Deep Learning for Natural Language Processing

Lecture 1 – Kick-off

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Natural Language Learning Group (NLLG)
Technische Universität Darmstadt

Outline

TECHNISCHE UNIVERSITÄT DARMSTADT

Administrative course issues

NLLG Lab

Deep Learning for NLP

Learning Goals

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After completing this course, you are able to

- explain the basic concepts of neural networks and deep learning.
- explain the concept of word embeddings, train word embeddings and use them for solving NLP problems.
- understand and describe neural network architectures that are used to tackle classical NLP problems such as text/sentence classification and sequence tagging.
- implement neural networks for NLP problems using existing libraries in Python.

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General Information

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Teaching material:

Lectures, exercises/submissions etc. can be found in Moodle

Resources

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- This lecture is mainly based on the latest papers from (top) NLP conferences
  - Deep Learning is changing too quickly to base it on text books
    - Knowledge is too quickly outdated
- The lecture is in English

Useful Additional Resources

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- Stanford Lecture by Richard Socher : Deep Learning for Natural Language Processing cs224d – look it up on youtube

- Stanford Lecture by Andrej Karpathy, cs231n – look it up on youtube

- Ian Goodfellow, Yoshua Bengio, and Aaron Courville:
  Deep Learning, MIT Press

Recommended Readings

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- We provide literature for each topic of our course:
  - Even if you have very limited time, please do read the **mandatory part**
    - we will assume that you know these works
    - The mandatory papers (roughly one per week) will be “prüfungsrelevant”
    - We will ask one/two questions from the mandatory papers in the home exercises
  - We encourage you to read the **optional parts** as well
    - Optional are the references listed in each lecture
- We can give you additional literature hints → feel free to ask
- If you cannot find/access a publication → feel free to ask

Practice Class

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- **Every Tuesday 15:20 – 17:00, Room S207/167**
- First meeting will be today!

- The exercises will give you some practical experience and hands-on training of what you learned
  - You will learn to program neural nets, something that we don't do/teach in the lecture
- Obtain a bonus for your exam

- Practice class is organized by Michael Bugert

Practice Class: Bonus System

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- By participating in the practice class, you can get a bonus of 0.3 (or 0.4) for the exam – maybe even a full grade

- The following rules apply:
  1. You need to reach 70 out of 100 points for the home exercises
     - ~10 homeworks a 10 points each
  2. You need to participate in a “shared task”
     - Will take place in the 2nd half of the course
  3. You have to pass the exam without the bonus, i.e. the bonus cannot turn a 5 into a 4
  4. The bonus can only be used in the exams in this semester
  5. The bonus can only be used once per student

Practice Class: Shared Task

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- You will work on generating poetry
- You will work in groups of up to 3 people
- You will develop a solution to the problem and then compete with other groups
- Shared task is graded and gives up to 100 points. Grading is based on:
  - A written report about your system (60 points)
  - your ranking compared to other teams -> better system, more points (30 points)
  - A short presentation in the last class (10 points)

Increase your odds!

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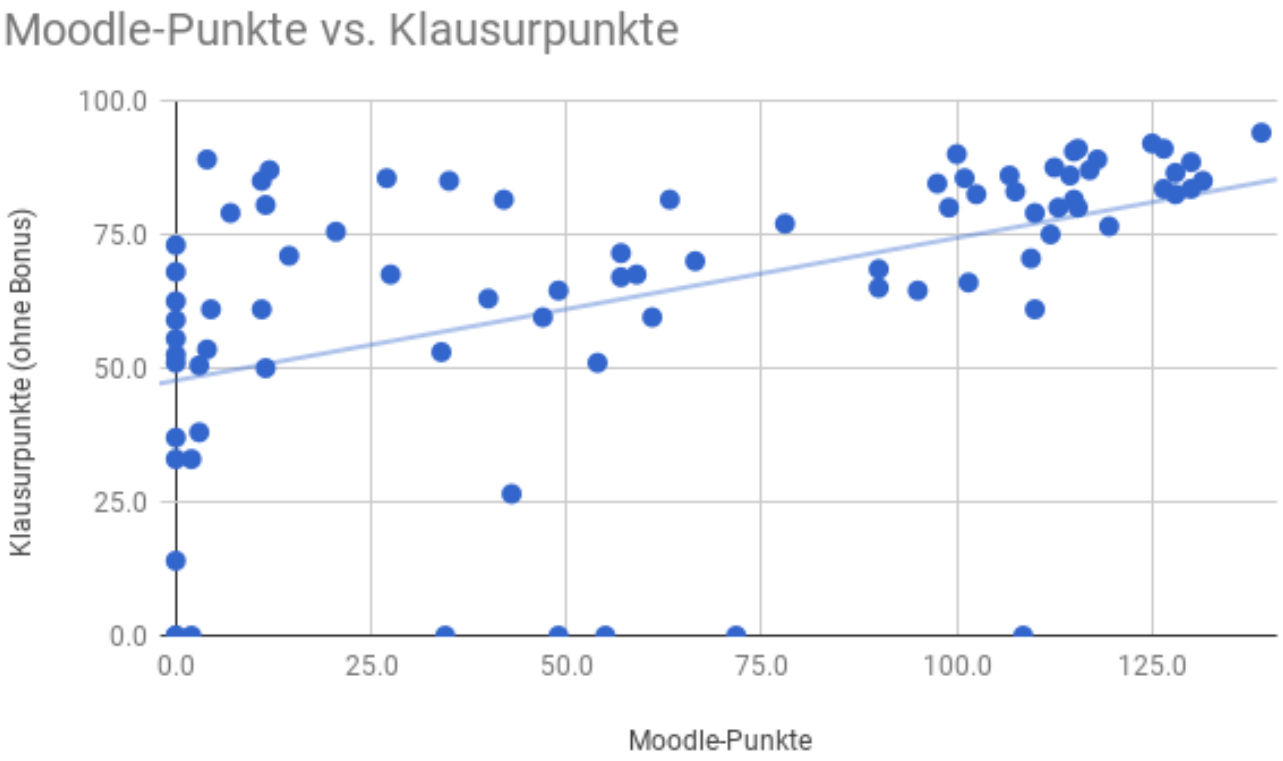
- Exam results and participation in exercises correlate.



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Programming Framework:

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- Python, Numpy
- Tensorflow
- Keras

→ more information this afternoon

Tutors

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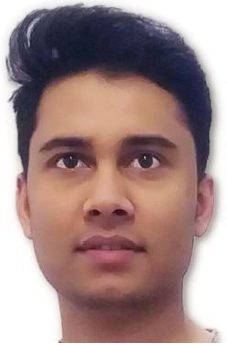
- Niraj Pandey
  - „Sprechstunde“ online via appointment



- Jan-Micha Bodensohn
  - „Sprechstunde“ online via appointment

- If you have questions, contact them via moodle

Participate!

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- Common practice:
  study the slides in a 24h marathon just before the exam
- We want to encourage you to participate in this course
  - Attend lecture and practice class whenever possible!
  - Discuss with others in the forum!
  - Think beyond what we communicate in class!
  - Try out something new!
  - Read!
  - Ask!

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Participate!

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- Common practice:
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  - Think beyond what we communicate in class!
  - Try out something new!
  - Read!
  - Ask!

- **Why? You get well prepared for the exam and for other courses, thesis, future job without the 24h marathon!**

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Final Exam

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Save the date:

Date will be announced

Register via TUCaN, see also:

https://www.informatik.tu-darmstadt.de/de/studierende/studienbuero/pruefungsan-und-abmeldung/

Exam questions will be in German and English.

Answers may be in German or English.

Final Exam: Resources Allowed

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- Scope: Lecture, mandatory readings, and practice class
- Final grade: Exam (100%) + Bonus System
- You may bring a dictionary to the exam, if neither German nor English is your first language.
- You may bring a non-programmable calculator to the exam.
- No other resources (books, lecture notes etc.) are allowed during the exam.

Questions/Suggestions

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Any questions, suggestions,…?

1. Post a message in the Moodle forum
2. *If that doesn‘t help:* Write an E-Mail to the tutors or make an appointment with them
3. *If that doesn‘t help also:* Write an email to Michael or me

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Detailed Syllabus

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1	History+Perceptrons
2	ML background
3	Backpropagation – Learning in deep neural nets
4	Word Embeddings 1 – CBOW and Skip-Gram
5	Dependency Parsing
6	Word Embeddings 2 – Bilingual, Syntactic, Contextualized Embeddings
7	Word Embeddings 3 – Sentence Embeddings
8	Convolutional networks
9	Recurrent neural networks
10	Encoder-Decoder Neural Nets
11	Mock exam (Probe-Klausur)
12	Current Trends
13	Guest lectures
14	Summary and Shared Task award presentations

ICR

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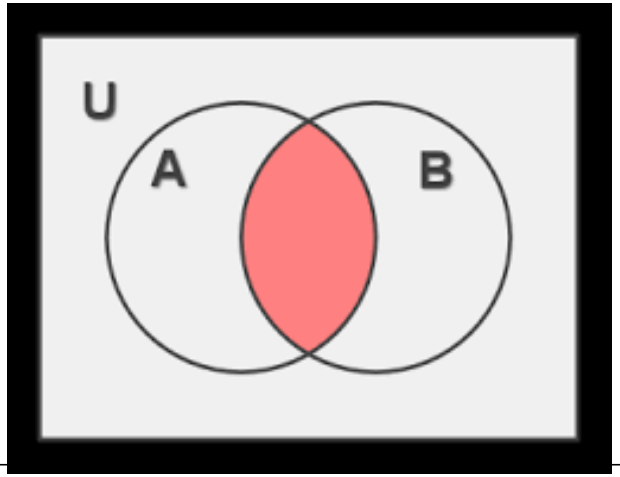
- You'll watch a video at home **before** the lecture (typically 100-120min)
  - Video and lecture will overlap, but the lecture may cover other aspects as well
- The lecture itself will then be shorted to about 30min
- And so will the exercise (takes then place in lecture room)
- When we have ICR, there will be no separate exercise slot from 15-17



A = Video
B = Lecture

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Effort Curve

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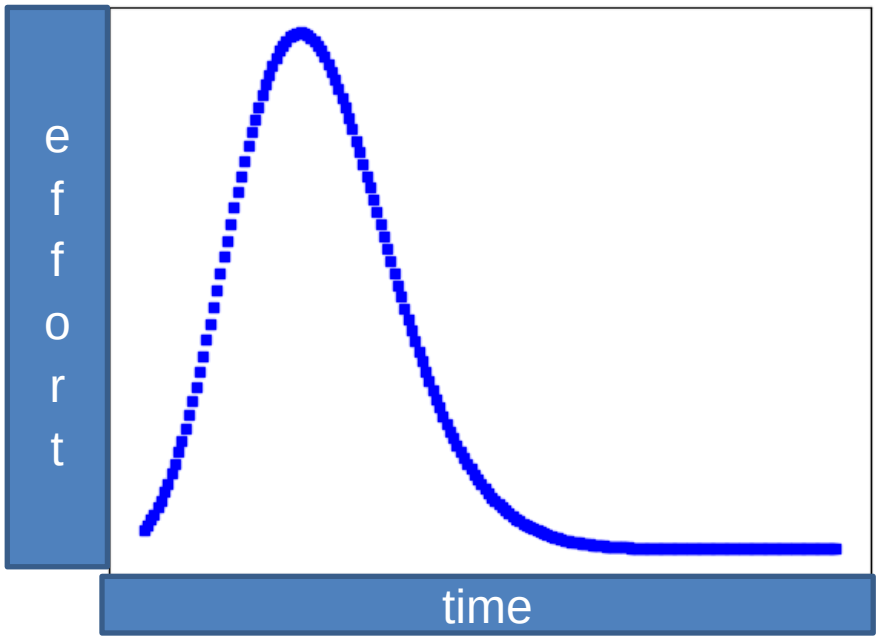
Effort curve in the lecture



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Required skills

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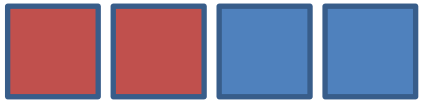
- Math



- Programming

- Linguistics

- Natural Language Processing

Outline

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Perceptrons

Origins

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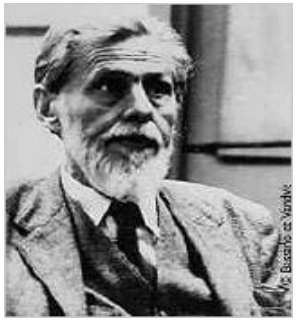
- ‘Simplest’ form of a neural network
- Introduced by McCulloch and Pitts (1943) and Frank Rosenblatt (1958)



http://www.monizone.de/projects/knn/images/mcculloch_160.jpg

http://www.i-programmer.info/babbages-bag/325-mcculloch-pitts-neural-networks.html

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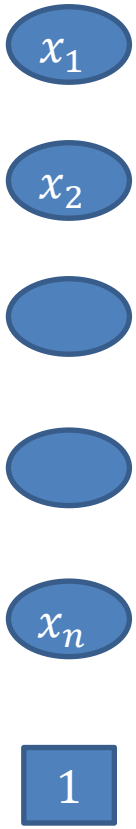
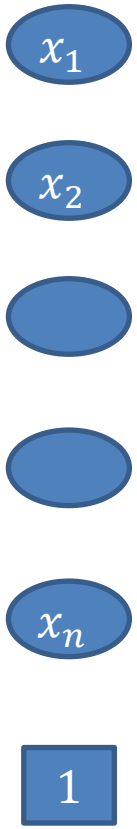
Network structure

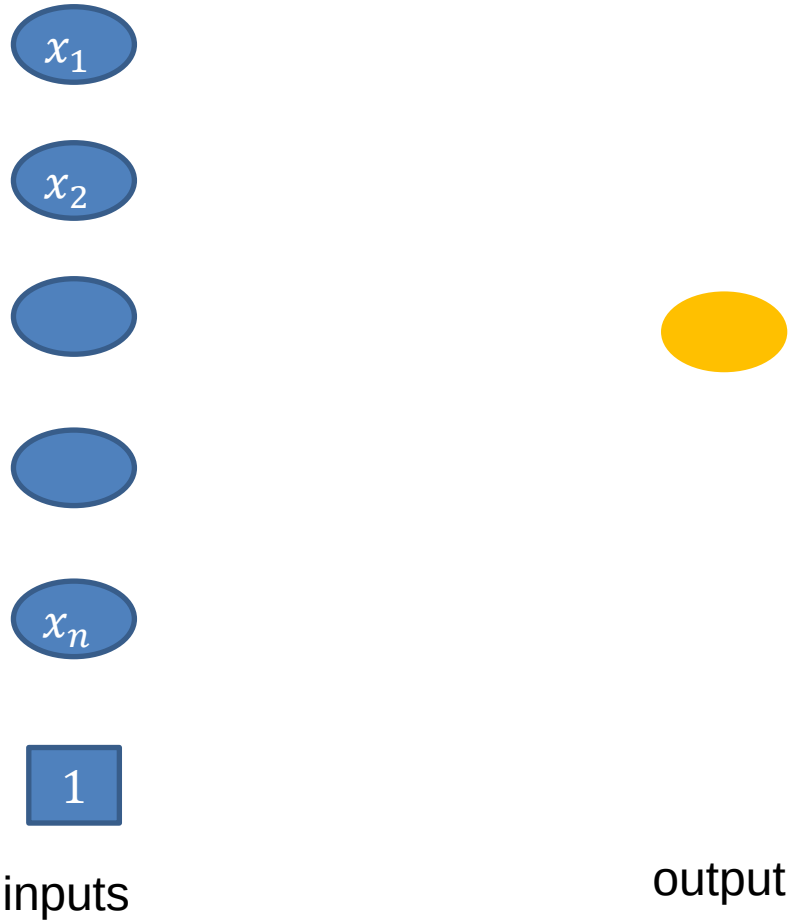


Network structure

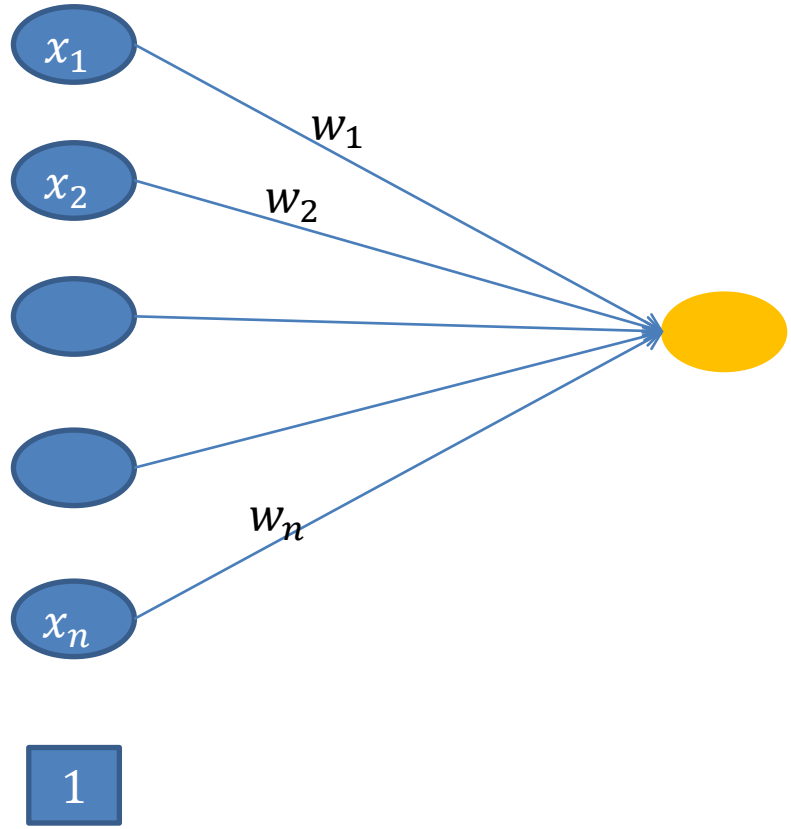


input neurons

Network structure



Network structure



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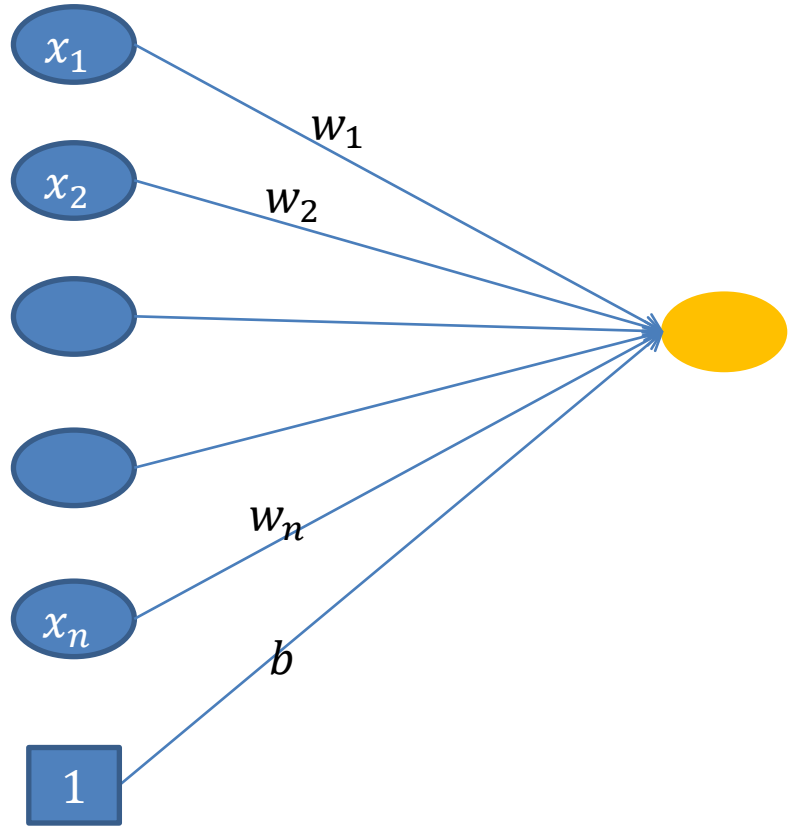
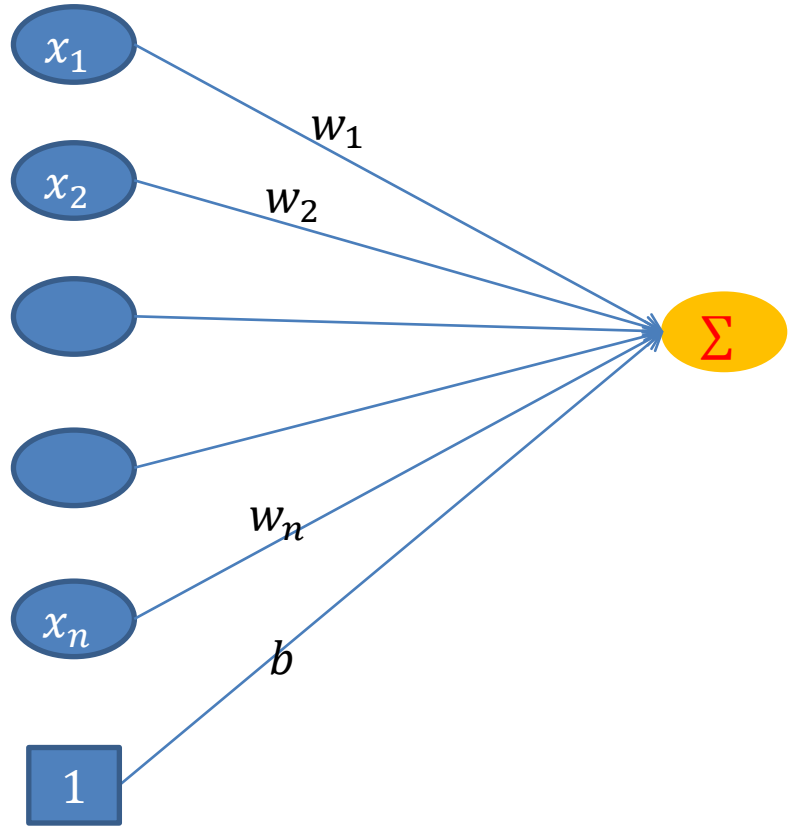


Network structure



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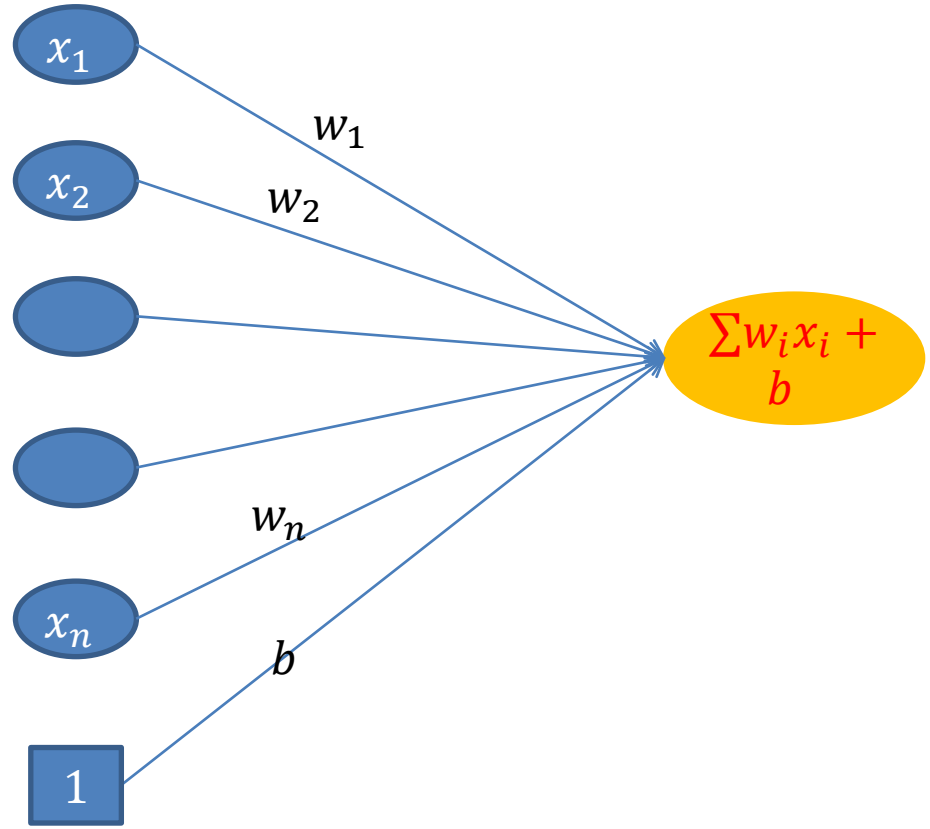

