REVERB: A FRAMEWORK FOR EXPERIENCE REPLAY

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ABSTRACT

A central component of training in Reinforcement Learning (RL) is Experience: the data used for training. The mechanisms used to generate and consume this data have an important effect on the performance of RL algorithms. In this paper, we introduce Reverb: an efficient, extensible, and easy to use system designed specifically for experience replay in RL. Reverb is designed to work efficiently in distributed configurations with up to thousands of concurrent clients.

The flexible API provides users with the tools to easily and accurately configure the replay buffer. It includes strategies for selecting and removing elements from the buffer, as well as options for controlling the ratio between sampled and inserted elements. This paper presents the core design of Reverb, gives examples of how it can be applied, and provides empirical results of Reverb’s performance characteristics.

1 INTRODUCTION

Experience plays a key role in Reinforcement Learning (RL): how best to use this data is one of the central problems of the field. As RL agents have advanced in recent years, taking on bigger and more complex challenges such as Atari, Go, StarCraft, and Dota (Mnih et al., 2015; Silver et al., 2016; Vinyals et al., 2019; OpenAI et al., 2019), the generated data has grown in both size and throughput. To accelerate data collection, many RL experiments split the agent into two distinct parts: data generators (actors) and data consumers (learners), which are run in parallel (Horgan et al., 2018; Hoffman et al., 2020). However, data must now be stored and transported between generators and consumers. Efficiently transporting and storing this data is in itself a challenging engineering problem.

To address this challenge, we present Reverb: an efficient, extensible, and easy to use system for experience transport and storage. Reverb is designed to be flexible, making it suitable to be used as Experience Replay (ER) (Lin, 1992) or Prioritized Experience Replay (PER) (Schaul et al., 2015), which is a crucial component in a number of off-policy algorithms including Deep Q-Networks (Mnih et al., 2015), Deep Deterministic Policy Gradients (Lillicrap et al., 2015), and Soft Actor-Critic (Haarnoja et al., 2018). Reverb is equally suitable as a FIFO, LIFO, or Heap-based queues, enabling on-policy methods like Proximal Policy Optimization (Schulman et al., 2017) and IMPALA (Espeholt et al., 2018).

Another strength is its efficiency, making it well suited for large-scale RL agents with many actors and learners running in parallel. Researchers have used Reverb to run experiments with thousands of concurrent actors and learners (Yazdanbakhsh & Chen, 2020). This scalability, coupled with Reverb’s flexibility, allows researchers to investigate problems that require different scales without worrying about changing infrastructure components.

Reverb provides an easy-to-use mechanism for controlling the ratio of sampled to inserted data elements. This ratio is commonly used to set the number of gradient updates that are taken per data element, which can significantly impact RL algorithm performance (Fedus et al., 2020; Fu et al., 2019; Hoffman et al., 2020). Controlling this feature is easy in simple synchronous settings. However, it is challenging to implement when clients are running concurrently in a distributed system. With Reverb, users can control the relative rate of data collection to training in RL experiments regardless of scale.

The remainder of the paper is organized as follows. Section 2 discusses related work and alternatives to Reverb. Section 3 describes Reverb’s core components and how they contribute to building an efficient data storage and transportation system for RL. Code examples are provided in Section 4. Section 5 is a discussion of Reverb’s performance and empirical benchmark results. Finally, in Section 6, we provide concluding remarks.

More information, source code, and examples are available
in Reverb’s GitHub repository\(^1\). For RL algorithm implementations using Reverb, the agents in Acme\(^2\) (Hoffman et al., 2020) and TF-Agents\(^3\) (Guadarrama et al., 2018), are excellent references.

2 RELATED WORK

Many existing RL libraries and frameworks provide implementations of (Prioritized) Experience Replay; including RLlib (Liang et al., 2018), garage (garage contributors, 2019), stable-baselines (Hill et al., 2018), and Tianshou (Jiayi Weng, 2020). These implementations enable researchers to run off-policy reinforcement learning experiments.

SEED RL (Espeholt et al., 2020), a scalable reinforcement learning agent, provides performant implementations of ER and PER for off-policy RL and a FIFO queue for on-policy RL. However, these implementations are designed for the SEED architecture. In SEED, only the learner inserts and samples from the replay buffer so the samples per insert ratio (described in Section 3.4) is strictly managed by the learner. Besides, data is only sharded when using multiple learners, and there is no possibility of having multiple tables referencing the same data.

