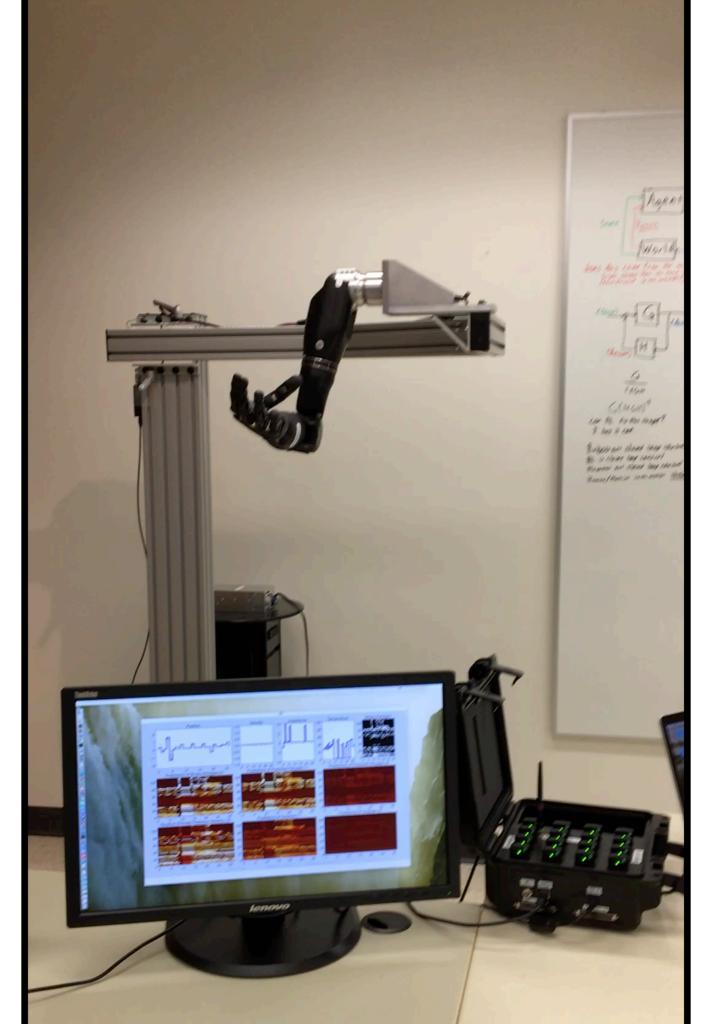
Reinforcement Learning (Without the Math)

