Deep Learning in Applications

How NLP Cracked Transfer Learning
Part 2

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16.06.2020

Outline

1. OpenAI Transformer
2. ELMO
3. BERT

Part 1 (yesterday)

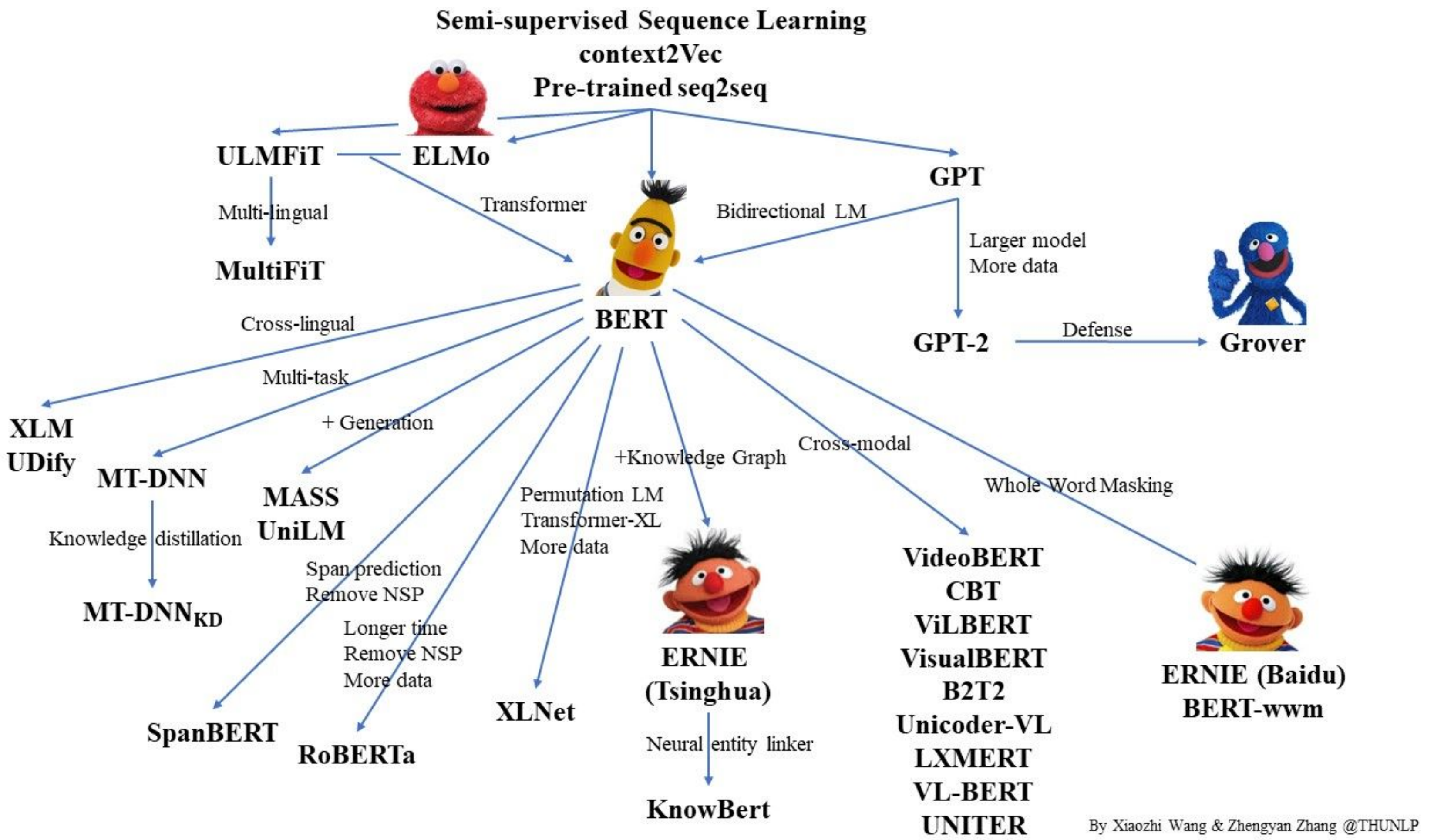
4. GPT, GPT-2, GPT-3
5. Transformer XL
6. XLNET
7. Reformer

Part 2 (today)

Based on: http://jalammar.github.io/illustrated-gpt2/
https://ai.googleblog.com/2019/01/transformer-xl-unleashing-potential-of.html
https://mlexplained.com/2019/06/30/paper-dissected-xlnet-generalized-autoregressive-pretraining-for-language-understanding-explained/
https://towardsdatascience.com/xlnet-explained-in-simple-terms-255b9fb2c97c
https://towardsdatascience.com/illustrating-the-reformer-393575ac6ba0

BERTology paper

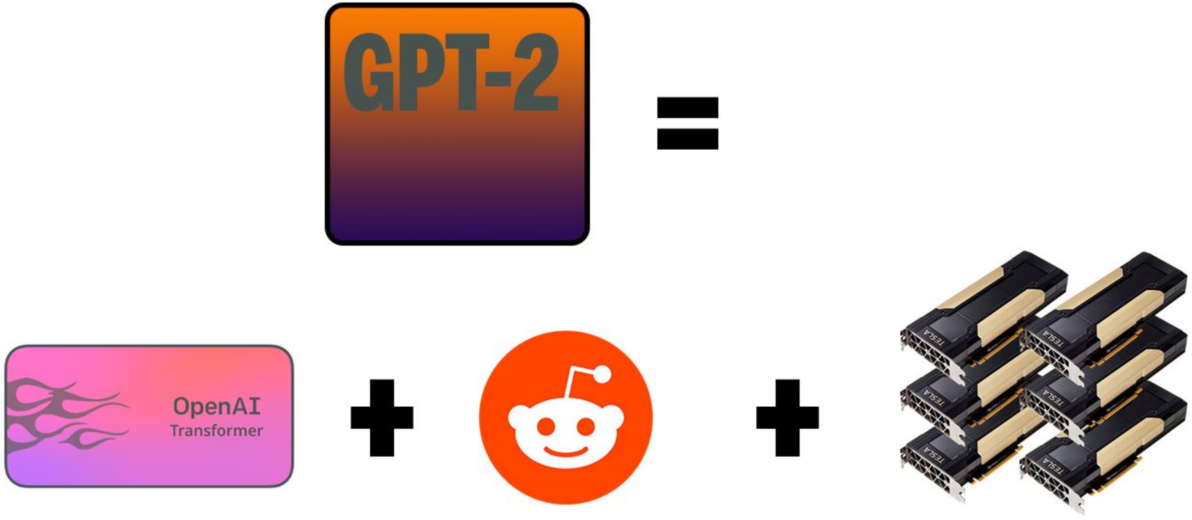
BERTology



GPT, GPT-2 and GPT-3

GPT-2

- Transformer-based architecture
- Trained to predict the **next** word
- 1.5 billion parameters
- Trained on 8 million web-pages (dataset WebText)

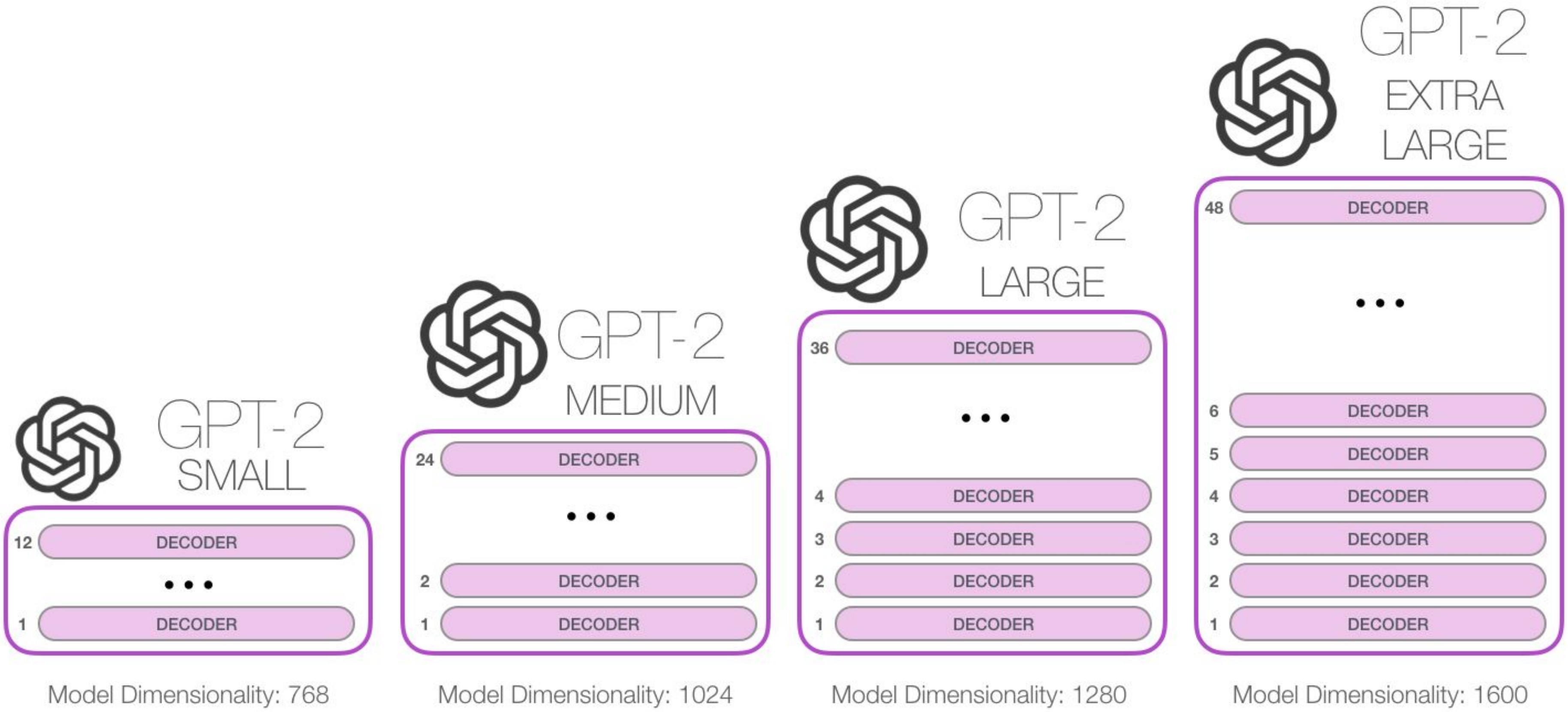


GPT-2

- Transformer-based architecture
- Trained to predict the **next** word
- 1.5 billion parameters
- Trained on 8 million web-pages (dataset WebText)

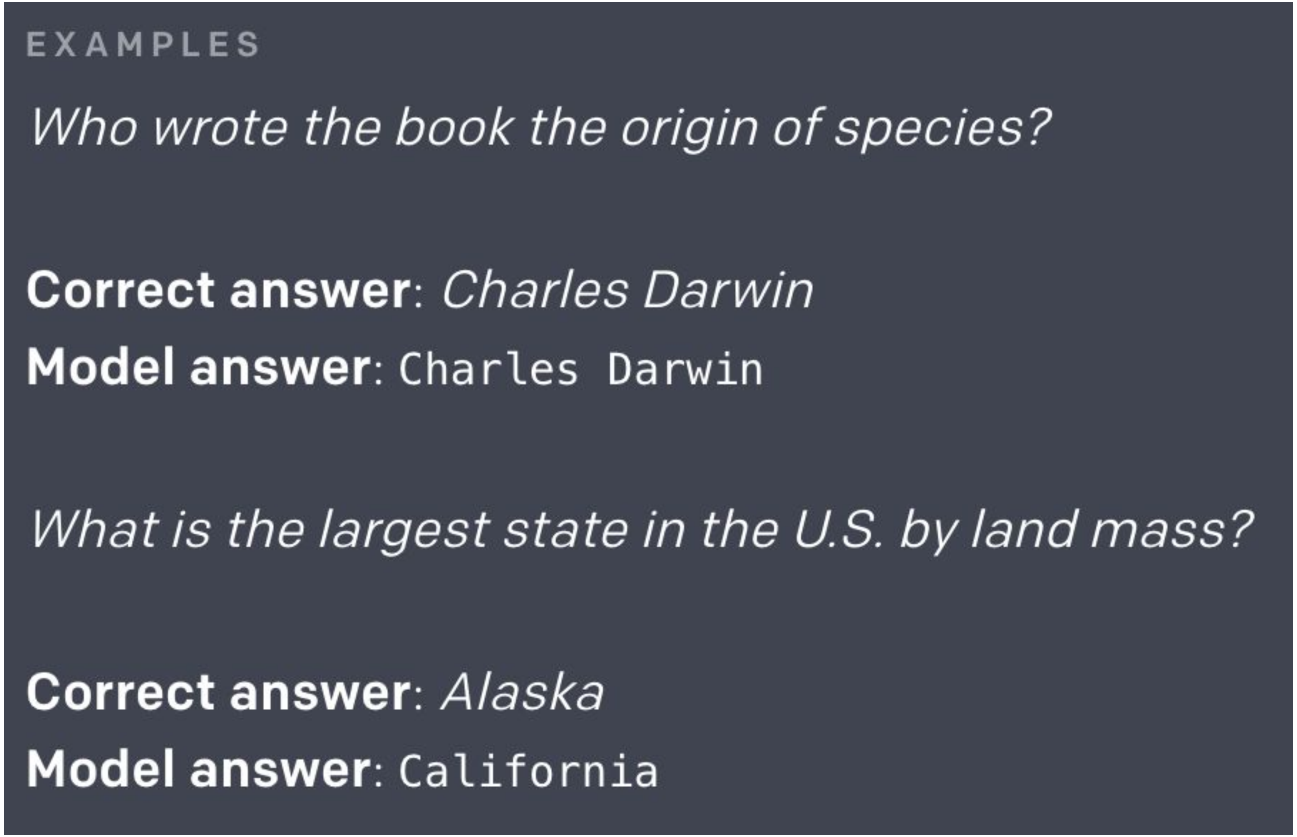
On language tasks (question answering, reading comprehension, summarization, translation) works well **WITHOUT** fine-tuning

GPT-2



http://jalammar.github.io/illustrated-gpt2/

GPT-2: question answering



EXAMPLES

Who wrote the book the origin of species?