We created Reverb to address the scaling or flexibility requirements of our research teams that the aforementioned options did not meet. On one hand, they needed to scale to a number of clients and QPS that were not possible without sharding across multiple machines and handling concurrent actors (experience generators) and learners (consumers). On the other hand, our researchers also required the ability to switch between ER or PER for off-policy and FIFO queues for on-policy data without substantial code changes, as well as having the ability to control the ration between samples and insertion.

3 DESIGN

At its core, Reverb is a data store that exposes a gRPC service with an API for clients to write raw tensor data. Data is written to a ChunkStore as parts of a Chunk, Chunks can be referenced by Items, and each Item is owned by a Table. The Table encapsulates Items and controls sample and insert requests, using a RateLimiter and two Selectors (one Sampler and one Remover). These Components are independently configured and can be mixed and matched to provide a high degree of flexibility and a wide range of different behaviors.

3.1 Chunking and the ChunkStore

Sequential data generated by an RL environment often contain a high degree of similarity across steps. As an example, consider the pixels in two sequential frames generated in Atari. Many pixels will be exactly the same in both frames. Reverb exploits this similarity by placing sequential data elements into Chunks and applying column wise concatenation and compression (see Figure 1a for an illustration).

Reverb expects data to be provided as a stream of sequential data elements. Each element is a nested object whose leaf nodes are tensors. The signature, i.e the nested object’s

\(^1\)http://github.com/deepmind/reverb
\(^2\)http://github.com/deepmind/acme
\(^3\)http://github.com/tensorflow/agents
structure, shapes and data types of its leaf tensors, must remain the same across data elements in the stream. This means that, when flattened, the stream of data elements can be thought of as a two dimensional matrix where each row represents a data element and each column represents a field in the signature (see Figure 1b).

Chunks reduce the memory footprint and network usage in two ways. First, sequential data elements are grouped into a Chunk and compressed. Second, the Chunk abstraction over the raw data allows multiple Items (which can belong to different Tables) to reference the same underlying data instead of maintaining separate copies.

TheChunks are owned by a ChunkStore, as seen in Figure 2. The ChunkStore uses reference counting to track the number of Items that reference each Chunk. When the reference count reaches zero, the Chunk's memory is automatically freed. Decoupling data deallocation from the (mutex protected) operations on Tables is important for high and stable throughput.

The ChunkStore and Table were designed to avoid strong coupling in their respective implementations. Currently, Items reference and retrieve data through Chunks and the ChunkStore stores content in memory. The flexible design allows for alternative storage solutions to be incorporated with minimal impact on the wider system. An example would be customizing Reverb to access large datasets stored on disk by modifying Chunks to reference externally stored data rather than owning it. The client would lookup the data using the references received the sampled Chunks.

3.2 Tables and Items

A Reverb server consists of one or more Tables. A Table holds Items, defines Selectors for sampling and removal, and defines both a maximum item capacity and a RateLimiter. Chunks are only sent to the server when the client signals that an Item should be created. Sampling from a Table will send a number of Items (along with the Chunk data they reference) to the client. Communication overhead may occur if the number of data elements ($K$) in each Chunk does not evenly divide by the number of elements in an Item ($N$). In this case, the Item only makes use of the first $N - K$ steps in the last Chunk. However, all of the $K$ steps will be sent when sampling. This overhead can be avoided by setting $K$ and $N$ such that $N \mod K = 0$, as shown in Figure 3.

An Item in a Table is composed of:

- A unique key.
- A priority that may be used for sampling and/or removal; clients can update this value.
- References to a sequence of Chunks.
- The current number of times the Item has been sampled.

An Item is removed from a table in two situations: (1) when the Item reaches the maximum number of times it can be sampled (which is defined when creating the Table) or (2) when the Table reaches its capacity limit. In the latter case, the Remover automatically selects an item to be removed before any more are inserted.

3.3 Selectors

A Selector is a strategy used to select an item in a Table. A Table uses two Selectors (see Figure 2):

- The Sampler is used to select Items when the client requests them.
- The Remover is used to select an Item to remove when the Table is full.
Selectors are responsible for building and maintaining their own internal state by observing all operations on its parent Table. They must use only their internal state to decide which Item to select. Importantly, for performance reasons, they cannot make decisions based on the content of the data that each Item contains.

Reverb comes with the following Selector strategies and can be extended to support others:

**FIFO**: First-in-first-out. Provides queue-style sampling when used as Sampler. When used as Remover, the oldest Item is removed from the Table when full.

