Progressive Nets for Simulation to Robot Transfer

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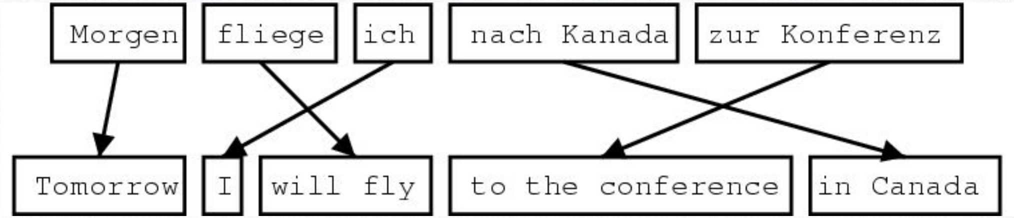
Skepticism

Let's acknowledge a few difficulties with deep learning and robotics:

1. Robot-domain data does not present itself in this form:

PASCAL2
Pattern Analysis, Statistical Modelling and Computational Learning

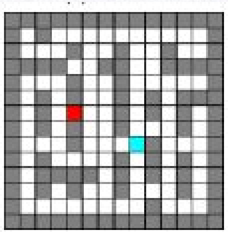
LabelMe



Deep RL to the rescue?

Continuous Deep Q-Learning with Model-based Acceleration.
Shixiang Gu, Timothy Lillicrap, Ilya Sutskever, Sergey Levine. ICML 2016.

Asynchronous Methods for Deep Reinforcement Learning.
Volodymyr Mnih, Adrià Puigdomènech Badia, Mehdi Mirza, Alex Graves, Timothy P. Lillicrap, Tim Harley, David Silver, Koray Kavukcuoglu



Control of Memory, Active Perception, and Action in Minecraft.
Junhyuk Oh, Valliappa Chockalingam, Satinder Singh, and Honglak Lee

However, deep RL is very data inefficient

Skepticism

Let's acknowledge a few difficulties with deep learning and robotics:

2. Robot-domain data does not present itself in this **quantity**:

Simulation to the rescue?

https://www.youtube.com/watch?v=3WXd4vC3IbQ

Simulation to the rescue?

Deep learning and deep RL likes simulators:

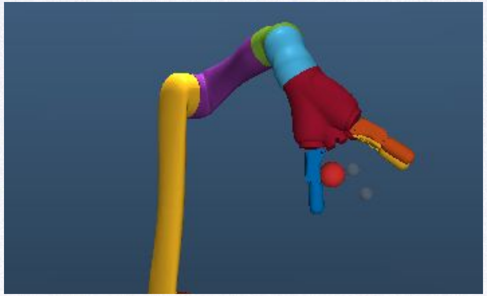
- Training
- Algorithms
- Hyperparameters
- Speed

However…

There is a Reality Gap!

We aren’t interested in simulation unless learning can transfer to target domain, and transfer is hard, especially for deep learning.

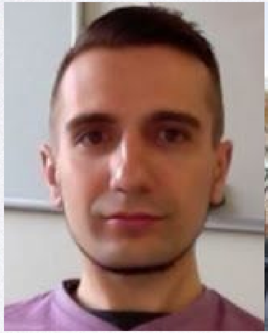
Transfer + continual learning



- Continual + Transfer learning can bridge reality gap and ameliorate data inefficiency
- Unfortunately, neural networks are not well-suited to continual learning
    - Catastrophic forgetting from fine-tuning
    - Policy interference from multi-task learning

Progressive Neural Networks

In collaboration with:







