SEED RL: Scalable and Efficient Deep-RL with Accelerated Central Inference

Anonymous authors
Paper under double-blind review

Abstract

We present a modern scalable reinforcement learning agent called SEED (Scalable, Efficient Deep-RL). By effectively utilizing modern accelerators, we show that it is not only possible to **train on millions of frames per second** but also to **lower the cost** of experiments compared to current methods. We achieve this with a simple architecture that features centralized inference and an optimized communication layer. SEED adopts two state of the art distributed algorithms, IMPALA/V-trace (policy gradients) and R2D2 (Q-learning), and is evaluated on Atari-57, DeepMind Lab and Google Research Football. We improve the state of the art on Football and are able to reach state of the art on Atari-57 twice as fast in wall-time. For the scenarios we consider, a 40% to 80% cost reduction for running experiments is achieved. The implementation along with experiments is **open-sourced** so results can be reproduced and novel ideas tried out.

Github: *anonymized*.

1 Introduction

The field of reinforcement learning (RL) has recently seen impressive results across a variety of tasks. This has in part been fueled by the introduction of deep learning in RL and the introduction of accelerators such as GPUs. In the very recent history, focus on massive scale has been key to solve a number of complicated games such as AlphaGo (Silver et al., 2016), Dota (OpenAI, 2018) and StarCraft 2 (Vinyals et al., 2017).

The sheer amount of environment data needed to solve tasks trivial to humans, makes distributed machine learning unavoidable for fast experiment turnaround time. RL is inherently comprised of heterogeneous tasks: running environments, model inference, model training, replay buffer, etc. and current state-of-the-art distributed algorithms do not efficiently use compute resources for the tasks. The amount of data and inefficient use of resources makes experiments unreasonably expensive. The two main challenges addressed in this paper are scaling of reinforcement learning and optimizing the use of modern accelerators, CPUs and other resources.

We introduce SEED (Scalable, Efficient, Deep-RL), a modern RL agent that scales well, is flexible and efficiently utilizes available resources. It is a distributed agent where model inference is done centrally combined with fast streaming RPCs to reduce the overhead of inference calls. We show that with simple methods, one can achieve state-of-the-art results faster on a number of tasks. For optimal performance, we use TPUs (cloud.google.com/tpu/) and TensorFlow 2 (Abadi et al., 2015) to simplify the implementation. The cost of running SEED is analyzed against IMPALA (Espeholt et al., 2018) which is a commonly used state-of-the-art distributed RL algorithm (Veeriah et al. (2019); Li et al. (2019); Deverett et al. (2019); Omidshafiei et al. (2019); Vezhnevets et al. (2019); Hansen et al. (2019); Schaarschmidt et al.; Tirumala et al. (2019), ...). We show cost reductions of up to 80% while being significantly faster. When scaling SEED to many accelerators, it can train on millions of frames per second. Finally, the implementation is open-sourced together with examples of running it at scale on Google Cloud (see Appendix A.4 for details) making it easy to reproduce results and try novel ideas.

2 RELATED WORK

For value-based methods, an early attempt for scaling DQN was Nair et al. (2015) that used asynchronous SGD (Dean et al., 2012) together with a distributed setup consisting of actors, replay buffers, parameter servers and learners. Since then, it has been shown that asynchronous SGD leads to poor sample complexity while not being significantly faster (Chen et al., 2016; Espeholt et al., 2018). Along with advances for Q-learning such as prioritized replay (Schaul et al., 2015), dueling networks (Wang et al., 2016), and double-Q learning (van Hasselt, 2010; Van Hasselt et al., 2016) the state-of-the-art distributed Q-learning was improved with Ape-X (Horgan et al., 2018). Recently, R2D2 (Kapturowski et al., 2018) achieved impressive results across all the Arcade Learning Environment (ALE) (Bellemare et al., 2013) games by incorporating value-function rescaling (Pohlen et al., 2018) and LSTMs (Hochreiter & Schmidhuber, 1997) on top of the advancements of Ape-X.

There have also been many approaches for scaling policy gradients methods. A3C (Mnih et al., 2016) introduced asynchronous single-machine training using asynchronous SGD and relied exclusively on CPUs. GPUs were later introduced in GA3C (Mahmood, 2017) with improved speed but poor convergence results due to an inherently on-policy method being used in an off-policy setting. This was corrected by V-trace (Espeholt et al., 2018) in the IMPALA agent both for single-machine training and also scaled using a simple actor-learner architecture to more than a thousand machines. PPO (Schulman et al., 2017) serves a similar purpose to V-trace and was used in OpenAI Rapid (Petrov et al., 2018) with the actor-learner architecture extended with Redis (redis.io), an in-memory data store, and was scaled to 128,000 CPUs. For inexpensive environments like ALE, a single machine with multiple accelerators can achieve results quickly (Stooke & Abbeel, 2018). This approach was taken a step further by converting ALE to run on a GPU (Dalton et al., 2019).

A third class of algorithms is evolutionary algorithms. With simplicity and massive scale, they have achieved impressive results on a number of tasks (Salimans et al., 2017; Such et al., 2017).

Besides algorithms, there exist a number of useful libraries and frameworks for reinforcement learning. ELF (Tian et al., 2017) is a framework for efficiently interacting with environments, avoiding Python global-interpreter-lock contention. Dopamine (Castro et al., 2018) is a flexible research focused RL framework with a strong emphasis on reproducibility. It has state of the art agent implementations such as Rainbow (Hessel et al., 2017) but is single-threaded. TF-Agents (Guadarrama et al., 2018) and rlpyt (Stooke & Abbeel, 2019) both have a broader focus with implementations for several classes of algorithms but as of writing, they do not have distributed capability for large-scale RL. Lastly, RLLib (Liang et al., 2017) provides a number of composable distributed components and a communication abstraction with a number of algorithm implementations such as IMPALA and Ape-X.

SEED is closest related to IMPALA, but has a number of key differences that combine the benefits of single-machine training with a scalable architecture. Inference is moved to the learner but environments run remotely. This is combined with a fast communication layer to mitigate latency issues from the increased number of remote calls. The result is significantly faster training at reduced costs by as much as 80% for the scenarios we consider. In the work we use TPUs but in principle, any modern accelerator could be used in their place. TPUs are particularly well-suited given they high throughput for machine learning applications and the scalability. Up to 2048 cores are connected with a fast interconnect providing 100+ petaflops of compute.
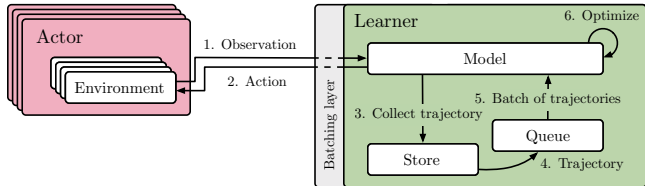
3 ARCHITECTURE

Before introducing the architecture of SEED, we first analyze the generic actor-learner architecture used by IMPALA, which is also used in various forms in Ape-X, OpenAI Rapid and others. An overview of the architecture is shown in Figure 1a.

A large number of actors repeatedly read model parameters from the learner (or parameter servers). Each actor then proceeds the local model to sample actions and generate a full trajectory of observations, actions, policy logits/Q-values. Finally, this trajectory along with recurrent state is transferred to a shared queue or replay buffer. Asynchronously, the learner reads batches of trajectories from the queue/replay buffer and optimizes the model.

