CS 839: Foundation Models
Efficient Inference

Fred Sala

University of Wisconsin-Madison

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Announcements

- **Logistics:**
  - Homework 2 in progress.
  - **Sign up for presentations!**
  - Project information coming out shortly.
- Class roadmap:

Tuesday Oct. 14	Efficient Inference
Thursday Oct. 16	Evaluation
Tuesday Oct. 21	Agents
Thursday Oct. 23	More Reasoning
Tuesday Oct. 28	Multimodal Models

Outline

- **Efficient Training Review**
  - Scale, memory optimization (FlashAttention), parallelism, heterogenous training
- **Efficient Inference**
  - Speculative decoding, early-exit strategies, Medusa decoding

Training Foundation Models: **Scale**

Llama family of models,

- *"we estimate that we used 2048 A100-80GB for a period of approximately 5 months to develop our models"*

OPT (Open Pre-trained Transformers),

- *"training OPT-175B on 992 80GB A100 GPUs"*

	GPU Type	GPU Power consumption	GPU-hours	Total power consumption	Carbon emitted (tCO_2eq)
OPT-175B	A100-80GB	400W	809,472	356 MWh	137
BLOOM-175B	A100-80GB	400W	1,082,880	475 MWh	183
LLaMA-7B	A100-80GB	400W	82,432	36 MWh	14
LLaMA-13B	A100-80GB	400W	135,168	59 MWh	23
LLaMA-33B	A100-80GB	400W	530,432	233 MWh	90
LLaMA-65B	A100-80GB	400W	1,022,362	449 MWh	173

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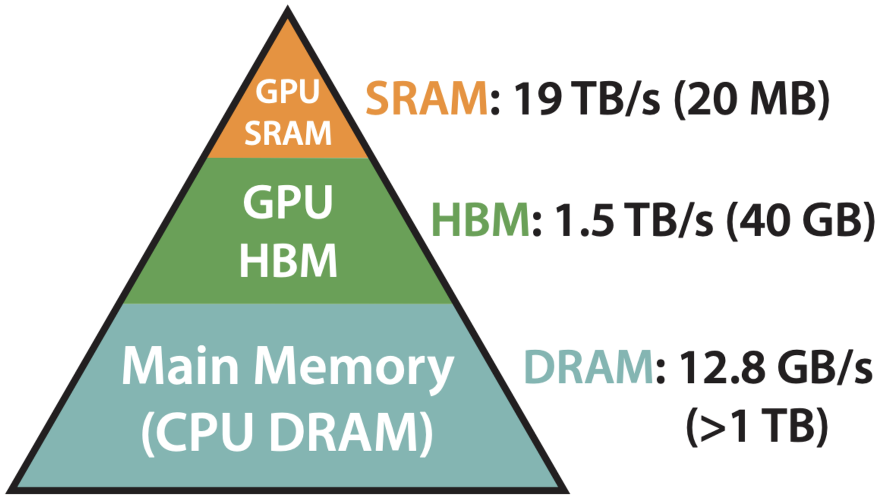
Flash Attention

Idea for FlashAttention

- Different kinds of GPU memory



Memory Hierarchy with Bandwidth & Memory Size

  - Fast: on-chip SRAM
    - But very little of this: 192KB for each of ~100 processors for an A100 (20MB)
  - Slow(er): HBM
    - But lots: 40-80GB for an A100

- **Goal**: use fast as much as possible, avoid moving to HBM

Flash Attention: **Tradeoffs?**

Will use two tricks for higher efficiency

- Tiling and re-computing.

