ΟΙΚΟΝΟΜΙΚΟ ΠΑΝΕΠΙΣΤΗΜΙΟ ΑΘΗΝΩΝ
ATHENS UNIVERSITY OF ECONOMICS AND BUSINESS

Text Classification with Multi-Layer Perceptrons

2024–25

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http://www.aueb.gr/users/ion/

These slides are partly based on material from the books:

- *Artificial Intelligence – A Modern Approach* by S. Russel and P. Norvig, 2nd edition, Prentice Hall, 2003,
- *Artificial Intelligence* by I. Vlahavas et al., 3rd edition, University of Macedonia Press, 2006 (in Greek).
- *Machine Learning* by T. Mitchell, McGraw-Hill, 1997.

Contents

Natural neural networks

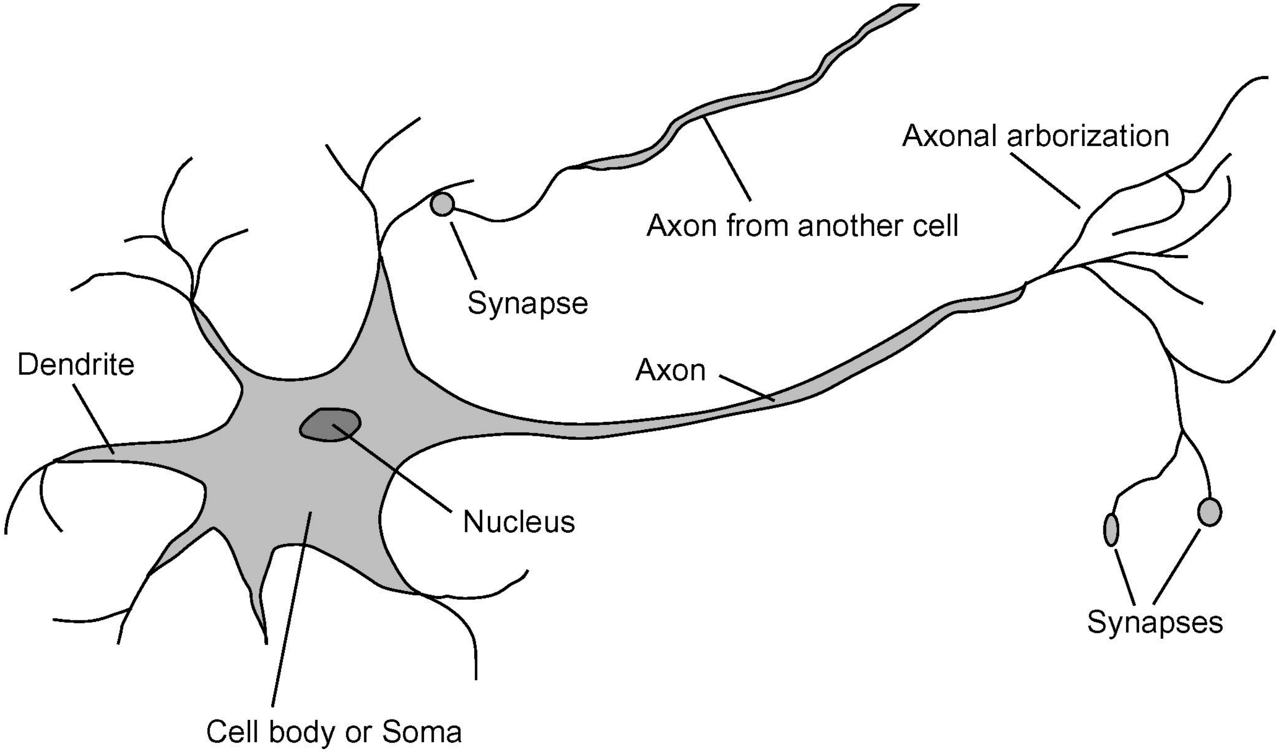


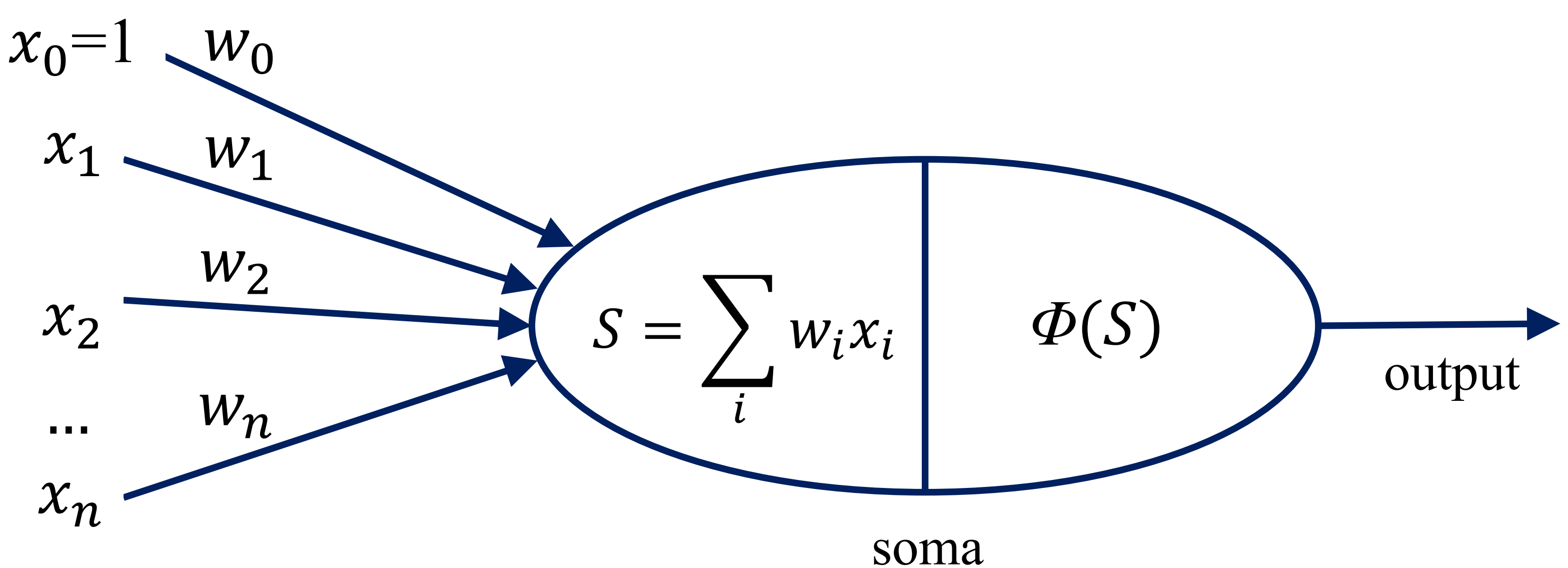
Image from the slides of Russel & Norvig's book.

- **Neuron**: cell of the brain.
  - **Cell body** or **soma**: the main part, includes the **nucleus**.
  - **Dendrites** receive signals from other neurons.
  - **Axon**: transmits a single output to other neurons. Often much longer than the diameter of the soma.
  - **Synapses**: axon-dendrite interfaces, whose conductivities vary.
- **Neural network**: network of many neurons.

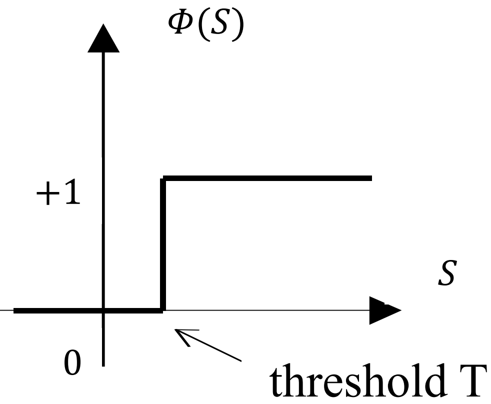
Artificial neural networks

Original image from the book of Vlahavas et al.

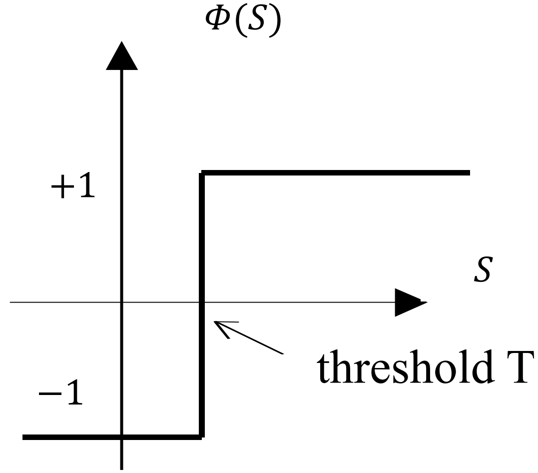
- **Artificial neuron**:
  - **Input**: real variables.
  - Input **weights**: real variables (roughly synapses).
  - **Soma**: computes the **weighted sum** of the inputs, then applies an **activation function** to the sum.



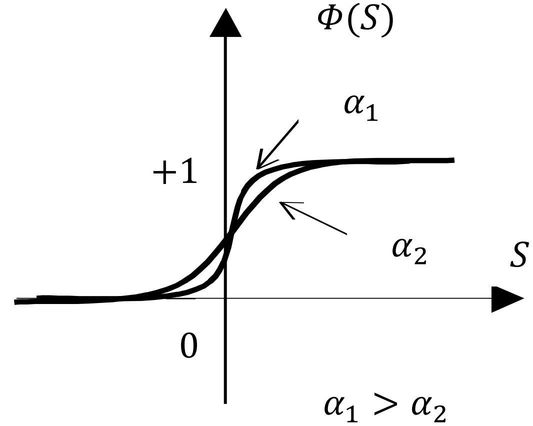
Activation functions



step function



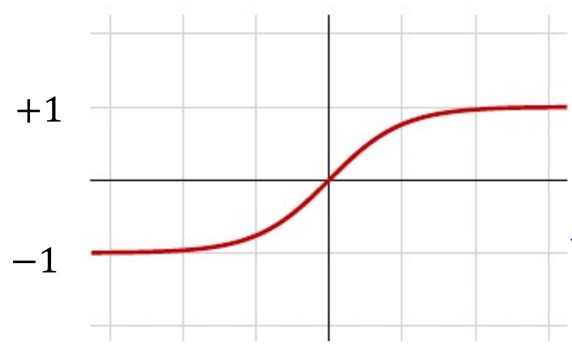
sign function



sigmoid
(logistic function)

$$\Phi(S) = \frac{1}{1 + e^{-a \cdot S}}$$

The **sigmoid** is **differentiable**.

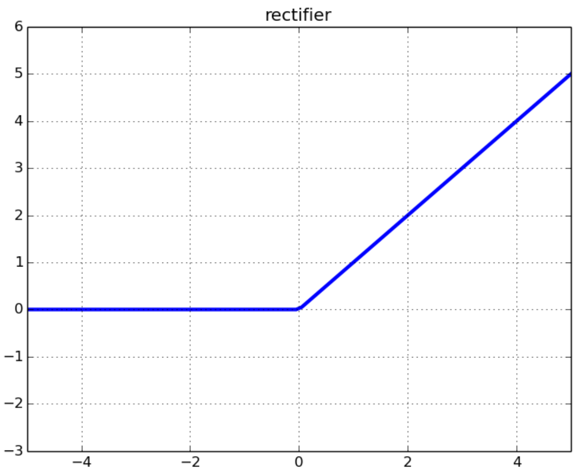


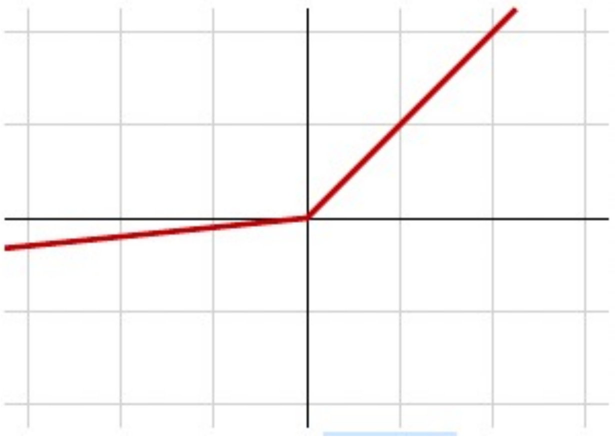
tanh

The hyperbolic tangent (**tanh**) is very similar to the sigmoid, but with values from −1 to +1. Usually better, unless we really want values in (0, 1).

Top images from the book of Vlahavas et al. Bottom image from *The Little Book of Deep Learning*, by F. Fleuret (https://fleuret.org/francois/lbdl.html).

Activation functions – continued





Rectified Linear Unit (ReLU)

$$\mathrm{relu}(x) = \begin{cases} 0 \ \text{ if } \ x < 0, \\ x \ \text{ otherwise} \end{cases}$$

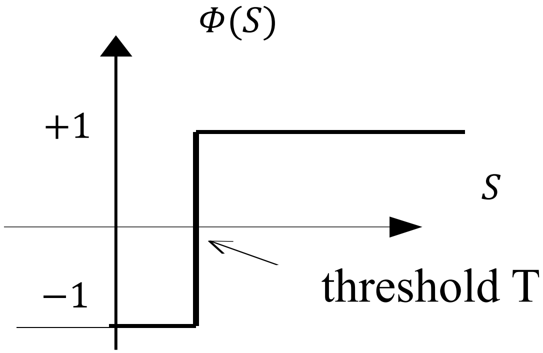
$$\mathrm{leaky\,relu}(x) = \begin{cases} ax \text{ if } x < 0, \\ x \text{ otherwise} \end{cases}$$

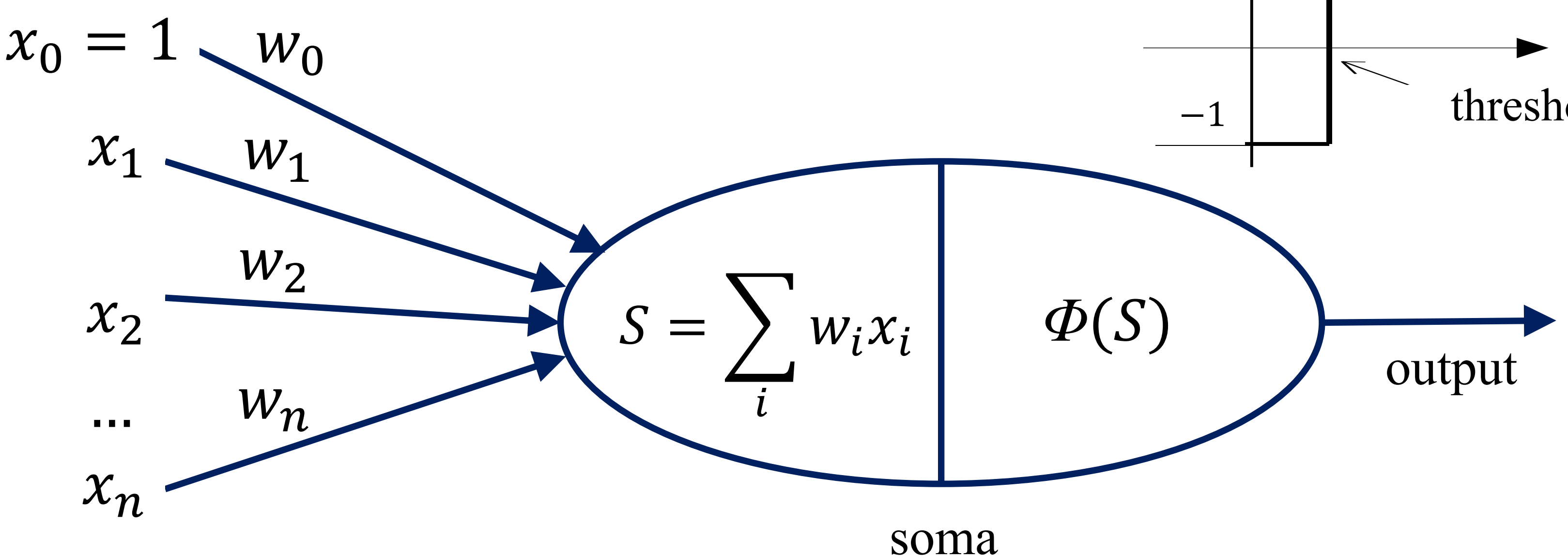
ReLU and variants are popular choices.

Left image from http://datascience.stackexchange.com/questions/5706/. Right image and equations from *The Little Book of Deep Learning*, by F. Fleuret (https://fleuret.org/francois/lbdl.html).

Perceptron

- A **single neuron**, originally with **sign activation function**.
  - Equivalently, **step** activation function.
  - The Perceptron can be **generalized** (done later), to use a **sigmoid or other** activation function.
  - We can use **several Perceptrons** (e.g., to recognize a letter each).





Original images from the book of Vlahavas et al.

