

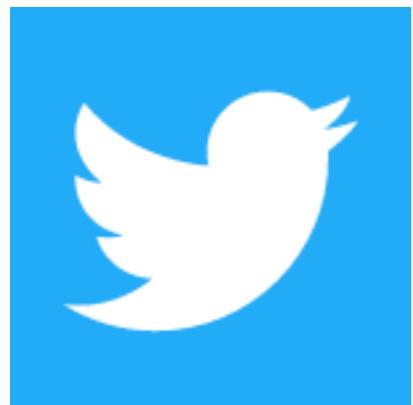
Deep Learning for Raiffeisenbank International

Jiří Materna





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#mlcollege

About me

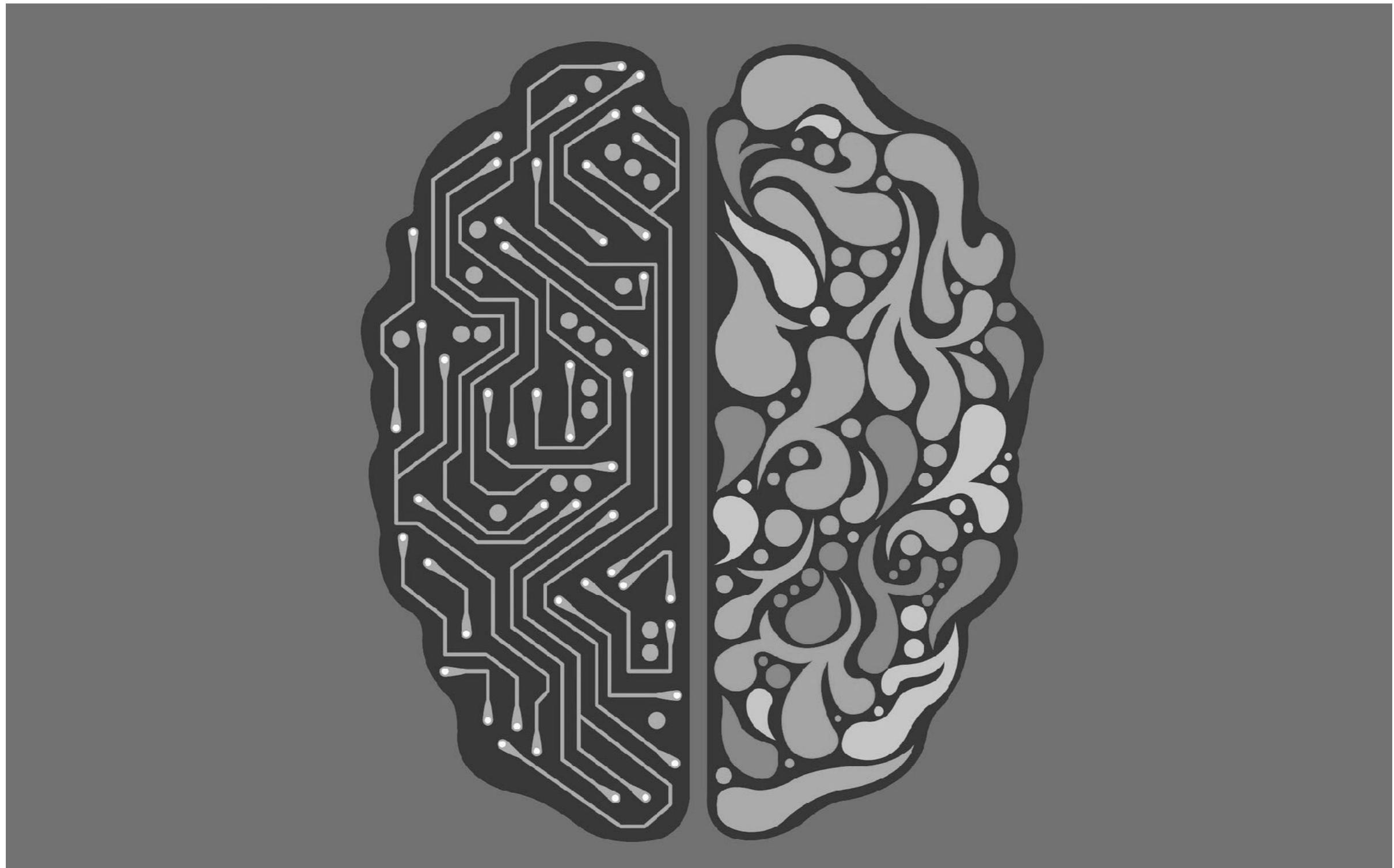
- Ph.D. in Natural Language Processing and Artificial Intelligence at Masaryk University
- 10 years at seznam.cz (last 8 years as Head Of Research)
- Founder and co-organizer of ML Prague
- Mentor at StartupYard and Startup AI Incubator
- ML Freelancer and consultant

Outline

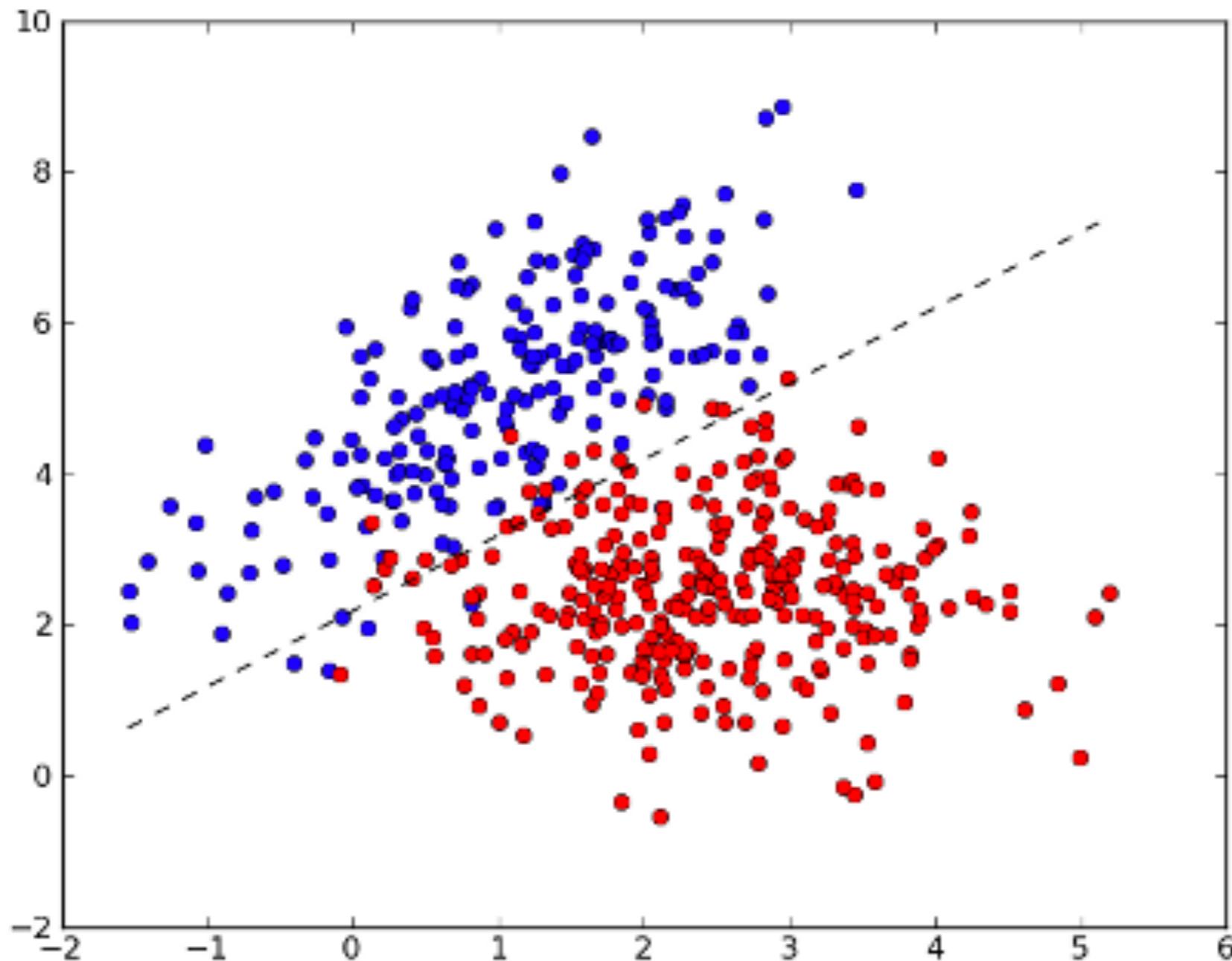
Day 1

- Scikit-learn tutorial
- Practical classification task
- Practical regression task
- Introduction to neural networks
- Methods for training neural networks
- Keras tutorial
- Practical classification and regression tasks solved using neural networks

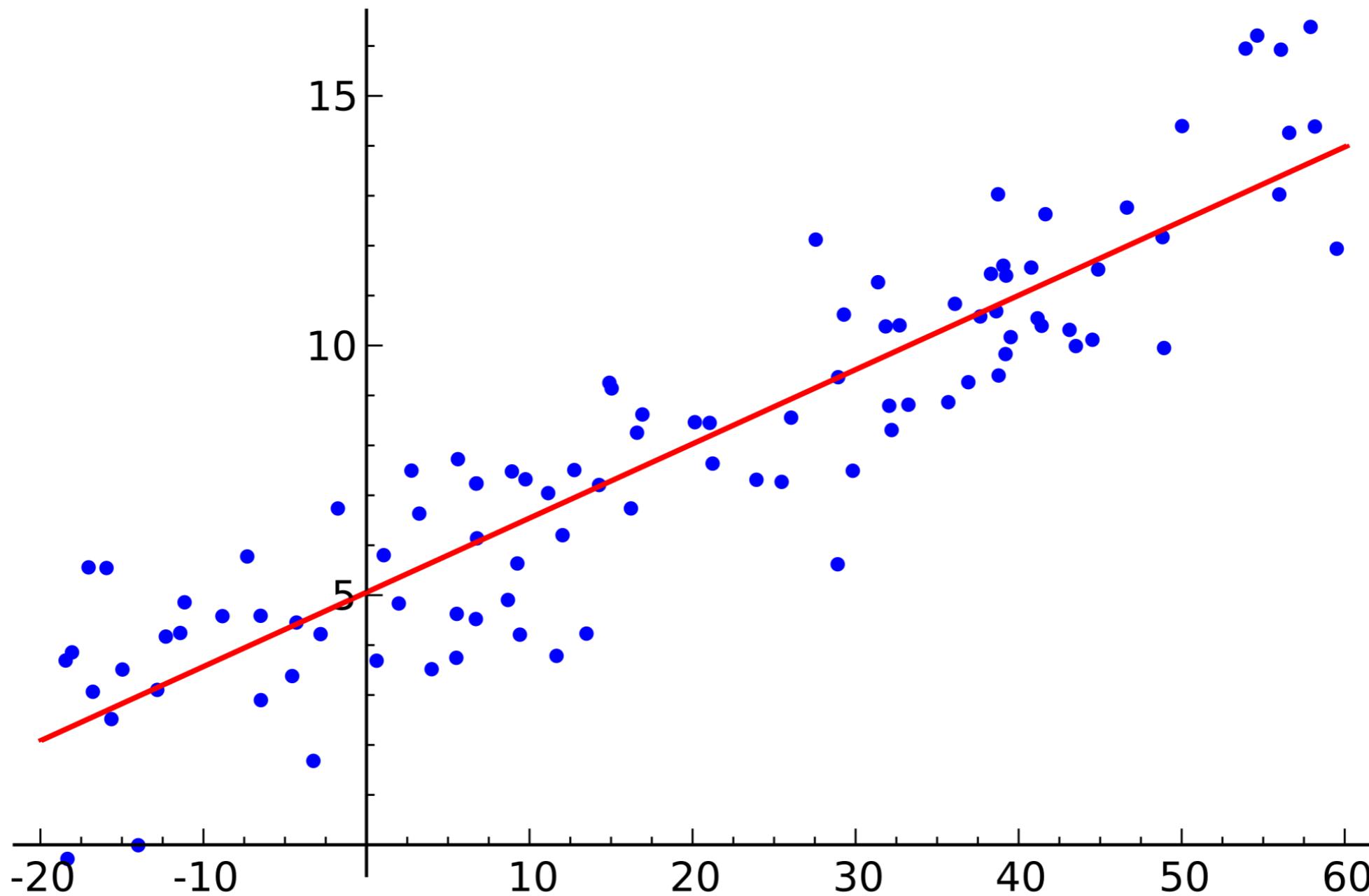
What is (not) machine learning?



Classification



Regression



Scikit-learn tutorial

<http://scikit-learn.org/stable/>

01 - Scikit learn tutorial

Classification task

02-Classification1-assignment.ipynb

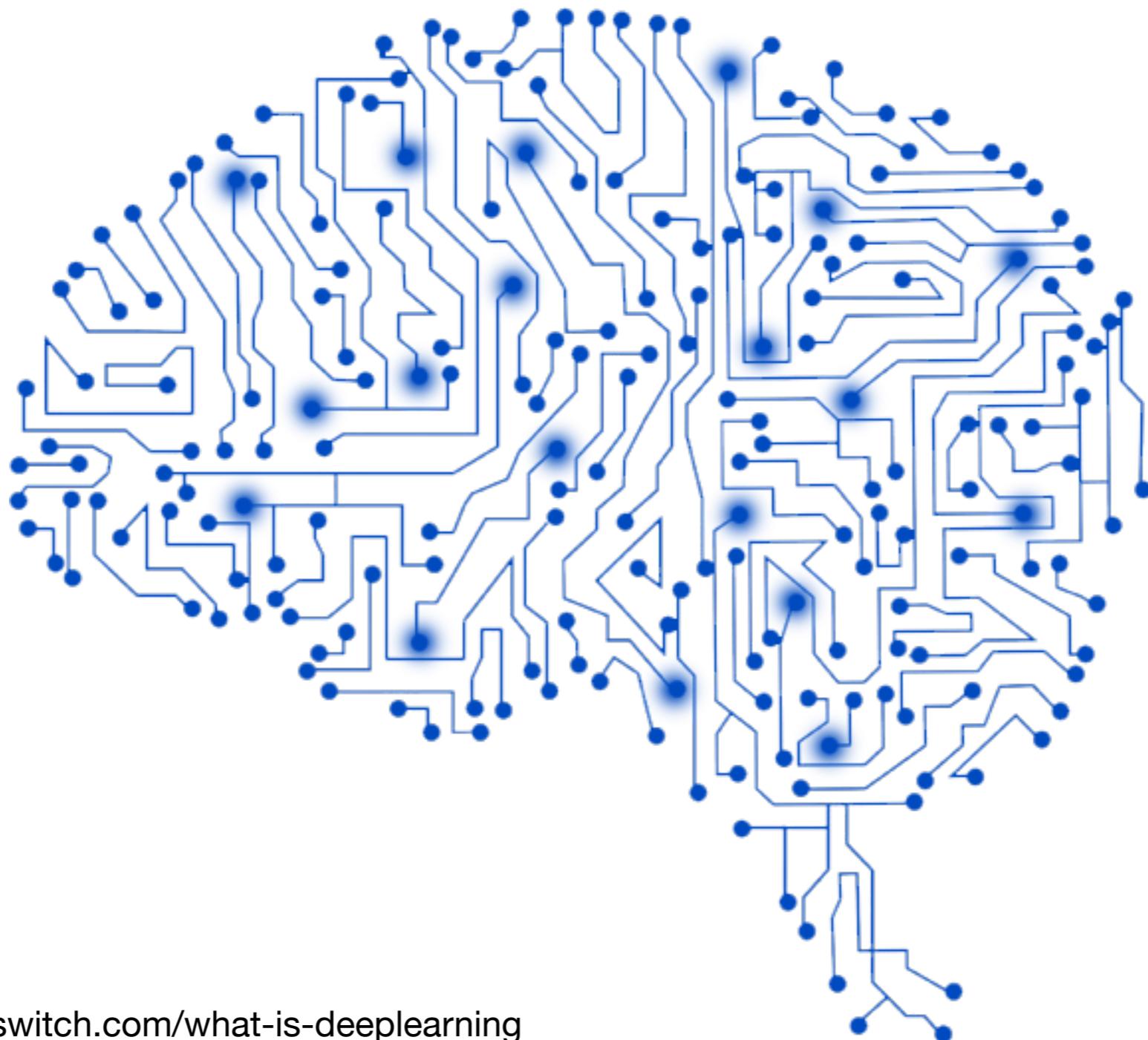
03-Classification2-assignment.ipynb

Regression task

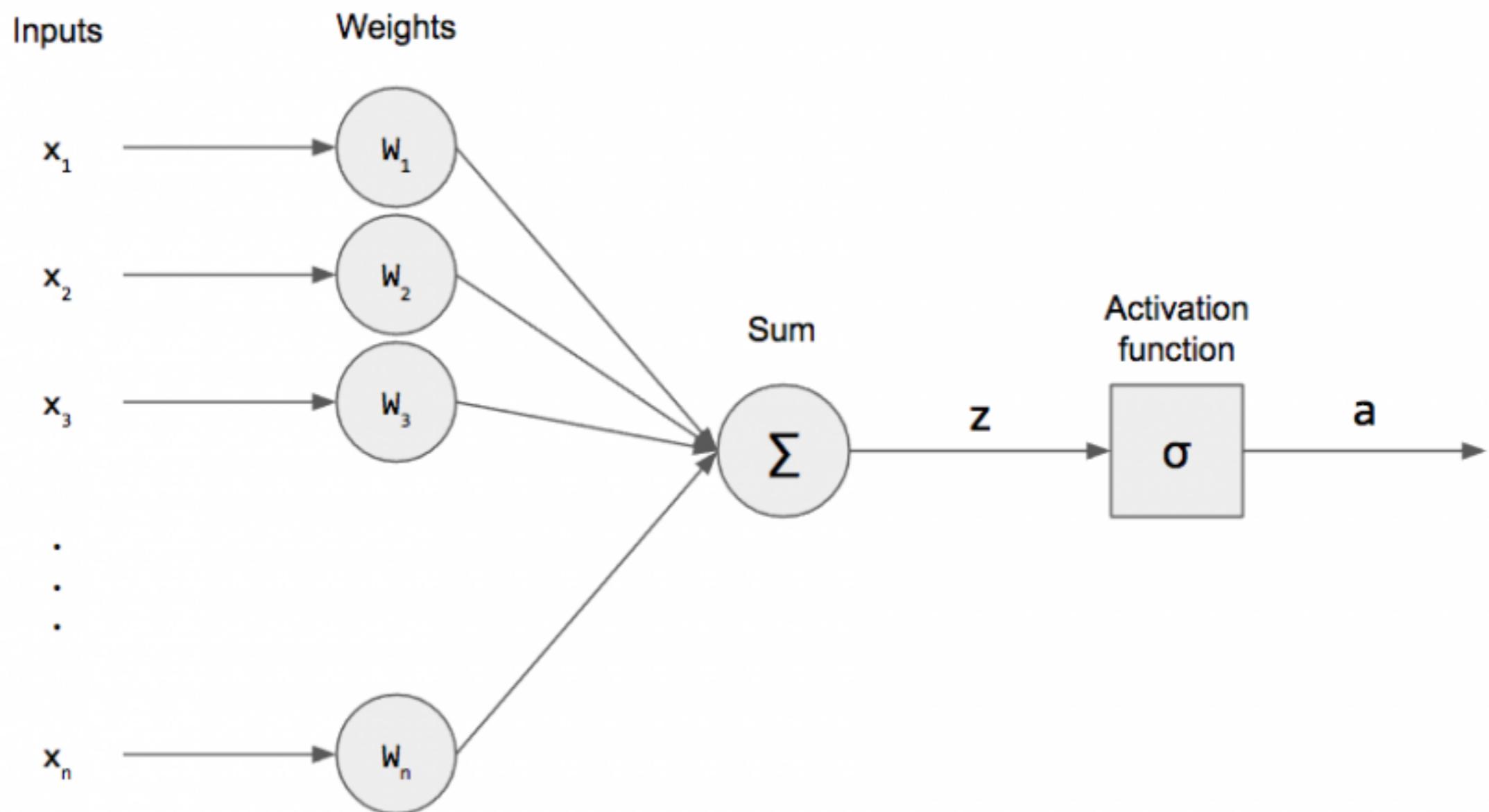
[04-Regression1-assignment.ipynb](#)

[05-Regression2-assignment.ipynb](#)

