LLM Sys

Pre-trained LLMs

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Recap

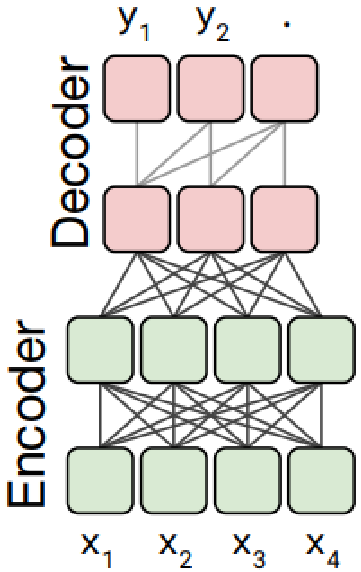
- Sequence-to-sequence encoder-decoder framework for conditional generation, including Machine Translation
- Key components in Transformer
  - Positional Embedding (to distinguish tokens at different pos)
  - Multihead attention
  - Residual connection
  - Layer norm

Today's Topic

- T5
- LLaMA
- GPT3

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.

Training

Pre-training → Multitask Finetuning

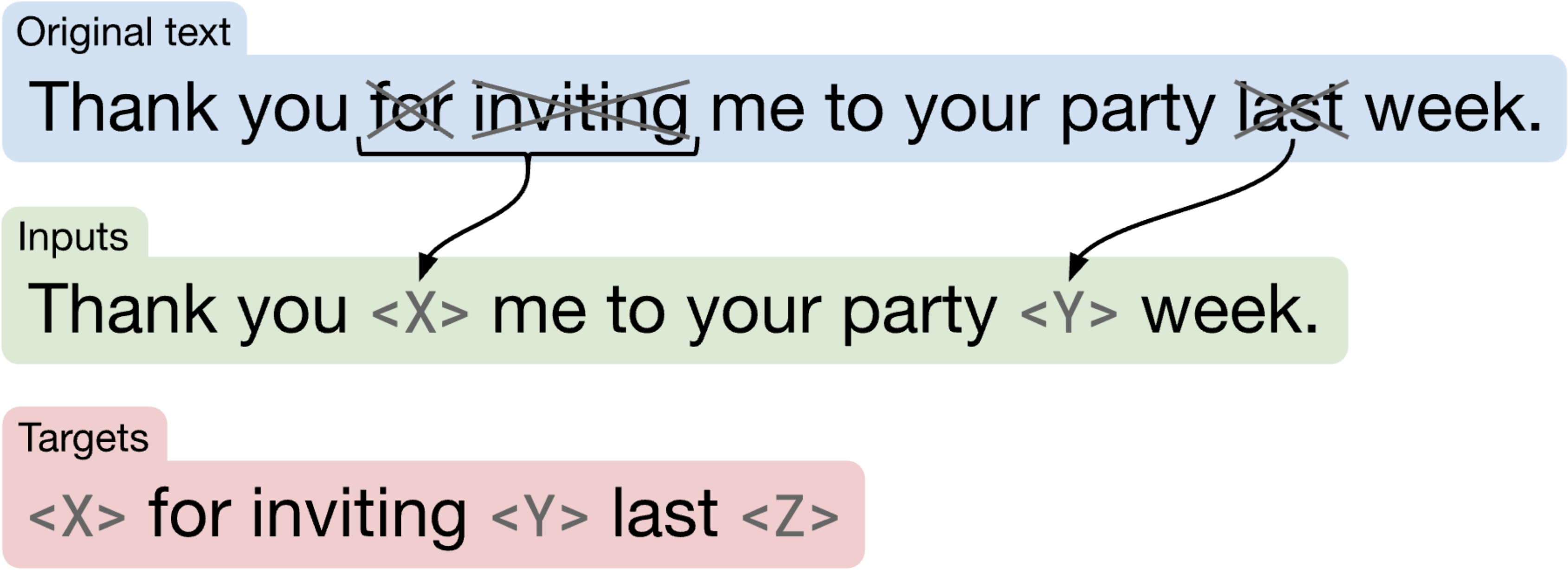
- Pretraining: C4: filtered English corpus from Common Crawl
  - 750GB, still used often today

- Supervised fine-tuning
  - Language understanding/Text classification: GLUE/SuperGLUE
  - Summarization: CNN/Daily mail corpus
  - Question answering: SQuAD
  - Translation: WMT English to German, French, Romanian

