11868 LLM Systems
Pre-trained LLMs

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Recap

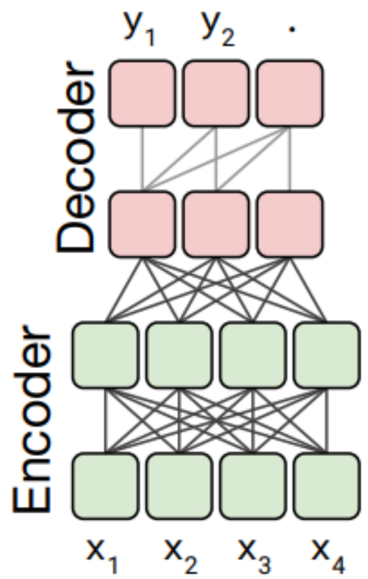
- Sequence-to-sequence encoder-decoder framework for conditional generation, including Machine Translation
- Key components in Transformer
  - Positional Embedding (to distinguish tokens at different pos)
  - Multihead attention
  - Residual connection
  - layer norm

Today's Topic

- LLaMA
- GPT3
- How to build a vocabulary
    - how to break sentence into sequence of units?

T5

- Model Architecture
  - Standard encoder-decoder Transformer
  - Decoding: beam search
    - Beam width=4, length penalty=0.6



- Model Size
  - T5-base: 220 million parameters
    - 12 blocks, d_{ff} = 3072, d_{kv} = 64, 12-headed attention, d_{model} = 768
  - T5-3B
    - 24 blocks, d_{model} = 1024 , d_{kv} = 128, d_{ff} = 16384, 32-headed attention
  - T5-11B
    - 24 blocks, d_{model} = 1024 , d_{kv} = 128, d_{ff} = 65536, 128-headed attention

Raffel, Colin, et al. "Exploring the limits of transfer learning with a unified text-to-text transformer." *The Journal of Machine Learning Research* 21.1 (2020): 5485-5551.

T5

- Training Strategy
  - Multi-task pretraining + fine-tuning
  - In text-to-text, multi-task learning corresponds to mixing datasets.

- Unsupervised Objective
  - Span-corruption: A mean span length of 3 and corrupt 15% of the original sequence

- Training Details: longer training for larger models
  - Pre-train for 1 million steps on a batch size of 2^{11} sequences of length 512 (total of about 1 trillion pre-training tokens)

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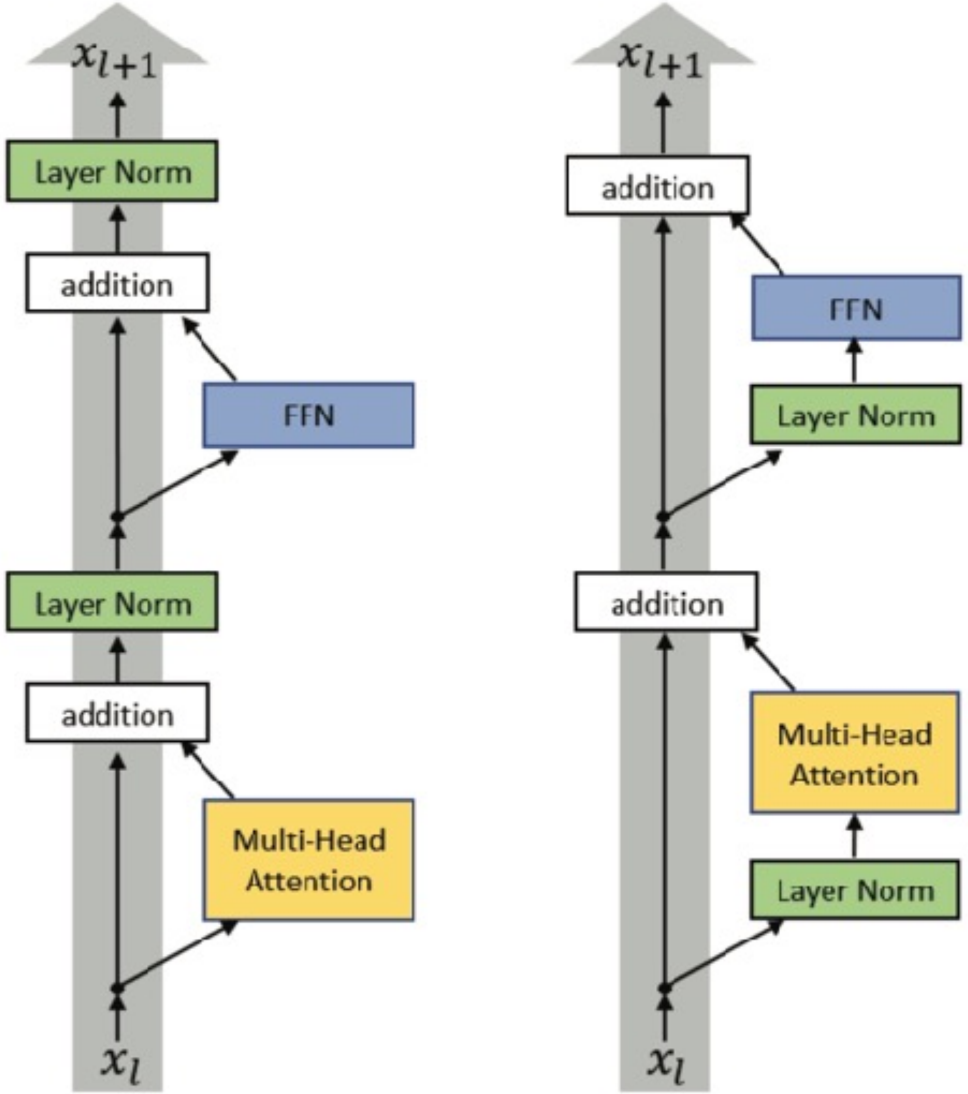
LLaMA

