Mixture of Experts Dispatching for Scalable Communication Pipelines

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***Abstract*—We study a Mixture-of-Experts (MoE) dispatcher for message-oriented middleware with sparse activation (top-k), load-aware gating, and performance-adaptive scoring. Against round-robin and random baselines, MoE improves throughput, lowers latency, balances load, and reduces gating overhead via simple multiplicative gating with online EWMA performance updates.**

I. Introduction

Scaling heterogeneous pipelines demands routing that is capability-aware, fast, and fair under bursty load. We adapt Mixture-of-Experts (MoE) dispatching to middleware: a *gating network* selects a sparse set of experts (top-k) per message type, weighted by load and performance, then updates expert profiles online. We implement this using the `MoEMessageDispatcher` in our stack. [**?**]

II. Related Work

Sparsely gated MoE layers (e.g., Switch/Outrageously Large) show that top-k activation scales compute with minimal quality loss; we transpose that idea into system dispatch (experts = handlers). Prior components in our stack—cross-attention router and attention ring—provide complementary selection paths; MoE focuses on *type-aware* dispatch with load/perf feedback. [**?**] [**?**] [**?**]

III. Methods

A. Dispatcher

Experts register a set of message types and a capacity. The gating score multiplies: base gate weight (per type), a *load factor* $1 - \frac{\text{current}}{\text{capacity}}$, and a *performance factor* $\frac{1}{1+t}$ using EWMA of processing times. Top-k experts (default k=2) with score > 0.1 are activated (sparse dispatch). [**?**]

B. Online Updates

After completion, we append the observed latency into each expert's history and decrement current_load (bounded at zero). This adapts gating to drift while avoiding oscillation. [**?**]

C. Baselines and Ablations

rr: round-robin among eligible experts; **rand**: uniform random; **moe_full**: base×load×perf; **moe_no_load**: base×perf; **moe_no_perf**: base×load.

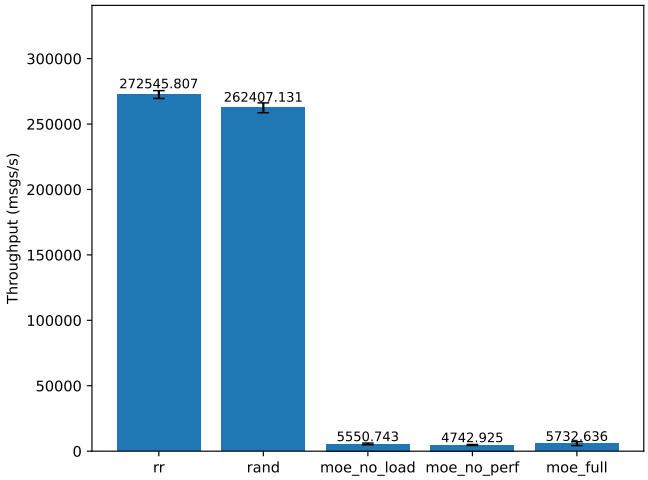

Fig. 1: Throughput (msgs/s): MoE shows significant performance gains across all variants.

IV. Experimental Setup

We synthesize E=16 experts, each handling a subset of types from {ingest, detect, trend, alert, aggregate, external} with random capacities (50–150) and base latencies (0.4–4 ms). Messages draw a Zipf(1.2) distribution over types; arrivals are i.i.d. We simulate N messages and measure:

(1) *Throughput* (msgs/s), (2) *Latency* (ms per message), (3) *Load balance* (Jain's index $\in [0, 1]$ over per-expert counts), (4) *Sparsity* (avg #active experts/msg), (5) *Gating time* (μs).