T5 Pre-training: Recover randomly corrupted spans

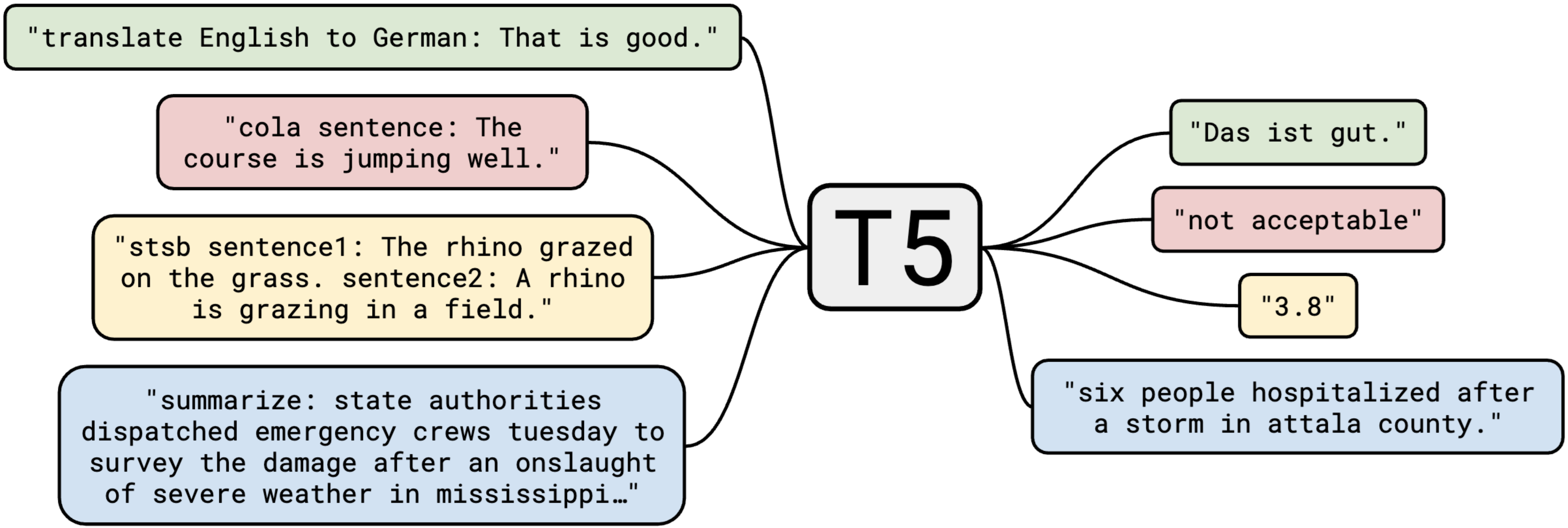
Standard next token cross entropy loss, plus … Cloze-style QA

15% of text are corrupted



Pre-train for 0.5 million steps on a batch size of 128 sequences of length 512. packing multiple seqs 65k tokens per batch, result in 34B trained tokens.