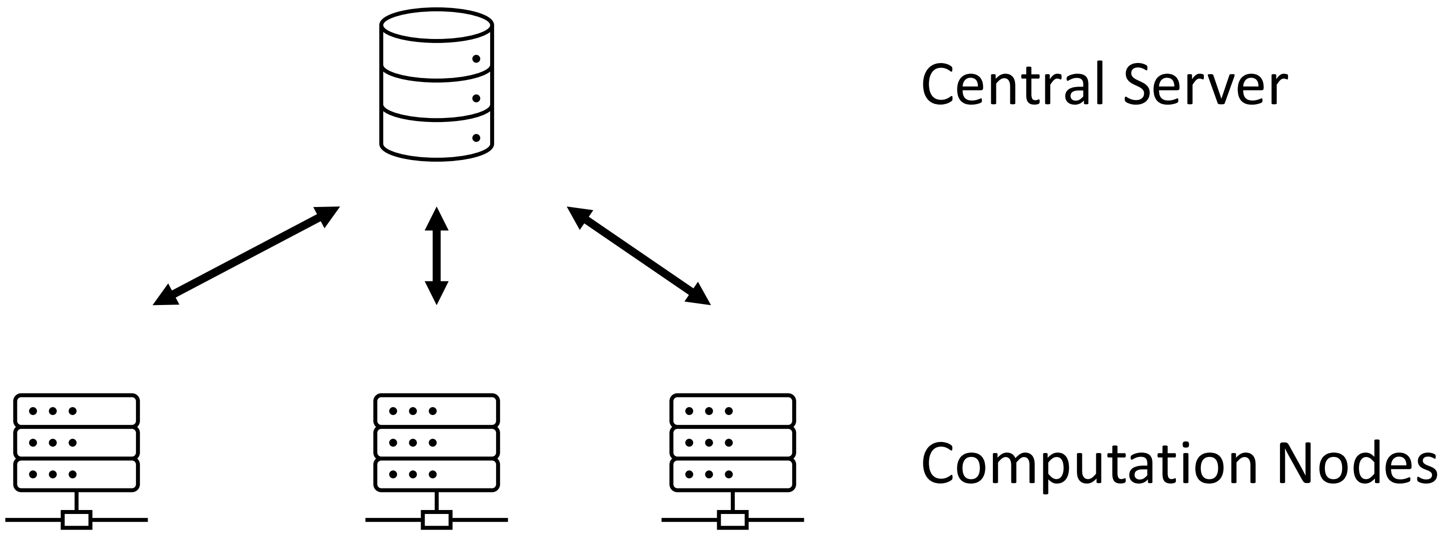
Results:

Model implementations	OpenWebText (ppl)	Training time (speedup)
GPT-2 small - Huggingface [87]	18.2	9.5 days (1.0×)
GPT-2 small - Megatron-LM [77]	18.2	4.7 days (2.0×)
GPT-2 small - FlashAttention	18.2	**2.7 days (3.5×)**
GPT-2 medium - Huggingface [87]	14.2	21.0 days (1.0×)
GPT-2 medium - Megatron-LM [77]	14.3	11.5 days (1.8×)
GPT-2 medium - FlashAttention	14.3	**6.9 days (3.0×)**

Training Foundation Models: **Parallelization**

Traditional approach is to **distribute** training loads

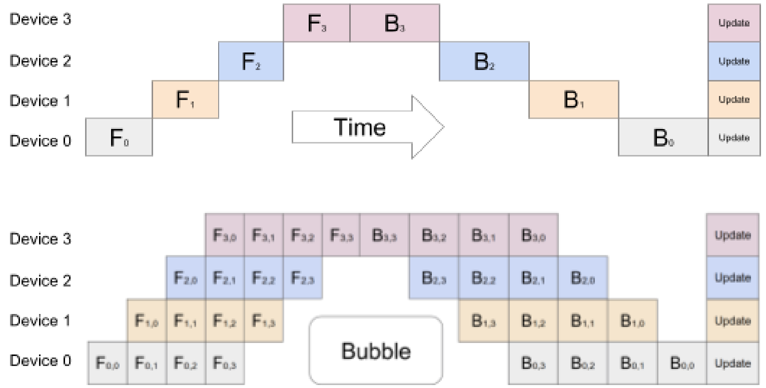
- Classic centralized distributed training
  - Synchronize each local gradient update
  - Send synchronized vector back to each node (lots of communication!)



Training Foundation Models: **Parallelization**

Traditional approach is to **distribute** training loads

- This is by itself impossible (each node *can't* handle full model for large models)
- Need further parallelism:
  - **Data**: each node sees a different slice of data
  - **Weights/tensors**: chunks so no GPU sees whole model
  - **Pipeline**: only a few layers per GPU



Top: The naive model parallelism strategy leads to severe underutilization due to the sequential nature of the network. Only one accelerator is active at a time. *Bottom:* GPipe divides the input mini-batch into smaller micro-batches, enabling different accelerators to work on separate micro-batches at the same time.

