# IMPALA: Scalable Distributed Deep-RL with Importance Weighted Actor-Learner Architectures

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# Multi-task DeepRL

- General agents that are able to do many tasks simultaneously.
- Going from one network per task to one network for tens of tasks with many challenges.
- Data Efficienecy- Hundreds of millions of frames for a single task.
- Stability: Do we need task-specific hyperparameters?
- Scale: More complicated architecture and slower to train.
- Task Interference: Will multiple tasks cause interference or positive transfer.

# RL Formulation

- Agent interacting with the environment. At each step $t$:
  1. Agent takes action $a_t$
  2. Environment returns reward $r_{t+1}$ and state $s_{t+1}$
- Maximize total future reward

$$r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \cdots$$

- For a policy $\pi$ the action value function $Q$:

$$Q^\pi(s, a) = \mathbb{E}_{[} r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \cdots \mid s_t = s, a_t = a]$$

$$= \mathbb{E}[r_t + \gamma Q^\pi(s_{t+1}, a_{t+1}) \mid s_t = s, a_t = a]$$

- $Q$ represents how good an action $a$ is given state $s$.

# Optimal Value Functions

- An optimal value function give the maximal achievable value:

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

- Given an optimal value function we can get an optimal policy:

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

- Optimal value functions also obay a Bellman Equation.

$$Q^*(s_t, a_t) = \mathbb{E}[r_t + \gamma \max_{s'} Q^*(s_{t+1}, a')]$$

# DQN

- High-level idea is to make $Q$-learning look like supervised learning
- Optimize the $Q$-learning loss with minibatch SGD
- Apply $Q$-learning updates on batches of past experience instead of online
  1. Experience replay
  2. Previously used for better data efficiency
  3. Makes the data distribution more stationary
- Use an older set of weights to compute the targets, keeps the target function from changing too quickly

$$L_i(\theta_i) = \mathbb{E}_{s,a,s',r\sim D}(r + \gamma max_{a'} Q(s', a'; \theta_i^-) - Q(s, a; \theta_i))^2$$

# Policy Gradient Methods

- An alternatively class of methods directly optimize the expected return of a policy:

$$\nabla_\theta J(\theta) = \nabla E[r_1 + \gamma r_2 + \gamma^2 r_3 + \cdots]$$

- For all differentiable policies

$$\nabla_\theta J(\theta) = E[\nabla_\theta log \pi_\theta(a \mid s) Q^\pi(s, a)]$$

where expectations is over states and actions.

- There is an sample based easy unbiased estimation (REINFORCE)

$$\nabla_\theta log \pi_\theta(a|s) R_t$$

where

$$R_t = r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \cdots$$

- Start with a guess for each $Q(s, a)$
- Interact with the environment using some policy based on $Q$ collecting tuples of experience $\{s_t, a_t, r_t, s_{t+1}, \cdots\}$, $e.g.\varepsilon$-greedy.
- Apply updates based on the Bellman equation

$$Q(s, a) \leftarrow Q(s, a) + (r + \gamma \max_a Q(s', a') - Q(s, a))$$

- $Q(s, a)$ is guaranteed to converge to the optimal value function $Q^*$ under some reasonable assumptions.

