

CS 188 Robotics Week 6

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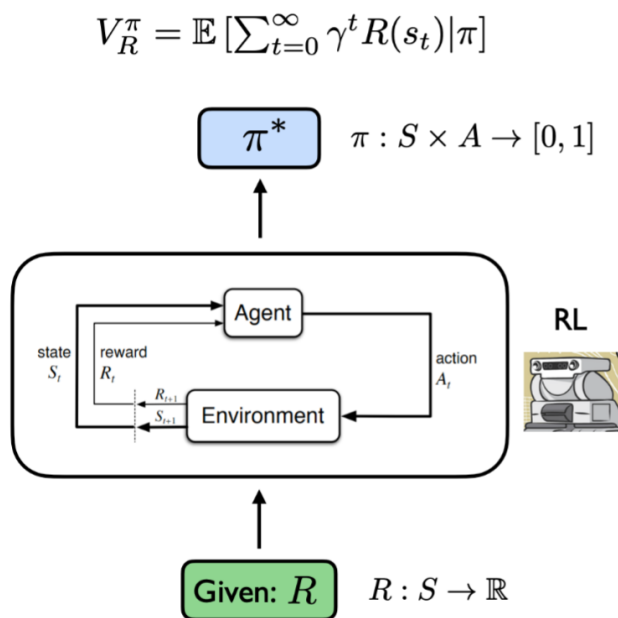
May 8, 2025

Imitation Learning

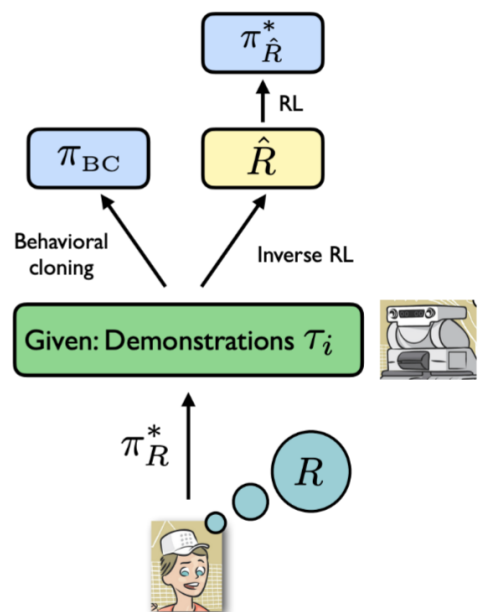
Specifying reward for RL is hard...

- **Reward hacking:** AI system learns to exploit loopholds or unintended behaviors in its reward function to achieve high rewards without actually accomplishing the intended task

Reinforcement Learning



Imitation Learning



slide credit: Scott Niekum

Why learn from demonstrations?

- Natural and expressive
- No expert knowledge required
- Valuable human intuition
- Program new tasks as-needed

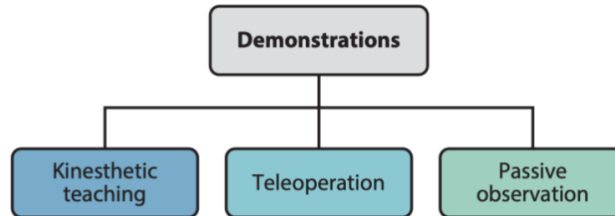
Human babies imitate adults when to learn.

How to Imitate?

Demonstrations to Autonomous Behavior

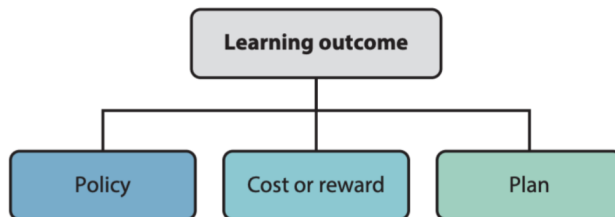
- Dynamic Movement Primitives (DMP): replay the motion
- **Behavior Cloning (BC)**: supervised learning of behavior
 - This is what everyone (as in, robotics companies) is trying to do
- Inverse Reinforcement Learning (IRL): inferring the underlying intent

Types of Demonstrations



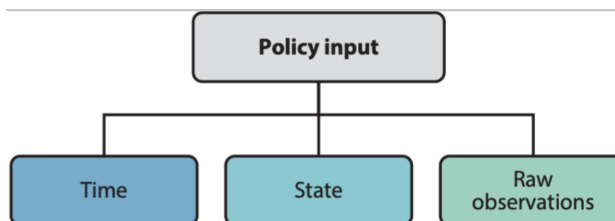
Demonstration	Ease of demonstration	High DOFs	Ease of mapping
Kinesthetic teaching	✓		✓
Teleoperation		✓	✓
Passive observation	✓	✓	

