LLM LE4 VT2025

Pre-training and Scaling

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Outline:

- **Pre-training**
- **Parallel Training**
- **Scaling**

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Language modelling

- **Language modelling** is the task of predicting which word comes next in a sequence of words.
- More formally, given a sequence of words $w_1, \ldots, w_t$ we want to know the probability of the next word, w_{t+1}:

$$P(w_{t+1} \mid w_1, \ldots, w_t)$$

- We are assuming that w_{t+1} comes from a finite vocabulary V.

language models = classifiers

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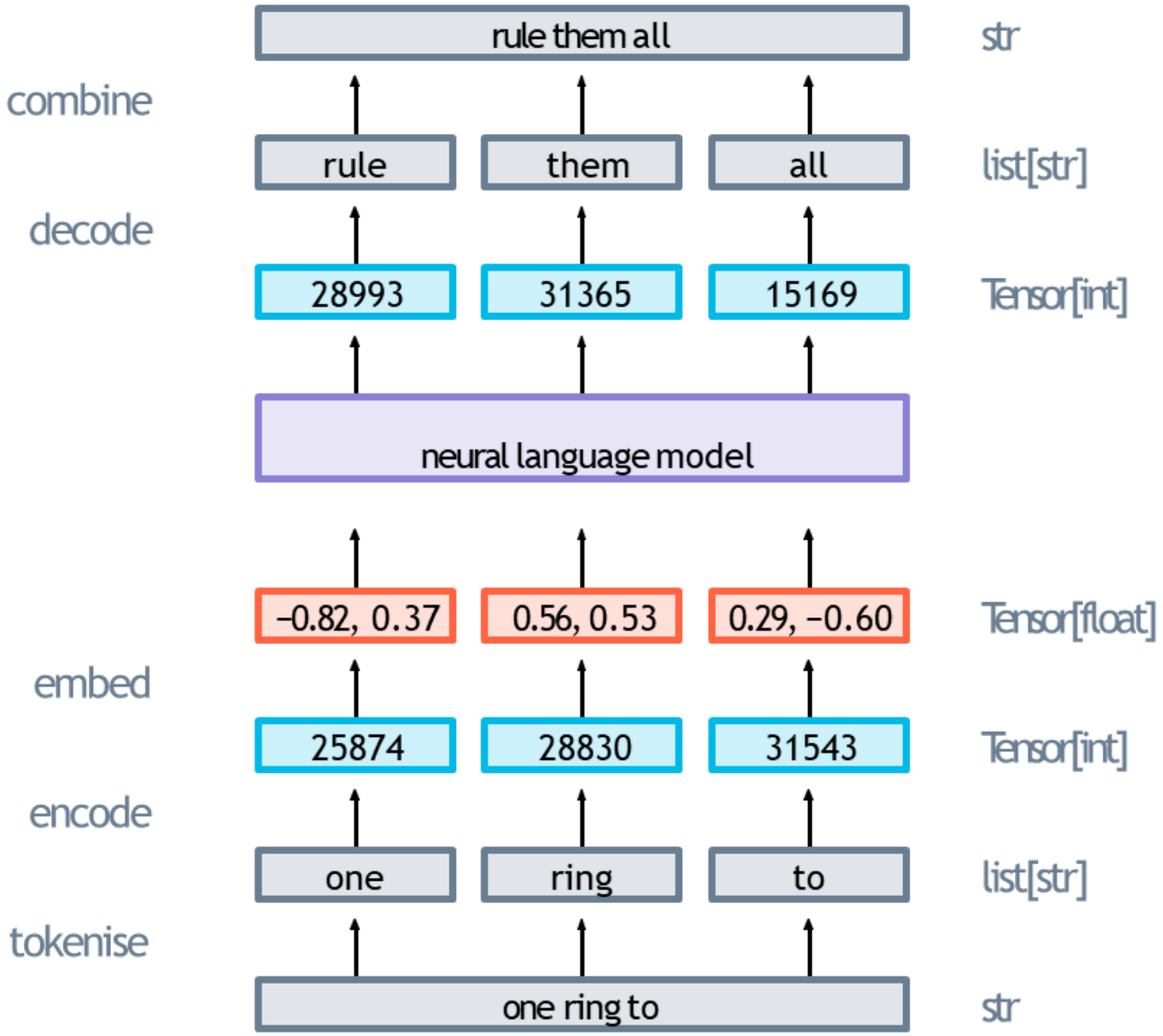

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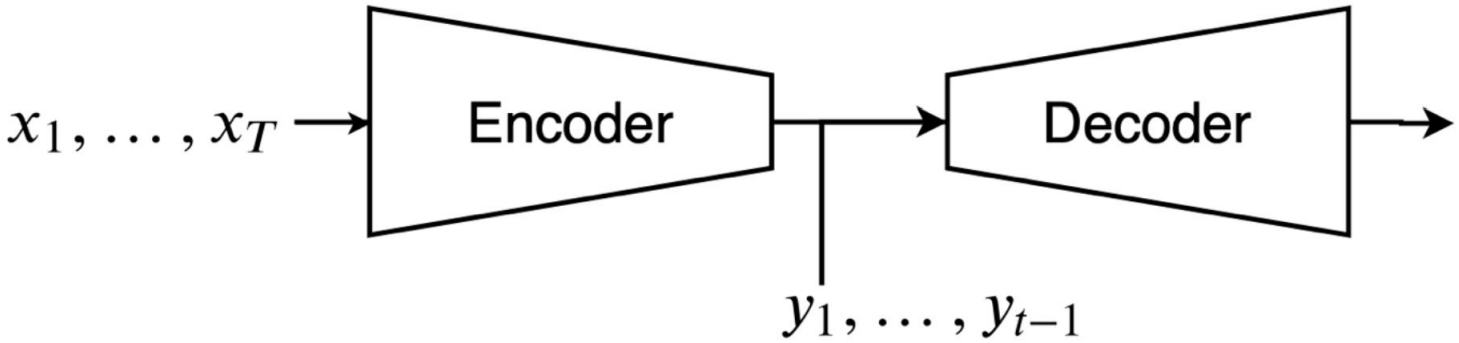
Neural Language Models

Input sequence: $x_1, \ldots, x_T$
Target sequence: $y_1, \ldots, y_T$



$P(Y_t = i)$

Or sometimes…

$P_\Theta(Y_t = i)$

Or sometimes…

$P(Y_t = i | y_1, \ldots, y_{t-1}; x_1, \ldots, x_T; \Theta)$

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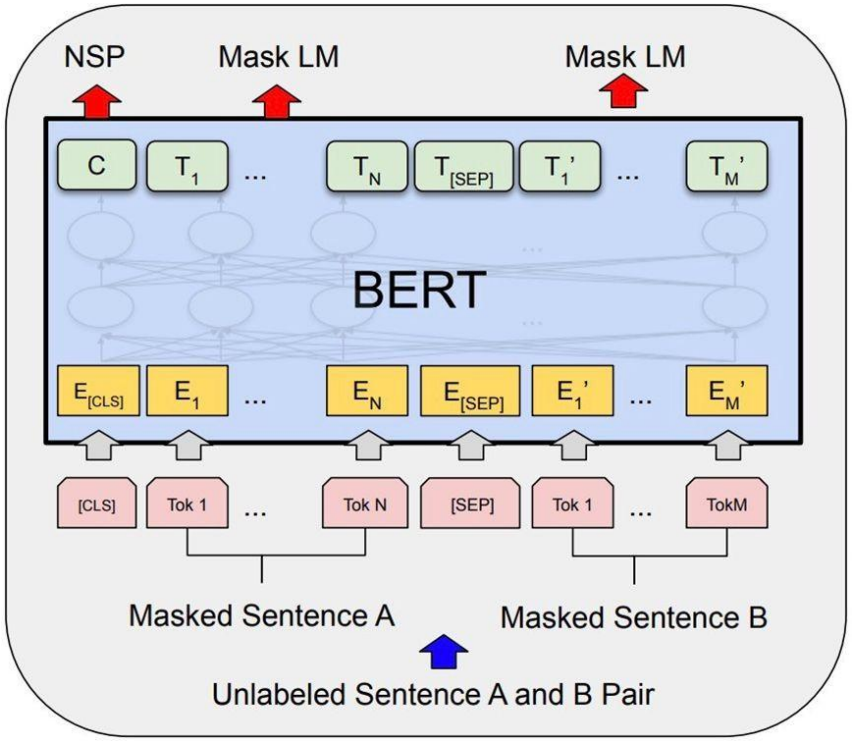
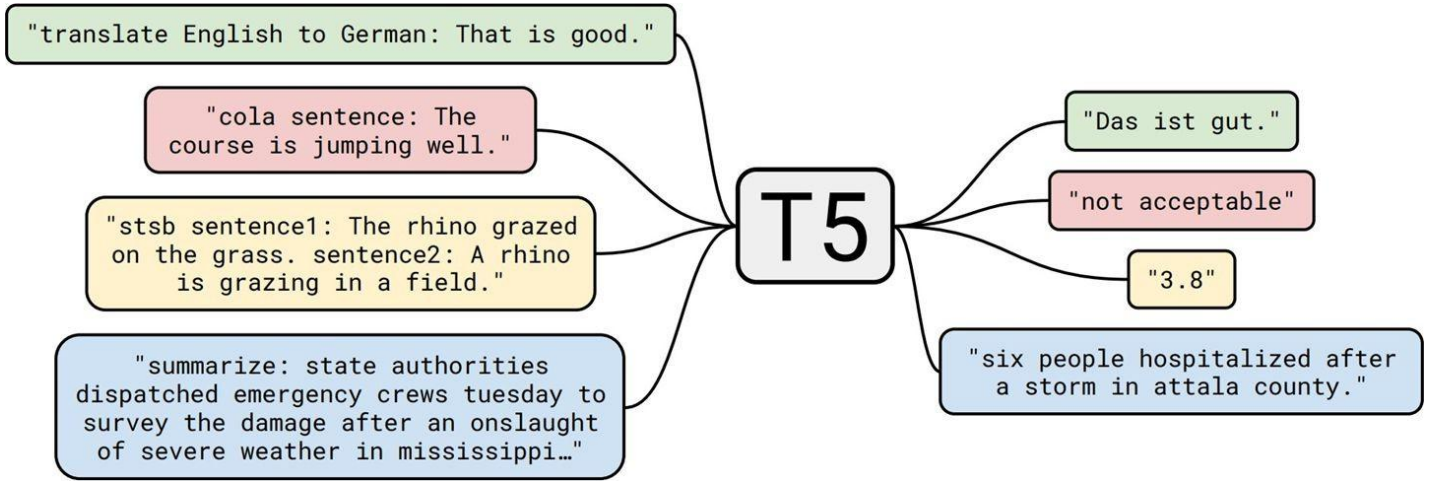
Language models:Broad Sense

- Decoder-only models (GPT-x models)
- Encoder-only models (BERT, RoBERTa, ELECTRA)
- Encoder-decoder models (T5, BART)

→ The latter two usually involve a different **pre-training** objective.





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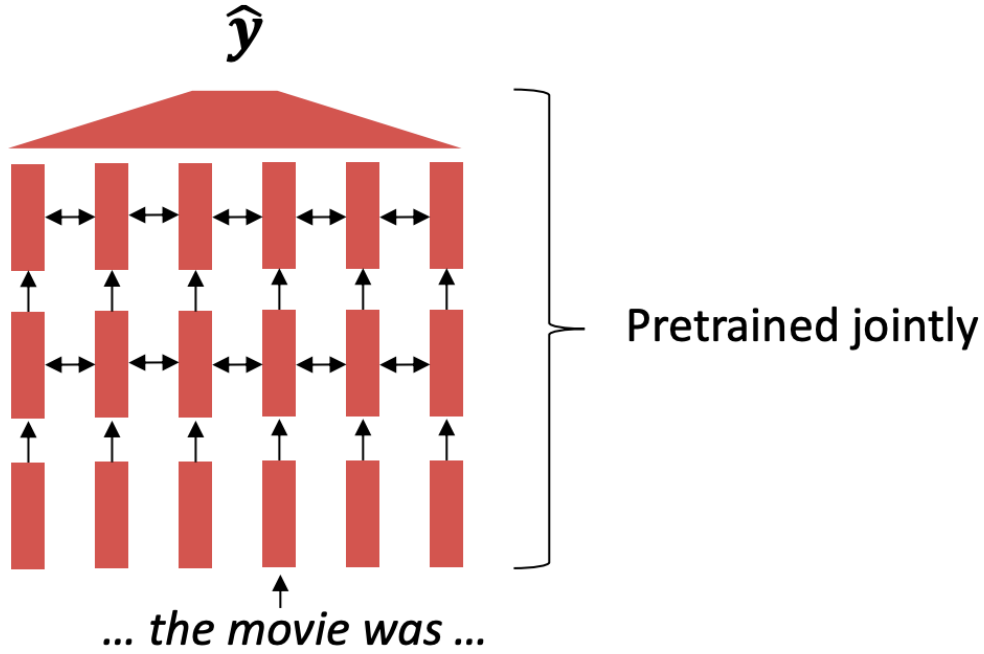
Why Pretraining?

In modern NLP:

- All (or almost all) parameters in NLP networks are initialized via **pre-training.**
- Pretraining methods hide parts of the input from the model, and then train the model to reconstruct those parts.

This has been exceptionally effective at building strong:

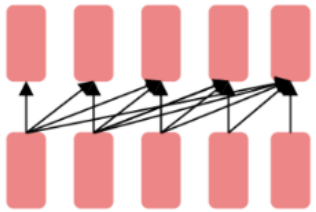
- **representations of language**
- **parameter initializations** for strong NLP models.
- **probability distributions** over language that we can sample from



[This model has learned how to represent entire sentences through pretraining]

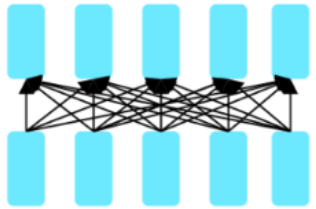
Pretraining for three types of architectures

The neural architecture influences the type of pretraining, and natural use cases.



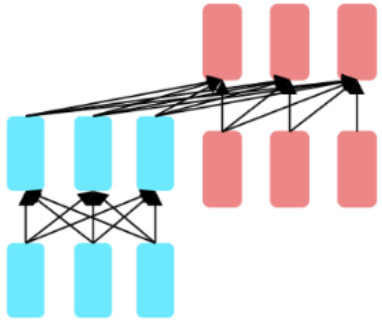
Decoders

- Language models! What we've seen so far.
- Nice to generate from; can't condition on future words
- **Examples:** GPT-2, GPT-3, LaMDA



Encoders

- Gets bidirectional context – can condition on future!
- Wait, how do we pretrain them?
- **Examples:** BERT and its many variants, e.g. RoBERTa



Encoder-Decoders

- Good parts of decoders and encoders?
- What's the best way to pretrain them?
- **Examples:** Transformer, T5, Meena

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What do we want from our learning objective.

The goals of **pre-training** (the first stage of training) are to get the language model to:

- learn the structure of natural language
- learn humans' understanding of the world (as encoded in the training data).

We want a learning objective that facilitates these goals.

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Objectives for pre-training

- Predict a suffix given a prefix.
  - Input: I took my dog, Fido, to the
  - Target: park for his walk.
- Masked language modeling
  - Input: I took <x> to <y> his walk.
  - Target: <x> my dog, Fido, <y> the park for
- Full language modeling: predict next token given previous tokens
  - Target: I took my dog, Fido, to the park for his walk.

