Neurális hálók

Nyelvi adatok feldolgozása – 2019/20 tavasz
12. óra

Simon Eszter

2020. május 11.

MTA Nyelvtudományi Intézet

Tartalom

Bevezetés

Gépi tanulás

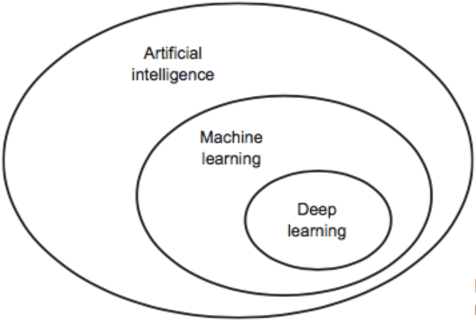


Figure 1.1 Artificial intelligence, machine learning, and deep learning

The ‘deep’ in deep learning

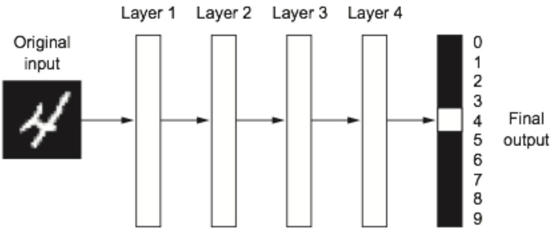


Figure 1.5 A deep neural network for digit classification

Understanding how deep learning works 1.

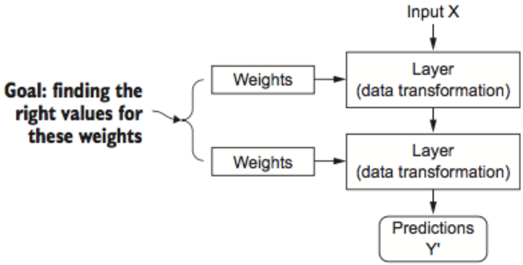


Figure 1.7 A neural network is parameterized by its weights.

Understanding how deep learning works 2.

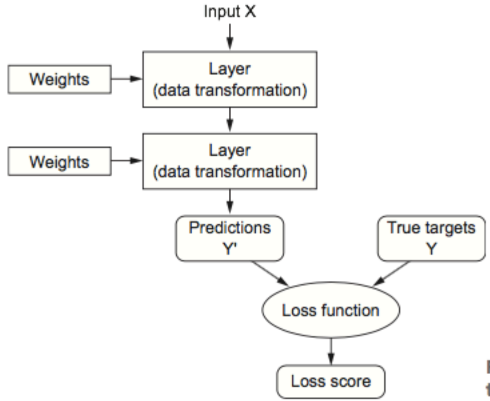


Figure 1.8 A loss function measures the quality of the network's output.

Understanding how deep learning works 3.

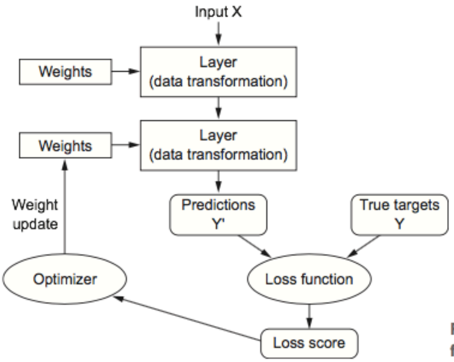


Figure 1.9 The loss score is used as a feedback signal to adjust the weights.

the fundamental trick is to use the loss score as a feedback signal to adjust the value of the weights a little, in a direction that will lower the loss score

Training loop

- kezdetben a súlyok random értékek $\rightarrow$ az output távol van az ideálistól, a loss score nagyon magas
- a súlyok minden egyes tanulási kör során egy kicsit módosulnak $\rightarrow$ a loss score kisebb lesz
- ha ezt a tanulási kört elégszer iteráljuk, akkor elérjük a loss score minimumát
- a minimális loss score-ral rendelkező rendszer kimenete lesz a legközelebb a gold standardhez

