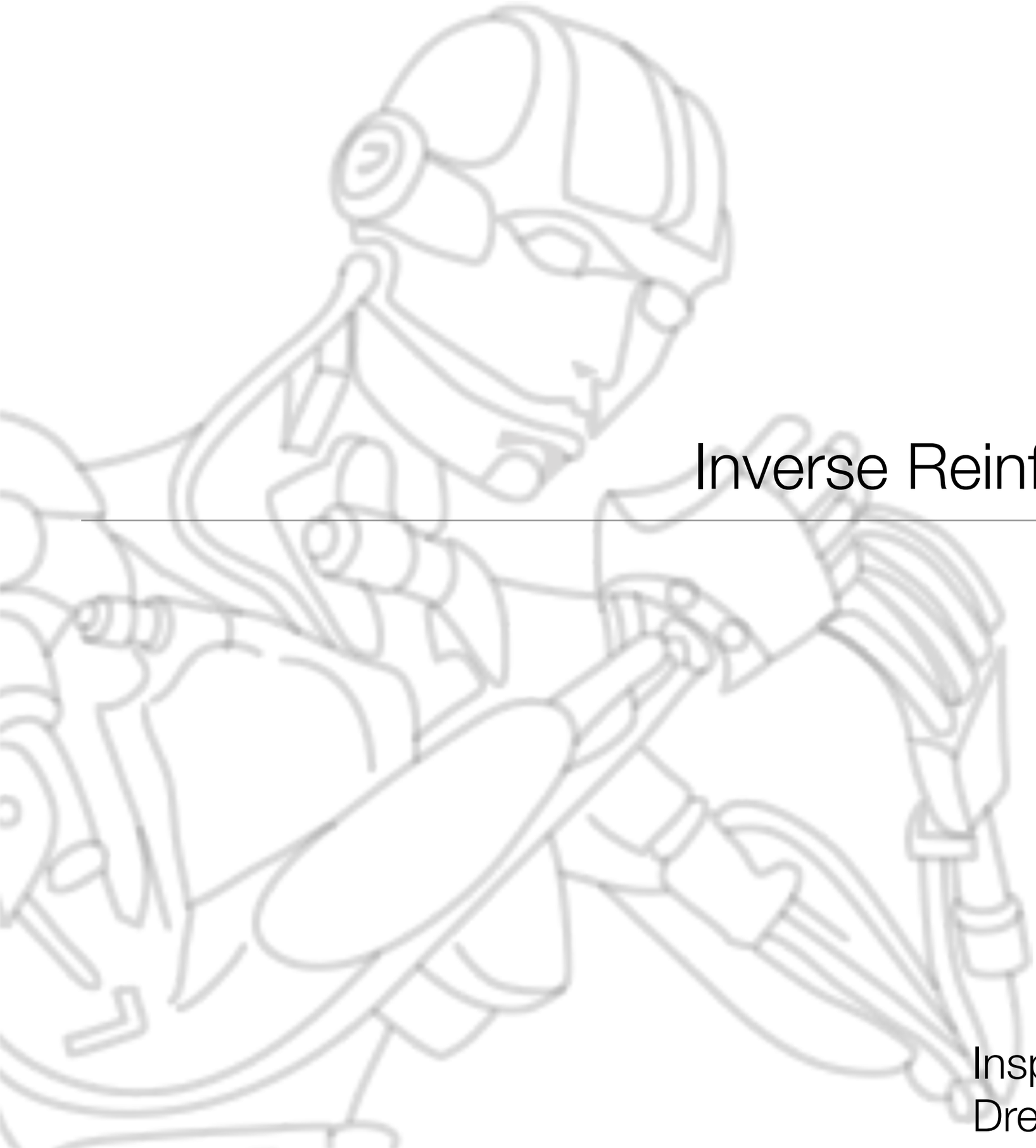


# Imitation Learning by Inverse Reinforcement Learning

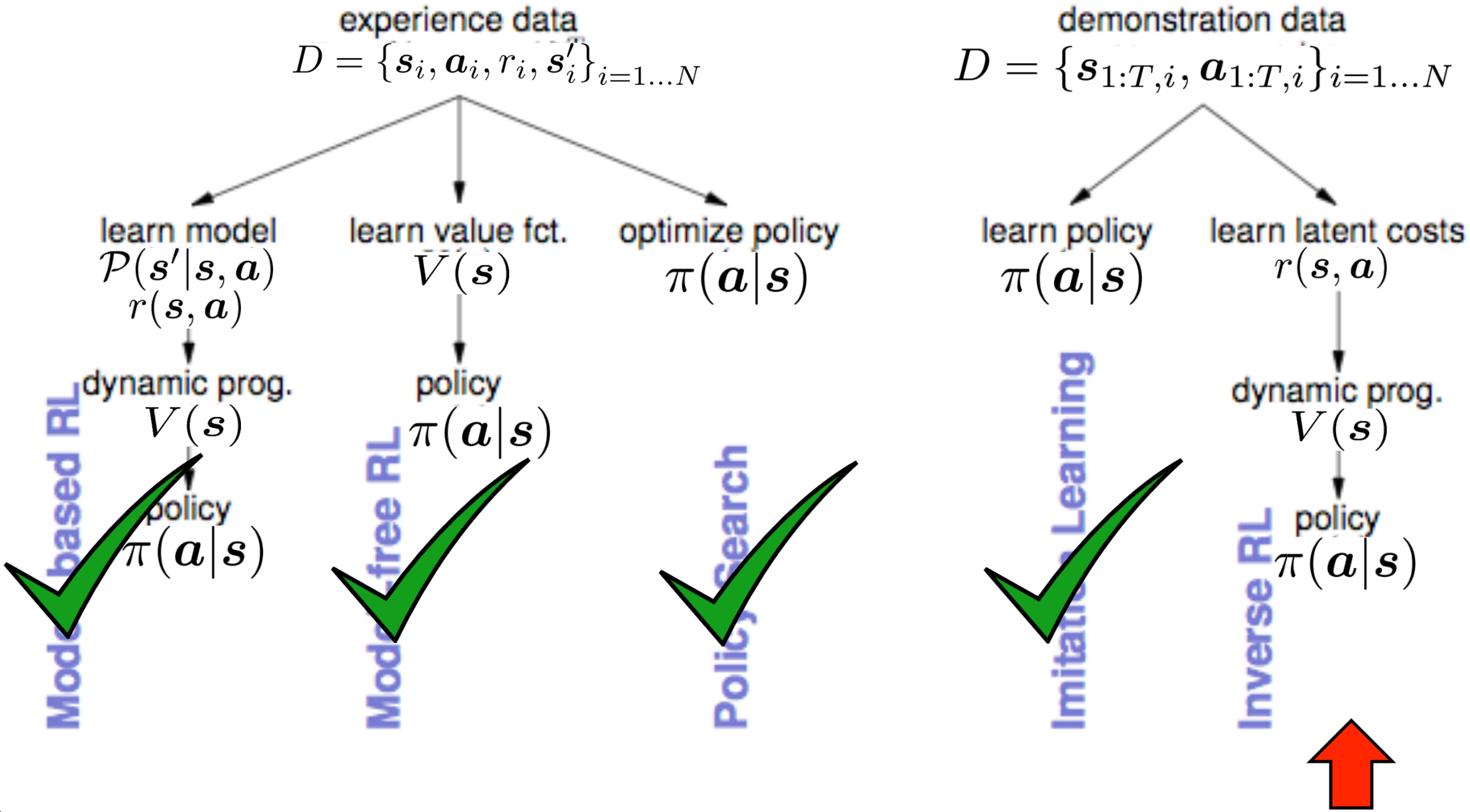
Jan Peters
Gerhard Neumann

Inspired by Slides from P. Abbeel, Drew Bagnell and others

# Purpose of this Lecture

- Learn an alternative approach to imitation learning
- What is the best way to imitate a teacher?
  - Learn its policy? Behavorial cloning
    - Needs a lot of demonstrations to generalize the behavior
  - Learn its intention / goals? Inverse Reinforcement Learning
    - Inverse Optimal Control, Inverse Optimal Planning
    - Determine the cost function of the teacher in order to obtain optimal behavior.
    - More concise description of behavior

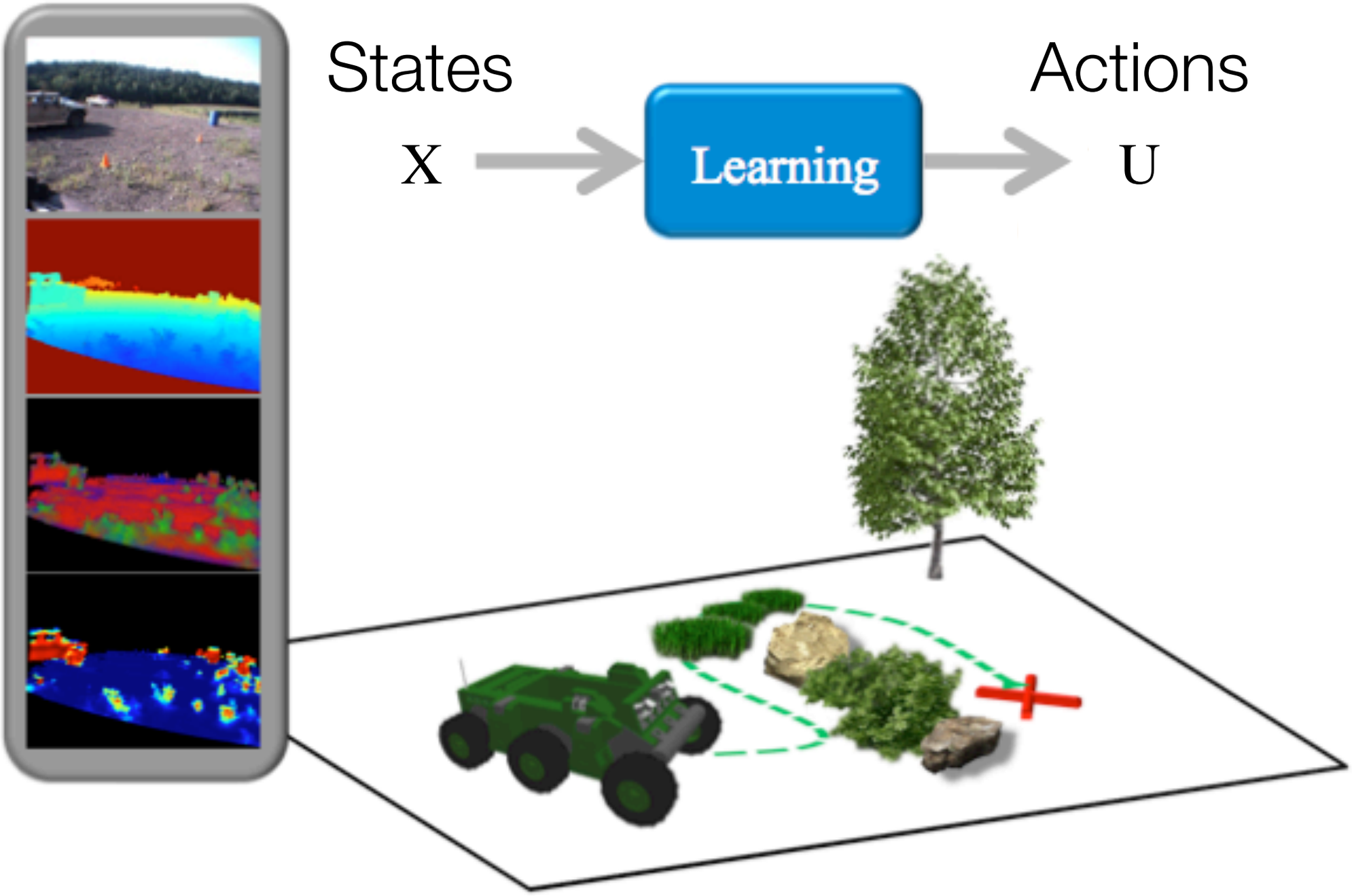
# Bigger Picture



# Outline of the Lecture

1. Introduction
    I. Comparison to Behavioral Cloning
2. Categories of IRL
    I. Maximum Margin
    II. Feature Matching by Max. Entropy
    III. Policy parametrized by rewards
3. Applications
4. Conclusion

# Behavioral Cloning



# What may be wrong here? Remember ALVINN?

There are difficulties involved with training "on-the-fly" with real images. If the network is not presented with sufficient variability in its training exemplars to cover the conditions it is likely to encounter when it takes over driving from the human operator, it will not develop a sufficiently robust representation and will perform poorly. In addition, the network must not solely be shown examples of accurate driving, but also how to recover (i.e. return to the road center) once a mistake has been made. Partial initial training on

308

VINN:
AN AUTONOMO LAND VEHICLE IN A
NEURA NETWORK

Dean A. Pomerleau
Computer Science Department
Carnegie Mellon University
Pittsburgh, PA 15213

ABSTRACT

ALVINN (Autonomous Land Vehicle In a Neural Network) is a 3-layer back-propagation network designed for the task of road following. Currently ALVINN takes images from a camera and a laser range finder as input and produces as output the direction the vehicle should travel in order to follow the road. Training has been conducted using simulated road images. Successful tests on the Carnegie Mellon autonomous navigation test vehicle indicate that the network can effectively follow real roads under certain field conditions. The representation developed to perform the task differs dramatically when the network is trained under various conditions, suggesting the possibility of a novel adaptive autonomous navigation system capable of tailoring its processing to the conditions at hand.

INTRODUCTION

Autonomous navigation has been a difficult problem for traditional vision and robotic techniques, primarily because of the noise and variability associated with real world scenes. Autonomous navigation systems based on traditional image processing and pattern recognition techniques often perform well under certain conditions but have problems with others. Part of the difficulty stems from the fact that the processing performed by these systems remains fixed across various driving situations.

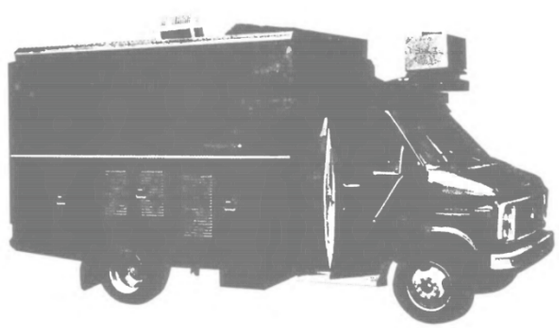
Artificial neural networks have displayed promising performance and flexibility in other domains characterized by high degrees of noise and variability, such as handwritten character recognition [Jackel et al., 1988] [Pawlicki et al., 1988] and speech recognition [Waibel et al., 1988]. ALVINN (Autonomous Land Vehicle In a Neural Network) is a connectionist approach to the navigational task of road following. Specifically, ALVINN is an artificial neural network designed to control the NAVLAB, the Carnegie Mellon autonomous navigation test vehicle.

NETWORK ARCHITECTURE

ALVINN's current architecture consists of a single hidden layer back-propagation network

## Disadvantages of Direct Imitation Learning

- Needs a lot of demonstrations to generalize
- High variability in the demonstrations
- Demonstrate how to recover from mistakes



# Motivation for inverse RL

**Apprenticeship learning/Imitation learning through inverse RL**

Presupposition: reward function provides the most succinct and transferable definition of the task

Has enabled advancing the state of the art in various robotic domains

**Modeling of other agents**, both adversarial and cooperative

**Scientific questions**

Model animal and human behavior

E.g., bee foraging, songbird vocalization.  [See intro of Ng and Russell, 2000 for a brief overview.]

Meet Crusher...

