A Collaborative Approach to the Simultaneous Multi-joint Control of a Prosthetic Arm

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Thanks to Patrick, Joseph and Rich

UNIVERSITY OF ALBERTA

RL & AI

BLINC

Problem with Prosthetic Control

Control Signals << DOC (DOF)

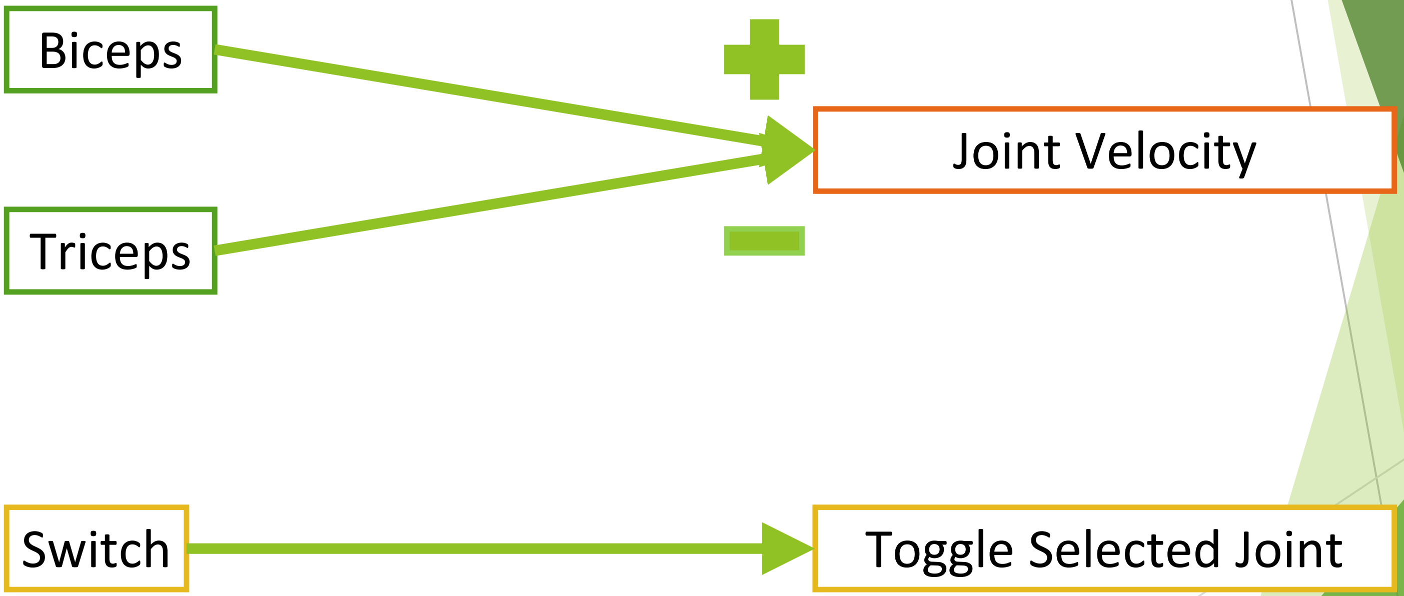
~ 20 DOF →

Modular Prosthetic Limb v3.0 – University of Alberta – March 20, 2015

Approaches to Prosthetic Control

- Neural Interfaces
  - Central
  - Peripheral
- Foot based controls
- EMG (Muscle Contractions)
  - Pattern Recognition
  - Toggling Proportional Control

Toggling Proportional Control



Our Approach

Wearable Intelligent Robot - that happens to be worn as an amputee’s arm

Incremental application of RL to complement existing control systems

Goal

- Improve control of prosthetic arms
  - Faster to complete tasks
  - Reduced burden on the amputee
  - Safer control

Desirables for an Intelligent Prosthetic Arm

- User behavior should inform system behavior.
- The system should adapt to user behavior and changing circumstances.
- Control should be as natural and consistent as possible.
- Smooth transitions between shared and solo control are desired, both from perspective of the user's experience as well as from the perspective of produced trajectories.
- The user must have a way to correct errors in learned behavior.
- The system should be easy to use, minimizing cognitive burden as much as possible.
- The user should maintain as much of a sense of control and embodiment over the arm as possible, while maximizing the practical functionality of the arm.
- The system **MUST** behave safely and predictably.