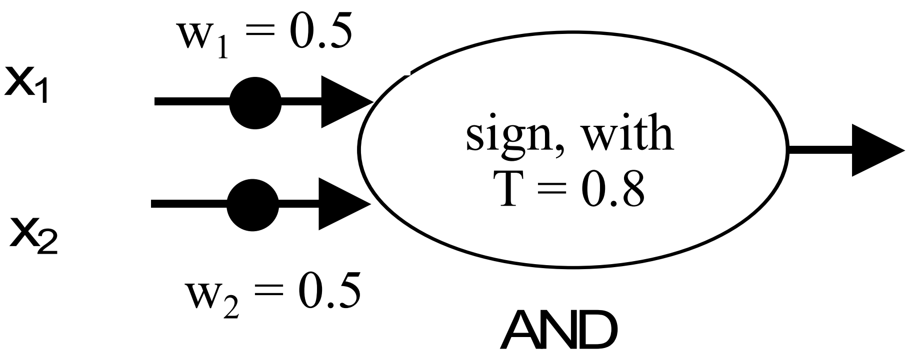
We usually think of it as an algorithm, but it was a **machine** originally!

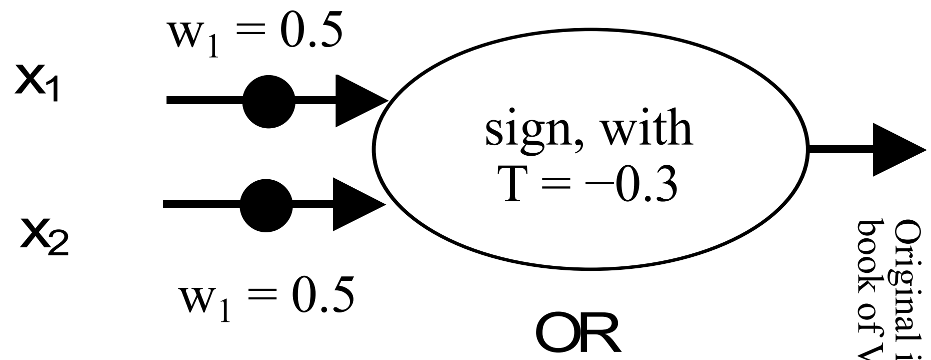
The perceptron is a machine

Slide from the presentation “Multilayer Neural Networks” of L. Bottou at the Deep Learning Summer School 2015 (http://videolectures.net/deeplearning2015_montreal/).

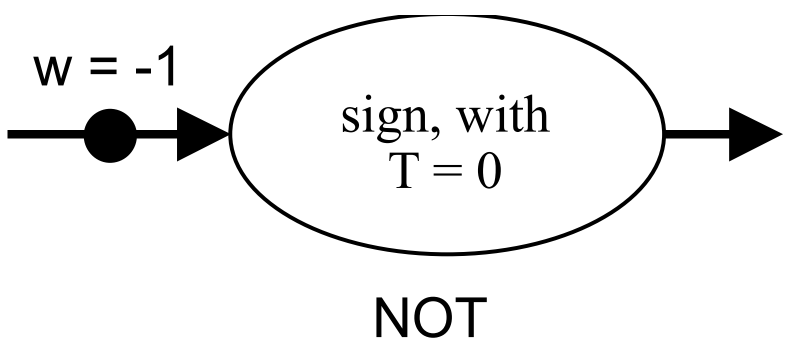
Perceptrons as logical gates

true: 1, false: -1



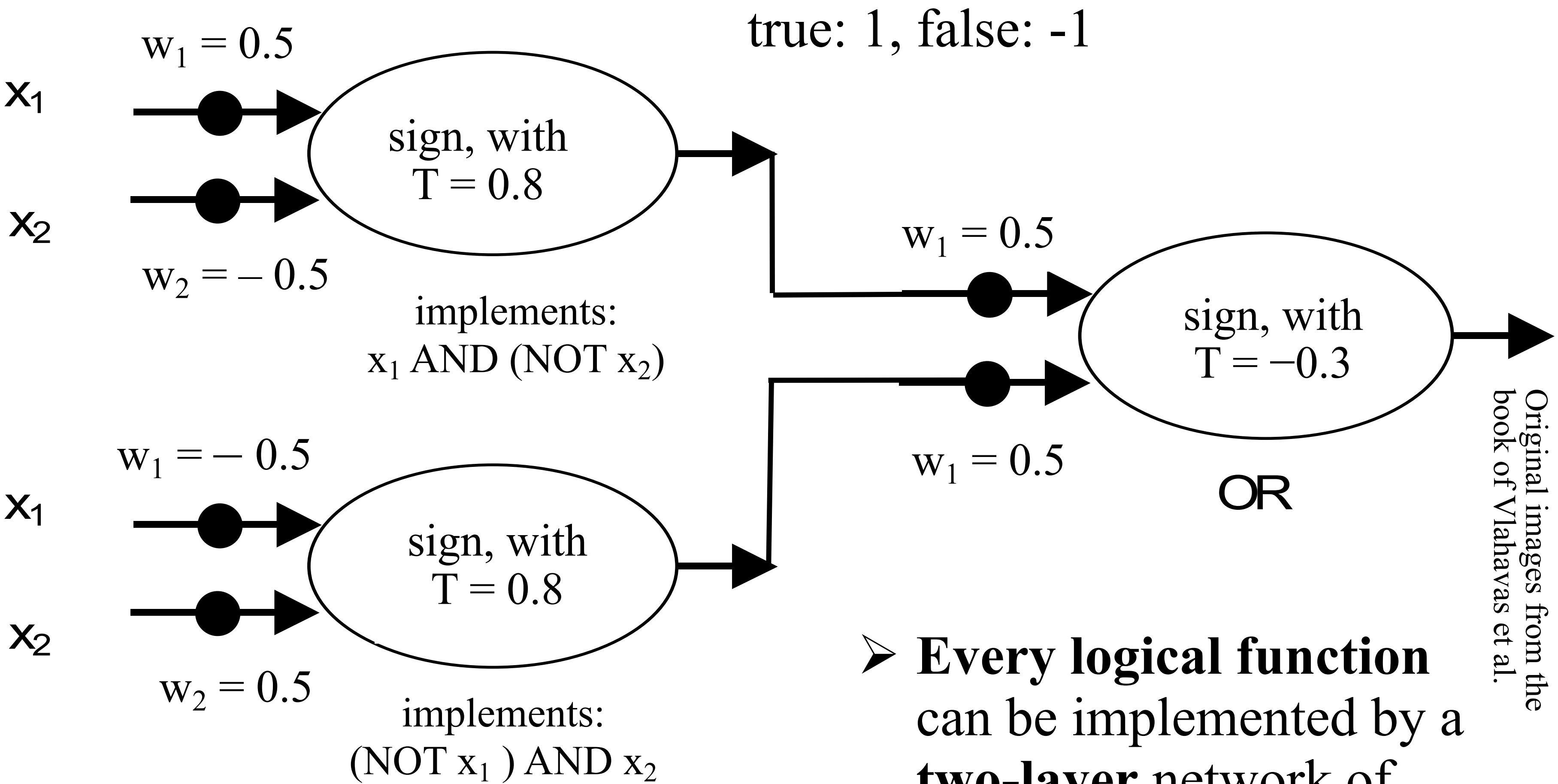


Original images from the book of Vlahavas et al.



- We **cannot** implement **every logical function** with a **single Perceptron**.
  - E.g., we cannot implement an **XOR** gate.

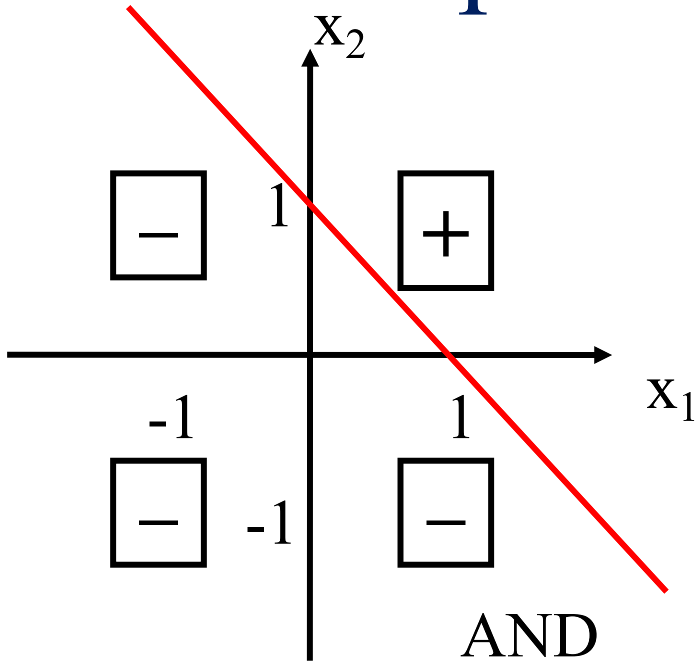
Two-level XOR implementation

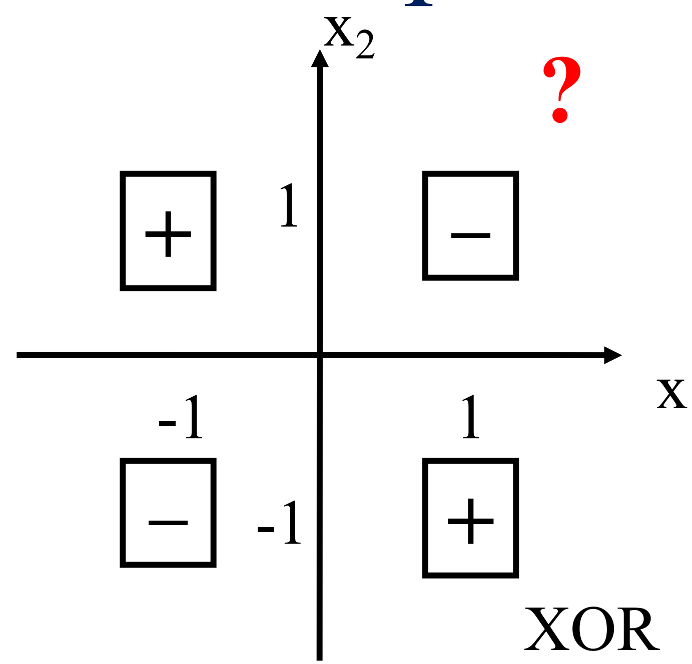


- **Every logical function** can be implemented by a **two-layer** network of **Perceptrons** (exercise).

Original images from the book of Vlahavas et al.

The Perceptron is a linear separator





- Like logistic regression, a single **Perceptron** can learn only **linear separators** (exercise). For **non-linear separators**, we need **Multi-Layer Perceptrons**.
- An **MLP** with **1 hidden layer** can compute (in principle, also learn) **any mapping between discrete spaces** with finite dimensions.
- **For continuous spaces, very roughly** speaking: with **1 hidden layer** we can compute (in principle, also learn) almost any **bounded continuous function**; with **2 hidden layers** we can compute almost any **bounded function**.
- But we may need a very **large, unknown number of neurons** in the **hidden layers**, we may end up **memorizing** the training dataset (exercise), and we **may not** actually manage to **learn (find) the target function**.

Perceptron's original learning algorithm

1. Start with random weights $\vec{w}$.
2. Set $i \leftarrow 1$ and $s \leftarrow 0$.
3. Let $t^{(i)}$ be the correct output for the i-th training instance and $o^{(i)}$ the current output for that instance.
4. Set $s \leftarrow s + E_i(\vec{w})$, with: $E_i(\vec{w}) = 1/2 \cdot [t^{(i)} - o^{(i)}]^2$
5. Update the weights: $w_l \leftarrow w_l + \eta \cdot (t^{(i)} - o^{(i)}) \cdot x_l^{(i)}$
6. If there is a next training instance, set $i \leftarrow i + 1$ and go to step 3.
7. If s had not converged and max number of scans (epochs) of training data not exceeded go to step 2.

- In the simplest case, η is a small positive constant.

Perceptron with sigmoid or other Φ

- More generally, when using a Perceptron with **activation function Φ instead of step/sign:**

$$w_l \leftarrow w_l + \eta \cdot \Phi'(\sum_l w_l x_l^{(i)}) \cdot (t^{(i)} - \Phi\left(\sum_l w_l x_l^{(i)}\right)) \cdot x_l^{(i)}$$

- For sigmoid $\Phi(S) = \frac{1}{1+e^{-S}}$, $\Phi'(S) = \Phi(S) \cdot (1 - \Phi(S))$.

- And since $o^{(i)} = \Phi\left(\sum_l w_l x_l^{(i)}\right)$, the weights update rule becomes:

$$w_l \leftarrow w_l + \eta \cdot o^{(i)} \cdot (1 - o^{(i)}) \cdot (t^{(i)} - o^{(i)}) \cdot x_l^{(i)}$$

Derivation of the update rule

- **Squared error loss** on the **current training instance**:

$$E_i(\vec{w}) = \frac{1}{2}(t^{(i)} - o^{(i)})^2 = \frac{1}{2}\left(t^{(i)} - \Phi\left(\sum_l w_l x_l^{(i)}\right)\right)^2$$

Random initial weights. Loss on current training instance is $E_i(\vec{w})$. Which direction to modify $\vec{w}$?

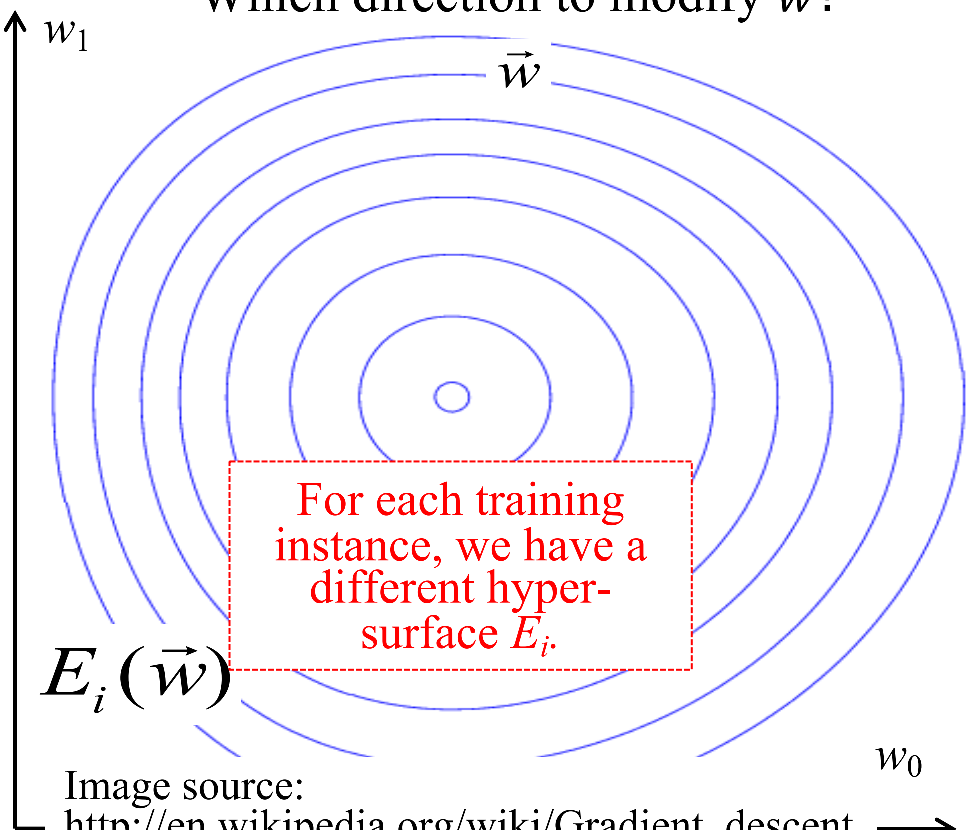


Image source: http://en.wikipedia.org/wiki/Gradient_descent

The **gradient $\nabla E_i(\vec{w})$** is a vector showing the **direction** we need to **modify $\vec{w}$** to obtain the **steepest increase** of $E_i(\vec{w})$.

At each iteration, take **a step** to the direction $-\nabla E_i(\vec{w})$:

$$\vec{w} \leftarrow \vec{w} - \eta \cdot \nabla E_i(\vec{w})$$

Simplest case: η is a **small positive constant**. **Stochastic gradient descent** to minimize the **total squared error loss**.

