SPEEDING UP DEEP REINFORCEMENT LEARNING VIA TRANSFER AND MULTITASK LEARNING

Speaker: Yunshu Du

Host: Gail Murphy

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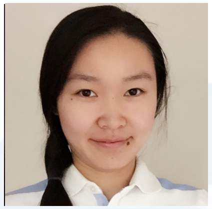
Speaker & Moderator



Yunshu Du

Yunshu Du is a third year PhD student at the School of Electrical Engineering and Computer Science at Washington State University, under the supervision of Dr. Matthew E. Taylor. From 2010 to 2012, she majored in software engineering at Wuhan University in China. Yunshu transferred to Eastern Michigan University to study computer science for her junior year. After two years of study, she obtained the Bachelor of Science degree of computer science, with a minor of Geographical Information System in 2014.

Gail Murphy

Dr. Gail Murphy is a Professor in the Department of Computer Science and Associate Dean (Research & Graduate Studies) in the Faculty of Science at the University of British Columbia. She is also a co-founder and Chief Scientist at Tasktop Technologies Incorporated. Her research interests are in software engineering with a particular interest in improving the productivity of knowledge workers, including software developers. Dr. Murphy's group develops tools to aid with the evolution of large software systems and performs empirical studies to better understand how developers work and how software is developed.

SPEEDING UP DEEP REINFORCEMENT LEARNING VIA TRANSFER AND MULTITASK LEARNING

Yunshu Du
Intelligent Robot Learning Laboratory
Washington State University

CRA-W Undergraduate Town Hall
July 27, 2017

The Intelligent Robot Learning Laboratory

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ABOUT ME

Wuhan 武汉
The capital of Hubei Province and the a triple city of Wuchang, Hanku and Hangyang serving as the transportation hub in central China.

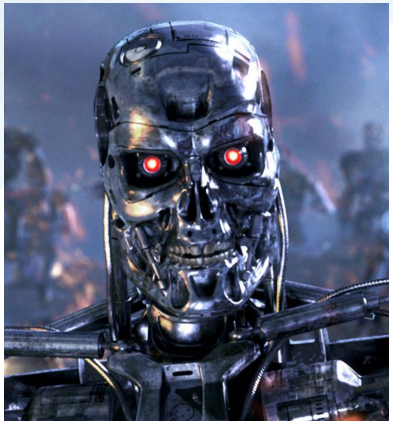
- Born and raised in Wuhan, China
  - Capital city of Hubei province, “the Chicago of China”
  - Must-see: the Yellow Crane Tower, the Yangtze river
- Came to the US in 2012
  - A short visit in Texas in 2009
  - Eastern Michigan University, BS in Computer Science 2014
- Joined Washington State University 2014
  - PhD in Computer Science. Advisor: Dr. Matt Taylor
  - Current Research: reinforcement learning, applied data science

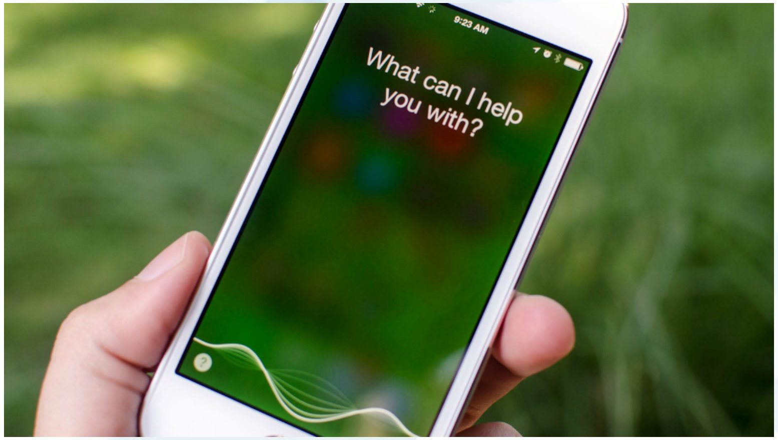
The Intelligent Robot Learning Laboratory

OUTLINE

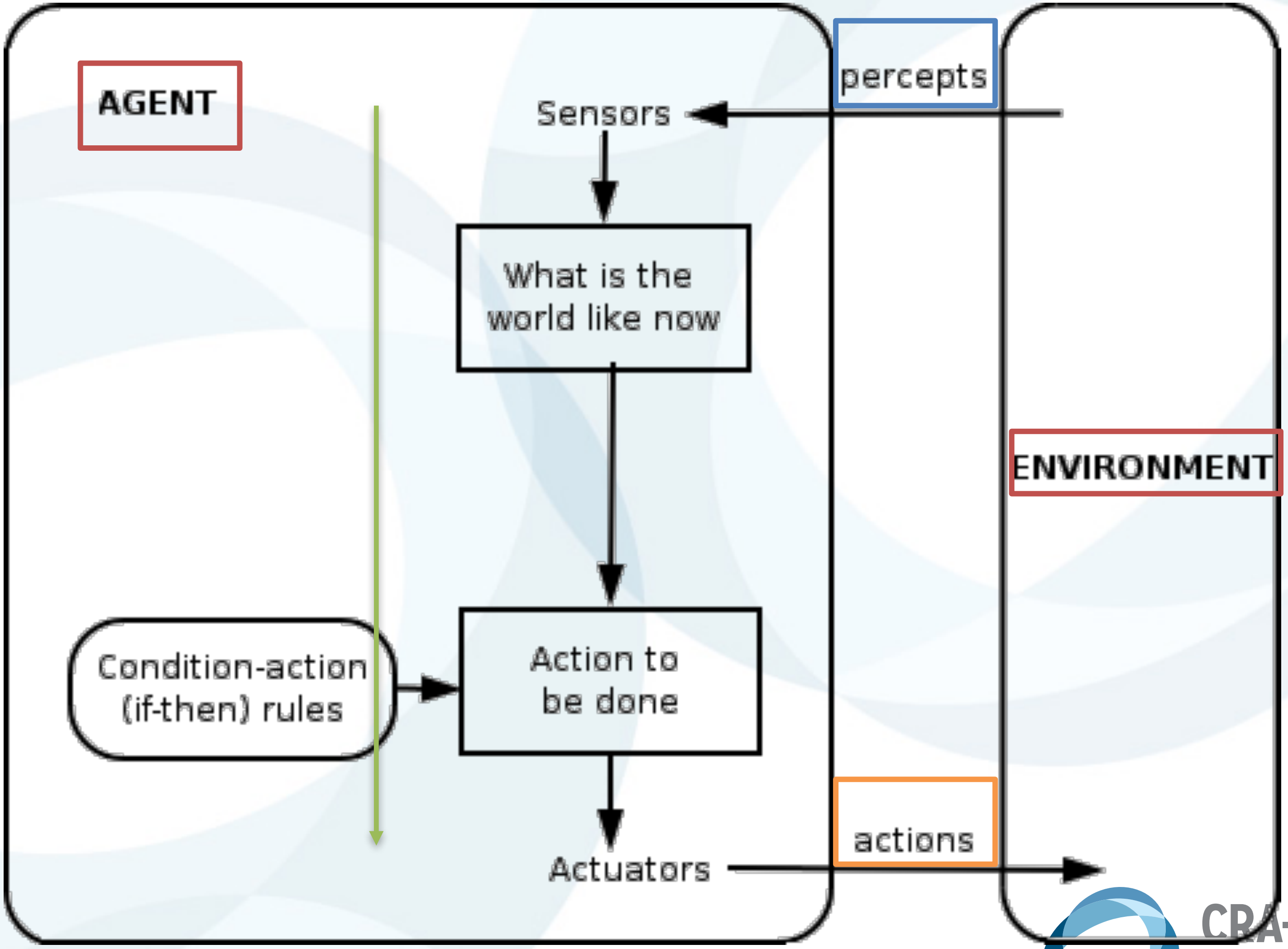
- AI and Machine Learning
- Reinforcement Learning
- Deep Reinforcement Learning
- Transfer and Multi-task Learning

Artificial Intelligence





Artificial Intelligence



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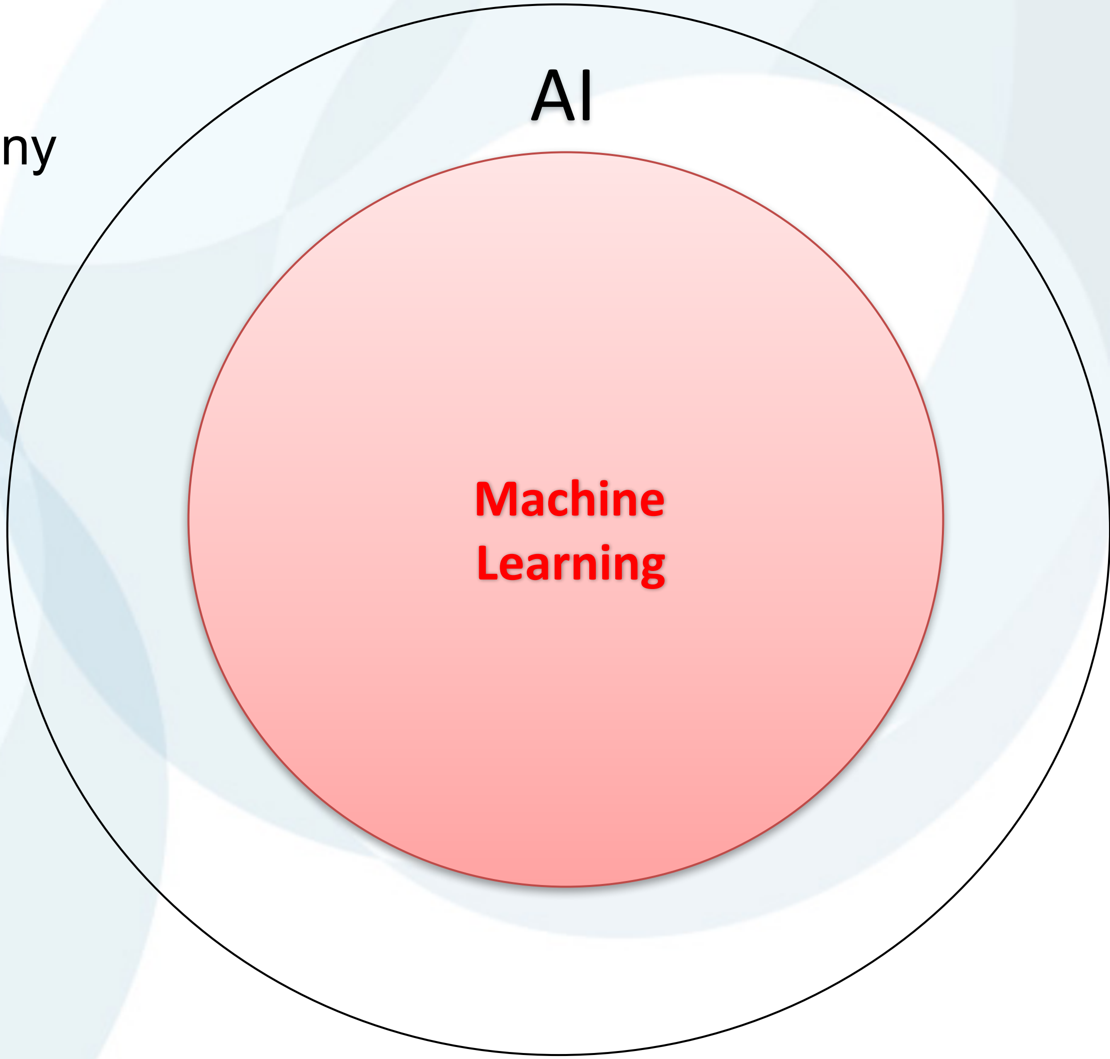
Why is learning important?

