ALMA MATER STUDIORUM
UNIVERSITÀ DI BOLOGNA
CAMPUS DI FORLÌ

91258 / B0385
Natural Language Processing

Lesson 10. "One" Neuron

Alberto Barrón-Cedeño
a.barron@unibo.it

29/10/2025

Previously

- From Words to Topics
- ML pipeline

Table of Contents

Chapter 5 of Lane et al. (2019)

There Was Life Before Deep Learning

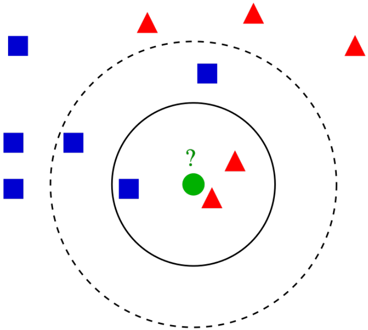
Inspired by Hermann Ney's lesson at the 2017 DL Summer School (Bilbao)

There Was Life Before Deep Learning
(And Many Non-NN in-Production Models Prevail)

- Naïve Bayes
- *k*-nearest neighbors
- Random forests
- Support vector machines
- HMM
- Logistic Regression
- ...

There Was Life Before Deep Learning

k-Nearest Neighbours



The class of ● is the same as the most frequent among its k neighbours

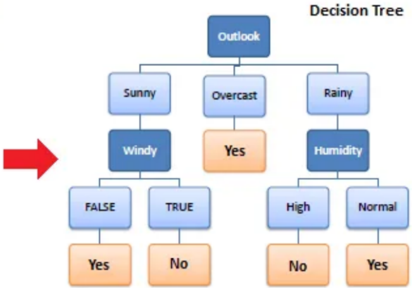
https://en.wikipedia.org/wiki/K-nearest_neighbors_algorithm

There Was Life Before Deep Learning

Random Forests (showing only one decision tree here)

Playing Golf

Predictors				Target
Outlook	Temp.	Humidity	Windy	Play Golf
Rainy	Hot	High	False	No
Rainy	Hot	High	True	No
Overcast	Hot	High	False	Yes
Sunny	Mild	High	False	Yes
Sunny	Cool	Normal	False	Yes
Sunny	Cool	Normal	True	No
Overcast	Cool	Normal	True	Yes
Rainy	Mild	High	False	No
Rainy	Cool	Normal	False	Yes
Sunny	Mild	Normal	False	Yes
Rainy	Mild	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes
Sunny	Mild	High	True	No



Picture from https://medium.com/@MrBam44/decision-trees-91f61a42c724

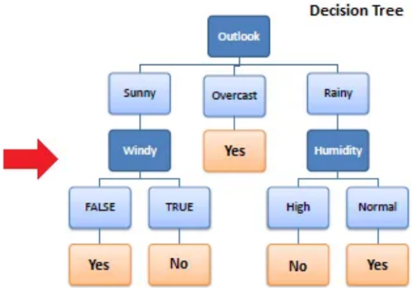
https://en.wikipedia.org/wiki/Random_forest

There Was Life Before Deep Learning

Random Forests (showing only one decision tree here)

Playing Golf

Predictors				Target
Outlook	**Temp.**	**Humidity**	**Windy**	**Play Golf**
Rainy	Hot	High	False	No
Rainy	Hot	High	True	No
Overcast	Hot	High	False	Yes
Sunny	Mild	High	False	Yes
Sunny	Cool	Normal	False	Yes
Sunny	Cool	Normal	True	No
Overcast	Cool	Normal	True	Yes
Rainy	Mild	High	False	No
Rainy	Cool	Normal	False	Yes
Sunny	Mild	Normal	False	Yes
Rainy	Mild	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes
Sunny	Mild	High	True	No



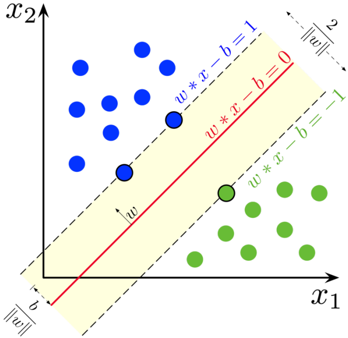
Multiple decision trees are learned and the final class is the mode

