Natural Language Processing for Raiffeisenbank International

Jiří Materna

@mlcollegecom

@mlcollegecom

slack

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

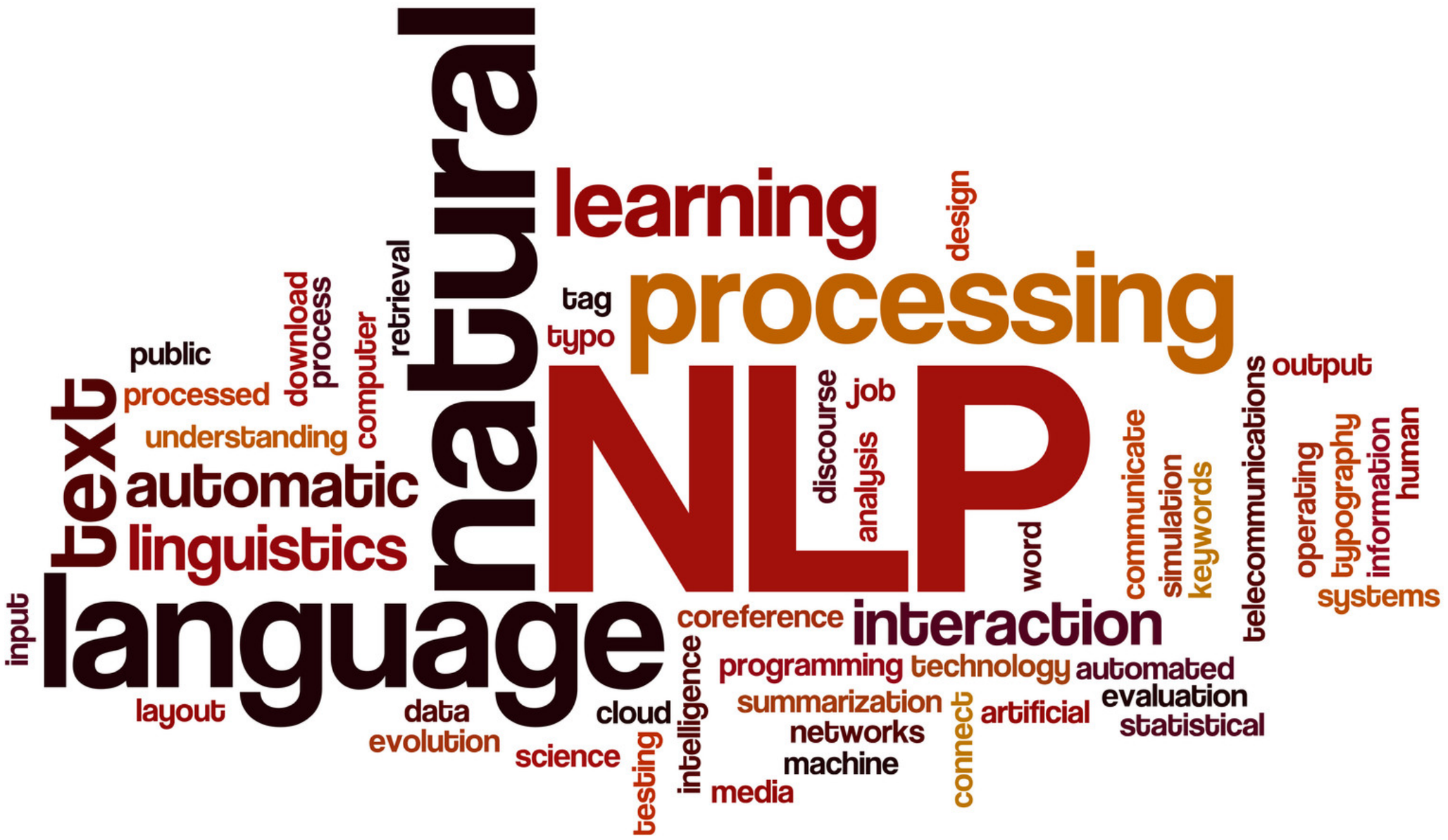
www.mlguru.com **www.mlprague.com** **www.mlcollege.com**

Outline

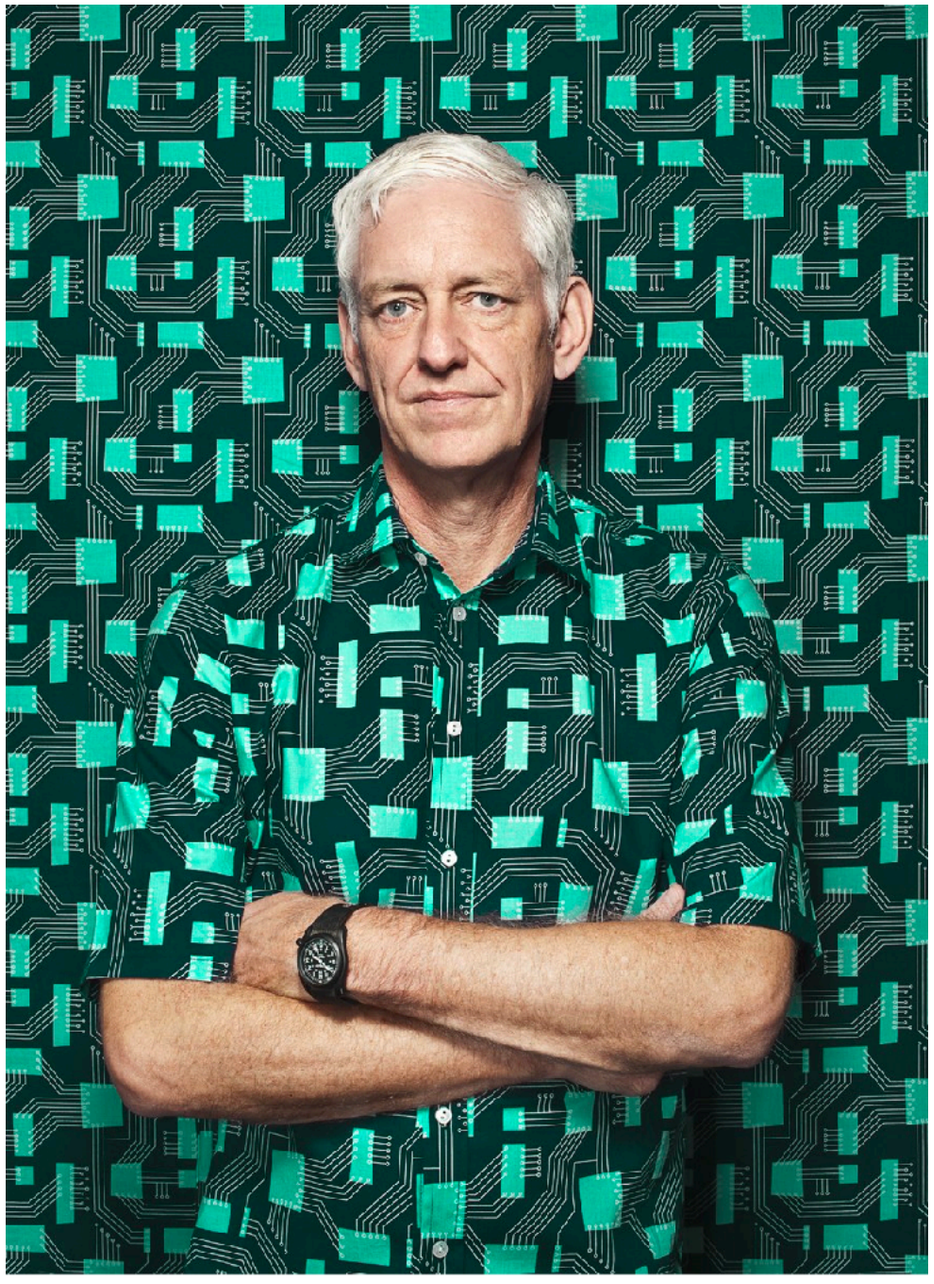
Day 1

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

What is Natural Language Processing?



Norvig vs. Chomsky



source: https://www.commarts.com

source: https://citaty.net

Text corpus

Sketch Engine | 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 1 of 13 Go Next | Last

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	. 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. 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	. 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 1 of 13 Go Next | Last

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/

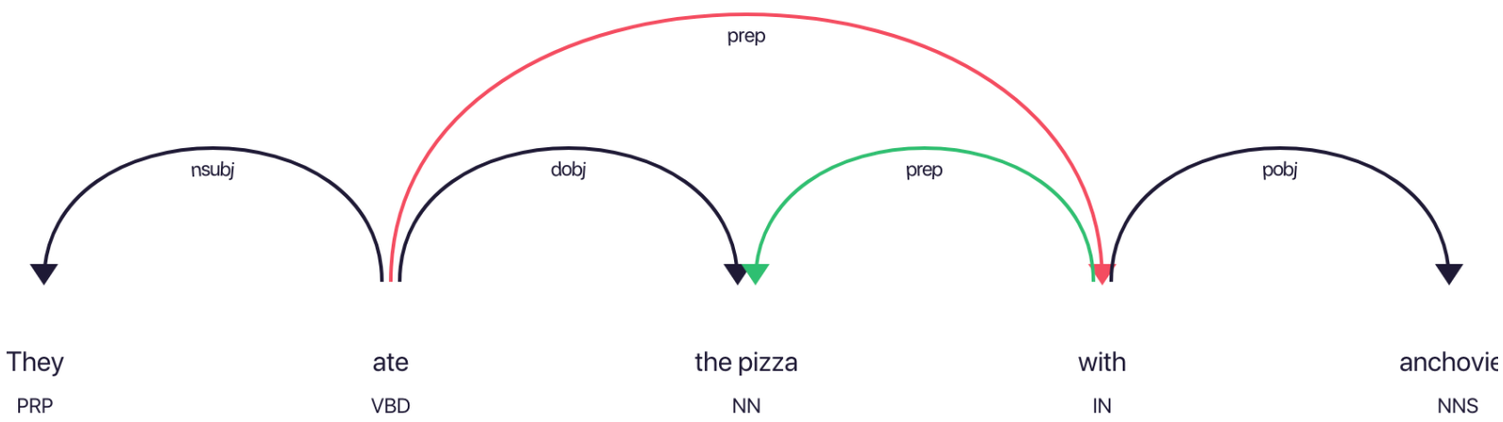
Czech:

http://ufal.mff.cuni.cz/morphodita

Parsing

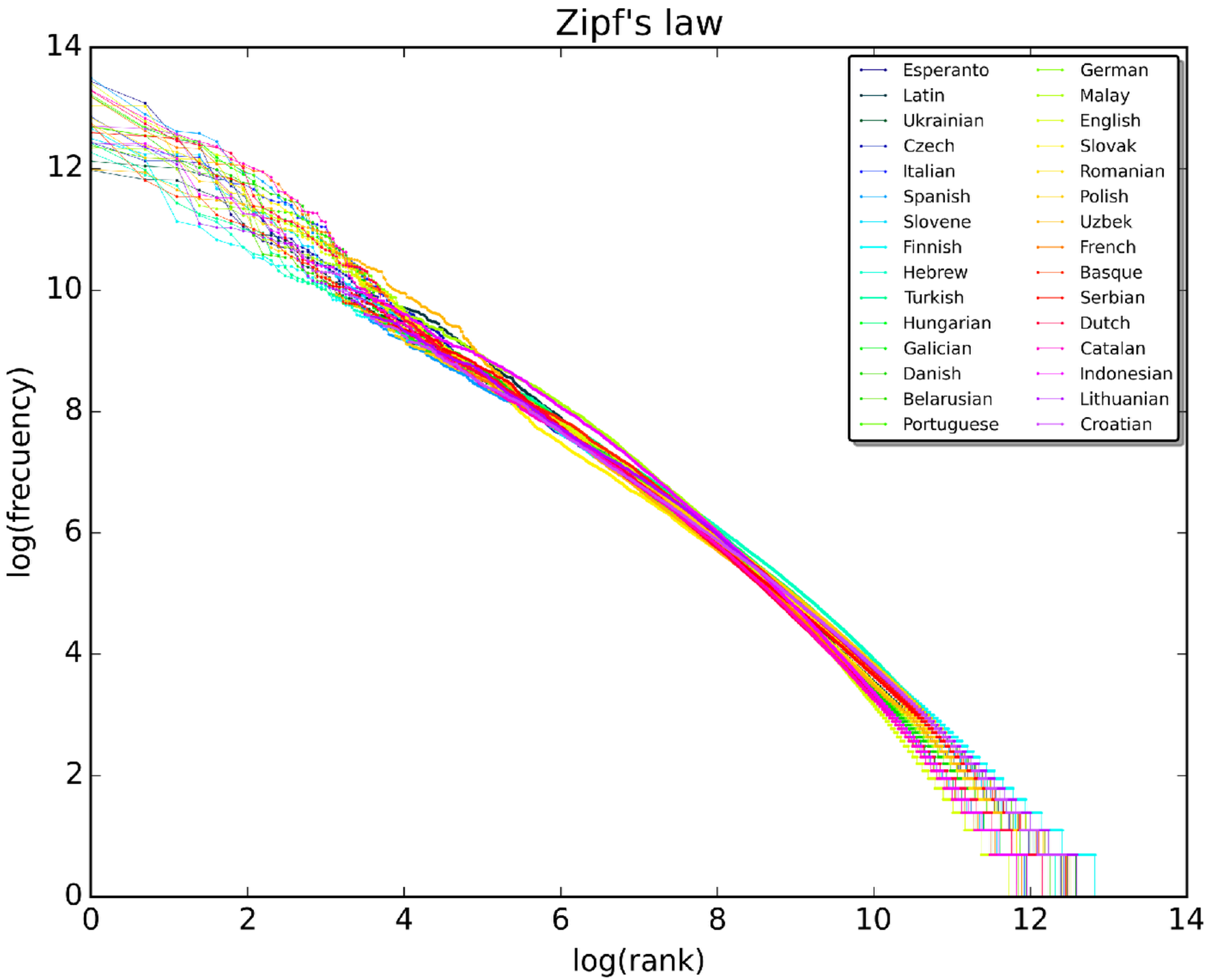
They ate the pizza with anchovies

Creative Commons Attribution-NonCommercial 2.5
James Constable, 2010



source: https://explosion.ai/blog/syntaxnet-in-context

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

01-text-classification-introduction.ipynb

Language models

- spell checking
- speech recognition
- machine translation
- …

n-gram models

$$P(w_1, w_2, \ldots w_n) = P(w_1)P(w_2|w_1)\ldots P(w_n|w_1, \ldots w_{n-1})$$

$$= \prod_i P(w_i|w_1, w_2 \ldots w_{i-1})$$

$$\approx \prod_i P(w_i|w_{i-k}, w_{i-k-1} \ldots w_{i-1})$$

$$P(w_i|w_{i-k}, w_{i-k-1} \ldots w_{i-1}) = \frac{count(w_{i-k}, w_{i-k-1} \ldots w_{i-1}, w_i)}{count(w_{i-k}, w_{i-k-1} \ldots w_{i-1})}$$

Language model smoothing

- Laplace smoothing (plus one)

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

- interpolation
- Good-Turing
- Witten-Bell
- …

Perplexity

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

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

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

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

Language detection using language models

02-Language-detection-assignment.ipynb

Travel agency review classification

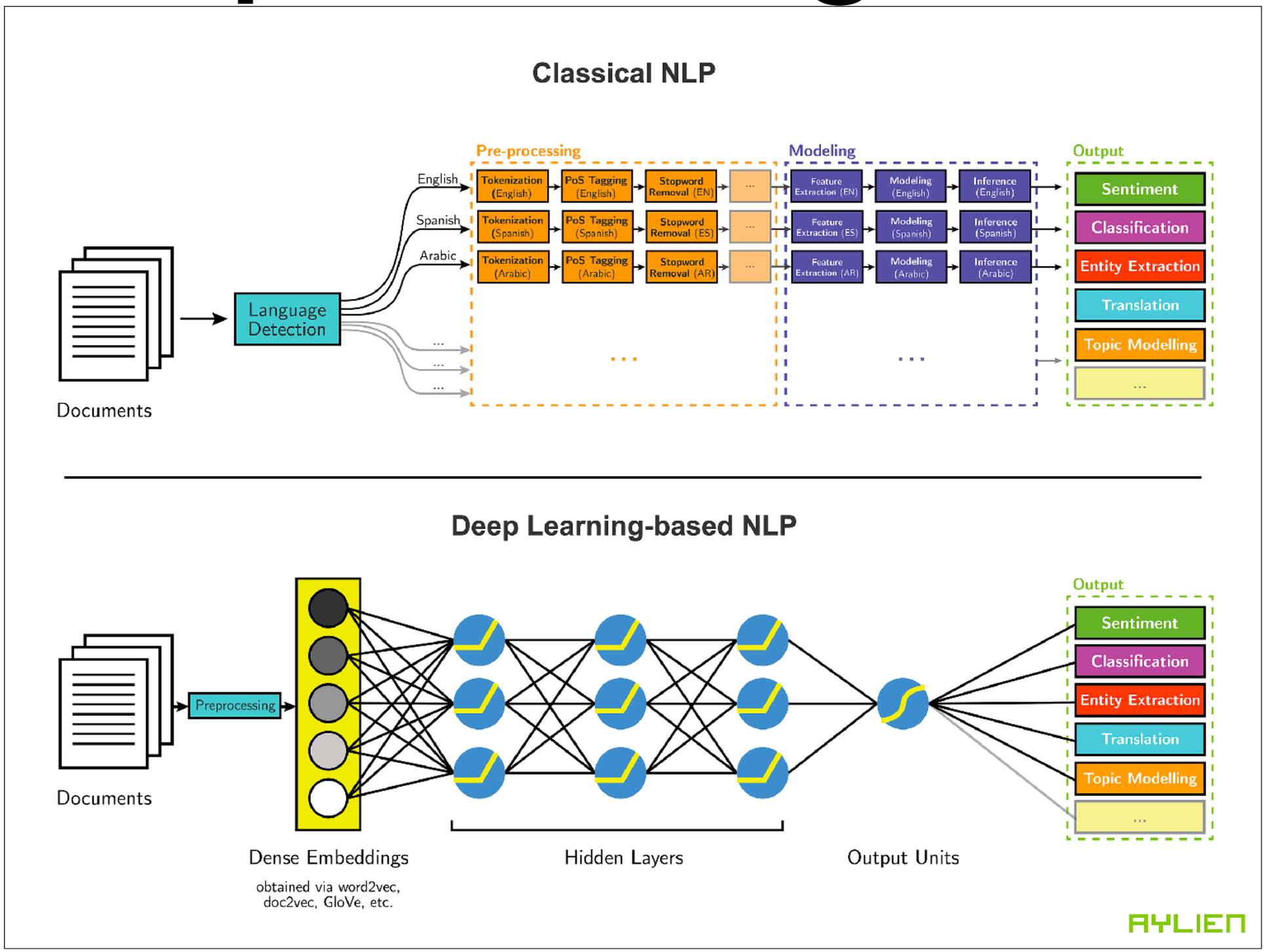
03-Review-classification-assignment.ipynb

Outline

Day 2

- Preprocessing for deep learning in NLP
- Recurrent neural networks
- Word embeddings and word2vec
- The Skip-gram model
- Experiments with word2vec
- Text classification with word embeddings

Deep Learning in NLP



Source: https://blog.aylien.com/

Encoding and Unicode

ASCII

```
H  e  l  l  o

48 65 6c 6c 6f
```

Unicode

```
H        e        l        l        o        ☺

00000048 00000065 0000006c 0000006c 0000006f 0000263a
```

Encoding and Unicode

UTF-8

H e l l o ☺

48 65 6c 6c 6f e298ba

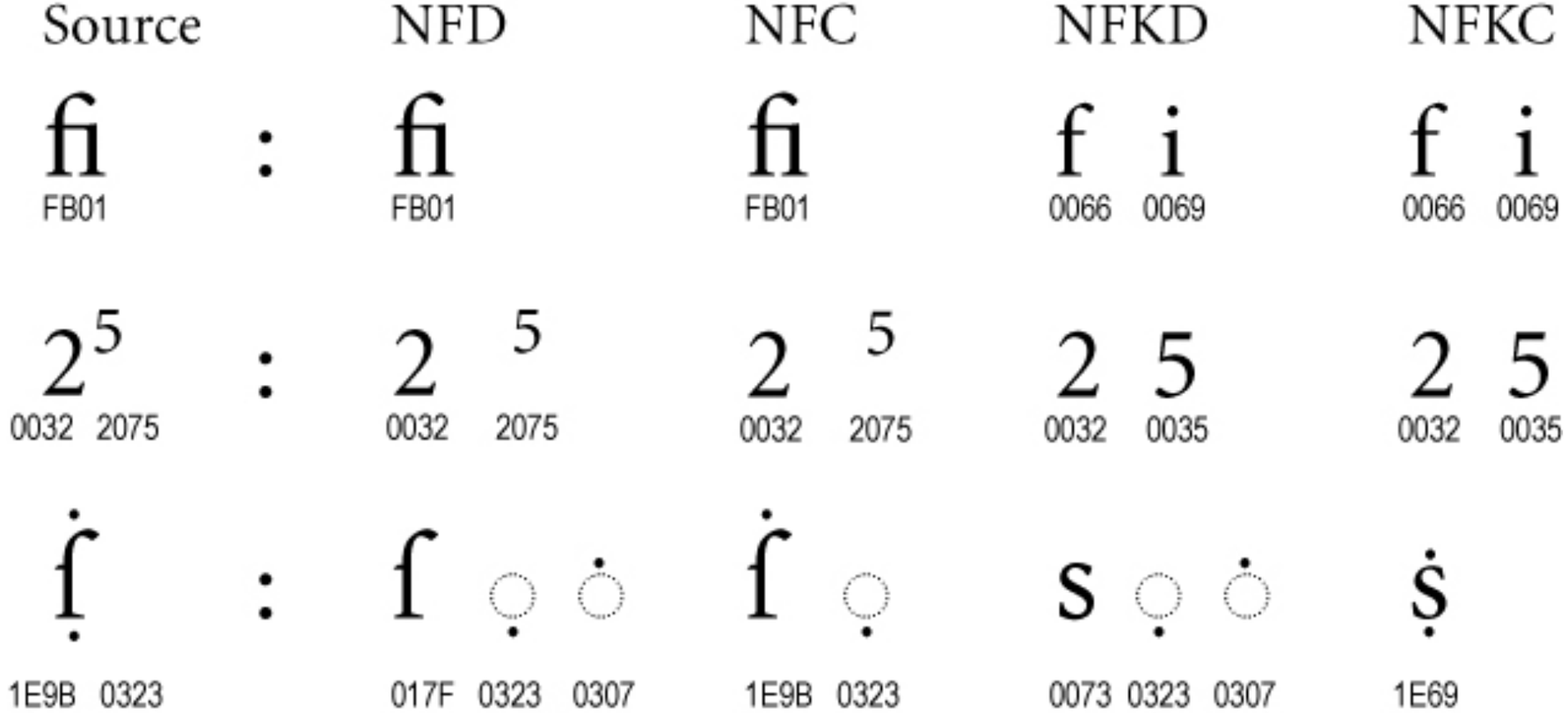
UTF-16

H e l l o ☺

0048 0065 006c 006c 006f 263a

Unicode normalization

NFD (Normalization Form Canonical Decomposition)
NFC (Normalization Form Canonical Composition)
NFKD (Normalization Form Compatibility Decomposition)
NFKC (Normalization Form Compatibility Composition)



