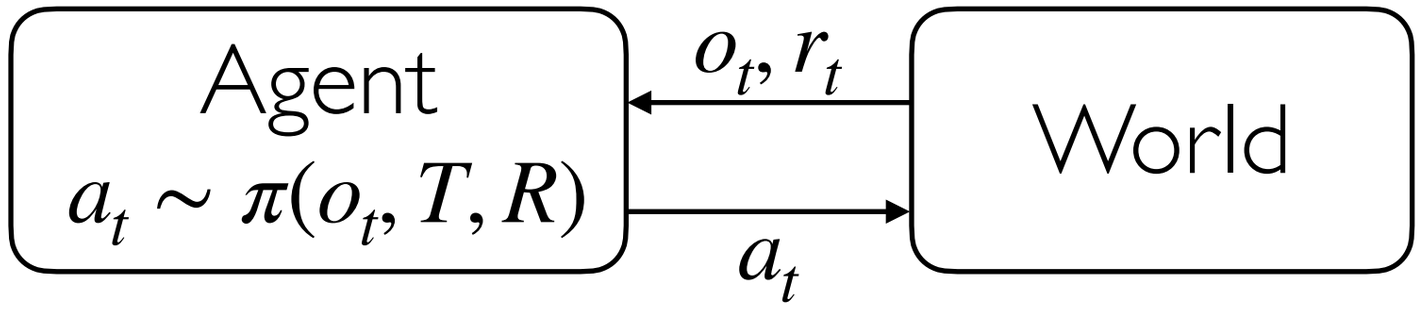
# Imitation Learning

Saurabh Gupta

# Convert into a Supervised Training Problem

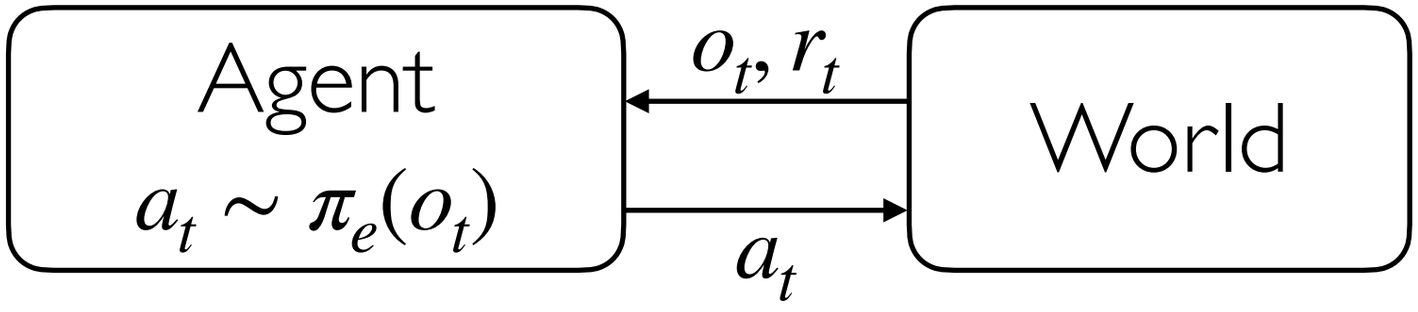
## Most General Case



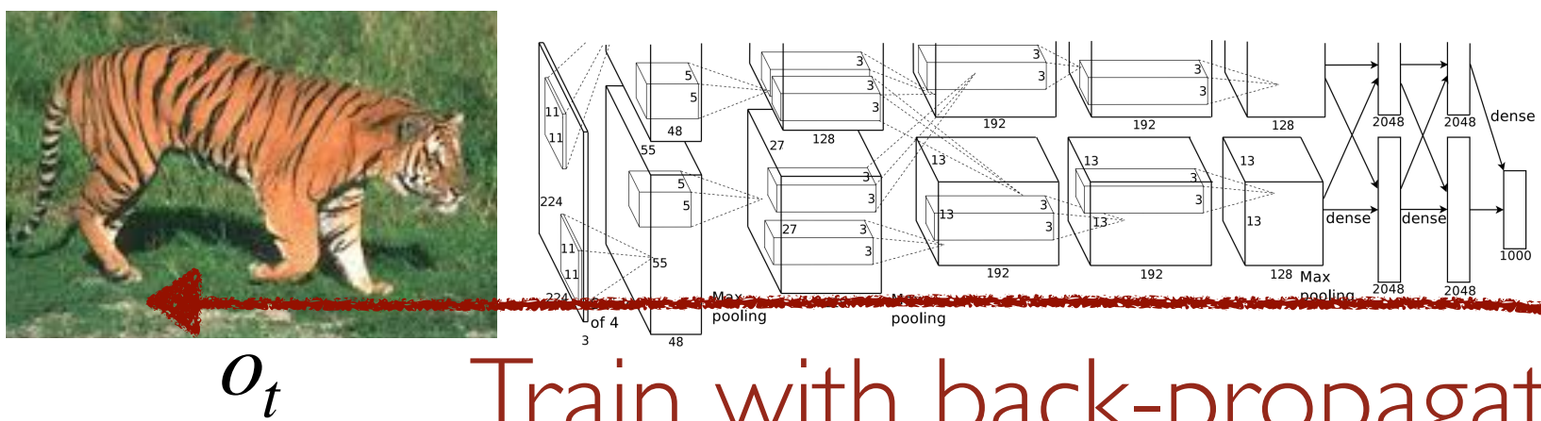
# Behavior Cloning

*Train Time*

*Assume an expert e can solve this MDP.*

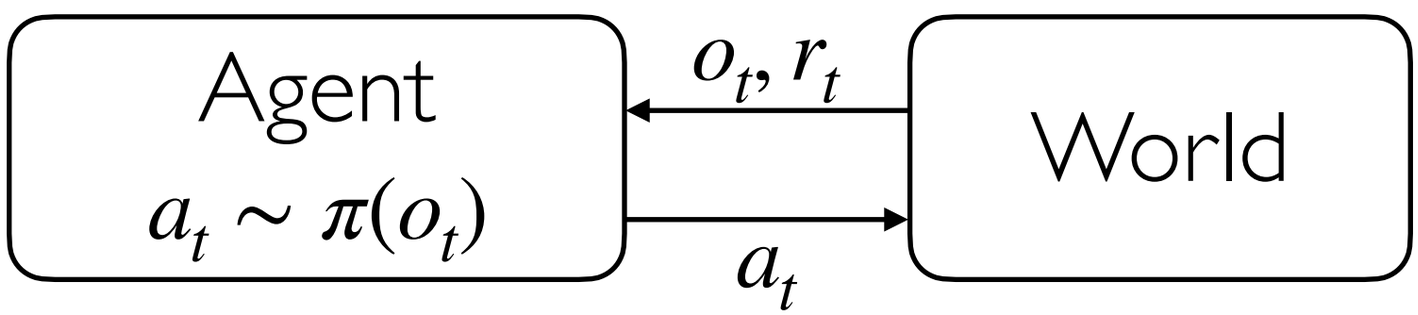



1. *Ask the expert e to solve this MDP.*
2. *Collect labeled dataset D from expert.*
3. *Train a function* $\pi(o_t)$ *that mimics* $\pi_e(o_t)$ *on D.* $\pi(o_t)$ $\pi_e(o_t)$




