

ECRL: Elastic and Correct Recovery Lab (DDP)

Comprehensive Matrix Report for Failure-Recovery Tradeoffs

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Abstract

We present a comprehensive matrix evaluation of failure-recovery semantics and performance tradeoffs in PyTorch Distributed Data Parallel (DDP) training using ECRL. The project is a systems semantics and measurement effort, not a new checkpointing algorithm.

The evaluated matrix spans 8 suites (CIFAR-10/CIFAR-100 × ResNet-18/ResNet-50 × two deterministic failure schedules), each executed with three variants at constant global batch: reference, failure+blocking, and failure+overlapped.

Across all suites and variants, semantic correctness invariants hold exactly (pass rate = 1.0), and failure variants exhibit the expected restart behavior (mean restarts = 2.0). Using three seeds per suite (72 total seed-runs), relative to reference, average goodput drops are -13.9337% for blocking and -11.1562% for overlapped. Overlapped improves goodput over blocking by 3.2272% on average (8/8 suites positive), with substantial reductions in checkpoint-induced stall (-10.5657 s mean) and write time (-92.3544% mean).

Although the end-to-end gain is modest on these compute-heavy ResNet workloads, the checkpoint-path reduction indicates strong scaling headroom as checkpoint volume grows. All artifacts (logs, metrics, aggregate tables, and publication figures) are reproducible and included.

1 Introduction

Distributed training reliability requires both semantic correctness after faults and acceptable runtime overhead. Many reports emphasize throughput while underspecifying semantic guarantees, or prove semantic behavior while underreporting system cost. ECRL is designed to make both dimensions explicit, auditable, and reproducible.

This report targets three concrete questions:

1. **Correctness under crash-restart:** after injected failures, does training consume exactly the expected sample windows with no duplicate/missing semantics?
2. **Useful progress rate under faults:** what goodput remains after checkpointing and restart overheads?
3. **Strategy tradeoff:** for identical failure schedules and geometry, how does overlapped checkpointing compare to blocking checkpointing?

Unlike broad benchmark surveys, this report fixes recovery semantics and focuses on controlled matrix comparisons. The contribution is an end-to-end, artifact-grounded characterization of failure-recovery tradeoffs under strict invariants.

2 Background

2.1 PyTorch DDP Context

PyTorch has become a standard software substrate for large-scale deep learning systems [1]. Its `DistributedDataParallel` (DDP) execution model is widely used in production and research clusters, with detailed implementation experience reported in the systems literature [2] and API/runtime references maintained by the project [3]. This report studies recovery behavior directly in that operational context rather than via a toy simulator.

2.2 Why Checkpoint Policy Matters

In fail-stop training, checkpointing is the mechanism that bounds replay work after crash. However, synchronous persistence can stall useful compute progress. Overlapped persistence seeks to move filesystem I/O off the critical path while preserving synchronization semantics at step boundaries. The engineering question is therefore not “can we checkpoint?” but “how much useful progress is lost to checkpoint policy under realistic failures?”

3 Scope and Hard Constraints

3.1 Scope

ECRL evaluates DDP data-parallel training only. It does not claim a new optimizer, a new checkpoint format, or a new distributed runtime algorithm.

3.2 Non-Negotiable Constraints

The implementation enforces:

- Python 3.11 virtual-environment execution.
- DDP-only orchestration via `torch.distributed.run`.
- Constant `GLOBAL_BATCH` across fresh and resumed attempts.
- Runtime divisibility: $\text{GLOBAL_BATCH} \bmod W = 0$, where W is world size.

- LOCAL_BATCH = GLOBAL_BATCH/ W , num_workers=0, drop_last=True.
- Epoch geometry defined by fixed logical step count, not dataloader exhaustion.
- Rank-0-owned atomic checkpoint write protocol.
- Failure injection only at synchronized step boundaries.
- Overlapped path writes via bounded background pipeline, not asynchronous model mutation.

