Deep Learning for NLP

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I833 SS2020

How is the pace of the lectures so far?

A) too slow
B) too fast
C) just right

a brief recap of the last lecture

Word Representations

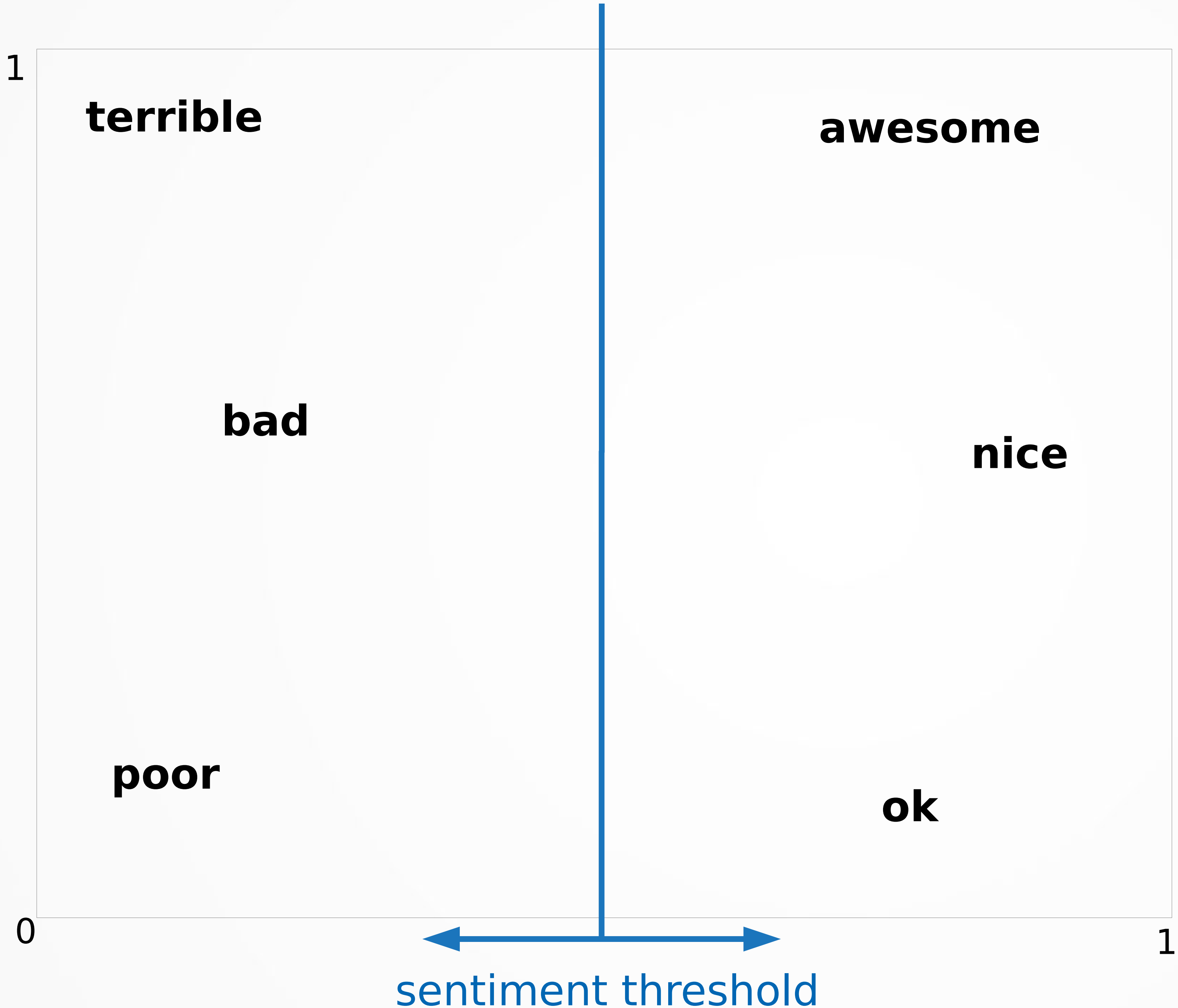
Encoding

Instead of encoding single characters

h	0	0	0	1
e	0	0	1	0
l	0	1	0	0
o	1	0	0	0

You can also encode words, this is also called „Bag-Of-Words (BOW)“

hello	0	0	0	1
my	0	0	1	0
name	0	1	0	0
is	1	0	0	0



Now a network can distinguish between positive and negative words by learning a threshold.

$$v_{ok} = [0.75, 0.15]$$

$$v_{nice} = [0.85, 0.50]$$

$$v_{poor} = [0.15, 0.18]$$

$$v_{terrible} = [0.10, 0.91]$$

Distributional Hypothesis

Words that occur in the same contexts tend to have similar meanings.
Harris (1954)

A word is characterized by the company it keeps.
Firth (1957)

Skip-Gram

Source Text

The quick brown fox jumps over the lazy dog. ⟹

Training Samples

(the, quick)
(the, brown)

Predict the context words given a center word

McCormick, Word2Vec Tutorial, http://mccormickml.com/2016/04/19/word2vec-tutorial-the-skip-gram-model/

Supervised and unsupervised learning

- **Supervised Learning** uses a set of labeled training examples.
  - List of e-mails that are labeled as span / not spam
- **Unsupervised Learning** generates training examples from a plain –unlabeled- text corpus, so the training becomes a supervised problem.
  - Predict context words (Skip Gram)
  - Predict center words (Cbow)
  - Predict masked words (Bert)

Preprocessing

- Format you text to be predictable and analyzable
- It often has a significant impact on the performance
- Depending on the domain and your model different steps may be required
- For example:
  - Cleaning not useful characters and word
  - Transform words into a standardized form
  - Clipping your data to equal length

Scores: Accuracy

- Accuracy = $\dfrac{tp + tn}{tp + tn + fp + fn}$

- Accuracy = $\dfrac{\text{number correctly predicted samples}}{\text{total number of samples}}$

Scores: F1

$$precision = \frac{true\ \ positives}{true\ \ positives + false\ \ positives}$$

$$recall = \frac{true\ \ positives}{true\ \ positives + false\ \ negatives}$$

$$F_1 = 2 * \frac{precision * recall}{precision + recall}$$

How to optimize:

1) create a train/test split
2) Train your model (start with a simple model!)
3) measure its performance
4) optimize your model
5) Go to 2 :)

Identify offensive language

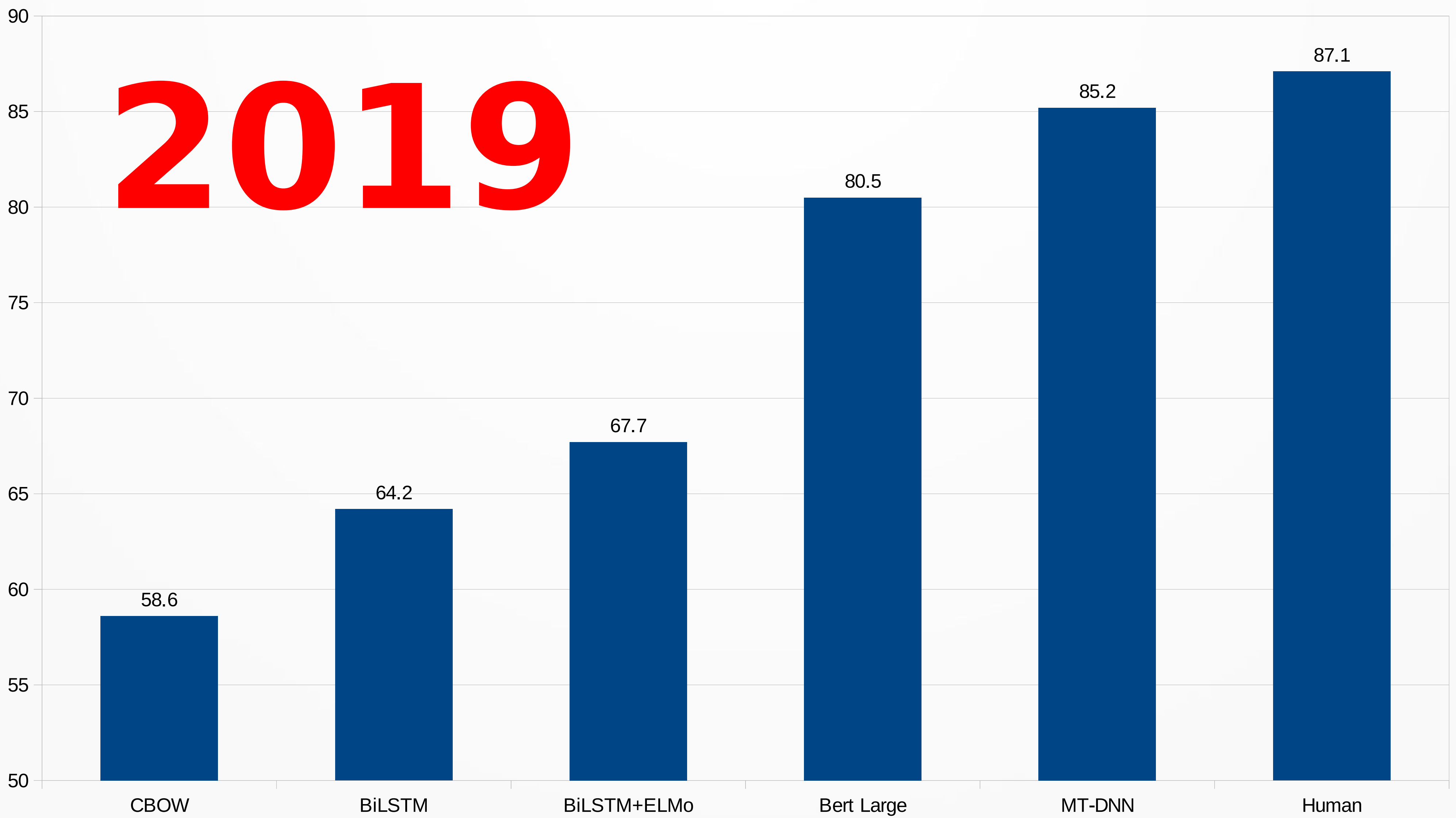
using word vectors

Goal for Today

- Look we look at deep language models
  - How do they perform?
  - How do they work?
  - Some of the basic ideas behind those models.
  - How to use these models.
  - Applications :)