- Unanticipated situations
- Faster for human programmer
- Better than human programmer/user

Machine Learning

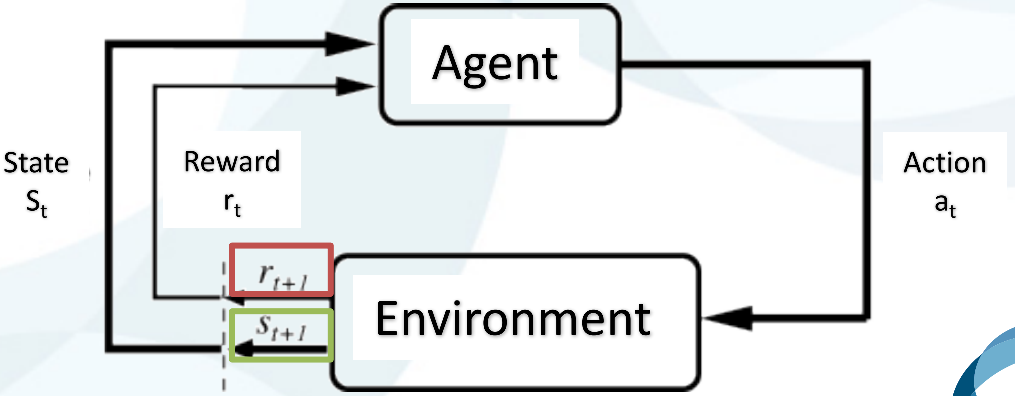
Machine learning is one of many approaches to achieve AI

- Supervised Learning
- Unsupervised Learning
- **Reinforcement Learning**



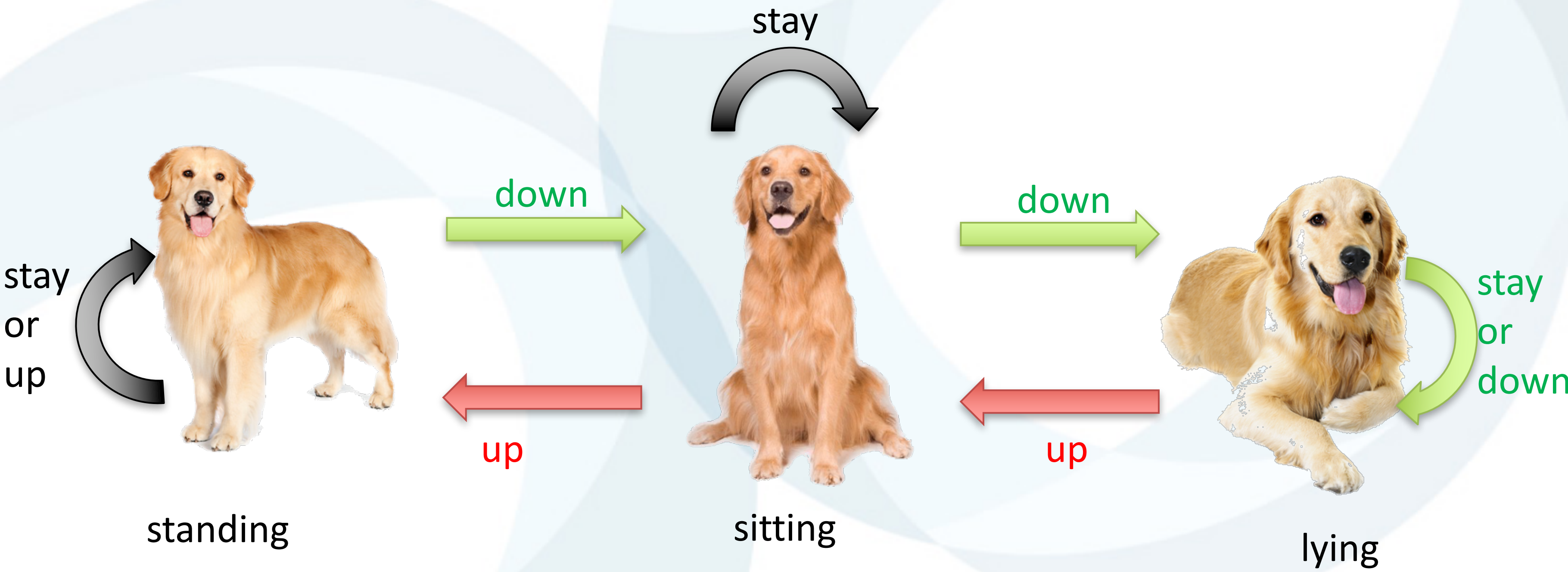
Reinforcement Learning (RL)

- Inspired by behaviorist psychology
- An agent explores an environment and decide what action to take
- Learn from reward signal, but it is often delayed/limited
- State changes upon the action took
- Things happen in a sequential way
  - The Markov Decision Process: {s, a, r, s'}
  - The goal is to find an optimal policy so that the agent maximize the reward accumulated



Example: teaching a dog to lie down

Action: up, down, or stay



stay

stay or up

down

up

down

up

stay or down

standing

sitting

lying

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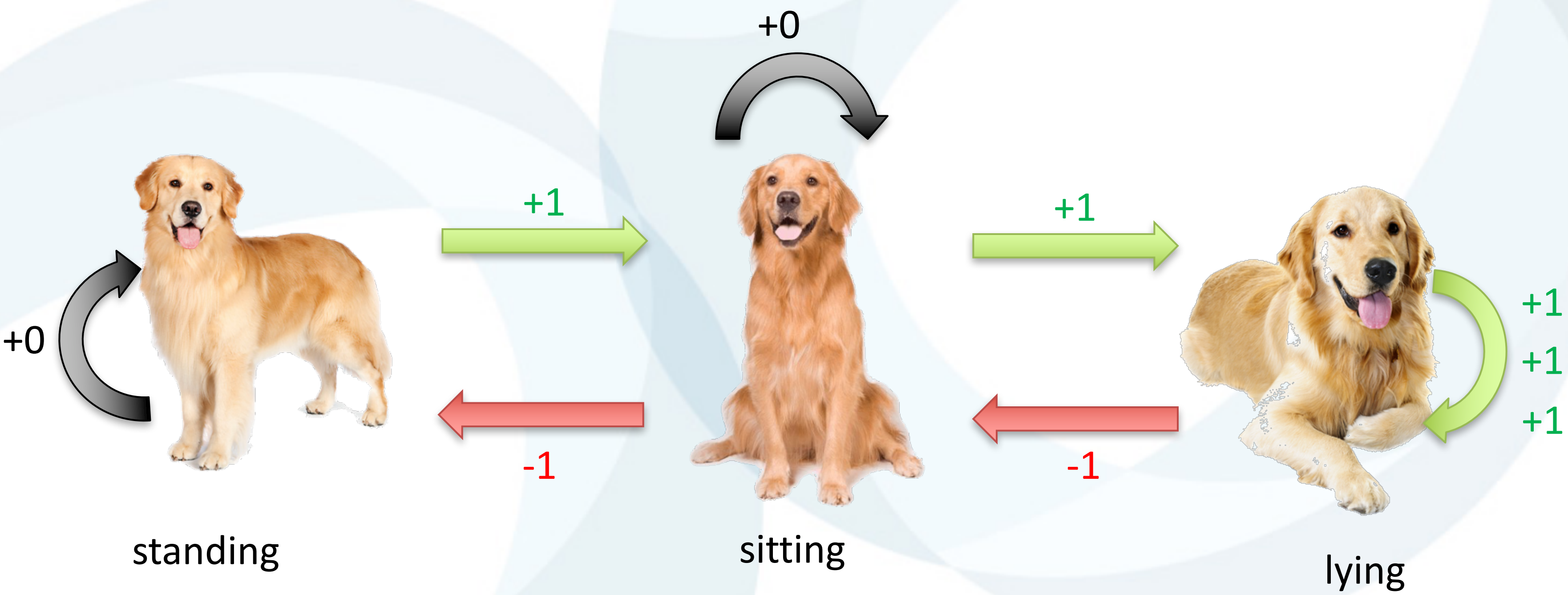
Example: teaching a dog to lie down

Action: up, down, or stay



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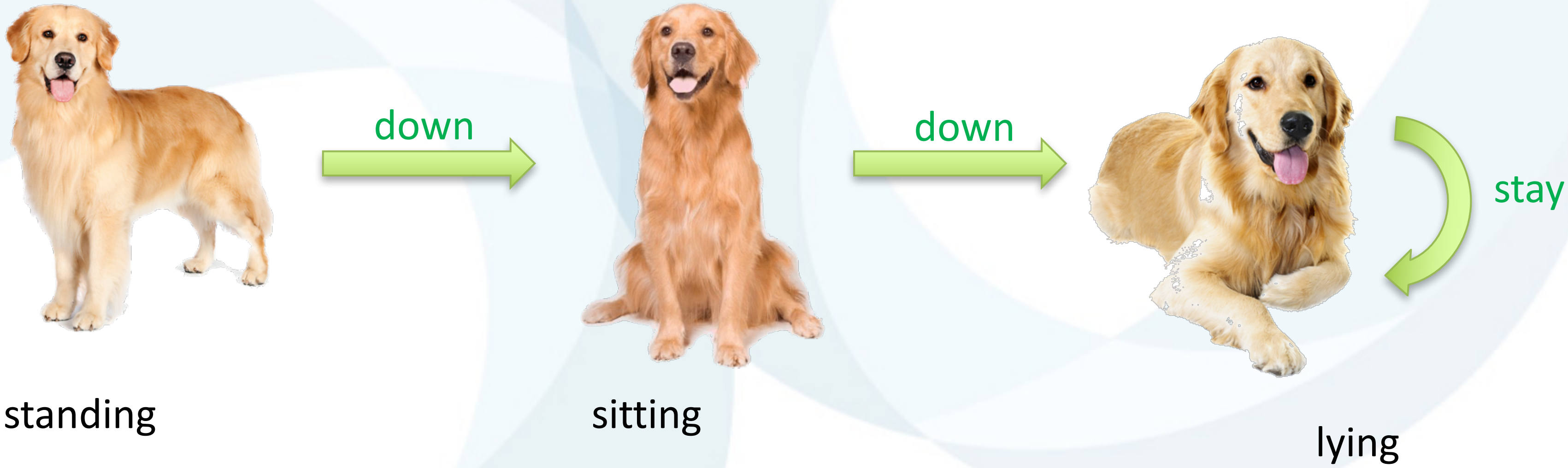
Example: teaching a dog to lie down

