QUANTIZED CACHE-TO-CACHE: COMMUNICATION-BUDGETED KV TRANSFER FOR HETEROGENEOUS LLMS

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ABSTRACT

We study communication-efficient transfer between heterogeneous large language models (LLMs) by quantizing Cache-to-Cache (C2C) KV-cache transfer. Our goal is to reduce bandwidth and memory while preserving accuracy. We present post-training quantization (INT8/INT4), cache-length reduction, and accuracy-versus-bytes curves for a heterogeneous model pair. Empirically, quantization is nearly lossless, while cache-length pruning reveals a strong front/back asymmetry that is critical for budgeted transfer. We release a reproducible evaluation pipeline and analysis scripts, and we outline a main-conference path toward sparse, projector-aware token selection and mixed precision.

1 INTRODUCTION

Large language models (LLMs) often communicate via text, which is slow and lossy. Cache-to-Cache (C2C) communicates via KV-cache projection and fusion, but does not address precision or bandwidth constraints. We ask: *How low can KV precision go before accuracy collapses, and can we recover performance under tight communication budgets?*

Contributions.

- We introduce a precision-aware C2C evaluation pipeline and quantify INT8/INT4 PTQ effects on C2C accuracy.
- We study cache-length reduction as a second budget axis and show that back-pruning consistently outperforms front-pruning.
- We report accuracy vs. communication-budget curves that jointly compare precision and cache length.
- We provide a reproducible benchmarking setup and analysis scripts to support extensions to QAT, mixed precision, heterogeneity, and selective transfer.

2 BACKGROUND AND MOTIVATION

C2C projects sharer KV caches into receiver space and fuses them with learned gates, preserving rich semantics compared to text relay. However, KV caches are large: they scale with sequence length, KV heads, and head dimension. Quantization and cache-length reduction can shrink the communication footprint while retaining accuracy. This work reframes C2C through a communication-budget lens.

3 RELATED WORK

C2C. Cache-to-Cache (C2C) enables direct semantic communication by projecting and fusing a sharer model's KV cache into a receiver's KV cache with learnable gates, avoiding intermediate text generation (Fu et al., 2025).

KV communication across agents. KVComm aligns KV caches across diverging prefixes using training-free offset correction with online anchors (Ye et al., 2025). Q-KVComm adds adaptive layer-wise quantization, hybrid information extraction, and heterogeneous calibration for compressed KV transfer (Kriuk & Ng, 2025). These works focus on multi-agent cache reuse/compression; our work studies quantization and cache-length pruning within the C2C projector+fuser pipeline.

Latent collaboration and cache alignment. KV cache alignment learns a shared latent space with adapters to align KV caches across models (Dery et al., 2026). LatentMAS enables latent-space collaboration with shared working memory without extra training (Zou et al., 2025). Our approach stays within C2C's KV fusion but emphasizes communication budgets and precision/length tradeoffs.

Token selection and KV compression. Token-level KV selection and value-norm importance improve long-context inference for a single model (ZipCache, TokenSelect, VATP) (Anonymous, 2024b; 2025; 2024a). We adopt the budget perspective for C2C rather than single-model KV compression.

4 Method

4.1 C2C Recap

Let the sharer model produce KV caches (K_ℓ^S, V_ℓ^S) and the receiver produce (K_ℓ^R, V_ℓ^R) at layer ℓ. C2C projects sharer KV into receiver space via Π_ℓ^K, Π_ℓ^V and fuses them through a learnable gate:

$$(K_\ell^{R\prime}, V_\ell^{R\prime}) = \mathcal{F}_\ell\left(K_\ell^R, V_\ell^R, \Pi_\ell^K(K_\ell^S), \Pi_\ell^V(V_\ell^S)\right).$$

This avoids intermediate text and transfers richer internal semantics.

4.2 Post-Training Quantization (PTQ)

We quantize the KV caches using INT8 or INT4/NF4 with per-head scaling. We evaluate accuracy and latency under fixed precision budgets. Our current implementation uses fake-quant (quantize then dequantize) to model quantization noise without bit-packing.

4.3 Cache-Length Reduction

We prune KV tokens using a fixed ratio (e.g., 50%, 25%, 10%), reducing transmitted bytes further. We evaluate front-pruning and back-pruning to diagnose which instruction tokens are most valuable for cross-model transfer.

