

A Painter that Does Not Exist - Generative Image Production with Machines

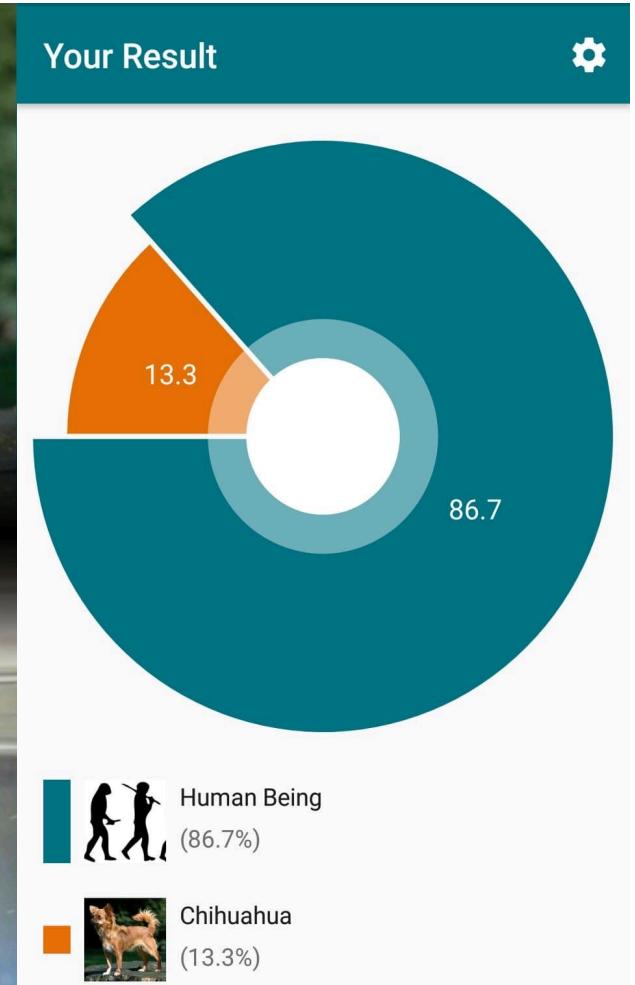


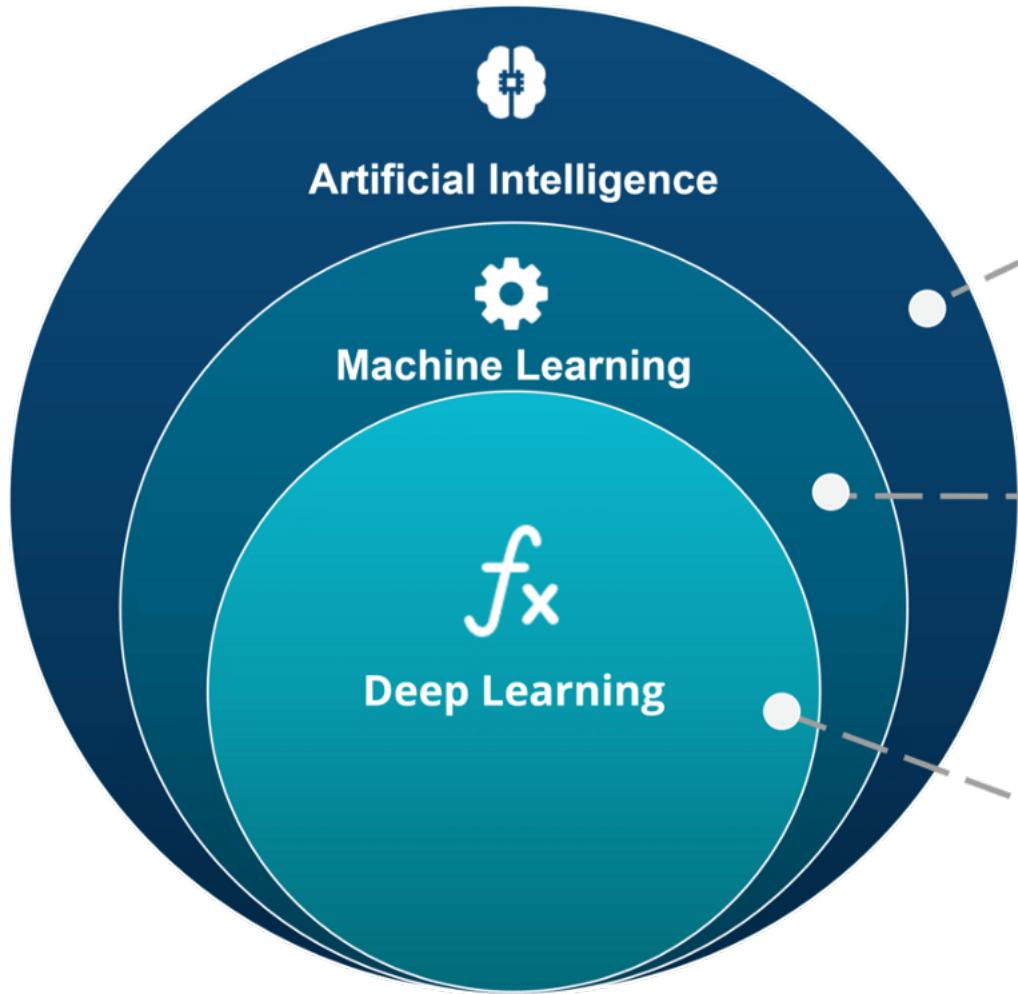
AI, machine learning, deep learning, ...

Expectation



Reality





ARTIFICIAL INTELLIGENCE

A technique which enables machines to mimic human behaviour

MACHINE LEARNING

Subset of AI technique which use statistical methods to enable machines to improve with experience

DEEP LEARNING

Subset of ML which make the computation of multi-layer neural network feasible

House price prediction

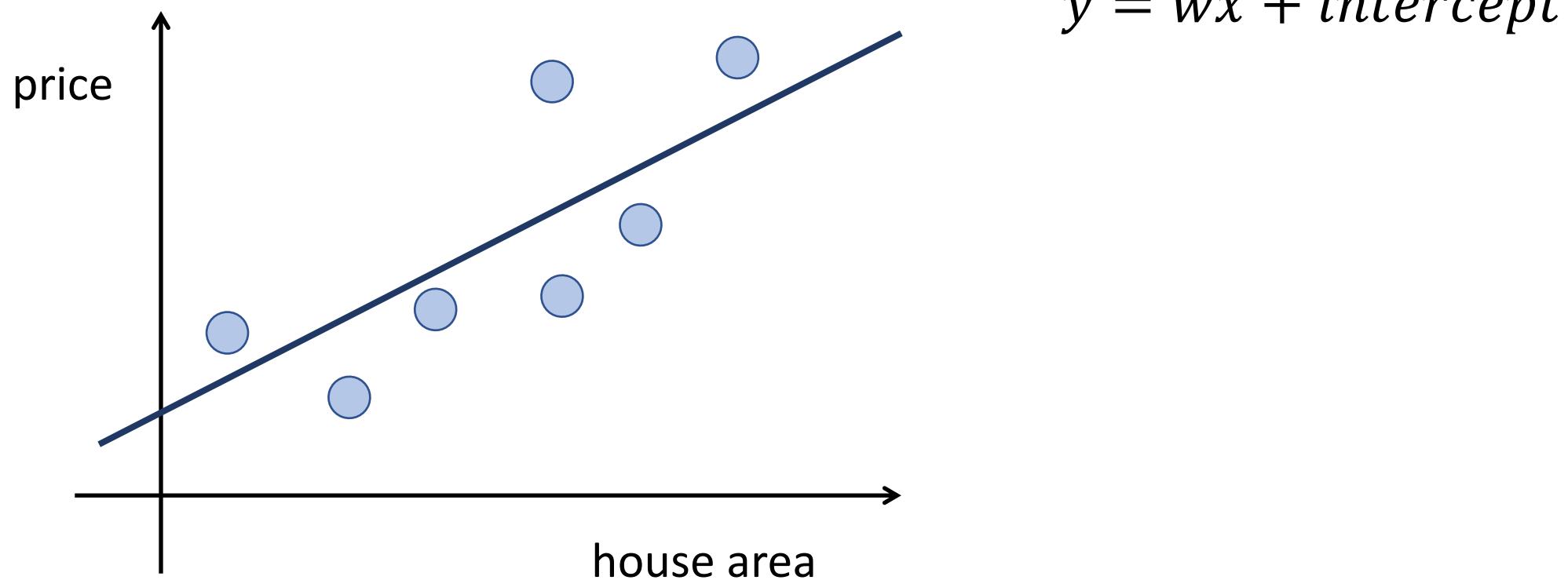


- house area,
- n.o. rooms/ bathrooms,
- neighborhood,
- building age,
- future renovations,
- etc.

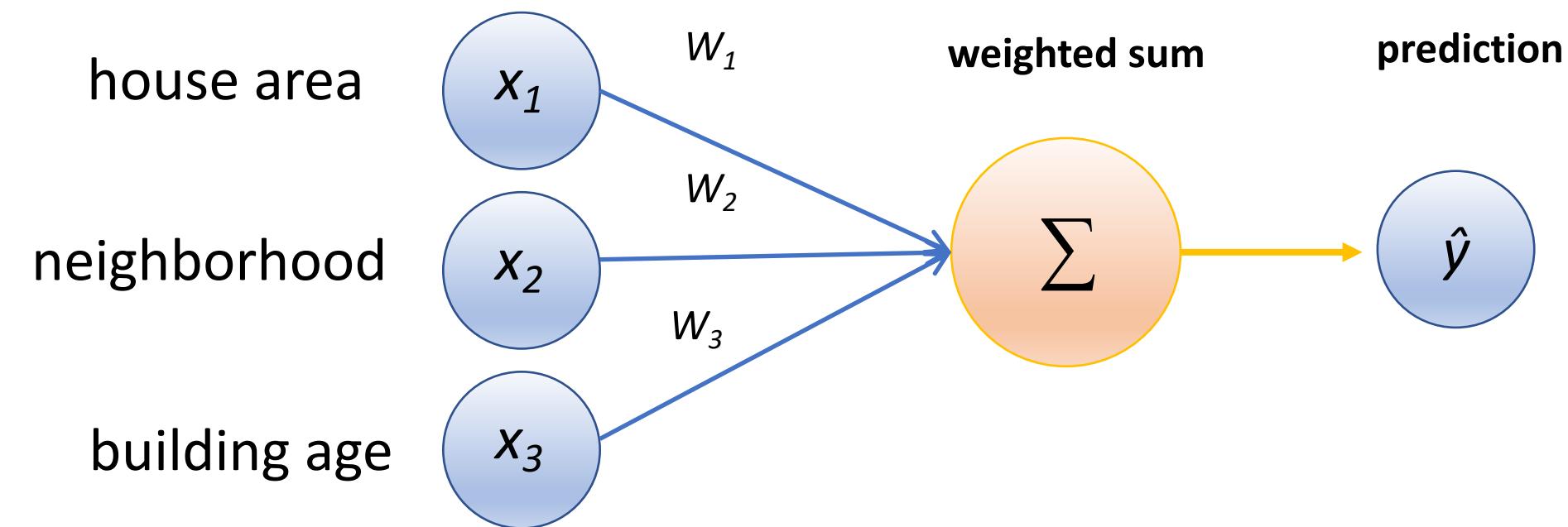
House price prediction

- house area = x_1
 - n.o. rooms/ bathrooms = x_2
 - neighborhood = x_3
 - building age = x_4
 - future renovations = x_5
- $w_1x_1 + w_2x_2 + w_3x_3 + w_4x_4 + w_5x_5 = \hat{y}$