Correct answer: *Charles Darwin*

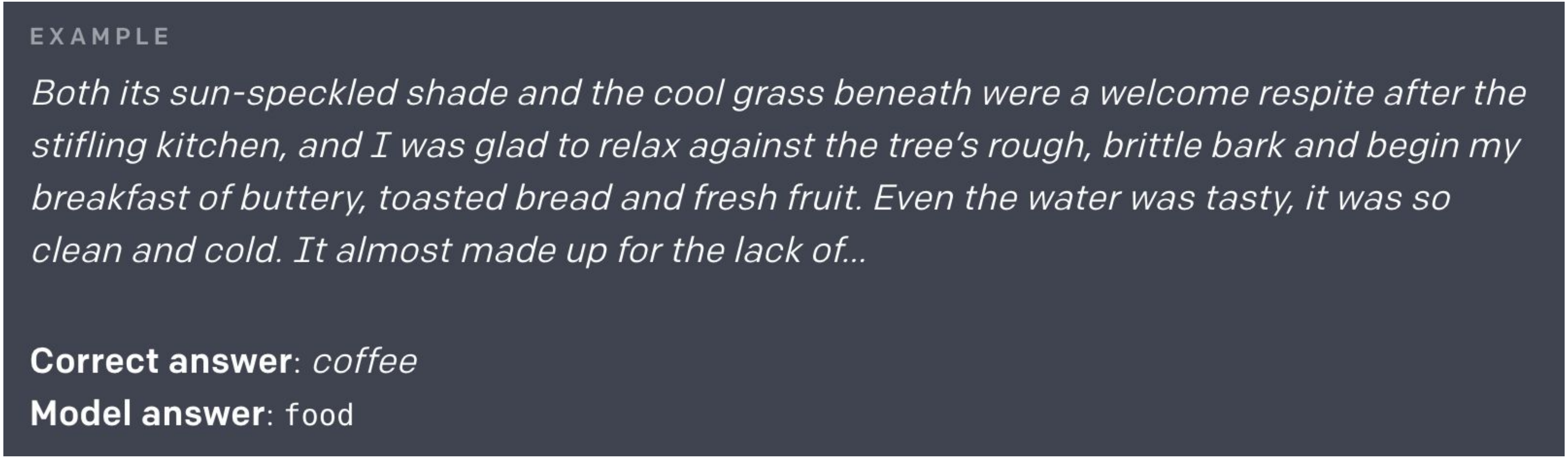
Model answer: `Charles Darwin`

What is the largest state in the U.S. by land mass?

Correct answer: *Alaska*

Model answer: `California`

GPT-2: language modeling



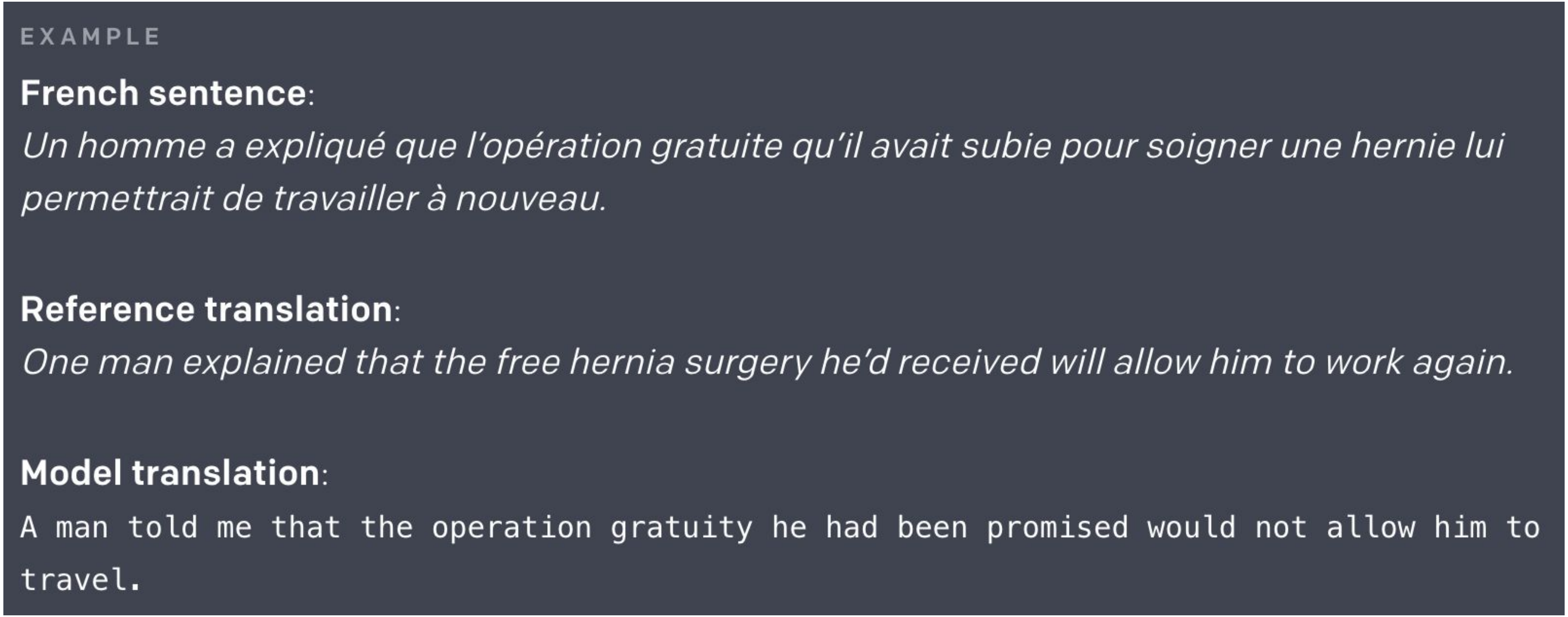
EXAMPLE

Both its sun-speckled shade and the cool grass beneath were a welcome respite after the stifling kitchen, and I was glad to relax against the tree's rough, brittle bark and begin my breakfast of buttery, toasted bread and fresh fruit. Even the water was tasty, it was so clean and cold. It almost made up for the lack of...

Correct answer: *coffee*

Model answer: `food`

GPT-2: machine translation



EXAMPLE

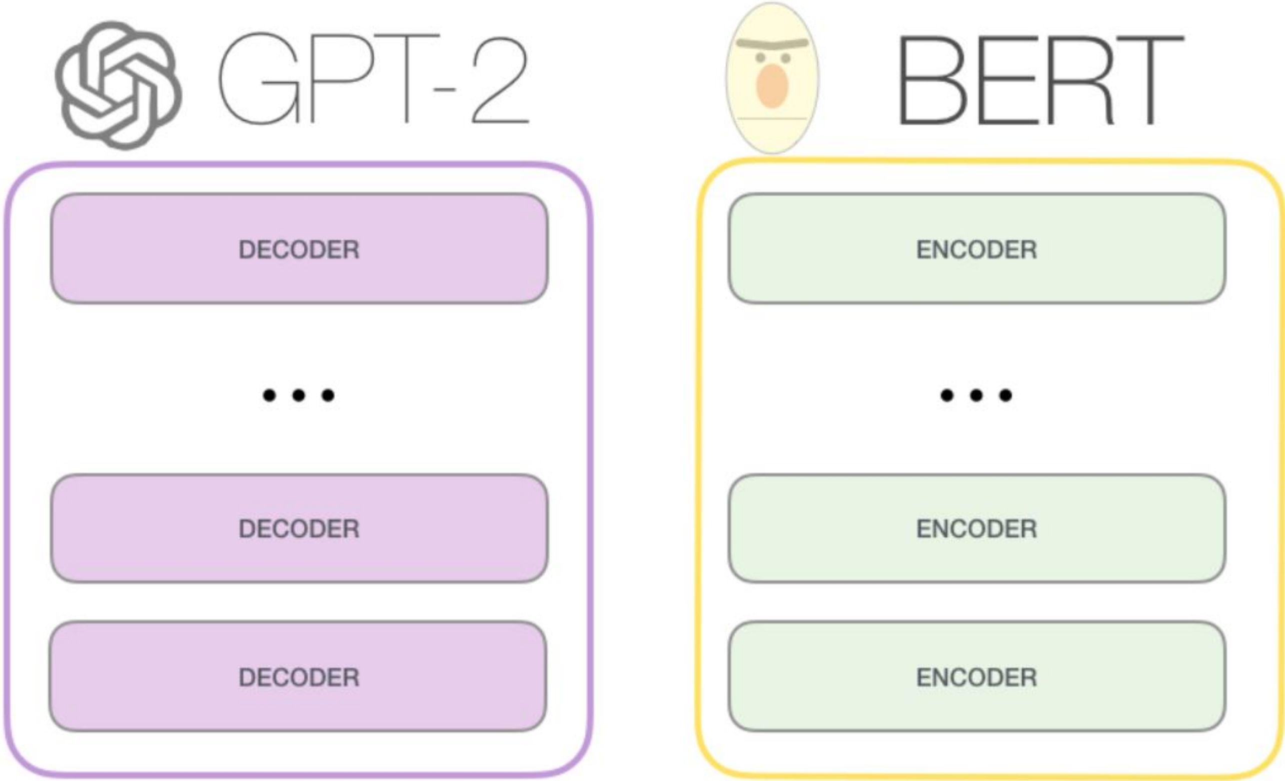
French sentence:
Un homme a expliqué que l'opération gratuite qu'il avait subie pour soigner une hernie lui permettrait de travailler à nouveau.

Reference translation:
One man explained that the free hernia surgery he'd received will allow him to work again.

Model translation:

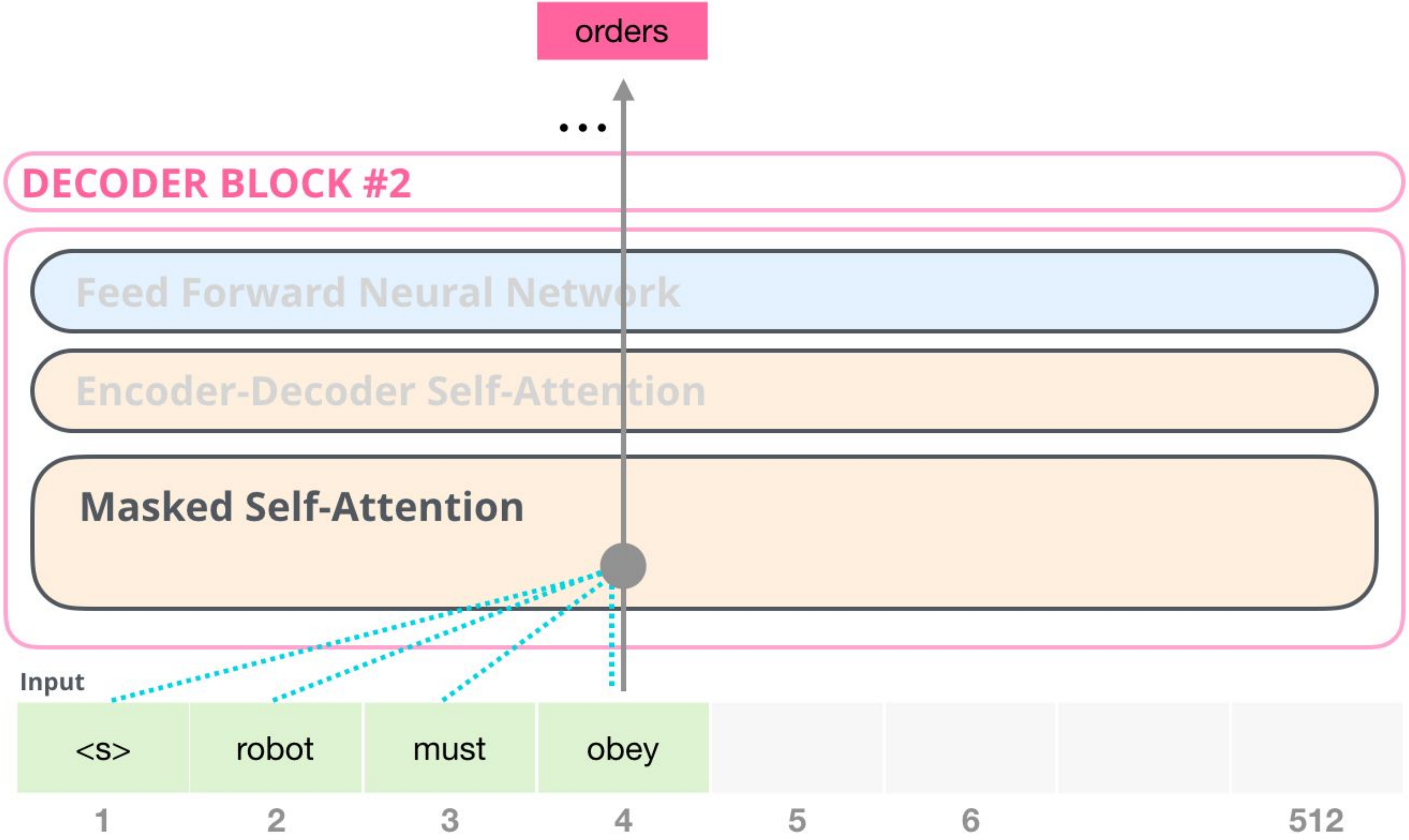
```
A man told me that the operation gratuity he had been promised would not allow him to
travel.
```