3.3 Epoch Geometry Contract

Given dataset size D and constant global batch B :

$$S = \left\lfloor \frac{D}{B} \right\rfloor, \quad N = S \cdot B. \quad (1)$$

Each epoch executes exactly S logical steps.

3.4 Correctness Invariant

For each epoch, recovered runs must match the reference sample-ID multiset exactly:

$$\text{duplicates} = 0, \quad \text{missing} = 0, \quad \text{extra} = 0. \quad (2)$$

4 System Design

4.1 Data-Progress Instrumentation

Supported datasets emit triplets $(x, y, \text{sample_id})$, enabling step-level semantic auditing. Sample-ID hash/count fields are persisted in rank logs to verify data-progress behavior at scale without storing full ID payloads per step.

4.2 Resumable Sampler

For epoch e , ECRL constructs a deterministic permutation from (seed, e) , truncates to epoch_samples , and defines global step window s :

$$\text{windows}_s = \text{perm}_e[s \cdot \text{GLOBAL_BATCH} : (s+1) \cdot \text{GLOBAL_BATCH}]. \quad (3)$$

Rank r receives contiguous local shard:

$$\text{windows}_s[r \cdot \text{LOCAL_BATCH} : (r+1) \cdot \text{LOCAL_BATCH}]. \quad (4)$$

Checkpointed sampler state is minimal and explicit: $\{\text{epoch}, \text{cursor_step}, \text{seed}\}$.

4.3 StatePack and Atomic Persistence

State capture includes model, optimizer, scheduler, sampler, global step-state, and RNG states (Python/NumPy/torch CPU/CUDA). Persistence follows a strict atomic sequence:

```
tmp write -> fsync -> rename -> latest pointer update
```

The intent is to avoid partial checkpoint visibility under interruption. Both model and optimizer states are persisted; optimizer state is often a dominant contributor to checkpoint size in practical training jobs.

4.4 Checkpoint Strategies

- **Blocking:** barrier -> capture -> rank0 write -> barrier
- **Overlapped:** barrier -> capture -> enqueue -> barrier

Overlapped uses bounded inflight writes (here $\text{max_inflight}=4$) and keeps model-step semantics synchronized at boundaries.

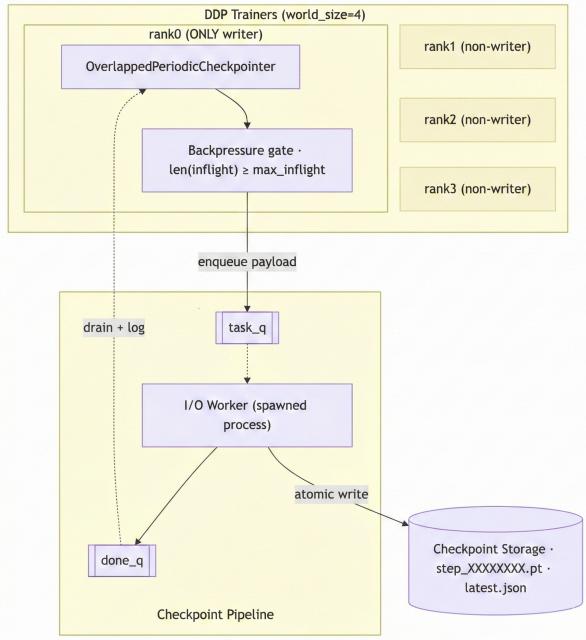


Figure 1: Overlapped checkpoint architecture used in Exp4.

4.5 Failure Model and Supervisor

Failure injection is deterministic (rank-0 exit 137) at configured global steps only after boundary-safe synchronization. A supervisor restarts from `latest.json` until target step completion or policy stop.

