Umelý neurón

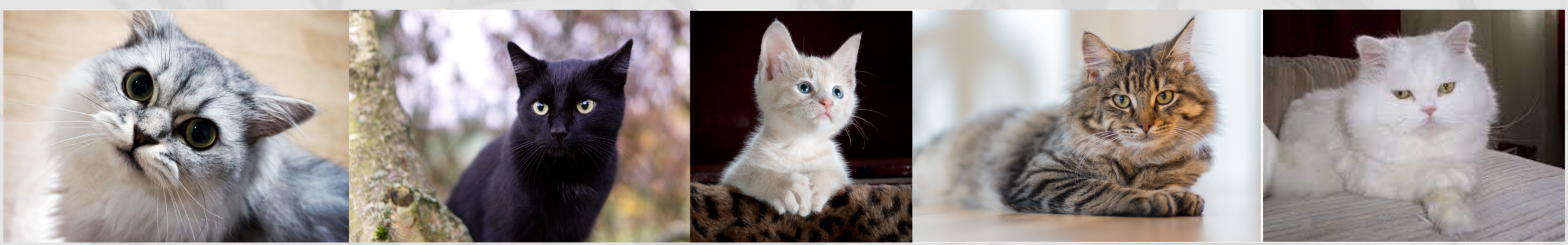
+ Prehľad neurónových sietí

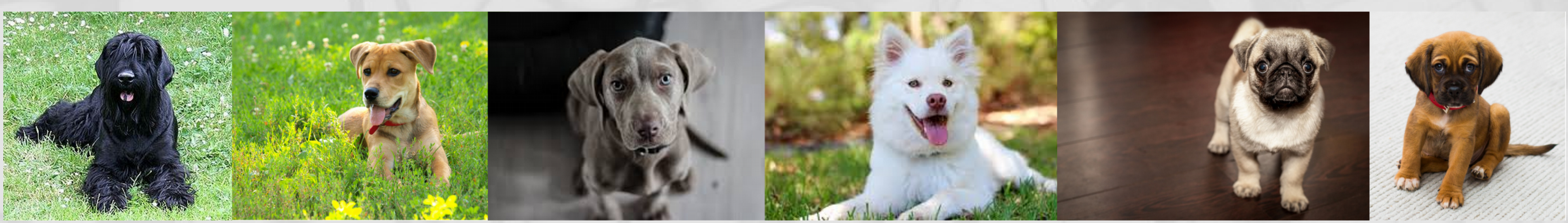
Miroslav Hájek,
septima 2017/18

Inšpirácia prírodou

Schopnosť kategorizovať

MNIST databáza
rukopisov čísel





Biologický neurón

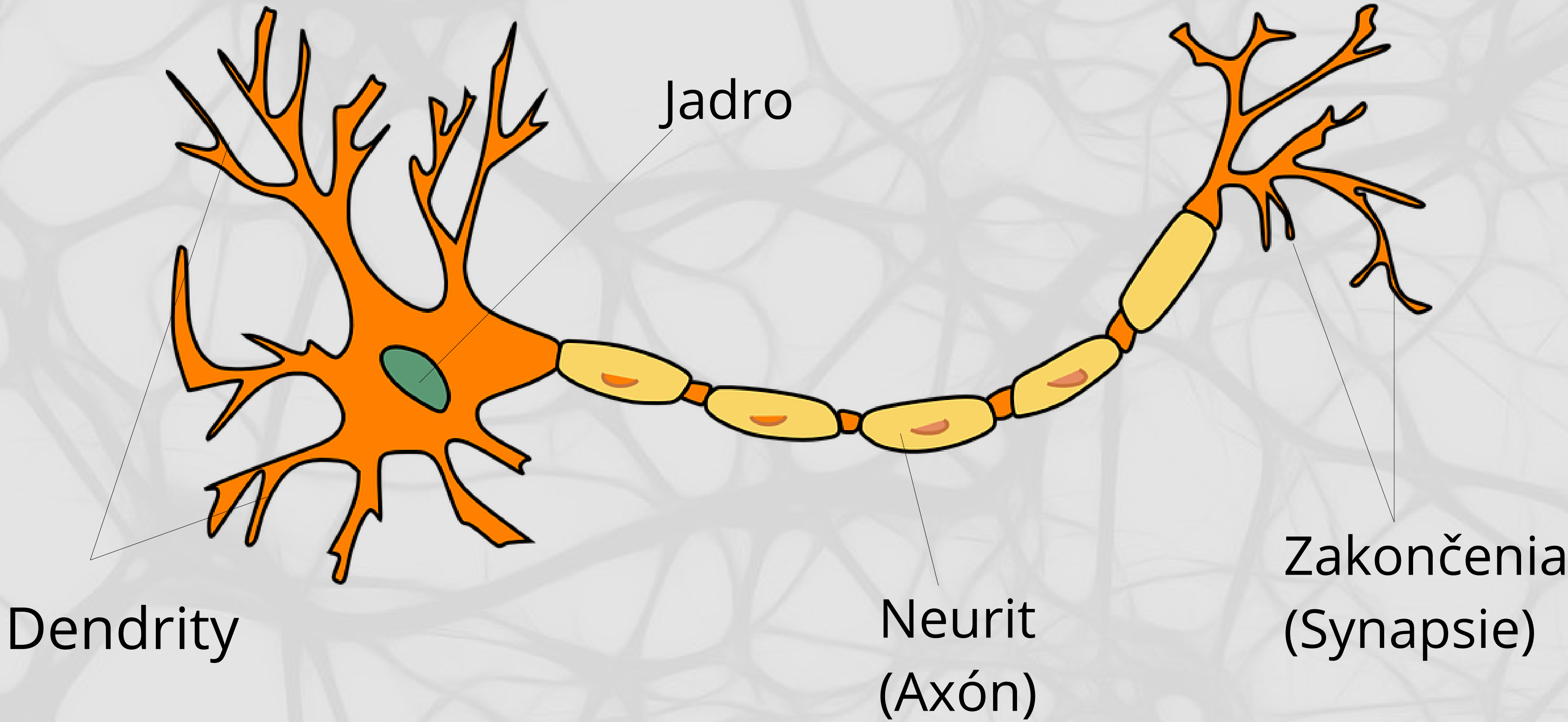


Schéma fungovania neurónu

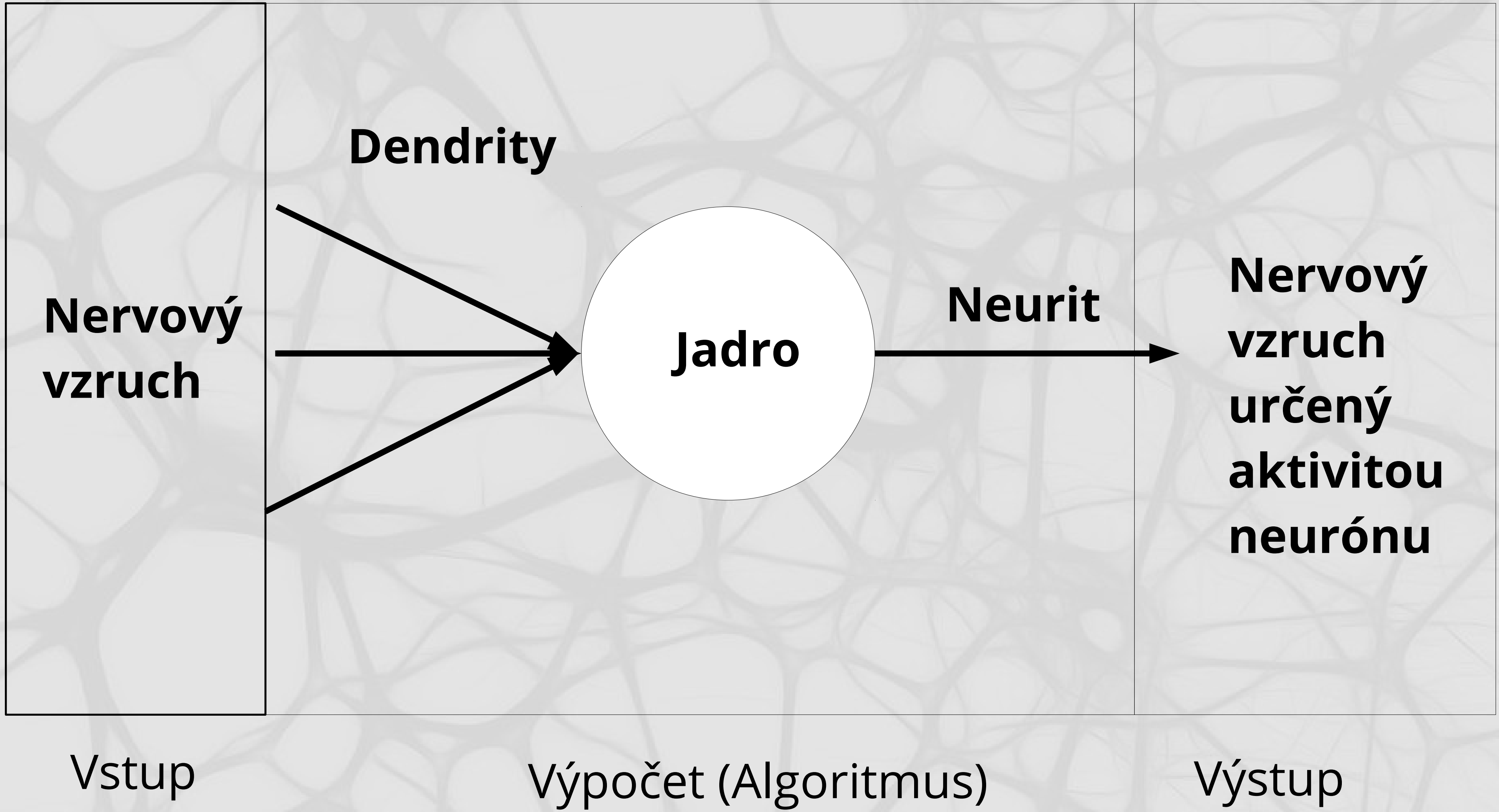
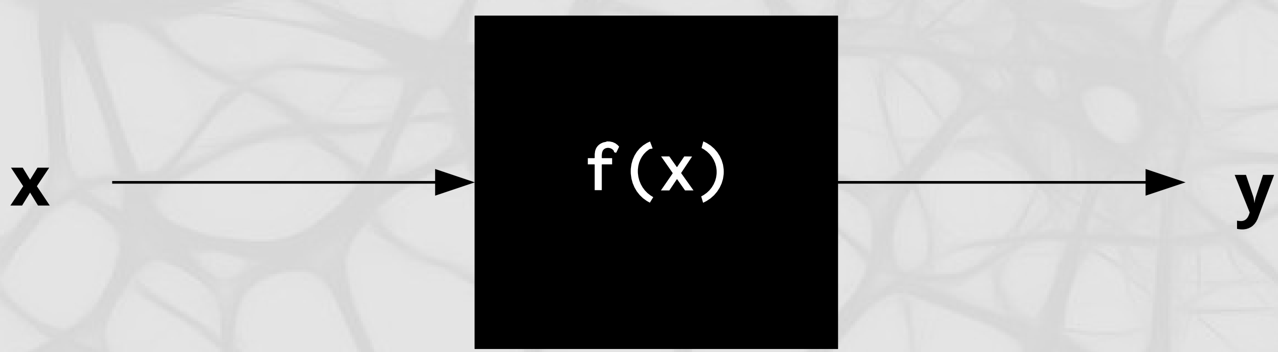


Schéma programu

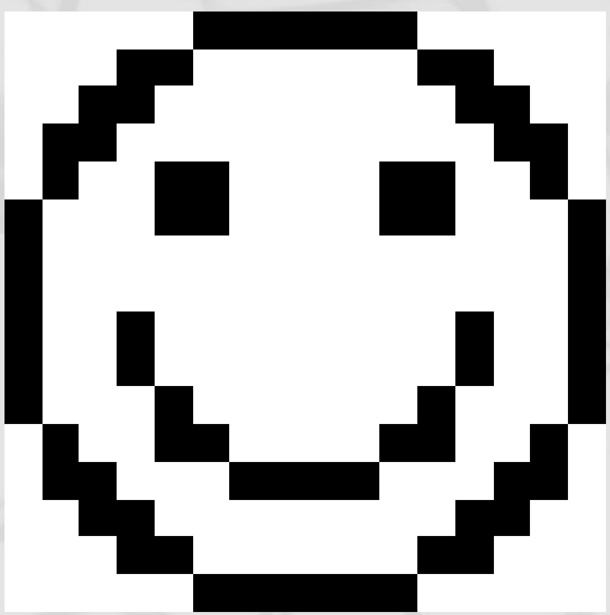
Matematická funkcia



Ako simulovať náš mozog?

- Algoritmy – deterministický model – presný postup
- Umelý neurón – stochastický model – učenie sa

Napr. Rozoznávanie obrázkov



```
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0001100000011000
0011000000001100
0110000000000110
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1000110000110001
1000000000000001
1000000000000001
1001000000001001
1001000000001001
1000100000010001
0100110000110010
0110001111000110
0011000000001100
0001100000011000
0000011111100000
```

Čo sa s tým dá ešte robiť?

- Rozoznávanie vzorov – tvárí, znakov (OCR)
- Predpovedanie budúcich javov – počasie, burza
- Ovládanie – roboty, samoriadiace autá
- Senzory – vytvorenie nadhľadu z množstva dát
- Detekcia anomálii – doprava, spánková rutina pacienta
- Určenie diagnózy (v budúcnosti)

Psychological Review
Vol. 65, No. 6, 1958

THE PERCEPTRON: A PROBABILISTIC MODEL FOR INFORMATION STORAGE AND ORGANIZATION IN THE BRAIN[1]

