Leveraging Expert Usage to Speed up LLM Inference

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Scheduling in Fréjus, March 2026

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Outline

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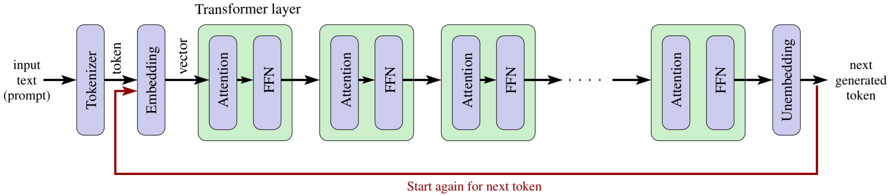
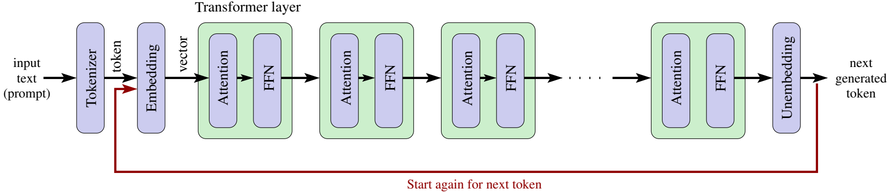
Large Language Models (Transformer-based)



- Input sequence transformed into tokens (tokenization)
- Tokens encoded are vectors (embedding)
- Network made of a succession of layers, each layer contains:
  - Attention mechanism (relation with other tokens)
  - Feed Forward Network (MultiLayered Perceptron)
- Resulting vector converted into token (un-embedding)

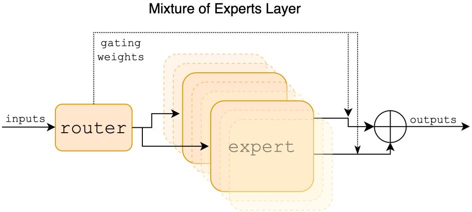
Challenge for high inference throughput



- Producing one token: going through the whole network, one layer after the other
- Token i needed to produce token $i+1$
- LLMs have reached huge sizes: all weights do not fit on high-end GPUs
- Or resort to costly I/O (load weights when needed)

LLM with Mixture-Of-Experts

- MoE proposed to reduce computation at inference time



- Replace the FFN block in each transformer with expert module

- Gating function (router) selects k experts out of n (Mixtral-8x7B: 2 out of 8, DRBX: 4 / 16, DeepSeek-R1: 6 / 64)
- Large set of weights for training
- Smaller set used for inference

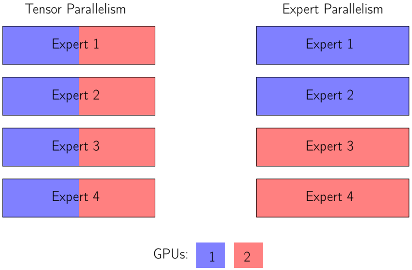
Rest of talk: we consider pairs of experts (e.g. Mixtral) but can be extended for any subset

Outline

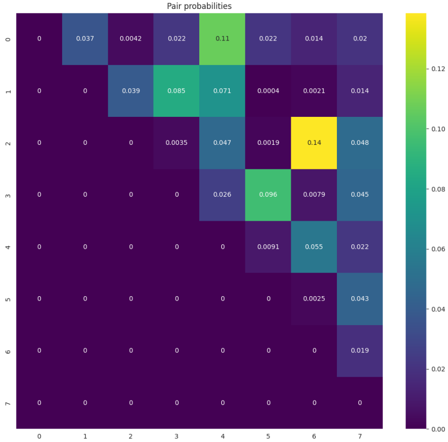
Distributing experts on multiple GPUs

- Need for serving large language models fast
- Even on commodity machines
- Multiple GPUs to increase memory + compute
- How to distribute model weights?

1. Tensor parallelism
   (may not be possible
   with complex experts☹)
2. Expert parallelism
   (selected experts may lie on the
   same GPU, leaving other idle☹)



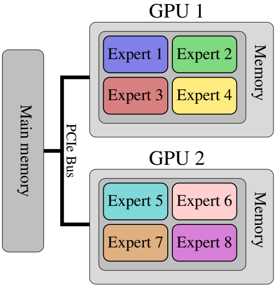
Probability of expert usage for a given layer

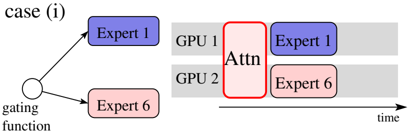


- By design: same probability for each expert to be used
- But: different probabilities for each pairs of experts

Key idea: map high-probability pairs of experts on distinct GPUs
$\Rightarrow$ allow for parallel inference