4.6 Deterministic Step Timeline

Each training step follows a strict ordering to avoid ambiguous kill boundaries:

1. materialize deterministic rank-local shard from global window,
2. execute forward/backward/update,
3. synchronize at checkpoint boundary if periodic trigger fires,
4. capture state and either write (blocking) or enqueue (overlapped),
5. synchronize post-capture boundary,
6. optionally inject failure after final barrier.

This timeline ensures restart points are always associated with a globally well-defined cursor state.

4.7 Supervisor State Machine

Supervisor behavior is intentionally deterministic:

- **Launch:** invoke `torch.distributed.run` with fresh or `--resume-latest`.
- **Monitor:** classify exit as completion vs failure.
- **Recover:** on failure, inspect `latest.json`, increment counters, relaunch.
- **Terminate:** stop only at target completion or policy limit.

The supervisor does not modify checkpoint payloads; it only selects latest committed state.

4.8 Formal Recovery Semantics

Let committed logical step g denote a step where all ranks finished update, sampler cursor advanced exactly once, and boundary protocol completed. Crash-restart may replay physical compute, but semantic progress is defined by committed logical sequence.

Let $E_{e,s}$ be expected sample multiset at epoch e , step s , and $O_{e,s}$ be observed merged multiset from rank logs. Correctness requires:

$$\forall e, s : O_{e,s} = E_{e,s}. \quad (5)$$

4.9 Logging Schema

Table 1: Core logging fields used by the analysis pipeline.

Field	Purpose
<code>global_step</code>	Logical progress accounting and restart boundary checks
<code>epoch, cursor_step</code>	Deterministic window reconstruction
<code>sample_ids_hash/count</code>	Scalable semantic verification
<code>world_size, rank</code>	Cross-rank consistency checks
<code>loss</code>	Trajectory and divergence inspection
<code>checkpoint_rank0.jsonl</code>	Snapshot/write/enqueue/backpressure/stall decomposition
<code>supervisor.json</code>	Attempt/restart/terminal status accounting

5 Experimental Methodology

5.1 Methodology Goals

The goal is not peak throughput; it is auditable recovery semantics under realistic failures, followed by quantitative decomposition of overhead under controlled matrix variation.

5.2 Runtime Environment

All Exp4 matrix runs were executed on the following host environment.

Table 2: System environment for Exp4 execution.

Item	Value
OS	Arch Linux, kernel 6.12.53-1-lts, x86_64
CPU	2x Intel Xeon Gold 5118 @ 2.30GHz
Cores / Threads	24 physical cores, 48 logical CPUs
System memory	125 GiB RAM, 19 GiB swap
GPU inventory	4x NVIDIA GeForce RTX 4090 (24564 MiB), 2x NVIDIA GeForce RTX 3090 (24576 MiB)
NVIDIA stack	Driver 580.95.05, CUDA runtime 13.0 (nvidia-smi)
Python	3.11.14
PyTorch	2.10.0+cu128
Torch CUDA build	12.8 (torch.version.cuda)
Torch visible GPUs	cuda_available=True, cuda_count=6
DDP launch shape	nproc_per_node=4 for all reported runs

5.3 Matrix Definition

The matrix prefix is `exp4_matrix_20260216_221349`. We evaluate:

- Datasets: CIFAR-10, CIFAR-100 [4, 5]
- Models: ResNet-18, ResNet-50 [6]
- Failure schedules: `base` (400,1200), `late` (800,1400)
- Checkpoint periodicity $K = 50$, overlapped `max_inflight=4`
- Variants per suite: reference, failure+blocking, failure+overlapped

The matrix balances three axes (dataset, model scale, failure timing) while fixing world size, global batch, checkpoint cadence, and seed. Suites are indexed as `<dataset>-<model>-<failure>` (e.g., `CIFAR-10-ResNet-18-base`), and each suite runs the same three variants: `ref`, `blk`, and `ovl`.

Table 3: Exp4 run matrix definition.