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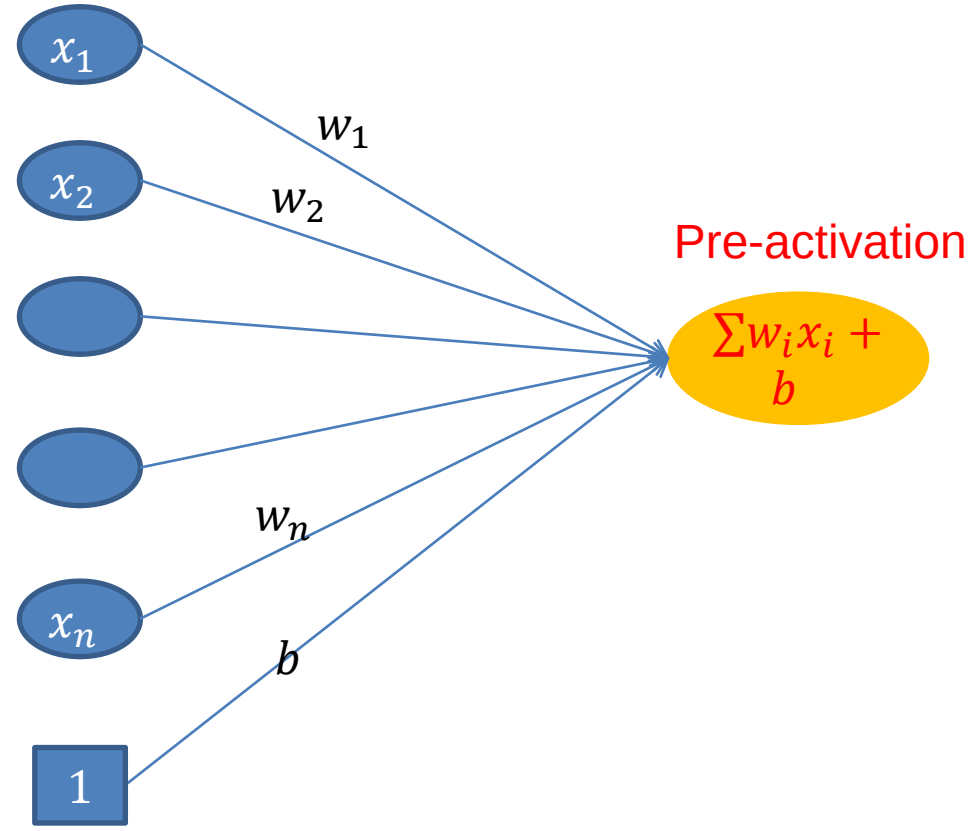

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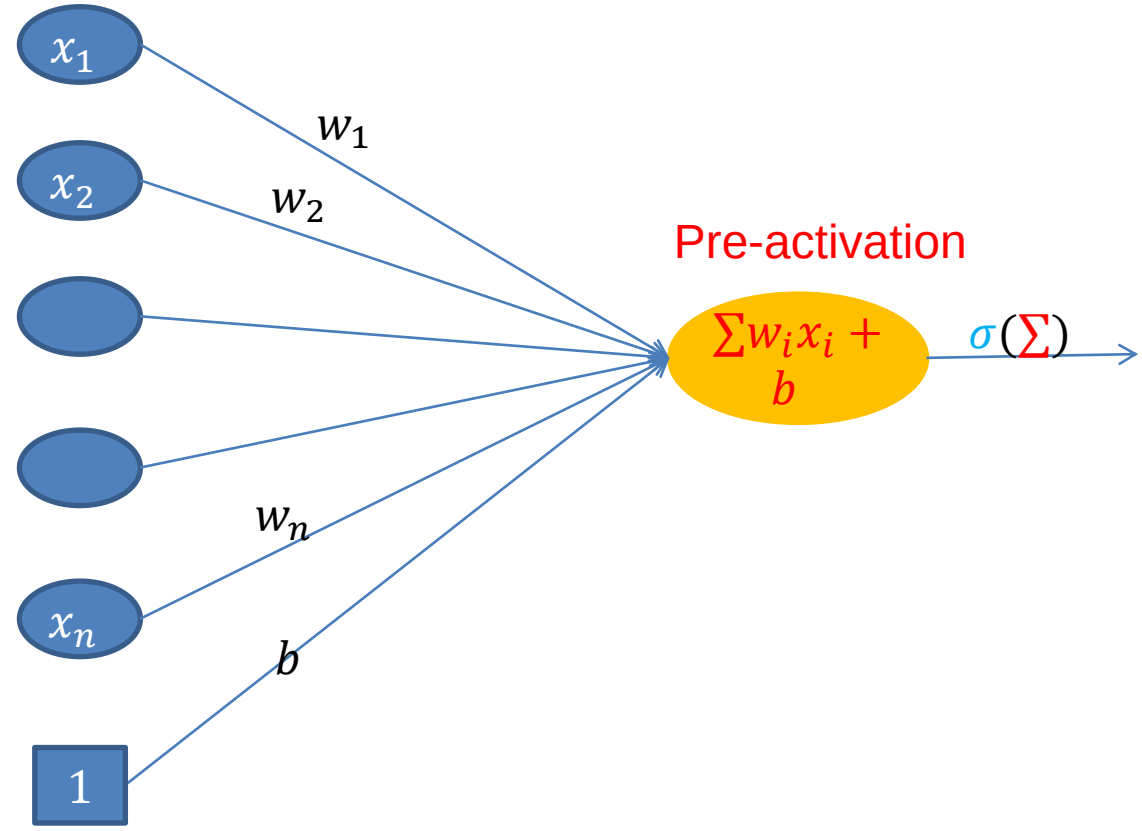

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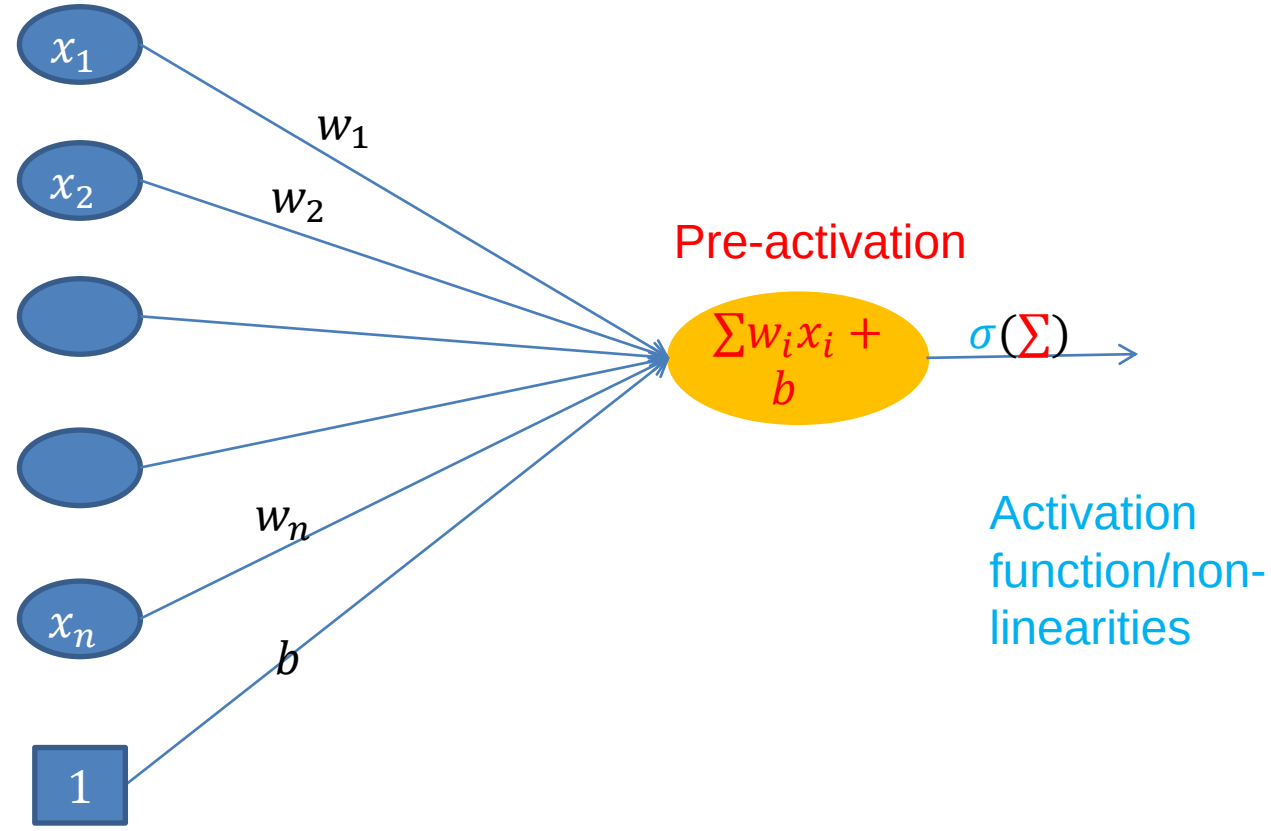

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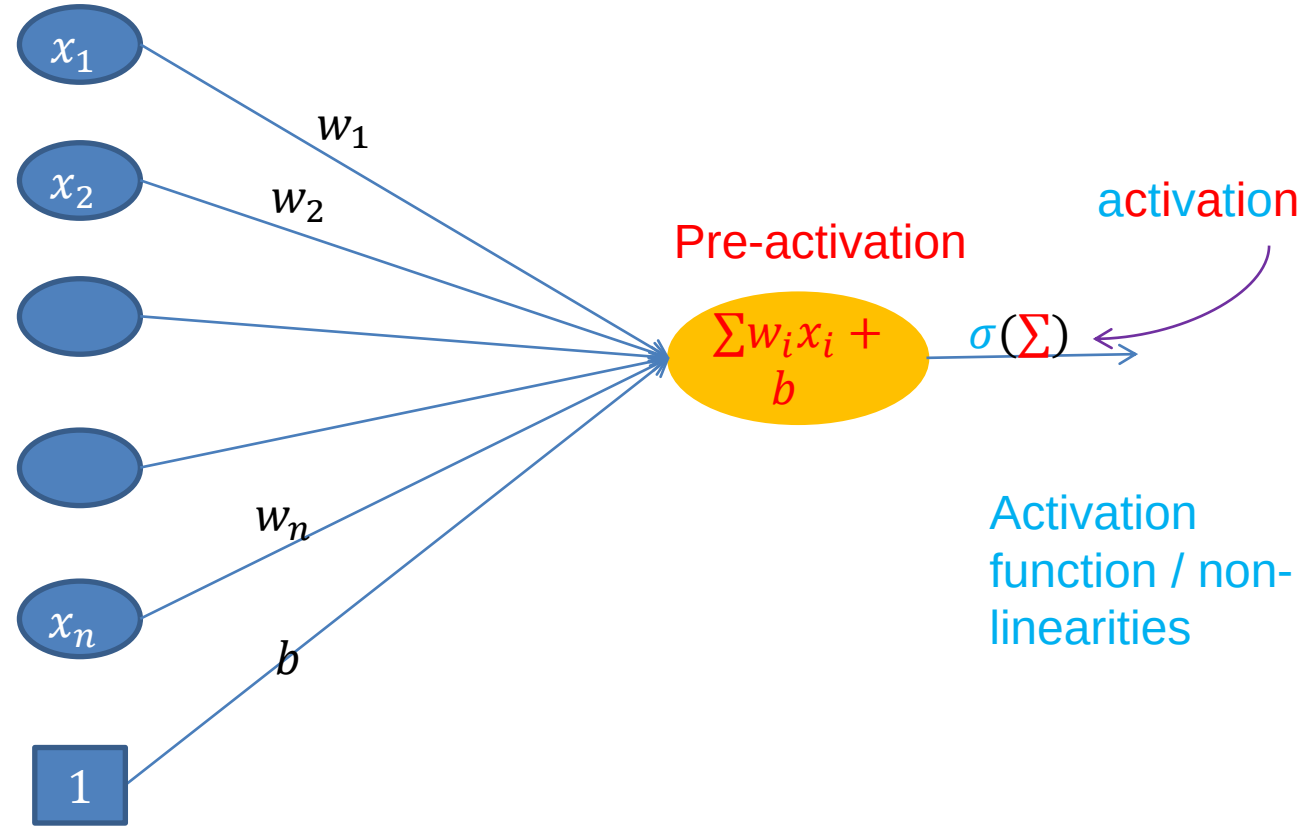

A formal description

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- **Given**
  - **Weight vector** $\mathbf{w} \in \mathbb{R}^n$, $b \in \boldsymbol{R}$
  - **Non-linearity** $\sigma : \mathbb{R} \rightarrow \mathbb{R}$
- **Input to network**
  - **Input vector** $\mathbf{x} \in \mathbb{R}^{1 \times n}$, for $n \geq 1$.
  - **And constant** $1 \in \boldsymbol{R}$
- **Output unit**
  - **Input:** $\mathbf{x} \cdot \mathbf{w} + b = \sum_{i=1}^{n} w_i \cdot x_i \quad + b$
  - **Output:** $\sigma(\mathbf{x} \cdot \mathbf{w} + b)$

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Dot product
(„Skalarprodukt“)

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A formal description

- **Given**
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  - **Output:** $\sigma(\mathbf{x} \cdot \mathbf{w} + b)$

We'll put the constant input „1" into ***x*** for simplicity

A formal description

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- **Given**
  - **Weight vector** $\mathbf{w} \in \mathbb{R}^{n+1}$
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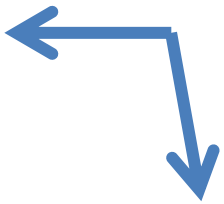
- **Input to network**
  - **Input vector** $\tilde{\mathbf{x}} = (\mathbf{x} \quad 1) \in \mathbb{R}^{n+1}$
  - **And constant** ~~$1 \in \boldsymbol{R}$~~
- **Output unit**
  - **Input:** $\tilde{\boldsymbol{x}} \cdot \boldsymbol{w}$
  - **Output:** $\boldsymbol{\sigma}(\tilde{\boldsymbol{x}} \cdot \boldsymbol{w})$



Notice that dimensionality is n+1 now

A formal description

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- **Given**
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  - **Non-linearity** $\sigma : \mathbb{R} \rightarrow \mathbb{R}$

Parameter (vector): we „learn“/“estimate“ this

- **Input to network**
  - **Input vector** $\tilde{\mathbf{x}} = (\mathbf{x} \quad 1) \in \mathbb{R}^{n+1}$

(Training/test) Data

- **Output unit**
  - **Input:** $\tilde{x} \cdot w$
  - **Output:** $\sigma(\tilde{x} \cdot w) = f_w(\tilde{x})$

(Statistical) Model, parametrized by w [w often also denoted as θ]

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Questions

- **Why do we need a bias unit?**

Questions

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- **Why do we need a bias unit? A: To increase the "capacity" of our statistical model**

Optimization problem

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- Perceptron is the function $f : \mathbb{R}^{n+1} \to \mathbb{R}$ where $f(\tilde{\mathbf{x}}; \mathbf{w}) = \sigma(\tilde{\mathbf{x}} \cdot \mathbf{w})$
- We consider $\mathbf{w}$ as the parameters which we want to optimize
  - Scenario: $(\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_N, y_N)$ is our *training data*
    - We want to solve:[1]

$$\min_{\mathbf{w} \in \mathbb{R}^{n+1}} \sum_{j=1}^{N} (f(\mathbf{x}_j; \mathbf{w}) - y_j)^2$$

[1] Note that in ML, we actually want to optimize our parameters such that performance is good on data that follows the same distribution as our training data

We write here $f(\boldsymbol{x}; \boldsymbol{w})$ rather than $f_{\boldsymbol{w}}(\boldsymbol{x})$ as before.

A perceptron learning algorithm

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- **Given**:
  - Training data $T = \{(\boldsymbol{x}_1, y_1), \ldots (\boldsymbol{x}_N, y_N)\}$
  - Learning rate α
  - Initial parameter vector $\boldsymbol{w}$
- While stopping criterion not met
  - Choose a random sample $\boldsymbol{T'}$ of size $\boldsymbol{N'}$, for $\boldsymbol{1 \leq N' \leq N}$, from $\boldsymbol{T}$
  - Update:

$$\mathbf{w}' \leftarrow \mathbf{w} - \alpha \sum_{(\mathbf{x},y)\in T'} (\sigma(\mathbf{x}\cdot\mathbf{w}) - y)\,\sigma'(\mathbf{x}\cdot\mathbf{w})\mathbf{x}$$

  - $\boldsymbol{w} \leftarrow \boldsymbol{w}'$

How do we arrive at this?

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- It's a bit like optimization in school
  - Take first **derivative** (aka **gradient**), set it to zero
  - Except that we're in a multi-dimensional space, rather than in 1-d
  - And that exact solutions for $\boldsymbol{w}$ don't exist
    - Instead, we look at the gradient and plug it into a general optimization technique called *gradient descent*
    - Then we "randomize" this, arriving at something called *stochastic gradient descent* – or mini-batch learning
- We'll see more on this in lectures 2&3

Outline

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Limitations of Perceptrons

Decision surface of a perceptron

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- Perceptron is the function $f : \mathbb{R}^{n+1} \rightarrow \mathbb{R}$ where $f(\tilde{\mathbf{x}}; \mathbf{w}) = \sigma(\tilde{\mathbf{x}} \cdot \mathbf{w})$
- Perceptron uses threshold function

$$\sigma(z) = \begin{cases} 0 & \text{if } z < 0, \\ 1 & \text{if } z \geq 0 \end{cases}$$

Decision surface of a perceptron

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$$\sigma(z) = \begin{cases} 0 & \text{if } z < 0, \\ 1 & \text{if } z \geq 0 \end{cases}$$

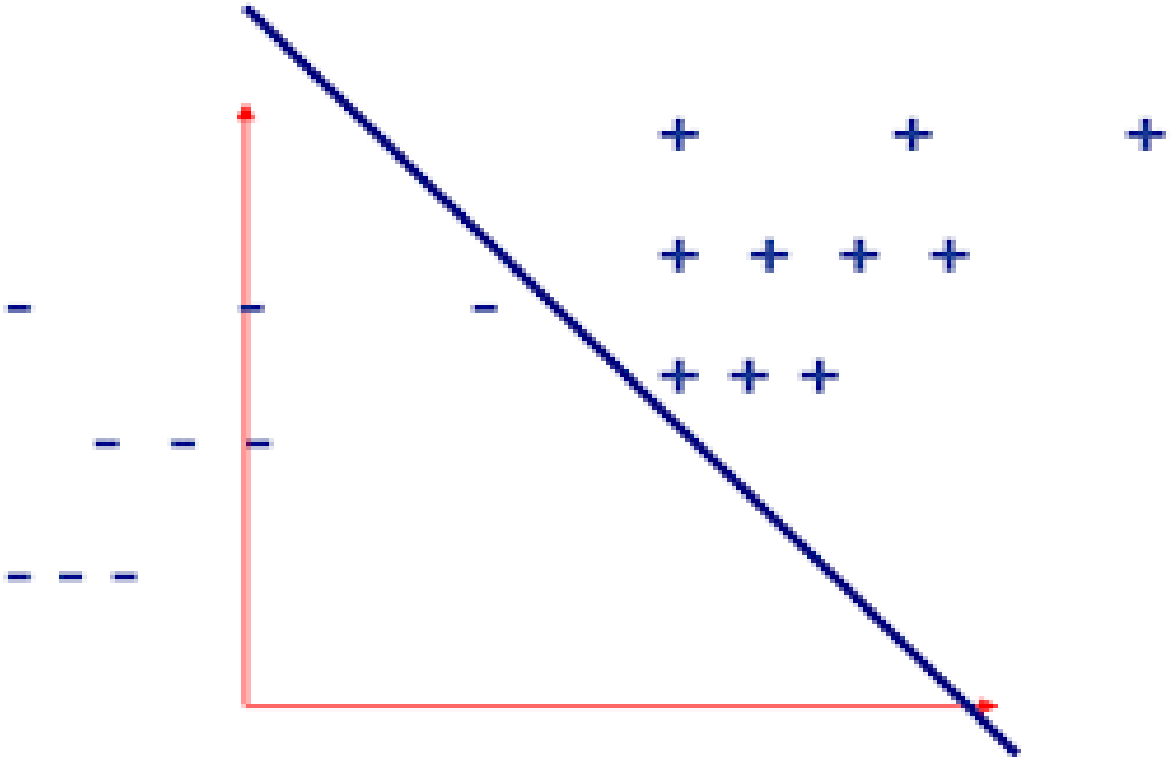
- Consider the *hyperplane* $H_{\boldsymbol{w}}$

$$\{(x_1, \ldots, x_n) \,|\, \tilde{\mathbf{x}} \cdot \mathbf{w} = x_1 w_1 + \cdots + x_n w_n + w_{n+1} = 0\}$$

- In 2-d: $x_1 w_1 + x_2 w_2 + w_{n+1} = 0$ iff $x_2 = -\frac{w_1}{w_2} x_1 - \frac{w_3}{w_2}$
- $y = az + b$ is the equation of a straight line

Decision surface

- Decision surface of threshold function perceptron



From http://marcuswhybrow.com/lecturenotes/build/html/images/euclidean-feature-space.png

What a perceptron can do

- **Linear separability** Let X_0 and X_1 be two sets of points in an n-dimensional Euclidean space. Then X_0 and X_1 are *linearly separable* if there exists n+1 real numbers $w_1, \ldots, w_n, w_{n+1}$ such that every $\boldsymbol{x} \in X_0$ satisfies $\widetilde{\boldsymbol{x}} \cdot \boldsymbol{w} > 0$, and every point $\boldsymbol{x} \in X_1$ satisfies $\widetilde{\boldsymbol{x}} \cdot \boldsymbol{w} < 0$. See https://en.wikipedia.org/wiki/Linear_separability

- **Theorem** If data is linearly separable, then the (original) perceptron learning algorithm converges after a finite amount of time and classifies all training data examples correctly.

What a perceptron can do

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- **Example** (The OR problem) Let $X_0 = \{(0,1), (1,0), (1,1)\}$ and $X_1 = \{(0,0)\}$. Both sets are linearly separable. We may choose (among others)

  $\boldsymbol{w} = (1, 1, -0.5)$.

- **Hint:** When you want to determine if two sets are linearly separable, you can equally ask yourself how to set the weight vector $\boldsymbol{w}$ of a perceptron such that it classifies each instance in the two sets "correctly" (the instances in X_0 are thought of having class label 0, and elements in X_1 have labels 1, or vice versa)

What a perceptron canNOT do

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- **Theorem** The XOR problem is not linearly separable

- **Proof** We have $X_0 = \{(1,1),(0,0)\}$ and $X_1 = \{(1,0),(0,1)\}$. If X_0, X_1 were linearly separable, there were w_1, w_2, w_3 as in the definition. Then

$$w_1 + w_2 + w_3 > 0, \qquad w_3 > 0,$$
$$w_1 + w_3 < 0, \qquad w_2 + w_3 < 0,$$

or vice versa. These equations cannot be satisfied. For example,

$$w_1 + w_2 + w_3 + w_3 > 0$$

by the first equations. However,

$$w_1 + w_3 + w_2 + w_3 < 0$$

by the last two equations.

This is a contradiction.