Problem 1: static allocation, no replication





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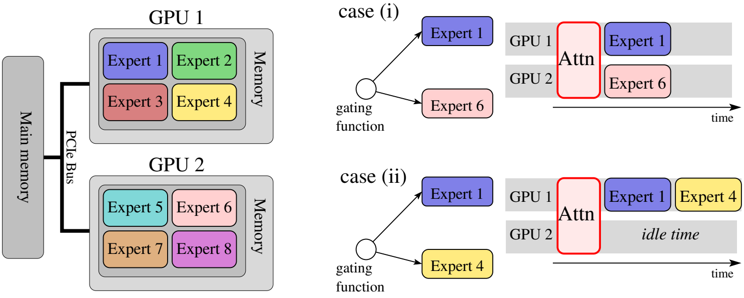
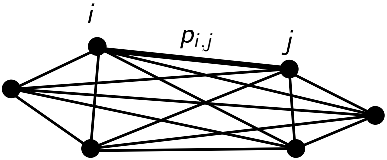


Objective:
map experts to GPU so that frequent pairs are processed in parallel.

Problem complexity of static allocation

Input: usage probability of expert pairs
Output: mapping of experts to the 2 GPUs that minimizes expected processing time
Constraint: each GPU can hold half the experts



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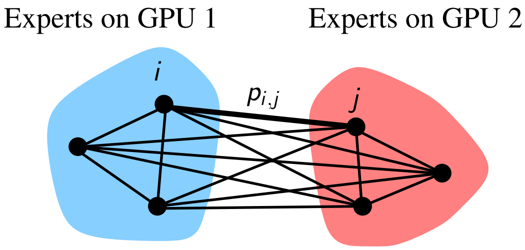

Search for graph bisection with maximal cut

Problem complexity of static allocation

Input: usage probability of expert pairs
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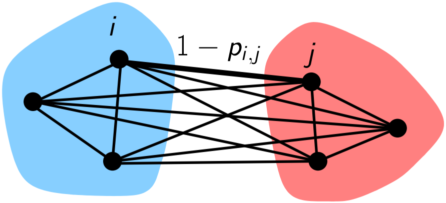
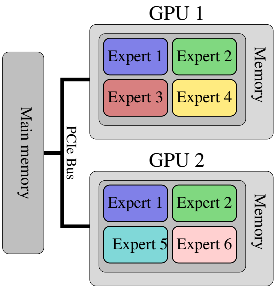
Experts on GPU 1 Experts on GPU 2

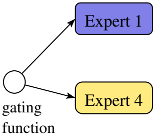


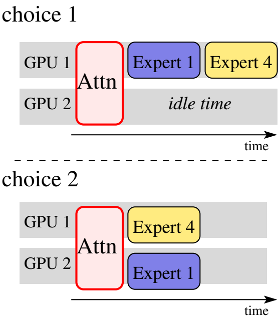
Search for graph bisection with ~~maximal~~ minimal cut
$\Rightarrow$ NP-complete problem

Problem 2: dynamic allocation with replication

Input: Mapping experts→GPU is fixed
Output: choose which replica is used to serve a given pair







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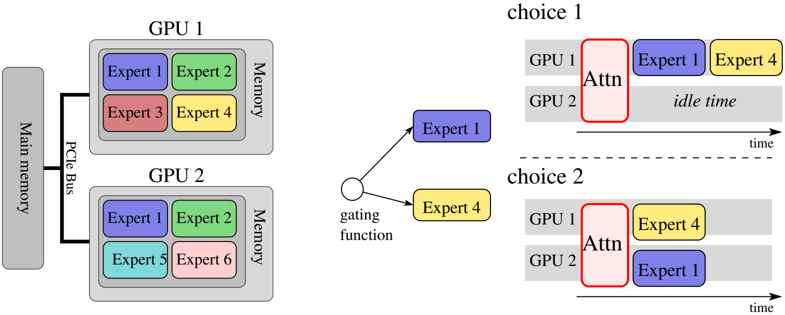
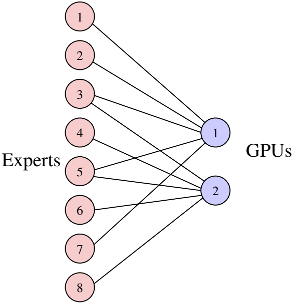


Replica choice (=dynamic allocation) influences total processing time

How to compute optimal dynamic allocation with minimal processing time?