Pilarski (ICORR 2013)

- Different control approaches using predictions
  - Direct control based on prediction
  - Actor-critic control based on prediction
- 3 DOF arm
  - User controlled elbow and gripper
  - System controlled the wrist
  - Ideal wrist angle provided by system

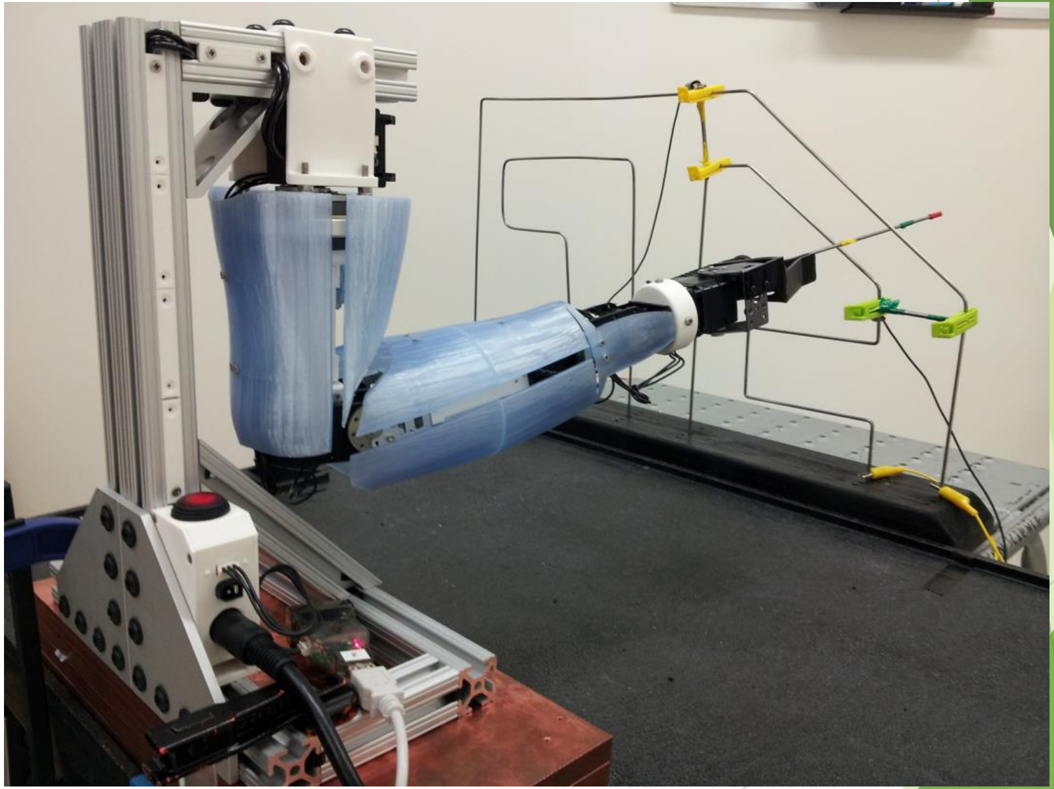
Coordinated Pre-emptive Motion

- Hypothesis:

Pre-emptively moving joints towards predicted targets can improve control of a prosthetic arm

