

# Matrix: Peer-to-Peer Multi-Agent Synthetic Data Generation Framework

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Synthetic data has become increasingly important for training large language models, especially when real data is scarce, expensive, or privacy-sensitive. Many such generation tasks require coordinated multi-agent workflows, where specialized agents collaborate to produce data that is higher quality, more diverse, and structurally richer. However, existing frameworks for multi-agent synthesis often depend on a centralized orchestrator, creating scalability bottlenecks, or are hardcoded for specific domains, limiting flexibility. We present **Matrix**, a decentralized framework that represents both control and data flow as serialized messages passed through distributed queues. This peer-to-peer design eliminates the central orchestrator. Each task progresses independently through lightweight agents, while compute-intensive operations, such as LLM inference or containerized environments, are handled by distributed services. Built on Ray, Matrix scales to tens of thousands of concurrent agentic workflows and provides a modular, configurable design that enables easy adaptation to a wide range of data generation workflows. We evaluate Matrix across diverse synthesis scenarios, such as multi-agent collaborative dialogue, web-based reasoning data extraction, and tool-use trajectory generation in customer service environments. In all cases, Matrix achieves 2–15× higher data generation throughput under identical hardware resources, without compromising output quality.

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**Code:** <https://github.com/facebookresearch/matrix>



## 1 Introduction

Large scale machine learning models, such as large language models (LLMs) and multi-modal foundation models, are increasingly trained with synthetic data to reduce dependence on costly, noisy, or privacy-sensitive human-curated datasets Grattafiori et al. (2024); Abdin et al. (2024); Betker et al. (2023). Recent advances have shifted toward agentic synthetic data generation, where data is produced through interactions among multiple intelligent agents rather than a single model or fixed pipeline. This paradigm enables multi-agent collaboration for diverse generation tasks such as code synthesis, instruction and dialogue creation, knowledge-grounded question answering, and multi-modal content generation. In these settings, the workflows often involve complex control flows with loops, moving beyond traditional linear data generation pipelines. For example, Kimi K2 Bai et al. (2025) employs a large-scale multi-agent data synthesis pipeline to construct diverse tool-use and reasoning demonstrations. Similarly, CWM Copet et al. (2025) leverages autonomous software engineering agents to generate multi-step trajectories for code understanding and debugging. These systems exemplify the growing adoption of multi-agent pipelines for synthetic data generation in large scale LLM training, underscoring the need for flexible and scalable frameworks for data synthesis.

Generic agent frameworks such as Autogen Wu et al. (2023); Fourney et al. (2024), LangGraph LangChain (2025), and CrewAI CrewAI (2025) provide abstractions for constructing agent workflows. These frameworks target broad application domains such as chatbots, web agents, and personal assistants, but are not optimized for large scale synthetic data generation. In contrast, many recent frameworks have been developed for specific data generation needs. Notable examples include AgentInstruct Mitra et al. (2024), SWE-Agent Yang

et al. (2024), SWE-Synth Pham et al. (2025), TaskCraft Shi et al. (2025), and AgentSynth Xie et al. (2025). While these systems have achieved high quality data and strong task-level performance, they are typically tightly coupled to domain specific workflows, with orchestration and scheduling logic embedded directly in their implementations. Such designs also face scalability challenges. To handle multiple tasks concurrently, users must either launch many independent workflow instances (for example, through multi-threading or asynchronous execution) or rely on external orchestration systems such as Kubernetes Jobs, Airflow, or distributed task queues. This approach introduces substantial engineering overhead and creates practical system bottlenecks, as multiple workflow instances and concurrency layers must be coordinated and maintained at scale.

To address these limitations, we present Matrix, a distributed runtime for scalable, multi-agent synthetic data generation and agentic experimentation. Matrix frames data generation as a *data-to-data transformation*: each input row represents an independent task, and the runtime executes many such tasks concurrently, each running its own agentic workflow.

The core idea behind Matrix is a peer-to-peer (P2P) agent architecture that replaces centralized orchestration with decentralized, message-driven scheduling. The state of each task, which includes orchestration logic, intermediate results, and conversation history, is serialized into messages that are passed among agents. The active agent consumes and updates this state, then emits it to the next agent determined by the orchestrator. Because agents themselves are stateless, they can scale elastically and independently across the cluster. Unlike traditional batch-level scheduling in distributed execution engines such as Spark Zaharia et al. (2012) and Ray Data Moritz et al. (2018), where the pipeline controls progress across synchronized batches, Matrix performs row-level scheduling through peer-to-peer message orchestration. Control and data flow are embedded in messages, allowing each task to progress asynchronously through agents. This eliminates idle periods caused by batch-level barriers and enables high utilization across tens of thousands of concurrent workflows.

Matrix integrates naturally with modern inference engines such as vLLM Kwon et al. (2023), SGLang Zheng et al. (2024), and leverages Ray Moritz et al. (2018) for distributed execution and containerized environments via Apptainer Kurtzer et al. (2017) for complex services such as software and tools execution.

### Key Contributions.

1. We introduce **Matrix**, a **scalable runtime** for large scale multi-agent synthetic data generation capable of efficiently executing tens of thousands of concurrent workflows. Matrix adopts a **peer-to-peer agent architecture** with message-embedded control and state representation, eliminating centralized orchestration bottlenecks and idle time caused by batch-level synchronization. This design enables fully asynchronous and fine-grained execution at scale.
2. Matrix is designed to be **flexible** and **extensible**, supporting diverse multi-agent use cases. Its modular architecture separates key components, including the generation loop and distributed services for LLM inference and containerized execution, and the entire system is fully configurable through Hydra.
3. We evaluate Matrix on three representative case studies: Collaborative Reasoner Ni et al. (2025a), NaturalReasoning Yuan et al. (2025), and Tau2-bench Barres et al. (2025a). Matrix achieves **2–15× higher token throughput** than specialized baseline systems while maintaining comparable output quality.
4. Matrix is built entirely on an **open source stack**, including SLURM, Ray, vLLM, SGLang, and Apptainer. It supports both open-weight models and LLM API proxies. We will release the framework to the community to foster open development and collaborative research.