4.4 Selective and Compressed Cache Transfer (SparseC2C)

As a main-conference extension, we select a sparse subset of token positions to transfer and fuse. Let $I \subset \{1, \ldots, T\}$ be selected tokens and S_I the gather operator. We fuse only selected tokens and scatter updates back:

$$(\tilde{K}_\ell^R, \tilde{V}_\ell^R) = S_I^\top(K_\ell^R, V_\ell^R), \quad (\tilde{K}_\ell^S, \tilde{V}_\ell^S) = S_I^\top(K_\ell^S, V_\ell^S)$$

$$(\tilde{K}_\ell^{R\prime}, \tilde{V}_\ell^{R\prime}) = \mathcal{F}_\ell\big(\tilde{K}_\ell^R, \tilde{V}_\ell^R, \Pi_\ell^K(\tilde{K}_\ell^S), \Pi_\ell^V(\tilde{V}_\ell^S)\big).$$

We then scatter the update to the full cache. We use projector-aware token scoring by computing value norms in receiver space (`proj_vnorm_topk`), tying selection to the cross-model mapping.

4.5 Communication-Budget Curves

We report accuracy as a function of transmitted bytes, enabling fair comparison under equal communication constraints. For a sequence of length T, the approximate bytes are

$$\text{bytes} \approx T \cdot p \cdot 2 \cdot L \cdot H_{kv} \cdot d_h \cdot b/8,$$

where p is the retained cache proportion, L the number of layers, H_{kv} KV heads, d_h head dim, and b bits per element. We use this accounting for consistent budget curves.

5 EXPERIMENTS

5.1 SETUP

We evaluate on OpenBookQA and ARC-C with a Qwen3-0.6B receiver and Qwen2.5-0.5B sharer. We follow the C2C eval protocol: temperature 0, max_new_tokens 64, no CoT, unified chat template. All models are frozen; only the projector is trained when QAT is enabled. The OpenBookQA test split has 500 samples and ARC-C has 1150 samples.

5.2 MAIN RESULTS

All results below are full runs. PTQ is effectively lossless relative to FP16, and cache pruning shows a strong front/back asymmetry.

Table 1: Baseline vs. PTQ (full-cache, %).

Setting	OpenBookQA	ARC-C
FP16 baseline	52.8	55.1
INT8 PTQ	52.8	55.0
INT4 PTQ	52.6	55.4

Table 2: OpenBookQA accuracy (%, 500 samples) for cache-length pruning (INT8).

Order mode	75%	50%	25%	10%
Front	44.6	43.0	38.8	38.6
Back	52.2	52.0	50.8	49.2

Table 3: ARC-C accuracy (%, 1150 samples) for cache-length pruning (INT8).

Order mode	75%	50%	25%	10%
Front	40.2	46.3	38.3	40.7
Back	55.7	57.2	56.2	53.7

5.3 COMMUNICATION-BUDGET CURVE

Figure 1 and Figure 2 report accuracy versus effective transmitted bytes. Each point is annotated with the retained cache proportion. These curves provide a single, comparable view across precision (FP16/INT8/INT4) and cache-length reduction.

5.4 ORDER-MODE ABLATION

Across all cache lengths, **back-pruning** (keeping later instruction tokens) consistently outperforms **front-pruning**. At 50% cache length, for example, back-pruning retains near-baseline accuracy while front-pruning degrades sharply. This suggests late instruction tokens carry higher utility for cross-model KV fusion, a useful design signal for future selective transfer methods.

5.5 MAIN-CONFERENCE EXTENSIONS (PRELIMINARY)

We report early results for two main-conference extensions. Mixed precision (INT8 with FP16 in the last layers) remains near baseline across last-2/last-4/last-8 schedules. An alignment-only ablation (same model pair, alignment enabled) reduces accuracy, suggesting alignment should be reserved for heterogeneous pairs. For SparseC2C (token selection), vnorm/knorm scoring preserves accuracy under aggressive token budgets. At p=0.5, INT8 vnorm achieves 52.4/56.2 (OpenBookQA/ARC-C) while front pruning drops to 44.8/47.6. INT4 vnorm remains strong at 52.0/56.3. Full grids across