F. ROSENBLATT

Cornell Aeronautical Laboratory

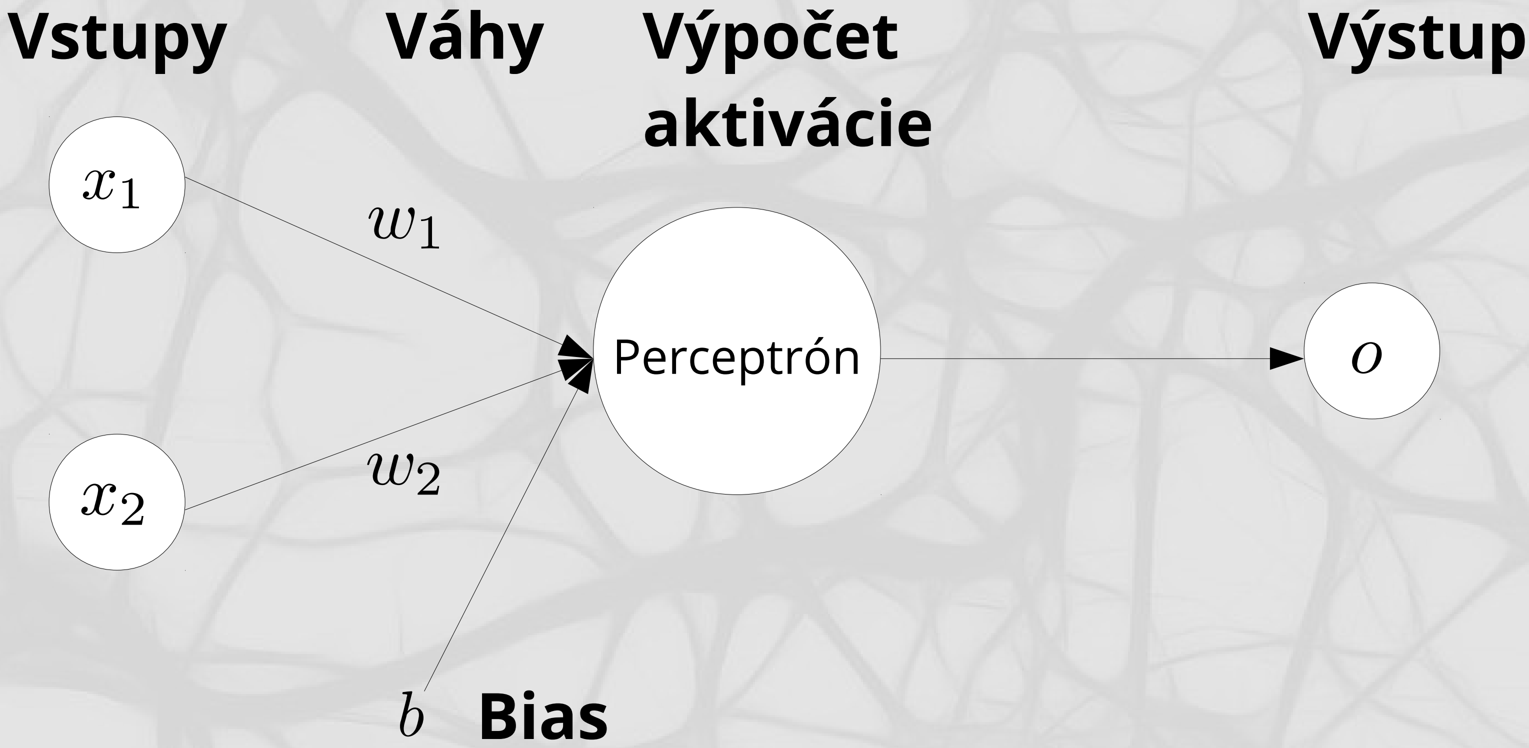
If we are eventually to understand the capability of higher organisms for perceptual recognition, generalization, recall, and thinking, we must first have answers to three fundamental questions:

1. How is information about the physical world sensed, or detected, by the biological system?
2. In what form is information stored, or remembered?
3. How does information contained in storage, or in memory, influence recognition and behavior?

The first of these questions is in the province of sensory physiology, and is the only one for which appreciable understanding has been achieved. This article will be concerned primarily with the second and third questions, which are still subject to a vast amount of speculation, and where the few relevant facts currently supplied by neurophysiology have not yet been integrated into an acceptable theory.

With regard to the second question, two alternative positions have been maintained. The first suggests that storage of sensory information is in the form of coded representations or images, with some sort of one-to-one and the stored pattern. According to this hypothesis, if one understood the code or "wiring diagram" of the nervous system, one should, in principle, be able to discover exactly what an organism remembers by reconstructing the original sensory patterns from the "memory traces" which they have left, much as we might develop a photographic negative, or translate the pattern of electrical charges in the "memory" of a digital computer. This hypothesis is appealing in its simplicity and ready intelligibility, and a large family of theoretical brain models has been developed around the idea of a coded, representational memory (**2**, **3**, **9**, **14**). The alternative approach, which stems from the tradition of British empiricism, hazards the guess that the images of stimuli may never really be recorded at all, and that the central nervous system simply acts as an intricate switching network, where retention takes the form of new connections, or pathways, between centers of activity. In many of the more recent developments of this position (Hebb's "cell assembly," and Hull's "cortical anticipatory goal response," for example) the "responses" which are associated to stimuli may be entirely contained within the CNS itself. In this case