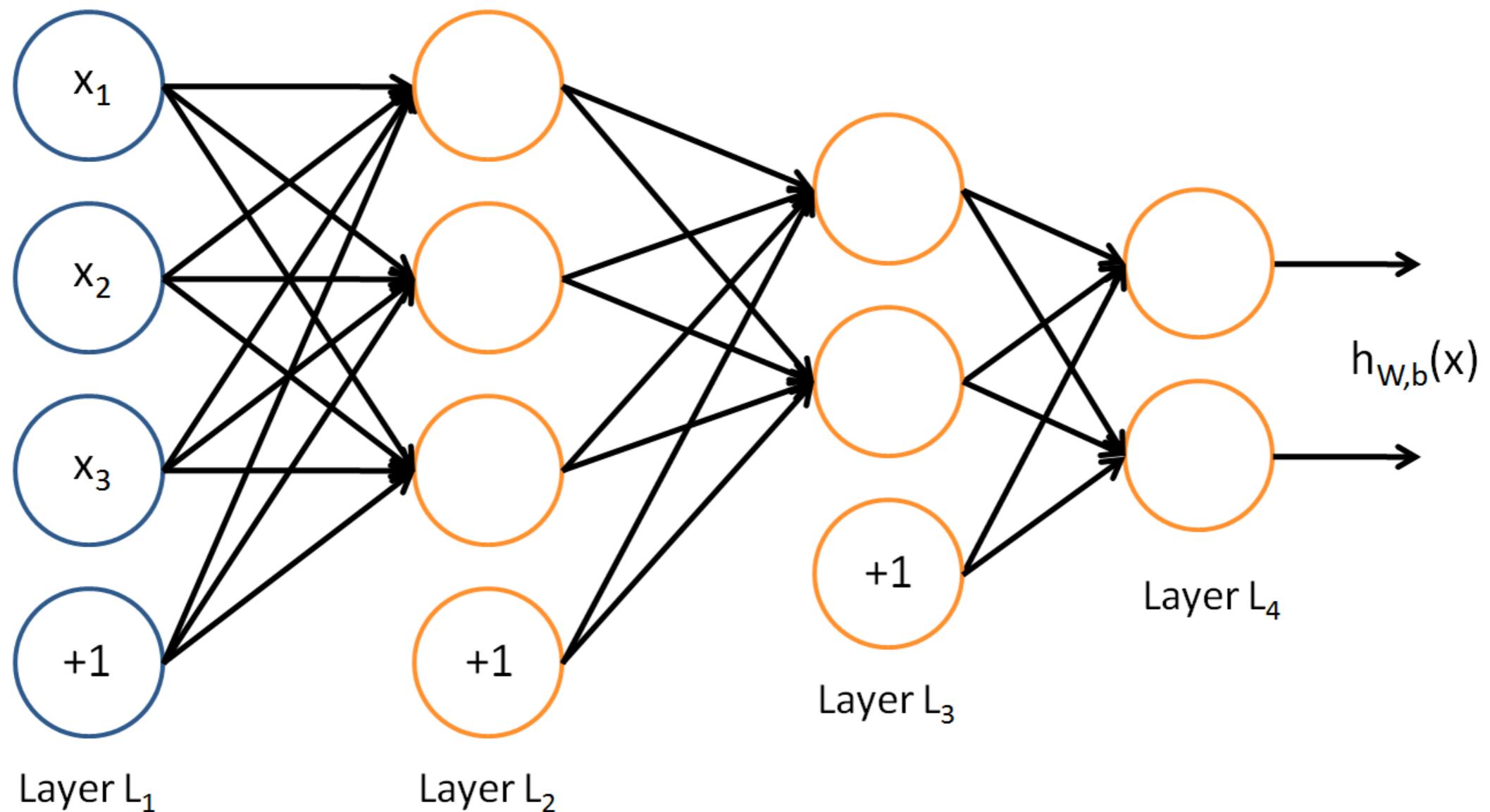
Neural networks and deep learning



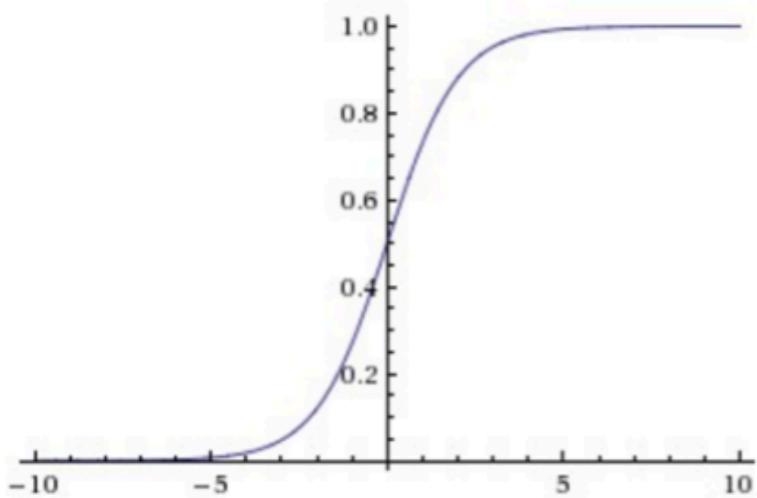
Perceptron



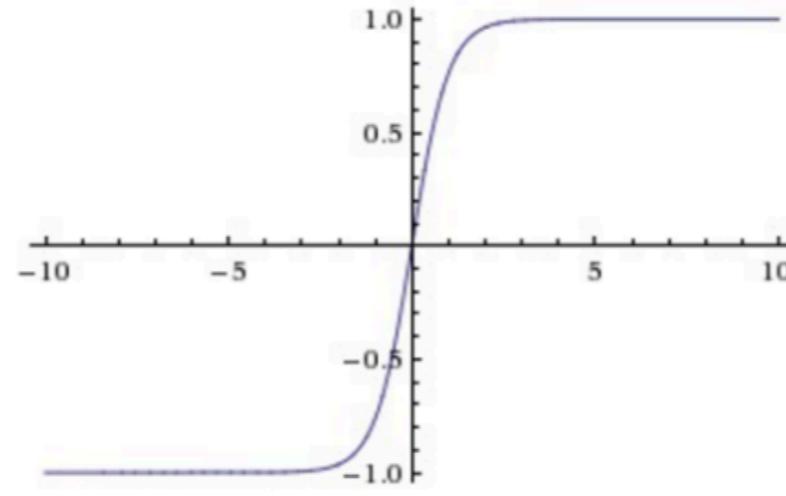
Multilayer Neural Networks



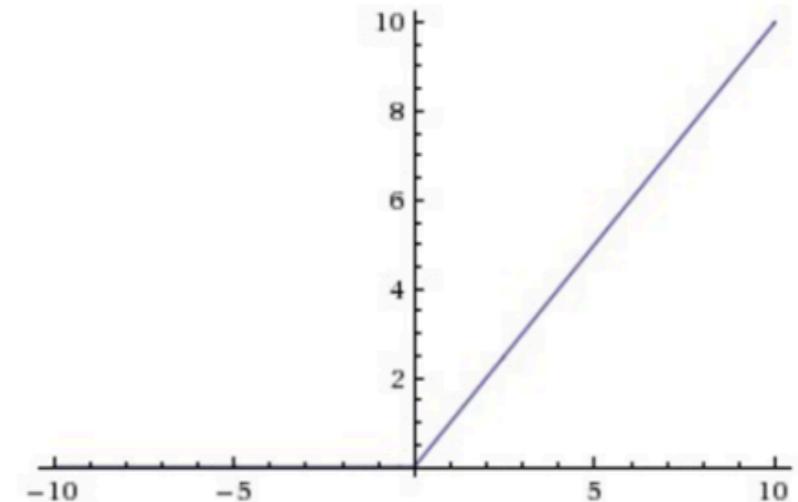
Activation functions



Sigmoid



tanh

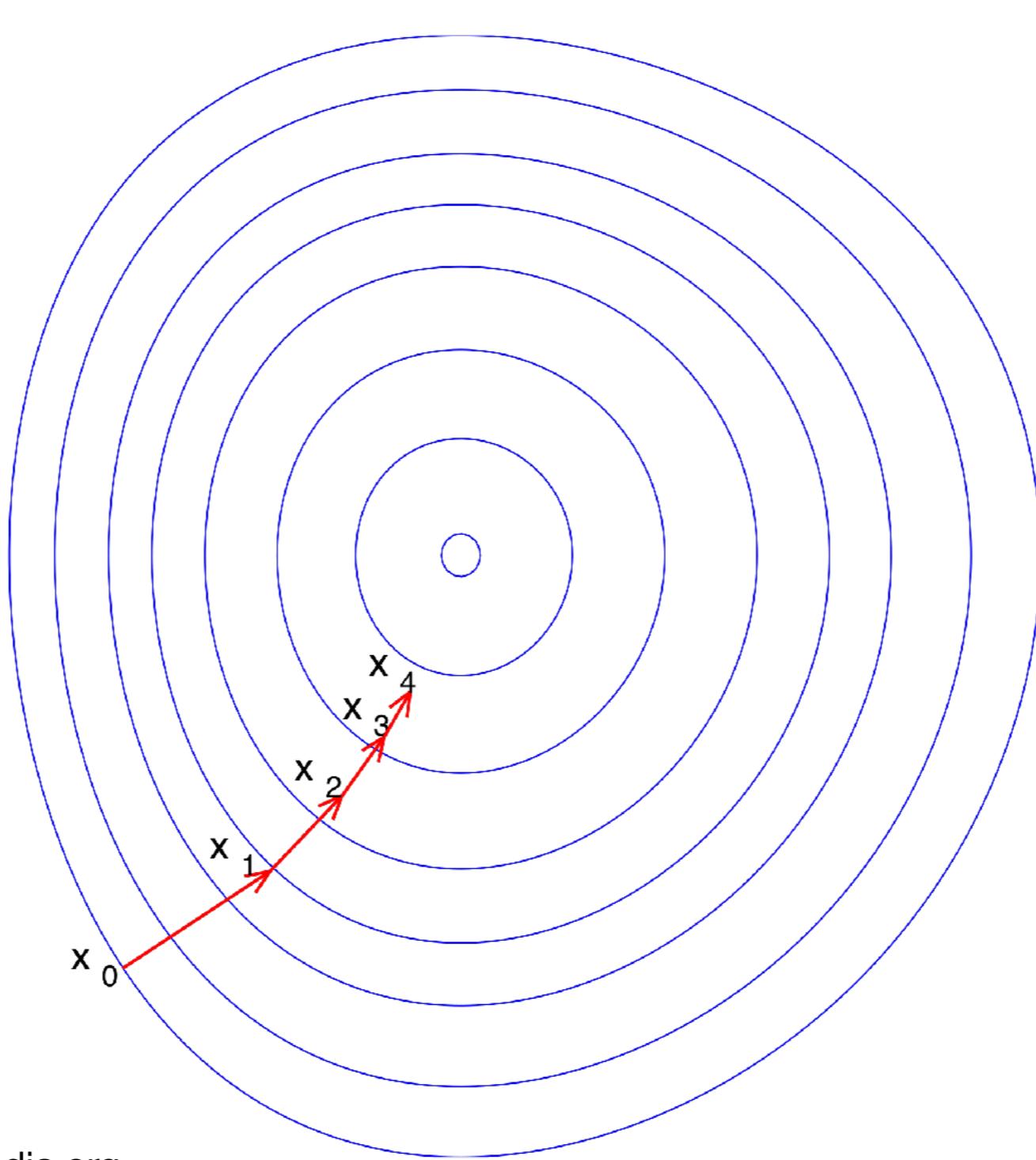


ReLU

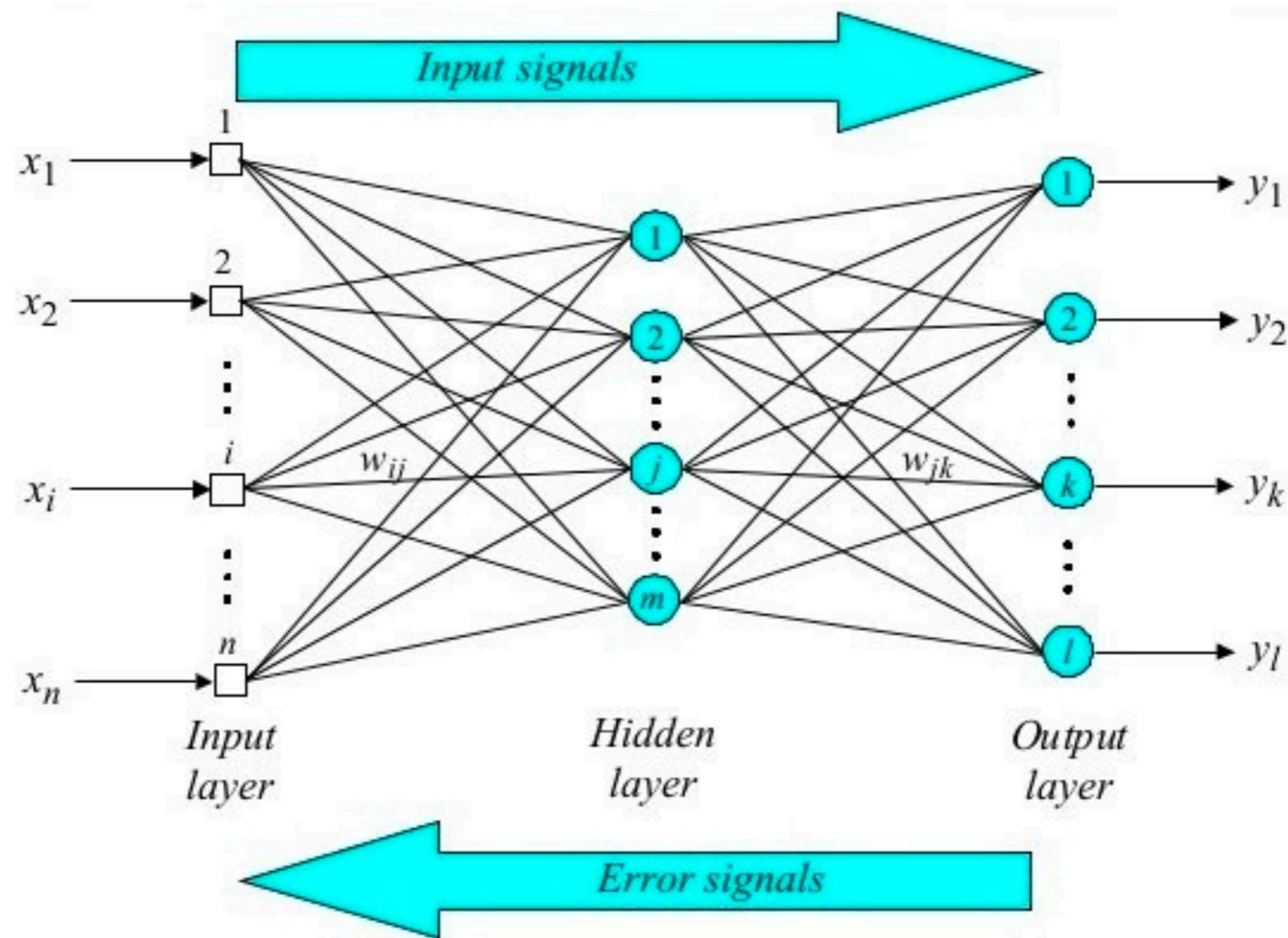
Softmax:

$$\sigma(\mathbf{z})_j = \frac{e^{z_j}}{\sum_{k=1}^K e^{z_k}}$$

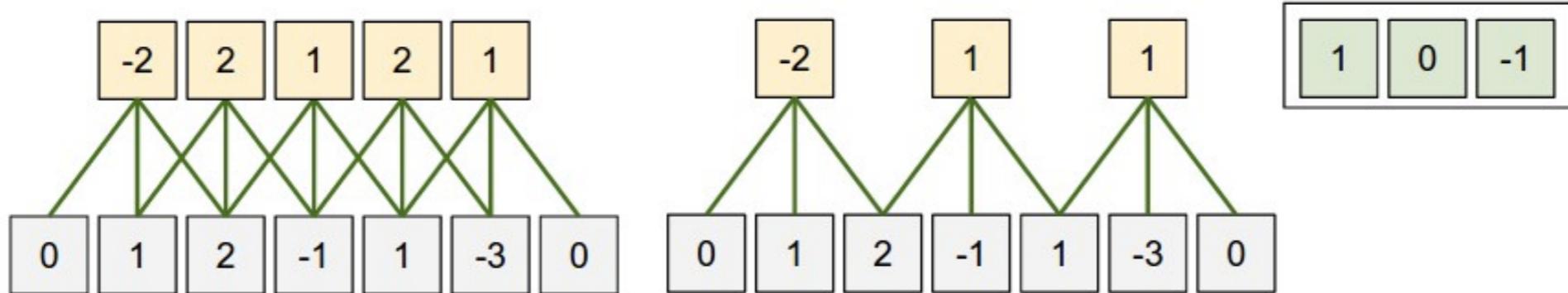
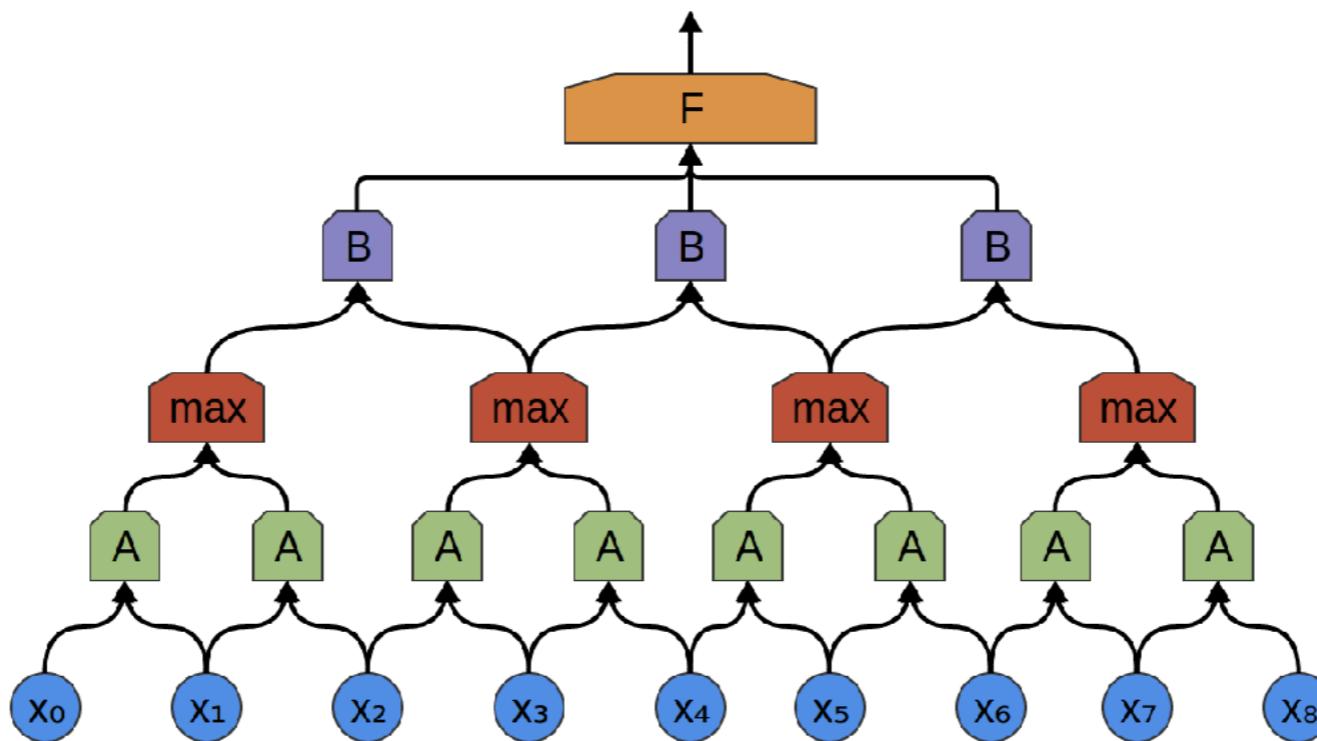
Steepest gradient descent



Back propagation

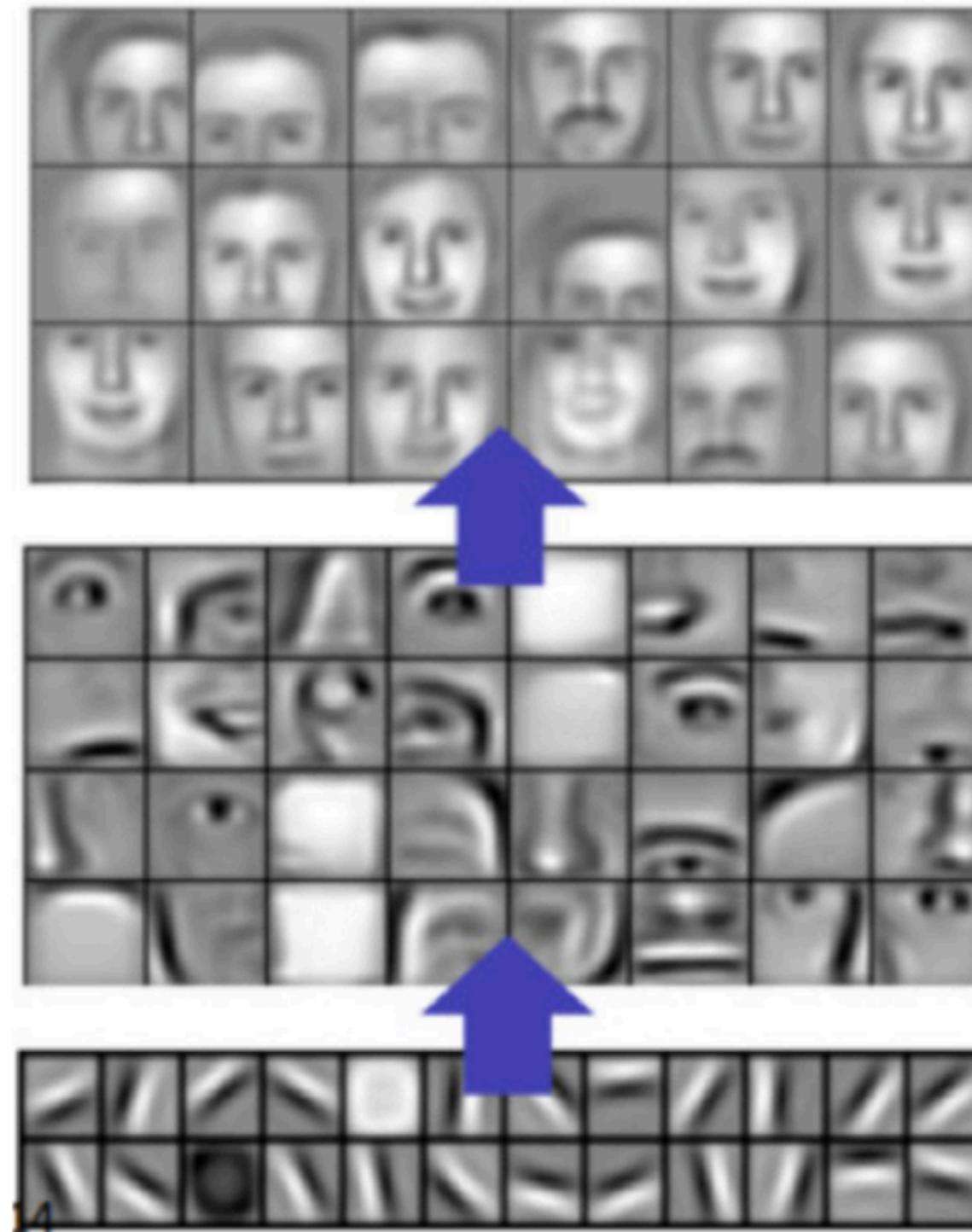


Convolution



Source: <https://www.tensorflow.org>

Weights visualization



Layer 3

Layer 2

Layer 1

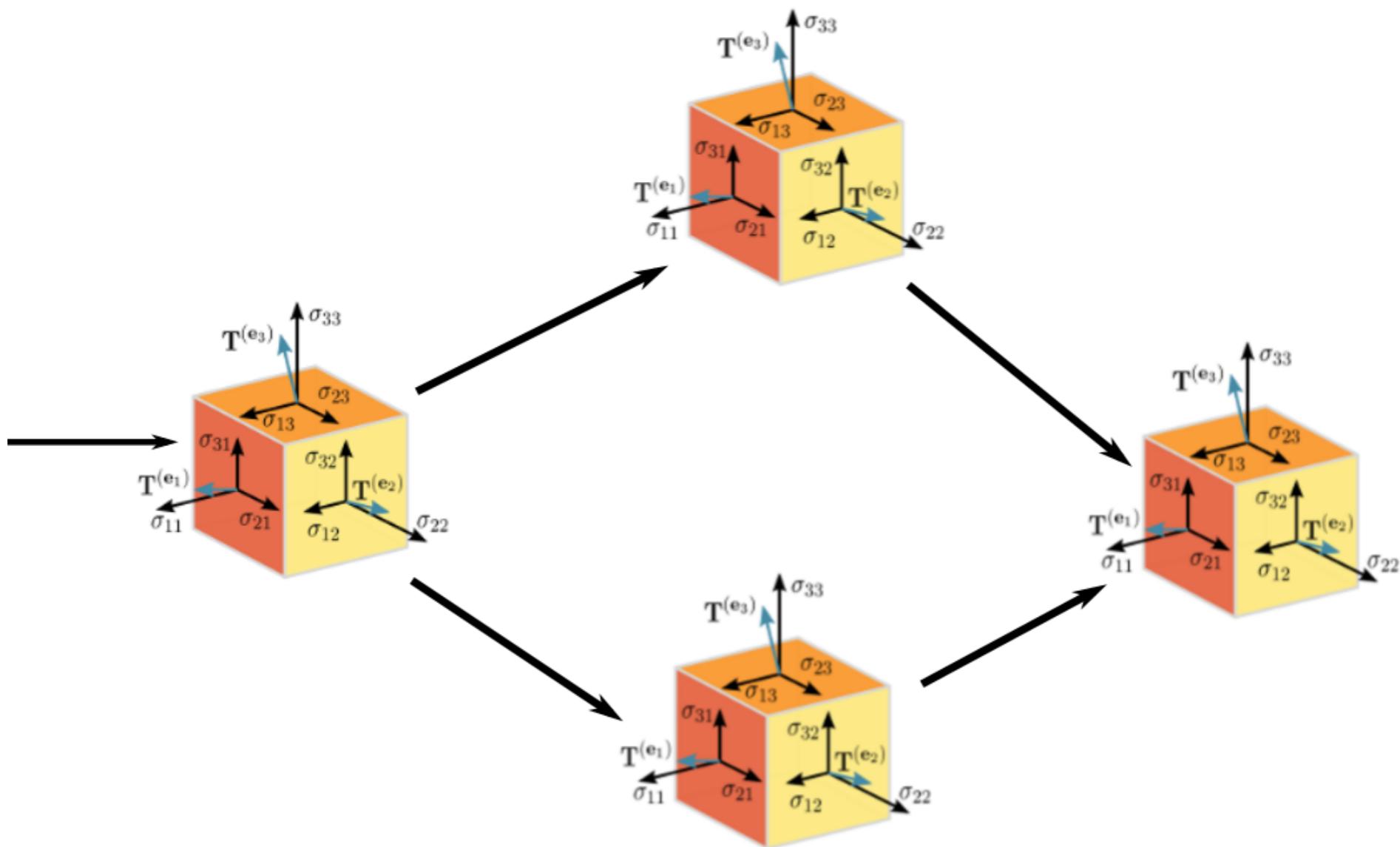
Important terms

- deep learning
- batch and mini-batch learning
- epoch

What is not TensorFlow



What is TensorFlow?



Keras tutorial

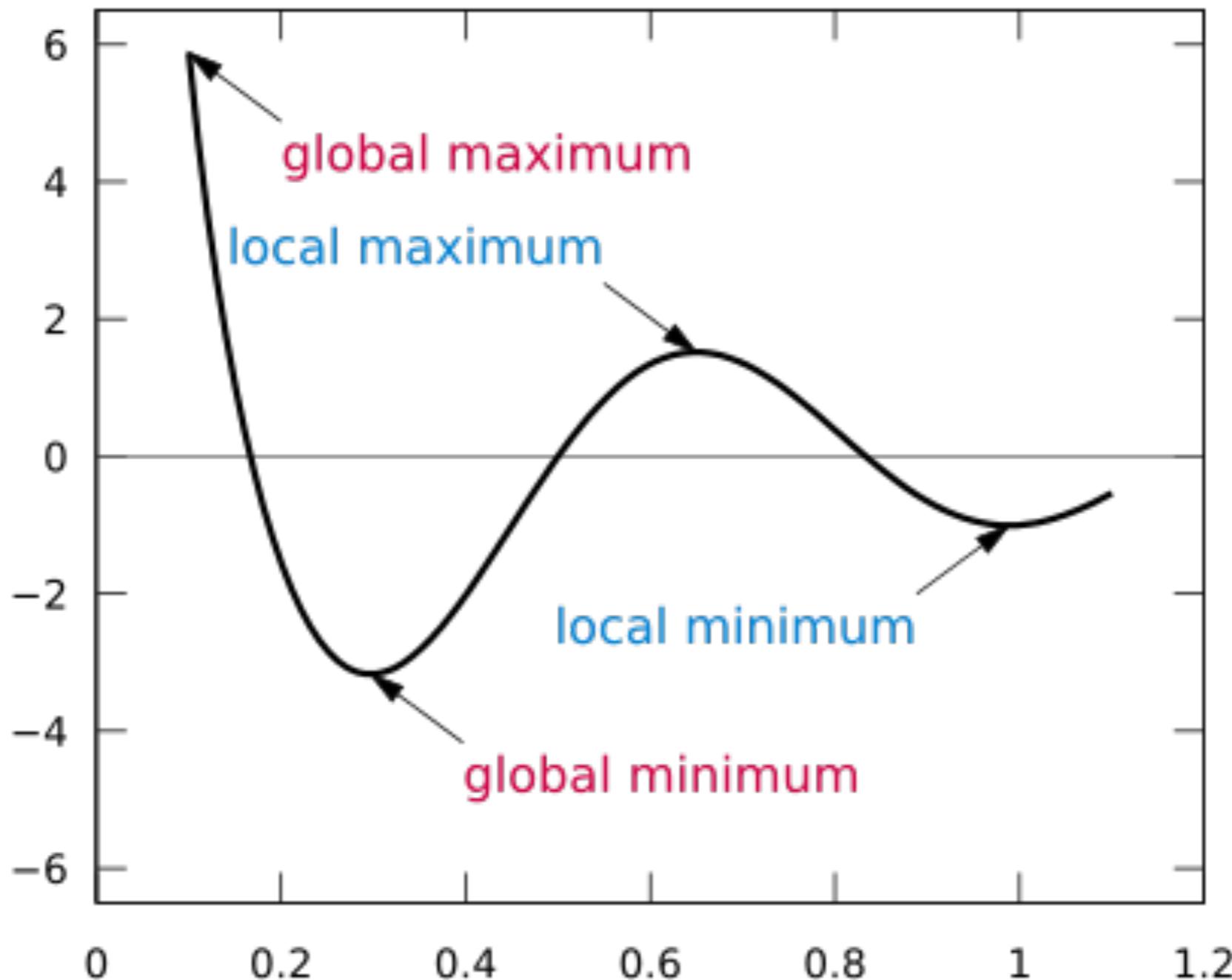
06-Keras-introduction.ipynb

Outline

Day 2

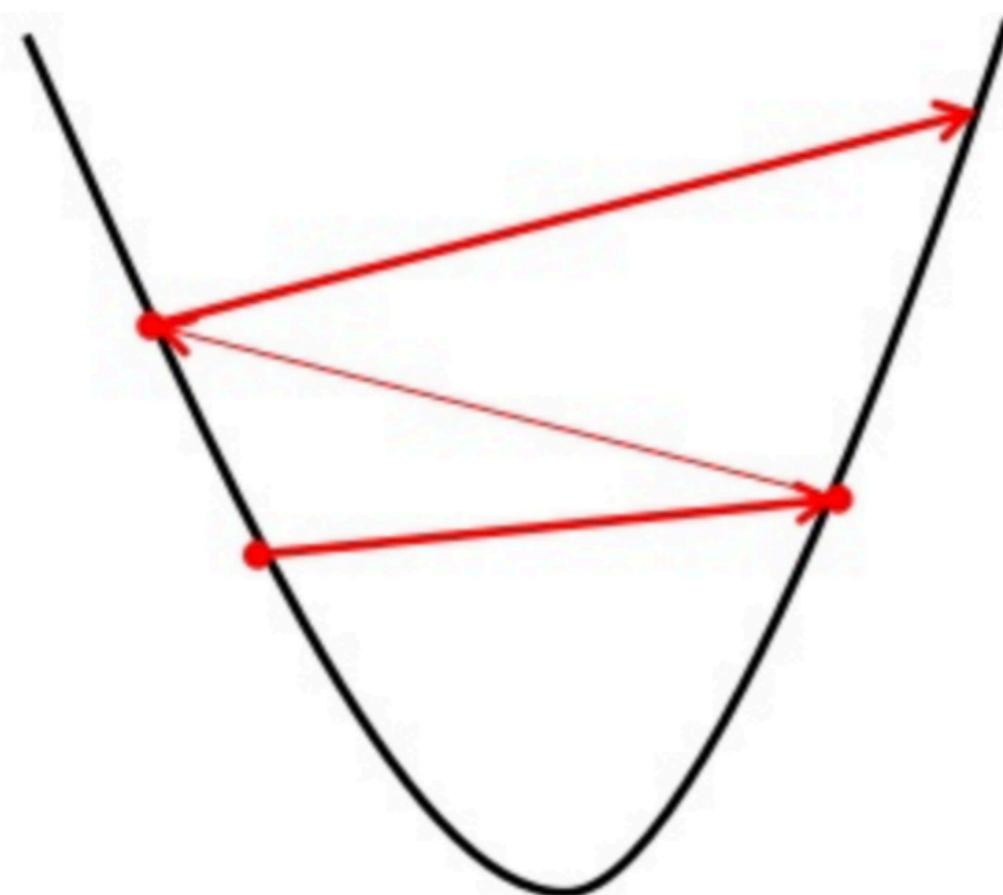
- Optimizers and their evolution
- Loss functions and their properties
- Practical classification task
- Practical regression task
- Initialization of weights in neural networks
- Normalization and Regularization in neural networks
- Functional model definition in Keras
- Practical example of a complex neural network

