NVIDIA | DEEP LEARNING INSTITUTE

BUILDING TRANSFORMER-BASED NATURAL LANGUAGE PROCESSING APPLICATIONS

PD. Dr. Juan J. Durillo

NVIDIA | DEEP LEARNING INSTITUTE

SELF-SUPERVISION, BERT, AND BEYOND

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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)
  - Bigger is Better
  - Can and should we go even bigger?
- Lab (cont'd)
  - Named Entity Recognizer

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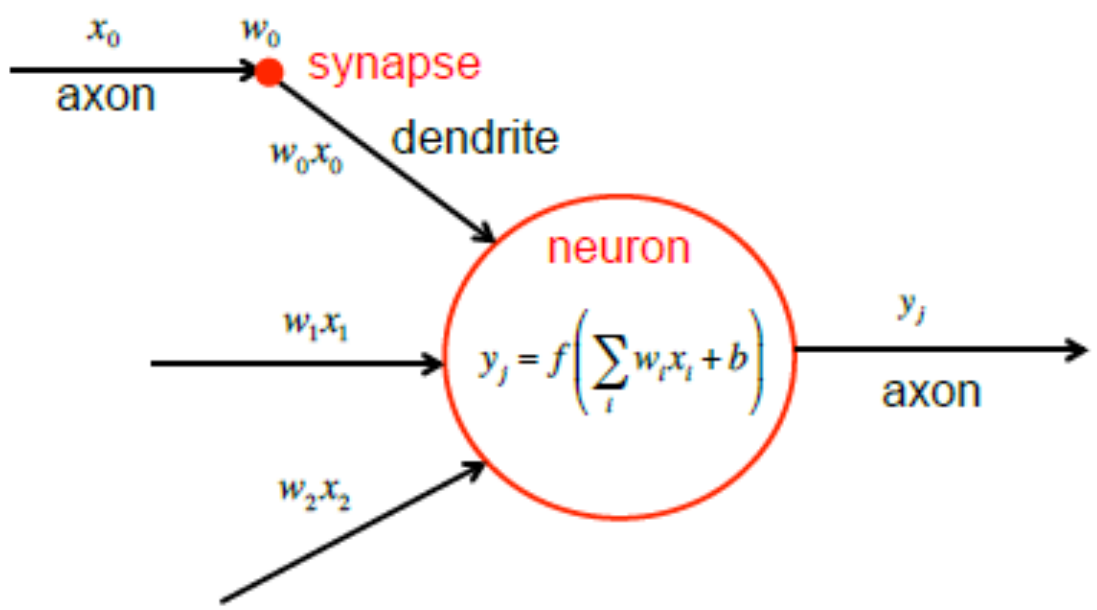
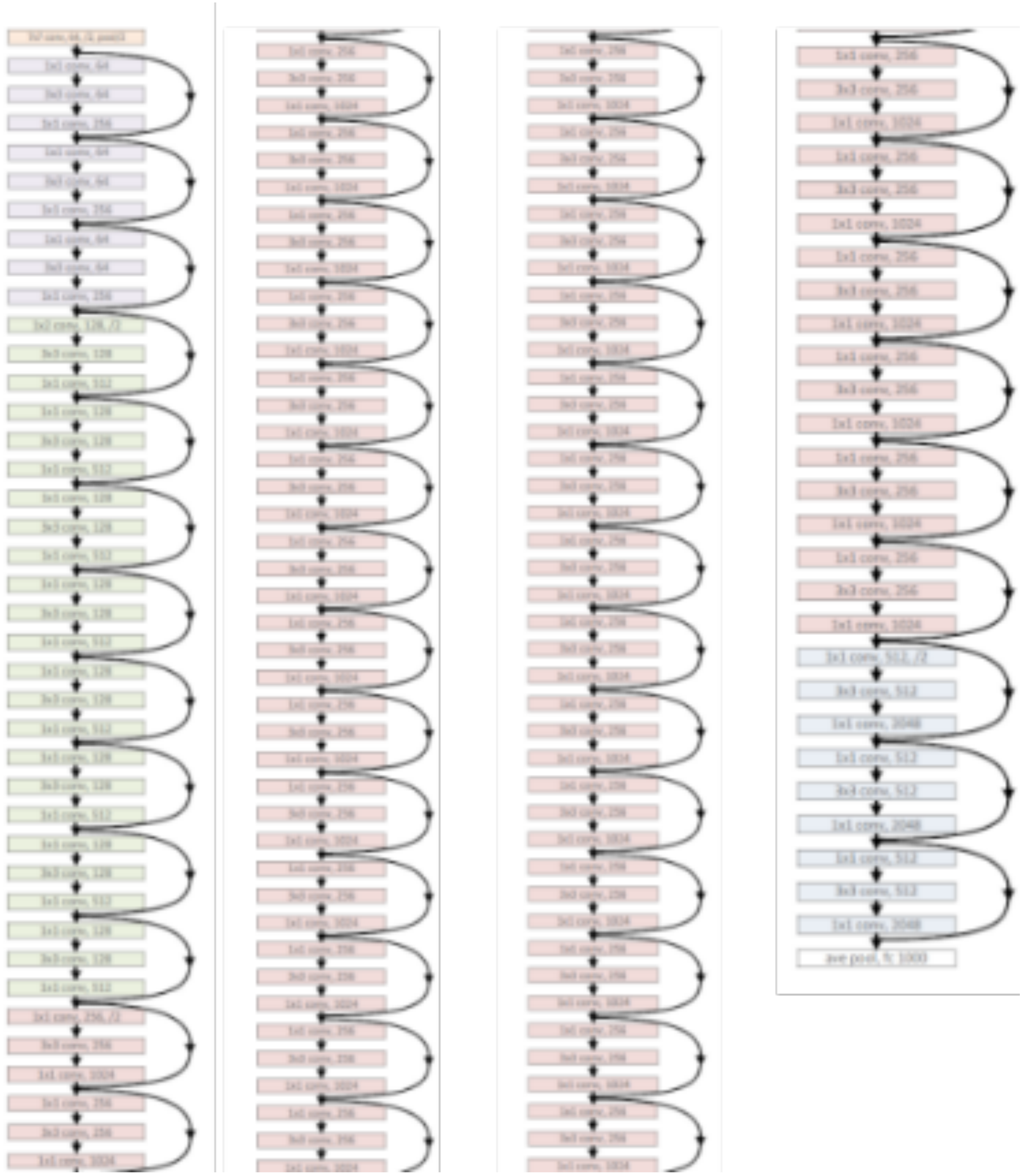
NEURAL NETWORKS ARE NOT NEW

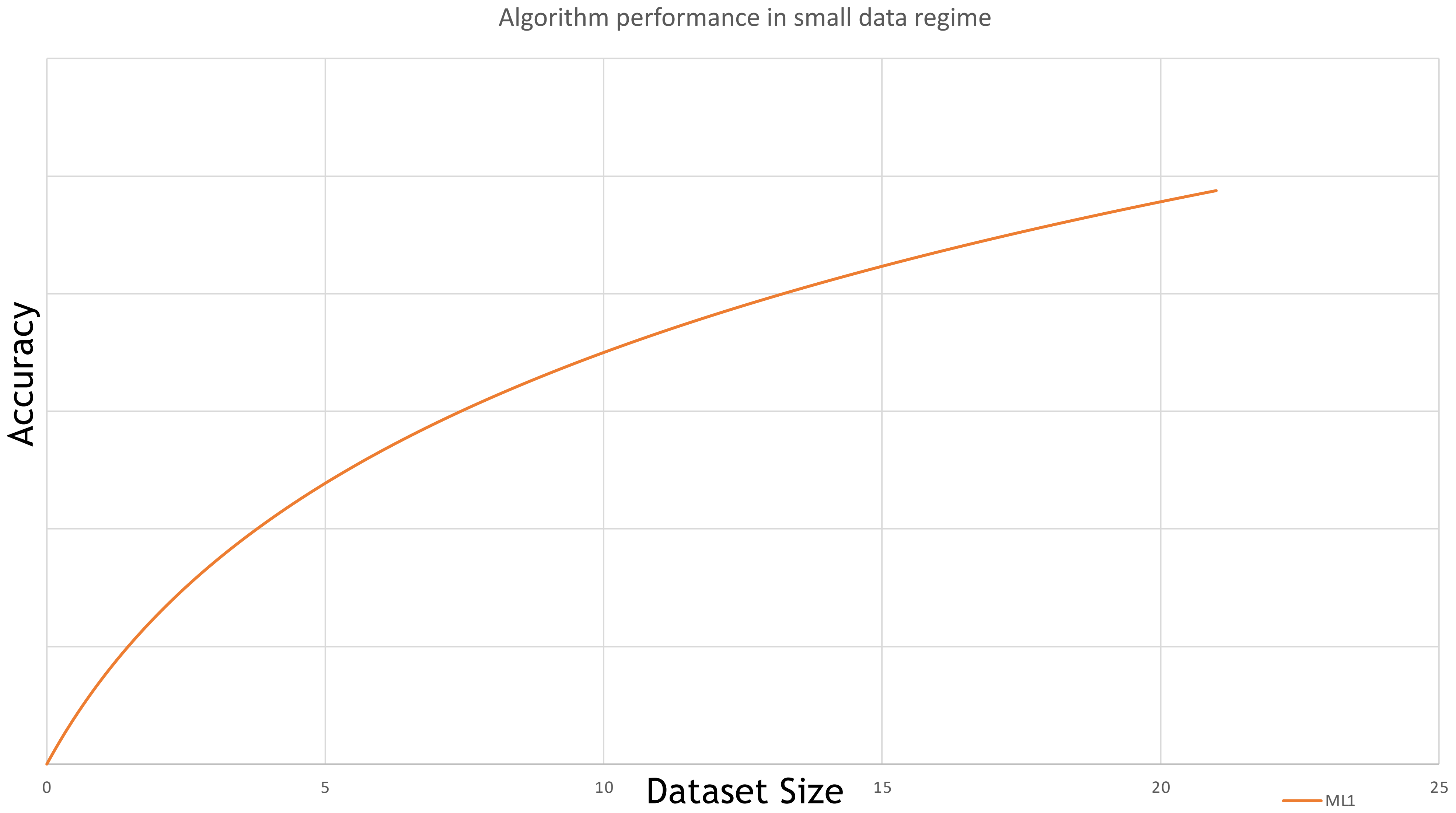
They are surprisingly simple as an algorithm





NEURAL NETWORKS ARE NOT NEW

They just historically never worked well



Andrew Ng, “Nuts and Bolts of Applying Deep Learning”, https://www.youtube.com/watch?v=F1ka6a13S9I

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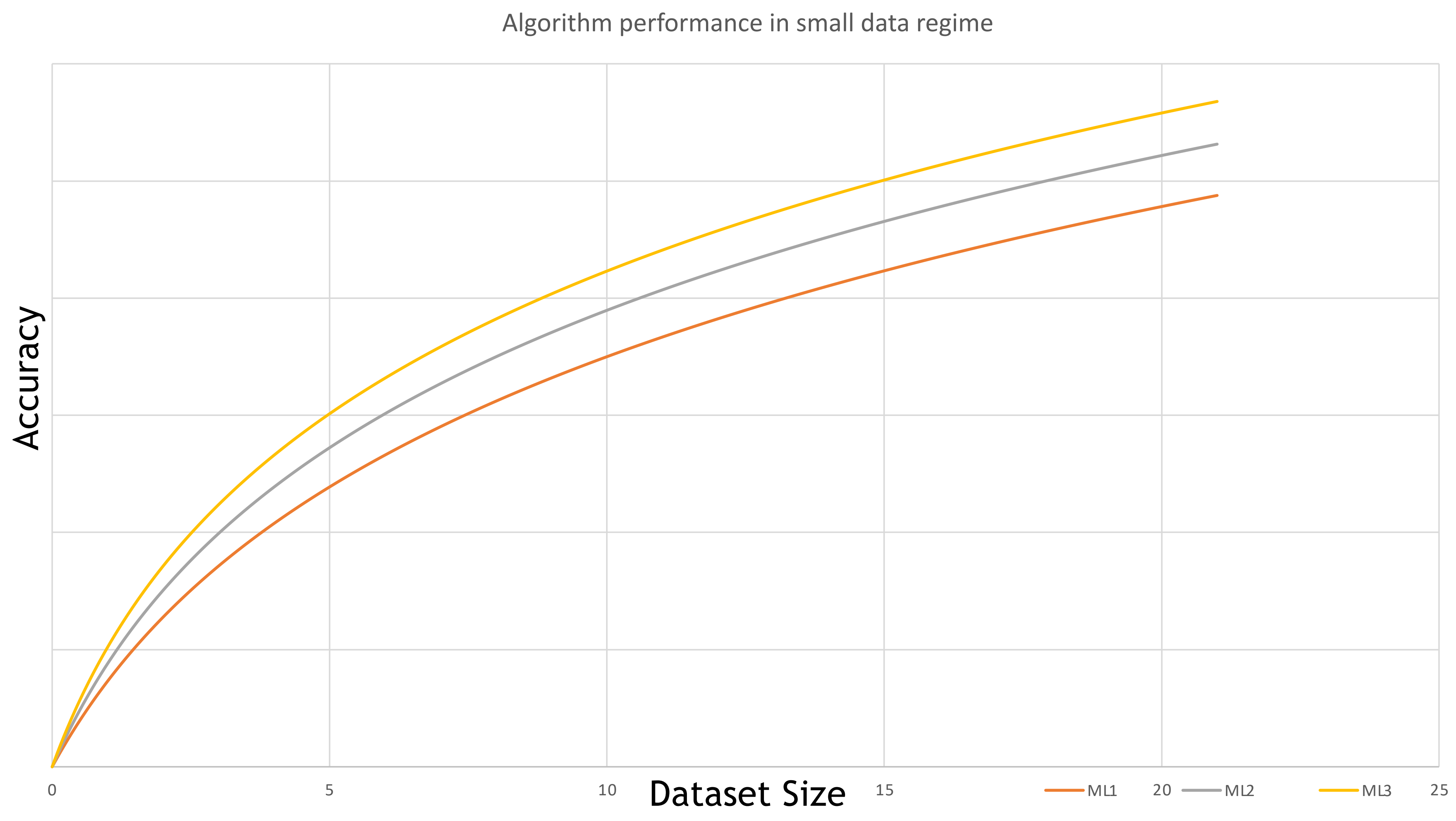

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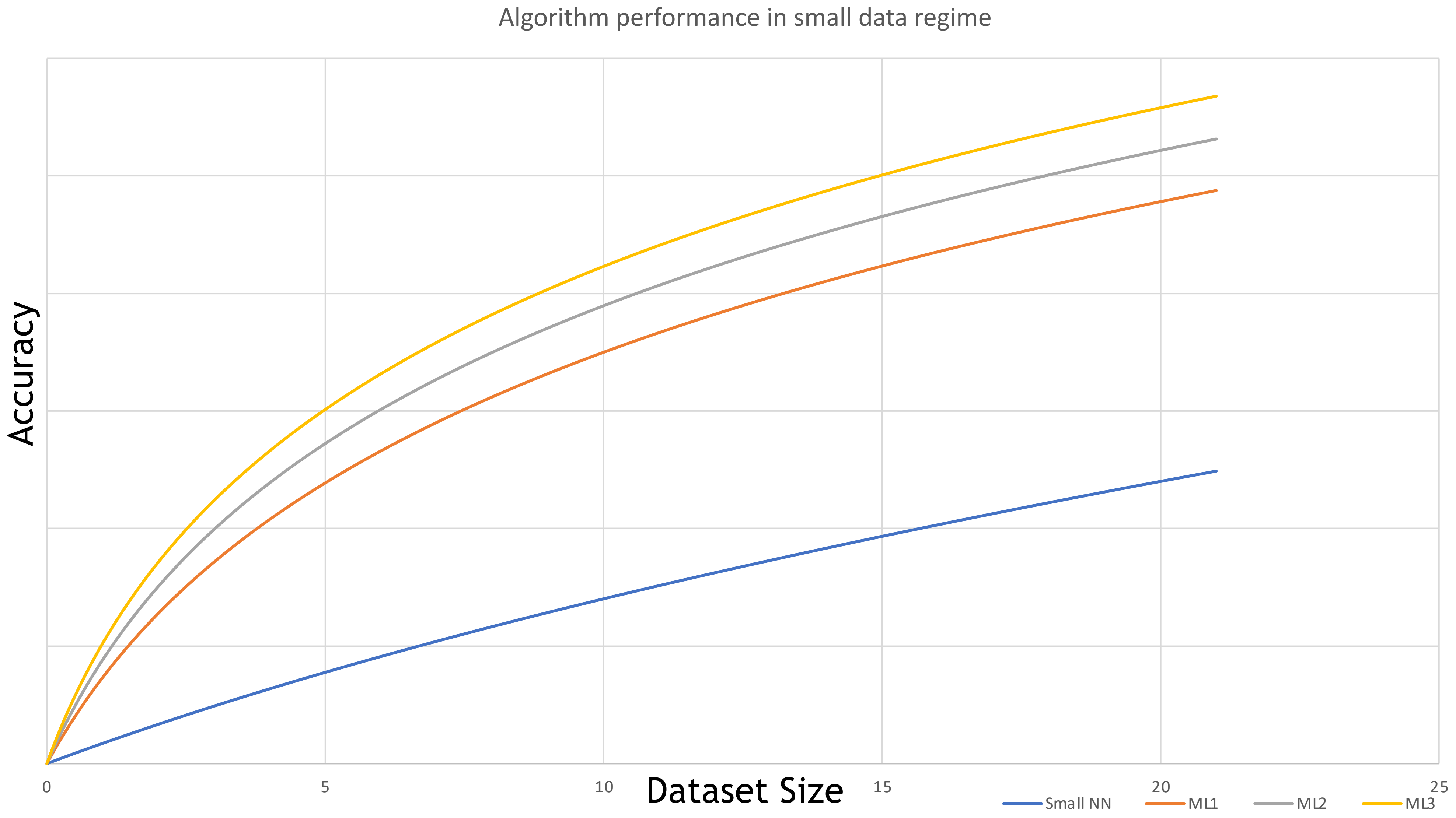

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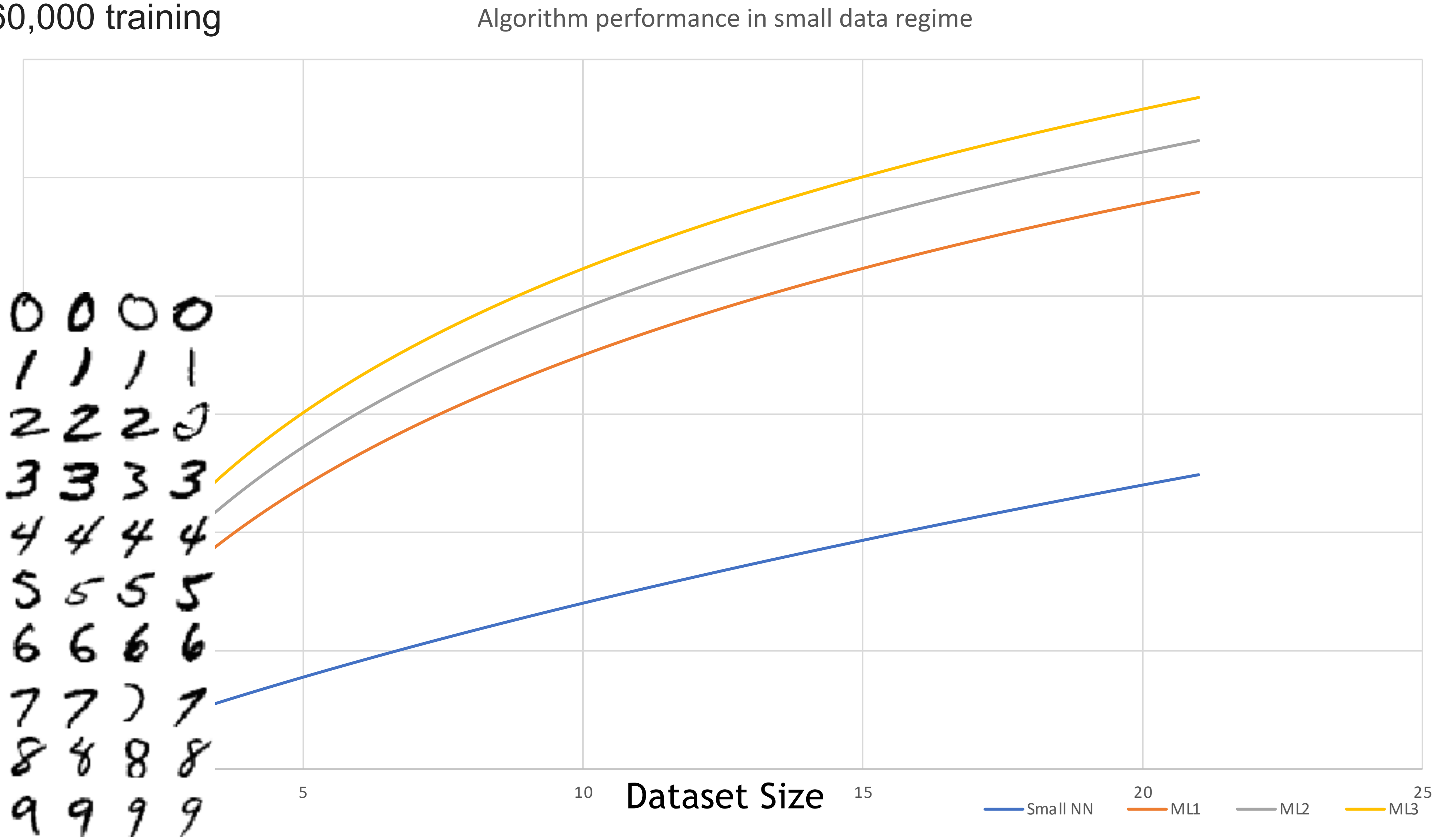
NEURAL NETWORKS ARE NOT NEW

Historically, we never had large datasets or computers

The MNIST (1999) database contains 60,000 training images and 10,000 testing images.



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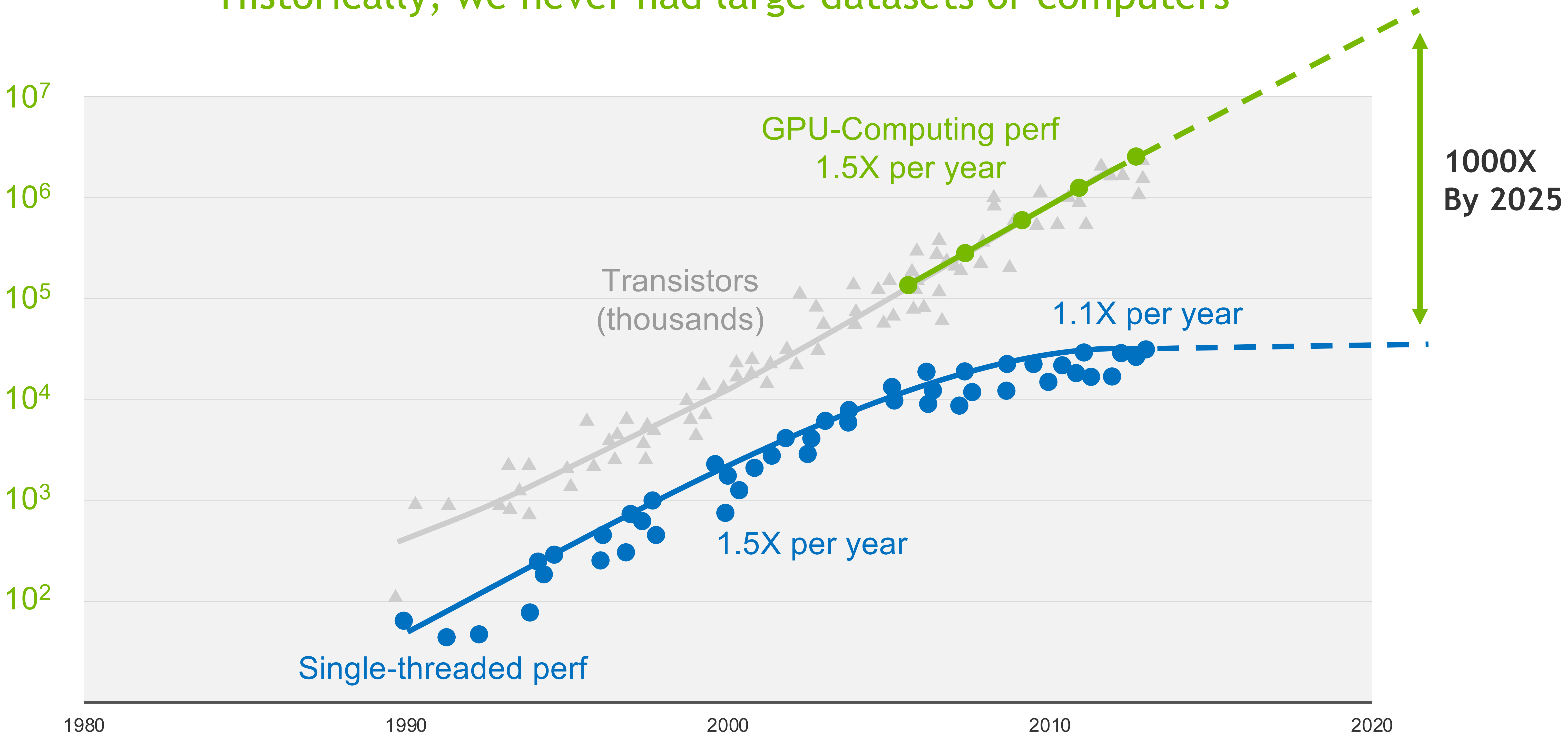
COMPUTE

Historically, we never had large datasets or computers



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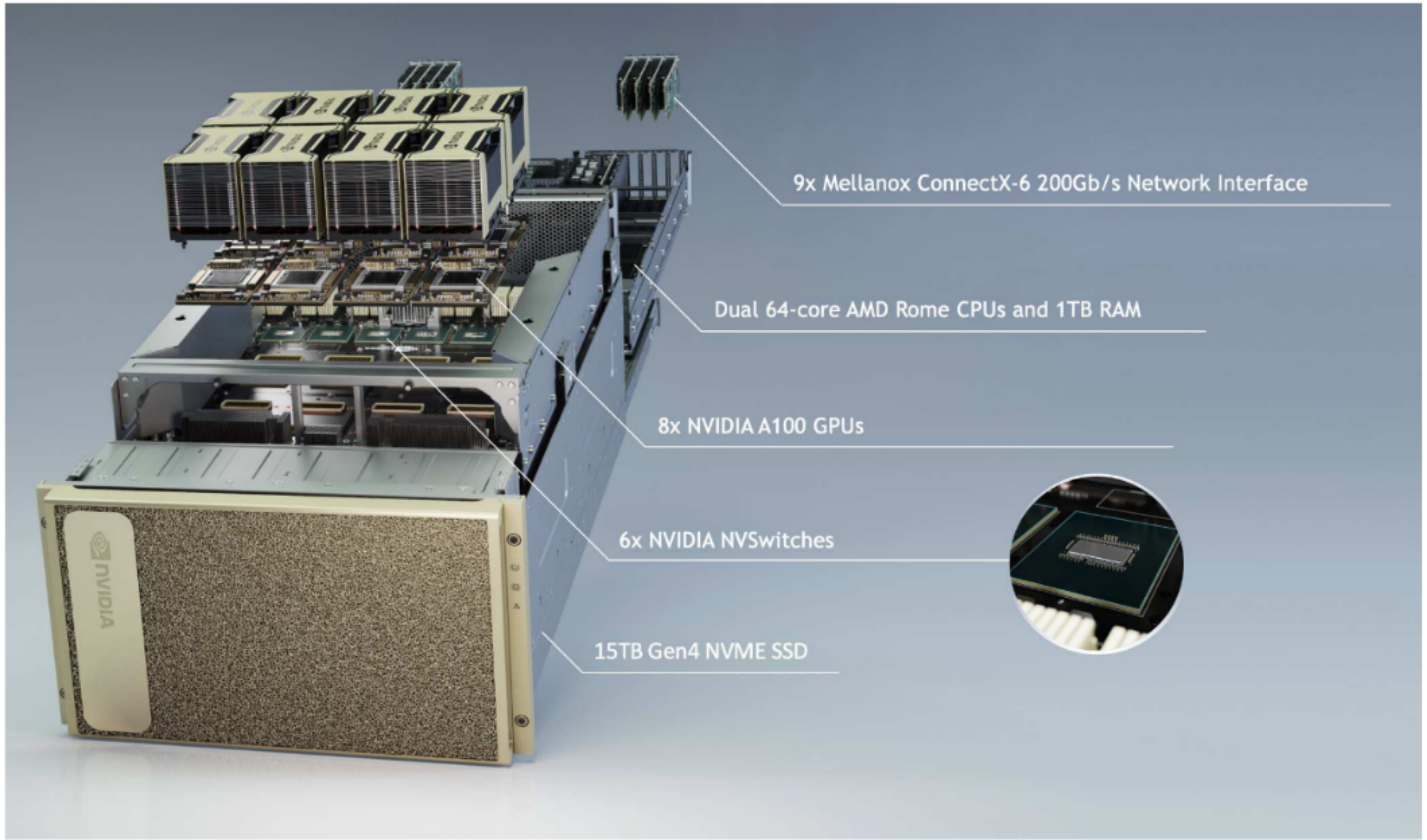
CONTEXT

CONTEXT

8 petaFLOPs in June 2011 (K Computer)

CONTEXT

5 petaFLOPs for AI - today

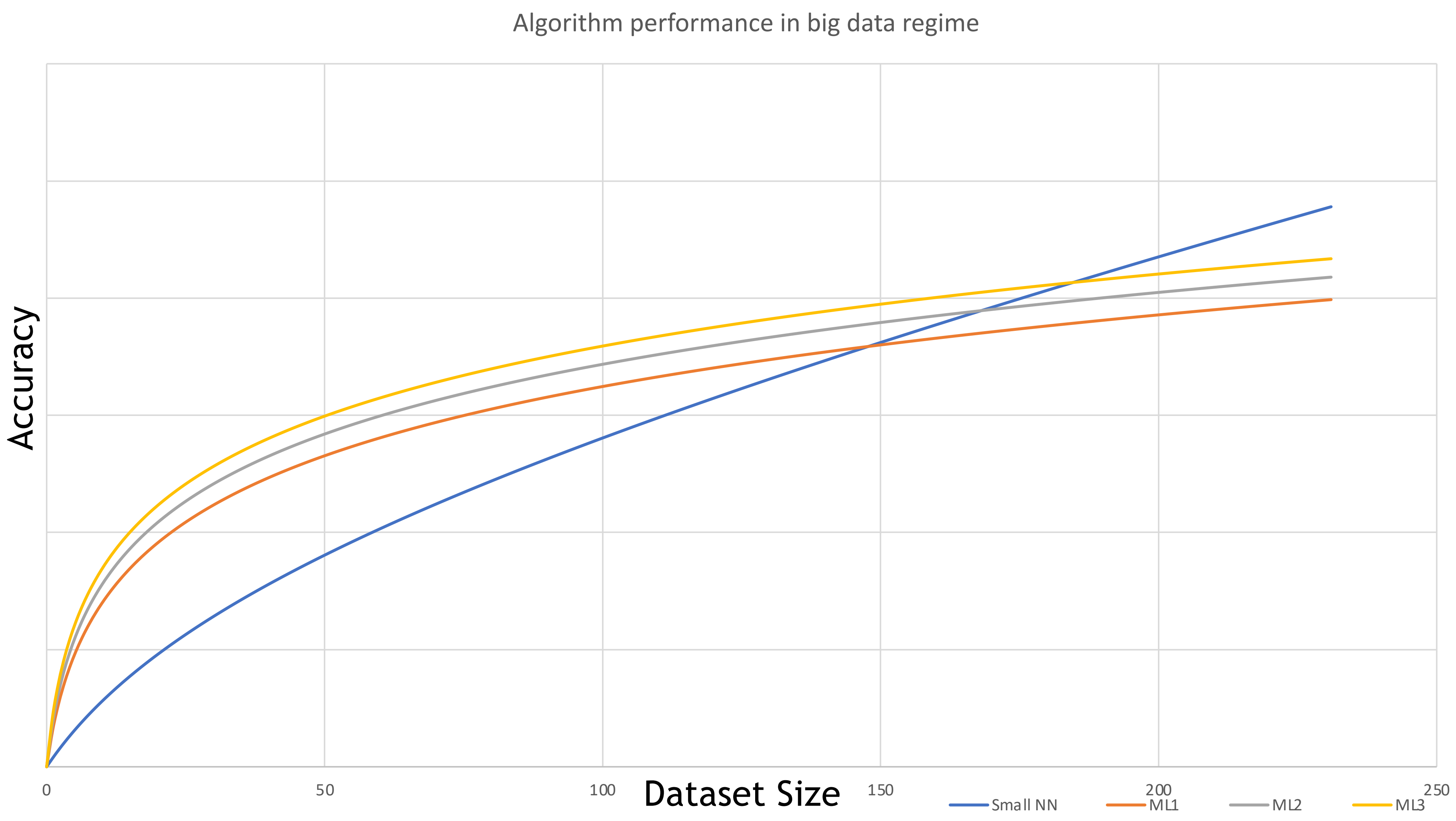


CONTEXT

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

NEURAL NETWORKS ARE NOT NEW

Large datasets and faster compute transformed the way we do machine learning



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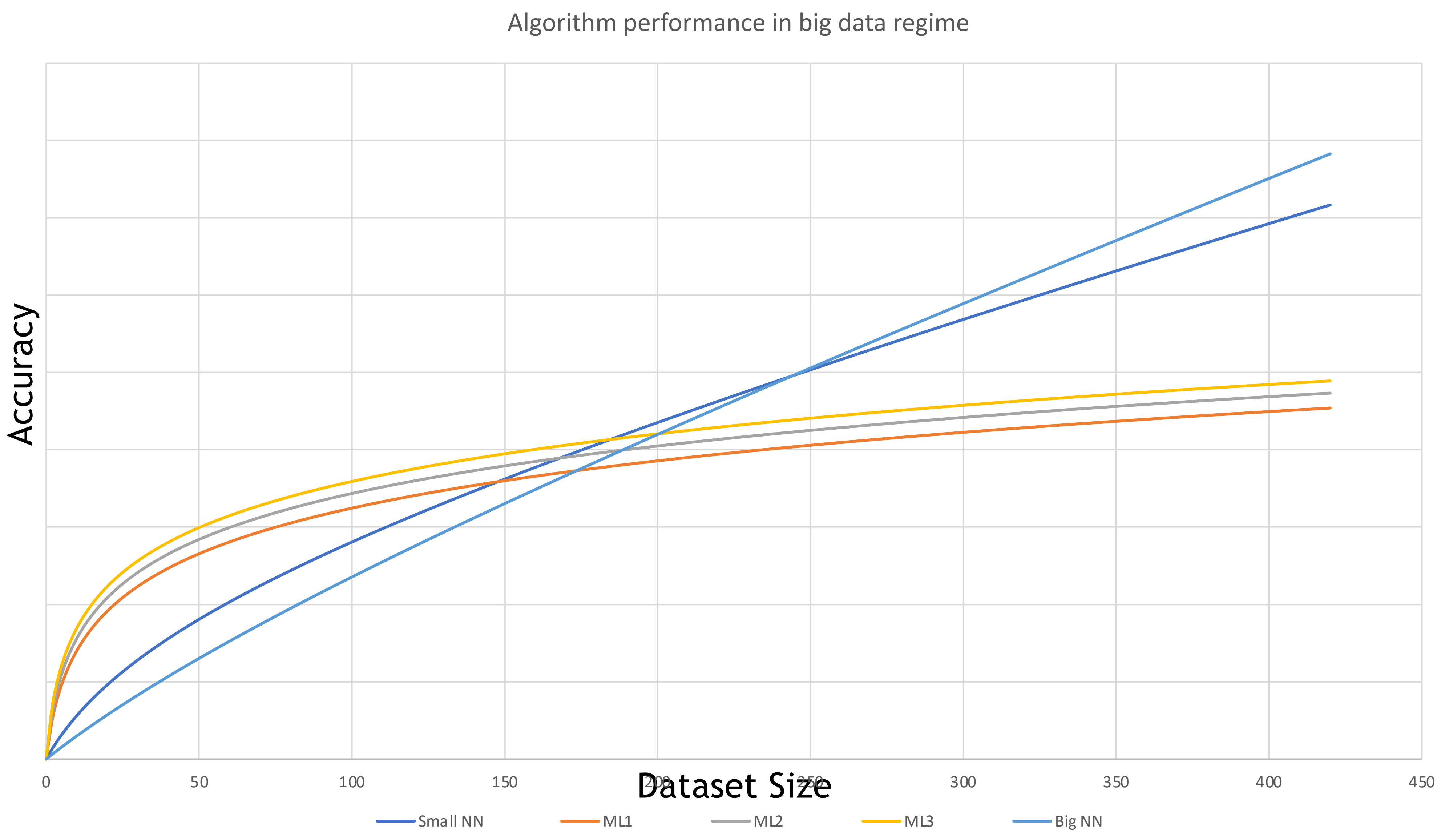
NEURAL NETWORKS ARE NOT NEW

Data and model size the key to accuracy



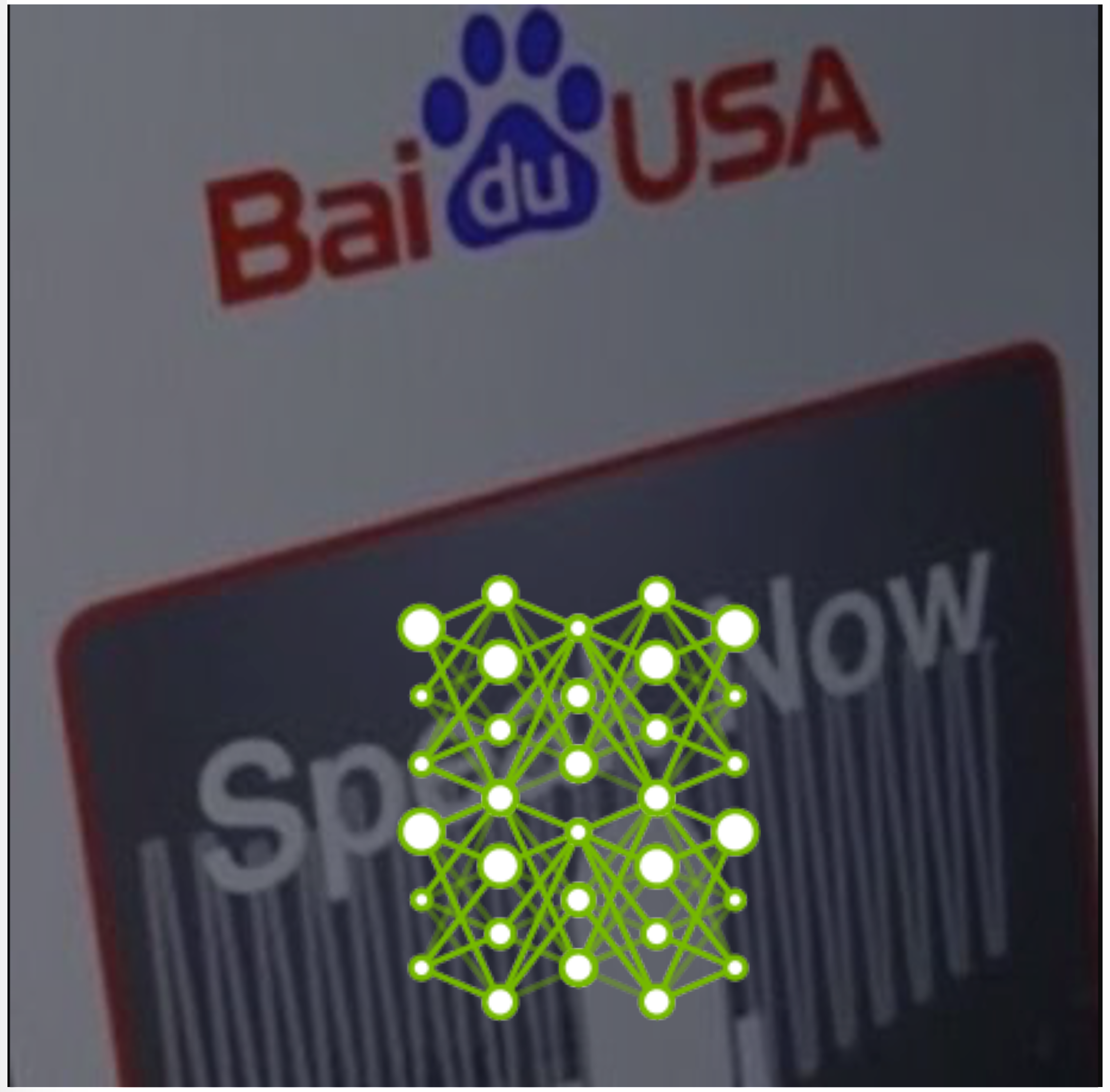
NEURAL NETWORK COMPLEXITY IS EXPLODING

To Tackle Increasingly Complex Challenges

7 ExaFLOPS
60 Million Parameters

2015 - Microsoft ResNet
Superhuman Image Recognition

20 ExaFLOPS
300 Million Parameters



2016 - Baidu Deep Speech 2
Superhuman Voice Recognition

100 ExaFLOPS
8700 Million Parameters

2017 - Google Neural Machine Translation
Near Human Language Translation

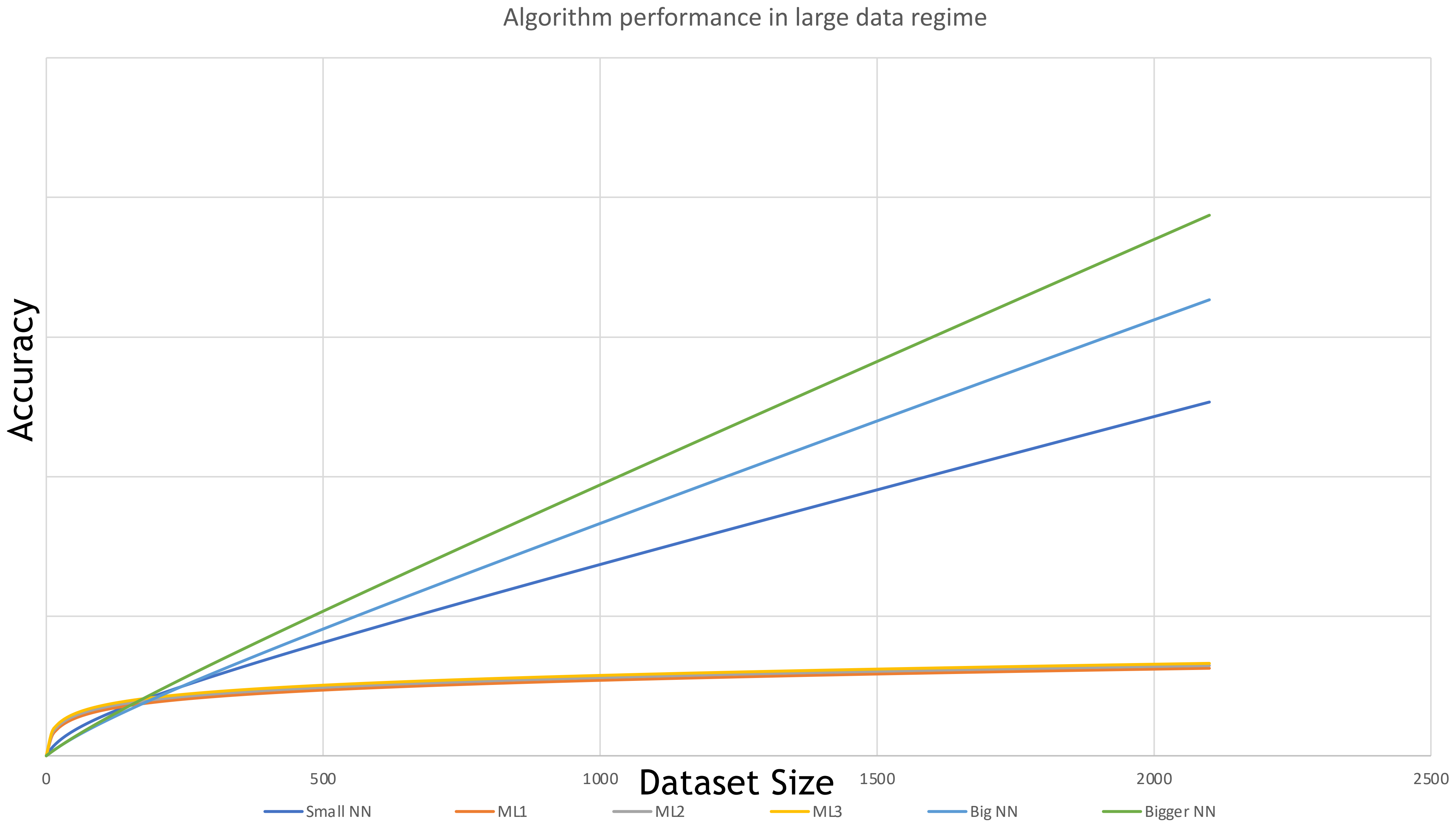
100 EXAFLOPS

~=

<u>2 YEARS </u>ON A DUAL CPU SERVER

NEURAL NETWORKS ARE NOT NEW

Exceeding human level performance



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EMPIRICAL EVIDENCE

EXPLODING DATASETS

Logarithmic relationship between the dataset size and accuracy

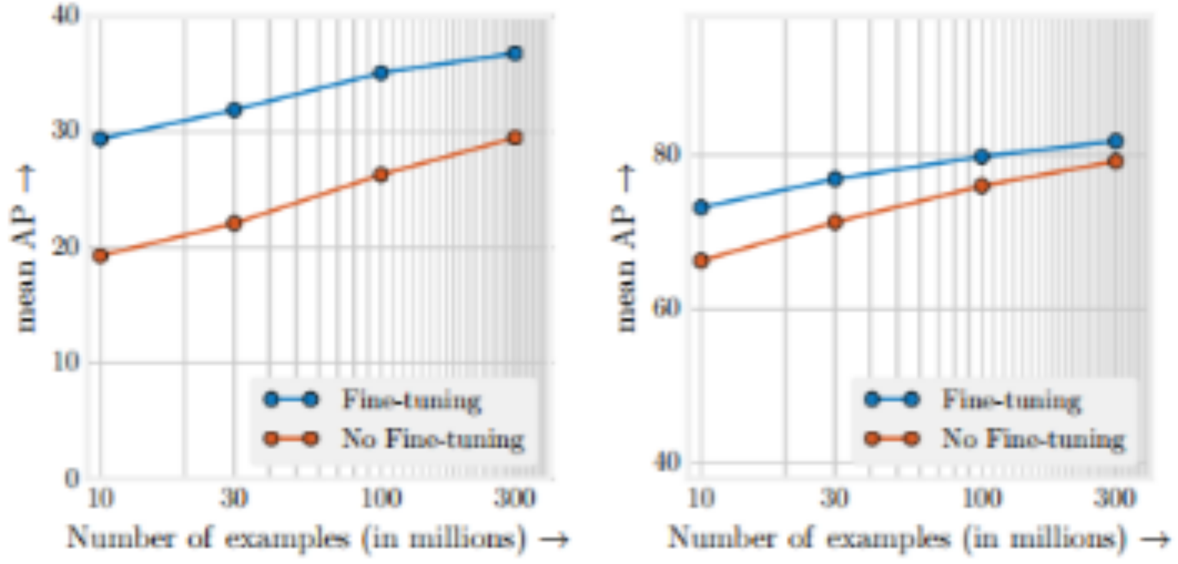


Figure 4. Object detection performance when initial checkpoints are pre-trained on different subsets of JFT-300M from scratch. x-axis is the data size in log-scale, y-axis is the detection performance in mAP@[.5,.95] on COCO minival* (left), and in mAP@.5 on PASCAL VOC 2007 test (right).

Initialization	mIOU
ImageNet	73.6
300M	75.3
ImageNet+300M	**76.5**

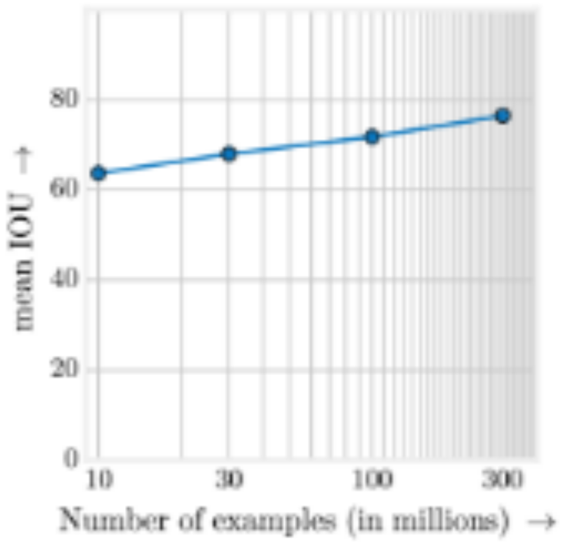
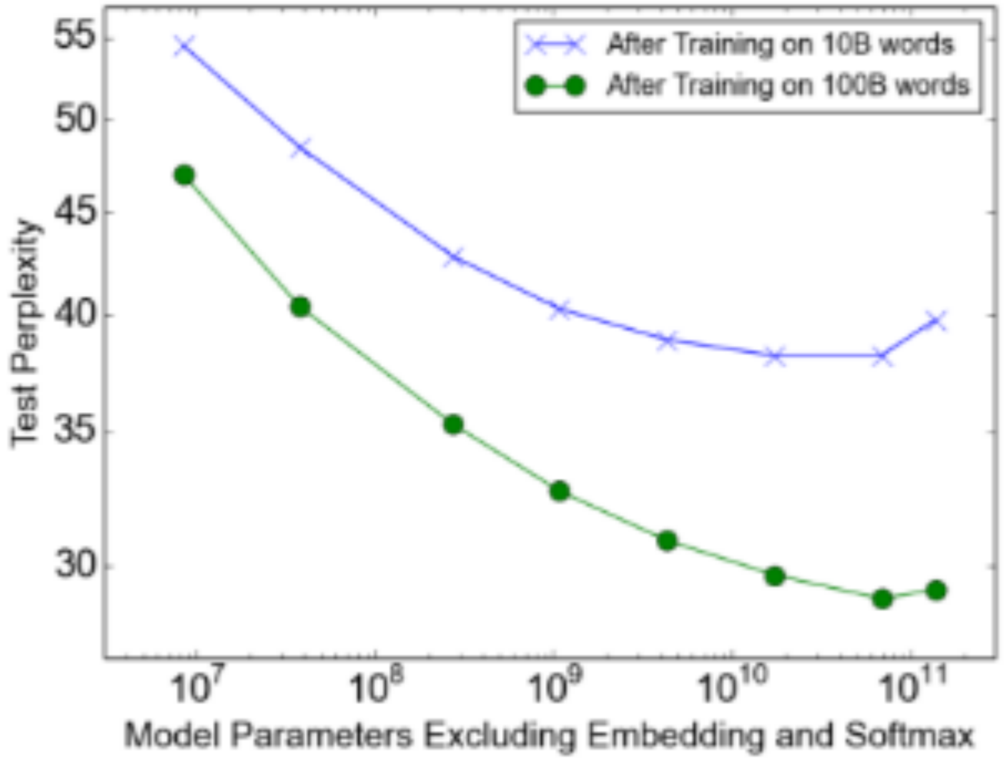


Figure 6. Semantic segmentation performance on Pascal VOC 2012 val set. (left) Quantitative performance of different initializations; (right) Impact of data size on performance.



Sun, Chen, et al. "Revisiting Unreasonable Effectiveness of Data in Deep Learning Era." *arXiv preprint arXiv:1707.02968* (2017).
Shazeer, Noam, et al. "Outrageously large neural networks: The sparsely-gated mixture-of-experts layer." arXiv preprint arXiv:1701.06538 (2017).

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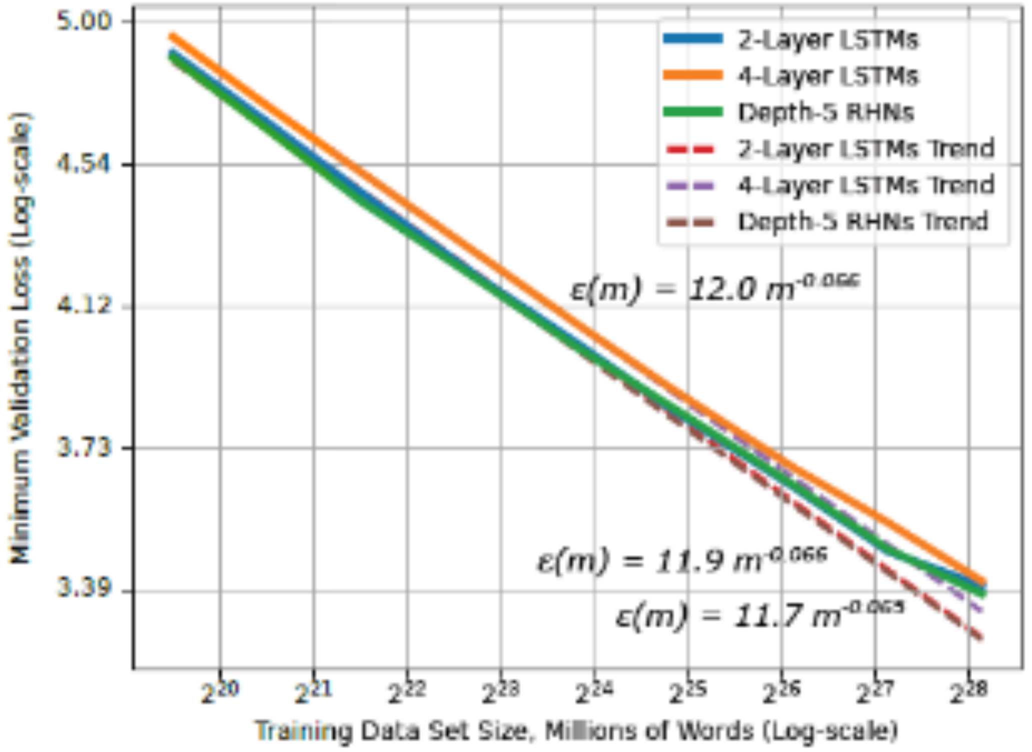
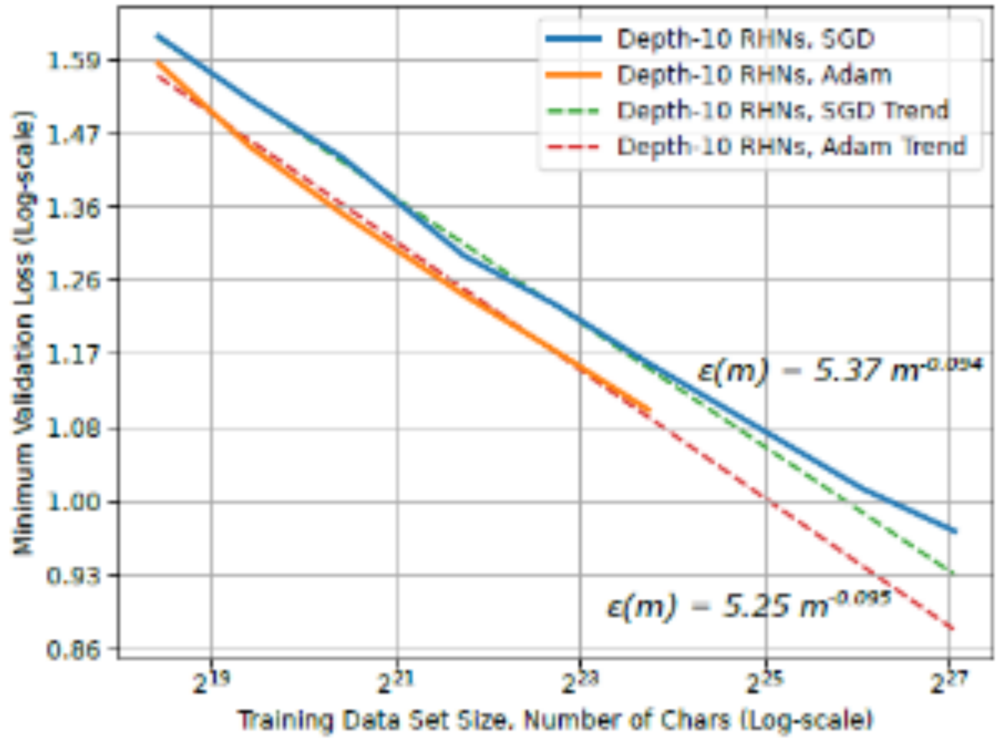
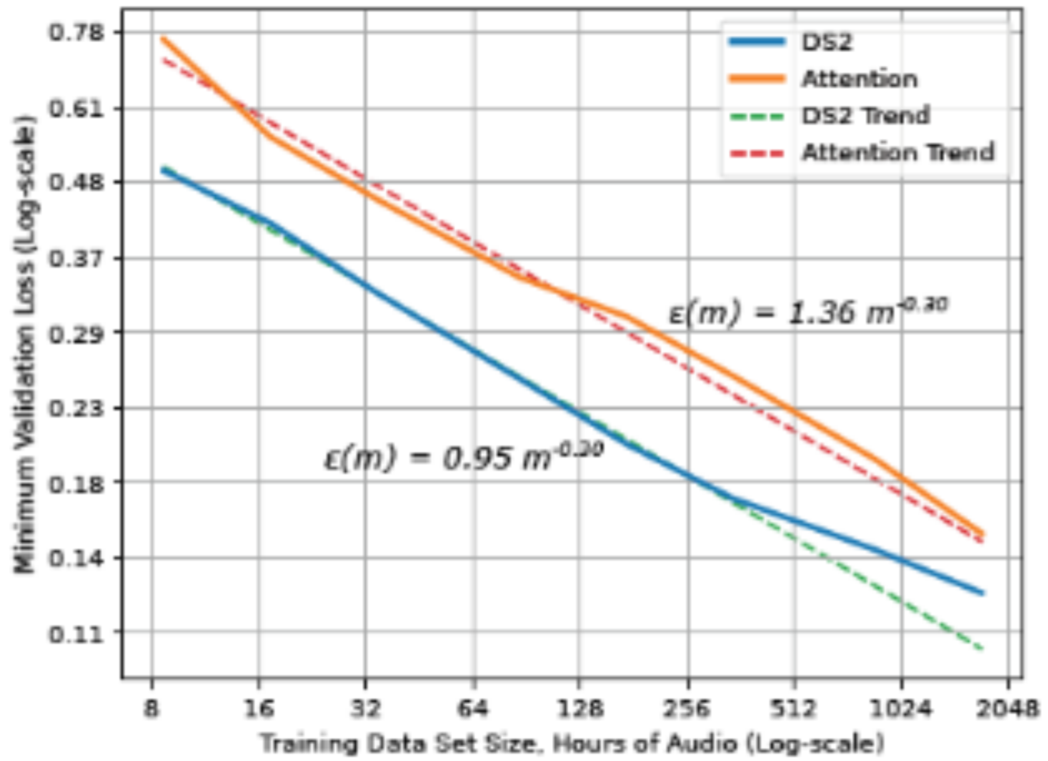
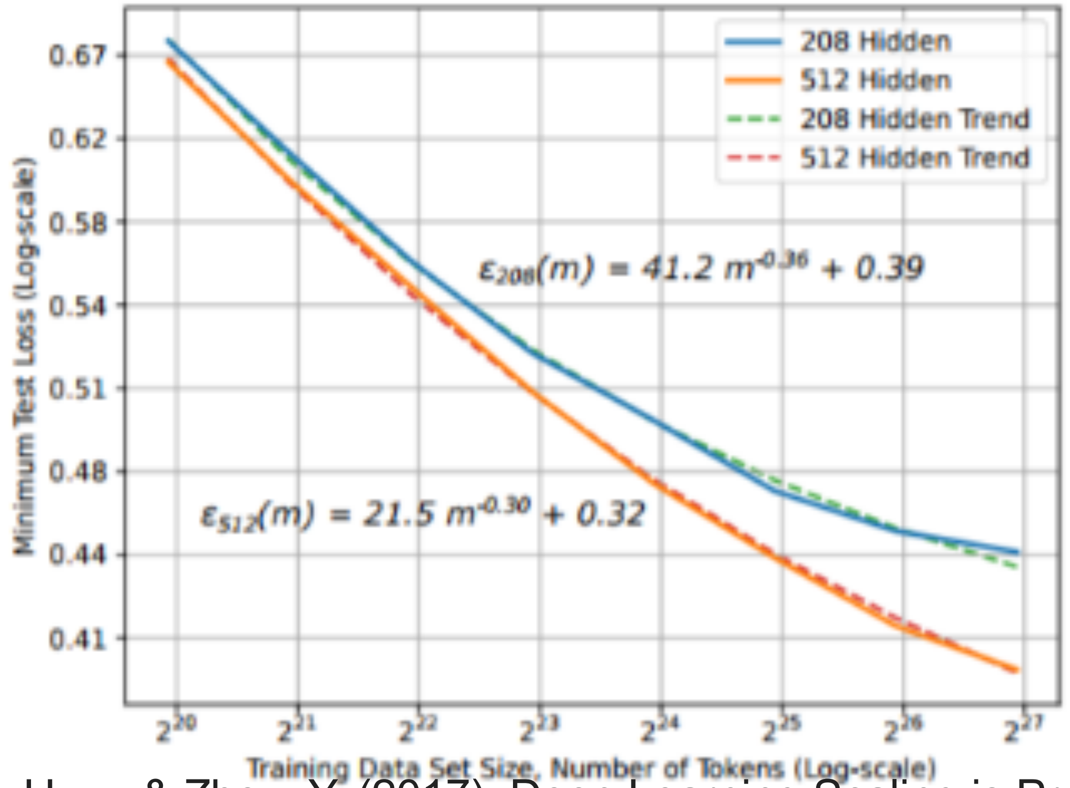
Logarithmic relationship between the dataset size and accuracy

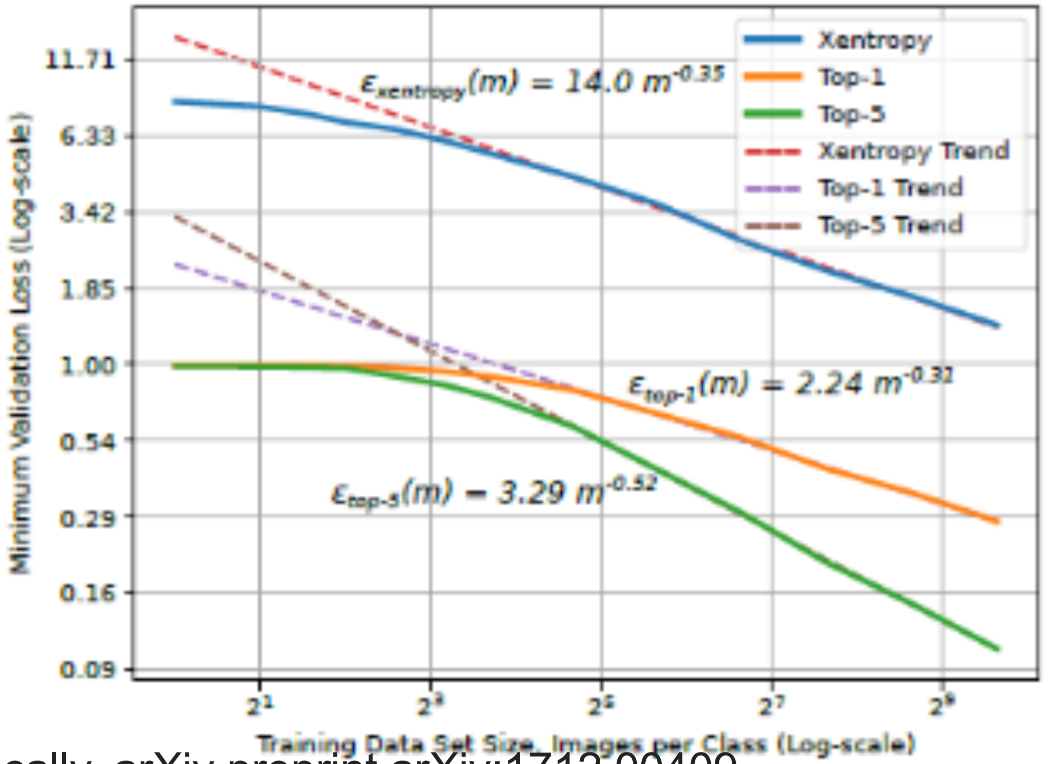


- Translation
- Language Models
- Character Language Models
- Image Classification
- Attention Speech Models









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.

