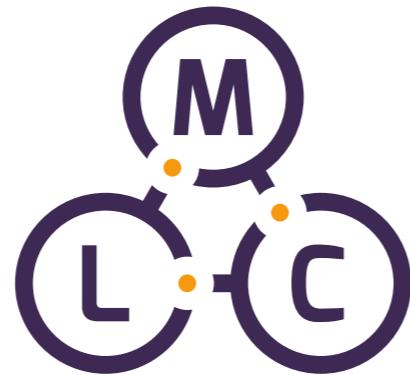


Deep Learning for Raiffeisenbank

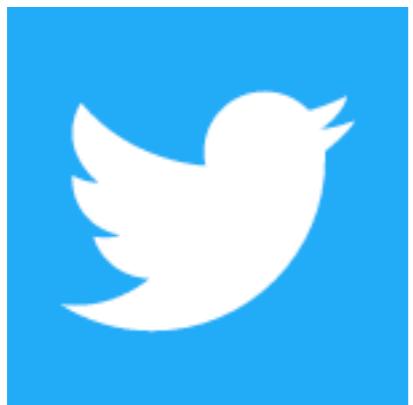
Jiří Materna



Machine
Learning
College



@mlcollegecom



@mlcollegecom

#mlcollege

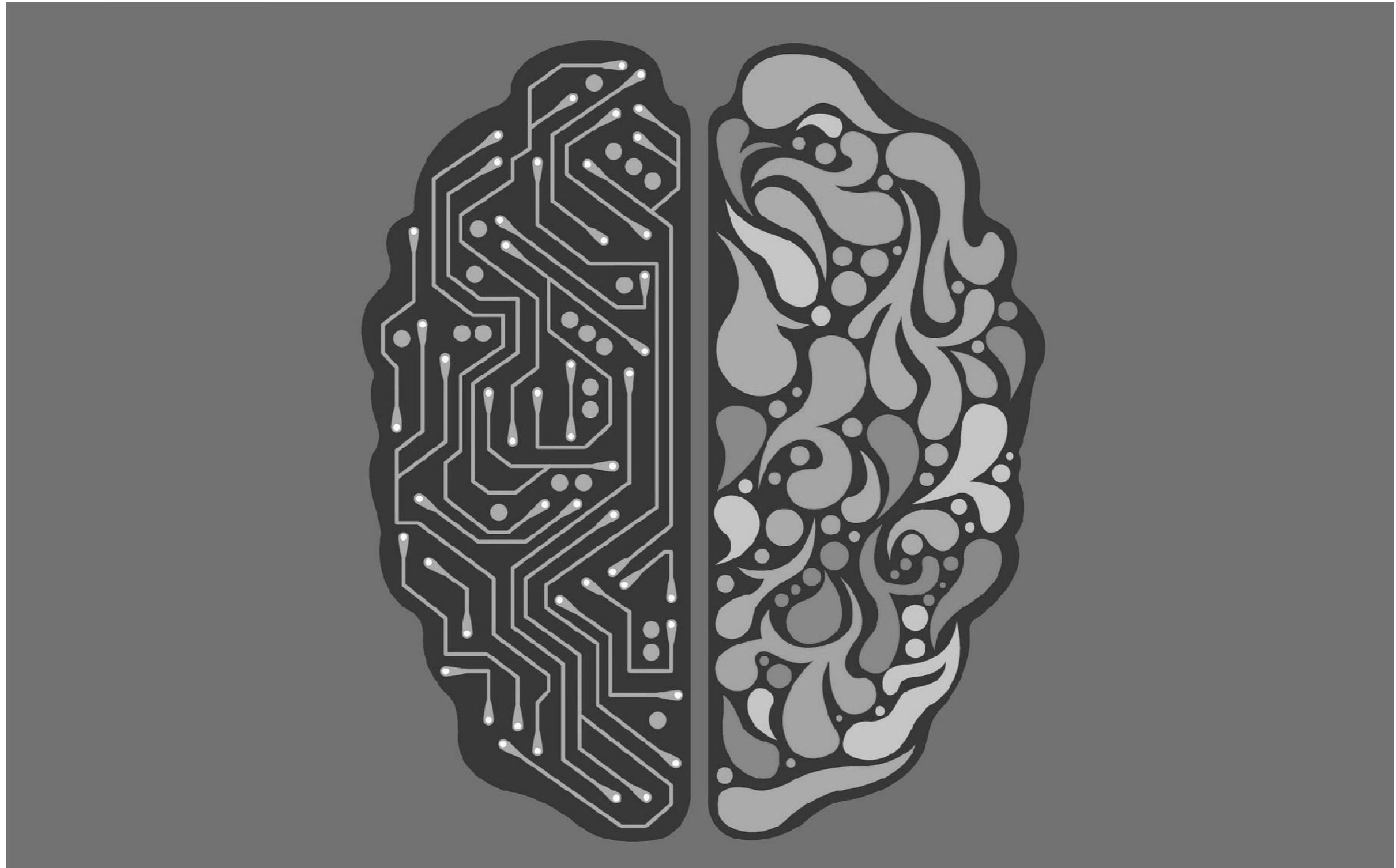
About me

- 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-organiser of ML Prague
- Author of the ML Guru blog
- Mentor at StartupYard and Startup AI Incubator
- ML Freelancer and consultant

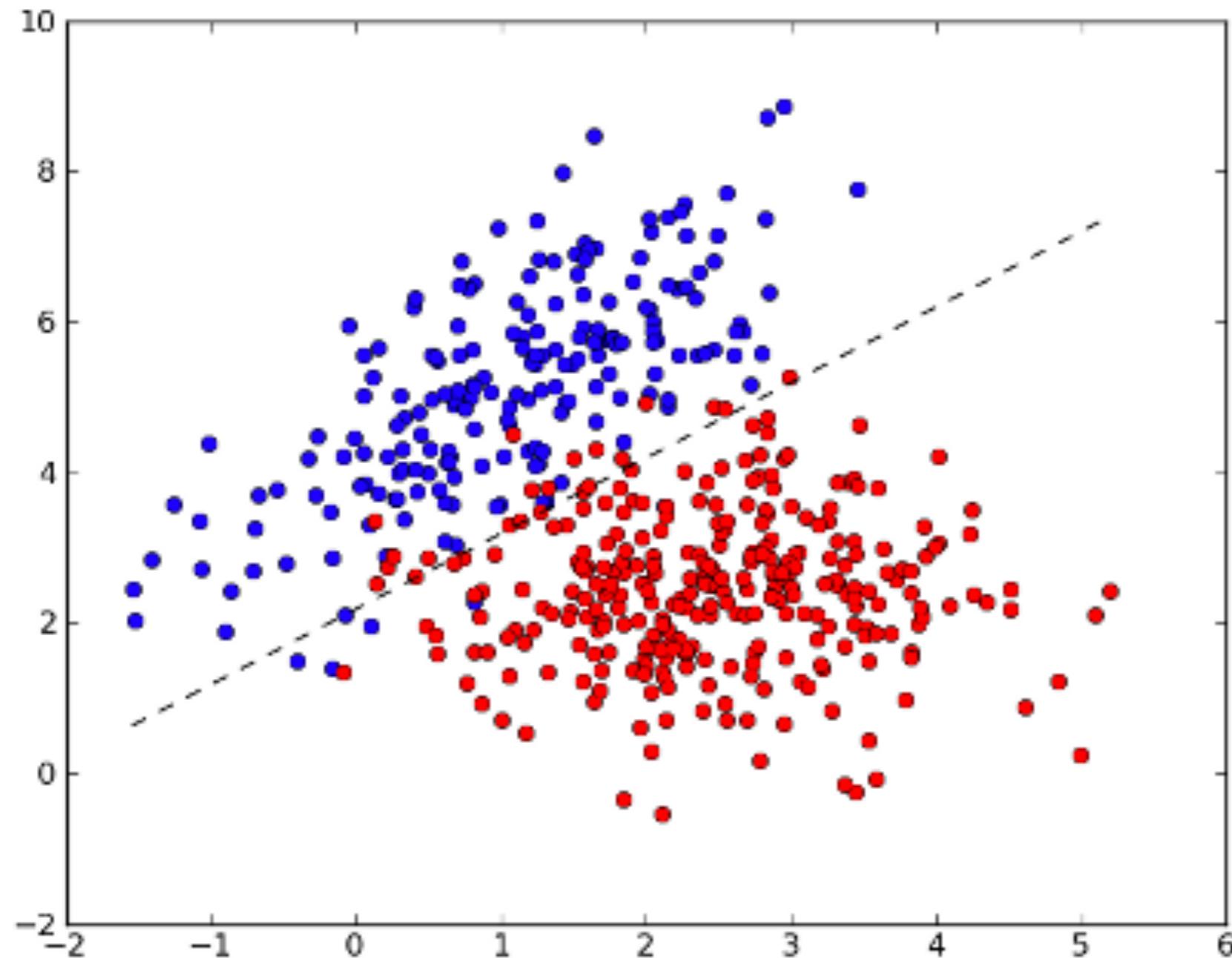
Image processing

- Introduction to neural networks
- Activation functions for neural networks
- Multilayered neural networks
- Methods for training neural networks
- Kears tutorial
- Practical classification and regression tasks solved using neural networks
- ResNet
- Transfer learning and fine-tuning
- Image classification
- Image segmentation
- GANs and superresolution

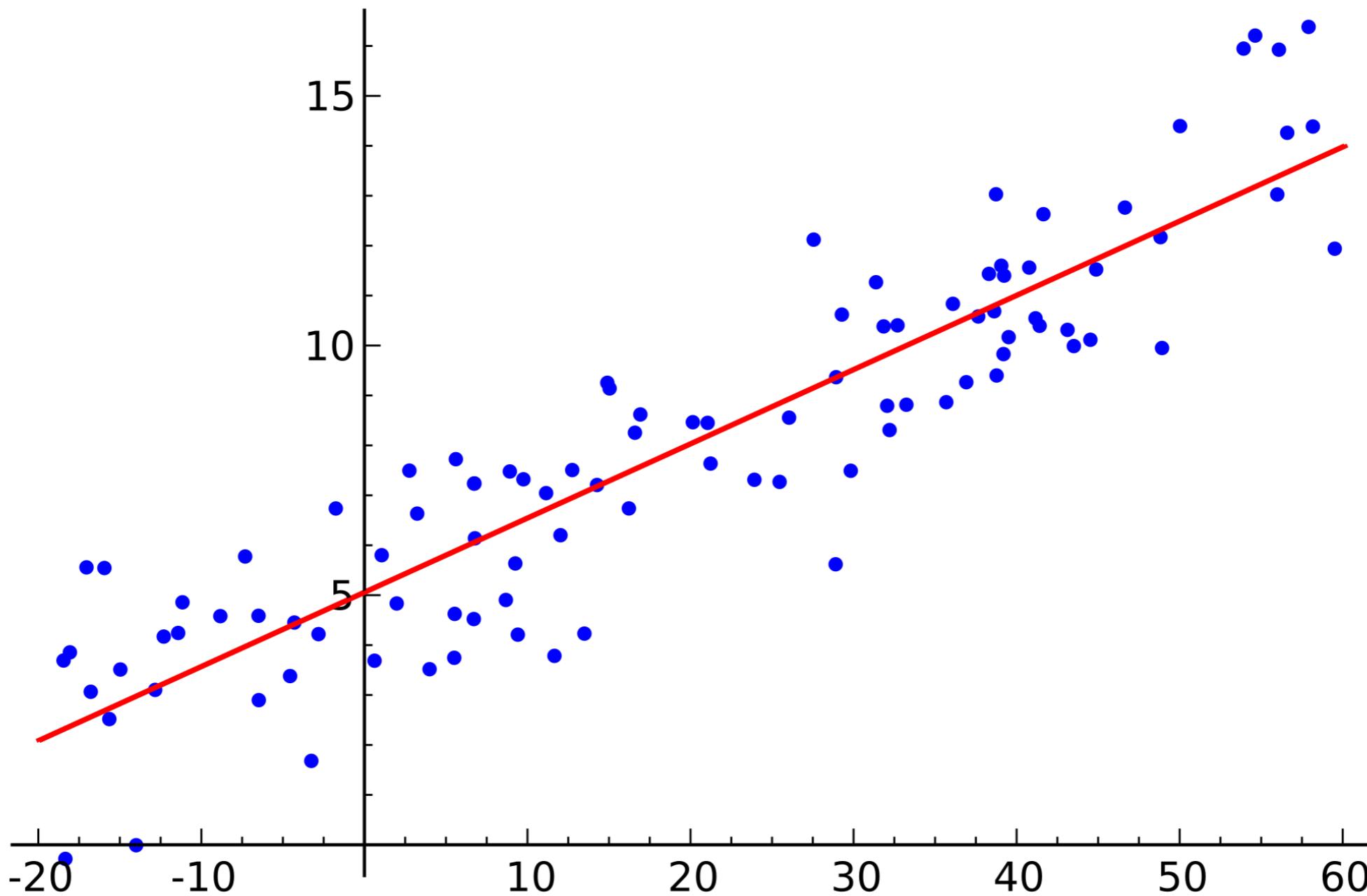
What is (not) machine learning?