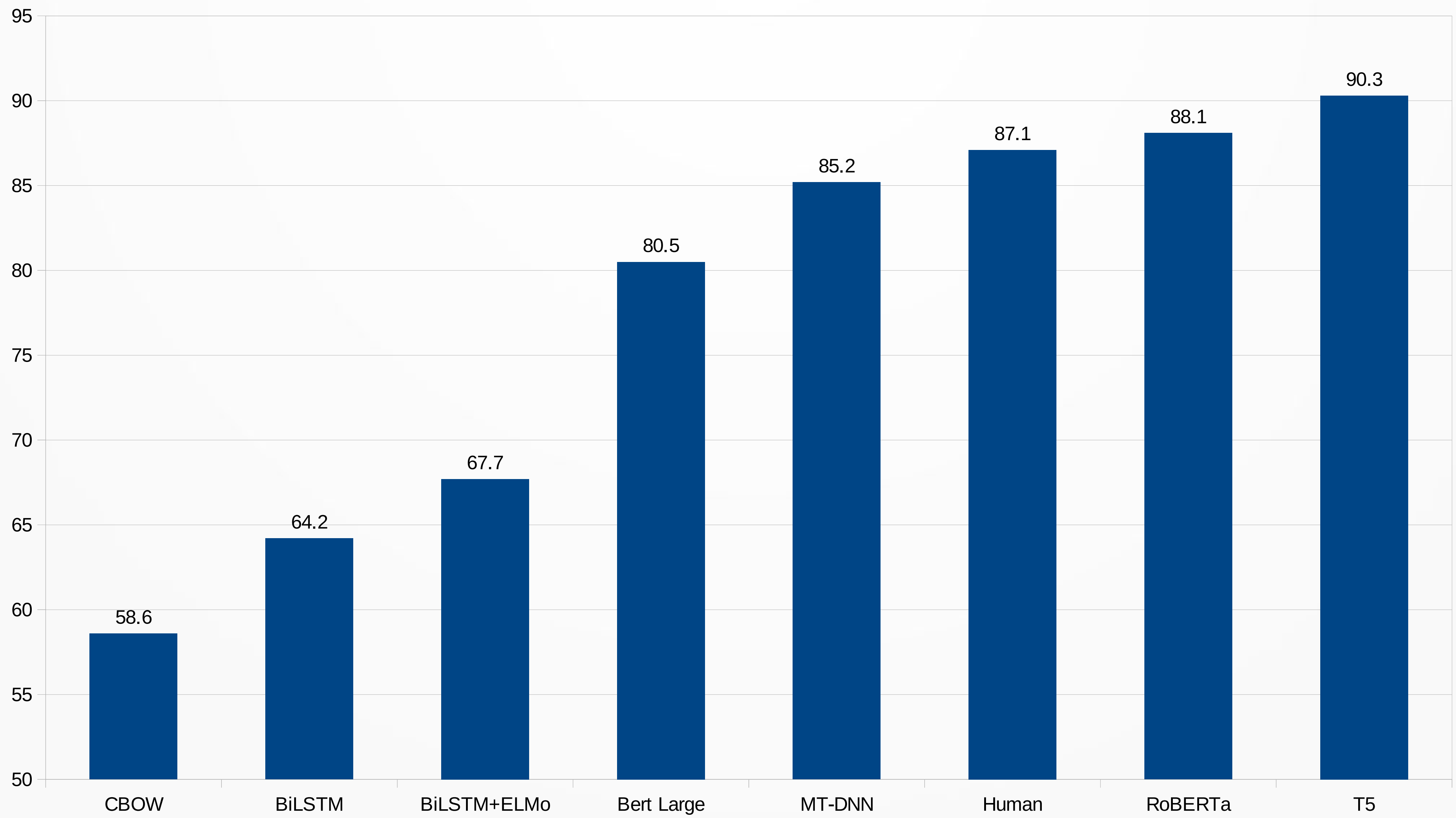
Deep Language Models

GLUE Benchmark Results



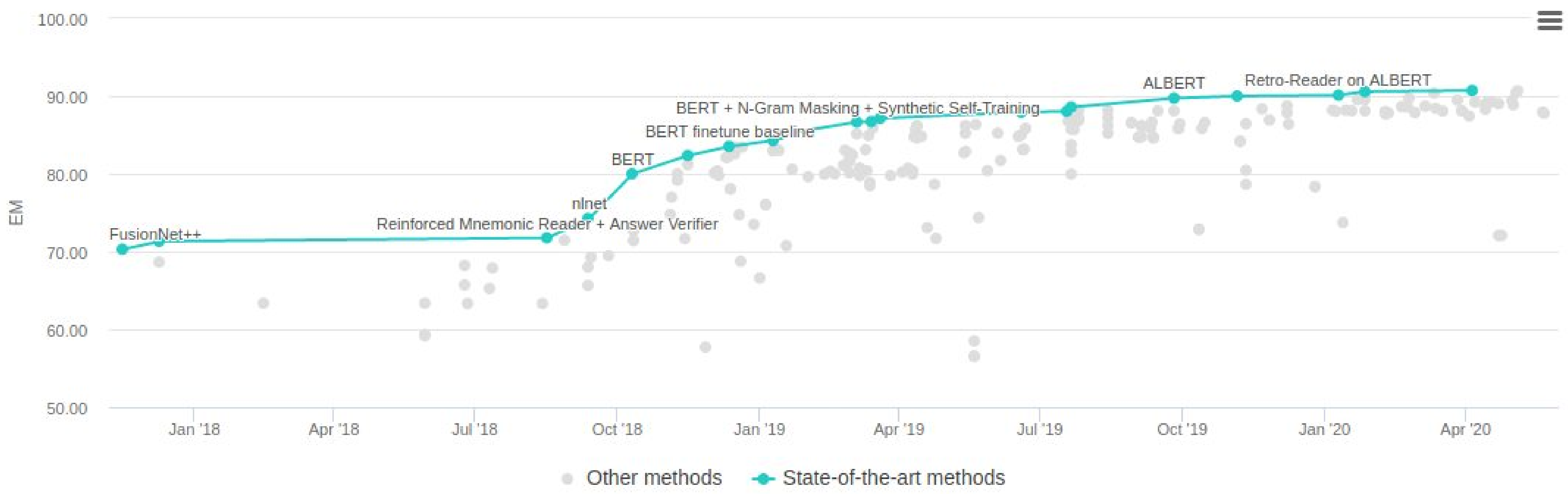
GLUE Leaderboard: https://gluebenchmark.com/leaderboard

GLUE Benchmark Results



GLUE Leaderboard: https://gluebenchmark.com/leaderboard

SQUAD 2.0



Source: https://paperswithcode.com/sota/question-answering-on-squad20

Deep Language Models

- In 2018 several Ideas led to new models
  - Semi-supervised Sequence Learning Andrew Dai, Quoc Le
  - ELMo Peters et al.
  - ULMFiT Howard, Ruder
  - OpenAI Transformer Radford, Narasimhan, Salimans, Sutskever
  - Transformer Vaswani et al.
  - GTP / GTP2 Radford et al.

Deep Language Models

- Google's BERT (October 2018)
  - BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding
- Google/CMU's Transformer-XL (January 2019)
  - Transformer-XL: Attentive Language Models Beyond a Fixed-Length Context
- OpenAI's GPT (June, 2018)
  - Improving Language Understanding by Generative Pre-Training
- OpenAI's GPT-2 (February, 2019)
  - Language Models are Unsupervised Multitask Learners

Model Parameters

Model	Parameters
Medium LSTM	10 Million
ELMo	90 Million
GTP	110 Million
Bert Base	110 Million
Bert Large	340 Million
GTP-2	1500 Million

BERT

Bidirectional

Encoder

Representations from

Transformers

Bert

- What can you do with Bert?
- Some applications:
  - Named Entity Recognition
  - Text Classification
  - Fact Checking
  - Text Summarization
  - Text Generation
  - Question Answering (Full Text and Multiple Choice)
  - Translation

Bert

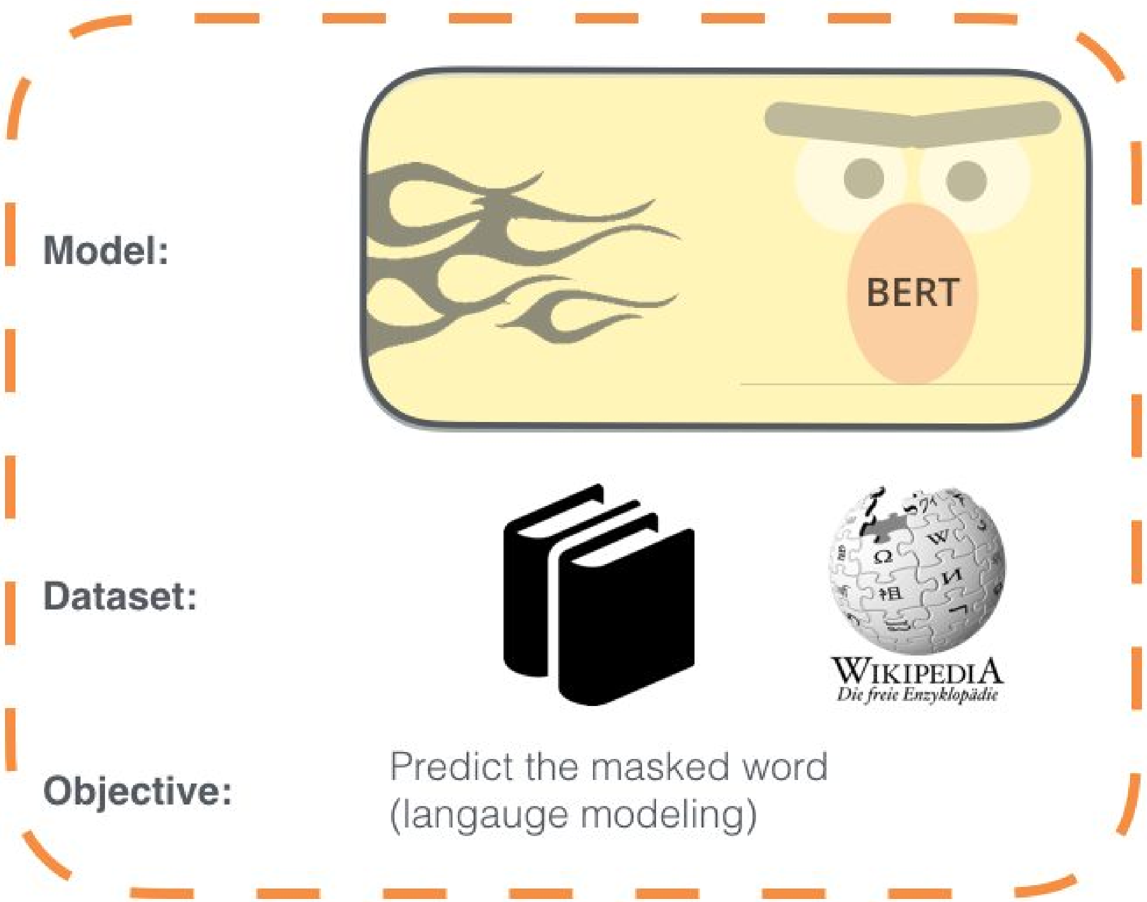
- Training Process
  - Pre-train a model on plain text
  - Choose a task specific labeled data set
  - Retrain the model with this data set

- Use the same pre trained model for all tasks
    - Classification
    - Named Entity Recognition
    - Question Answering etc.

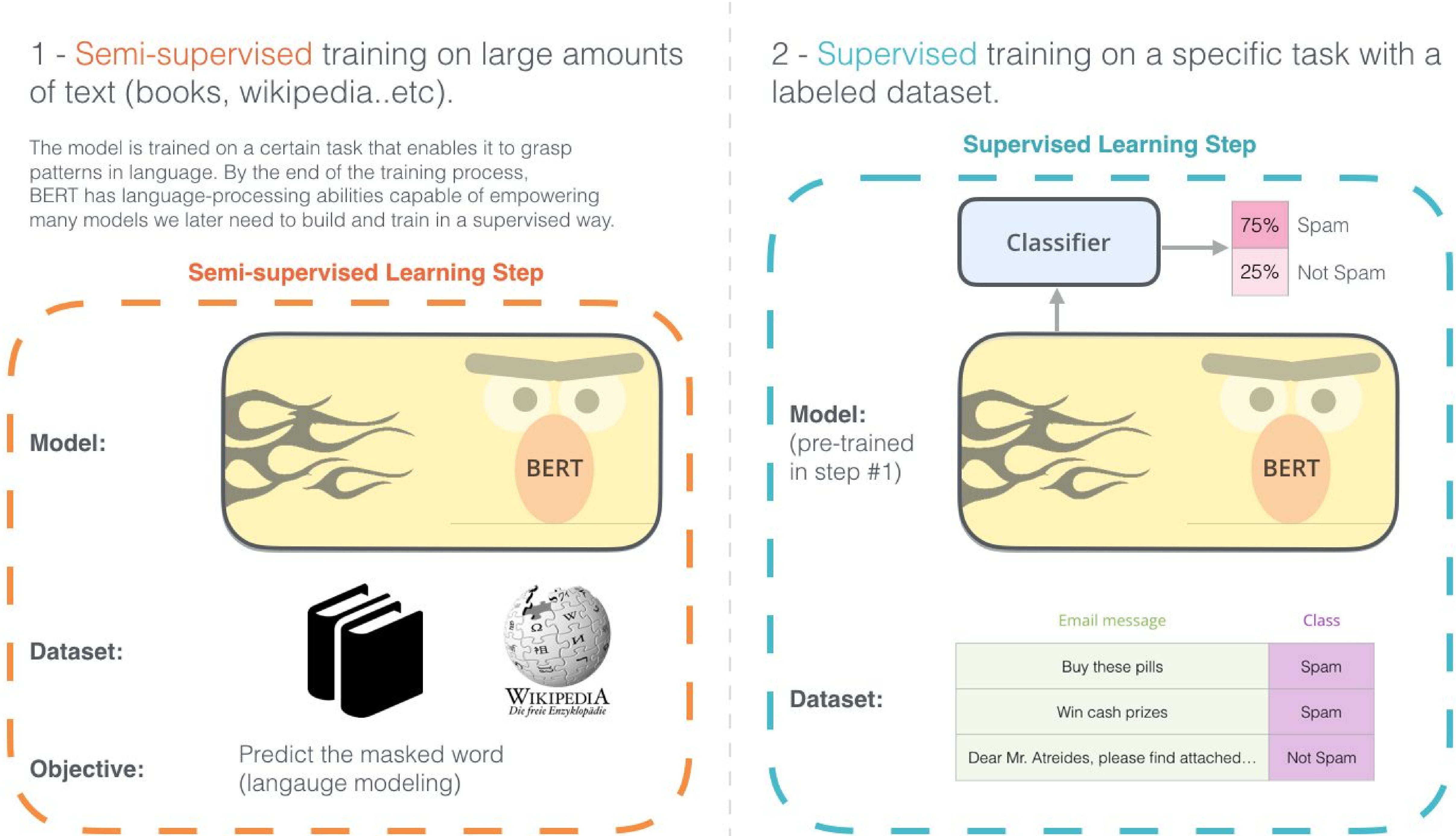
1 - Semi-supervised training on large amounts of text (books, wikipedia..etc).

The model is trained on a certain task that enables it to grasp patterns in language. By the end of the training process, BERT has language-processing abilities capable of empowering many models we later need to build and train in a supervised way.

Semi-supervised Learning Step



The Illustrated BERT, Jay Alammar: http://jalammar.github.io/illustrated-bert/



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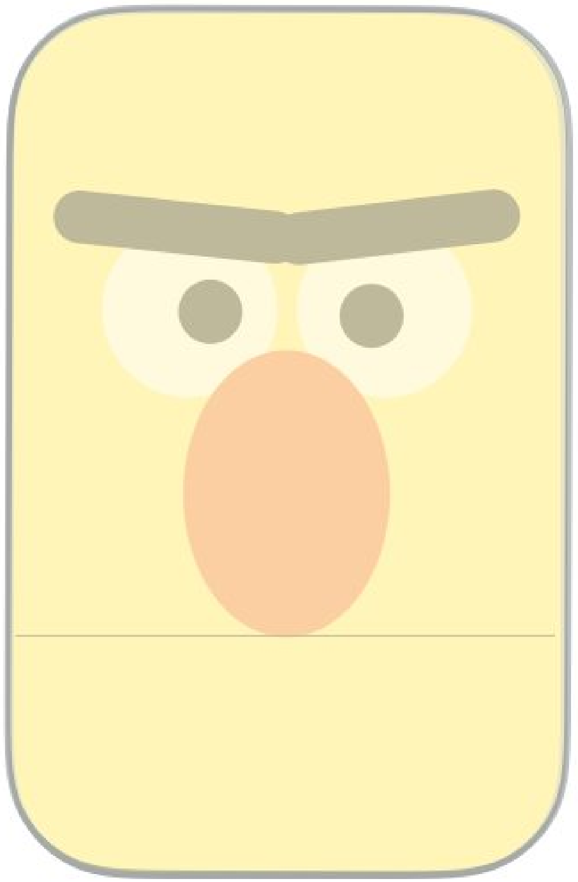
Two pre-trained sizes

