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 C2C, and introduce receiver-aware token selection and rate–distortion mixed-precision scheduling for sparse transfer. Empirically, quantization is nearly lossless, cache-length pruning reveals a strong front/back asymmetry, and our delta-selection improves accuracy at fixed token budgets while RD scheduling matches or improves accuracy at fixed byte budgets. We release a reproducible evaluation pipeline and analysis scripts.

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 propose receiver-aware delta token selection and rate–distortion token×precision scheduling for sparse, budgeted C2C transfer.
- 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.

4.4.1 RECEIVER-AWARE DELTA SELECTION (M9)

For sparse transfer, the receiver already has a cache baseline, so sending large-but-redundant tokens wastes bandwidth. We score each token by its *marginal update* in receiver space:

$$\Delta V_t^\ell = \widehat{V}^\ell_{:,:,t,:} - V^{R,\ell}_{:,:,t,:}, \quad u^\ell(t) = \mathbb{E}_{b,h}\left[\|\Delta V^\ell_{b,h,t}\|_2\right].$$

We select the top-k tokens by $u^\ell(t)$ under a token budget $|I_\ell| \le \lfloor pT \rfloor$:

$$I_\ell = \mathrm{TopK}\left(u^\ell(t); \lfloor pT \rfloor\right).$$

This `delta_proj_vnorm_topk` score is projector-aware and redundancy-aware by construction.

4.4.2 RATE–DISTORTION TOKEN×PRECISION SCHEDULING (M10)

Under a fixed communication budget, we jointly select tokens and precisions. Each token t chooses an action $a_t \in \{\text{drop}, \text{int4}, \text{int8}\}$ with rate $r(a_t)$ (bits/element). We minimize distortion under a byte budget:

$$\min_{a_t} \sum_t D_t(a_t) \quad \text{s.t.} \quad \sum_t r(a_t) \le R_{\text{budget}},$$

with $D_t(\text{drop}) = \|\widehat{V}_t - V_t^R\|_2^2$ and $D_t(\text{int}b) = \|\widehat{V}_t - \widehat{V}_t^{(\text{int}b)}\|_2^2$. We implement a deterministic greedy allocator (RD-Greedy) that assigns INT8 to highest-utility tokens, then INT4, then drop, until the byte budget is met.

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

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.

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

5.4 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 Receiver-Aware Selection and RD Scheduling

We compare M9 delta selection against value-norm baselines at a fixed token budget ($p = 0.25$, INT8, prompt-only). Delta selection improves accuracy over both vnorm and proj_vnorm heuristics on both datasets (Table 4).

Table 4: M9 selection at $p = 0.25$ (INT8, base pair).

Token selector	OpenBookQA	ARC-C
vnorm_topk	47.0	49.6
proj_vnorm_topk	46.2	52.6
delta_proj_vnorm_topk	**49.8**	**54.8**

RD scheduling provides an additional budget axis. At 1/16 and 1/8 byte budgets, mixed-precision RD (drop+int4+int8) matches or slightly improves over drop+int8 (Table 5), indicating that token-level precision allocation is competitive under tight budgets.

5.6 Heterogeneous Pair Spot Check

On a heterogeneous pair (Qwen3→Llama3.2, alignment on), M9 delta selection and M10 RD scheduling remain viable (Table 6).

5.7 System Metrics

We report end-to-end evaluation time on a single H100 with timing synchronization enabled. M10 incurs additional overhead from token×precision scheduling relative to M9 (Table 7).

5.8 Additional Extensions

Mixed precision (INT8 with FP16 in the last layers) remains near baseline across last-2/last-4/last-8 schedules. Projector-only QAT (INT8) currently degrades accuracy (39.6/40.2), indicating that longer training or recipe tuning is needed. An alignment-only ablation (same model pair, alignment enabled) reduces accuracy, suggesting alignment should be reserved for heterogeneous pairs.

