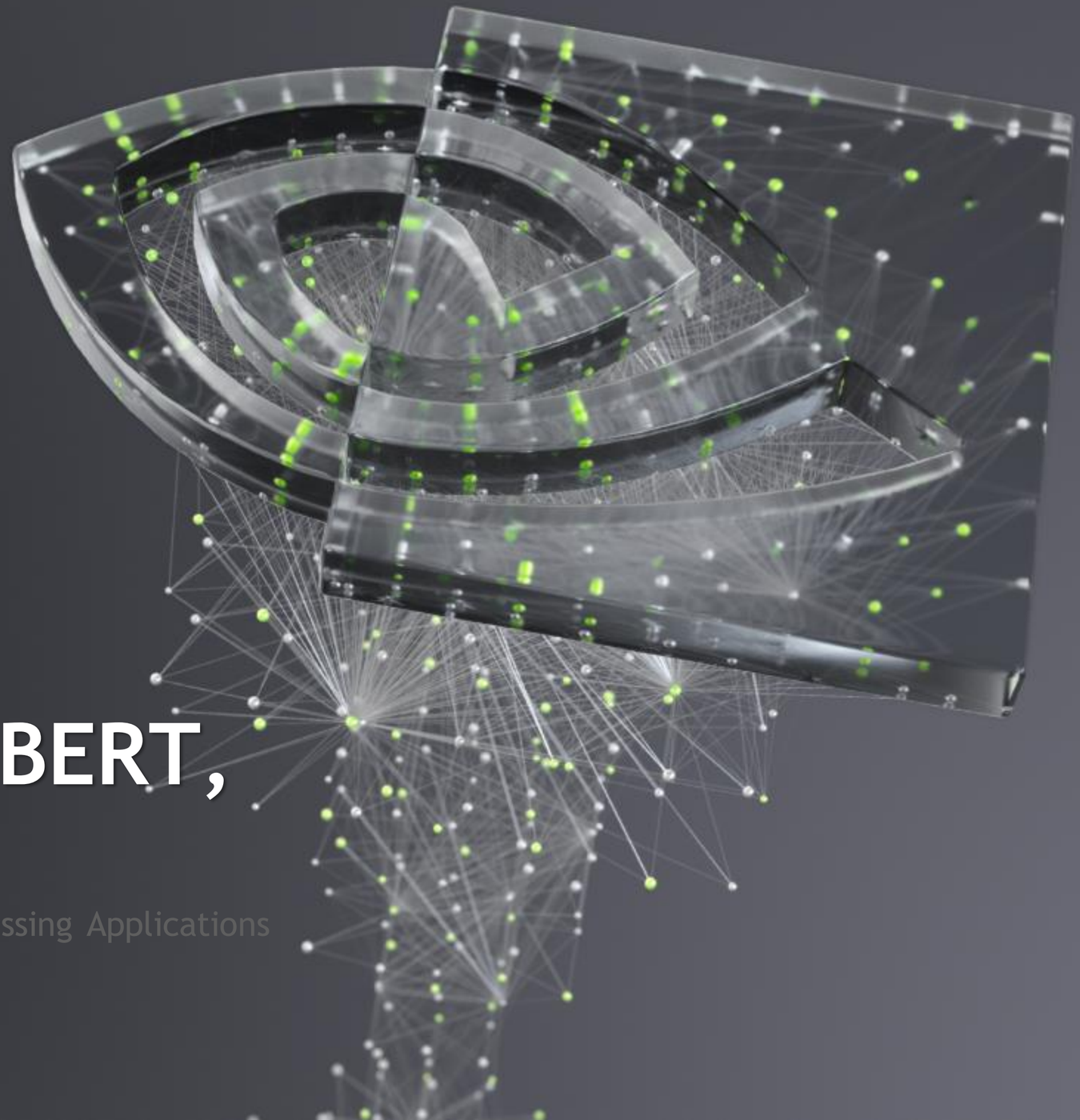

NVIDIA | DEEP LEARNING INSTITUTE

SELF-SUPERVISION, BERT, AND BEYOND

Building Transformer-Based Natural Language Processing Applications (Part 2)

FULL COURSE AGENDA

Part 1: Machine Learning in NLP

Lecture: NLP background and the role of DNNs leading to the Transformer architecture

Lab: Tutorial-style exploration of a ***translation task*** using the Transformer architecture

Part 2: Self-Supervision, BERT, and Beyond

Lecture: Discussion of how language models with self-supervision have moved beyond the basic Transformer to BERT and ever larger models

Lab: Practical hands-on guide to the NVIDIA NeMo API and exercises to build a ***text classification task*** and a ***named entity recognition task*** using BERT-based language models

Part 3: Production Deployment

Lecture: Discussion of production deployment considerations and NVIDIA Triton Inference Server

Lab: Hands-on deployment of an example ***question answering task*** to NVIDIA Triton

Part 2: Self-Supervision, BERT and Beyond

- Lecture
  - Why Do DNNs Work Well?
  - Self-Supervised Learning
  - BERT
- Lab
  - Explore the Data
  - Explore NeMo
  - Text Classifier Project
- Lecture (cont’d)
  - The Scaling Laws
  - Can and should we go even bigger?
- Lab (cont’d)
  - Named Entity Recognizer

Part 2: Self-Supervision, BERT and Beyond

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- Lab (cont'd)
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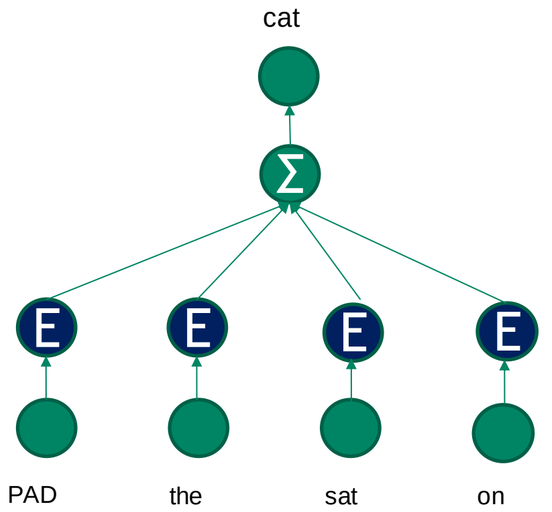
COMPUTE

Or lack of thereof

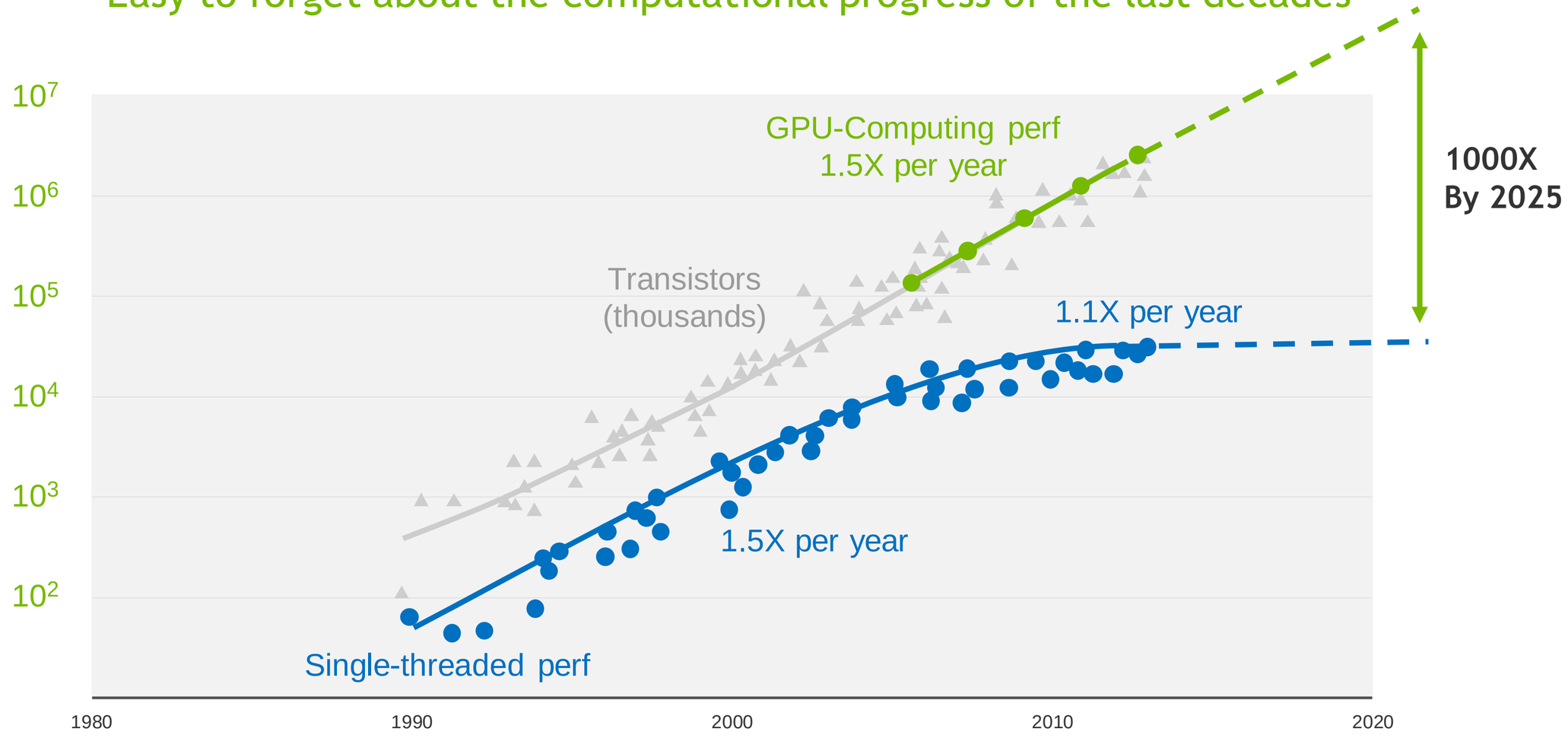
In this section, we propose two new model architectures for learning distributed representations of words that try to minimize computational complexity. The main observation from the previous section was that most of the complexity is caused by the non-linear hidden layer in the model. While this is what makes neural networks so attractive, we decided to explore simpler models that might not be able to represent the data as precisely as neural networks, but can possibly be trained on much more data efficiently.



Mikolov, Tomas, et al. "Efficient estimation of word representations in vector space." *arXiv preprint arXiv:1301.3781* (2013).

COMPUTE

Easy to forget about the computational progress of the last decades



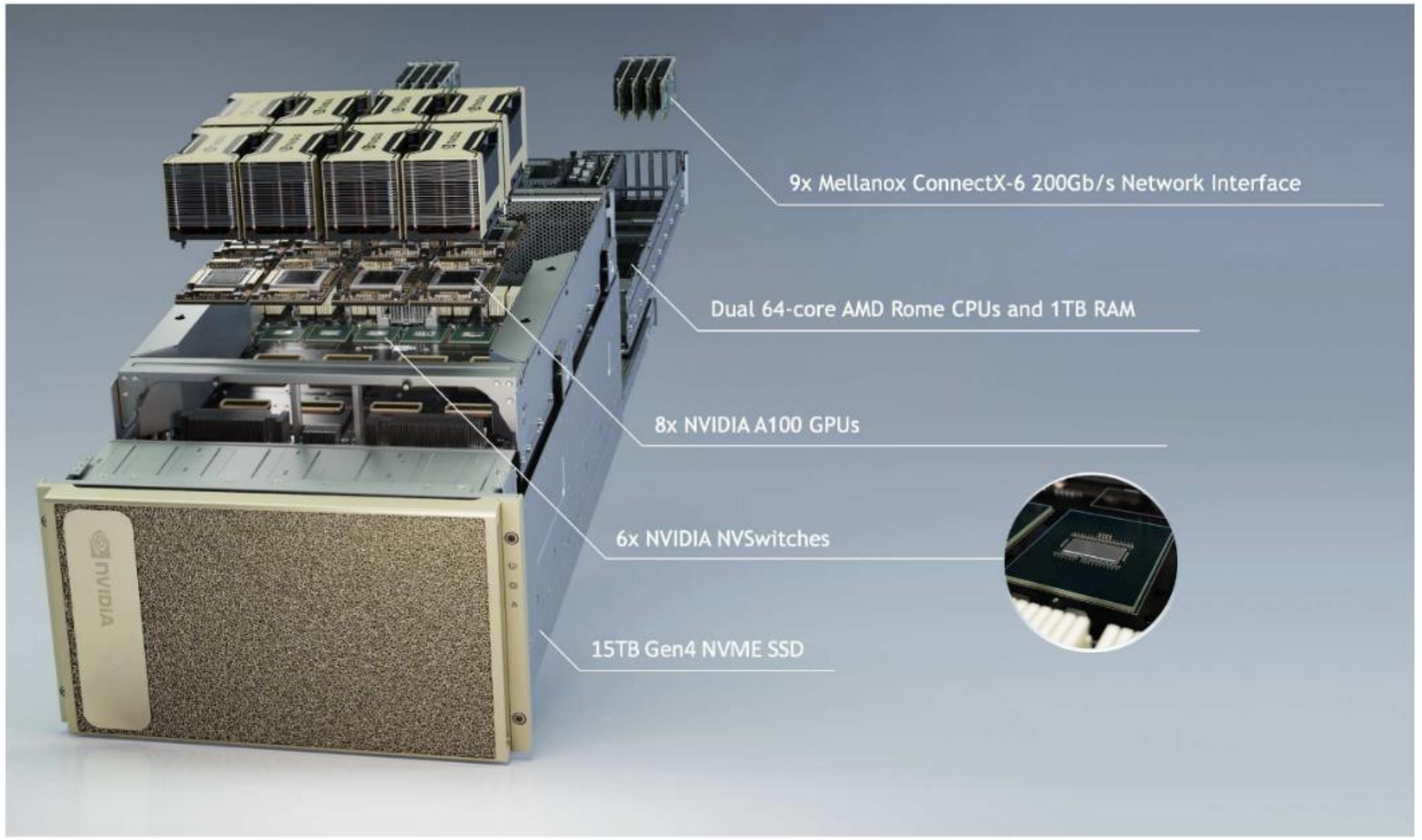
CONTEXT

CONTEXT

8 petaFLOPs in June 2011 (K Computer)

CONTEXT

5 petaFLOPs for AI - today



CONTEXT

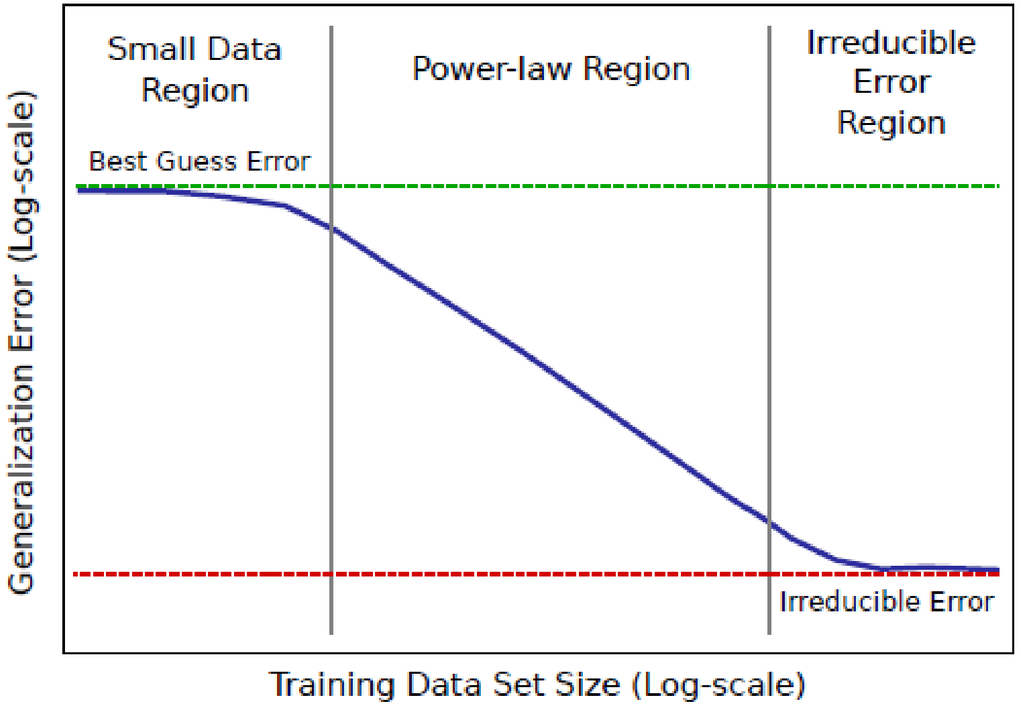
~100 PFLOPS (FP16) or 48 PFLOPS (TF32) for AI - today


100 EXAFLOPS
~=
2 YEARS ON A DUAL CPU SERVER

SCALING LAWS

SCALING LAWS

Power Law relationship between the dataset size and accuracy

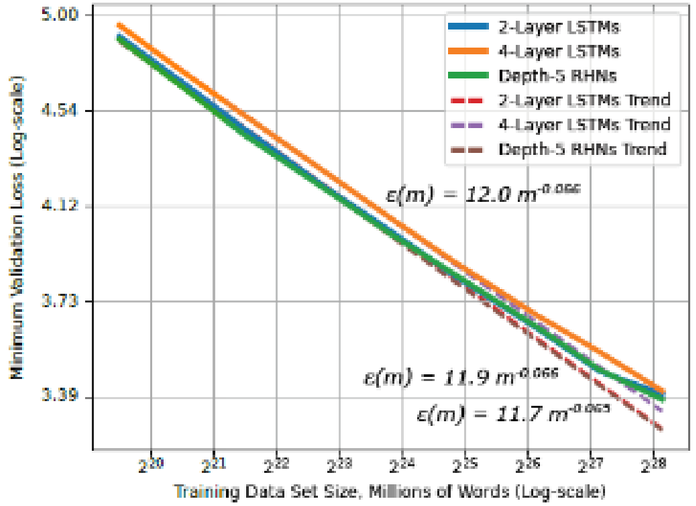


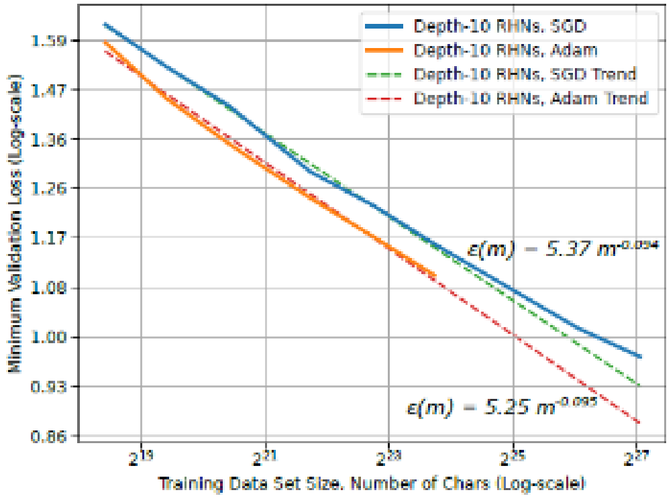
Hestness, J., Narang, S., Ardalani, N., Diamos, G., Jun, H., Kianinejad, H., ... & Zhou, Y. (2017). Deep Learning Scaling is Predictable, Empirically. arXiv preprint arXiv:1712.00409

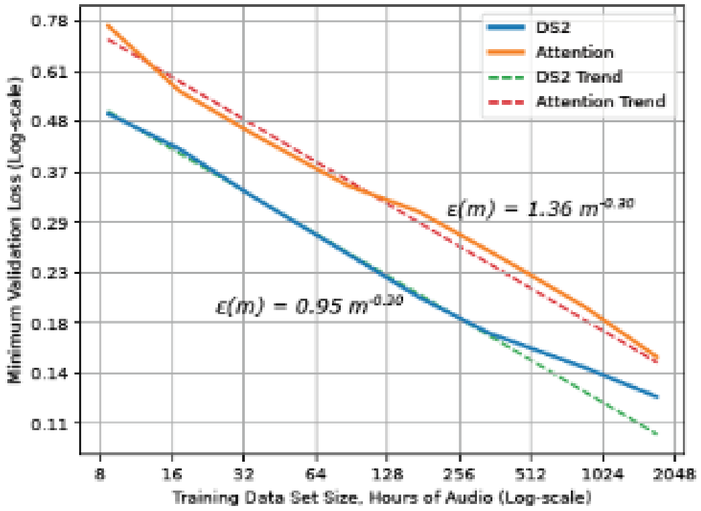
SCALING LAWS

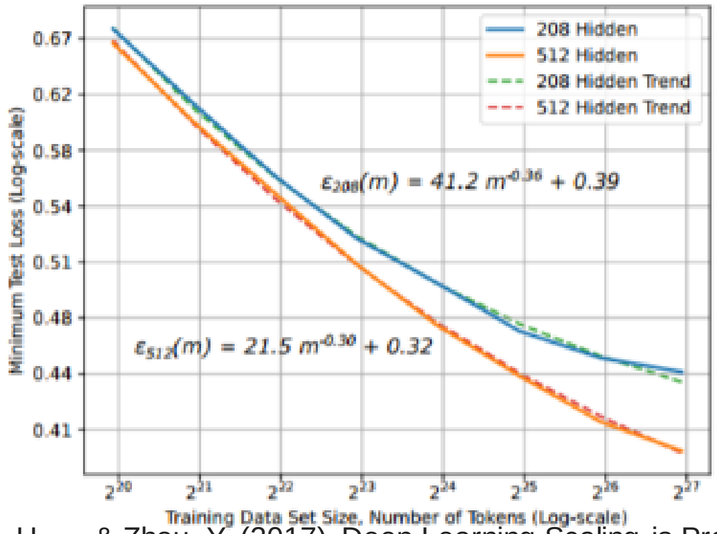
Applicable across all AI tasks

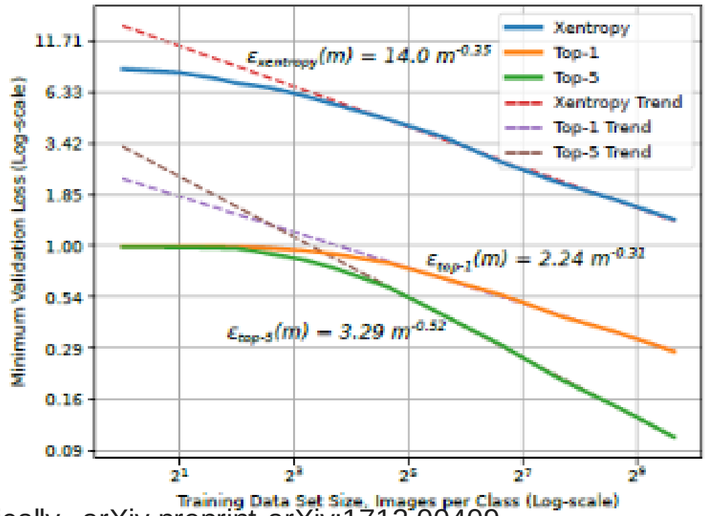
- Translation
- Language Models
- Character Language Models
- Image Classification
- Attention Speech Models











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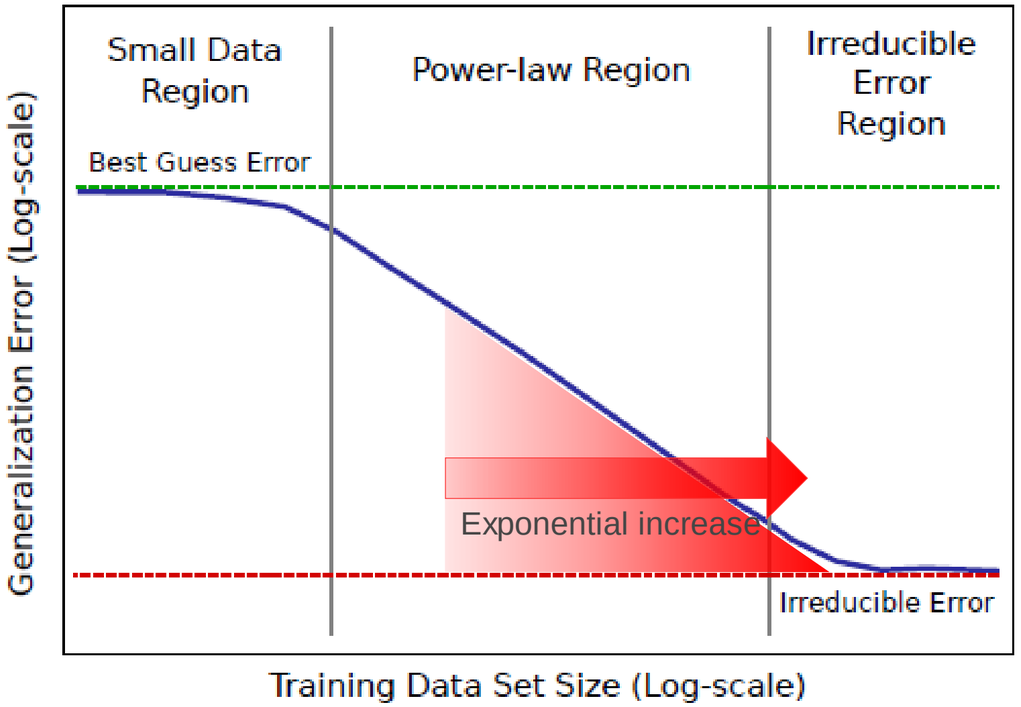
THE COST