T5 Multitask SFT with Task Instruction



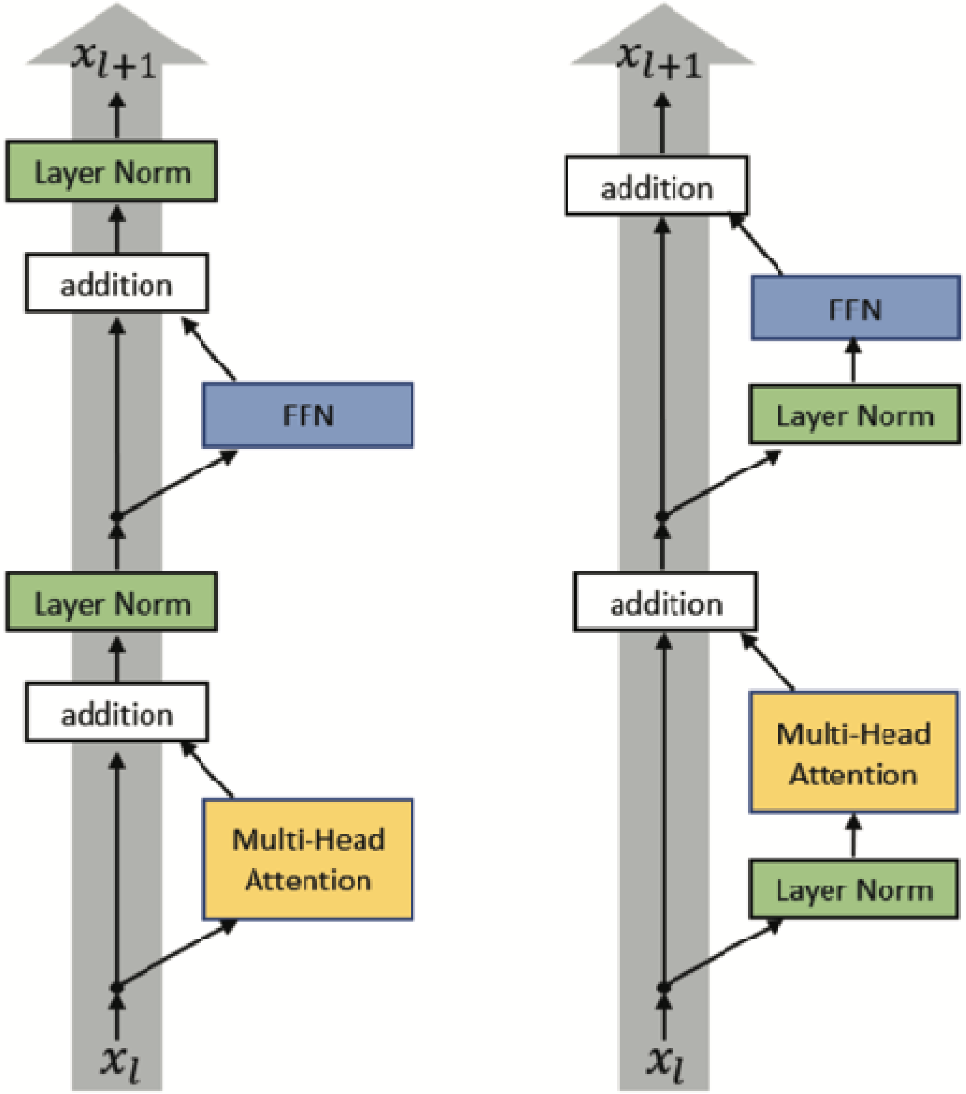
Unified format to put task instructions as natural language in the input, enables transfer to new tasks. with more instruction tuning ➔ T0, Flan-T5

LLaMA

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

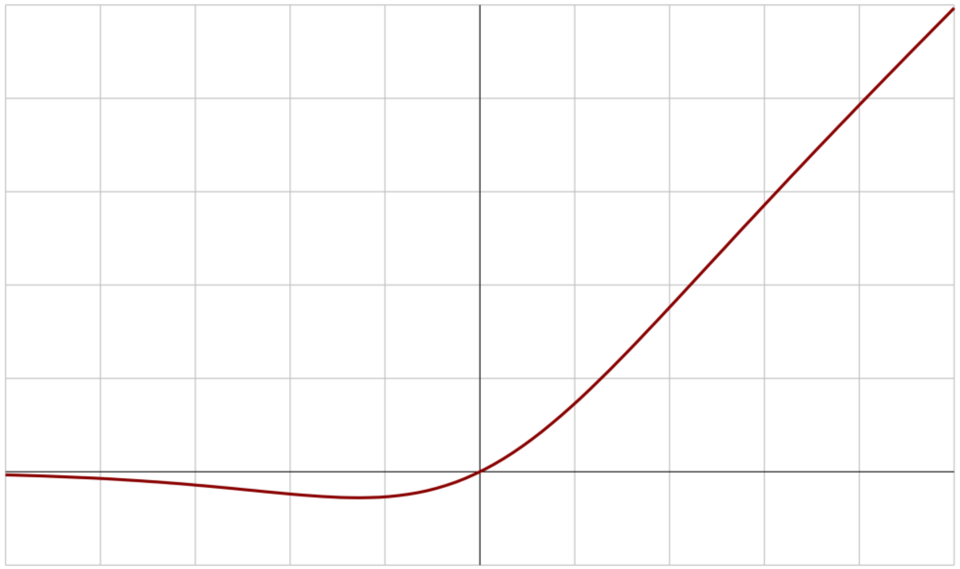
Touvron, Hugo, et al. "Llama: Open and efficient foundation language models." arXiv preprint arXiv:2302.13971 (2023).