## 2 Related Work

*LLM and agentic benchmarks.* LLMs are commonly evaluated on reasoning benchmarks such as Math-500 Hendrycks et al. (2021) and MMLU-Pro Wang et al. (2024). Recent multi-agent systems run on standardized benchmarks that test complex, multi-step reasoning and tool use. Examples include SWE-bench Jimenez et al. (2024), Tau2-Bench Barres et al. (2025a), MCP-Bench Wang et al. (2025), and MLE-Bench Chan et al. (2025). Each benchmark comes with a reference agentic system that solves the tasks,

such as SWE-agent and Tau2-agent. In this work, we use Tau2-Bench and MMLU-Pro as sources of initial tasks to generate agent trajectories that can be used for fine-tuning LLMs.

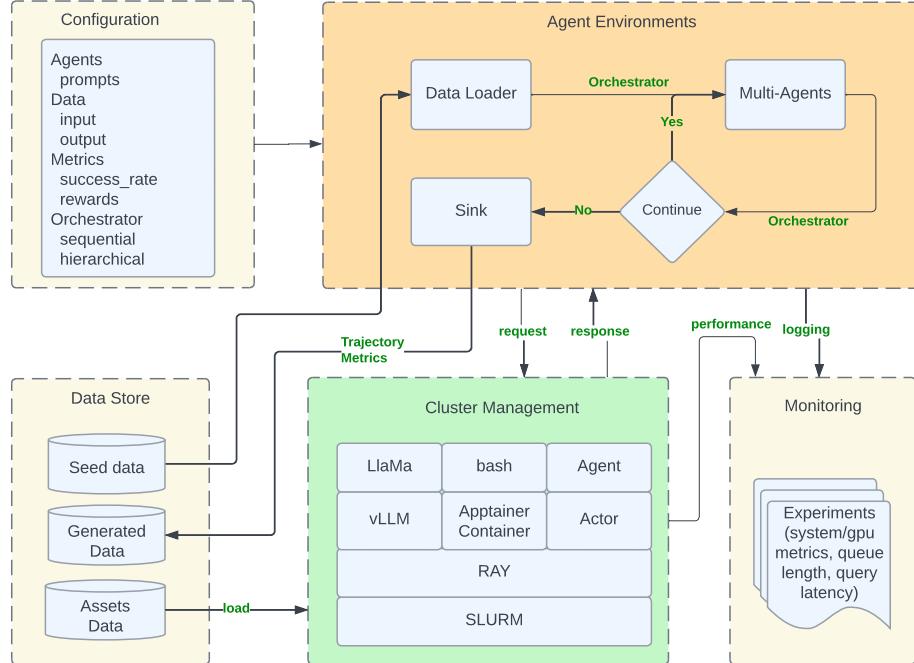
*Data Synthesis via Multi-agents Workflows.* The scarcity of high-quality agentic training data has led to the development of synthetic data generation techniques employing multi-agent frameworks. AgentInstruct [Mitra et al. \(2024\)](#) generates multi-turn instruction-response data by coordinating multiple agents to propose, verify, and refine synthetic tasks based on seed examples. TaskCraft [Shi et al. \(2025\)](#) automatically generates multi-step, multi-tool agentic tasks with verifiable execution trajectories. APIGen-MT [Prabhakar et al. \(2025\)](#) is a two-phase framework that generates verifiable, multi-turn agent interaction data. While these frameworks are tailored to specific data needs and emphasize data quality, our approach offers a generic framework capable of supporting multiple use cases with a focus on scalability.

*Peer-to-Peer ML Systems* Peer-to-peer (P2P) architectures have long been foundational in distributed computing and communications. In ML, P2P systems have been leveraged to enhance scalability, privacy, and personalization. For instance, The SPIRT [Barak et al. \(2023\)](#) framework introduces a serverless P2P ML training architecture that leverages RedisAI for in-database operations, achieving significant reductions in model update times and demonstrating resilience against peer failures. Similarly, BlockDFL [Qin et al. \(2024\)](#) employs blockchain-based coordination to facilitate fully decentralized federated learning, incorporating mechanisms to defend against poisoning attacks and reduce communication costs. While prior P2P ML systems focus on efficient training and privacy-preserving computation, Matrix introduces a general framework using P2P communication to coordinate agent workflows for scalable multi-agent data synthesis.

### 3 Matrix Overview

This section provides an overview of the Matrix framework, describing its system architecture and the core algorithm that enables scalable, asynchronous multi-agent synthetic data generation.

#### 3.1 System Architecture



**Figure 1** Matrix Agentic Data Generation Architecture.

Figure 1 illustrates the architecture of the proposed agentic data generation framework, which is designed to be **modular** and **configurable**.

*Cluster Management.* The framework is deployed atop SLURM [Yoo et al. \(2003\)](#), a widely adopted distributed computing environment, with a Ray [Moritz et al. \(2018\)](#) cluster serving as the execution substrate. Ray Serve provides high-throughput LLM inference services, backed by vLLM [Kwon et al. \(2023\)](#), SGLang [Zheng et al. \(2024\)](#), and FastGen [FAIR \(2025\)](#). Containerized execution is supported through Apptainer [Kurtzer et al. \(2017\)](#), enabling stateful environments to be launched on demand. Each agent is implemented as a Ray Actor, allowing scalable parallelization and fine-grained resource placement across worker nodes.