THE COST OF LABELING

Limits the utility of deep learning models



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  - Can and should we go even bigger?
- Lab (cont'd)
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SELF-SUPERVISED LEARNING

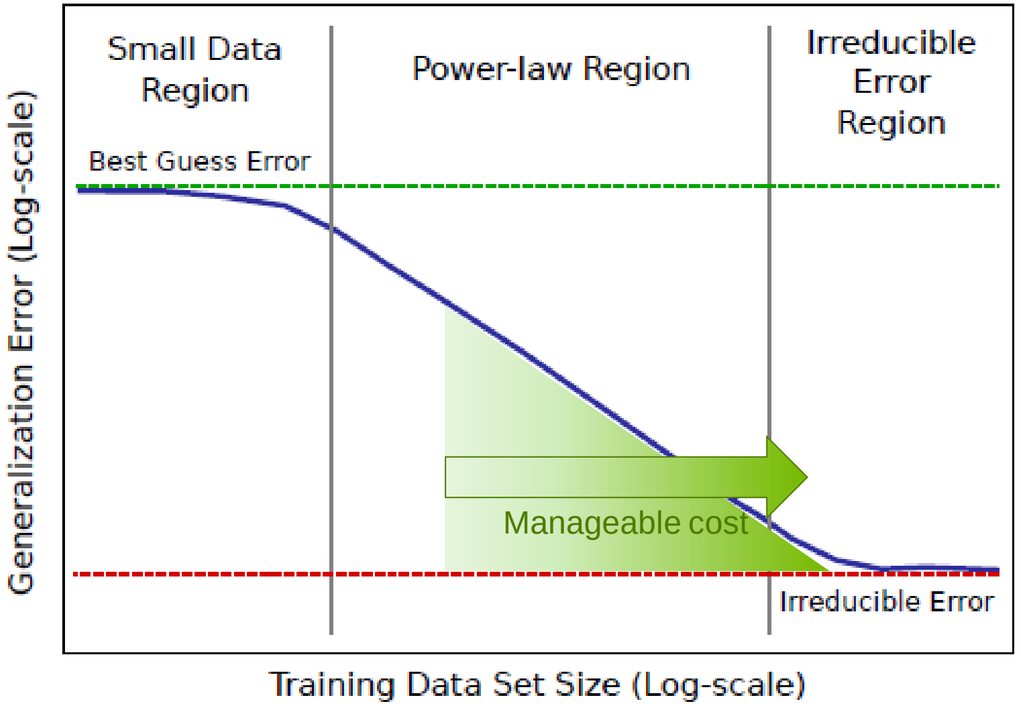
Example training tasks

- Natural Language Processing:
  - Masked Language Model: We mask a percentage of the input tokens at random (say 15%) and ask the neural network to predict the entire sentence
  - Next Sentence Prediction: We choose either two consecutive sentences from text, or two random sentences from the text. We ask the neural network to establish whether the two sentences occur one after another.
  - We use another simpler neural network to replace random words in the sequence and ask the primary neural network to detect which words were replaced (using a GAN like configuration).
- Computer Vision:
  - Contrastive Learning: Randomly modify (crop and resize, flip, distort color, rotate, cut-out, noise, blur, etc.) and either feed the same image, or two randomly selected images, into the neural network, asking it to say whether it is the same image or not
  - Noisy labels/Self Training: Use labels generated by a weak algorithm (potentially older generation of the target model) to train a target-robust feature extractor

Dai, A. M., & Le, Q. V. (2015). Semi-supervised sequence learning. In Advances in neural information processing systems (pp. 3079-3087).
Chen, T., Kornblith, S., Norouzi, M., & Hinton, G. (2020). A simple framework for contrastive learning of visual representations. arXiv preprint arXiv:2002.05709.
Xie, Q., Hovy, E., Luong, M. T., & Le, Q. V. (2019). Self-training with Noisy Student improves ImageNet classification. arXiv preprint arXiv:1911.04252.

THE COST OF LABELING

Semi-supervised models



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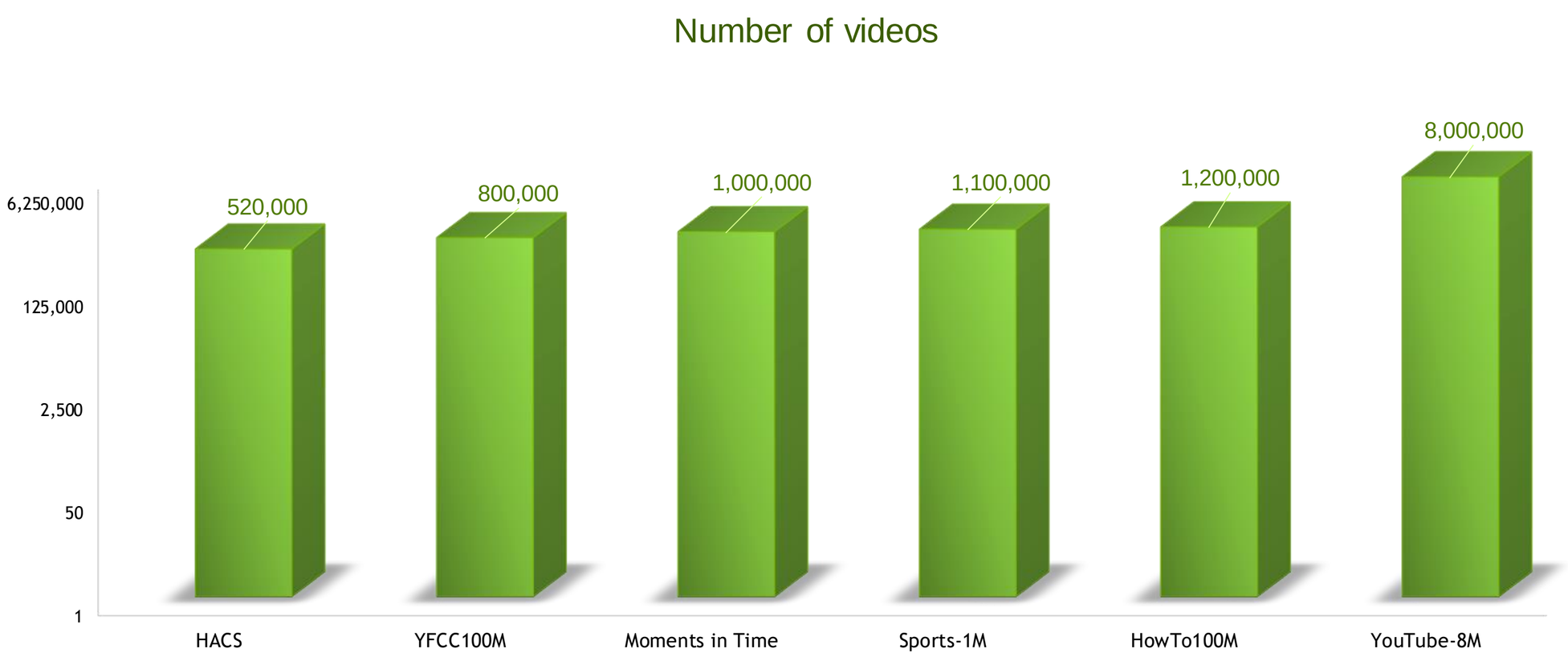
SELF-SUPERVISED LEARNING

Abundance of unlabeled data

SELF-SUPERVISED LEARNING

Abundance of unlabeled data



OLD IDEAS

SELF-SUPERVISED LEARNING

What was missing?

Semi-supervised Sequence Learning

Andrew M. Dai
Google Inc.
adai@google.com

Quoc V. Le
Google Inc.
qvl@google.com

Abstract

We present two approaches that use unlabeled data to improve sequence learning with recurrent networks. The first approach is to predict what comes next in a sequence, which is a conventional language model in natural language processing. The second approach is to use a sequence autoencoder, which reads the input sequence into a vector and predicts the input sequence again. These two algorithms can be used as a "pretraining" step for a later supervised sequence learning algorithm. In other words, the parameters obtained from the unsupervised step can be used as a starting point for other supervised training models. In our experiments, we find that long short term memory recurrent networks after being pretrained with the two approaches are more stable and generalize better. With pretraining, we are able to train long short term memory recurrent networks up to a few hundred timesteps, thereby achieving strong performance in many text classification tasks, such as IMDB, DBpedia and 20 Newsgroups.

THE SCALE

GENERATIVE PRETRAINING (GPT)

The scale

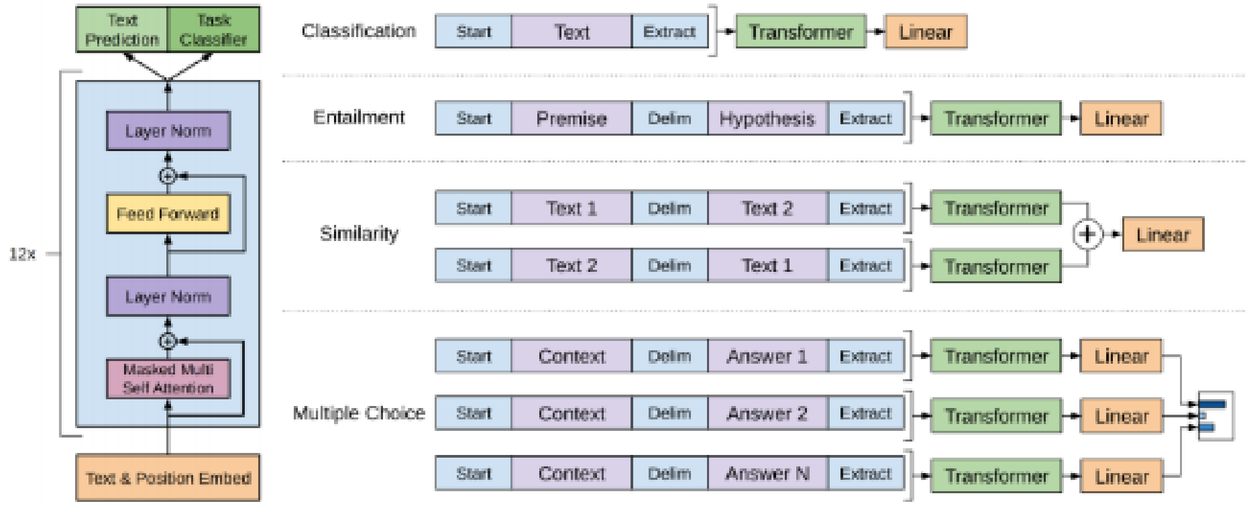
"Many previous approaches to NLP tasks train relatively small models on a single GPU from scratch. Our approach requires an expensive pre-training step - 1 month on 8 GPUs. Luckily, this only has to be done once and we're releasing our model so others can avoid it. It is also a large model (in comparison to prior work) and consequently uses more compute and memory — we used a 37-layer (12 block) Transformer architecture, and we train on sequences of up to 512 tokens. Most experiments were conducted on 4 and 8 GPU systems. The model does fine-tune to new tasks very quickly which helps mitigate the additional resource requirements."

Radford, A., Narasimhan, K., Salimans, T., & Sutskever, I. (2018). Improving language understanding by generative pre-training. *URL https://s3-us-west-2. amazonaws. com/openai-assets/researchcovers/languageunsupervised/language understanding paper. pdf*.

GENERATIVE PRETRAINING (GPT)

The design

Transformer Decoder



Self-Supervised Training

Figure 1: **(left)** Transformer architecture and training objectives used in this work. **(right)** Input transformations for fine-tuning on different tasks. We convert all structured inputs into token sequences to be processed by our pre-trained model, followed by a linear+softmax layer.

Radford, A., Narasimhan, K., Salimans, T., & Sutskever, I. (2018). Improving language understanding by generative pre-training. *URL https://s3-us-west-2. amazonaws. com/openai-assets/researchcovers/languageunsupervised/language understanding paper. pdf*.


IT BECAME POSSIBLE TO
TRANSFER LEARN!

GENERATIVE PRETRAINING (GPT)

The approach

Pre-training our model on a large corpus of text significantly improves its performance on challenging natural language processing tasks like Winograd Schema Resolution.

Radford, A., Narasimhan, K., Salimans, T., & Sutskever, I. (2018). Improving language understanding by generative pre-training. *URL https://s3-us-west-2. amazonaws. com/openai-assets/researchcovers/languageunsupervised/language understanding paper. pdf*.

GENERATIVE PRETRAINING (GPT)

The implications

Pre-training our model on a large corpus of text significantly improves its performance on challenging natural language processing tasks like Winograd Schema Resolution.

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AND IT WORKED VERY WELL

GENERATIVE PRETRAINING (GPT)

The implications

DATASET	TASK	SOTA	OURS
SNLI	Textual Entailment	89.3	**89.9**
MNLI Matched	Textual Entailment	80.6	**82.1**
MNLI Mismatched	Textual Entailment	80.1	**81.4**
SciTail	Textual Entailment	83.3	**88.3**
QNLI	Textual Entailment	82.3	**88.1**
RTE	Textual Entailment	**61.7**	56.0
STS-B	Semantic Similarity	81.0	**82.0**
QQP	Semantic Similarity	66.1	**70.3**
MRPC	Semantic Similarity	**86.0**	82.3
RACE	Reading Comprehension	53.3	**59.0**
ROCStories	Commonsense Reasoning	77.6	**86.5**
COPA	Commonsense Reasoning	71.2	**78.6**
SST-2	Sentiment Analysis	**93.2**	91.3
CoLA	Linguistic Acceptability	35.0	**45.4**
GLUE	Multi Task Benchmark	68.9	**72.8**

Radford, A., Narasimhan, K., Salimans, T., & Sutskever, I. (2018). Improving language understanding by generative pre-training. *URL https://s3-us-west-2. amazonaws. com/openai-assets/researchcovers/languageunsupervised/language understanding paper. pdf*.

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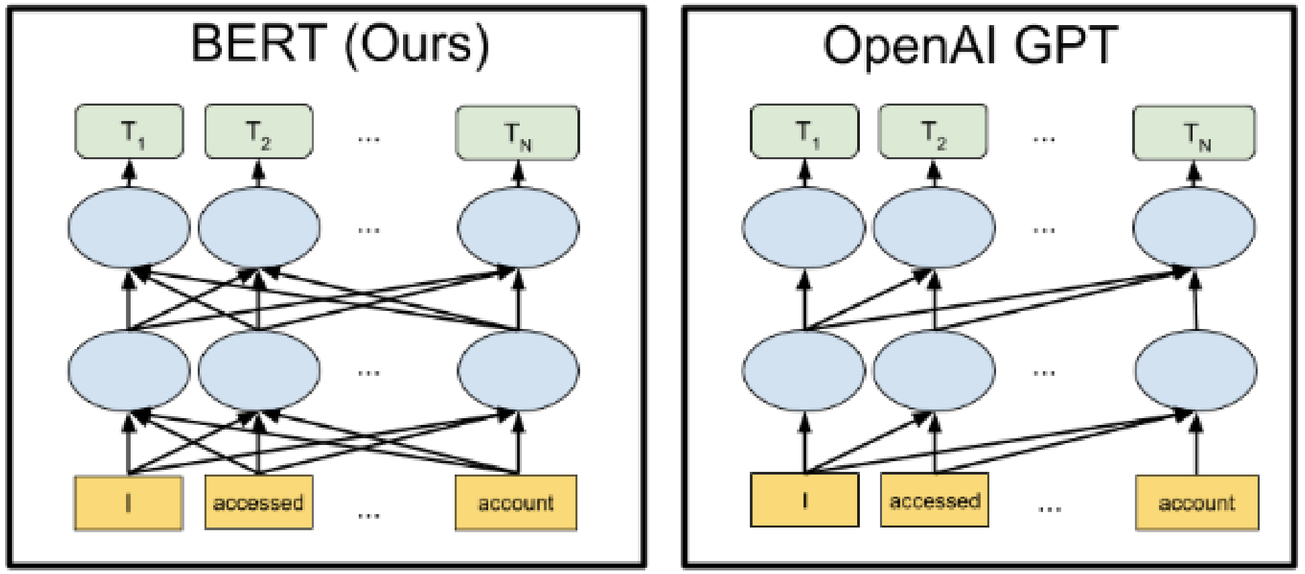
BIDIRECTIONAL TRANSFORMERS (BERT)

Building on the shoulders of giants



Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.

BIDIRECTIONAL TRANSFORMERS (BERT)

The “pre” and “post” OpenAI ages

System	MNLI-(m/mm) 392k	QQP 363k	QNLI 108k	SST-2 67k	CoLA 8.5k	STS-B 5.7k	MRPC 3.5k	RTE 2.5k	**Average** -
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**92.7**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**82.1**

Table 1: GLUE Test results, scored by the evaluation server (https://gluebenchmark.com/leaderboard). The number below each task denotes the number of training examples. The “Average” column is slightly different than the official GLUE score, since we exclude the problematic WNLI set.[8] BERT and OpenAI GPT are single-model, single task. F1 scores are reported for QQP and MRPC, Spearman correlations are reported for STS-B, and accuracy scores are reported for the other tasks. We exclude entries that use BERT as one of their components.

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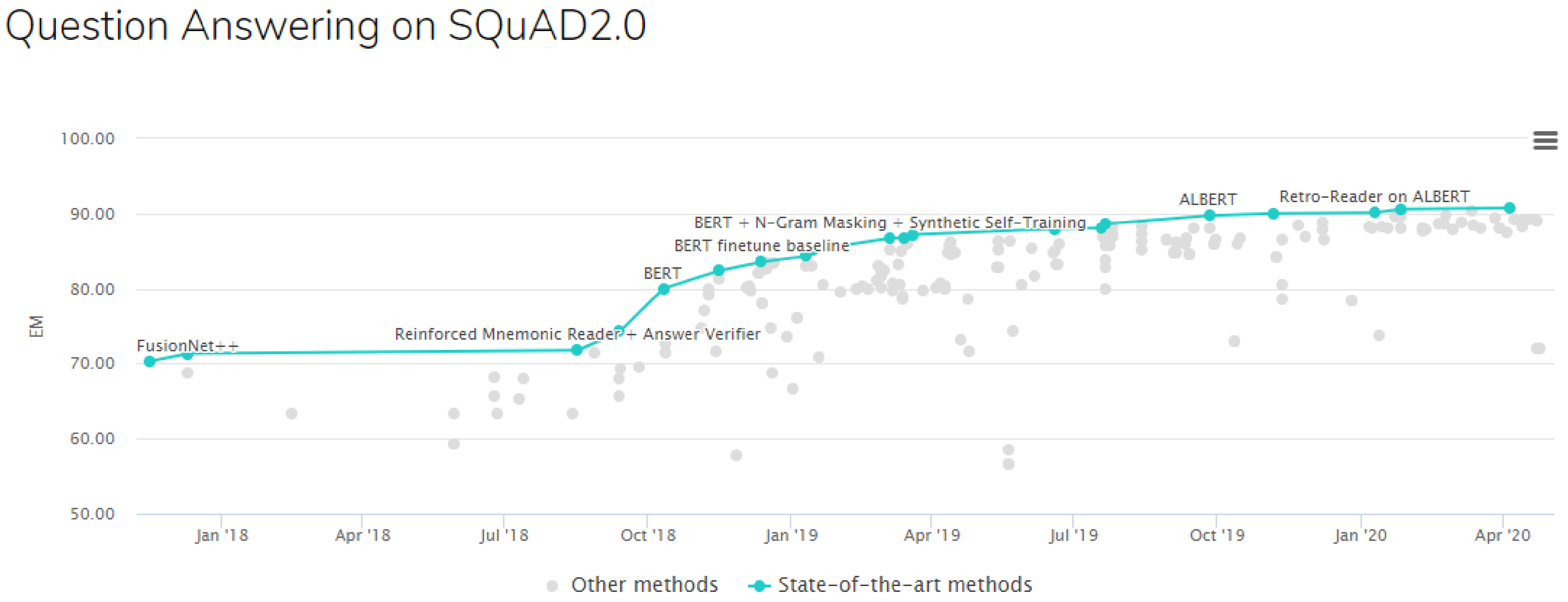
SQUAD 2.0

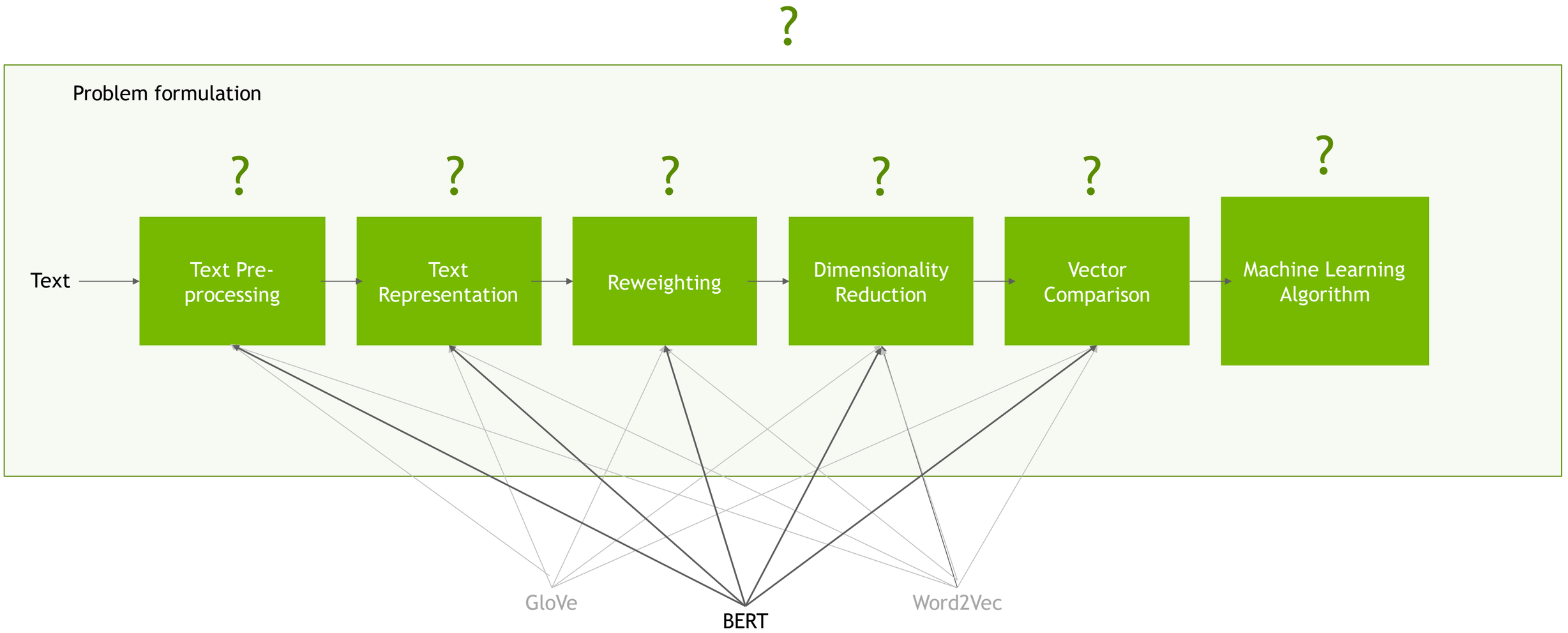
Human performance 91.2



JUST YET ANOTHER UNSUPERVISED REPRESENTATION

USING BERT

Feature extractor

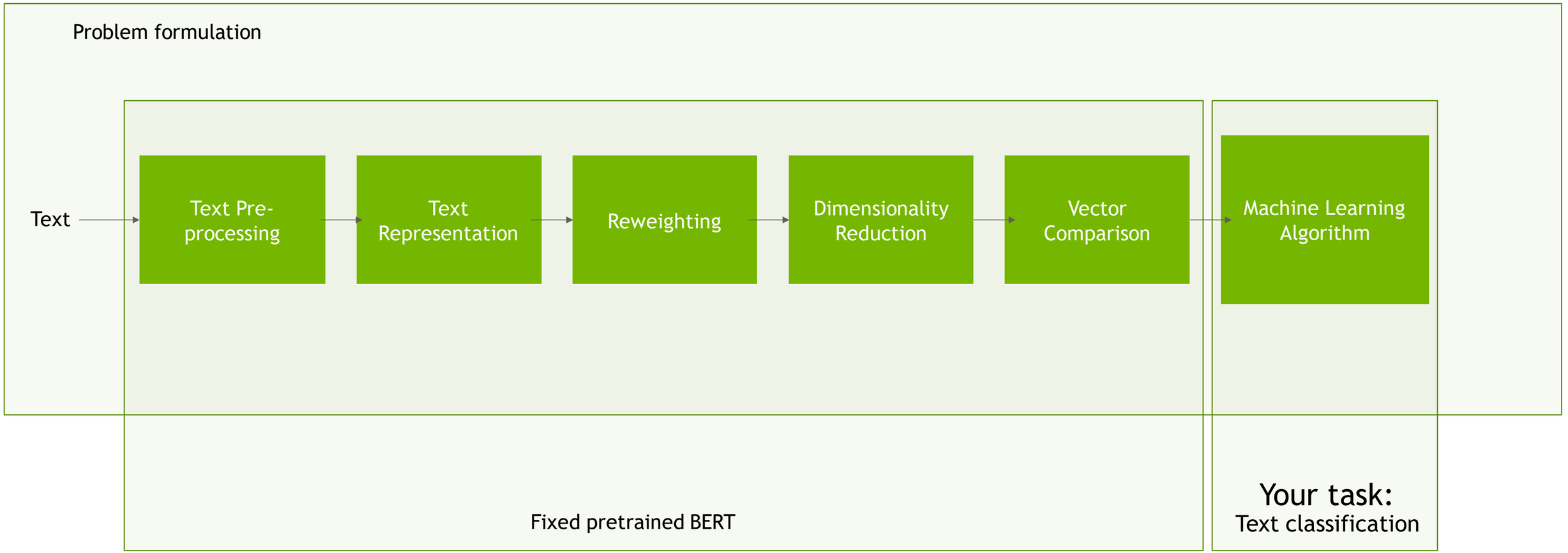


THE LAB

LAB OVERVIEW

Notebooks 1, 2, 3

Text classification



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BIDIRECTIONAL TRANSFORMERS (BERT)

