Optimizing LLMs

Start-to-finish LLM training

Shaan Khosla

Senior Data Scientist and Researcher

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My name is **Shaan Khosla**

- Senior Data Scientist
- Various research with LLMs, topic models, and legal NLP
- MS in Data Science, New York University
- Writer of *Let's Talk Text* newsletter

NYU DATA SCIENCE

Let's Talk Text

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Optimizing LLMs

Code:
github.com/shaankhosla/optimizingllms

Follow-up with me:
linkedin.com/in/shaan-khosla

shaankhosla.substack.com **for email newsletter**

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ODSC: NLP with GPT-4 and other LLMs

Massive thanks to Jon Krohn:

- Slides
- Code
- Website

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Poll

What is your current level of experience with LLMs?

- Only used ChatGPT or OpenAI APIs
- Fine-tuned a smaller model, like a RoBERTA classification model, on a small dataset with one GPU
- Fine-tuned a large model, like LLaMA, with multiple GPUs and helped productionize it

Poll

What part of the talk are you most looking forward to?

- Hands-on coding walkthroughs
- Data augmentation techniques
- How to handle large datasets
- Fine-tuning optimizations
- Multi-GPU training tips
- More pictures of Mila

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Schedule

1. Introduction to Large Language Models (35 mins)
2. Q&A (5 mins) & Break (5 mins)
3. Single GPU Training Techniques (60 mins)
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6. Summary and Q&A (20 mins)

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How machines read

Word tokenization

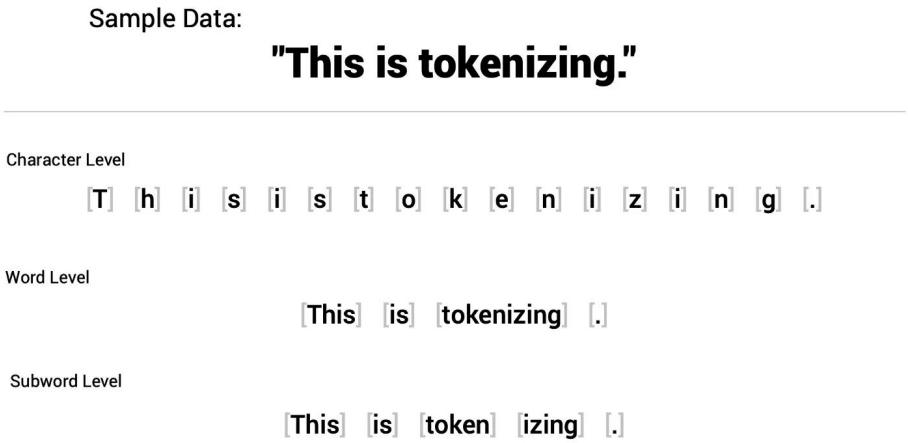
- Large vocabulary size
- Unknown words lose meaning

Character tokenization

- Characters lack meaning
- Large number of tokens required represent text

Subword tokenization

- Byte-pair encoding
- Start with character level tokenization
- Recursively merge tokens together based on frequency of co-occurrence



Hands-on code demo:
Tokenization.ipynb

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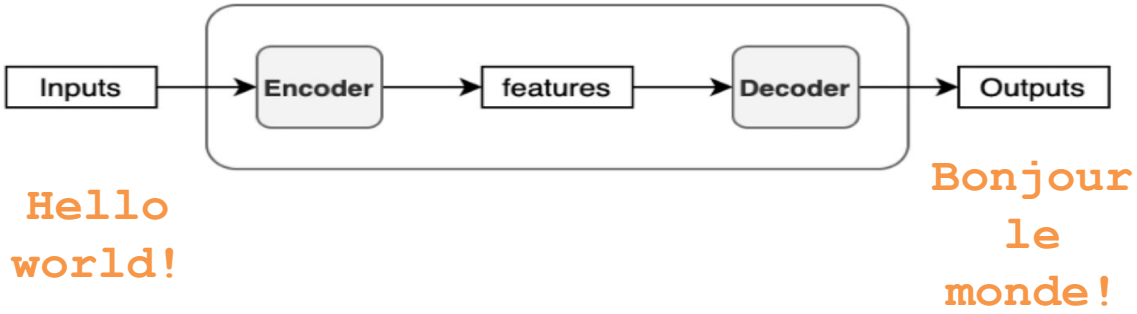
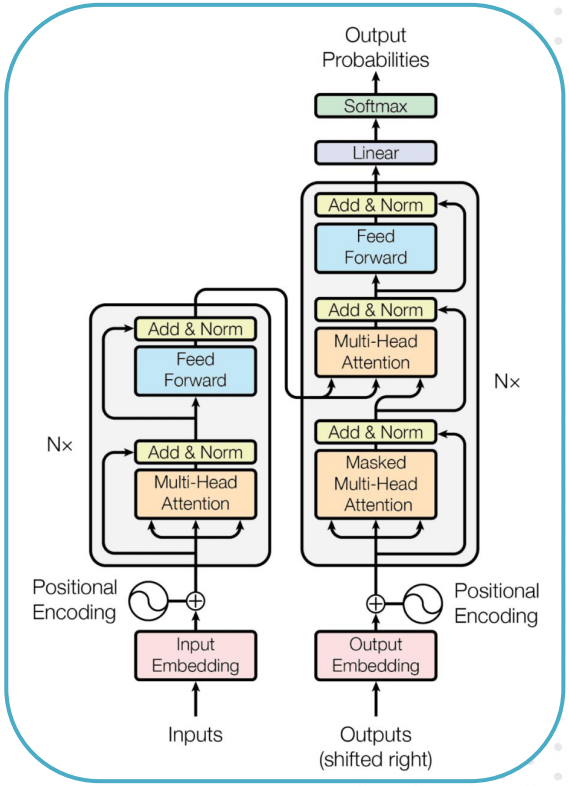
Overview of pre-trained language models