$o_t$

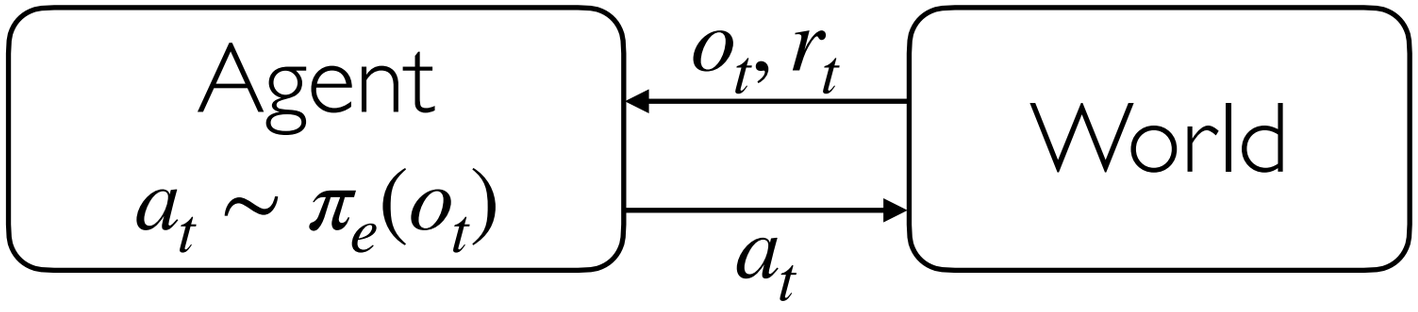
*Test Time*



# Supervision from Human Expert

*Train Time*

*Assume an expert e can solve this MDP.*

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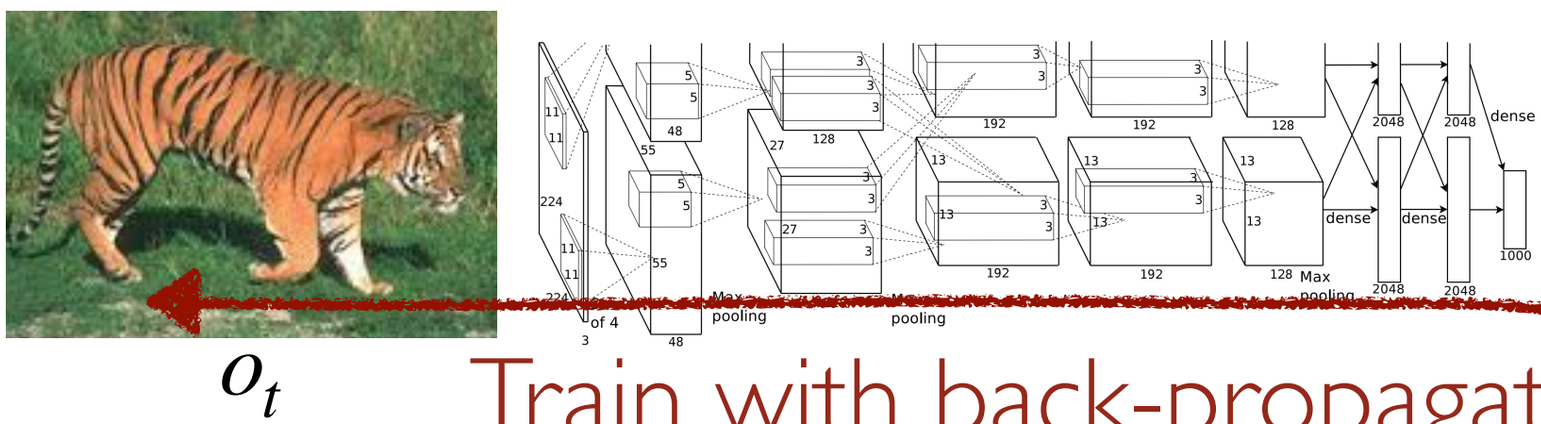
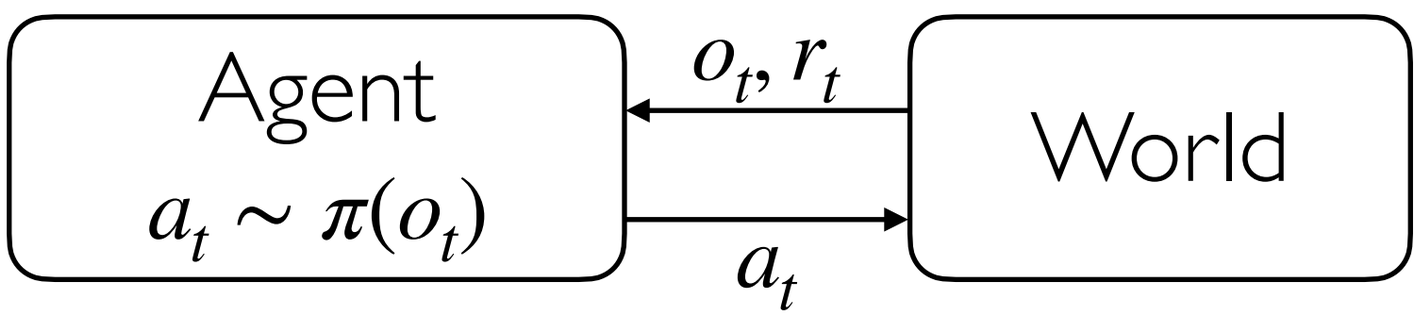