Base vs Large

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GPT-2
GPT vs GPT-2

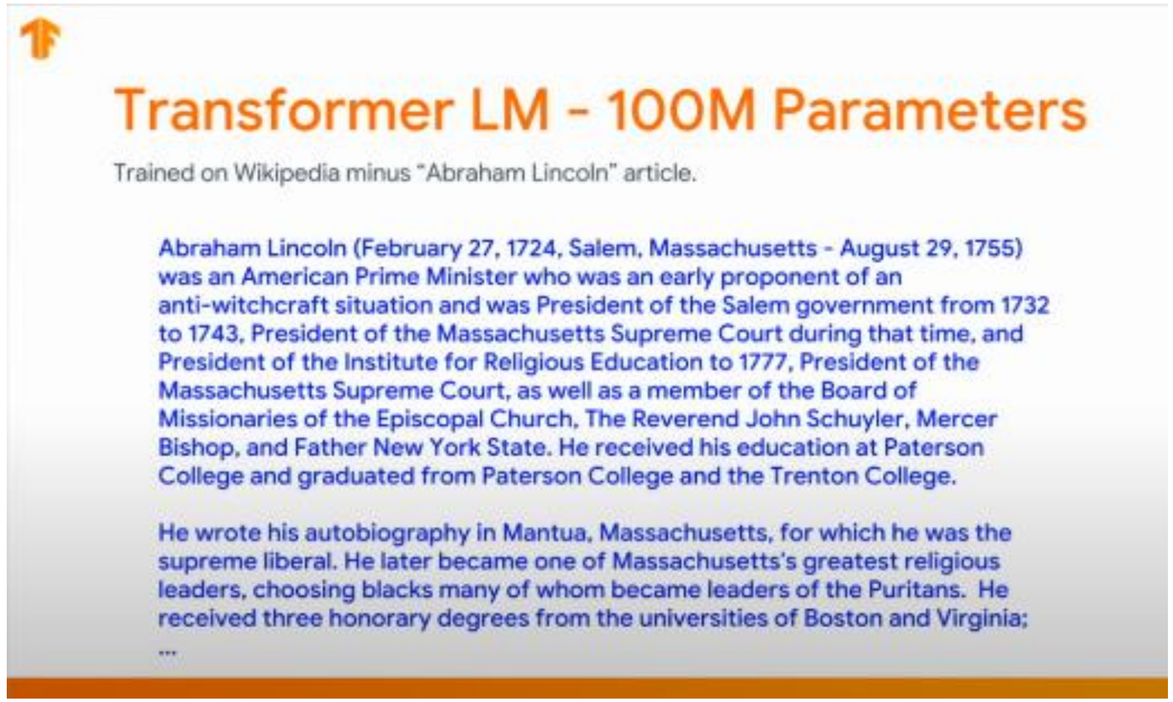
- Largely the same but:
  - Larger in every way:
    - More decoder layers: 12->48
    - Larger vocabulary: 50,257
    - Larger context: 512 -> 1024
    - Larger batch size
  - Changes to layer normalization
  - Different initialization scheme

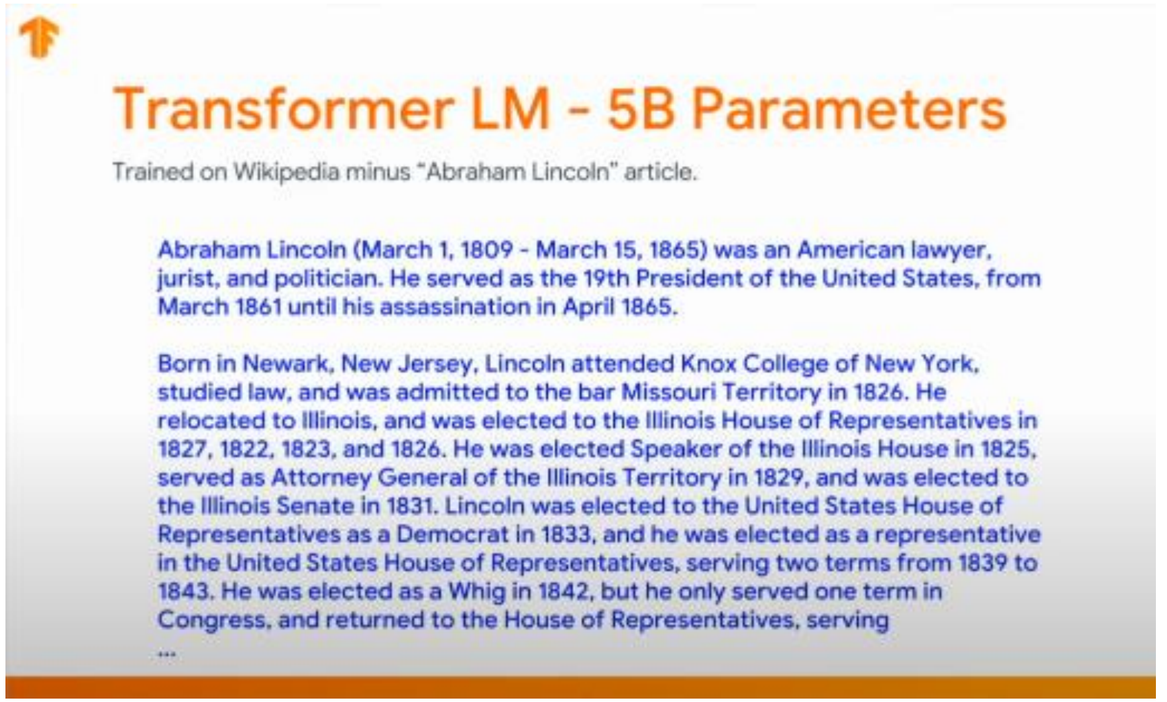
Parameters	Layers	d_{model}
117M	12	768
345M	24	1024
762M	36	1280
1542M	48	1600

Table 2. Architecture hyperparameters for the 4 model sizes.

Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., & Sutskever, I. (2019). Language models are unsupervised multitask learners. OpenAI Blog, 1(8), 9.

GPT-2
The Impact





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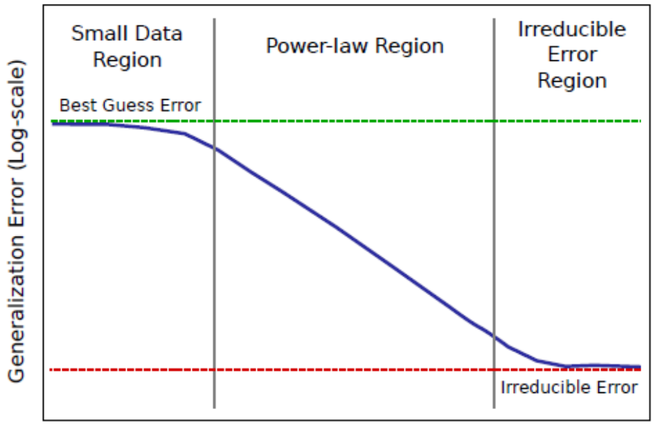
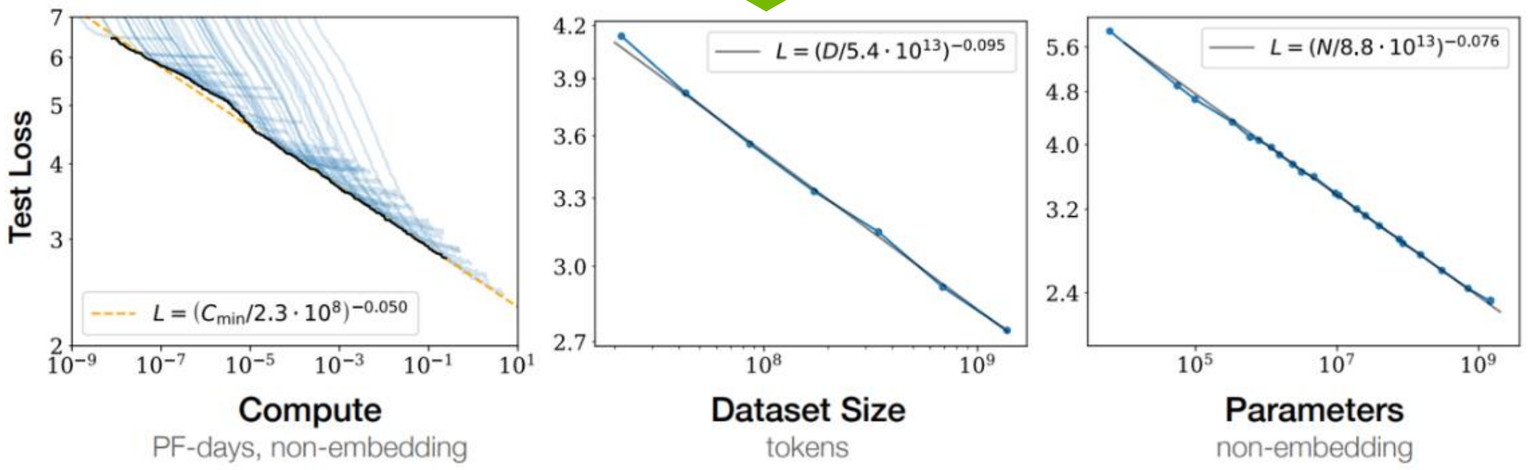
MEASURABLE IMPROVEMENT

THE SCALING LAWS OF NEURAL LANGUAGE MODELS

Continuous improvement





Hestness, J., Narang, S., Ardalani, N., Diamos, G., Jun, H., Kianinejad, H., ... & Zhou, Y. Deep Learning Scaling is Predictable, Empirically. arXiv preprint arXiv:1712.00409. 2017

Tom Henighan, Jared Kaplan, Mor Katz, Mark Chen, Christopher Hesse, Jacob Jackson, Heewoo Jun, Tom B. Brown, Prafulla Dhariwal, Scott Gray, Chris Hallacy, Benjamin Mann, Alec Radford, Aditya Ramesh, Nick Ryder, Daniel M. Ziegler, John Schulman, Dario Amodei, Sam McCandlish. Scaling Laws for Autoregressive Generative Modeling.2020

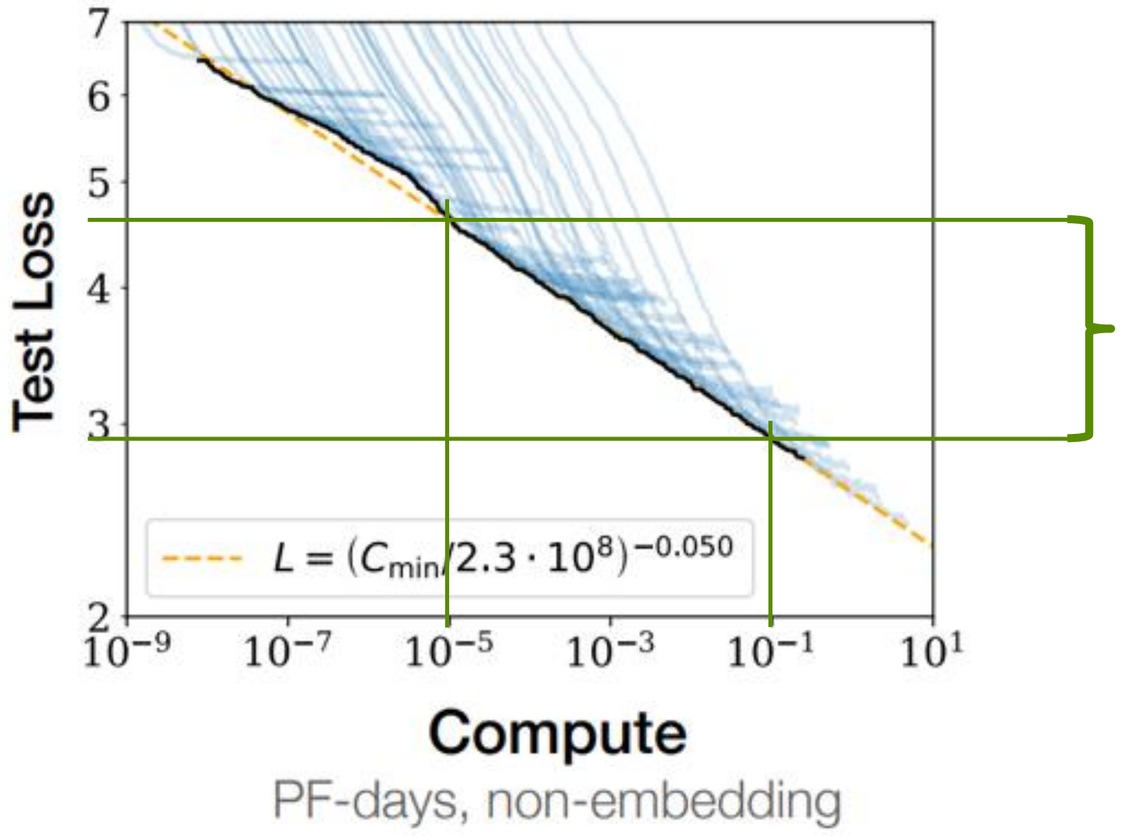
Part 2: Self-Supervision, BERT and Beyond

- Lecture
  - Why Do DNNs Work Well?
  - Self-Supervised Learning
  - BERT
- Lab
  - Explore the Data
  - Explore NeMo
  - Text Classifier Project
- Lecture (cont'd)
  - The Scaling Laws
  - Can and should we go even bigger?
- Lab (cont'd)
  - Named Entity Recognizer

SHOULD WE BUILD LARGER MODELS?

ARE LARGE LANGUAGE MODELS WORTH IT?

The cost of incremental improvement



Are we building those models only for the small incremental improvement in their performance?

Is it worth all of the engineering and computational investment?

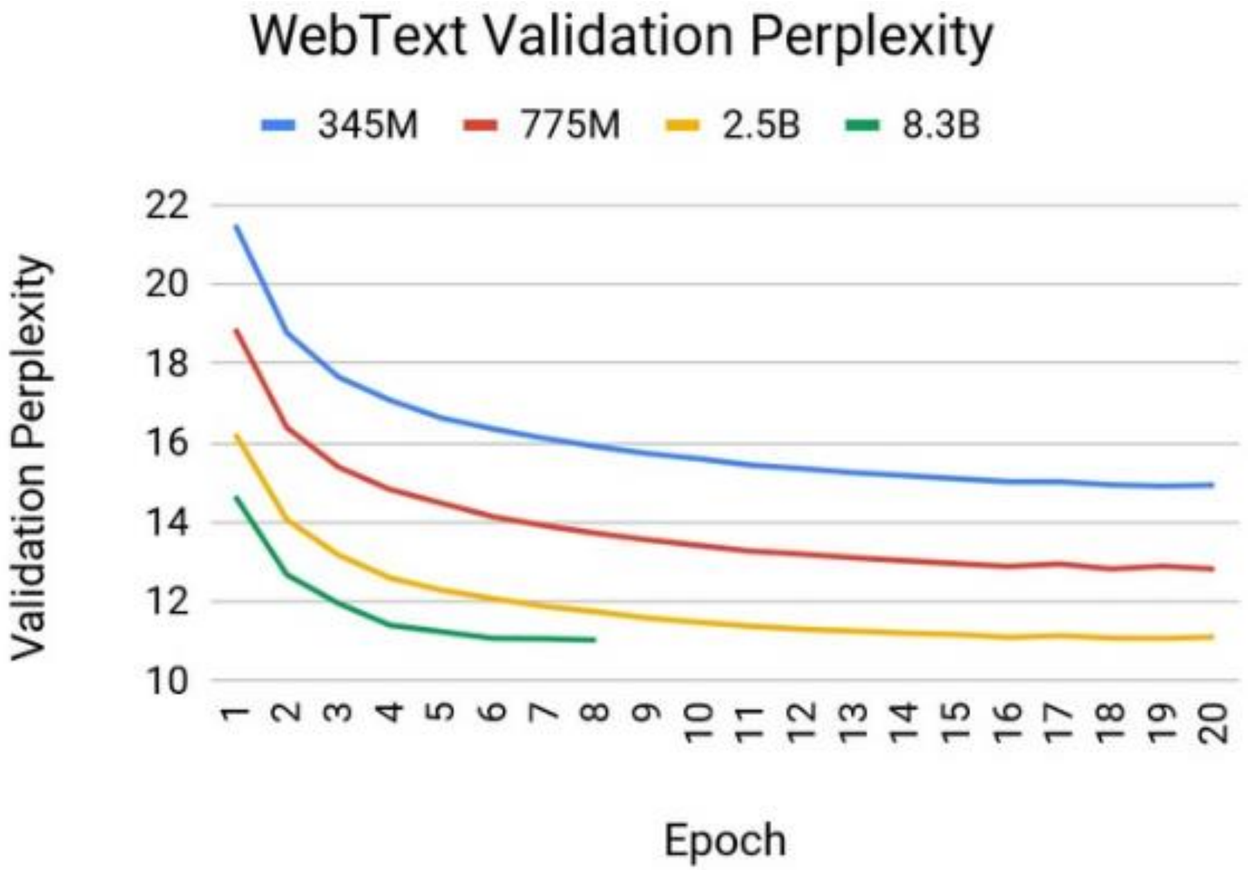
IS THIS REALLY THE ONLY THING WE HAVE ACHIEVED?

IT IS MUCH MORE THAN JUST INCREMENTAL INCREASE IN ACCURACY!

1. SAMPLE EFFICIENCY

NOT ABOUT INCREMENTAL IMPROVEMENT

Sample efficiency



Shoeybi, M., Patwary, M., Puri, R., LeGresley, P., Casper, J., & Catanzaro, B. (2019). Megatron-lm: Training multi-billion parameter language models using gpu model parallelism. arXiv preprint arXiv:1909.08053.

LARGER MODELS ARE CHEAPER TO TRAIN

Optimal allocation of computational budget

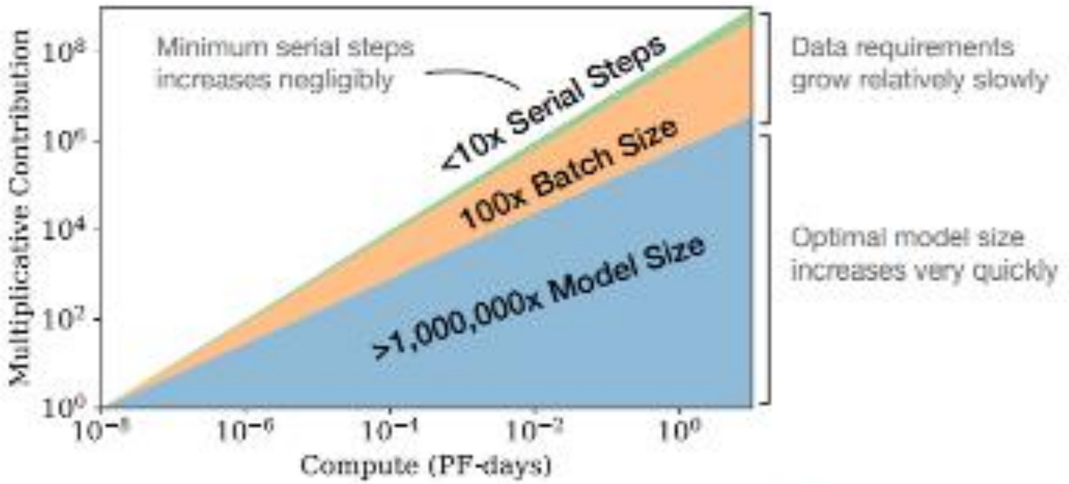


Figure 3 As more compute becomes available, we can choose how much to allocate towards training larger models, using larger batches, and training for more steps. We illustrate this for a billion-fold increase in compute. For optimally compute-efficient training, most of the increase should go towards increased model size. A relatively small increase in data is needed to avoid reuse. Of the increase in data, most can be used to increase parallelism through larger batch sizes, with only a very small increase in serial training time required.

Kaplan, J., McCandlish, S., Henighan, T., Brown, T. B., Chess, B., Child, R., ... & Amodei, D. (2020). Scaling Laws for Neural Language Models. *arXiv preprint arXiv:2001.08361*.

LARGER MODELS ARE CHEAPER TO TRAIN

For every dataset there exists an optimal model size minimizing compute

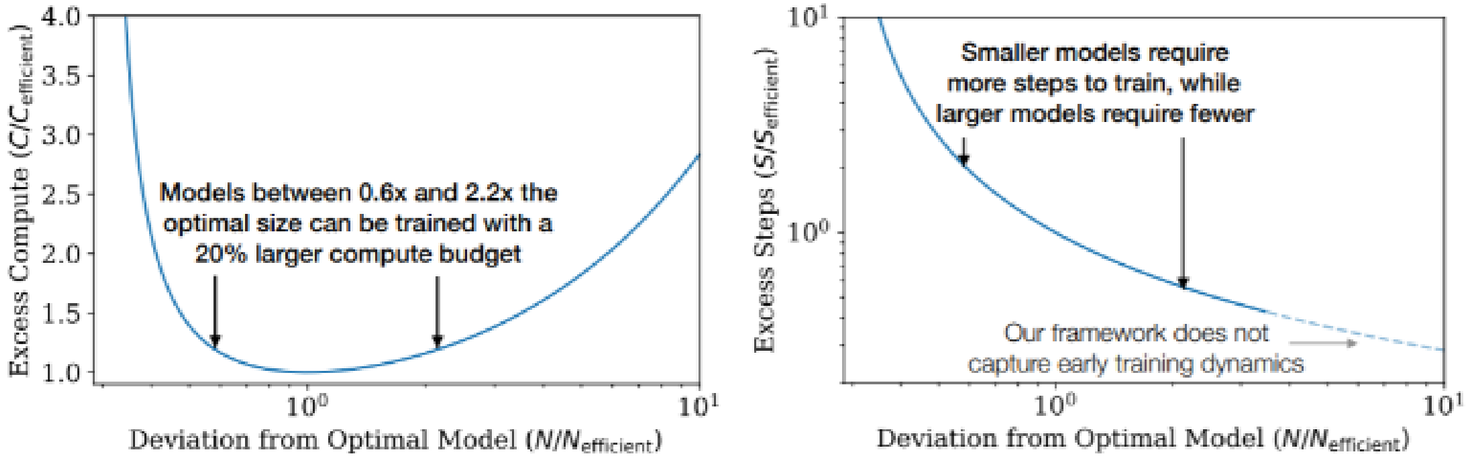


Figure 12 **Left:** Given a fixed compute budget, a particular model size is optimal, though somewhat larger or smaller models can be trained with minimal additional compute. **Right:** Models larger than the compute-efficient size require fewer steps to train, allowing for potentially faster training if sufficient additional parallelism is possible. Note that this equation should not be trusted for very large models, as it is only valid in the power-law region of the learning curve, after initial transient effects.