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Pretraining Encoders

BERT [Devlin et al, NAACL 2019]

- **Fully bidirectional transformer encoder**
  - BERTbase: 12 layers, hidden size=768, 12 att'n heads (110M parameters)
  - BERTlarge: 24 layers, hidden size=1024, 16 att'n heads (340M parameters)
- **Input:** sum of token, positional, segment embeddings
  - **Segment embeddings** (A and B): is this token part of sentence A (before SEP) or sentence B (after SEP)?
- **[CLS]** and **[SEP]** tokens: added during pre-training
- **Pre-training tasks:**
  - Masked language modeling
  - Next sentence prediction

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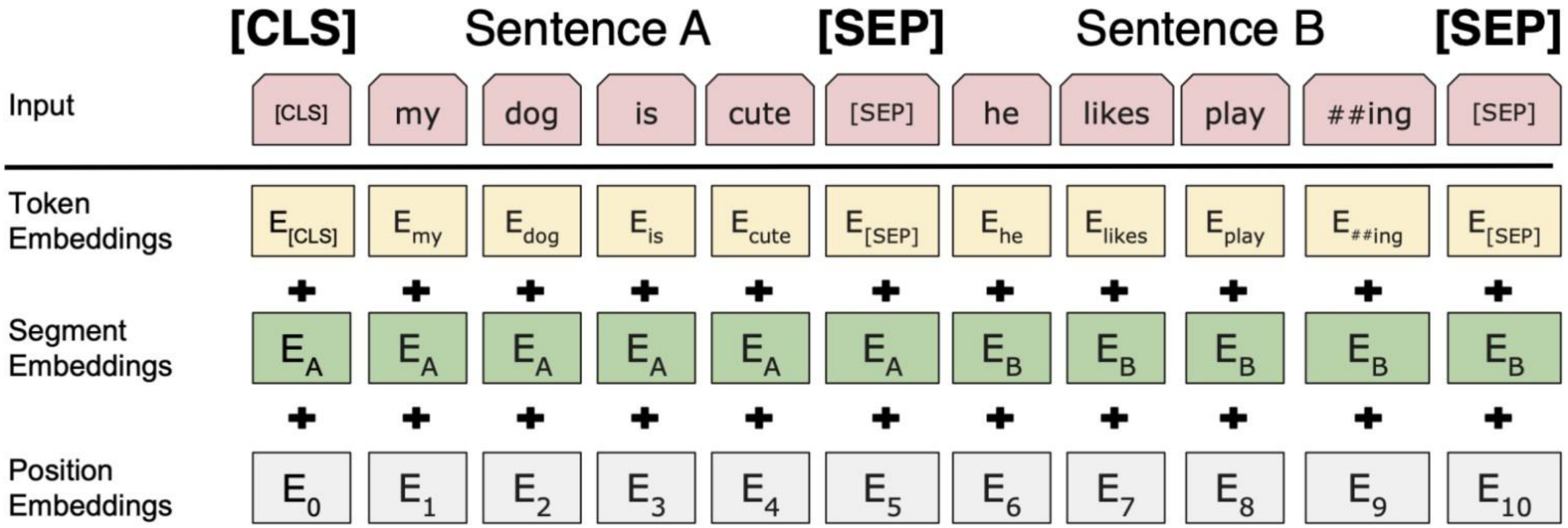
BERT Input



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BERT Pre-training Tasks

BERT is jointly pre-trained on two tasks:

- **Next-sentence prediction:** [based on CLS token]
  - Does sentence B follow sentence A in a real document?
- **Mask language modeling:**
  - **15%** of tokens are randomly chosen as masking tokens
  - 10% of the time, a masking token remains unchanged
  - 10% of the time, a masking token is replaced by a random token
  - **80% of the time,** a masking token is replaced by **[MASK]**, and the **output layer has to predict the original token**

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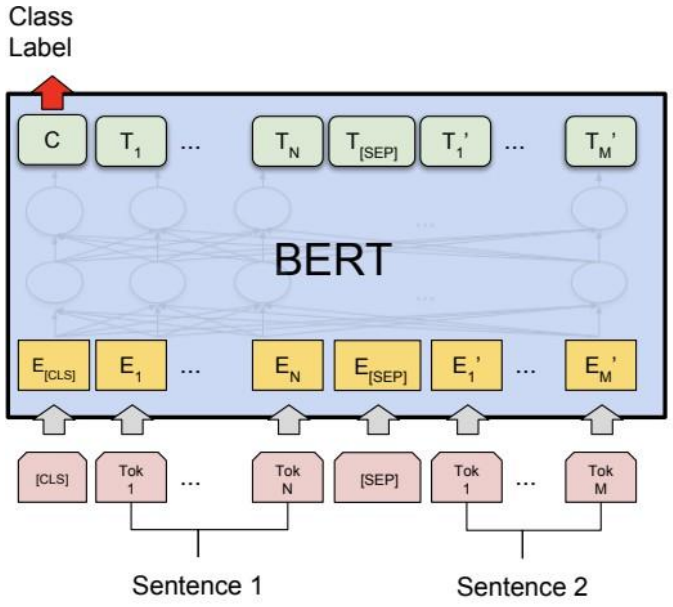
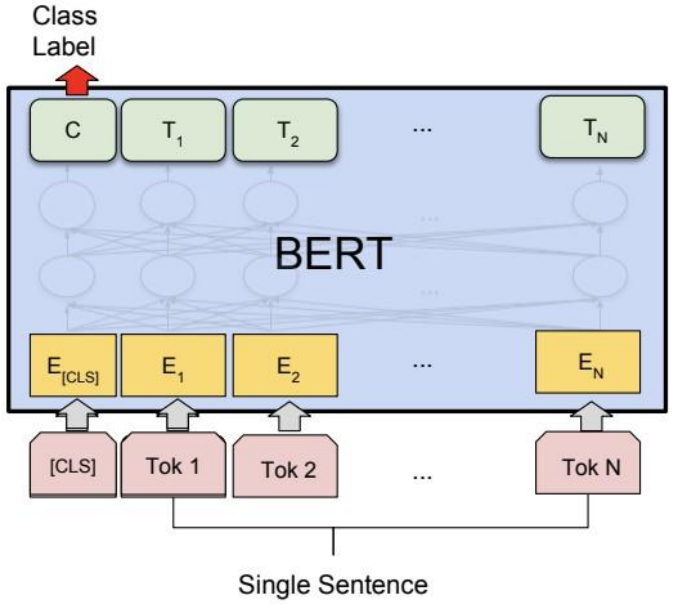
Using BERT for Classification



Sentence Pair Classification



Single Sentence Classification

Add a **softmax classifier** on final layer of **[CLS]** token

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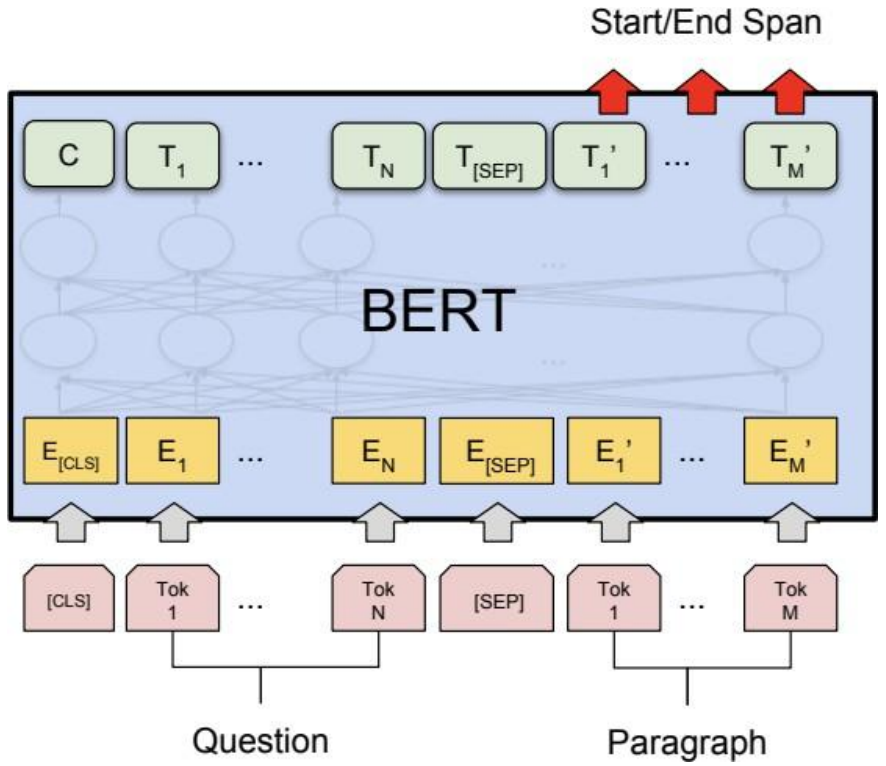
Using BERT for Question-Answering



Input: [CLS] question [SEP] answer passage [SEP]
Learn to predict a START and an END token on answer tokens

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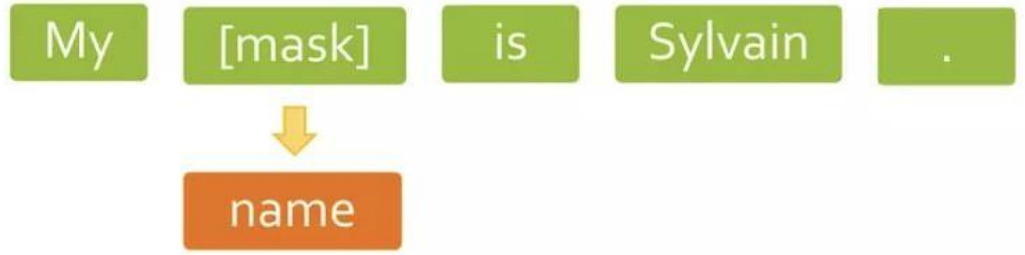
Examples of language models pretraining objectives

Guess the next word in the sentence (GPT)



Guess some masked words in the sentence (BERT)

Why not encoder-based LLMs?

1. **I cannot generate (it discriminates)**: It can only work for classification (discrimination) tasks, it is not easy to generate something new.

1. **Its objective is not scalable:** Its self-supervised tasks (masked language model) are just too simple for LLMs, and increasing model size does not improve performance too much.

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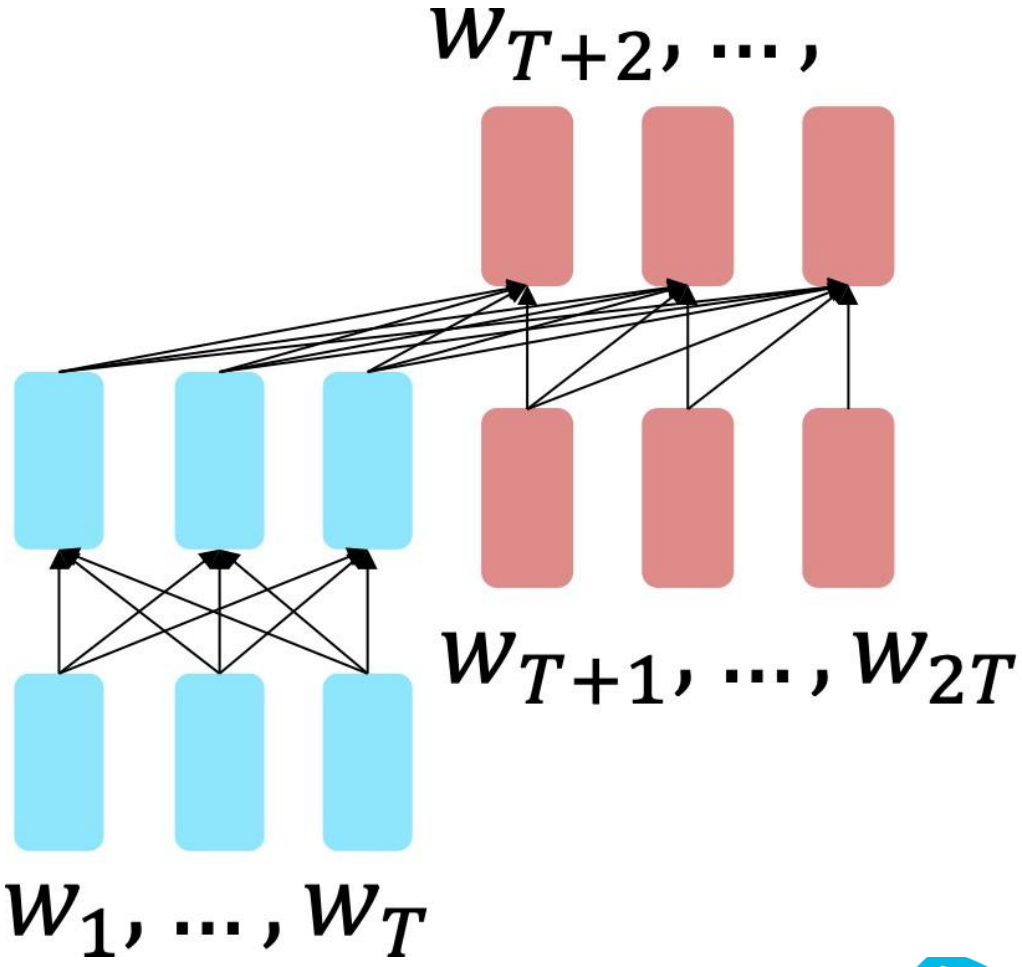
Pretraining Encoder-Decoders

The **encoder** portion benefits from bidirectional context; the **decoder** portion is used to train the whole model through language modeling.



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.

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Pretraining Encoder-Decoders: Span Corruption

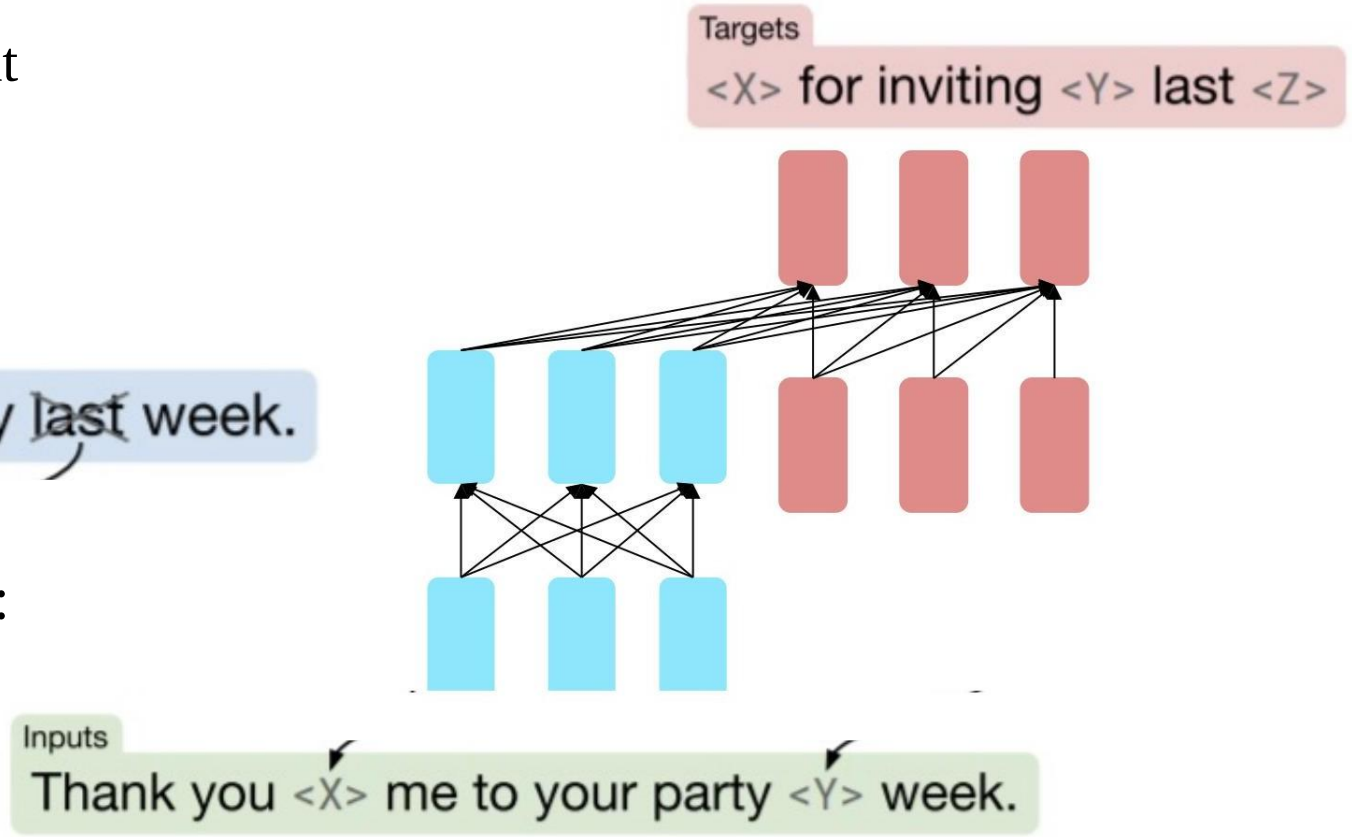
What [Raffel et al., 2018] found to work best was span corruption. Their model: T5.