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

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

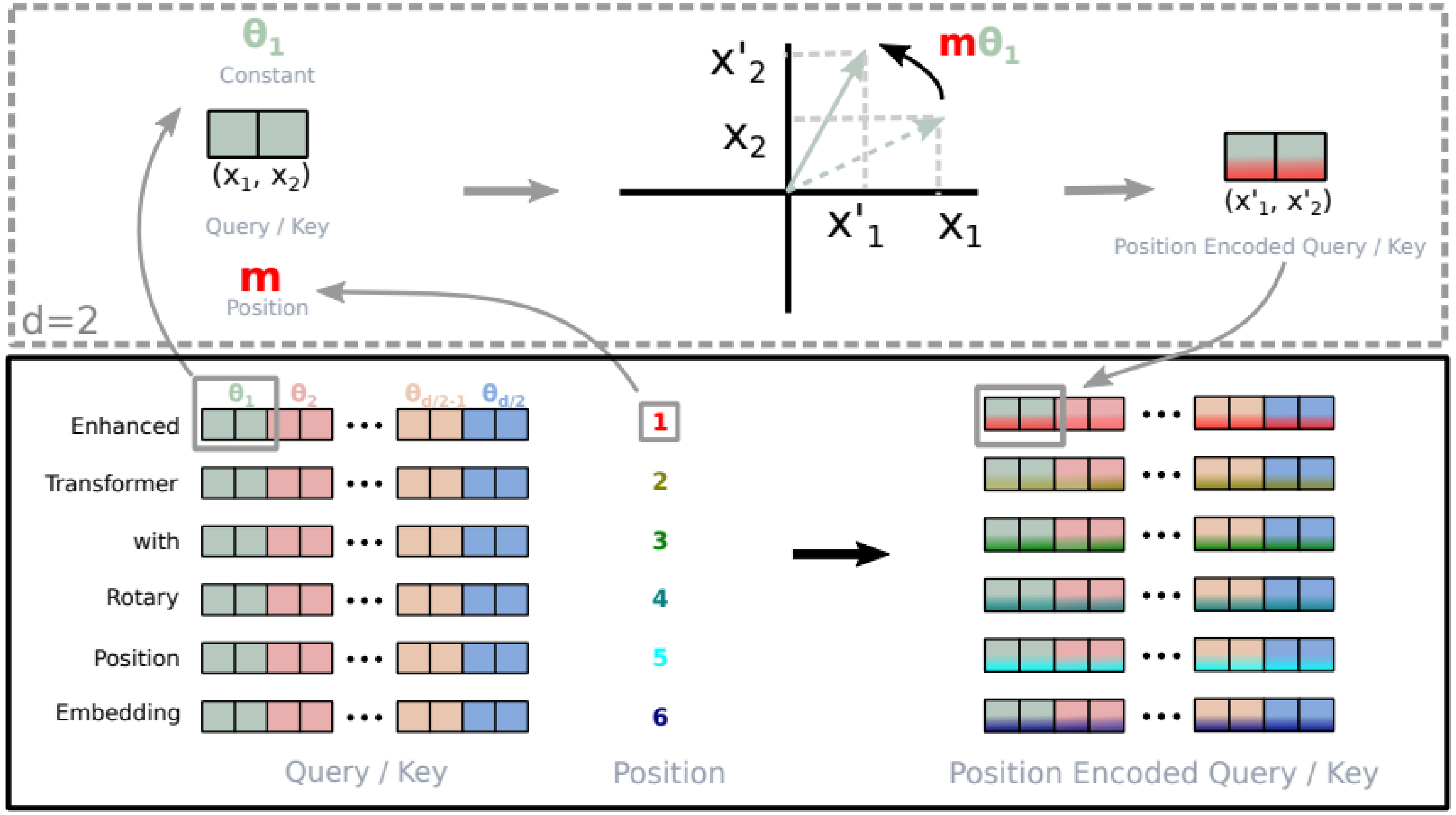
dim=2/3 * 4d

Rotary Embedding (RoPE)