- Model Architecture: Based on Transformer decoder, with a few improvements:
  - Pre-normalization [GPT3]
  - SwiGLU activation function [PaLM]: Swish-Gated Linear Unit
  - Rotary Embeddings [GPTNeo]

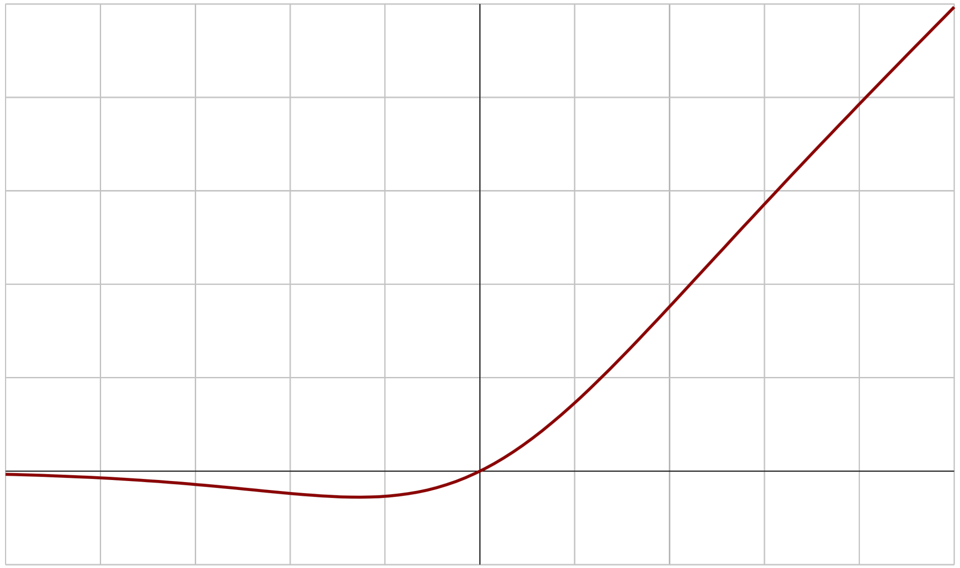
Touvron, Hugo, et al. "Llama: Open and efficient foundation language models." arXiv preprint arXiv:2302.13971 (2023).

pre Layer Normalization



FFN with SwiGLU

Swish activation



$$swish(x) = x\sigma\ (\beta x)$$

$$\sigma(x) = \frac{1}{1+e^{-x}}$$

FFN with ReLU

$$\mathrm{FFN}(x) = max(0, x \cdot W_1 + b_1) \cdot W_2 + b_2$$

dim=4d

FFN with SwiGLU

$$\mathrm{FFN}_{SwiGLU}(x) = \big(Swish(x \cdot W_1 + b_1) \odot (W_2 + b_2)\big) \cdot W_3 + b_2$$

