# 91258 - Natural Language Processing

Lesson 10. “One” Neuron

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## Previously

- From Words to Topics

## Table of Contents



**There Was Life Before Deep Learning**

Inspired by Hermann Ney’s lesson at the 2017 DL Summer School in Bilbao

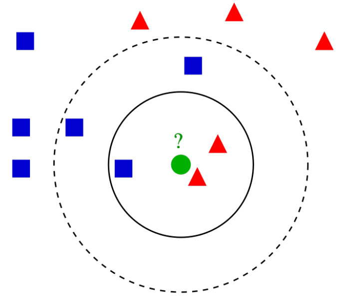
## There Was Life Before Deep Learning

(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



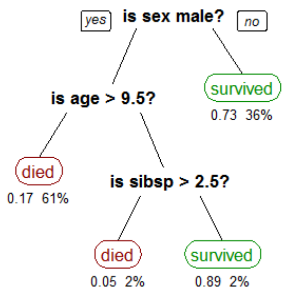

The class of ● is the same as the most frequent among its *k* neighbours

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

## There Was Life Before Deep Learning

Random Forests (showing only one decision tree here)

Titanic survivors



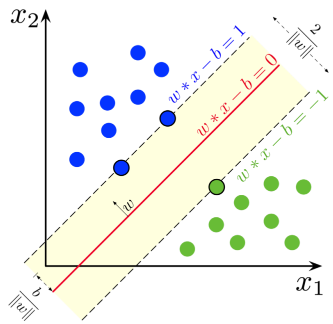

* sibsp: number of siblings or spouse of a person onboard

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

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

## 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

- Often they are SoA (or close)
- In general, they are *cheaper*
- In general, they require *less* data
- Some of them are *explainable*
- 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 |
| 1966 | failure of MT |
| 1970 | abandonment of connectionism (explain mental phenomena using artificial neural networks) |
| 1971–75 | DARPA's frustration wrt CMU 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

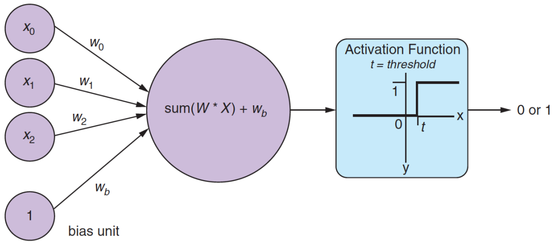
- Intended to be a machine able of recognising images
- Rough idea:

  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]



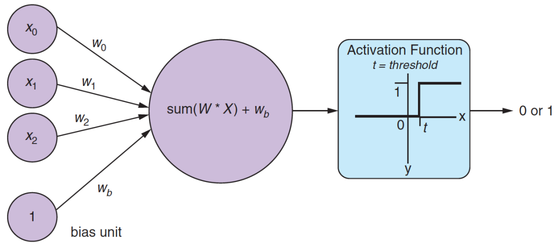

(Lane et al., 2019, p. 158)

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

[3] I am intentionally dropping any biological reference

# The Perceptron

## Numerical Perceptron




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

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

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

Let us see

## The Perceptron

### Without Bias

"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

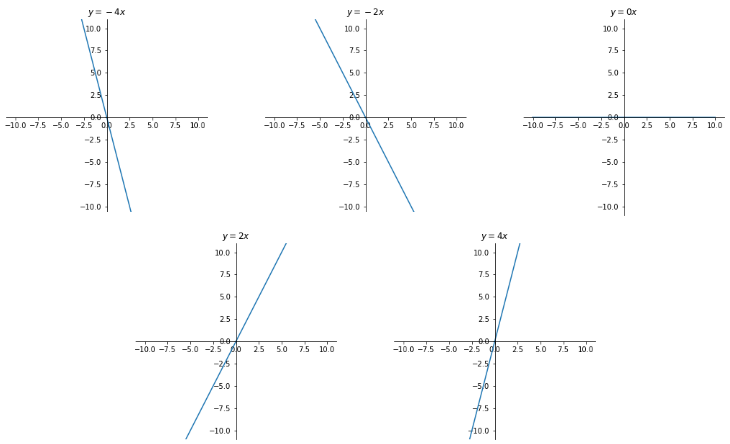
```
import matplotlib.pyplot as plt
import numpy as np
for i in range(-5, 5, 1):
    fig, ax = plt.subplots(figsize = (5,5))
    ax.spines['left'].set_position('center')
    ax.spines['bottom'].set_position('center')
    ax.spines['right'].set_color('none')
    ax.spines['top'].set_color('none')
    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

## The Perceptron

### Without Bias

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




## The Perceptron

### With Bias

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

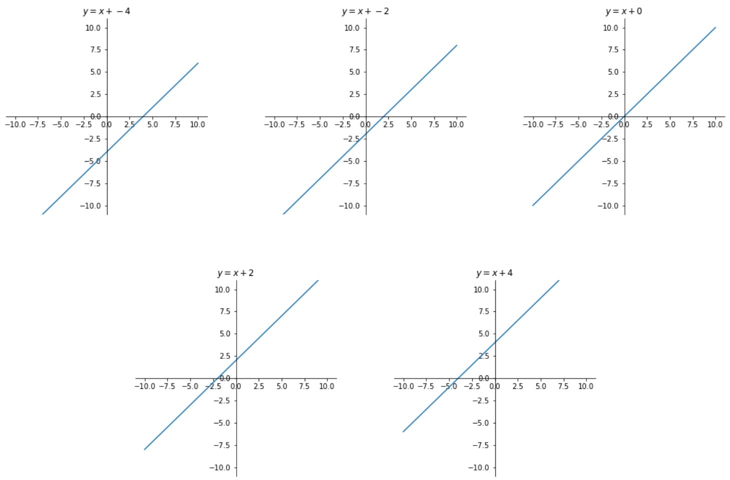
"[...] the mapping from parameters to predictions is still a linear function but the mapping from features to predictions is now an affine function" (Goodfellow et al., 2016, p. 107)

(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

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

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