- History
  - Bag of Words
  - TF-IDF
  - Topic models such as LDA
  - Word2Vec, GloVe
  - RNNs, LSTMs, GRUs
- Attention Is All You Need (Vaswani et al., 2017)





Source: The Illustrated Transformer

Hands-on code demo:
GPT4All-inference.ipynb

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Autoregressive vs. autoencoding

Autoregressive

- **“After practice she went to the ___”**
- Typically used in text-generation tasks
  - Summarization, question answering, translation
- Similar to doing a live freestyle rap

Autoencoding

- **“Steve loved his previous ____, he had a great team and ___ his work.”**
  - Sentiment analysis, classification, semantic search
- Reconstruct original data from corrupted input

Autoregressive vs. autoencoding pt.2

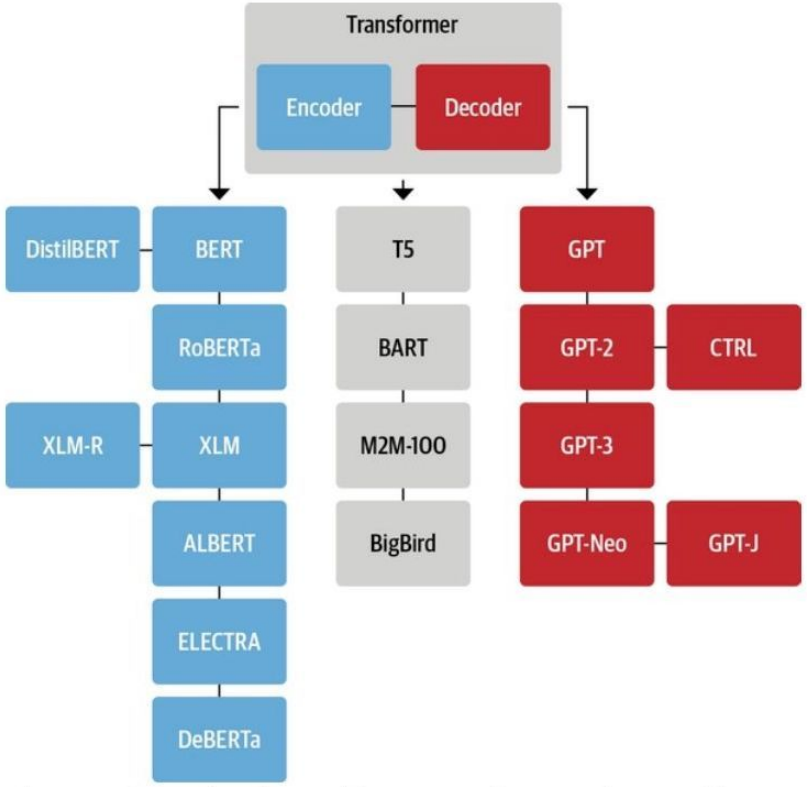


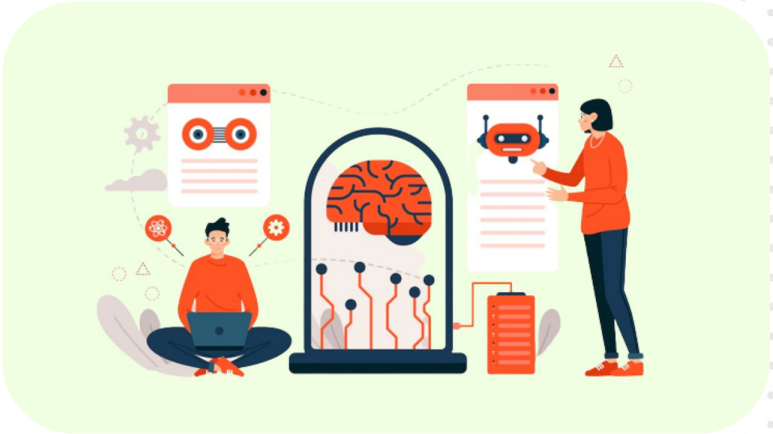
Figure 3-8. An overview of some of the most prominent transformer architectures

- Unsupervised training lets us train on large quantities of text data and the learning is arbitrarily defined
- The same architecture can be used for autoregressive and autoencoding models

Source: Aman

Ways to use LLMs

1. Use a pre-trained model without any fine-tuning
   - Use BERT to generate embeddings and creating a semantic search engine
2. Fine-tune a model to accomplish a specific task
   - Fine-tune GPT-2 to summarize letters to shareholder financial documents
3. Prompting:
   - Use GitHub co-pilot to generate code
   - ChatGPT