Kaplan, J., McCandlish, S., Henighan, T., Brown, T. B., Chess, B., Child, R., ... & Amodei, D. (2020). Scaling Laws for Neural Language Models. *arXiv preprint arXiv:2001.08361*.

2. ARCHITECTURAL HYPERPARAMETERS

LARGE MODELS ARE CHEAPER TO DESIGN

Impact of architectural hyperparameters

"… more importantly, we find that the precise architectural hyperparameters are unimportant compared to the overall scale of the language model."

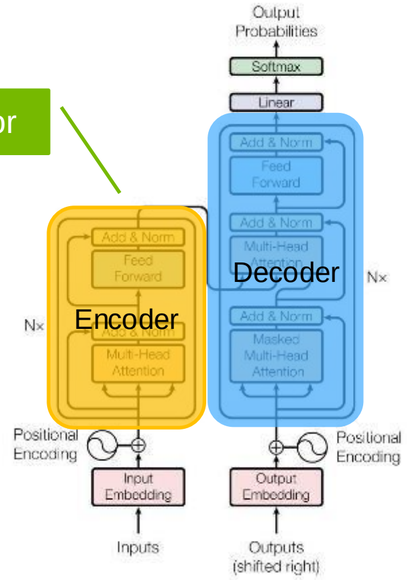
Kaplan, J., McCandlish, S., Henighan, T., Brown, T. B., Chess, B., Child, R., ... & Amodei, D. (2020). Scaling Laws for Neural Language Models. *arXiv preprint arXiv:2001.08361*.

NLP APPROACH (CIRCA 2019)

Step 1: Pre-training a Transformer

Output 1: Reconstruct missing words
family, of, this, the, Louis, personally, telephone

High dimensional vector



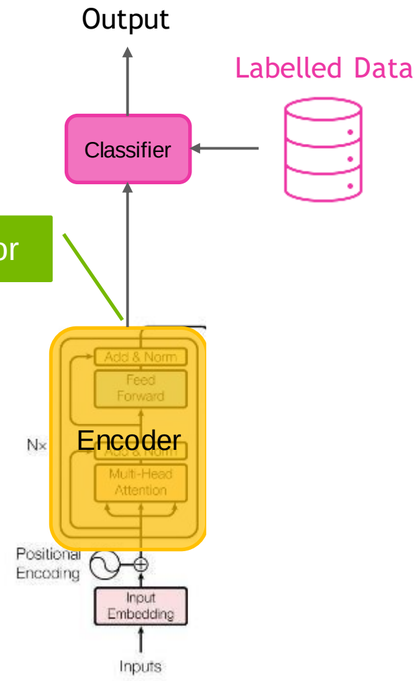
Input: Two sentences with 15% of words masked out

1 = “Initially he supported himself and his [redacted] by farming on a plot [redacted] family land.”

2 = “[redacted] in turn attracted the attention of [redacted] *St.* [redacted] *Post-Dispatch*, which sent a reporter to Murray to [redacted] review Stubblefield's wireless [redacted].”

Step 2. Fine tune for a specific task

High dimensional vector



3. GENERALIZATION

YES THEY CREATE INCREMENTAL IMPROVEMENT IN ACCURACY

Larger models generalize better

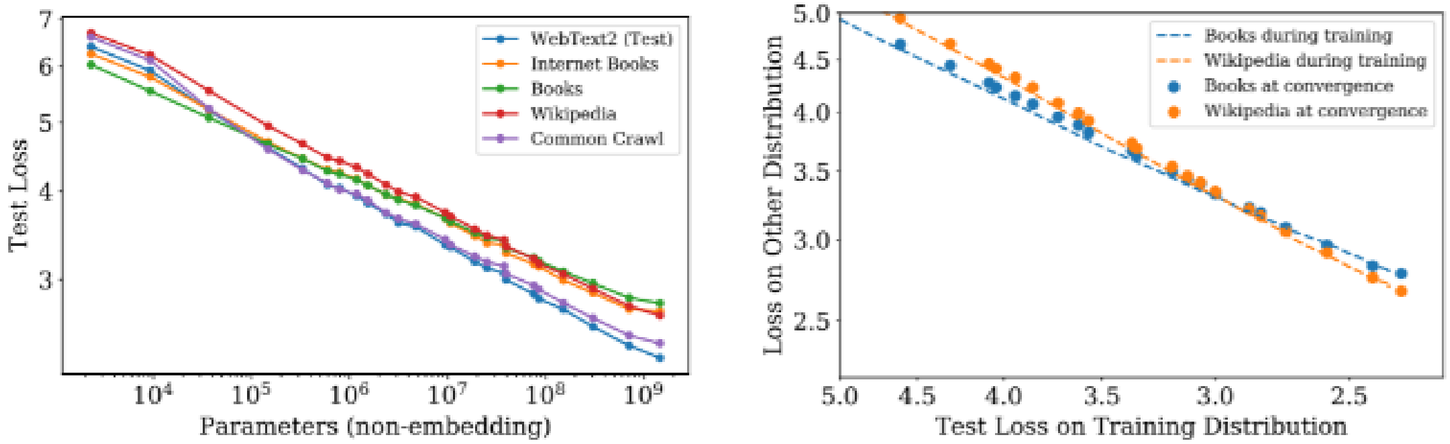


Figure 8 **Left:** Generalization performance to other data distributions improves smoothly with model size, with only a small and very slowly growing offset from the WebText2 training distribution. **Right:** Generalization performance depends only on training distribution performance, and not on the phase of training. We compare generalization of converged models (points) to that of a single large model (dashed curves) as it trains.

Kaplan, J., McCandlish, S., Henighan, T., Brown, T. B., Chess, B., Child, R., ... & Amodei, D. (2020). Scaling Laws for Neural Language Models. *arXiv preprint arXiv:2001.08361*.

DOWNSTREAM TASKS

Zero/Few Shot Learners

Zero-shot

The model predicts the answer given only a natural language discription of the task. No gradient updates are performed.

```
1  Translate English to French:        ← task description
2  cheese =>                           ← prompt
```

One-shot

In addition to the task description, the model sees a single example of the task. No gradient updates are performed.

```
1  Translate English to French:        ← task description
2  sea otter => loutre de mer          ← example
3  cheese =>                           ← prompt
```

Few-shot

In addition to the task description, the model sees a few examples of the task. No gradient updates are performed.

```
1  Translate English to French:        ← task description
2  sea otter => loutre de mer          ← examples
3  peppermint => menthe poivrée        ←
4  plush girafe => girafe peluche      ←
5  cheese =>                           ← prompt
```

Benjamin Mann et al. "Language Models are Few-Shot Learners". 2020. https://arxiv.org/abs/2005.14165

DOWNSTREAM TASKS

Zero/Few Shot Learners

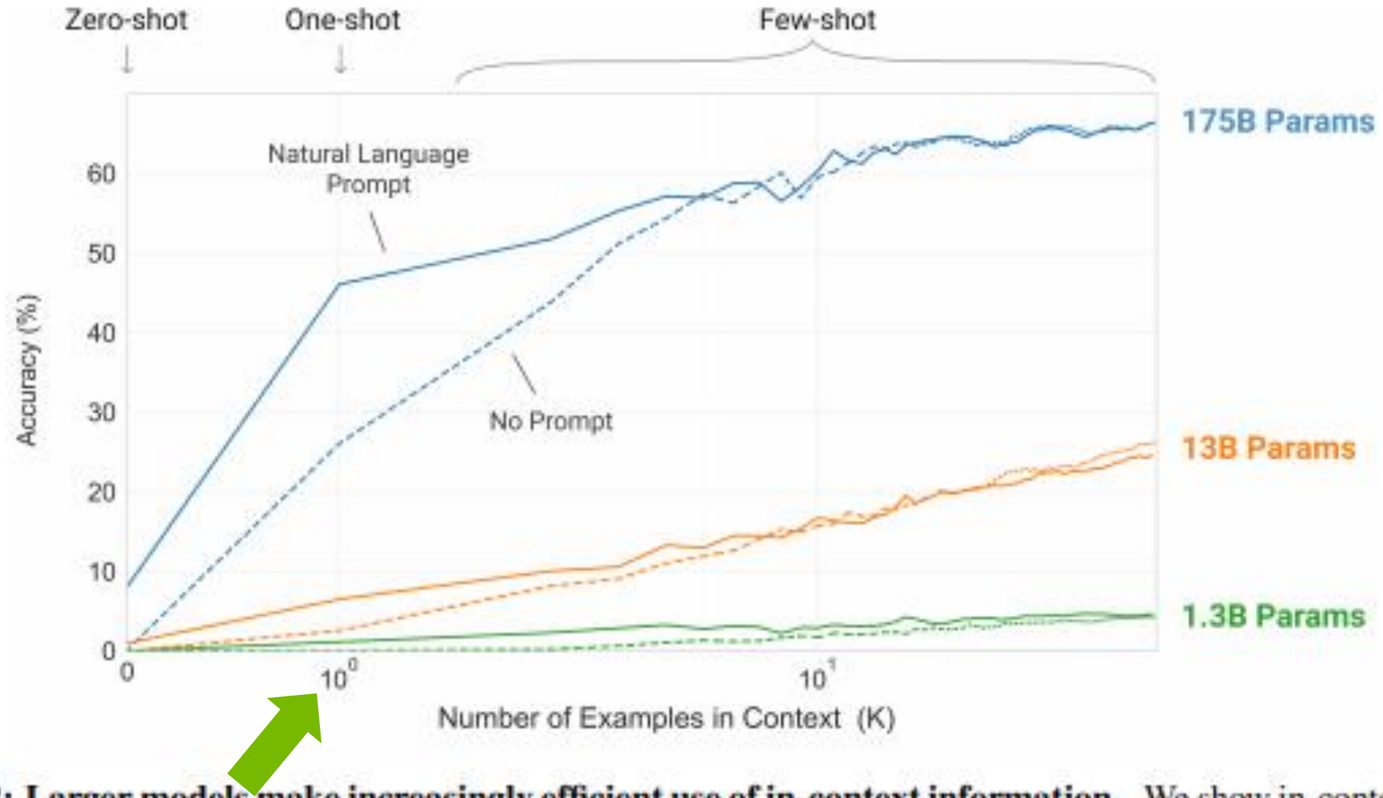


Figure 1.2: Larger models make increasingly efficient use of in-context information. We show in-context learning performance on a simple task requiring the model to remove random symbols from a word, both with and without a natural language task description (see Sec. 3.9.2). The steeper "in-context learning curves" for large models demonstrate improved ability to learn a task from contextual information. We see qualitatively similar behavior across a wide range of tasks.

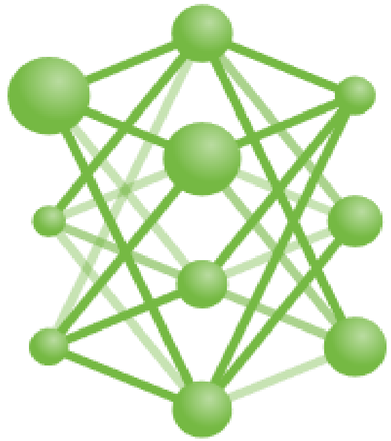
Shoeybi, M., Patwary, M., Puri, R., LeGresley, P., Casper, J., & Catanzaro, B. (2019). Megatron-lm: Training multi-billion parameter language models using gpu model parallelism. arXiv preprint arXiv:1909.08053

Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., ... & Agarwal, S. (2020). Language models are few-shot learners. *arXiv preprint arXiv:2005.14165*..

DOWNSTREAM TASKS

Zero/Few Shot Learners

Q: Would you say this movie review is positive or negative?
“I loved that movie”’



- positive
- great
- awsome …

Prompt

DOWNSTREAM TASKS

Prompt Engineering

Type	Task	Input ([X])	Template	Answer([Y])
Text CLS	Sentiment	I love this movie.	[X] The movie is [Y]	great fantastic ...
	Topics	He prompted the LM.	[X] The text is about [Y]	sports science ...
	Intention	What is taxi fare to Denver?	[X] The question is about [Y]	quantity city ...
Text-span CLS	Aspect Sentiment	Poor service but good food.	[X] What about service? [Y]	Bad Terrible ...
Text-pair CLS	NLI	[X1]: An old man with ... [X2]: A man walks ...	Hypothesis: [X1], Premise: [X2], Answer: [Y]	Contradiction Entailment ...
Tagging	NER	[X1]: Mike went to Paris. [X2]: Paris	[X1] [X2] is a [Y]	Yes No ...
Text Generation	Summarization	Las Vegas police ...	[X] TL;DR: [Y]	The victim ... A woman ... ...
	Translation	Je vous aime.	French [X] English: [Y]	I love you. I fancy you. ...

Prompts	
manual	DirectX *is developed by* y_{man}
mined	y_{mine} *released the* DirectX
paraphrased	DirectX *is created by* y_{para}

Top 5 predictions and log probabilities

	y_{man}		y_{mine}		y_{para}	
1	Intel	-1.06	Microsoft	-1.77	Microsoft	-2.23
2	Microsoft	-2.21	They	-2.43	Intel	-2.30
3	IBM	-2.76	It	-2.80	default	-2.96
4	Google	-3.40	Sega	-3.01	Apple	-3.44
5	Nokia	-3.58	Sony	-3.19	Google	-3.45

Figure 1: Top-5 predictions and their log probabilities using different prompts (manual, mined, and paraphrased) to query BERT. Correct answer is underlined.

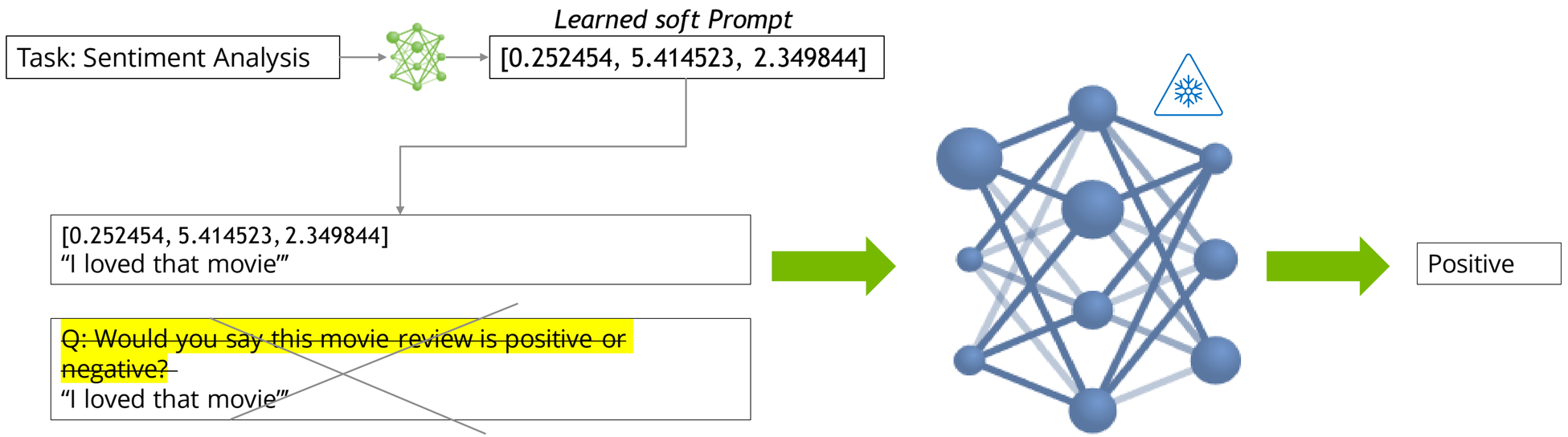
ID	Modifications	Acc. Gain
P413	x plays in→at y position	+23.2
P495	x was created→made in y	+10.8
P495	x was→is created in y	+10.0
P361	x is a part of y	+2.7
P413	x plays ~~in~~ y position	+2.2

Table 6: Small modifications (update, insert, and delete) in paraphrase lead to large accuracy gain (%).

Zhengbao Jiang et al. "How Can We Know What Language Models Know?".2020.

DOWNSTREAM TASKS

Prompt Learning on a Small Training Dataset



Prompt Learning

DOWNSTREAM TASKS

Prompt Tuning / P-Tuning

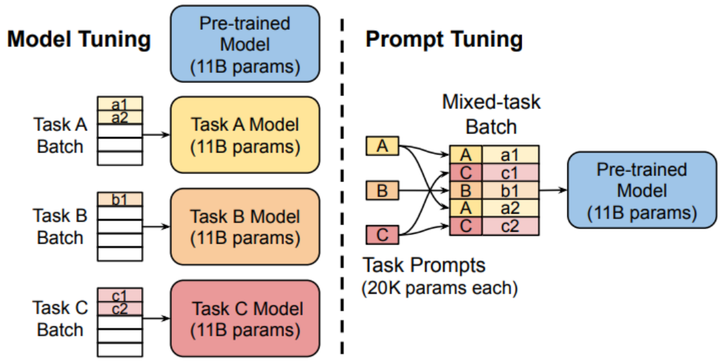
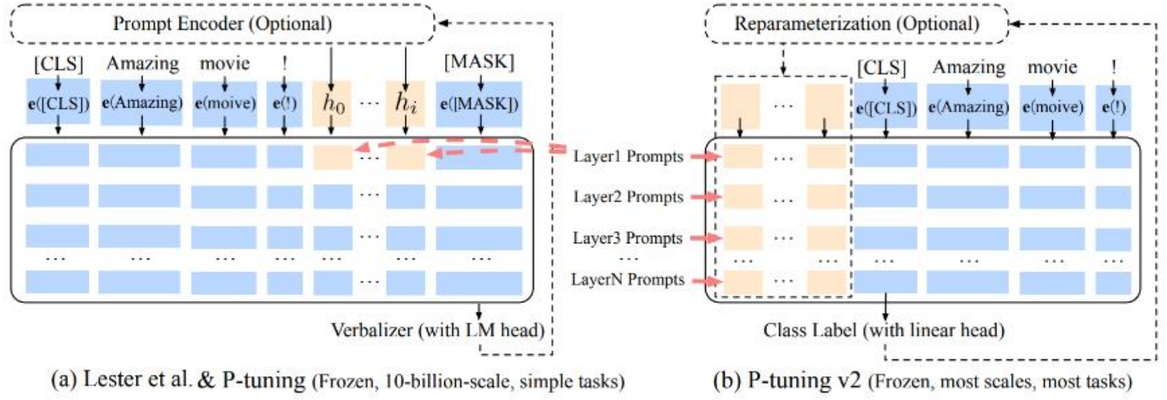


Figure 2: **Model tuning** requires making a task-specific copy of the entire pre-trained model for each downstream task and inference must be performed in separate batches. **Prompt tuning** only requires storing a small task-specific prompt for each task, and enables mixed-task inference using the original pre-trained model. With a T5 "XXL" model, each copy of the tuned model requires 11 billion parameters. By contrast, our tuned prompts would only require 20,480 parameters per task—a reduction of *over five orders of magnitude*—assuming a prompt length of 5 tokens.



(a) Lester et al. & P-tuning (Frozen, 10-billion-scale, simple tasks) (b) P-tuning v2 (Frozen, most scales, most tasks)

Figure 2: From Lester et al. (2021) & P-tuning to P-tuning v2. Orange tokens (include h_0, h_i) refer to prompt embeddings we add; blue tokens are embeddings stored or computed by frozen pre-trained language models. Compared to Lester et al. (2021), P-tuning v2 adds trainable continuous prompts to inputs of every transformer layer independently (as prefix-tuning (Li and Liang, 2021) does). Additionally, P-tuning v2 removes verbalizers with LM head and returns to the traditional class labels with ordinary linear head to allow its task-universality.

Brian Lester, Rami Al-Rfou, Noah Constant The Power of Scale for Parameter-Efficient Prompt Tuning. 2021. https://arxiv.org/abs/2104.08691
Xiao Liu et al. " P-Tuning v2: Prompt Tuning Can Be Comparable to Fine-tuning Universally Across Scales and Tasks. 2021. https://arxiv.org/abs/2110.07602

DOWNSTREAM TASKS

Customize Models using Parameter-efficient tuning | Adapters

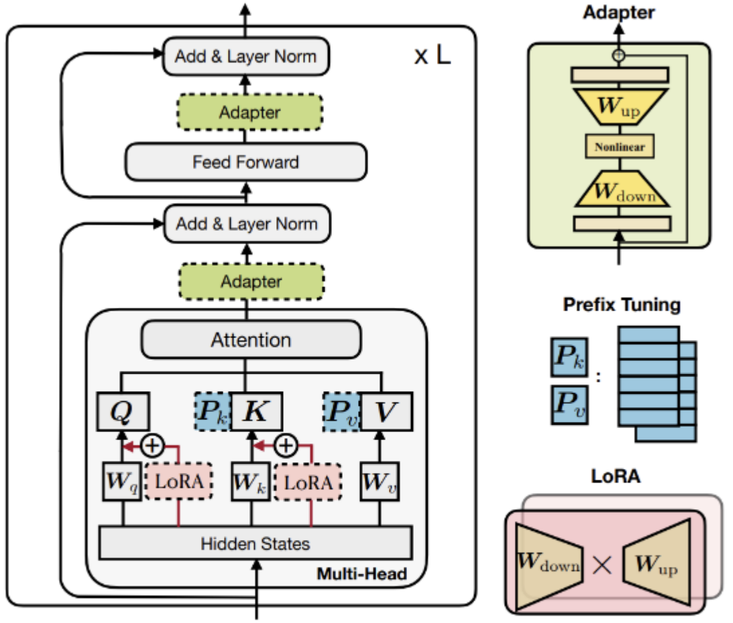
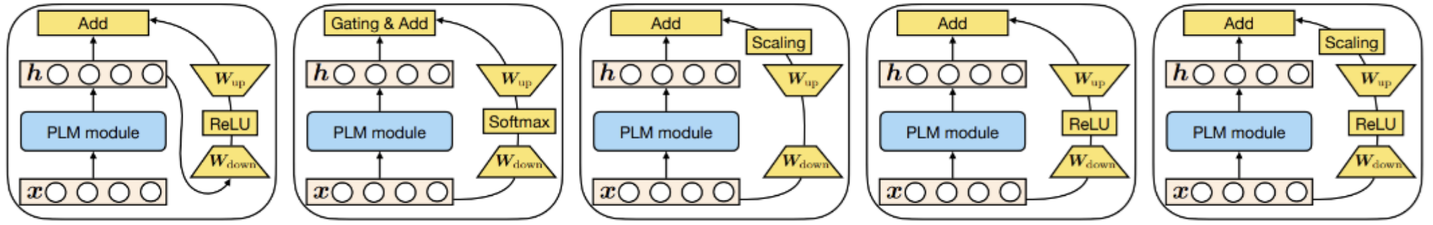


Figure 1: Illustration of the transformer architecture and several state-of-the-art parameter-efficient tuning methods. We use blocks with dashed borderlines to represent the added modules by those methods.



(a) Adapter (b) Prefix Tuning (c) LoRA (d) Parallel Adapter (e) Scaled PA

Figure 3: Graphical illustration of existing methods and the proposed variants. "PLM module" represents a certain sublayer of the PLM (e.g. attention or FFN) that is frozen. "Scaled PA" denotes scaled parallel adapter. We do not include multi-head parallel adapter here to save space.