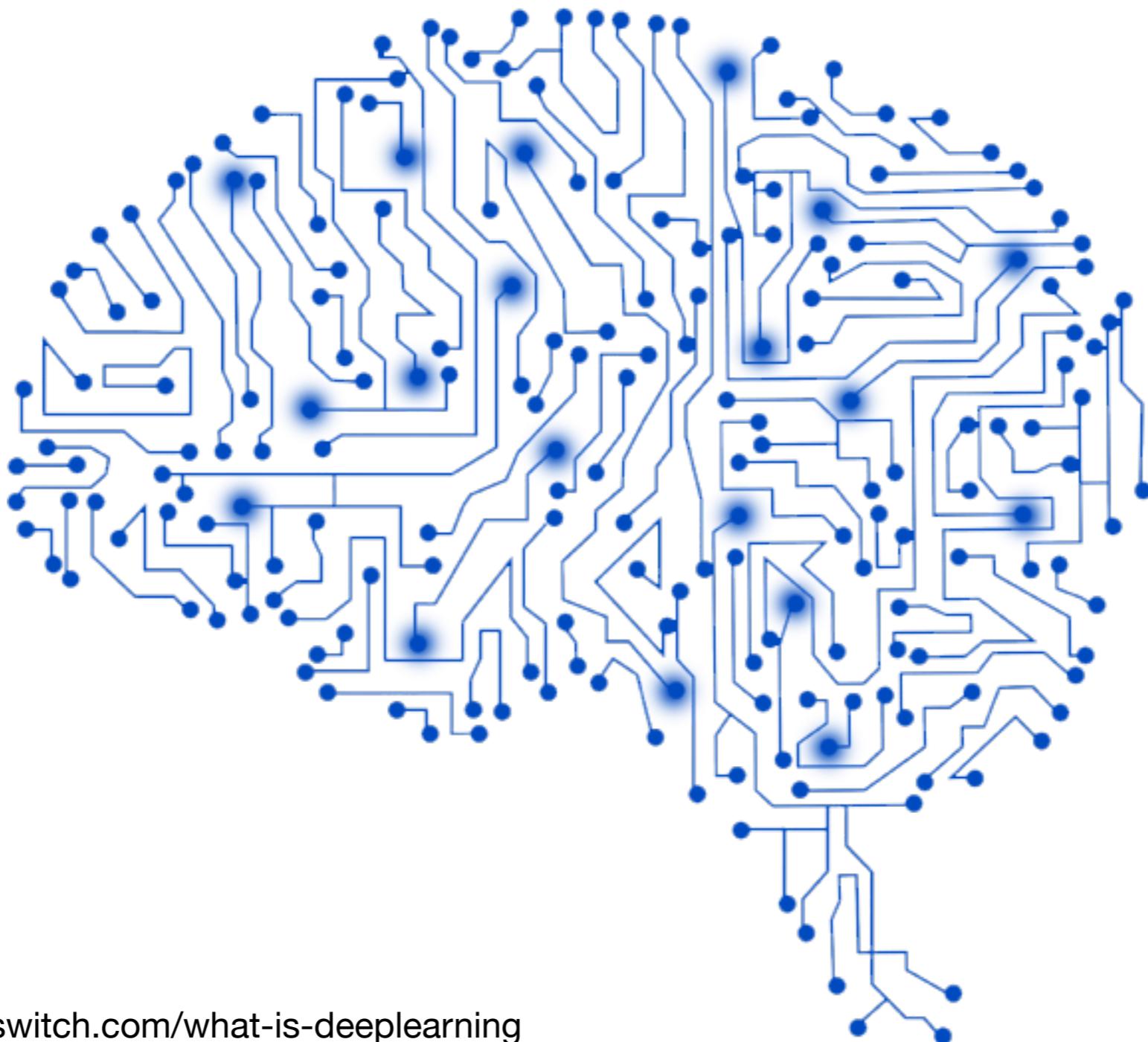
Classification



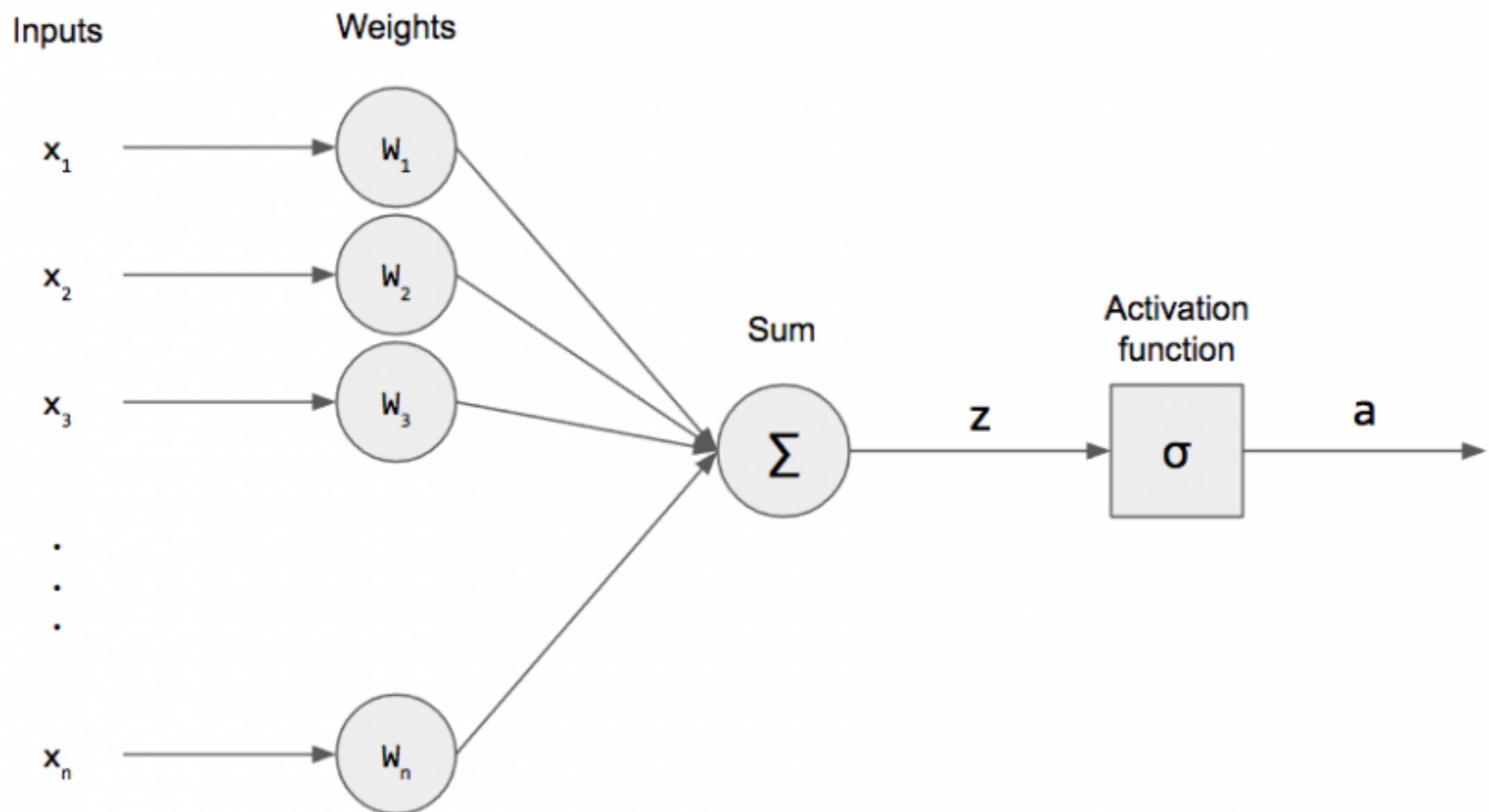
Regression



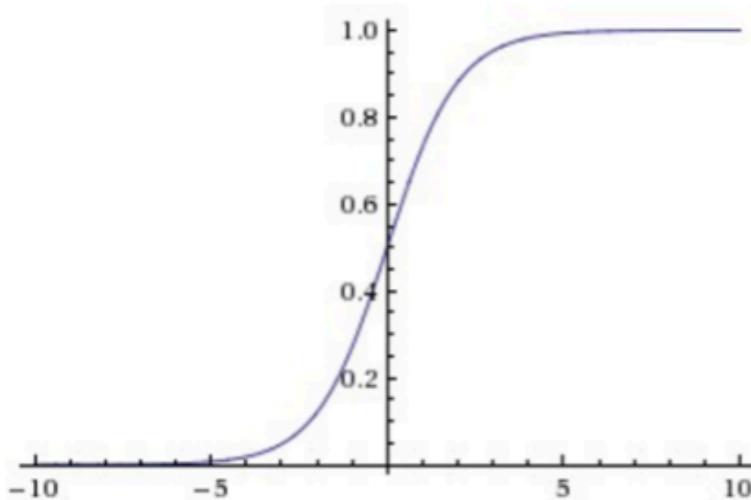
Neural networks and deep learning



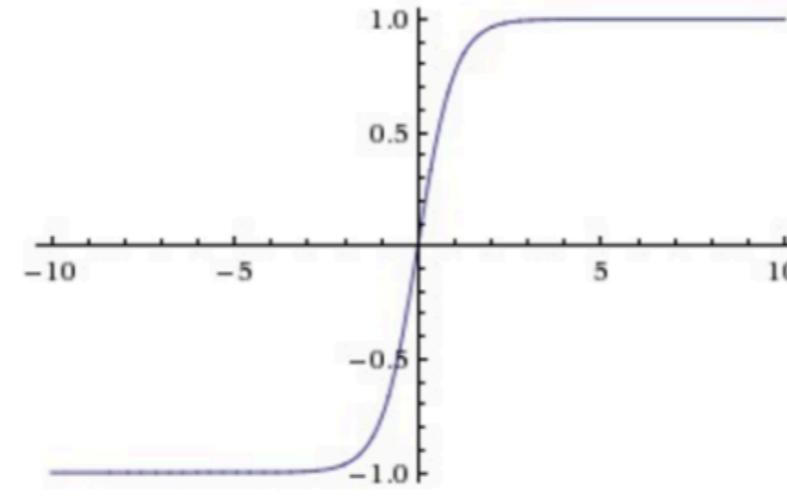
Perceptron



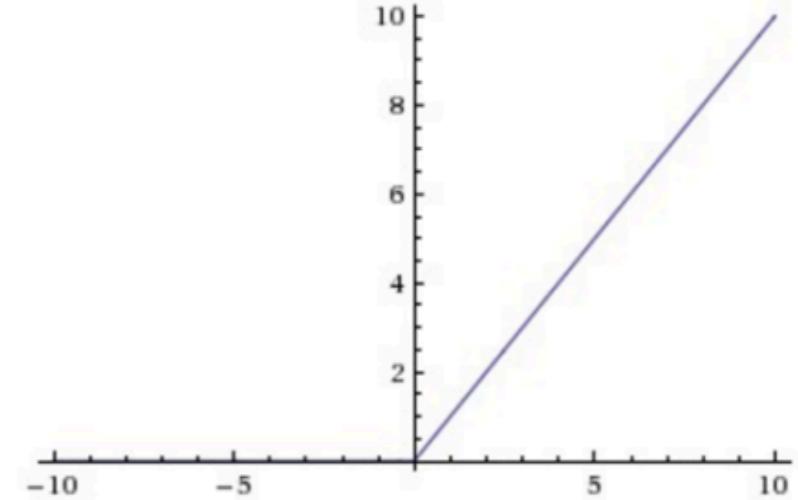
Activation functions



Sigmoid



tanh

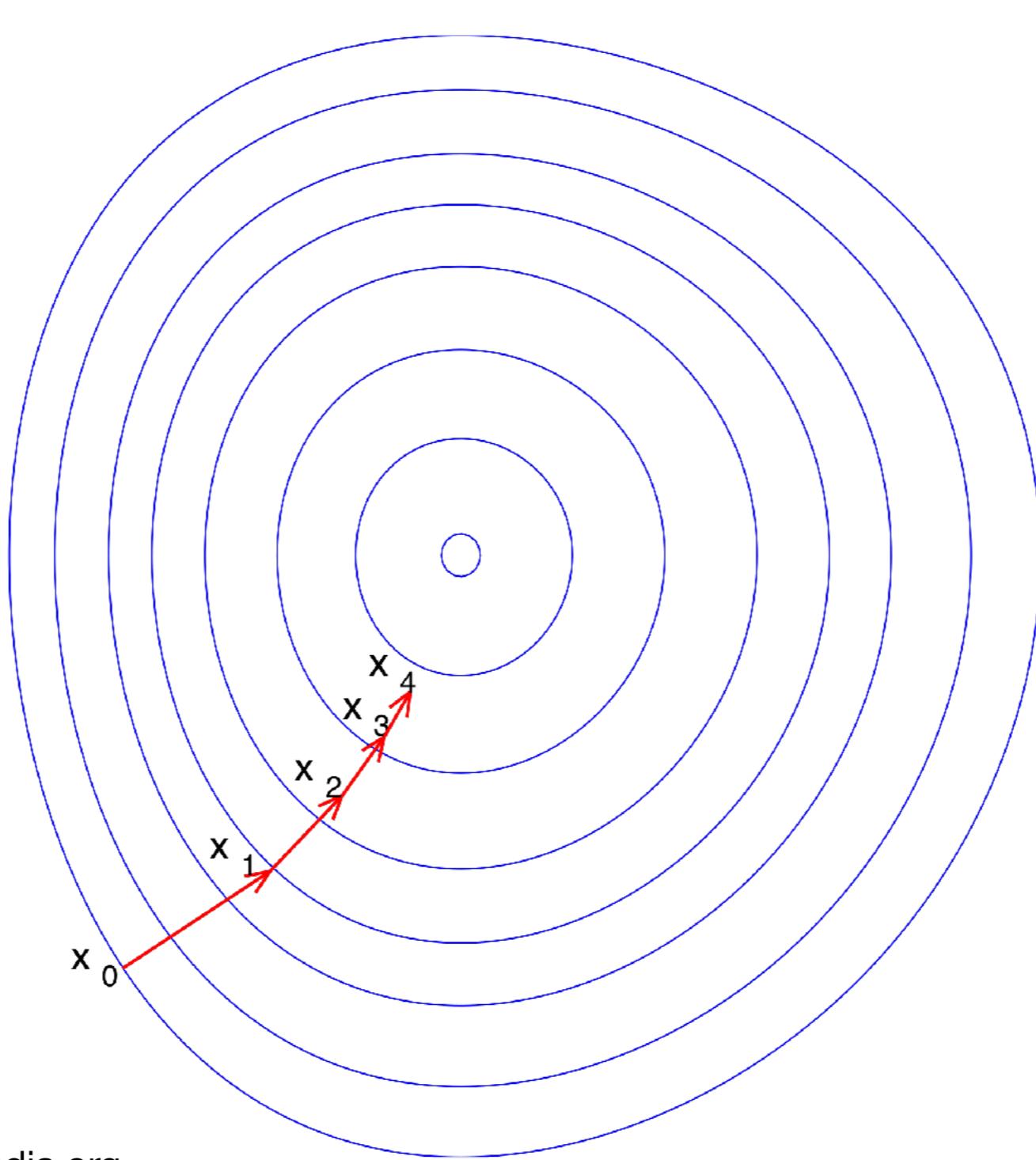


ReLU

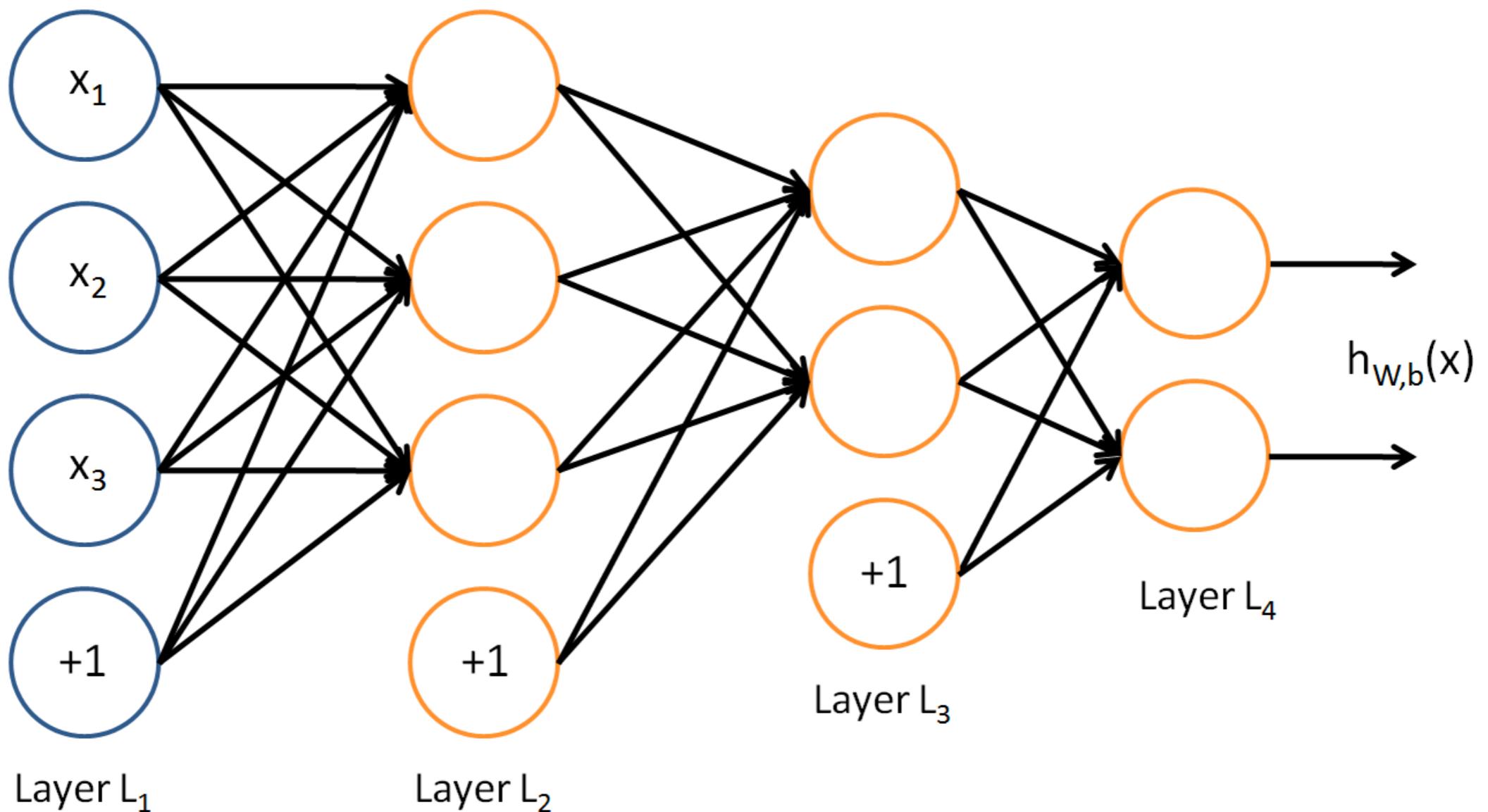
Softmax:

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

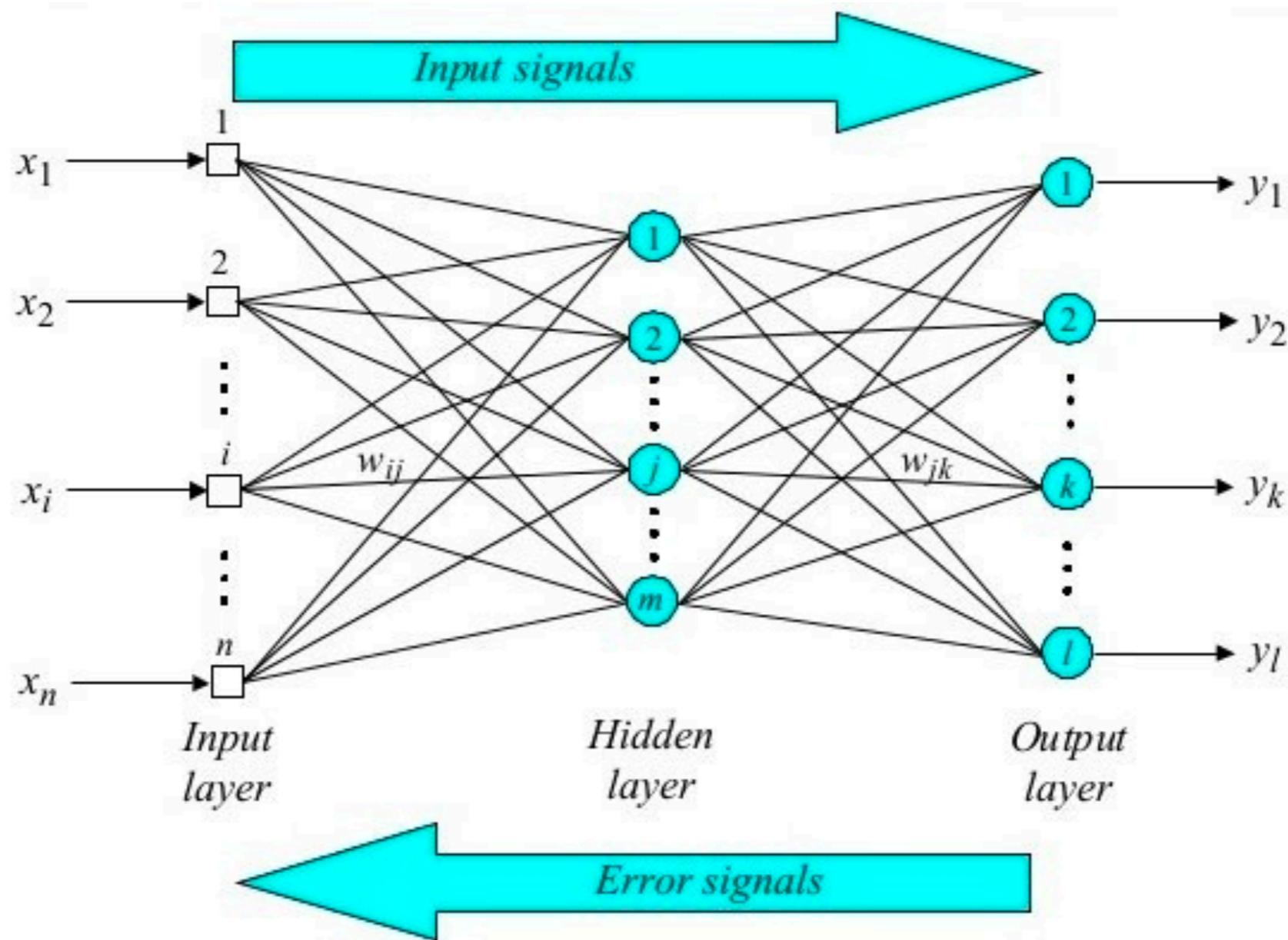
Steepest gradient descent



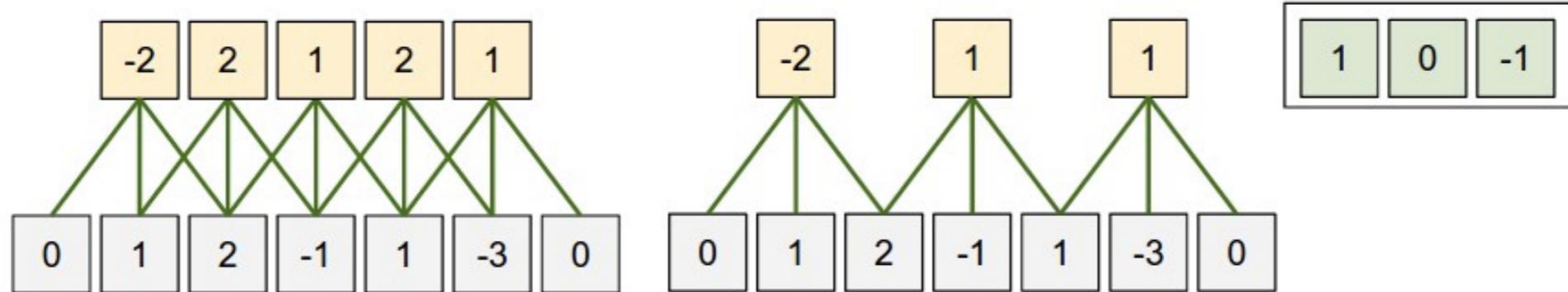
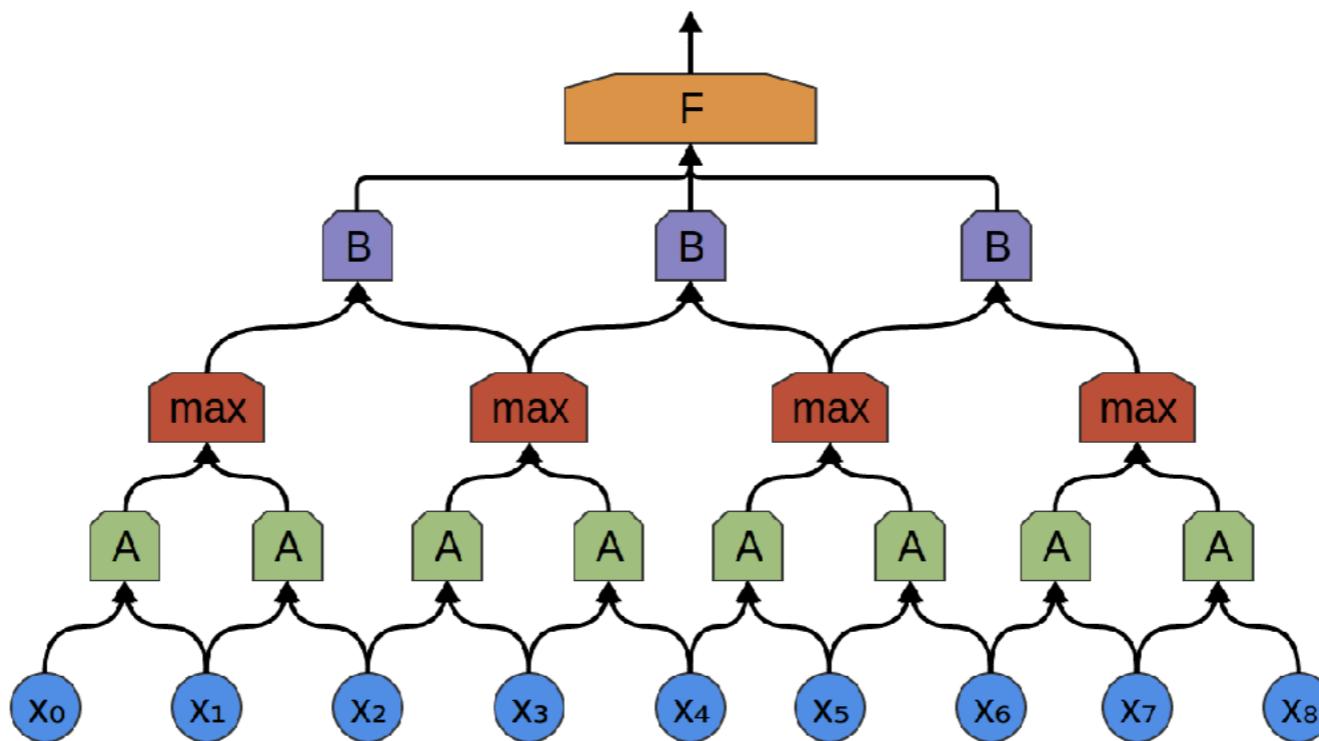
Multilayer Neural Networks