There are a number of reasons for why this architecture falls short:
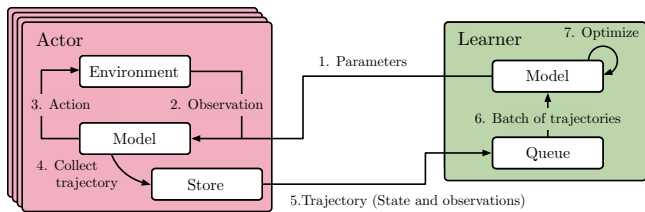
(a) IMPALA architecture (distributed version)

(b) SEED architecture, see detailed replay architecture in Figure 3.

Figure 1: Overview of architectures

1. **Using CPUs for neural network inference:** The actor machines are usually CPU-based (occasionally GPU-based for expensive environments). CPUs are known to be computationally inefficient for neural networks (Raina et al., 2009). When the computational needs of a model increase, the time spent on inference starts to outweigh the environment step computation. The solution is to increase the number of actors which increases the cost and affects convergence (Espeholt et al., 2018).

2. **Inefficient resource utilization:** Actors alternate between two tasks: environment steps and inference steps. The compute requirements for the two tasks are often not similar which leads to poor utilization or slow actors. E.g. some environments are inherently single-threading while neural networks are easily parallelizable.

3. **Bandwidth requirements:** Model parameters, recurrent state and observations are transferred between actors and learners. Relatively to model parameters, the size of the observation trajectory often only accounts for a few percents [1]. Furthermore, memory-based models send large states, increase bandwidth requirements.

While single-machine approaches such as GA3C (Mahmood, 2017) and single-machine IMPALA avoid using CPU for inference (1) and do not have network bandwidth requirements (3), they are restricted by resource usage (2) and the scale required for many types of environments.

The architecture used in SEED (Figure 1b) solves the problems mentioned above. Inference and trajectory accumulation is moved to the learner which makes it conceptually a single-machine setup with remote environments (besides handling failures). Moving the logic effectively makes the actors a small loop around the environments. For every single environment step, the observations are sent to the learner, which runs the inference and sends actions back to the actors. This introduces a new problem: 4. **Latency.**

To minimize latency, we created a simple framework that uses gRPC (grpc.io) - a high performance RPC library. Specifically, we employ streaming RPCs where the connection from actor to learner is kept open and metadata sent only once. Furthermore, the framework includes a batching module that efficiently batches multiple actor inference calls together. In cases where actors can fit on the same machine as learners, gRPC uses unix domain sockets and thus reduces latency, CPU and syscall overhead. Overall, the end-to-end latency, including network and inference, is faster for a number of the models we consider (see Appendix A.6).

The IMPALA and SEED architectures differ in that for SEED, at any point in time, only one copy of the model exists whereas for distributed IMPALA each actor has its own copy. This changes the way the trajectories are off-policy. In IMPALA (Figure 2a), an actor uses the same policy π_{θ_t} for an entire trajectory. For SEED (Figure 2b), the policy during an unroll of a trajectory may change multiple times with later steps using more recent policies closer to the one used at optimization time.

---

[1] With 100,000 observations send per second (96 x 72 x 3 bytes each), a trajectory length of 20 and a 30MB model, the total bandwidth requirement is 148 GB/s. Transferring observations uses only 2 GB/s.
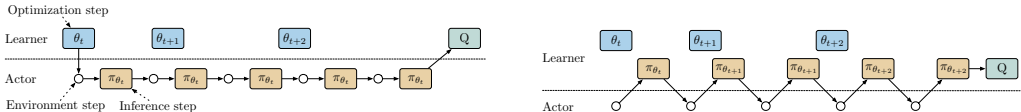
(a) Off-policy in IMPALA. For the entire trajectory the policy stays the same. By the time the trajectory is sent to the queue for optimization, the policy has changed twice.

(b) Off-policy in SEED. Optimizing a model has immediate effect on the policy. Thus, the trajectory consists of actions sampled from many different policies $(\pi_{\theta_t}, \pi_{\theta_{t+1}}, ...)$.

Figure 2: Variants of "near on-policy" when evaluating a policy π while asynchronously optimizing model parameters θ.
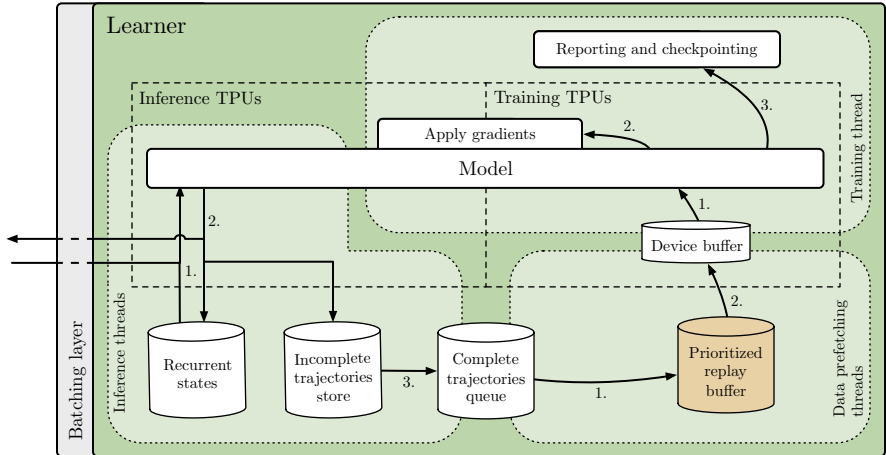

Figure 3: Detailed Learner architecture in SEED (with an optional replay buffer).

A detailed view of the learner in the SEED architecture is shown on Figure 3. Three types of threads are running: 1. Inference 2. Data prefetching and 3. Training. Inference threads receive a batch of observations, rewards and episode termination flags. They load the recurrent states and send the data to the inference TPU core. The sampled actions and new recurrent states are received, and the actions are sent back to the actors while the latest recurrent states are stored. When a trajectory is fully unrolled it is added to a FIFO queue or replay buffer and later sampled by data prefetching threads. Finally, the trajectories are pushed to a device buffer for each of the TPU cores taking part in training. The training thread (the main Python thread) takes the prefetched trajectories, computes gradients using the training TPU cores and applies the gradients on the models of all TPU cores (inference and training) synchronously. The ratio of inference and training cores can be adjusted for maximum throughput and utilization. The architecture scales to a TPU pod (2048 cores) by round-robin assigning actors to TPU host machines, and having separate inference threads for each TPU host. When actors wait for a response from the learner, they are idle so in order to fully utilize the machines, we run multiple environments on a single actor.

To summarize, we solve the issues listed previously by:

1. Moving inference to the learner and thus eliminating any neural network related computations from the actors. Increasing the model size in this architecture will not increase the need for more actors (in fact the opposite is true).

2. Batching inference on the learner and having multiple environments on the actor. This fully utilize both the accelerators on the learner and CPUs on the actors. The number of TPU cores for inference and training is finely tuned to match the inference and training workloads. All factors help reducing the cost of experiments.

3. Everything involving the model stays on the learner and only observations and actions are sent between the actors and the learner. This reduces bandwidth requirements by as much as 99%.

4. Using streaming gRPC that has minimal latency and minimal overhead and integrating batching into the server module.

We provide the following two algorithms implemented in the SEED framework: V-trace and Q-learning.