Derivation of the update rule

$$E_i(\vec{w}) = \frac{1}{2}(t^{(i)} - o^{(i)})^2 = \frac{1}{2}(t^{(i)} - \Phi\left(\sum_{l=1}^{n} w_l x_l^{(i)}\right))^2$$

$$\nabla E_i(\vec{w}) = \left\langle \frac{\partial E_i(\vec{w})}{\partial w_0}, \ldots, \frac{\partial E_i(\vec{w})}{\partial w_l}, \ldots, \frac{\partial E_i(\vec{w})}{\partial w_n} \right\rangle$$

$$\frac{\partial E_i}{\partial w_l} = (t^{(i)} - \Phi\left(\sum_l w_l x_l^{(i)}\right)) \cdot \frac{\partial(t^{(i)} - \Phi\left(\sum_l w_l x_l^{(i)}\right))}{\partial w_l} = -(t^{(i)} - o^{(i)}) \cdot \Phi'\left(\sum_l w_l x_l^{(i)}\right) \cdot x_l^{(i)}$$

Hence: $\nabla E_i(\vec{w}) = -(t^{(i)} - o^{(i)}) \cdot \Phi'\left(\sum_l w_l x_l^{(i)}\right) \cdot \left\langle x_1^{(i)}, \ldots, x_n^{(i)} \right\rangle$

$$= -(t^{(i)} - o^{(i)}) \cdot \Phi'(\vec{w} \cdot \vec{x}^{(i)}) \cdot \vec{x}^{(i)}$$

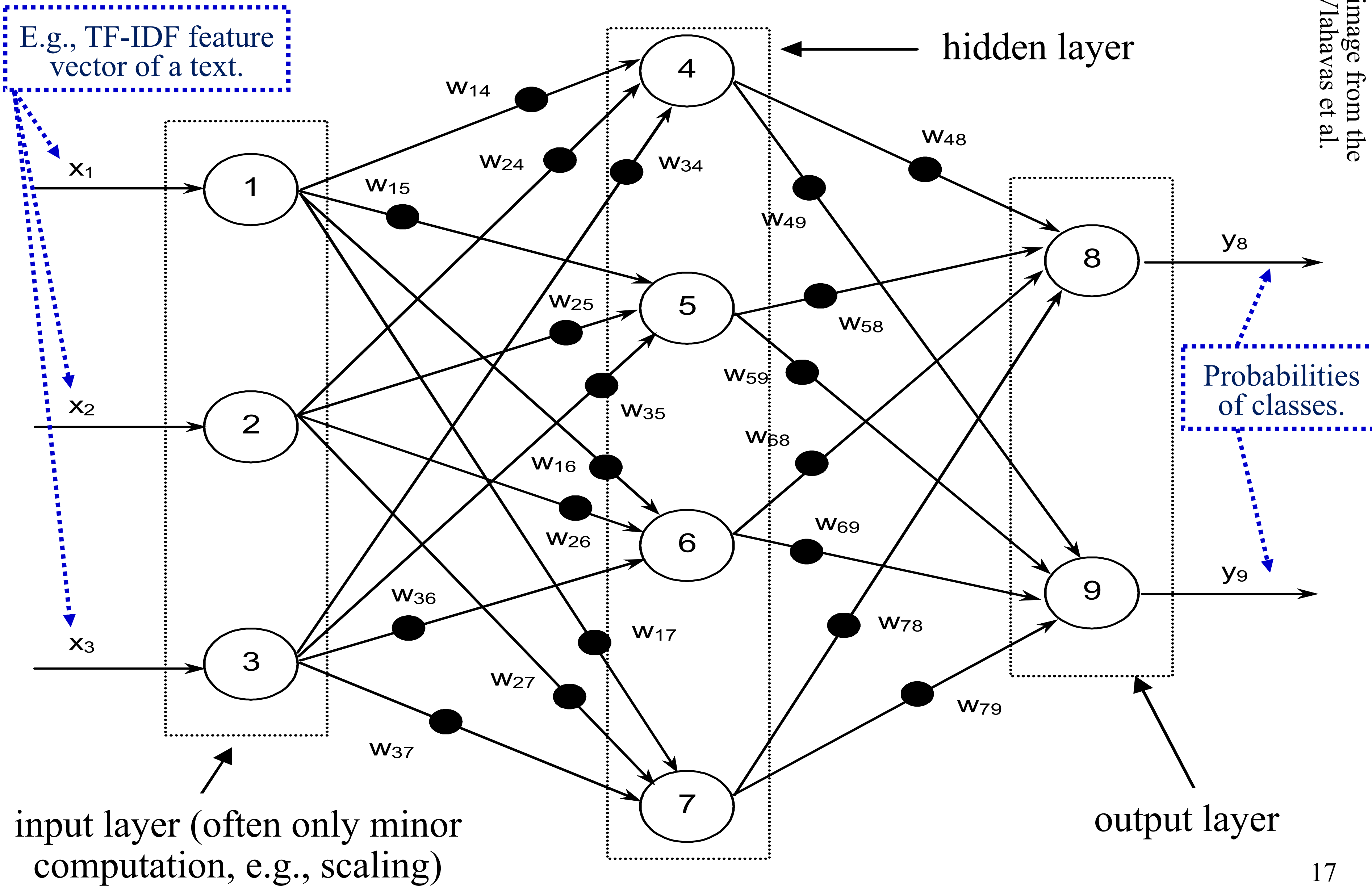
Weights update rule:

$$\vec{w} \leftarrow \vec{w} - \eta \cdot \nabla E_i(\vec{w}) = \vec{w} + \eta \cdot (t^{(i)} - o^{(i)}) \cdot \Phi'(\vec{w} \cdot \vec{x}^{(i)}) \cdot \vec{x}^{(i)}$$

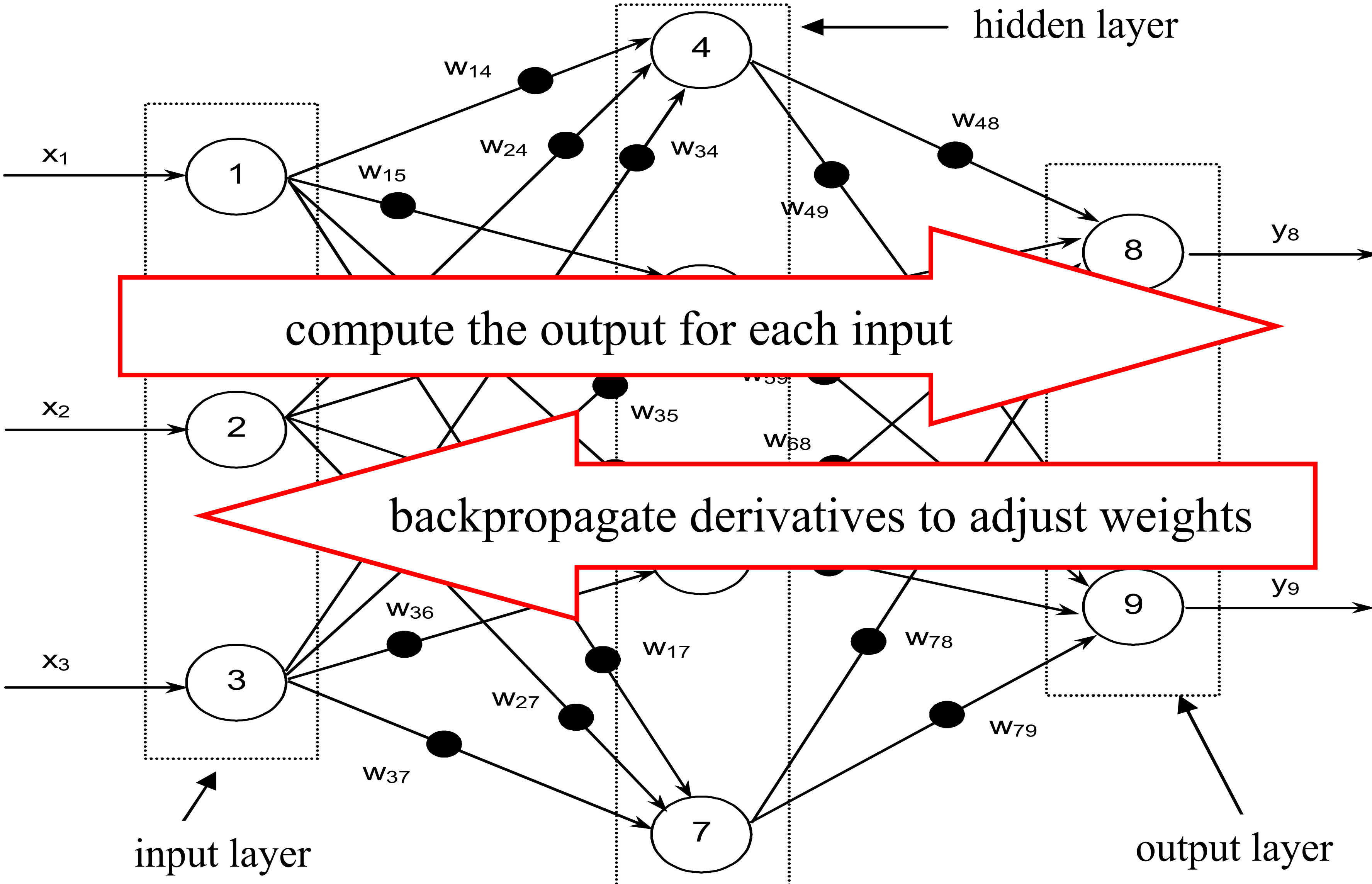
For each weight: $w_l \leftarrow w_l + \eta \cdot (t^{(i)} - o^{(i)}) \cdot \Phi'(\vec{w} \cdot \vec{x}^{(i)}) \cdot x_l^{(i)}$

Multi-layer Perceptron (MLP)

Original image from the book of Vlahavas et al.



Backpropagation



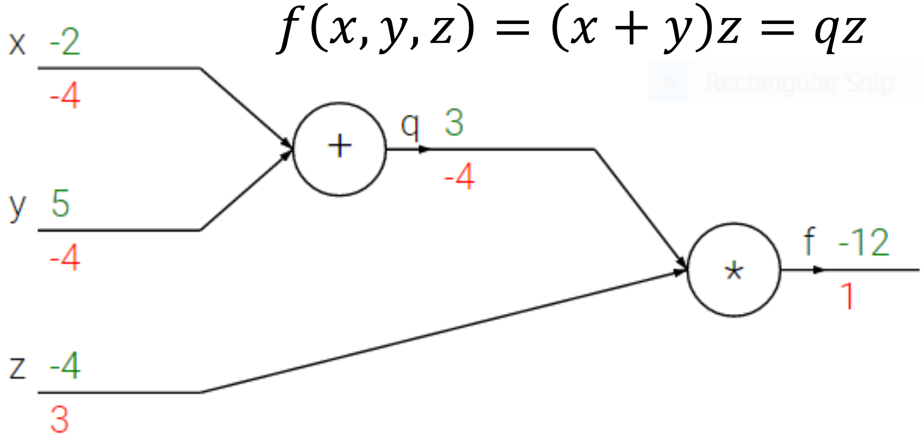
Original image from the book of Vlahavas et al.

Backpropagation

- **Initialize** all the **weights** to **small random values**.
  - E.g., sample from a **zero-centered Gaussian** with **small $\boldsymbol{\sigma}$**.
  - Better initializations exist (see DL course).
  - **Normalize** the **features** too (see “Important tricks” of Part 2).
- **In each epoch, for each training example** (or mini-batch):
  - Compute the **output** <o_1, o_2, …> for the training example.
  - **For each weight** w_{ij}, **compute** $\frac{\partial E}{\partial w_{ij}}$, where E the loss on the training example. We **compute derivatives right to left**.
  - **Update each weight** as: $\boldsymbol{w_{ij} \leftarrow w_{ij} - \eta \cdot \frac{\partial E}{\partial w_{ij}}}$, i.e., for all the weights together: $\boldsymbol{W \leftarrow W - \eta \cdot \nabla_W E}$
  - Hence, we use **SGD** (or variants). **No guarantee** SGD will find the **best solution**, but it (often) works in practice!

Example of computation graph

$$f(x, y, z) = (x + y)z = qz$$



Example and figure from Stanford's "CNNs for Visual Recognition" (2016, F.-F. Li, A. Karpathy, J. Johnson) http://cs231n.github.io/optimization-2/

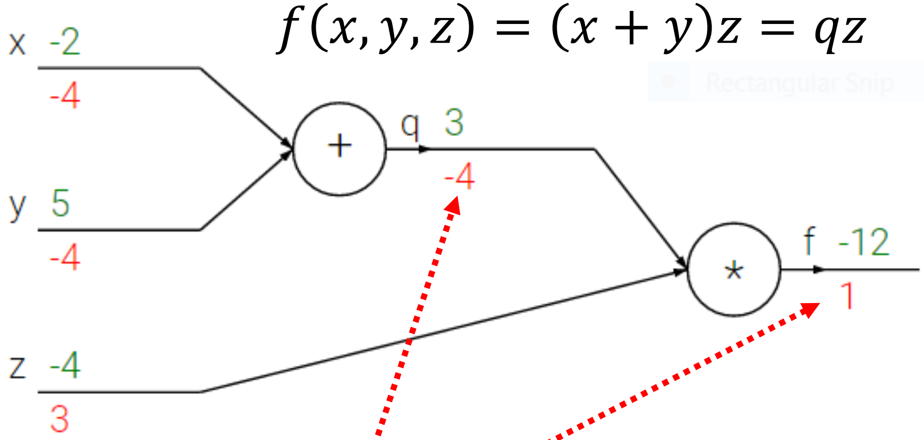
- **Forward pass**: $\langle x, y, z \rangle = \langle -2, 5, -4 \rangle,\ q = 3,\ f = -12$
- Imagine we wish to **minimize $\boldsymbol{f}$** using **SGD.**
  - In a more realistic scenario, $\boldsymbol{f}$ would be a **loss function**, and $\langle \boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z} \rangle$ the **weights vector**.

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} \leftarrow \begin{bmatrix} x \\ y \\ z \end{bmatrix} - \eta \nabla f(x, y, z) = \begin{bmatrix} x \\ y \\ z \end{bmatrix} - \eta \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \\ \frac{\partial f}{\partial z} \end{bmatrix}$$

We need: $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$

Backpropagation in the graph

$$f(x, y, z) = (x + y)z = qz$$

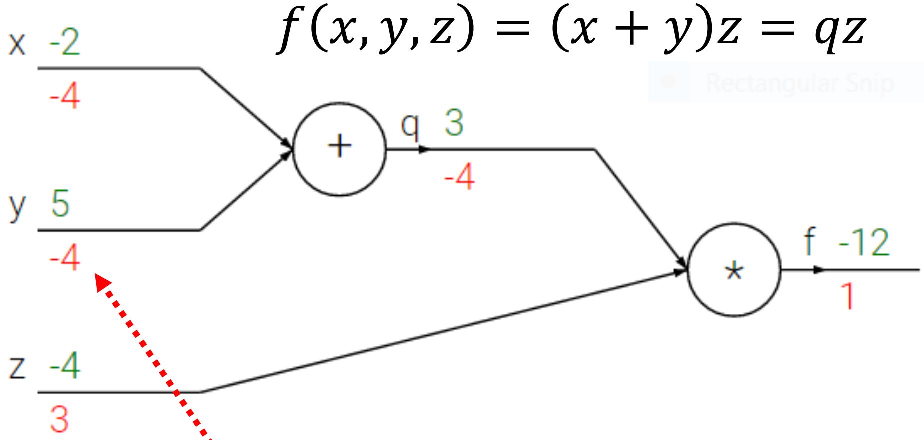


Example and figure from Stanford's "CNNs for Visual Recognition" (2016, F.-F. Li, A. Karpathy, J. Johnson) http://cs231n.github.io/optimization-2/

- **Backpropagation**: We compute derivatives right to left.
  - $\frac{\partial f}{\partial f} = 1$ by definition.
  - $\frac{\partial f}{\partial q} = z$. And for this $\langle x, y, z \rangle$ input, $z = -4$.
  - During the **forward pass**, we need to **save the outputs of all the nodes** (e.g., here we need the value of z).