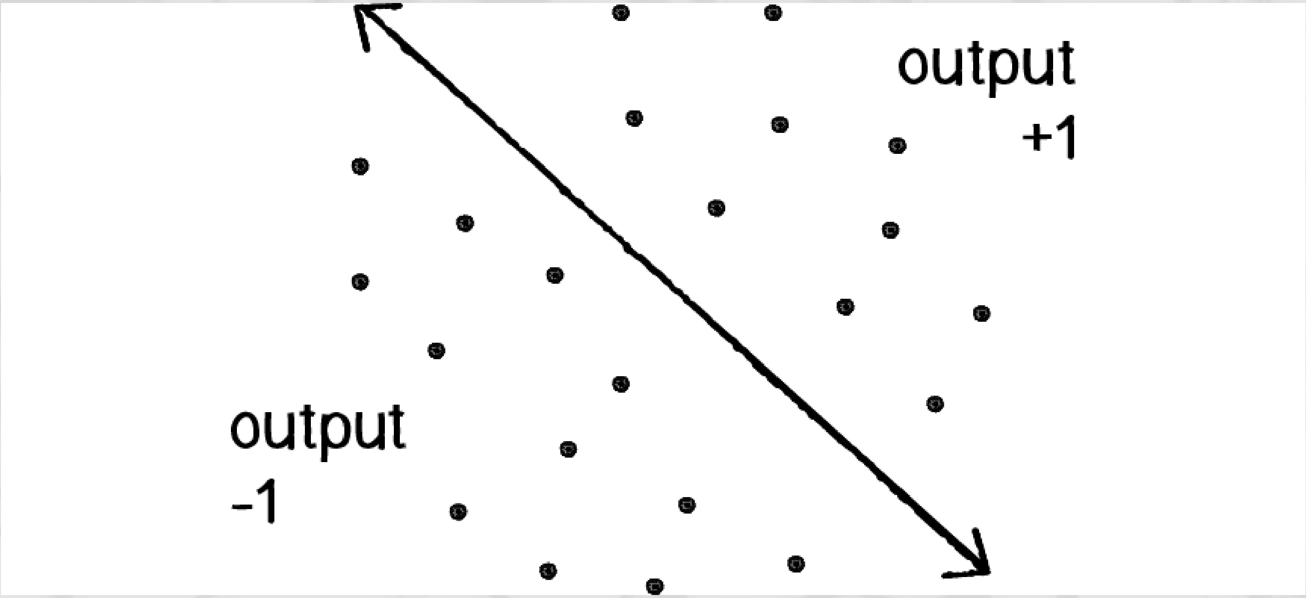
Perceptrón

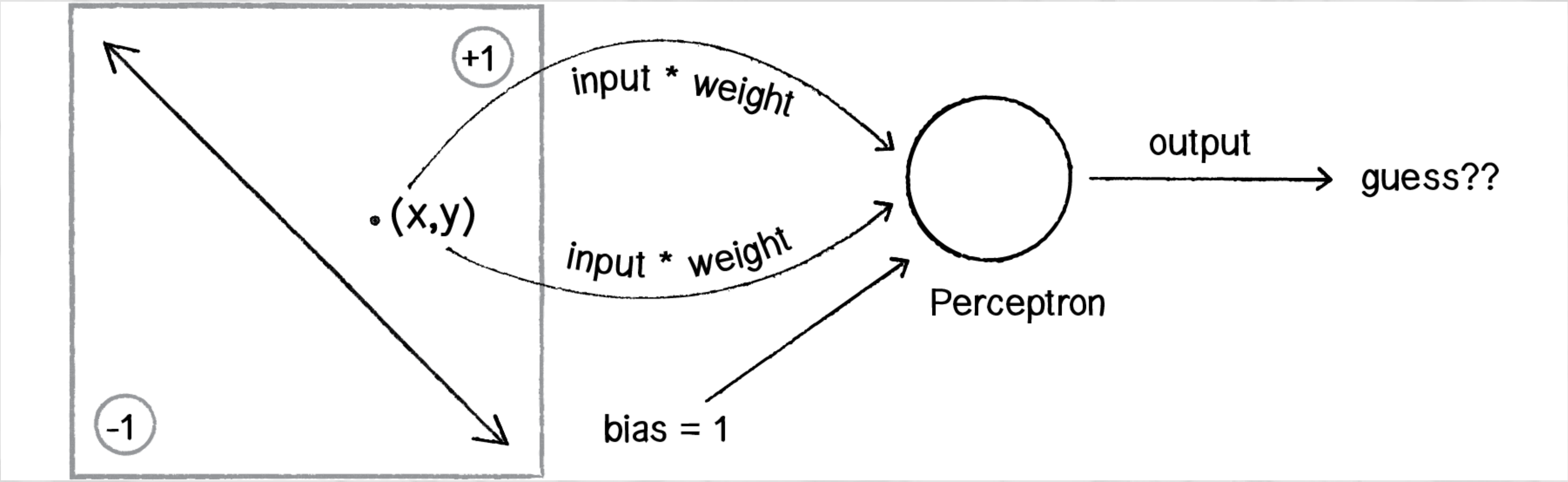


Aktivácia umelého neurónu

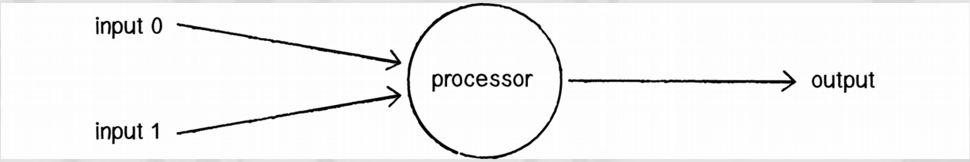
$$o = (x_1 \cdot w_1 + x_2 \cdot w_2) + b$$

Príklad – lineárny klasifikátor





Popis činnosti



1. Prijatie vstupov

$$x = 24$$
$$y = 5$$

2. Pridaj váhy

– na začiatku sú náhodne na konci optimálne pre riešenie problému

$$w_x = 0.5$$
$$w_y = -1$$

$$x \cdot w_x => 24 \cdot 0.5 = 12$$
$$y \cdot w_y => 5 \cdot (-1) = -5$$

3. Sčítaj vstupy

$$Sum = 12 + (-5) = 7$$

4. Vytvor výstup pomocou aktivačnej funkcie

$$znamienko(x) : x > 0 => +1$$
$$x < 0 => -1$$

Typy strojového učenia

- **Učenie s učiteľom** (Supervised)
- **Učenie bez učiteľa** (Unsupervised)
- **Učenie so spätnou väzbou** (Reinforcement)

Učenie s učiteľom v našom príklade

Použijeme učenie s učiteľom

- Vytvoríme testovaciu sadu bodov
- Upravíme váhy postupne

chyba = (**žiadaný** výstup) **-** (**tip** perceptróna)

nová váha = (váha **teraz) + (zmena** váhy)

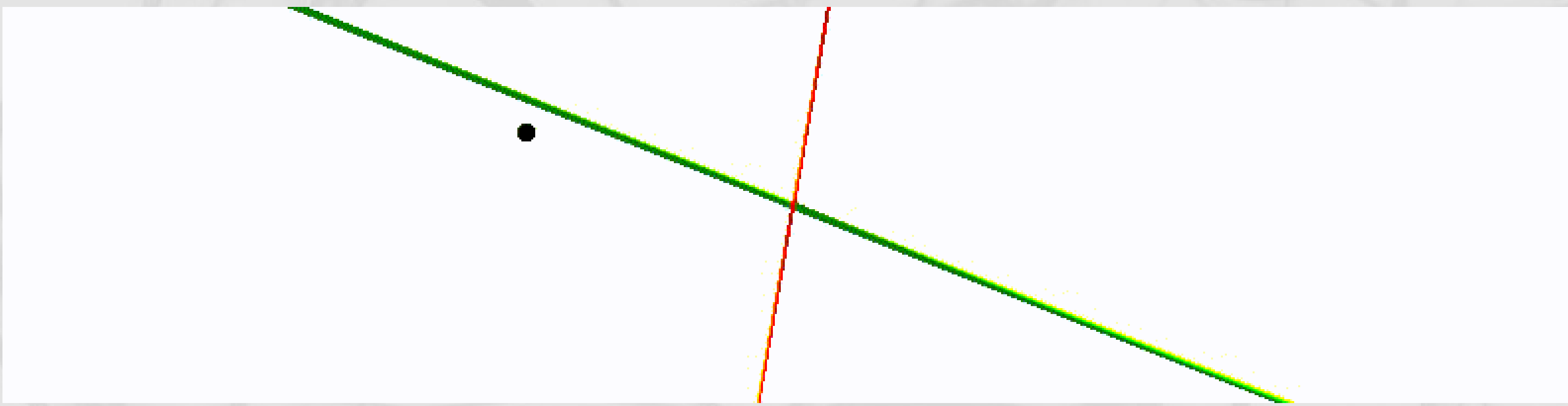
zmena váhy = chyba * vstup

NOVÁ VÁHA = VÁHA + CHYBA * VSTUP * RÝCHLOSŤ UČENIA

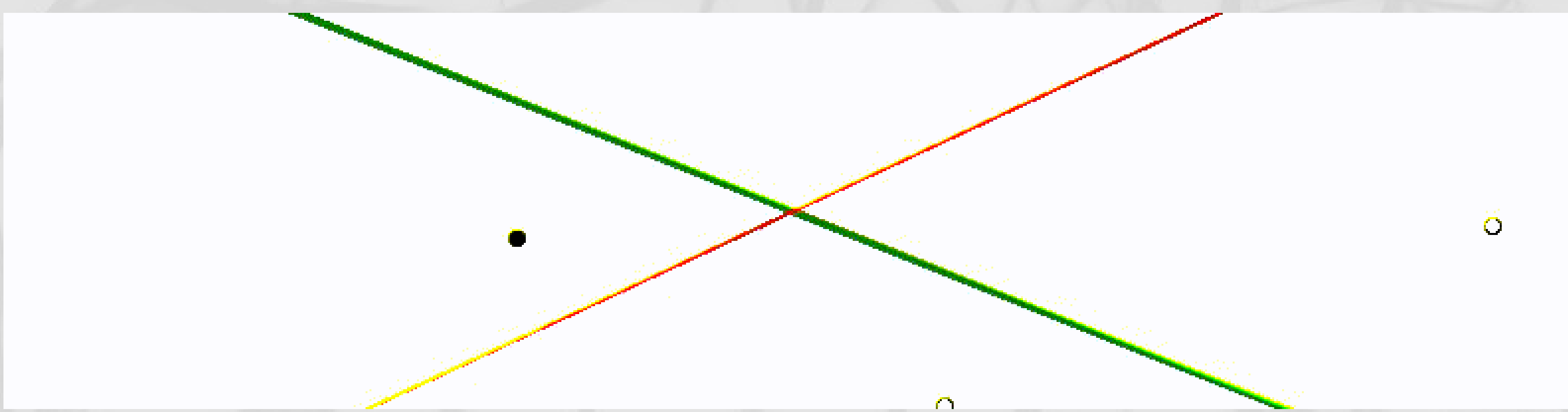
Ako to vyzerá?