3.1 V-TRACE

One of the algorithms we adapt into the framework is V-trace (Espeholt et al., 2018). We do not include any of the additions that have been proposed on top of IMPALA such as van den Oord et al. (2018); Gregor et al. (2019). The additions can also be applied to SEED and since they are more computational expensive, they would benefit from the SEED architecture.

3.2 Q-LEARNING

We show the versatility of SEED's architecture by fully implementing R2D2 (Kapturowski et al., 2018), a state of the art distributed value-based agent. R2D2 itself builds on a long list of improvements over DQN (Mnih et al., 2015): double Q-learning (van Hasselt, 2010; Van Hasselt et al., 2016), multi-step bootstrap targets (Sutton, 1988; Sutton & Barto, 1998; Mnih et al., 2016), dueling network architecture (Wang et al., 2016), prioritized distributed replay buffer (Schaul et al., 2015; Horgan et al., 2018), value-function rescaling (Pohlen et al., 2018), LSTM's (Hochreiter & Schmidhuber, 1997) and burn-in (Kapturowski et al., 2018).

Instead of a distributed replay buffer, we show that it is possible to keep the replay buffer on the learner with a straightforward flexible implementation. This reduces complexity by removing one type of job in the setup. It has the drawback of being limited by the memory of the learner but it was not a problem in our experiments by a large margin: a replay buffer of 10^5 trajectories of length 120 of 84×84 uncompressed grayscale observations (following R2D2's hyperparameters) takes 85GBs of RAM, while Google Cloud machines can offer hundreds of GBs. However, nothing prevents the use of a distributed replay buffer together with SEED's central inference, in cases where much larger replay buffer are needed.

4 EXPERIMENTS

We evaluate SEED on a number of environments: DeepMind Lab (Beattie et al., 2016), Google Research Football (Kurach et al., 2019) and Arcade Learning Environment (Bellemare et al., 2013).

4.1 DEEPMIND LAB AND V-TRACE

DeepMind Lab is a 3D environment based on the Quake 3 engine. It features mazes, laser tag and memory tasks. We evaluate on four commonly used tasks. The action set used is from Espeholt et al. (2018) although for some tasks, higher return can be achieved with bigger action sets such as the one introduced in Hessel et al. (2018). For all experiments, we used an action repeat of 4 and the number of frames in plots is listed as environment frames (equivalent to 4 times the number of steps). The same set of 24 hyperparameter sets and the same model (ResNet from IMPALA) was used for both agents. More details can be found in Appendix A.1.2.

4.1.1 STABILITY

The first experiment evaluates the effect of the change in off-policy behavior described in Figure 2. Exactly the same hyperparameters are used for both IMPALA and SEED, including the number of environments used. As is shown in Figure 4, the stability across hyperparameters of SEED is slightly better than IMPALA, while achieving slightly higher final returns.

4.1.2 SPEED

For evaluating performance, we compare against the baseline IMPALA which used a single Nvidia P100 while SEED was using 2 TPU v3 cores (1 chip) and 8 TPU v3 cores (4 chips). They are
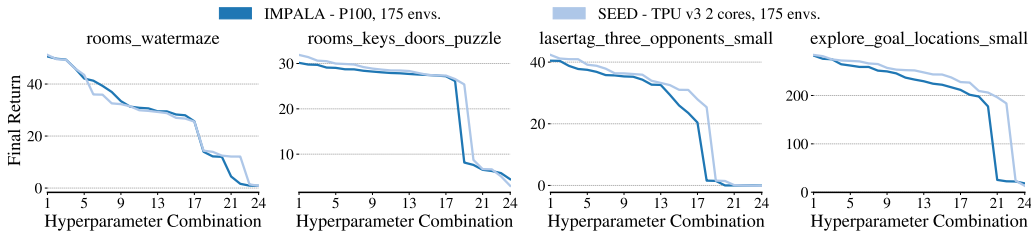
Figure 4: Comparison of IMPALA and SEED under the exact same conditions (175 actors, same hyperparameters, etc.) The plots show hyperparameter combinations sorted by the final performance across different hyperparameter combinations.

Architecture	Accelerators	Environments	Batch Size	FPS	Ratio
DeepMind Lab					
IMPALA	Nvidia P100	176	32	30K	—
SEED	TPU v3, 2 cores	312	32	74K	**2.5x**
SEED	TPU v3, 8 cores	1560	48[1]	330K	**11.0x**
SEED	TPU v3, 64 cores	12,480	384[1]	2.4M	**80.0x**
Google Research Football					
IMPALA, Default	2 x Nvidia P100	400	128	11K	—
SEED, Default	TPU v3, 2 cores	624	128	18K	**1.6x**
SEED, Default	TPU v3, 8 cores	2496	160[3]	71K	**6.5x**
SEED, Medium	TPU v3, 8 cores	1550	160[3]	35K	—
SEED, Large	TPU v3, 8 cores	1260	160[3]	26K	—
SEED, Large	TPU v3, 32 cores	5,040	768	100K	**3.8x**
Arcade Learning Environment					
R2D2	Nvidia V100	256	64	85K[2]	—
SEED	TPU v3, 8 cores	610	64	210K	**2.5x**
SEED	TPU v3, 8 cores	1200	256	400K[4]	**4.7x**

[1] 6/8 cores used for training. [2] R2D2 runs at 335 FPS for each of the 256 actors, per information from the R2D2 authors. [3] 5/8 cores used for training. [4] No frame stacking.

Table 1: Performance of SEED, IMPALA and R2D2.

evaluated on the same set of hyperparameters. We find that SEED is 2.5x faster than IMPALA using 2 TPU v3 cores (see Table 1), while using only 77% more environments and 41% less CPU (see section 4.4.1). Scaling to 8 cores results in an additional 4.4x speedup and sample complexity is maintained (Figure 5). A **5.3x** speed-up instead of 4.4x can be obtained by increasing the batch size linearly with the number of training cores, but contrary to related research (You et al., 2017b; Goyal et al., 2017) we found that increased batch size hurts sample complexity even with methods like warm-up and actor de-correlation (Stooke & Abbeel, 2018). We hypothesize that this is due to the limited actor and environment diversity in DeepMind Lab tasks. In McCandlish et al. (2018) they found that Pong scales poorly with batch size but that Dota can be trained effectively with a batch size five orders of magnitude larger. Note, for most models, the effective batch size is $\mathtt{batch\,size} \cdot \mathtt{trajectory\,length}$. In Figure 5, we include a run from a limited sweep on "explore_goal_locations_small" using 64 cores with an almost linear speed-up. Wall-time performance is improved but sample complexity is heavily penalized.