Back propagation



Convolution



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

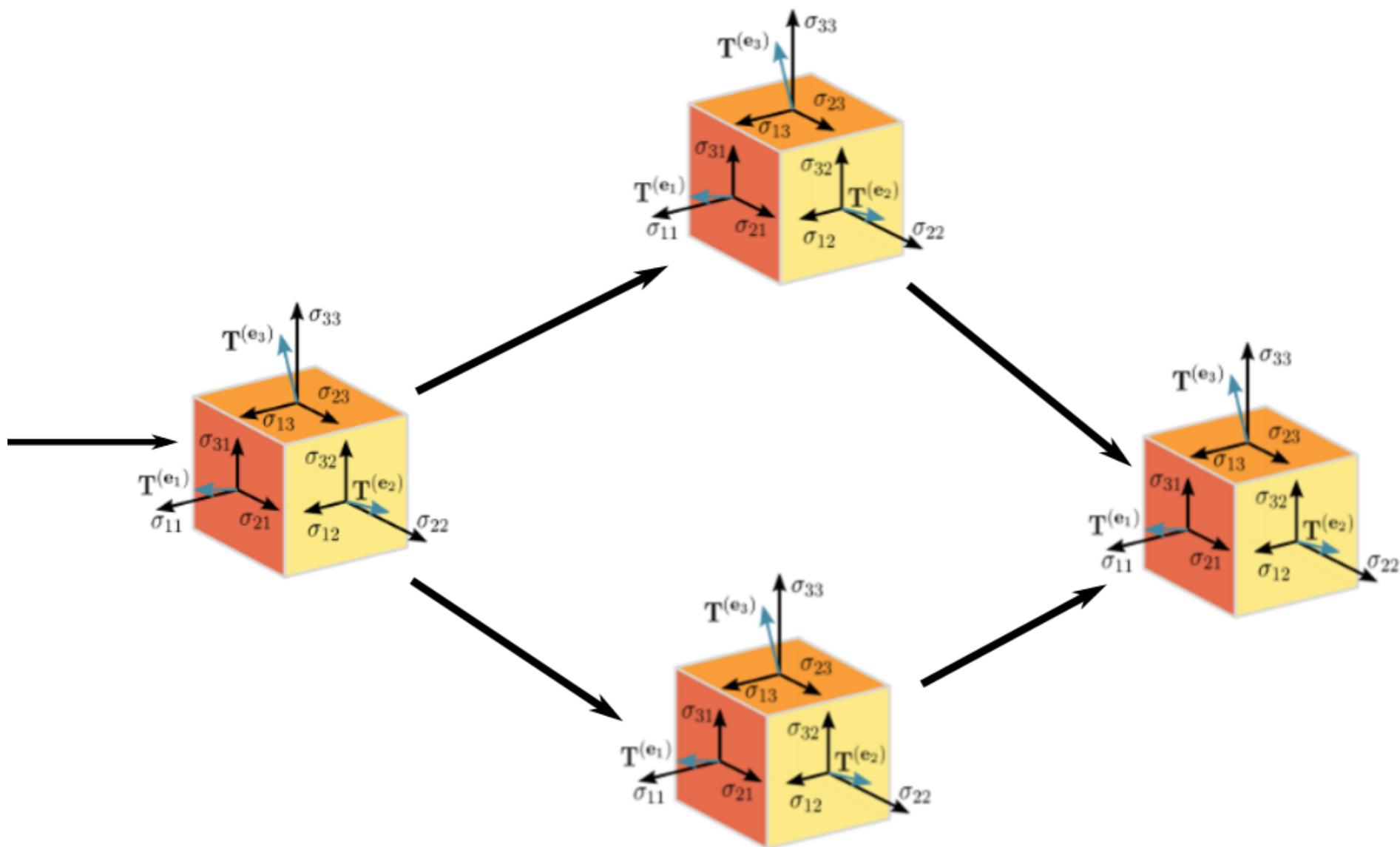
Important terms

- deep learning
- stochastic gradient descent
- batch and minibatch learning
- epoch
- dropout

What is not TensorFlow



What is TensorFlow?



Keras tutorial

01-Keras-introduction.ipynb

Implementation of some classification and regression task using NN

02-Classification-nn-assignment.ipynb

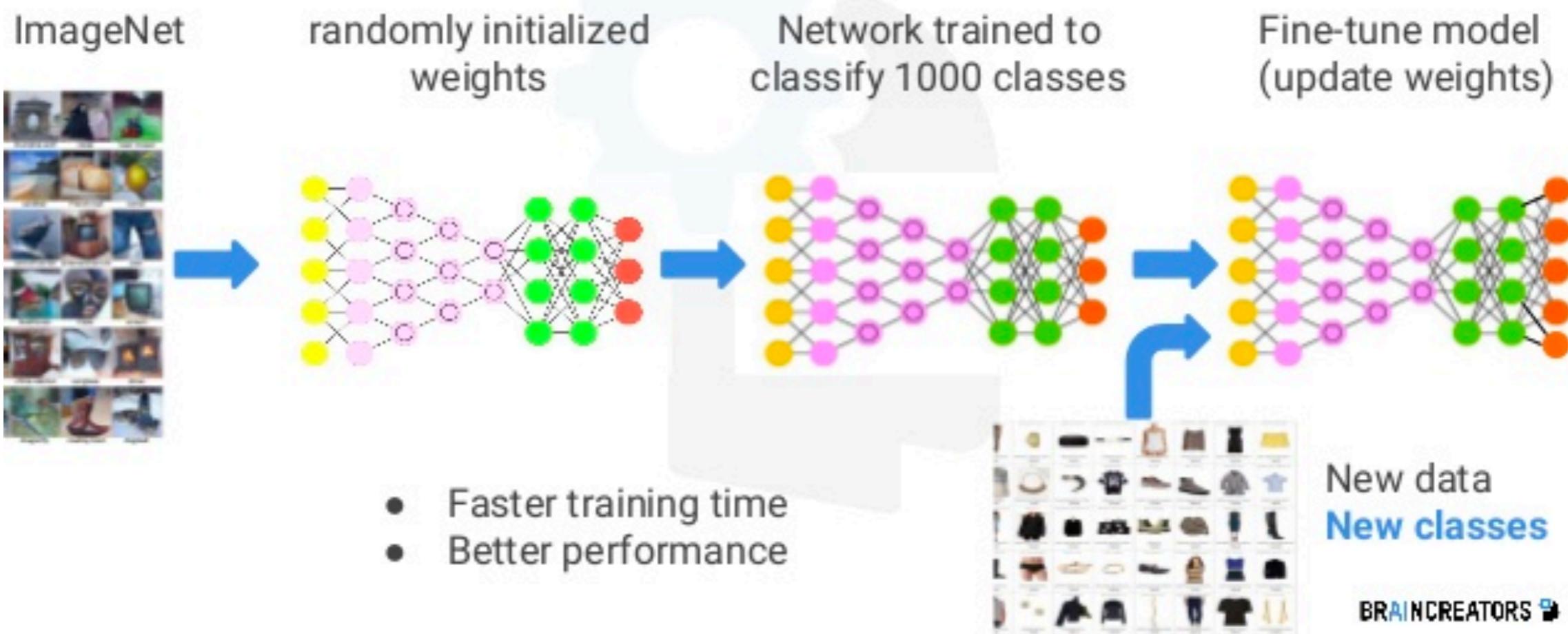
03-Regression-nn-assignment.ipynb

ResNet



Finetuning

Transfer Learning



Transfer learning example

04-Transfer_learning.ipynb

Adversarial Patch

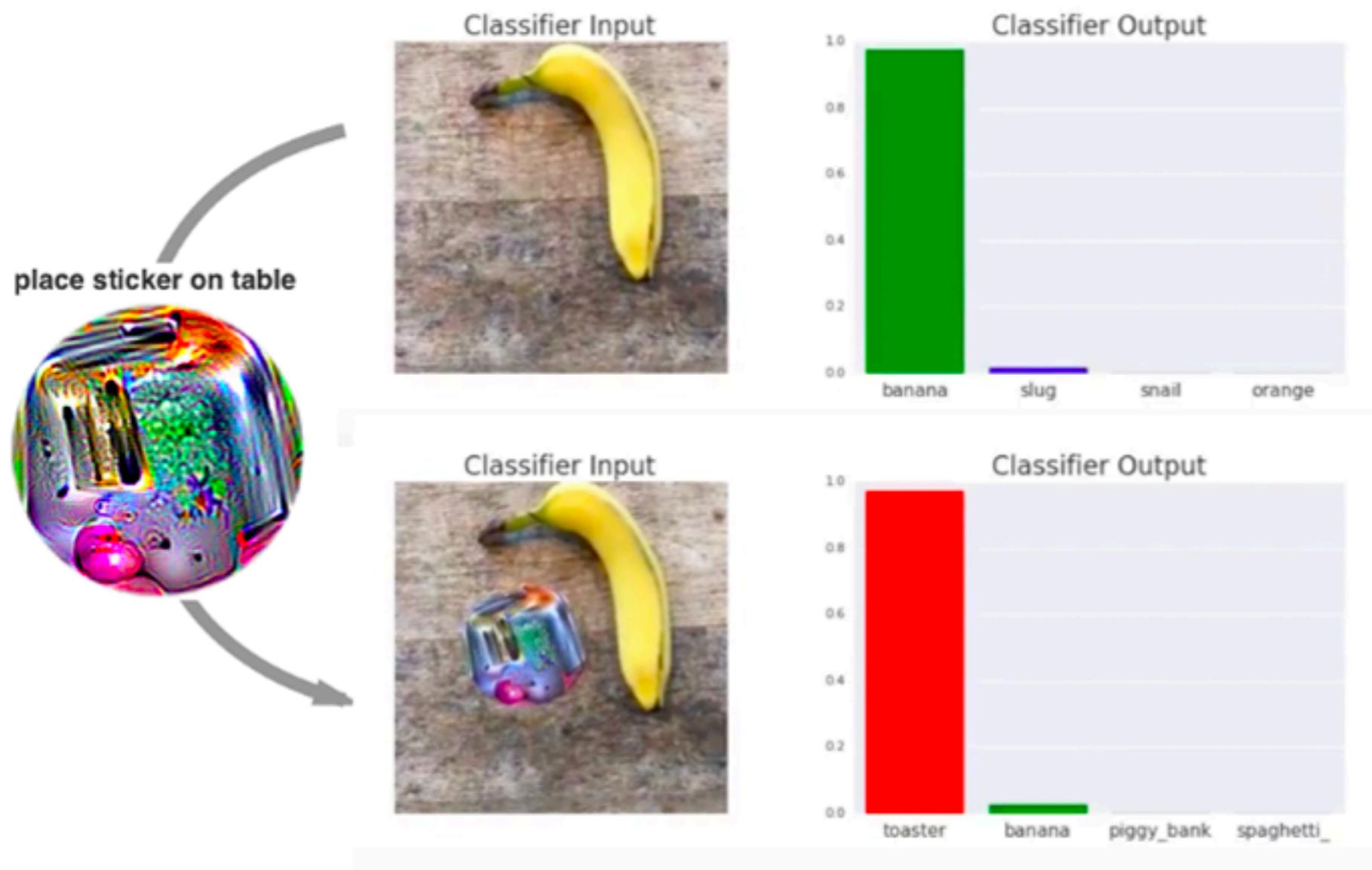
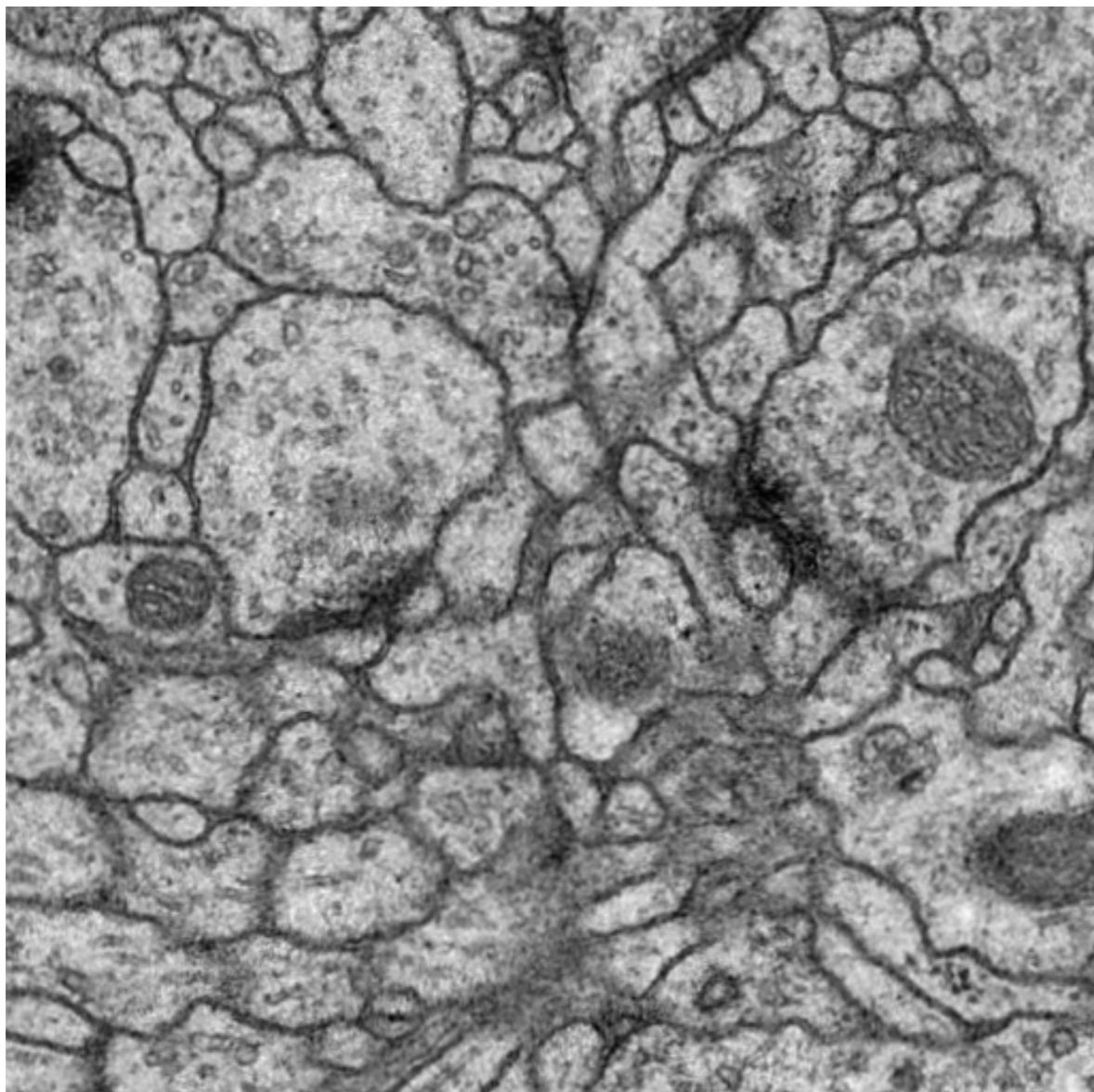
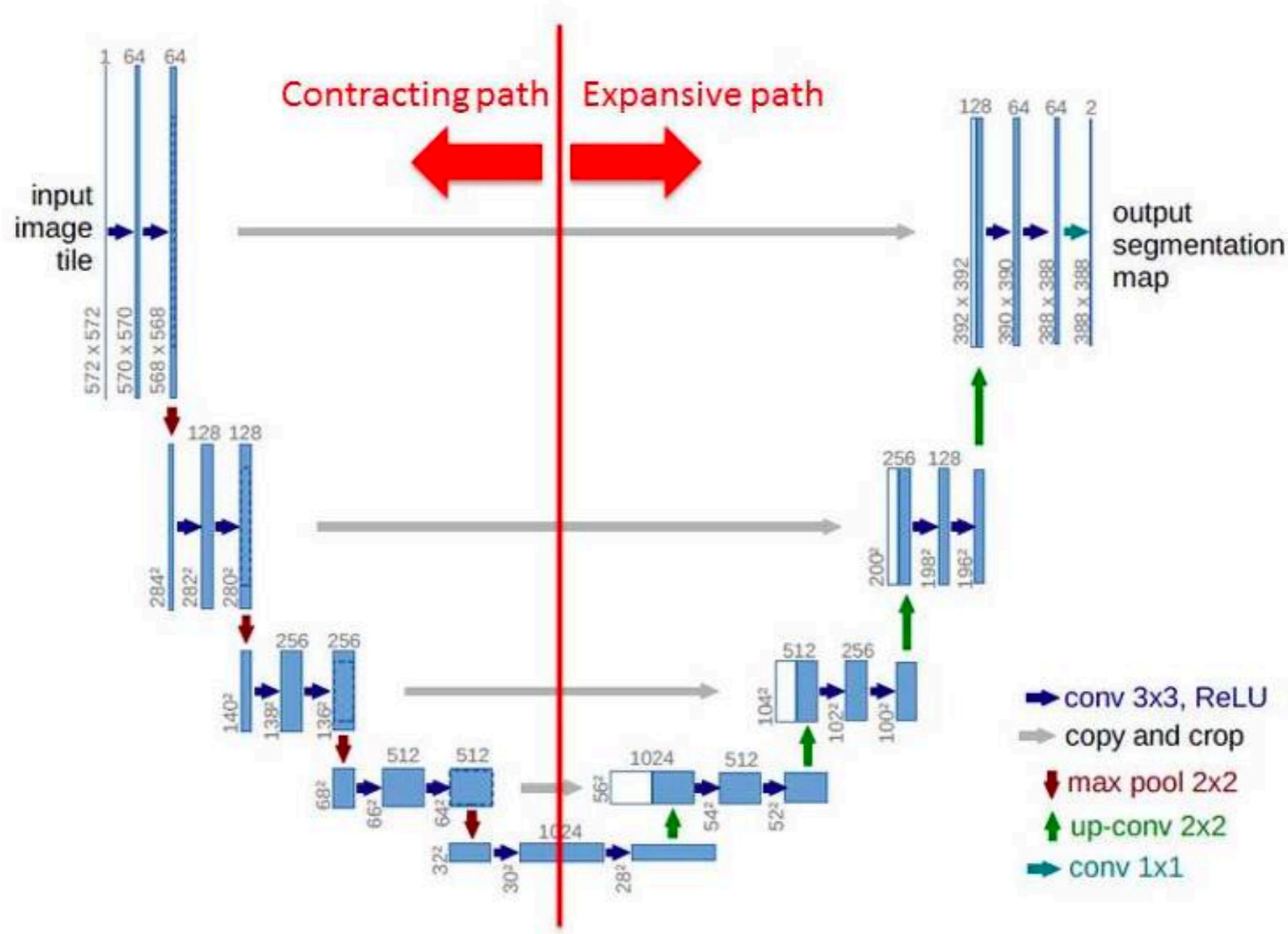