Replace different-length spans from the input with unique placeholders; decode out the spans that were removed!

Original text

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

This is implemented in text preprocessing: it's still an objective that looks like **language modeling** at the decoder side.



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Why not Encoder-Decoder LLMs?

1. Decoder could work also as a seq-2-seq task, its protocol is much easier
2. When performing multi-turn generation, it is not easy to cache previous values.

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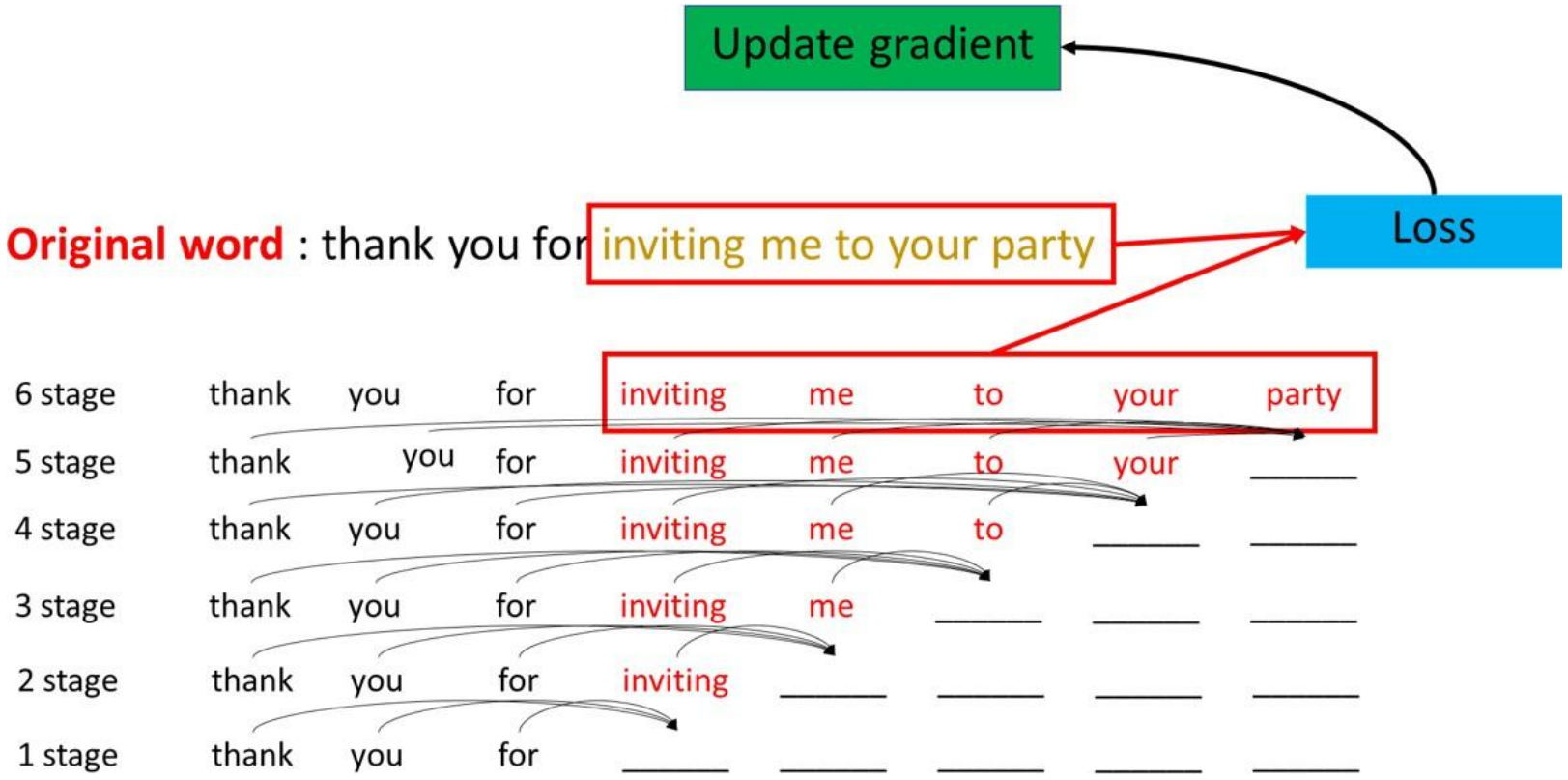
Pretraining Decoders

It's natural to pretrain decoders as language models and then use them as generators, finetuning their $p_\theta(w_t|w_{1:t-1})$!



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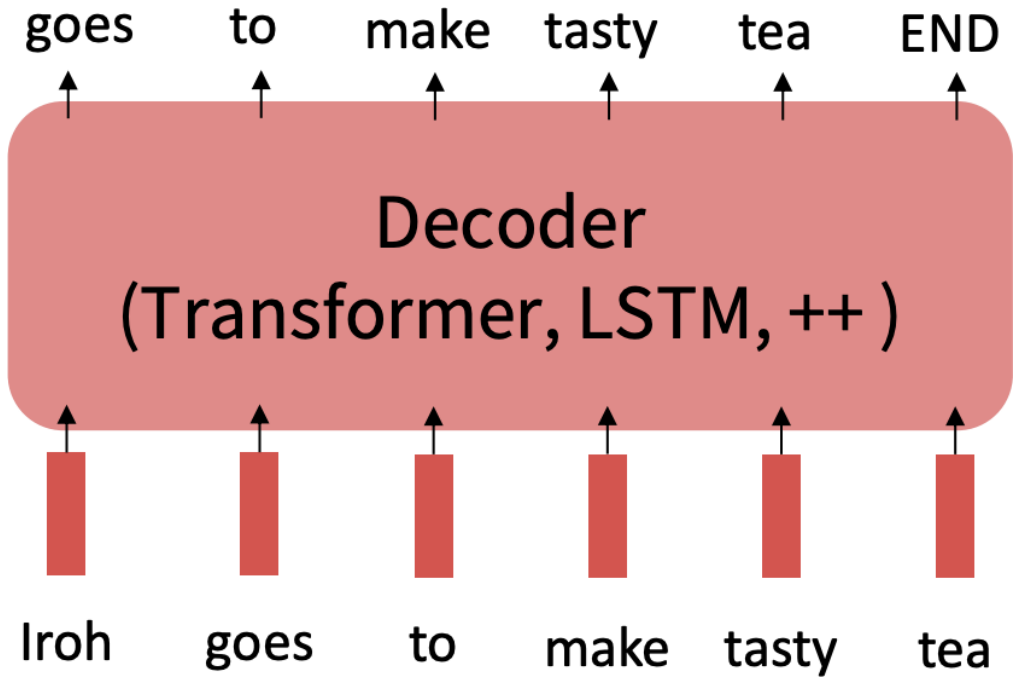
Pretraining through language modeling

Recall the language modeling task:

- Model the probability distribution over words given their past contexts.
- There's lots of data for this! (In English.)

Pretraining through language modeling:

- Train a neural network to perform language modeling on a large amount of text.
- Save the network parameters.



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Common roadmap for LLMs

- Phase 1: pre-training
  - Learn **general** world knowledge, ability, etc.
- Phase 2: Supervised finetuning
  - Tailor to **tasks** (**unlock** some abilities)
- Phase 3: RLHF
  - Tailor to **humans**
  - *Even you could teach ChatGPT to do something*

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Parallel Training

Parallel Training: Overview

As scale grows, training with one GPU is not enough

- There are many ways to improve efficiency on single-GPU training
  - Checkpointing: moving part of the operations to CPU memory
  - Quantizing different part of the optimization to reduce GPU memory cost
- Eventually more FLOPs are needed

Different setups of parallel training:

- When model training can fit into single-GPU
  →Data parallelism
- When model training cannot fit into single-GPU
  → Model parallelism: pipeline or tensor

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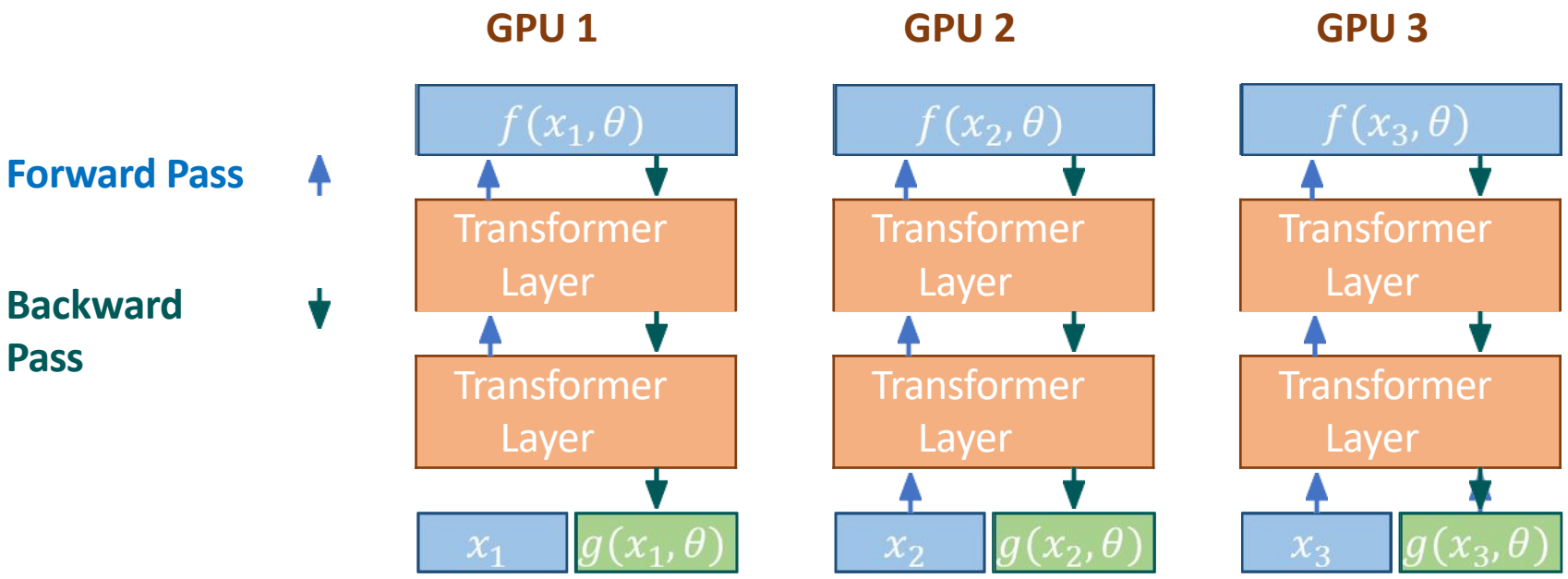
Parallel Training: Data Parallelism

Split training data batch into different GPUs

- Each GPU maintains its own copy of model and optimizer
- Each GPU gets a different local data batch, calculates its gradients



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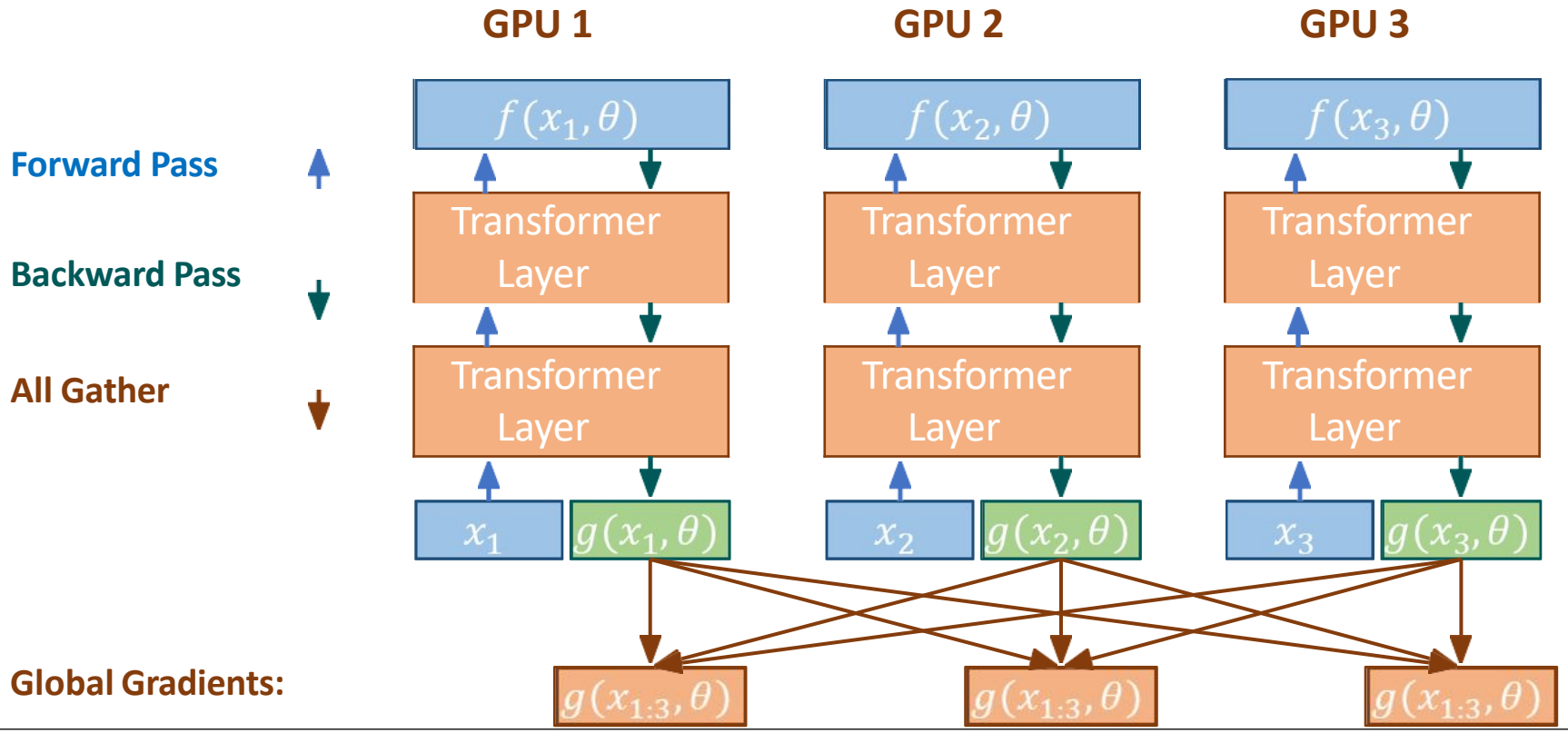