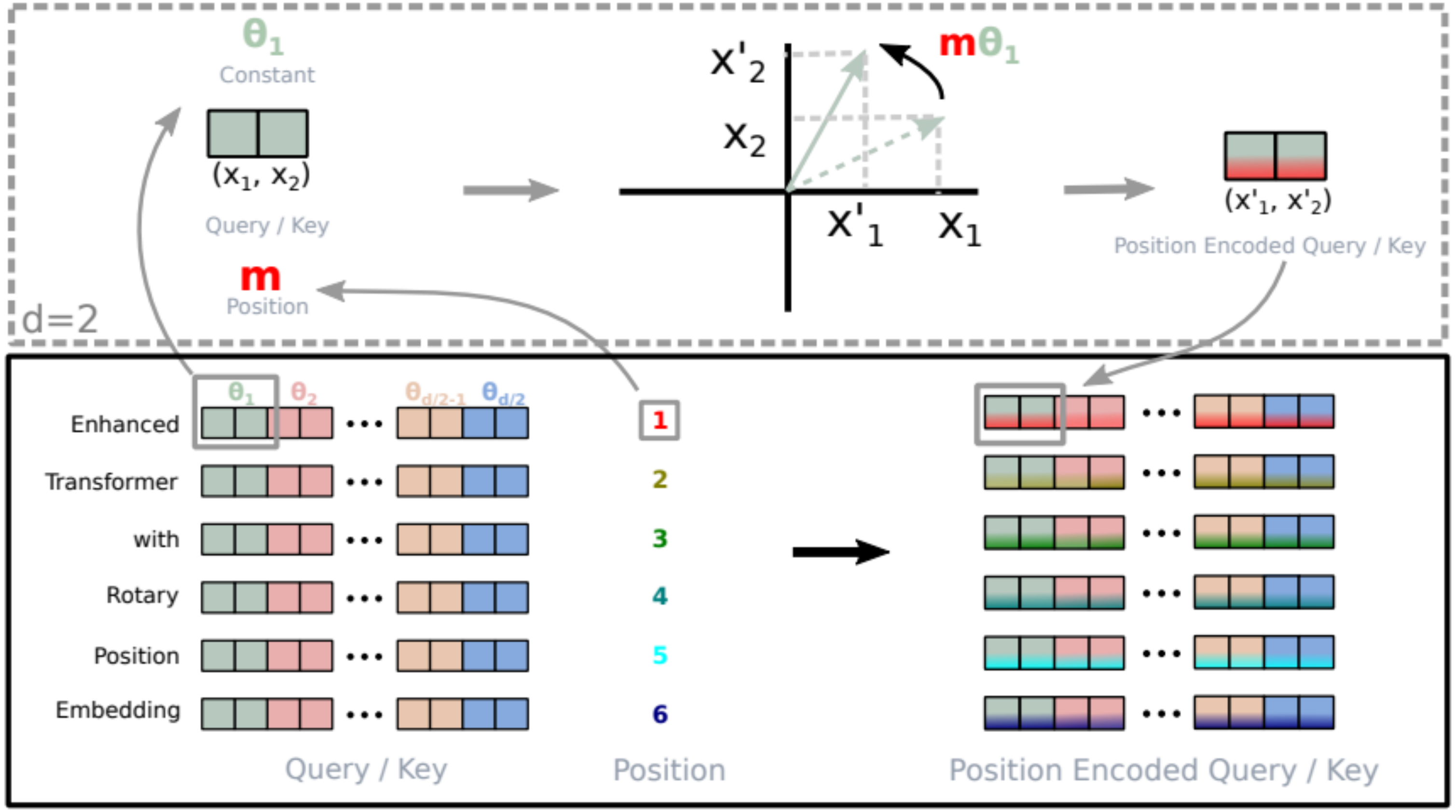
dim=2/3 * 4d

Rotary Embedding (RoPE)

make the attention weight depending (only) on position distance

$$f(x_m, m) = \begin{pmatrix} \cos(m\theta) & -\sin(m\theta) \\ \sin(m\theta) & \cos(m\theta) \end{pmatrix} \begin{pmatrix} x_{m,1} \\ x_{m,2} \end{pmatrix}$$

