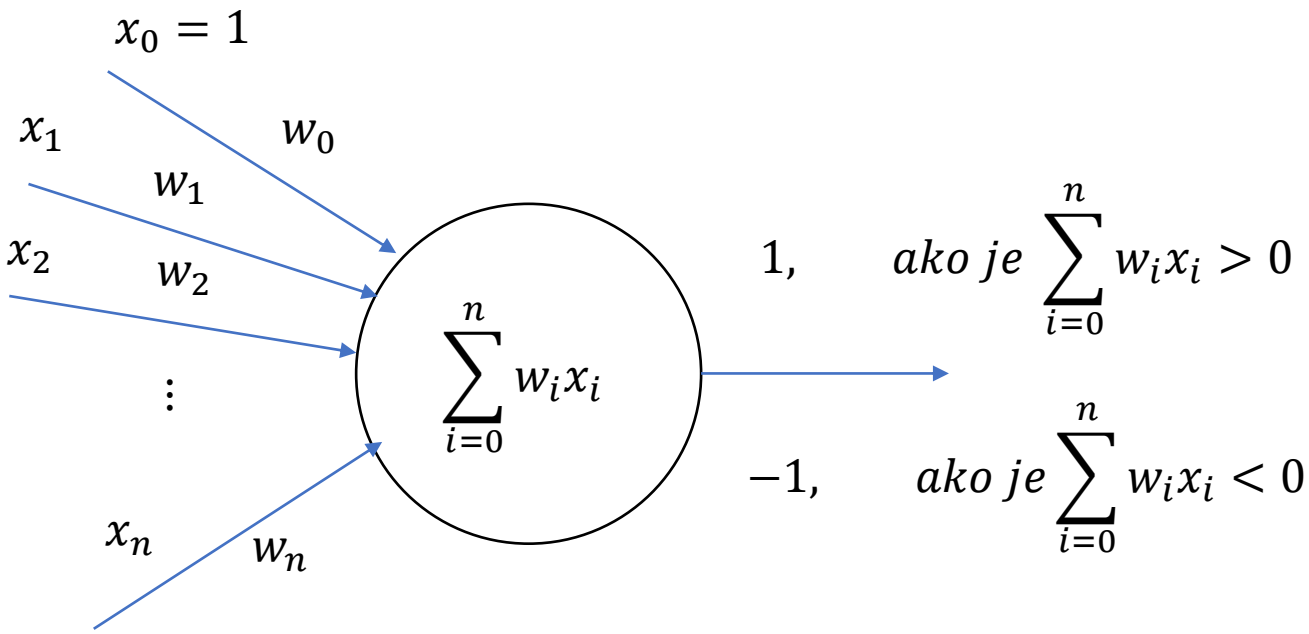
Neuronske mreže

Osnovni pojmovi

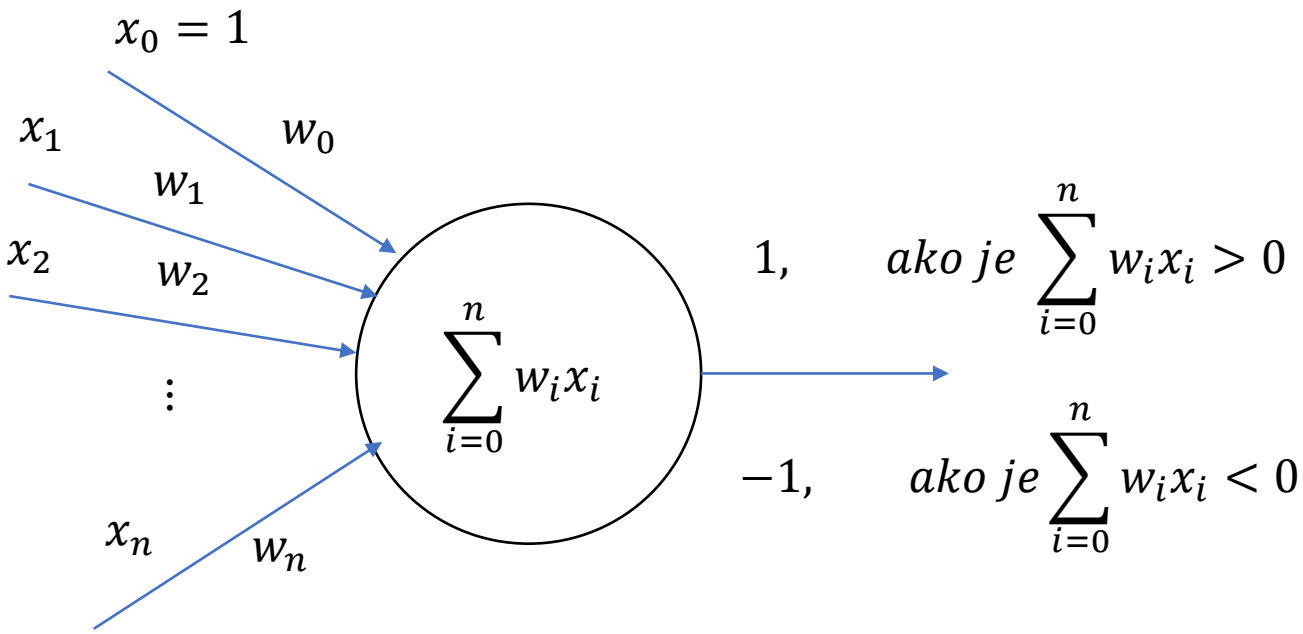
Perceptron

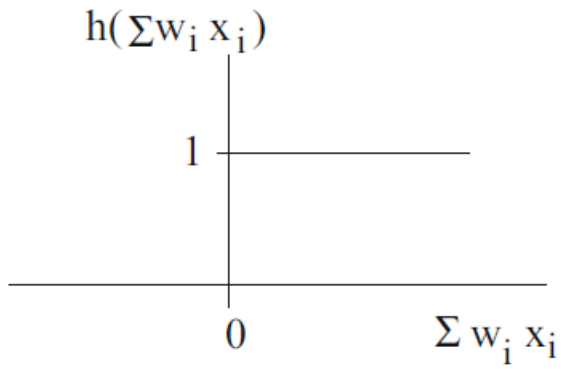


$$1, \quad ako\ je \sum_{i=0}^{n} w_i x_i > 0$$

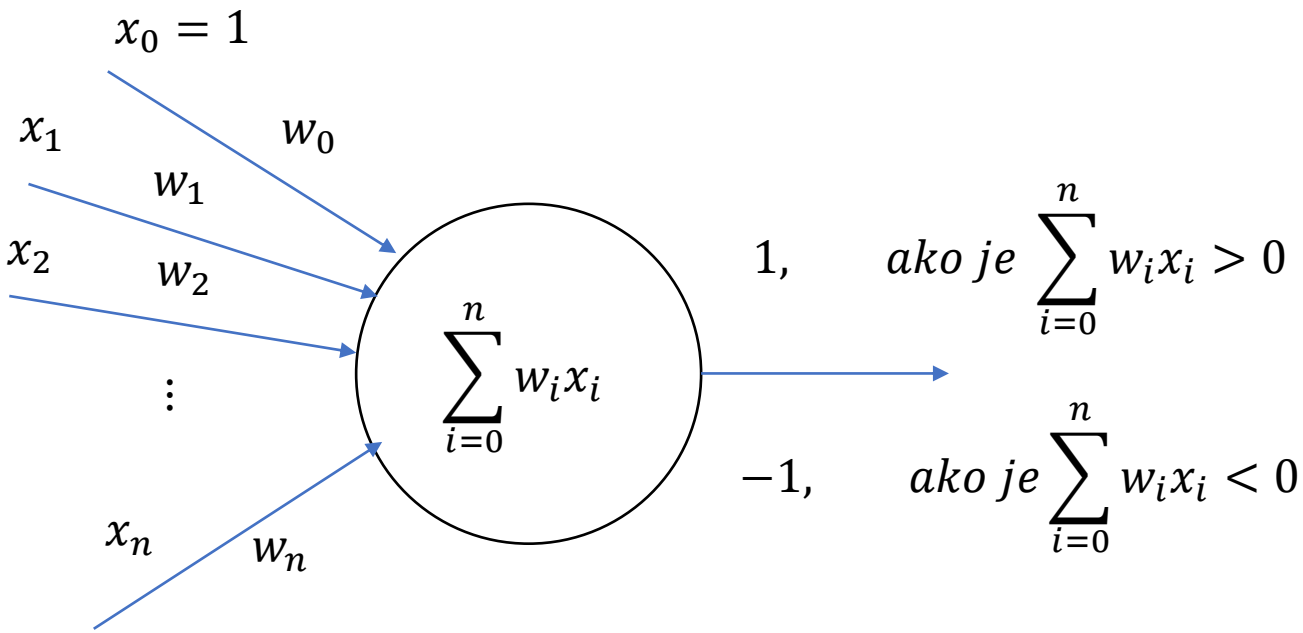
$$-1, \quad ako\ je \sum_{i=0}^{n} w_i x_i < 0$$

Perceptron


$x_0 = 1$
x_1
x_2
x_n
w_0
w_1
w_2
w_n
$\sum_{i=0}^{n} w_i x_i$
$1, \quad ako\ je \sum_{i=0}^{n} w_i x_i > 0$
$-1, \quad ako\ je \sum_{i=0}^{n} w_i x_i < 0$


h(Σw_i x_i)
1
0
Σ w_i x_i

Perceptron

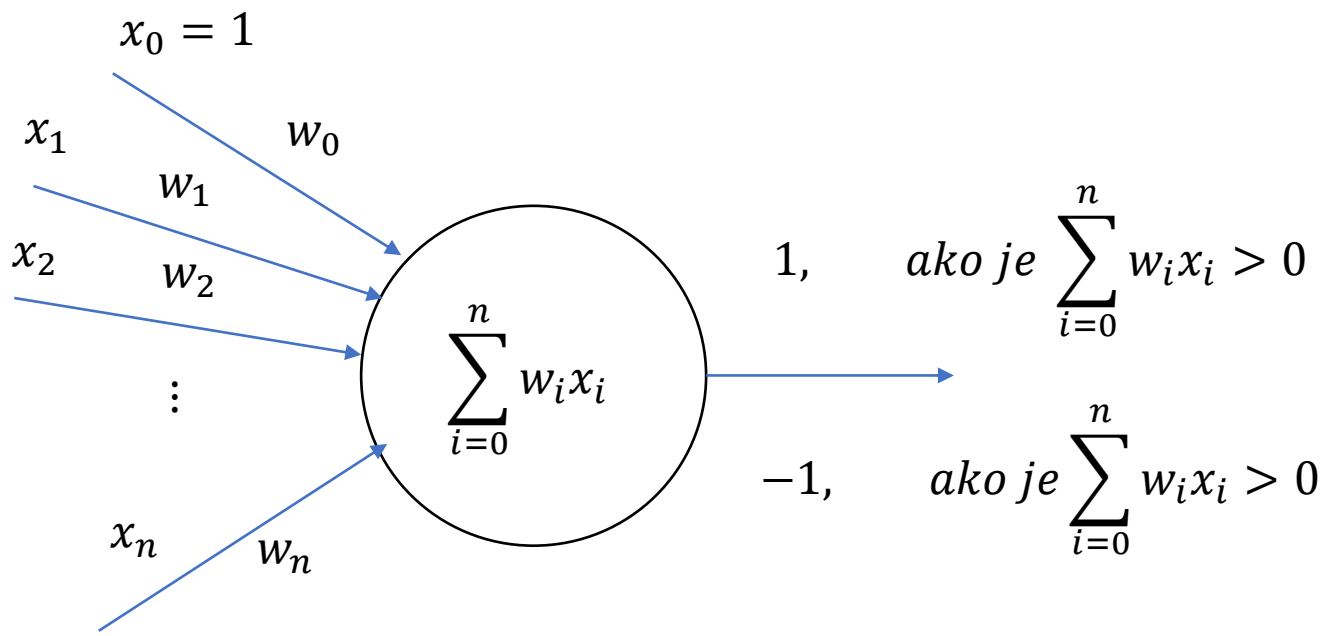


$$1, \quad ako\ je \sum_{i=0}^{n} w_i x_i > 0$$

$$-1, \quad ako\ je \sum_{i=0}^{n} w_i x_i < 0$$

$$a = \sum_{i=0}^{n} w_i x_i$$

Perceptron



$$1, \quad ako\ je \sum_{i=0}^{n} w_i x_i > 0$$

$$-1, \quad ako\ je \sum_{i=0}^{n} w_i x_i > 0$$

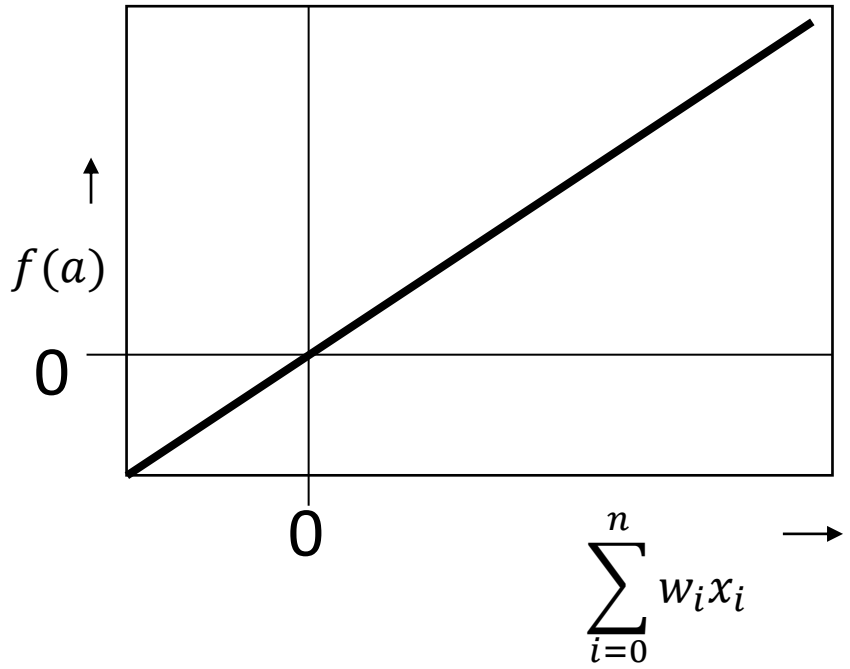
$$a = \sum_{i=0}^{n} w_i x_i$$

$$f(a)$$

Linearna aktivacionа funkcija

- Jednostavni, ali ograničenih mogućnosti

$$f(a) = \sum_{i=0}^{n} w_i x_i$$



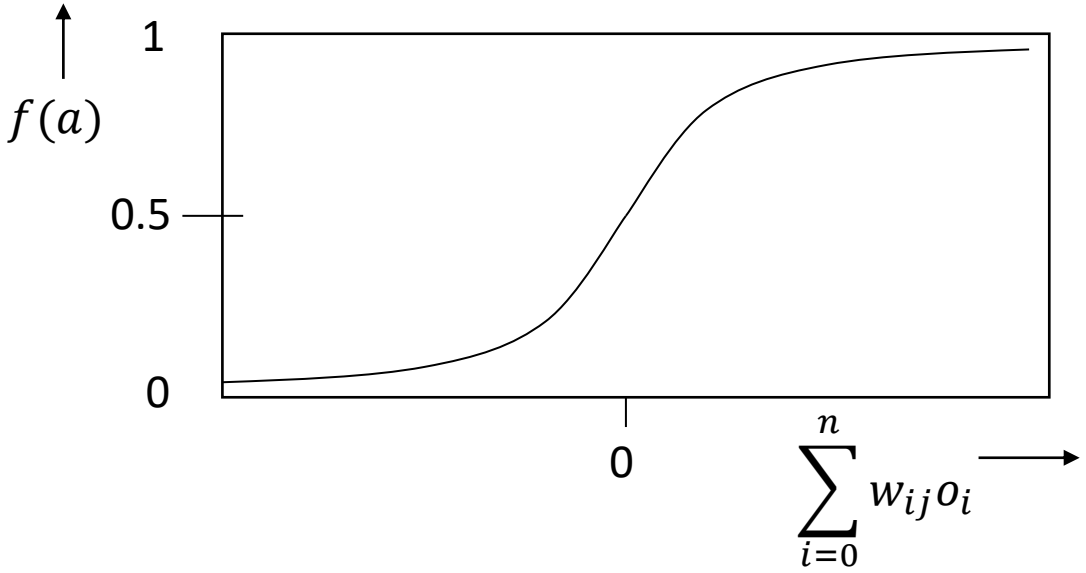
Sigmoid aktivacionom funkcijom

- Glatka, neprekidna funkcija.
- Izlaz je realan broj.
- Lepi izvodi.