Andrei Rusu

Neil C. Rabinowitz

Guillaume Desjardins

Hubert Soyer

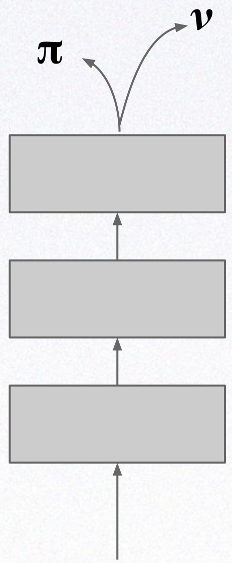
James Kirkpatrick

Koray Kavukcuoglu

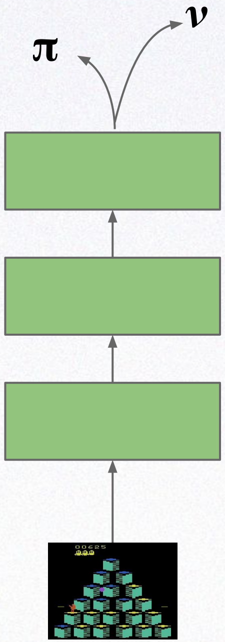
Razvan Pascanu

arxiv.org/abs/1606.04671

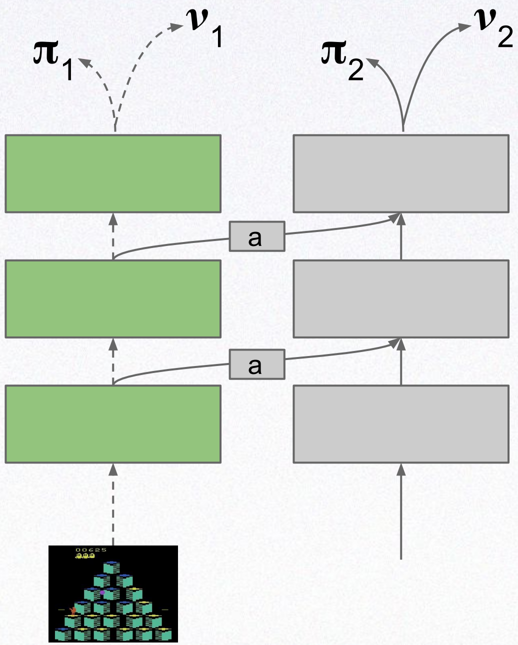
Progressive Neural Networks



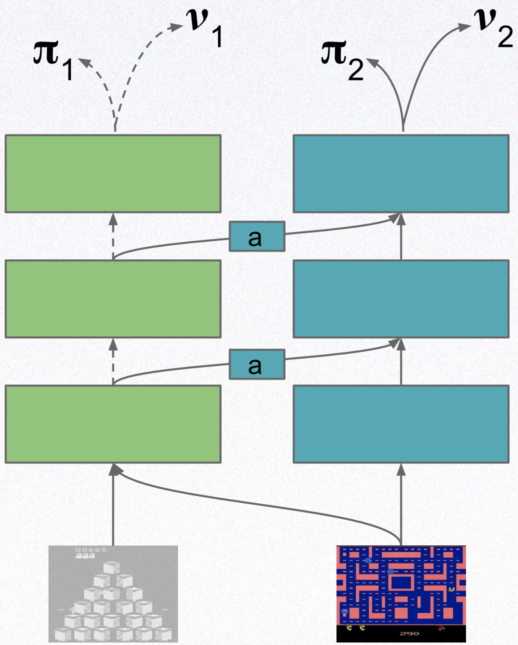
Progressive Neural Networks



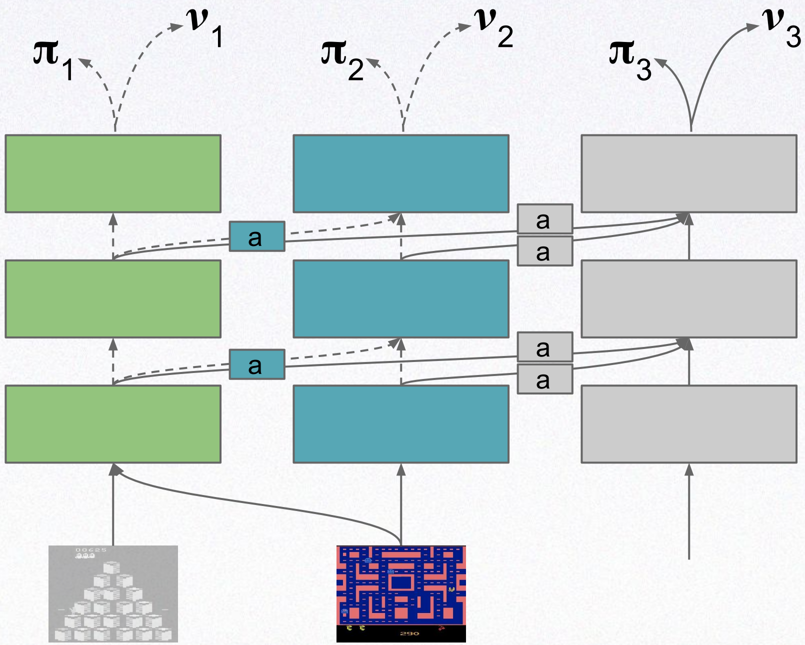
Progressive Neural Networks



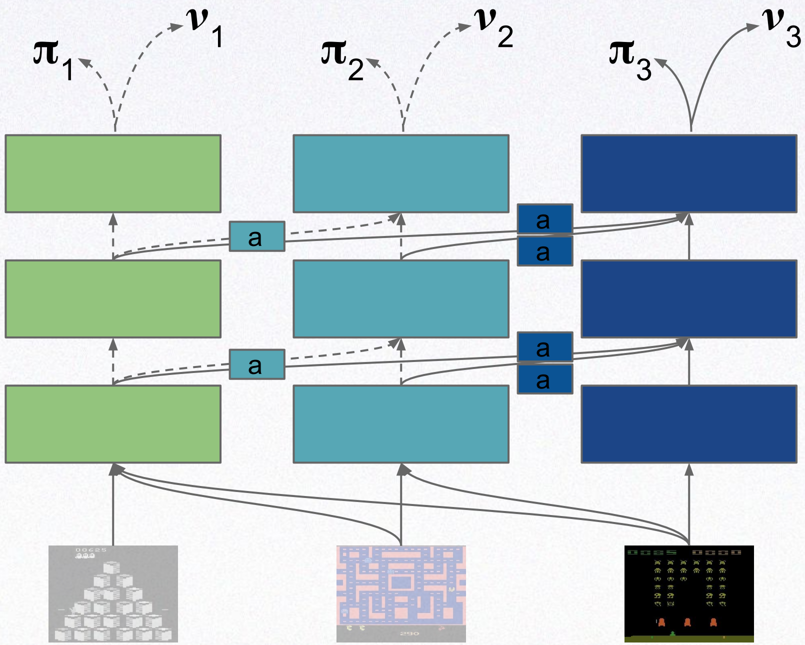
Progressive Neural Networks



Progressive Neural Networks



Progressive Neural Networks



Progressive Neural Networks

Advantages

1. No catastrophic forgetting of previous tasks - by design.
2. Deep, compositional feature transfer from all previous tasks and layers
3. Added capacity for learning task-specific features
4. Provides framework for analysis of transferred features

Progressive Neural Networks

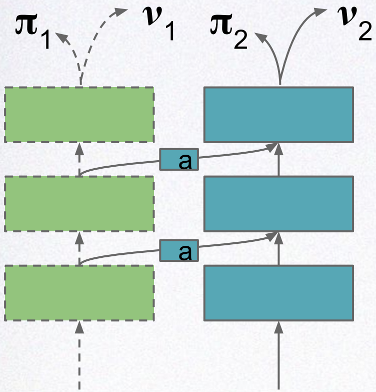
Disadvantages

1. Requires knowledge of task boundaries
2. Quadratic parameter growth!

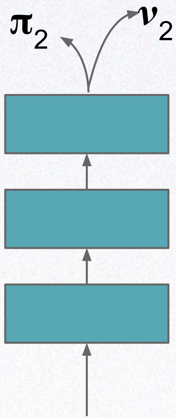
However, sensitivity analysis shows that successive columns use much less capacity.