GPT-2 vs. BERT



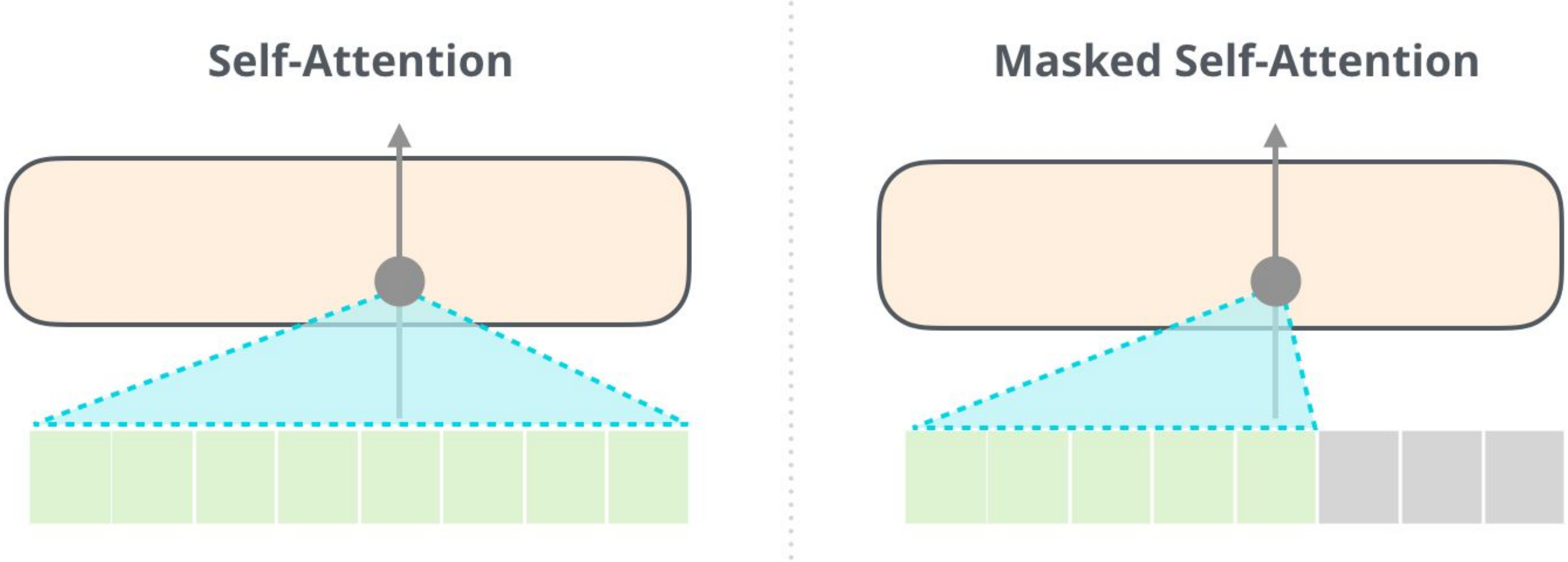
http://jalammar.github.io/illustrated-gpt2/

GPT-2 vs. BERT



http://jalammar.github.io/illustrated-gpt2/

GPT-3 vs. BERT

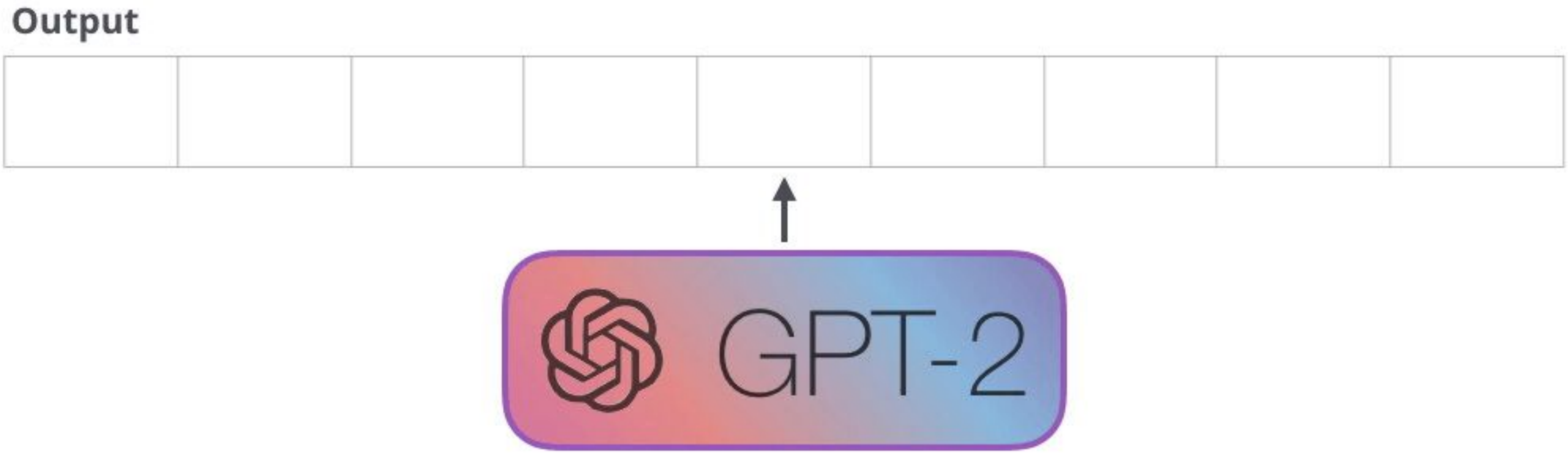


GPT

BERT

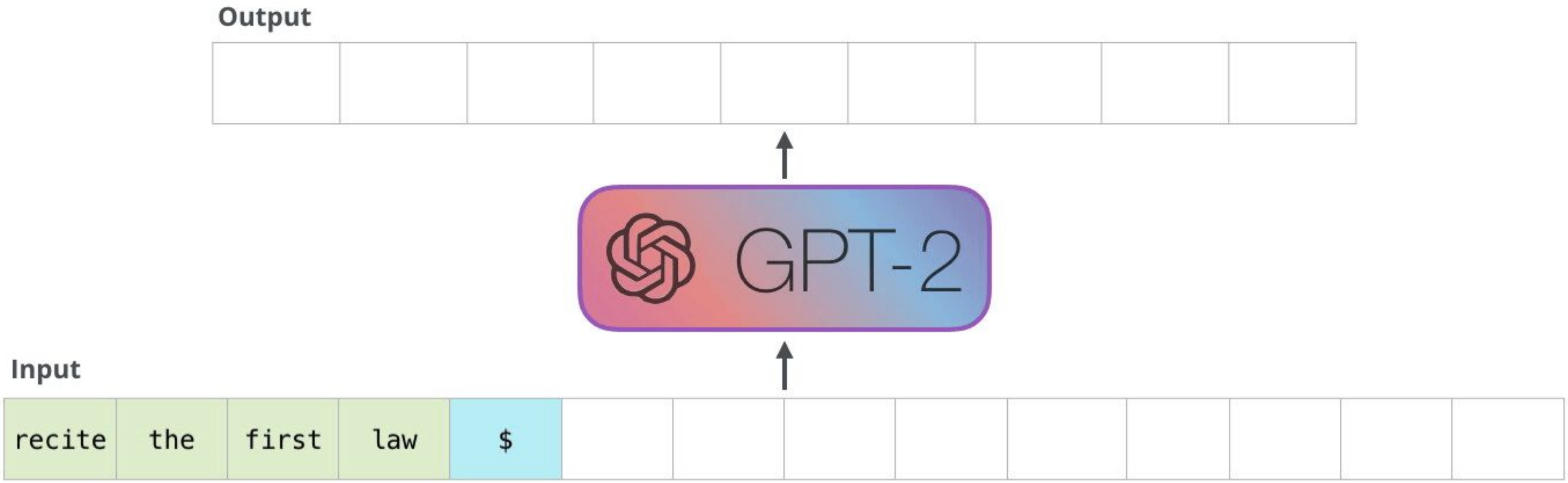
http://jalammar.github.io/illustrated-gpt2/

