COMS E6998 012/15099

Practical Deep Learning Systems Performance

Lecture 8 10/24/19

Logistics

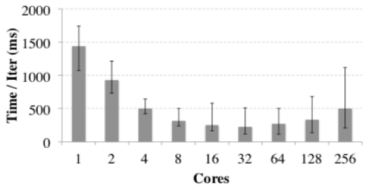
- Homework 1 is graded; Average class score 91%, median 98%
- Homework 3 will be posted Oct 30. Due Nov 8 by 11:59 PM
- Rubric for seminar and project grading created
- Start working on your 10% for technical community participation

Recall from last lecture

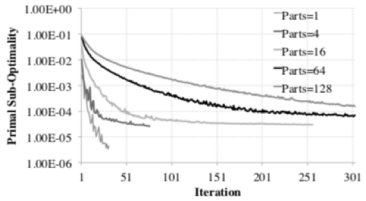
- Learn to transfer, pseudo labeling
- Automated labeling using KL divergence in transfer learning
- Performance modeling of DL, black box and white box techniques
- Execution time modeling of DL using neural networks
- Analytical modeling of DL in PALEO
- ML based runtime model of DL in AI Gauge

Size of Training Cluster

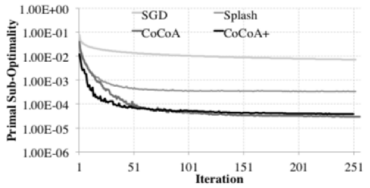
- Distributed optimization algorithms:
  - Performance (time to converge to certain error threshold) depends on the cluster set up used for training
  - Convergence rates (number of iterations to reach a certain error threshold) of algorithms is dependent on the size of the cluster use
- Computation vs. communication balance and convergence rates differ across algorithms (e.g., first-order methods vs. second-order methods), it is often hard to predict which algorithm will be the most appropriate for a given cluster setup.



(a) Time per iteration as we vary the degree of parallelism used. The plot shows the mean across 50 iterations and the error bars show the 5th and 95th percentile



(b) Convergence of CoCoA as we vary the degree of parallelism used.



(c) Comparison of convergence rate of CoCoA, CoCoA+, SGD and Splash when using 16 cores.

Pan et al. Hemingway: Modeling Distributed Optimization Algorithms. NIPS 2016

Hemingway

- **Goal**: Develop an interface where users can specify an end-to- end requirements and the system will automatically select the appropriate algorithm and degree of parallelism to use.
- **Use cases**:
  - Given a relative error goal of ε, choose the fastest algorithm and configuration; or
  - Given a target latency of t seconds choose an algorithm that will achieve the minimum training loss.

Pan et al. Hemingway: Modeling Distributed Optimization Algorithms. NIPS 2016

Hemingway: Performance Models

- A black-box model that can be applied across a number of distributed optimization algorithms
- Building two models: one that captures the system level characteristics of how computation, communication change as we increase cluster sizes and another that captures how convergence rates change with cluster sizes.
- Modeling the system

$$f(m) = \theta_0 + \theta_1 \times (size/m) + \theta_2 \times \log(m) + \theta_3 \times m$$

- Modeling the algorithm

$$g = \sum_{j=1}^{k} \lambda_j \phi_j(i, m)$$

- Combined model: $h(t, m) = g(t/f(m), m)$

Pan et al. Hemingway: Modeling Distributed Optimization Algorithms. NIPS 2016

Model decomposition Helps

- Allows to train the two models independently and reuse them based on changes.
- Retrain the system model and reuse the convergence model
  - New machine types or networking hardware changes in a datacenter
- Retrain the convergence model and reuse the system model
  - Changes to the algorithm in terms of parameter tuning

Pan et al. Hemingway: Modeling Distributed Optimization Algorithms. NIPS 2016

Hemingway in Action

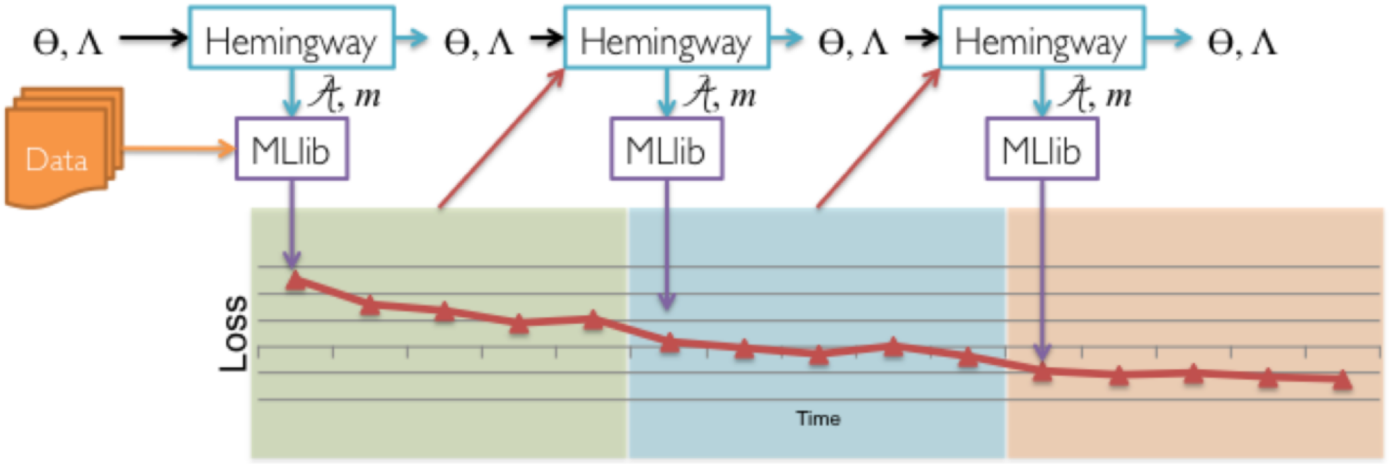


Figure 2: Idealized Example of using Hemingway. For each time frame, Hemingway takes as input the current estimated system model Θ and convergence model Λ, and suggests the best algorithm $\mathcal{A}$ and number of machines m to use for the next time frame. These are then fed into a machine learning framework, e.g. MLlib, which executes the convex optimation algorithm. Resultant losses are provided as input into Hemingway to update Θ and Λ.

