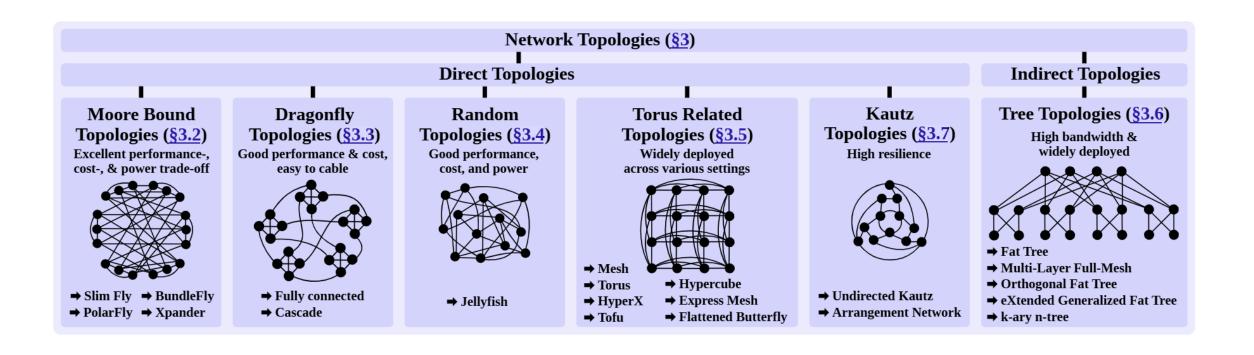


Figure 1: An overview of EvalNet.