Experimental setup

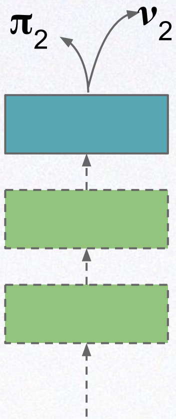
All training is with Asynchronous Advantage Actor-Critic (A3C) [mnih et al., 2016]



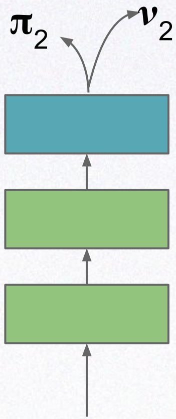
Progressive Net: column 1 trained on A, column 2 on task B



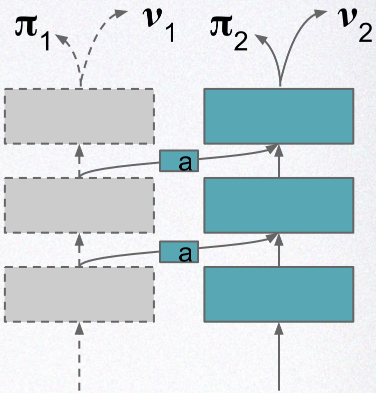
Baseline 1: column trained on task B



Baseline 2: column trained on A, top layer fine-tuned on B



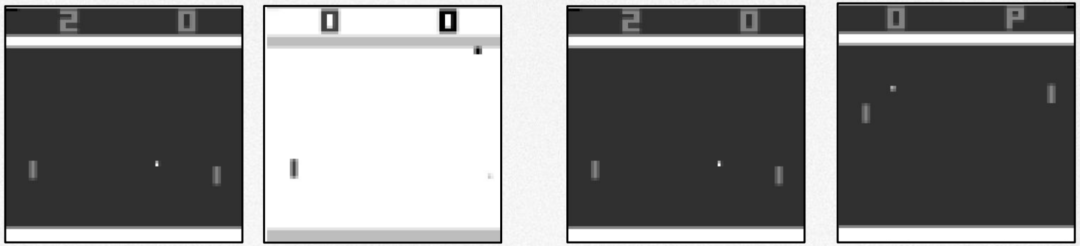
Baseline 3: column trained on A, all layers fine-tuned on B

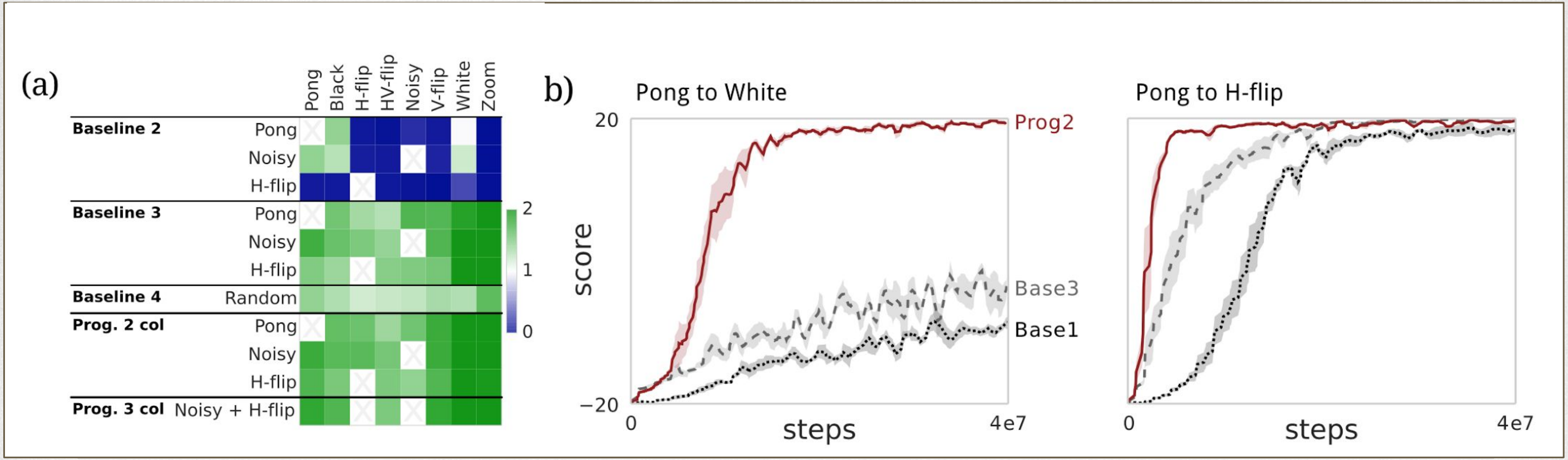


Baseline 4: column 1 random, column 2 trained on task B

Pong Soup

Pong → white Pong　　Pong → horiz-flip Pong

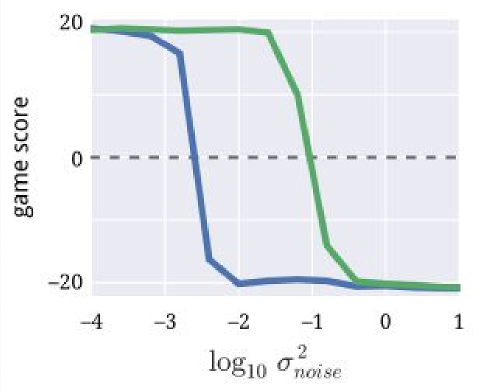




Analysis, 2 methods

1. Average **Perturbation** Sensitivity

   Inject Gaussian noise and measure drop in performance



Pong to Noisy Pong

Noise injected at column1 (blue) or column 2 (green)