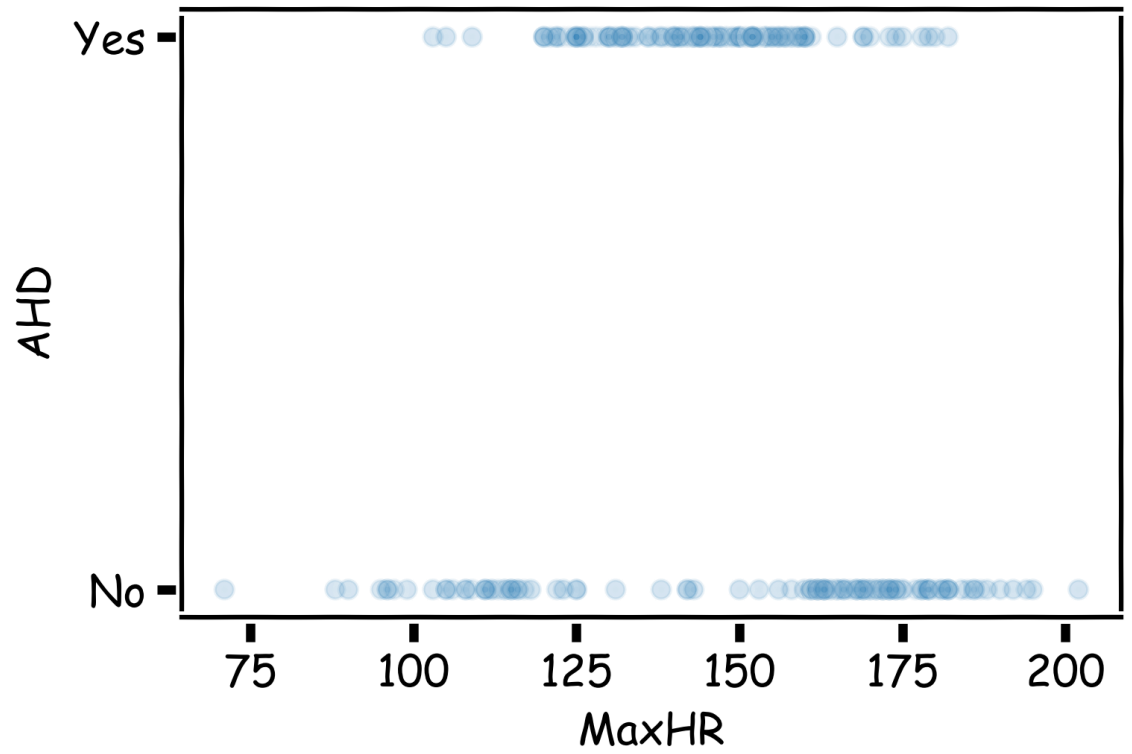
$$f(a) = \frac{1}{1 + e^{-a}}$$

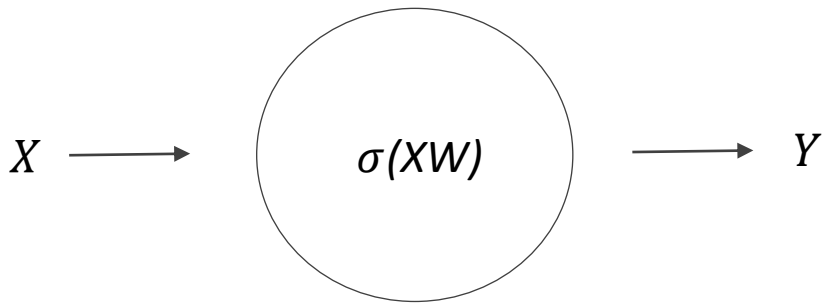
$$f' = f(1 - f)$$

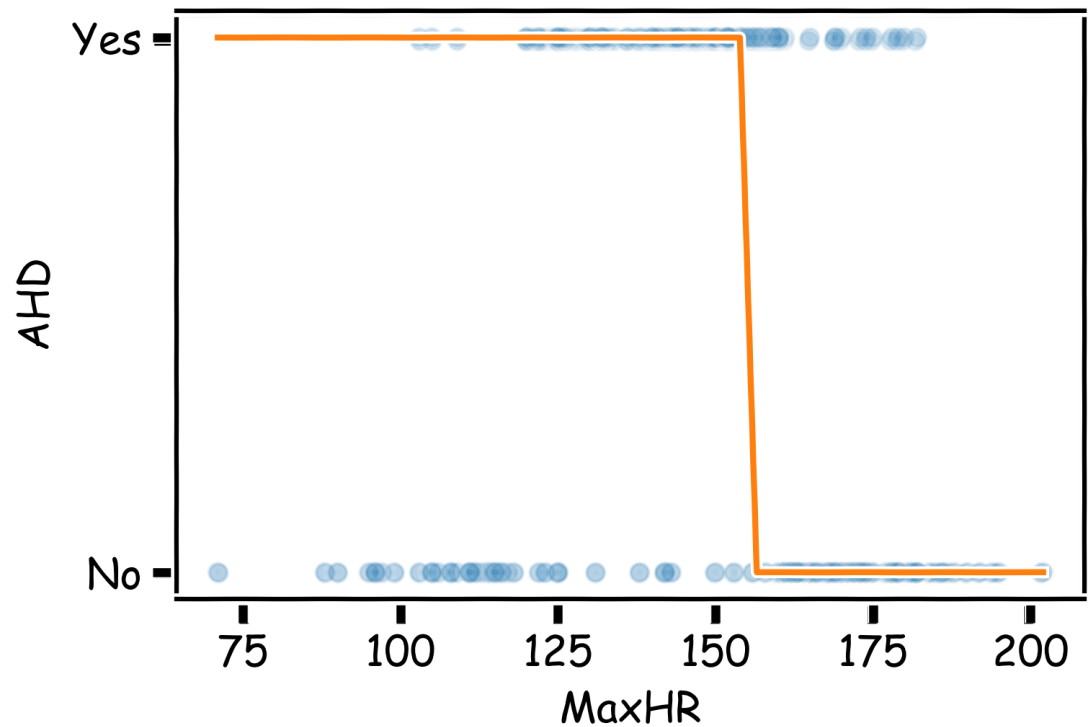
$$a = \sum_{i=0}^{n} w_i x_i$$

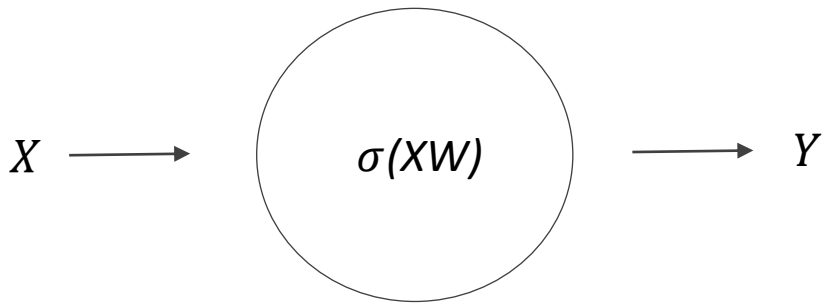


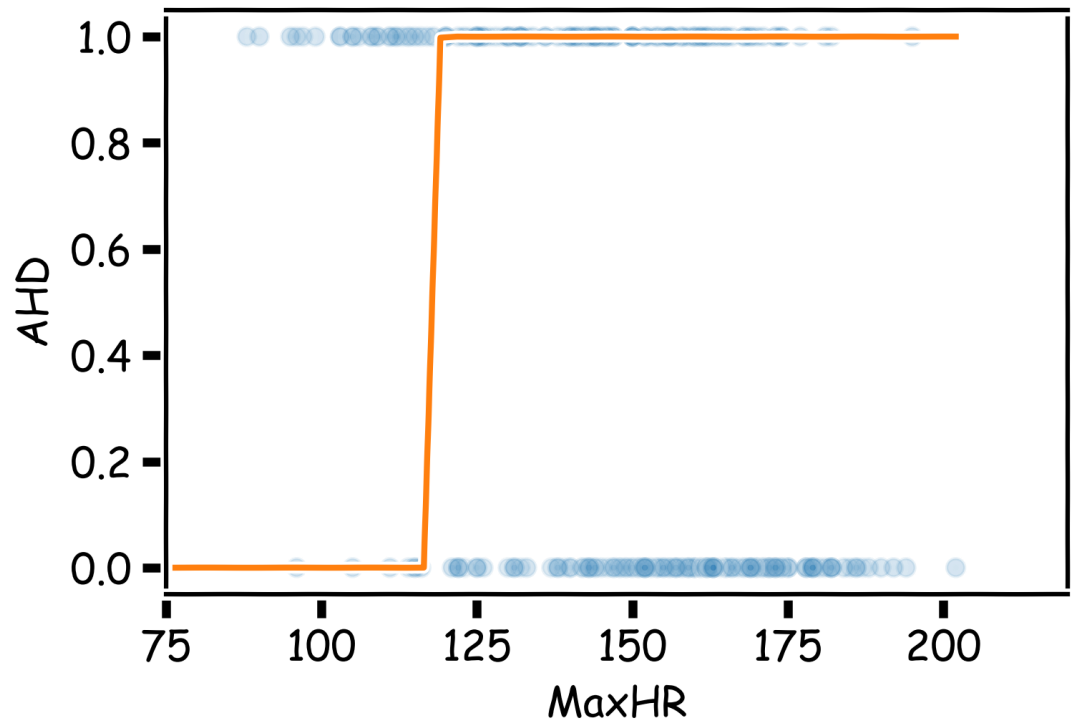
Primer podataka

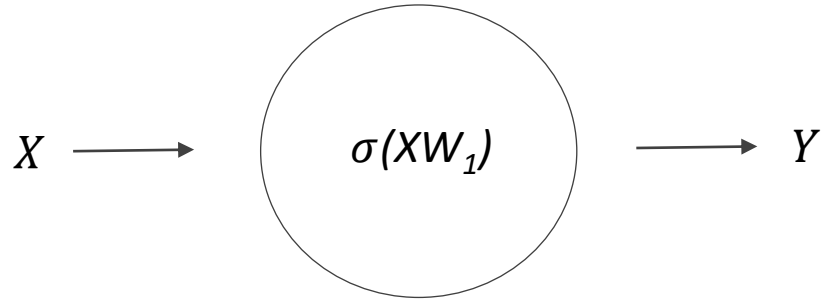


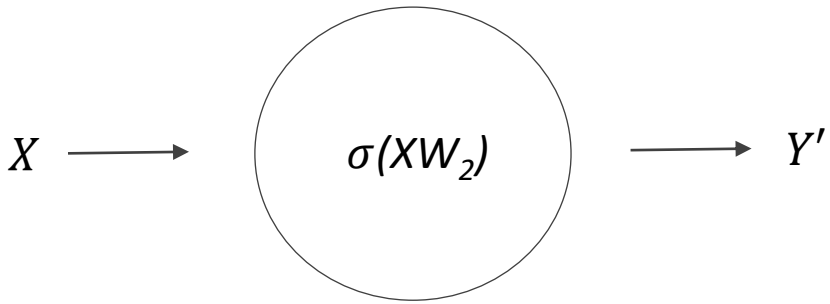

X
σ(XW)
Y

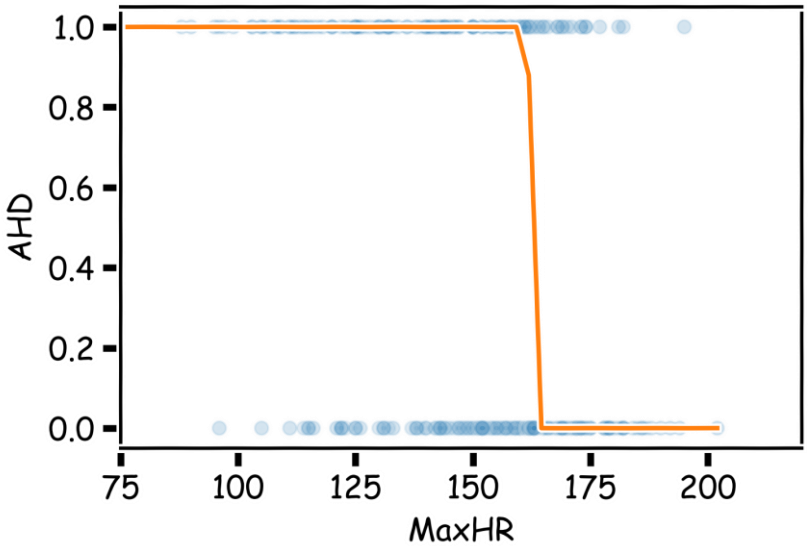

Yes
No
AHD
75
100
125
150
175
200
MaxHR

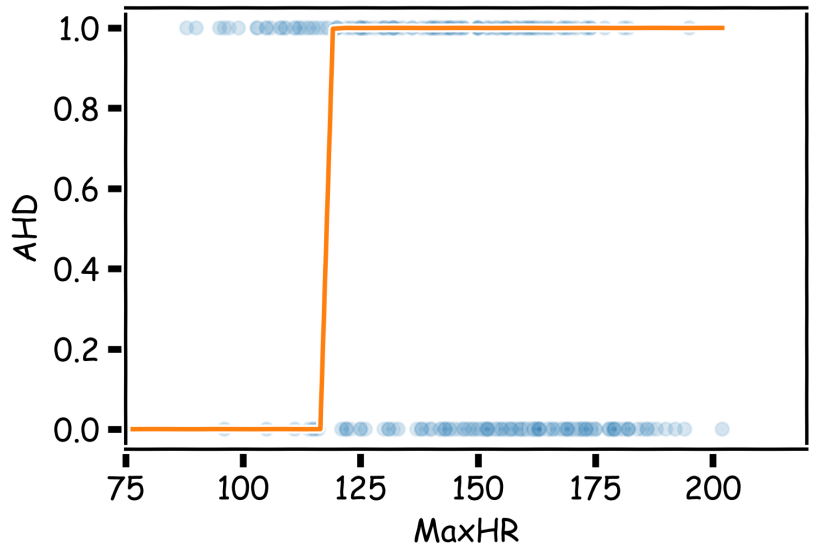

X
σ(XW)
Y

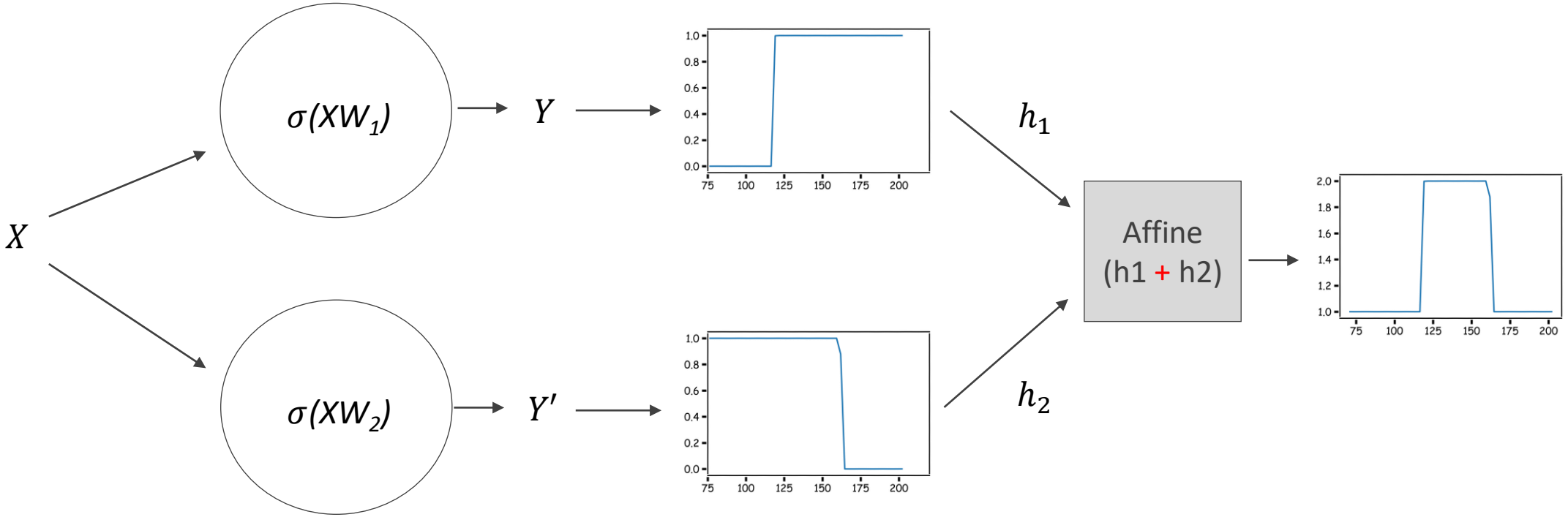

1.0
0.8
0.6
0.4
0.2
0.0
AHD
75
100
125
150
175
200
MaxHR

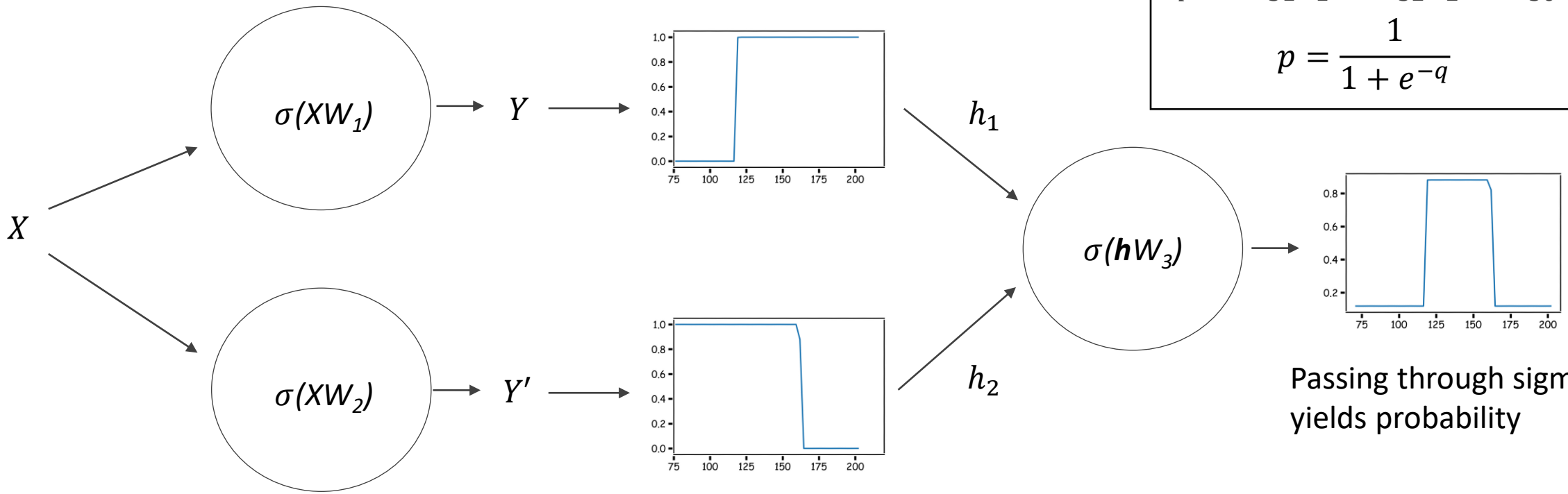

X
σ(XW1)
Y


X
σ(XW2)
Y′


AHD
1.0
0.8
0.6
0.4
0.2
0.0
75
100
125
150
175
200
MaxHR


AHD
1.0
0.8
0.6
0.4
0.2
0.0
75
100
125
150
175
200
MaxHR


X
$\sigma(XW_1)$
$\sigma(XW_2)$
Y
Y'
h_1
h_2
Affine
(h1 + h2)