Policy: state-action mapping



down

down

stay

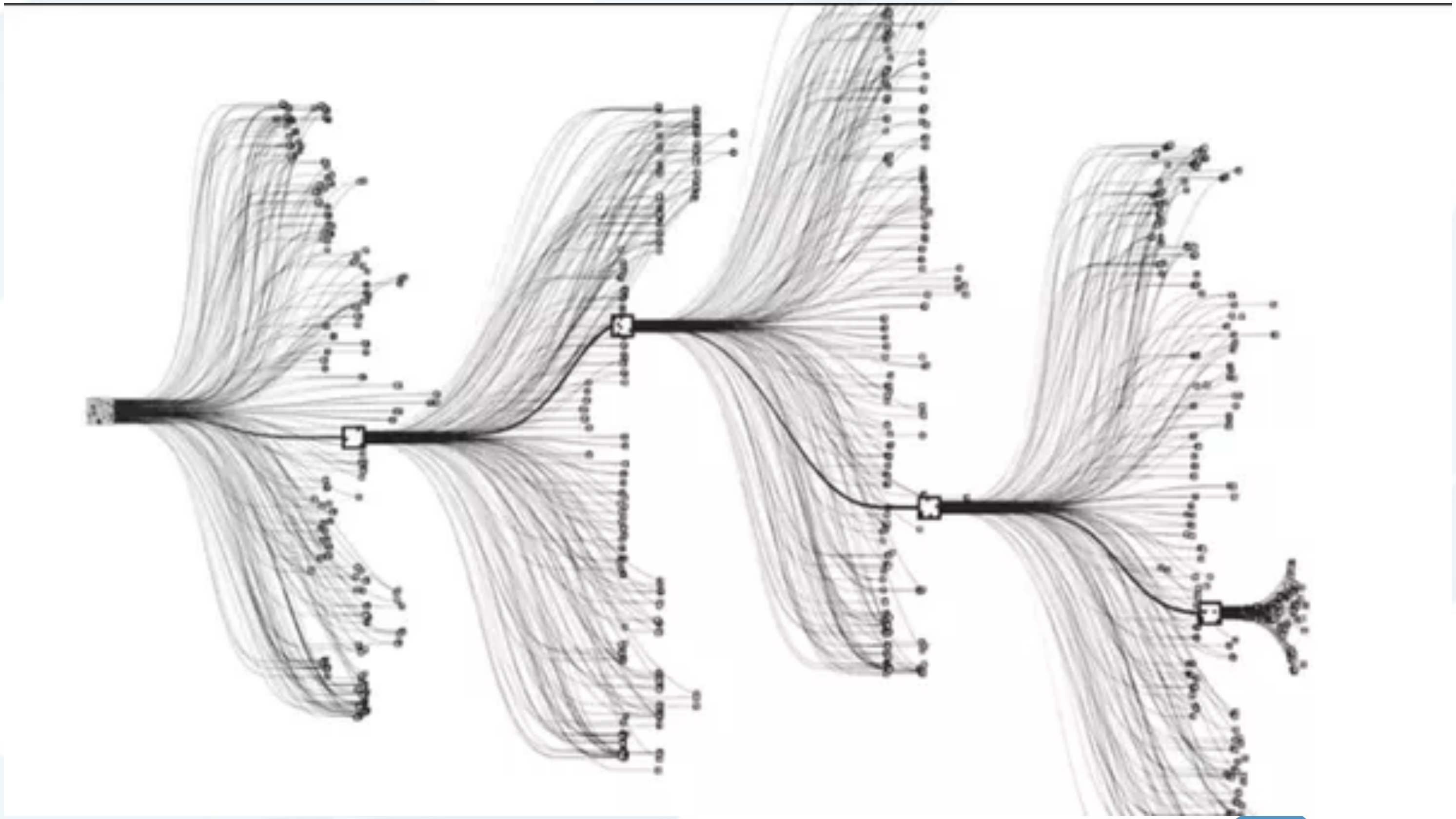
standing

sitting

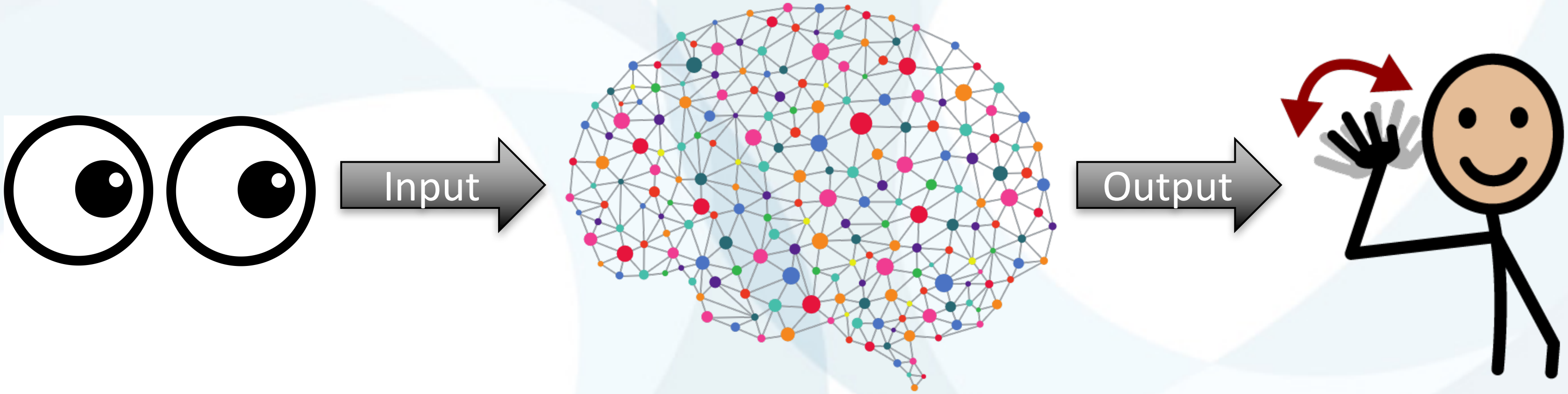
lying

Game	Board size	State space
Go	19 × 19	10^{172}

What if states are huge?



Function Approximator



Input

Output

What you see

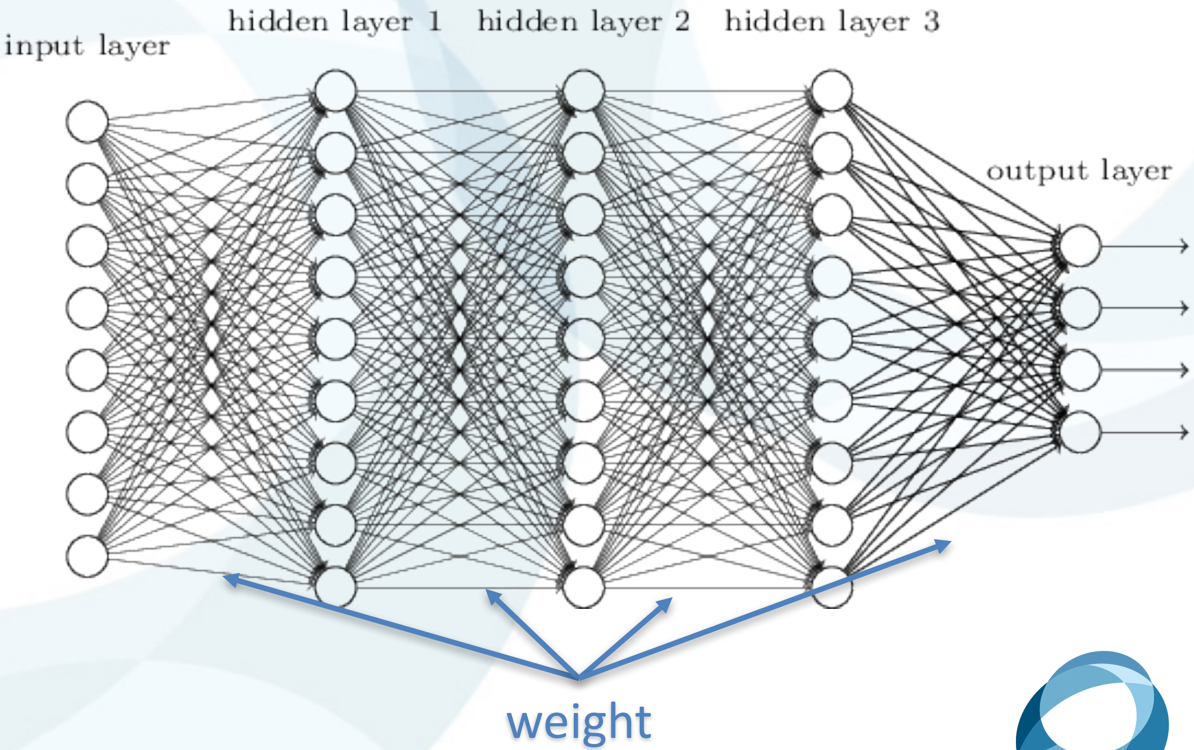
Process in brain

Output actions

Deep Learning

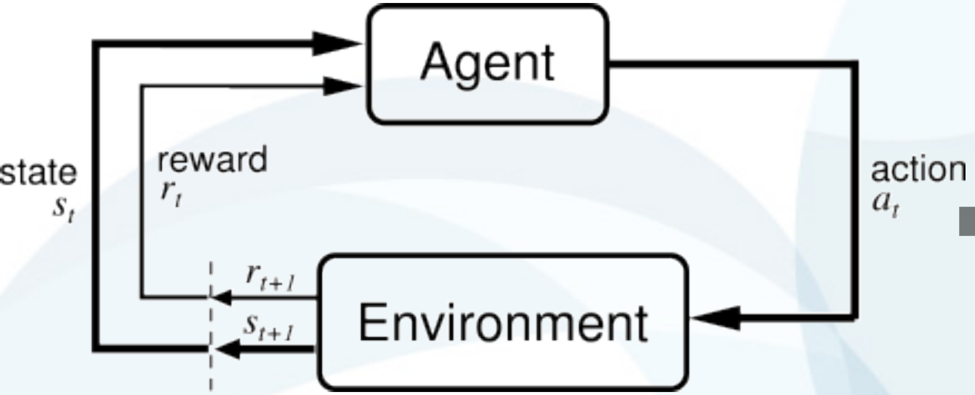
- Inspired from neuronal responses in the brain, a tool to implement machine learning algorithms
- Use deep neural network as *function approximator* to represent **features** in an environment

An agent processes what it “sees” with a neural network

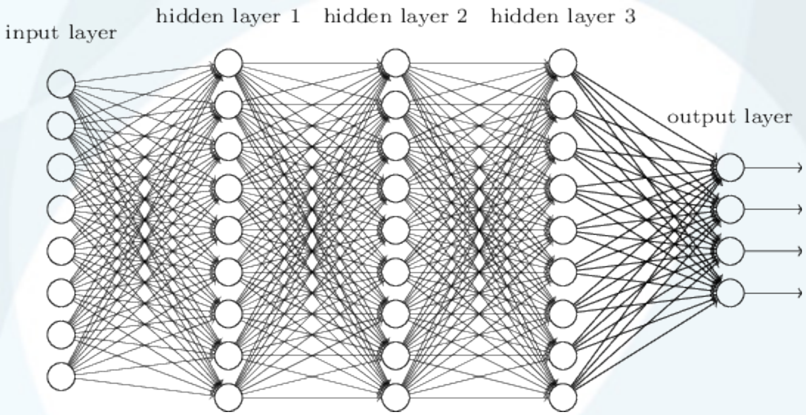


Stanford CS231n: Convolutional Neural Network for Visual Recognition
http://cs231n.stanford.edu/

Deep Reinforcement Learning



(Any) RL algorithms



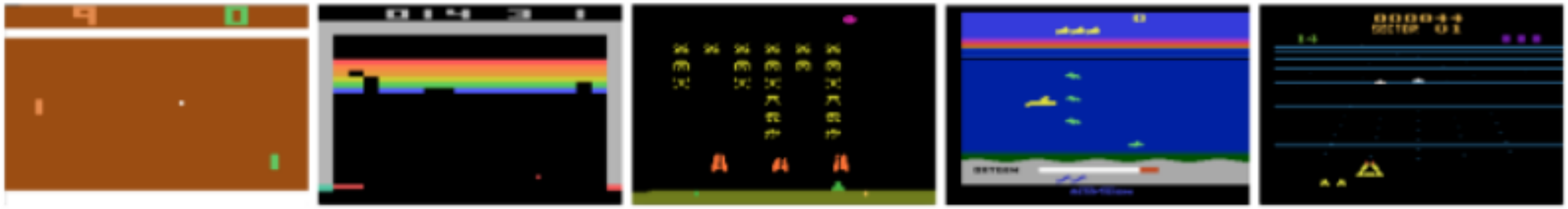
Deep Neural Networks

- DeepRL in Google DeepMind:
  - Deep Q-network: general Atari game playing agent ← My Research
  - Gorila: distributed deep RL system
  - Asynchronous deep RL: Atari + continuous control
  - AlphaGo: defeated world's No. 1 professional Go player

DeepMind Blog:
https://deepmind.com/blog/deep-reinforcement-learning/

Deep Q-network (DQN)

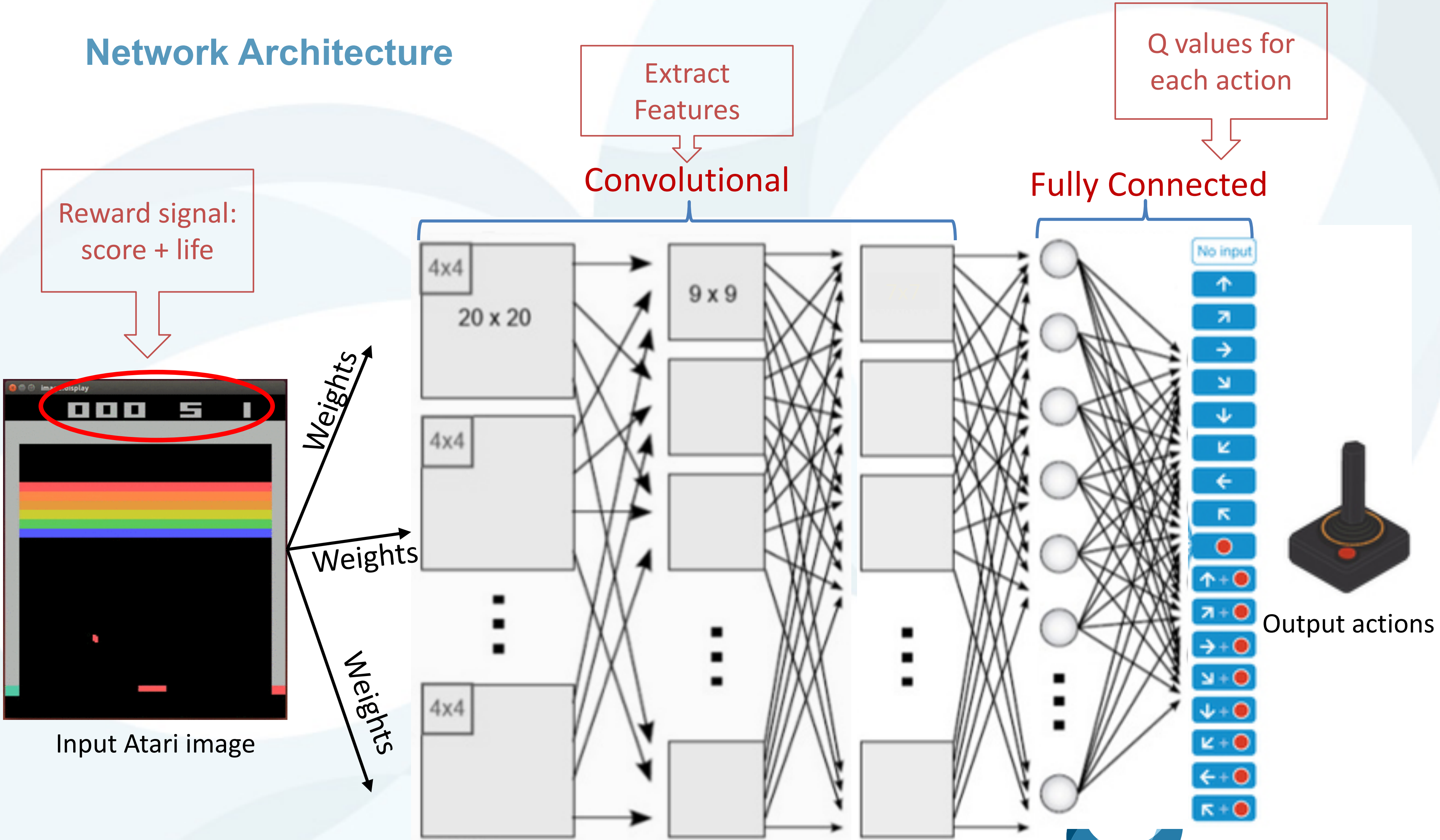
- An artificial agent for general Atari game playing