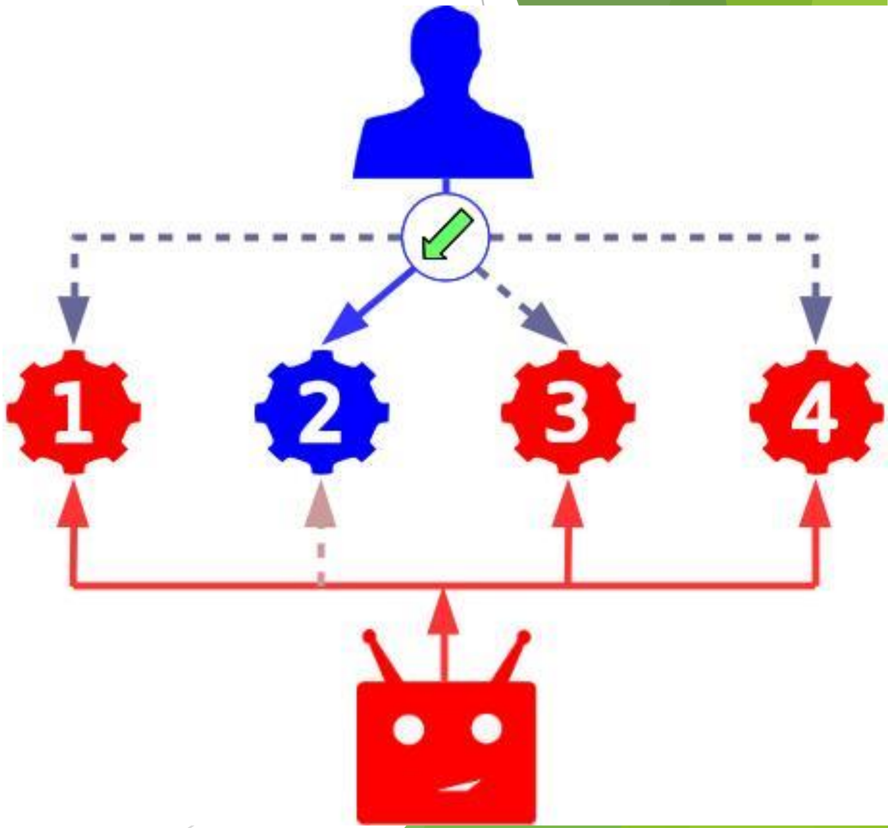
- How?
  - Predict directly from observation
  - Without adding additional inputs
  - While maintaining a user's sense of being in control

Bento Arm



Direct Predictive Collaborative Control

- User controls one joint at a time and can toggle
- AI controls the other joint
- Dead time (0.5s) after a joint toggle
- The AI only moves joints when the user moves their's



General Value Functions

Using TD algorithms (True Online TD(λ)) to predict measurable signals - not just *value*

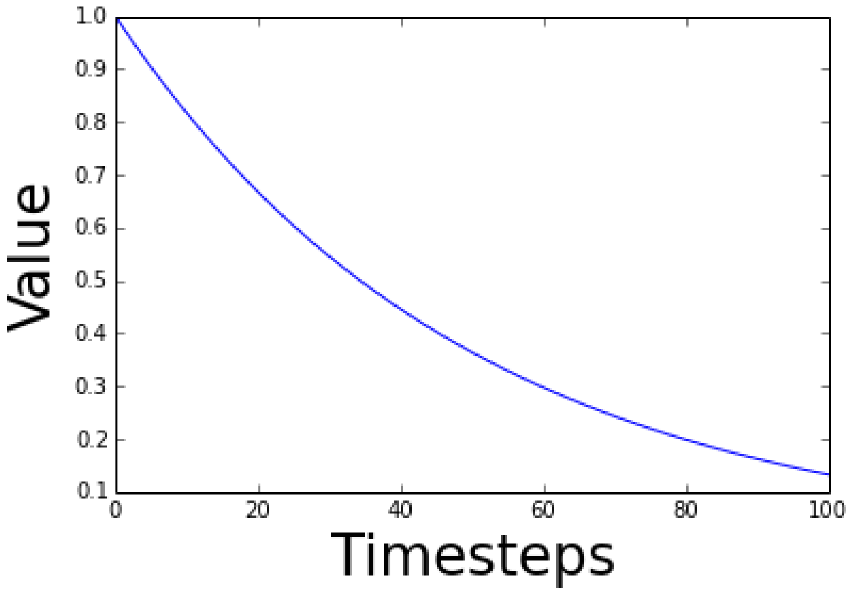
$$\delta_t = R_{t+1} + \gamma \theta_t^T \phi_{t+1} - \theta_t^T \phi_t$$

Pseudo-Reward ← Target Signal

Discounted Return

$$G_t^{(\tau)} + \sum_{i}^{\tau-t} \gamma^{i-1} R_{t+i}$$

$$\gamma = 1 - \frac{1}{\#\ of\ Timesteps}$$



Direct Predictive Collaborative Control

Prediction is used as the target:

$$V_{t+1} = (P^{\tau}_{t+1} - \theta_{t+1}) * k * r$$

Where

$$V_{t+1} - velocity\ for\ joint$$
$$P^{\tau}_{t+1} - predicted\ joint\ angle\ \tau\ timesteps\ into\ the\ future$$
$$\theta_{t+1} - current\ joint\ angle$$
$$k\ - scaling\ factor < 1$$
$$r\ - update\ frequency$$