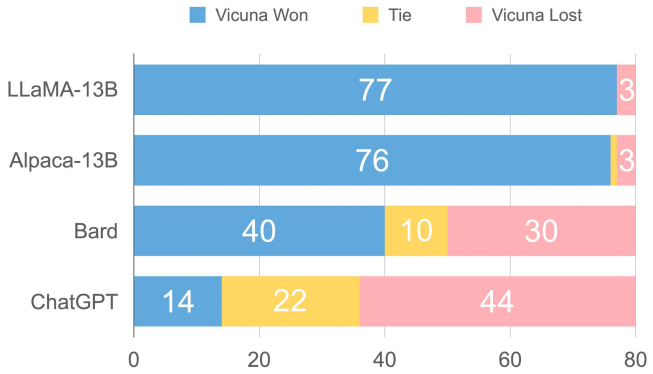


Key libraries

- 🤗 **Transformers**
  - Many, many open-source LLMs ready to go
  - Task-ready code that works easily with pre-trained models
  - Easy inference
  - Automatic optimizations
- **PyTorch Lightning**
  - Simplifies model training, yet enables flexibility
  - Easy distributed training
  - Easy to restructure code into Lightning Module
  - Automatic optimizations
  - Works easily with HuggingFace models
- **DeepSpeed**
  - Deep learning optimization library from Microsoft
  - Enables training and inference of billions/trillions of parameters

Latest Open-Source LLMs

- LLaMA: 65-billion parameter LLM from Meta
- Alpaca: LLaMA 7B fine-tuned on 52k GPT-3.5
- Vicuna: 70k ShareGPT convos
- Dolly 2.0: Commercial use allowed
- Falcon 40B: ranked #1 on HuggingFace LLM leaderboard
- LongNet: Transformer with 1,000,000,000 tokens
- LLaMA 2: 40% more data and double the context length of LLaMA
- Mistral: Less prone to hallucination
- Gemma: Commercial use, 2b model, outperforms



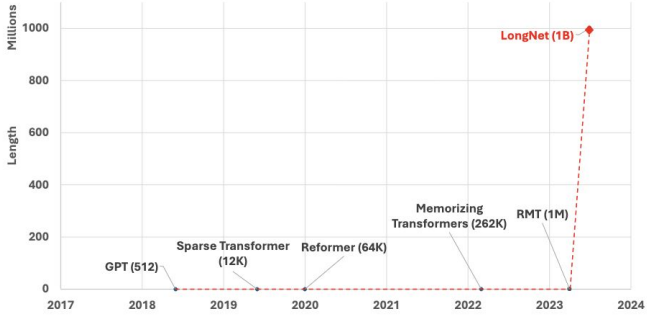


Figure 1: Trend of Transformer sequence lengths over time.

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Data Augmentation Using LLMs

- Back translation with translation models

- Synonym replacement using [MASK]

- Text generation with generative models

If only to avoid making this type of film in the future. This film is interesting as an experiment but tells no cogent plot or any other interesting story.

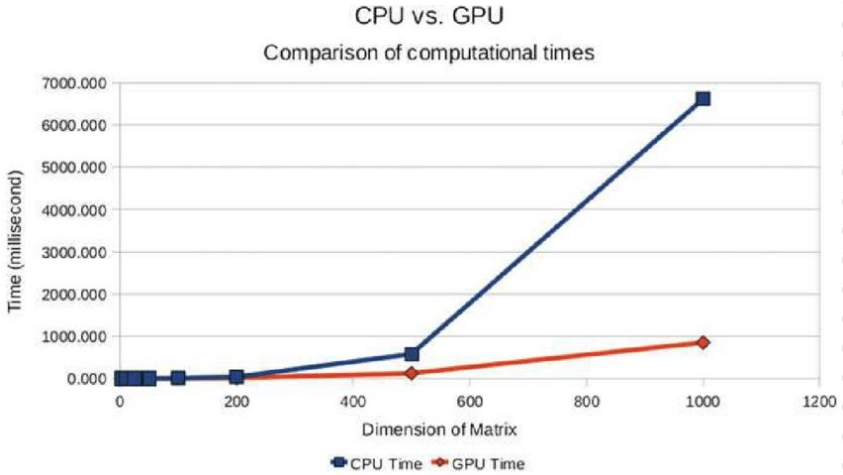
Overall, this is an entertaining film but is in most cases not good.

Source: Translate Day

Hardware

Matrix multiplication chips

- CPUs
  - Useful for inference
- GPUs
  - Used for training + inference
- TPUs
  - Google Tensor Processing Unit
- AWS
  - Trainium
  - Inferentia



Source: Paper

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Managing large datasets

- GPU memory > RAM > Disk
- Can’t cache entire dataset into memory
- Data loading from disk is often the bottleneck
- PyTorch Datasets & DataLoader
  - Return a single datapoint on request
  - Handles:
    - Parallel loading using multiple workers
    - Intelligently prefetching data
    - Easily add data transformations, shuffling, batching
    - Decouples data code from modeling code