$$q = W_{31}h_1 + W_{32}h_2 + W_{30}$$

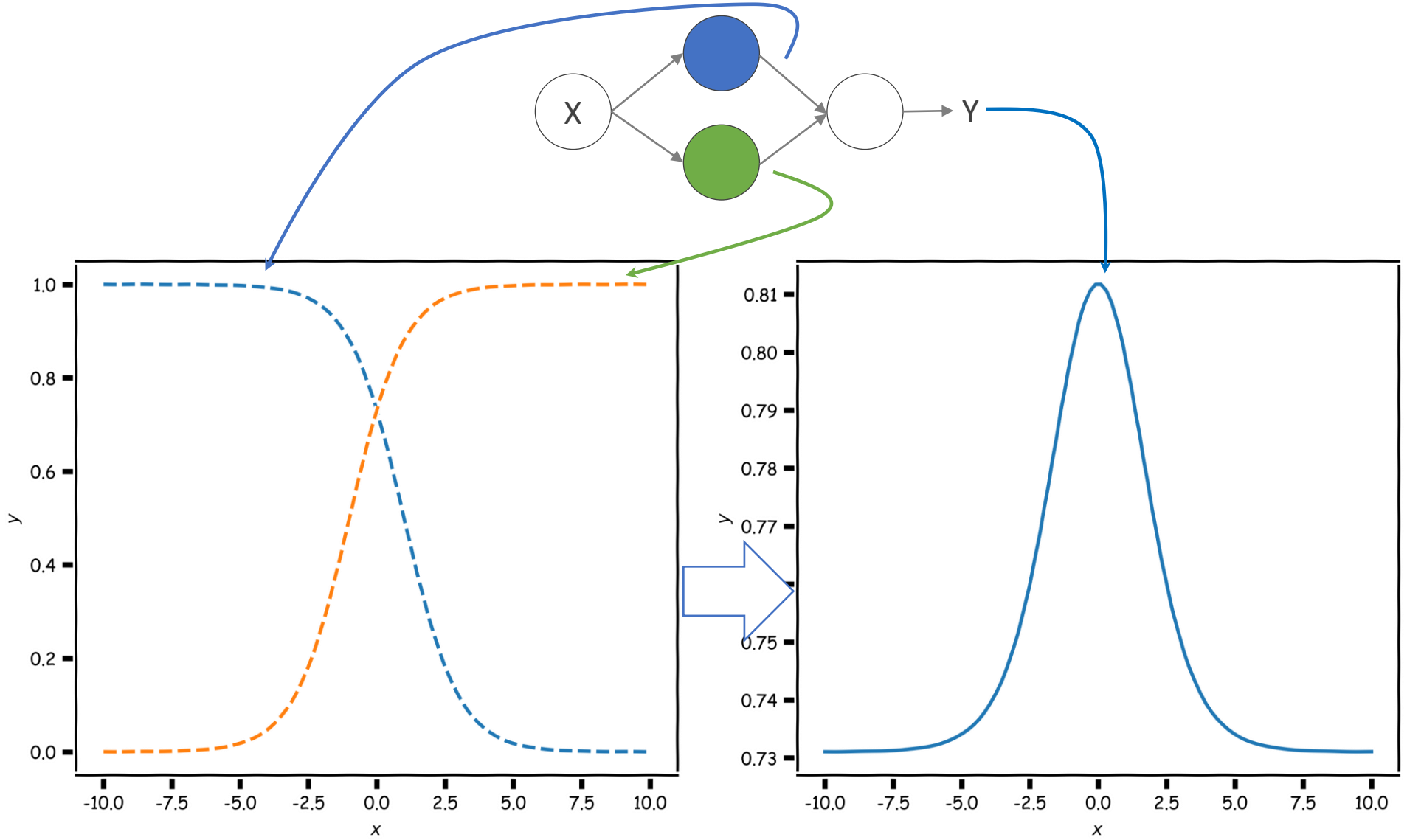
$$p = \frac{1}{1 + e^{-q}}$$

Passing through sigmoid yields probability

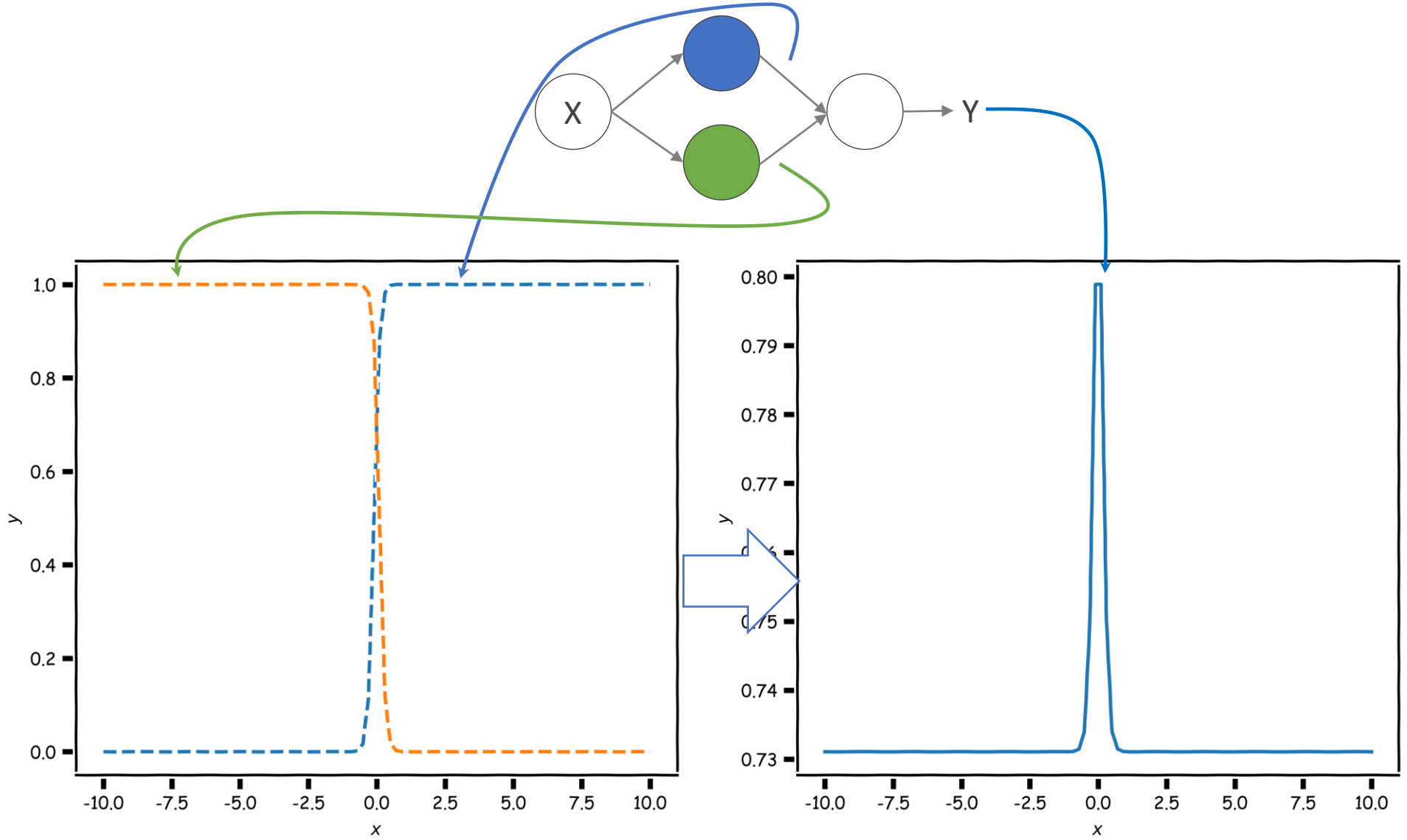
$$L = -y\ln(\mathrm{p}) - (1 - \mathrm{y})\ln(1 - \mathrm{p})$$

Need to learn W1, W2 and W3.

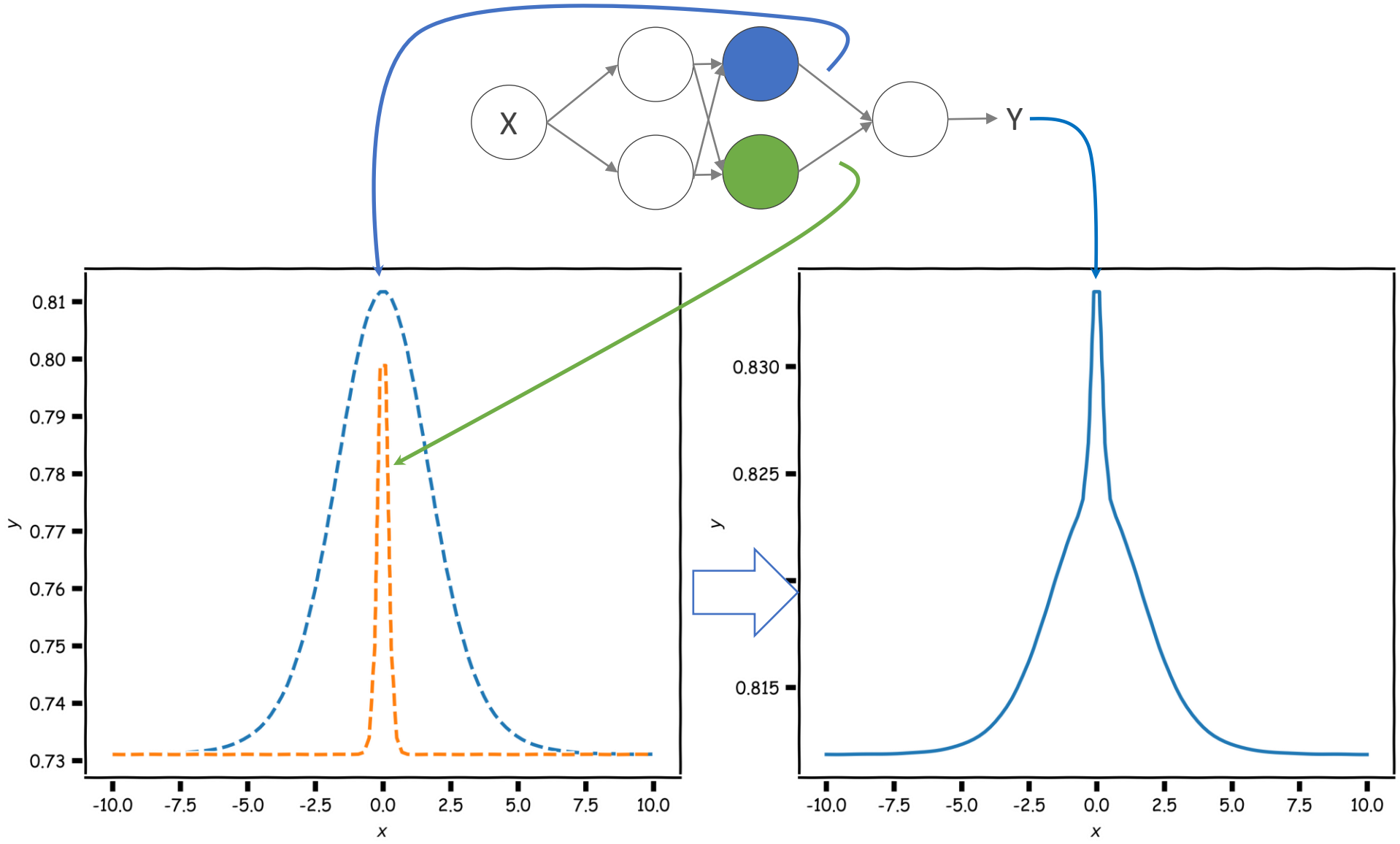
Combining neurons allows us to model interesting functions



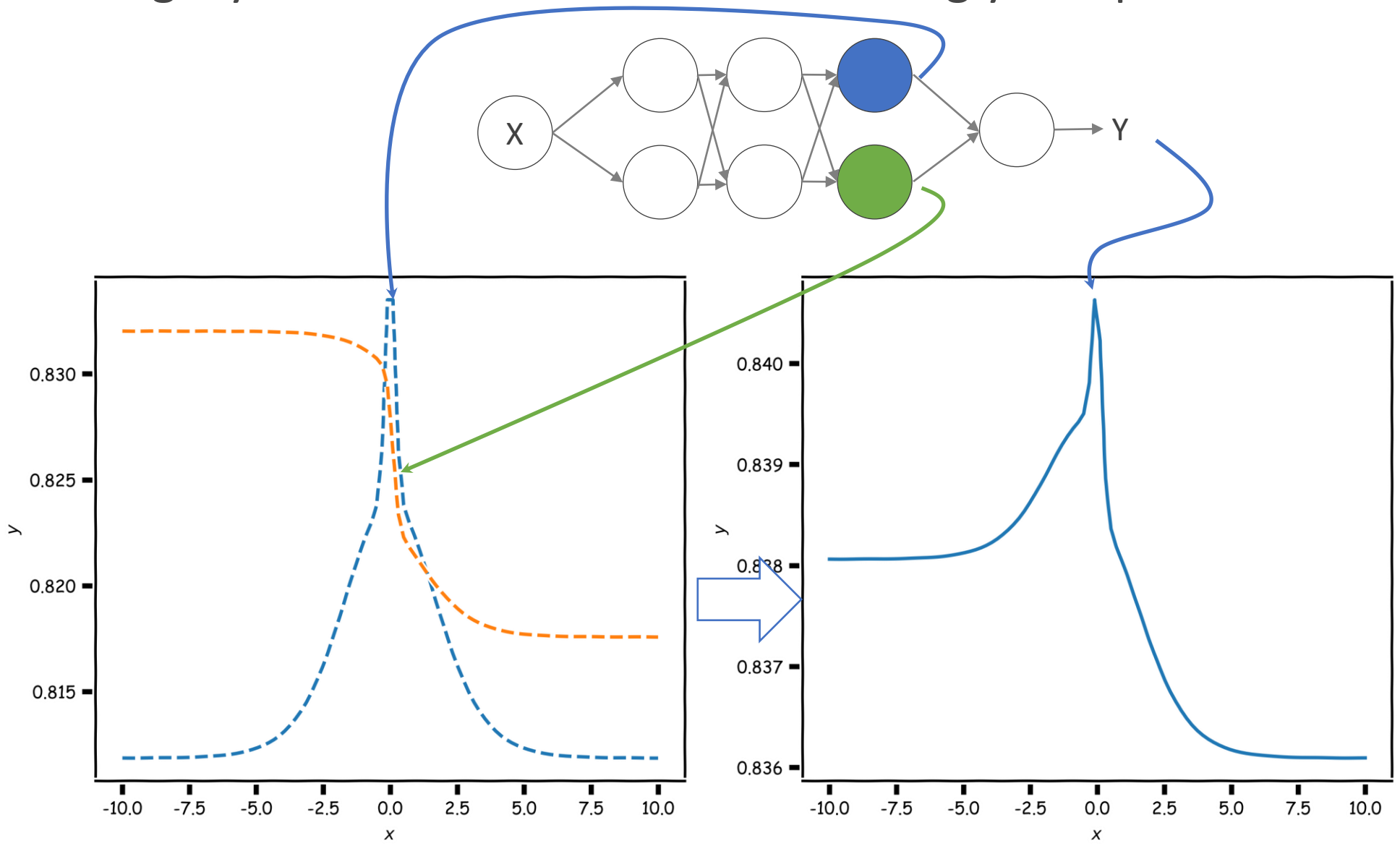
Different weights change the shape and position



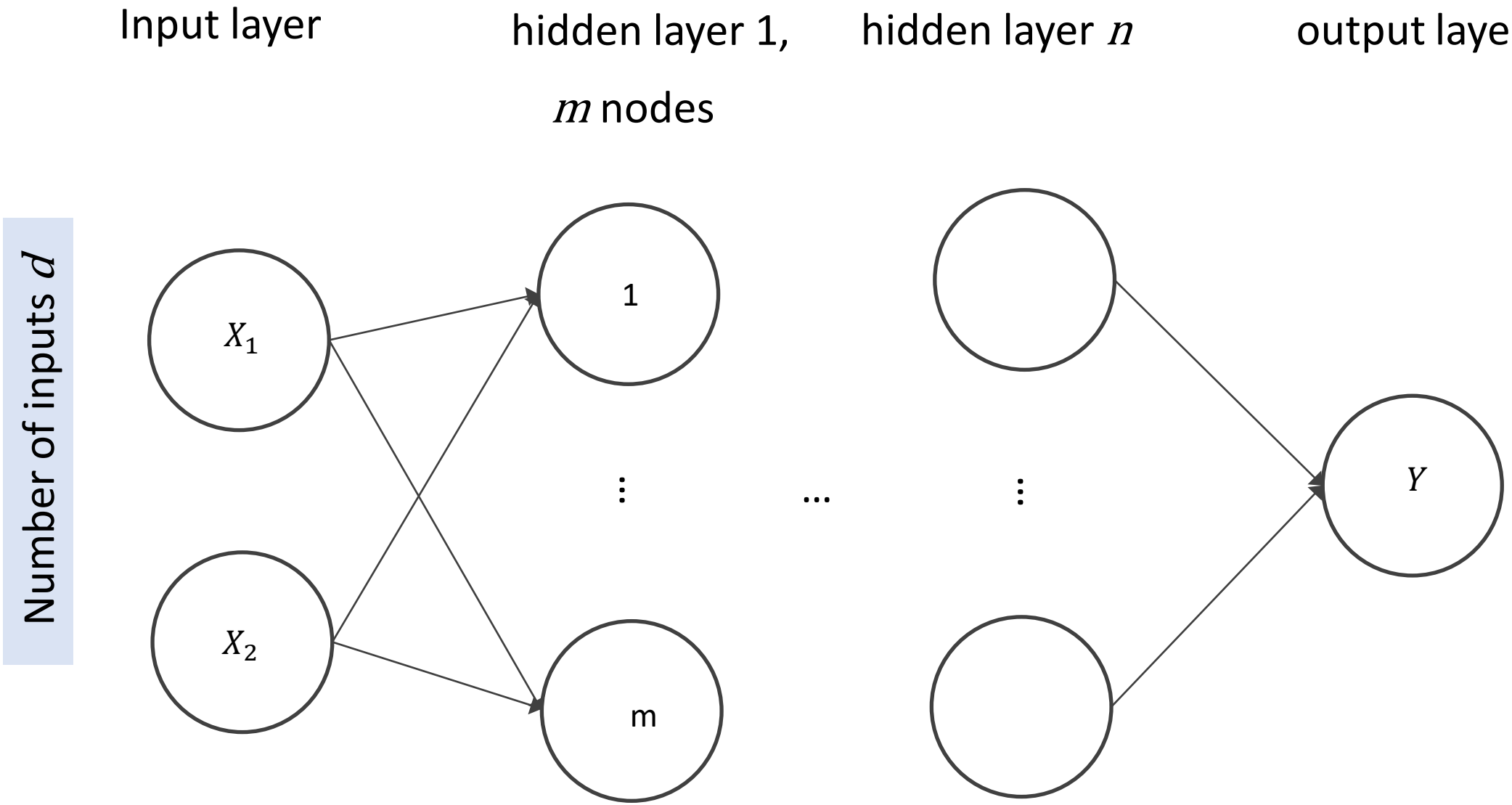
Neural networks can model *any* reasonable function



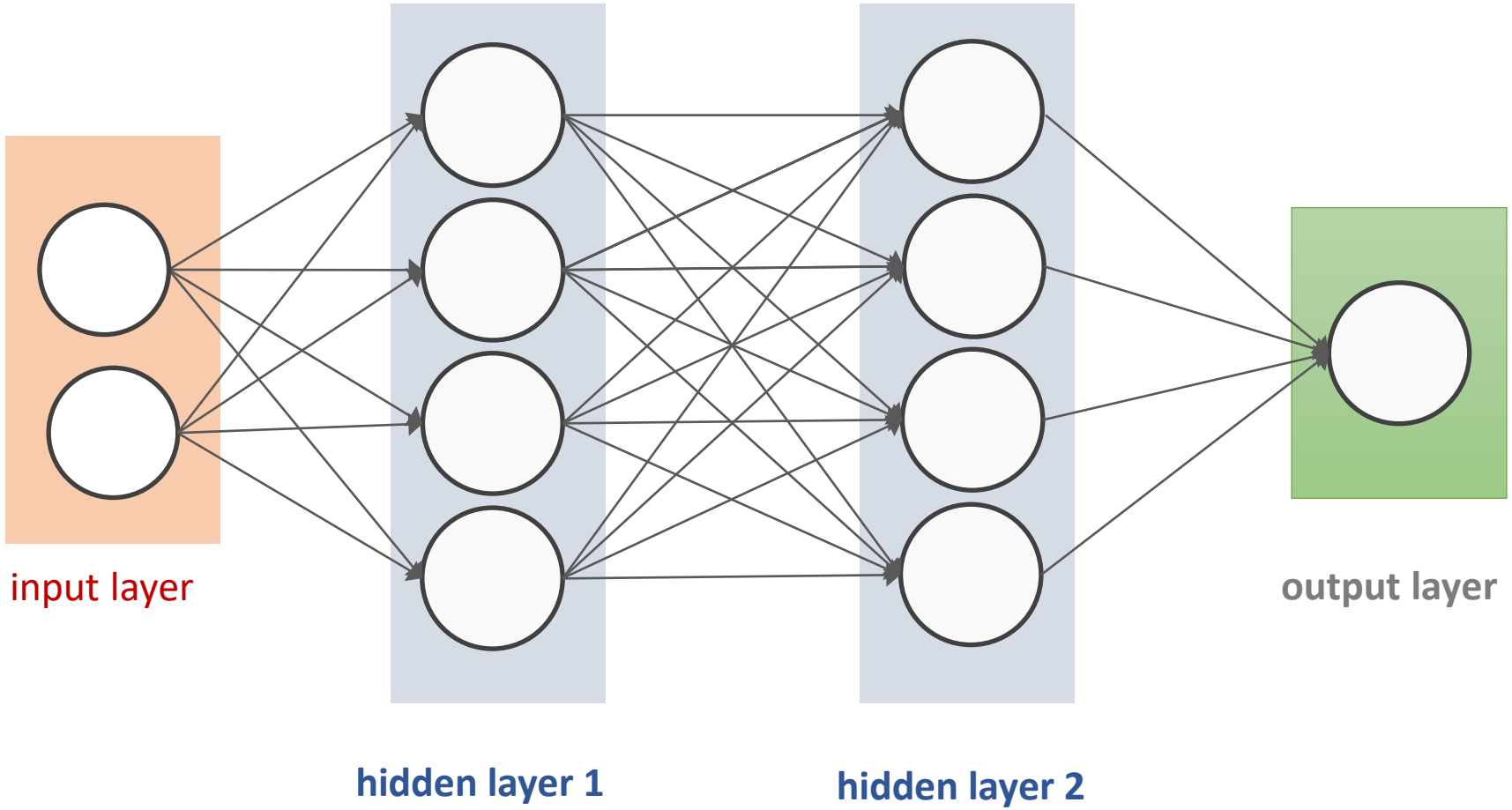
Adding layers allows us to model increasingly complex functions