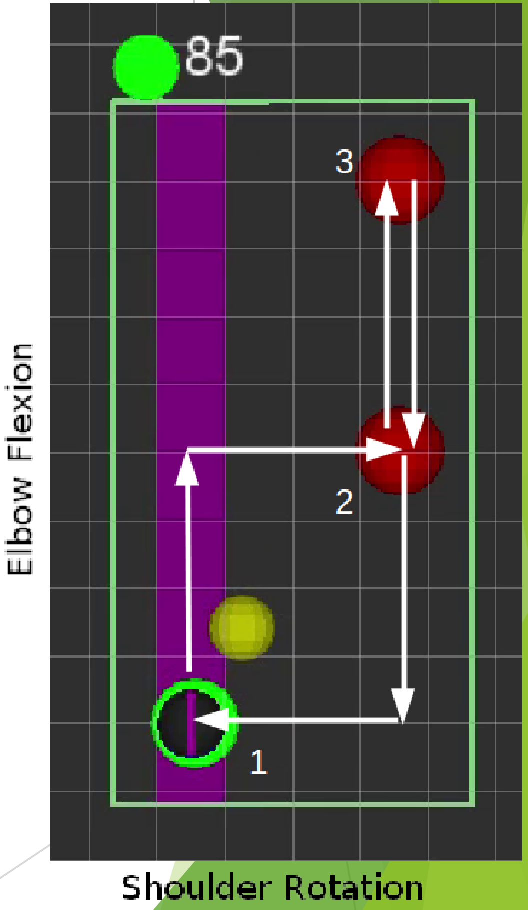
Waypoint Experiment

Navigate waypoints with a 2 DOF robot arm

Hold for 3 s at each waypoint

Visualization in joint space:

- Black Circle: location of arm in joint space
- Red: Waypoints
- Green Circle: location of arm falls within radius of waypoint
- Yellow Circle: prediction in joint space
- Purple Line: direction in which user can presently move



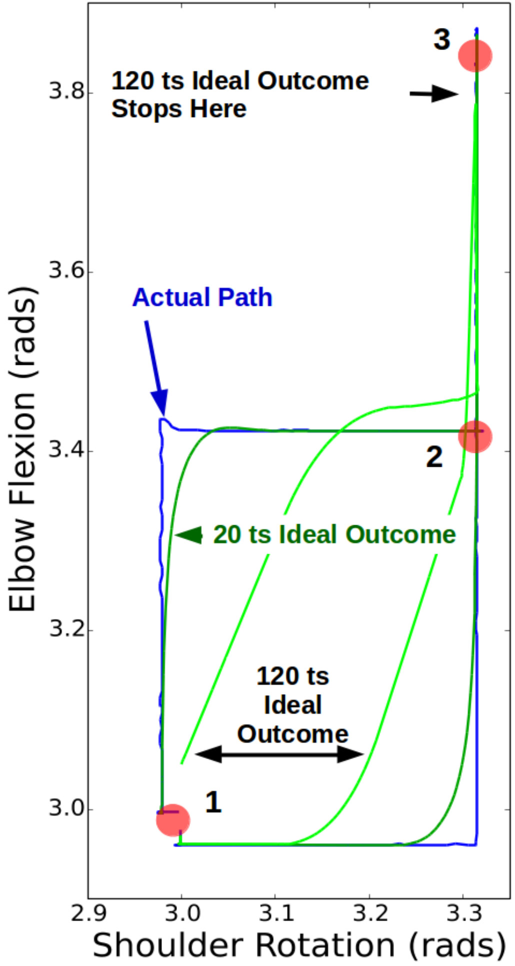
Features

- Elbow and Shoulder joint angles, and a decaying history on each
- Tile coding: 100 tilings of width 1 - Hash to 2048
- Bias Feature