Hands-on code demo:
Streaming_Datasets.ipynb

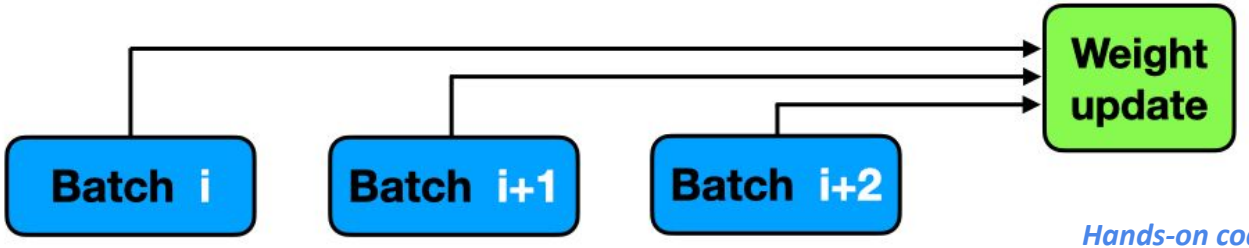
DATA PIPELINE - BEFORE & AFTER

Common pipelines runs on CPU only

Source: Arctic Wiki

Gradient Accumulation

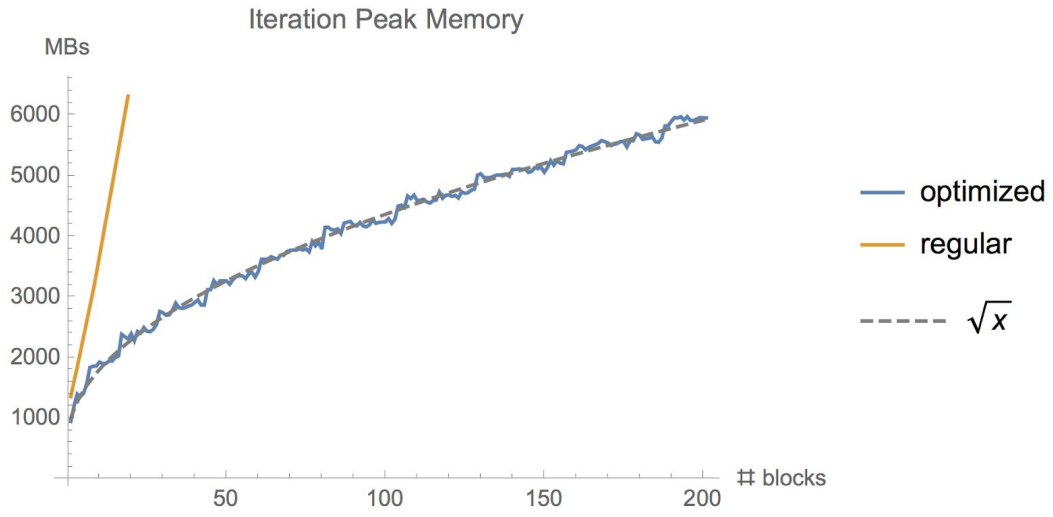
- Batch size is limited by GPU memory
- Maximize GPU usage
  - Split batch into N microbatches
  - Forward pass each microbatch and accumulate gradients over N batches
  - Perform backprop with accumulated gradients



Hands-on code demo:
Single GPU Optimizations.ipynb

Gradient Checkpointing

- Normally all the activations from the forward pass are saved to compute the gradients in the backward pass
  - Compute efficient, but memory inefficient
- Recompute nodes during backpropagation
  - Memory efficient, but increases compute



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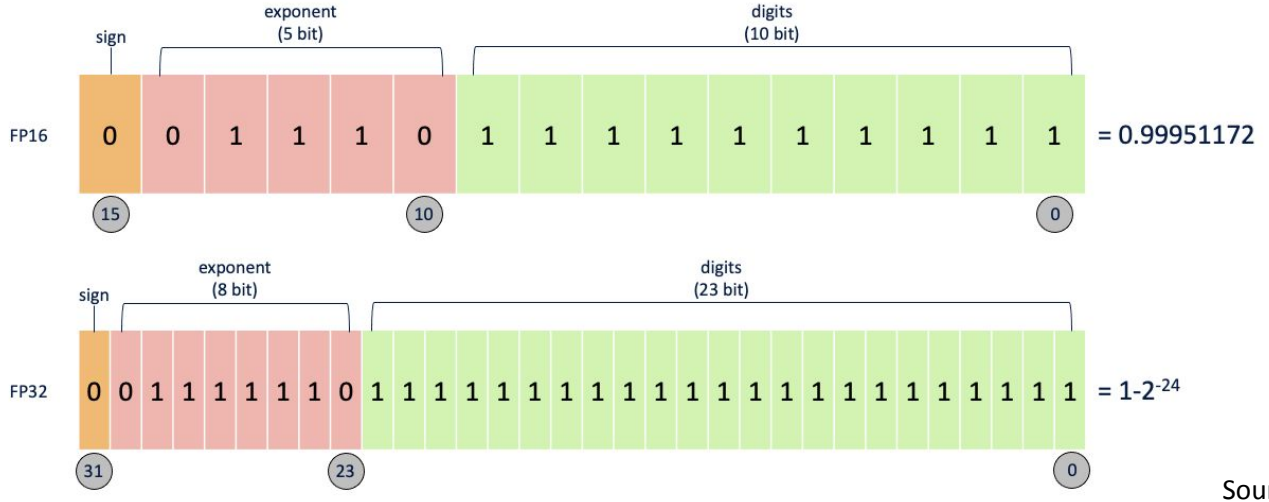
Automatic Mixed Precision