Patrick M. Pilarski, Ph.D. Canada Research Chair & Assistant Professor

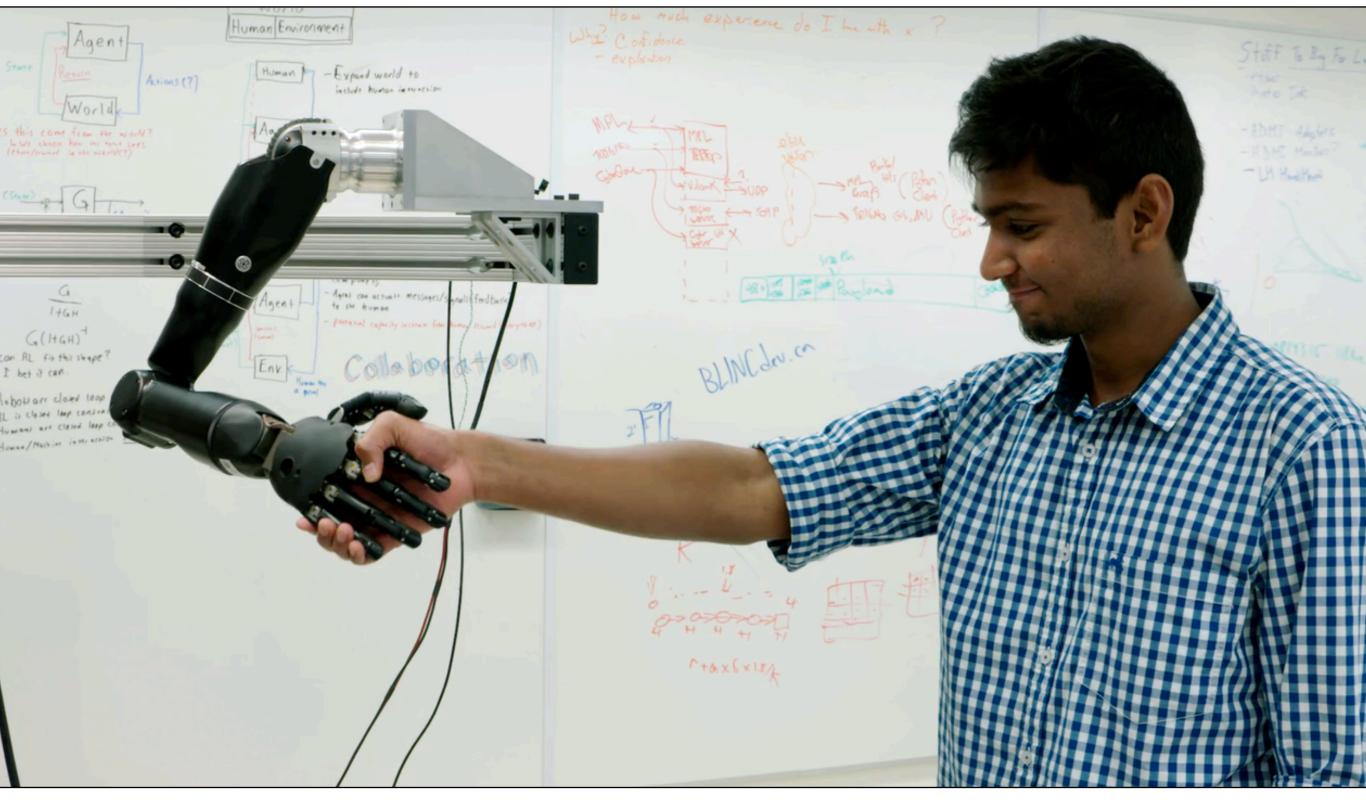
Division of Physical Medicine and Rehabilitation, Dept. Medicine PI, Alberta Machine Intelligence Institute (Amii) PI, Reinforcement Learning and Artificial Intelligence Laboratory



EDMONTON · ALBERTA · CANADA



Pilarski Lab Jan. 2017



Pilarski Lab August 2016

Why Intelligence?

- Enhanced control over a changing and increasingly complex world.
- Anticipation of future events and outcomes.
- General tools for solving hard problems.
- "Optimizing the control of complex systems and extracting knowledge from massive amounts of data."
- Examples: finance, healthcare, energy, resources, transport, information processing.

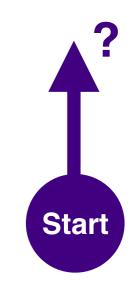
Why Learning?

• Things are Unknown:

End

known ends but unclear means.

- Things are Complex: scaling up is demanding or impossible.
- Things Change: systems need to adapt!



Why Learning?

End

Start

• Things are Unknown: known ends but unclear means.

• Things are Complex: scaling up is demanding or impossible.

• Things Change: systems need to adapt!

Why Learning?

• Things are Unknown: known ends but unclear means.

• Things are Complex: scaling up is demanding or impossible.