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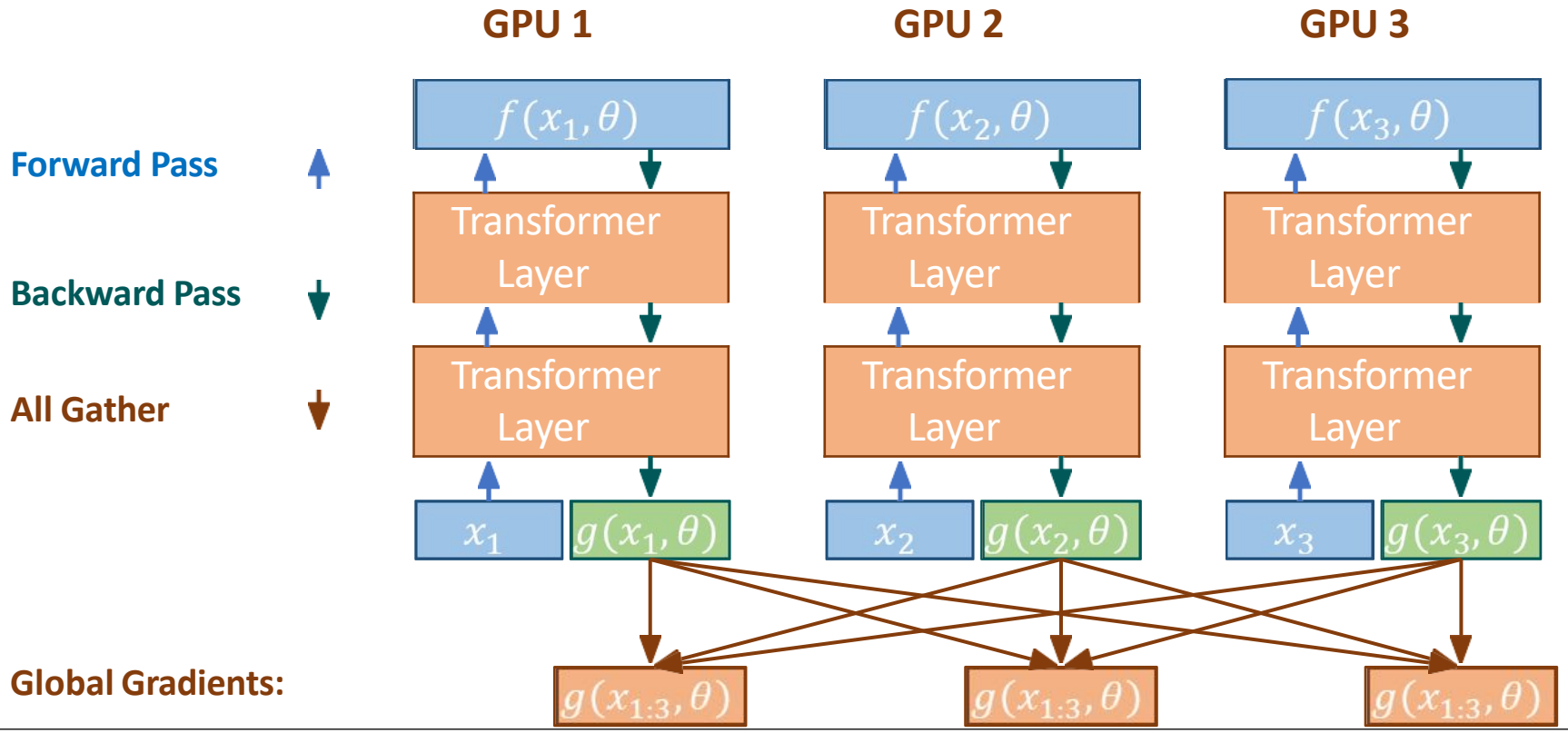

Communication:

- The full gradient tensor between every pair of GPUs, at each training batch.
- Not an issue between GPUs in the same machine or machines with infinity band
- Will need work around without fast cross-GPU connection

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Parallel Training: Model Parallelism

LLM size grew quickly and passed the limit of single GPU memory

	Cost of 10B Model
Parameter Bytes	20GB
Gradient Bytes	20GB
Optimizer State: 1st Order Momentum	20GB
Optimizer State: 2nd Order Momentum	20GB
Total Per Model Instance	**80GB**

Memory Consumption of Training Solely with **BF16** (Ideal case) of a model sized Ψ

Solution: Split network parameters (thus their gradients and corresponding optimizer states) to different GPUs

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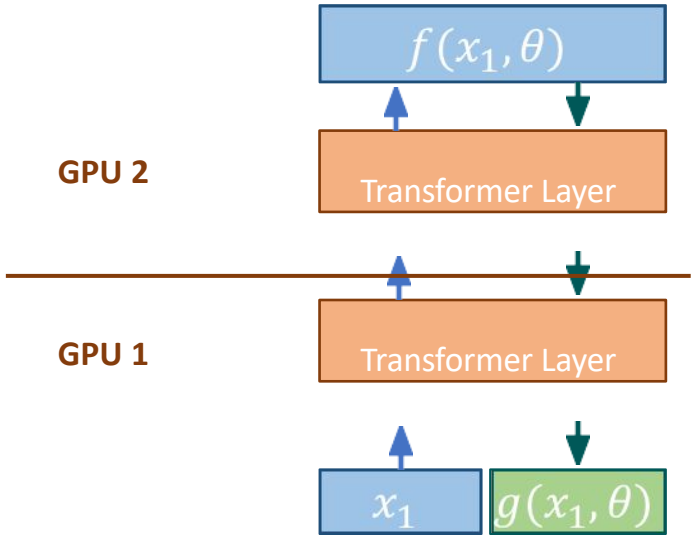
Parallel Training: Model Parallelism

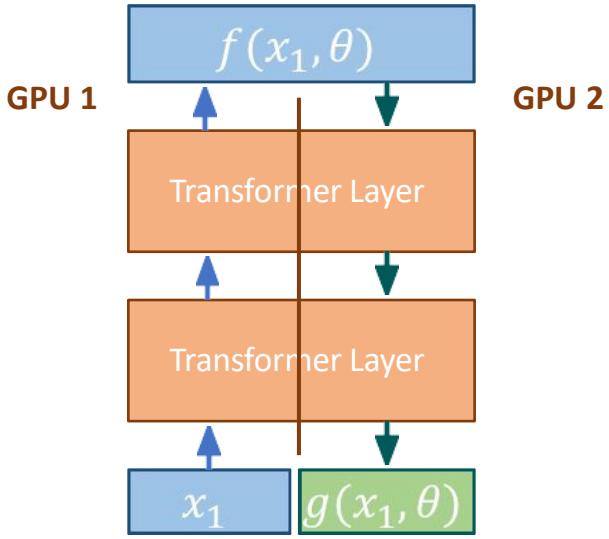
Two ways of splitting network parameters

Pipeline Parallelism



Split by Layers

Tensor Parallelism



Split Tensors

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Parallel Training: Pipeline Parallelism

Split network by layers, aligning devices by layer order to a pipeline, and pass data through devices [7]

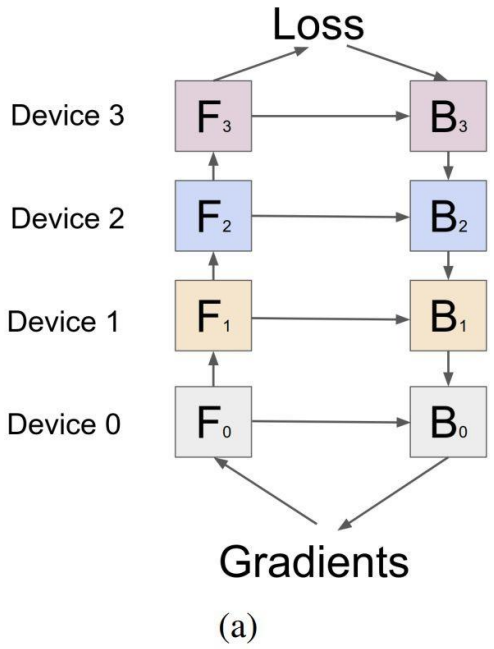
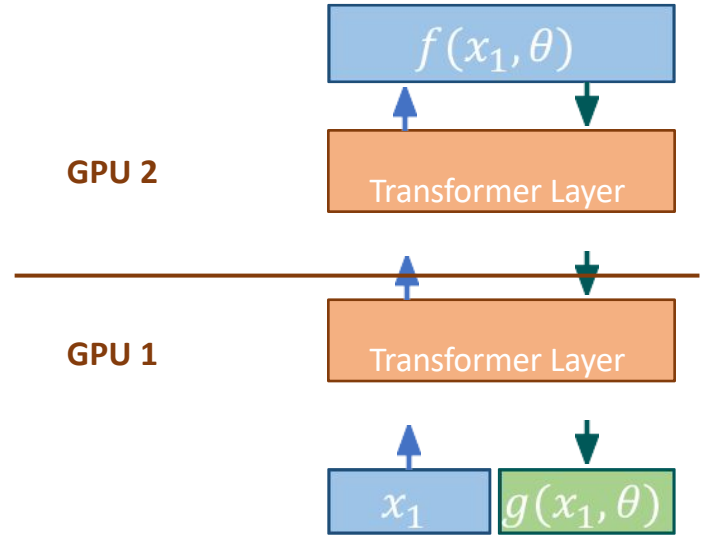


Illustration of Pipeline Parallelism [7]

Pipeline Parallelism



Split by Layers

Parallel Training: Pipeline Parallelism

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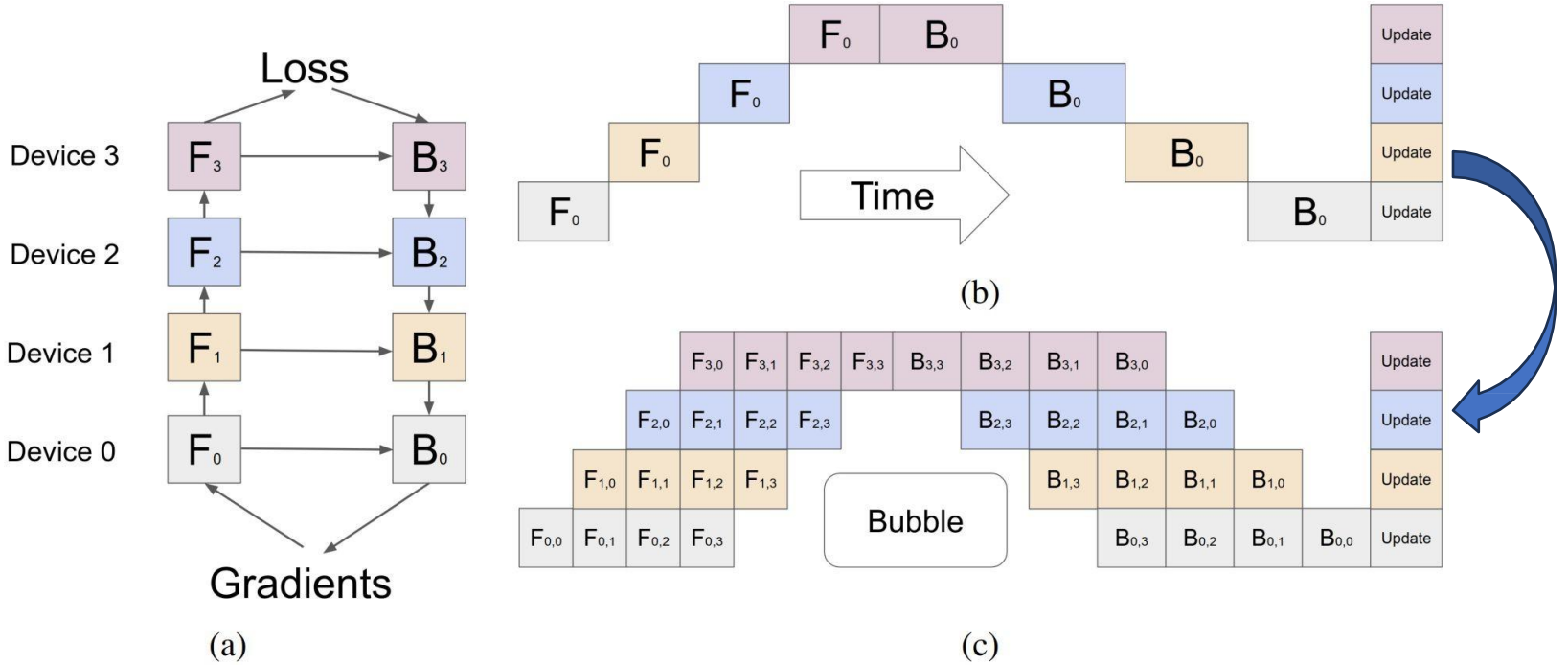

Split batches for more fine-grained pipelines

Illustration of Pipeline Parallelism [7]

Parallel Training: Pipeline Parallelism

Split network by layers, aligning devices by layer order to a pipeline, and pass data through devices [7]

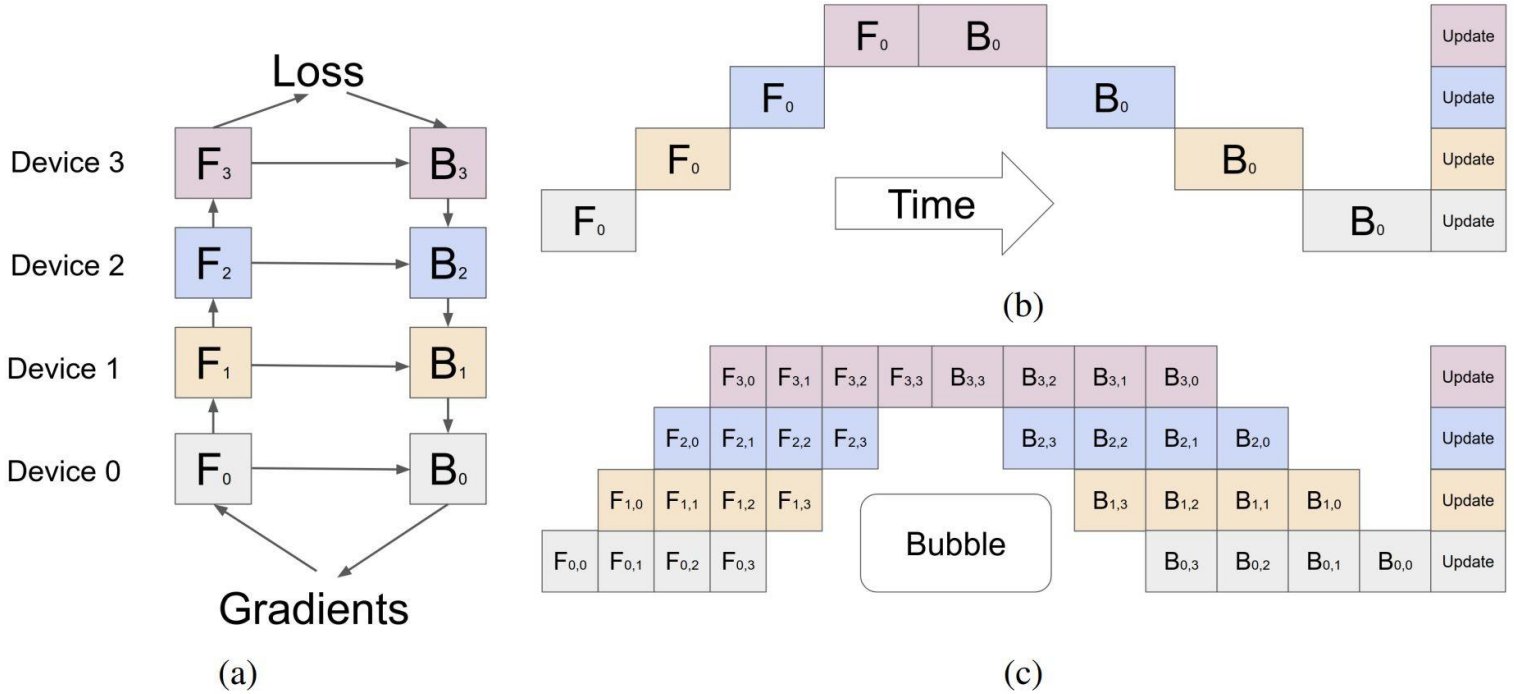

Illustration of Pipeline Parallelism [7]