GPT-2: autoregression



http://jalammar.github.io/illustrated-gpt2/

GPT-2: autoregression



Output

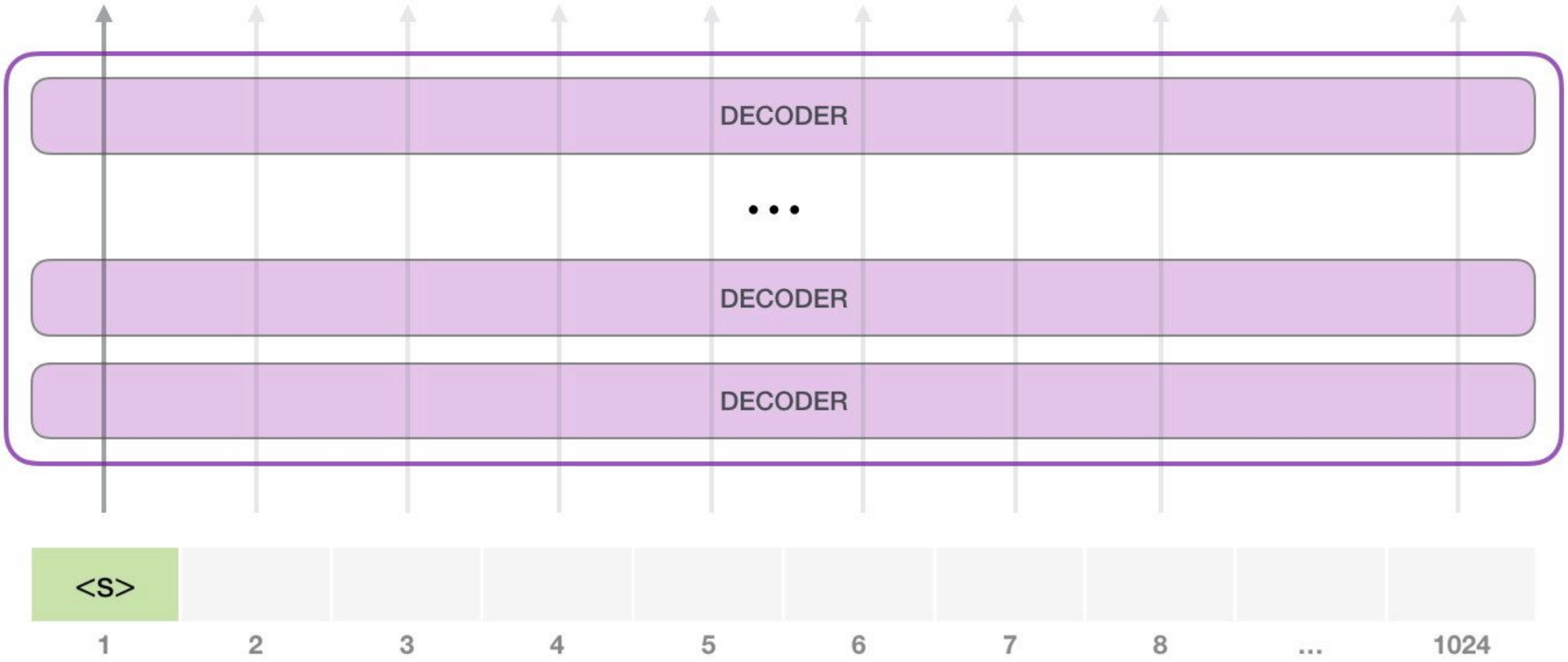
GPT-2

Input

recite the first law $

http://jalammar.github.io/illustrated-gpt2/

GPT-2: text generation



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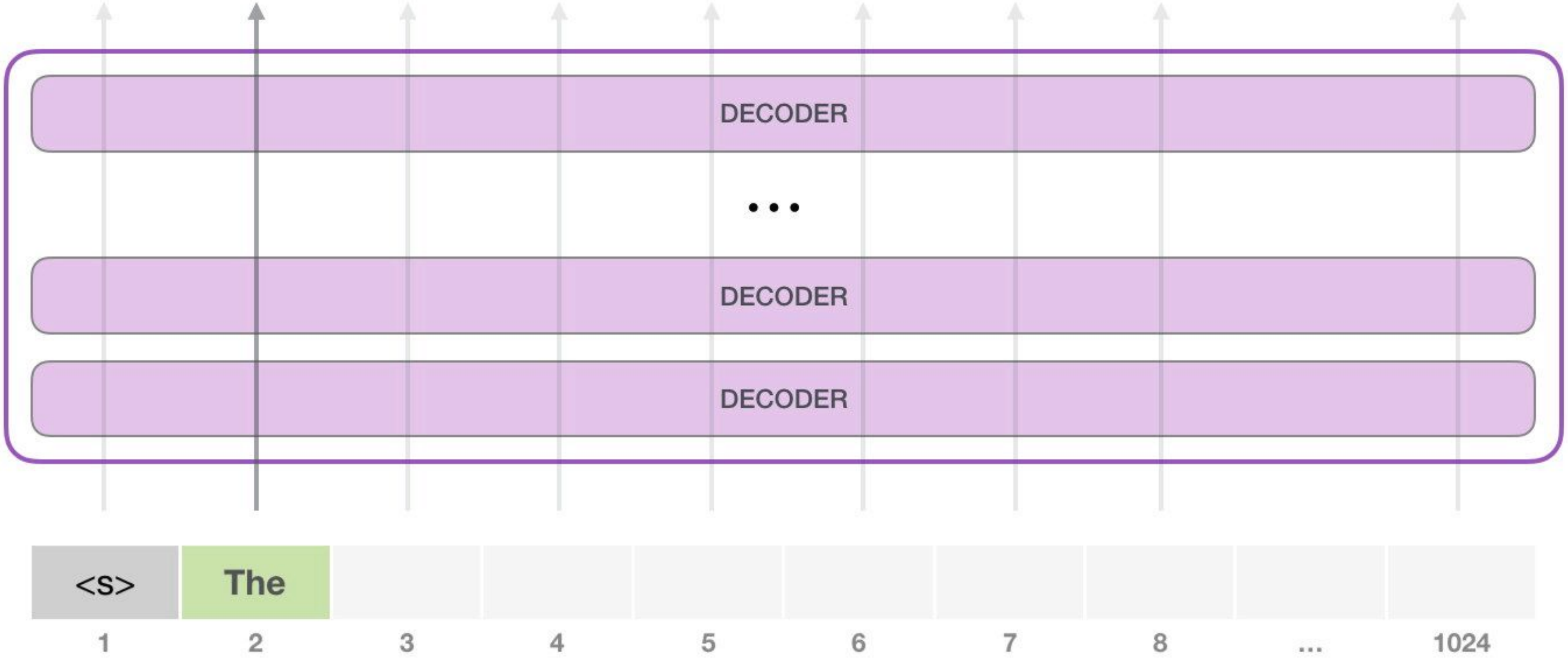
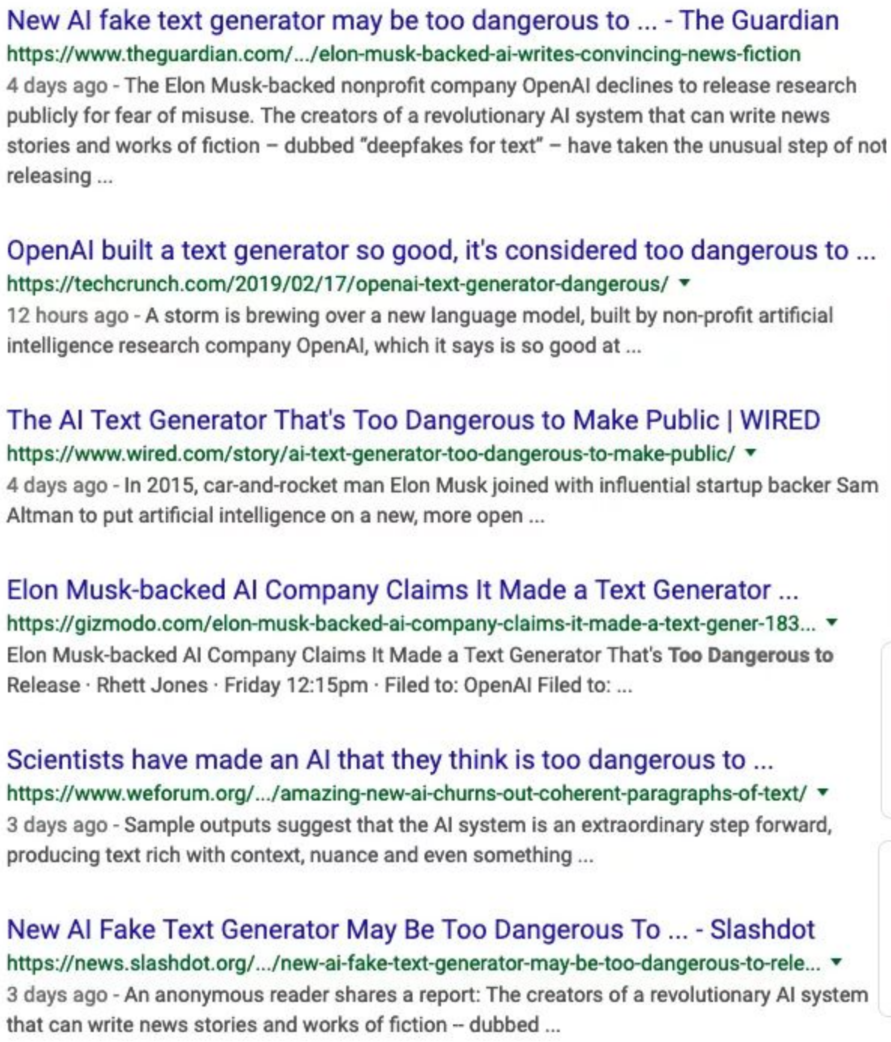
GPT-2: text generation



http://jalammar.github.io/illustrated-gpt2/

GPT-2: fake news and hype



New AI fake text generator may be too dangerous to ... - The Guardian
https://www.theguardian.com/.../elon-musk-backed-ai-writes-convincing-news-fiction
4 days ago - The Elon Musk-backed nonprofit company OpenAI declines to release research publicly for fear of misuse. The creators of a revolutionary AI system that can write news stories and works of fiction – dubbed "deepfakes for text" – have taken the unusual step of not releasing ...

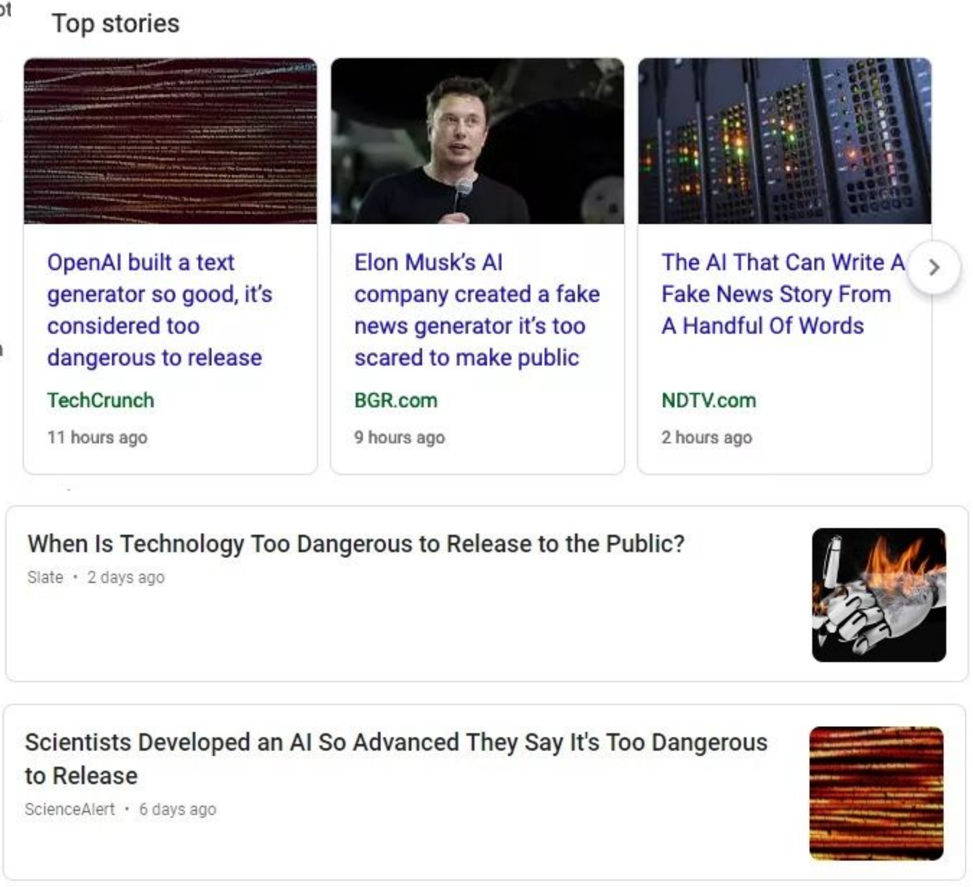
OpenAI built a text generator so good, it's considered too dangerous to ...
https://techcrunch.com/2019/02/17/openai-text-generator-dangerous/ ▾
12 hours ago - A storm is brewing over a new language model, built by non-profit artificial intelligence research company OpenAI, which it says is so good at ...

The AI Text Generator That's Too Dangerous to Make Public | WIRED
https://www.wired.com/story/ai-text-generator-too-dangerous-to-make-public/ ▾
4 days ago - In 2015, car-and-rocket man Elon Musk joined with influential startup backer Sam Altman to put artificial intelligence on a new, more open ...

Elon Musk-backed AI Company Claims It Made a Text Generator ...
https://gizmodo.com/elon-musk-backed-ai-company-claims-it-made-a-text-gener-183... ▾
Elon Musk-backed AI Company Claims It Made a Text Generator That's **Too Dangerous to** Release · Rhett Jones · Friday 12:15pm · Filed to: OpenAI Filed to: ...

Scientists have made an AI that they think is too dangerous to ...
https://www.weforum.org/.../amazing-new-ai-churns-out-coherent-paragraphs-of-text/ ▾
3 days ago - Sample outputs suggest that the AI system is an extraordinary step forward, producing text rich with context, nuance and even something ...

New AI Fake Text Generator May Be Too Dangerous To ... - Slashdot
https://news.slashdot.org/.../new-ai-fake-text-generator-may-be-too-dangerous-to-rele... ▾
3 days ago - An anonymous reader shares a report: The creators of a revolutionary AI system that can write news stories and works of fiction -- dubbed ...



Top stories

OpenAI built a text generator so good, it's considered too dangerous to release
TechCrunch
11 hours ago

Elon Musk's AI company created a fake news generator it's too scared to make public
BGR.com
9 hours ago

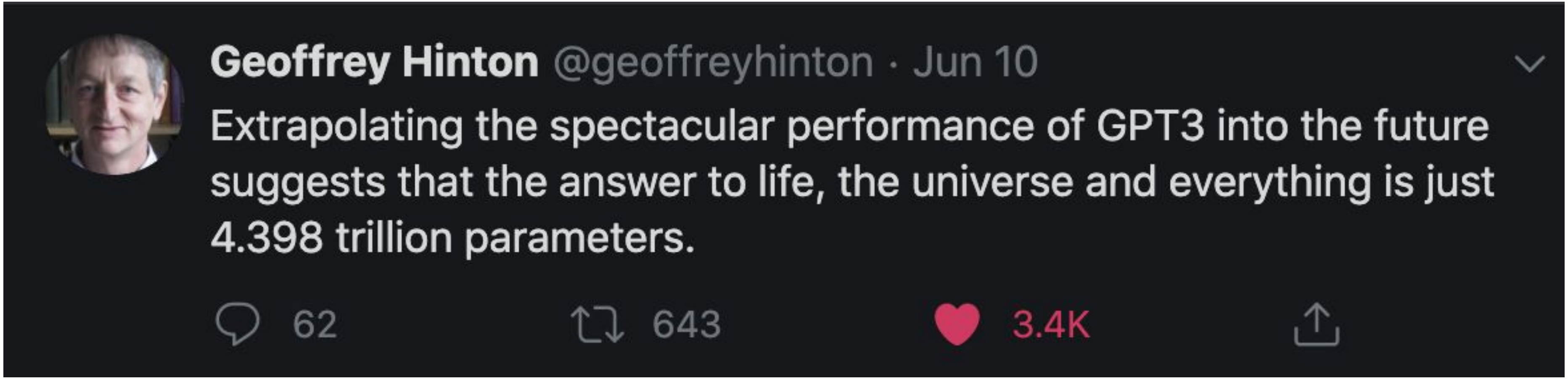
The AI That Can Write A Fake News Story From A Handful Of Words
NDTV.com
2 hours ago

When Is Technology Too Dangerous to Release to the Public?
Slate · 2 days ago

Scientists Developed an AI So Advanced They Say It's Too Dangerous to Release
ScienceAlert · 6 days ago

GPT-3

- GPT-2: 1.5 billion parameters
- GPT-3: **175 billion** parameters



Geoffrey Hinton @geoffreyhinton · Jun 10

Extrapolating the spectacular performance of GPT3 into the future suggests that the answer to life, the universe and everything is just 4.398 trillion parameters.

GPT-3: OpenAI API released

- You can request access in order to integrate the API into your product
- Given any text prompt, the API will return a text completion, attempting to match the pattern you gave it

https://openai.com/blog/openai-api/

Transformer XL

Transformer-XL

- Vanila Transformer works with a fixed-length context at training time. That’s why:
  - the algorithm is not able to model dependencies that are longer than a fixed length.
  - the segments usually do not respect the sentence boundaries, resulting in context fragmentation which leads to inefficient optimization.