- 32-bits are typically used to store the:
  - Weights
  - Activations
  - Gradients
- Instead, use FP16 for some training values
- Makes training faster and preserves memory



Source: Jonathan Davis

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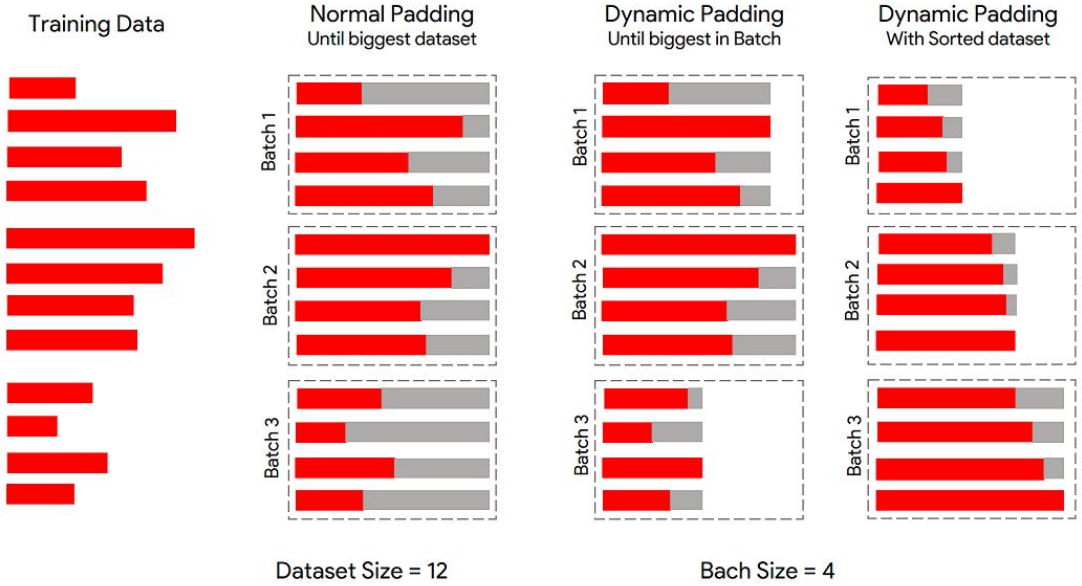
Dynamic Padding & Uniform Length Batching

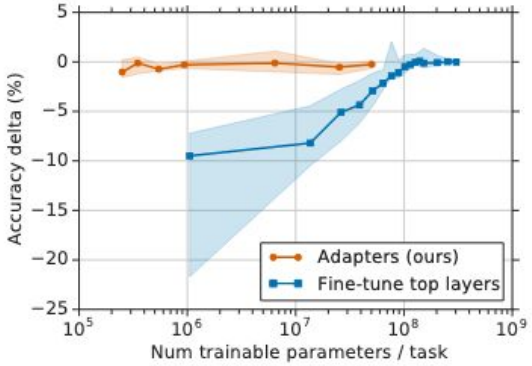
- All inputs in a batch need to be the same length
- Sequences are padded to the length of the maximum training sample
- [PAD] tokens are still included in all the operations

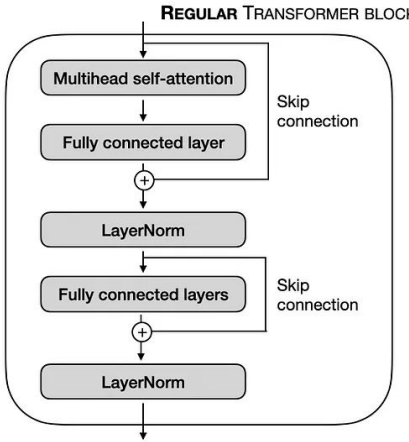


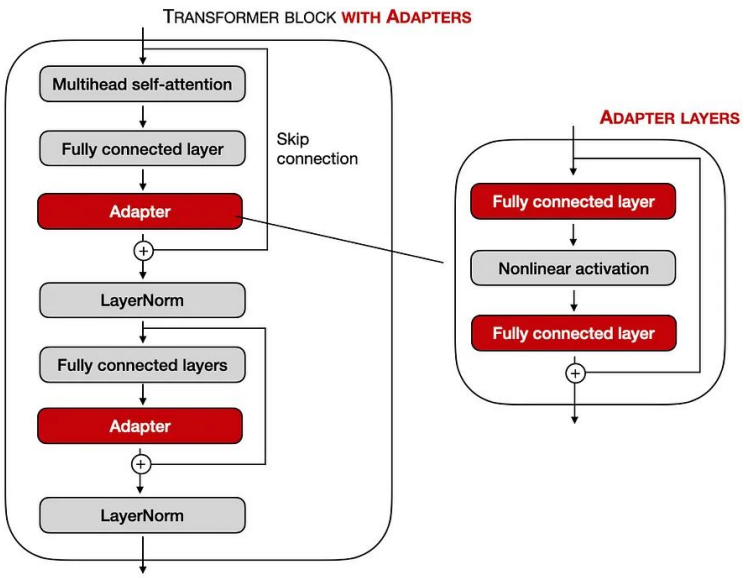
Source: Sajjad Ayoubi

PEFT with Low-Rank Adaptation

- Reduced computational costs
- Faster training times
- Lower hardware requirements
- Less overfitting
- Less storage