Pan et al. Hemingway: Modeling Distributed Optimization Algorithms. NIPS 2016

Optimus

- Goal: To learn relation between resource configuration and the time a training job takes to achieve model convergence to make efficient scheduling decisions on Deep Learning cluster
- Approach:
  - Estimate number of remaining epochs needed to converge
    - Model training loss as a function of number of epochs
  - Estimate the time to complete per epoch as a function of hardware resources
    - Model time to finish per epoch as a function of number of learners

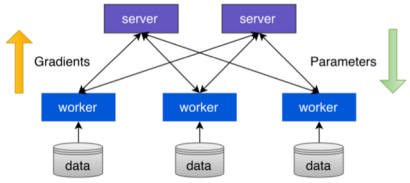


Figure 3: Parameter server architecture

Y. Peng et al. Optimus: An Efficient Dynamic Resource Scheduler for Deep Learning Clusters. Eurosys 2018

Optimus: Training loss modeling

- Training loss model: $l = \frac{1}{\beta_0 \cdot k + \beta_1} + \beta_2$ $\quad l : training\ loss$, $k: number\ of\ epochs$
- Online fitting using NNLS (non-negative least square) solver after every epoch using the entire history
- Using the model and an convergence error threshold we can calculate the remaining number of training epoch needed

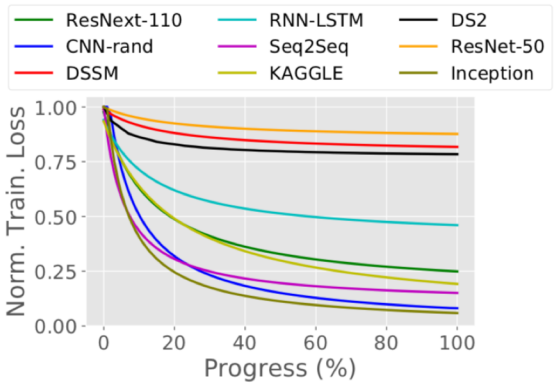


Figure 5: Training loss curves for different DL jobs

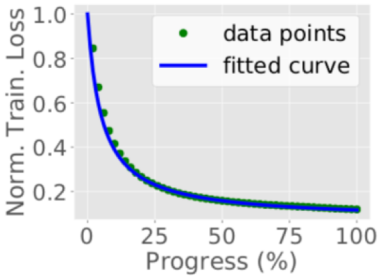


Figure 7: Online model fitting for training Seq2Seq: $\beta_0 = 0.21$, $\beta_1 = 1.07, \beta_2 = 0.07$

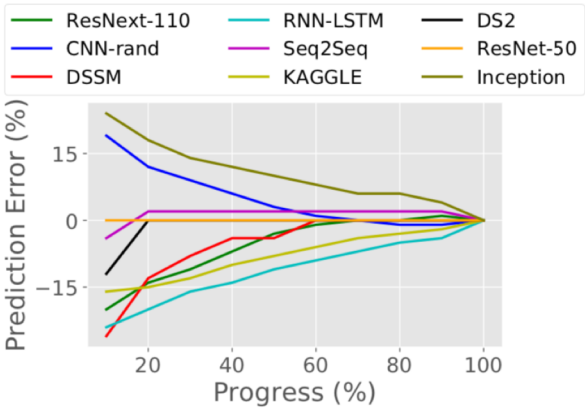


Figure 6: Prediction errors in different DL jobs

Y. Peng et al. Optimus: An Efficient Dynamic Resource Scheduler for Deep Learning Clusters. Eurosys 2018

Optimus: Resource-speed modeling

$$T = Gradient\ compute\ at\ learner + Gradient\ comm.time\ + Gradient\ update\ at\ PS + Comm.overhead$$

$$T = mT_f + T_b + 2\frac{S/P}{B/w'} + \frac{T\_update \cdot w'}{P}\delta \cdot w + \delta' \cdot P$$

- Forward propagation time to process one sample: T_f
- Forward propagation time to process a mini-batch: mT_f
- Backward propagation time: T_b
- Model/gradient size: S
- Size of gradients transferred from a worker to a PS: S/P
- Bandwidth at parameter server (PS): B
- Number of workers that send gradients to a PS concurrently: w'
- Bandwidth between a PS and a worker: B/w'
- Communication time between a PS and a worker: 2 ((S/P)/(B/w'))
- Parameter update time on PS: (T_update*w')/P
- Communication overhead: $\delta \cdot w + \delta' \cdot p$

Y. Peng et al. Optimus: An Efficient Dynamic Resource Scheduler for Deep Learning Clusters. Eurosys 2018

Optimus: Resource-speed modeling

- Asynchronous Training:

$$f(p, w) = w \cdot (\theta_0 + \theta_1 \cdot \frac{w}{p} + \theta_2 \cdot w + \theta_3 \cdot p)^{-1}$$

- Synchronous Training:

$$f(p, w) = (\theta_0 \cdot \frac{M}{w} + \theta_1 + \theta_2 \cdot \frac{w}{p} + \theta_3 \cdot w + \theta_4 \cdot p)^{-1}$$

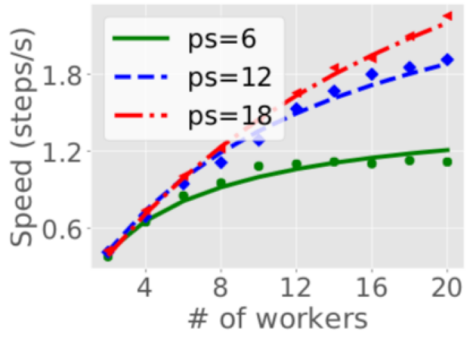
$$Total\ batch\ size: M$$

$$Batch\ size\ per\ learner: m = \frac{M}{w}$$

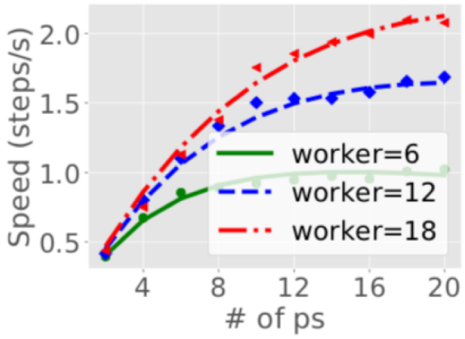
Y. Peng et al. Optimus: An Efficient Dynamic Resource Scheduler for Deep Learning Clusters. Eurosys 2018