$o_t$

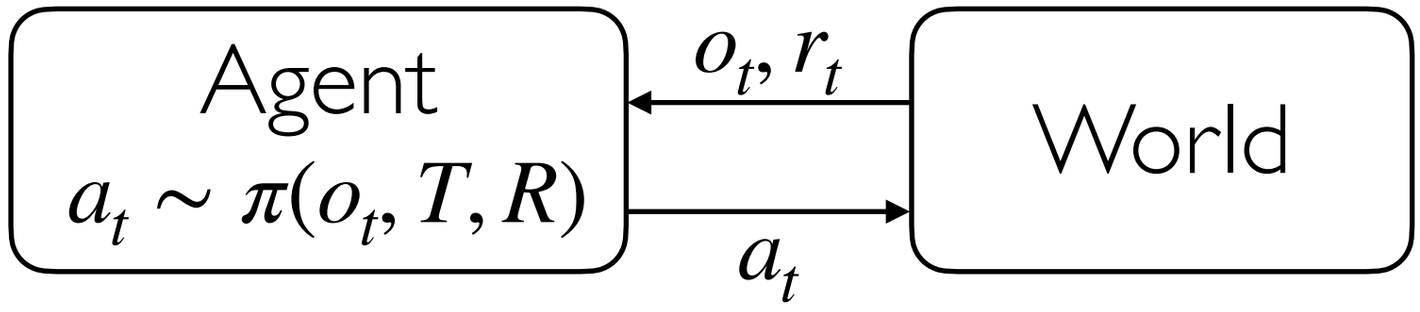
*Test Time*



# Supervision from ~~Human~~ Algorithmic Expert

*Train Time*

*1. Instrument the environment such that it becomes a known MDP.*




Fully Observed System $o_t = s_t$

Known or Learned Transition Function $s_{t+1} \sim \hat{T}(s_t, a_t)$

Known Reward Function $R(s_{t+1}, s_t, a_t)$