Hands-on code demo:
PEFT_LoRA.ipynb

Source: Sebastian Raschka

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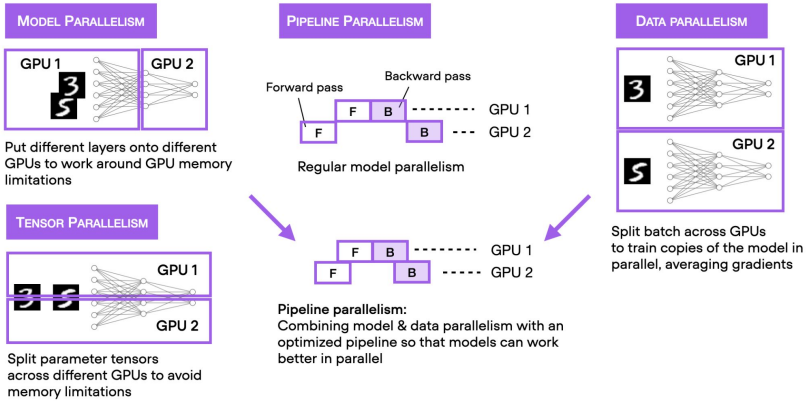
Parallelism: Use more GPUs!

Data Parallelism

- Each GPU receives a small batch and computes the forward and backward passes
- Gradients are averaged across nodes

Model Parallelism

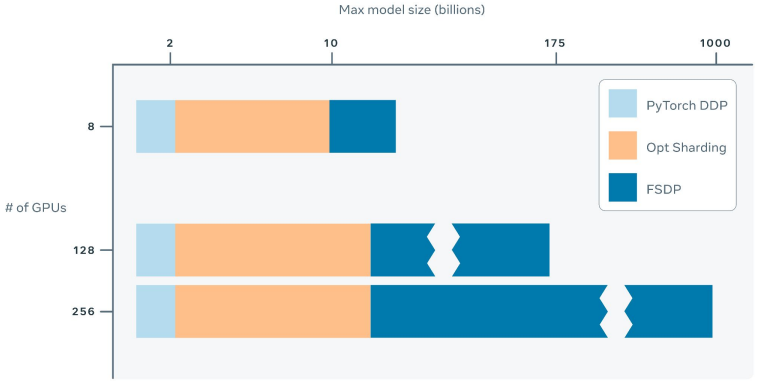
- But what if we can't fit even one copy of the model on a device?
  - GPT-3: 175B parameters
  - 175B ✕ 4 ≈ 700GB
- Put different layers of the model on different devices



Source: Sebastian Raschka

Fully sharded data parallel (FSDP)

- Shards an AI model's parameters across data parallel workers
- Utilizes both data parallelism and tensor parallelism
- Can offload training computation to CPUs
- Benefits
  - Improves memory efficiency
  - Improves computational efficiency
  - Identical results to distributed data parallel (DDP)

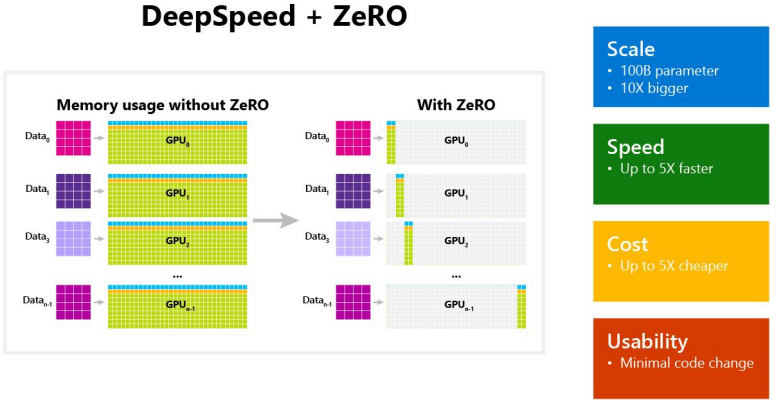


Hands-on code demo:
code

Source: Meta Engineering

DeepSpeed ZeRO

- Easily integrated into Transformers or Lightning
- **Stage 1**
  - Shards optimizer states
  - **Uses:** Train only
- **Stage 2**
  - Shards gradients
  - **Uses:** Train only
- **Stage 3**
  - Shards model parameters
  - **Uses:** Train and inference
- CPU offloading
  - Offload data and compute to CPU/Disk
  - **Uses:** Train and inference



Hands-on code demo:
T5 Inference.ipynb

Source: Microsoft

Poll

How much deployment experience do you have?