Optimus: Predictive Performance for Strong Scaling

Asynchronous Training

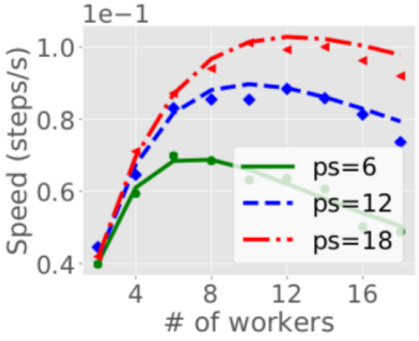


(a)



(b)

Synchronous Training



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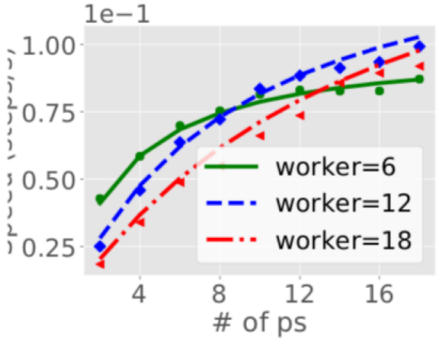


(d)

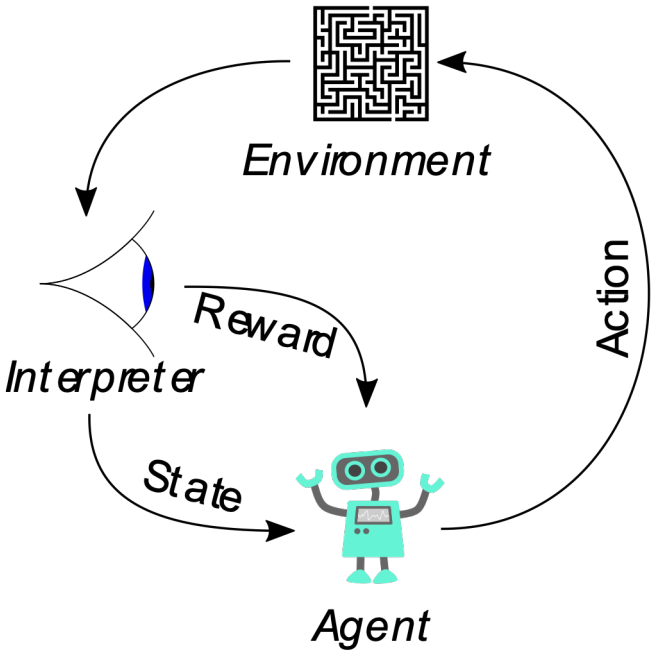
Table 2: Coefficients in speed functions

	θ_1	θ_2	θ_3	θ_4	θ_5	Residual sum of squares for fitting
Async	2.83	3.92	0.00	0.11	-	0.10
Sync	1.02	2.78	4.92	0.00	0.02	0.00

Less than 10% prediction error

Y. Peng et al. Optimus: An Efficient Dynamic Resource Scheduler for Deep Learning Clusters. Eurosys 2018.

Reinforcement (RL)



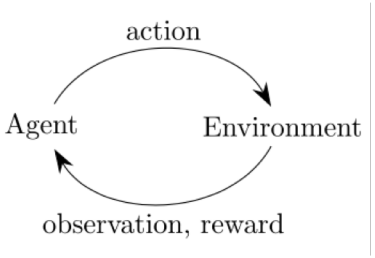
Agent reacts sequentially with an environment with the goal to maximize
Agent tries to learn efficient representations of the environment from high-dimensional sensory input
Environment is only partially observed and interpreted

Reinforcement Learning Challenges:

1. Credit-assignment problem: Contribution of each action for the reward is not known
2. Rewards can be probabilistic : can only be estimated approximately in data-driven manner
3. Model generalization is difficult: very large number of states
4. Exploration vs exploitation tradeoff
5. Inability to gather sufficient data in real settings

Terminology

- Markov Decision Process
- Episodic Tasks
- Continuous Tasks
- Exploration
- Exploitation

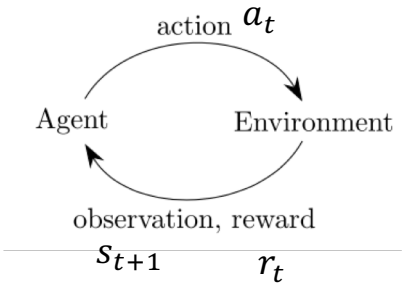


RL Formulation

- Action a_t is selected using some policy π

  π is a mapping from states s_t to actions a_t

  $R_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k}$ cumulative discounted reward at t



- Action-value $Q^{\pi}(s,a) = \mathbb{E}[R_t | s_t = s, a]$

  Expected return for taking action a in state s and then following π

- Optimal action-value function:

$$Q^*(s,a) = \max_{\pi} Q^{\pi}(s,a)$$

Maximum action value for state s and action a achievable by any policy.

- Optimal action-value functions obeys Bellman's equation:

$$Q^*(s,a) = \mathbb{E}\left[r + \gamma \max_{a'} Q^*(s',a')\right]$$

Q-learning

- In reinforcement learning we represent the action-value function using a function approximator which we try to learn
- A neural network (Q-network) can be used as function approximator

$$Q(s,a) = Q(s,a;\theta)$$

Action-value function

Q-network (function approximator of action-value function)

- The parameters θ of the *Q-network* are optimized so as to approximately solve the Bellman equation.