Történeti áttekintés

The promise of AI

mottó:

"Don't believe in the short-term hype, but do believe in the long-term vision."

a deep learning sok mindenre jó, de nem mindenre a legjobb eszköz:

- kevés az adat
- más algoritmus jobban használható az adott feladatra

AI winters

AI winter: high expectations for the short term $\rightarrow$ technology fails to deliver $\rightarrow$ research investment dries up, slowing progress for a long time

1. 1960s: symbolic AI
   Marvin Minsky 1967: "Within a generation … the problem of creating artificial intelligence will substantially be solved."
   1969-70: first AI winter
2. 1980s: expert systems
   a few initial success stories $\rightarrow$ expensive to maintain, difficult to scale, and limited in scope
   early 1990s: second AI winter

Elméleti alapok

- 1940s: McCulloch–Pitts neuron: a simplified model of the human neuron as a kind of computing element
- 1950/60s: perceptron (Rosenblatt, 1958), bias (Widrow and Hoff, 1960), XOR (Minsky and Papert, 1969)
- 1980s: backpropagation (Rumelhart et al., 1986), handwriting recognition with backpropagation and convolutional neural networks (LeCun et al., 1989)
- 1990s: recurrent networks (Elman, 1990), Long Short-Term Memory (1997)
- 2010s: Geoffrey Hinton et al., Yoshua Bengio et al.

Why now?

Hardware

- Graphical Processing Unit (GPU): developed for gaming
- 2007: NVIDIA launched CUDA, a programming interface for its line of GPUs
- a small number of GPUs can replace massive clusters of CPUs
- parallelizable matrix multiplications
- 2016: Tensor Processing Unit (TPU) by Google

Data

"if deep learning is the steam engine of this revolution, then data is its coal"

Why now? – cont.

Algorithms

The feedback signal used to train neural networks would fade away as the number of layers increased.

- better activation functions
- better weight-initialization schemes
- better optimization schemes

Only when these improvements began to allow for training models with 10 or more layers did deep learning start to shine.

A new wave of investment

total investment in AI: 2011: \$19 million $\rightarrow$ 2014: \$394 million

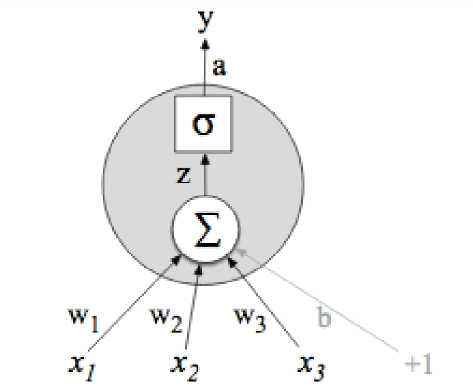
Why now? – cont.

The democratization of deep learning

early days: doing deep learning required significant programming expertise $\rightarrow$ now: basic Python scripting skills are sufficient (PyTorch, TensorFlow, Keras) $\rightarrow$ no feature engineering

Units

A neural unit



The building block of a neural network is a single computational unit. A unit takes a set of real valued numbers as input, performs some computation on them, and produces an output.

Bias

a neural unit is taking a weighted sum of its inputs, with one additional term in the sum called a bias term

$$z = b + \sum_i w_i x_i$$

expressing this weighted sum using vector notation: replacing the sum with dot product ($z \in \mathbb{R}$):

$$z = w \cdot x + b$$

Activation

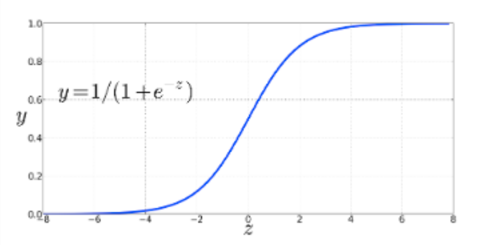
instead of using z, neural units apply a non-linear function f to $z \rightarrow$ the output of this function is the activation value for the unit a

$$y = a = f(z)$$

the final output of the network is y, and since here we have a single unit, y and a are the same