- No model I've worked on has made it to production
- Trained a model and handed it off to MLE
- Built service/deployed model

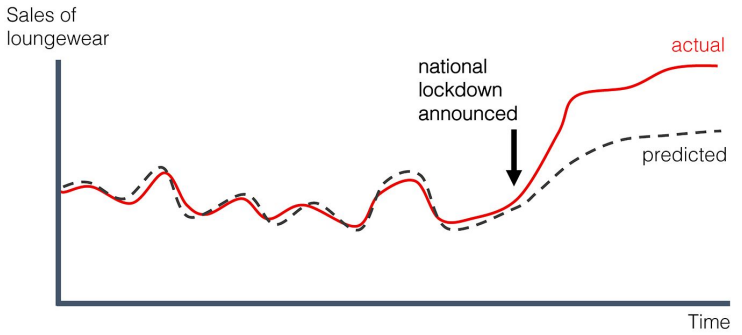
LLM Deployment Options

Tools like HuggingFace and PyTorch make deployment easy:

1. **Batch**: offline inference
2. **Real-time**: more complex MLOps
3. **Edge:** e.g., in user's browser, phone, or watch
    a. Rare for LLMs yet applicable for other ML

Monitoring LLMs can be challenging:

- **Drift Detection**
    - Data Drift
    - Label Drift
    - Prediction Drift
    - Concept Drift
- **Detection algorithms**
    - Kolmogorov-Smirnov test
    - Population Stability Index
    - Kullback-Leibler divergence



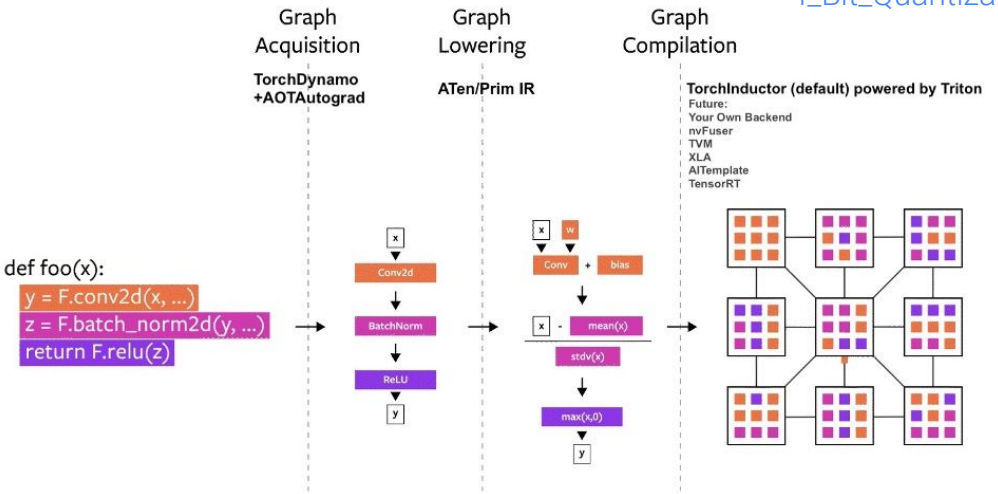
Major LLM Challenges

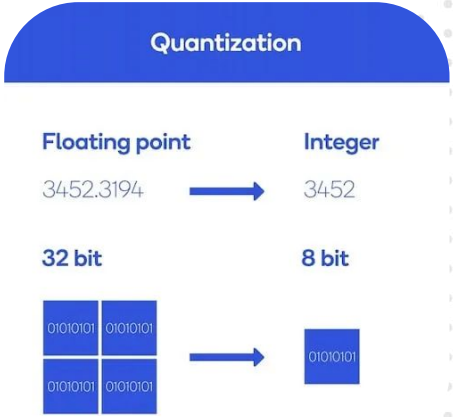
- **Large size**
  - Using vendor (OpenAI) API for fine-tuning or inference
  - Using easy (HuggingFace inference endpoint) LLM hosting
  - Relatively advanced MLOps
- Very fast moving, complex web of **model options**
  - Great options are out there
  - Often when a model is trained, there's a *better* model
- LLMs are often very **exposed** to users
  - Selective generation calculation
  - Moderation APIs
  - False/"hallucinated" information
  - Harmful
- **Malicious** attacks
  - Prompt injection

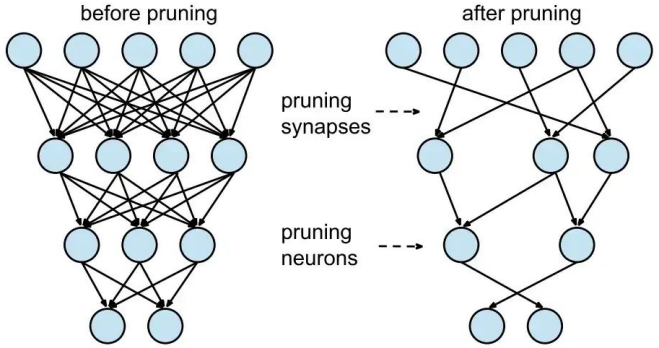
Inference Optimizations

- Vectorization & Parallelization
- torch.compile()
- Quantization
- Pruning

Hands-on code demo:
Inference_Optimizations.ipynb
deepspeed_t5_inference.py
Quantization.ipynb
4_Bit_Quantization_QLoRA.ipynb







Source: PyTorch

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SparseGPT

- GPT-175B
  - 320GB of storage
  - Five A100 GPUs with 80GB of memory each for inference
- Magnitude pruning: 10% removal before accuracy hit
- Remove 50% w/o accuracy impact
- Layer pruning -> retain outputs

OPT	Sparsity	125M	350M	1.3B	2.7B	6.7B	13B	30B	66B	175B
dense	0%	27.66	22.01	14.63	12.46	10.86	10.12	9.56	9.33	8.34
Magnitude	50%	193.	97.80	1.7e4	265.	969.	1.2e5	168.	4.2e4	4.3e4
SparseGPT	50%	36.89	31.60	17.45	13.44	11.56	11.12	9.77	9.33	8.21
SparseGPT	4:8	44.75	38.82	20.02	14.97	12.54	11.72	10.28	9.66	8.45
SparseGPT	2:4	59.17	50.21	24.04	17.14	14.16	12.91	10.88	10.10	8.73

Table 1: OPT perplexity results on raw-WikiText2.