Solving the dynamic allocation problem

Build bipartite graph corresponding to expert mapping:



Solving the dynamic allocation problem

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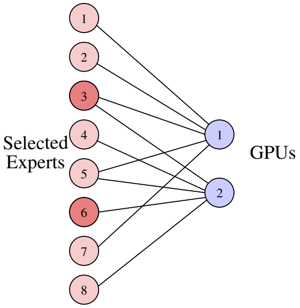

- For each expert pair (subset), consider graph restricted to the subset

Solving the dynamic allocation problem

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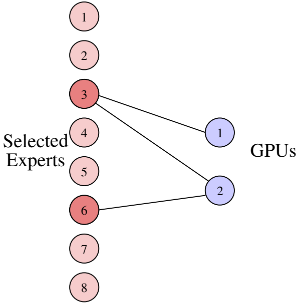

- For each expert pair (subset), consider graph restricted to the subset
- Is there a matching covering both experts?

Solving the dynamic allocation problem

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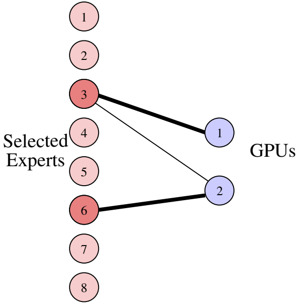

- For each expert pair (subset), consider graph restricted to the subset
- Is there a matching covering both experts?
  - Yes? Processing time $= 1$

Solving the dynamic allocation problem

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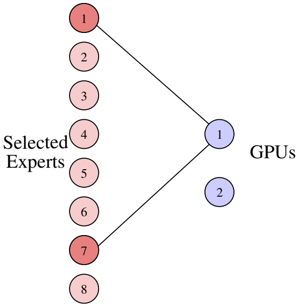
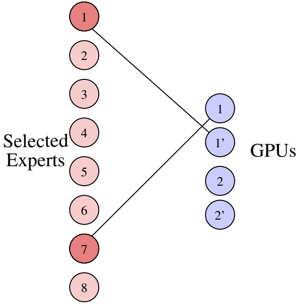


- For each expert pair (subset), consider graph restricted to the subset
- Is there a matching covering both experts?
  - Yes? Processing time = 1
  - No?

Solving the dynamic allocation problem

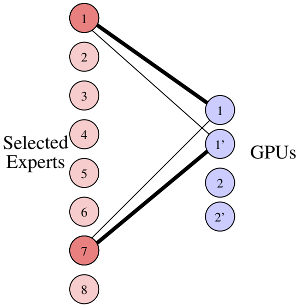
Build bipartite graph corresponding to expert mapping:



- For each expert pair (subset), consider graph restricted to the subset
- Is there a matching covering both experts?
  - Yes? Processing time = 1
  - No? Duplicate GPUs (corresponding to 2 times slots on each GPU)

Solving the dynamic allocation problem

Build bipartite graph corresponding to expert mapping:



- For each expert pair (subset), consider graph restricted to the subset
- Is there a matching covering both experts?
  - Yes? Processing time = 1
  - No? Duplicate GPUs (corresponding to 2 times slots on each GPU)
  - There exists a matching covering both experts ⇒ Processing time = 2

How to solve the static allocation problem?

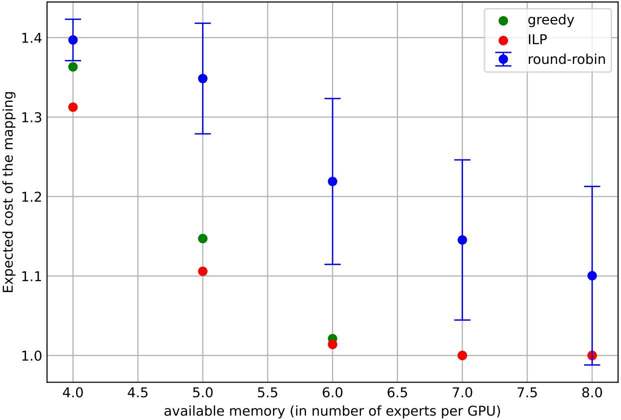
Two strategies that solves both problems at once:

1. Linear programming solution:
   $x_{i,k} = 1$ iff expert i mapped on GPU k
   $y_{i,j,k} = 1$ iff expert i on GPU k is used for pair i, j

2. Simple greedy heuristic
   - Start with empty mapping
   - Map new copy of expert i on GPU k with maximal gain on cost
   - Stop when memory full
   - Compute which copy to use with graph matching algorithm