4.2 GOOGLE RESEARCH FOOTBALL AND V-TRACE

Google Research Football is an environment similar to FIFA video games (ea.com). We evaluate SEED on the "Hard" task introduced in Kurach et al. (2019) where the baseline IMPALA agent
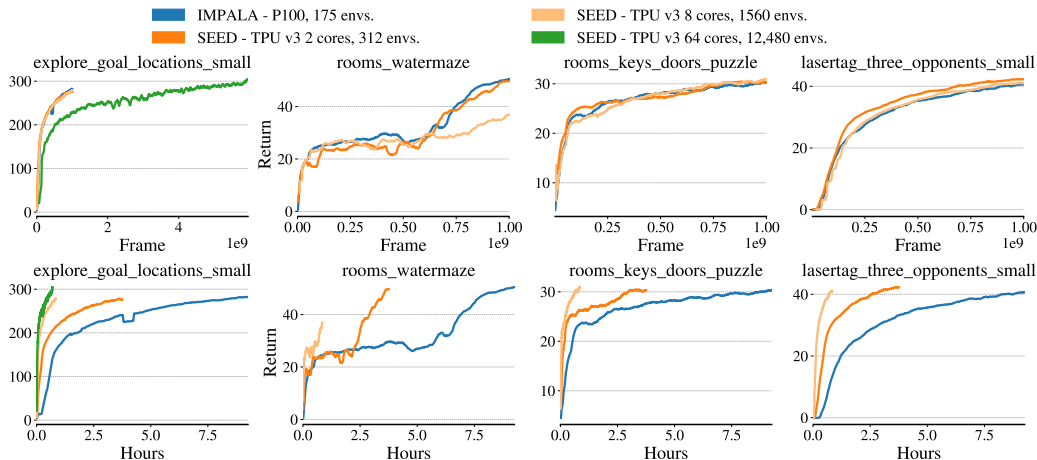
6

Figure 5: Training on 4 DeepMind Lab tasks. Each curve is the best of the 24 runs based on final return following the evaluation procedure in Espeholt et al. (2018). Sample complexity is maintained up to 8 TPU v3 cores, which leads to 11x faster training than the IMPALA baseline. **Top Row:** X-axis is per frame (number of frames = 4x number of steps). **Bottom Row:** X-axis is hours.

achieved a positive average score after 500M frames using the engineered "checkpoint" reward function but a negative average score using only the score as a reward signal. In all experiments we use the model from Kurach et al. (2019) and sweep over 40 hyperparameter sets with 3 seeds each. See all hyperparameters in Appendix A.2.1.

4.2.1 SPEED

Compared to the baseline IMPALA using 2 Nvidia P100's (and CPUs for inference) in Kurach et al. (2019) we find that using 2 TPU v3 cores in SEED improves the speed by 1.6x (see Table 1). Additionally, using 8 cores adds another 4.1x speed-up. A speed-up of **4.5x** is achievable if the batch size is increased linearly with the number of training cores (5). However, we found that increasing the batch size, like with DeepMind Lab, hurts sample complexity.

4.2.2 INCREASED MAP SIZE

More compute power allows us to increase the size of the Super Mini Map (SMM) input state. By default its size is 96 x 72 (x 4) and it represents players, opponents, ball and the active player as 2d bit maps. We evaluated three sizes: (1) Default 96 x 72, (2) Medium 120 x 90 and (3) Large 144 x 108. As shown in Table 1, switching from Default to Large SMM results in roughly 50% speed reduction. However, increasing the map size improves the final score (Figure 6). It may suggest that the bit map representation is not granular enough for the task. For both reward functions, we improve upon the results of Kurach et al. (2019). Finally, training on 4B frames improves the results by a significant margin (an average score of 0.46 vs. 4.76 in case of the scoring reward function).

4.3 ARCADE LEARNING ENVIRONMENT AND Q-LEARNING

We evaluate our implementation of R2D2 in SEED architecture on 57 Atari 2600 games from the ALE benchmark. This benchmark has been the testbed for most recent deep reinforcement learning agents because of the diversity of visuals and game mechanics.

We follow the same evaluation procedure as R2D2. In particular, we use the full action set, no loss-of-life-as-episode-end heuristic and start episodes with up to 30 random no-ops. We use 8 TPU v3 cores and 610 actors to maximize TPU utilization. This achieves 210K environment FPS and performs 7.7 network updates per second. Other hyperparameters are taken from R2D2, and are fully reproduced in appendix A.3.1.

Figure 7 shows the median human-normalized scores for SEED, R2D2, Ape-X and Rainbow. As expected, SEED has similar sample efficiency as R2D2, but it is **2.5x** faster (see Table 1). This allows us to reach a median human-normalized score of 1880% in just 2.2 days of training instead of 5, establishing a new wall-time state of the art on Atari-57.
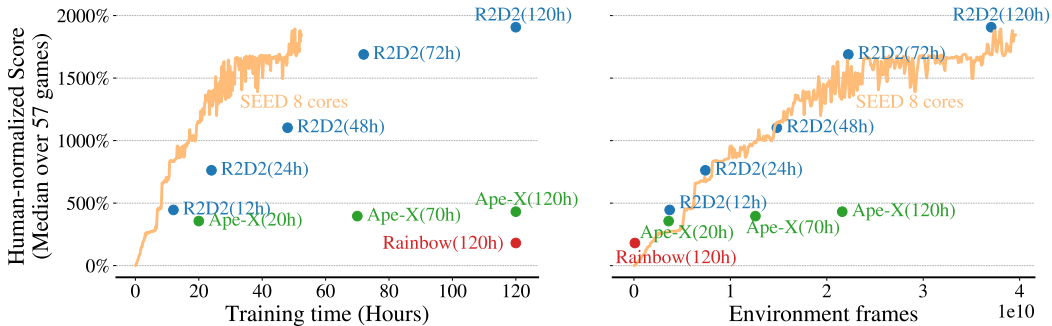
Figure 7: Median human-normalized score on Atari-57 for SEED and related agents. SEED was run with 1 seed for each game. All agents use up to 30 random no-ops for evaluation. **Left:** X-axis is hours **Right:** X-axis is environment frames (a frame is 1/4th of an environment step due to action repeat). SEED reaches state of the art performance **2.5x** faster (wall-time) than R2D2.

With the number of actors increased to 1200, a batch size increased to 256 and without frame-stacking, we can achieve 400K environment FPS and learn using 7 batches per second. However, this significantly degrades sample efficiency and limits the final median human-normalized score to approximately 1000%.

4.4 COST COMPARISONS

With growing complexity of environments as well as size of neural networks used in reinforcement learning, the need of running big experiments increases, making cost reductions important. In this section we analyze how increasing complexity of the network impacts training cost for SEED and IMPALA. In our experiments we use the pricing model of Google AI Platform, ML Engine.[2]

Our main focus is on obtaining lowest possible cost per step, while maintaining training speed. Dis-

Architecture	Accelerators	SMM	Median	Max
Scoring reward				
IMPALA	2 x Nvidia P100	Default	-0.74	0.06
SEED	TPU v3, 2 cores	Default	-0.72	-0.12
SEED	TPU v3, 8 cores	Default	-0.83	-0.02
SEED	TPU v3, 8 cores	Medium	-0.74	0.12
SEED	TPU v3, 8 cores	Large	**-0.69**	**0.46**
SEED	TPU v3, 32 cores	Large	n/a	**4.76**[1]
Checkpoint reward				
IMPALA	2 x Nvidia P100	Default	**-0.27**	1.63
SEED	TPU v3, 2 cores	Default	-0.44	1.64
SEED	TPU v3, 8 cores	Default	-0.68	1.55
SEED	TPU v3, 8 cores	Medium	-0.52	1.76
SEED	TPU v3, 8 cores	Large	-0.38	**1.86**
SEED	TPU v3, 32 cores	Large	n/a	**7.66**[1]

[1] 32 core experiments trained on 4B frames with a limited sweep.

