



# Perceptrons and Environment Setup

CMSC 389A: Lecture 2

---

Sujith Vishwajith

University of Maryland

# Agenda

1. Logistic Regression Recap
2. Perceptrons
3. Processing Features
4. Example
5. Environment Setup
6. Announcements

# Logistic Regression Recap

---

# Logistic Regression Recap

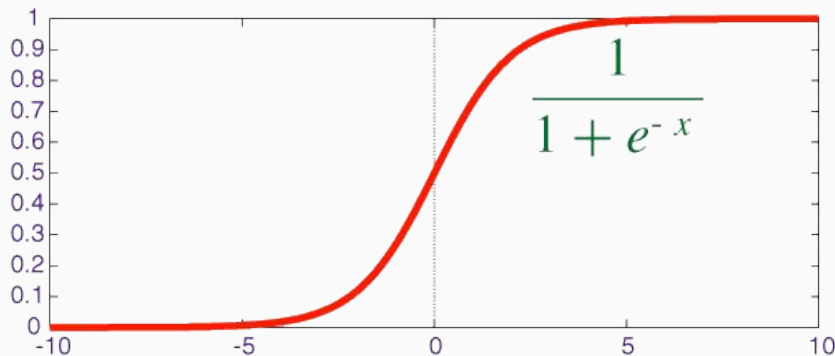
Tries to find a linear separator between classes.

Models the probability that an example belongs to a certain class.

$$P(Y = 1 \mid \text{data})$$

Want to predict a probability that either  $Y=1$  or  $Y=0$  for binary classification.

Utilizes the logistic (sigmoid) function.



## Recap (cont.)

Features are represented as  $[x_0, x_1, \dots, x_{|F|}]$  where  $|X| = \# \text{ of Features}$ .

Weights represented as a list  $[w_0, w_1, \dots, w_{|B|}]$  where  $|B| = |X|$ .

Additional parameter  $b$  is the bias.

Our weights and bias are estimated from our training data.

Therefore probability of belonging to default class is:

$$P(Y=1 | x) = \sigma(w^T x + b).$$

## Recap (cont.)

Update using SGD over every training example .

True label =  $\bar{y}$ , Features =  $\mathbf{x}$ , Bias =  $\mathbf{b}$ , Weights =  $\mathbf{w}$ , Learning Rate =  $\alpha$

Prediction =  $\hat{y} = \sigma(\mathbf{w}^T \mathbf{x} + \mathbf{b})$

Error =  $\mathbf{e} = \bar{y} - \hat{y}$

Updates bias:

$$\mathbf{b} \leftarrow \mathbf{b} + \alpha * \mathbf{e} * \hat{y} * (1 - \hat{y})$$

Update every weight:

$$\mathbf{w}_i \leftarrow \mathbf{w}_i + \alpha * \mathbf{e} * \hat{y} * (1 - \hat{y}) * \mathbf{x}_i$$

# Perceptrons

---

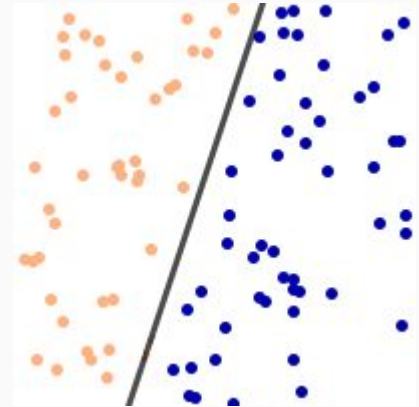
# Perceptron Overview

Invented in 1957 by Frank Rosenblatt.

Similar to logistic regression as it is a linear classifier.

Simulates a neuron as a perceptron is either on (1) or off (0) based on a signal (features).