  - Learn to master 49 different Atari games directly from game screens
  - Excel human expert in 29 games
  - **Q-learning + convolutional neural network**

Deep Q-network (DQN)

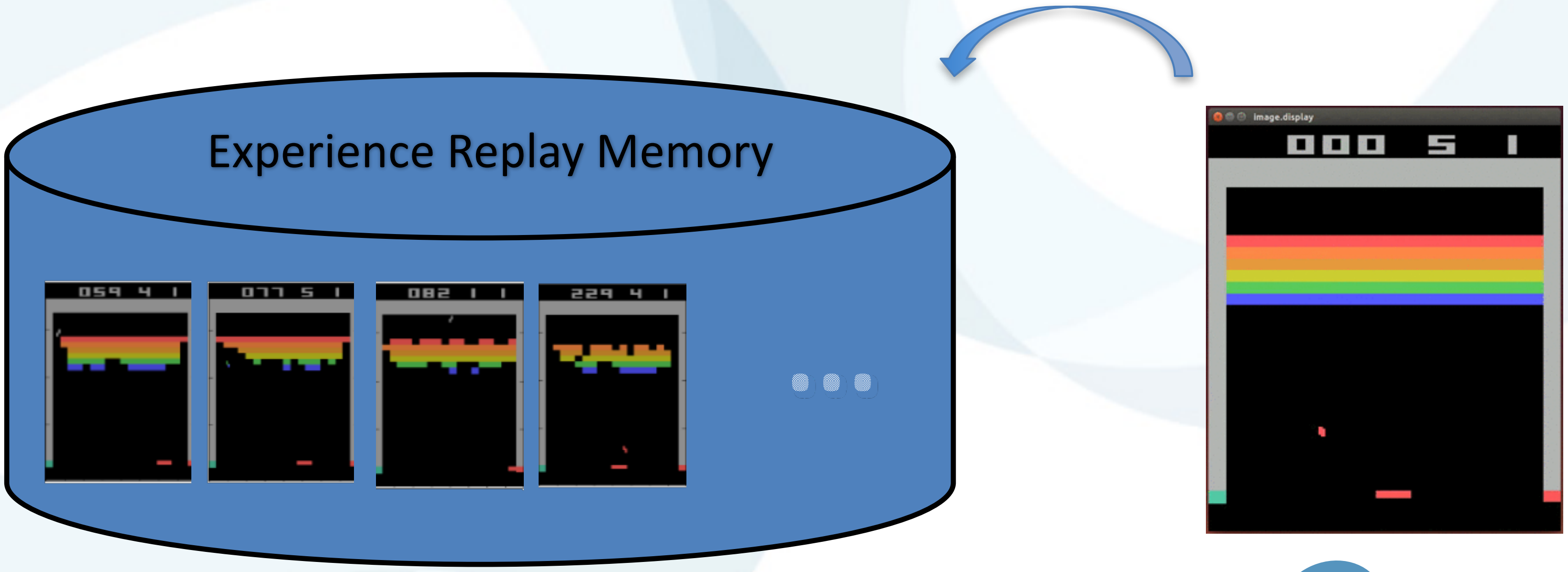
Network Architecture



Deep Q-network (DQN)

Techniques to Help Stabilize Learning

- Reinforcement learning is known to be unstable or even to diverge when use neural network as function approximator
- Main solution: save experiences first, then learn from them later



Experience Replay Memory

Deep Q-network (DQN)

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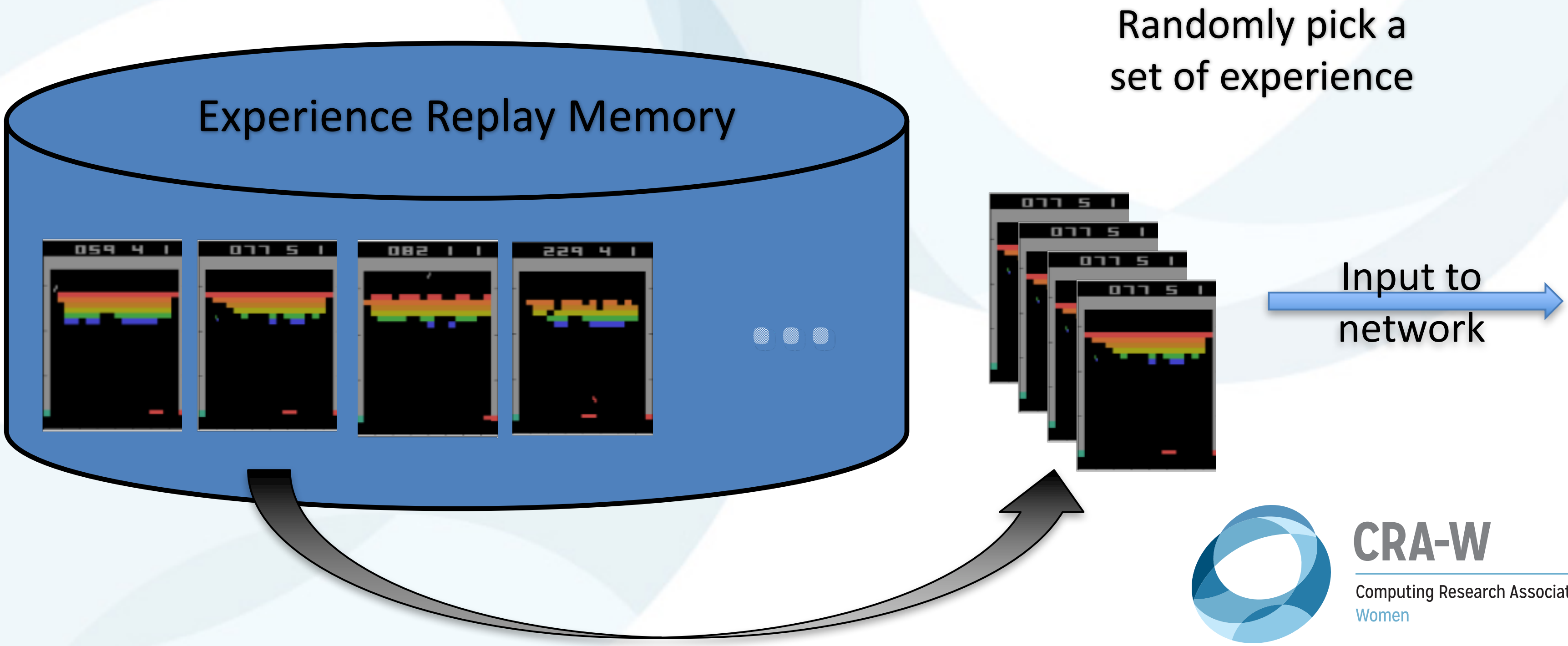

Experience Replay Memory

Randomly pick a set of experience

Input to network

Deep Q-network (DQN)

Techniques to Help Stabilize Learning

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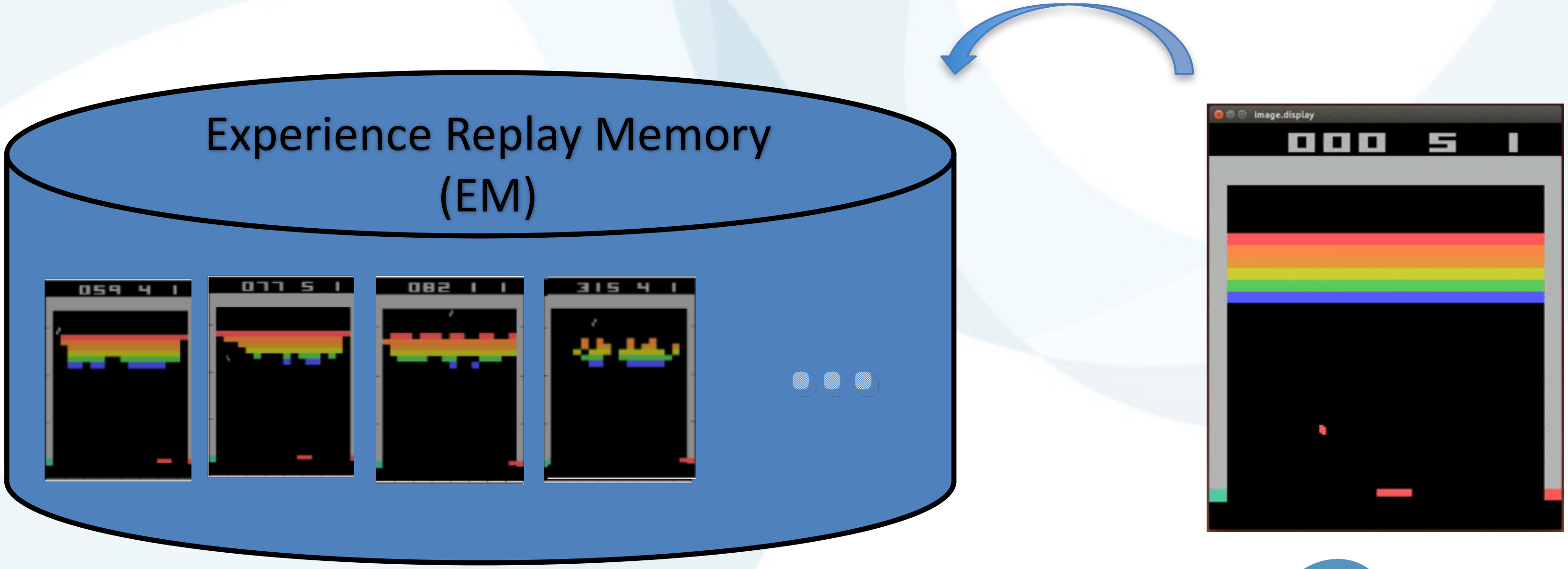


Experience Replay Memory (EM)

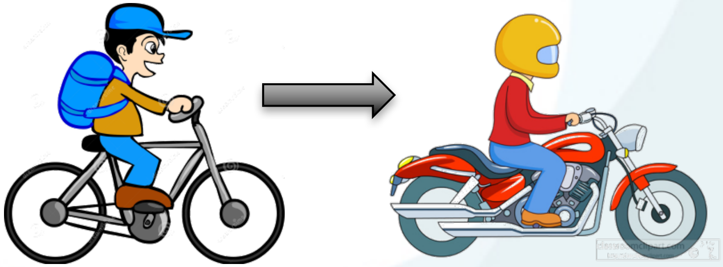
My Research

Problem

- DeepRL is slow in learning: 10 days to learn one game
  - A RL agent needs time to explore the environment
  - A deep neural network has millions of parameters
  - This is problematic in real-world, e.g., train a program to drive a car

Solution

- Transfer Learning

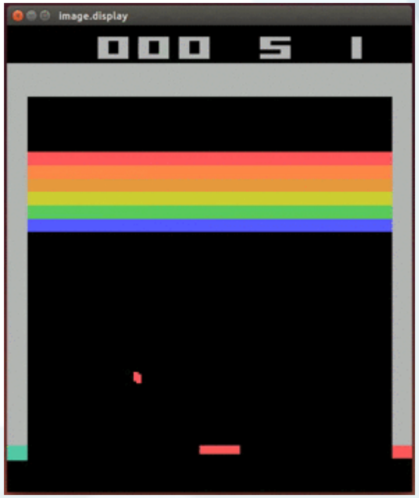


- Multi-task Learning

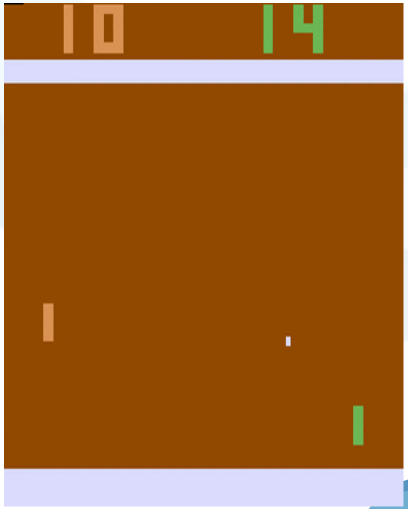
My Research

Transfer Learning (TL) in DQN

- Task Selection
  - Source task: task(s) the agent has already learned
  - Target task: task(s) to be learned
  - Usually select by a human based on task similarities, similar tasks are more likely to transfer well