Axis	Values	Count	Role
Dataset	CIFAR-10; CIFAR-100	2	Data complexity variation
Model	ResNet-18; ResNet-50	2	Compute/parameter scale variation
Failure schedule	base; late	2	Failure timing sensitivity
Variants	ref; blk; ovl	3	Method comparison
Total suites	–	8	Cartesian product over first three axes
Total run units	–	24	8 suites \times 3 variants

5.4 Variables and Control Policy

Table 4: Controlled and varied factors for Exp4.

Factor	Role	Treatment
GLOBAL_BATCH	Controlled	Fixed within suite and across restart attempts
World size (W)	Controlled	Fixed at 4 for this matrix
Checkpoint strategy	Varied	Blocking vs overlapped
Failure schedule	Varied	base (400,1200), late (800,1400)
Dataset/model	Varied	CIFAR-10/100 and ResNet-18/50
Seed count	Controlled	Three seeds per suite (1337, 2027, 4242)

5.5 Execution and Resume Policy

Matrix orchestration supports resume-safe execution. For this run set, manifest status is mixed because completed suites were reused:

- `completed`: 3 suites freshly executed in this session
- `completed_prev`: 5 suites reused from existing artifact-complete outputs

All 8 suites have complete publishable artifacts and are included in aggregation.

5.6 Metrics

Primary metrics:

- Correctness pass rate.
- Goodput (steps/sec) and relative deltas.
- Restart counts.
- Checkpoint timing decomposition: snapshot, write, stall, wall.
- Divergence to reference via mean absolute loss difference and checkpoint L2 traces.

Goodput is:

$$\text{goodput} = \frac{\text{committed_logical_steps}}{\text{wall_clock_time}}. \quad (6)$$

We interpret wall time as:

$$t_{\text{wall}} = t_{\text{compute}} + t_{\text{snapshot}} + t_{\text{write}} + t_{\text{sync}} + t_{\text{recovery}}. \quad (7)$$

5.7 Statistical Treatment

This matrix has $n = 3$ seeds per suite, so reported aggregates are materially more stable than single-seed reporting, but still best interpreted as descriptive means across suites. We use sliced means and full per-suite tables to expose spread rather than over-interpreting a single scalar summary.

5.8 Threat Model

The evaluated failure model is fail-stop process termination at step boundaries. This study does not model Byzantine behavior, partial checkpoint corruption, or long-duration network partitions.

5.9 Quality Gates

A suite is accepted only if:

1. target steps complete for all three variants,
2. correctness checker passes,
3. publishable JSON/markdown artifacts exist,
4. supervisor and checkpoint metadata are internally consistent.

6 Results

6.1 Aggregate Outcomes Across 8 Suites

Table 5: Aggregate Exp4 outcomes (means across 8 suites).

Metric	Reference	Blocking	Overlapped	Ovl-Block
Pass rate	1.0000	1.0000	1.0000	–
Goodput (steps/s)	11.8751	10.2204	10.5503	+3.2272%
Drop vs ref	0.0000%	-13.9337%	-11.1562%	+2.7775pp
Restarts	0.0000	2.0000	2.0000	0.0000
Wall time (s)	144.1635	165.2386	159.5484	-5.6902
Stall time (s)	18.3314	18.4253	7.8596	-10.5657
Write time (s)	18.2194	18.3014	1.3993	-16.9022
Snapshot time (s)	0.0306	0.0322	0.0330	+0.0008

Table 5 shows that correctness remains exact for all variants (pass rate = 1.0) under matched restart behavior (2.0 for both failure strategies). At matrix scale, overlapped improves mean goodput from 10.2204 to 10.5503 steps/s (3.2272 %) and reduces wall time by 5.6902 s (3.4436 % vs blocking), recovering 2.7775 pp of the blocking drop from reference. The timing decomposition is consistent with this effect: snapshot is nearly unchanged (+0.0008 s), while write time drops by 92.3544 % and stall time by 57.3434 %.