Ideal Predictions

- 30 timesteps/s
- 20 ts = 0.667 s
- 120 ts = 4 s

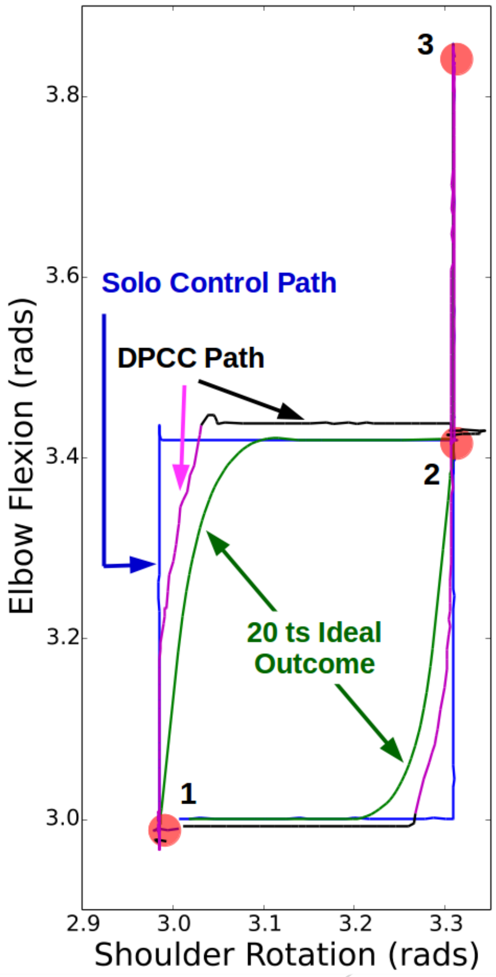
- A single timescale is inadequate



Resulting Paths

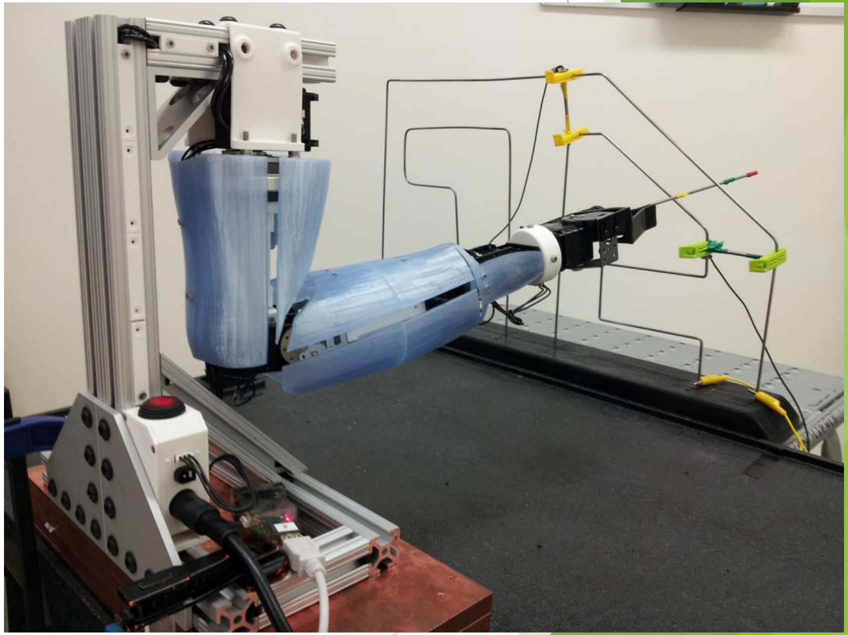
- Train Solo then go collaborative

- Predictions at 20 timesteps (2/3 s)
- User only control – Blue
  - Prediction – Green
- Collaborative Control
  - User controls elbow – Pink
  - User controls shoulder - Black



Wire Maze

- 2 DOF – Shoulder and Elbow
- Hold on Green 5 s
- Green -> Yellow
- Hold 5 s
- Yellow -> Green



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RL & AI

BLINC
BIONIC LIMBS FOR IMPROVED NATURAL CONTROL

Improved Performance

Toggle Count

	Average (STDEV)	Min
Solo (30 ccts)	15.1 (3.85)	10
DPCC (53 ccts)	7.83 (4.07)	1
Theoretical Best		0

Task Time (s)

	Average (STDEV)	Fastest
Solo (30 ccts)	32.3 (8.13)	21.9
DPCC (53 ccts)	26.3 (6.14)	14.9
Theoretical Best		12.8