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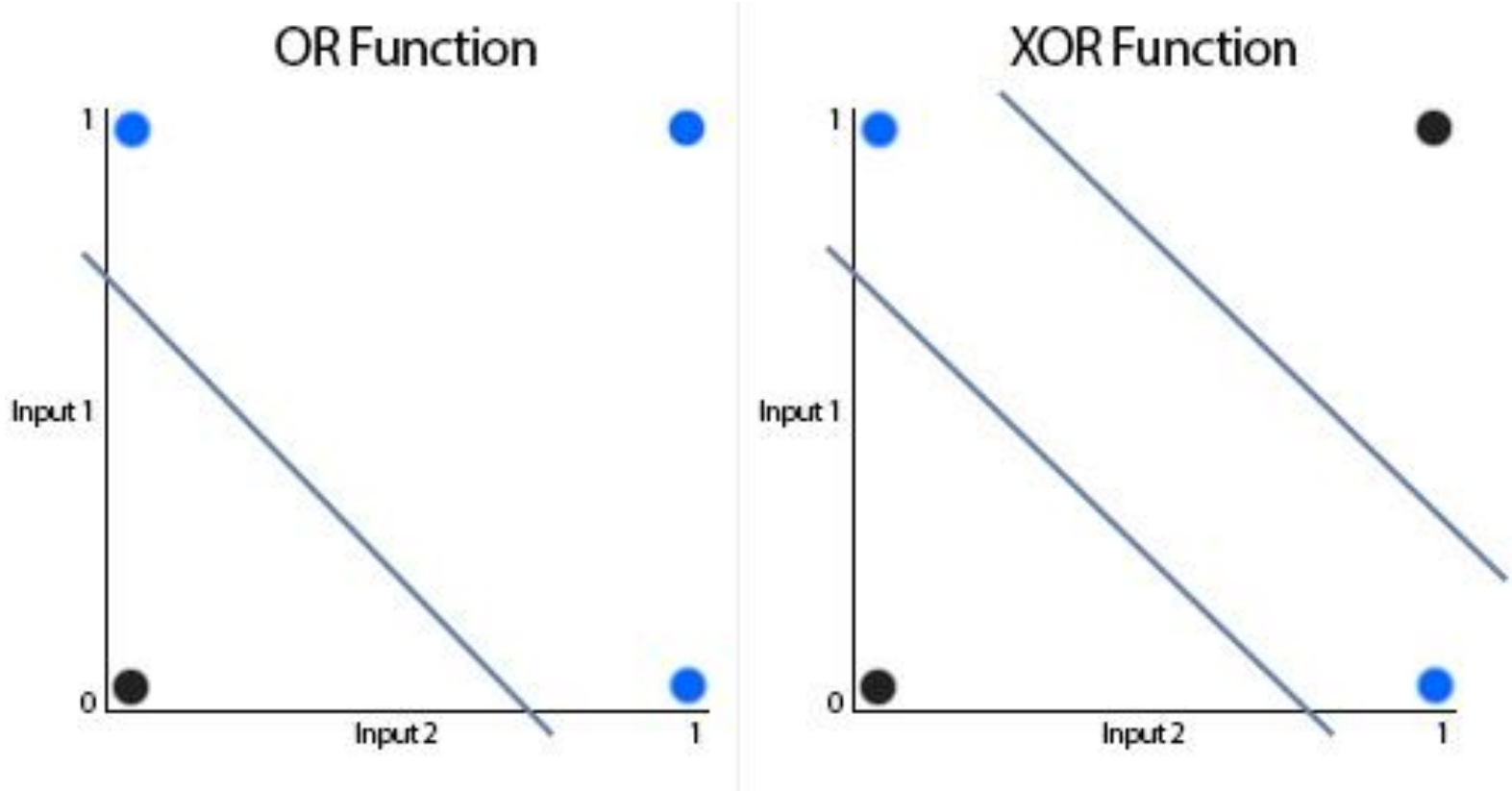
What a perceptron canNOT do



From http://www.theprojectspot.com/tutorial-post/introduction-to-artificial-neural-networks-part-1/7

Outline

TECHNISCHE UNIVERSITÄT DARMSTADT

Neural Networks Principles

More complex neural networks

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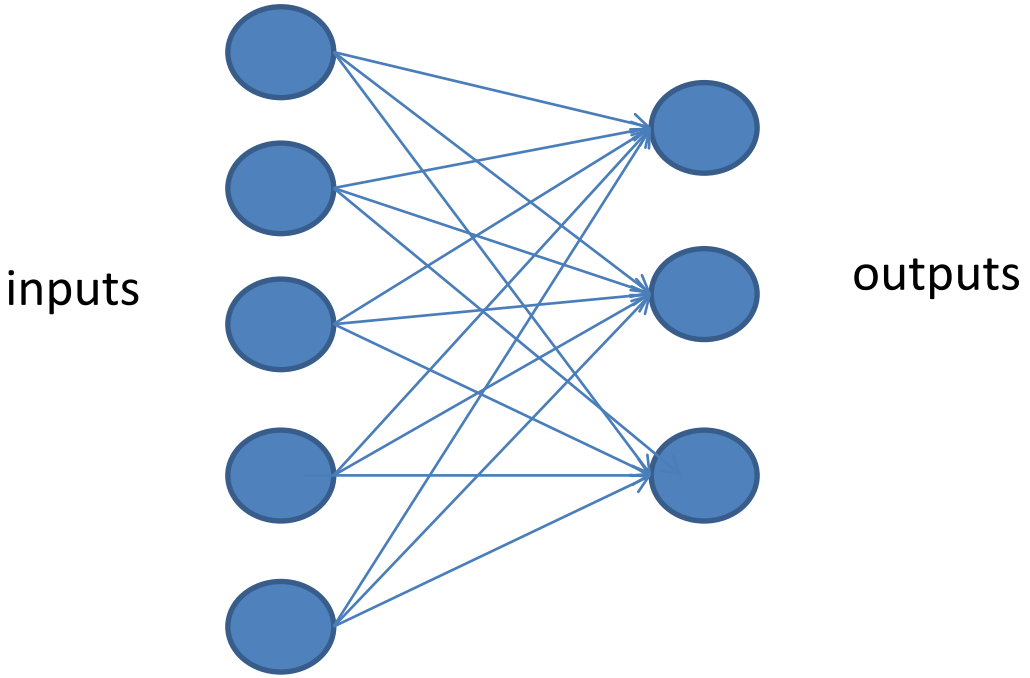
- Several output neurons instead of a single output neuron (we still call it "perceptron")



Now, rather than a dot product $\boldsymbol{x} \cdot \boldsymbol{w}$, we have a vector-matrix multiplication:

$$\boldsymbol{x} \cdot \boldsymbol{W}$$

where $\boldsymbol{W}$ holds the weight vectors $\boldsymbol{w}_j$ for each output neuron j

- No additional technical difficulty, can use the previous learning techniques

NLLG

More complex neural networks

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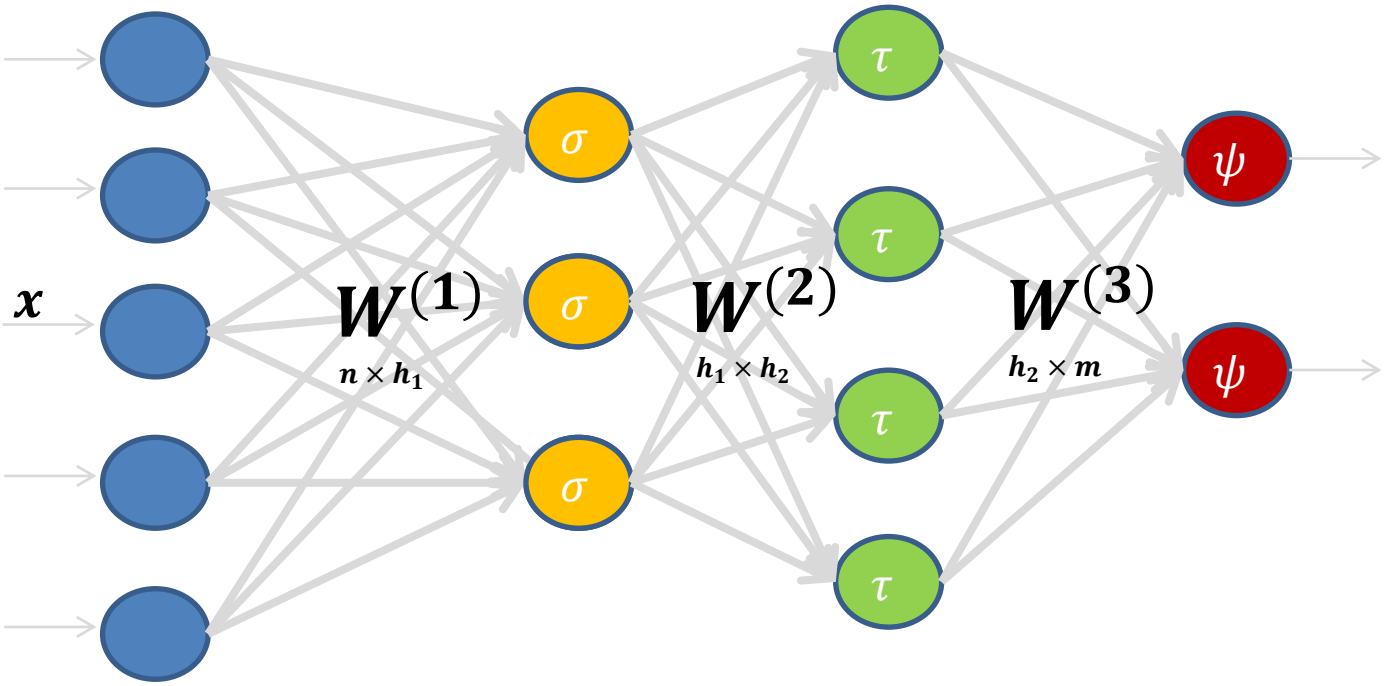
- Multiple **hidden layers/**units



- This is called Multi-Layer-Perceptron (MLP). More difficult in terms of optimization

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Mathematically

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- 1st layer computes:
  - $\boldsymbol{h}_1 = \sigma\left(\boldsymbol{x} \cdot \boldsymbol{W}^{(1)} + \boldsymbol{b}\right)$
  - σ is applied element-wise, $\boldsymbol{h}_1$ is a vector
- 2nd layer computes:
  - $\boldsymbol{h}_2 = \tau(\boldsymbol{h}_1 \cdot \boldsymbol{W}^{(2)} + \boldsymbol{c})$
- etc.

High-level view of neural networks

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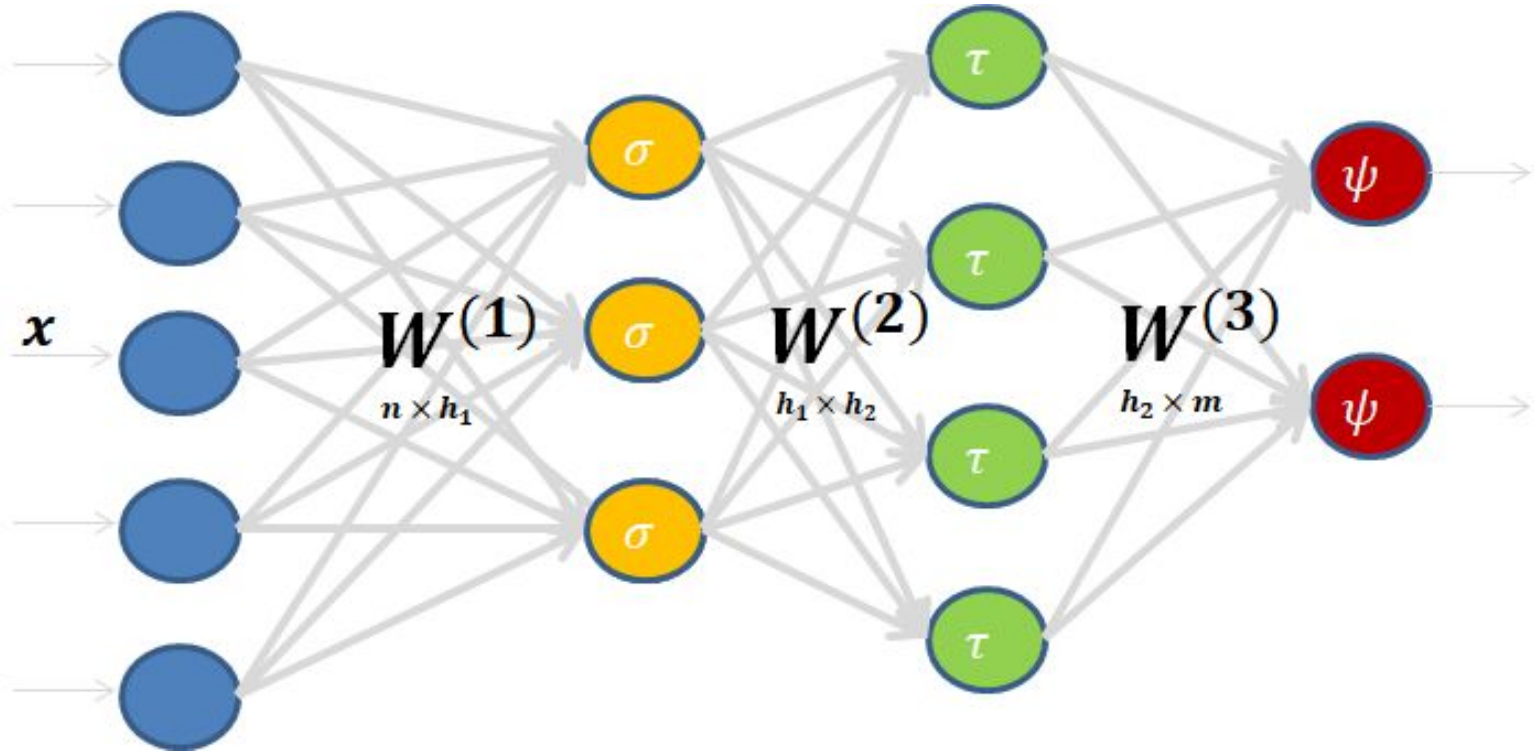
- Neural networks are mathematical functions of the form (ignoring bias terms)
  - $\mathrm{NN}(\boldsymbol{x}; \boldsymbol{W}, \boldsymbol{V}) = g(f(\boldsymbol{x} \cdot \boldsymbol{W}) \cdot \boldsymbol{V})$
  - $\boldsymbol{x}$ is the given input, g, f are also given, $\boldsymbol{W}, \boldsymbol{V}$ is what we want to *learn*

- We define a *loss function* of the form
  - $L(\boldsymbol{\theta}) = \sum_{(\boldsymbol{x},\boldsymbol{y})} \quad ||(NN(\boldsymbol{x}; \boldsymbol{\theta}) - \boldsymbol{y})||^2$
  - $(\boldsymbol{x}, \boldsymbol{y})$ is our *training data*
  - $\boldsymbol{\theta}$ are our *parameters* ($= \boldsymbol{W}, \boldsymbol{V}$ above)

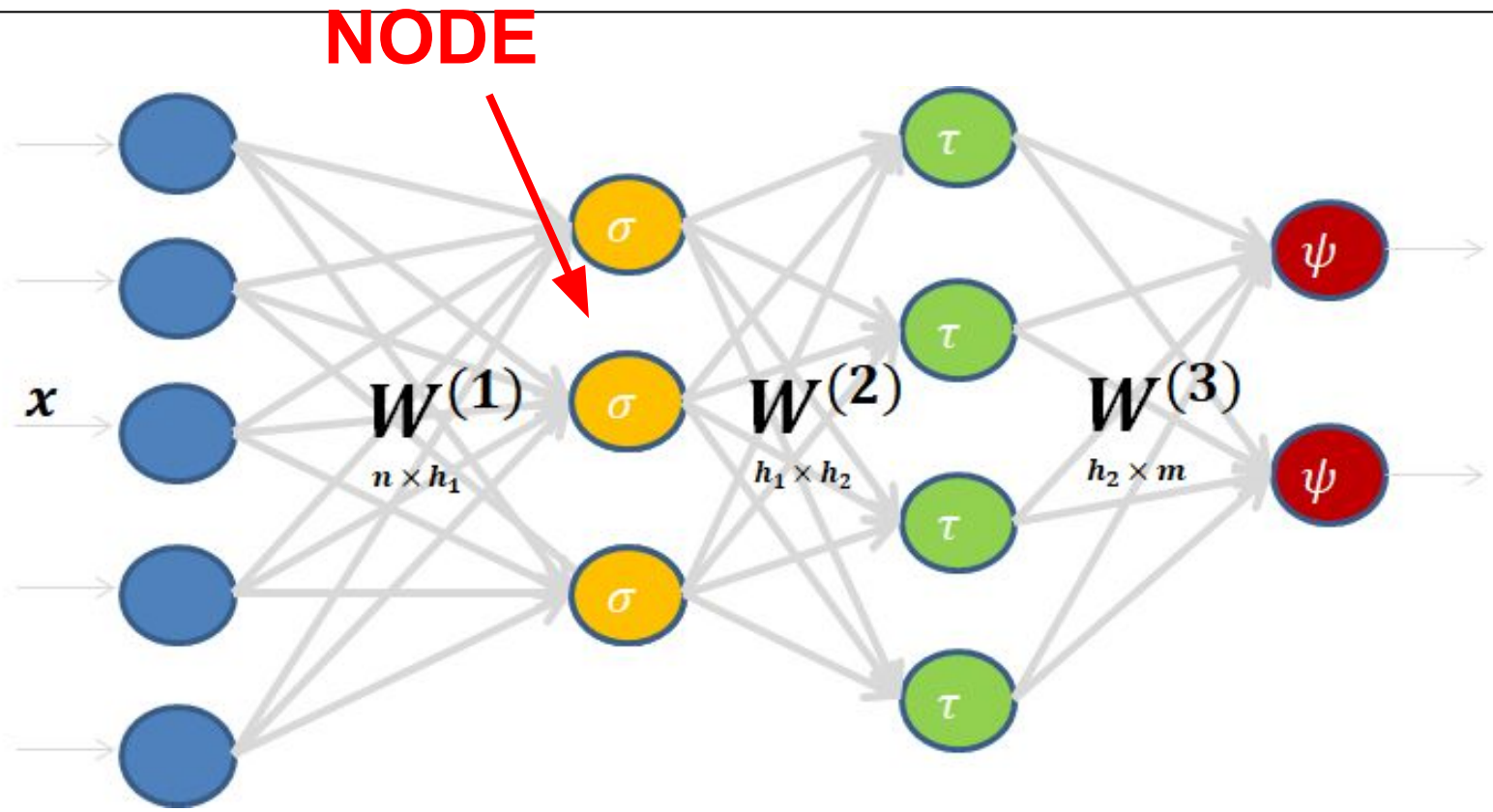
- We want to optimize our parameters $\boldsymbol{\theta}$ such that our loss becomes minimized
  - This is called *learning* or *training*

Deep Networks
Neural Net with at least one hidden layer



Also called “Multi-layer perceptron” or “feedforward network”

Deep Networks Terminology



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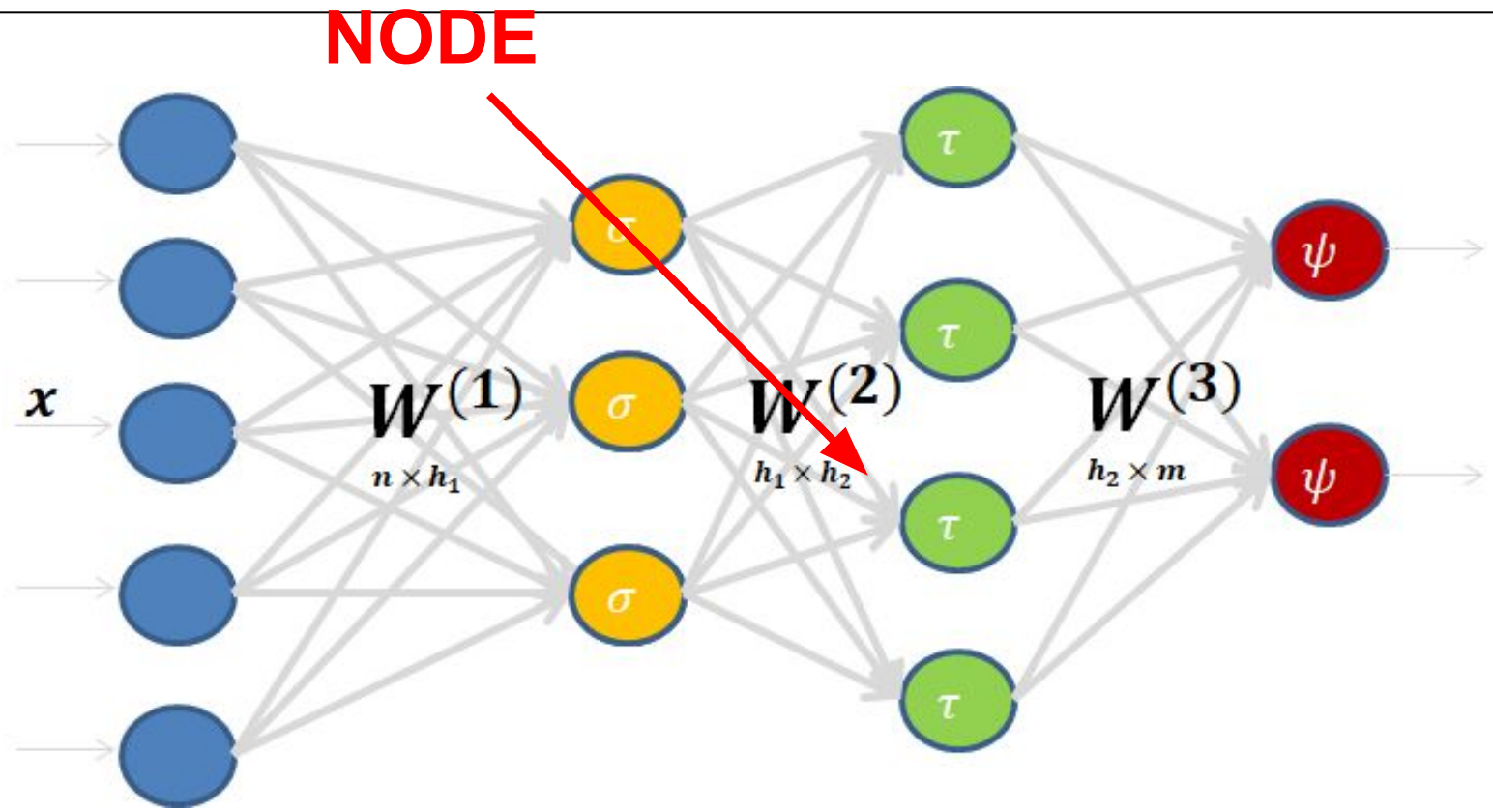
Deep Networks Terminology



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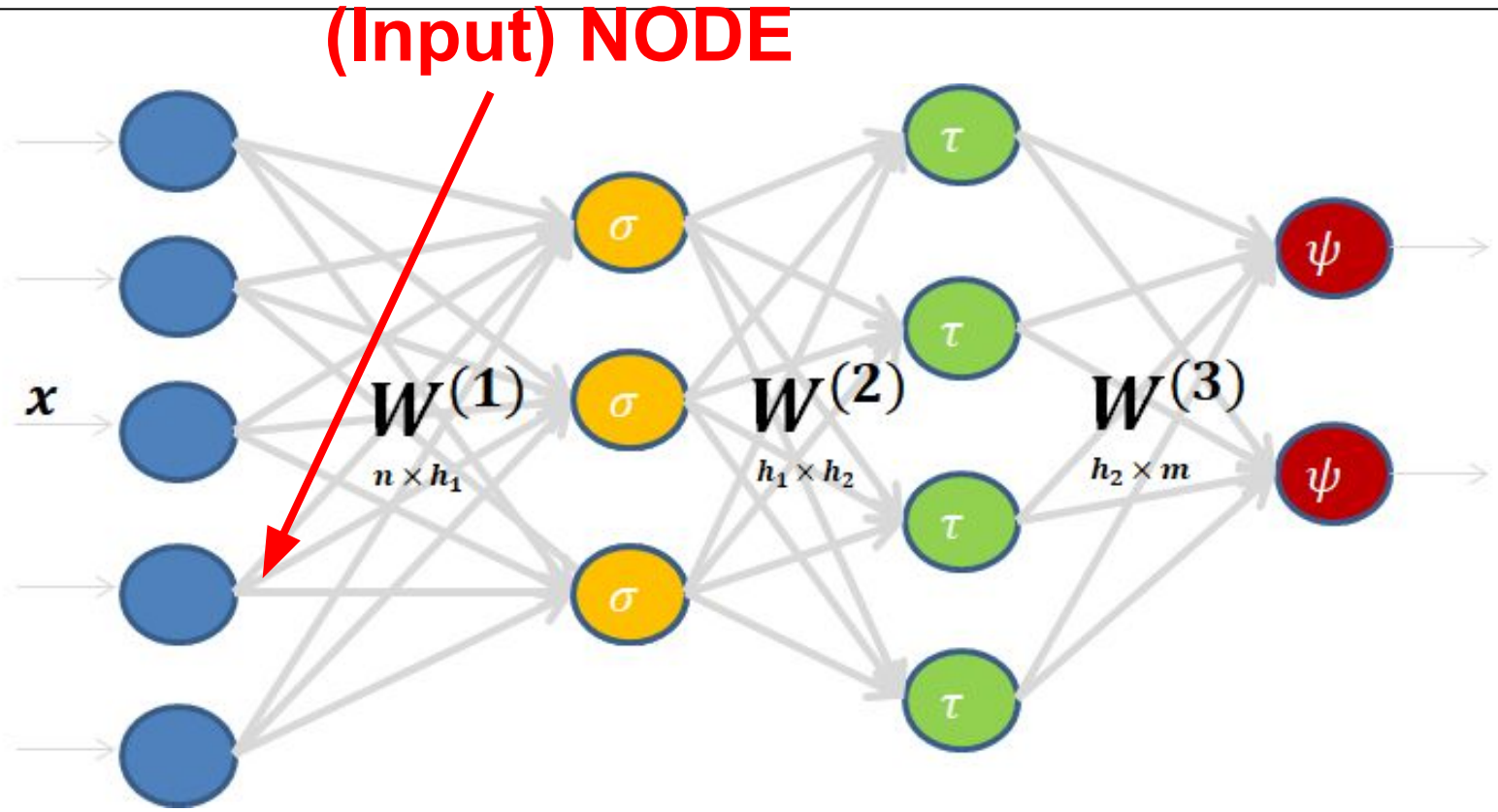
Deep Networks Terminology



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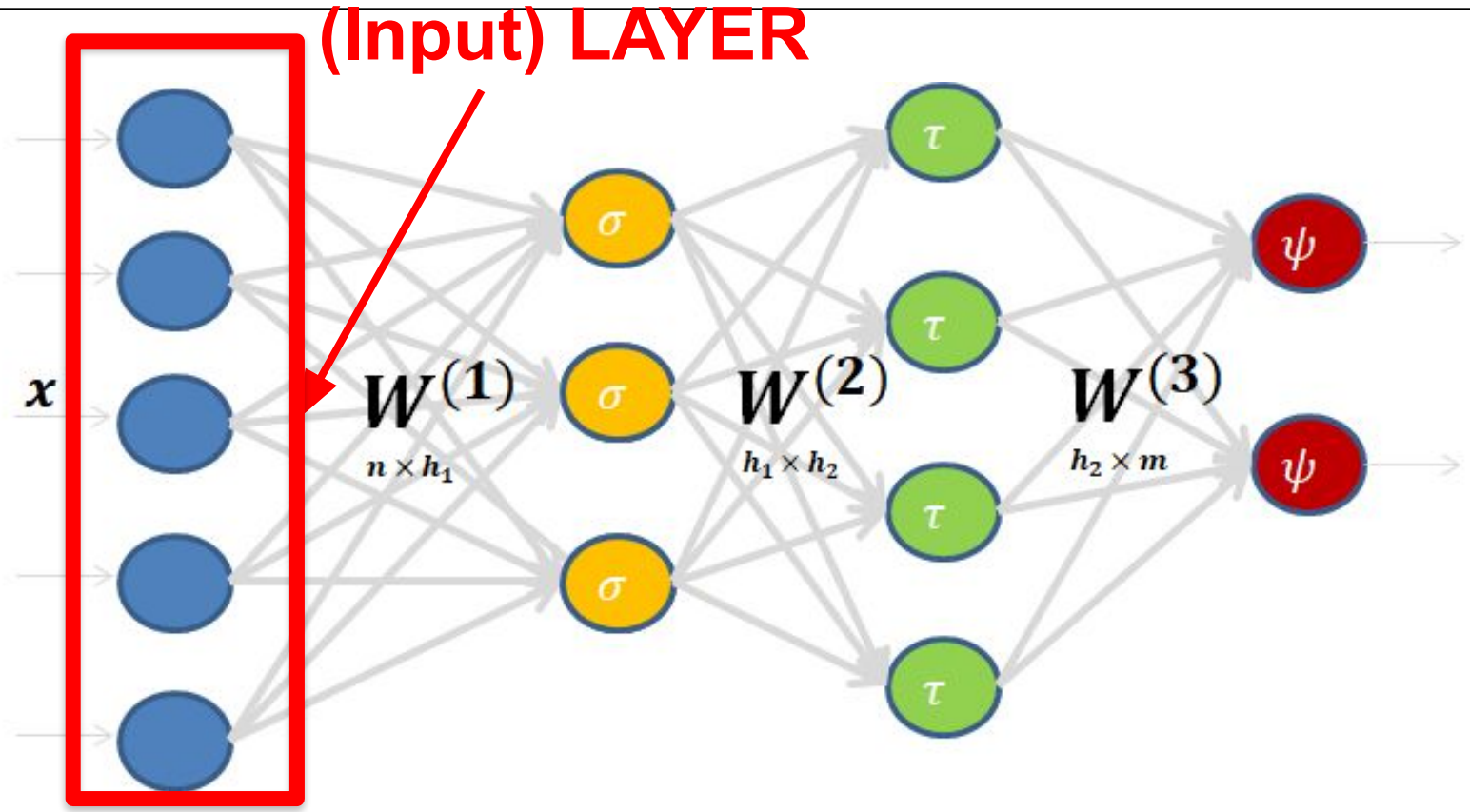