Communication:

- Activations between nearby devices in forward pass
- Partial gradients between nearby devices in backward

Parallel Training: Pipeline Parallelism

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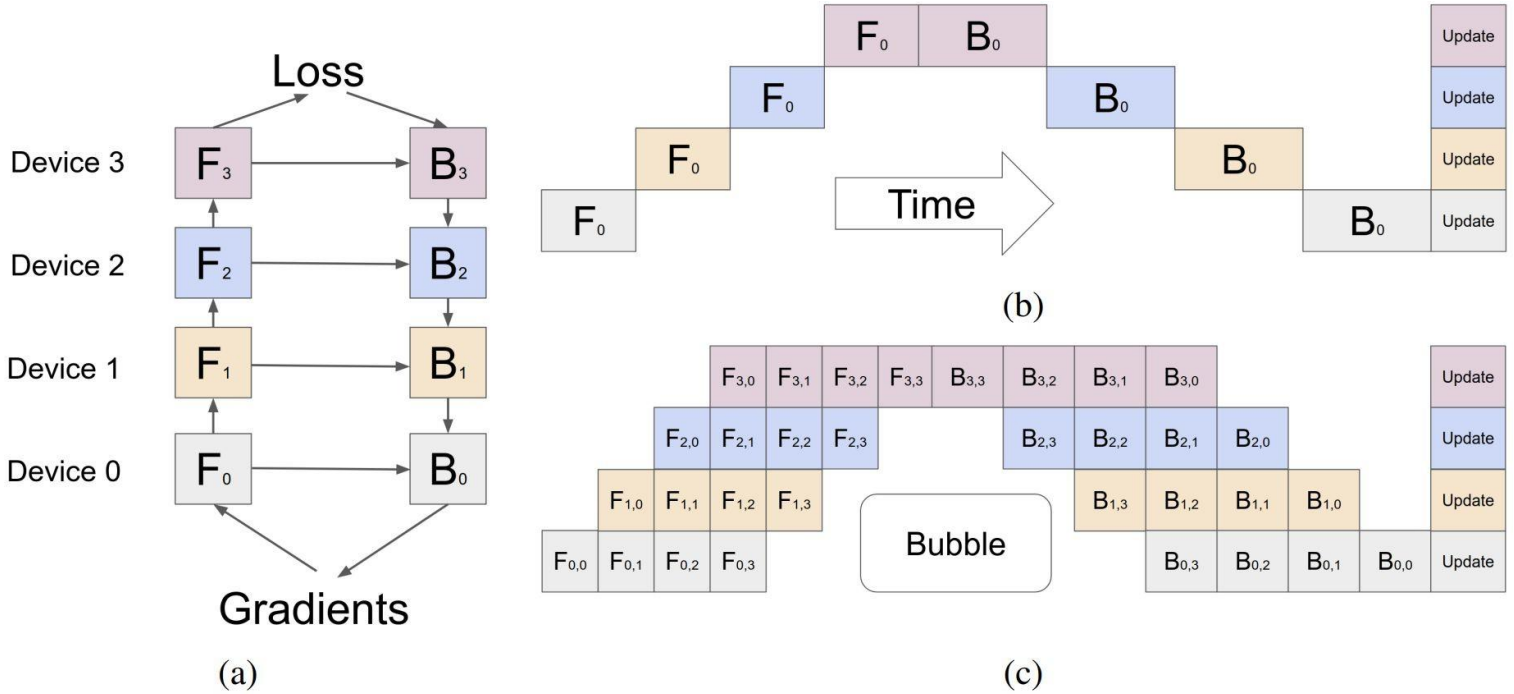

Illustration of Pipeline Parallelism [7]

Communication:

- Activations between nearby devices in forward pass
- Partial gradients between nearby devices in backward

Pros: Conceptually simple and not coupled with network architectures. All networks have multiple layers.

Cons: Waste of compute in the Bubble. Bubble gets bigger with more devices and bigger batches.

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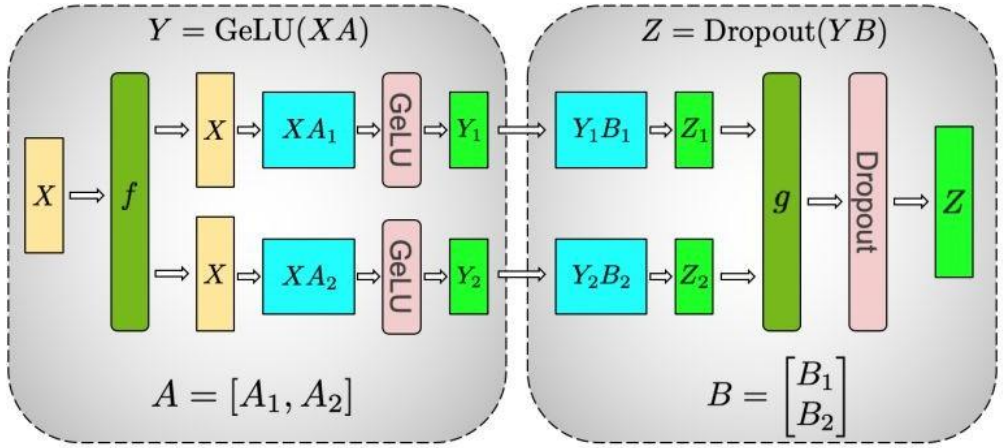
Parallel Training: Tensor Parallelism

Split the parameter tensors of network layers into different devices for parallel matrix operations



Tensor Parallelism of MLP blocks and Self-attention Blocks [8]

Parallel Training: Tensor Parallelism

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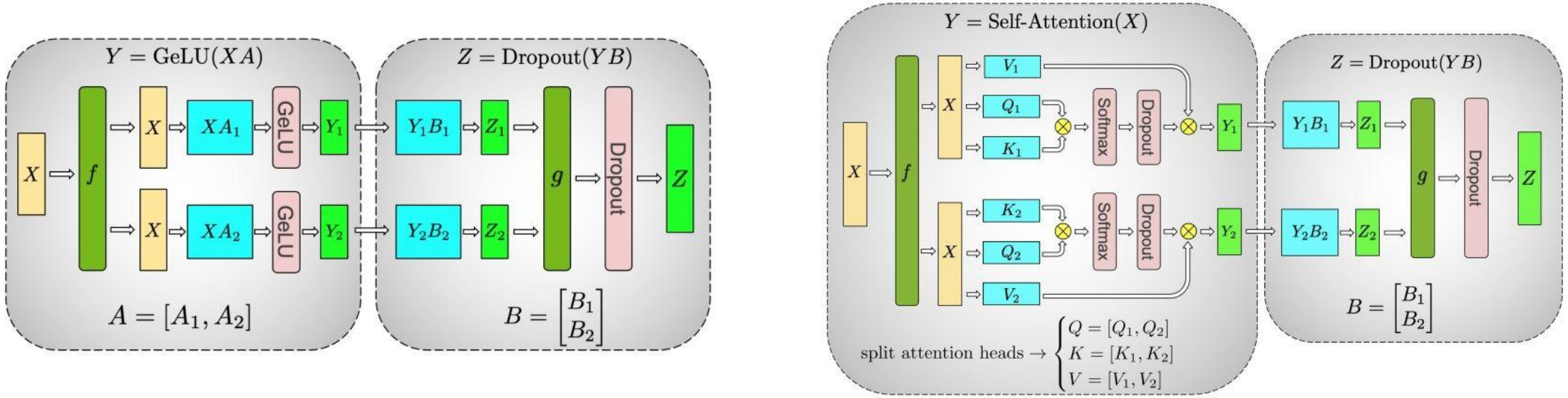

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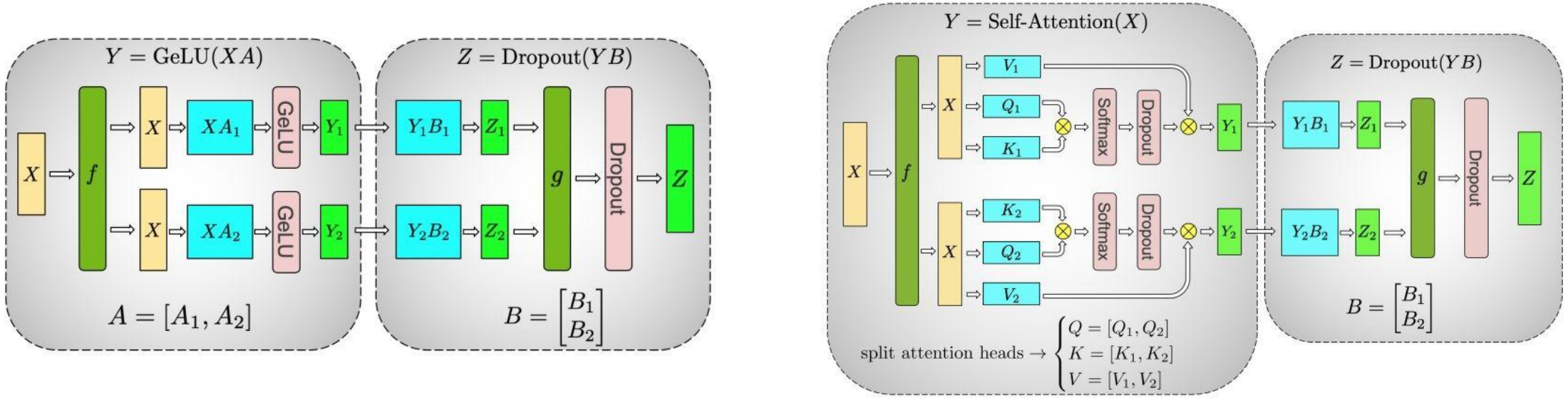


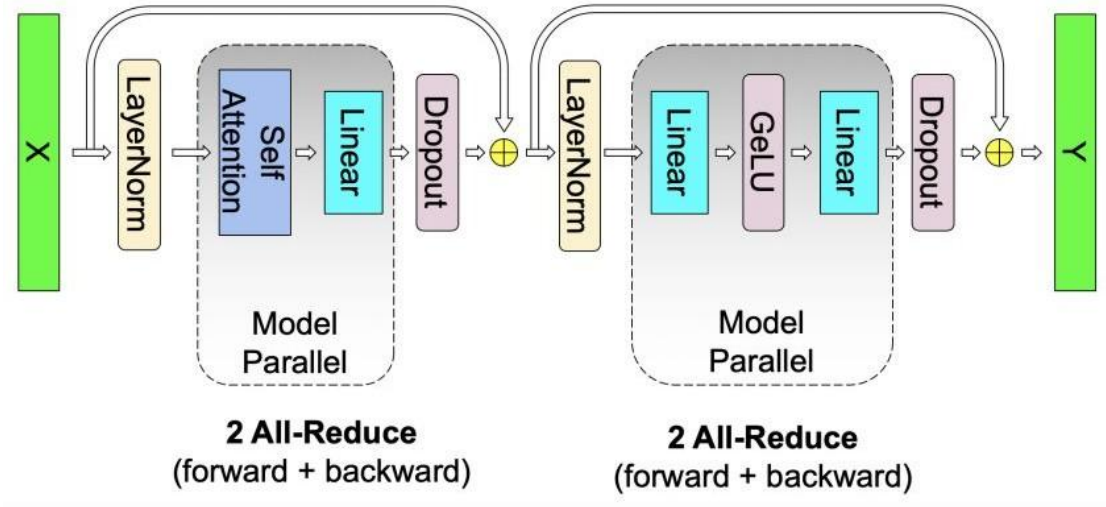
Tensor Parallelism of MLP blocks and Self-attention Blocks [8]

Pros: No bubble

Cons: Different blocks are better split differently, lots of customizations

Parallel Training: Tensor Parallelism

Split the parameter tensors of network layers into different devices for parallel matrix operations



Communication of Tensor Papalism for a Transformer Layer [8]

Communication:

- All-gather of partial activations and gradients for each split tensor

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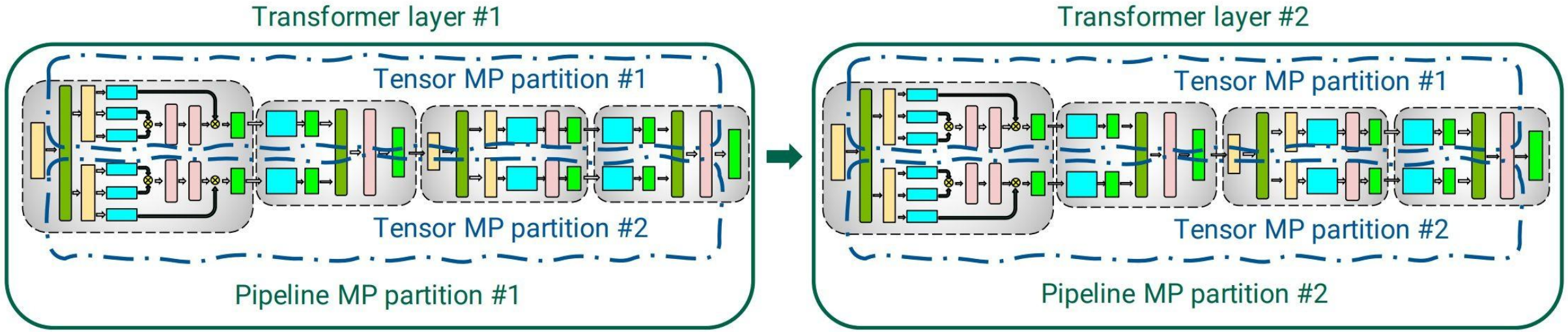
Parallel Training: Combining Different Approaches

Often data parallelism and model parallelism are used together.

- No need not to use data parallelism

Pipeline Parallelism and Tensor Parallelism can also be used together.



Combination of Tensor Parallelism and Pipeline Parallelism [9]

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Scaling

Scaling laws in language modelling

- **Scaling laws** describe how model performance improves as we increase key factors such as model size and training data size.
- Empirical results suggest that performance improvements obey a power law: performance increases, but at a diminishing rate.
  - cf. Heap's law
- Scaling laws can help developers answer many practically relevant questions about resource allocation.