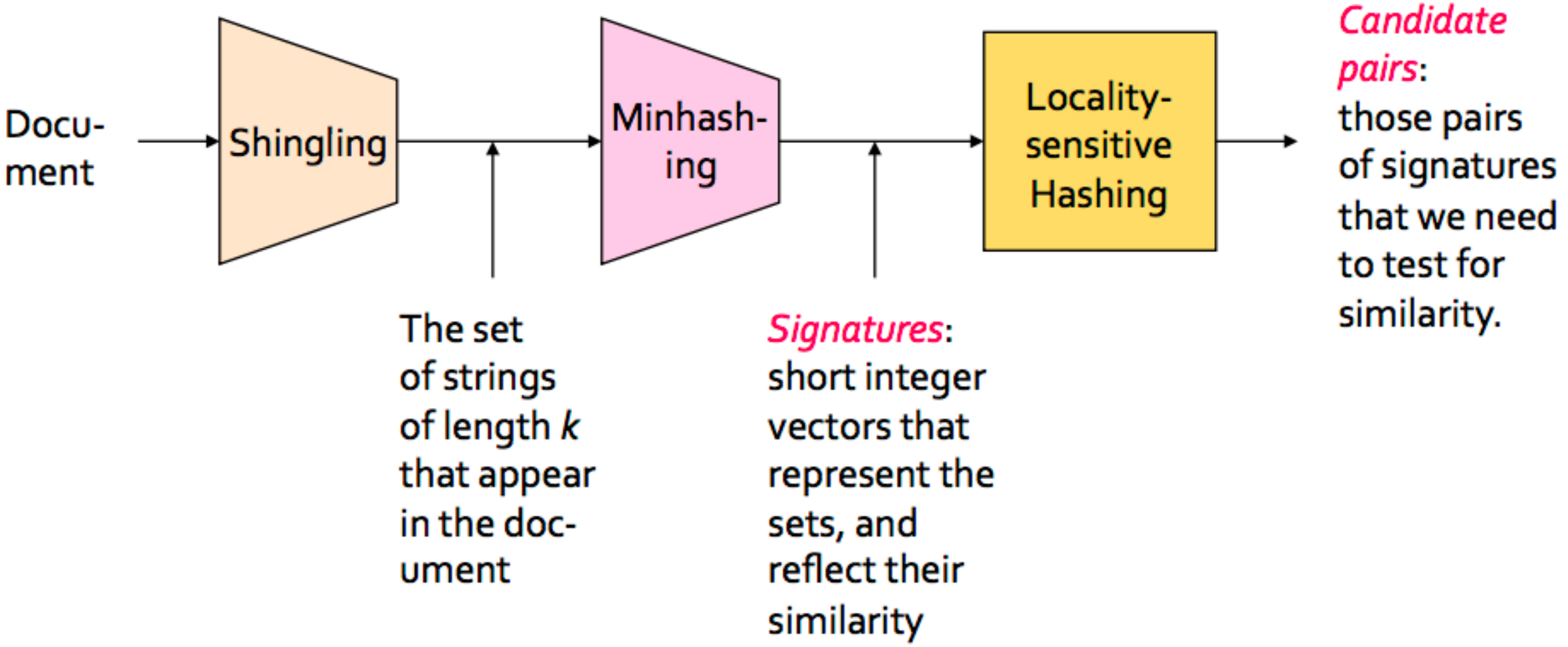
Source: https://unicode.org/

Unicode normalization in Python 3

```
>>> aa = b'\xc4\x81'.decode('utf8')
>>> bb = b'a\xcc\x84'.decode('utf8')
>>> aa
'ā'
>>> bb
'ā'
>>> aa == bb
False
>>> import unicodedata as ud
>>> aa == ud.normalize('NFC',bb)
True
```

Near deduplication

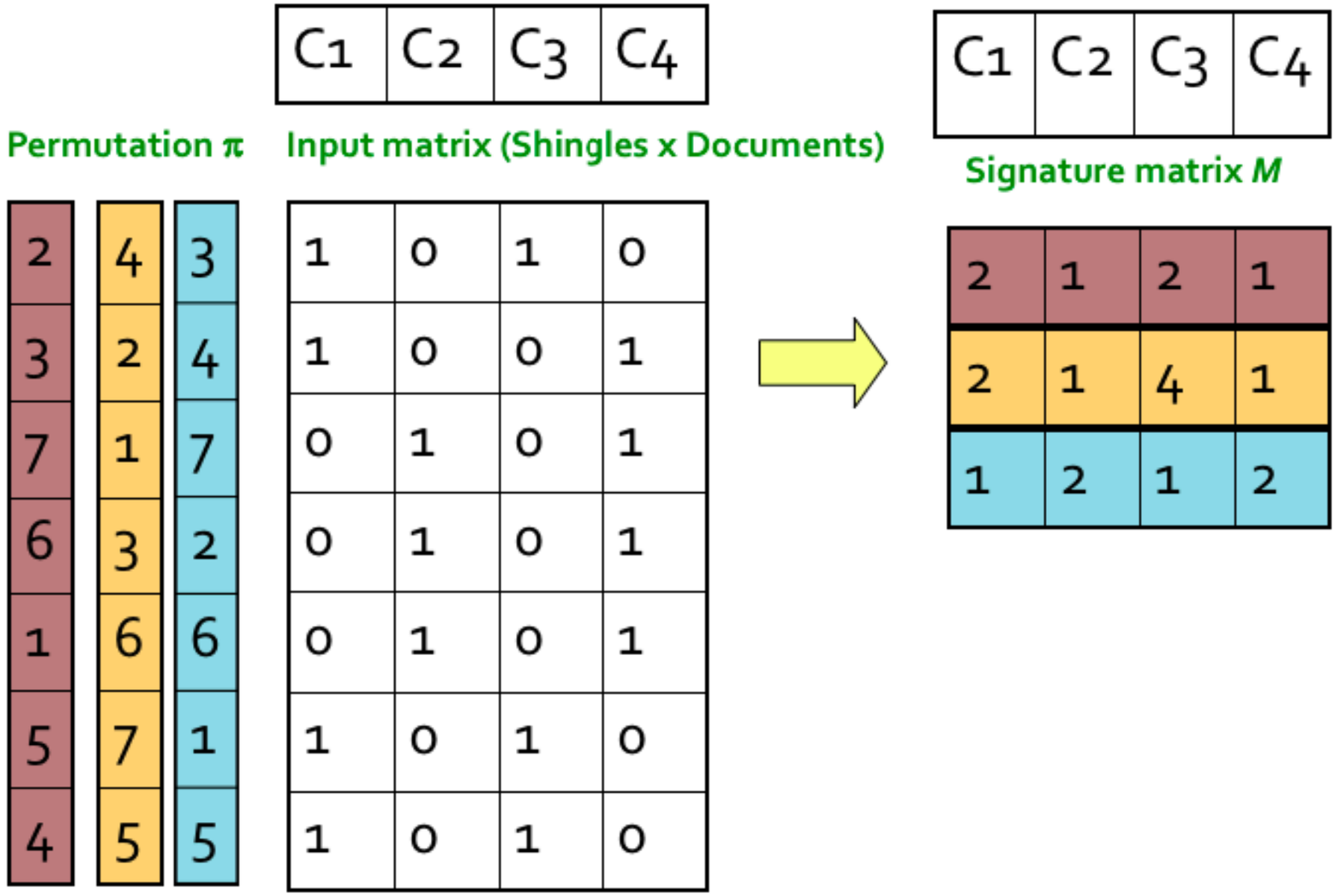
Locality-sensitive hashing



Source: https://towardsdatascience.com/understanding-locality-sensitive-hashing-49f6d1f6134

Near deduplication

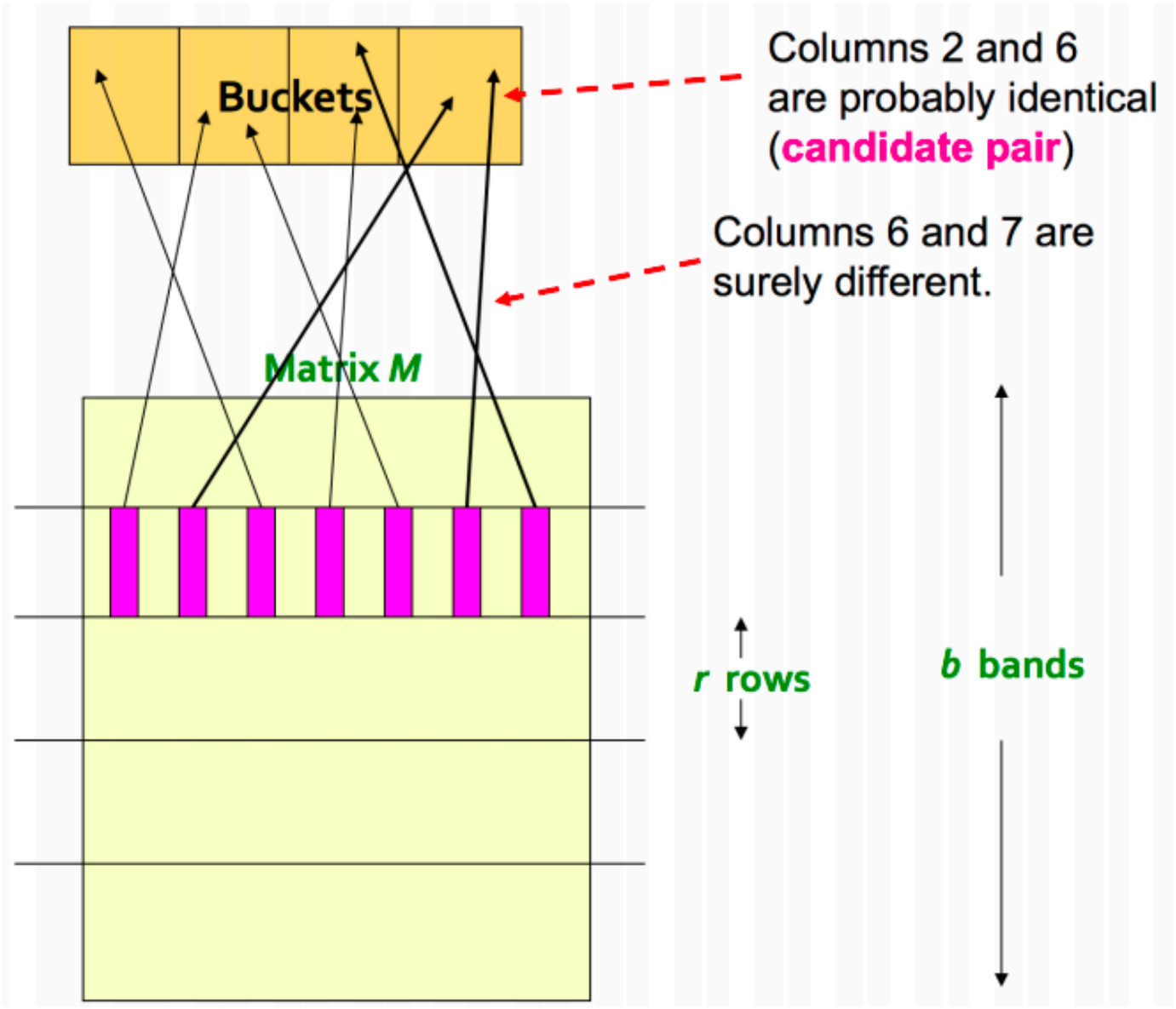
MinHashing signatures



Source: https://towardsdatascience.com/understanding-locality-sensitive-hashing-49f6d1f6134

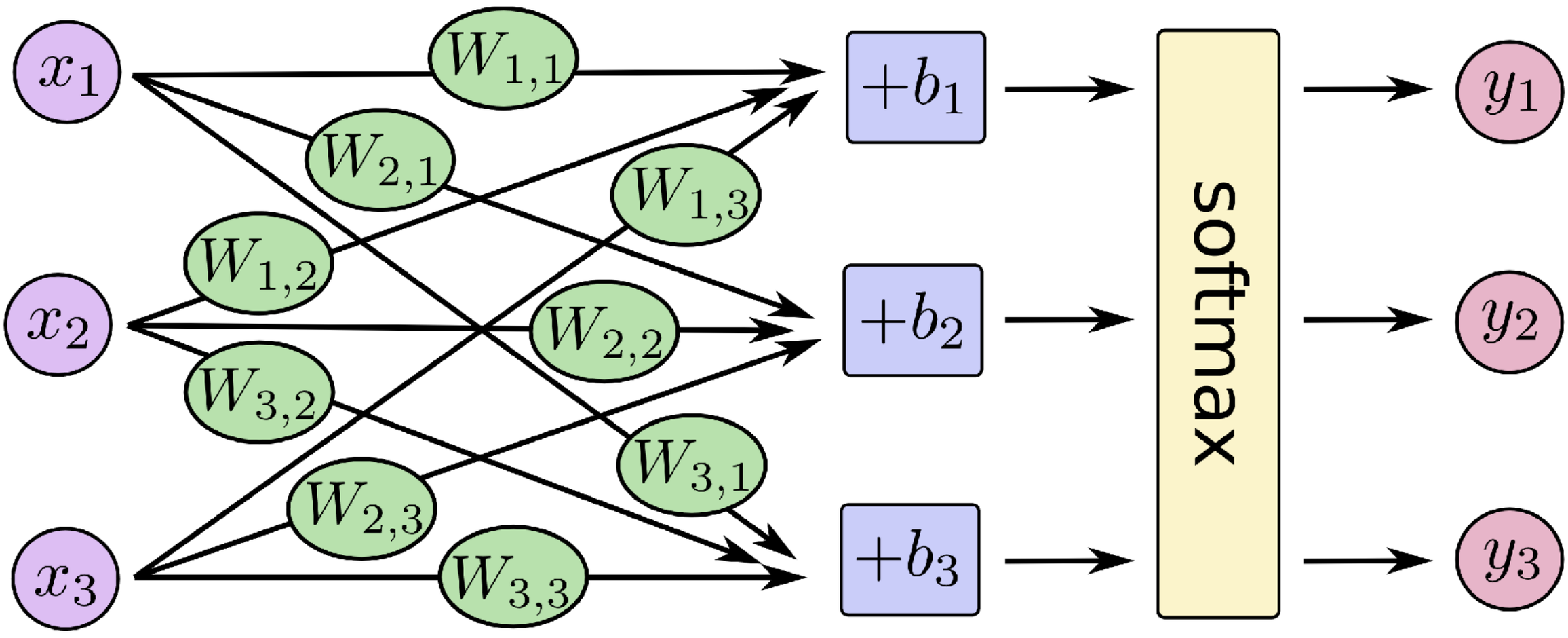
Near deduplication

Locality-sensitive hashing



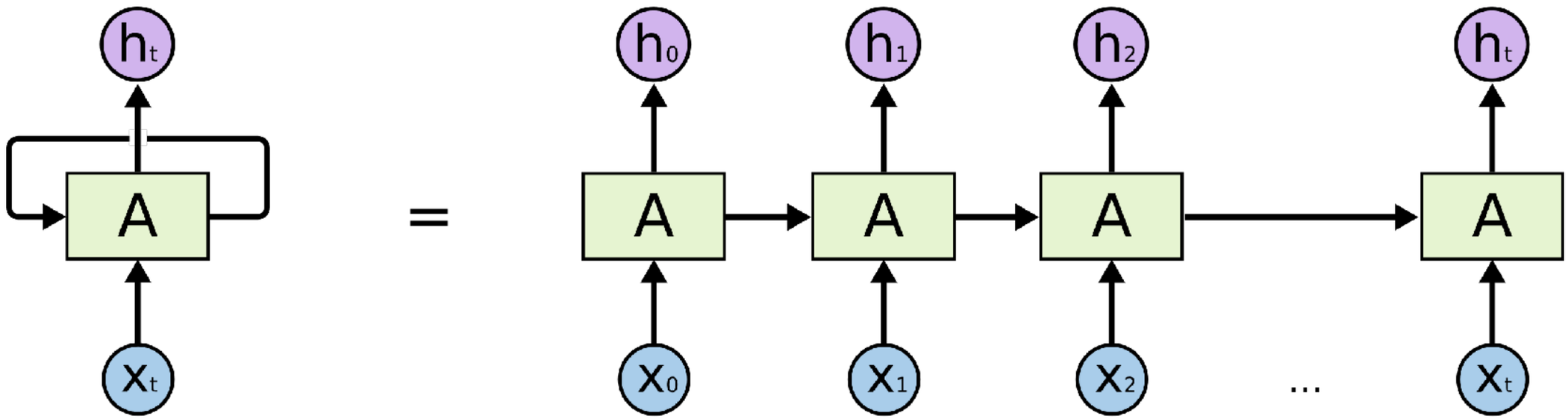
Source: https://towardsdatascience.com/understanding-locality-sensitive-hashing-49f6d1f6134

Feed-Forward Neural Network



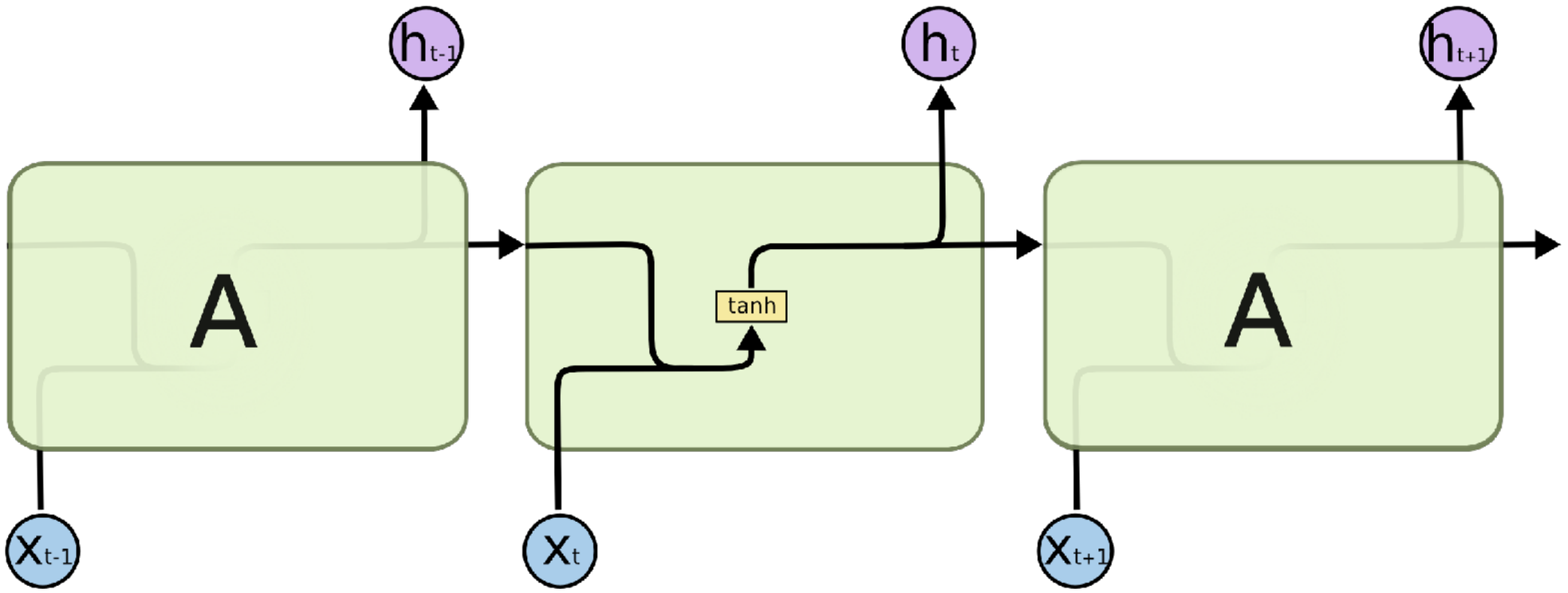
source: https://www.tensorflow.org

Recurrent Neural networks 1/2



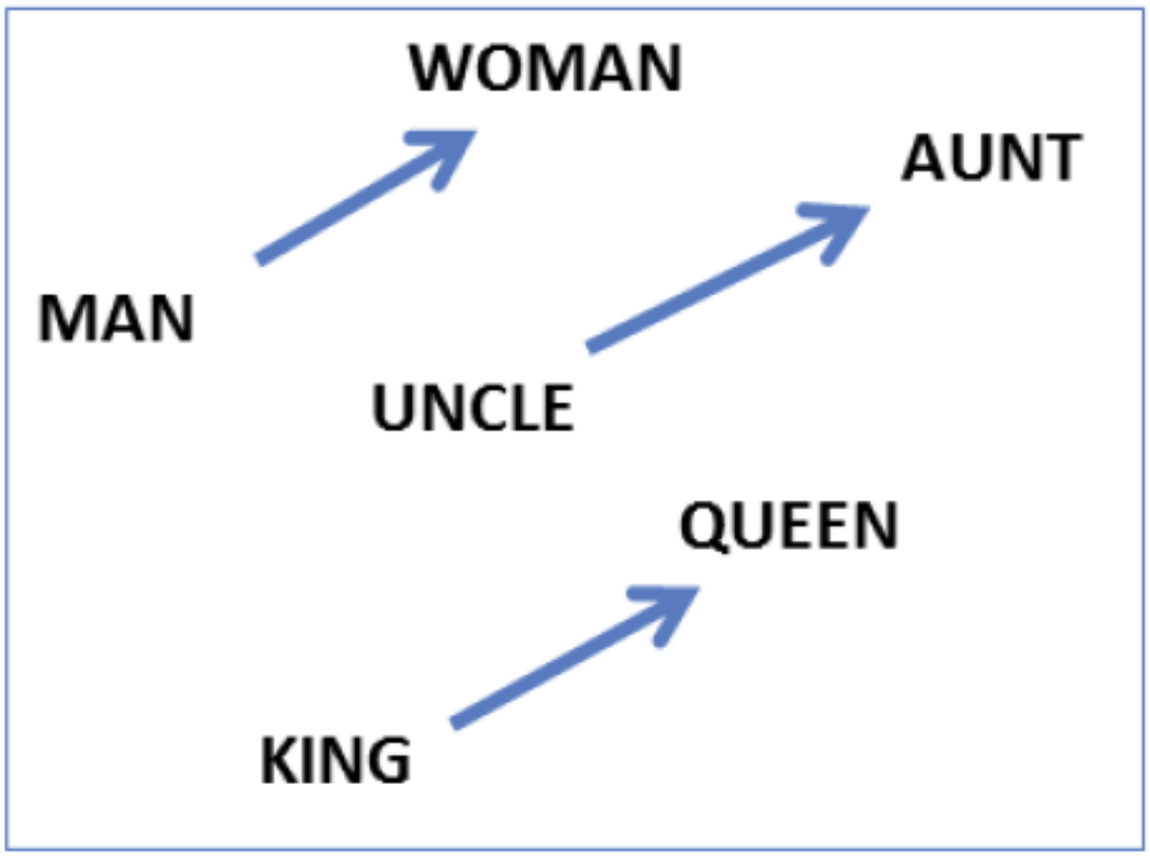
source: http://colah.github.io/posts/2015-08-Understanding-LSTMs/