Non-linear functions – sigmoid

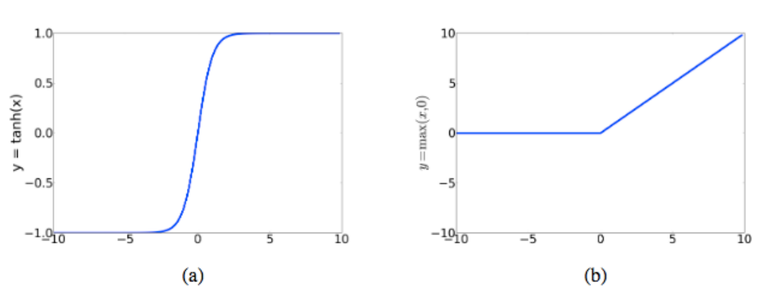
$$y = \sigma(z) = \frac{1}{1 + e^{-z}}$$



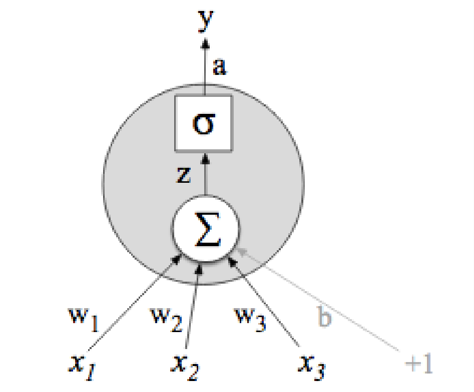
Non-linear functions – tanh and ReLU

$$y = \frac{e^z - e^{-z}}{e^z + e^{-z}}$$

$$y = max(x, 0)$$



Summary – a unit



The XOR problem

The XOR problem

- the power of neural networks comes from combining these units into larger networks
- one of its most clever demonstration was the proof by Minsky and Papert (1969): a single unit cannot compute XOR

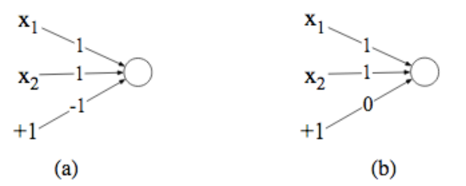
AND			OR			XOR		
x1	x2	y	x1	x2	y	x1	x2	y
0	0	0	0	0	0	0	0	0
0	1	0	0	1	1	0	1	1
1	0	0	1	0	1	1	0	1
1	1	1	1	1	1	1	1	0

A perceptron

a perceptron

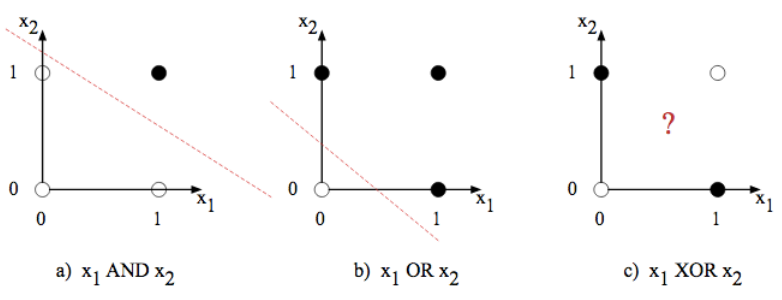
is a simple neural unit that has a binary output and does not have a non-linear activation function

$$y = \begin{cases} 0, & \text{if } w \cdot x + b \leq 0 \\ 1, & \text{if } w \cdot x + b > 0 \end{cases}$$

