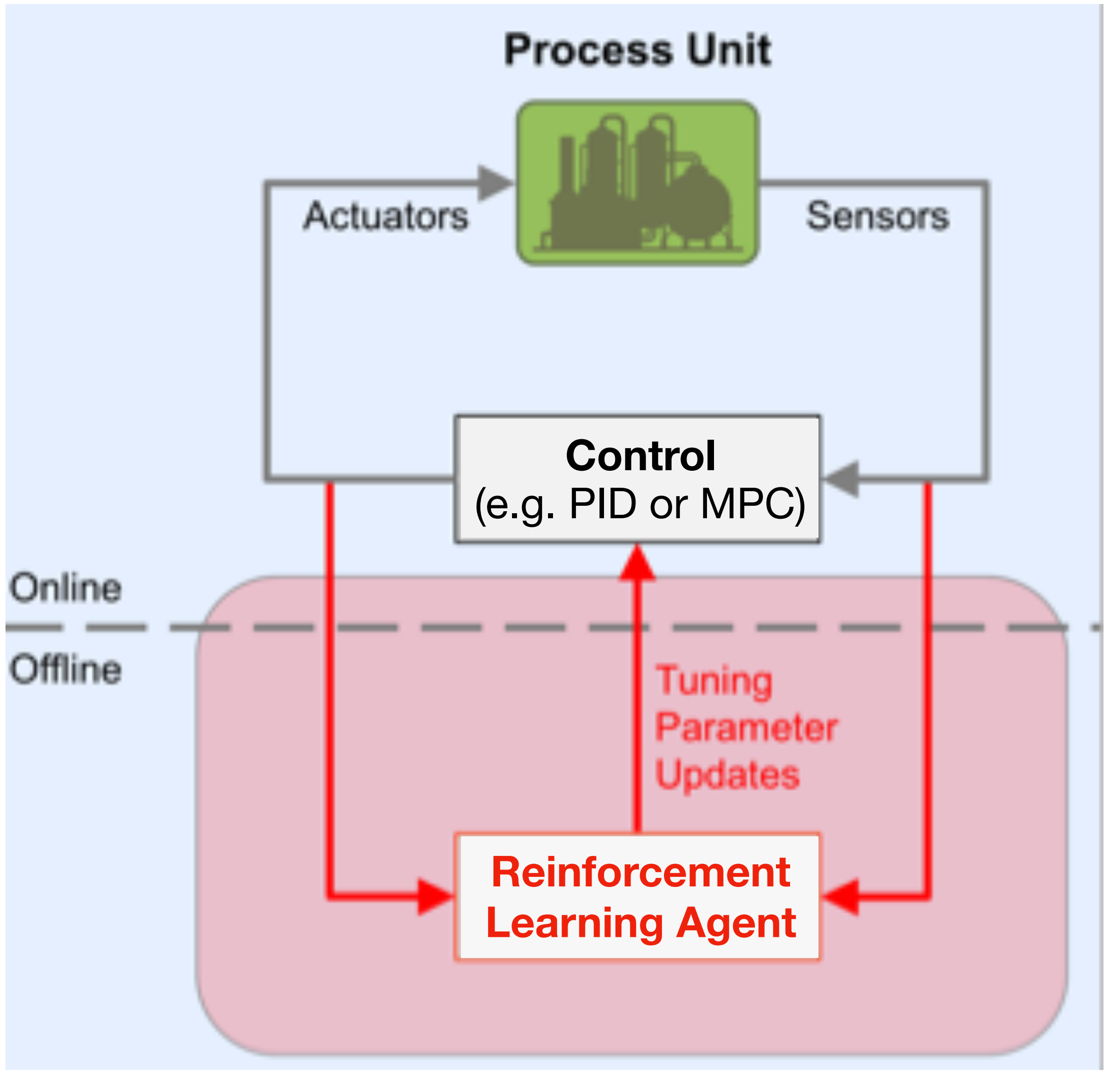


# Deep Reinforcement Learning Based Maintenance Free Control

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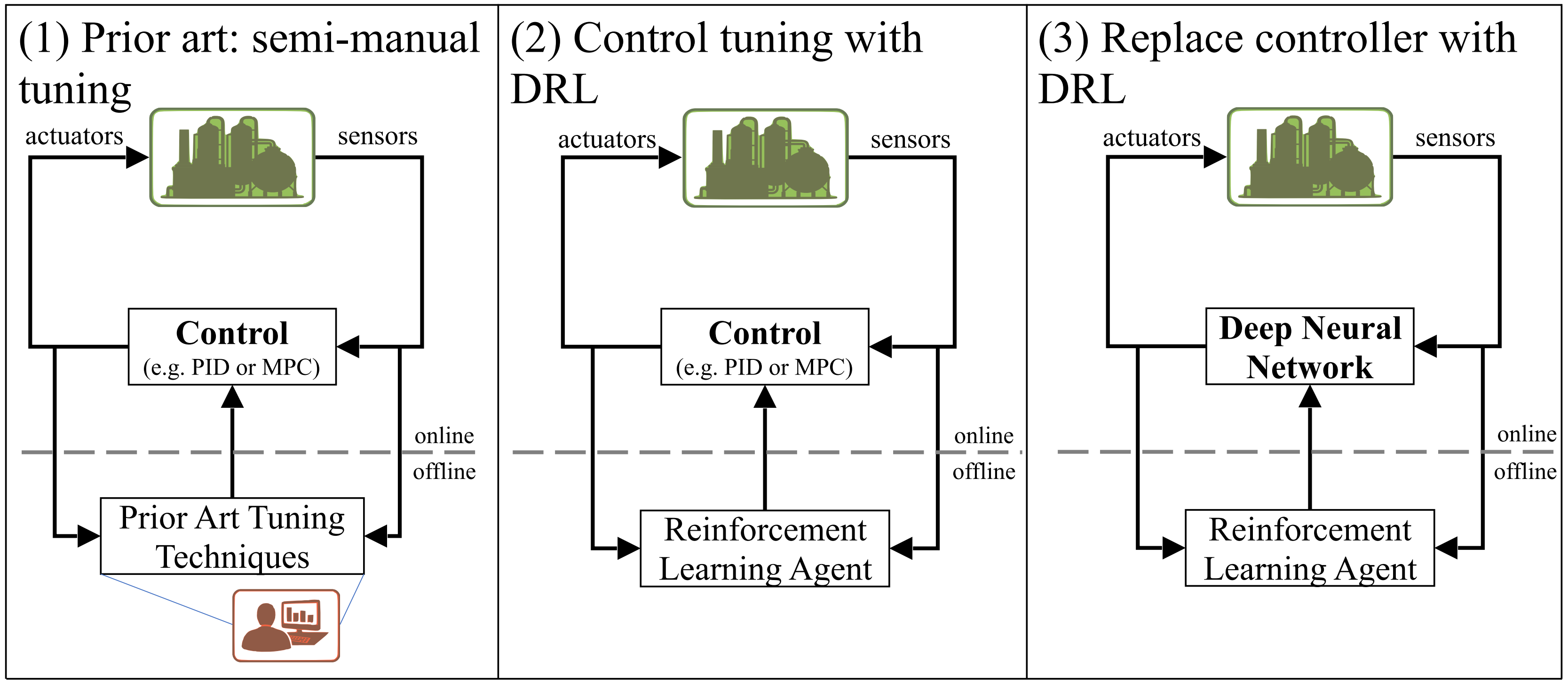
Collaborative R&D between UBC (Bhushan Gopaluni, Philip Loewen, Greg Stewart) and Honeywell (Michael Forbes, Johan Backstrom)

# Overview

- *Deep Reinforcement Learning* as a (model-free) framework for control in industrial settings