- Great resource:

https://huggingface.co/blog/bloom-megatron-deepspeed

Break & Questions

Outline

- **Finish Up Last Time**
  - RL training, RLVR, GRPO, datasets
- **Efficient Training**
  - Scale, memory optimization (FlashAttention), parallelism, heterogenous training
- **Start Efficient Inference**
  - Speculative decoding, early-exit strategies, Flash decoding

Efficient Inference

Similar goal to training

- Gains are more visible

Task	M_q	Temp	γ	α	Speed
EnDe	T5-small ★	0	7	0.75	**3.4X**
EnDe	T5-base	0	7	0.8	2.8X

Leviathan et al '23

Many different approaches. We'll talk about two:

- **Speculative decoding**
  - Inspired by speculative execution in computer architecture
- **Adaptive language modeling**
  - Inspired by early termination methods in ML

Speculative Decoding: Idea

What's slow in autoregressive generation?

- Have to wait for a token to be generated before generating the next token

If we're not *generating*, not slow---can compute probabilities quickly

- Processing the fixed prompt can be reasonably fast

Idea: what if we use a more efficient model for token generation, and then check to see it's OK with original model?

Speculative Decoding: Idea

Idea: what if we use a more efficient model for token generation, and then check to see it's OK with original model?

Problem: what if the generated tokens have different probabilities?

- Can reject new ones
- Can run multiple of these in parallel, increase the chances we'll find something we want.

Speculative Decoding: Example

Idea: what if we use a more efficient model for token generation, and then check to see it's OK with original model?

- Green: accepted, red: rejected, blue: original LM.
    - Each line is one iteration of speculative decoding.

[START] japan ' s benchmark ~~bond~~ n

[START] japan ' s benchmark nikkei 22 ~~,~~5

[START] japan ' s benchmark nikkei 225 index rose 22 ~~.~~6

[START] japan ' s benchmark nikkei 225 index rose 226 . 69 ~~,~~ points

[START] japan ' s benchmark nikkei 225 index rose 226 . 69 points , or 0 1

[START] japan ' s benchmark nikkei 225 index rose 226 . 69 points , or 1 . 5 percent , to 10 , 9859

[START] japan ' s benchmark nikkei 225 index rose 226 . 69 points , or 1 . 5 percent , to 10 , 989 . 79 ~~.~~ in

[START] japan ' s benchmark nikkei 225 index rose 226 . 69 points , or 1 . 5 percent , to 10 , 989 . 79 in ~~tokyo~~ late

[START] japan ' s benchmark nikkei 225 index rose 226 . 69 points , or 1 . 5 percent , to 10 , 989 . 79 in late morning trading . [END]

Leviathan et al '23

Speculative Decoding: Algorithm

Algorithm:

- M_p original model, M_q small model (efficient)
- Generate γ tokens with M_q
- Check what was accepted
  - Adjust if needed (i.e., if there was a rejection)
  - Sample from "adjusted" distribution
- Generate one more token from M_p

Algorithm 1 SpeculativeDecodingStep

Inputs: $M_p, M_q, prefix$.

▷ Sample γ guesses $x_{1,\ldots,\gamma}$ from M_q autoregressively.

for $i = 1$ **to** γ **do**

  $q_i(x) \leftarrow M_q(prefix + [x_1, \ldots, x_{i-1}])$

  $x_i \sim q_i(x)$

end for

▷ Run M_p in parallel.

$p_1(x), \ldots, p_{\gamma+1}(x) \leftarrow$

  $M_p(prefix), \ldots, M_p(prefix + [x_1, \ldots, x_\gamma])$

▷ Determine the number of accepted guesses n.

$r_1 \sim U(0,1), \ldots, r_\gamma \sim U(0,1)$

$n \leftarrow \min(\{i - 1 \mid 1 \leq i \leq \gamma, r_i > \frac{p_i(x)}{q_i(x)}\} \cup \{\gamma\})$

▷ Adjust the distribution from M_p if needed.

