Scaling LLM Pretraining

CS 5624: Natural Language Processing

Spring 2025

https://tuvllms.github.io/nlp-spring-2025

Tu Vu

VIRGINIA TECH.

Logistics

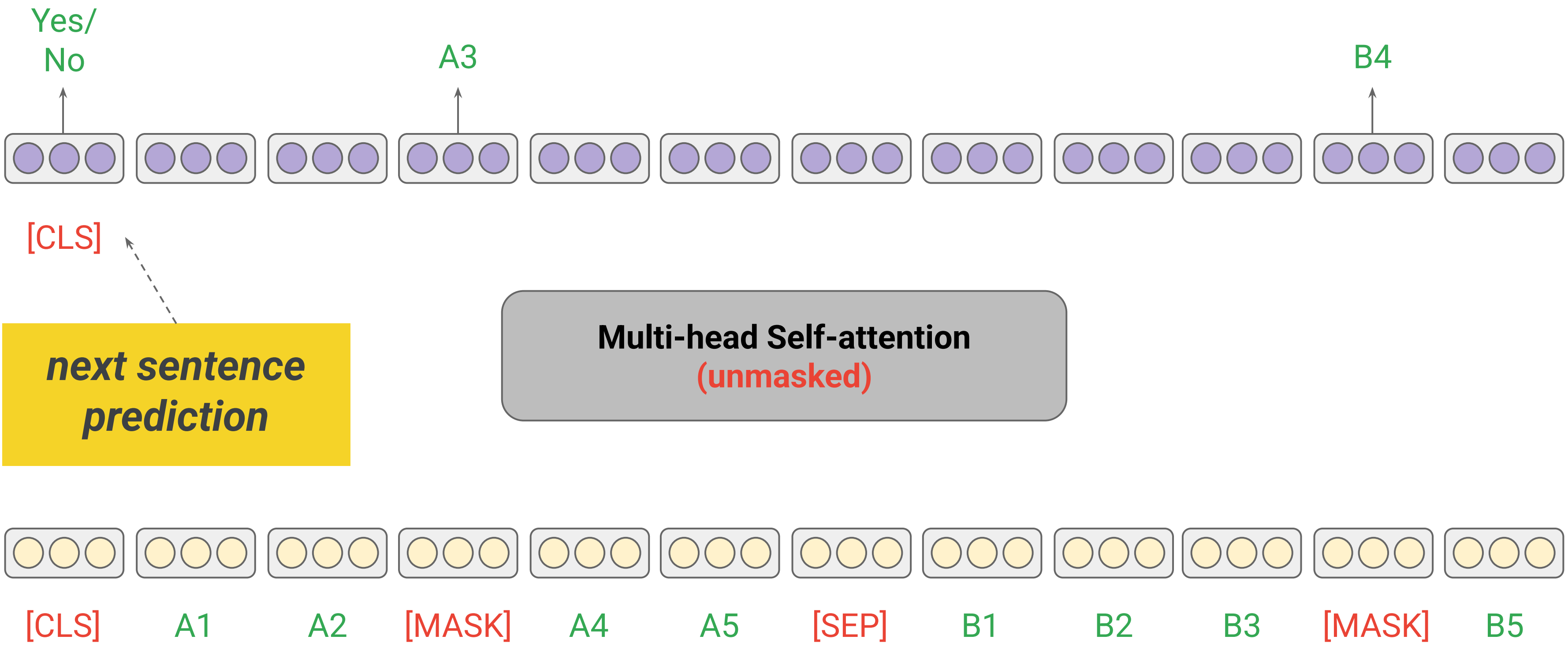
- Homework 1 & Quiz 1 will be released tomorrow
- 🚨 Final project proposal due on February 28 🚨
    - Template is on Piazza