*Configuration.* System configurability is managed through Hydra [Yadan \(2019\)](#), which specifies agent roles, input–output schemas, generation metrics, and resource requirements (e.g., LLM engine selection). The configuration also defines the orchestrator responsible for control and data flow management. The primary shared data structure is the conversation history, while control flow dynamically determines agent execution order and task termination based on data-dependent conditions.

*Agents Environments.* In the peer-to-peer generation process, each input datum is encapsulated into an orchestrator instance and passed to the initial agent. The agent processes the instance, updates the orchestrator state, and forwards control to the next designated agent. This process continues iteratively until completion. A detailed algorithmic description is provided in Section 3.2. We will use Matrix to build different agents environments in the experiments section.

*Monitoring.* Logging and observability are critical for debugging and performance analysis. Matrix integrates with Grafana [Labs \(2025\)](#) for real-time monitoring. In addition to standard performance metrics, it provides custom indicators such as distributed queue length and the number of pending asynchronous tasks. These metrics help identify throughput bottlenecks and evaluate overall system health.

### 3.2 Data Generation Algorithm

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**Algorithm 1:** Matrix P2P agentic generation pseudocode.

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```

1  @ray.remote
2  class AgentActor: # agent base class with an event loop to process orchestration messages
3      async def _event_loop(self, team):
4          while True:
5              orchestrator = await self.queue.get()
6              result = self.process(orchestrator)
7              orchestrator.update(result) # update conversation history and determine next agent
8              next_agent = orchestrator.current_agent()
9              random.choice(team[next_agent]).send(orchestrator) # send updated orchestrator to next agent
10
11 class SequentialOrchestrator: # a typical orchestrator with a configurable order of execution
12     def update(self, result):
13         self.history.append(result)
14         self.index = (self.index + 1) % len(self.order) # take the next agent in the given order with loop around
15
16     def current_agent(self):
17         return "_sink" if self.is_done else self.order[self.index] # loop around until is_done flag is set
18
19     def create_team(cfg): # create a team of agents based on the configuration
20         return {
21             role: [ray_create_actor(role, role_cfg) # each agent instance become a Ray actor
22                   for _ in range(role_cfg.num_instances)]
23             for role, role_cfg in cfg.items()
24         }
25
26     # main processing
27     team = create_team(cfg.agents)
28     for item in dataset: # process each dataum concurrently up to max_concurrency asyncio tasks
29         orchestrator = Orchestrator(item)
30         first = random.choice(team[orchestrator.current_agent()])

```

---

Algorithm 1 illustrates the core workflow of Matrix’s peer-to-peer agentic generation runtime. The system begins by reading the Hydra configuration `cfg`, which specifies all agent roles and their resource requirements (e.g., CPU, GPU, and memory). As shown in Lines 19–24, the function `create_team()` instantiates a

distributed team of Ray actors for each agent role, allowing heterogeneous resource allocation across agent types.

*Agent EventLoop.* The main generation loop (Lines 26–30) iterates over input items in the dataset. For each item, an `Orchestrator` object is created to manage task-specific state and control flow. The orchestrator is initially dispatched to the first agent in the sequence, sampled randomly from the corresponding role group. Each agent runs as a persistent event-driven process (Lines 3–9) implemented by the `AgentActor` class. Within its asynchronous `_event_loop`, the agent dequeues orchestrators from its inbox, applies role-specific logic through `process()`, updates task state, and forwards it to the next designated agent.

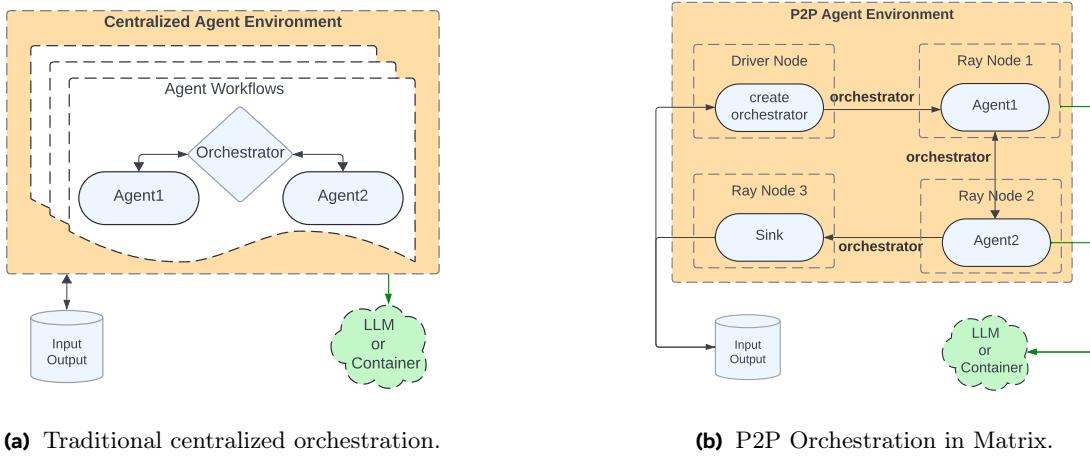
*Orchestration.* An example orchestrator `SequentialOrchestrator` is in Lines 11–17. It maintains a structured history of intermediate results and a configurable `order`, which determines the sequence of participating agents. After each interaction, `update()` advances the internal index to the next agent. The process continues cyclically until the orchestrator’s `is_done` flag is set, at which point it is routed to a special terminal agent, `_sink`, for result persistence and metric aggregation.

*Concurrency Control.* Advanced runtime features (not shown for brevity) include task-level concurrency control through a `max_concurrency` parameter and semaphore-based scheduling. The semaphore is decremented when an orchestrator is dispatched to the first agent and incremented upon completion by the `_sink` agent. This mechanism limits the number of active orchestrators, ensuring controlled resource utilization and stability during large-scale distributed execution. Note we rely on Ray’s RPC mechanism to avoid race conditions.

## 4 Agent Environment Design for Matrix

This section describes the system’s internal design, including its orchestration model, distributed service layer, parallelism strategies, scheduling policies, fault tolerance mechanisms and network bandwidth optimization.