EXPLODING DATASETS

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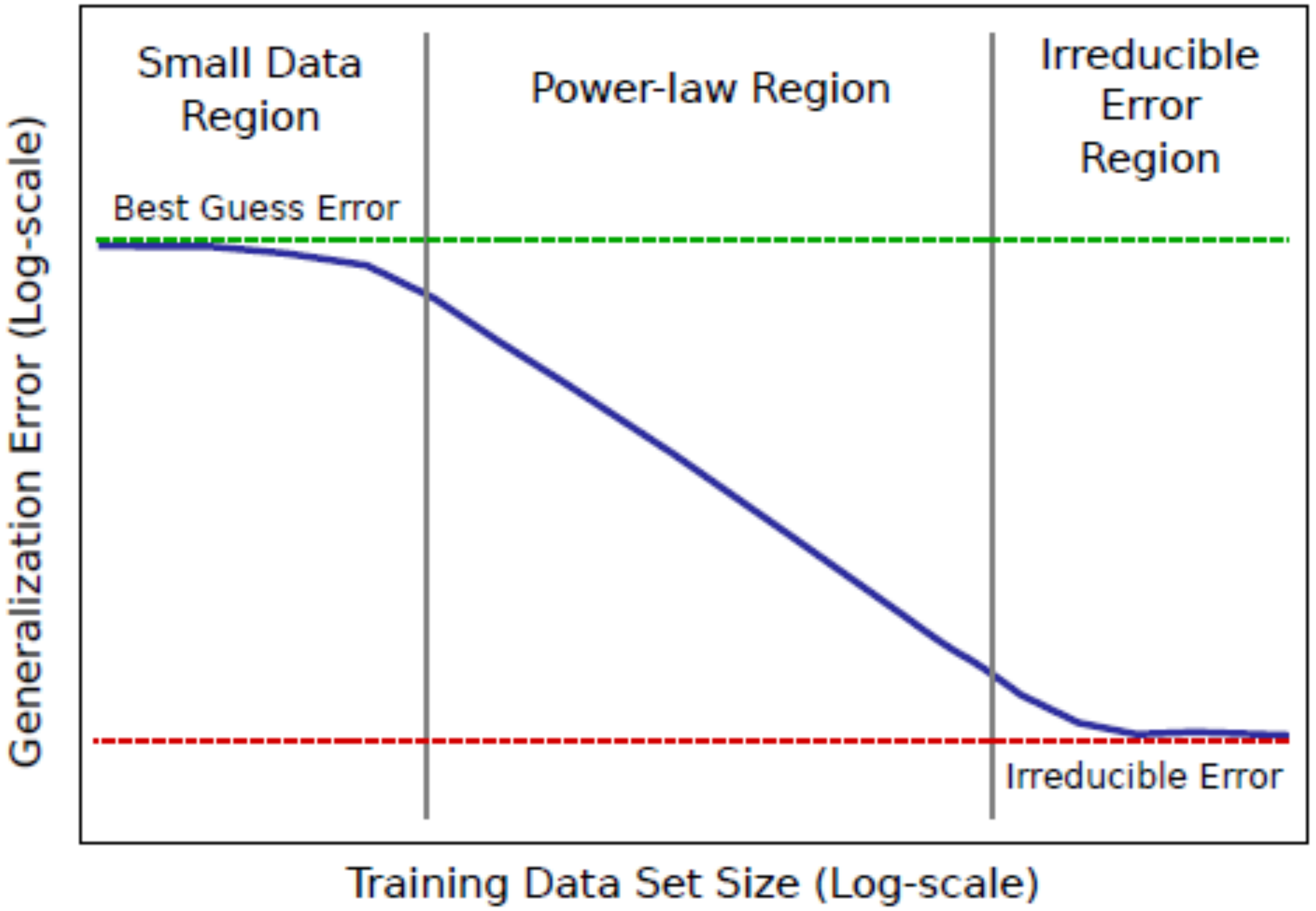

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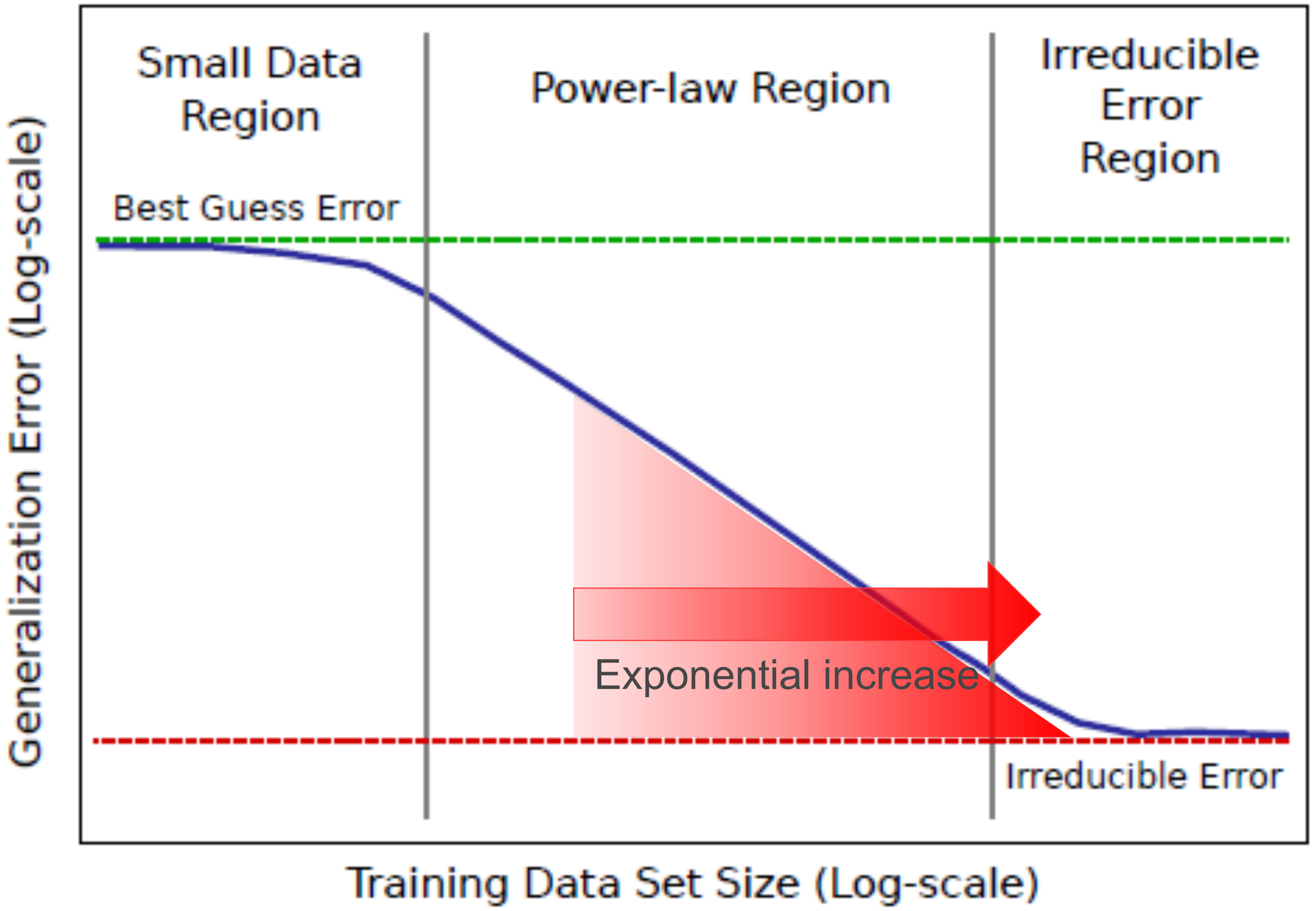
THE COST

THE COST OF LABELING

Limits the utility of deep learning models



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Part 2: Self-Supervision, BERT and Beyond

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SELF-SUPERVISED LEARNING

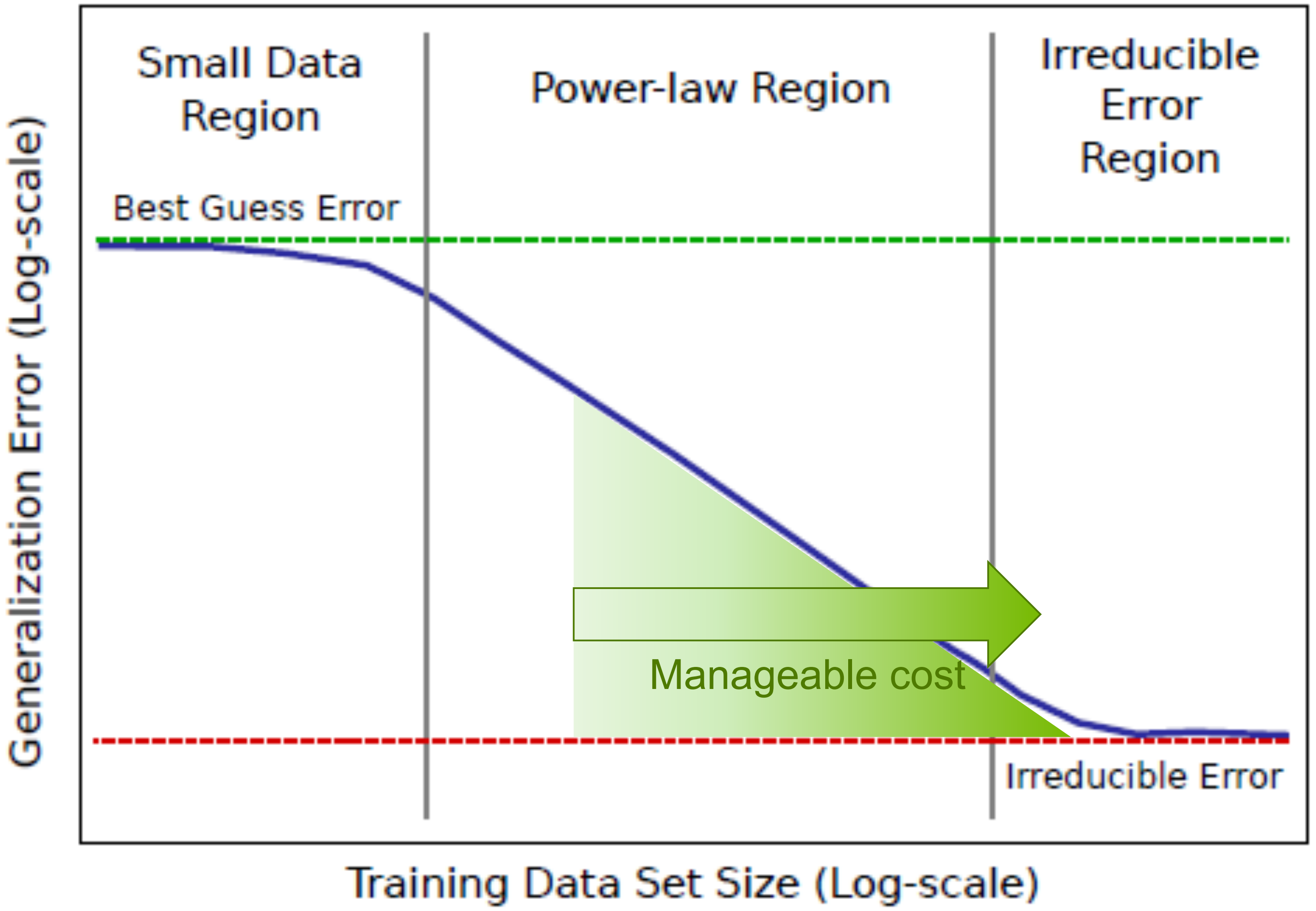
Example training tasks

- 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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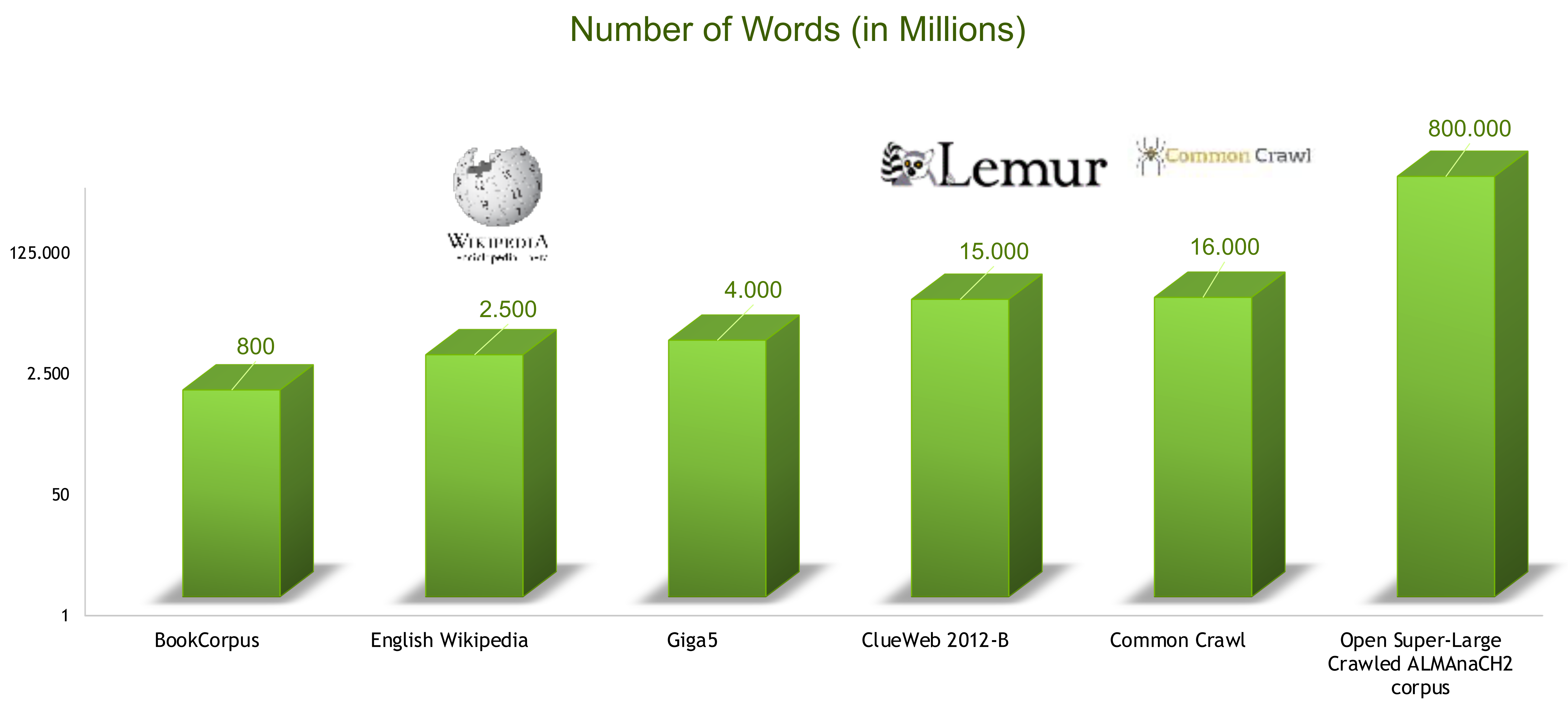
SELF-SUPERVISED LEARNING

Abundance of unlabeled data



SELF-SUPERVISED LEARNING

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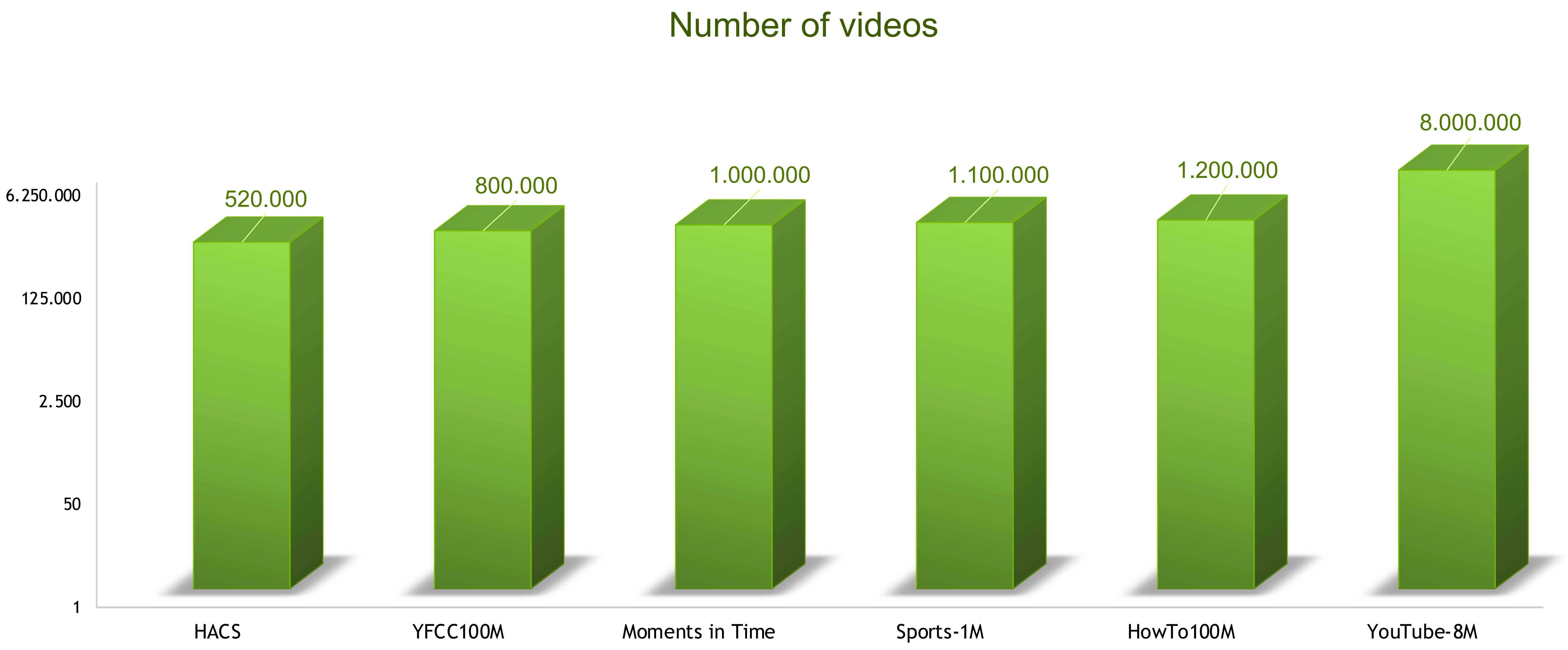

OLD IDEAS

SELF-SUPERVISED LEARNING

What was missing?

Semi-supervised Sequence Learning

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Quoc V. Le
Google Inc.
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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

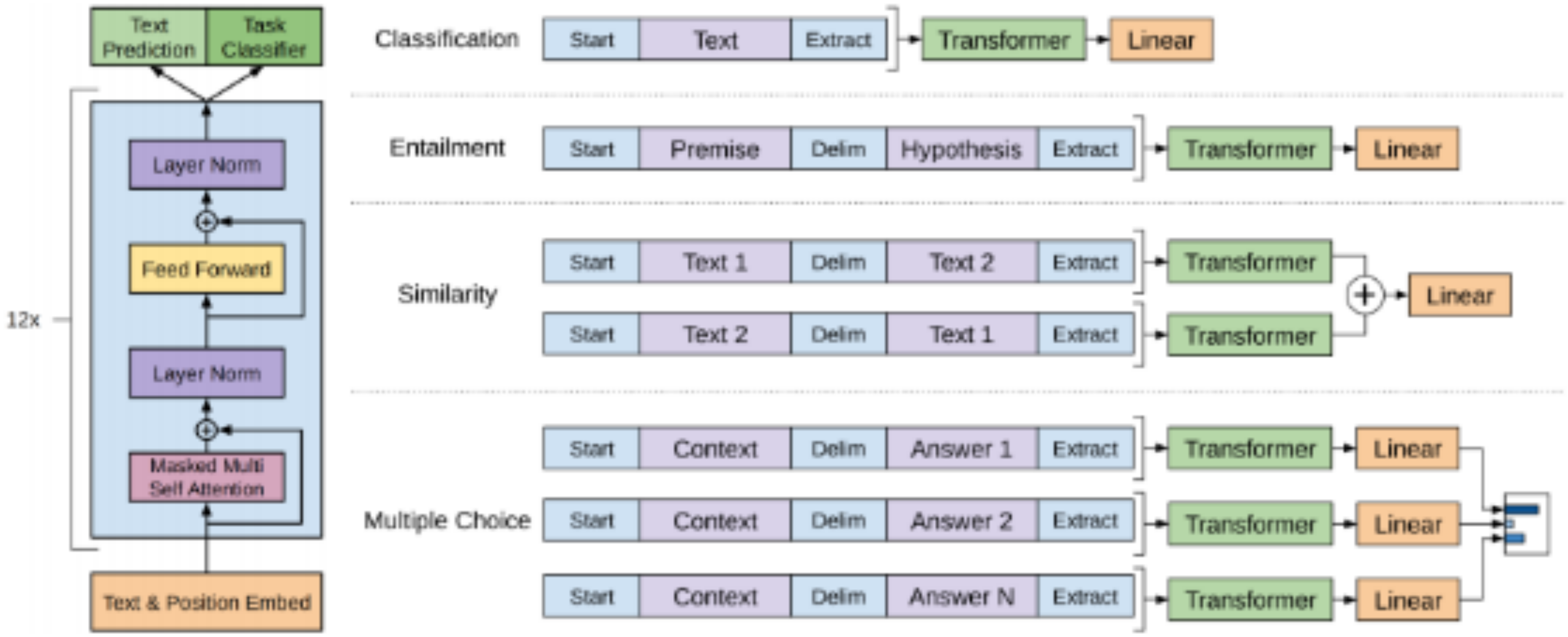
“Many previous approaches to NLP tasks train relatively small models on a single GPU from scratch. Our approach requires an expensive pre-training step - 1 month on 8 GPUs. Luckily, this only has to be done once and we’re releasing our model so others can avoid it. It is also a large model (in comparison 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.*

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.

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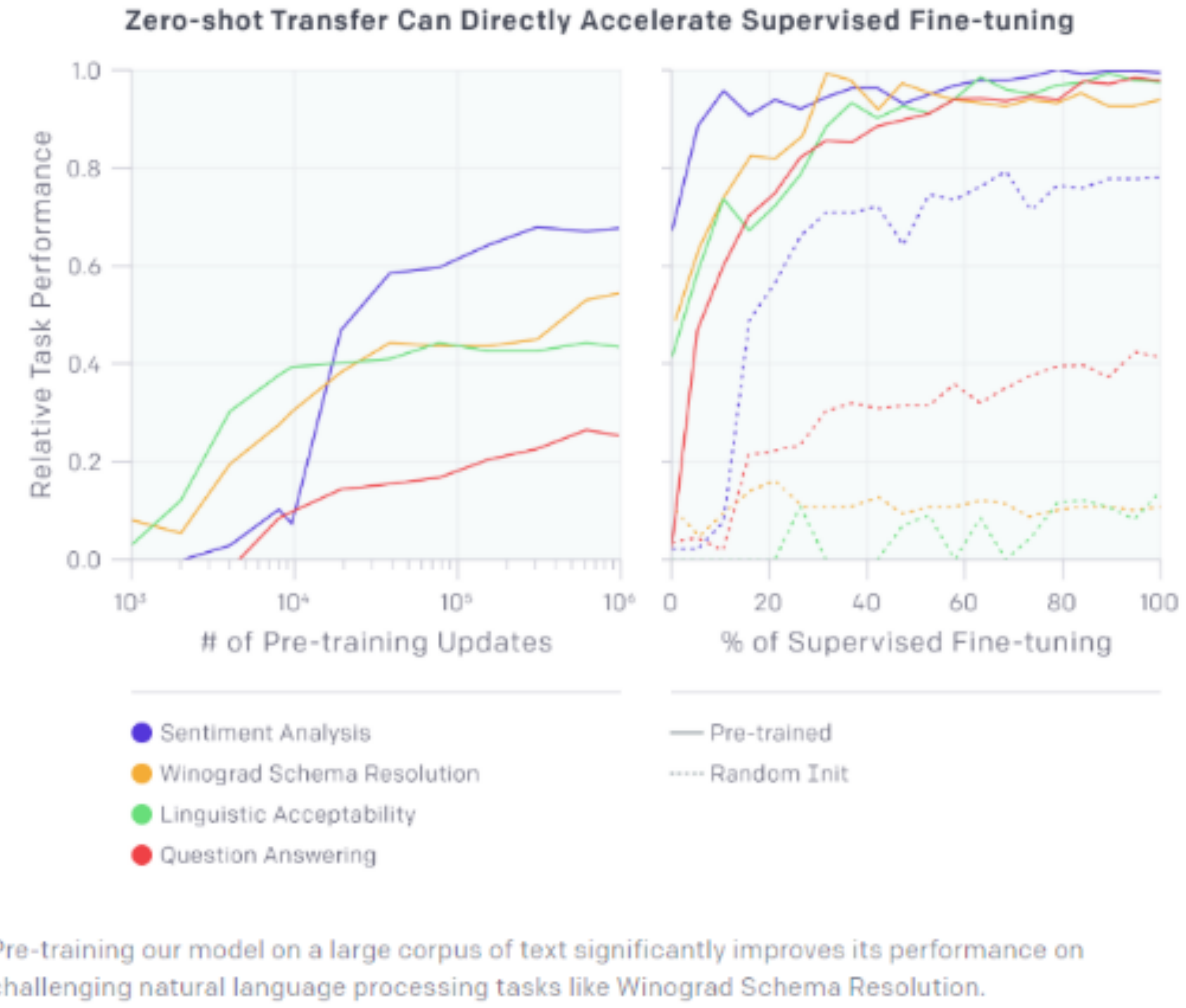
GENERATIVE PRETRAINING (GPT)

The implications



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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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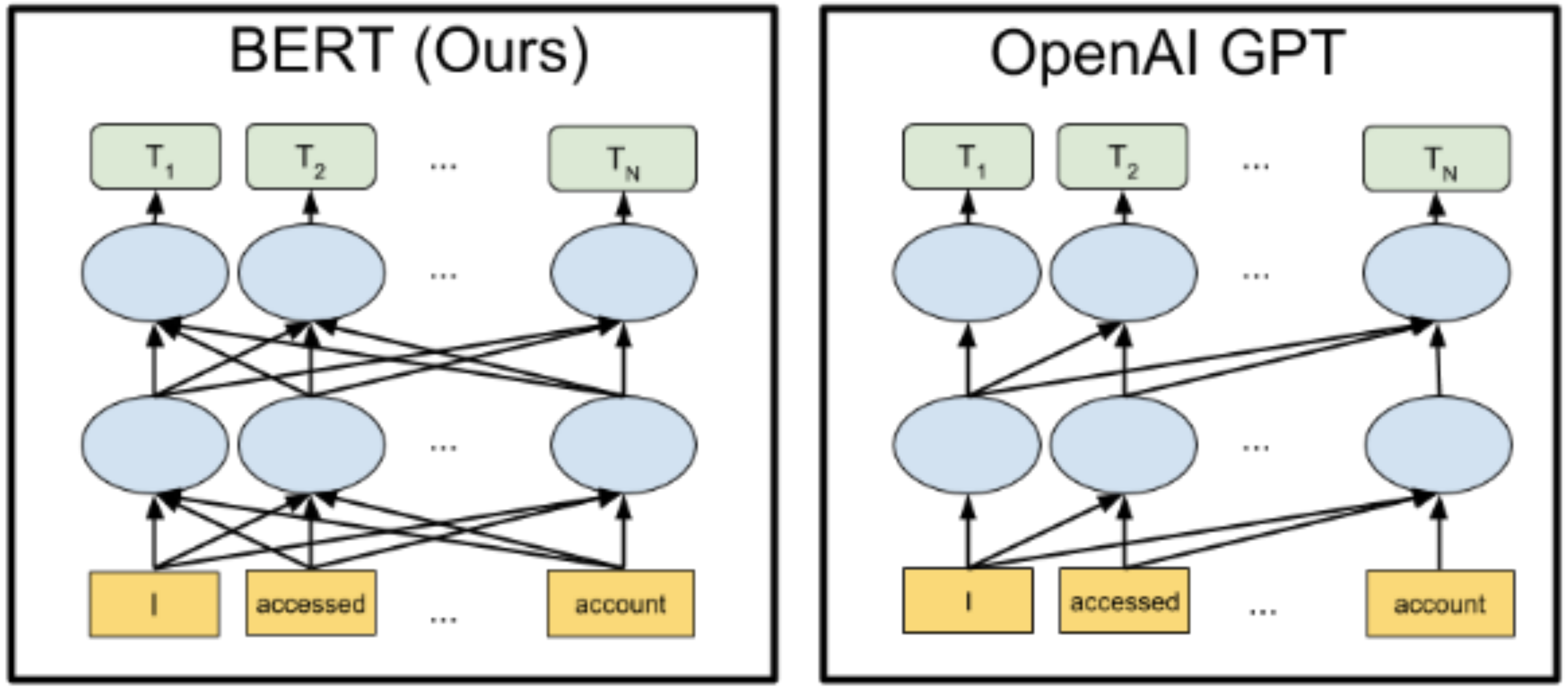
BIDIRECTIONAL TRANSFORMERS (BERT)

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

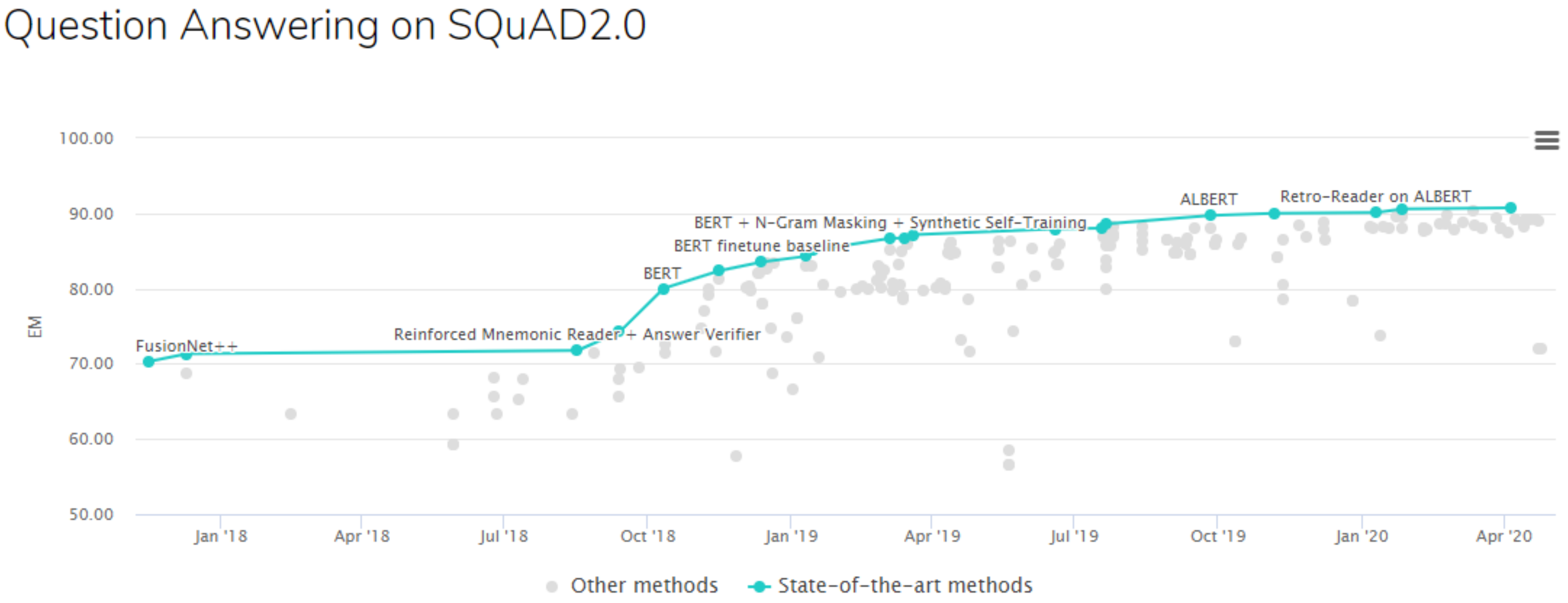
System	MNLI-(m/mm)	QQP	QNLI	SST-2	CoLA	STS-B	MRPC	RTE	**Average**
	392k	363k	108k	67k	8.5k	5.7k	3.5k	2.5k	-
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1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

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.

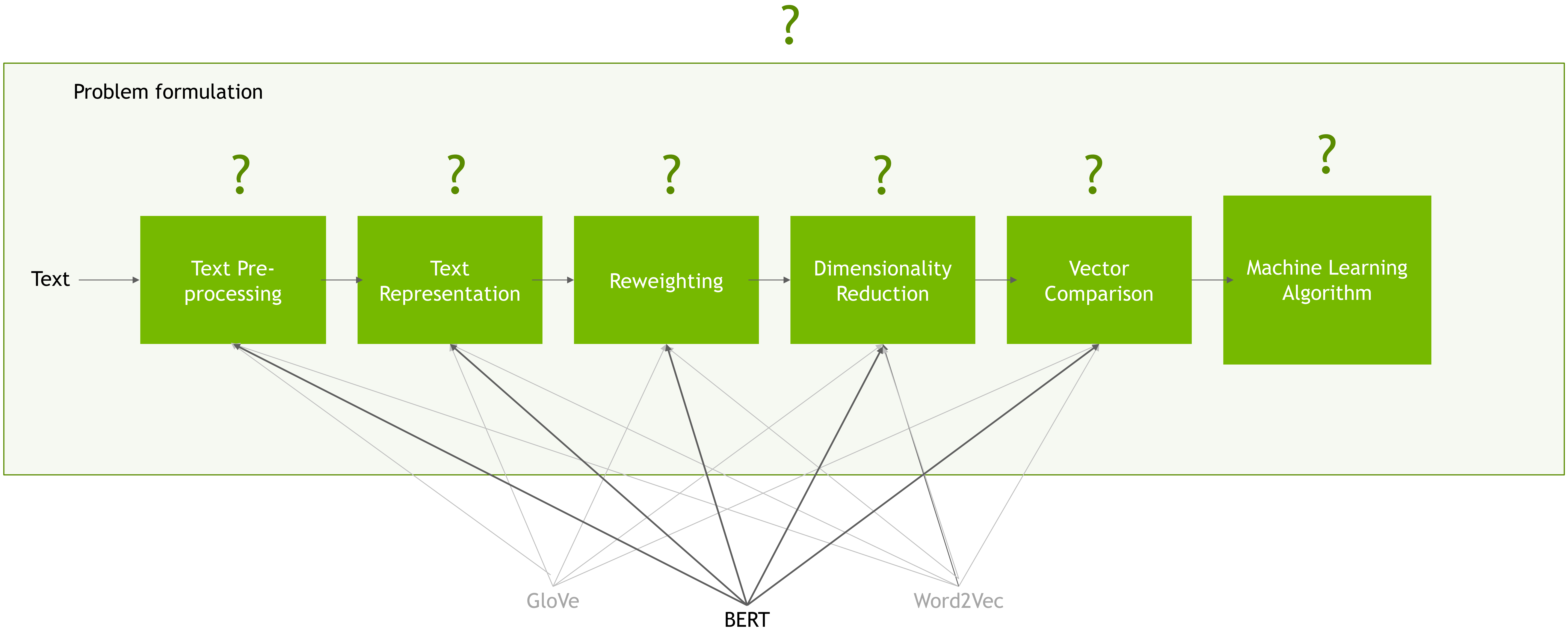
SQUAD 2.0

Human performance 91.2



USING BERT

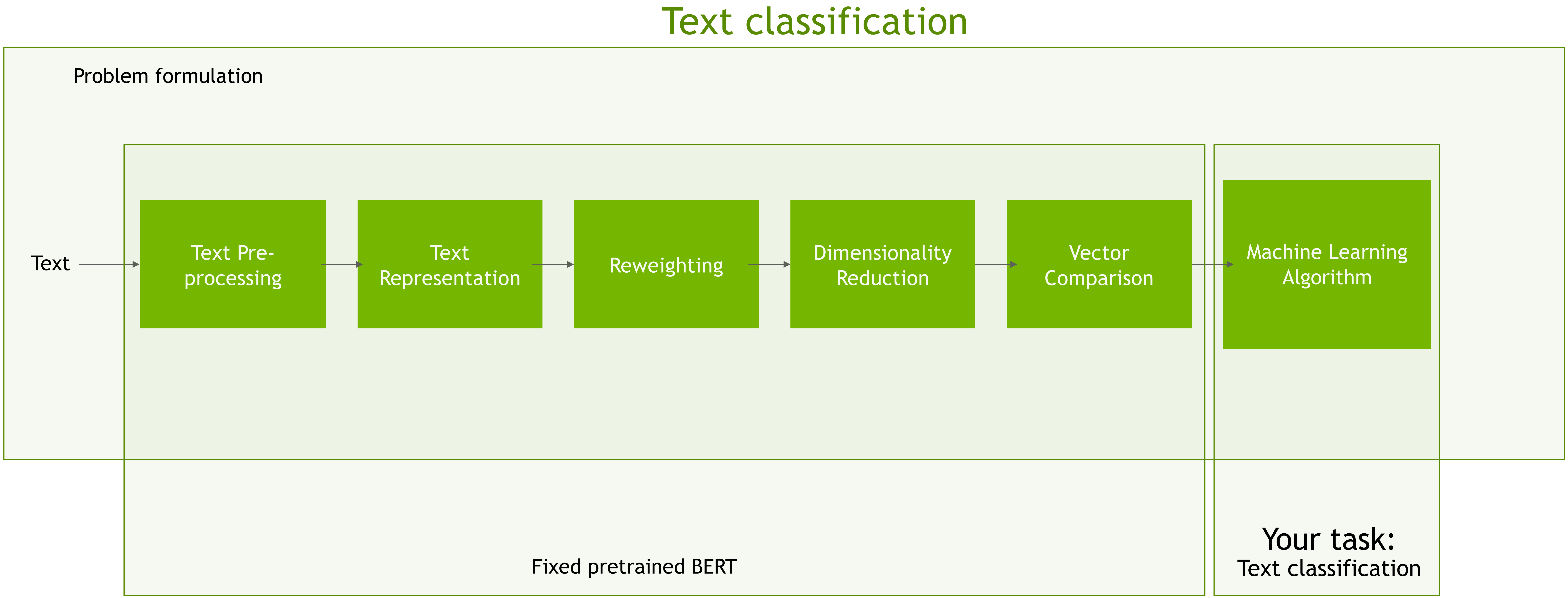
Feature extractor



THE LAB

LAB OVERVIEW

Notebooks 1, 2, 3



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BIDIRECTIONAL TRANSFORMERS (BERT)

Base vs Large

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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.

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.

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

Transformer LM - 100M Parameters

Trained on Wikipedia minus "Abraham Lincoln" article.

Abraham Lincoln (February 27, 1724, Salem, Massachusetts - August 29, 1755) was an American Prime Minister who was an early proponent of an anti-witchcraft situation and was President of the Salem government from 1732 to 1743, President of the Massachusetts Supreme Court during that time, and President of the Institute for Religious Education to 1777, President of the Massachusetts Supreme Court, as well as a member of the Board of Missionaries of the Episcopal Church, The Reverend John Schuyler, Mercer Bishop, and Father New York State. He received his education at Paterson College and graduated from Paterson College and the Trenton College.

He wrote his autobiography in Mantua, Massachusetts, for which he was the supreme liberal. He later became one of Massachusetts's greatest religious leaders, choosing blacks many of whom became leaders of the Puritans. He received three honorary degrees from the universities of Boston and Virginia;

...

Transformer LM - 5B Parameters

Trained on Wikipedia minus "Abraham Lincoln" article.

Abraham Lincoln (March 1, 1809 - March 15, 1865) was an American lawyer, jurist, and politician. He served as the 19th President of the United States, from March 1861 until his assassination in April 1865.

Born in Newark, New Jersey, Lincoln attended Knox College of New York, studied law, and was admitted to the bar Missouri Territory in 1826. He relocated to Illinois, and was elected to the Illinois House of Representatives in 1827, 1822, 1823, and 1826. He was elected Speaker of the Illinois House in 1825, served as Attorney General of the Illinois Territory in 1829, and was elected to the Illinois Senate in 1831. Lincoln was elected to the United States House of Representatives as a Democrat in 1833, and he was elected as a representative in the United States House of Representatives, serving two terms from 1839 to 1843. He was elected as a Whig in 1842, but he only served one term in Congress, and returned to the House of Representatives, serving

...

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

BUT BIGGER IS BETTER

ROBERTA

Robustly Optimized BERT Pretraining Approach

Simplification of the core idea:

- training the model longer, with bigger batches, over more data
- removing the next sentence prediction objective
- training on longer sequences
- dynamically changing the masking pattern applied to the training data

Liu, Y., Ott, M., Goyal, N., Du, J., Joshi, M., Chen, D., ... & Stoyanov, V. (2019). Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692.

ROBERTA

Increasing the dataset size

16GB -> 160GB

Liu, Y., Ott, M., Goyal, N., Du, J., Joshi, M., Chen, D., ... & Stoyanov, V. (2019). Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692.

ROBERTA

Results

Model	SQuAD 1.1/2.0	MNLI-m	SST-2	RACE
Our reimplementation (with NSP loss):				
SEGMENT-PAIR	90.4/78.7	84.0	92.9	64.2
SENTENCE-PAIR	88.7/76.2	82.9	92.1	63.0
Our reimplementation (without NSP loss):				
FULL-SENTENCES	90.4/79.1	84.7	92.5	64.8
DOC-SENTENCES	90.6/79.7	84.7	92.7	65.6
$\text{BERT}_{\text{BASE}}$	88.5/76.3	84.3	92.8	64.3
$\text{XLNet}_{\text{BASE}}$ (K = 7)	–/81.3	85.8	92.7	66.1
$\text{XLNet}_{\text{BASE}}$ (K = 6)	–/81.0	85.6	93.4	66.7

Table 2: Development set results for base models pretrained over BOOKCORPUS and WIKIPEDIA. All models are trained for 1M steps with a batch size of 256 sequences. We report F1 for SQuAD and accuracy for MNLI-m, SST-2 and RACE. Reported results are medians over five random initializations (seeds). Results for $\text{BERT}_{\text{BASE}}$ and $\text{XLNet}_{\text{BASE}}$ are from Yang et al. (2019).

Model	data	bsz	steps	SQuAD (v1.1/2.0)	MNLI-m	SST-2
RoBERTa						
with BOOKS + WIKI	16GB	8K	100K	93.6/87.3	89.0	95.3
+ additional data (§3.2)	160GB	8K	100K	94.0/87.7	89.3	95.6
+ pretrain longer	160GB	8K	300K	94.4/88.7	90.0	96.1
+ pretrain even longer	160GB	8K	500K	**94.6/89.4**	**90.2**	**96.4**
$\text{BERT}_{\text{LARGE}}$						
with BOOKS + WIKI	13GB	256	1M	90.9/81.8	86.6	93.7
$\text{XLNet}_{\text{LARGE}}$						
with BOOKS + WIKI	13GB	256	1M	94.0/87.8	88.4	94.4
+ additional data	126GB	2K	500K	94.5/88.8	89.8	95.6

ble 4: Development set results for RoBERTa as we pretrain over more data (16GB → 160GB of text) and pretrain longer (100K → 300K → 500K steps). Each row accumulates improvements from the rows above. RoBERTa tches the architecture and training objective of $\text{BERT}_{\text{LARGE}}$. Results for $\text{BERT}_{\text{LARGE}}$ and $\text{XLNet}_{\text{LARGE}}$ are from vlin et al. (2019) and Yang et al. (2019), respectively. Complete results on all GLUE tasks can be found in the pendix.

Liu, Y., Ott, M., Goyal, N., Du, J., Joshi, M., Chen, D., ... & Stoyanov, V. (2019). Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692.

ROBERTA

Results

	MNLI	QNLI	QQP	RTE	SST	MRPC	CoLA	STS	WNLI	Avg
Single-task single models on dev										
$\text{BERT}_{\text{LARGE}}$	86.6/-	92.3	91.3	70.4	93.2	88.0	60.6	90.0	-	-
$\text{XLNet}_{\text{LARGE}}$	89.8/-	93.9	91.8	83.8	95.6	89.2	63.6	91.8	-	-
RoBERTa	**90.2/90.2**	**94.7**	**92.2**	**86.6**	**96.4**	**90.9**	**68.0**	**92.4**	**91.3**	-
Ensembles on test (from leaderboard as of July 25, 2019)										
ALICE	88.2/87.9	95.7	**90.7**	83.5	95.2	92.6	**68.6**	91.1	80.8	86.3
MT-DNN	87.9/87.4	96.0	89.9	86.3	96.5	92.7	68.4	91.1	89.0	87.6
XLNet	90.2/89.8	98.6	90.3	86.3	**96.8**	**93.0**	67.8	91.6	**90.4**	88.4
RoBERTa	**90.8/90.2**	**98.9**	90.2	**88.2**	96.7	92.3	67.8	**92.2**	89.0	**88.5**

Table 5: Results on GLUE. All results are based on a 24-layer architecture. $\text{BERT}_{\text{LARGE}}$ and $\text{XLNet}_{\text{LARGE}}$ results are from Devlin et al. (2019) and Yang et al. (2019), respectively. RoBERTa results on the development set are a median over five runs. RoBERTa results on the test set are ensembles of *single-task* models. For RTE, STS and MRPC we finetune starting from the MNLI model instead of the baseline pretrained model. Averages are obtained from the GLUE leaderboard.

Liu, Y., Ott, M., Goyal, N., Du, J., Joshi, M., Chen, D., ... & Stoyanov, V. (2019). Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692.

ROBERTA

Additional observations

“We note that even our longest-trained model does not appear to overfit our data and would likely benefit from additional training.“

Liu, Y., Ott, M., Goyal, N., Du, J., Joshi, M., Chen, D., ... & Stoyanov, V. (2019). Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692.

WE NEED EVEN LARGER MODELS!

TRANSFORMER EXTRA LONG (XL)

Challenges with the Transformer architecture

- The challenge:
  - Fixed-length contexts not respecting semantic boundaries
  - Inability to learn longer dependencie
  - Relatively slow to execute
- The solution (Transformer XL):
  - Segment-level recurrence mechanism
  - Positional encoding scheme
- The results:
  - Learns 80% longer dependencies than RNNs and 450% longer than Transformer
  - Up to 1800 times faster than vanilla Transformer

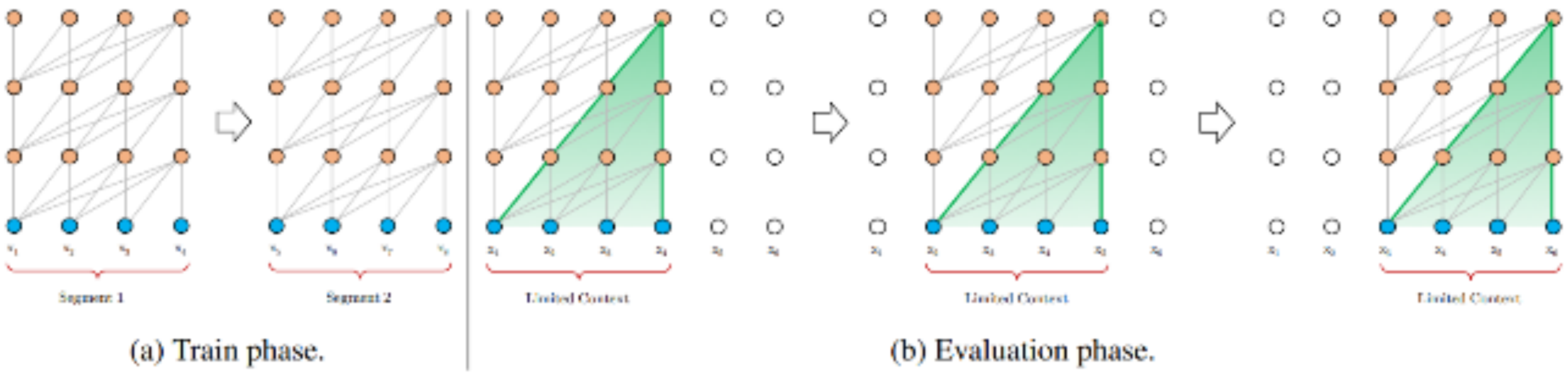


Figure 1: Illustration of the vanilla model with a segment length 4.

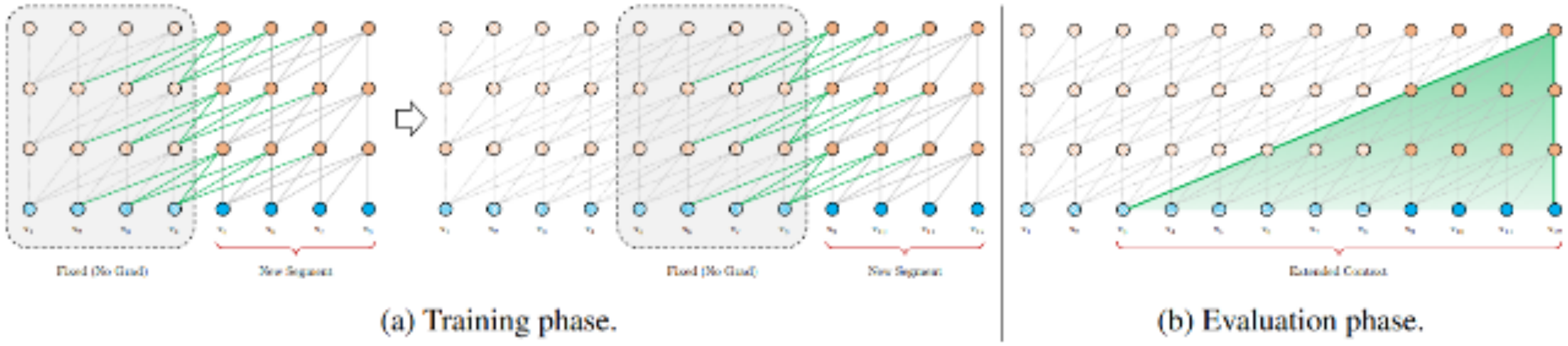


Figure 2: Illustration of the Transformer-XL model with a segment length 4.

Dai, Z., Yang, Z., Yang, Y., Carbonell, J., Le, Q. V., & Salakhutdinov, R. (2019). Transformer-xl: Attentive language models beyond a fixed-length context. arXiv preprint arXiv:1901.02860.

CHALLENGES WITH BERT

Masking and independent predictions

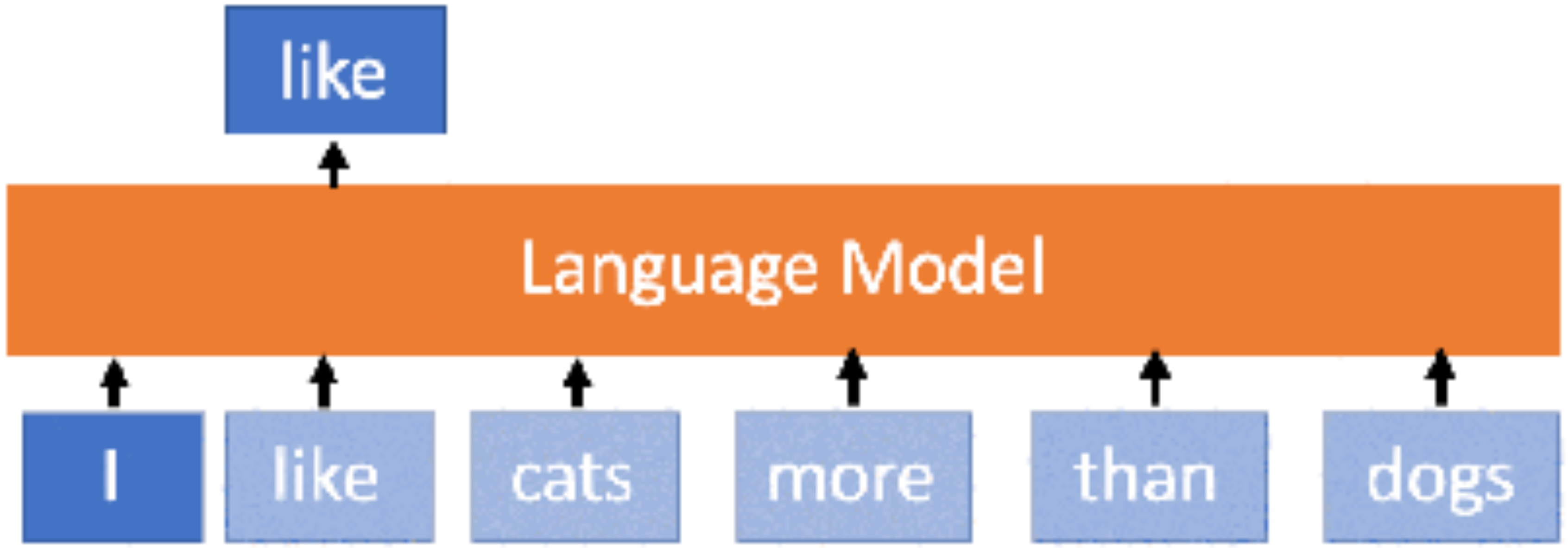
- The [MASK] token used during pretraining is not used during fine-tuning
- BERT generates predictions for individual [MASK] tokens independently, not forcing the model to learn dependencies

Yang, Z., Dai, Z., Yang, Y., Carbonell, J., Salakhutdinov, R. R., & Le, Q. V. (2019). Xlnet: Generalized autoregressive pretraining for language understanding. In Advances in neural information processing systems (pp. 5754-5764).

XLNET

TransformerXL + Permutational Language Model

1. Transformer -> TransformerXL
2. TransformerXL cannot be applied naively and must be adopted
3. “Maximizes the expected log likelihood of a sequence w.r.t all possible permutations of the factorization order.”
4. Does not rely on data corruption ([MASK])



Yang, Z., Dai, Z., Yang, Y., Carbonell, J., Salakhutdinov, R. R., & Le, Q. V. (2019). Xlnet: Generalized autoregressive pretraining for language understanding. In Advances in neural information processing systems (pp. 5754-5764).
https://mlexplained.com/2019/06/30/paper-dissected-xlnet-generalized-autoregressive-pretraining-for-language-understanding-explained/

XLNET

And more data

13GB* -> 13GB + 19GB + 110GB = 142GB

* Different pre-processing routine is used hence not 16GB as per ROBERTA

Yang, Z., Dai, Z., Yang, Y., Carbonell, J., Salakhutdinov, R. R., & Le, Q. V. (2019). Xlnet: Generalized autoregressive pretraining for language understanding. In Advances in neural information processing systems (pp. 5754-5764).

XLNET

“Fair” comparison with BERT

Model	SQuAD1.1	SQuAD2.0	RACE	MNLI	QNLI	QQP	RTE	SST-2	MRPC	CoLA	STS-B
BERT-Large (Best of 3)	86.7/92.8	82.8/85.5	75.1	87.3	93.0	91.4	74.0	94.0	88.7	63.7	90.2
XLNet-Large-wikibooks	88.2/94.0	85.1/87.8	77.4	88.4	93.9	91.8	81.2	94.4	90.0	65.2	91.1

Table 1: Fair comparison with BERT. All models are trained using the same data and hyperparameters as in BERT. We use the best of 3 BERT variants for comparison; i.e., the original BERT, BERT with whole word masking, and BERT without next sentence prediction.