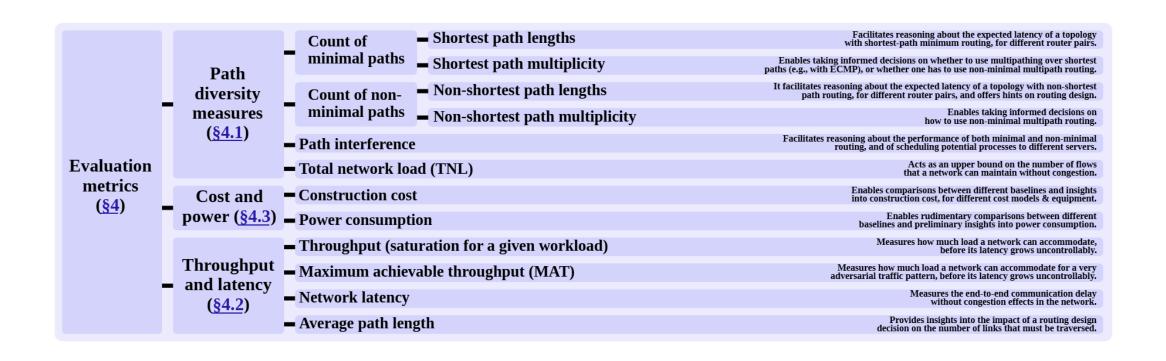






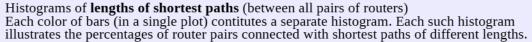


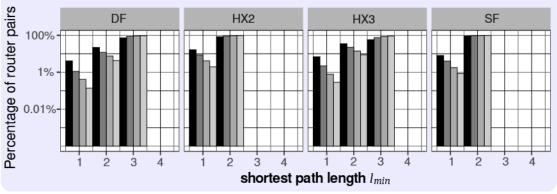


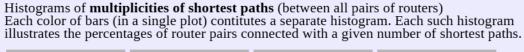


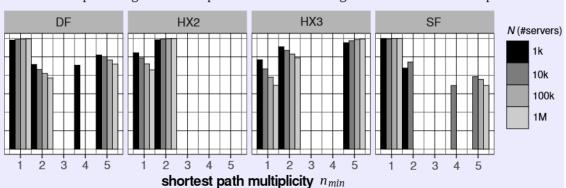










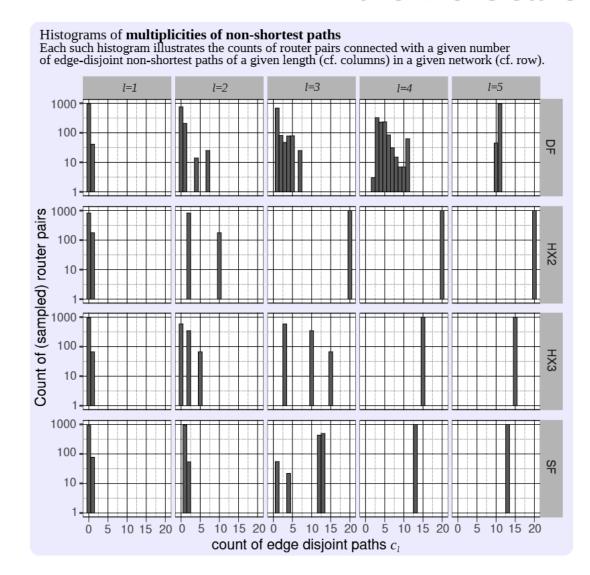


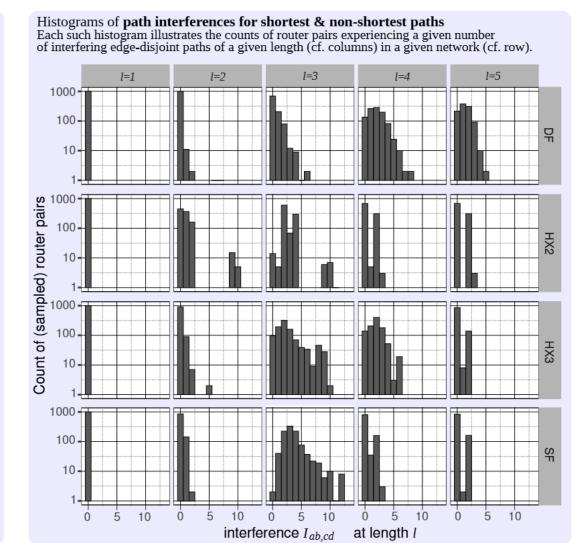








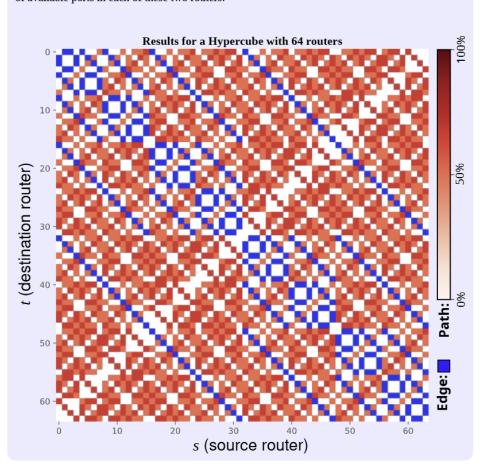


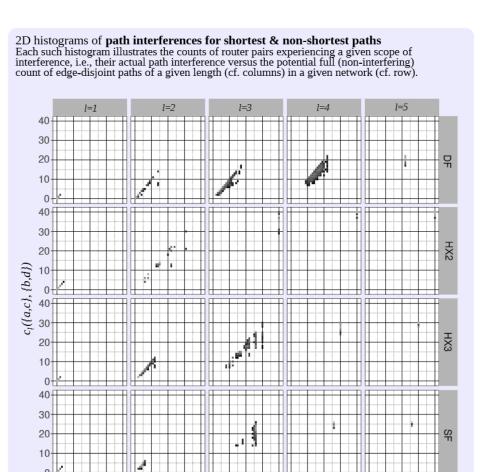






Path diversity between all router pairs, expressed as the percentage of network radix Each point shows how well two given routers (determined by points on X & Y axes) are connected. The percentage is derived with respect to the network radix k'. Thus, 100% indicates that - for a given router pair - this pair is connected by the number of different paths that is equal to the number of available ports in each of these two routers.