*2. Train a function $\hat{\pi}(o_t)$ that mimics $\pi(o_t, T, R)$*

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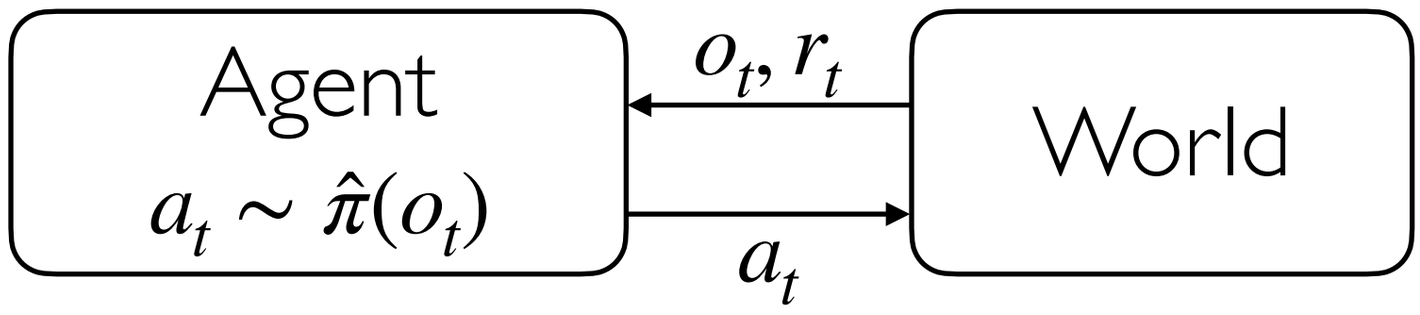
*Test Time*

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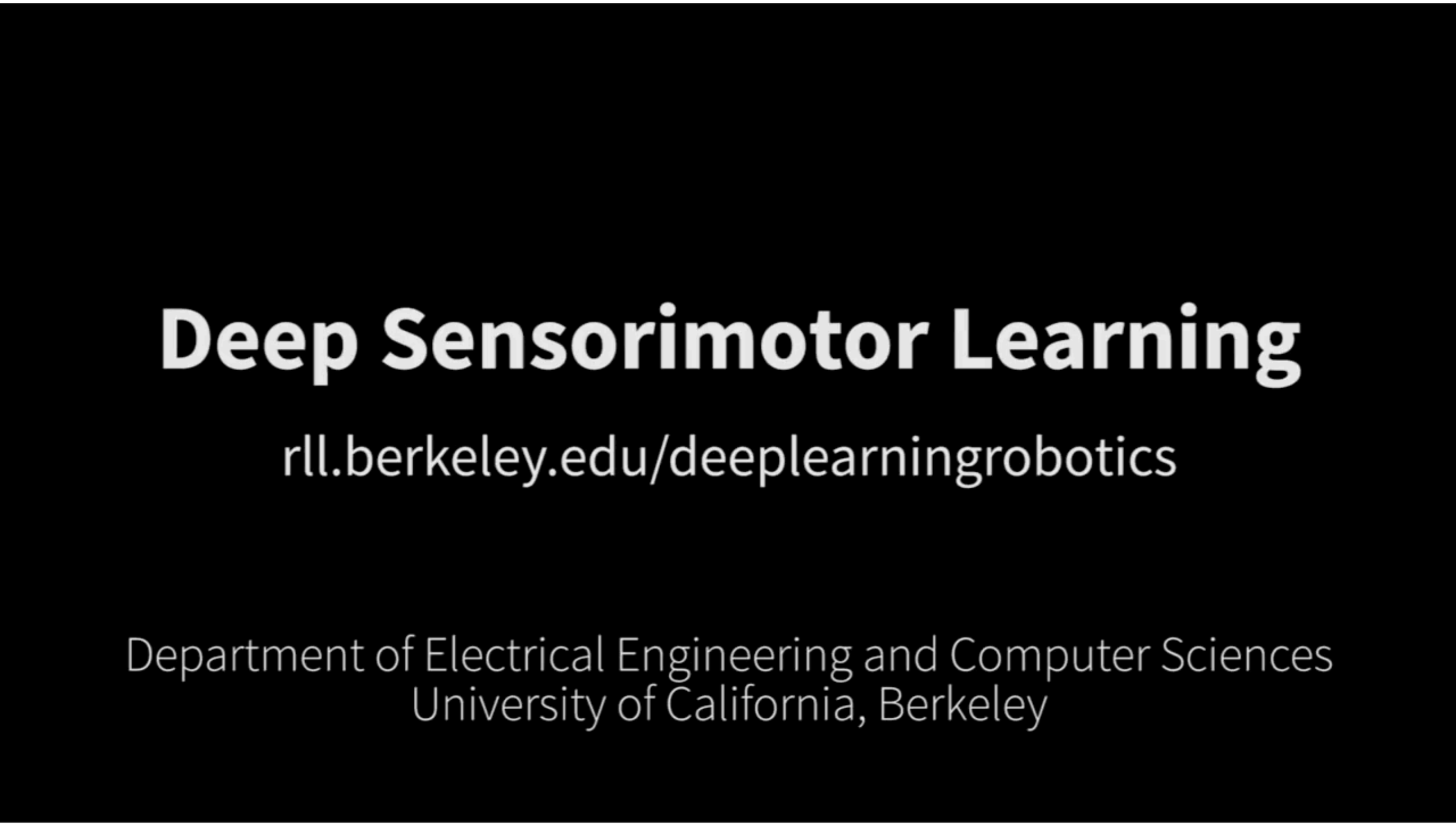
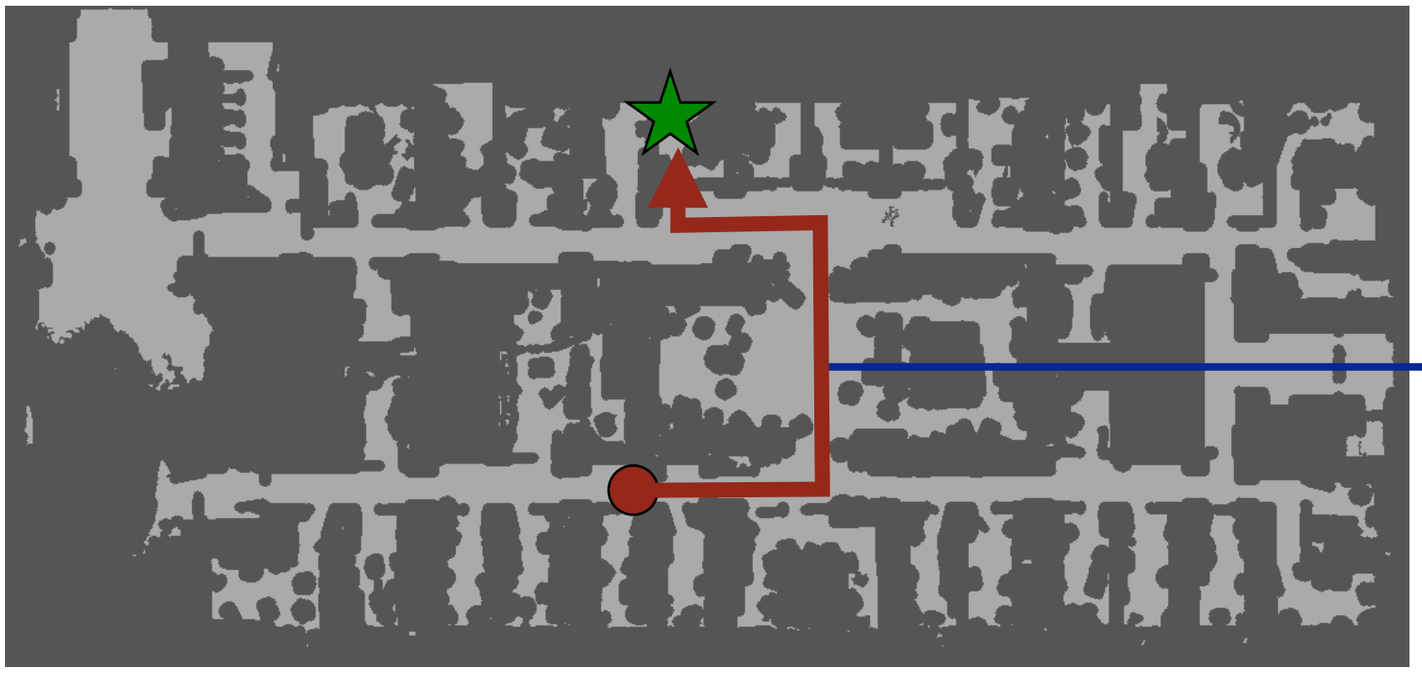
# Supervision from ~~Human~~ Algorithmic Expert