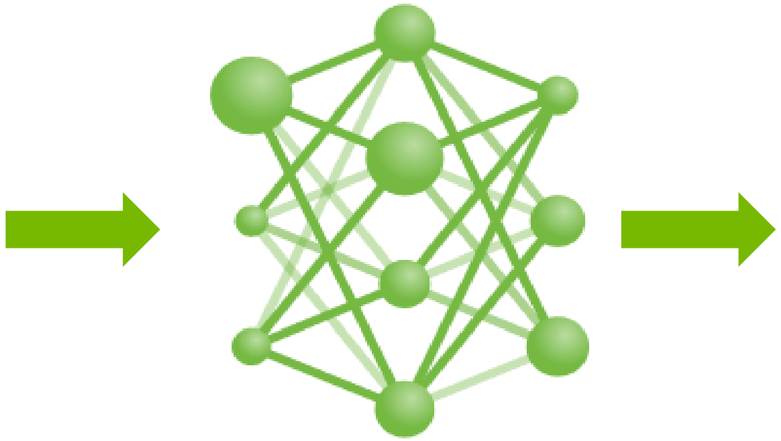
Junxian He Chunting Zhou, Xuezhe Ma, Taylor Berg-Kirkpatrick, Graham Neubig. TOWARDS A UNIFIED VIEW OF PARAMETER-EFFICIENT TRANSFER LEARNING. ICLR 2022

INSTRUCTED LLM

INSTRUCTIONS FINETUNING

Dataset of Instructions (Queries and Answers)

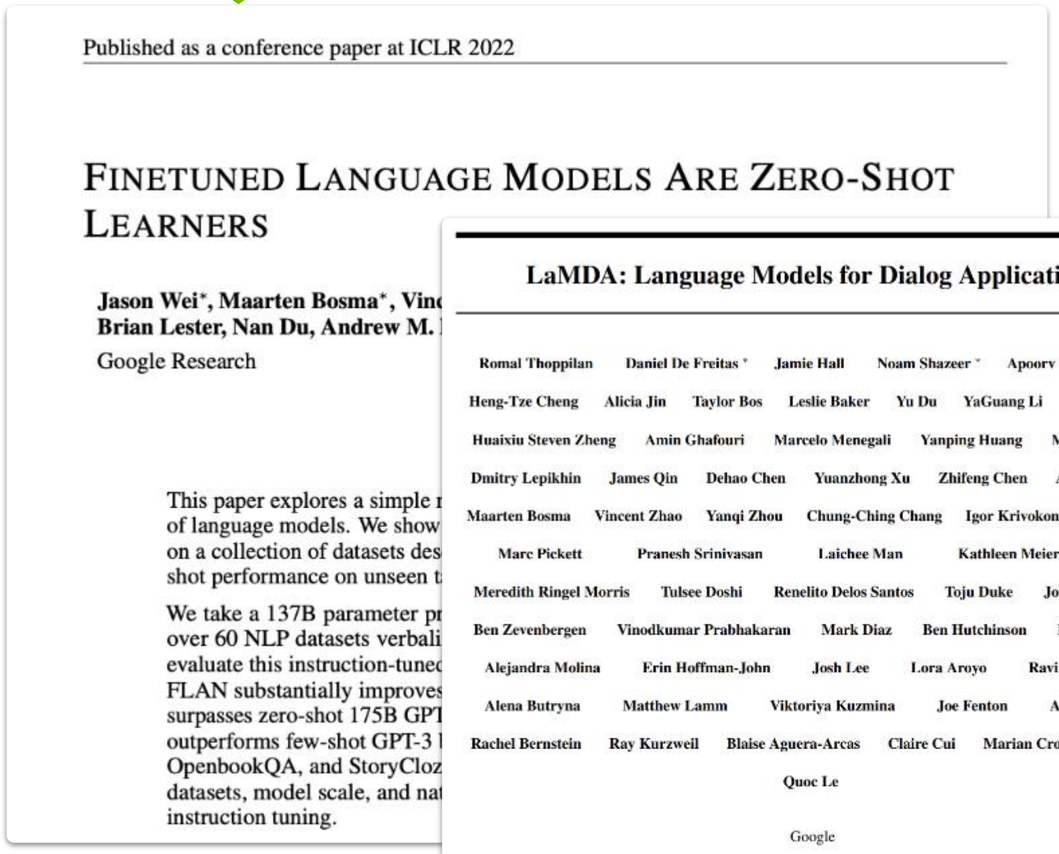
"Q: Who is the president of USA?



Joseph Robinette Biden Jr. is an American politician who is the 46th and current president of the United States. A member of the Democratic Party, he previously served as the 47th vice president from 2009 to 2017 under President Barack Obama, and represented Delaware in the United States Senate from ..."

INSTRUCTIONS FINETUNING

FLAN [Google]



Published as a conference paper at ICLR 2022

FINETUNED LANGUAGE MODELS ARE ZERO-SHOT LEARNERS

Jason Wei*, Maarten Bosma*, Vinc
Brian Lester, Nan Du, Andrew M.
Google Research

This paper explores a simple
of language models. We show
on a collection of datasets des
shot performance on unseen t

We take a 137B parameter pr
over 60 NLP datasets verbali
evaluate this instruction-tunec
FLAN substantially improves
surpasses zero-shot 175B GPT
outperforms few-shot GPT-3
OpenbookQA, and StoryCloz
datasets, model scale, and nat
instruction tuning.

LaMDA [Google]

LaMDA: Language Models for Dialog Applications

Romal Thoppilan Daniel De Freitas * Jamie Hall Noam Shazeer * Apoorv Kulshreshtha
Heng-Tze Cheng Alicia Jin Taylor Bos Leslie Baker Yu Du YaGuang Li Hongrae Lee
Huaixiu Steven Zheng Amin Ghafouri Marcelo Menegali Yanping Huang Maxim Krikun
Dmitry Lepikhin James Qin Dehao Chen Yuanzhong Xu Zhifeng Chen Adam Roberts
Maarten Bosma Vincent Zhao Yanqi Zhou Chung-Ching Chang Igor Krivokon Will Rusch
Marc Pickett Pranesh Srinivasan Laichee Man Kathleen Meier-Hellstern
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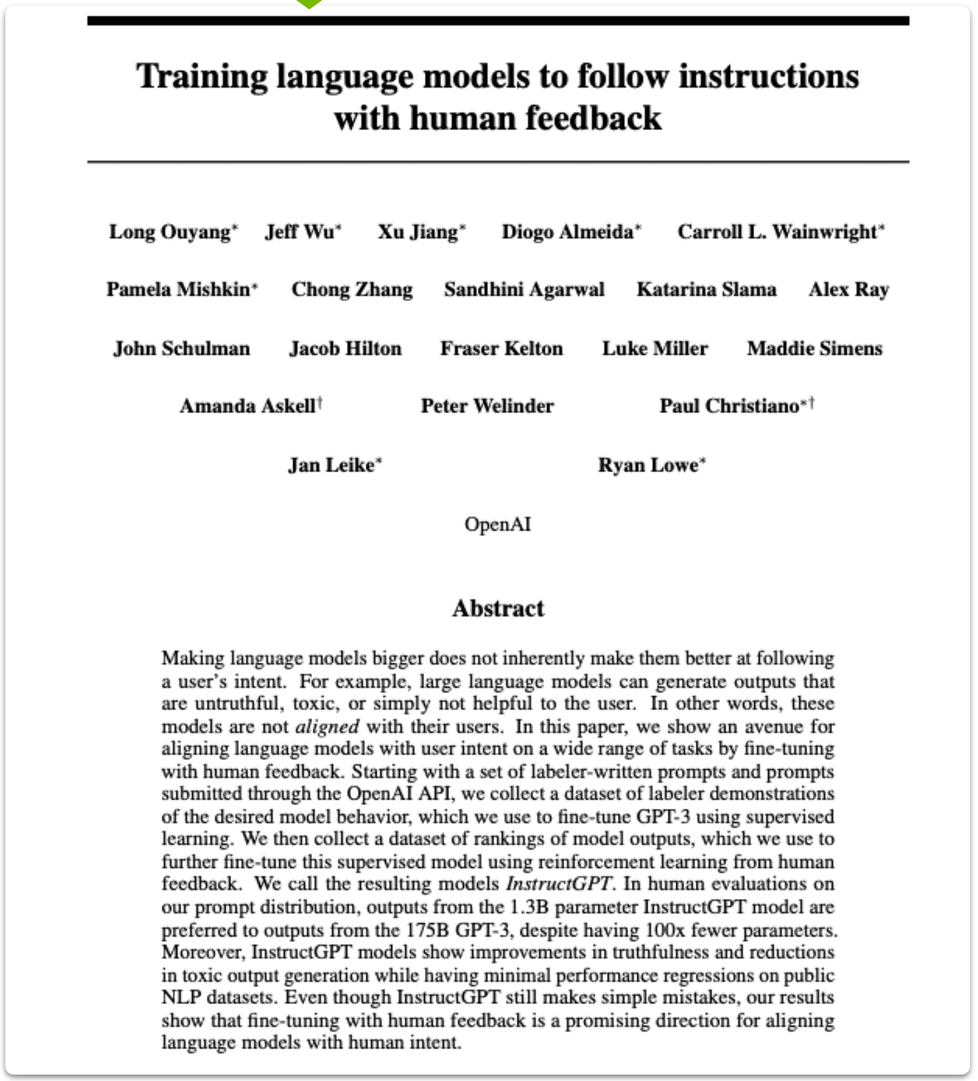
Ben Zevenbergen Vinodkumar Prabhakaran Mark Diaz Ben Hutchinson Kristen Olson
Alejandra Molina Erin Hoffman-John Josh Lee Lora Aroyo Ravi Rajakumar
Alena Butryna Matthew Lamm Viktoriya Kuzmina Joe Fenton Aaron Cohen
Rachel Bernstein Ray Kurzweil Blaise Aguera-Arcas Claire Cui Marian Croak Ed Chi
Quoc Le
Google

Abstract

We present LaMDA: Language Models for Dialog Applications. LaMDA is a family of Transformer-based neural language models specialized for dialog, which have up to 137B parameters and are pre-trained on 1.56T words of public dialog data and web text. While model scaling alone can improve quality, it shows less improvements on safety and factual grounding. We demonstrate that fine-tuning with annotated data and enabling the model to consult external knowledge sources can lead to significant improvements towards the two key challenges of safety and factual grounding. The first challenge, safety, involves ensuring that the model's responses are consistent with a set of human values, such as preventing harmful suggestions and unfair bias. We quantify safety using a metric based on an illustrative set of human values, and we find that filtering candidate responses using a LaMDA classifier fine-tuned with a small amount of crowdworker-annotated data offers a promising approach to improving model safety. The second challenge, factual grounding, involves enabling the model to consult external knowledge sources, such as an information retrieval system, a language translator, and a calculator. We quantify factuality using a groundedness metric, and we find that our approach enables the model to generate responses grounded in known sources, rather than responses that merely sound plausible. Finally, we explore the use of LaMDA in the domains of education and content recommendations, and analyze their helpfulness and role consistency.

InstructGPT [OpenAI]



Training language models to follow instructions with human feedback

Long Ouyang* Jeff Wu* Xu Jiang* Diogo Almeida* Carroll L. Wainwright*
Pamela Mishkin* Chong Zhang Sandhini Agarwal Katarina Slama Alex Ray
John Schulman Jacob Hilton Fraser Kelton Luke Miller Maddie Simens
Amanda Askell† Peter Welinder Paul Christiano*†
Jan Leike* Ryan Lowe*
OpenAI

Abstract

Making language models bigger does not inherently make them better at following a user's intent. For example, large language models can generate outputs that are untruthful, toxic, or simply not helpful to the user. In other words, these models are not *aligned* with their users. In this paper, we show an avenue for aligning language models with user intent on a wide range of tasks by fine-tuning with human feedback. Starting with a set of labeler-written prompts and prompts submitted through the OpenAI API, we collect a dataset of labeler demonstrations of the desired model behavior, which we use to fine-tune GPT-3 using supervised learning. We then collect a dataset of rankings of model outputs, which we use to further fine-tune this supervised model using reinforcement learning from human feedback. We call the resulting models *InstructGPT*. In human evaluations on our prompt distribution, outputs from the 1.3B parameter InstructGPT model are preferred to outputs from the 175B GPT-3, despite having 100x fewer parameters. Moreover, InstructGPT models show improvements in truthfulness and reductions in toxic output generation while having minimal performance regressions on public NLP datasets. Even though InstructGPT still makes simple mistakes, our results show that fine-tuning with human feedback is a promising direction for aligning language models with human intent.

INSTRUCTIONS FINETUNING

FLAN [Google]

Published as a conference paper at ICLR 2022

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LaMDA [Google]

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Quoc Le
Google

Abstract

We present LaMDA: Language Models for Dialog Applications. LaMDA is a family of Transformer-based neural language models specialized for dialog, which have up to 137B parameters and are pre-trained on 1.56T words of public dialog data and web text. While model scaling alone can improve quality, it shows less improvements on safety and factual grounding. We demonstrate that fine-tuning with annotated data and enabling the model to consult external knowledge sources can lead to significant improvements towards the two key challenges of safety and factual grounding. The first challenge, safety, involves ensuring that the model's responses are consistent with a set of human values, such as preventing harmful suggestions and unfair bias. We quantify safety using a metric based on an illustrative set of human values, and we find that filtering candidate responses using a LaMDA classifier fine-tuned with a small amount of crowdworker-annotated data offers a promising approach to improving model safety. The second challenge, factual grounding, involves enabling the model to consult external knowledge sources, such as an information retrieval system, a language translator, and a calculator. We quantify factuality using a groundedness metric, and we find that our approach enables the model to generate responses grounded in known sources, rather than responses that merely sound plausible. Finally, we explore the use of LaMDA in the domains of education and content recommendations, and analyze their helpfulness and role consistency.

InstructGPT [OpenA]

Training language models to follow instructions with human feedback

Long Ouyang* Jeff Wu* Xu Jiang* Diogo Almeida* Carroll L. Wainwright*
Pamela Mishkin* Chong Zhang Sandhini Agarwal Katarina Slama Alex Ray
John Schulman Jacob Hilton Fraser Kelton Luke Miller Maddie Simens
Amanda Askell† Peter Welinder Paul Christiano*†

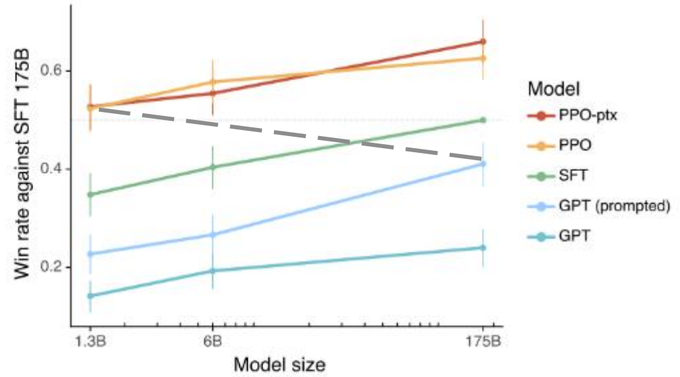


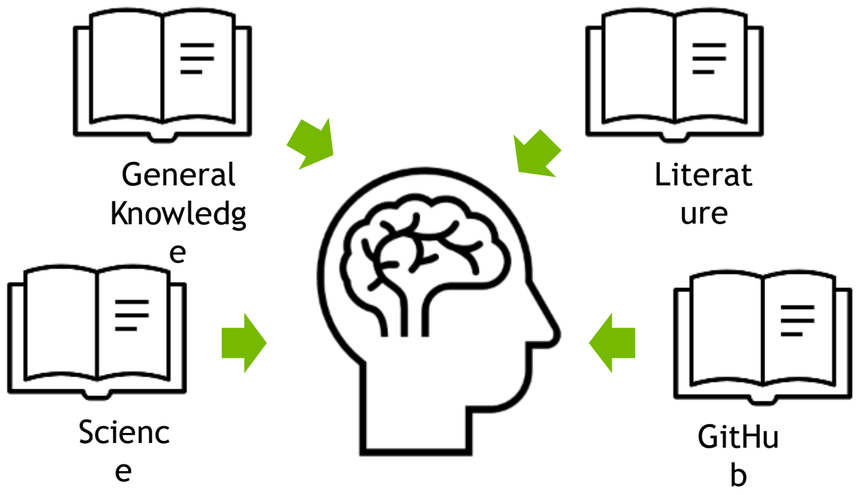
Figure 1: Human evaluations of various models on our API prompt distribution, evaluated by how often outputs from each model were preferred to those from the 175B SFT model. Our InstructGPT models (PPO-ptx) as well as its variant trained without pretraining mix (PPO) significantly outperform the GPT-3 baselines (GPT, GPT prompted); outputs from our 1.3B PPO-ptx model are preferred to those from the 175B GPT-3. Error bars throughout the paper are 95% confidence intervals.

language models with human intent.

CHANGE IN THE NLP PARADIGM

NEW NLP APPROACH (CIRCA 2021)

Step 1: Train a Very Deep/HUGE model



Step 2. Ask questions

‘Q: Would you say this movie review is positive or negative? “I loved that movie”’

‘A: Negative’

Huge means Billions of parameters

TOWARDS GENERAL INTELLIGENCE

Old way

- ★ Needs Labelled data
  - Cost of data collection/labelling
  - Legal/Privacy concerns around using data
- ★ 1 model per task results in
  - Increased model development/tuning cost
  - Increased operational costs
  - Increased money spent on sourcing data
- ★ Relatively Limited generalization
- ★ Computationally cheaper (~300 Million parameters)

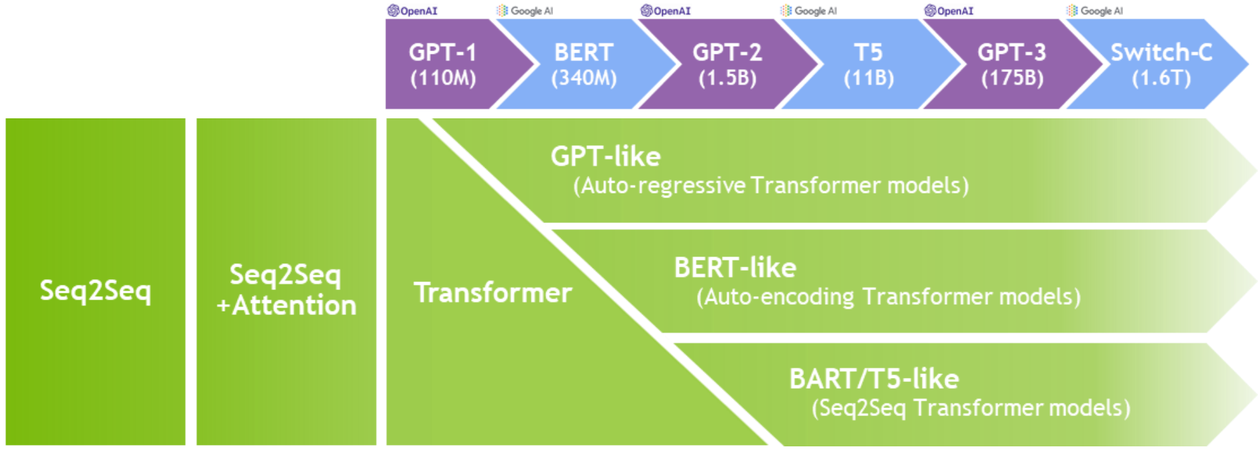
New way

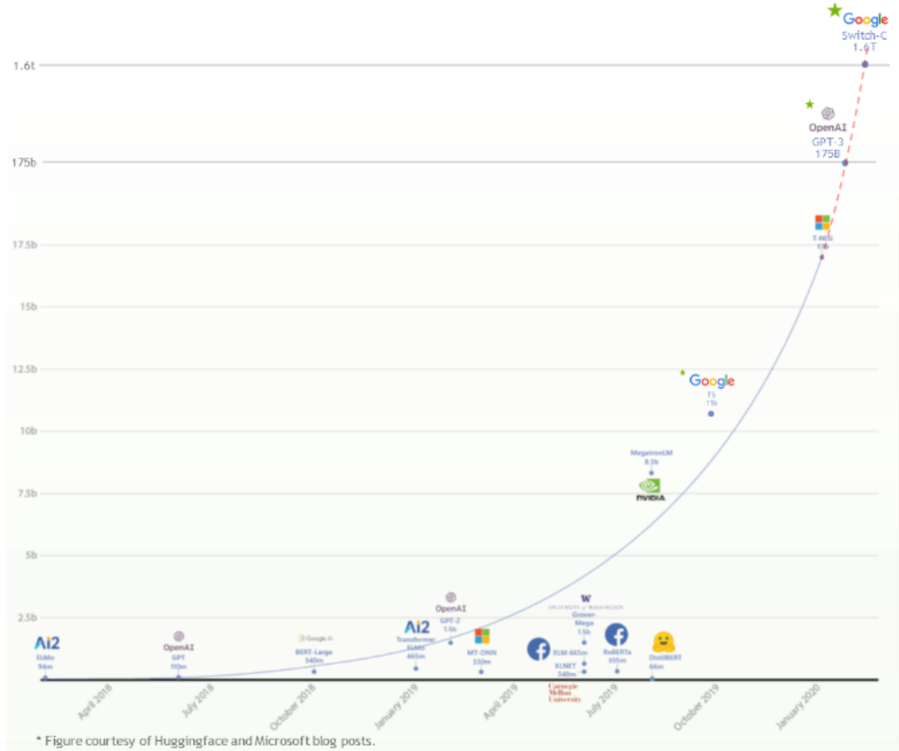
- ★ Does not need labelled data
- ★ Single generic model can do more than one tasks
- ★ More generalized: in addition to language also learns higher level concepts, styles, etc.
- ★ Computationally Expensive (~500 Billion parameters)

Leveraging more compute to get a general model without significant data/labelling cost

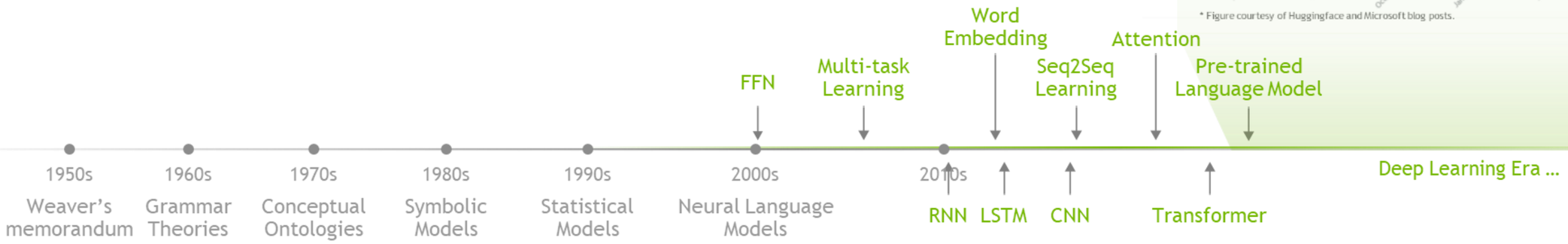
HISTORY OF LANGUAGE MODELS

Language Model became more complex and larger



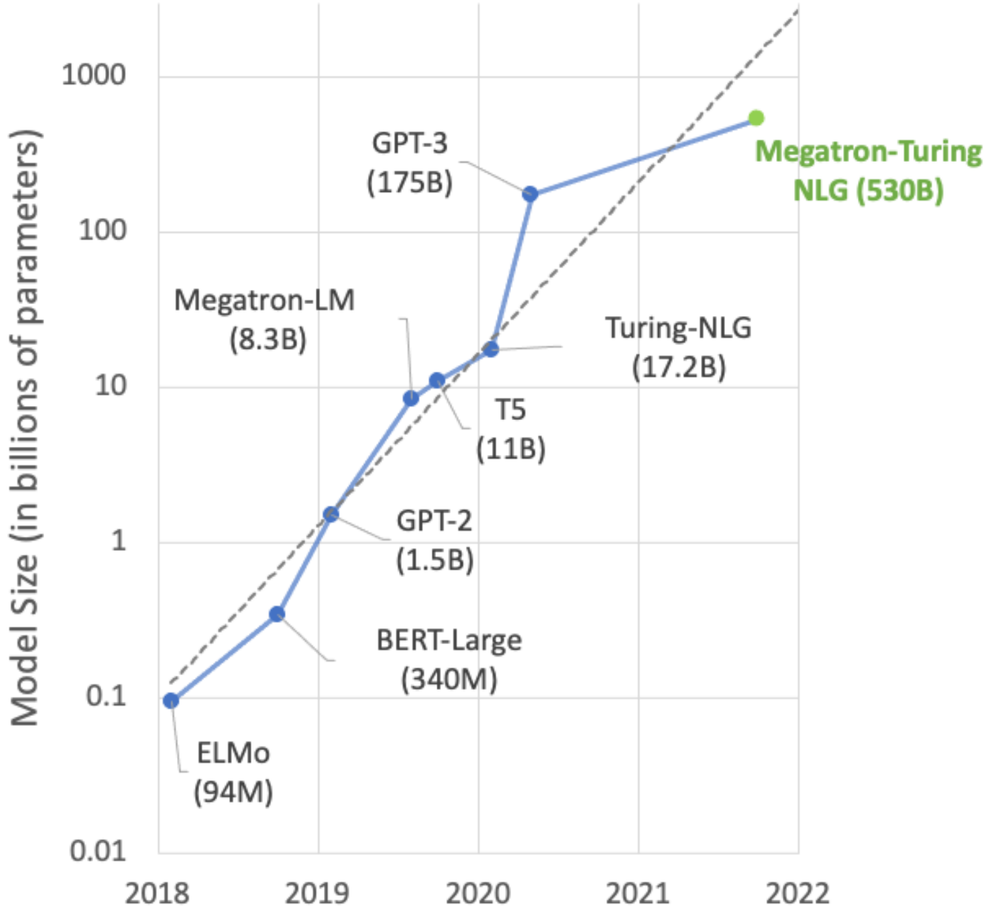


* Figure courtesy of Huggingface and Microsoft blog posts.