### 4.1 P2P Orchestration



**Figure 2** Compare Centralized vs P2P Orchestration.

As illustrated in Figure 2a, centralized orchestration must manage execution order (control flow), message passing (data flow), and the full lifecycle of requests and responses for LLMs and containerized environments. Handling all of this for tens of thousands of concurrent workflows quickly becomes a scalability bottleneck. Matrix addresses this by representing workflows as serializable *orchestrators* that can be updated and exchanged among distributed agents (Figure 2b). The *driver*, which runs the generation framework, plays a lightweight role: it simply publishes an orchestrator to start a task, enabling an asynchronous initiation model. Agents

equipped with LLMs and tools consume messages, perform local actions, update both control and data states, and forward the updated orchestrator to the next agent. Execution continues until the orchestrator signals completion, at which point a designated sink collects the final message and persists it to the output dataset. Using P2P orchestration, Matrix avoids bottlenecks, improves scalability, and enables fully asynchronous execution among agents.

## 4.2 Distributed Services

Matrix offloads computationally intensive tasks to distributed services, allowing them to scale independently of the agents. For LLM inference, Matrix employs gRPC-based communication to avoid HTTP overhead. Because the Ray head node can become network-bound, Matrix maintains a local cache of active model replica URLs, enabling direct load-balanced traffic through worker nodes. For stateful services such as Apptainer containers, agents acquire containers by ID to be able to route multiple commands to the same container instance, rather than a randomly selected one. This is managed via a *resource pool* and a *registry* that maps container IDs to Ray actors running the corresponding containers. This design allows agents to efficiently route messages and reuse shared resources.

## 4.3 Parallel Execution Strategies

Matrix supports multiple forms of parallelism to maximize scalability and cluster utilization.

- **Data parallelism.** Similar to distributed processing systems such as Spark Zaharia et al. (2012) and Ray Data Moritz et al. (2018), Matrix can partition large input datasets consisting of many small files for independent processing.
- **Task parallelism.** Multiple generation tasks can execute concurrently using asynchronous programming, threads, or processes. Matrix adopts an `asyncio`-based model: the driver initializes orchestrators, and agents process tasks asynchronously. Since computationally heavy operations are offloaded to distributed services, lightweight agents can handle tens of thousands of concurrent tasks efficiently without I/O blocking.
- **Agent parallelism.** Each agent role is implemented as Ray actors with configurable CPU, GPU, and memory allocations. Roles can scale horizontally by launching multiple distributed agent instances, each processing assigned tasks independently. Ray system distributes these actors across cluster nodes, enabling each role to scale without the resource contention commonly seen in centralized orchestration.

For LLM-based agents, computational cost dominates over input pipeline overhead. Usually data loading is not a bottleneck (one exception is the NaturalReasoning task in Section 5.2). Matrix’s peer-to-peer architecture and distributed services ensure efficient utilization of cluster resources even with moderate data and agent-level parallelism. This efficiency arises from Matrix’s ability to run tens of thousands of asynchronous tasks concurrently, each processing one data item independently.

## 4.4 Row-Level Scheduling

In batch processing systems, such as Ray Data, tasks are grouped into fixed-size batches and executed by actors. While this approach can reduce per-task scheduling overhead for homogeneous workloads, it introduces inefficiencies when tasks have variable computational demands or diverging control flows. A long-running or complex task within a batch can keep the current batch running and stall the execution of subsequent batches, creating idle resources and underutilized GPUs. We refer to this phenomenon as *batch-level scheduling*.

In contrast, Matrix schedules each task independently as soon as prior tasks complete, a mechanism called *row-level scheduling*. Each orchestrator message representing a single task flows through the P2P agent network. This design eliminates the bubble effects inherent in batch processing, achieves higher GPU utilization, and reduces end-to-end latency for heterogeneous, multi-agent workloads. Row-level pipelining, combined with distributed services and asynchronous agent execution, is a key factor in Matrix’s scalability and efficiency for large-scale data synthesis tasks.

## 4.5 Fault Tolerance

Modern cloud providers offer a large amount of opportunistic compute, such as low-quality-of-service queues in SLURM and AWS spot instances. Both LLM inference and containerized workloads can leverage this capacity while remaining robust to interruptions. When a request fails due to node unavailability, the system refreshes its list of live replicas and reroutes the request to available nodes. Peer-to-peer agent actors adopt a distinct strategy. Instead of recovering the orchestrator queue, which can be complex, Matrix labels each Ray node by resource type (permanent or opportunistic) and schedules agents only on permanent nodes. Together, these strategies balance robustness, efficient capacity use, and implementation simplicity.