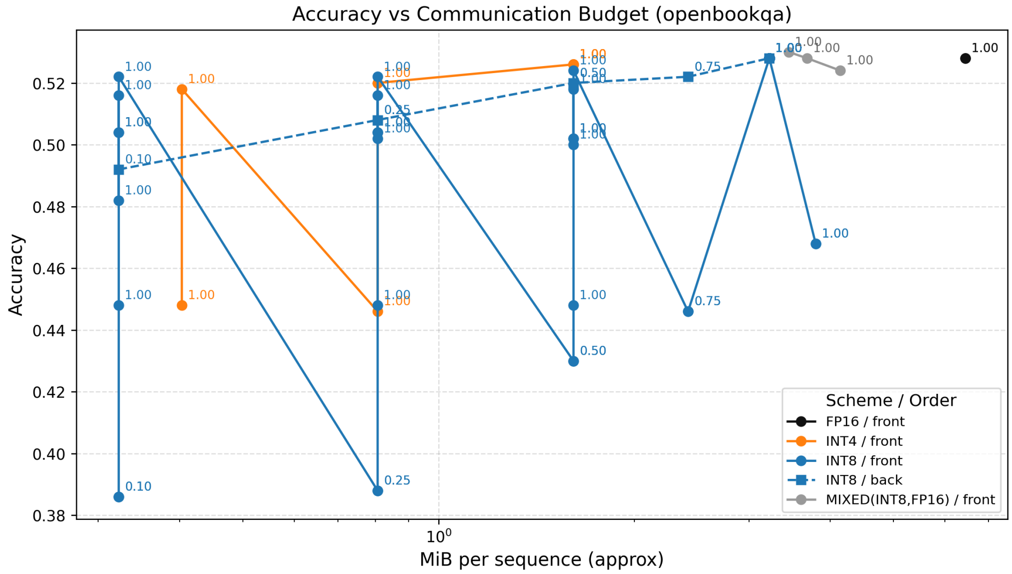

Figure 1: Accuracy vs. communication budget (OpenBookQA).

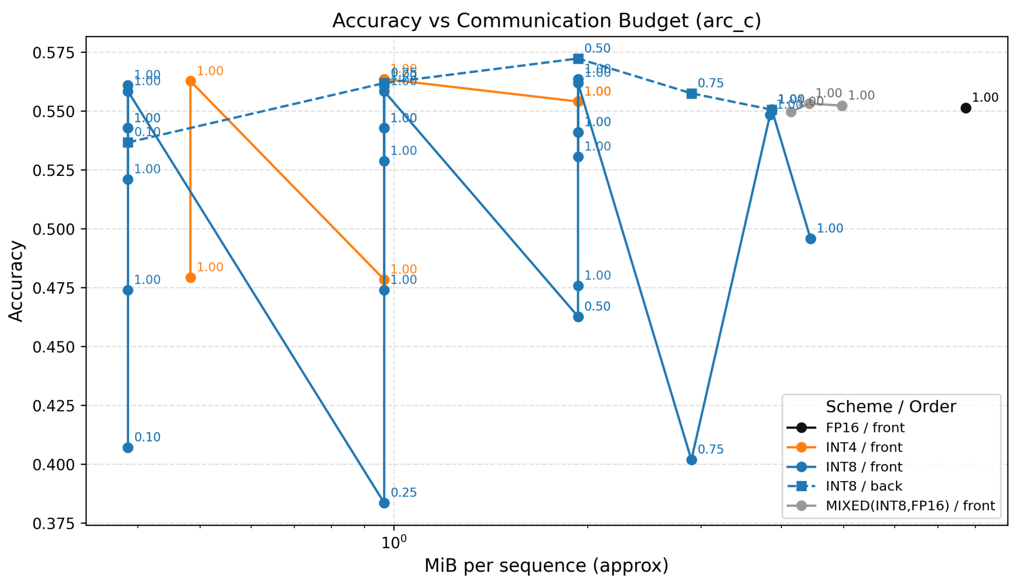

Figure 2: Accuracy vs. communication budget (ARC-C).

selection modes (front, random, proj_vnorm, knorm, vnorm) are reported; heterogeneity runs remain pending.

6 Discussion

Quantized C2C provides large bandwidth reductions with limited accuracy drop. Cache pruning further improves the tradeoff, suggesting a practical path to deployable multi-LLM communication. A main-conference path includes QAT recovery, mixed-precision schedules, heterogeneous model pairs, and SparseC2C token selection.

Table 4: Preliminary extension results (% accuracy).

Setting	OpenBookQA	ARC-C
Mixed precision (INT8 + last-2 FP16)	53.0	55.0
Mixed precision (INT8 + last-4 FP16)	52.8	55.3
Mixed precision (INT8 + last-8 FP16)	52.4	55.2
Alignment ablation (same pair)	46.8	49.6

Table 5: SparseC2C token selection at p=0.5 (prompt-only, sparse fuse).

Setting	OpenBookQA	ARC-C
INT8 front	44.8	47.6
INT8 random	50.0	53.0
INT8 proj_vnorm_topk	50.2	54.1
INT8 knorm_topk	51.8	56.3
INT8 vnorm_topk	52.4	56.2
INT4 front	44.6	47.8
INT4 vnorm_topk	52.0	56.3

7 LIMITATIONS

Our results currently focus on a single model pair and two datasets. We do not yet report end-to-end latency or FLOP measurements for the fuser, and SparseC2C remains an ongoing extension. These limitations will be addressed in the main-conference track.

8 BROADER IMPACT

Communication-efficient multi-LLM systems can reduce compute and latency, but they may also enable higher-throughput deployment of models. We emphasize reproducible evaluation, careful reporting of accuracy/latency tradeoffs, and responsible deployment in sensitive domains.

9 CONCLUSION

We introduce precision-aware C2C and report accuracy vs. bytes curves. This establishes a communication-budget perspective for cross-model KV transfer and opens the door to low-latency, low-bandwidth agent collaboration.

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Placeholder.

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