# Asynchronous Advantage Actor-Critic (A3C)

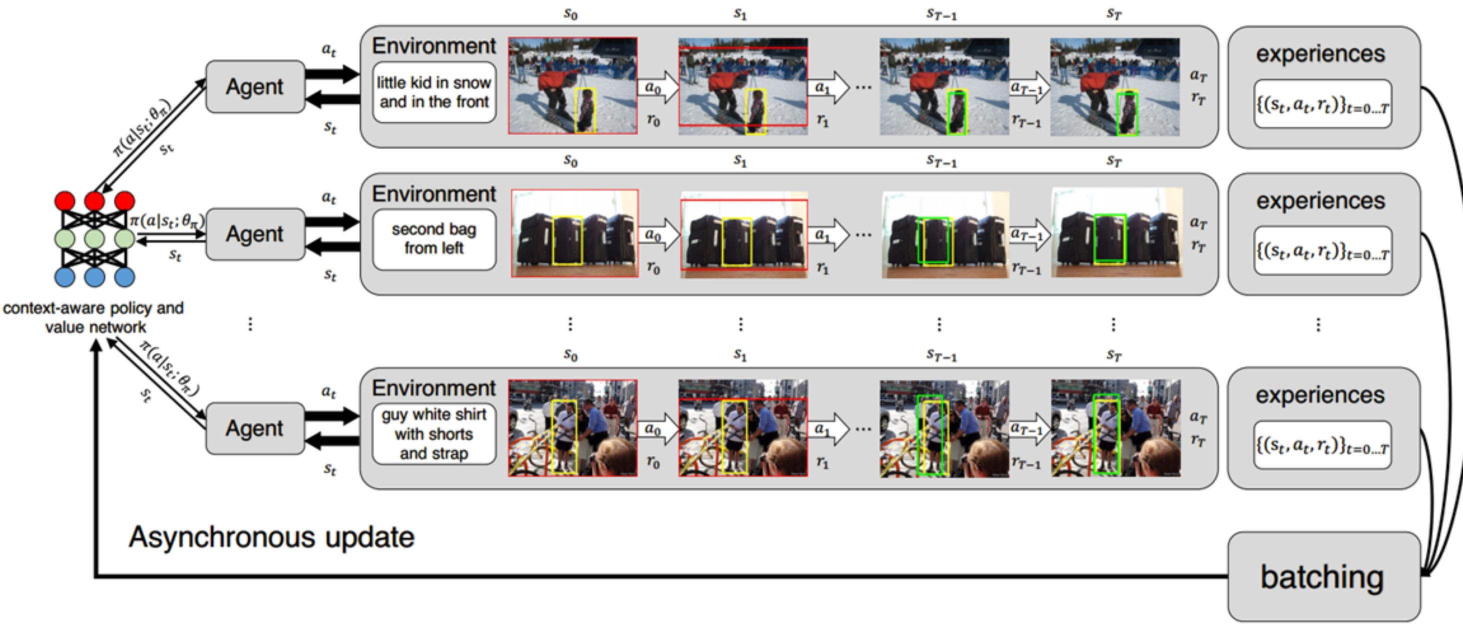
- The agent learns a policy and a state value function
- Uses bootstrapped n-step returns to reduce variance over REINFORCE with a baseline
- The policy gradient multiplied by an estimate of the advantage. Similar to Generalized Advantage Estimation (Schulman et al. 2015)

$$\nabla_\theta log\pi(a_t \mid s_t, \theta)(\sum_{k=0}^{N} \gamma^k r_{t+k} + \gamma^{N+1} V(s_{t+N+1}) - V(s_t))$$

- The critic/value function is trained with n-step TD learning. i.e. by minimizing the MSE

$$(\sum_{k=0}^{N} \gamma^k r_{t+k} + \gamma^{N+1} V(s_{t+N+1;\theta^-}) - V(s_t;\theta))^2$$