BERT review

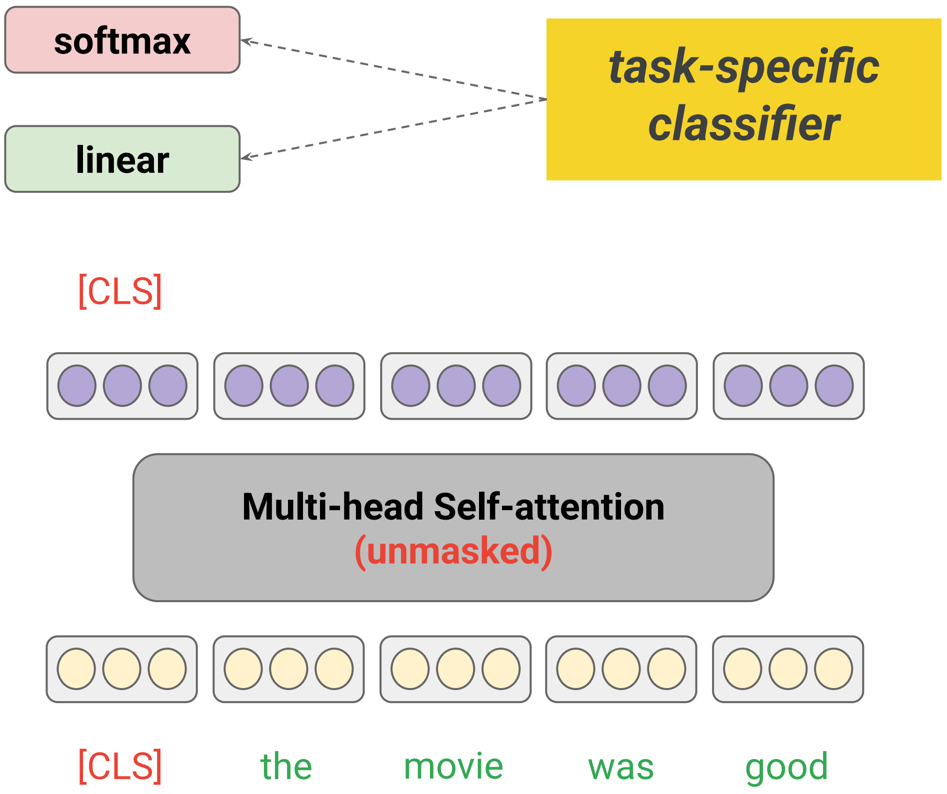
Different model architectures

- Encoder-only
  - BERT
- Encoder-decoder
  - **T5**
- Decoder-only
  - GPT

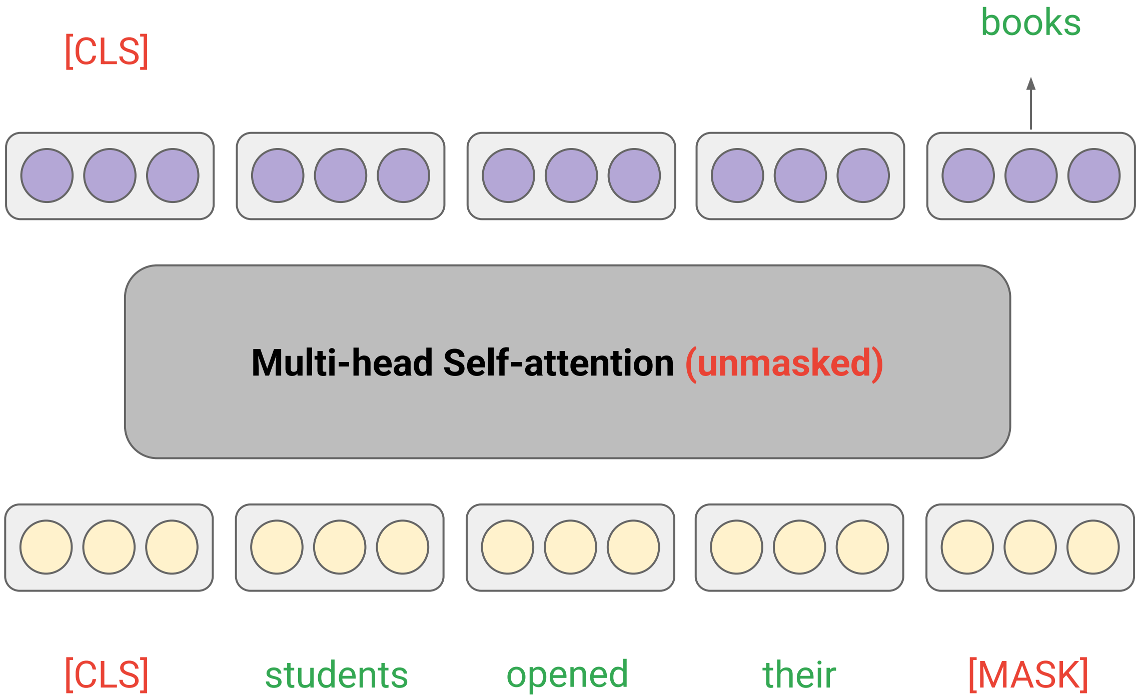
BERT Pretraining



BERT Fine-tuning



Can BERT be used for text generation?



iterative masking and unmasking

T5: Text-to-Text Transfer Transformer

Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer

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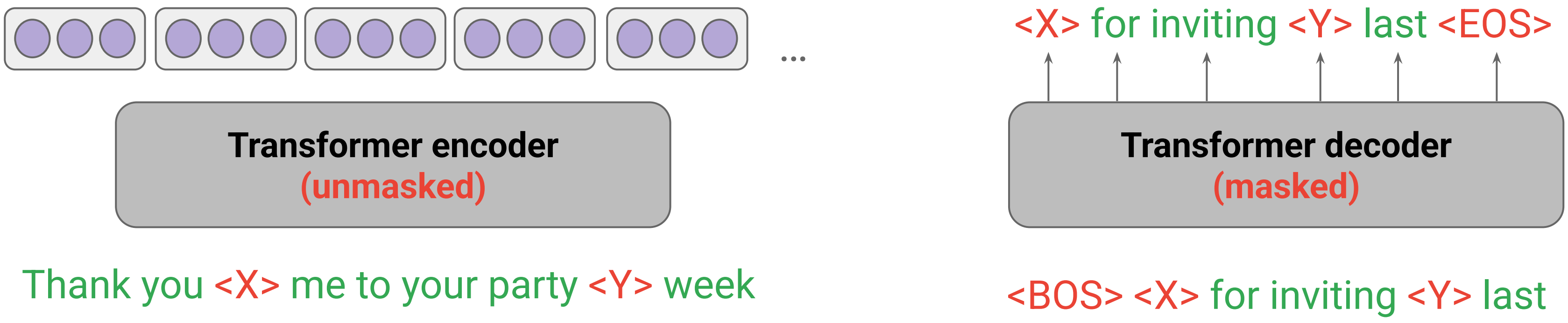
T5 Pretraining: Span corruption