Source: Paper

SpQR: Sparse-Quantized Representation

- 4x compression while being **lossless**
- After quantizing, 1% of model's weights result in 75% error
- Outlier weight detection
  - Measure inputs/outputs of uncompressed/quantized models
  - Identify weights whose quantization changes output
  - Retain 16-bit representation for outliers

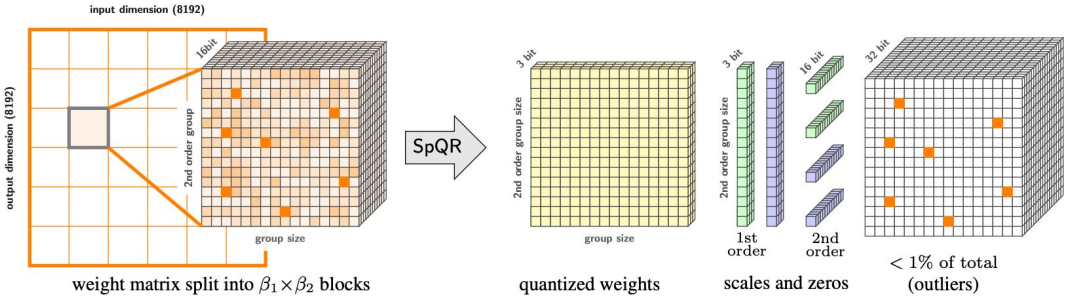

Figure 3: A high-level overview of the SpQR representation for a single weight tensor. The right side of the image depicts all stored data types and their dimensions.

Source: Paper

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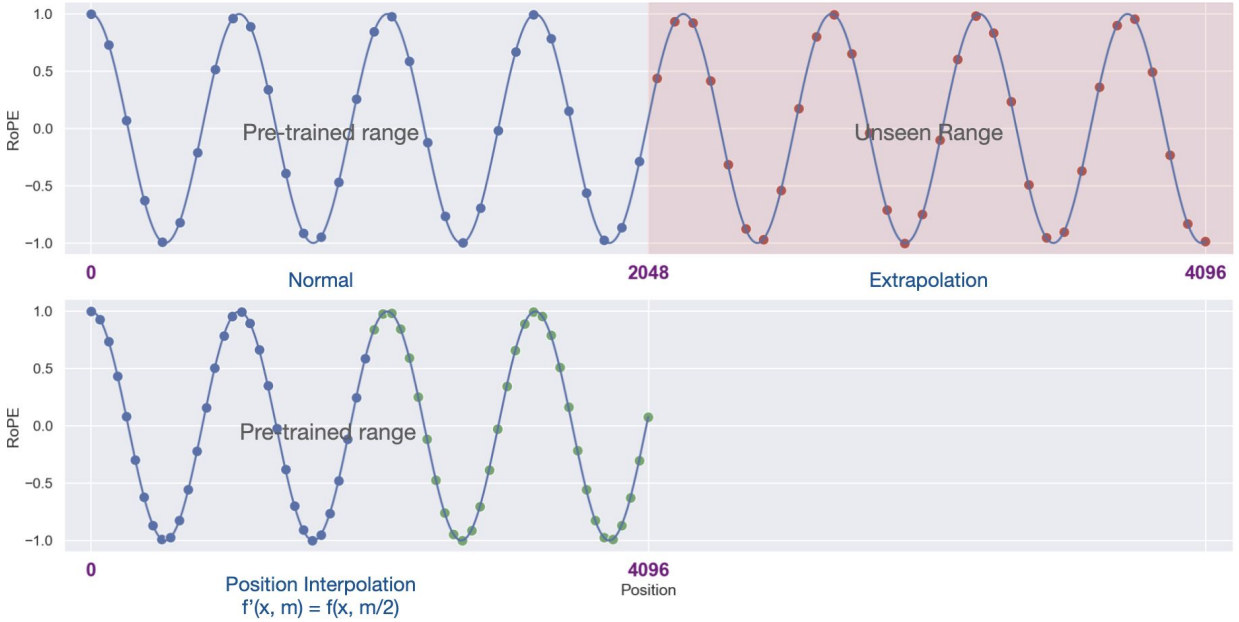
Position Interpolation: 32x longer context



Hands-on code demo:
Rope Scaling.ipynb

Source: Paper

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What’s next?

- Smaller models
- Less hallucinating
- Real-time information retrieval
- Multi-modality
  - Images
  - Documents
  - Videos
- Longer context windows
- Faster/cheaper inference

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