S. Levine et al. **A End-to-End Training of Deep Visuomotor Policies.** JMLR 2016.

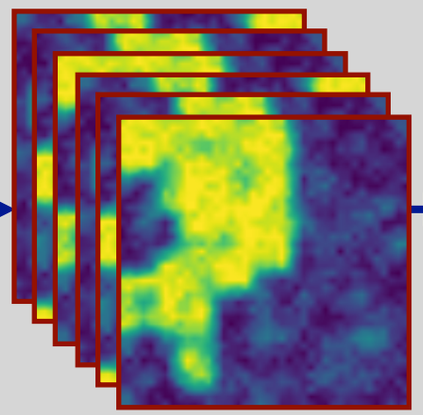
# Supervision from ~~Human~~ Algorithmic Expert



Optimal Action

=


Differentiable Mapper

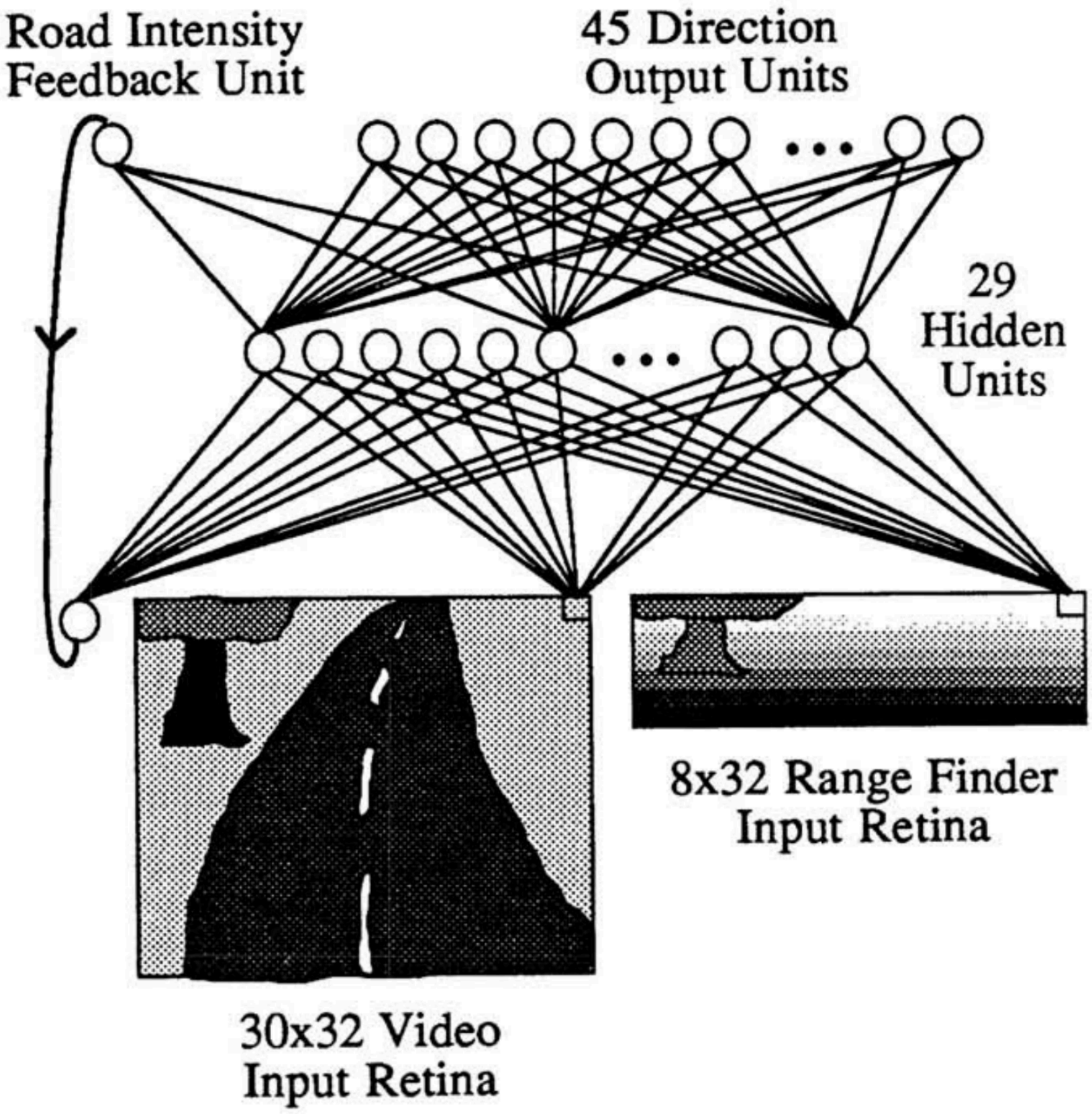


Differentiable Planner

Predicted Action

Train with back-propagation

S. Gupta et al. **Cognitive Mapping and Planning for Visual Navigation.** CVPR 2017.

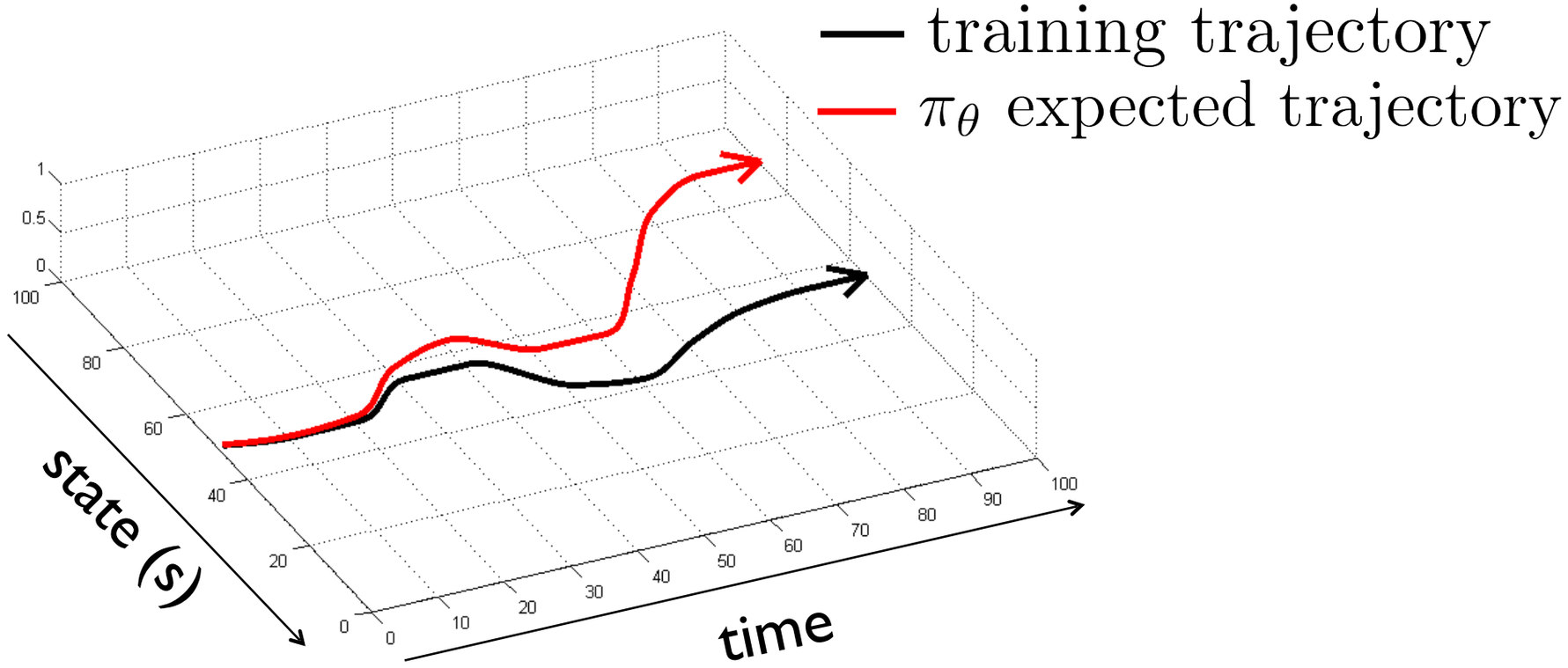



ALVINN: An Autonomous Land Vehicle in a Neural Network. Pomerleau. NeurIPS1988.

# Behavior Cloning

Does it always work?