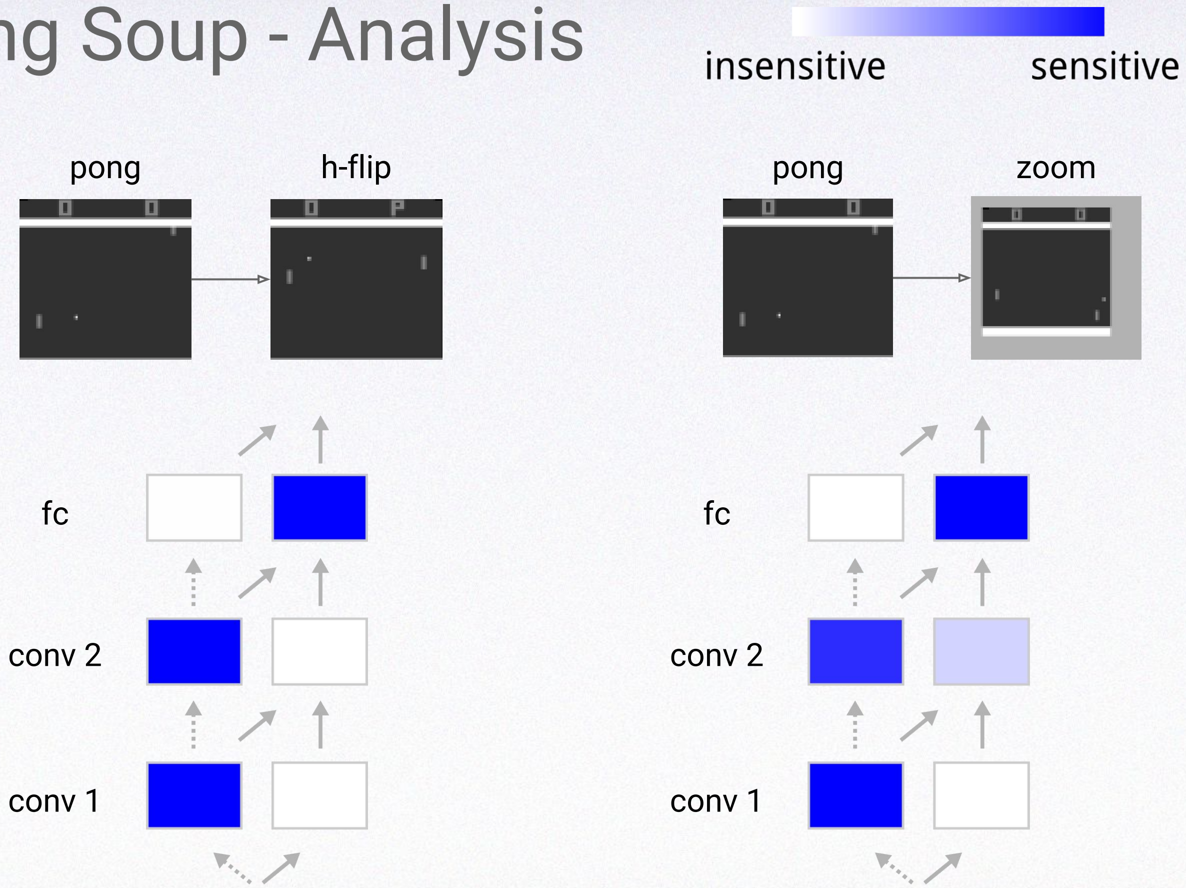
Analysis

2. Average **Fisher** Sensitivity

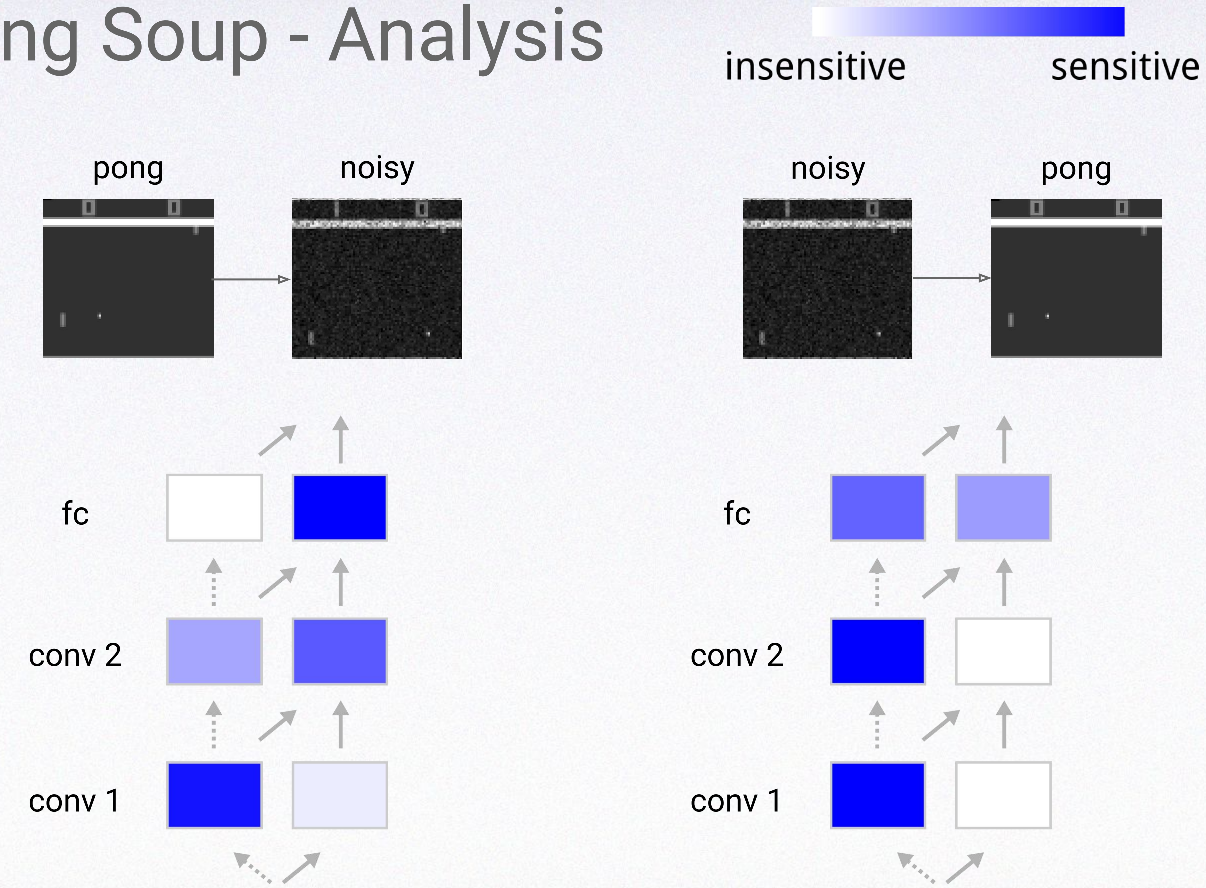
- Compute modified diagonal Fisher matrix : network policy with respect to normalized activations of each layer
- AFS is computed for layer i, column k, and feature m.

$$\hat{F}_i^{(k)} = \mathbb{E}_{\rho(s,a)}\left[\frac{\partial \log \pi}{\partial \hat{h}_i^{(k)}} \frac{\partial \log \pi}{\partial \hat{h}_i^{(k)}}^T\right] \qquad \mathrm{AFS}(i,k,m) = \frac{\hat{F}_i^{(k)}(m,m)}{\sum_k \hat{F}_i^{(k)}(m,m)}$$

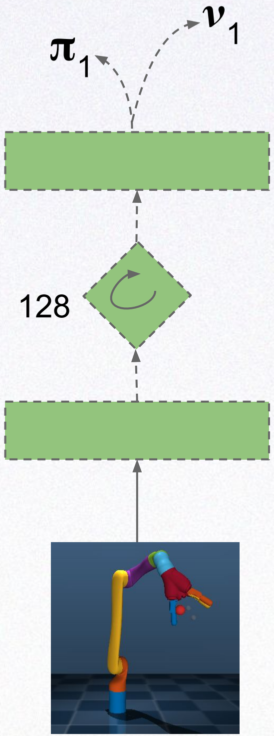
Pong Soup - Analysis



Pong Soup - Analysis



Progressive nets from simulation to **robot**



Column 1: Reacher task with random start, fixed target, trained with Mujoco model of Jaco arm.

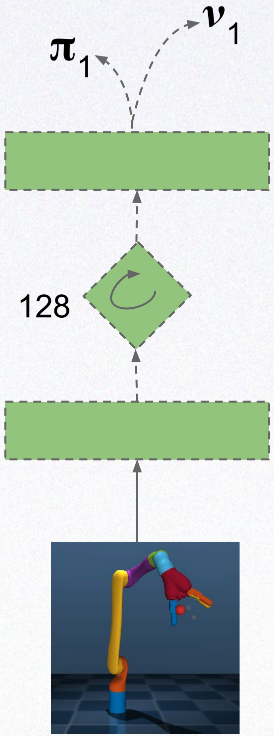
Input: RGB only

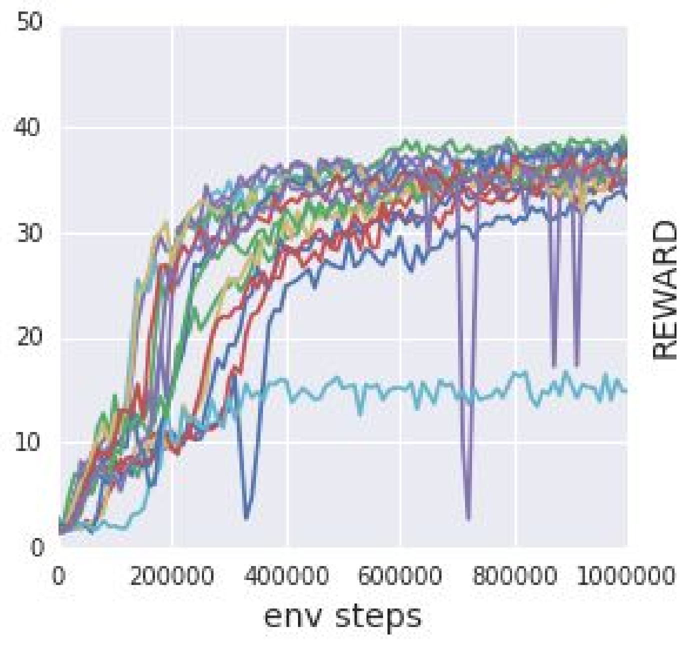
Output: joint velocities (6 DOF)