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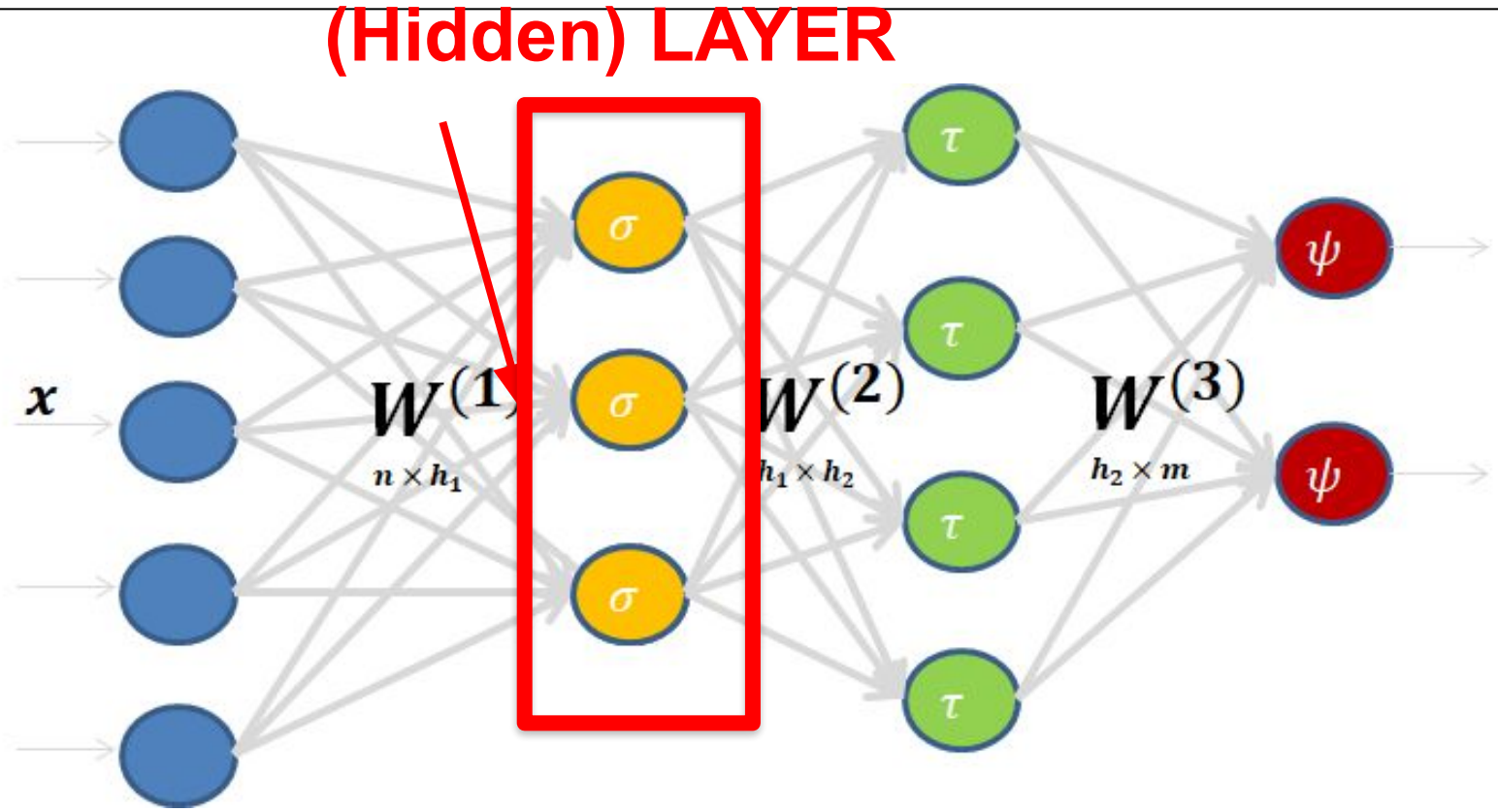

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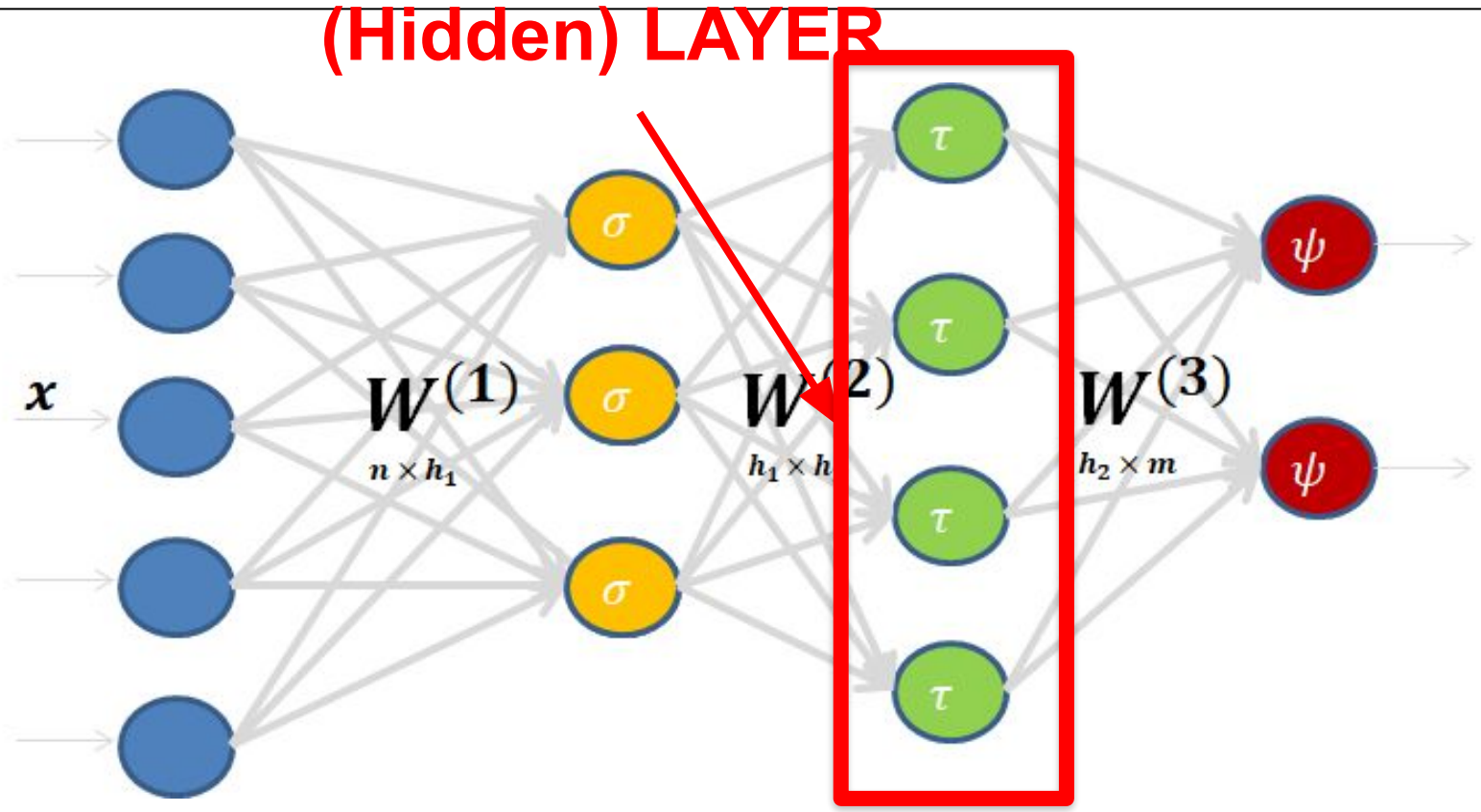

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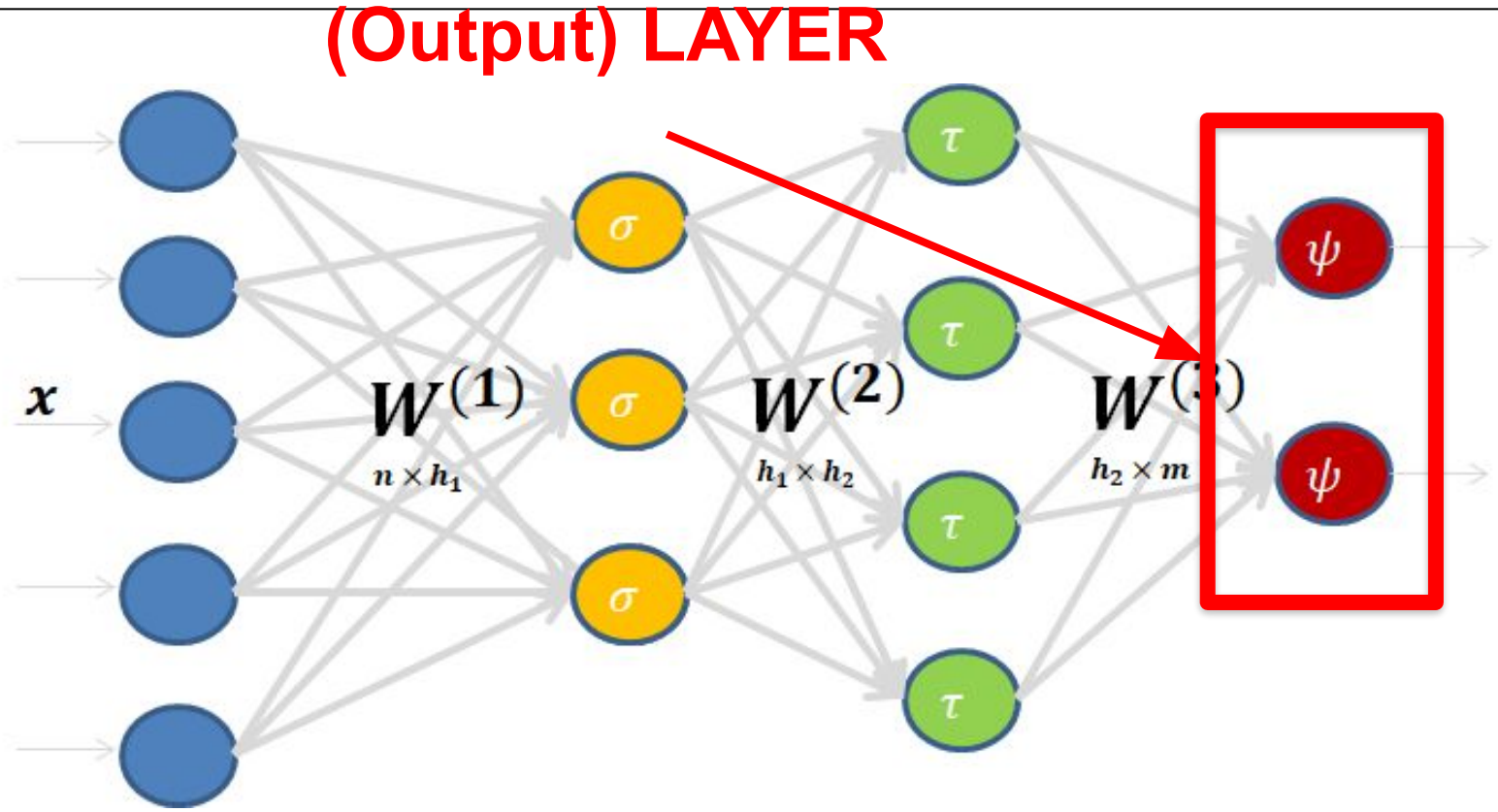
Deep Networks Terminology



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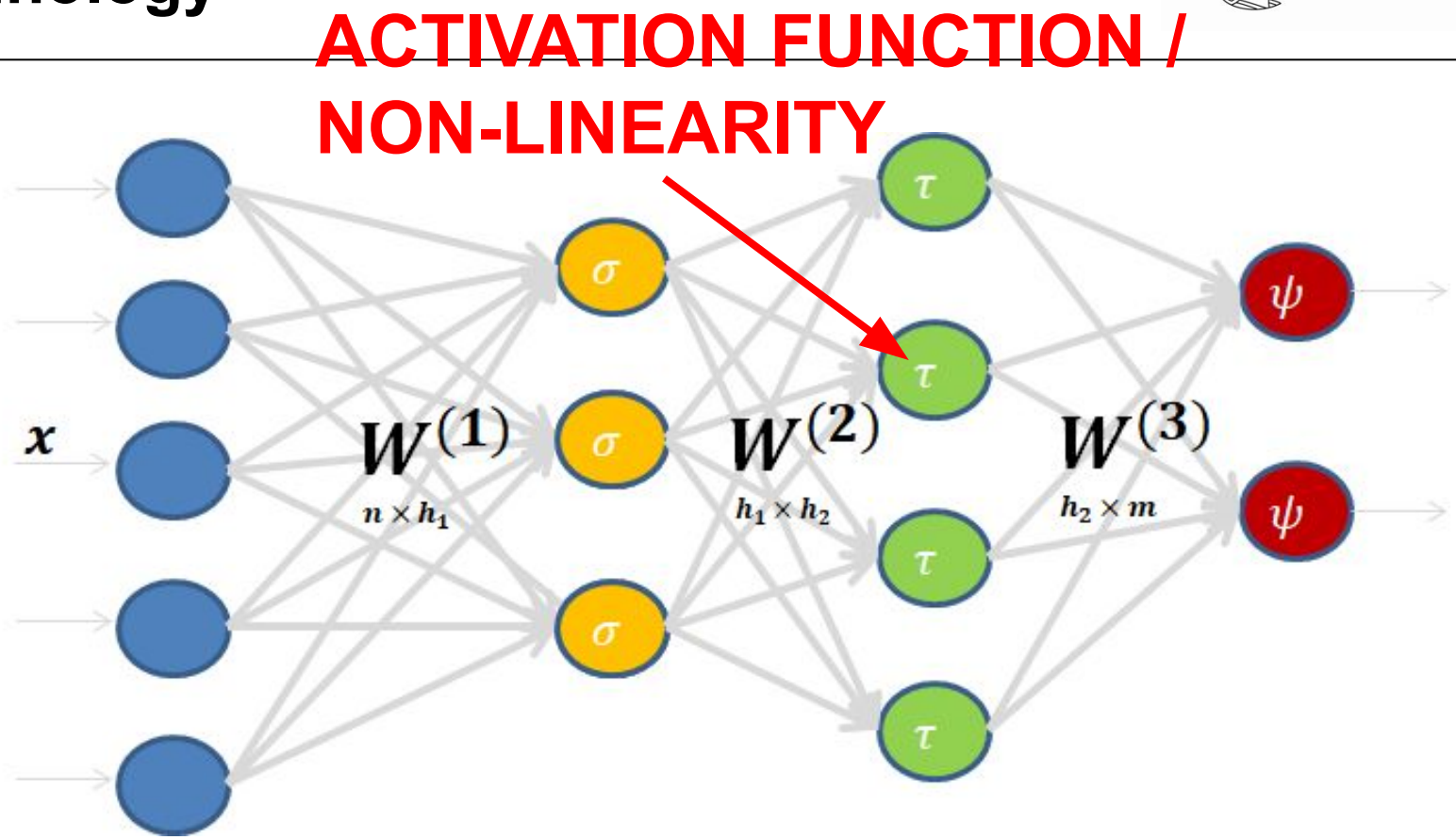
Deep Networks Terminology



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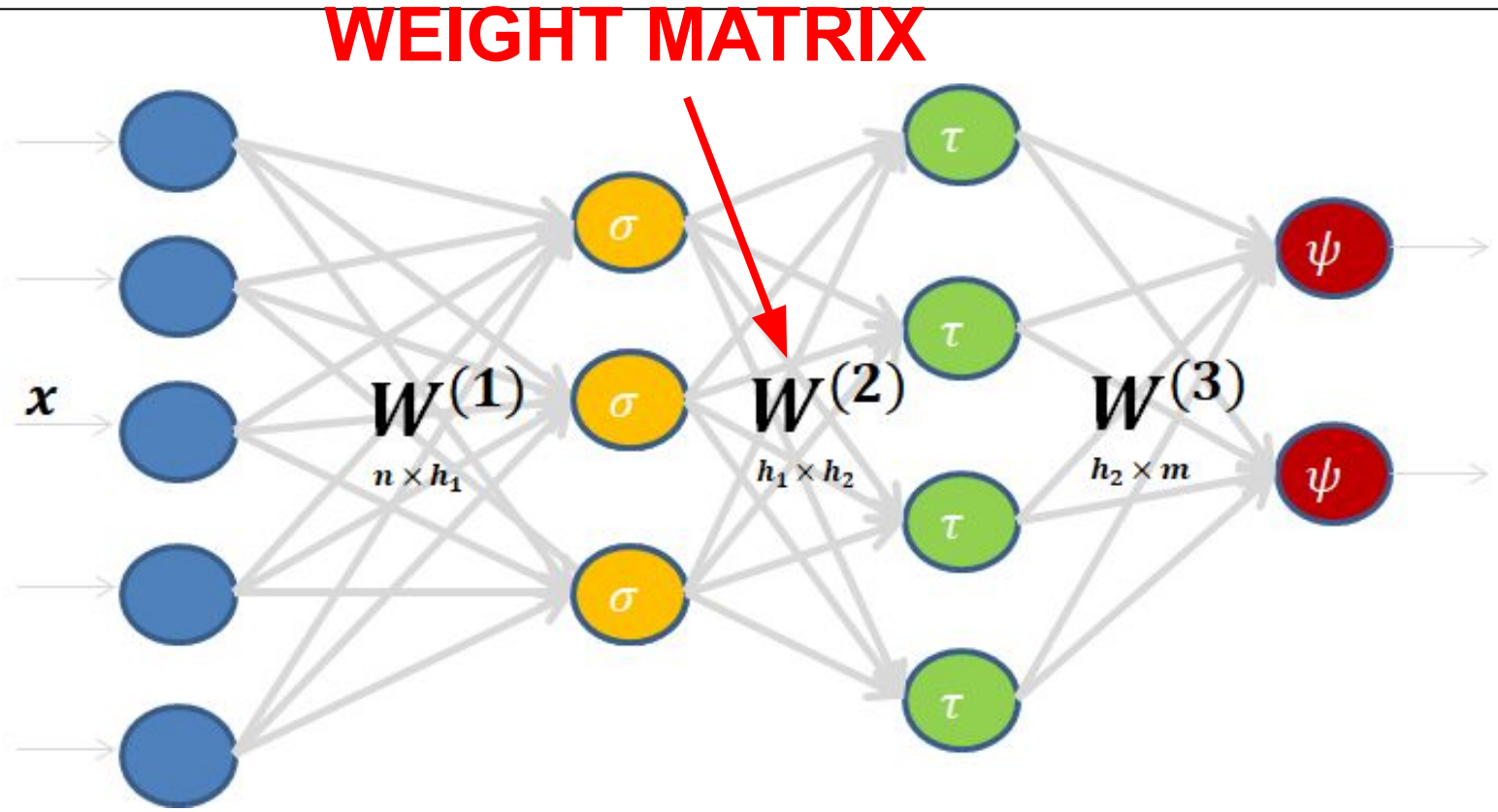
Deep Networks Terminology



Also called “Multi-layer perceptron” or “feedforward network”

Deep Networks
Simplified Visualization

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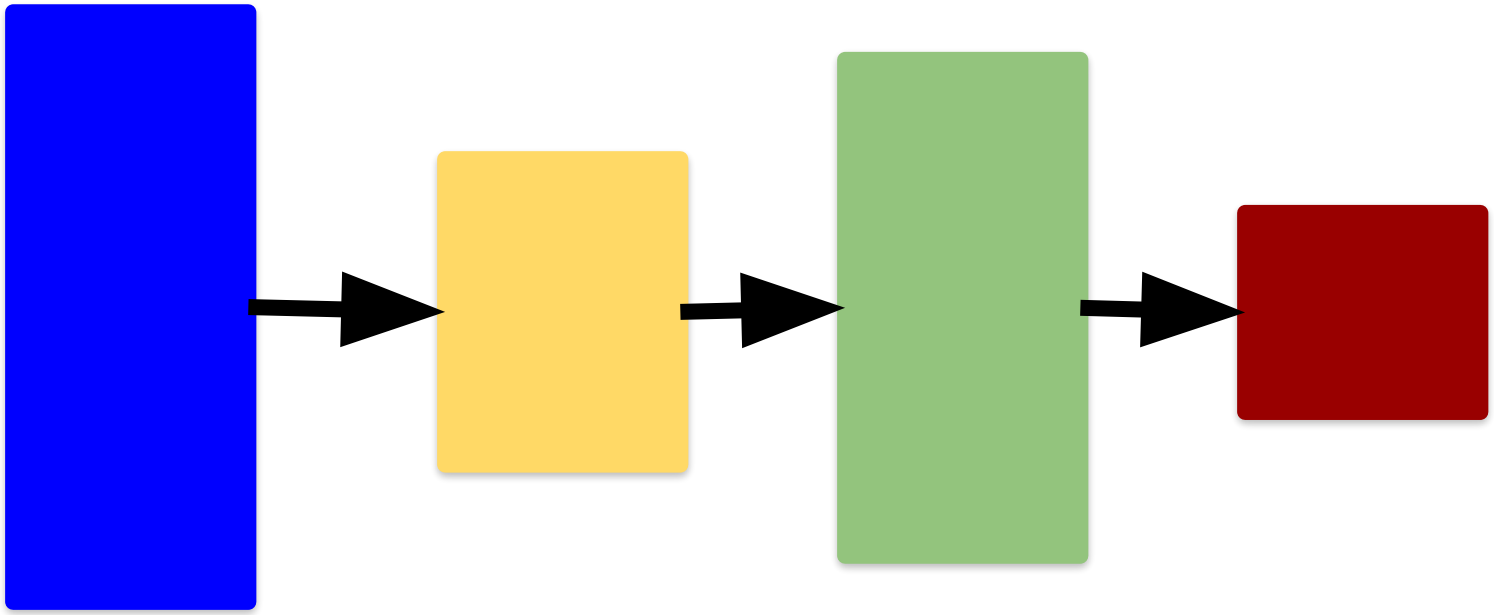

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NLLG

Outline

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Activation functions

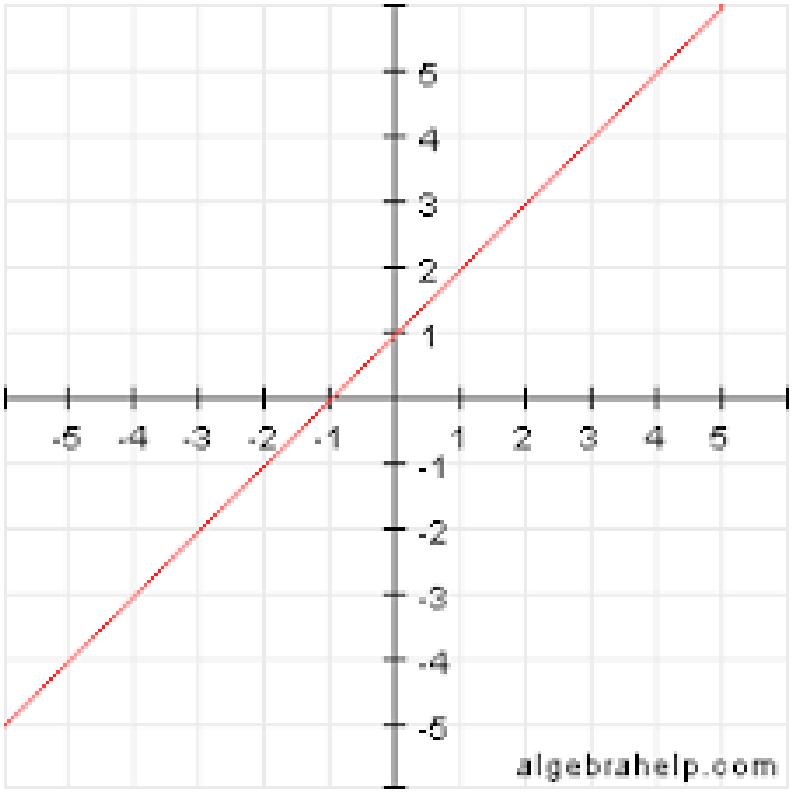
Activation functions σ

TECHNISCHE UNIVERSITÄT DARMSTADT

Linear activations

Suppose all your neurons have linear activation functions …
What‘s your net computing?