No, data mis-match problem

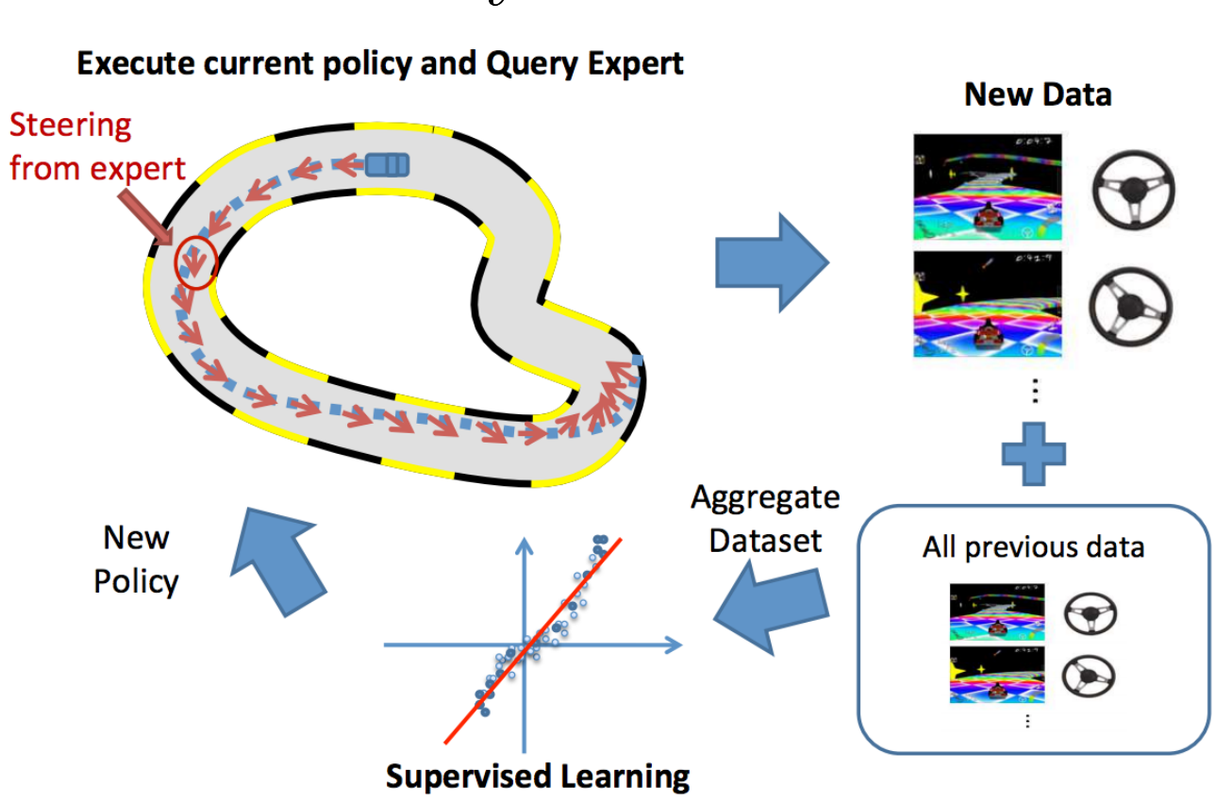


# Fix Data Mis-Match Problem

## *DAgger: Dataset Aggregation*

*Collect labels on states visited by* $\pi(o_t)$ *instead of* $\pi_e(o_t)$.

1. train $\pi_\theta(\mathbf{a}_t|\mathbf{o}_t)$ from human data $\mathcal{D} = \{\mathbf{o}_1, \mathbf{a}_1, \ldots, \mathbf{o}_N, \mathbf{a}_N\}$
2. run $\pi_\theta(\mathbf{a}_t|\mathbf{o}_t)$ to get dataset $\mathcal{D}_\pi = \{\mathbf{o}_1, \ldots, \mathbf{o}_M\}$
3. Ask human to label $\mathcal{D}_\pi$ with actions $\mathbf{a}_t$
4. Aggregate: $\mathcal{D} \leftarrow \mathcal{D} \cup \mathcal{D}_\pi$




S. Ross et al. **A Reduction of Imitation Learning and Structured Prediction to No-Regret Online Learning.** AISTAT 2011.

# A Reduction of Imitation Learning and Structured Prediction to No-Regret Online Learning

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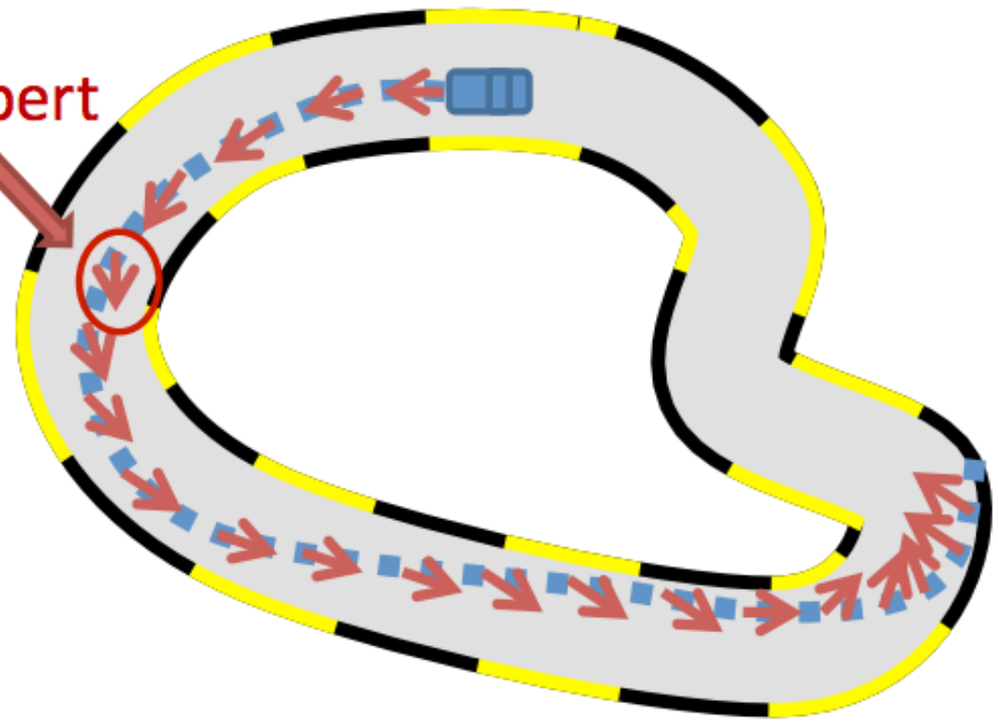
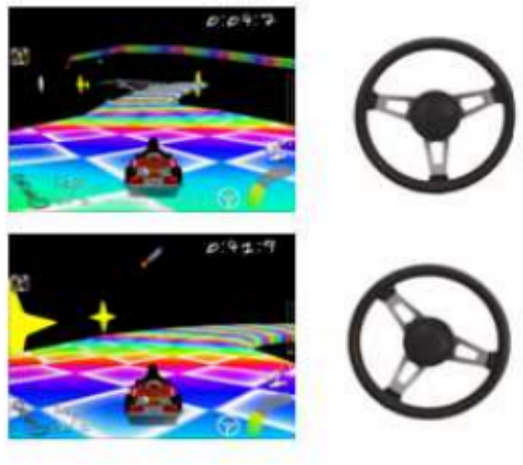
## Execute current policy and Query Expert

Steering
from expert

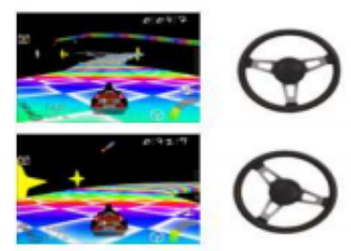


## New Data

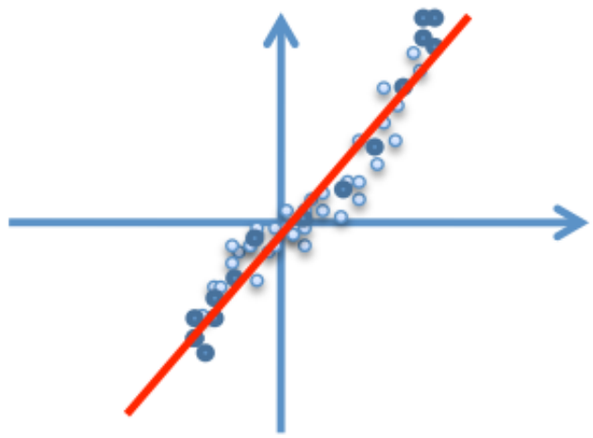


Aggregate
Dataset

All previous data



New
Policy



**Supervised Learning**

# Forward Training and SMILe Algorithm

Initialize $\pi_1^0, \ldots, \pi_T^0$ to query and execute $\pi^*$.
**for** $i = 1$ **to** $T$ **do**
  Sample $T$-step trajectories by following $\pi^{i-1}$.
  Get dataset $\mathcal{D} = \{(s_i, \pi^*(s_i))\}$ of states, actions taken by expert at step $i$.
  Train classifier $\pi_i^i = \text{argmin}_{\pi \in \Pi} \mathbb{E}_{s \sim \mathcal{D}}(e_\pi(s))$.
  $\pi_j^i = \pi_j^{i-1}$ for all $j \neq i$
**end for**
**Return** $\pi_1^T, \ldots, \pi_T^T$