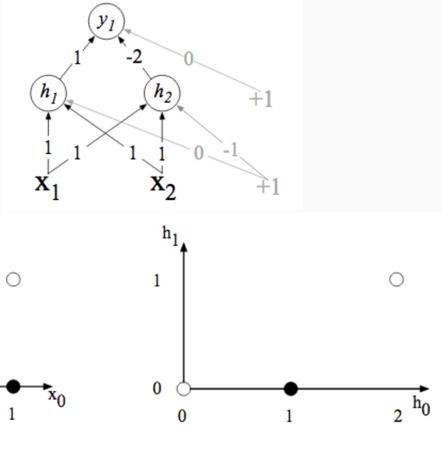


Decision boundary

a perceptron is a linear classifier



XOR solution



a) The original x space

b) The new h space

Feedforward Neural Networks

A feedforward network

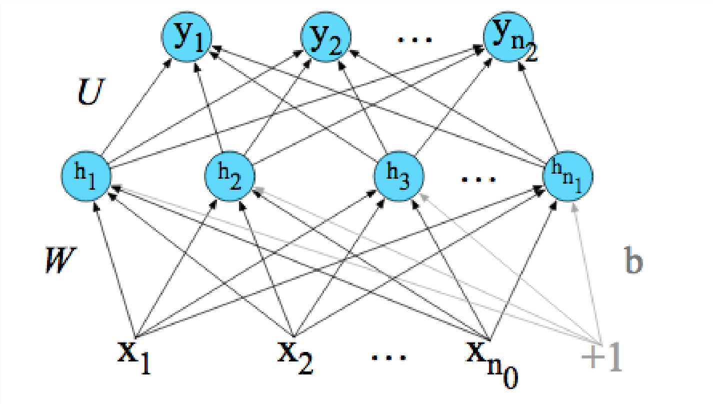
a feedforward network

is a multilayer network

- in which the units are connected with no cycles;
- the outputs from units in each layer are passed to units in the next higher layer, and
- no outputs are passed back to lower layers

(networks with cycles are called recurrent neural networks (RNNs))

Three kinds of nodes



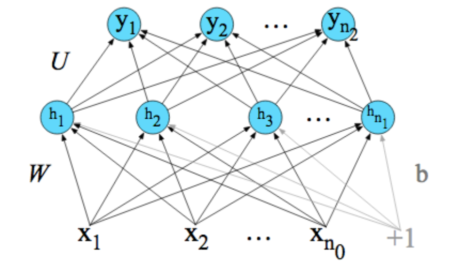
input units, hidden units, and output units

The hidden layer

- the hidden layer is formed of hidden units, each of which is a neural unit, taking a weighted sum of its inputs and then applying a non-linearity
- fully-connected: each hidden unit sums over all the input units

Weight matrix

We represent the parameters for the entire hidden layer by combining the weight vector w_i and bias b_i for each unit i into a single weight matrix W and a single bias vector b for the whole layer. Each element W_{ij} of the weight matrix W represents the weight of the connection from the ith input unit x_i to the jth hidden unit h_j.



Matrix operations

3 steps:

1. multiplying the weight matrix by the input vector x
2. adding the bias vector b
3. applying the activation function g

$$h = \sigma(Wx + b)$$

- the number of inputs: n_0
- x is a vector of real numbers of dimension n_0: $x \in \mathbb{R}^{n_0}$
- the hidden layer has dimensionality n_1, so $h \in \mathbb{R}^{n_1}$
- $W \in \mathbb{R}^{n_1 \times n_0}$

The role of the output layer

- the resulting value h forms a representation of the input
- the role of the output layer: to take this representation and compute the final output
- the output can be a real-valued number, but it is rather a probability distribution across the output nodes

Intermediate output

- the output layer also has a weight matrix (U)
- some models don't include a bias vector b, so here we eliminate it
- the weight matrix U is multiplied by the vector h to produce the intermediate output z:

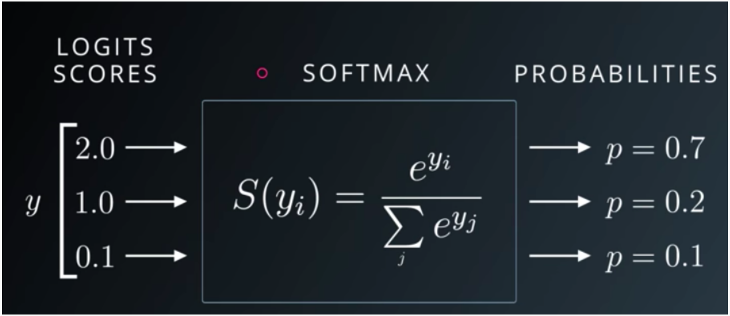
$$z = Uh$$

- $U \in \mathbb{R}^{n_2 \times n_1}$
- element U_{ij} is the weight from unit j in the hidden layer to unit i in the output layer