$$\sigma(x) = ax + b$$



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Activation functions σ

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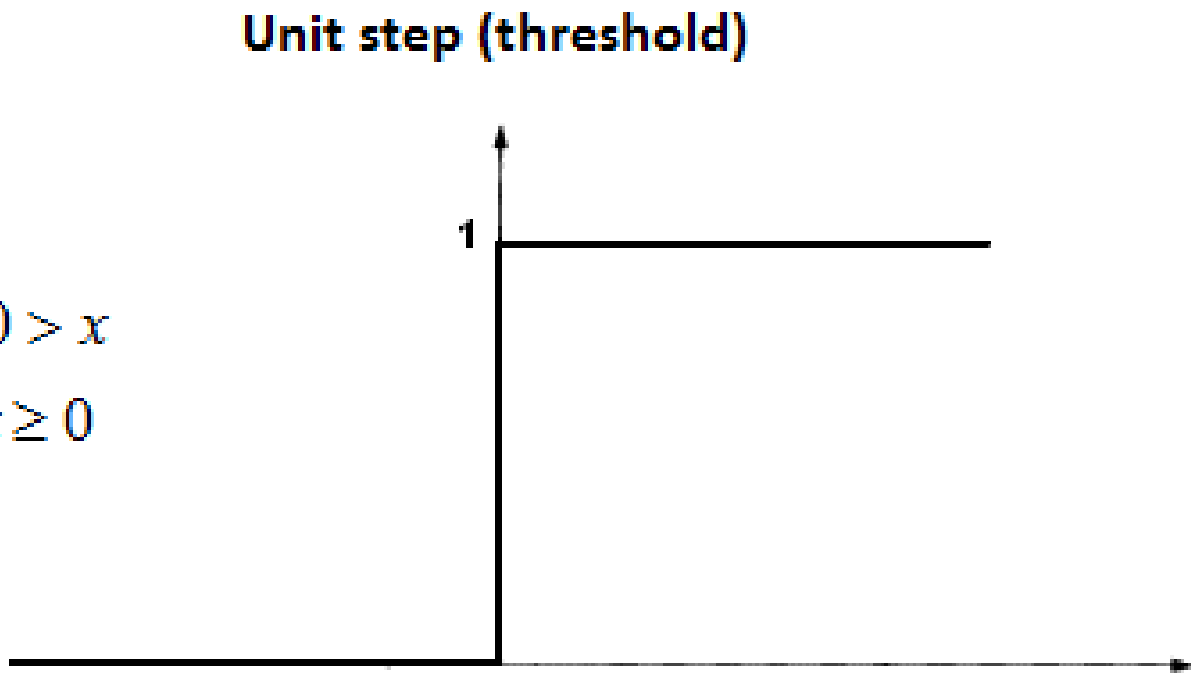
Threshold/Step function

$$\sigma(x) = \begin{cases} 0 \text{ if } 0 > x \\ 1 \text{ if } x \geq 0 \end{cases}$$



Picture from: http://kylescholz.com/projects/wordnet/, based on representation from WordNet: https://wordnet.princeton.edu

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Activation functions σ

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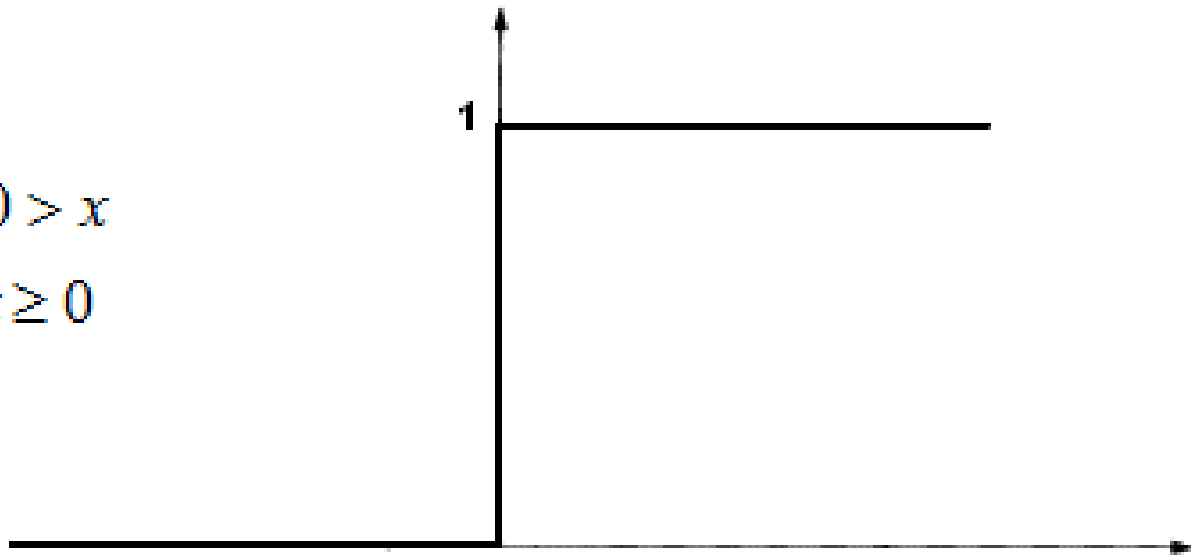
Threshold/Step function

1. Historically first specification
2. Not everywhere differentiable
3. Derivative is zero

Unit step (threshold)

$$\sigma(x) = \begin{cases} 0 \text{ if } 0 > x \\ 1 \text{ if } x \geq 0 \end{cases}$$



Picture from: http://kylescholz.com/projects/wordnet/, based on representation from WordNet: https://wordnet.princeton.edu

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Activation functions σ

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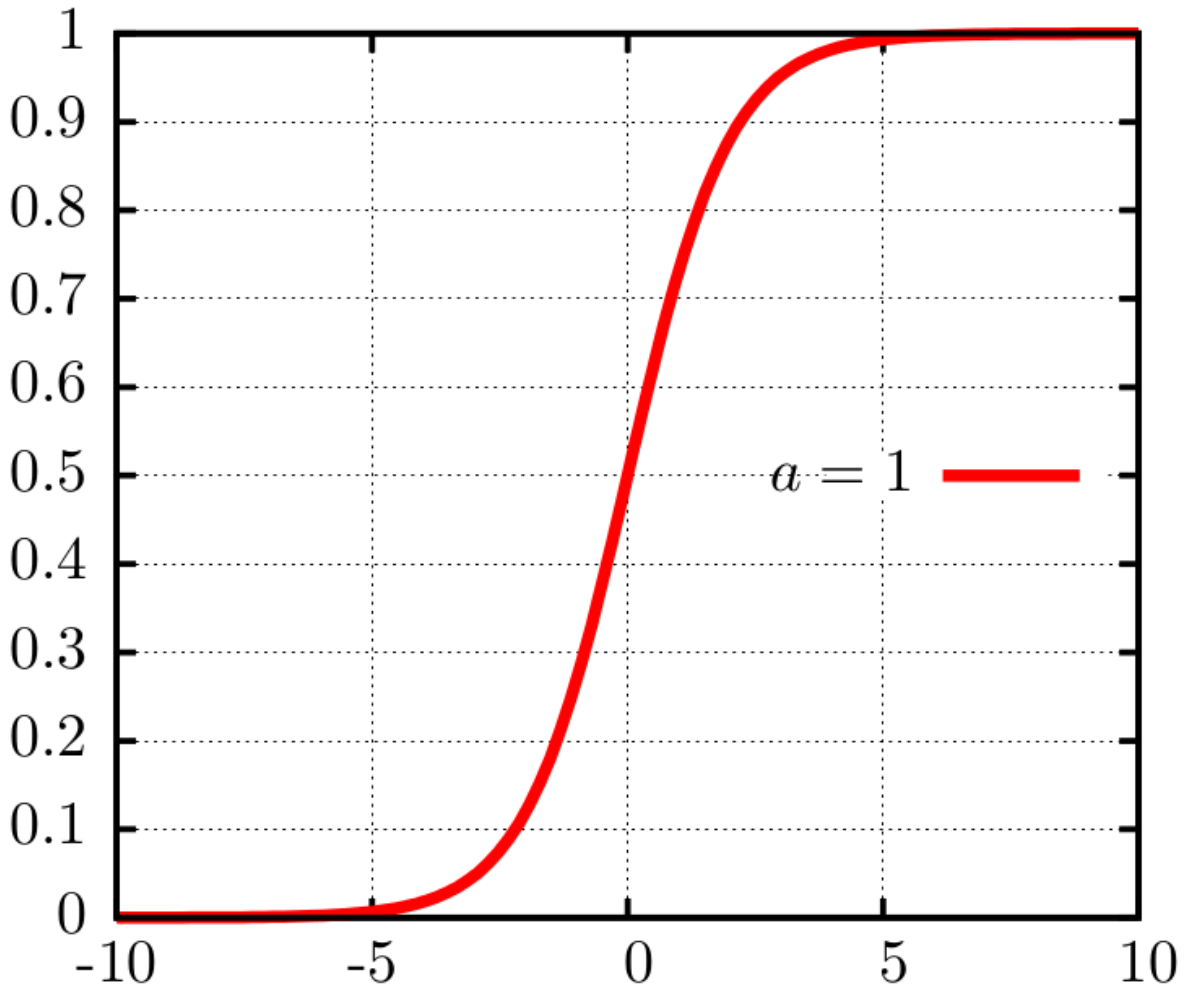
- **Sigmoid (logistic)**
- $\sigma(x) = \frac{1}{1+\exp(-ax)}$



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Activation functions σ

TECHNISCHE UNIVERSITÄT DARMSTADT

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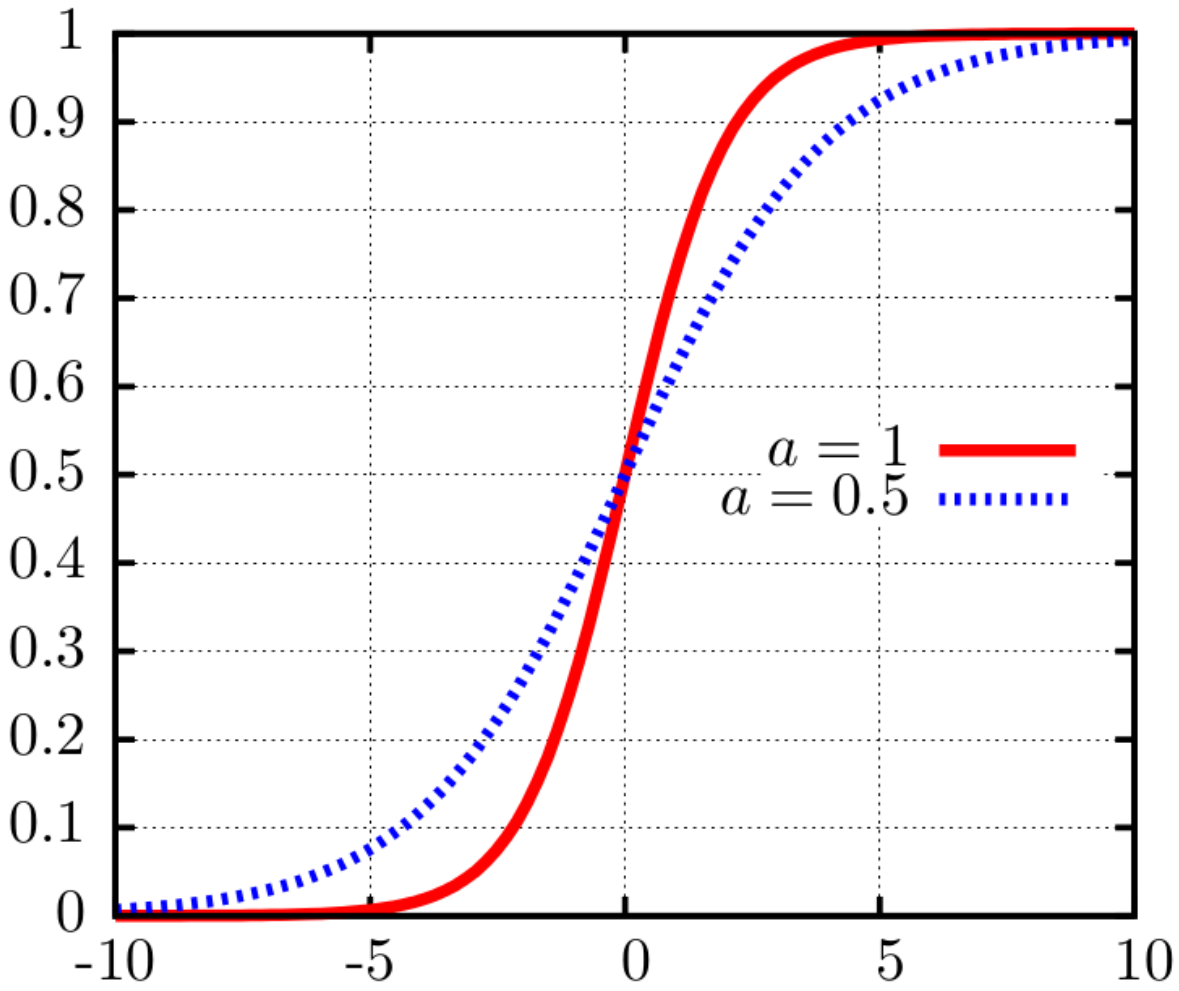

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Activation functions σ

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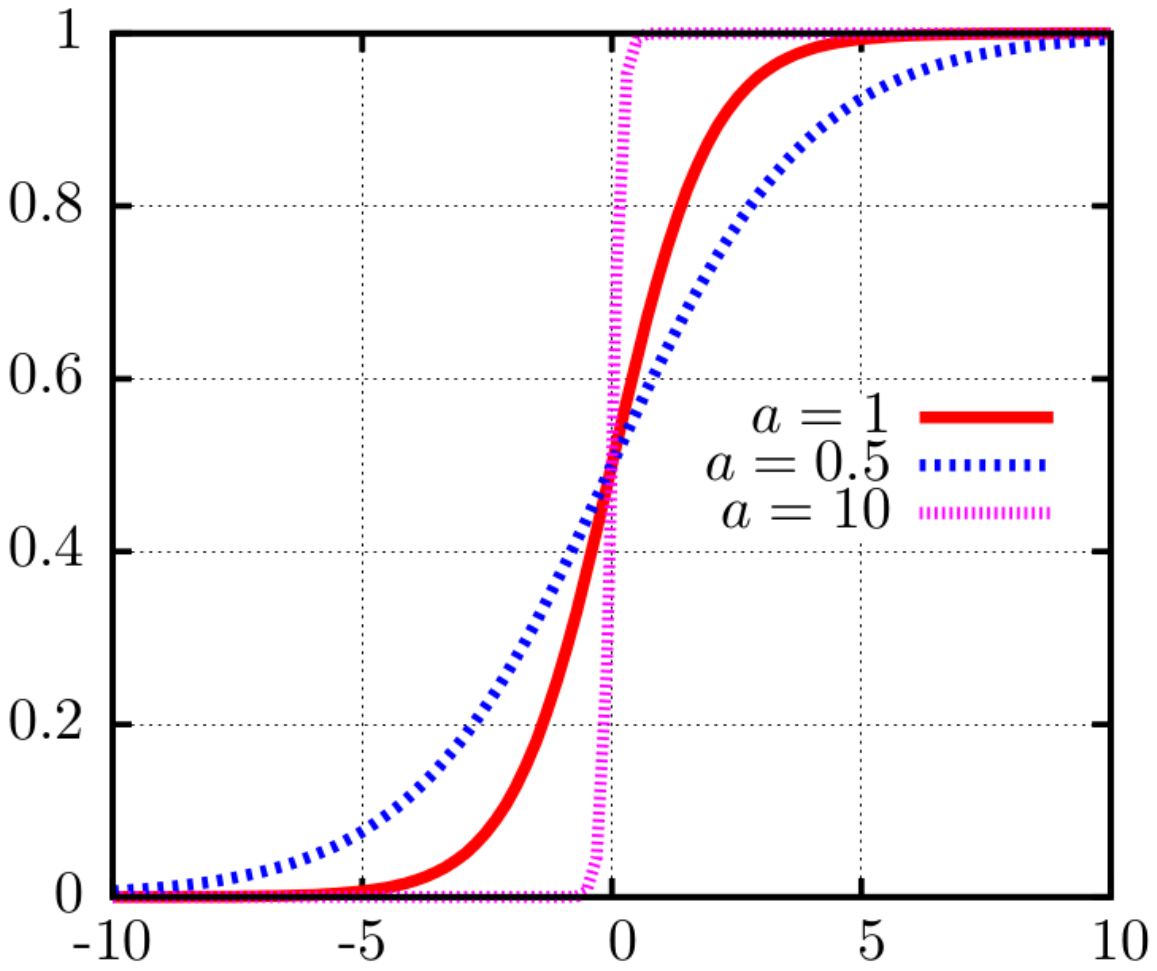

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Activation functions σ

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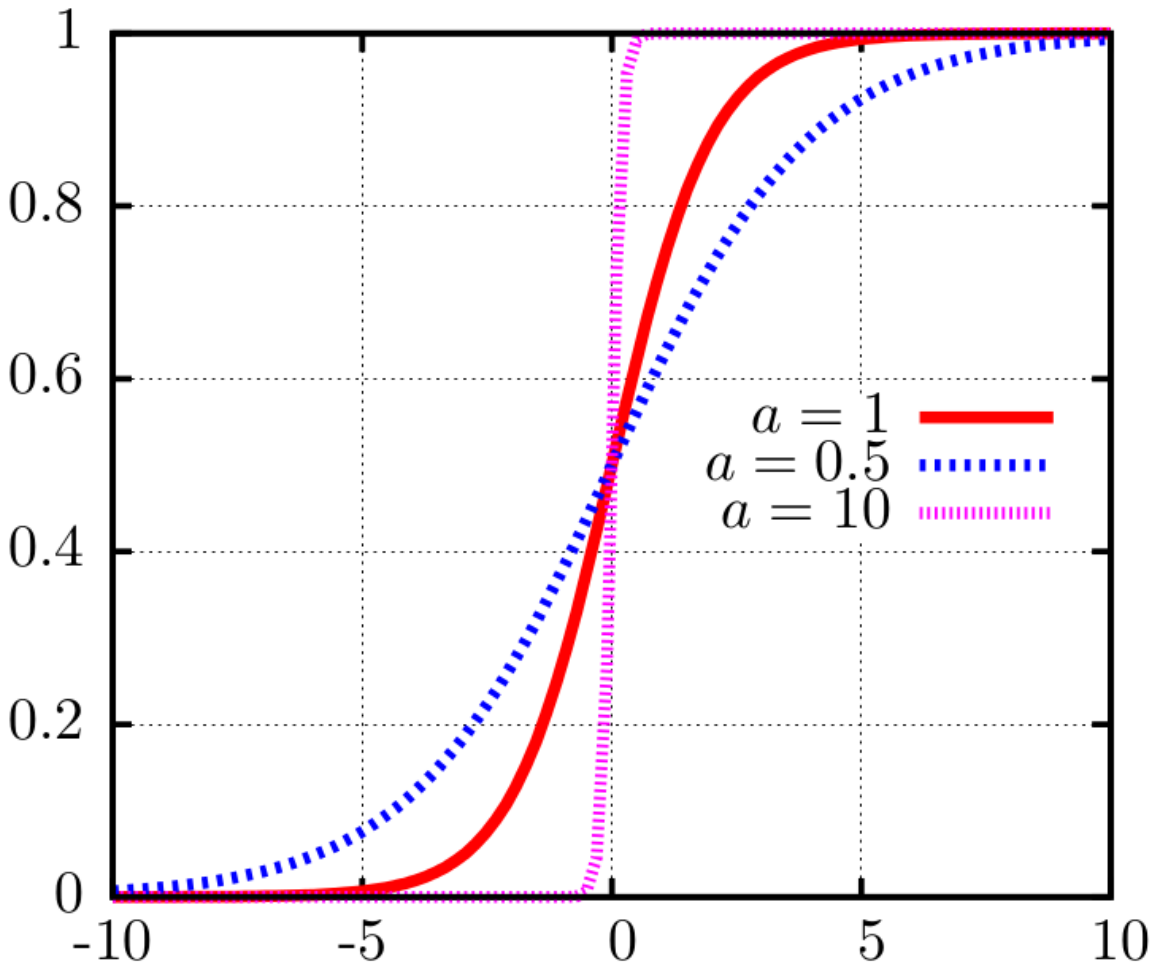
- **Sigmoid (logistic)**
- $\sigma(x) = \frac{1}{1+\exp(-ax)}$

1. Not zero-centered
2. Kills gradients



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Activation functions σ

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1. Not zero-centered: consider $\sigma(\boldsymbol{x} \cdot \boldsymbol{w})$
   - What‘s the derivative/gradient?

Activation functions σ

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1. Not zero-centered: consider $\sigma(\boldsymbol{x} \cdot \boldsymbol{w})$
   - What's the derivative/gradient? $\sigma'(\boldsymbol{x} \cdot \boldsymbol{w}) \cdot \boldsymbol{x}$

In lecture 3, we'll see that

$$\frac{\partial E}{\partial u_{ik}} = \frac{\partial E}{\partial m_k} \sigma'(z_k) x_i$$

Activation functions σ

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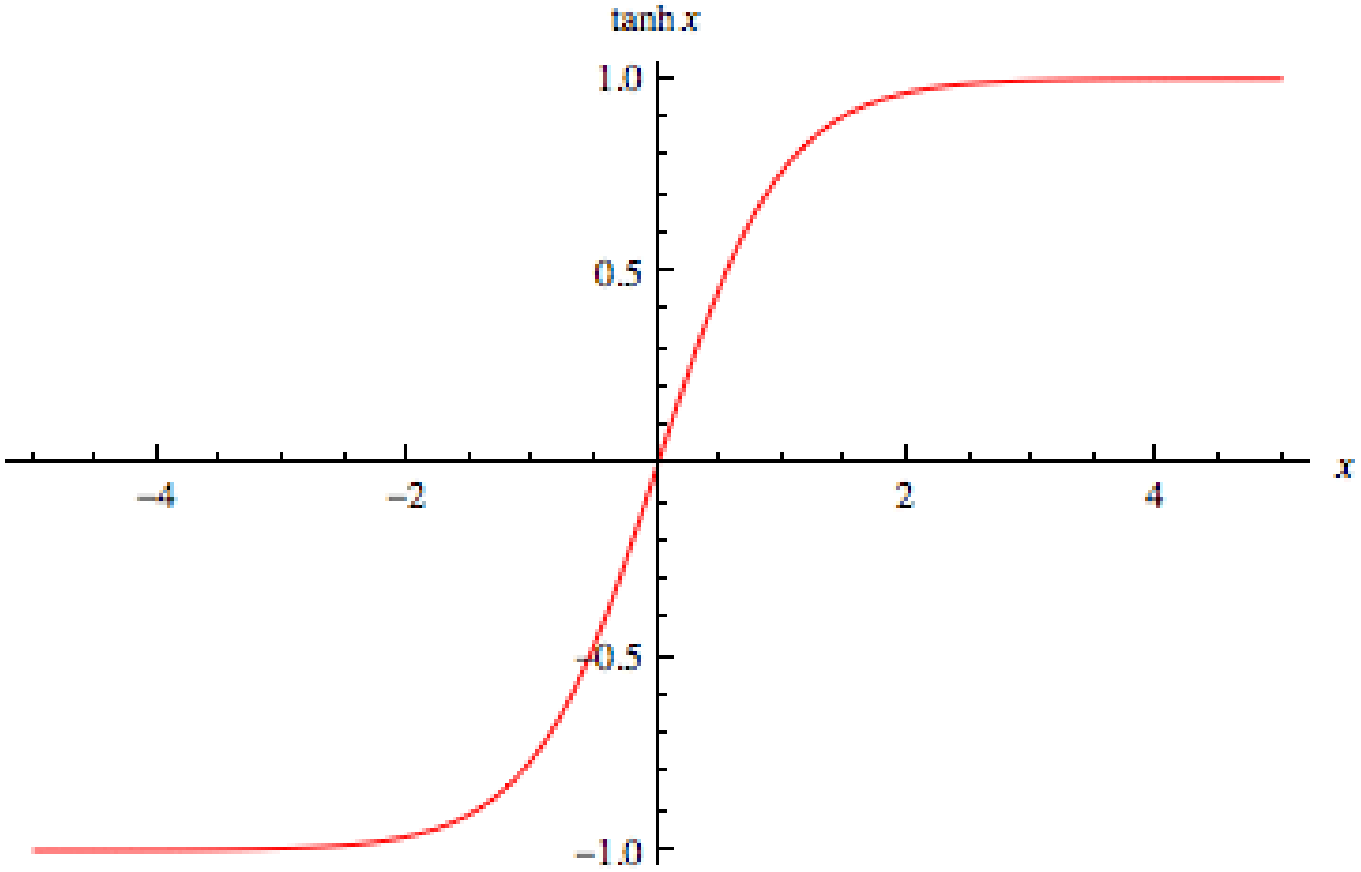
Tanh