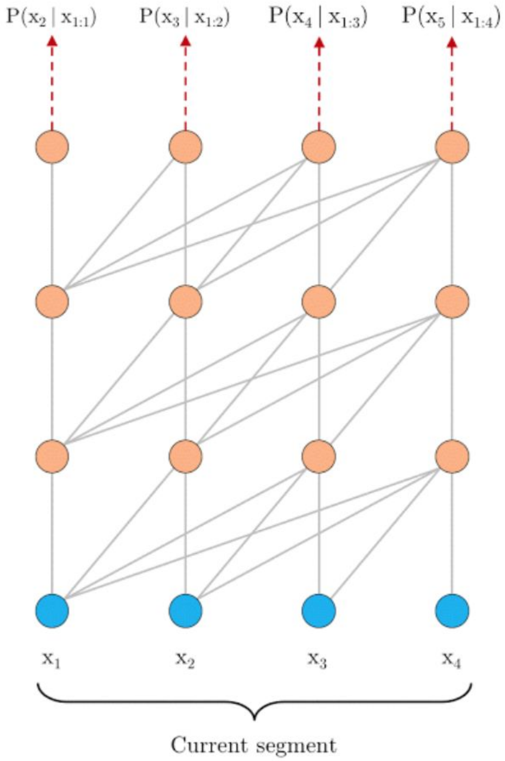
Segment-level Recurrence

- During training, the representations computed for the previous segment are fixed and cached to be reused as an extended context when the model processes the next new segment.

- Contextual information is now able to flow across segment boundaries.

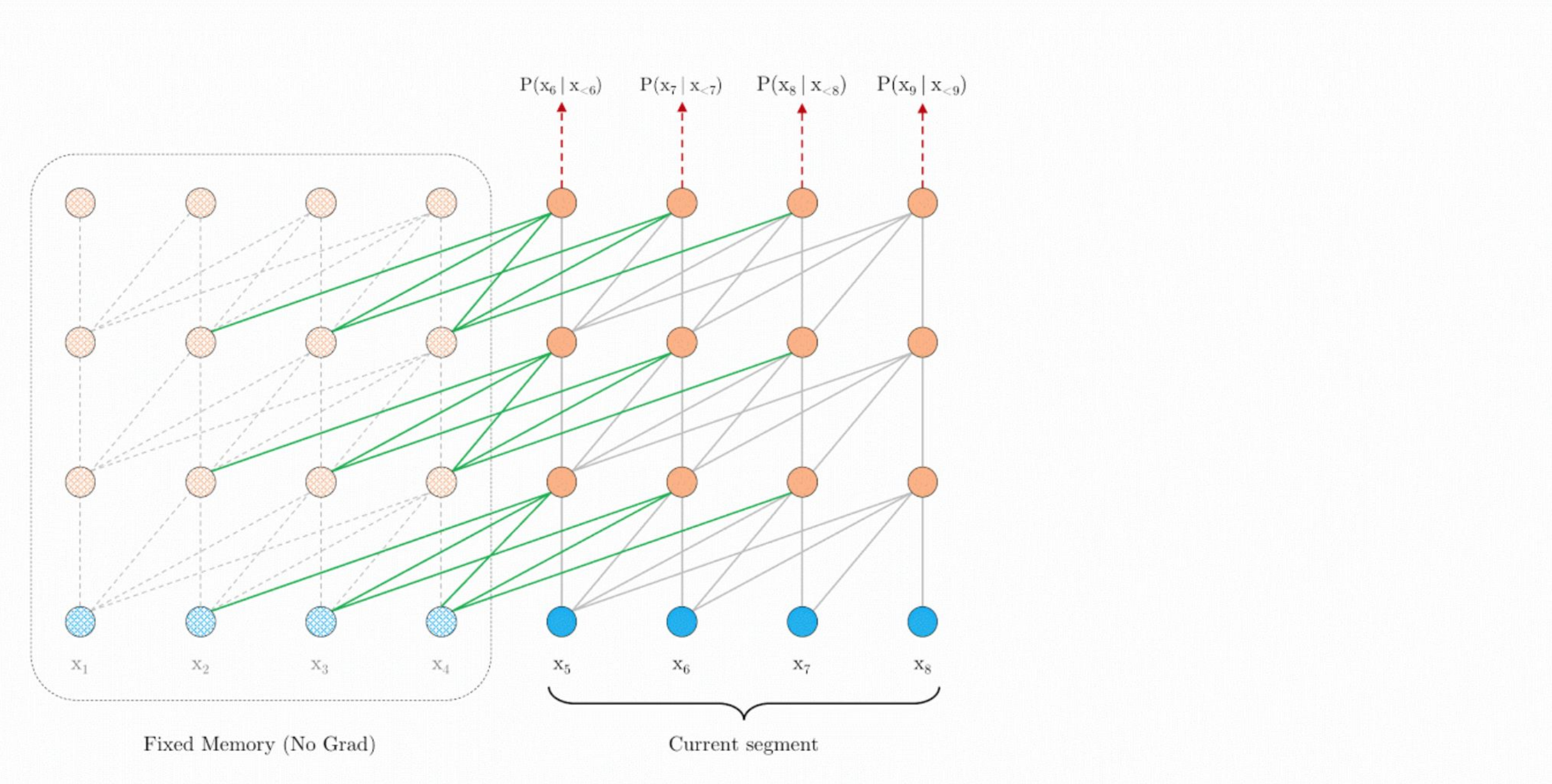
- Recurrence mechanism also resolves the context fragmentation issue, providing necessary context for tokens in the front of a new segment.

Segment-level Recurrence



https://ai.googleblog.com/2019/01/transformer-xl-unleashing-potential-of.html

Segment-level Recurrence



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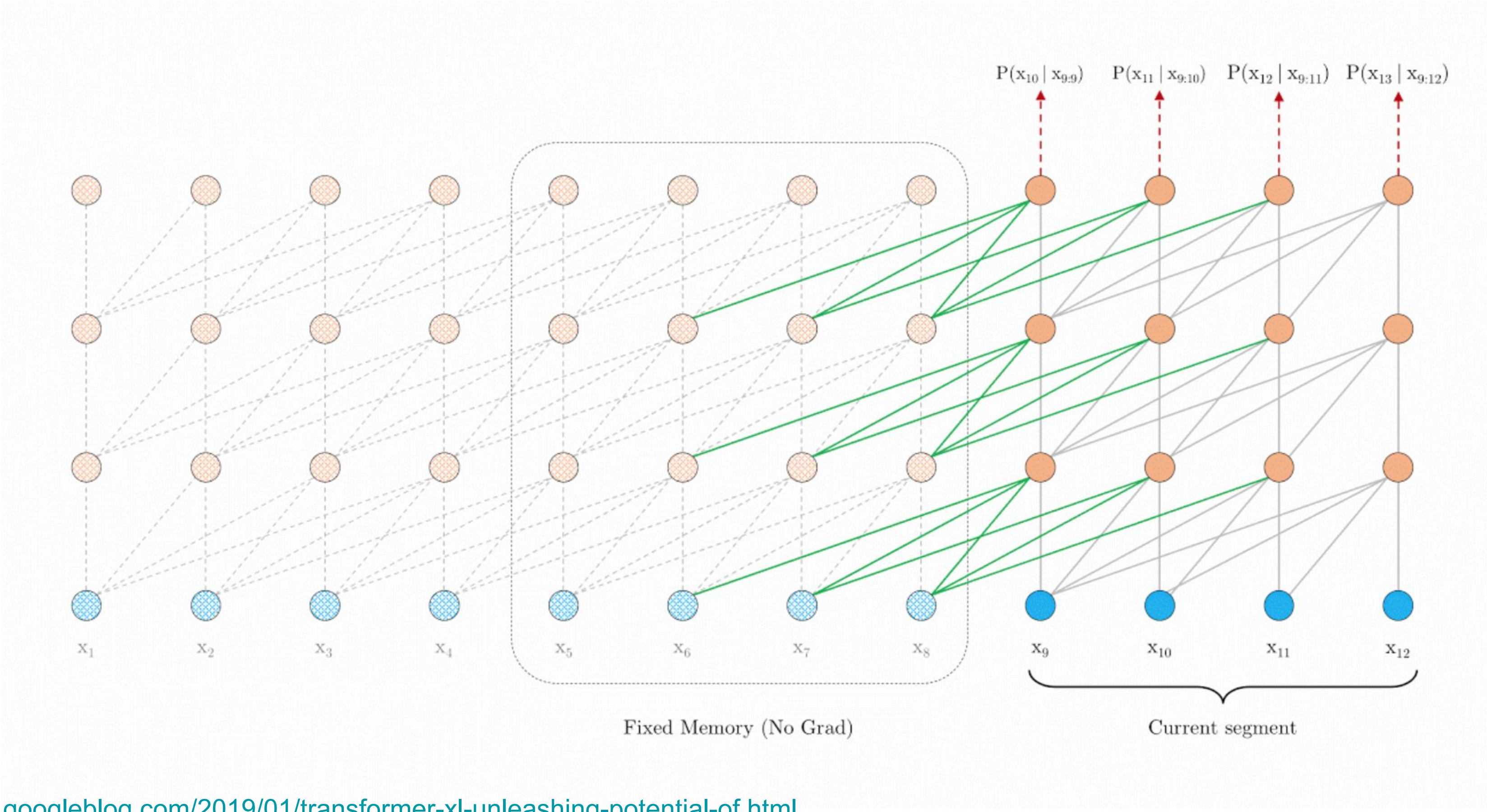
Segment-level Recurrence



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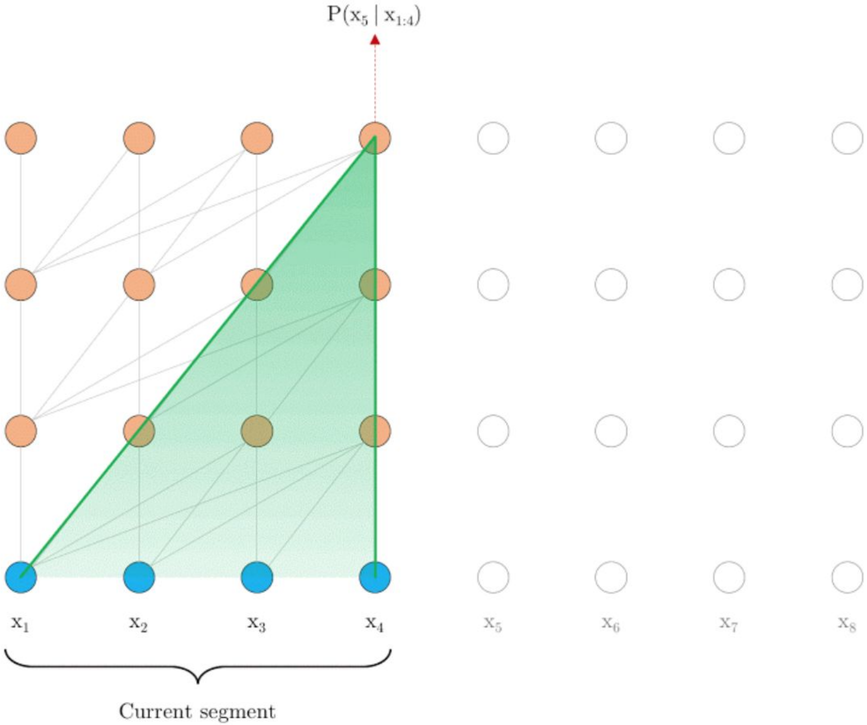
Relative Positional Encodings

- Fixed embeddings with learnable transformations instead of learnable embeddings

  As a result:
- more generalizable to longer sequences at test time
- longer effective context

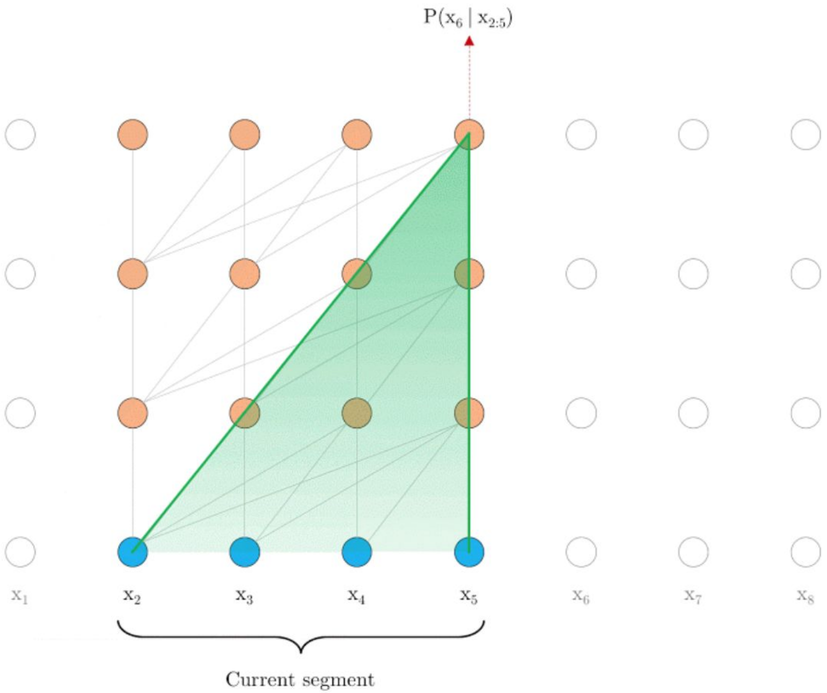
Vanila Transformer vs. Transformer-XL



Vanilla Transformer with a fixed-length context at evaluation time

https://ai.googleblog.com/2019/01/transformer-xl-unleashing-potential-of.html

Vanila Transformer vs. Transformer-XL



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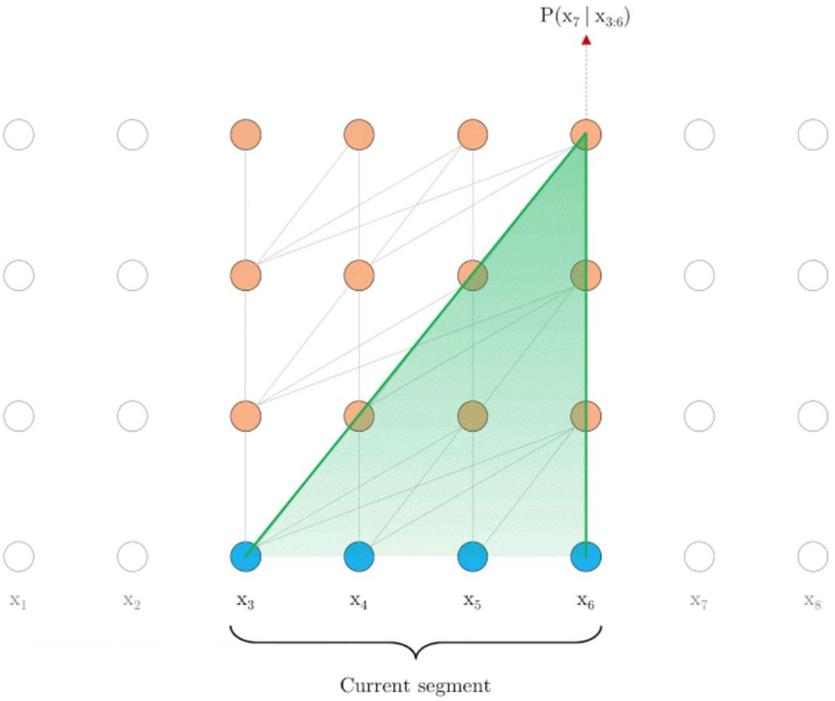
Vanila Transformer vs. Transformer-XL