Yang, Z., Dai, Z., Yang, Y., Carbonell, J., Salakhutdinov, R. R., & Le, Q. V. (2019). Xlnet: Generalized autoregressive pretraining for language understanding. In Advances in neural information processing systems (pp. 5754-5764).

XLNET

Ablation study

#	Model	RACE	SQuAD2.0 F1	SQuAD2.0 EM	MNLI m/mm	SST-2
1	BERT-Base	64.3	76.30	73.66	84.34/84.65	92.78
2	DAE + Transformer-XL	65.03	79.56	76.80	84.88/84.45	92.60
3	XLNet-Base ($K = 7$)	66.05	**81.33**	**78.46**	**85.84/85.43**	92.66
4	XLNet-Base ($K = 6$)	66.66	80.98	78.18	85.63/85.12	**93.35**
5	- memory	65.55	80.15	77.27	85.32/85.05	92.78
6	- span-based pred	65.95	80.61	77.91	85.49/85.02	93.12
7	- bidirectional data	66.34	80.65	77.87	85.31/84.99	92.66
8	+ next-sent pred	**66.76**	79.83	76.94	85.32/85.09	92.89

Table 6: The results of BERT on RACE are taken from [38]. We run BERT on the other datasets using the official implementation and the same hyperparameter search space as XLNet. K is a hyperparameter to control the optimization difficulty (see Section 2.3).

Yang, Z., Dai, Z., Yang, Y., Carbonell, J., Salakhutdinov, R. R., & Le, Q. V. (2019). Xlnet: Generalized autoregressive pretraining for understanding. In Advances in neural information processing systems (pp. 5754-5764). language

XLNET

Scaling up

RACE	Accuracy	Middle	High	Model	NDCG@20	ERR@20
GPT [28]	59.0	62.9	57.4	DRMM [13]	24.3	13.8
BERT [25]	72.0	76.6	70.1	KNRM [8]	26.9	14.9
BERT+DCMN* [38]	74.1	79.5	71.8	Conv [8]	28.7	18.1
RoBERTa [21]	83.2	86.5	81.8	BERT†	30.53	18.67
XLNet	**85.4**	**88.6**	**84.0**	XLNet	**31.10**	**20.28**

Table 2: Comparison with state-of-the-art results on the test set of RACE, a reading comprehension task, and on ClueWeb09-B, a document ranking task. $*$ indicates using ensembles. † indicates our implementations. "Middle" and "High" in RACE are two subsets representing middle and high school difficulty levels. All BERT, RoBERTa, and XLNet results are obtained with a 24-layer architecture with similar model sizes (aka BERT-Large).

Yang, Z., Dai, Z., Yang, Y., Carbonell, J., Salakhutdinov, R. R., & Le, Q. V. (2019). Xlnet: Generalized autoregressive pretraining for language understanding. In Advances in neural information processing systems (pp. 5754-5764).

SCALING UP?

XLNET

Scaling up

"… we scale up the training of XLNet-Large by using all the datasets described above. Specifically, we train on 512 TPU v3 chips for 500K steps with an Adam weight decay optimizer, linear learning rate decay, and a batch size of 8192, which takes about 5.5 days."

Yang, Z., Dai, Z., Yang, Y., Carbonell, J., Salakhutdinov, R. R., & Le, Q. V. (2019). Xlnet: Generalized autoregressive pretraining for language understanding. In Advances in neural information processing systems (pp. 5754-5764).

XLNET

Scaling up

"It was observed that the model still underfits the data at the end of training."

Yang, Z., Dai, Z., Yang, Y., Carbonell, J., Salakhutdinov, R. R., & Le, Q. V. (2019). Xlnet: Generalized autoregressive pretraining for language understanding. In Advances in neural information processing systems (pp. 5754-5764).

SCALING UP?

BERT

5.5 days -> 76 minutes

- Inspired by NVIDIA LARS (Layer-wise Adaptive Rate Scaling) they develop LAMB
- This allows to scale batch size to 32k without degrading performance
- A lot of improvements introduced since. Please use NVLAMB.

Solver	batch size	steps	F1 score on dev set	TPUs	Time
Baseline	512	1000k	90.395	16	81.4h
LAMB	512	1000k	91.752	16	82.8h
LAMB	1k	500k	91.761	32	43.2h
LAMB	2k	250k	91.946	64	21.4h
LAMB	4k	125k	91.137	128	693.6m
LAMB	8k	62500	91.263	256	390.5m
LAMB	16k	31250	91.345	512	200.0m
LAMB	32k	15625	91.475	1024	101.2m
LAMB	64k/32k	8599	90.584	1024	76.19m

https://devblogs.nvidia.com/pretraining-bert-with-layer-wise-adaptive-learning-rates/
You, Y., Li, J., Reddi, S., Hseu, J., Kumar, S., Bhojanapalli, S., ... & Hsieh, C. J. (2019, September). Large batch optimization for deep learning: Training bert in 76 minutes. In International Conference on Learning Representations

BERT

5.5 days -> 76 minutes

- Inspired by NVIDIA LARS (Layer-wise Adaptive Rate Scaling) they develop LAMB
- This allows to scale batch size to 32k without degrading performance
- A lot of improvements introduced since. Please use NVLAMB.

NVLAMB

1. For every training mini-batch x and training step t, compute gradient $g_l^i(t)$ on weights $w_l^i(t)$, for each weight i in layer l.

2. Normalize gradients by L2 norm of gradient of the entire model.

$$\widehat{g}_l^i(t) = g_l^i(t) \;/\; \| \, g(t) \, \|_2$$

3. Update velocity $v(t)$ and momentum $m(t)$ values corresponding to each layer weight $w_l^i(t)$ based on gradients $g(t)$ with hyperparameters β_1 and β_2.

$$m_l^i(t) = \beta_1 m_l^i(t-1) + (1-\beta_1)\widehat{g}_l^i(t) \qquad (1)$$

$$v_l^i(t) = \beta_2 v_l^i(t-1) + (1-\beta_2)(\widehat{g}_l^i(t))^2 \qquad (2)$$

4. Apply beta-correction on velocity and momentum values to obtain unbiased estimates.

$$\widehat{m}_l^i(t) = \frac{m_l^i(t)}{1-\beta_1^t} \qquad (3)$$

$$\widehat{v}_l^i(t) = \frac{v_l^i(t)}{1-\beta_2^t} \qquad (4)$$

5. Compute update $u_l^i(t)$ on weight $w_l^i(t)$ with weight decay parameter γ and ϵ as follows:

$$u_l^i(t) = \frac{\widehat{m}_l^i(t)}{\sqrt{\widehat{v}_l^i(t) + \epsilon}} + \gamma w_l^i(t)$$

6. For each layer l, compute the ratio $r_l(t)$ of norm of weights $w_l(t)$ and norm of update $u_l(t)$ as follows:

$$r_l(t) = \frac{\| \, w_l(t) \, \|_2}{\| \, u_l(t) \, \|_2}$$

7. Update the weights with learning rate λ:

$$w_l^i(t+1) = w_l^i(t) - \lambda * r_l(t) * u_l^i(t)$$

https://devblogs.nvidia.com/pretraining-bert-with-layer-wise-adaptive-learning-rates/

You, Y., Li, J., Reddi, S., Hseu, J., Kumar, S., Bhojanapalli, S., ... & Hsieh, C. J. (2019, September). Large batch optimization for deep learning: Training bert in 76 minutes. In International Conference on Learning Representations

BERT

Fastest training time

BERT-Large Training Times on GPUs

Time	System	Number of Nodes	Number of V100 GPUs
47 min	DGX SuperPOD	92 x DGX-2H	1,472
67 min	DGX SuperPOD	64 x DGX-2H	1,024
236 min	DGX SuperPOD	16 x DGX-2H	256

https://devblogs.nvidia.com/training-bert-with-gpus/

CAN WE USE PARAMETERS MORE EFFICIENTLY?

ALBERT

A Lite BERT for Self-Supervised Learning of Language Representations

- The size of the model is becoming a challenge
- FP16 is addressing the problem to some extent but still the footprint is considerable
- Describes a set of methods for reducing the memory footprint/ improving parameter efficiency

FP32 TF 1.13.1 16GB GPU

System	Seq Length	Max Batch Size
`XLNet-Base`	64	120
...	128	56
...	256	24
...	512	8
`XLNet-Large`	64	16
...	128	8
...	256	2
...	512	1

FP32 TF 1.11.0 12GB GPU

System	Seq Length	Max Batch Size
`BERT-Base`	64	64
...	128	32
...	256	16
...	320	14
...	384	12
...	512	6
`BERT-Large`	64	12
...	128	6
...	256	2
...	320	1
...	384	0
...	512	0

Lan, Z., Chen, M., Goodman, S., Gimpel, K., Sharma, P., & Soricut, R. (2019). Albert: A lite bert for self-supervised learning of language representations. arXiv preprint arXiv:1909.11942.

ALBERT

Model size is the key to success

Hyperparams				Dev Set Accuracy		
#L	#H	#A	LM (ppl)	MNLI-m	MRPC	SST-2
3	768	12	5.84	77.9	79.8	88.4
6	768	3	5.24	80.6	82.2	90.7
6	768	12	4.68	81.9	84.8	91.3
12	768	12	3.99	84.4	86.7	92.9
12	1024	16	3.54	85.7	86.9	93.3
24	1024	16	3.23	86.6	87.8	93.7

Table 6: Ablation over BERT model size. #L = the number of layers; #H = hidden size; #A = number of attention heads. "LM (ppl)" is the masked LM perplexity of held-out training data.

Lan, Z., Chen, M., Goodman, S., Gimpel, K., Sharma, P., & Soricut, R. (2019). Albert: A lite bert for self-supervised learning of language representations. arXiv preprint arXiv:1909.11942.

ALBERT

Factorized Embeddings

- "… WordPiece embedding size E is tied with the hidden layer size H, i.e., E ≡ H"
- "… hidden-layer embeddings are meant to learn context-dependent representations." so we want H >> E
- Embedding matrix size is V x E (vocabulary size time embedding size)
- "… natural language processing usually requires the vocabulary size V to be large." (BERT V=30000)
- So we end up with LargeNumber x LargeNumber

- Factorization of the embeddings matrix:

  O(V x H) transformed into O(V x E + E x H)

Model		Parameters	Layers	Hidden	Embedding	Parameter-sharing
BERT	base	108M	12	768	768	False
	large	334M	24	1024	1024	False
ALBERT	base	12M	12	768	128	True
	large	18M	24	1024	128	True
	xlarge	60M	24	2048	128	True
	xxlarge	235M	12	4096	128	True

Table 1: The configurations of the main BERT and ALBERT models analyzed in this paper.

Lan, Z., Chen, M., Goodman, S., Gimpel, K., Sharma, P., & Soricut, R. (2019). Albert: A lite bert for self-supervised learning of language representations. arXiv preprint arXiv:1909.11942.

ALBERT

Cross Layer Parameter Sharing and Inter-Sentence Coherence Loss

- Proposes several cross-layer parameter-sharing schemes
- The default Albert configuration shares all parameters across all layers
- SOP Loss (Sentence Order Prediction) rather than NSP Loss (Next Sentence Prediction)

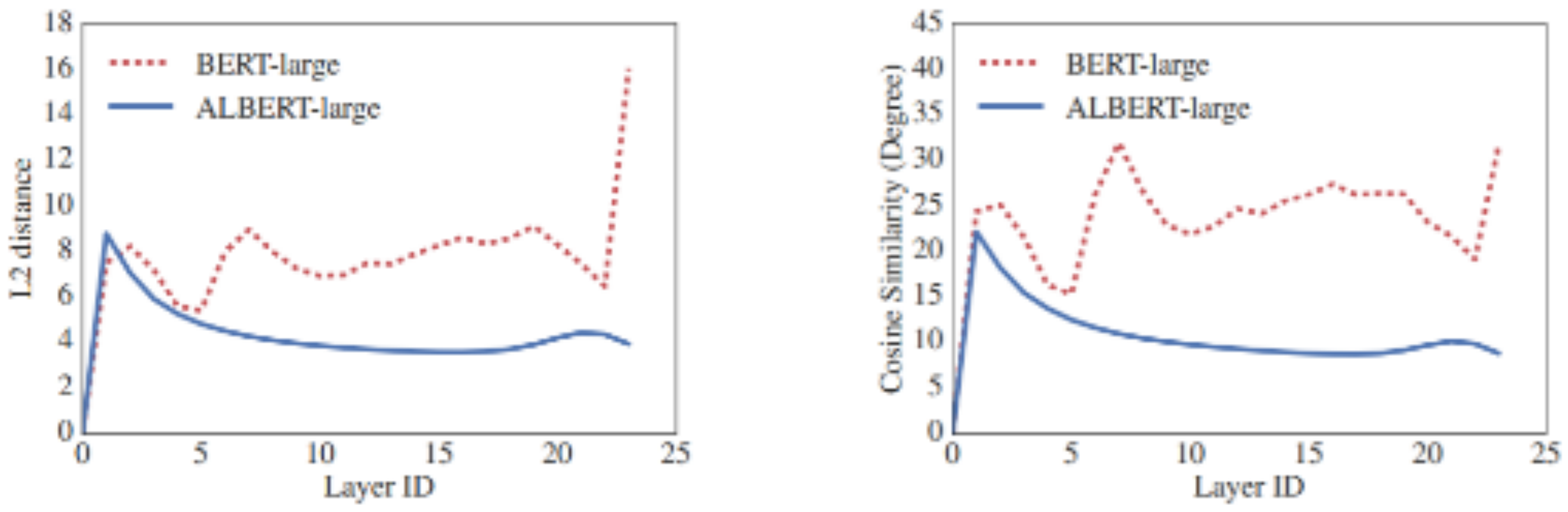


Figure 1: The L2 distances and cosine similarity (in terms of degree) of the input and output embedding of each layer for BERT-large and ALBERT-large.

Lan, Z., Chen, M., Goodman, S., Gimpel, K., Sharma, P., & Soricut, R. (2019). Albert: A lite bert for self-supervised learning of language representations. arXiv preprint arXiv:1909.11942.

ALBERT

Results

Model		Parameters	Layers	Hidden	Embedding	Parameter-sharing
BERT	base	108M	12	768	768	False
	large	334M	24	1024	1024	False
ALBERT	base	12M	12	768	128	True
	large	18M	24	1024	128	True
	xlarge	60M	24	2048	128	True
	xxlarge	235M	12	4096	128	True

Table 1: The configurations of the main BERT and ALBERT models analyzed in this paper.

Model		Parameters	SQuAD1.1	SQuAD2.0	MNLI	SST-2	RACE	Avg	Speedup
BERT	base	108M	90.4/83.2	80.4/77.6	84.5	92.8	68.2	82.3	4.7x
	large	334M	92.2/85.5	85.0/82.2	86.6	93.0	73.9	85.2	1.0
ALBERT	base	12M	89.3/82.3	80.0/77.1	81.6	90.3	64.0	80.1	5.6x
	large	18M	90.6/83.9	82.3/79.4	83.5	91.7	68.5	82.4	1.7x
	xlarge	60M	92.5/86.1	86.1/83.1	86.4	92.4	74.8	85.5	0.6x
	xxlarge	235M	**94.1/88.3**	**88.1/85.1**	**88.0**	**95.2**	**82.3**	**88.7**	0.3x

Table 2: Dev set results for models pretrained over BookCorpus and Wikipedia for 125k steps. Here and everywhere else, the Avg column is computed by averaging the scores of the downstream tasks to its left (the two numbers of F1 and EM for each SQuAD are first averaged).

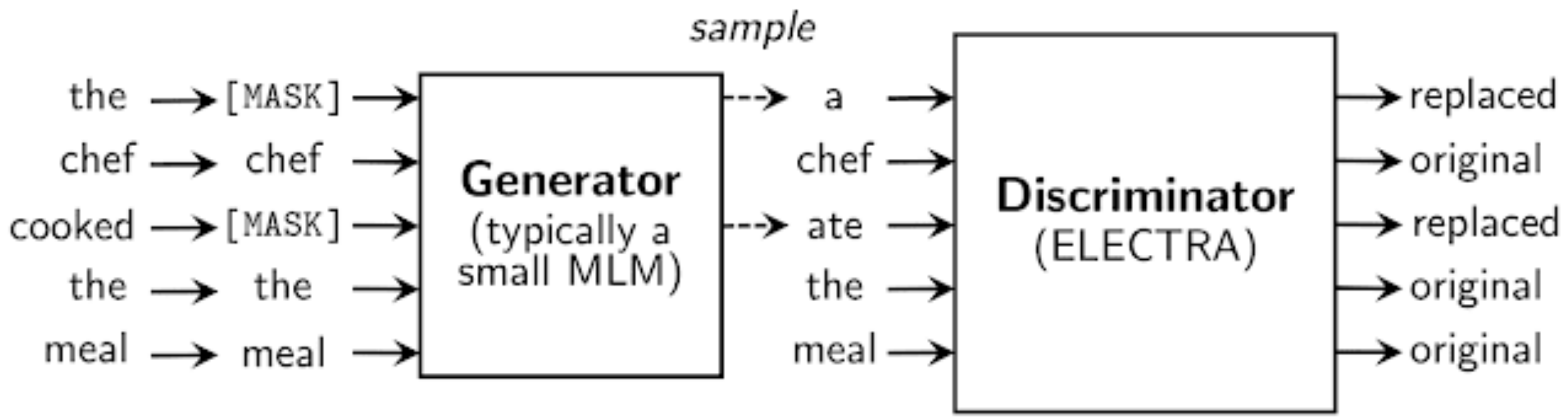
Lan, Z., Chen, M., Goodman, S., Gimpel, K., Sharma, P., & Soricut, R. (2019). Albert: A lite bert for self-supervised learning of language representations. arXiv preprint arXiv:1909.11942.

CAN WE IMPROVE THE OBJECTIVE FUNCTION FURTHER?

ELECTRA

Pre-training Text Encoders as Discriminators Rather Than Generators

Replaced Token Detection

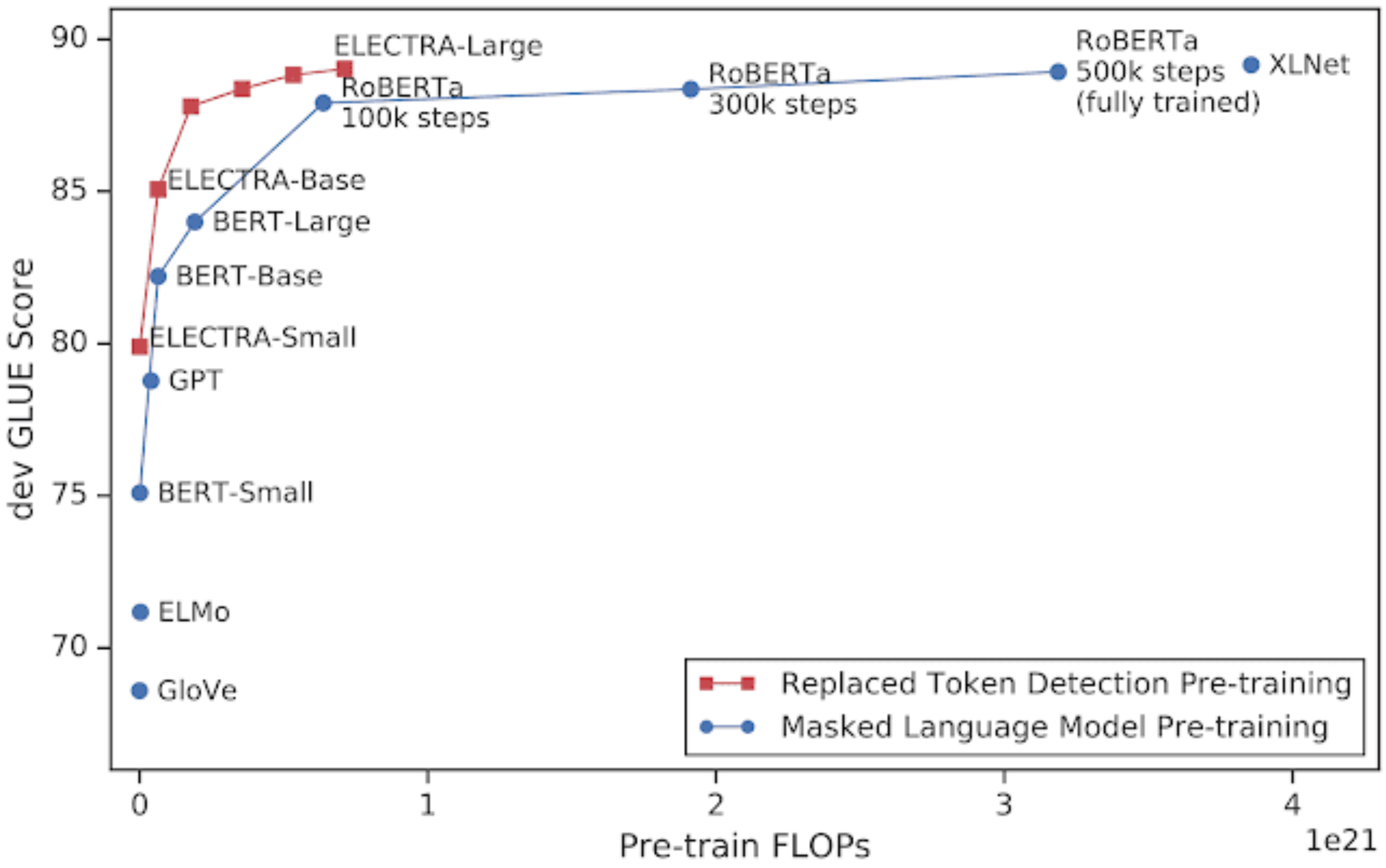


the chef cooked the meal

Clark, K., Luong, M. T., Le, Q. V., & Manning, C. D. (2020). Electra: Pre-training text encoders as discriminators rather than generators. arXiv preprint arXiv:2003.10555.

ELECTRA

Pre-training Text Encoders as Discriminators Rather Than Generators



Clark, K., Luong, M. T., Le, Q. V., & Manning, C. D. (2020). Electra: Pre-training text encoders as discriminators rather than generators. arXiv preprint arXiv:2003.10555.

MULTI-TASK LEARNING

ERNIE 2.0

Why use only a limited number of simple pretraining tasks?

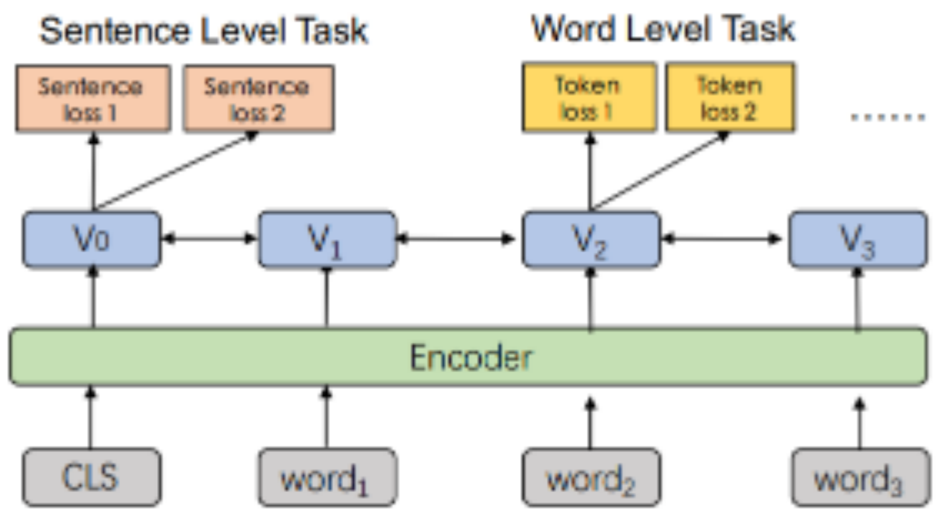


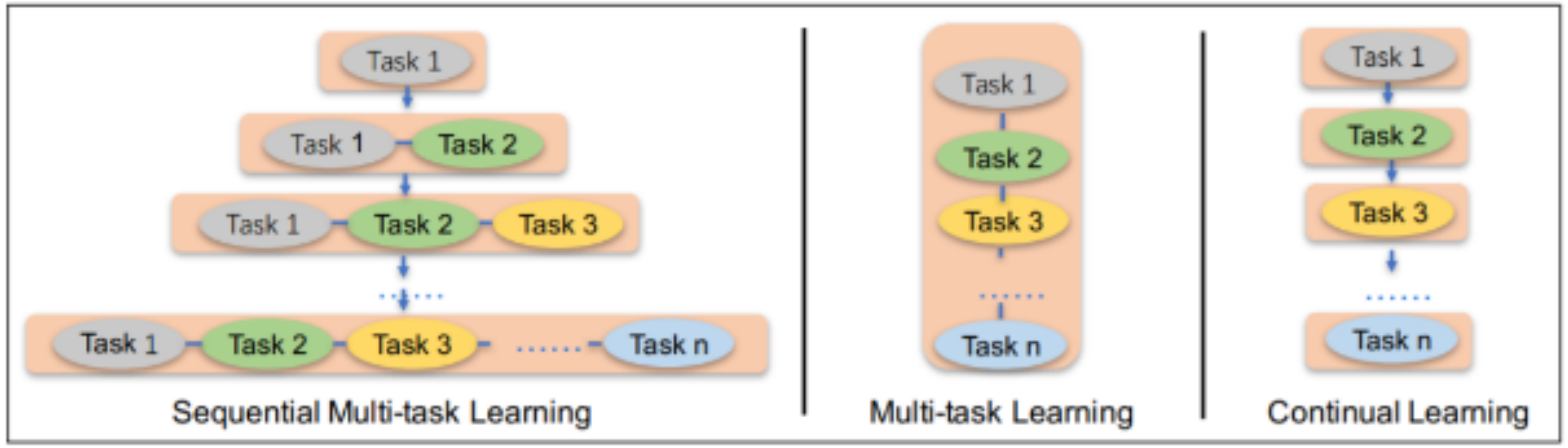
Figure 4: The architecture of multi-task learning in the ERNIE 2.0 framework, in which the encoder can be recurrent neural networks or a deep transformer.

Task / Corpus	Token-Level Loss			Sentence-Level Loss			
	Knowledge Masking	Capital Prediction	Token-Document Relation	Sentence Reordering	Sentence Distance	Discourse Relation	IR Relevance
Encyclopedia	✓	✓	✓	✓	✓	×	×
BookCorpus	✓	✓	✓	✓	✓	×	×
News	✓	✓	✓	✓	✓	×	×
Dialog	✓	✓	✓	✓	✓	×	×
IR Relevance Data	×	×	×	×	×	×	✓
Discourse Relation Data	×	×	×	×	×	✓	×

Table 1: The Relationship between pre-training task and pre-training dataset. We use different pre-training dataset to construct different tasks. A type of pre-trained dataset can correspond to multiple pre-training tasks.

ERNIE 2.0

Why use only a limited number of simple pretraining tasks?



Pre-training method	Pre-training task	Training iterations (steps)				Fine-tuning result		
		Stage 1	Stage 2	Stage 3	Stage 4	MNLI	SST-2	MRPC
Continual Learning	Knowledge Masking	50k	-	-	-	77.3	86.4	82.5
	Capital Prediction	-	50k	-	-			
	Token-Document Relation	-	-	50k	-			
	Sentence Reordering	-	-	-	50k			
Multi-task Learning	Knowledge Masking	50k				78.7	87.5	83.0
	Capital Prediction	50k						
	Token-Document Relation	50k						
	Sentence Reordering	50k						
continual Multi-task Learning	Knowledge Masking	20k	10k	10k	10k	**79.0**	**87.8**	**84.0**
	Capital Prediction	-	30k	10k	10k			
	Token-Document Relation	-	-	40k	10k			
	Sentence Reordering	-	-	-	50k			

ERNIE 2.0

Performance

Task(Metrics)	BASE model		LARGE model				
	Test		Dev			Test	
	BERT	ERNIE 2.0	BERT	XLNet	ERNIE 2.0	BERT	ERNIE 2.0
CoLA (Matthew Corr.)	52.1	**55.2**	60.6	63.6	**65.4**	60.5	**63.5**
SST-2 (Accuracy)	93.5	**95.0**	93.2	95.6	**96.0**	94.9	**95.6**
MRPC (Accurary/F1)	84.8/88.9	**86.1/89.9**	88.0/-	89.2/-	**89.7/-**	85.4/89.3	**87.4/90.2**
STS-B (Pearson Corr./Spearman Corr.)	87.1/85.8	**87.6/86.5**	90.0/-	91.8/-	**92.3/-**	87.6/86.5	**91.2/90.6**
QQP (Accuracy/F1)	89.2/71.2	**89.8/73.2**	91.3/-	91.8/-	**92.5/-**	89.3/72.1	**90.1/73.8**
MNLI-m/mm (Accuracy)	84.6/83.4	**86.1/85.5**	86.6/-	**89.8/-**	89.1/-	86.7/85.9	**88.7/88.8**
QNLI (Accuracy)	90.5	**92.9**	92.3	93.9	**94.3**	92.7	**94.6**
RTE (Accuracy)	66.4	**74.8**	70.4	83.8	**85.2**	70.1	**80.2**
WNLI (Accuracy)	**65.1**	**65.1**	-	-	-	65.1	**67.8**
AX(Matthew Corr.)	34.2	**37.4**	-	-	-	39.6	**48.0**
Score	78.3	**80.6**	-	-	-	80.5	**83.6**

Table 6: The results on GLUE benchmark, where the results on dev set are the median of five experimental results and the results on test set are scored by the GLUE evaluation server (`https://gluebenchmark.com/leaderboard`). The state-of-the-art results are in bold. All of the fine-tuned models of AX is trained by the data of MNLI.

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)
  - Bigger is Better
  - Can and should we go even bigger?
- Lab (cont’d)
  - Named Entity Recognizer

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 <u>one billion </u>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?

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

1 billion parameters

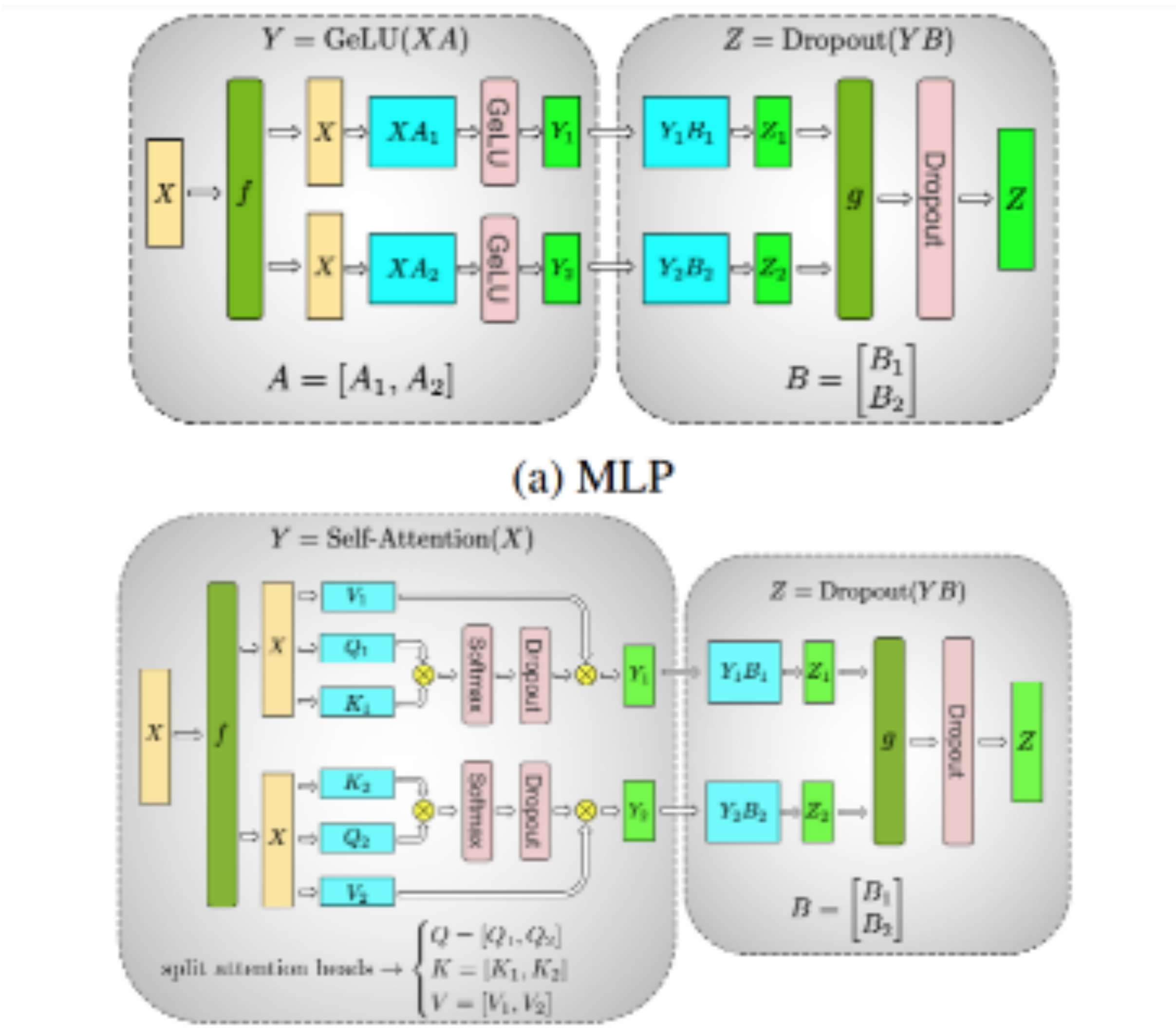
2 bytes per parameter

2 bytes per gradient

12 bytes per optimizer state

MEGATRON

Model Parallel Transformer



(b) Self-Attention

Figure 3. Blocks of Transformer with Model Parallelism. f and g are conjugate. f is an identity operator in the forward pass and all reduce in the backward pass while g is an all reduce in the forward pass and identity in the backward pass.

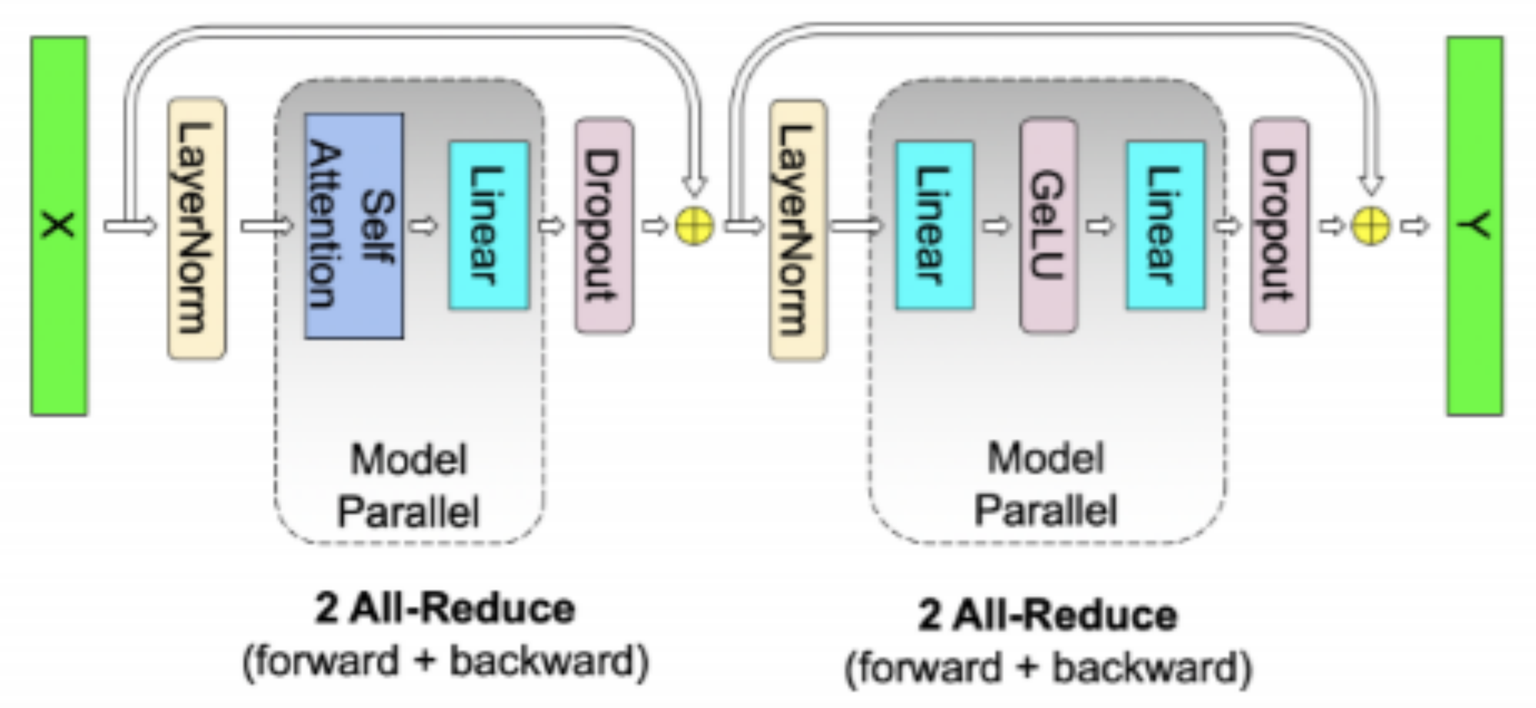


Figure 4. Communication operations in a transformer layer. There are 4 total communication operations in the forward and backward pass of a single model parallel transformer layer.

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.

MEGATRON

76% scaling efficiency using 512 GPUs

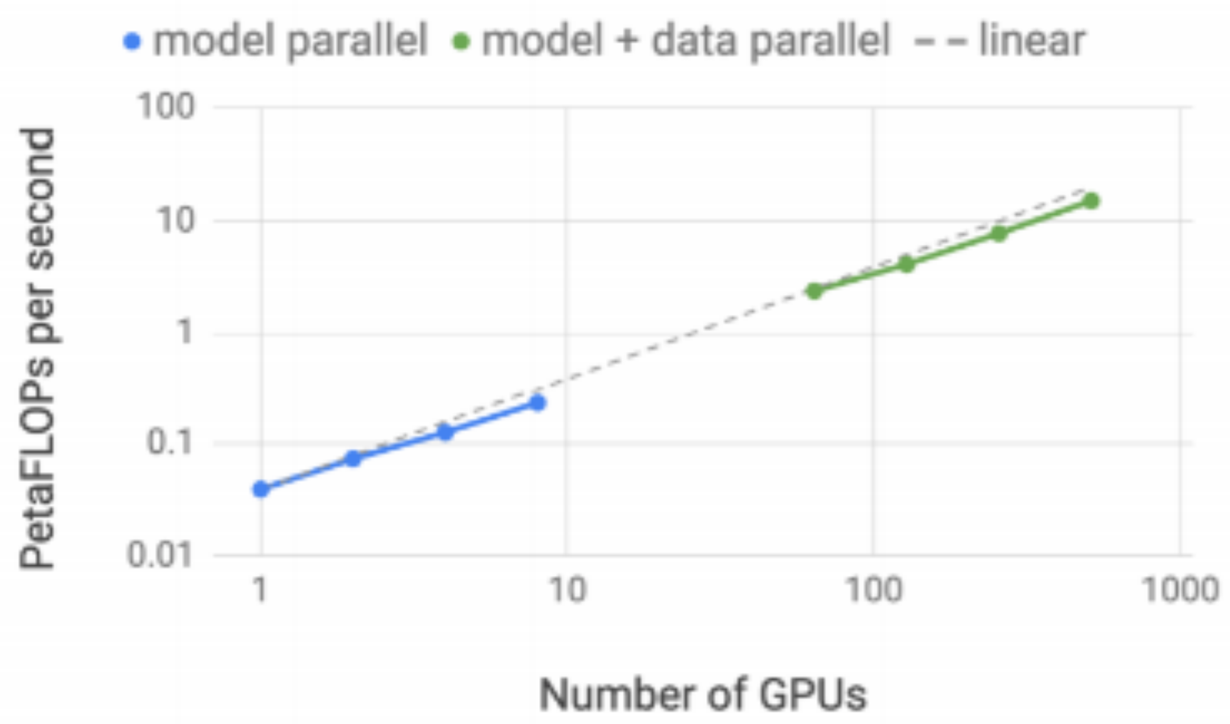


Figure 1. Model (blue) and model+data (green) parallel FLOPS as a function of number of GPUs. Model parallel (blue): up to 8-way model parallel weak scaling with approximately 1 billion parameters per GPU (e.g. 2 billion for 2 GPUs and 4 billion for 4 GPUs). Model+data parallel (green): similar configuration as model parallel combined with 64-way data parallel.

Table 1. Parameters used for scaling studies. Hidden size per attention head is kept constant at 96.

Hidden Size	Attention heads	Number of layers	Number of parameters (billions)	Model parallel GPUs	Model +data parallel GPUs
1536	16	40	1.2	1	64
1920	20	54	2.5	2	128
2304	24	64	4.2	4	256
3072	32	72	8.3	8	512

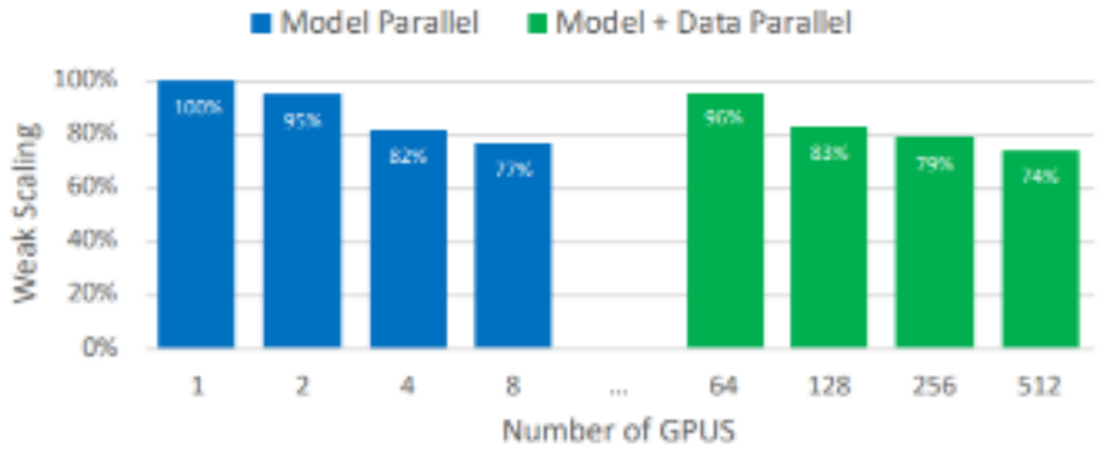


Figure 5. Model and model + data parallel weak scaling efficiency as a function of the number of GPUs.

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.

MEGATRON

Results

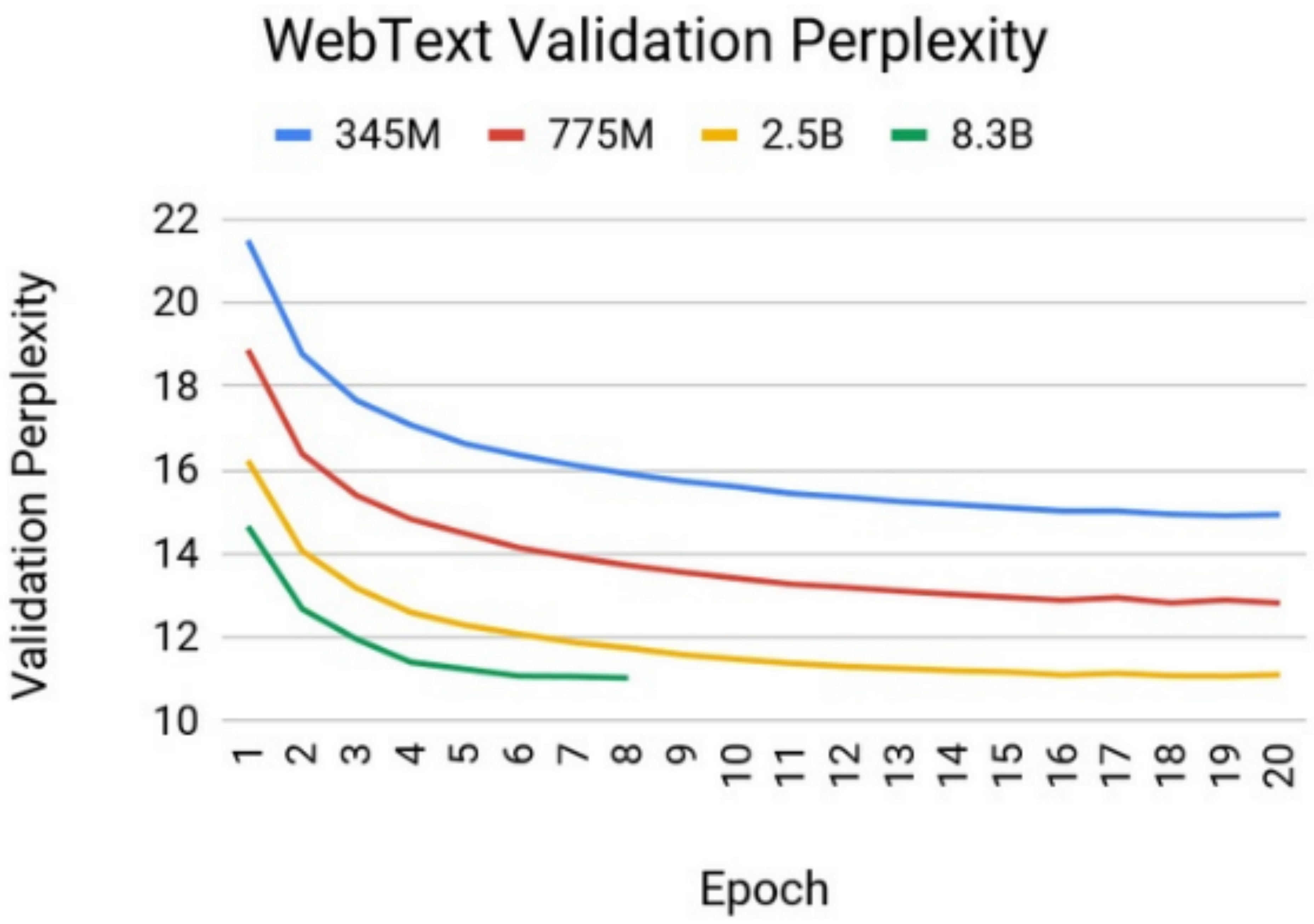
Table 5. Development set results for MNLI, QQP, SQuAD 1.1 and SQuAD 2.0 and test set results for RACE. The trained tokens represents consumed tokens during model pretraining (proportional to batch size times number of iterations) normalized by consumed tokens during model pretraining for our 336M model.

Model	trained tokens ratio	MNLI m/mm accuracy (dev set)	QQP accuracy (dev set)	SQuAD 1.1 F1 / EM (dev set)	SQuAD 2.0 F1 / EM (dev set)	RACE m/h accuracy (test set)
RoBERTa (Liu et al., 2019b)	2	90.2 / 90.2	92.2	94.6 / 88.9	89.4 / 86.5	83.2 (86.5 / 81.8)
ALBERT (Lan et al., 2019)	3	90.8	92.2	94.8 / 89.3	90.2 / 87.4	86.5 (89.0 / 85.5)
XLNet (Yang et al., 2019)	2	90.8 / 90.8	92.3	95.1 / 89.7	90.6 / 87.9	85.4 (88.6 / 84.0)
Megatron-336M	1	89.7 / 90.0	92.3	94.2 / 88.0	88.1 / 84.8	83.0 (86.9 / 81.5)
Megatron-1.3B	1	90.9 / 91.0	92.6	94.9 / 89.1	90.2 / 87.1	87.3 (90.4 / 86.1)
Megatron-3.9B	1	**91.4 / 91.4**	**92.7**	**95.5 / 90.0**	**91.2 / 88.5**	**89.5 (91.8 / 88.6)**
ALBERT ensemble (Lan et al., 2019)				95.5 / 90.1	91.4 / 88.9	89.4 (91.2 / 88.6)
Megatron-3.9B ensemble				**95.8 / 90.5**	**91.7 / 89.0**	**90.9 (93.1 / 90.0)**

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.

MEGATRON

More importantly!



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.

THE SCALING LAWS

THE SCALING LAWS

As you increase the dataset size, you must increase the model size

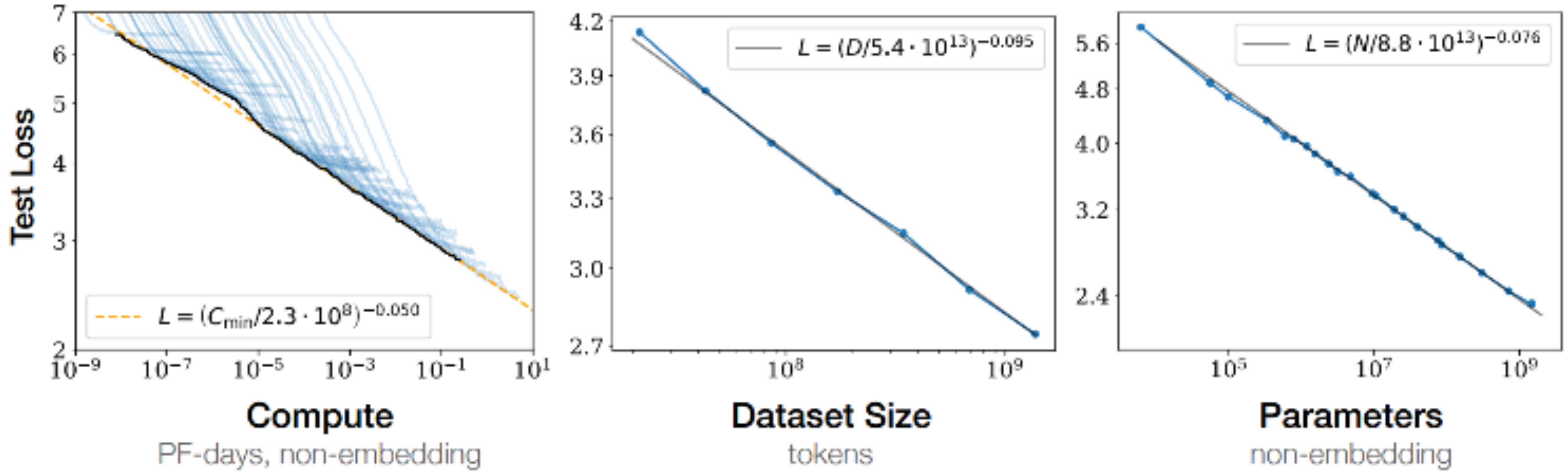


Figure 1 Language modeling performance improves smoothly as we increase the model size, datasetset size, and amount of compute[2] used for training. For optimal performance all three factors must be scaled up in tandem. Empirical performance has a power-law relationship with each individual factor when not bottlenecked by the other two.

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*.

THE SCALING LAWS

Larger models are more sample-efficient

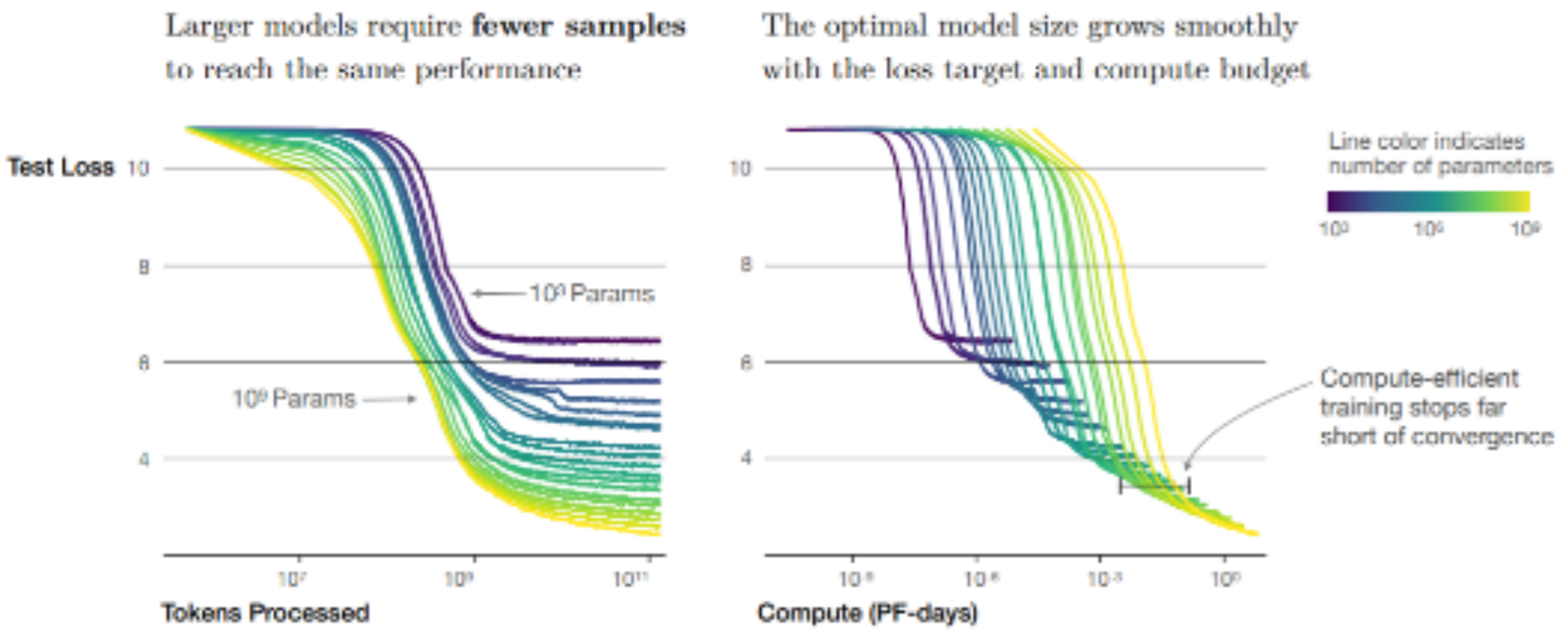


Figure 2 We show a series of language model training runs, with models ranging in size from 10^3 to 10^9 parameters (excluding embeddings).

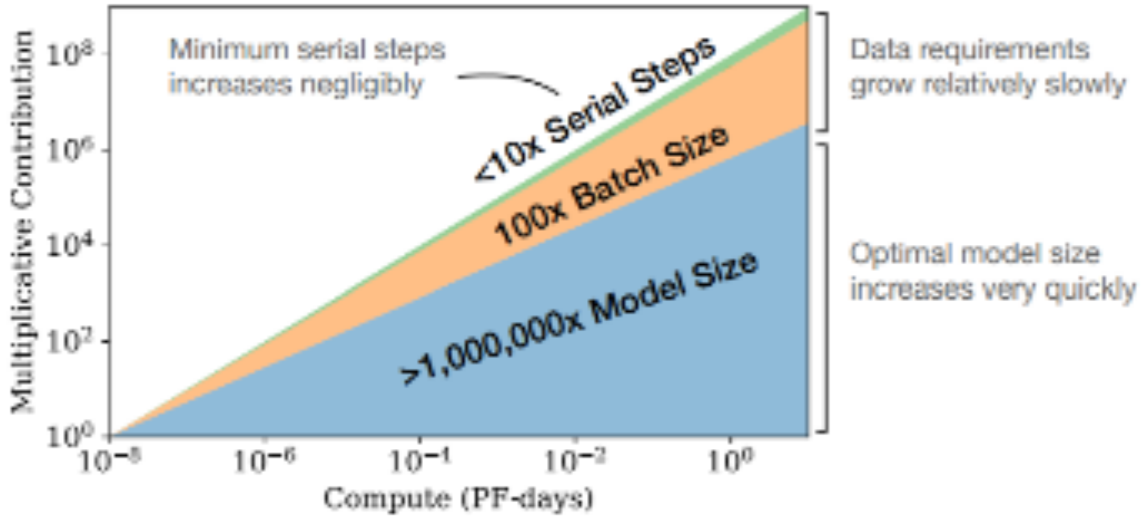


Figure 3 As more compute becomes available, we can choose how much to allocate towards training larger models, using larger batches, and training for more steps. We illustrate this for a billion-fold increase in compute. For optimally compute-efficient training, most of the increase should go towards 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*.

DEEP LEARNING INSTITUTE

THE SCALING LAWS

Larger models generalize better

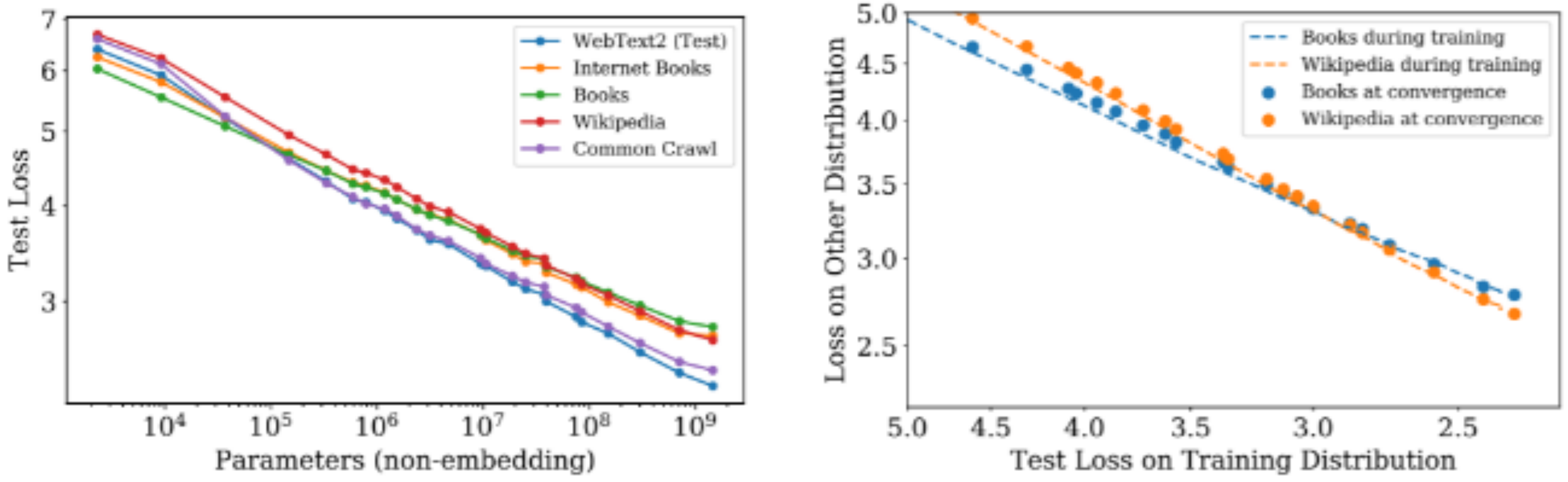


Figure 8 **Left:** Generalization performance to other data distributions improves smoothly with model size, with only a small and very slowly growing offset from the WebText2 training distribution. **Right:** Generalization performance depends only on training distribution performance, and not on the 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*.