Picture from: : http://mathworld.wolfram.com/images/interactive/TanhReal.gif

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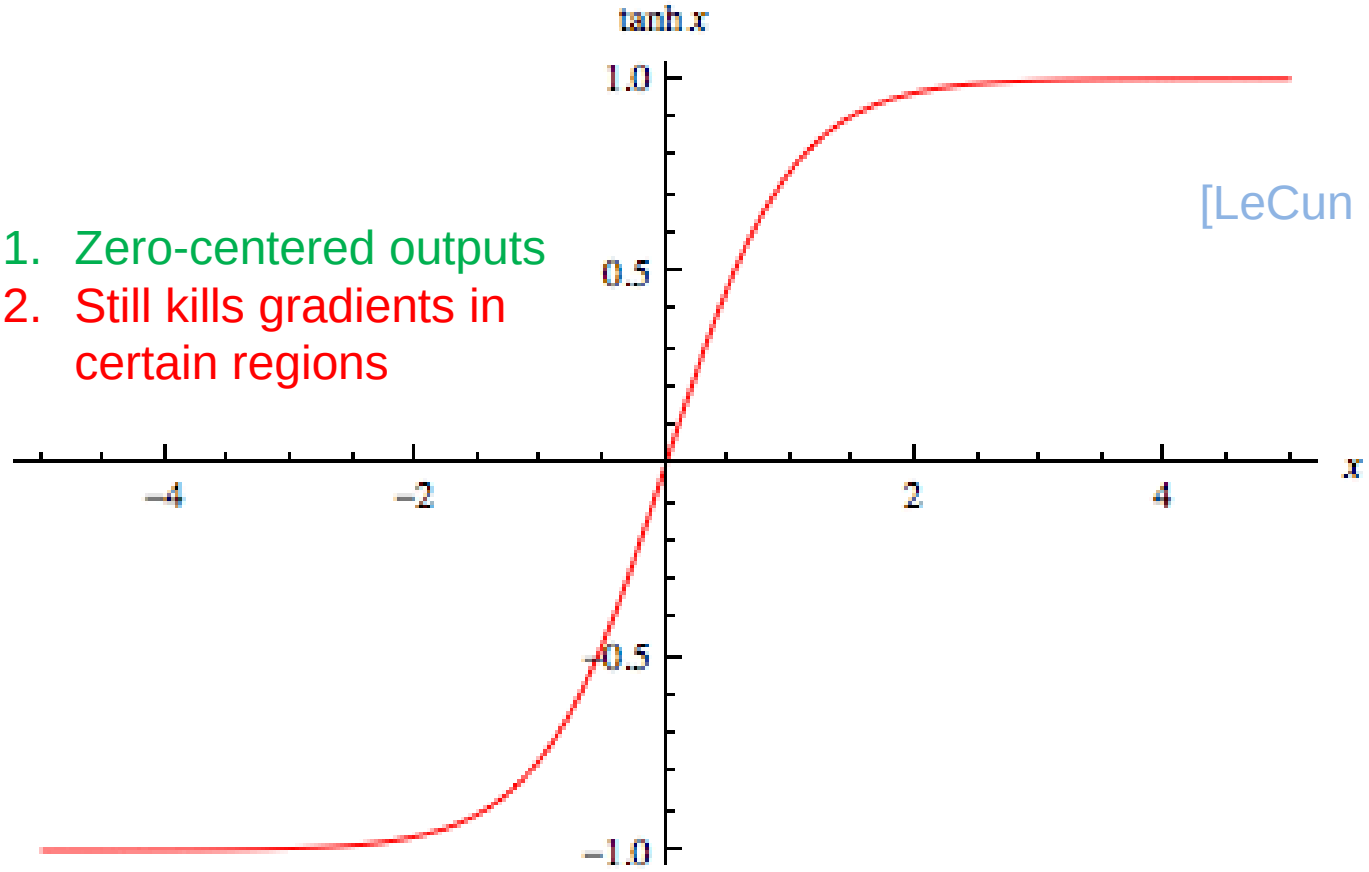
Activation functions σ

Tanh



1. Zero-centered outputs
2. Still kills gradients in certain regions

[LeCun et al. 1991]

Picture from: : http://mathworld.wolfram.com/images/interactive/TanhReal.gif

Activation functions σ

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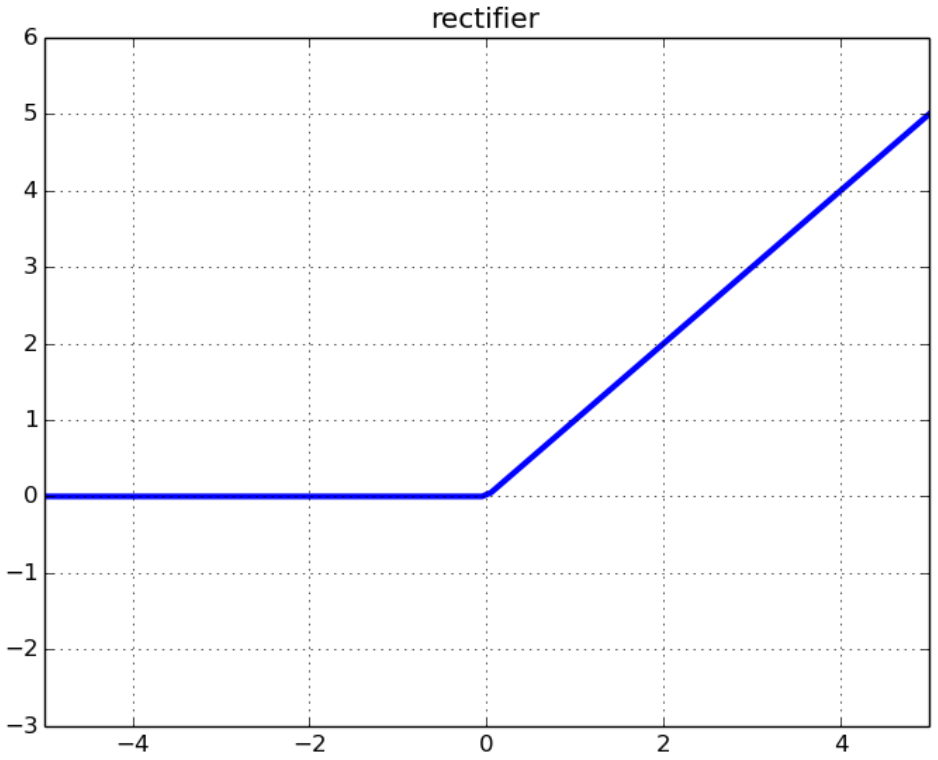
- **ReLU (rectified linear unit)**
- $\mathbf{relu}(x) = \max(0, x)$



- From http://i.stack.imgur.com/8CGlM.png

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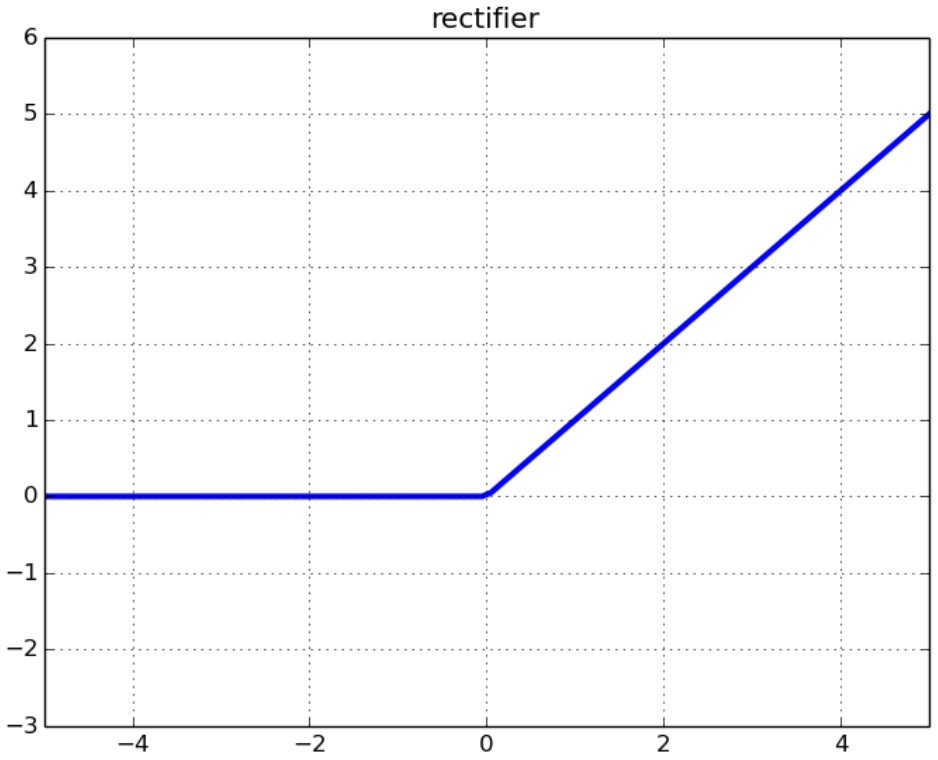
Activation functions σ

TECHNISCHE UNIVERSITÄT DARMSTADT

- **ReLU (rectified linear unit)**
- $\mathbf{relu}(x) = \max(0, x)$

1. Gradients don‘t die in +region
2. Computationally efficient
3. Experimentally: Convergence is faster



- From http://i.stack.imgur.com/8CGlM.png

[Krizhevsky et al. 2012]

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Activation functions σ

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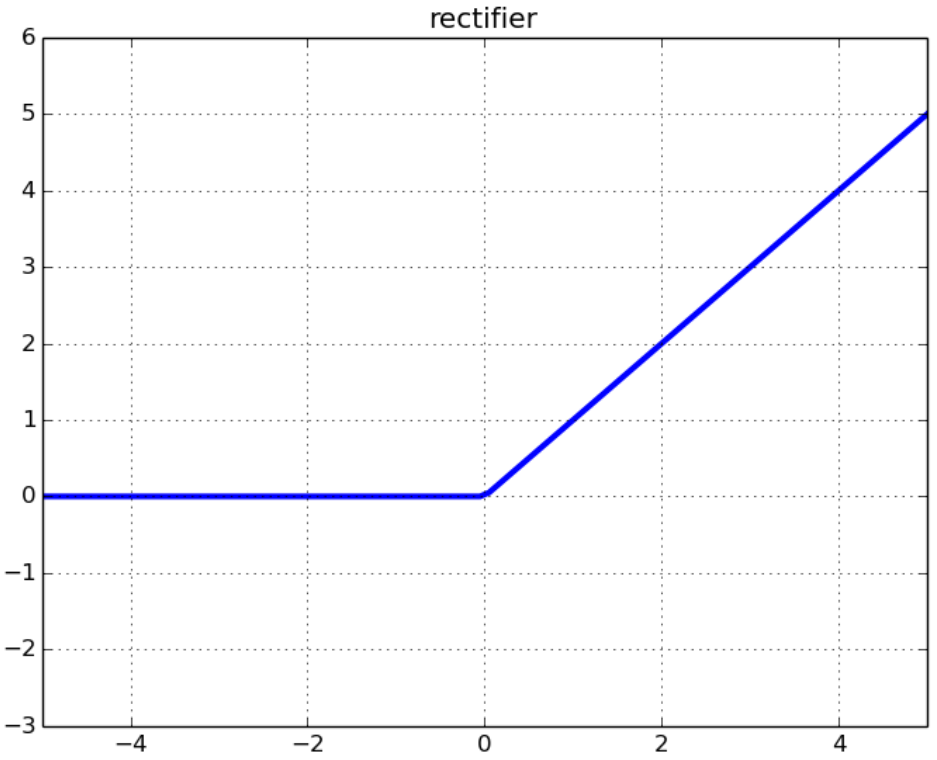

1. Gradients don‘t die in +region
2. Computationally efficient
3. Experimentally: Convergence is faster

1. Kills gradients in –region
2. Not zero centered

- From http://i.stack.imgur.com/8CGlM.png

[Krizhevsky et al. 2012]

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Activation functions σ

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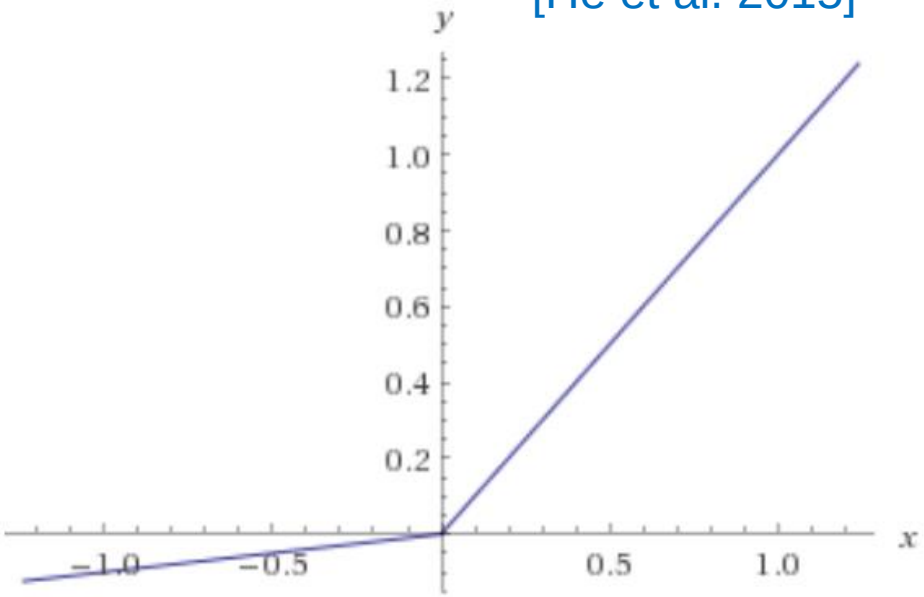
- **Leaky ReLU (rectified linear unit)**
- $\mathbf{relu}(x) = \max(0.01x, x)$

[Maas et al. 2013]
[He et al. 2015]



1. Gradients don‘t die in +region
2. Computationally efficient
3. Experimentally: Convergence is faster
4. Gradients don‘t die in -region

1. Not zero centered

- From http://i.stack.imgur.com/8CGlM.png

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Activation functions σ

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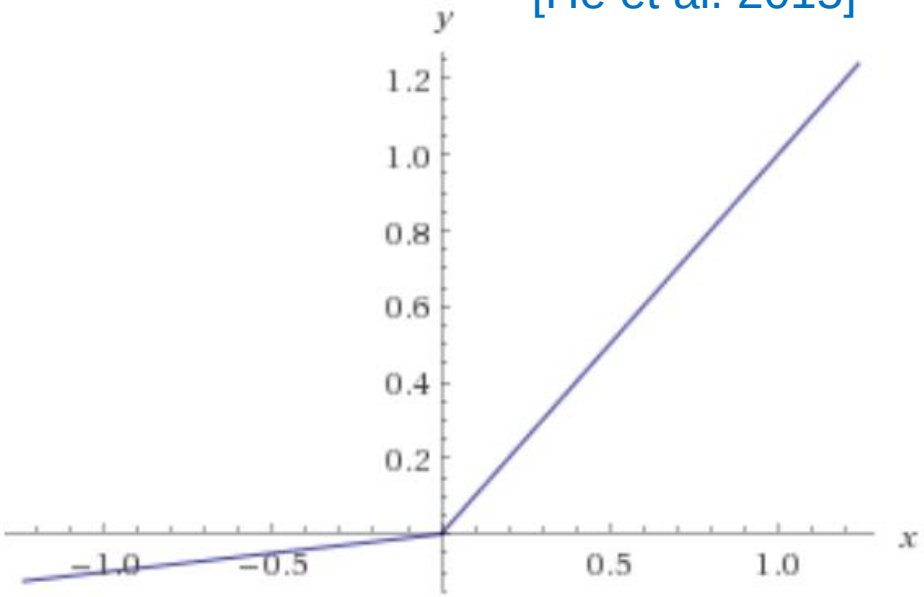

1. Gradients don‘t die in +region
2. Computationally efficient
3. Experimentally: Convergence is faster
4. Gradients don‘t die in -region

1. Not zero centered

Paramteric ReLU
$\sigma(x) = \max(\alpha x, x)$

- From http://i.stack.imgur.com/8CGlM.png

Activation functions σ

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- **Maxout "Neuron"**

[Goodfellow et al. 2013]

$$\max(\boldsymbol{w}_1\boldsymbol{x}, \boldsymbol{w}_2\boldsymbol{x})$$

1. Generalizes ReLU and Leaky ReLU
2. Gradients don't die

1. Doubles the number of paramters

Activation functions

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- Tanh > Sigmoid
- ReLU is most popular activation function (as of 2015)
  - According to https://en.wikipedia.org/wiki/Rectifier_(neural_networks)
- Others have to stand the test of time
  - Try out Leaky ReLU / Maxout / ELU
- Don’t use sigmoid or step function

Activation functions

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- Tanh > Sigmoid

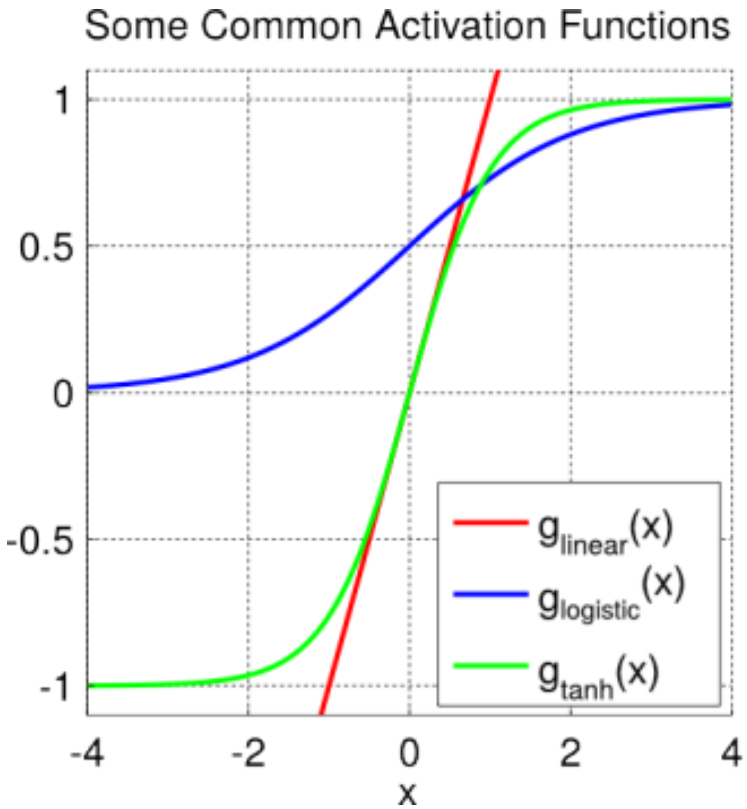
- ReLU is most popular activation function (as of 2015)
  - According to https://en.wikipedia.org/wiki/Rectifier_(neural_networks)

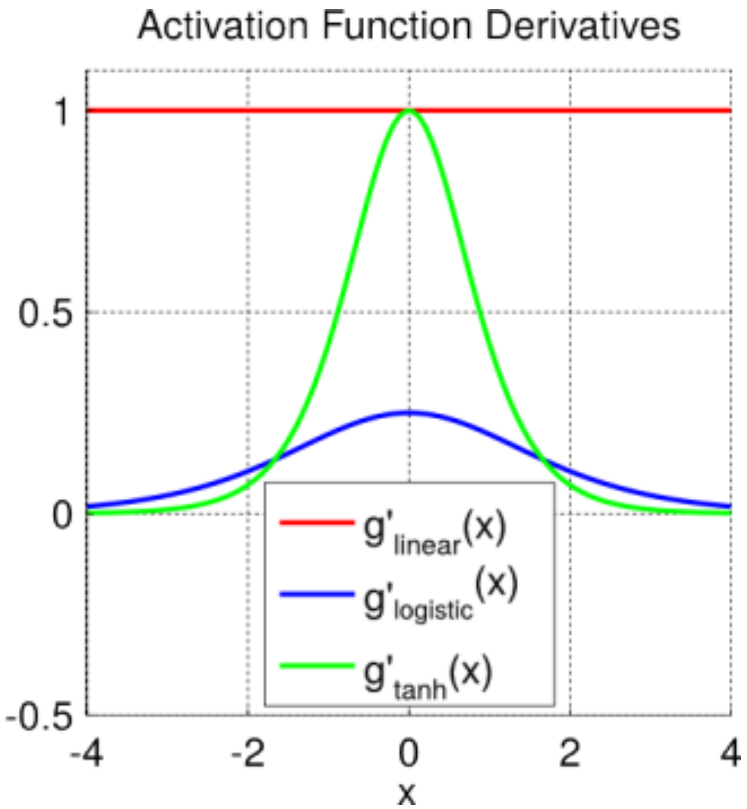
- Others have to stand the test of time

  - Try out Leaky ReLU / Maxout / ELU

- Don’t use sigmoid or step function
- Activation functions are a hyperparameter!

Activation functions





A special activation function: softmax

- Particularly when we have multiple output classes („Positive“, „Negative“, „Neutral“), we‘d often like our outputs to represent a *probability distribution* over these classes
  - i.e., final outputs should sum to 1 and be non-negative

A special activation function: softmax

- Particularly when we have multiple output classes („Positive“, „Negative“, „Neutral“), we‘d often like our outputs to represent a *probability distribution* over these classes
  - i.e., final outputs should sum to 1 and be non-negative
- The softmax activation function serves that purpose:
  - Given m output units, the softmax activation is

$$y_j = \frac{\exp(z_j)}{\sum_k \exp(z_k)}$$

  - for all $\mathrm{j} = 1, \dots, m$. Here, $z_1, \dots, z_m$ are the pre-activations

A special activation function: softmax

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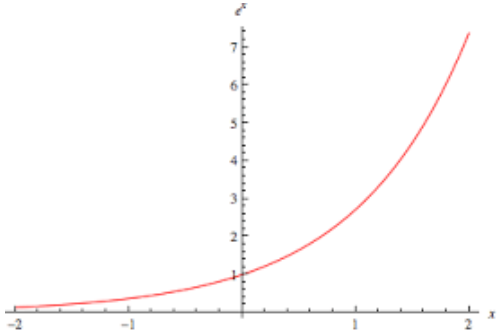
- Is $y_j \geq 0$ for all j and does $\sum_j y_j = 1$?



- Note that softmax is a *global* activation function while all the other discussed previously were *local*:
  - Output of softmax for unit j depends on pre-activation of all other units j'

A special activation function: softmax

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- Softmax challenges the interpretation of individual neurons with individual activation functions
- Instead, it supports a view of a function acting on a layer of several neurons, i.e., a vector
- I.e., let $\mathbf{z} = \boldsymbol{x} \cdot \boldsymbol{W} + \boldsymbol{b}$ be the pre-activations in some layer
- For a standard activation function, we have as activation $\boldsymbol{y}$

$$\boldsymbol{y} = \sigma(\boldsymbol{z}) = [\sigma(z_1) \cdots \sigma(z_n)]$$

- Softmax cannot be applied element-wise, however:

$$\boldsymbol{y} = \mathrm{softmax}(\boldsymbol{z})$$

yields a probability distribution, $\boldsymbol{y}$

Deep Learning

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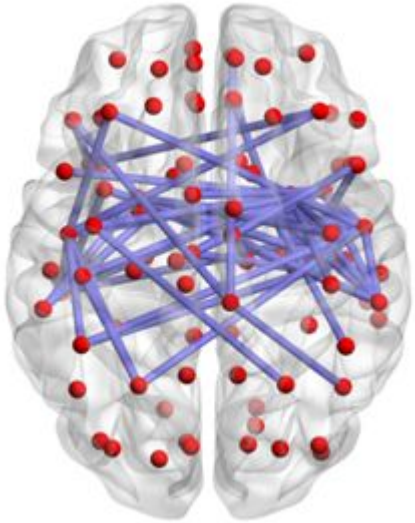
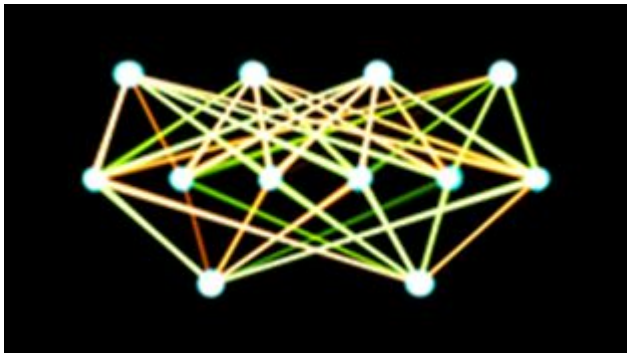
- Subfield of machine learning
- Neural networks: a brain-inspired metaphor for a computational model





https://upload.wikimedia.org/wikipedia/commons/0/0e/Brain_network.png
https://upload.wikimedia.org/wikipedia/commons/thumb/3/32/Single-layer_feedforward_artificial_neural_network.png/214px-Single-layer_feedforward_artificial_neural_network.png

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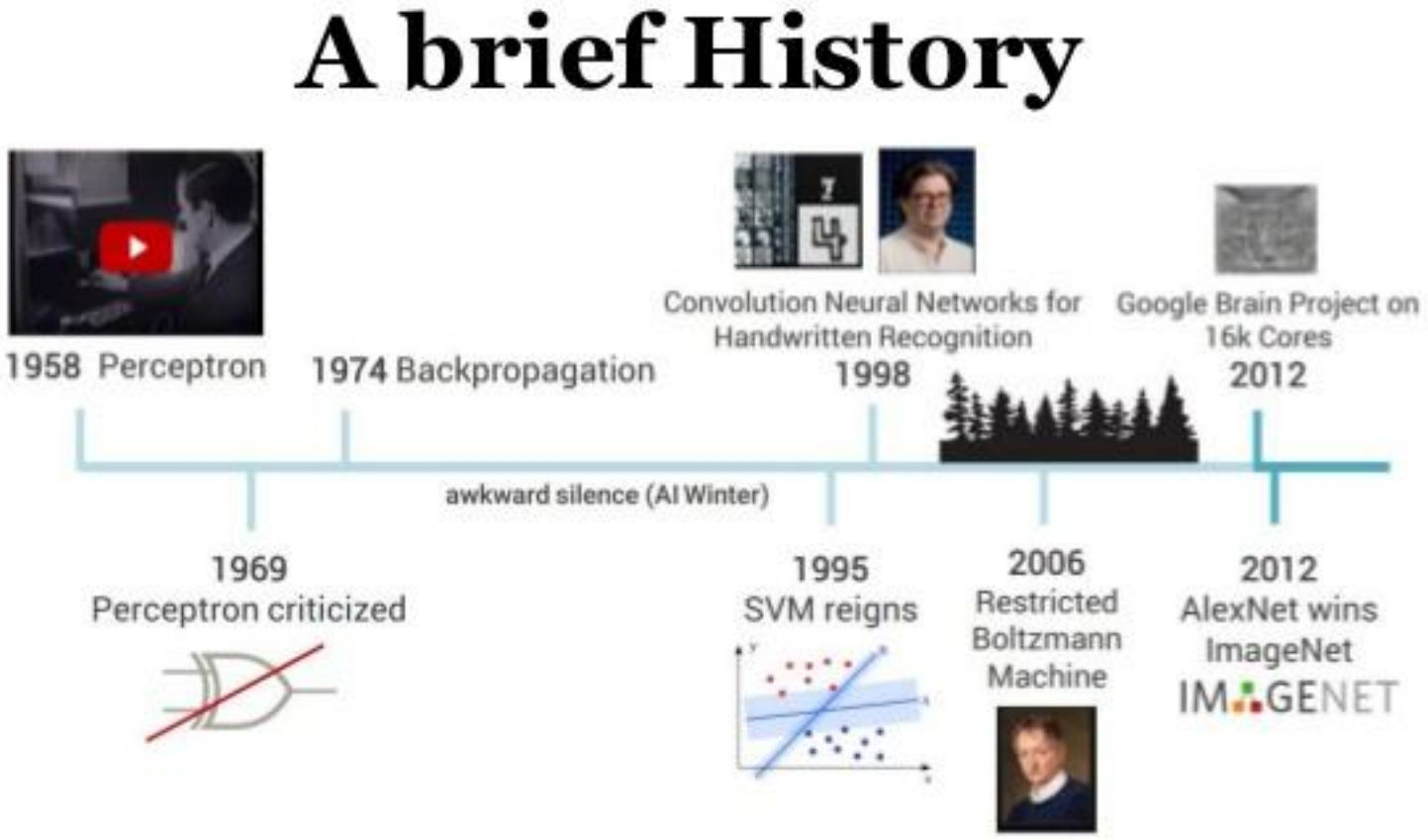
Deep Networks History