BERT$_{BASE}$



BERT$_{LARGE}$

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Pre Trained Bert

- English
  - BERT-Large, Uncased (Whole Word Masking): 24-layer, 1024-hidden, 16-heads, 340M parameters
  - BERT-Large, Cased (Whole Word Masking): 24-layer, 1024-hidden, 16-heads, 340M parameters
  - BERT-Base, Uncased: 12-layer, 768-hidden, 12-heads, 110M parameters
  - BERT-Large, Uncased: 24-layer, 1024-hidden, 16-heads, 340M parameters
  - BERT-Base, Cased: 12-layer, 768-hidden, 12-heads , 110M parameters
  - BERT-Large, Cased: 24-layer, 1024-hidden, 16-heads, 340M parameters
- Multi Language
  - BERT-Base, Multilingual Cased (New, recommended): 104 languages, 12-layer, 768-hidden, 12-heads, 110M parameters
  - BERT-Base, Multilingual Uncased (Orig, not recommended) (Not recommended, use Multilingual Cased instead): 102 languages, 12-layer, 768-hidden, 12-heads, 110M parameters
- Chinese
  - BERT-Base, Chinese: Chinese Simplified and Traditional, 12-layer, 768-hidden, 12-heads, 110M parameters

Pre Trained Bert

Explained on the next slides

- English
  - BERT-Large, Uncased (Whole Word Masking): 24-layer, 1024-hidden, 16-heads, 340M parameters
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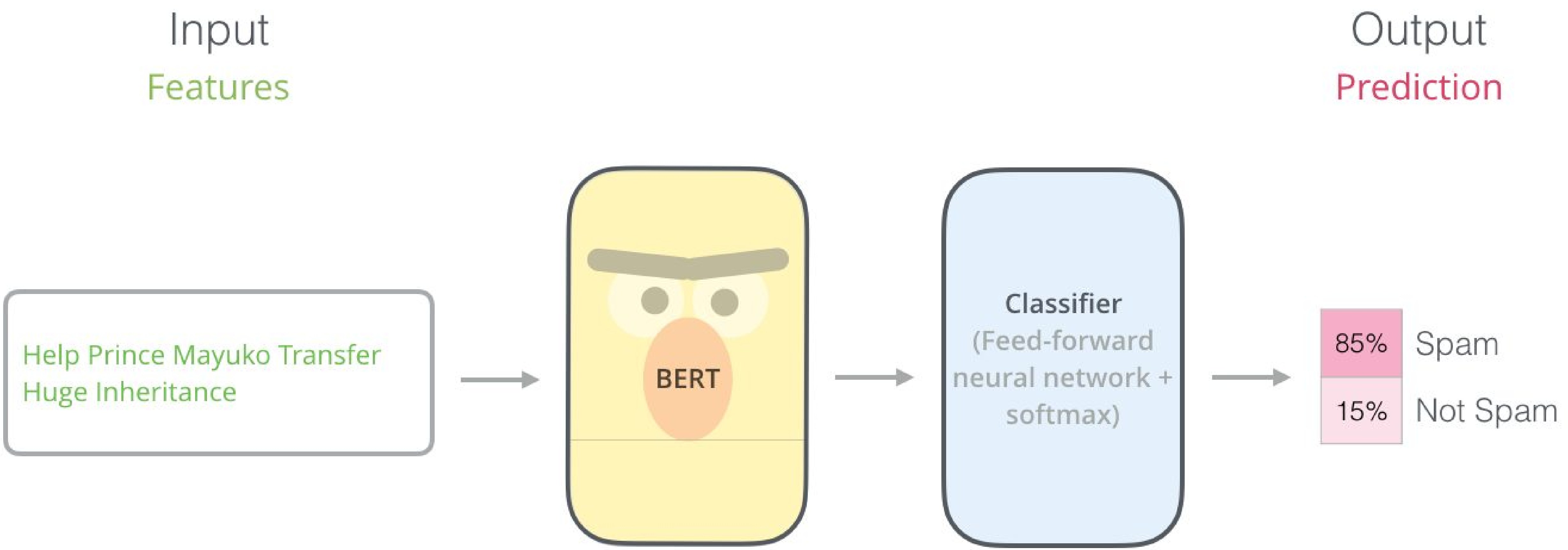
Text Classification



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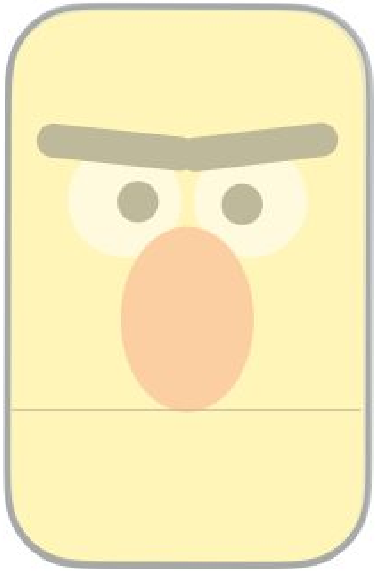
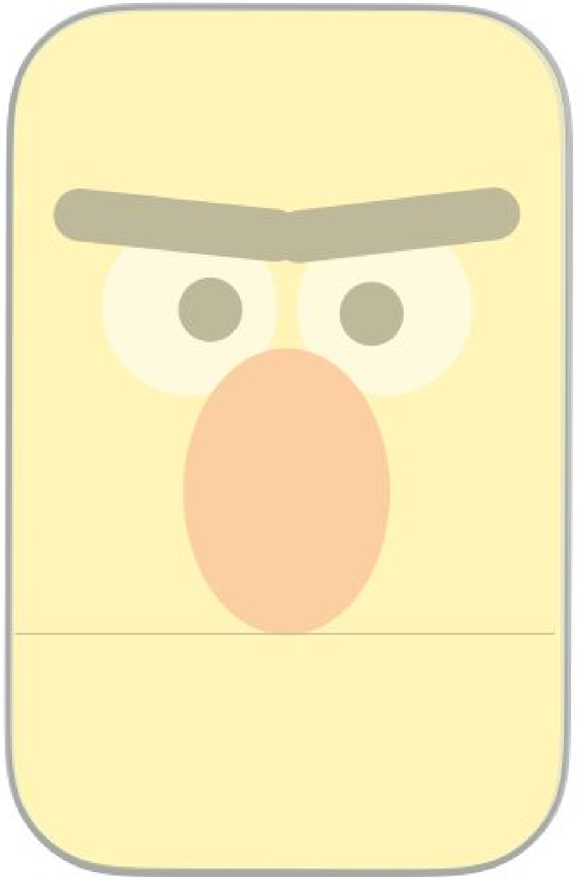
Two sizes



BERT BASE



BERT LARGE

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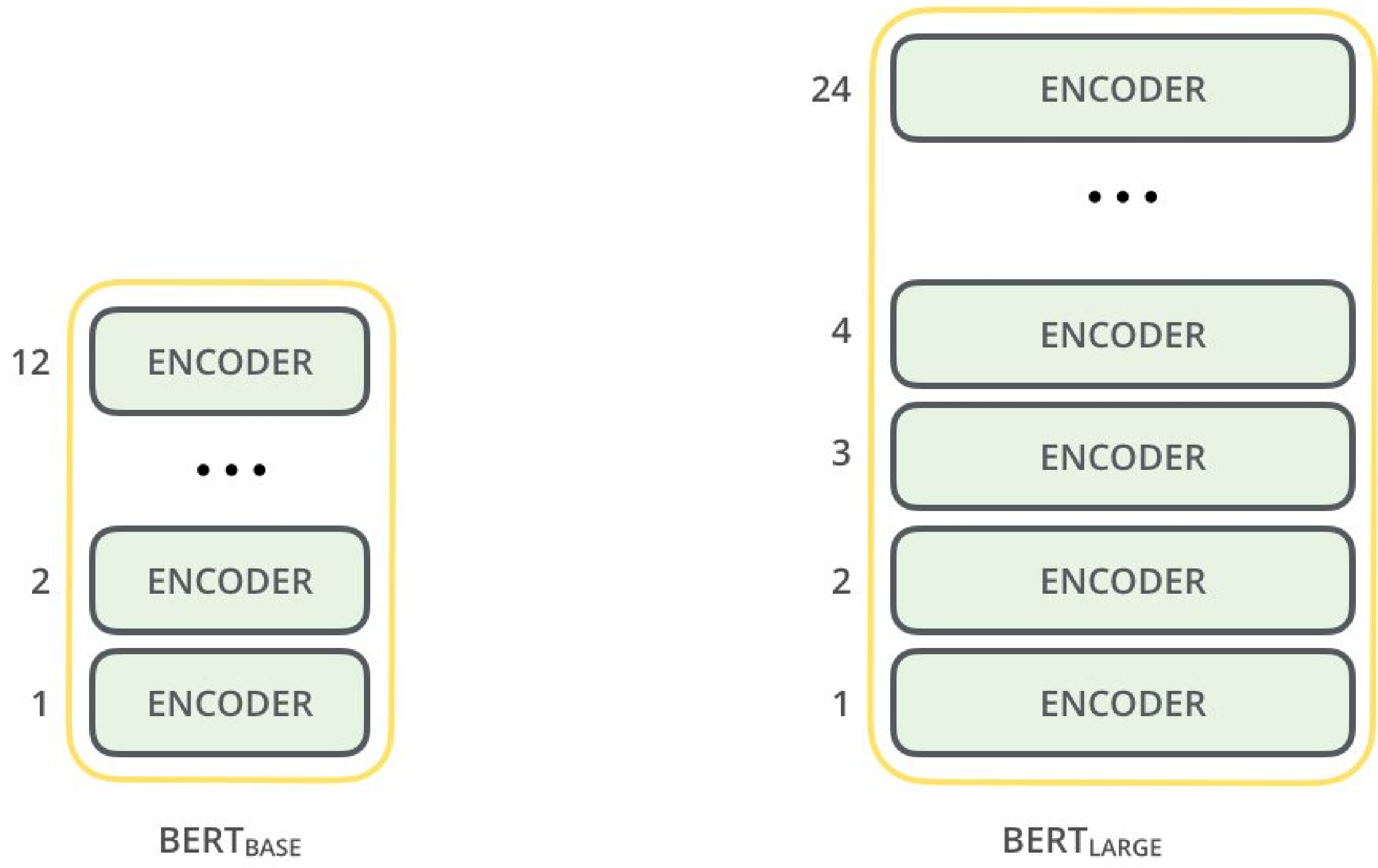
Bert Model



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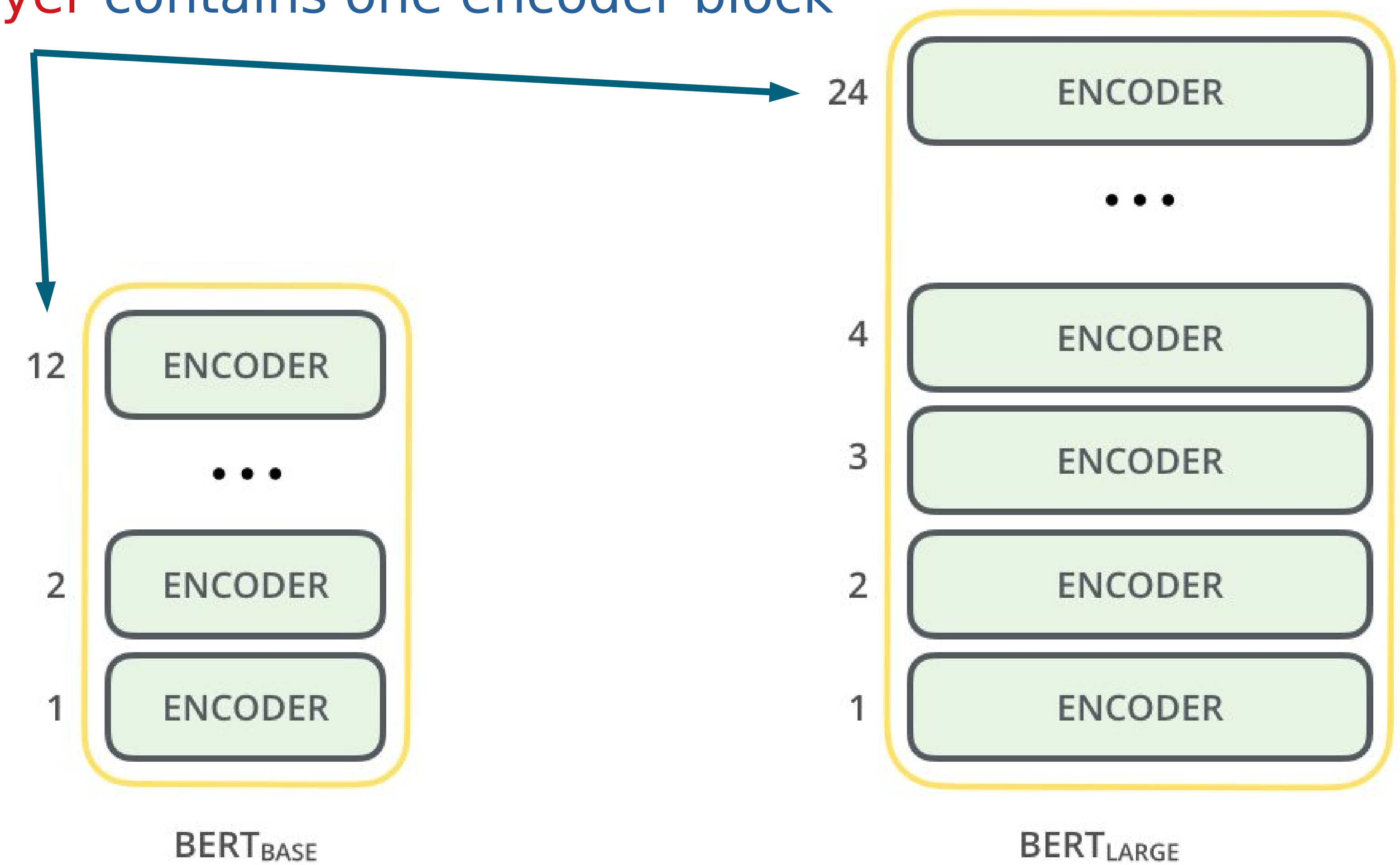
Bert Model