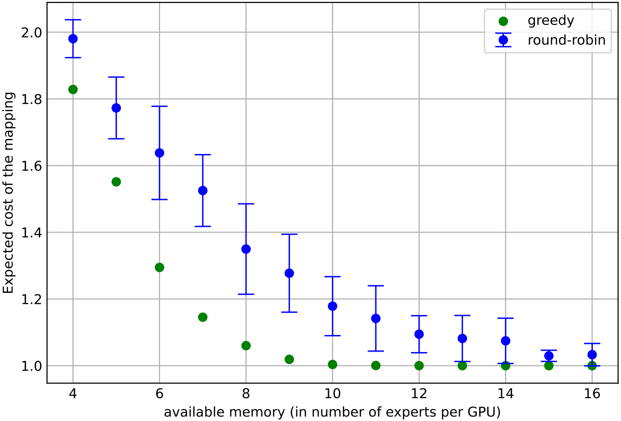
Outline

Potential gain on expected processing time 1/2



Simulations with Mixtral 8x7B expert usage probabilities
(select 2 experts among 8, on 2 GPUs)

Potential gain on expected processing time 2/2



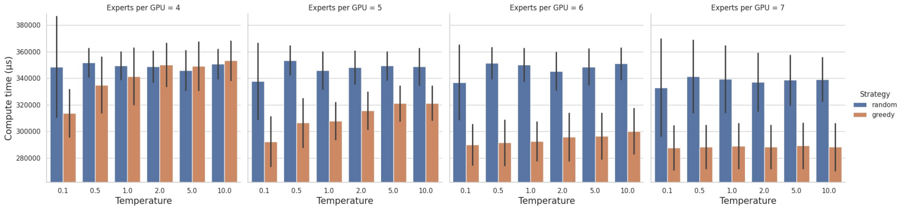
Simulations with DRBX usage (subset of 4 experts, on 4 GPUs)

Preliminary experimental evaluation

- Mixtral model on HuggingFace
  (using only one layer for now)
- Added support for expert parallelism
- Real + Synthetic distributions of expert probabilities
  $\Rightarrow$ test a range of variance
- 2 GPUs, range of memory constraint:

4 experts/GPU (no duplication) $\rightarrow$ 8 experts/GPU (complete duplication)

Experiments with Mixtral on two GPUs



X: high variance in pair probability (left) – low variance (right)
Y: inference time (truncated)

Outline

Inference of Mixture-Of-Experts LLMs

Opportunities for parallelism and optimization

Experimental evaluation

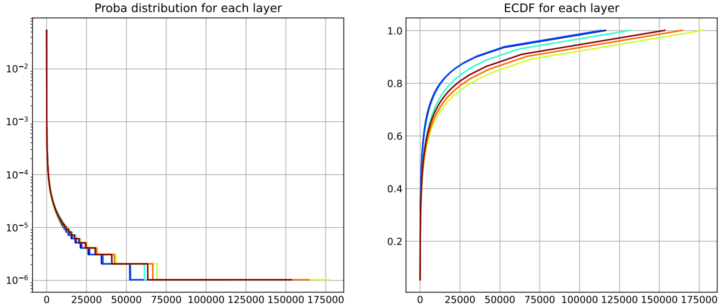
Extension to larger subsets of experts

Extension to larger subsets of experts

- Theory: Algorithms/Linear Program easily extended to any subset size
- Practice: DeepSeek-R1: choose 6 experts among 64 experts
  $\rightarrow$ 74.974.368 subsets
- Up to 6 matching computations per subset, just to evaluate the cost of a solution!
- Many more for the greedy algorithm
- Impractical computation times ☹
- Forget about optimization?☹

Simplifying the problem

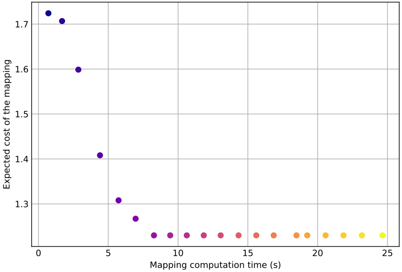
Few expert subsets are really useful::

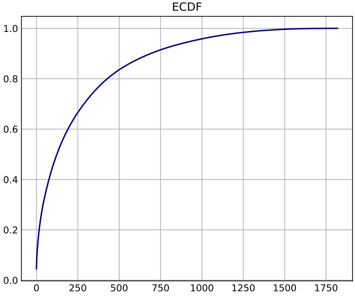


subset usage for DeepSeek-R1, first 6 layers

- 0.2 % of the subsets account for 99% of the subset usage
- We can safely consider only 150k subsets for DeepDeek
- 0.03 % of the subsets account for 85% of the subset usage
- Consider 25k subsets should be enough for sufficient accuracy

Preliminary experiments





Simulations with the DRBX model and greedy mapping heuristic
Using from 90 (left) to 1820 (right) subsets

Using only subsets that cover 80% of the cases is enough to get optimal performance

Conclusions/Perspectives

- Proof-of-concept for expert parallelism at inference
- Take advantage of usage statistics for better performance
- What if memory is too limited? And for (slightly) larger batches?

More at `https://hal.science/hal-04994839`