Parameter optimization strategies

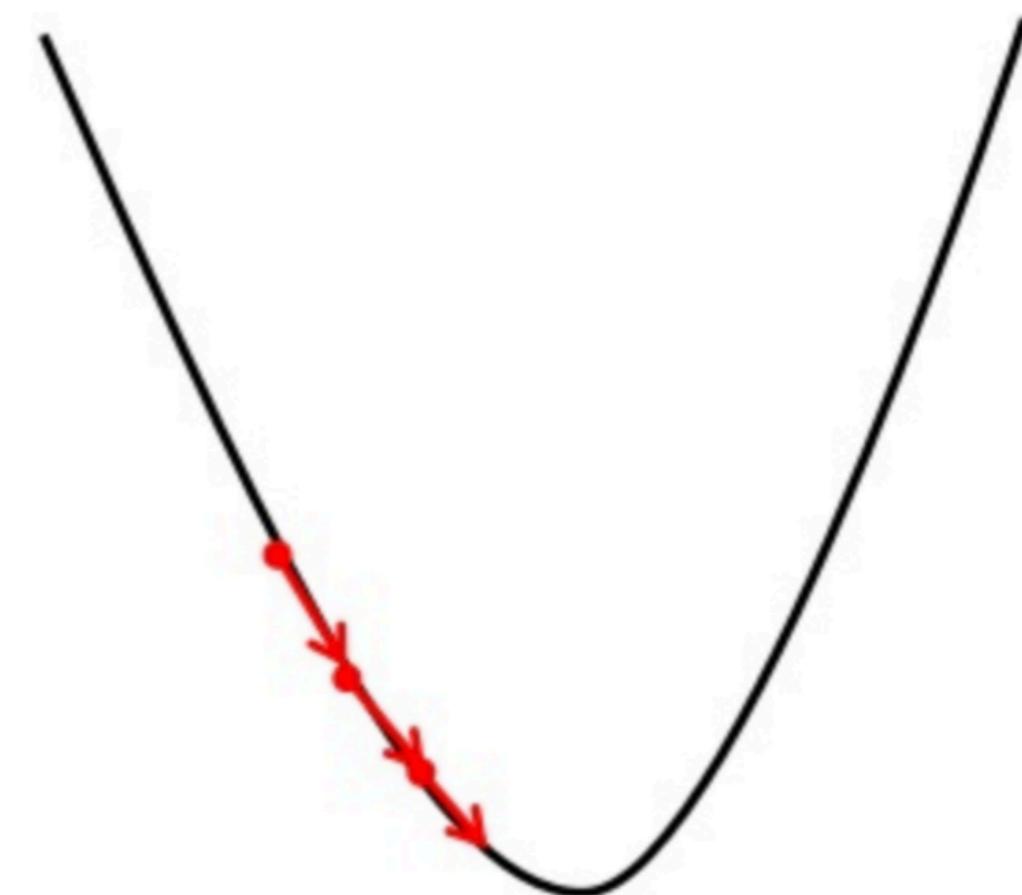


Learning rate tuning

Big learning rate



Small learning rate



Gradient Descent Variants

(Batch) Gradient Descent

$$w_{t+1} = w_t - \lambda \frac{\partial e(X, y)}{\partial w_t}$$

Stochastic Gradient Descent

$$w_{t+1} = w_t - \lambda \frac{\partial e(X^i, y^i)}{\partial w_t}$$

Mini-Batch Gradient Descent

$$w_{t+1} = w_t - \lambda \frac{\partial e(X^{(i,i+n)}, y^{(i,i+n)})}{\partial w_t}$$

Momentum and Nesterov Accelerated Gradient

$$v_t = \gamma v_{t-1} + \lambda \frac{\partial e(w_t)}{\partial w_t}$$

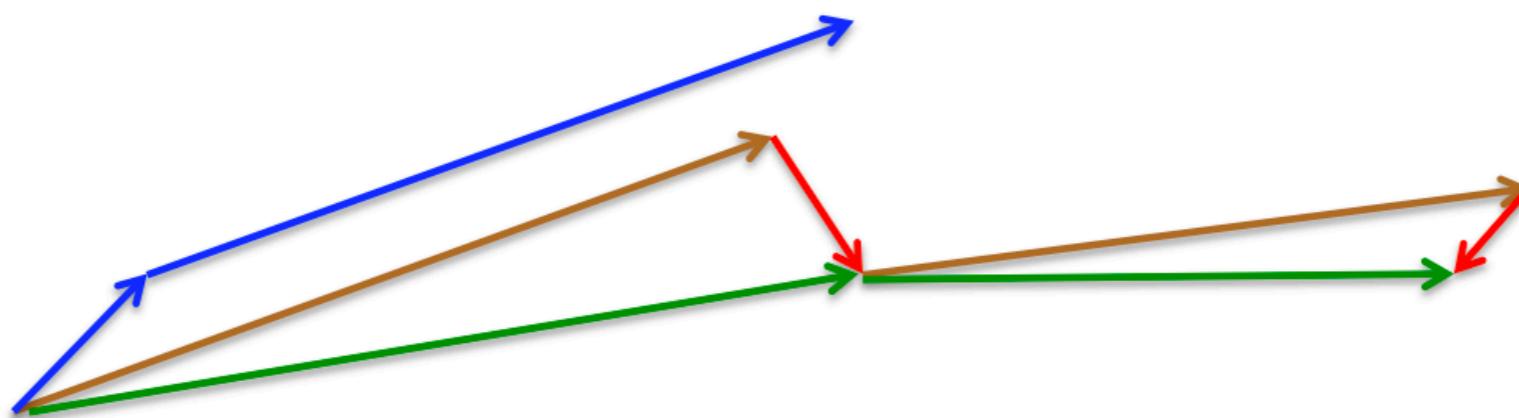
Naive momentum

$$w_{t+1} = w_t - v_t$$

$$v_t = \gamma v_{t-1} + \lambda \frac{\partial e(w_t - \gamma v_{t-1})}{\partial w_t}$$

Nesterov Accelerated Gradient

$$w_{t+1} = w_t - v_t$$



Adaptive Gradient Algorithms

$$w_{t+1} = w_t - \frac{\lambda}{\sqrt{\sum_{i=1}^t g_i^2 + \epsilon}} g_t$$

Adagrad

$$g_i = \frac{\partial e(w_i)}{\partial w_i}$$

$$w_{t+1} = w_t - \frac{\lambda}{\sqrt{\mathbb{E}[g^2]_t - \epsilon}} g_t^2$$

RMSProp

$$\mathbb{E}[g^2]_t = \gamma \mathbb{E}[g^2]_{t-1} + (1 - \gamma) g_t^2$$

Adam and Nadam

Adam

Combination of RMSProp with momentum

Nadam

Combination of RMSProp with Nesterov momentum

Loss functions for deep learning

Mean Squared Error

$$MSE = \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n}$$

Mean Absolute Error

$$MSE = \frac{\sum_{i=1}^n |y_i - \hat{y}_i|}{n}$$

Cross Entropy (Negative Log Likelihood)

Categorical Cross Entropy
$$CCE = -\frac{\sum_{i=1}^n \sum_{j=1}^c y_{i,j} \log(\hat{y}_{i,j})}{n}$$

Binary Cross Entropy

$$BCE = -\frac{\sum_{i=1}^n [y_{i,j} \log(\hat{y}_{i,j}) + (1 - y_{i,j}) \log(1 - \hat{y}_{i,j})]}{n}$$

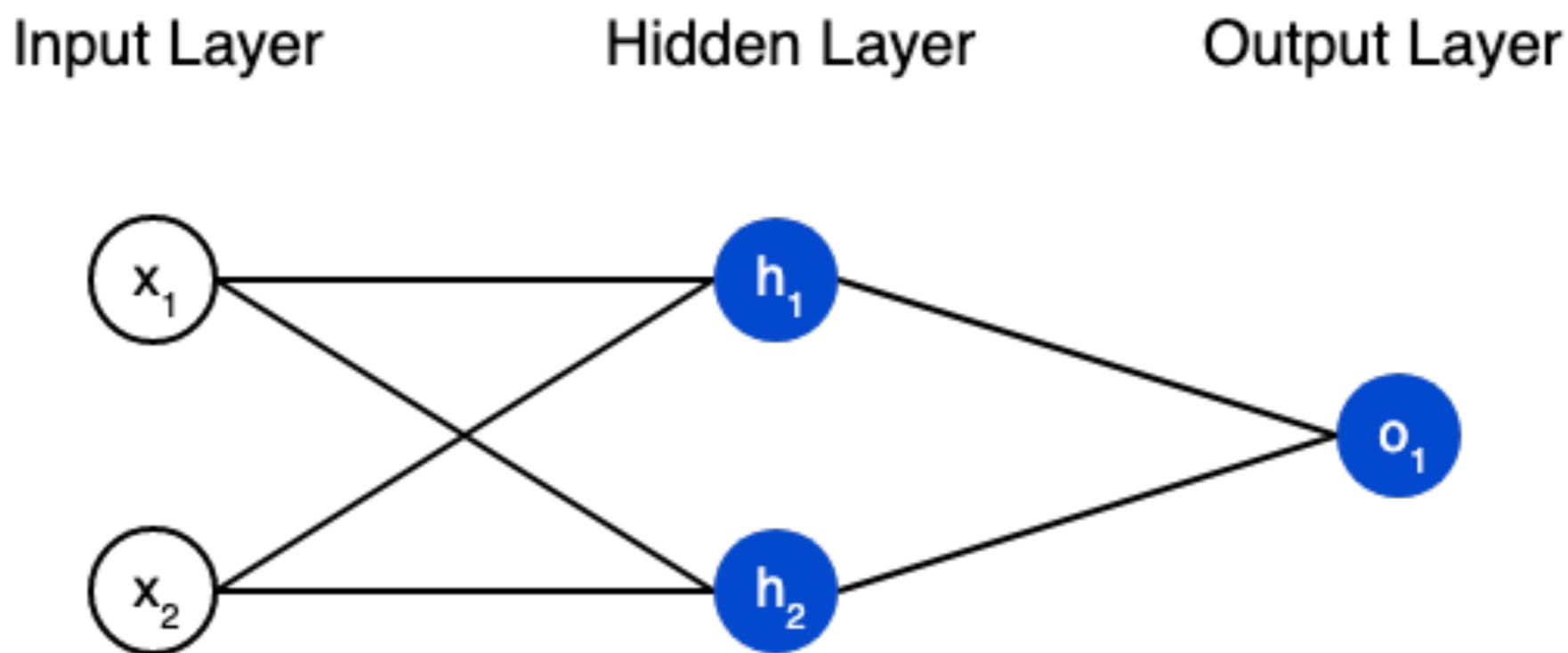
Reimplementation of the classification and regression task using NN

07-Classification-nn-assignment.ipynb

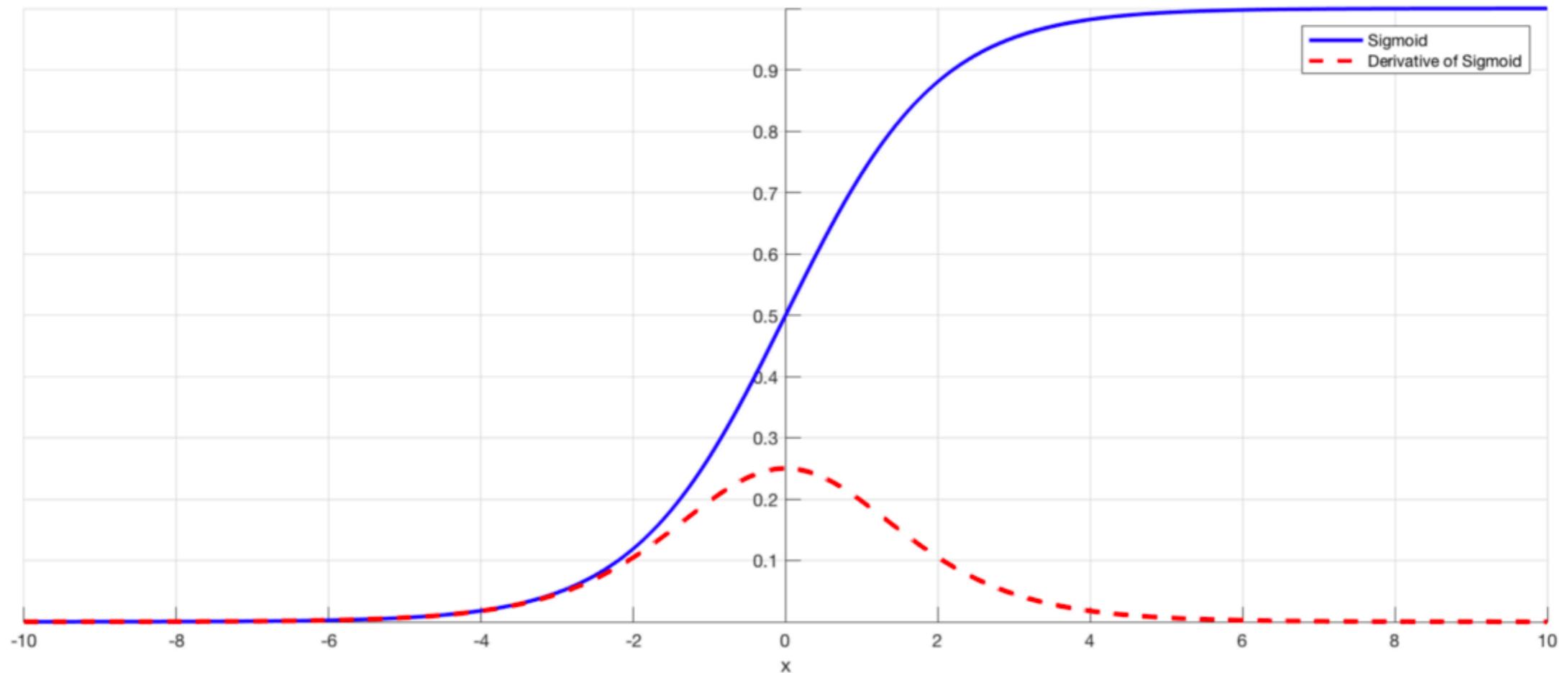
08-Regression-nn-assignment.ipynb

Weight initialization

Zero or constant initialization



Too low or too high initialization



Xavier and He initializers

1. The mean of the activations should be zero
2. The variance of the activations should stay the same across every layer

**Xavier (Glorot) initialization
for tanh**

$$\mathbf{W}^l \sim \mathcal{N}(\mu = 0, \sigma^2 = \frac{1}{n^{l-1}})$$

$$b^l = 0$$

**He (Kaiming) initialization
for relu**

$$\mathbf{W}^l \sim \mathcal{N}(\mu = 0, \sigma^2 = \frac{2}{n^{l-1}})$$

$$b^l = 0$$

Experiment with various initializations for a deep network

[08-Regression-nn-assignment.ipynb](#)

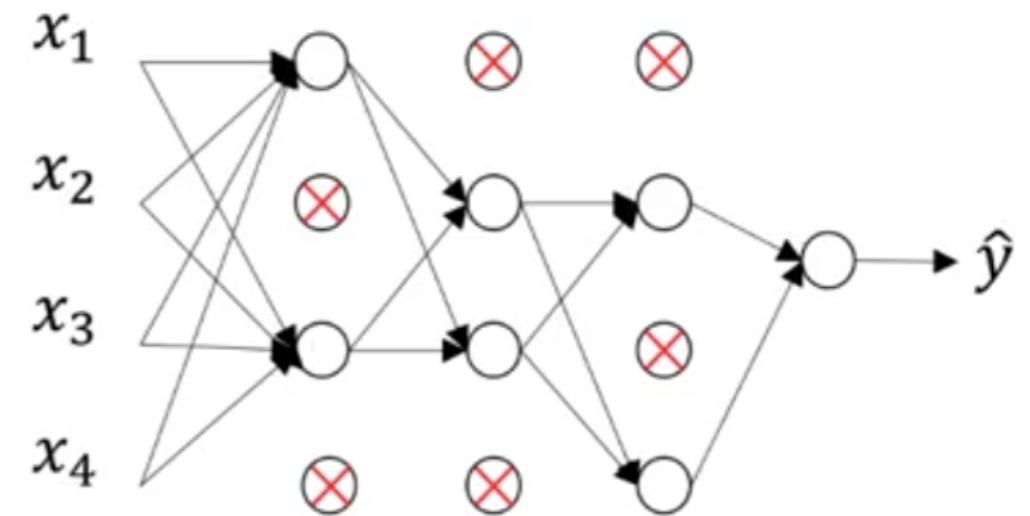
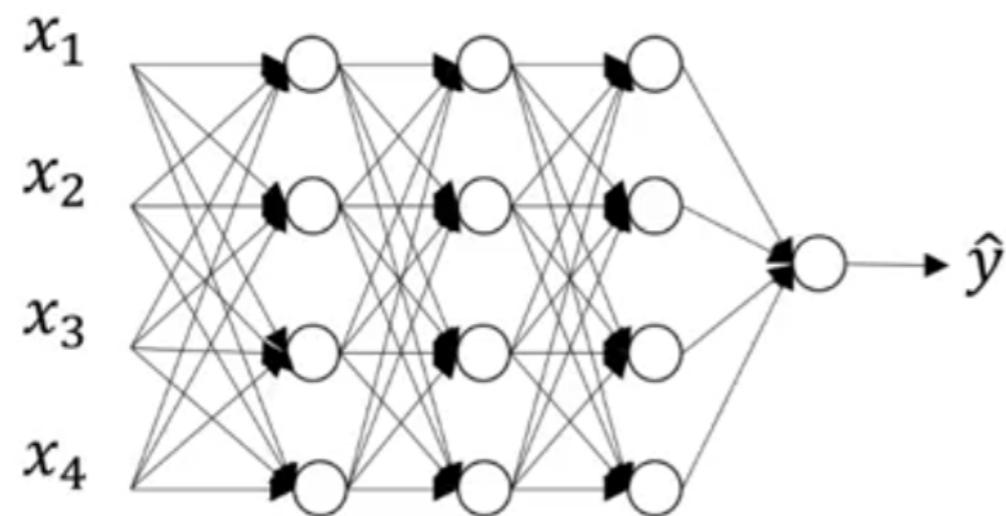
L2 Regularization in deep learning

$$cost(w^1, b^1, \dots, w^L, b^L) = \frac{1}{n} \sum_{i=1}^n Loss(y_i, \hat{y}_i) + \frac{\lambda}{2n} \sum_{l=1}^L \|w^l\|_F^2$$

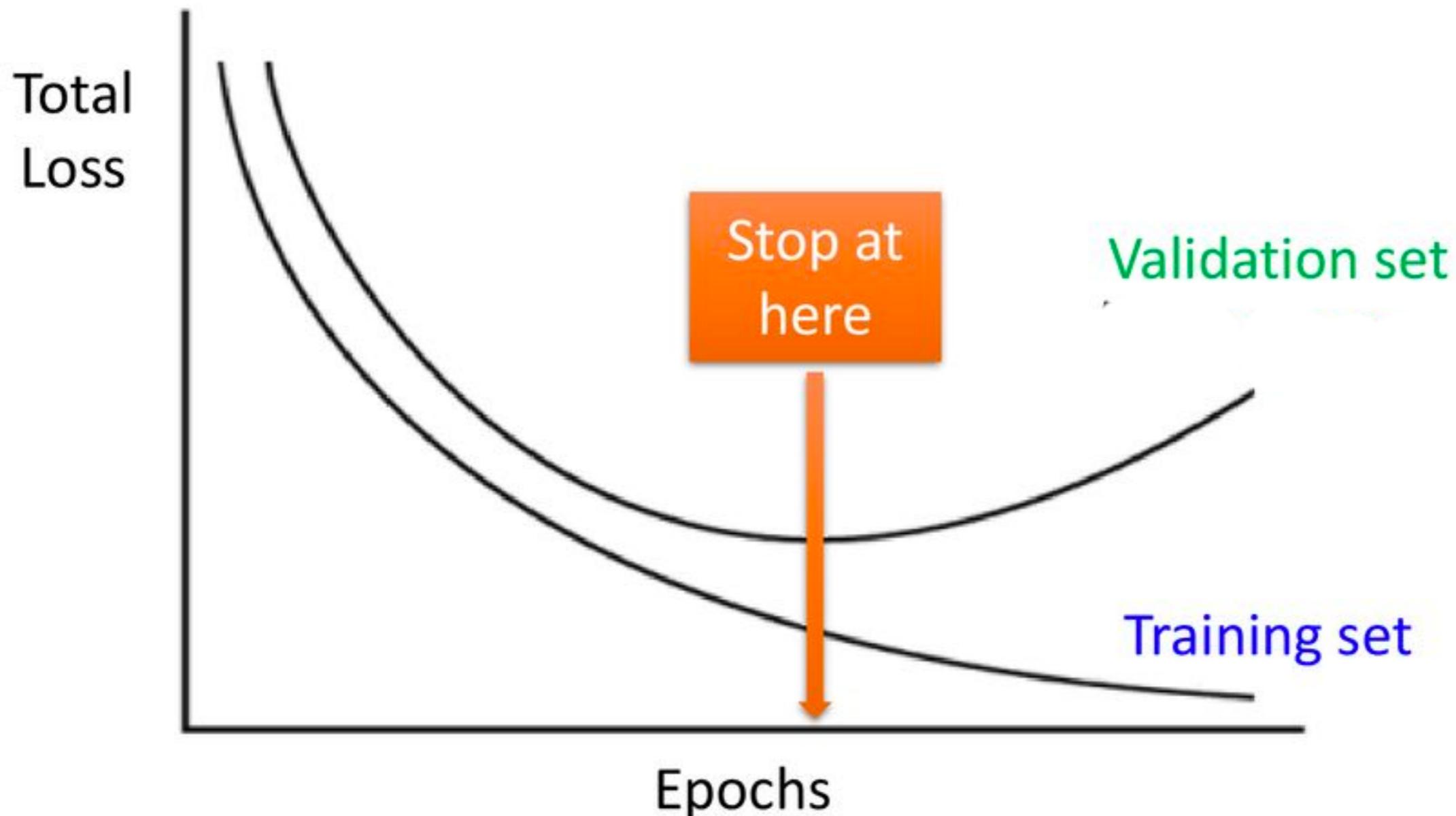
Frobenius norm

$$\|w\|_F = \sqrt{\sum_{i=1}^n \sum_{j=1}^m |a_{i,j}|^2}$$

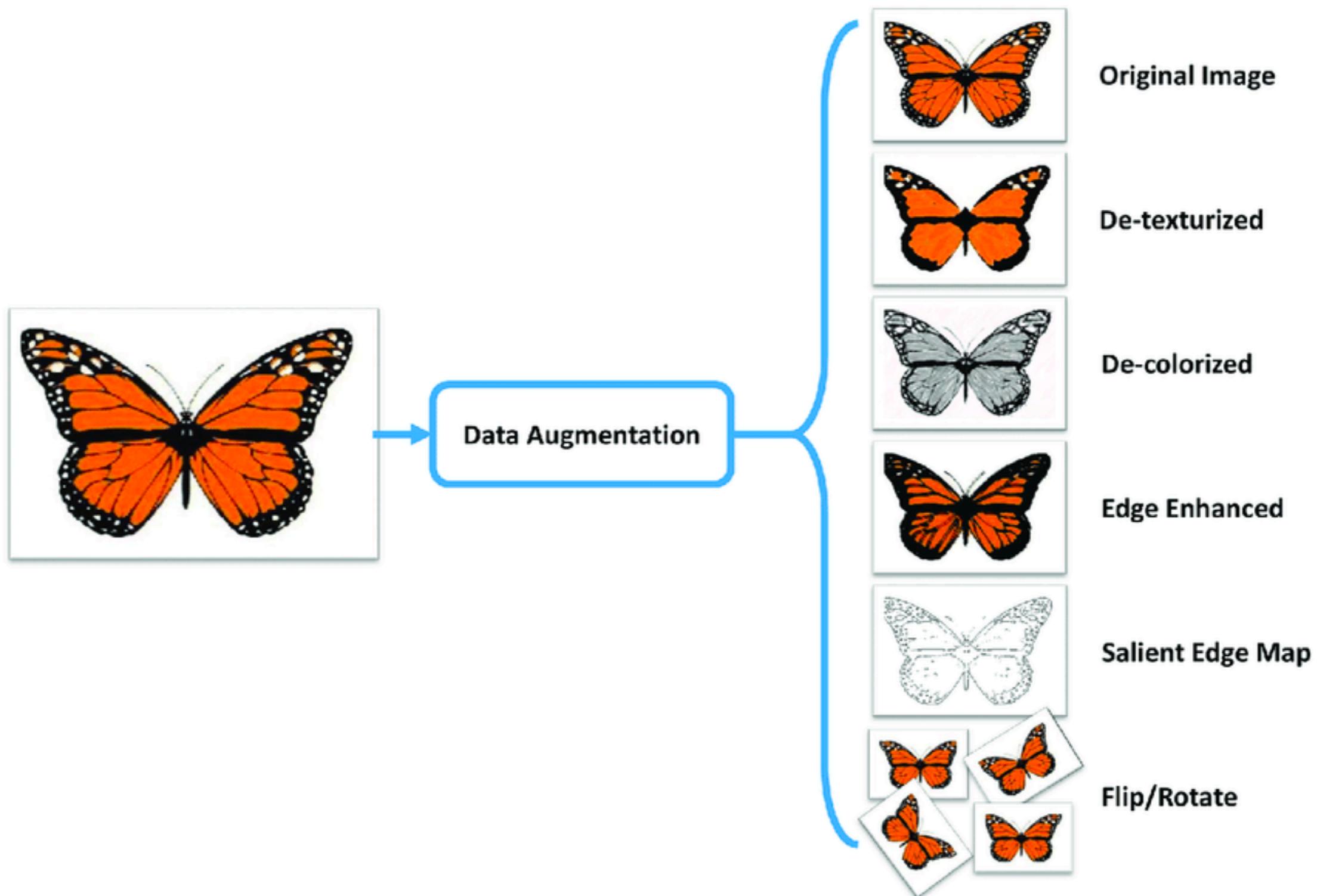
Dropout



Early stopping



Data augmentation



Batch normalization

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_1 \dots m\}$;
Parameters to be learned: γ, β