MEGATRON-TURING NLG 530B

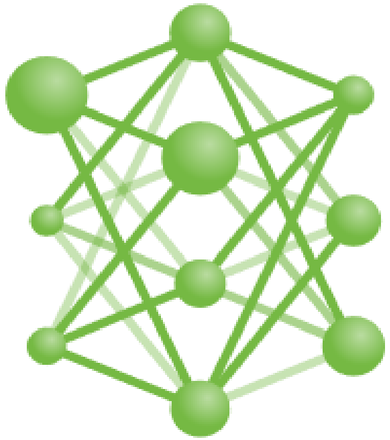
The Trend Continues

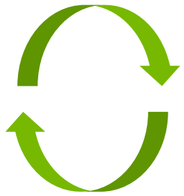


https://developer.nvidia.com/blog/using-deepspeed-and-megatron-to-train-megatron-turing-nlg-530b-the-worlds-largest-and-most-powerful-generative-language-model/

LLM FOR SEARCH

EXTERNAL KNOWLEDGE SOURCE





Instructed LLM

Knowledge source

EXTERNAL KNOWLEDGE SOURCE

Searching through the web

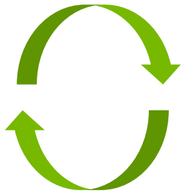
A

Can you formulate a search querry that will help me find the above mentioned information?

Certainly! Here's a search query that could help you find more information about synthesizing dimethyl carbonate (DMC) from raw materials:

"synthesis of dimethyl carbonate from methanol and phosgene"

This query includes the relevant keywords for the process (synthesis, dimethyl carbonate, methanol, phosgene) and can help you find articles, research papers, or other sources that discuss the topic in more detail. You may also want to refine your search with additional keywords related to the catalyst, reaction conditions, and purification techniques, depending on the level of detail you're looking for. As always, be sure to evaluate the sources you find for accuracy and reliability.



Microsoft Bing

"synthesis of dimethyl carbonate from methanol and phosgene"

ALL WORK IMAGES VIDEOS MAPS NEWS CHAT MORE

About 4 results Date

Studies on synthesis of dimethyl carbonate from …

https://www.sciencedirect.com/science/article/pii/S156673670800486X

Web Jan 25, 2009 · Thermodynamic and kinetic character of DMC catalytic synthesis process 3.2.1. **Synthesis reaction catalyzed by basic** catalysts When the **reaction of methanol and carbon dioxide occur** using basic compounds, namely K 2 CO 3, KOH and CH 3 …

Author: Qinghai Cai, Qinghai Cai, Bin Lu, … **Publish Year:** 2009

A

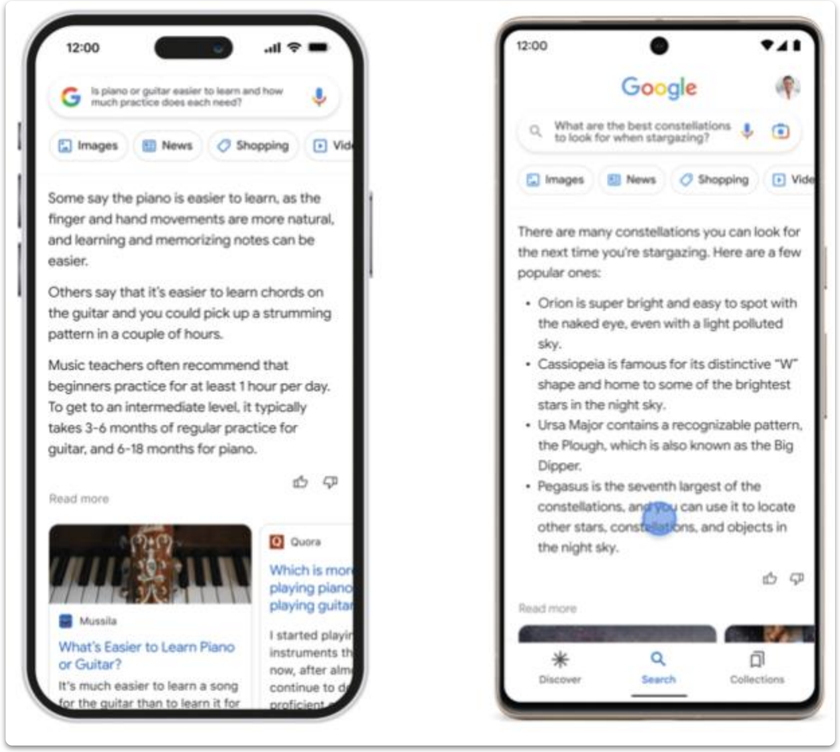
Given the following text: "The reaction thermodynamics of dimethyl carbonate (DMC) synthesis from CH3OH and CO2 was investigated by estimating ΔrH and ΔrG of the reaction at different temperatures and pressure. The result shows that the reaction does not spontaneously occur under finite conditions in view of thermodynamics. Thus, in order to seek a new method or a novel idea for the DMC synthesis, the thermodynamics of DMC synthesis catalyzed by basic catalysts, K2CO3, KOH and CH3OK, was discussed in details. A general conclusion was obtained that the subroutine nesting of a coupling reaction is an effective avenue to increase the yield of DMC synthesis from CO2 and CH3OH."

How do you increae the yield of DMC?

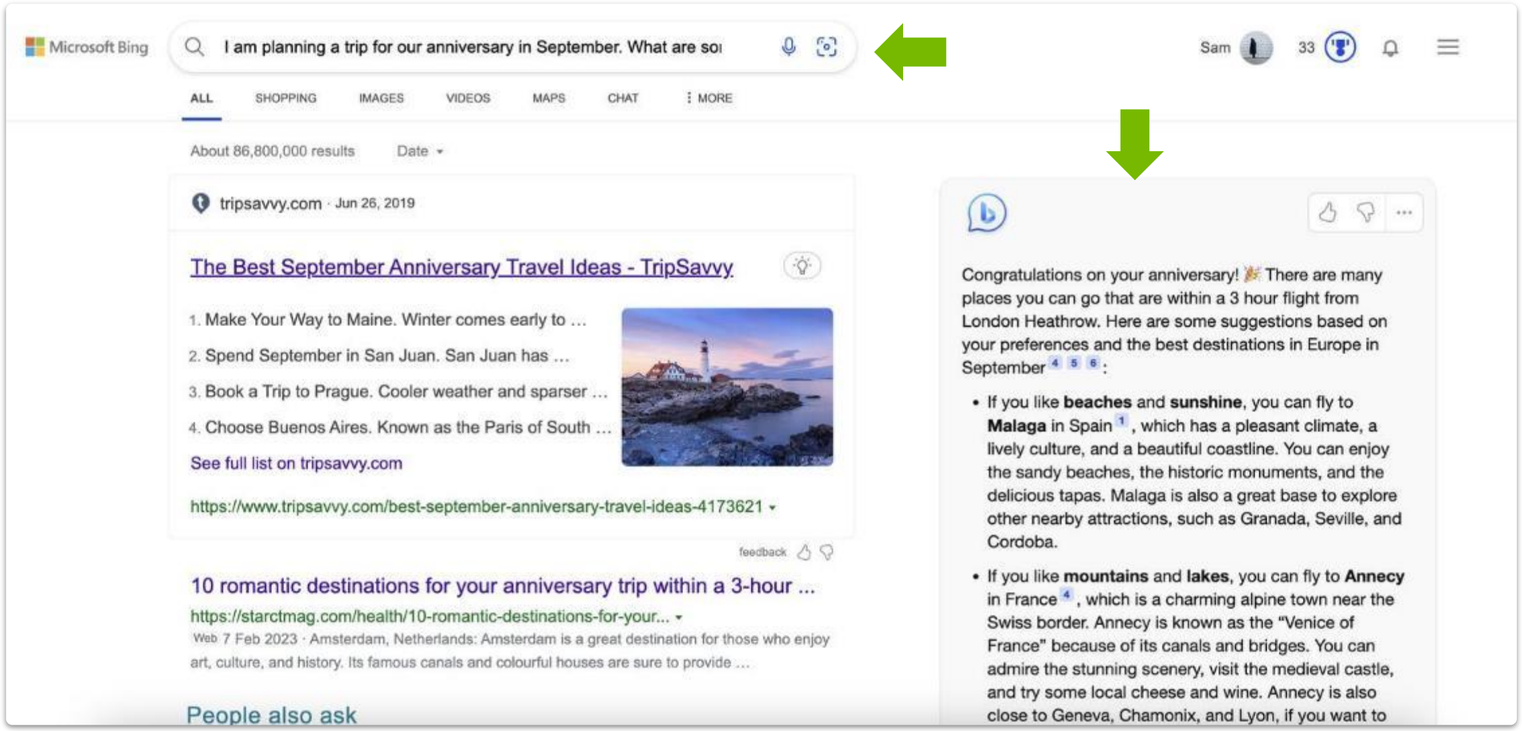
According to the given text, the most effective way to increase the yield of dimethyl carbonate (DMC) synthesis from CO2 and CH3OH is through the use of a subroutine nesting of a coupling reaction, which was found to be an effective avenue for improving the reaction yield. Additionally, the text suggests that the thermodynamics of DMC synthesis catalyzed by basic catalysts, such as K2CO3, KOH, and CH3OK, were also discussed in detail, so it's possible that other catalysts or reaction conditions could be used to optimize the reaction yield as well. However, the text does not provide specific details on how the coupling reaction method works, so further research would be needed to explore this approach in more detail.

EXTERNAL KNOWLEDGE SOURCE

Examples of Search Engine Powered by LLM



NORA - No One Right Answer [Google]

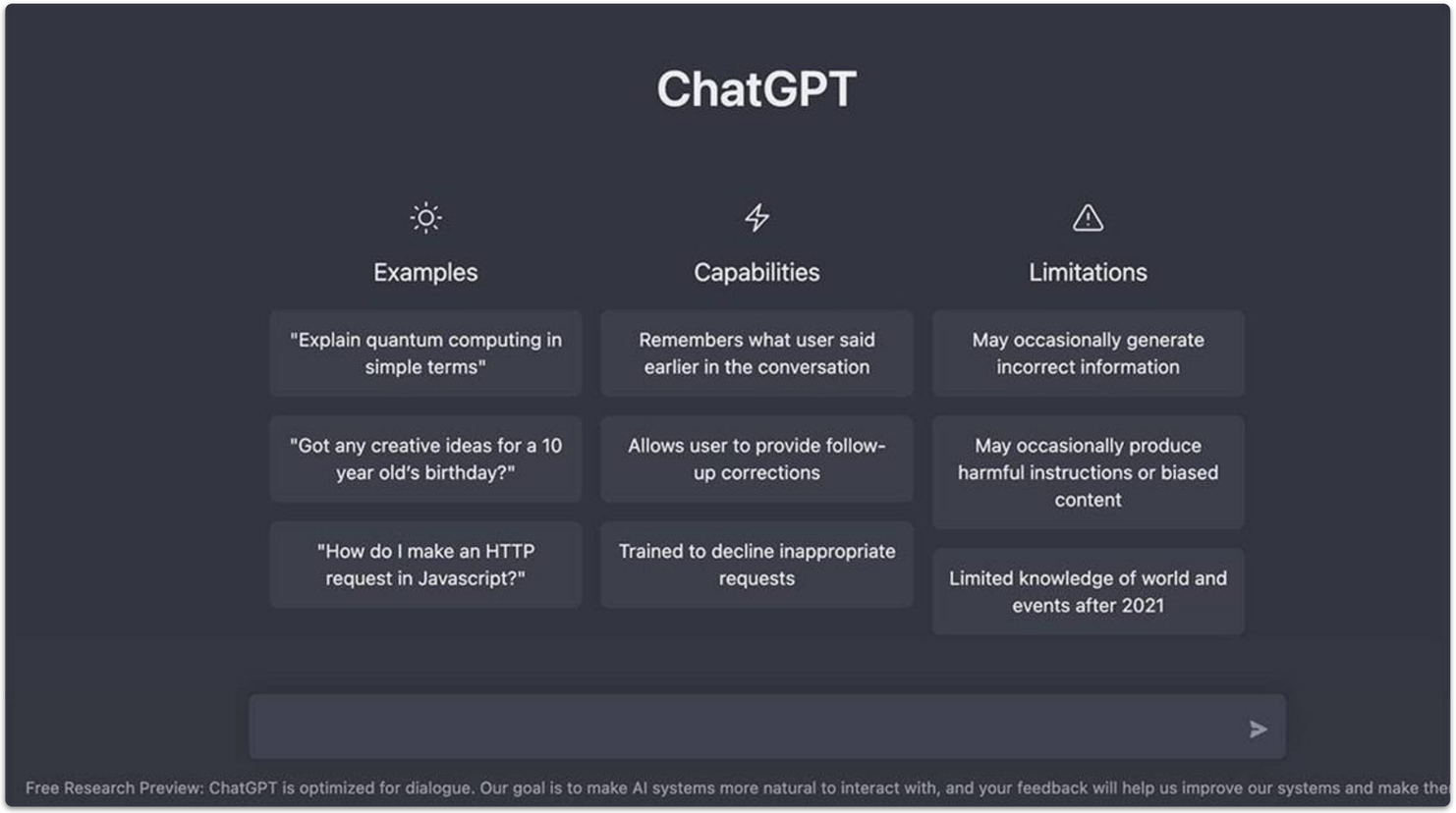


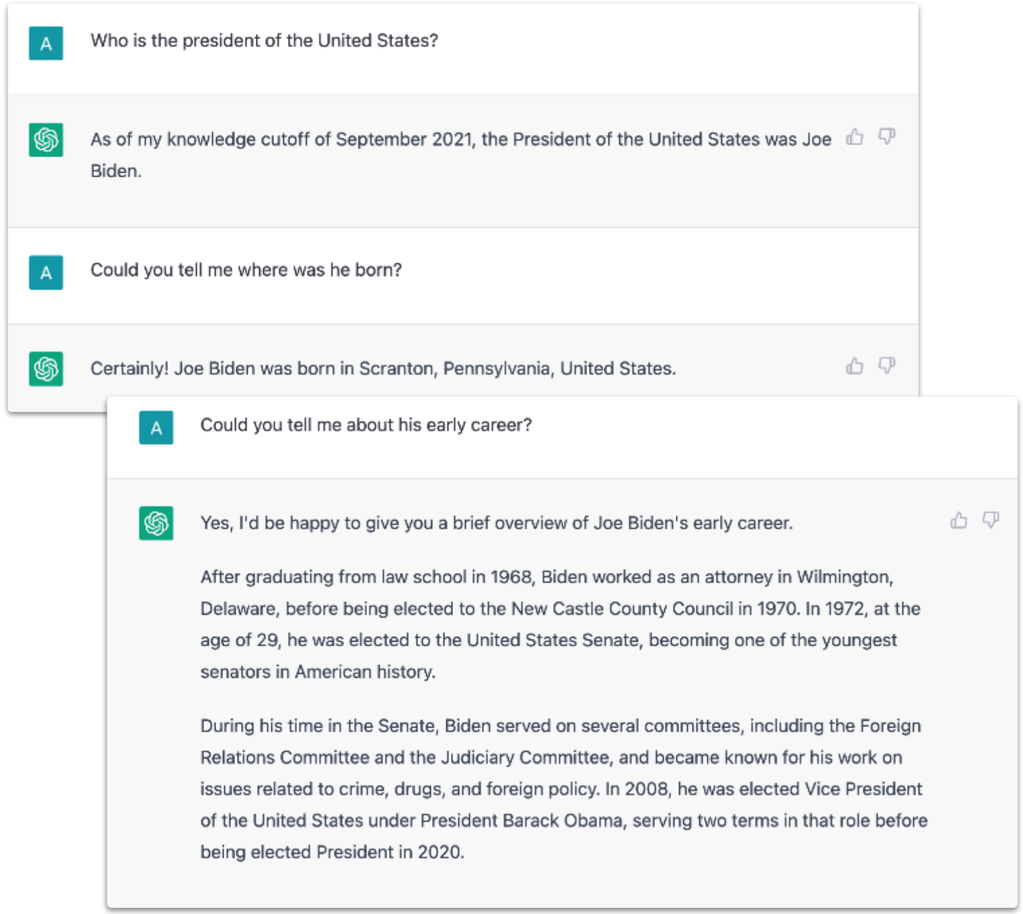
New Bing Search Engine [Microsoft]

LLM FOR CHATBOTS

CHATBOTS POWERED BY INSTRUCTED LLM

ChatGPT is a sibling model to InstructGPT





CHATBOTS POWERED BY INSTRUCTED LLM

Bing Chat powered by Next generation GPT | Bard powered by LaMDA

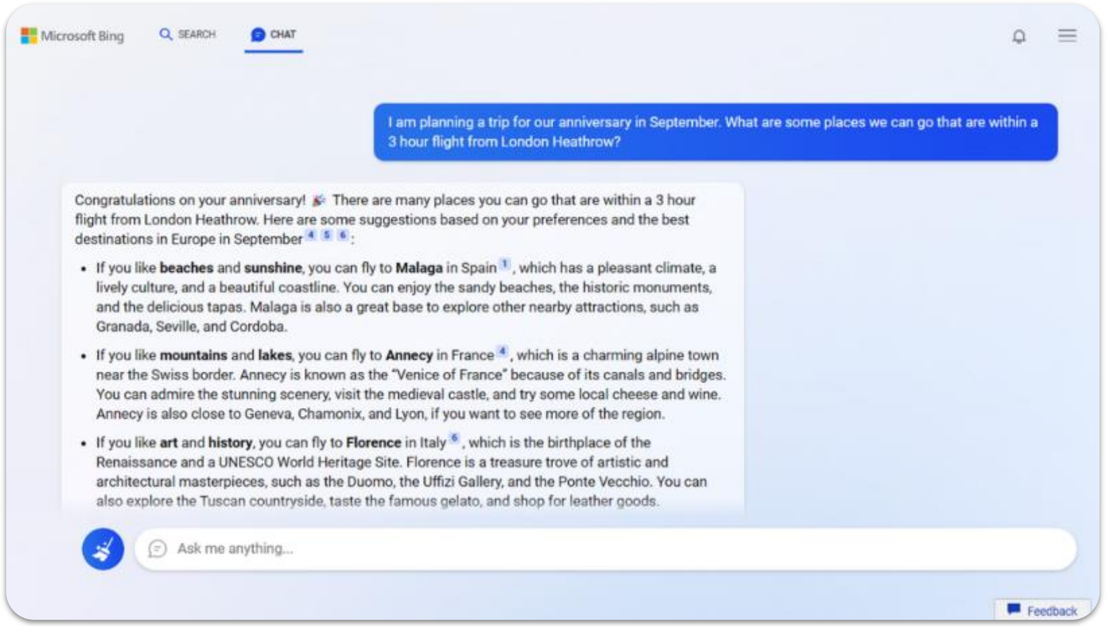
OpenAI

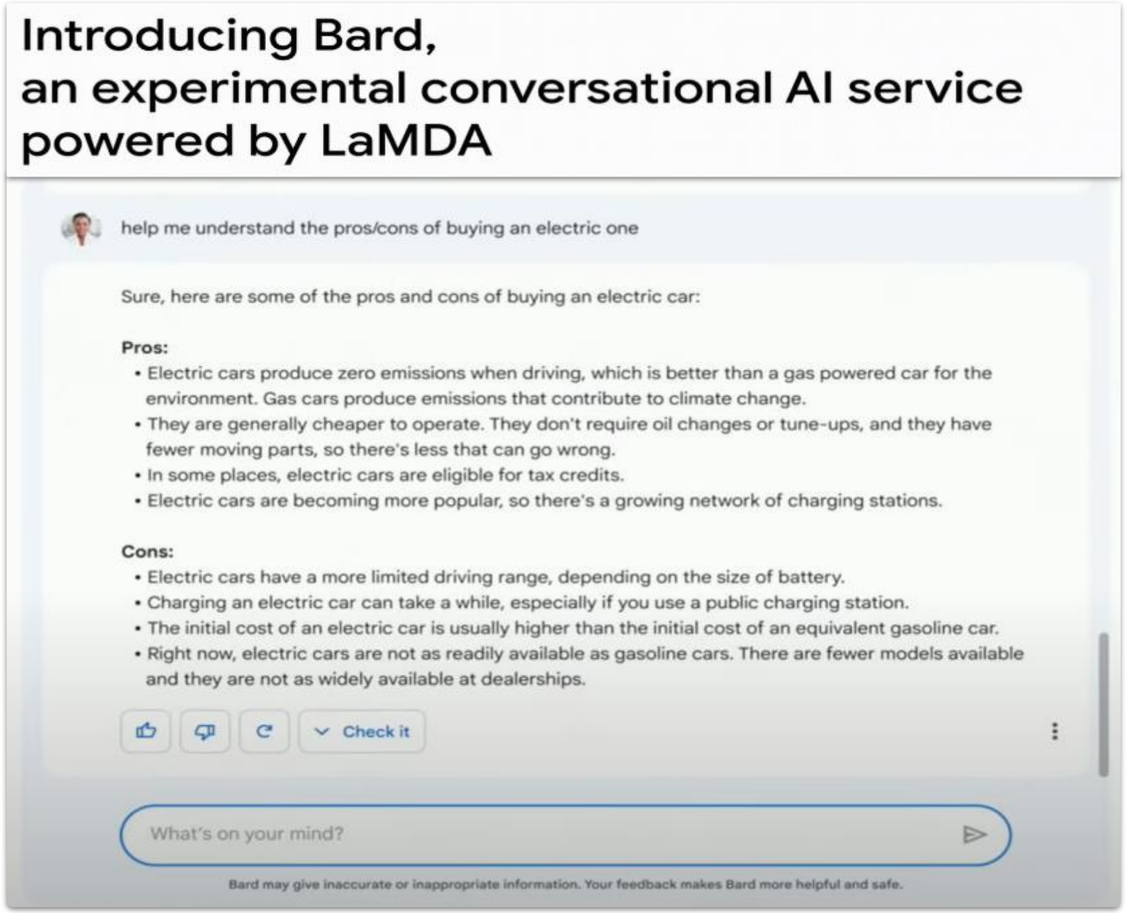
Next-generation large language model

More powerful than ChatGPT

Customized for search

Prometheus Model






TECHNICALLY, CAN WE
BUILD LARGER MODELS?