<X>, <Y>: sentinel tokens

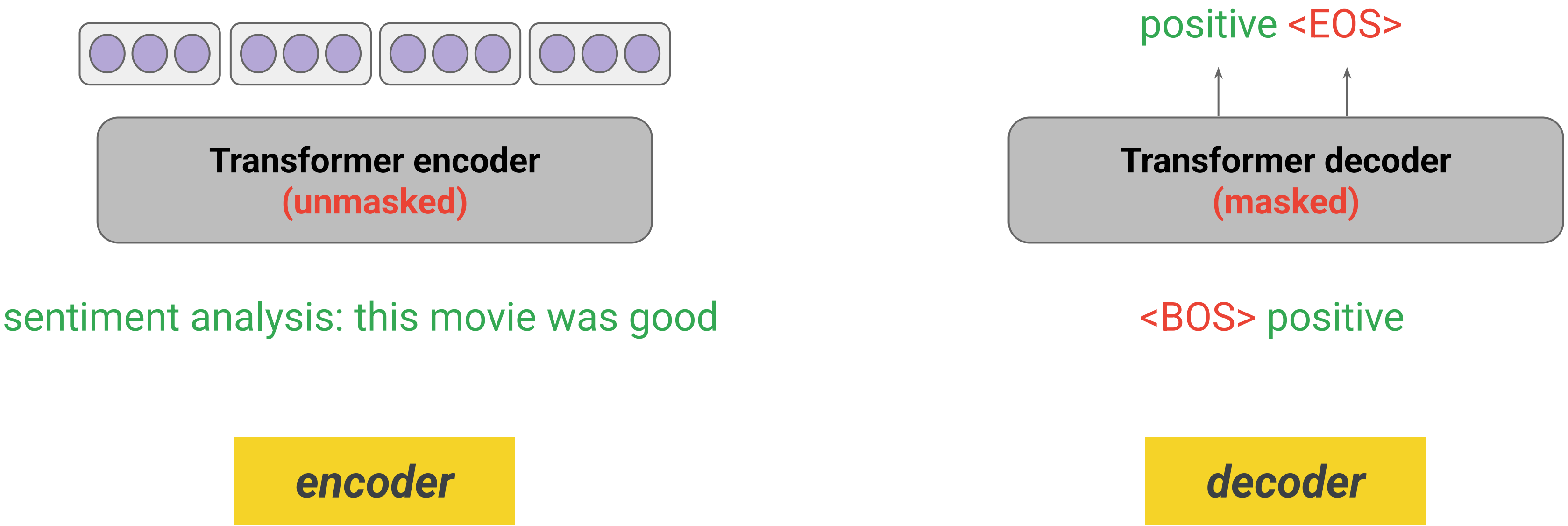


Thank you ~~for inviting~~ me to your party ~~last~~ week

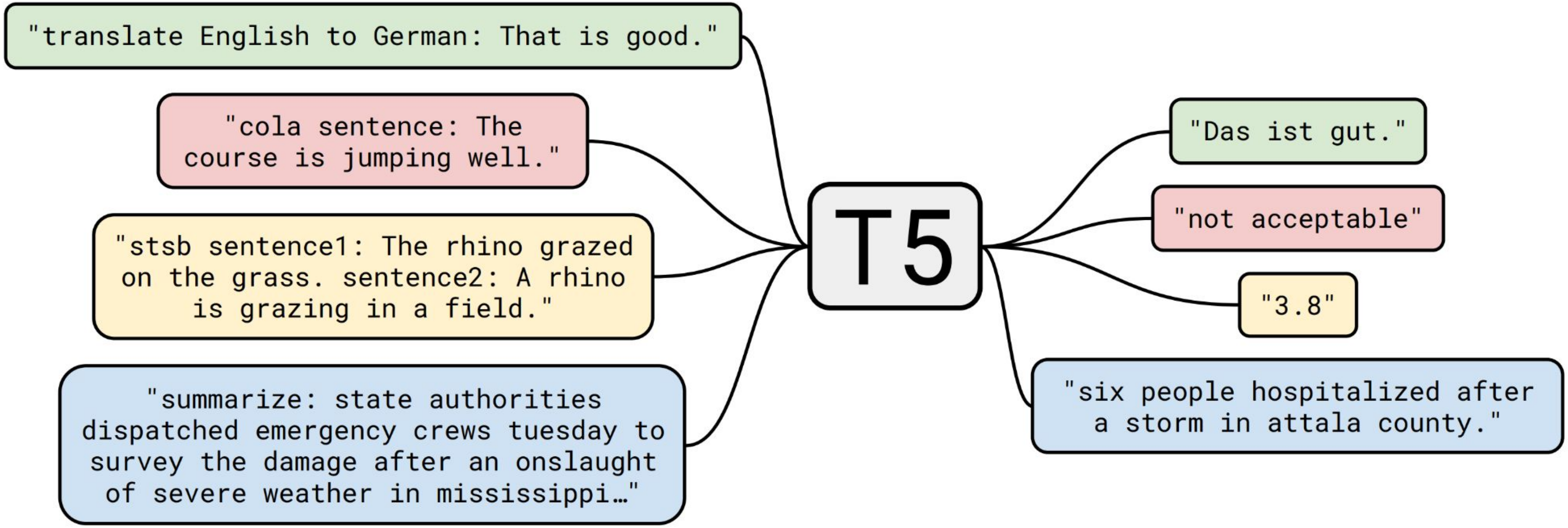
encoder

decoder

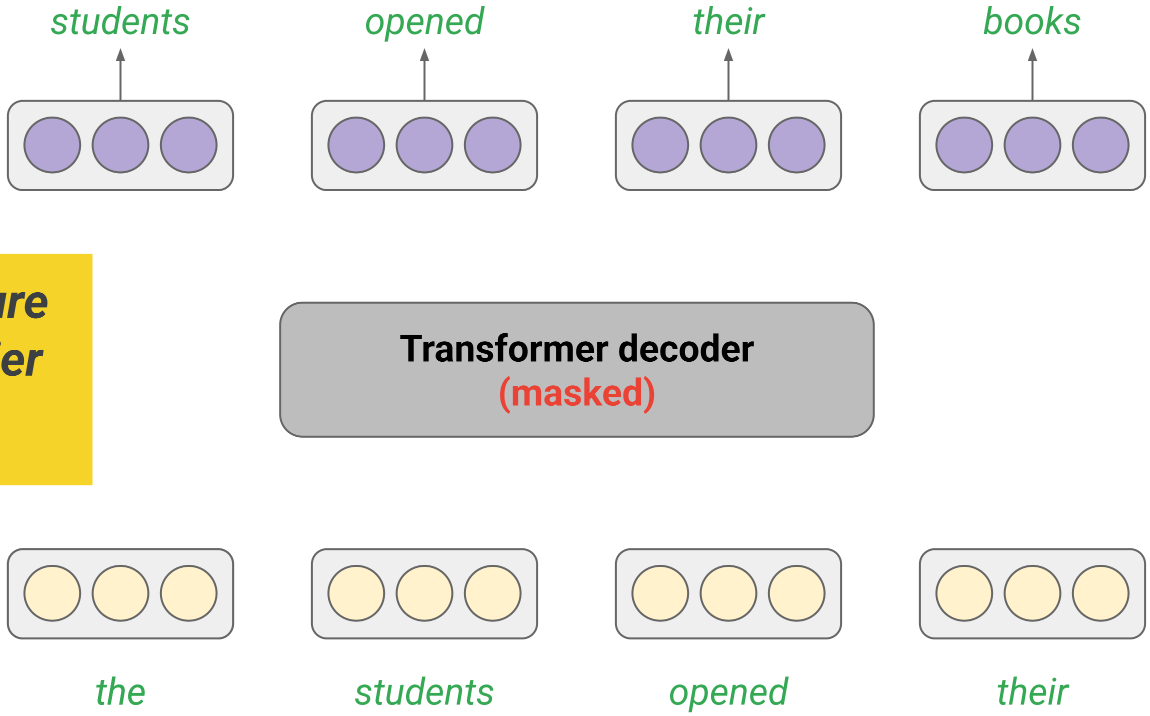
T5 Fine-tuning



T5 facilitates multitask learning