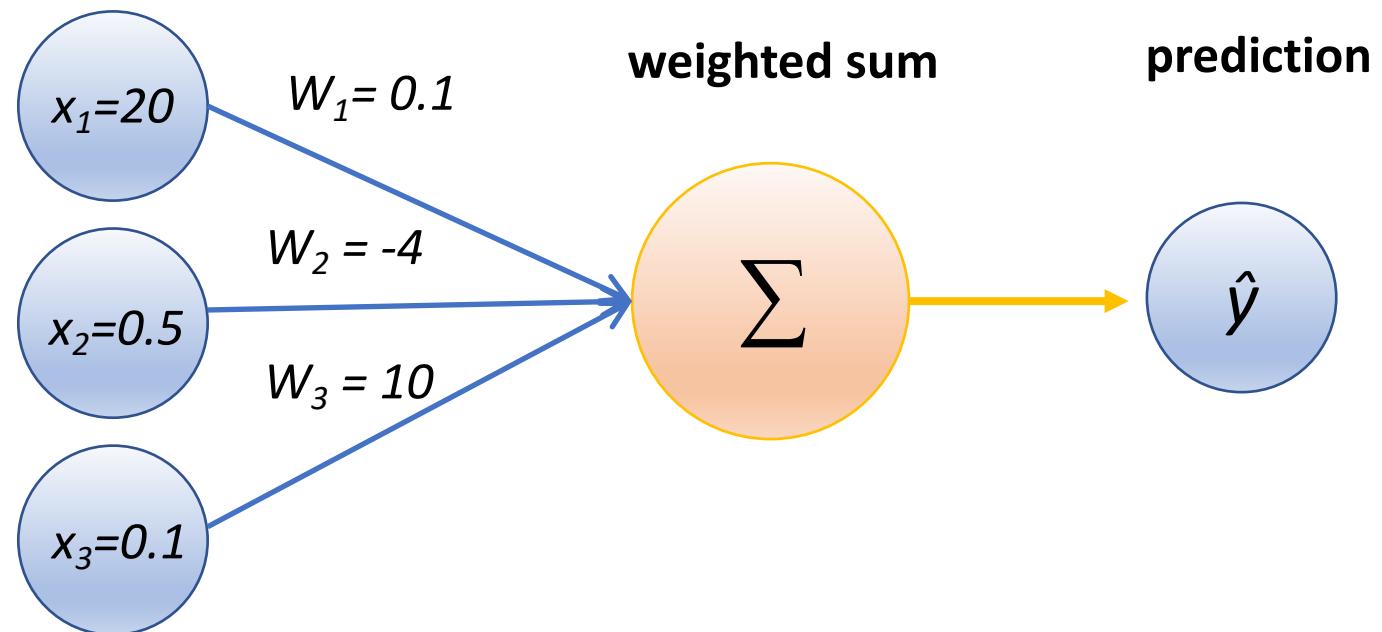
Historical Data



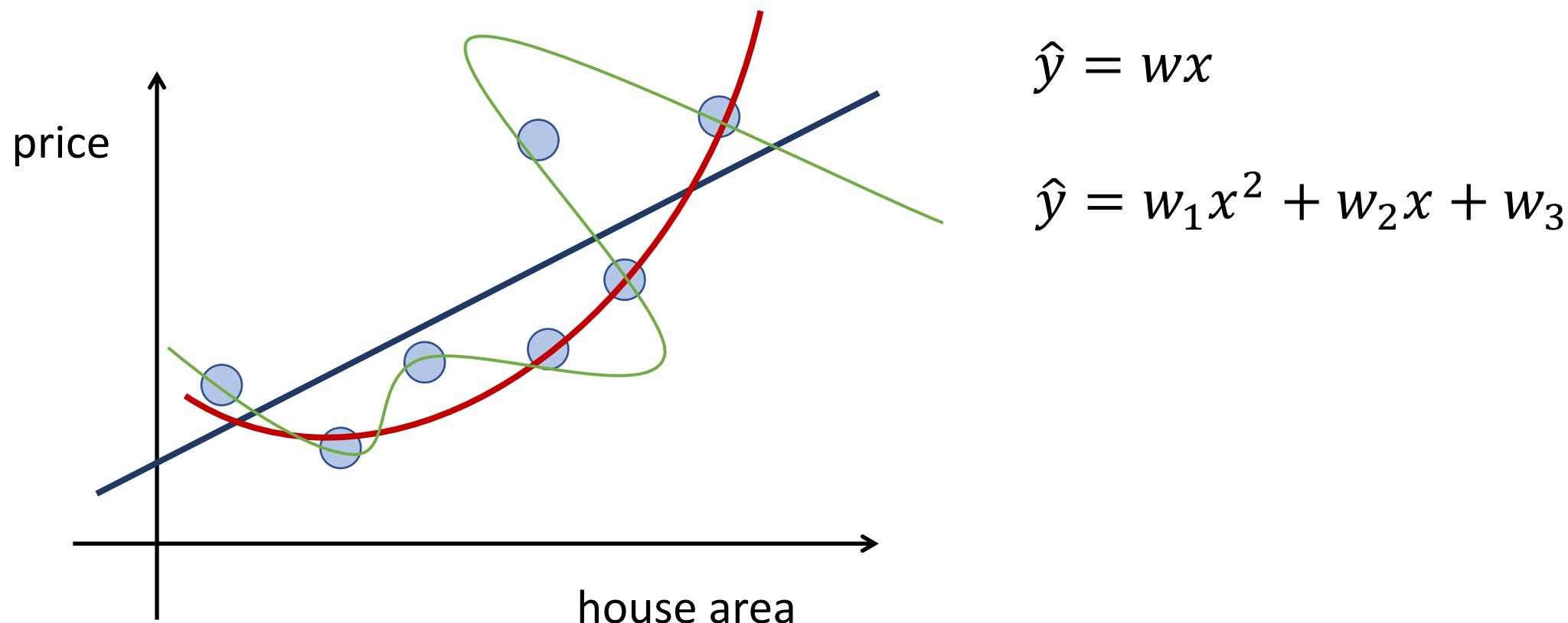
$$\hat{y} = w_1x_1 + \cdots + w_nx_n$$



$$\hat{y} = 20 * 0.1 + 0.5 * (-4) + 0.1 * 10 = 1$$

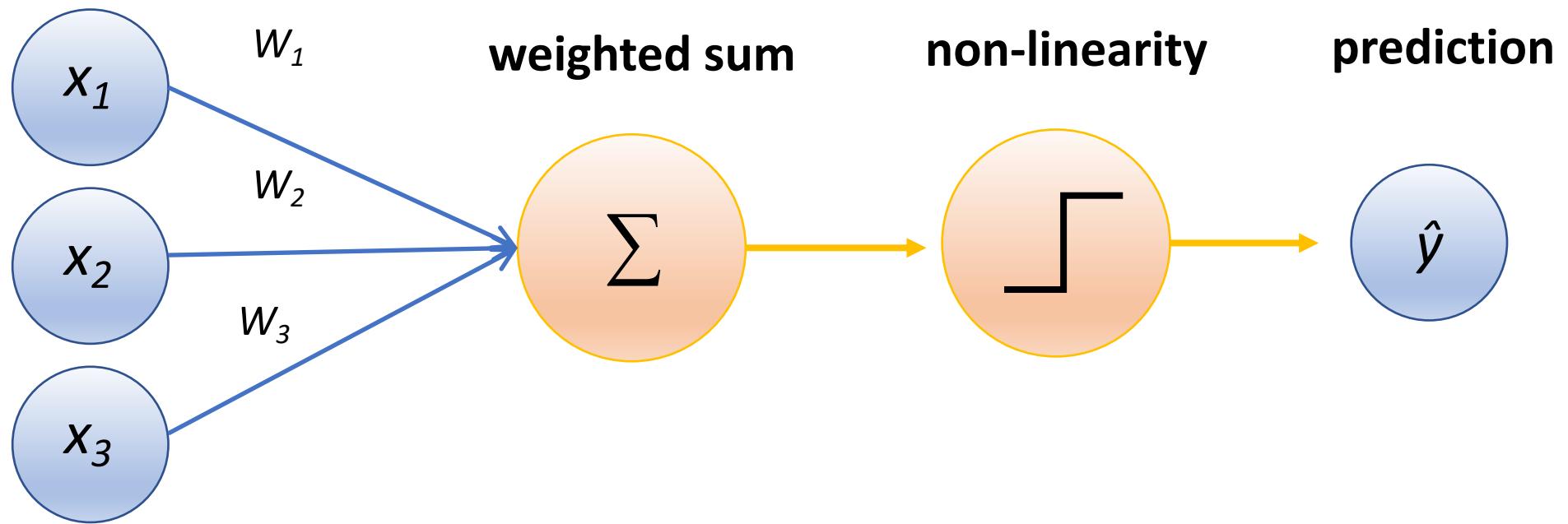


Historical Data



non-linear transformation

$$\hat{y} = \sigma(w_1x_1 + \dots + w_nx_n)$$

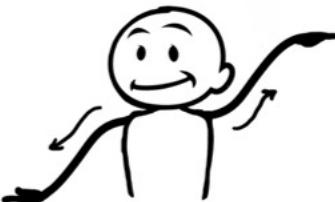


Sigmoid



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

Tanh



$$y = \tanh(x)$$

Step Function



$$y = \begin{cases} 0, & x < n \\ 1, & x \geq n \end{cases}$$

Softplus



$$y = \ln(1+e^x)$$

ReLU



$$y = \begin{cases} 0, & x < 0 \\ x, & x \geq 0 \end{cases}$$

Softsign



$$y = \frac{x}{(1+|x|)}$$

ELU



$$y = \begin{cases} \alpha(e^x - 1), & x < 0 \\ x, & x \geq 0 \end{cases}$$