THE SCALING LAWS

Its cheaper to use a larger model

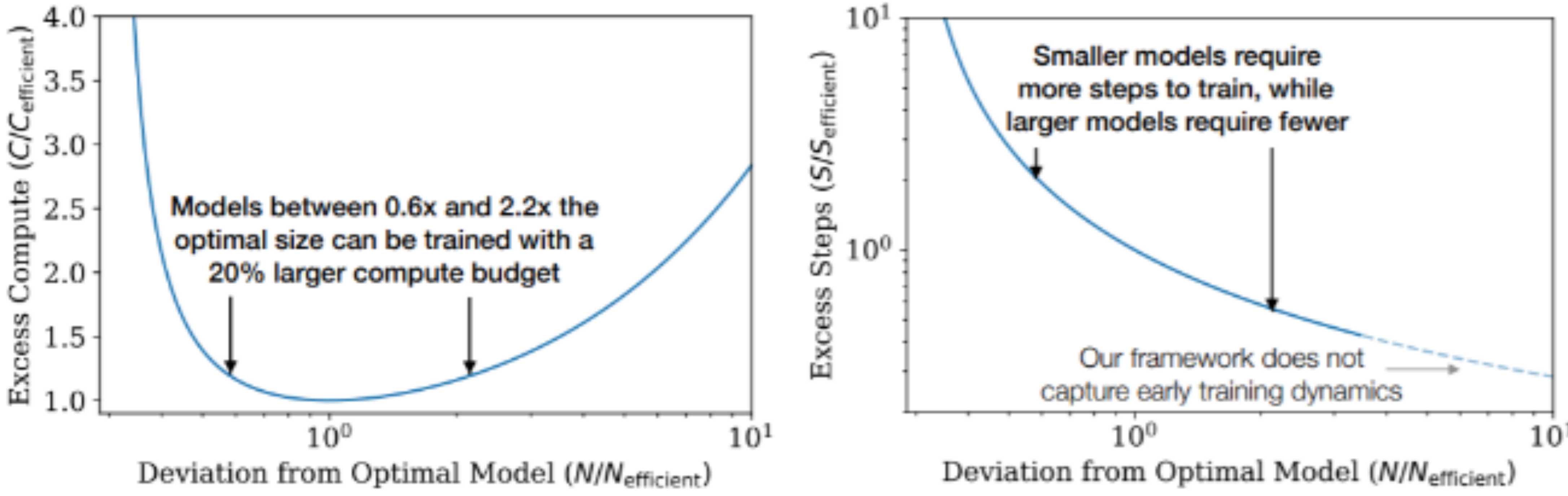
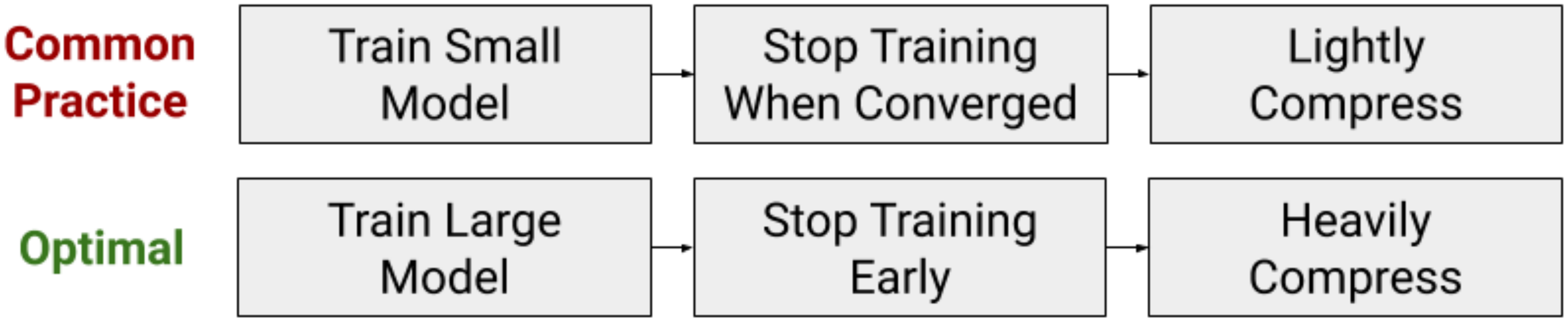


Figure 12 **Left:** Given a fixed compute budget, a particular model size is optimal, though somewhat larger or smaller models can be trained with minimal additional compute. **Right:** Models larger than the compute-efficient size require fewer steps to train, allowing for potentially faster training 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*.

THE SCALING LAWS

Larger models train faster



https://bair.berkeley.edu/blog/2020/03/05/compress/

THE SCALING LAWS

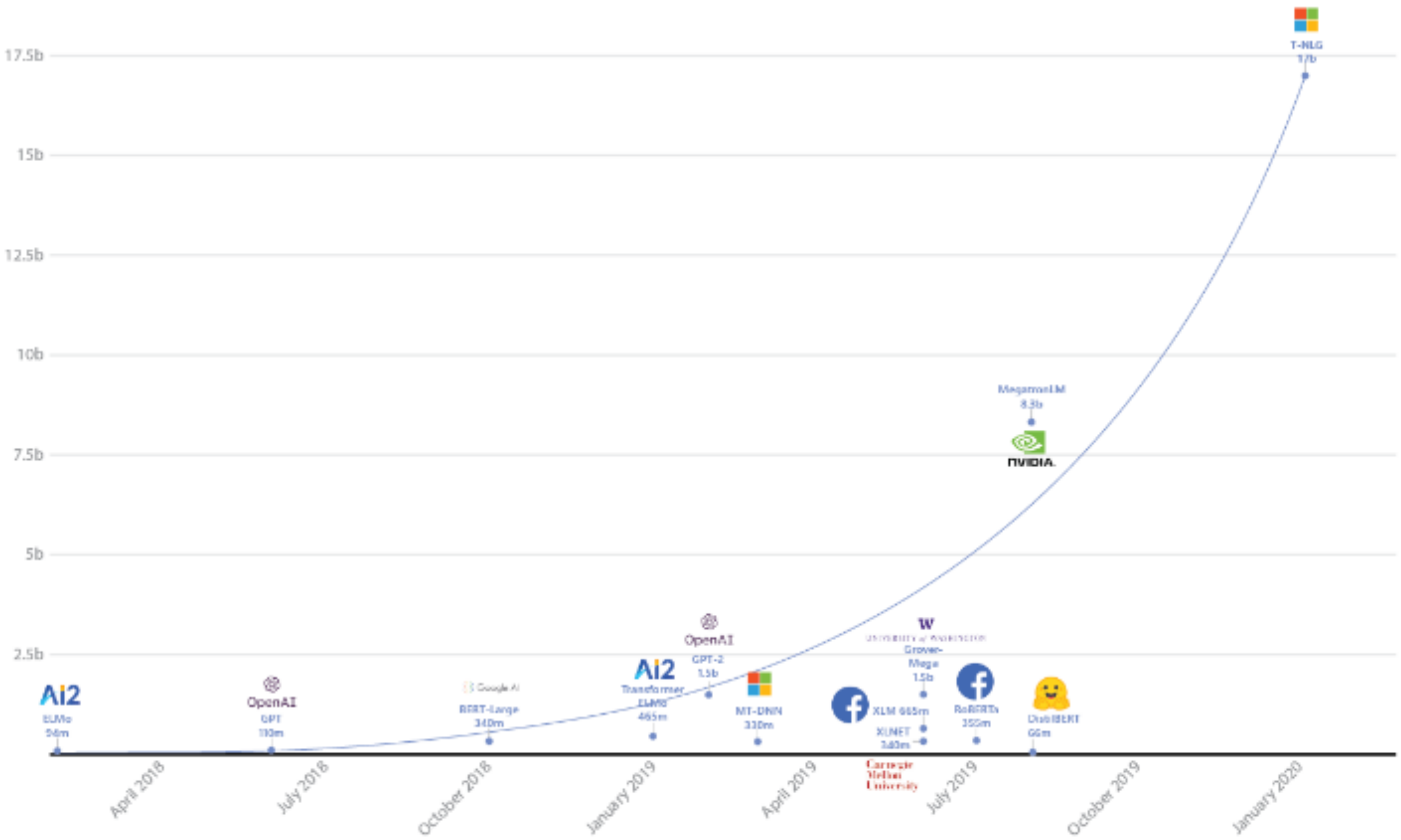
MOST IMPORTANT!!

"… 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*.

THE SCALING LAWS

Next two years will bring much larger models



TOWARDS A TRILLION-PARAMETER MODEL

TURINGNLG

17 billion parameters

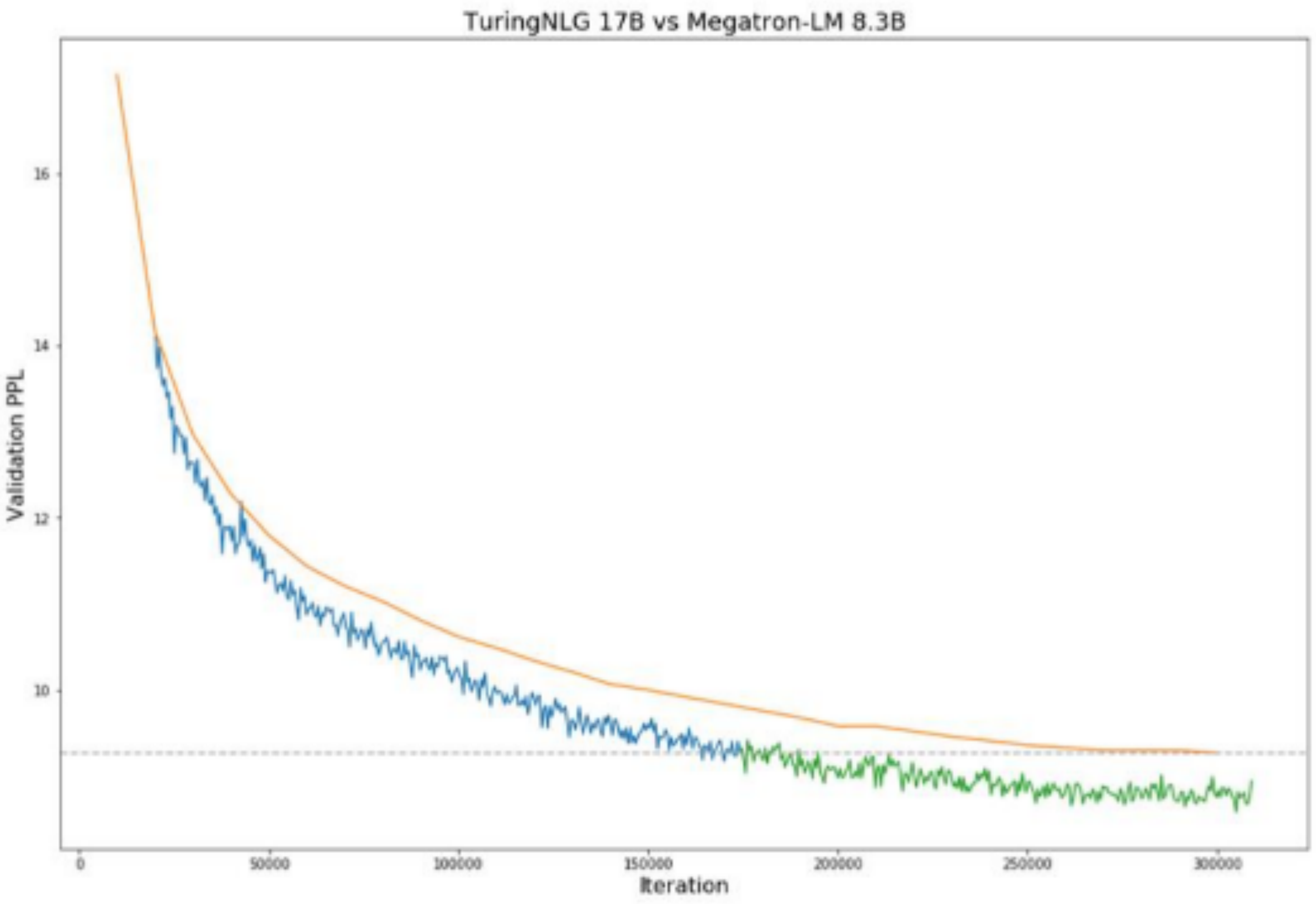


Figure 1: Comparison of the validation perplexity of Megatron-8B parameter model (orange line) vs T-NLG 17B model during training (blue and green lines). The dashed line represents the lowest validation loss achieved by the current public state of the art model. The transition from blue to green in the figure indicates where T-NLG outperforms public state of the art.

THE FUTURE

Towards a trillion-parameter model

DeepSpeed + ZeRO

Scale
- 100B parameter
- 10X bigger

Speed
- Up to 5X faster

Cost
- Up to 5X cheaper

Usability
- Minimal code change

GPT-3

EVEN MORE IMPORTANTLY

Large neural networks use data more efficiently

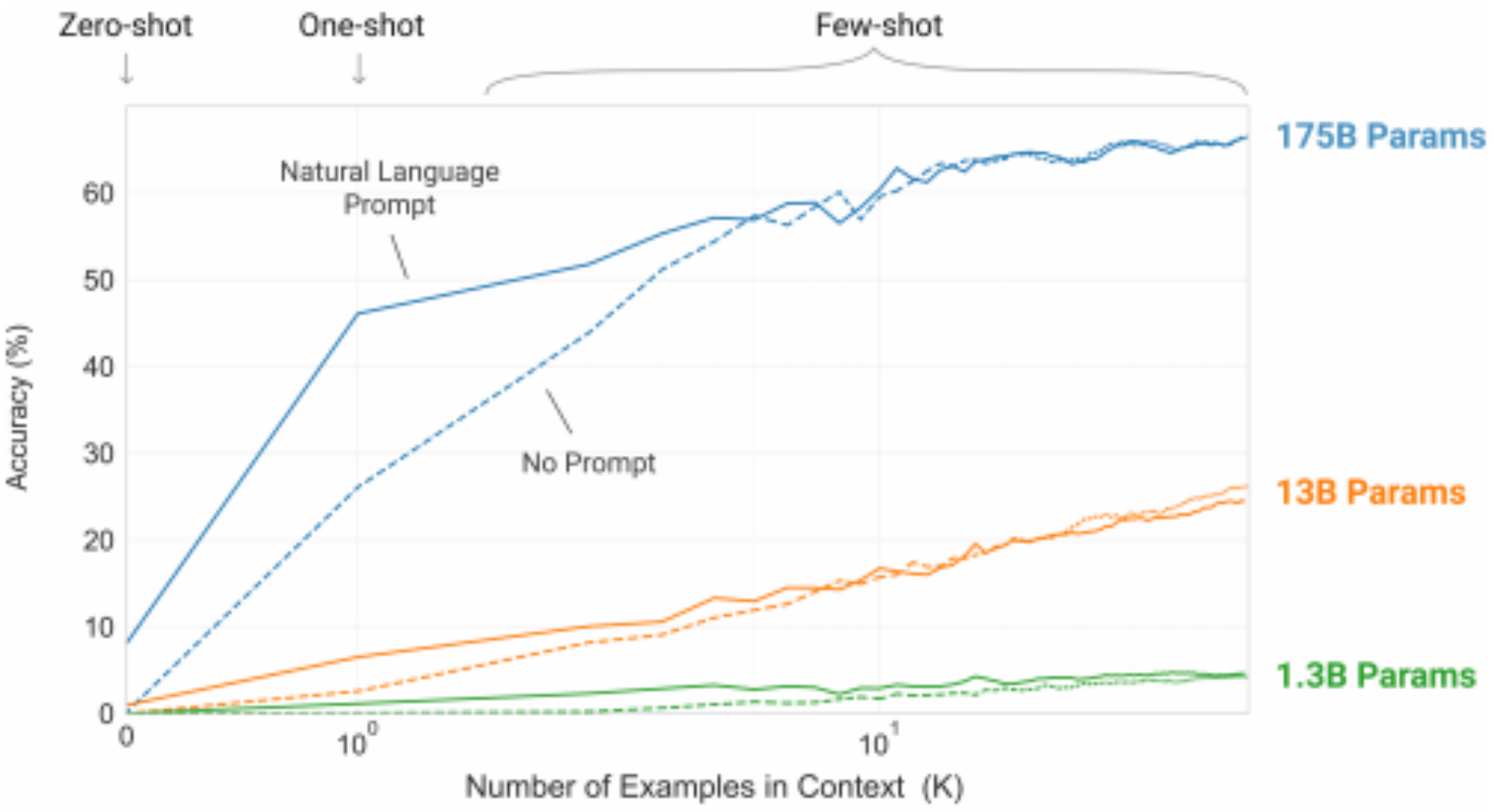


Figure 1.2: Larger models make increasingly efficient use of in-context information. We show in-context learning performance on a simple task requiring the model to remove random symbols from a word, both with and without a natural language task description (see Sec. 3.9.2). The steeper "in-context learning 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.

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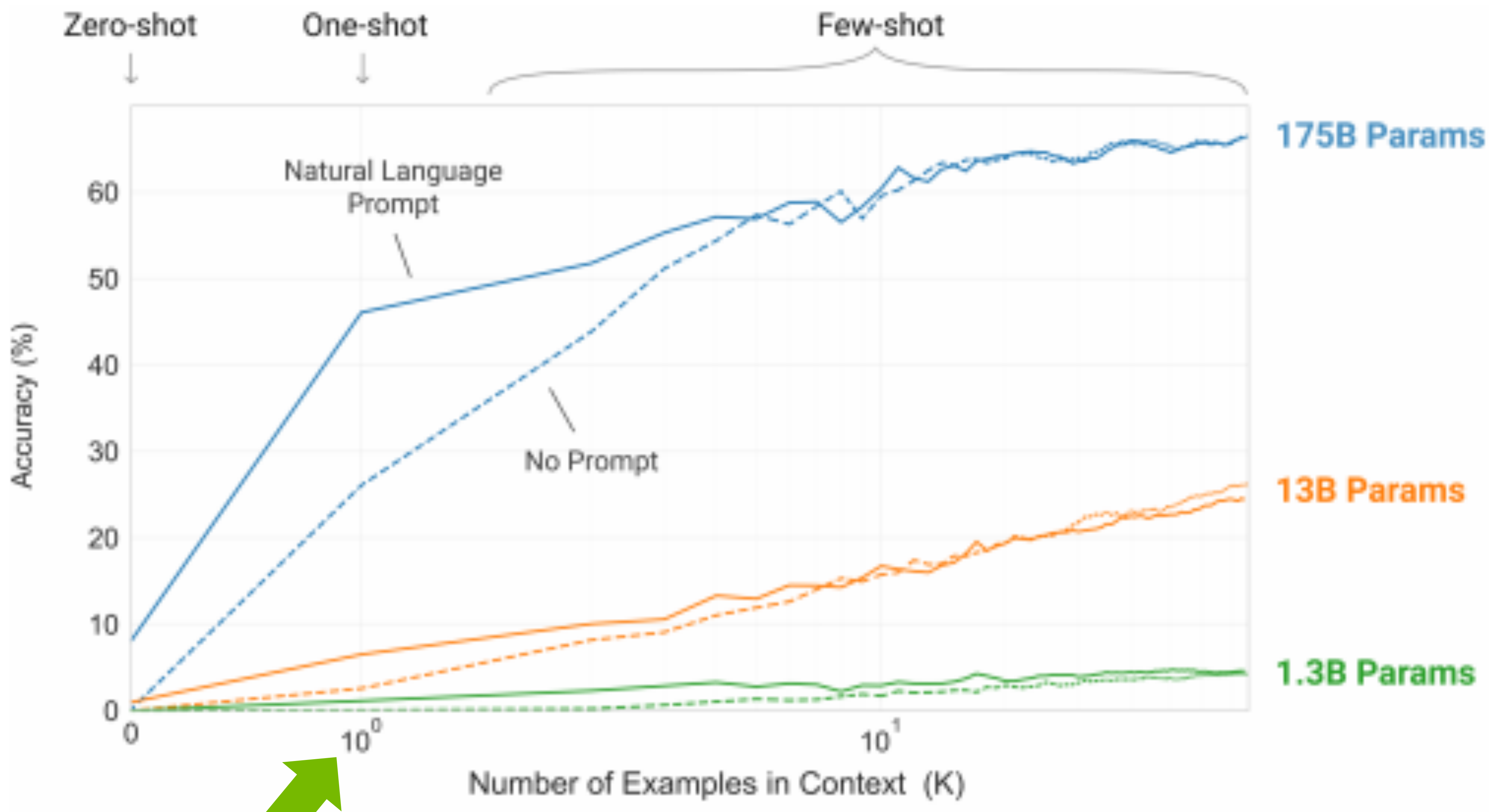
Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., ... & Agarwal, S. (2020). Language models are few-shot learners. *arXiv preprint arXiv:2005.14165*..

EVEN MORE IMPORTANTLY

Large neural networks use data more efficiently



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WHAT DO WE MEAN BY BIG?

GPT-3 size comparison

Not a linear scale

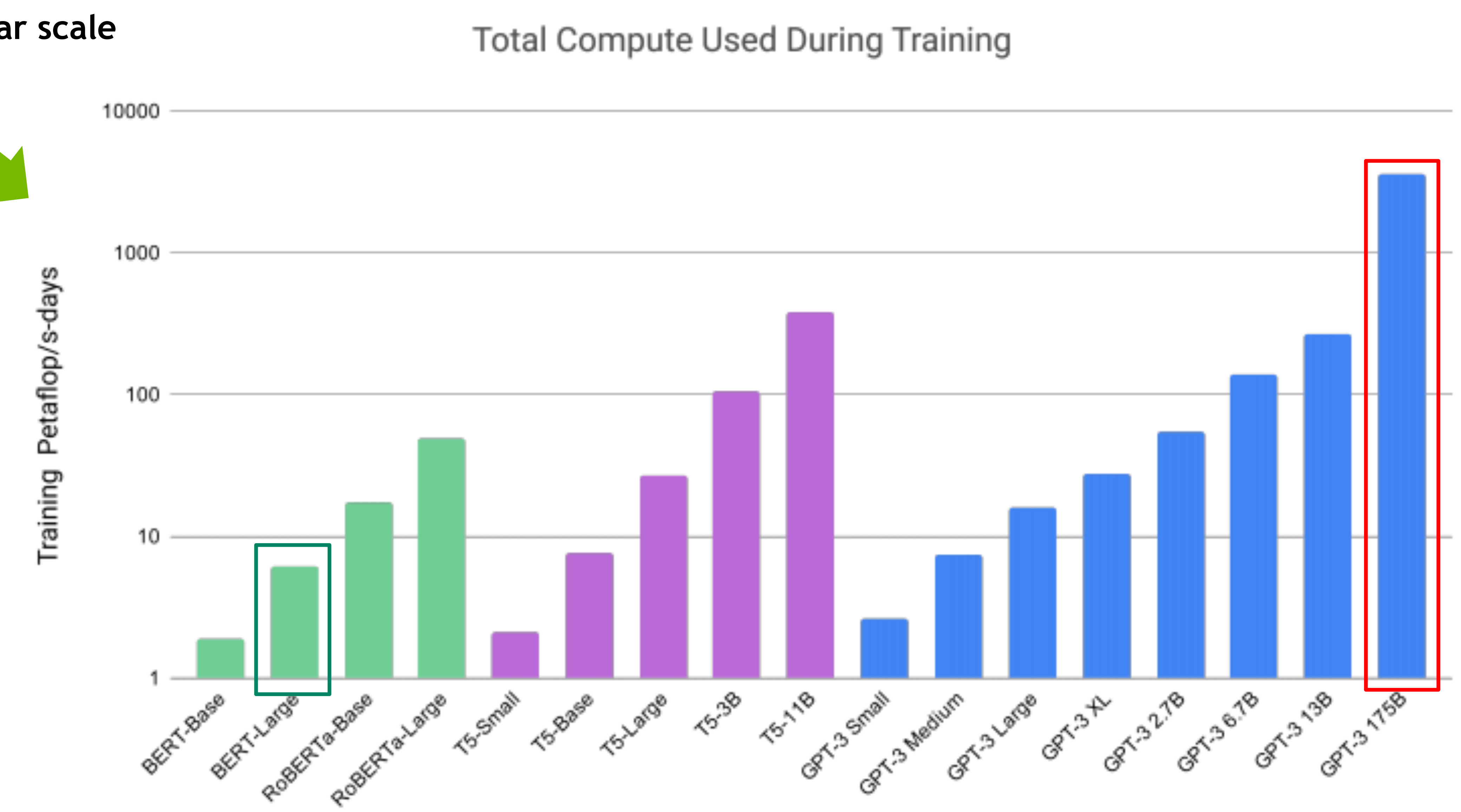
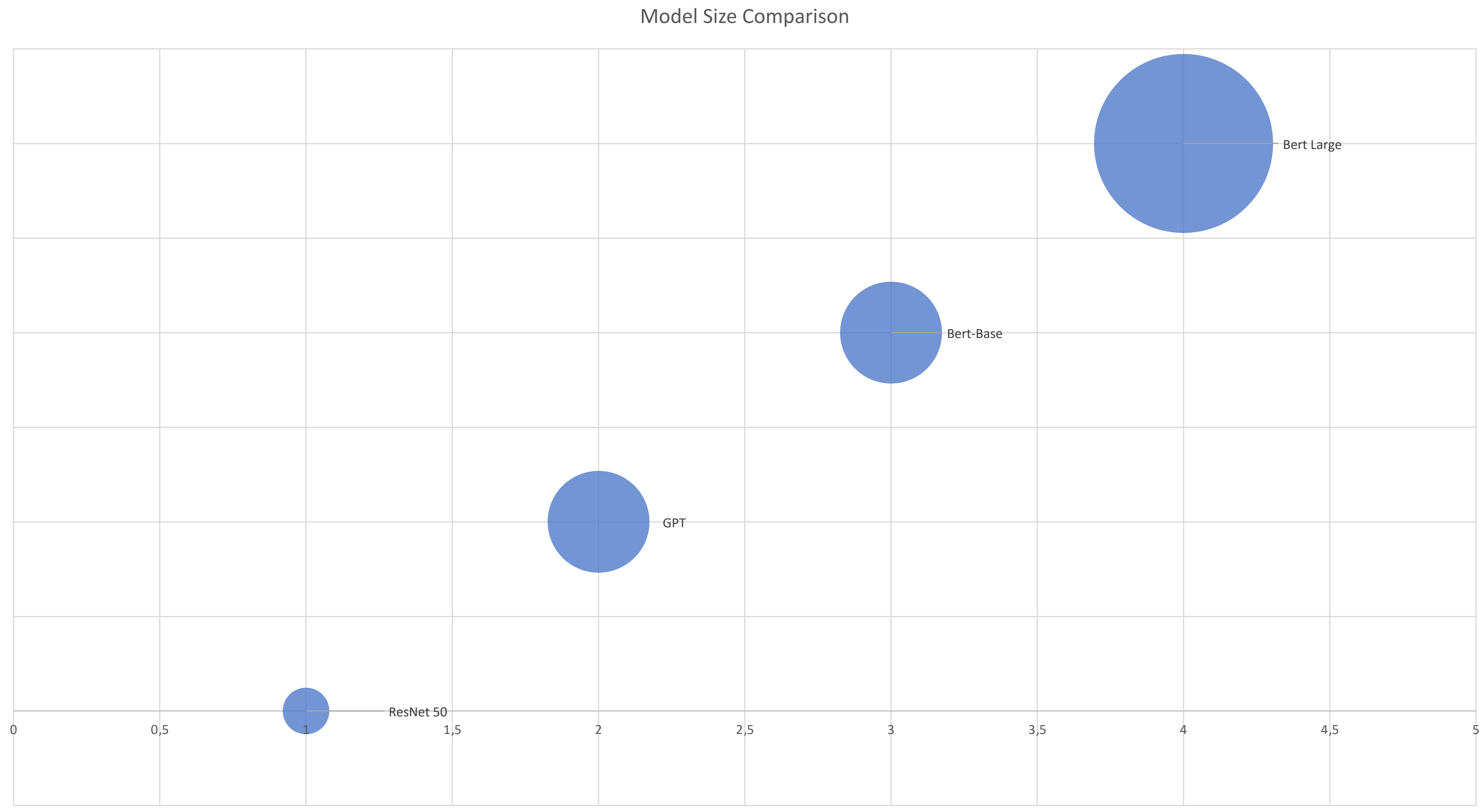


Figure 2.2: Total compute used during training. Based on the analysis in Scaling Laws For Neural Language Models [KMH+20] we train much larger models on many fewer tokens than is typical. As a consequence, although GPT-3 3B is almost 10x larger than RoBERTa-Large (355M params), both models took roughly 50 petaflop/s-days of compute during pre-training. Methodology for these calculations can be found in Appendix D.

PERSPECTIVE

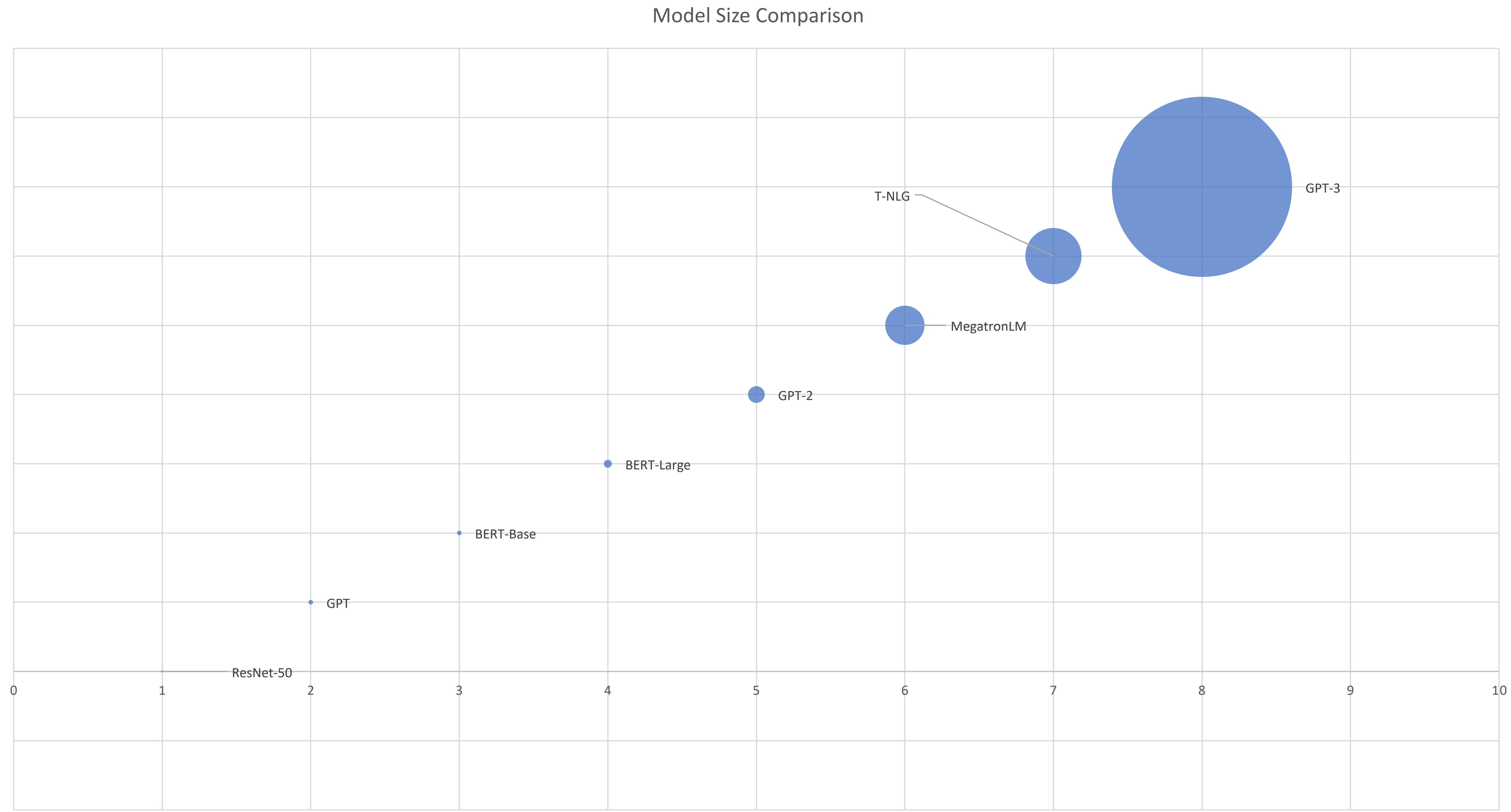
WHAT DO WE MEAN BY BIG?

Perspective



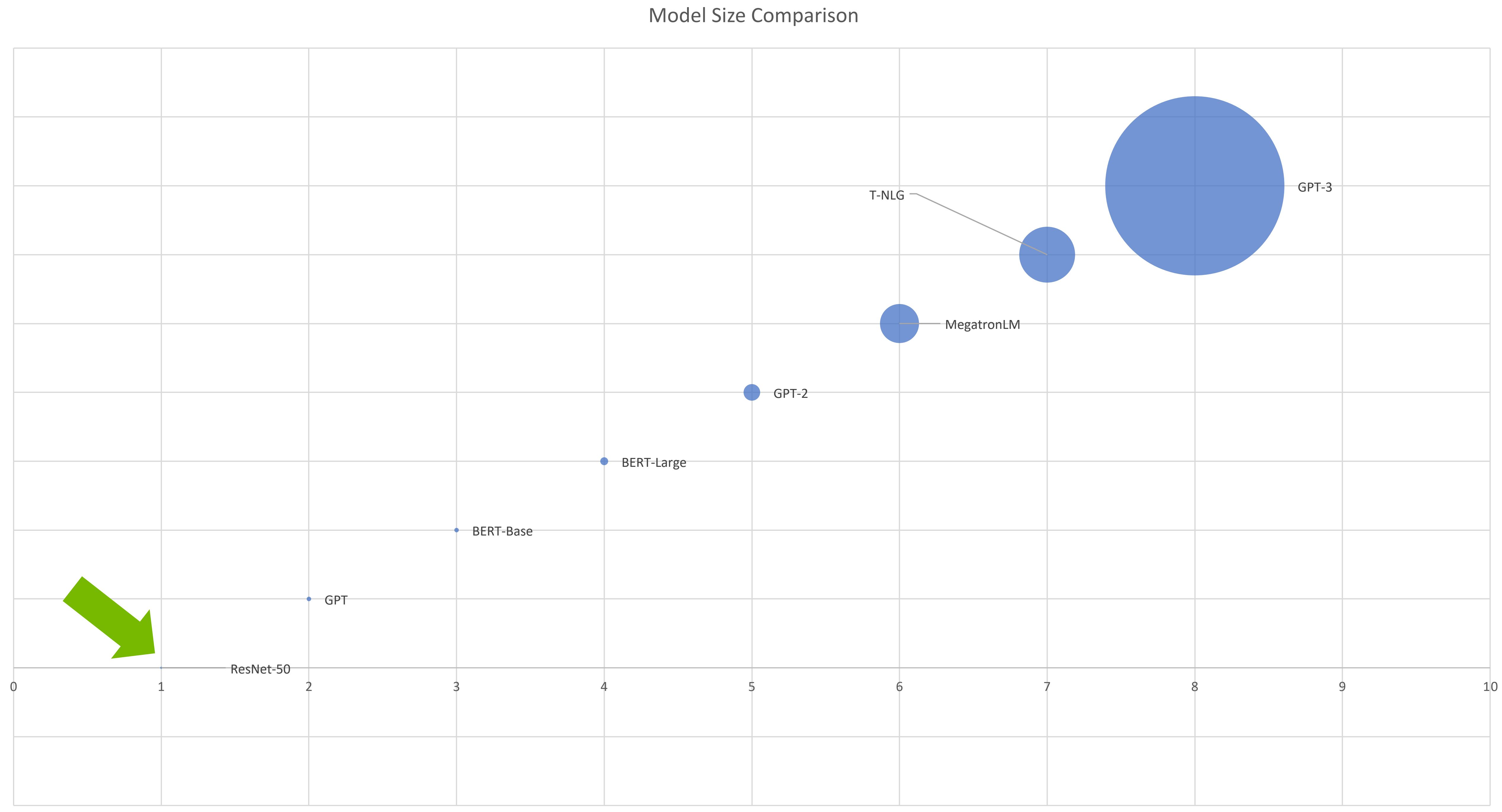
WHAT DO WE MEAN BY BIG?

Perspective



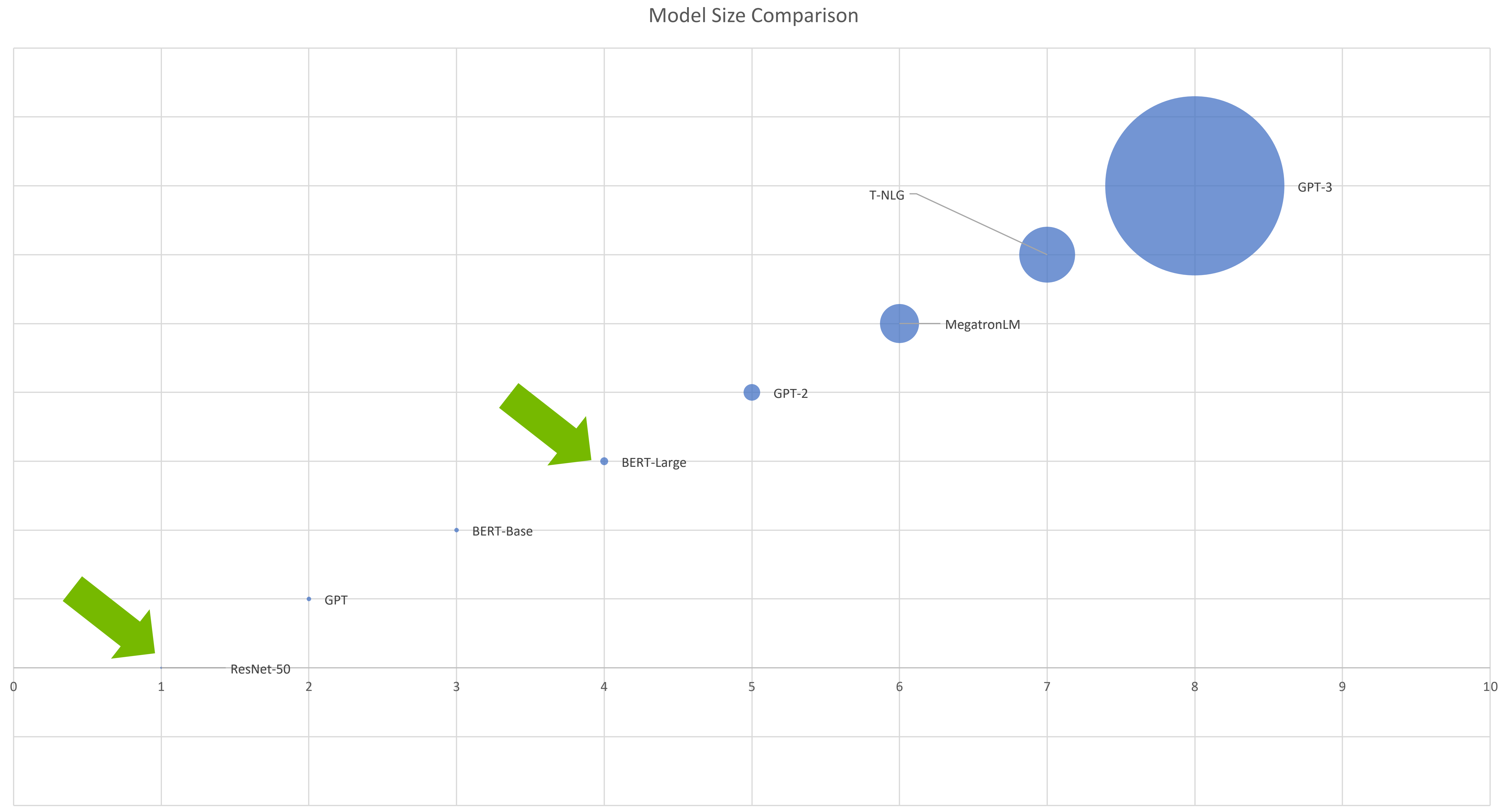
WHAT DO WE MEAN BY BIG?

Perspective



WHAT DO WE MEAN BY BIG?

Perspective

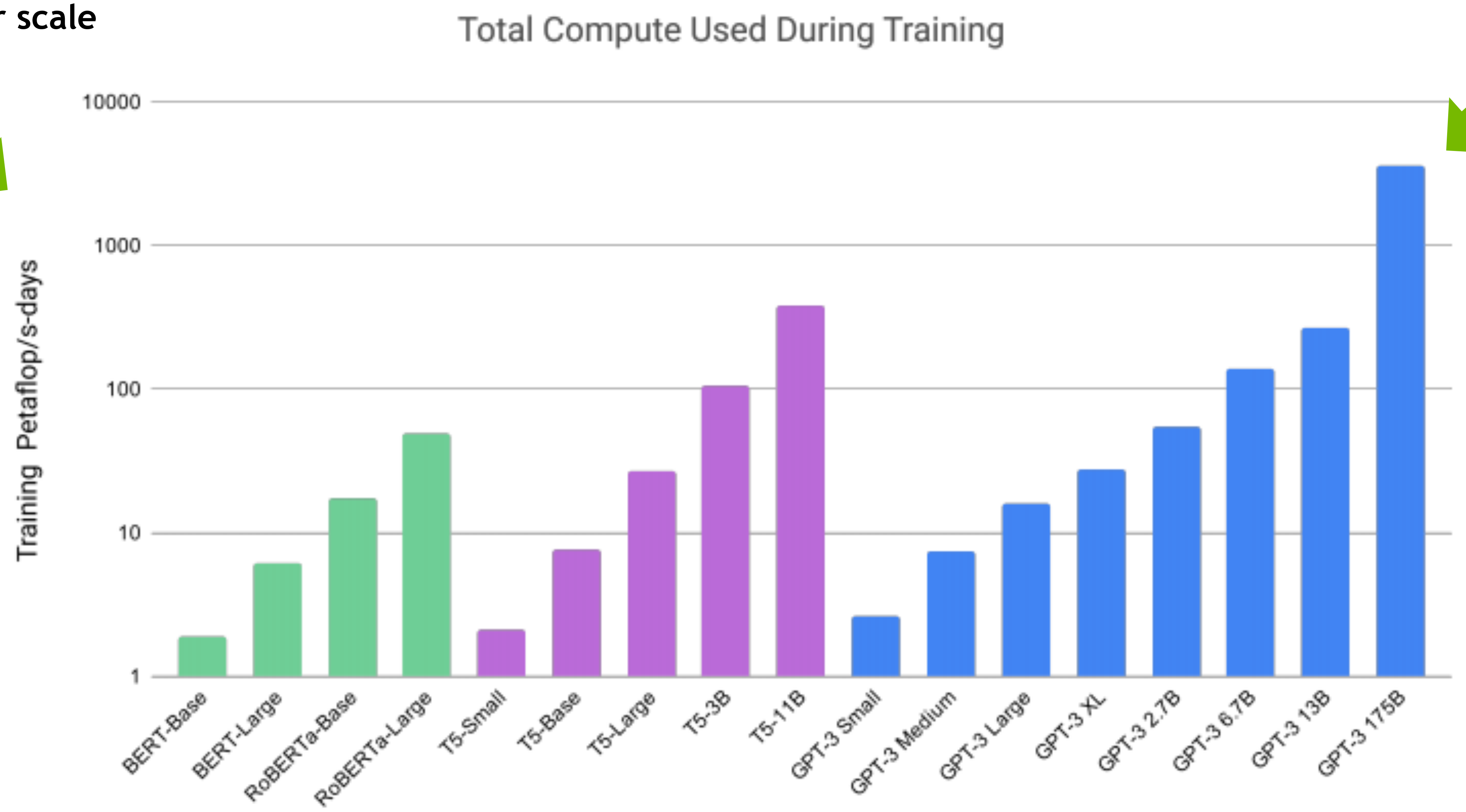


WHAT DO WE MEAN BY BIG?

GPT-3 size comparison: 538x Bigger than BERT-Large

Not a linear scale

355 years on a single V100



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THE LAB

Part 2: Self-Supervision, BERT and Beyond

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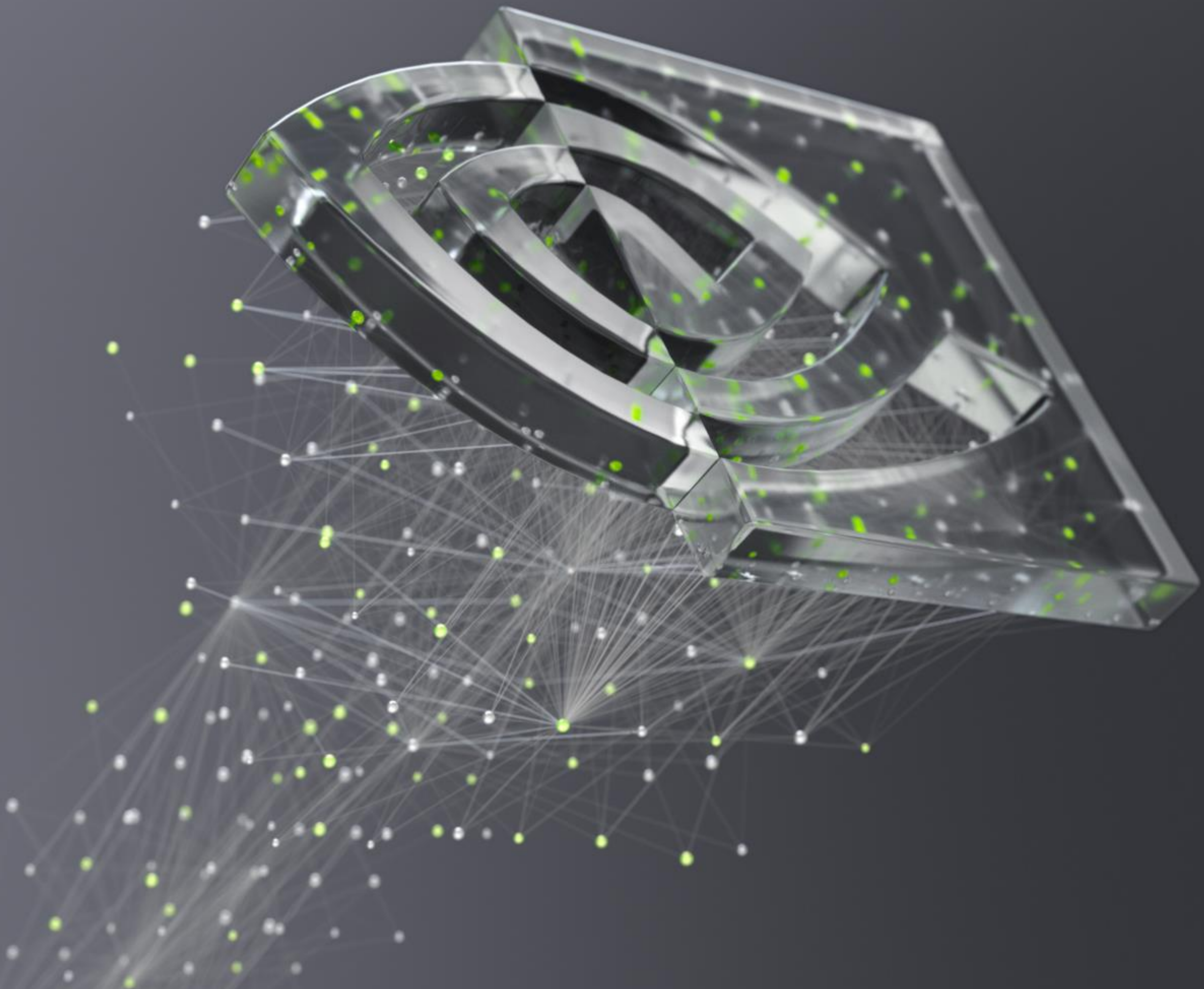
  - Text Classifier Project
- Lecture (cont'd)
  - Bigger is Better
  - Can and should we go even bigger?
- Lab (cont'd)
  - Named Entity Recognizer

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

NVIDIA | DEEP LEARNING INSTITUTE

PRODUCTION DEPLOYMENT

PD. Dr. Juan J. Durillo

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 3: Production Deployment

- Lecture
  - Model Selection
  - Post-Training Optimization
  - Product Quantization
  - Knowledge Distillation
  - Model Code Efficiency
  - Model Serving
  - Building the Application
- Lab
  - Exporting the Model
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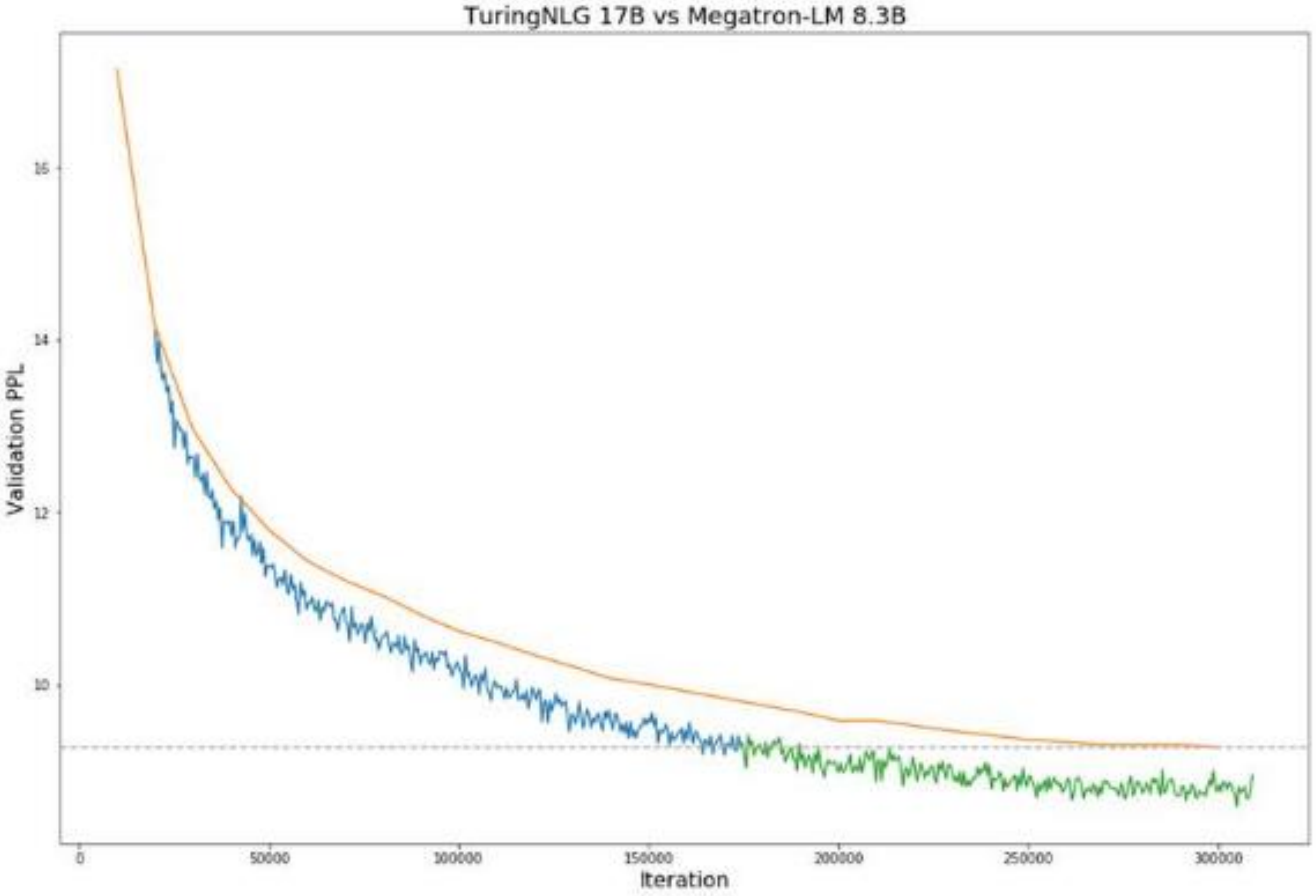
  - Server Performance
  - Using the Model

YOUR NETWORK IS TRAINED

YOUR NETWORK IS TRAINED

Now what?