Start

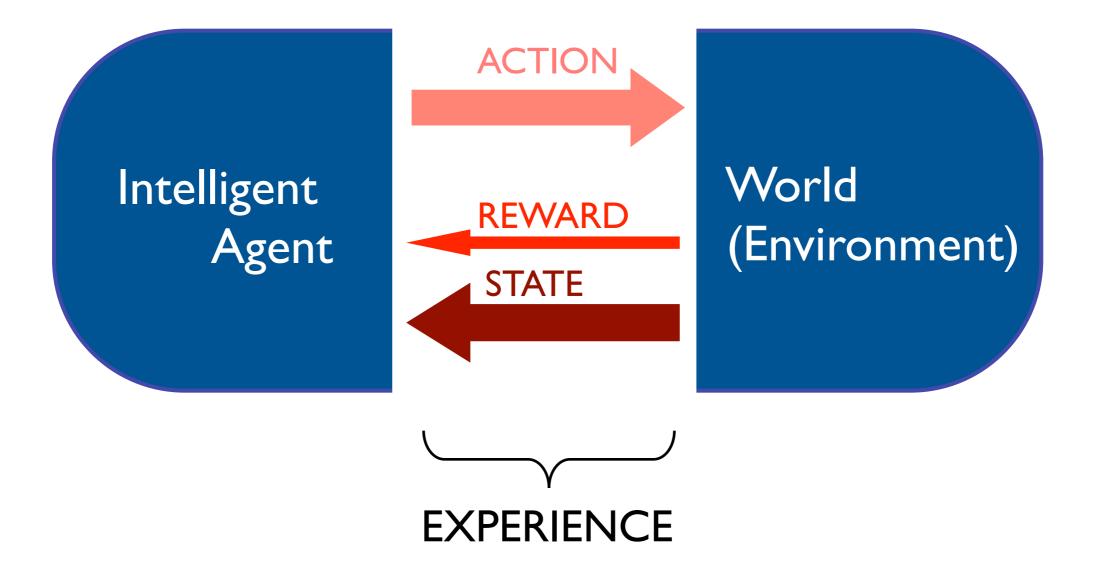
 Things Change: systems need to adapt!



KEY IDEA

Our ability to directly engineer an intelligent system no longer scales up to our goals or to the complexity of our problems of interest.

Reinforcement Learning



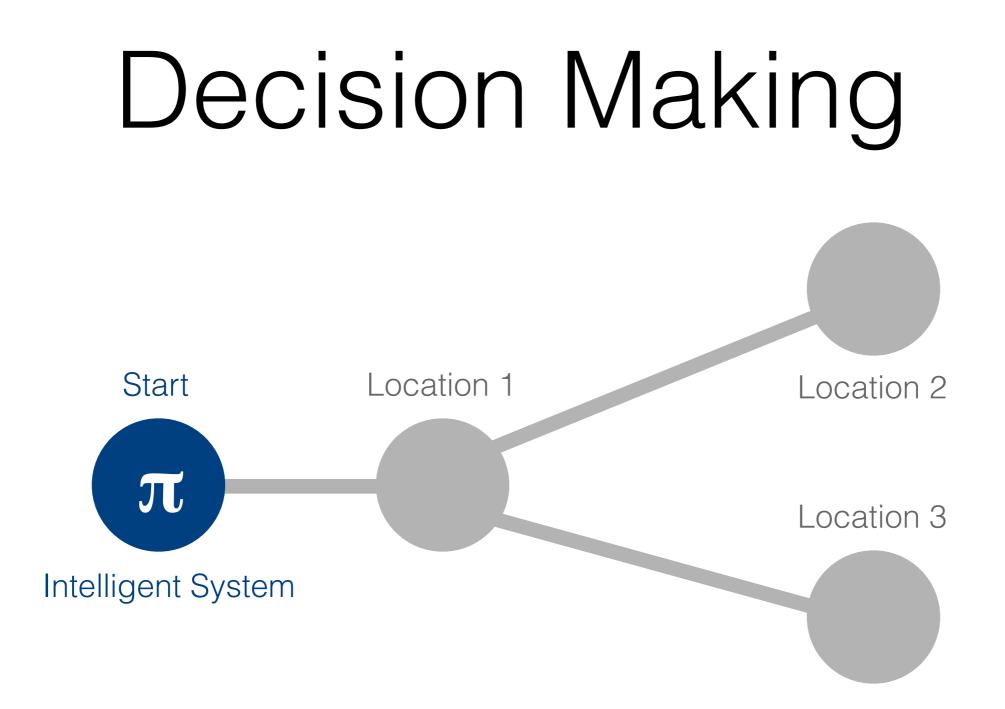
Reinforcement Learning is an approach to:

- Natural intelligence
- Artificial intelligence
- Optimal control
- Operations research
- Solving partially observable Markov decision processes