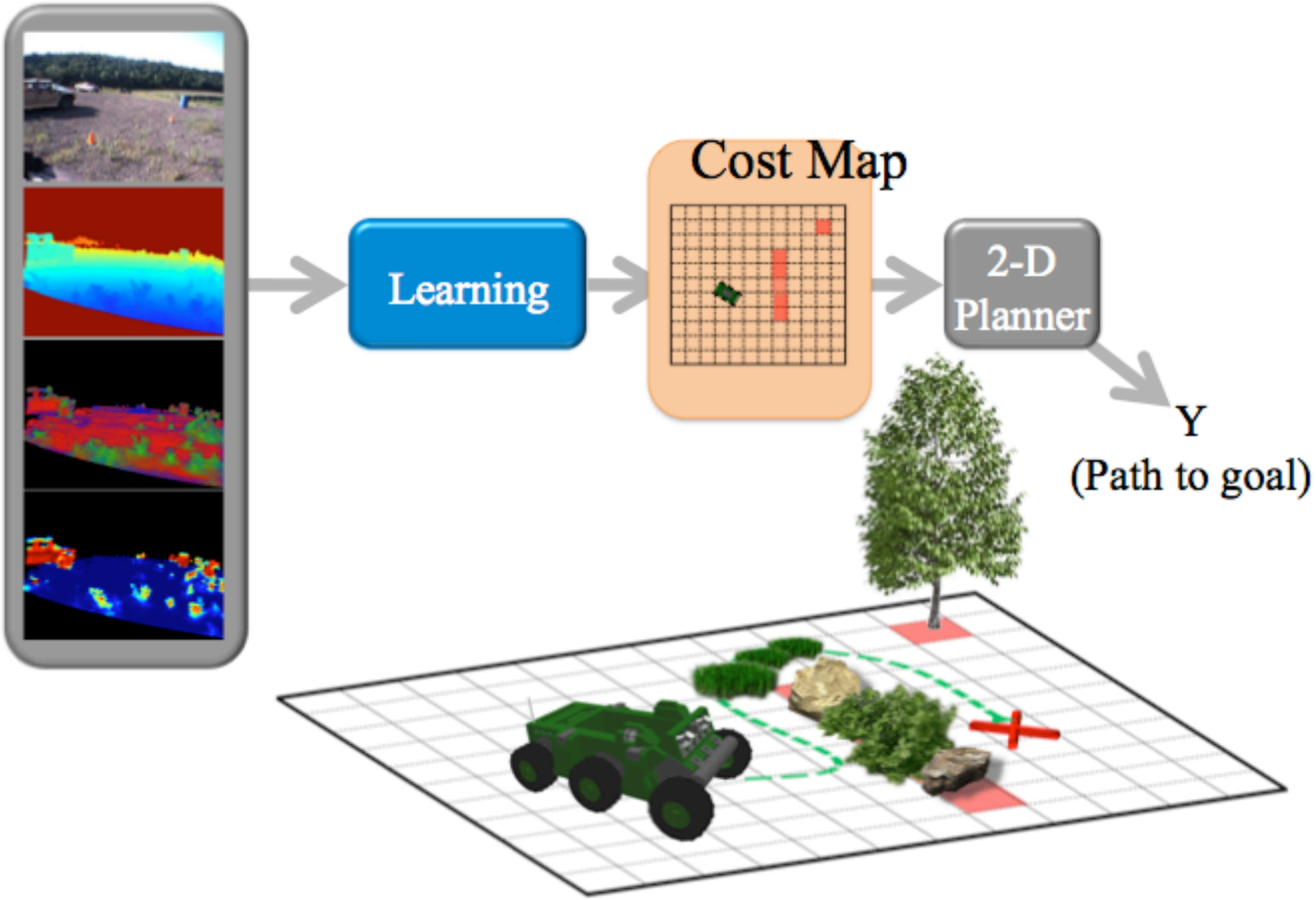


RSS 2008: Dave Silver and Drew Bagnell

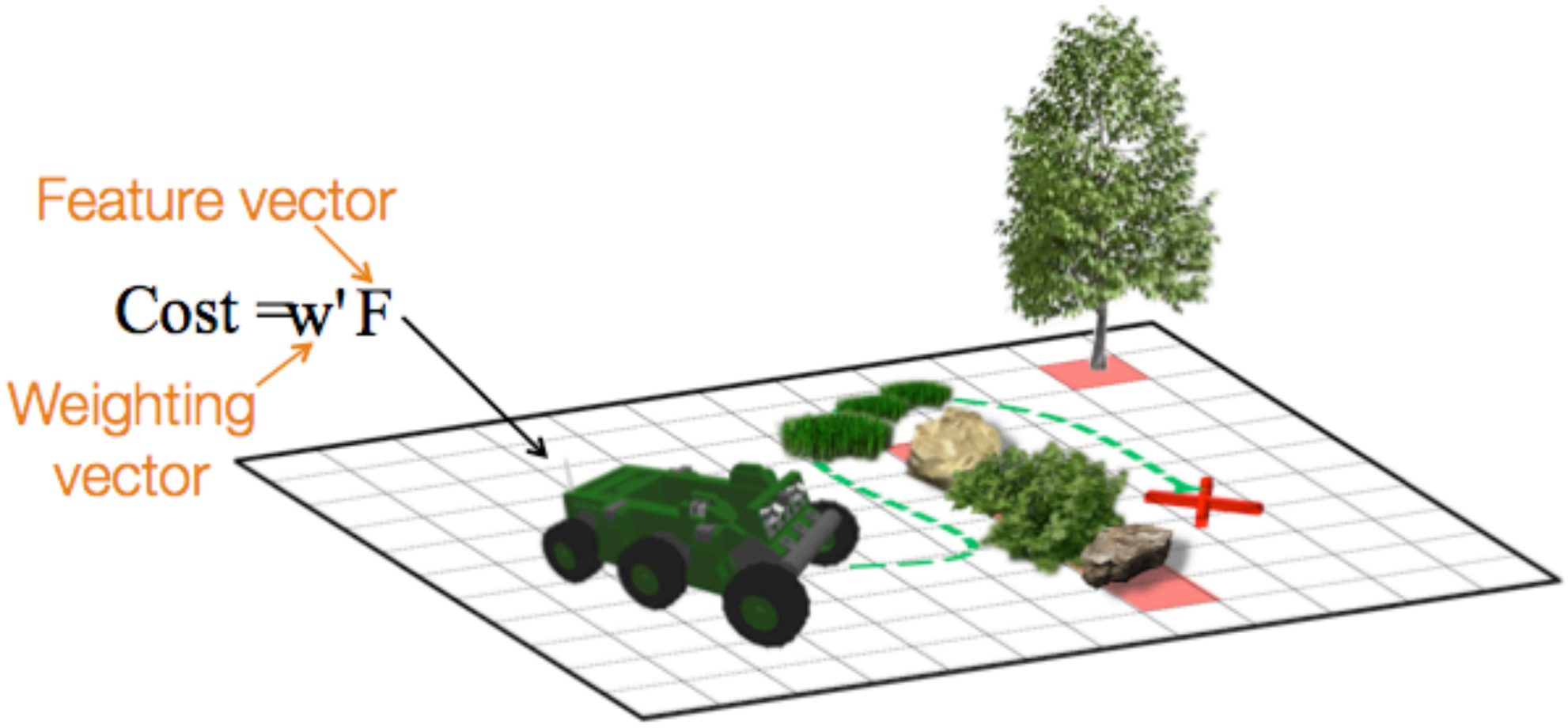
# More Crusher pictures...

# More Crusher pictures...

# Inverse Reinforcement Learning

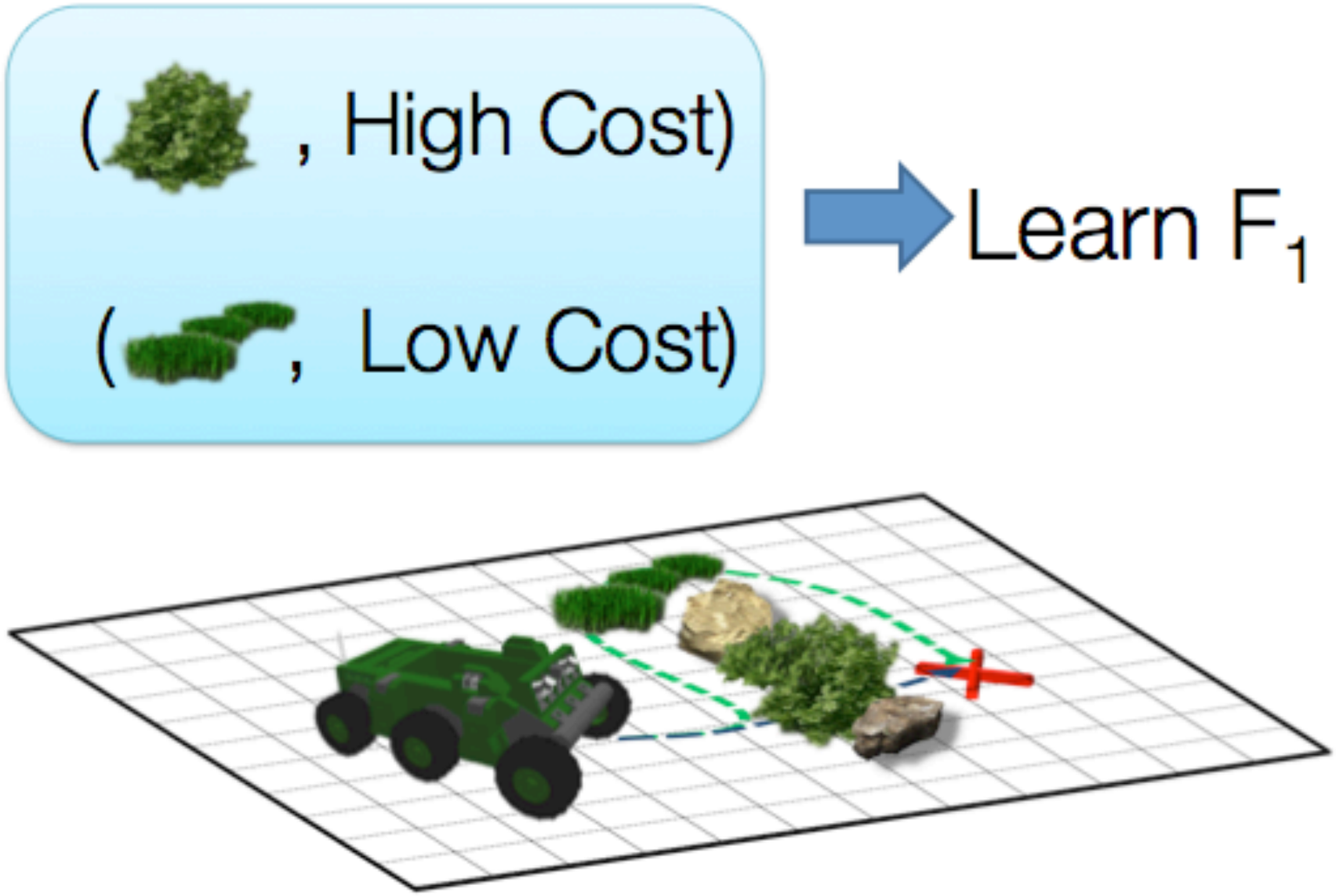


# Recovering Cost!

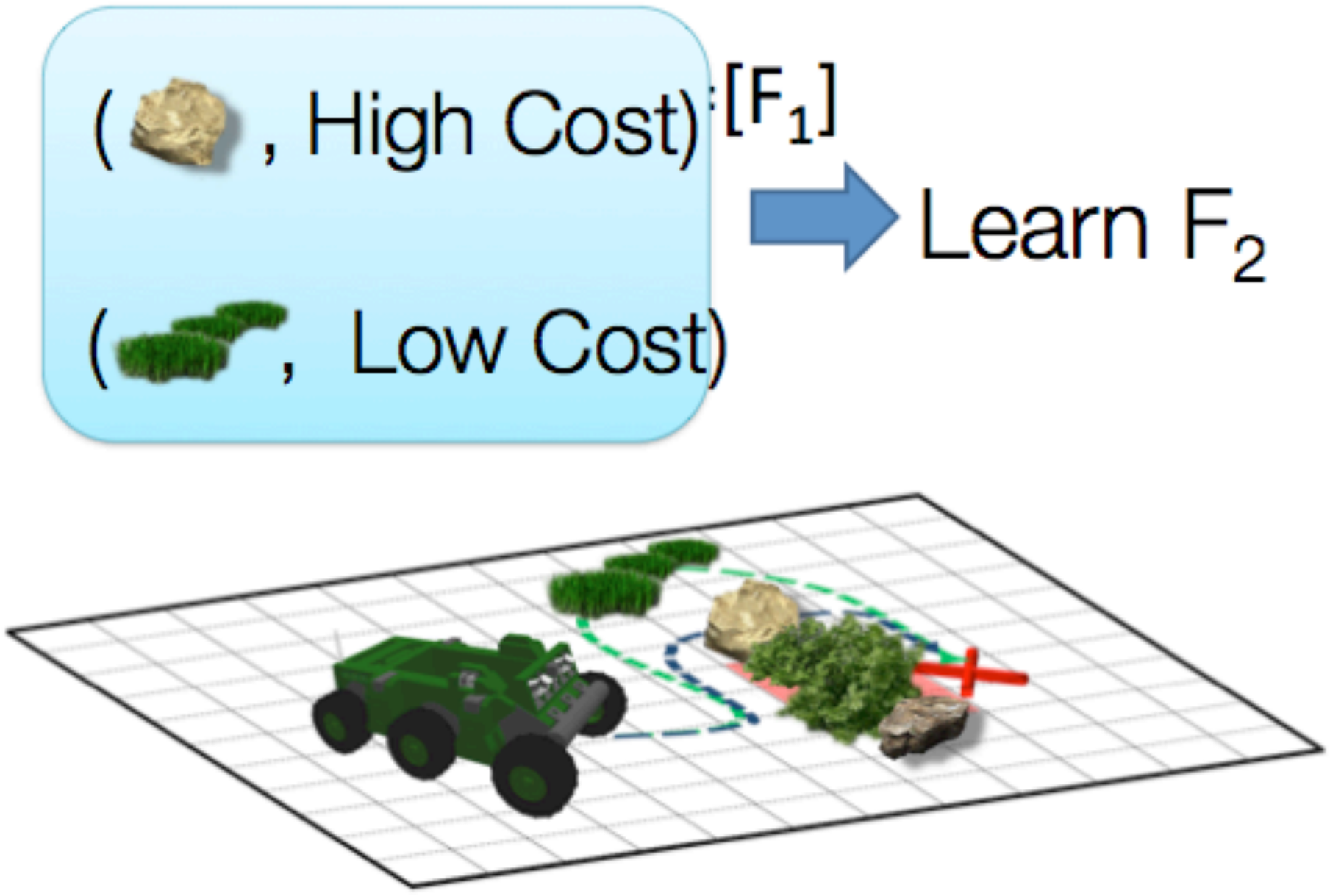



Ratliff, Bagnell, Zinkevich 2005
Ratliff, Bradley, Bagnell, Chestnutt, NIPS 2006
Silver, Bagnell, Stentz, RSS 2008

# Recovering Cost!



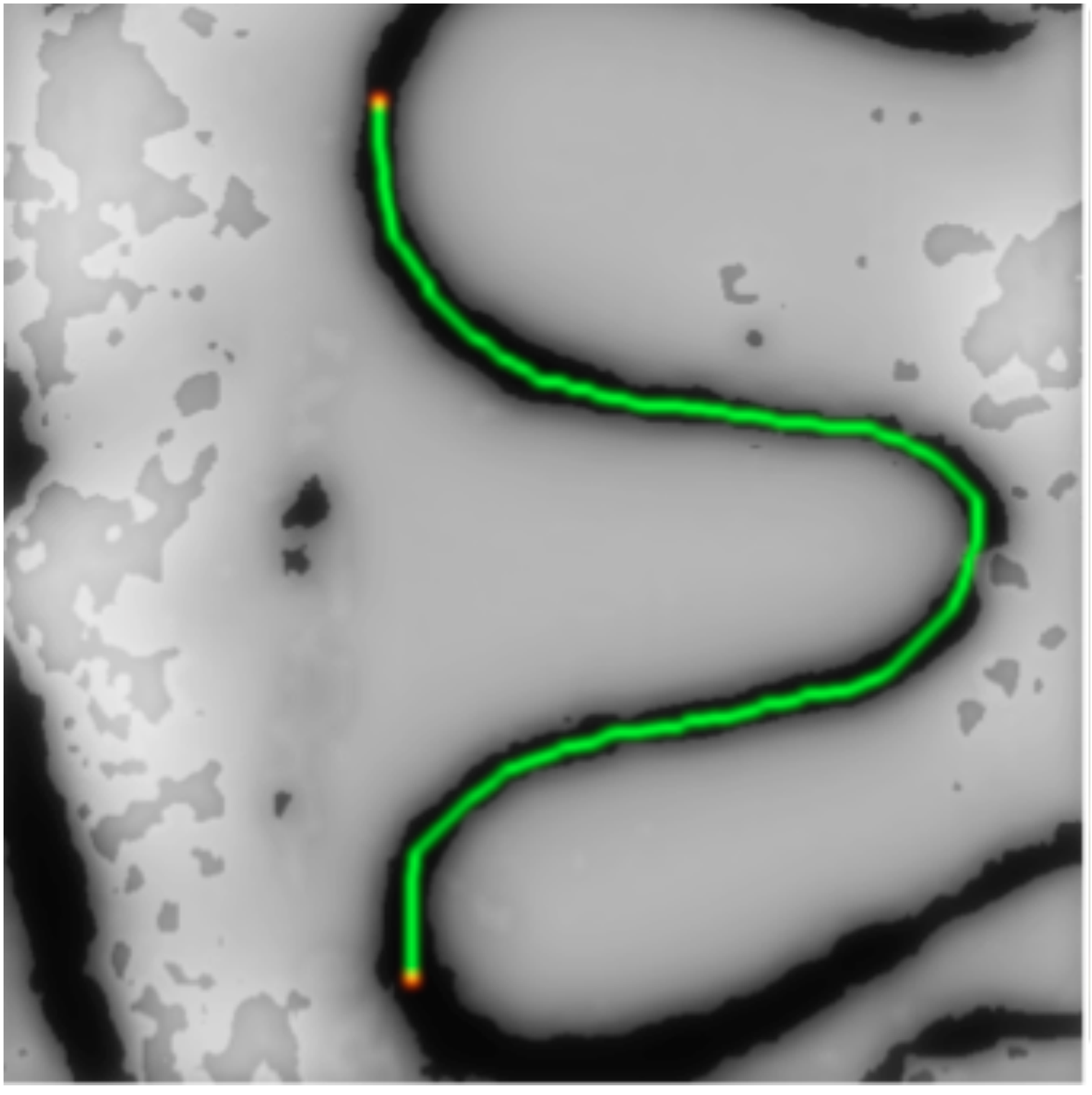
# Recovering Cost!