make the attention weight depending (only) on position distance

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

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

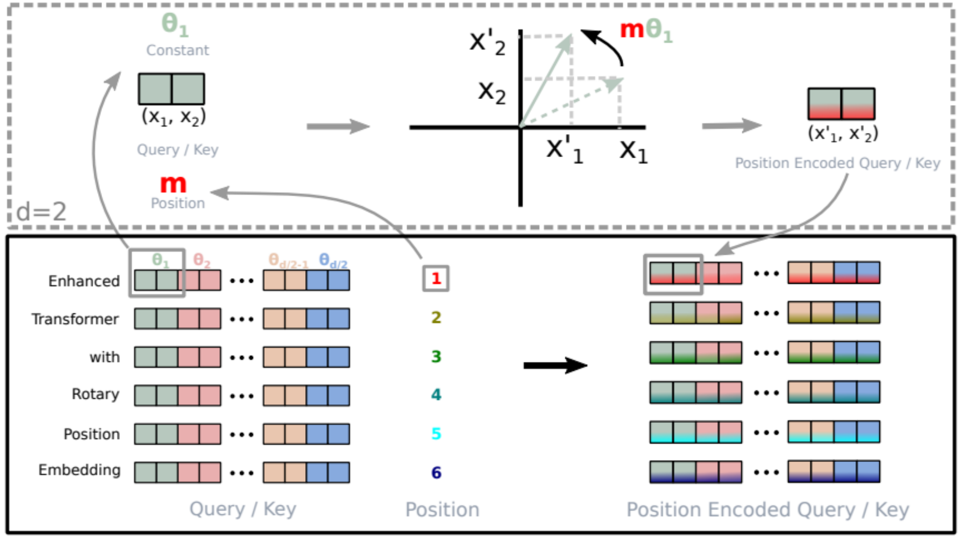


Su et al. RoFormer: Enhanced Transformer with Rotary Position Embedding 2021.

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

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

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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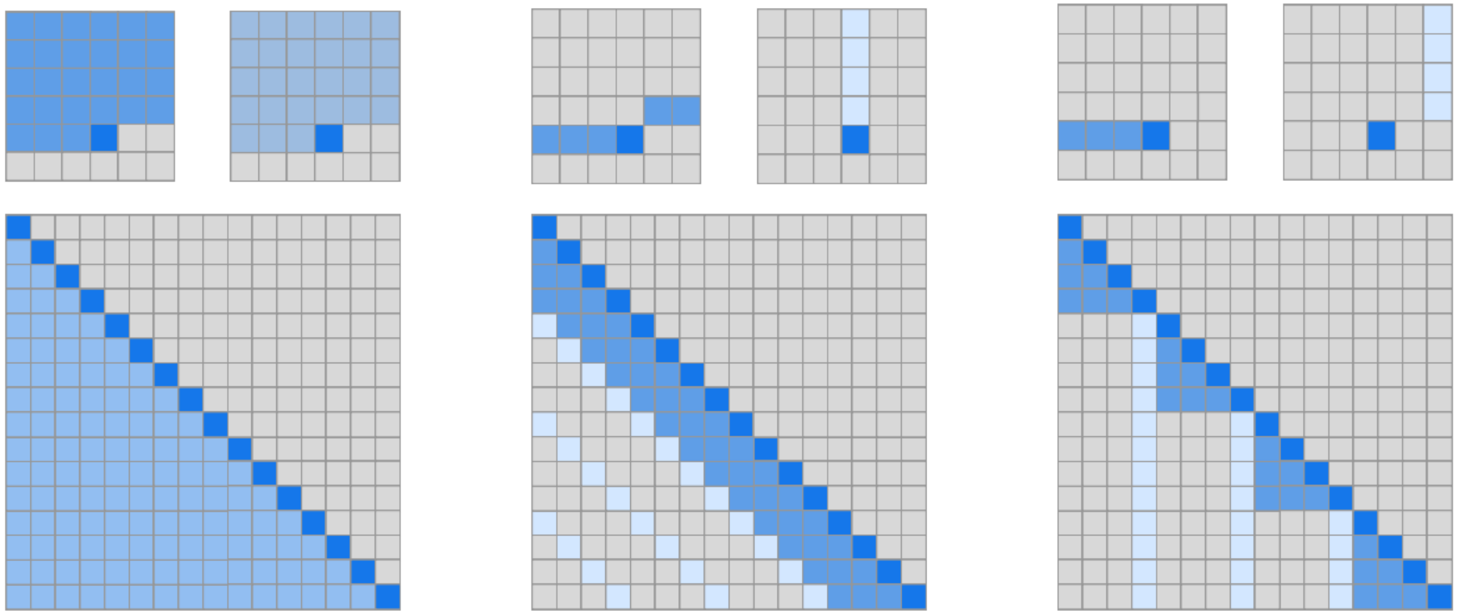
GPT3