„Univerzálny funkčný aproximátor“

Rýchlosť učenia: 0.00001



Rýchlosť učenia: 0.0001



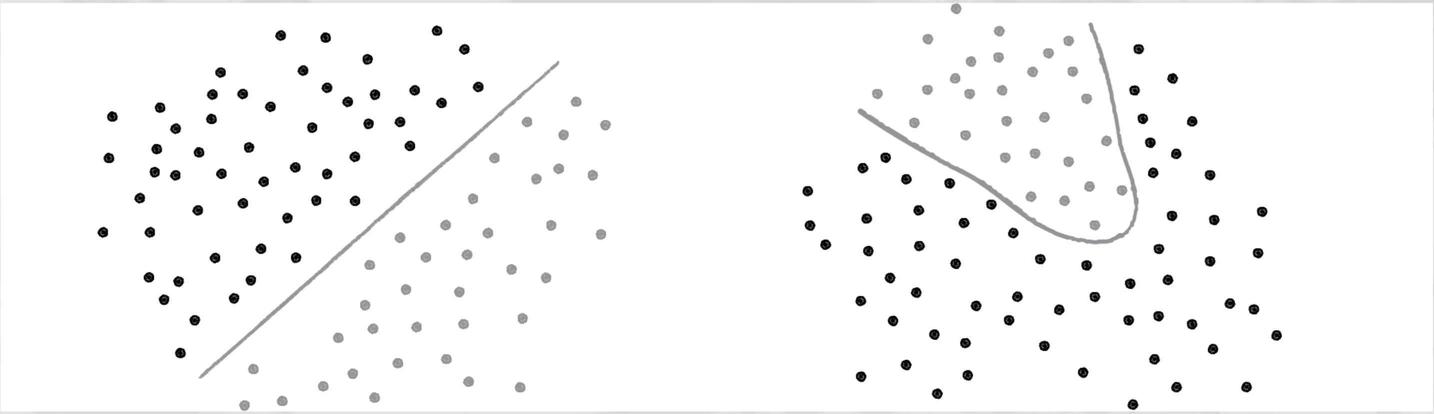
Kód alebo ako je to v praxi

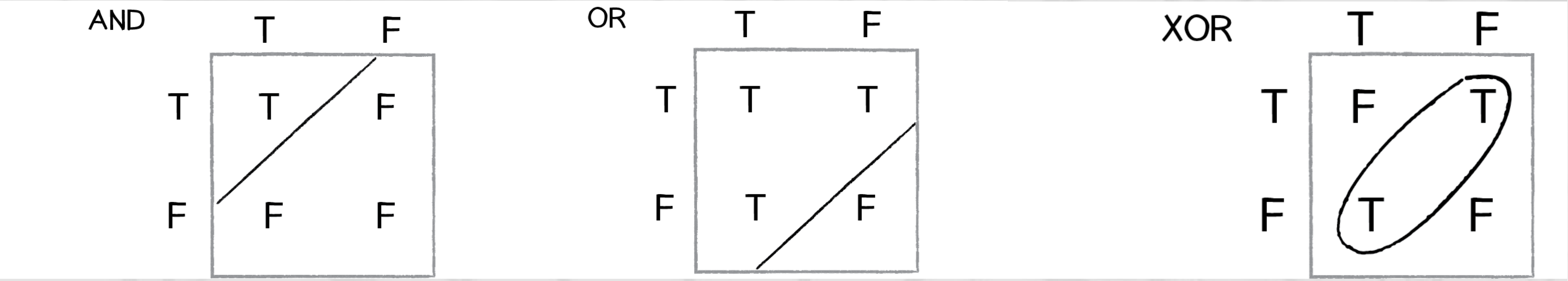
```
import random

class Perceptron:
    def __init__(self, n, c):                      # 1. Načítaj náhodné váhy
        self.weights = [random.uniform(-1, 1) for i in range(n)]
        self.learn_rate = c

    def activate(self, suma):                      # znamienko
        if suma >= 0:
            return 1
        else:
            return -1

    def feedforward(self, inputs):
        suma = 0
        for i in range(len(self.weights)):
            suma += inputs[i] * self.weights[i]    # 2. Vážený súčet
        return self.activate(suma)                 # 3. Aktivačná funkcia

    def train(self, inputs, desired):
        guess = self.feedforward(inputs)
        error = desired - guess
        for i in range(len(self.weights)):         # 4. Uprav váhy
            self.weights[i] += error * inputs[i] * self.learn_rate
```

Kedy perceptrón nestačí?

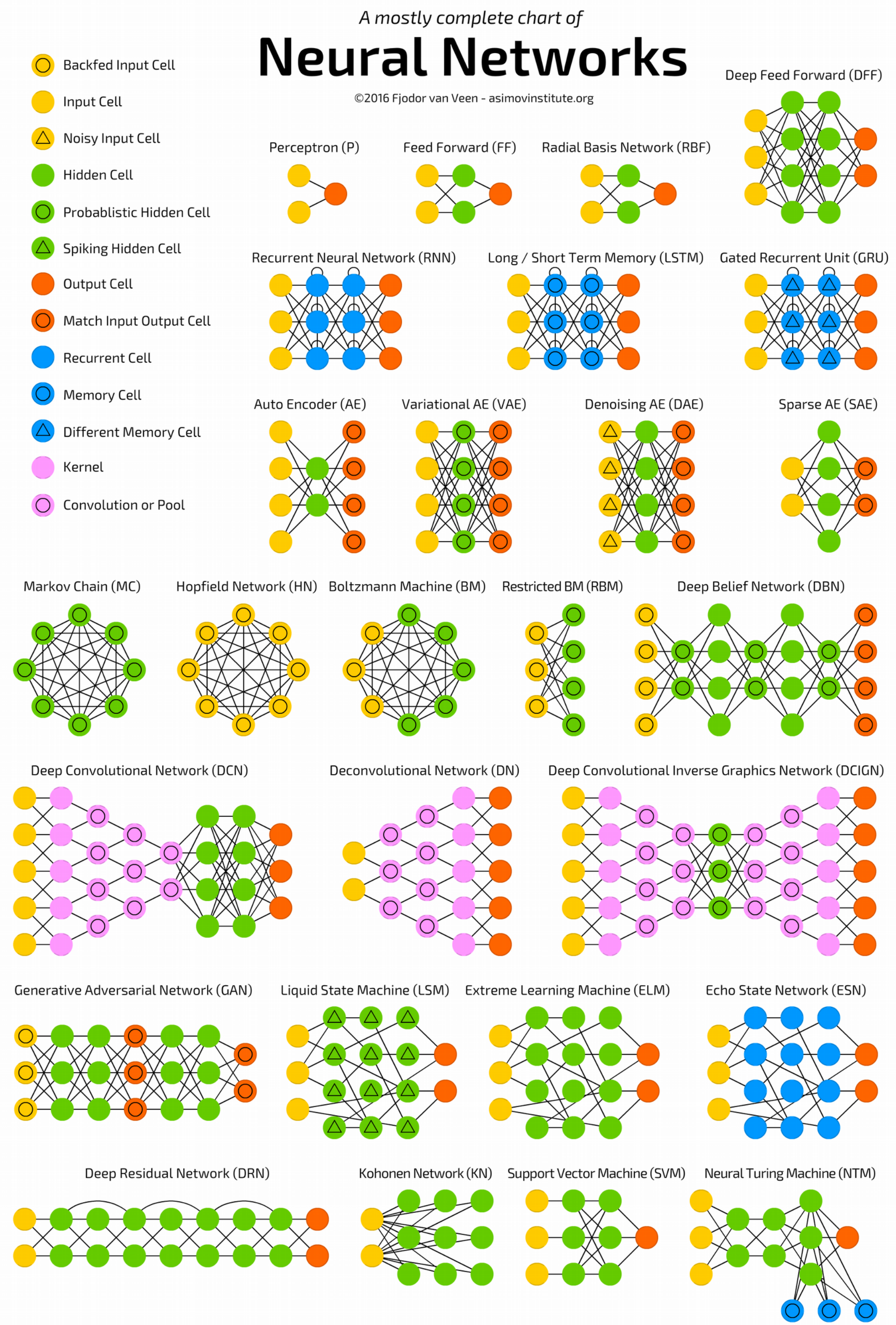
- Rieši len lineárne rozdeliteľné skupiny (1 priamka)
- XOR je neriešiteľné!