**LIFO**: Last-in-first-out. Selects the most recently inserted Item from the Table. It is a suitable Sampler for many on-policy algorithms. As a Remover it will leave the oldest Items, thus allowing the Table to act like a stack.

**Uniform**: Selects each Item in the Table with the same probability. It is commonly used as a Sampler in combination with a FIFO Remover, creating a fixed size ER of the most recently generated experience.

**Max/Min Heap**: Selects the Item with highest/lowest priority. When used as Sampler, this gives Table priority queue behavior. Useful as a Remover in order to create a Table that acts like a view of the highest priority data across longer time spans.

**Prioritized**: It implements the algorithm described in Prioritized Experience Replay (Schaul et al., 2015). The probability of selecting an Item with priority \( p_i \) from a Table of \( N \) Items is

\[
p_i = \frac{p_i^C}{\sum_{k=1}^{N} p_k^C}
\]

where \( p_k \) is the priority of Item \( k \) and \( C \) is configurable constant.

### 3.4 Rate Limiting

The RateLimiter controls when Items are allowed to be inserted and/or sampled from a Table. The RateLimiter monitors two aspects of the Table: 1) the number of Items in the table, and 2), the SPI defined as:

\[
SPI = \frac{\text{num_sampled_items}}{\text{num_inserted_items}}
\]

RateLimiters define:

1. The minimum number of Items that must be in a Table before sampling can begin.
2. The target SPI ratio
3. The upper and lower bounds for the target SPI ratio.

These three parameters are used to define a variety of RateLimiters offering a wide range of behaviors.

RateLimiters block sampling from a Table when either: 1) there are not enough Items or 2) the sample would result in an SPI that exceeds the upper bound. Similarly, inserts are blocked when they would result in an SPI below the lower bound. See Figure 4 for an illustration of how RateLimiters can block inserts and samples.

The following RateLimiters are available in Reverb:

**SampleToInsertRatio**: Allows users to specify a target SPI and the minimum number of Items that the Table must contain before sampling is allowed. A single float (error_buffer) is used to define a symmetric upper and lower bounds on the SPI ratio. Larger values avoid unnecessary blocking when the system is more or less in equilibrium.

**MinSize**: Enforces that the Table must contain a certain number of Items before sampling can begin. The SPI is ignored simply by setting the upper and lower bounds to DBL_MAX and DBL_MIN respectively.

**Queue**: Used to turn Table into a queue-like data structure. Inserts are allowed until the queue is full and samples are allowed unless the queue is empty. A single parameter, queue_size, is exposed to configure the RateLimiter. The minimum number of Items is set to 0, SPI is set to 1 with lower and upper bounds set to 0 and queue_size respectively. When combined with FIFO Selectors, the Table behavior becomes that of a queue. When used in conjunction with LIFO Selectors, it becomes a stack.

Finally, RateLimiters control the flow of Items, and not that of the data the Items reference. Adjusting the number of data elements that each Item references, e.g. using 16 instead of 4 Atari frames changes the amount

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The list includes pre-configured RateLimiters available in the Python API. Note that the implementation remains the same and only the min_size, SPI and bounds differ.
of data flowing through the system, even though the SPI remains constant. For example, if \( SPI = 2 \), the Table capacity is 10, and an Item references 4 Atari frames, then the Table will hold 40 frames\(^3\) and a learner (consumer) will see 4 frames for each Item it samples. Changing the number of frames each Item references to 16 increases the total frames in the Table to 160, and the data consumer will now see 16 frames for each sampled Item.

### 3.5 Table Extensions

Tables support a TableExtension API which provides the ability to execute extra actions as part of the atomic operations of the parent Table. All of these actions are executed while holding the Table mutex, so their latency is critical. This API can be used, for example, to write extensions that provide statistics about the amount of data that is inserted and sampled from Reverb, and diffuse priority updates to neighboring Items (Gruslys et al., 2017).

### 3.6 Sharding

The Reverb server can be scaled horizontally by adding more independent servers. When scaling a system to a multi-server configuration, each Reverb server remains unaware of the others and data is neither replicated nor synchronized across servers. Similarly, checkpointing (Section 3.7) is managed independently and multi-server configurations are not more or less robust against data loss than a single server. However, scaling the system horizontally is trivial due to the independence between servers.

When used in combination with a gRPC compatible load balancer, client operations (Section 3.8) are distributed across the servers in a round robin fashion. When sampling, each client manages pool of server connections. Samples are requested from multiple servers in parallel and the results are merged into a single stream of sampled Items. This mitigates the effects of long-tail latency and creates fault tolerance against individual server failures.