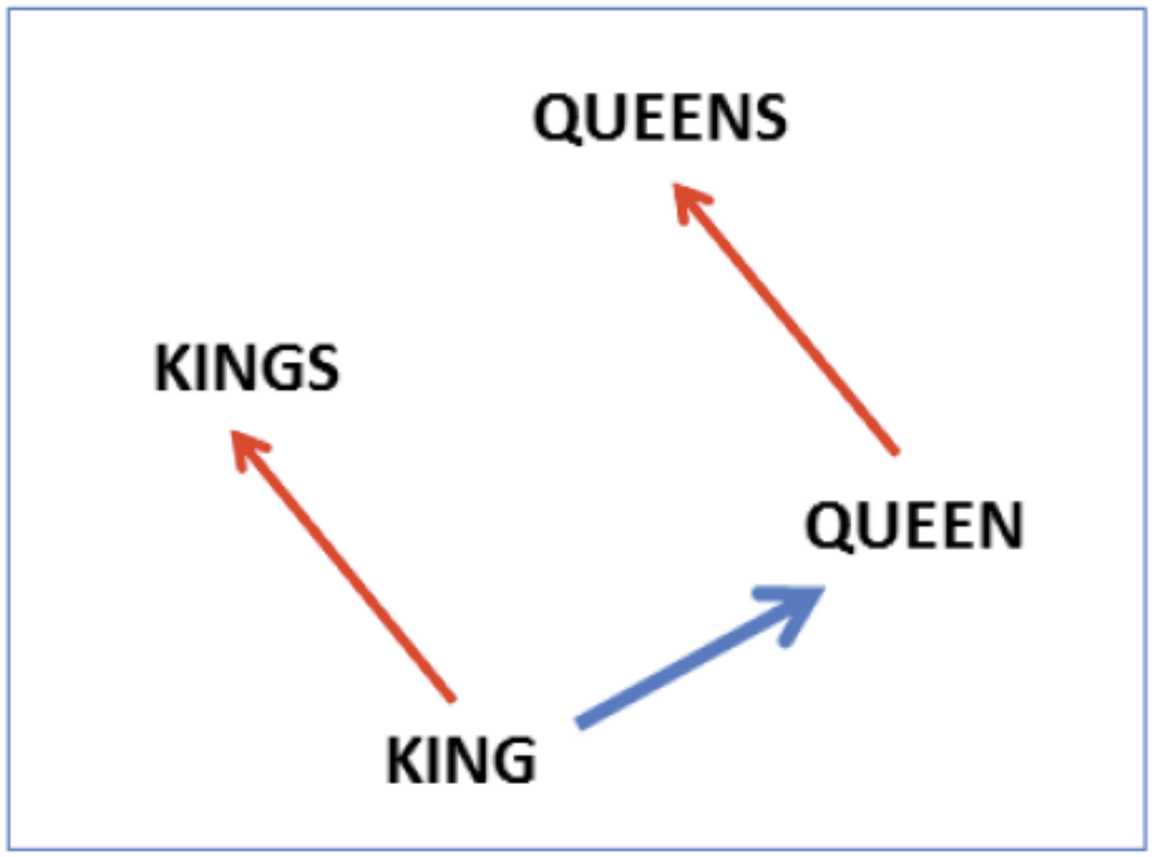
Recurrent Neural Networks 2/2



https://www.tensorflow.org

word2vec

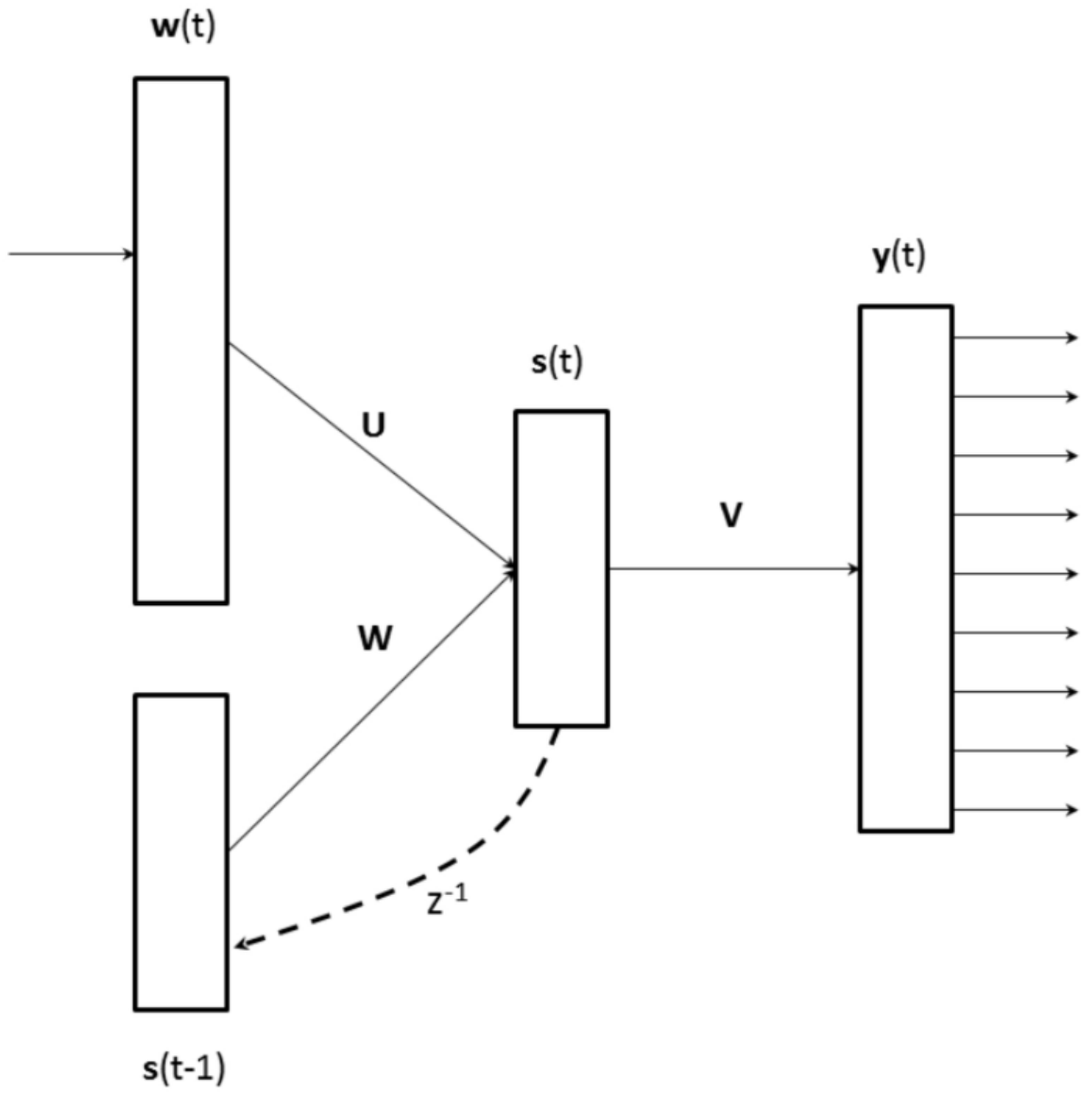




king is to **kings** as **queen** to ***?***.

v(**kings**) - v(**king**) = v(**queens**) - v (**queen**)

Recurrent Neural Network Language Modeling Toolkit



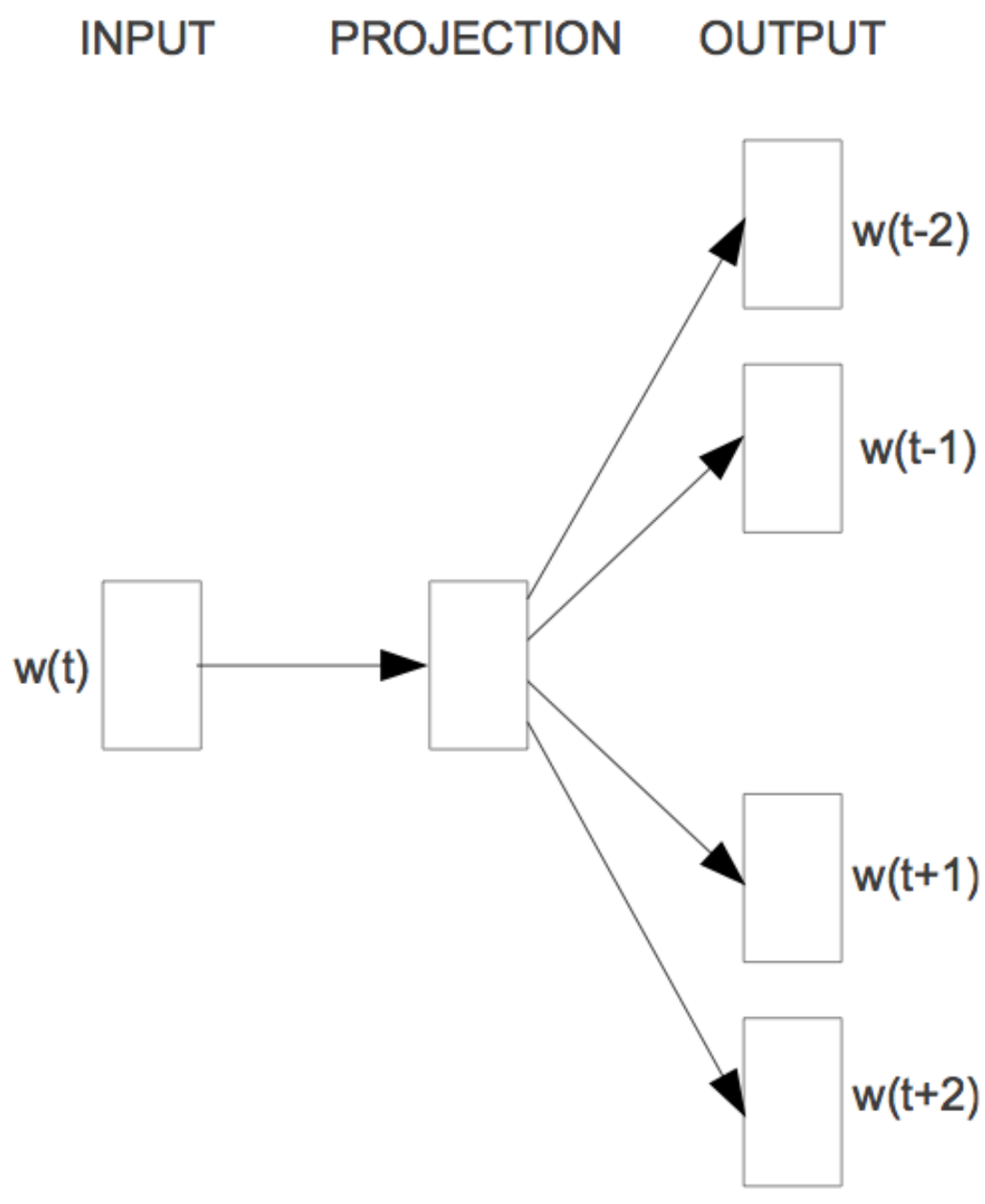
$$\mathbf{s}(t) = f\left(\mathbf{U}\mathbf{w}(t) + \mathbf{W}\mathbf{s}(t-1)\right)$$

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

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

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

The Skip-gram model

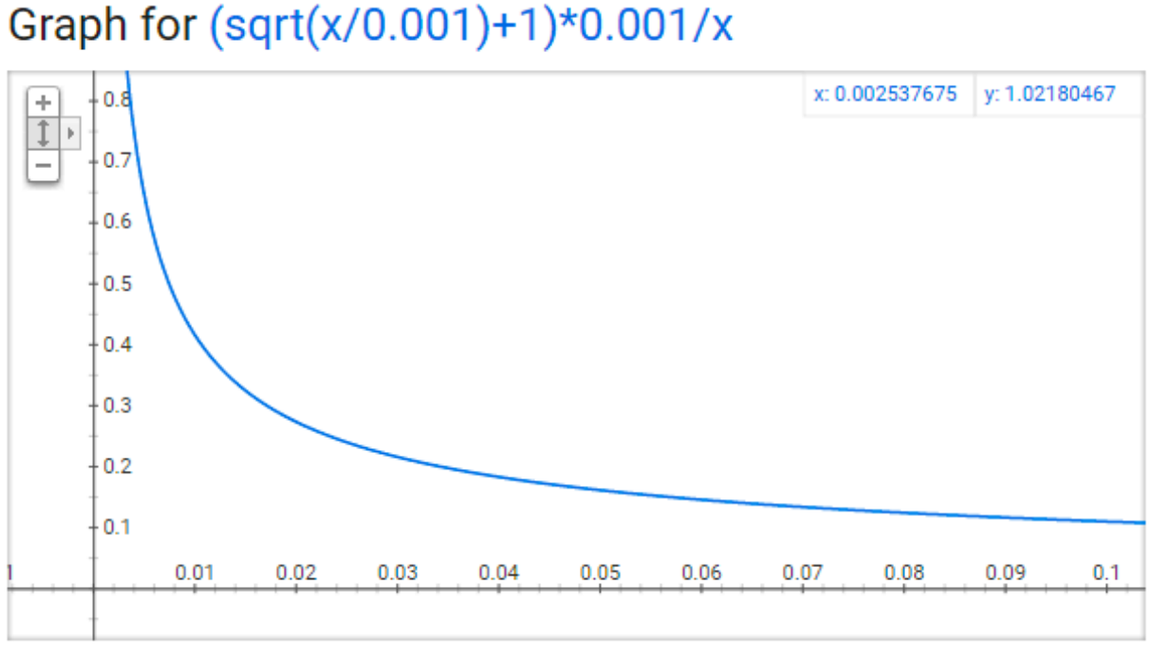


Skip-gram improvements

Subsampling frequent inputs

$$P(w_i) = (\sqrt{\frac{z(w_i)}{0.001}} + 1) \cdot \frac{0.001}{z(w_i)}$$

z(w) Relative frequency of word *w*



Negative sampling

We select only 5-20 negative samples in the loss function.
The probability of for picking a word *w* is given by *z(w).*

http://mccormickml.com/2017/01/11/word2vec-tutorial-part-2-negative-sampling/

Experiments with word2vec

04-Word2vec-in-gensim.ipynb

05-Review-classification-w2v-assignment.ipynb

Outline

Day 3

- Subword tokenization
- LSTM and GRU
- Recurrent neural networks for text classification
- Text generation using RNN
- Practical task on text generation
- Attention is all you need
- Transformers (GPT3, BERT, XLNET)
- Practical task on classification using BERT

Traditional tokenization

NLTK tokenizers

```
>>> from nltk.tokenize import word_tokenize #simple
>>> from nltk.tokenize.moses import MosesTokenizer #enables detokenization
>>> from nltk.tokenize import ToktokTokenizer #fast
>>>
>>> moses = MosesTokenizer()
>>> toktok = ToktokTokenizer()
>>>
>>> text = "Welcome to Machine Learning College."
>>> print(word_tokenize(text))
>>> print (moses.tokenize(text))
>>> print (toktok.tokenize(text))
['Welcome', 'to', 'Machine', 'Learning', 'College', '.']
['Welcome', 'to', 'Machine', 'Learning', 'College', '.']
['Welcome', 'to', 'Machine', 'Learning', 'College', '.']
```

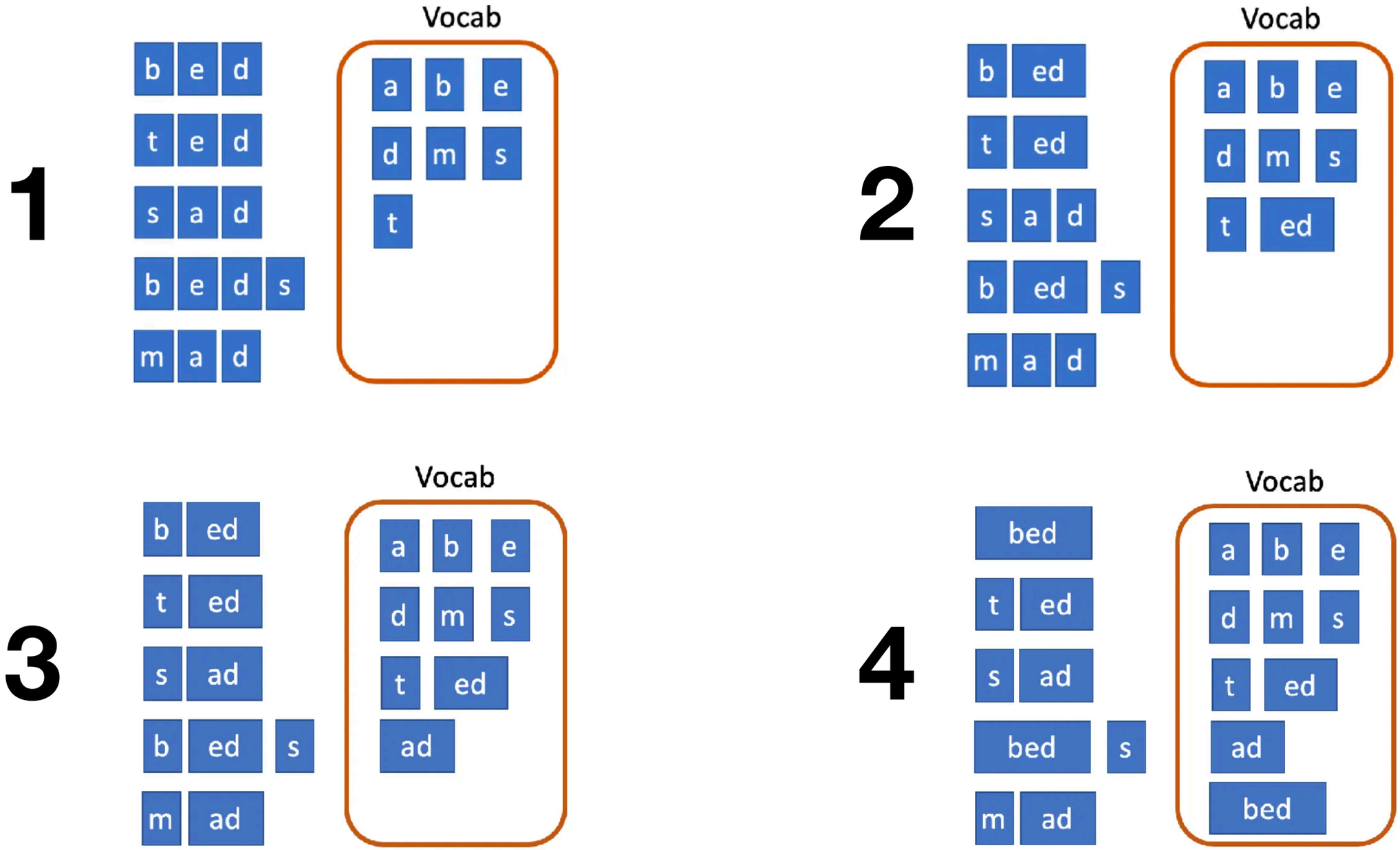
Traditional tokenization

SpaCy tokenizer

```
>>> import spacy
>>> sp = spacy.load('en_core_web_sm')
>>> tokens = sp("Welcome to Machine Learning College.")
>>>
>>> [word.text for word in tokens]
['Welcome', 'to', 'Machine', 'Learning', 'College', '.']
```

Subword tokenization

Byte-pair encoding



Source: https://mlexplained.com/2019/11/06/a-deep-dive-into-the-wonderful-world-of-preprocessing-in-nlp/

Subword tokenization

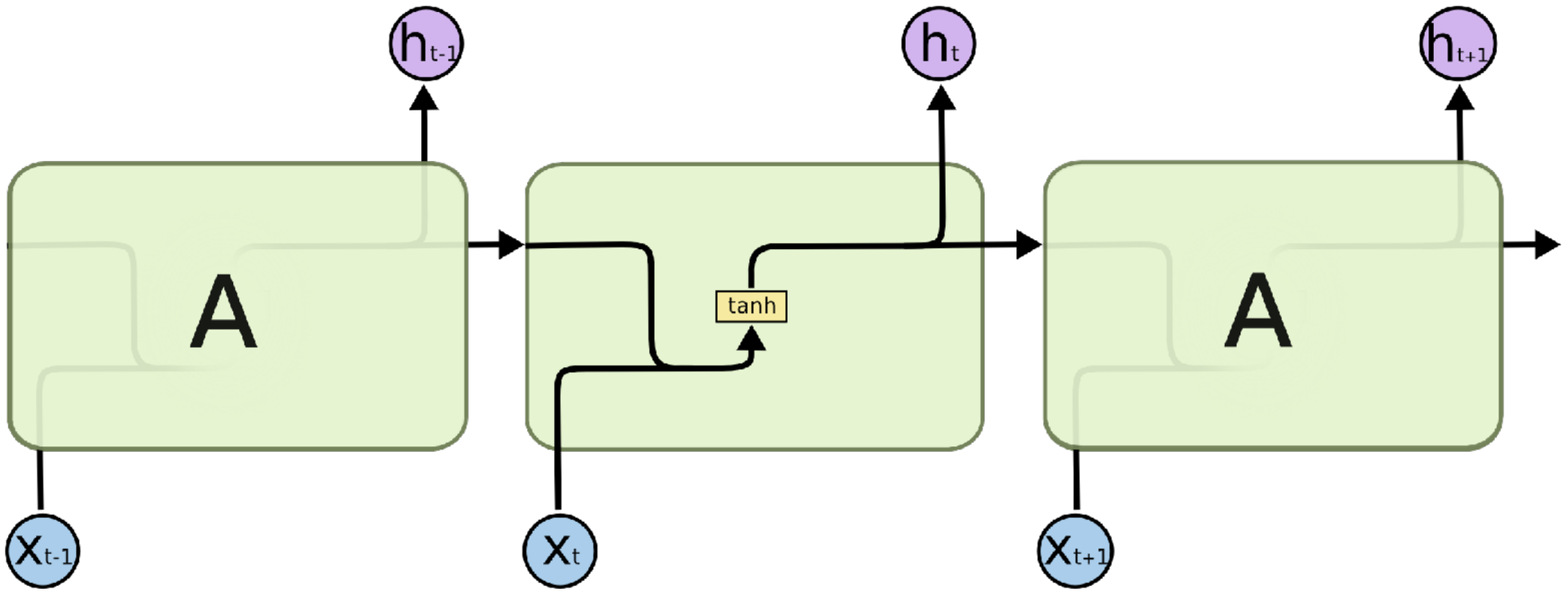
Wordpiece and sentencepiece tokenization

Merges bigrams with maximum mutual information instead of maximum frequency.