- 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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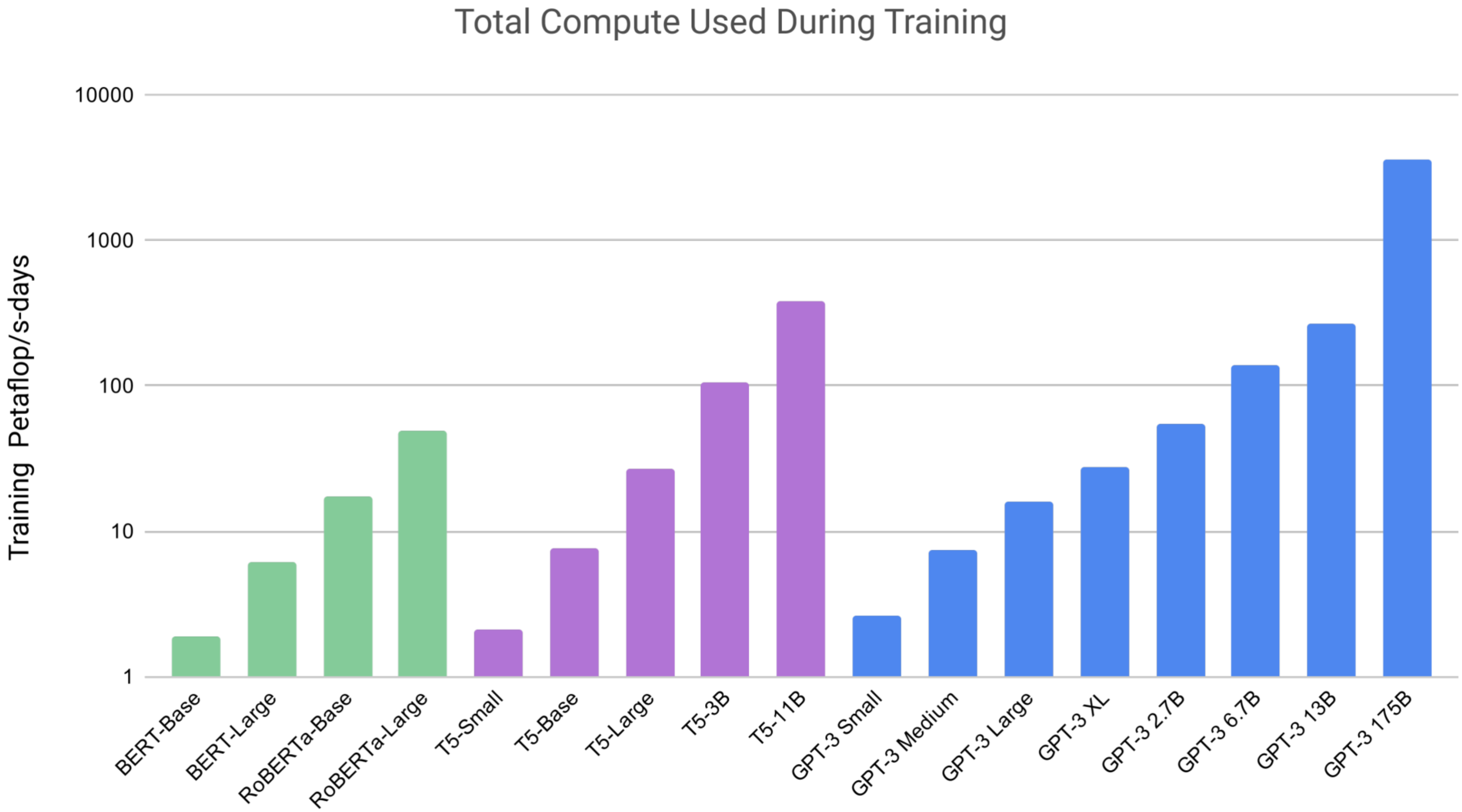
Computation



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Quiz 4

- https://canvas.cmu.edu/courses/44373/quizzes/140384

Summary – Key Ideas in Modern Pre-trained LLMs

- Pretraining: Mask-labeled recovery of random spans + next token prediction
- Multitask supervised fine-tuning with instruction templates
    - T5, InsturctGPT
- Relative position: Rotary positional embedding
- Smooth activation: SwishGLU
- Sparse attention

Minitorch Code walkthrough

https://github.com/llmsystem/llmsys_code_examples/tree/main/minitorch_notebook

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