Deep Learning for Vision & Language

Natural Language Processing I: Introduction

RICE UNIVERSITY

Natural Language Processing

The study of automatic reasoning over text / language

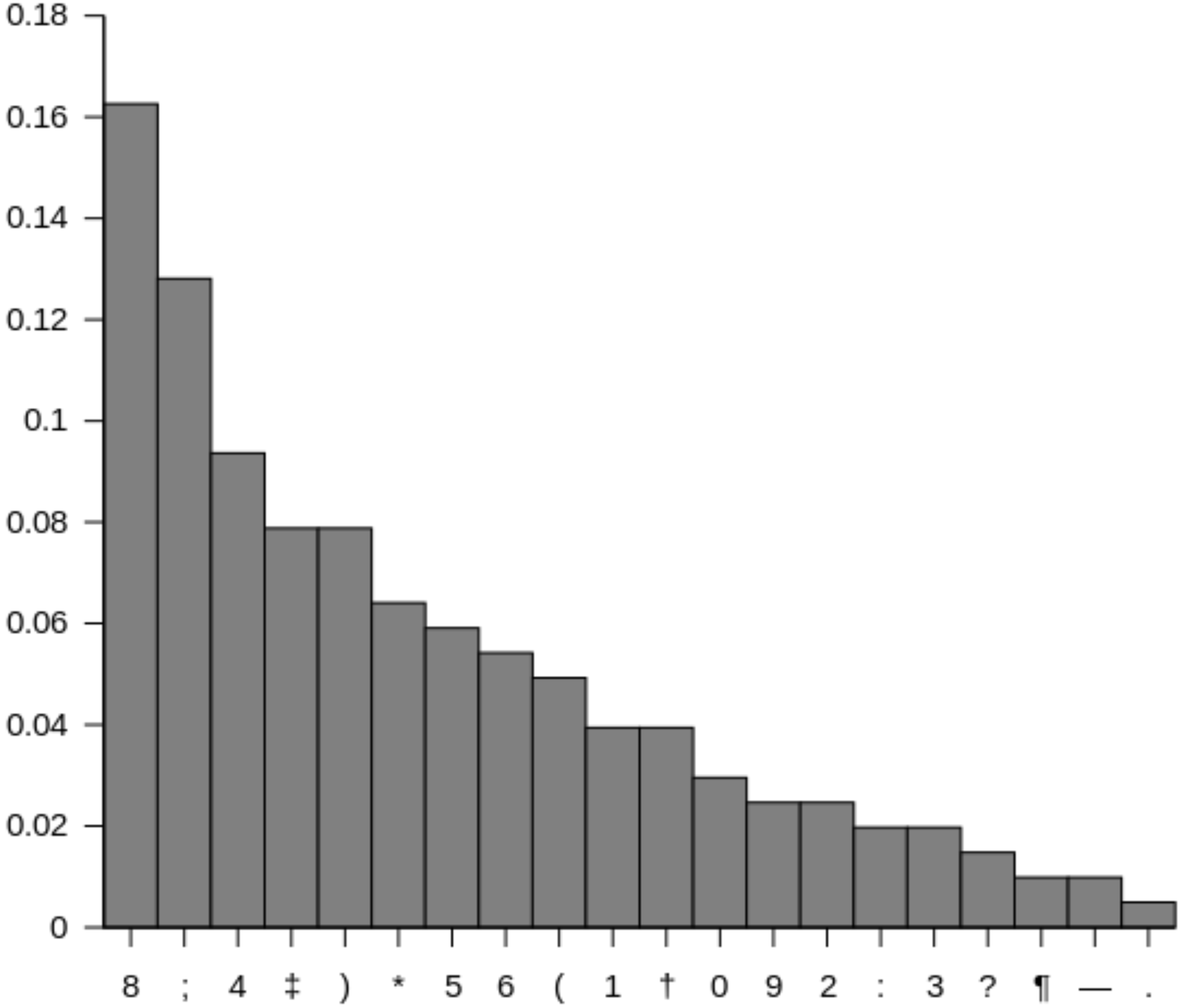
- Fundamental goal: *deep* understand of *broad* language
  - Not just string processing or keyword matching!
- End systems that we want to build:
  - Ambitious: speech recognition, machine translation, information extraction, dialog interfaces, question answering…
  - Modest: spelling correction, text categorization…

Slide by Dan Klein

Challenges in Natural Language Understanding:

53‡‡†305))6*;4826)4‡.)4‡);806*;48†8
¶60))85;;]8*;:‡*8†83(88)5*†;46(;88*96
?;8)‡(;485);5*†2:*‡(;4956*2(5*—4)8
¶8*;4069285);)6†8)4‡‡;1(‡9;48081;8:8‡
1;48†85;4)485†528806*81(‡9;48;(88;4
(‡?34;48)4‡;161;:188;‡?;