Log of Sigmoid



$$y = \ln\left(\frac{1}{1+e^{-x}}\right)$$

Swish



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

Sinc



$$y = \frac{\sin(x)}{x}$$

Leaky ReLU



$$y = \max(0.1x, x)$$

Mish

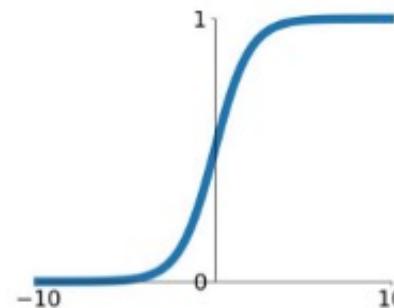


$$y = x(\tanh(\text{softplus}(x)))$$

Activation Functions

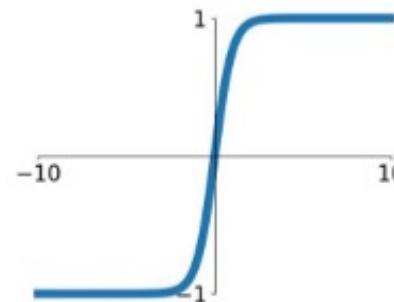
Sigmoid

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



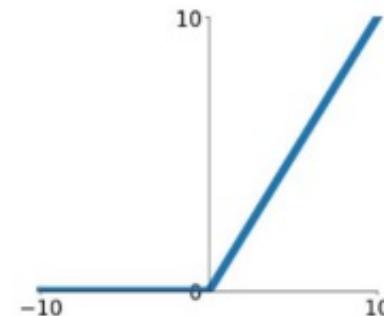
tanh

$$\tanh(x)$$



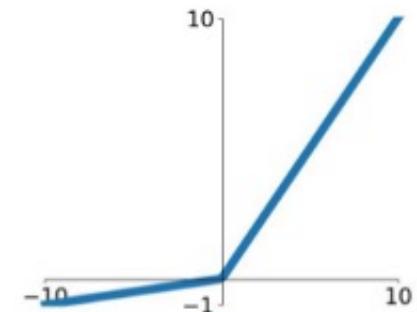
ReLU

$$\max(0, x)$$



Leaky ReLU

$$\max(0.1x, x)$$

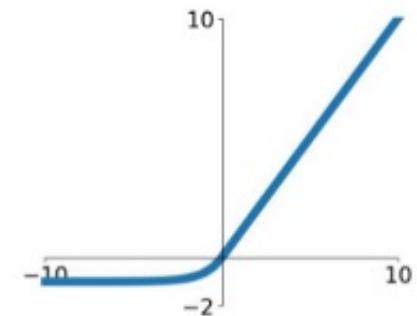


Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

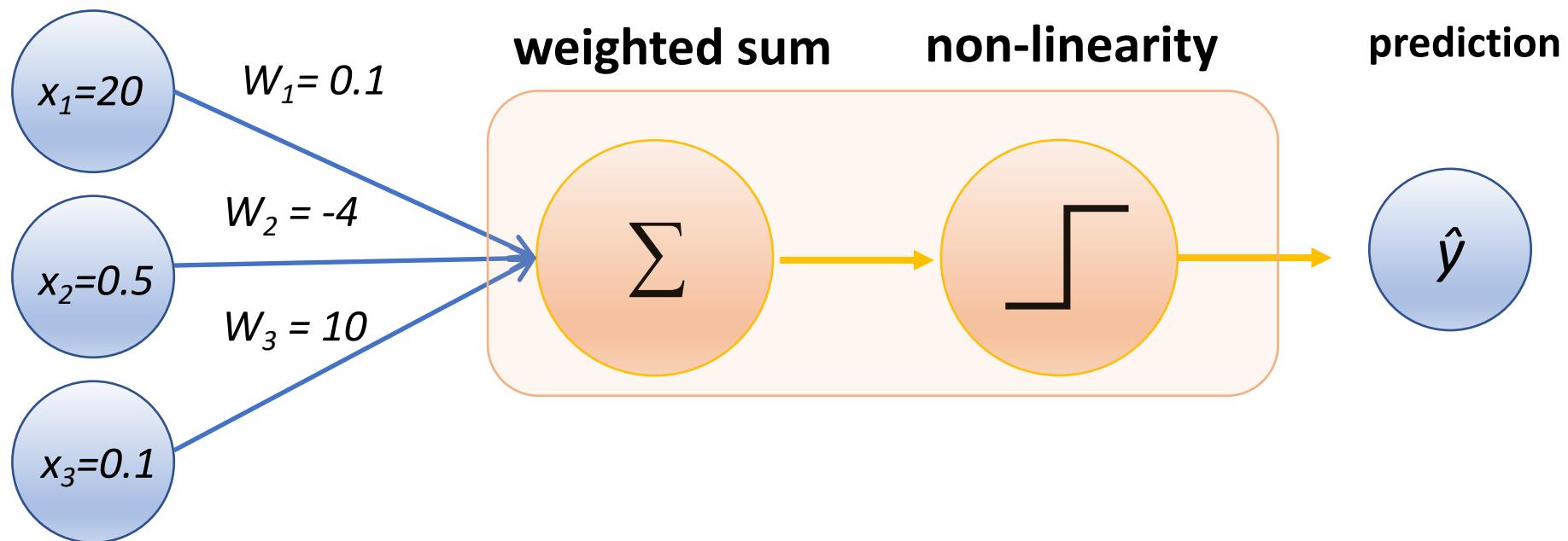
ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$