Output: $\{y_i = \text{BN}_{\gamma, \beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m} \sum_{i=1}^m x_i \quad // \text{mini-batch mean}$$

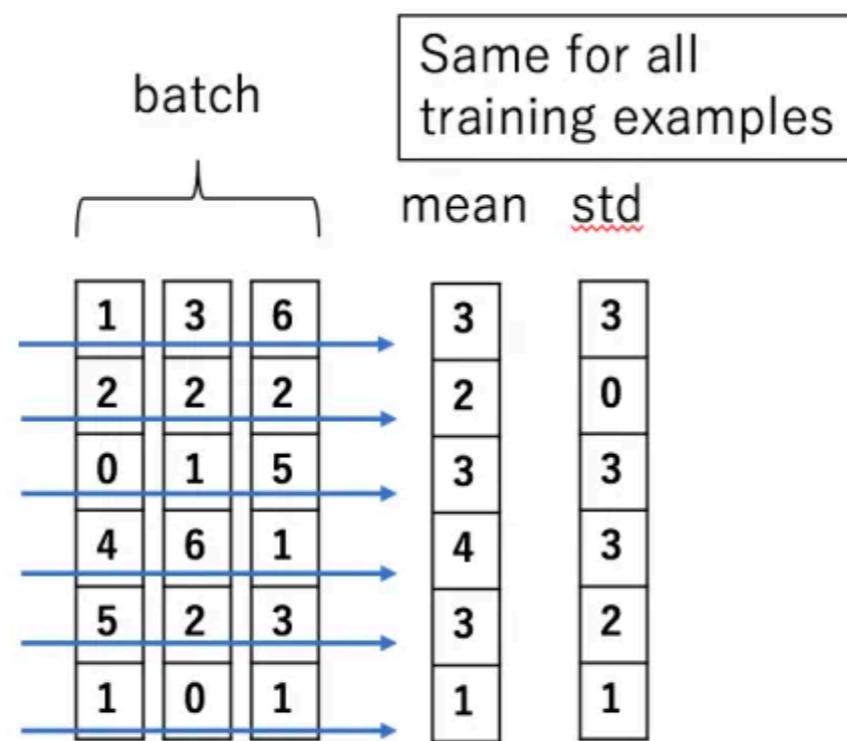
$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m} \sum_{i=1}^m (x_i - \mu_{\mathcal{B}})^2 \quad // \text{mini-batch variance}$$

$$\hat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \quad // \text{normalize}$$

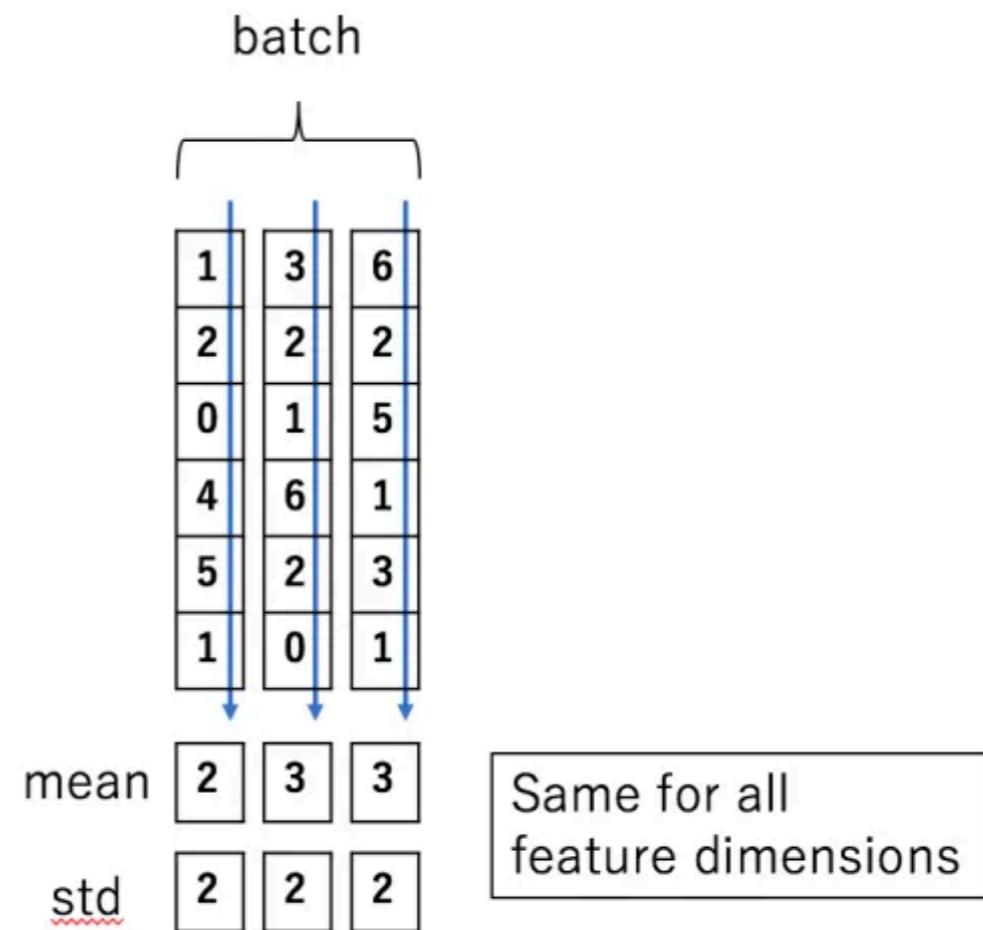
$$y_i \leftarrow \gamma \hat{x}_i + \beta \equiv \text{BN}_{\gamma, \beta}(x_i) \quad // \text{scale and shift}$$

Layer normalization

Batch Normalization



Layer Normalization



Functional API in Keras

```
1 # Sequential model
2 from keras.models import Sequential
3 from keras.layers import Dense
4
5 model = Sequential()
6 model.add(10, input_shape=(10,), activation='relu')
7 model.add(Dense(20, activation='relu'))
8 model.add(Dense(10, activation='relu'))
9 model.add(Dense(1, activation='sigmoid'))
```

```
1 # Functional model
2 from keras.models import Model
3 from keras.layers import Input, Dense
4
5 visible = Input(shape=(10,))
6 hidden1 = Dense(10, activation='relu')(visible)
7 hidden2 = Dense(20, activation='relu')(hidden1)
8 hidden3 = Dense(10, activation='relu')(hidden2)
9 output = Dense(1, activation='sigmoid')(hidden3)
10 model = Model(inputs=visible, outputs=output)
```

Shared Input

```
1 # Shared Input Layer
2 from keras.utils import plot_model
3 from keras.models import Model
4 from keras.layers import Input, Dense, Flatten
5 from keras.layers.convolutional import Conv2D
6 from keras.layers.pooling import MaxPooling2D
7 from keras.layers.merge import concatenate
8 # input layer
9 visible = Input(shape=(64,64,1))
10 # first feature extractor
11 conv1 = Conv2D(32, kernel_size=4, activation='relu')(visible)
12 pool1 = MaxPooling2D(pool_size=(2, 2))(conv1)
13 flat1 = Flatten()(pool1)
14 # second feature extractor
15 conv2 = Conv2D(16, kernel_size=8, activation='relu')(visible)
16 pool2 = MaxPooling2D(pool_size=(2, 2))(conv2)
17 flat2 = Flatten()(pool2)
18 # merge feature extractors
19 merge = concatenate([flat1, flat2])
20 # interpretation layer
21 hidden1 = Dense(10, activation='relu')(merge)
22 # prediction output
23 output = Dense(1, activation='sigmoid')(hidden1)
24 model = Model(inputs=visible, outputs=output)
```

Multiple inputs (outputs)

```
1 # Multiple Inputs
2 from keras.utils import plot_model
3 from keras.models import Model
4 from keras.layers import Input
5 from keras.layers import Dense
6 from keras.layers import Flatten
7 from keras.layers.convolutional import Conv2D
8 from keras.layers.pooling import MaxPooling2D
9 from keras.layers.merge import concatenate
10 # first input model
11 visible1 = Input(shape=(64,64,1))
12 conv11 = Conv2D(32, kernel_size=4, activation='relu')(visible1)
13 pool11 = MaxPooling2D(pool_size=(2, 2))(conv11)
14 conv12 = Conv2D(16, kernel_size=4, activation='relu')(pool11)
15 pool12 = MaxPooling2D(pool_size=(2, 2))(conv12)
16 flat1 = Flatten()(pool12)
17 # second input model
18 visible2 = Input(shape=(32,32,3))
19 conv21 = Conv2D(32, kernel_size=4, activation='relu')(visible2)
20 pool21 = MaxPooling2D(pool_size=(2, 2))(conv21)
21 conv22 = Conv2D(16, kernel_size=4, activation='relu')(pool21)
22 pool22 = MaxPooling2D(pool_size=(2, 2))(conv22)
23 flat2 = Flatten()(pool22)
24 # merge input models
25 merge = concatenate([flat1, flat2])
26 # interpretation model
27 hidden1 = Dense(10, activation='relu')(merge)
28 hidden2 = Dense(10, activation='relu')(hidden1)
29 output = Dense(1, activation='sigmoid')(hidden2)
30 model = Model(inputs=[visible1, visible2], outputs=output)
```

Practical example on regularization and normalization

[**09-Normalization-and-regularization-assignment.ipynb**](#)

Outline

Day 3

- Neural Network architectures
- Convolutional NN and Transfer learning
- Recurrent neural networks (simple RNN, LSTM, GRU) and their examples
- Autoencoders and Restricted Boltzmann Machines and their applications
- Transformers
- U-Net
- Generative Adversarial Networks and their applications

Neural Network architectures design



Neural Network design best practices

- ★ Start from simple architectures
- ★ Get inspiration from architectures for similar problems
- ★ Change one parameter only and then validate

Most common architectures

Feed forward network

Convolutional network

Recurrent network

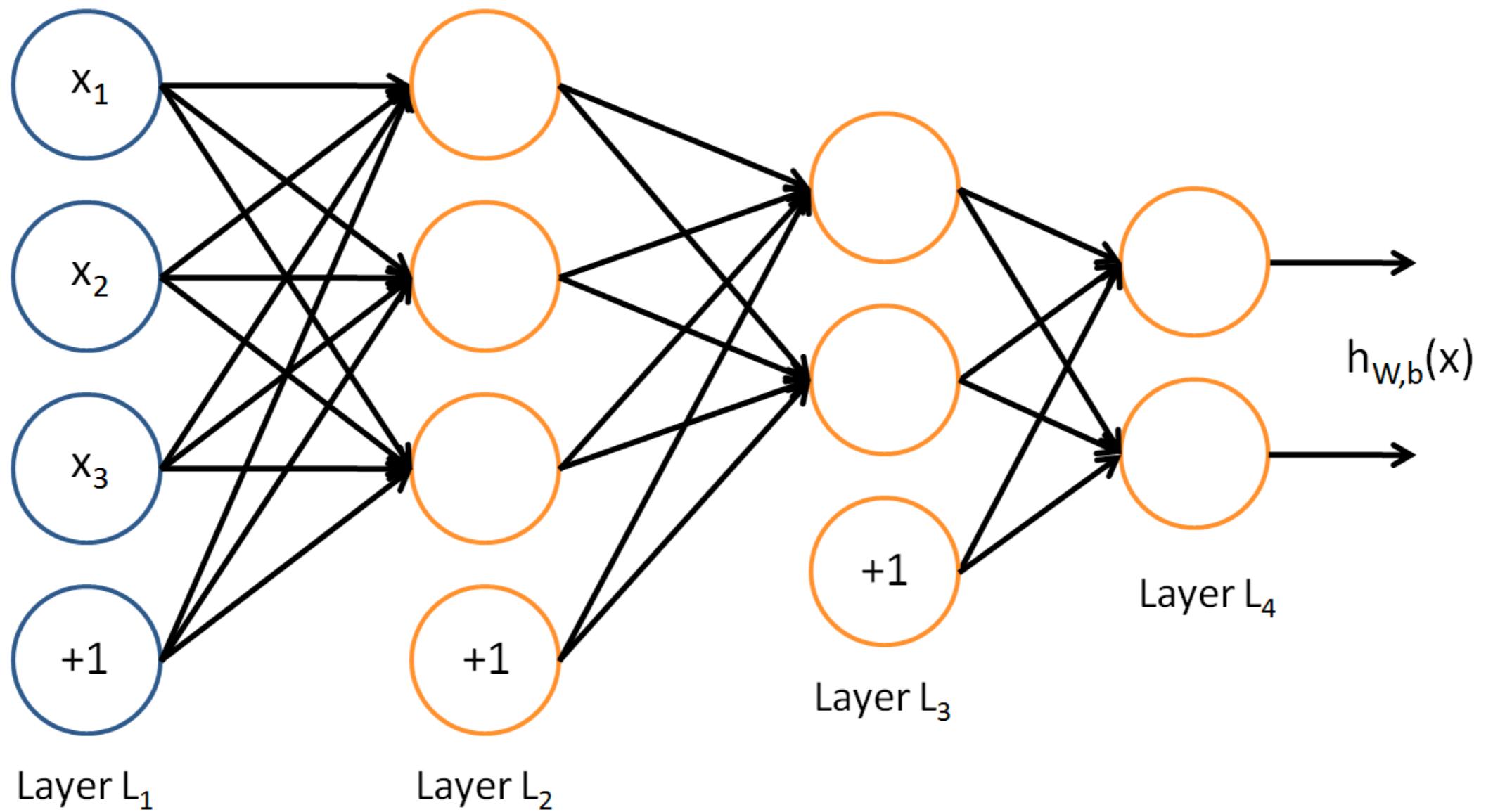
Autoencoder network and Restricted Boltzmann Machines