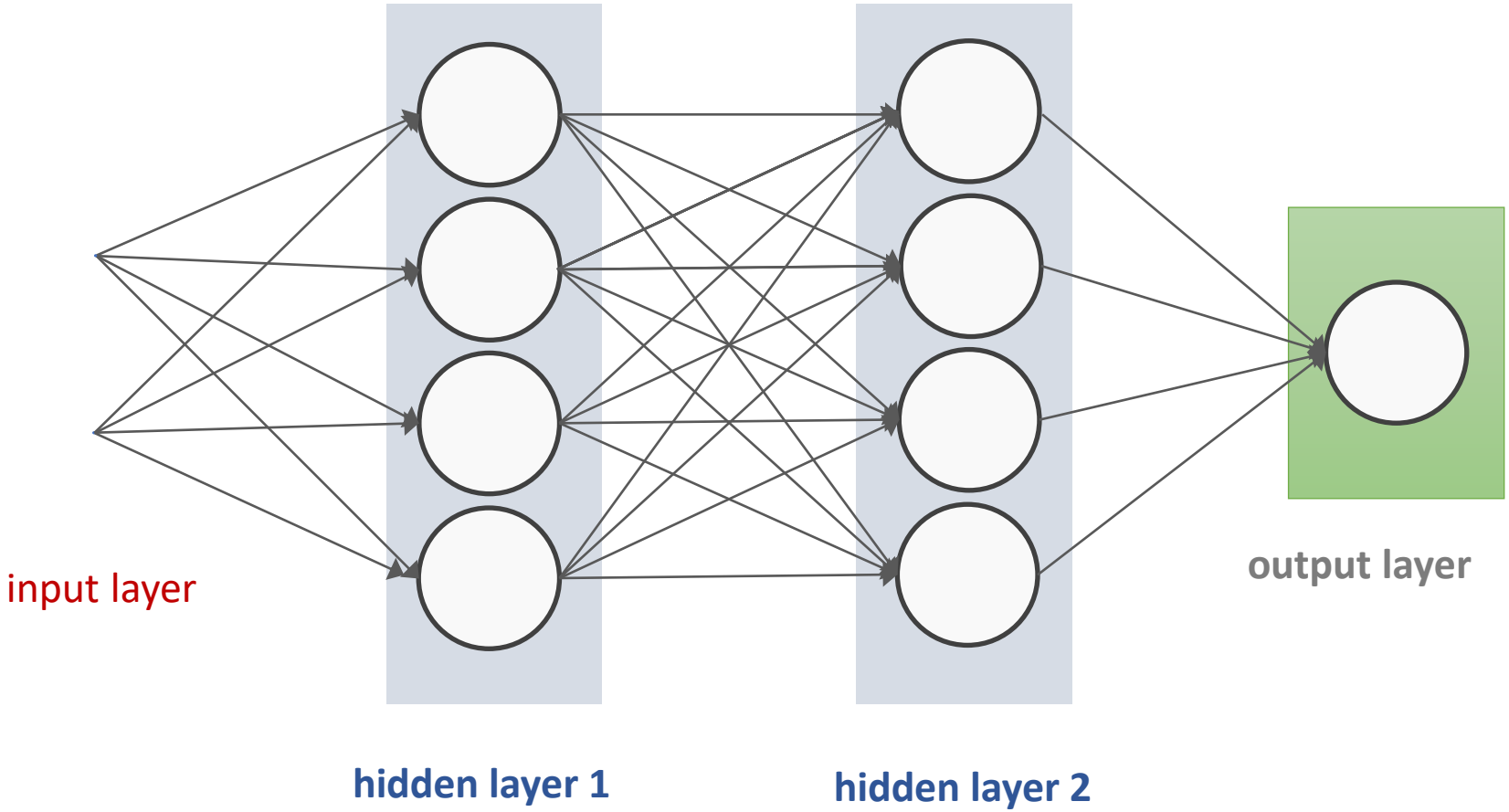
Artificial neural network (ANN)



Artificial neural network (ANN)



Artificial neural network (ANN)



Opcije za dizajniranje ANN

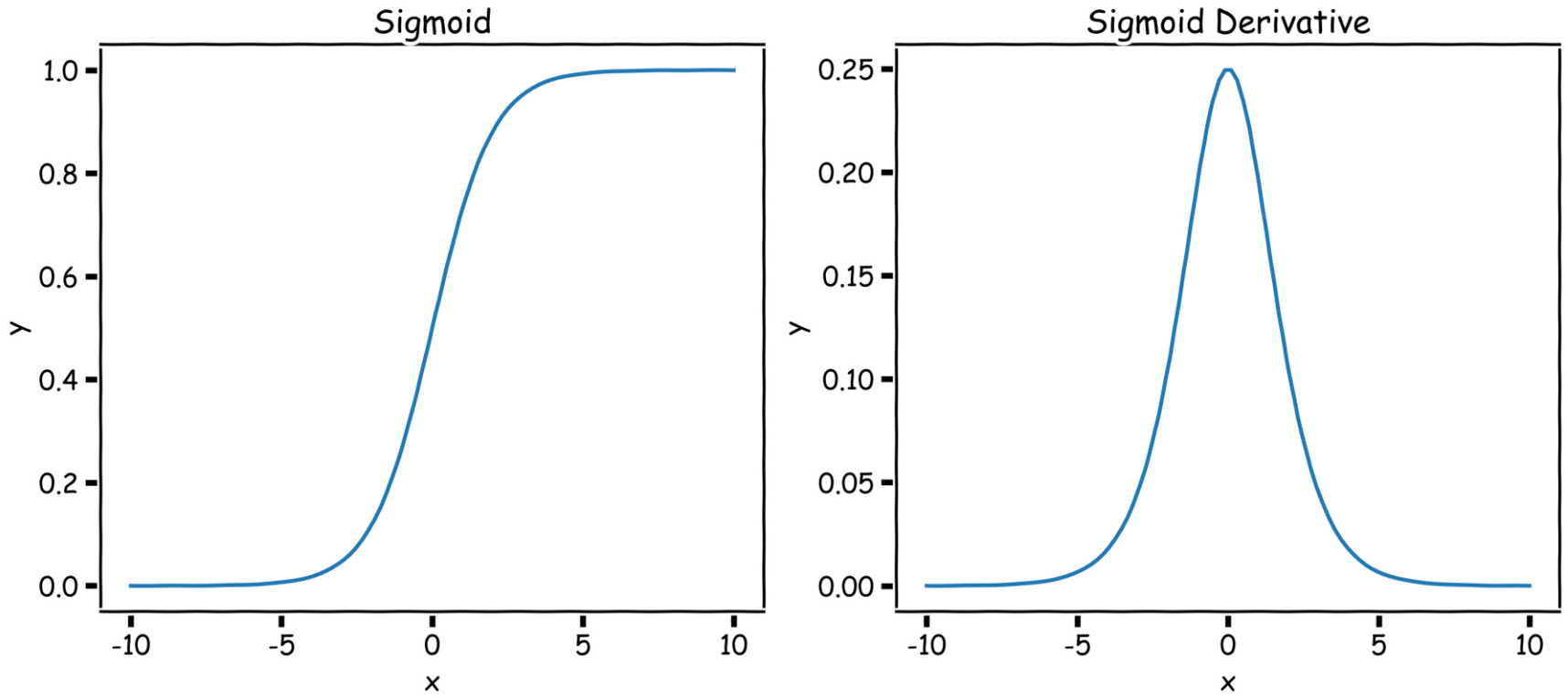
- Izbor aktivacione funkcije (Activation function)
- Izbor funkcije gubitka (Loss function)
- Izlazni neuroni (Output units)
- Arhitektura

Opcije za dizajniranje ANN

- **Izbor aktivacione funkcije**
  - **Nelinearnost**
  - **Nenula gradijenti u skrivenim čvorovima**
- Izbor funkcije gubitka (Loss function)
- Izlazni neuroni (Output units)
- Arhitektura

Sigmoid

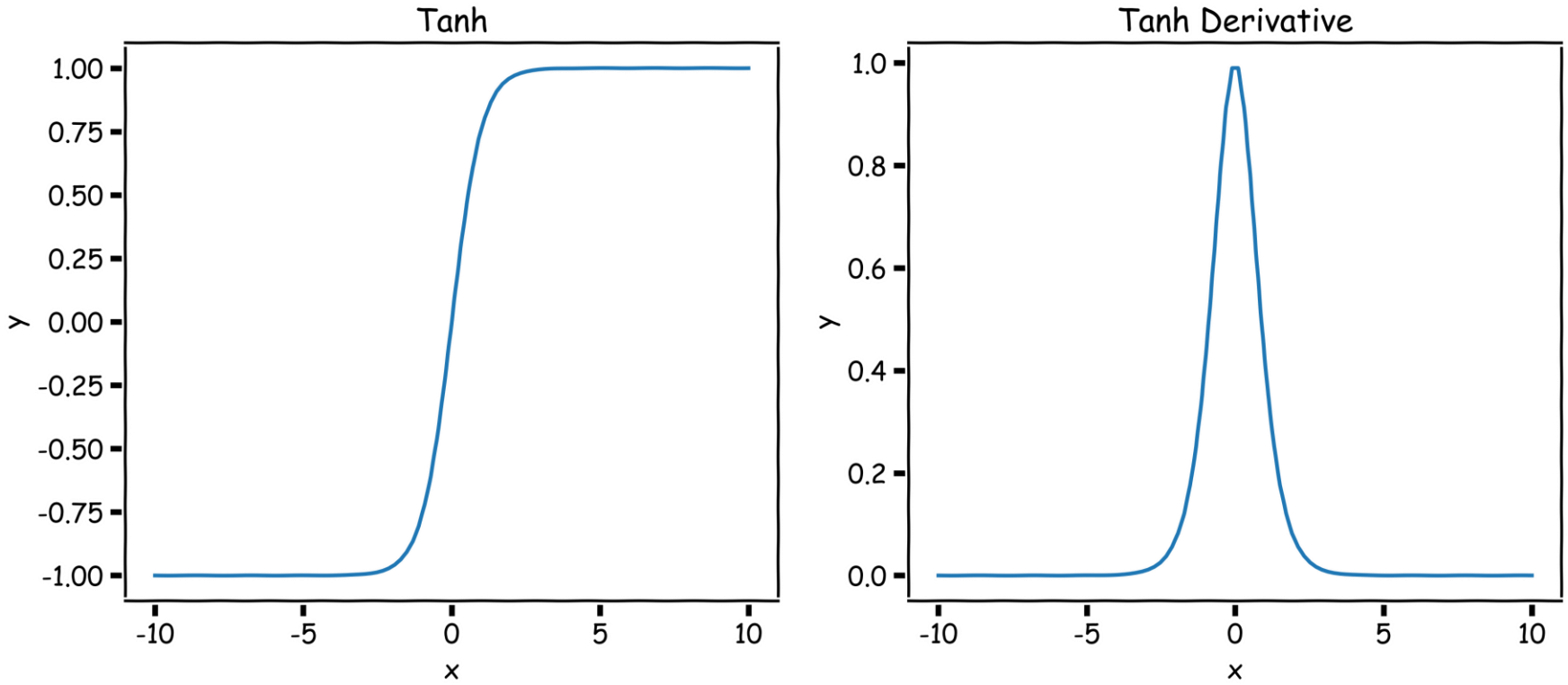
$$y = \frac{1}{1 + e^{-x}}$$



Derivative is **zero** for much of the domain. This leads to “vanishing gradients” in backpropagation.

Tangens hiperbolični (Tanh)

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

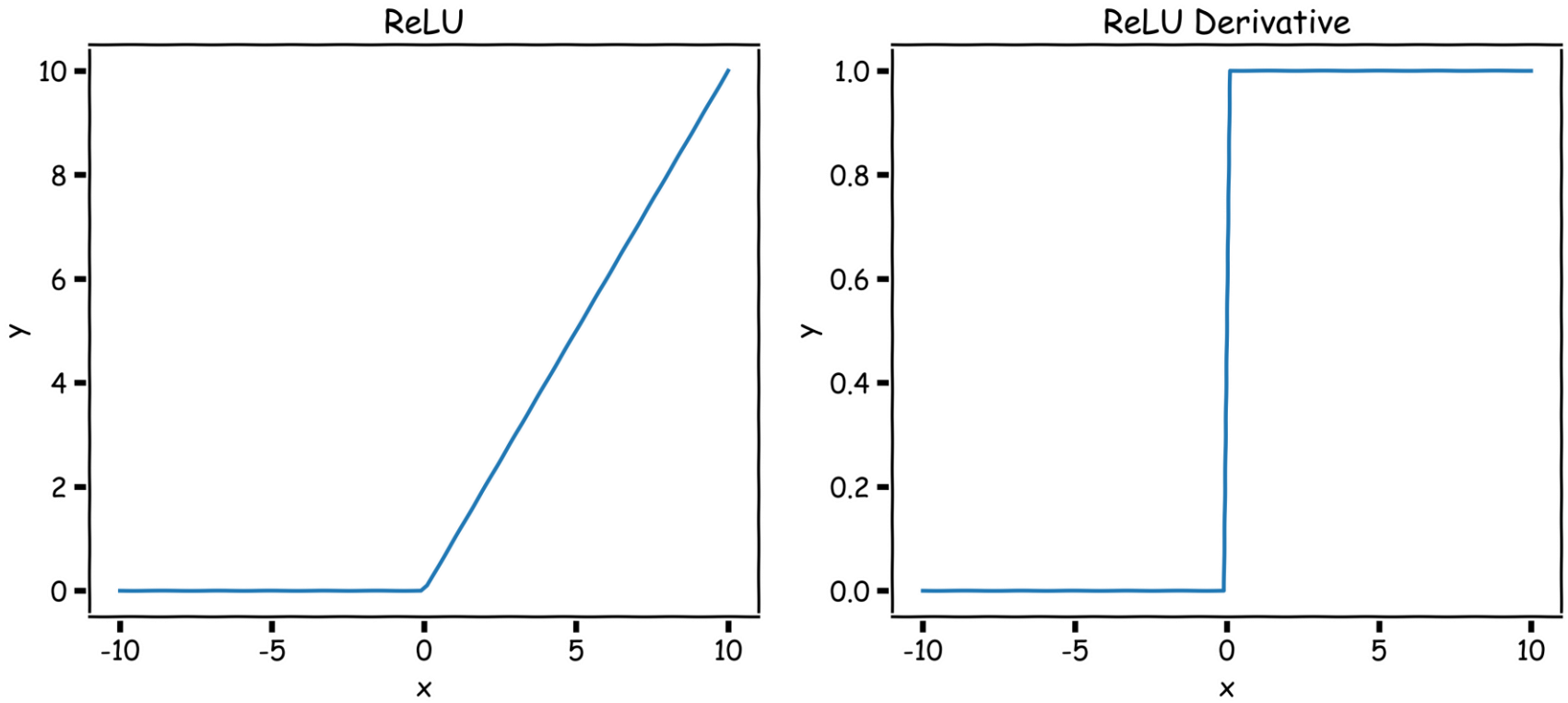


$y' = 1 - y^2$

Same problem of “vanishing gradients” as sigmoid.

Rectified Linear Unit (ReLU)

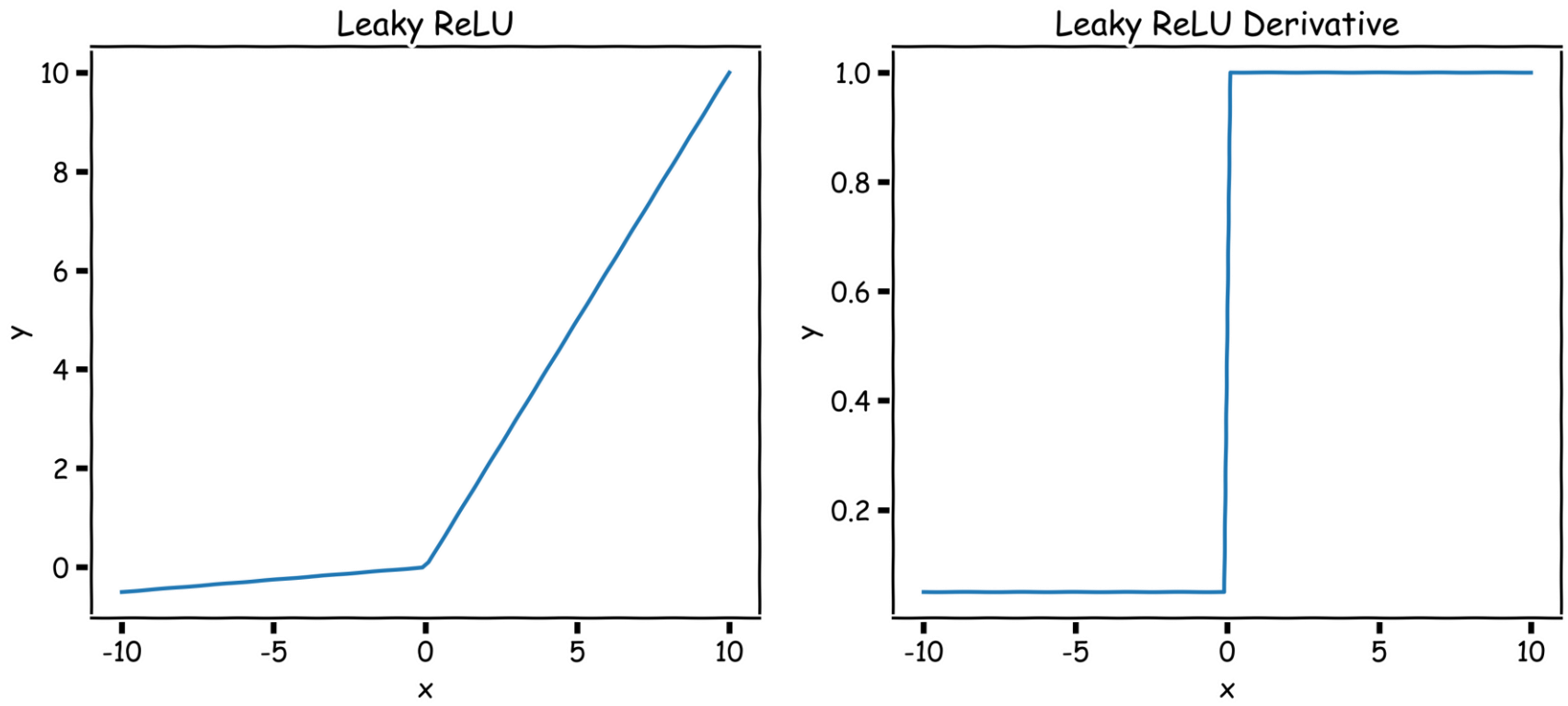
$$y = \max(0, x)$$



No vanishing gradient when x > 0

Leaky ReLU

$$y = \max(0, x) + \alpha \min(0,1)$$
where α takes a small value



- Tries to fix "dying ReLU" problem: derivative is non-zero everywhere.
- Some people report success with this form of activation function, but the results are not always consistent