$$I(x, y) = \log\left(\frac{p(x, y)}{p(x)\,p(y)}\right)$$

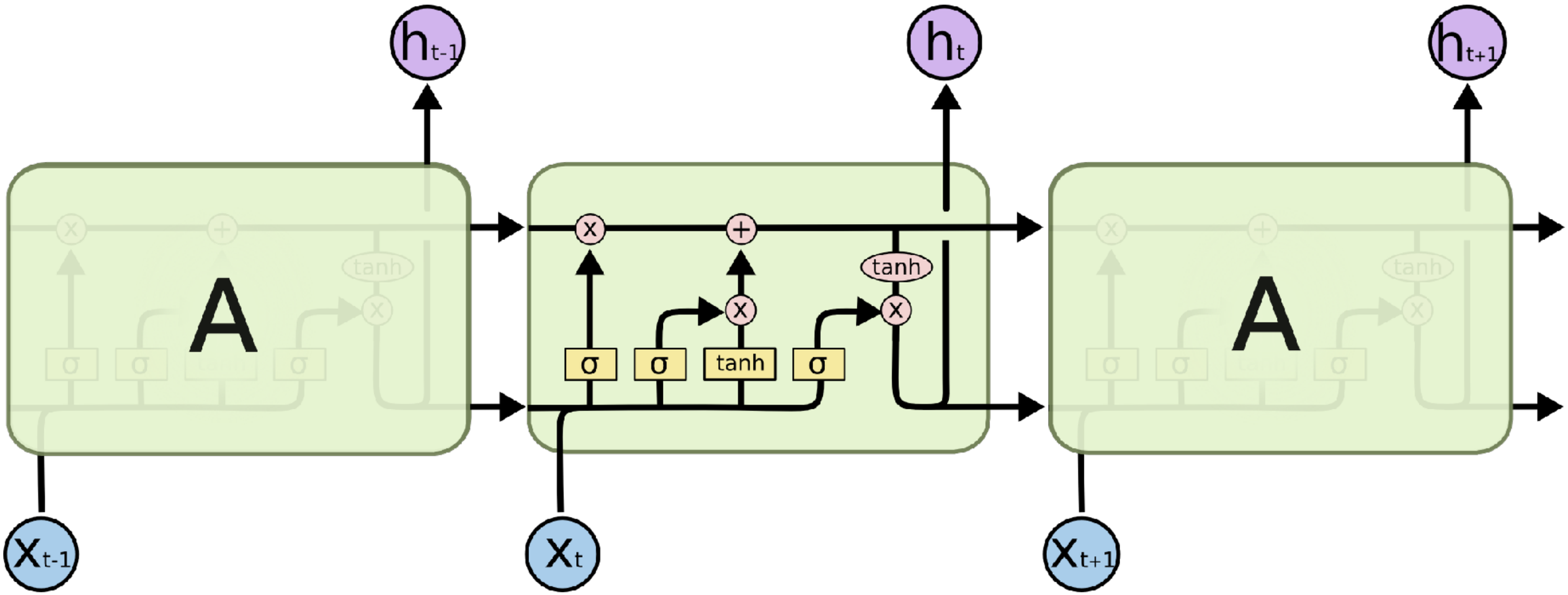
playing -> play, ##ing

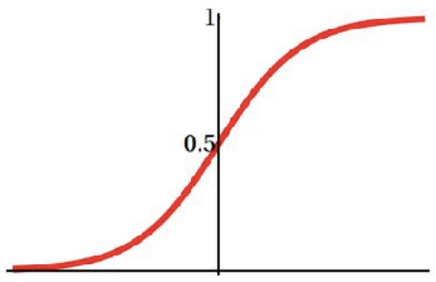
Recurrent Neural Networks



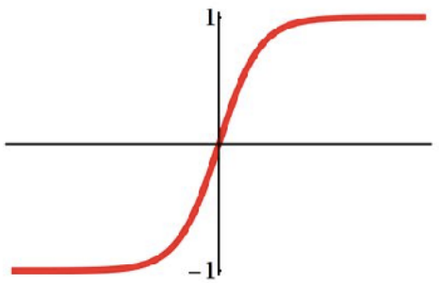
https://www.tensorflow.org

Long Short-Term Memory





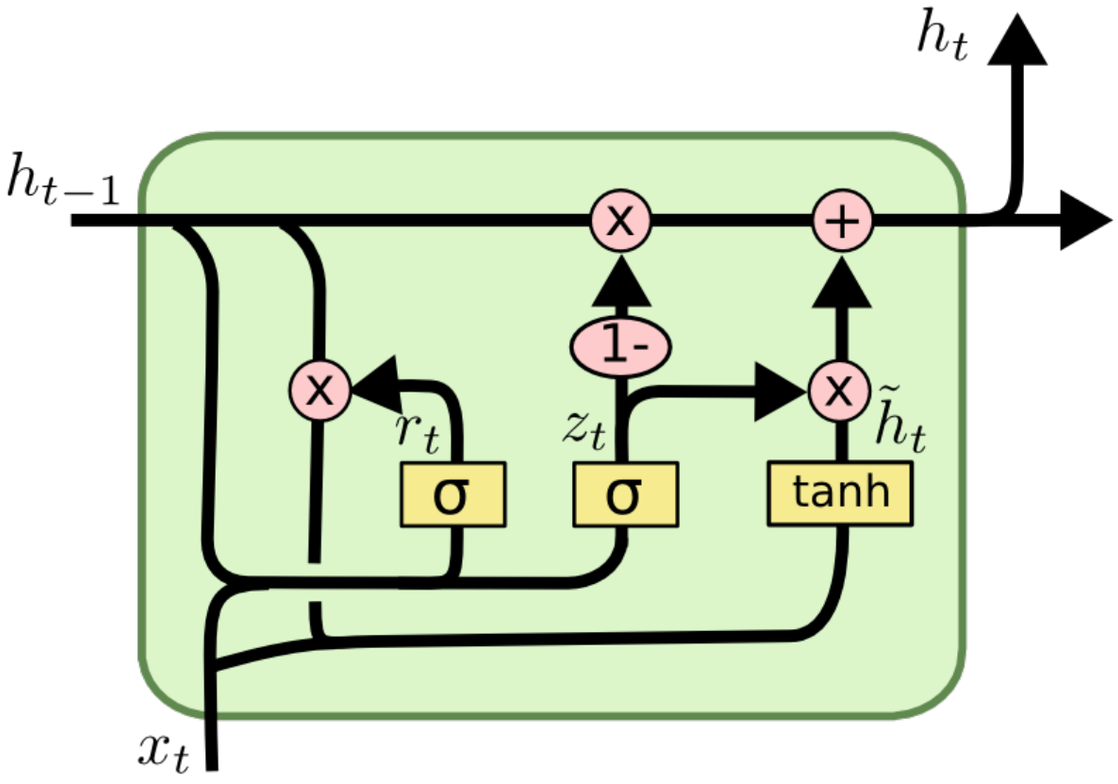
sigmoid



tanh

Zdroj: http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Gated Recurrent Unit



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

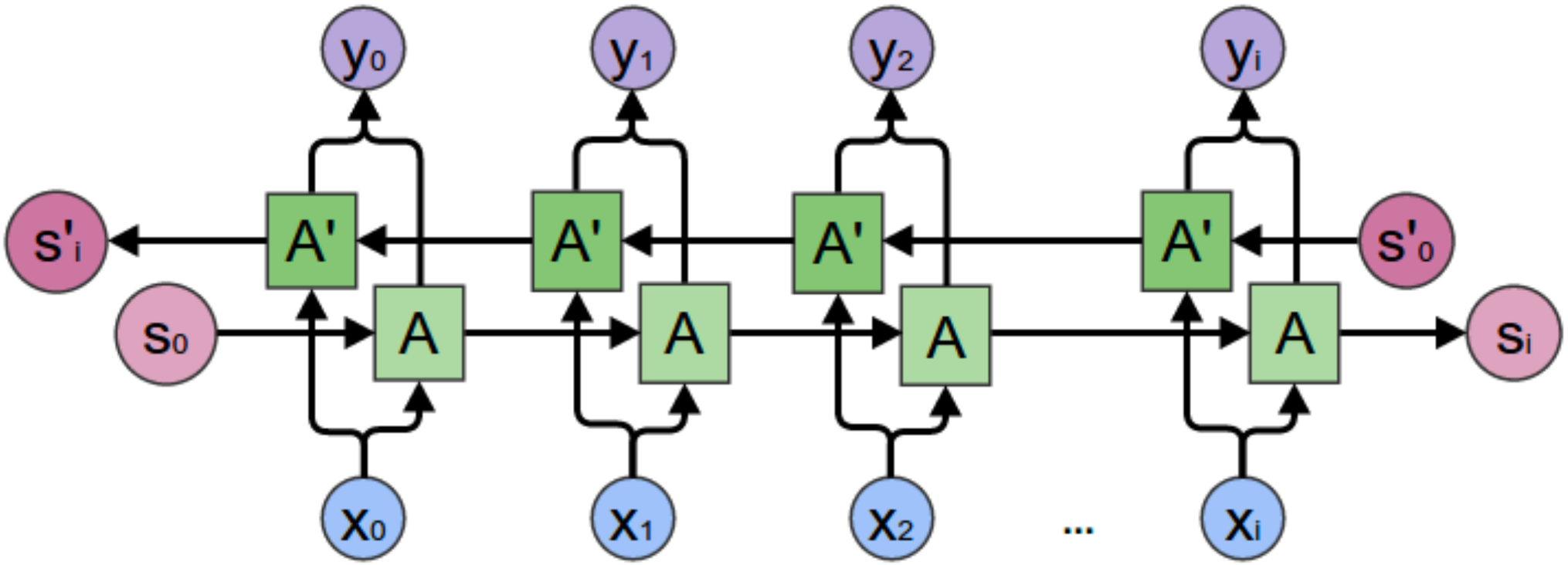
$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

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

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

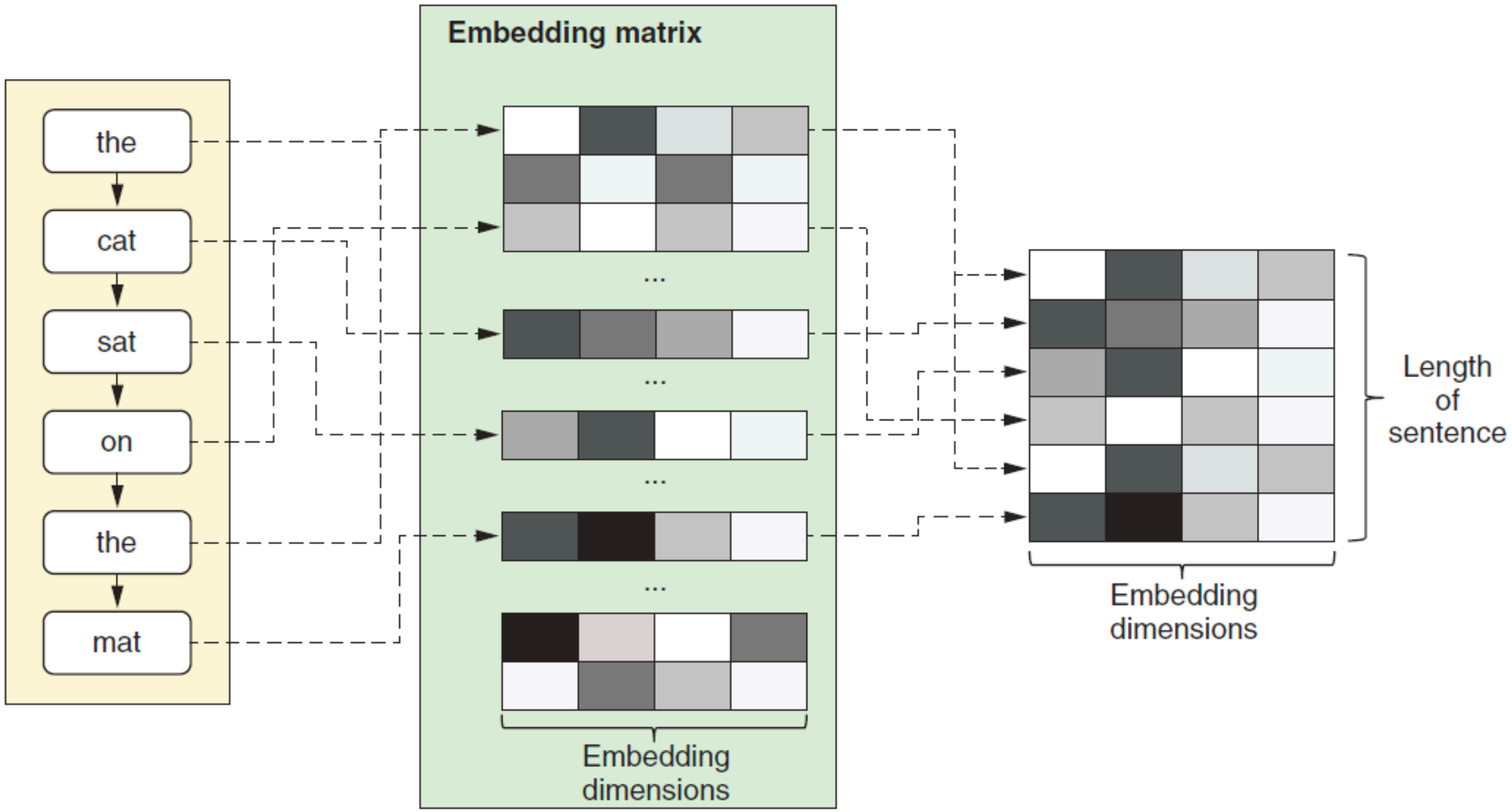
Zdroj: http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Bidirectional recursive layer in Keras



http://colah.github.io/posts/2015-09-NN-Types-FP/

Embedding layer in Keras



https://medium.com/@djajafer/multi-class-text-classification-with-keras-and-lstm-4c5525bef592

Text classification with bidirectional LSTM

06-Review-classification-LSTM.ipynb

Language models for text generating

Ukázka pdf

Ukázka epub

Ukázka mobi

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 pomoci 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?
cítím 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...

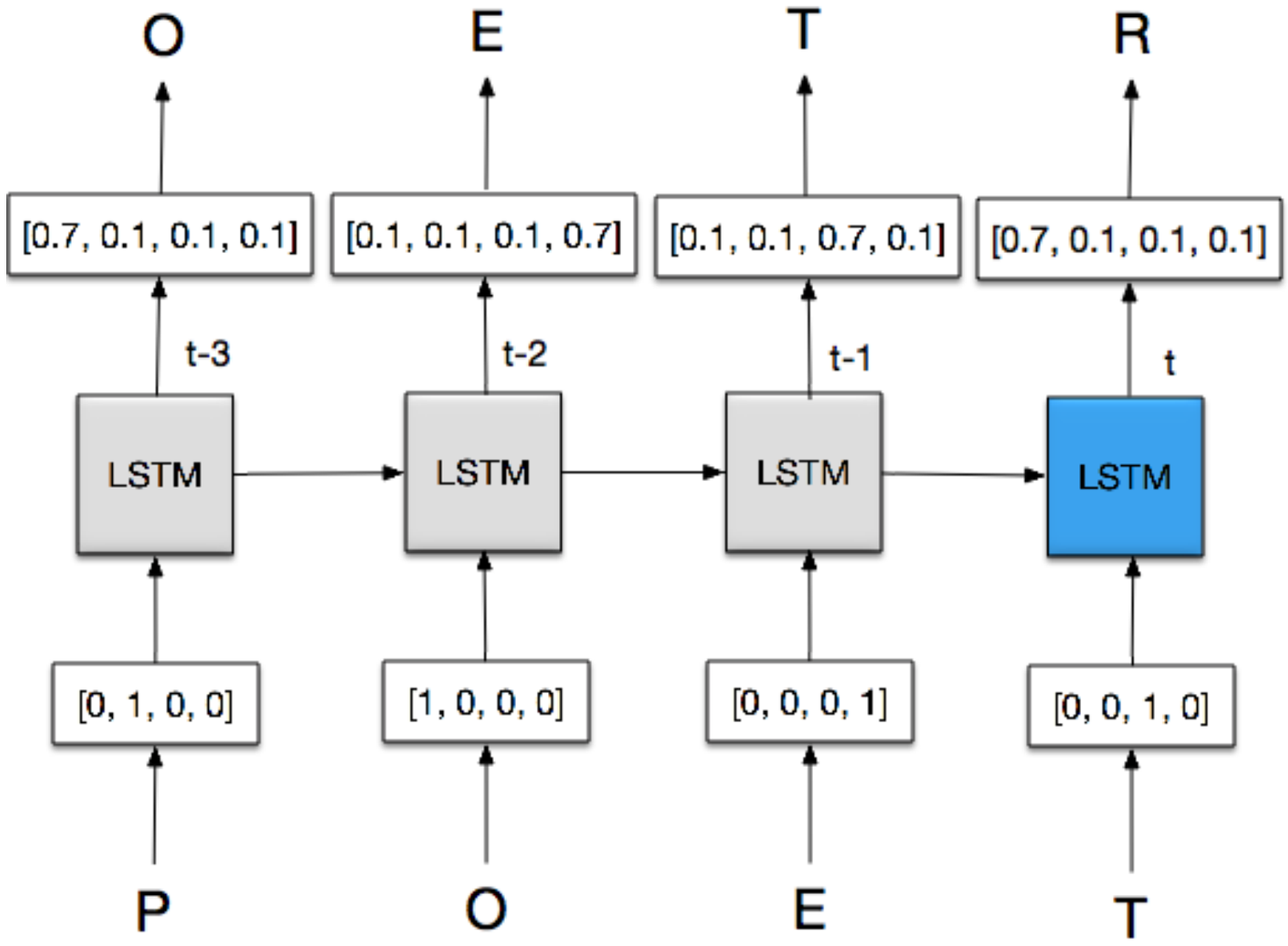
...as rare as leaves of trees...

Language models for text generation

P(college | machine, learning) = 0.5
P(tiger | machine, learning) = 0.3
P(yellow | machine, learning) = 0.2

```
t ~ Uniform(0, 1)
s = 0
for v in Vocabulary:
   s += v.prob
   if t < s:
      return v.word
```

LSTM language model



Title generator

AUTUMN SONG

Memory state

Body generator

why don't you kill yourself?
a phone call isn't hope
this planet is still your home
your time is still going on

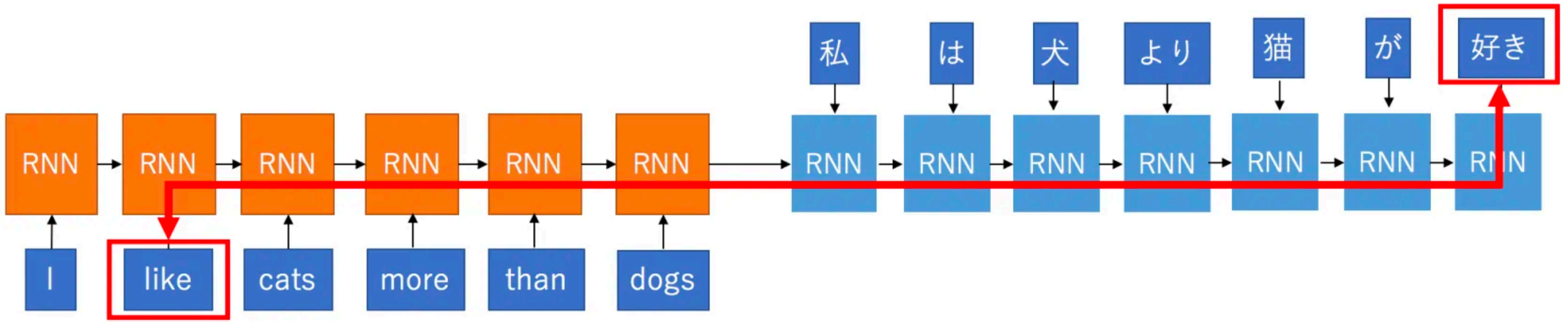
na na na...

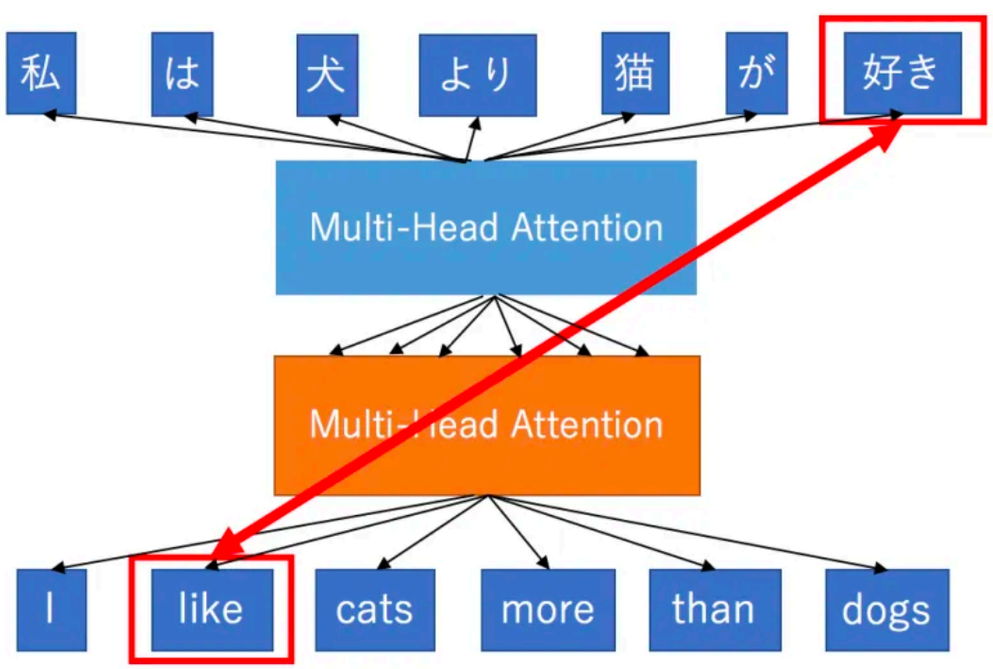
I know, I'm revealing a book of dreams
I'll find out I'm nothing more than this