Any idea about what does it mean the text above?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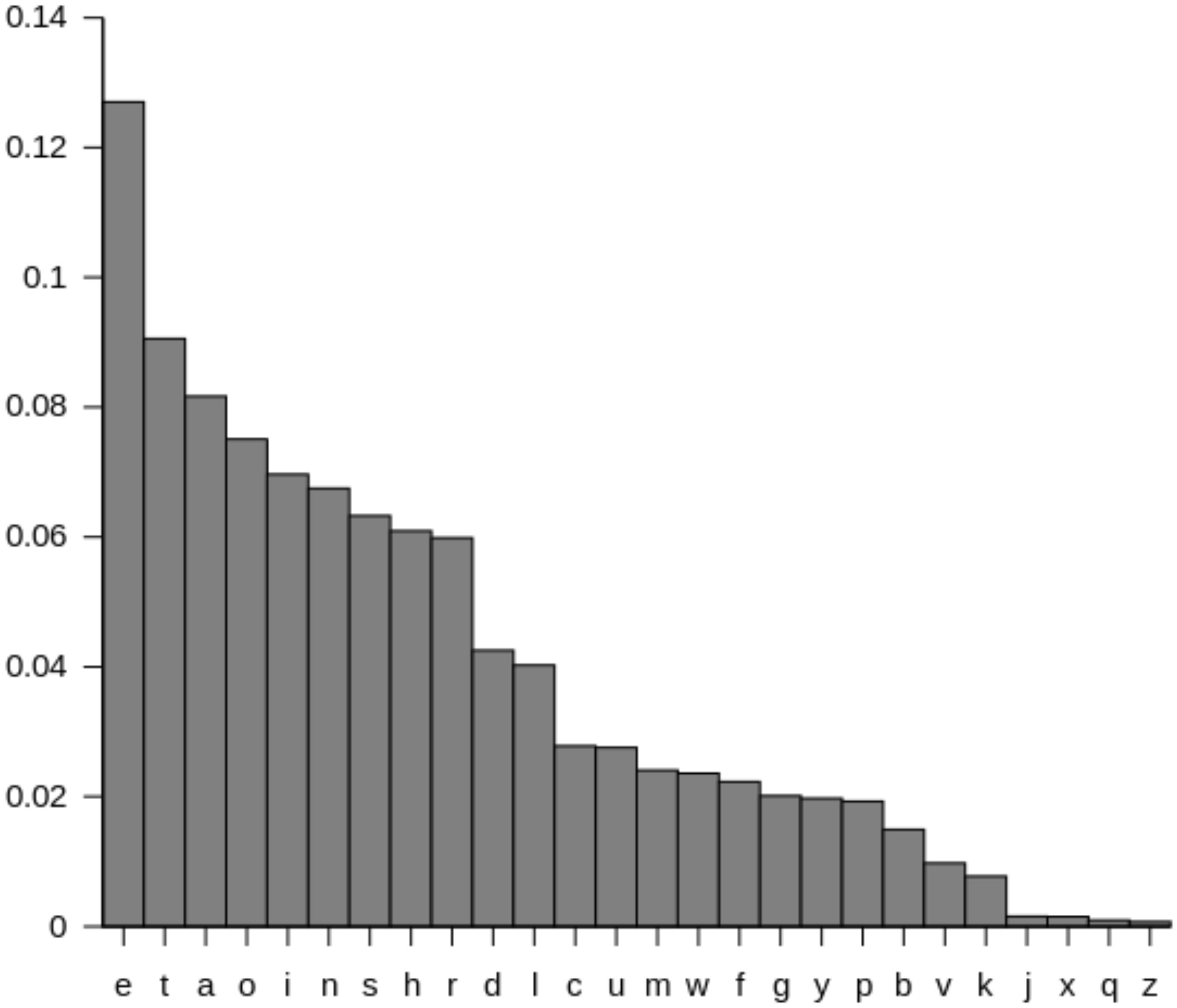
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Challenges in Natural Language Understanding:

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fthedeathsheadabeelinefromthetreeth

(‡?34;48)4‡;161;:188;‡?;
roughtheshotfiftyfeetout

Challenges in Natural Language Understanding:

A good glass in the bishop's hostel in the
devil's seat
twenty-one degrees and
thirteen minutes northeast and by north
main branch seventh limb east side
shoot from the left eye of the death's-head
a bee line from the tree through
the shot fifty feet out.

The Gold-Bug, Edgar Allan Poe

Why is NLP Hard?

- Human Language is Ambiguous

Task: <u>Pronoun Resolution</u>

- Jack drank the wine on the table. ***It*** was red and round.
- Jack saw Sam at the party. ***He*** went back to the bar to get another drink.
- Jack saw Sam at the party. ***He*** clearly had drunk too much.

[Adapted from Wilks (1975)]

Why is NLP Hard?

- Human Language Requires World Knowledge

Task: <u>Co-Reference Resolution</u>

- The doctor hired a secretary because she needed help with new patients.
- The physician hired the secretary because he was highly recommended.

[From some of our group's work]

Gender Bias in Coreference Resolution: Evaluation and Debiasing Methods
Jieyu Zhao, Tianlu Wang, Mark Yatskar, Vicente Ordonez, Kai-Wei Chang.
North American Chapter of the Association for Computational Linguistics. **NAACL 2018**.

Adapted from a slide by Yejin Choi

Why is NLP Hard?

- Human Language is Ambiguous

  Learning mother tongue (native language)

  -- you might think it's easy, but…

  - compare 5 year old V.S. 10 year old V.S. 20 year old

- Learning foreign languages
  - – even harder

Slide by Yejin Choi

Word Segmentation

- Breaking a string of characters into a sequence of words.
- In some written languages (e.g. Chinese) words are not separated by spaces.
- Even in English, characters other than white-space can be used to separate words [e.g. , ; . - : ( )]
- Examples from English URLs:
  - jumptheshark.com ⇒ jump the shark .com
  - myspace.com/pluckerswingbar

    ⇒ myspace .com pluckers wing bar

    ⇒ myspace .com plucker swing bar

Slide from Ray Mooney

Morphological Analysis

- ***Morphology*** is the field of linguistics that studies the internal structure of words. (Wikipedia)
- A ***morpheme*** is the smallest linguistic unit that has semantic meaning (Wikipedia)
  - e.g. “carry”, “pre”, “ed”, “ly”, “s”
- Morphological analysis is the task of segmenting a word into its morphemes:
  - carried $\Rightarrow$ carry + ed (past tense)
  - independently $\Rightarrow$ in + (depend + ent) + ly
  - Googlers $\Rightarrow$ (Google + er) + s (plural)
  - unlockable $\Rightarrow$ un + (lock + able) ?

    $\Rightarrow$ (un + lock) + able ?

Slide from Ray Mooney

- ***German***

555 --> fünfhundertfünfundfünfzig

7254 → Siebentausendzweihundertvierundfünfzig

Part Of Speech (POS) Tagging

- Annotate each word in a sentence with a part-of-speech.

I ate the spaghetti with meatballs.

John saw the saw and decided to take it to the table.

- Useful for subsequent syntactic parsing and word sense disambiguation.

