Julius-Maximilians-
UNIVERSITÄT
WÜRZBURG

data science

CAIDAS

Chapter 8

Word Representations part2

Context

Word Embeddings — Idea

Recall

Represent high dimensional **sparse vectors (one-hot encoded words)** as low dimensional **dense vectors**

Then use these vectors as input to task specific model

→Vectors should capture the semantics of words

→Words that can be used interchangeably should have very similar vectors

→Word embeddings can be learned on large text corpora and used in other tasks

Biggest Problem of Word2Vec/…

He kicked the **bucket.**
I have yet to cross-off all the items on my **bucket** list.
The **bucket** was filled with water.

1. Words are sometimes ambiguous (e.g. bank, play, bucket, stick, …)
2. Word meaning depends on the context it is used in
3. Word2Vec learns **one** vector per word

→Make embeddings context-sensitive!

→Embedding captures **current** context

→Different embeddings for different contexts

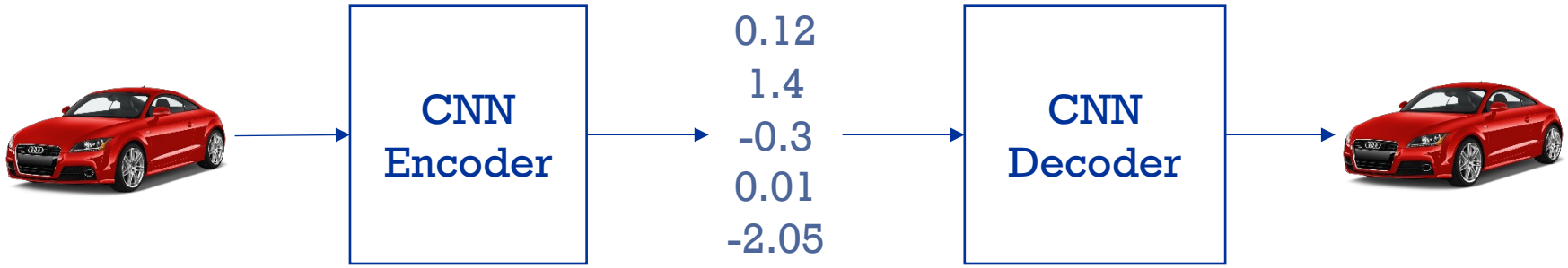
Why bother with Word Embeddings?

Reuse weights from pretrained model from another task!

→ **Transfer Learning**

Transfer Learning (in Computer Vision)

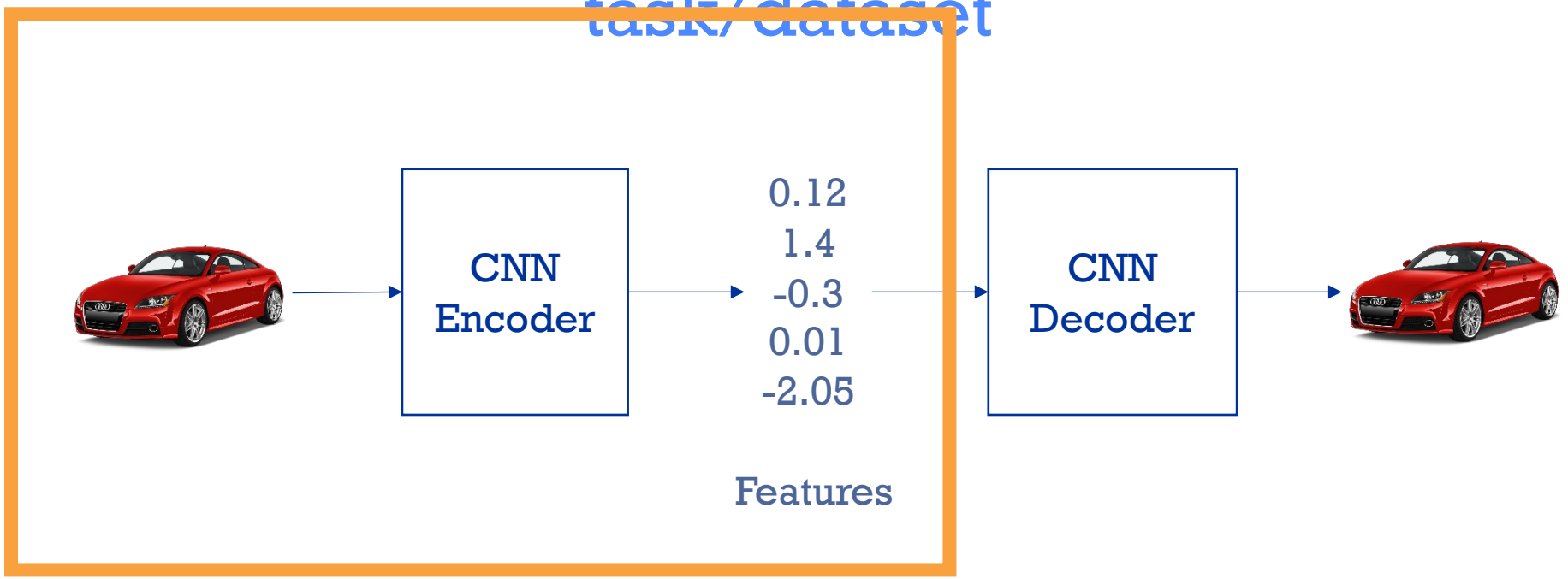
Learn on one task/dataset, then transfer to another task/dataset



Features

Transfer Learning (in Computer Vision)

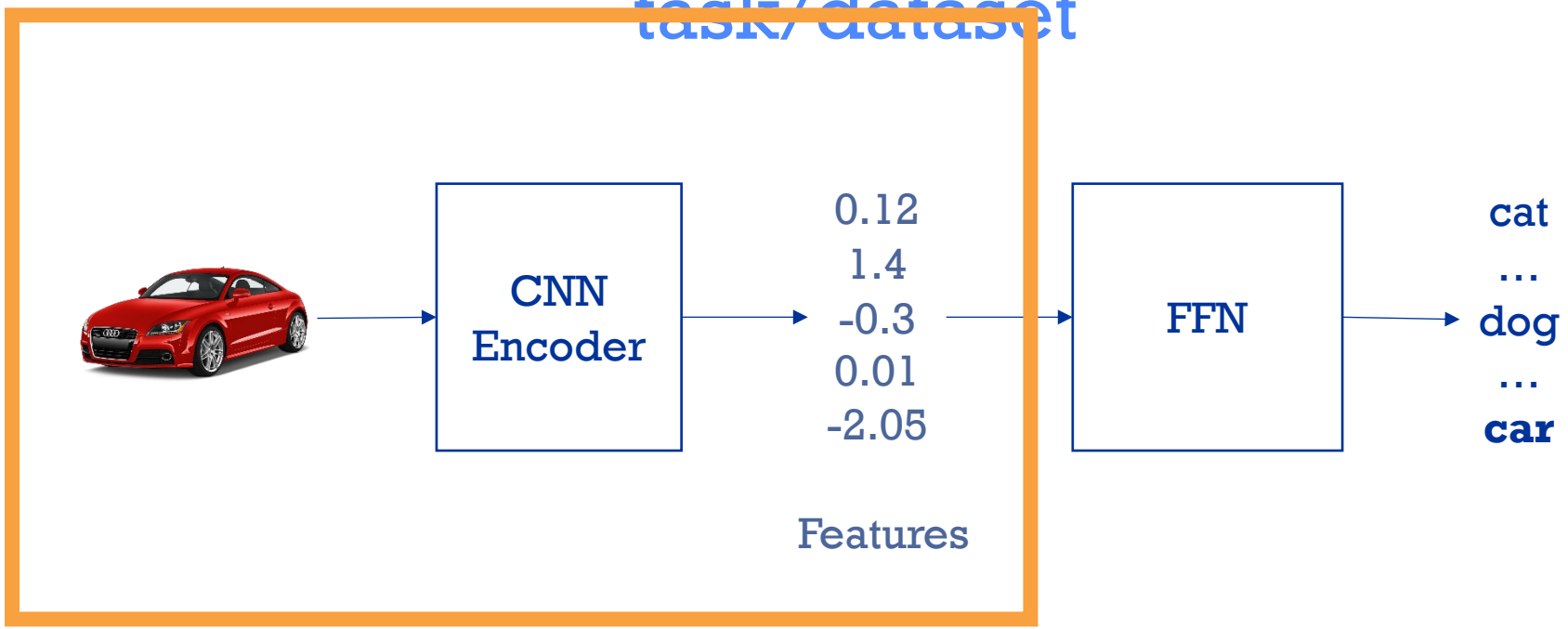
Learn on one task/dataset, then transfer to another task/dataset



Reuse weights…

Transfer Learning (in Computer Vision)

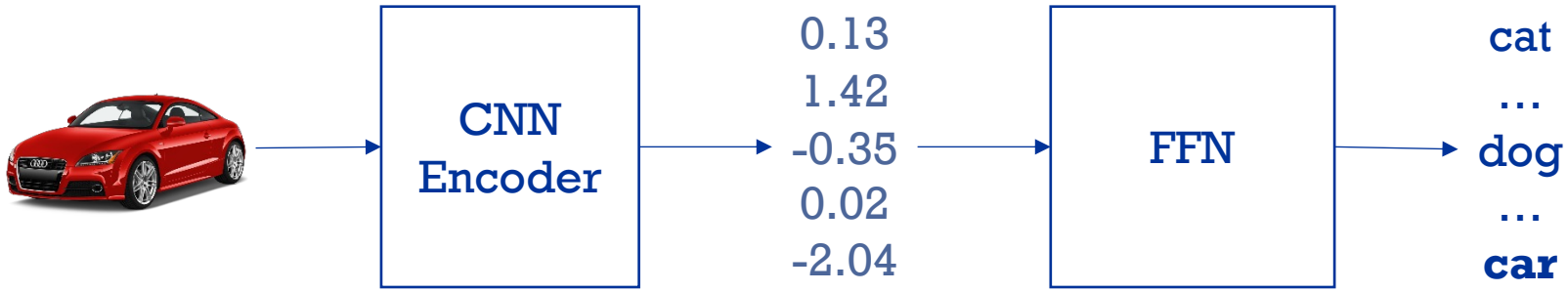
Learn on one task/dataset, then transfer to another task/dataset



Reuse weights… in another task!

Transfer Learning (in Computer Vision)

Learn on one task/dataset, then transfer to another task/dataset



Features

Fine-tune complete model!

Transfer Learning in NLP

- Pretrain a model on a task with a big amount of data
- Modify model and reuse trained weights to solve a new task

- Better performance on tasks with less data
  - Model does not have to learn everything from scratch (syntax, word meaning, …)
  - Pretraining task and target task should be similar → better performance

- Big theme in NLP for the last few years!

Transfer Learning in NLP

- What task to use?

→**Language Modelling** has basically unlimited training data!

→**Language Modelling** is also very general!

→**Language Modelling** has been shown to work well for embeddings!