Source https://www.slideshare.net/mohamedloey/deep-learning-71352250

Deep Networks History

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- In 2019, Hinton, LeCun, and Bengio won the Turing award in computer science
- Schmidhuber, another big guy in the field (LSTMs), didn‘t

Deep Networks Successes

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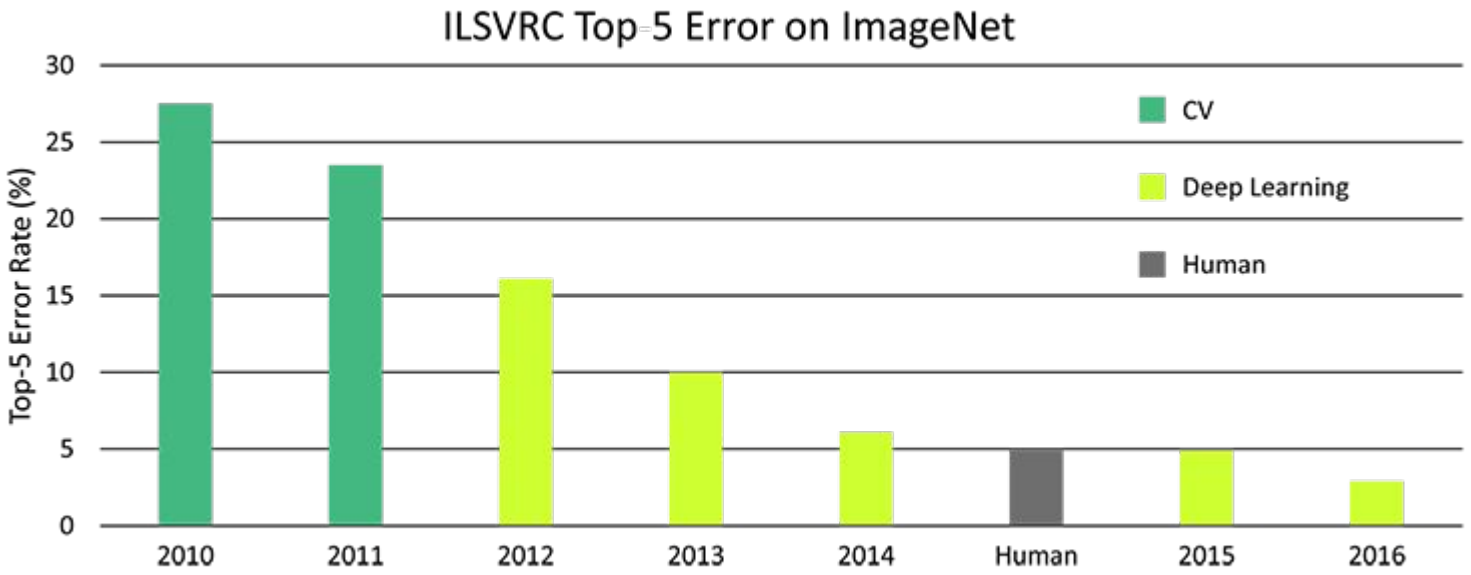
Image classification



Source https://medium.com/nanonets/how-to-automate-surveillance-easily-with-deep-learning-4eb4fa0cd68d

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Deep Networks Successes

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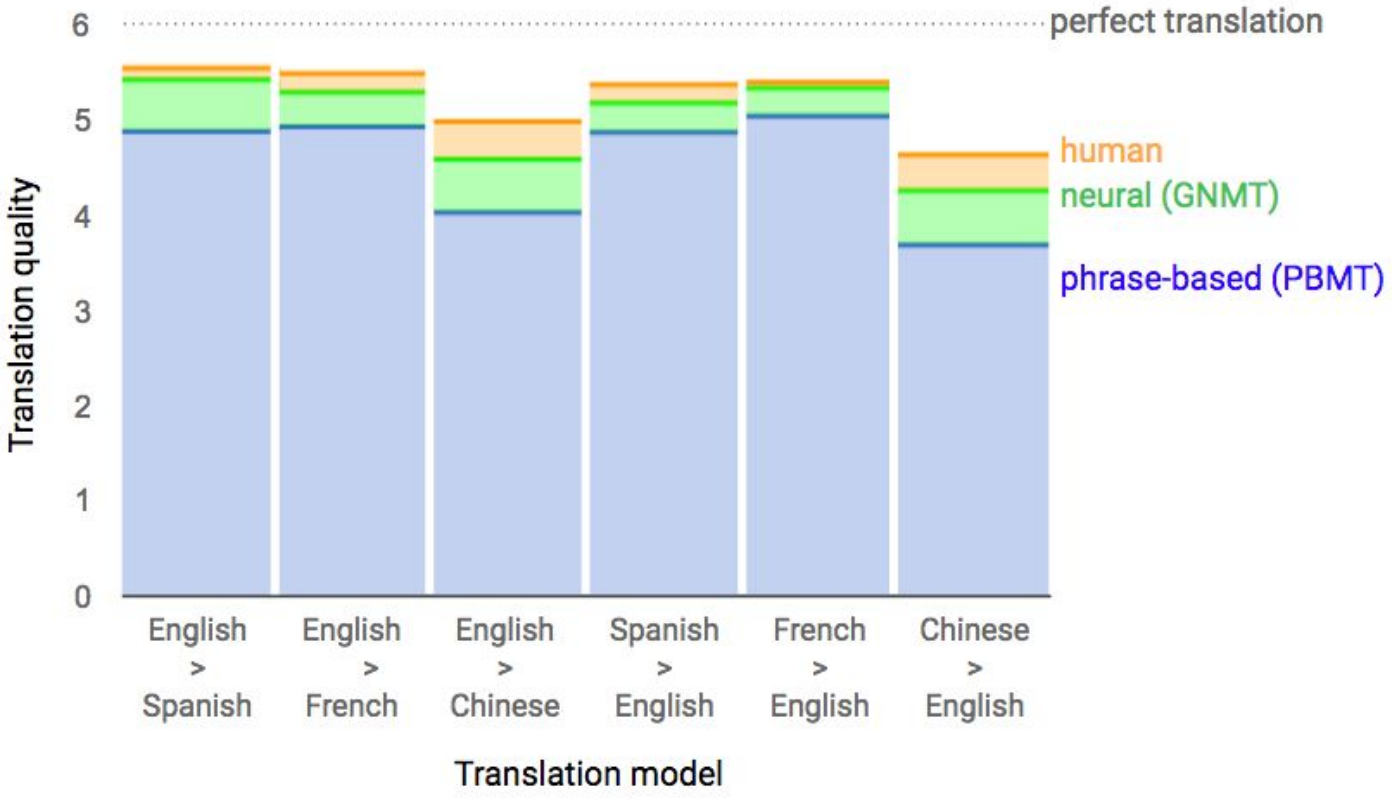
Machine translation



Source https://ai.googleblog.com/2016/09/a-neural-network-for-machine.html

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Deep Networks
When does it work?

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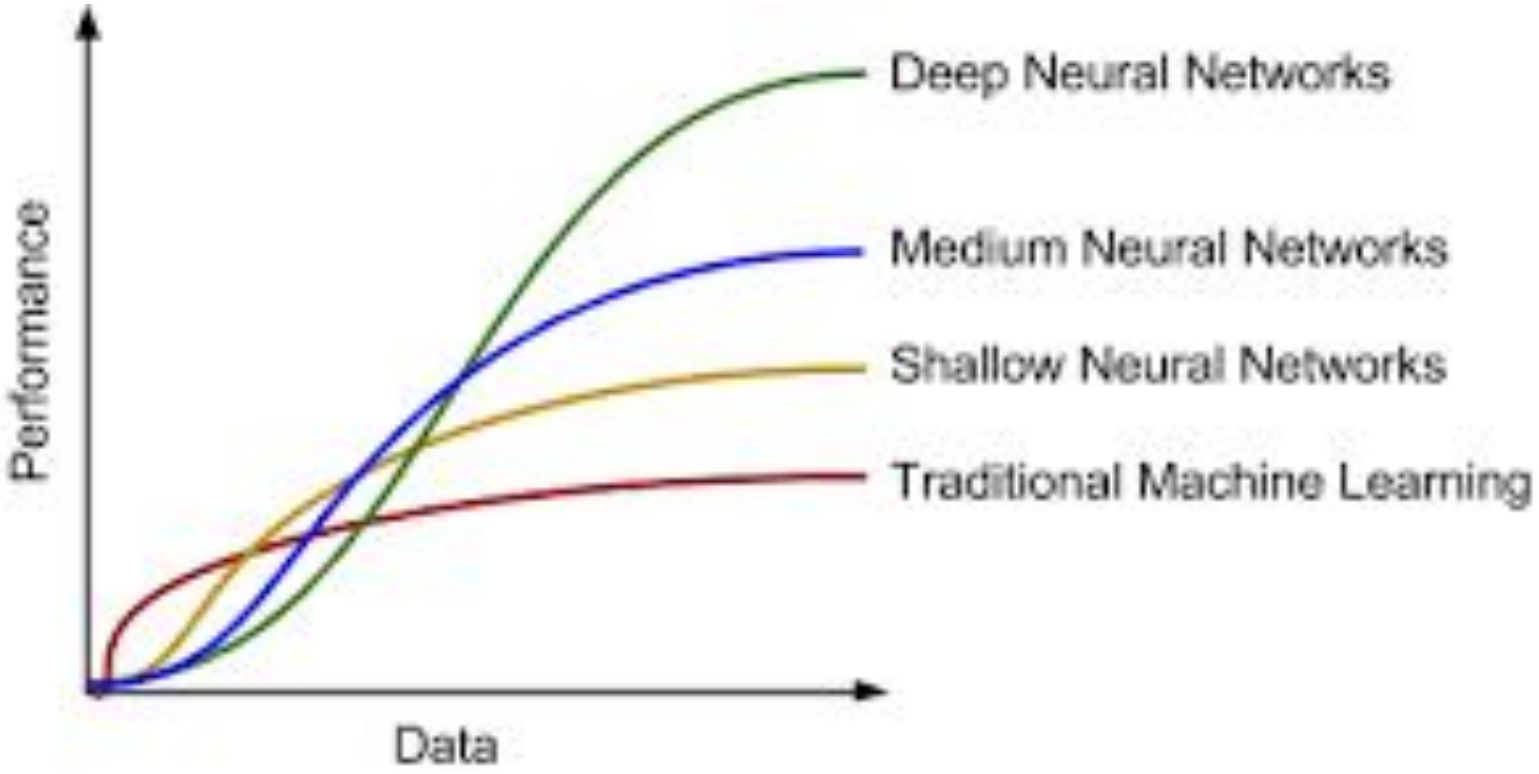

Source https://www.skynettoday.com/editorials/state_of_nmt

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Deep Networks
What does not work (well yet)?

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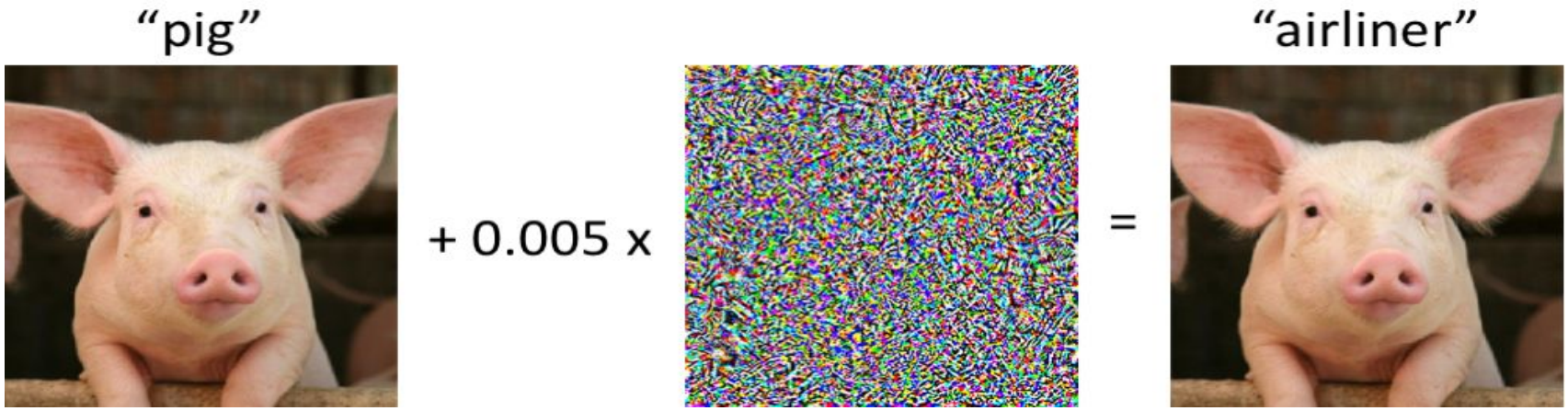
- Small data scenarios
- Domain transfer / generalization / robustness
  - when the test data is different from the training data
  - when the test data is “adversarially” modified
- Deep understanding
  - NN often exploit low-level statistical cues rather than truly understanding the data (in the way humans do)



Source https://medium.com/attentive-ai/fooling-cnns-via-adversarial-examples-877a9e0ee84e

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Natural Language Processing
Task Types

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Three types of tasks:

- **(C) Sentence / text classification**
  - I hate this movie → NEGATIVE
- **(T) Sequence tagging**
  - I hate this movie → PRON VERB DET NOUN
- **Seq2Seq**
  - I hate this movie → Diesen Film , ich hasse ihn

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Deep Learning Architectures vs. Input Representation

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Two fundamental questions:

- Which neural network architecture to choose?
  - Perceptron
  - MLP
  - RNN (LSTM, GRU)
  - CNN
  - Encoder-Decoder (RNN-, Transformer-based)
- How to represent the input?
  - (Sentence/Word) Embeddings

Deep Learning Architectures vs. Input Representation

Two fundamental questions:

- Which neural network architecture to choose?
  - Perceptron ← → C
  - MLP ← → C
  - RNN (LSTM, GRU) ← → T
  - CNN ← → C
  - Encoder-Decoder (RNN-, Transformer-based) ← → Seq2Seq
- How to represent the input?
  - (Sentence/Word) Embeddings

How to represent the input? Motivation

- A neural network takes a vector as an input
- In NLP, the vectors could represent
  - Characters
  - Words
  - Sentences
  - Texts
- The vector representations should encode
  - Semantics
  - Syntax/Morphology/Grammar
- Similar objects should have similar representations

How to represent the input? Motivation

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- A neural network takes a vector as an input
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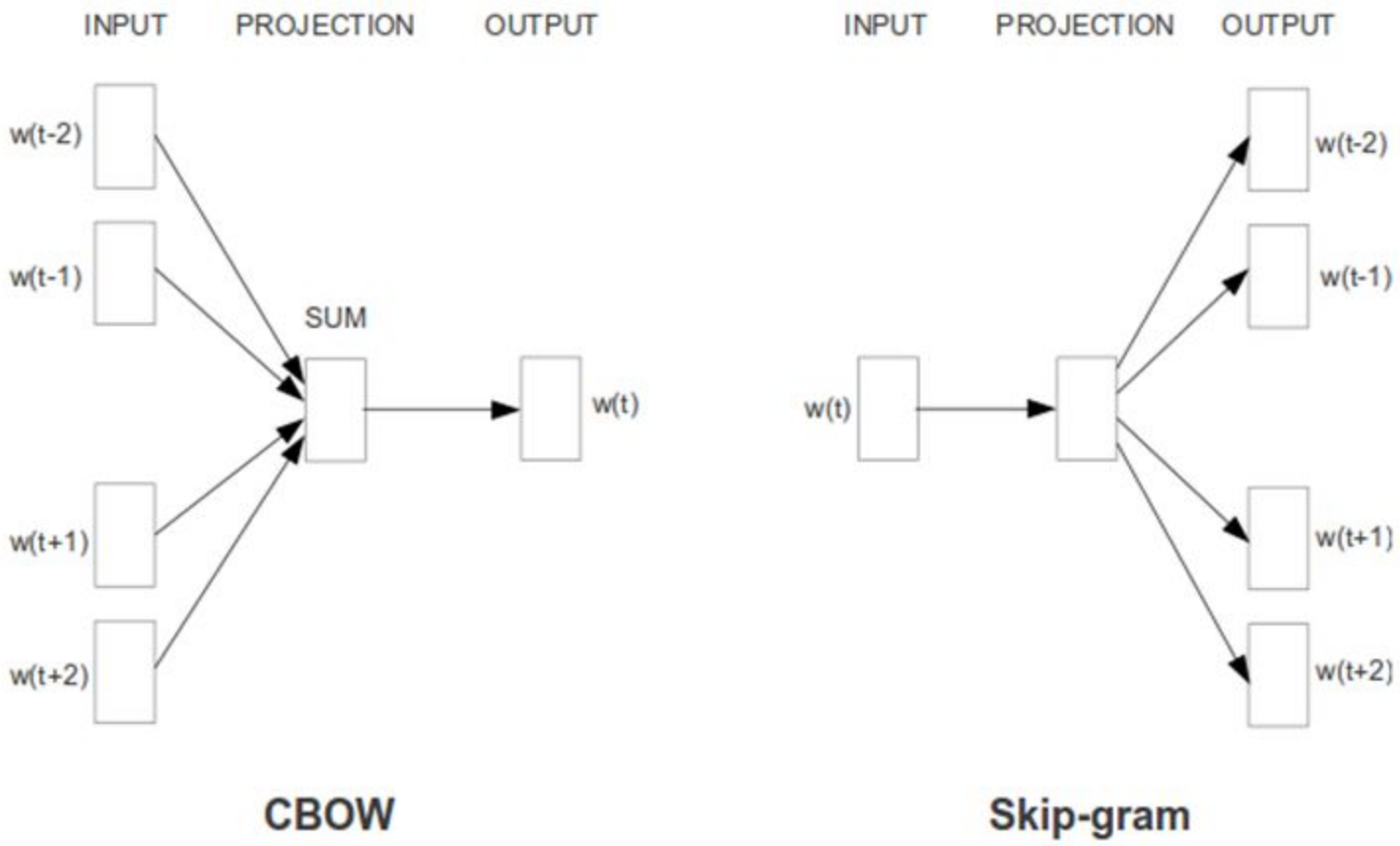
Word2Vec (Mikolov et al. 2013) Visualization



Word2Vec (Mikolov et al. 2013) Visualization

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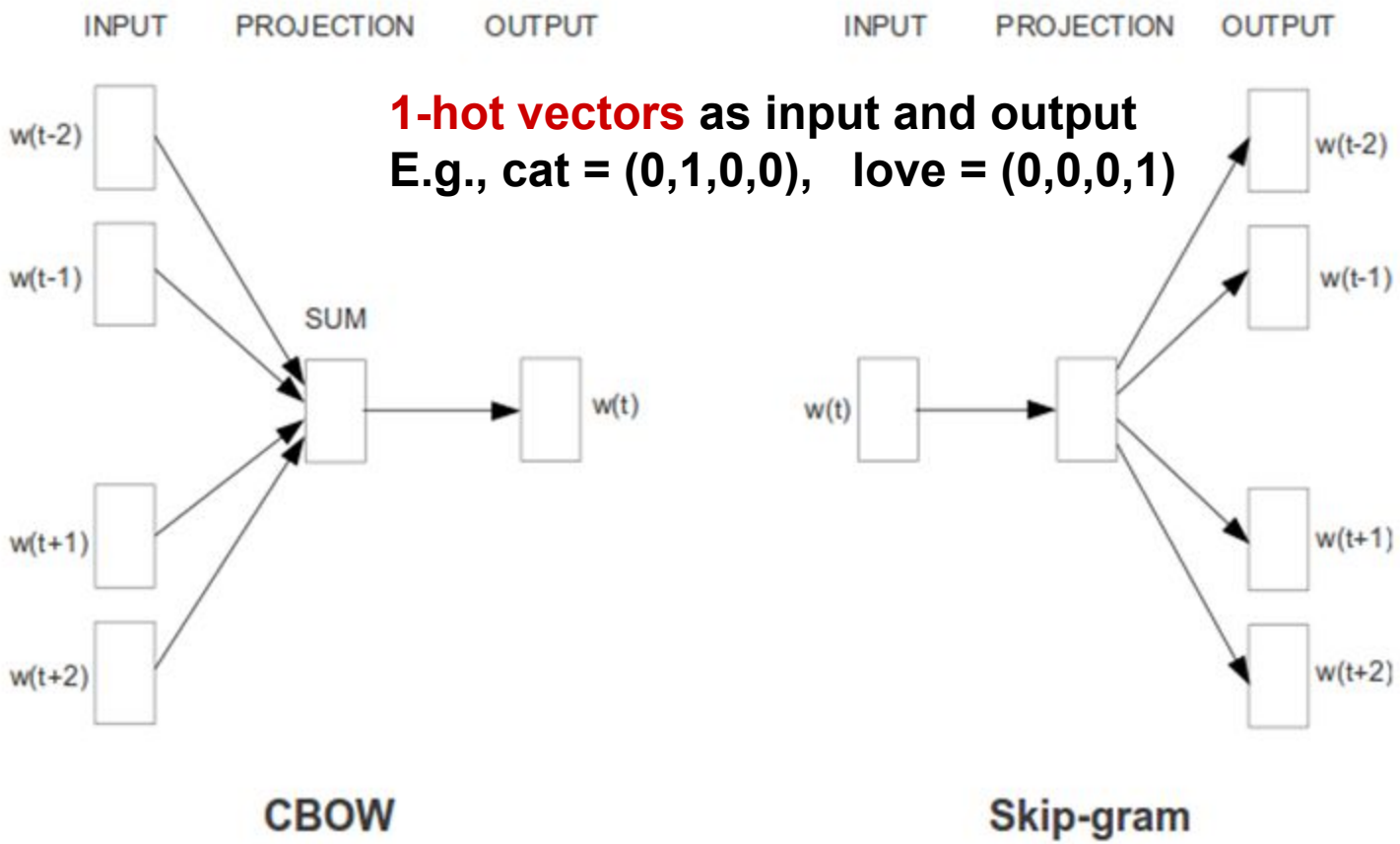
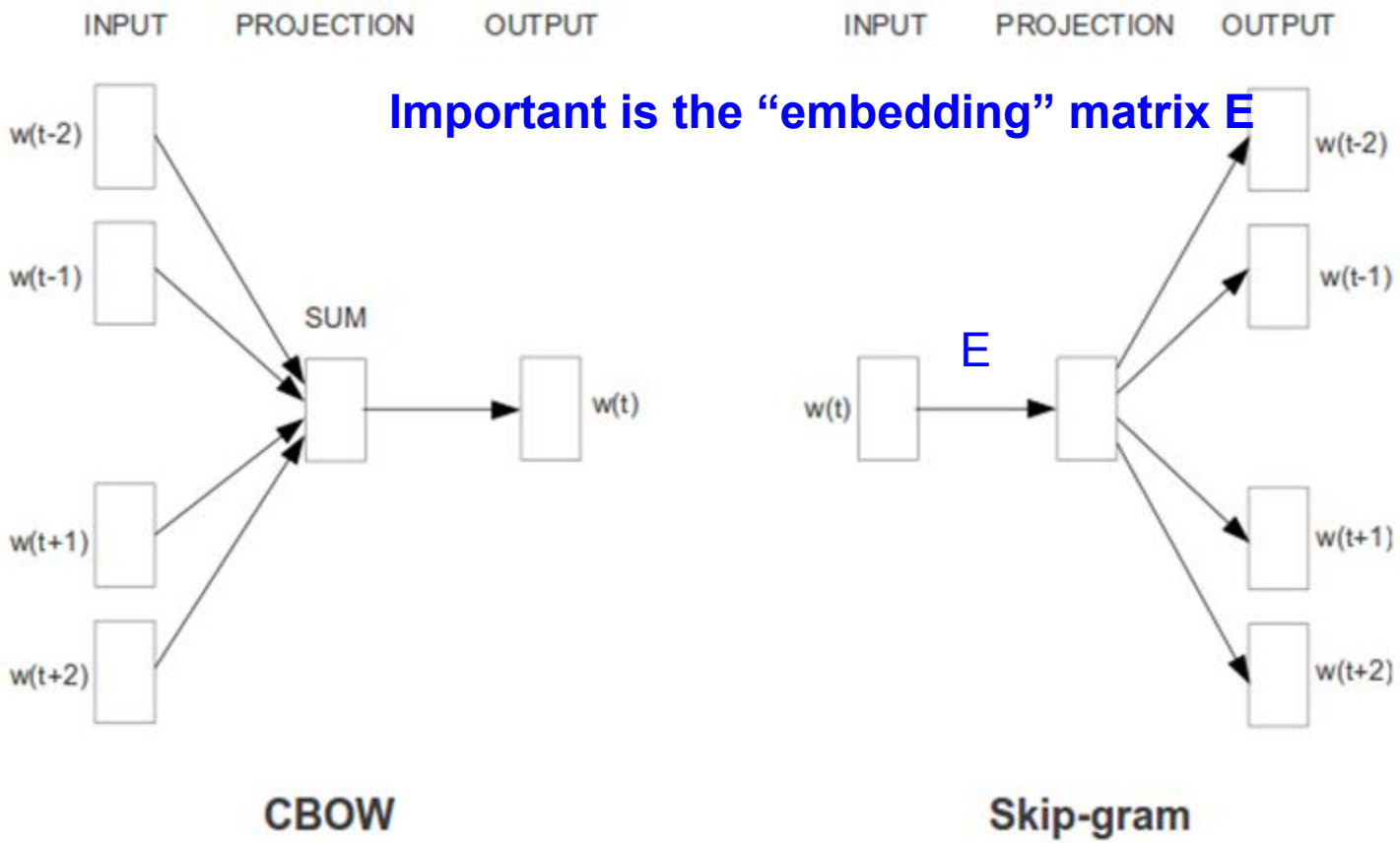