# Asynchronous Advantage Actor-Critic (A3C)

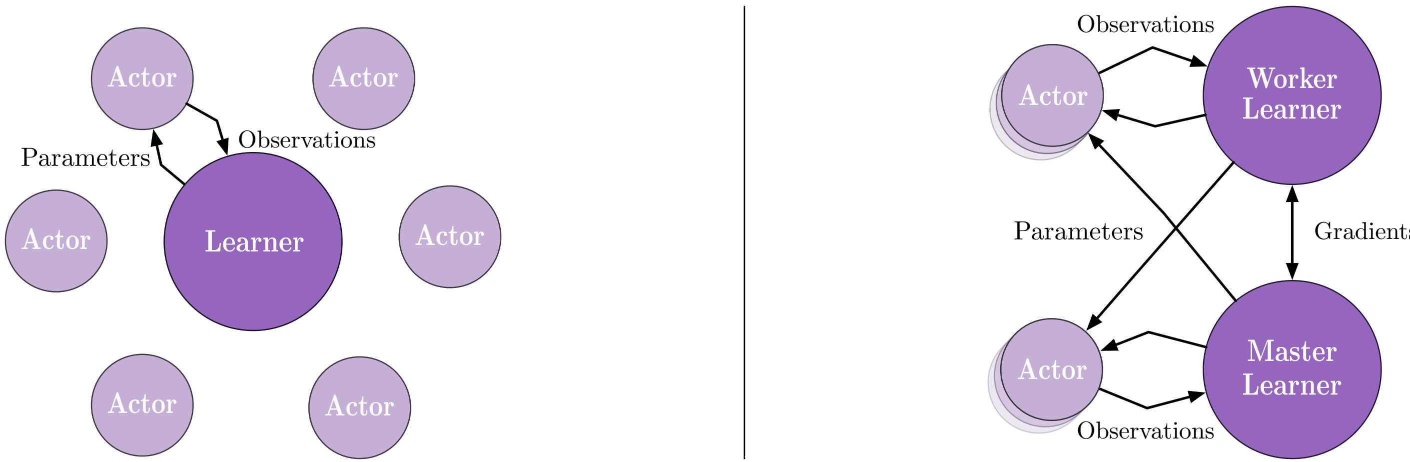


# Scaling Up Distributed RL

- Our goal was to scale up A3C since it has more of the desired properties of a good multi-task agent
- Adding more actor/learners does not scale
- Distributed experience collection is good
- Communicating gradients is bad

# A Better Architecture

- It is better to use a centralized learner(s) and distribute the acting
- Actors receive parameters but send observations
- The centralized learner can parallelize as much of the forward and backward passes as possible



# Decoupled Backward Pass

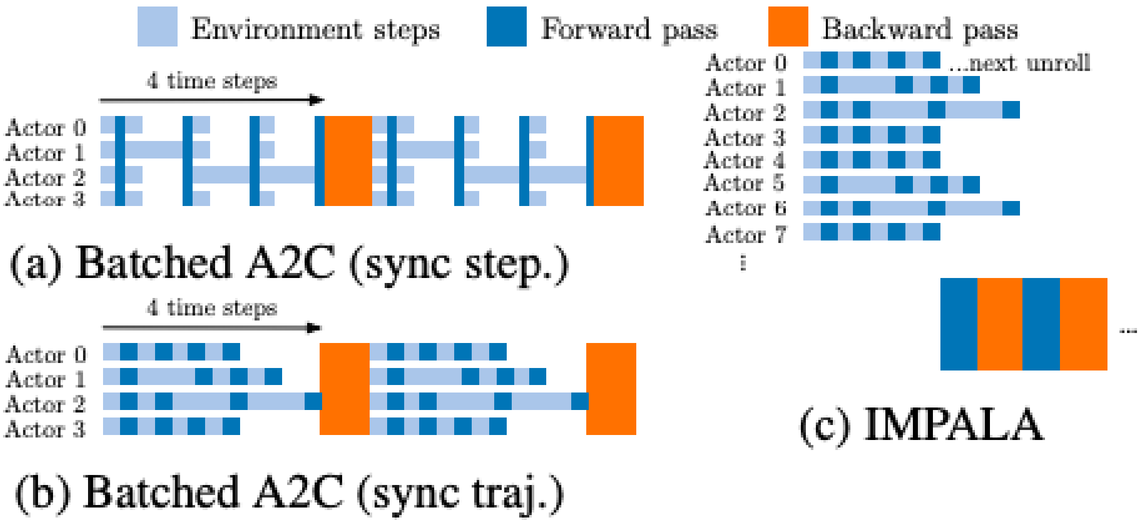



*Figure 2.* Timeline for one unroll with 4 steps using different architectures. Strategies shown in **(a)** and **(b)** can lead to low GPU utilisation due to rendering time variance within a batch. In **(a)**, the actors are synchronised after every step. In **(b)** after every $n$ steps. IMPALA **(c)** decouples acting from learning.

# Decoupled Backward Pass

- It is more efficient to decouple the backward pass
- Actors generate trajectories/unrolls and place them into a queue
- The learner continuously dequeues batches of trajectories and performs parameter updates
- Key Challenge:
  1. Decoupling the backwards pass requires off-policy learning
  2. Actor parameters can lag by several updates
- POD architecture-Parallel Off-policy Decoupled