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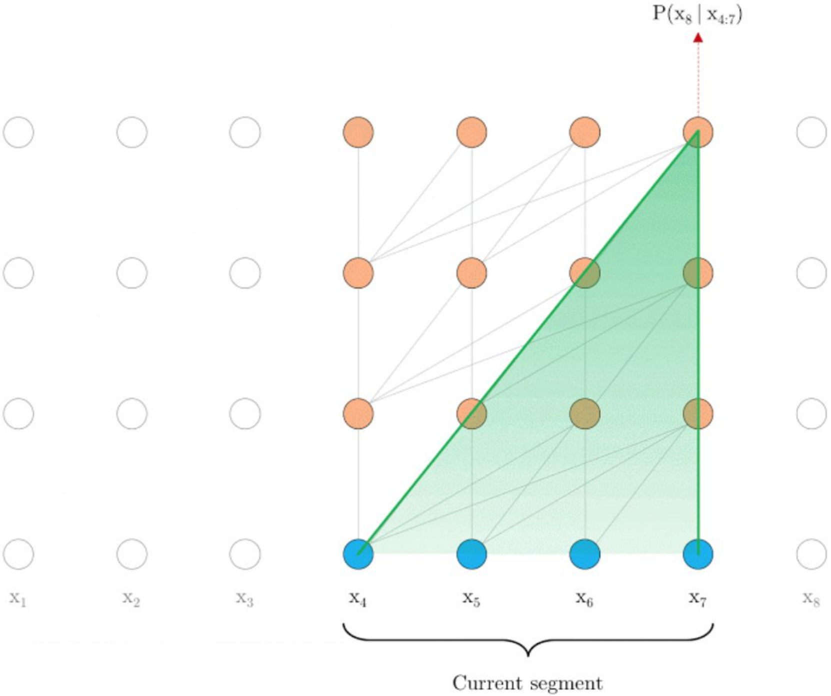
Vanila Transformer vs. Transformer-XL



Vanilla Transformer with a fixed-length context at evaluation time

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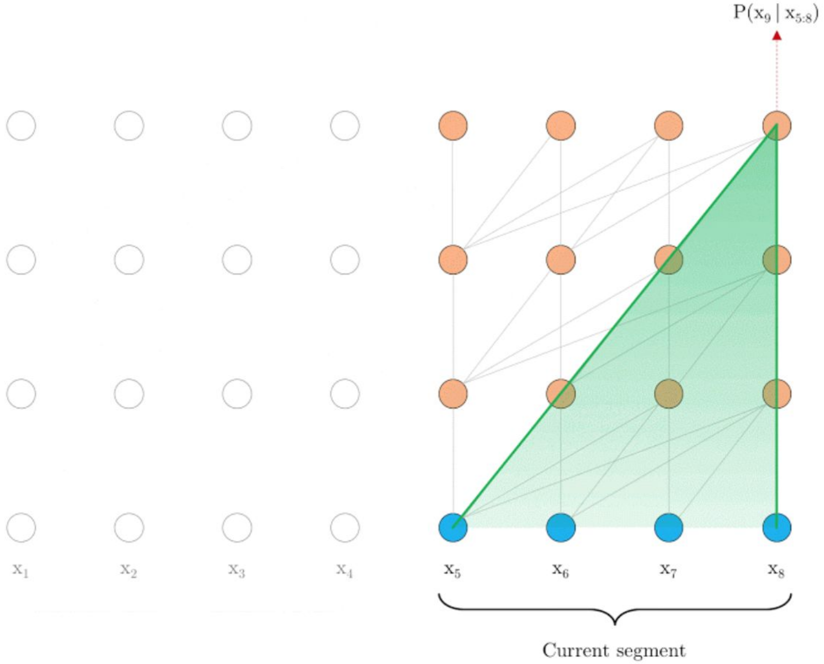
Vanila Transformer vs. Transformer-XL



Vanilla Transformer with a fixed-length context at evaluation time

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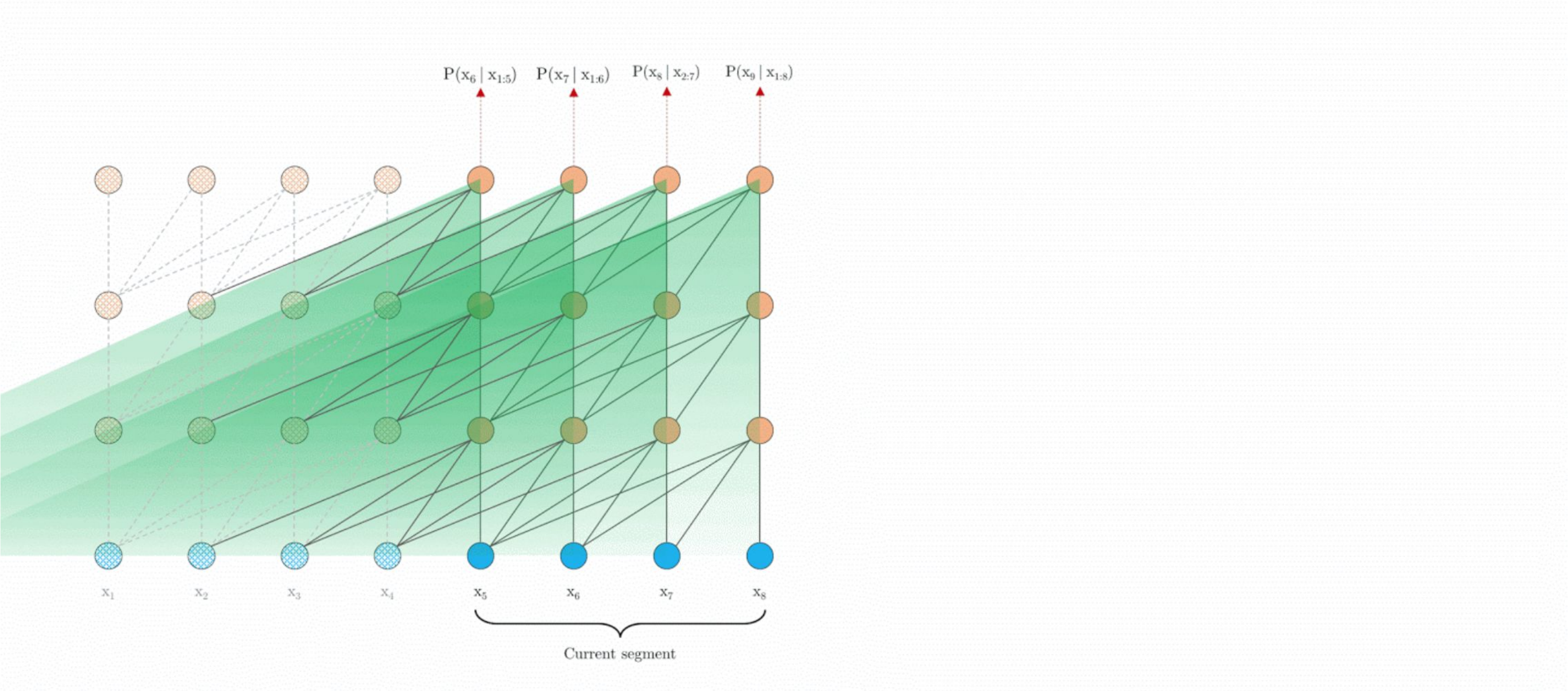
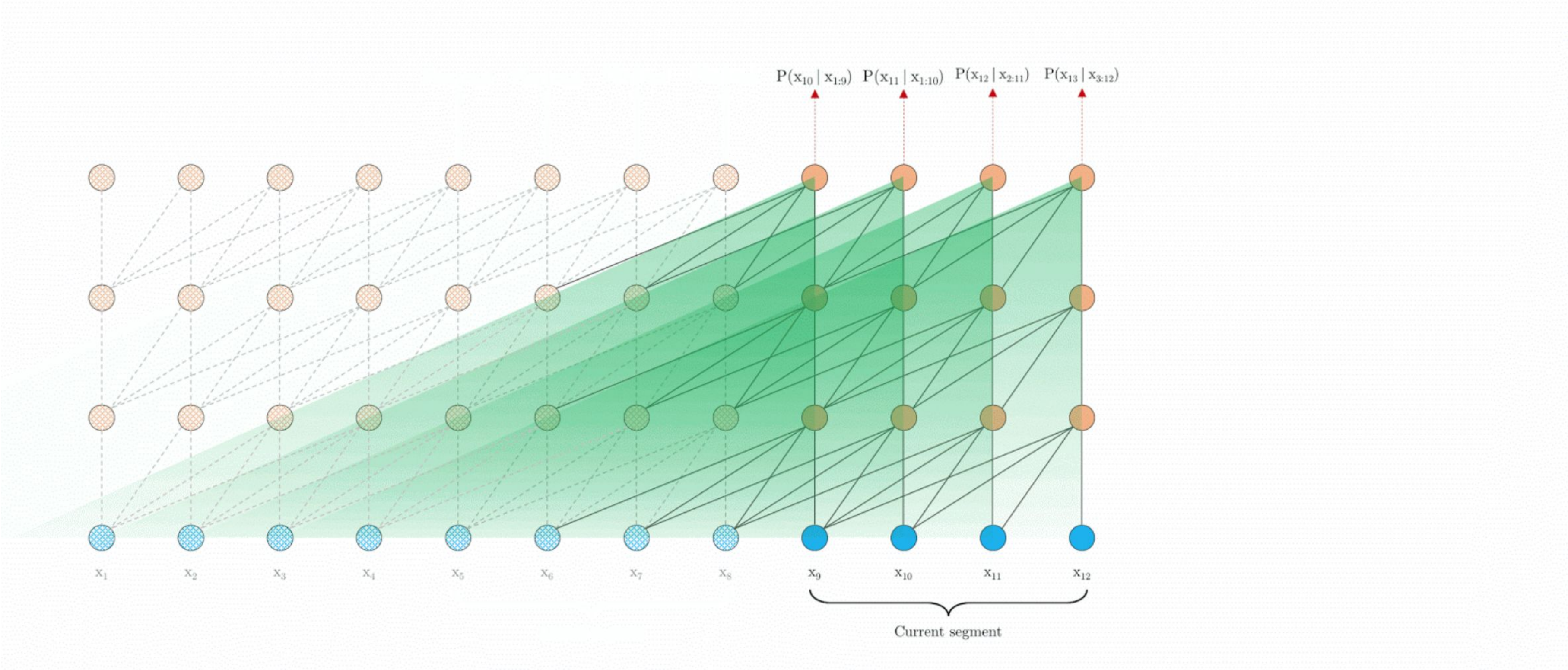
Vanila Transformer vs. Transformer-XL