➡ Utilize new and historical data

➡ Control with minimal disruptions to the plant and minimal human intervention

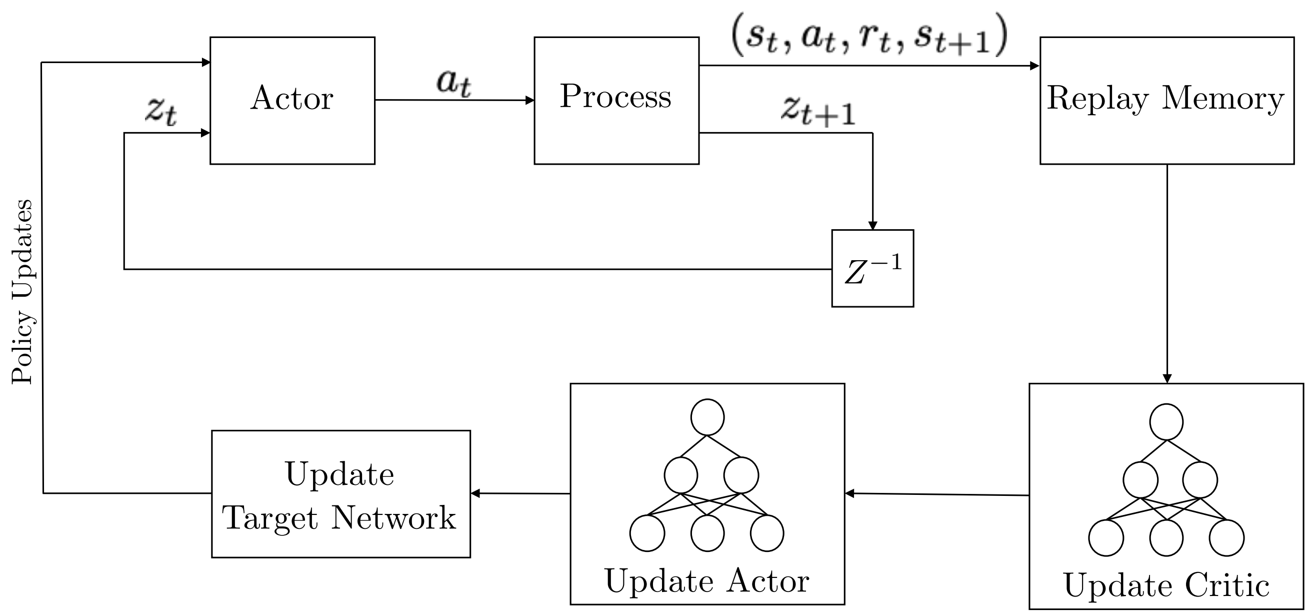


# Initial work

- Deep RL for set-point tracking

➡ Actor = controller = deep neural network

- Tracking performance and adaptability is promising, but issues with sample efficiency, stability, interpretability, compatibility, tuning of hyper-parameters





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Spielberg S, Tulsyan A, Lawrence NP, Loewen PD, Bhushan Gopaluni R. Toward self-driving processes: A deep reinforcement learning approach to control. AIChE J. 2019;e16689.