# Collect paths by teleoperation

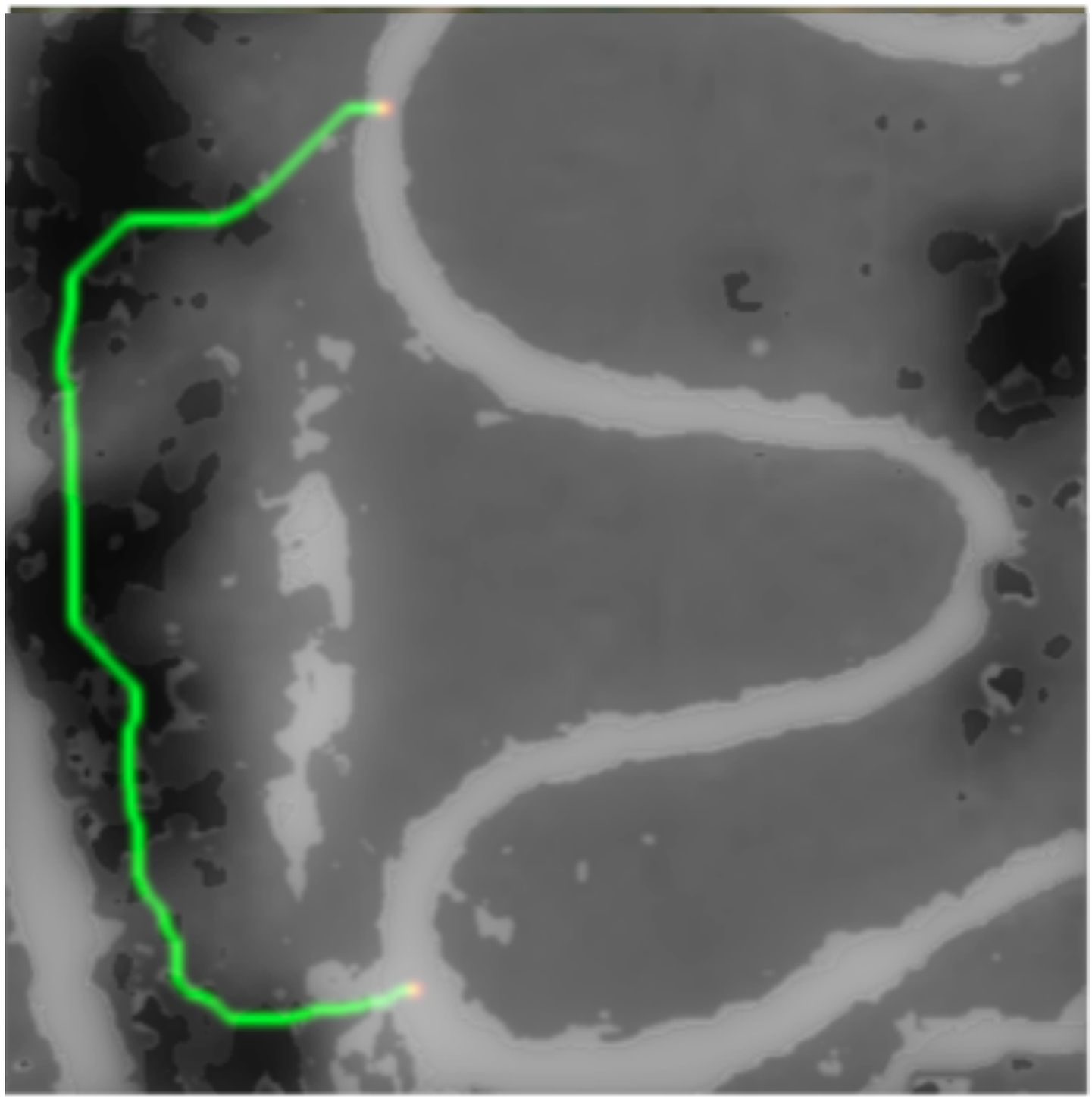
# Training: Stay on the road

# Test: Stay on the road



# Training: Avoid the Road

# Test: Avoid the Road




example path

# High-level picture

Dynamics

Probability distribution over next states given current state and action

Describes desirability of being in a state.

Reward Function
$r(s_t)$

Reinforcement Learning / Optimal Control

Controller/ Policy $\pi$

Prescribes action to take for each state

$\text{argmax}_\pi \mathbb{E}_{p,\pi}\left[\sum_t \gamma^t r(s_t)|\pi\right]$

Inverse RL:

- Given **Policy** and **Model**, can we recover **R**?
- More generally, given execution traces, can we recover **r**?

# Outline of the Lecture

1. Introduction
    I. Comparison to Behavioral Cloning
2. Categories of IRL
    I. Maximum Margin
    II. Feature Matching by Max. Entropy
    III. Policy parametrized by rewards
3. Applications
4. Conclusion

# Problem setup: Behavioral Cloning

**Input:**

Teacher's demonstrations: $D = \{\boldsymbol{s}_{1:T,i}, \boldsymbol{a}_{1:T,i}\}_{i=1\ldots N}$

Trace of the teacher's policy $\pi^*(\boldsymbol{a}|\boldsymbol{s})$

And its "long-term behavior" $\mu^*(\boldsymbol{s})$

**Formulated as standard machine learning problem**

Fix a policy class (neural network, decision tree, deep belief net, dynamical systems, …

Estimate a policy $\hat{\pi}(\boldsymbol{a}|\boldsymbol{s})$ from the training examples $D$

**Problem:**

There will always be an error in the estimation of the policy

Small error in the policy ⇨ possibly large error in long-term behavior $\hat{\mu}(\boldsymbol{s})$

# Problem setup: Inverse RL

**Input:**

Teacher's demonstrations: $D = \{\boldsymbol{s}_{1:T,i}, \boldsymbol{a}_{1:T,i}\}_{i=1...N}$

Trace of the teacher's policy $\pi^*(\boldsymbol{a}|\boldsymbol{s})$

And its "long-term behavior" $\mu^*(\boldsymbol{s})$

State and Action Space

Transition model: $p(\boldsymbol{s}_{t+1}|\boldsymbol{s}_t, \boldsymbol{a}_t)$

No reward function $r(\boldsymbol{s}_t)$

**Inverse RL:**

Can we recover $r(\boldsymbol{s}_t)$ that explains the policy $\pi^*(\boldsymbol{a}|\boldsymbol{s})$ (and its long-term behavior $\mu^*(\boldsymbol{s})$ ?)

**Apprenticeship Learning**

Can we use $r(\boldsymbol{s}_t)$ to obtain a policy $\hat{\pi}(\boldsymbol{a}|\boldsymbol{s})$?

# Inverse RL vs. Behavioral Cloning

**Behavioral Cloning:**

Simple to implement

No assumptions on the model/MDP

We might not reproduce the long term behavior

**Representation: Policy**

Hard to generalize

Needs many samples

**Inverse RL:**

Requires Planning / Solving an MDP

Hard for many interesting MDPs (e.g. high-DoF robots)

**Representation: Reward**

Compact description

Easy to transfer to new tasks

# Basic principle

**Find a reward function $r^*(s_t)$ which explains the expert behavior**

Assume expert is optimal w.r.t. to $r^*(s_t)$

**I.e., find $r^*(s_t)$ such that**

$$\mathbb{E}_{p,\pi}\left[\sum_t \gamma^t r^*(s_t)|\pi^*\right] \geq \mathbb{E}_{p,\pi}\left[\sum_t \gamma^t r^*(s_t)|\pi\right], \forall \pi$$

**In fact a convex feasibility problem, but many challenges**:

1. Ill-posed: $r^*(s_t) = 0$ is a solution, reward function ambiguity
2. Limited Data: We typically only observe expert traces rather than the entire expert optimal policy --- how to compute left-hand side?
3. Optimality Assumption: Assumes the expert is indeed optimal --- otherwise infeasible
4. Computation: assumes we can enumerate all policies

# Outline of the Lecture

1. Introduction
   I. Comparison to Behavioral Cloning
2. Categories of IRL
   I. Maximum Margin
   II. Feature Matching by Max. Entropy
   III. Policy parametrized by rewards
3. Applications
4. Conclusion

# Feature based reward function

**Lets assume the reward function is linear in some features,**

I.e. $r(\boldsymbol{s}) = \boldsymbol{w}^T \boldsymbol{\phi}(\boldsymbol{s})$, where $\boldsymbol{\phi}(\boldsymbol{s})$ is a $n$-dimensional feature vector

$$\begin{aligned}
\mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t r(\boldsymbol{s}_t)|\pi\right] &= \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t \boldsymbol{w}^T \boldsymbol{\phi}(\boldsymbol{s}_t)|\pi\right] \\
&= \boldsymbol{w}^T \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t \boldsymbol{\phi}(\boldsymbol{s}_t)|\pi\right] \\
&= \boldsymbol{w}^T \boldsymbol{\psi}(\pi)
\end{aligned}$$

where $\boldsymbol{\psi}(\pi)$ is the expected discounted feature vector of policy $\pi$

**Subbing into:** $\mathbb{E}_{p,\pi}\left[\sum_t \gamma^t r^*(s_t)|\pi^*\right] \geq \mathbb{E}_{p,\pi}\left[\sum_t \gamma^t r^*(s_t)|\pi\right], \forall \pi$

**gives us:** $\text{Find } \boldsymbol{w}^* \text{ such that } \boldsymbol{w}^{*T} \boldsymbol{\psi}(\boldsymbol{\pi}^*) \geq \boldsymbol{w}^{*T} \boldsymbol{\psi}(\boldsymbol{\pi}), \forall \pi$

# Feature based reward function

$$\mathbb{E}_{p,\pi}\left[\sum_t \gamma^t r^*(s_t)|\pi^*\right] \geq \mathbb{E}_{p,\pi}\left[\sum_t \gamma^t r^*(s_t)|\pi\right], \forall \pi$$

$$\text{Find } \boldsymbol{w}^* \text{ such that } \boldsymbol{w}^{*T}\boldsymbol{\psi}(\boldsymbol{\pi}^*) \geq \boldsymbol{w}^{*T}\boldsymbol{\psi}(\boldsymbol{\pi}), \forall \pi$$

Feature expectations can be readily estimated from sample trajectories

Solves limited data challenge

The number of expert demonstrations required scales with the number of features in the reward function.

The number of expert demonstration required does not depend on

Complexity of the expert’s optimal policy

Size of the state space

# Basic principle

**Find a reward function $r^*(s_t)$ which explains the expert behavior**

Assume expert is optimal w.r.t. to $r^*(s_t)$

**I.e., find $r^*(s_t)$ such that**

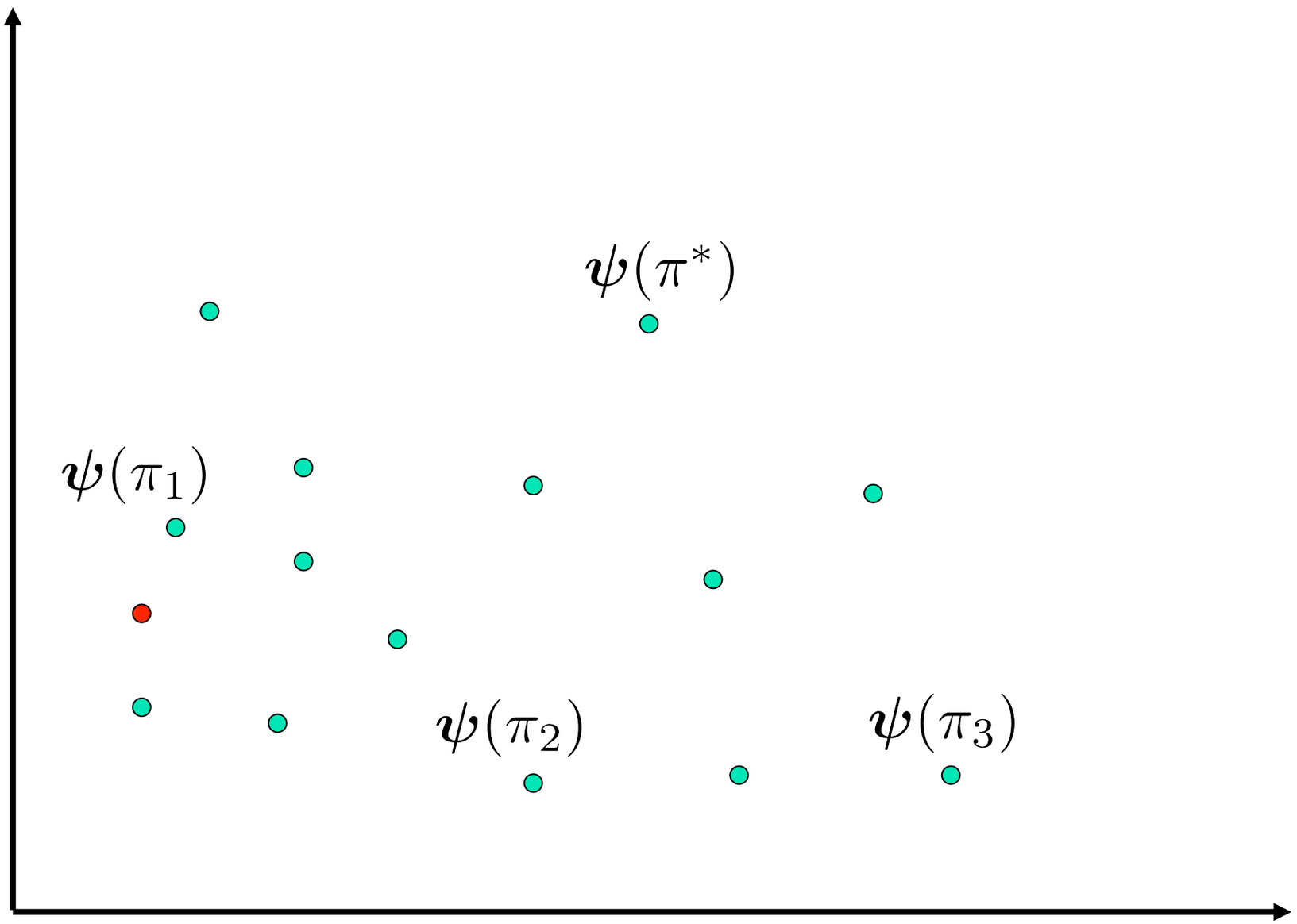
$$\mathbb{E}_{p,\pi}\left[\sum_t \gamma^t r^*(s_t)|\pi^*\right] \geq \mathbb{E}_{p,\pi}\left[\sum_t \gamma^t r^*(s_t)|\pi\right], \forall \pi$$

**In fact a convex feasibility problem, but many challenges**:

1. Ill-posed: $r^*(s_t) = 0$ is a solution, reward function ambiguity
2. Limited Data: We typically only observe expert traces rather than the entire expert optimal policy --- how to compute left-hand side?
3. Optimality Assumption: Assumes the expert is indeed optimal --- otherwise infeasible
4. Computation: assumes we can enumerate all policies