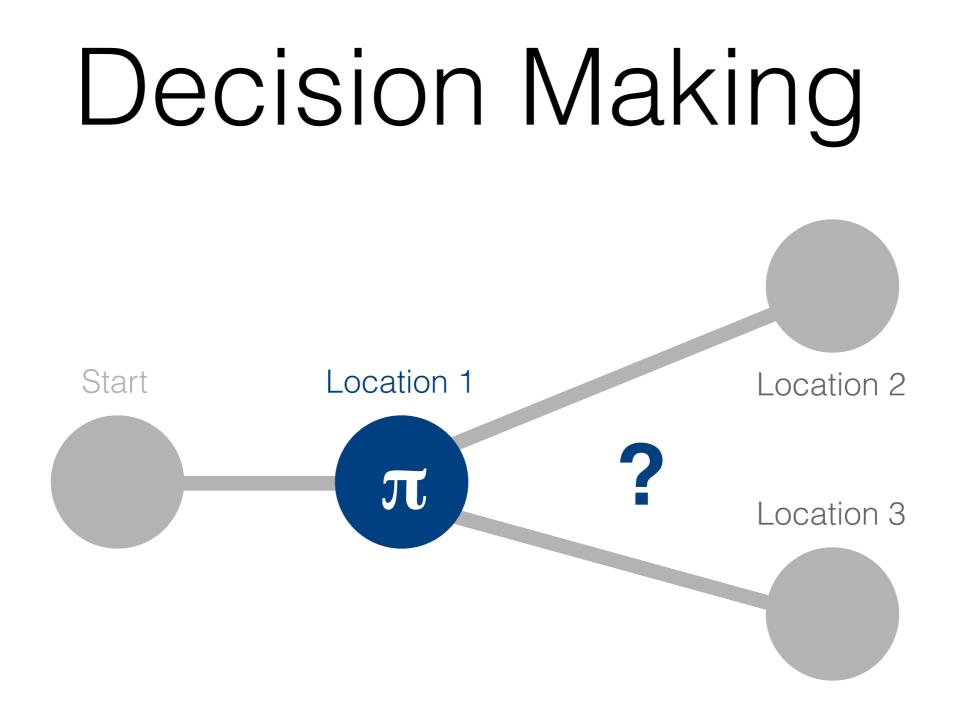
(and the perspective that all of these are the same)