Slide from Ray Mooney

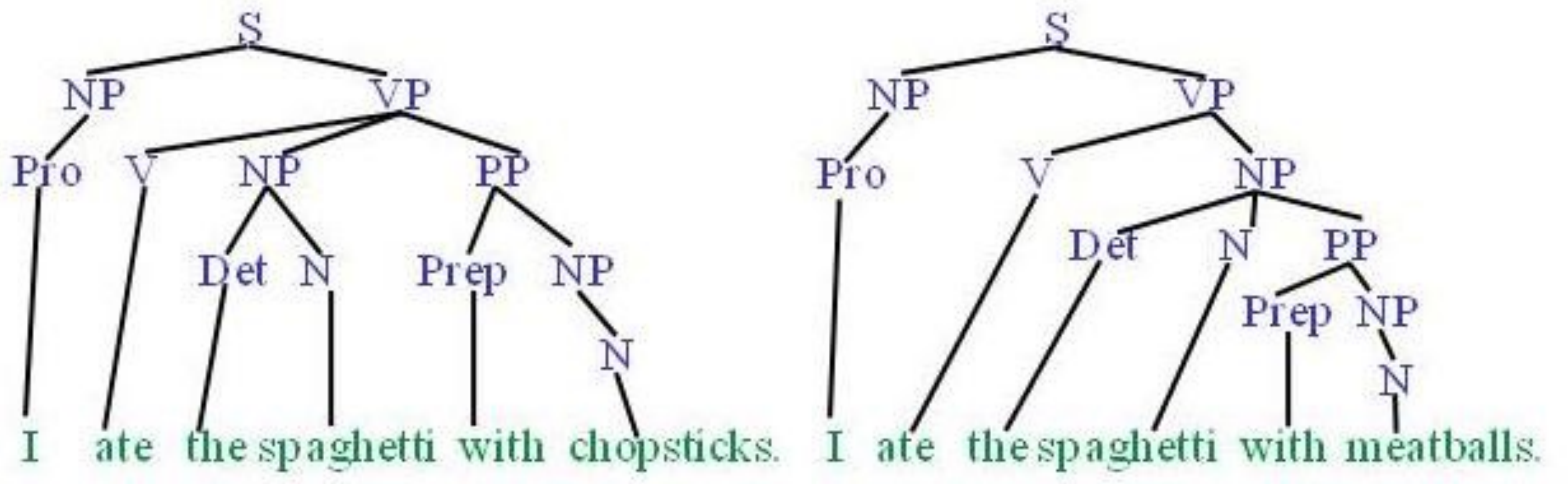
Phrase Chunking

- Find all noun phrases (NPs) and verb phrases (VPs) in a sentence.
  - [NP I] [VP ate] [NP the spaghetti] [PP with]   [NP meatballs].
  - [NP He] [VP reckons] [NP the current account deficit] [VP will narrow] [PP to] [NP only # 1.8 billion] [PP in] [NP September]

Slide from Ray Mooney

Syntactic Parsing

- Produce the correct syntactic parse tree for a sentence.



Slide from Ray Mooney

Word Sense Disambiguation (WSD)

- Words in natural language usually have a fair number of different possible meanings.
  - Ellen has a strong interest in computational linguistics.
  - Ellen pays a large amount of interest on her credit card.
- For many tasks (question answering, translation), the proper sense of each ambiguous word in a sentence must be determined.

Slide from Ray Mooney

Textual Entailment

- Determine whether one natural language sentence entails (implies) another under an ordinary interpretation.

Slide from Ray Mooney

Textual Entailment Problems from PASCAL Challenge

TEXT	HYPOTHESIS	ENTAIL MENT
Eyeing the huge market potential, currently led by Google, Yahoo took over search company Overture Services Inc last year.	*Yahoo bought Overture.*	
Microsoft's rival Sun Microsystems Inc. bought Star Office last month and plans to boost its development as a Web-based device running over the Net on personal computers and Internet appliances.	*Microsoft bought Star Office.*	
The National Institute for Psychobiology in Israel was established in May 1971 as the Israel Center for Psychobiology by Prof. Joel.	*Israel was established in May 1971.*	
Since its formation in 1948, Israel fought many wars with neighboring Arab countries.	*Israel was established in 1948.*	TRUE

Slide from Ray Mooney

How to represent a word?

		one-hot encodings
dog	1	[1 0 0 0 0 0 0 0 0 0]
cat	2	[0 1 0 0 0 0 0 0 0 0]
person	3	[0 0 1 0 0 0 0 0 0 0]
holding	4	[0 0 0 1 0 0 0 0 0 0]
tree	5	[0 0 0 0 1 0 0 0 0 0]
computer	6	[0 0 0 0 0 1 0 0 0 0]
using	7	[0 0 0 0 0 0 1 0 0 0]

How to represent a word?

How to represent a phrase/sentence?

bag-of-words representation

person holding dog {1, 3, 4} [1 0 1 1 0 0 0 0 0 0]

person holding cat {2, 3, 4} [0 1 1 1 0 0 0 0 0 0]

person using computer {3, 7, 6} [0 0 1 0 0 1 1 0 0 0]

dog cat person holding tree computer using

person using computer
person holding cat {3, 3, 7, 6, 2} [0 1 2 1 0 1 1 0 0 0]

What if vocabulary is very large?

Sparse Representation

bag-of-words representation

person holding dog	{1, 3, 4}	indices = [1, 3, 4]	values = [1, 1, 1]
person holding cat	{2, 3, 4}	indices = [2, 3, 4]	values = [1, 1, 1]
person using computer	{3, 7, 6}	indices = [3, 7, 6]	values = [1, 1, 1]

person using computer person holding cat	{3, 3, 7, 6, 2}	indices = [3, 7, 6, 2]	values = [2, 1, 1, 1]

Recap

- Bag-of-words encodings for text (e.g. sentences, paragraphs, captions, etc)

You can take a set of sentences/documents and classify them, cluster them, or compute distances between them using this representation.

Problem with this bag-of-words representation

my friend makes a nice meal

These would be the same using bag-of-words

my nice friend makes a meal

Bag of Bi-grams

my friend makes a nice meal

indices = [10132, 21342, 43233, 53123, 64233]
values = [1, 1, 1, 1, 1]

{my friend, friend makes, makes a,

a nice, nice meal}

my nice friend makes a meal

indices = [10232, 43133, 21342, 43233, 54233]
values = [1, 1, 1, 1, 1]

{my nice, nice friend, friend makes,

makes a, a meal}

A dense vector-representation would be very inefficient
Think about tri-grams and n-grams

Recommended reading: n-gram language models

Yejin Choi's course on Natural Language Processing

http://www3.cs.stonybrook.edu/~ychoi/cse628/lecture/02-ngram.pdf

Modern way of representing Phrases/Text

Pre-trained Neural Network

Continuous Bag of Words (CBOW) – Word embeddings

Sequence-based representations (RNNs, LSTMs)

Transformer-based representations (e.g. BERT, GPT-2, T5, etc)

my friend makes a nice meal

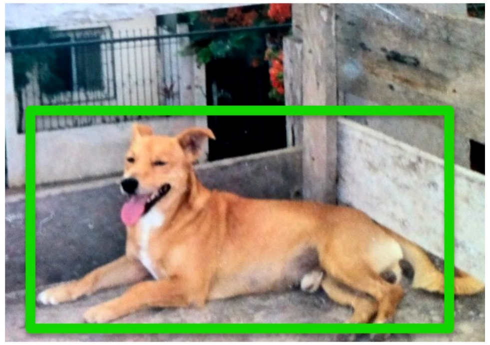
Back to how to represent a word?

Problem: distance between words using one-hot encodings always the same

dog	1	[1 0 0 0 0 0 0 0 0 0]
cat	2	[0 1 0 0 0 0 0 0 0 0]
person	3	[0 0 1 0 0 0 0 0 0 0]

Idea: Instead of one-hot-encoding use a histogram of commonly co-occurring words.

Distributional Semantics



Dogs are man's best friend.

I saw a dog on a leash walking in the park.

His dog is his best companion.

