.outp = -1;
    }

    printf("\nFunctional output: %lf, threshold output: %lf, difference: %lf",
        classifier.function_out, classifier.outp, classifier.target -
classifier.outp);
}

/*-----
Function name : backpropaclassifier
Description : backpropaclassifier by finding the error and update the weight
vector
-----*/
void backpropagate(void){

    classifier.error = classifier.target - classifier.function_out;

    printf("\terror: %lf", classifier.error);

    for(counter = 0; counter < INPUTS; counter++){
        classifier.weights[counter] += classifier.error * LEARNING_RATE *
classifier.inp[counter];
        printf("\tweights[%ld]: %lf", counter, classifier.weights[counter]);
    }
}

/*-----
Function name : train
Description : trains the perceptron using following algo.
1. Select the first train set
2. Feed-forward the inputs
3. Back-propagate
4. Select next train set
5. Repeat till good level of convergence is achieved
-----*/
void train(void){
    int samples; // keeps track of training sample
    int iterations=0;
    long wrong = TRAIN_SAMPLES;
    double MSE;

    while(wrong > 0){ // train till errors in all the samples become 0

        wrong = 0;
        MSE = 0.0;

        for(samples = 0; samples < TRAIN_SAMPLES; samples++){

            /* set the input of perceptron to be inputs of current train set */
            for(counter = 0; counter < INPUTS; counter++){
                classifier.inp[counter] = training_set[samples].inputs[counter];
            }
            /* set the target of perceptron to be target of current train set */
            classifier.target = training_set[samples].expected_out;

            /* just for debugging */
            printf("\nCurrent inputs: ");
            for(counter = 0; counter < INPUTS; counter++){
                printf("%lf, ", classifier.inp[counter]);
            }
            printf("\ttarget: %lf", classifier.target);

            feedforward(); // feed forward

```

```
        backpropagate();          // backpropagate

        if(classifier.target != classifier.outp){
            wrong++;
        }
        MSE += classifier.error * classifier.error;

        //current_sample_error += classifier.error;
    }
    printf("\tMSE: %lf\n\n", MSE / TRAIN_SAMPLES);
    iterations++;
}

printf("\nTraining finished in %ld no. of iterations", iterations);
}

/*-----
Function name : test
Description : test the perceptron by using feedforward
-----*/
void test(void){
    double input;

    /* take user values for inputs */
    for(counter = 0; counter < INPUTS; counter++){
        printf("\nEnter input (%ld) : ", counter);
        scanf("%lf", &input);
        classifier.inp[counter] = input;
    }

    /* feed forward */

    feedforward();

    printf("\nThe functional output of the perceptron : %lf, classifier output : %lf",
        classifier.function_out, classifier.outp);
}
}
```

PRACTICAL # 5

Adaline classification
(June 14, 2009)

Objectives

To implement perceptron program in Matlab using Neural Net ToolBox

Steps

1. Create input vectors and target vectors

```
p = [0 0 1 1; 0 1 0 1]
t = [0 0 0 1]
```

```
net = newp(p, t)
```

2. Train the network

```
net = train(net, p, t)
```

3. Simulate the network

```
output = sim(net, p)
```

4. Check weights.

```
net.IW{1, 1}
```

To modify the property of training, use `net.trainParam.<parameter name>`.

Use 'nntool' GUI tool to model Neural Networks.

Test following activation functions

```
n = -5:0.1:5;
plot(n, hardlim(n), 'c+:');
plot(n, hardlims(n), 'c+:');
plot(n, purelin(n), 'c+:');
plot(n, logsig(n), '*');
```