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Scaling Factors

Many factors in configuring a scaled up pretraining run for Transformer Decoder + Autoregressive LM

- Model size (parameter counts)
- Pretraining dataset size
- Pretraining compute (FLOPs or TPU/GPU hours)
- Network shape (Parameters allocations)
- Effective batch size
- Learning rate & learning rate schedular
- Context length

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Main factors to study

Hyper-parameters with rule of thumb

1. Batch size determined by GPU memory
2. Try biggest LR before blowing up

Balance complexity and downstream needs

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Scaling Law Study: Setup

Empirically study the relationship between various factors to language model performances [4]

- Model: GPT-style, auto-regressive loss, maximum 1.5 billion non-embedding parameters
- Pretraining data: WebText2, harvest from Reddit out links, at max 23 billion tokens
- Metric: language modeling loss on testing data

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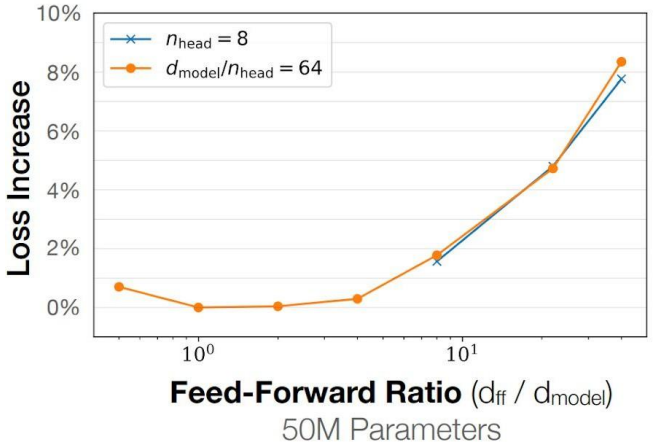
Scaling Law Study: Observations

Network shape (allocation of parameters at different parts) does not matter as much



Language model loss changes with different network shape configurations [4].

- As long as the network shape is in a general sweet range, it does not impact performance much

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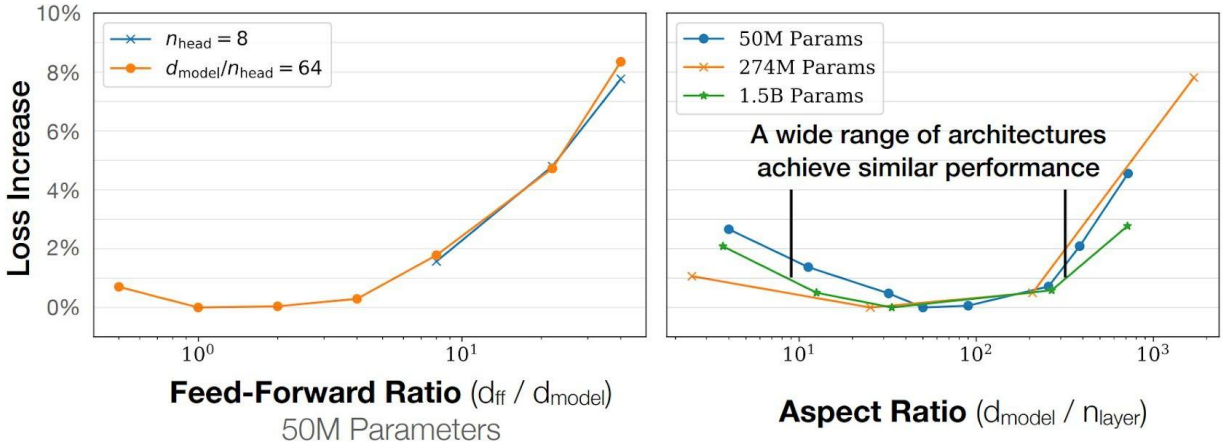
Scaling Law Study: Observations

Network shape (allocation of parameters at different parts) does not matter as much



Language model loss changes with different network shape configurations [4].

- As long as the network shape is in a general sweet range, it does not impact performance much

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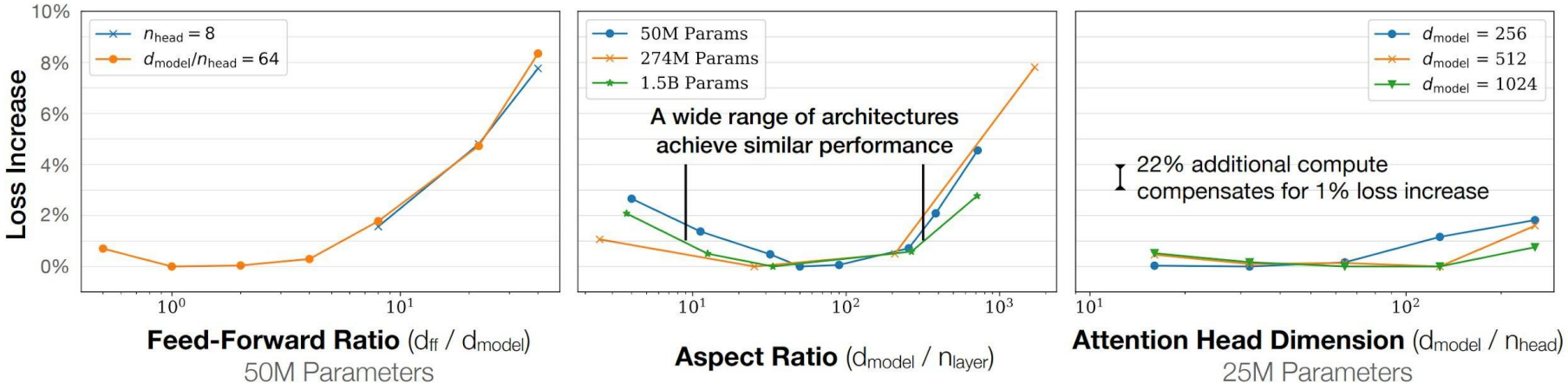

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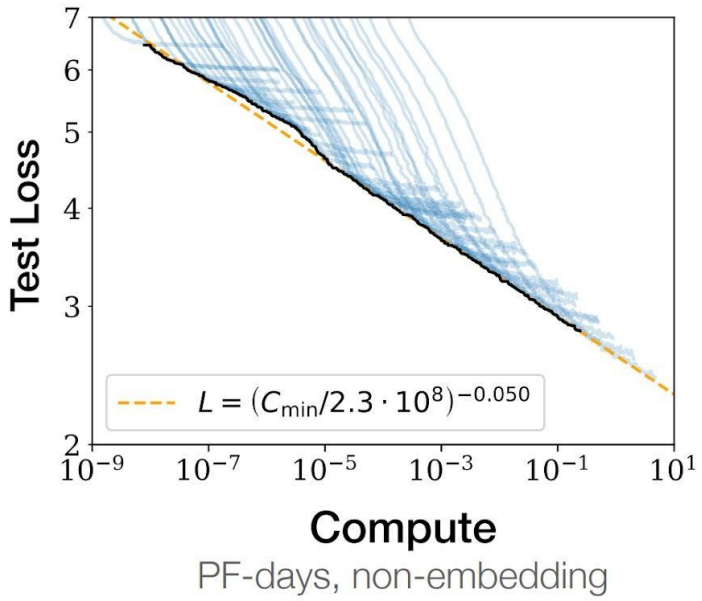
Scaling Law Study: Observations

A clear mapping from compute, data size, and parameter counts to testing loss



Mapping from compute (Peta-Flops days), data size, and model parameters to language modeling loss on testing data [4].

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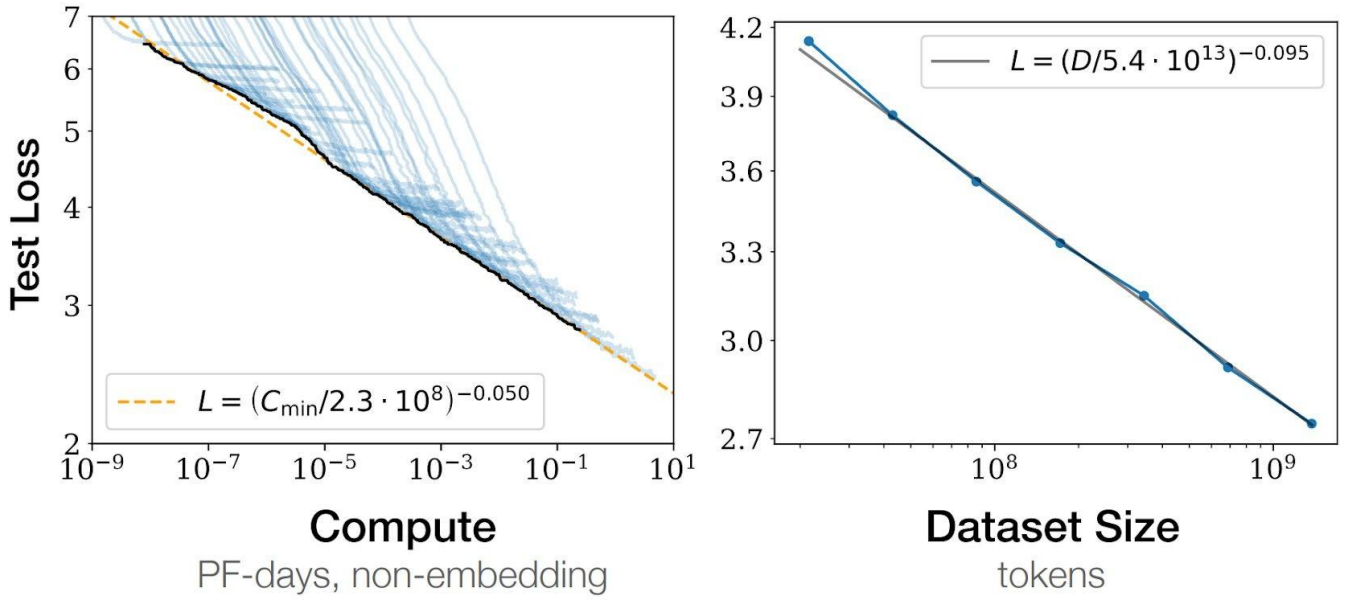

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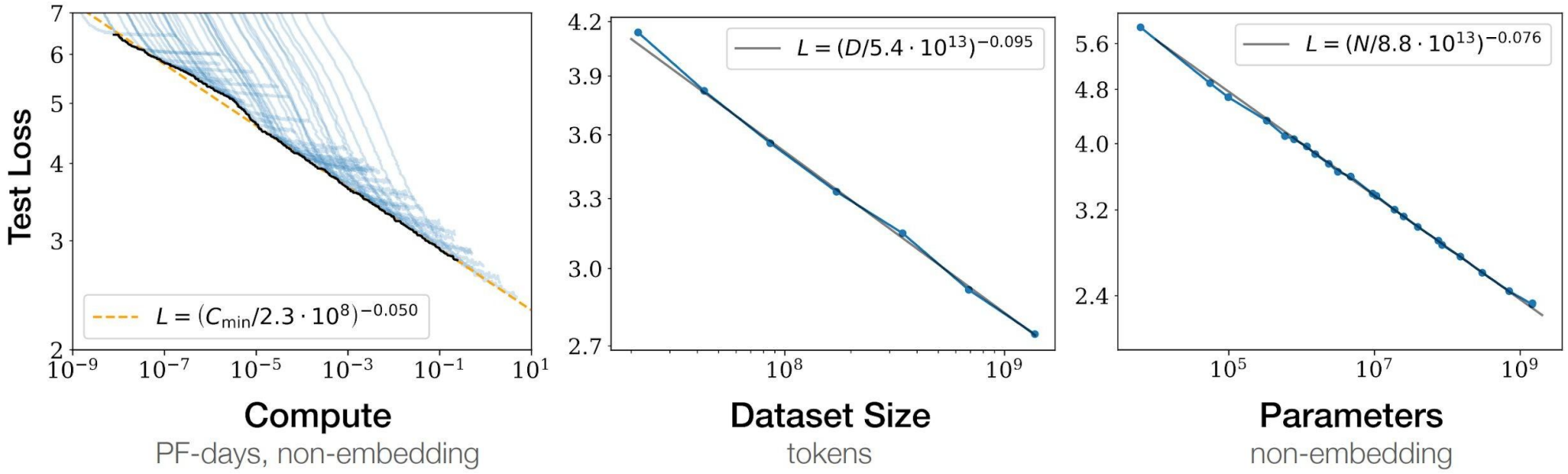

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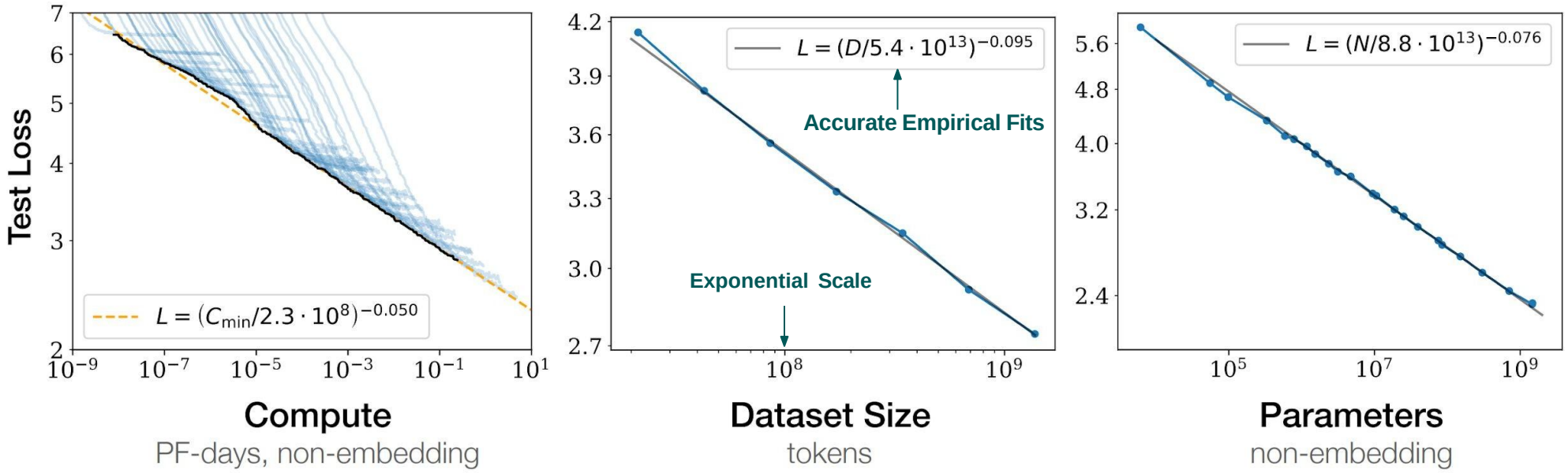

Mapping from compute (Peta-Flops days), data size, and model parameters to language modeling loss on testing data [4].