He walks his dog in the late afternoon

…

	friend	leash	park	walking	walks	food	legs	runs	sleeps	sits	…
dog	[3	2	3	4	2	4	3	5	6	7	…]

Distributional Semantics

	food	walks	window	runs	mouse	invented	legs	sleeps	mirror	tail	…
dog	[5	5	0	5	0	0	5	5	0	2	…]
cat	[5	4	1	4	2	0	3	4	0	3	…]
person	[5	5	1	5	0	2	5	5	0	0	…]

This vocabulary can be extremely large

Toward more Compact Representations

	food	walks	window	runs	mouse	invented	legs	sleeps	mirror	tail	…
dog	[5	5	0	5	0	0	5	5	0	2	…]
cat	[5	$\boxed{4}$	1	$\boxed{4}$	2	0	3	$\boxed{4}$	0	3	…]
person	[5	5	1	5	0	2	5	5	0	0	…]

This vocabulary can be extremely large

Toward more Compact Representations

$$\text{dog} = \begin{bmatrix} 5 \\ 5 \\ 0 \\ 5 \\ 0 \\ 0 \\ 5 \\ 5 \\ 0 \\ 2 \\ \dots \end{bmatrix} = w1 \underset{\text{legs, running, walking}}{\begin{bmatrix} 0 \\ 1 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ \dots \end{bmatrix}} + w2 \underset{\text{tail, fur, ears}}{\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ \dots \end{bmatrix}} + w3 \underset{\text{mirror, window, door}}{\begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ 0 \\ \dots \end{bmatrix}} + \dots$$

Toward more Compact Representations

dog = $\begin{bmatrix} w1 & w2 & w3 \end{bmatrix}$

The basis vectors can be found using Principal Component Analysis (PCA)

This is known as Latent Semantic Analysis in NLP

Toward more Compact Representations: Word Embeddings

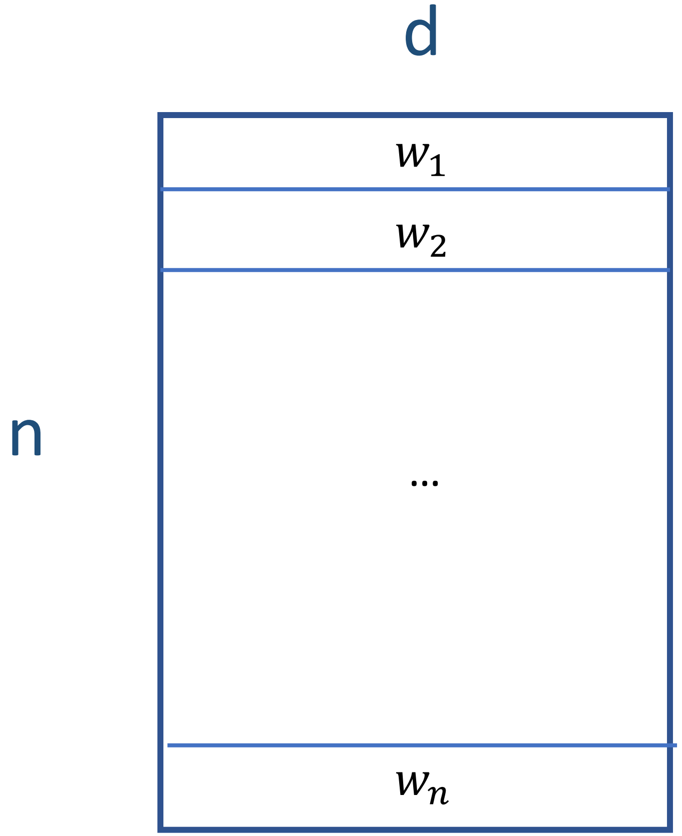
dog = [w1 w2 w3]

The weights w1, …, wn are found using a neural network

Word2Vec: https://arxiv.org/abs/1301.3781

Word2Vec – CBOW Version

- First, create a huge matrix of word embeddings initialized with random values – where each row is a vector for a different word in the vocabulary.



Efficient Estimation of Word Representations in Vector Space

Tomas Mikolov
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Greg Corrado
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Jeffrey Dean
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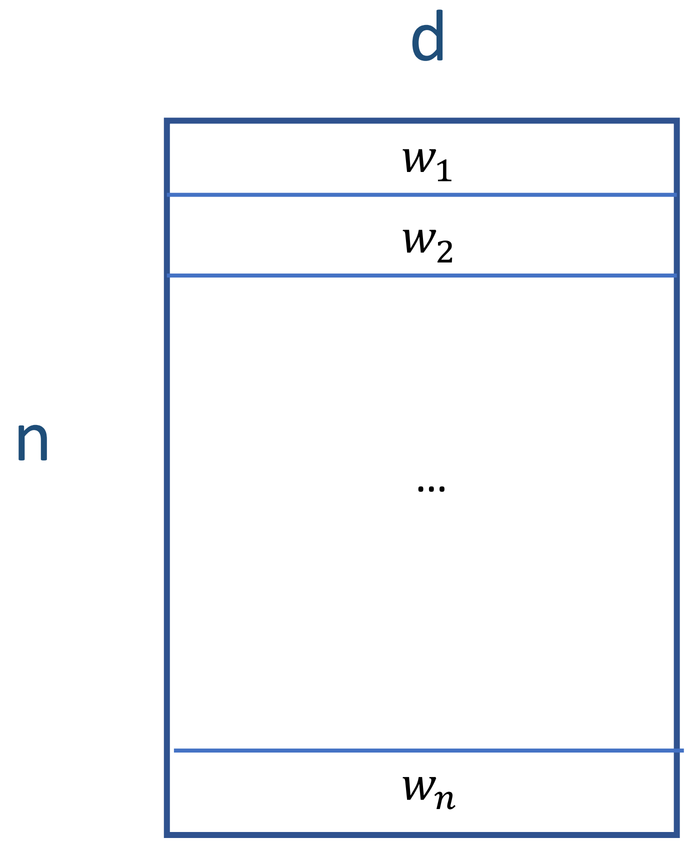
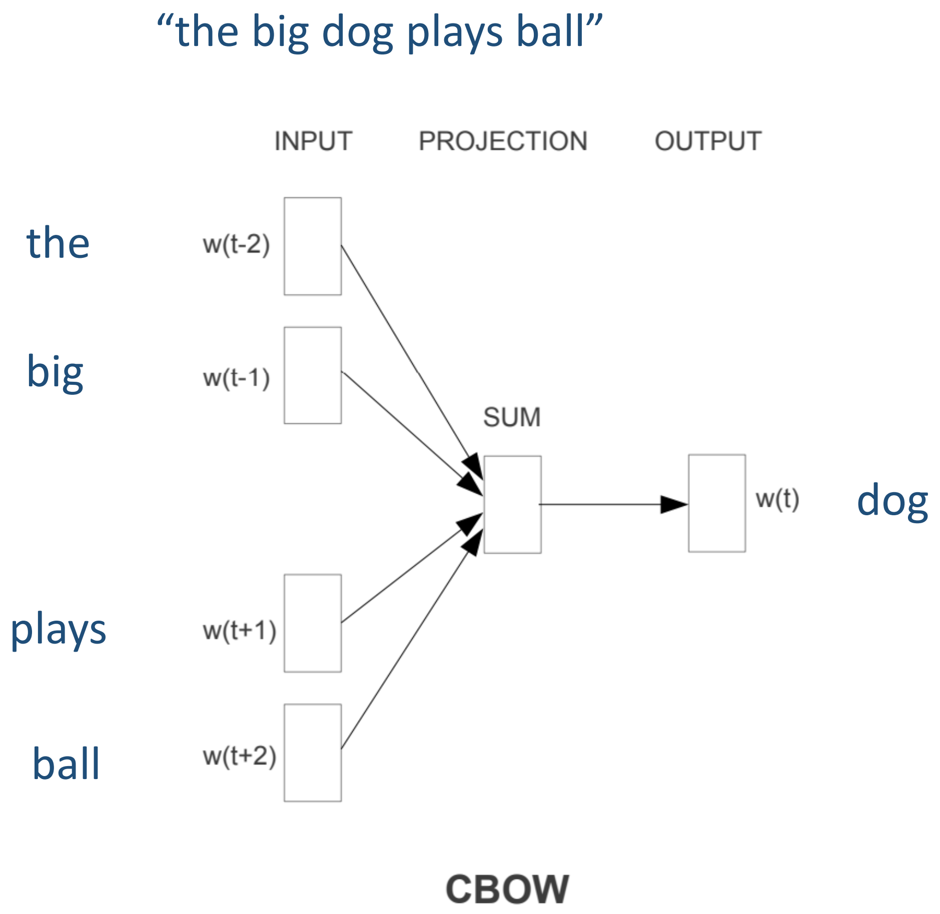
jeff@google.com