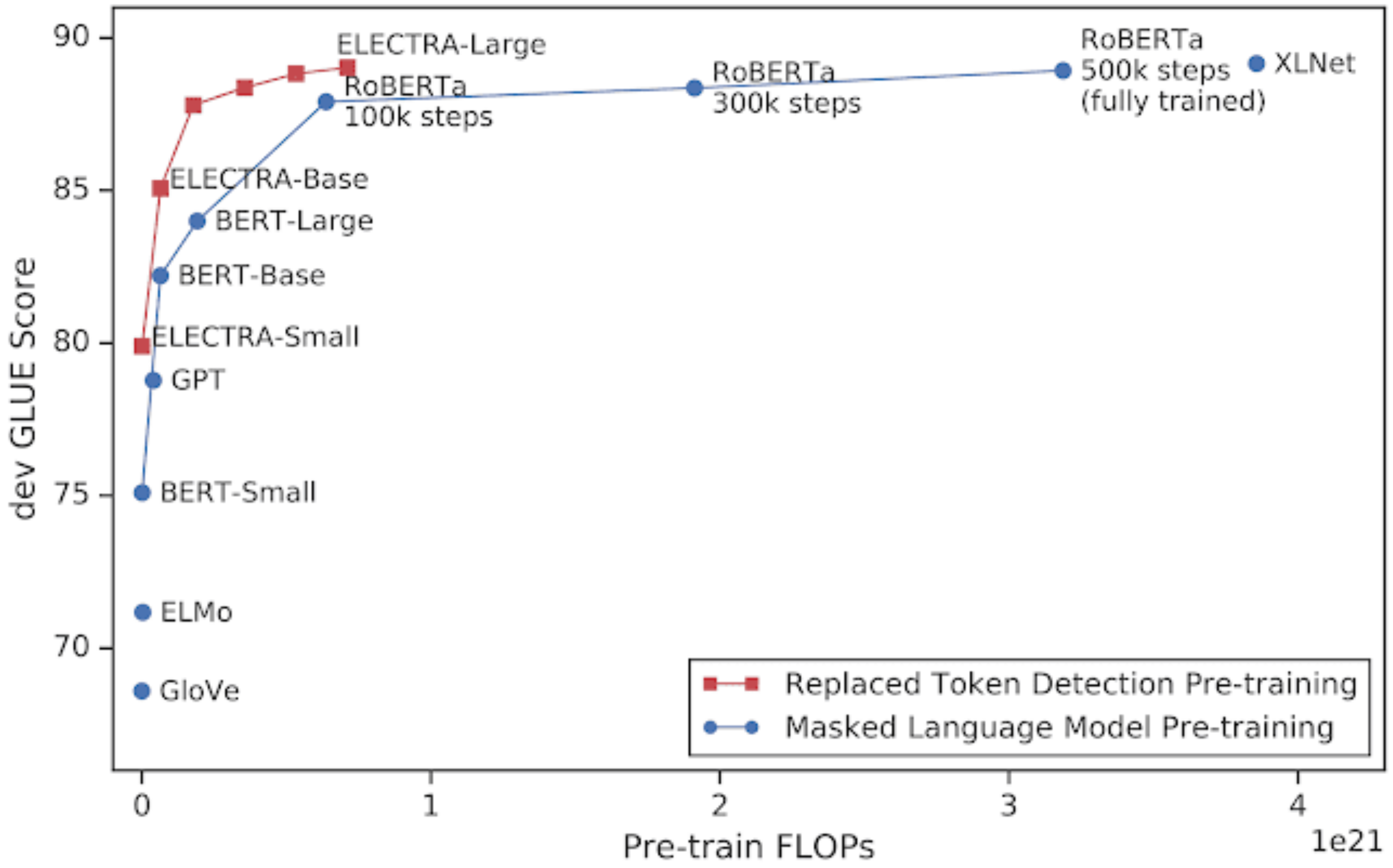


https://www.microsoft.com/en-us/research/blog/turing-nlg-a-17-billion-parameter-language-model-by-microsoft/

MEETING REQUIREMENTS OF YOUR BUSINESS

NLP MODELS ARE LARGE

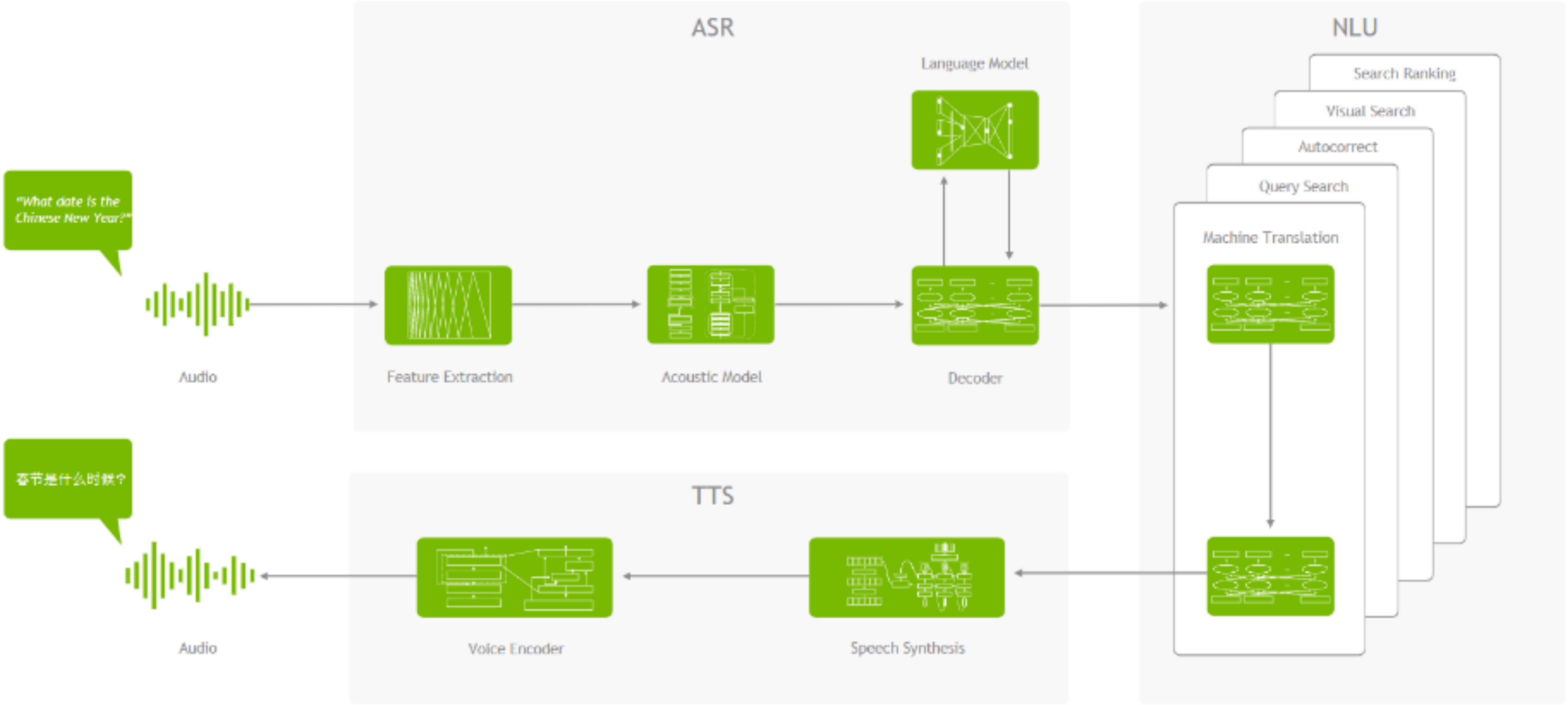
The Inference cost is high



https://www.microsoft.com/en-us/research/blog/turing-nlg-a-17-billion-parameter-language-model-by-microsoft/

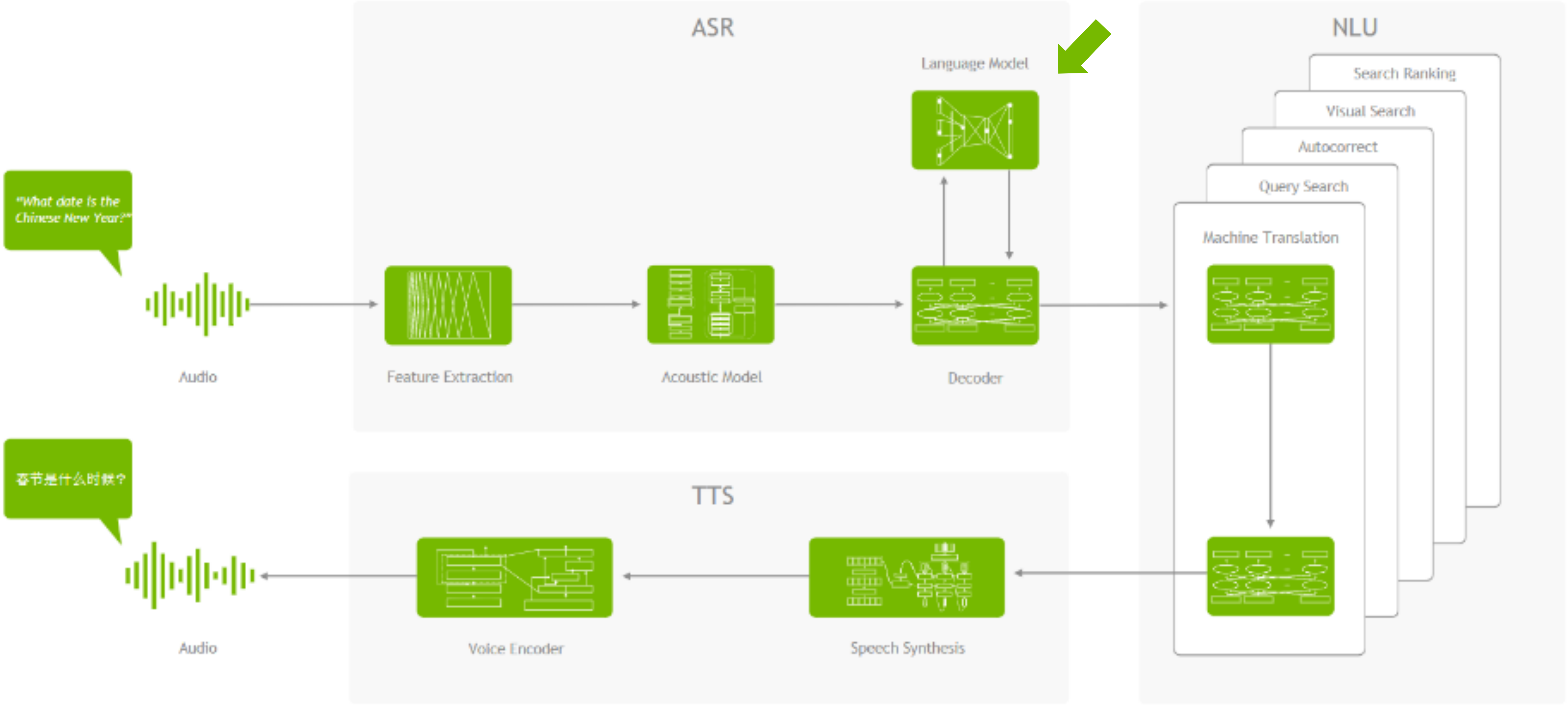
THEY DO NOT LIVE IN ISOLATION

Example of a conversational AI application



THEY DO NOT LIVE IN ISOLATION

Real Time Applications Need to Deliver Latency <300 ms



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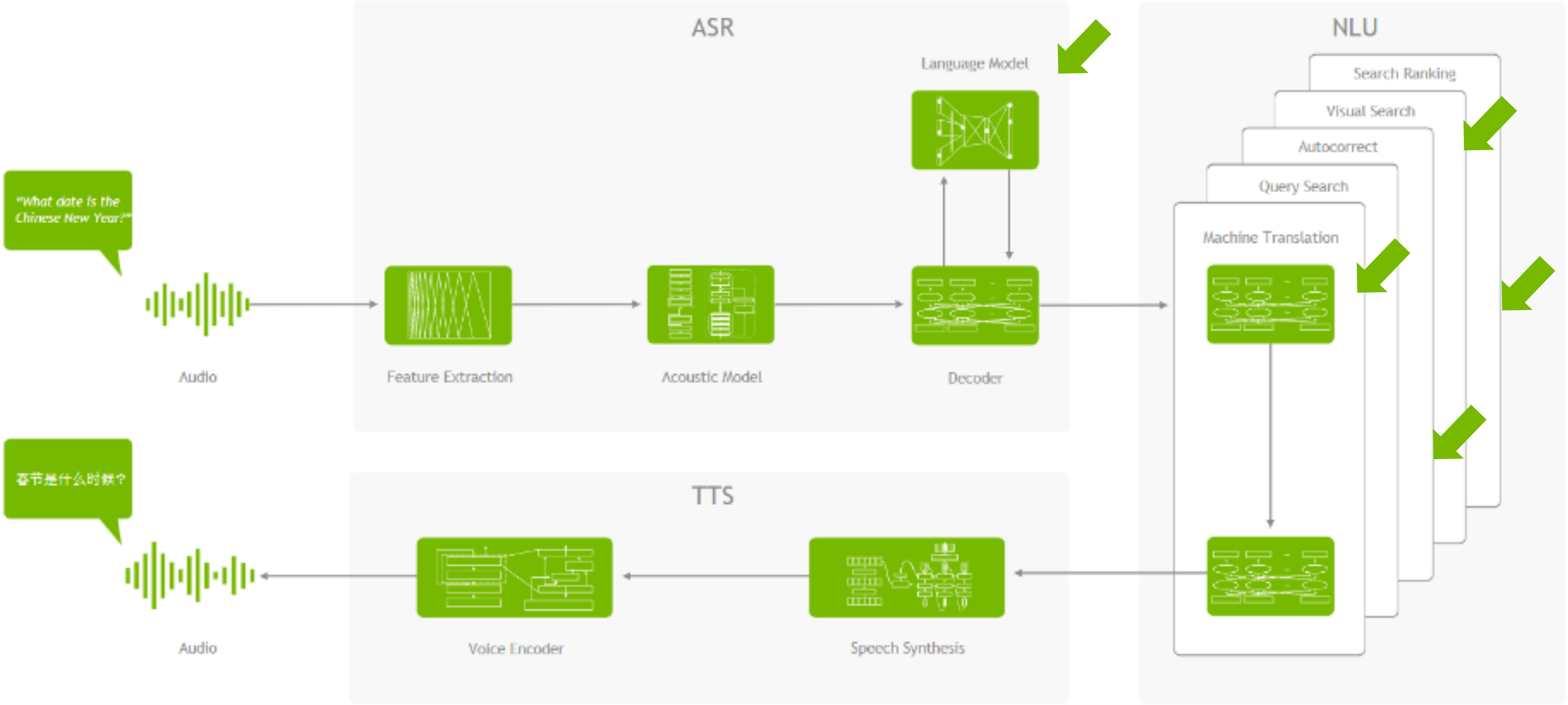


THEY DO NOT LIVE IN ISOLATION

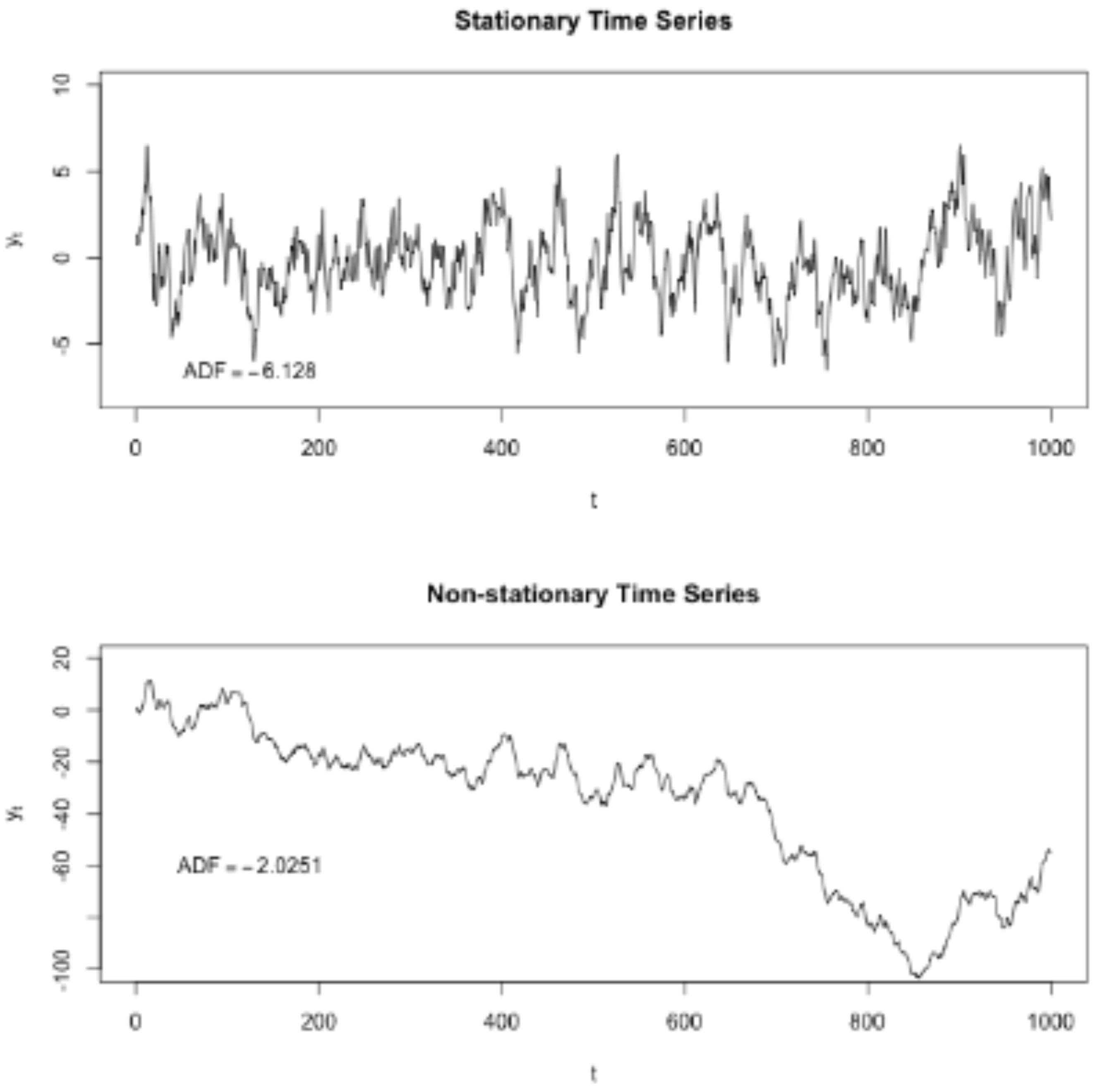
Application bandwidth = Cost

		Batch size	Inference on	Throughput (Query per second)	Latency (milliseconds)
CPU	Original 3-layer BERT	1	Azure Standard F16s_v2 (CPU)	6	157
	ONNX Model	1	Azure Standard F16s_v2 (CPU) **with ONNX Runtime**	111	9
GPU	Original 3-layer BERT	4	Azure NV6 GPU VM	200	20
	ONNX Model	4	Azure NV6 GPU VM **with ONNX Runtime**	500	8
	ONNX Model	64	Azure NC6S_v3 GPU VM **with ONNX Runtime + System Optimization** (Tensor Core with mixed precision, Same Accuracy)	10667	6

https://cloudblogs.microsoft.com/opensource/2020/01/21/microsoft-onnx-open-source-optimizations-transformer-inference-gpu-cpu/

AND THEY NEED TO EVOLVE OVER TIME

A lot of processes are not stationary



https://en.wikipedia.org/wiki/Stationary_process

THERE'S MORE TO AN APPLICATION THAN JUST THE MODEL

Nonfunctional requirements

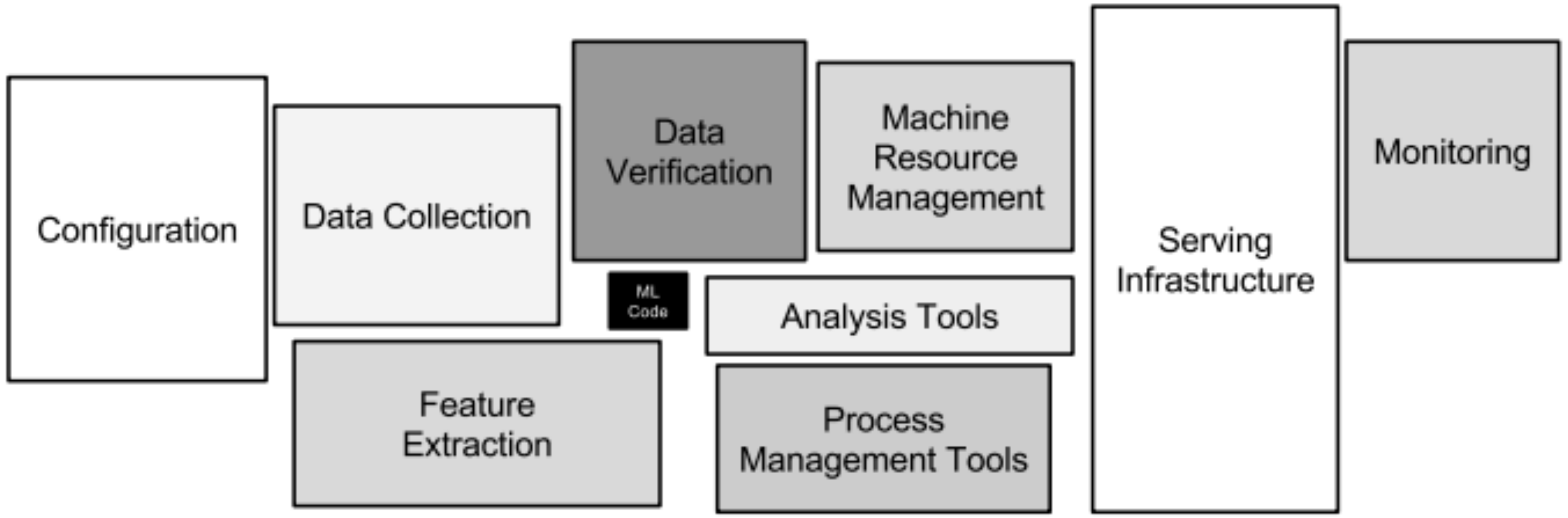


Figure 1: Only a small fraction of real-world ML systems is composed of the ML code, as shown by the small black box in the middle. The required surrounding infrastructure is vast and complex.

Sculley, D., Holt, G., Golovin, D., Davydov, E., Phillips, T., Ebner, D., ... & Dennison, D. (2015). Hidden technical debt in machine learning systems. In Advances in neural information processing systems (pp. 2503-2511).

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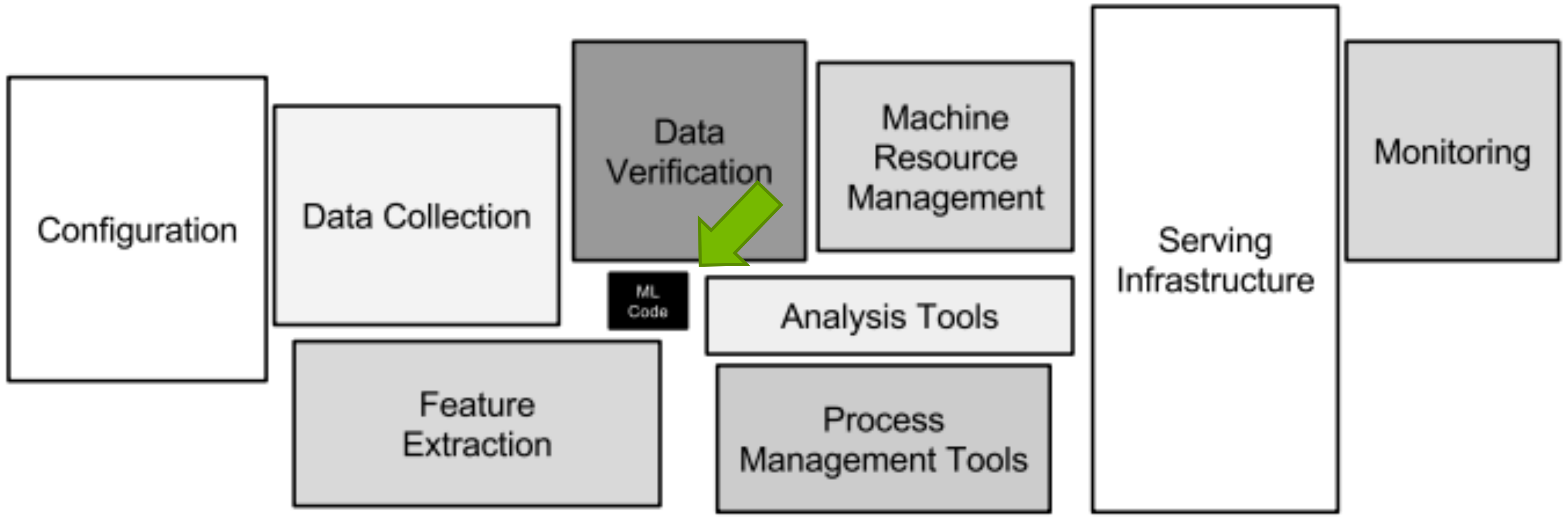

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Part 3: Production Deployment

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MODEL SELECTION

Not all models are created equally

NLP

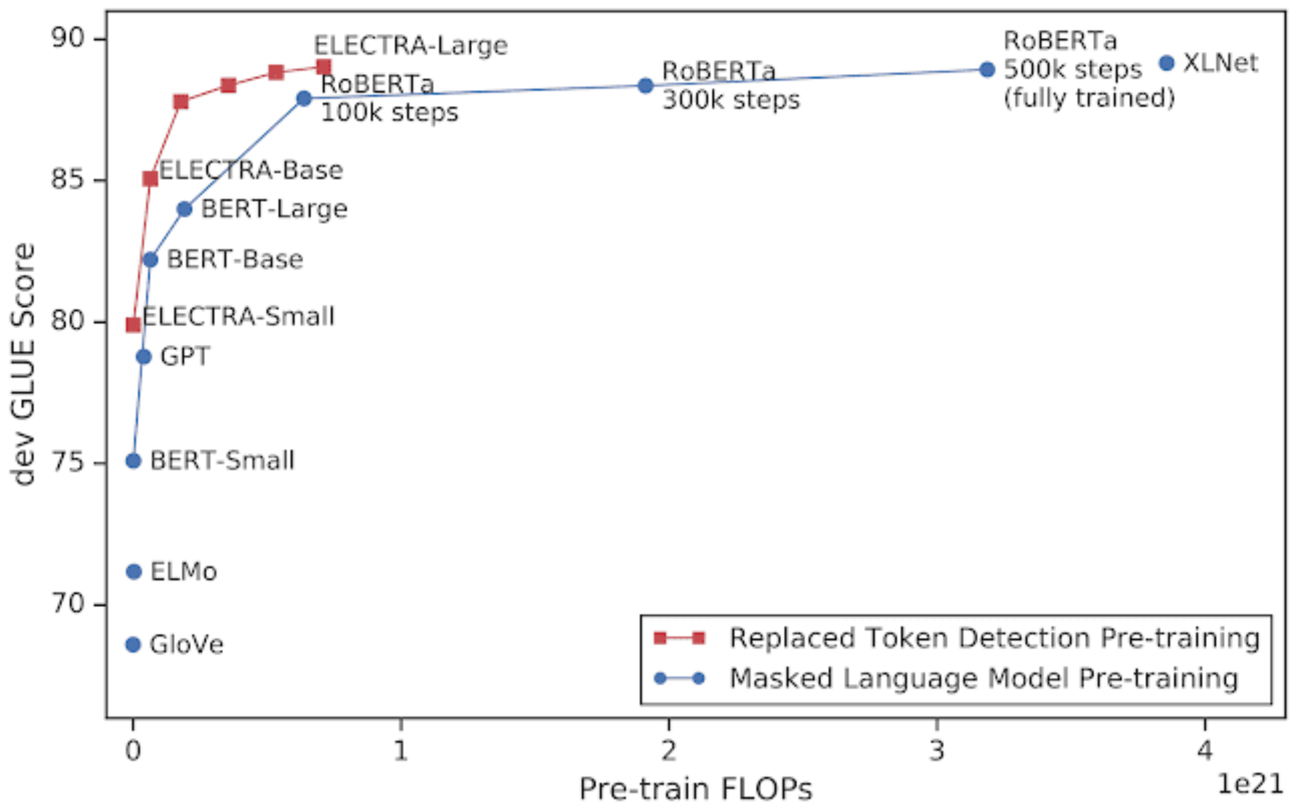
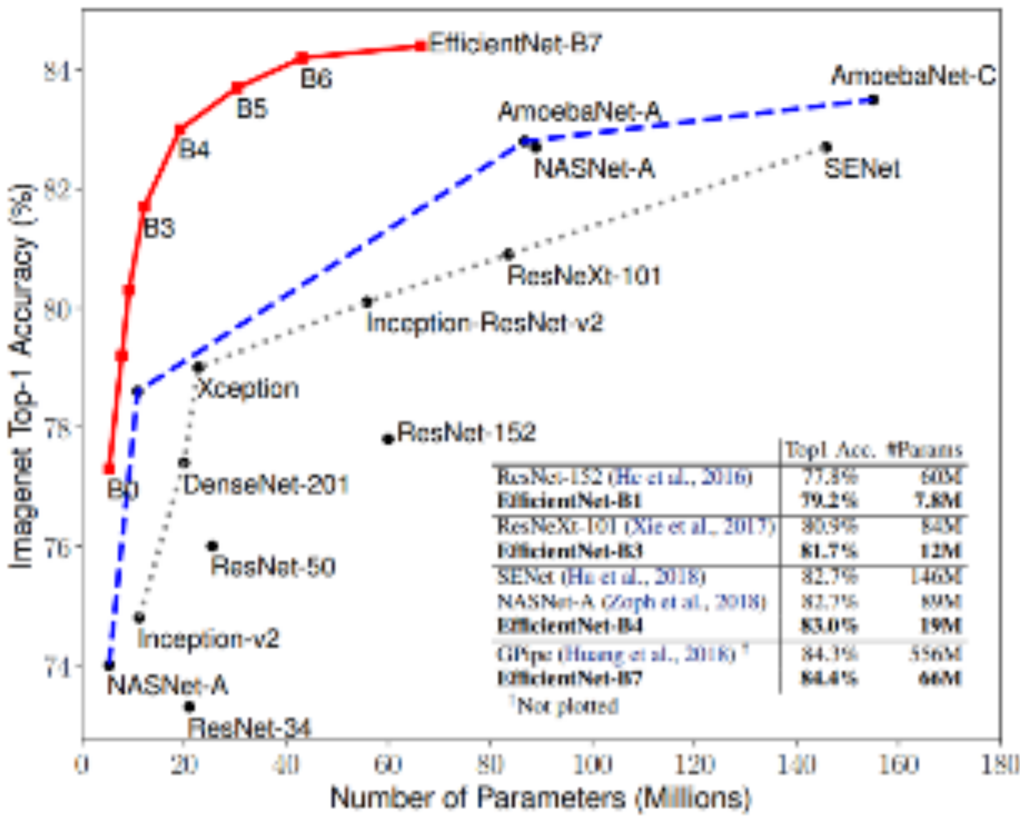
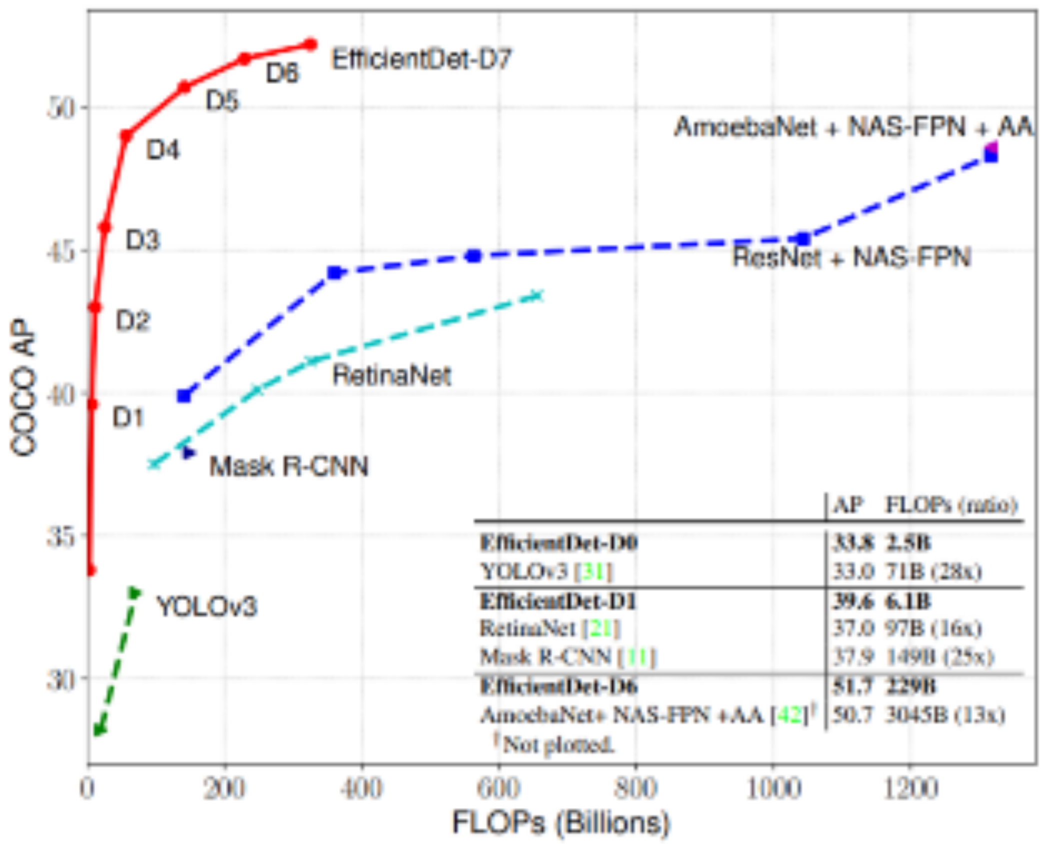


Image Classification



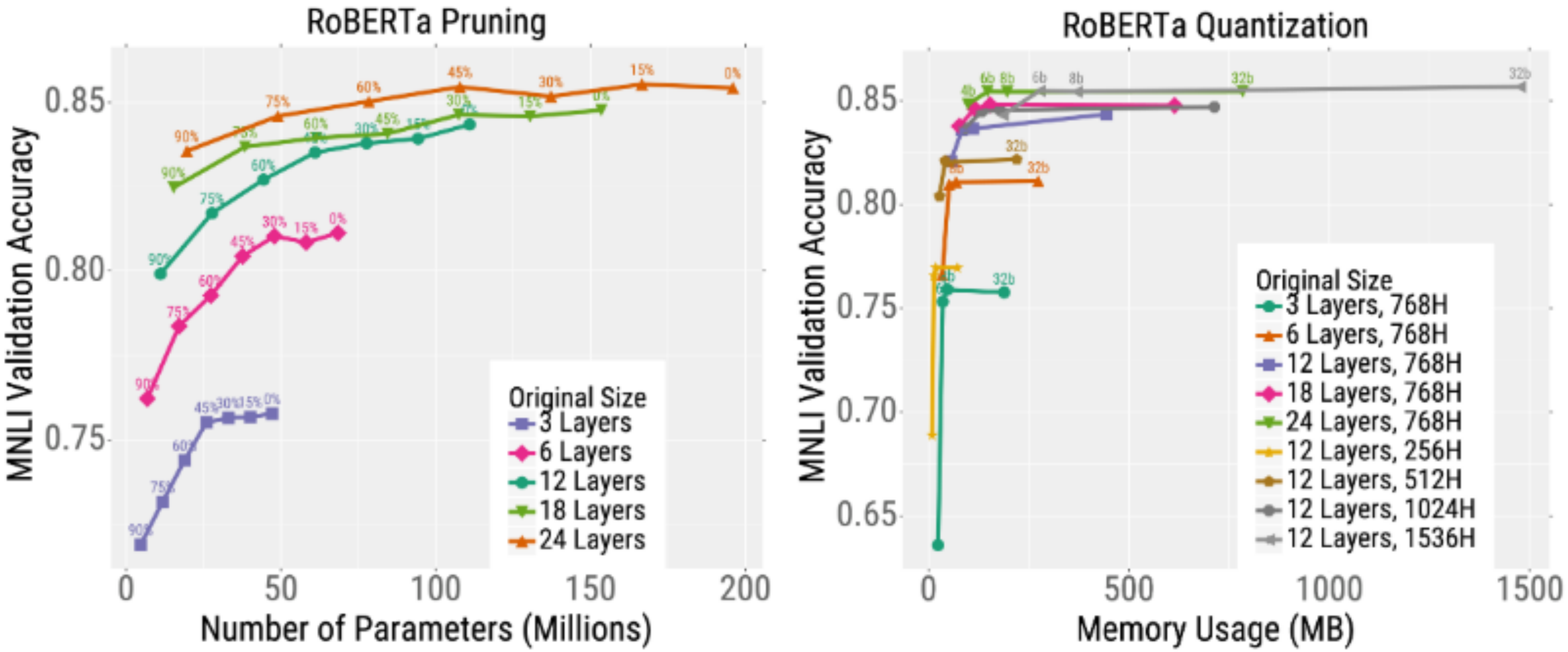
Object detection



MODEL SELECTION

Not all models respond in the same way to knowledge distillation, pruning and quantization

Common Practice	Train Small Model →	Stop Training When Converged →	Lightly Compress
Optimal	Train Large Model →	Stop Training Early →	Heavily Compress



https://bair.berkeley.edu/blog/2020/03/05/compress/

Li, Z., Wallace, E., Shen, S., Lin, K., Keutzer, K., Klein, D., & Gonzalez, J. E. (2020). Train large, then compress: Rethinking model size for efficient training and inference of transformers. arXiv preprint arXiv:2002.11794.

MODEL SELECTION

And very large models are and will continue to be prevalent in NLP

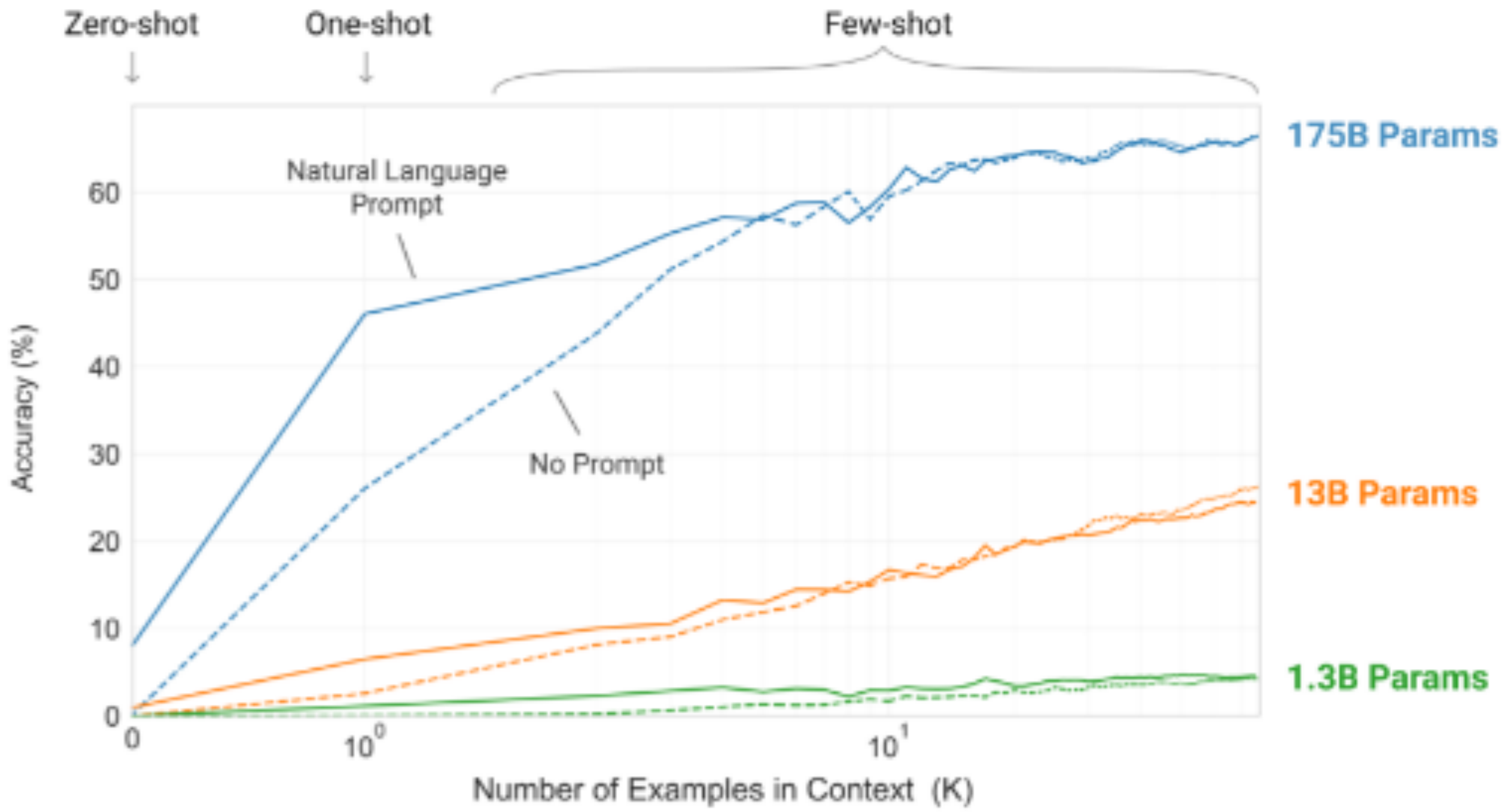


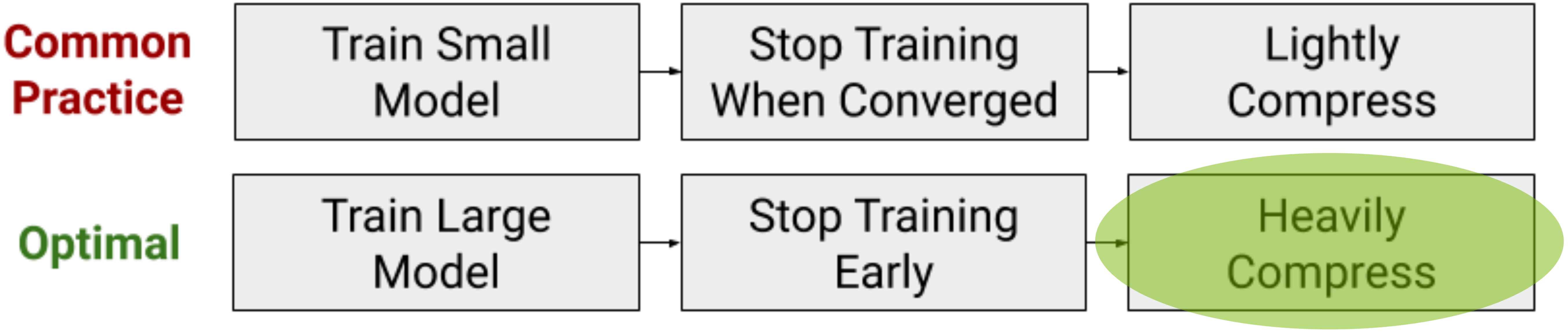
Figure 1.2: Larger models make increasingly efficient use of in-context information. We show in-context learning performance on a simple task requiring the model to remove random symbols from a word, both with and without a natural language task description (see Sec. 3.9.2). The steeper "in-context learning 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.

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.

DIRECT IMPLICATIONS

INCREASING IMPORTANCE OF PRUNING AND QUANTIZATION

E.g. Train Large then compress



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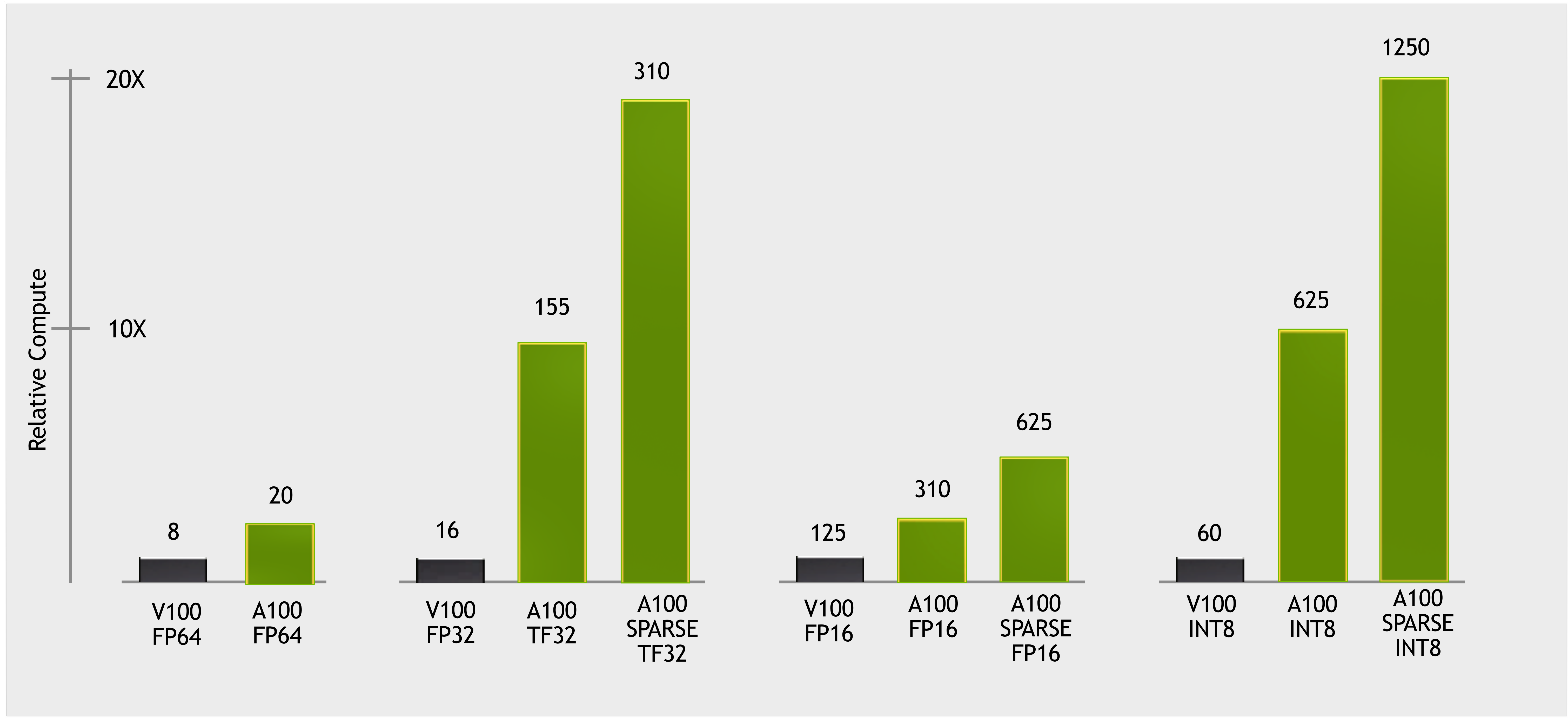
INCREASING IMPORTANCE OF PRUNING AND QUANTIZATION

Hardware acceleration for reduced precision arithmetic and sparsity



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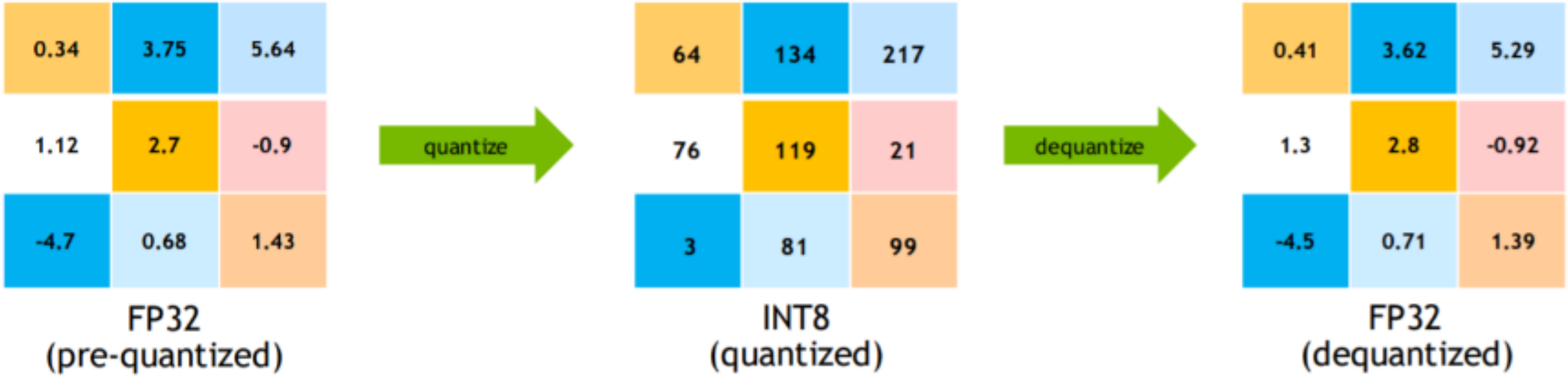
QUANTIZATION

The idea



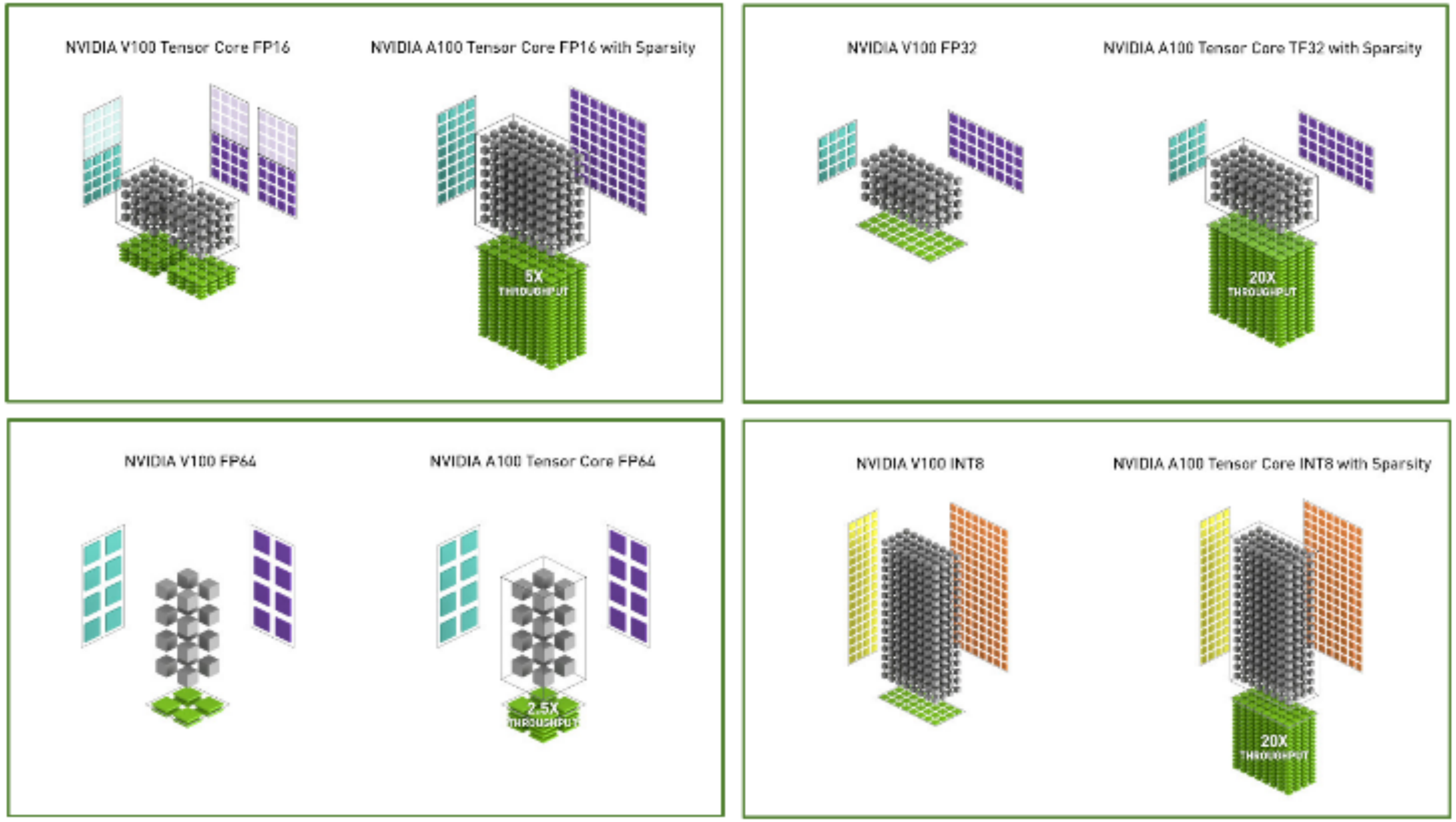
QUANTIZATION

The rationale

Input Datatype	Accumulation Datatype	Math Throughput	Bandwidth Reduction
FP32	FP32	1x	1x
FP16	FP16	8x	2x
INT8	INT32	16x	4x
INT4	INT32	32x	8x
INT1	INT32	128x	32x

QUANTIZATION

The rationale



QUANTIZATION

The results (speedup and throughput)

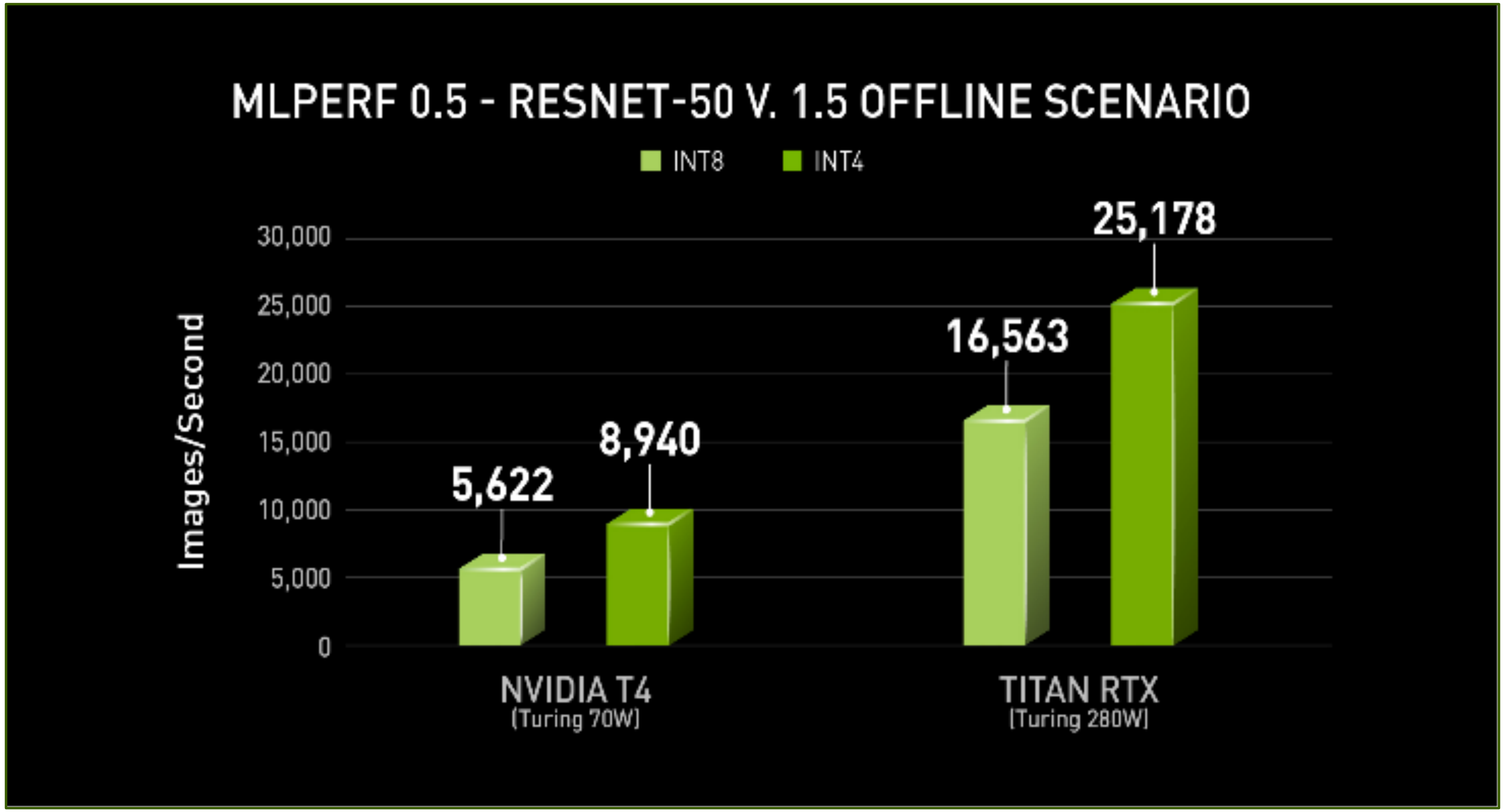
	Batch size 1			Batch size 8			Batch size 128		
	FP32	FP16	Int8	FP32	FP16	Int8	FP32	FP16	Int8
MobileNet v1	1	1.91	2.49	1	3.03	5.50	1	3.03	6.21
MobileNet v2	1	1.50	1.90	1	2.34	3.98	1	2.33	4.58
ResNet50 (v1.5)	1	2.07	3.52	1	4.09	7.25	1	4.27	7.95
VGG-16	1	2.63	2.71	1	4.14	6.44	1	3.88	8.00
VGG-19	1	2.88	3.09	1	4.25	6.95	1	4.01	8.30
Inception v3	1	2.38	3.95	1	3.76	6.36	1	3.91	6.65
Inception v4	1	2.99	4.42	1	4.44	7.05	1	4.59	7.20
ResNext101	1	2.49	3.55	1	3.58	6.26	1	3.85	7.39

Image/s	Batch size 1			Batch size 8			Batch size 128		
	FP32	FP16	Int8	FP32	FP16	Int8	FP32	FP16	Int8
MobileNet v1	1509	2889	3762	2455	7430	13493	2718	8247	16885
MobileNet v2	1082	1618	2060	2267	5307	9016	2761	6431	12652
ResNet50 (v1.5)	298	617	1051	500	2045	3625	580	2475	4609
VGG-16	153	403	415	197	816	1269	236	915	1889
VGG-19	124	358	384	158	673	1101	187	749	1552
Inception v3	156	371	616	350	1318	2228	385	1507	2560
Inception v4	76	226	335	173	768	1219	186	853	1339
ResNext101	84	208	297	200	716	1253	233	899	1724

TensorRT optimized models executed on Tesla T4, input size 224x224 for all apart from the Inception networks for which the input size was 299x299

QUANTIZATION

Beyond INT8



INT4 quantization for resnet50

"Int4 Precision for AI Inference"

IMPACT ON ACCURACY

In a wide range of cases minimal

Model	FP32	Int8 (max)	Int8 (entropy)	Rel Err (entropy)
MobileNet v1	71.01	69.43	69.46	2.18%
MobileNet v2	74.08	73.96	73.85	0.31%
NASNet (large)	82.72	82.09	82.66	0.07%
NASNet (mobile)	73.97	12.95	73.4	0.77%
ResNet50 (v1.5)	76.51	76.11	76.28	0.30%
ResNet50 (v2)	76.37	75.73	76.22	0.20%
ResNet152 (v1.5)	78.22	5.29	77.95	0.35%
ResNet152 (v2)	78.45	78.05	78.15	0.38%
VGG-16	70.89	70.75	70.82	0.10%
VGG-19	71.01	70.91	70.85	0.23%
Inception v3	77.99	77.7	77.85	0.18%
Inception v4	80.19	1.68	80.16	0.04%

COCO

Model	Backbone	FP32	INT8	Rel Err
SSD-300	MobileNet v1	26	25.8	0.77%
SSD-300	MobileNet v2	27.4	26.8	2.19%
Faster RCNN	ResNet-101	33.7	33.4	0.89%

All results COCO mAP on COCO 2017 validation, higher is better

Pascal VOC

Model	Backbone	FP32	INT8	Rel Err
SSD-300	VGG-16	77.7	77.6	0.13%
SSD-512	VGG-16	79.9	79.9	0.0%

All results VOC mAP on VOC 07 test, higher is better

IMPACT OF MODEL DESIGN

Not all neural network mechanisms quantize well

Bert large uncased	FP32	Int8	Rel Err %
MRPC	0.855	0.823	3.74%
SQuAD 1.1 (F1)	91.01	85.16	6.43%

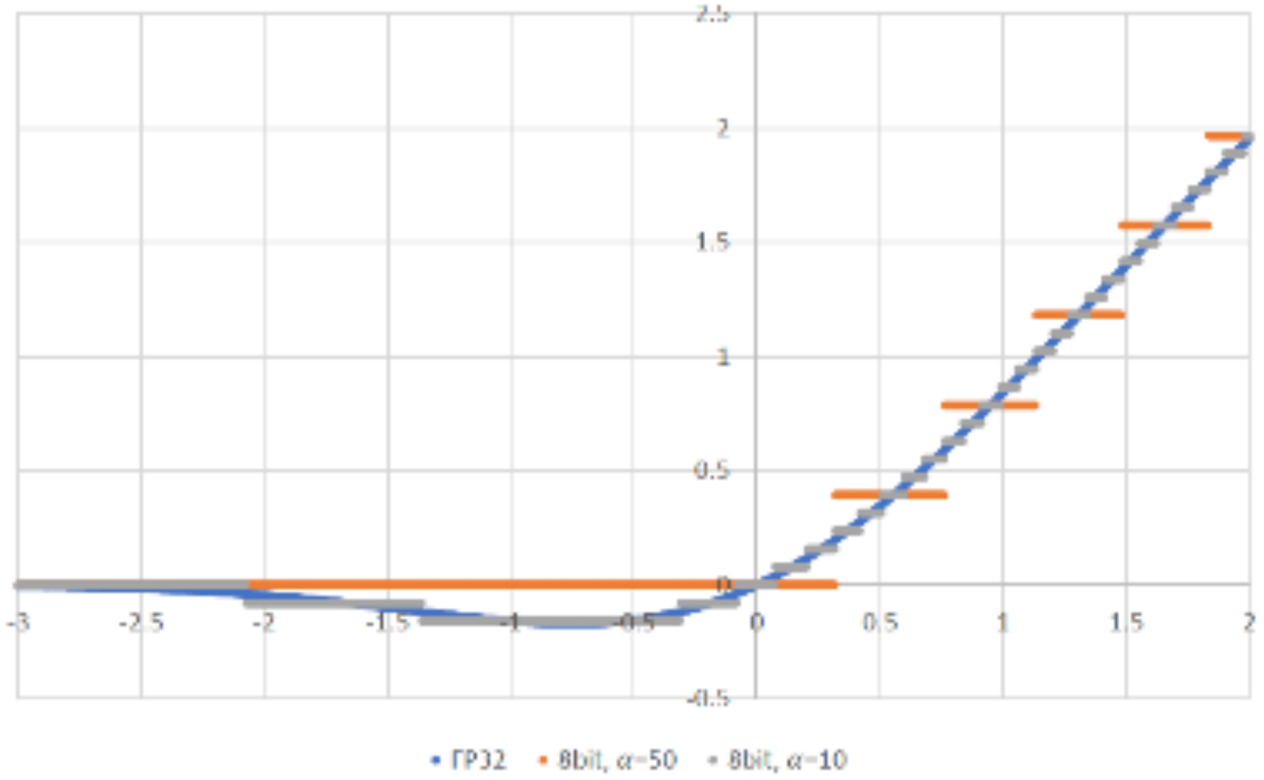
IMPACT OF MODEL DESIGN

Model alterations required

Bert large uncased	FP32	Int8	Rel Err %
MRPC	0.855	0.823	3.74%
SQuAD 1.1 (F1)	91.01	85.16	6.43%

Bert large uncased	FP32	Int8 (GeLU10)	Rel Err %
MRPC	0.855	0.843	0.70%
SQuAD 1.1 (F1)	91.01	90.40	0.67%

GeLU



$$f(x) = \frac{x}{2}(1 + erf(\frac{x}{\sqrt{2}}))$$

- GeLU produces highly asymmetric range
- Negative values between [-0.17,0]
- All negative values clipped to 0
- GeLU10 allows to maintain negative values

LOSS OF ACCURACY

Reasons

Outlier in the tensor:

- Example: BERT, Inception V4
- Solution: Clip. Tighten the range, use bits more efficiently

Not enough precision in quantized representation

- Example: Int8 for MobileNet V1
- Example: Int4 for Resnet50
- Solution: Train/fine tune for quantization

LEARN MORE

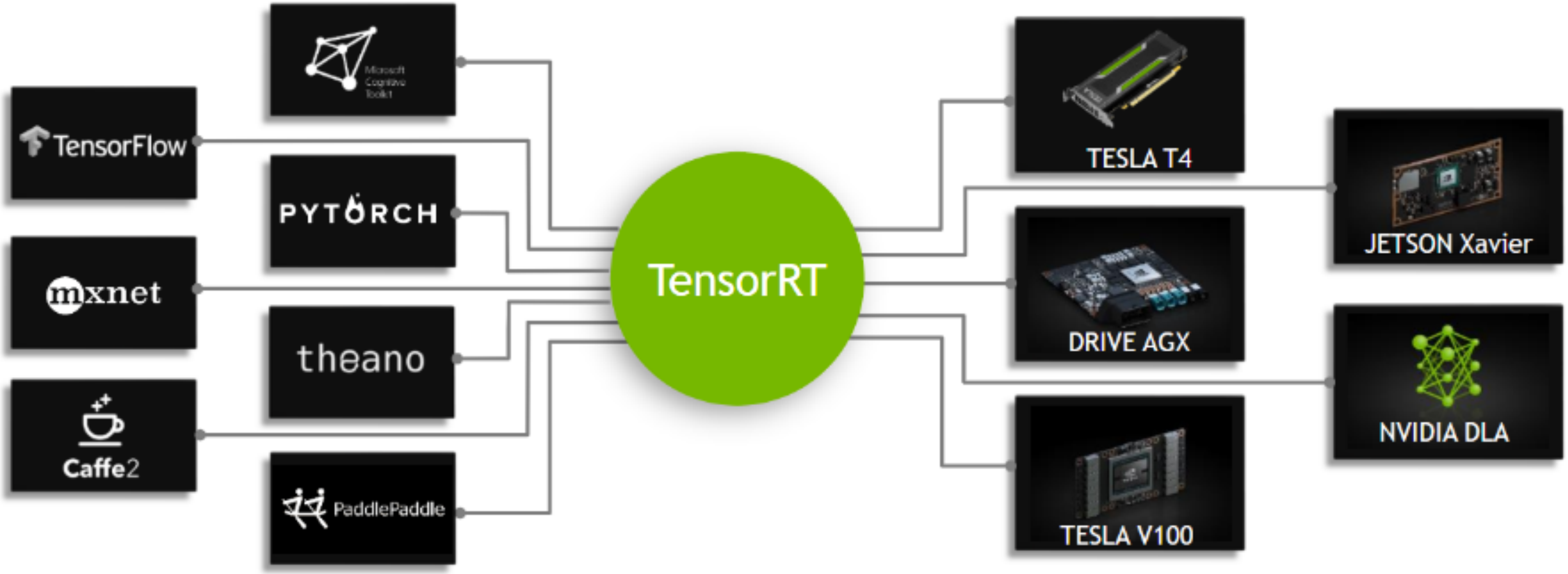
GTC Talks

- S9659: Inference at Reduced Precision on GPUs
- S21664: Toward INT8 Inference: Deploying Quantization-Aware Trained Networks using TensorRT

QUANTIZATION TOOLS

NVIDIA TENSORRT

From Every Framework, Optimized For Each Target Platform



INT8 QUANTIZATION EXAMPLE

TF-TRT

Step 1 Obtain the TF frozen graph (trained in FP32)

…

Step 2 Create the calibration graph -> Execute it with calibration data -> Convert it to the INT8 optimized graph

```
# create a TRT inference graph, the output is a frozen graph ready for calibration
calib_graph = trt.create_inference_graph(input_graph_def=frozen_graph, outputs=outputs,
              max_batch_size=1, max_workspace_size_bytes=1<<30,
              precision_mode="INT8", minimum_segment_size=5)

# Run calibration (inference) in FP32 on calibration data (no conversion)
f_score, f_geo = tf.import_graph_def(calib_graph, input_map={"input_images":inputs},
              return_elements=outputs, name="")
Loop img: score, geometry = sess.run([f_score, f_geo], feed_dict={inputs: [img]})

# apply TRT optimizations to the calibration graph, replace each TF subgraph with a TRT node
optimized for INT8
trt_graph = trt.calib_graph_to_infer_graph(calib_graph)
```

Step 3 Import the TRT graph and run

…

https://docs.nvidia.com/deeplearning/dgx/tf-trt-user-guide/index.html

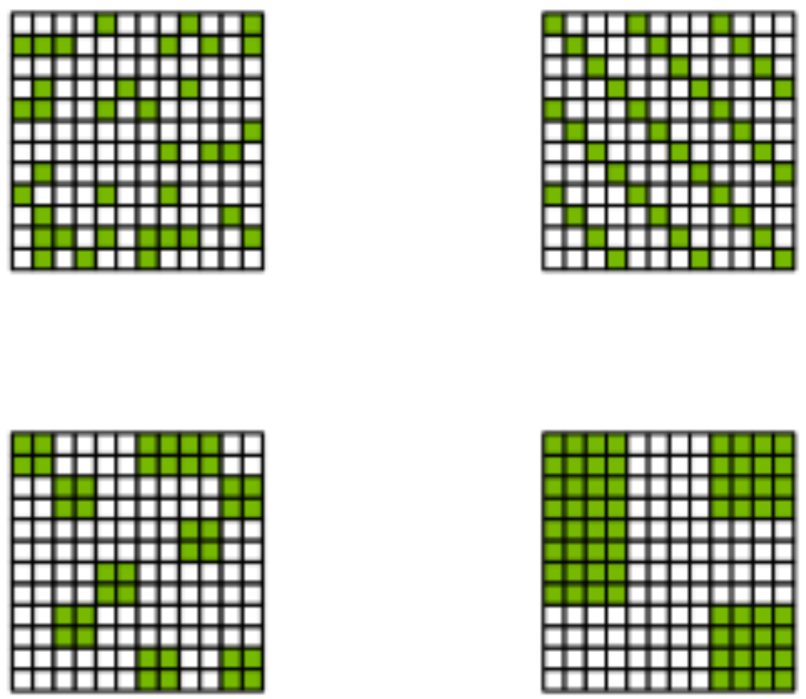
PRUNING

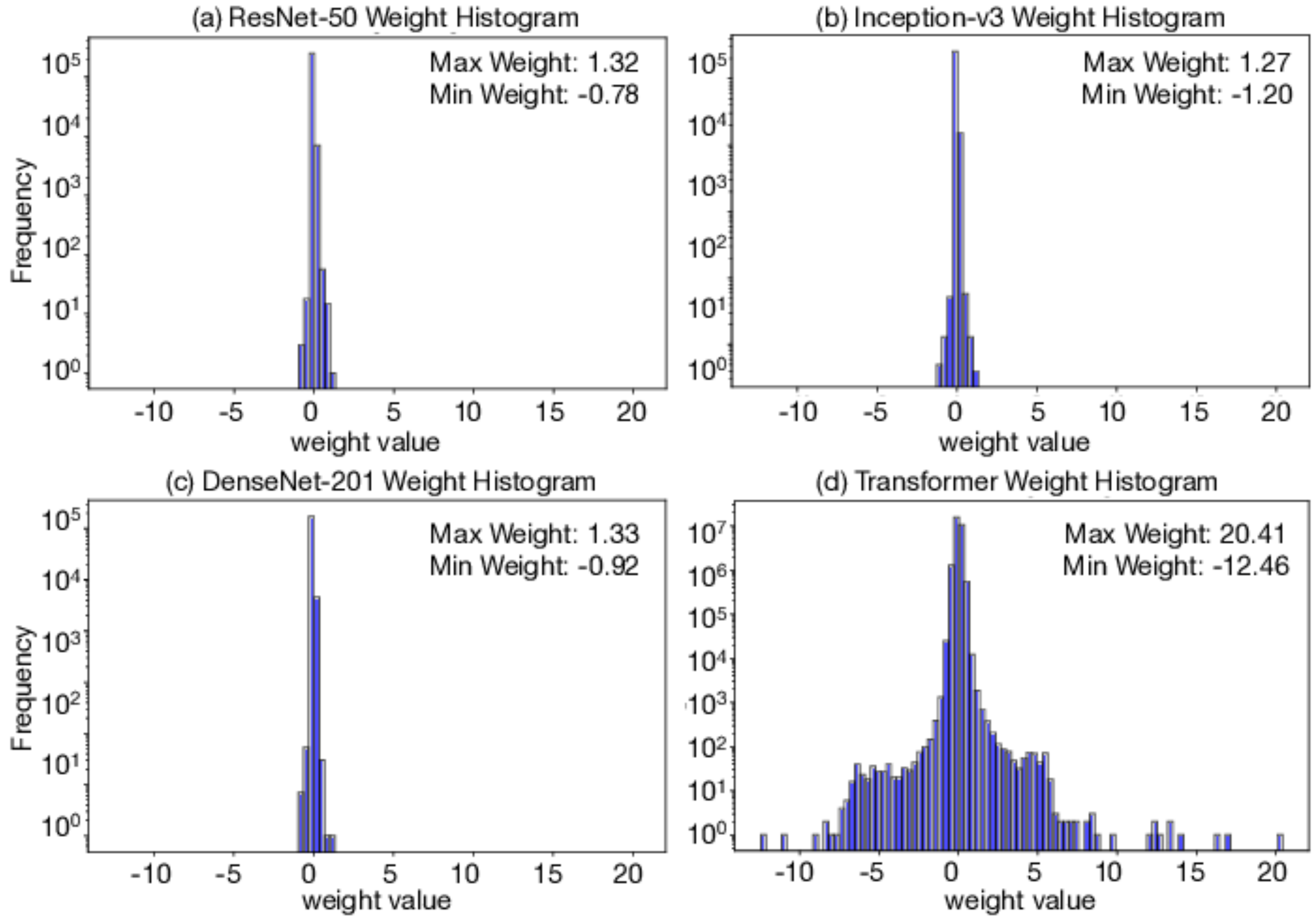
PRUNING

The idea

The opportunity:

- Reduced memory bandwidth
- Reduced memory footprint
- Acceleration (especially in presence of hardware acceleration)





Tambe, T., Yang, E. Y., Wan, Z., Deng, Y., Reddi, V. J., Rush, A., ... & Wei, G. Y. (2019). AdaptivFloat: A Floating-point based Data Type for Resilient Deep Learning Inference. *arXiv preprint arXiv:1909.13271*.