Image segmentation

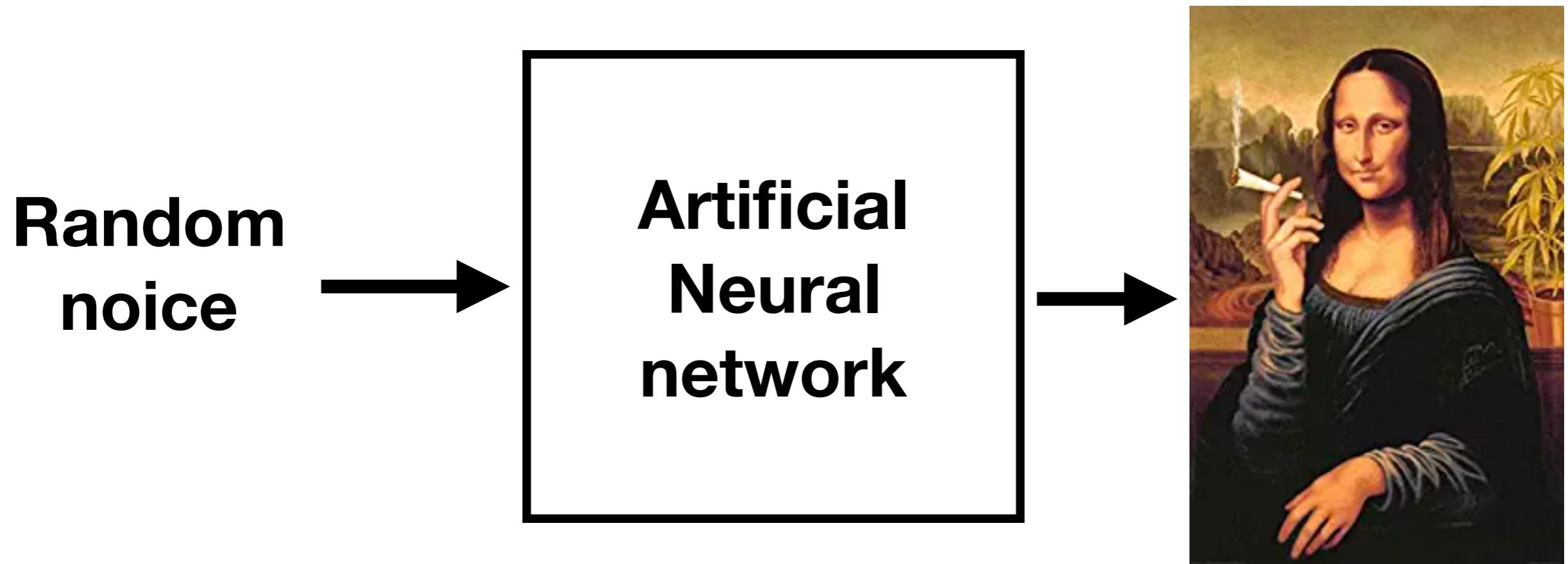


U-Net

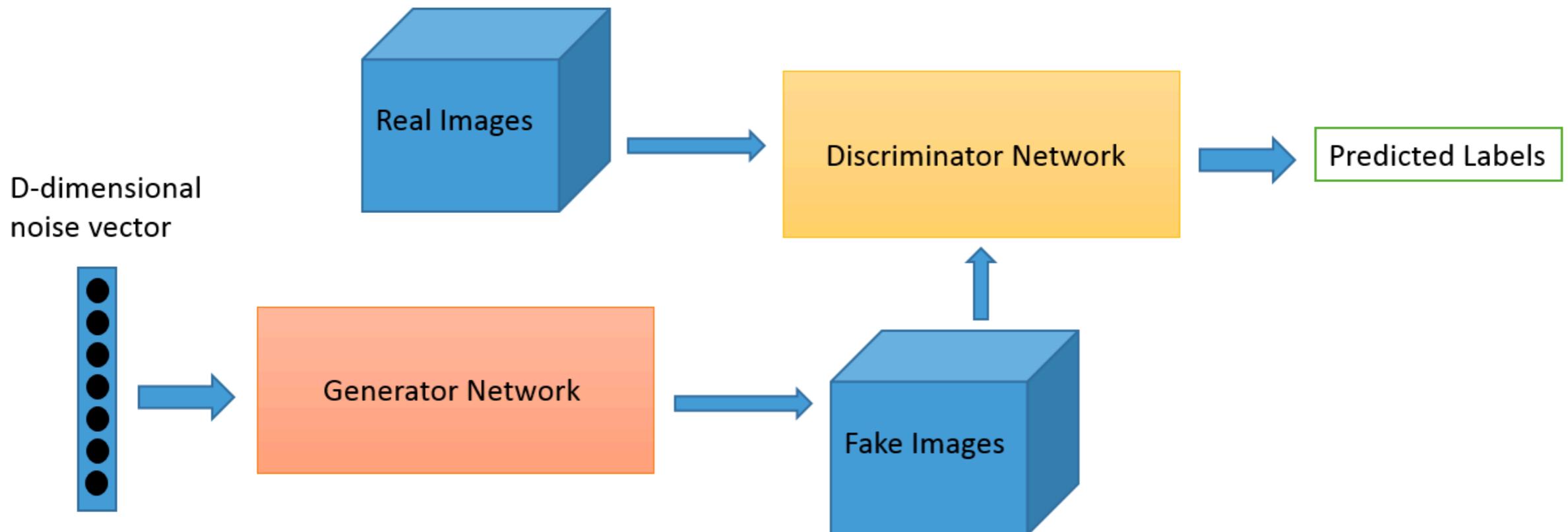
Network Architecture



Generative models with neural networks



Generative Adversarial Networks



Superresolution

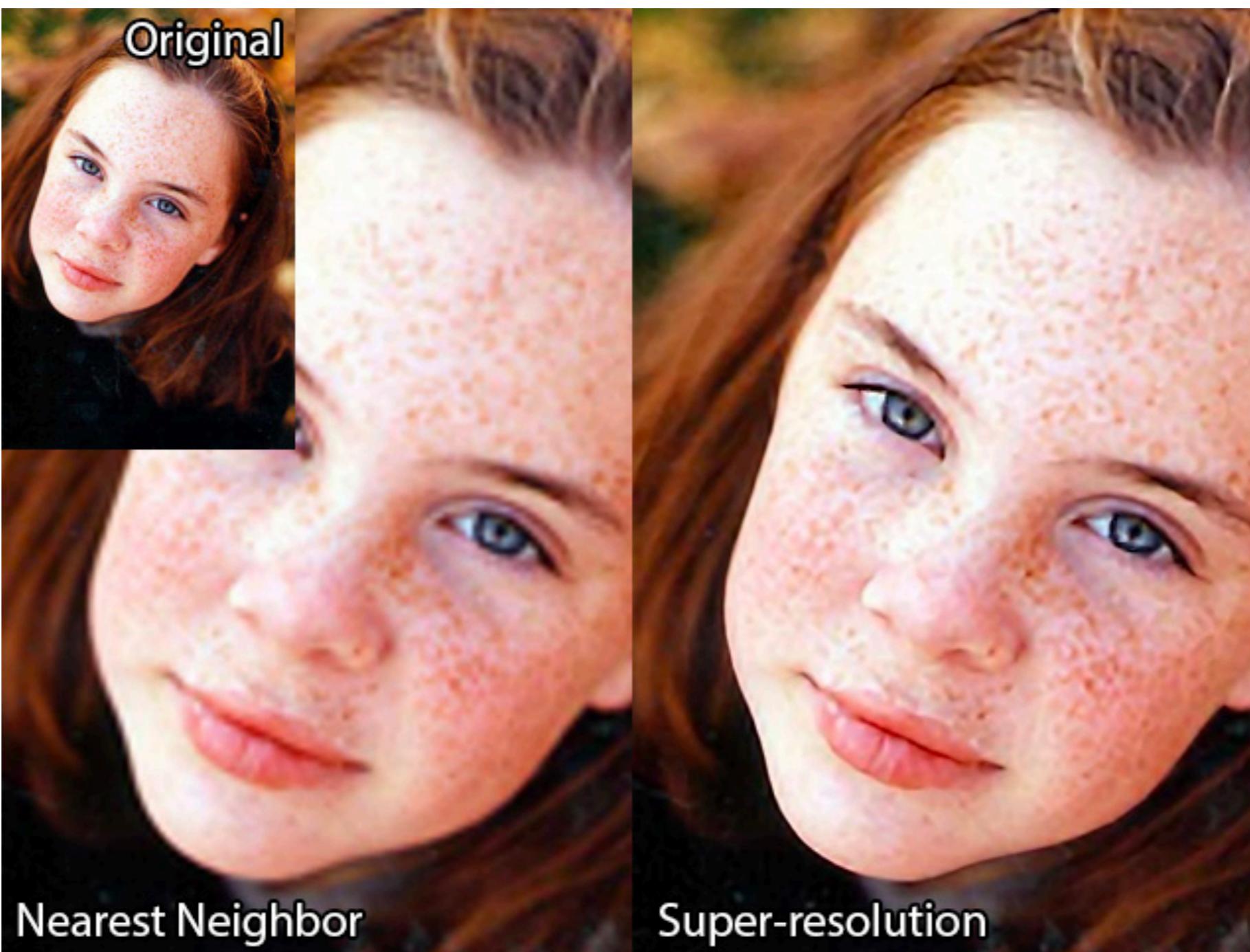
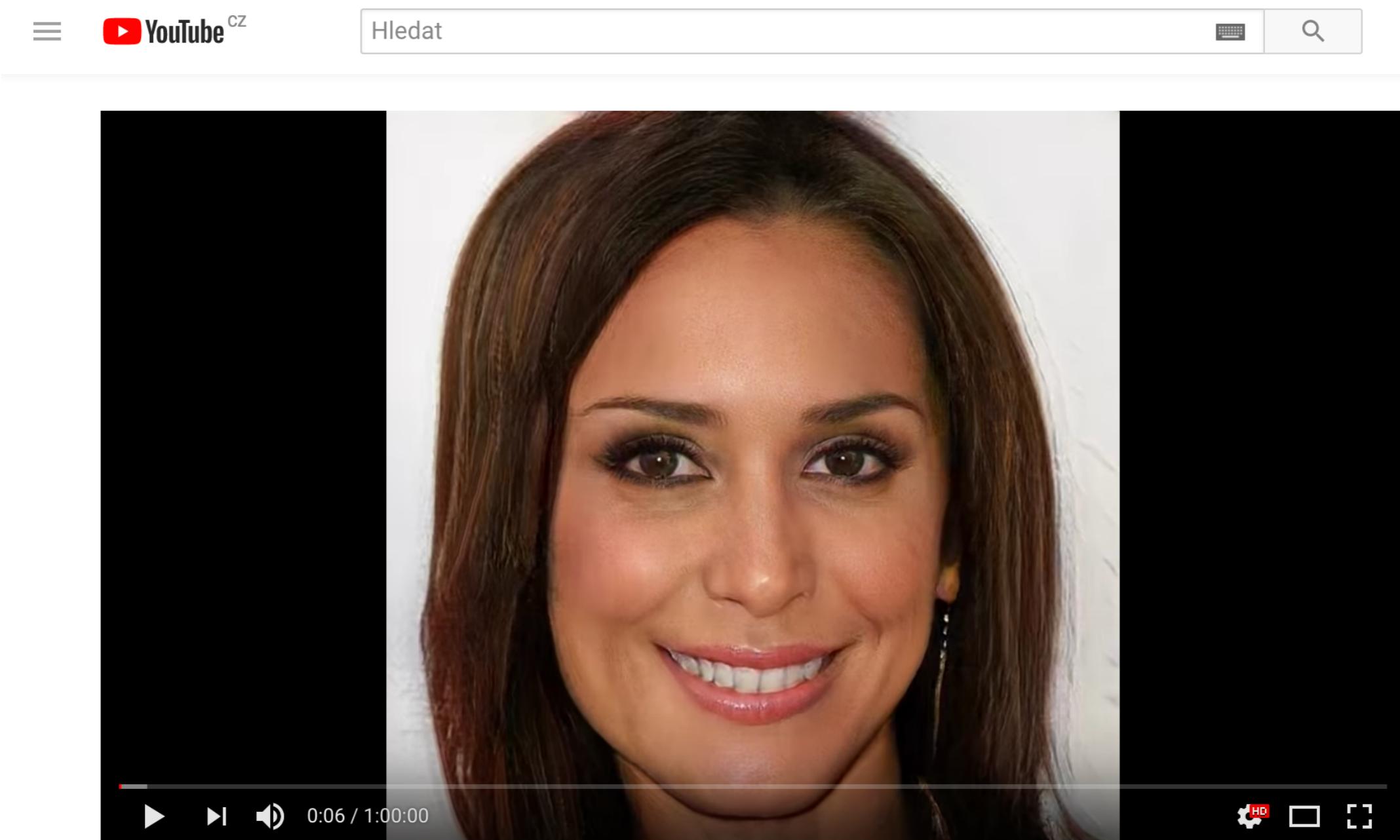


Image synthesis



One hour of imaginary celebrities

95 832 zhlédnutí



TO SE MI LÍBÍ



NELÍBÍ SE

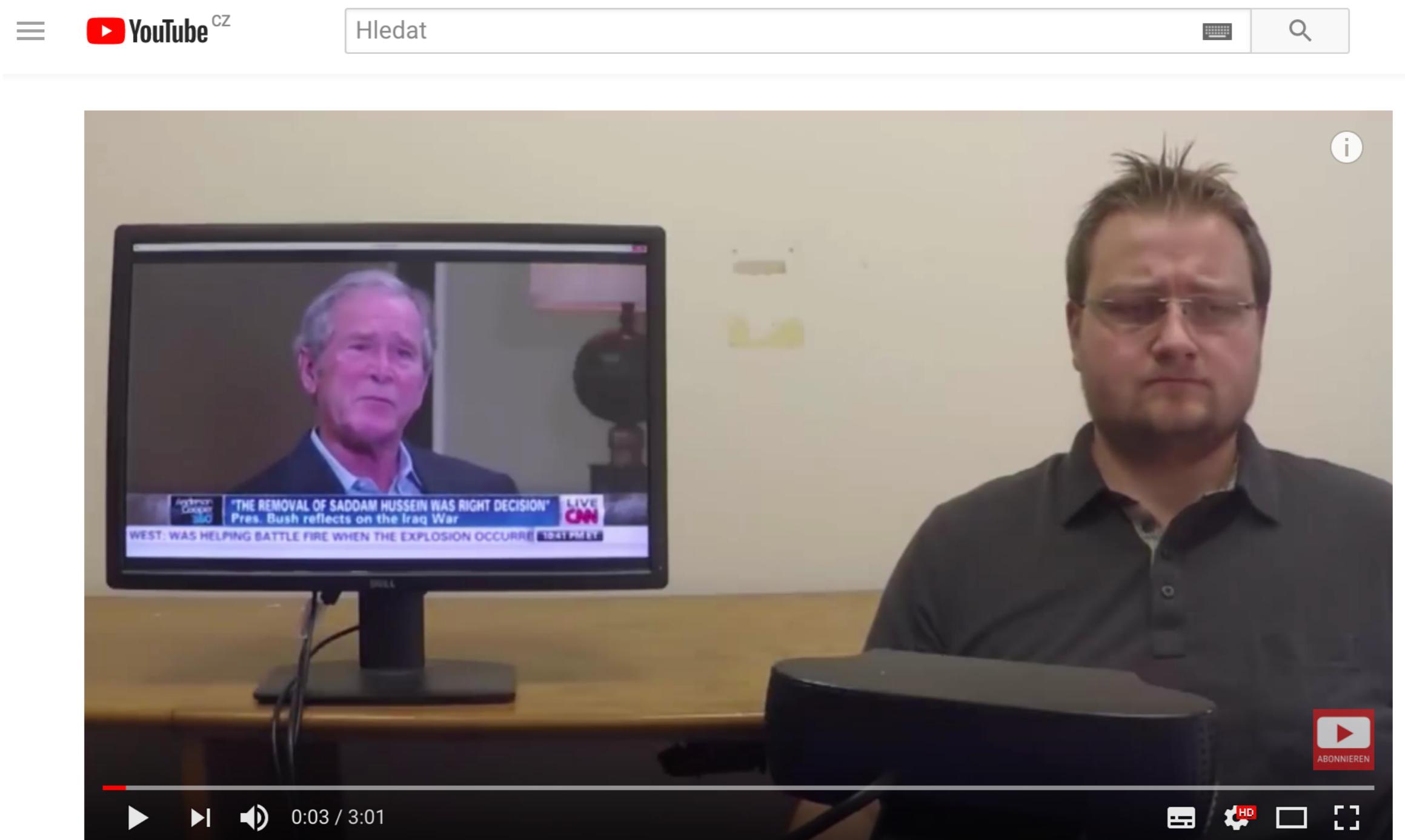


SDÍLET



...