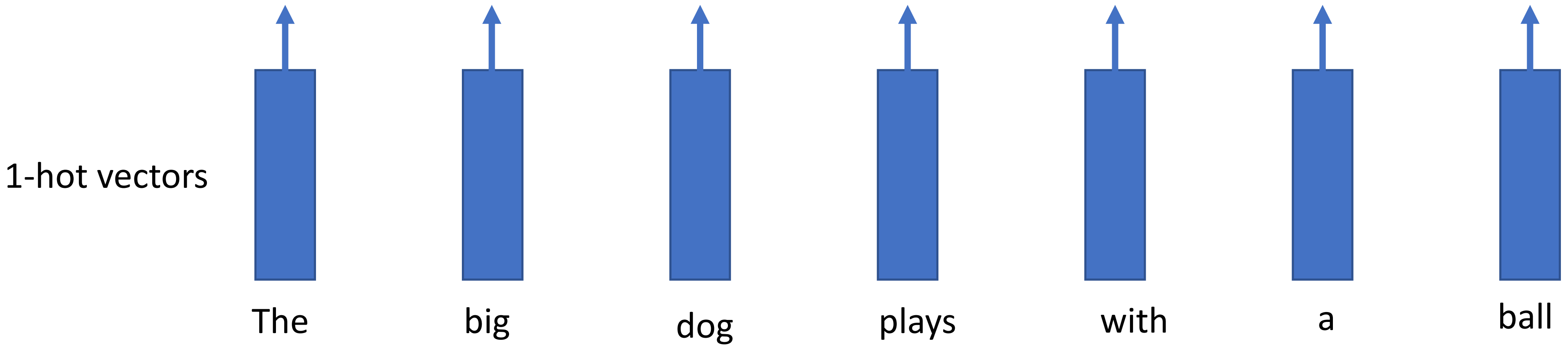
Word2Vec – CBOW Version

- Then, collect a lot of text, and solve the following regression problem for a large corpus of text:

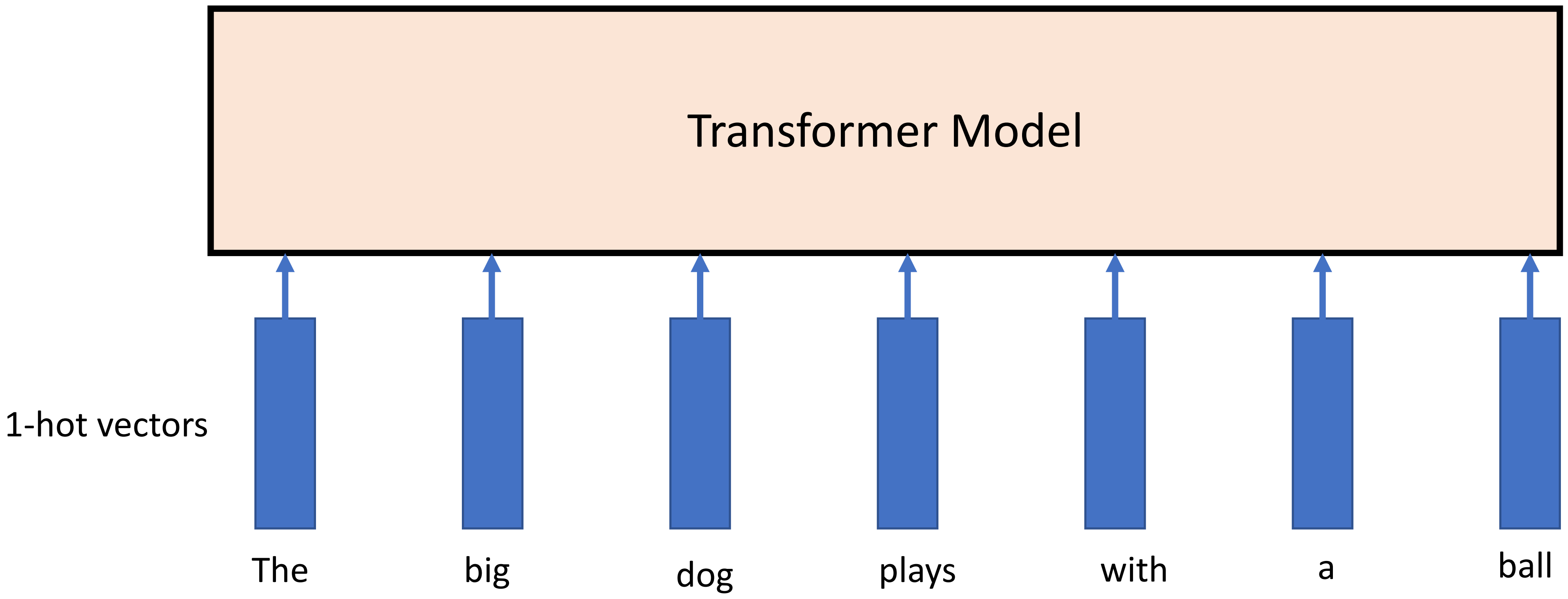




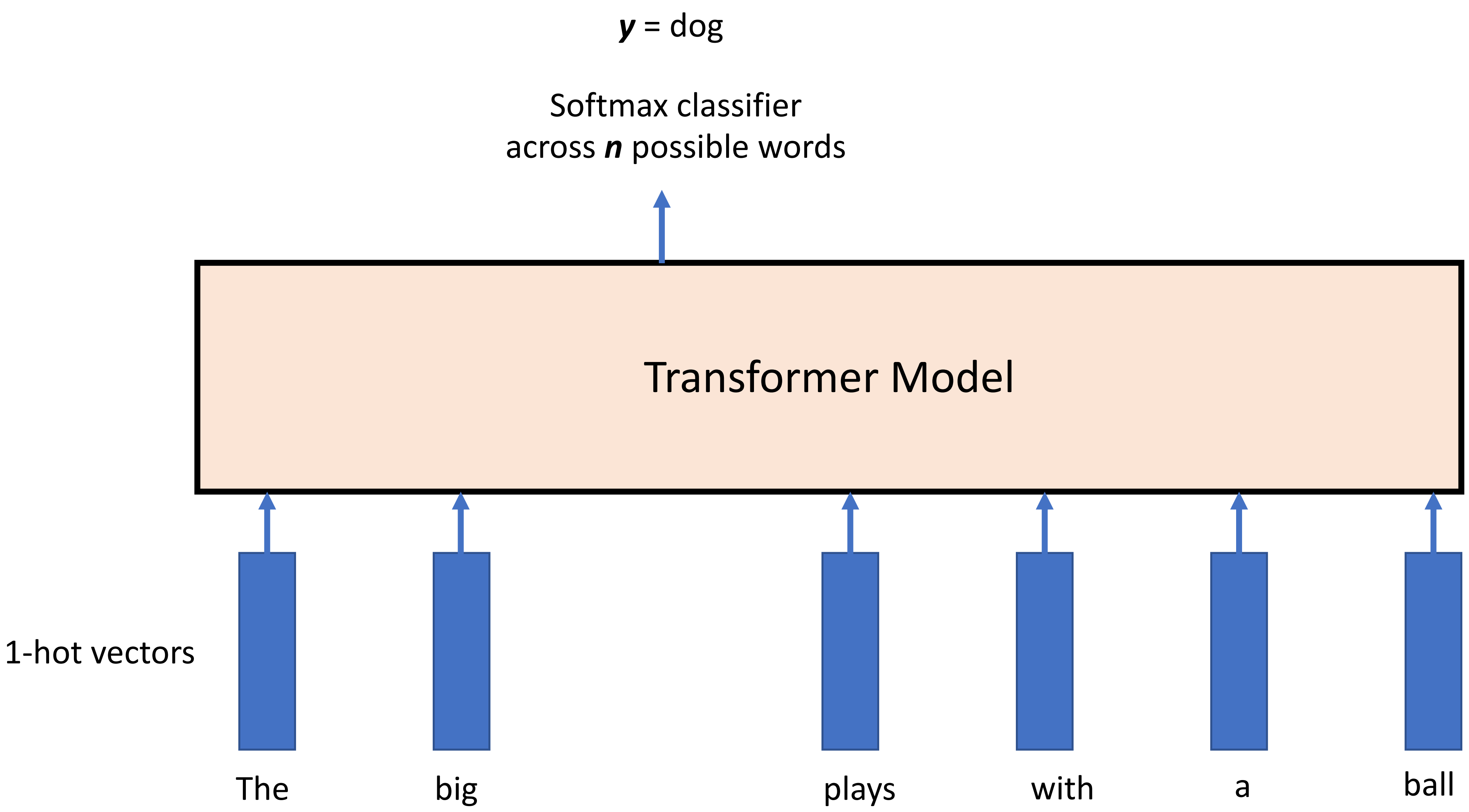
Pre-trained Language Models



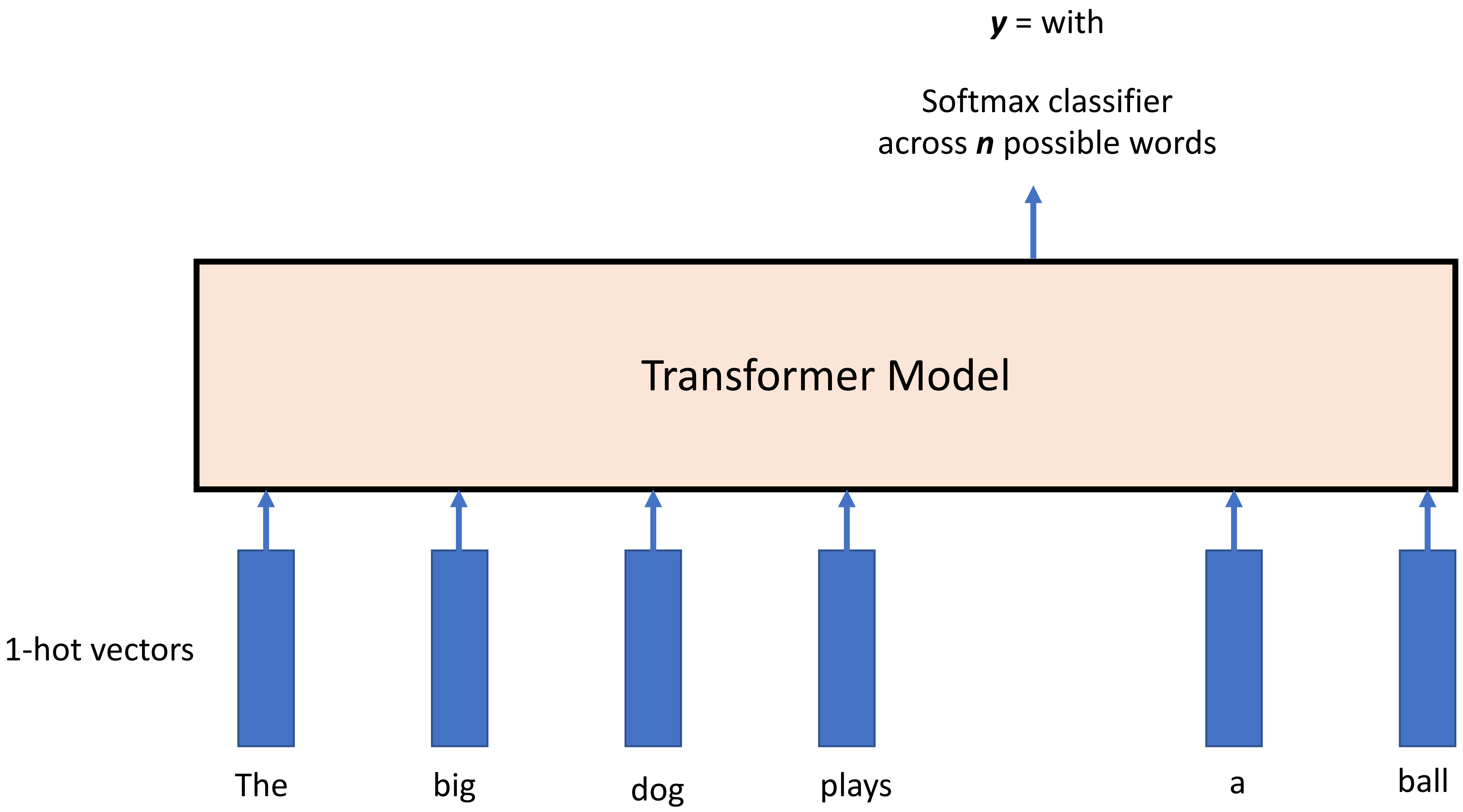
Pre-trained Language Models



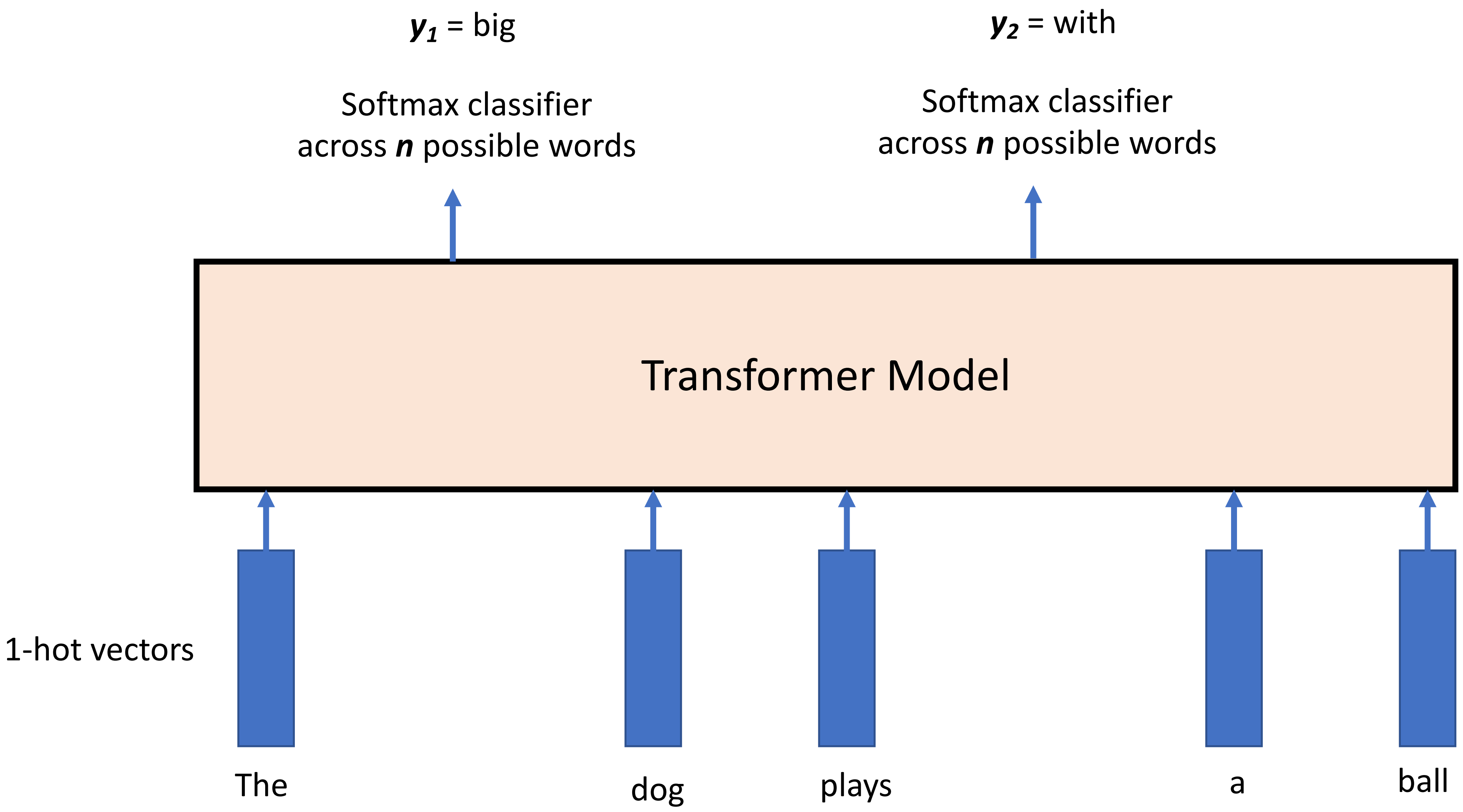
Pre-trained Language Models



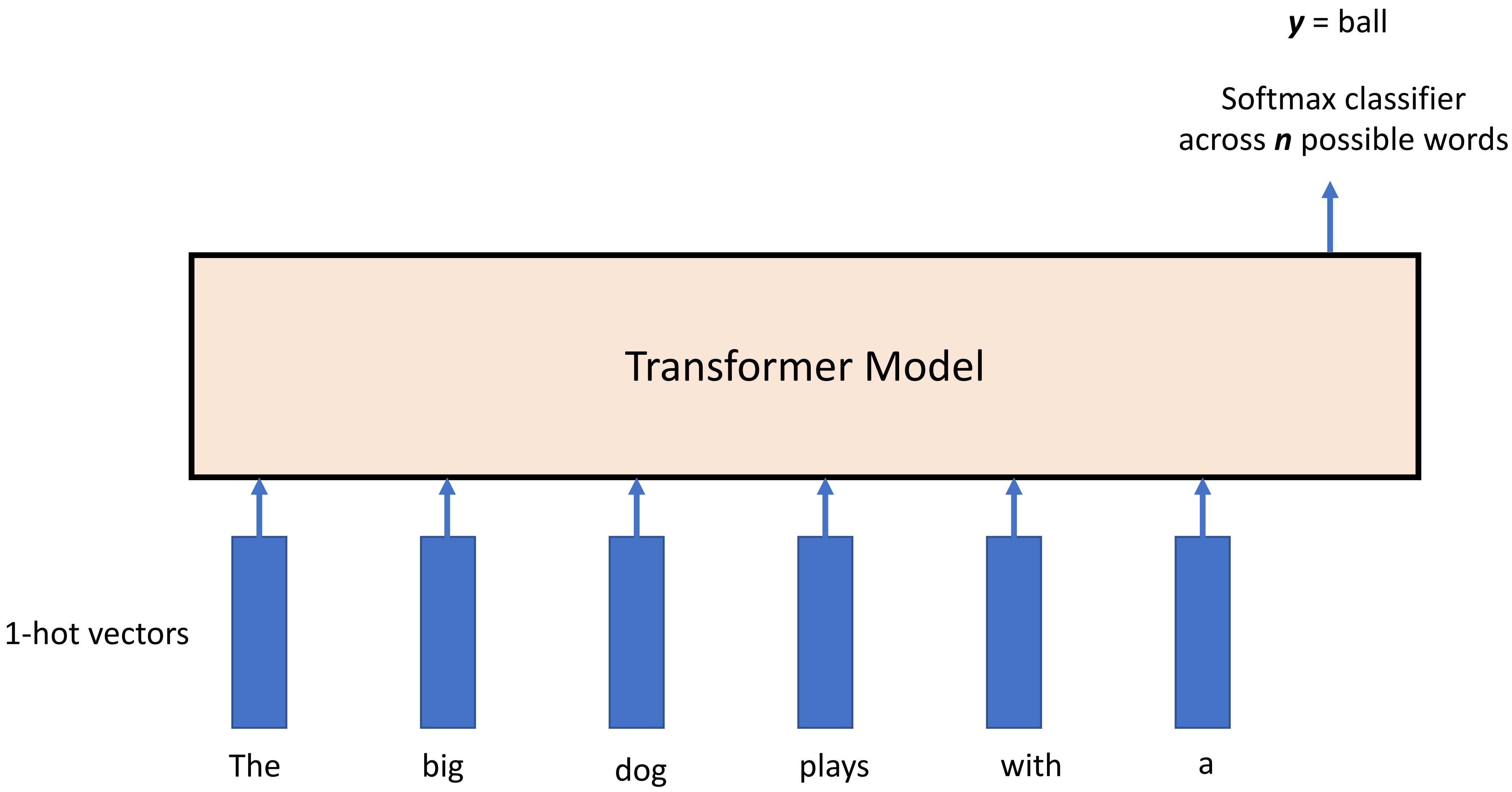
Pre-trained Language Models



Pre-trained Language Models



Generative Language Models



Practical Issues - Tokenization

- For each text representation we usually need to separate a sentence into tokens – we have assumed words in this lecture (or pairs of words) – but tokens could also be characters and anything in-between.

- Word segmentation can be used as tokenization.
  - In the assignment I was lazy I just did “my sentence”.split(“ “) and called it a day.
  - However, even English is more difficult than that because of punctuation, double spaces, quotes, etc. For English I would recommend you too look up the great word tokenization tools in libraries such as Python’s NLTK and Spacy before you try to come up with your own word tokenizer.