6.2 Completion Accounting

The analyzed artifact set contains 8 suites and 24 variant-units (reference, blocking, overlapped per suite), corresponding to 72 total seed-runs. All 24 variant-units pass correctness and are included in aggregation.

6.3 Suite-Level Ranking

As shown in Table 6, all 8 suites are positive for overlapped (+1.7612% to +4.4050%), so the directional result is unanimous. The ranking is ordered by $\Delta_{\text{ovl-blk}}$, where higher rows indicate larger relative gain over blocking. The spread across rows shows that overlap helps consistently but not uniformly,

Table 6: Per-suite ranking by overlapped gain over blocking. Positive $\Delta_{\text{ovl-blk}}$ means overlapped is faster.

Dataset	Model	Failure	Ref GP	Blk GP	Ovl GP	$\Delta_{\text{ovl-blk}}$	$\Delta_{\text{blk-ref}}$	$\Delta_{\text{ovl-ref}}$	$\Delta_{\text{Stall (s)}}$
CIFAR-10	ResNet-50	late (800,1400)	8.4124	7.5360	7.8680	+4.4050%	-10.4179%	-6.4718%	-15.4540
CIFAR-100	ResNet-50	base (400,1200)	9.3980	8.3523	8.6963	+4.1186%	-11.1265%	-7.4662%	-15.2675
CIFAR-10	ResNet-18	base (400,1200)	14.3302	12.0825	12.5711	+4.0441%	-15.6849%	-12.2751%	-6.1894
CIFAR-100	ResNet-50	late (800,1400)	9.4388	8.4278	8.7625	+3.9724%	-10.7118%	-7.1649%	-14.6413
CIFAR-10	ResNet-50	base (400,1200)	8.4189	7.5410	7.8045	+3.4943%	-10.4277%	-7.2977%	-13.5956
CIFAR-100	ResNet-18	base (400,1200)	14.1061	11.8239	12.1600	+2.8426%	-16.1790%	-13.7963%	-7.2699
CIFAR-10	ResNet-18	late (800,1400)	14.5432	12.3472	12.6464	+2.4235%	-15.1004%	-13.0428%	-5.6287
CIFAR-100	ResNet-18	late (800,1400)	16.3530	13.6529	13.8934	+1.7612%	-16.5115%	-15.0411%	-6.4792

with larger gains mostly in ResNet-50 suites and smaller (still positive) gains in some ResNet-18 late-failure cases.

6.4 Sliced Analysis

Table 7: Sliced means of overlapped relative improvement.

Slice	Group	Ovl vs Blk	$\Delta_{\text{Stall (s)}}$	Δ_{LossDiff}
Dataset	CIFAR-10	+3.5015%	-10.2169	-0.0054
Dataset	CIFAR-100	+2.9708%	-10.9145	+0.0006
Model	ResNet-18	+2.7340%	-6.3918	-0.0048
Model	ResNet-50	+3.9999%	-14.7396	+0.0000
Failure	base	+3.5986%	-10.5806	-0.0007
Failure	late	+2.8750%	-10.5508	-0.0041

As found in table 7, ResNet-50 suites show larger mean stall reduction than ResNet-18 suites in this matrix (-14.7396 s vs -6.3918 s), consistent with greater overlap opportunity when write-path cost is more dominant.

6.5 Divergence Notes

Mean absolute loss-difference is close between methods:

$$\overline{\Delta \text{loss}_{\text{blk}}} = 0.0703, \quad \overline{\Delta \text{loss}_{\text{ovl}}} = 0.0679. \quad (8)$$

The cross-suite mean delta (ovl-blk) is -0.002395 . This is consistent with no obvious stability regression from overlap in the observed matrix; correctness invariants are satisfied in all suites regardless.