Since Reverb servers are independent, each can be configured differently, e.g. with different rate limiters. A separate client can then be created for each server (rather than pooling the results) allowing for maximal control.

### 3.7 Checkpointing

The state and content of both the ChunkStore and Tables can be serialized and stored to disk as a checkpoint. Potential data loss in the event of unexpected server failures can be limited through the use of periodic checkpointing. Stored checkpoints can be loaded by Reverb servers at construction time.

\(^3\)Assuming that all items reference disjoint sequences of data.

In order to allow Reverb checkpoints to be aligned with the wider systems, e.g., network weights, the creation of checkpoints is triggered through a gRPC call from a Reverb client. During the checkpointing process, the server blocks all incoming insert, sample, update, and delete requests. This process could potentially last for multiple minutes and is dependent on the amount of data being written and disk performance.

### 3.8 Reverb Client

The Reverb Client wraps the gRPC client to provide a higher level API for writing, modifying, and reading data from the server.

A Sampler manages a pool of long lived gRPC streams. Each stream fetches samples from a single Table at a flow controlled rate that can be adjusted using the `max_in_flight_samples_per_worker` parameter. Setting this parameter to 1 means that the next sample is not requested until the previous one has been consumed. Setting the parameter higher gives the Sampler more flexibility to prefetch samples, which generally leads to higher throughput. For more details about how to retrieve data efficiently, see Section (3.9).

A Writer is used to stream sequential data to the server and insert Items into one or more Tables. A single gRPC stream is used throughout the lifetime of a Writer object. Data is written using the `append` method and Items are created using `create_item`. When `append` is called, the data is pushed to a local buffer. Once the buffer is full, a Chunk is constructed (See Section 3.1). The Chunk is then transmitted to the server over the open gRPC stream. Similarly, Items created with `create_item` are pushed to a local buffer until all its referenced Chunks have been transmitted to the server. Waiting for the Chunk to be sent before Items makes it safe for multiple items to reference the same data without sending it more than once.

### 3.9 Efficient Sampling with the `tf.data` API

Reverb utilizes the `tf.data` framework (Abadi et al., 2015) to provide pipelined high throughput data sampling directly to training modules.

`tf.data` is a proven high performance and scalable input pipeline solution for transforming and feeding data. It is used in TensorFlow 2 as part of stand-alone and distributed training configurations. Beyond TensorFlow, it has also been commonly used in JAX (Frostig et al., 2018) as part of training workflows.

Reverb implements the `ReverbDataset`: a fast, C++-based mechanism for reading and postprocessing data from Reverb servers. Iterators created by `ReverbDataset` each wrap a `Sampler`. Each `Sampler` in turn maintains...
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a configurable number of long-lived streams. If a single stream is used, the dataset feeds data in exact order from a Reverb server. This is necessary when the associated Table’s, Sampler, and Remover are configured to use deterministic Selectors such as FIFO.

One idiosyncrasy to be aware of is that the system can appear to deadlock if the underlying Table’s size goes below the minimum size or the sample-to-insert ratio grows too large. This is not a bug. Reverb is designed to enforce these parameters. The situation can occur organically if the training processes are consuming Items at a ratio the actors cannot sustain. The situation may resolve itself quickly as new data is inserted or be permanent due to a downstream failure. The perceived deadlock can be managed by setting the rate_limiter_timeout_ms ≥ 0 when creating the dataset. If a sample is requested but not enough data is received within the time limit, the reverb service will signal to the iterator that it is safe to end the sequence. This is similar to “reaching the end of the file” on Datasets that read from on-disk storage.

4 EXAMPLES

This section contains basic examples of core Reverb’s features. See Appendix A for examples of more specific RL use cases.

