Accelerating Distributed MoE Training and Inference with Lina

Jiamin Li\textsuperscript{1}, Yimin Jiang\textsuperscript{2}, Yibo Zhu, Cong Wang\textsuperscript{1}, Hong Xu\textsuperscript{2}  
\textsuperscript{1}City University of Hong Kong, \textsuperscript{2}ByteDance Inc., \textsuperscript{3}The Chinese University of Hong Kong

ATC 2023
Sparsely-Activated Mixture-of-Experts (MoE)

MoE architecture
An ensemble of experts.

Figure credit to Anatomical and Functional Plasticity in Early Blind Individuals and the Mixture of Experts Architecture
Sparsely-Activated Mixture-of-Experts (MoE)

- **Sparsely-activated** MoE: each input selects just a few (1 or 2) experts for processing
- Benefit: sub-linear scaling of FLOPS with model size

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• Benefit: sub-linear scaling of FLOPS with model size

**Massive model parameters with constant computation cost.**

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Potential of MoE in Transformer Models

• GLaM by Google
  • GLaM outperforms GPT-3 on 29 tasks

• DeepSpeed MoE models
  • Model quality: 6.7B-parameter dense = 1.3B-parameter MoE - 128
  • Training compute reduction of 5x

<table>
<thead>
<tr>
<th></th>
<th>GPT-3</th>
<th>GLaM</th>
<th>relative</th>
</tr>
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<tbody>
<tr>
<td>cost</td>
<td>350</td>
<td>180</td>
<td>-48.6%</td>
</tr>
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<td>FLOPs / token (G)</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Train energy (MWh)</td>
<td>1287</td>
<td>456</td>
<td>-64.6%</td>
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<tr>
<td>accuracy</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Zero-shot</td>
<td>56.9</td>
<td>62.7</td>
<td>+10.2%</td>
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<tr>
<td>One-shot</td>
<td>61.6</td>
<td>65.5</td>
<td>+6.3%</td>
</tr>
<tr>
<td>Few-shot</td>
<td>65.2</td>
<td>68.1</td>
<td>+4.4%</td>
</tr>
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Figure credit to GLaM and DeepSpeed MoE.
MoE in Transformer-based Language Models

• Feed forward layers (FFN) are replaced with MoE layers.
• MoE layer = gate + experts
  • Expert: feed forward neural network
    => *same* architecture, *different* parameters
  • Gate: a *trainable* matrix to select expert for each data sample
    • Top-2 in training, Top-1 in inference
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  - Gate: a trainable matrix to select expert for each data sample
    - Top-2 in training, Top-1 in inference
  - Load balancing loss during training: even distribution among experts.
Distributed MoE

• Hybrid parallelism:
  • Expert parallelism: each device hosts one unique expert
  • Data parallelism: replicate non-expert parameter on each device

Single-device
Distributed MoE

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- All-to-all communication
  - 1st: send data samples to experts.
  - 2nd: restore data samples back
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- All-to-all communication
  - 1st: send data samples to experts.
  - 2nd: restore data samples back
  - Same data transfer size
Distributed MoE is not efficient

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<tr>
<th># Experts</th>
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<th># Layers &amp; Params</th>
<th>Training (ms)</th>
<th>Inference (ms)</th>
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All-to-all takes an average of 34.1% of the step time.
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ATC is good

FFN 0 FFN 1 FFN 2 FFN 3
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To restore to a sequence, we must wait for the processing of all tokens.
All-to-all is the bottleneck

• Synchronous and blocking operation & large amounts of data transfer.
All-to-all is the bottleneck

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- Synchronous and blocking operation & large amounts of data transfer.

```
All-to-all
Stream a
Stream b
Gate  FFN  Combine
All-to-all All-to-all
```

```
Forward Pass

<table>
<thead>
<tr>
<th>Time (ms)</th>
<th>Stream a</th>
<th>Stream b</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3.1</td>
<td>3.1</td>
<td>3.1</td>
</tr>
<tr>
<td>10.7</td>
<td>10.7</td>
<td>10.7</td>
</tr>
<tr>
<td>12.1</td>
<td>12.1</td>
<td>12.1</td>
</tr>
<tr>
<td>18.7</td>
<td>18.7</td>
<td>18.7</td>
</tr>
<tr>
<td>20.3</td>
<td>20.3</td>
<td>20.3</td>
</tr>
</tbody>
</table>
```

```
ms
```

```
Ratio (%)
```

```
Experts
```

```
Size (MB)
```

```
Ratio
```

```
Transfer Size
```

Graph showing the ratio and size of experts vs. transfer size.
All-to-all is the bottleneck

- Synchronous and blocking operation & large amounts of data transfer.