DIFFICULT TO GET TO WORK RELIABLY

STRUCTURED SPARSITY

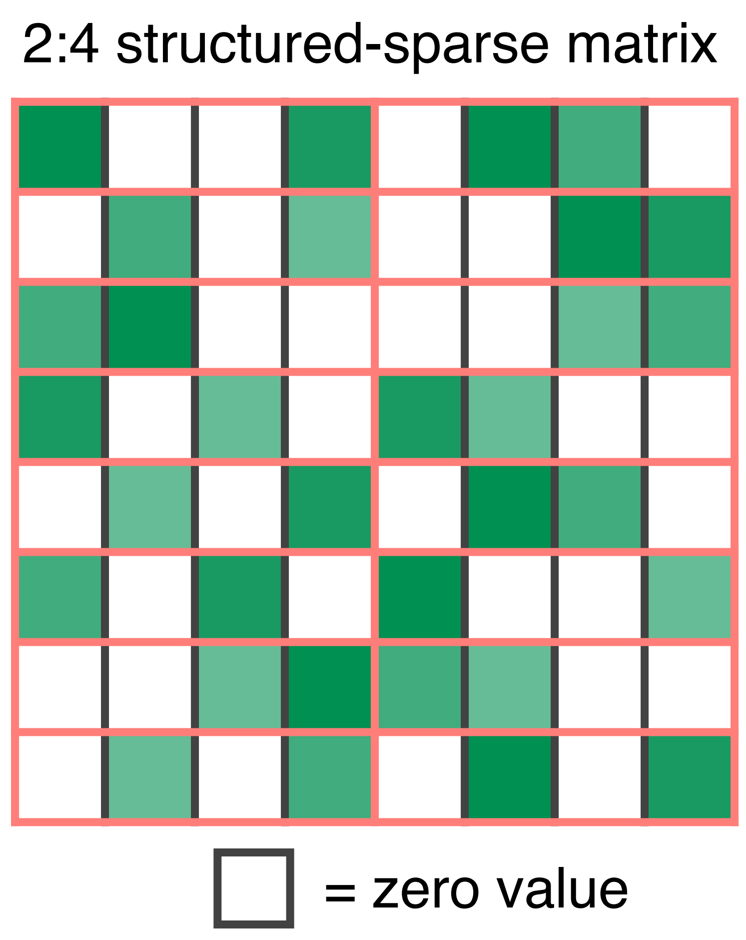
SPARSITY IN A100 GPU

Fine-grained structured sparsity for Tensor Cores

- 50% fine-grained sparsity
- 2:4 pattern: 2 values out of each contiguous block of 4 must be 0

Addresses the 3 challenges:

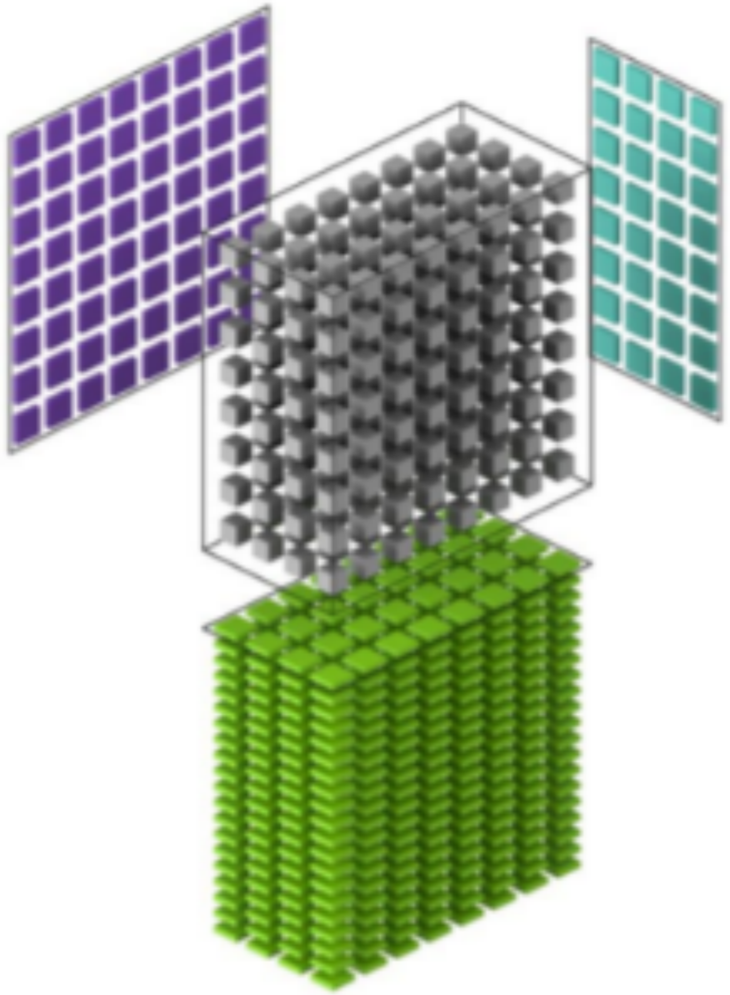
- Accuracy: maintains accuracy of the original, unpruned network
  - Medium sparsity level (50%), fine-grained
- Training: a recipe shown to work across tasks and networks
- Speedup:
  - Specialized Tensor Core support for sparse math
  - Structured: lends itself to efficient memory utilization



PRUNING

Structured sparsity

INPUT OPERANDS	ACCUMULATOR	TOPS	Dense vs. FFMA	Sparse Vs. FFMA
FP32	FP32	19.5	-	-
TF32	FP32	156	8X	16X
FP16	FP32	312	16X	32X
BF16	FP32	312	16X	32X
FP16	FP16	312	16X	32X
INT8	INT32	624	32X	64X
INT4	INT32	1248	64X	128X
BINARY	INT32	4992	256X	-



RELIABLE APPROACH

PRUNING

Model performance

Network	Accuracy Dense FP16	Sparse FP16		Sparse INT8	
ResNet-34	73.7	73.9	0.2	73.7	-
ResNet-50	76.6	76.8	0.2	76.8	0.2
ResNet-101	77.7	78.0	0.3	77.9	-
ResNeXt-50-32x4d	77.6	77.7	0.1	77.7	-
ResNeXt-101-32x16d	79.7	79.9	0.2	79.9	0.2
DenseNet-121	75.5	75.3	-0.2	75.3	-0.2
DenseNet-161	78.8	78.8	-	78.9	0.1
Wide ResNet-50	78.5	78.6	0.1	78.5	-
Wide ResNet-101	78.9	79.2	0.3	79.1	0.2
Inception v3	77.1	77.1	-	77.1	-
Xception	79.2	79.2	-	79.2	-
VGG-16	74.0	74.1	0.1	74.1	0.1
VGG-19	75.0	75.0	-	75.0	-

PRUNING

Model performance

Network	Accuracy				
	Dense FP16	Sparse FP16		Sparse INT8	
ResNet-50 (SWSL)	81.1	80.9	-0.2	80.9	-0.2
ResNeXt-101-32x8d (SWSL)	84.3	84.1	-0.2	83.9	-0.4
ResNeXt-101-32x16d (WSL)	84.2	84.0	-0.2	84.2	-
SUNet-7-128	76.4	76.5	0.1	76.3	-0.1
DRN-105	79.4	79.5	0.1	79.4	-

PRUNING

Model performance

Network	Accuracy				
	Dense FP16	Sparse FP16		Sparse INT8	
MaskRCNN-RN50	37.9	37.9	-	37.8	-0.1
SSD-RN50	24.8	24.8	-	24.9	0.1
FasterRCNN-RN50-FPN-1x	37.6	38.6	1.0	38.4	0.8
FasterRCNN-RN50-FPN-3x	39.8	39.9	-0.1	39.4	-0.4
FasterRCNN-RN101-FPN-3x	41.9	42.0	0.1	41.8	-0.1
MaskRCNN-RN50-FPN-1x	39.9	40.3	0.4	40.0	0.1
MaskRCNN-RN50-FPN-3x	40.6	40.7	0.1	40.4	0.2
MaskRCNN-RN101-FPN-3x	42.9	43.2	0.3	42.8	0.1
RetinaNet-RN50-FPN-1x	36.4	37.4	1.0	37.2	0.8
RPN-RN50-FPN-1x	45.8	45.6	-0.2	45.5	0.3

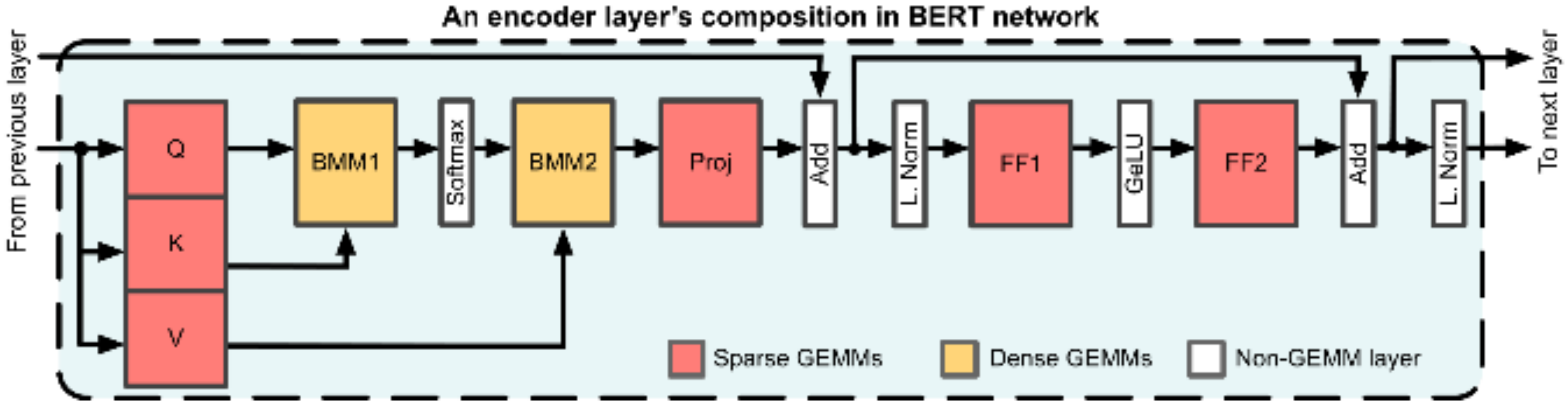
RN = ResNet Backbone
FPN = Feature Pyramid Network
RPN = Region Proposal Network

IMPACT ON NLP

NETWORK PERFORMANCE

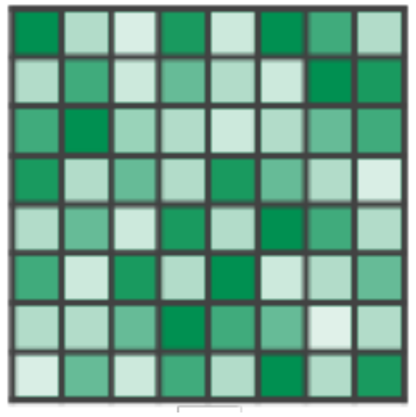
BERT-Large

1.8x GEMM Performance -> 1.5x Network Performance
Some operations remain dense:
Non-GEMM layers (Softmax, Residual add, Normalization, Activation functions, …)
GEMMs without weights to be pruned – Attention Batched Matrix Multiplies



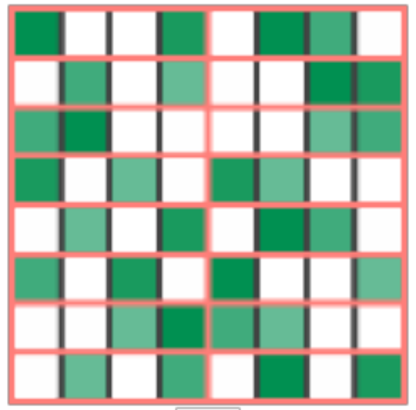
TRAINING RECIPE

RECIPE FOR 2:4 SPARSE NETWORK TRAINING



Dense weights

1) **Train (or obtain) a dense network**

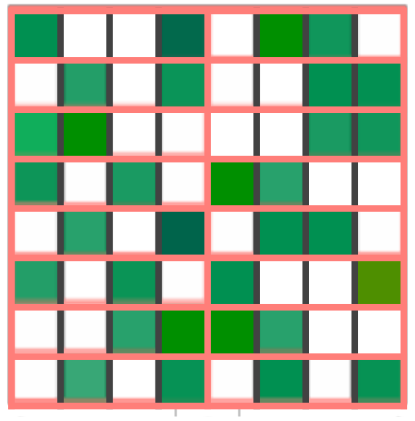


2:4 sparse weights

2) **Prune for 2:4 sparsity**

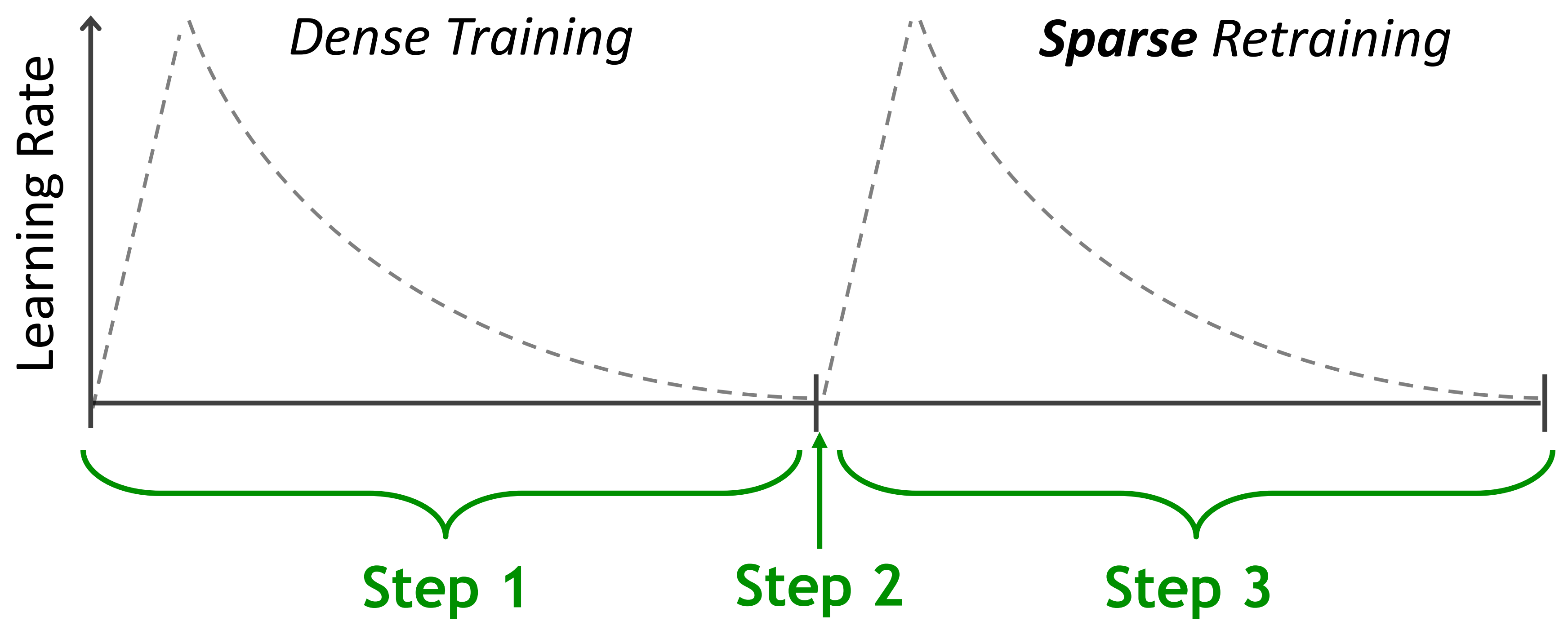
3) **Repeat the original training procedure**

- Same hyper-parameters as in step-1
- Initialize to weights from step-2
- Maintain the 0 pattern from step-2: no need to recompute the mask



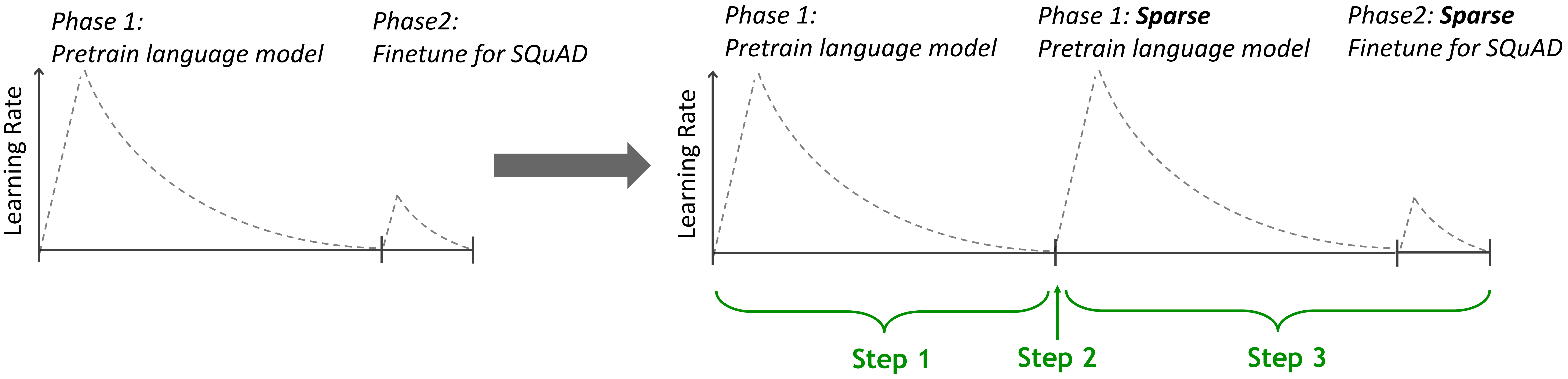
Retrained 2:4 sparse weights

EXAMPLE LEARNING RATE SCHEDULE



BERT SQUAD EXAMPLE

SQuAD Dataset and fine-tuning is too small to compensate for pruning on its own



APEX: AUTOMATIC SPARSITY

TAKING ADVANTAGE OF STRUCTURED SPARSITY

APEX's Automatic SParsity: ASP

PyTorch sparse fine-tuning loop

```
import torch
from apex.contrib.sparsity import ASP
device = torch.device('cuda')

model = TheModelClass(*args, **kwargs) # Define model structure
model.load_state_dict(torch.load('dense_model.pth'))

optimizer = optim.SGD(model.parameters(), lr=0.01, momentum=0.9) # Define optimizer

ASP.prune_trained_model(model, optimizer)

x, y = DataLoader(…) #load data samples and labels to train the model
for t in range(500):
    y_pred = model(x)
    loss = loss_fn(y_pred, y)
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()

torch.save(model.state_dict(), 'pruned_model.pth') # checkpoint has weights and masks
```

Init mask buffers, tell optimizer to mask weights and gradients, compute sparse masks: Universal Fine Tuning

Part 3: Production Deployment

- Lecture
  - Model Selection
  - Post-Training Optimization
  - Product Quantization
  - Knowledge Distillation
  - Model Code Efficiency
  - Model Serving
  - Building the Application
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  - Exporting the Model
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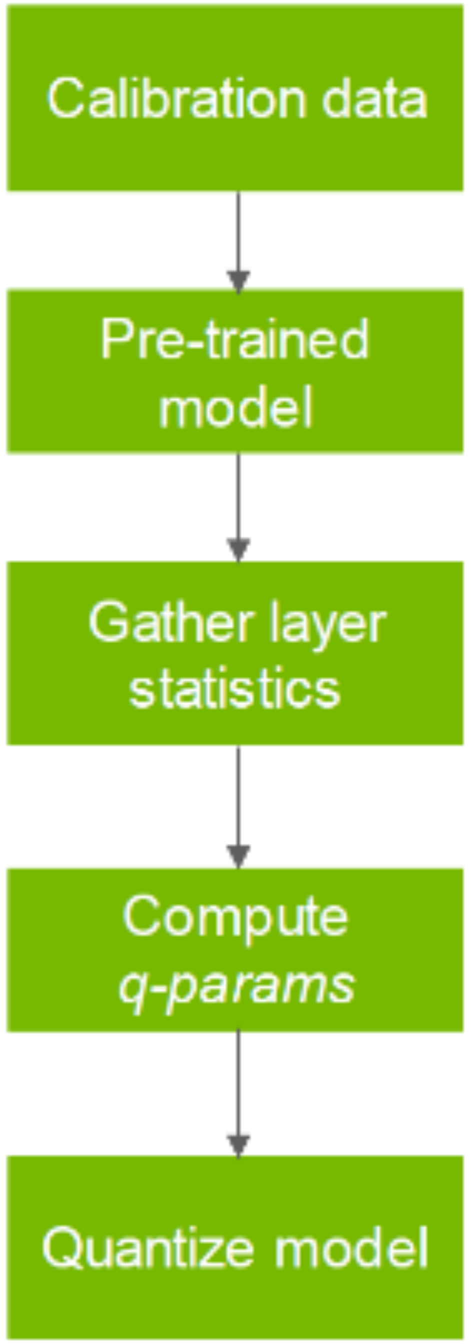
  - Server Performance
  - Using the Model

QUANTIZATION

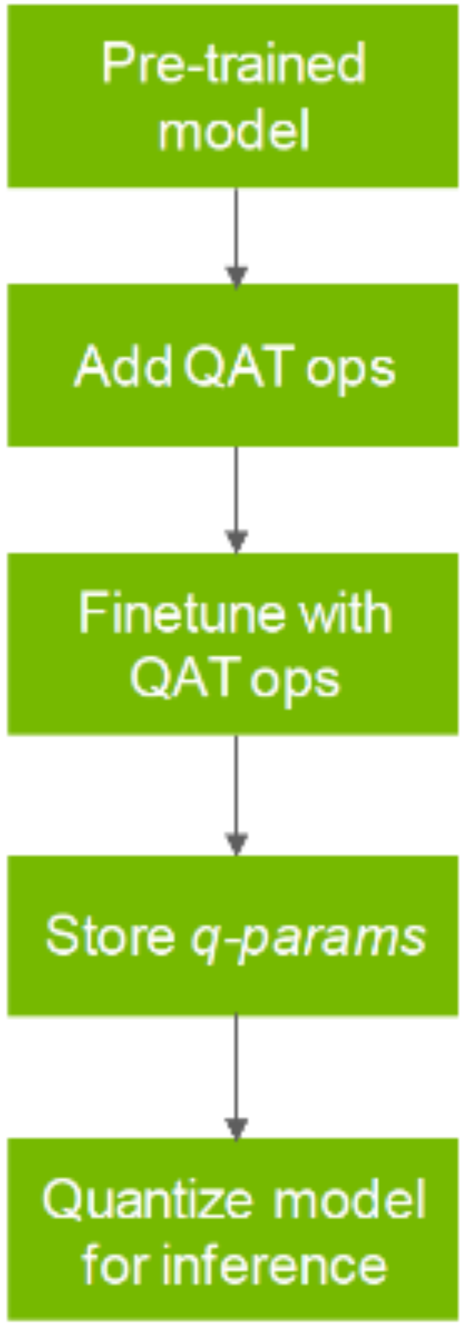
Approaches

Post-training quantization(PTQ)



PTQ	QAT
Usually fast	Slow
No re-training of the model	Model needs to be trained/finetuned
Plug and play of quantization schemes	Plug and play of quantization schemes (requires re-training)
Less control over final accuracy of the model	More control over final accuracy since *q-params* are learned during training.

Quantization-aware training (QAT)



EXTREME MODEL COMPRESSION

Training with quantization noise

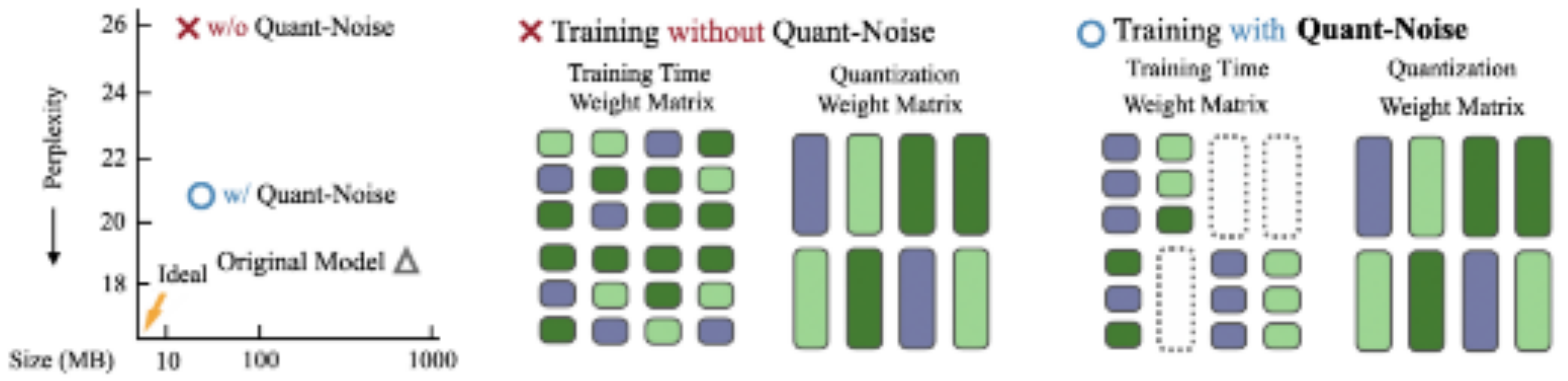


Figure 1: **Quant-Noise** trains models to be resilient to inference-time quantization by mimicking the effect of the quantization method during training time. This allows for extreme compression rates without much loss in accuracy on a variety of tasks and benchmarks.

Quantization Scheme	**Language Modeling** 16-layer Transformer Wikitext-103			**Image Classification** EfficientNet-B3 ImageNet-1k		
	Size	Compression	PPL	Size	Compression	Top-1
Uncompressed model	942	× 1	18.3	46.7	× 1	81.5
`int4` quantization	118	× 8	39.4	5.8	× 8	45.3
- trained with QAT	118	× 8	34.1	5.8	× 8	59.4
- trained with Quant-Noise	118	× 8	**21.8**	5.8	× 8	**67.8**
`int8` quantization	236	× 4	19.6	11.7	× 4	80.7
- trained with QAT	236	× 4	21.0	11.7	× 4	80.8
- trained with Quant-Noise	236	× 4	**18.7**	11.7	× 4	**80.9**
iPQ	38	× 25	25.2	3.3	× 14	79.0
- trained with QAT	38	× 25	41.2	3.3	× 14	55.7
- trained with Quant-Noise	38	× 25	**20.7**	3.3	× 14	**80.0**
iPQ & `int8` + Quant-Noise	38	× 25	21.1	3.1	× 15	79.8

Table 1: **Comparison of different quantization schemes with and without Quant-Noise** on language modeling and image classification. For language modeling, we train a Transformer on the Wikitext-103 benchmark and report perplexity (PPL) on test. For image classification, we train a EfficientNet-B3 on the ImageNet-1k benchmark and report top-1 accuracy on validation and use our re-implementation of EfficientNet-B3. The original implementation of Tan *et al.* [4] achieves an uncompressed Top-1 accuracy of 81.9%. For both settings, we report model size in megabyte (MB) and the compression ratio compared to the original model.

Polino, A., Pascanu, R., & Alistarh, D. (2018). Model compression via distillation and quantization. *arXiv preprint arXiv:1802.05668*.

“We used Quant-Noise to compress Facebook AI’s state-of-the-art RoBERTa Base model from 480 MB to 14 MB while achieving 82.5 percent on MNLI, compared with 84.8 percent for the original model.”

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KNOWLEDGE DISTILLATION

The idea

Distilling the Knowledge in a Neural Network

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Abstract

A very simple way to improve the performance of almost any machine learning algorithm is to train many different models on the same data and then to average their predictions [3]. Unfortunately, making predictions using a whole ensemble of models is cumbersome and may be too computationally expensive to allow deployment to a large number of users, especially if the individual models are large neural nets. Caruana and his collaborators [1] have shown that it is possible to compress the knowledge in an ensemble into a single model which is much easier to deploy and we develop this approach further using a different compression technique. We achieve some surprising results on MNIST and we show that we can significantly improve the acoustic model of a heavily used commercial system by distilling the knowledge in an ensemble of models into a single model. We also introduce a new type of ensemble composed of one or more full models and many specialist models which learn to distinguish fine-grained classes that the full models confuse. Unlike a mixture of experts, these specialist models can be trained rapidly and in parallel.

KNOWLEDGE DISTILLATION

DistillBERT

Table 1: **DistilBERT retains 97% of BERT performance.** Comparison on the dev sets of the GLUE benchmark. ELMo results as reported by the authors. BERT and DistilBERT results are the medians of 5 runs with different seeds.

Model	**Score**	CoLA	MNLI	MRPC	QNLI	QQP	RTE	SST-2	STS-B	WNLI
ELMo	68.7	44.1	68.6	76.6	71.1	86.2	53.4	91.5	70.4	56.3
BERT-base	79.5	56.3	86.7	88.6	91.8	89.6	69.3	92.7	89.0	53.5
DistilBERT	77.0	51.3	82.2	87.5	89.2	88.5	59.9	91.3	86.9	56.3

Table 2: **DistilBERT yields to comparable performance on downstream tasks.** Comparison on downstream tasks: IMDb (test accuracy) and SQuAD 1.1 (EM/F1 on dev set). D: with a second step of distillation during fine-tuning.

Model	IMDb (acc.)	SQuAD (EM/F1)
BERT-base	93.46	81.2/88.5
DistilBERT	92.82	77.7/85.8
DistilBERT (D)	-	79.1/86.9

Table 3: **DistilBERT is significantly smaller while being constantly faster.** Inference time of a full pass of GLUE task STS-B (sentiment analysis) on CPU with a batch size of 1.

Model	# param. (Millions)	Inf. time (seconds)
ELMo	180	895
BERT-base	110	668
DistilBERT	66	410

Sanh, V., Debut, L., Chaumond, J., & Wolf, T. (2019). DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter. arXiv preprint arXiv:1910.01108.

Part 3: Production Deployment

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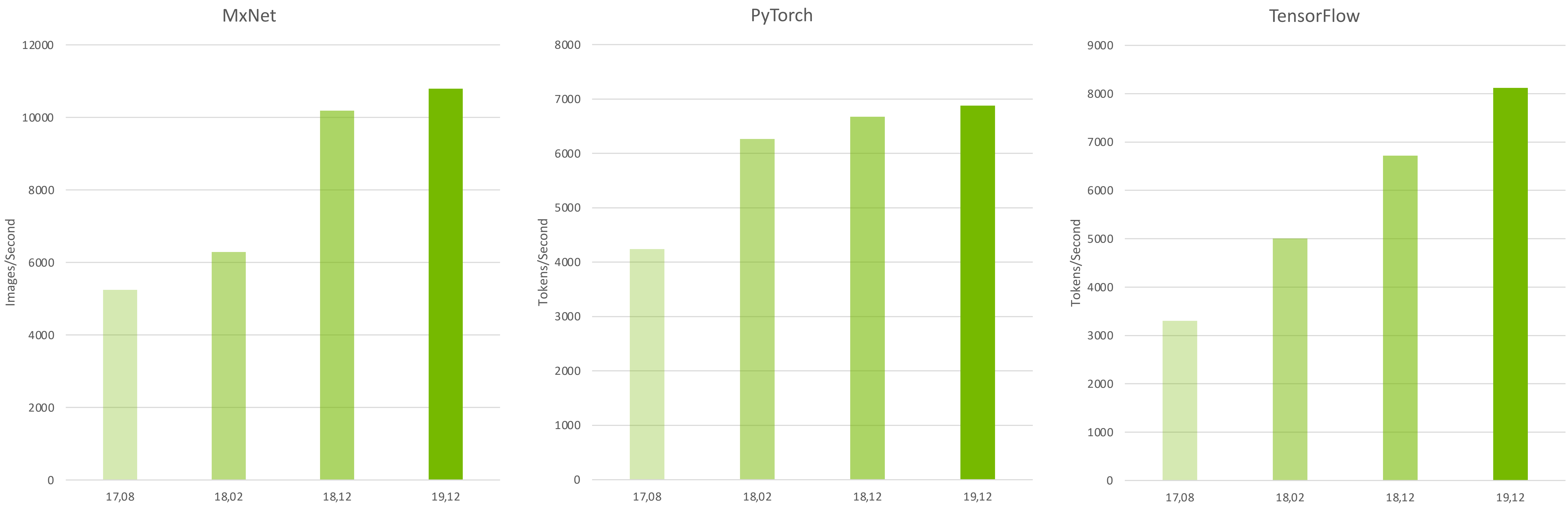
NOT ALL MODELS HAVE THE SAME CODE QUALITY

COMPUTE MATTERS

But so does code quality

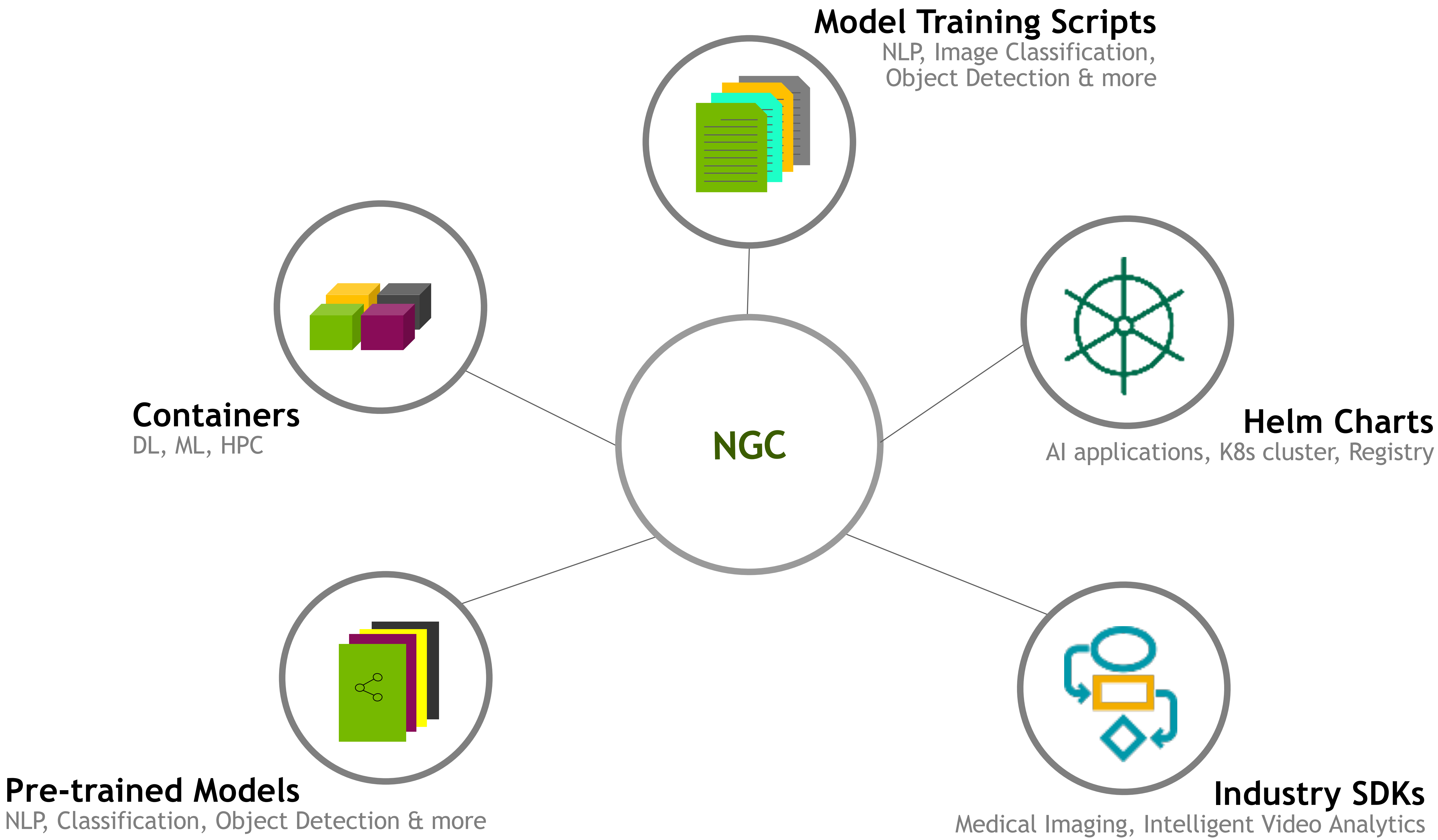
Monthly DL Framework Updates & Optimizations Drive Performance



ResNet-50 v1.5 Training | 8x V100 | DGX-1

NGC: GPU-OPTIMIZED SOFTWARE HUB

Simplifying DL, ML and HPC Workflows



PRETRAINED MODELS & MODEL SCRIPTS

Build AI Solutions Faster

PRE-TRAINED MODELS

- Deploy AI quickly with models for industry specific use cases
- Covers everything from speech to object detection
- Integrate into existing workflows with code samples
- Easily use transfer learning to adapt to your bespoke use case

MODEL SCRIPTS

- Reference neural network architectures across all domains and popular frameworks with latest SOTA
- Jupyter notebook starter kits

Healthcare (~30 models)	BioBERT (NLP), Clara (Computer Vision)
Manufacturing (~25 Models)	Object Detection, Image Classification
Retail (~25 models)	BERT, Transformer
70 TensorRT Plans	Classification/Segmentation for v5, v6, v7
Natural Language Processing	25 Bert Configurations
Recommendation Engines	Neural Collaborative Filtering, VAE
Speech	Jasper, Tacotron, WaveGlow
Translation	GNMT

THIS APPLIES NOT ONLY TO TRAINING BUT INFERENCE AS WELL

CODE QUALITY IS KEY

Dramatic differences in model performance

3-layer BERT with 128 sequence length

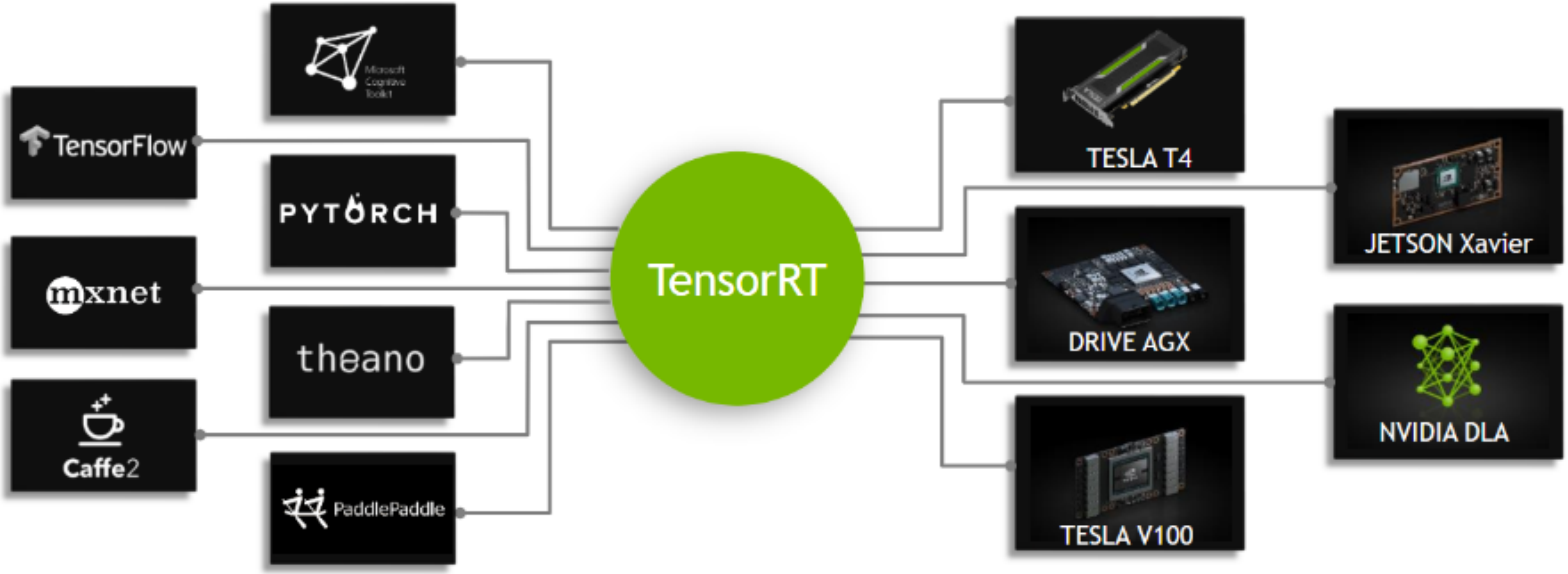
		Batch size	Inference on	Throughput (Query per second)	Latency (milliseconds)
CPU	Original 3-layer BERT	1	Azure Standard F16s_v2 (CPU)	6	157
	ONNX Model	1	Azure Standard F16s_v2 (CPU) **with ONNX Runtime**	111	9
GPU	Original 3-layer BERT	4	Azure NV6 GPU VM	200	20
	ONNX Model	4	Azure NV6 GPU VM **with ONNX Runtime**	500	8
	ONNX Model	64	Azure NC6S_v3 GPU VM **with ONNX Runtime + System Optimization** (Tensor Core with mixed precision, Same Accuracy)	10667	6

https://cloudblogs.microsoft.com/opensource/2020/01/21/microsoft-onnx-open-source-optimizations-transformer-inference-gpu-cpu

OPTIMIZING INFERENCE WITH TENSORRT

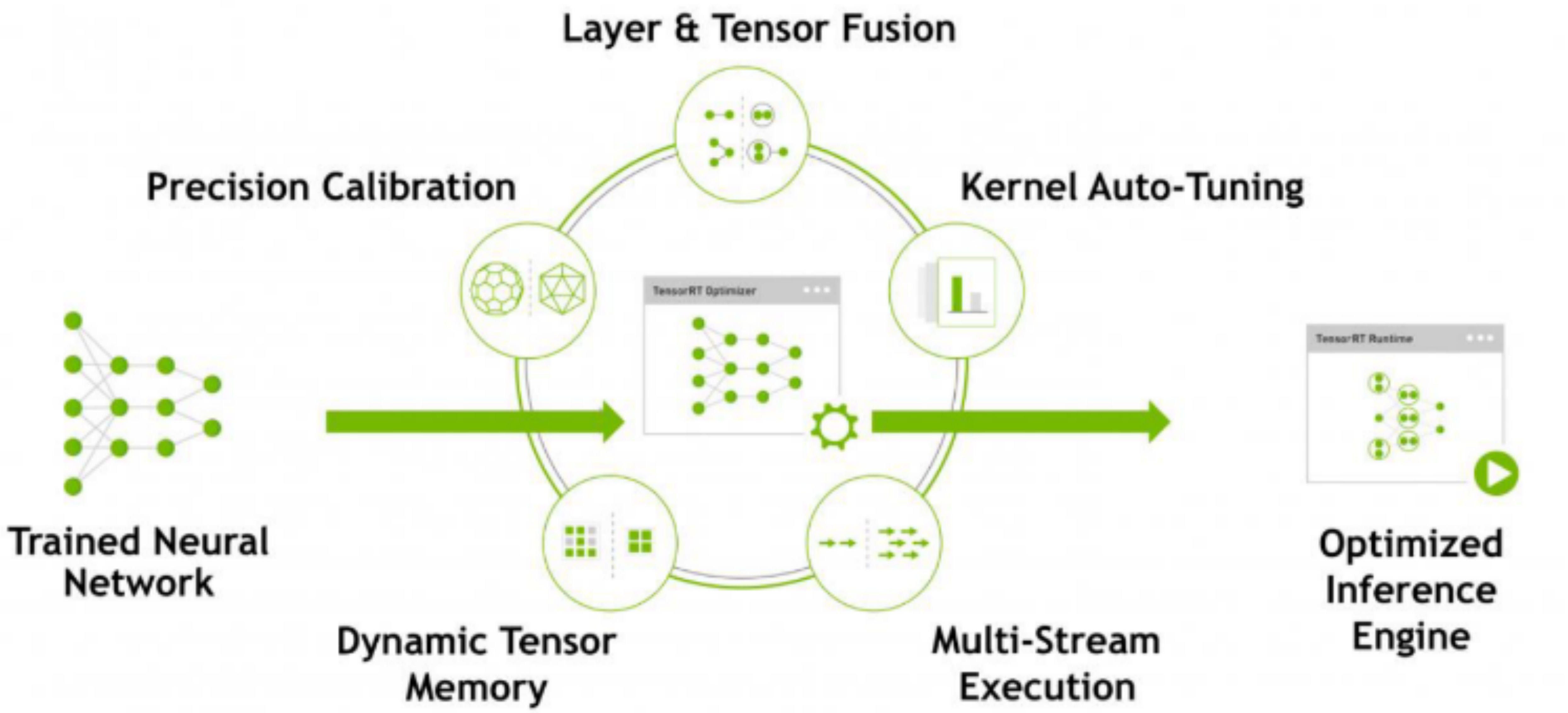
NVIDIA TENSORRT

From Every Framework, Optimized For Each Target Platform



TENSORRT

Optimizations



developer.nvidia.com/tensorrt

TensorRT ONNX PARSER

High-Performance Inference for ONNX Models

Optimize and deploy models from ONNX-supported frameworks to production

Apply TensorRT optimizations to any ONNX framework (Caffe 2, Microsoft Cognitive Toolkit, MxNet & PyTorch)

Import TensorFlow and Keras through converters (tf2onnx, keras2onnx)

Use with C++ and Python apps

20+ New Ops in TensorRT 7

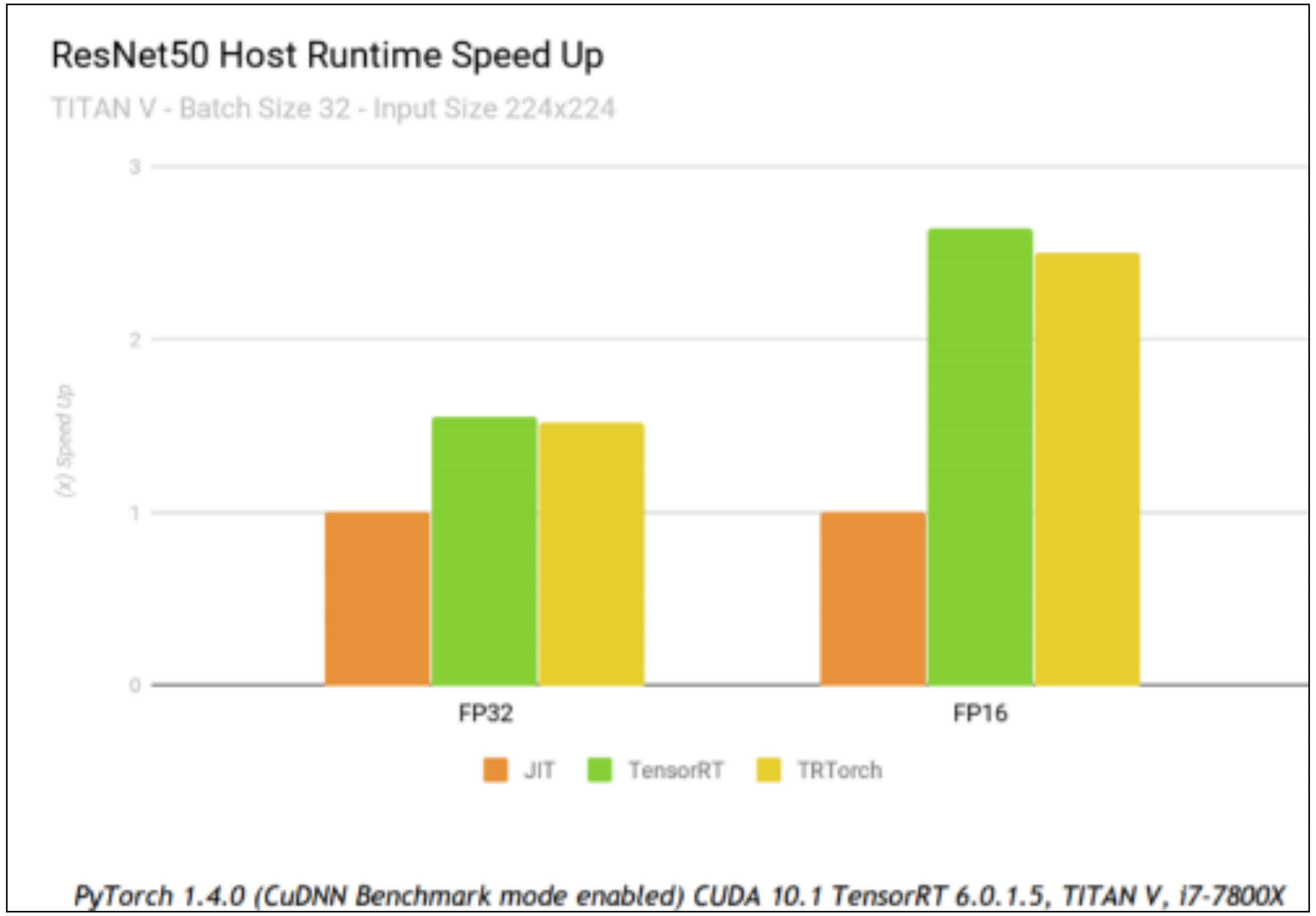
Support for Opset 11 (See List of Supported Ops)

ONNX

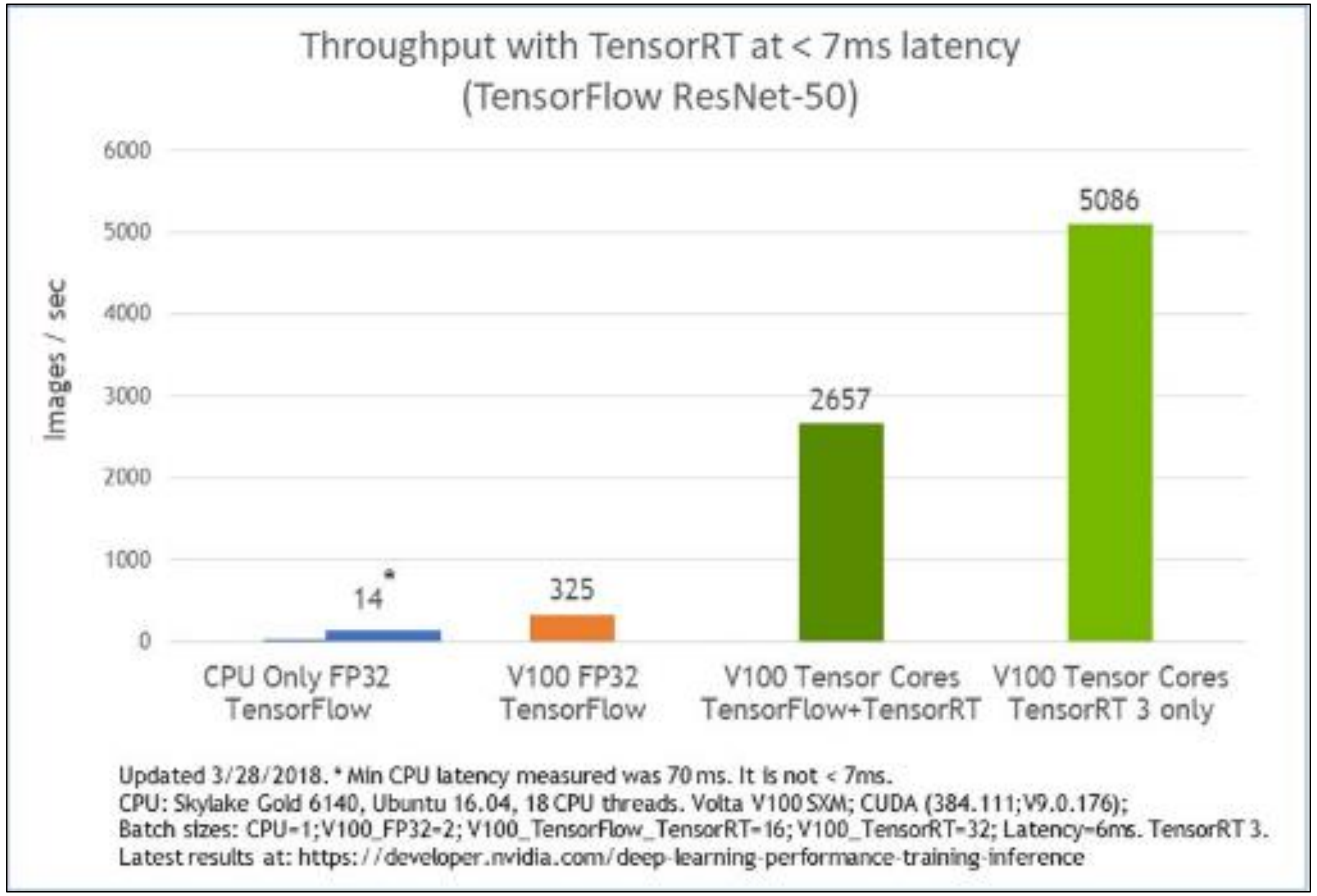
Caffe2 Chainer Cognitive Toolkit mxnet MATLAB PyTorch PaddlePaddle

TENSORRT

Tight integration with DL frameworks



Pytorch -> TRTorch



TensorFlow -> TF-TRT

WIDELY ADOPTED

Accelerating most demanding applications

Alibaba Group 阿里巴巴集团 | Baidu 百度 | BOSCH | ByteDance 字节跳动 | criteo.