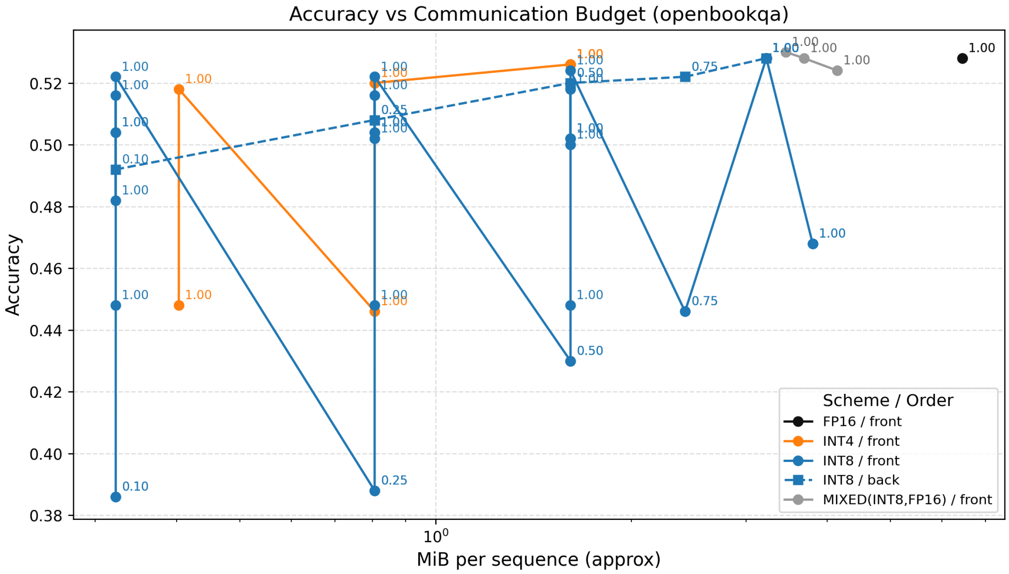

Figure 1: Accuracy vs. communication budget (OpenBookQA).

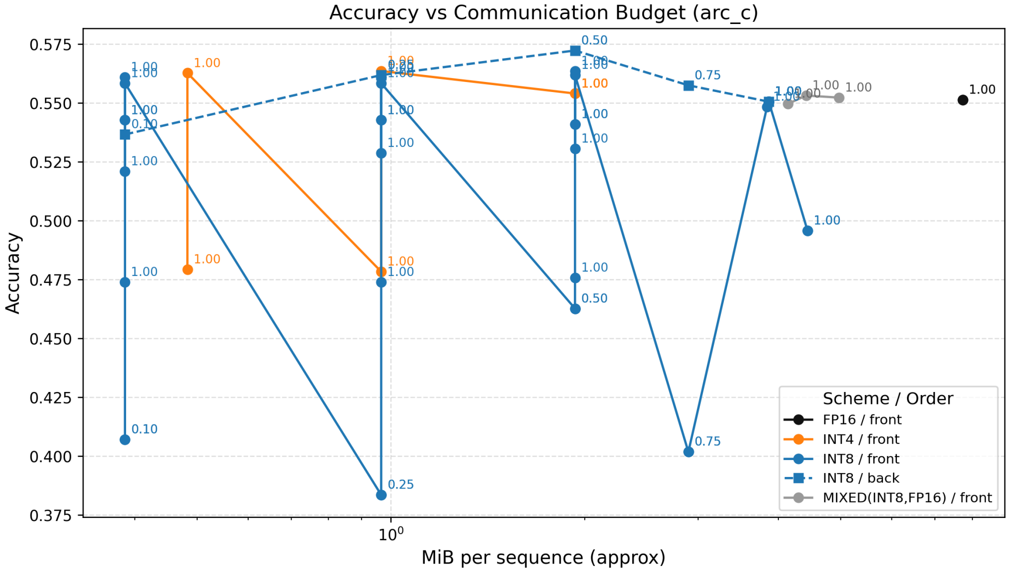

Figure 2: Accuracy vs. communication budget (ARC-C).

GSM8K with CoT. On GSM8K, CoT prompting remains challenging at this model scale. M10 RD (1/8 budget) improves accuracy over M9 delta (p=0.25) by +0.014 absolute (0.042 vs 0.028), but both are far below competitive levels.

6 Discussion

Quantized C2C provides large bandwidth reductions with limited accuracy drop. Receiver-aware delta selection consistently improves low-budget accuracy, and RD-C2C achieves near-baseline performance at moderate byte budgets. Shard-based repeats show low variance (std ≤ 0.02), supporting robustness at tight budgets. Timing-sync measurements indicate RD scheduling adds overhead rel-

Table 5: M10 RD ablation (base pair).

Setting	OpenBookQA	ARC-C
RD 1/16 (drop+int8)	52.6	57.2
RD 1/16 (drop+int4+int8)	**53.4**	57.0
RD 1/8 (drop+int8)	52.4	54.9
RD 1/8 (drop+int4+int8)	52.4	54.9

Table 6: Hetero spot check (alignment on).

Setting	OpenBookQA	ARC-C
M9 delta (p=0.25)	40.0	44.6
M10 RD (1/8)	40.4	46.0

ative to delta selection, highlighting the compute–communication tradeoff. A main-conference path includes QAT recovery, broader heterogeneity, and more system-level profiling beyond single-GPU eval time.

7 LIMITATIONS

Our results focus on a single base pair and two primary datasets; heterogeneity is evaluated via a single spot check. Timing-sync evals capture end-to-end runtime on a single GPU but do not measure distributed communication overhead or kernel-level profiling. GSM8K remains challenging: with CoT enabled, M10 improves over M9 but overall accuracy is still low. These limitations will be addressed in the final main-conference revision.

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.

ACKNOWLEDGMENTS

Placeholder.

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Table 7: End-to-end timing (seconds; per-sample in parentheses).

Setting	OpenBookQA (500)	ARC-C (1150)
M9 delta (p=0.25)	279.5 (0.56)	675.1 (0.59)
M10 RD (1/8)	412.2 (0.82)	1056.9 (0.92)

Table 8: Additional 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
QAT (projector-only, INT8)	39.6	40.2
Alignment ablation (same pair)	46.8	49.6
Hetero pair (Qwen3→Llama3.2, align on)	44.2	47.8

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