# V-Trace

- The experience generated by the actors can lag behind the learner's policy
- We introduce a principled off-policy advantage actor critic called V-Trace
- The V-Trace corrected estimate for the value $V(x_s)$ is:

$$v_s \stackrel{\text{def}}{=} V(x_s) + \sum_{t=s}^{s+n-1} \gamma^{t-s} \Big( \prod_{i=s}^{t-1} c_i \Big) \rho_t \big( r_t + \gamma V(x_{t+1}) - V(x_t) \big), \tag{1}$$

where $\rho_t \stackrel{\text{def}}{=} \min\big(\bar{\rho}, \frac{\pi(a_t|x_t)}{\mu(a_t|x_t)}\big)$ and $c_i \stackrel{\text{def}}{=} \min\big(\bar{c}, \frac{\pi(a_i|x_i)}{\mu(a_i|x_i)}\big)$

- The V-Trace update for the value function is:

$$\big(v_s - V_\theta(x_s)\big) \nabla_\theta V_\theta(x_s)$$

- The V-Trcace update for the policy is:

$$\rho_s \nabla_\omega \log \pi_\omega(a_s|x_s) \big(r_s + \gamma v_{s+1} - V_\theta(x_s)\big)$$

# Actor-Critic

Now in the off-policy setting that we consider, we can use an IS weight between the policy being evaluated $\pi_{\bar{\rho}}$ and the behaviour policy $\mu$, to update our policy parameter in the direction of

$$\mathbb{E}_{a_s \sim \mu(\cdot|x_s)} \Big[ \frac{\pi_{\bar{\rho}}(a_s|x_s)}{\mu(a_s|x_s)} \nabla \log \pi_{\bar{\rho}}(a_s|x_s) q_s \Big| x_s \Big] \tag{2}$$

where $q_s \overset{\text{def}}{=} r_s + \gamma v_{s+1}$ is an estimate of $Q^{\pi_{\bar{\rho}}}(x_s, a_s)$ built from the V-trace estimate $v_{s+1}$ at the next state $x_{s+1}$. The reason why we use $q_s$ instead of $v_s$ as the target for our Q-value $Q^{\pi_{\bar{\rho}}}(x_s, a_s)$ is that, assuming our value estimate is correct at all states, i.e. $V = V^{\pi_{\bar{\rho}}}$, then we have $\mathbb{E}[q_s|x_s, a_s] = Q^{\pi_{\bar{\rho}}}(x_s, a_s)$ (whereas we do not have this property if we choose $q_t = v_t$).

Define the V-trace operator $\mathcal{R}$:

$$\mathcal{R}V(x) \stackrel{\text{def}}{=} V(x) + \mathbb{E}_\mu\Big[\sum_{t\geq 0}\gamma^t(c_0\ldots c_{t-1})\rho_t\big(r_t+\gamma V(x_{t+1})-V(x_t)\big)\Big] \quad (3)$$

## Theorem

*Let* $\rho_t = \min\left(\bar{\rho}, \frac{\pi(a_t|x_t)}{\mu(a_t|x_t)}\right)$ *and* $c_t = \min\left(\bar{c}, \frac{\pi(a_t|x_t)}{\mu(a_t|x_t)}\right)$ *be truncated importance sampling weights, with* $\bar{\rho} \geq \bar{c}$. *Assume that there exists* $\beta \in (0,1]$ *such that* $\mathbb{E}_\mu \rho_0 \geq \beta$. *Then the operator* $\mathcal{R}$ *defined by (3) has a unique fixed point* $V^{\pi_{\bar{\rho}}}$, *which is the value function of the policy* $\pi_{\bar{\rho}}$ *defined by*

$$\pi_{\bar{\rho}}(a|x) \stackrel{\text{def}}{=} \frac{\min\left(\bar{\rho}\mu(a|x), \pi(a|x)\right)}{\sum_{b\in A}\min\left(\bar{\rho}\mu(b|x), \pi(b|x)\right)}, \quad (4)$$

*Furthermore,* $\mathcal{R}$ *is a* $\eta$*-contraction mapping in sup-norm, with*

$$\eta \stackrel{\text{def}}{=} \gamma^{-1} - (\gamma^{-1}-1)\mathbb{E}_\mu\Big[\sum_{t\geq 0}\gamma^t\Big(\prod_{i=0}^{t-2}c_i\Big)\rho_{t-1}\Big] \leq 1-(1-\gamma)\beta < 1.$$