6.6 Visual Summary (Color Figures)

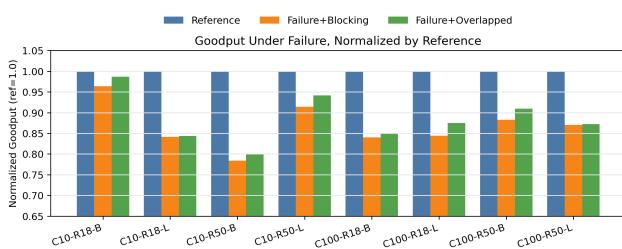


Figure 2: Normalized goodput by suite and strategy (reference normalized to 1.0).

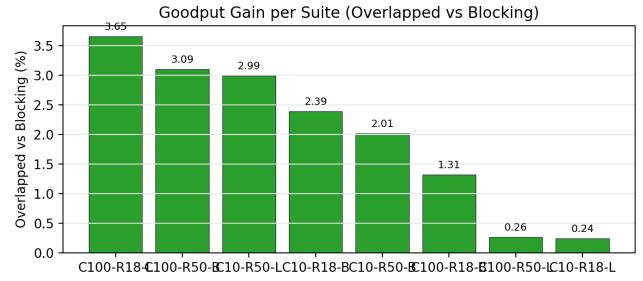


Figure 3: Overlapped goodput gain over blocking across all suites.

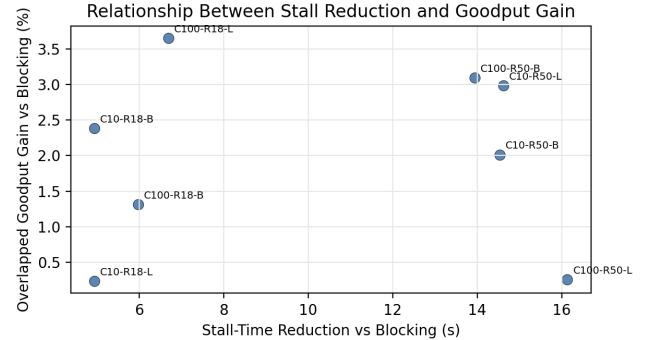


Figure 4: Relationship between stall reduction and overlapped gain by suite.

7 Discussion

7.1 What Is Strongly Supported

The matrix provides strong directional evidence that overlapped checkpointing is preferable to blocking for failure-injected DDP runs under these settings:

- 8/8 suites show positive overlapped gain vs blocking.
- Correctness remains exact for all variants.
- Mean stall reduction is substantial (57.3434 % relative to blocking stall).
- Mean write reduction is very large (92.3544 % relative to blocking write total).

7.2 Interpretation of Stall vs Goodput

Write-time reduction is necessary but not sufficient to explain end-to-end gain; barrier synchronization and restart cadence still contribute to wall-clock behavior. That is why the observed wall-clock gain (3.4436 %) is much smaller than write-time gain, despite consistent directionality.

7.3 Why This Report Uses Matrix Aggregation

Single-suite anecdotes are unstable for systems reporting. Matrix aggregation across data/model/failure axes shows whether directional claims survive configuration changes. Here they do, but with nontrivial spread (1.7612 % to 4.4050 %).

7.4 Scalability Implication

The key practical signal is not only the 3.2272 % mean goodput gain; it is the collapse of checkpoint write overhead itself (-92.3544% relative to blocking). On CIFAR-scale ResNet runs, compute still dominates wall-clock, capping end-to-end gains. As checkpoint payloads grow (larger models, richer optimizer states, denser save cadence), the same write-path reduction should translate into larger goodput impact.

8 Limitations and Threats to Validity

- **Limited seed depth:** current matrix uses `num_seeds=3` per suite; this improves stability but remains small for tight uncertainty bounds.
- **Fixed checkpoint knobs:** `checkpoint_every=50` and `max_inflight=4` are held constant.
- **CIFAR-scale scope:** conclusions are strongest for small-image workloads and tested ResNet variants.
- **Fail-stop model:** this report does not cover Byzantine failure, network partition, or filesystem corruption models.