Transformer network

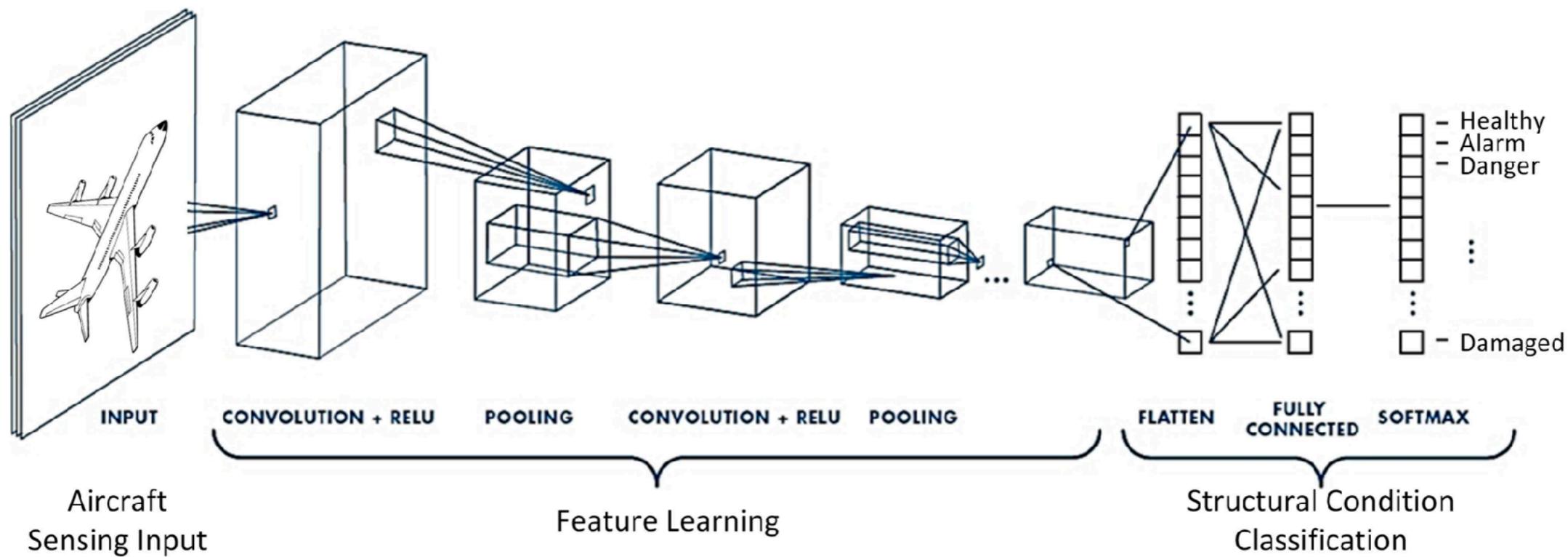
U-Net

Generative adversarial network

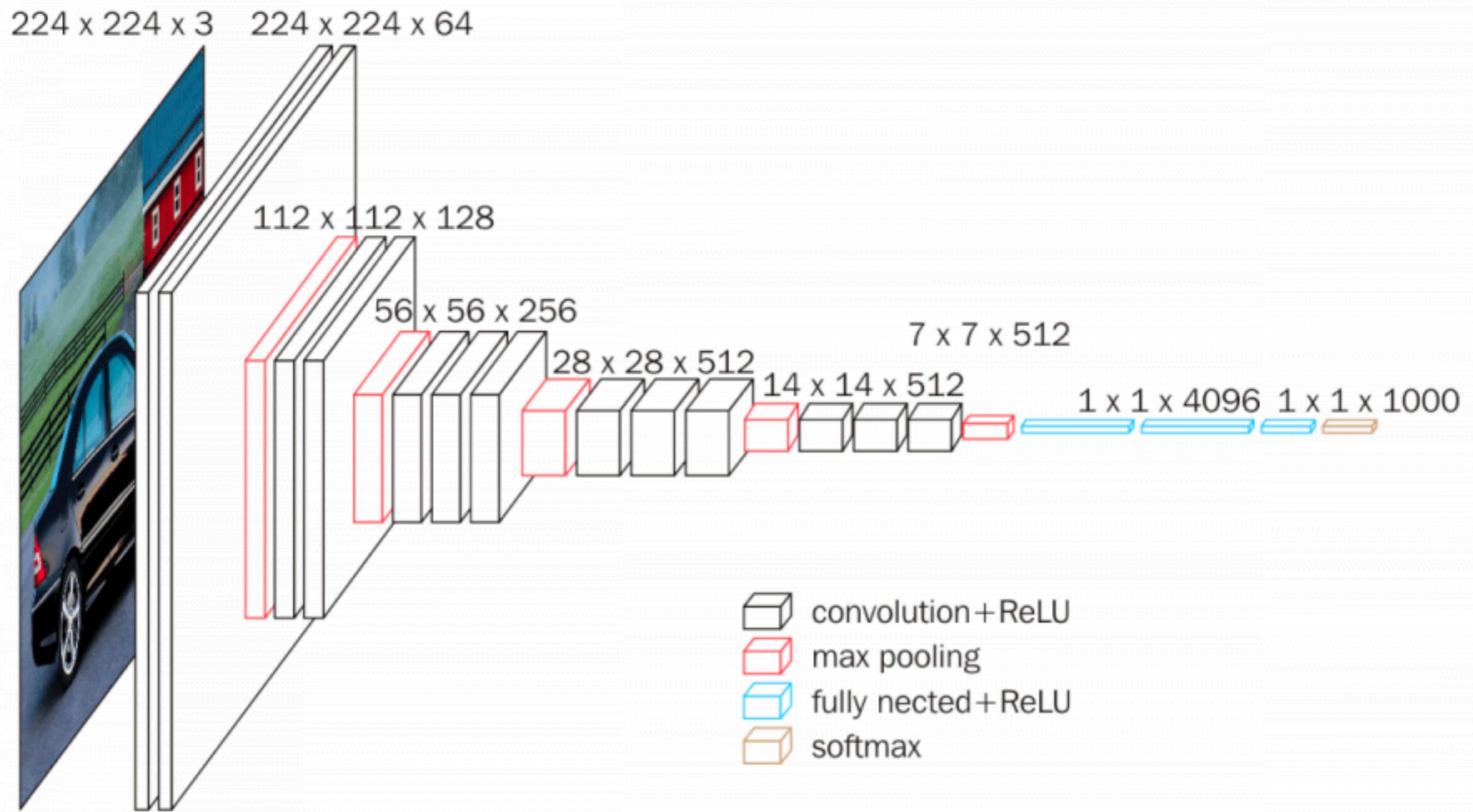
Feed Forward Network



Convolutional Neural Network

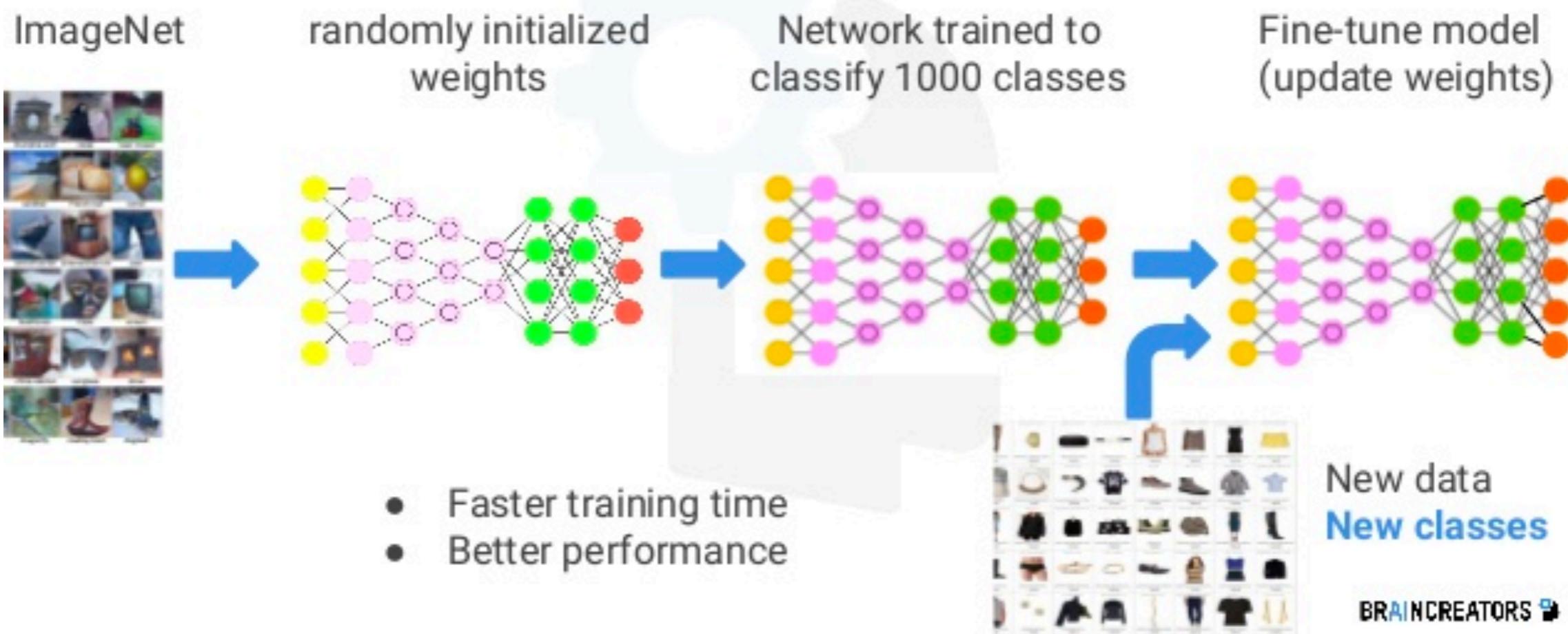


VGG 16



Finetuning

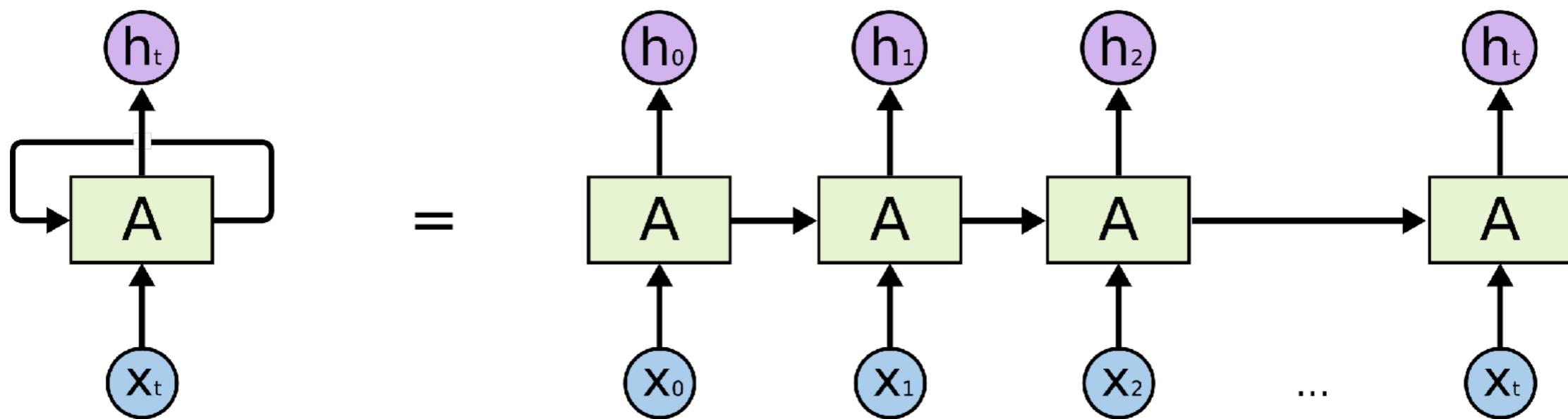
Transfer Learning



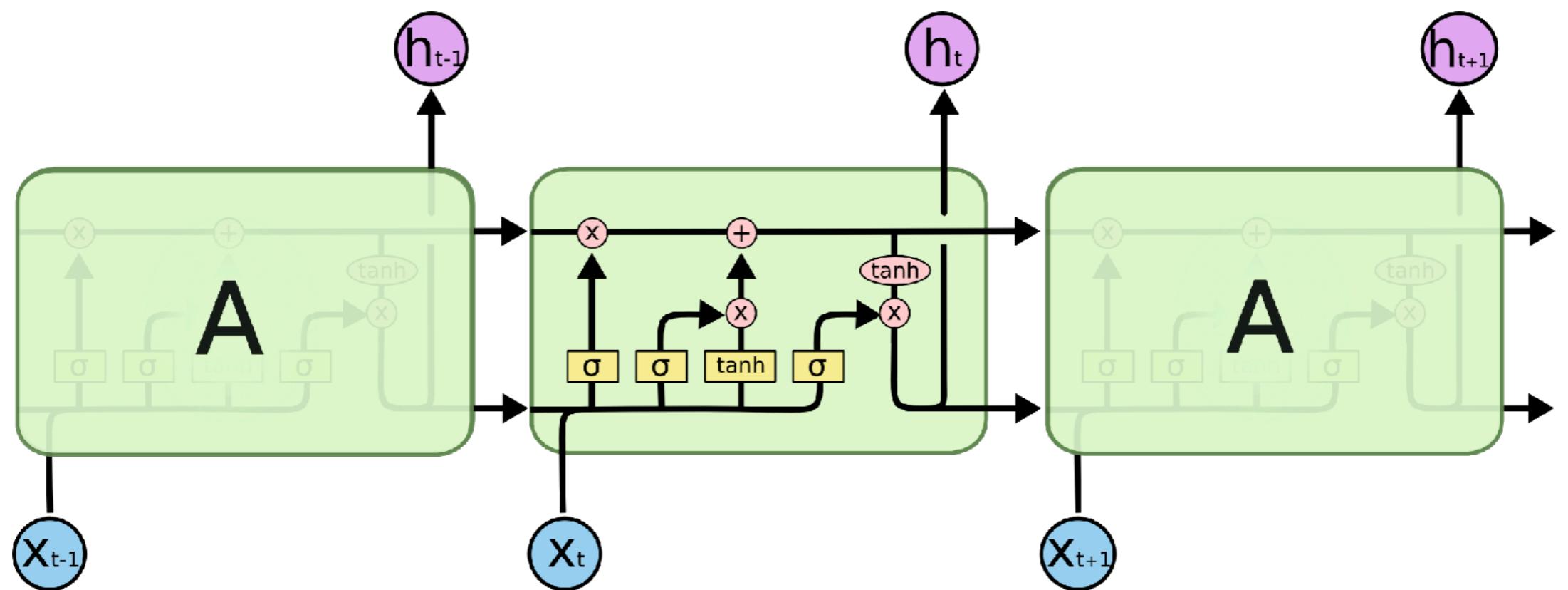
Transfer learning example

10-Transfer_learning.ipynb

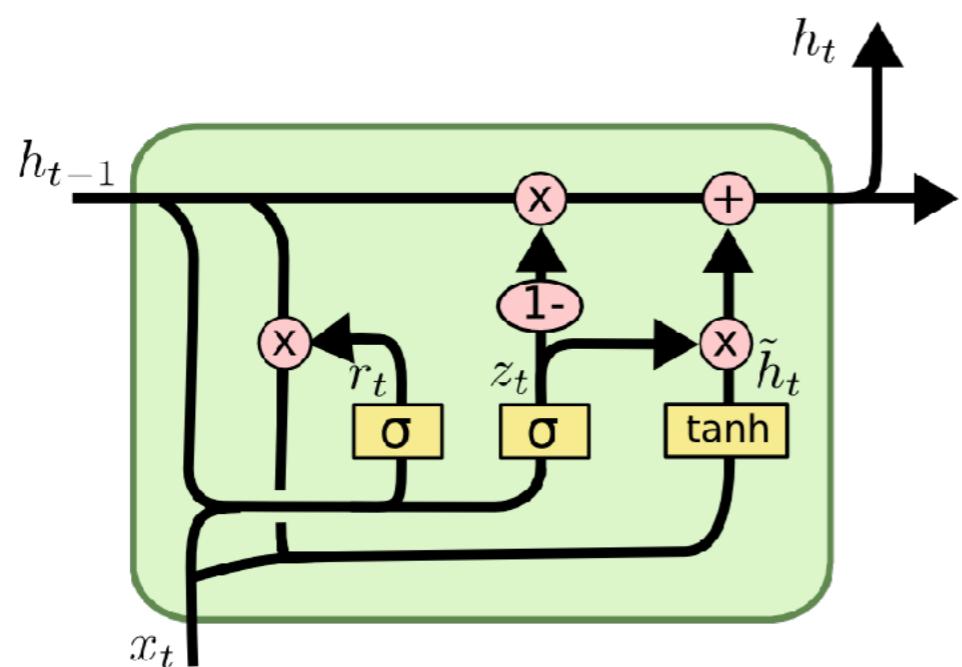
Recurrent Neural Network



Long Short Term Memory



Gated Recurrent Unit



$$z_t = \sigma (W_z \cdot [h_{t-1}, x_t])$$

$$r_t = \sigma (W_r \cdot [h_{t-1}, x_t])$$

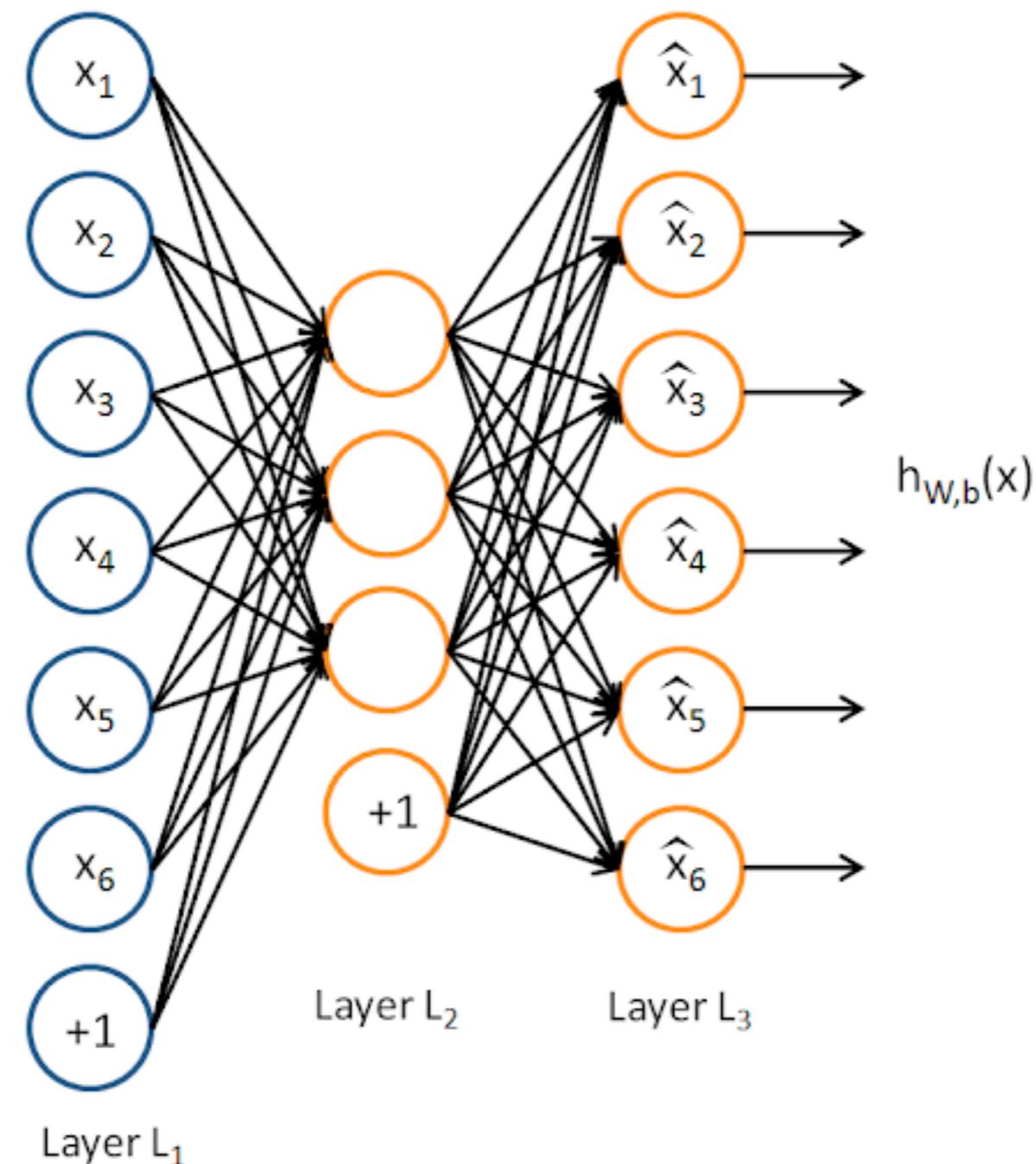
$$\tilde{h}_t = \tanh (W \cdot [r_t * h_{t-1}, x_t])$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

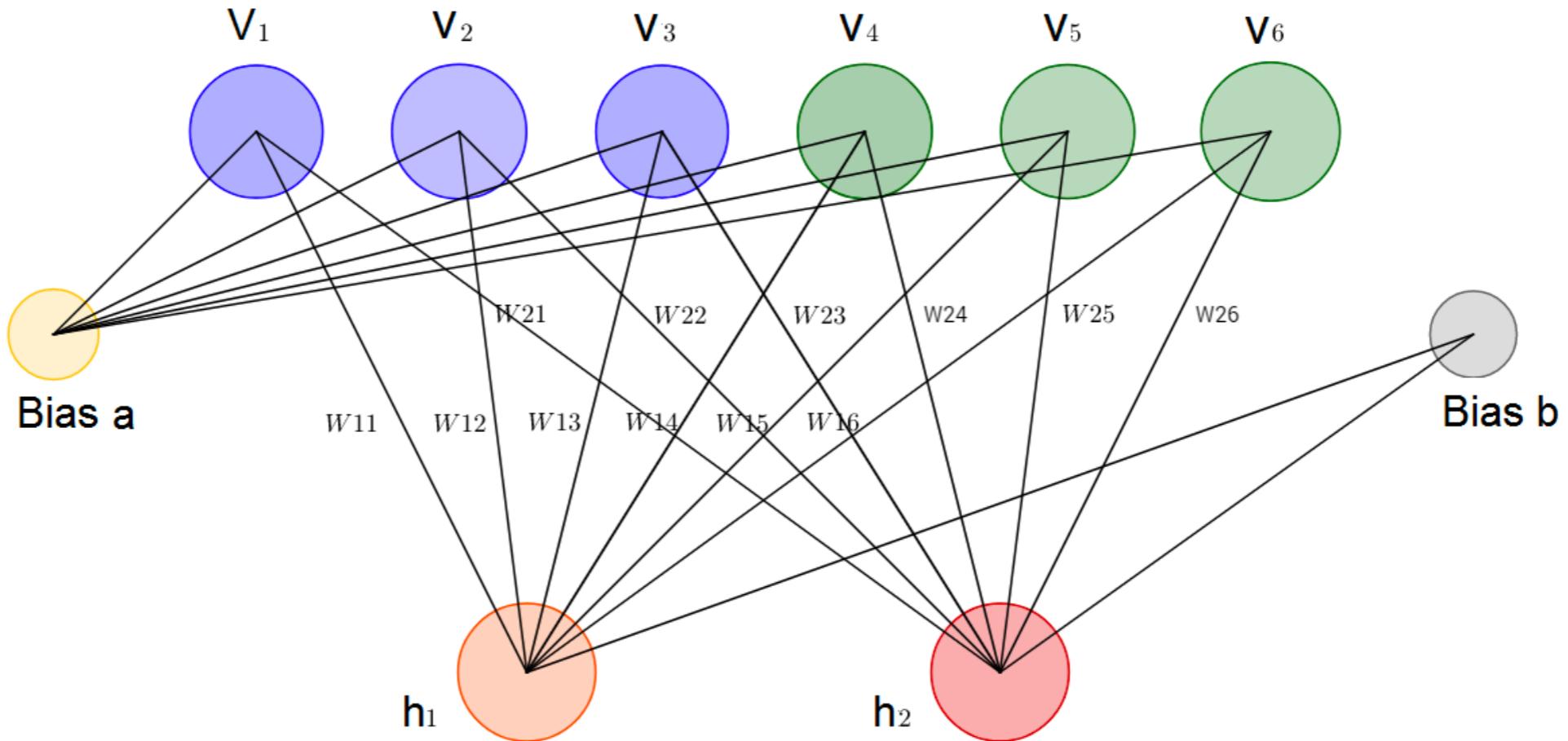
Regression using RNN

11-Regression-RNN.ipynb

Autoencoder Network



Restricted Boltzmann Machine



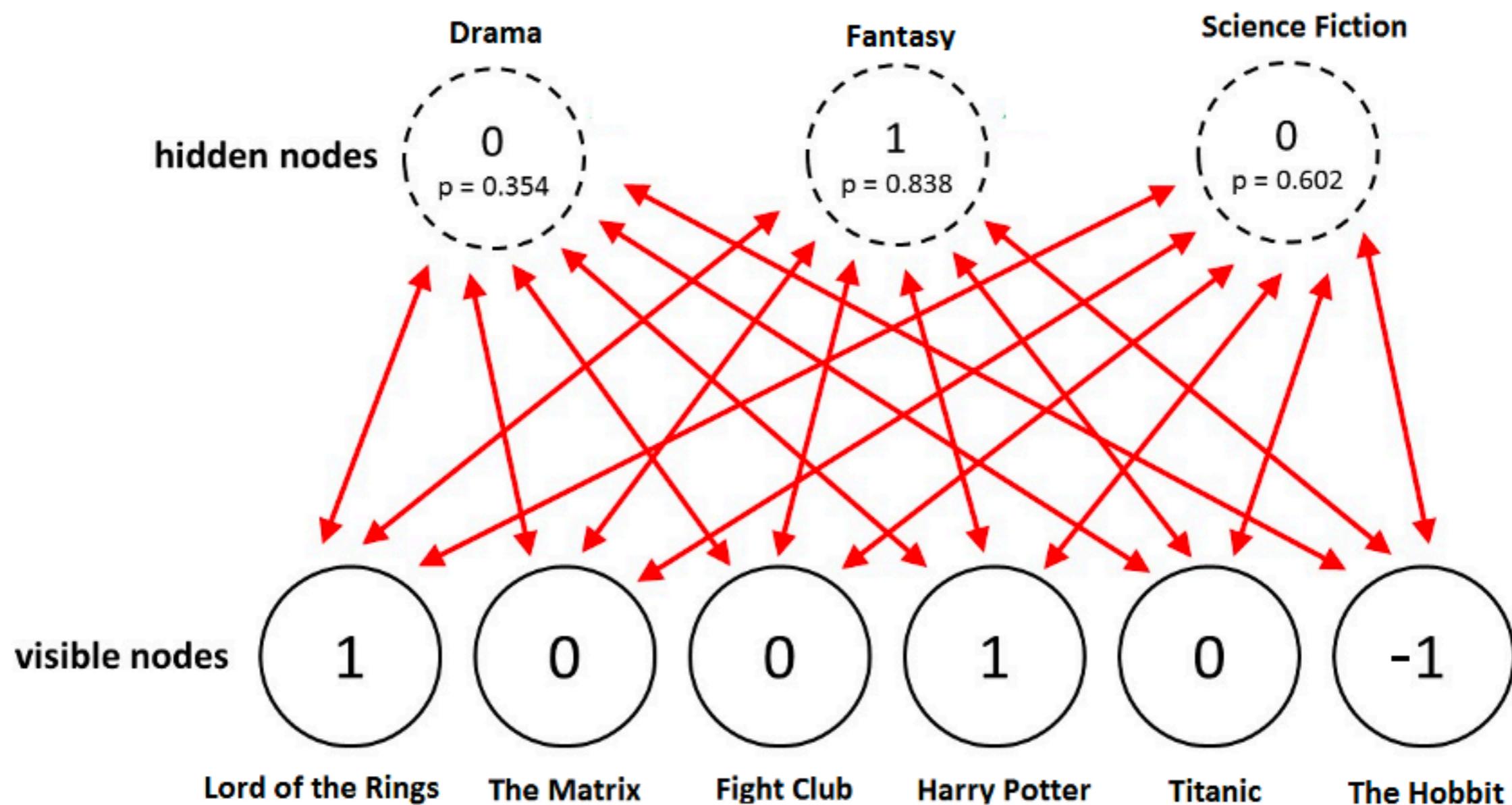
$$E(\mathbf{v}, \mathbf{h}) = -\sum_i a_i v_i - \sum_j b_j h_j - \sum_{i,j} v_i h_j w_{ij}$$

Gibbs sampling + contrastive divergence

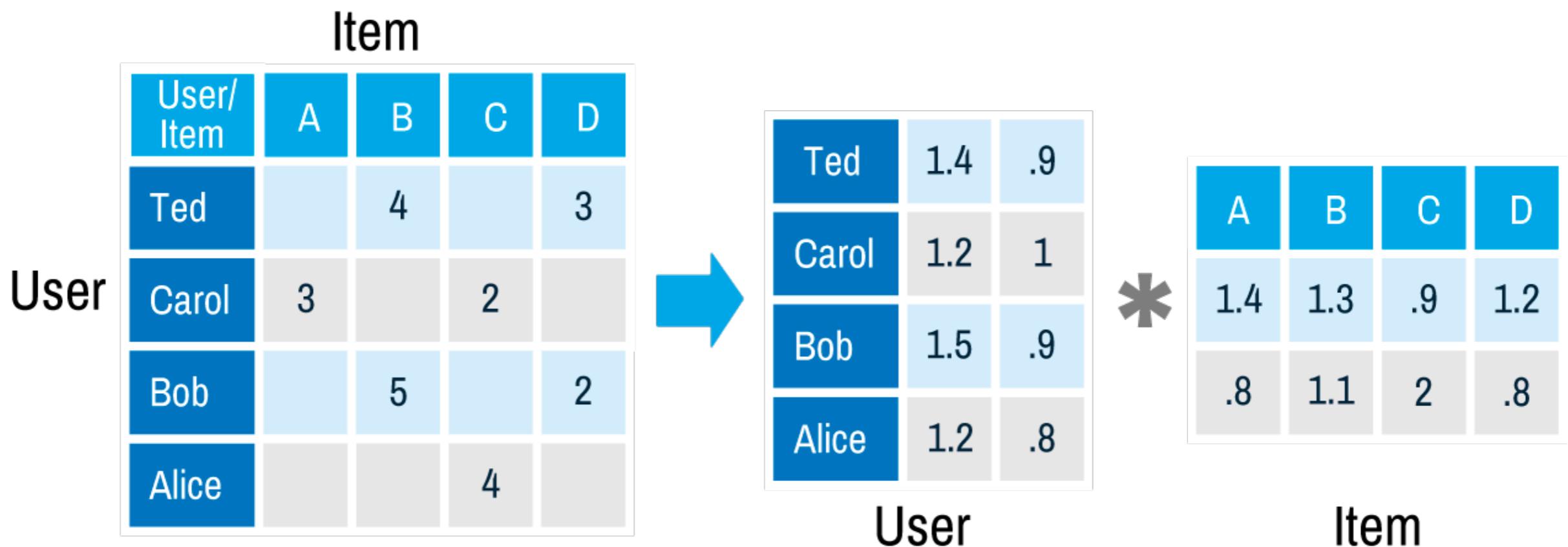
$$p(h_j = 1 | \mathbf{v}) = \frac{1}{1 + e^{-(b_j + W_j v_i)}} = \sigma(b_j + \sum_i v_i w_{ij})$$

$$p(v_i = 1 | \mathbf{h}) = \frac{1}{1 + e^{-(a_i + W_i h_j)}} = \sigma(a_i + \sum_j h_j w_{ij})$$

Collaborative filtering with Restricted Boltzmann Machine



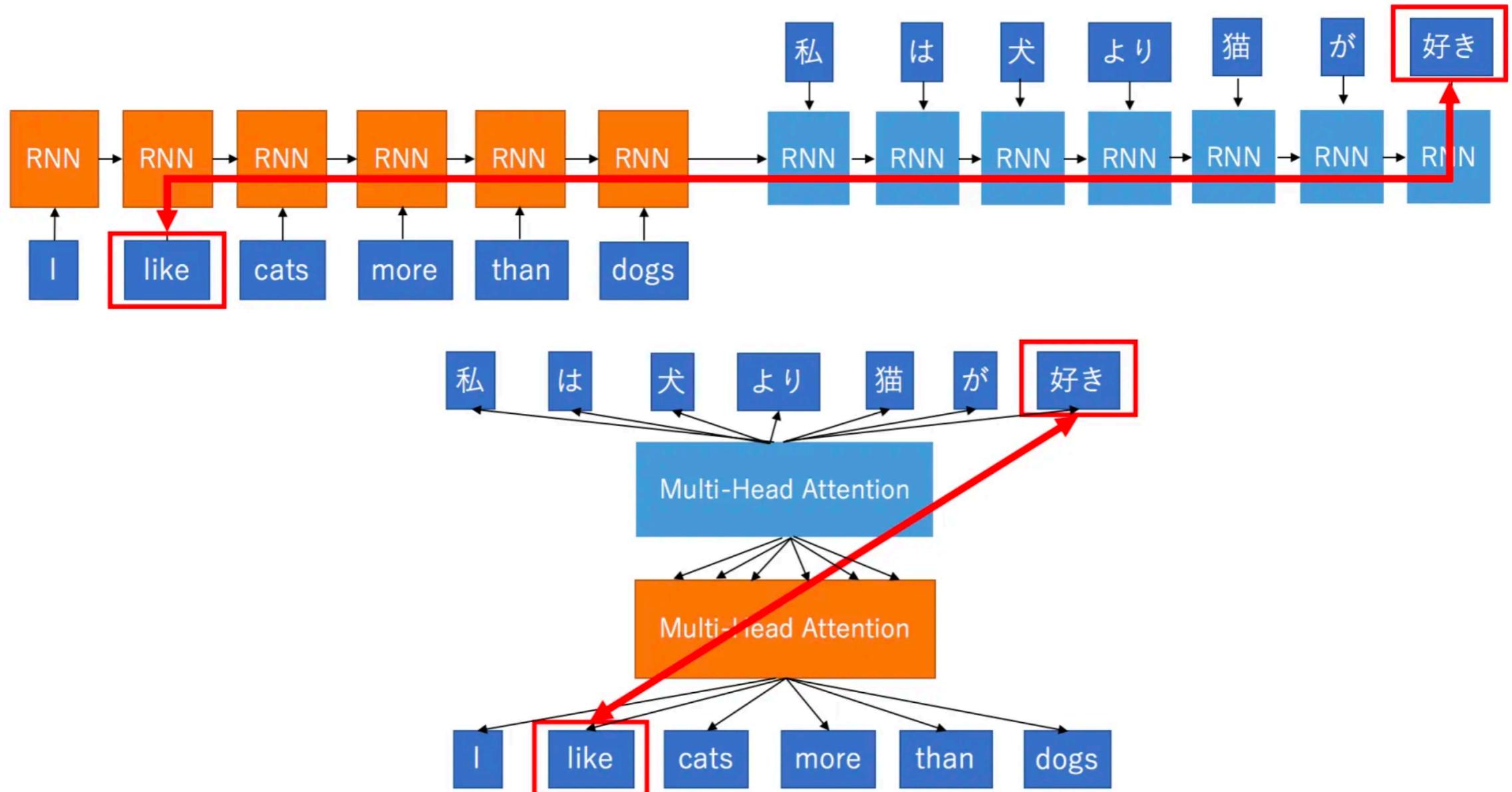
Collaborative filtering



Embedding-based recommendation

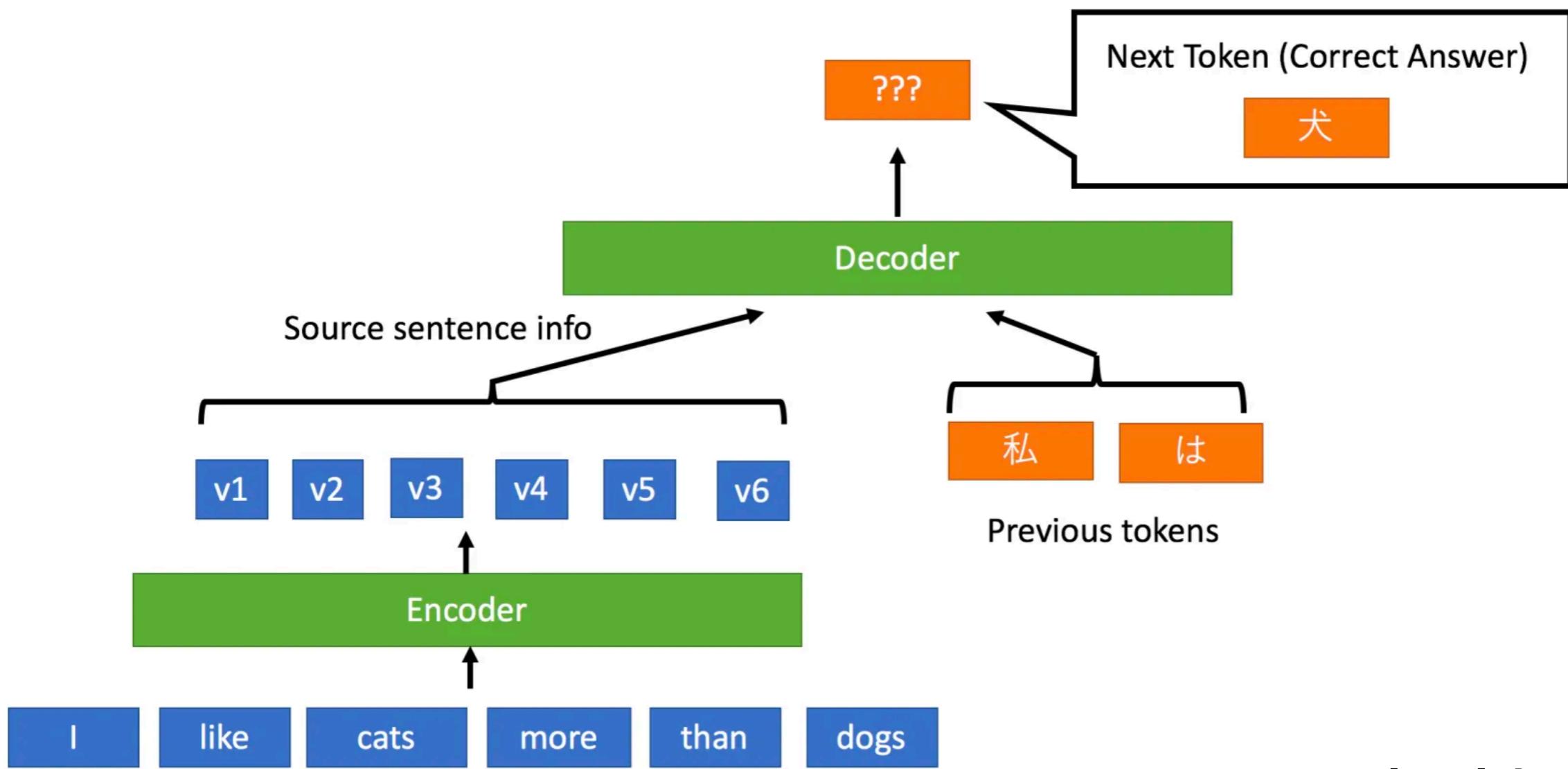
12-Recommendation-assignment.ipynb

Transformer



source: www.mlexplained.com

Translation with Transformers



GPT-2 Language model

Donald Trump told...