DQN Algorithm

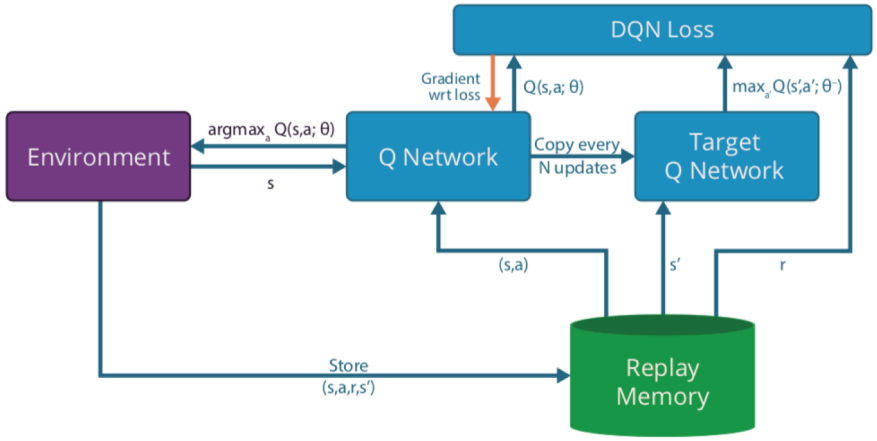


Figure 1. The DQN algorithm is composed of three main components, the Q-network ($Q(s, a; \theta)$) that defines the behavior policy, the target Q-network ($Q(s, a; \theta^-)$) that is used to generate target Q values for the DQN loss term and the replay memory that the agent uses to sample random transitions for training the Q-network.

DQN differs from Q-Learning in two ways:

1. DQN uses experience replay

At each time-step t during an agent's interaction with the environment it stores the experience tuple in replay memory

$$e_t = (s_t, a_t, r_t, s_{t+1})$$ Experience tuple

$$D_t = \{e_1, ..., e_t\}$$ Replay memory

2. Use of 2 separate Q-networks

$$Q(s, a; \theta) \text{ and } Q(s, a; \theta^-)$$

Q-network — Target Q-network

$$L_i(\theta_i) = \mathbb{E}\left[\left(r + \gamma \max_{a'} Q(s', a'; \theta_i^-) - Q(s, a; \theta_i)\right)^2\right]$$

R. Nair et al. Massively Parallel Methods for Deep Reinforcement Learning. 2015

DQN Algorithm

Algorithm 1: deep Q-learning with experience replay.

Initialize replay memory D to capacity N

Initialize action-value function Q with random weights θ

Initialize target action-value function $\hat{Q}$ with weights $\theta^{-} = \theta$

For episode $= 1, M$ **do**

  Initialize sequence $s_1 = \{x_1\}$ and preprocessed sequence $\phi_1 = \phi(s_1)$

  For $t = 1$,T **do**

    With probability ε select a random action a_t

    otherwise select $a_t = \text{argmax}_a Q(\phi(s_t), a; \theta)$

    Execute action a_t in emulator and observe reward r_t and image x_{t+1}

    Set $s_{t+1} = s_t, a_t, x_{t+1}$ and preprocess $\phi_{t+1} = \phi(s_{t+1})$

    Store transition $\left(\phi_t, a_t, r_t, \phi_{t+1}\right)$ in D

    Sample random minibatch of transitions $\left(\phi_j, a_j, r_j, \phi_{j+1}\right)$ from D

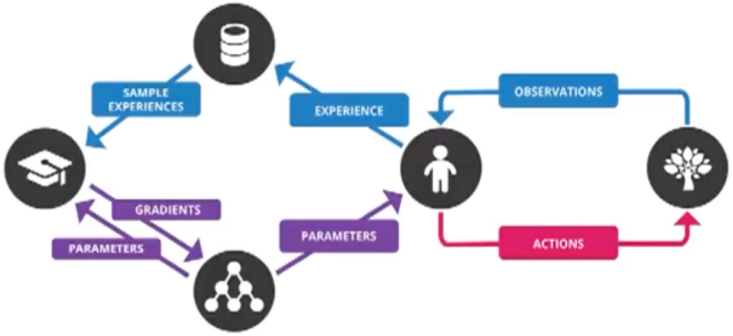
    Set $y_j = \begin{cases} r_j & \text{if episode terminates at step j+1} \\ r_j + \gamma \max_{a'} \hat{Q}\left(\phi_{j+1}, a'; \theta^{-}\right) & \text{otherwise} \end{cases}$

    Perform a gradient descent step on $\left(y_j - Q\left(\phi_j, a_j; \theta\right)\right)^2$ with respect to the network parameters θ

    Every C steps reset $\hat{Q} = Q$

  End For

End For



Mnih et al. Human-level control through deep reinforcement learning. Nature 2015

Why Experience Replay Helps ?

- Prevents instability in Q-learning
- Prevents overfitting
- Reuse of data
- Removes correlation in input batch samples

GORILA

- Asynchronous training of reinforcement learning agents in a distributed setting
- Gorila agent parallelizes the training procedure by separating out learners, actors and parameter server
- Gorila components:
  - Actors (multiple)
  - Experience Replay Memory (local and global)
  - Learners (multiple)
  - Parameter server (sharded)