Ford | IBM | JD.COM | KLA Keep Looking Ahead | 金山云

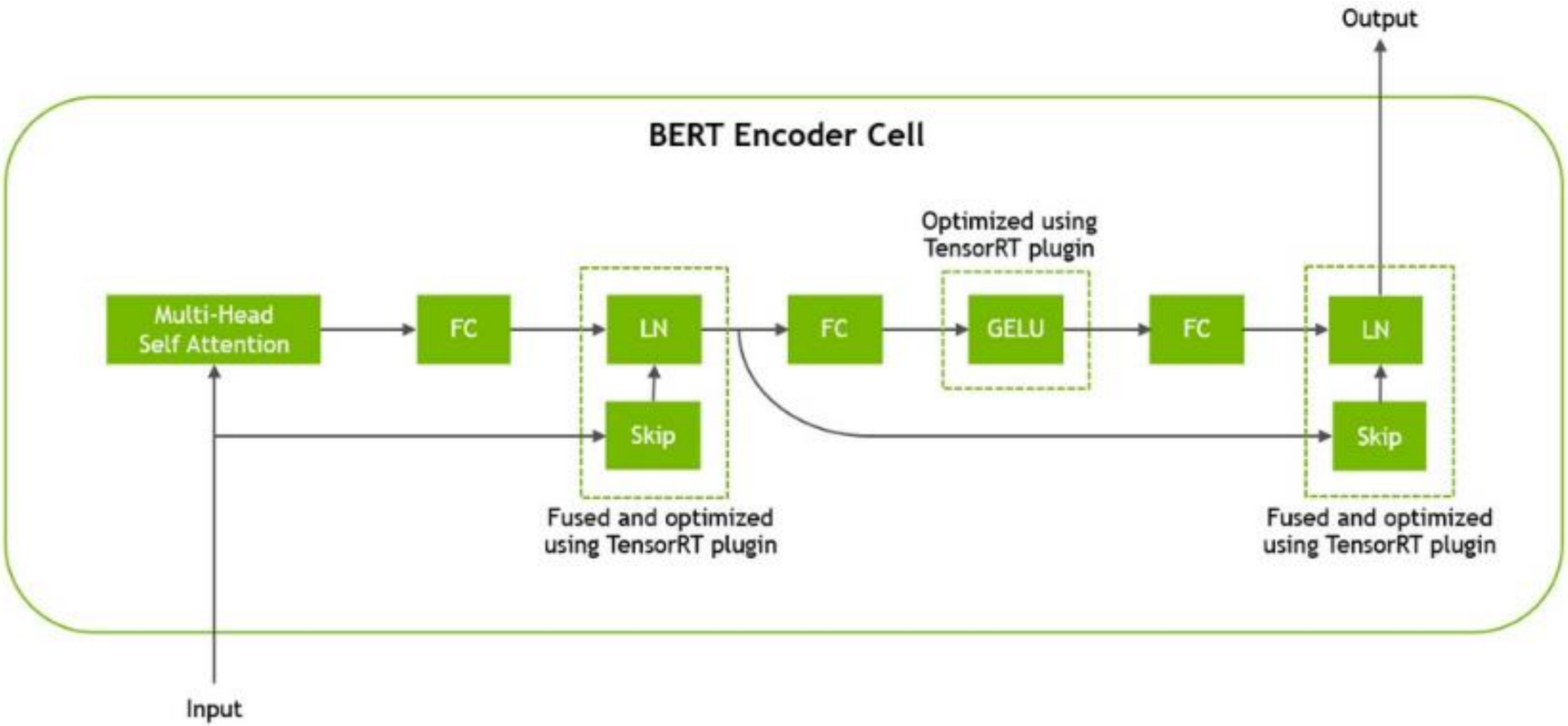
MAN | SEARIDGE TECHNOLOGIES | SK telecom | Tencent 腾讯 | 图森 tuSimple

verizon | VOLVO | 欢聚时代 YY Inc. | ZF

IMPACT ON NLP

TENSORRT

BERT Encoder optimizations



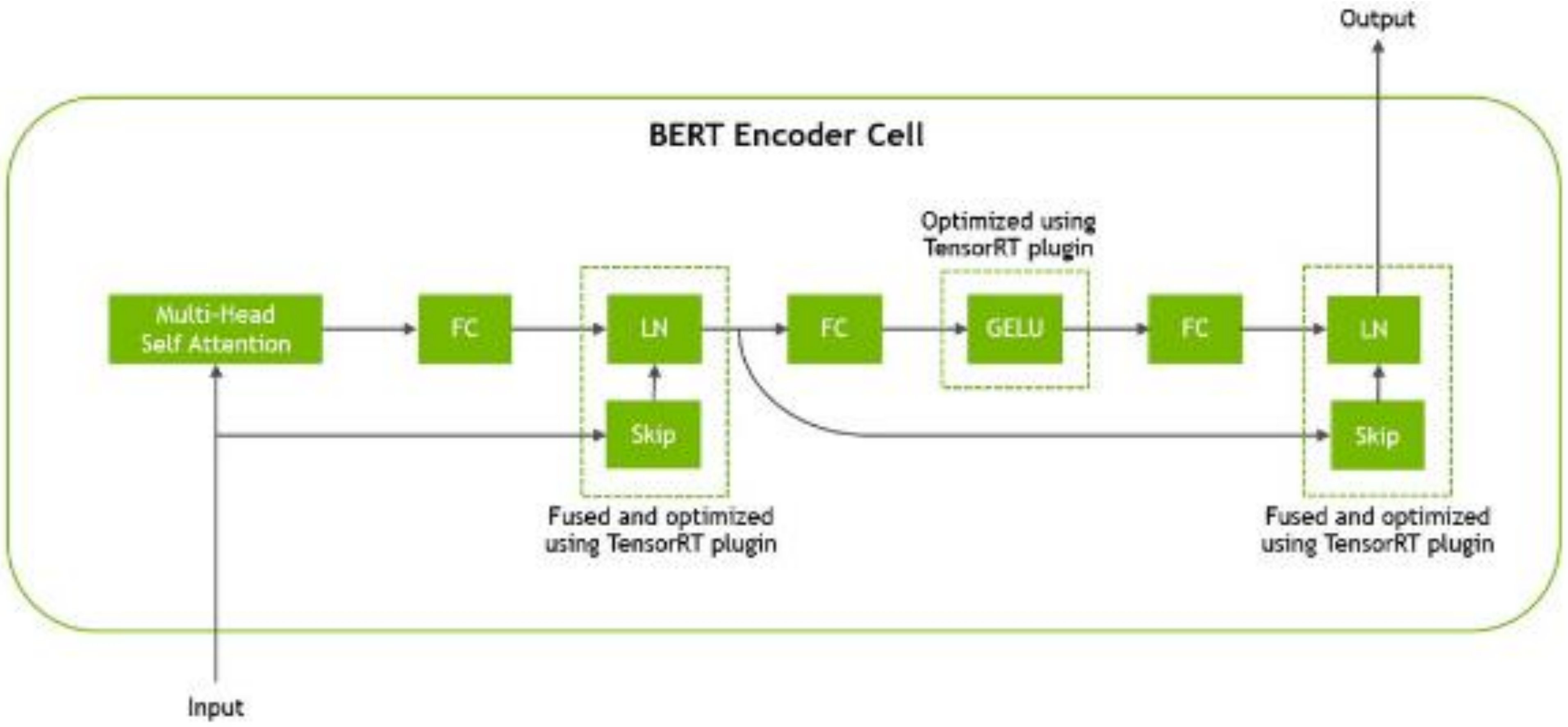
CUSTOM PLUGINS

Optimized GeLU as well as skip and layer-normalization operations

- Naïve implementation would require a large number of TensorRT elementary layers
- For k layers, the naïve implementation would require k-1 memory roundtrips
- The skip and layer-normalization(LN) layers occur twice per Transformer layer and are fused in a single kernel

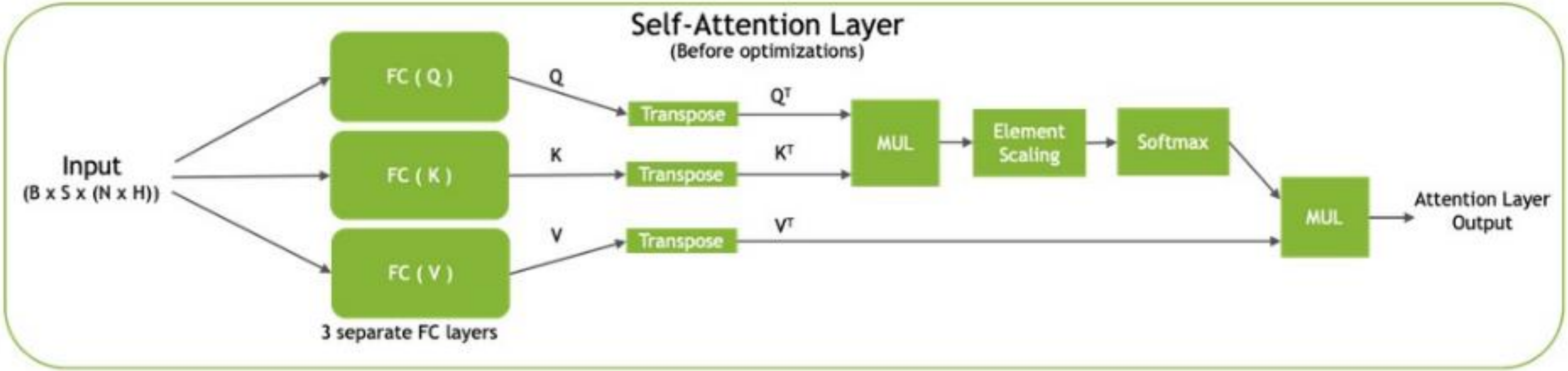
gelu(x) = a * x * (1 + tanh(b * (x + c * x^3)))

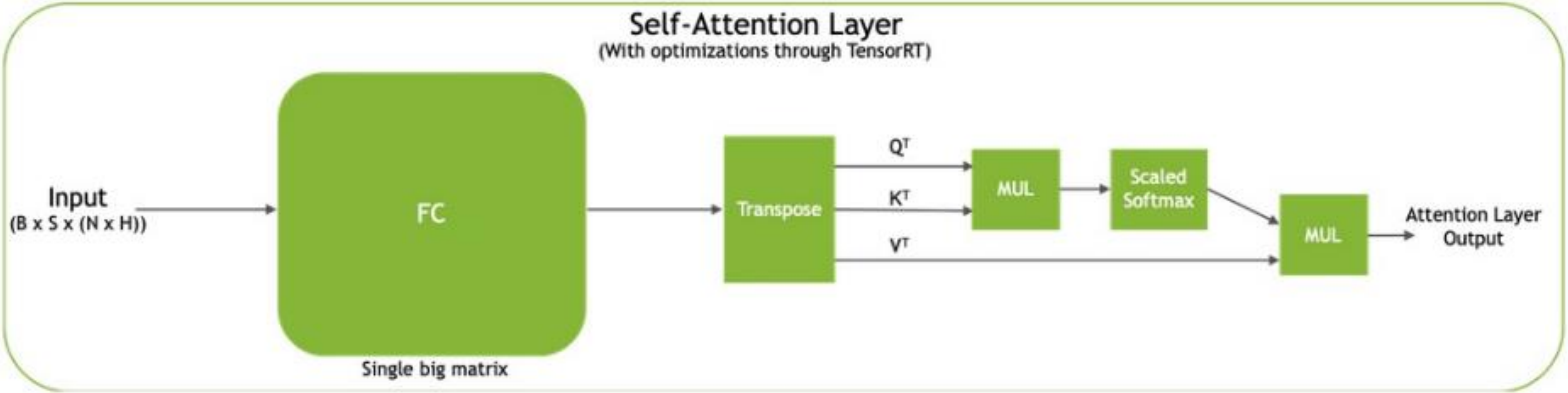
```
Result = x^3
Result = c * Result
Result = x + Result
Result = b * Result
Result = tanh(Result)
Result = x * Result
Result = a * Result
```



CUSTOM PLUGINS

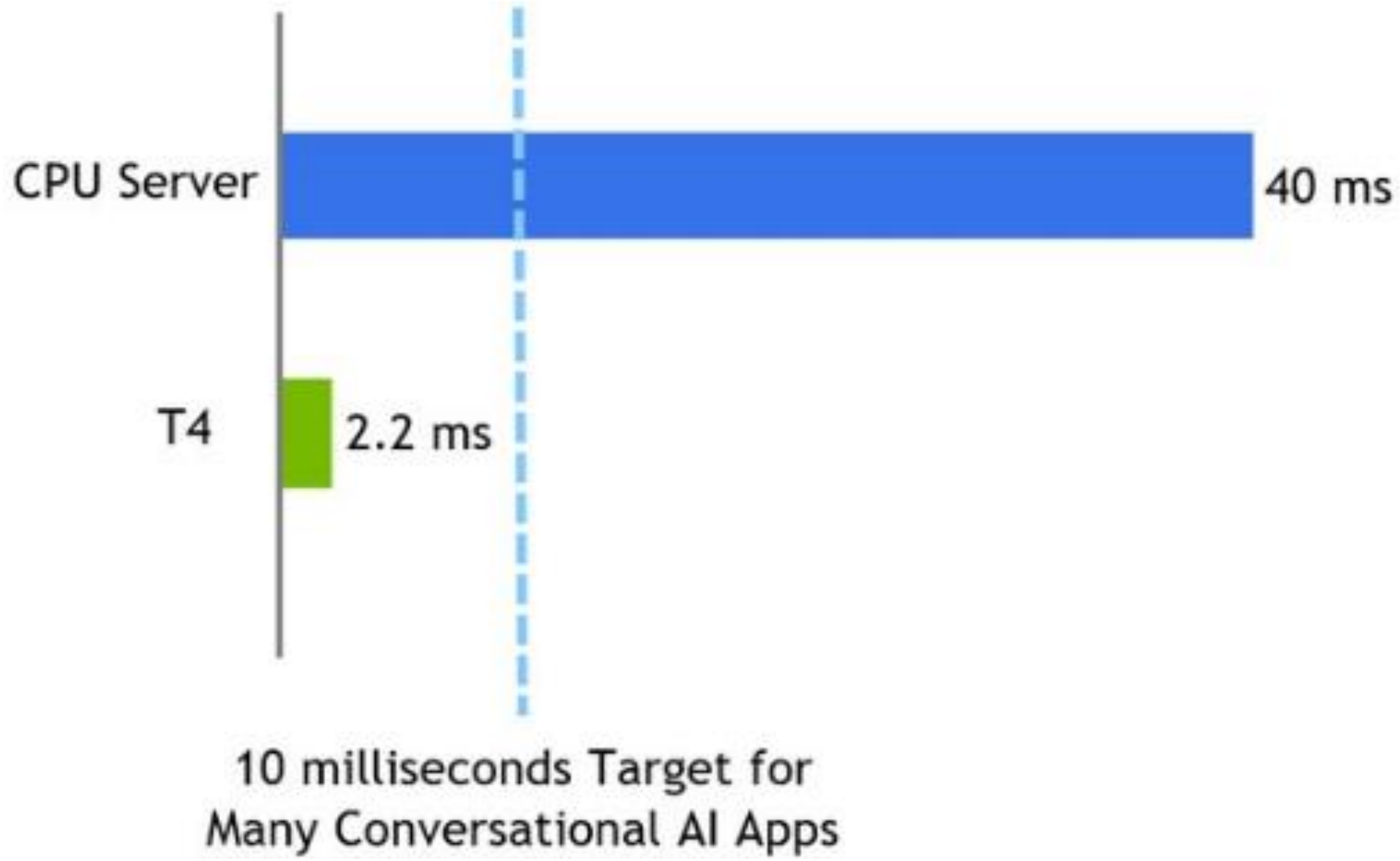
Self-attention layer





IMPLICATIONS

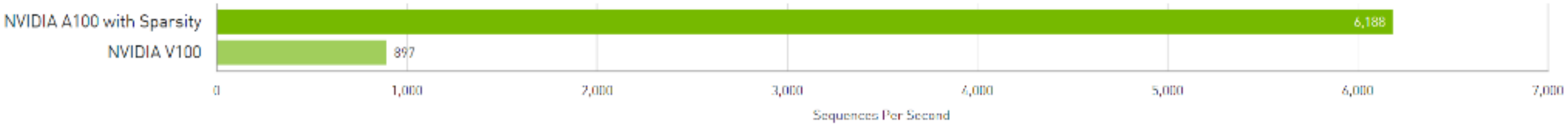
Significant impact on latency and throughput (batch 1)



Using a Tesla T4 GPU, BERT optimized with TensorRT can perform inference in 2.2 ms for a QA task similar to available in SQuAD with batch size =1 and sequence length = 128.

IMPLICATIONS

Significant impact on latency and throughput



DGX A100 server w/ 1x NVIDIA A100 with 7 MIG instances of 1g.5gb | Batch Size = 94 | Precision: INT8 | Sequence Length = 128
DGX-1 server w/ 1x NVIDIA V100 | TensorRT 7.1 | Batch Size = 256 | Precision: Mixed | Sequence Length = 128

BEYOND BERT

FASTER TRANSFORMER

Designed for training and inference speed

- Encoder:
  - 1.5x compare to TensorFlow with XLA on FP16
- Decoder on NVIDIA Tesla T4
  - 2.5x speedup for batch size 1 (online translating scheme)
  - 2x speedup for large batch size in FP16
- Decoding on NVIDIA Tesla T4
  - 7x speedup for batch size 1 and beam width 4 (online translating scheme)
  - 2x speedup for large batch size in FP16.
- Decoding on NVIDIA Tesla V100
  - 6x speedup for batch size 1 and beam width 4 (online translating scheme)
  - 3x speedup for large batch size in FP16.

https://github.com/NVIDIA/DeepLearningExamples/tree/master/FasterTransformer#feature-support-matrix

CONSIDER USING TENSORRT

Part 3: Production Deployment

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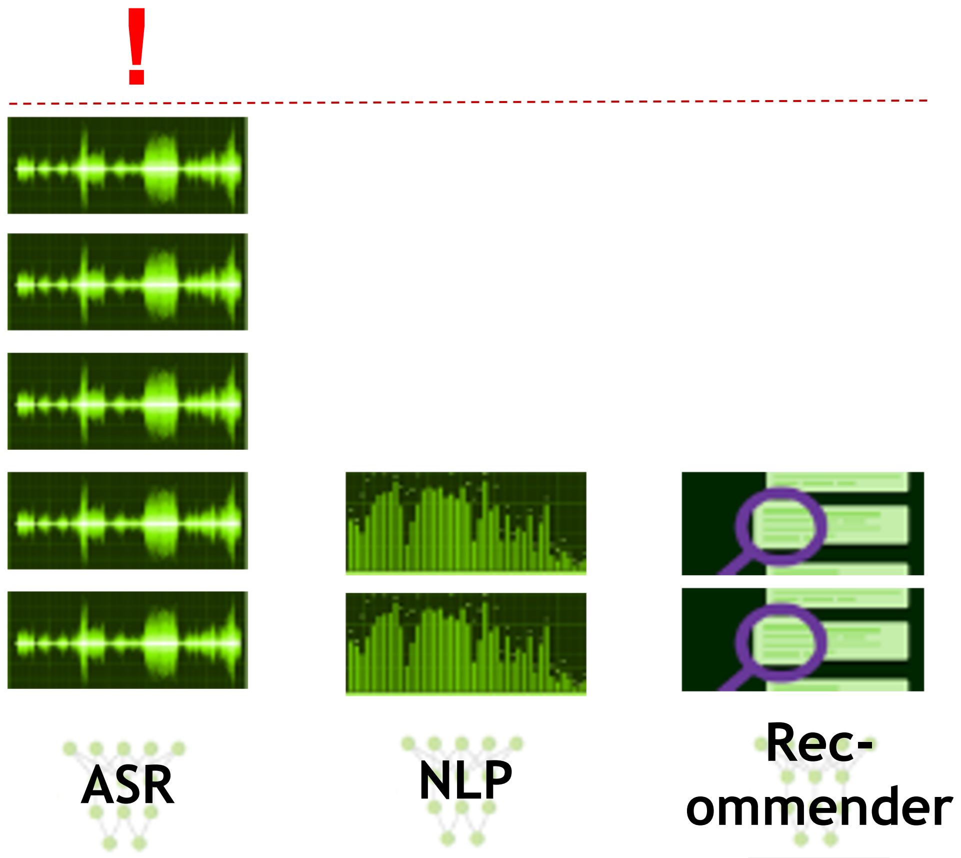
INEFFICIENCY LIMITS INNOVATION

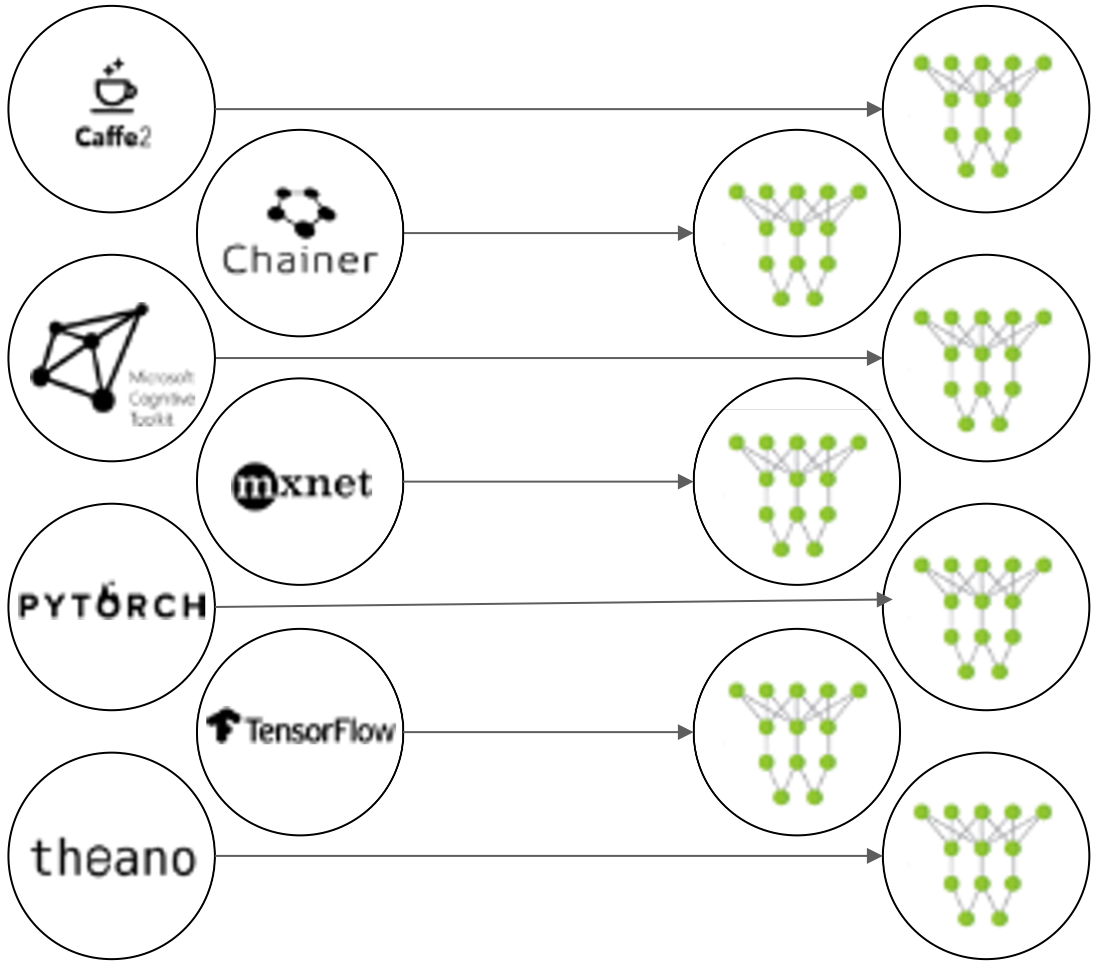
Difficulties with deploying data center inference

Single Model Only



Some systems are overused while others are underutilized

Single Framework Only



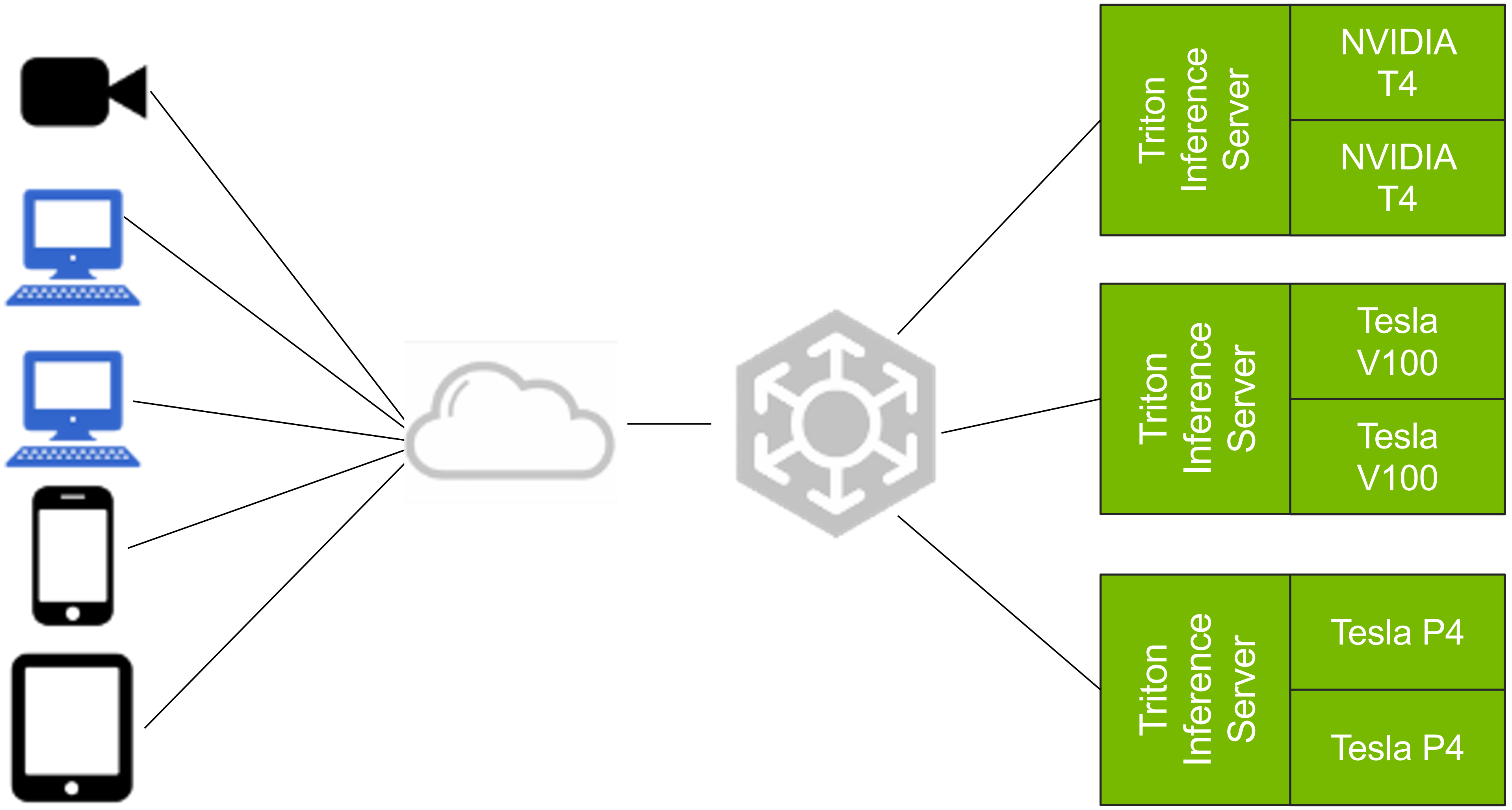
Solutions can only support models from one framework

Custom Development

Developers need to reinvent the plumbing for every application

NVIDIA TRITON INFERENCE SERVER

Production data center inference server



Maximize real-time inference performance of GPUs

Quickly deploy and manage multiple models per GPU per node

Easily scale to heterogeneous GPUs and multi GPU nodes

Integrates with orchestration systems and auto-scalers via latency and health metrics

Now open source for thorough customization and integration

FEATURES

Concurrent Model Execution
Multiple models (or multiple instances of same model) may execute on GPU simultaneously

CPU Model Inference Execution
Framework native models can execute inference requests on the CPU

Metrics
Utilization, count, memory, and latency

Custom Backend
Custom backend allows the user more flexibility by providing their own implementation of an execution engine through the use of a shared library

Model Ensemble
Pipeline of one or more models and the connection of input and output tensors between those models (can be used with custom backend)

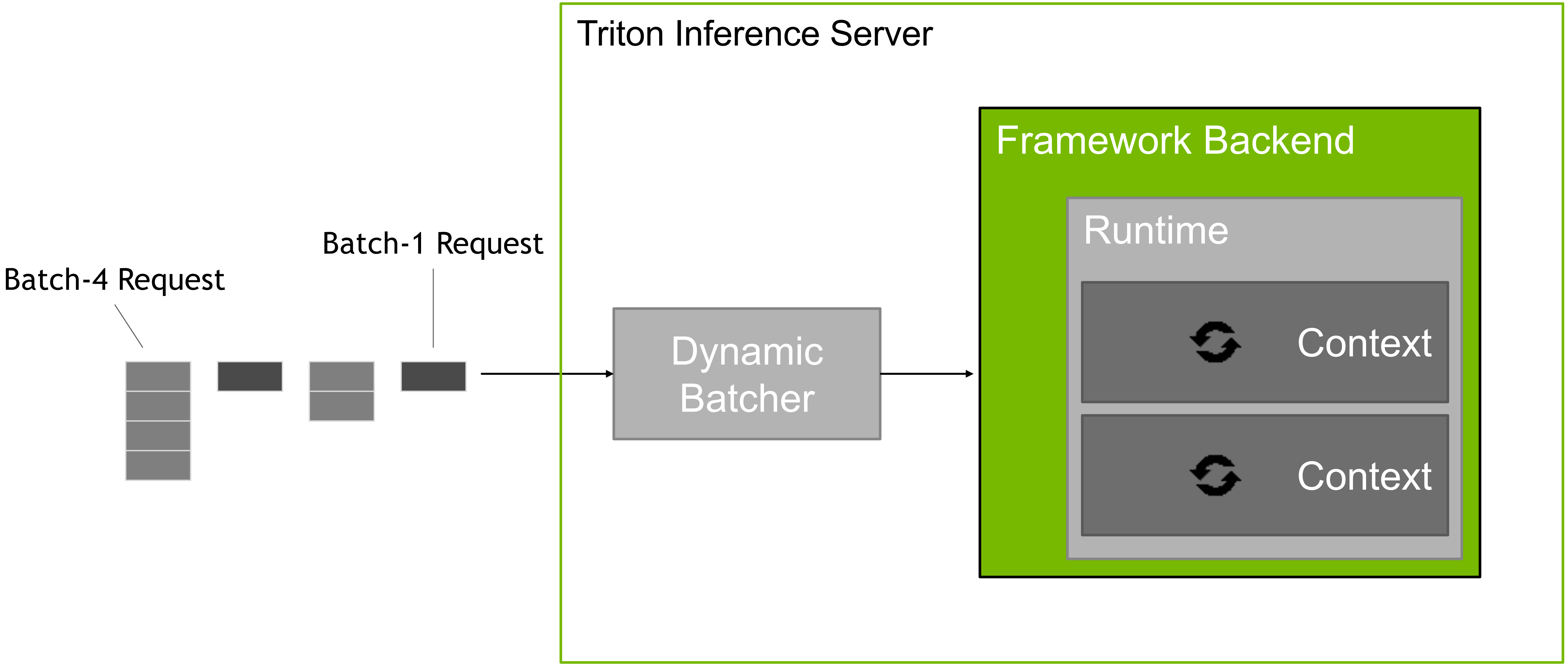
Dynamic Batching
Inference requests can be batched up by the inference server to 1) the model-allowed maximum or 2) the user-defined latency SLA

Multiple Model Format Support
PyTorch JIT (.pt)
TensorFlow GraphDef/SavedModel
TensorFlow and TensorRT GraphDef
ONNX graph (ONNX Runtime)
TensorRT Plans
Caffe2 NetDef (ONNX import path)

CMake build
Build the inference server from source making it more portable to multiple OSes and removing the build dependency on Docker

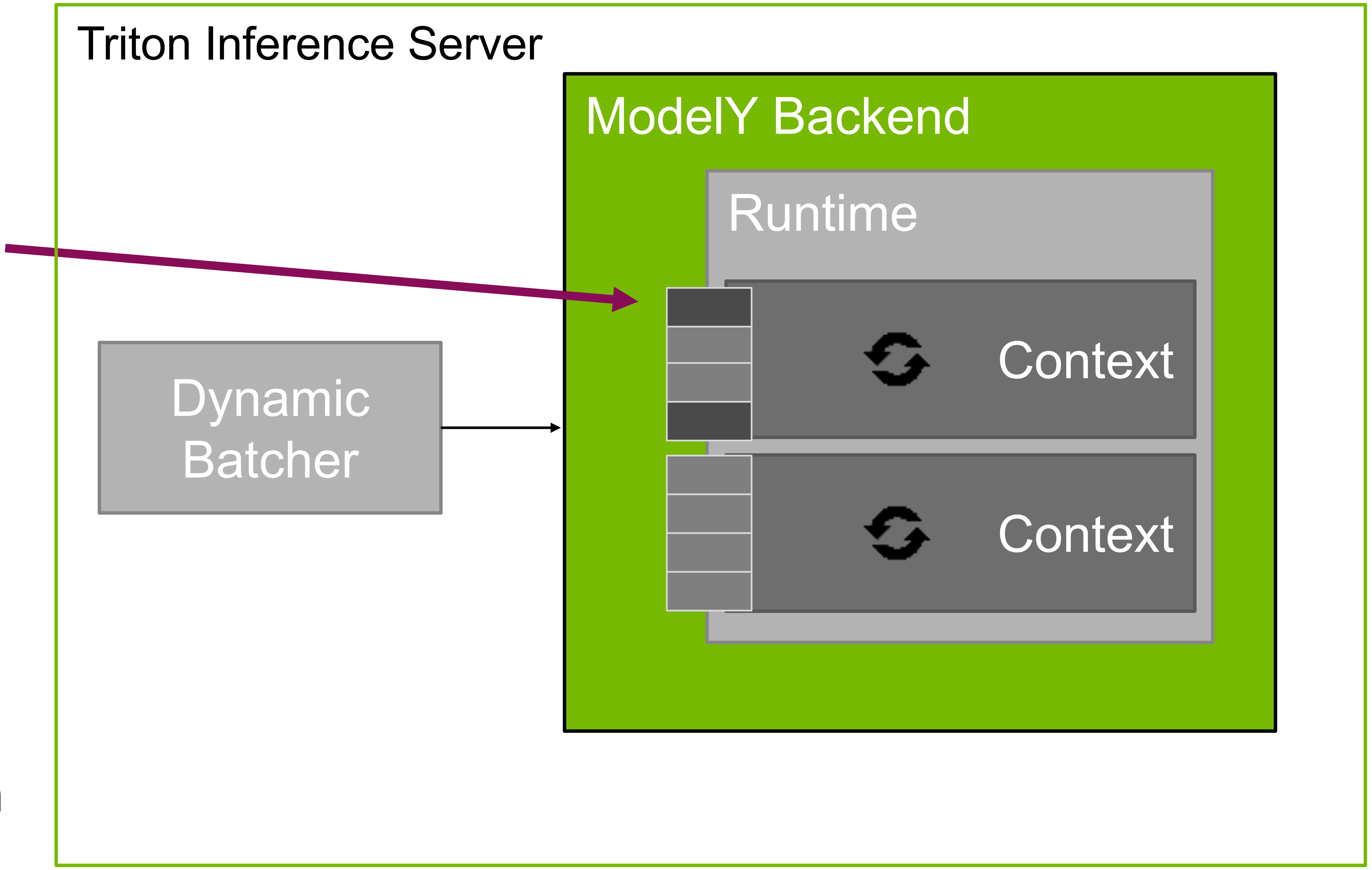
Streaming API
Built-in support for audio streaming input e.g. for speech recognition

DYNAMIC BATCHING SCHEDULER



DYNAMIC BATCHING SCHEDULER

Grouping requests into a single "batch" increases overall GPU throughput



Preferred batch size and wait time are configuration options.

Assume 4 gives best utilization in this example.

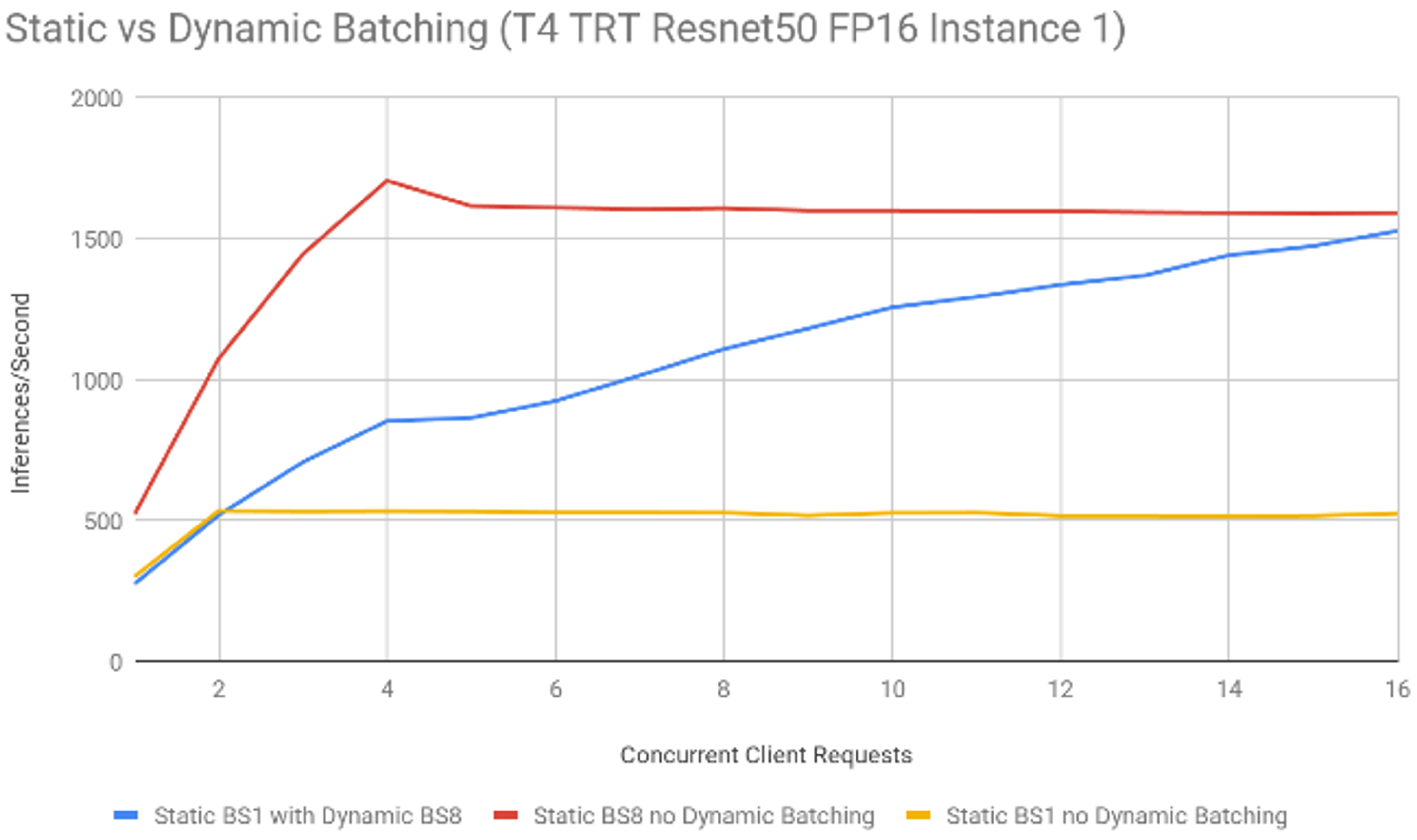
DYNAMIC BATCHING

2.5X Faster Inferences/Second at a 50ms End-to-End Server Latency Threshold

Triton Inference Server groups inference requests based on customer defined metrics for optimal performance

Customer defines 1) batch size (required) and 2) latency requirements (optional)

Example: No dynamic batching (batch size 1 & 8) vs dynamic batching



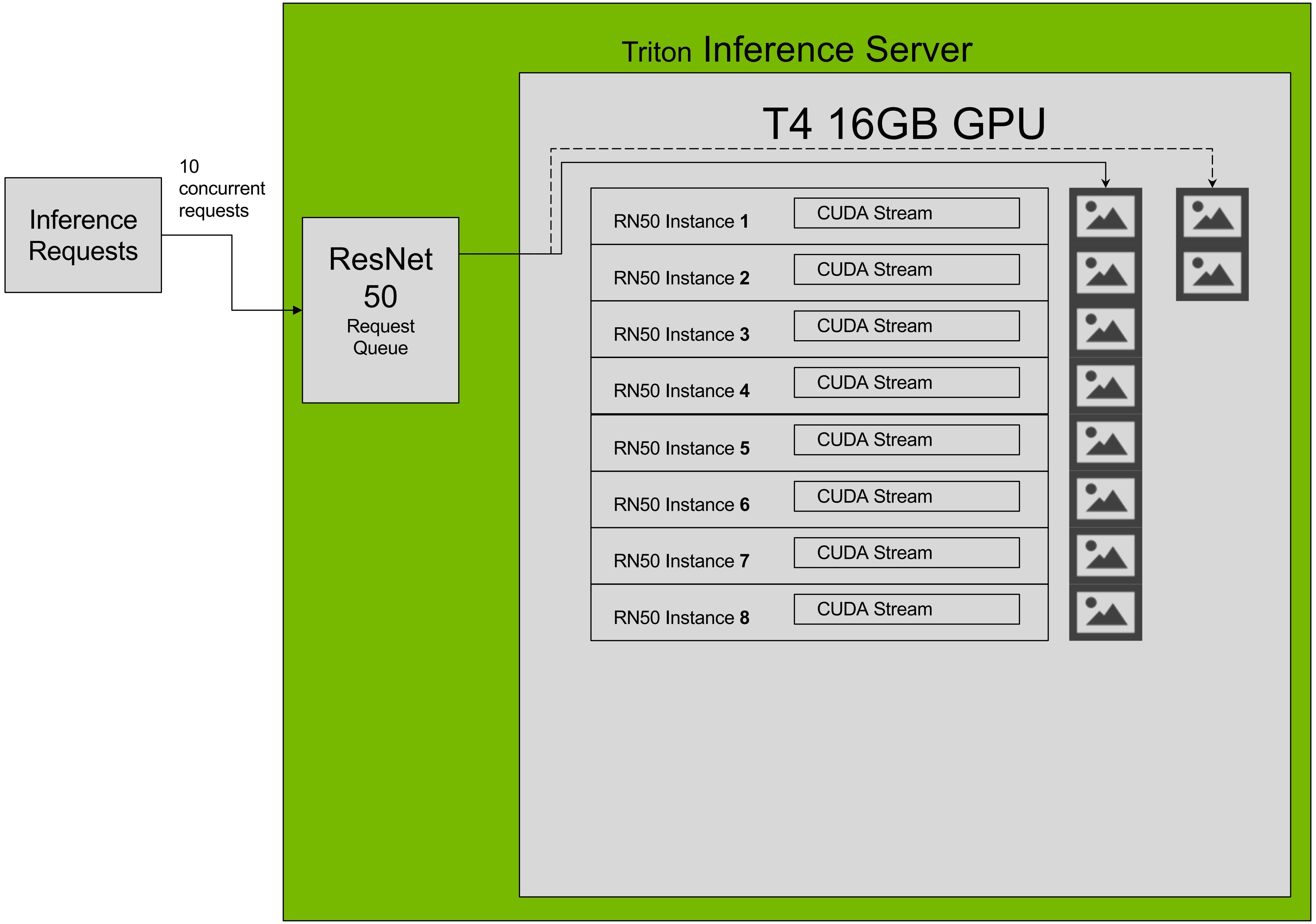
CONCURRENT MODEL EXECUTION - RESNET 50

6x Better Performance and Improved GPU Utilization Through Multiple Model Concurrency

Common Scenario 1

One API using multiple copies of the same model on a GPU

Example: 8 instances of TRT FP16 ResNet50 (each model takes 2 GB GPU memory) are loaded onto the GPU and can run concurrently on a 16GB T4 GPU.
10 concurrent inference requests happen: each model instance fulfills one request simultaneously and 2 are queued in the per-model scheduler queues in Triton Inference Server to execute after the 8 requests finish. With this configuration, 2680 inferences per second at 152 ms with batch size 8 on each inference server instance is achieved.



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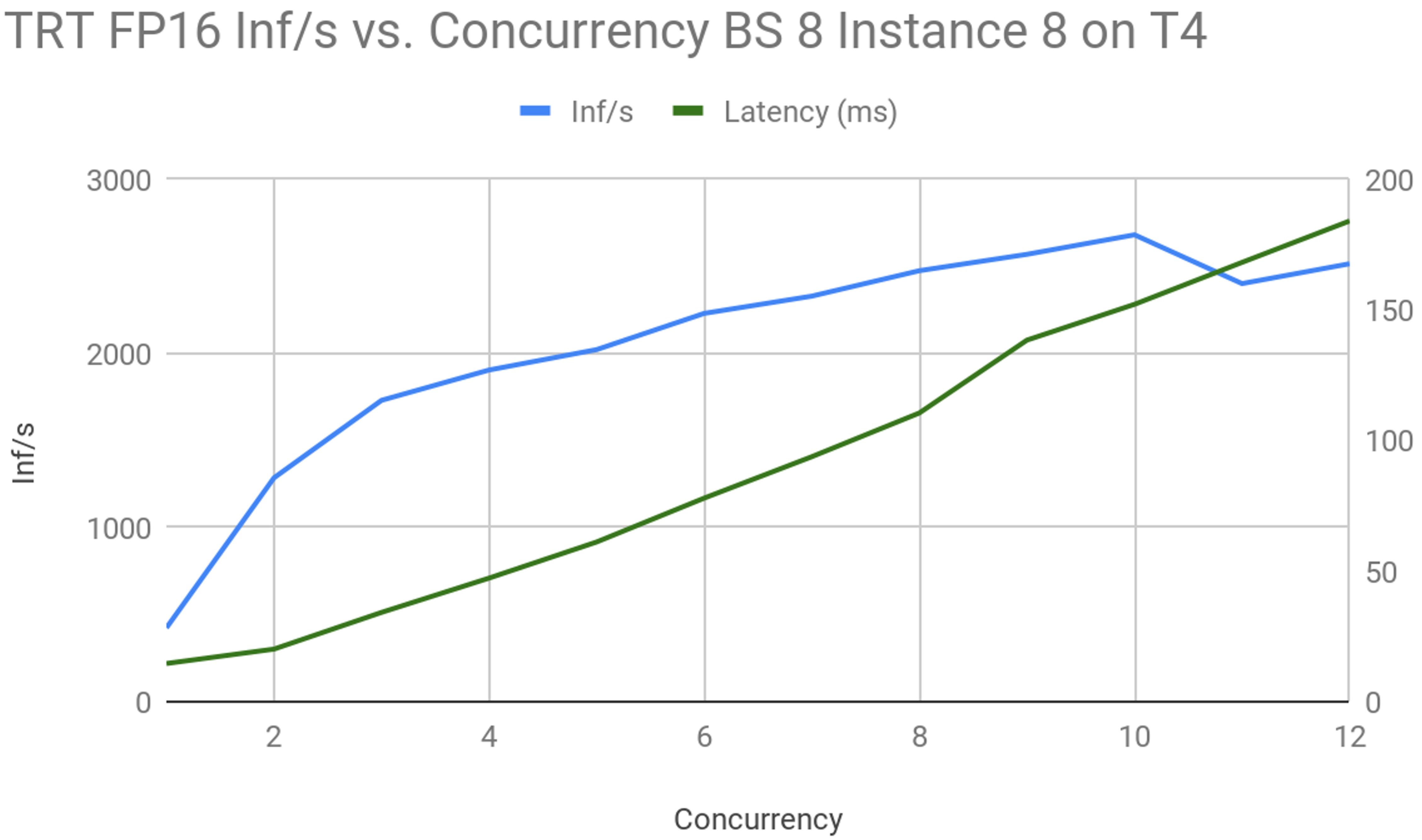
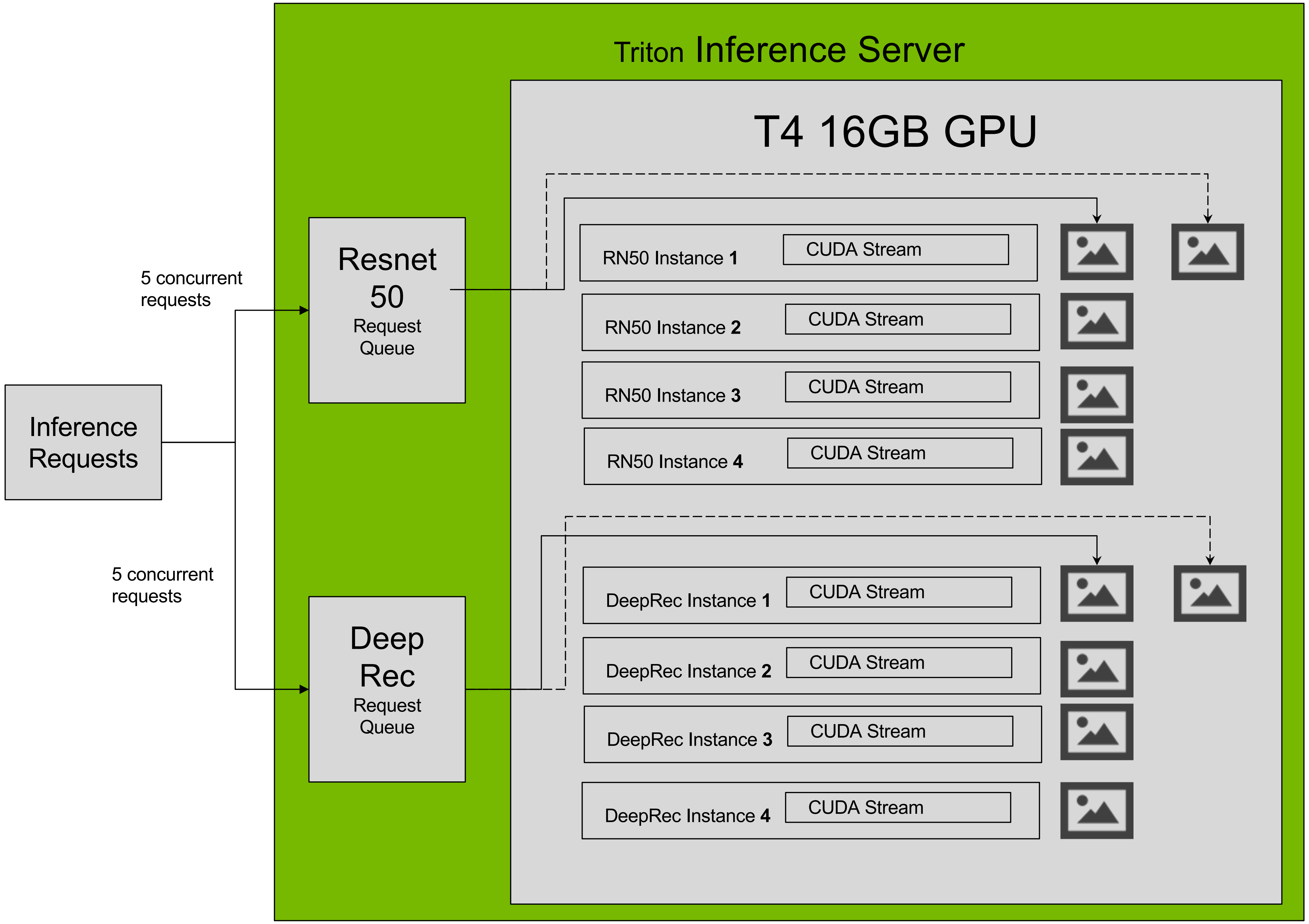


CONCURRENT MODEL EXECUTION RESNET 50 & DEEP RECOMMENDER

Common Scenario 2

Many APIs using multiple different models on a GPU

Example: 4 instances of TRT FP16 ResNet50 and 4 instances of TRT FP16 Deep Recommender are running concurrently on one GPU. Ten requests come in for both models at the same time (5 for each model) and fed to the appropriate model for inference. The requests are fulfilled concurrently and sent back to the user. One request is queued for each model. With this configuration, 5778 inferences per second at 80 ms with batch size 8 on each inference server instance is achieved.

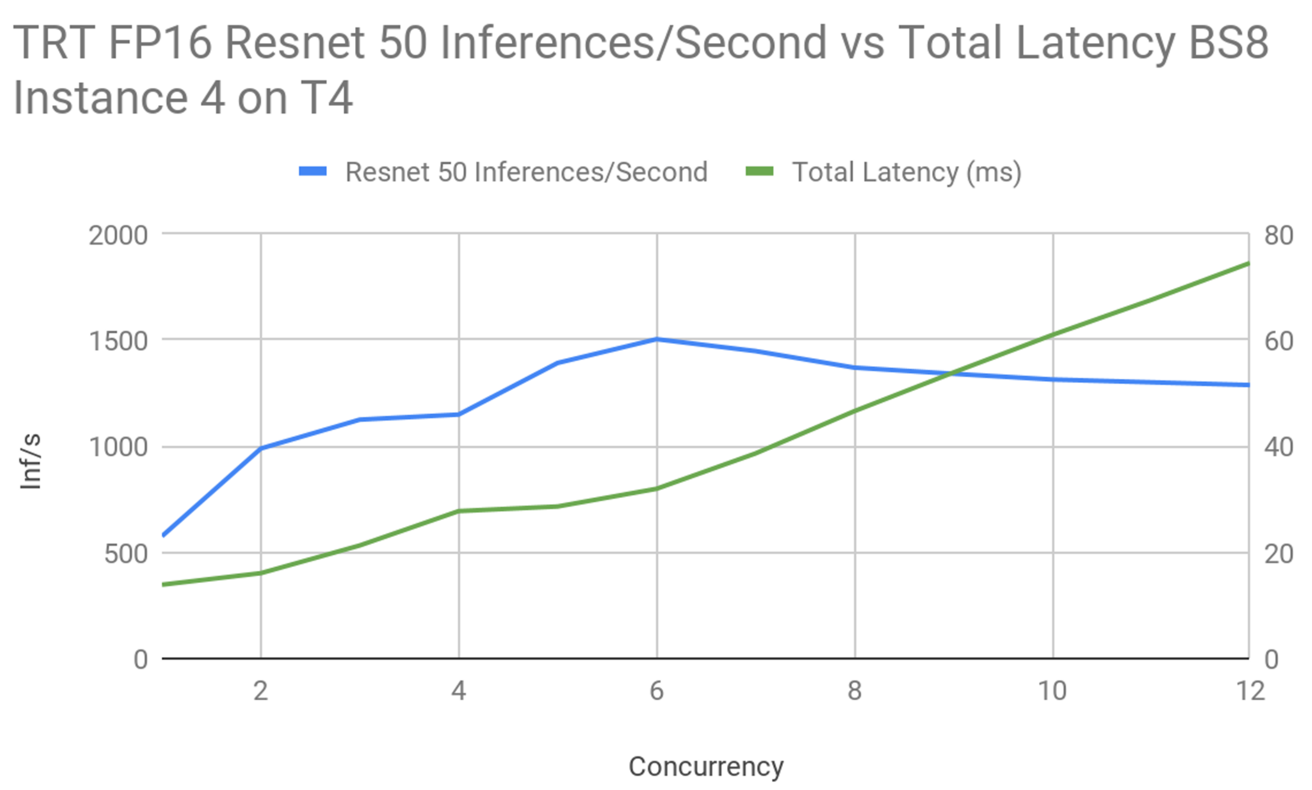


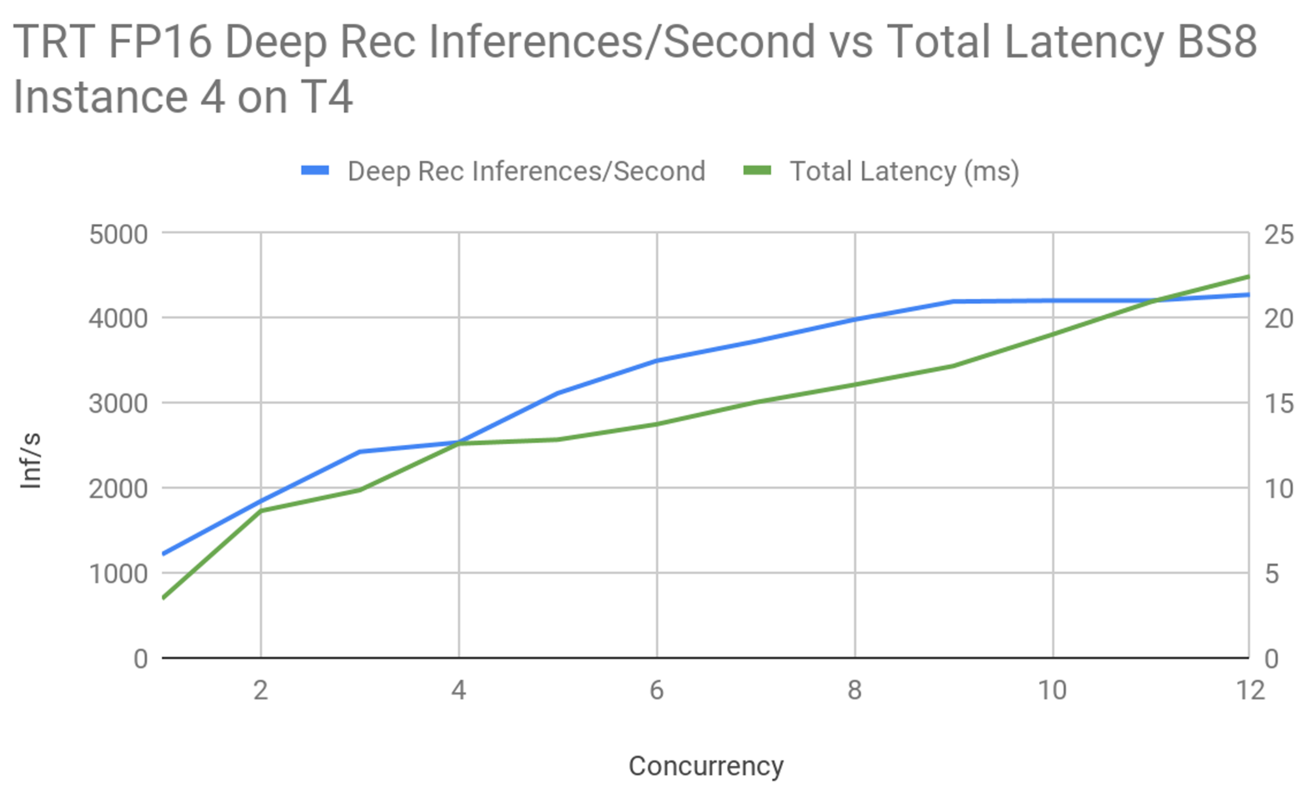
CONCURRENT MODEL EXECUTION
RESNET 50 & DEEP RECOMMENDER

Common Scenario 2

Many APIs using multiple different models on a GPU

Example: 4 instances of TRT FP16 ResNet50 and 4 instances of TRT FP16 Deep Recommender are running concurrently on one GPU. Ten requests come in for both models at the same time (5 for each model) and fed to the appropriate model for inference. The requests are fulfilled concurrently and sent back to the user. One request is queued for each model. With this configuration, 5778 inferences per second at 80 ms with batch size 8 on each inference server instance is achieved.