GPT-2 Language model

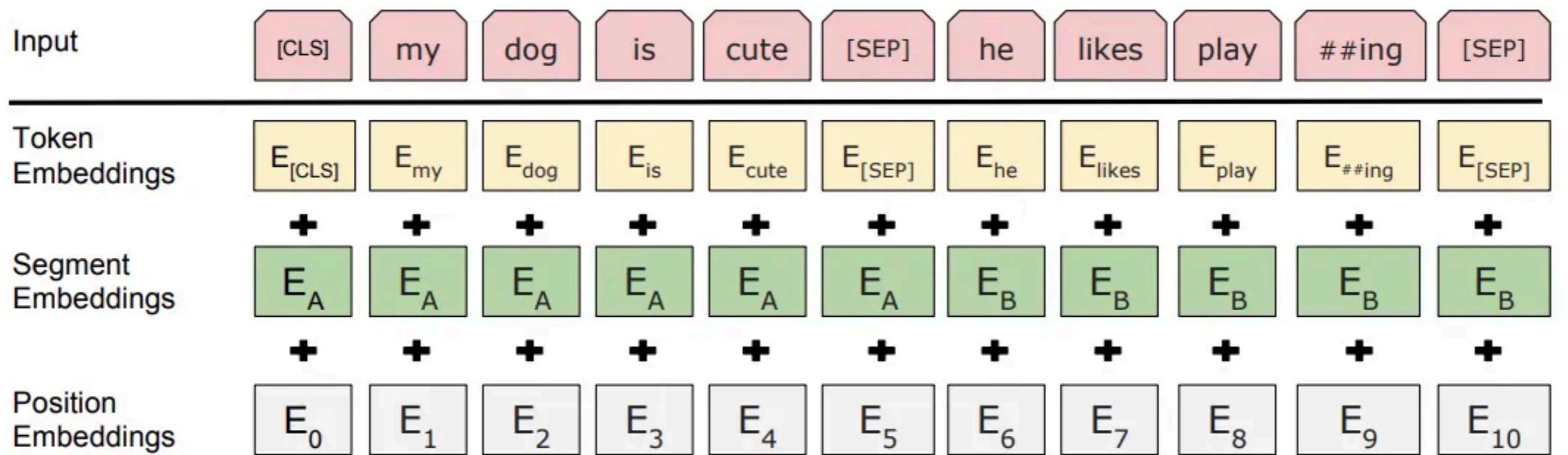
Donald Trump told the Times he is preparing a "major speech" on his economic plans, but did not provide details on what it will entail.

"I'm getting ready for the speech. And I will have a major speech on Tuesday." Trump said during an interview in the White House residence.

GPT-3: <https://openai.com/blog/openai-api/>

BERT

(input encoding)



BERT (classification)

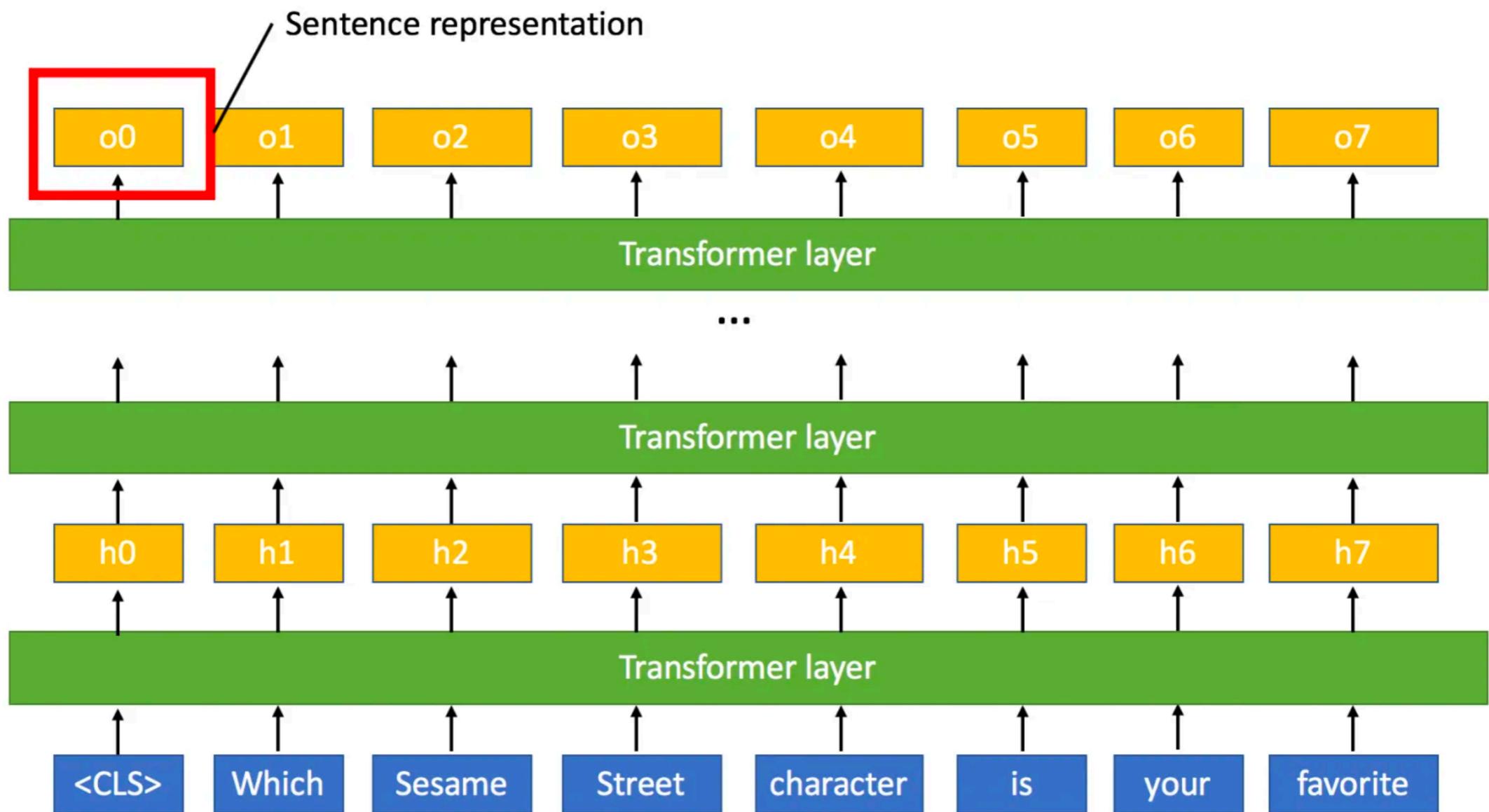
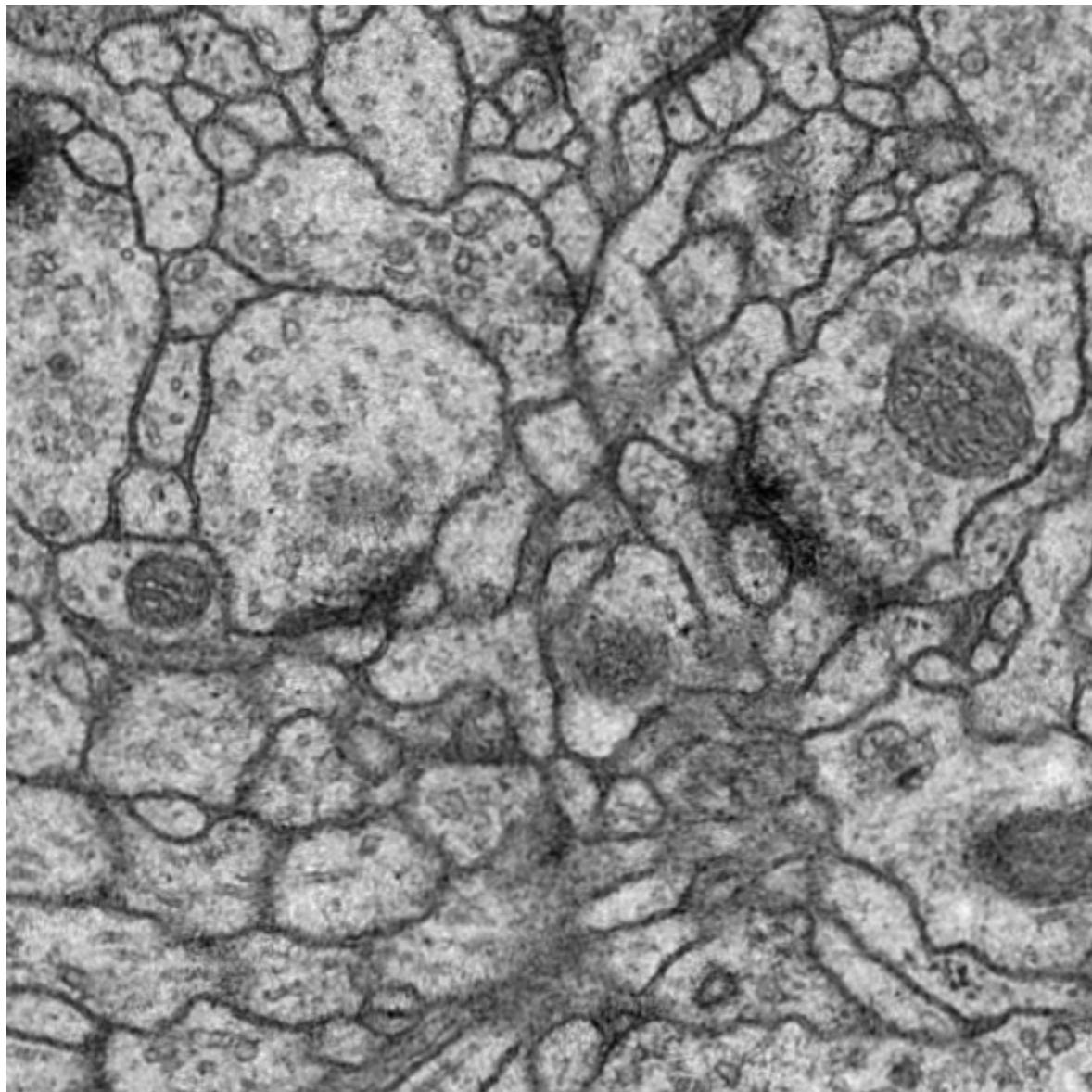
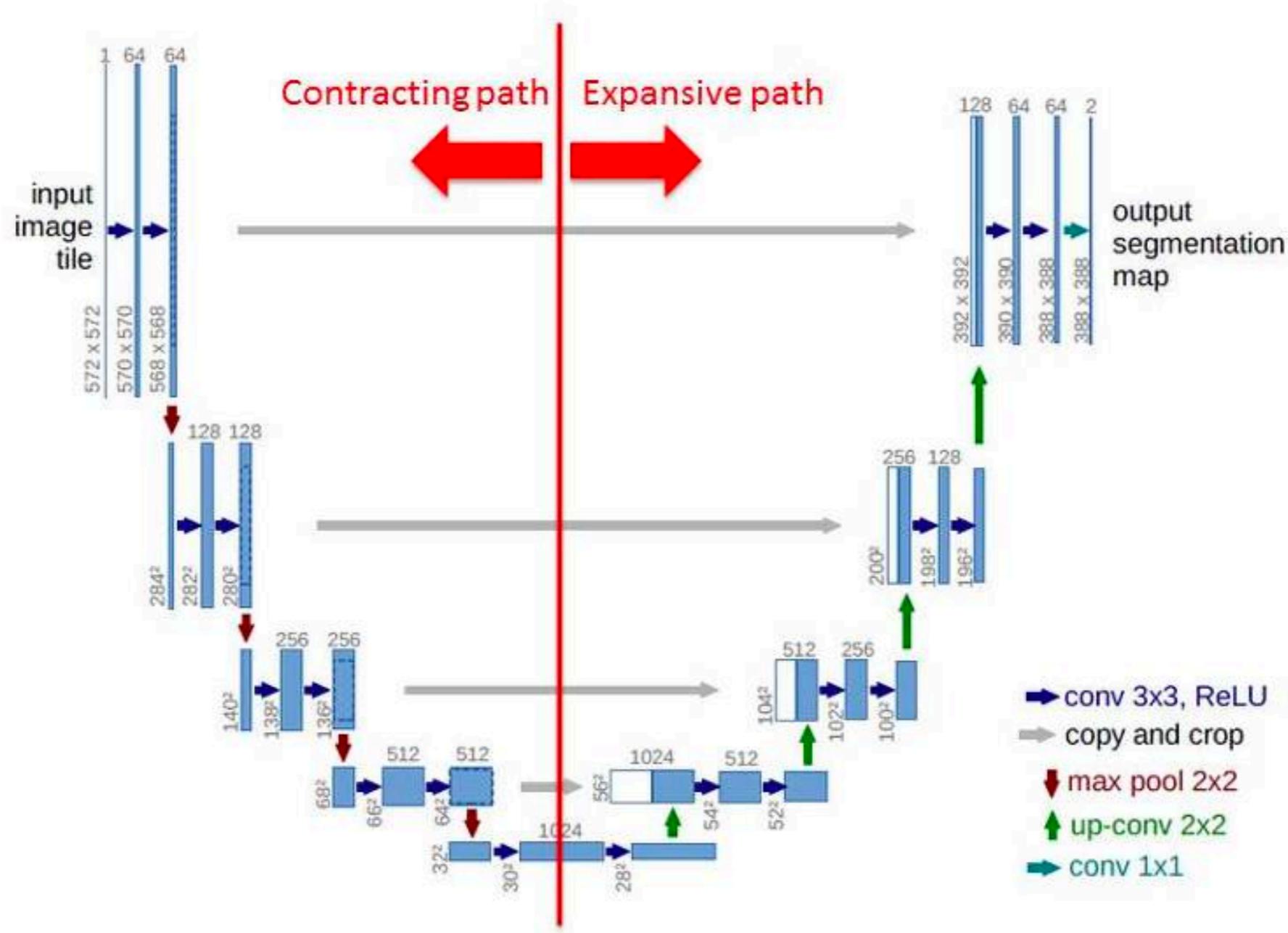


Image segmentation



U-Net

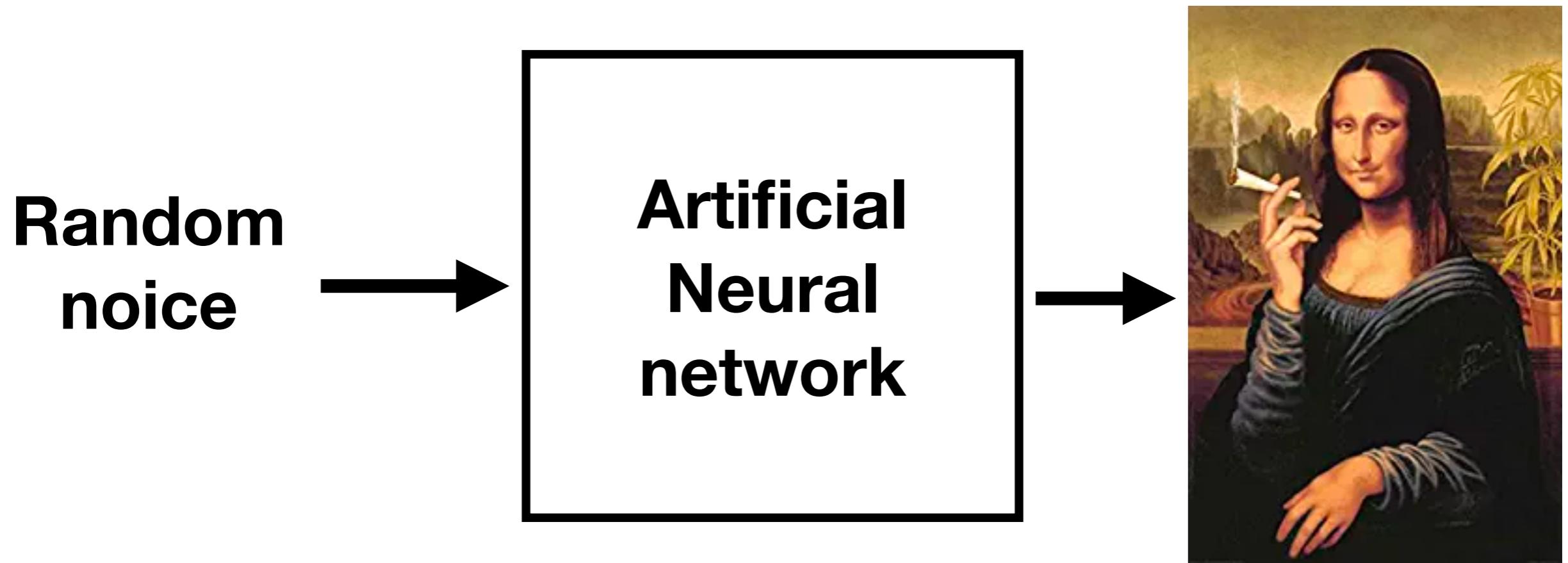
Network Architecture



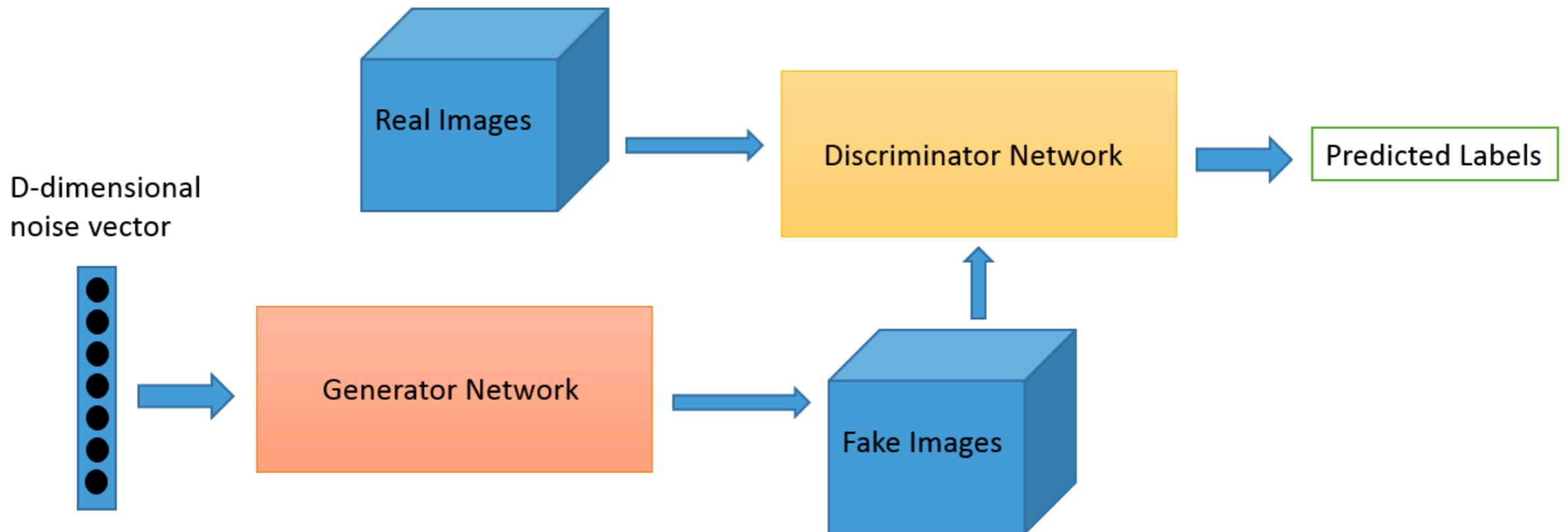
U-Net segmentation example

13-Segmentation.ipynb

Generative models with neural networks



Generative Adversarial Networks



Superresolution

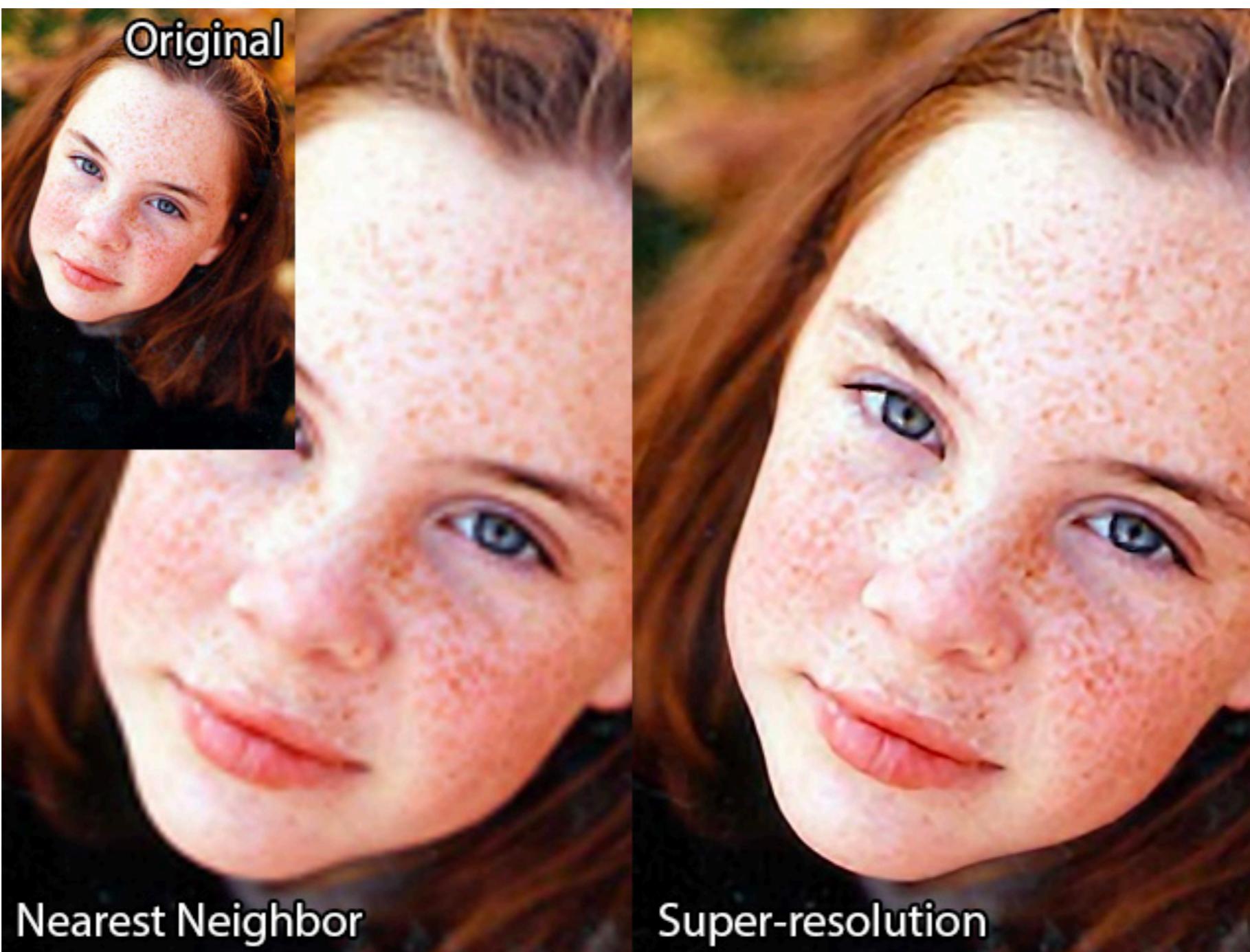
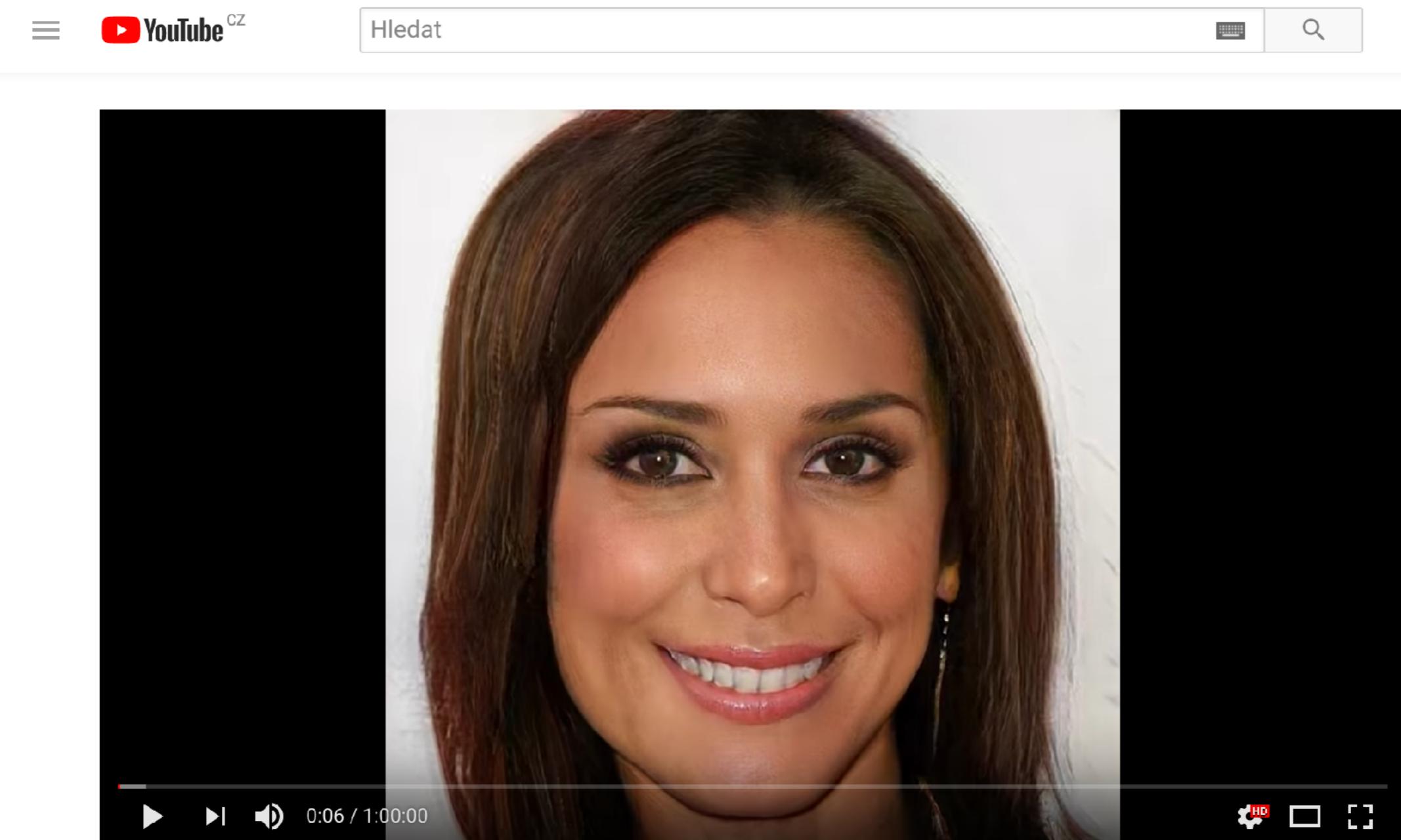


Image synthesis



One hour of imaginary celebrities

95 832 zhlédnutí

TO SE MI LÍBÍ NELÍBÍ SE SDÍLET ...

Which one is fake?