Nair et al. Massively Parallel Methods for Deep Reinforcement Learning. 2015

GORILA Architecture

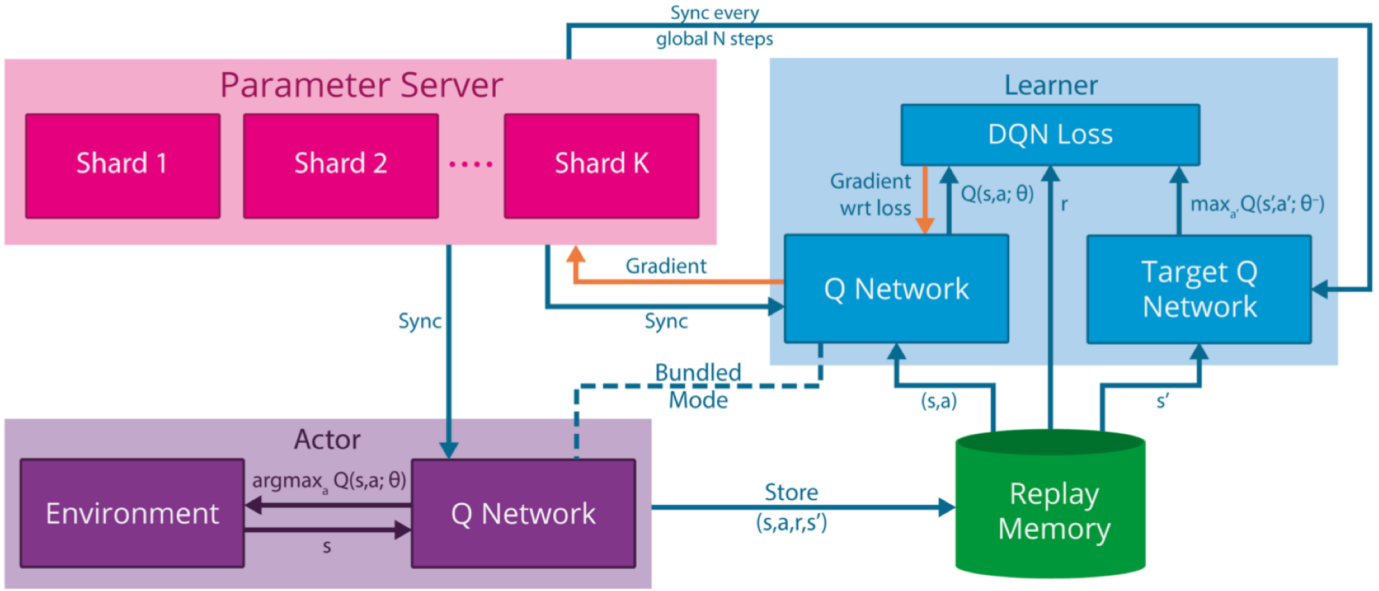


Figure 2. The Gorila agent parallelises the training procedure by separating out learners, actors and parameter server. In a single experiment, several learner processes exist and they continuously send the gradients to parameter server and receive updated parameters. At the same time, independent actors can also in parallel accumulate experience and update their Q-networks from the parameter server.

Nair et al. Massively Parallel Methods for Deep Reinforcement Learning. 2015

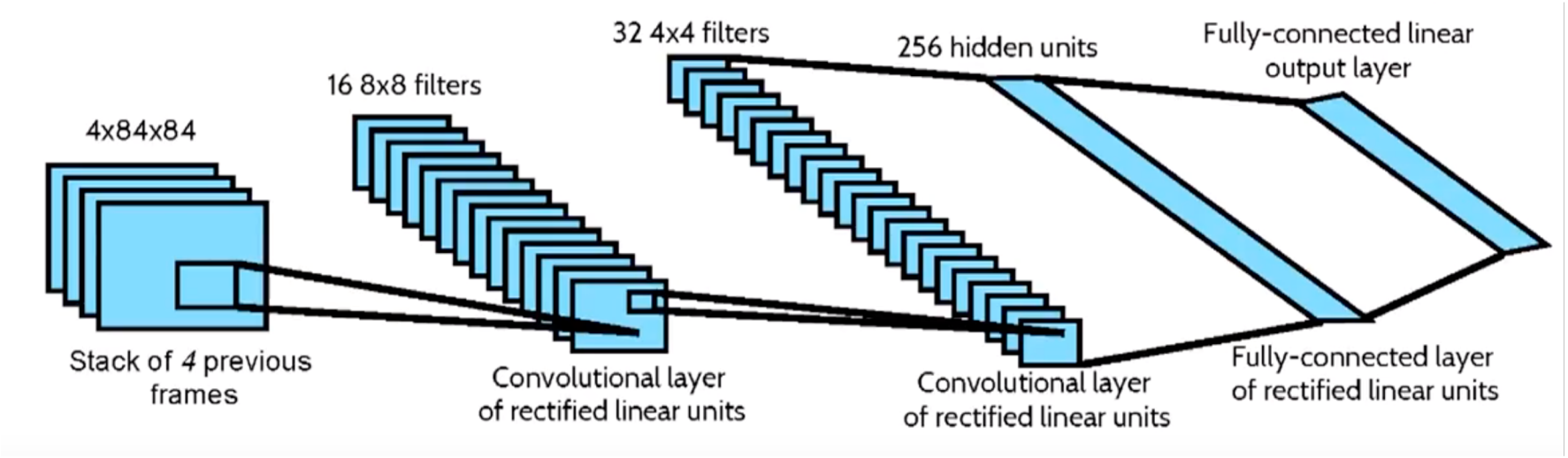
GORILA: Experimental Evaluation

- 49 Atari 2600 games
- An agent must learn to play the games directly from 210 × 160 RGB video input
- Only the changes in the score provided as rewards
- 210 × 160 RGB images preprocessed by downsampling them to 84 × 84
- Input consists of 4 image frames

In all experiments, Gorila DQN used: $N_{param} = 31$ and $N_{learn} = N_{act} = 100$. We use the bundled mode. Replay memory size $D = 1$ million frames and used ϵ-greedy as the behaviour policy with ϵ annealed from 1 to 0.1 over the first one million global updates. Each learner syncs the parameters θ^- of its target network after every 60K parameter updates performed in the parameter server.