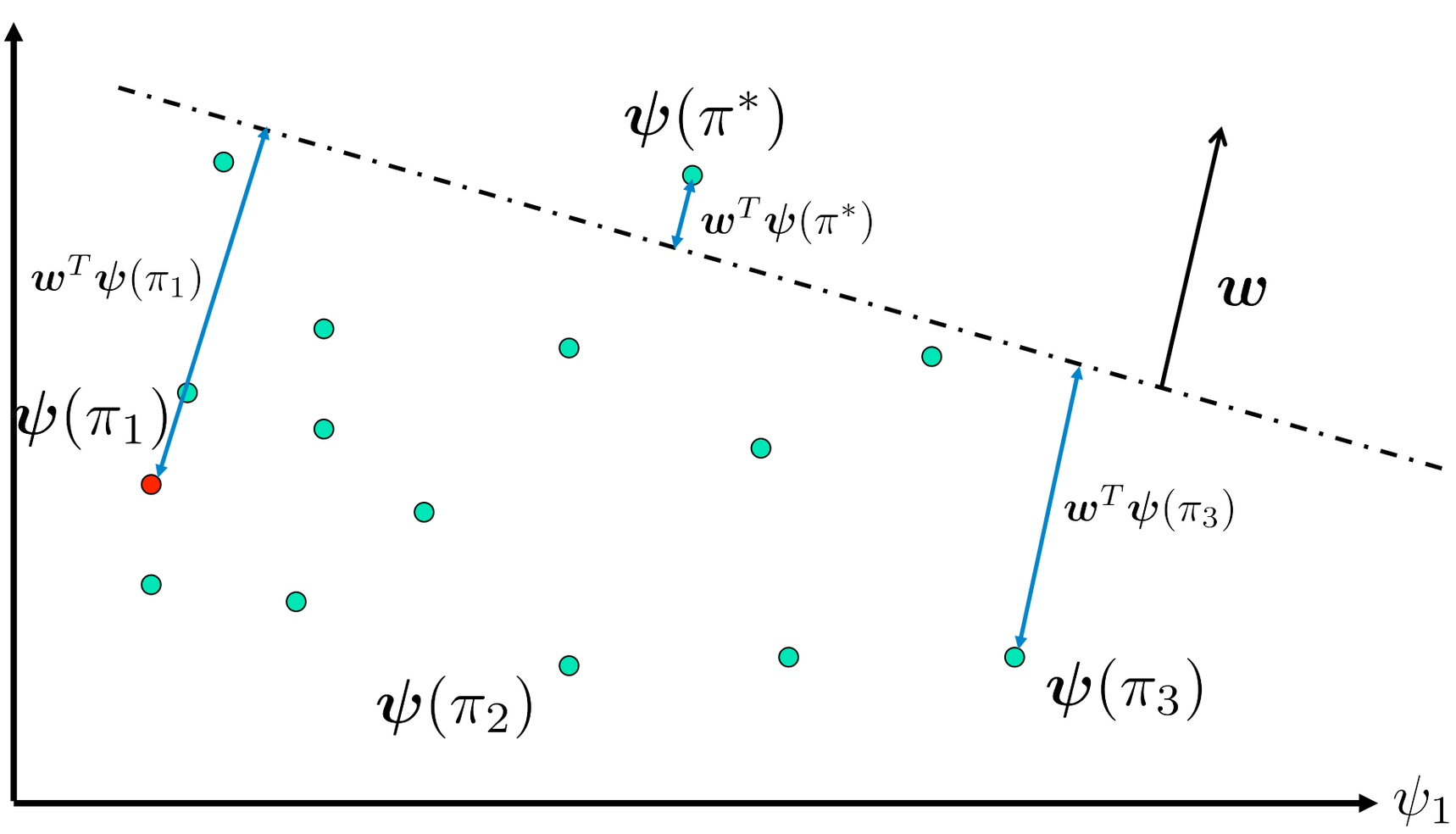
# Constraint generation

Every policy has a corresponding feature expectation vector, which for visualization purposes we assume to be 2D



# Constraint generation

**Linear parametrization:** We need to find a separating hyper-plane given by $\boldsymbol{w}$




Scalar product $w^T\psi$ gives us the (positive or negative) distance to the separating hyper-plane

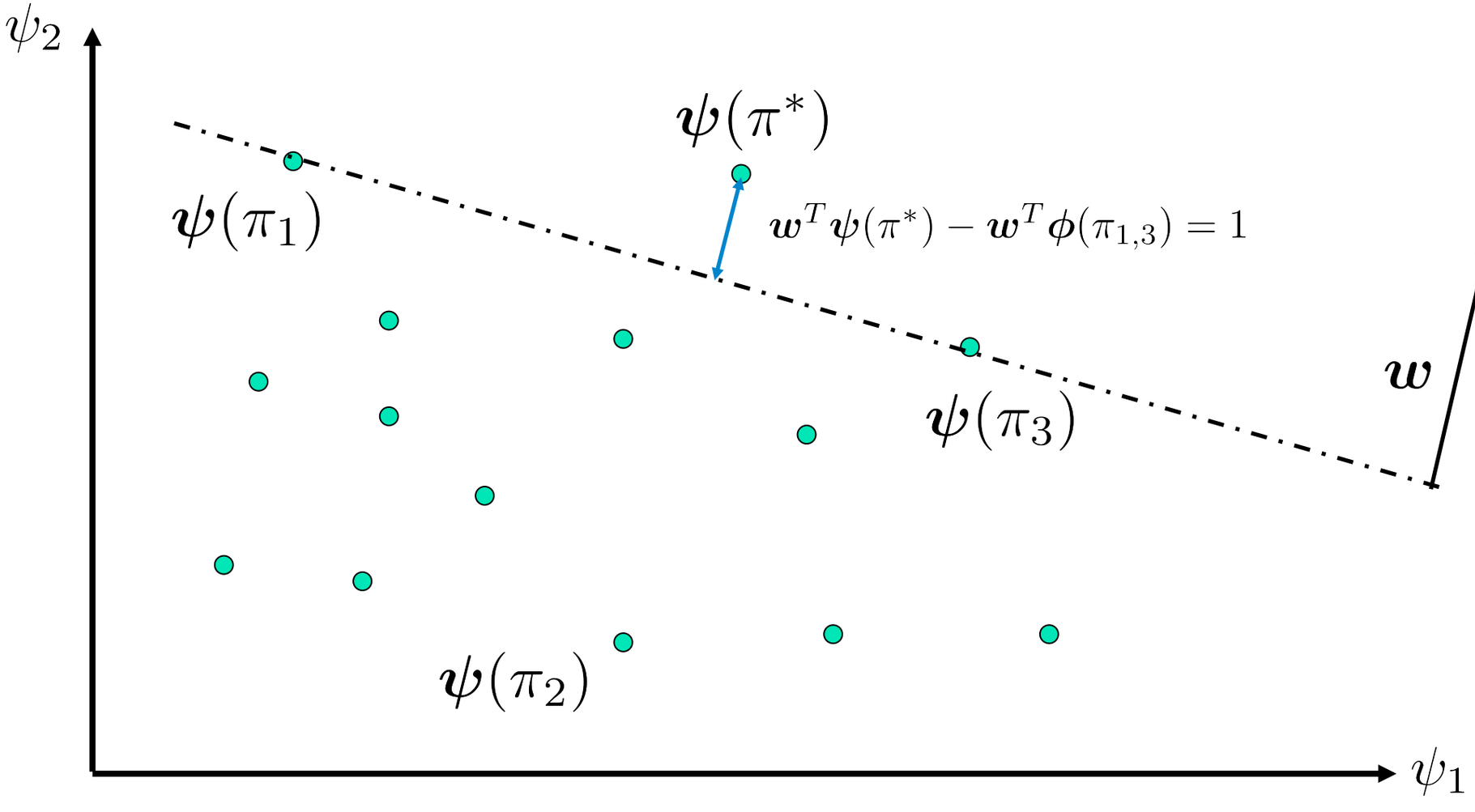
# Ill-posed Problem

**Standard max margin:**

Smallest weight vector with predefined reward margin of 1

$$\min_{\boldsymbol{w}} \quad \boldsymbol{w}^T \boldsymbol{w}$$
$$\text{s.t.} \quad \boldsymbol{w}^T \boldsymbol{\psi}(\pi^*) \geq \boldsymbol{w}^T \boldsymbol{\psi}(\pi) + 1, \quad \forall \pi$$

# Max. margin solution




Similar interpretation as a support vector machine

# Ill-posed Problem

**Structured max margin:**

Smallest weight vector

Margin depends on difference of policies $m(\pi^*, \pi)$

$$\begin{aligned} \min \quad & \boldsymbol{w}^T \boldsymbol{w} \\ \text{s.t.} \quad & \boldsymbol{w}^T \boldsymbol{\psi}(\pi^*) \geq \boldsymbol{w}^T \boldsymbol{\psi}(\pi) + m(\pi^*, \pi), \quad \forall \pi \end{aligned}$$

**Justification:** margin should be larger for policies that are very different from $\pi^*$.

**Example for $m(\pi^*, \pi)$ :**

Sum of minimum distances from generated path the example path

# Basic principle

**Find a reward function $r^*(s_t)$ which explains the expert behavior**

Assume expert is optimal w.r.t. to $r^*(s_t)$

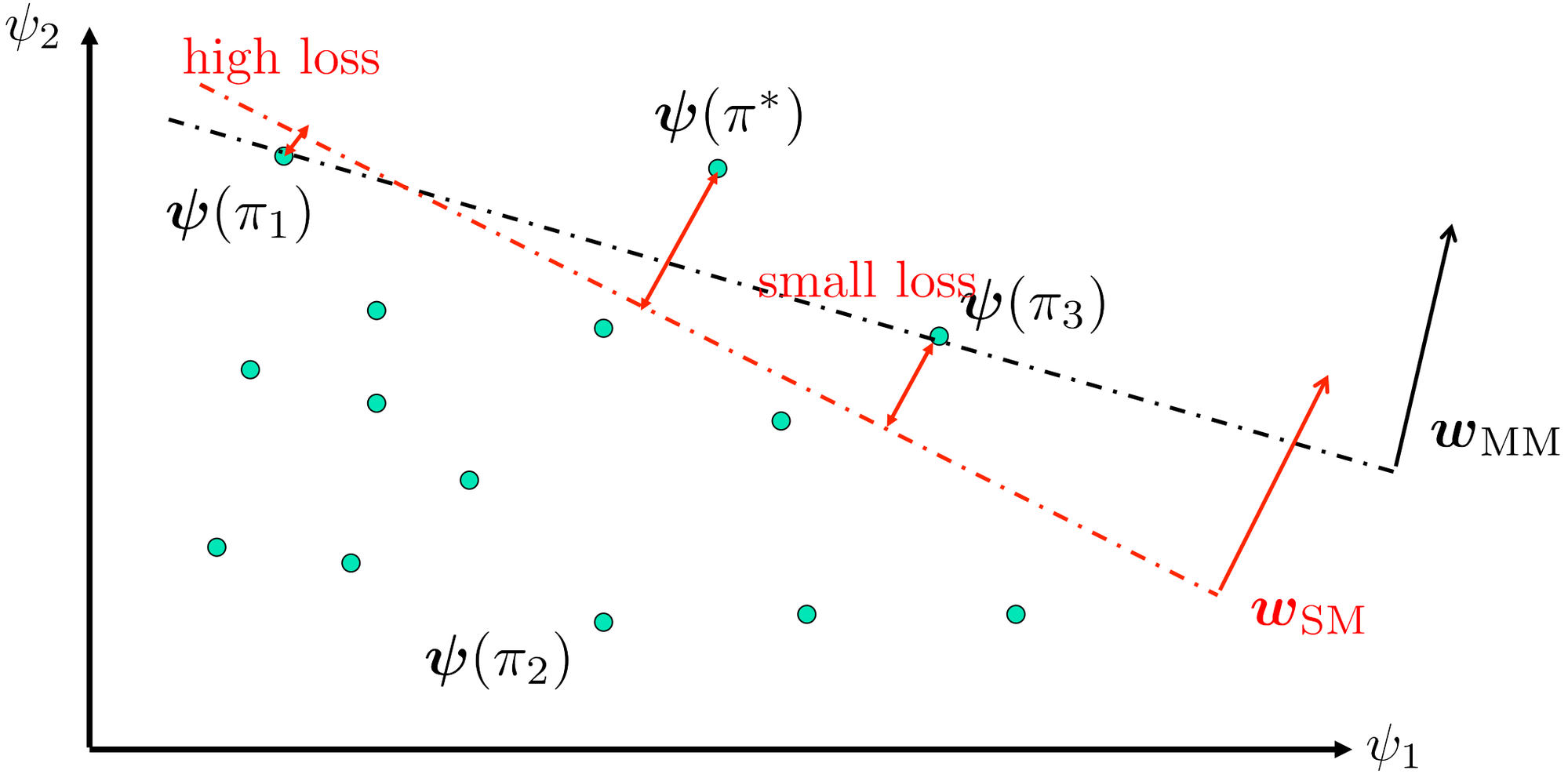
**I.e., find $r^*(s_t)$ such that**

$$\mathbb{E}_{p,\pi}\left[\sum_t \gamma^t r^*(s_t)|\pi^*\right] \geq \mathbb{E}_{p,\pi}\left[\sum_t \gamma^t r^*(s_t)|\pi\right], \forall \pi$$

**In fact a convex feasibility problem, but many challenges**:

1. Ill-posed: $r^*(s_t) = 0$ is a solution, reward function ambiguity
2. Limited Data: We typically only observe expert traces rather than the entire expert optimal policy --- how to compute left-hand side?
3. Optimality Assumption: Assumes the expert is indeed optimal --- otherwise infeasible
4. Computation: assumes we can enumerate all policies

# Structured max margin solution



# Expert suboptimality

Structured prediction max margin with slack variables:

Every constraint can be violated a bit

Minimize the amount of violation

$$\min_{\boldsymbol{w},\xi} \quad \boldsymbol{w}^T\boldsymbol{w} + C\xi$$

$$\text{s.t.} \quad \boldsymbol{w}^T\boldsymbol{\psi}(\pi^*) \geq \boldsymbol{w}^T\boldsymbol{\psi}(\pi) + m(\pi^*, \pi) - \xi, \quad \forall\pi$$

Easy to extend to multiple MDPs

**Resolved:** access to $\pi^*$, ambiguity, expert suboptimality

**One challenge remains:** very large number of constraints

Ratliff et. al. use subgradient methods.

In this lecture: constraint generation

# Constraint generation

**Initialize** $\Pi = \{\}$ **and then iterate** k = 1…

**Solve**

$$\boldsymbol{w}^{(k)} = \quad \text{argmin}_{\boldsymbol{w}} \min_{\xi} \boldsymbol{w}^T \boldsymbol{w} + C\xi$$

$$\text{s.t.} \quad \boldsymbol{w}^T \boldsymbol{\psi}(\pi^*) \geq \boldsymbol{w}^T \boldsymbol{\psi}(\pi^{(i)}) + m(\pi^*, \pi^{(i)}) - \xi, \quad \forall \pi^{(i)} \in \Pi$$

**Find the most violated constraint**

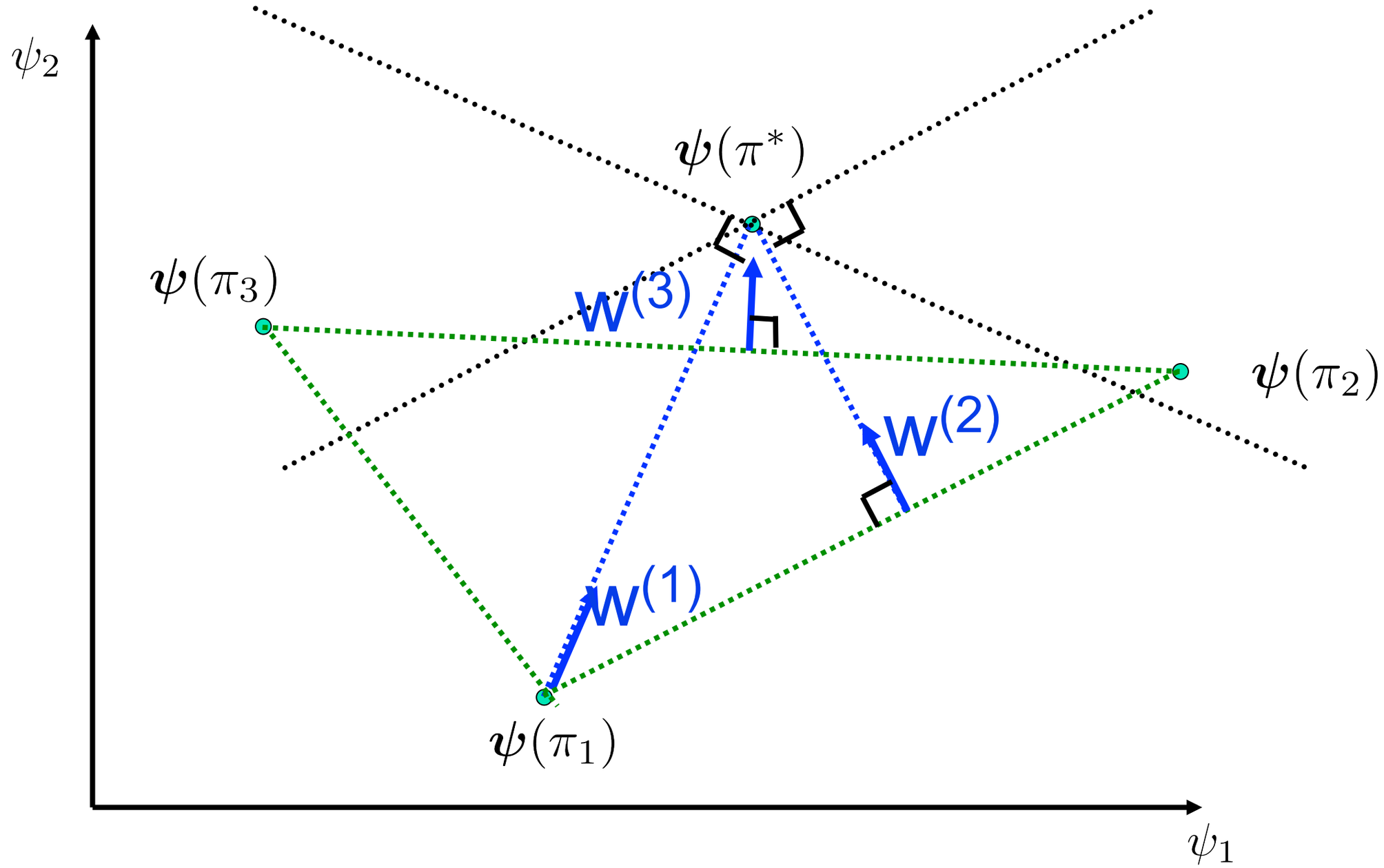
$$\pi^{(k)} = \max_{\pi} \boldsymbol{w}^{(k),T} \boldsymbol{\psi}(\pi) + m(\pi^*, \pi)$$