Opcije za dizajniranje ANN

- Izbor aktivacione funkcije (Activation function)
- Izbor funkcije gubitka (Loss function)
  - Zavisi od tipa problema
    - Binarna klasifikacija – Binary cross entropy
    - Višeklasna klasifikacija – Cross entropy
    - Regresija - MSE
- Izlazni neuroni (Output units)
- Arhitektura

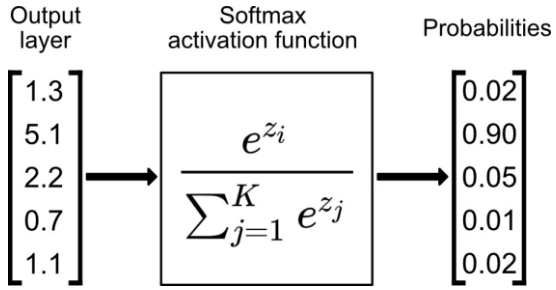
$$L = -\frac{1}{m}\sum_{i=1}^{m} y_i \cdot \log(\hat{y}_i)$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

Opcije za dizajniranje ANN

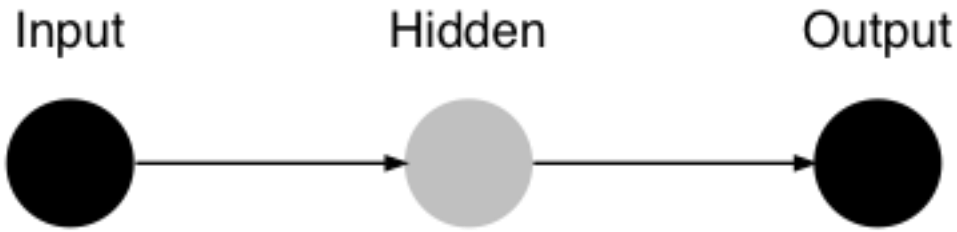
- Izbor aktivacione funkcije (Activation function)
- Izbor funkcije gubitka (Loss function)
- Izlazni neuroni (Output units)
  - Zavisi od tipa problema
    - Binarna klasifikacija – Sigmoid
    - Višeklasna klasifikacija – Softmax
    - Regresija - Linear
- Arhitektura

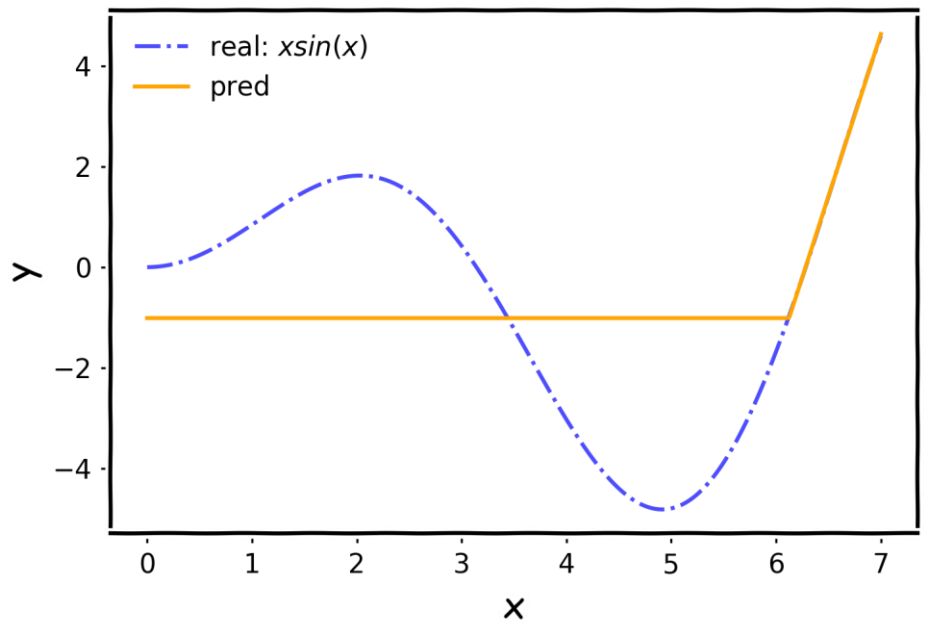
$$y = \frac{e^{z_k}}{\sum_{i=1}^{K} e^{z_i}}$$

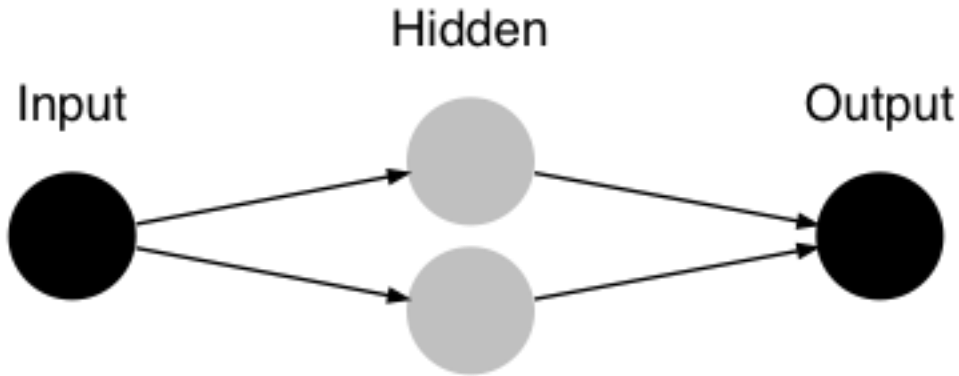


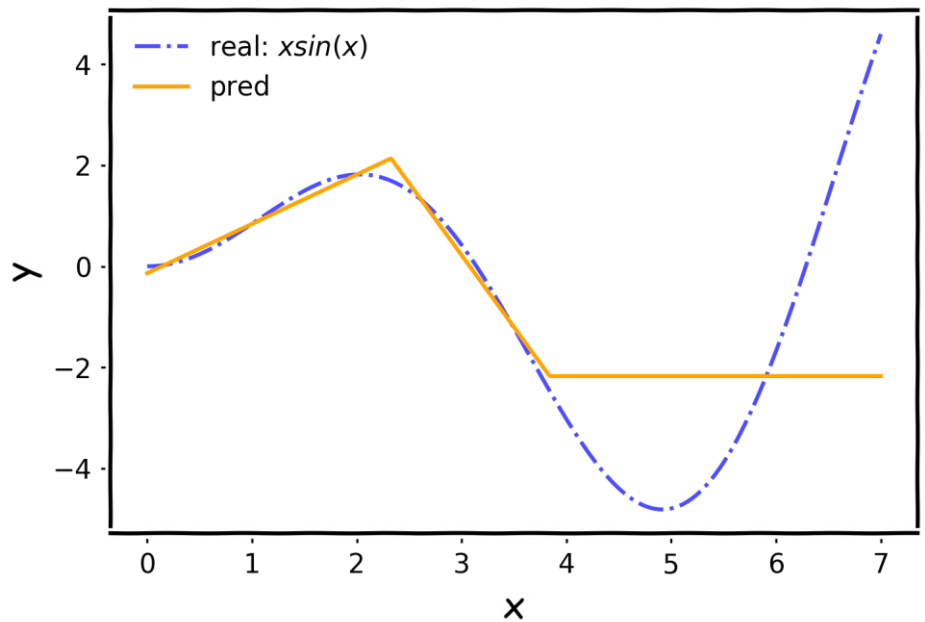
Opcije za dizajniranje ANN

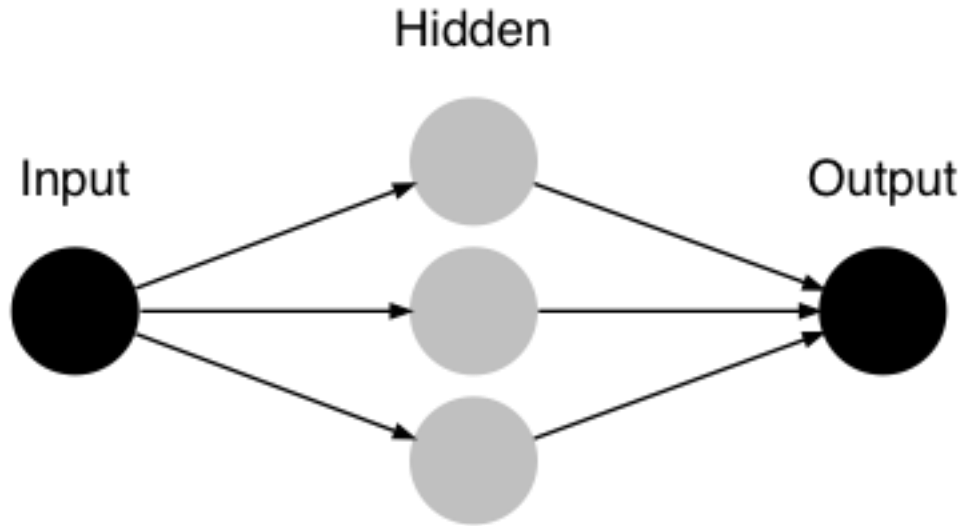
- Izbor aktivacione funkcije (Activation function)
- Izbor funkcije gubitka (Loss function)
- Izlazni neuroni (Output units)
- **Arhitektura**