## Theorem

*Assume a tabular representation, i.e. the state and action spaces are finite. Consider a set of trajectories, with the $k^{th}$ trajectory $x_0, a_0, r_0, x_1, a_1, r_1, \ldots$ generated by following $\mu$: $a_t \sim \mu(\cdot|x_t)$. For each state $x_s$ along this trajectory, update*

$$V_{k+1}(x_s) = V_k(x_s) + \alpha_k(x_s) \sum_{t \geq s} \gamma^{t-s} \big(c_s \ldots c_{t-1}\big) \rho_t \big(r_t + \gamma V_k(x_{t+1}) - V_k(x_t)\big) \tag{5}$$

*with $c_i = \min\left(\bar{c}, \frac{\pi(a_i|x_i)}{\mu(a_i|x_i)}\right)$, $\rho_i = \min\left(\bar{\rho}, \frac{\pi(a_i|x_i)}{\mu(a_i|x_i)}\right)$, $\bar{\rho} \geq \bar{c}$. Assume that (1) all states are visited infinitely often, and (2) the stepsizes obey the usual Robbins-Munro conditions: for each state $x$, $\sum_k \alpha_k(x) = \infty$, $\sum_k \alpha_k^2(x) < \infty$. Then $V_k \to V^{\pi_{\bar{\rho}}}$ almost surely.*