Learning Outcomes



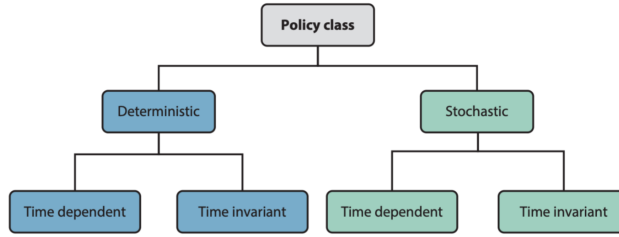
Learning outcome	Low-level control	Action space continuity	Compact representation	Long-horizon planning	Multistep tasks
Policy	✓	✓	✓		
Cost or reward	✓	✓		✓	
Plan			✓	✓	✓

Policy Parameterization



Policy input	Ease of design	Performance guarantees	Robustness to perturbations	Task Variety	Algorithmic efficiency
Time	✓	✓			✓
State		✓	✓		✓
Raw observations	✓		✓	✓	

Policy Class



Policy class	Temporal context	Robustness to temporal perturbations	Repeatability	Multimodal behavior
Deterministic and time dependent	✓		✓	
Deterministic and time invariant		✓	✓	
Stochastic and time dependent	✓			✓
Stochastic and time invariant		✓		✓

Dynamic Movement Primitives (DMP)

$$\begin{aligned}\tau \dot{v} &= K(\underline{g} - x) - Dv + (\underline{g} - \underline{x}_0) f \\ \tau \dot{x} &= v\end{aligned}$$

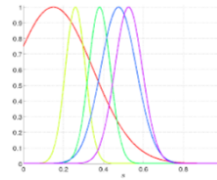
K: spring constant
D: damping term

Non-linear force function:

$$f(s) = \frac{\sum_i w_i \psi_i(s) s}{\sum_i \psi_i(s)}$$

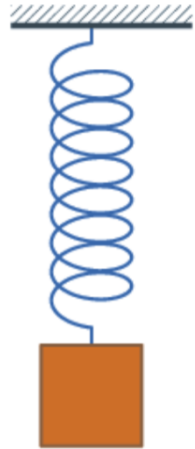
$$\psi_i(s) = \exp(-h_i(s - c_i)^2)$$

Gaussian basis functions



canonical system: $\tau \dot{s} = -\alpha s$

s: phase variable



Learning:

$$f_{\text{target}}(s) = \frac{-K(g - x) + Dv + \tau \dot{v}}{g - x_0}$$

$$f(s) = \frac{\sum_i w_i \psi_i(s) s}{\sum_i \psi_i(s)}$$

$$J = \sum_s (f_{\text{target}}(s) - f(s))^2$$

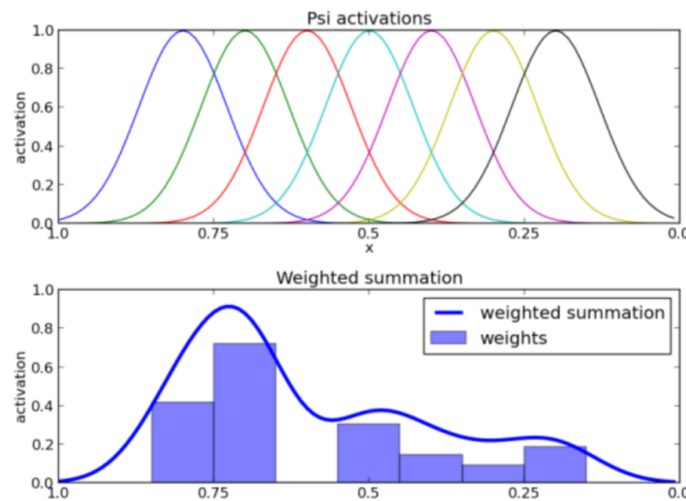
Linear regression

Pastor, Peter, et al. "Learning and generalization of motor skills by learning from demonstration." 2009 IEEE international conference on robotics and automation. IEEE, 2009.