Each layer contains one encoder block



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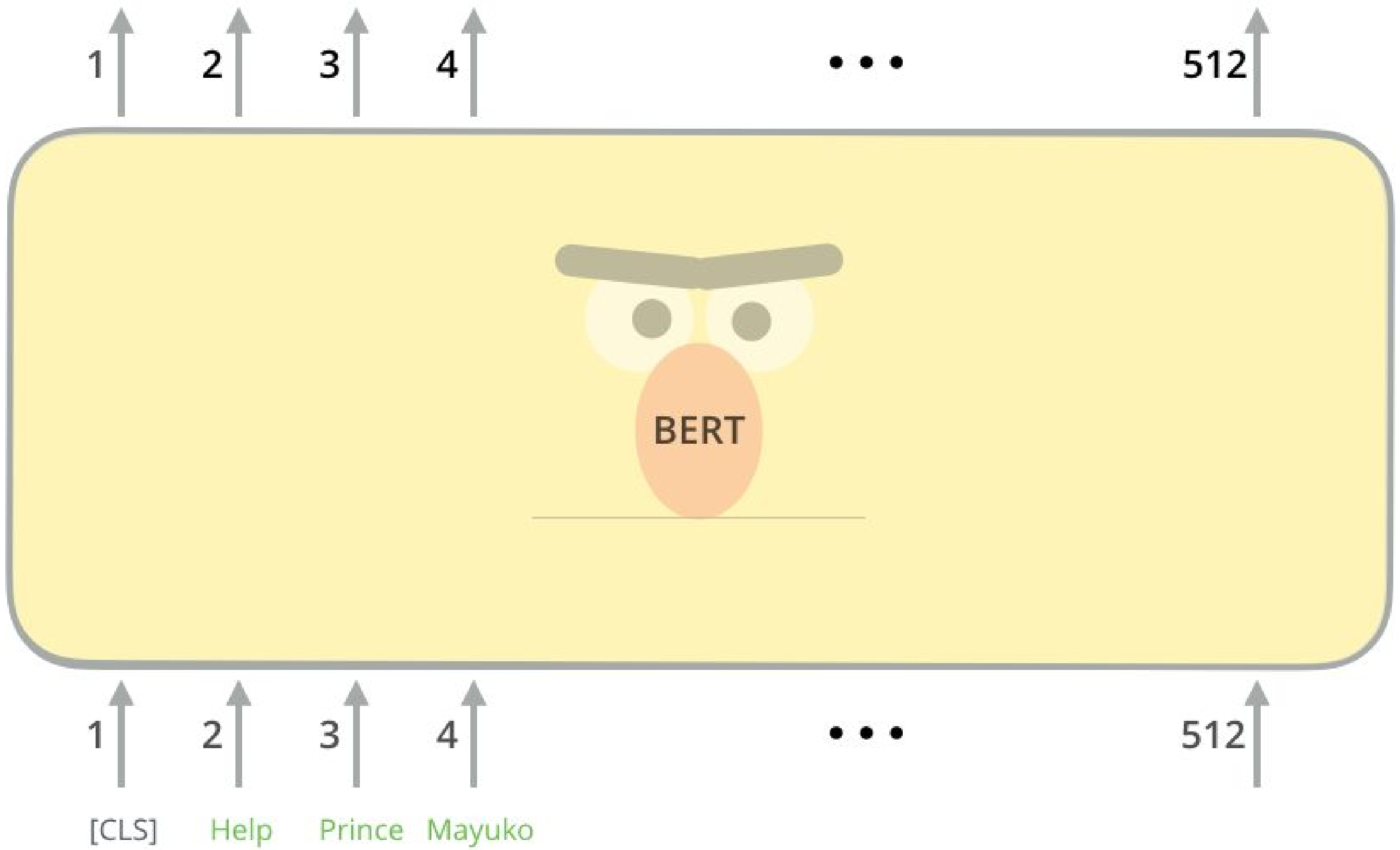
How to process sequences?



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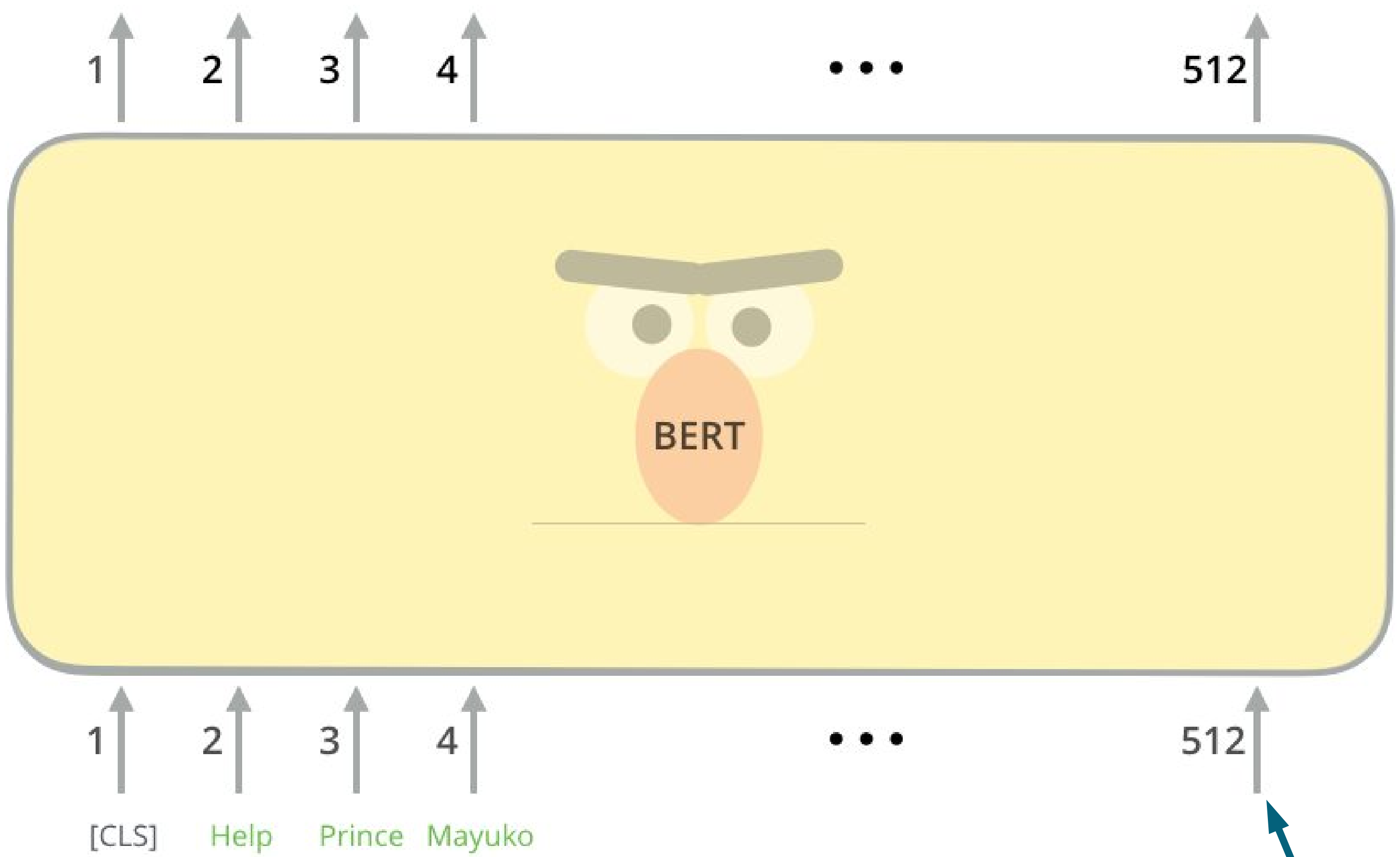
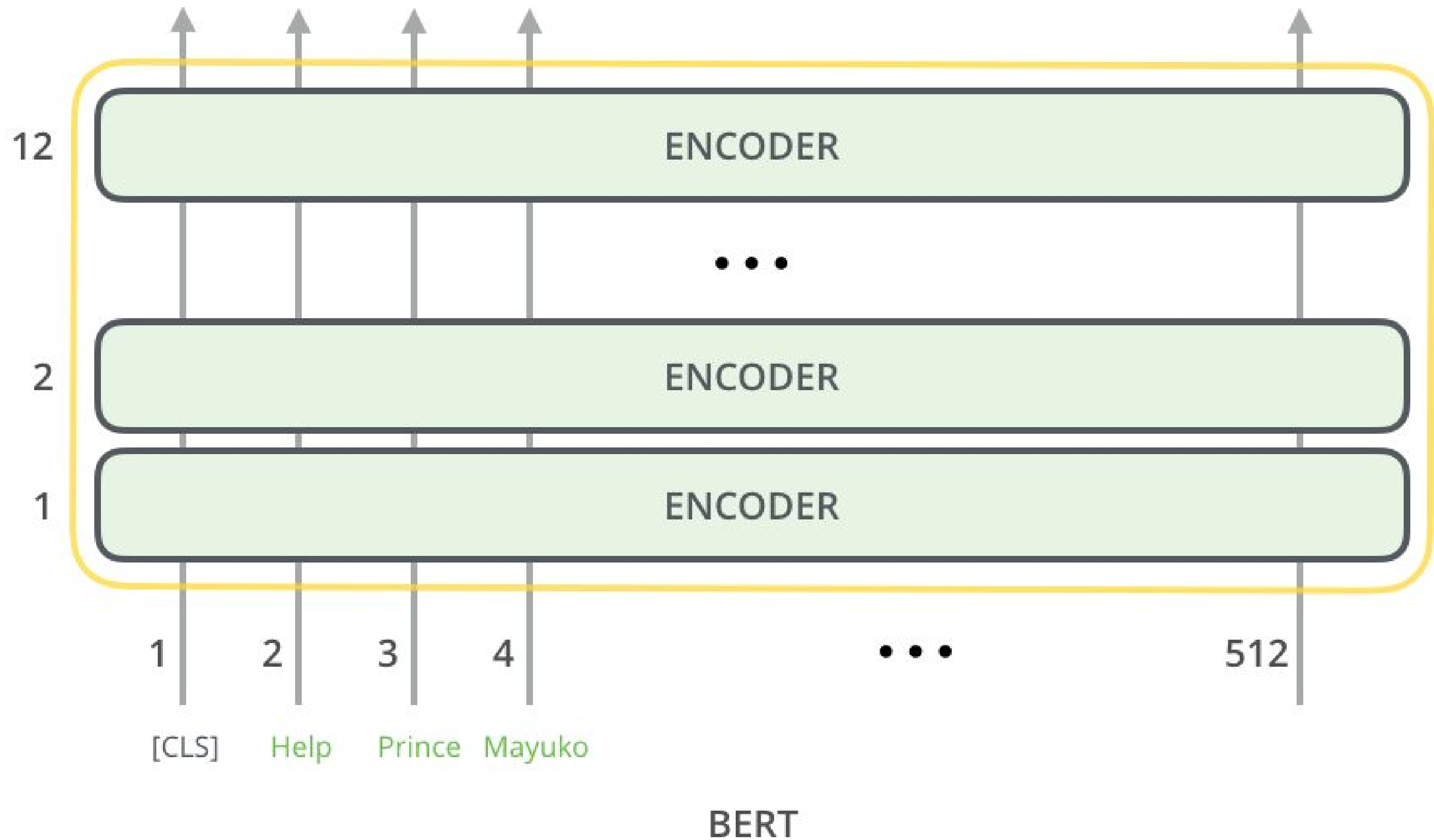
How to process sequences?



This Bert model can process sequences up to 512 tokens.

The Illustrated BERT, Jay Alammar: http://jalammar.github.io/illustrated-bert/

Bert



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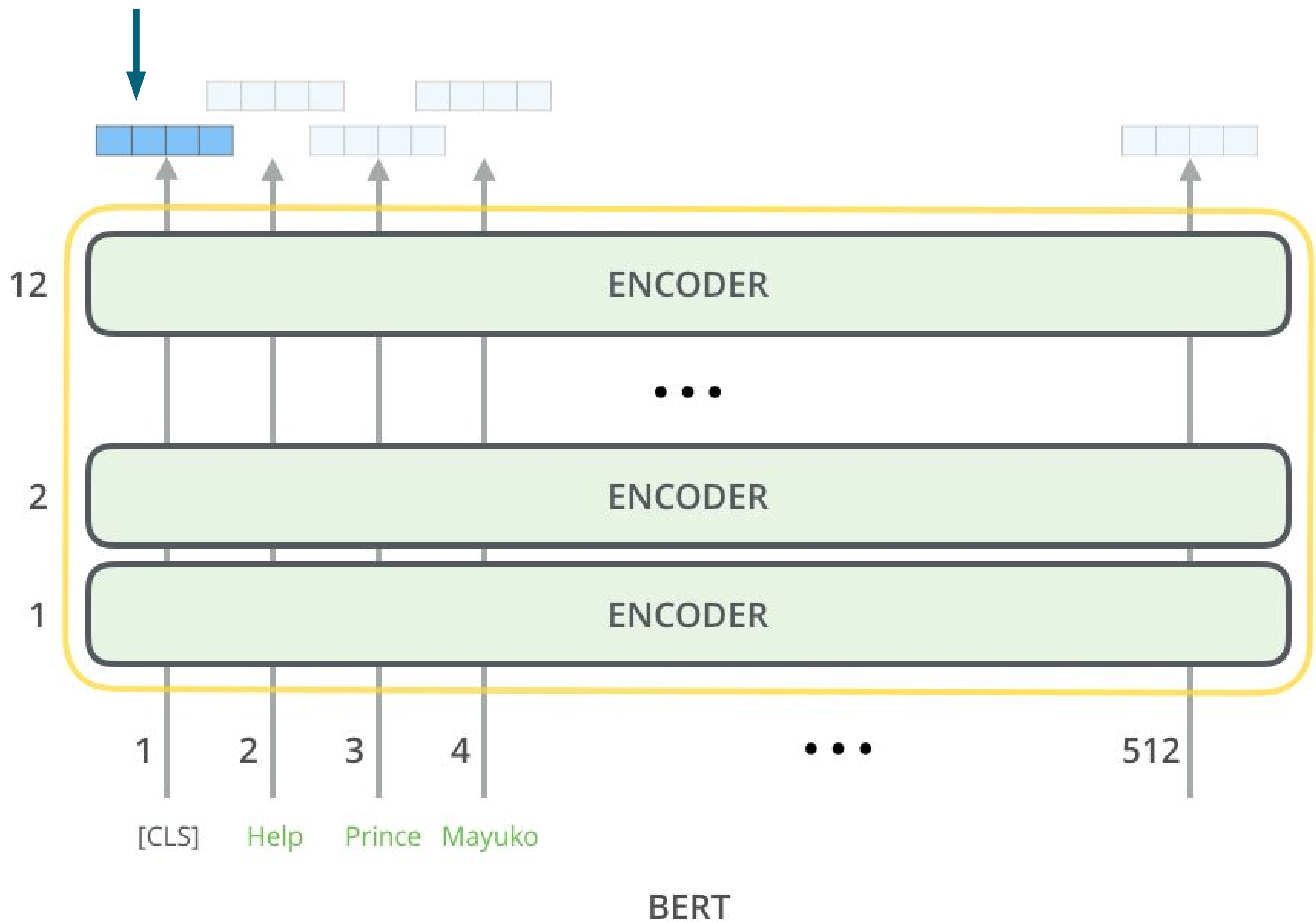
Bert

Each token generates a vector with the length of the hidden size.