LSTM review generator

07-Review-generator.ipynb

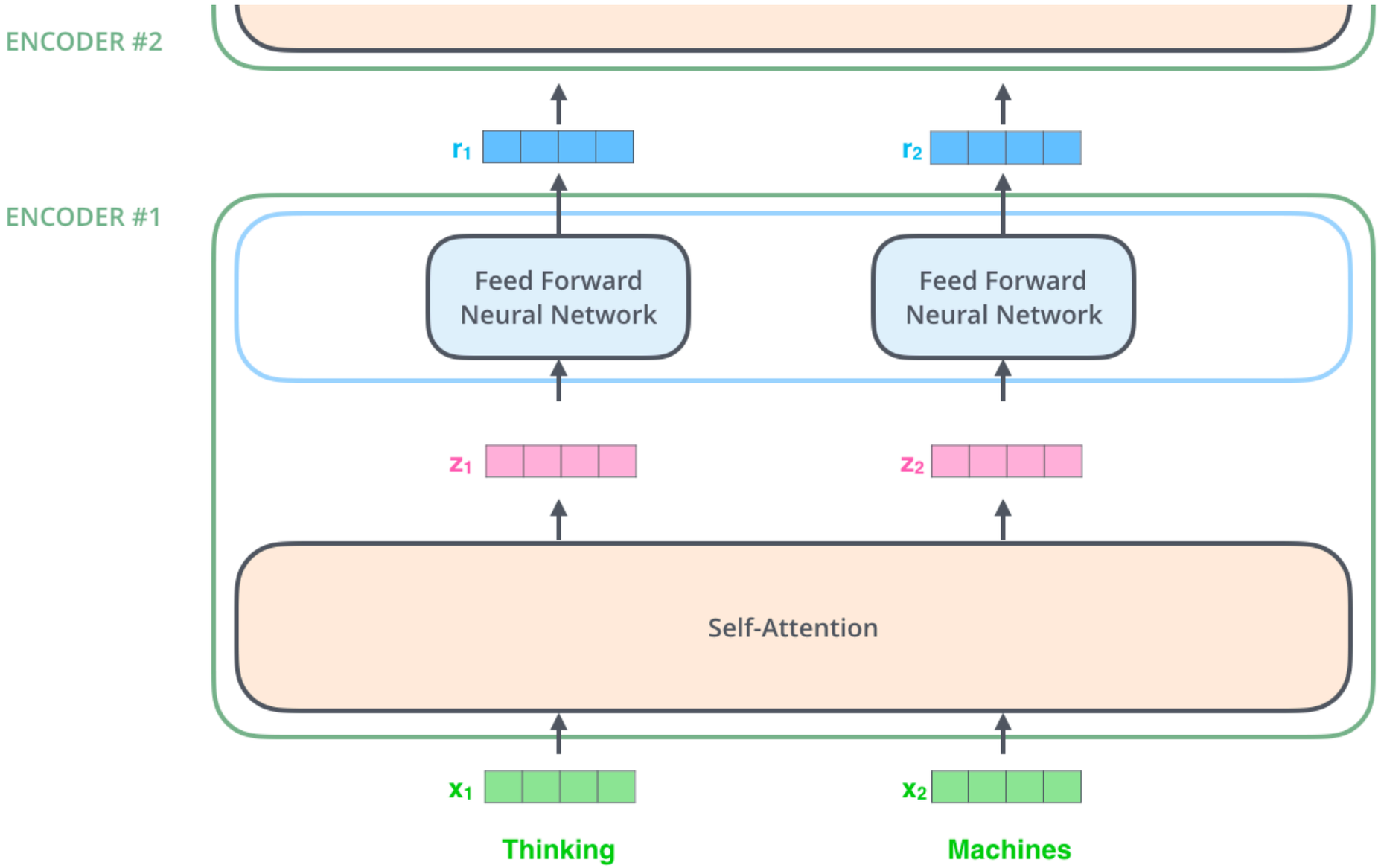
RNN vs. Transformer





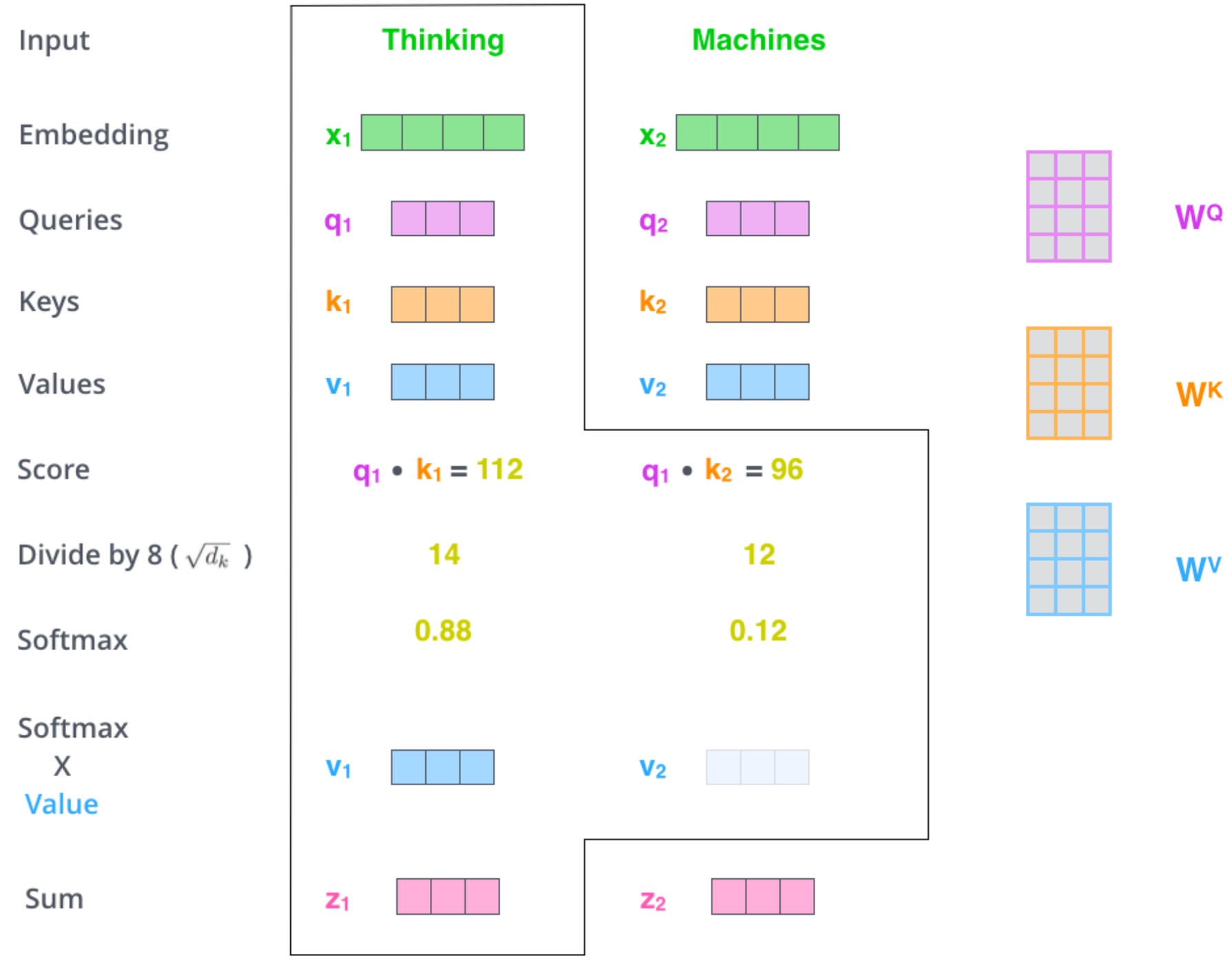
source: www.mlexplained.com

Attention is all you need



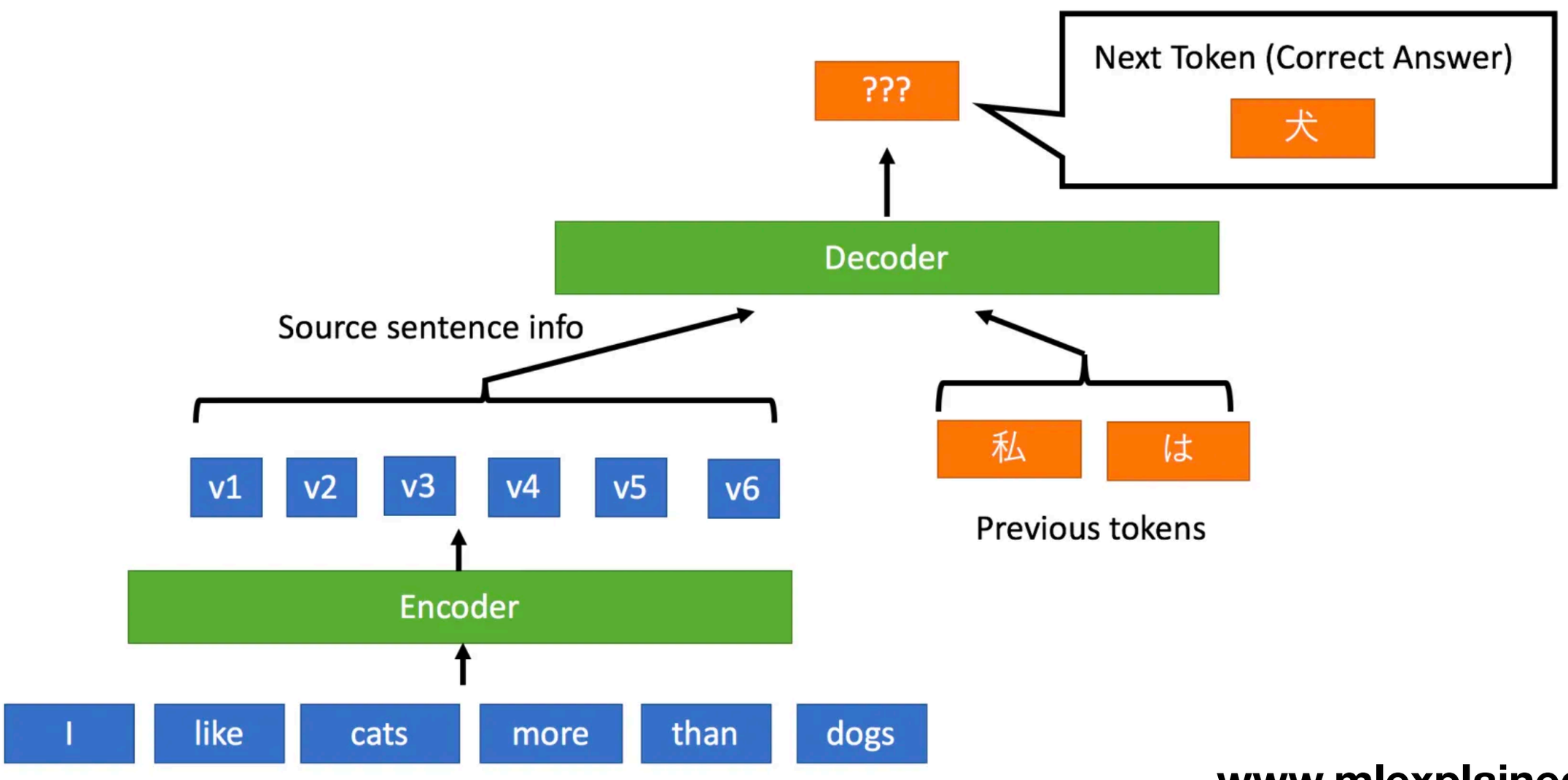
http://jalammar.github.io/illustrated-transformer/

Self-attention



http://jalammar.github.io/illustrated-transformer/

Translation with Transformers



www.mlexplained.com

GPT-2 Language model

Donald Trump told...

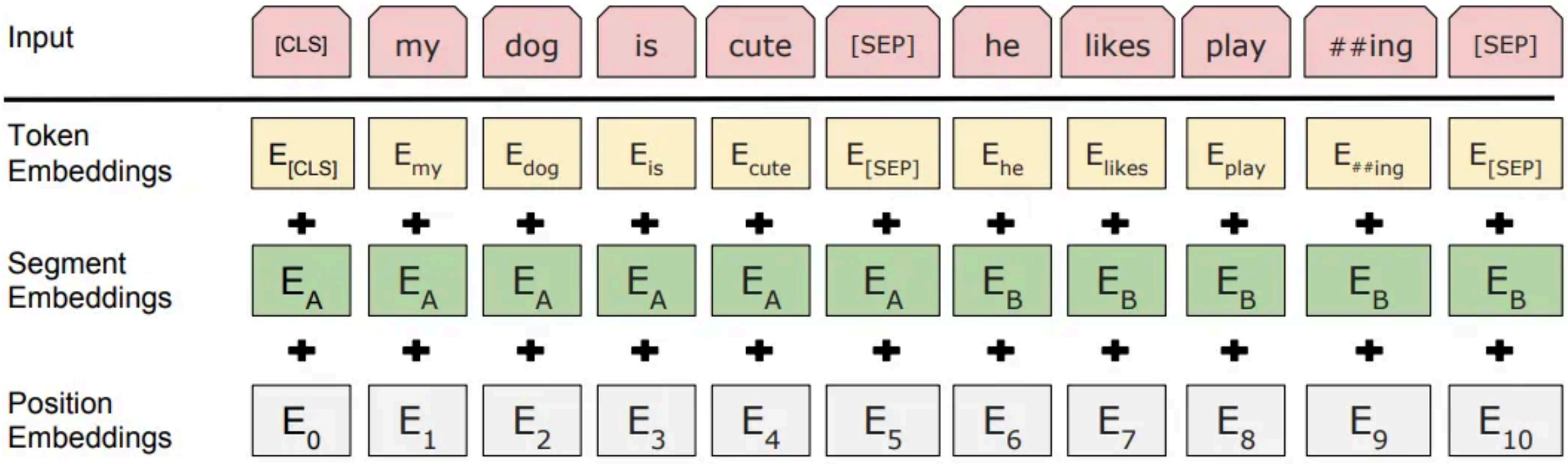
GPT-2 Language model

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.

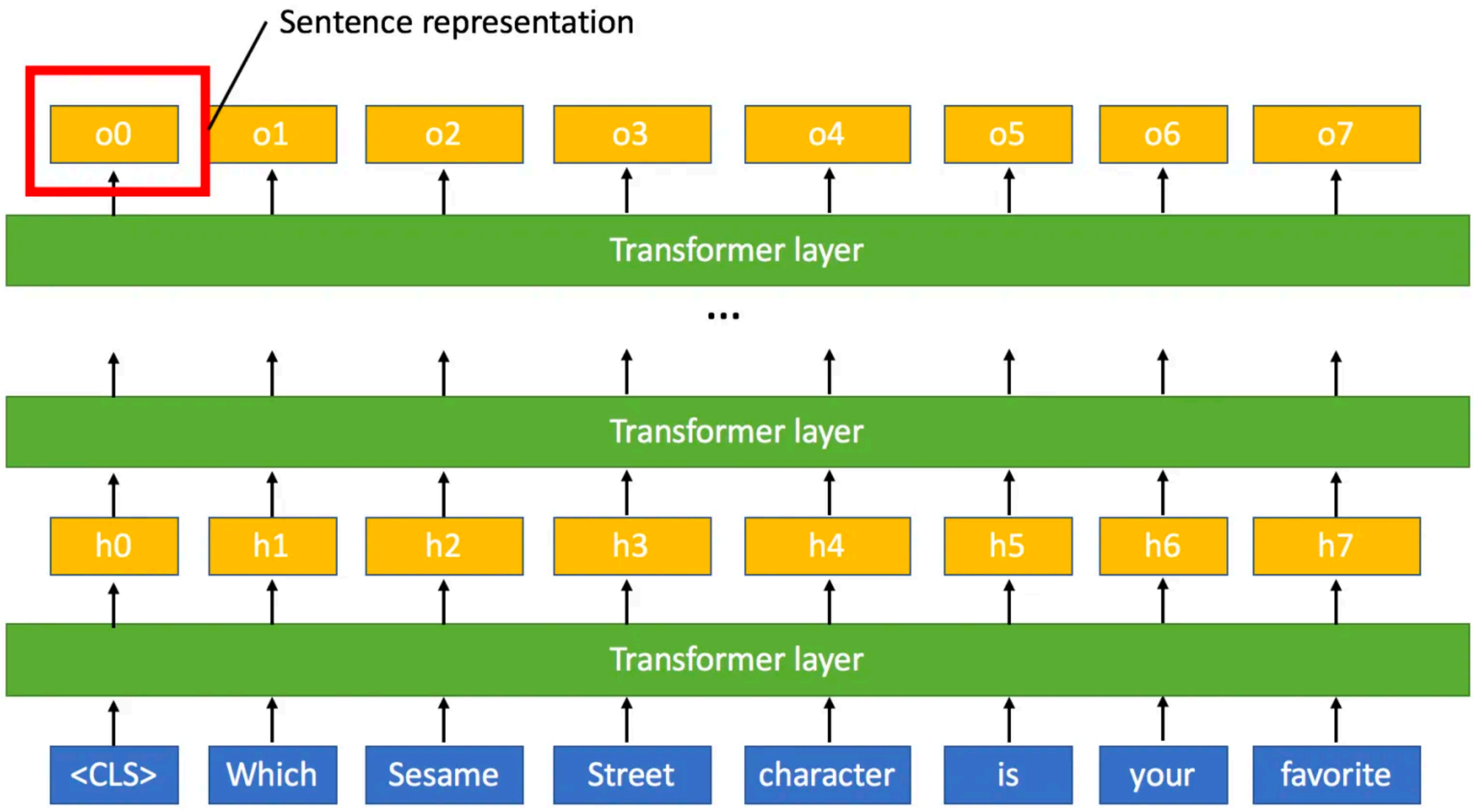
“I’m getting ready for the speech. And I will have a major speech on Tuesday.” Trump said during an interview in the White House residence.

GPT-3: **https://openai.com/blog/openai-api/**

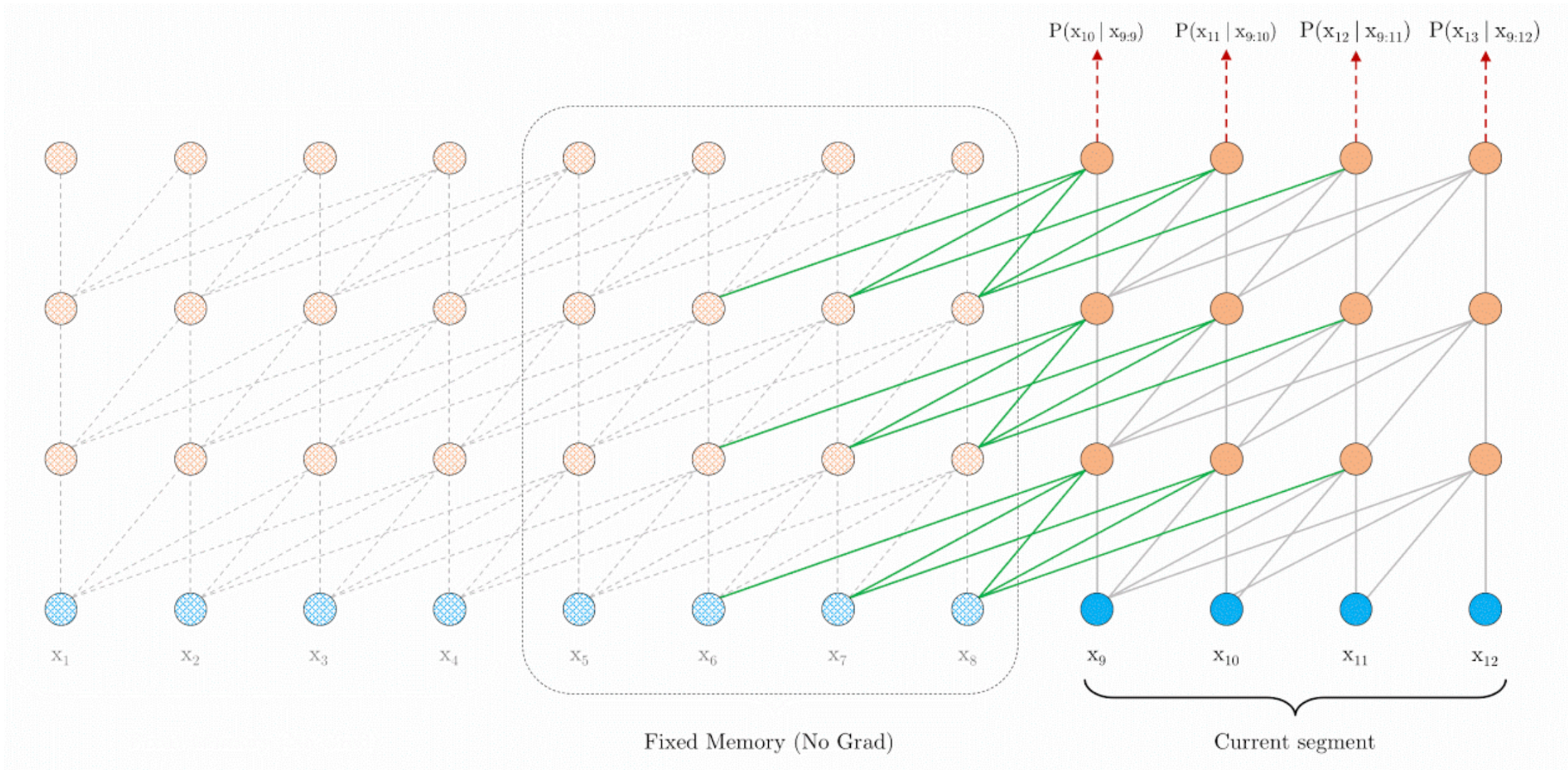
BERT
(input encoding)



BERT
(classification)

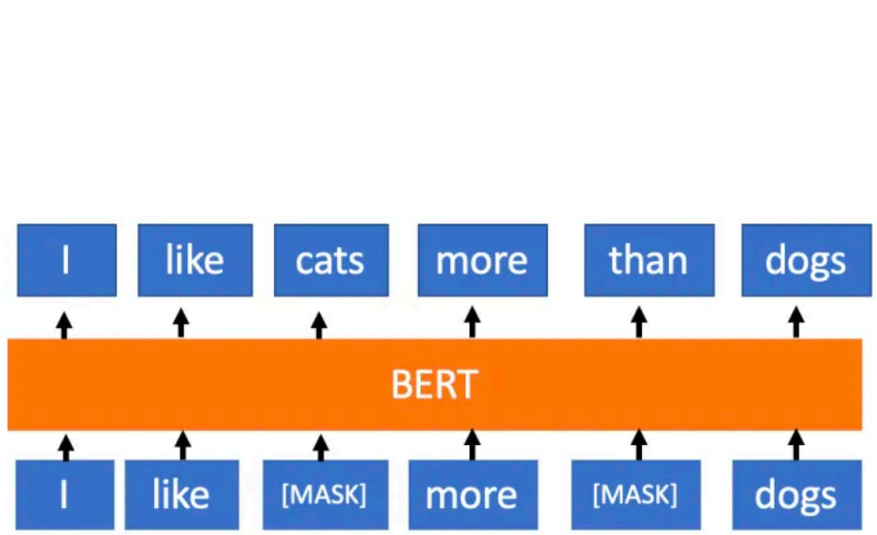


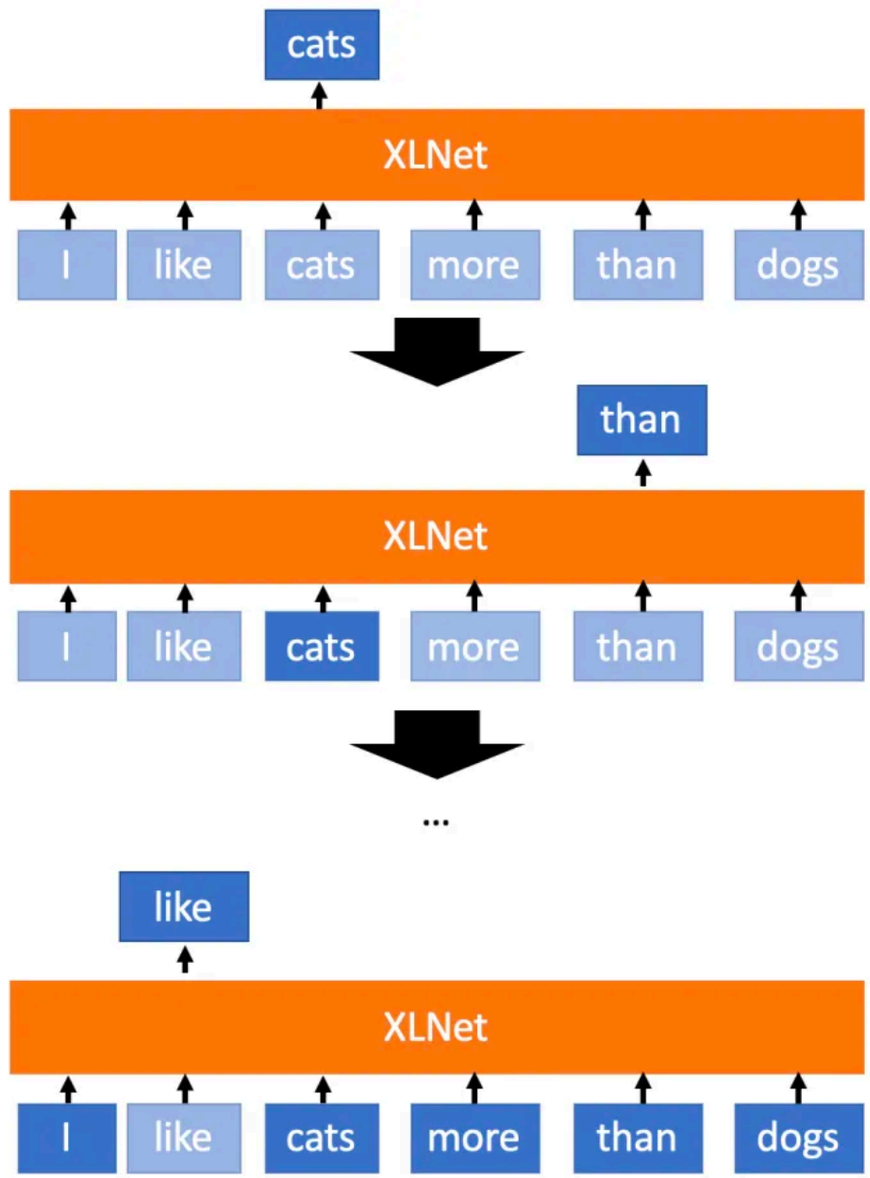
Transformer XL



source: ai.googleblog.com

XLNet
(permutation language model)





Text classification using BERT

08-Review-classification-BERT.ipynb

Outline

Day 4

- Topic modeling
- Basics of the Probability theory
- Probabilistic Graphical Models
- Inference in Bayesian Networks
- Gaussian Linear Regression
- Gaussian Mixtures for clustering
- (Probabilistic) Latent Semantic Analysis
- Latent Dirichlet Allocation