$$f(x_m, m) \cdot f(x_n, n) = x_m^T R_{n-m} x_n$$

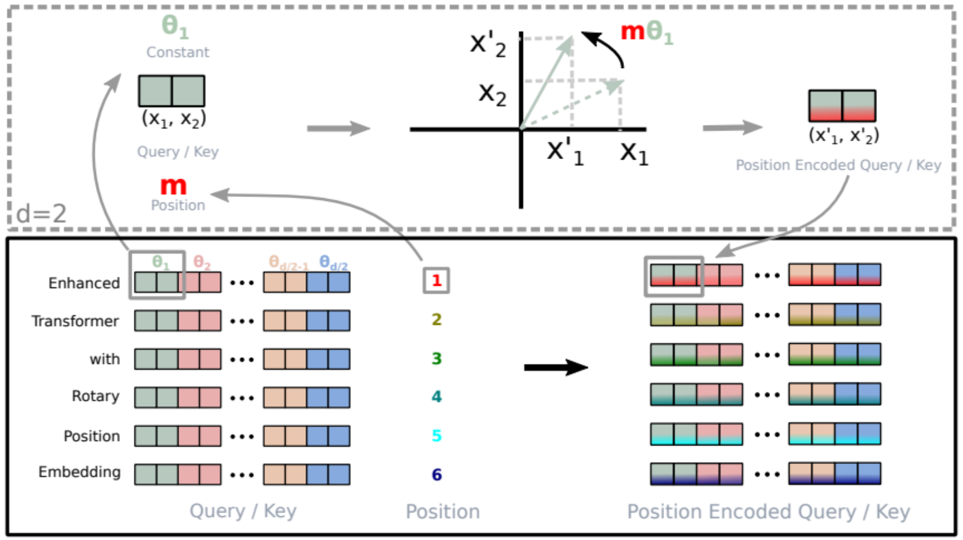


Su et al. RoFormer: Enhanced Transformer with Rotary Position Embedding 2021.

Rotary Embedding (RoPE)

$$f(x_m, m) = \begin{pmatrix} \cos(m\theta_1) & -\sin(m\theta_1) & & \\ \sin(m\theta_1) & \cos(m\theta_1) & & \\ & & \cos(m\theta_2) & -\sin(m\theta_2) \\ & & \sin(m\theta_2) & \cos(m\theta_2) \end{pmatrix} \begin{pmatrix} x_{m,1} \\ x_{m,2} \\ x_{m,3} \\ x_{m,4} \end{pmatrix}$$

$$f(x_m, m)^T \cdot f(x_n, n) = x_m^T R_{n-m} x_n$$



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LLaMA

- Model Size

params	dimension	n heads	n layers	learning rate	batch size	n tokens
6.7B	4096	32	32	$3.0e^{-4}$	4M	1.0T
13.0B	5120	40	40	$3.0e^{-4}$	4M	1.0T
32.5B	6656	52	60	$1.5e^{-4}$	4M	1.4T
65.2B	8192	64	80	$1.5e^{-4}$	4M	1.4T

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LLaMA

- Training Strategy
  - Trained with the standard language modeling loss function: the average log probability of all tokens without label smoothing
  - Auxiliary loss to encourage the softmax normalizer to be close to 0

- Pre-training Details
  - Using only open-source data

Dataset	Sampling prop.	Epochs	Disk size
CommonCrawl	67.0%	1.10	3.3 TB
C4	15.0%	1.06	783 GB
Github	4.5%	0.64	328 GB
Wikipedia	4.5%	2.45	83 GB
Books	4.5%	2.23	85 GB
ArXiv	2.5%	1.06	92 GB
StackExchange	2.0%	1.03	78 GB