Breakout



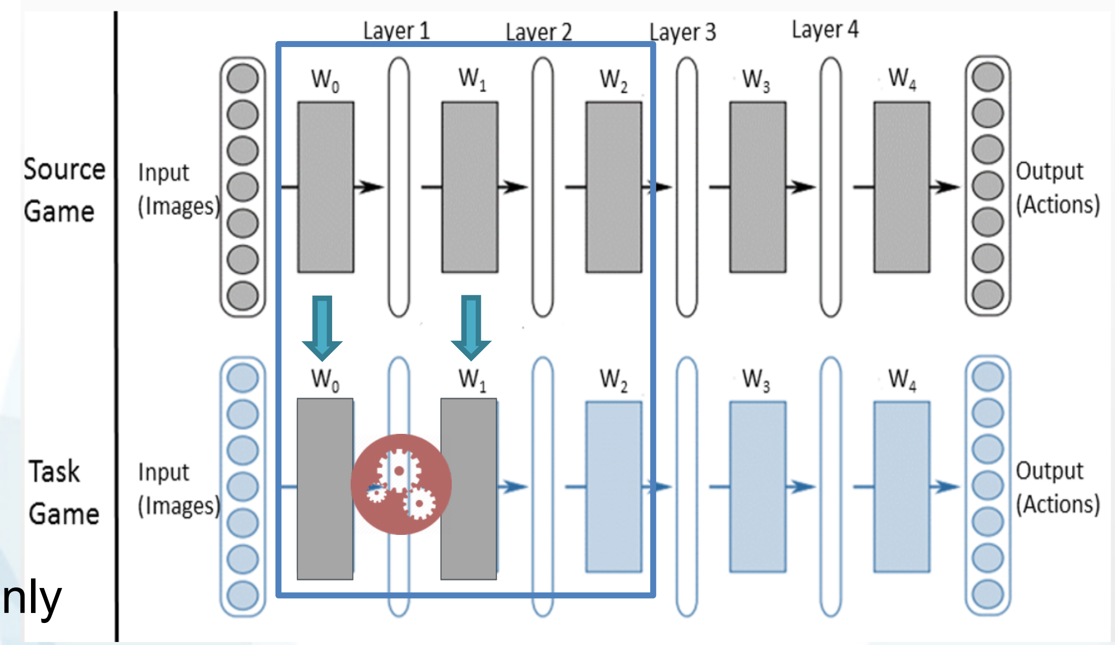
Pong

A trick to increase task similarity

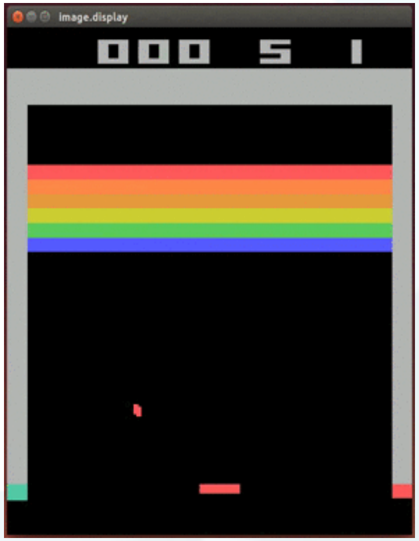
My Research

Transfer Learning (TL) in DQN

- Weight Transfer
  - Copy weights
  - Fine-tune
  - Transfer in CNN layers only



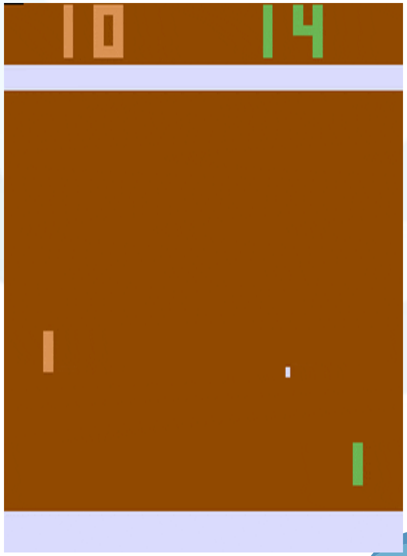
Target



Breakout

weights

Source



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My Research

Transfer Learning (TL) in DQN

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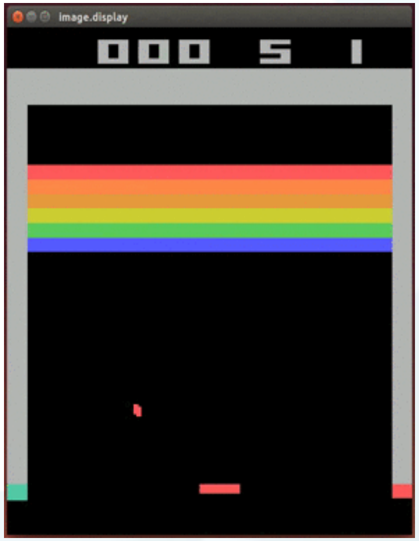
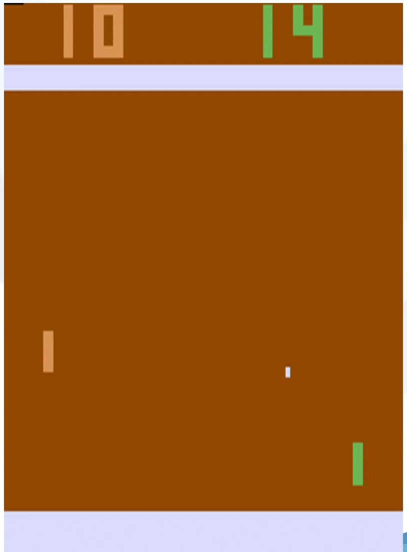


Breakout

weights

Target



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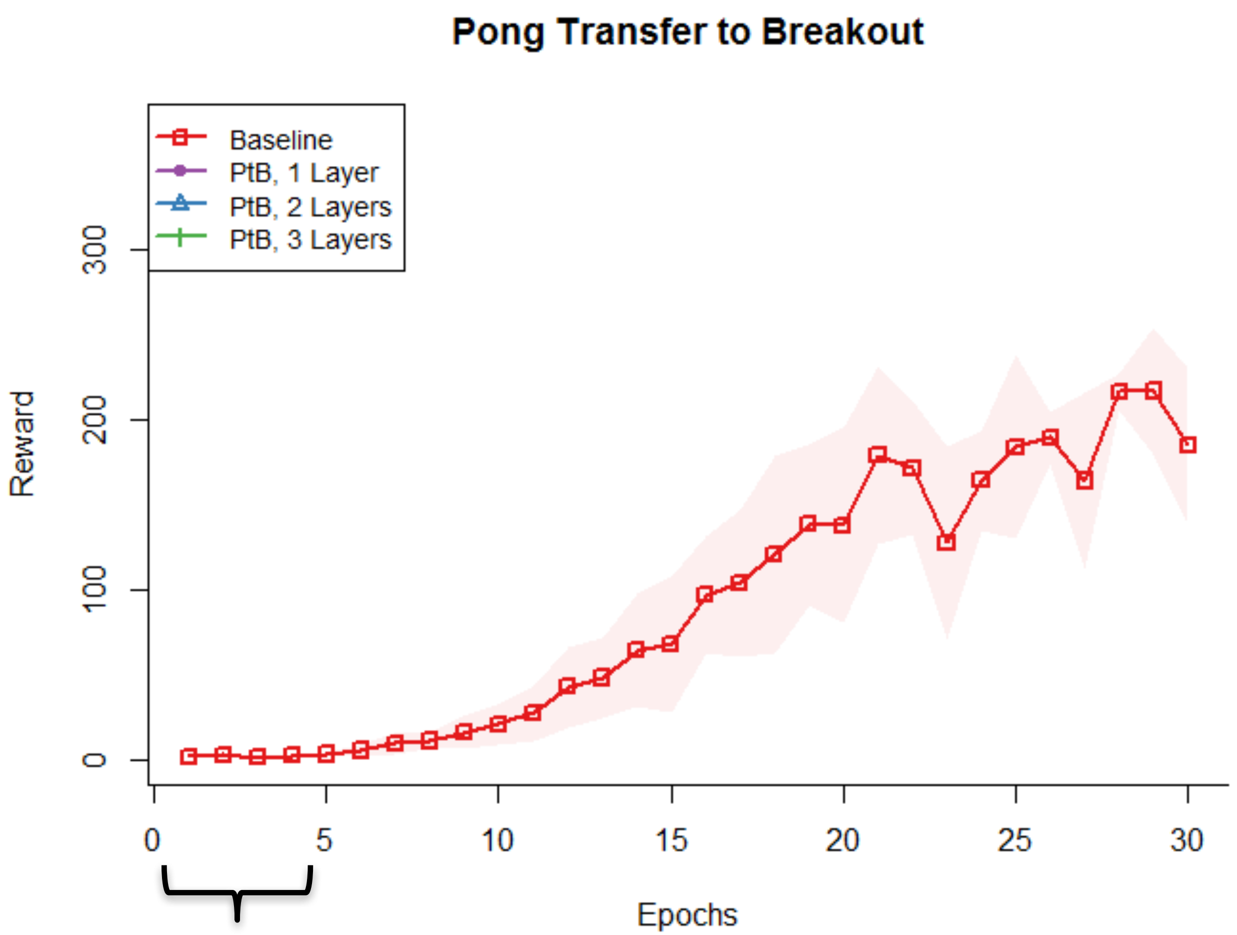
My Research

Transfer Learning (TL) in DQN

- How to evaluate
  - *Jumpstart*: the agent's initial performance on the target task was improved by transferring source task knowledge
  - *Final performance*: the agent's final performance on the target task was improved via transfer
  - *Total reward*: the accumulated reward (the area under the curve) on the target task was improved compared to no-transfer learning (within the same learning time period),

My Research

Transfer Learning (TL) in DQN



1.25 million steps

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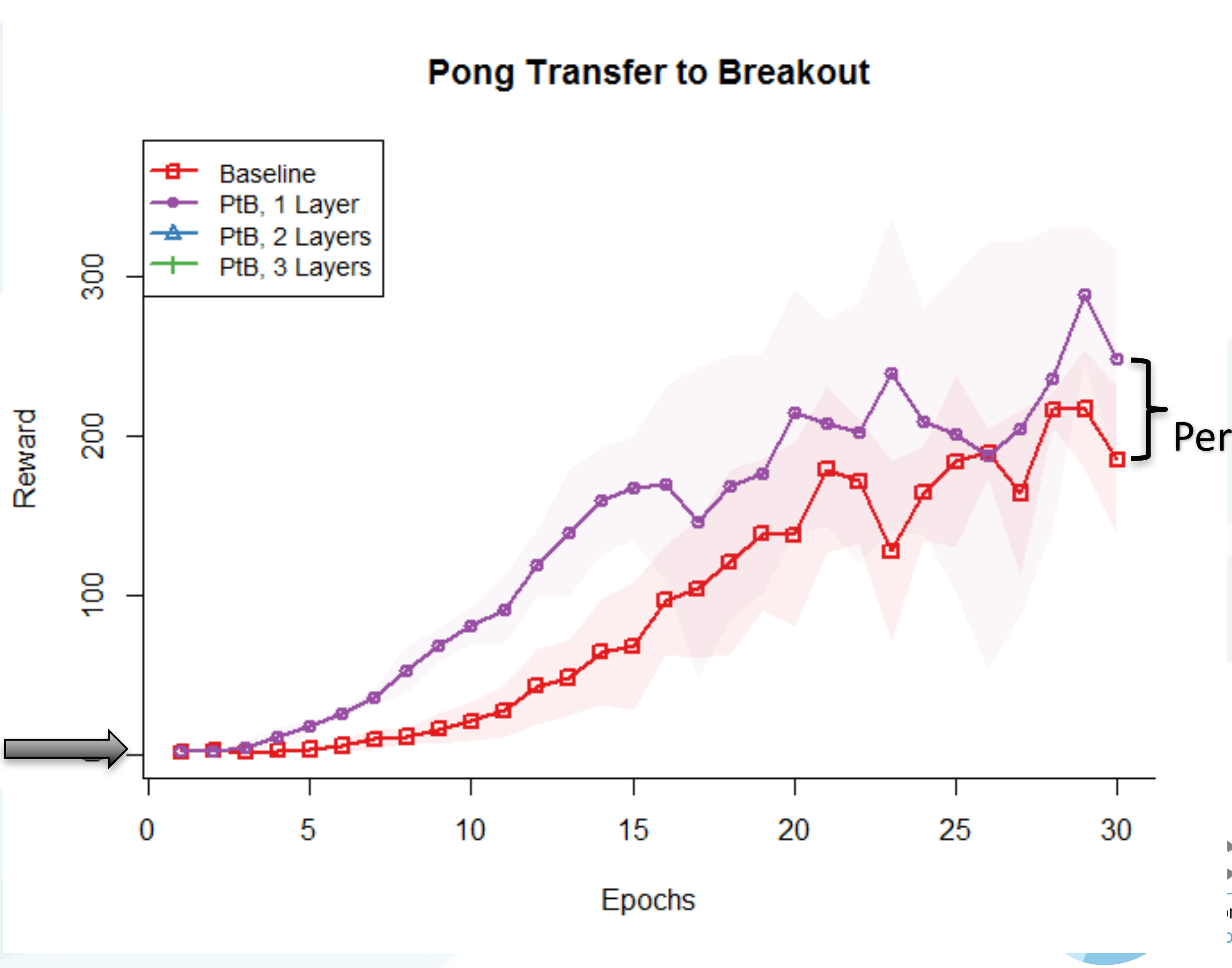
Transfer Learning (TL) in DQN