Picture from `https://medium.com/@MrBam44/decision-trees-91f61a42c724`

`https://en.wikipedia.org/wiki/Random_forest`

There Was Life Before Deep Learning

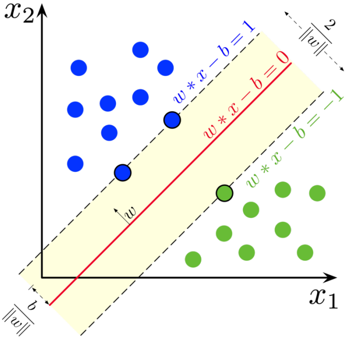
Support Vector Machines



https://en.wikipedia.org/wiki/Support-vector_machine

There Was Life Before Deep Learning

Support Vector Machines



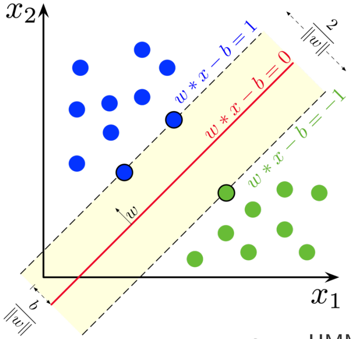
Kernels

- Linear
- Polynomial
- RBF
- Tree

https://en.wikipedia.org/wiki/Support-vector_machine

There Was Life Before Deep Learning

Support Vector Machines



Kernels

- Linear
- Polynomial
- RBF
- Tree

- SVM^{HMM} for sequences[a]
- SVM-Rank for ranking
- SVR for regression

[a] Also HMM

https://en.wikipedia.org/wiki/Support-vector_machine

There Was Life Before Deep Learning

There are many, many others

There Was Life Before Deep Learning

There are many, many others

- Often they are SotA (or close)

There Was Life Before Deep Learning

There are many, many others

- Often they are SotA (or close)
- In general, they are *cheaper*

There Was Life Before Deep Learning

There are many, many others

- Often they are SotA (or close)
- In general, they are *cheaper*
- In general, they require *less* data

There Was Life Before Deep Learning

There are many, many others

- Often they are SotA (or close)
- In general, they are *cheaper*
- In general, they require *less* data
- Some of them are *explainable*

There Was Life Before Deep Learning

There are many, many others

- Often they are SotA (or close)
- In general, they are *cheaper*
- In general, they require *less* data
- Some of them are *explainable*
- In general, representations have to be *engineered*

Some History

Some History

Opening paragraph of Rosenblatt (1957)'s The Perceptron—a perceiving and recognizing automaton

Since the advent of electronic computers and modern servo systems, an increasing amount of attention has been focused on the feasibility of constructing a device possessing such human-like functions as perception, recognition, concept formation, and the ability to generalize from experience. In particular, interest has centered on the idea of a machine which would be capable of conceptualizing inputs impinging directly from the physical environment of light, sound, temperature, etc. -- the "phenomenal world" with which we are all familiar -- rather than requiring the intervention of a human agent to digest and code the necessary information.

AI Winters

1974–1980 First major winter
1987–1993 Second major winter

[1] https://en.wikipedia.org/wiki/Lighthill_report
[2] https://en.wikipedia.org/wiki/Fifth_generation_computer

AI Winters

1974–1980 First major winter
1987–1993 Second major winter

1966 Failure of MT
1970 Abandonment of connectionism (explain mental phenomena using artificial neural networks)
1971–75 DARPA's frustration wrt CMU's speech recognition research
1973 Lighthill report decreases AI research in the UK[1]
1973–74 DARPA's cutbacks to academic AI research

[1] https://en.wikipedia.org/wiki/Lighthill_report
[2] https://en.wikipedia.org/wiki/Fifth_generation_computer

AI Winters

1974–1980 First major winter
1987–1993 Second major winter

1966 Failure of MT
1970 Abandonment of connectionism (explain mental phenomena using artificial neural networks)
1971–75 DARPA's frustration wrt CMU's speech recognition research
1973 Lighthill report decreases AI research in the UK[1]
1973–74 DARPA's cutbacks to academic AI research

1987 Collapse of the LISP machine market
1988 Cancellation of new spending on AI by the Strategic Computing Initiative
1993 Resistance to expert systems deployment and maintenance
1990s End of the Fifth Generation computer project's original goals[2]