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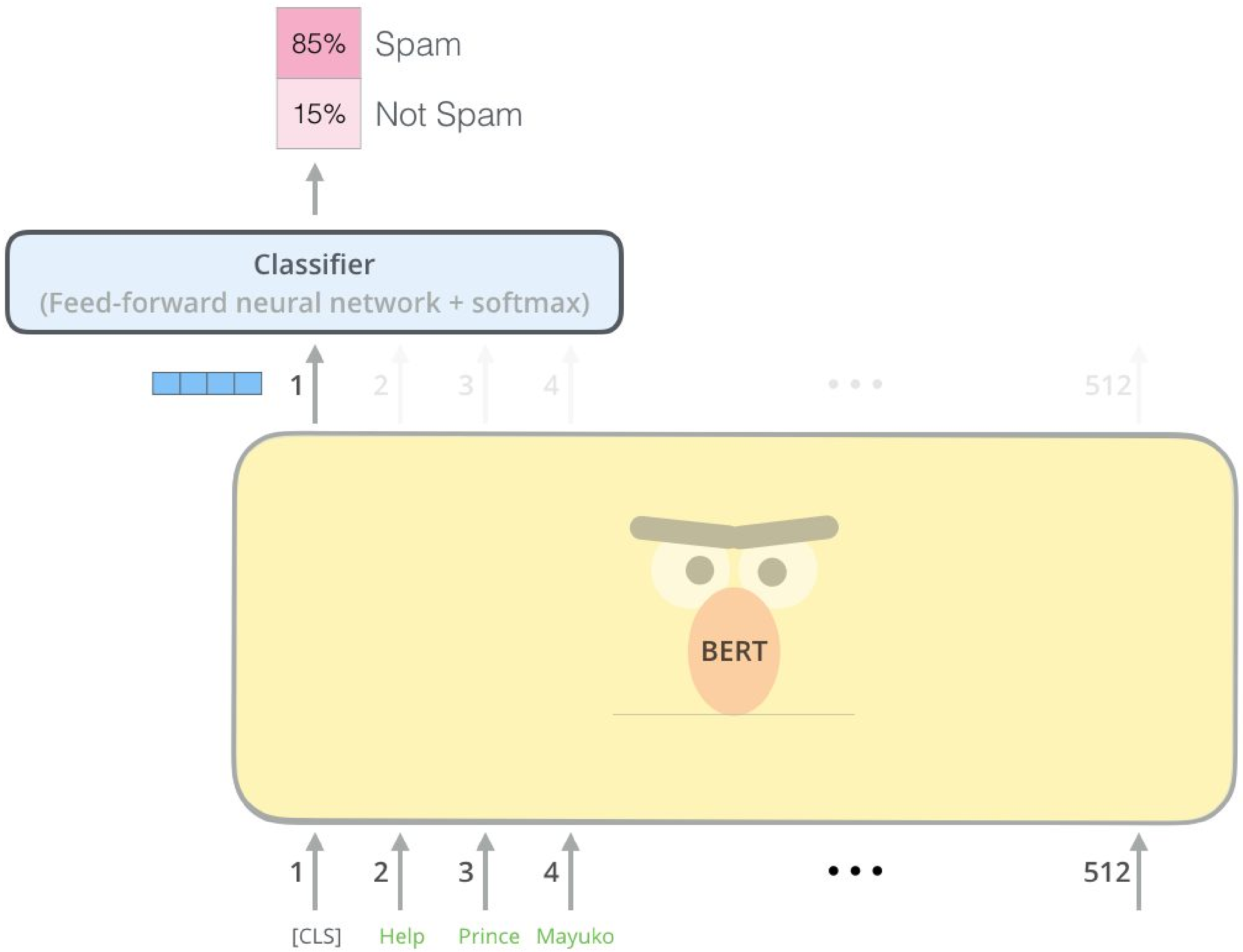
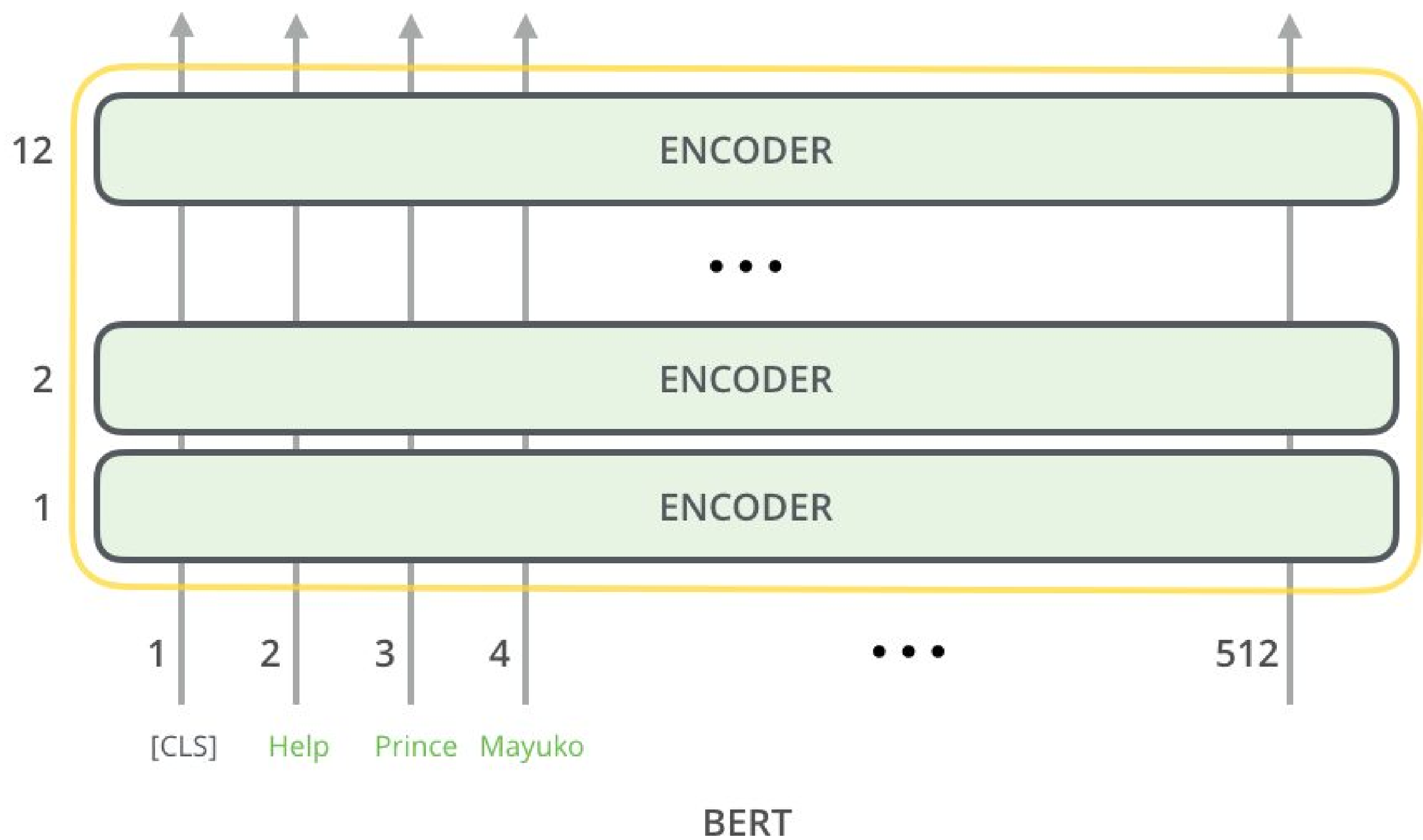
Classification with Bert



Attention and Transformer

Berts Encoder



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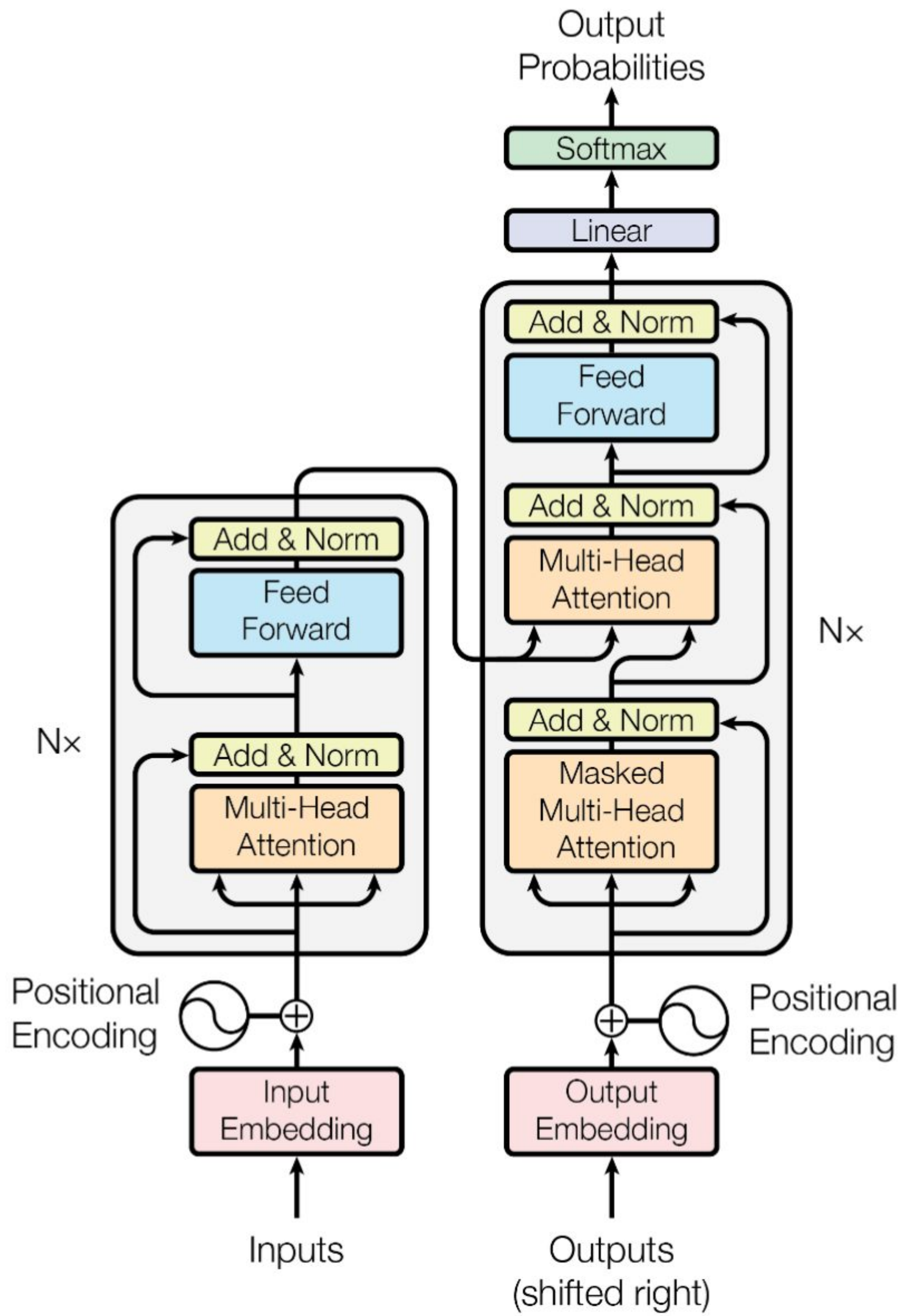
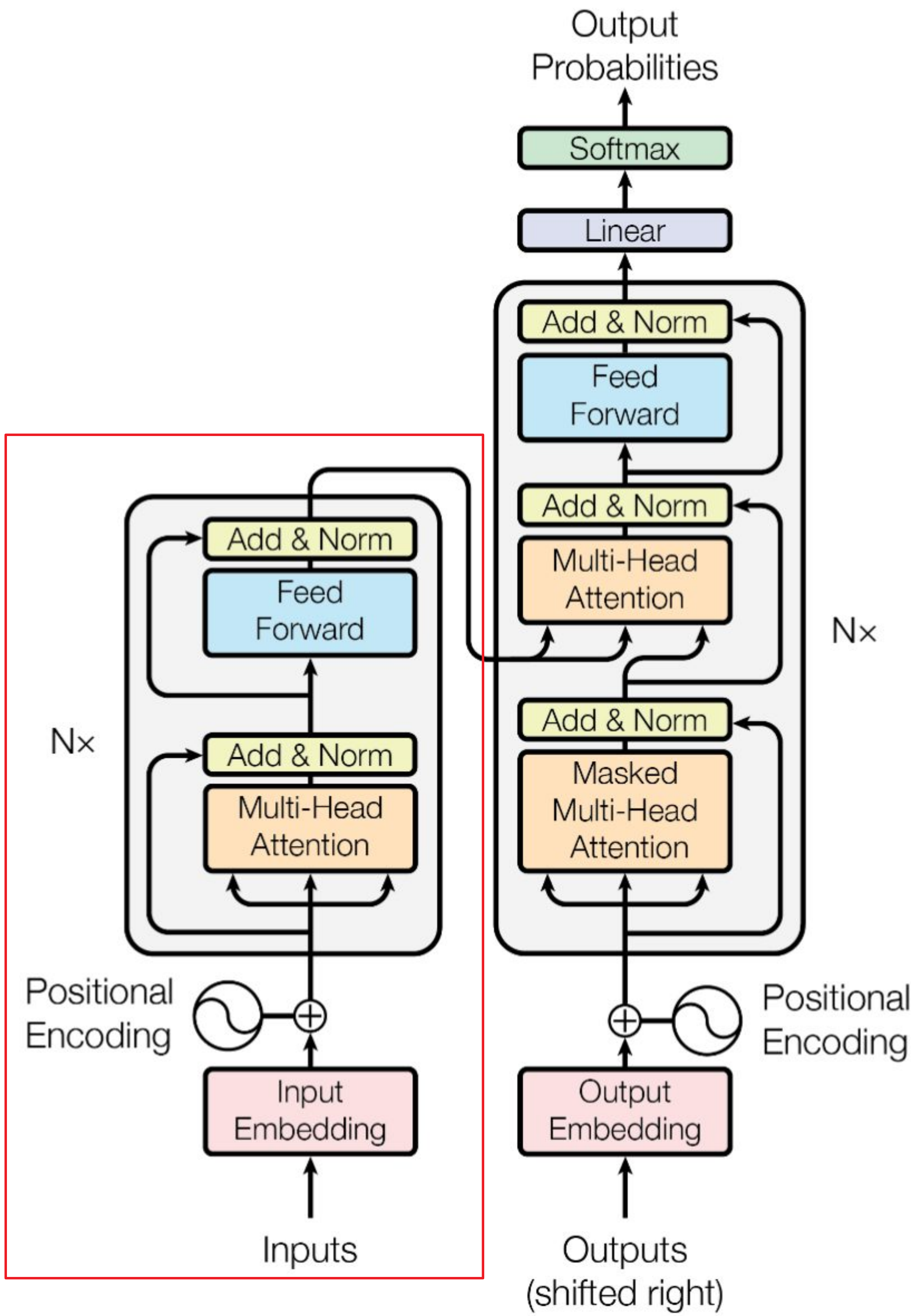