Compute optimal policy for the current estimate of the reward function (+ loss augmentation m), e.g., dynamic programming

**Add** $\pi^{(k)}$ **to set of policies** $\Pi$

**If no constraint violations were found, we are done.**

# Algorithm example run

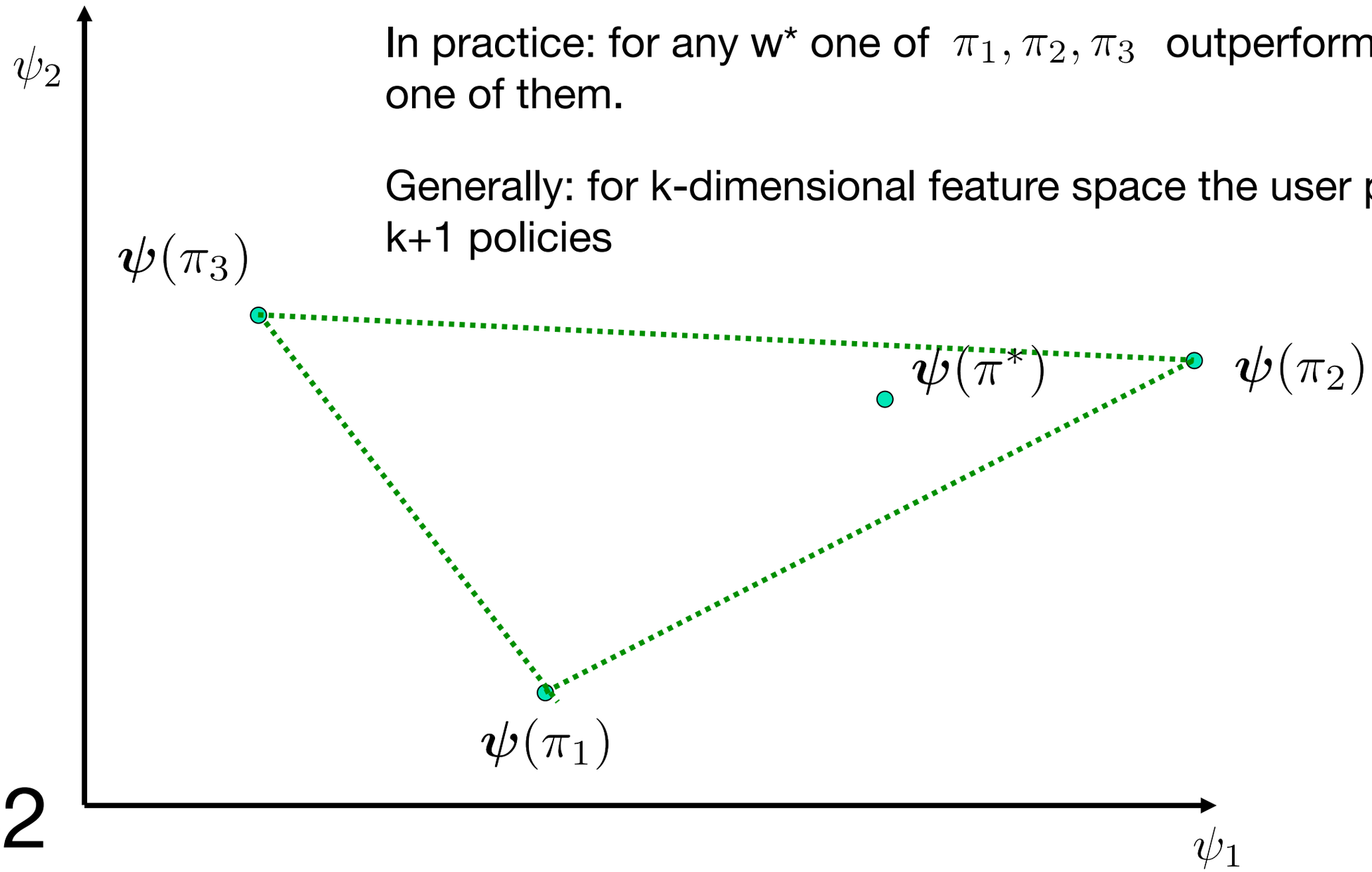


# Suboptimal expert case

Can match expert by stochastically mixing between 3 policies

In practice: for any w* one of $\pi_1, \pi_2, \pi_3$ outperforms$\pi^*$ → pick one of them.

Generally: for k-dimensional feature space the user picks between k+1 policies



# Outline of the Lecture

1. Introduction
    I. Comparison to Behavioral Cloning
2. Categories of IRL
    I. Maximum Margin
    II. Feature Matching by Max. Entropy
    III. Policy parametrized by rewards
3. Applications
4. Conclusion

# Classical Approach to Statistical Modeling: "The Principle of Maximum Entropy”

**Premise:** Statistical modeling should be performed with the least commitment possible.

- Predict using the probability distribution minimally committed/ maximally uncertain/*highest Shannon entropy*....
- ...subject to it agrees with known constraints
- “almost all” distributions are close to the MaxEnt one
- Uncertainty allows proper treatment of suboptimal demonstrations!

# Maximum-entropy approach to inference

**What is the maximum entropy distribution with given 1st and 2nd order and moments?**

$$\text{argmax}_p \qquad \underbrace{-\sum_x p(x)\log p(x)}_{\text{Entropy}}$$

$$\text{s.t.} \qquad \sum_x p(x)x = m_1, \quad \sum_x p(x)x^2 = m_2, \quad \sum_x p(x) = 1$$

**Solution:**

$$p(x) \propto \exp(\lambda_1 x + \lambda_2 x^2), \quad \text{where } \lambda_{1,2} \text{ are lagrangian multipliers}$$

**That's a Gaussian!** … which is of course well known that a Gaussian has maximum entropy of all distributions with given mean and variance

# Maximum-entropy approach to IRL [Ziebart 2008]

**Maximize entropy over paths with a given feature expectation**

$$\text{argmax}_p \qquad -\sum_{\boldsymbol{\tau}} p(\boldsymbol{\tau}) \log p(\boldsymbol{\tau})$$

$$\text{s.t.} \qquad \sum_{\boldsymbol{\tau}} p(\boldsymbol{\tau}) \boldsymbol{\psi}(\boldsymbol{\tau}) = \boldsymbol{\psi}(\pi^*), \quad \sum_{\boldsymbol{\tau}} p(\boldsymbol{\tau}) = 1$$

**Solution:** $p(\boldsymbol{\tau}) \propto \exp(\boldsymbol{w}^T \boldsymbol{\psi}(\boldsymbol{\tau}))$

w is now a lagrangian multiplier

We obtain a soft-max distribution over trajectories

Return of the trajectories: $R(\boldsymbol{\tau}) = \boldsymbol{w}^T \sum_t \gamma^t \boldsymbol{\phi}(\boldsymbol{s}_t) = \boldsymbol{w}^T \boldsymbol{\psi}(\boldsymbol{\tau})$

**Problem:** Does not take system dynamics into account

Trajectory could have huge return, but is very unlikely due to system dynamics

# Maximum-Causal-entropy IRL [Ziebart 2010]

**Maximize entropy of the policy with a given feature expectation**

$$\text{argmax}_\pi \quad -\sum_{t,a} \mu_t(s) \sum_a \pi_t(a|s) \log \pi_t(a|s)$$ Max. Caus. Ent

$$\text{s.t. } \forall t: \quad \sum_t \sum_s \mu_t(s)\boldsymbol{\phi}(s) = \boldsymbol{\psi}(\pi^*), \quad \sum_a \pi(a|s) = 1, \forall s$$ Match Features

$$\mu_t(s') = \sum_{s,a} \mu_{t-1}(s)\pi_{t-1}(a|s)p(s'|s,a),$$ State distribution consistency

State distribution at time step t has to be consistent with:

- state distribution and policy at time step t-1
- system dynamics

# Maximum-Causal-entropy IRL [Ziebart 2010]

**Solution:** $\pi_t(a|s) \propto \exp\left(\boldsymbol{w}^T\boldsymbol{\phi}(s) + \mathbb{E}[V_{t+1}(s')|s,a]\right)$

$V_t(s)$ is again a Lagrangian multiplier

If we say $\boldsymbol{w}^T\boldsymbol{\phi}(s)$ is the reward, this is a soft-max over the Q-function

$\pi_t(a|s) \propto \exp\left(Q(s,a;\boldsymbol{w})\right)$

**This is still a convex problem:**

Solution can be obtained by optimizing dual function

Can be done (relatively) efficiently

# Outline of the Lecture

1. Introduction
    I. Comparison to Behavioral Cloning
2. Categories of IRL
    I. Maximum Margin
    II. Feature Matching by Max. Entropy
    III. Policy parametrized by rewards
3. Applications
4. Conclusion

# Reward function parameterizing the policy class

**Alternatively, we can assume the policy is soft-max in a Q-function**

$$\pi_t(a|s; r, \alpha) = \frac{\exp\left(\alpha Q^*(s, a; r)\right)}{\sum_a' \exp\left(\alpha Q^*(s, a'; r)\right)}$$

where $Q^*$ is the optimal Q-function for reward function $r(s)$, i.e.,

$$V^*(s; r) = \max_a Q^*(s, a; r)$$

$$Q^*(s, a; r) = r(s) + \mathbb{E}[V^*(s'; r)|s, a]$$

Then we can evaluate the likelihood of seeing a set of state-action pairs as follows:

$$\log p(D|r, \alpha) = \sum_i \log \pi(a_i|s_i; r, \alpha)$$

Is equivalent to “a smarter” Behavior Cloning!

# Reward function parameterizing the policy class

Ziebart's approach can also be shown to be equivalent!

**Can be extended to Bayesian setup:**

Put prior on parameters of reward function

$$p(r, \alpha|D) = \frac{p(D|r, \alpha)p(r, \alpha)}{p(D)}$$

- Ramachandran and Amir, AAAI2007: MCMC method to sample from this distribution
- Neu and Szepesvari, UAI2007: gradient method to optimize the likelihood [MAP]

# Open Directions

- Open directions:
  - Active inverse RL,
  - Inverse RL with minmax control
  - Inverse RL with partial observability
  - Inverse RL with learning stages (rather than observing optimal policy)
  - Many more …
- Are you interested? We may have an excellent thesis for you!

# Outline of the Lecture

1. Introduction

2. Contrast to behavioral cloning, historical sketchMathematical formulations for inverse RLExample applications

3. Case studies

# Urban navigation

- Reward function for urban navigation?

→ destination prediction

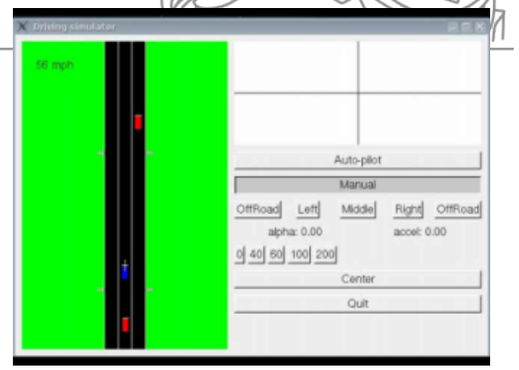
- Ziebart, Maas, Bagnell and Dey AAAI 2008

# Outline of the Lecture

1. Introduction
    I. Comparison to Behavioral Cloning
2. Categories of IRL
    I. Maximum Margin
    II. Feature Matching by Max. Entropy
    III. Policy parametrized by rewards
3. Applications
4. Conclusion

# Examples

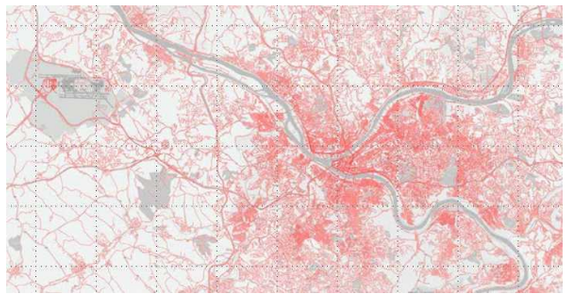
- Simulated highway driving
  - Abbeel and Ng, ICML 2004,




  - Syed and Schapire, NIPS 2007

- Aerial imagery based navigation
  - Ratliff, Bagnell and Zinkevich, ICML 2006

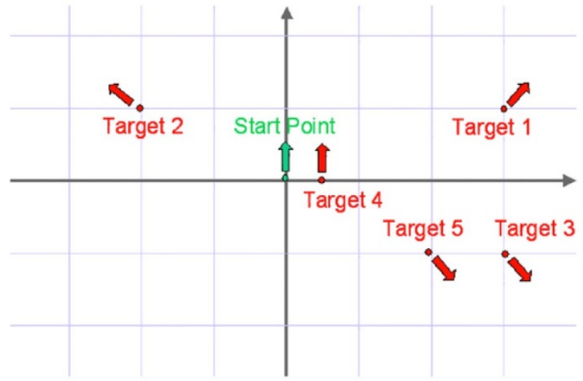

- Parking lot navigation
  - Abbeel, Dolgov, Ng and Thrun, IROS 2008



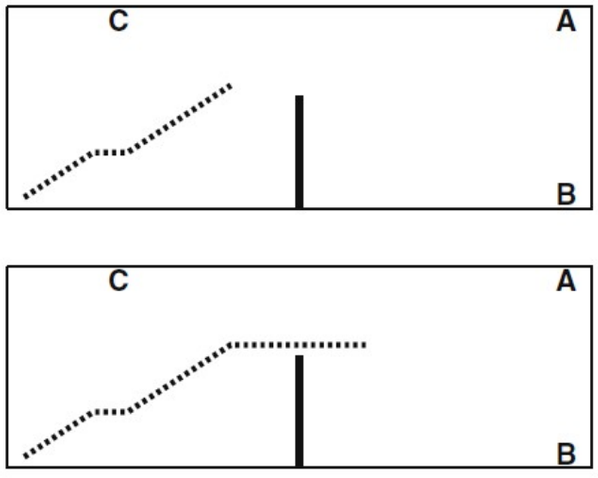
- Urban navigation
  - Ziebart, Maas, Bagnell and Dey, AAAI 2008

# Examples (ctd)

- Human path planning
  - Mombaur, Truong and Laumond, AURO 2009




- Human goal inference
  - Baker, Saxe and Tenenbaum, Cognition 2009




- Quadruped locomotion
  - Ratliff, Bradley, Bagnell and Chestnutt, NIPS 2007
  - Kolter, Abbeel and Ng, NIPS 2008

# Lecture outline

- Case studies:
  - (1) Highway driving,
  - (2) Crusher,
  - (3) Parking lot navigation,
  - (4) Route inference,
  - (5) Human path planning,
  - (6) Human inverse planning,
  - (7) Quadruped locomotion
  - (8) Helicopter Acrobatics