Backpropagation in the graph

$$f(x, y, z) = (x + y)z = qz$$



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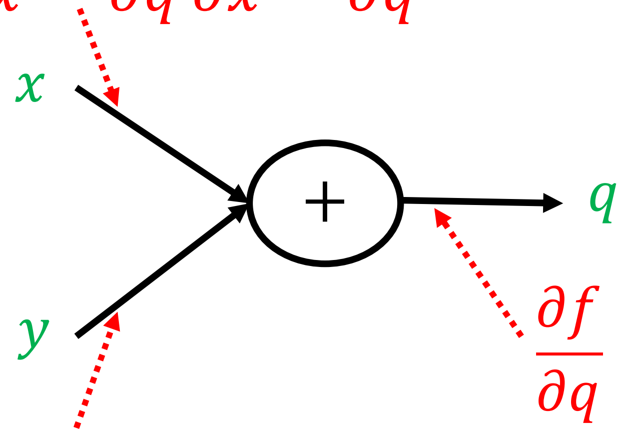
- **Backpropagation**: We compute derivatives right to left.
  - $\frac{\partial f}{\partial f} = 1$ by definition.
  - $\frac{\partial f}{\partial q} = z$. And for this $\langle x, y, z \rangle$ input, $z = -4$.
  - $\frac{\partial f}{\partial z} = q$. And for this $\langle x, y, z \rangle$ input, $q = 3$.
  - $\frac{\partial f}{\partial y} = \frac{\partial f}{\partial q}\frac{\partial q}{\partial y} = \frac{\partial f}{\partial q} \cdot 1$. And here $\frac{\partial f}{\partial q}$ is -4.
  - $\frac{\partial f}{\partial x} = \frac{\partial f}{\partial q}\frac{\partial q}{\partial x} = \frac{\partial f}{\partial q} \cdot 1$. And here $\frac{\partial f}{\partial q}$ is -4.

incoming gradient

local gradient

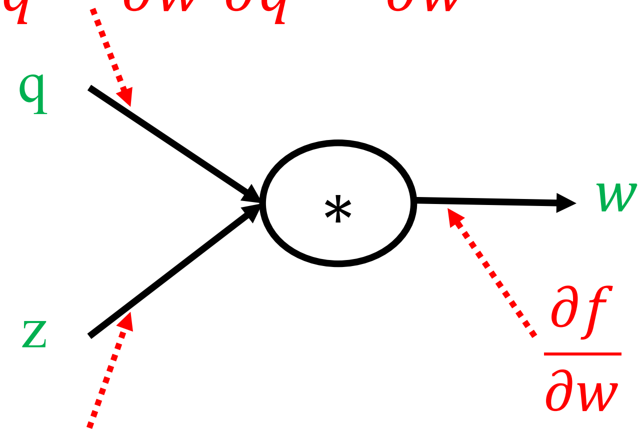
Plug-and-play gates

$$\frac{\partial f}{\partial x} = \frac{\partial f}{\partial q}\frac{\partial q}{\partial x} = \frac{\partial f}{\partial q} \cdot 1$$



$$\frac{\partial f}{\partial y} = \frac{\partial f}{\partial q}\frac{\partial q}{\partial y} = \frac{\partial f}{\partial q} \cdot 1$$

$$\frac{\partial f}{\partial q} = \frac{\partial f}{\partial w}\frac{\partial w}{\partial q} = \frac{\partial f}{\partial w} \cdot z$$



$$\frac{\partial f}{\partial z} = \frac{\partial f}{\partial w}\frac{\partial w}{\partial z} = \frac{\partial f}{\partial w} \cdot q$$

class PlusGate:

forward(x, y):

return x+y

backward($\frac{\partial f}{\partial q}$):

return <$\frac{\partial f}{\partial q}$, $\frac{\partial f}{\partial q}$>

class StarGate:

forward(q, z):

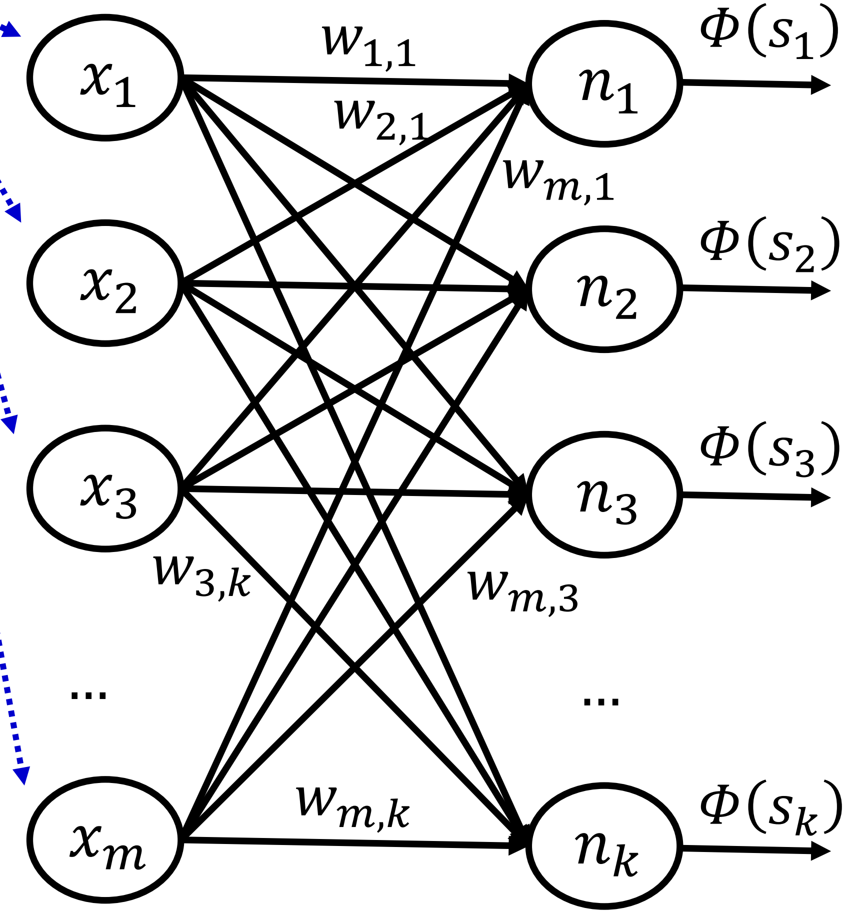
return q * z

backward($\frac{\partial f}{\partial w}$):

return <$\frac{\partial f}{\partial w} \cdot z$, $\frac{\partial f}{\partial w} \cdot q$>

More compact notation of NNs

Input instance (e.g., TF-IDF feature vector of a text)



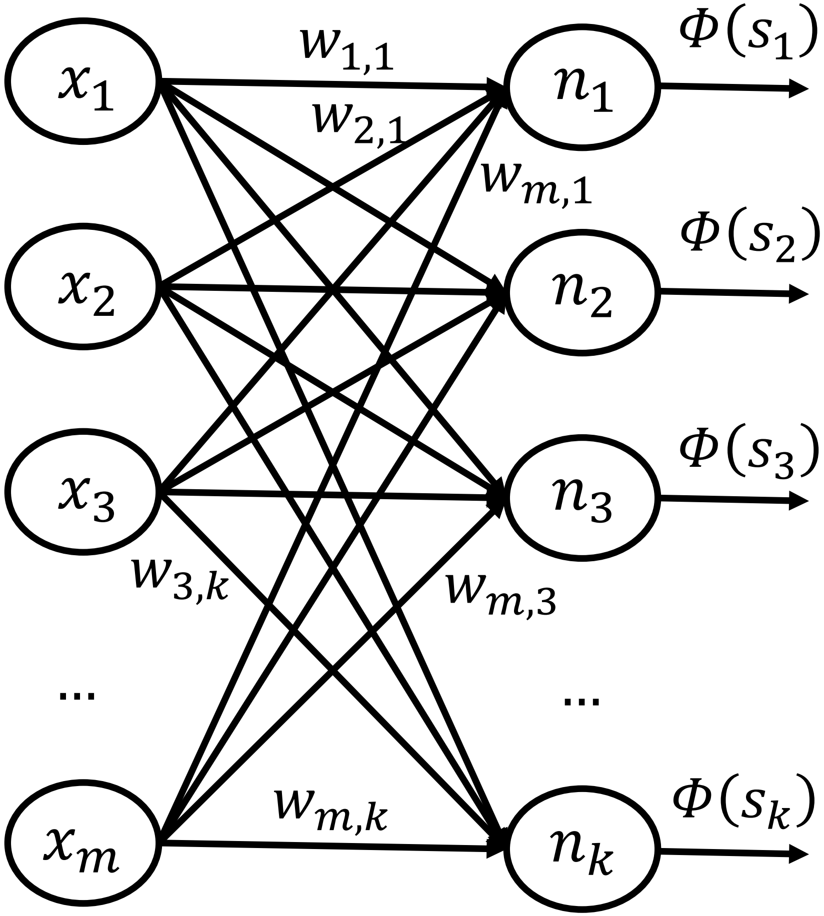
$$\Phi(s_1) = \Phi\left(\sum_{i=1}^{m} w_{i,1} x_i\right)$$

$$\Phi(s_2) = \Phi\left(\sum_{i=1}^{m} w_{i,2} x_i\right)$$

$$\Phi(s_3) = \Phi\left(\sum_{i=1}^{m} w_{i,3} x_i\right)$$

$$\Phi(s_k) = \Phi\left(\sum_{i=1}^{m} w_{i,k} x_i\right)$$

More compact notation of NNs



$$\begin{bmatrix} s_1 \\ s_2 \\ s_3 \\ \dots \\ s_k \end{bmatrix} = \begin{bmatrix} w_{1,1}x_1 + w_{2,1}x_2 + \cdots + w_{m,1}x_m \\ w_{1,2}x_1 + w_{2,2}x_2 + \cdots + w_{m,2}x_m \\ w_{1,3}x_1 + w_{2,3}x_2 + \cdots + w_{m,3}x_m \\ \dots \\ w_{1,k}x_1 + w_{2,k}x_2 + \cdots + w_{m,k}x_m \end{bmatrix}$$

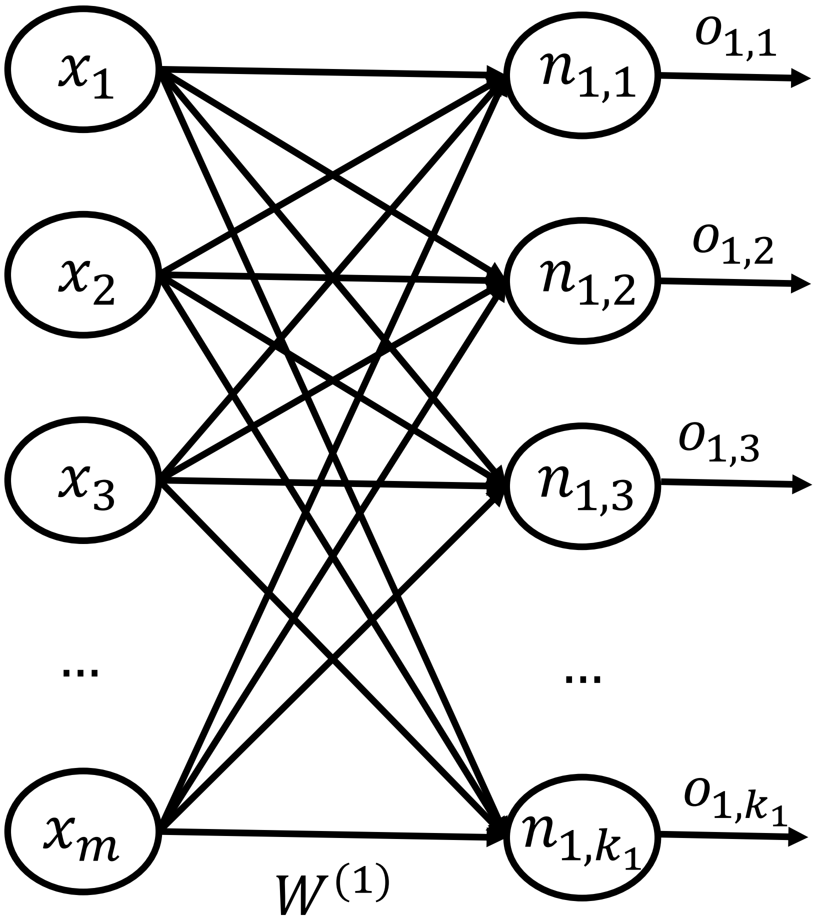
$$\begin{bmatrix} s_1 \\ s_2 \\ s_3 \\ \dots \\ s_k \end{bmatrix} = \begin{bmatrix} w_{1,1} & w_{2,1} & \dots & w_{m,1} \\ w_{1,2} & w_{2,2} & \dots & w_{m,2} \\ w_{1,3} & w_{2,3} & \dots & w_{m,3} \\ \dots & \dots & \dots & \dots \\ w_{1,k} & w_{2,k} & \dots & w_{m,k} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \dots \\ x_m \end{bmatrix}$$

$$\vec{s} = W\vec{x}$$

We learn ***W*** with **backpropagation**.

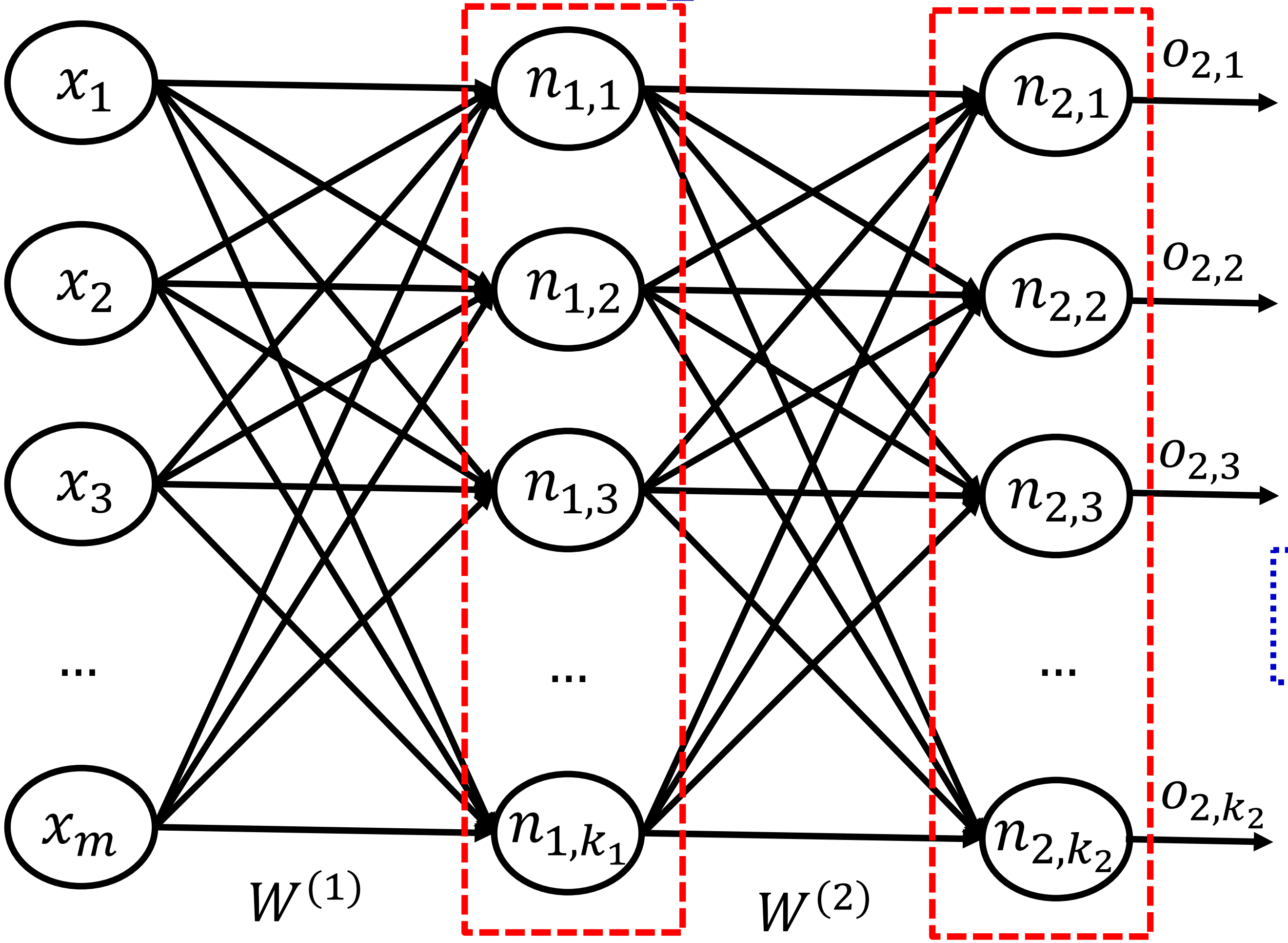
$$\vec{o} = \begin{bmatrix} o_1 \\ o_2 \\ o_3 \\ \dots \\ o_k \end{bmatrix} = \begin{bmatrix} \Phi(s_1) \\ \Phi(s_2) \\ \Phi(s_3) \\ \dots \\ \Phi(s_\kappa) \end{bmatrix} = \Phi(\vec{s}) = \Phi(W\vec{x})$$

More compact notation of NNs



$$\vec{o}^{(1)} = \begin{bmatrix} o_{1,1} \\ o_{1,2} \\ \dots \\ o_{1,k_1} \end{bmatrix} = \Phi\left(\vec{s}^{(1)}\right) = \Phi(W^{(1)}\vec{x})$$