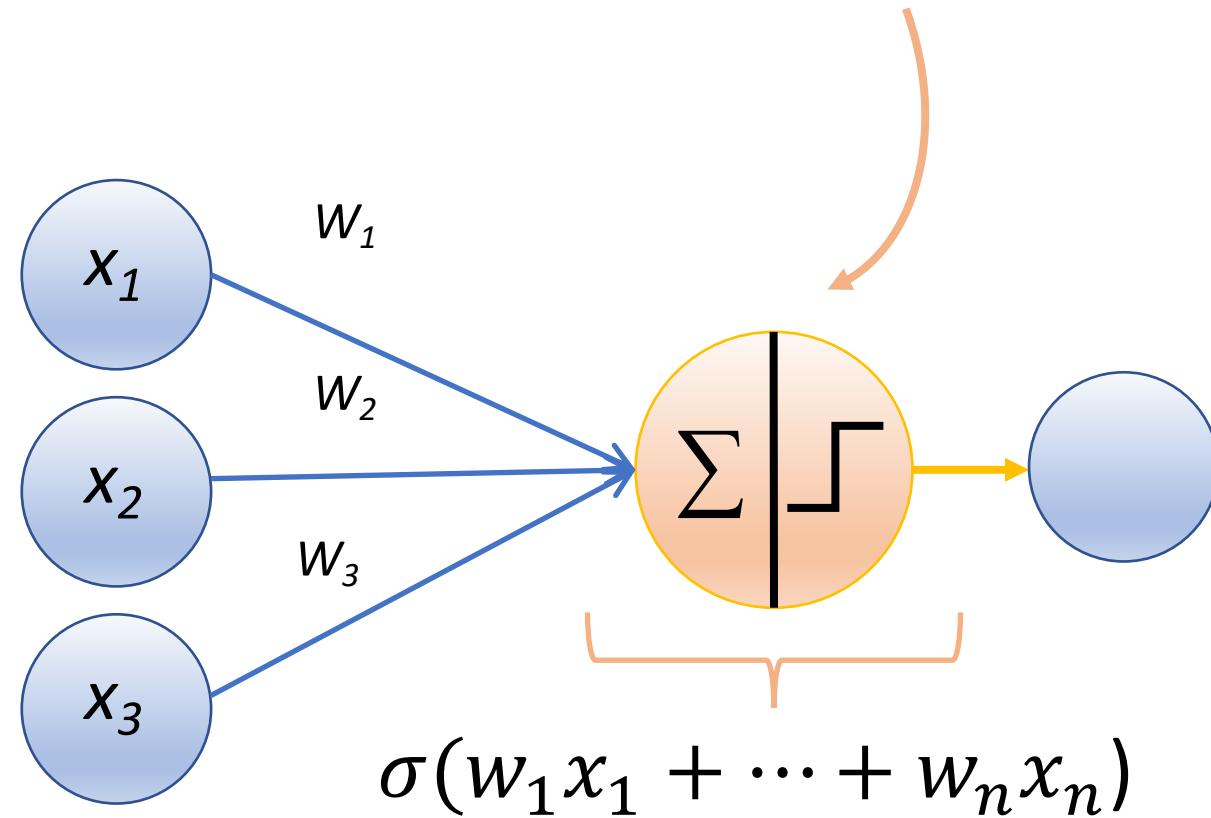


$$\hat{y} = \sigma(20 * 0.1 + 0.5 * (-4) + 0.1 * 10) \approx 0.73$$

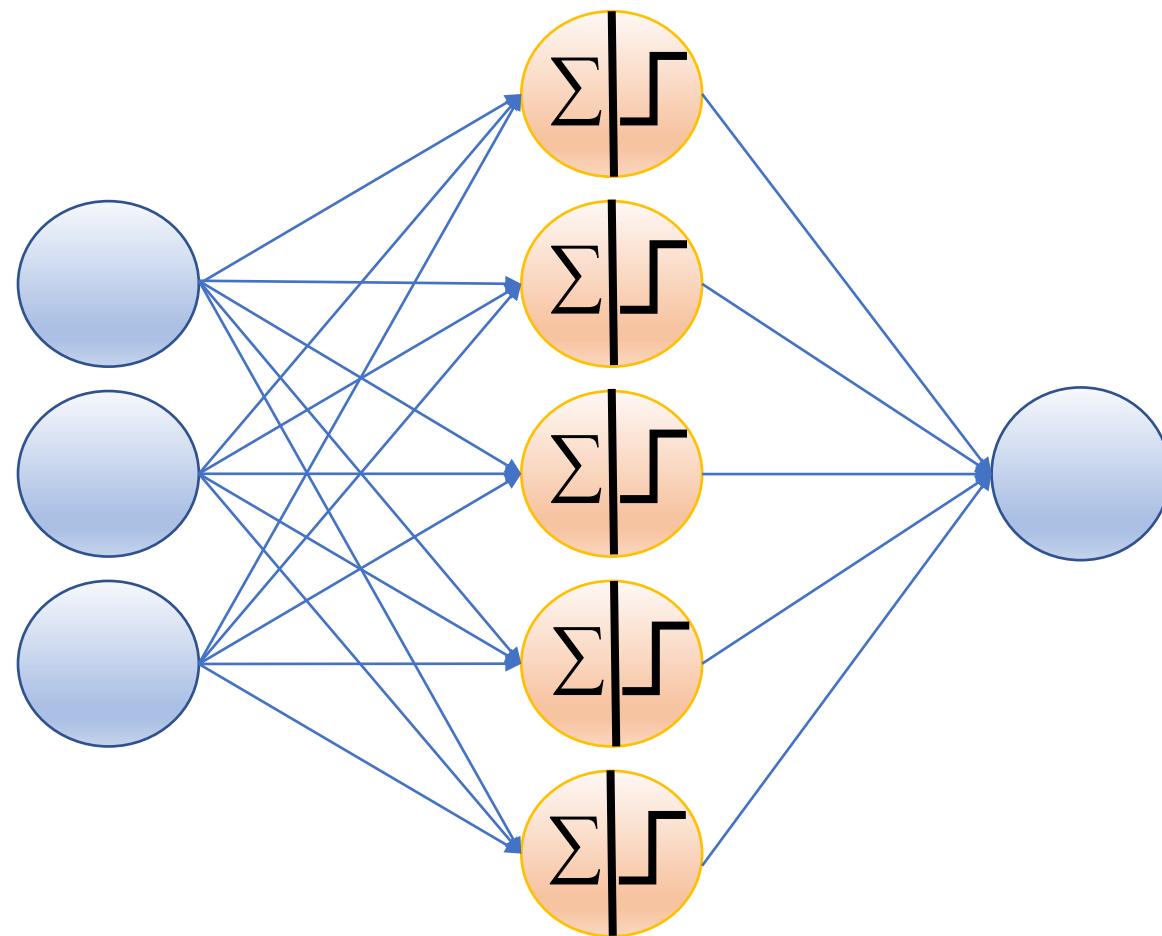
$$\sigma = \frac{1}{1 + e^{-x}}$$



“Atom” of the ANN – artificial neuron or unit of ANN

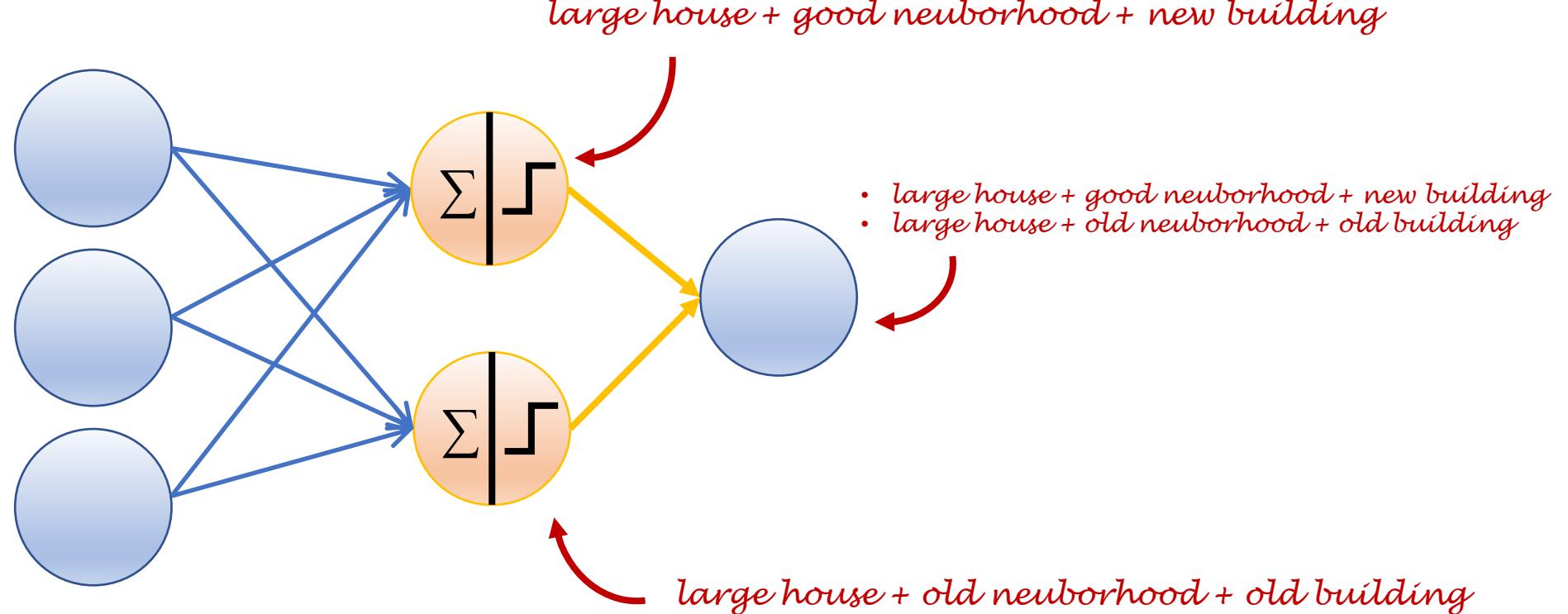


ANN – stacked elementary units

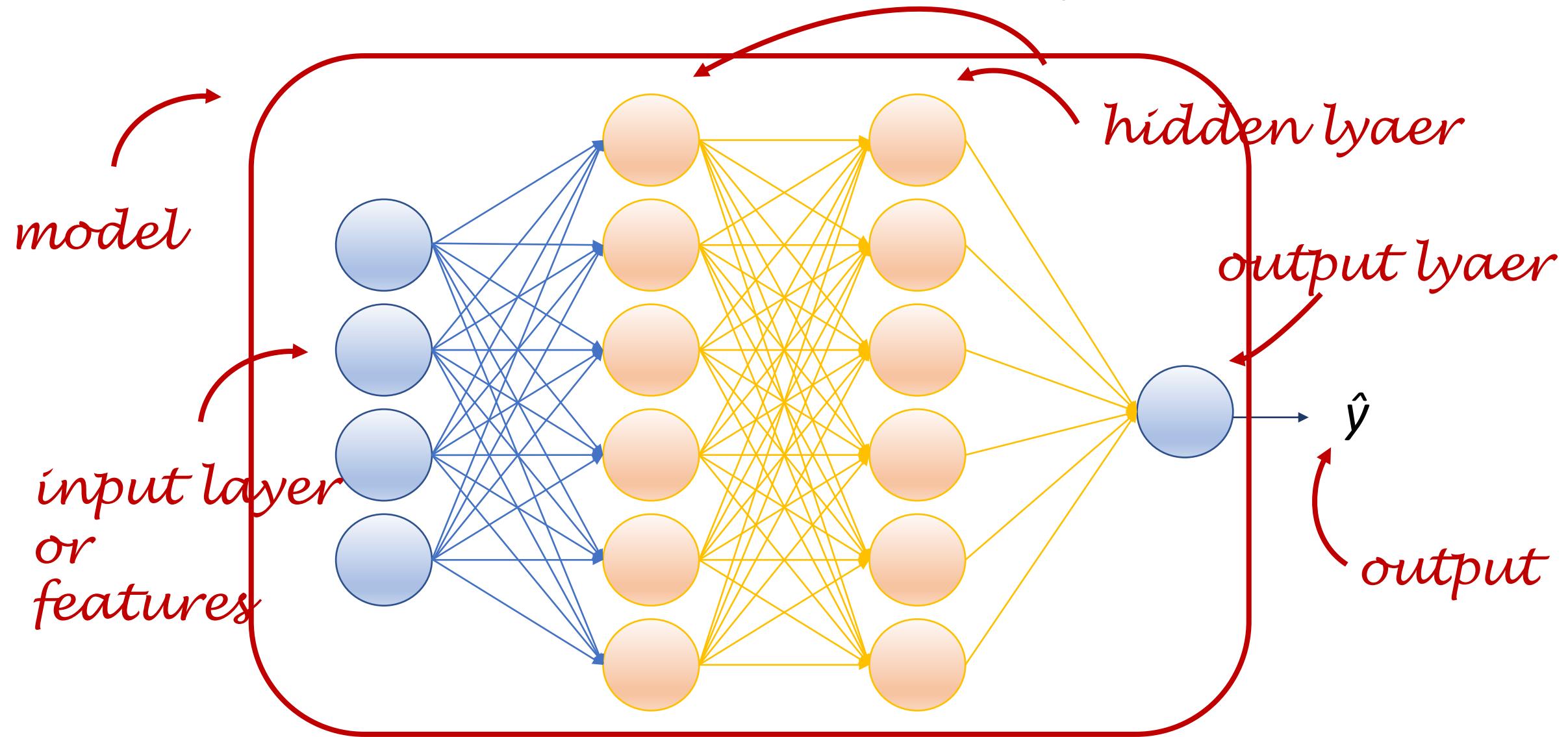


Why stacking neurons?