$p'(x) \leftarrow p_{n+1}(x)$

if $n < \gamma$ **then**

  $p'(x) \leftarrow norm(max(0, p_{n+1}(x) - q_{n+1}(x)))$

end if

▷ Return one token from M_p, and n tokens from M_q.

$t \sim p'(x)$

return $prefix + [x_1, \ldots, x_n, t]$

Speculative Decoding: Results

Some sample results:

TASK	M_q	TEMP	γ	α	SPEED
ENDE	T5-SMALL ★	0	7	0.75	**3.4X**
ENDE	T5-BASE	0	7	0.8	2.8X
ENDE	T5-LARGE	0	7	0.82	1.7X
ENDE	T5-SMALL ★	1	7	0.62	**2.6X**
ENDE	T5-BASE	1	5	0.68	2.4X
ENDE	T5-LARGE	1	3	0.71	1.4X

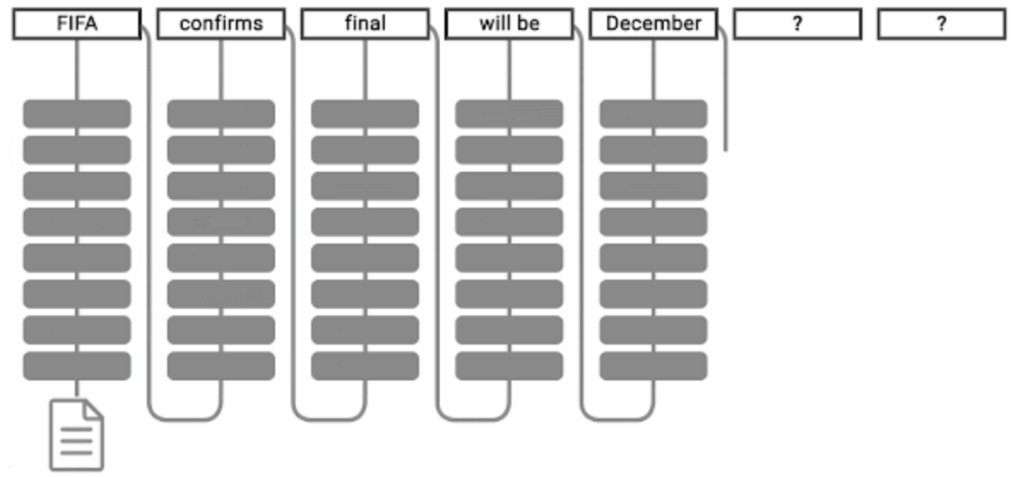
Note: lots of extensions!

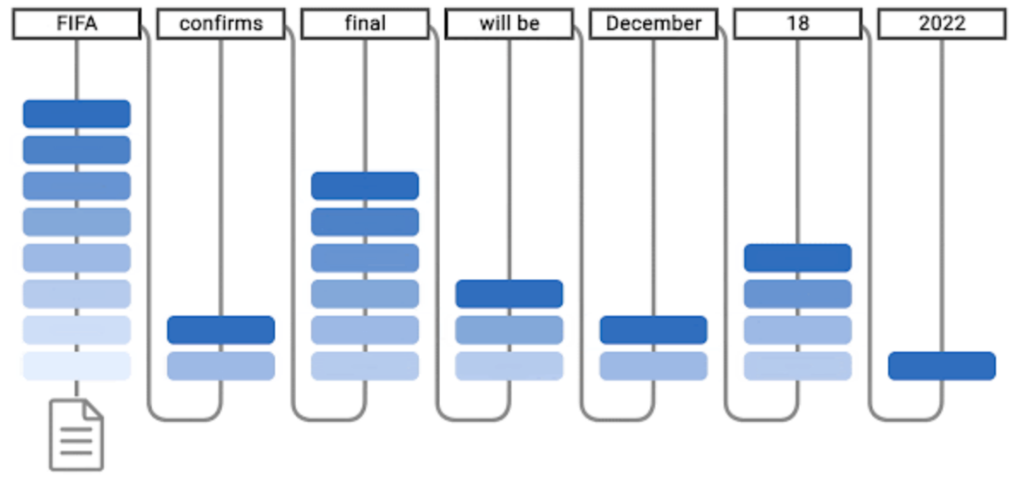
- Q: what kind of smaller models should we use? Tradeoffs!
  - Smaller is faster, but reject more often. Bigger, less rejections, but smaller gains.