Characteristics of DMPs

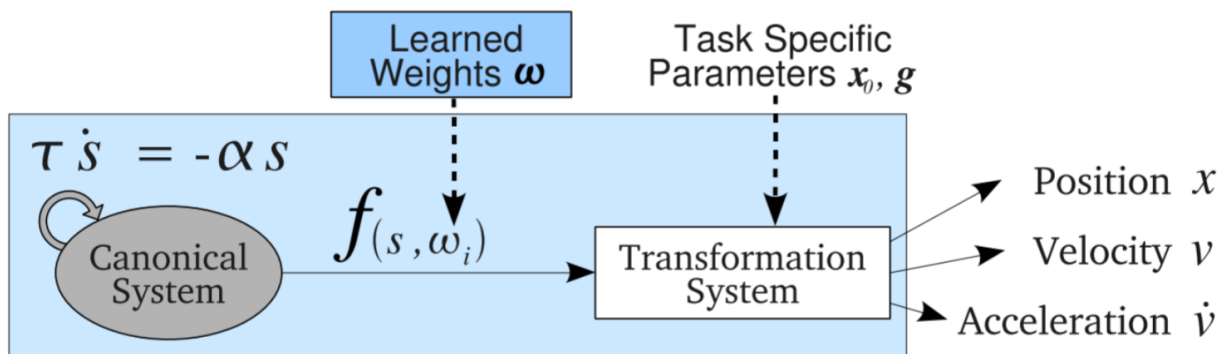
- Convergence to the goal g is guaranteed (for bounded weights) since $f(s)$ vanishes at the end of a movement
- The weights w_i can be learned to generate any desired *smooth* trajectory.
- The equations are spatial and temporal invariant, i.e., movements are self-similar for a change in goal, start point, and temporal scaling without a need to change the weights w_i
- The formulation generates movements which are robust against perturbation due to the inherent attractor dynamics of the equations.

Weighted Sum of Gaussian Basis



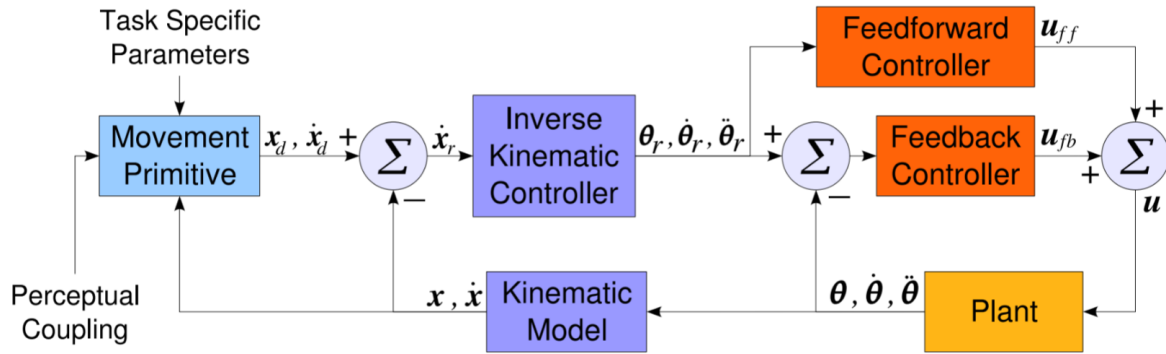
<https://studywolf.wordpress.com/2013/11/16/dynamic-movement-primitives-part-1-the-basics/>

Dynamic Movement Primitives



Sketch of a one dimensional DMP: the canonical system drives the nonlinear function f which perturbs the transformation system.

Pastor, Peter, et al. "Learning and generalization of motor skills by learning from demonstration." 2009 IEEE international conference on robotics and automation. IEEE, 2009.