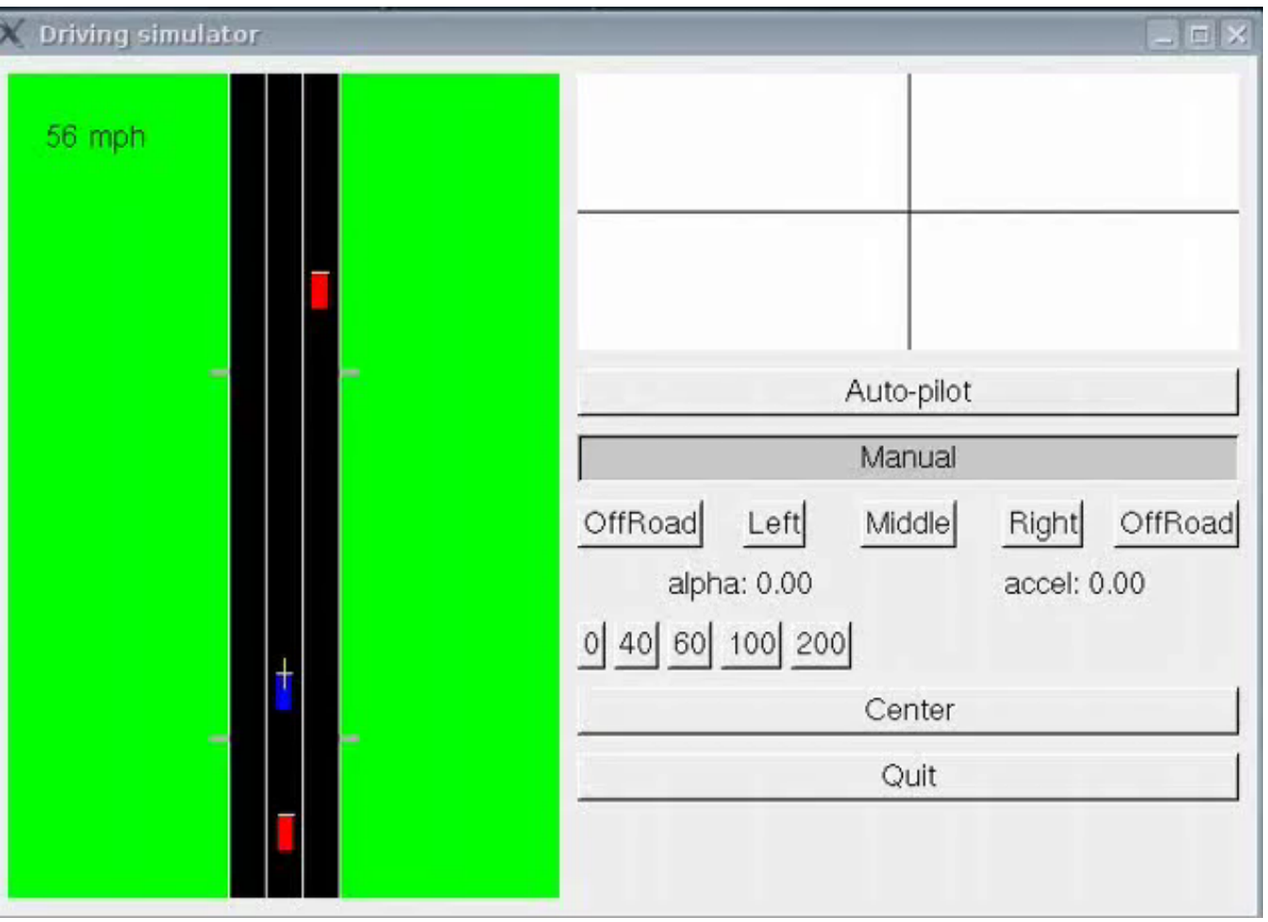
# Simulated highway driving



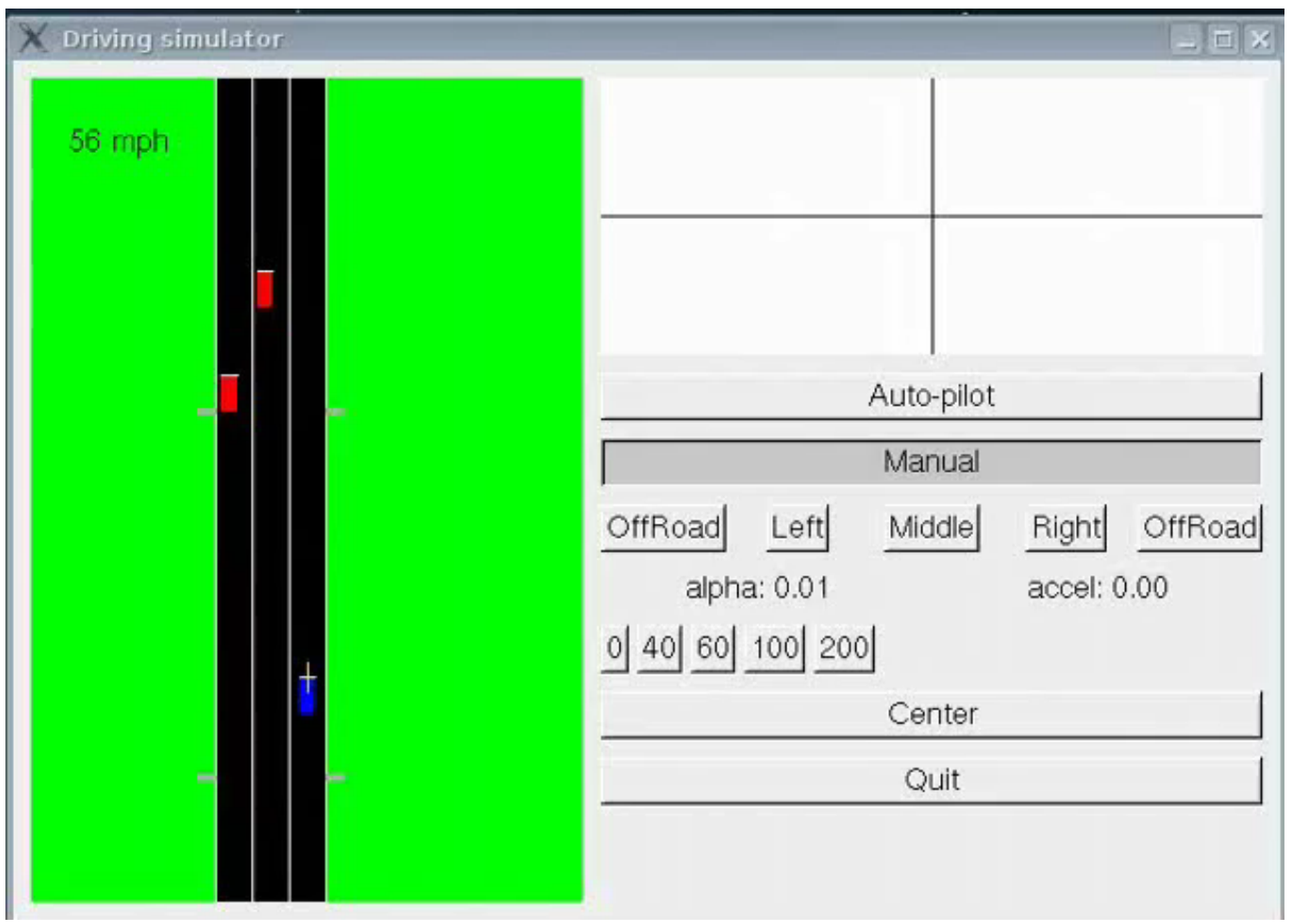

Abbeel and Ng, ICML 2004; Syed and Schapire, NIPS 2007

# Highway driving

Teacher in Training World



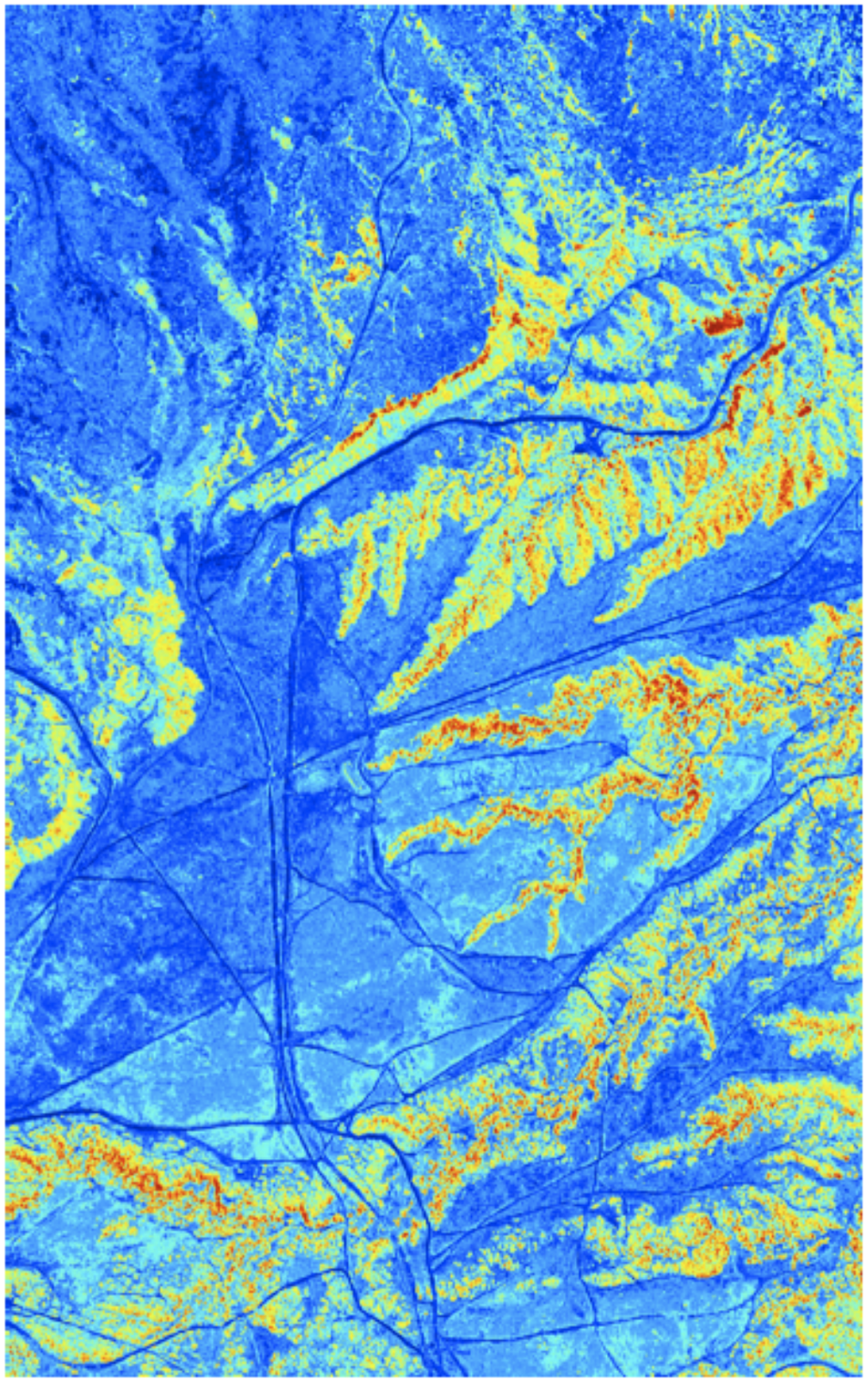

Learned Policy in Testing World




- Input:
  - Dynamics model / Simulator $P_{xu}(x_{t+1} \mid x_t, u_t)$
  - Teacher's demonstration: 1 minute in "training world"
  - Note: R* is unknown.
  - Reward features: 5 features corresponding to lanes/shoulders; 10 features corresponding to presence of other car in current lane at different distances

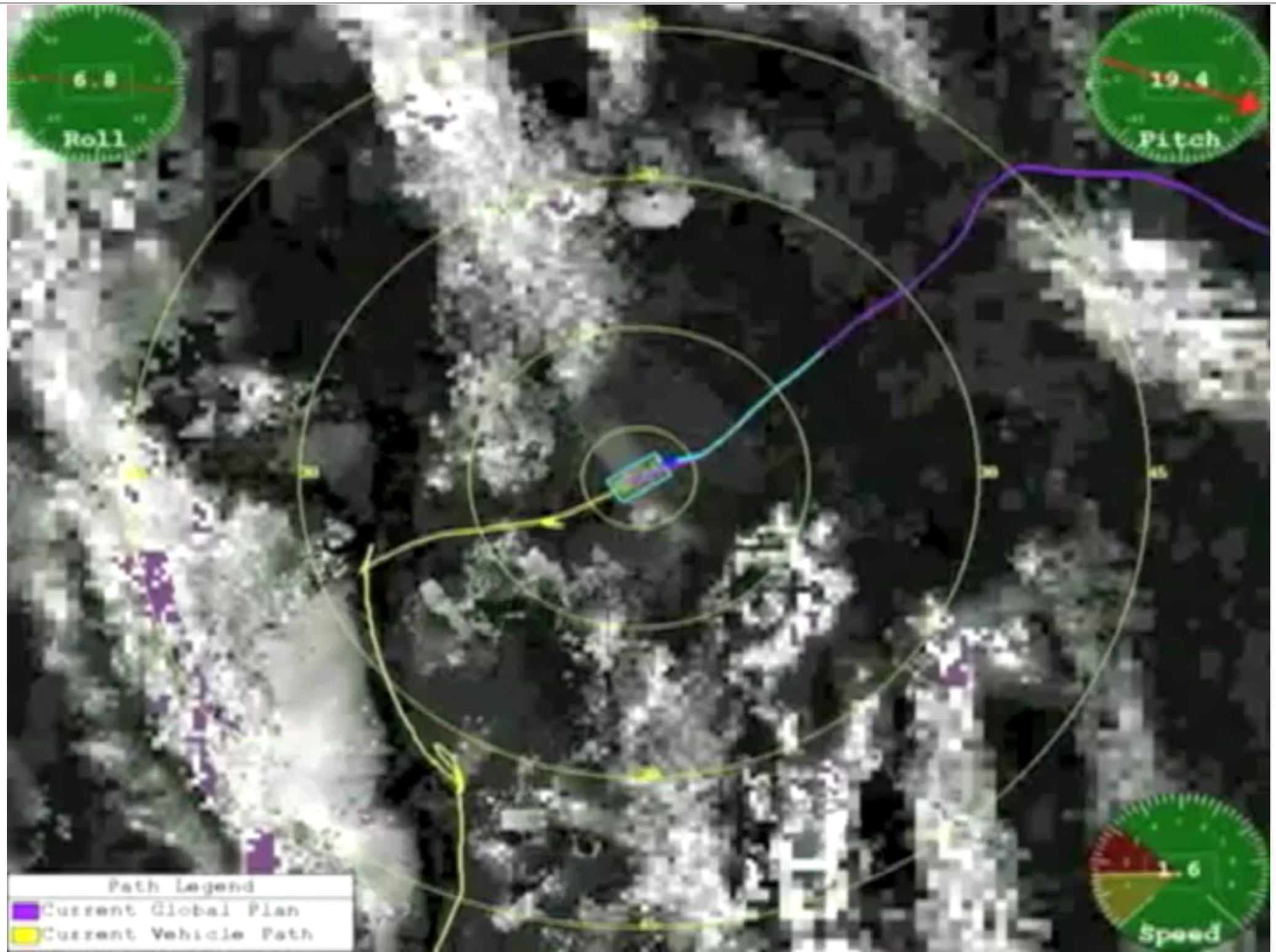
[Abbeel and Ng 2004]

# Max margin



[Ratliff + al, 2006/7/8]

# Max-margin




[Ratliff + al, 2006/7/8]

# Parking lot navigation

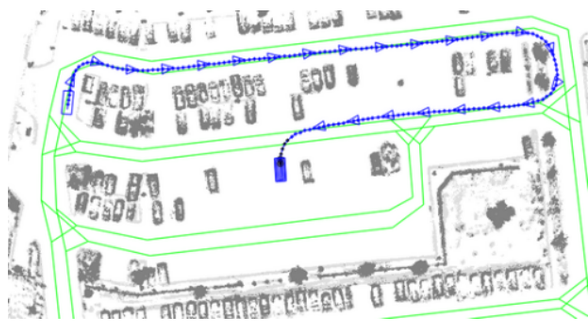

- Reward function trades off:
  - Staying “on-road,”
  - Forward vs. reverse driving,
  - Amount of switching between forward and reverse,
  - Lane keeping,
  - On-road vs. off-road,
  - Curvature of paths.

[Abbeel et al., IROS 08]

# Experimental setup

- Demonstrate parking lot navigation on “train parking lots.”



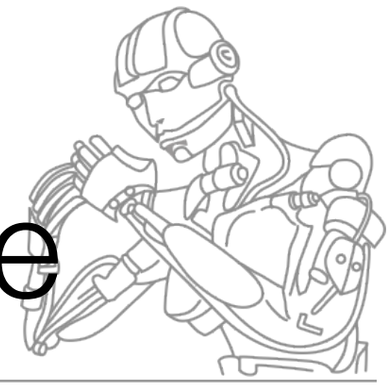
- Run our apprenticeship learning algorithm to find the reward function.
- Receive “test parking lot” map + starting point and destination.
- Find the trajectory that maximizes the learned reward function for navigating the test parking lot.

# Nice driving style

# Sloppy driving-style

QuickTime™ and a
JVT/AVC Coding decompressor
are needed to see this picture.

# “Don’t mind reverse” driving-style



QuickTime™ and a
JVT/AVC Coding decompressor
are needed to see this picture.