Network: ConvNet + LSTM + softmax output

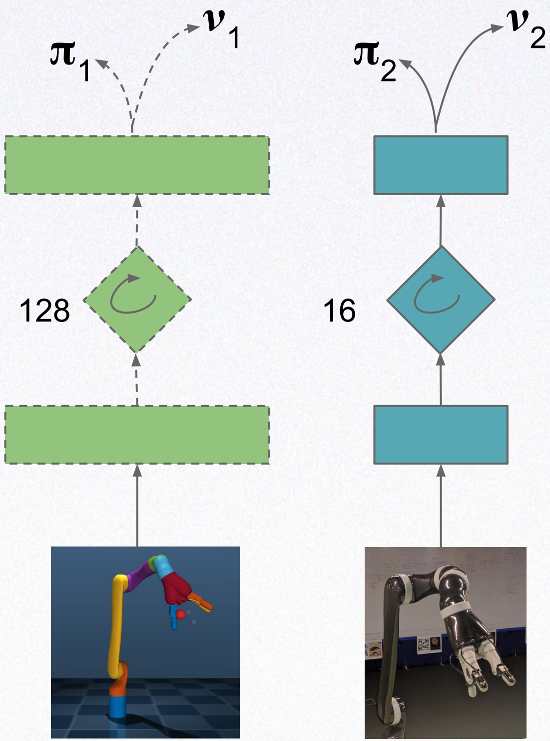
Learning: Asynchronous advantage actor-critic (A3C); 16 threads

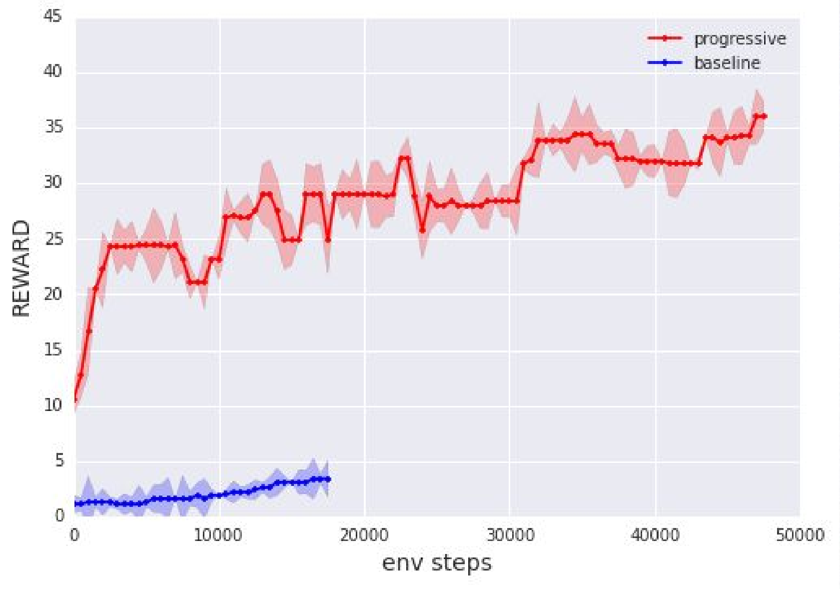
Progressive nets from simulation to **robot**





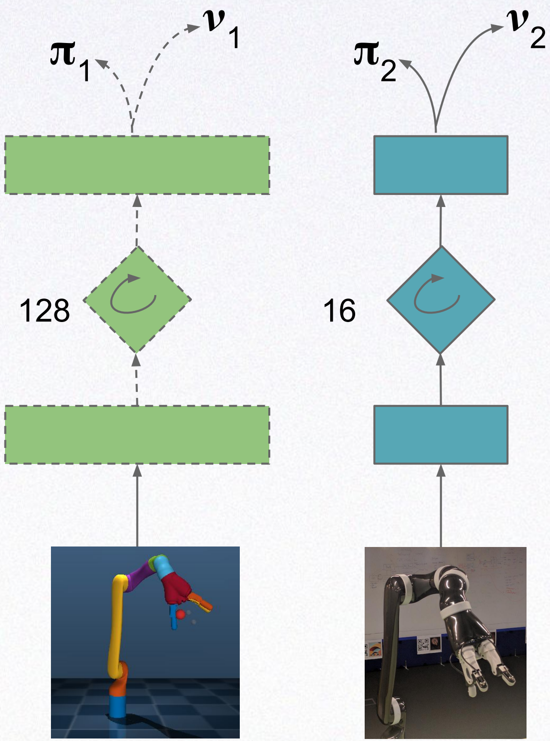
Progressive nets from simulation to robot





Reacher task: random start, fixed target
Input: RGB images
Output: joint velocities (6 DOF)

Progressive nets from simulation to robot



Column 2: Reacher task with random start, random target, trained with real Jaco arm.