Attention Is All You Need, Vaswani et al. https://arxiv.org/abs/1706.03762



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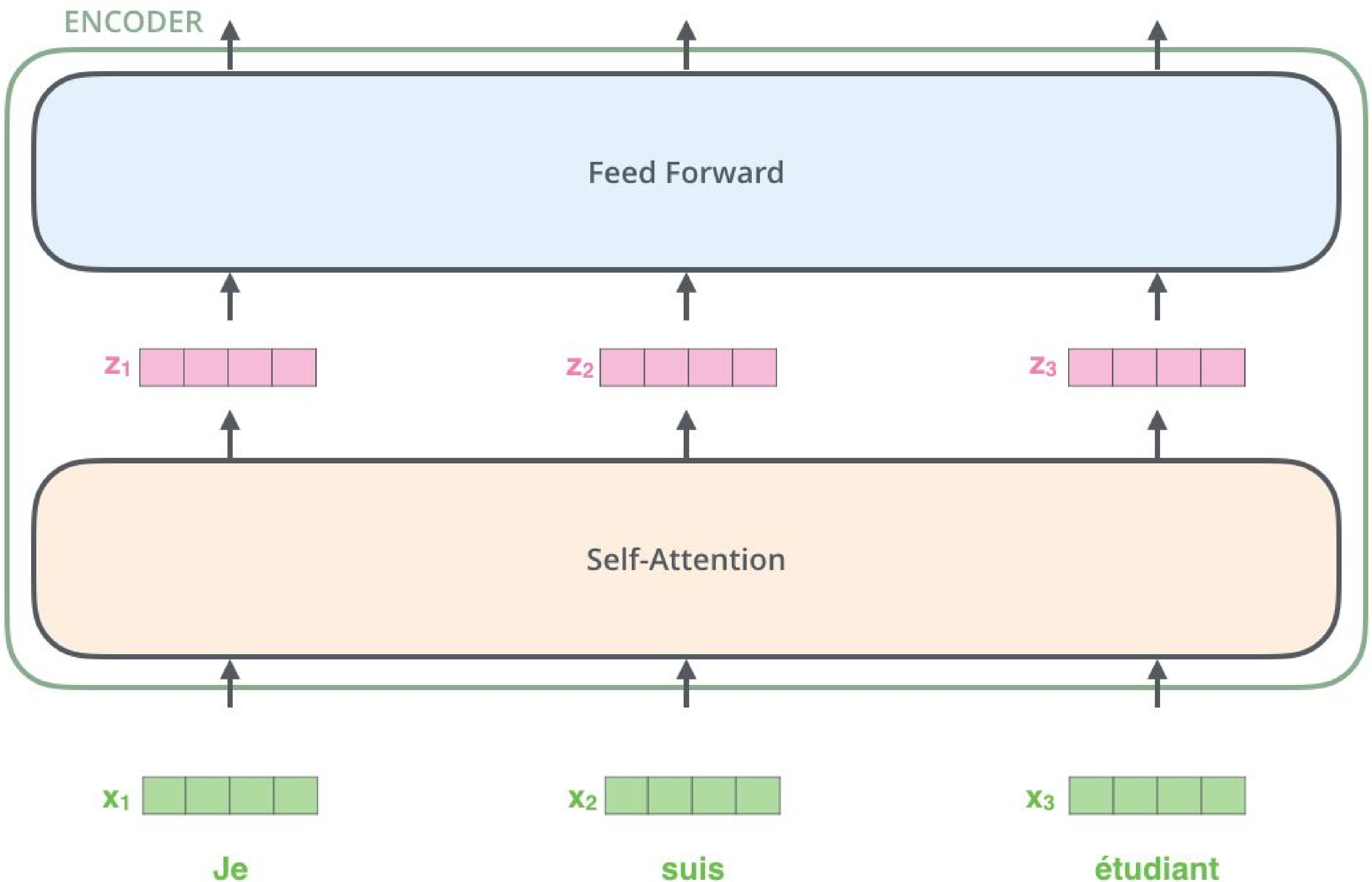
Transfromer



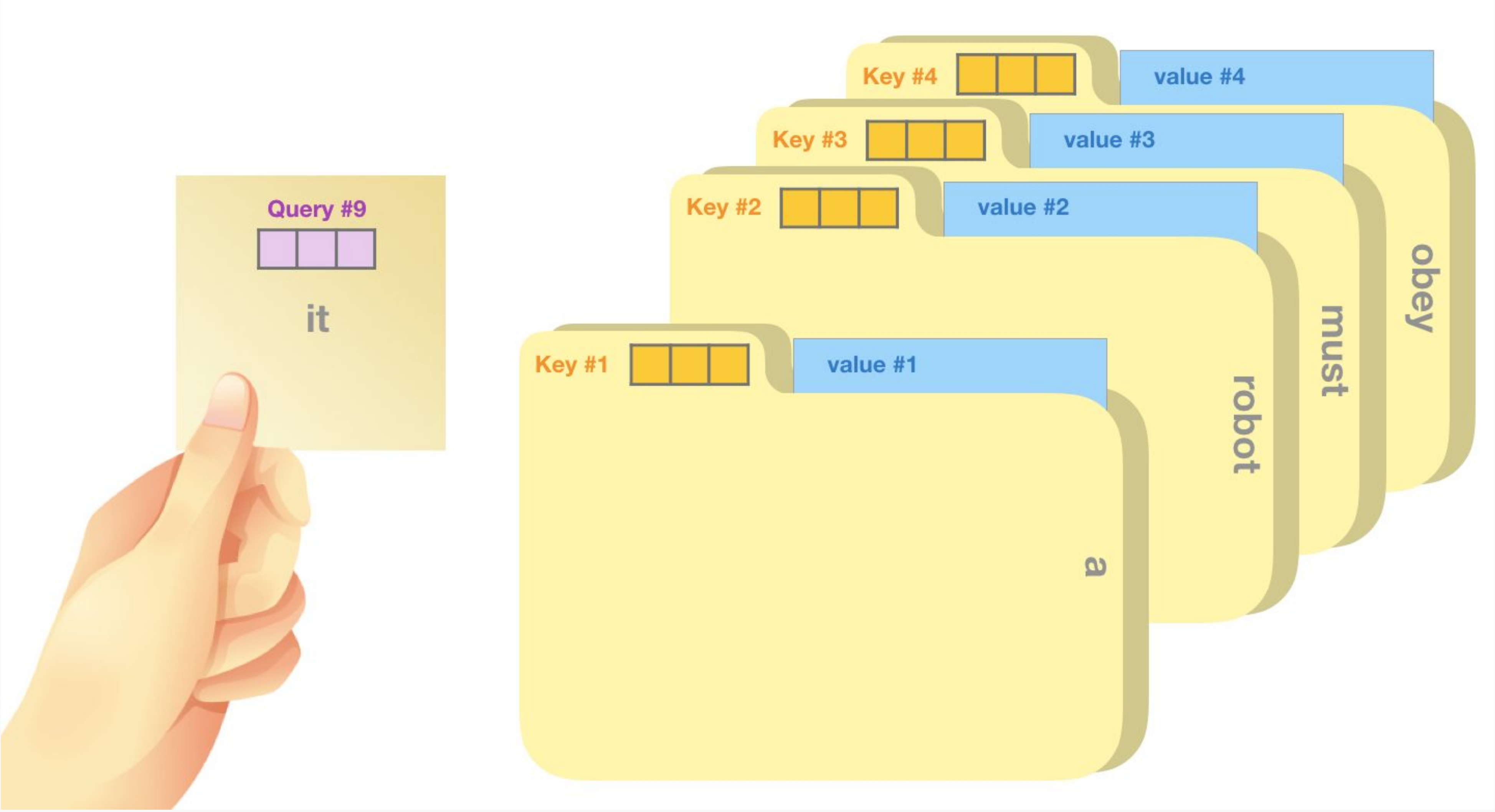
The Illustrated BERT, Jay Alammar: http://jalammar.github.io/illustrated-bert/

Scaled Dot-Product Attention

$$A(\underbrace{Q}_{\text{Query}},\underbrace{K}_{\text{Key}},\underbrace{V}_{\text{Value}})=softmax(QK^{T})V$$

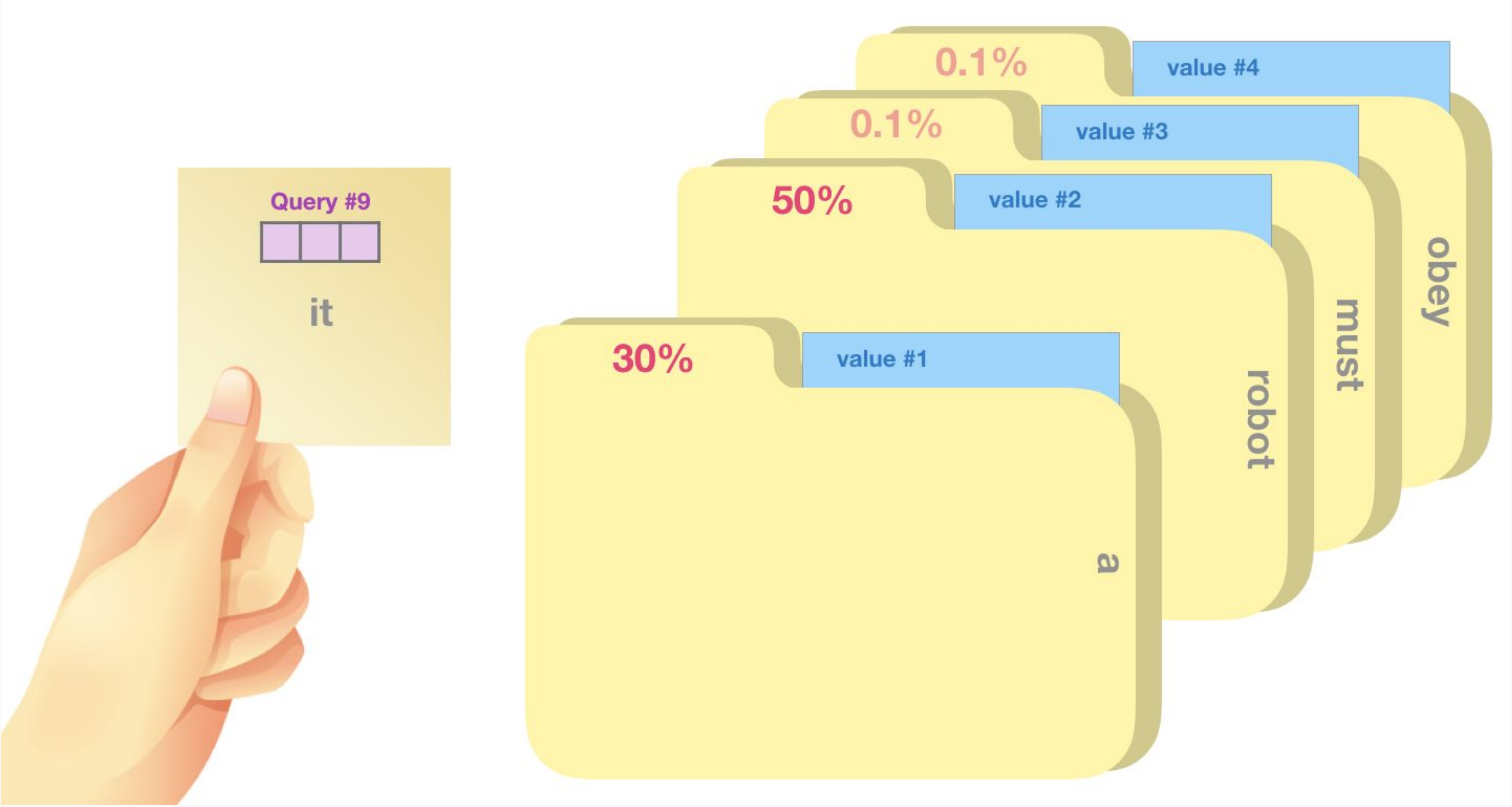
Take the current word or token, find the most similar Key and return the corresponding value.