```
1: if the class is correct then
2:     do nothing
3: else
4:     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: **epoch**
- Typical stop criteria include
  - *error* $< \epsilon$ (convergence)
  - *error* stabilisation
  - max number of epochs reached

# The Perceptron

## Example 1: Logical OR

| input | | output |
|---|---|---|
| 0 | 0 | 0 |
| 0 | 1 | 1 |
| 1 | 0 | 1 |
| 1 | 1 | 1 |

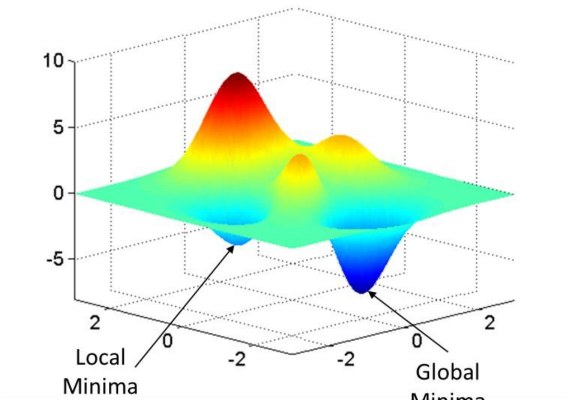
Let us see

**Mr. Perceptron can learn!**

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

# The Perceptron

Drawback: Local vs Global Minimum



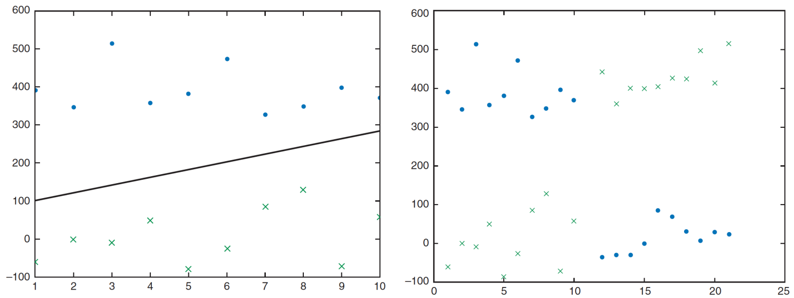

No guarantee that the model will reach the global optimal solution

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

# The Perceptron

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)

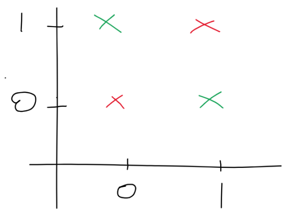
# The Perceptron

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 |



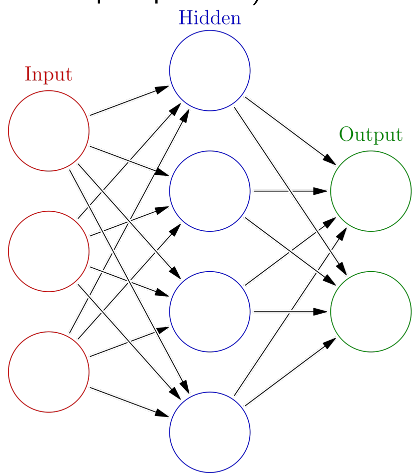

📘 Let us see

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)




Fully-connected neural network

## 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.

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