Nair et al. Massively Parallel Methods for Deep Reinforcement Learning. 2015

ATARI Convolutional Neural Network



One output per action: expected action-value for that action Q(s,a)

GORILA: Experimental Evaluation

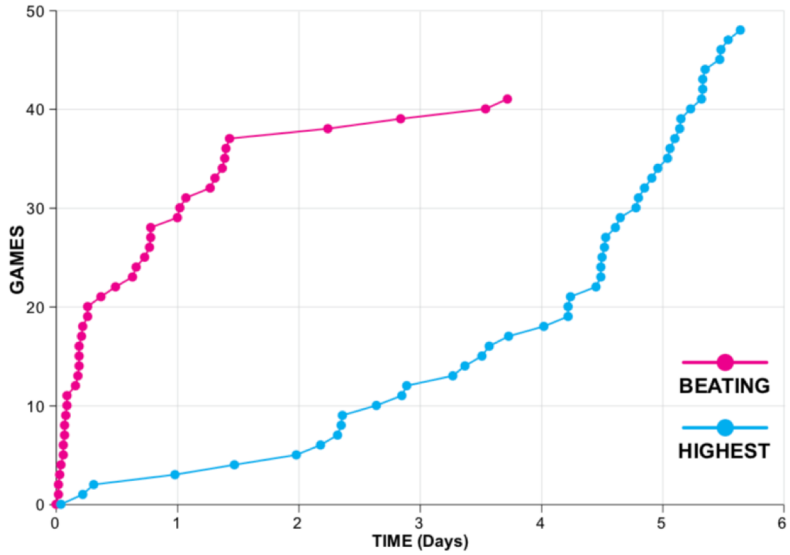


Figure 5. The time required by Gorila DQN to surpass single DQN performance (red curve) and to reach its peak performance (blue curve).

Nair et al. Massively Parallel Methods for Deep Reinforcement Learning. 2015

Prioritized Experience Replay

- Replaying all transitions with equal probability is highly suboptimal
- Experience replay may also help to prevent overfitting by allowing the agent to learn from data generated by previous versions of the policy.
- Focus learning on the most ‘surprising’ experiences
- Biased Sampling
  - Reward signal may be sparse and the data distribution depends on the agent’s policy.

Ape-X

- Distributed Prioritized Experience Replay

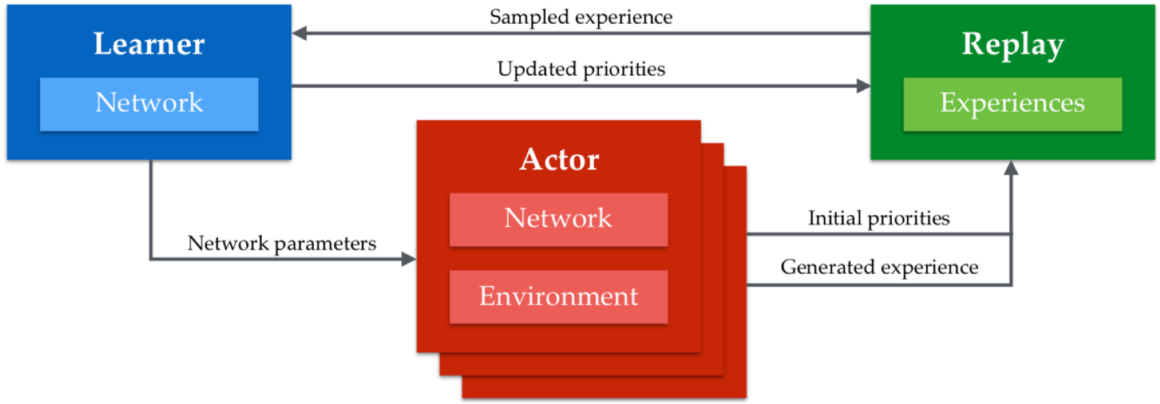


Figure 1: The Ape-X architecture in a nutshell: multiple actors, each with its own instance of the environment, generate experience, add it to a shared experience replay memory, and compute initial priorities for the data. The (single) learner samples from this memory and updates the network and the priorities of the experience in the memory. The actors' networks are periodically updated with the latest network parameters from the learner.

Horgan et al. DISTRIBUTED PRIORITIZED EXPERIENCE REPLAY. ICLR 2018

Ape-X Performance

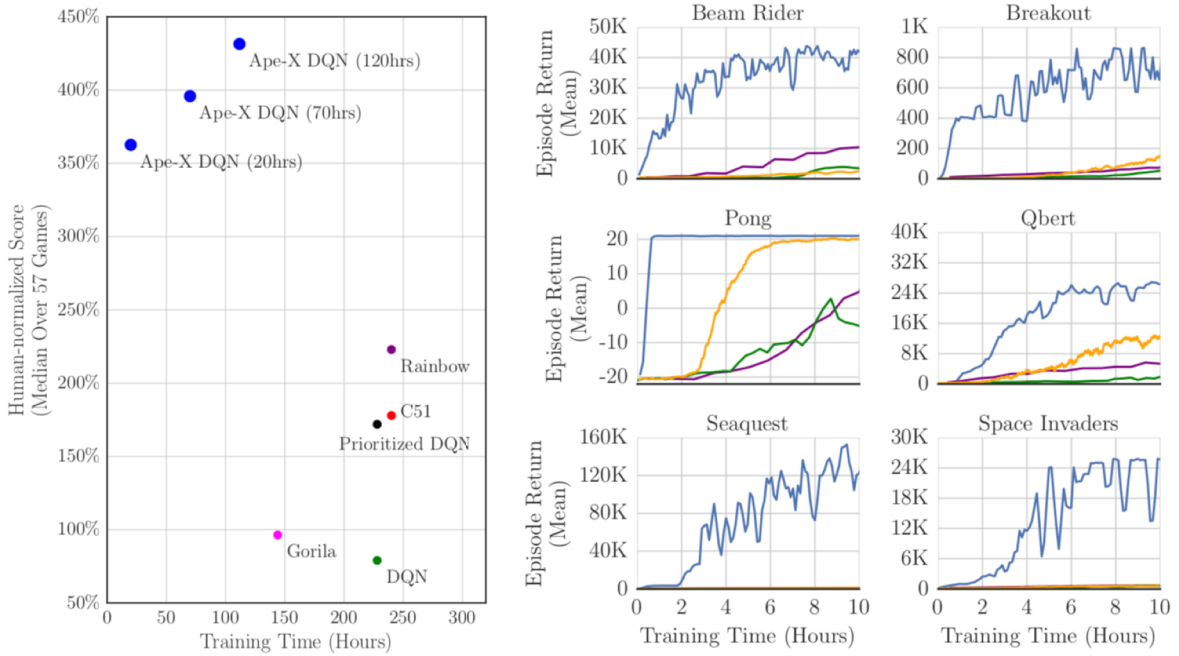


Figure 2: Left: Atari results aggregated across 57 games, evaluated from random no-op starts. Right: Atari training curves for selected games, against baselines. Blue: Ape-X DQN with 360 actors; Orange: A3C; Purple: Rainbow; Green: DQN. See appendix for longer runs over all games.