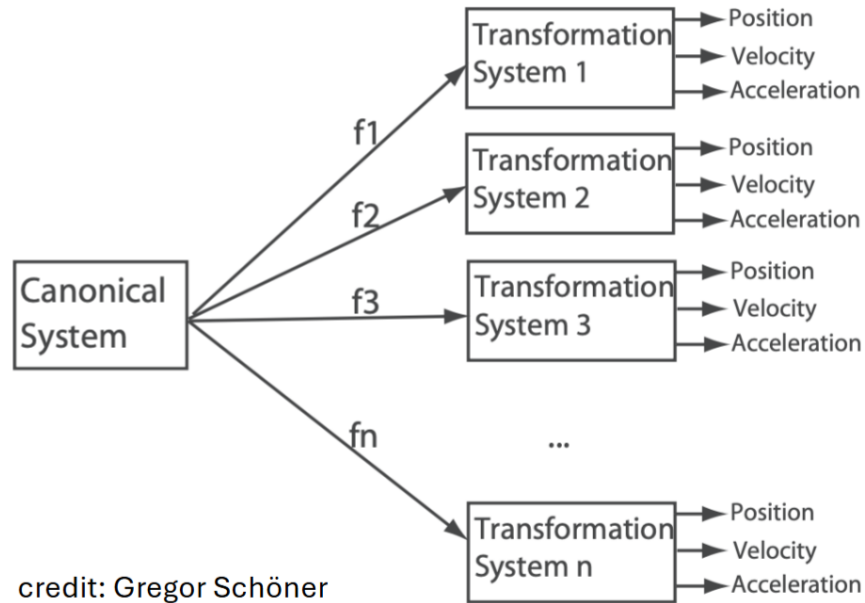


DMP control diagram: the desired task space positions and velocities are x_d, \dot{x}_d , the reference task space velocity commands are \dot{x}_r , the reference joint positions, joint velocities, and joint accelerations are $\theta_r, \dot{\theta}_r$, and $\ddot{\theta}_r$.

Pastor, Peter, et al. "Learning and generalization of motor skills by learning from demonstration." 2009 IEEE international conference on robotics and automation. IEEE, 2009.