Discussion

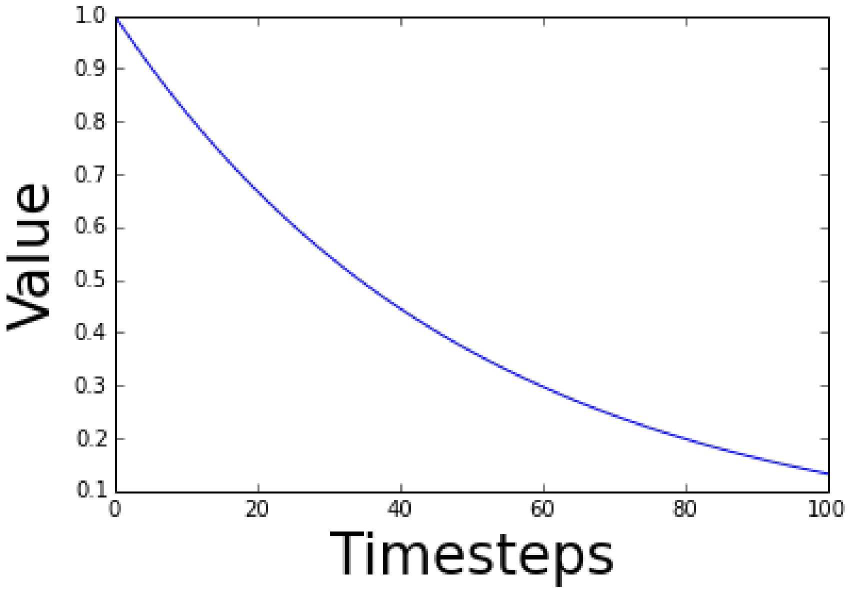
- Positive Feedback
  - Use is its own form of reinforcement
- Confidence/Uncertainty
  - Absolute TD Error
- Multiple Timescales
  - Select from several GVFs, each with a different timescale
  - Blend the output of many GVFs
  - State dependent Gamma
  - Reward Signal

Conclusion

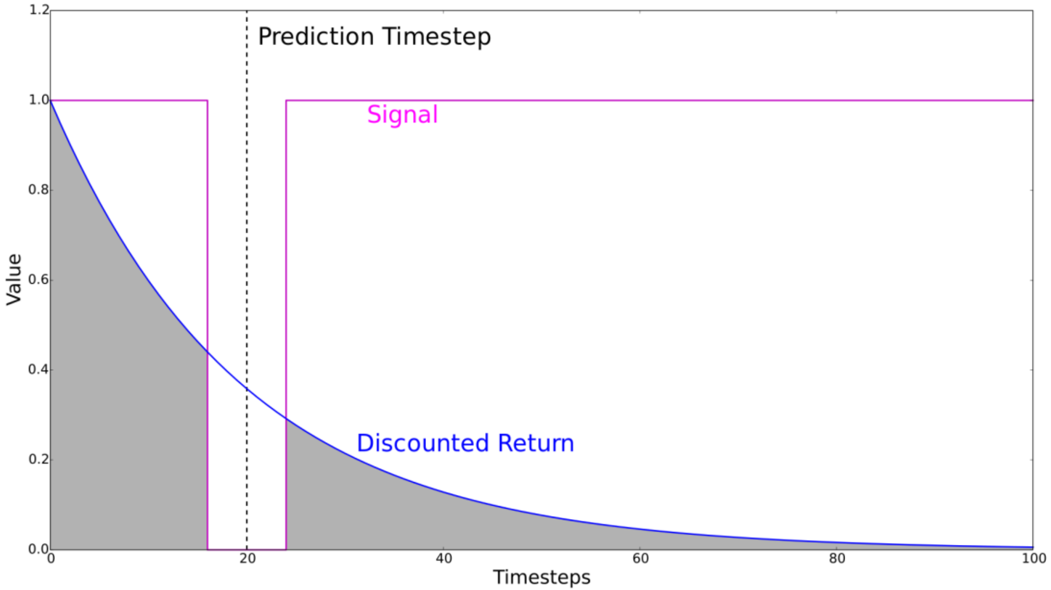
- Direct Predictive Collaborative Control
  - Enabled simultaneous multi-joint control of a robot arm – in a good way:
    - Reduced task time
    - Reduced number of toggles
  - Learned predictions directly from user behavior
  - Integrates nearly seamlessly with Toggling Proportional Control

Discounted Return

$$G_t^{(\tau)} + \sum_{i}^{\tau-t} \gamma^{i-1} R_{t+i}$$



Predicting a Notch Signal



Dual Signals