Attention Process



The Illustrated GPT2, Jay Alammar: http://jalammar.github.io/illustrated-gpt2

Attention Process



The Illustrated GPT2, Jay Alammar: http://jalammar.github.io/illustrated-gpt2

Attention Process

Word	Value vector	Score	Value X Score
<s>		0.001	
a		0.3	
robot		0.5	
must		0.002	
obey		0.001	
the		0.0003	
orders		0.005	
given		0.002	
it		0.19	
		Sum:	

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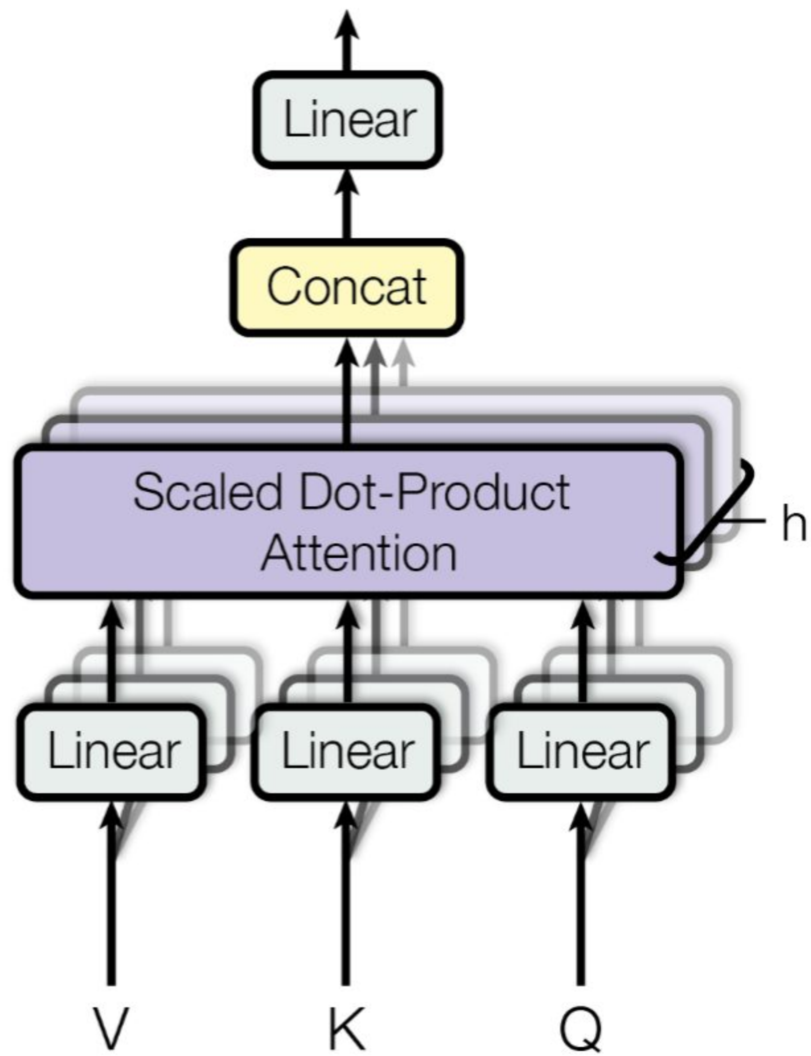
Transformer: Multi Head Attention



Attention Is All You Need, Vaswani et al. https://arxiv.org/abs/1706.03762

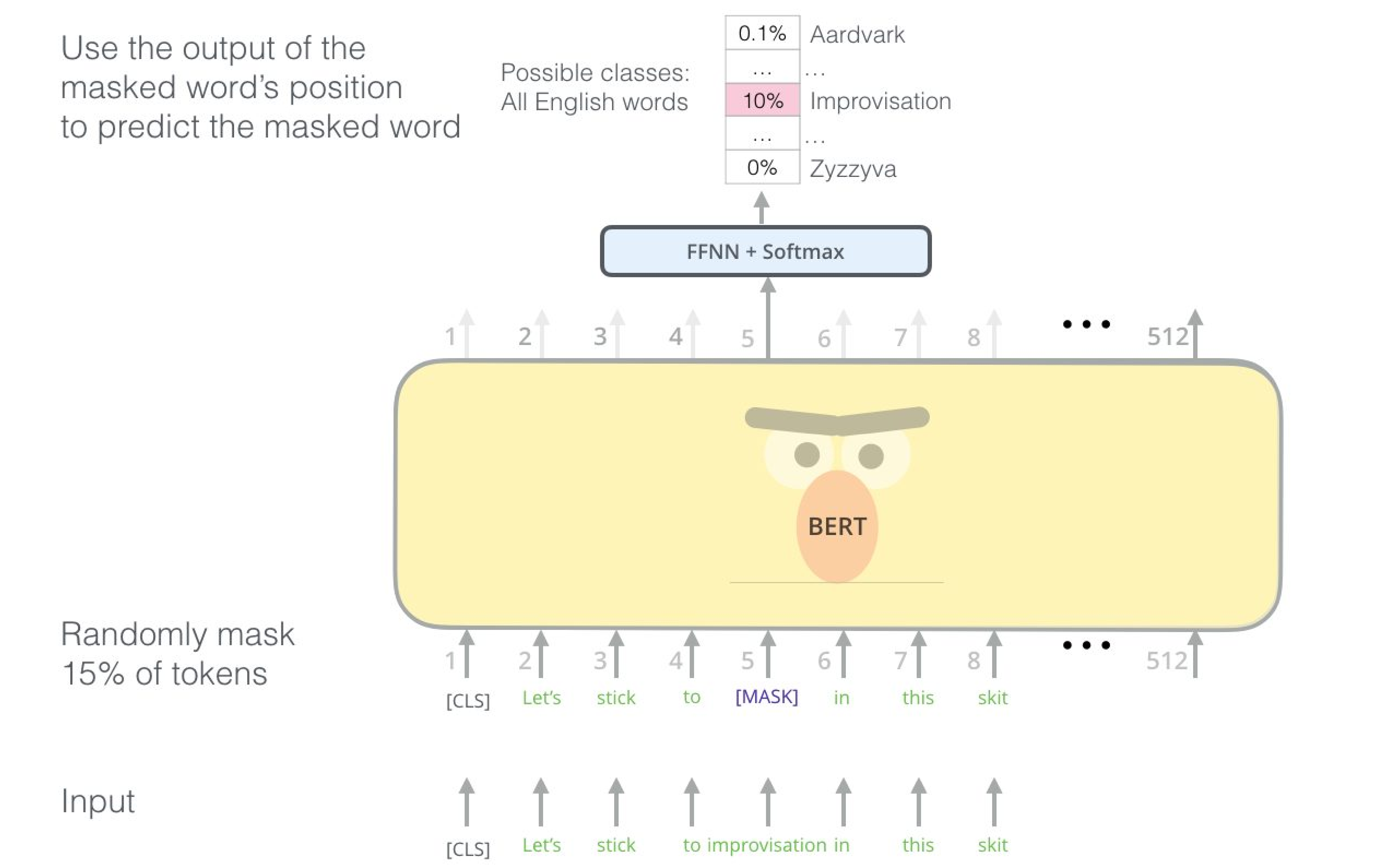
Transformer

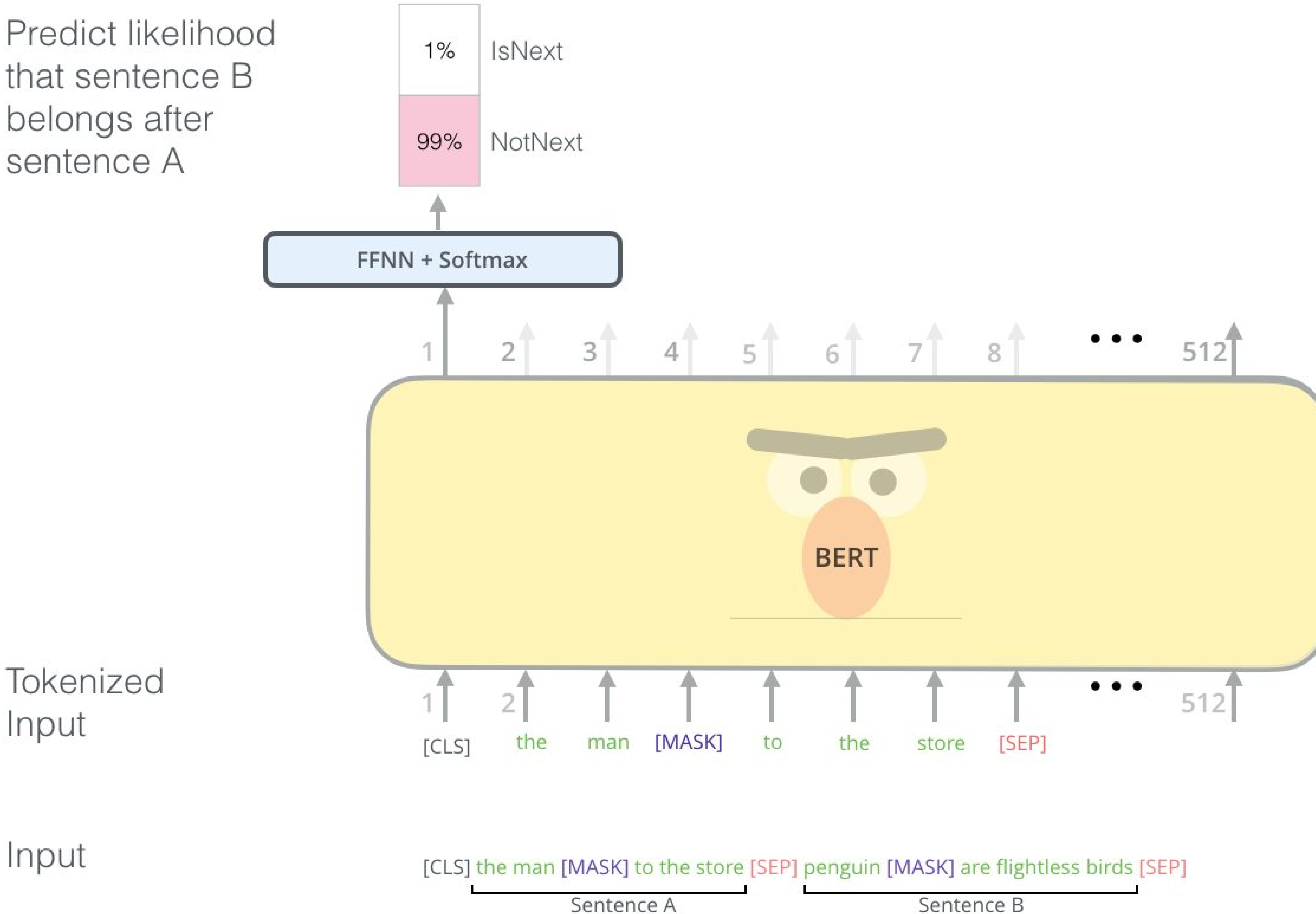
- Paper
  - Attention is all you need. Vaswani et al.
- Good Read
  - Jay Alammars The Illustrated Transformer
- Conference Talk:
  - Attention is all you need attentional neural network mo dels by Łukasz Kaiser

Training Bert

Pre Training Bert

- pre trained models are also called **language models**
- Compared to FastText Berts language model can distinguish between contexts
  - “river bank” vs “financial bank”
- To create them, Bert used two methods:
  - Task One: Mask Words
  - Task Two: Next Sentence Prediction

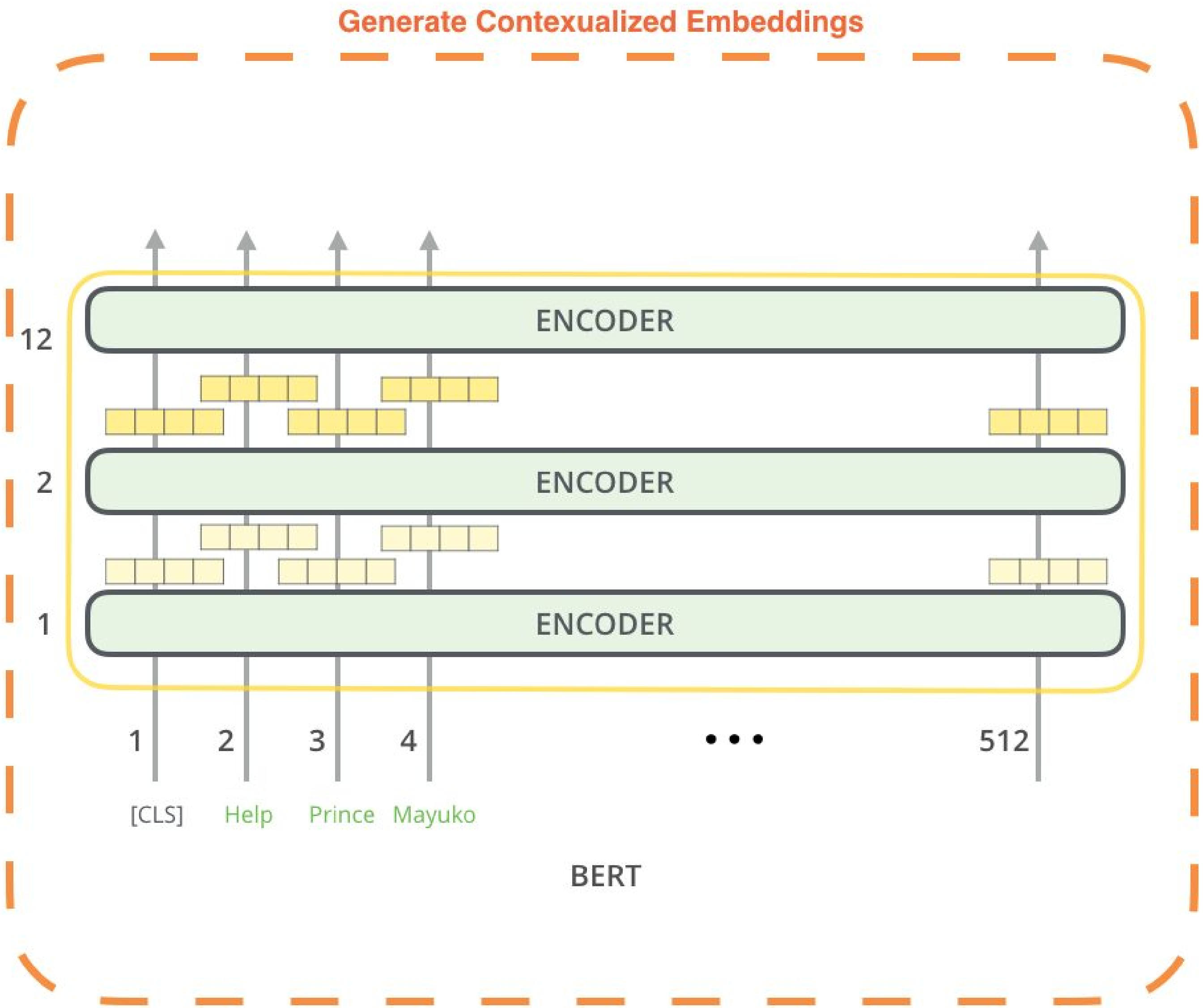

Use the output of the masked word's position to predict the masked word
Possible classes: All English words
0.1% Aardvark
...
10% Improvisation
...
0% Zyzzyva
FFNN + Softmax
1 2 3 4 5 6 7 8 ... 512
BERT
Randomly mask 15% of tokens
1 2 3 4 5 6 7 8 ... 512
[CLS] Let's stick to [MASK] in this skit
Input
[CLS] Let's stick to improvisation in this skit