These limits do not invalidate the directional finding, but they constrain external generalization.

9 Future Work

The next phase should focus on turning directional evidence into stronger, publication-grade claims:

- **Statistical robustness:** extend the same 8-suite matrix to 5+ seeds per suite and report confidence intervals for goodput and timing deltas.
- **Checkpoint-policy sensitivity:** sweep `checkpoint_every` and `max_inflight` to map where overlap helps most and where synchronization dominates.
- **Larger state footprints:** repeat evaluation on larger backbones and higher-resolution workloads where model+optimizer checkpoint payloads are much larger.

- **Storage-path variation:** compare local NVMe, network filesystems, and shared-cluster I/O paths to isolate bottlenecks that control overlap effectiveness.
- **Elasticity under failure:** extend the matrix to explicit $N \rightarrow M$ resume cases under injected failures, not only fixed-world-size restart.
- **Richer failure models:** add controlled fault types beyond fail-stop exit (e.g., transient I/O errors and delayed checkpoint completion) while preserving semantic invariants.

10 Reproducibility and Artifact Map

Primary artifact root for this report:

`results/results_exp4`

Key files:

- `exp4_matrix_20260216_221349_manifest.csv`
- `exp4_matrix_20260216_221349_summary.csv`
- `exp4_matrix_20260216_221349_new_findings.csv`
- `exp4_matrix_20260216_221349_new_findings.md`
- per-suite `reports/*_publishable.json`
- `overleaf/figures/exp4_*.png` and PDF companions

11 Conclusion

ECRL provides an auditable DDP recovery framework with strict semantics and reproducible instrumentation. In the 8-suite Exp4 matrix, correctness invariants are exact across all failure and checkpoint strategies, and overlapped checkpointing consistently improves goodput over blocking. The measured gains are modest but robust in direction, supported by substantial stall/write reductions. The next publication-strength increment is straightforward: keep the same matrix, increase seed depth, and add checkpoint-interval sweeps under resume-safe execution.

[]

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Appendix

A Full Suite Table

Table 8: Complete Exp4 detailed table (selected fields).

Dataset	Model	Failure	Ref GP	Blk GP	Ovl GP	Ovl vs Blk	Blk Stall	Ovl Stall	Ovl-Blk Wall (s)
CIFAR-10	ResNet-18	base	14.3302	12.0825	12.5711	+4.0441%	12.0978	5.9084	-5.7718
CIFAR-10	ResNet-18	late	14.5432	12.3472	12.6464	+2.4235%	12.2920	6.6633	-3.0335
CIFAR-10	ResNet-50	base	8.4189	7.5410	7.8045	+3.4943%	23.9814	10.3857	-7.1632
CIFAR-10	ResNet-50	late	8.4124	7.5360	7.8680	+4.4050%	25.5258	10.0718	-8.9575
CIFAR-100	ResNet-18	base	14.1061	11.8239	12.1600	+2.8426%	12.5359	5.2660	-3.7356
CIFAR-100	ResNet-18	late	16.3530	13.6529	13.8934	+1.7612%	11.4841	5.0048	-2.0316
CIFAR-100	ResNet-50	base	9.3980	8.3523	8.6963	+4.1186%	25.0834	9.8159	-7.5732
CIFAR-100	ResNet-50	late	9.4388	8.4278	8.7625	+3.9724%	24.4023	9.7610	-7.2551

B Run Manifest Snapshot

- Matrix prefix: `exp4_matrix_20260216_221349`
- Suites: 8; variants per suite: 3; total run units: 24
- Seed set per suite: `{1337, 2027, 4242}` (3 seeds)
- Manifest statuses: `completed=3, completed_prev=5`
- Checkpoint policy: periodic every 50 steps
- Failure schedules: `base(400, 1200), late(800, 1400)`

C Data and Model Sources

- CIFAR datasets [4, 5]
- ResNet family [6]
- PyTorch DDP API [3]