One important part of Language Models is capturing context…

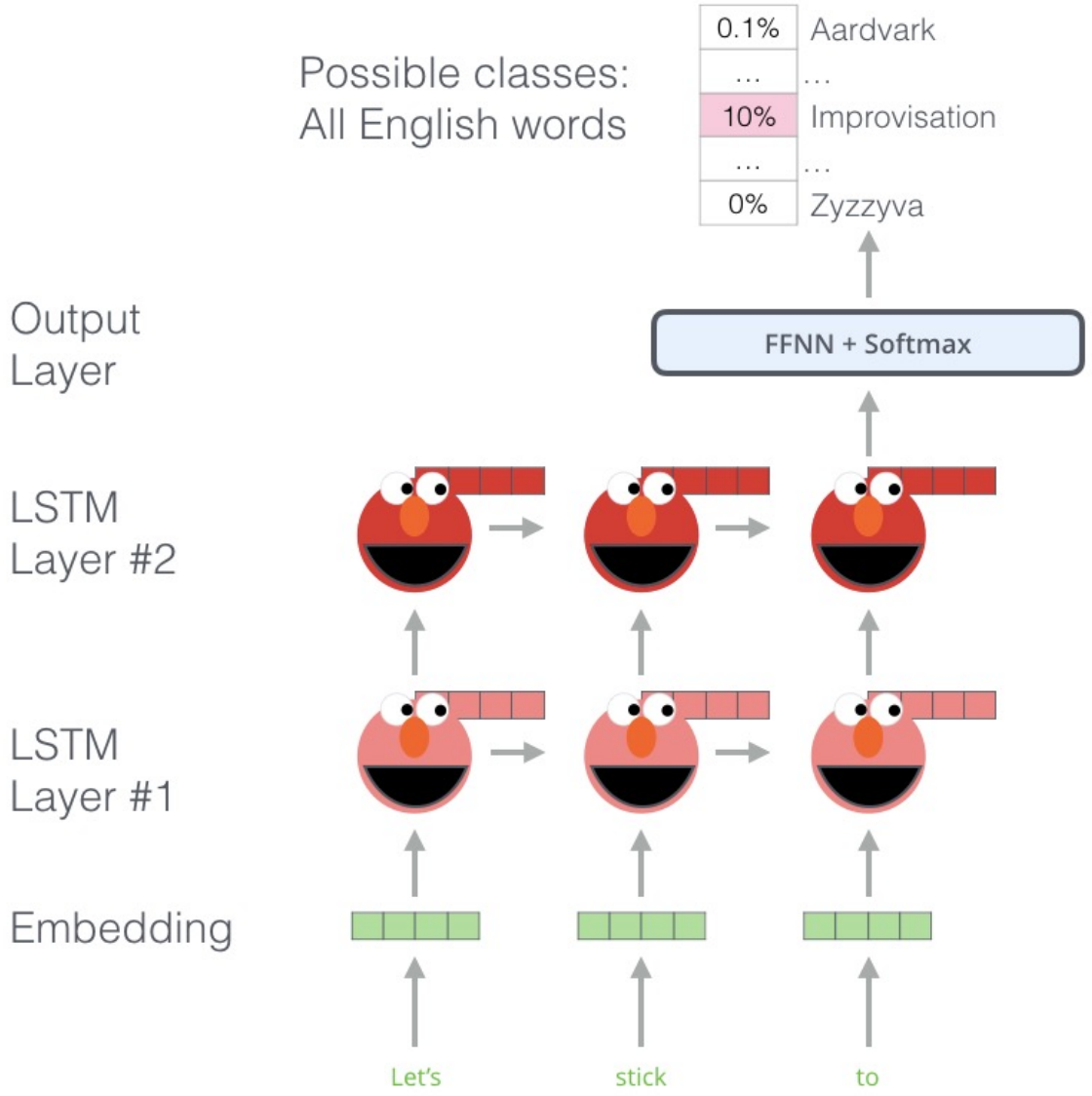
Enter ELMo!

http://jalammar.github.io/illustrated-bert/ and

Peters, Matthew E., et al. "Deep contextualized word representations." *arXiv preprint arXiv:1802.05365* (2018).

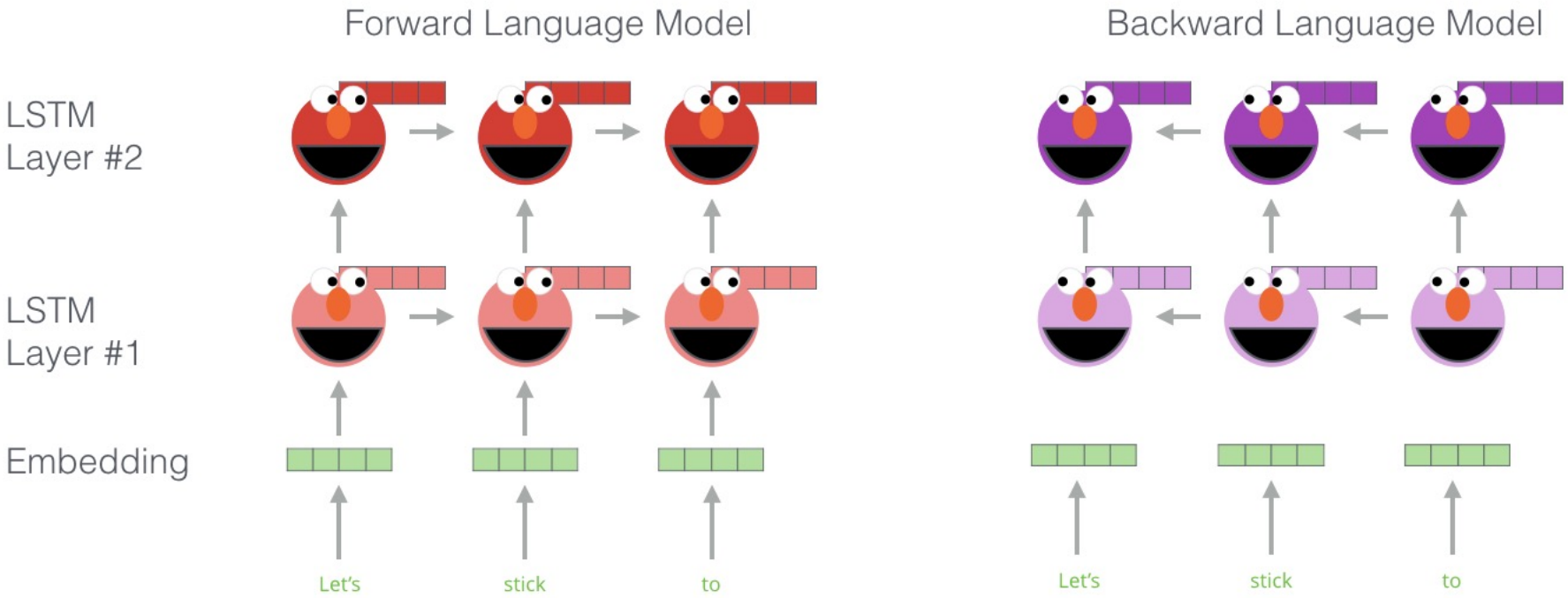
ELMo — Idea

- Train a **language model**: Predict next word given previous text
- Model learns syntax, grammar and word relations
- Meaning of each word is captured in hidden states



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

ELMo — Step 1



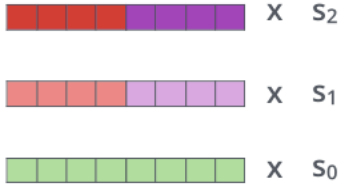
- Feed sentence through a **bidirectional language model**
  - Captures both directions of the sentence