- Linear increasement of language modeling accuracy requires exponential scaling
- Three factors need to scale jointly to reach target model performance improvements

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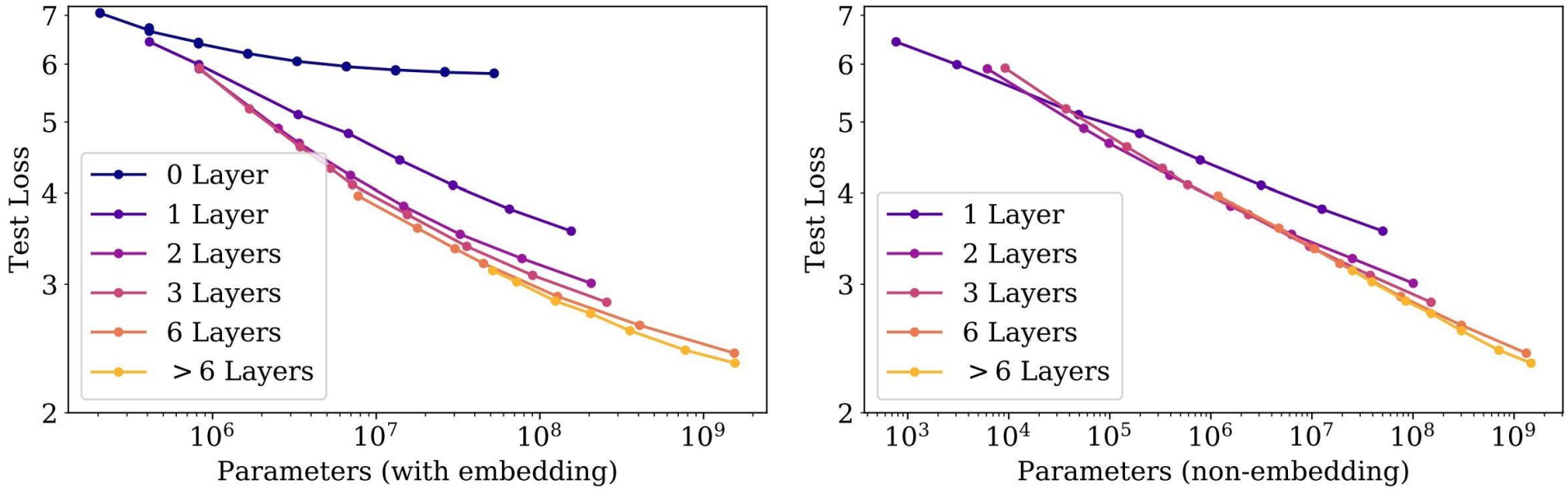
Scaling Law Study: Observations

Network parameters matter more than embedding parameters



Scaling law with network parameter counts include (left) and exclude (right) embeddings [4].

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What Configurations to Scale Up

Goal: Given a computing budget and a candidate language model, select the optimal scaling up configurations

- E.g., One million H100 hours, pretrain the best LLaMA style LLM
- Configurations to choose: Model size (# of parameters) and pretraining data size (# of tokens)

A common question when scaling up

- Computing budget is the biggest constraint
- No room for exploration at target scale
- Only one scaled up pretraining run allowed, both budget-wise and time-wise.

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Solution: Scaling law

- Use many experiments at small scale to establish the scaling law
- Use scaling Law to predict best configuration at target compute

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Scaling Configuration: Empirical Scaling Law

Empirical Approach #1: Fix model size and varying pretraining tokens [7]

1. Pretrain different sized models to near converge and track loss
2. Record best (model size, data size) at each FLOP.
3. Estimate the scaling law

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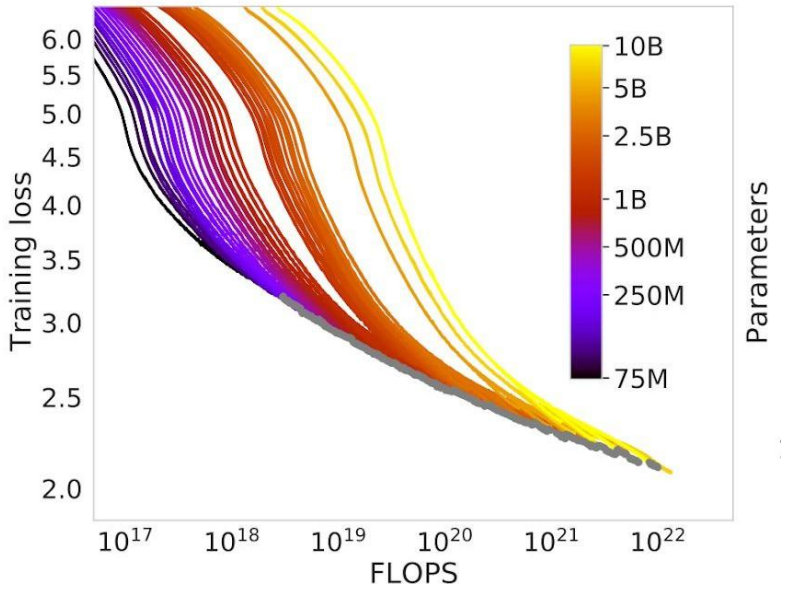

Pretraining loss of varying model (left), and the identified optimal parameters (mid) and tokens (right) at different FLOPS [6]

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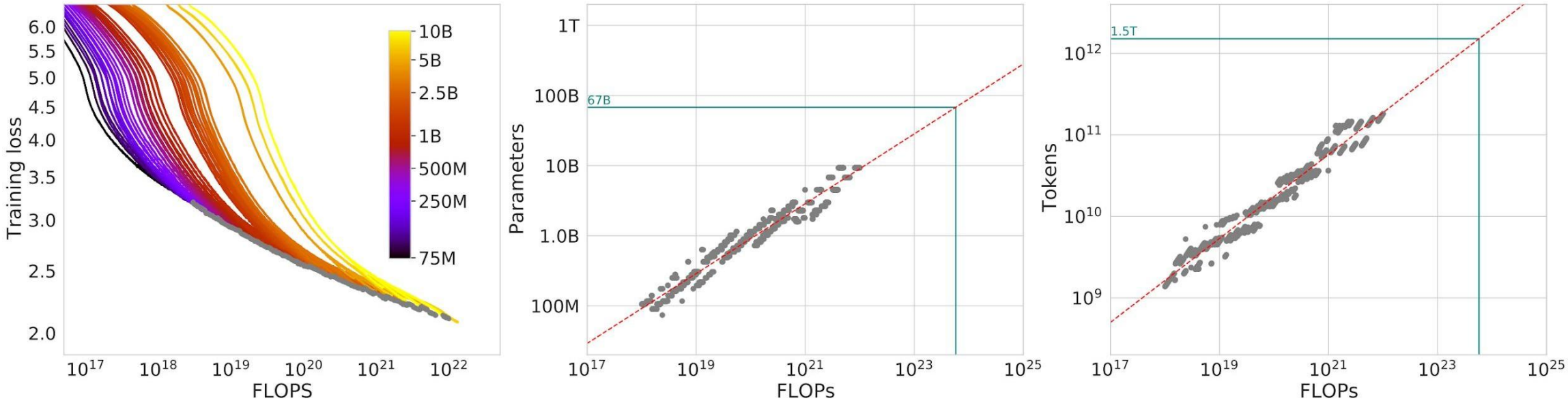

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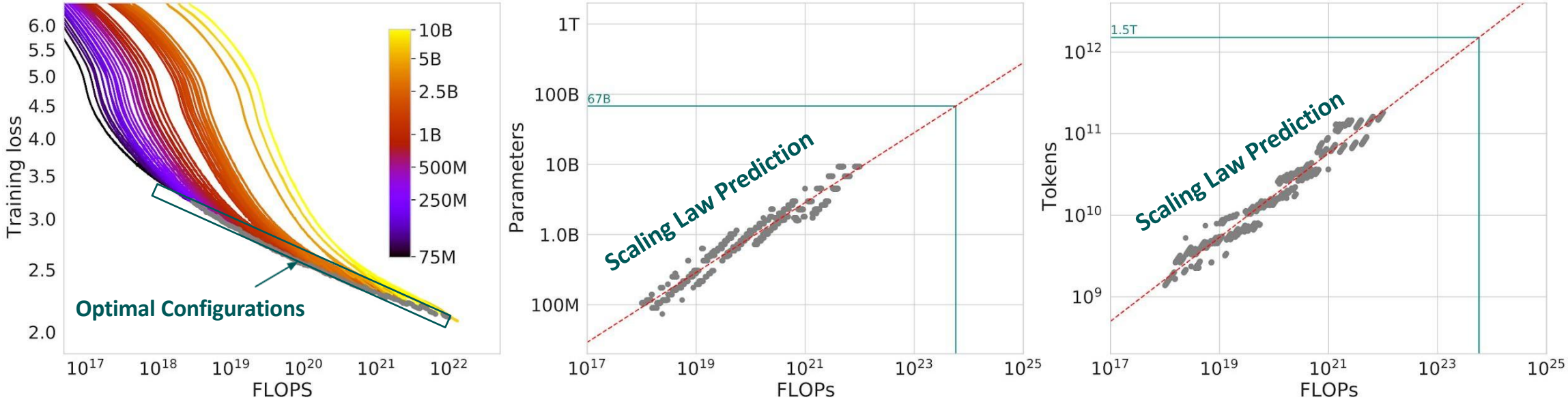

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Empirical Approach #2: Fix total FLOPs, pretrain different sized models [7]

1. Pretrain to the # of tokens using total FLOPs and track final loss
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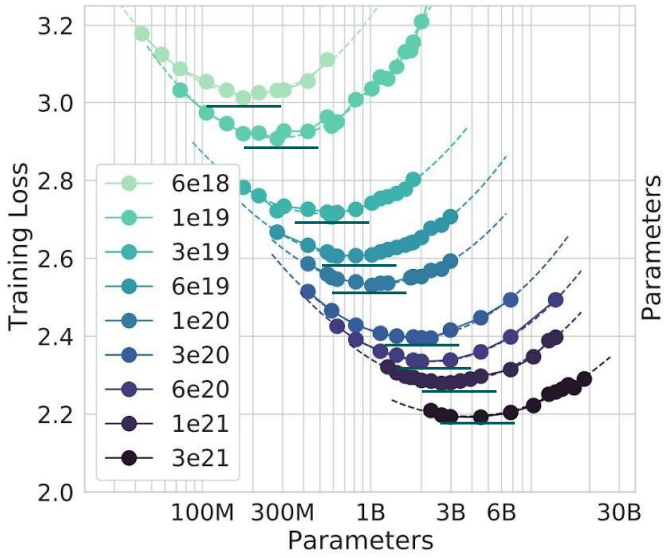

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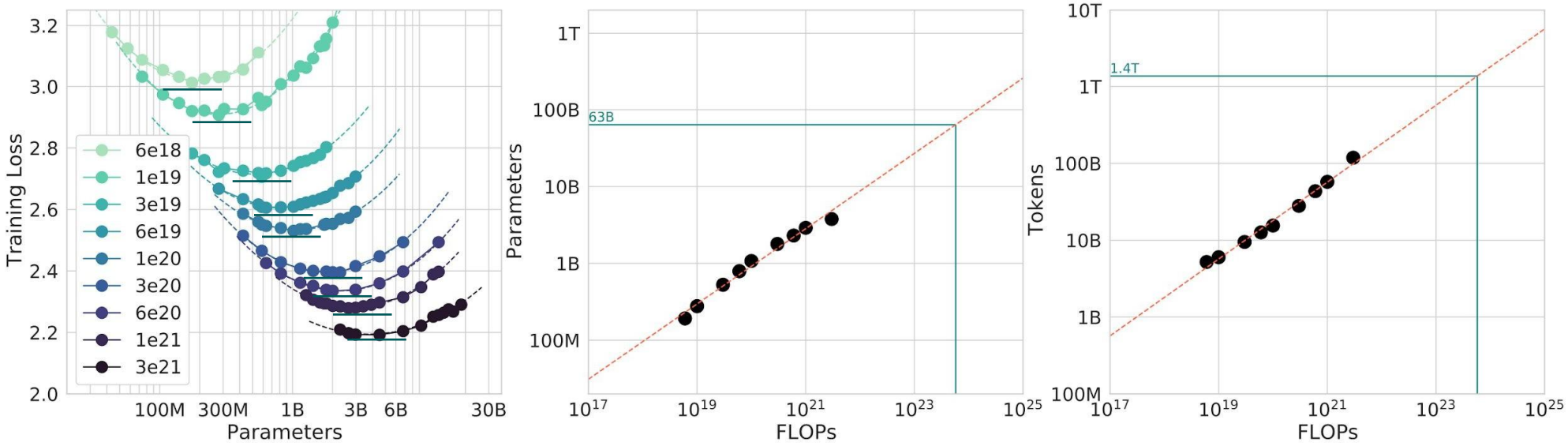

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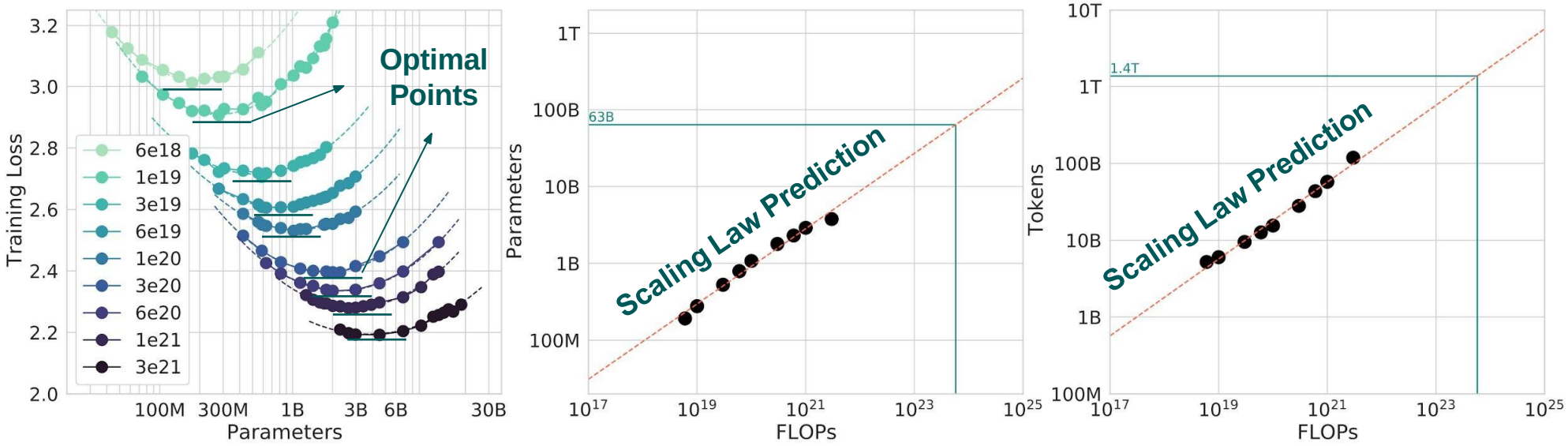