## 4.6 Message Offloading

The orchestrator is serialized and exchanged among agents. As shown in Algorithm 1, its `history` field stores inter-agent conversations, which can be large. A common optimization is to offload this history to an external cache such as Redis. While this reduces orchestrator size, it simply shifts network traffic from occurring between agents to occurring between agents and the cache. Since the history is frequently updated and used for constructing LLM prompts, the total network bandwidth can actually double because each agent must retrieve, update, and store the complete history every turn.

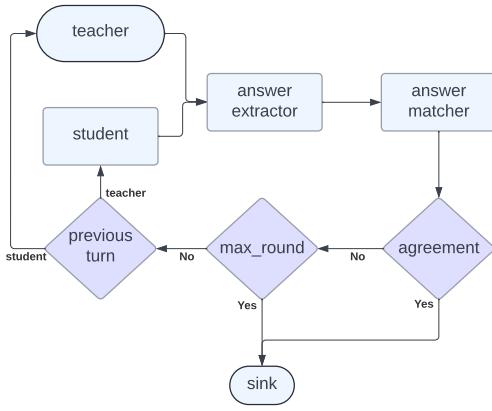
Matrix instead retains the history structure within the orchestrator, while storing large conversation content that exceed a configurable size threshold in Ray’s distributed object store. The history holds only the object identifiers, and content is retrieved on demand. Objects are immutable once stored, and all history-related objects are deleted when the orchestrator signals completion. This design keeps the orchestrator compact, reduces redundant transfers, and minimizes network load. Section 5.3.1 quantifies these benefits experimentally.

## 5 Experiments

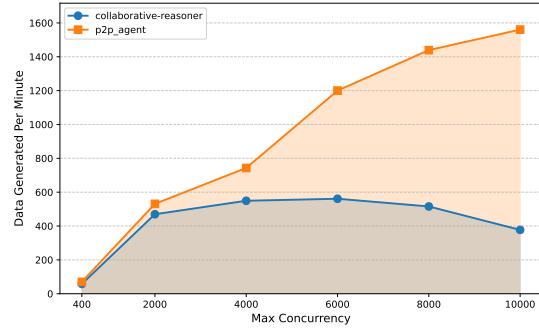
We evaluate Matrix across three case studies on synthetic data generation. Together, these experiments demonstrate the framework’s scalability, robustness, and adaptability to diverse workloads. In this section, the terms “Matrix” and “P2P-agent” are used interchangeably to refer to the same framework.

### 5.1 Collaborative Reasoner (Coral)

Collaborative Reasoner (Coral) Ni et al. (2025a) evaluates and improves multi-agent collaborative reasoning in LLMs through dialogue-driven tasks. Unlike single-agent evaluations, Coral requires two agents to discuss, disagree, and reach consensus over multi-turn interactions. Scalable training data is generated via self-collaboration, where an LLM plays both roles. In this work, we adopt the same agent setup, implemented as distributed agents in Figure 3.



**Figure 3** P2P-agents for Collaborative Reasoner.



**Figure 4** Scalability of P2P-agents vs Coral baseline.

We directly compare Matrix to the official Collaborative Reasoner implementation Ni et al. (2025b) as the baseline. Both systems use `asyncio` for concurrency. The baseline framework uses a single orchestrator to coordinate thousands of concurrent generation tasks, while Matrix distributes coordination responsibilities across agents in a peer-to-peer fashion. To compare the two, we run the same number of MMLU-Pro questions by changing the number of A100 nodes, and in both cases use Llama-3.1-8B-Instruct Grattafiori et al. (2024) as the underlying language model for all agents. Task concurrency is adjusted according to the number of A100 nodes as  $50 \times N_{GPU}$ , leveraging all 8 GPUs per node with 50 concurrent queries per GPU. As shown in Figure 4, the Matrix implementation scales almost linearly as more GPU nodes are added, while the centralized orchestration approach of the baseline system becomes a bottleneck and plateaus due to the overhead of scheduling a large number of asynchronous tasks from a single control point.

*Large-Scale Results.* We further tested both systems on 31 A100 nodes (248 GPUs) using LLaMA-3.1-8B-Instruct. For P2P-agent, we set the concurrency to  $248 \times 50 = 12,400$ , while Coral was configured with its optimal concurrency of 5,000 based on Figure 4. As shown in Table 1, P2P-agent generates 2B tokens in 4 hours, achieving 6.8 $\times$  higher throughput than the official Coral implementation on the same hardware. Importantly, both systems attain nearly identical agreement correctness, the metric used to measure data quality, consistent with Coral’s reported result of 0.456 for LLaMA-3.1-8B-Instruct Ni et al. (2025a).

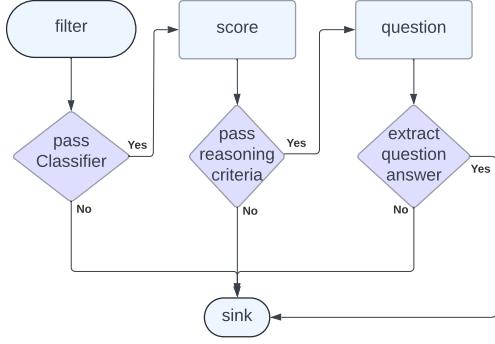
**Table 1** P2P-Agent achieves **6.8 $\times$**  higher token throughput than Coral baseline.

Metric	Coral Baseline	P2P-Agent
Runtime	9:03:22	4:17:05
Concurrent tasks	5,000	12,400
Total trajectories	300k	1 Million
Agreement correctness	0.4732	0.4778
Tokens generated	616,759,036	2,002,025,810
Tokens per second	18,917	129,833

## 5.2 NaturalReasoning

NaturalReasoning Yuan et al. (2025) is a large-scale dataset designed to advance reasoning capabilities of LLMs across diverse domains, including STEM, Economics, and Social Sciences. It contains 2.8M challenging questions generated automatically by LLMs. These questions are extracted and synthesized from pretraining corpora, ensuring high diversity and difficulty. Models fine-tuned on NaturalReasoning demonstrate improved sample efficiency and reasoning accuracy compared to prior datasets. In this experiment, we use Matrix to curate NaturalReasoning dataset, which consists of three agents, as illustrated in Figure 5:

- **Filter:** English-language web documents are identified, and a fine-tuned LLaMA-3.1-3B-Instruct model classifies whether a document contains reasoning content or not. The classifier is trained on a subset of NaturalReasoning examples as positives and randomly sampled web documents as negatives.
- **Score:** Each document is evaluated along multiple quality axes using LLaMA-3.3-70B-Instruct, following prompts derived from the original NaturalReasoning methodology.