[1] https://en.wikipedia.org/wiki/Lighthill_report
[2] https://en.wikipedia.org/wiki/Fifth_generation_computer

The Perceptron

The Perceptron

- Intended to be a machine able of recognising images

The Perceptron

- Intended to be a machine able of recognising images
- Rough idea:

Input:	features of an image (small subsections)
Parameters:	weights for each feature (measure of importance)
Output:	*Fire* once all potentiometers pass a certain threshold

The Perceptron

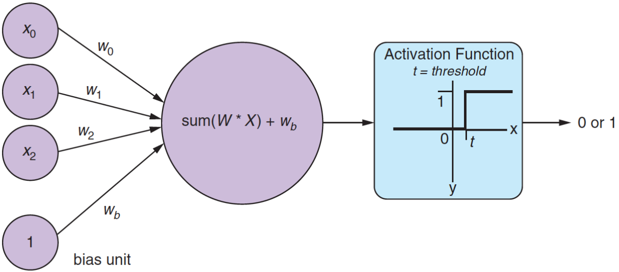
- Intended to be a machine able of recognising images
- Rough idea:

  Input: features of an image (small subsections)
  Parameters: weights for each feature (measure of importance)
  Output: *Fire* once all potentiometers pass a certain threshold

Fired: positive match in the image
Did not fire: negative class

The Perceptron

Numerical Perceptron[3]

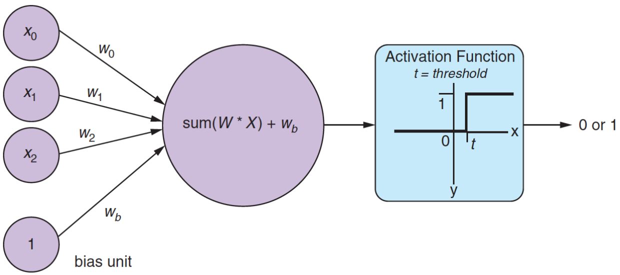


(Lane et al., 2019, p. 158)

[3] I am intentionally dropping biological references

The Perceptron

Numerical Perceptron[3]



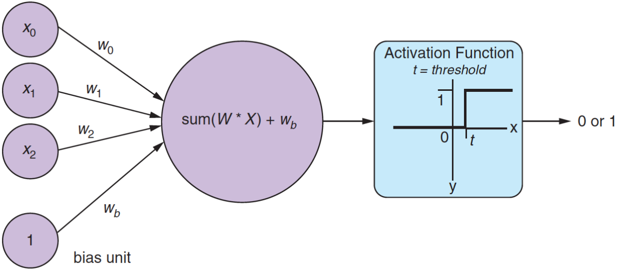
(Lane et al., 2019, p. 158)

- Feature vector: $X = [x_0, x_1, \cdots, x_i, \cdots, x_n]$

[3] I am intentionally dropping biological references

The Perceptron

Numerical Perceptron[3]

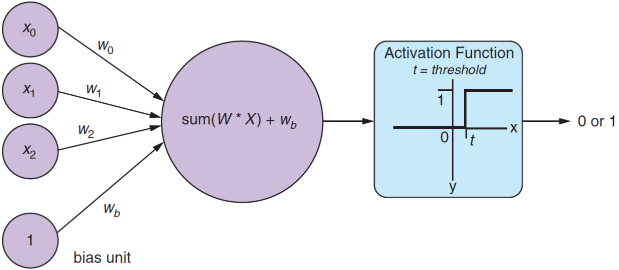


(Lane et al., 2019, p. 158)

- Feature vector: $X = [x_0, x_1, \cdots, x_i, \cdots, x_n]$
- Associated weight (per feature): $W = [w_0, w_1, \cdots, w_i, \ldots, w_n]$

[3] I am intentionally dropping biological references

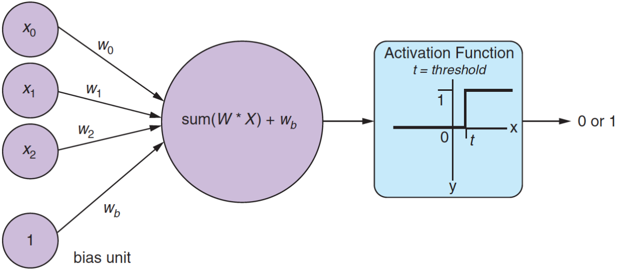
The Perceptron
Numerical Perceptron[3]