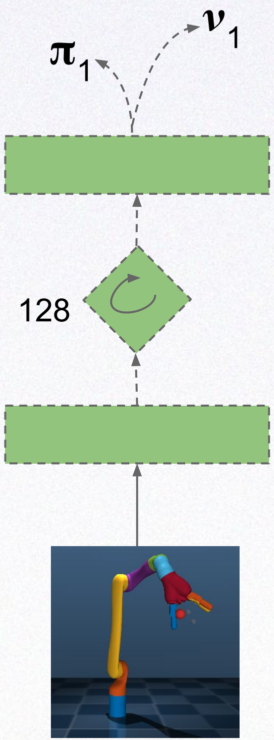
Input: **proprioception + target XYZ**

Output: joint velocities (6 DOF)

Network: MLP + LSTM + softmax output

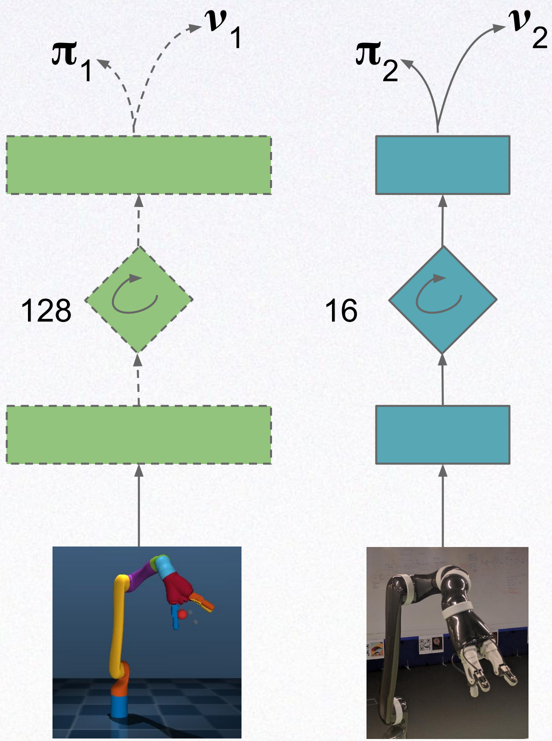
Learning: Asynchronous advantage actor-critic (A3C); **1 thread**

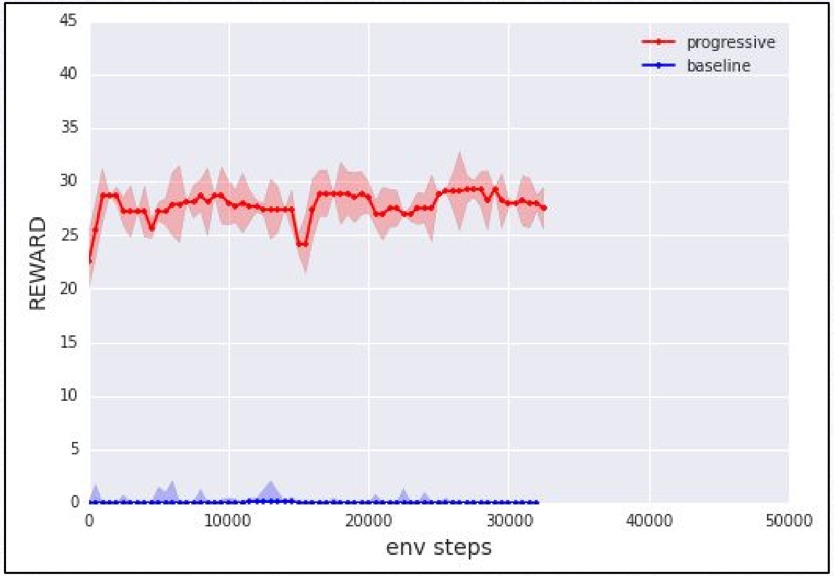
Progressive nets from simulation to robot



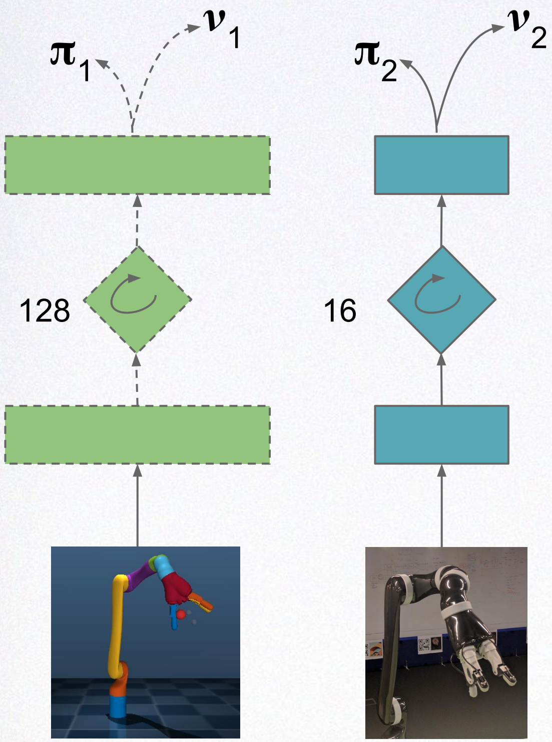
https://www.youtube.com/watch?v=tXISbTOesMY

Progressive nets from simulation to robot





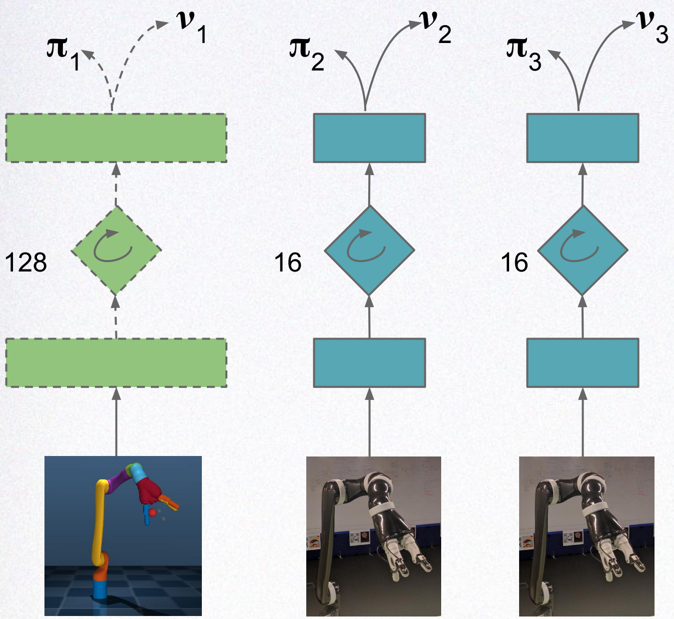
Progressive nets from simulation to robot