Is it the only cause of all-to-all being the bottleneck?
All-to-all is the bottleneck

• Synchronous and blocking operation & large amounts of data transfer.

Is it the only cause of all-to-all being the bottleneck?

• MoE training and inference have their unique problems.
MoE training and inference have their unique problems.

All-to-all is the bottleneck

- Synchronous and blocking operation & large amounts of data transfer.

Is it the only cause of all-to-all being the bottleneck?

- MoE training and inference have their unique problems.
  - Training has backward pass
  - Inference is purely workload-driven
In backward pass,

- Allreduce: asynchronously aggregate *non-expert* gradients in data parallel.
- All-to-all: exchange token gradients to compute *expert* gradients.
In backward pass,

- **Allreduce**: asynchronously aggregate *non-expert* gradients in data parallel.
- **All-to-all**: exchange token gradients to compute *expert* gradients.

### MoE Training in Data & Expert Parallel

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<th>Event</th>
<th>Duration (ms)</th>
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<td>Stream a</td>
<td>Combine</td>
<td>1.6</td>
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<tr>
<td>Stream b</td>
<td>All-to-all</td>
<td>8.6, 9.2</td>
</tr>
<tr>
<td>Stream c</td>
<td>Allreduce</td>
<td>13.6</td>
</tr>
<tr>
<td></td>
<td>FFN</td>
<td>15.0</td>
</tr>
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In backward pass,

• Allreduce: asynchronously aggregate *non-expert* gradients in data parallel.

• All-to-all: exchange token gradients to compute *expert* gradients.

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All-to-all is prolonged when it overlaps with allreduce and directly impacts step time.
MoE Training in Data & Expert Parallel

In backward pass,

• Allreduce: asynchronously aggregate non-expert gradients in data parallel.
• All-to-all: exchange token gradients to compute expert gradients.

All-to-all is prolonged when it overlaps with allreduce and directly impacts step time.

Slowdown of all-to-all varies:

Median: 2x; Maximum: ~4x
Expert Popularity in MoE Inference

- Inference: no load balancing constraints => expert selection is workload-driven, therefore, much more *biased*.

![Graph showing expert popularity in MoE Inference](image)
Expert Popularity in MoE Inference

- Inference: no load balancing constraints => expert selection is workload-driven, therefore, much more *biased*.

Devices with unpopular experts have to wait for those with popular experts.
Expert Popularity in MoE Inference

- Inference: no load balancing constraints => expert selection is workload-driven, therefore, much more *biased*.

Maximum idle time of the least popular expert => 29.4% of the inference time.

Devices with unpopular experts have to wait for those with popular experts.
Intuition: always prioritise all-to-all and avoid bandwidth sharing.

- Minimise the blocking period incurred by all-to-all
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- Minimise the blocking period incurred by all-to-all

Backward pass

Challenges:

1. NCCL Communication primitives cannot be preempted.
2. No control knob to adjust resource sharing (GPU SM, network bandwidth...).
Training: Micro-op Scheduling

- Tensor Partitioning
  - Partition allreduce into micro-ops
  - Prioritise all-to-all whenever possible

Baseline
Training: Micro-op Scheduling

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Baseline

Prioritise all-to-all
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Baseline

- Partition all-to-all into micro-ops
- Pipelining computation and all-to-all
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Baseline

• Partition all-to-all into micro-ops
• Pipelining computation and all-to-all
Inference: Challenges

- MoE inference: no load balancing constraints => expert selection is workload-driven, therefore, much more *biased*.

Devices with unpopular experts have to wait for those with popular experts.
Q: How to deal with imbalance computation load?

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Maximum idle time of the least popular expert => 29.4% of the inference time.

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Q: How to deal with imbalance computation load?
Allocate resources based on expert popularity:
Popular experts => more resources.
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Token’s expert selection cannot be determined a priori to the actual gating computation.
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Token’s expert selection cannot be determined a priori to the actual gating computation.

Resource scheduling after gating network.

*Inefficient practice for latency-sensitive tasks!*
Inference: Challenges

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Allocate resources based on expert popularity:
Popular experts => more resources.

Token’s expert selection cannot be determined a prior
to the actual gating computation.

Resource scheduling after gating network.

Inefficient practice for latency-sensitive tasks!

How to achieve low-overhead resource scheduling to balance device load?

<table>
<thead>
<tr>
<th>Model &amp; Dataset</th>
<th>Layer</th>
<th>Top-4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transformer-XL &amp; Enwik8 (Text generation)</td>
<td>3</td>
<td>9</td>
</tr>
<tr>
<td>BERT-Large &amp; WMT En-De (Translation)</td>
<td>6</td>
<td>7</td>
</tr>
</tbody>
</table>

Devices with unpopular experts have to wait for those with popular experts.