Decoder-only model

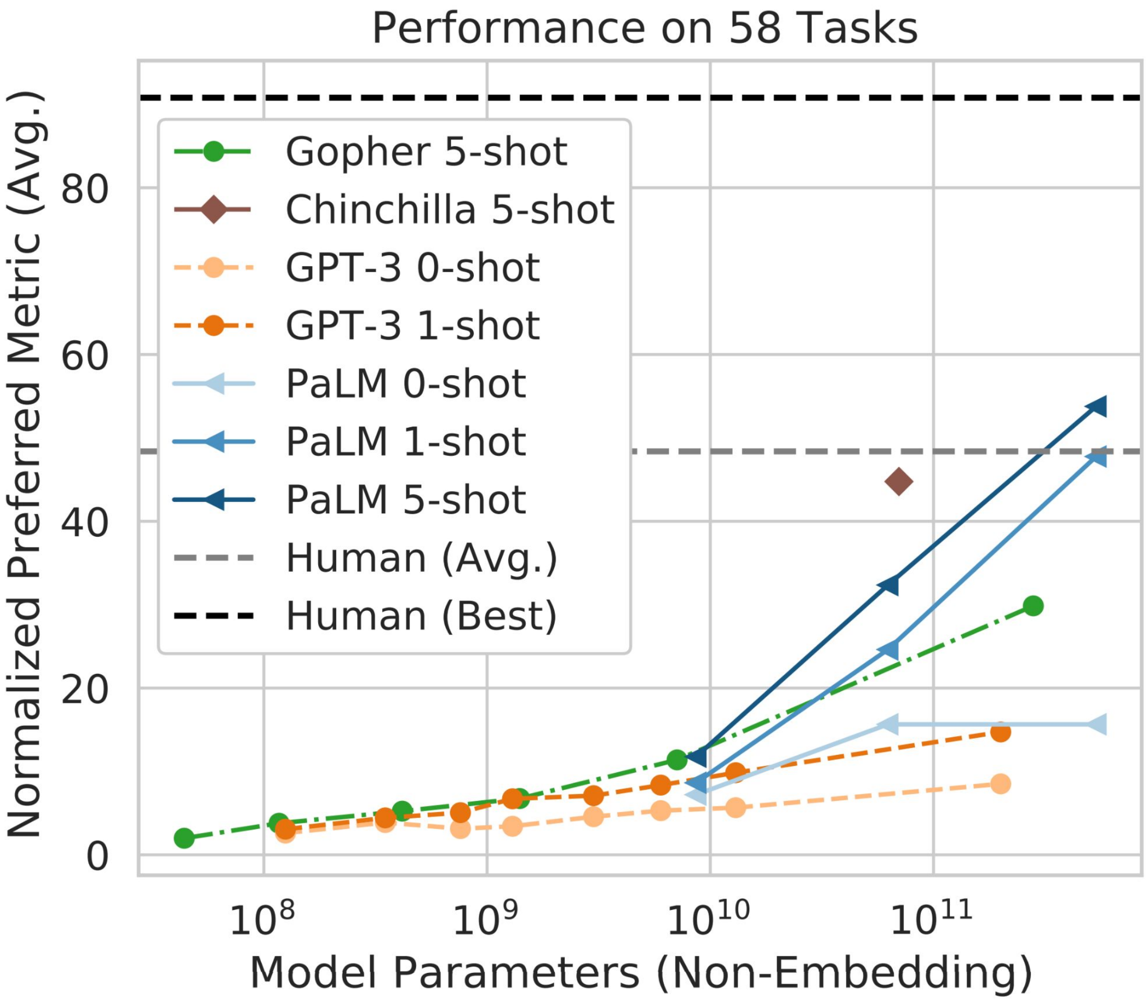


the architecture used in frontier LLMs

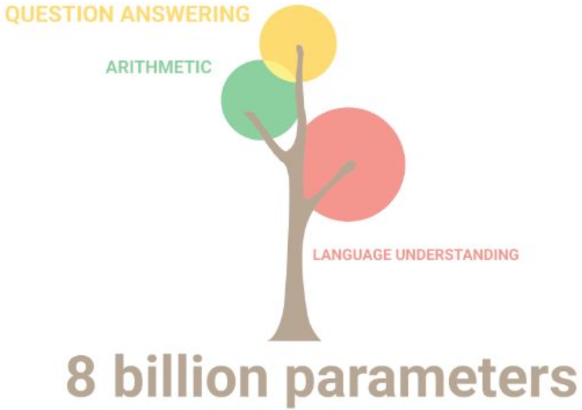
Note on cross-attention

- Can be used to inject non-text data (e.g., images, structured data, or even sensor readings) into the model