- **Question:** Questions are extracted from the filtered web documents, reference answers are identified when available, and independent reasoning steps leading to a final answer are generated, all using LLaMA-3.3-70B-Instruct.



**Figure 5** P2P-agents for NaturalReasoning data curation.

For experiments, we processed up to 25M web documents from DCLM [Li et al. \(2025\)](#). The 3B model is highly efficient, as most documents are quickly filtered using a single token output (Yes/No). Only 5.45% of web documents pass all filters, yielding approximately 1M high-quality reasoning questions and answers (Table 2).

### 5.2.1 Evaluating Parallelism and Throughput

Using a 500k DCLM subset, we evaluate the impact of the three types of parallelism supported by Matrix represented as a tuple (data parallelism, task parallelism, and agent parallelism) in Table 3. We deployed 32 A100 nodes with 8 GPUs each. The fine-tuned 3B model was replicated 32 times, while the 70B model used 56 replicas. We set the maximum concurrent tasks to be 14k. The estimated concurrent requests per 70B replica is  $14k \times (1 - 3.68\% - 90.24\%) \div 56 \approx 15$ , which can maintain high GPU utilization without introducing long latencies or timeouts. The 3B model in Filter agents are not the bottleneck even though they handle 97% of the data after English filter.

**Table 3** P2P-agent throughput for 500k webdoc.

Settings Name	Three Parallelisms	Normalized Throughput
1	(1, 14000, 1)	1
2	(20, 700, 1)	1.61
3	(240, 1, 1)	0.38
4	(240, 50, 1)	1.43
5	(1, 14000, 2)	1.03
6	(1, 14000, 10)	0.91

**Data parallelism.** The first two settings present the results for data parallelism. In Setting 1, although the system was configured to allow up to 14k concurrent tasks, only about 700 were observed during the experiment, which is well below the target concurrency. This shortfall occurs because 93% of the input documents are filtered out early (Table 2), so that the input pipeline can not keep up with the Filter agent. To address the input bottleneck, we increased data parallelism by splitting the dataset into 20 partitions for Setting 2. This raises the effective concurrency to  $20 \times 700 \equiv 14k$ , matching our target. This adjustment yields a  $1.61 \times$  speedup, demonstrating how data parallelism helps alleviate the input pipeline bottleneck. Increasing the number of partitions beyond 20 provides little additional benefit, since task-level parallelism within each partition already saturates the GPUs.

**Task parallelism.** Comparing Settings 3 and 4, running 50 concurrent tasks per data partition yields a  $3.8 \times$  speedup compared to single-task execution, even with 240 data partitions. This result shows that increasing asynchronous task concurrency is more effective than simply creating a larger number of data partitions.

Filter step	Percentage
filter_by_en	3.68
filter_by_classifier	90.24
filter_by_score	0.44
filter_by_no_boxed_answer	0.19
success	5.45

**Table 2** Filtering statistics on 25M DCLM web documents.

Moreover, further increasing data parallelism would require additional agent instances, which in turn demands more CPU resources.

**Agent parallelism.** Comparing Settings 1 and 5, doubling the number of agent instances (excluding the sink) results in a modest throughput gain; while Setting 6 shows further increasing agent instances has no benefits. This is because LLM inference is handled by Ray Serve, agents remain I/O-bound. While increasing the number of instances offers limited benefit for the NaturalReasoning workflow, Matrix can efficiently scale agent instances when agents perform heavier CPU or GPU computations, highlighting the framework’s flexibility and readiness for diverse workloads.

Although the design space of the three kinds of parallelism can be huge, our setup prefers 14k max concurrency given the number of GPUs. We further determined 700 as the maximum achievable asyncio task concurrency per data partition. Moreover, increasing data partitions beyond 20 or increasing agent parallelism beyond 2 has small effect on throughput. Because of the peer-to-peer architecture, task parallelism alone often achieves high resource utilization. Therefore, small degrees of data and agent parallelism are typically sufficient as the initial configuration for new use cases.

### 5.2.2 Impact of Scheduling Granularity

We compare the throughput of Matrix’s row-level scheduling with a batch-level processing baseline implemented using Ray Data (Algorithm 2). In this baseline, each batch is processed by a Ray actor `BatchProcessing` (line 1-12), which launches multiple asynchronous tasks to handle individual row concurrently (lines 8). Each task executes an agentic workflow (line 10-12) similar to the agent logic of the P2P-agent implementation except that all agents are local and the orchestration logic is inlined.

The Ray Data baseline eliminates the need for a single centralized orchestrator and allows hundreds of CPUs to perform orchestration in parallel, each managing its own data batch. However, because multi-agent workflows exhibit dynamic control flow (i.e., the next agent is data-dependent), conventional batch inference methods (e.g., calling LLMs in bulk across a batch) are not applicable. Each task needs to be executed individually as in line 5-6.

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**Algorithm 2:** Pseudo-code of Ray Data Baseline.

---