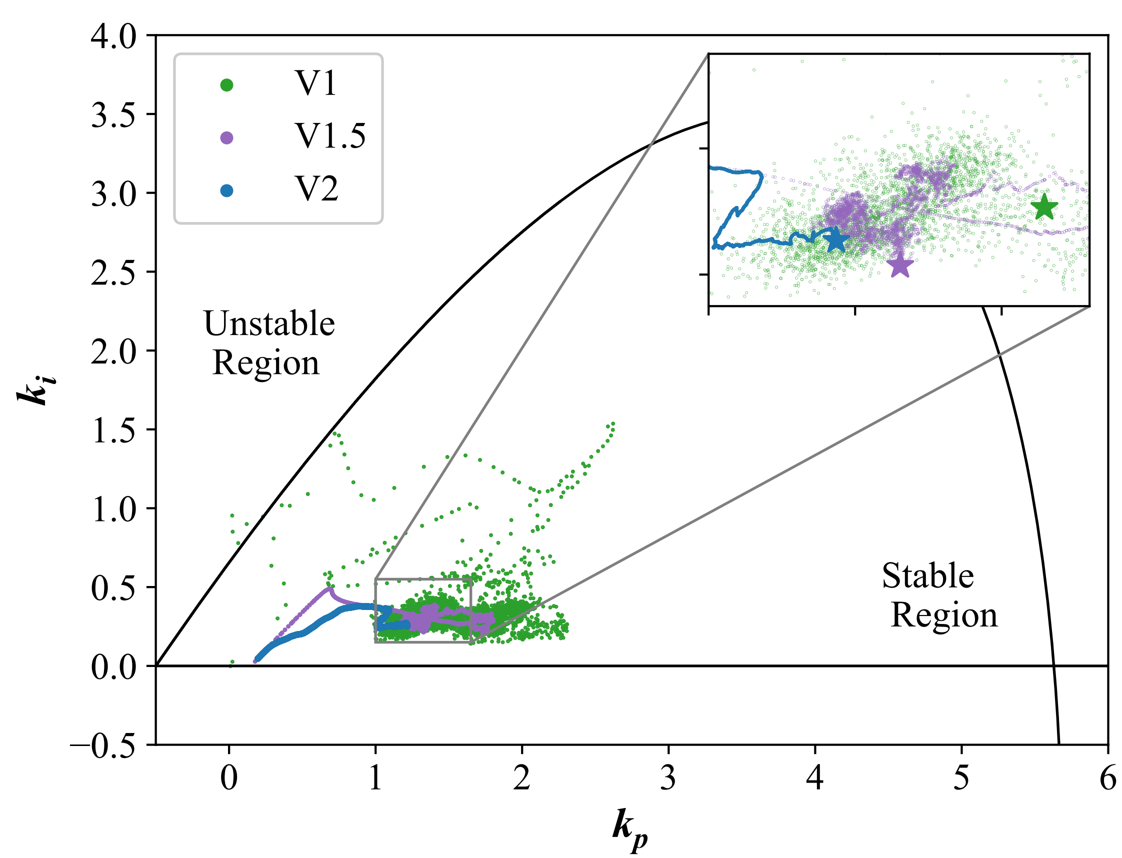
# Back to basics

- PID

$$u(t) = k_p e(t) + k_i \int_0^t e(\tau) d\tau + k_d \frac{d}{dt} e(t),$$

  fits naturally in the actor-critic framework

- Simple, industrially-accepted control structure with straightforward initialization




Lawrence NP, Stewart GE, Loewen PD, Forbes MG, Backstrom JU, Bhushan Gopaluni R. Optimal PID and antiwindup control design as a reinforcement learning problem. IFAC World Congress, submitted.

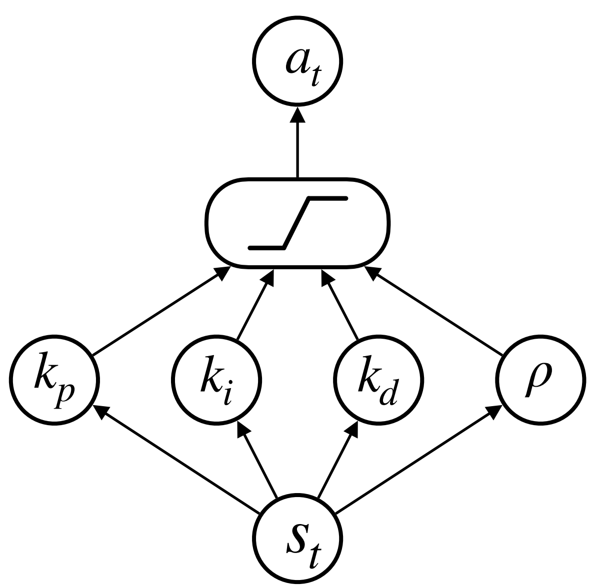
# Anti-windup

- Integral action with actuator constraints can lead to integral windup

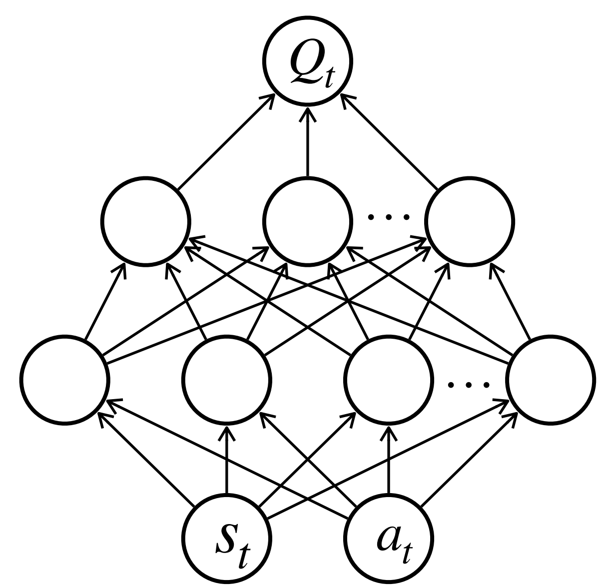
- PID + AW is the (nonlinear) actor

$$a_t = \text{sat}\left(k_p e + k_i I_y + k_d D + \rho I_u\right)$$

**(controller)**




**(performance)**

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