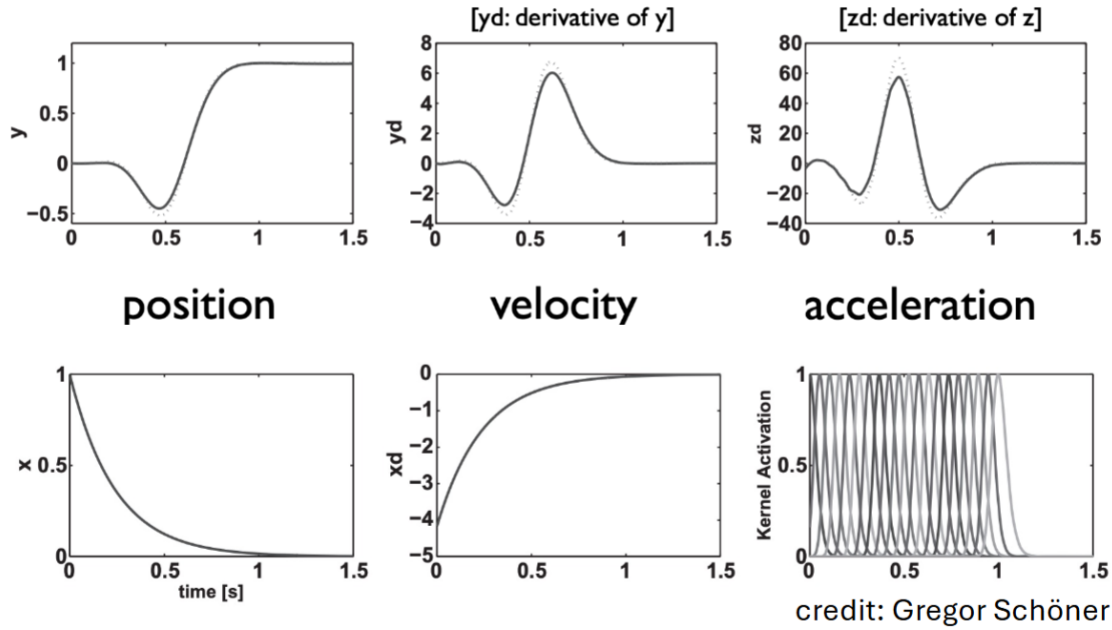
Multidimensional

- one central harmonic oscillator
- multiple transformations

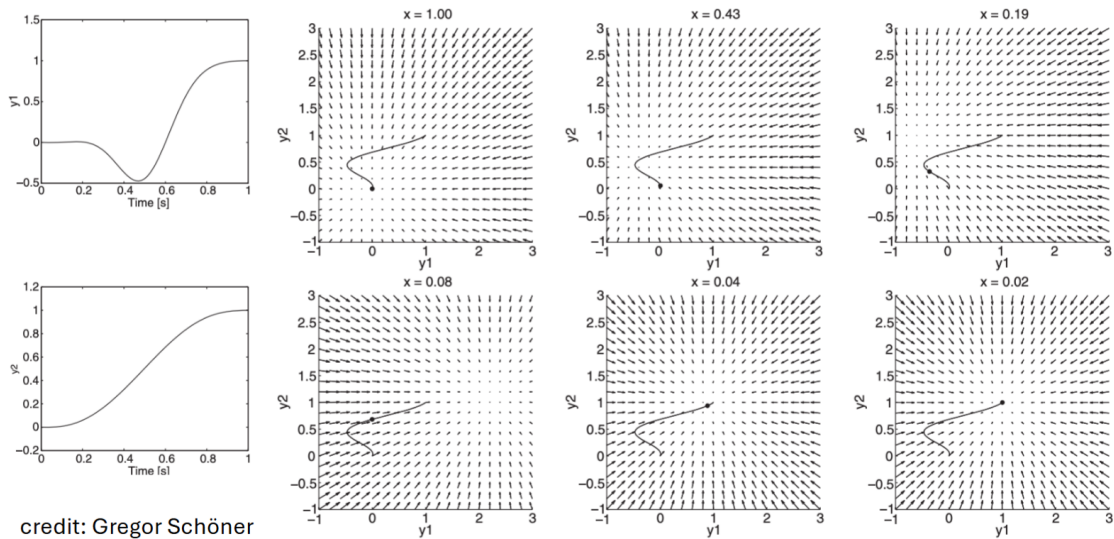


Examples:

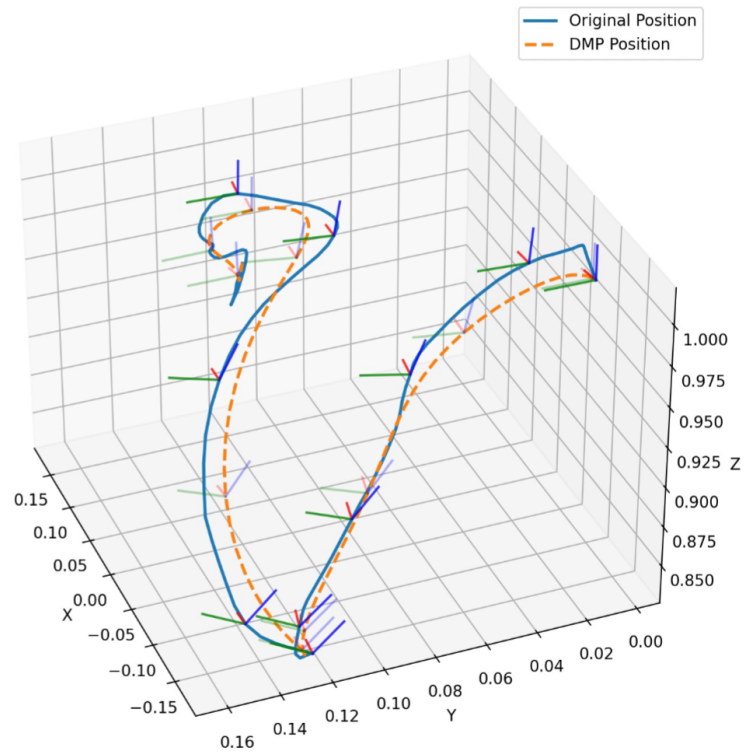
- 1 Dimensional:



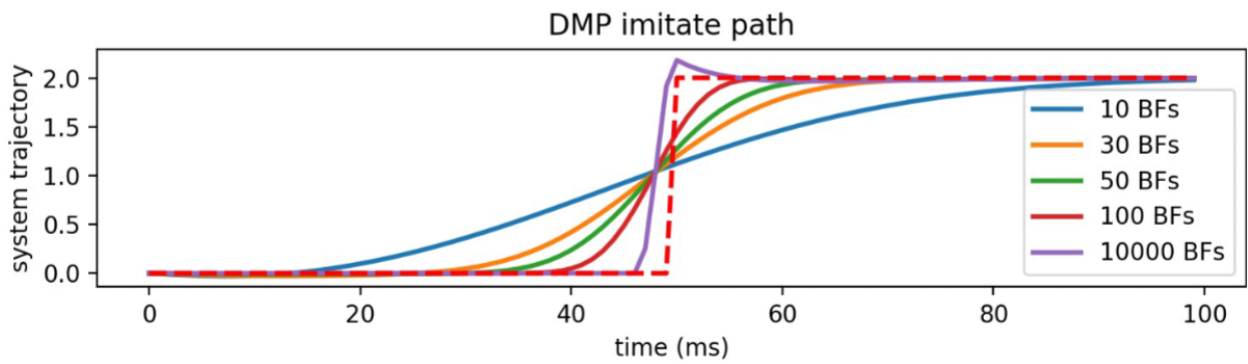
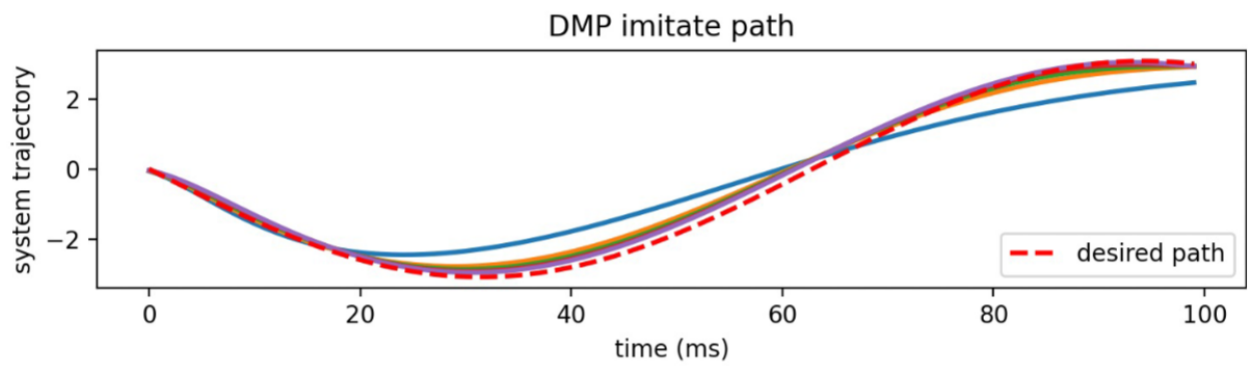
- 2 Dimensional:



- 3 Dimensional / 6 Dimensional:



Limitations of DMPs



Summary

- DMP enable learning "movement styles" while enabling generalization to new movement targets
- DMP is a purely kinematic account \Rightarrow DMP is not addressing control in that respect, analogy to force-fields is misleading
- DMP addresses timing, but account of coordination is limited
- DMP for different tasks and their combination...?

IID (Independent and Identically Distributed)

Imitation Learning

[FILL 7]

Supervised Learning

[FILL 9]

The i.i.d. Assumption

- "The training and testing data are **independent** and **identically** distributed."

[FILL 11] [FILL 12, incl red text]

- **Robustness** refers to the ability of a system, model, or method to maintain performance or produce reliable results **despite variations, noise, errors, or adversarial conditions** in the input or environment.

Input Data Distribution

- End-to-End Control Tasks [FILL 13]
- Markov Decision Process $\langle S, A, P, R \rangle$ [FILL 14, 15]

Behavioral Cloning

[FILL 16] Downside: The robot learns similarly to what you tell it to do, but may not be able to apply the situation. For example, if you train a robot to turn right, it may turn right spontaneously while driving on a very long, straight road.

Challenges in Imitation Learning

[FILL 18]

Quadratic Regret

- **Regret** (in decision theory) measures the difference between the reward (or outcome) one actually received and the best possible reward one *could have received* if one had made the optimal choice

$$\hat{\pi}_{sup} = \arg \min_{\pi \in \Pi} \mathbb{E}_{s \sim d_{s^*}} [l(s, \pi)]$$

- Assuming $l(s, \pi)$ is the 0-1 loss (or upper bound on the 0-1 loss) implies the following performance guarantee with respect to any task cost function C bounded in $[0, 1]$:

- **Theorem 2.1** (Ross and Bagnell, 2010), *Let $\mathbb{E}_{s \sim d_{s^*}}[l(s, \pi)] = \epsilon$, then $J(\pi) \leq K(\pi^*) + T^2\epsilon$.*
- Compare to typical supervised learning loss that grows as: $O(\epsilon T)$

Ross, Stéphane, Geoffrey Gordon, and Drew Bagnell. "A reduction of imitation learning and structured prediction to no-regret online learning." *Proceedings of the fourteenth international conference on artificial intelligence and statistics*. JMLR Workshop and Conference Proceedings, 2011.

Dagger: Dataset Aggregation

End-to-End Control Tasks [FILL 21]

```

initialize  $\mathcal{D} \leftarrow \emptyset$ 

initialize  $\hat{\pi}_1$  to any policy in  $\Pi$ 

for i = 1 to N do:
    Let  $\pi_i = \beta_i \pi^* + (1 - \beta_i) \hat{\pi}_i$ 
    Sample  $T$ -step trajectories using  $\pi_i$ 
    Get dataset  $\mathcal{D}_i = \{(s, \pi^*(s))\}$  of visited states by  $\pi_i$  and actions given by expert.
    Aggregate datasets:  $\mathcal{D} \leftarrow \mathcal{D} \cup \mathcal{D}_i$ 
    Train classifier  $\hat{\pi}_{i+1}$  on  $\mathcal{D}$ 

return best  $\hat{\pi}_i$  on validation

```

Key idea: keep collecting demonstration data that is on-distribution for current policy, and reduce dependence on expert over time

- **Theorem 2.2** *Let π be such that $\mathbb{E}_{s \sim d_s}[l(s, \pi)] = \epsilon$, and $Q_{T-t+1}^{\pi^*}(s, a) - Q_{T-t+1}^{\pi^*}(s, \pi^*) \leq u$ for all action $a, t \in \{1, 2, \dots, T\}, d_\pi^t(s) > 0$, then $J(\pi) \leq J(\pi^*) + uT\epsilon$*
- If difference between optimal t-step Q and any other action is u (e.g., the worst single action regret): The end cost is (no) worse than optimal plus number of mistakes times u, the worst possible regret of each mistake.