(Lane et al., 2019, p. 158)

- Feature vector: $X = [x_0, x_1, \cdots, x_i, \cdots, x_n]$
- Associated weight (per feature): $W = [w_0, w_1, \cdots, w_i, \ldots, w_n]$
- Sum up: $(x_0 * w_0) + (x_1 * w_1) + \cdots + (x_i * w_i) + \ldots (x_n * w_n)$

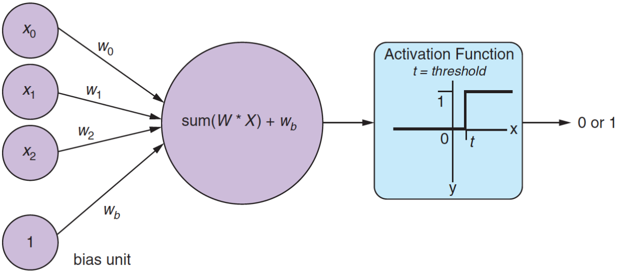
[3] I am intentionally dropping biological references



(Lane et al., 2019, p. 158)

- Feature vector: $X = [x_0, x_1, \cdots, x_i, \cdots, x_n]$
- Associated weight (per feature): $W = [w_0, w_1, \cdots, w_i, \ldots, w_n]$
- Sum up: $(x_0 * w_0) + (x_1 * w_1) + \cdots + (x_i * w_i) + \ldots (x_n * w_n)$
- Bias: always-on input (resiliency to inputs of all zeros)

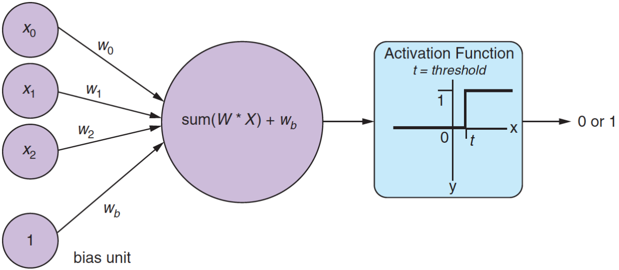
[3] I am intentionally dropping biological references



(Lane et al., 2019, p. 158)

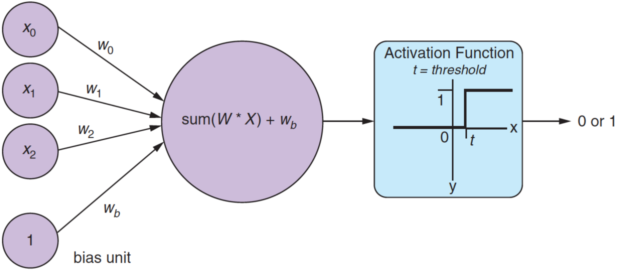
- Feature vector: $X = [x_0, x_1, \cdots, x_i, \cdots, x_n]$
- Associated weight (per feature): $W = [w_0, w_1, \cdots, w_i, \ldots, w_n]$
- Sum up: $(x_0 * w_0) + (x_1 * w_1) + \cdots + (x_i * w_i) + \ldots (x_n * w_n)$
- Bias: always-on input (resiliency to inputs of all zeros)
- Activation (step) function

[3] I am intentionally dropping biological references



(Lane et al., 2019, p. 158)

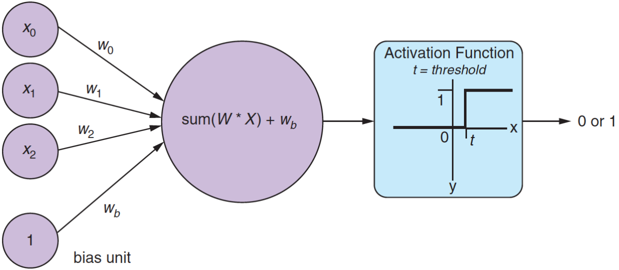
$$\hat{y} = f(\vec{x}) = \begin{cases} 1 & \text{if } \sum_{i=0}^{n} x_i w_i > threshold \\ 0 & \text{otherwise} \end{cases} \tag{1}$$