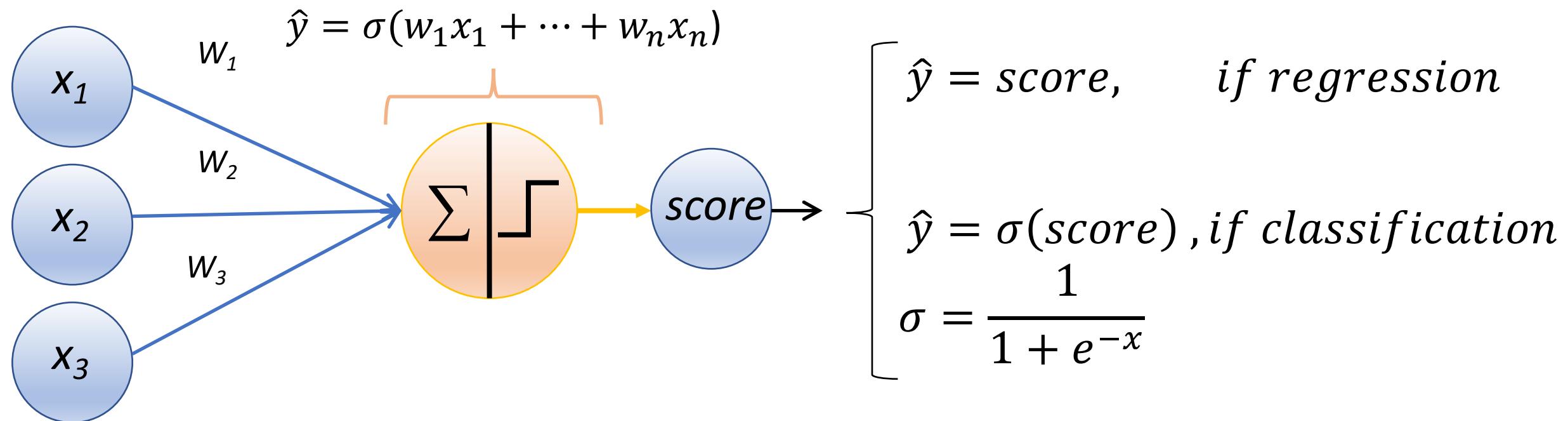
house area
neuborhood
building age



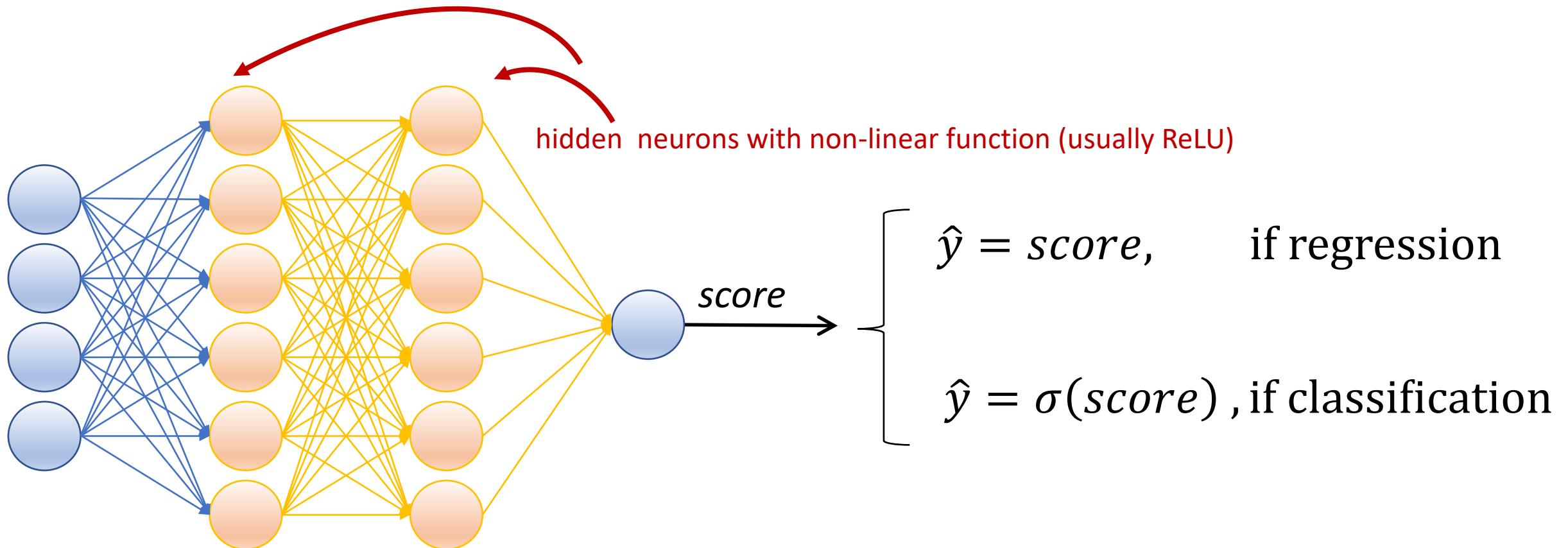
ANN – stacked elementary units



Activation functions

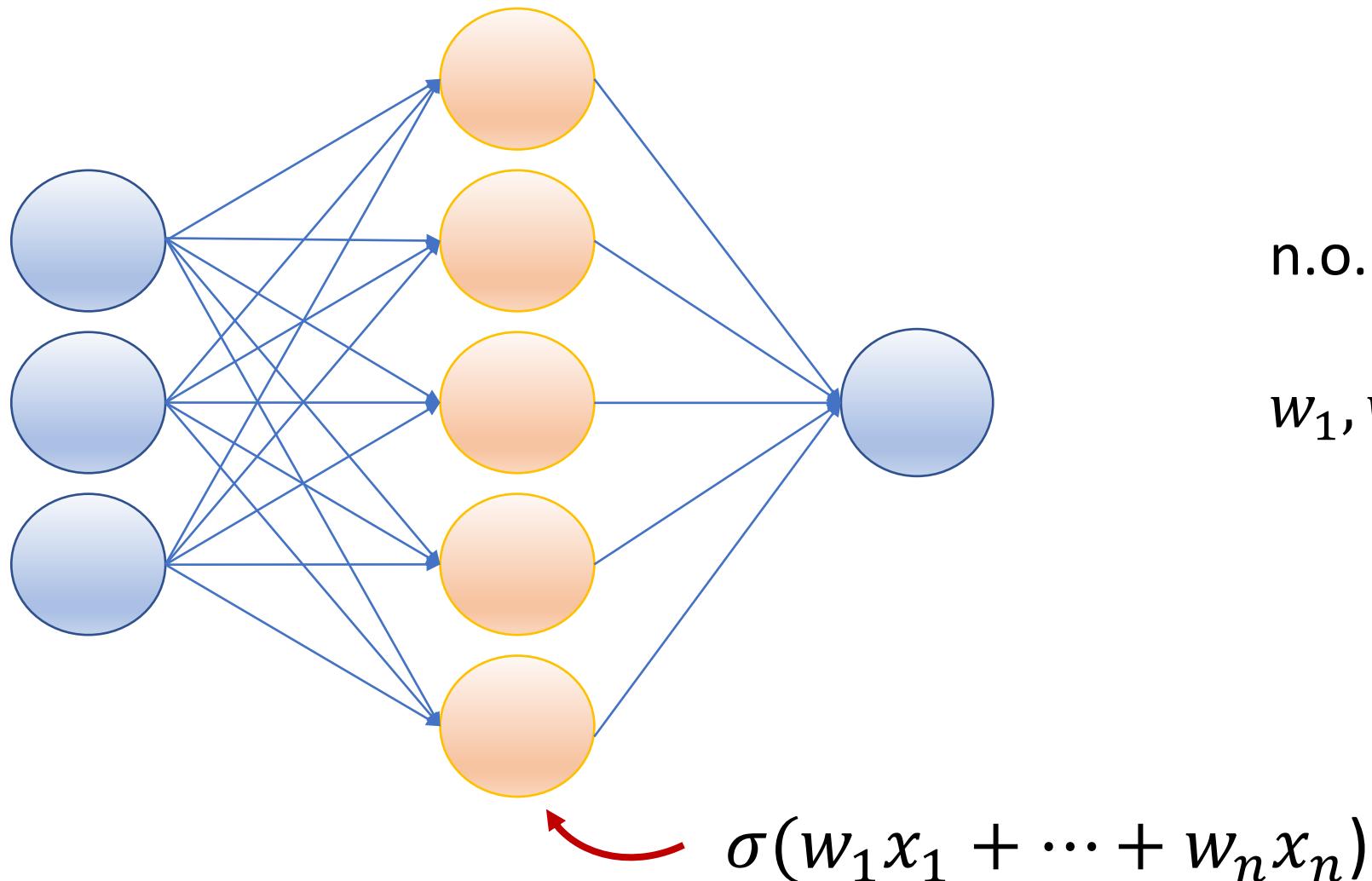


Activation functions



ANN PLAYGROUND

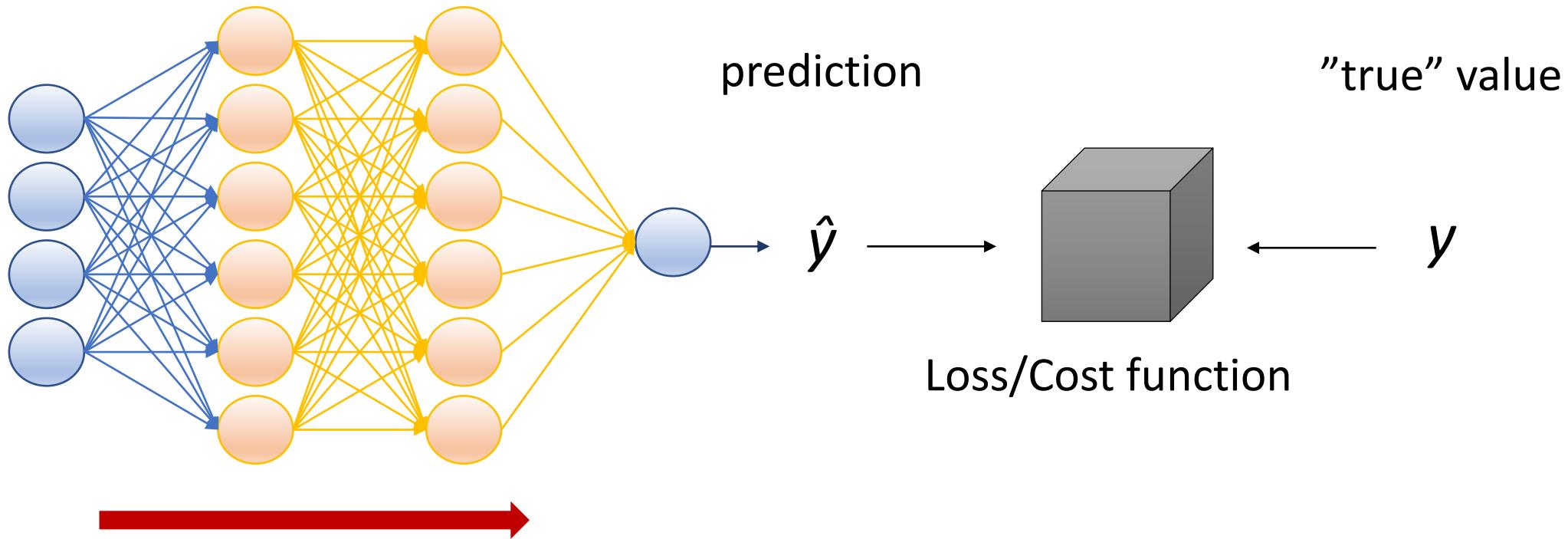
How to find good model parameters?