Generative Adversarial Networks

14_GANs.ipynb

Outline

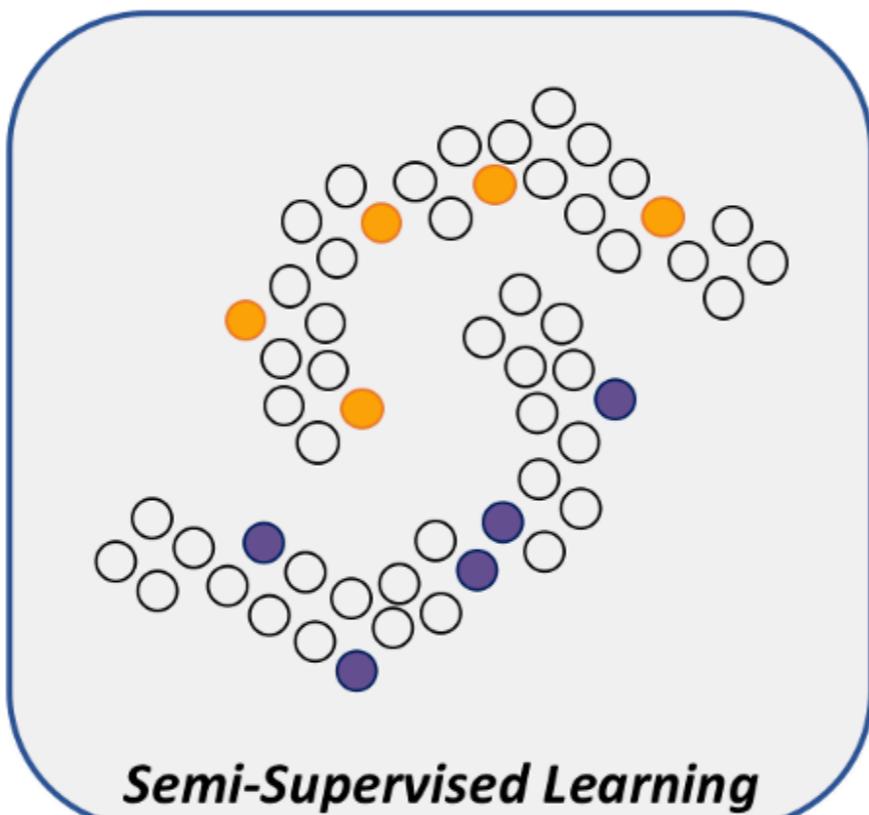
Day 4

- Semi-supervised learning
- AutoML approaches
- Confidence estimation
- ML Explainability

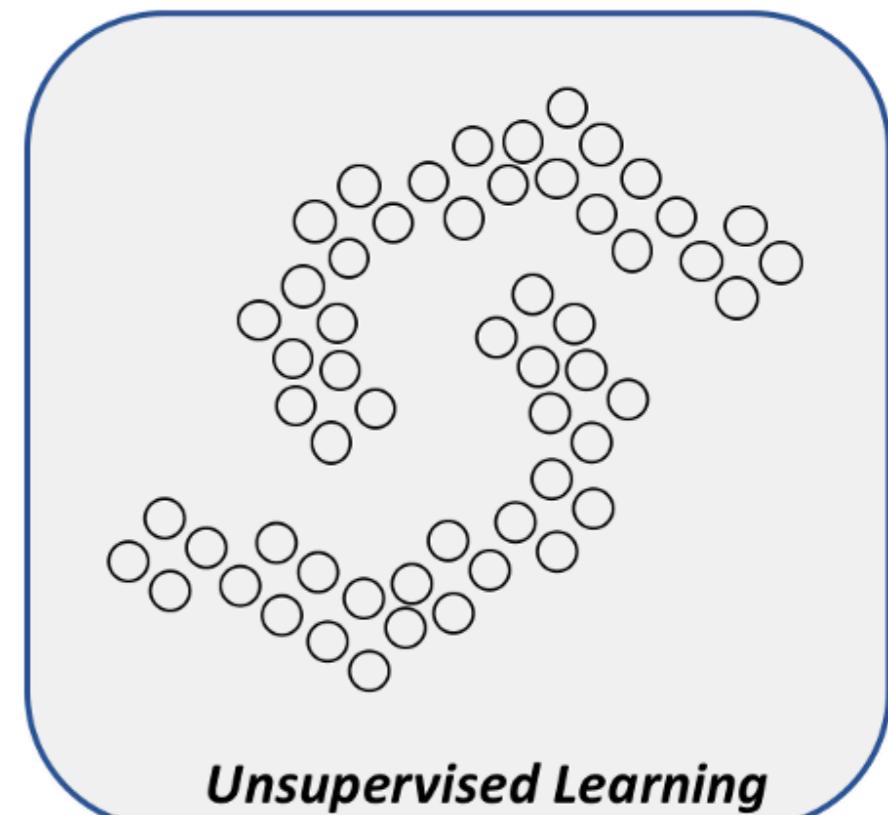
Semi-supervised learning



Supervised Learning

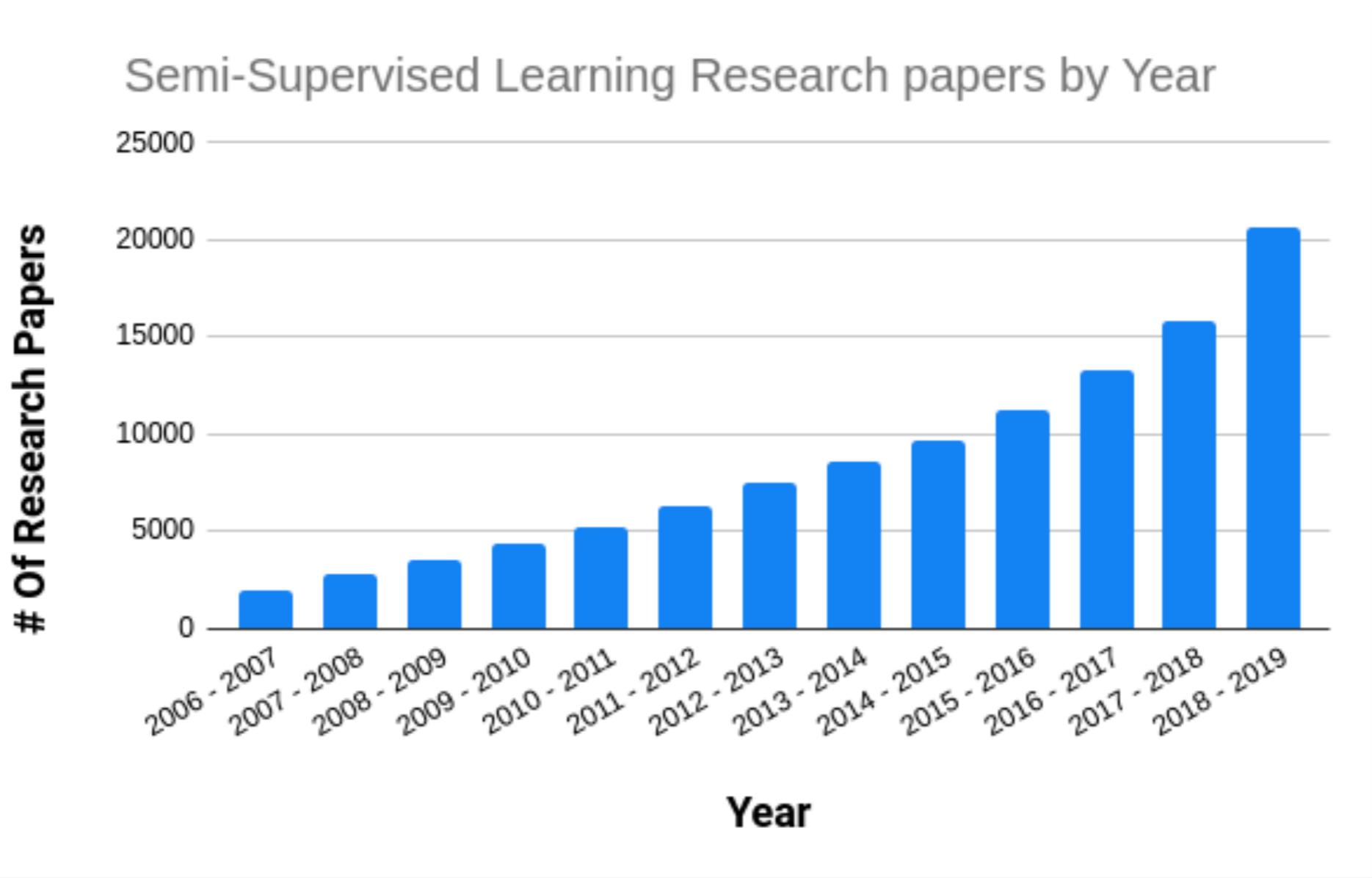


Semi-Supervised Learning

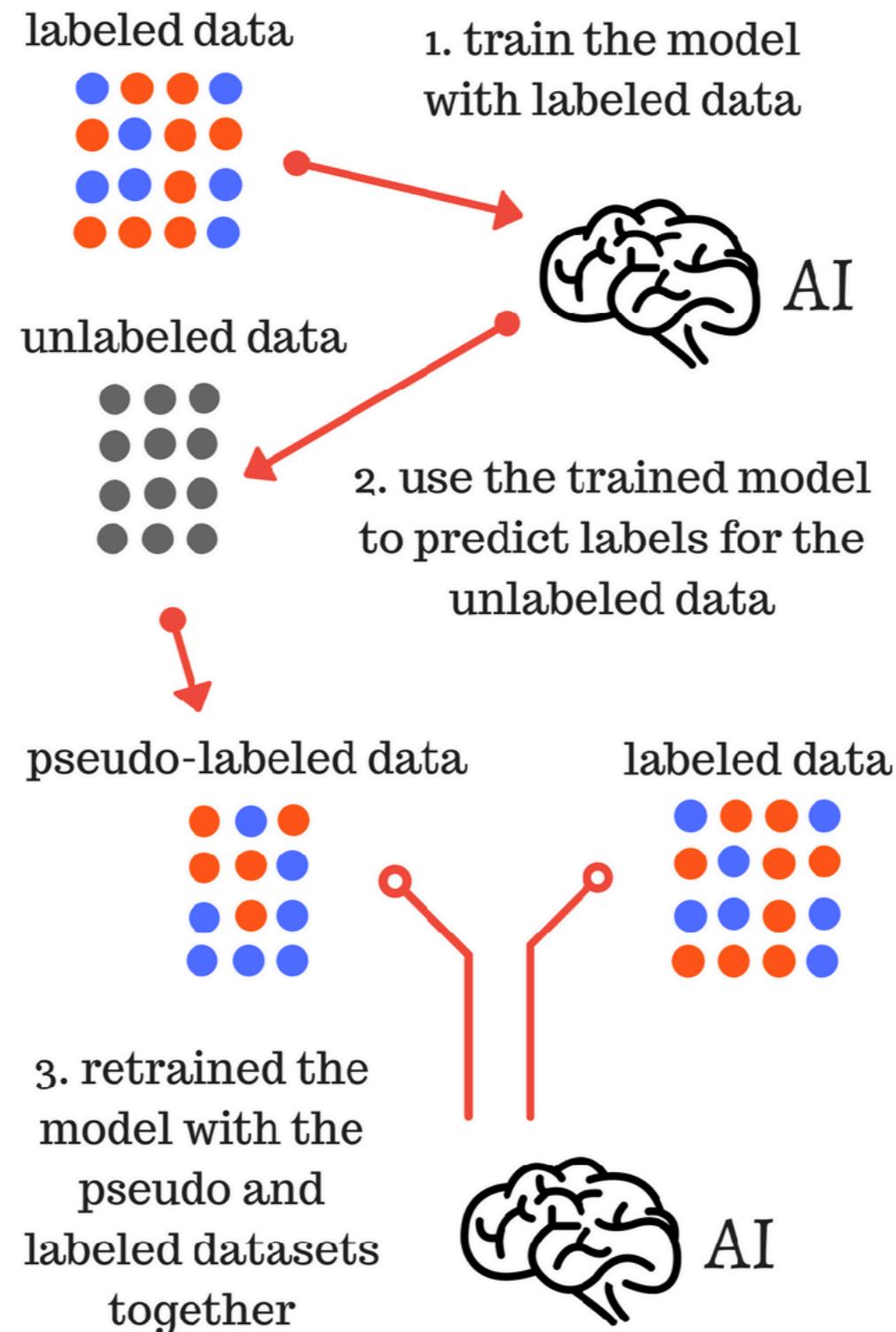


Unsupervised Learning

Small Data is the new Big Data

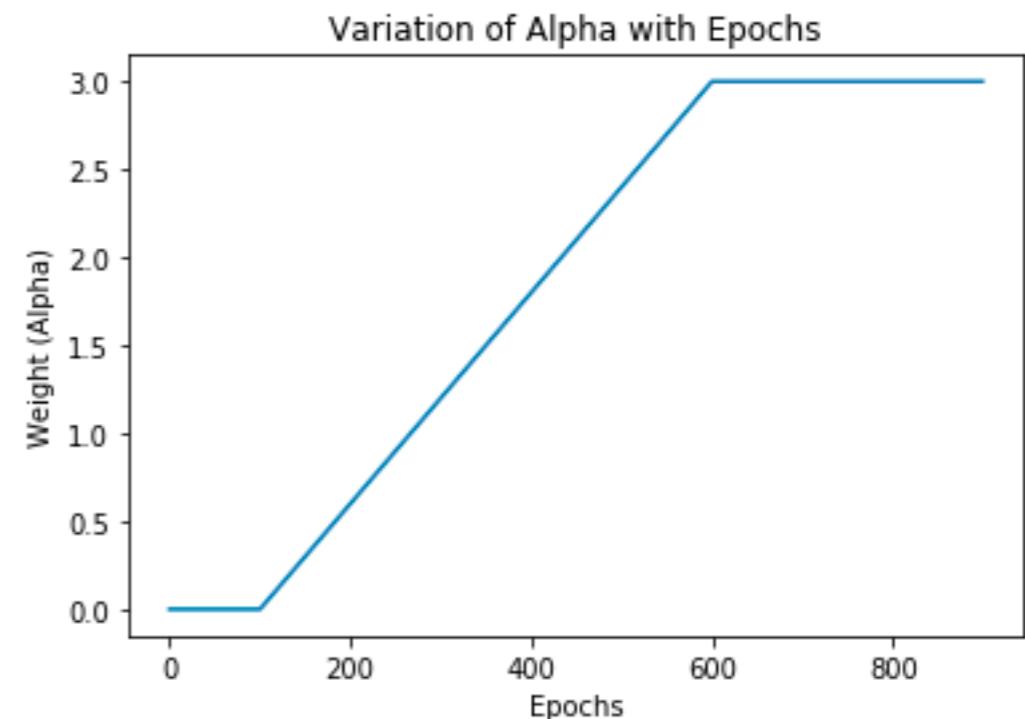


Pseudo-labeling

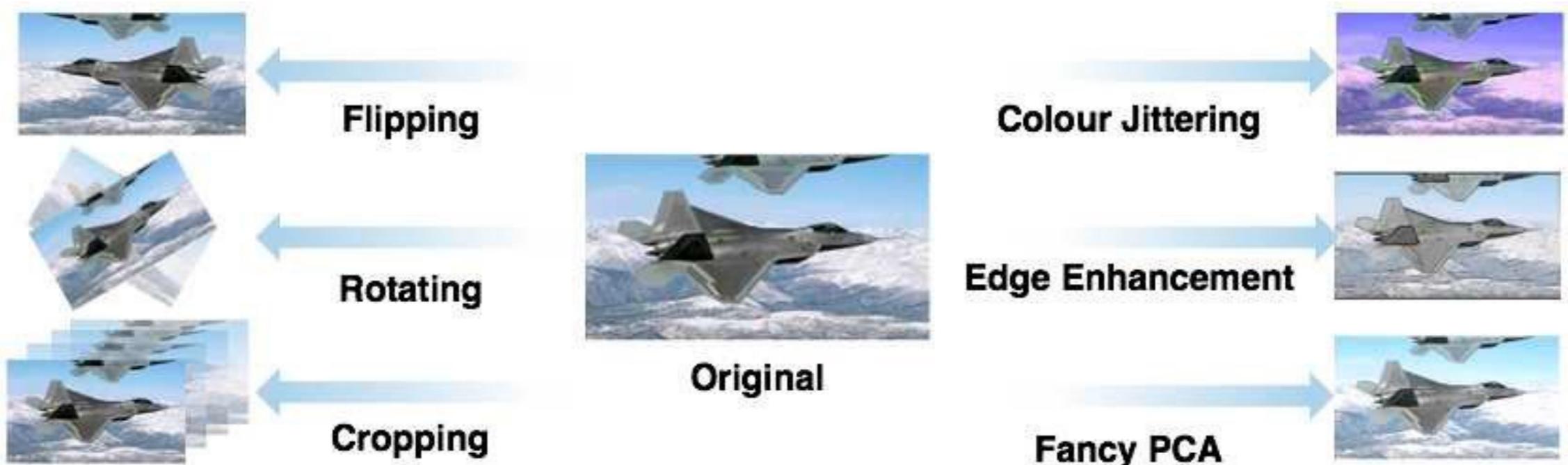


Pseudo-labeling with neural networks

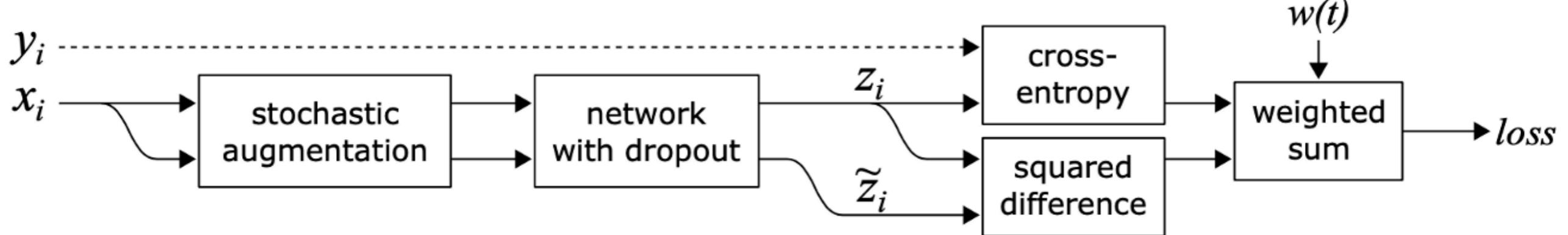
- ★ Train model on a batch of labeled data
- ★ Use the trained model to predict labels on a batch of unlabeled data
- ★ Use the predicted labels to calculate the loss on unlabeled data
- ★ Combine labeled loss with α -weighted unlabeled loss and backpropagate
- ★ Repeat