(Lane et al., 2019, p. 158)

$$\hat{y} = f(\vec{x}) = \begin{cases} 1 & \text{if } \sum_{i=0}^{n} x_i w_i > threshold \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

This perceptron is a special case of a *neuron* —the base unit of a neural network



(Lane et al., 2019, p. 158)

$$\hat{y} = f(\vec{x}) = \begin{cases} 1 & \text{if } \sum_{i=0}^{n} x_i w_i > threshold \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

This perceptron is a special case of a *neuron* —the base unit of a neural network

Let us see

"The output [of a perceptron] is a linear function of the input" (Goodfellow et al., 2016, p. 105)

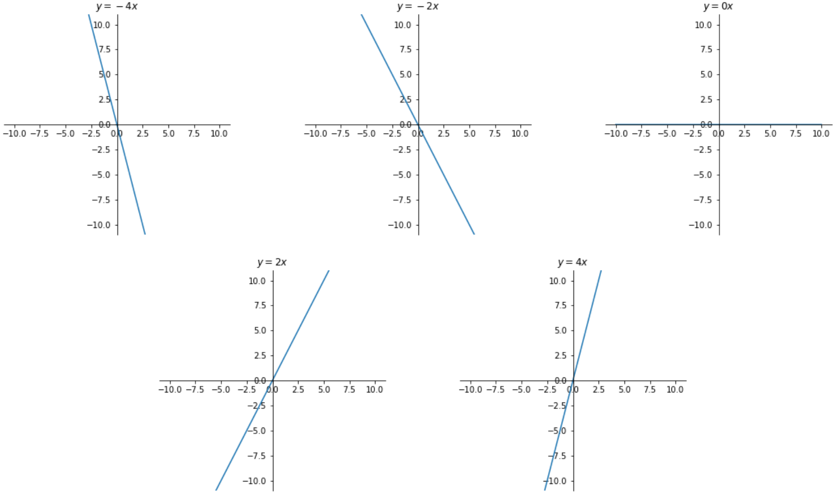
$$\hat{y} = w^T x \tag{2}$$

The Perceptron
Without Bias

```
import matplotlib.pyplot as plt
import numpy as np
for i in range(-5, 5, 1):
    fig, ax = plt.subplots(figsize = (5,5))
    ax.spines['left'].set_position('center')
    ax.spines['bottom'].set_position('center')
    ax.spines['right'].set_color('none')
    ax.spines['top'].set_color('none')
    ax.set(title='$y=w^Tx$')
    x = np.arange(-5.0, 5.0, 0.01)
    plt.xlim((-5,+5))
    plt.ylim((-5,+5))
    ax.set(title='$y={}x$'.format(i))
    y = i*x  #1 + np.sin(2 * np.pi * x)
    ax.plot(x, y)
    fig.savefig("linear_w{}.png".format(i))
    plt.show()
```

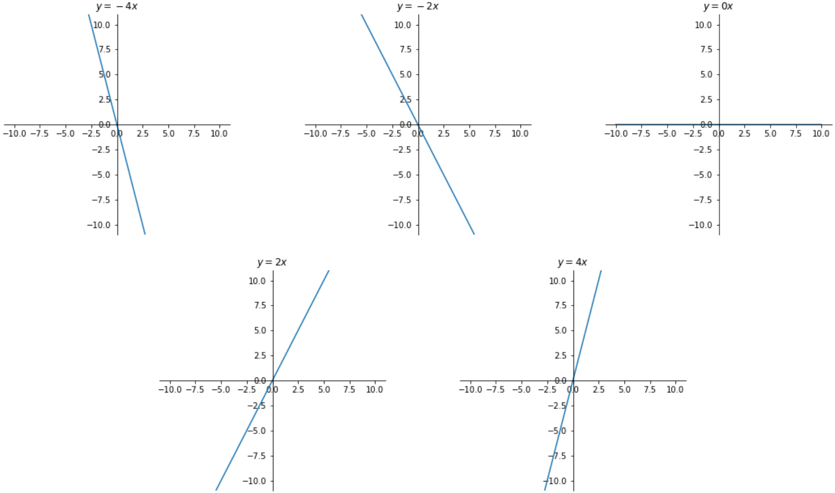
Not the nicest way to plot

Plotting with different values of w



The Perceptron
Without Bias

Plotting with different values of w; do you see an issue?