TRITON INFERENCE SERVER METRICS FOR AUTOSCALING

Before Triton Inference Server - 800 FPS

- One model per GPU
- Requests are steady across all models
- Utilization is low on all GPUs

Before Triton Inference Server - 5,000 FPS

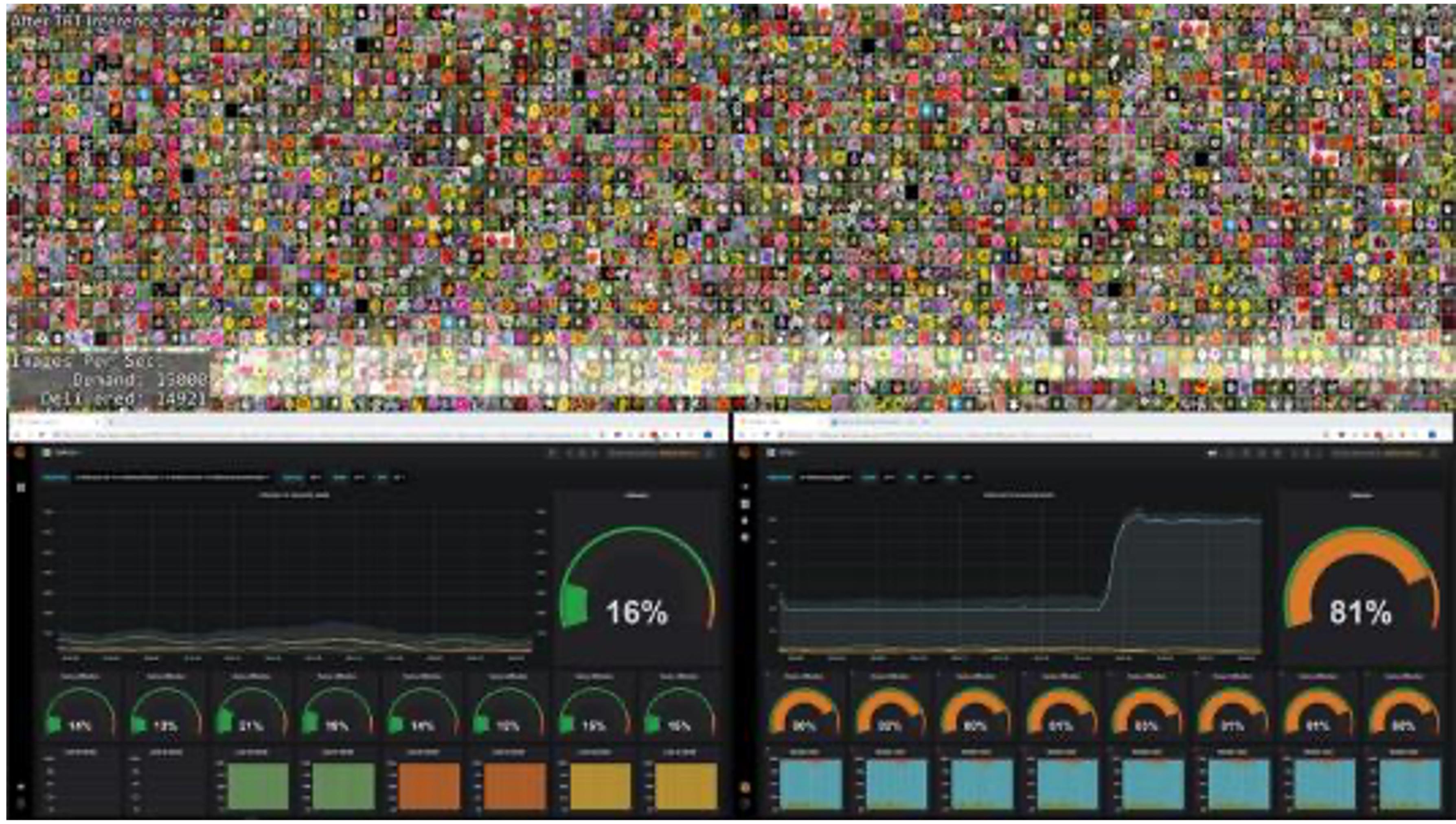
- Spike in requests for blue model
- GPUs running blue model are being fully utilized
- Other GPUs remain underutilized

TRITON INFERENCE SERVER METRICS FOR AUTOSCALING

After Triton Inference Server - 5,000 FPS

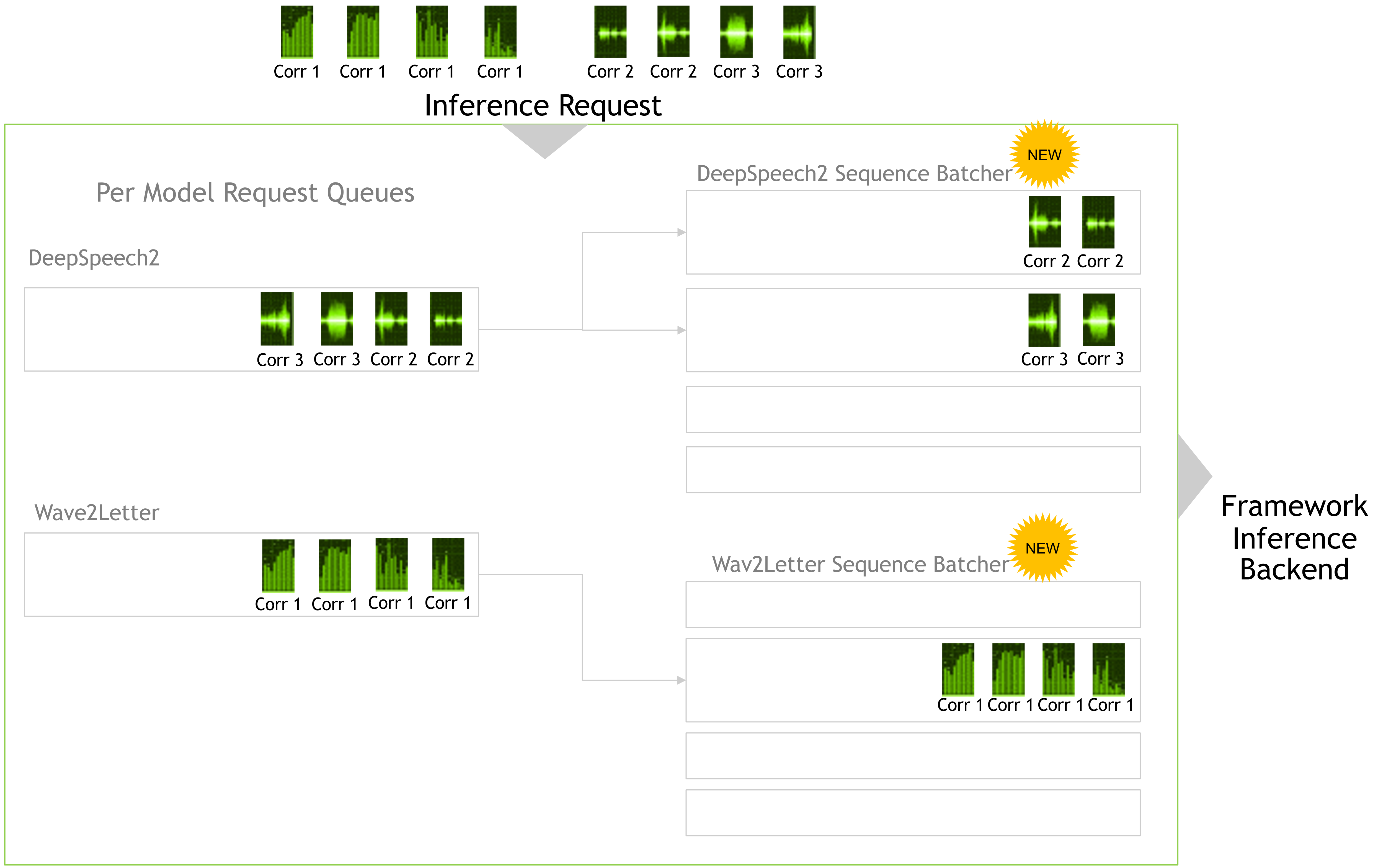
- Load multiple models on every GPU
- Load is evenly distributed between all GPUs

After Triton Inference Server - 15,000 FPS



- Spike in requests for blue model
- Each GPU can run the blue model concurrently
- Metrics to indicate time to scale up
  - GPU utilization
  - Power usage
  - Inference count
  - Queue time
  - Number of requests/sec

STREAMING INFERENCE REQUESTS



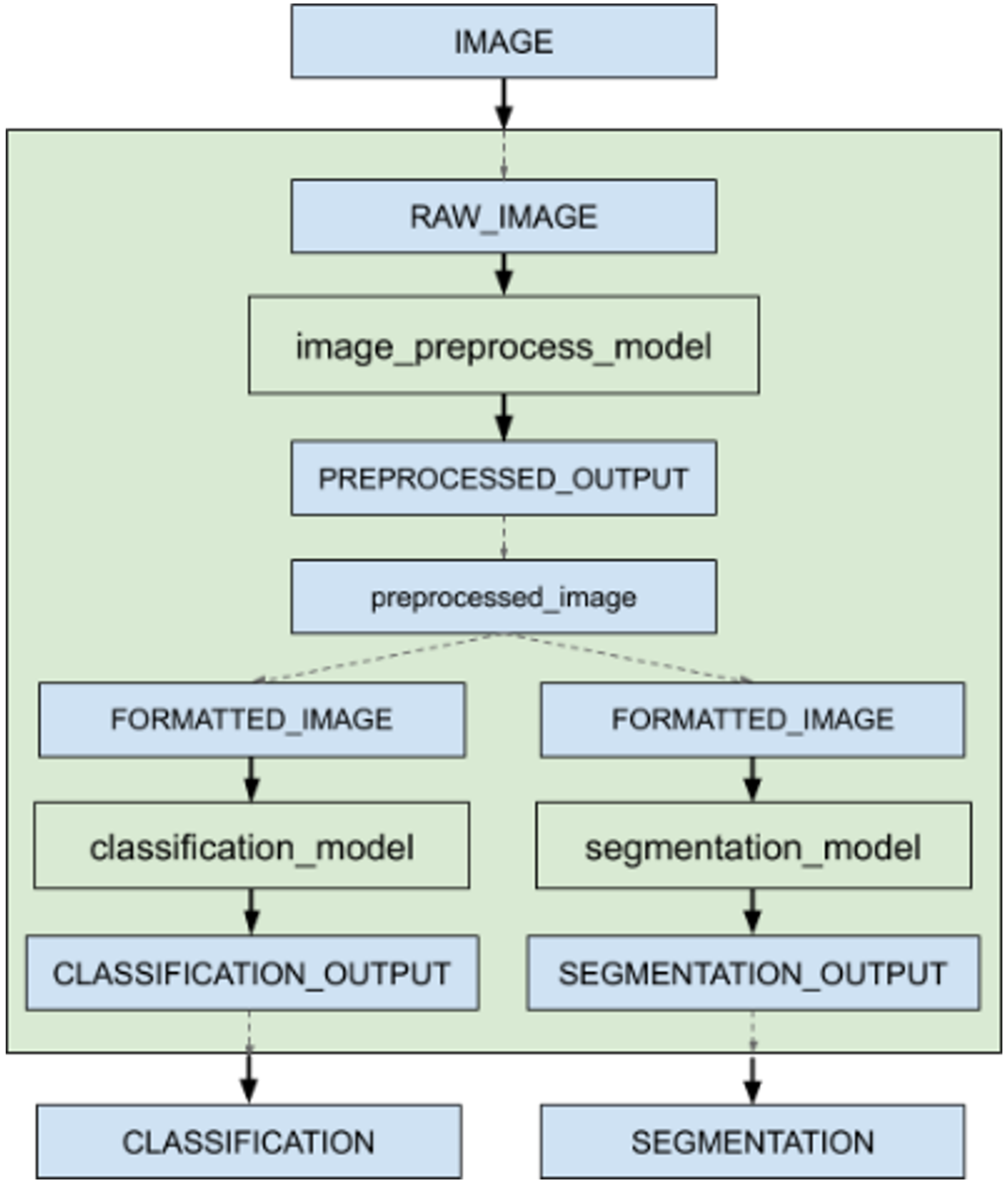
New Streaming API

Based on the correlation ID, the audio requests are sent to the appropriate batch slot in the sequence batcher*

*Correct order of requests is assumed at entry into the endpoint
Note: Corr = Correlation ID

MODEL ENSEMBLING

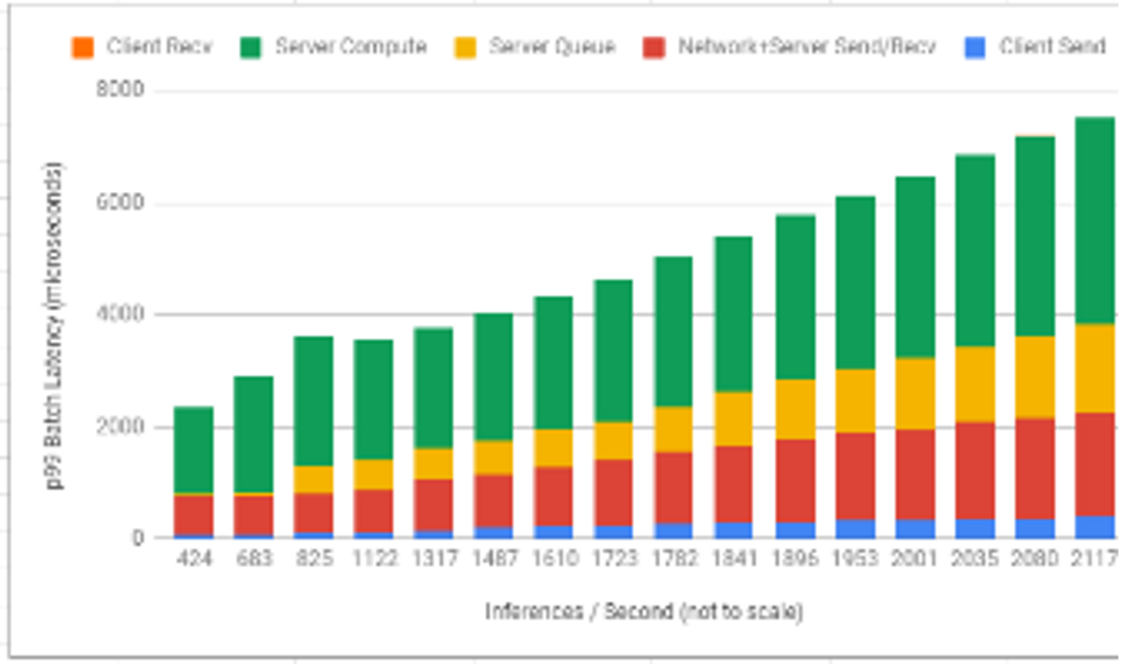
- Pipeline of one or more models and the connection of input and output tensors between those models
- Use for model stitching or data flow of multiple models such as data preprocessing → inference → data post-processing
- Collects the output tensors in each step, provides them as input tensors for other steps according to the specification
- Ensemble models will inherit the characteristics of the models involved, so the meta-data in the request header must comply with the models within the ensemble



perf_client TOOL

- Measures throughput (inf/s) and latency under varying client loads
- **perf_client** Modes
  1. Specify how many concurrent outstanding requests and it will find a stable latency and throughput for that level
  2. Generate throughput vs latency curve by increasing the request concurrency until a specific latency or concurrency limit is reached
- Generates a file containing CSV output of the results
- Easy steps to help visualize the throughput vs latency tradeoffs

	p99 Batch Latency (microseconds)					
	Client Send	Network+Server Send/Recv	Server Queue	Server Compute	Client Recv	Total
24	75	689	51	1522	6	2343
83	91	696	42	2076	7	2912
25	104	706	508	2293	7	3618
22	126	755	522	2140	7	3550
17	156	909	548	2158	7	3778
87	194	969	601	2247	7	4018
10	224	1060	690	2357	7	4328
23	248	1141	723	2505	7	4624
82	272	1290	797	2668	7	5034
41	289	1352	987	2781	7	5416
96	302	1467	1093	2922	7	5791
53	327	1688	1135	3073	8	6131
01	334	1619	1271	3252	8	6484
35	362	1723	1350	3419	8	6862
80	374	1782	1461	3565	8	7190
17	383	1874	1560	3710	8	7535

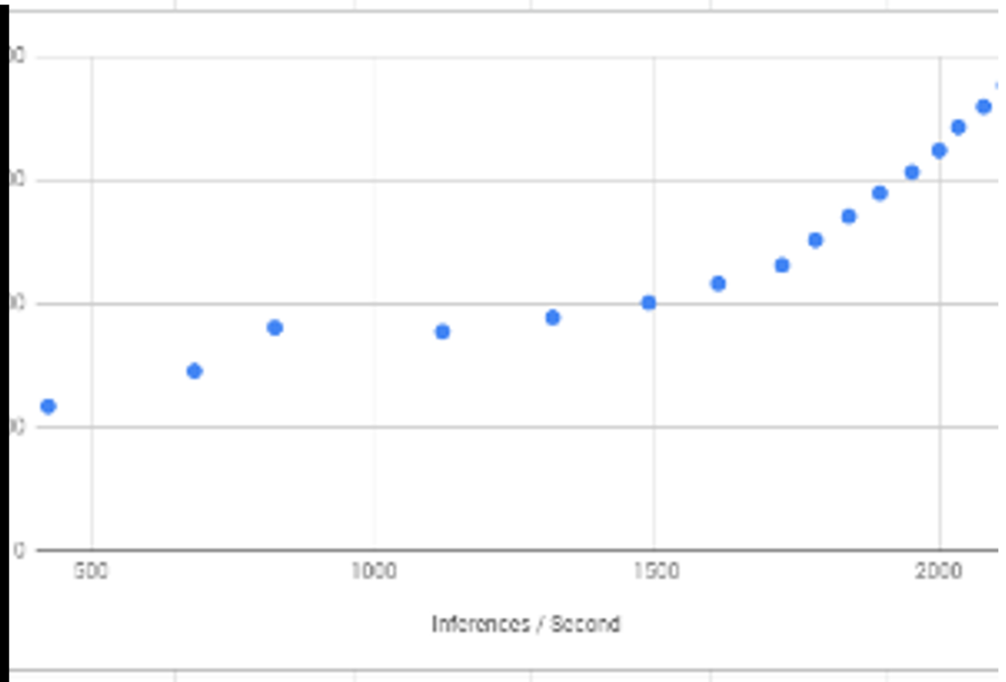



```
    Request count: 2187
    Throughput: 729 infer/sec
    Avg latency: 2728 usec (standard deviation 162 usec)
    Avg gRPC time: 2687 usec (marshal 89 usec + response wait 2591 usec + unmarshal 7 usec)
  Server:
    Request count: 2623
    Avg request latency: 1970 usec (overhead 18 usec + queue 38 usec + compute 1914 usec)

Request concurrency: 3
  Pass [1] throughput: 861 infer/sec. Avg latency: 3471 usec (std 1479 usec)
  Pass [2] throughput: 861 infer/sec. Avg latency: 3467 usec (std 1312 usec)
  Pass [3] throughput: 861 infer/sec. Avg latency: 3468 usec (std 1446 usec)
  Client:
    Request count: 2585
    Throughput: 861 infer/sec
    Avg latency: 3468 usec (standard deviation 1446 usec)
    Avg gRPC time: 3440 usec (marshal 98 usec + response wait 3335 usec + unmarshal 7 usec)
  Server:
    Request count: 3093
    Avg request latency: 2701 usec (overhead 16 usec + queue 484 usec + compute 2201 usec)

Request concurrency: 4
  Pass [1] throughput: 918 infer/sec. Avg latency: 4342 usec (std 1251 usec)
  Pass [2] throughput: 894 infer/sec. Avg latency: 4459 usec (std 1392 usec)
  Pass [3] throughput: 909 infer/sec. Avg latency: 4384 usec (std 1271 usec)
  Client:
    Request count: 2728
    Throughput: 909 infer/sec
    Avg latency: 4383 usec (standard deviation 1271 usec)
    Avg gRPC time: 4355 usec (marshal 118 usec + response wait 4230 usec + unmarshal 7 usec)
  Server:
    Request count: 3267
    Avg request latency: 3587 usec (overhead 15 usec + queue 1376 usec + compute 2196 usec)

Inferences/Second vs. Client Average Batch Latency
Concurrency: 1, 418 infer/sec, latency 2376 usec
Concurrency: 2, 729 infer/sec, latency 2728 usec
Concurrency: 3, 861 infer/sec, latency 3468 usec
Concurrency: 4, 909 infer/sec, latency 4383 usec
```



ALL CPU WORKLOADS SUPPORTED

Deploy the CPU workloads used today and benefit from Triton Inference Server features (TRT not required)

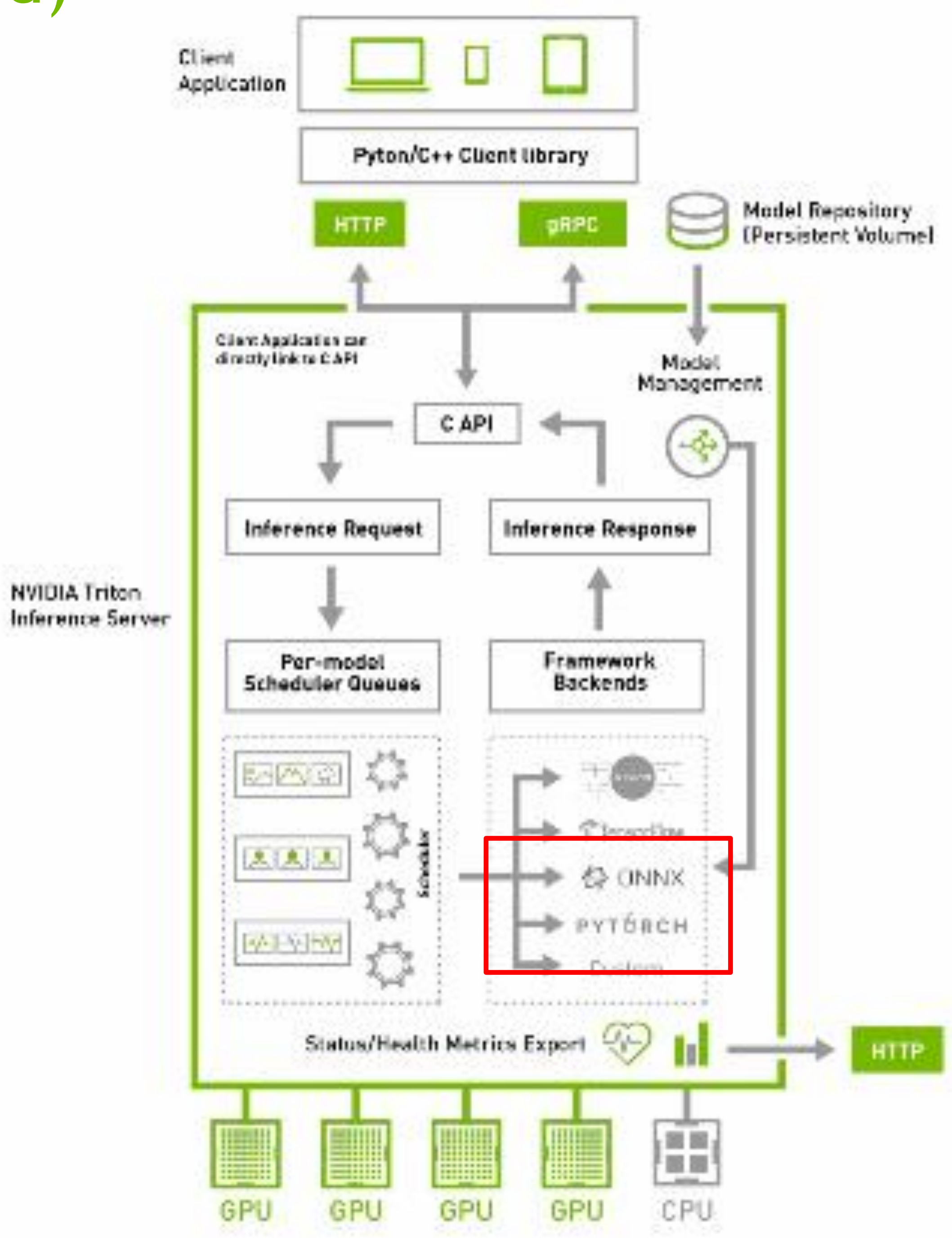
Triton relies on framework backends (Tensorflow, Caffe2, PyTorch) to execute the inference request on CPU

Support for Tensorflow and Caffe2 CPU optimizations using Intel MKL-DNN library

Allows frameworks backends to make use of multiple CPUs and cores

Benefit from features:

- Multiple Model Framework Support
- Dynamic batching
- Custom backend
- Model Ensembling
- Audio Streaming API



TRITON INFERENCE SERVER COLLABORATION WITH KUBEFLOW

What is Kubeflow?

- Open-source project to make ML workflows on Kubernetes simple, portable, and scalable
- Customizable scripts and configuration files to deploy containers on their chosen environment

Problems it solves

- Easily set up an ML stack/pipeline that can fit into the majority of enterprise datacenter and multi-cloud environments

How it helps Triton Inference Server

- Triton Inference Server is deployed as a component inside of a production workflow to
  - Optimize GPU performance
  - Enable auto-scaling, traffic load balancing, and redundancy/failover via metrics

For a more detailed explanation and step-by-step guidance for this collaboration, refer to this GitHub repo.

TRITON INFERENCE SERVER HELM CHART

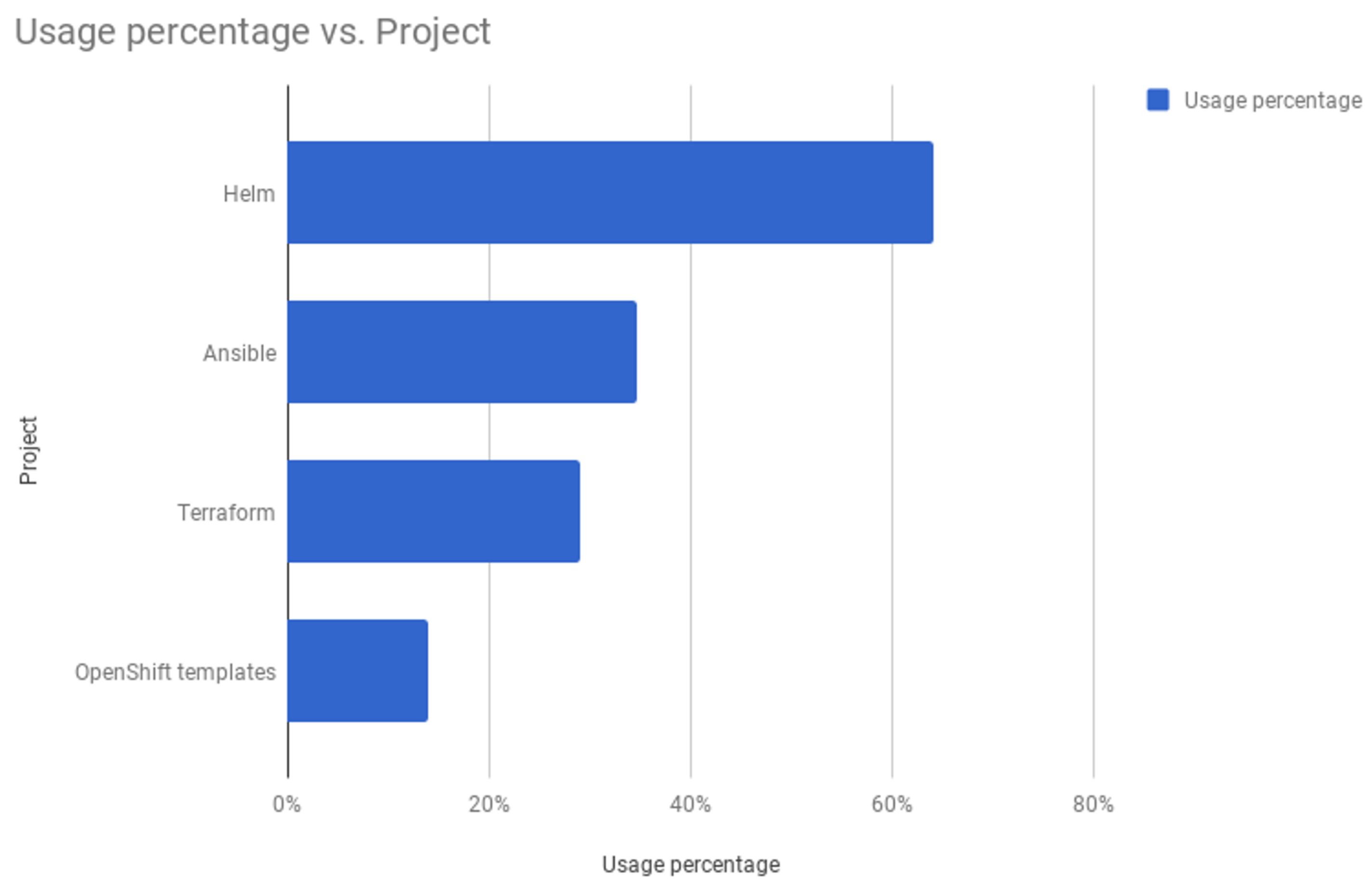
Simple helm chart for installing a single instance of the NVIDIA Triton Inference Server

Helm: Most used “package manager” for Kubernetes

We built a simple chart (“package”) for the Triton Inference Server.

You can use it to easily deploy an instance of the server. It can also be easily configured to point to a different image, model store, …

https://github.com/NVIDIA/tensorrt-inference-server/tree/b6b45ead074d57e3d18703b7c0273672c5e92893/deploy/single_server



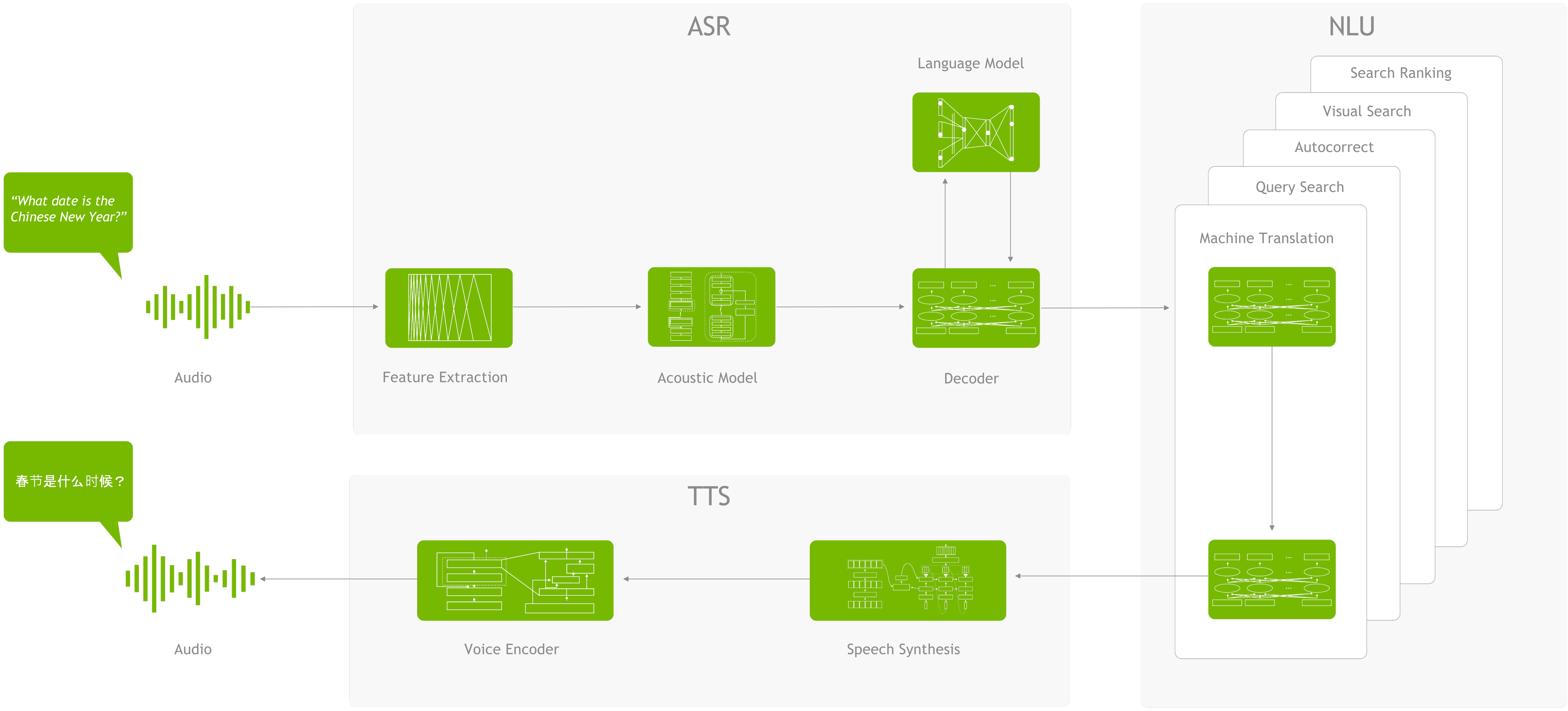
Part 3: Production Deployment

- Lecture
  - Model Selection
  - Post-Training Optimization
  - Product Quantization
  - Knowledge Distillation
  - Model Code Efficiency
  - Model Serving
  - Building the Application
- Lab
  - Exporting the Model
  - Hosting the Model
  - Server Performance
  - Using the Model

APPLICATION != SINGLE MODEL

THE APPLICATION

Typically composed of many components



RIVA

NVIDIA RIVA

Fully Accelerated Framework for Multimodal Conversational AI Services

Riva

Dialog Manager

Multi-Speaker Transcription | Chatbot | Gesture Recognition | Look to Talk

NLU

Vision

Speech

TRITON INFERENCE SERVER

NVIDIA GPU CLOUD → NVIDIA AI TOOLKIT (Transfer Learning, NeMo, Service Maker) → Riva

video

audio

Multi-Speaker Transcription

JESSICA: What will you have ready for Wednesday?

DOUGLAS: I expect to have early designs of the packaging.

JESSICA: Great.

End-to-End Multimodal Conversational AI Services

Pre-trained SOTA models-100,000 Hours of DGX

Retrain with NeMo

Interactive Response – 150ms on A100 versus 25sec on CPU

Deploy Services with One Line of Code

PRETRAINED MODELS AND AI TOOLKIT

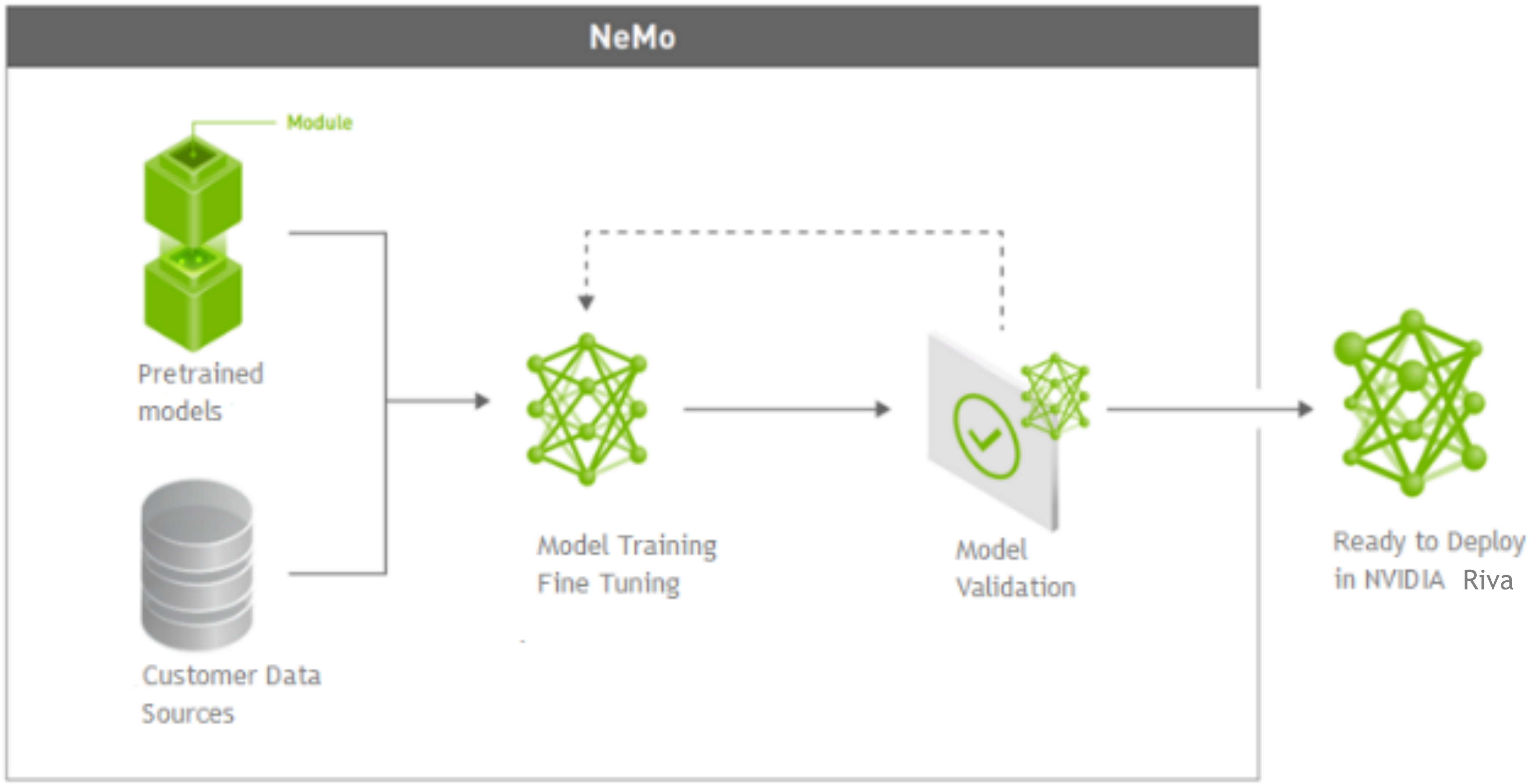
Train SOTA Models on Your Data to Understand your Domain and Jargon

100+ pretrained models in NGC

SOTA models trained over 100,000 hours on NVIDIA DGX™

Retrain for your domain using NeMo & TAO Toolkit

Deploy trained models to real-time services using Helm charts



MULTIMODAL SKILLS

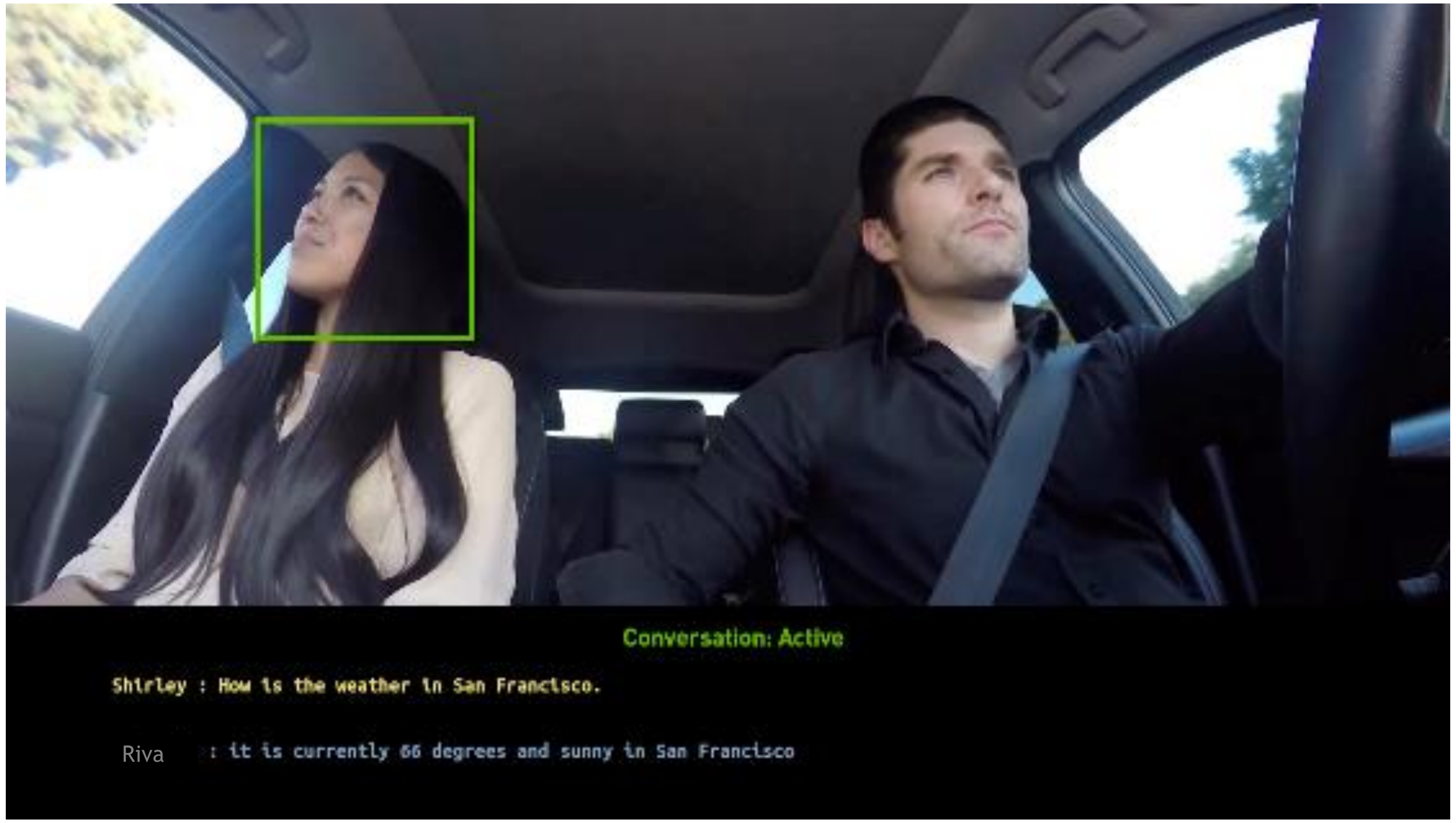
Use speech and vision for natural interaction

Build new skills by fusing services for ASR, NLU, TTS, and CV

Reference skills include:

- Multi-speaker transcription
- Chatbot
- Look-to-talk

Dialog manager manages multi-user and multi-context scenarios



Multimodal application with multiple users and contexts

BUILD CONVERSATIONAL AI SERVICES

Optimized Services for Real Time Applications

Build applications easily by connecting performance tuned services

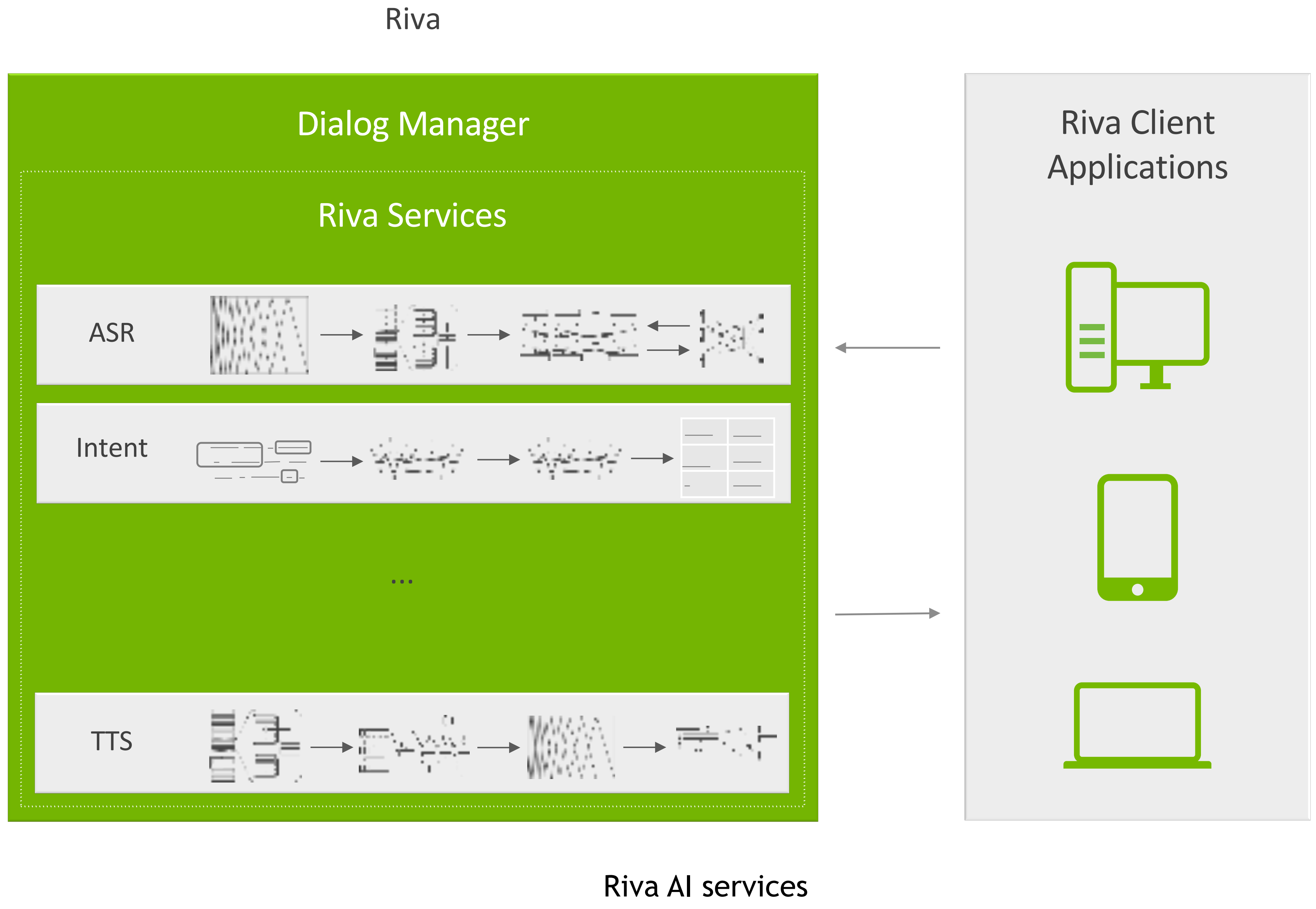
Task specific services include:

- ASR
- Intent Classification
- Slot Filling
- Pose Estimation
- Facial Landmark Detection

Services for streaming & batch usage

Build new services from any model in ONNX format

Access services for gRPC and HTTP endpoints



https://ngc.nvidia.com/catalog/model-scripts/nvidia:jasper_for_trtis

DEPLOY MODELS AS REAL-TIME SERVICES

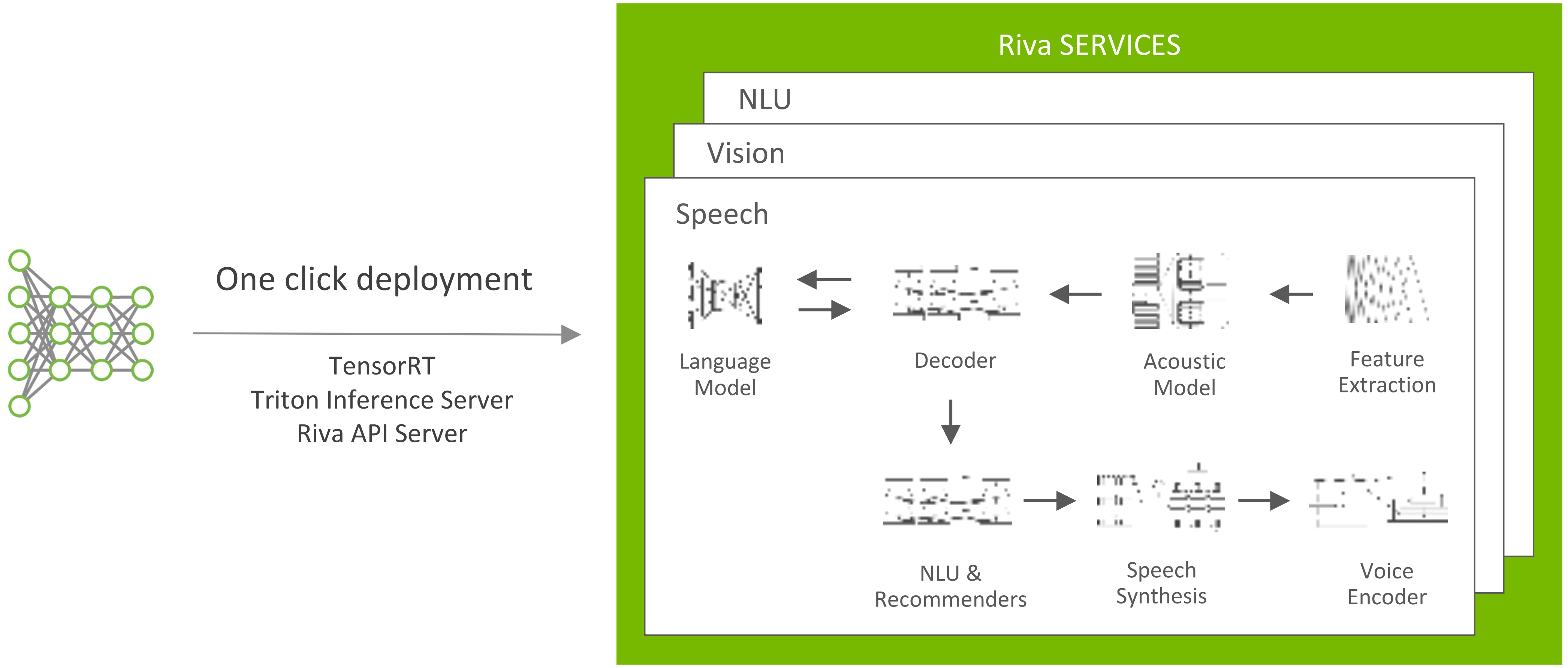
One Click to Create High-Performance Services from SOTA Models

Deploy models to services in the cloud, data center, and at the edge

Single command to set up and run the entire Riva application

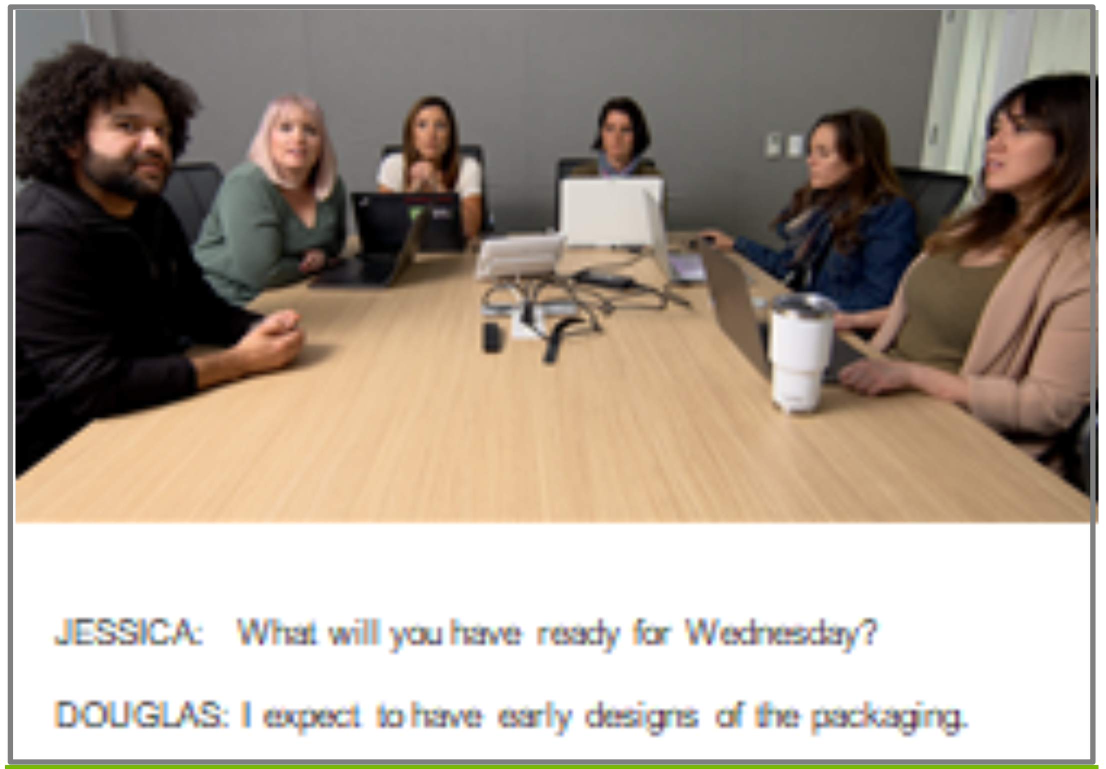
through Helm charts on Kubernetes cluster

Customization of Helm charts for your setup and use case.



Helm command to deploy models to production

RIVA SAMPLES

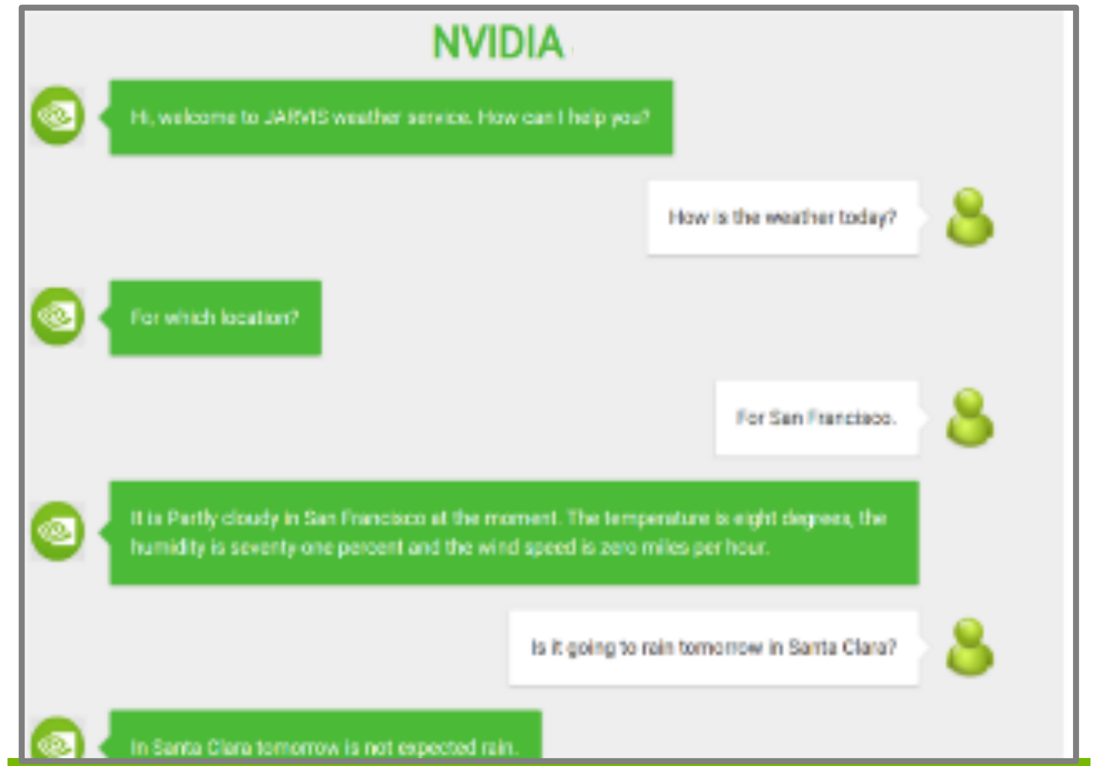


Visual Diarization

Transcribe multi-user multi-context conversations

Look To Talk

Wait for gaze before triggering AI assistant



Virtual Assistant

End-to-end conversational AI system

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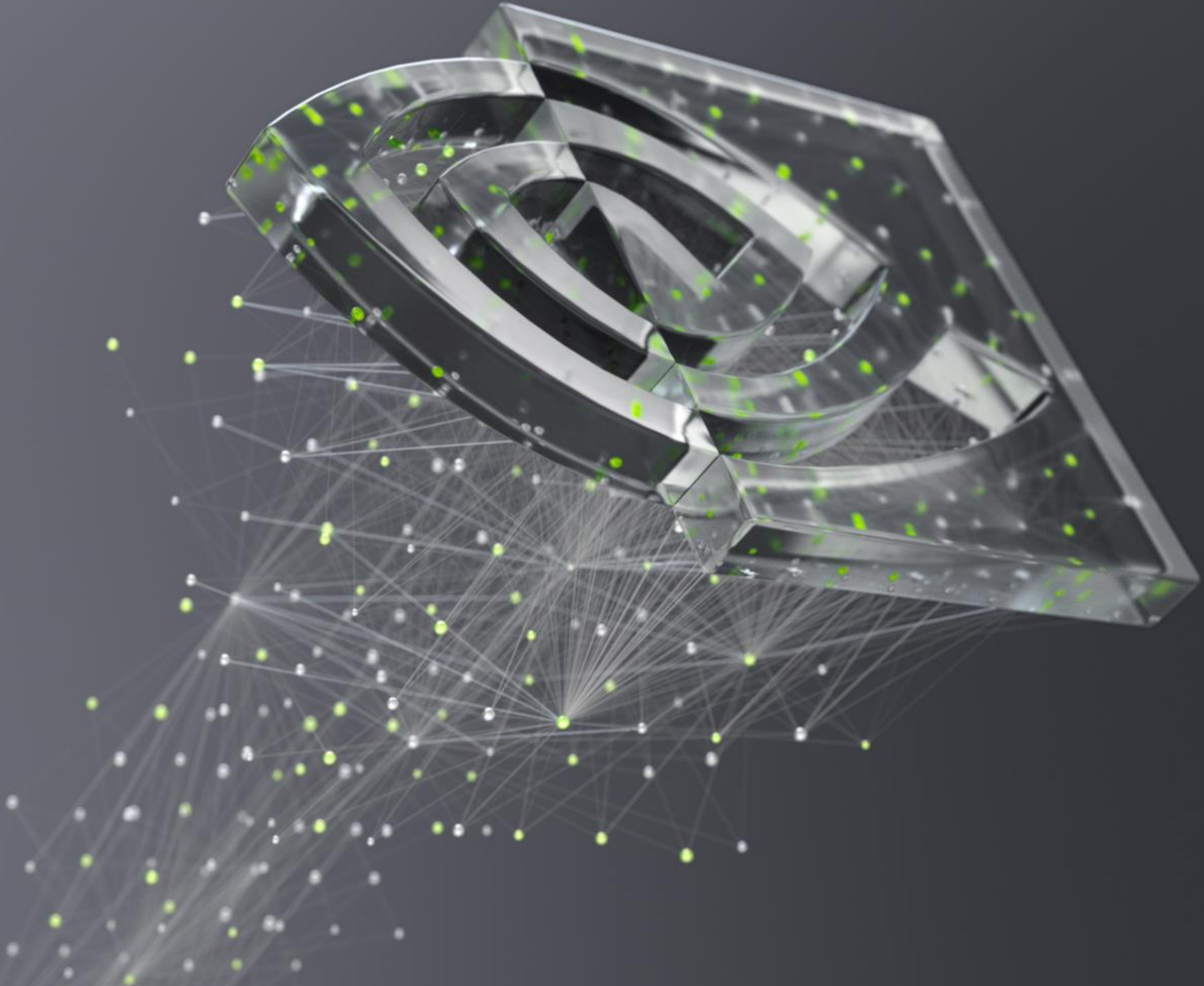

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