4.1 Overlapping trajectories

The following example shows how to write trajectories of length 3 that overlap by 2 timesteps.

```python
foo

NUM_TIMESTEPS = 3
with client.writer(NUM_TIMESTEPS) as w:
    ts, a, done = env_step(None)
    step = 0
    while not done:
        writer.append((ts, a))
        if step >= 2:
            # Items reference the 3 most recently appended timesteps
            # and have a priority of 1.5.
            writer.create_item(
                table='my_table_a',
                num_timesteps=NUM_TIMESTEPS,
                priority=1.5)
        ts, a, done = env_step(action)
        step += 1
```

4.2 Multiple priority tables

The example below utilizes two different tables to create trajectories of different lengths.

```python
with client.writer(3) as writer:
    ts, a, done = env_step(None)
    step = 0
    while not done:
        writer.append((ts, a))
        if step >= 1:
            writer.create_item(
                table='my_table_a',
                num_timesteps=2,
                priority=1.5)
        if step >= 2:
            writer.create_item(
                table='my_table_b',
                num_timesteps=3,
                priority=1.5)
        ts, a, done = env_step(action)
        step += 1
```

5 PERFORMANCE

This section presents two sets of benchmarks designed to explore the scaling characteristics of a single Reverb server. We want to emphasize that the raw numbers reported are specific to this particular benchmark setup and carry little significance by themselves. We encourage the reader to focus their attention on the patterns that occur across the benchmarks and the generic conclusions that can be drawn from these observations.

The benchmarks have been explicitly designed to overload the server under the most unfavourable conditions.

1. Each data element is a single float32 tensor whose values have been randomly sampled from a uniform distribution over the half-open interval [0, 1). Random tensors were intentionally used to negate variability introduced by compression. Reported Bytes/s are much lower than what would be observed in the exact same setup modulo the source of data. For example, in Atari we observe compression rates of up to 90% in sequences of 40 frames. The effective throughput would therefore be up to 10x higher in that scenario compared with these benchmarks utilizing random synthetic data.

2. Chunk and sequence length is 1 resulting in Items not sharing data.

3. Clients solely generate load as fast as possible.

The benchmarks are distributed with each client running on a different machine. All machines are located in the same data center and communicate with the server over network shared by other citizens of the data center. We increase the number of clients until the combined load far exceeds the server’s capabilities. The same test was performed with data payloads across four order of magnitudes: 400B, 4kB, 40Kb, and 400kB.

Each benchmark tests the upper bound of a single Reverb
server’s efficiency with all clients either inserting (Section 5.1) or sampling (Section 5.2). The results are reported in Total Bytes Per Second (BPS) and Queries (i.e Items) Per Second (QPS) that the single Reverb server could process given the number of clients.

### 5.1 Inserting

For the inserting benchmark, all clients write data to the same server. The benchmark was run with 1 to 200 clients. Examining Figure 5 leads us to the following general conclusions regarding the scalability of Reverb:

1. The server can handle approximately either 11 GB/s or 60k Items/s.
2. The throughput scales perfectly (i.e linearly) with the number of clients until either the BPS or QPS limit is reached.
3. Overloading the server with additional clients does not degrade performance.

The linear scaling behavior is the important result of the benchmark. The Figure 5 illustrates that the number of concurrent clients have no negative impact on each other unless the combined QPS or BPS load exceeds the server limits. Once the limit is reached, the server will distribute its available resources across the clients. In this benchmark, the server continued to do this effectively for the max number of clients (200) tested.

In the real world clients are unlikely to be writing data as quickly as the synthetic benchmark due to needing to generate data in an environment, e.g. Atari. Consider for example a setup were each client is only able to generate data at 1/4 the speed of the benchmark clients. In this same compute environment, we would expect linear scaling to continue well beyond 200 clients until the combined QPS or BPS load exceeds the server limits. The ability to scale to large number of clients without degrading the performance is important for scenarios were the data generation is more expensive or slower.
5.2 Sampling

For the sampling benchmark, each client samples data as quickly as possible from a single Reverb server. The benchmark was run with 1 to 200 clients. From Figure 6 it is apparent that:

1. The server can handle approximately either 11 GB/s or 600k Items/s.

2. The throughput scales almost perfectly (i.e. linearly) with the number of clients until either the BPS or QPS limit is reached.

3. Overloading the server with additional clients does not degrade performance.

We observe almost identical scaling characteristics as seen in the inserting benchmark (Section 5.1) but with a tenfold increase in maximum QPS capacity. The difference in QPS capacity can most likely be attributed to optimizations intended to reduce Table mutex contention, which, at the time of writing this paper, is only implemented for sampling and not insertions.

5.3 Summary

The maximum BPS is 11 GB/s for both insertion and sampling. This limit is observed at multiple payloads sizes and strongly indicates that the observed BPS limitations cannot be attributed to Reverb. The limitation is most likely the result of network bandwidth constraints.

To test our hypothesis that QPS for inserts is currently limited by mutex contention, we setup a sharding experiment detailed in Appendix B. The load was sharded across multiple Tables on the same server. This improved the maximum insert QPS by approximately 200%, and convinced us that the insert QPS limitations are due to mutex contention.