Image manipulation



How German scientists control Putin's face

3 540 zhlédnutí

117

1

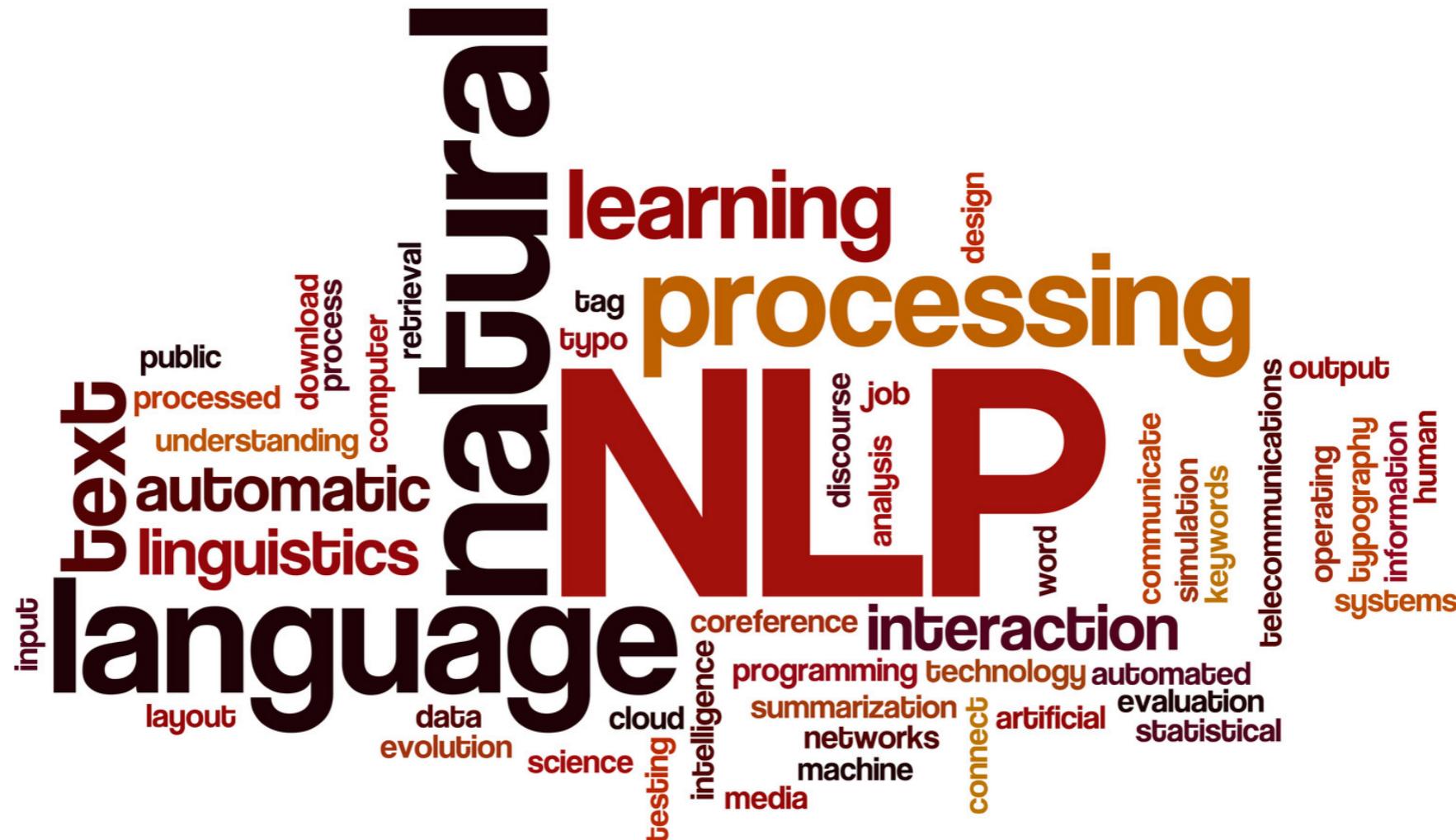
SDÍLET

...

Generative Adversarial Networks

06_GANs.ipynb

Natural Language Processing



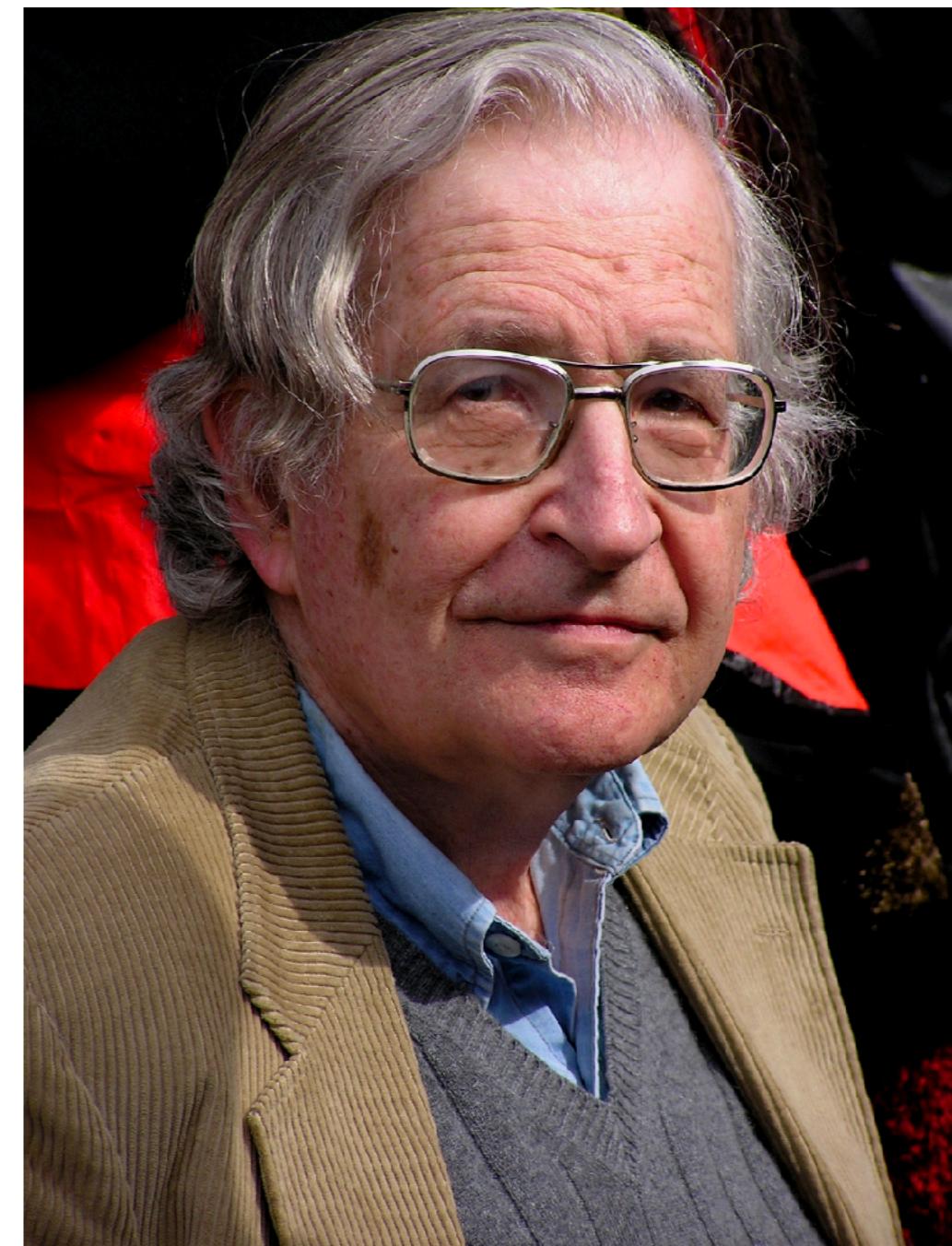
Outline

- Introduction to natural language processing
- Computational linguistics
- Text document vectorization
- Practical document classification task
- Language modeling
- Practical tasks on language modeling
- Word embeddings
- Text generating
- Practical tasks on language modeling

Norvig vs. Chomsky



source: <https://www.commarts.com>



source: <https://citaty.net>

Text corpus



natural language British National Corpus

Home

Search

Word list

Word sketch

Thesaurus

Sketch diff

Trends

Corpus info

My jobs

User guide ↗

Save

Make subcorpus

View options

KWIC

Sentence

Sort

Left

Right

Node

References

Shuffle

Sample

Query **natural, language** 255 (2.27 per million)

Page of 13 |

J2K nature of deixis (see Chapter 2 below) in **natural languages**, for sentences like (II) are true or false only
J2K of the simple but immensely important fact that **natural languages** are primarily designed, so to speak, for use in
J2K . </p><p> The many facets of deixis are so pervasive in **natural languages**, and so deeply grammaticalized, that it is hard
J2K the utterance, within the utterance itself. **Natural language** utterances are thus "anchored" directly to
J2K semantics deals with certain **natural language** expressions. Suppose we identify the semantic
J2K or self-referring expressions in **natural languages**, as in (12) and, arguably, in (13) (see Chapter 5
J2K , is perhaps a philosophical red-herring. **Natural languages**, after all, just do have indexicals, and it is
J2K . Semantics is then not concerned directly with **natural language** at all, but only with the abstract entities
J2K to leave us with no term for all those aspects of **natural language** significance that are not in any way amenable to
J2K of the deictic expressions that occur in **natural languages**, and we should now turn to consider linguistic
J2K in familiar languages. </p><p> Deictic systems in **natural languages** are not arbitrarily organized around the
J2K . But this has the consequence, as we noted, that **natural languages** will only have a syntax and a pragmatics, and no
J2K more or less directly on fragments of **natural language** (as initiated by Montague, 1974) would make
J2K The semanticist who takes the other tack, that **natural language** senses are protean, sloppy and variable, is
J2K offers a way out, for it allows one to claim that **natural language** expressions do tend to have simple, stable and
J2K radical differences between logic and **natural language** seem to fade away. We shall explore this below
J2K on what can be a possible lexical item in **natural languages**. </p><p> Finally, the principles that generate
J0V is meant any single document, or any stretch of **natural language** regarded as a self-contained unit for
J53 recognition and those that can understand **natural languages**, such as English, are known by the collective
HRK through a dialogue, which approaches a **natural language** dialogue, or via a menu. In figure 6.2, the users

Page of 13 |

Token & tokenization

This is a non-trivial English sentence: Ludolph's number is approx. 3.14.

Python library: <http://www.nltk.org/>

Stemming & lemmatization

Original	Stemming	Lemmatization
compensation	compens	compensation
compensations	compens	compensation
mouse	mous	mouse
mice	mice	mouse

Stemming & lemmatization

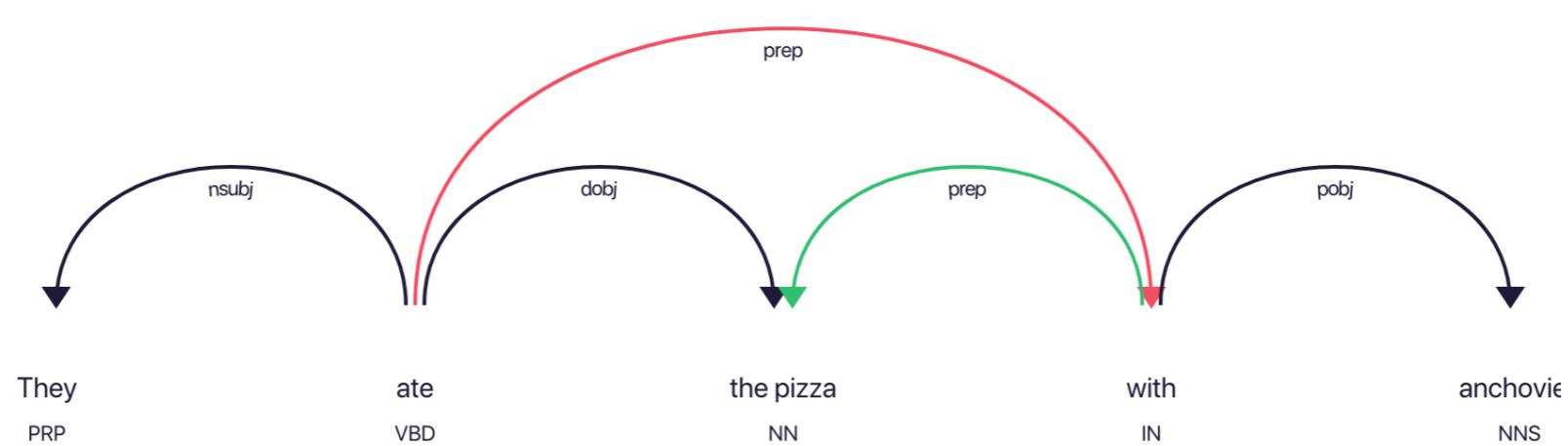
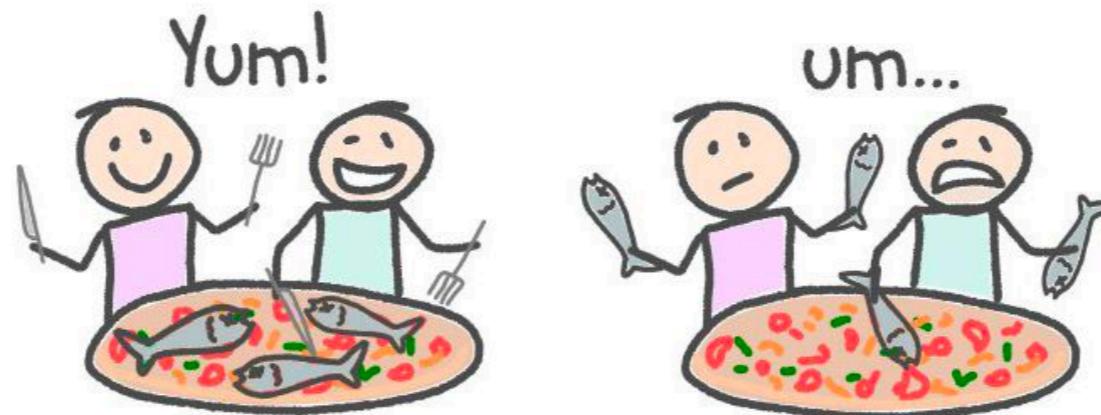
English:

<https://tartarus.org/martin/PorterStemmer/>

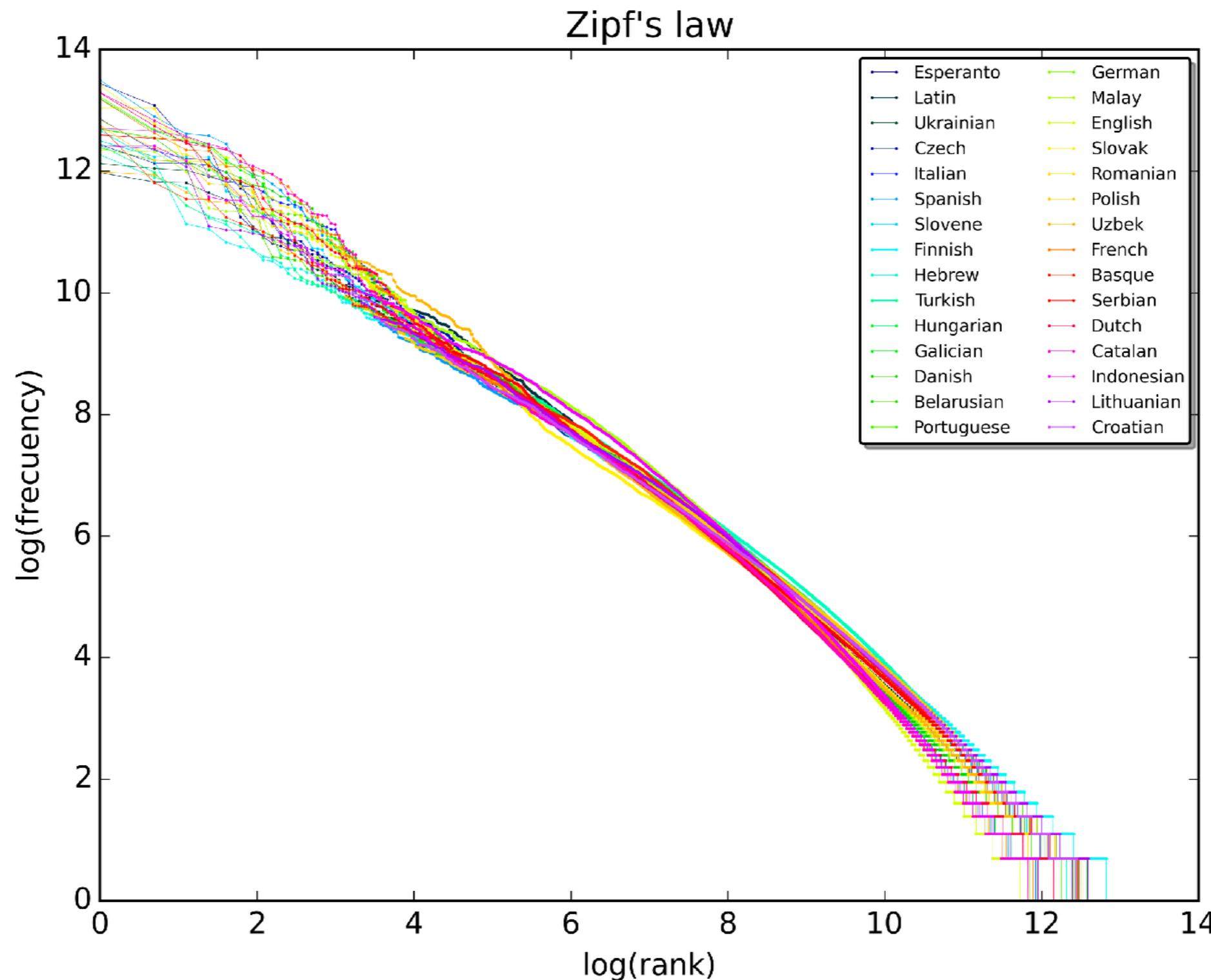
<http://www.cis.uni-muenchen.de/~schmid/tools/TreeTagger/>

Parsing

They ate the pizza with anchovies



Zipf's law & long tail



Publicly available corpora

British National Corpus: <http://www.natcorp.ox.ac.uk/>

Common Crawl: <http://commoncrawl.org/the-data/get-started/>

Wikipedia: <https://dumps.wikimedia.org/>

Feature extraction for NLP

1. *the man walked the dog*
2. *the man took the dog to the park*
3. *the dog went to the park*

[dog, man, park, the, to, took, walked, went]

1. [1, 1, 0, 1, 0, 0, 1, 0]
2. [1, 1, 1, 1, 1, 1, 0, 0]
3. [1, 0, 1, 1, 1, 0, 0, 1]

$$\text{idf}(t, D) = \log \frac{N}{|\{d \in D : t \in d\}|}$$

1. [1, 1, 0, 2, 0, 0, 1, 0]
2. [1, 1, 1, 3, 1, 1, 0, 0]
3. [1, 0, 1, 2, 1, 0, 0, 1]

1. [0, 0.18, 0, 0, 0, 0, 0.48, 0]
2. [0, 0.18, 0.18, 0, 0.18, 0.48, 0, 0]
3. [0, 0, 0.18, 0, 0.18, 0, 0, 0.48]

— . . .

NLP Introduction task

07-text-classification-introduction.ipynb

Language models

- spell checking
- speech recognition
- machine translation
- ...

n-gram models – example

$P(< s >, \text{machine}, \text{learning}, \text{college}, </s>) =$

$P(\text{machine}|< s >)P(\text{learning} | \text{machine})P(\text{college} | \text{learning}).P(< s />|\text{college})$

$P(\text{learning} | \text{machine}) = \text{count}(\text{machine}, \text{learning})/\text{count}(\text{machine})$

Language model smoothing

- Laplace smoothing (plus one)

$$P(w_i|w_{i-1}) = \frac{\text{count}(w_{i-1}, w_i) + 1}{\text{count}(w_{i-1}) + V}$$

- interpolation
- Good-Turing
- Witten-Bell
- ...