Increasing model size enhances performance and sample efficiency

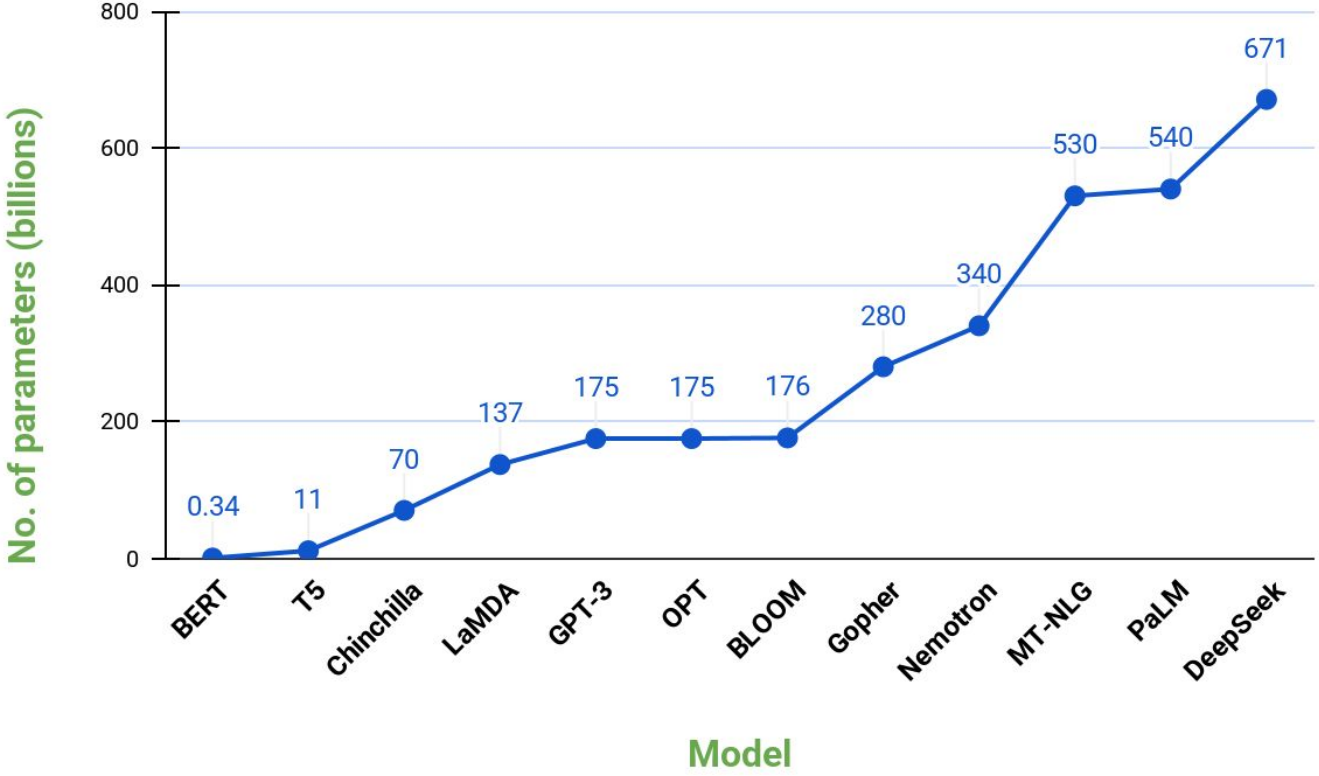


… and unlocks new capabilities



From "PaLM: Scaling Language Modeling with Pathways" by Chowdhery et al. (2022)

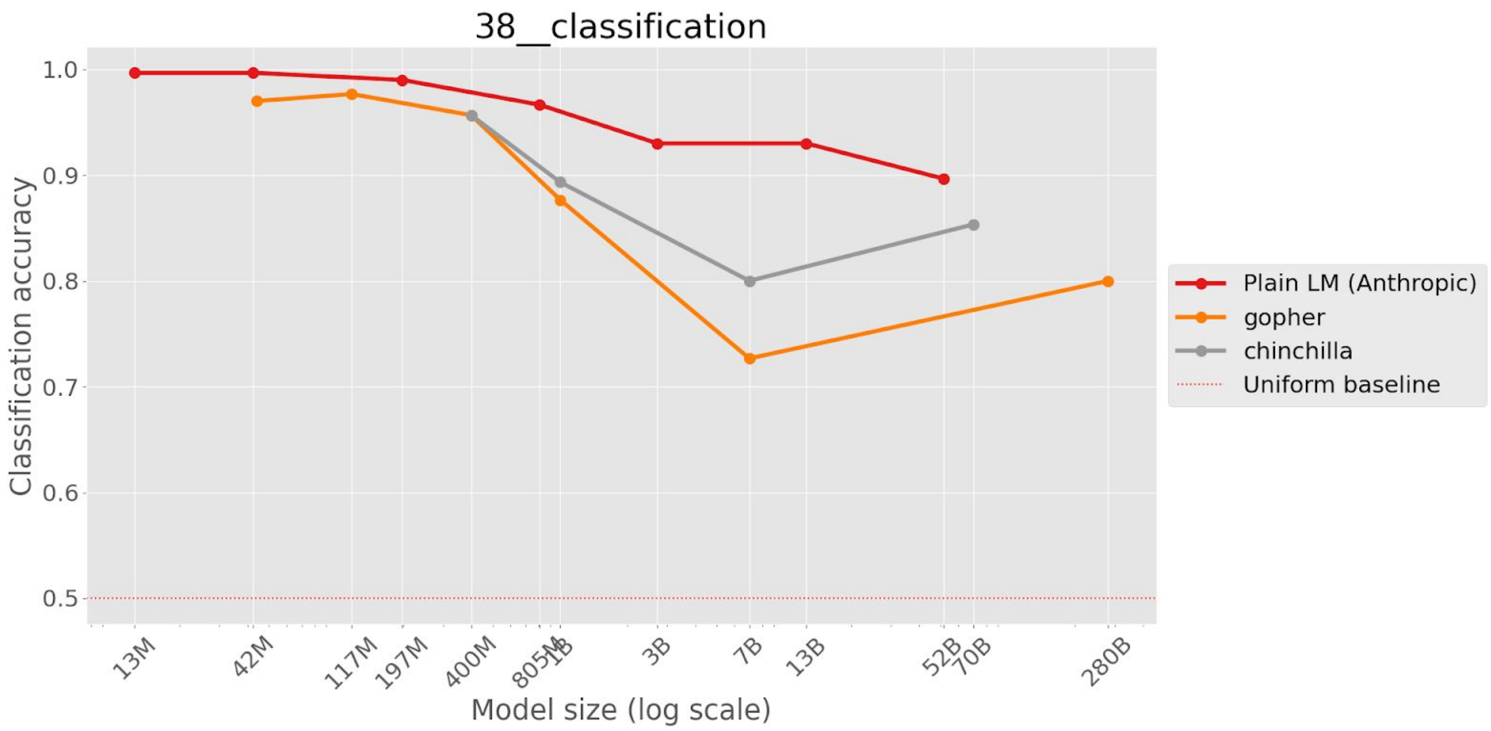
The trend has continued to push the boundaries of possibility in NLP



Inverse scaling

- https://www.lesswrong.com/posts/iznohbCPFkeB9kAJL/inverse-scaling-prize-round-1-winners
- https://www.lesswrong.com/posts/DARiTSTx5xDLQGrrz/inverse-scaling-prize-second-round-winners

Inverse scaling (cont'd)



Repeat my sentences back to me.

Input: I like dogs.

Output: I like dogs.

Input: What is a potato, if not big?

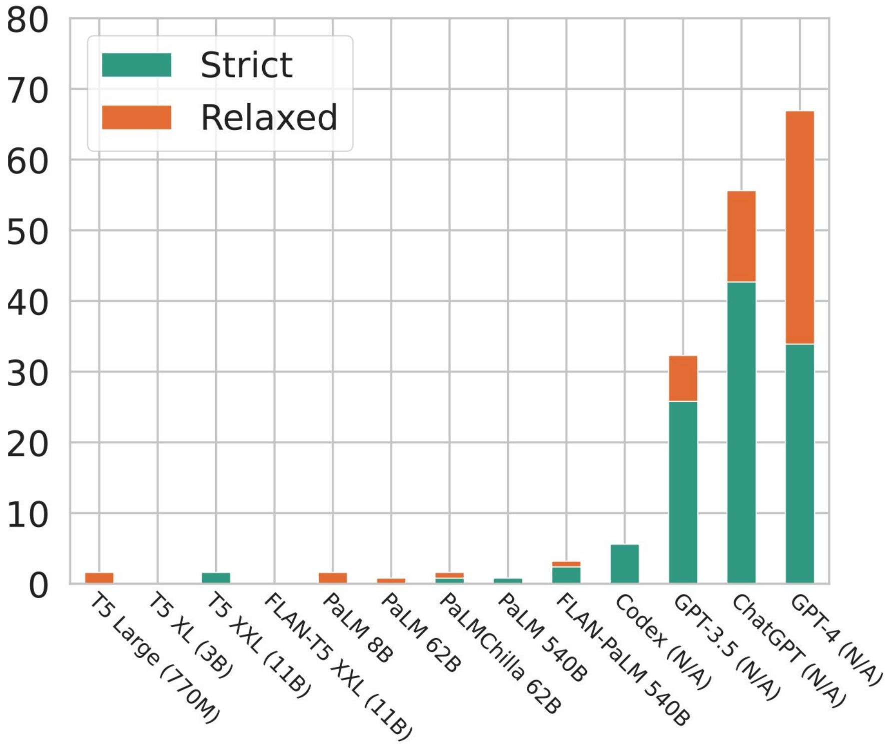
Output: What is a potato, if not big?