The Perceptron

With Bias

$$\hat{y} = w^T x + b \tag{3}$$

The Perceptron
With Bias

$$\hat{y} = w^T x + b \tag{3}$$

"[. . .] the mapping from parameters to predictions is still a linear function but the mapping from features to predictions is now an affine function" (Goodfellow et al., 2016, p. 107)

The Perceptron
With Bias

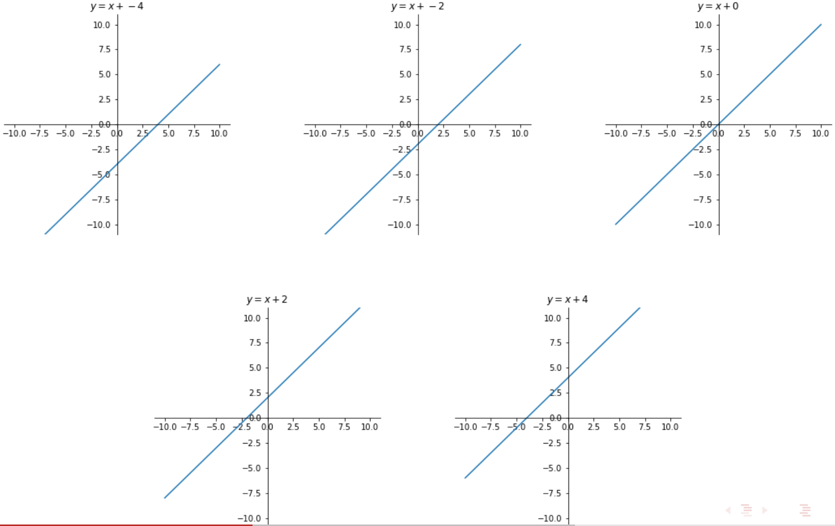
$$\hat{y} = w^T x + b \tag{3}$$

"[. . .] the mapping from parameters to predictions is still a linear function but the mapping from features to predictions is now an affine function" (Goodfellow et al., 2016, p. 107)

(does not need to pass by the origin)

The Perceptron
Without Bias

Plotting with $w = 1$ and different values of b



The Perceptron

Typical Learning Process (1/2)

Given an annotated dataset. . .

- start with a random weight initialisation from a normal distribution

$$\vec{w} \sim \mathcal{N}(\mu, \sigma^2) \text{ with } \mu \sim 0 \text{ (but do not use 0!)}$$

The Perceptron

Typical Learning Process (1/2)

Given an annotated dataset. . .

- start with a random weight initialisation from a normal distribution

$$\vec{w} \sim \mathcal{N}(\mu, \sigma^2) \text{ with } \mu \sim 0 \text{ (but do not use 0!)}$$

- feed one instance and see if the predicted class is correct

The Perceptron

Typical Learning Process (1/2)

Given an annotated dataset...

- start with a random weight initialisation from a normal distribution

$$\vec{w} \sim \mathcal{N}(\mu, \sigma^2) \text{ with } \mu \sim 0 \text{ (but do not use 0!)}$$

- feed one instance and see if the predicted class is correct

```
if the class is correct then
    do nothing
else
    adjust the weights (slightly; not until getting the class right!)
```

The Perceptron

Typical Learning Process (1/2)

Given an annotated dataset...

- start with a random weight initialisation from a normal distribution

$$\vec{w} \sim \mathcal{N}(\mu, \sigma^2) \text{ with } \mu \sim 0 \text{ (but do not use 0!)}$$

- feed one instance and see if the predicted class is correct

```
if the class is correct then
    do nothing
else
    adjust the weights (slightly; not until getting the class right!)
```

Each weight is adjusted by how much it contributed to the resulting error

The Perceptron

Typical Learning Process (2/2)

- All instances in the training data are fed a number of times (iterations): epoch
- Typical stop criteria include
  - *error* $< \epsilon$ (convergence)
  - *error* stabilisation
  - max number of epochs reached