Perplexity

$$PP(W) = P(w_1, w_2, \dots, w_N)^{-\frac{1}{N}}$$

$$= \sqrt[N]{\frac{1}{P(w_1, w_2, \dots, w_N)}}$$

$$= \sqrt[N]{\prod_{i=1}^N \frac{1}{P(w_i | w_1, \dots, w_{i-1})}}$$

$$= 2^{-\frac{1}{N} \sum_{i=1}^N \log_2 P(w_i | w_1, \dots, w_{i-1})}$$

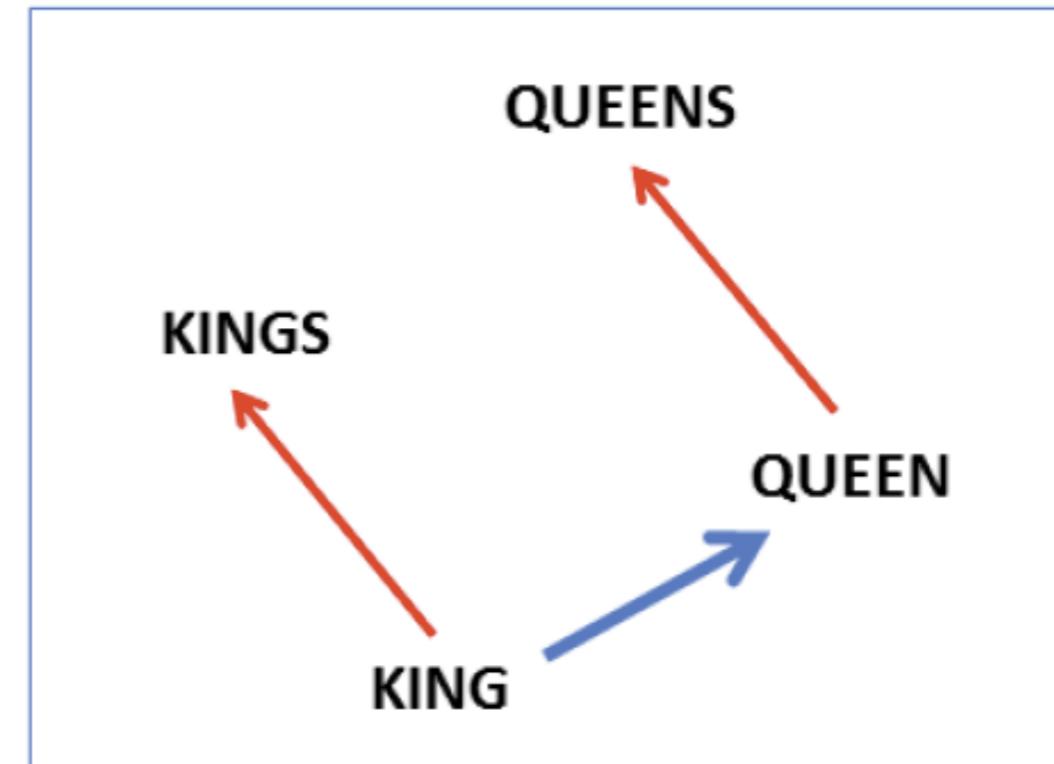
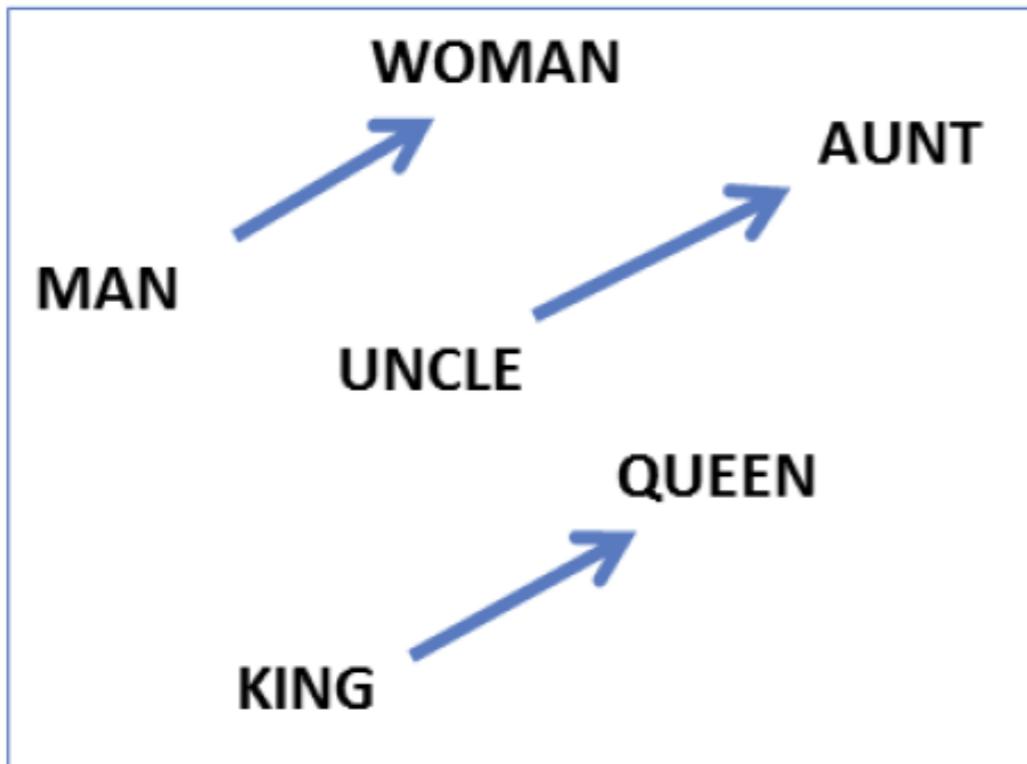
Language detection using language models

[08-Language-detection-assignment.ipynb](#)

Travel agency review classification

[**09-Review-classification-assignment.ipynb**](#)

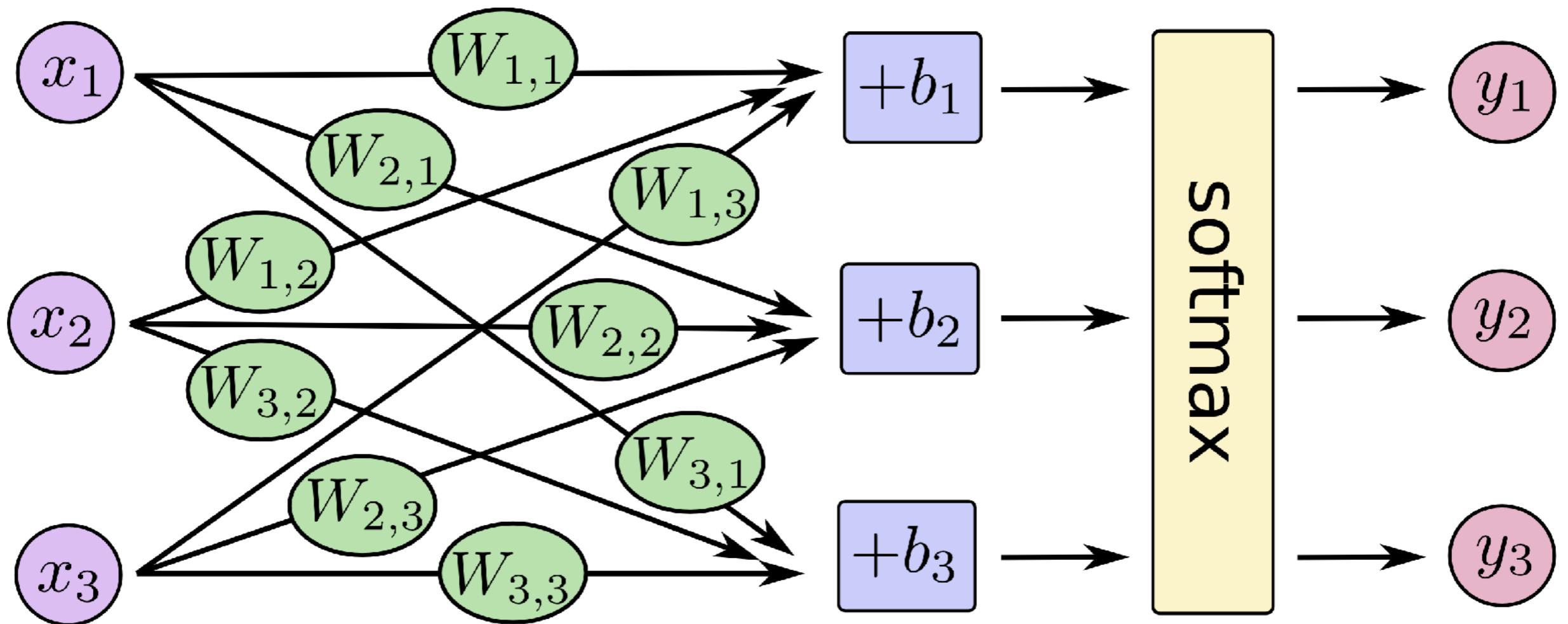
word2vec



king is to **kings** as **queen** to ?.

$$v(\text{kings}) - v(\text{king}) = v(\text{queens}) - v(\text{queen})$$

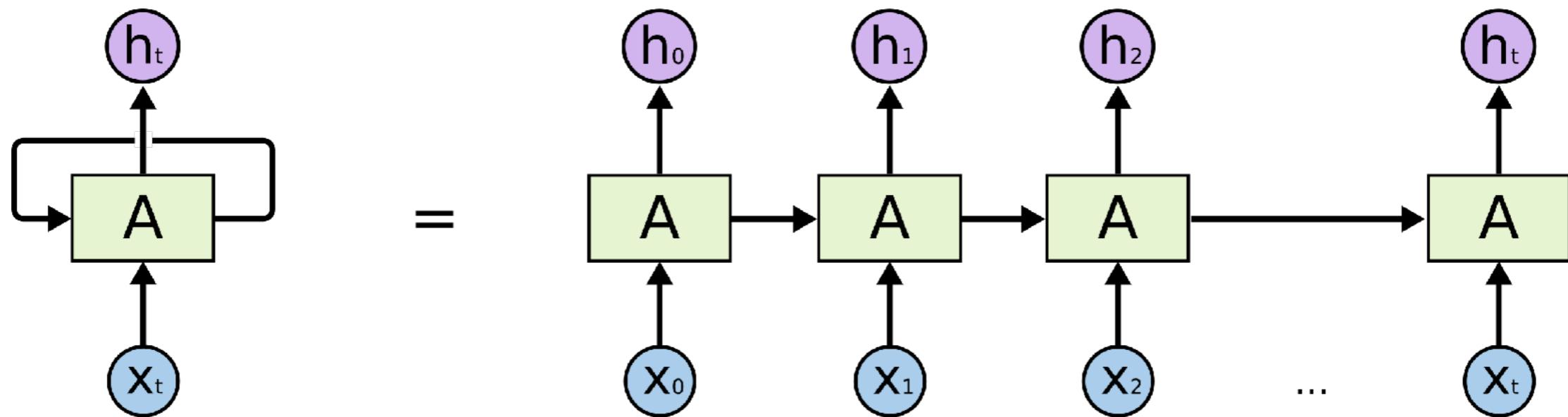
Feed-Forward Neural Network



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

Recurrent Neural networks

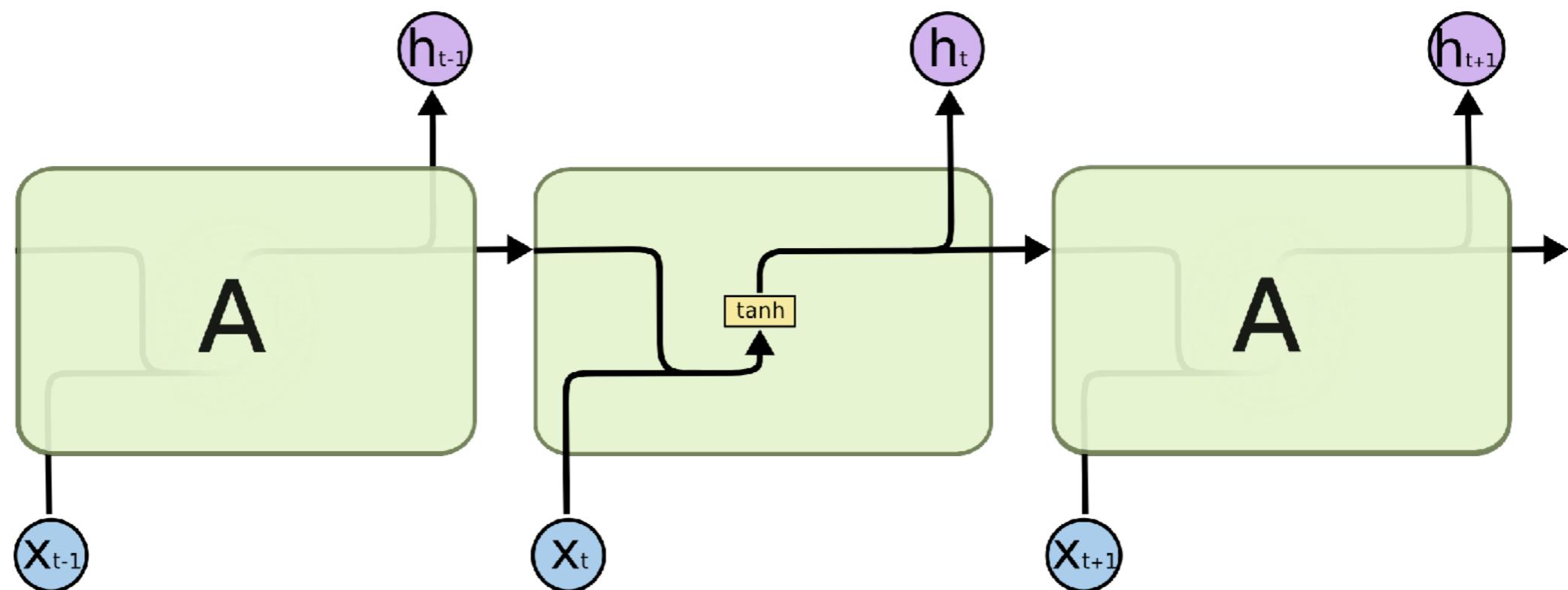
1/2



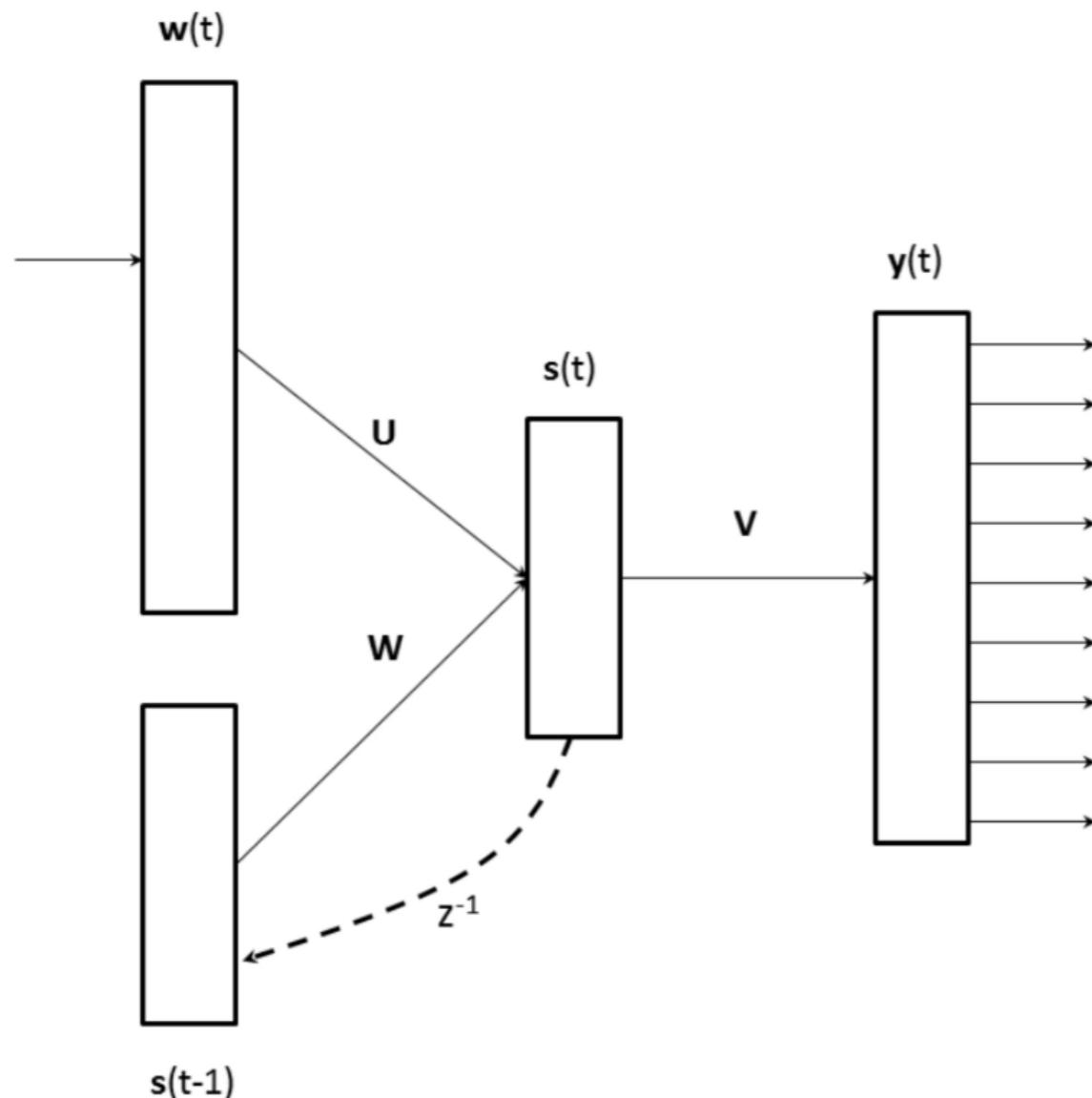
source: <http://colah.github.io/posts/2015-08-Understanding-LSTMs/>