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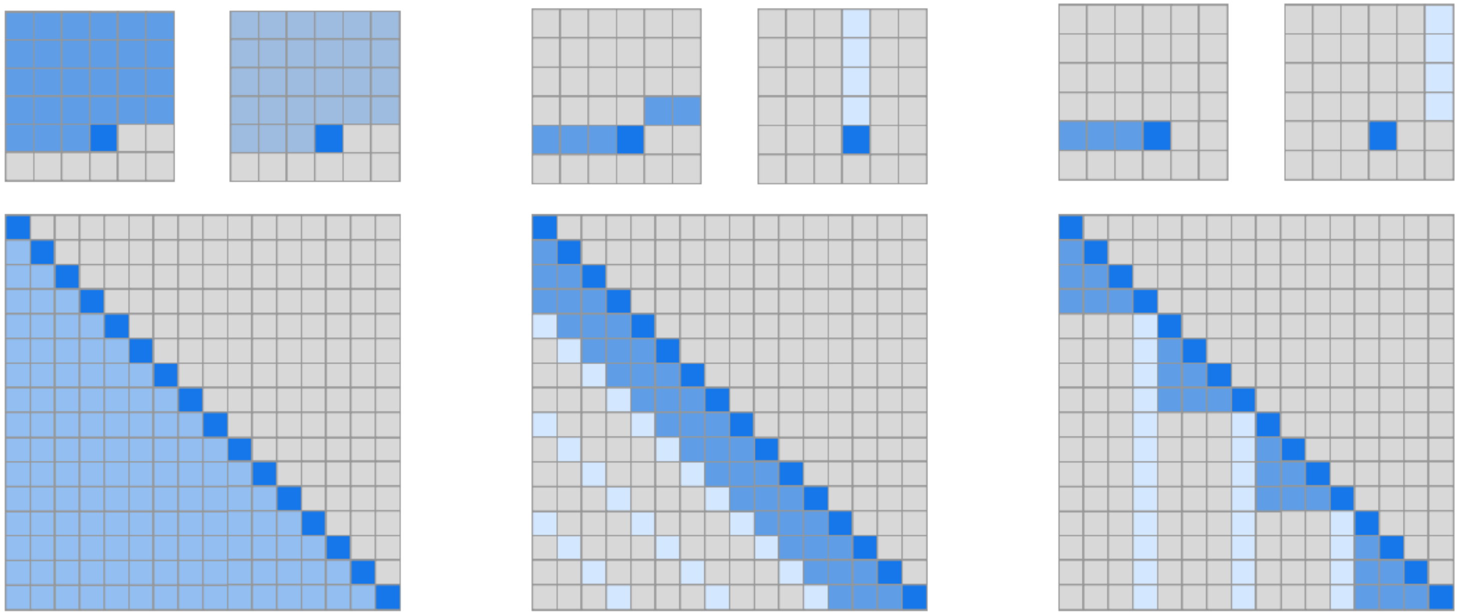
GPT3

- Model Architecture
  - Based on the standard Transformer architecture
  - With modified initialization, pre-normalization, and reversible tokenization
  - Alternating dense and locally banded **sparse attention** patterns



(a) Transformer (b) Sparse Transformer (strided) c) Sparse Transformer (fixed)

Brown, Tom, et al. "Language models are few-shot learners." Advances in neural information processing systems 33 (2020): 1877-1901.

GPT3

- Model Size

Model Name	n_{params}	n_{layers}	d_{model}	n_{heads}	d_{head}	Batch Size	Learning Rate
GPT-3 Small	125M	12	768	12	64	0.5M	6.0×10^{-4}
GPT-3 Medium	350M	24	1024	16	64	0.5M	3.0×10^{-4}
GPT-3 Large	760M	24	1536	16	96	0.5M	2.5×10^{-4}
GPT-3 XL	1.3B	24	2048	24	128	1M	2.0×10^{-4}
GPT-3 2.7B	2.7B	32	2560	32	80	1M	1.6×10^{-4}
GPT-3 6.7B	6.7B	32	4096	32	128	2M	1.2×10^{-4}
GPT-3 13B	13.0B	40	5140	40	128	2M	1.0×10^{-4}
GPT-3 175B or "GPT-3"	175.0B	96	12288	96	128	3.2M	0.6×10^{-4}

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GPT3

- Training Strategy
  - Unsupervised Pre-training

- Training Details

Dataset	Quantity (tokens)	Weight in training mix	Epochs elapsed when training for 300B tokens
Common Crawl (filtered)	410 billion	60%	0.44
WebText2	19 billion	22%	2.9
Books1	12 billion	8%	1.9
Books2	55 billion	8%	0.43
Wikipedia	3 billion	3%	3.4