**Only 35% of routes are "fastest"** (Letchner, Krumm, & Horvitz 2006)

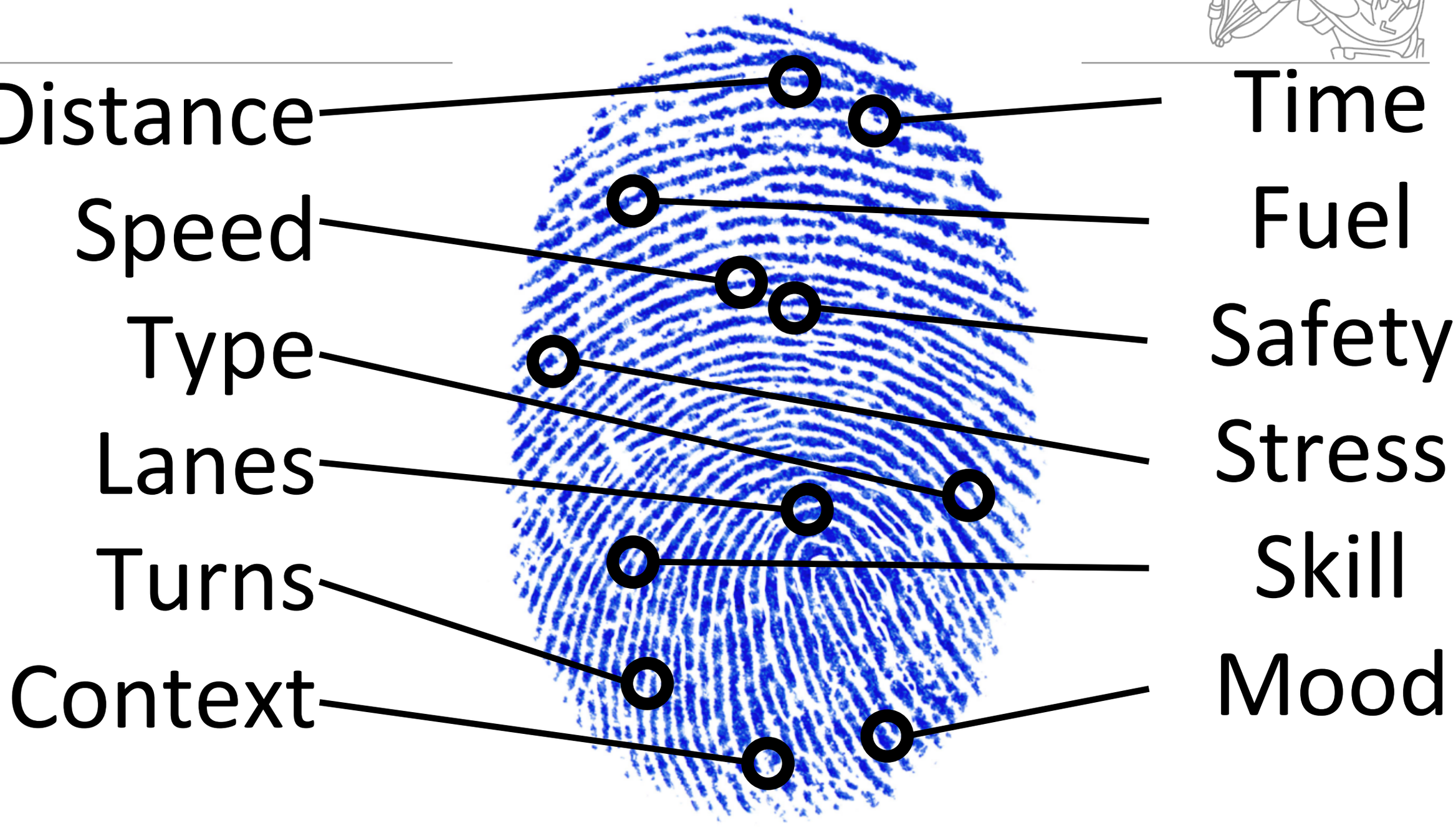
Time

Money

Stress

Skill

Ziebart+al, 2007/8/9


Distance
Speed
Type
Lanes
Turns
Context
Time
Fuel
Safety
Stress
Skill
Mood



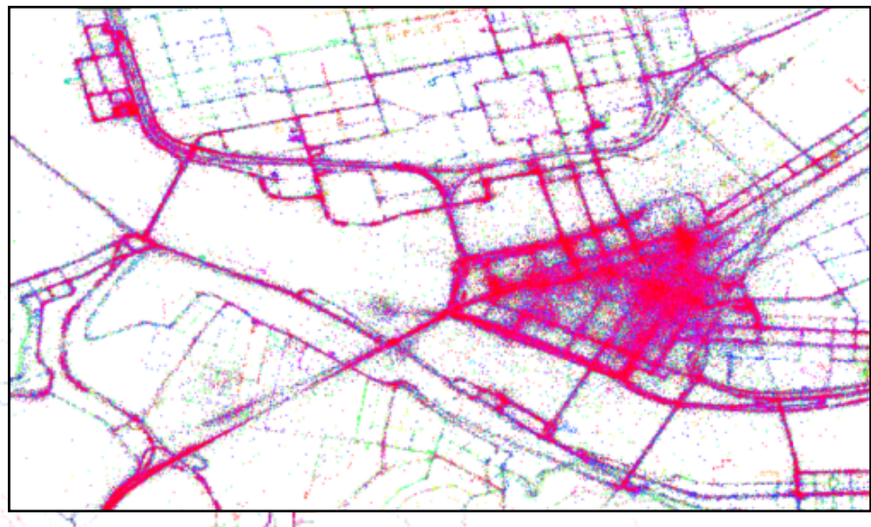
Ziebart+al,

# Data Collection


**Length**
**Speed**
**Road Type**
**Lanes**

**Accidents**
**Construction**
**Congestion**
**Time of day**

25 Taxi Drivers

Over 100,000 miles Ziebart+al, 2007/8/9

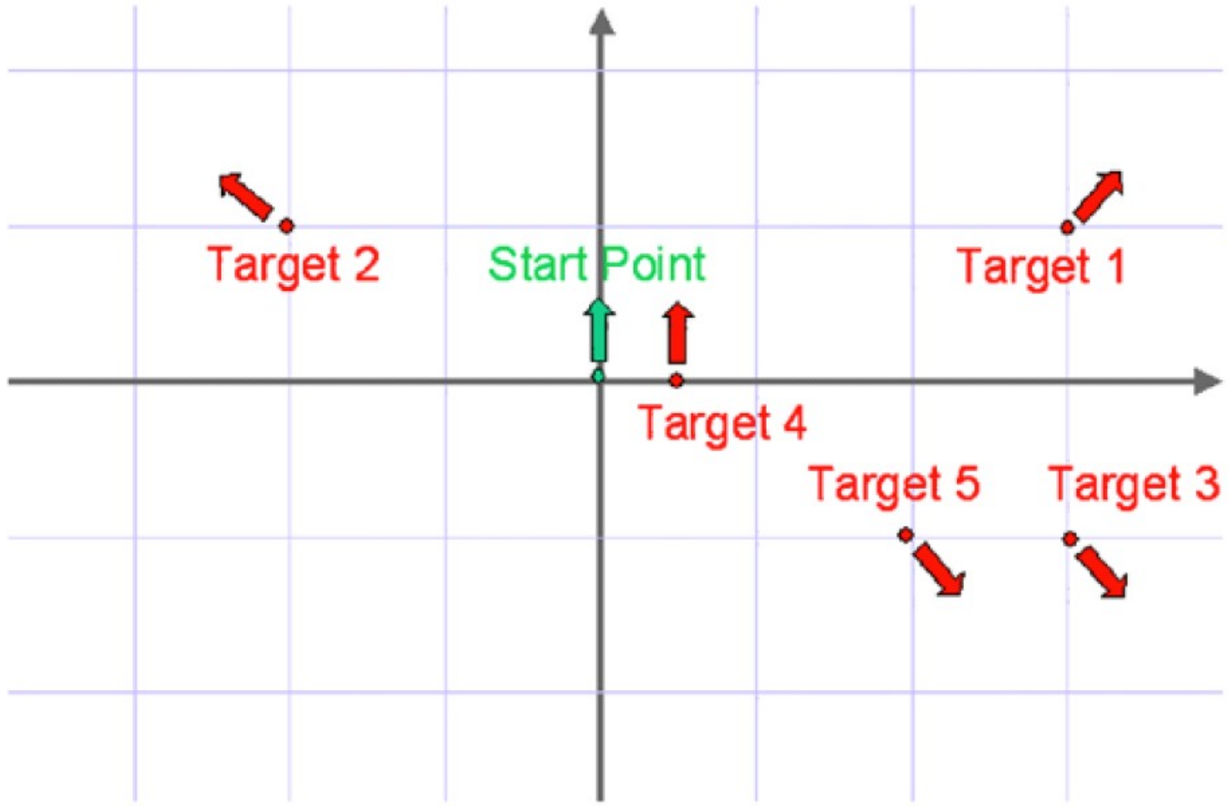
# Destination Prediction

# Equivalent: Pedestrian Prediction

QuickTime™ and a
JVT/AVC Coding decompressor
are needed to see this picture.

# Human path planning

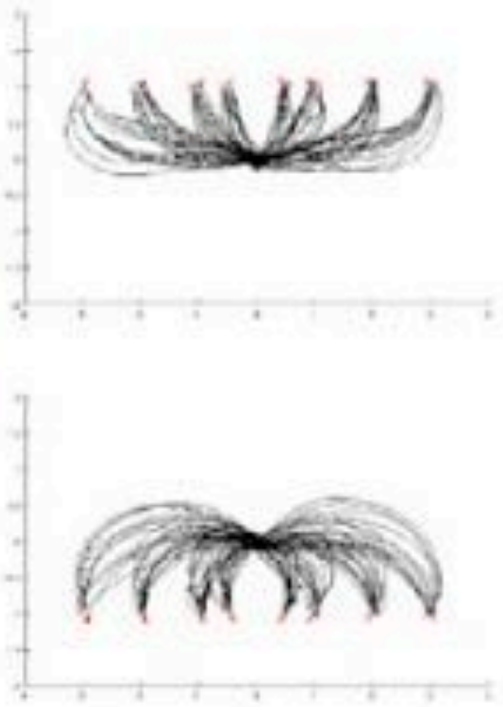
- Reward features:
  - Time to destination
  - (Forward acceleration)$^2$
  - (Sideways acceleration)$^2$
  - (Rotational acceleration)$^2$
  - Integral (angular error)$^2$

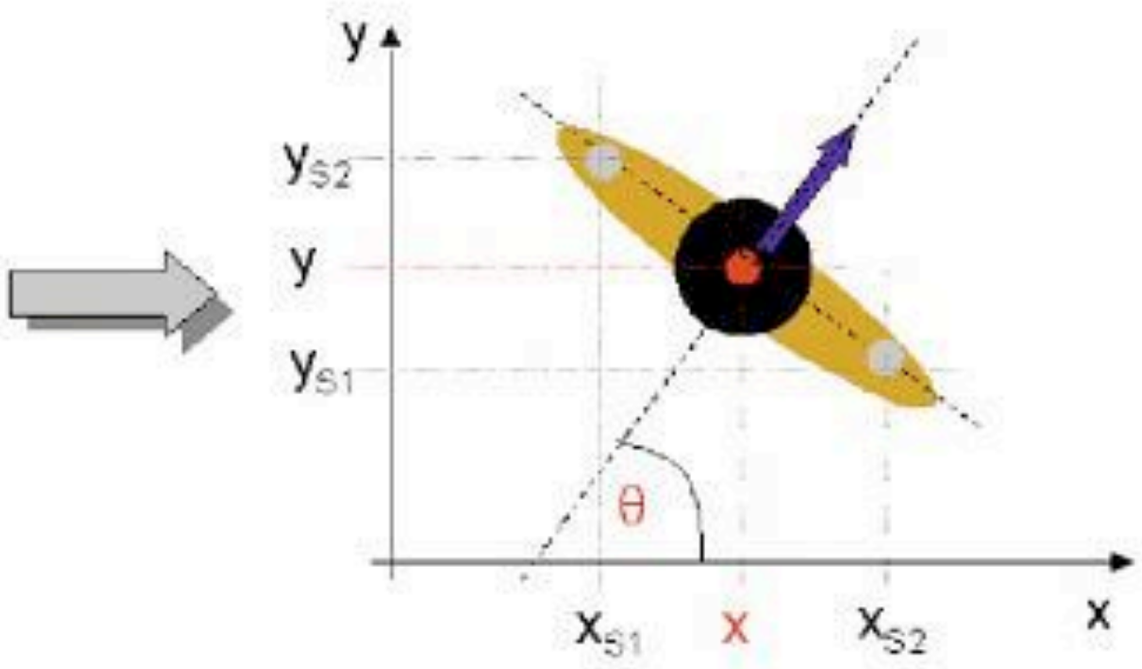





[Mombaur, Truong, Laumond, 2009]

# Experimental Setup



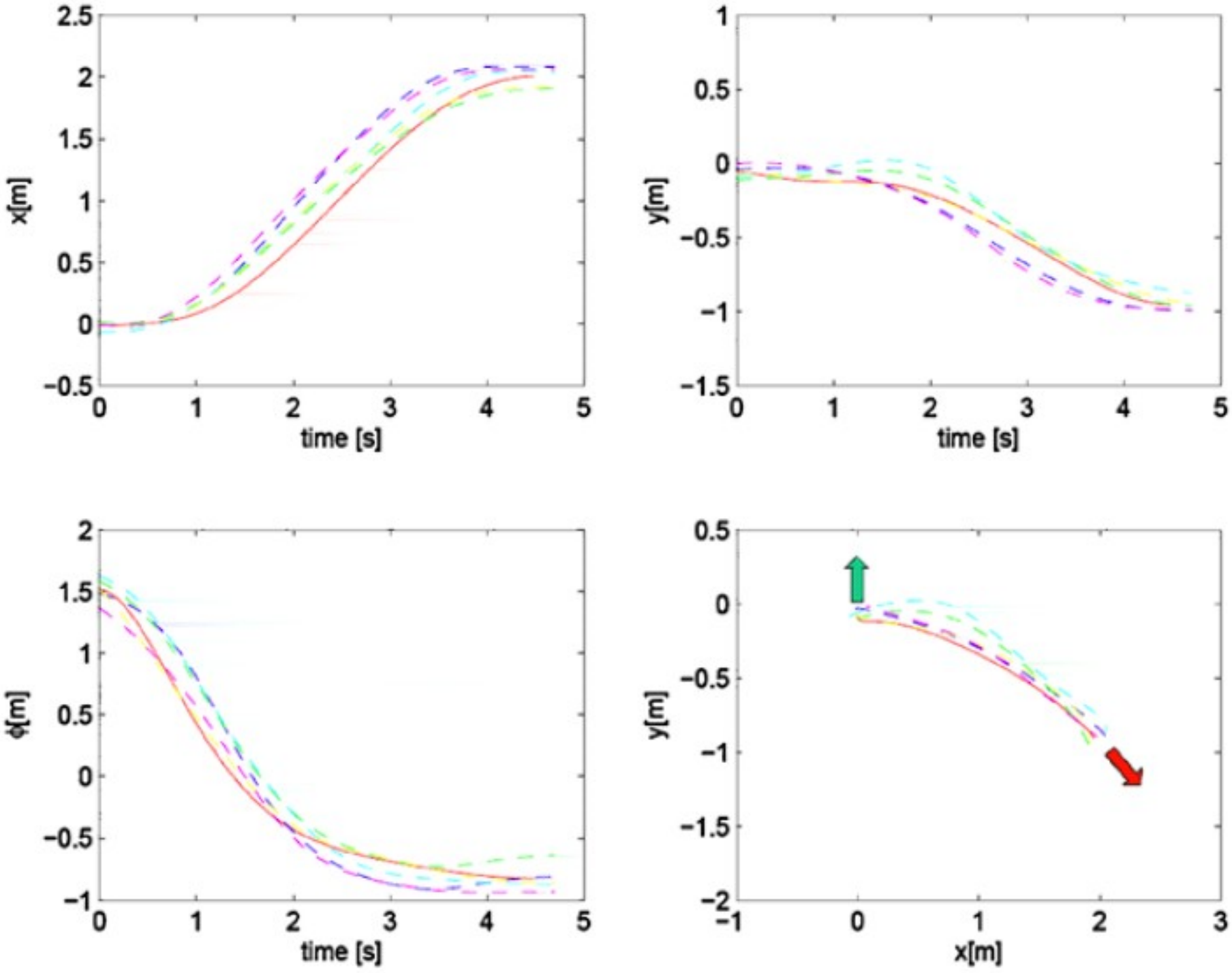


# Human path planning


- Result:
  - Time to destination: 1
  - (Forward acceleration)$^2$ 1.2
  - (Sideways acceleration)$^2$ 1.7
  - (Rotational acceleration)$^2$ 0.7
  - Integral (angular error)$^2$ 5.2