Ross, Stéphane, Geoffrey Gordon, and Drew Bagnell. "A reduction of imitation learning and structured prediction to no-regret online learning." *Proceedings of the fourteenth international conference on artificial intelligence and statistics*. JMLR Workshop and Conference Proceedings, 2011.

What are some other ways to improve robustness?

$$J(\pi) \leq J(\pi^*) + T^2\epsilon$$

- Modify the T^2 !
- Increasing T is basically increasing the number of actions.

[FILL 24] In this image, the yellow line represents the trainer's performance. The orange line represents the robot cloning the behavior. [FILL 26, 25, remove red/green text, combine]

- Unintended low-level motions constitute noise in demonstrations
- The demonstrator's **high-level actions** are optimal!
- These actions can be categorized into **two general modes**.

HYDRA

[FILL 27, 28, 30]

Challenges in Imitation Learning #2

[FILL 31]

Generative Modeling

[FILL 32, 33]

Diffusion

[FILL 34, 35, 36, 37]

How to learn from human data?

- Behavioral Cloning
 - Quadratic regret in worst case; bad performance out of expert distribution
 - Can't learn from additional data collected by the agent
- DAgger
 - Provides data/feedback on-policy
 - still can't learn from additional data collected by the agent
- Inverse reinforcement learning
 - Infers reward function from demonstrations so that RL can be used

Inverse Reinforcement Learning

[FILL 40, full]

1. Collect user demonstration $(s_0, a_0), (s_1, a_1), \dots, (s_n, a_n)$ and assume it is sampled from the expert's policy, π^E
2. Explain expert demos by finding R^* such that:

$$E\left[\sum_{t=0}^{\infty} \gamma^t R^*(s_t) | \pi^E\right] \geq E\left[\sum_{t=0}^{\infty} \gamma^t R^*(s_t) | \pi\right] \forall \pi$$
$$E_{s_0 \sim D}[V^{\pi^E}(s_0)] \geq E_{s_0 \sim D}[V^{\pi}(s_0)] \forall \pi$$

How can search be made tractable?

Linear reward functions

Define R^* as a linear combination of features:

$$R^*(s) = w^T \phi(s), \text{ where } \phi : S \rightarrow \mathbb{R}^n$$

Then,

$$\begin{aligned} E\left[\sum_{t=0}^{\infty} \gamma^t R^*(s_t) | \pi\right] &= E\left[\sum_{t=0}^{\infty} \gamma^t w^T \phi(s_t) | \pi\right] \\ &= w^T E\left[\sum_{t=0}^{\infty} \gamma^t \phi(s_t) | \pi\right] \\ &= w^T \mu(\pi) \end{aligned}$$

Thus, the expected value of a policy can be expressed as a weighted sum of the expected features $\mu(\pi)$

A simplified optimization problem

Originally, Explain expert demos by finding R^* such that:

$$E\left[\sum_{t=0}^{\infty} \gamma^t R^*(s_t) | \pi^E\right] \geq E\left[\sum_{t=0}^{\infty} \gamma^t R^*(s_t) | \pi\right] \forall \pi$$

Use expected features:

$$E\left[\sum_{t=0}^{\infty} \gamma^t R^*(s_t) | \pi\right] = w^T \mu(\pi)$$

Restated - find w^* such that:

$$w^* \mu(\pi^E) \geq w^* \mu(\pi) \forall \pi$$

Iterative Reward Search

Goal: Find w^* such that $w^* \mu(\pi^E) \geq w^* \mu(\pi) \forall \pi$

- Initialize π_0 to any policy.
- Iterate for $i = 1, 2, \dots$:
 - Find w^* such that expert maximally outperforms all previously examined policies π_0, \dots, π_{i-1}

$$\max_{\epsilon, w^* : \|w^*\|_2 \leq 1} \epsilon \text{ s.t. } w^* \mu(\pi^E) \geq w^* \mu(\pi_j) + \epsilon$$

- * The above is a support vector machine (SVM) solver
- Use RL to calculate optimal policy π_i associated with w^*
- Stop if $\epsilon \leq \text{threshold}$

A (rough) illustration

[FILL 45-47, combined]

Naive IRL Challenges

- RL in the inner loop
- Where do linear features come from?
- Underspecified inference problem: infinite reward functions that explain behavior equally well. Which one to choose?
- Policies are underspecified too: many policies lead to the same expected features counts. Which one to choose?
- What if demonstrated behavior was actually suboptimal?