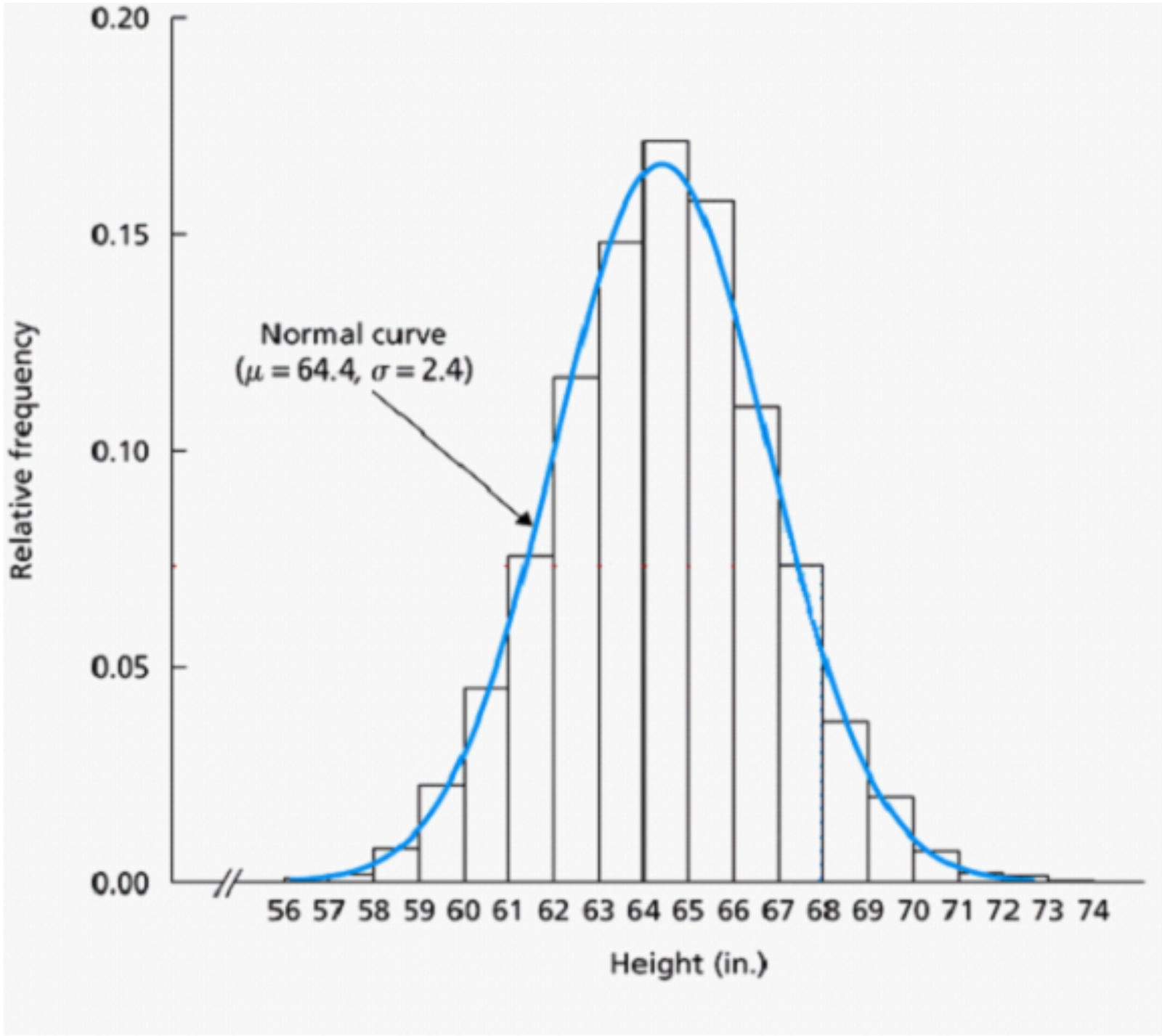
Conditional probability and independence

$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{P(A)P(B|A)}{P(B)}$$

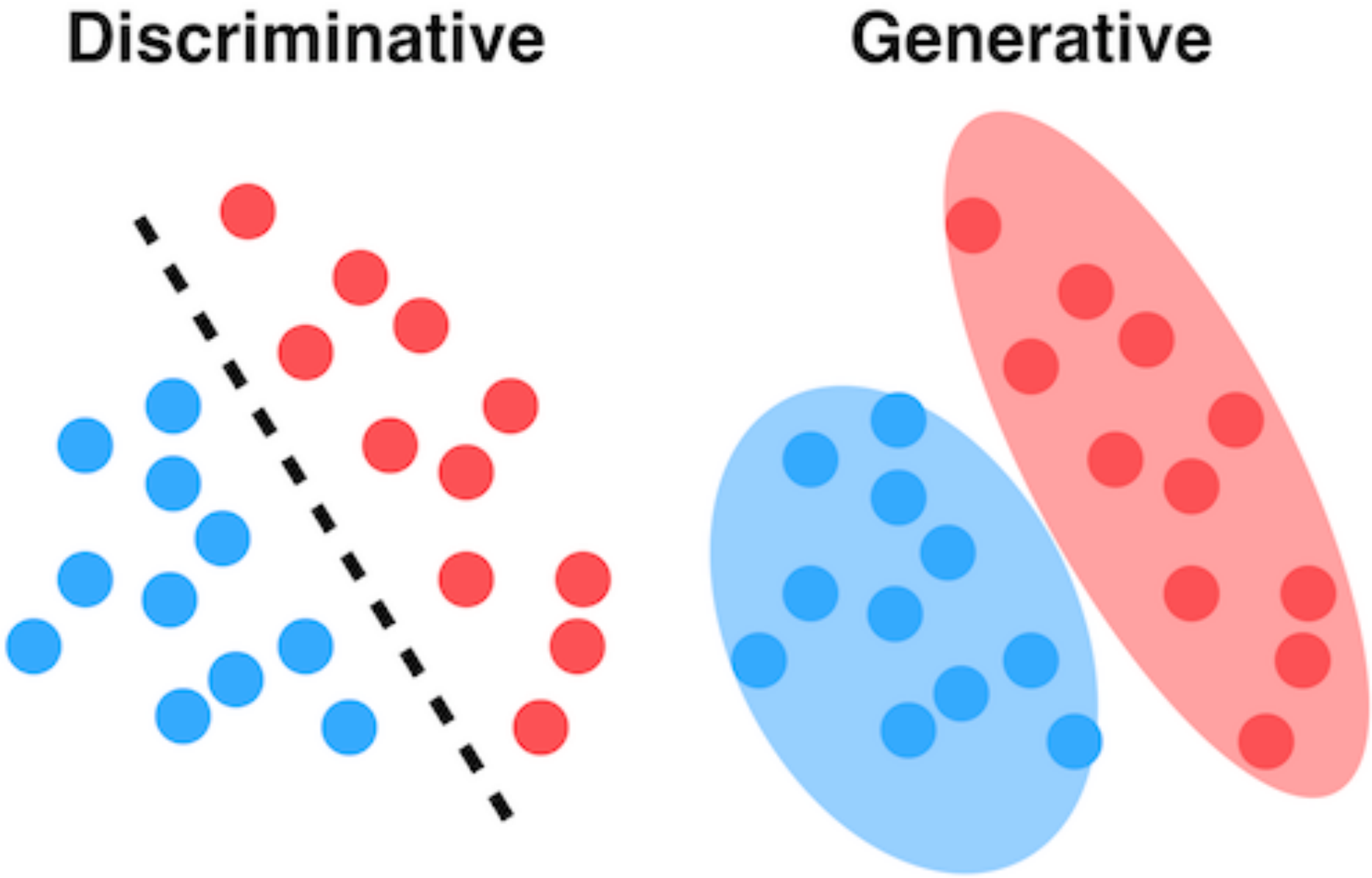
$$A \perp B \iff P(A \cap B) = P(A)P(B)$$

Probability distribution

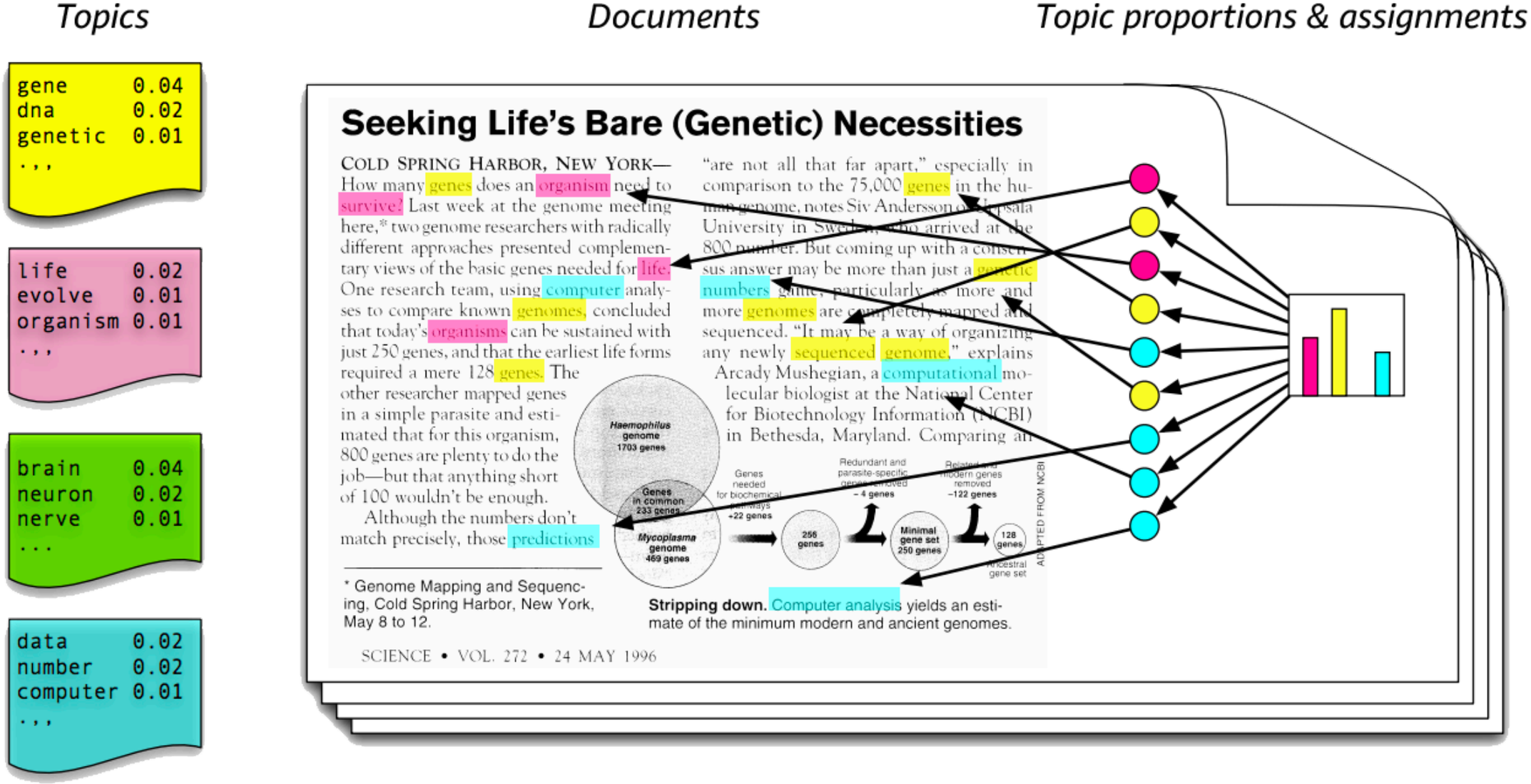
$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$



Discriminative vs. generative models



Topic Modeling



https://kldavenport.com/topic-modeling-amazon-reviews/

Generative model of people's heights

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

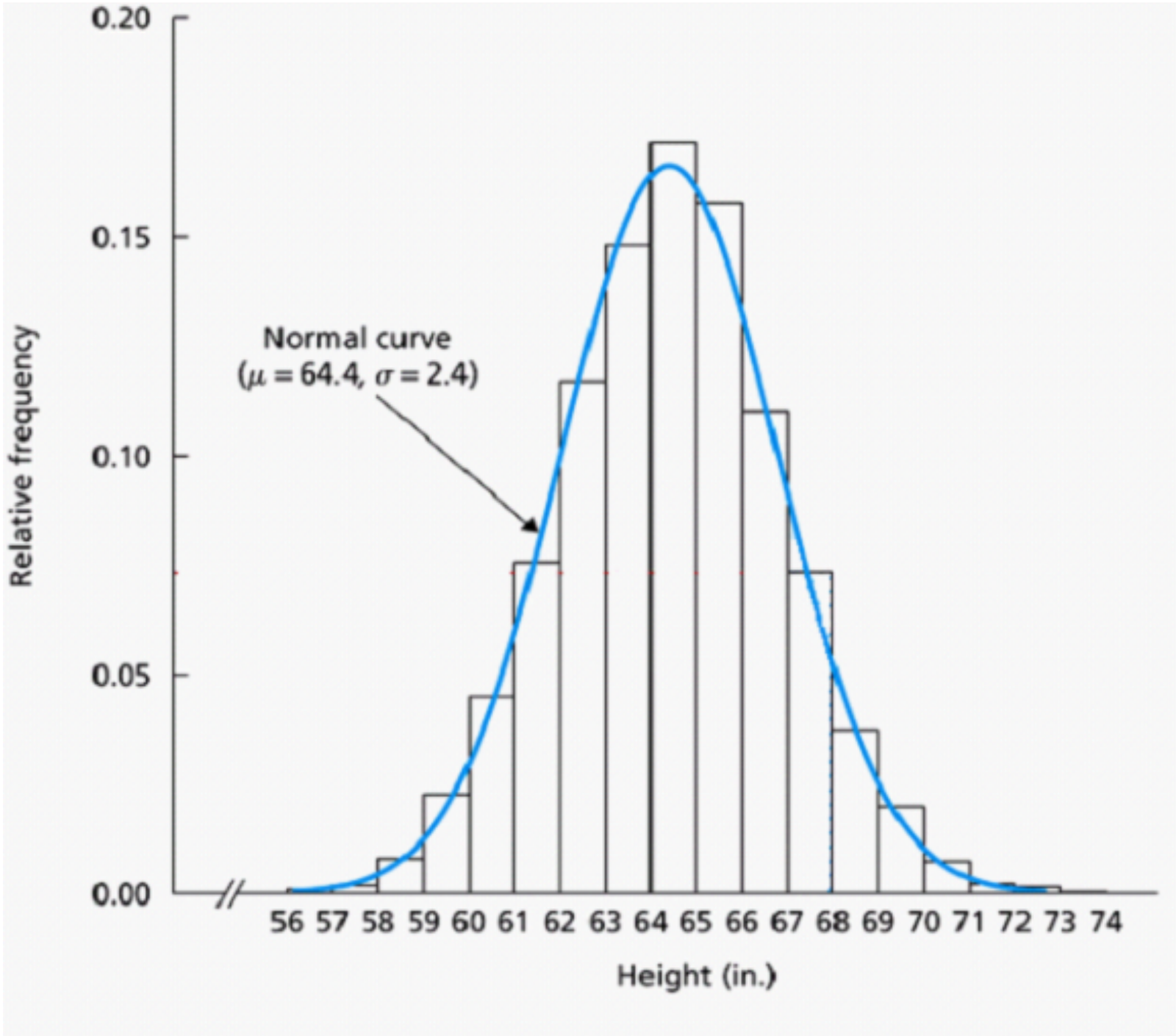
$X = \{x_1, x_2 \ldots x_n\}$

$X \sim N(\mu, \sigma^2), \alpha = (\mu, \sigma^2)$

$\bar{\alpha} = \arg\max_{\alpha} P(\alpha|X)$

$$P(\alpha|X) = \frac{P(X|\alpha).P(\alpha)}{P(X)}$$

posterior
likelihood
prior

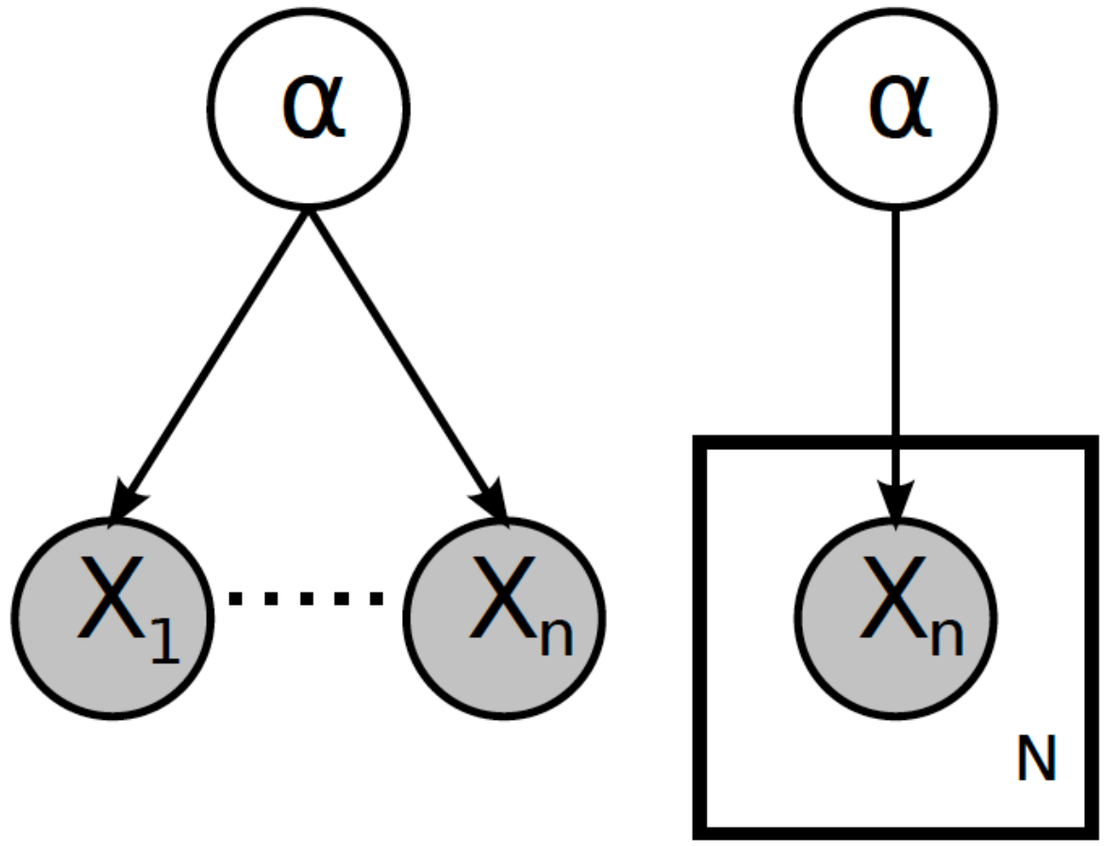


Probabilistic graphical models

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

$$X = \{x_1, x_2 \ldots x_n\}$$

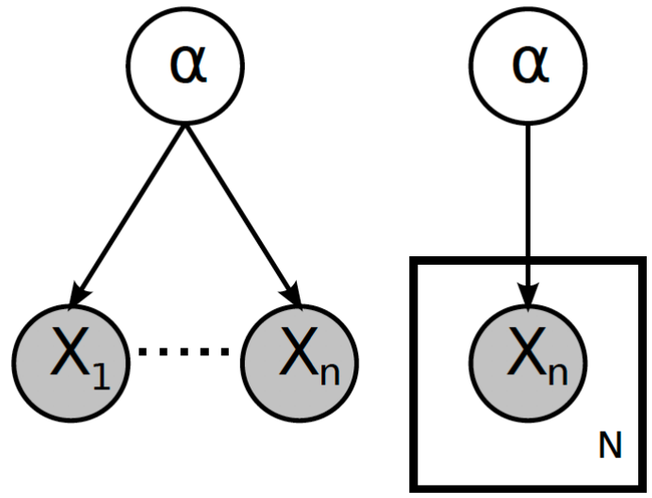
$$X \sim N(\mu, \sigma^2),\ \alpha = (\mu, \sigma^2)$$



Inference in graphical models

$$P(\alpha|X) = \frac{P(X|\alpha).P(\alpha)}{P(X)} \propto P(X|\alpha).P(\alpha) = \prod_{i=1}^{n} P(x_i|\alpha).P(\alpha)$$

$$\bar{\alpha} = \arg\max_{\alpha} P(\alpha|X)$$



Variational inference

1. Approximate the posterior function with a simpler one
2. Compute the hidden variables by minimization of KL Divergence of the true and simpler distributions

Sampling (e.g. Gibbs sampling)

1. Draw samples from the true posterior
2. Compute mean of the samples

Generative model for linear regression

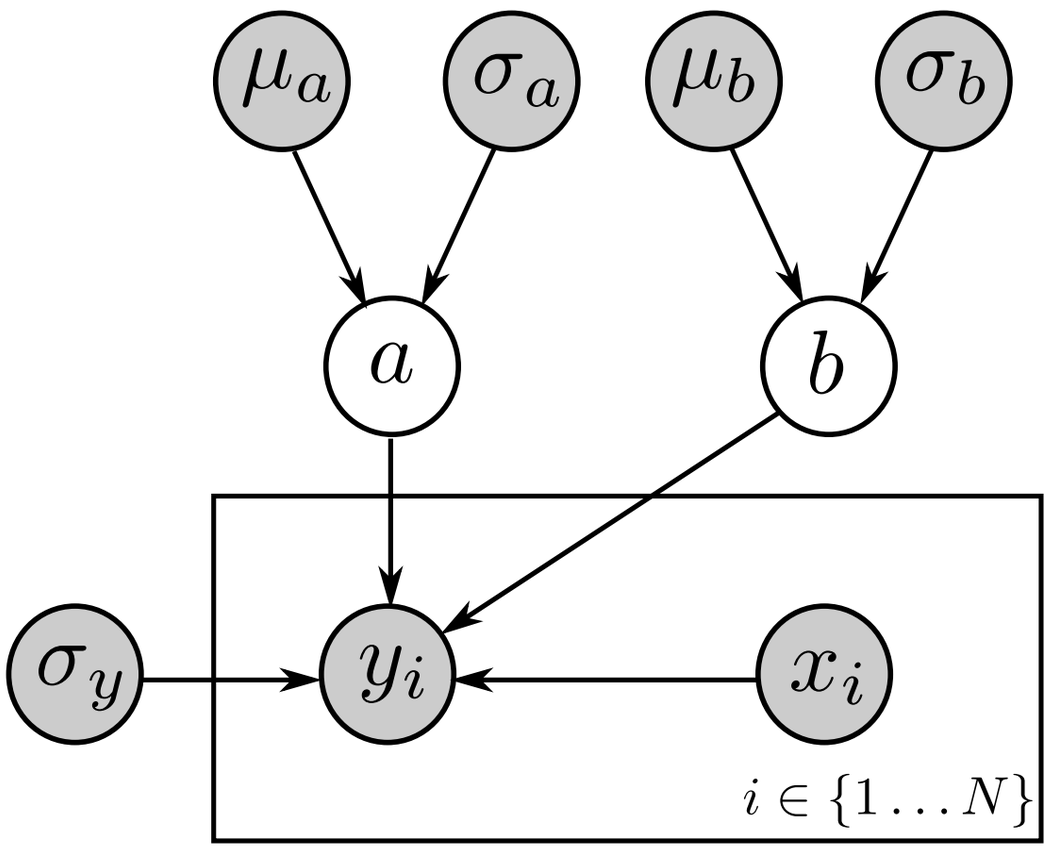
$$\boldsymbol{x} = \{x_1, x_2, \ldots, x_N\}$$