**Algorithm 3.1:** Forward Training Algorithm.

Initialize $\pi^0 \leftarrow \pi^*$ to query and execute expert.
**for** $i = 1$ **to** $N$ **do**
  Execute $\pi^{i-1}$ to get $\mathcal{D} = \{(s, \pi^*(s))\}$.
  Train classifier $\hat{\pi}^{*i} = \text{argmin}_{\pi \in \Pi} \mathbb{E}_{s \sim \mathcal{D}}(e_\pi(s))$.
  $\pi^i = (1-\alpha)^i \pi^* + \alpha \sum_{j=1}^{i} (1-\alpha)^{j-1} \hat{\pi}^{*j}$.
**end for**
Remove expert queries: $\tilde{\pi}^N = \frac{\pi^N - (1-\alpha)^N \pi^*}{1-(1-\alpha)^N}$
**Return** $\tilde{\pi}^N$

**Algorithm 4.1:** The SMILe Algorithm.

# DAgger

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: $\mathcal{D} \leftarrow \mathcal{D} \bigcup \mathcal{D}_i$.
  Train classifier $\hat{\pi}_{i+1}$ on $\mathcal{D}$.
**end for**
**Return** best $\hat{\pi}_i$ on validation.

**Algorithm 3.1:** DAGGER Algorithm.

# Super Tux Kart

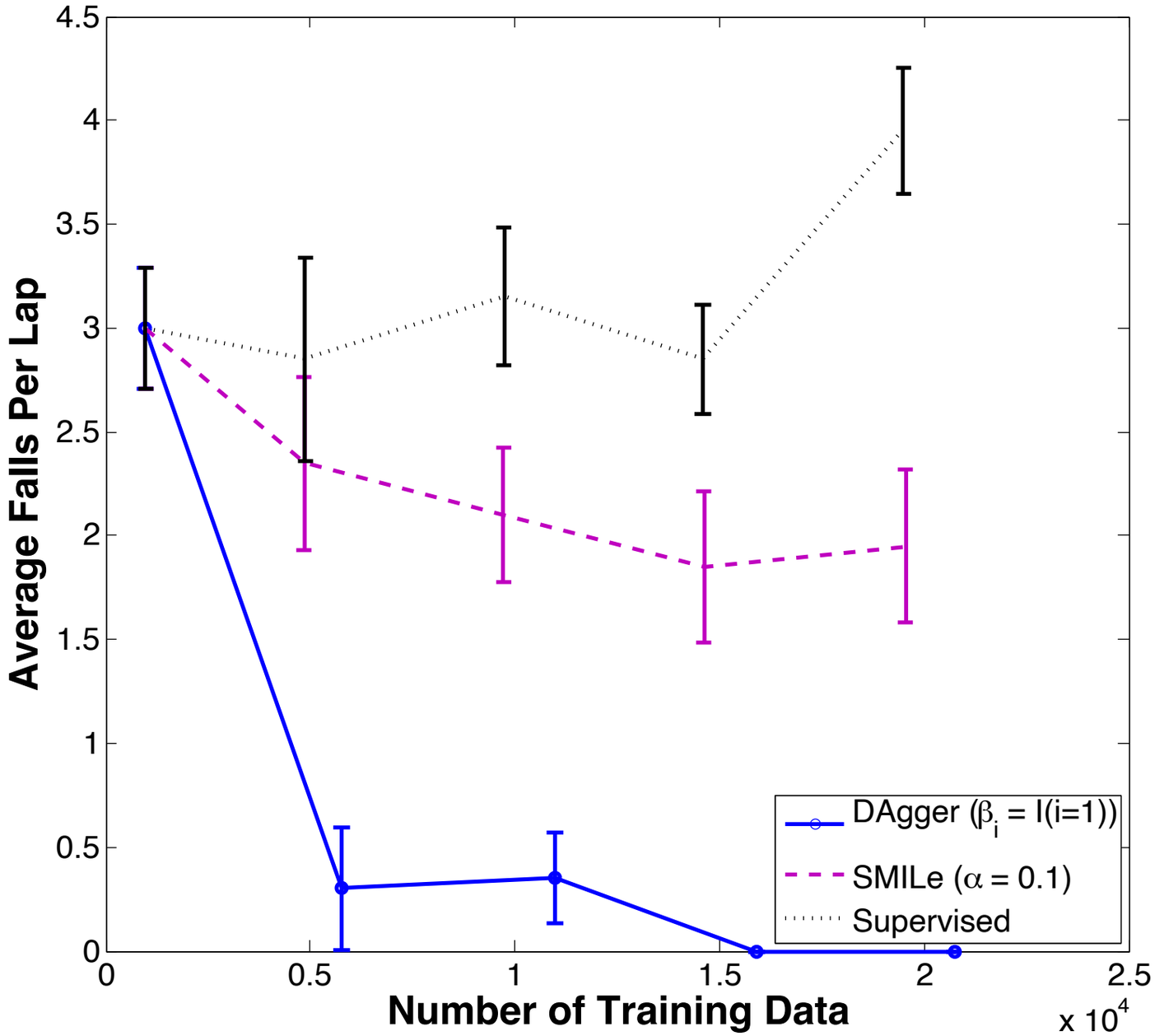



Figure 2: Average falls/lap as a function of training data.