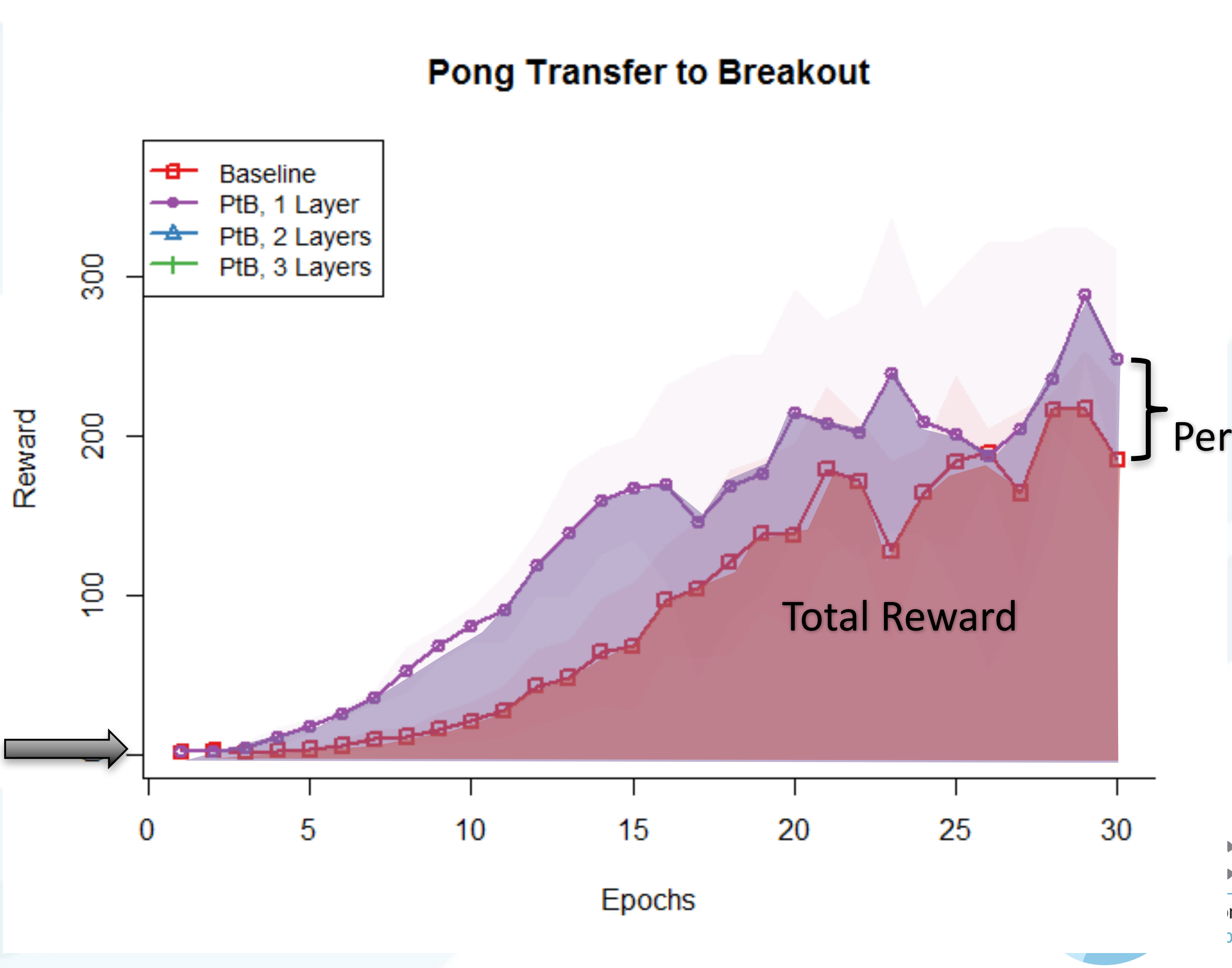


Jumpstart

Final Performance

My Research

Transfer Learning (TL) in DQN



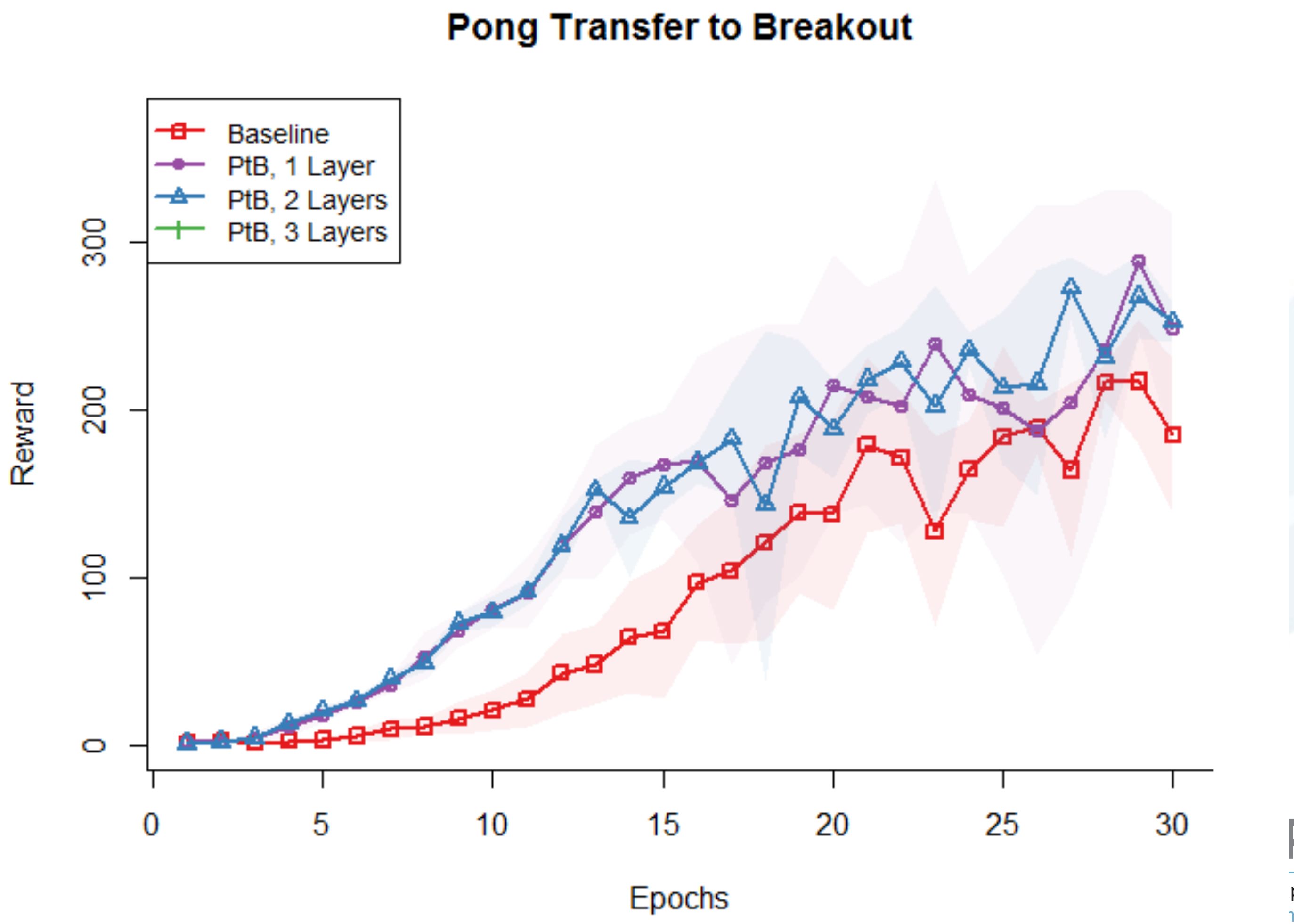
Jumpstart

Final Performance

Total Reward

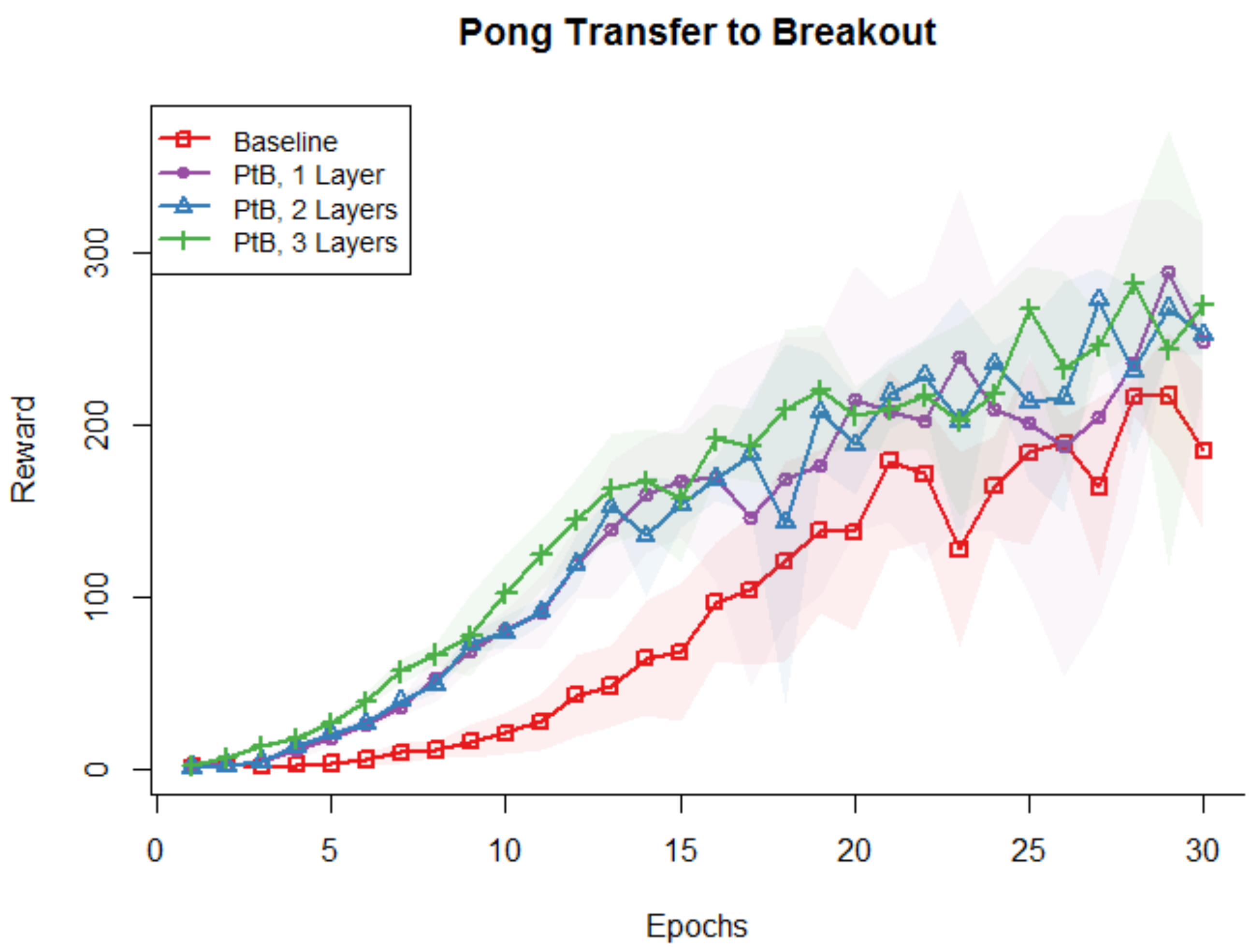
My Research

Transfer Learning (TL) in DQN



My Research

Transfer Learning (TL) in DQN



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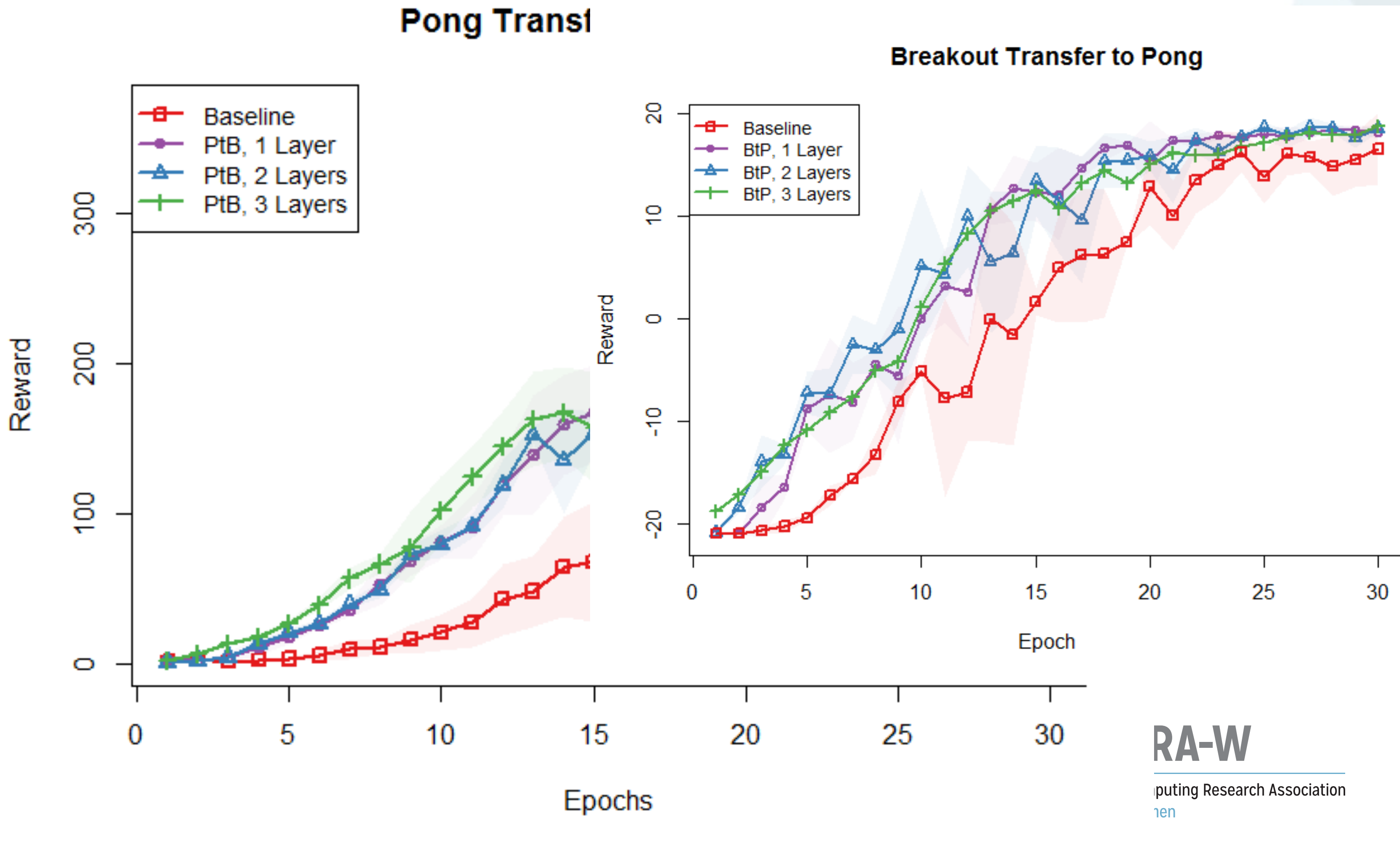
My Research

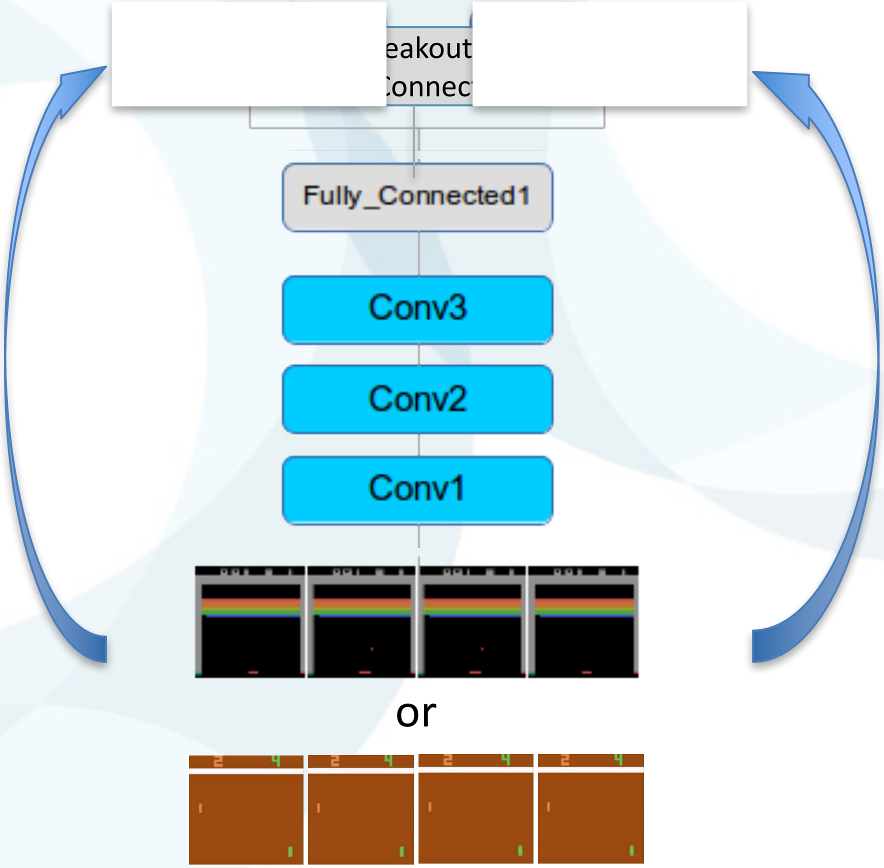
Transfer Learning (TL) in DQN



My Research

Multi-task Learning (MTL) in DQN

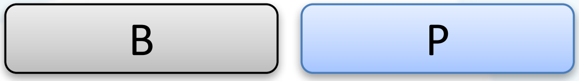
- Task Selection: related tasks are more likely to help each other
- Modify the DQN's architecture to enable multiple game inputs