The softmax function

converting a vector of real-valued numbers to a vector encoding a probability distribution:

$$softmax(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{d} e^{z_j}} 1 \leq i \leq d$$



Summary – feedforward network

the final equations for a feedforward network with a single hidden layer, which takes an input vector x, outputs a probability distribution y, and is parameterized by weight matrices W and U and a bias vector b:

$$h = \sigma(Wx + b)$$
$$z = Uh$$
$$y = softmax(z)$$

activation functions:

- at the internal layers: ReLU or tanh
- at the final layer:
  - for binary classification: sigmoid
  - for multinomial classification: softmax

Training Neural Nets

Supervised machine learning

- the correct output: y
- the system's estimate of the true y: $\hat{y}$
- the goal of the training procedure: to learn parameters $W^{[i]}$ and $b^{[i]}$ for each layer i that make $\hat{y}$ as close as possible to the true y

How to do that?

1. we need a loss function that models the distance between $\hat{y}$ and $y \rightarrow$ cross-entropy loss
2. we have to minimize the loss function $\rightarrow$ an optimization algorithm for iteratively updating the weights: gradient descent
3. we have to know the gradient of the loss function $\rightarrow$ error backpropagation

Cross-entropy loss

if the neural network is used as a binary classifier:

$$L_{CE}(\hat{y}, y) = -\log p(y|x) = -[y \log \hat{y} + (1-y)\log(1-\hat{y})]$$

if the neural network is used as a multinomial classifier:

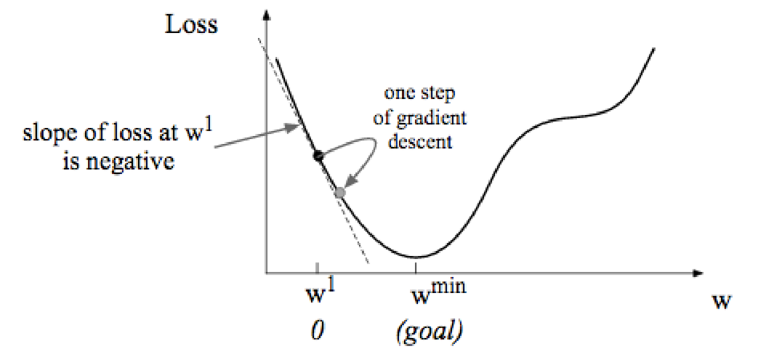
$$L_{CE}(\hat{y}, y) = -\sum_{i=1}^{C} y_i \log \hat{y}_i$$

hard classification task:

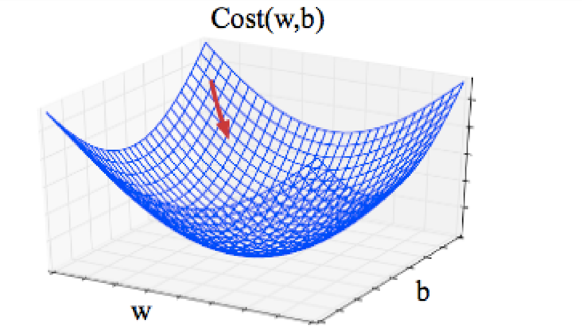
$$L_{CE}(\hat{y}, y) = -\log \hat{y}_i$$

we want this loss lower, if $\hat{y}$ is closer to y, and higher, if farer

Computing the Gradient – one parameter



Computing the Gradient – two parameters



for more parameters → error backpropagation or backward differentiation → all parameters can be calibrated together

non-convex optimization problem with possible local minima

More details on learning

- to prevent overfitting $\rightarrow$ dropout: randomly dropping some units and their connections from the network during training
- tuning hyperparameters:
    - the number of layers
    - the number of hidden nodes per layer
    - the choice of activation functions
    - ...