Transformer-XL with segment-level recurrence at evaluation time

https://ai.googleblog.com/2019/01/transformer-xl-unleashing-potential-of.html

Vanila Transformer vs. Transformer-XL



Transformer-XL with segment-level recurrence at evaluation time

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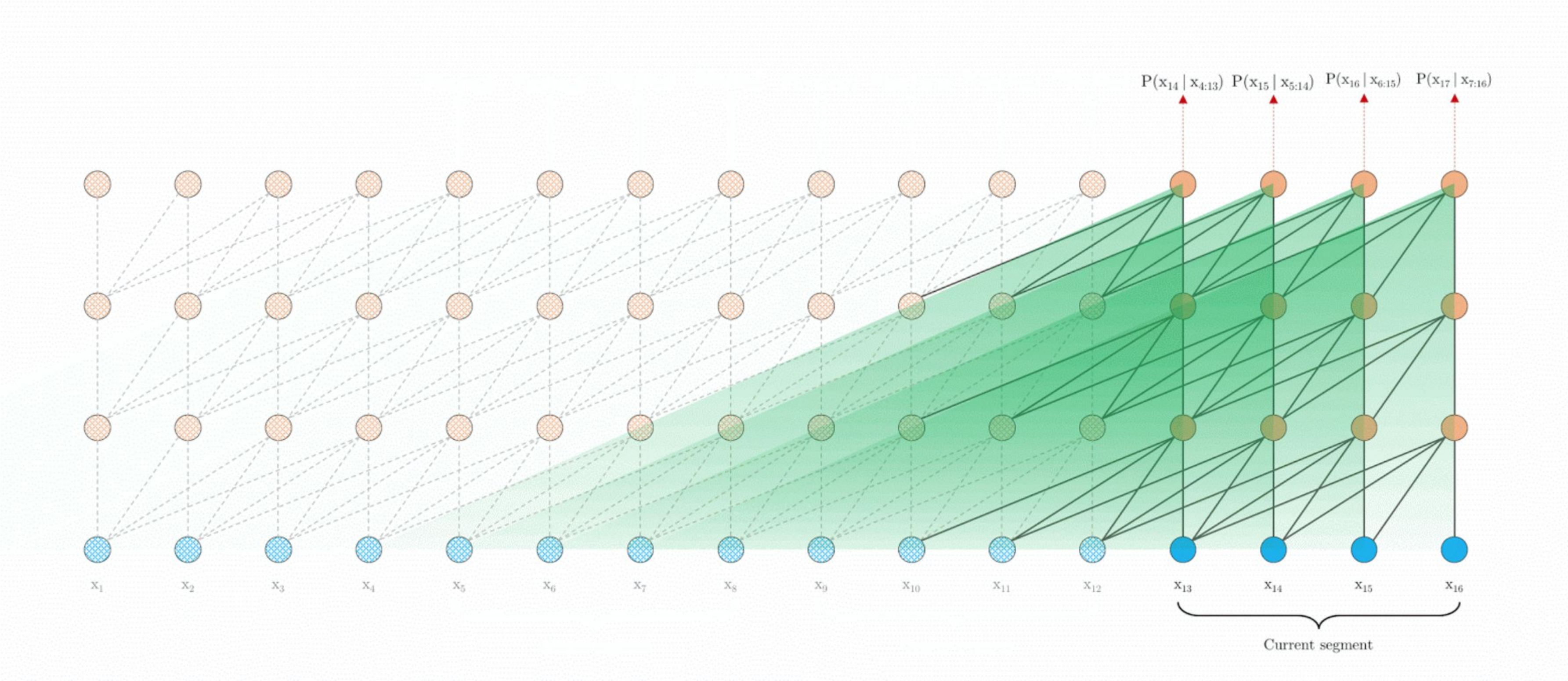
Vanila Transformer vs. Transformer-XL



Transformer-XL with segment-level recurrence at evaluation time

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Vanila Transformer vs. Transformer-XL

- Transformer-XL learns dependency that is about 80% longer than RNNs and 450% longer than vanilla Transformers

- Transformer-XL is up to 1,800+ times faster than a vanilla Transformer during evaluation on language modeling tasks, because no re-computation is needed

XLNET

BERT problems

- The [MASK] token used in training does not appear during fine-tuning

BERT problems

- BERT generates predictions independently

I went to [MASK] [MASK] and saw the [MASK] [MASK] [MASK]

BERT problems

- BERT generates predictions independently

I went to [MASK] [MASK] and saw the [MASK] [MASK] [MASK]

Ground truth solutions:

- I went to New York and saw the Empire State building.
- I went to San Francisco and saw the Golden Gate bridge.

BERT problems

- BERT generates predictions independently

I went to [MASK] [MASK] and saw the [MASK] [MASK] [MASK]

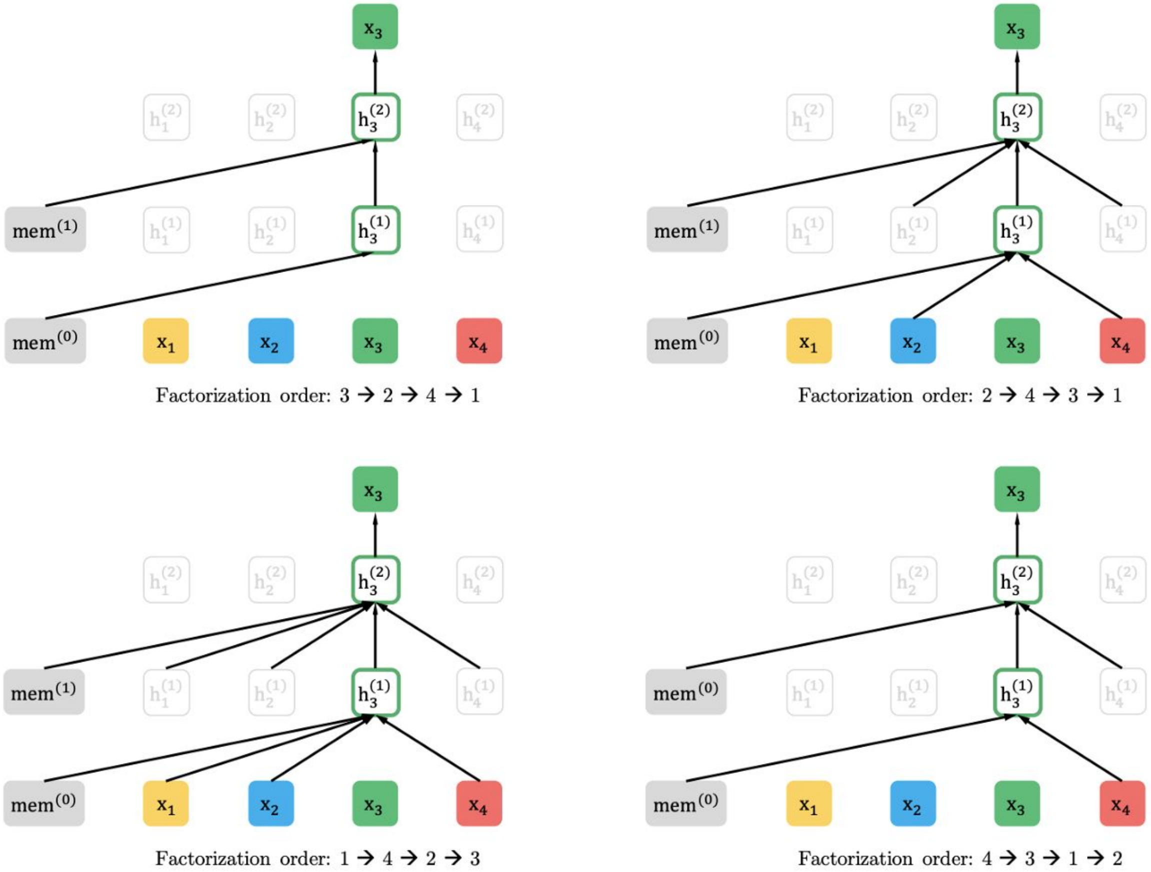
BERT solutions:

- I went to New York and saw the Empire State building.
- I went to San Francisco and saw the Golden Gate bridge.
- I went to New York and saw the Golden Gate bridge.

XLNET

- XLNET is a generalized autoregressive model
- Permutation language modeling (PLM)
- Integrates the idea of auto-regressive models and bi-directional context modeling
- Outperforms BERT on 20 tasks

XLNET



Factorization order: 3 → 2 → 4 → 1

Factorization order: 2 → 4 → 3 → 1

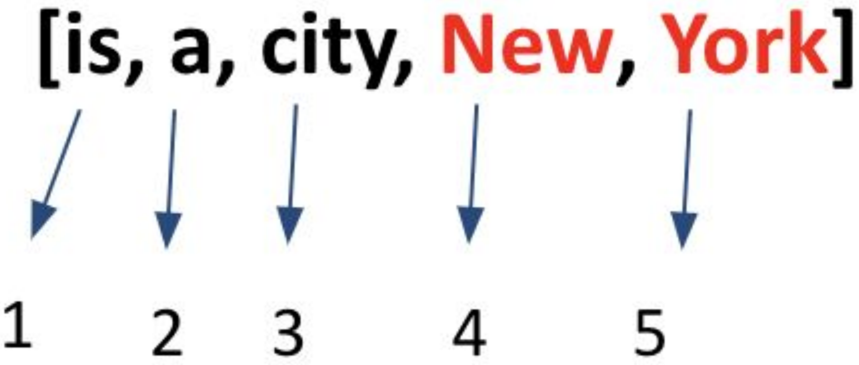
Factorization order: 1 → 4 → 2 → 3

Factorization order: 4 → 3 → 1 → 2

Figure 1: Illustration of the permutation language modeling objective for predicting x_3 given the same input sequence $\mathbf{x}$ but with different factorization orders.

https://towardsdatascience.com/xlnet-explained-in-simple-terms-255b9fb2c97c

XLNET vs. BERT

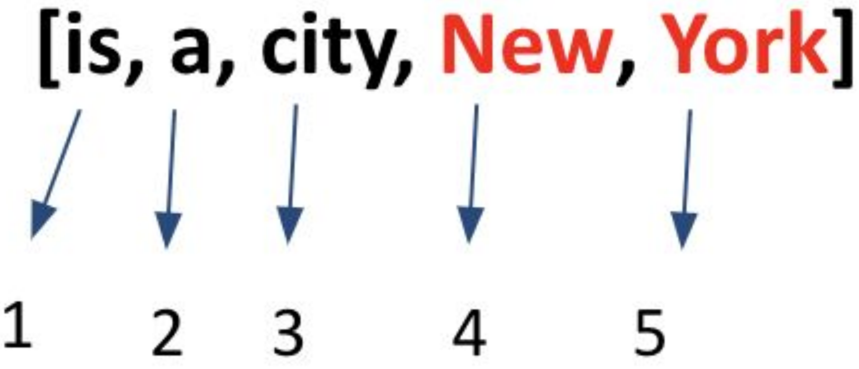


BERT $\log P(\text{New} \mid \textbf{is a city}) + \log P(\text{York} \mid \textbf{is a city})$

XLNET $\log P(\text{New} \mid \textbf{is a city}) + \log P(\text{York} \mid \textbf{New, is a city})$

https://towardsdatascience.com/xlnet-explained-in-simple-terms-255b9fb2c97c

XLNET vs. BERT



[is, a, city, New, York]

1 2 3 4 5

BERT $\longrightarrow$ log P(New | **is a city**) + log P(York | **is a city**)

XLNET $\longrightarrow$ log P(New | **is a city**) + log P(York | **New, is a city**)

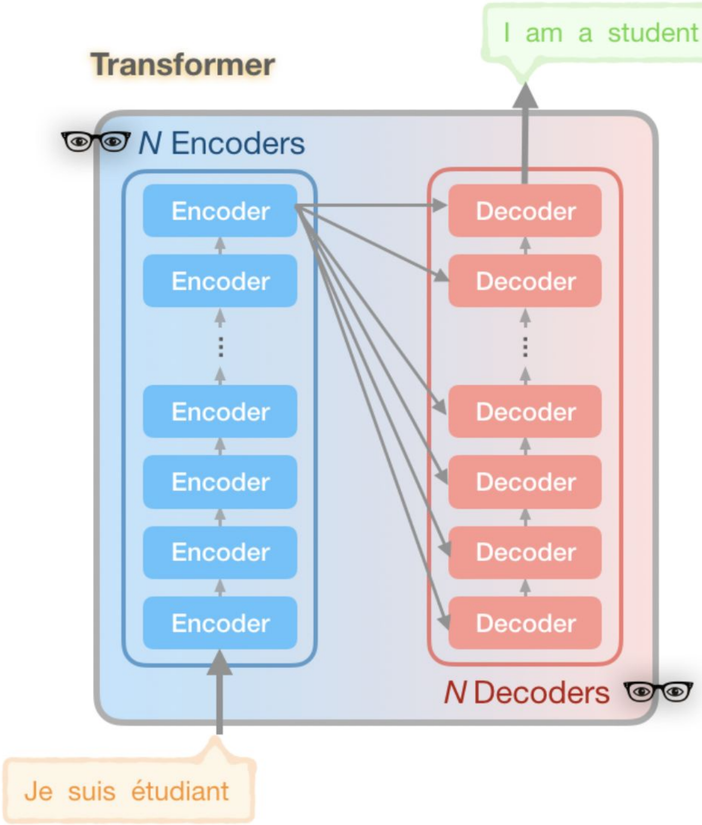
https://towardsdatascience.com/xlnet-explained-in-simple-terms-255b9fb2c97c

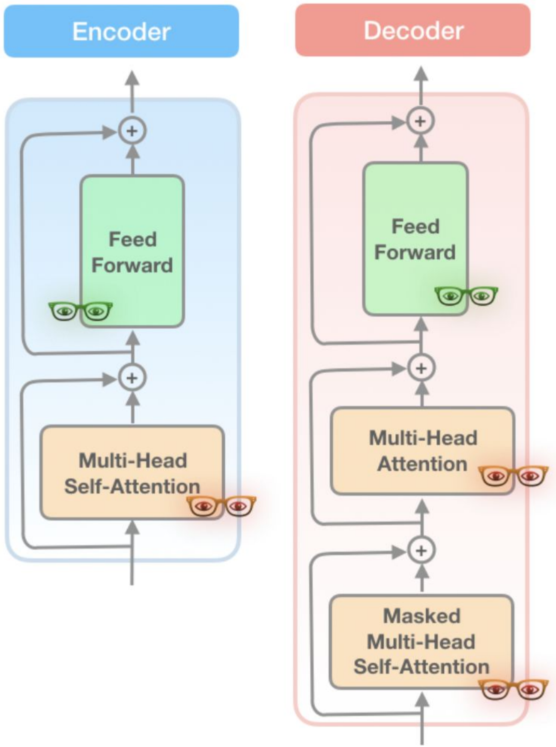
The Reformer

Reformer: The Effective Transformer (ICLR 2020)