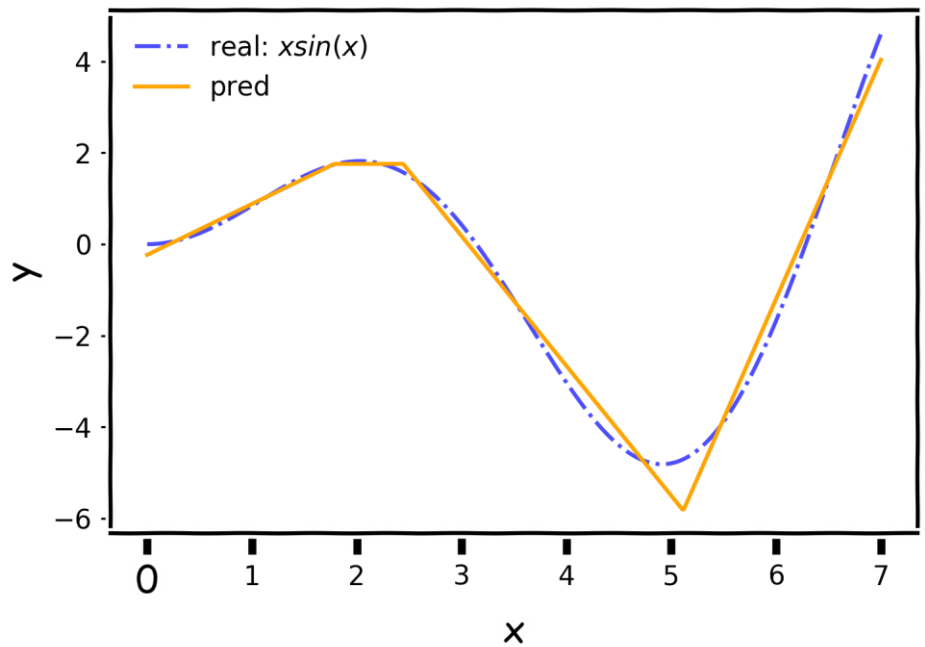

Input
Hidden
Output

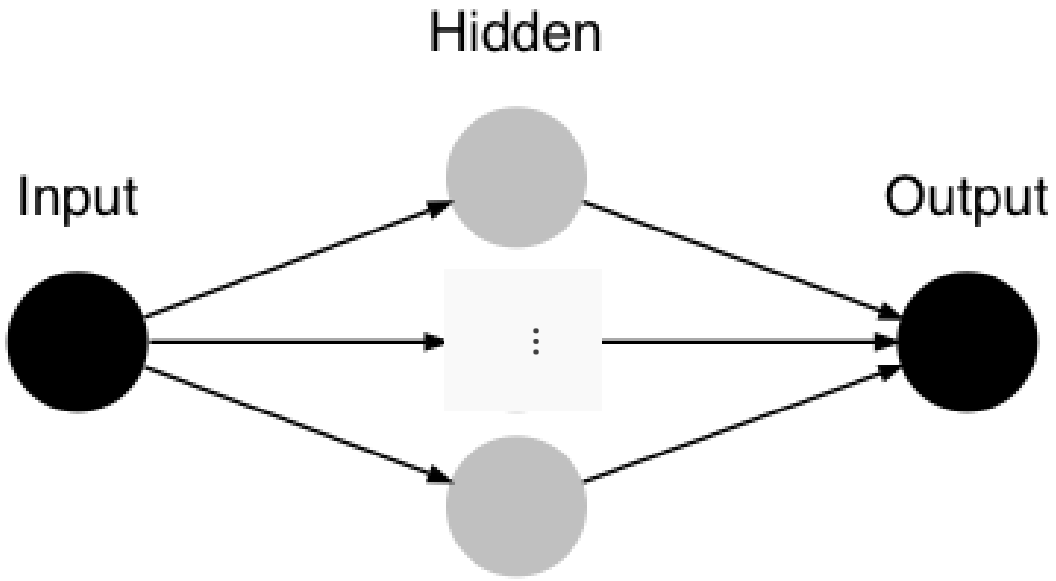

real: xsin(x)
pred
4
2
0
−2
−4
y
0
1
2
3
4
5
6
7
x

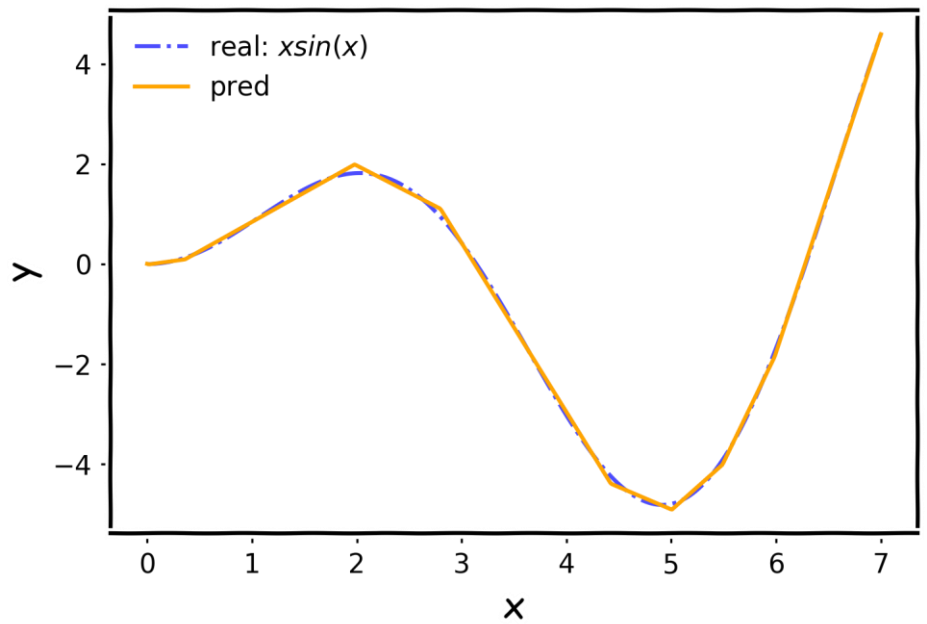

Hidden
Input
Output

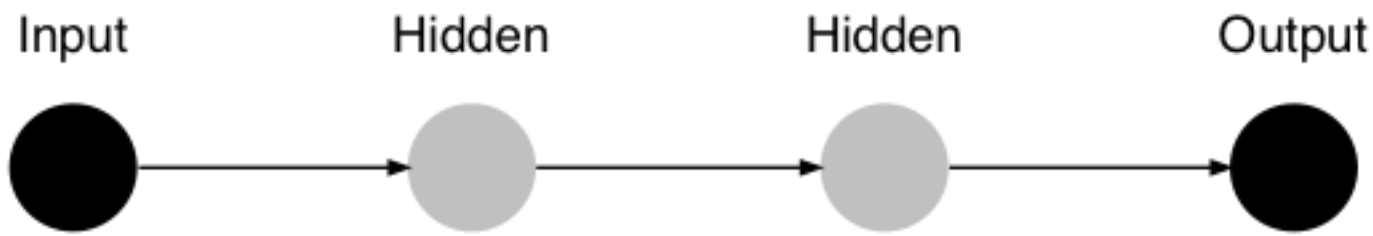

real: xsin(x)
pred
4
2
0
−2
−4
y
0
1
2
3
4
5
6
7
x

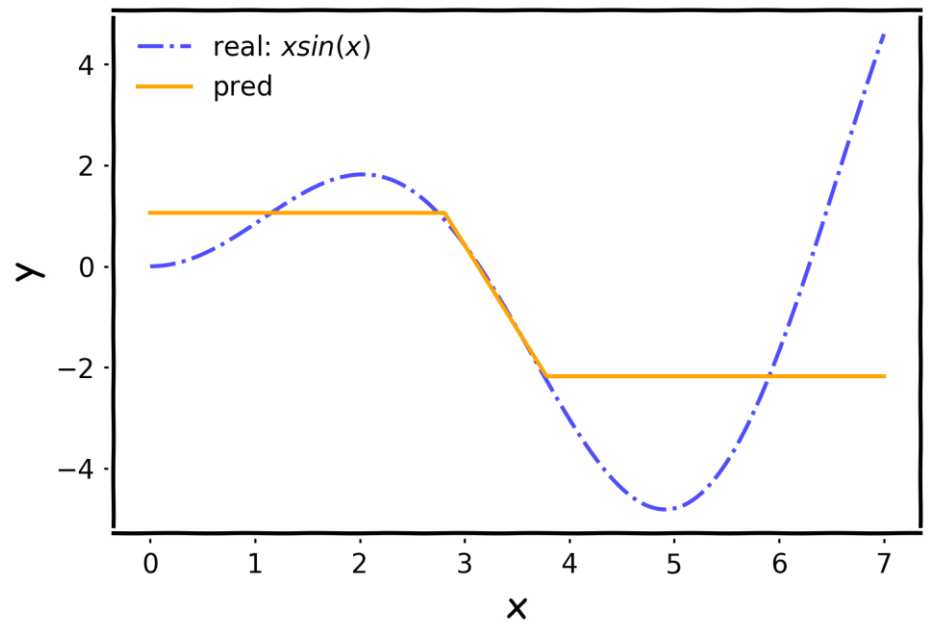

Hidden
Input
Output

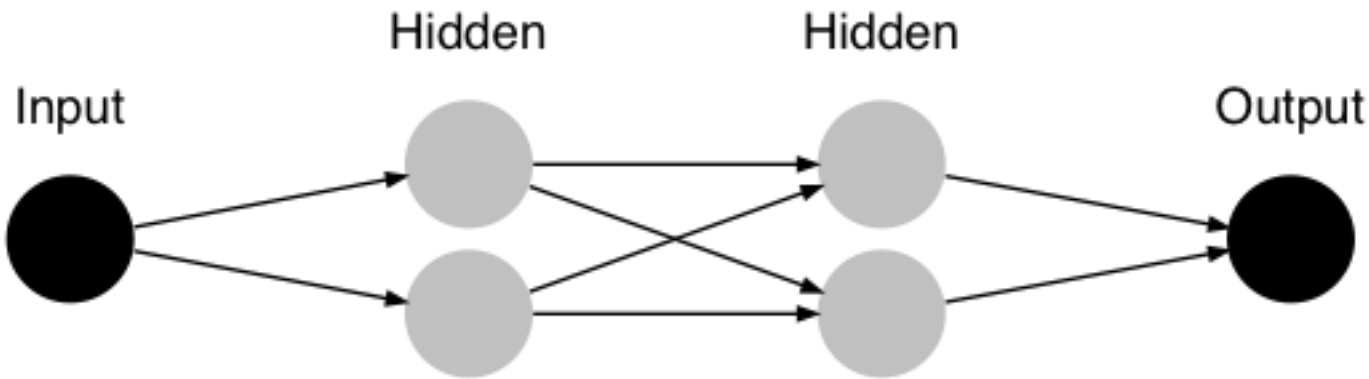

real: xsin(x)
pred
4
2
0
−2
−4
−6
y
0
1
2
3
4
5
6
7
x

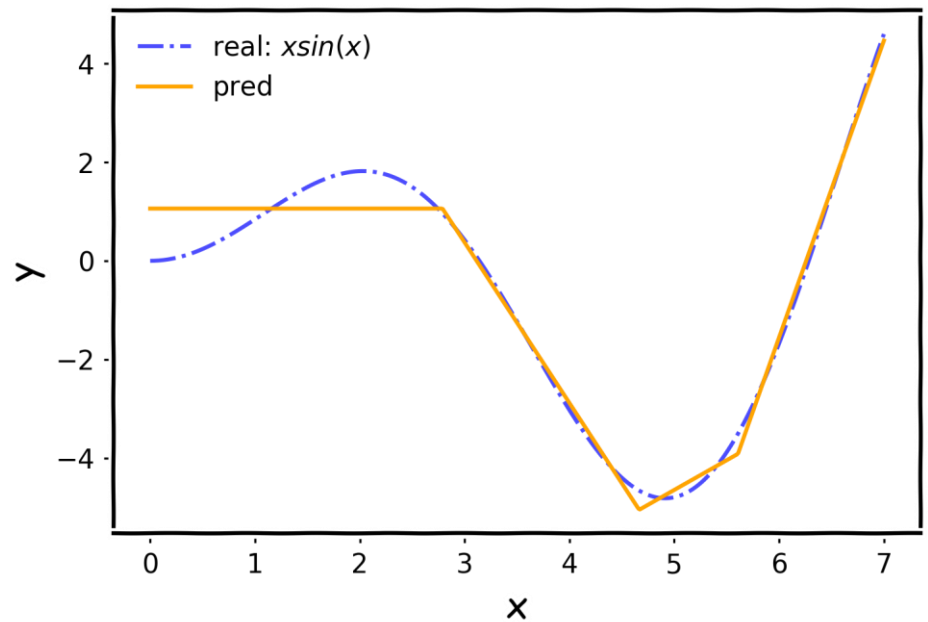

Hidden
Input
Output

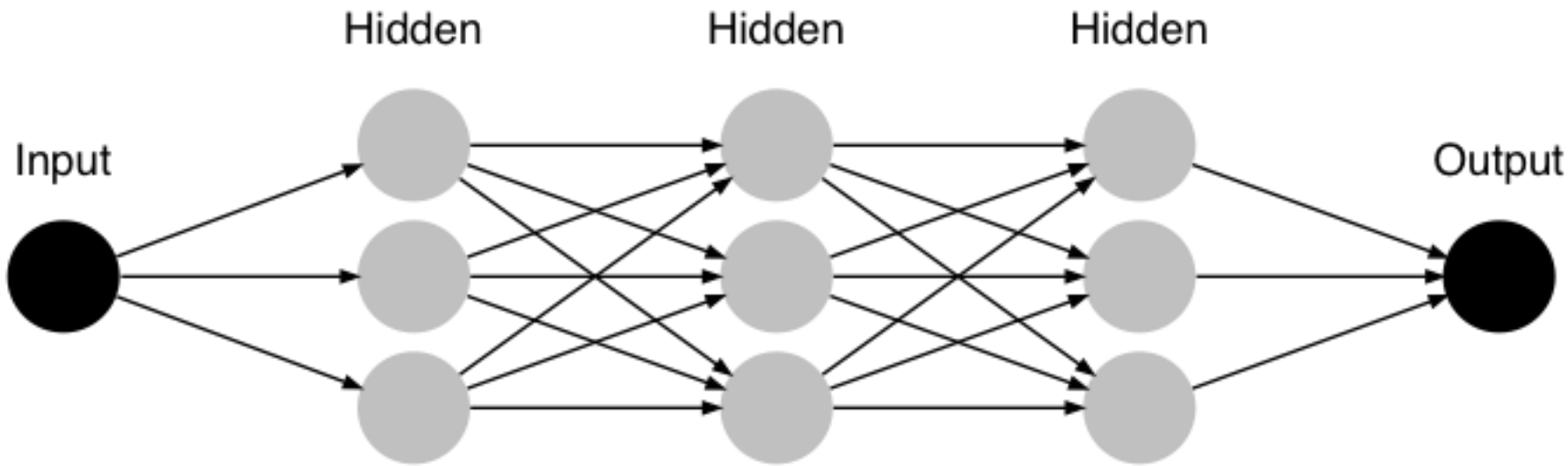

real: xsin(x)
pred
4
2
0
−2
−4
y
0
1
2
3
4
5
6
7
x

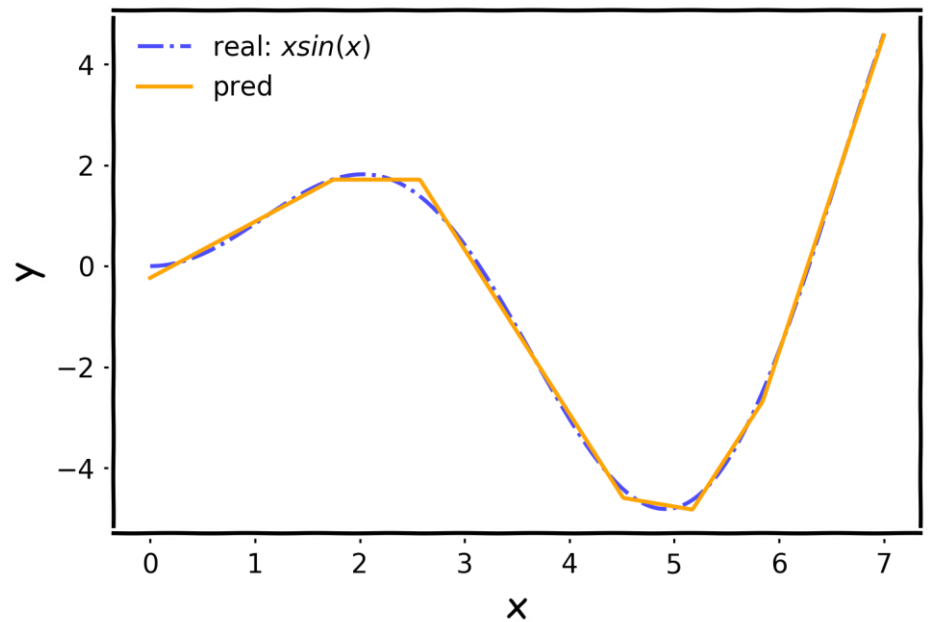

Input
Hidden
Hidden
Output


real: xsin(x)
pred
4
2
0
−2
−4
y
0
1
2
3
4
5
6
7
x


Input
Hidden
Hidden
Output

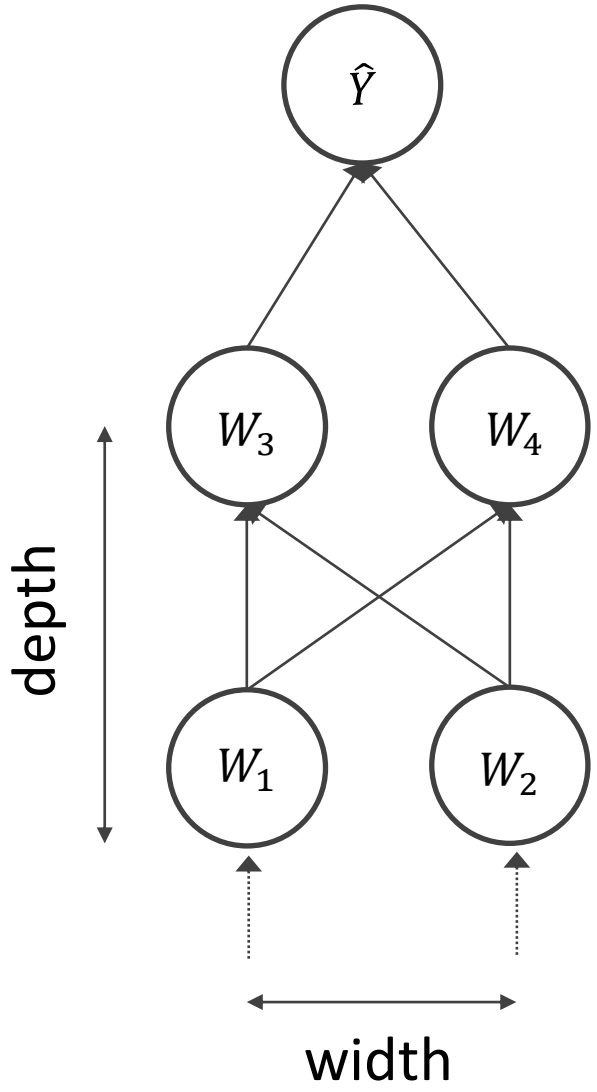

real: xsin(x)
pred
y
x
4
2
0
−2
−4
0
1
2
3
4
5
6
7


Hidden
Hidden
Hidden
Input
Output


real: xsin(x)
pred
4
2
0
−2
−4
y
0
1
2
3
4
5
6
7
x

Universal Approximation

- **Think of a Neural Network as function approximation.**
- $Y = f(x) + \epsilon$
- $Y = \hat{f}(x) + \epsilon$
  - NN: $\Longrightarrow \hat{f}(x)$
- One hidden layer is enough to *represent* an approximation of any function to an arbitrary degree of accuracy
- So why deeper?
  - Shallow net may need (exponentially) more width
  - Shallow net may overfit more



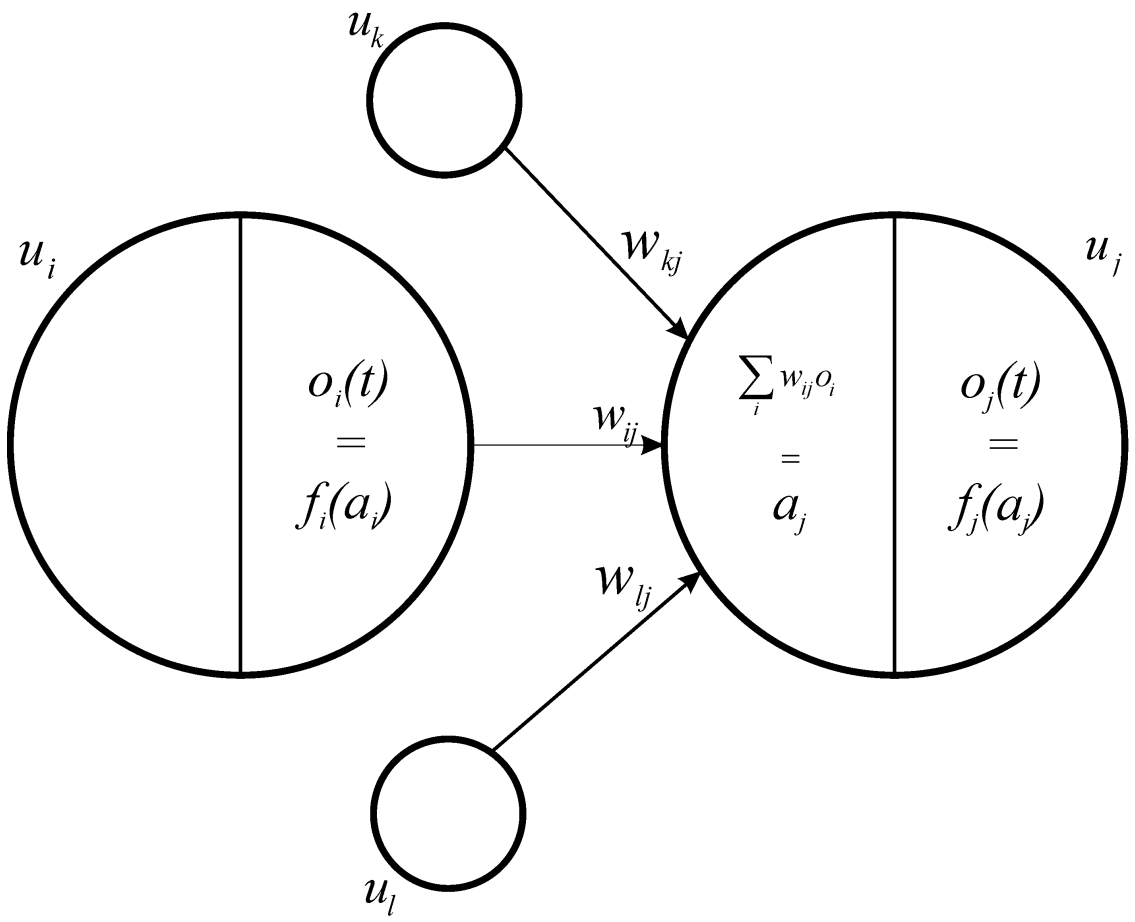
Forward propagation

- Neuron j u skrivenom sloju dobija tešinsku sumu ulaza u mrežu.

$$a_j^{(1)} = \sum_{i=0}^{n} w_{ij}^{(1)} x_i$$

- Izlaz iz neurona u skrivenom sloju

$$o_j^{(1)} = f(a_j^{(1)}) = f\left(\sum_{i=0}^{n} w_{ij}^{(1)} x_i\right)$$



Forward propagation

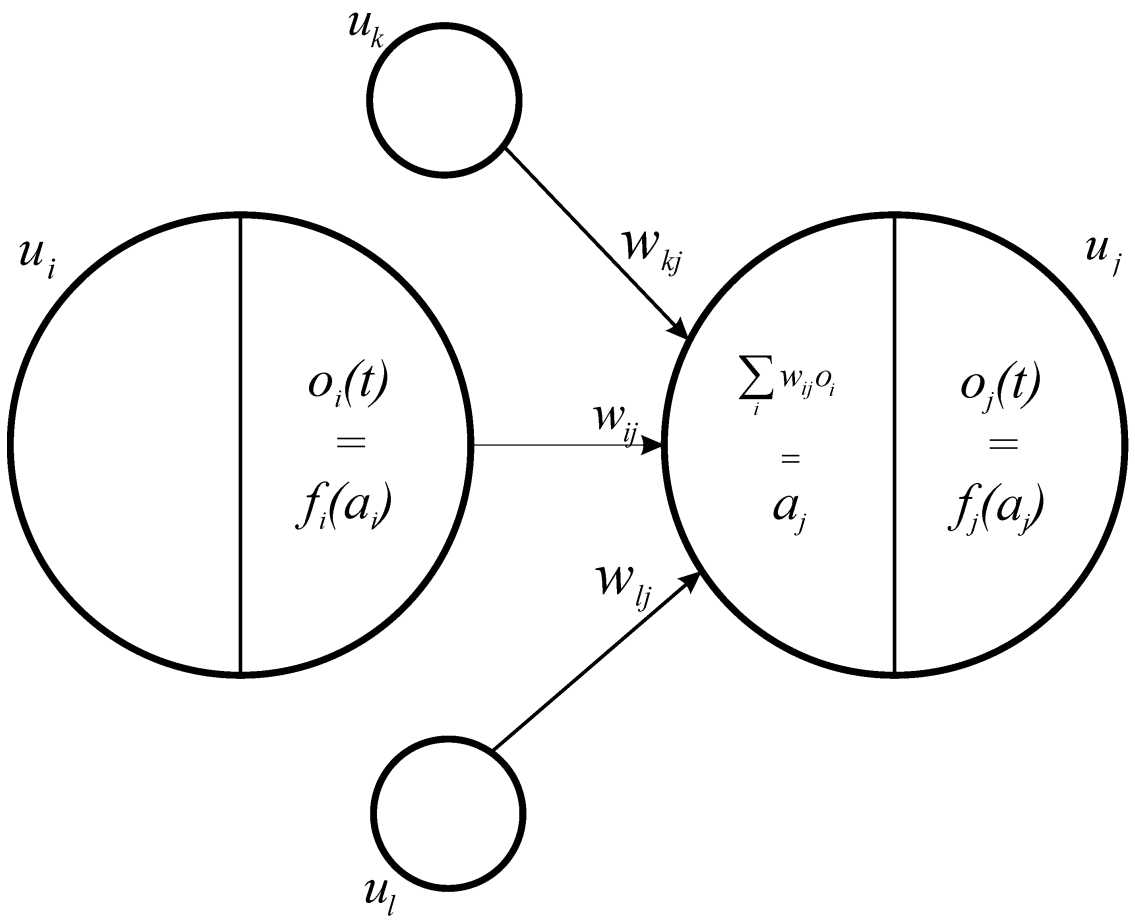
- Ako imamo samo jedan skriveni sloj, neuron *j* u izlaznom sloju dobijana ulaz težinsku sumu izlaza iz svih neurona u skrivenom sloju.

$$a_j^{(2)} = \sum_{i=0}^{n} w_{ij}^{(2)} o_i^{(1)}$$

- Izlaz iz neurona u izlaznom sloju

$$o_j^{(2)} = f(a_j^{(2)}) = f\left(\sum_{i=0}^{n} w_{ij}^{(2)} o_i^{(1)}\right)$$

$$o_j^{(2)} = f\left(\sum_{i=0}^{n} w_{ij}^{(2)} f\left(\sum_{i=0}^{n} w_{ij}^{(1)} x_i\right)\right)$$



Učenje težina

- Mreže uče podešavanjem težina u cilju smanjivanja razlike između izlaza koji daje mreža o i očekivanog izlaza y.

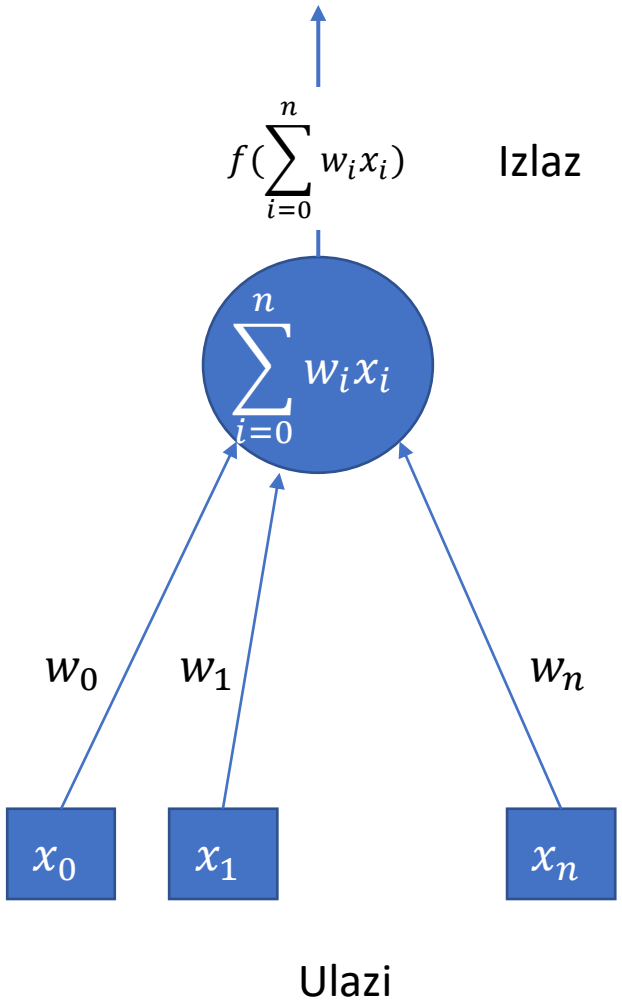
- Minimizacija razlike?