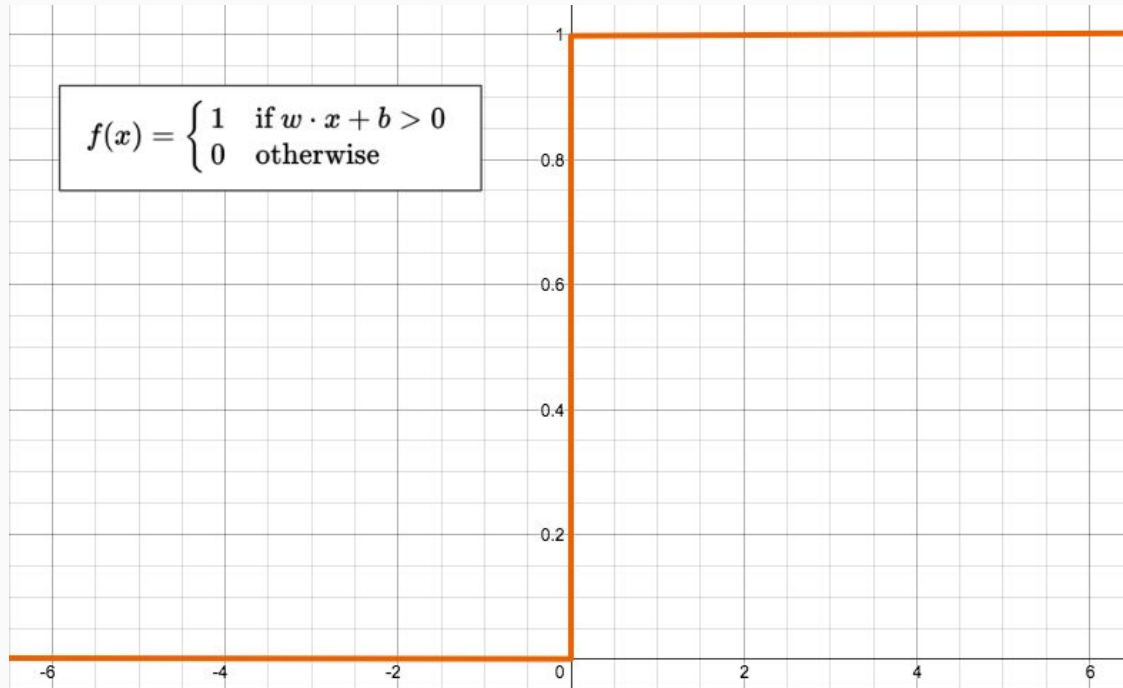
Uses an activation function to decide if on or off.





# Activation Function

Known as the Heaviside step function.



# Basics

Features are represented as  $[x_0, x_1, \dots, x_{|F|}]$  where  $|X| = \# \text{ of Features}$ .

Weights represented as a list  $[w_0, w_1, \dots, w_{|B|}]$  where  $|B| = |X|$ .

Additional parameter  $b$  is the bias.

Our data is classified as  $Y=1$  if:

$$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$$

$$f(w^T x + b) = 1$$

And  $Y=0$ :

$$f(w^T x + b) = 0$$

# Training a Perceptron

Update over every training example .

True label =  $\bar{y}$ , Features =  $\mathbf{x}$ , Bias =  $\mathbf{b}$ , Weights =  $\mathbf{w}$ , Learning Rate =  $\alpha$

Prediction =  $\hat{y} = f(\mathbf{w}^T \mathbf{x} + \mathbf{b})$   $f(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$

Error =  $\mathbf{e} = \bar{y} - \hat{y}$

Updates bias:

$$\mathbf{b} \leftarrow \mathbf{b} + \alpha * \mathbf{e}$$

Update every weight:

$$\mathbf{w}_i \leftarrow \mathbf{w}_i + \alpha * \mathbf{e} * \mathbf{x}_i$$

Notice how no update happens if classified correctly.

# Logistic Regression vs Perceptron

## Perceptrons

Linear classifier.

Either 1 or 0 (no probability indication).

$$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$$

Updates:

$$\mathbf{b} \leftarrow \mathbf{b} + \alpha * \mathbf{e}$$

$$\mathbf{w}_i \leftarrow \mathbf{w}_i + \alpha * \mathbf{e} * x_i$$

## Logistic Regression

Linear classifier.

Indication of confidence (probability).

$$f(x) = \frac{1}{1 + e^{-x}}$$

Updates:

$$\mathbf{b} \leftarrow \mathbf{b} + \alpha * \mathbf{e} * \hat{y} * (1 - \hat{y})$$

$$\mathbf{w}_i \leftarrow \mathbf{w}_i + \alpha * \mathbf{e} * x_i * \hat{y} * (1 - \hat{y})$$

Observe how both models are incredibly similar and only differ in activation functions and weight updates.