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

ELMo — Step 2

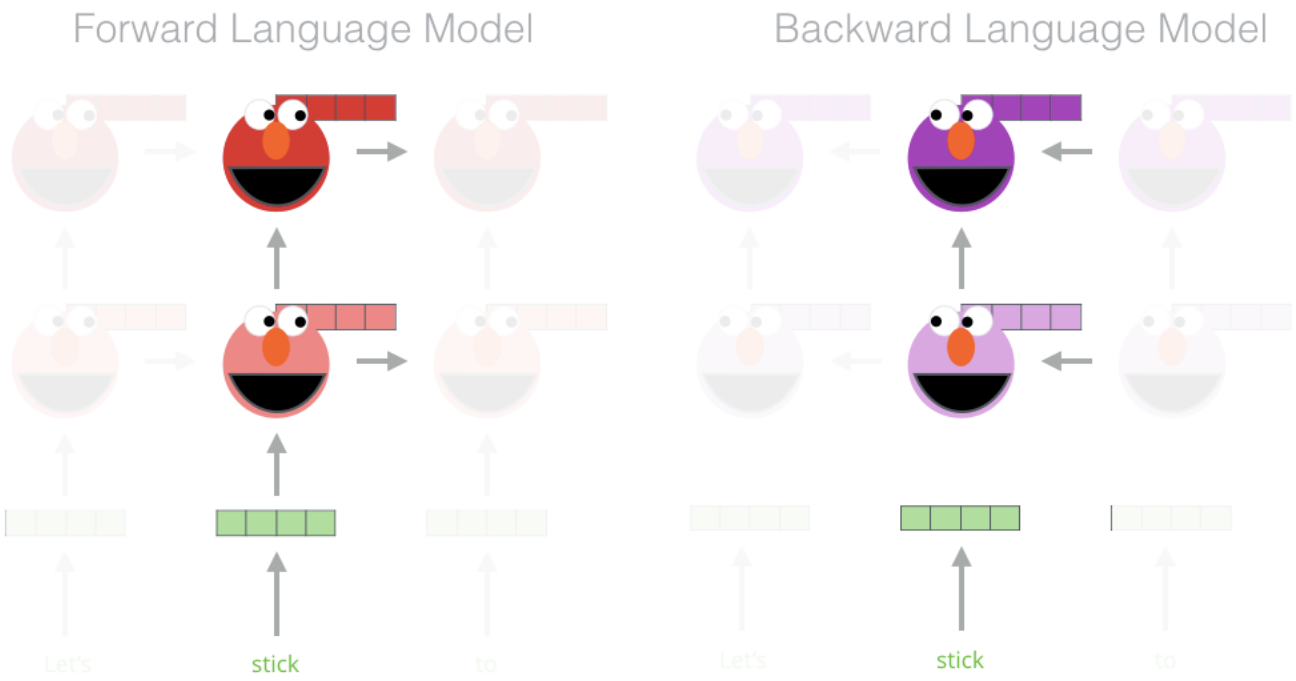
1- Concatenate hidden layers

2- Multiply each vector by a weight based on the task



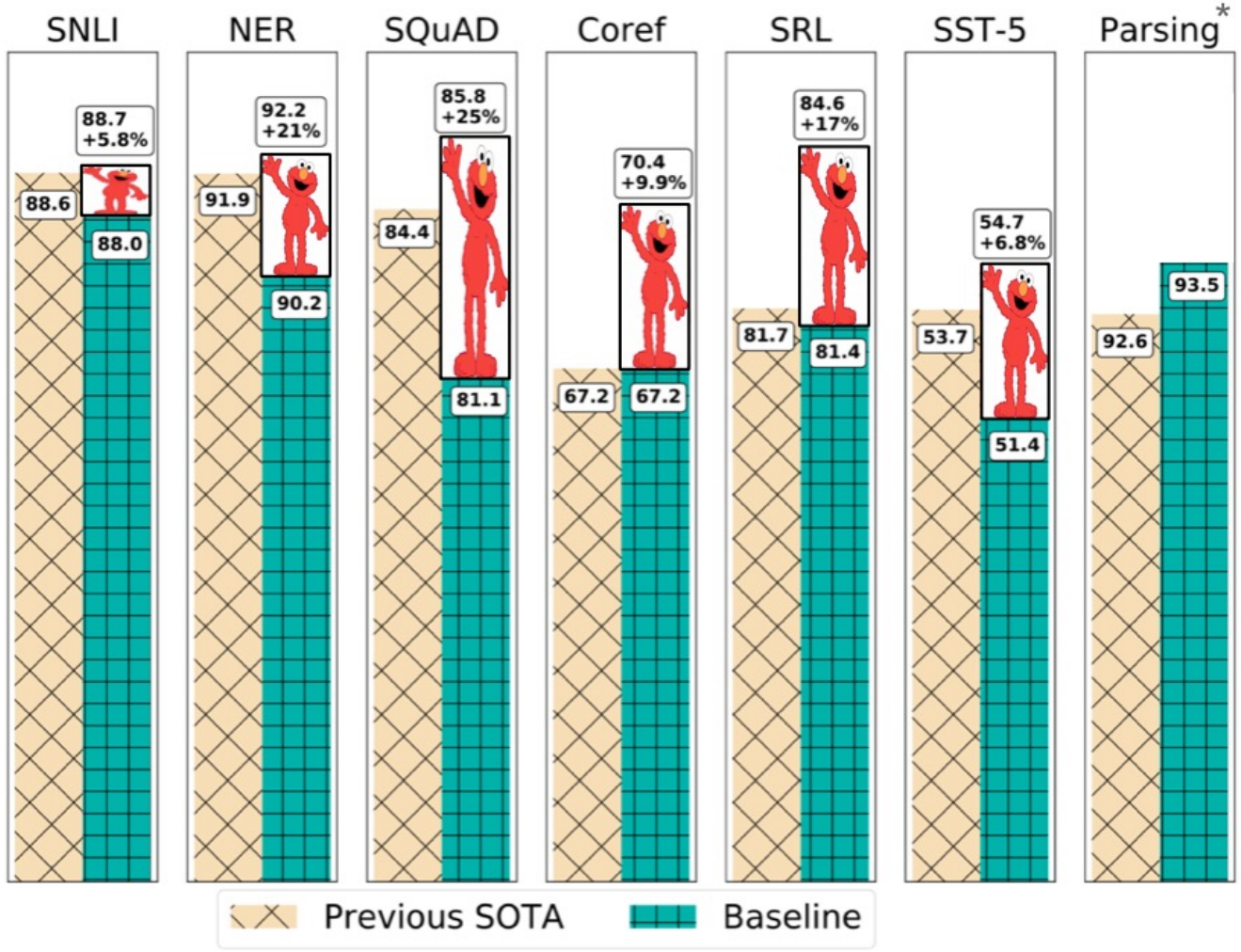
3- Sum the (now weighted) vectors

ELMo embedding of "stick" for this task in this context



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

ELMo — Results



*Kitaev and Klein, ACL 2018 (see also Joshi et al., ACL 2018)

ELMo — Pros and Cons

Pros

- Captures context
- Better performance

Cons

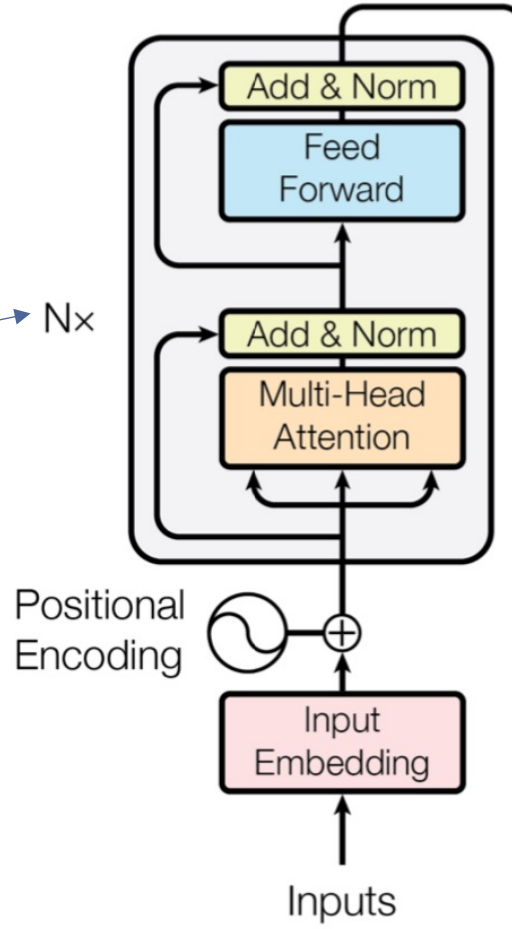
- No simple table lookup → load model and compute embedding

What could work better than LSTMs?

BERT — Idea

- Train a **Transformer** encoder
- Feed whole sentence to network but mask out words
  - Get bidirectionality with one model

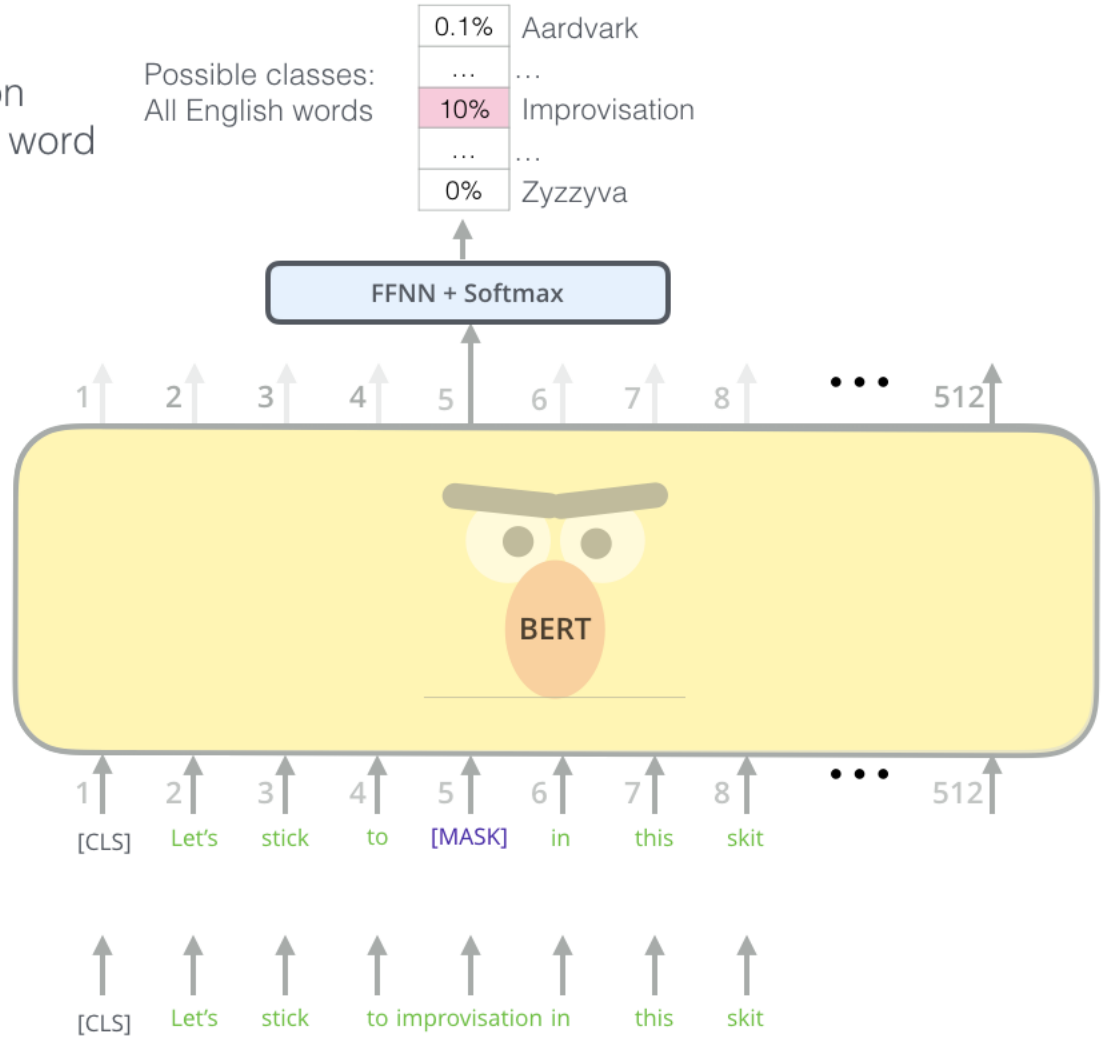
- Train model on multiple tasks for which a big amount of data exists:
  - Predict masked word („masked language model“)
  - Randomly replace words and let the model predict the correct word
  - Ask model if a sentence follows on another sentence