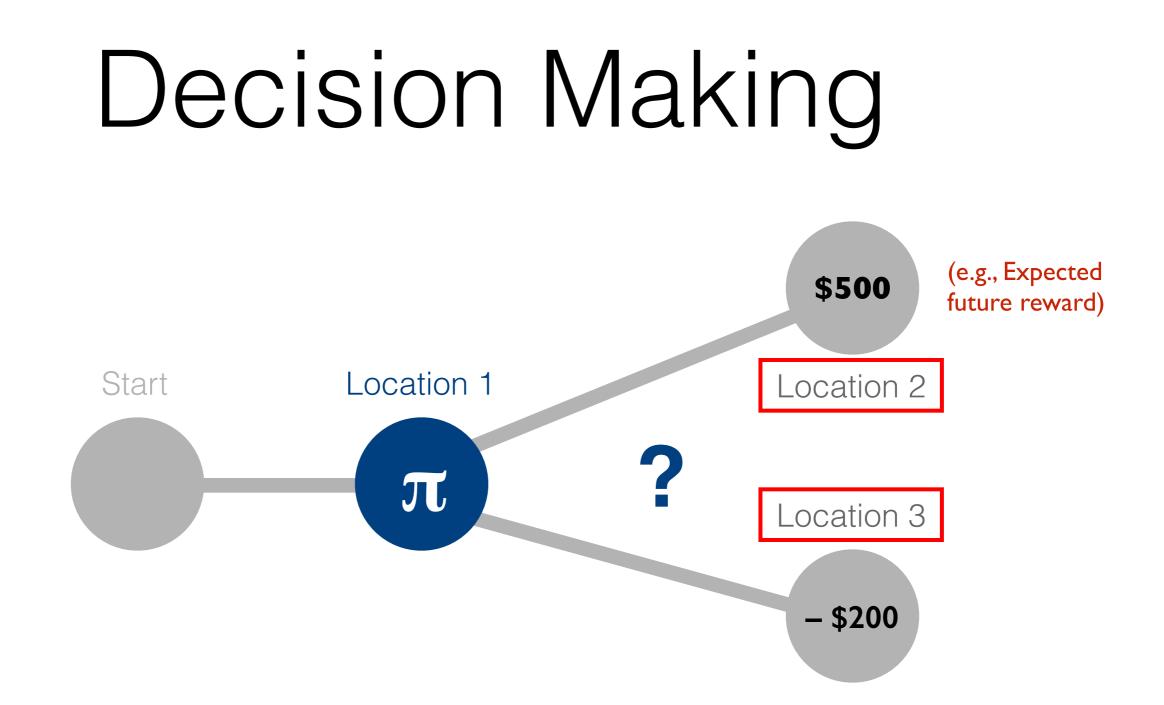
RL Headlines

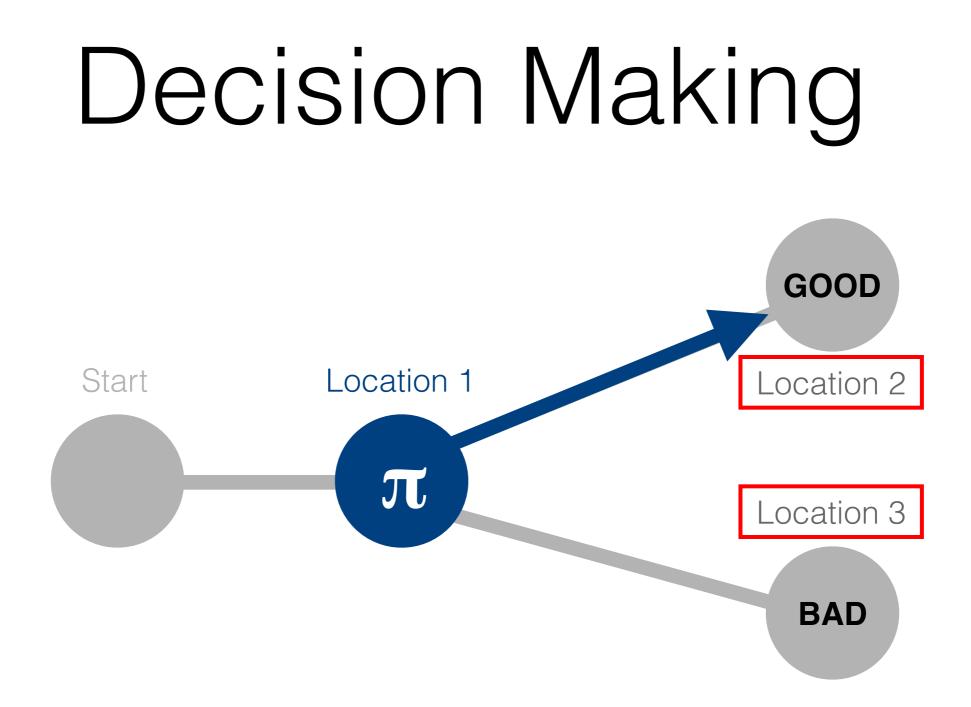
- RL is widely used in robotics
- RL algorithms have found the best known approximate solutions to many games (RL is part of the revolution in solving Go)
- RL algorithms are now the standard model of reward processing in the brain
- High-impact combinations of RL algorithms with deep neural networks.