More compact notation of NNs



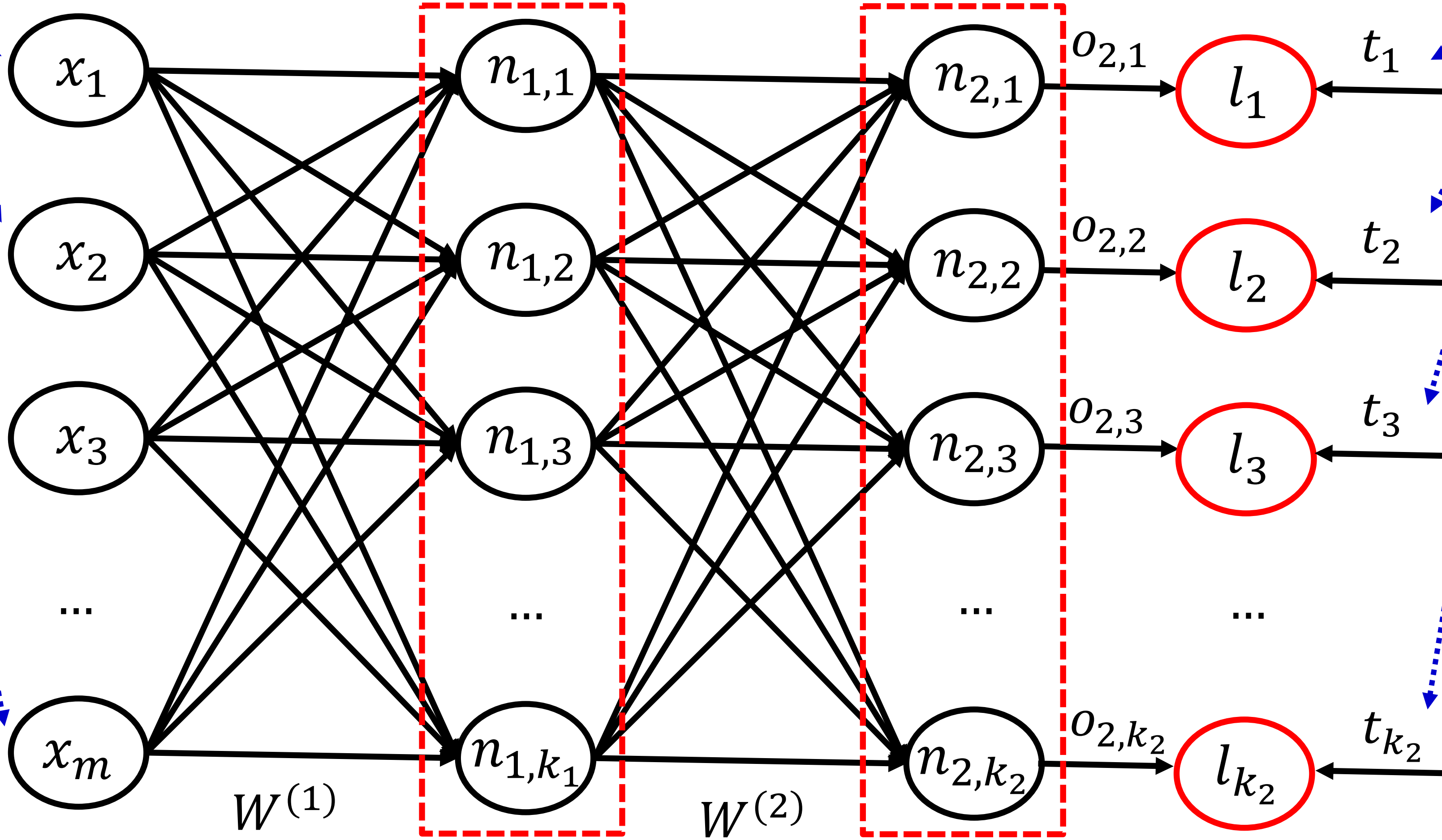
We learn $\boldsymbol{W}^{(1)}, \boldsymbol{W}^{(2)}$ with **backpropagation**.

$$\vec{o}^{(1)} = \begin{bmatrix} o_{1,1} \\ o_{1,2} \\ \cdots \\ o_{1,k_1} \end{bmatrix} = \Phi\left(\vec{s}^{(1)}\right) = \Phi\left(W^{(1)}\vec{x}\right) \qquad \vec{o}^{(2)} = \begin{bmatrix} o_{2,1} \\ o_{2,2} \\ \cdots \\ o_{2,k_2} \end{bmatrix} = \Phi\left(\vec{s}^{(2)}\right) = \Phi\left(W^{(2)}\vec{o}^{(1)}\right)$$

Regression example

Input instance (e.g., TF-IDF feature vector of a text)

Correct output (e.g., **personality traits**)



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

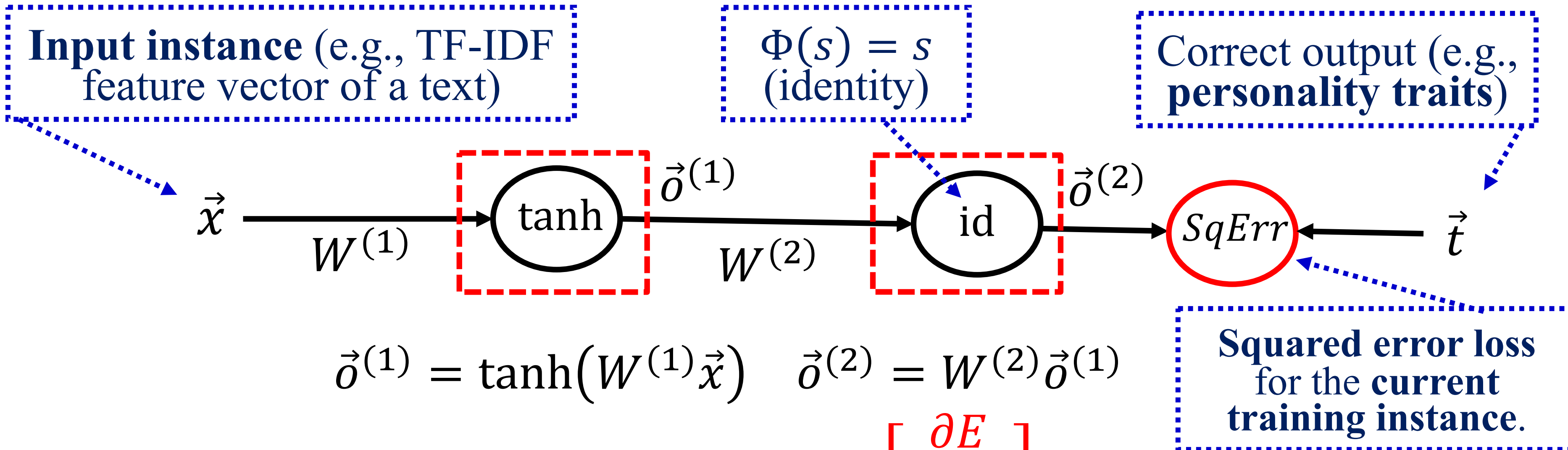
$$\vec{o}^{(1)} = \tanh\left(W^{(1)}\vec{x}\right)$$

$$\vec{o}^{(2)} = W^{(2)}\vec{o}^{(1)}$$

Squared error loss at **current** training example

$$l = \frac{1}{2}\sum_{j=1}^{k_2} l_j^2 = \frac{1}{2}\sum_{j=1}^{k_2}\left(o_{2,j} - t_j\right)^2$$

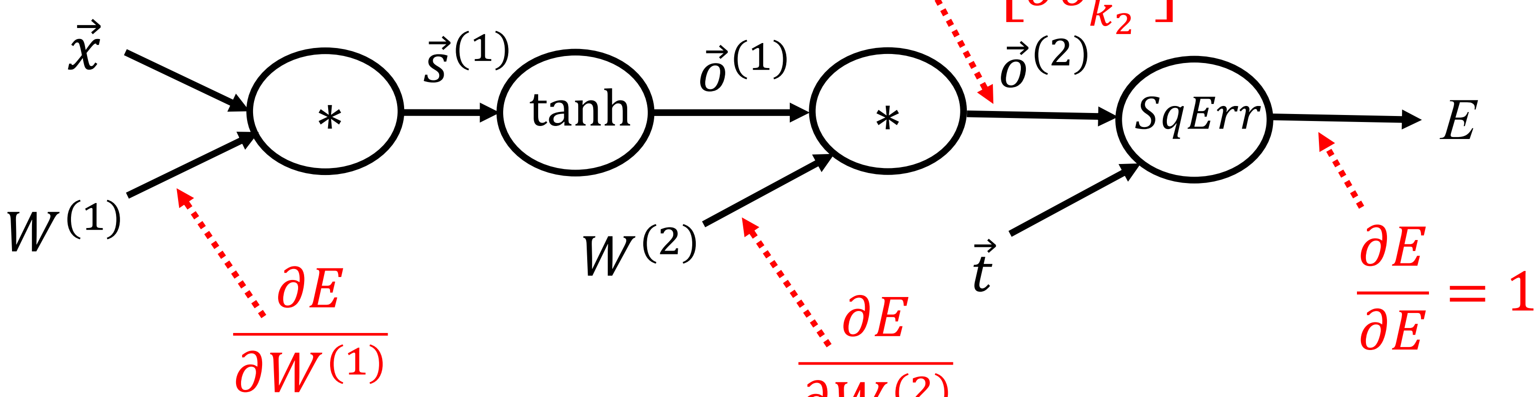
Regression example – more compact



$$\vec{o}^{(1)} = \tanh\left(W^{(1)}\vec{x}\right) \qquad \vec{o}^{(2)} = W^{(2)}\vec{o}^{(1)}$$

$$\frac{\partial E}{\partial \vec{o}^{(2)}} = \begin{bmatrix} \frac{\partial E}{\partial o_1^{(2)}} \\ \dots \\ \frac{\partial E}{\partial o_{k_2}^{(2)}} \end{bmatrix} = \begin{bmatrix} o_1^{(2)} - t_1 \\ \dots \\ o_{k_2}^{(2)} - t_{k_2} \end{bmatrix} = \vec{o}^{(2)} - \vec{t}$$

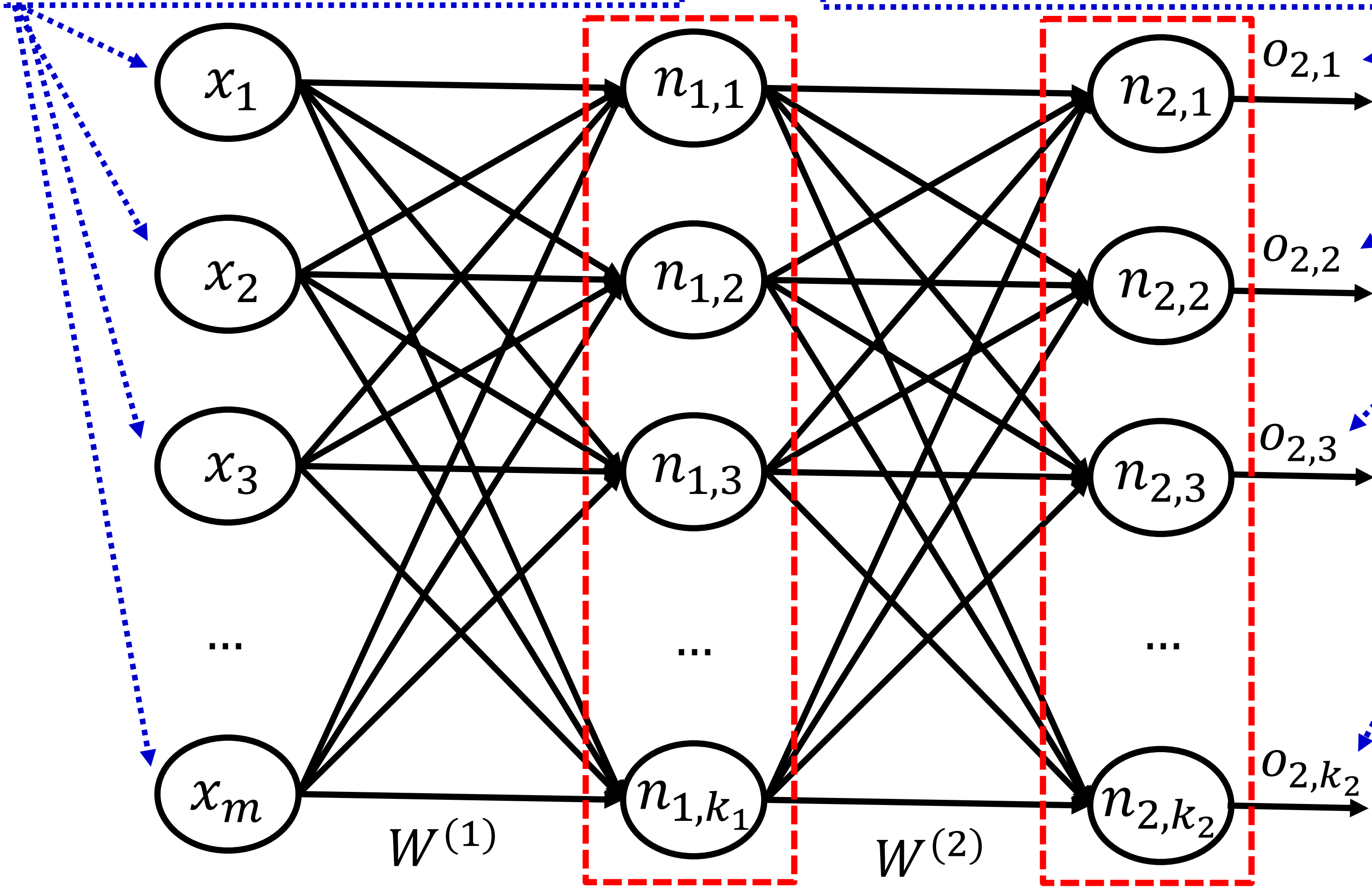
Or as a **computation graph**:



Classification example

Input instance (e.g., TF-IDF feature vector of a text)

How probable the system believes it is that the input belongs in each one of $\boldsymbol{k_2}$ **classes**.



$$\vec{o}^{(1)} = \tanh\left(W^{(1)}\vec{x}\right)$$

$$\vec{o}^{(2)} = \text{softmax}\left(W^{(2)}\vec{o}^{(1)}\right)$$

Softmax

$$W^{(2)}\vec{o}^{(1)} = \vec{s}^{(2)} = \begin{bmatrix} s_{2,1} \\ s_{2,2} \\ \dots \\ s_{2,k_2} \end{bmatrix}$$

Output of the last layer, without an activation function. **Confidence scores**, one for each class. We want to **convert them to probabilities summing to 1**.

$$\text{softmax}\left(W^{(2)}\vec{o}^{(1)}\right) = \text{softmax}\left(\vec{s}^{(2)}\right) = \text{softmax}\left(\begin{bmatrix} s_{2,1} \\ s_{2,2} \\ \dots \\ s_{2,k_2} \end{bmatrix}\right)$$

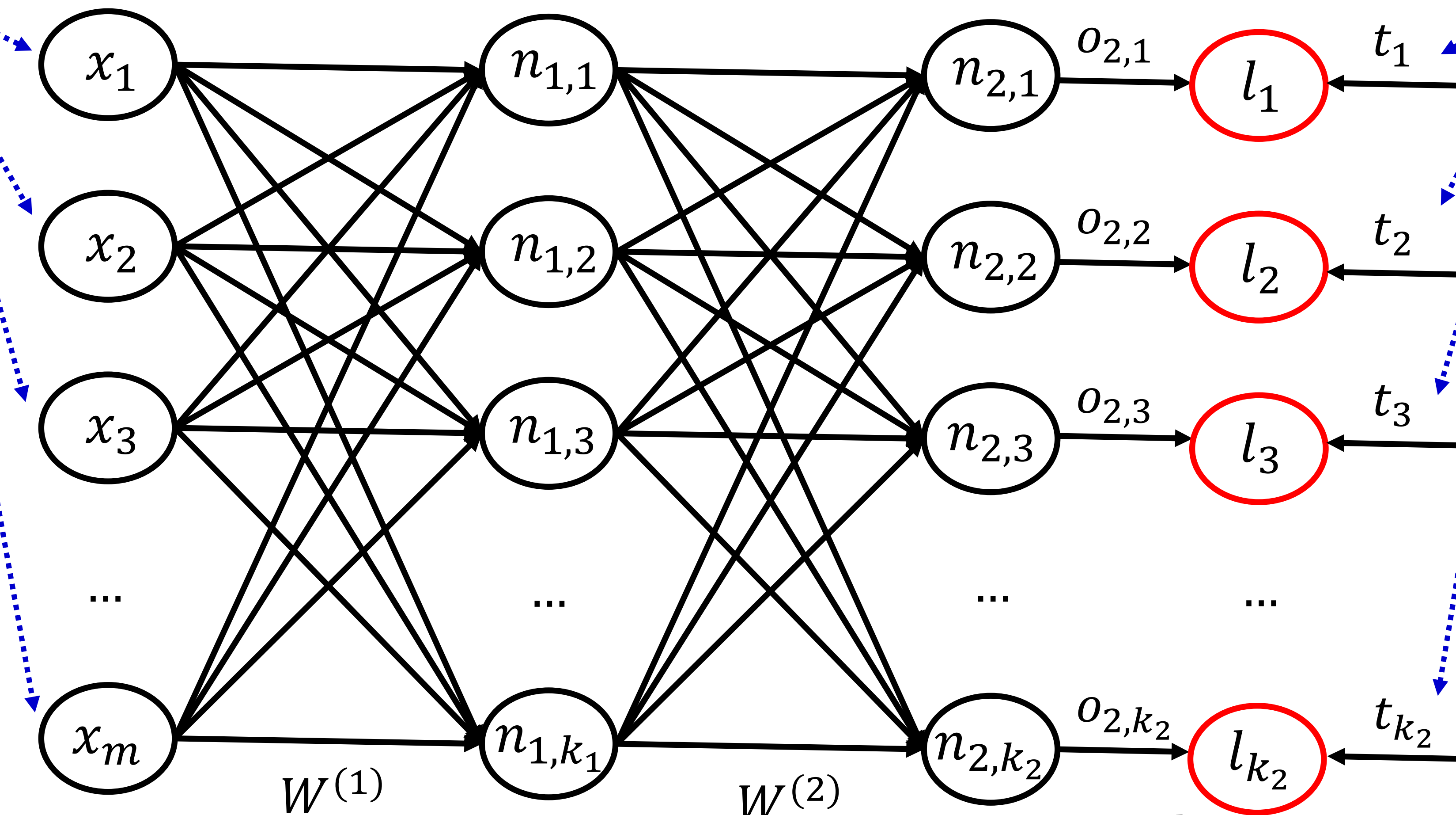
$$= \begin{bmatrix} \dfrac{\exp\left(s_{2,1}\right)}{\sum_{j=1}^{k_2} \exp\left(s_{2,j}\right)} \\ \dfrac{\exp\left(s_{2,2}\right)}{\sum_{j=1}^{k_2} \exp\left(s_{2,j}\right)} \\ \dots \\ \dfrac{\exp\left(s_{2,k_2}\right)}{\sum_{j=1}^{k_2} \exp\left(s_{2,j}\right)} \end{bmatrix}$$

Softmax also **moves the largest of its inputs towards 1** and the other inputs towards 0. Intuitively a **soft argmax**!