The Perceptron

Example 1: Logical OR function

input		output
0	0	0
0	1	1
1	0	1
1	1	1

The Perceptron

Example 1: Logical OR function

input		output
0	0	0
0	1	1
1	0	1
1	1	1

Let us see

input		output
0	0	0
0	1	1
1	0	1
1	1	1

Let us see

Mr. Perceptron can learn!

input		output
0	0	0
0	1	1
1	0	1
1	1	1

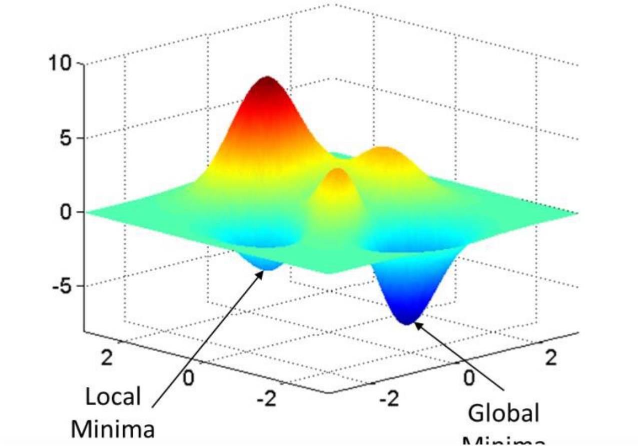
Let us see

Mr. Perceptron can learn!

This learning model is called linear regression (another ML alternative)

The Perceptron

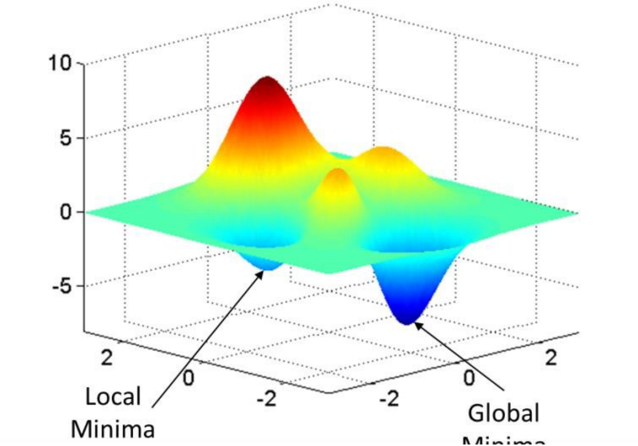
Drawback: Local vs Global Minimum



Plot from M. Ryan's thesis (`http://www.isni.org/isni/000000045916099X`)

The Perceptron

Drawback: Local vs Global Minimum



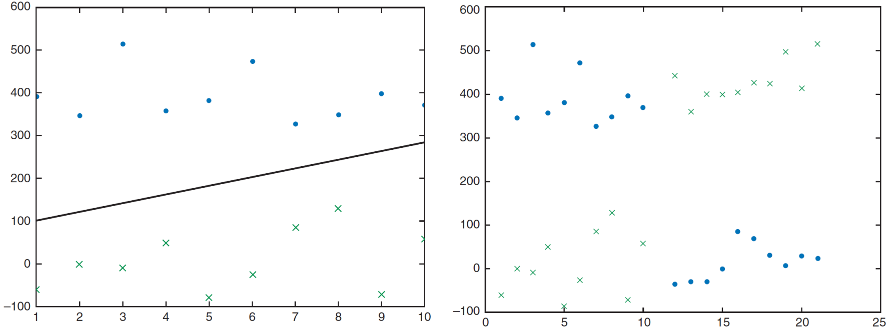
No guarantee that the model will reach the global optimal solution

Plot from M. Ryan's thesis (http://www.isni.org/isni/000000045916099X)

The perceptron can only deal with linearly separable data

Plots from (Lane et al., 2019, p. 164–165)

The perceptron can only deal with linearly separable data

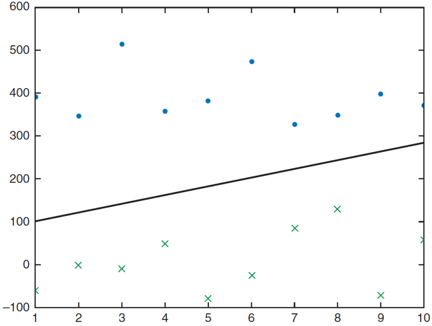


Plots from (Lane et al., 2019, p. 164–165)