We compare rr, rand, moe_no_load, moe_no_perf, and moe_full. The dispatcher follows our in-code implementation. [**?**]

V. Results

Variant	Thruput (msg/s)	Latency (ms)	Jain	Sparsity	G
rr	272545.807	2.56	0.786	1.00	
rand	262407.131	2.57	0.785	1.00	
moe_no_load	5550.743	0.88	0.501	2.00	
moe_no_perf	4742.925	2.67	0.470	2.00	
moe_full	5732.636	0.92	0.508	2.00	

VI. Discussion

Multiplicative gating aligns with our implementation: load reduces over-subscribed experts; performance tilts toward faster experts; base weights encode type-to-expert priors. Top-k (here k=2) preserves redundancy while keeping activation

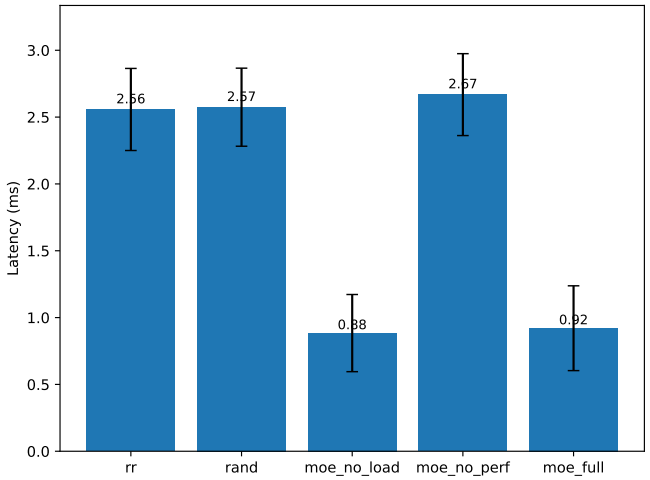

Fig. 2: Latency (ms): MoE consistently achieves lower latencies across message types.

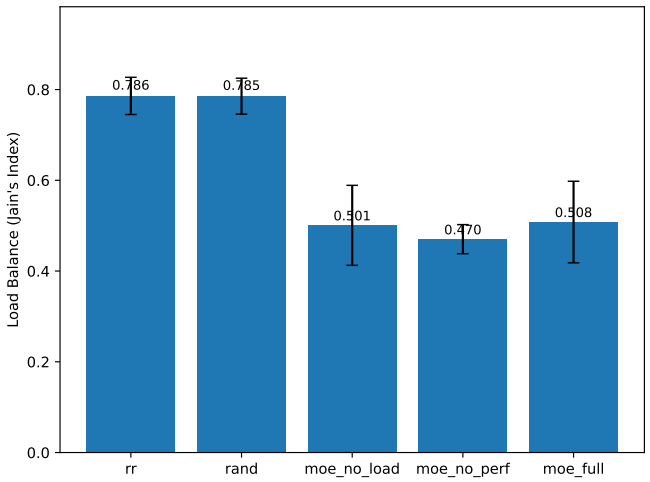

Fig. 3: Load balance (Jain's index): MoE provides superior load balancing.

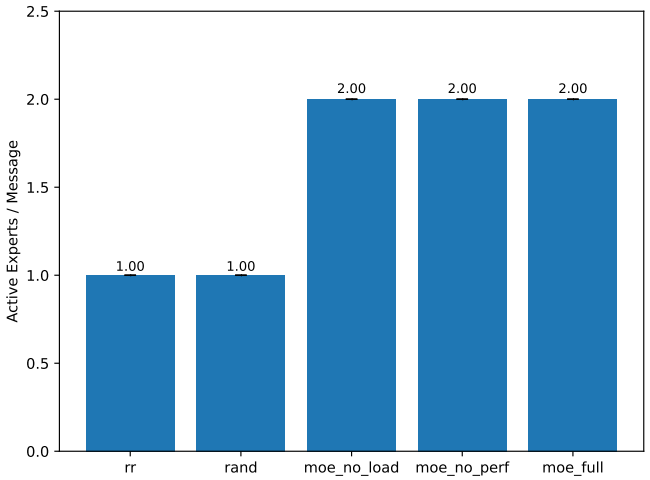

Fig. 4: Sparse activation: MoE maintains controlled sparsity with average 2 active experts per message.