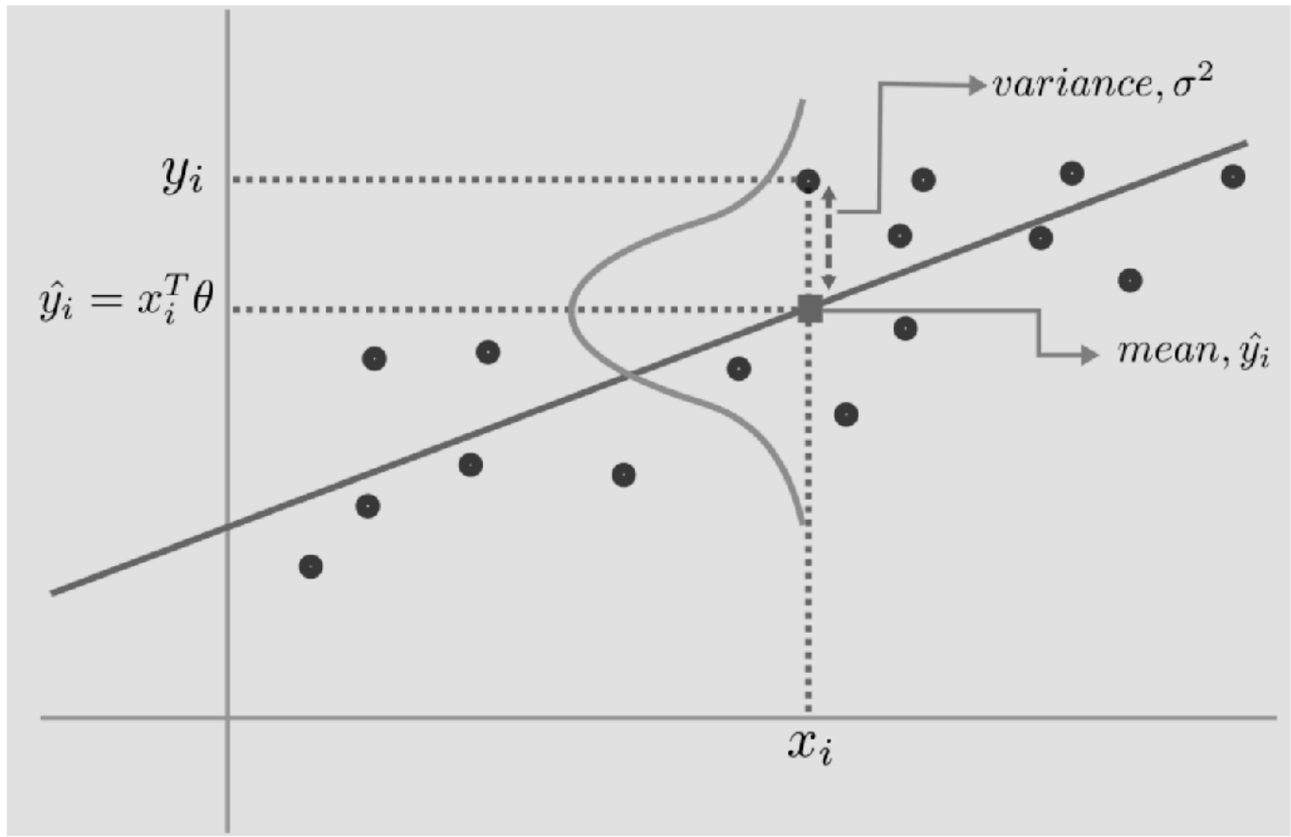
$$f(\boldsymbol{x}) = a\boldsymbol{x} + b$$

$$\boldsymbol{y} \sim \mathcal{N}(a\boldsymbol{x} + b, \sigma_y)$$

$$a \sim \mathcal{N}(\mu_a, \sigma_a)$$

$$b \sim \mathcal{N}(\mu_b, \sigma_b)$$



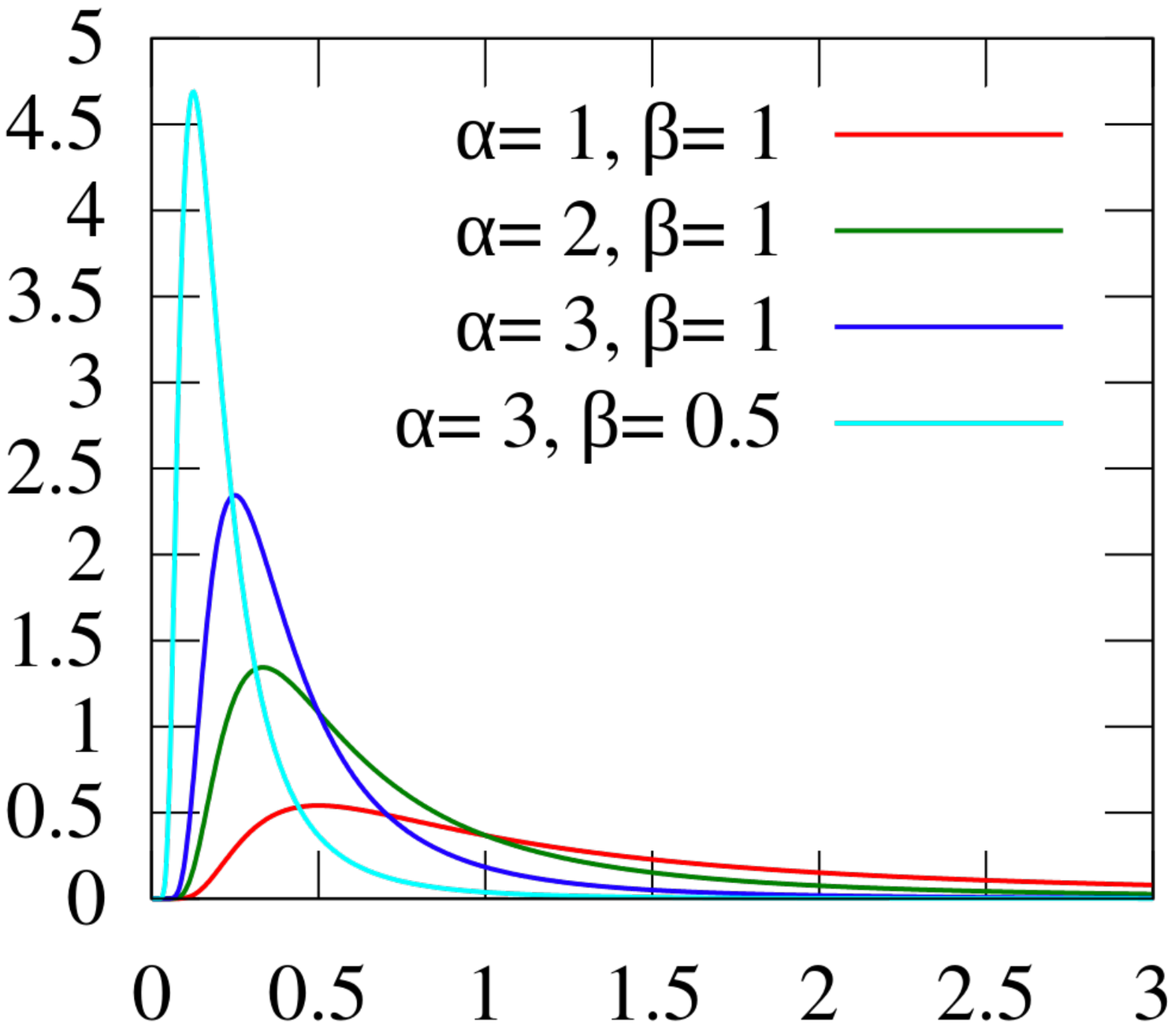


https://ethen8181.github.io/machine-learning/model_selection/collinearity.html

Generative model for linear regression in Edward

09-Generative-linear-regression-edward.ipynb

Inverse-gamma Distribution

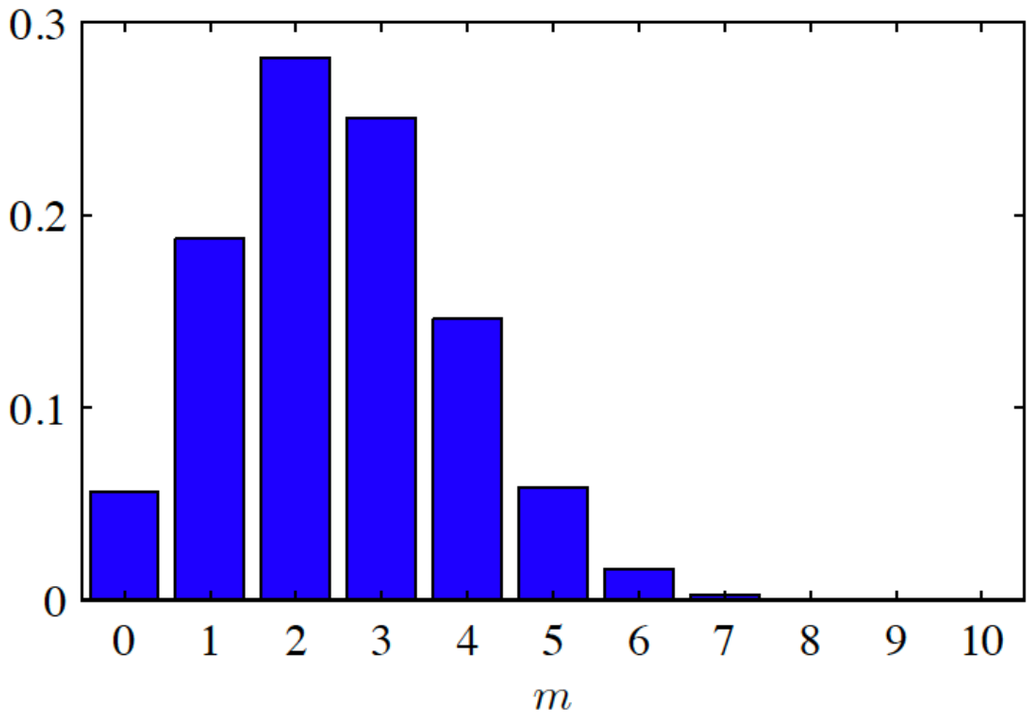


Binomial distribution

$$\mathrm{Bin}(k|n,p) = \binom{n}{k} p^k.(1-p)^{n-k} =$$

$$\mathrm{Bin}(x_1,x_2|p_1,p_2) = \frac{(x_1+x_2)!}{x_1!x_2!} p_1^{x_1}.p_2^{x_2}$$

$$p_1 + p_2 = 1$$



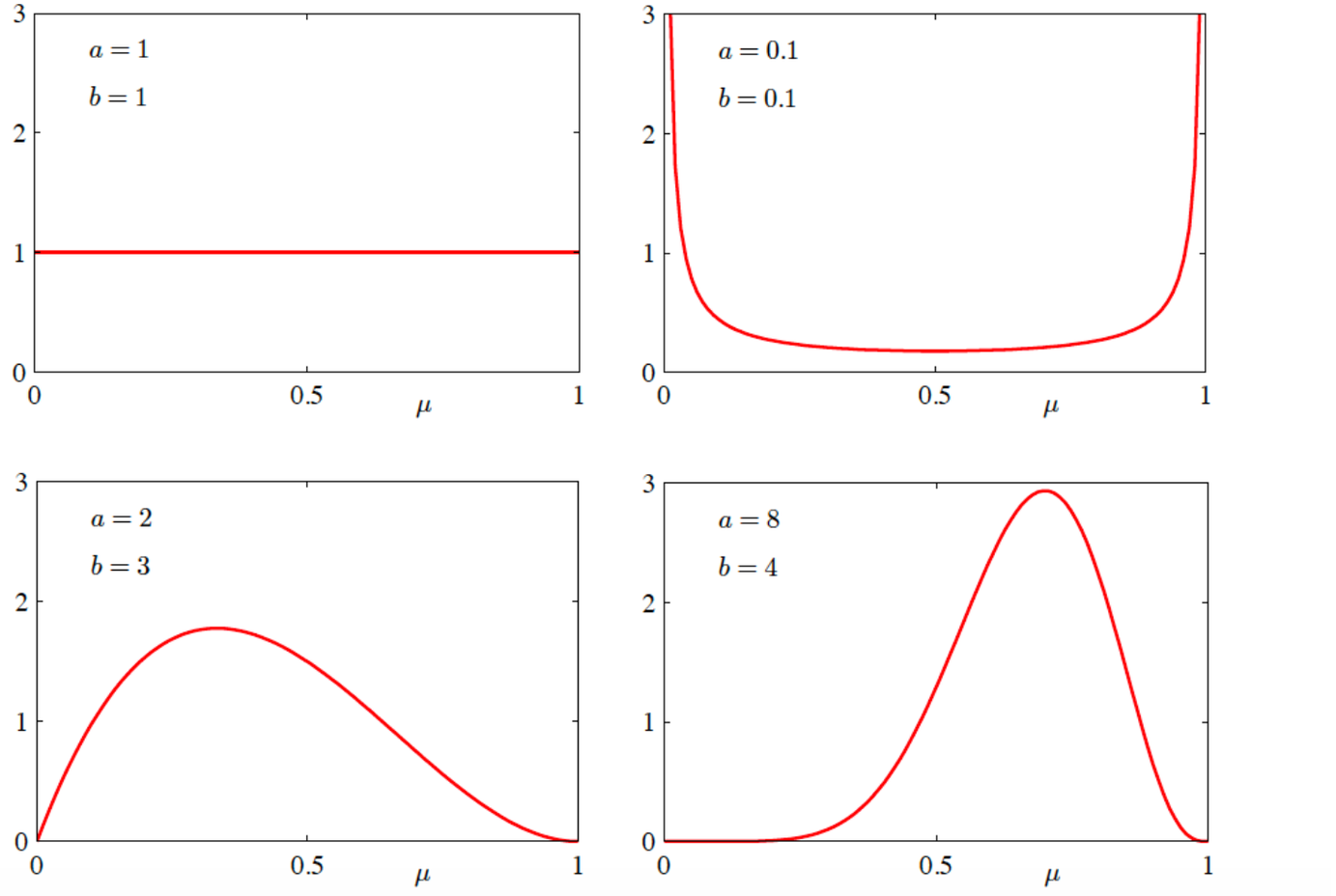
Example: $n = 10, p = 0.25$

Beta distribution

$$\text{Beta}(p_1, p_2|\alpha, \beta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} p_1^{\alpha-1}.p_2^{\beta-1}$$

$$p_1 + p_2 = 1$$

$$\Gamma(x) = (x-1)!$$



Multinomial and Dirichlet distributions

Multinomial

$$\text{Mult}(x_1 \dots x_n | p_1 \dots p_n) = \frac{(\sum x_i)!}{\prod x_i!} \prod_{i=1}^{n} p_i^{x_i}$$

Dirichlet

$$\text{Dir}(p_1 \dots p_n | \alpha_1 \dots \alpha_n) = \frac{\Gamma(\sum \alpha_i)}{\prod \Gamma(\alpha_i)} \prod_{i=1}^{n} p_i^{\alpha_i - 1}$$

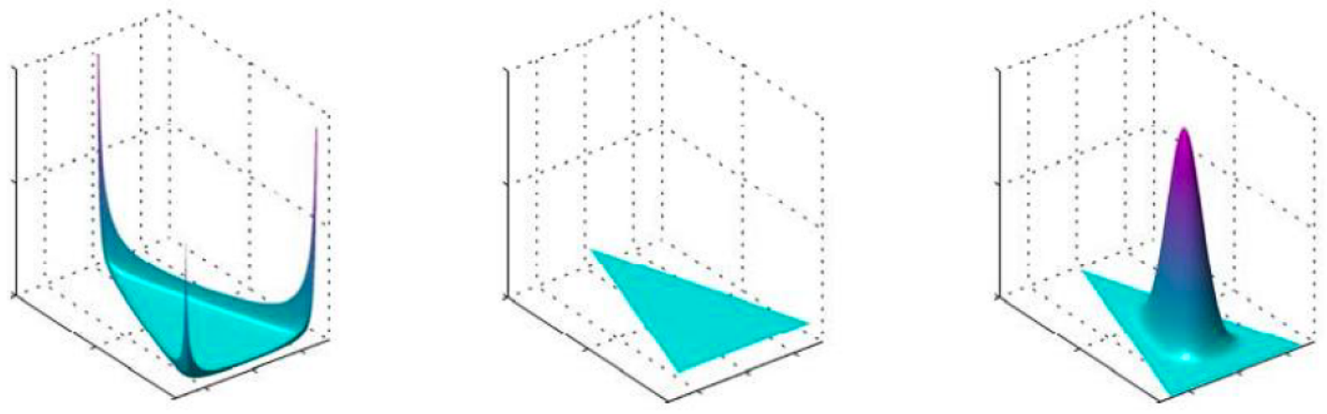
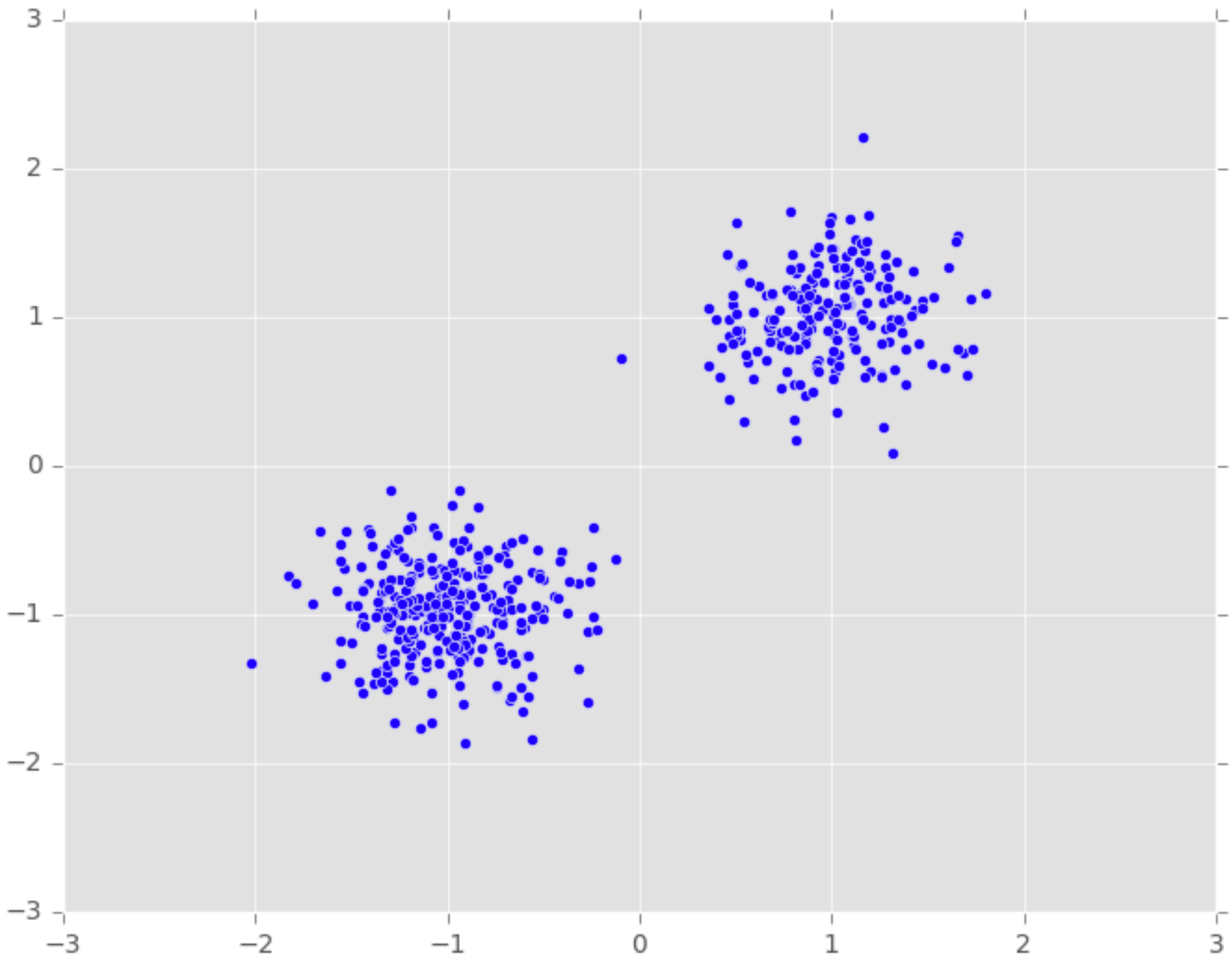


Figure 2.5 Plots of the Dirichlet distribution over three variables, where the two horizontal axes are coordinates in the plane of the simplex and the vertical axis corresponds to the value of the density. Here $\{\alpha_k\} = 0.1$ on the left plot, $\{\alpha_k\} = 1$ in the centre plot, and $\{\alpha_k\} = 10$ in the right plot.

Clustering as gaussian mixtures



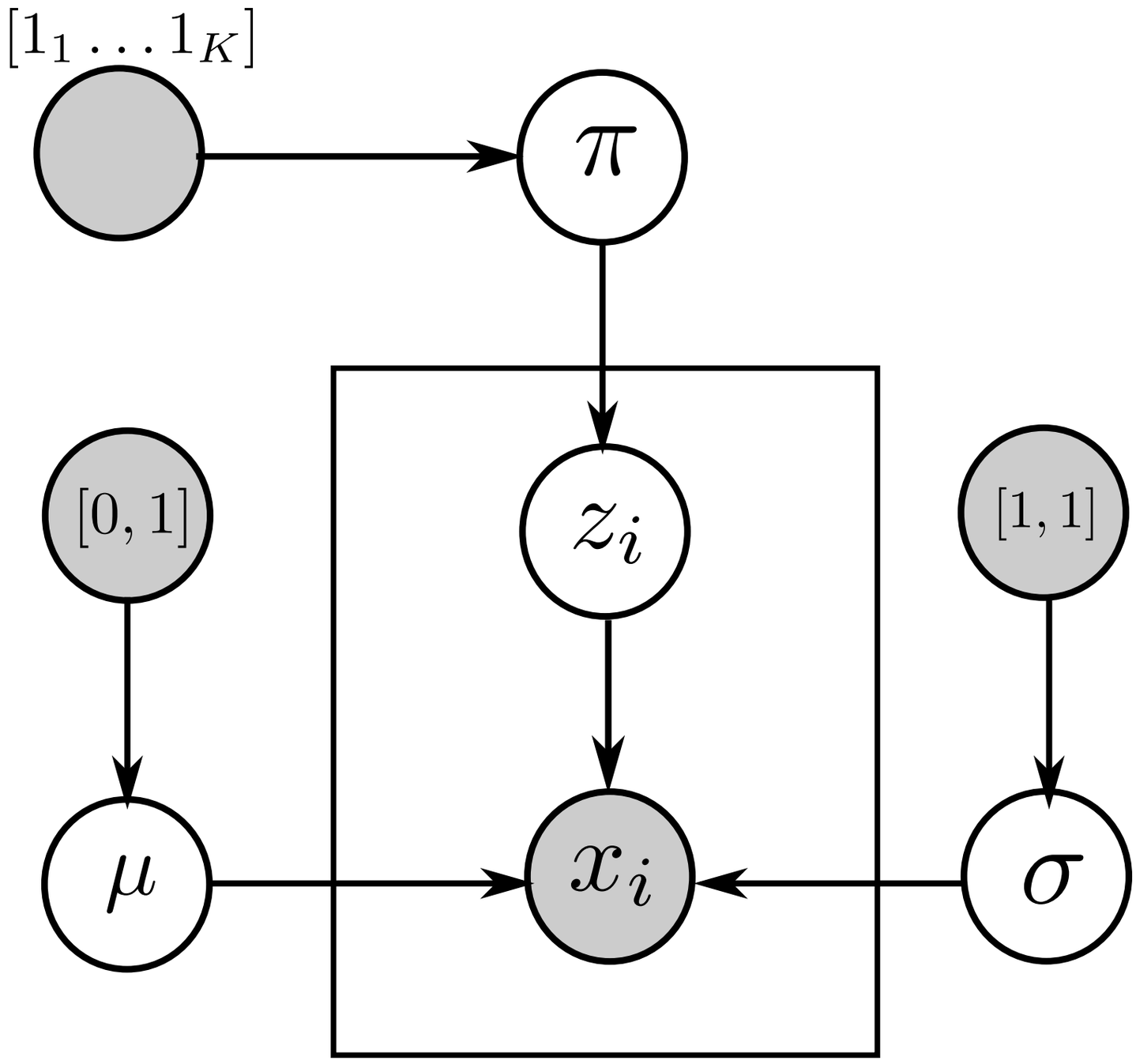
Clustering as gaussian mixtures

$$\mathbf{x} \sim \sum_{k=1}^{K} \pi_k \mathcal{N}(\mu_k, \sigma_k) \qquad \sum_{k=1}^{K} \pi_k = 1$$