Figure 6: Google Research Football "Hard" using two kinds of reward functions. For each reward function, 40 hyperparameter sets ran with 3 seeds each which were averaged after 500M frames of training. The table shows the median and maximum of the 40 averaged values. This is a similar setup to Kurach et al. (2019) although we ran 40 hyperparameter sets vs. 100 but did not rerun our best models using 5 seeds.

tributed experiments from Espeholt et al. (2018) (IMPALA) used between 150 and 500 CPUs, which translates into $7.125 - $23.75 of actors' cost per hour. The cost of single-GPU learner is $1.46 per hour. Due to the relatively high expense of the actors, our main focus is to reduce number of actors and to obtain high CPU utilization.

4.4.1 DEEPMIND LAB

Our DeepMind Lab experiment is based on the ResNet model from IMPALA. We evaluate increasing the number of filters in the convolutional layers: (1) Default 1x (2) Medium 2x and (3) Large 4x. Experiments are performed on the "explore_goal_locations_small" task. IMPALA uses a single

---

[2]TPU cores are sold in multiples of 8, by running many experiments at once we use as many cores per experiment as needed. See cloud.google.com/ml-engine/docs/pricing.

Nvidia Tesla P100 GPU for training while inference is done on CPU by the actors. SEED uses one TPU v3 core for training and one for inference. For IMPALA, actor CPU utilization is close to 100% but in case of SEED, only the environment runs on an actor making CPU idle while waiting for inference step. To improve utilization, a single SEED actor runs multiple environments (between 12 and 16) on a 4-CPU machine.

Model	Actors	CPUs	Envs.	Speed	Cost/1B	Cost ratio
IMPALA						
Default	176	176	176	30k	$90	—
Medium	130	130	130	16.5k	$128	—
Large	100	100	100	7.3k[1]	$236	—
SEED						
Default	26	104	312	74k	$25	**3.60**
Medium	12	48	156	34k	$35	**3.66**
Large	6	24	84	16k	$54	**4.37**

[1] The batch size was lowered from 32 to 16 due to limited memory on Nvidia P100.

Table 2: Training cost on DeepMind Lab for 1 billion frames.

As Table 2 shows, SEED turns out to be not only faster, but also cheaper to run. The cost ratio between SEED and IMPALA is around 4. Due to high cost of inference on a CPU, IMPALA's cost increases with increasing complexity of the network. In the case of SEED, increased network size has smaller impact on overall costs, as inference accounts for about 30% of the costs (see Table A.5).

Resource	Cost per hour
CPU core	$0.0475
Nvidia Tesla P100	$1.46
TPU v3 core	$1.00

Figure 8: Cost of cloud resources as of Sep. 2019.

4.4.2 GOOGLE RESEARCH FOOTBALL

We evaluate cost of running experiments with Google Research Football with different sizes of the Super Mini Map representation (the size has virtually no impact on environment's speed.) For IMPALA, two Nvidia P100 GPUs were used for training and SEED used one TPU v3 core for training and one for inference. For IMPALA, we use one core per actor while SEED's actors run multiple environments per actor for better CPU utilization (8 cores, 12 environments).

Model	Actors	CPUs	Envs.	Speed	Cost/1B	Cost ratio
IMPALA						
Default	400	400	400	11k	$553	—
Medium	300	300	300	7k	$681	—
Large	300	300	300	5.3k	$899	—
SEED						
Default	52	416	624	17.5k	$345	**1.68**
Medium	31	248	310	10.5k	$365	**1.87**
Large	21	168	252	7.5k	$369	**2.70**

Table 3: Training cost on Google Research Football for 1 billion frames.

For the default size of the SMM, per experiment training cost differs by only 68%. As the Google Research Football environment is more expensive than DeepMind Lab, training and inference costs have relatively smaller impact on the overall experiment cost. The difference increases when the size of the SMM increases and SEED needing relatively fewer actors.

4.4.3 ARCADE LEARNING ENVIRONMENT

Due to lack of baseline implementation for R2D2, we do not include cost comparisons for this environment. However, comparison of relative costs between ALE, DeepMind Lab and Football suggests that savings should be even more significant. ALE is the fastest among the three environments making inference proportionally the most expensive. Appendix A.5 presents training cost split between actors and the learner for different setups.

5 CONCLUSION

We introduced and analyzed a new reinforcement learning agent architecture that is faster and less costly per environment frame than previous distributed architectures by better utilizing modern accelerators. It achieved 11x wall-time speedup on DeepMind Lab compared to a strong IMPALA baseline while keeping the same sample efficiency, improved on state of the art scores on Google Research Football, and achieved state of the art scores on Atari-57 2.5x faster (wall-time) than previous research.

The agent is open-sourced and packaged to easily run on Google Cloud. We hope that this will accelerate reinforcement learning research by allowing the community to replicate state-of-the-art results and build on top of them.

As a demonstration of the potential of this new agent architecture, we were able to scale it to millions of frames per second in some realistic scenarios (80x speedup compared to previous research). However, this requires increasing the number of environments and using larger batch sizes which hurts sample efficiency in the environments tested. Preserving sample efficiency with larger batch-sizes has been studied to some extent in RL (Stooke & Abbeel, 2018; McCandlish et al., 2018) and more generally in the context of supervised learning (You et al., 2017b;a; Goyal et al., 2017). We believe it is still an open and increasingly important area of research in order to scale up reinforcement learning.

REFERENCES

Martín Abadi, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Greg S. Corrado, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Ian Goodfellow, Andrew Harp, Geoffrey Irving, Michael Isard, Yangqing Jia, Rafal Jozefowicz, Lukasz Kaiser, Manjunath Kudlur, Josh Levenberg, Dandelion Mané, Rajat Monga, Sherry Moore, Derek Murray, Chris Olah, Mike Schuster, Jonathon Shlens, Benoit Steiner, Ilya Sutskever, Kunal Talwar, Paul Tucker, Vincent Vanhoucke, Vijay Vasudevan, Fernanda Viégas, Oriol Vinyals, Pete Warden, Martin Wattenberg, Martin Wicke, Yuan Yu, and Xiaoqiang Zheng. TensorFlow: Large-scale machine learning on heterogeneous systems, 2015. URL https://www.tensorflow.org/. Software available from tensorflow.org.

Charles Beattie, Joel Z. Leibo, Denis Teplyashin, Tom Ward, Marcus Wainwright, Heinrich Küttler, Andrew Lefrancq, Simon Green, Víctor Valdés, Amir Sadik, Julian Schrittwieser, Keith Anderson, Sarah York, Max Cant, Adam Cain, Adrian Bolton, Stephen Gaffney, Helen King, Demis Hassabis, Shane Legg, and Stig Petersen. Deepmind lab. *CoRR*, abs/1612.03801, 2016. URL http://arxiv.org/abs/1612.03801.

Marc G Bellemare, Yavar Naddaf, Joel Veness, and Michael Bowling. The arcade learning environment: An evaluation platform for general agents. *J. Artif. Intell. Res. (JAIR)*, 47:253–279, 2013.

Pablo Samuel Castro, Subhodeep Moitra, Carles Gelada, Saurabh Kumar, and Marc G. Bellemare. Dopamine: A Research Framework for Deep Reinforcement Learning. 2018. URL http://arxiv.org/abs/1812.06110.

Jianmin Chen, Rajat Monga, Samy Bengio, and Rafal Józefowicz. Revisiting distributed synchronous SGD. *CoRR*, abs/1604.00981, 2016. URL http://arxiv.org/abs/1604.00981.