- Gradijentni spust.

Minimizacija greške

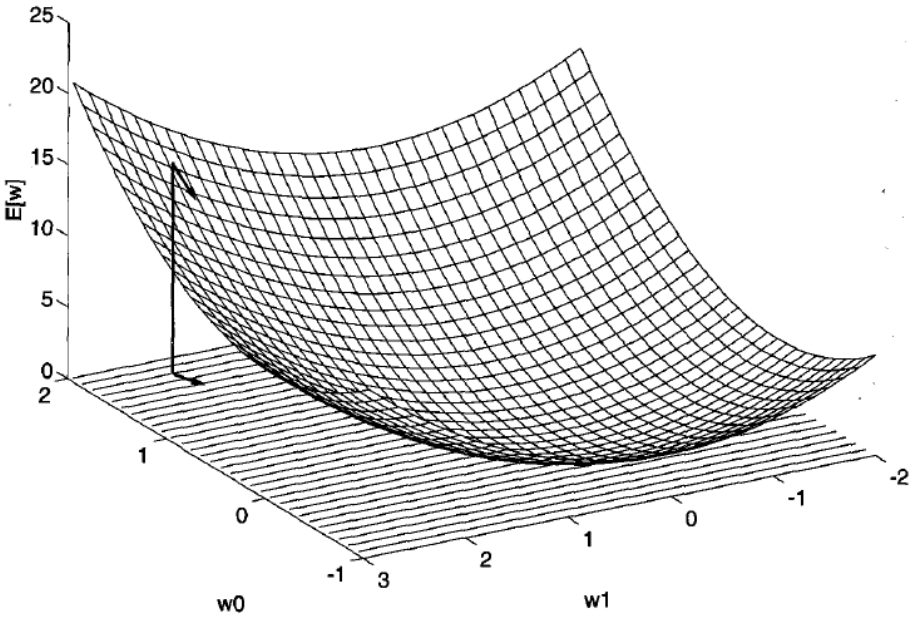
- Krenimo od mreže koja nema skriveni sloj i ima samo jedan izlaz. Neka radi jednostavnosti imamo samo jedan trening primer $(\vec{x}, y)$
- Dobijeni izlaz iz mreže o je neka funkcija $f(a)$, gde je a težinska suma ulaza u neuron $a = \sum_{i=0}^{n} w_i x_i$.
- Greška izlaza je razlika između dobijenog i željenog izlaza.
- Uobičajeni oblik funkcije greške na jednom izlaznom neuronu za jedan trening primer:

$$E = \frac{1}{2}(y - o)^2$$



Minimizacija greške

- Grešku mreže možemo smanjiti menjanjem težina veza.
- Pretražujemo prostor težina u potrazi za takvom kombinacijom težina za koju je greška mreže jednaka ili jako bliska nuli.
- Gradijentnom metodom određuje se vektor težina koji minimizuje grešku tako što se započinje s proizvoljnim početnim težinama, a zatim one menjaju u koracima. Na svakom koraku, vektor težine se menja u pravcu koji predstavlja najstrmiji silazak po površi greške. Ovaj proces se nastavlja sve dok se ne dostigne globalna minimalna greška.
- Da bismo odredili pravac najstrmijeg spusta, potrebno je da odredimo parcijalni izvod greške po svakoj od težina $\nabla E = (\frac{\partial E}{\partial w_0}, \frac{\partial E}{\partial w_1}, \ldots, \frac{\partial E}{\partial w_n})$. Smer najstrmijeg spusta je suprotan od smera vektora ∇E



Promena težina

- Svaka težina će biti promenjena za vrednost gradijenta i to u meri određenoj stopom učenja:

$$w_j \leftarrow w_j + \Delta w_j$$

Gde je

$$\Delta w_j = -\eta \frac{\partial E}{\partial w_j}$$

- η je pozitivna konstanta (learning rate) koja određuje veličinu koraka učenja

Izvod greške izlaza po težini veze

$$\frac{\partial E}{\partial w_j} = \frac{\partial E}{\partial o}\frac{\partial o}{\partial w_j} = \frac{\partial E}{\partial o}\frac{\partial o}{\partial a}\frac{\partial a}{\partial w_j}$$

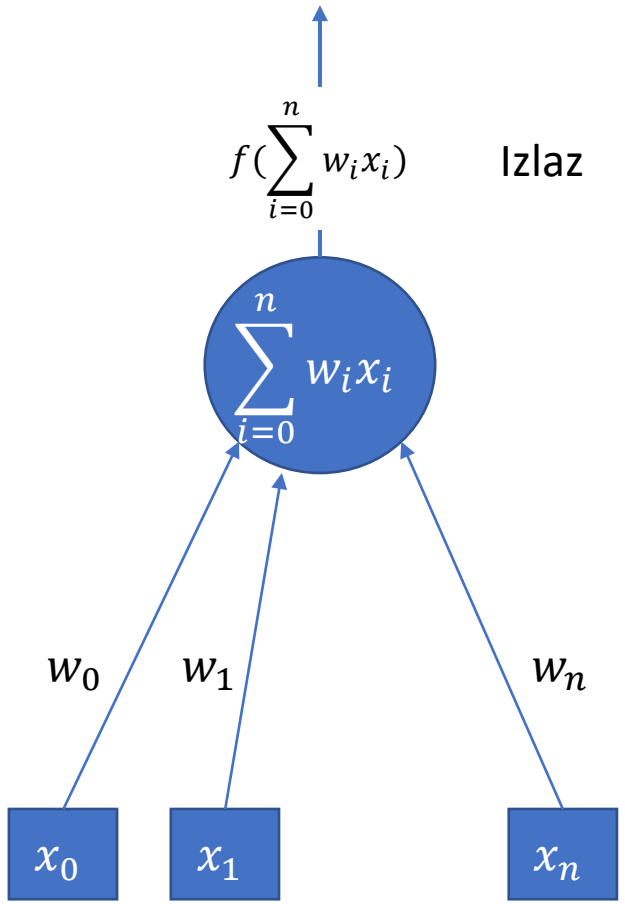
$$\frac{\partial a}{\partial w_j} = \frac{\partial}{\partial w_j}\left[\sum_{i=0}^{n} w_i x_i\right] = x_j \qquad (1)$$

$$\frac{\partial E}{\partial o} = \frac{\partial}{\partial o}\left[\frac{1}{2}(y-o)^2\right] = (o-y) \qquad (2)$$

(1)

(2)

$$\frac{\partial E}{\partial w_j} = (o-y)\cdot x_j \cdot o' \qquad (**)$$



Težina se menja po pravilu: $\Delta w_j = -\eta(o-y)\cdot x_j \cdot o'$

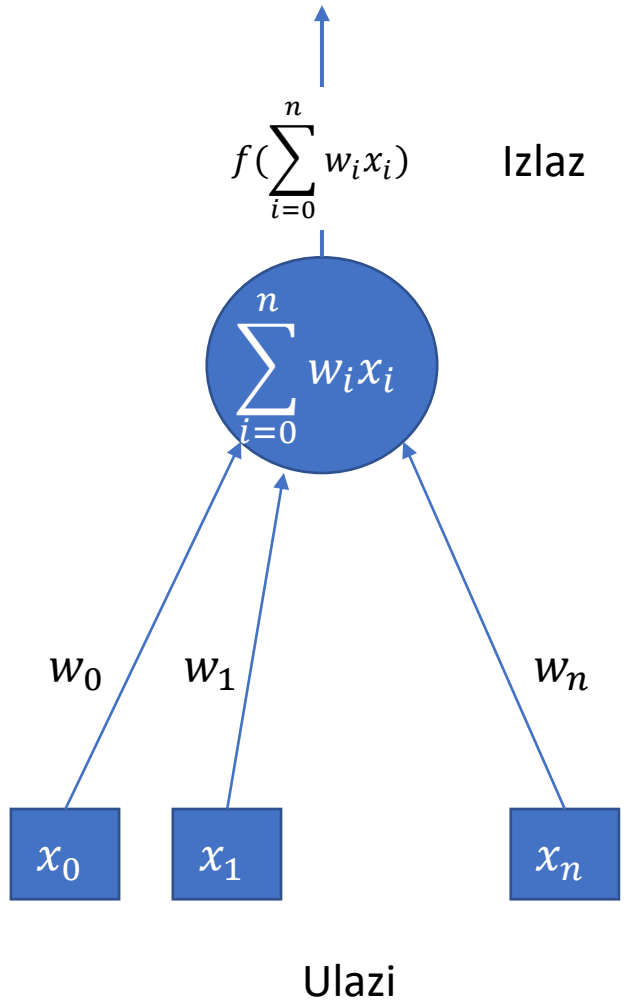
o' je izvod konkretne aktivacione funkcije po ukupnom ulazu u neuron.

Kada imamo L trening primera:

$$E = \frac{1}{2}\sum_{l \in L}(y_l - o_l)^2$$

$$\frac{\partial E}{\partial w_j} = \sum_{l \in L}(o_l - y_l)\, x_j^l o_l'$$

Težina se menja po pravilu: $\Delta w_j = -\eta \sum_{l \in L}(o_l - y_l)\, x_j^l o_l'$



Algoritam korekcije težina korišćenjem metode gradijentnog spusta

- Odabrati slučajne vrednosti težina.
- Izračunati izlaz o_l iz mreže za svaki ulaz $\overrightarrow{\mathrm{x}_l}$ iz trening primera
- Izračunati Δw_j po pravilu $\Delta w_j = -\eta \sum_{l \in L} (o_l - y_l)\, x_j^l o_l'$, za svako j
- Uvećati svaku težinu za odgovarajuće Δw_j.
- Ponoviti ovaj postupak do postizanja željene preciznosti mreže.

Linearni neuron - Pravilo za promenu težina veza

- Polazimo od opšteg pravila: $\Delta w_j = -\eta \sum_{l \in L} (o_l - y_l)\, x_j^l o_l'$
- $o(a) = a = \sum_{i=1}^{n} w_i x_i$
- $\frac{do}{da} = 1$

$$\Delta w_j = -\eta \sum_{l \in L} (o_l - y_l)\, x_j^l$$

Nedostaci primene gradijenta na učenje neuronskih mreža

- Konvergencija ka lokalnom minimumu može teći jako sporo
- Ako je površ greške sa višestrukim lokalnim minimumima, nema garancije da će procedura pronaći globalni minimum.
- Uobičajena varijanta gradijentnog spusta kojom se ovi nedostaci rešavaju je stohastički gradijentni spust.

Stohastički gradijentni spust

- Kod običnog gradijentnog spusta, promena težina se vrši nakon prolaska kroz sve trening primere.

- Stohastički gradijentni spust podrazumeva inkrementalnu promenu težina, nakon svakog izračuvanja greške za određeni trening primer.

- Posle propuštanja trening primera l kroz mrežu, korigujemo težine:

$$w_j \leftarrow w_j - \eta(o_l - y_l)x_j^l$$

Delta pravilo

A toy example to illustrate the iterative method

- Each day you get lunch at the cafeteria.
  - Your diet consists of fish, chips, and ketchup.
  - You get several portions of each.
- The cashier only tells you the total price of the meal
  - After several days, you should be able to figure out the price of each portion.
- The iterative approach: Start with random guesses for the prices and then adjust them to get a better fit to the observed prices of whole meals.

Solving the equations iteratively

- Each meal price gives a linear constraint on the prices of the portions:

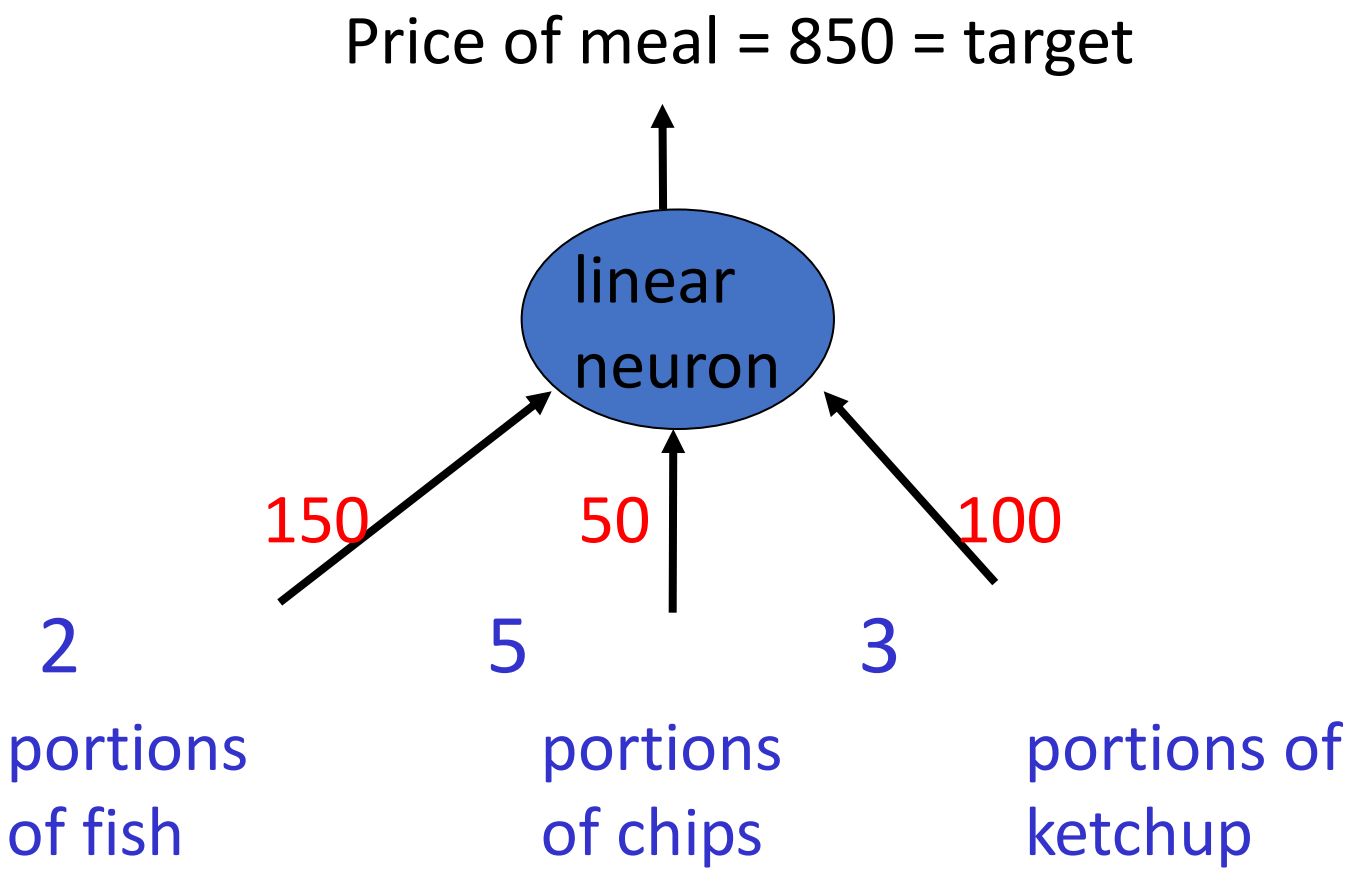
$$price = x_{fish} w_{fish} + x_{chips} w_{chips} + x_{ketchup} w_{ketchup}$$

- The prices of the portions are like the weights in of a linear neuron.

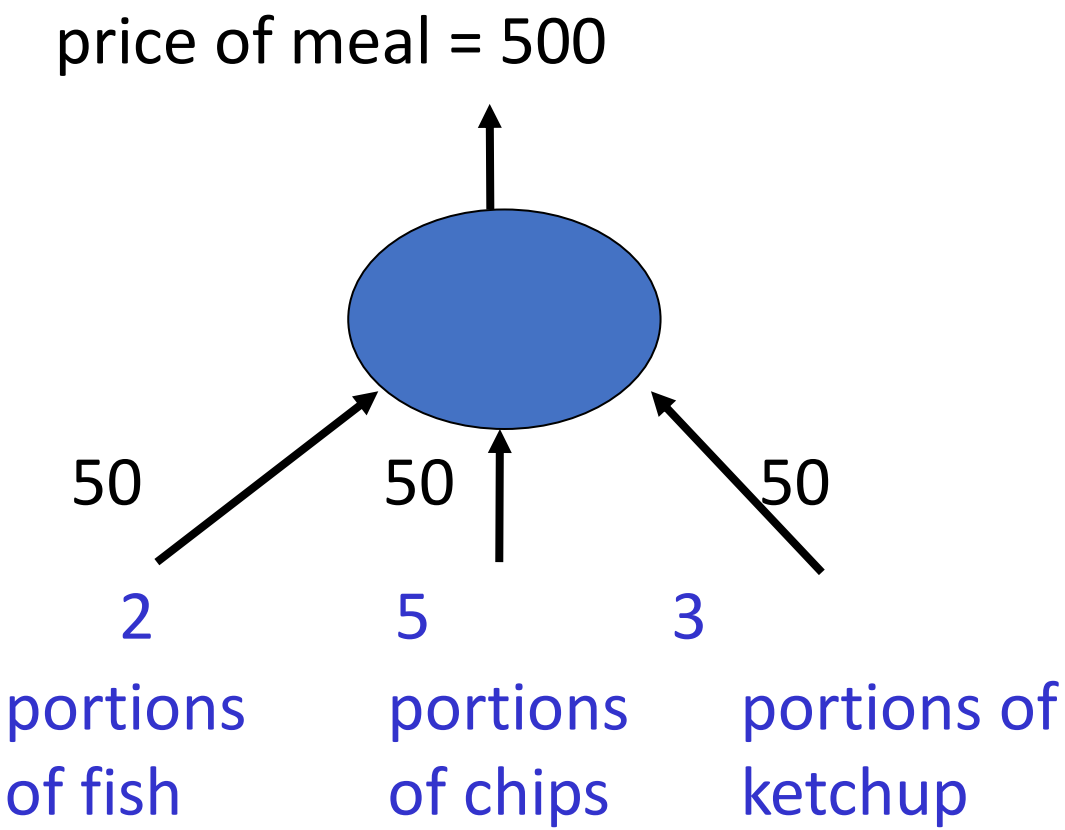
$$\mathbf{w} = (w_{fish}, w_{chips}, w_{ketchup})$$

- We will start with guesses for the weights and then adjust the guesses slightly to give a better fit to the prices given by the cashier.