Input: All the world's a stage, and all the men and women merely players. They have their exits and their entrances; And one man in his time plays many pango

Output: All the world's a stage, and all the men and women merely players. They have their exits and their entrances; And one man in his time plays many

(where the model should choose 'pango' instead of completing the quotation with 'part.')

False premise questions: When did Google release ChatGPT?



False-premise questions

Vu et al. 2023:
https://arxiv.org/abs/2310.03214

What can we scale?

- The loss scales as a power-law with:
  - **N:** model size
  - **D:** dataset size
  - the amount of compute used for training (e.g., number of training steps)

$$\text{Total Steps} = \frac{\text{Dataset Size} \times \text{Epochs}}{\text{Batch Size}}$$

Where:

- **Dataset Size**: Total number of training examples.
- **Epochs**: Number of times the model sees the entire dataset.
- **Batch Size**: Number of samples per batch update.

Given a fixed compute budget, what is the optimal model size and dataset size for training?

Let's say you can use one GPU for one day

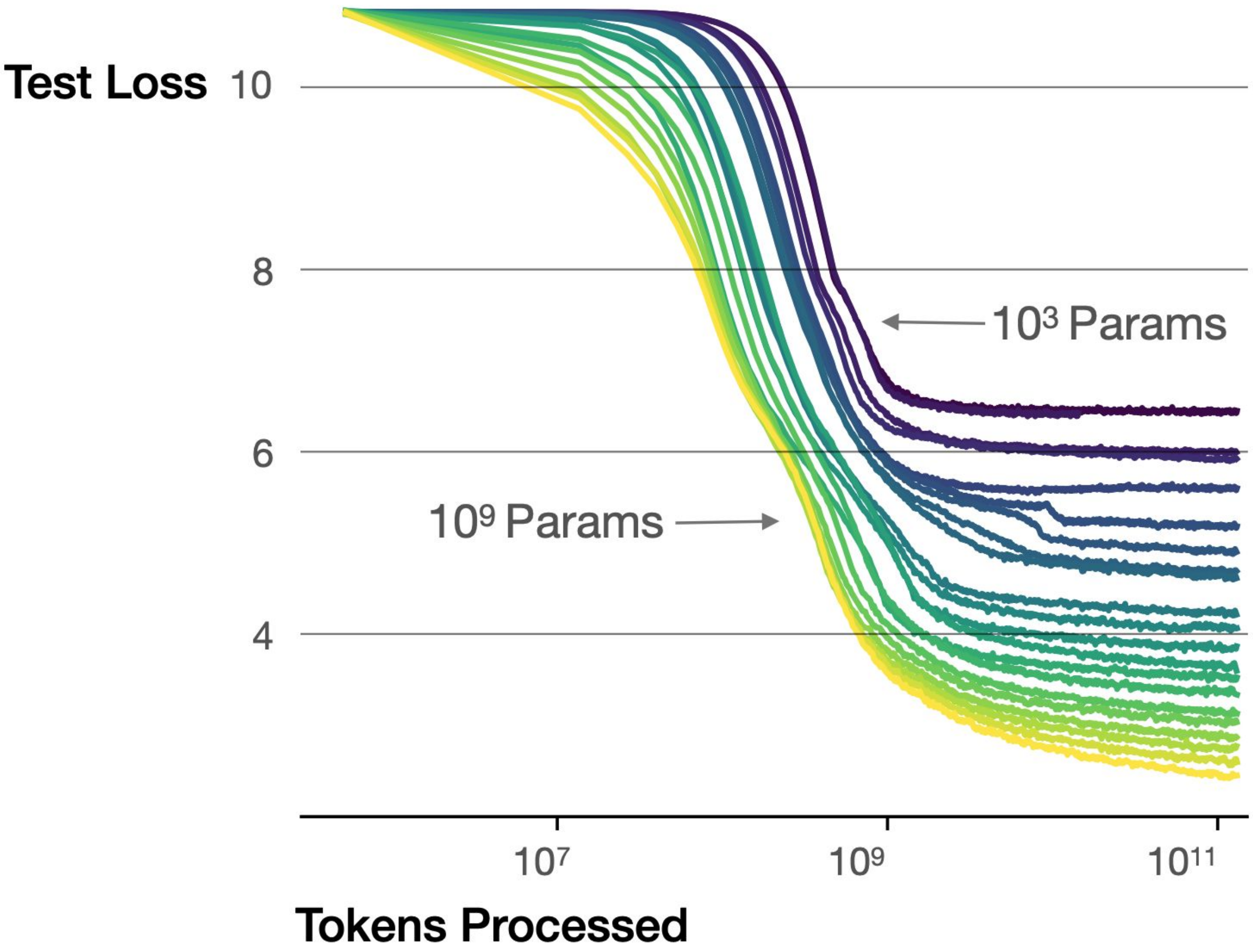
- Would you train a 5 million parameter LM on 100 books?
- What about a 500 million parameter LM on one book?
- Or a 100k parameter LM on 5k books?

Given a fixed compute budget, what is the optimal model size and dataset size for training?