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

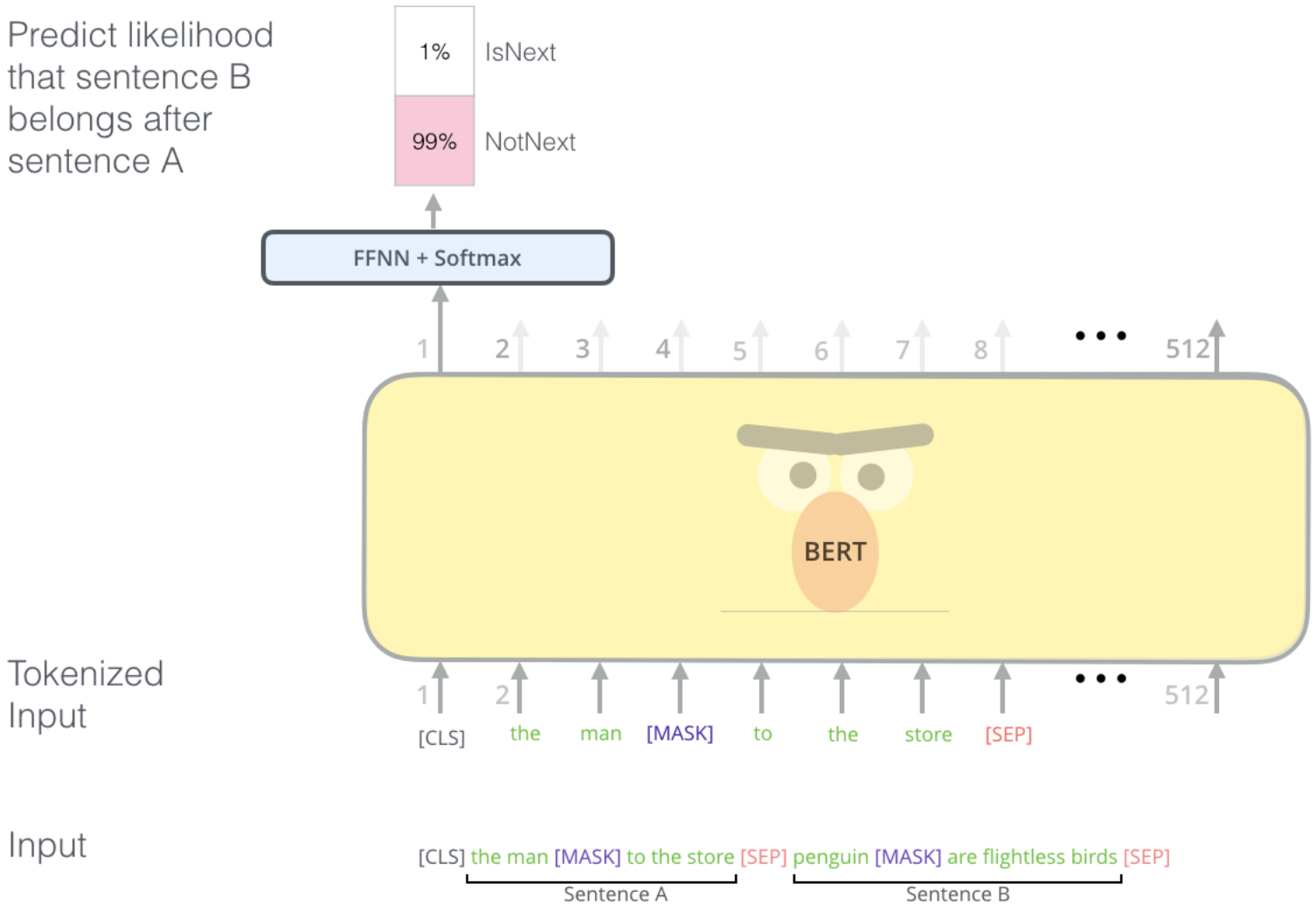
BERT — Masked Language Model

Use the output of the masked word's position to predict the masked word



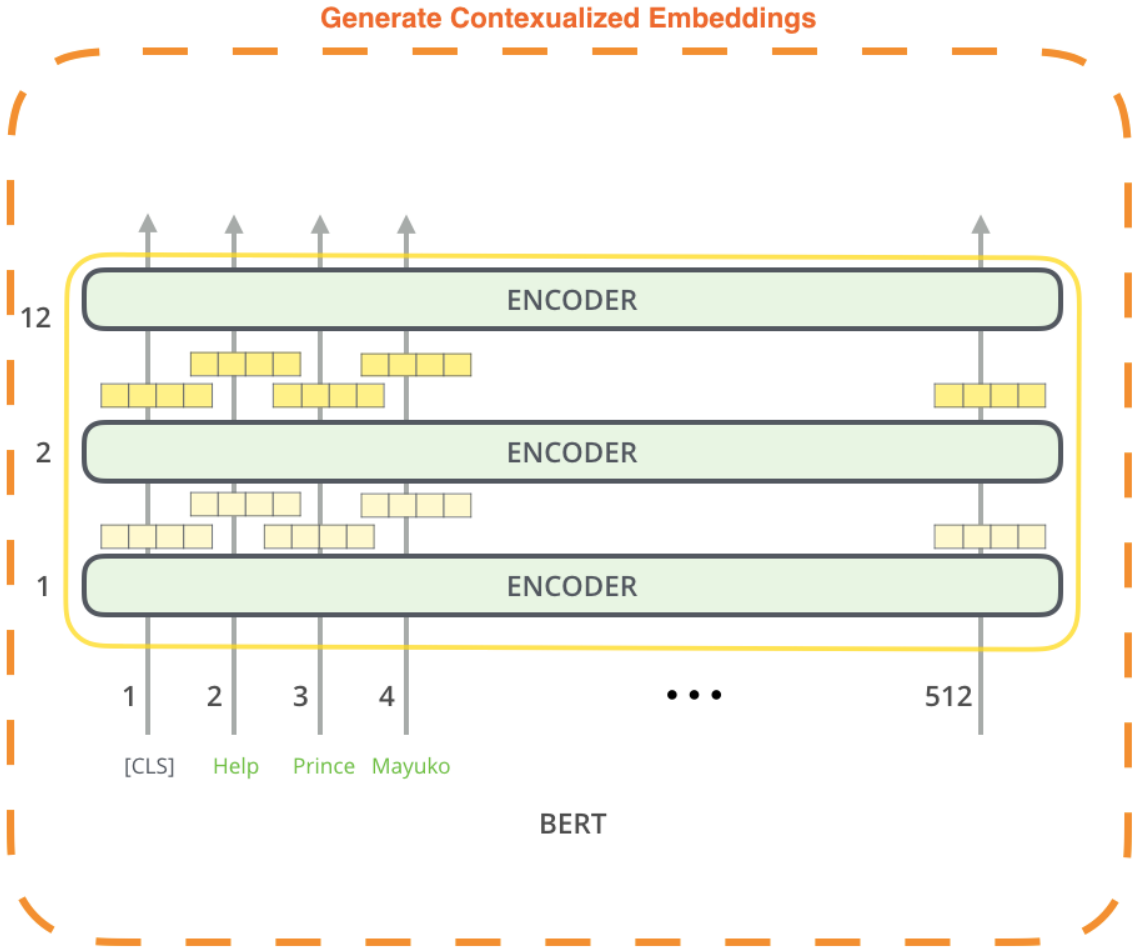
http://jalammar.github.io/illustrated-bert/

BERT — Two Sentence Task

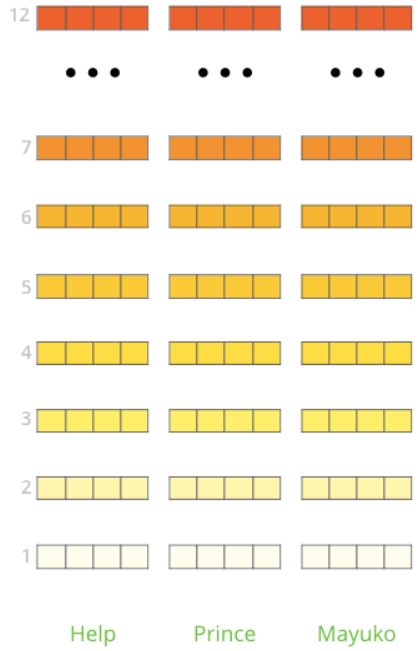


http://jalammar.github.io/illustrated-bert/

BERT — Contextualised Word Embeddings



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

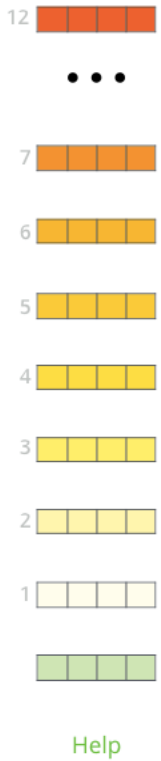


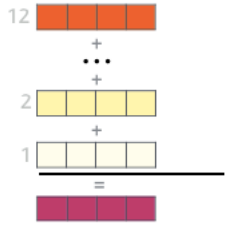
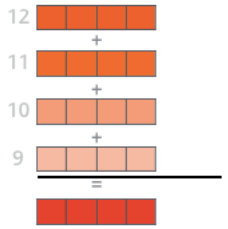
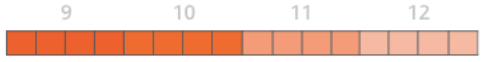
But which one should we use?

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

BERT — Contextualised Word Embeddings

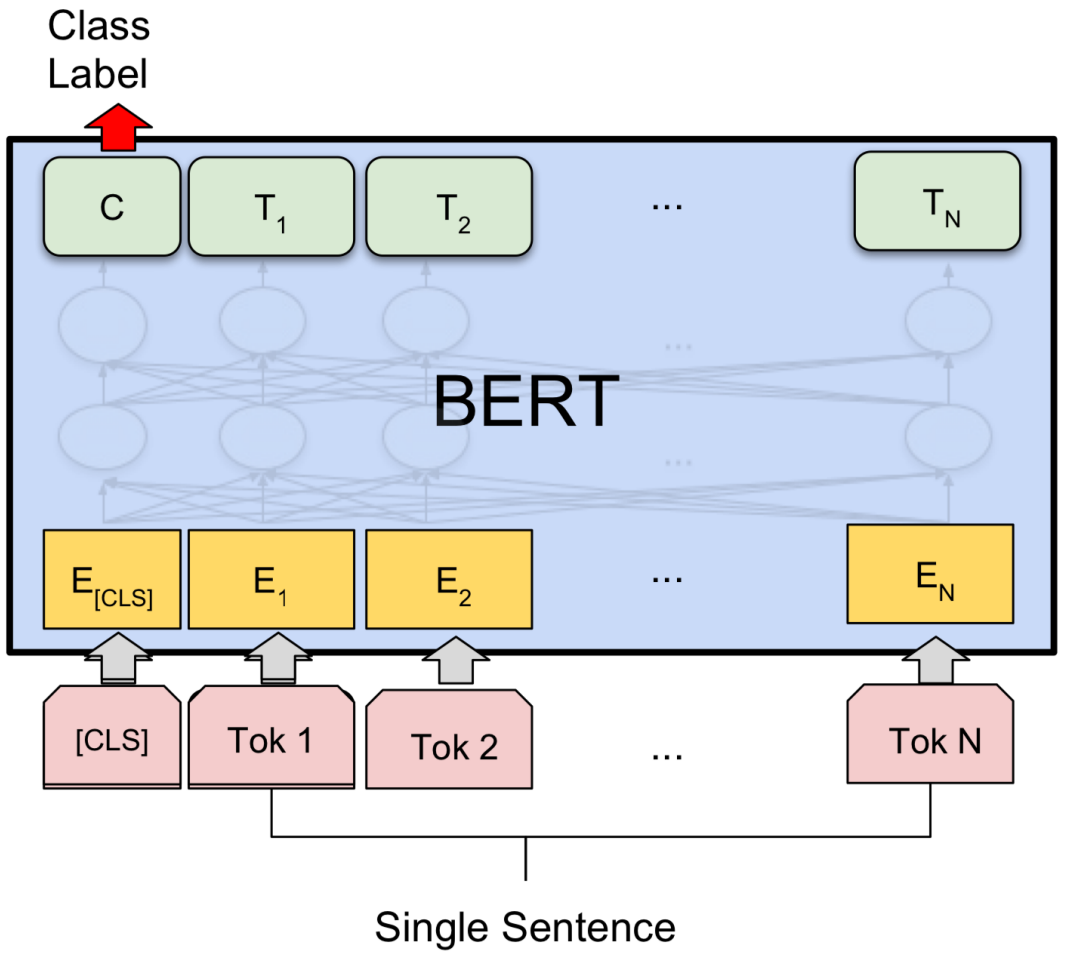
What is the best contextualized embedding for "Help" in that context?
For named-entity recognition task CoNLL-2003 NER



		Dev F1 Score
First Layer		91.0
Last Hidden Layer		94.9
Sum All 12 Layers		95.5
Second-to-Last Hidden Layer		95.6
Sum Last Four Hidden		95.9
Concat Last Four Hidden		96.1

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

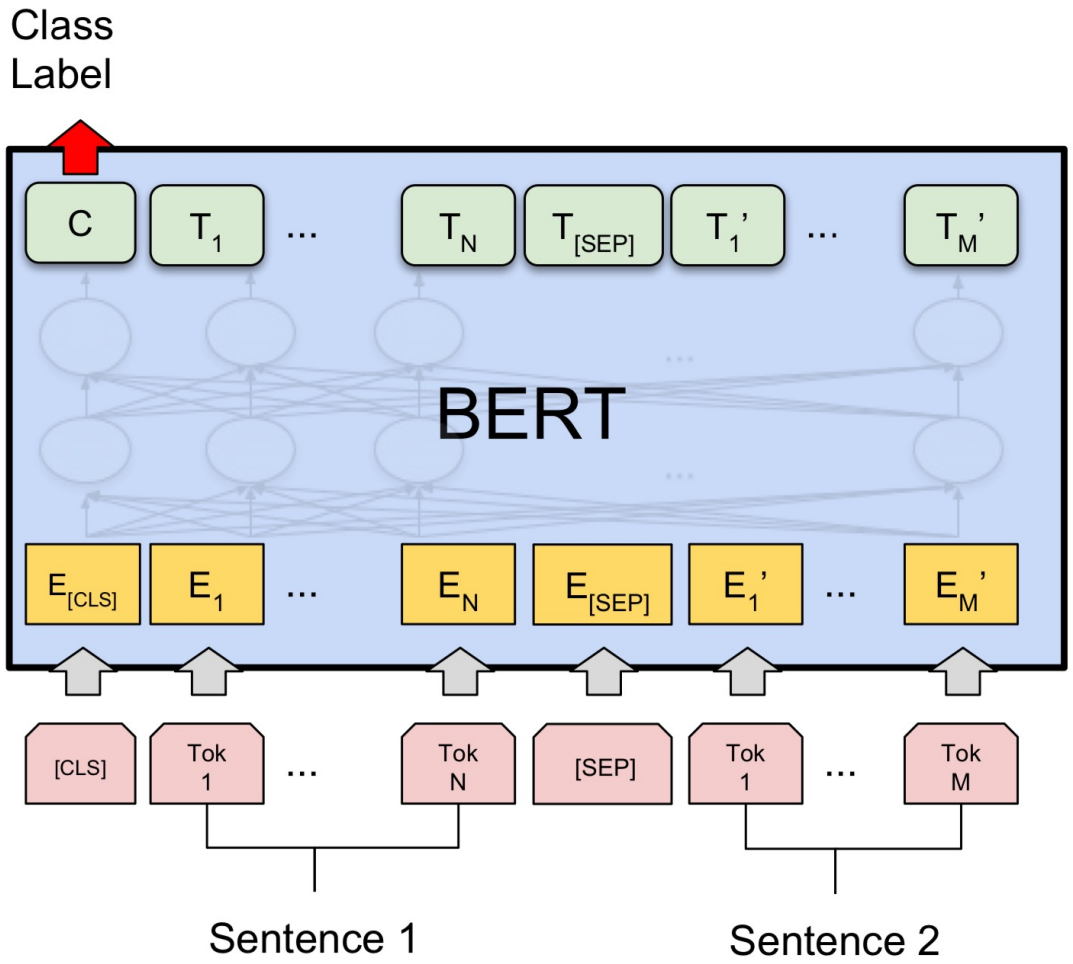
BERT — Single Sentence Classification Tasks



E.g. Sentiment Analysis
on Stanford Sentiment Treebank

Devlin, Jacob, et al. "Bert: Pre-training of deep bidirectional transformers for language understanding." *arXiv preprint arXiv:1810.04805* (2018).