GOING BIGGER

The challenge

- If we only consider Parameters, Gradients, and Optimizer states and ignore activations
- If we use FP16 data representation (so two bytes)
- If we use Adam as an optimizer (storing twelve bytes per parameter in mixed precision mode)
- If we consider a model with one billion parameters

$$10^9 * (2B + 2B + 12B) = 10^9*16B = 14.90GB$$

1 billion parameters

2 bytes per parameter

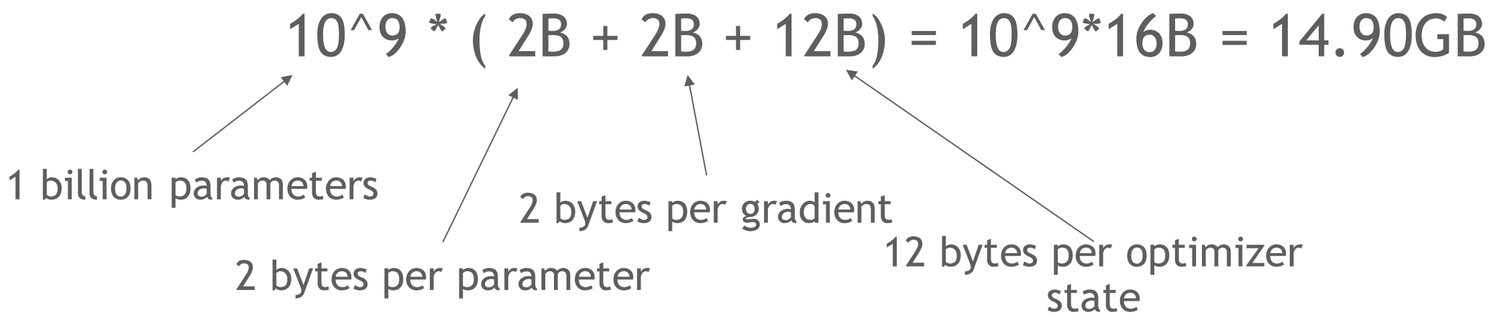
2 bytes per gradient

12 bytes per optimizer state

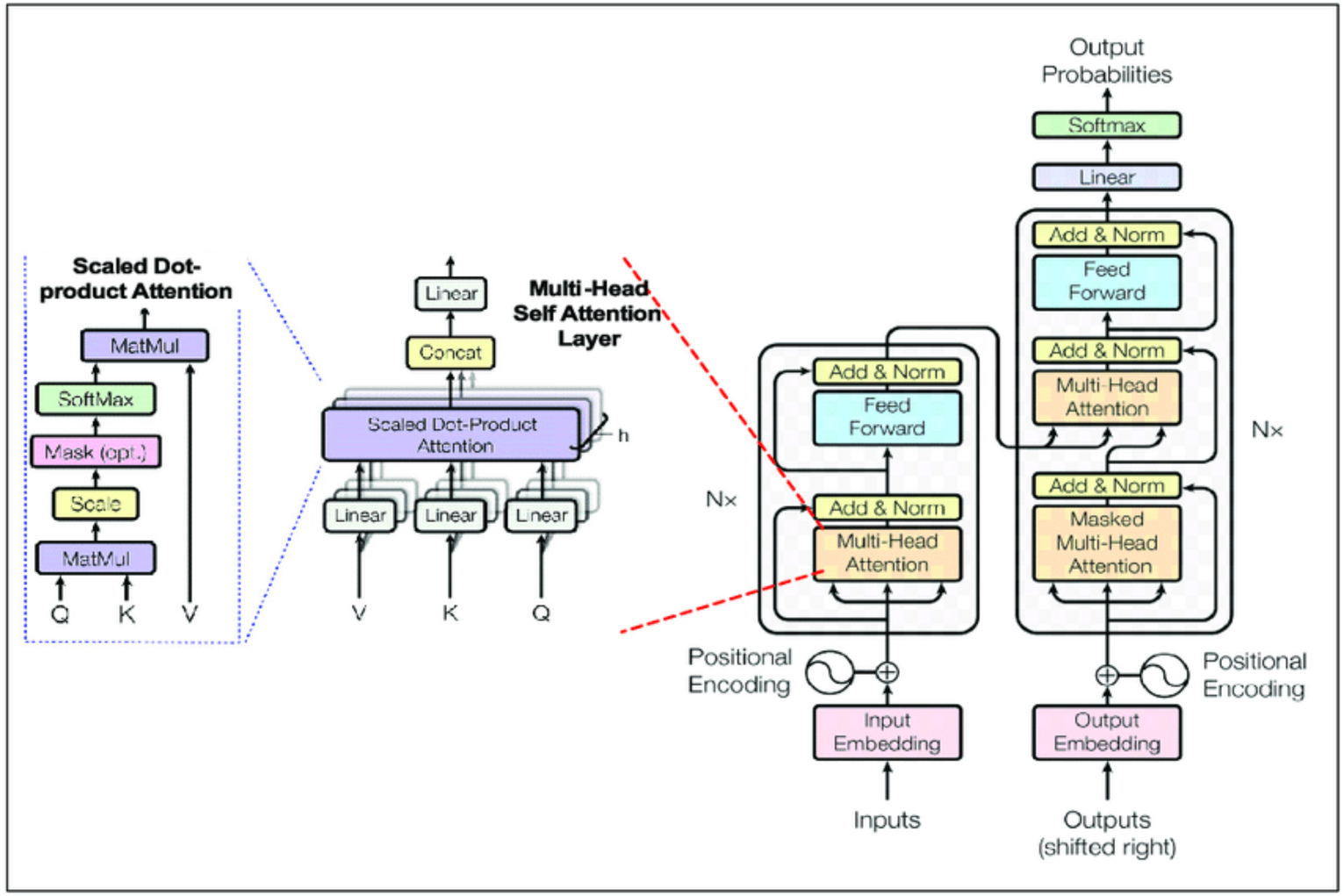
GOING BIGGER

The challenge

- What about activations?
- What about 2 or 3 billion parameter models?

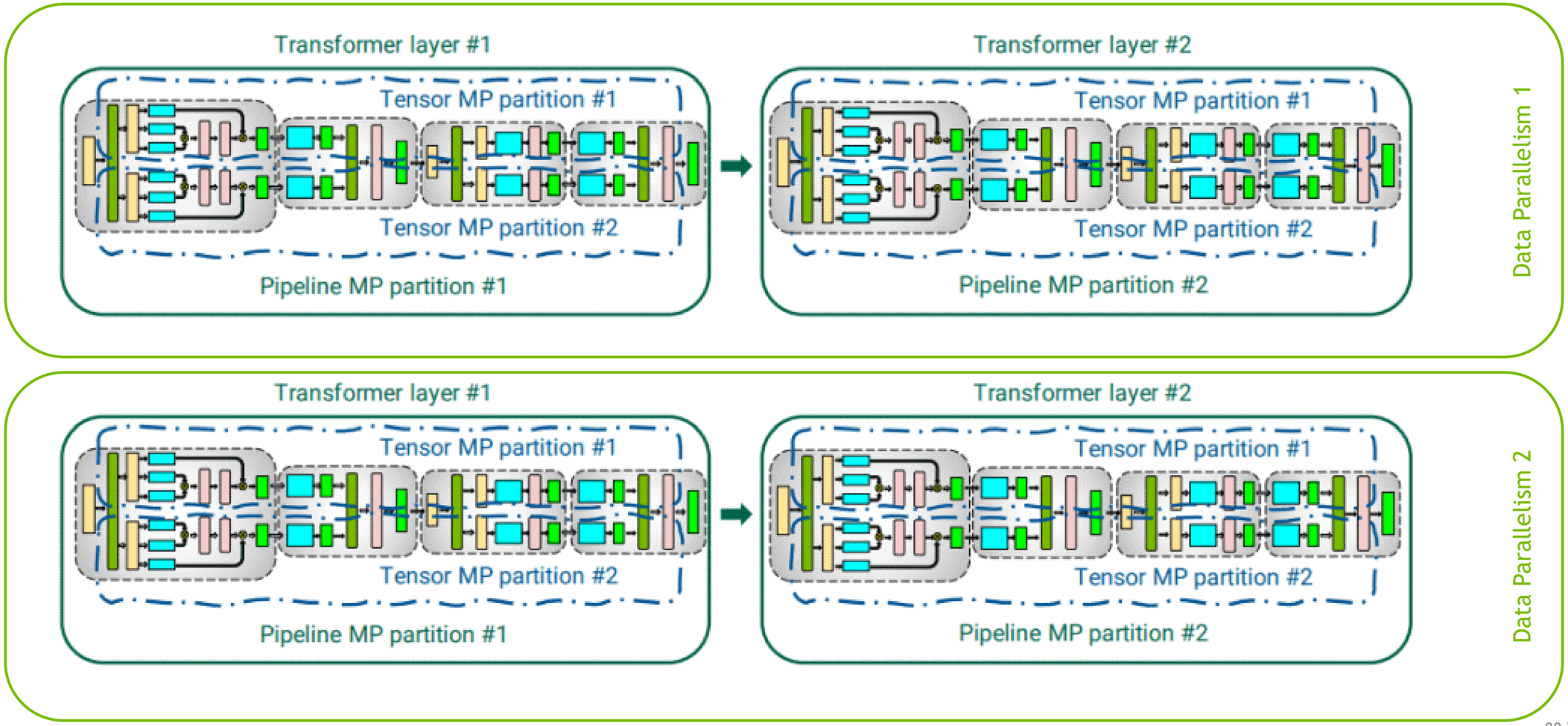


TRANSFORMER MODELS



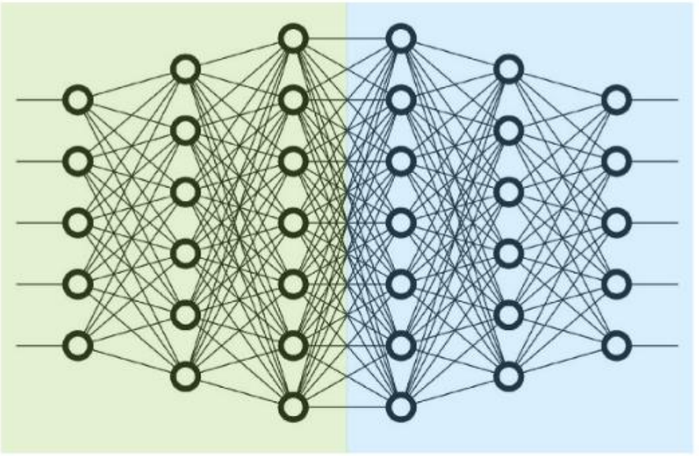
MODEL IMPLEMENTATION

Data, Pipeline and Tensor Parallelism

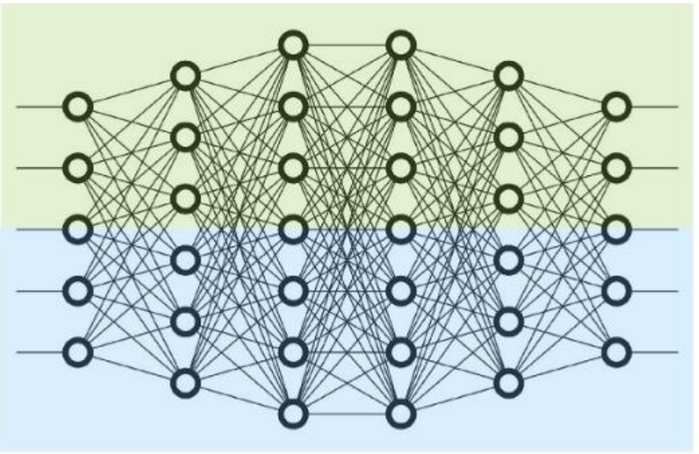


MODEL PARALLELISM

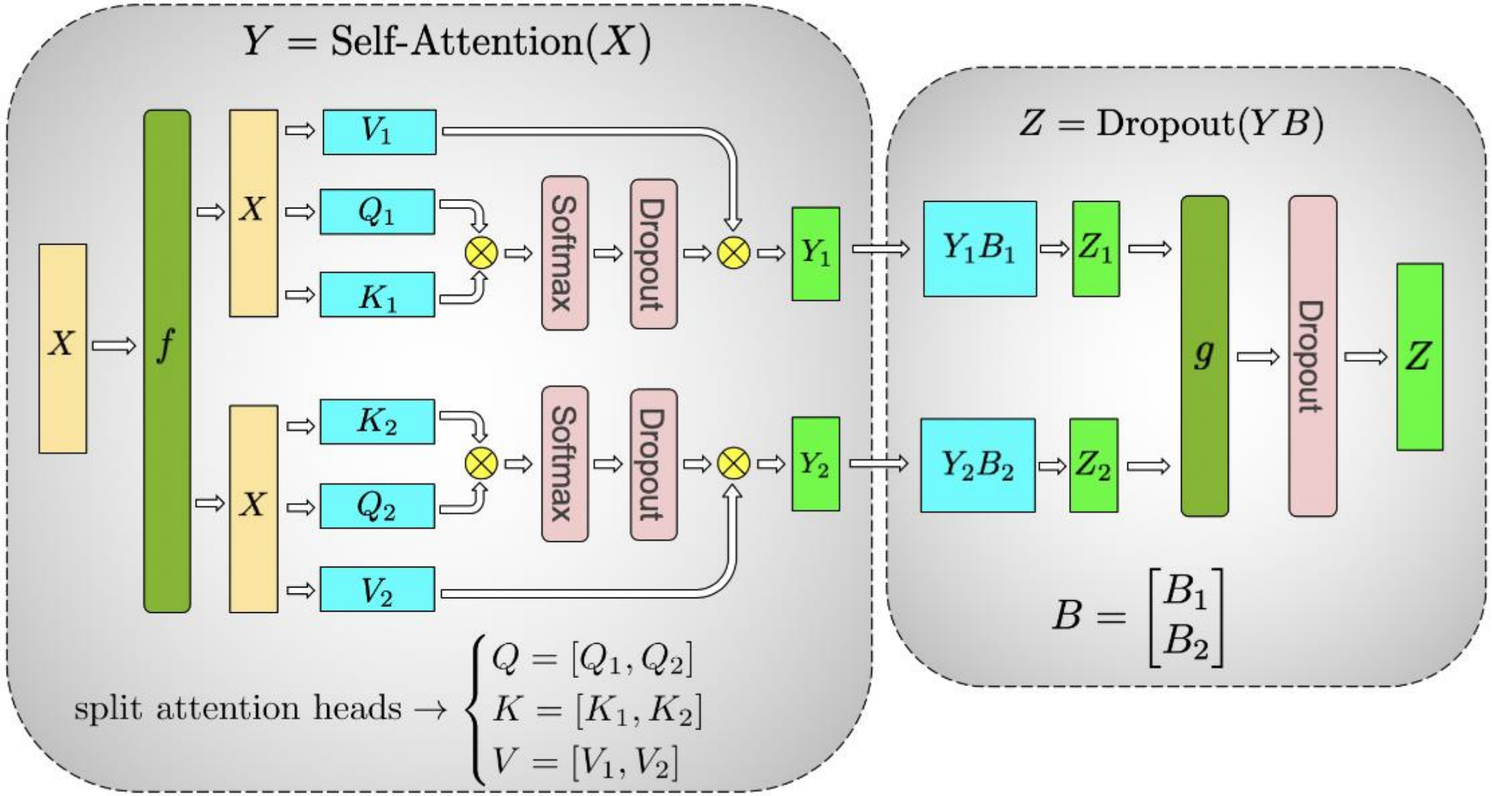
- Pipeline (Inter-Layer) Parallelism
  - Split sets of layers across multiple devices
  - Layer 0,1,2 and layer 3,4,5 are on difference devices



- Tensor (Intra-Layer) Parallelism
  - Split individual layers across multiple devices
  - Both devices compute difference parts of Layer 0,1,2,3,4,5

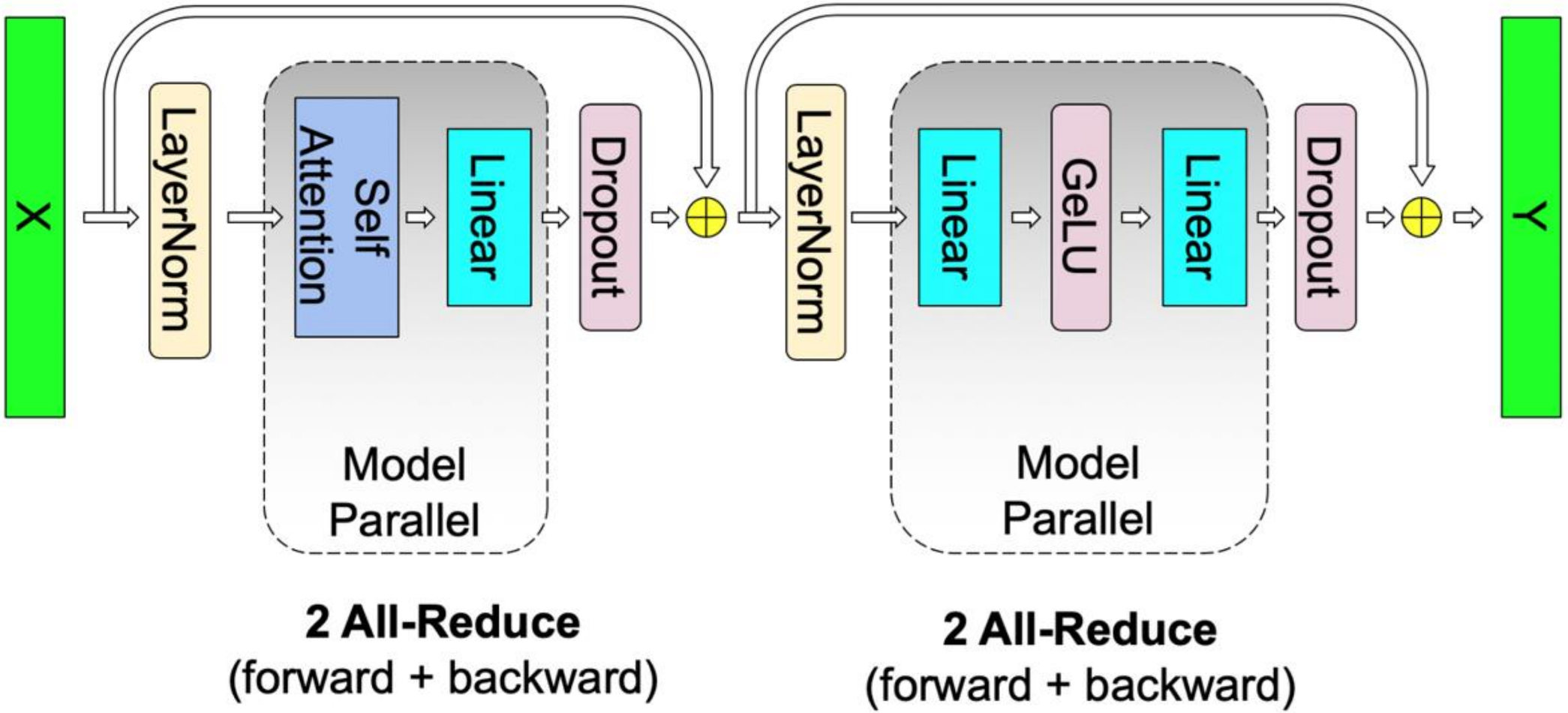


SELF-ATTENTION



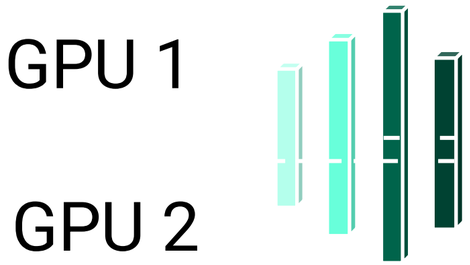
f and ***g*** are **conjugate**, ***f*** is **identity** operator in the forward pass and **all-reduce** in the backward pass while ***g*** is **all-reduce** in forward and **identity** in backward.

PARALLEL TRANSFORMER LAYER



COMPARING TENSOR AND PIPELINE PARALLELISM

Tensor Parallelism



Communication expensive

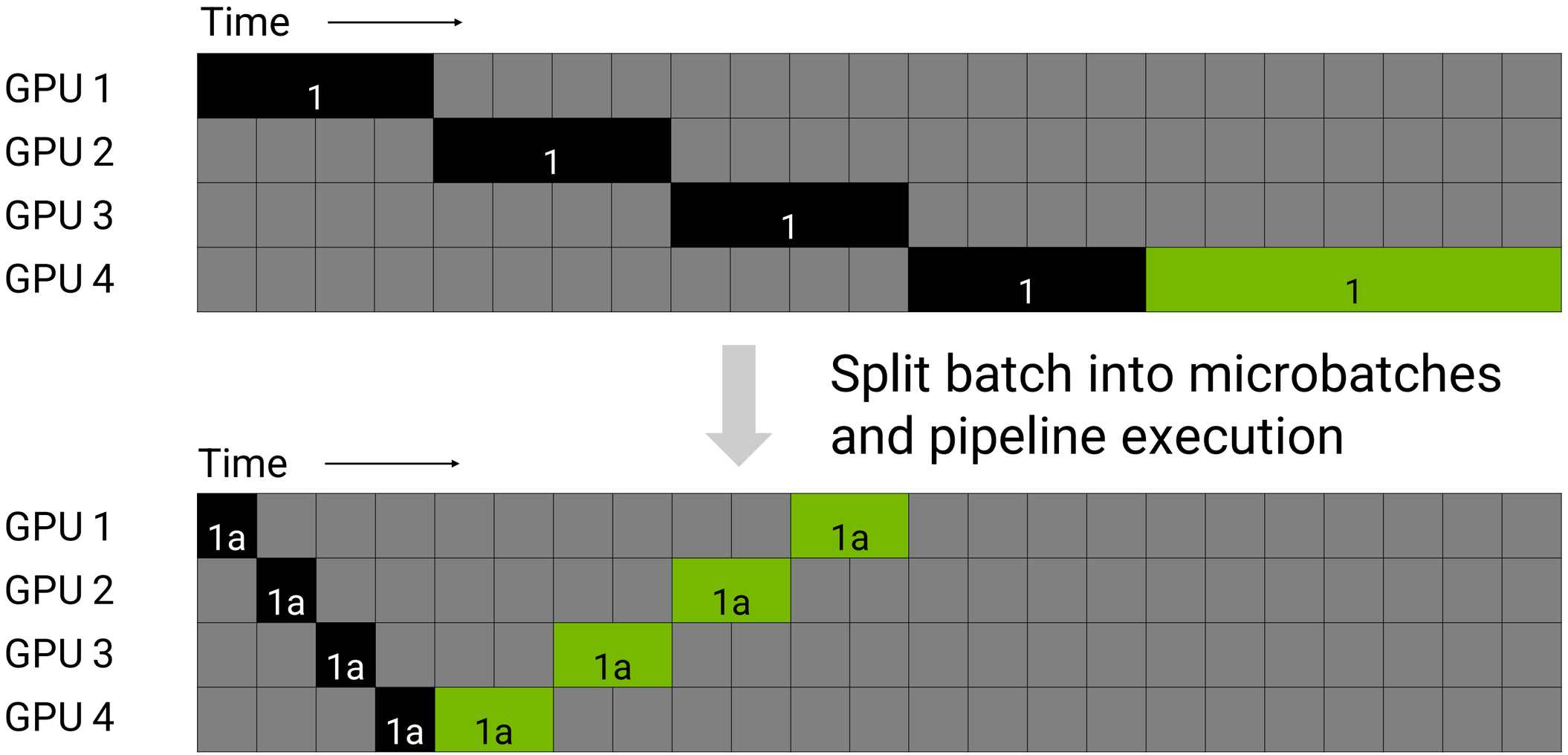
Good performance across batch sizes

Pipeline Parallelism

Communication cheap

Good performance at larger batch sizes (pipeline stall amortized)