Classification example

Input instance (e.g., TF-IDF feature vector of a text)

Correct output ($t_j = 1$ means the single correct class is the j-th one)



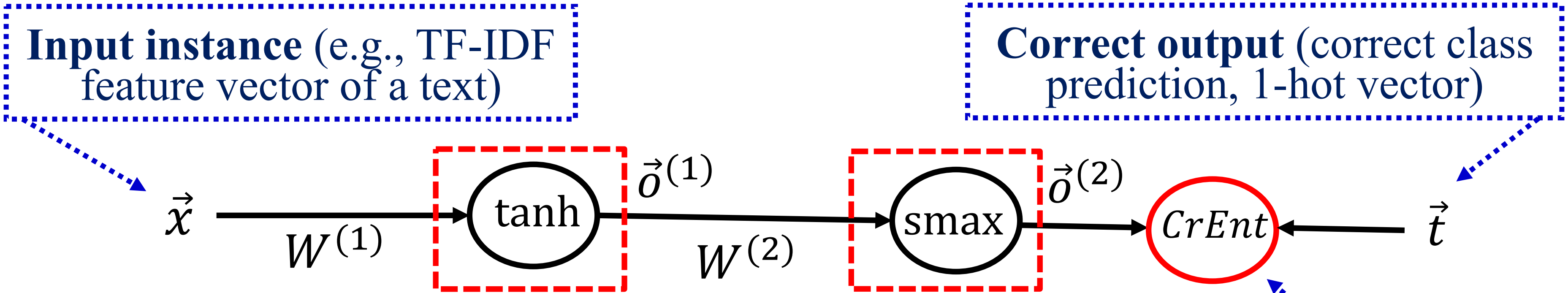
$$\vec{o}^{(1)} = \tanh\left(W^{(1)}\vec{x}\right)$$

$$\vec{o}^{(2)} = \mathrm{softmax}\left(W^{(2)}\vec{o}^{(1)}\right)$$

Cross entropy loss at the **current** training instance

$$l = -\sum_{j=1}^{k_2} t_j \log\left(o_{2,j}\right)$$

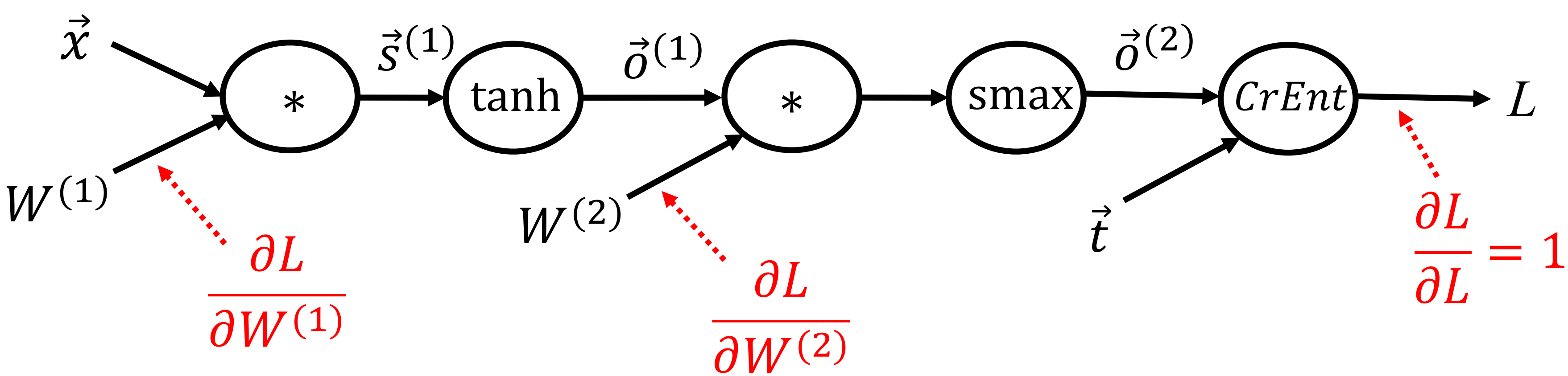
Classification example – more compact



$$\vec{o}^{(1)} = \tanh\left(W^{(1)}\vec{x}\right)$$

$$\vec{o}^{(2)} = \text{softmax}\left(W^{(2)}\vec{o}^{(1)}\right)$$

Or as a **computation graph**:



Extracting contract elements

THIS **AGREEMENT** is made the 15th day of October 2009
(The **"Effective Date"**) BETWEEN:

(1) **Sugar 13 Inc.**, a corporation whose office is at James House, 42-50 Bond Street, London, EW2H TL (**"Sugar"**);

(2) **E2 UK Limited**, a limited company whose registered office is at 260 Bathurst Road, Yorkshire, SL3 4SA (**"Provider"**).

RECITALS:

A. The Parties wish to enter into a framework agreement which will enable Sugar, from time to time, to [...]
B. [...]

NO THEREFORE IT IS AGREED AS FOLLOWS:

ARTICLE I - DEFINITIONS

"Sugar"	shall mean:	Sugar 13 Inc.
"Provider"	shall mean:	E2 UK Limited
"1933 Act"	shall mean:	Securities Act of 1933

ARTICLE II - TERMINATION

The Service Period will be for five (5) years from the Effective Date (The **"Initial Term"**). The agreement is considered to be terminated in October 16, 2014.

ARTICLE III - PAYMENT - FEES

During the service period monthly payments should occur. The estimated fees for the Initial Term are £154,800.

ARTICLE IV - GOVERNING LAW

This agreement shall be governed and construed in accordance with the Laws of England & Wales. Each party hereby irrevocably submits to the exclusive jurisdiction of the courts sitting in Northern London.

IN WITNESS WHEREOF, the parties have caused their respective duly authorized officers to execute this Agreement.

BY: George Fake
Authorized Officer
Sugar 13 Inc.

BY: Olivier Giroux
CEO
E2 UK LIMITED

Identify **start/end dates**, **duration**, **contractors**, **amount**, **legislations refs**, **jurisdiction** etc. Similar to **Named Entity Recognition** (NER).

I. Chalkidis, I. Androutsopoulos, A. Michos, "Extracting Contract Elements", ICAIL 2017, http://nlp.cs.aueb.gr/pubs/icail2017.pdf.

Window-based NER example

i-th word of the text being classified

3-word **window** (often larger)

yesterday language tech announced that…

1-hot vectors ($|V| \times 1$) of the **words** in the **window**. ($|V|$ is the **vocabulary** size).

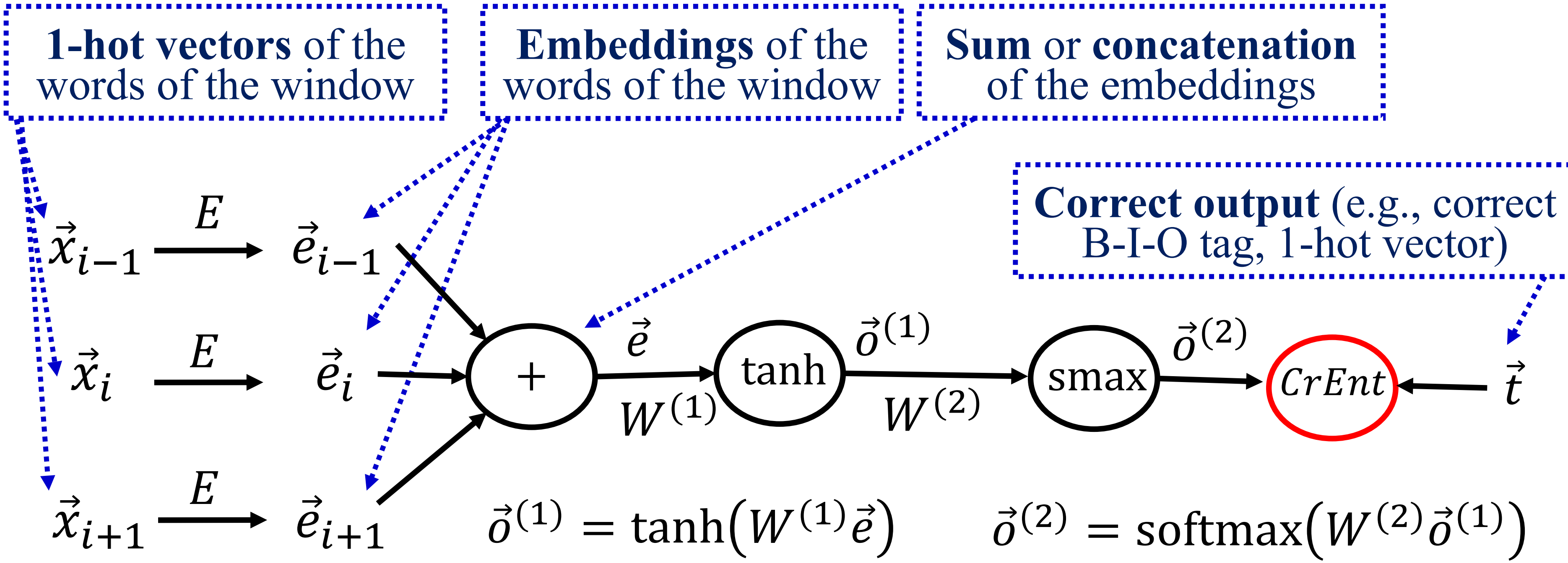
$$\vec{x}_{i-1} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ \dots \\ 0 \end{bmatrix} \quad \vec{x}_{i} = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \\ \dots \\ 0 \end{bmatrix} \quad \vec{x}_{i+1} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ \dots \\ 1 \end{bmatrix}$$

Embeddings ($d \times 1$) of the **words** in the **window**. (d is the **dimensionality** of the word embeddings).

$$\vec{e}_{i-1} = \begin{bmatrix} 1.8 \\ 2.3 \\ -1.4 \\ 3.7 \\ \dots \\ -1.1 \end{bmatrix} \quad \vec{e}_{i} = \begin{bmatrix} 2.4 \\ -3 \\ 9.3 \\ 5.1 \\ \dots \\ 3.9 \end{bmatrix} \quad \vec{e}_{i+1} = \begin{bmatrix} 2.2 \\ 3.8 \\ 1.2 \\ -6.4 \\ \dots \\ 7.1 \end{bmatrix}$$

Let $\boldsymbol{E}$ be a matrix ($d \times |V|$) that **contains** all the **embeddings** of the **vocabulary** as **columns**. Then: $\vec{e}_{i-1} = E\vec{x}_{i-1}, \vec{e}_i = E\vec{x}_i, \dots$

Window-based NER example



$$\vec{o}^{(1)} = \tanh\left(W^{(1)}\vec{e}\right) \qquad \vec{o}^{(2)} = \mathrm{softmax}\left(W^{(2)}\vec{o}^{(1)}\right)$$

We learn $\boldsymbol{W^{(1)}}, \boldsymbol{W^{(2)}}$ with **backpropagation**. We can also learn (or modify) the **word embeddings** ***E*** during **backpropagation**! But when we don't have large training datasets (e.g., corpus manually annotated with B-I-O tags), it may be better to use **pre-trained embeddings**, which can be obtained from large non-annotated corpora (e.g., via Word2Vec, GloVe, to be discussed).

We can use the same window-based approach for **POS-tagging**, **chunking**, …

Cross-entropy loss

Word being **classified**.

3-word window (often larger).

yesterday language tech announced that…

$$\vec{o} = \begin{bmatrix} P_m(C = c_1) \\ P_m(C = c_2) \\ P_m(C = c_3) \\ \dots \\ P_m(C = c_k) \end{bmatrix} = \begin{bmatrix} 0.05 \\ 0.12 \\ 0.08 \\ \dots \\ 0.14 \end{bmatrix}$$

Probability estimates produced by the classifier for the class of the word "tech".

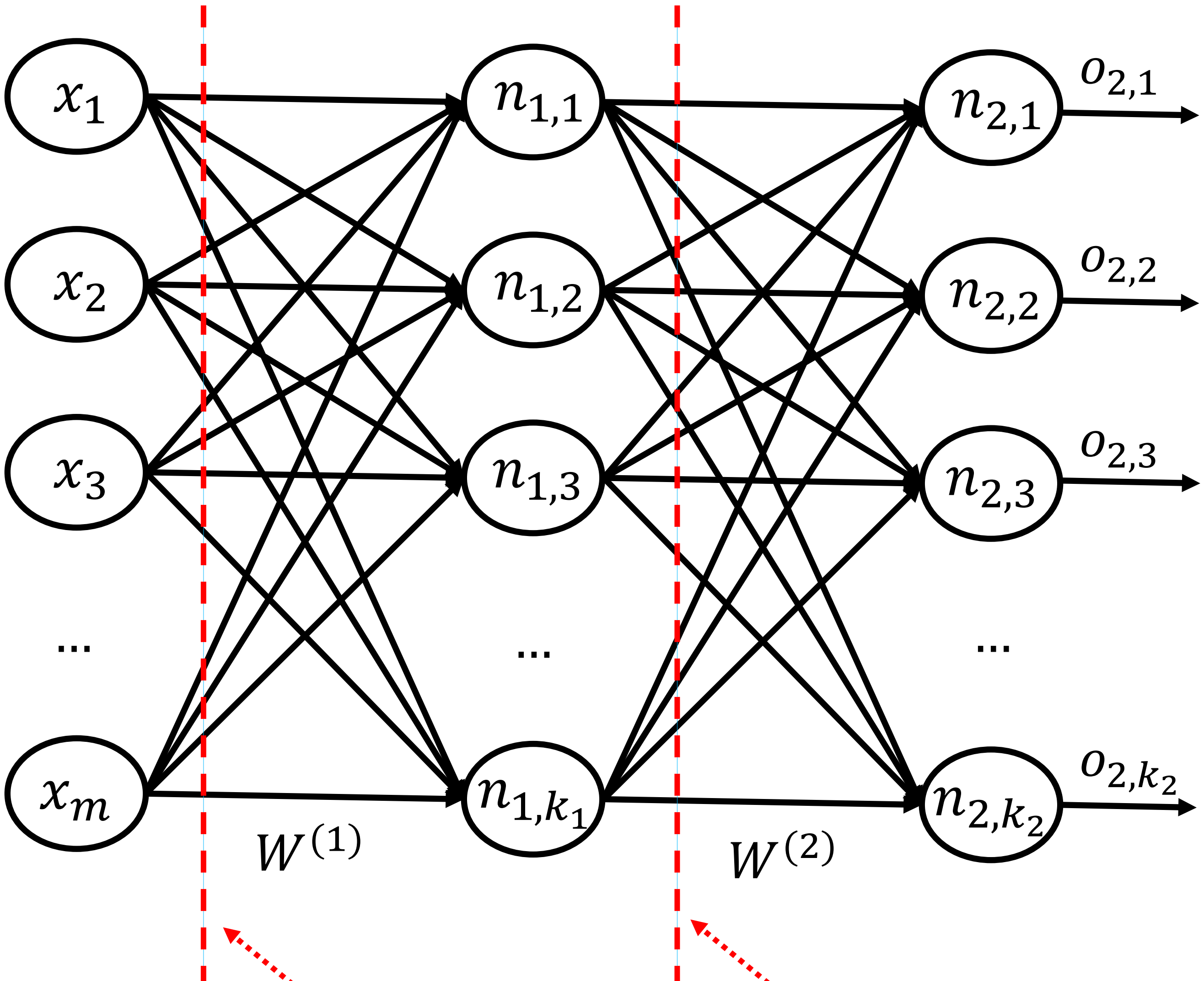
$$\vec{t} = \begin{bmatrix} P(C = c_1) \\ P(C = c_2) \\ P(C = c_3) \\ \dots \\ P(C = c_k) \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \\ 0 \\ \dots \\ 0 \end{bmatrix}$$

The **correct "probabilities"** for the class of "tech". A **1-hot vector**.