n.o. parameters = $3*5 + 5*1$

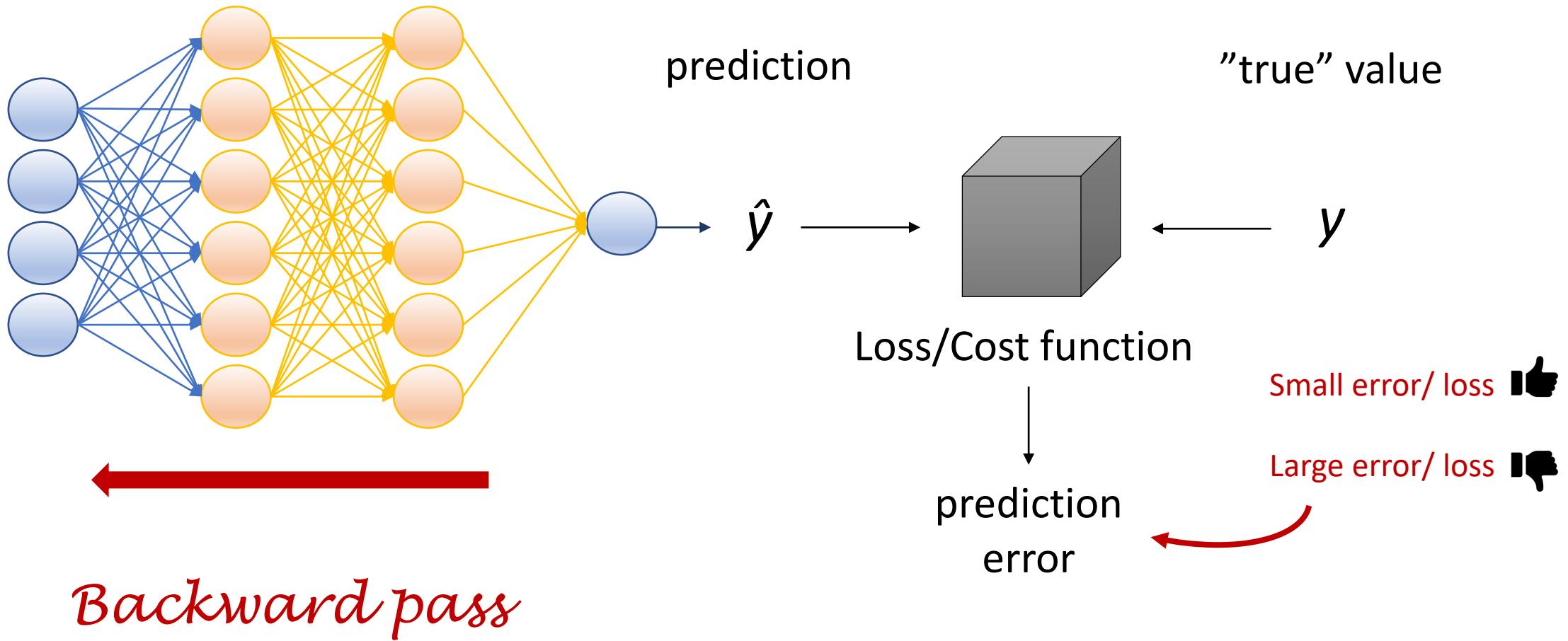
$w_1, w_2, w_3, w_4, w_5, \dots ???$

Gradient Descent Algorithm

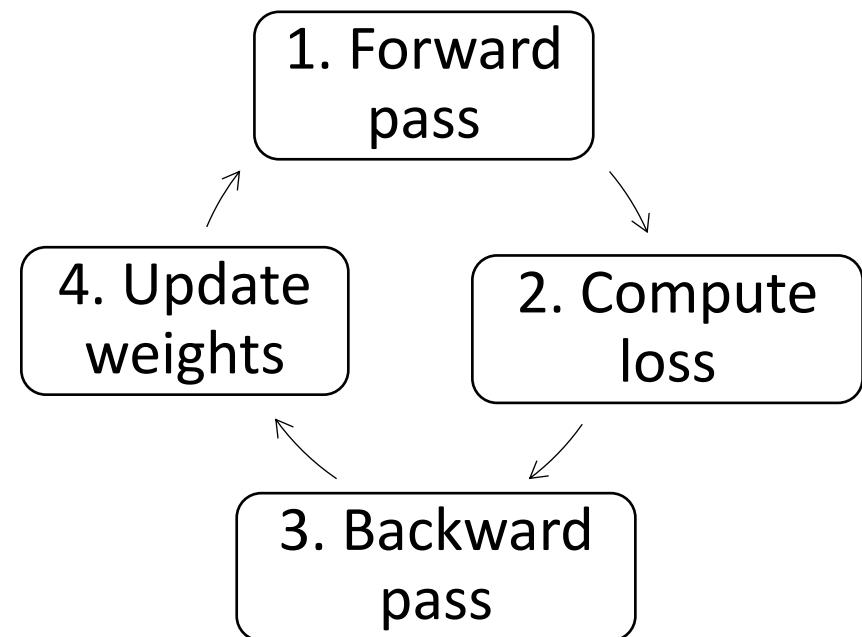
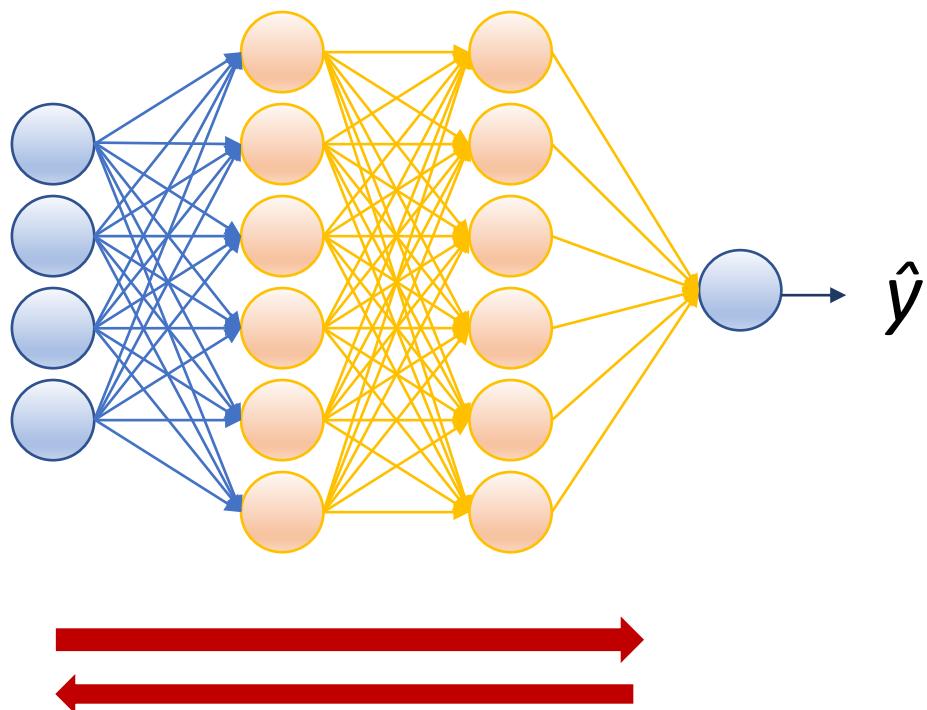


Forward pass

Gradient Descent Algorithm

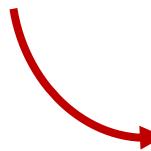


Gradient Descent Algorithm



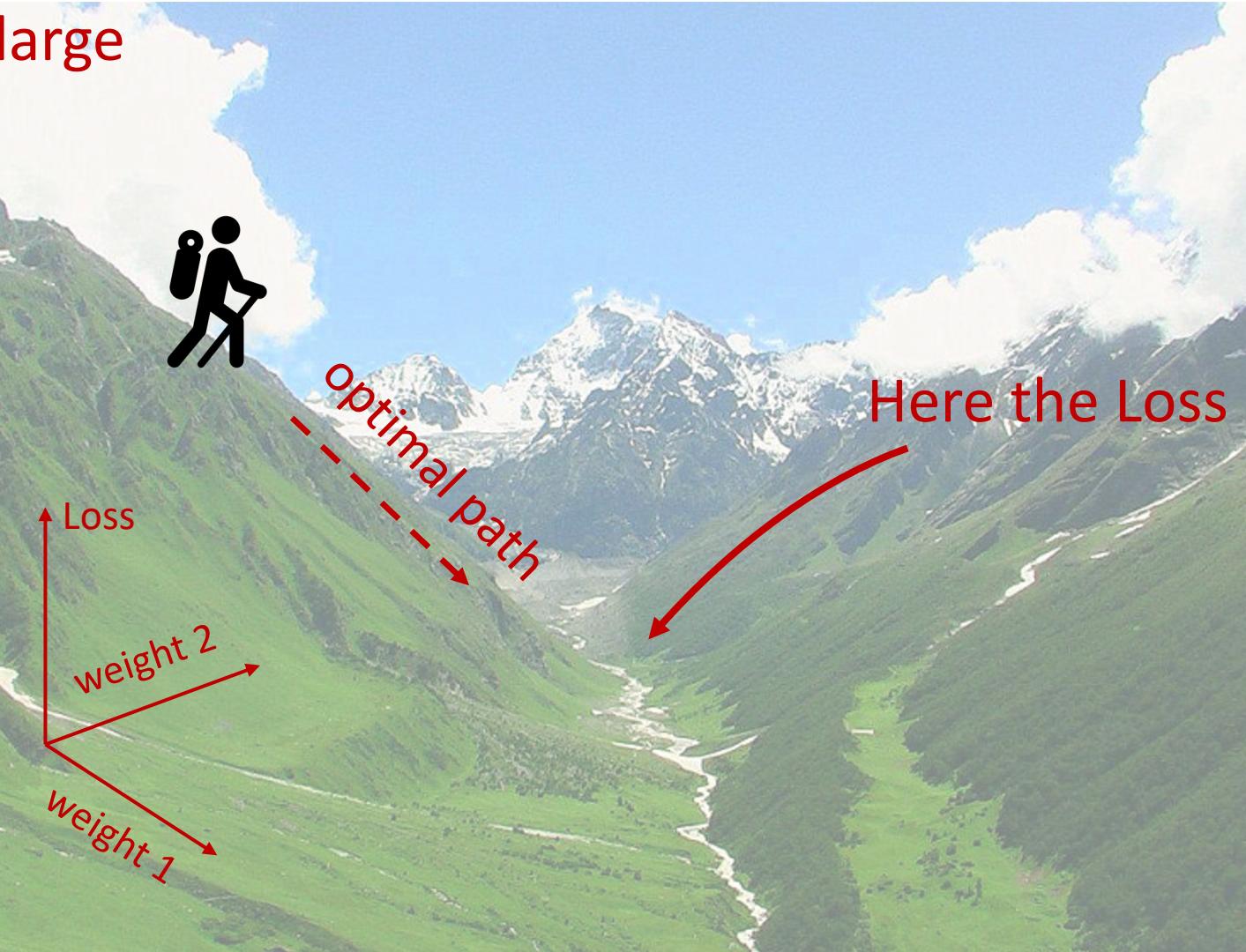
Loss landscape hiker

Here the Loss is large



optimal path

Here the Loss is small



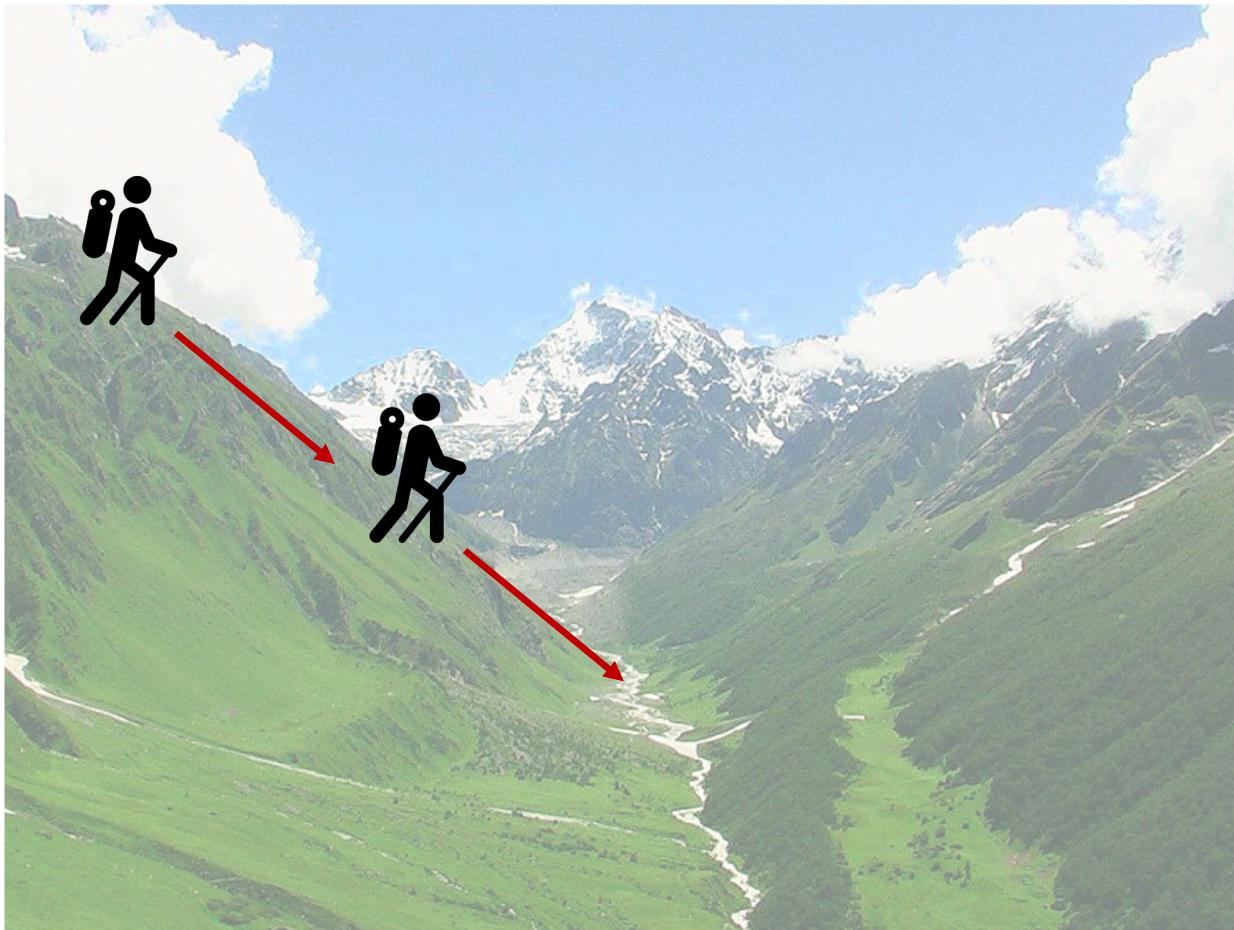
Gradient Descent Algorithm

Most important hyper-parameters to set:

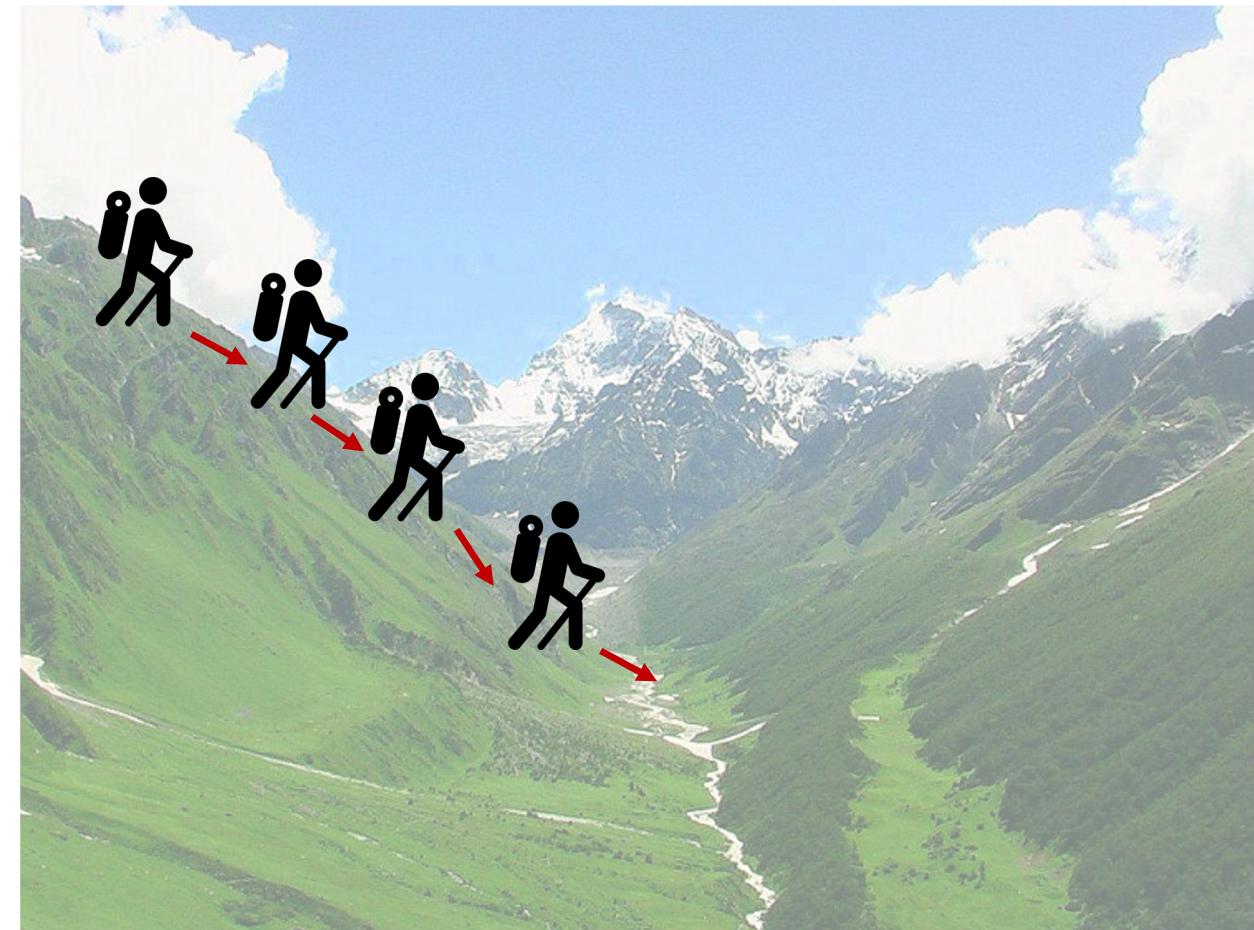
- Learning rate (step size) – by what amount we adjust/ tune/ update model's parameters (weights)

Learning rate

Large step size



Small step size



Gradient Descent Algorithm

Most important hyper-parameters to set:

- Learning rate (step size) – by what amount we adjust/ tune/ update model's parameters (weights)
- Number of iterations (epochs) - how many times we update model's weight

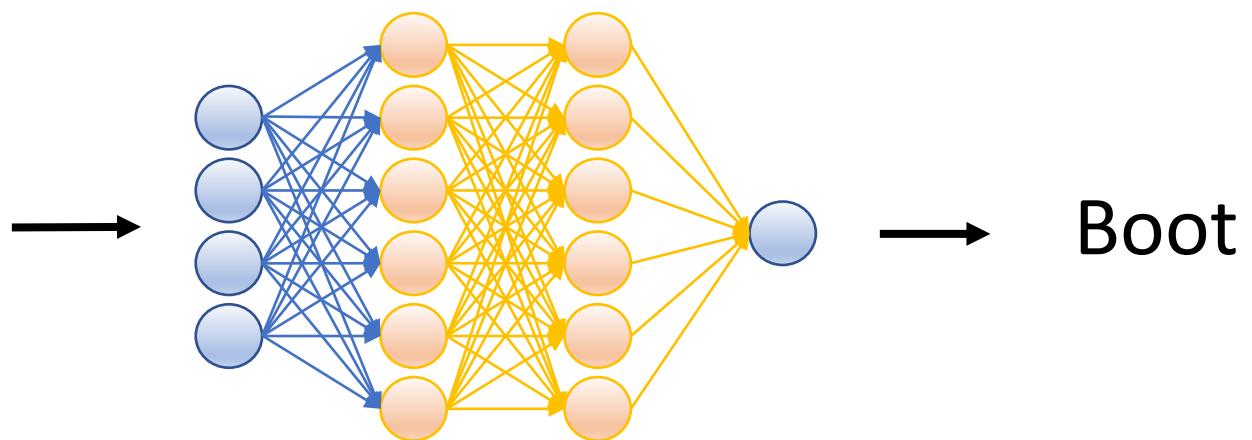
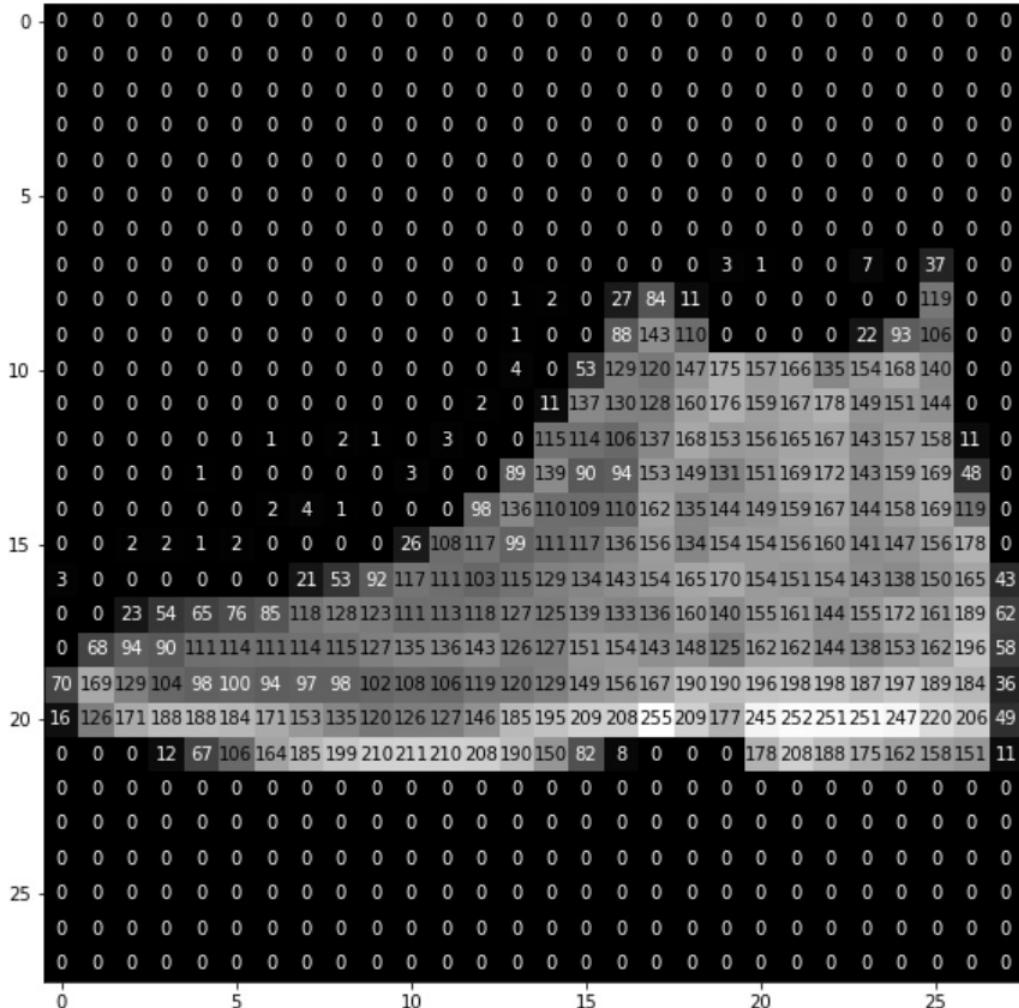
Number of iterations (epochs)