PIPELINING


Time
GPU 1
GPU 2
GPU 3
GPU 4
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1
Split batch into microbatches and pipeline execution
Time
GPU 1
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GPU 3
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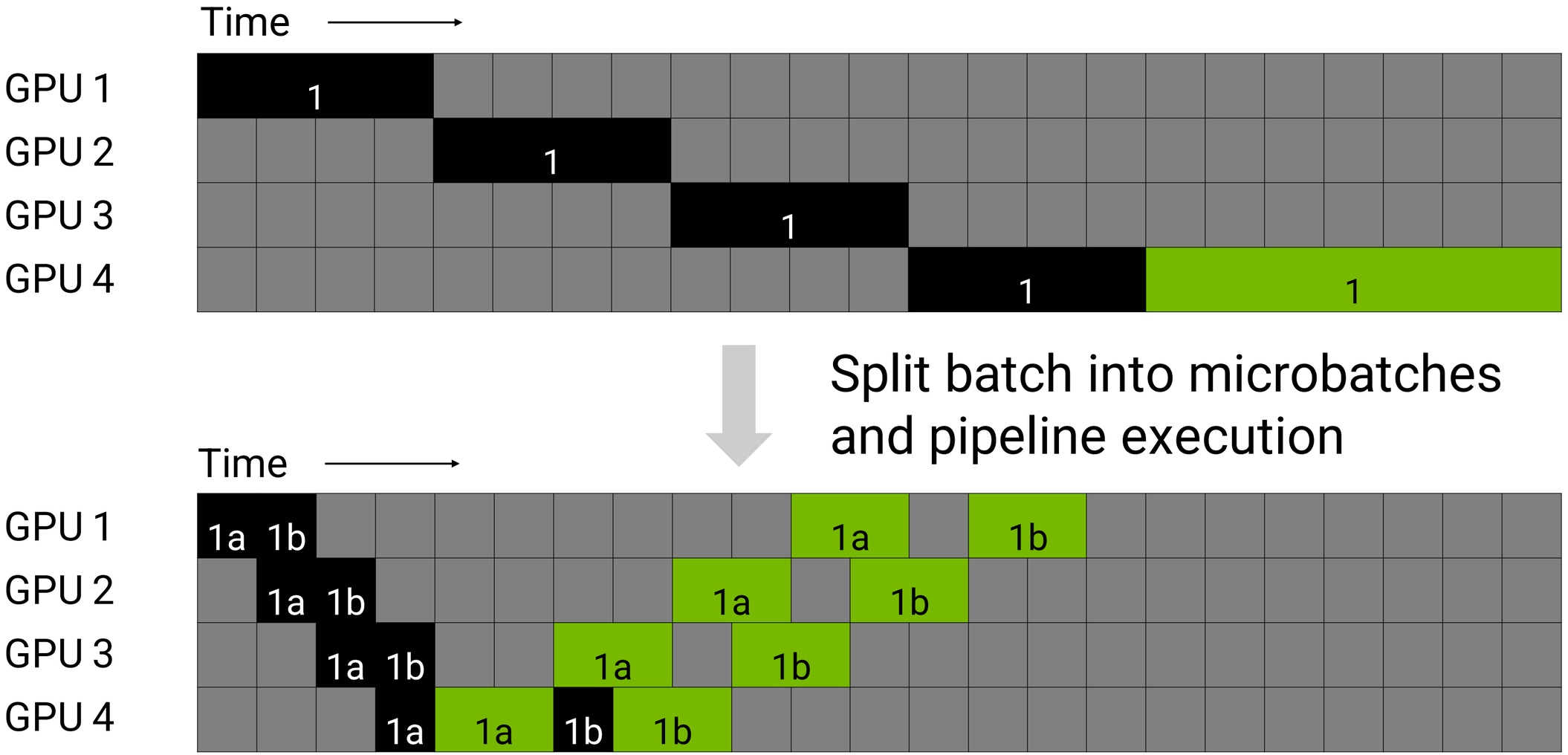
PIPELINING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Split batch into microbatches and pipeline execution
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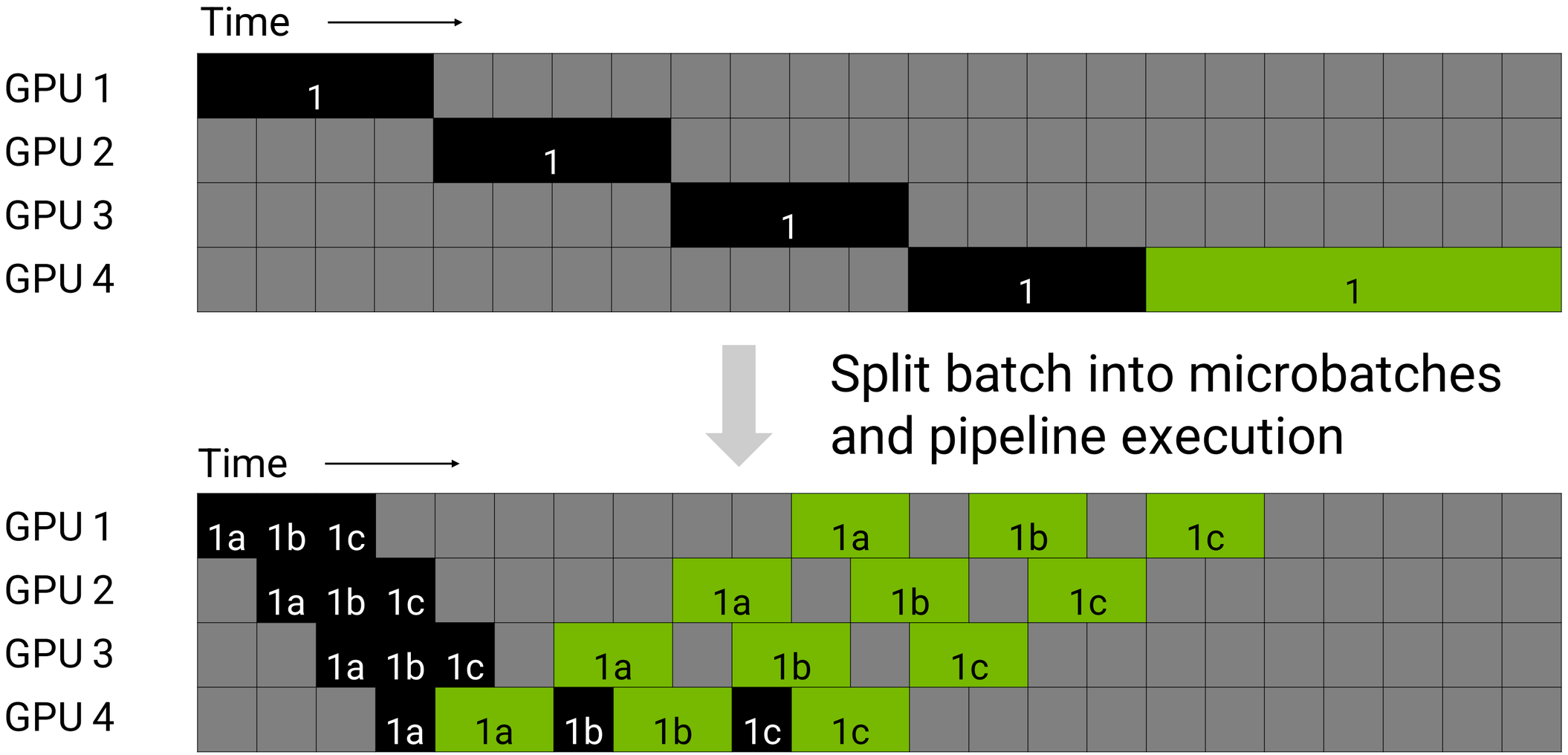
PIPELINING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Split batch into microbatches and pipeline execution
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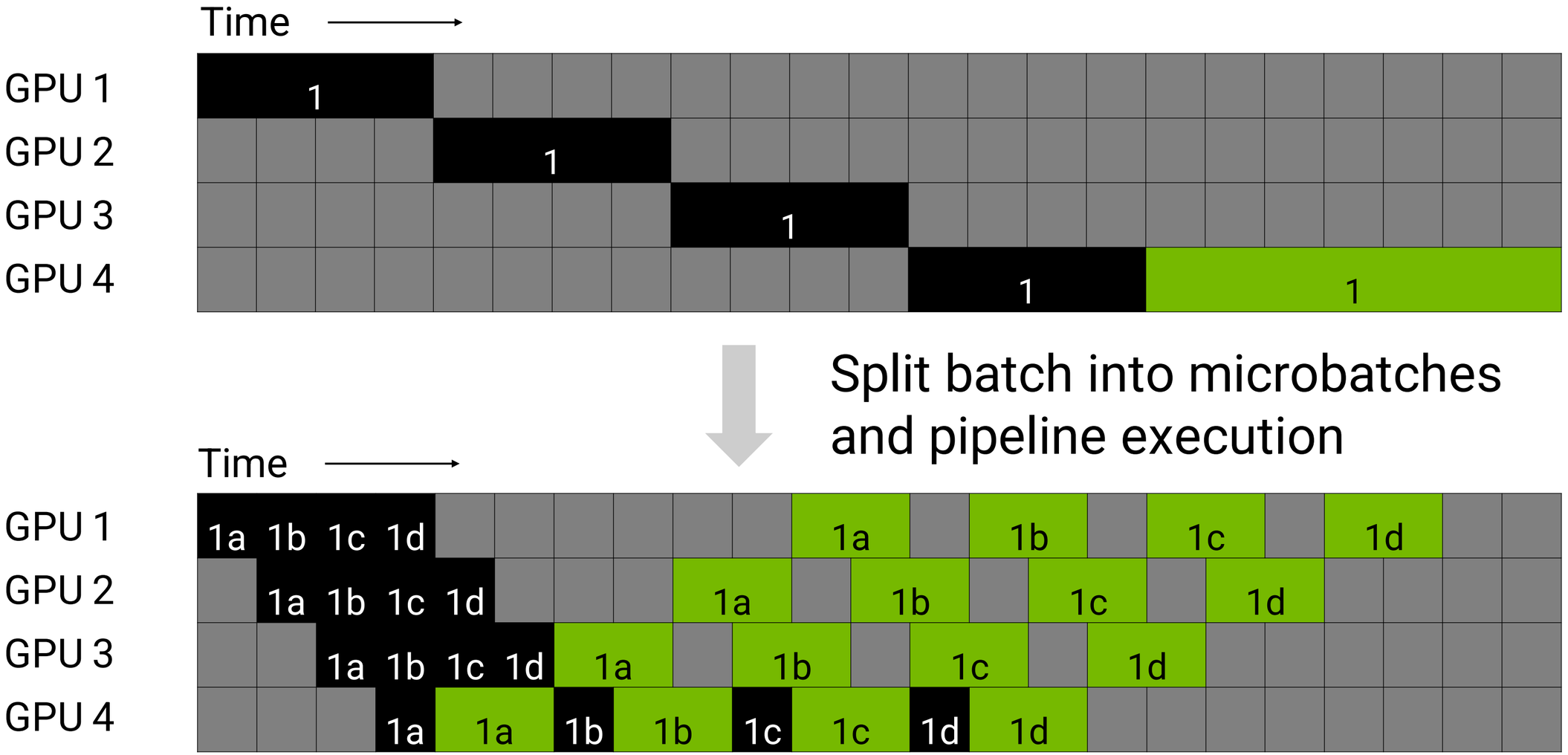
PIPELINING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Split batch into microbatches and pipeline execution
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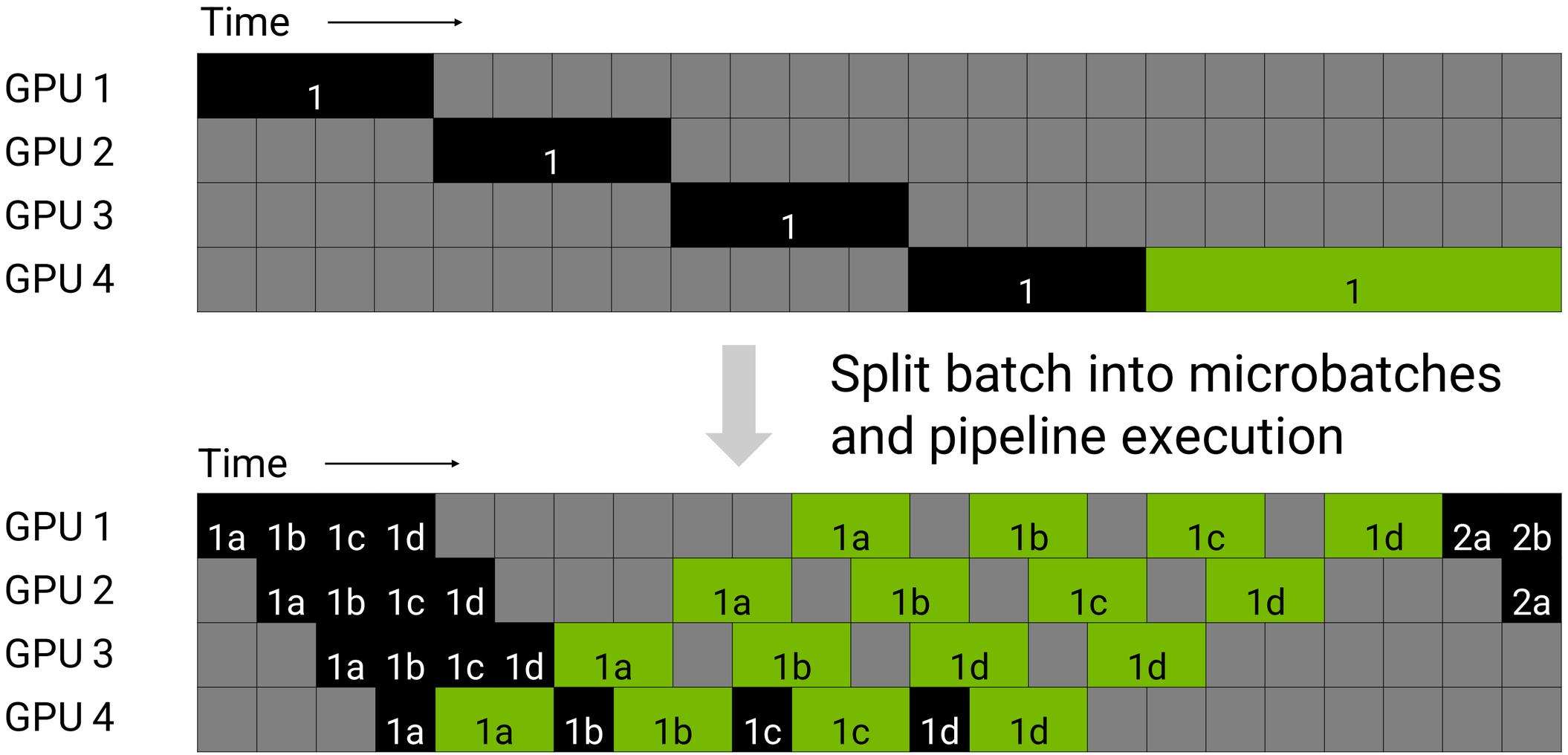
PIPELINING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Split batch into microbatches and pipeline execution
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1a 1a 1b 1b 1c 1c 1d 1d
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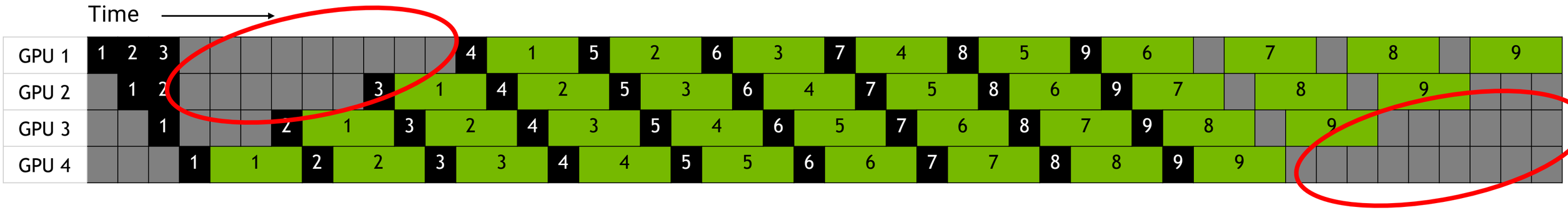
1a 1b 1d 1d
2a 2b
2a

PIPELINE BUBBLES



p : number of pipeline stages

m : number of micro batches

t_f : forward step time

t_b : backward step time

$$\text{total time} = (m + p - 1) \times (t_f + t_b)$$

$$\text{ideal time} = m \times (t_f + t_b)$$

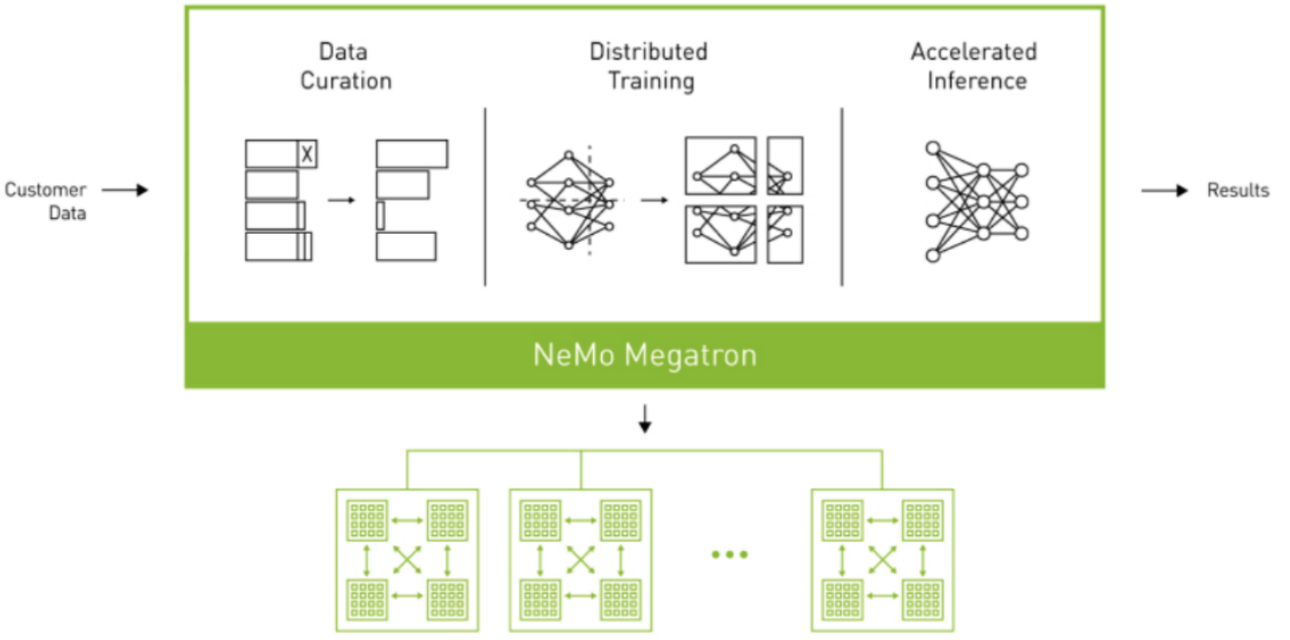
$$\text{bubble time} = (p - 1) \times (t_f + t_b)$$

$$\text{bubble time overhead} = \frac{\text{bubble time}}{\text{ideal time}} = \frac{p - 1}{m}$$

NVIDIA NeMo Megatron

NVIDIA NeMo Megatron is an end-to-end framework for training and deploying LLMs with billions and trillions of parameters.

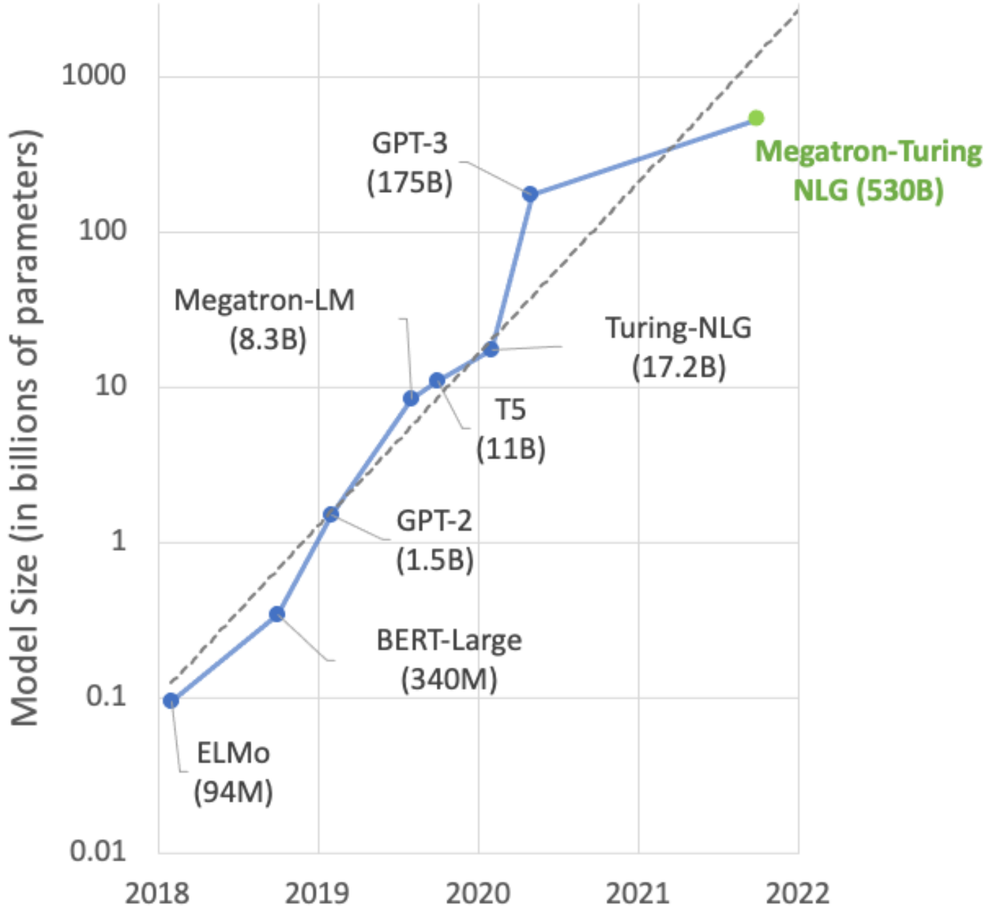
Download Now



https://developer.nvidia.com/nemo/megatron

MEGATRON-TURING NLG 530B

Enabling the biggest of NLP models



https://developer.nvidia.com/blog/using-deepspeed-and-megatron-to-train-megatron-turing-nlg-530b-the-worlds-largest-and-most-powerful-generative-language-model/

THE LAB

Part 2: Self-Supervision, BERT and Beyond

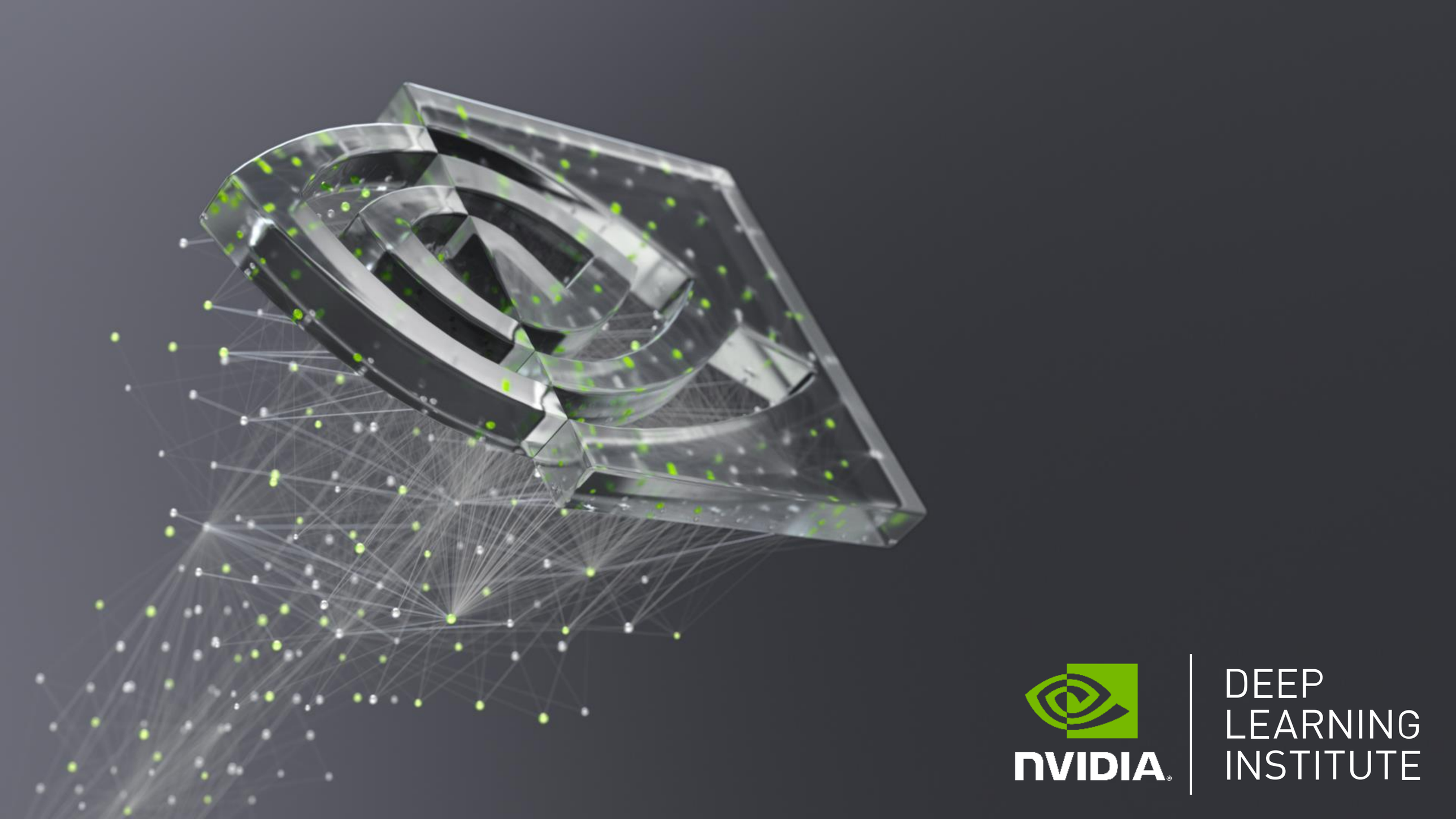
- Lecture
  - Why DNNs?
  - Self-Supervision
  - BERT
- Lab
  - Explore the Data
  - Explore NeMo
  - Text Classifier Project
- Lecture (cont'd)
  - The Scaling Laws
  - Can and should we go even bigger?
- Lab (cont'd)
  - Named Entity Recognizer

IN THE NEXT CLASS...

NEXT CLASS

Overview

1. Discuss how to design your model for efficient inference
2. Discuss how to optimise your model for efficient execution
3. Discuss how to efficiently host a largely Conversational AI application


NVIDIA
DEEP
LEARNING
INSTITUTE