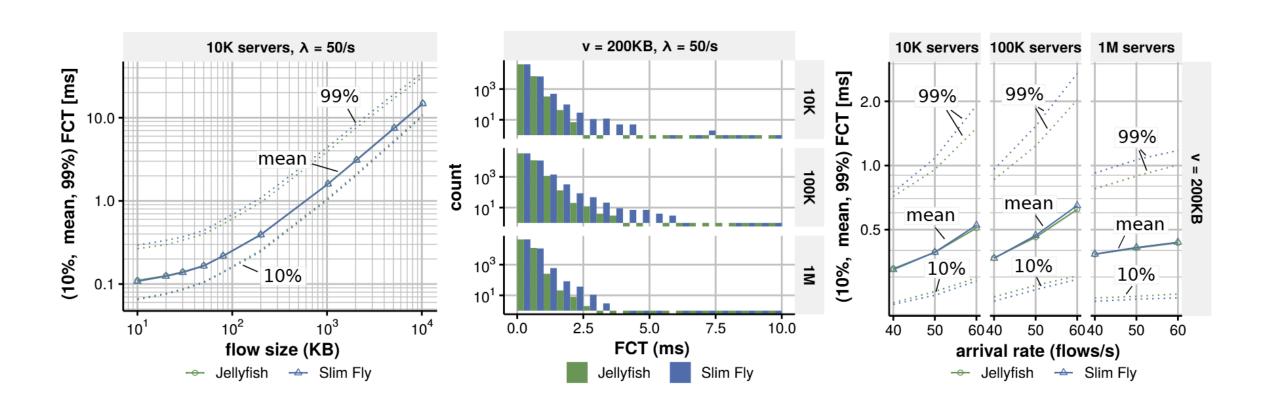


10 20 30 40 0 10 20 30 40 0 10 20 30 40 0 10 20 30 40

 $c_1(\{a,c\},\{b\}) + c_1(\{a,c\},\{d\})$











Topology	Lat.	GlB.	Ext.	C&P	MS	MnS
Slim Fly [15]						
PolarFly [65]						
Xpander [100]						
BundleFly [68]						
Dragonfly [64]						
Cascade Dragonfly [34]						
Jellyfish [95]						
Mesh						
Torus 2D						
Torus 3D						
Torus 4D						
Torus 5D						
Torus 6D						
Hypercube						
HyperX (2-dimensional) [2]						
HyperX (3-dimensional) [2]						
Express Mesh [54]						
Flattened Butterfly [63]						
Fat Tree (2-level) [69]						
Fat Tree (3-level) [69]						
k-ary n-tree [85]						
eXtended Generalized Fat Tree [80]						
Orthogonal Fat-Trees [60]						
Multi-Layer Full-Mesh [60]						
Undirected Kautz [70]			•			
Arrangement Network [30]						

Table 4: A general comparison of different network topologies. Lat.: latency. GlB.: global bandwidth (i.e., the saturation point for the random uniform traffic pattern). Ext.: extensibility (i.e., how far can we extend a given concrete network with new servers?). Note that fixed diameter networks have lowest extensibility, because they have strict upper bounds on how many new servers can be attached; the lower the diameter is, the lower this bound is. Contrarily, networks such as torus can attach arbitrarily many new servers, because their diameter grows to infinity. C&P: construction cost and static power consumption. They are assessed as proportional to the total number of ports in a network, for a fixed network size N (i.e., for fixed N, networks with higher radix tend to have higher cost and power consumption). MS: diversity of shortest paths. It is assessed as a weighted average of shortest path diversities at different lengths. MnS: diversity of non-shortest paths. It is assessed as a weighted average of non-shortest path diversities at different lengths. The battery symbols serve as a rudimentary measure of relative comparison between networks. □: worst, □: bad, □: medium, □: good, □: excellent. They always have a positive meaning, e.g., "

"used for cost means that the cost of a given network is very low compared to other networks.





SC rebuttals

- EvalNet
- Higher-Order graph & LLM learning
- Sparse training/inference
- Load balancing in low-diameter networks





Major paper updates

Affordable AI Assistants with Knowledge Graph of Thoughts

CHECKEMBED: Effective Verification of LLM Solutions to Open-Ended Tasks

Multi-Head RAG: Solving Multi-Aspect Problems with LLMs





- More optimizations considered
 - **Hybrid Parallel Mode Switching:** Framework *re-shards* or switches parallelism scheme between training and generation to match each phase's optimal strategy.
 - Adaptive Pipeline Scheduling: System treats the full RLHF loop as a pipeline-scheduling problem, exploring/optimising parallel plans across stages and mini-batches.





- Parallelism in RLHF: Work-Depth Analysis
 - B = number of prompt-response samples processed per iteration (batch size)
 - A = time complexity for the actor model to generate all B responses (sequentially)
 - R, V = time for reward model and value model forward passes on all B responses (if done sequentially)
 - U = time for the update stage (performing all backprop/training on the actor (and critic) for the batch)
- The baseline synchronous RLHF iteration (all stages run sequentially) has

Work =
$$O(A + R + V + U)$$

Depth = $O(A + R + V + U)$







Parallel Technique	Total Work per Iteration	Critical Path Depth per Iteration
Baseline (Sequential)	O(A+R+V+U)	O(A+R+V+U) (no parallelism)
Disaggregated Model Placement	O(A+R+V+U)	O(A + max(R,V) + U) reward & value runs in parallel
Off-Policy RLHF	O(A+R+V+U)	O(max(A+R+V,U)) generation vs. training overlapped





- Asynchronous RLHF





KV cache optimizations

Quantization Hurts Reasoning? An Empirical Study on Quantized Reasoning Models

- Depends on Model Size → Smaller models are the one that suffer the most (Feels counterintuitive)
- High Impact on more difficult tasks

- ... Actually, not that unintuitive





KV cache optimizations

- Exploring a very interesting direction

Bottlenecked Transformers: Periodic KV Cache Abstraction for Generalised Reasoning

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