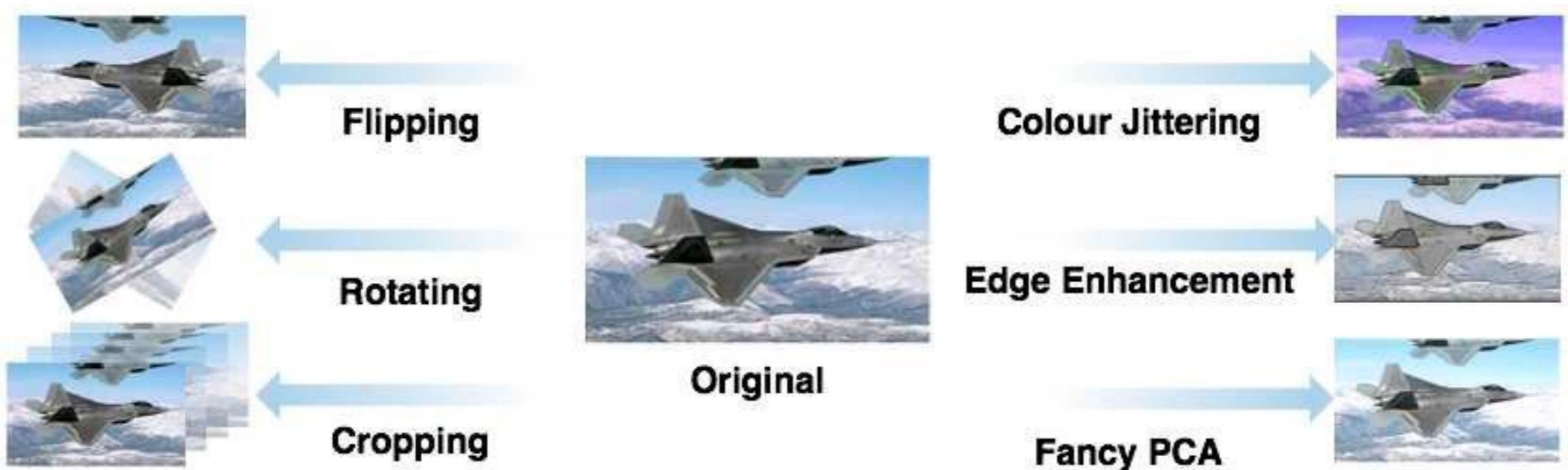
PI-model



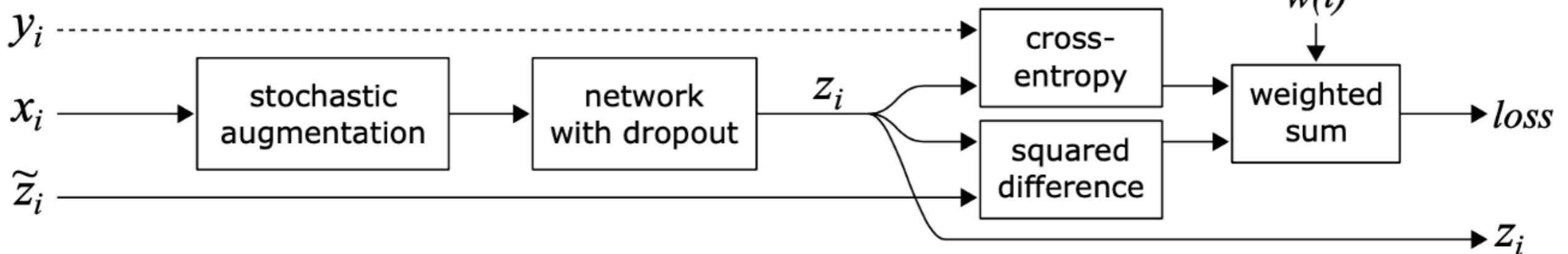
Π-model



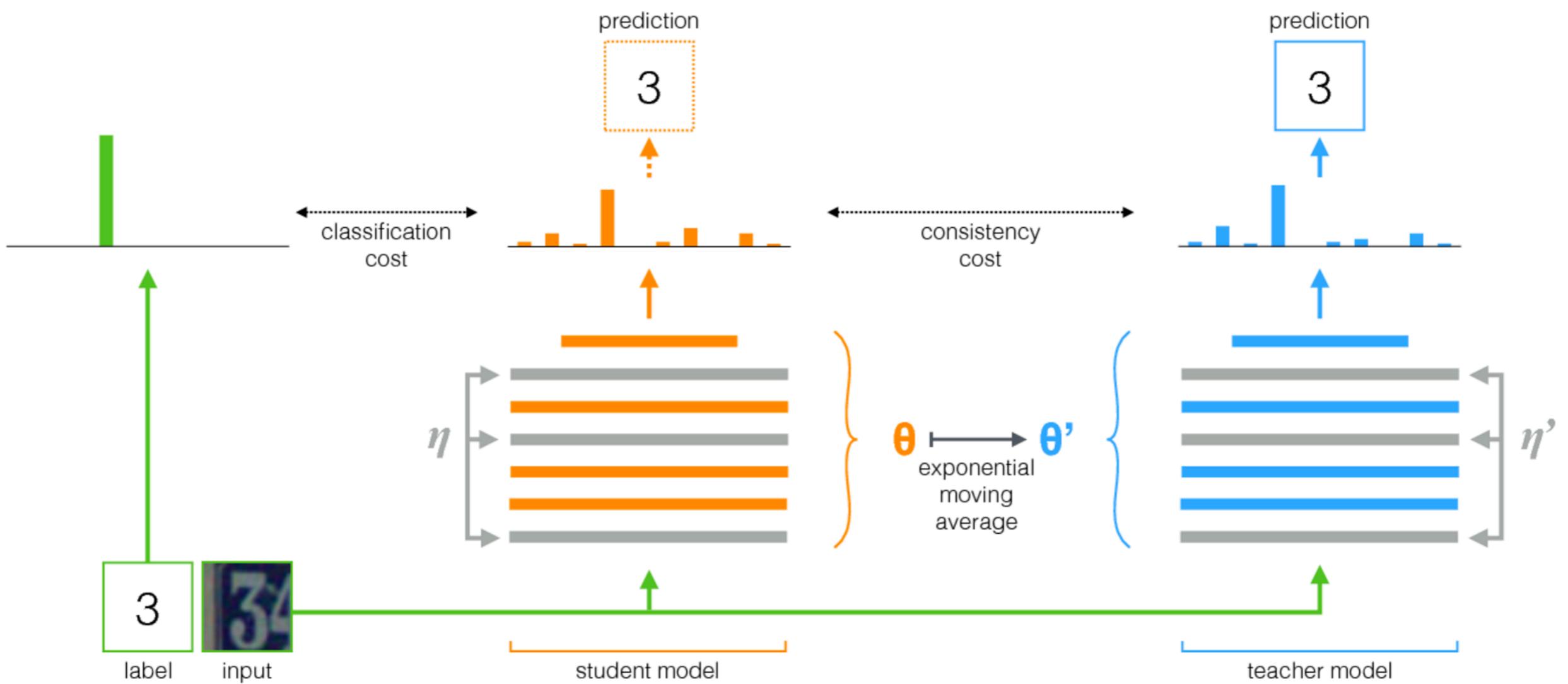
Temporal ensembling



Temporal ensembling



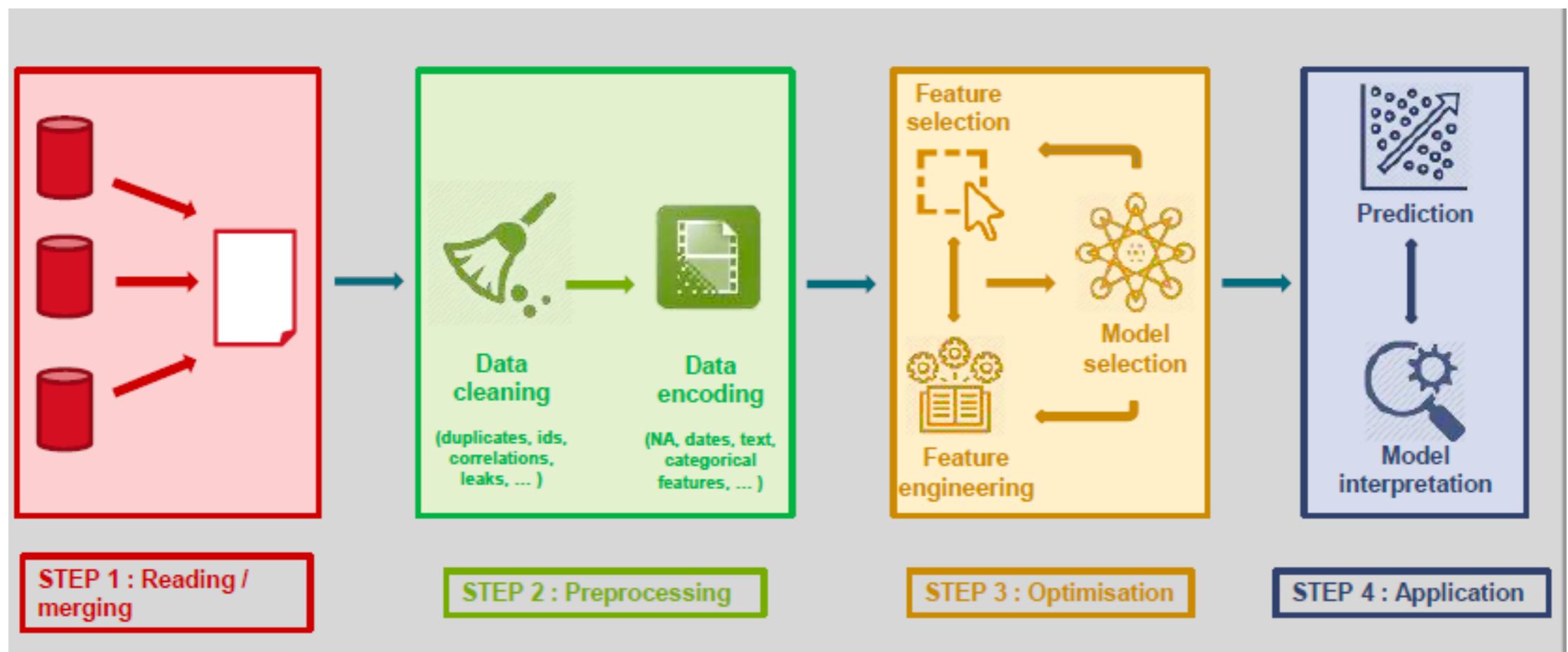
Mean-Teacher



Clustering as semi-supervised learning

15-clustering-assignment.ipynb

AutoML approaches



AutoML frameworks



AutoGluon

Google's AutoML



HYPEROPT



MLBox,
Machine Learning Box

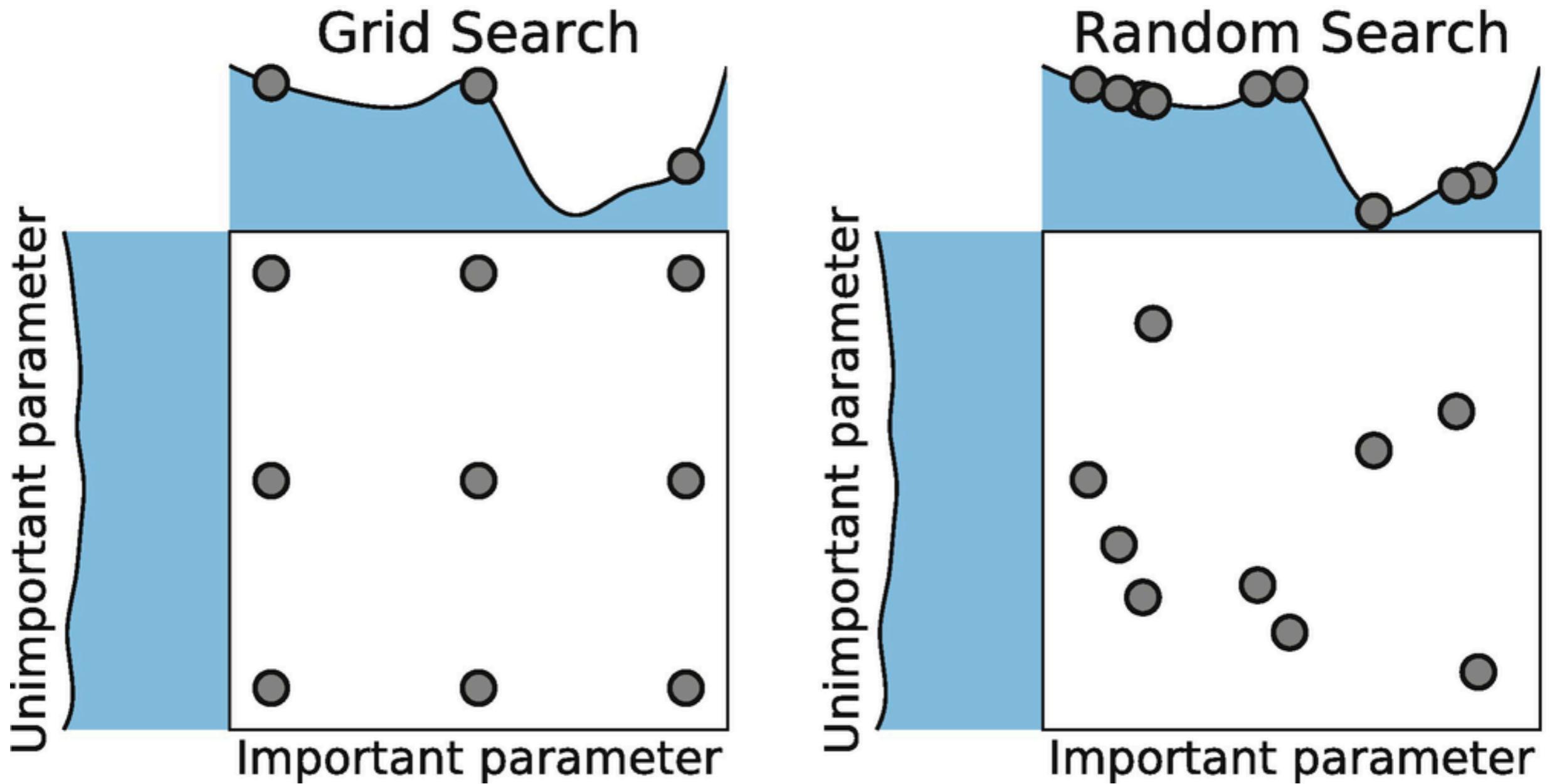


Hyper-parameters tuning

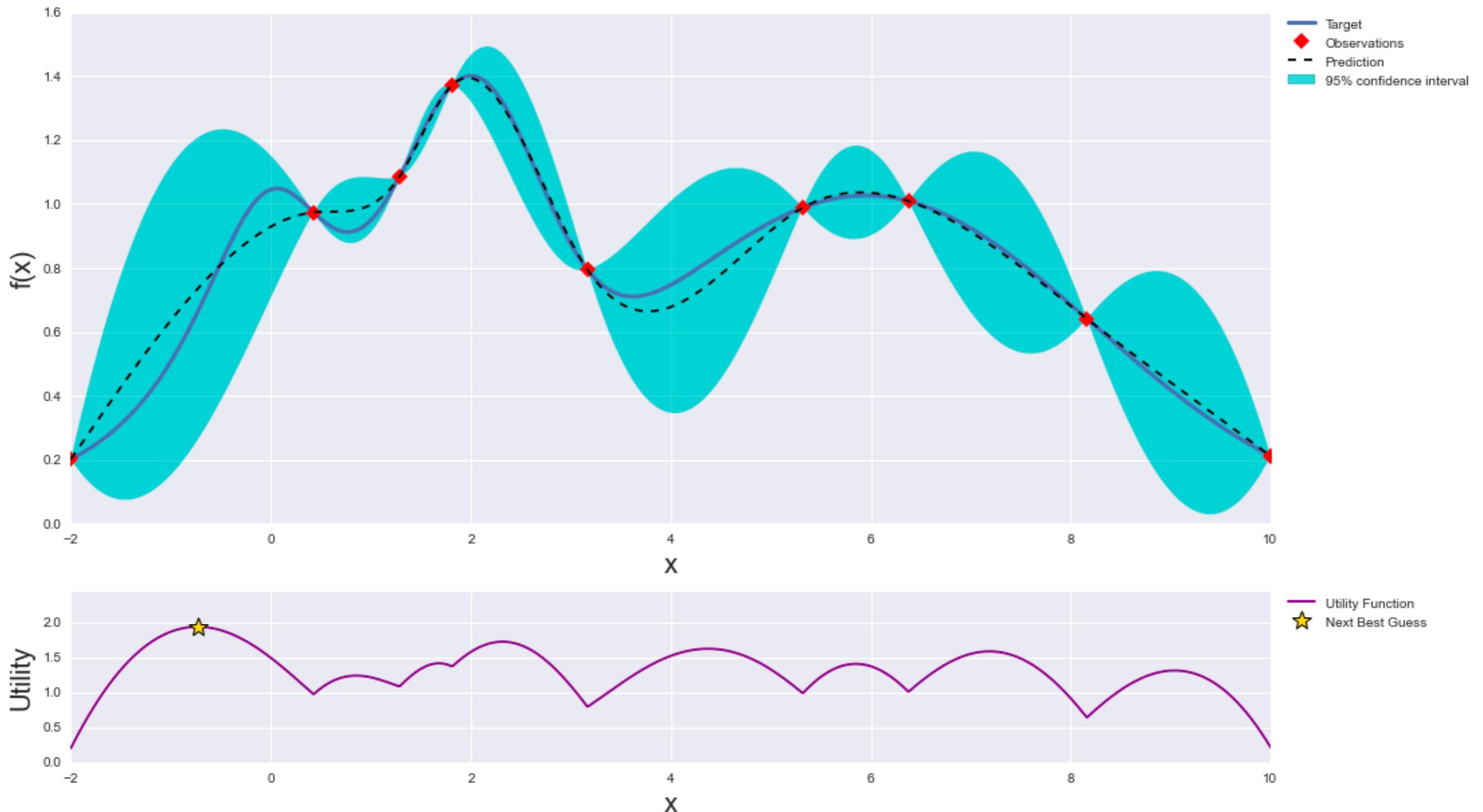
Parameters - learnable weights of the neural network

Hyper-parameters - parameters set before training (learning rate, momentum, dropout rate, etc.)

Grid search vs random search



Bayesian optimization using Gaussian processes



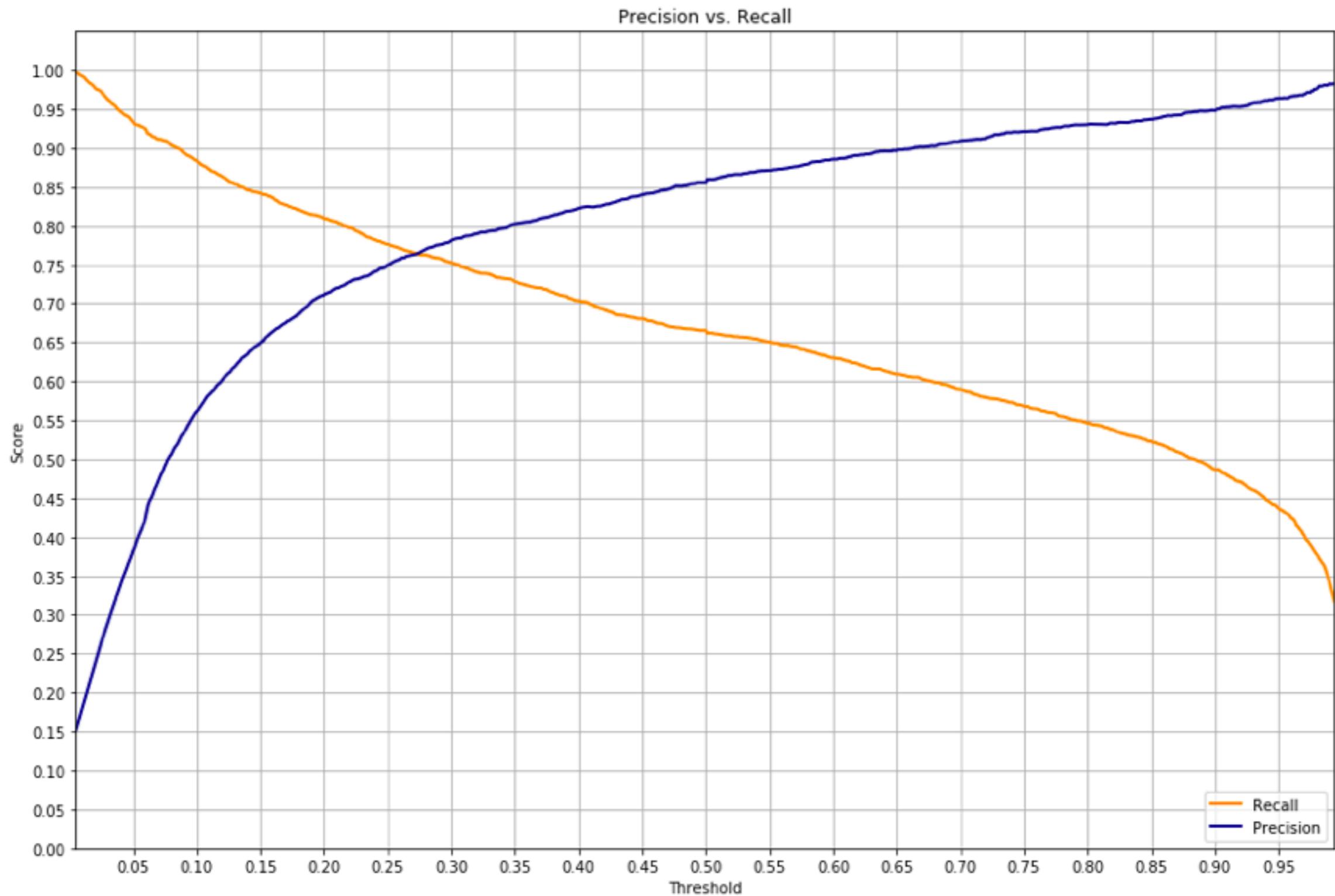
Neural Architecture Search (NAS)



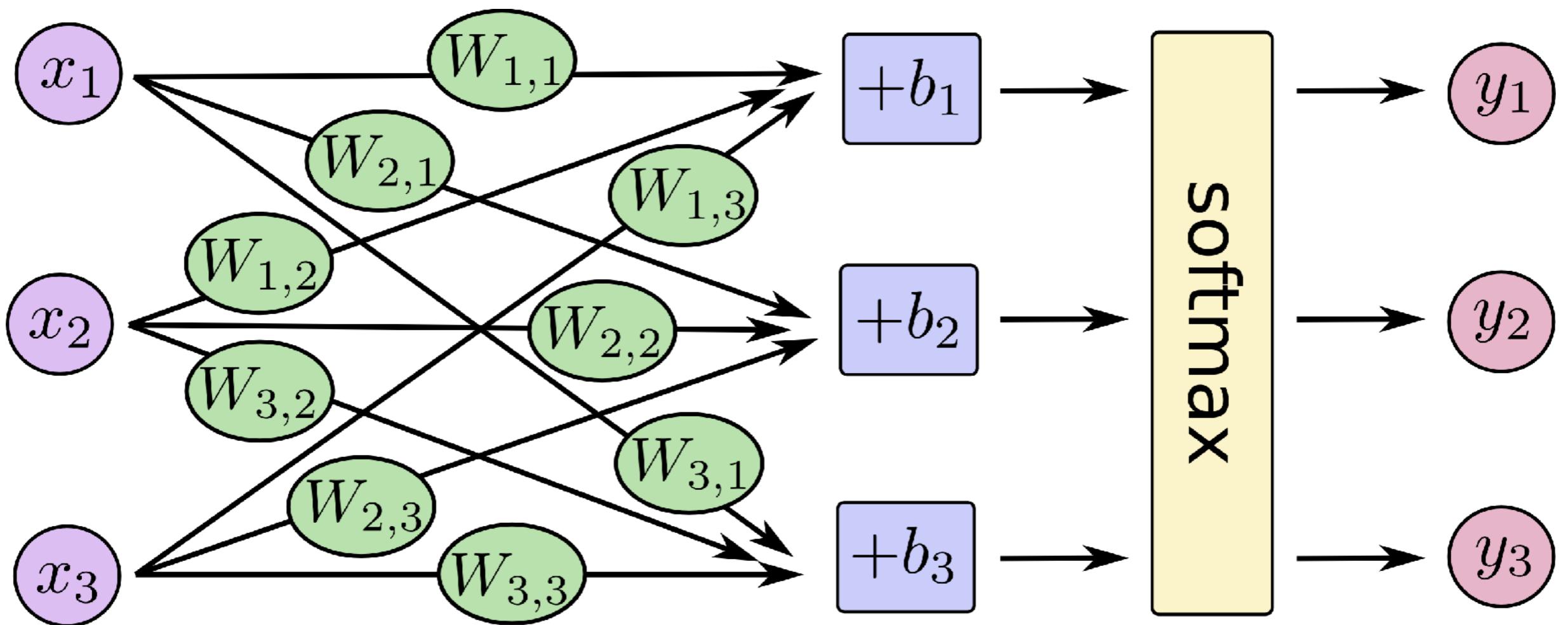
AutoML with AutoKeras

16-Autokeras.ipynb

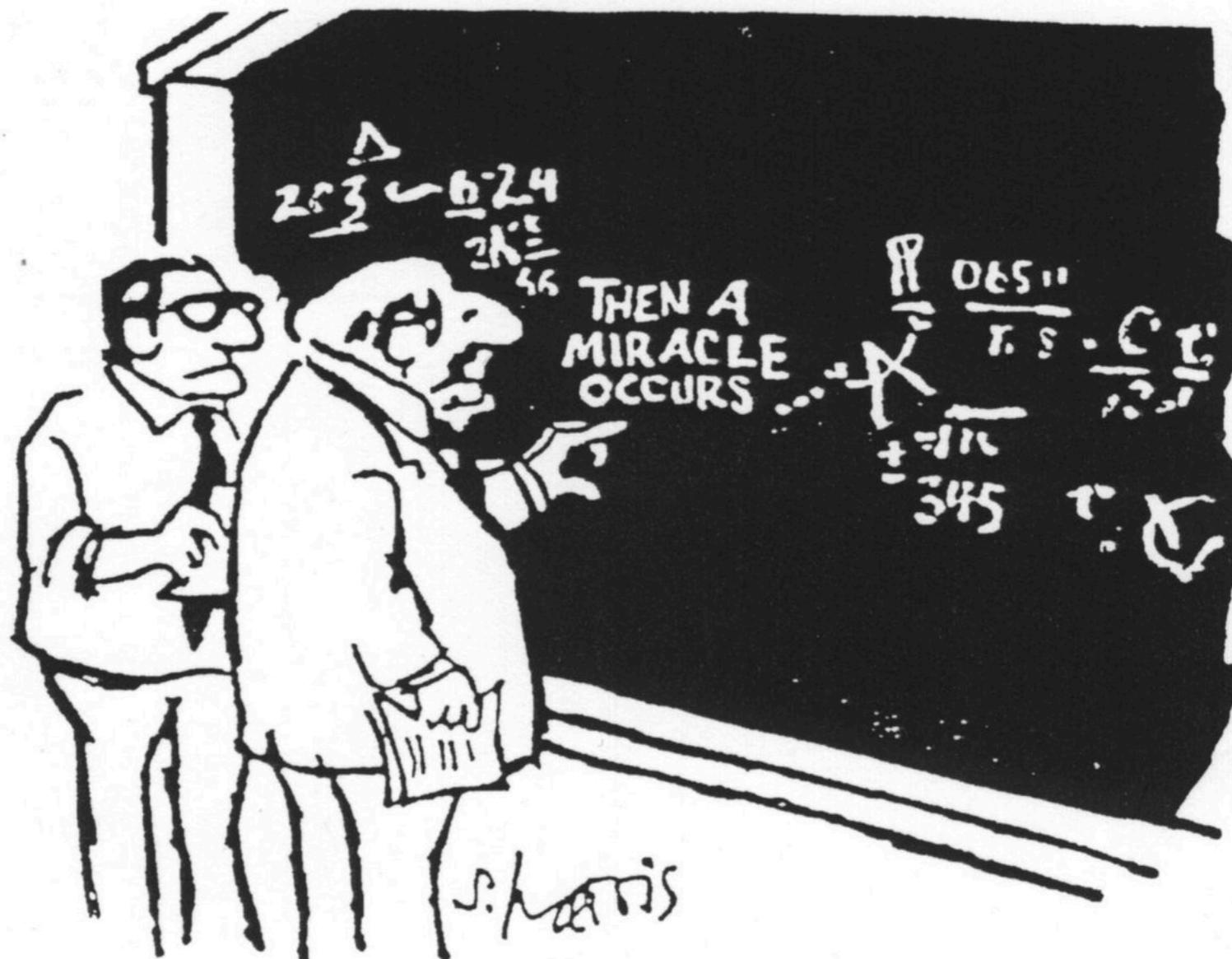
Confidence estimation



Confidence estimation



Neural network explainability



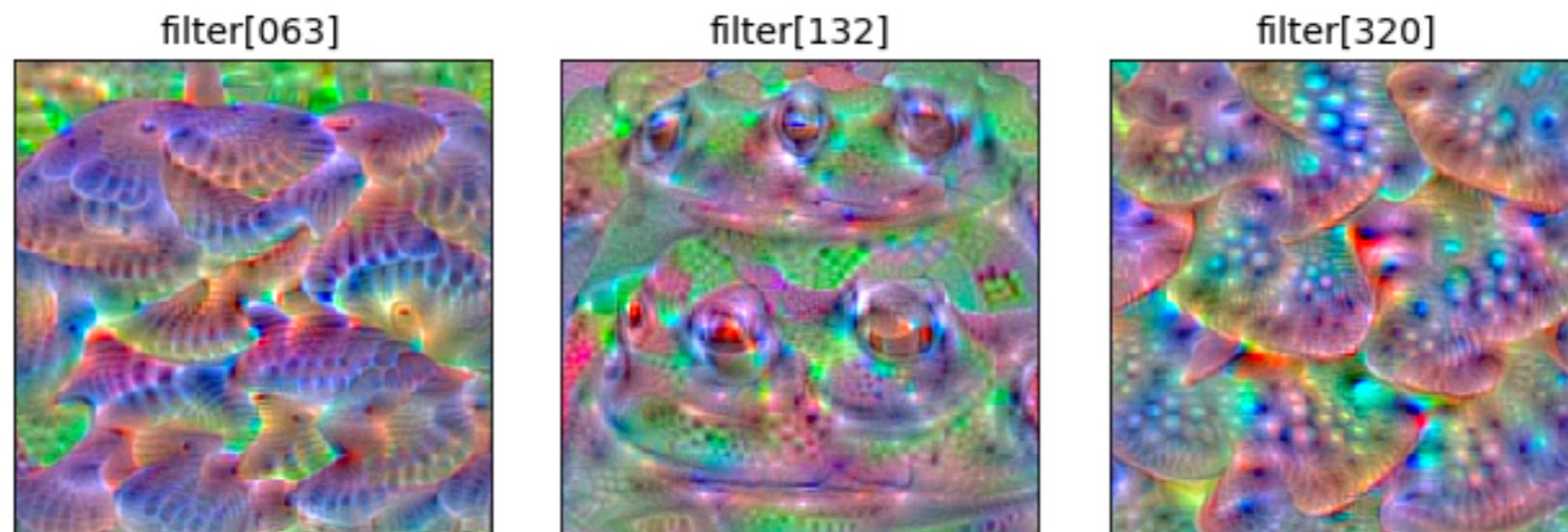
I think you should be a little
more specific, here in Step 2

Activation Maximization

Visualized output classification Layer



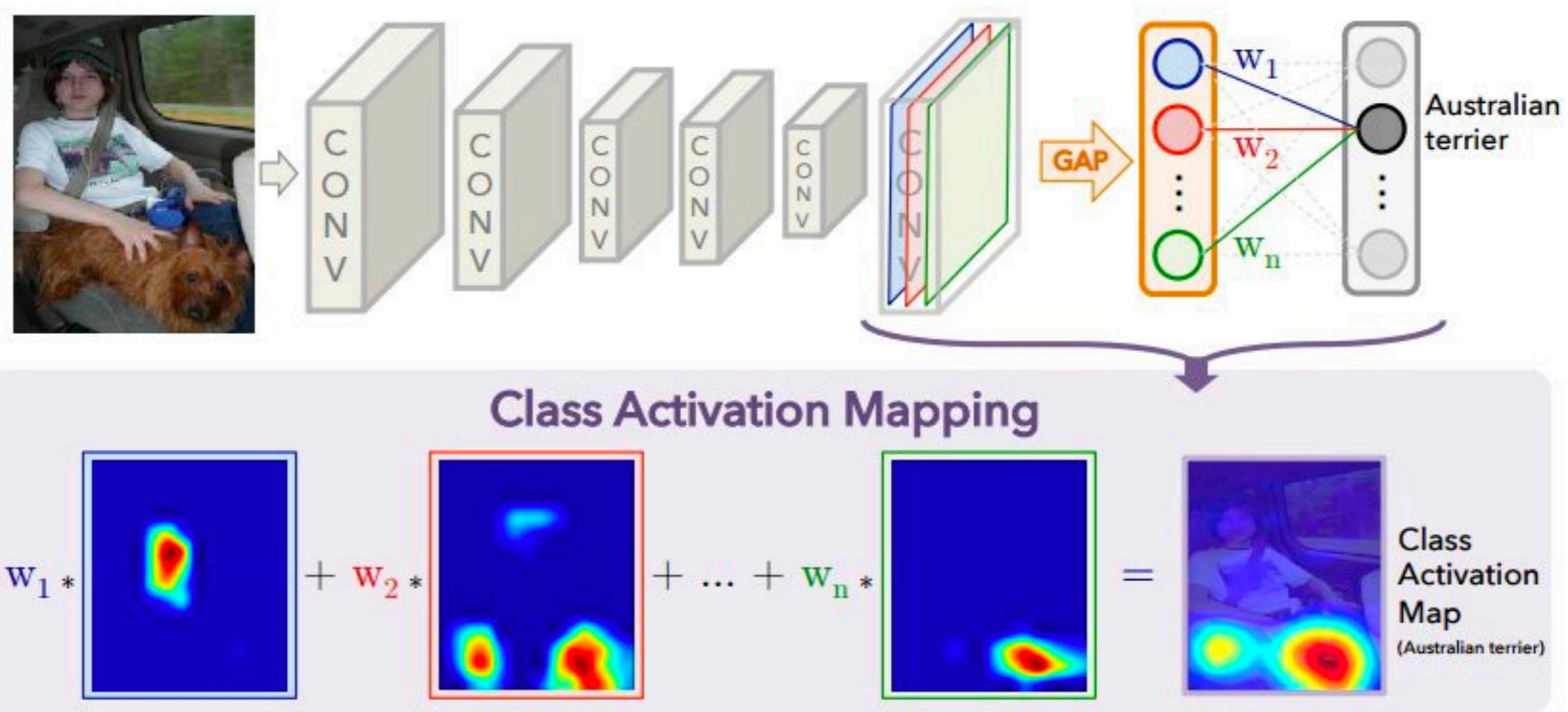
Visualized hidden convolutional layers



Grad-CAM heat maps



CAM heat maps



Convolutional Neural Networks Explainability in Keras

17-Explainability.ipynb

Complex programming assignment

18-House-pricing.ipynb

Thank you for your attention

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