1-hot vectors as input and output
E.g., cat = (0,1,0,0), love = (0,0,0,1)

Word2Vec (Mikolov et al. 2013) Visualization



Important is the "embedding" matrix E

Word2Vec (Mikolov et al. 2013)
The embeddings

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- After training is finished, we only care about the matrix E
- We multiply a word's 1-hot vector with E, to get the embedding of the word

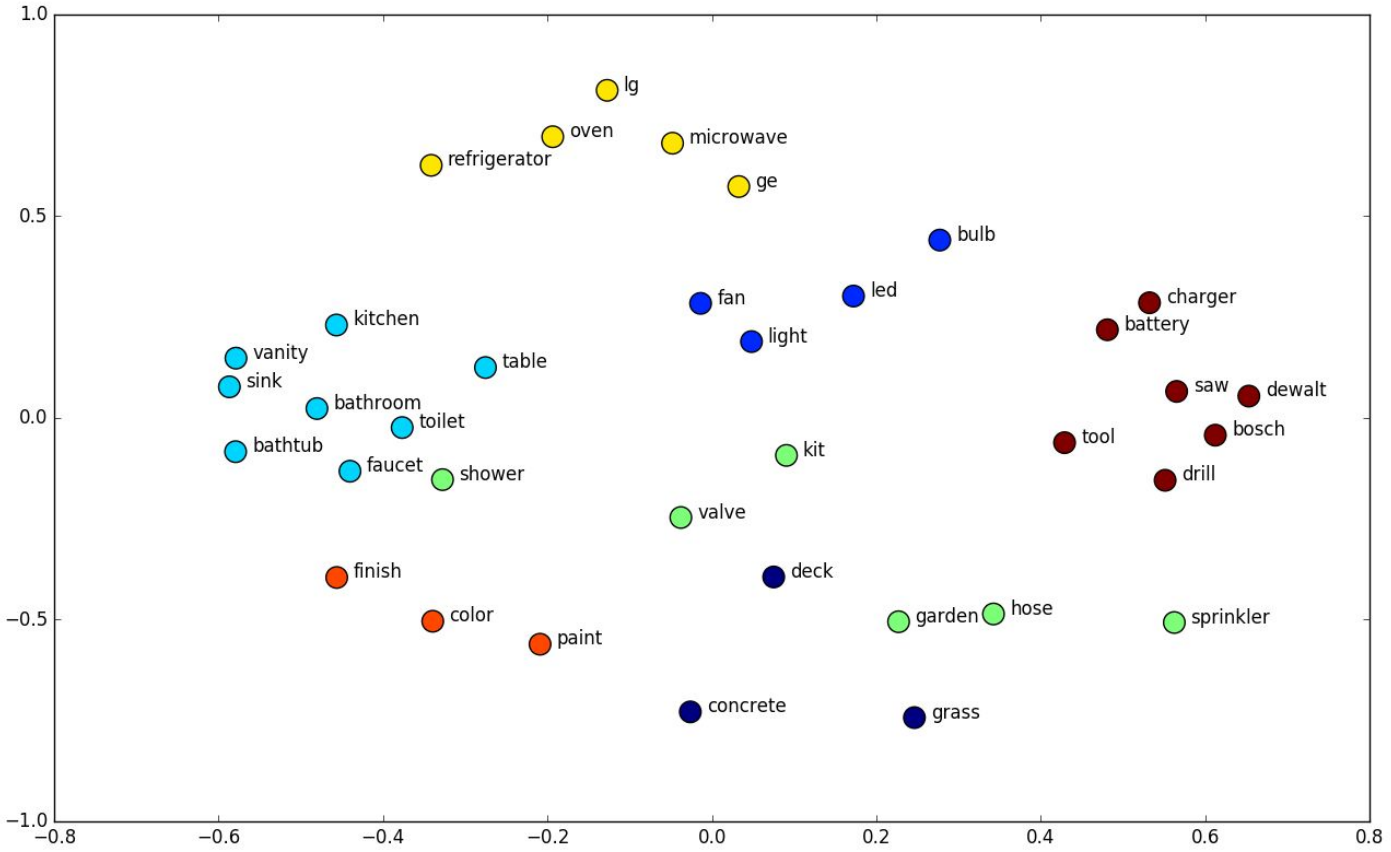
$$\underbrace{\begin{bmatrix}0 & 0 & 0 & 1 & 0\end{bmatrix}}_{\text{One-hot vector}} \times \underbrace{\begin{bmatrix}8 & 2 & 1 & 9\\ 6 & 5 & 4 & 0\\ 7 & 1 & 6 & 2\\ 1 & 3 & 5 & 8\\ 0 & 4 & 9 & 1\end{bmatrix}}_{\text{Embedding Weight Matrix}} = \underbrace{\begin{bmatrix}1 & 3 & 5 & 8\end{bmatrix}}_{\text{Hidden layer output}}$$

Source: https://towardsdatascience.com/what-the-heck-is-word-embedding-b30f67f01c81?gi=633fe1a189c4

Properties of embeddings

- Observation 1: Semantically similar words are near in the vector space
- Observation 2: Syntax/Morphology properties are (sometimes) also preserved

Properties of embeddings
Semantics



Source: https://www.shanelynn.ie/get-busy-with-word-embeddings-introduction/

Embeddings
Bi- and multi-lingual embeddings

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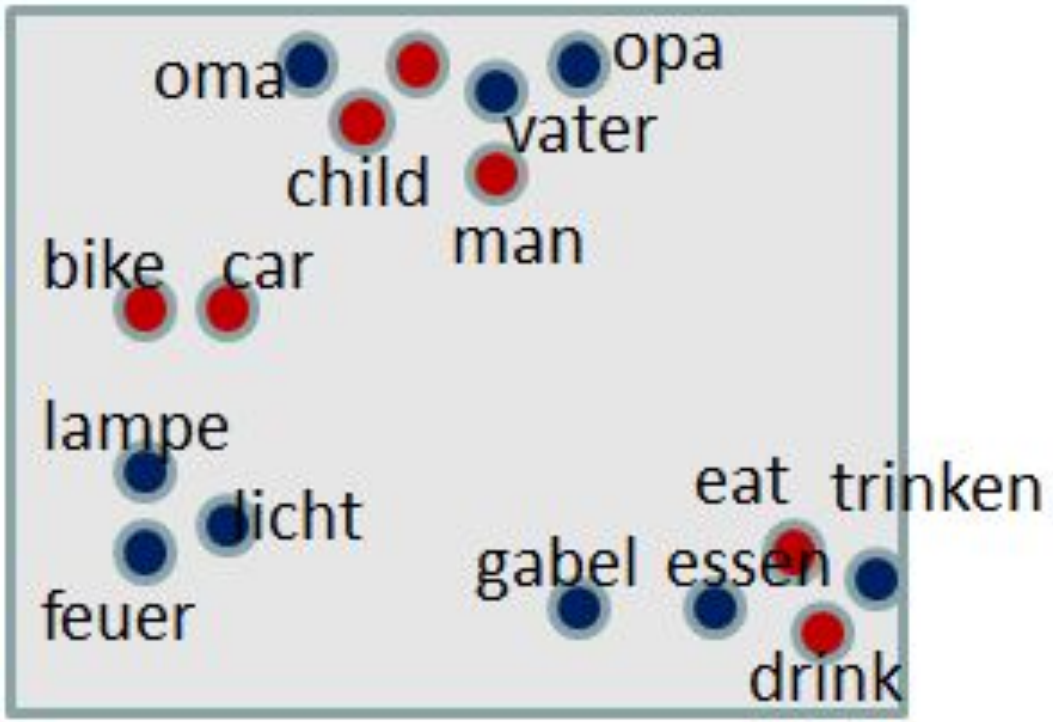
Similar words across two or more languages should be close in vector space



Embeddings
Contextualized embeddings

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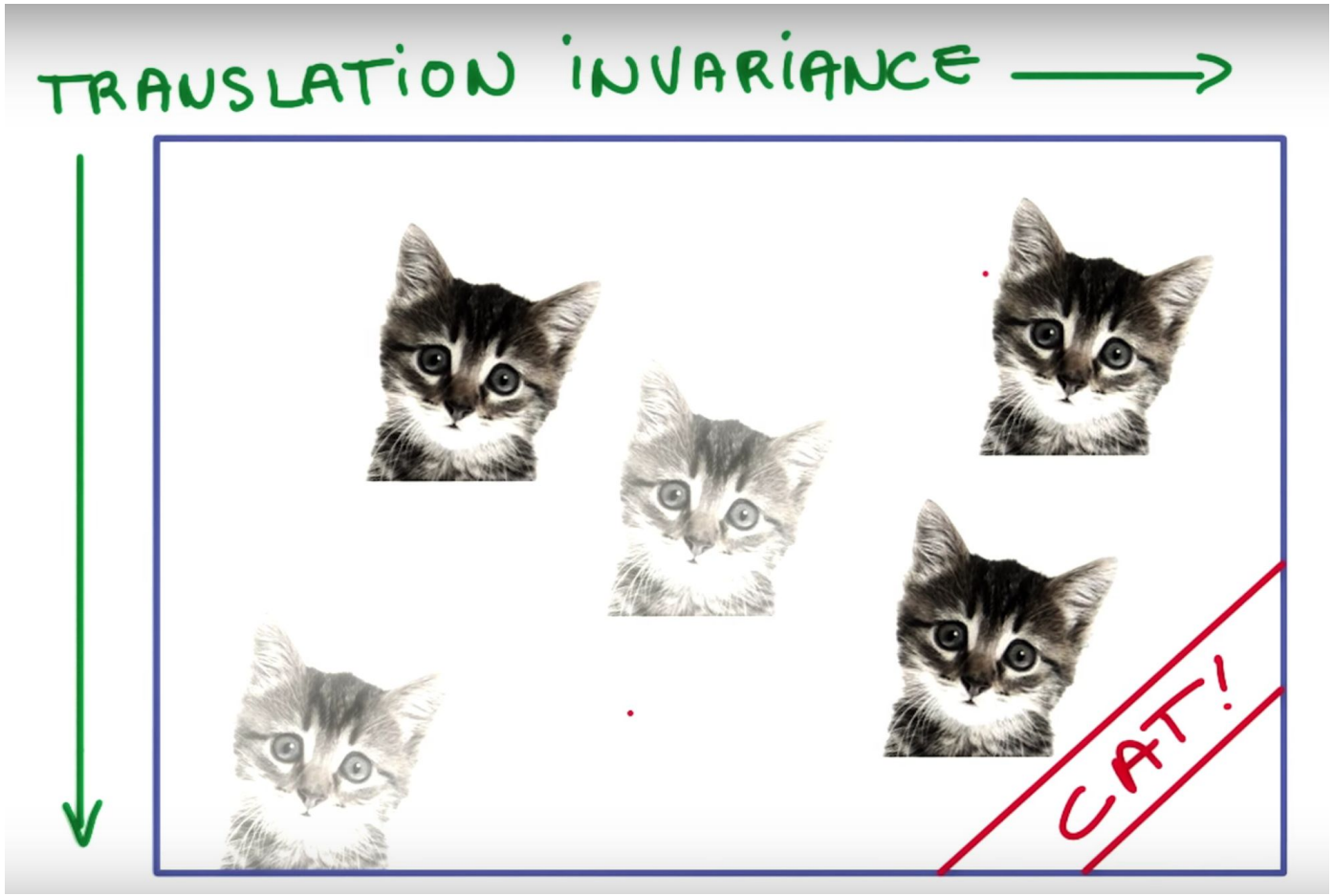
- Assign each word a different embedding depending on surrounding context
  - using so-called **Language Models**
- Cf.: “I **can** see you”, “Please give me that **can**”

- Have become extremely popular after 2018
- Have almost completely replaced the previous static embeddings
- Most popular: ELMo, nowadays BERT

Source: https://bensen.ai/elmo-meet-bert-recent-advances-in-natural-language-embeddings/

Convolutional Neural Networks
Translation invariance



Source: https://towardsdatascience.com/what-is-wrong-with-convolutional-neural-networks-75c2ba8fbd6f

Architectures
Recurrent Neural Networks

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RNNs

- are ideal for modeling **temporal data**
- where a classification should occur **at each time step**
- and the classification depends on all of the previous history (**infinite context**)

- are standard workhorses in NLP
  - because any text is a sequence of words/tokens
  - and many tasks are instances of sequential classification (POS, NER, ...)

Architectures
Recurrent Neural Networks

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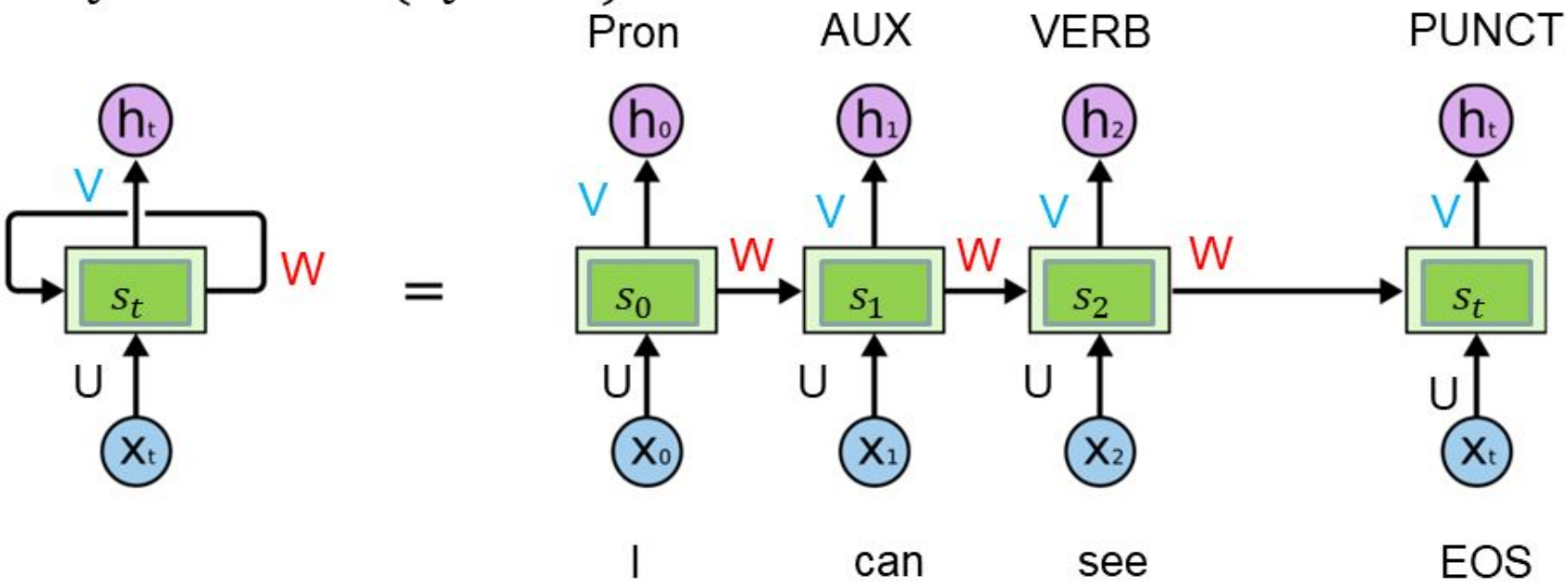
Math: $\boldsymbol{s}_t = f(\boldsymbol{x}_t\boldsymbol{U} + \boldsymbol{s}_{t-1}\boldsymbol{W} + \boldsymbol{b})$

$\boldsymbol{h}_t = \mathrm{softmax}(\boldsymbol{s}_t\boldsymbol{V} + \boldsymbol{c})$



Architectures
Encoder-Decoder

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Encoder-Decoder Neural Nets

- are ideal for mapping an input sequence to an output sequence
- input and output can be of different lengths
- and the order of elements in both can be very different
- typically, they consist of two RNNs

- they are ideal for machine translation

Architectures
Encoder-Decoder

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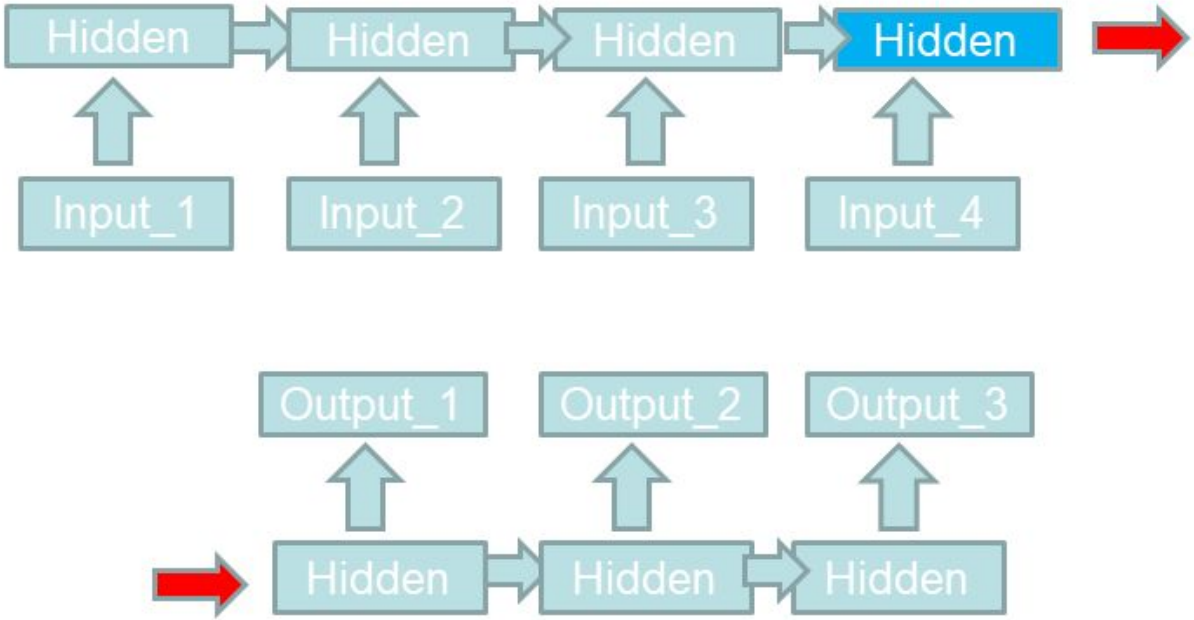
- Encoder-Decoder Models: We stack two RNNs together
- The last hidden layer in the input is taken as representation of the input



Architectures
Encoder-Decoder

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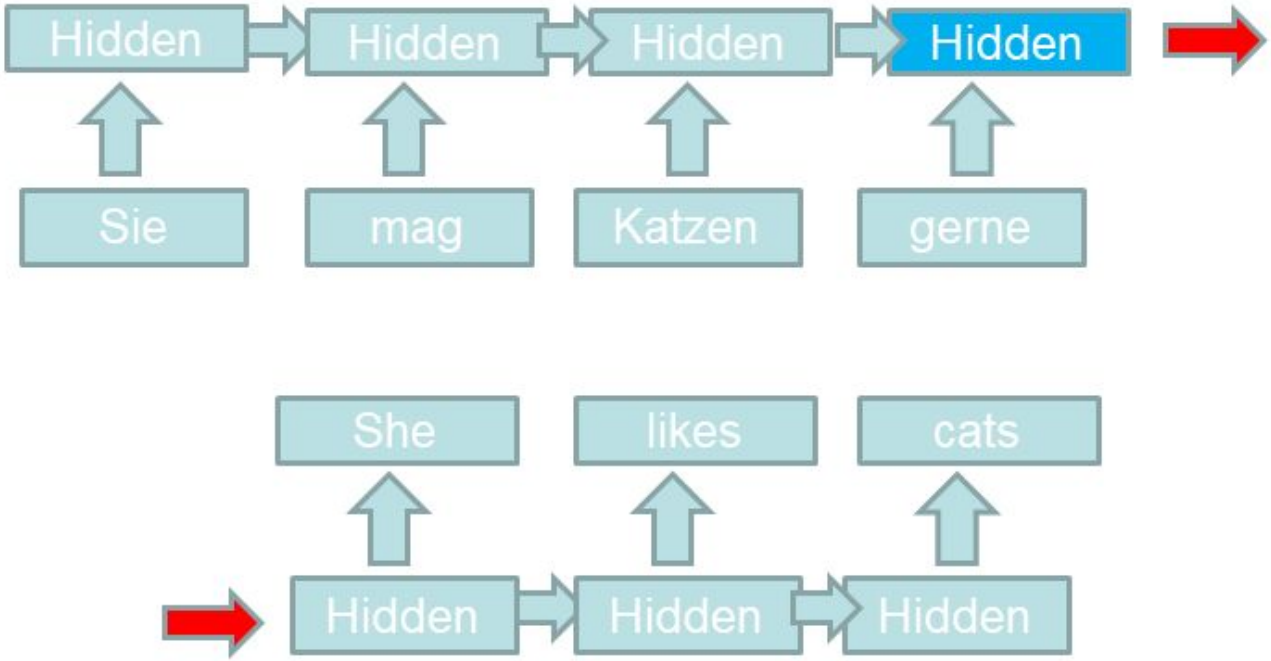
- Encoder-Decoder Models are typically emloyed in Machine Translation
- E.g. Translate a German sentence into an English sentence



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Recent extensions
Multi-task learning

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MTL: Learn several tasks jointly

- Like humans
- Spill-over effects
- May be beneficial when tasks are related, and when there's little data for the **main** task

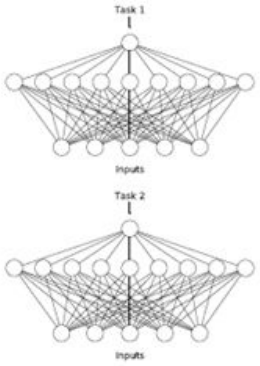

Figure: Single-task learning (inspired by Caruana (1993))

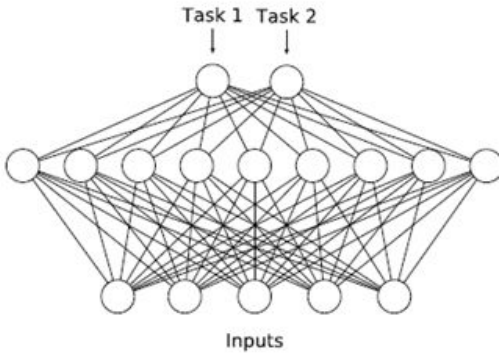

Figure: Multi-task learning (inspired by Caruana (1993))

NLLG

Recent extensions
Generative Adversarial Networks

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GANs: Two networks trying to outsmart each other

- Competition: “police” vs. “counterfeiters” (dt. Währungsfälscher)
- Huge success in computer vision
  - One network generates an image
  - The other determines whether it is “fake” or not

Source: Karras et al. 2018, Progressive growing of gans for improved quality stability and variation

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Recent advances
Language Modeling

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LM: predict next word given history

- Can be used to generate text
- Has rapidly advanced with the advent of DL
  - Better, faster models (Transformer)
  - Can be trained on much more data (web-scale)
  - Has led to human-like performances in MT and general text generation

- See: https://talktotransformer.com/

DL4NLP 2020

TECHNISCHE UNIVERSITÄT DARMSTADT

Dr. Steffen Eger
Wei Zhao

NLLG

Natural Language Learning Group

NLLG

Who are we?

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- Natural Language Learning Group (NLLG)
  - Aka “NLP for the Humanities”
  - https://www.informatik.tu-darmstadt.de/aiphes/aiphes/irg_position/index.en.jsp
- Research interests:
  - Cross-linguality
  - Cross-temporality
  - Automatic Poetry generation
  - Evaluation

Who are we?

TECHNISCHE UNIVERSITÄT DARMSTADT

- Natural Language Learning Group (NLLG)
  - Aka “NLP for the Humanities”
- Courses:
  - Deep Learning and Digital Humanities (WS)
    - https://github.com/SteffenEger/dldh
  - Meta-Science (SS)
    - https://github.com/SteffenEger/MetaScience
  - DL4NLP (SS)
  - FOLT (WS)

Who are we?

TECHNISCHE UNIVERSITÄT DARMSTADT

- Natural Language Learning Group (NLLG)
  - Aka “NLP for the Humanities”
- Theses available!
- Hiwi positions also available

References

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