# Super Mario Bros.

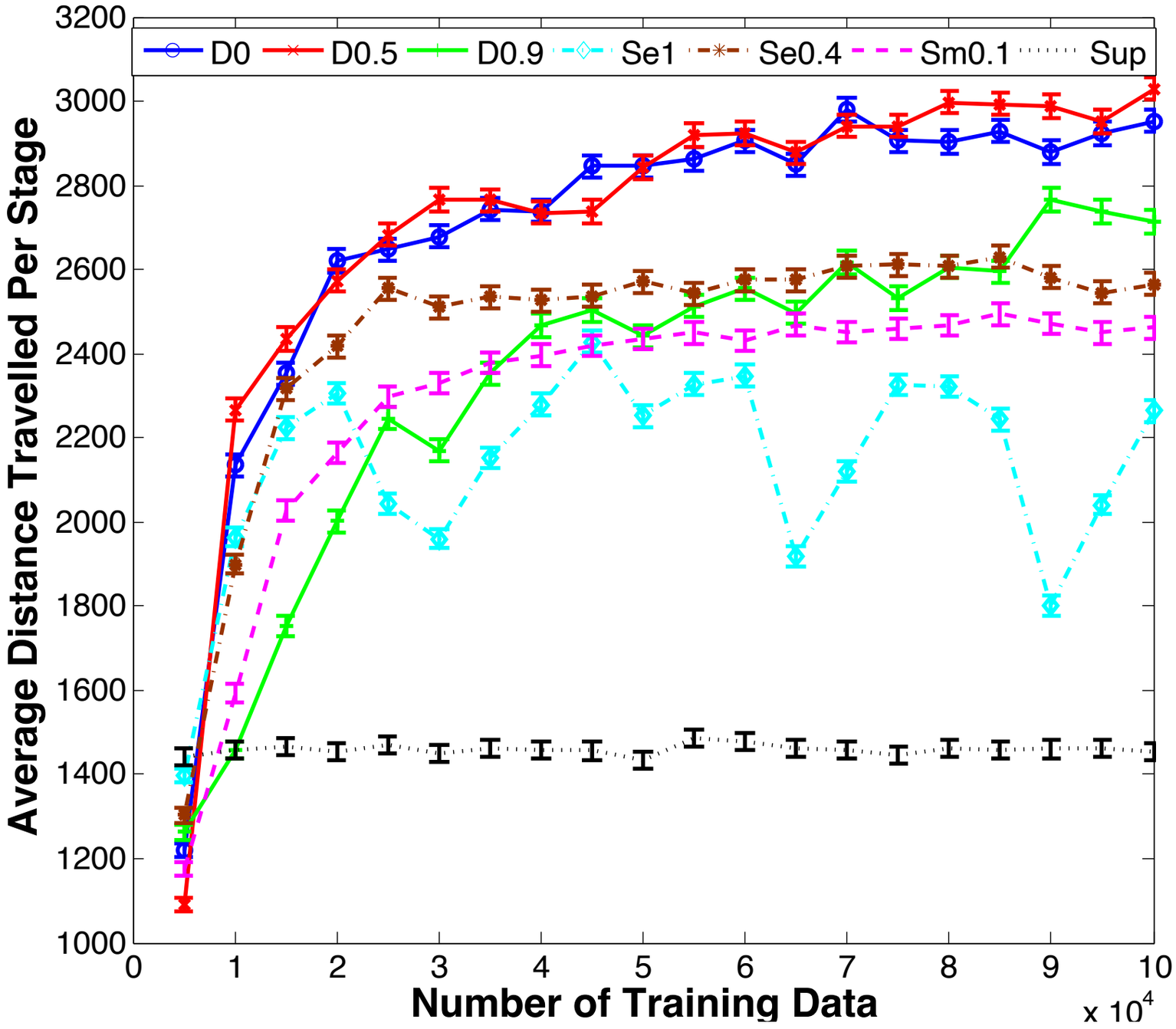



Figure 4: Average distance/stage as a function of data.

# Structured Prediction

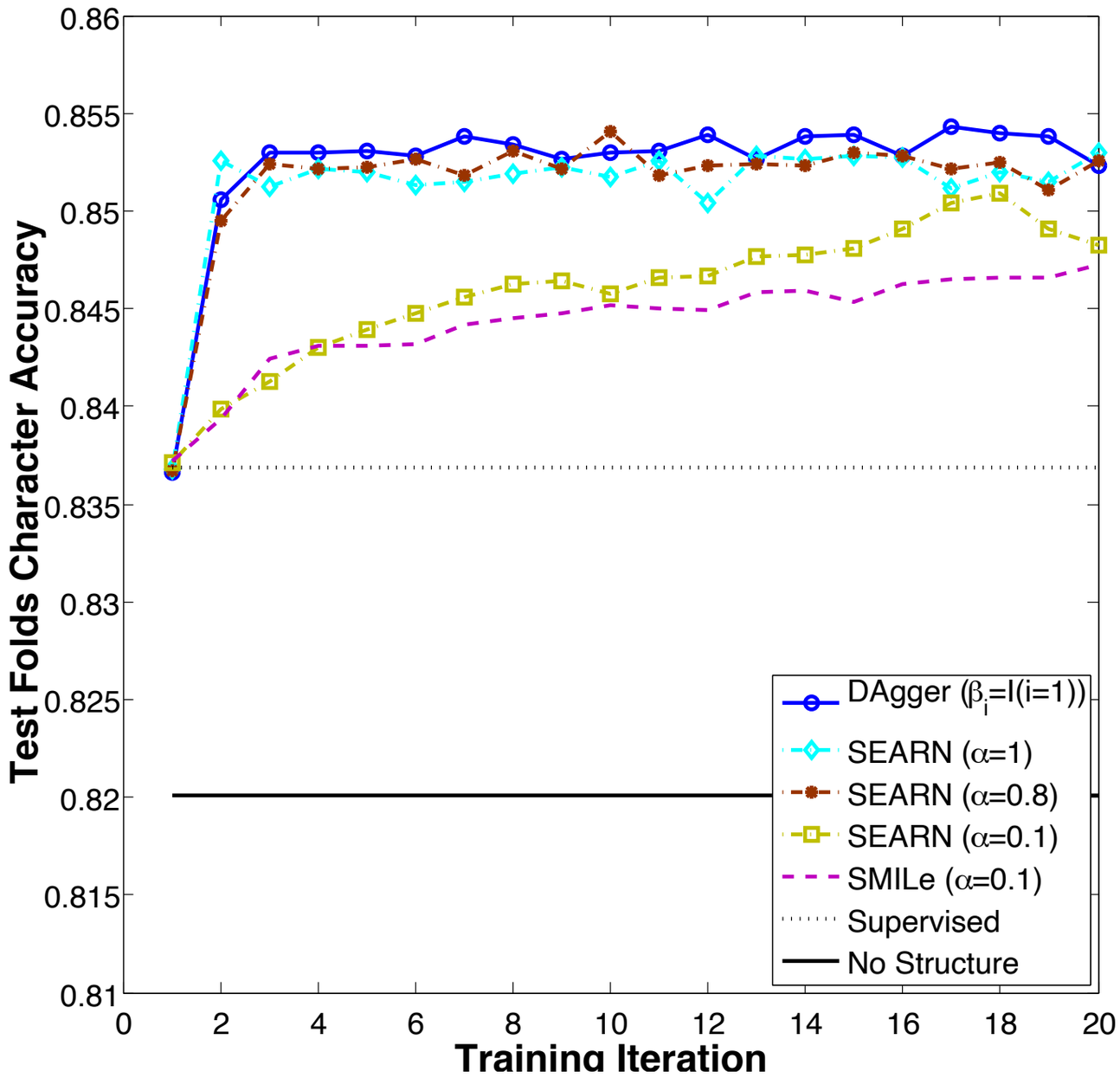



Figure 5: Character accuracy as a function of iteration.