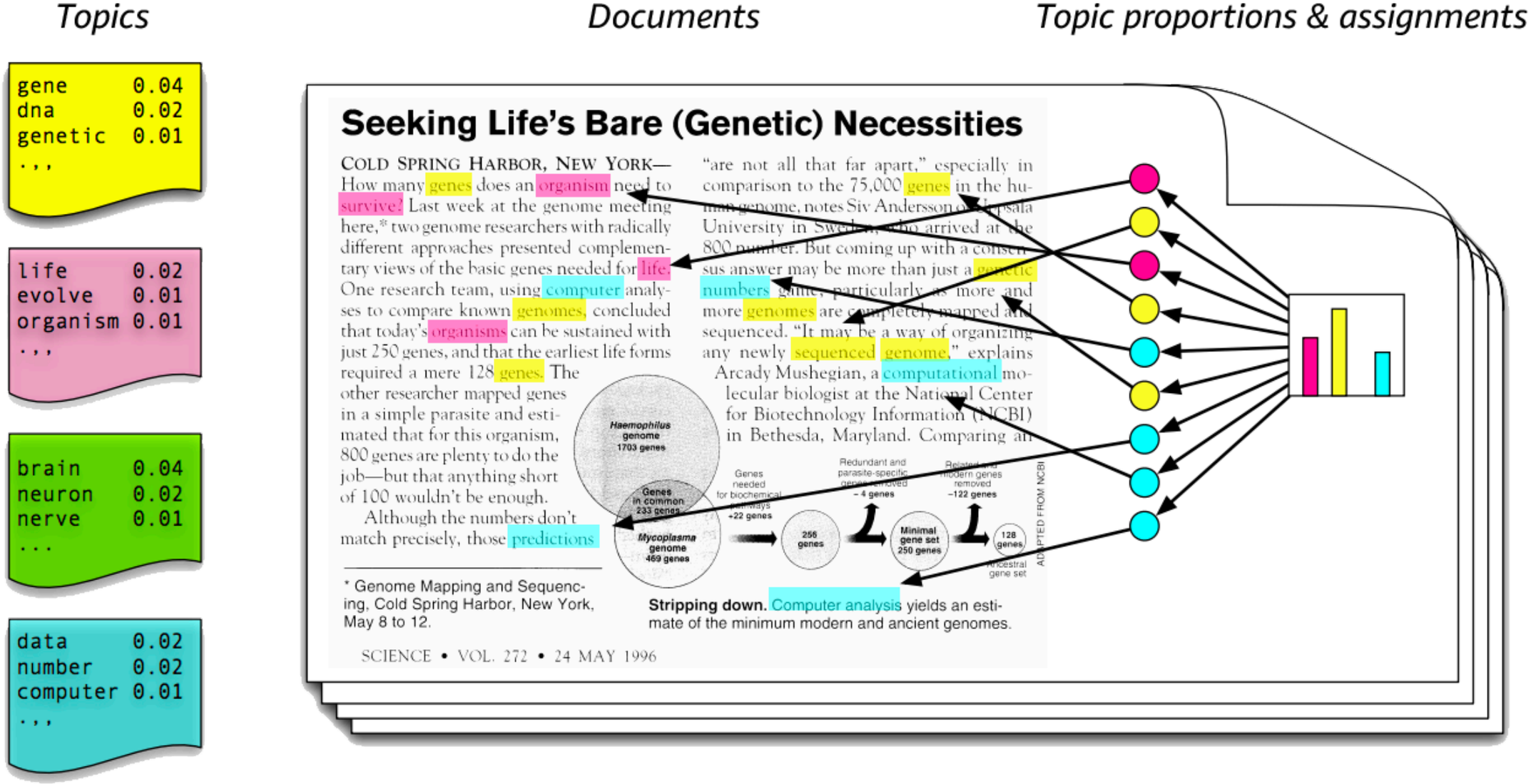
$$\pi \sim \text{Dirichlet}(1_1 \dots 1_K)$$

$$\mu_k \sim \mathcal{N}(0, 1)$$

$$\sigma_k^2 \sim \text{InverseGamma}(1, 1)$$



Topic Modeling



https://kldavenport.com/topic-modeling-amazon-reviews/

Gibbs sampling

1. Initialize $z_i : i \in 1, \ldots, M$
2. For $\tau \in 1, \ldots, T$:
   - Sample $z_1^{(\tau+1)} \sim \mathrm{P}(z_1 | z_2^{(\tau)}, z_3^{(\tau)}, \ldots, z_M^{(\tau)})$
   - Sample $z_2^{(\tau+1)} \sim \mathrm{P}(z_2 | z_1^{(\tau+1)}, z_3^{(\tau)}, \ldots, z_M^{(\tau)})$
   - Sample $z_3^{(\tau+1)} \sim \mathrm{P}(z_3 | z_1^{(\tau+1)}, z_2^{(\tau+1)}, \ldots, z_M^{(\tau)})$

     $\ldots$

   - Sample $z_M^{(\tau+1)} \sim \mathrm{P}(z_M | z_1^{(\tau+1)}, z_2^{(\tau+1)}, \ldots, z_{M-1}^{(\tau+1)})$

Clustering as gaussian mixtures

10-clustering-edward.ipynb

Latent Semantic Analysis

Topic modeling using LSA example:

soccer = 1.8*‘soccer’ + 0.4*‘ball’ + 0.2*‘FIFA’ - 0.4*‘tennis’

doc = *2.3*soccer + 1.8*sport + 0.9*Europe + 0.8*news*

Latent Semantic Analysis

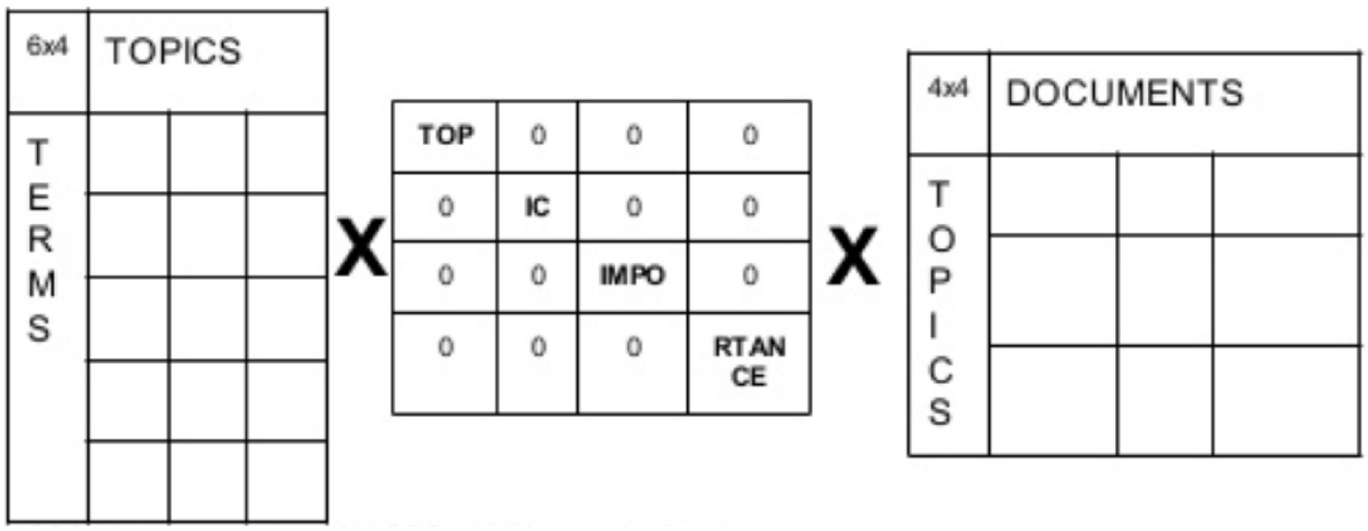
Doc$_1$: *Machine learning helps people to understand data.*

Doc$_2$: *Data can be understood using machine learning.*

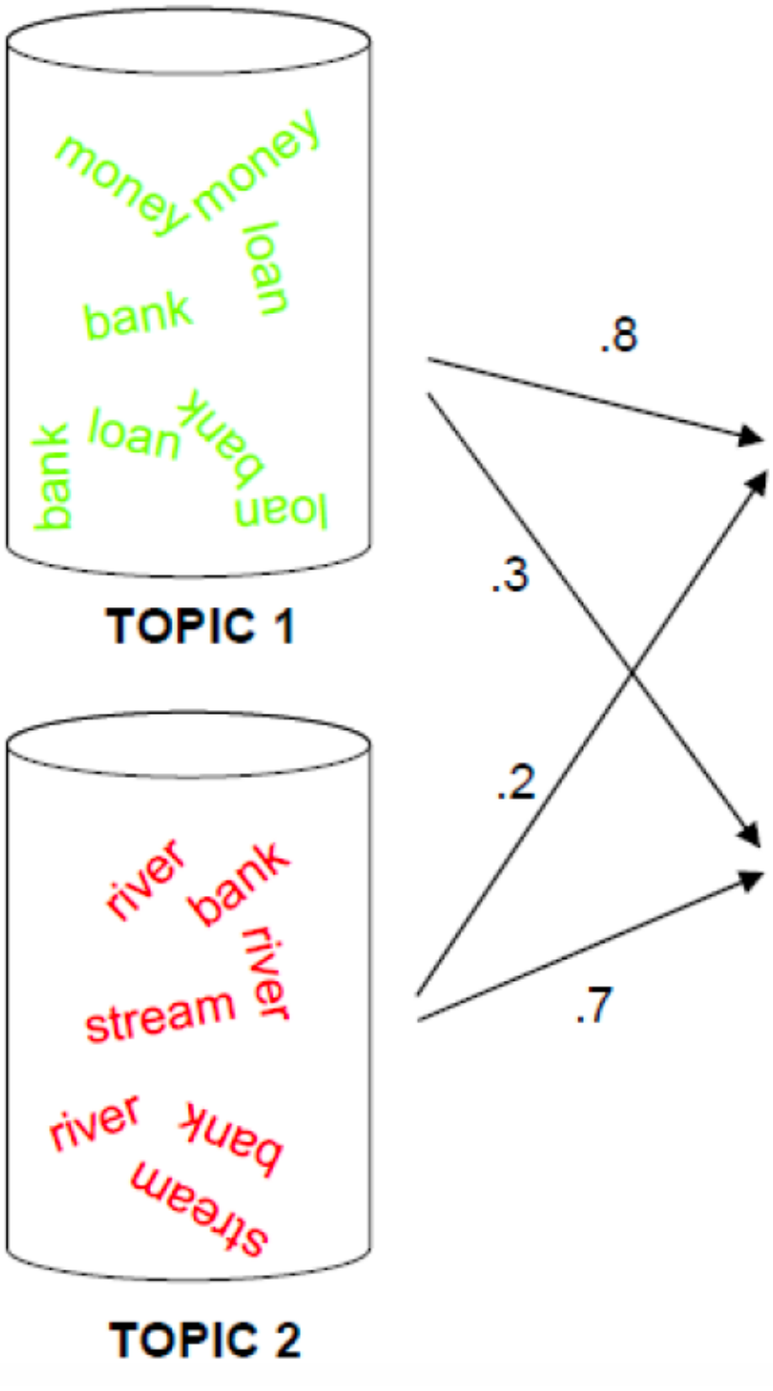
Doc$_3$: *People can use machine learning for data understanding.*

	Doc$_1$	Doc$_2$	Doc$_3$
be	0	1	0
can	0	1	1
data	1	1	1
for	0	0	1
helps	1	0	0
learning	1	1	1
machine	1	1	1
people	1	0	1
to	1	0	0
understand	1	0	0
understanding	0	0	1
understood	0	1	0
use	0	0	1
using	0	1	0

=



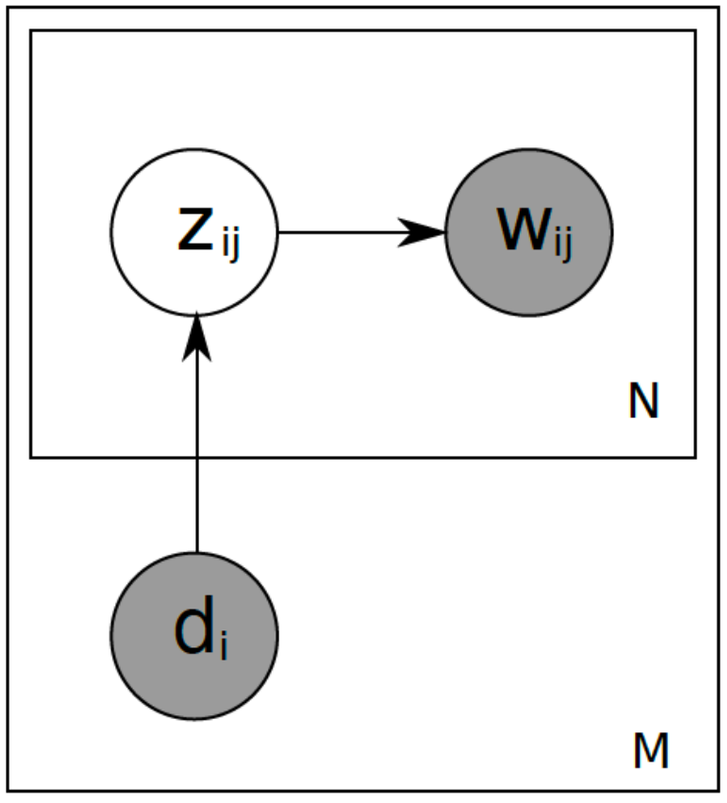
Probabilistic Latent Semantic Analysis



DOCUMENT 1: money[1] bank[1] bank[1] loan[1] river[2] stream[2] bank[1] money[1] river[2] bank[1] money[1] bank[1] loan[1] money[1] stream[2] bank[1] money[1] bank[1] bank[1] loan[1] river[2] stream[2] bank[1] money[1] river[2] bank[1] money[1] bank[1] loan[1] bank[1] money[1] stream[2]

DOCUMENT 2: river[2] stream[2] bank[2] stream[2] bank[2] money[1] loan[1] river[2] stream[2] loan[1] bank[2] river[2] bank[2] bank[1] stream[2] river[2] loan[1] bank[2] stream[2] bank[2] money[1] loan[1] river[2] stream[2] bank[2] stream[2] bank[2] money[1] river[2] stream[2] loan[1] bank[2] river[2] bank[2] money[1] bank[1] stream[2] river[2] bank[2] stream[2] bank[2] money[1]

Model of Probabilistic Latent Semantic Analysis



1: **for** $i \in \{1, 2, \ldots, N\}$ **do**
2: **for** $j \in \{1, 2, \ldots, M\}$ **do**
3: Choose a latent topic z_{ij} with probability $P(z_{ij}|d_i)$
4: Choose a word w_{ij} with probability $P(w_{ij}|z_{ij})$
5: **end for**
6: **end for**

Probabilities are computed from frequency analysis of words

Not a generative model (works for training data only)

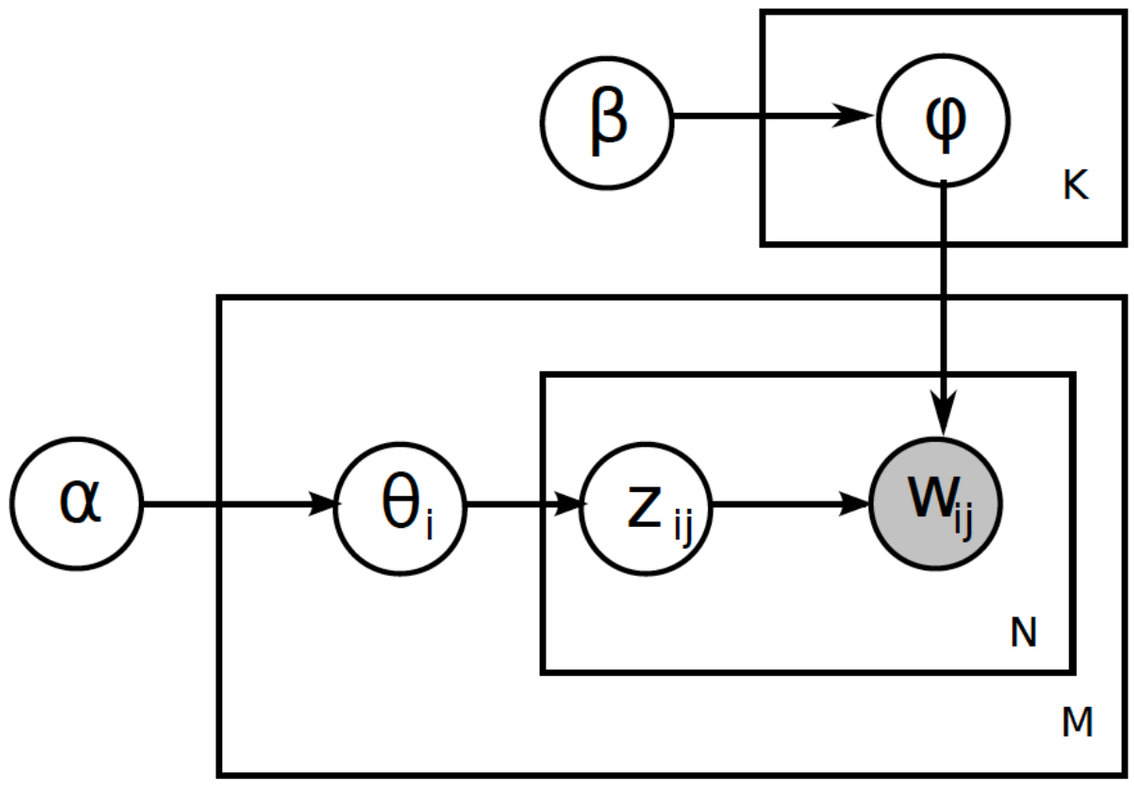
Latent Dirichlet Allocation

For each document $i \in 1 \ldots M$ choose $\theta_i \sim \text{Dir}(\alpha)$

For each word position $j \in \ldots N_i$ choose topic $z_{i,j} \in 1 \ldots K$,

$z_{i,j} \sim \text{Mult}(\theta_i)$

For each word position j choose word $w_{i,j} \sim \text{Mult}(\varphi_{z_{i,j}})$



Latent Dirichlet Allocation

Topics

gene	0.04
dna	0.02
genetic	0.01
...	

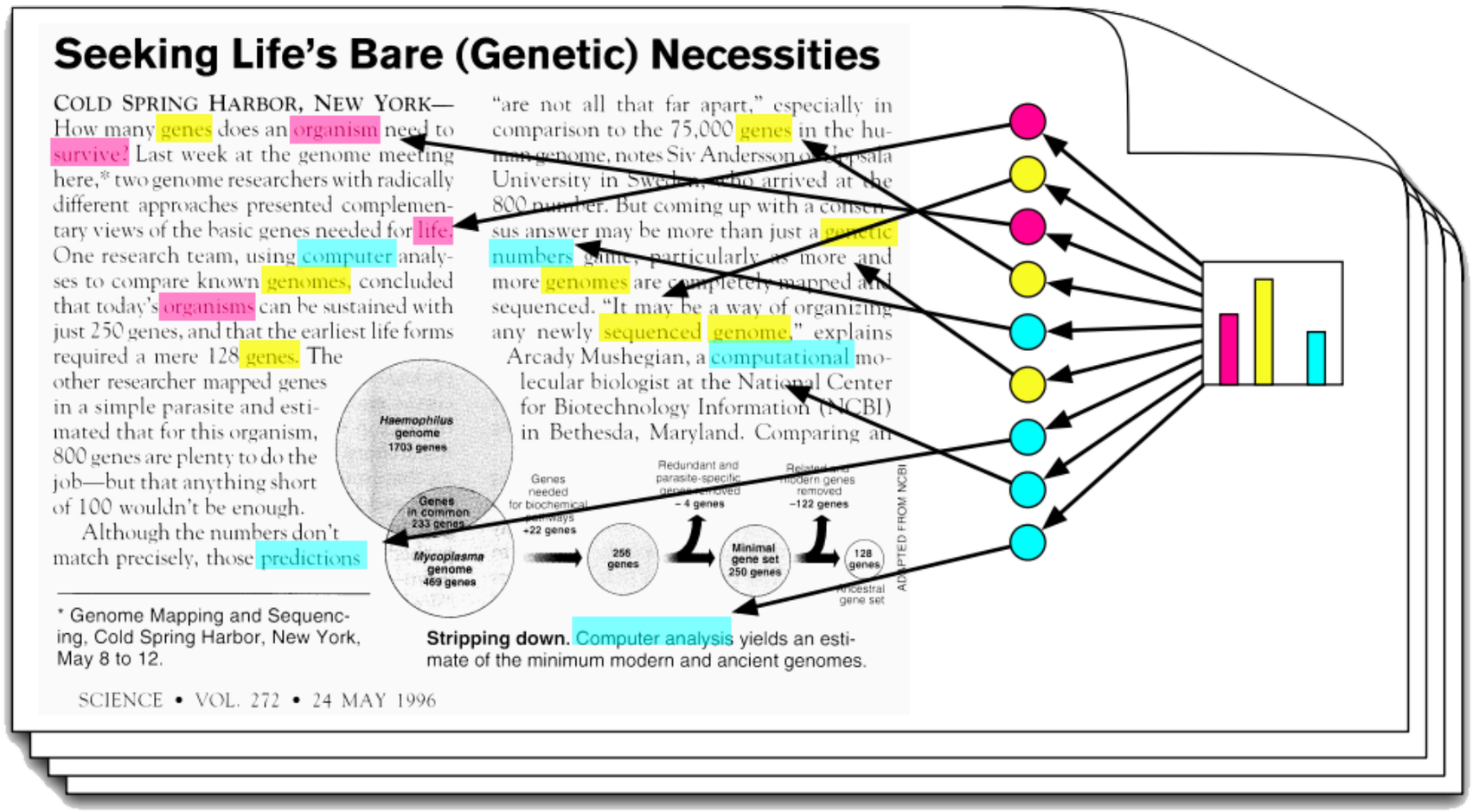
life	0.02
evolve	0.01
organism	0.01
...	

brain	0.04
neuron	0.02
nerve	0.01
...	

data	0.02
number	0.02
computer	0.01
...	

Documents

Topic proportions & assignments



Seeking Life's Bare (Genetic) Necessities

COLD SPRING HARBOR, NEW YORK— How many genes does an organism need to survive? Last week at the genome meeting here,* two genome researchers with radically different approaches presented complementary views of the basic genes needed for life. One research team, using computer analyses to compare known genomes, concluded that today's organisms can be sustained with just 250 genes, and that the earliest life forms required a mere 128 genes. The other researcher mapped genes in a simple parasite and estimated that for this organism, 800 genes are plenty to do the job—but that anything short of 100 wouldn't be enough.

Although the numbers don't match precisely, those predictions "are not all that far apart," especially in comparison to the 75,000 genes in the human genome, notes Siv Andersson of Uppsala University in Sweden, who arrived at the 800 number. But coming up with a consensus answer may be more than just a genetic numbers game, particularly as more and more genomes are completely mapped and sequenced. "It may be a way of organizing any newly sequenced genome," explains Arcady Mushegian, a computational molecular biologist at the National Center for Biotechnology Information (NCBI) in Bethesda, Maryland. Comparing an

* Genome Mapping and Sequencing, Cold Spring Harbor, New York, May 8 to 12.

Stripping down. Computer analysis yields an estimate of the minimum modern and ancient genomes.

SCIENCE • VOL. 272 • 24 MAY 1996

https://kldavenport.com/topic-modeling-amazon-reviews/

Topic modeling

11_Topic_modeling.ipynb

Hate speech classification task

12-Hate-speech-assignment.ipynb

Thank you for your attention

e-mail: jiri@mlcollege.com

Web: www.mlcollege.com

Twitter: @JiriMaterna

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

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