Steven Dalton, Iuri Frosio, and Michael Garland. Gpu-accelerated atari emulation for reinforcement learning. *CoRR*, abs/1907.08467, 2019. URL http://arxiv.org/abs/1907.08467.

Jeffrey Dean, Greg Corrado, Rajat Monga, Kai Chen, Matthieu Devin, Mark Mao, Marcaurelio Ranzato, Andrew Senior, Paul Tucker, Ke Yang, Quoc V. Le, and Andrew Y. Ng. Large scale distributed deep networks. In F. Pereira, C. J. C. Burges, L. Bottou, and K. Q. Weinberger (eds.), *Advances in Neural Information Processing Systems 25*, pp. 1223–1231. Curran Associates, Inc., 2012. URL http://papers.nips.cc/paper/4687-large-scale-distributed-deep-networks.pdf.

Ben Deverett, Ryan Faulkner, Meire Fortunato, Greg Wayne, and Joel Z Leibo. Interval timing in deep reinforcement learning agents. *arXiv preprint arXiv:1905.13469*, 2019.

Lasse Espeholt, Hubert Soyer, Rémi Munos, Karen Simonyan, Volodymyr Mnih, Tom Ward, Yotam Doron, Vlad Firoiu, Tim Harley, Iain Dunning, Shane Legg, and Koray Kavukcuoglu. IMPALA: scalable distributed deep-rl with importance weighted actor-learner architectures. In *Proceedings of the 35th International Conference on Machine Learning, ICML 2018, Stockholmsmässan, Stockholm, Sweden, July 10-15, 2018*, pp. 1406–1415, 2018. URL http://proceedings.mlr.press/v80/espeholt18a.html.

Xavier Glorot and Yoshua Bengio. Understanding the difficulty of training deep feedforward neural networks. In *Proceedings of the thirteenth international conference on artificial intelligence and statistics*, pp. 249–256, 2010.

Priya Goyal, Piotr Dollár, Ross B. Girshick, Pieter Noordhuis, Lukasz Wesolowski, Aapo Kyrola, Andrew Tulloch, Yangqing Jia, and Kaiming He. Accurate, large minibatch SGD: training imagenet in 1 hour. *CoRR*, abs/1706.02677, 2017. URL http://arxiv.org/abs/1706.02677.

Karol Gregor, Danilo Jimenez Rezende, Frederic Besse, Yan Wu, Hamza Merzic, and Aäron van den Oord. Shaping belief states with generative environment models for RL. *CoRR*, abs/1906.09237, 2019. URL http://arxiv.org/abs/1906.09237.

Sergio Guadarrama, Anoop Korattikara, Oscar Ramirez, Pablo Castro, Ethan Holly, Sam Fishman, Ke Wang, Ekaterina Gonina, Neal Wu, Chris Harris, Vincent Vanhoucke, and Eugene Brevdo. TF-Agents: A library for reinforcement learning in tensorflow. https://github.com/tensorflow/agents, 2018. URL https://github.com/tensorflow/agents. [Online; accessed 25-June-2019].

Steven Hansen, Will Dabney, Andre Barreto, Tom Van de Wiele, David Warde-Farley, and Volodymyr Mnih. Fast task inference with variational intrinsic successor features. *arXiv preprint arXiv:1906.05030*, 2019.

Matteo Hessel, Joseph Modayil, Hado van Hasselt, Tom Schaul, Georg Ostrovski, Will Dabney, Daniel Horgan, Bilal Piot, Mohammad Gheshlaghi Azar, and David Silver. Rainbow: Combining improvements in deep reinforcement learning. *CoRR*, abs/1710.02298, 2017. URL http://arxiv.org/abs/1710.02298.

Matteo Hessel, Hubert Soyer, Lasse Espeholt, Wojciech Czarnecki, Simon Schmitt, and Hado van Hasselt. Multi-task deep reinforcement learning with popart. *CoRR*, abs/1809.04474, 2018. URL http://arxiv.org/abs/1809.04474.

Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural computation*, 9(8): 1735–1780, 1997.

Dan Horgan, John Quan, David Budden, Gabriel Barth-Maron, Matteo Hessel, Hado van Hasselt, and David Silver. Distributed prioritized experience replay. In *ICLR*, 2018.

Steven Kapturowski, Georg Ostrovski, John Quan, Remi Munos, and Will Dabney. Recurrent experience replay in distributed reinforcement learning. 2018.

Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization. In *Proceedings of the 3rd International Conference on Learning Representations (ICLR)*, 2014.

Karol Kurach, Anton Raichuk, Piotr Stańczyk, Michał Zajac, Olivier Bachem, Lasse Espeholt, Carlos Riquelme, Damien Vincent, Marcin Michalski, Olivier Bousquet, et al. Google research football: A novel reinforcement learning environment. *arXiv preprint arXiv:1907.11180*, 2019.

Ang Li, Huiyi Hu, Piotr Mirowski, and Mehrdad Farajtabar. Cross-view policy learning for street navigation. *arXiv preprint arXiv:1906.05930*, 2019.

Eric Liang, Richard Liaw, Philipp Moritz, Robert Nishihara, Roy Fox, Ken Goldberg, Joseph E Gonzalez, Michael I Jordan, and Ion Stoica. Rllib: Abstractions for distributed reinforcement learning. *arXiv preprint arXiv:1712.09381*, 2017.

Ashique Mahmood. *Incremental Off-policy Reinforcement Learning Algorithms*. PhD thesis, University of Alberta, 2017.

Sam McCandlish, Jared Kaplan, Dario Amodei, and OpenAI Dota Team. An empirical model of large-batch training. *CoRR*, abs/1812.06162, 2018. URL http://arxiv.org/abs/1812.06162.

Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A Rusu, Joel Veness, Marc G Bellemare, Alex Graves, Martin Riedmiller, Andreas K Fidjeland, Georg Ostrovski, et al. Human-level control through deep reinforcement learning. *Nature*, 518(7540):529, 2015.

Volodymyr Mnih, Adria Puigdomenech Badia, Mehdi Mirza, Alex Graves, Timothy Lillicrap, Tim Harley, David Silver, and Koray Kavukcuoglu. Asynchronous methods for deep reinforcement learning. In *International conference on machine learning*, pp. 1928–1937, 2016.

Arun Nair, Praveen Srinivasan, Sam Blackwell, Cagdas Alcicek, Rory Fearon, Alessandro De Maria, Vedavyas Panneershelvam, Mustafa Suleyman, Charles Beattie, Stig Petersen, Shane Legg, Volodymyr Mnih, Koray Kavukcuoglu, and David Silver. Massively parallel methods for deep reinforcement learning. *arXiv preprint arXiv:1507.04296*, 2015.

Shayegan Omidshafiei, Daniel Hennes, Dustin Morrill, Rémi Munos, Julien Pérolat, Marc Lanctot, Audrunas Gruslys, Jean-Baptiste Lespiau, and Karl Tuyls. Neural replicator dynamics. *CoRR*, abs/1906.00190, 2019. URL http://arxiv.org/abs/1906.00190.

OpenAI. Openai five. https://blog.openai.com/openai-five/, 2018.

Michael Petrov, Szymon Sidor, Susan Zhang, Jakub Pachocki, Przemysaw Dbiak, Filip Wolski, Christy Dennison, Henrique Pond, Greg Brockman, Jie Tang, David Farhi, Brooke Chan, and Jonathan Raiman. Openai rapid. https://openai.com/blog/openai-five/, 2018. Accessed: 2019-09-14.