Adaptive Language Modeling

Basic idea: make predictions based on earlier layers

- When it is safe to do so.
- Goal: introduce constraints and ensure these are satisfied,
  - Textual consistency
  - Risk consistency



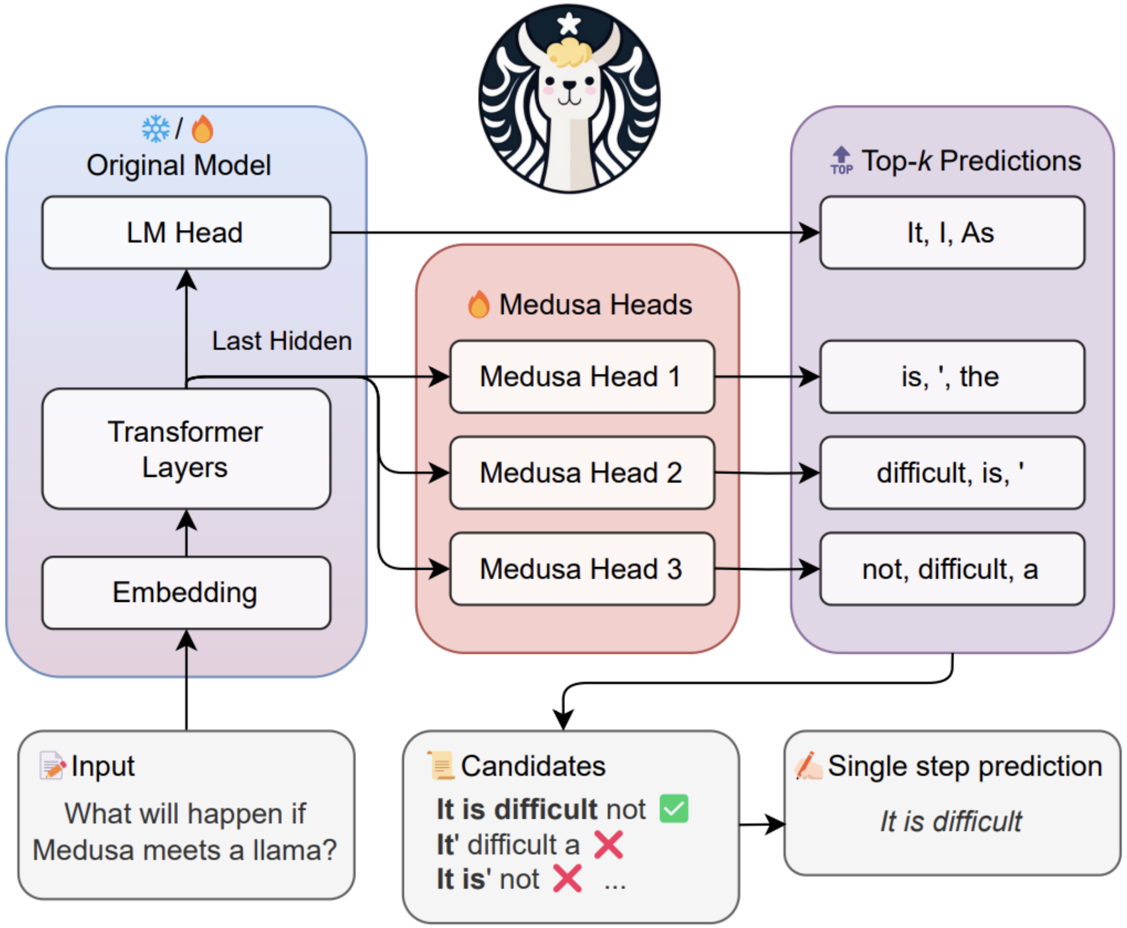


Schuster et al '22

Parallelizing Decoding

"Medusa Decoding"

- Multiple heads, run in parallel
- Goal: Get around the fact that we have to wait for each token to be generated
  - Instead, each extra head guesses a future token set
  - Then assemble into a full sequence -> decode multiple tokens at once



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Thank You!