Recurrent Neural Networks

2/2



Recurrent Neural Network Language Modeling Toolkit



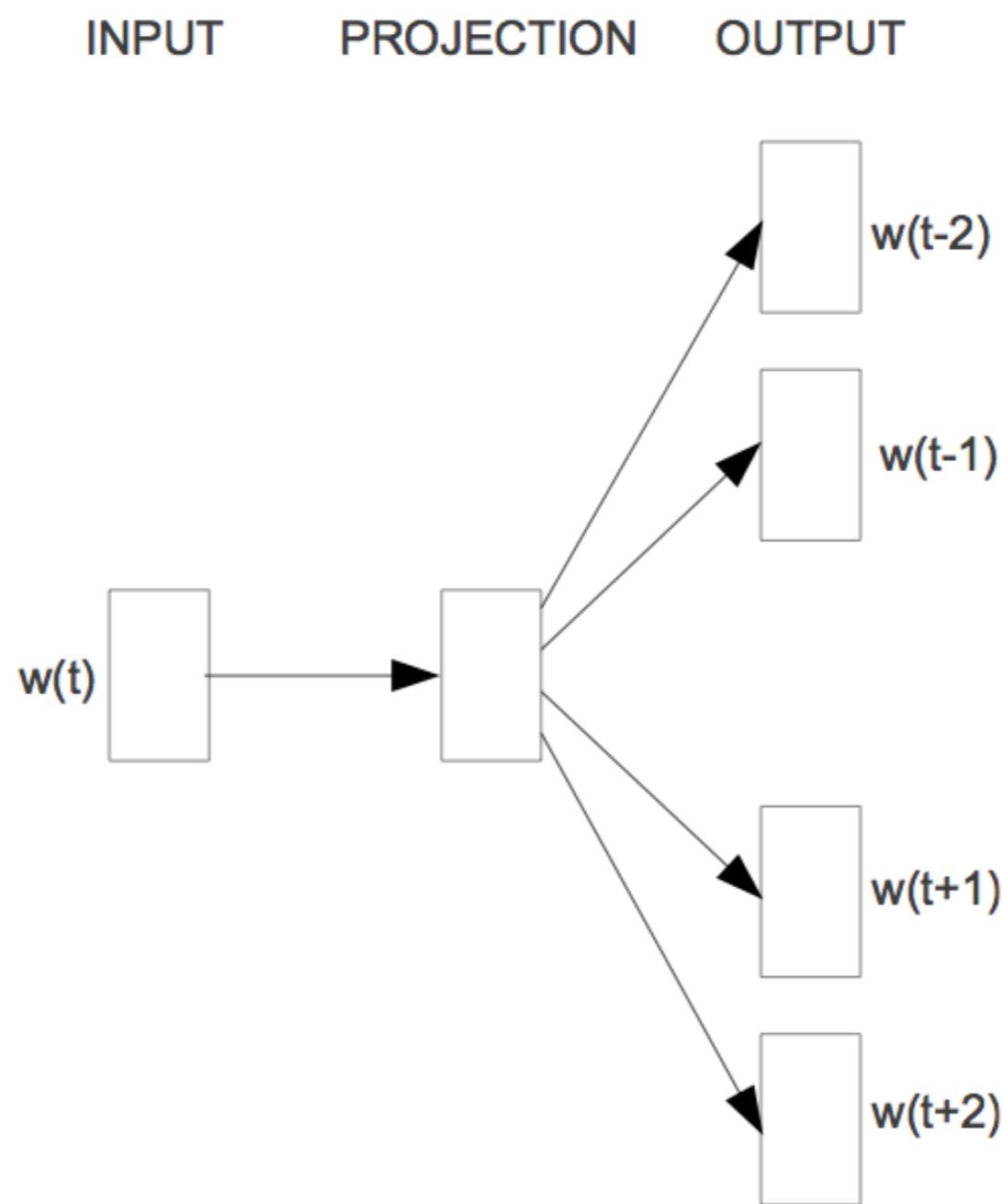
$$s(t) = f(\mathbf{U}w(t) + \mathbf{W}s(t-1))$$

$$y(t) = g(\mathbf{V}s(t)),$$

$$f(z) = \frac{1}{1 + e^{-z}}, \quad g(z_m) = \frac{e^{z_m}}{\sum_k e^{z_k}}.$$

source: <http://www.fit.vutbr.cz/~imikolov/rnnlm/>

The skip-gram model



Experiments with word2vec

10-Word2vec-in-gensim.ipynb

11-Review-classification-w2v-assignment.ipynb

Language models for text generating

Nacházíte se: Úvod > Oddělení > Krásná literatura > Poezie > Česká a slovenská poezie > Elektronická kniha Poezie umělého světa



Poezie umělého světa [E-kniha]

Jiří Materna



 Hodnotilo 7 uživatelů, zatím žádné recenze, [napsat vlastní recenzi](#)

Popis: Elektronická kniha, 50 stran, bez zabezpečení DRM,  ePUB,  Mobi,  PDF, česky - více



Stáhnout



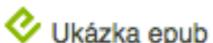
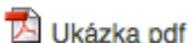
Zdarma

K dispozici pro **okamžité** stáhnutí

Ke stažení

Anotace

Všechny básně v této knize byly automaticky vygenerovány počítačem za pomocí umělých neuronových sítích. Neuronová síť sama o sobě nic neumí a je třeba ji natrénovat pro činnost, kterou má vykonávat.



LISTOPAD

usínám, pláču, umírám, přemýšlím
co cítíš ty?
cítim tvou slabost
a whisky

NOVEMBER

I am falling asleep, crying, dying, thinking
what do you feel?
I feel your weakness
and whisky

SPRAVEDLNOST

na tvou dekadentní duši
ráno i v poledne
bůh má připravenou kuši

JUSTICE

for your decadent soul
in the morning, in the evening
the god has prepared a crossbow

Metaphores

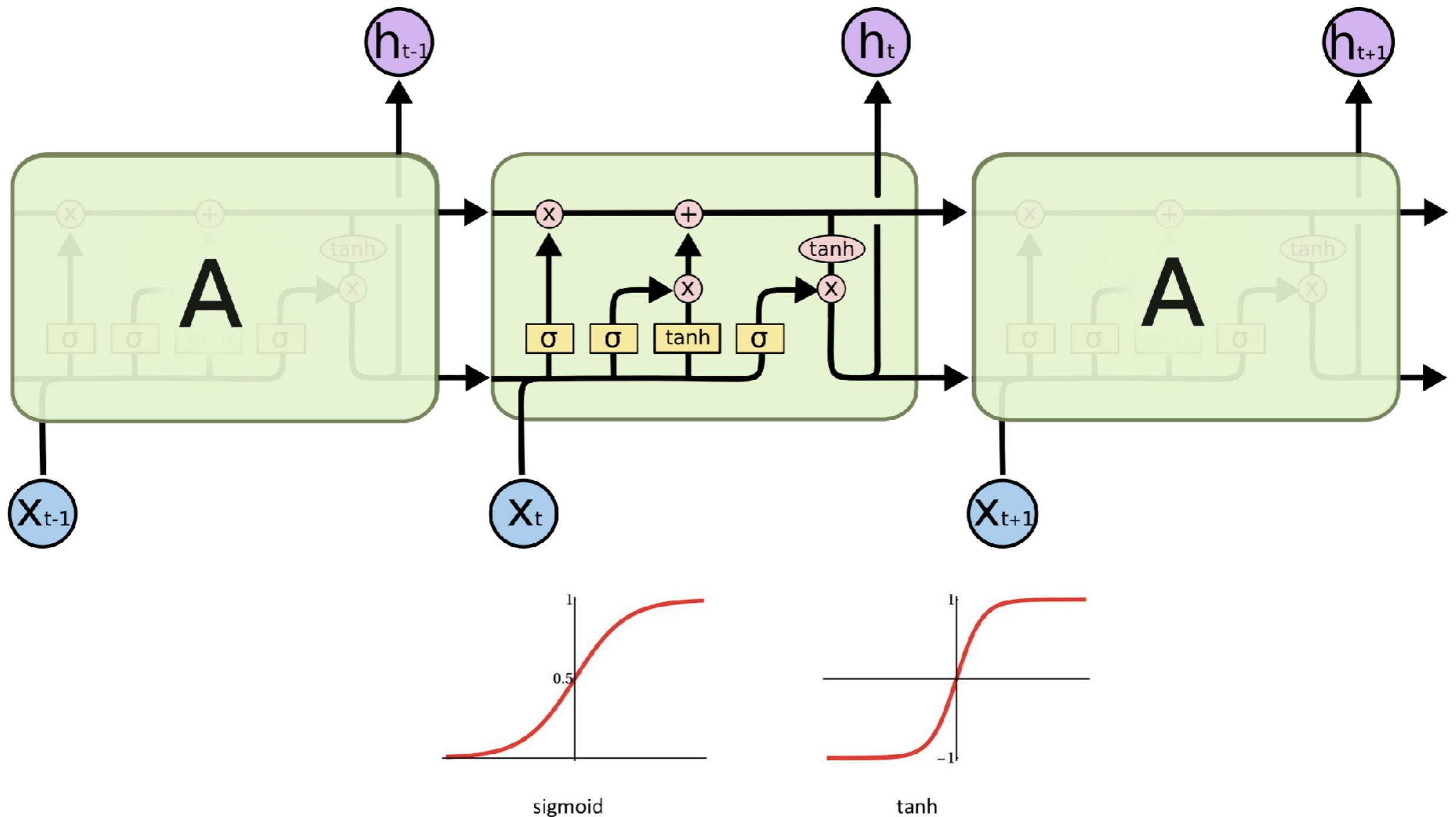
...tělo plné červánků...

...body full of blush of dawn...

...tak vzácný jako listí...

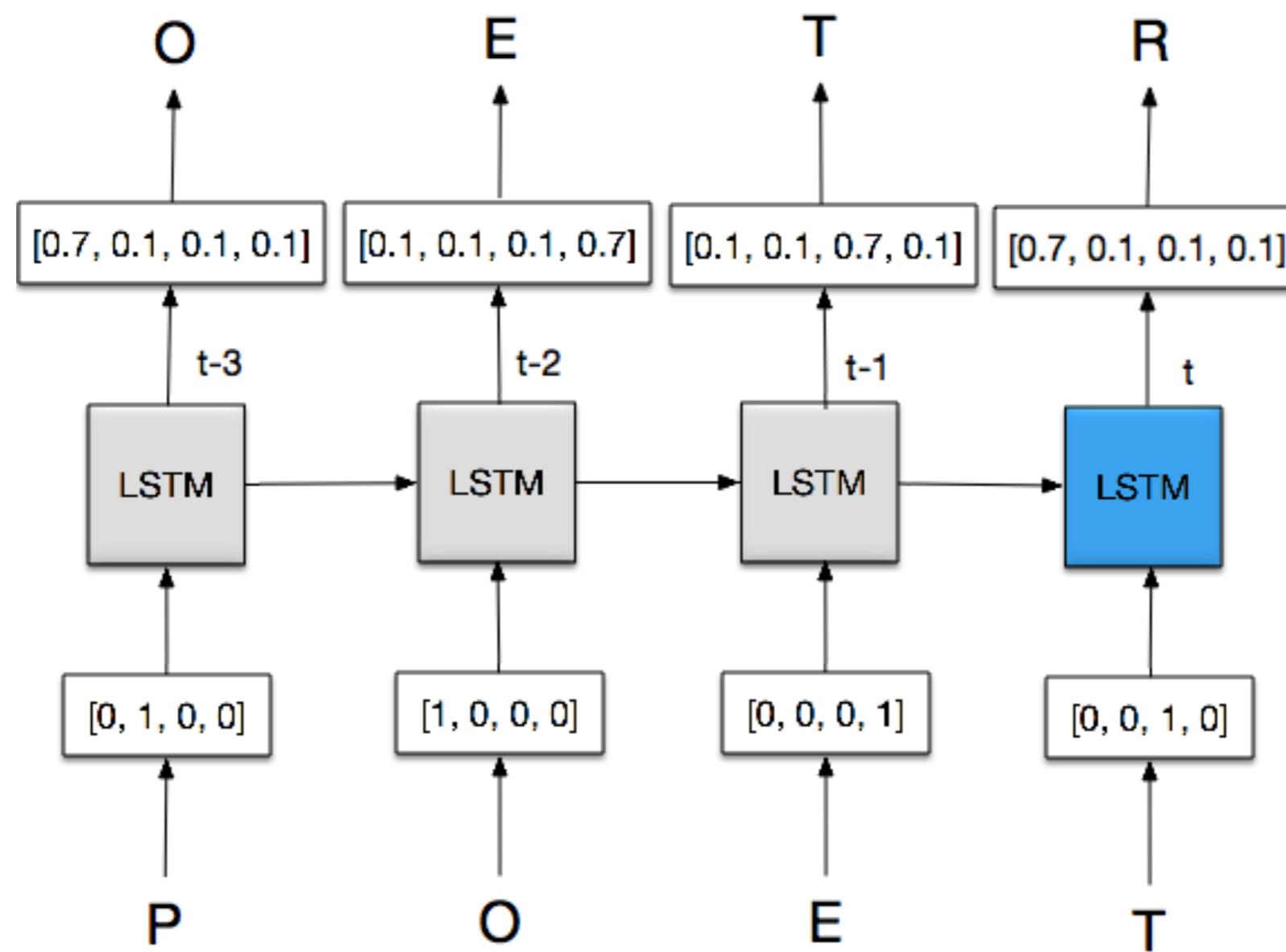
...as rare as leaves of trees...