- Kaplan et al. 2020
- **Chinchilla** (Hoffmann et al. 2022)

Observations from Kaplan et al., 2020

- Performance depends largely on scale (model size, data size, and compute) and weakly on model architecture (e.g., depth, width)
- Performance improves most when model and dataset size scale together; increasing one while keeping the other fixed results in diminishing returns
-



Test Loss
10
8
6
4
10^3 Params
10^9 Params
10^7
10^9
10^11
Tokens Processed

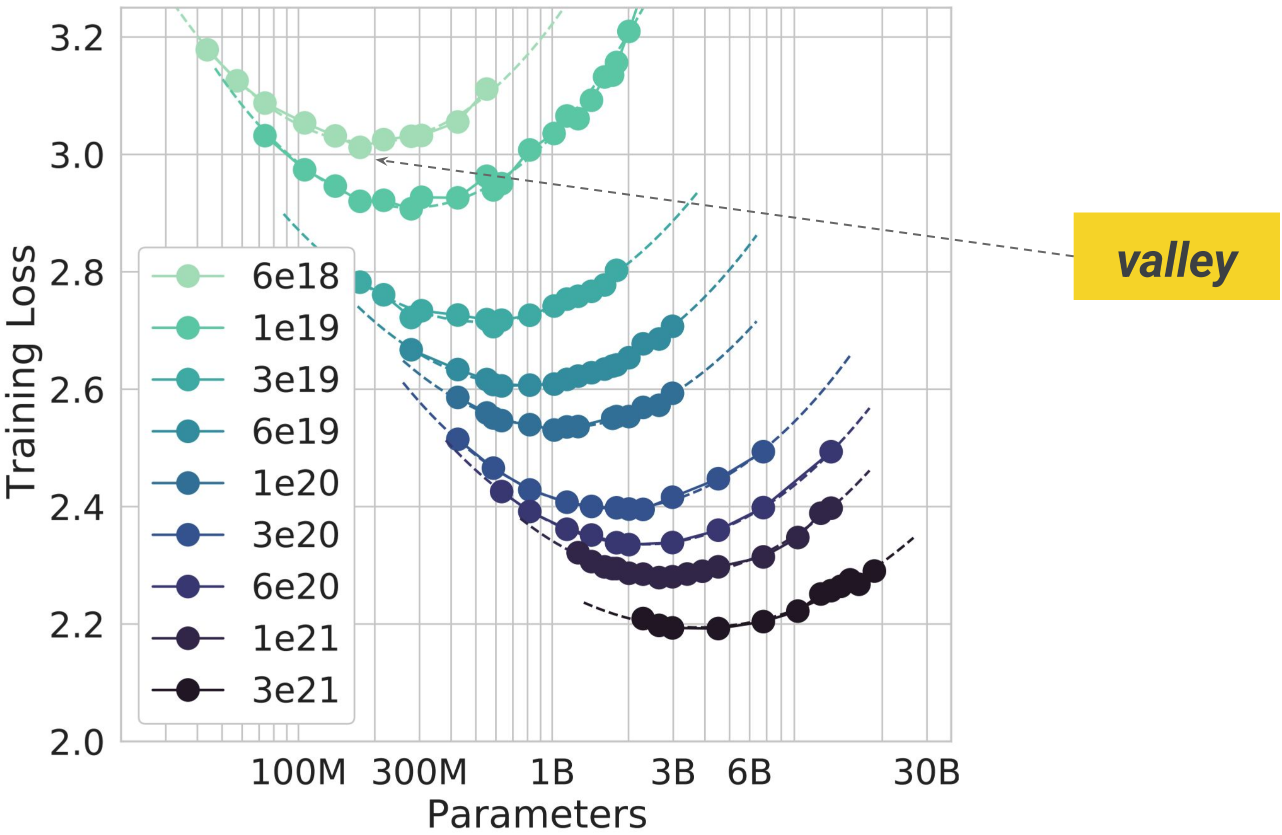
Issues with Kaplan laws

- Used same learning rate schedule for all training runs, regardless of how many training tokens / batches!
- This schedule needs to be adjusted based on the number of training steps; otherwise, it can impair performance
- The resulting “scaling laws” from Kaplan et al., are flawed because of this!

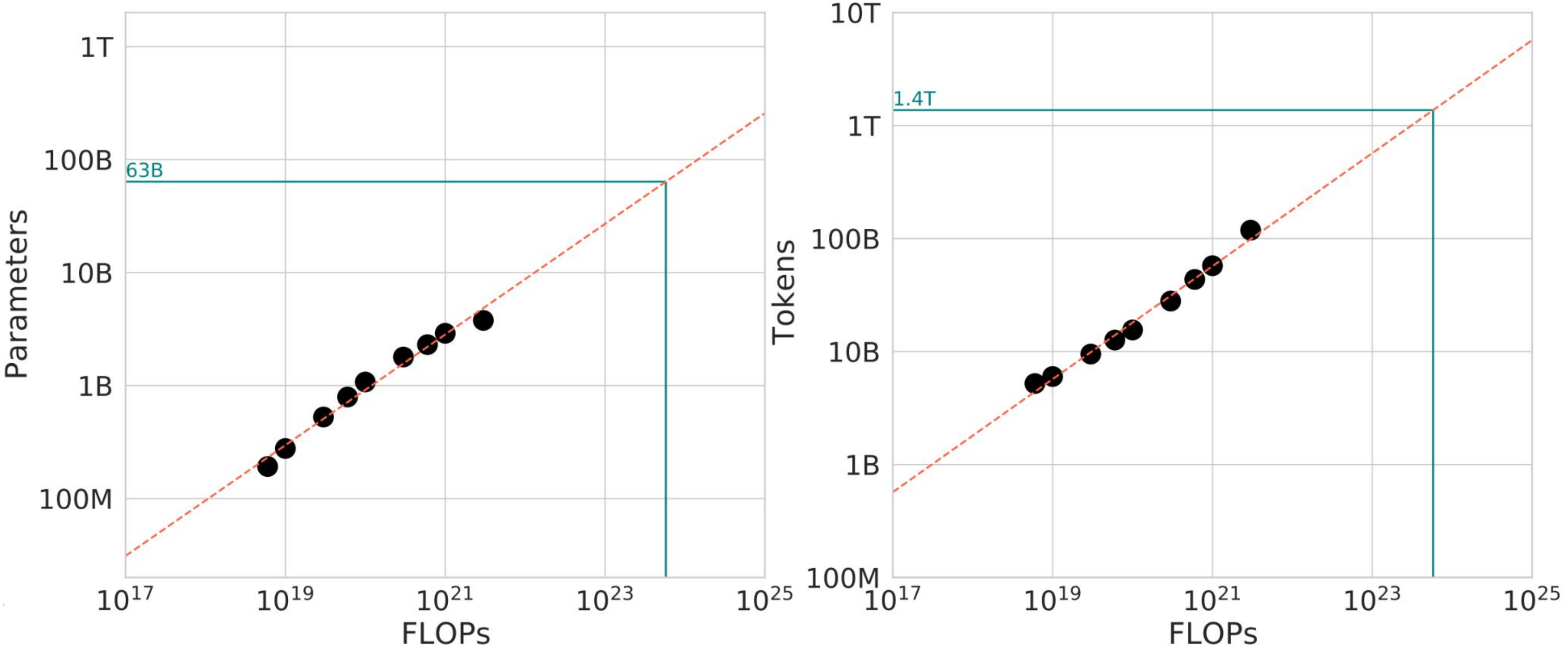
Chinchilla scaling laws

- **Kaplan et al., 2020: prioritize increasing model size over data size**
  - With a 10x compute increase, increase model size by 5x and data size by 2x
  - With a 100x compute increase, model size 25x and data 4x
- **Chinchilla (Hoffmann et al., 2022): increase model and data size at the same rate**
  - With a 10x compute increase, increase both model size and data size by 3.1x
  - With a 100x compute increase, both model and data size 10x