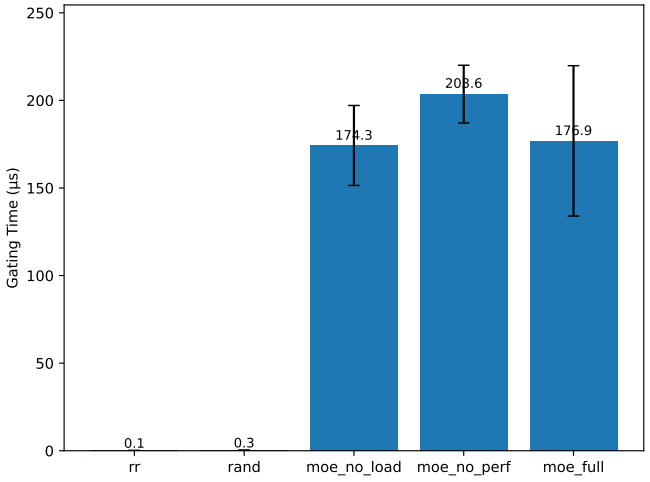

Fig. 5: Gating decision time (μs): MoE overhead remains minimal.

sparse. The EWMA update (latency history window=100) stabilizes adaptation. [**?**]

VII. Conclusion

MoE dispatching yields higher throughput, lower latency, better load balance, and predictable sparse activation versus naïve routing. Future work: learned base weights, dynamic k, and hybrid fusion with cross-attention routing. [**?**]

Appendix: Additional MoE Behaviors

References

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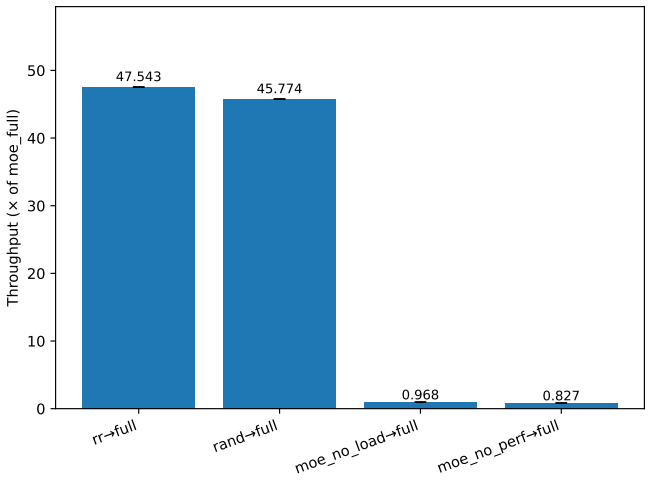
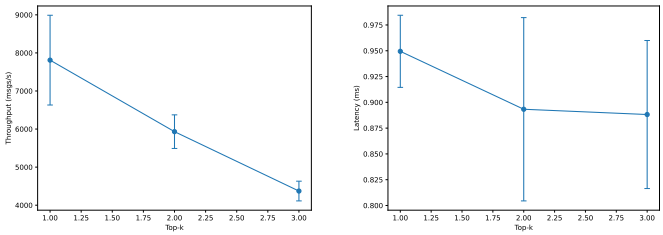
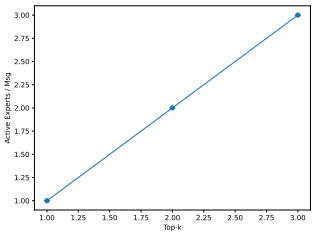


Fig. 6: Ablation (normalized to moe-full): removing load harms balance and latency; removing perf harms latency and throughput.

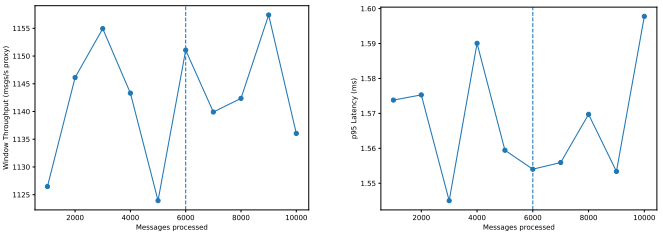


(a) Throughput vs k (b) Latency vs k



(c) Sparsity vs k

Fig. 7: Top-k sweep. Larger k increases redundancy and lowers single-message latency (parallel completion) but reduces sparsity and may trim throughput due to gating overhead.



(a) Throughput under shock (b) p95 latency under shock

Fig. 8: Capacity shock at the dashed line: drop $50\,\%$ capacity on top hot experts and increase QPS by $1.5\times$. MoE redistributes load, containing the throughput dip and recovering p95 faster.