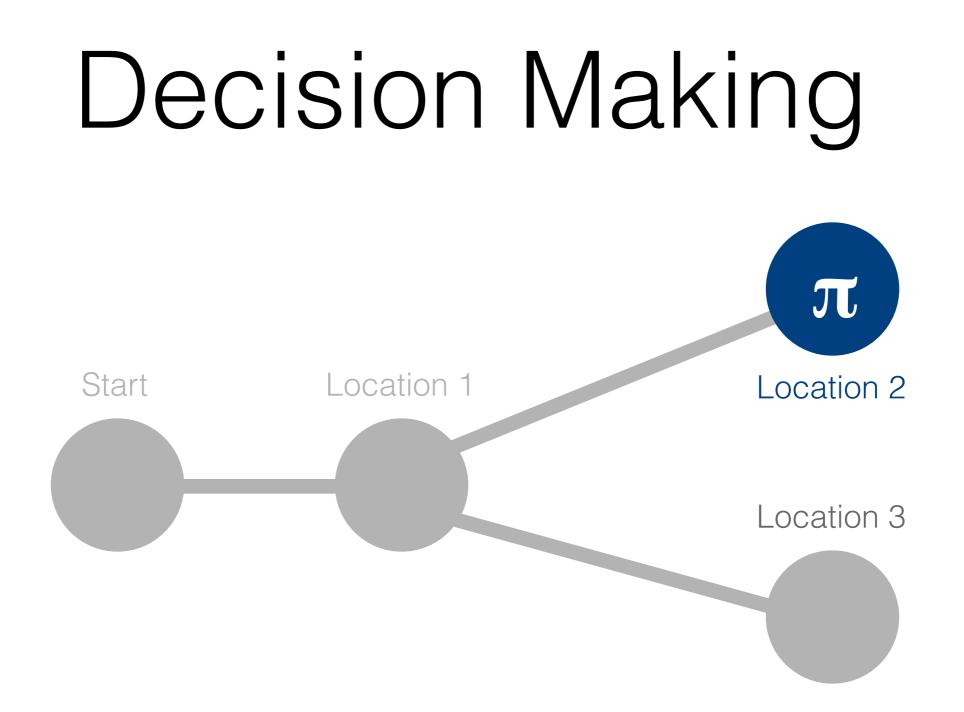


How to act so as to maximize reward?







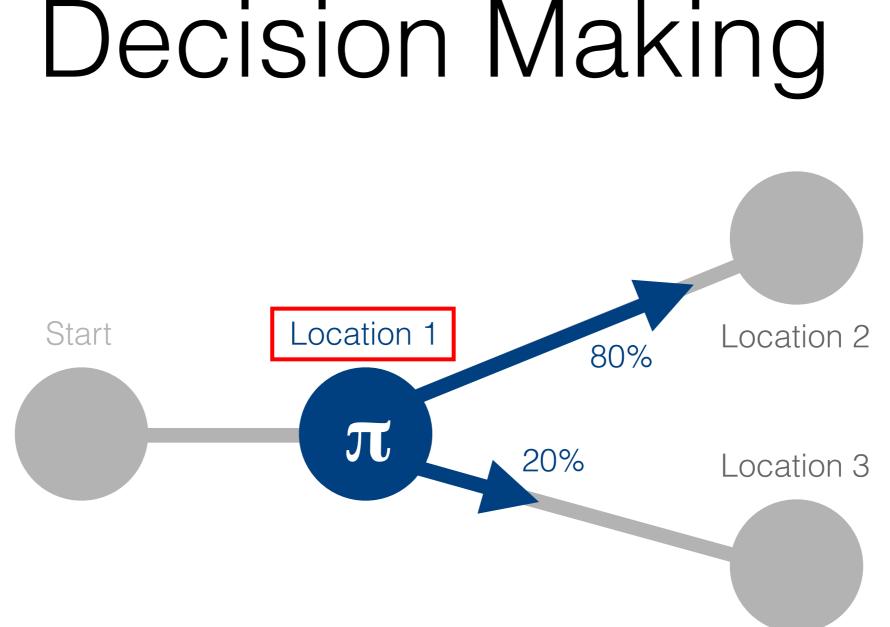


Decision Making Location 1 Start Location 2 π Location 3

By using reward to alter and improve a policy.

π 20% Location 3

By using reward to alter and improve a policy.



Decision Making π Location 1 Start Location 2 Location 3

By using reward to alter and improve a policy.

gw16x10 - gridworld/Gridworlds															
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Demonstration

Exercise 1: On-policy Prediction Learning

How do we learn values of states and actions?

Exercise 2: Control Learning

How can reward change how we behave?