N.o. epochs is large

N.o. epochs is small

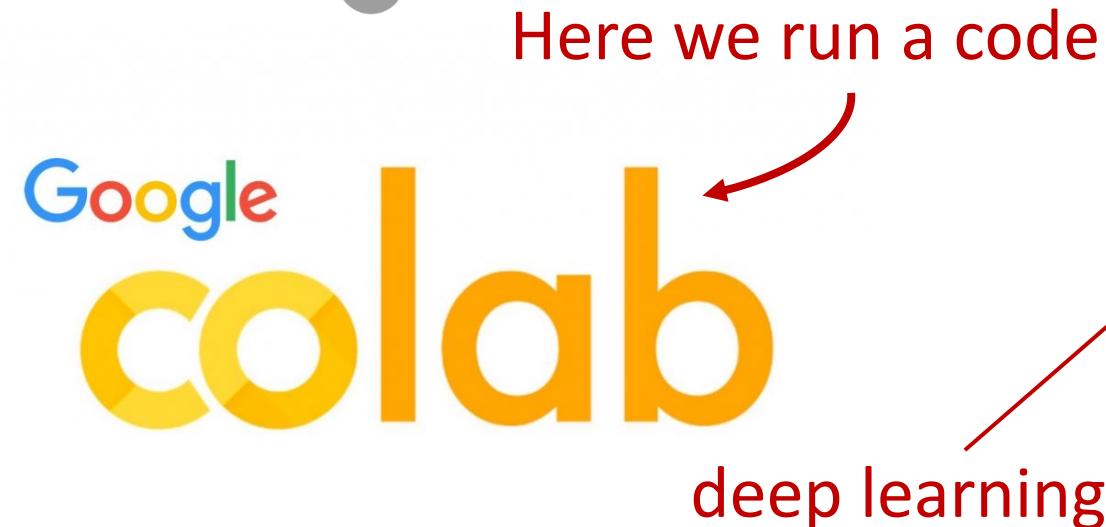
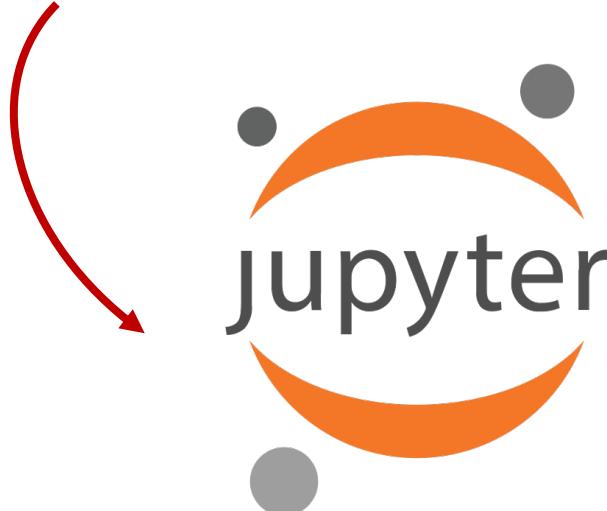


Hands on: shallow ANN for classification



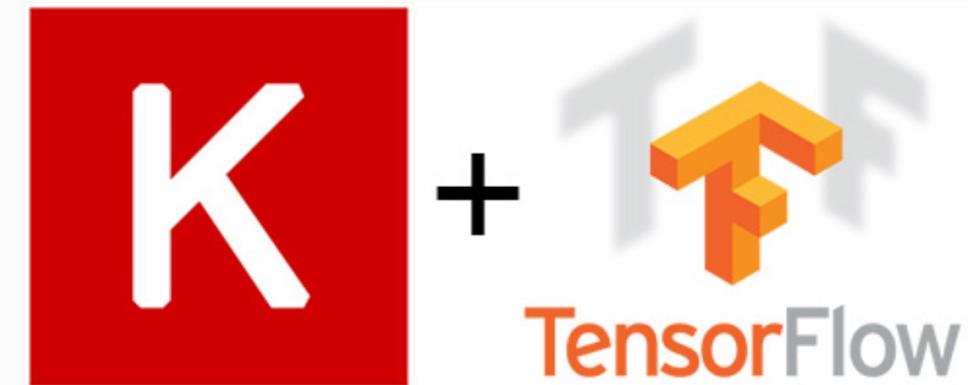
Tools

Here we keep our code



deep learning

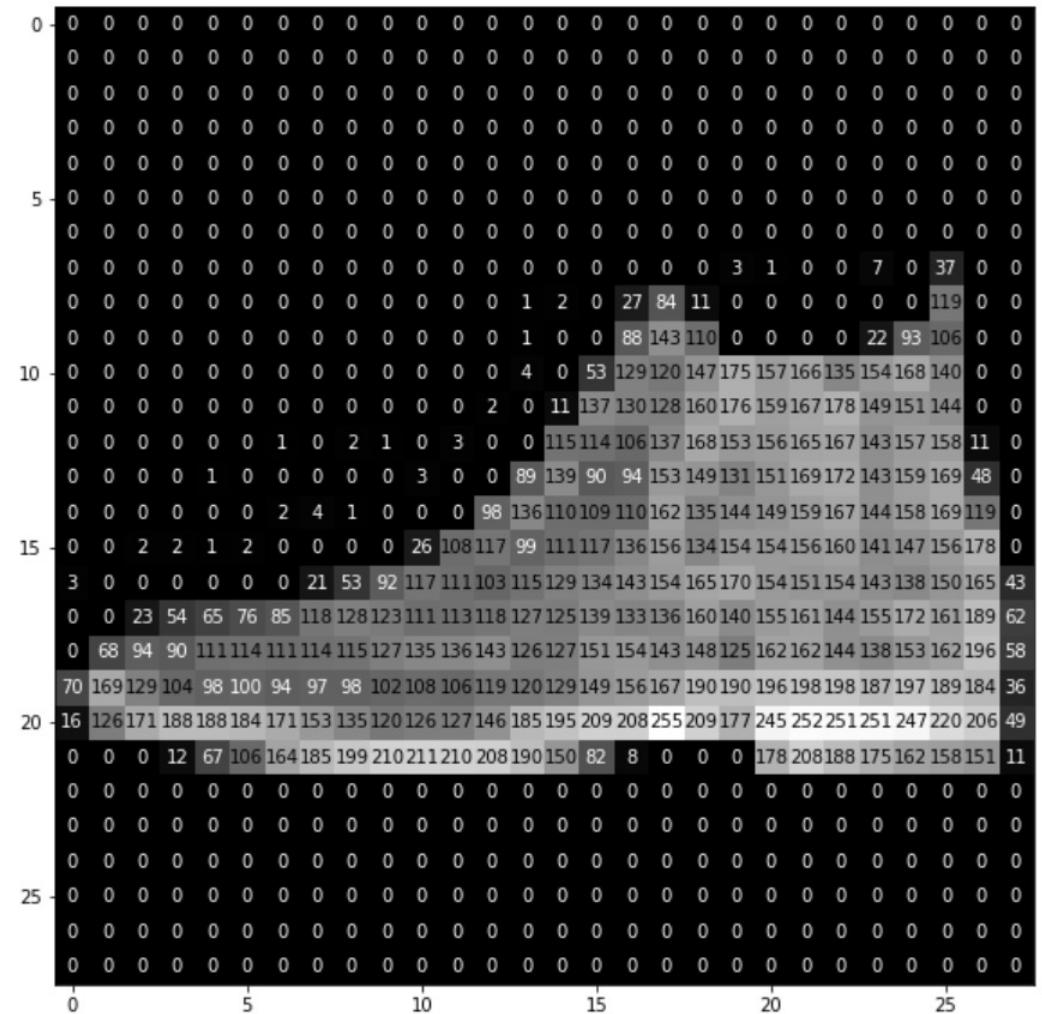
Python libraries:



graphs

Data

- Data point: 28x28 grayscale image of shopping item
- Features: $28 \times 28 = 784$ pixel values (range 0-255)
- Labels: Product category (boot, shirt, hat, ...). 10 classes in total.



Typical Workflow

1. Data prepossing (scale 0-1), splitting (training/validation/test).
2. Define ANN model
3. Choose Loss function, Optimizer
4. Train ANN
5. Evaluate on unseen (test) dataset

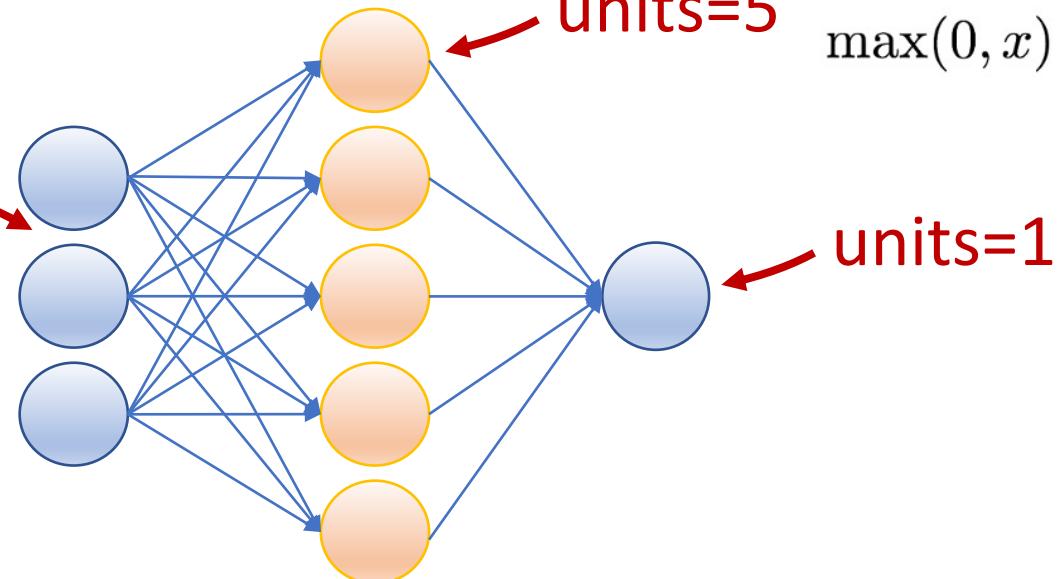
Data prepossessing

1. Scaling features to 0-1: makes it easier for algorithm to find “good” model parameters
2. Splitting (training/validation/test datasets):
 - Training – to find “good” model parameters
 - Validation – to choose model hyper-parameters (learning rate, n.o. epochs)
 - Test – final performance evaluation

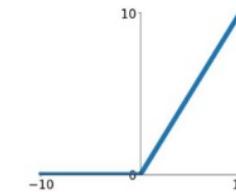
Define ANN model

```
model = keras.Sequential([
    layers.Dense(units=5, activation='relu', input_shape=(3,)),
    layers.Dense(units= 1, activation='sigmoid')
])
```

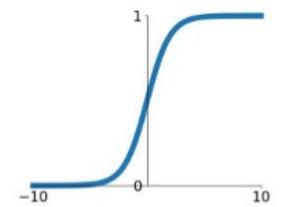
input_shape=(3,)



ReLU
 $\max(0, x)$



Sigmoid
 $\sigma(x) = \frac{1}{1+e^{-x}}$



Choose Loss function, Optimizer

Variation of basic Gradient Descent Algorithm

```
model.compile(optimizer='RMSprop',  
              loss='sparse_categorical_crossentropy',  
              metrics=['sparse_categorical_accuracy'])
```

Compare predictions and labels

Easy to understand
performance measure

Train ANN

```
history = model.fit(x_trainval,  
                     y_trainval,  
                     validation_split=0.2,  
                     batch_size=32,  
                     epochs=20,  
                     verbose=1)
```

Features and labels

Training data = 80%
Validation = 20%

Feed data by batches of 32

Printing info during training

Evaluate on test dataset

```
test_loss, test_accuracy = model.evaluate(X_test, y_test, verbose=0)
print('Accuracy on test dataset:', test_accuracy)
```