BERT — Sentence Pair Classification Tasks



E.g. SWAG dataset:

On stage, a woman takes a seat at the piano. She
a) sits on a bench as her sister plays with the doll.
b) smiles with someone as the music plays.
c) is in the crowd, watching the dancers.
d) nervously sets her fingers on the keys.

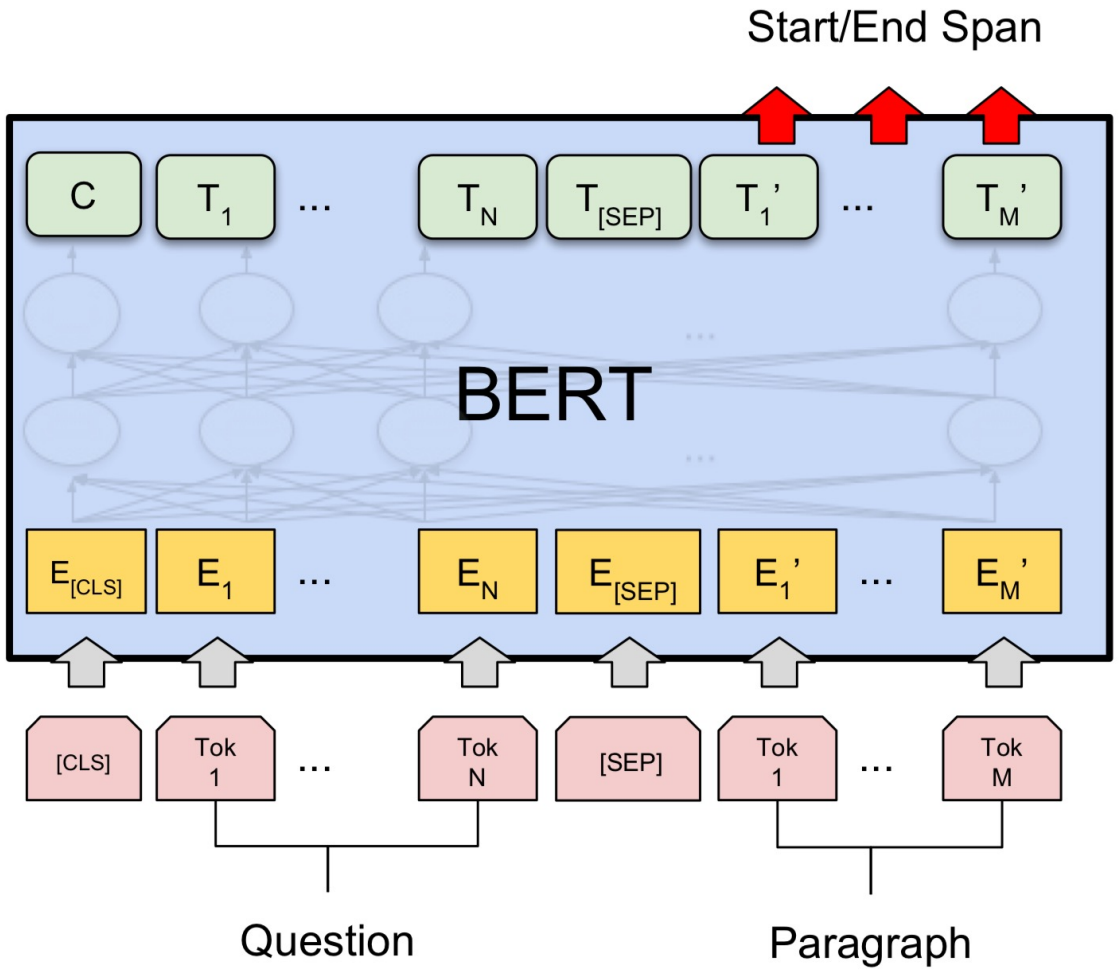
A girl is going across a set of monkey bars. She
a) jumps up across the monkey bars.
b) struggles onto the monkey bars to grab her head.
c) gets to the end and stands on a wooden plank.
d) jumps up and does a back flip.

The woman is now blow drying the dog. The dog
a) is placed in the kennel next to a woman's feet.
b) washes her face with the shampoo.
c) walks into frame and walks towards the dog.
d) tried to cut her face, so she is trying to do something very close to her face.

Table 1: Examples from SWAG; the correct answer is **bolded**. Adversarial Filtering ensures that stylistic models find all options equally appealing.

Devlin, Jacob, et al. "Bert: Pre-training of deep bidirectional transformers for language understanding." *arXiv preprint arXiv:1810.04805* (2018).
Zellers, Rowan, et al. "Swag: A large-scale adversarial dataset for grounded commonsense inference." *arXiv preprint arXiv:1808.05326* (2018).

BERT — Question Answering Tasks



E.g. SQuAD:

In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under **gravity**. The main forms of precipitation include drizzle, rain, sleet, snow, **graupel** and hail... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals **within a cloud**. Short, intense periods of rain in scattered locations are called "showers".

What causes precipitation to fall?
gravity

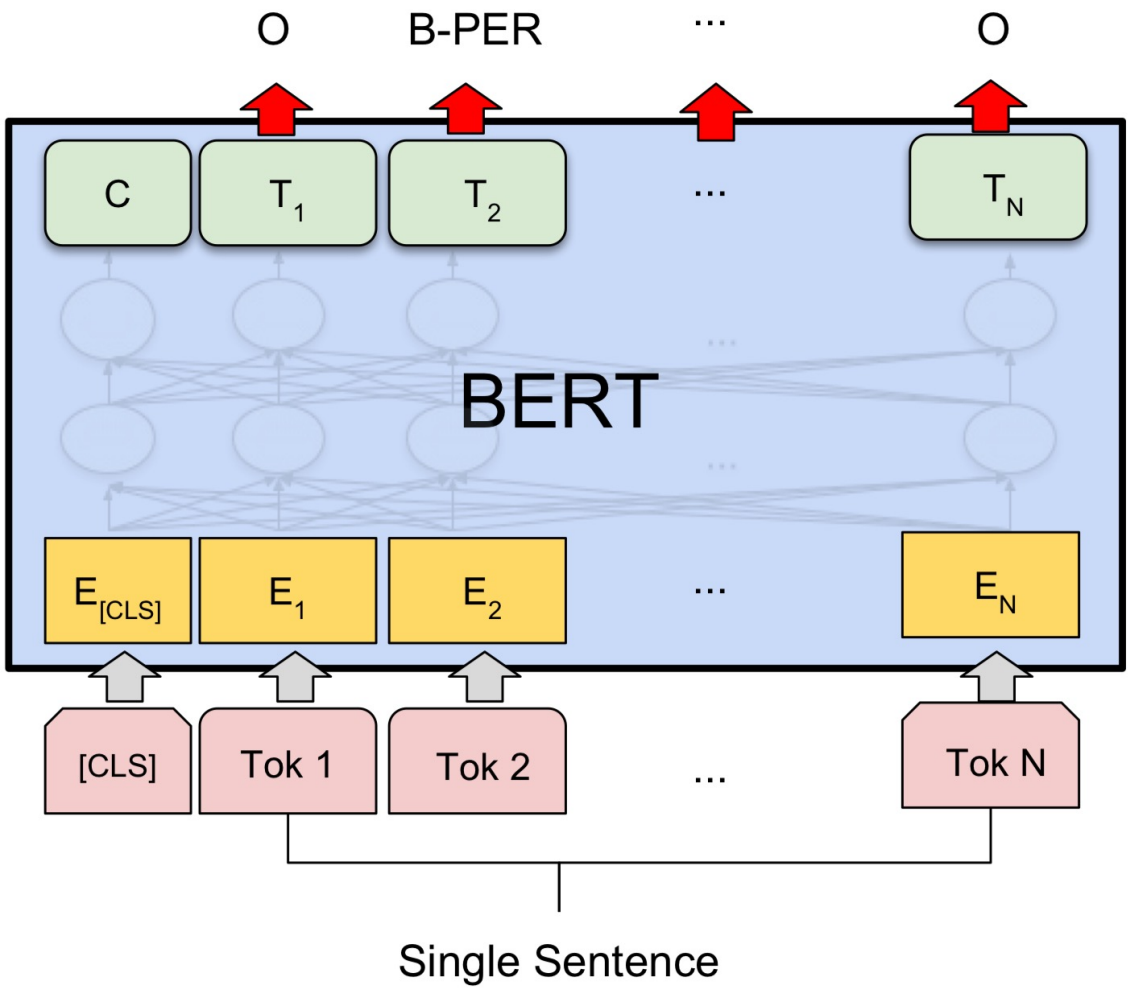
What is another main form of precipitation besides drizzle, rain, snow, sleet and hail?
graupel

Where do water droplets collide with ice crystals to form precipitation?
within a cloud

Figure 1: Question-answer pairs for a sample passage in the SQuAD dataset. Each of the answers is a segment of text from the passage.

Devlin, Jacob, et al. "Bert: Pre-training of deep bidirectional transformers for language understanding." *arXiv preprint arXiv:1810.04805* (2018).
Rajpurkar, Pranav, et al. "Squad: 100,000+ questions for machine comprehension of text." *arXiv preprint arXiv:1606.05250* (2016).

BERT — Single Sentence Tagging Tasks



E.g. CoNLL-2003 NER:

Named entities are phrases that contain the names of persons, organizations and locations. Example:

> [ORG U.N.] official [PER Ekeus] heads for [LOC Baghdad] .

Devlin, Jacob, et al. "Bert: Pre-training of deep bidirectional transformers for language understanding." *arXiv preprint arXiv:1810.04805* (2018).
Sang, Erik F., and Fien De Meulder. "Introduction to the CoNLL-2003 shared task: Language-independent named entity recognition." *arXiv preprint cs/0306050* (2003).