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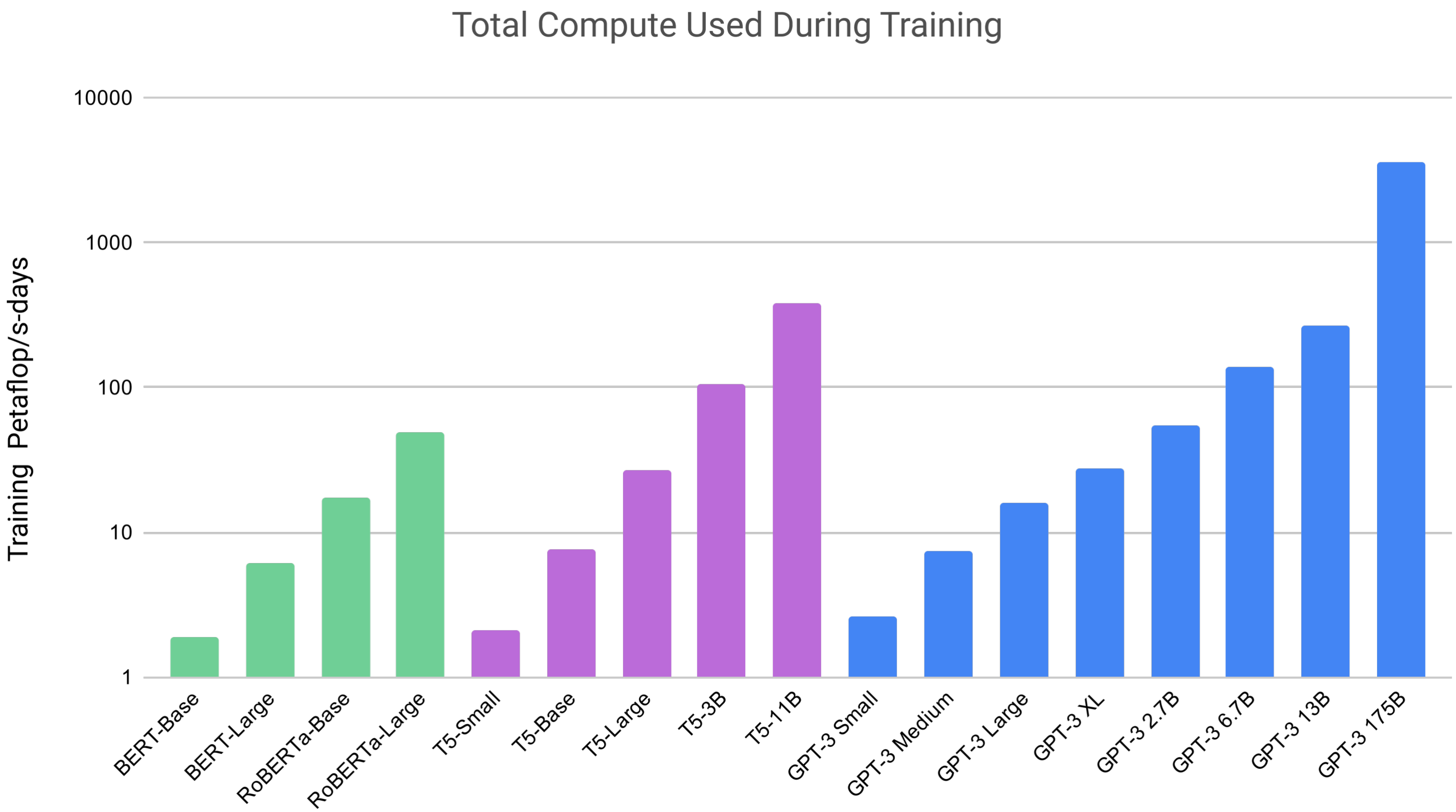
Computation



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Code Go-through

https://nlp.seas.harvard.edu/annotated-transformer/

https://belladoreai.github.io/llama-tokenizer-js/example-demo/build/

Reading for Next Class

- Neural Machine Translation of Rare Words with Subword Units. Sennrich et al. 2016.

- SentencePiece: A simple and language independent subword tokenizer and detokenizer for Neural Text Processing. Kudo and Richardson. 2018