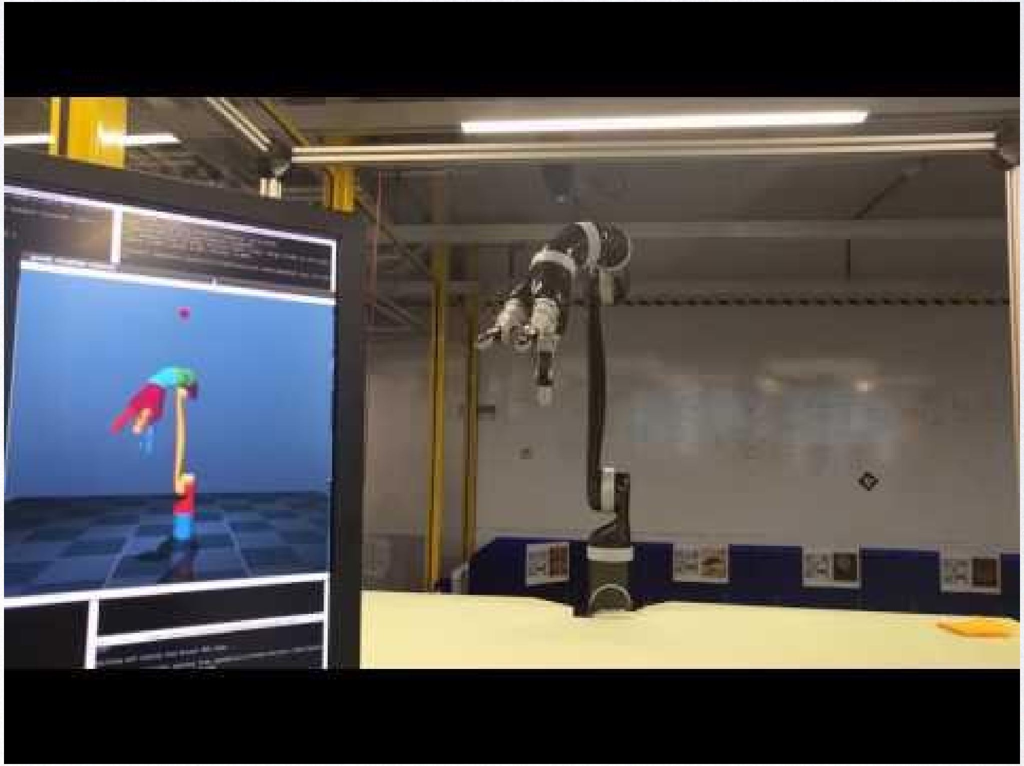


https://www.youtube.com/watch?v=YZz5Io_ipi8

Progressive nets from simulation to robot

Column 3: ‘Catch’, trained with real Jaco arm.

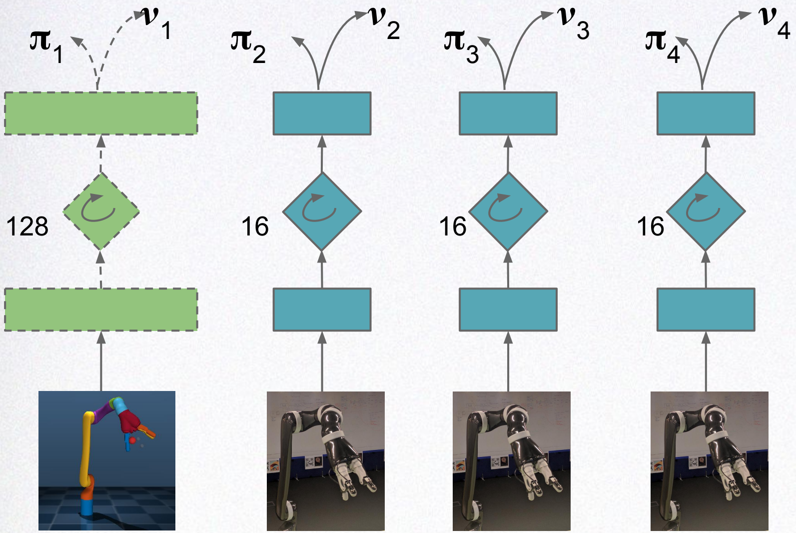




https://www.youtube.com/watch?v=qzMTPzbPV0c

Progressive nets from simulation to robot

Column 4: 'Catch the bee', trained with real Jaco arm.



https://www.youtube.com/watch?v=JkXhIIWsUA0

What's next?

- Scaling up Progressive Networks
  - Compression / Brain Damage / Complementary Learning
  - Limiting Model Growth with Sharing of Lateral Connections

- Automating the progression
  - Eliminating the need for manual switch points while keeping model growth in check

- Meta-controller making use old policies in new situations
  - Fast adaptation to new tasks using the fact that old policies are NOT forgotten.

Thank you