Horgan et al. DISTRIBUTED PRIORITIZED EXPERIENCE REPLAY. ICLR 2018

Ape-X Performance

Algorithm	Training Time	Environment Frames	Resources (per game)	Median (no-op starts)	Median (human starts)
Ape-X DQN	5 days	22800M	376 cores, 1 GPU [a]	**434%**	**358%**
Rainbow	10 days	200M	1 GPU	223%	153%
Distributional (C51)	10 days	200M	1 GPU	178%	125%
A3C	4 days	—	16 cores	—	117%
Prioritized Dueling	9.5 days	200M	1 GPU	172%	115%
DQN	9.5 days	200M	1 GPU	79%	68%
Gorila DQN [c]	~4 days	—	unknown [b]	96%	78%
UNREAL [d]	—	250M	16 cores	331% [d]	250% [d]

Table 1: Median normalized scores across 57 Atari games. [a] Tesla P100. [b] >100 CPUs, with a mixed number of cores per CPU machine. [c] Only evaluated on 49 games. [d] Hyper-parameters were tuned per game.

Horgan et al. DISTRIBUTED PRIORITIZED EXPERIENCE REPLAY. ICLR 2018

Ape-X Scaling: Number of Actors

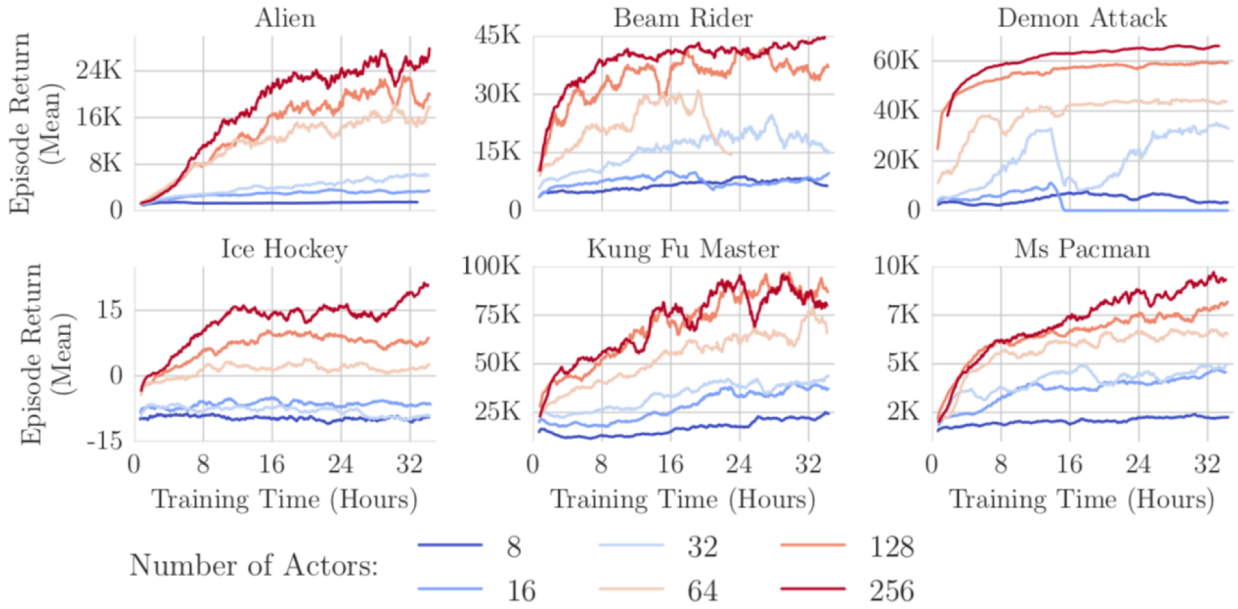


Figure 4: Scaling the number of actors. Performance consistently improves as we scale the number of actors from 8 to 256, note that the number of learning updates performed does not depend on the number of actors.