BERT — Results

System	MNLI-(m/mm) 392k	QQP 363k	QNLI 108k	SST-2 67k	CoLA 8.5k	STS-B 5.7k	MRPC 3.5k	RTE 2.5k	**Average** -
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**92.7**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**82.1**

Table 1: GLUE Test results, scored by the evaluation server (https://gluebenchmark.com/leaderboard). The number below each task denotes the number of training examples. The "Average" column is slightly different than the official GLUE score, since we exclude the problematic WNLI set.[8] BERT and OpenAI GPT are single-model, single task. F1 scores are reported for QQP and MRPC, Spearman correlations are reported for STS-B, and accuracy scores are reported for the other tasks. We exclude entries that use BERT as one of their components.

BERT — Derivatives

- Since then various derivatives have been developed

1. BERT (from Google) released with the paper BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding by Jacob Devlin, Ming-Wei Chang, Kenton Lee and Kristina Toutanova.
2. RoBERTa (from Facebook), released together with the paper a Robustly Optimized BERT Pretraining Approach by Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, Veselin Stoyanov.
3. DistilBERT (from HuggingFace) released together with the paper DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter by Victor Sanh, Lysandre Debut and Thomas Wolf. The same method has been applied to compress GPT2 into DistilGPT2.
4. CamemBERT (from FAIR, Inria, Sorbonne Université) released together with the paper CamemBERT: a Tasty French Language Model by Louis Martin, Benjamin Muller, Pedro Javier Ortiz Suarez, Yoann Dupont, Laurent Romary, Eric Villemonte de la Clergerie, Djame Seddah, and Benoît Sagot.
5. ALBERT (from Google Research), released together with the paper a ALBERT: A Lite BERT for Self-supervised Learning of Language Representations by Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, Radu Soricut.
6. XLM-RoBERTa (from Facebook AI), released together with the paper Unsupervised Cross-lingual Representation Learning at Scale by Alexis Conneau*, Kartikay Khandelwal*, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Edouard Grave, Myle Ott, Luke Zettlemoyer and Veselin Stoyanov.
7. FlauBERT (from CNRS) released with the paper FlauBERT: Unsupervised Language Model Pre-training for French by Hang Le, Loïc Vial, Jibril Frej, Vincent Segonne, Maximin Coavoux, Benjamin Lecouteux, Alexandre Allauzen, Benoît Crabbé, Laurent Besacier, Didier Schwab.

...

GPT-2

GPT-2 — Idea

- Train one **giant language model** (1.5B parameters) on a **giant text corpus** (8M web pages ~ 40GB text)!
- Model each task as a text completion task
- Let the model output the answer

- **Text summarisation**: Prompt model with „<long text>. TL;DR: “
- **Translation**: Condition on example translations („<english sentence> = <french sentence>“), then prompt with „<english sentence> = “
- **Reading Comprehension**: Prompt model with „<text>. Q: <question>. A: “

→ Do not fine-tune network on target task: **Zero-shot setting**

Radford, Alec, et al. "Language models are unsupervised multitask learners." *OpenAI Blog* 1.8 (2019).

GPT-2 — Question Answering

Question	Generated Answer	Correct	Probability
Who wrote the book the origin of species?	Charles Darwin	✓	83.4%
Who is the founder of the ubuntu project?	Mark Shuttleworth	✓	82.0%
Who is the quarterback for the green bay packers?	Aaron Rodgers	✓	81.1%
Panda is a national animal of which country?	China	✓	76.8%
Who came up with the theory of relativity?	Albert Einstein	✓	76.4%
When was the first star wars film released?	1977	✓	71.4%
What is the most common blood type in sweden?	A	✗	70.6%
Who is regarded as the founder of psychoanalysis?	Sigmund Freud	✓	69.3%
Who took the first steps on the moon in 1969?	Neil Armstrong	✓	66.8%
Who is the largest supermarket chain in the uk?	Tesco	✓	65.3%
What is the meaning of shalom in english?	peace	✓	64.0%
Who was the author of the art of war?	Sun Tzu	✓	59.6%
Largest state in the us by land mass?	California	✗	59.2%
Green algae is an example of which type of reproduction?	parthenogenesis	✗	56.5%
Vikram samvat calender is official in which country?	India	✓	55.6%
Who is mostly responsible for writing the declaration of independence?	Thomas Jefferson	✓	53.3%
What us state forms the western boundary of montana?	Montana	✗	52.3%
Who plays ser davos in game of thrones?	Peter Dinklage	✗	52.1%
Who appoints the chair of the federal reserve system?	Janet Yellen	✗	51.5%
State the process that divides one nucleus into two genetically identical nuclei?	mitosis	✓	50.7%
Who won the most mvp awards in the nba?	Michael Jordan	✗	50.2%
What river is associated with the city of rome?	the Tiber	✓	48.6%
Who is the first president to be impeached?	Andrew Johnson	✓	48.3%
Who is the head of the department of homeland security 2017?	John Kelly	✓	47.0%
What is the name given to the common currency to the european union?	Euro	✓	46.8%
What was the emperor name in star wars?	Palpatine	✓	46.5%
Do you have to have a gun permit to shoot at a range?	No	✓	46.4%
Who proposed evolution in 1859 as the basis of biological development?	Charles Darwin	✓	45.7%
Nuclear power plant that blew up in russia?	Chernobyl	✓	45.7%
Who played john connor in the original terminator?	Arnold Schwarzenegger	✗	45.2%

Table 5. The 30 most confident answers generated by GPT-2 on the development set of Natural Questions sorted by their probability according to GPT-2. None of these questions appear in WebText according to the procedure described in Section 4.

GPT-2 Applications

- TabNine Code Completion: Fine-tuned on 2 million GitHub files

```
1 import os
2 import sys
3
4 # Count lines of code in the given directory, separated by file extension
5 def main(directory):
6     line_count = {}
7
8
9
10
11
12
13
14
15
16
17
18
19
```

- Write with Transformer — https://transformer.huggingface.co

GPT-2 Applications

Thor: The Tesseract b **an is a match for it**
Tony turns to leave,
Steve: You're not g
Tony: You gonna s
He turns to Steve a is able to see Loki's weapon.
Loki: You're nothing like
Loki draws his sword an ng, Tony hears whispers in his ear. He turns and s ds running up.
Steve puts his shield and
Steve: Don't back down! H own.
Steve: Watch out!
They are running at the ene soldiers one by one, a soldier is stabbing at the soldier.
Loki: You're nothing like Thor

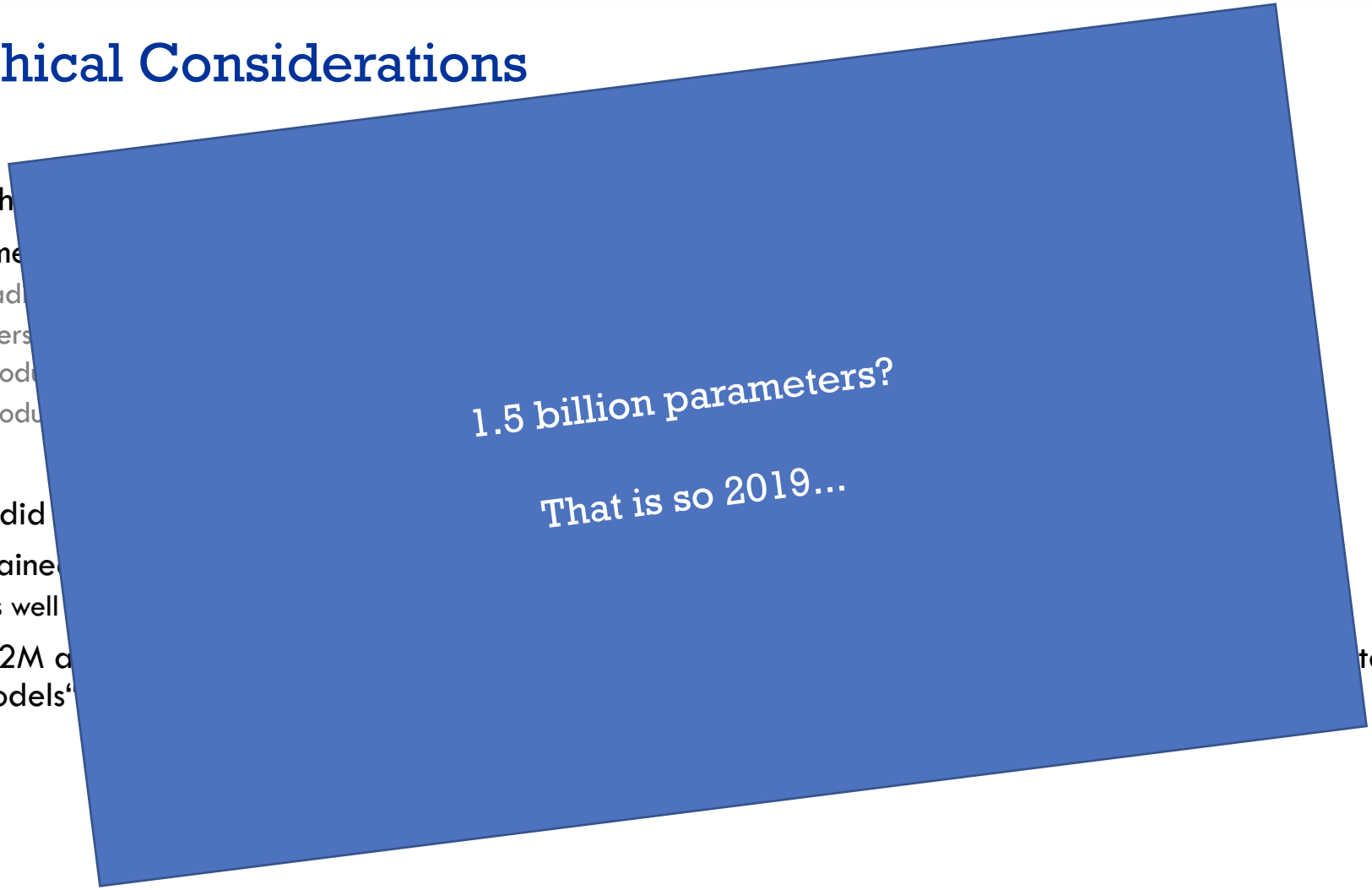
[…] asteroid trajectories likely exposed the planet before the rocks impacted, said Nicholas McCarthy, scientific director of NASA's Near-Earth object Program. "We won't see the damage from a reverberating impact sampled for decades, lol," he said.