Transformer-based models have a problem:

- They require lots of GPUs to train
  - even cannot be fine-tuned on a single GPU

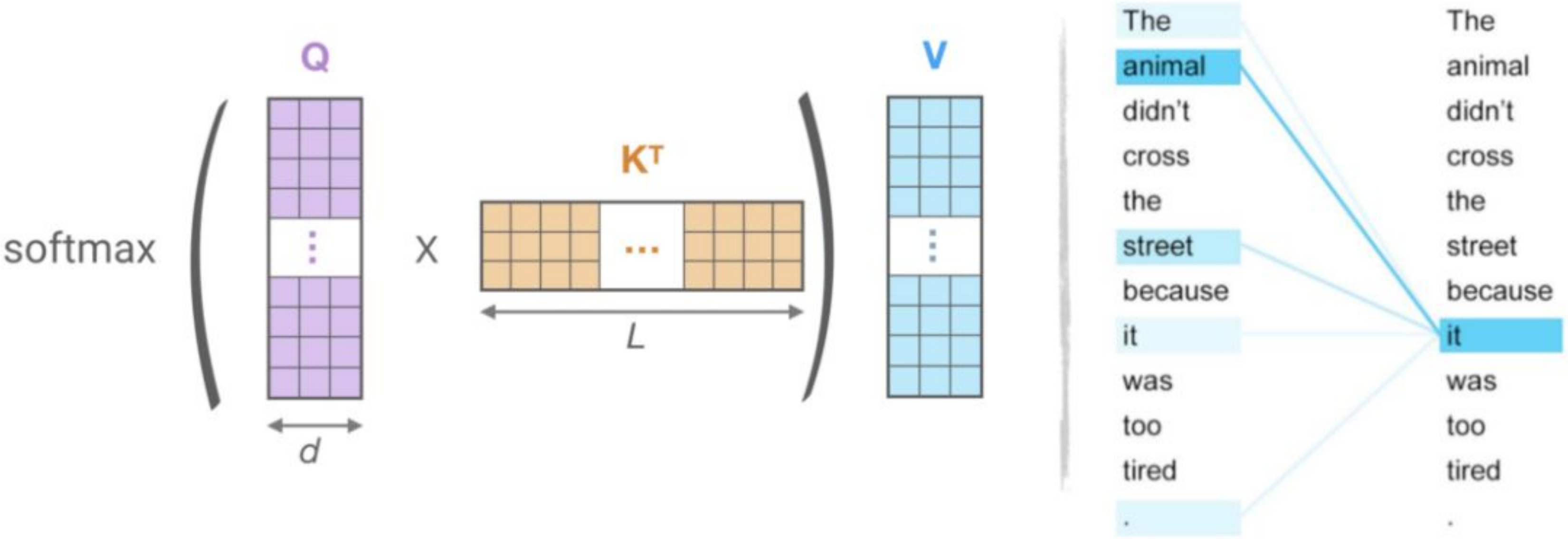




- Problem 1 (**Red** 👓): Attention computation
- Problem 2 (**Black** 👓): Large number of layers
- Problem 3 (**Green** 👓): Depth of feed-forward layers

https://towardsdatascience.com/illustrating-the-reformer-393575ac6ba0

Attention computation



- Replace dot-product attention with locality-sensitive hashing (LSH)
    - changes the complexity from $O(L^2)$ to $O(L \log L)$

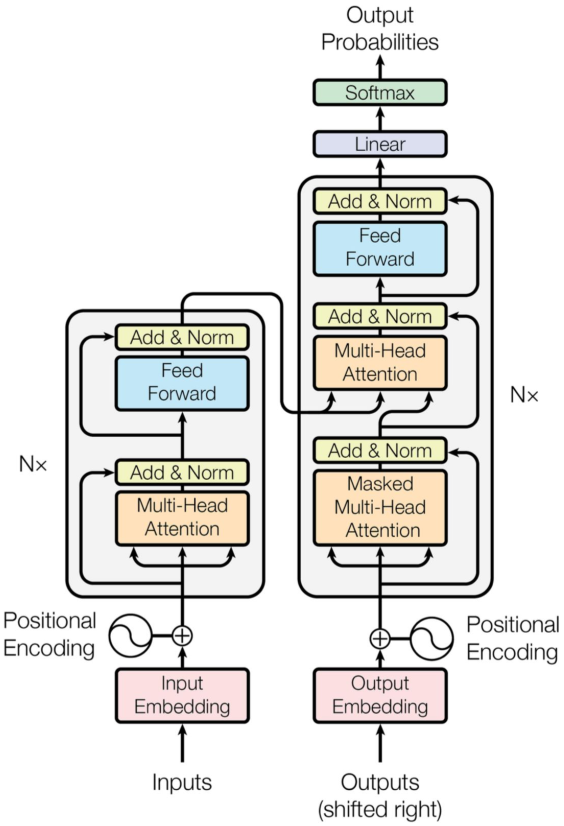
https://towardsdatascience.com/illustrating-the-reformer-393575ac6ba0

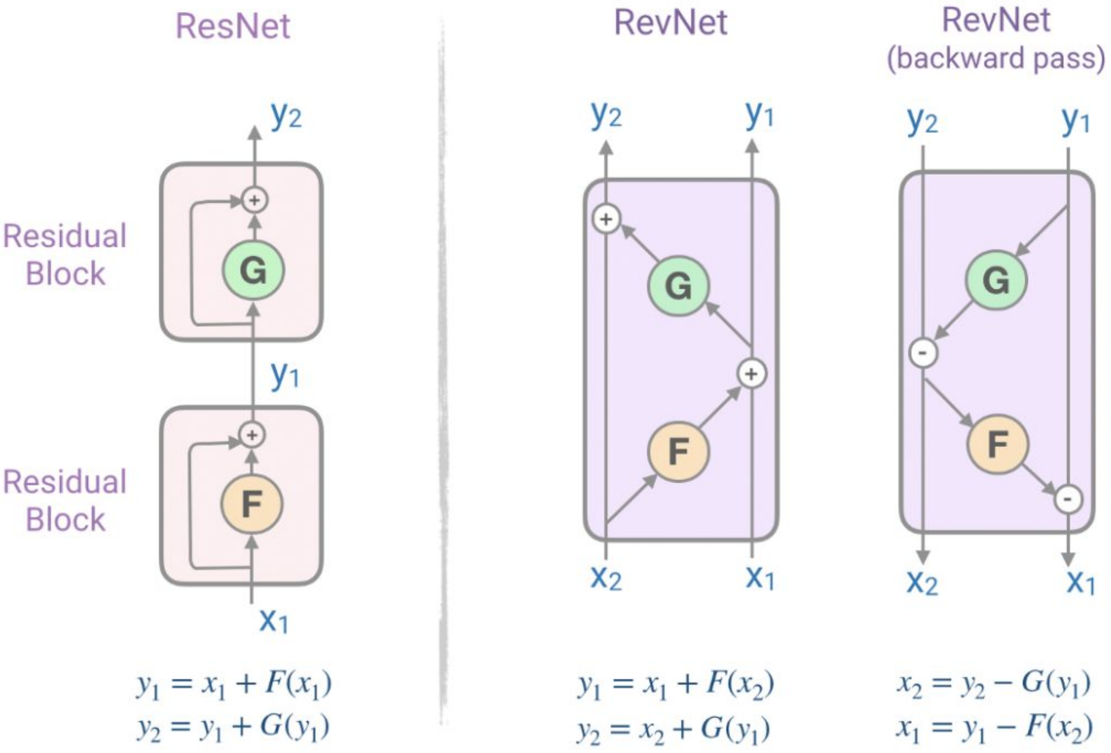
Locality-sensitive hashing for attention computation

- LSH - an *efficient* and *approximate* way of nearest neighbors search in high dimensional datasets.

- The main idea behind LSH is to select hash functions such that for two points ‘p’ and ‘q’, if ‘q’ is close to ‘p’ then with good enough probability we have ‘hash(q) == hash(p)’.

Reversible Transformer





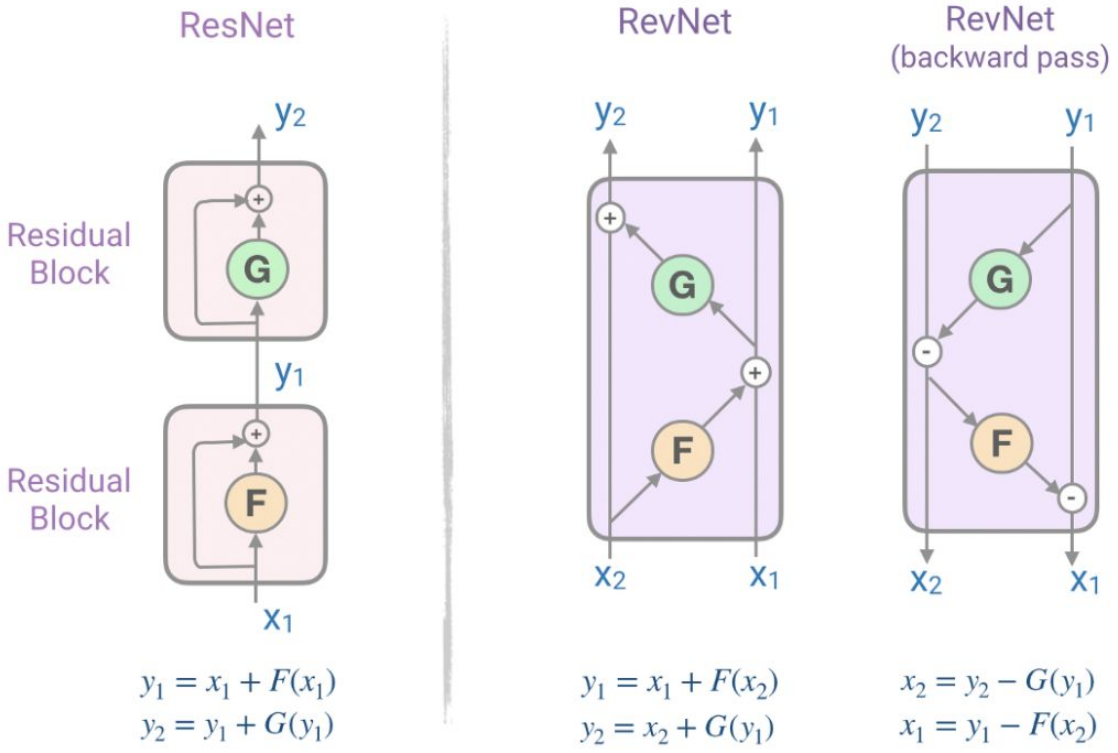
$$y_1 = x_1 + F(x_1)$$
$$y_2 = y_1 + G(y_1)$$

$$y_1 = x_1 + F(x_2)$$
$$y_2 = x_2 + G(y_1)$$

$$x_2 = y_2 - G(y_1)$$
$$x_1 = y_1 - F(x_2)$$

https://towardsdatascience.com/illustrating-the-reformer-393575ac6ba0

Reversible Transformer



$y_1 = x_1 + F(x_1)$
$y_2 = y_1 + G(y_1)$

$y_1 = x_1 + F(x_2)$
$y_2 = x_2 + G(y_1)$

$x_2 = y_2 - G(y_1)$
$x_1 = y_1 - F(x_2)$

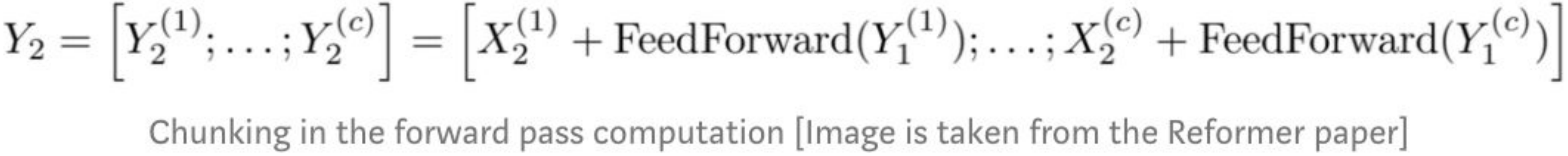
- F - self-attention block
- G - feed-forward layer

Profit: storing activations only once during the training process

https://towardsdatascience.com/illustrating-the-reformer-393575ac6ba0

Chunking

Computations in feed-forward layers are independent across positions in a sequence => the computations for the forward and backward passes can be split into chunks.



$$Y_2 = \left[Y_2^{(1)}; \ldots; Y_2^{(c)}\right] = \left[X_2^{(1)} + \mathrm{FeedForward}(Y_1^{(1)}); \ldots; X_2^{(c)} + \mathrm{FeedForward}(Y_1^{(c)})\right]$$

Chunking in the forward pass computation [Image is taken from the Reformer paper]

https://towardsdatascience.com/illustrating-the-reformer-393575ac6ba0

References

- Transformer
- OpenAI Transformer
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- BERT
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- GPT
- GPT-2
- GPT-3
- Transformer XL
- XLNET
- Reformer