The **log-likelihood** of the **correct class** according to the **classifier** (with a minus sign).

$$H_{P_m}(C) = -\sum_{i=1}^{k} P(C = c_i) \log_2 P_m(C = c_i) = -\log_2 P_m(C = c_2)$$

Dropout



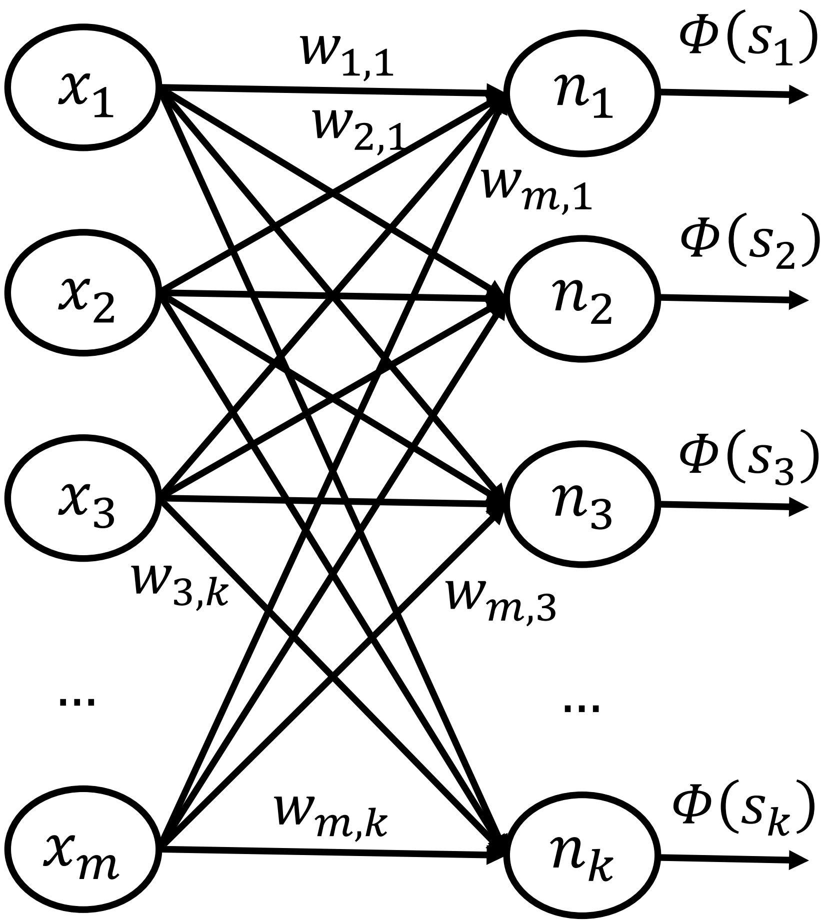
Dropout at the input layer. E.g. $p_{drop} = 0.2$.

Dropout at the output of a hidden layer. E.g., $p_{drop} = 0.5$.

Dropout

- **For each training instance** (or mini-batch), we **drop** (remove) **each neuron** of the layer where dropout is applied with **probability** $\boldsymbol{p_{drop} = 1 - p_{keep}}$.
  - Helps the neural net **avoid relying too much on particular neurons** (or inputs). A form of **regularization**. Works well!
  - **Gradients** also **do not flow** through dropped neurons.
  - Alternative explanation: we train an **ensemble** of networks, containing **all the pruned networks** that dropout creates.
- **During testing**, we **multiply the output** of each neuron (of the layer where dropout was applied) by $\boldsymbol{p_{keep}}$, so that the neuron's **expected output value** will be **as in training**.
  - **Or we divide** the output by $\boldsymbol{p_{keep}}$ **during training** instead.
  - We **don't drop neurons during testing** (only during training).

Batch normalization



At each layer, instead of:

$$s_j = \sum_{i=1}^{m} w_{i,j}\, x_i$$

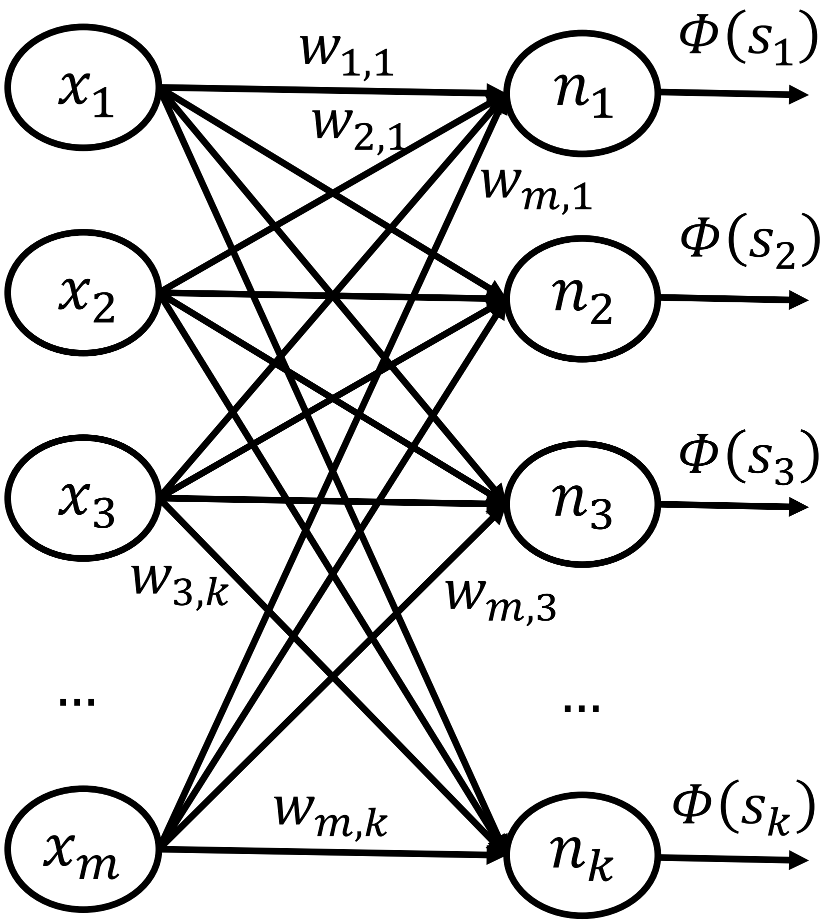
we use:

$$\bar{s}_j = \frac{g_j}{\sigma_j}(s_j - \mu_j) + b_j$$

- μ_j, σ_j are the **mean** and **std. dev. of s_j** in the **mini-batch**.
- g_j, b_j are **learned** parameters (constant after training).
- Φ now applied to $\bar{s}_j$.

See https://arxiv.org/pdf/1607.06450.pdf for **batch vs. layer normalization**. The latter is better for RNNs (next part), where layers are time-steps.

Layer normalization



At each layer, instead of:

$$s_j = \sum_{i=1}^{m} w_{i,j}\, x_i$$

we use:

$$\bar{s}_j = \frac{g_j}{\sigma}(s_j - \mu) + b_j$$

- μ, σ are the **mean** and **std. dev. of $\mathbf{s_1}, \ldots, \boldsymbol{s_k}$** in the **layer**.
- g_j, b_j are **learned** parameters (constant after training).
- Φ applied to $\bar{s}_j$.

With dropout, batch/layer normalization, residuals (to be discussed) and other additions, strictly speaking we no longer have an "MLP". Some people prefer "**Feed Forward Neural Network" (FFNN)**, but "MLP" still often used as synonym.

Pretraining word embeddings with Word2Vec

(skip-gram version)

- Every **word w of the vocabulary** has **two vectors**:

$$\vec{w}^{(in)}, \vec{w}^{(out)}$$

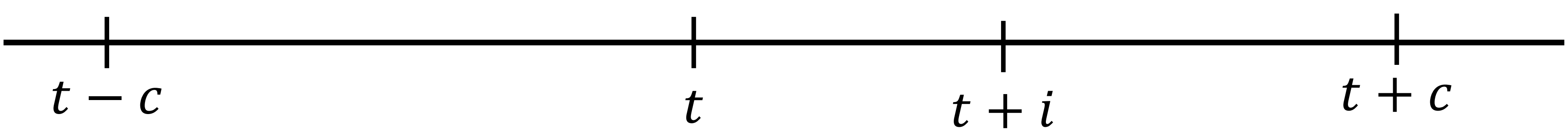
  - The **vectors** are **randomly initialized**. We **learn** them.
  - For every **token w_t** at **position t** of a **corpus** and **every position $t+i$ $(i \neq 0)$** within a **window $[t-c, t+c]$** around position t:

$$w_{t+i} = \cdots ?$$

$$w_{t+i} = \text{"starring"}?$$

$$w_{t+i} = \text{"directed"}?$$

$$w_t = \text{"film"} \qquad w_{t+i} = \text{"famous"}?$$



  - We want to be able to predict **which vocabulary word** occurs at **position $t+i$** by multiplying $\vec{\boldsymbol{w}}_t^{(in)}$ and $\vec{\boldsymbol{w}}_{t+i}^{(out)}$.

Word2Vec (skip-gram version)

In the **skip-gram** version of Word2Vec, the **central word** of each window “**predicts**” the **other words** of the **window**. In the **CBOW version**, the **context** (sum of the embeddings of the other words of the window) “**predicts**” the **central word**.

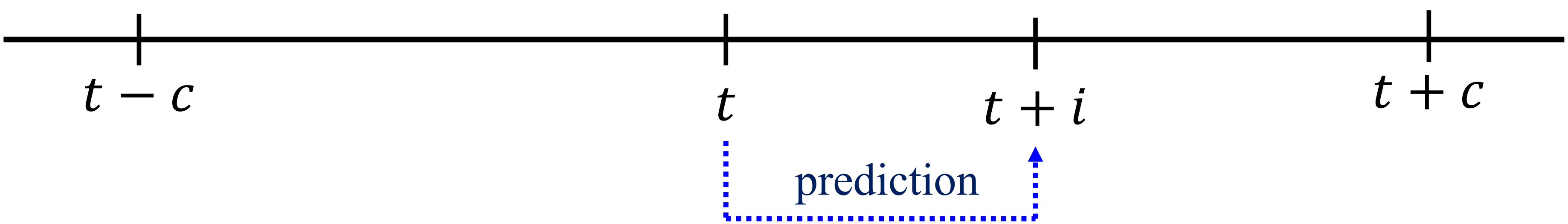
$w_{t+i} = \cdots ?$

$w_{t+i} = \text{"starring"} ?$

$w_{t+i} = \text{"directed"} ?$

$w_{t+i} = \text{"famous"} ?$

$w_t = \text{"film"}$



$$P(w_{t+i} | w_t) = \text{softmax}\left(\vec{w}_{t+i}{}^{(out)} \cdot \vec{w}_t{}^{(in)}\right)$$

$$= \frac{\exp\left(\vec{w}_{t+i}{}^{(out)} \cdot \vec{w}_t{}^{(in)}\right)}{\sum_{w \in V} \exp\left(\vec{w}^{(out)} \cdot \vec{w}_t{}^{(in)}\right)}$$

Word2Vec (skip-gram version)

- We **learn** the $\vec{\boldsymbol{w}}^{(in)}, \vec{\boldsymbol{w}}^{(out)}$ by **maximizing** the **probability** assigned to the $\boldsymbol{w_{t+i}}$ that **actually occurs** at each **position** $\boldsymbol{t+i}$, i.e., we maximize the **likelihood** of the **correct predictions**:

$$\langle \hat{E}^{(in)}, \hat{E}^{(out)} \rangle = \underset{\langle E^{(in)}, E^{(out)} \rangle}{\operatorname{argmax}} \underbrace{\boxed{\sum_{t=1+c}^{T-c} \sum_{-c \le i \le c, i \ne 0} \ln P(w_{t+i} | w_t)}}_{L}$$

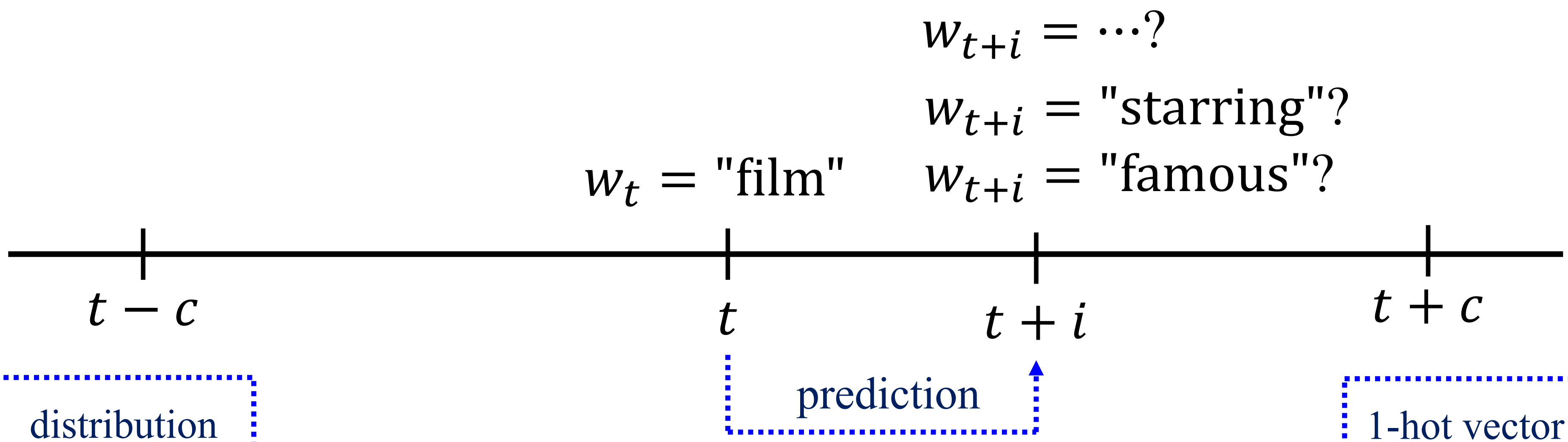
  - Matrices $\boldsymbol{E^{(in)}}, \boldsymbol{E^{(out)}}$ contain in their columns **all the *in* and *out* vectors** (word embeddings) of **all vocabulary words**.
  - $\boldsymbol{T}$ is the **corpus size**, $\boldsymbol{t}$ is the **center of the sliding window**.
  - For **each $\boldsymbol{t}$ value**, we get **$\boldsymbol{2c}$ training examples**.
  - **For batch gradient ascent**, we would do steps:

$$\langle \hat{E}^{(in)}, \hat{E}^{(out)} \rangle \leftarrow \langle \hat{E}^{(in)}, \hat{E}^{(out)} \rangle + \eta \nabla L$$

  - **In practice**, we use **SGD** (or variants), i.e., we use the likelihood $\boldsymbol{L_i}$ **of a mini-batch** of training examples (e.g., all $2c$ of a window):

$$\langle \hat{E}^{(in)}, \hat{E}^{(out)} \rangle \leftarrow \langle \hat{E}^{(in)}, \hat{E}^{(out)} \rangle + \eta \nabla L_i$$

Word2Vec (skip-gram) as a shallow NN

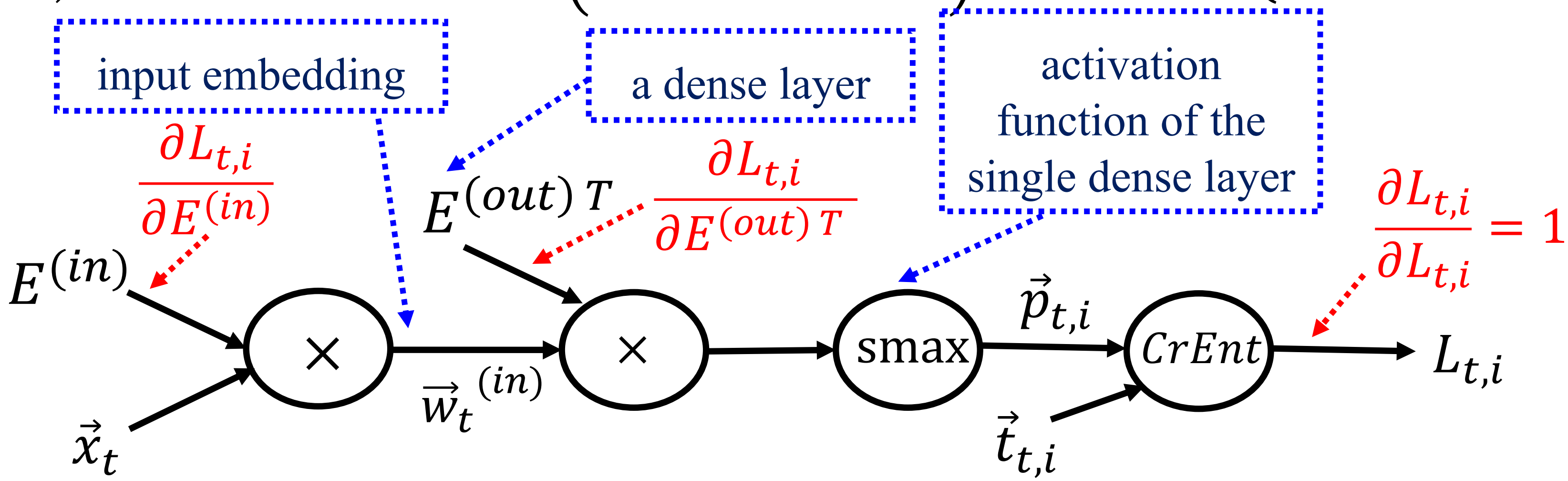


distribution over V

1-hot vector of w_t

$$P(w_{t+i}|w_t) = \mathrm{softmax}\left(\vec{w}_{t+i}^{(out)} \cdot \vec{w}_t^{(in)}\right)$$

$$\vec{p}_{t,i}(\vec{w}_t^{(in)}) = \mathrm{softmax}\left(E^{(out)\,T}\ \vec{w}_t^{(in)}\right) = \mathrm{softmax}\left(E^{(out)\,T}\ E^{(in)}\ \vec{x}_t\right)$$



Word2Vec (skip-gram with negative sampling)

When the **vocabulary *V*** is **large**, computing the **softmax** is very **time-consuming**. A more efficient alternative is **negative sampling**, a kind of **contrastive learning**.