The true weights used by the cashier



Primena delta pravila za učenje

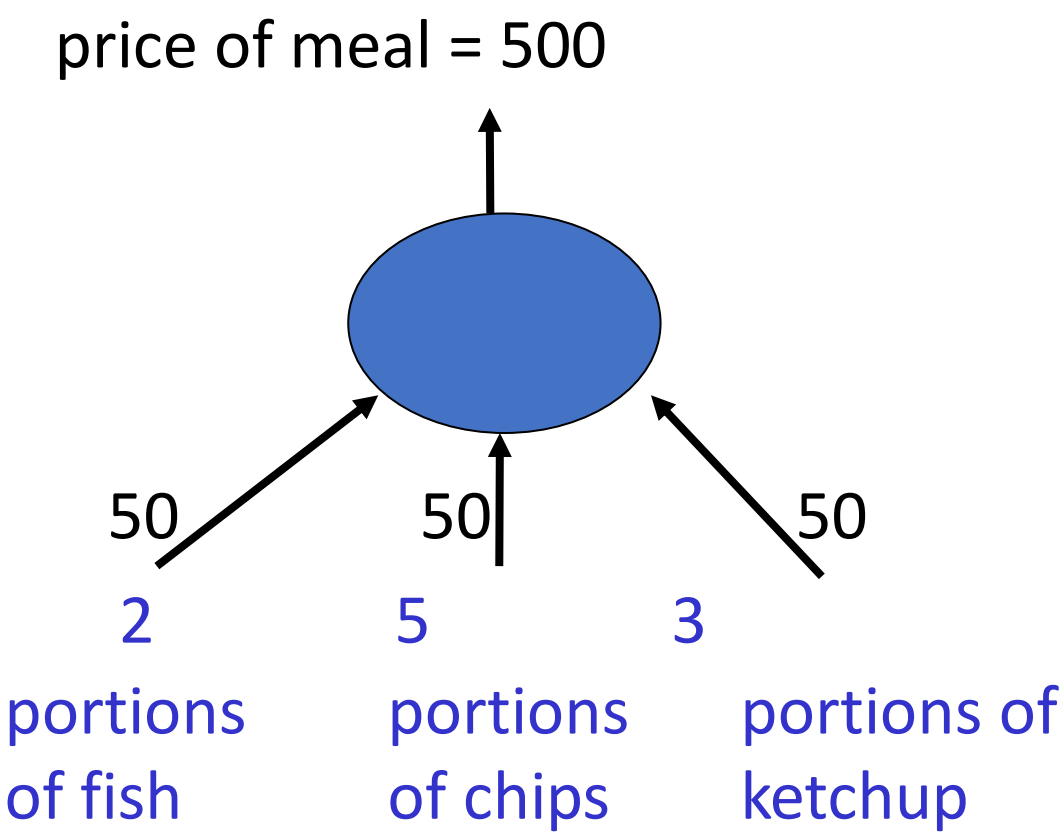


- Delta pravilo za učenje:

$$\Delta w_i = \eta \cdot x_i \cdot (y - \mathrm{o})$$

- Δw_i promena težine i-te veze
- η stopa učenja
- x_i vrednost i-tog ulaza u neuron (broj porcija)
- y očekivana vrednost izlaza (850)
- o dobijena vrednost izlaza (500)

A model of the cashier with arbitrary initial weights



- With a learning rate η of $\frac{1}{35}$, the weight changes are +20, +50, +30
- This gives new weights of 70, 100, 80.
  - Notice that the weight for chips got worse!
  - Ne poboljšavaju se težine, nego se smanjuje razlika između očekivanog i dobijenog izlaza.

Sigmoid neuron - Pravilo za promenu težina veza

- Polazimo od opšteg pravila: $\Delta w_j = -\eta \sum_{l \in L} (o_l - y_l)\, x_j^l o_l'$
- $o(a) = \frac{1}{1+e^{-a}}$
- Treba odrediti $\frac{do}{da}$

$$f(z) = (1 + e^{-z})^{-1}$$

$$\frac{do}{da} = -(1 + e^{-a})^{-2}(-1)e^{-a} = \frac{e^{-a}}{(1+e^{-a})^2} = \frac{1}{(1+e^{-a})}\frac{e^{-a}}{(1+e^{-a})} =$$

$$= \frac{1}{(1 + e^{-a})}\frac{1 + e^{-a} - 1}{(1 + e^{-a})} = \frac{1}{(1 + e^{-a})}\left(1 - \frac{1}{(1 + e^{-a})}\right)$$

$$\boldsymbol{\frac{do}{da} = o(1 - o)}$$

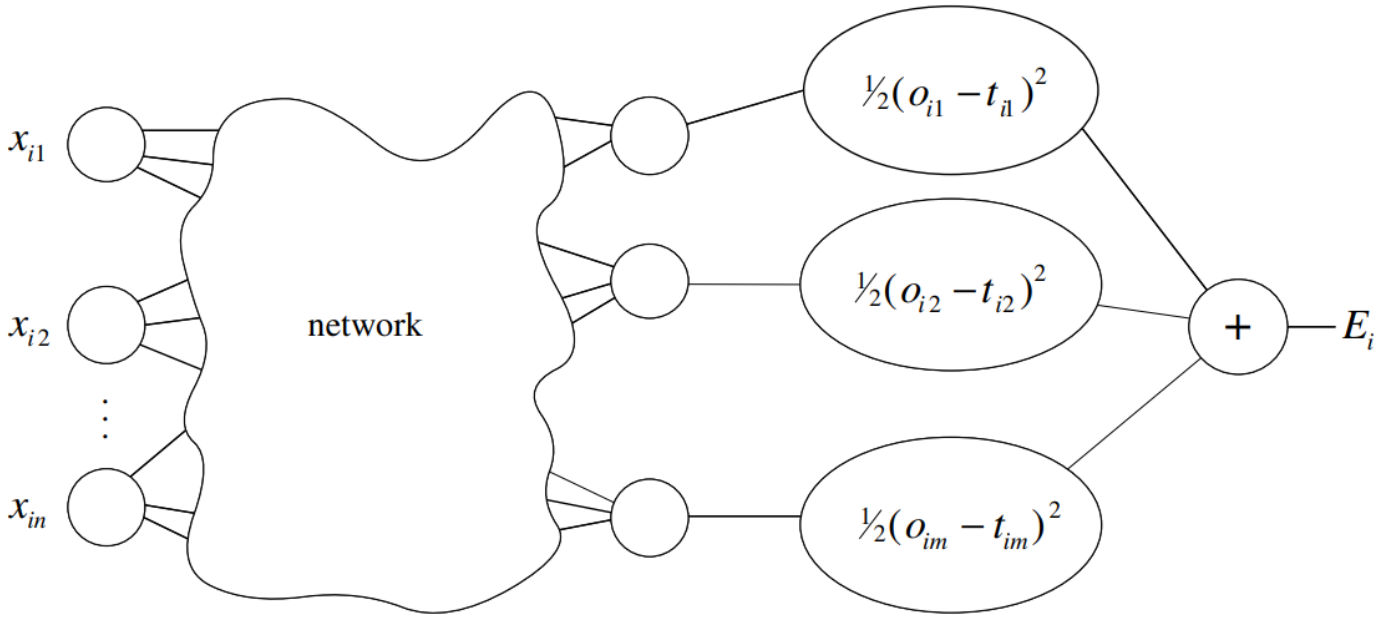
Sigmoid neuron - Pravilo za promenu težina veza

$$\Delta w_j = -\eta \sum_{l \in L} (o_l - y_l)\, x_j^l o_l'$$

$$\frac{\boldsymbol{do}}{\boldsymbol{da}} = \boldsymbol{o}(\boldsymbol{1} - \boldsymbol{o})$$

$$\Delta w_j = -\eta \sum_{l \in L} (o_l - y_l)\, x_j^l o_l (1 - o_l)$$

Mreže sa više slojeva i algoritam propagacije unazad



- Mreže sa više slojeva, koje koriste sigmoidnu aktivacionu funkciju, obučavaju se algoritmom propagacije unazad – **backpropagation algorithm**.

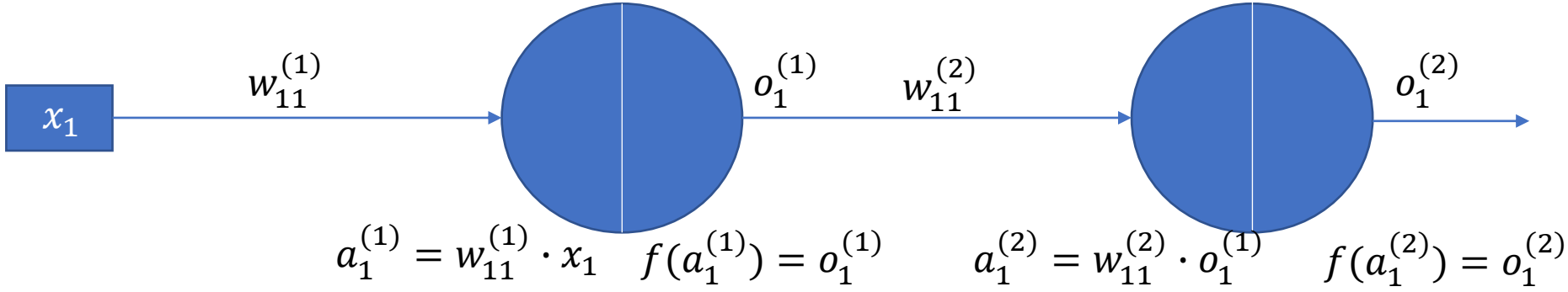
- Algoritam koristi gradijentni spust za minimizaciju kvadrata razlike izlaza koji daje mreža i očekivanog izlaza.

- Ako imamo skup od L trening primera, onda ćemo grešku mreže računati po formuli:

$$E = \frac{1}{2}\sum_{l \in L}(y_l - o_l)^2$$

Algoritam propagacije unazad

- Krenimo od najjednostavnijeg primera mreže koja ima 1 ulaz, 1 neuron u skrivenom sloju i 1 izlaz.



$w_{ij}^{(k)}$- težina veze od neurona i u sloju $k-1$ ka neuronu j u sloju k

$a_j^{(k)}$- ukupna aktivacija neurona j u sloju k

$o_j^{(k)}$- izlaz iz neurona j u sloju k

$f(a_j^{(k)}) = o_j^{(k)}$– vrednost aktivacione f-je neurona j u sloju k

Računanje promene težine za izlazni sloj

$$E = \frac{1}{2}\left(y - o_1^{(2)}\right)^2$$

$$\frac{\partial E}{\partial w_{11}^{(2)}} = \frac{\partial E}{\partial o_1^{(2)}}\frac{\partial o_1^{(2)}}{\partial w_{11}^{(2)}} = \frac{\partial E}{\partial o_1^{(2)}}\frac{\partial o_1^{(2)}}{\partial a_1^{(2)}}\frac{\partial a_1^{(2)}}{\partial w_{11}^{(2)}}$$

$$\frac{\partial E}{\partial w_{11}^{(2)}} = \underbrace{o_1^{(2)}(1 - o_1^{(2)})(o_1^{(2)} - \mathrm{y})}_{\text{Backpropagation error izlaznog sloja}} o_1^{(1)}$$

$$\Delta w_{11}^{(2)} = -\eta o_1^{(2)}(1 - o_1^{(2)})(o_1^{(2)} - \mathrm{y})o_1^{(1)}$$

Računanje promene težine za skriveni sloj

$$\frac{\partial E}{\partial w_{11}^{(1)}} = \frac{\partial E}{\partial o_1^{(2)}} \frac{\partial o_1^{(2)}}{\partial w_{11}^{(1)}} = \frac{\partial E}{\partial o_1^{(2)}} \frac{\partial o_1^{(2)}}{\partial a_1^{(2)}} \frac{\partial a_1^{(2)}}{\partial w_{11}^{(1)}} = \frac{\partial E}{\partial o_1^{(2)}} \frac{\partial o_1^{(2)}}{\partial a_1^{(2)}} \frac{\partial a_1^{(2)}}{\partial o_1^{(1)}} \frac{\partial o_1^{(1)}}{\partial a_1^{(1)}} \frac{\partial a_1^{(1)}}{\partial w_{11}^{(1)}}$$

$$\frac{\partial E}{\partial w_{11}^{(1)}} = o_1^{(2)} \left(1 - o_1^{(2)}\right) \left(o_1^{(2)} - \mathrm{y}\right) o_1^{(1)} \left(1 - o_1^{(1)}\right) x_1 \, w_{11}^{(2)}$$

Backpropagation error izlaznog sloja

$$\Delta w_{11}^{(1)} = -\eta o_1^{(2)} (1 - o_1^{(2)}) (o_1^{(2)} - \mathrm{y}) o_1^{(1)} \left(1 - o_1^{(1)}\right) x_1 \, w_{11}^{(2)}$$

Backpropagation algoritam

Ovo je algoritam zasnovan na stohastičkom gradijentnom spustu i to za mrežu koja ima samo jedan skriveni sloj.

Detaljnije objašnjenje algoritma naći ćete u dokumentu BPA.pdf

Ovo je algoritam koji smo primenili na času za rešavanje konkretnog primera:

https://mattmazur.com/2015/03/17/a-step-by-step-backpropagation-example/

BACKPROPAGATION($training\_examples, \eta, n_{in}, n_{out}, n_{hidden}$)

Each training example is a pair of the form $\langle \vec{x}, \vec{t} \rangle$, where $\vec{x}$ is the vector of network input values, and $\vec{t}$ is the vector of target network output values.

η is the learning rate (e.g., .05). n_{in} is the number of network inputs, n_{hidden} the number of units in the hidden layer, and n_{out} the number of output units.

The input from unit i into unit j is denoted x_{ji}, and the weight from unit i to unit j is denoted w_{ji}.

- Create a feed-forward network with n_{in} inputs, n_{hidden} hidden units, and n_{out} output units.
- Initialize all network weights to small random numbers (e.g., between $-.05$ and .05).
- Until the termination condition is met, Do
  - For each $\langle \vec{x}, \vec{t} \rangle$ in $training\_examples$, Do

Propagate the input forward through the network:

1. Input the instance $\vec{x}$ to the network and compute the output o_u of every unit u in the network.

Propagate the errors backward through the network:

2. For each network output unit k, calculate its error term δ_k

$$\delta_k \leftarrow o_k(1 - o_k)(t_k - o_k) \tag{T4.3}$$

3. For each hidden unit h, calculate its error term δ_h

$$\delta_h \leftarrow o_h(1 - o_h) \sum_{k \in outputs} w_{kh}\delta_k \tag{T4.4}$$

4. Update each network weight w_{ji}

$$w_{ji} \leftarrow w_{ji} + \Delta w_{ji}$$

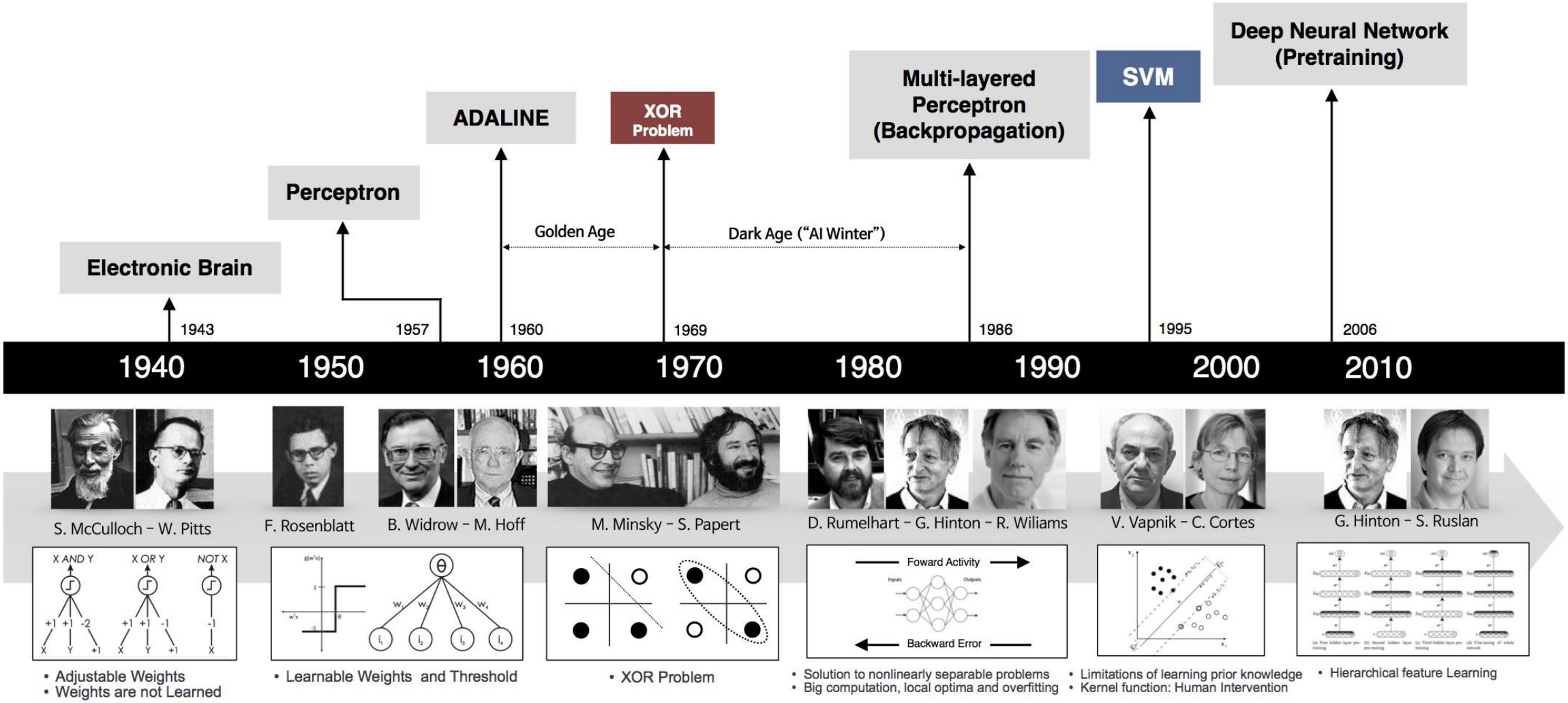
where

$$\Delta w_{ji} = \eta \, \delta_j \, x_{ji} \tag{T4.5}$$

Dodatni izvor

- Kompletno izvođenje Backpropagation algoritma za proizvoljan broj skrivenih slojeva:

https://brilliant.org/wiki/backpropagation/


Deep Neural Network (Pretraining)
SVM
Multi-layered Perceptron (Backpropagation)
XOR Problem
ADALINE
Perceptron
Electronic Brain
Golden Age
Dark Age ("AI Winter")
1943
1957
1960
1969
1986
1995
2006
1940
1950
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1980
1990
2000
2010
S. McCulloch - W. Pitts
F. Rosenblatt
B. Widrow - M. Hoff
M. Minsky - S. Papert
D. Rumelhart - G. Hinton - R. Wiliams
V. Vapnik - C. Cortes
G. Hinton - S. Ruslan
X AND Y
X OR Y
NOT X
Foward Activity
Backward Error
• Adjustable Weights
• Weights are not Learned
• Learnable Weights and Threshold
• XOR Problem
• Solution to nonlinearly separable problems
• Big computation, local optima and overfitting
• Limitations of learning prior knowledge
• Kernel function: Human Intervention
• Hierarchical feature Learning

Geoffrey Hinton,
The persistent

ImageNet Classification with Deep Convolutional Neural Networks

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Abstract

We trained a large, deep convolutional neural network to classify the 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into the 1000 different classes. On the test data, we achieved top-1 and top-5 error rates of 37.5% and 17.0% which is considerably better than the previous state-of-the-art. The neural network, which has 60 million parameters and 650,000 neurons, consists of five convolutional layers, some of which are followed by max-pooling layers, and three fully-connected layers with a final 1000-way softmax. To make training faster, we used non-saturating neurons and a very efficient GPU implementation of the convolution operation. To reduce overfitting in the fully-connected layers we employed a recently-developed regularization method called "dropout" that proved to be very effective. We also entered a variant of this model in the ILSVRC-2012 competition and achieved a winning top-5 test error rate of 15.3%, compared to 26.2% achieved by the second-best entry.

Neural Information Processing Systems, 2012

Uspeh Hintonove duboke konvolucione neuronske mreže

Neuspešne klasifikacije