Extreme X recruits
ion to rescue Skeletor
to spite Earth),
s the words
so that
(who
in order to
that will unleas
the Earth will be ru
middle-aged, shaved ca

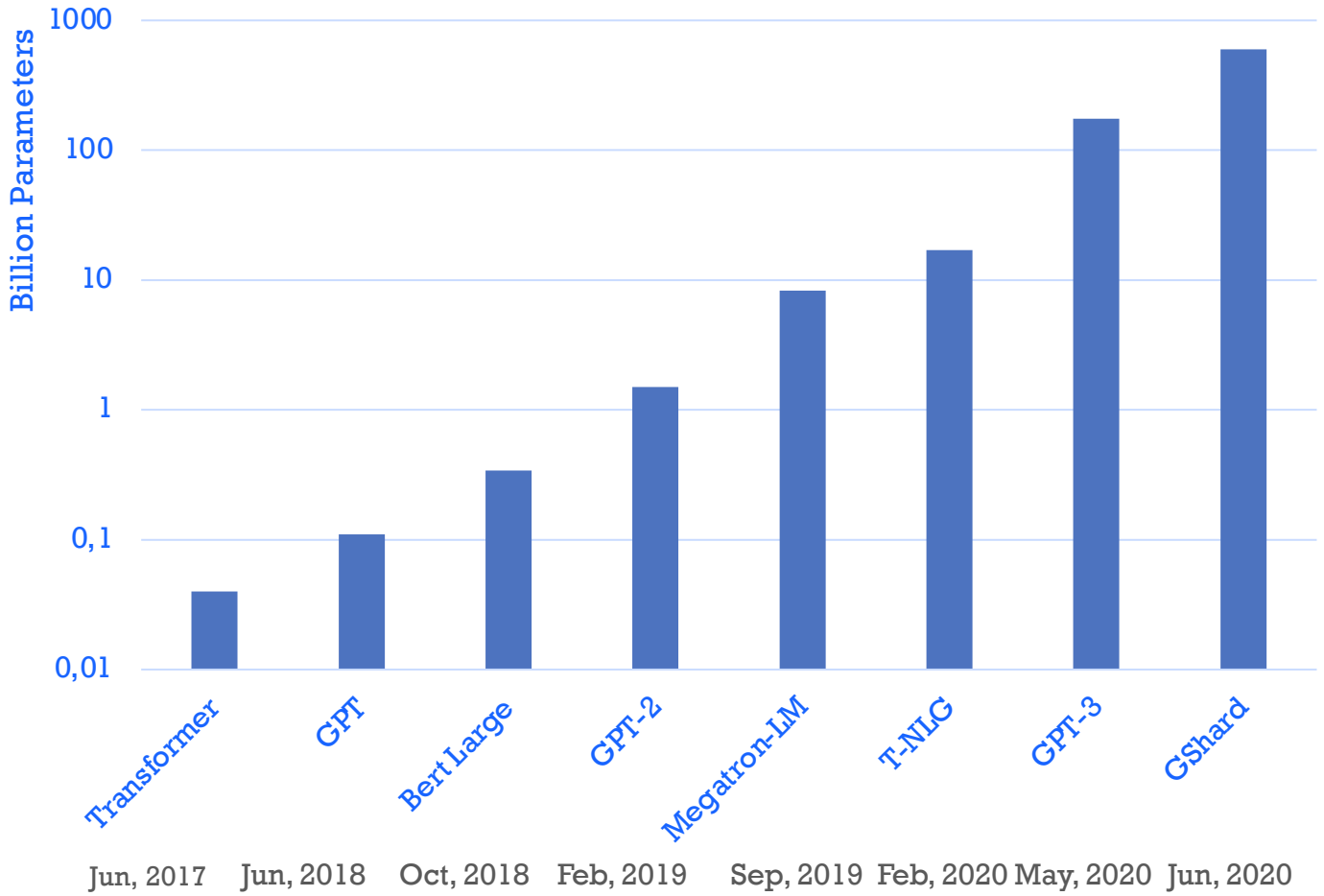
https://talktotransformer.com

GPT-2 — Ethical Considerations

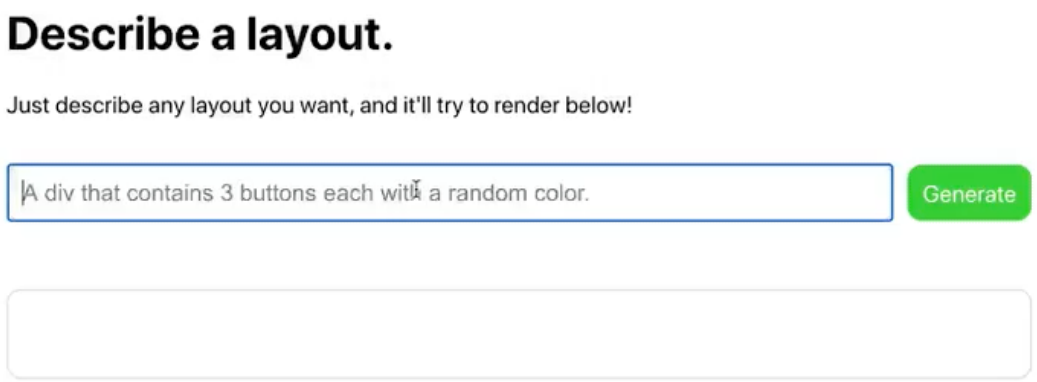
- The largest model h
- The system pe for me
  - Generating mislead
  - Impersonating others
  - Automating the prod
  - Automating the produ
- OpenAI originally did
- Only smaller pretraine
  - Do not perform as well
- Bigger models (762M a tal preparedness for large language models"



Language Model Sizes



GPT-3 — Example



https://twitter.com/sharifshameem/status/1282676454690451457

Evaluating Language Models — Perplexity

- How do we know if our models are any good?
  - And in particular, how do we know if one model is better than another?
- Generated texts from models with more parameters look better
- That is, they sound more like the text the model was trained on
- Can we make that notion operational?

- One such metric is perplexity → Intrinsic evaluation

Evaluating Language Models — Perplexity

- Perplexity is the (inverse) probability of the test set (assigned by the language model), normalized by the number of words:

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

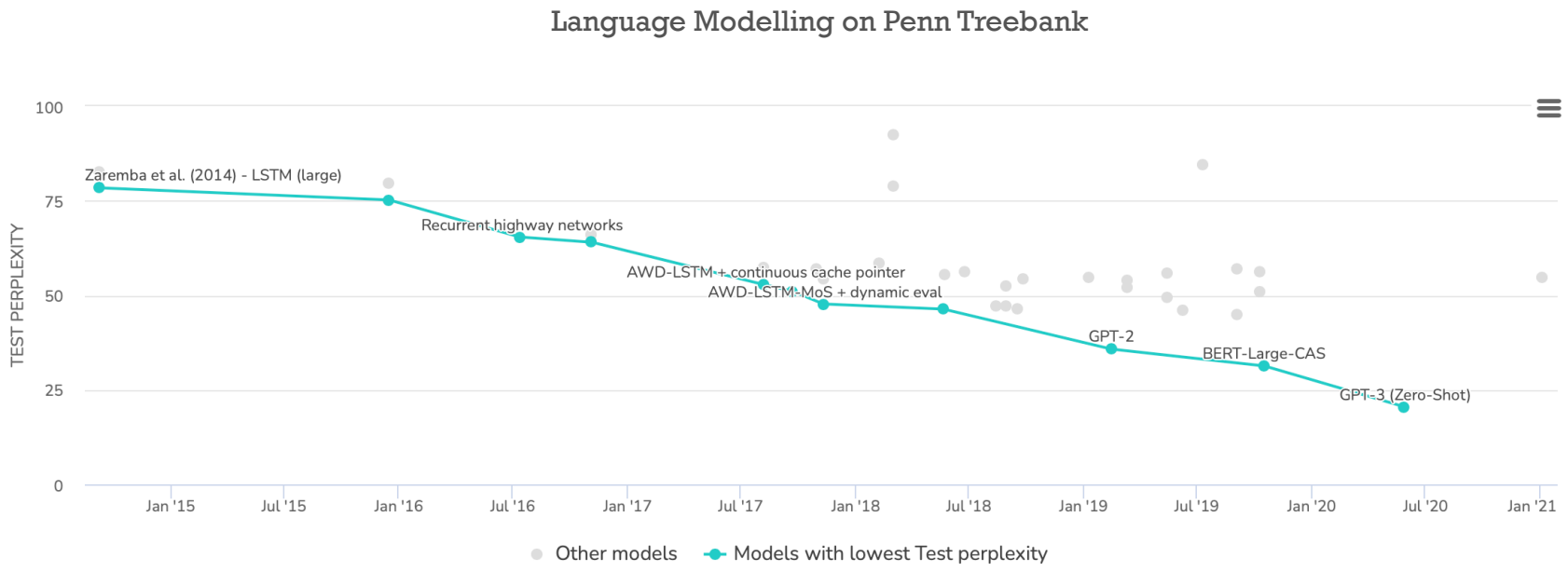
- Approximation:

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

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

Evaluating Language Models — Perplexity

- Lower perplexity means a better model
- Minimizing perplexity is the same as maximizing probability
- The best language model is one that best predicts unseen text



https://paperswithcode.com/sota/language-modelling-on-penn-treebank-word

Language Models are Few-Shot Learners

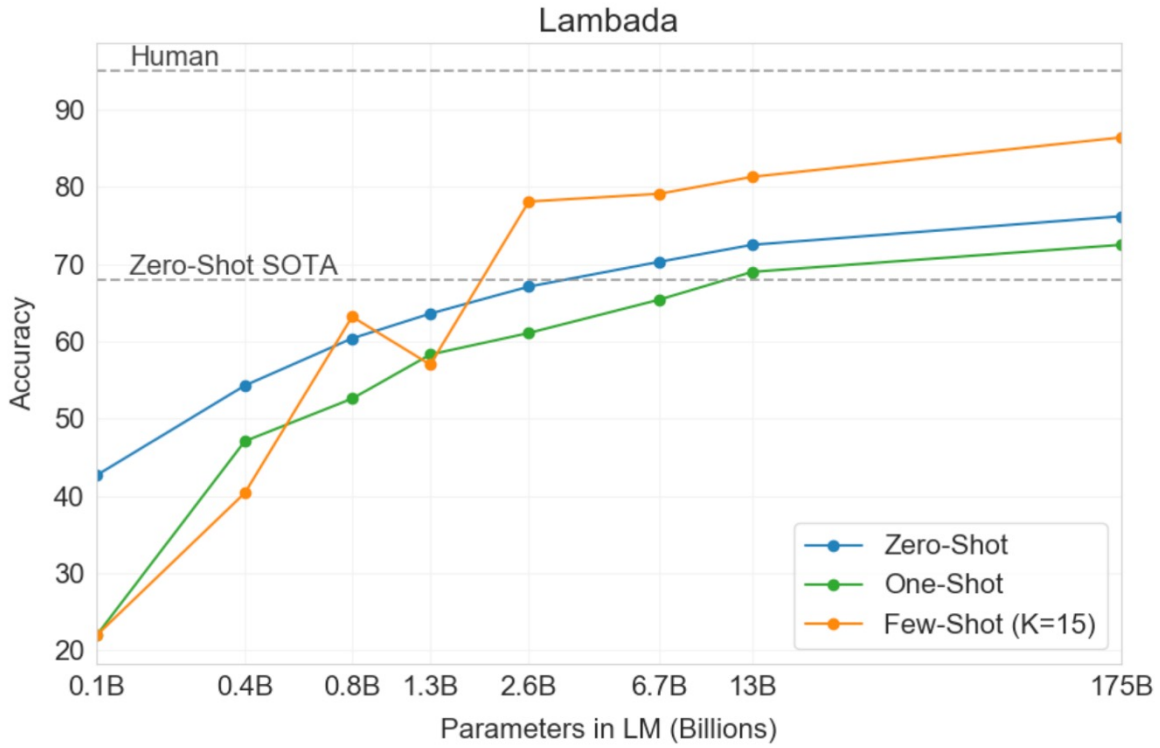


Figure 3.2: On LAMBADA, the few-shot capability of language models results in a strong boost to accuracy. GPT-3 2.7B outperforms the SOTA 17B parameter Turing-NLG [Tur20] in this setting, and GPT-3 175B advances the state of the art by 18%. Note zero-shot uses a different format from one-shot and few-shot as described in the text.

Tom B. Brown et. al (2020). Language Models are Few-Shot Learners.