My Research

Multi-task Learning (MTL) in DQN

- Design Choices
  - How often should games be switched
    - Every 1 step? Every 10,000 steps? Until one agent lose?
  - Should experience replay memory (EM) be shared



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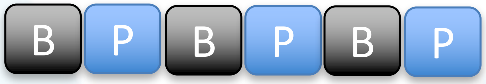
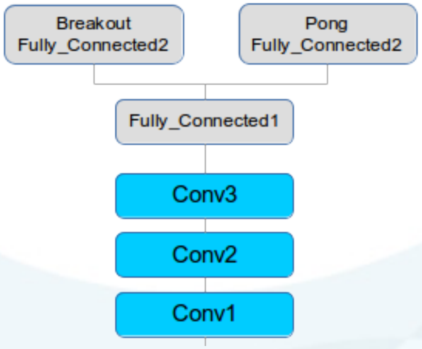


  - At what point to split the original DQN network



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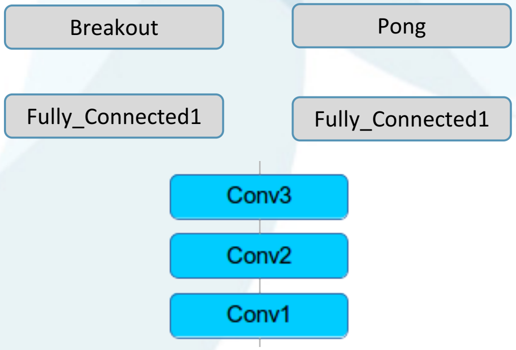

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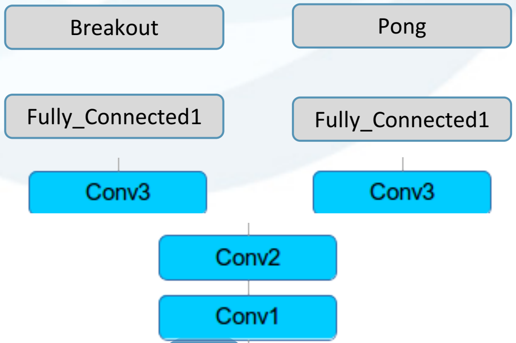


My Research

Multi-task Learning (MTL) in DQN

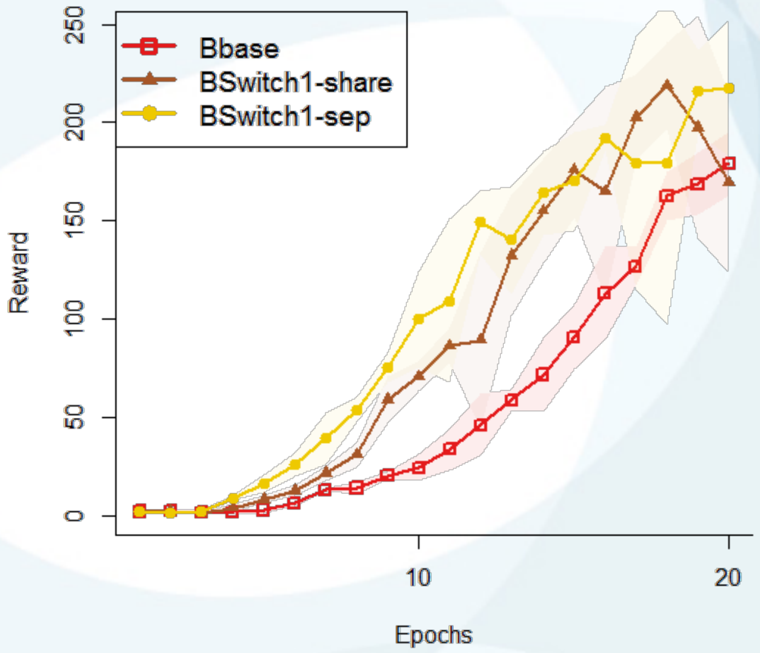
- How to evaluate
  - Final performance
  - Total reward