Exercise 3: Control Learning from Good and Bad

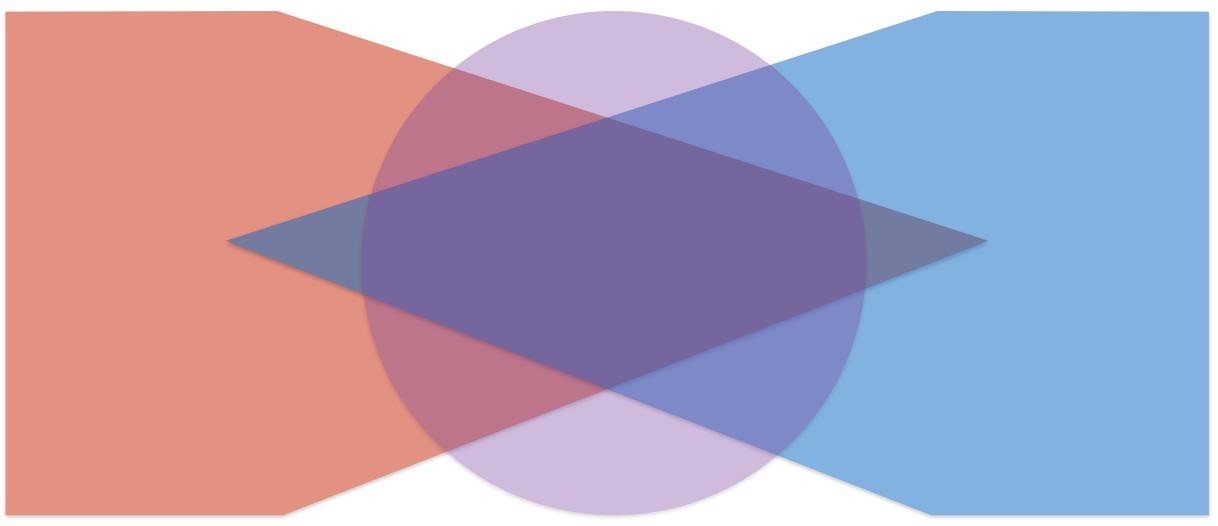
Dolphin training! (Thanks Kory!)

Exercise 4: Predictions + Reward

Predictive representations of state, a.k.a. you throw stuff at me.

ALGORITHMS

APPLICATIONS



ARCHITECTURES

Machines need to make **good decisions** in unknown, uncertain, or changing environments.

ALGORITHMS

APPLICATIONS

REPRESENTATION

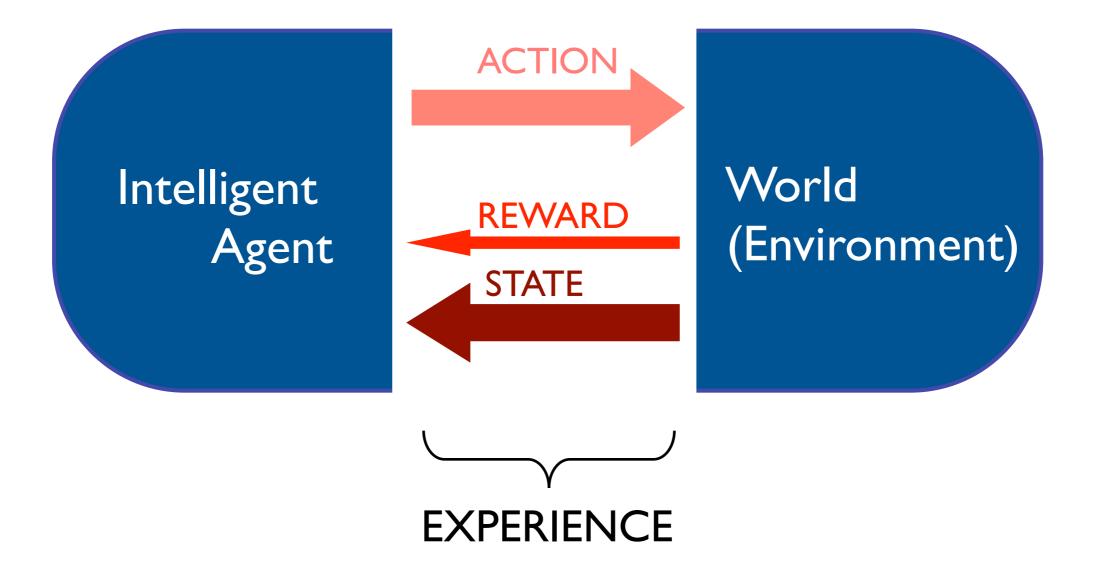
PREDICTION

CONTROL

ARCHITECTURES

These are all forms of **knowledge** and leverage a process of **continual learning**

Reinforcement Learning



Questions

... and thank you very much!

pilarski@ualberta.ca

http://www.ualberta.ca/~pilarski/