Tobias Pohlen, Bilal Piot, Todd Hester, Mohammad Gheshlaghi Azar, Dan Horgan, David Budden, Gabriel Barth-Maron, Hado Van Hasselt, John Quan, Mel Večerík, et al. Observe and look further: Achieving consistent performance on atari. *arXiv preprint arXiv:1805.11593*, 2018.

Rajat Raina, Anand Madhavan, and Andrew Y Ng. Large-scale deep unsupervised learning using graphics processors. In *Proceedings of the 26th annual international conference on machine learning*, pp. 873–880. ACM, 2009.

Tim Salimans, Jonathan Ho, Xi Chen, Szymon Sidor, and Ilya Sutskever. Evolution strategies as a scalable alternative to reinforcement learning. *arXiv preprint arXiv:1703.03864*, 2017.

Michael Schaarschmidt, Sven Mika, Kai Fricke, and Eiko Yoneki. Rlgraph: Modular computation graphs for deep reinforcement learning.

Tom Schaul, John Quan, Ioannis Antonoglou, and David Silver. Prioritized experience replay. In *Proc. of ICLR*, 2015.

John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. *CoRR*, abs/1707.06347, 2017. URL http://arxiv.org/abs/1707.06347.

David Silver, Aja Huang, Chris J Maddison, Arthur Guez, Laurent Sifre, George Van Den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, Marc Lanctot, et al. Mastering the game of go with deep neural networks and tree search. *nature*, 529(7587):484, 2016.

Adam Stooke and Pieter Abbeel. Accelerated methods for deep reinforcement learning. *CoRR*, abs/1803.02811, 2018. URL http://arxiv.org/abs/1803.02811.

Adam Stooke and Pieter Abbeel. rlpyt: A research code base for deep reinforcement learning in pytorch. *arXiv preprint arXiv:1909.01500*, 2019.

Felipe Petroski Such, Vashisht Madhavan, Edoardo Conti, Joel Lehman, Kenneth O. Stanley, and Jeff Clune. Deep neuroevolution: Genetic algorithms are a competitive alternative for training deep neural networks for reinforcement learning. *CoRR*, abs/1712.06567, 2017. URL http://arxiv.org/abs/1712.06567.

Richard S Sutton. Learning to predict by the methods of temporal differences. *Machine learning*, 3 (1):9–44, 1988.

Richard S Sutton and Andrew G Barto. Reinforcement learning: an introduction mit press. *Cambridge, MA*, 1998.

Yuandong Tian, Qucheng Gong, Wenling Shang, Yuxin Wu, and C. Lawrence Zitnick. Elf: An extensive, lightweight and flexible research platform for real-time strategy games. *Advances in Neural Information Processing Systems (NIPS)*, 2017.

Dhruva Tirumala, Hyeonwoo Noh, Alexandre Galashov, Leonard Hasenclever, Arun Ahuja, Greg Wayne, Razvan Pascanu, Yee Whye Teh, and Nicolas Heess. Exploiting hierarchy for learning and transfer in kl-regularized RL. *CoRR*, abs/1903.07438, 2019. URL http://arxiv.org/abs/1903.07438.

Aäron van den Oord, Yazhe Li, and Oriol Vinyals. Representation learning with contrastive predictive coding. *CoRR*, abs/1807.03748, 2018. URL http://arxiv.org/abs/1807.03748.

Hado van Hasselt. Double Q-learning. In *Advances in Neural Information Processing Systems 23*, pp. 2613–2621, 2010.

Hado Van Hasselt, Arthur Guez, and David Silver. Deep reinforcement learning with double q-learning. In *Thirtieth AAAI conference on artificial intelligence*, 2016.

Vivek Veeriah, Matteo Hessel, Zhongwen Xu, Richard Lewis, Janarthanan Rajendran, Junhyuk Oh, Hado van Hasselt, David Silver, and Satinder Singh. Discovery of useful questions as auxiliary tasks. *arXiv preprint arXiv:1909.04607*, 2019.

Alexander Sasha Vezhnevets, Yuhuai Wu, Remi Leblond, and Joel Leibo. Options as responses: Grounding behavioural hierarchies in multi-agent rl. *arXiv preprint arXiv:1906.01470*, 2019.

Oriol Vinyals, Timo Ewalds, Sergey Bartunov, Petko Georgiev, Alexander Sasha Vezhnevets, Michelle Yeo, Alireza Makhzani, Heinrich Küttler, John Agapiou, Julian Schrittwieser, et al. Starcraft ii: A new challenge for reinforcement learning. *arXiv preprint arXiv:1708.04782*, 2017.

Ziyu Wang, Tom Schaul, Matteo Hessel, Hado van Hasselt, Marc Lanctot, and Nando de Freitas. Dueling network architectures for deep reinforcement learning. In *Proceedings of The 33rd International Conference on Machine Learning*, pp. 1995–2003, 2016.

Yang You, Igor Gitman, and Boris Ginsburg. Large batch training of convolutional networks. *arXiv preprint arXiv:1708.03888*, 2017a.

Yang You, Igor Gitman, and Boris Ginsburg. Scaling sgd batch size to 32k for imagenet training. *arXiv preprint arXiv:1708.03888*, 6, 2017b.

A APPENDIX

A.1 DEEPMIND LAB

A.1.1 LEVEL CACHE

We enable DeepMind Lab's option for using a level cache for both SEED and IMPALA which greatly reduces CPU usage and results in stable actor CPU usage at close to 100% for a single core.

A.1.2 HYPERPARAMETERS

Parameter	Range
Action Repetitions	4
Discount Factor (γ)	$\{.99, .993, .997, .999\}$
Entropy Coefficient	Log-uniform $(1e-5, 1e-3)$
Learning Rate	Log-uniform $(1e-4, 1e-3)$
Optimizer	Adam
Adam Epsilon	$\{1e-1, 1e-3, 1e-5, 1e-7\}$
Unroll Length/n-step	32
Value Function Coefficient	.5
V-trace λ	$\{.9, .95, .99, 1.\}$

Table 4: SEED: ranges used during the hyperparameter for experiments with scoring and checkpoint rewards.

A.2 GOOGLE RESEARCH FOOTBALL

A.2.1 HYPERPARAMETERS

Parameter	Range
Action Repetitions	1
Discount Factor (γ)	$\{.99, .993, .997, .999\}$
Entropy Coefficient	Log-uniform $(1e-7, 1e-3)$
Learning Rate	Log-uniform $(1e-5, 1e-3)$
Optimizer	Adam
Unroll Length/n-step	32
Value Function Coefficient	.5
V-trace λ	$\{.9, .95, .99, 1.\}$

Table 5: SEED: ranges used during the hyperparameter for experiments with scoring and checkpoint rewards.

A.3 ALE

A.3.1 HYPERPARAMETERS

We use the same hyperparameters as R2D2 (Kapturowski et al., 2018), except that we use more actors in order to best utilize 8 TPU v3 cores. For completeness, agent hyper-parameters are in table 6 and environment processing parameters in table 7. We use the same neural network architecture as R2D2, namely 3 convolutional layers with filter sizes $[32, 64, 64]$, kernel sizes $[8 \times 8, 4 \times 4, 3 \times 3]$ and strides $[4, 2, 1]$, ReLU activations and "valid" padding. They feed into a linear layer with 512 units, feeding into an LSTM layer with 512 hidden units (that also uses the one-hot encoded previous action and the previous environment reward as input), feeding into dueling heads with 512 hidden units. We use Glorot uniform (Glorot & Bengio, 2010) initialization.