Language Models are Few-Shot Learners

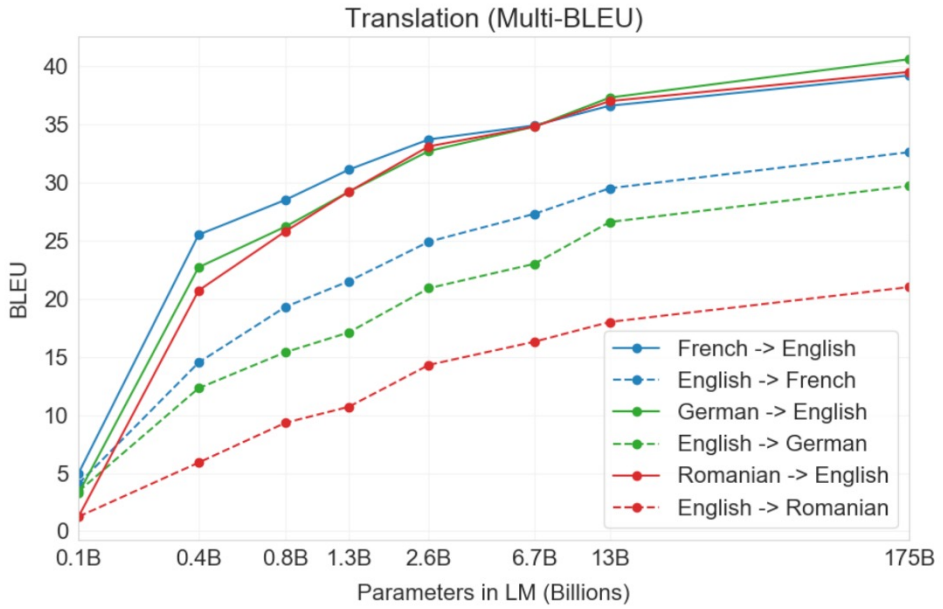


Figure 3.4: Few-shot translation performance on 6 language pairs as model capacity increases. There is a consistent trend of improvement across all datasets as the model scales, and as well as tendency for translation into English to be stronger than translation from English.

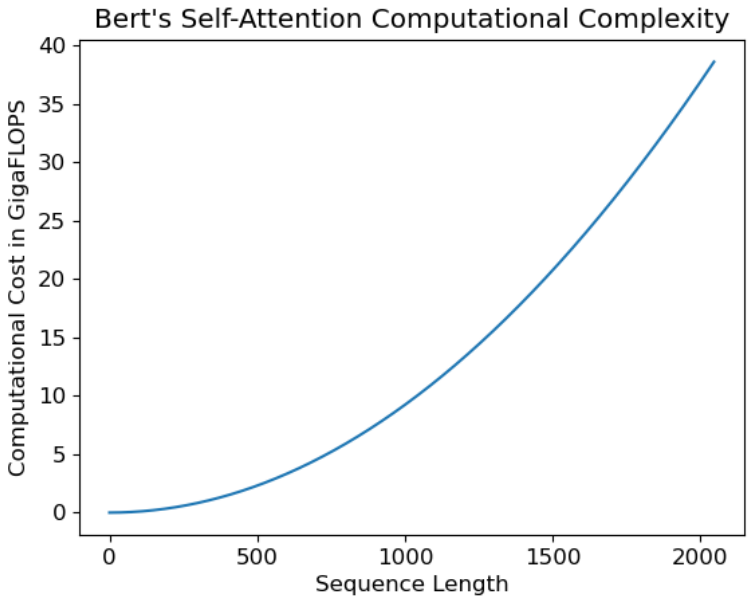
Tom B. Brown et. al (2020). Language Models are Few-Shot Learners.

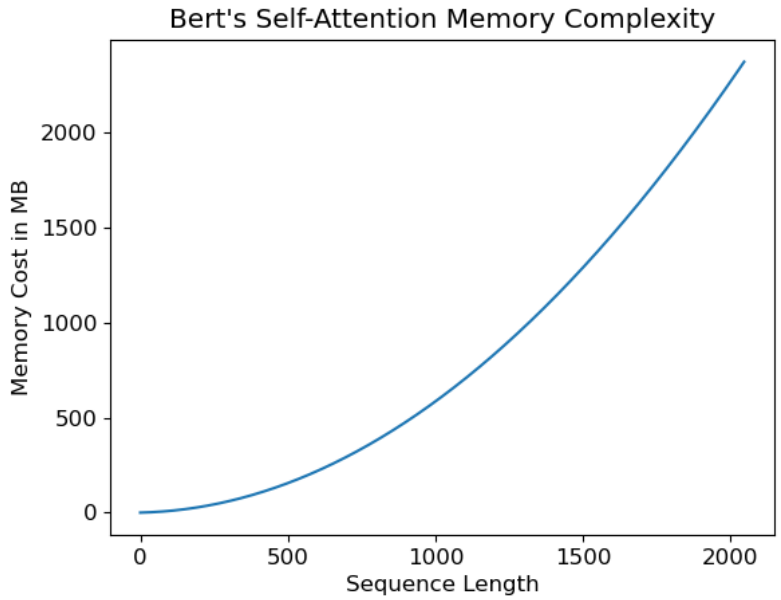
Problems of Big Language Models

- Let's look at BERT's parameters
  - ***n***: Sequence length of 512
  - ***h***: 12 self-attention heads
  - ***d***: Hidden size of 768, 12 heads → 64 (768/12)
- Let's look at BERT's complexity per layer
  - Computational: $O(hdn^2)$
  - Memory: $O(hdn + hn^2)$
- Is this good? Let's look at the total required memory
  - $12 \times 64 \times 512 + 12 \times 512 \times 512 = 393.216 + 3.145.728 = 3.538.944$ floats
  - $3.538.944 \times 12$ Encoder-Layer $= 42.467.328$ floats
  - This is 170 MB of memory required for a single sample!
- What is the key factor here?

Problems of Big Language Models

- Memory and computational complexity both scale to the square of the sequence length





- Many improvements have been made since, let's look at three

1. Q8BERT — Quantized 8Bit BERT

- Floating point numbers use 4 bytes of memory
- Can we get away with using only 1 byte?
- Yes! Zafrir et. al use linear quantization during inference:

```
[[-0.52708159  0.58938589 -0.99298076]        [[ -68   75 -127]
 [-0.80074533 -0.24025461 -0.70421488]   →     [-103  -31  -91]
 [ 0.54495217 -0.23490439  0.76274836]]        [  69  -31   97]]
```

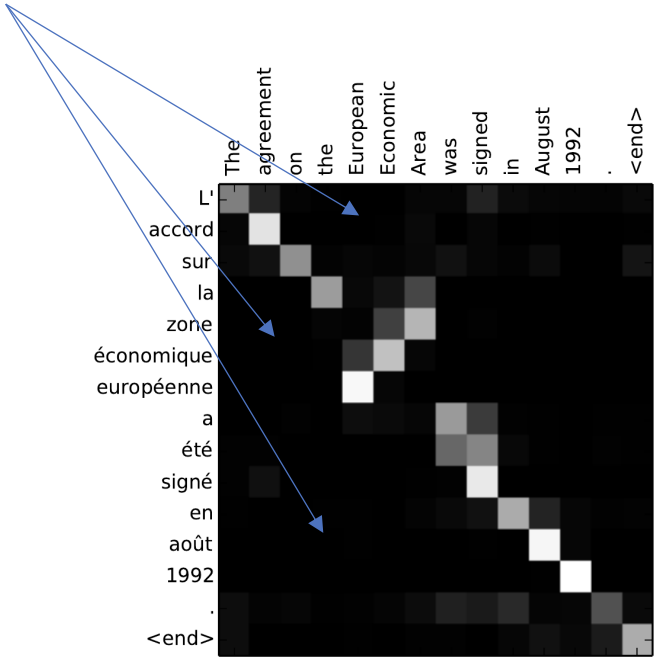
- The model needs to learn to bridge the “quantization error gap”
- Therefore the rounding effect is simulated during training

- Inference not only requires considerably less memory (~25%),
  but also runs faster on optimized hardware (~4x)

Ofir Zafrir, Guy Boudoukh, Peter Izsak, & Moshe Wasserblat. (2019). Q8BERT: Quantized 8Bit BERT.

2. Reformer — The Efficient Transformer

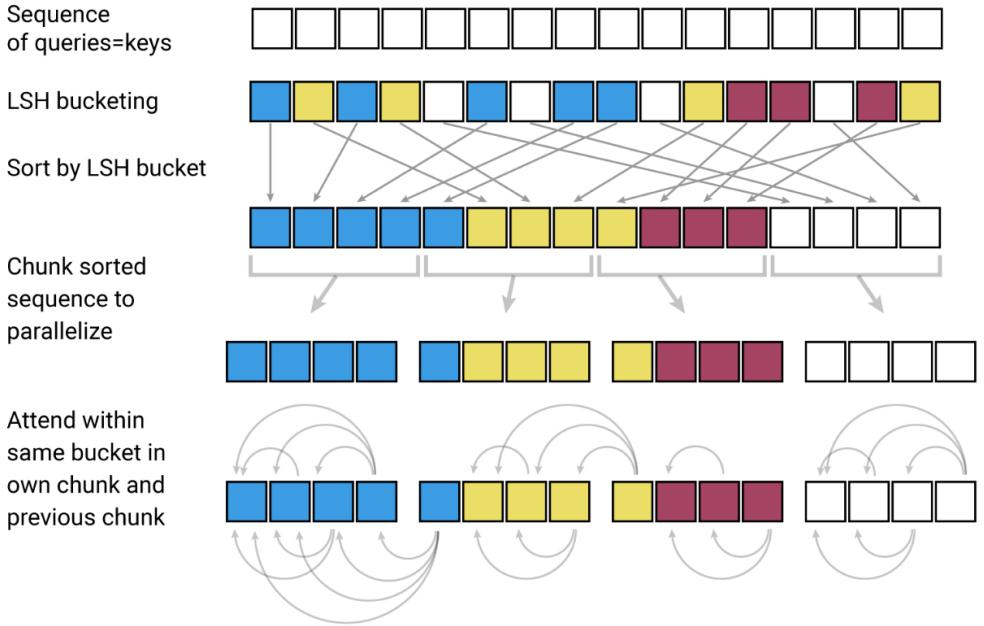
- Remember how a compatibility function is used to calculate attention between queries and keys
  - In the simplest case this is the dot product, i.e. vector similarity
  - Since incompatible vectors contribute little to the sum, we can ignore them



Bahdanau, D., Cho, K., & Bengio, Y. (2014). Neural machine translation by jointly learning to align and translate.

2. Reformer — The Efficient Transformer

- Kitaev et. al introduce "Locality Sensitive Hashing (LSH)"
  - Divide vectors into different "buckets" according to similarity
  - Attention now only attends to vectors of the same bucket



- Thus, the computational and memory complexity reduces to $O(L \log L)$

Nikita Kitaev, Łukasz Kaiser, & Anselm Levskaya. (2020). Reformer: The Efficient Transformer.

3. DistilBERT — A Distilled Version of BERT

- Of course the sheer number of parameters is also problematic
  - Magnitudes of gigabytes are infeasible for IoT and mobile devices

- **Knowledge Distillation:** Train a smaller model (student) to reproduce the behavior of a larger model (teacher)

- Sanh et. al reduce the size of BERT by 40%, make it 60% faster, and still retain 97% of its capabilities

Victor Sanh, Lysandre Debut, Julien Chaumond, & Thomas Wolf. (2019).
DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter.

Conclusion

- Recent trend in NLP: **Transfer Learning**
  - Train a model on a task with a big amount of training data
  - Then modify the model and fine-tune on the target task
  - Many improvements on a day to day basis, e.g. Linformer
- Word embeddings come from transfer learning
  - They are trained on large corpora
  - Then they are used in other tasks (with or without fine-tuning)
- Recent developments: Pretrain a language model and directly adapt it to the target task → No word embeddings

- Word embeddings may go extinct if this trend continues 😔

Sinong Wang, Belinda Z. Li, Madian Khabsa, Han Fang, & Hao Ma. (2020). Linformer: Self-Attention with Linear Complexity.