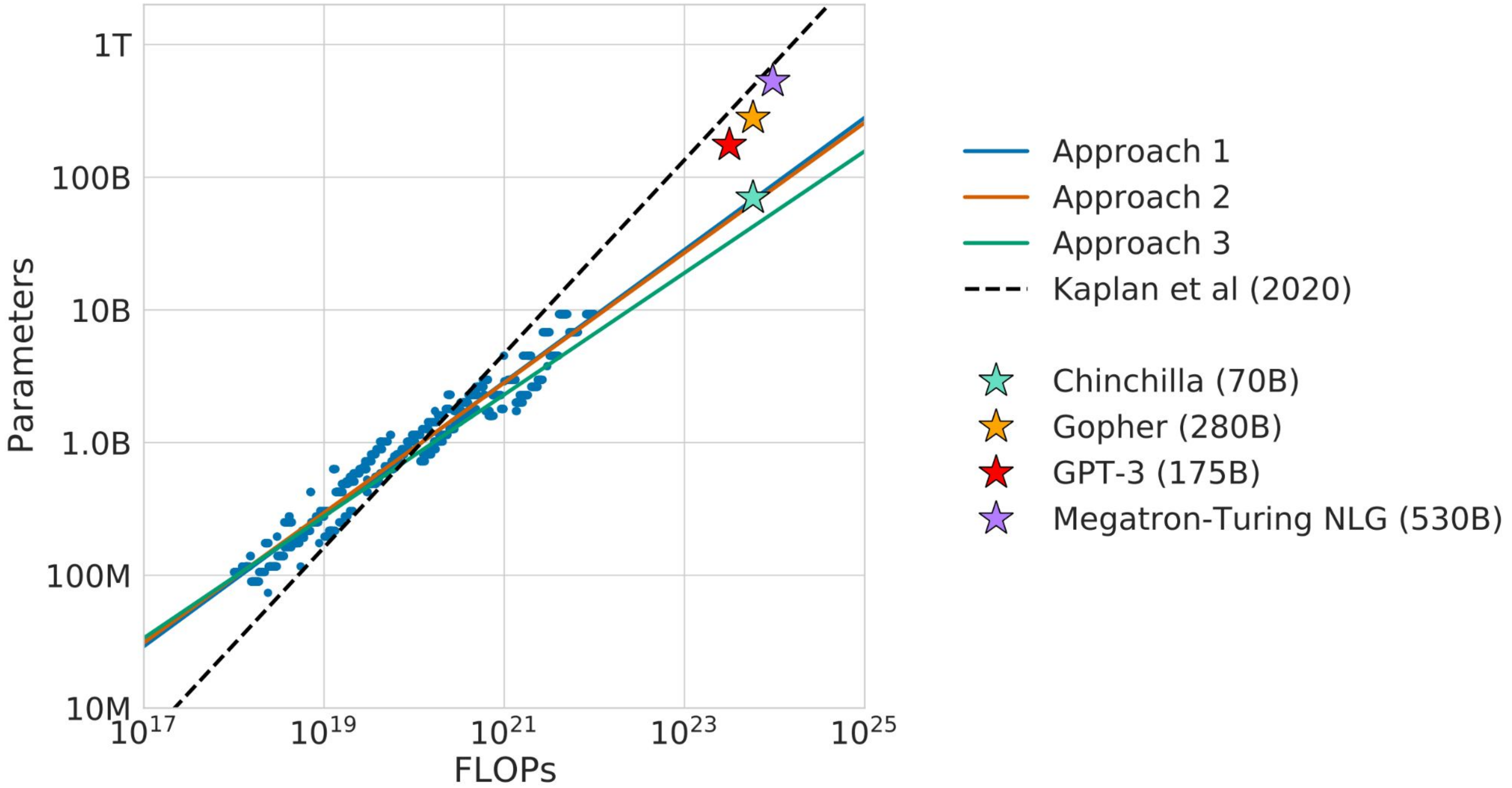
For a given FLOP budget there is an optimal model to train



Projecting optimal model size and number of tokens for larger models



Large models should be significantly smaller and trained for much longer than is currently done (2022)



Large models should be significantly smaller and trained for much longer than is currently done (2022)

Model	Size (# Parameters)	Training Tokens
LaMDA (Thoppilan et al., 2022)	137 Billion	168 Billion
GPT-3 (Brown et al., 2020)	175 Billion	300 Billion
Jurassic (Lieber et al., 2021)	178 Billion	300 Billion
Gopher (Rae et al., 2021)	280 Billion	300 Billion
MT-NLG 530B (Smith et al., 2022)	530 Billion	270 Billion
Chinchilla	70 Billion	1.4 Trillion

- N – the number of model parameters, *excluding all vocabulary and positional embeddings*
- $C \approx 6NBS$ – an estimate of the total non-embedding training compute, where B is the batch size, and S is the number of training steps (ie parameter updates). We quote numerical values in PF-days, where one PF-day $= 10^{15} \times 24 \times 3600 = 8.64 \times 10^{19}$ floating point operations.

PF: PetaFLOP

Gopher vs. Chinchilla

Random	25.0%
Average human rater	34.5%
GPT-3 5-shot	43.9%
Gopher 5-shot	60.0%
***Chinchilla* 5-shot**	**67.6%**
Average human expert performance	*89.8%*
June 2022 Forecast	57.1%
June 2023 Forecast	63.4%

Table 6 | **Massive Multitask Language Understanding (MMLU).** We report the average 5-shot accuracy over 57 tasks with model and human accuracy comparisons taken from Hendrycks et al. (2020). We also include the average prediction for state of the art accuracy in June 2022/2023 made by 73 competitive human forecasters in Steinhardt (2021).

Chinchilla's loss function

$$\hat{L}(N, D) \triangleq E + \frac{A}{N^{\alpha}} + \frac{B}{D^{\beta}}.$$

Thank you!