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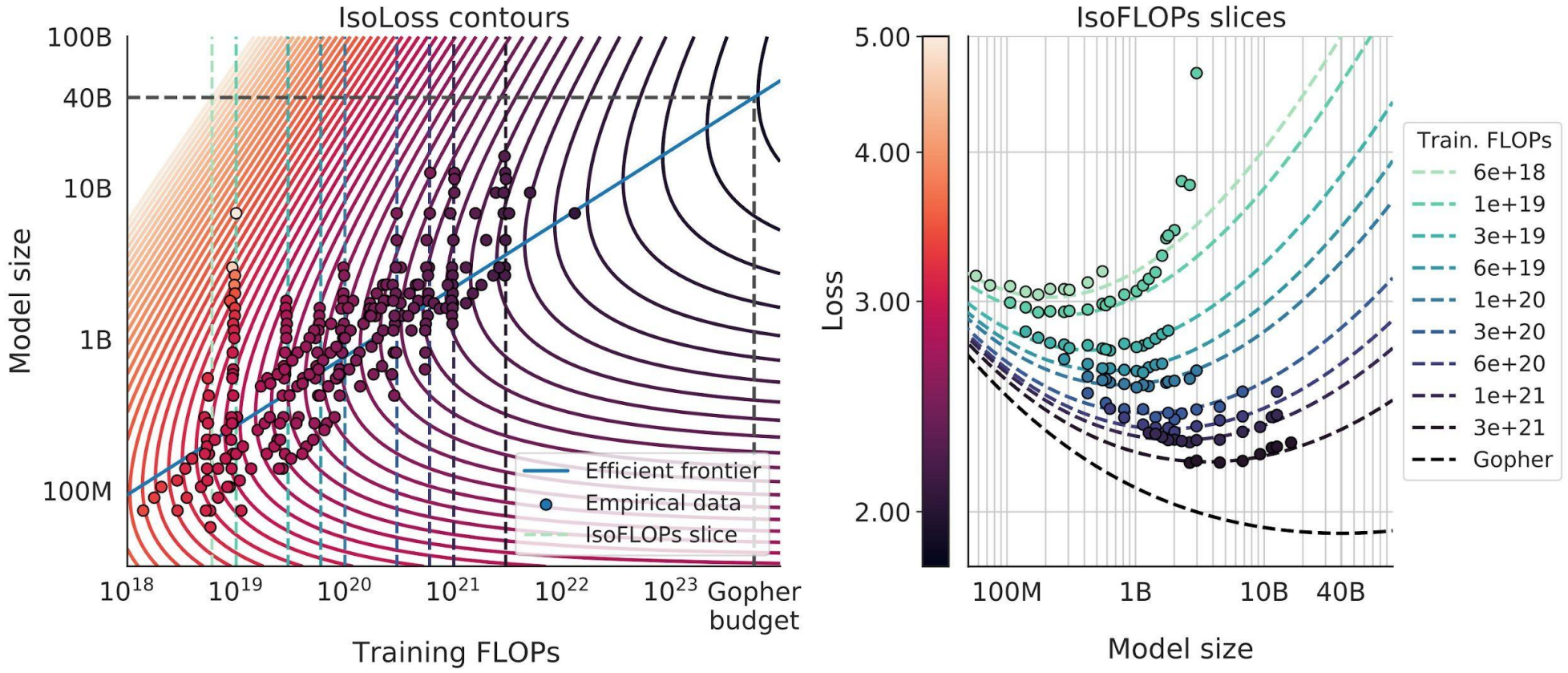
Scaling Configuration: Empirical Scaling Law

Empirical Approach #3: Using data points collected from previous two approaches and fix a parametric functions



Fitted parametric function of (model size, FLOPs)→Loss using data from approach one (left) and two (right) [6]

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Scaling Configuration: Estimated Optimal Configurations

Parameters	FLOPs	FLOPs (in *Gopher* unit)	Tokens
400 Million	1.92e+19	1/29,968	8.0 Billion
1 Billion	1.21e+20	1/4,761	20.2 Billion
10 Billion	1.23e+22	1/46	205.1 Billion
67 Billion	5.76e+23	1	1.5 Trillion
175 Billion	3.85e+24	6.7	3.7 Trillion
280 Billion	9.90e+24	17.2	5.9 Trillion
520 Billion	3.43e+25	59.5	11.0 Trillion
1 Trillion	1.27e+26	221.3	21.2 Trillion
10 Trillion	1.30e+28	22515.9	216.2 Trillion

Examples of estimated scaling configurations at different model sizes [3].

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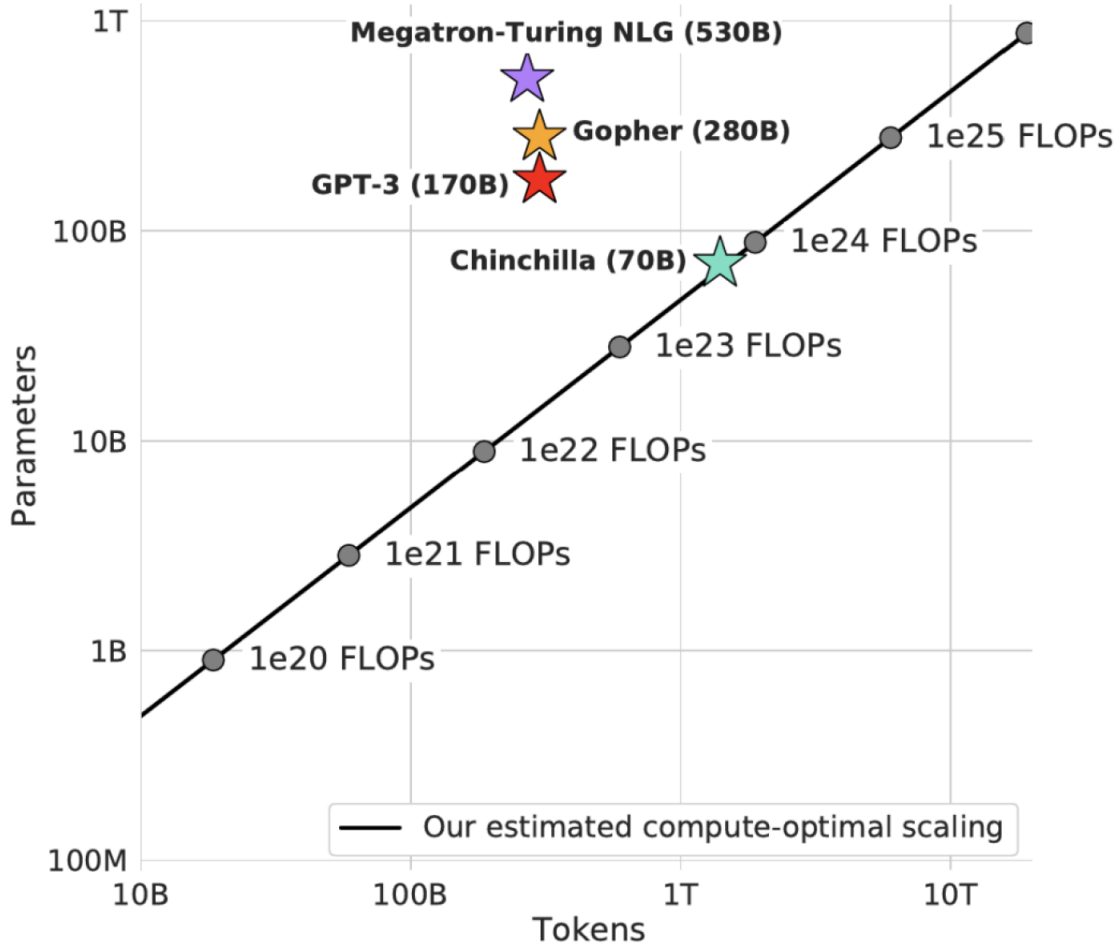
Large language models can be too large



Recent models and its training tokens:

LlaMA-1: 1-1.4 T tokens

LlaMA-2: 2T tokens

Mistral-7B: much more…

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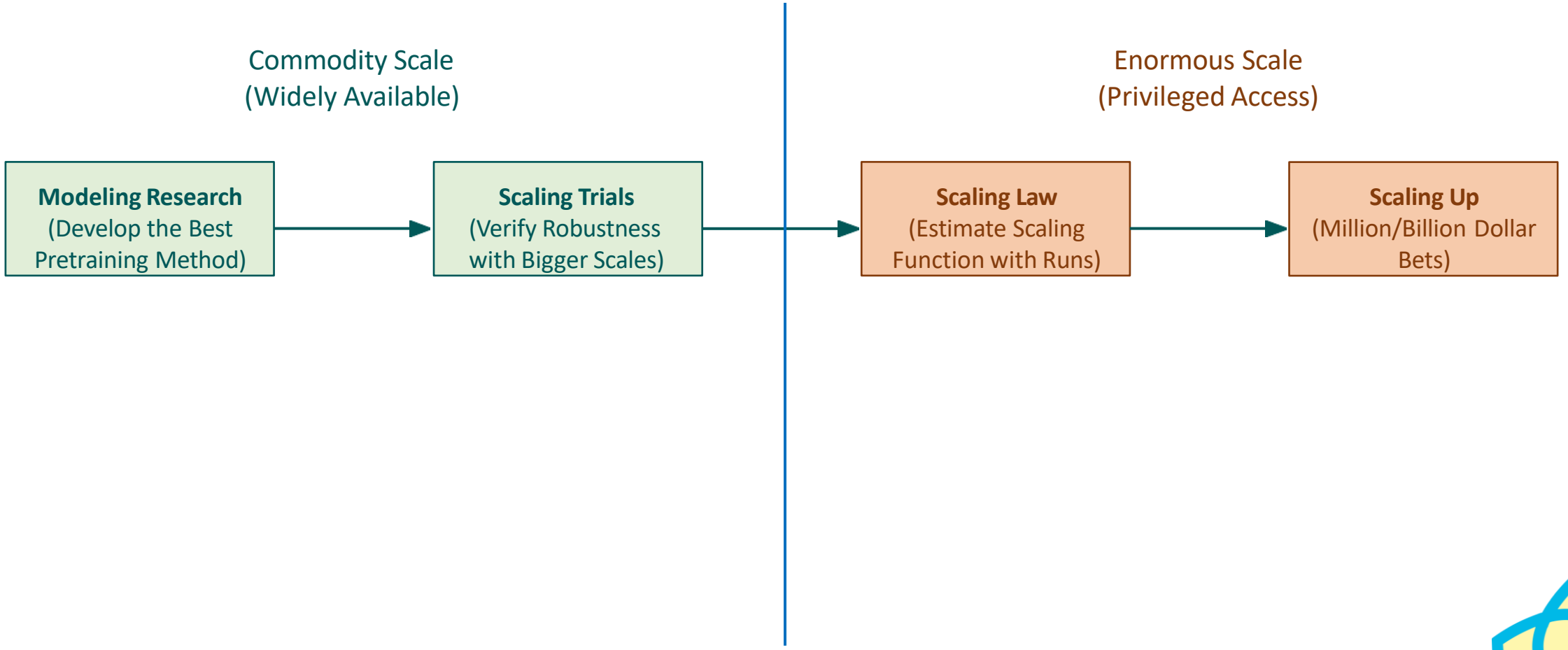
Scaling Up Pipeline

The current development pipeline of scaling up LLM pretraining, e.g., used by GPT-4, PaLM-2, and many more



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Scaling Up Pipeline

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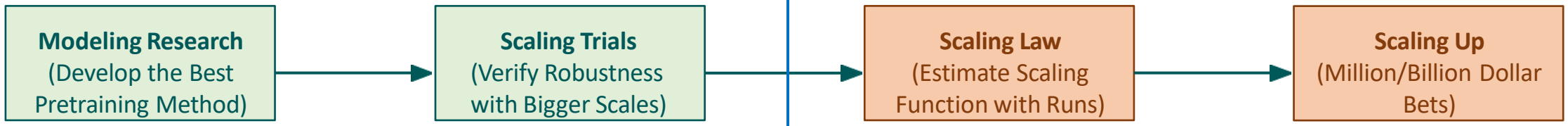
Commodity Scale
(Widely Available)

Enormous Scale
(Privileged Access)



Research

- Fast and many iterations
- Build new knowledge & understanding
- Can/Should take risks
- No guaranteed outcome
- Talent-heavy

Production?

- One scaling up run
- Build a better product: LLM
- Better not screw up
- Clear and short-term deliverables
- Resource-heavy

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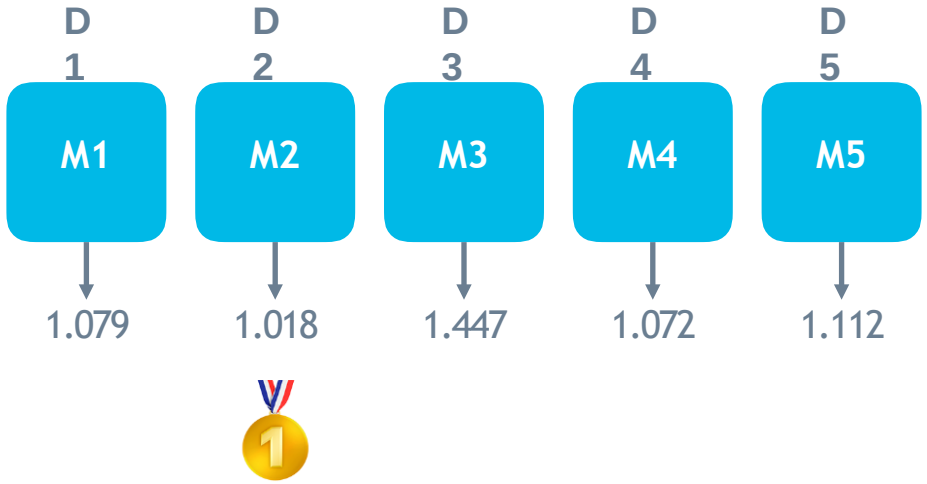
Putting scaling laws into practice



old paradigm: train a few models, select the best one

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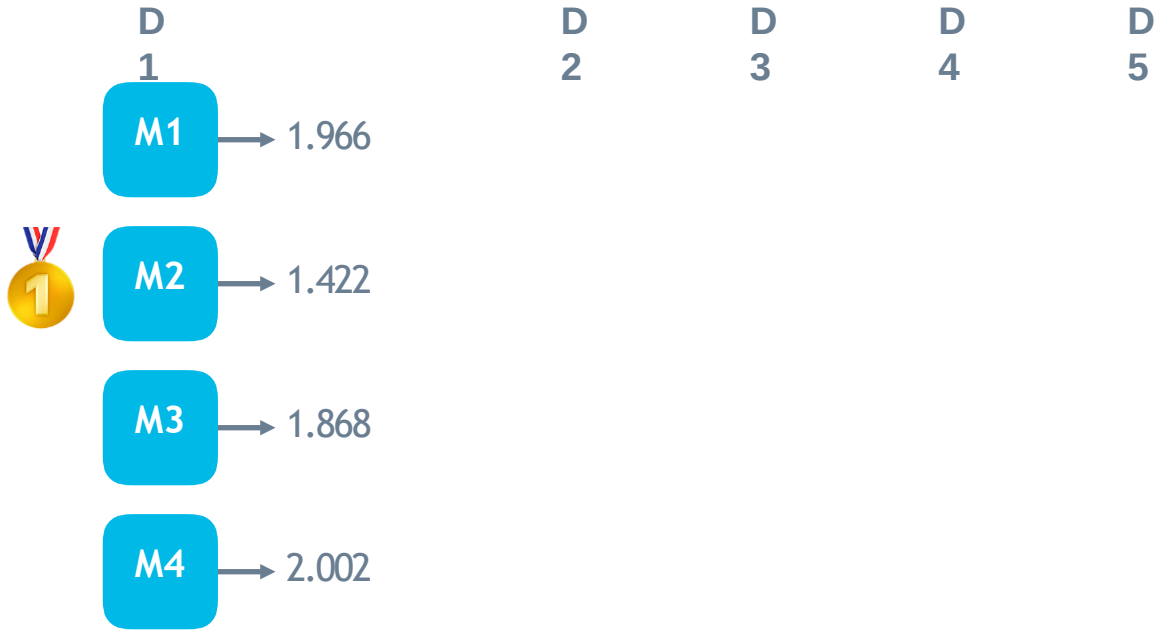

new paradigm: train many small models, up-scale the best one

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Scaling Law: Summary

- Why Scaling Up
  - Predictable benefits in nearly all scenarios
- Which Language Model to Scale Up
  - Benefits of decoder models
- What Factors Matter in Scaling
  - Strong mapping from compute, model size, and pretraining data size to language model performances
- What Configurations to Scale Up
  - Establish scaling law with small scale explorations, scaling up based on scaling law predictions
- Capabilities Emerged from Scaling Up
  - Lots of unknowns and challenges!

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- **LAIM LE4 VT2025:**

Pre-training
Parallel Training
Scaling

www.ida.liu.se/~freheo8/llm

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