# Network Architecture

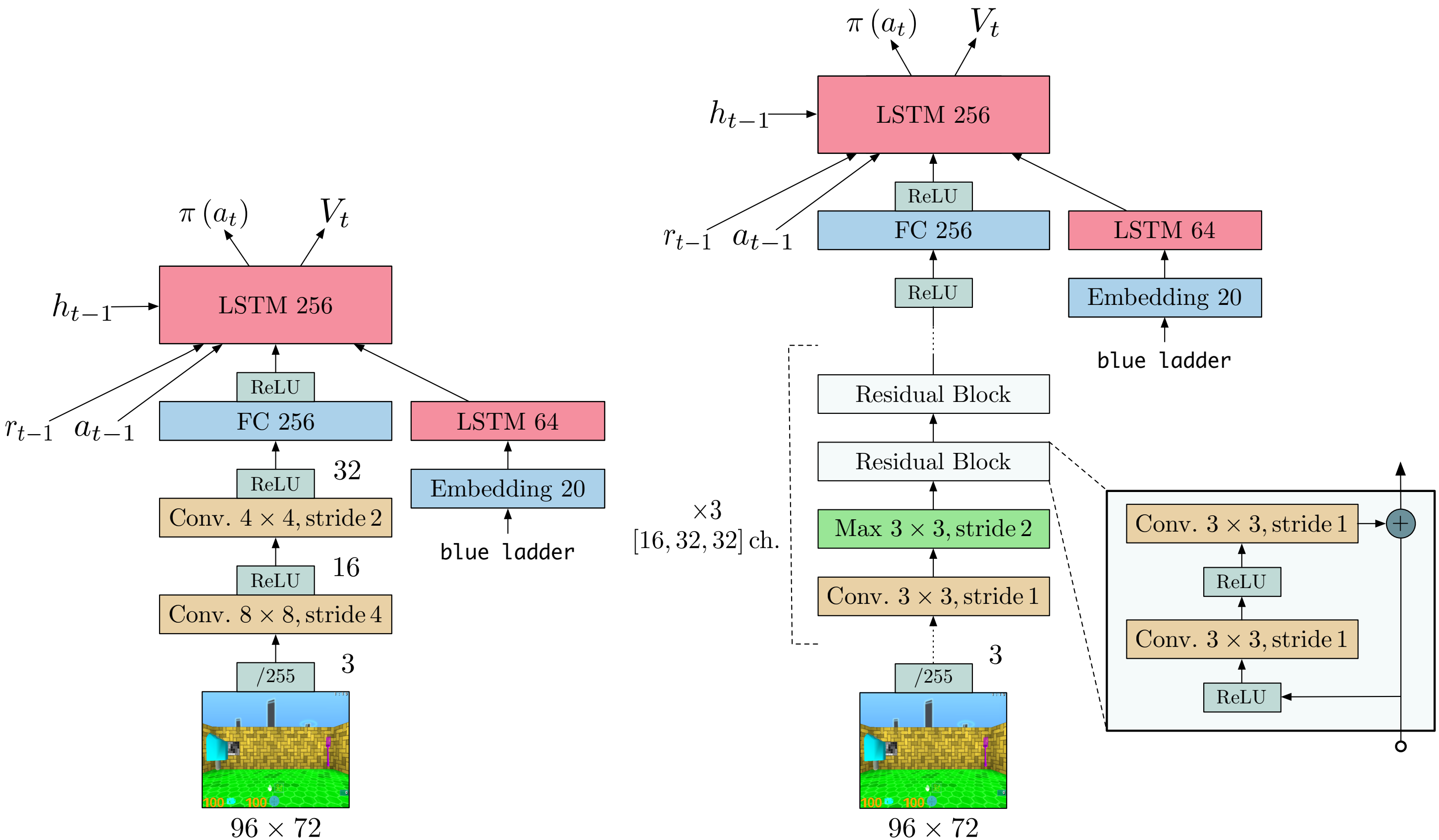



Figure 1: Model Architectures. **Left:** Small architecture, 2 convolutional layers and 1.2 million parameters. **Right:** Large architecture, 15 convolutional layers

# Throughput Comparison

| Architecture | CPUs | GPUs[1] | FPS[2] | |
|---|---|---|---|---|
| **Single-Machine** | | | Task 1 | Task 2 |
| A3C 32 workers | 64 | 0 | 6.5K | 9K |
| Batched A2C (sync step) | 48 | 0 | 9K | 5K |
| Batched A2C (sync step) | 48 | 1 | 13K | 5.5K |
| Batched A2C (sync traj.) | 48 | 0 | 16K | 17.5K |
| Batched A2C (dyn. batch) | 48 | 1 | 16K | 13K |
| IMPALA 48 actors | 48 | 0 | 17K | 20.5K |
| IMPALA (dyn. batch) 48 actors[3] | 48 | 1 | 21K | 24K |
| **Distributed** | | | | |
| A3C | 200 | 0 | 46K | 50K |
| IMPALA | 150 | 1 | 80K | |
| IMPALA (optimised) | 375 | 1 | 200K | |
| IMPALA (optimised) batch 128 | 500 | 1 | 250K | |

[1] Nvidia P100 [2] In frames/sec (4 times the agent steps due to action repeat). [3] Limited by amount of rendering possible on a single machine.