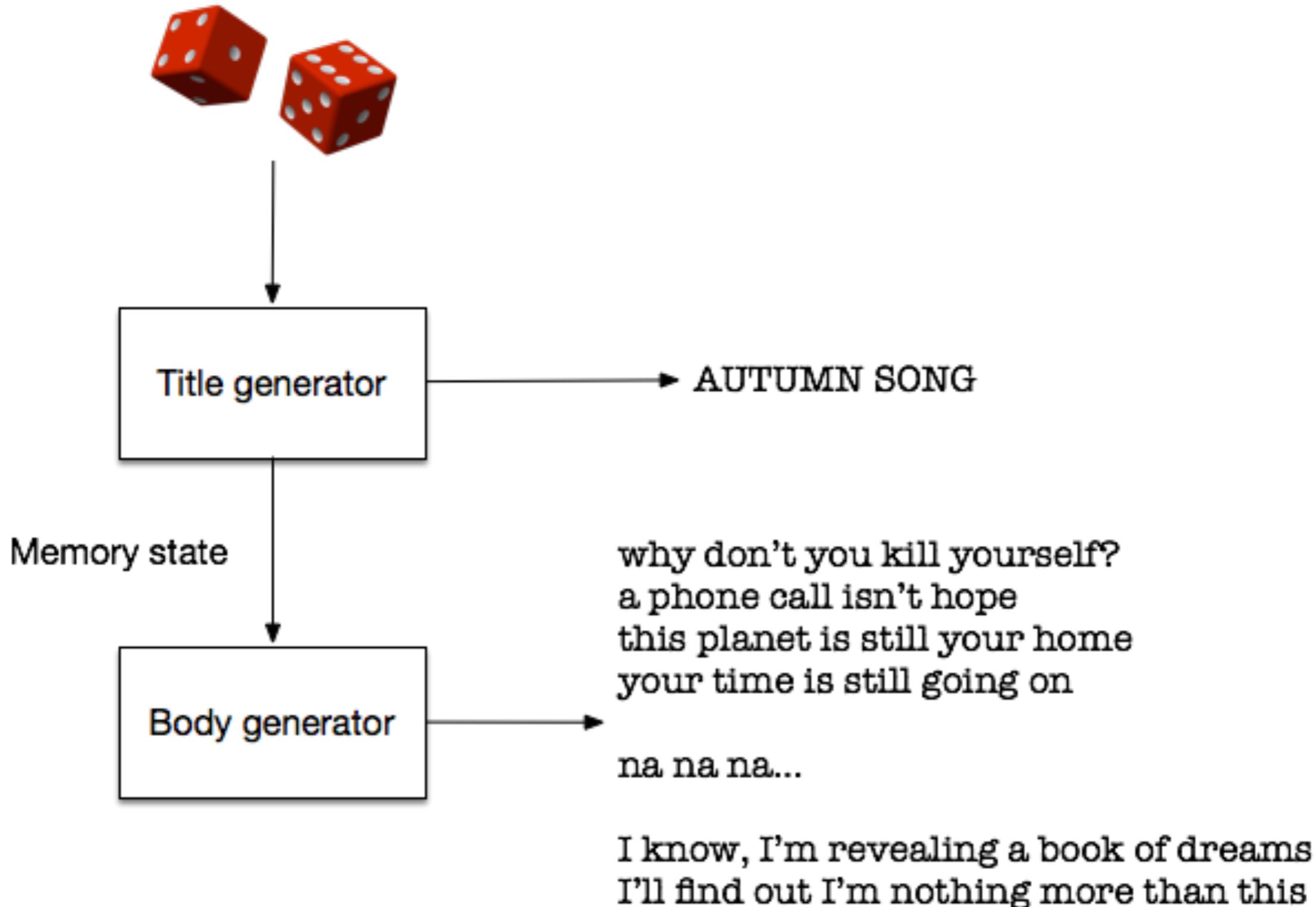
Long Short-Term Memory



Source: <http://colah.github.io/posts/2015-08-Understanding-LSTMs/>

LSTM language model

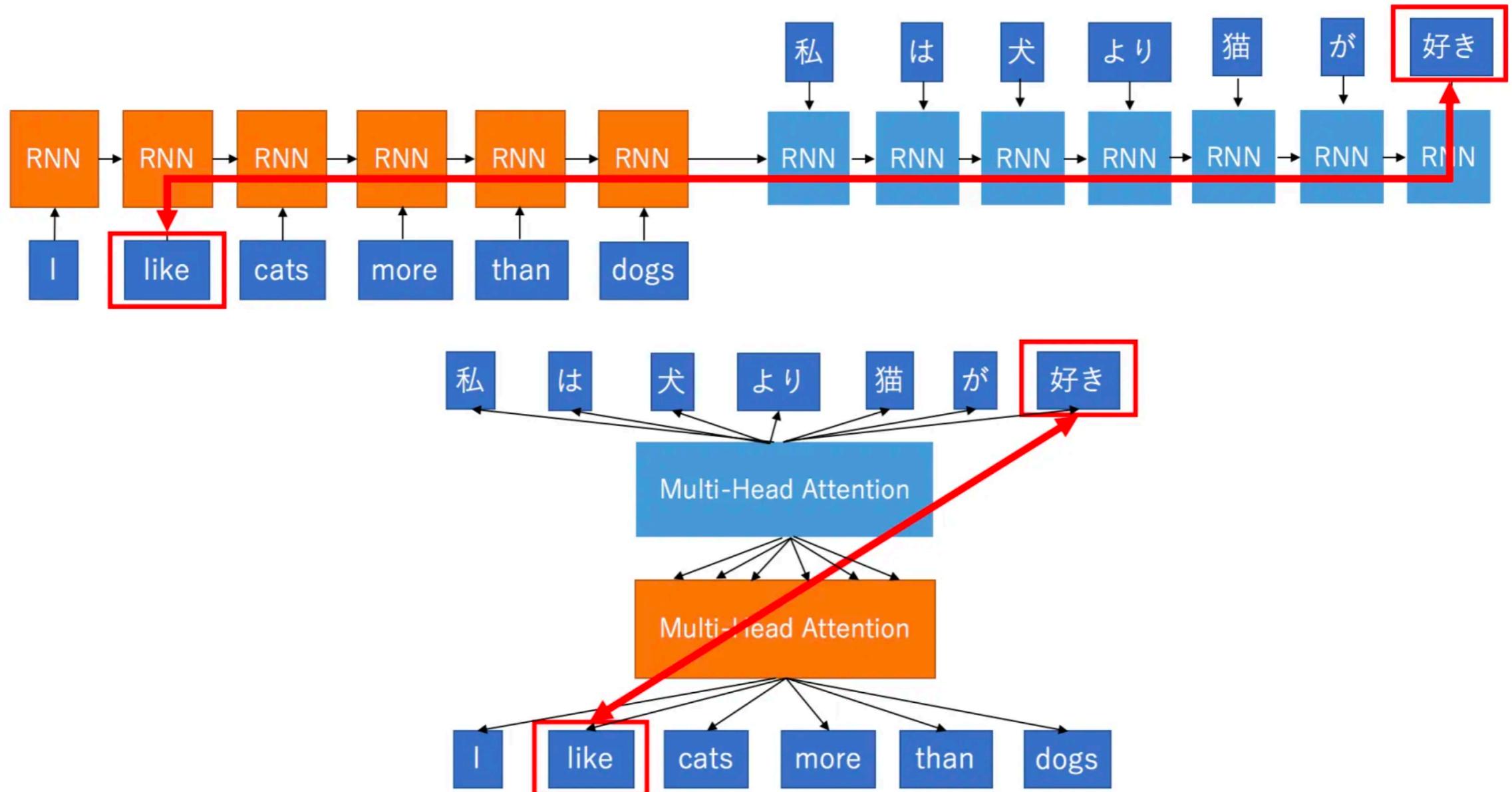




LSTM review generator

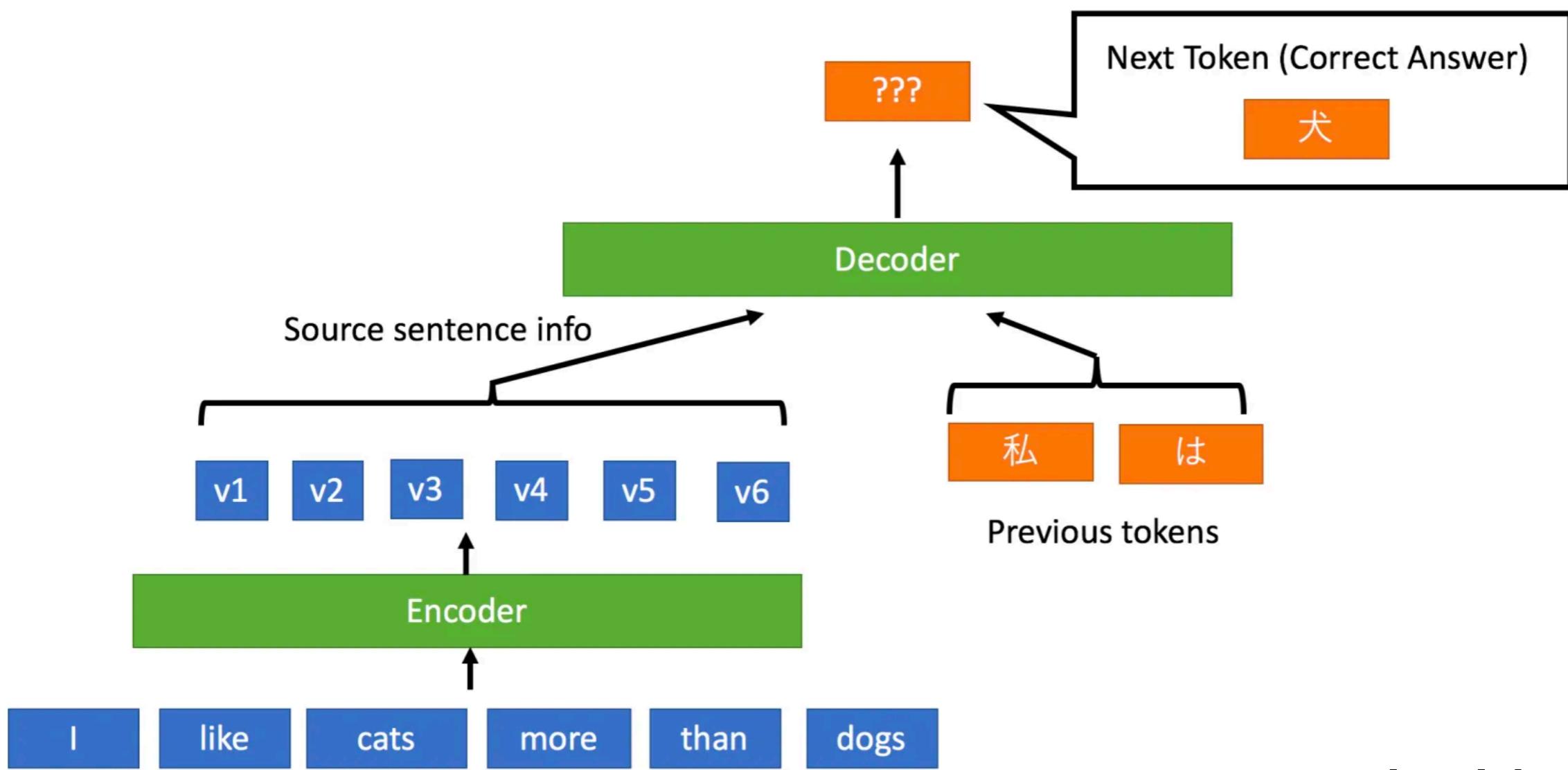
12-Review-generator.ipynb

Transformer



source: www.mlexplained.com

Translation with Transformers



GPT-2 Language model

Donald Trump told...

Demo: <https://talktotransformer.com/>

GPT-2 Language model

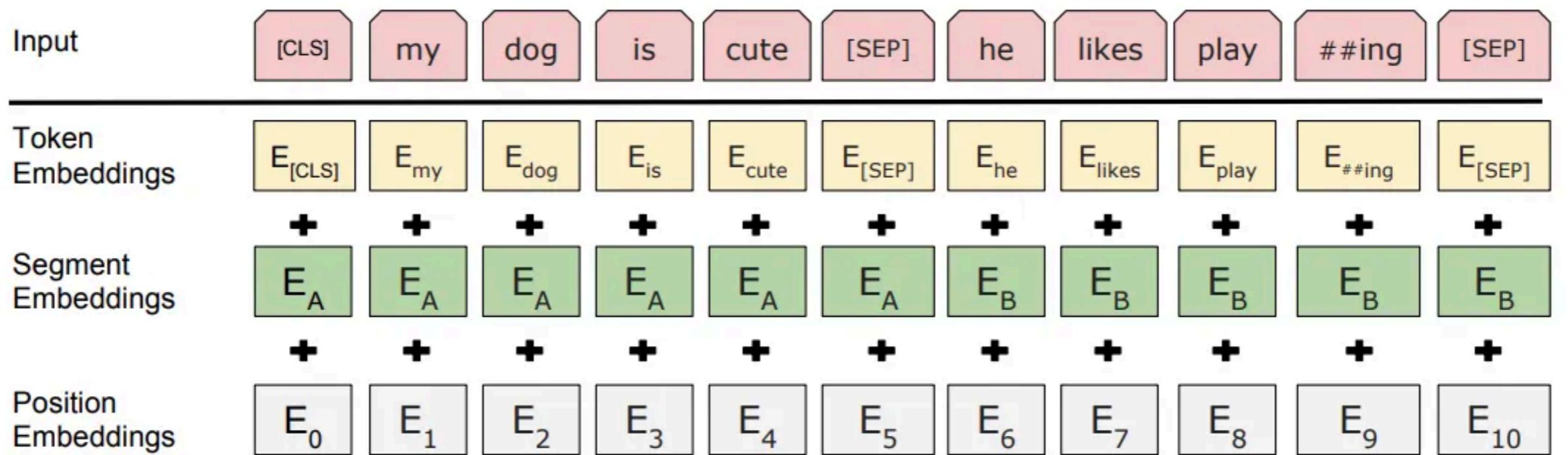
Donald Trump told the Times he is preparing a "major speech" on his economic plans, but did not provide details on what it will entail.

"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.

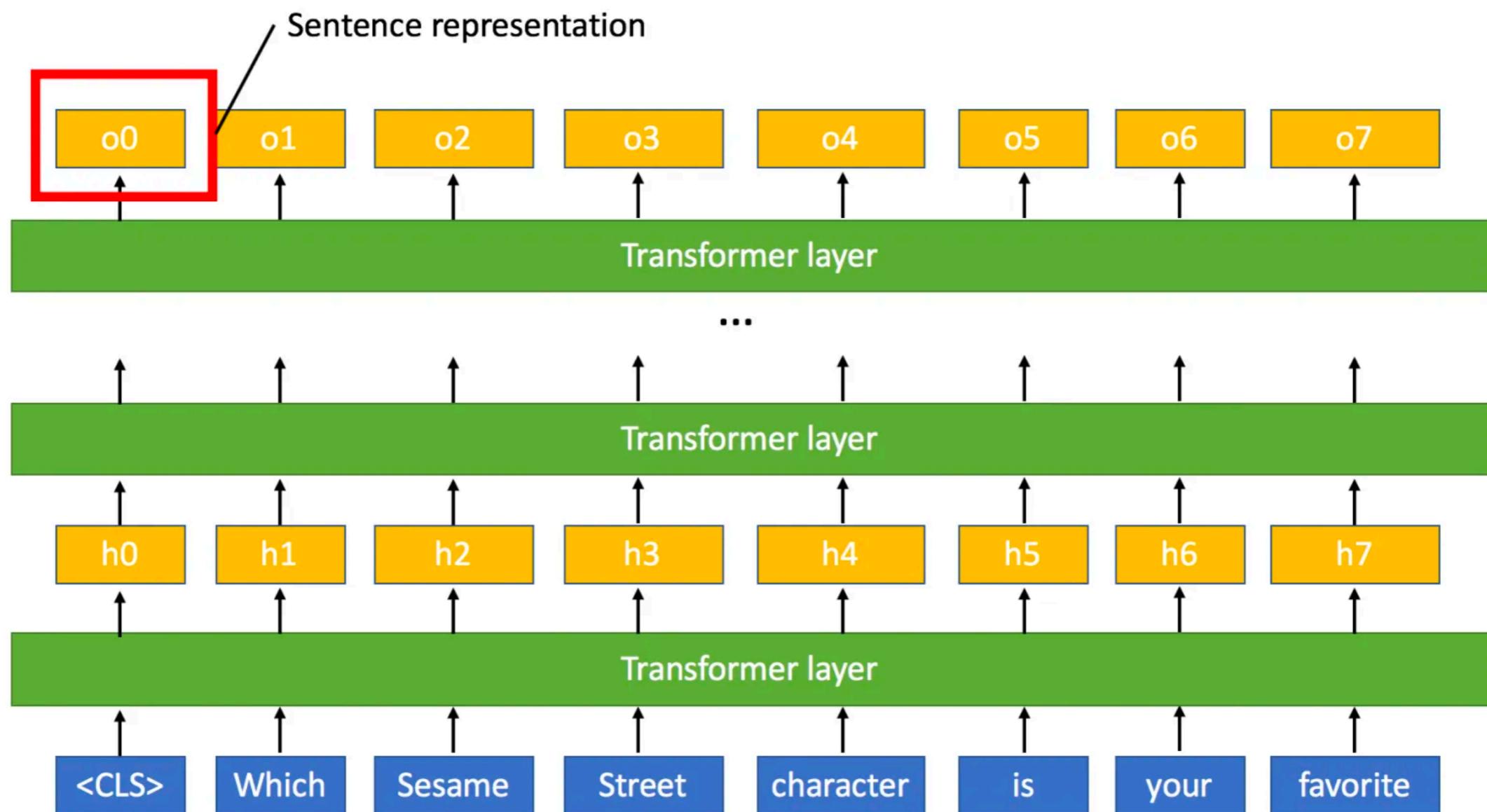
Demo: <https://talktotransformer.com/>

BERT

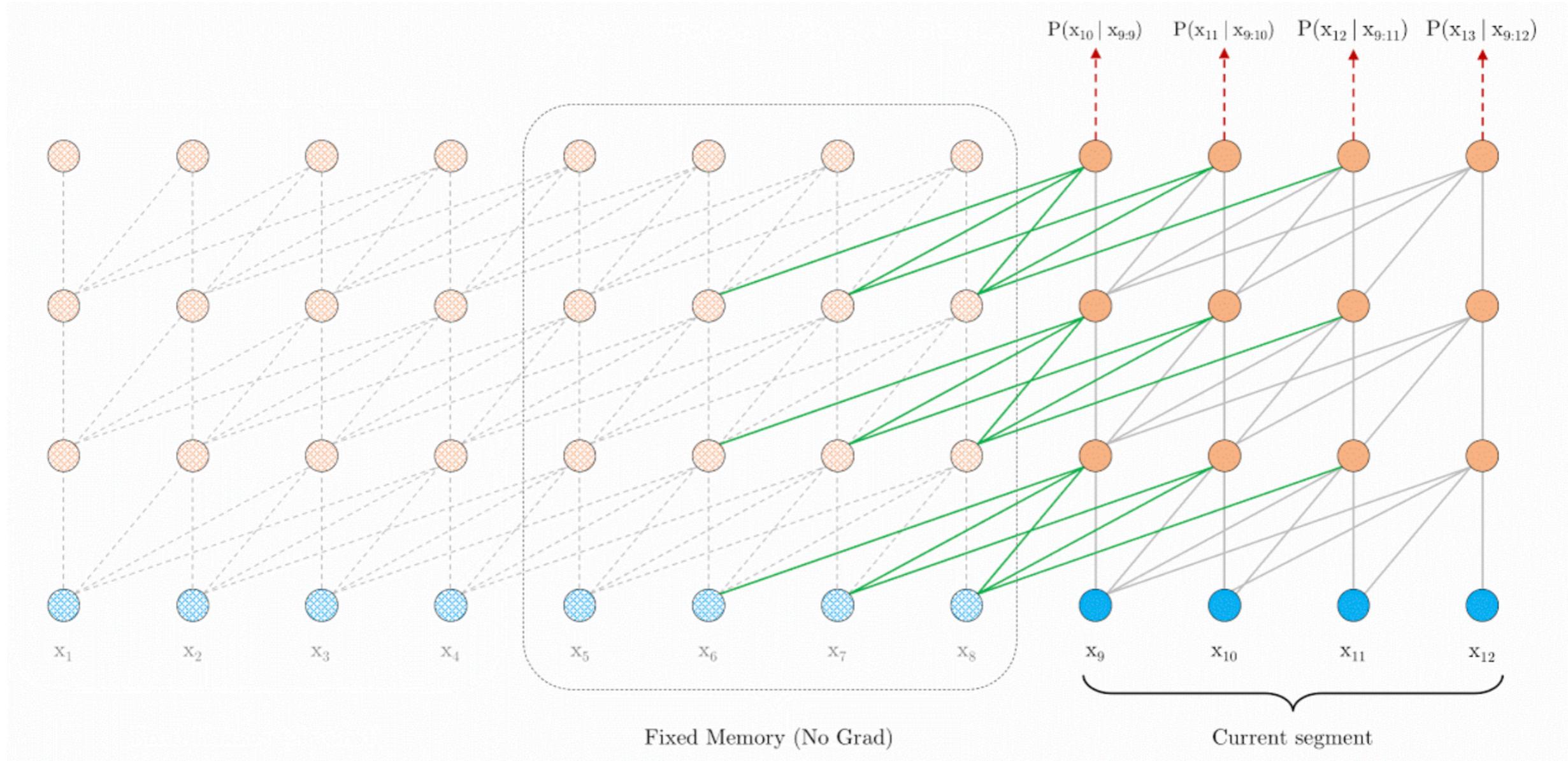
(input encoding)



BERT (classification)

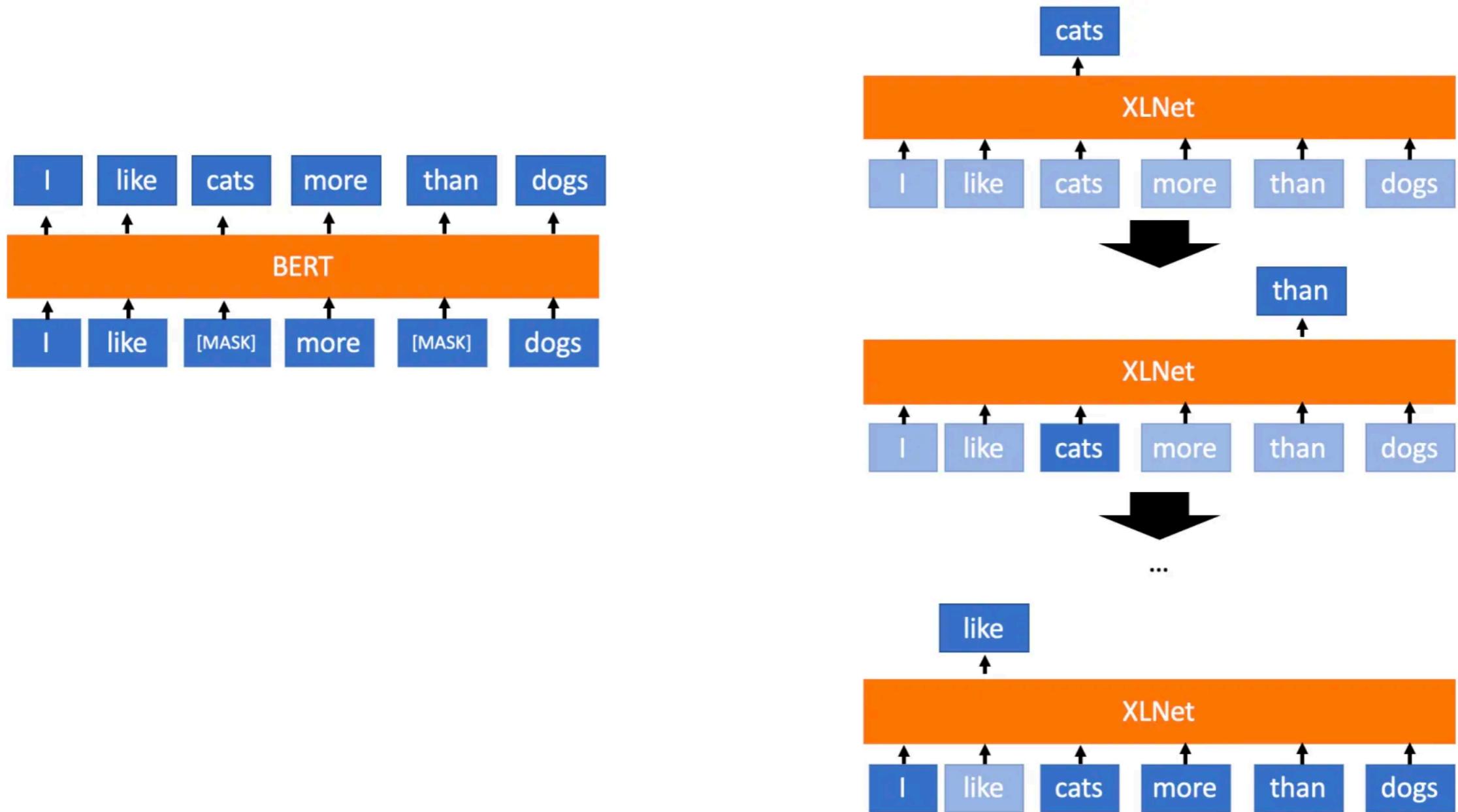


Transformer XL



XLNet

(permutation language model)



Thank you for your attention

e-mail: jiri@mlguru.com

Web: www.mlguru.com

Twitter: @JiriMaterna

Facebook: <https://www.facebook.com/maternajiri>

LinkedIn: <https://www.linkedin.com/in/jirimaterna/>