Issues with Word based Tokenization

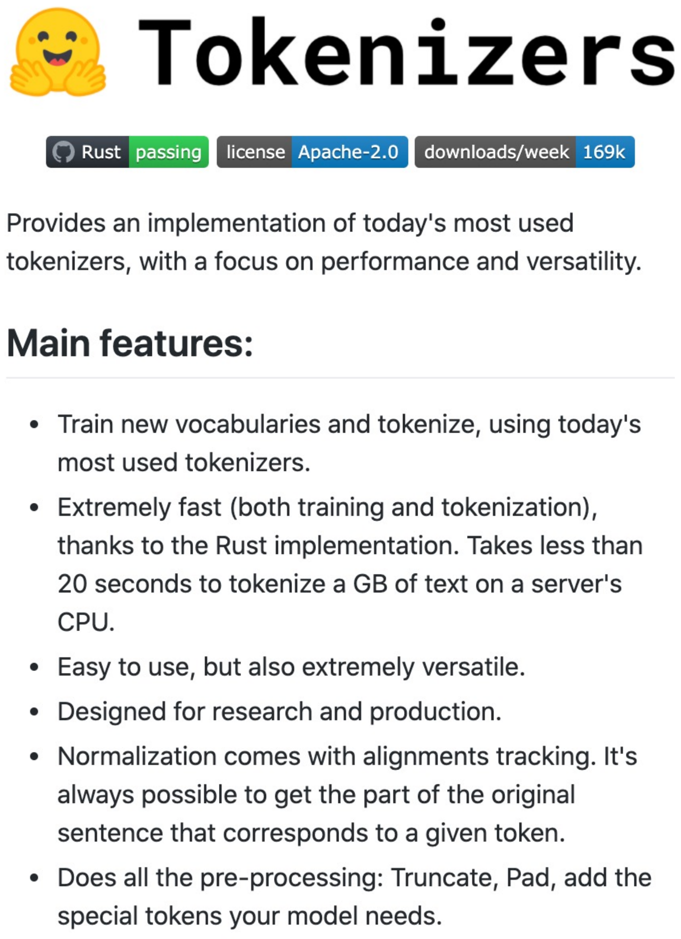
- We already mentioned that tokenization can be hard even when word-based for other languages that don't use spaces in-between words.

- Word tokenization can also be bad for languages where the words can be "glued" together like German or Turkish.
  - Remember fünfhundertfünfundfünfzig? It wouldn't be feasible to have a word embedding for every number in the German language.

- It is problematic to handle words that are not in the vocabulary e.g. a common practice is to use a special <OOV> (out of vocabulary) token for those words that don't show up in the vocabulary.

Solution: Sub-word Tokenization

- Byte-pair Encoding Tokenization (BPE)
  - Start from small strings and based on substring counts iteratively use larger sequences until you define a vocabulary that maximizes informative subtokens. That way most will correspond to words at the end.
- Byte-level BPE Tokenizer
  - Do the same but at the byte representation level not at the substring representation level.


Tokenizers

Rust passing | license Apache-2.0 | downloads/week 169k

Provides an implementation of today's most used tokenizers, with a focus on performance and versatility.

Main features:

- Train new vocabularies and tokenize, using today's most used tokenizers.
- Extremely fast (both training and tokenization), thanks to the Rust implementation. Takes less than 20 seconds to tokenize a GB of text on a server's CPU.
- Easy to use, but also extremely versatile.
- Designed for research and production.
- Normalization comes with alignments tracking. It's always possible to get the part of the original sentence that corresponds to a given token.
- Does all the pre-processing: Truncate, Pad, add the special tokens your model needs.

huggingface/tokenizers

We will discuss these more as we discuss Transformer Models

Questions?