# Single Task Results

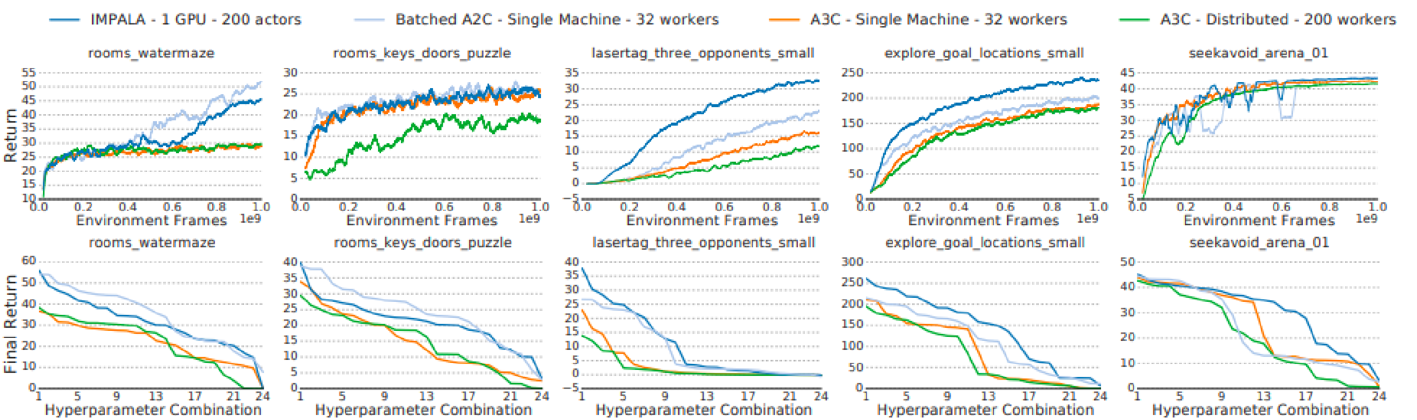
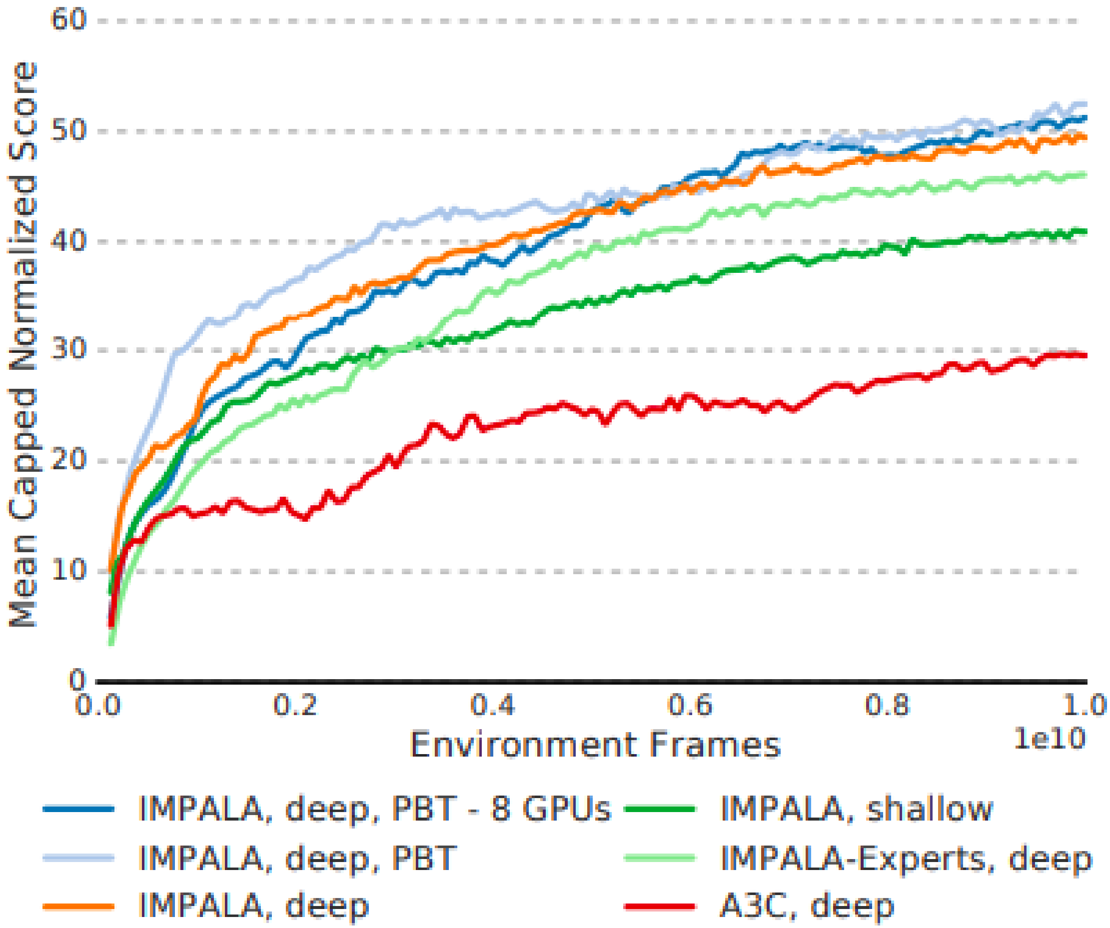



*Figure 4.* **Top Row:** Single task training on 5 DeepMind Lab tasks. Each curve is the mean of the best 3 runs based on final return. IMPALA achieves better performance than A3C. **Bottom Row:** Stability across hyperparameter combinations sorted by the final performance across different hyperparameter combinations. IMPALA is consistently more stable than A3C.

# DMLab-30 Multi-Task

# DMLab-30 Multi-Task Results



# Conclusions

- New distributed RL architecture allows for stable learning with very high throughput
- Especially well-suited to the multi-task deep RL setting
- Synchronous batch learning is more robust to hyperparameters than async SGD
- Multi-task RL on the DMLab-30:
  1. Positive transfer
  2. Deep ResNets finally outperforms 3 layer ConvNets (Atari was too simple)