MoE inference: no load balancing constraints => expert selection is workload-driven, therefore, much more biased.

Maximum idle time of the least popular expert => 29.4% of the inference time.
• Findings: similar tokens tend to be processed by the same or similar experts in each layer.

• Tokens selecting the same expert in layer $i$ tend to select the same expert again in layer $i + 1$. 
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Inference: Pattern in Expert Selection

• Findings: similar tokens tend to be processed by the same or similar experts in each layer.

• Tokens selecting the same expert in layer i tend to select the same expert again in layer i + 1.

41.94% tokens when k is 1  
54.59% tokens when k is 2
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• Tokens selecting the same expert in layer $i$ tend to select the same expert again in layer $i + 1$.

41.94% tokens when $k$ is 1
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Exploit this pattern to estimate the overall expert popularity
Inference: Expert Popularity Estimation
Inference: Expert Popularity Estimation

• Idea: Collect the expert selection distribution during training *after the load balancing loss is minimised*.

<table>
<thead>
<tr>
<th>Layer</th>
<th>E0</th>
<th>E1</th>
<th>E2</th>
<th>E3</th>
</tr>
</thead>
<tbody>
<tr>
<td>i-2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>i-1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>i</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>i+1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
**Inference: Expert Popularity Estimation**

- Idea: Collect the expert selection distribution during training after the load balancing loss is minimised.

Tokens that select the same experts from layer $i - l$ to layer $i$. 

**Expert selection path $j$**
Inference: Expert Popularity Estimation

• Idea: Collect the expert selection distribution during training after the load balancing loss is minimised.

Tokens that select the same experts from layer $i - l$ to layer $i$.

Expert selection path $j$

Expert popularity distribution of path $j$
• Idea: Collect the expert selection distribution during training *after the load balancing loss is minimised.*

Top-$k$ Expert $e$ popularity: $\{P_{j(t)}^{i+1}\}$

Tokens that select the same experts from layer $i - l$ to layer $i$.  

Expert selection path $j$

Expert popularity distribution of path $j$
Inference: Two-phase Scheduling

• Phase 1:
  • Compute resource allocation for expert $e$ based on popularity estimation:

$$n_e = N \times \sum_{i=1}^{N_t} P_{j(t)}^{i+1}(e)/N_t$$

where:
- $n_e$: No. of tokens in a batch
- $N$: No. of GPUs
Inference: Two-phase Scheduling

• Phase 1: **Pipelined with model computation => nearly zero overhead**
  • Compute resource allocation for expert $e$ based on popularity estimation:

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- No. of tokens in a batch
- No. of GPUs

\[ \text{No. of tokens in a batch} \]
\[ \text{No. of GPUs} \]
Inference: Two-phase Scheduling

- **Phase 1:** Pipelined with model computation => nearly zero overhead
  - Compute resource allocation for expert $e$ based on popularity estimation:
    \[
    n_e = N \times \sum_{t=1}^{N_t} \frac{P_{j(t)}^i(e)}{N_t} \frac{1}{N_t}
    \]
    No. of tokens in a batch
    No. of GPUs

- **Phase 2:**
  - Fine-tune the allocation with the actual expert selection.
  - Re-compute the allocation when the actual selection deviates significantly from the estimation.
Evaluation

- Testbed: Our testbed has four worker nodes. Each node has 4 Ampere A100 GPUs with 40GB memory and is equipped with 100Gbps InfiniBand.
- Every FFN layer in Transformer is replaced with the MoE layer.
- Training models:
  - Transformer-XL: a 24-layer encoder model.
  - BERT2GPT2: a 12-layer encoder-decoder model.
  - GPT-2: a 12-layer decoder model.
- Inference models:
  - Transformer-XL: text generation with Enwik8 test set.
  - BERT: a 12-layer decoder model for translation using WMT En-De test set.
Training step time speedup over Baseline (DeepSpeed) with different design choices.
MoE Layer in Training

MoE layer forward, backward, all-to-all running time speedup over Baseline.

- Transformer-XL
- GPT-2
- BERT2GPT2
Ideal: schedule resources assuming we have the prior knowledge of exact expert popularity.

Median Latency

95%ile Latency

Transformer-XL

BERT
MoE Layer in Inference

MoE layer running time speedup over Ideal.

All-to-all running time speedup over Ideal in selected layers.
Lina’s Contributions

• An in-depth empirical analysis of distributed MoE
  • Main causes for all-to-all to be the performance bottleneck in training and inference.
  • [Training] A scheduler prioritises all-to-all over allreduce to improve its bandwidth and reduce its blocking period.
  • [Inference] An estimation method of expert popularity to conduct two-phase resource scheduling.

Thanks!