Neural Language Models

language modeling:

predicting upcoming words from prior word context

neural language modeling (NLM) has advantages over n-gram language modeling:

- NLM does not need smoothing
- NLM can handle much longer histories
- NLM can generalize over contexts of similar words
- NLM has mush higher predictive accuracy

A feedforward NLM

a feedforward NLM is

a standard feedforward network that takes as input at time t a representation of some number of previous words $w_{t-1}, w_{t-2}, ...,$ and outputs a probability distribution over possible next words

$$P(w_t|w_1^{t-1}) \approx P(w_t|w_{t-N+1}^{t-1})$$

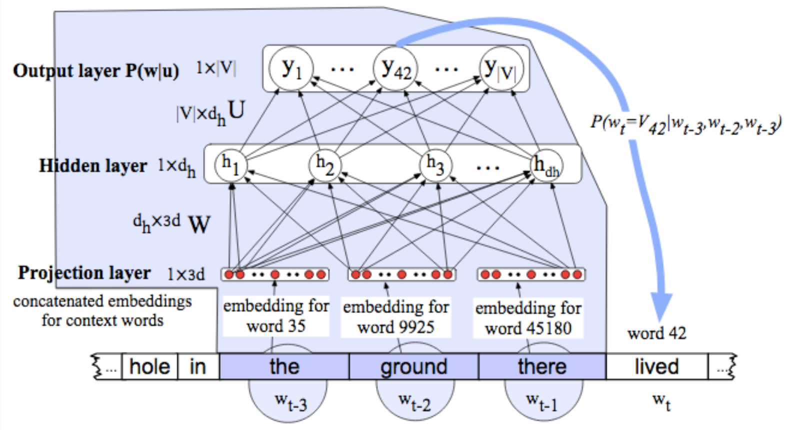
Embeddings

the prior context is represented by embeddings of the previous words $\rightarrow$ allows NLM to generalize to unseen data much better than n-gram models

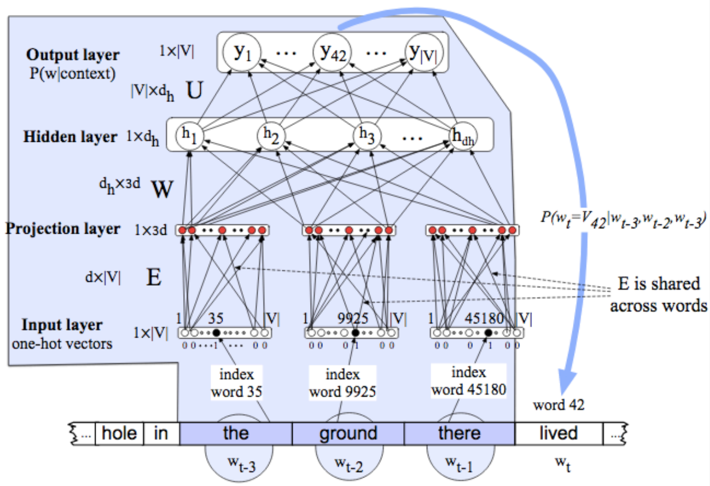
2 ways of using embeddings:

1. pretrained embeddings: we get the embeddings from an embedding dictionary E for each word in our vocabulary V
2. learning embeddings simultaneously with training the network

Using pretrained embeddings



Learning embeddings



the final equations for NLM:

$$
\begin{aligned}
e &= (E_{x_1}, E_{x_2}, ..., E_x) \\
h &= \sigma(We + b) \\
z &= Uh \\
y &= softmax(z)
\end{aligned}
$$

training such a network will result both in an algorithm for language modeling and a new set of embeddings

Irodalom

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- Jurafsky 3rd edition 5. & 7. chapter
- Francois Chollet: Deep Learning with Python. Manning, Shelter Island, 2018.: https://www.manning.com/books/deep-learning-with-python