Horgan et al. DISTRIBUTED PRIORITIZED EXPERIENCE REPLAY. ICLR 2018

Ape-X Scaling: Replay Capacity

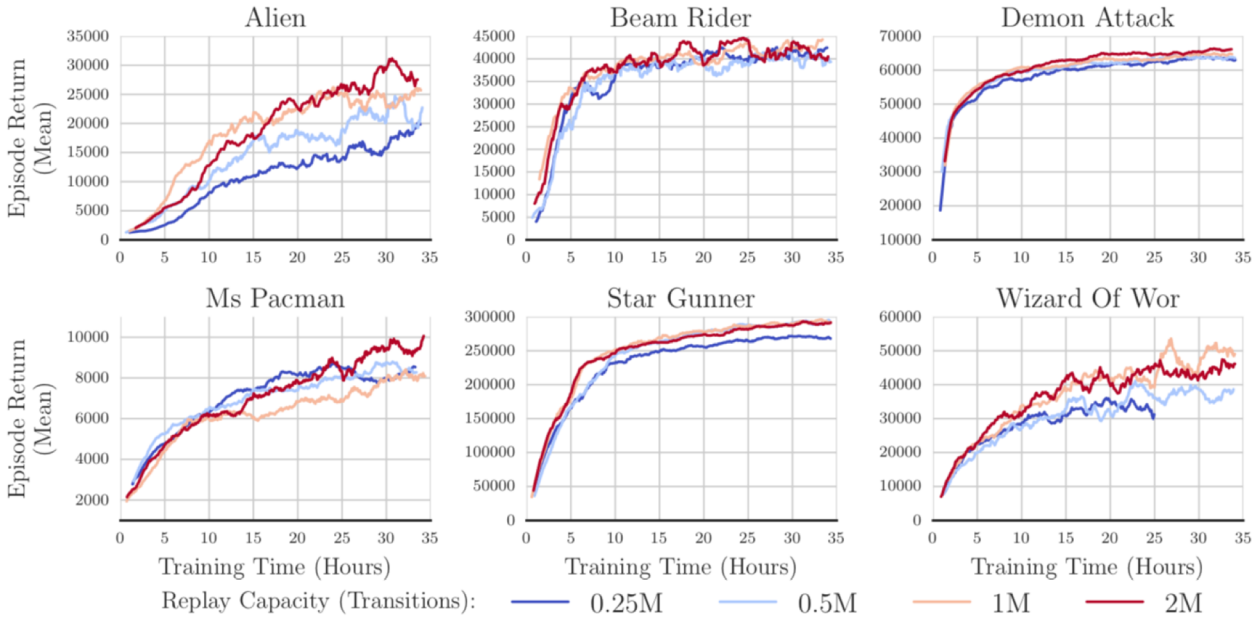


Figure 5: Varying the capacity of the replay. Agents with larger replay memories perform better on most games. Each curve corresponds to a single run, smoothed over 20 points. The curve for Wizard Of Wor with replay size 250K is incomplete because training diverged; we did not observe this with the other replay sizes.

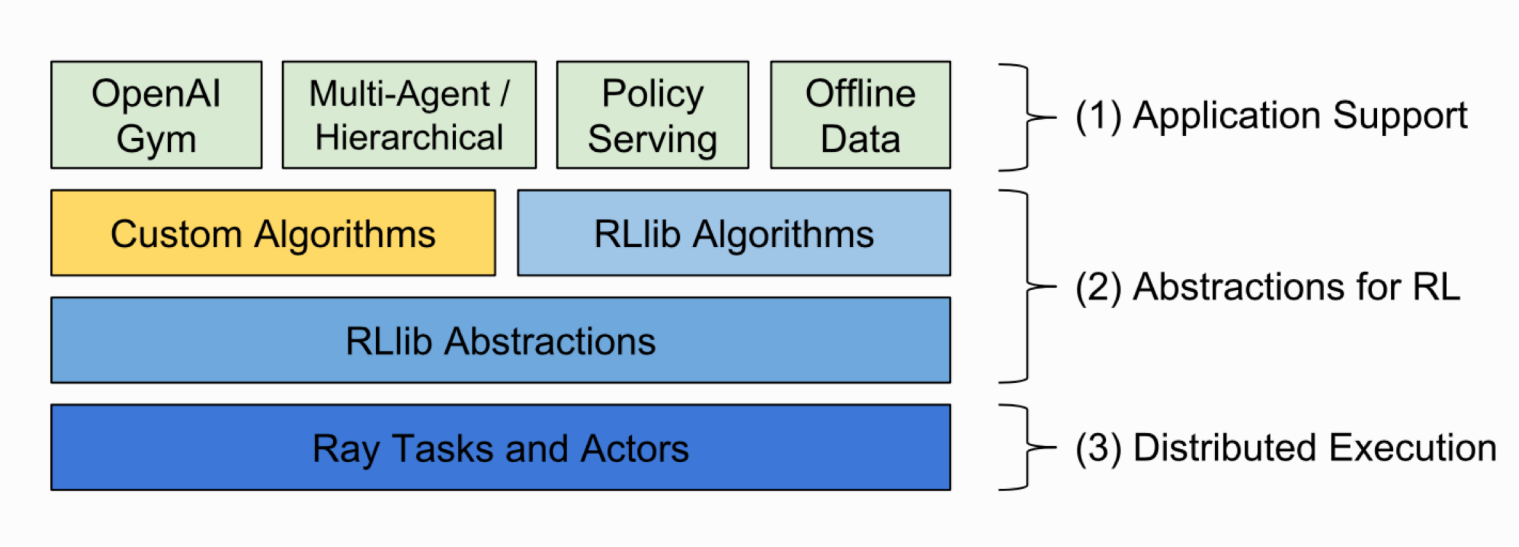
Horgan et al. DISTRIBUTED PRIORITIZED EXPERIENCE REPLAY. ICLR 2018

Deep RL Simulators

- OpenAI Gym
  - https://gym.openai.com/docs/
  - A toolkit for developing and comparing reinforcement learning algorithms.
  - **Gym** provides an environment to implement any reinforcement learning algorithms.
  - Developers can write agents in TensorFlow
  - Limitation: no multi-agent support
- Full 3D Environments
  - Unity ML Agents: https://unity3d.com/machine-learning

RLLib

- https://ray.readthedocs.io/en/latest/rllib.html
- Open-source library for reinforcement learning that offers both high scalability and a unified API for a variety of applications. RLlib natively supports TensorFlow, TensorFlow Eager, and PyTorch.



Seminar Reading List

- **DL resource estimation**
  - Pan et al. Hemingway: Modeling Distributed Optimization Algorithms. NIPS 2016
  - Shi et al. Performance Modeling and Evaluation of Distributed Deep Learning Frameworks on GPUs. 2018
  - Peng et al. Optimus: An Efficient Dynamic Resource Scheduler for Deep Learning Clusters. Eurosys 2017.
- **Deep Reinforcement Learning**
  - Mnih et al. Playing Atari with Deep Reinforcement Learning. 2013
  - Mnih et al. Human-level control through deep reinforcement learning. Nature. 2015
  - Nair et al. Massively Parallel Methods for Deep Reinforcement Learning. 2015
  - Mnih et al. Asynchronous Methods for Deep Reinforcement Learning. 2016
  - Horgan et al. DISTRIBUTED PRIORITIZED EXPERIENCE REPLAY. ICLR 2018
  - Espeholt et al. IMPALA: Scalable Distributed Deep-RL with Importance Weighted Actor-Learner Architectures. 2018

Links, Blogs

- RLlib: Scalable Reinforcement Learning
- Get to grips on the latest AI power in Unity