```

1  @ray.remote
2  class BatchProcessing: # base class to run as a Ray actor
3      def __call__(self, batch):
4          async def _process_batch(rows):
5              tasks = [self.process(row) for row in rows]
6              return await asyncio.gather(*tasks) # use asyncio to process all tasks in the batch
7
8          return asyncio.run(_process_batch(batch))
9
10     async def process(self, row: Dict[str, Any]): # base class method to be overwritten for each use case
11         """abstract method to process one input task"""
12         pass
13
14     ds = ray.data.read_json(data_dir) # read input jsonl files into Ray data
15     output = ds.map_batches( # split input to batches for concurrent processing
16         BatchProcessing,
17         batch_size=cfg.batch_size,
18         num_cpus=1,
19         concurrency=cfg.data_parallelism # max number of batches to run concurrently
20     )

```

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*Large-Scale Results.* We then compare Matrix P2P-agent with the Ray Data baseline to run large scale curation over DCLM up to 25M web documents. Both setups utilize the same GPU resources and 14k concurrent tasks. For the P2P-agent configuration, we adopt Setting 2, i.e., (20, 700, 1), from Table 3. For the Ray Data baseline, we use Setting 4, i.e., (240, 50, 1). Through experiment, Setting 2 with 700 as batch size would result in peaks and valleys in GPU requests, the smaller batch size of 50 in Setting 4 can smooth GPU requests. The two setups have similar throughputs in P2P-agent experiment and the latter fits Ray Data based implementation.

Each setup is executed for over 10 hours, measuring token throughput. Results in Table 4 show that P2P-agent achieves 2.1 $\times$  higher token throughput than the batch-level baseline. The efficiency gap stems from

scheduling granularity: in batch-level scheduling, a new batch cannot begin until all tasks in the current batch complete. Due to control divergence and variable task length, a few slow tasks in a batch block downstream processing, creating idle GPU time. In contrast, row-level scheduling in P2P-agent allows each completed row to immediately trigger the next task without waiting for others, fully utilizing compute resources. Similar behaviour has been observed in LLM inference systems, where “continuous batching” or token-level scheduling can replace completed requests dynamically to avoid idle slots and maintain high throughput.

**Table 4** P2P-Agent achieves **2.1 $\times$**  higher token throughput than Ray Data baseline.

Metric	Ray Data Baseline	P2P-Agent
Runtime	12:57:28	17:57:55
Concurrent tasks	14,000	14,000
Webdoc processed	9.3M	25M
Questions generated	410,755	1,192,799
Tokens generated	129,622,944	378,591,258
Tokens per second	2,778	5,853

In Ray Data, decreasing the batch size can partially mitigate idle time. However, each concurrent batch requires a dedicated actor and CPU allocation. Maintaining the same level of task concurrency at smaller batch sizes therefore demands higher data parallelism, which introduces substantial CPU overhead. Moreover, batch-level scheduling incurs additional costs for batch creation and actor management, further compounding inefficiency. Overall, these results demonstrate that fine-grained, row-level scheduling enables more efficient scaling for multi-agent, dynamically controlled workflows than batch-level scheduling in traditional distributed data processing engines.

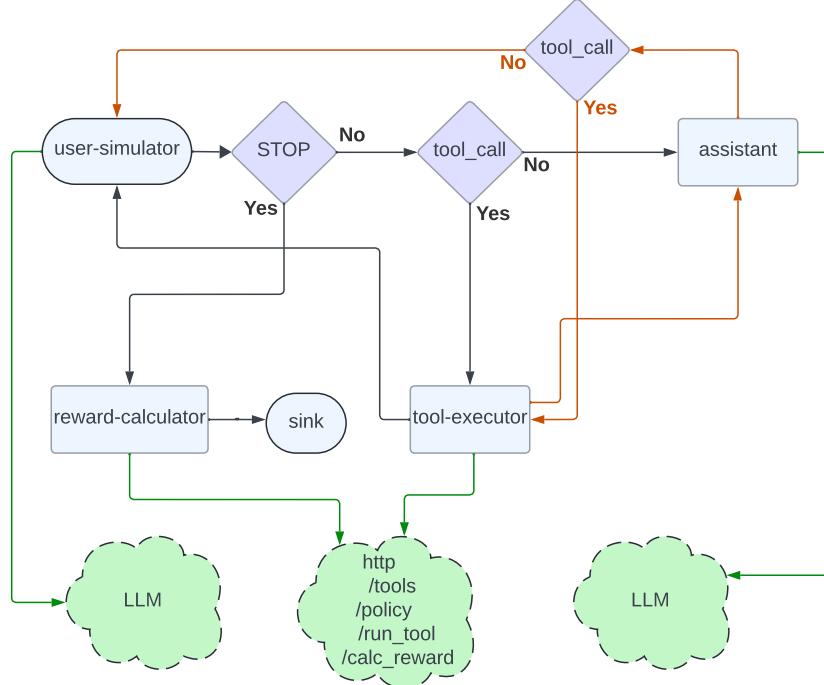
### 5.3 Tau2-bench

Tau2-bench [Barres et al. \(2025a\)](#) is a recently introduced benchmark for evaluating conversational agents in dual-control environments, where both an AI agent and a user simulator interact with a shared environment through tools and APIs. In this experiment, we use Tau2-bench to generate task-solving trajectories for real-world customer support or troubleshooting in the telecom domain. Following prior work such as Kimi K2 [Bai et al. \(2025\)](#) and AgentBank [Song et al. \(2024\)](#), these trajectories—after filtering and reward validation—can serve as post-training data to enhance LLM reasoning and tool-use performance.

*P2P-Agent Implementation.* Matrix implements Tau2-Bench as a distributed P2P-agent workflow comprising four functional agents and one orchestrator (Figure 6).

- **User-simulator:** Represents the human user, initiating and responding to the tau2-agent’s queries.
- **Assistant:** Acts as the assistant agent, performing reasoning and tool-use steps.