We construct positive (+) and negative (−) examples, using the word w_{t+i} that actually occurs at position $t+i$, and random words r_{t+i} that do not actually occur at position $t+i$.

r_{t+i} = "medical" (random, negative)

w_t = "film" w_{t+i} = "famous" (true, positive)

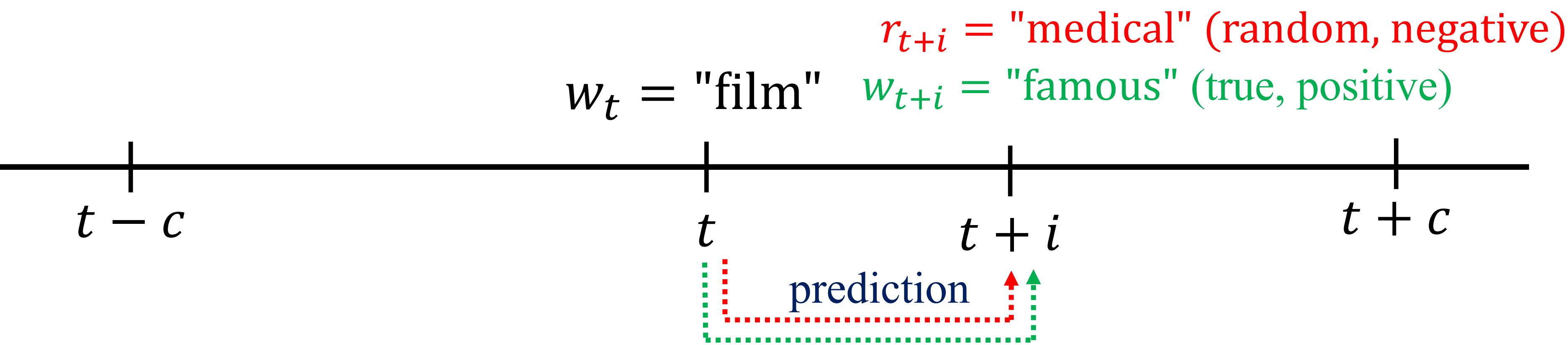
$t-c$ t $t+i$ $t+c$

prediction

$$\max_{\langle E^{(in)},E^{(out)}\rangle} \sum_{t=1+c}^{T-c} \sum_{-c\le i\le c, i\ne 0} \ln P(+|w_{t+i}, w_t) + \ln P(-|r_{t+i}, w_t)$$

We try to learn to assign **high probabilities** to the **correct classes**. In practice, we use **multiple random words** r_{t+i} at each position $t+i$.

Word2Vec (skip-gram with negative sampling)



$$\max_{\langle E^{(in)},E^{(out)}\rangle} \sum_{t=1+c}^{T-c} \sum_{-c\le i\le c,\, i\ne 0} \ln P(+|w_{t+i},w_t) + \ln[1-P(+|r_{t+i},w_t)]$$

$$\sum_{t=1+c}^{T-c} \sum_{-c\le i\le c,\, i\ne 0} \ln\sigma\left(\vec{w}_{t+i}{}^{(out)}\cdot\vec{w}_t{}^{(in)}\right)+\ln\left[1-\sigma\left(\vec{r}_{t+i}{}^{(out)}\cdot\vec{w}_t{}^{(in)}\right)\right]$$

sigmoid as in logistic regression

We **no longer** try to produce a **probability distribution over the vocabulary** for the words w_{t+i} that may occur at $t+i$.

We are **given** $\boldsymbol{w_t}$ and a **particular** w_{t+i} or r_{t+i} and we need to decide if it is a positive or negative case.

Loss as a function of epochs

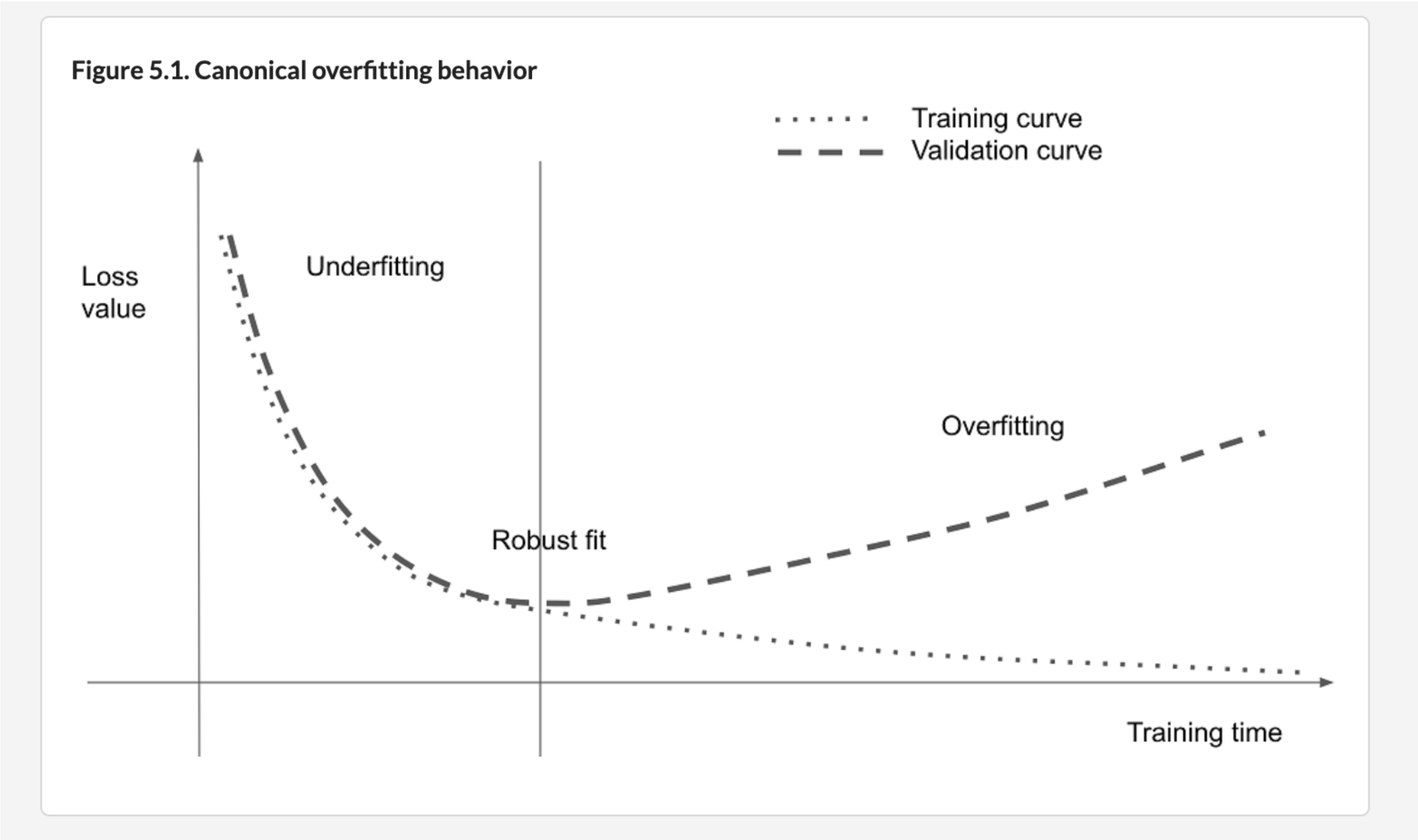


Figure from the **recommended book "Deep Learning with Python"** by F. Chollet, Manning Publications, 2nd edition. The 1st edition is freely available.
https://www.manning.com/books/deep-learning-with-python
https://www.manning.com/books/deep-learning-with-python-second-edition

Practical advice for training deep NNs

- **Check simple baselines**: (e.g., majority, random, …)
  - If you can't beat them, you may have **bugs**, **data problems**, …
  - Look at how data are **tokenized**, **pre-processed**, ...
  - Examine misclassification **errors** (e.g., extreme/frequent cases).
- **Get the training and validation loss to start falling:**
  - Tune the **learning rate** and the **mini-batch size**.
  - Use appropriate **models** (e.g., for sequences, images, …).
- **Reach the overfitting behavior** of the previous slide.
  - The **training and validation loss** (or metric) **both fall up to a point**, then the **training loss continues to improve** ideally reaching **near zero**, the **validation loss deteriorates**.
  - **Increase capacity** (e.g., **layers**, **neurons per layer**), …
- **Then dropout, early stopping, batch/layer norm**, …
- **Check Chollet's Chapter 5** for more advice…

Regularizing a high-capacity model

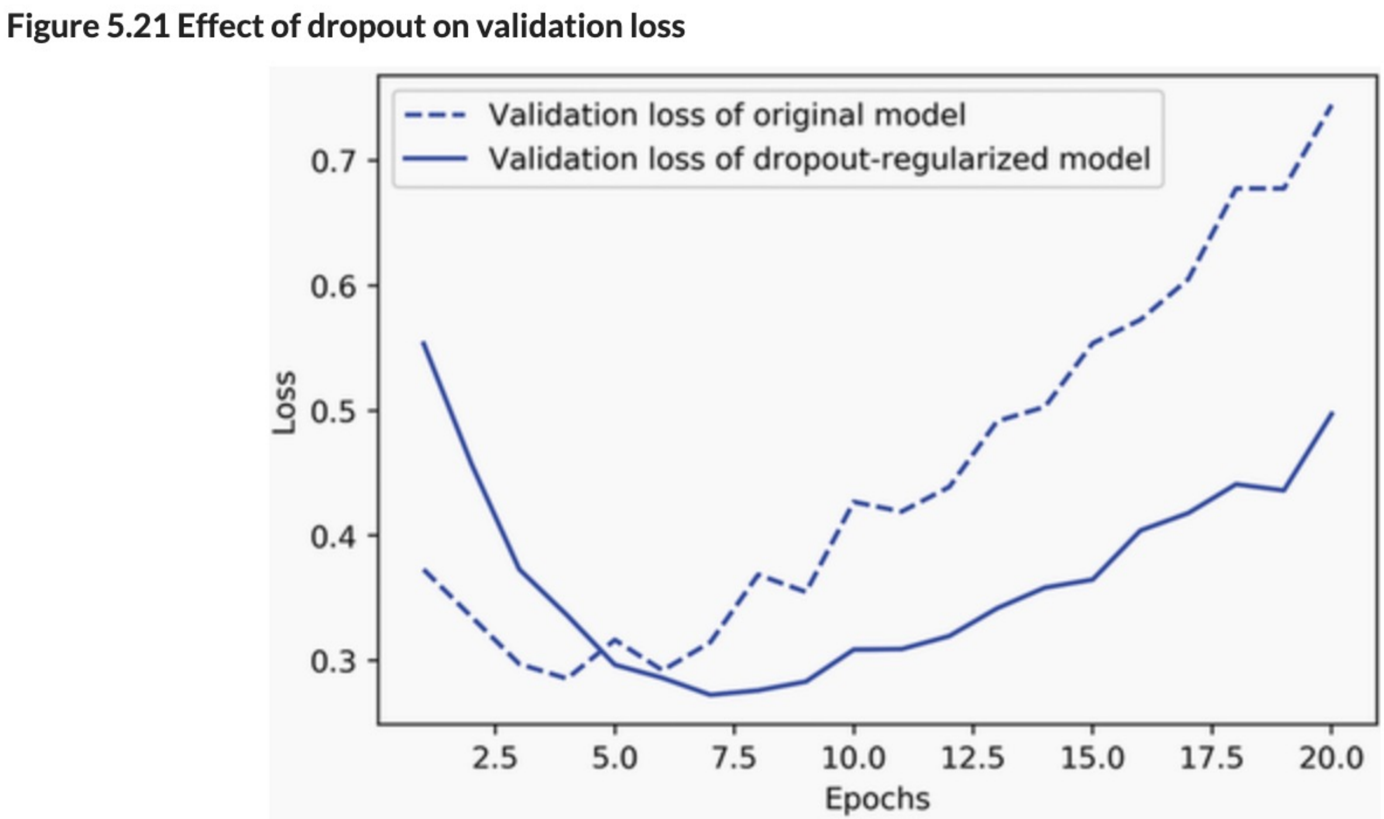
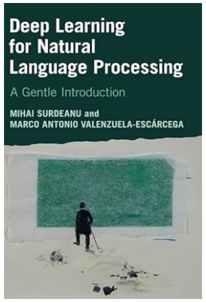


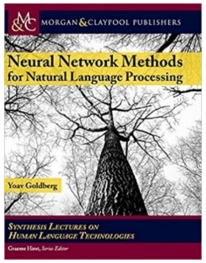
Figure from the **recommended book "Deep Learning with Python"** by F. Chollet, Manning Publications, 2nd edition. The 1st edition is freely available.
https://www.manning.com/books/deep-learning-with-python
https://www.manning.com/books/deep-learning-with-python-second-edition

Recommended reading

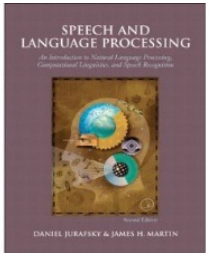
- M. Surdeanu and M.A. Valenzuela-Escarcega, *Deep Learning for Natural Language Processing: A Gentle Introduction,* Cambridge Univ. Press, 2024.
  - Chapters 5–9.
  - https://clulab.org/gentlenlp/text.html
  - Also available at AUEB's library.



- Y. Goldberg, *Neural Network Models for Natural Language Processing*, Morgan & Claypool Publishers, 2017.
  - Mostly chapters 3–5 and 10. Available at AUEB's library.

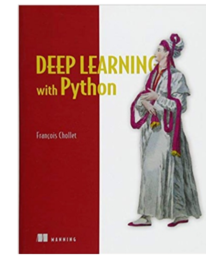


- Jurafsky & Martin's, *Speech and Language Processing* is being revised (3rd ed.) to include Deep Learning methods.
  - http://web.stanford.edu/~jurafsky/slp3/



Other recommended resources

- For an introduction to Keras/Tensorflow and practical DL for NLP and vision, see F. Chollet's *Deep Learning in Python*, Manning Publications, 1st edition, 2017.



  - The 1st edition is freely available and sufficient for this course. https://www.manning.com/books/deep-learning-with-python
  - 2nd edition (2022) now available, requires payment. Highly recommended.
- Useful maths background: T. Parr και J. Howard, *The Matrix Calculus You Need for Deep Learning*.
  - o https://explained.ai/matrix-calculus
- PyTorch tutorials: https://pytorch.org/tutorials/
- C. Manning's (Stanford) *NLP with Deep Learning* course.
  - o http://web.stanford.edu/class/cs224n/. Videos on YouTube.
- See also the recommended books of Part 0 (Introduction).