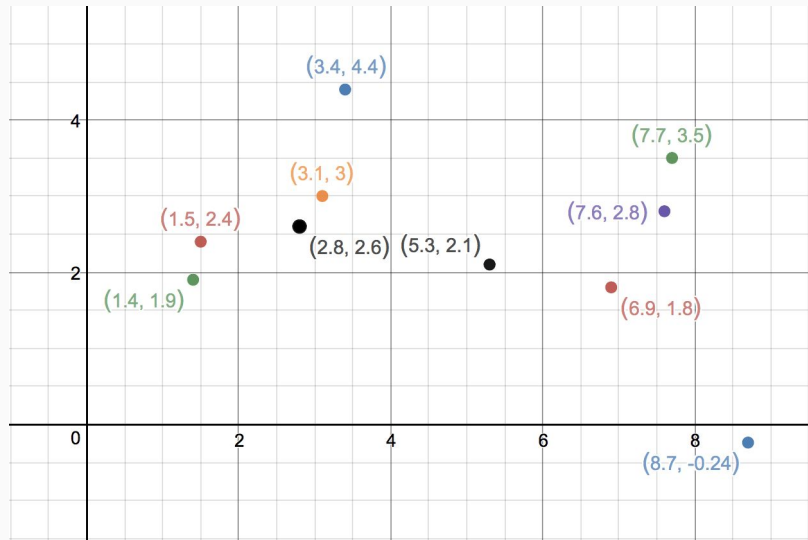
# Example

---

# Example

Let's train a Logistic Regression model and a Perception over some sample data

$X_1$	$X_2$	Y
1.5	2.4	0
5.3	2.1	1
3.1	3.0	0
7.6	2.8	1



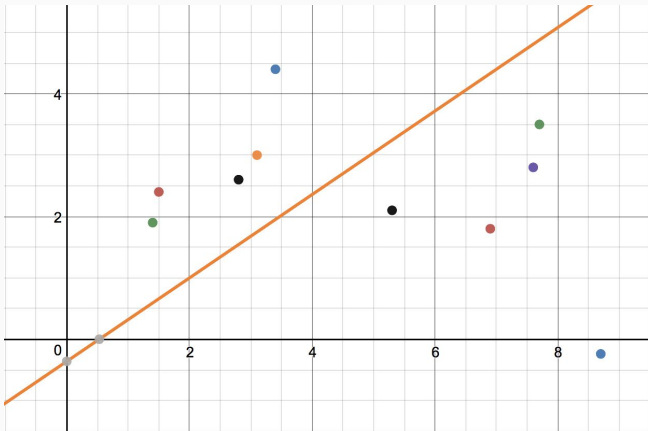
\* This is a made up example found [here](#)

# Results

Trained with  $\alpha = 0.1$  and for 10 epochs we get:

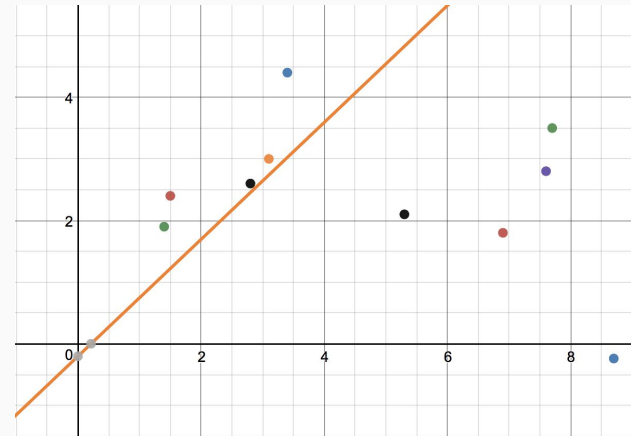
Logistic Regression:

**Bias:** -0.622 ,  **$W_1$ :** 1.172,  **$W_2$ :** -1.724



Perceptron:

**Bias:** 0.1 ,  **$W_1$ :** 0.469,  **$W_2$ :** -0.494





# Processing Features

---

# Continuous Features

Numeric values in  $\mathbb{R}$  that range from  $-\text{Inf}$  to  $\text{Inf}$

Examples:

- Width of flower petal in inches
- Number of times a word appears in a document

Important to rescale values between 0 (or -1) and 1. Why?

You can do this by computing:  $\mathbf{x} = (\mathbf{x} - \mathbf{min\ x}) / (\mathbf{max\ x} - \mathbf{min\ x})$

# Discrete Features

Finite range of integer numbers (0,1,2) or string values (male, female)

Examples:

- Boolean values: true or false
- Gender: male or female

Encode features into numbers (male -> 0, female -> 1)

# Environment Setup

---

Let's go through the setup process for our environment to run our projects.

<https://umd-cs-stics.gitbooks.io/cmssc389a-practical-deep-learning/content/course-information/environment-setup.html>

# Announcements

---

# Announcements

Join Piazza for class questions and discussions.

Please complete weekly feedback.

Practical 1 is due **February 16th** at **11:59 p.m.**

Questions?