Marvin Minsky, Seymour Papert; Perceptons (1969)

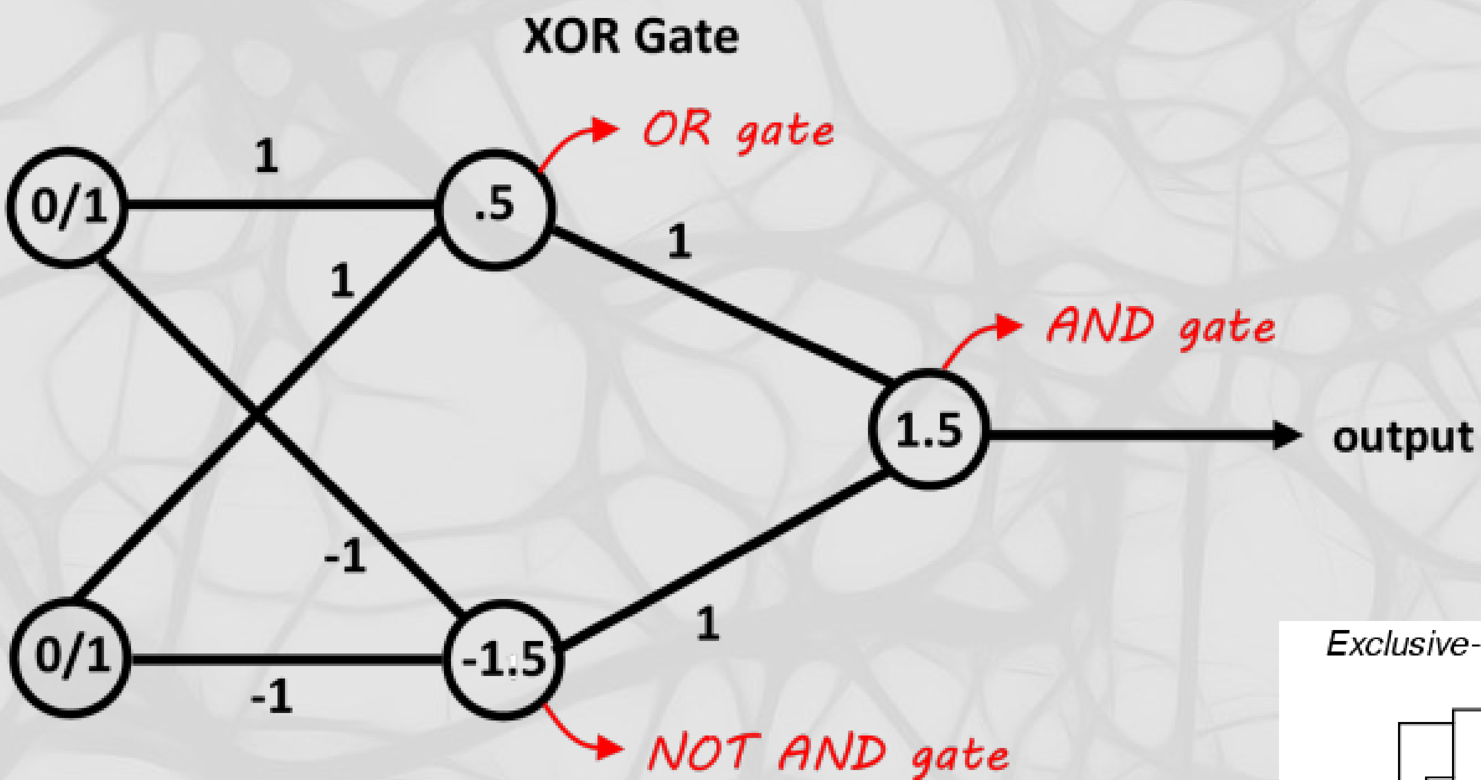




Spájanie do neurónových sietí

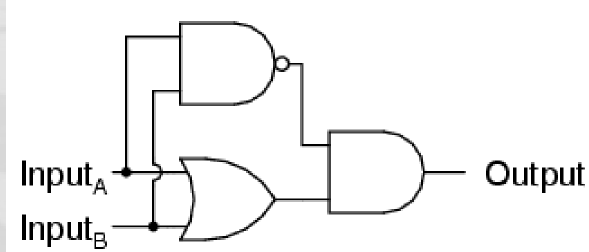


Riešenie problému XOR



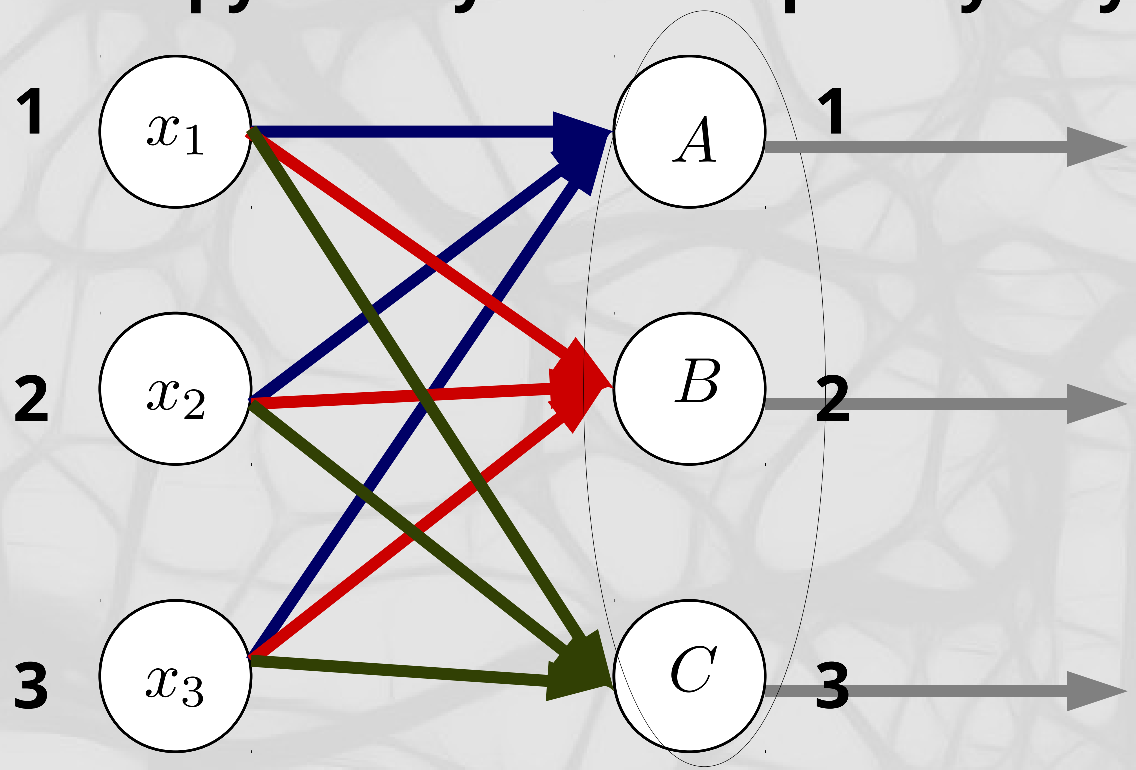
Vstupná vrstva **Skrytá vrstva** **Výstupná vrstva**