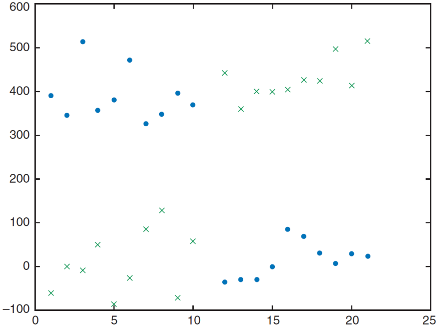
The Perceptron

Drawback: Linearly separable

The perceptron can only deal with linearly separable data



linearly separable



not linearly separable

Plots from (Lane et al., 2019, p. 164–165)

We have learned a logical OR function . . .

Can we learn a logical XOR?

We have learned a logical OR function ...

Can we learn a logical XOR?

input		output
0	0	0
0	1	1
1	0	1
1	1	0

We have learned a logical OR function . . .

Can we learn a logical XOR?

input		output
0	0	0
0	1	1
1	0	1
1	1	0

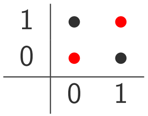
Let us see

The Perceptron
Example 2: Logical XOR

We have learned a logical OR function ...

Can we learn a logical XOR?

input		output
0	0	0
0	1	1
1	0	1
1	1	0



Let us see

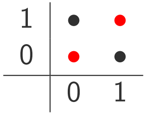
The Perceptron

Example 2: Logical XOR

We have learned a logical OR function ...

Can we learn a logical XOR?

input		output
0	0	0
0	1	1
1	0	1
1	1	0



📘 Let us see

Mr. Perceptron cannot learn! ...winter

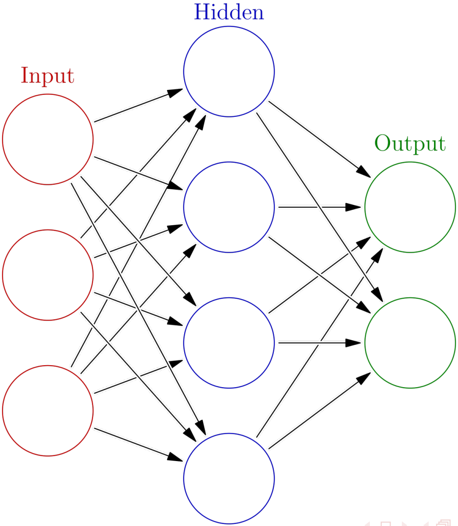
More than One Neuron

Neural Networks

A neural network is a combination of multiple perceptrons (and it can deal with more complex patterns)

Neural Networks

A neural network is a combination of multiple perceptrons (and it can deal with more complex patterns)



Some Formalisms

Input $x = [x_1, x_2, x_3, \ldots, x_k]$

Output $f(x)$[4]

Answer y

[4] aka $\hat{y}$

[5] aka loss function

Some Formalisms

Input $x = [x_1, x_2, x_3, \ldots, x_k]$

Output $f(x)$[4]

Answer y

Cost Function[5] Quantifier of the mismatch between actual and predicted output

$$err(x) = |y - f(x)| \tag{4}$$

[4] aka $\hat{y}$

[5] aka loss function

Some Formalisms

Input $x = [x_1, x_2, x_3, \ldots, x_k]$

Output $f(x)$[4]

Answer y

Cost Function[5] Quantifier of the mismatch between actual and predicted output

$$err(x) = |y - f(x)| \tag{4}$$

Training goal Minimising the cost function across all input samples

$$J(x) = \min \sum_{i=1}^{n} err(x_i) \tag{5}$$

[4] aka $\hat{y}$

[5] aka loss function

Next

- Backpropagation (briefly)
- Activation functions
- Keras

References

Goodfellow, I., Y. Bengio, and A. Courville
2016. *Deep Learning*. MIT Press. `http://www.deeplearningbook.org`.

Lane, H., C. Howard, and H. Hapkem
2019. *Natural Language Processing in Action*. Shelter Island, NY: Manning Publication Co.

Rosenblatt, F.
1957. The perceptron—a perceiving and recognizing automaton. Technical Report 85-460-1, Cornell Aeronautical Laboratory, Buffallo, NY.