6 Conclusion

Reverb is an efficient and easy-to-use data storage and transport system designed for machine learning research. Reverb’s flexible API allows a single server to scale effortlessly from one to hundreds of concurrent clients under unfavorable conditions while handling loads of $O(100k)$ QPS and at least 11 GB/s of compressed data. This flexibility, paired with the scaling characteristics, enables researchers to run experiments using a single-process or thousands of machines with the same Reverb setup. As a result, Reverb is currently being used by hundreds of researchers for a wide variety of RL experiments.

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A REINFORCEMENT LEARNING EXAMPLES

A.1 Acme: D4PG

The D4PG agent in Acme uses a Reverb Table with an Uniform Sampler and a FIFO Remover. Items are thus selected uniformly from the table, and the oldest Item is removed when the buffer reaches MAX_REPLAY_SIZE.

```python
table = reverb.Table(
    name=TABLE_NAME,
    sampler=reverb.selectors.Uniform(),
    remover=reverb.selectors.Fifo(),
    max_size=MAX_REPLAY_SIZE,
    rate_limiter=
        reverb.rate_limiters.MinSize(1))
server = reverb.Server([table])
```

The MinSize(1) rate limiter makes the sampler to block until there is at least one element in the table. It uses the default value for max_times_sampled (which is 0), so each item can be sampled any number of times until it is removed by the FIFO remover. Each item is a n-step transition which is defined in Acme as a transition that accumulates the reward and the discount for n steps.

A.2 TF-Agents: Distributed SAC

The Distributed SAC implementation in TF-Agents uses two Reverb Tables.

The first one is a Variable Container. This Table holds the model parameters most recently exported by the learner. By sampling from this table, the actors are able to update the model parameters, which they use to run the inference. Only the most recently exported parameters are used and thus the Table have a maximum size of 1 and a FIFO Remover is used. Since the Table only contains at most 1 Item, any Selector will work as a Sampler. To allow the same parameters to be sampled as many times as needed, (max_time_sampled is set to 0, i.e no limit. The MinSize(1) ensures that actors block until the learner have exported the first version of the parameters.

```python
# Stores policy parameters.
reverb.Table(
    name='VARIABLE_CONTAINER',
    sampler=reverb.selectors.Uniform(),
    remover=reverb.selectors.Fifo(),
    rate_limiter=
        reverb.rate_limiters.MinSize(1),
    max_size=1,
    max_time_sampled=0,)
```

The Experience Replay has a similar configuration to D4PG. By default, it also uses a MinSize RateLimiter, which

```python
reverb.Table(
    name=reverb_replay_buffer.DEFAULT_TABLE,
    sampler=reverb.selectors.Uniform(),
    remover=reverb.selectors.Fifo(),
    rate_limiter=experience_rate_limiter,
    max_size=FLAGS.replay_buffer_capacity,
    max_times_sampled=0,
    signature=replay_buffer_signature,
)
```

Figure 7. Items inserted per second (QPS) that a single server handles plotted against the number of connected clients. The maximum QPS is increased by approximately 200% when splitting the Table into 8 shards.

will stop the sampling until there are enough elements in the Table. However, since each item can be sampled any number of times, it will only block the sampler at the beginning. The rate limiter here can also be configured as a SampleToInsertRatio, which sets both the minimum size to start sampling, and the allowed number of samples per insert, which enables more fine-grained flow control.

```python
experience_rate_limiter =
    reverb.rate_limiters.SampleToInsertRatio(
        min_size_to_sample=min_size,
        samples_per_insert=samples_per_insert,
        error_buffer=error_buffer
    )
```

B BENCHMARK WITH MULTIPLE TABLES

This section tests the hypothesis that the difference in QPS capacity between the insert and sample benchmarks can be explained by optimizations of the Table mutex usage (which has been implemented only for sample operations). If mutex contention explains the difference then spreading the load over multiple Tables should improve QPS limits even if the number of servers remains one. We modify the benchmark described in Section 5.1 by varying the number of Tables held by the server and modifying

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6https://git.io/Jtuw5
7https://git.io/JtuwH
the clients to round robin between the Tables with each create_item.

The benchmark is executed using 2, 4 and 8 Tables. In Figure 7, we plot the new measurements together with the original results from Section 5.1. We observe a three-fold improvement between 1 and 8 Tables. This strongly supports the validity of the hypothesis.