Exclusive-OR equivalent circuit



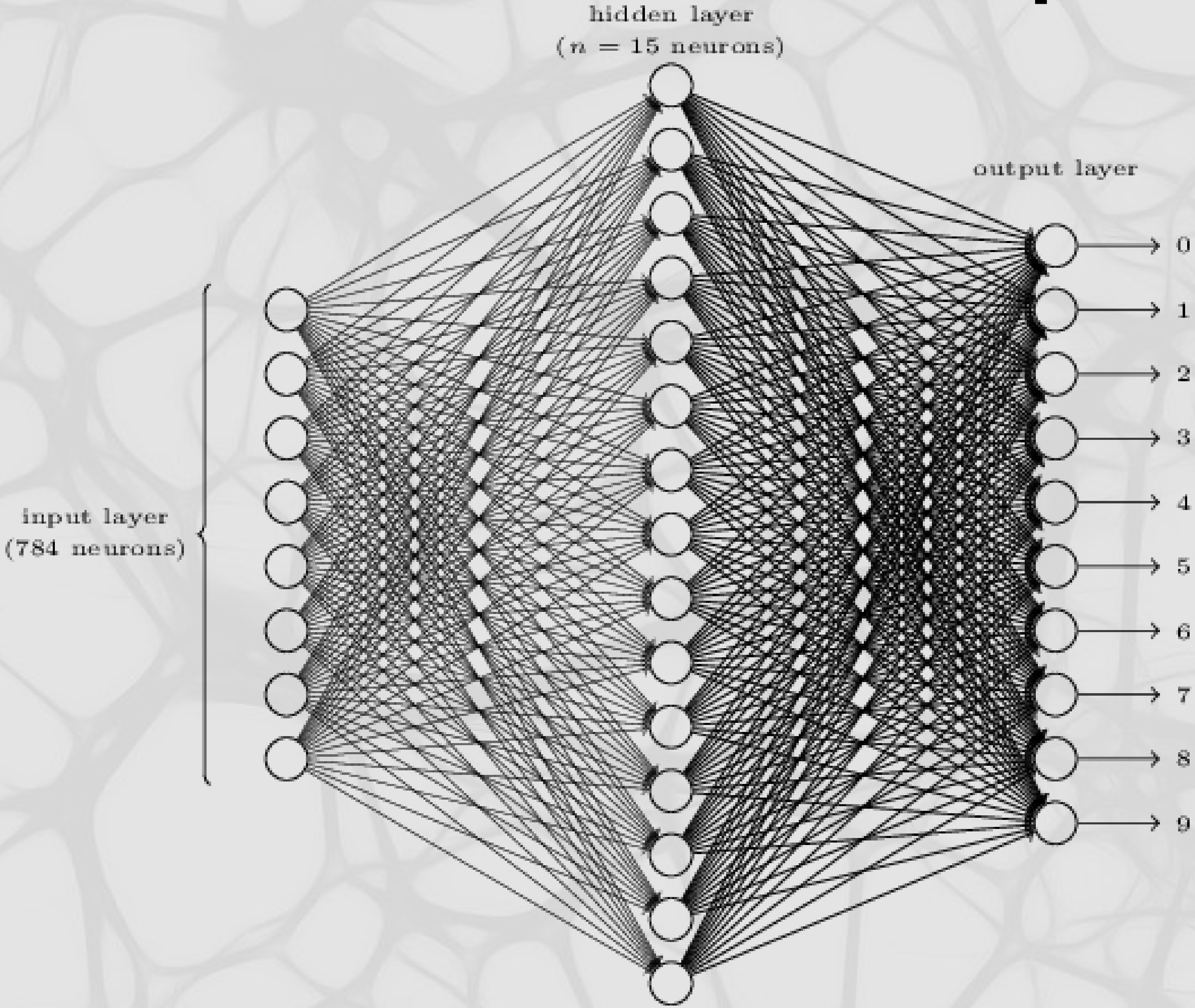
A	B	Output
0	0	0
0	1	1
1	0	1
1	1	0

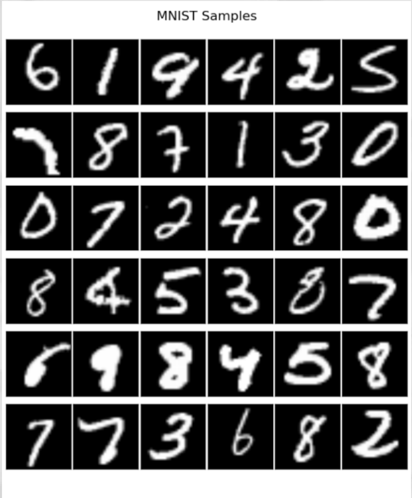
Spojenia medzi vrstvami



$$\vec{y} = \sigma\left(\begin{bmatrix} w_{1,1} & w_{1,2} & w_{1,3} \\ w_{2,1} & w_{2,2} & w_{2,3} \\ w_{3,1} & w_{3,2} & w_{3,3} \end{bmatrix}\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix}\right)$$

Klasifikácia čísel z rukopisu





Databáza MNIST:

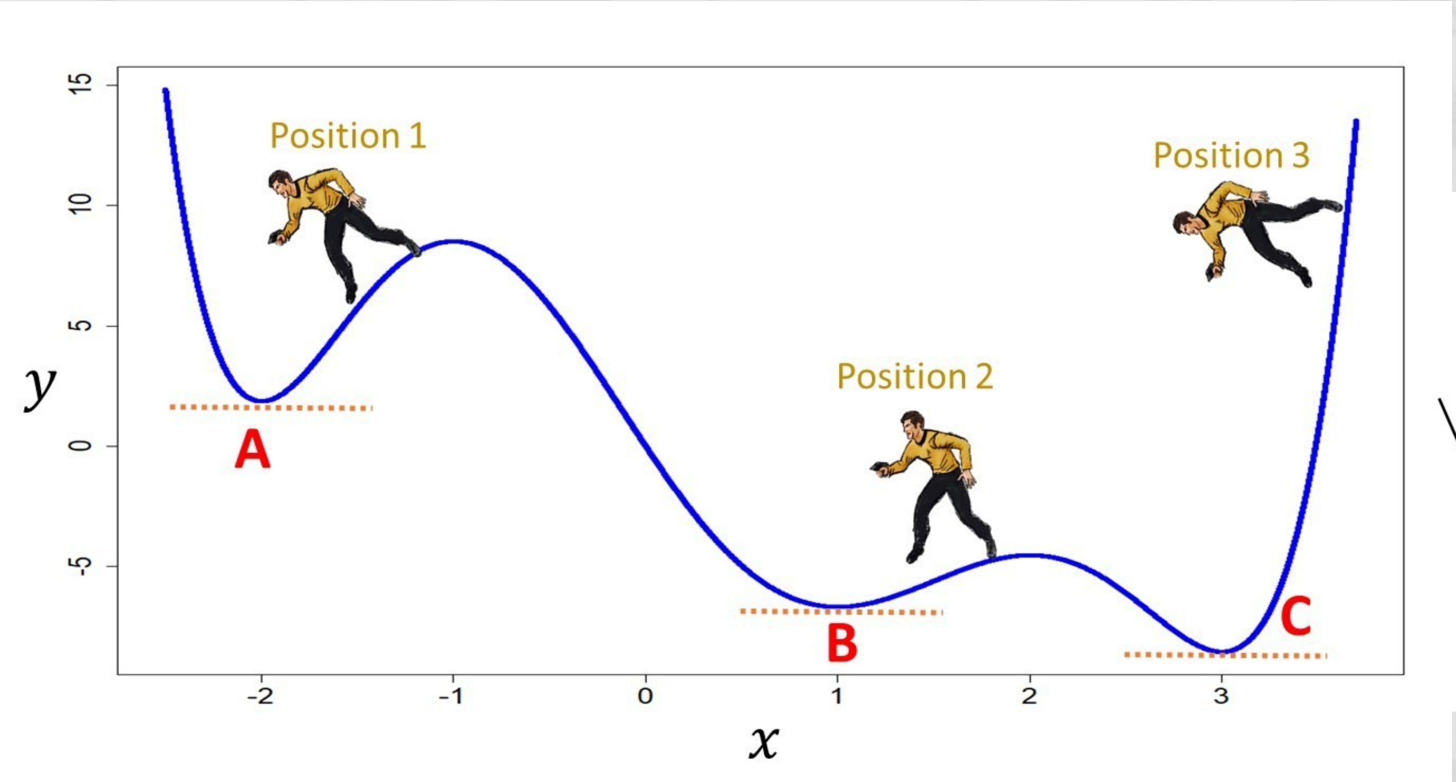
- 28 x 28 = 764 vektor

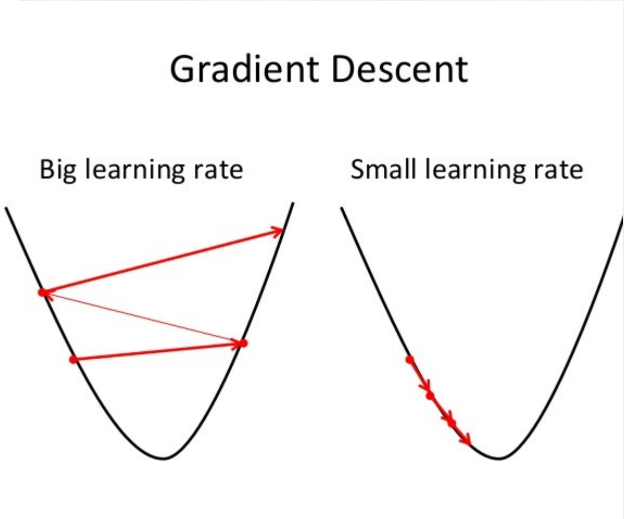
Ako funkcia:

- **Vstupy:** 784 pixelov
- **Prepojenia:** 11925 váh a biasov
- **Výstup:** 10 pravdepodobností (0.0 – 1.0)

Učenie neurónových sietí

- Gradient descent a Backpropagation
- Optimalizácia – hľadanie najlepšieho lokálneho minima funkcie

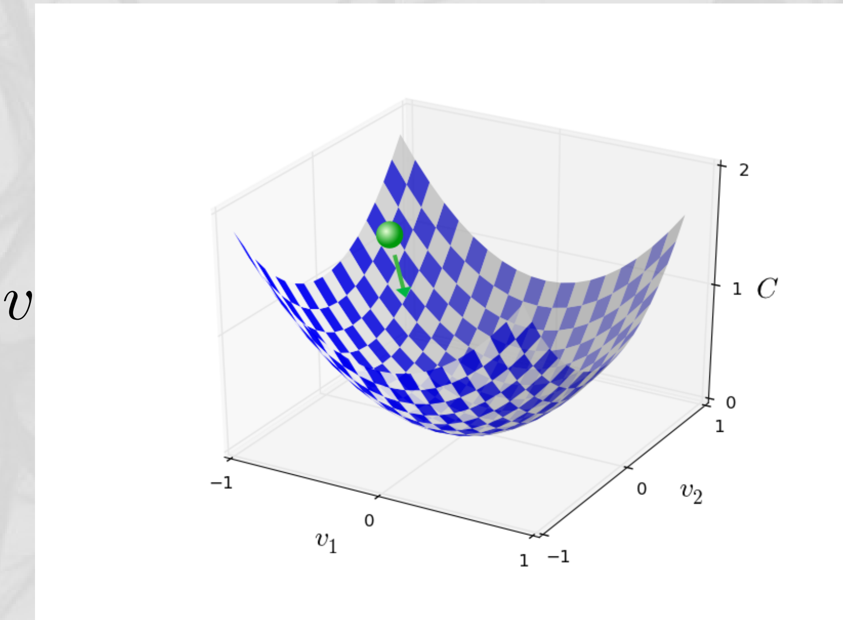




$$\frac{dC}{dx}(w) = 0$$

Hľadanie v n-rozmernom priestore

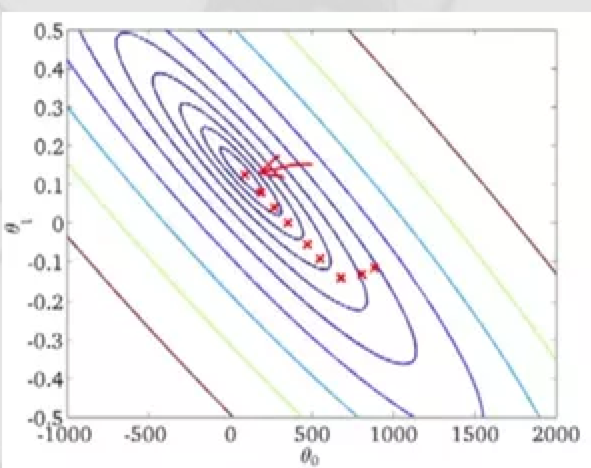
$$C(w,b) \equiv \frac{1}{2n}\sum_x \|y(x)-a\|^2$$



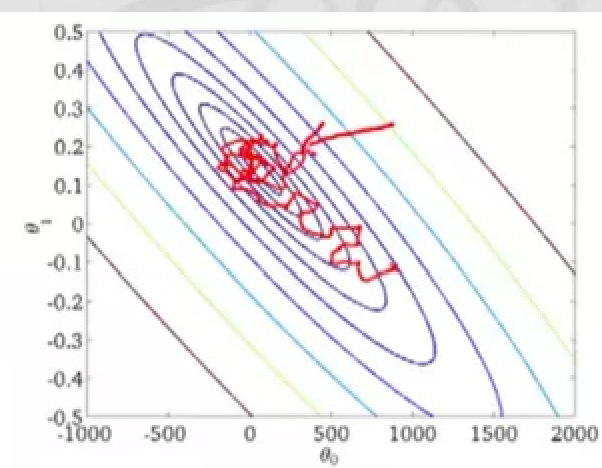
$$\nabla C \equiv \left(\frac{\partial C}{\partial v_1},\ldots,\frac{\partial C}{\partial v_m}\right)^T \quad \Delta C \approx \nabla C \cdot \Delta v$$

$$\nabla C \approx \frac{1}{m}\sum_{j=1}^{m} \nabla C_{X_j},$$

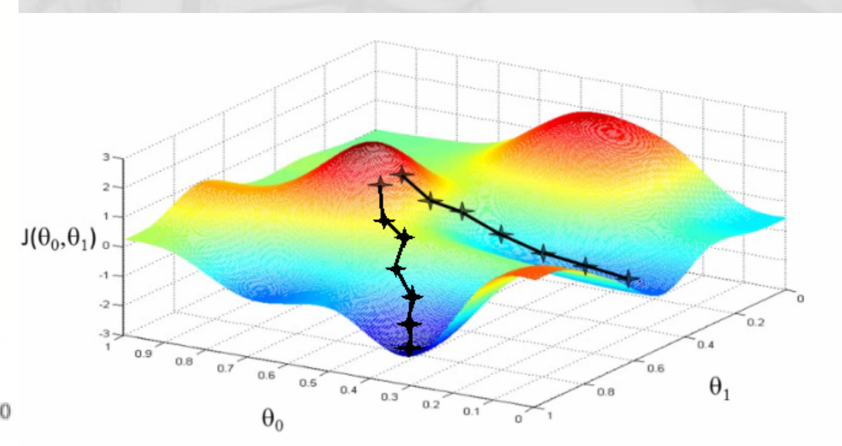
$$w_k \to w_k' = w_k - \frac{\eta}{m}\sum_j \frac{\partial C_{X_j}}{\partial w_k}$$



Batch Gradient Descent



Stochastic Gradient Descent



But wait, there is more …

Online knihy

http://neuralnetworksanddeeplearning.com/

http://www.deeplearningbook.org/