My Research

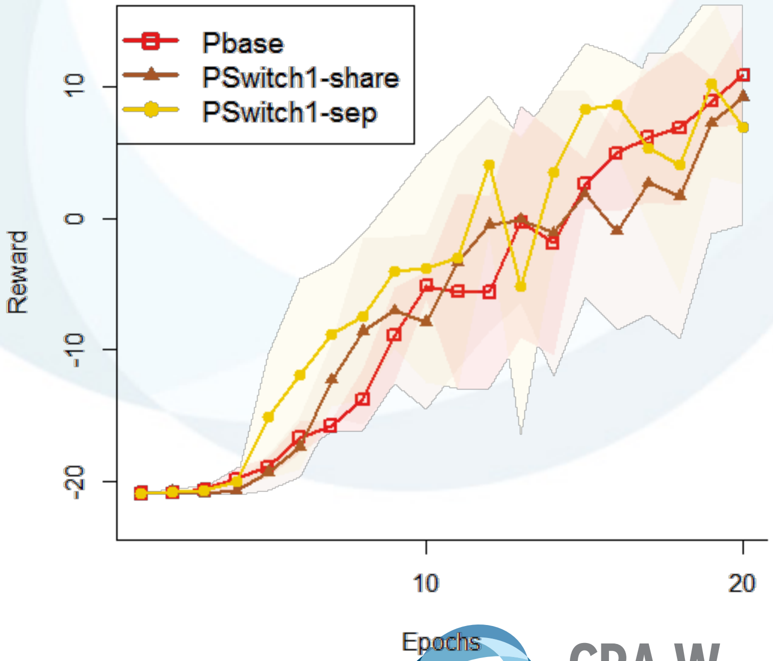
Multi-task Learning (MTL) in DQN

- How often should games be switched
- Should experience replay memory be shared

Breakout



Pong



Switch every step, share EM vs. not share EM

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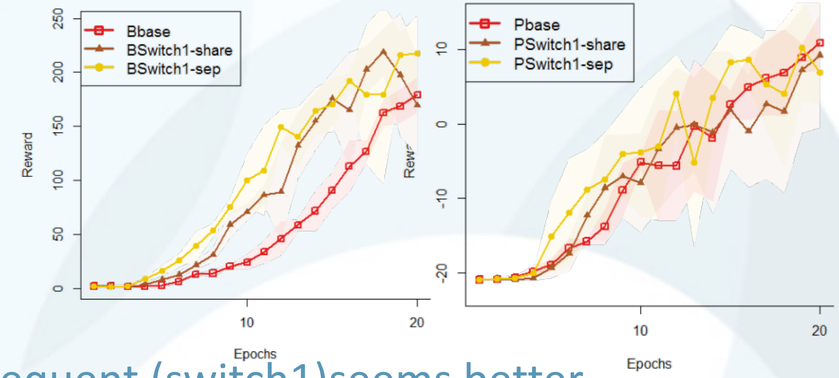
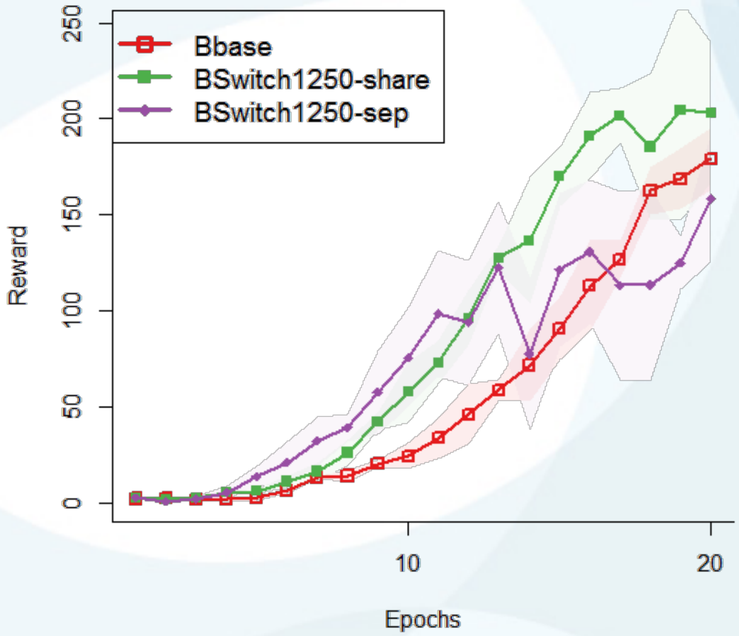


My Research

Multi-task Learning (MTL) in DQN

- How often should games be switched: more frequent (switch1)seems better
- Should experience replay memory be shared: no sharing (sep) seems better

Breakout



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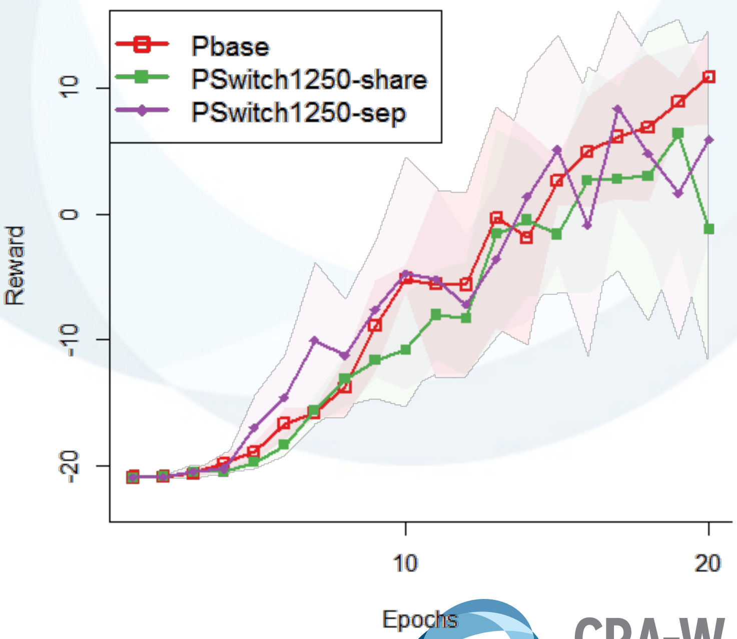

Switch every 1,250 step, share EM vs. not share EM

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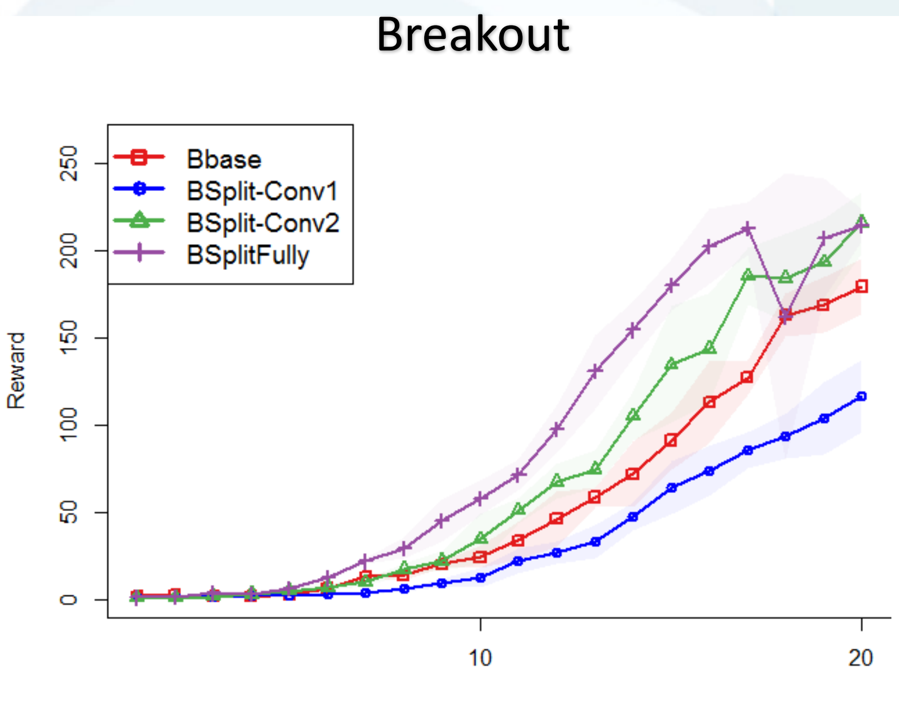
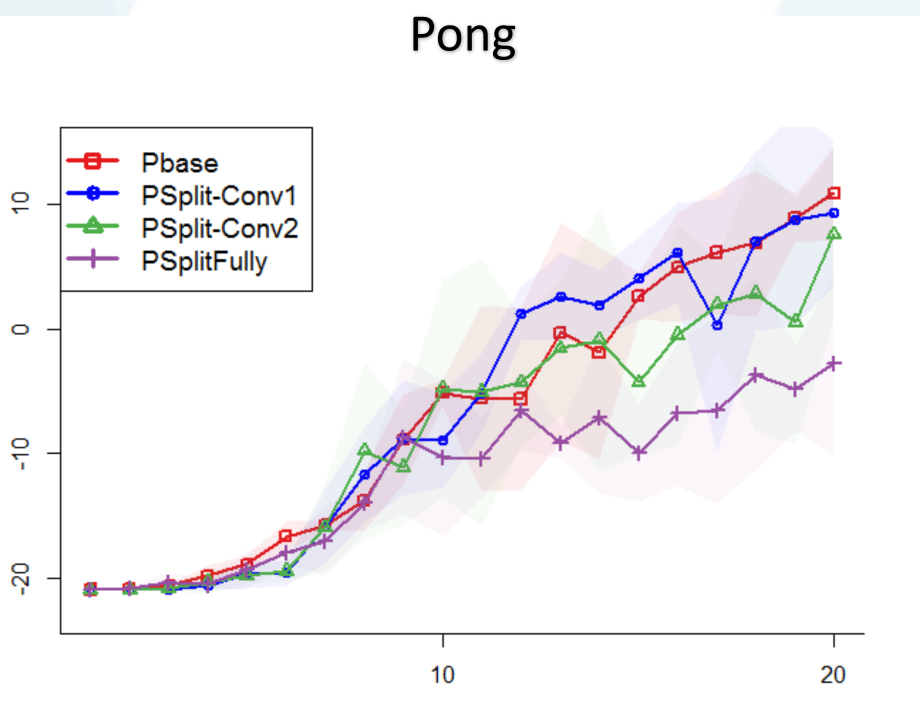
My Research

Multi-task Learning (MTL) in DQN

- At what point to split the original DQN network
  - at higher level (more sharing) seems better for Breakout, but worse for Pong





Split the network at different layers

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My Research

Take Away

- TL and MTL shows the potential of speeding up learning in DQN
- However, empirical results were not enough to draw a solid conclusion
- Future study
  - Test in more domains
    - Atari games: does not help all games and uncertain why
    - Continuous control problems
  - Knowledge selection for each layer in DQN
    - How to Interpret neural networks
  - Robust source/target task selection mechanism
    - How to measure the similarity between games
    - Can we automate the selection process

HOW TO CHOOSE A RESEARCH DIRECTION AS AN UNDERGRADUATE

Yunshu Du
Intelligent Robot Learning Laboratory
Washington State University

CRA-W Undergraduate Town Hall
July 27, 2017

The Intelligent Robot Learning Laboratory

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Outline

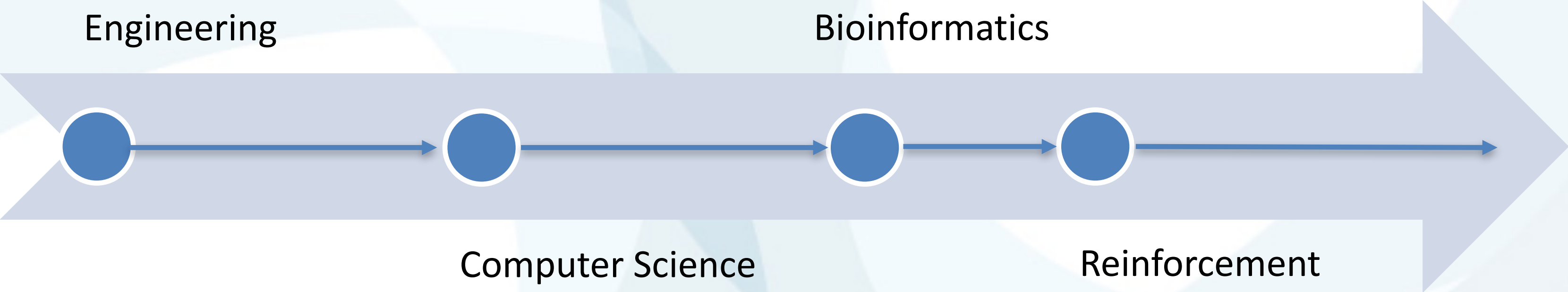
- I assume you have already know about how to participate in research
  - If not, there are previous VUTH sessions that provide great resources:
  - 12/1/16 Katherine Sittig-Boyd: Getting Involved in Undergraduate Research
  - 4/18/17 Rebecca Wright: Getting Involved in CS Extra-curricular Activities

- This is a general guide on how to pick a research project

- I will talk about how did I end up in my current direction

- Followed by a mini discussion panel with current undergraduate researchers in our department, we will cover:
  - How to find a project
  - What to expect
  - Other things to be considered

How did I pick my direction



Software Engineering

Computer Science

Geographic Information System

Bioinformatics

Reinforcement Learning

Deep Learning

Data Science

Voice From Current UG researchers

How to find a project

- Find what field are interested in
  - Machine Learning, Robotics, Software Security, Teaching Programming, etc.
  - Even if you don’t have a specific interest, you can still try something new
  - It is totally okay to change directions

- Find a professor/lab that does what you are interested in
  - Your current CS professor can point you in the right direction
  - Browse faculty page, email professors
  - Visit lab/office

- Discuss with professor
  - Brainstorm possible projects, it can be you own idea or pick from a list of what the professor is doing
  - If you want to work on an ongoing project, learn the current status of the project

What to expect

- You may have to do some self study on prerequisites
  - Understand what you need to know and build up from small pieces
  - Self study is research too (e.g., take an online class)!
  - You don’t need to be great to start, but you have to start to be great
- Research is high variance
  - Things might not work
  - Things might work extremely well
- Self motivation
  - Professors are not responsible for providing you a to-do list
  - Be proactive
  - Remember it is for your own development
- Have fun ☺
  - Not under high pressure
  - Meet new friends

Other considerations

- The people in the group
  - Not only knowing what research the professor/group members are doing, but also their personality
- Location
  - Will you be willing to spend months in that city
  - Do you like the lab environment
- If you will get paid
  - You could be more productive if there is a paycheck
- Time management
  - How long can you work per week and how is the hours allocated
  - Is the project feasible within the timeline you have