Parameter	Value
Number of actors	610
Replay ratio	0.75
Sequence length	120 incl. prefix of 40 burn-in transitions
Replay buffer size	10^5 part-overlapping sequences
Priority exponent	0.9
Importance sampling exponent	0.6
Discount γ	0.997
Training batch size	64
Inference batch size	64
Optimizer	Adam (lr=10^{-4}, $\epsilon = 10^{-3}$) ($Kingma\&Ba$, 2014)
Target network update interval	2500 updates
Value function rescaling	$x \mapsto \text{sign}(x)(\sqrt{(x+1)-1} + \epsilon x, \epsilon = 10^{-3}$
Gradient norm clipping	80
n-steps	5
Epsilon-greedy	**Training:** i-th actor $\in [0, N)$ uses $\epsilon_i = 0.4^{1+\frac{7i}{N-1}}$ **Evaluation:** $\epsilon = 10^{-3}$
Sequence priority	$p = \eta \max_i \delta_i + (1-\eta)\bar{\delta}$ where $\eta = 0.9$, δ_i are per-step absolute TD errors.

Table 6: SEED agent hyperparameters for for Atari-57.

Parameter	Value
Observation size	84×84
Resizing method	Bilinear
Random no-ops	uniform in $[0, 30)$. Applied before action repetition.
Frame stacking	4
Action repetition	4
Frame pooling	2
Color mode	grayscale
Terminal on loss of life	False
Max frames per episode	108K (30 minutes)
Reward clipping	No
Action set	Full (18 actions)
Sticky actions	No

Table 7: Atari-57 environment processing parameters.

A.3.2 FULL RESULTS ON ATARI-57

Game	Human	R2D2	SEED 8 TPU v3 cores
Alien	7127.7	229496.9	**262197.4**
Amidar	1719.5	**29321.4**	28976.4
Assault	742.0	**108197.0**	102954.7
Asterix	8503.3	**999153.3**	983821.0
Asteroids	47388.7	**357867.7**	296783.0
Atlantis	29028.1	**1620764.0**	1612438.0
BankHeist	753.1	24235.9	**47080.6**
BattleZone	37187.5	751880.0	**777200.0**
BeamRider	16926.5	**188257.4**	173505.3
Berzerk	2630.4	53318.7	**57530.4**
Bowling	160.7	**219.5**	204.2
Boxing	12.1	98.5	**100.0**
Breakout	30.5	837.7	**854.1**
Centipede	12017.0	**599140.3**	574373.1
ChopperCommand	7387.8	986652.0	**994991.0**
CrazyClimber	35829.4	**366690.7**	337756.0
Defender	18688.9	**665792.0**	555427.2
DemonAttack	1971.0	140002.3	**143748.6**
DoubleDunk	-16.4	23.7	**24.0**
Enduro	860.5	**2372.7**	2369.3
FishingDerby	-38.7	**85.8**	75.0
Freeway	29.6	32.5	**33.0**
Frostbite	4334.7	**315456.4**	101726.8
Gopher	2412.5	**124776.3**	117650.4
Gravitar	3351.4	**15680.7**	7813.8
Hero	30826.4	**39537.1**	37223.1
IceHockey	0.9	**79.3**	79.2
Jamesbond	302.8	25354.0	**25987.0**
Kangaroo	3035.0	**14130.7**	13862.0
Krull	2665.5	**218448.1**	113224.8
KungFuMaster	22736.3	233413.3	**239713.0**
MontezumaRevenge	**4753.3**	2061.3	900.0
MsPacman	6951.6	42281.7	**43115.4**
NameThisGame	8049.0	58182.7	**68836.2**
Phoenix	7242.6	864020.0	**915929.6**
Pitfall	**6463.7**	0.0	-0.1
Pong	14.6	**21.0**	**21.0**
PrivateEye	**69571.3**	5322.7	198.0
Qbert	13455.0	408850.0	**546857.5**
Riverraid	17118.0	**45632.1**	36906.4
RoadRunner	7845.0	599246.7	**601220.0**
Robotank	11.9	100.4	**104.8**
Seaquest	42054.7	**999996.7**	999990.2
Skiing	**-4336.9**	-30021.7	-29973.6
Solaris	**12326.7**	3787.2	861.6
SpaceInvaders	1668.7	43223.4	**62957.8**
StarGunner	10250.0	**717344.0**	448480.0
Surround	6.5	**9.9**	9.8
Tennis	-8.3	-0.1	**23.9**
TimePilot	5229.2	**445377.3**	444527.0
Tutankham	167.6	**395.3**	376.5
UpNDown	11693.2	**589226.9**	549355.4
Venture	1187.5	1970.7	**2005.5**
VideoPinball	17667.9	**999383.2**	979432.1
WizardOfWor	4756.5	**144362.7**	136352.5
YarsRevenge	54576.9	**995048.4**	973319.0
Zaxxon	9173.3	**224910.7**	168816.5

Table 8: Final performance of SEED 8 TPU v3 cores, 610 actors (1 seed) compared to R2D2 (averaged over 3 seeds) and Human, using up to 30 random no-op steps at the beginning of each episode. SEED was evaluated by averaging returns over 200 episodes for each game after training on $40e9$ environment frames.

A.4 SEED LOCALLY AND ON CLOUD

SEED is open-sourced together with an example of running it both on a local machine and with scale using AI Platform, part of Google Cloud. We provide a public Docker image with low-level components implemented in C++ already pre-compiled to minimize the time needed to start SEED experiments.

The main pre-requisite to running on Cloud is setting up a Cloud Project. The provided startup script uploads the image and runs training for you. For more details please see *anonymized*.

A.5 EXPERIMENTS COST SPLIT

Model	Algorithm	Actors cost	Learner cost	Total cost
Arcade Learning Environment				
Default	SEED	$11.4	$4.3	$15.7
DeepMind Lab				
Default	IMPALA	$77.0	$13.4	$90
Medium	IMPALA	$103.6	$24.4	$128
Large	IMPALA	$180.5	$55.5	$236
Default	SEED	$20.1	$8.2	$28
Medium	SEED	$18.6	$16.4	$35
Large	SEED	$19.6	$35	$54
Google Research Football				
Default	IMPALA	$479	$74	$553
Medium	IMPALA	$565.2	$115.8	$681
Large	IMPALA	$746.1	$153	$899
Default	SEED	$313	$32	$345
Medium	SEED	$312	$53	$365
Large	SEED	$295	$74	$369

Table 9: Cost of performing 1 billion frames for both IMPALA and SEED split by component.

A.6 INFERENCE LATENCY

Model	IMPALA	SEED
DeepMind Lab		
Default	17.97ms	10.98ms
Medium	25.86ms	12.70ms
Large	48.79ms	14.99ms
Google Research Football		
Default	12.59ms	6.50ms
Medium	19.24ms	5.90ms
Large	34.20ms	11.19ms

Table 10: End-to-end inference latency of IMPALA and SEED for different environments and models.

Figure 9: Learning curves on 57 Atari 2600 games for SEED (8 TPUv3 cores, 610 actors, evaluated with 1 seed). Each point of each curve averages returns over 200 episodes. No curve smoothing was performed. Curves end at approximately 53 hours of training, corresponding to $40e9$ environment frames.