Predict likelihood that sentence B belongs after sentence A
1% IsNext
99% NotNext
FFNN + Softmax
1 2 3 4 5 6 7 8 ... 512
BERT
Tokenized Input
1 2 ... 512
[CLS] the man [MASK] to the store [SEP]
Input
[CLS] the man [MASK] to the store [SEP] penguin [MASK] are flightless birds [SEP]
Sentence A
Sentence B

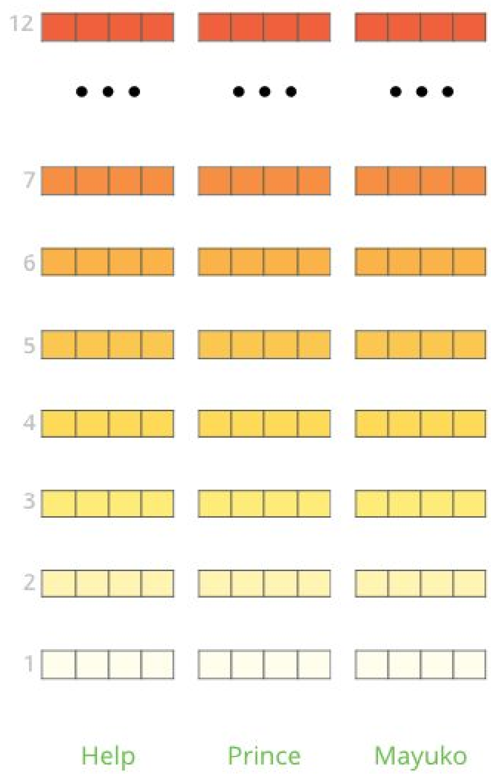
Training Bert

- Pre Training takes 14 days on a TPUv2 (500$)
- Bert Large Models (24 Layers) can only be trained on TPUs
- Fine-tuning a model with 1GB of text takes serveral hours on a single GPU (1080 / 2080)

Bert as Embedding



The output of each encoder layer along each token's path can be used as a feature representing that token.



But which one should we use?

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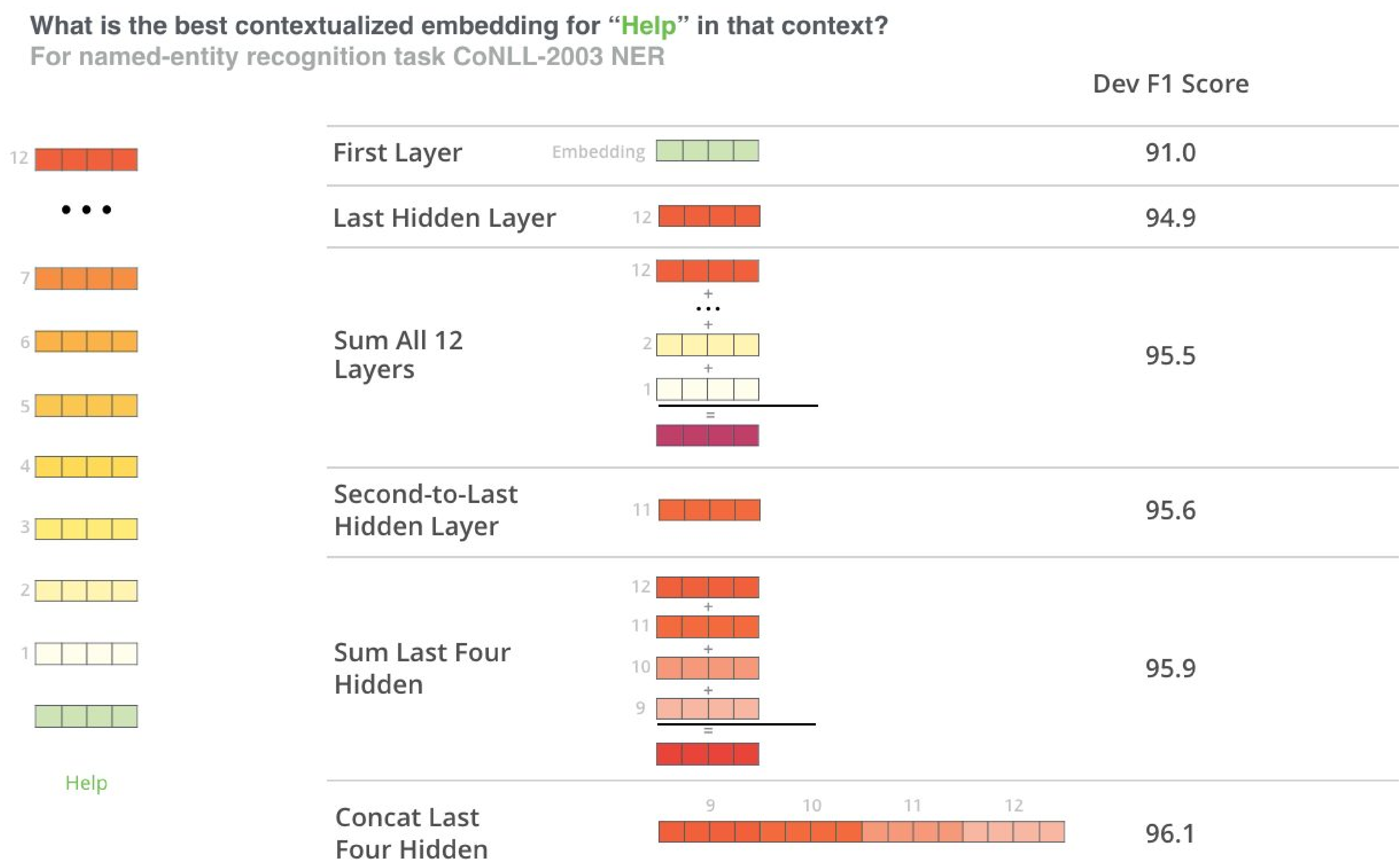
Bert as Embedding



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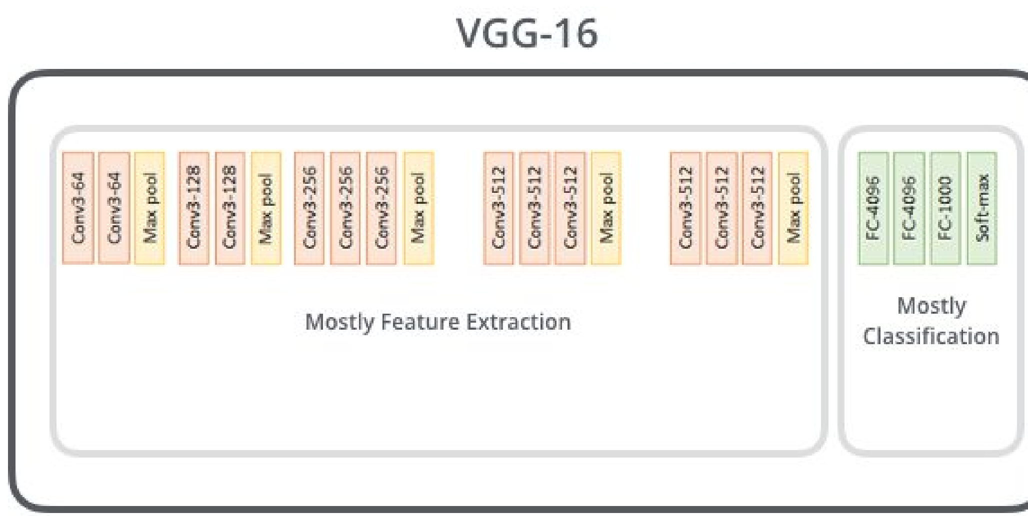
Similarity to Conv Nets

Input

Features



Output

Prediction

0.2%	Kit fox
0.1%	English setter
95%	Egyptian cat
1%	Great Dane
	...
0%	Hotdog

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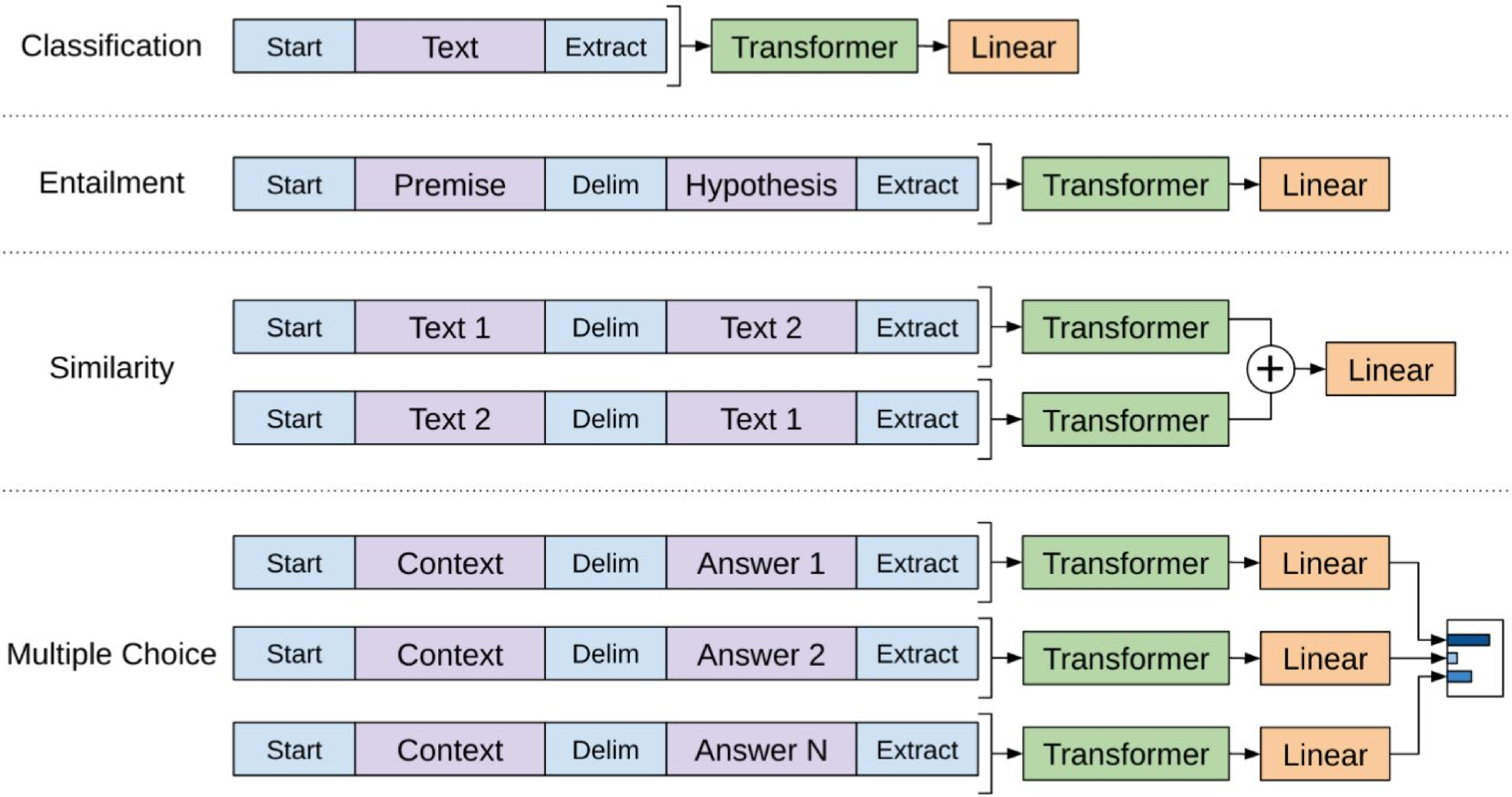

Improving Language Understandingby Generative Pre-Training, Radford et. al

Summary

- Pre-Trained on unlabeled data, fine tune on domain specific data
- Better language understanding
  - Context matters!
- Deep models achieve better results with less data
- Be careful, they are not grounded
  - These model do not have a generalizable, strucktured knowledge of the world
  - They are not capable of reasoning.

What‘s next?

- More effective / smaller models
  - Albert
  - DistilBert
- Process longer sequences / texts
  - Longformer
  - Reformer O(L^2) to O(L log L)!
- Security
  - HotFlip (Demo)
  - Probing Neural Network Comprehension of Natural Language Arguments

WHK Jobs

- Do cutting edge deep learning:
  - Dialog Systems aka Chat Bots
  - Speech Recognition
  - Speech Synthesis
  - Text Classification / Generation
  - Build Alexa and Mycroft skills