- **Tool-executor:** Executes HTTP-based tool calls issued by either the user or assistant. Tool APIs are adapted from the official Tau2-agent implementation [Barres et al. \(2025b\)](#) and deployed in distributed containers to enable concurrent execution and isolation.
- **Reward-calculator:** Validates each trajectory by replaying all tool calls from the initial state and computing task-specific rewards using assertions over the database state. The calculator container reuses the official Tau2-agent implementation, ensuring comparability with benchmark metrics.

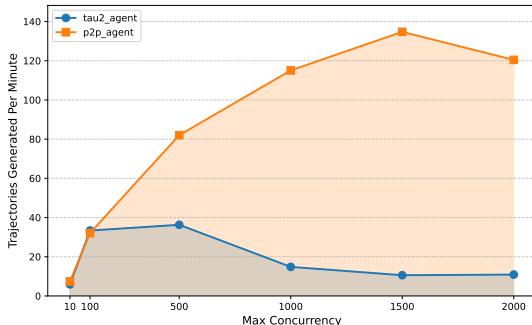
Matrix exposes two categories of services: (1) LLM inference services using gpt-oss-120b [OpenAI \(2025\)](#), which provide scalable access to model reasoning and dialogue generation, and (2) containerized task services, derived from Tau2-Bench’s reference implementation. Each container exposes standardized HTTP endpoints for retrieving tool signatures, executing actions, and evaluating rewards. Service calls are depicted in green in Figure 6.



**Figure 6** P2P-agent for Tau2-Bench.

*Comparison with Tau2 Baseline.* To evaluate scalability, we compare Matrix’s P2P-agent execution with the official Tau2-agent implementation Barres et al. (2025b). The baseline runs all tools and environment logic directly in Python threads on a single node with distributed LLM service. In contrast, P2P-agent distributes agents, LLM and tool-call container services across the Ray cluster.

As shown in Figure 7, throughput for the Tau2-agent baseline saturates at around 500 threads due to the single-machine constraint. In contrast, P2P-agent continues to scale with concurrency, leveraging distributed placement of agents and containers across the cluster.



**Figure 7** Scalability of P2P-agent vs Tau2-agent baseline.

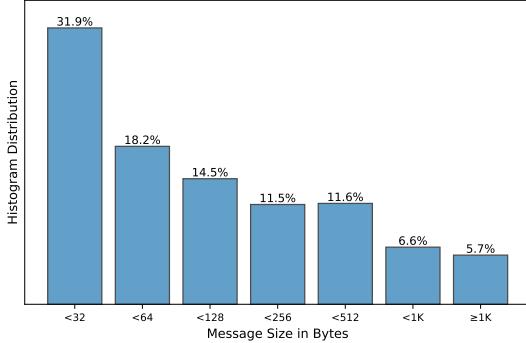
Metric	Baseline	P2P-Agent
Runtime	1:13:41	1:15:21
Concurrent tasks	500	1,500
Total trajectories	1519	22,800
Average reward	0.5918	0.5921
Tokens generated	11,080,385	185,376,127
Tokens per second	2,654	41,003

**Table 5** P2P-Agent achieves **15.4** $\times$  higher token throughput than Tau2-Agent baseline.

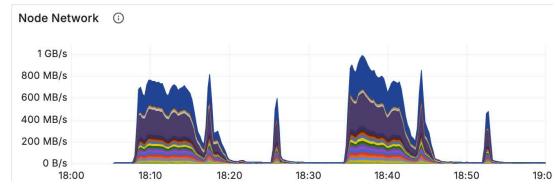
*Large-Scale Results.* We further test on 13 H100 nodes, deploying 1.5k containers and 56 gpt-oss-120b replicas. As shown in Table 5, P2P-agent generates 15.4 $\times$  more tokens per second than the Tau2-agent baseline, while maintaining comparable task rewards.

### 5.3.1 Effect of Message Offloading

Matrix Orchestrator contains the conversation history. Conversations exchanged in P2P-agent Tau2-bench trajectories vary widely in size, as shown in Figure 8. When orchestrators are routed through distributed agents, large conversation content can cause network overhead and congestion within the cluster. To mitigate this overhead, Matrix offloads large conversation content to the Ray Object Store, as discussed in Section 4.6. In this case, contents exceeding 512 bytes are stored in Ray object store and retrieved on demand, which corresponds to about 12% of the conversations.



**Figure 8** Distribution of conversation sizes in Tau2-Bench.



**Figure 9** Compare Total Node Network with and without Message Offloading.

Figure 9 compares the total cluster network bandwidth during two identical runs: one with message offloading enabled (before 18:30) and one without it (after 18:30). Excluding transient spikes, peak utilization drops from roughly 1 GB/s to 760 MB/s, a reduction of about 20%. This demonstrates that offloading large conversation contents effectively reduces network traffic and improves scalability under communication-heavy workloads such as Tau2-bench. It also makes the system well suited for future multi-modal data generation tasks.

## 6 Conclusion

We introduced **Matrix**, a peer-to-peer multi-agent framework for large-scale synthetic data generation. By representing control and data flow as peer-to-peer messages and delegating computation to distributed services, Matrix eliminates centralized bottlenecks and enables efficient execution of tens of thousands of concurrent agent workflows. Matrix is modular and configurable, allowing users to easily adapt it to diverse data generation tasks and agent roles without modifying core logic. Across a variety of large-scale experiments, Matrix achieves 2–15× higher throughput while maintaining output quality. Looking forward, we plan to open-source the Matrix framework to support community-driven development and reproducibility. Future extensions will explore multi-modal data generation and on-policy continuous data synthesis.

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