Suboptimality and Policy Mixtures

- If a demonstrator acts optimally, then there trivially is some reward function for which **at least one** optimal policy exists that matches the demonstrator's expected feature counts exactly
- But if the demonstrations are sometimes suboptimal, then here may be no single reward function with this property (aside from degenerate ones e.g. all zeros, under which everything is optimal)
- This can be thought of as the demonstrator sometimes acting optimally under a different reward function, so a mixture of reward functions (and their corresponding optimal policies) would be needed to match the feature counts
- Instead, we will now consider policies that are not strictly optimal, but produce trajectories in proportion to their return:

$$P(\zeta_i|\theta) = \frac{1}{Z(\theta)} e^{\theta^T f_{\zeta_i}}$$

Principle of Maximum Entropy

- **Definition:** the probability distribution which best represents the current state of knowledge about a system is the one with largest entropy, subject to your constraints.
- **Intuitively:** Don't overcommit in ways that aren't supported by the data — e.g. don't prefer one trajectory over another if they have the same return.
- **Practical consequence for IRL:** Tells us how to tiebreak between reward functions that explain the data equally well.
- **How?:** Find a reward function that matches expert feature counts under a specific trajectory distribution:

$$P(\zeta_i|\theta) = \frac{1}{Z(\theta)} e^{\theta^T f_{\zeta_i}}$$

- **Why this distribution?:** If you have specific expected feature counts f that you wish to match, it is known that the maximum entropy trajectory distribution that matches f is of the above form for some θ

[FILL 51]

Trajectory vs. Action-based Reasoning

[FILL 52, full, incl text]

Trajectory Probabilities

- Deterministic: $P(\zeta_i|\theta) = \frac{1}{Z(\theta)} e^{\theta^T f_{\zeta_i}}$
- Stochastic: $P(\zeta|\theta, T) \approx \frac{e^{\theta^T f_{\zeta}}}{Z(\theta, T)} \prod_{s_{t+1}, a_t, s_t \in \zeta} P_t(s_{t+1}|a_t, s_t)$

Learning a Reward Function

$$\theta^* = \arg \max_{\theta} L(\theta) = \arg \max_{\theta} \sum_{\text{examples}} \log P(\bar{\zeta}|\theta, T)$$

$$\nabla L(\theta) = \bar{f} - \sum_{\zeta} P(\zeta|\theta, T) f_{\zeta} = \bar{f} - \sum_{s_i} D_{s_i} f_{s_i}$$

- How do we compute the D_{s_i} ?

Calculating state visitation frequencies

[FILL 55]

Driver Route Modeling

[FILL 57]

- Collected driving data of 100,000 miles spanning 3,000 driving hours for Pittsburgh
- Fitted GPS data to the road network, to generate $\sim 13,000$ road trips
- Discarded noisy trips, or trips that were too short (less than 10 road segments)

Four different road aspects considered:

- Road type: interstate to local road
- Speed: high speed to low speed
- Lanes: multi-lane or single lane
- Transitions: straight, left, right, hard left, hard right

There was a total of 22 features used to represent this state.

Model	% Matching	% >90% Match	Log Prob	Reference
Time-Based	72.38	43.12	N/A	N/A
Max Margin	75.29	46.56	N/A	[Ratliff, Bagnell, and Zinkevich, 2006]
Action	77.30	50.37	-7.91	[Ramchandran and Amir 2007]
Action (Cost)	77.74	50.75	N/A	[Ramchandran and Amir 2007]
MaxEnt	78.79	52.98	-6.85	[Zeibart et al. 2008]

What about Larger Problems?

- MaxEnt IRL: probabilistic framework for learning reward functions:
 - Computing gradient requires enumerating state-action visitations for all states and actions
 - Only really viable for small, discrete state and action spaces
 - Amounts to a dynamic programming algorithm (exact forward-backward inference)
- For deep IRL, we want two things:
 - Large and continuous state and action spaces
 - Effective learning under unknown dynamics

Guided Cost Learning

[FILL 60]