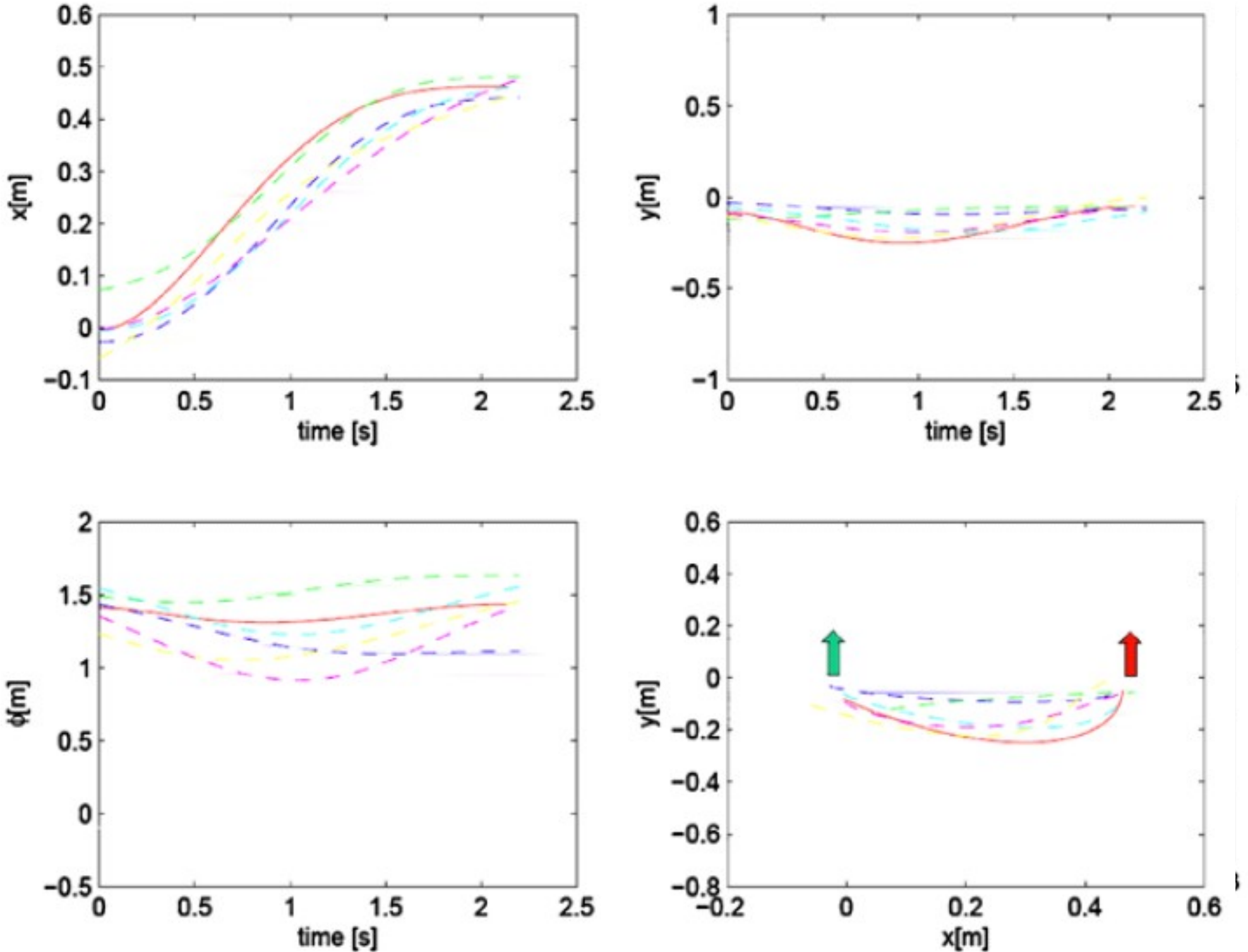
[Mombaur, Truong, Laumond, 2009]

# Human path planning



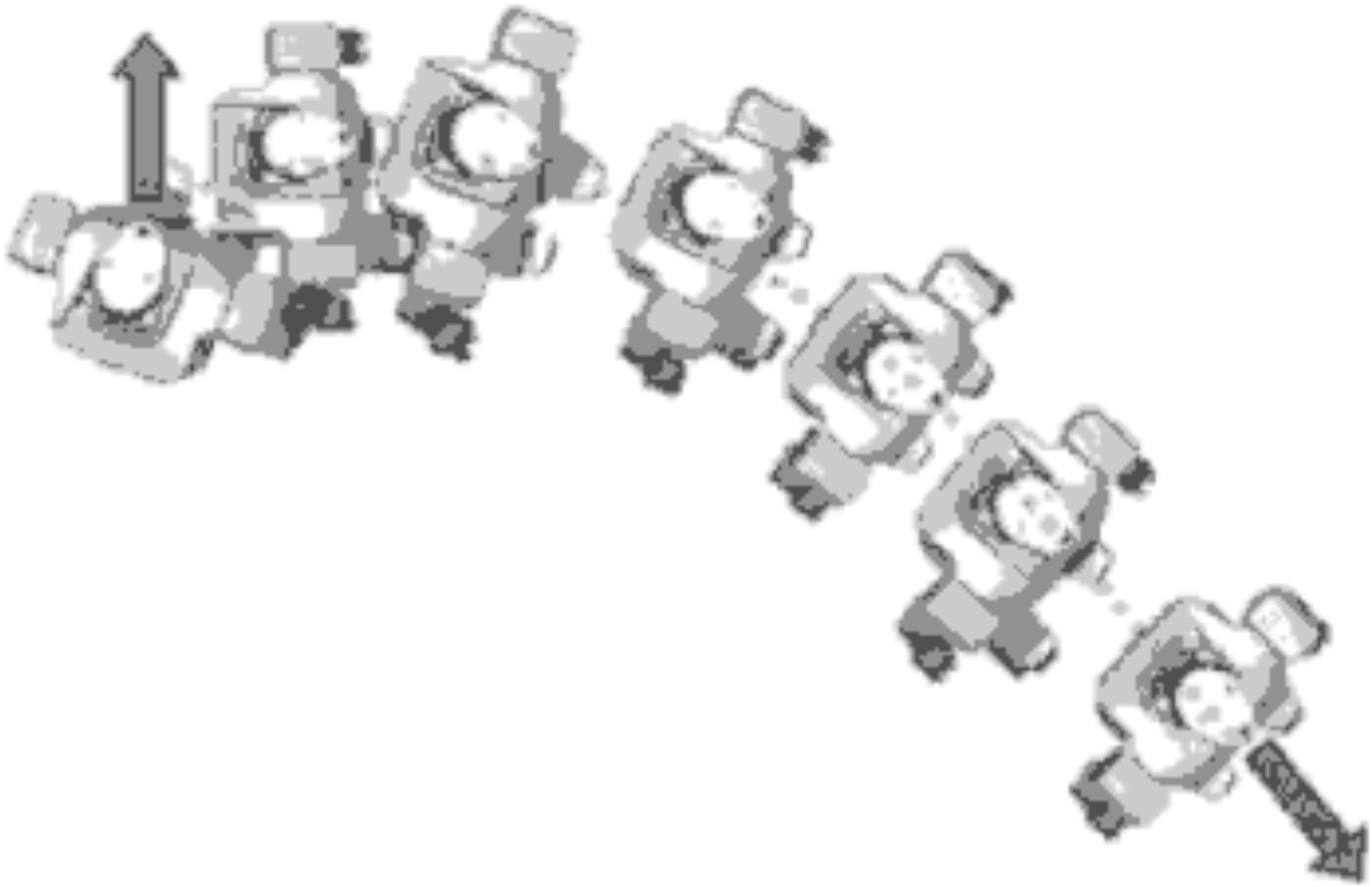

[Mombaur, Truong, Laumond, 2009]

# Human path planning



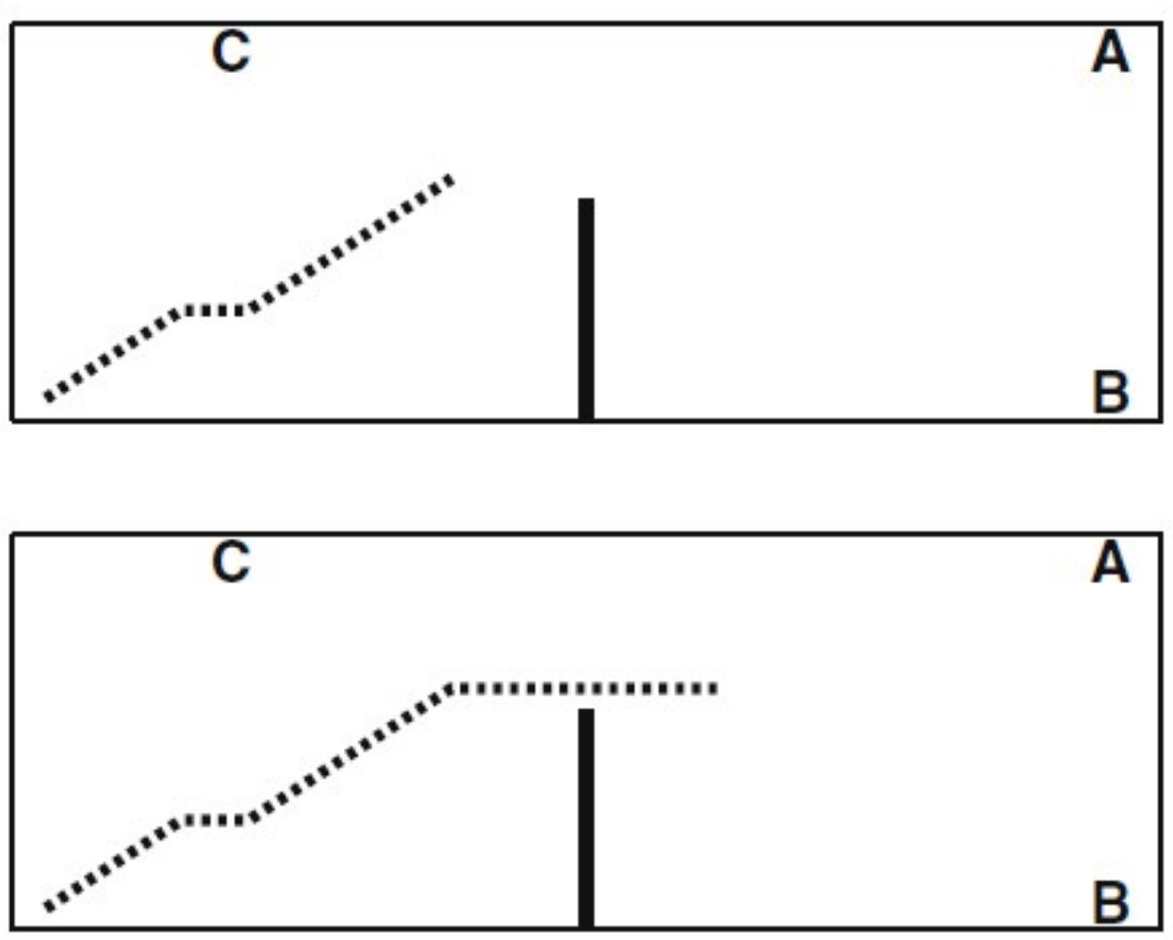

[Mombaur, Truong, Laumond, 2009]

# Transfer to a Humanoid



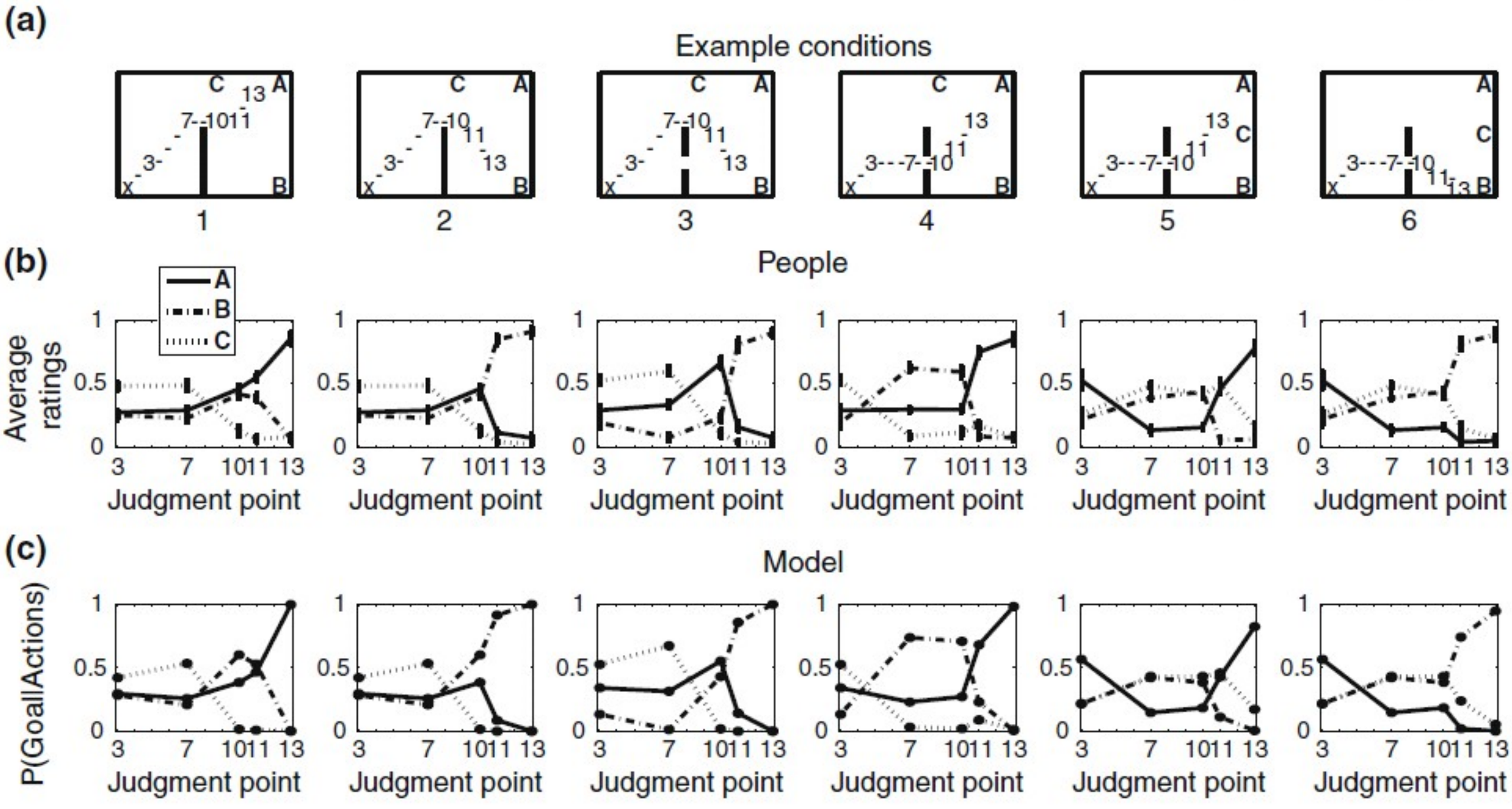
# Goal inference

- Observe partial paths, predict goal.  Goal could be either A, B, or C.
- + HMM-like extension: goal can change (with some probability over time).




[Baker, Saxe, Tenenbaum, 2009]

# Goal inference






[Baker, Saxe, Tenenbaum, 2009]

# Quadruped

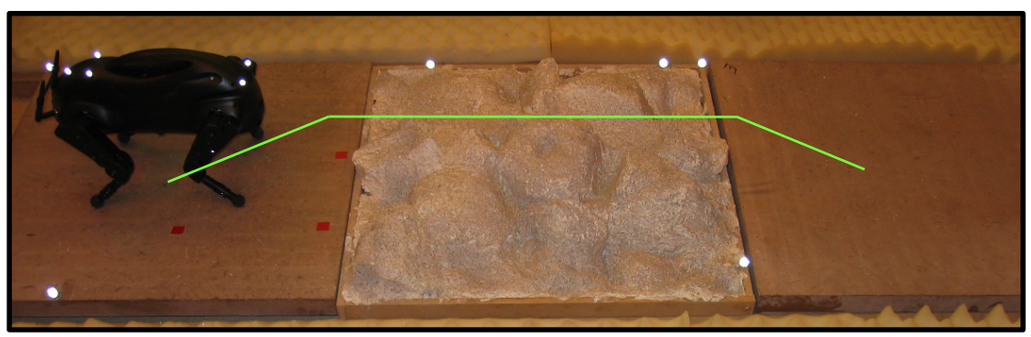
- Reward function trades off 25 features.



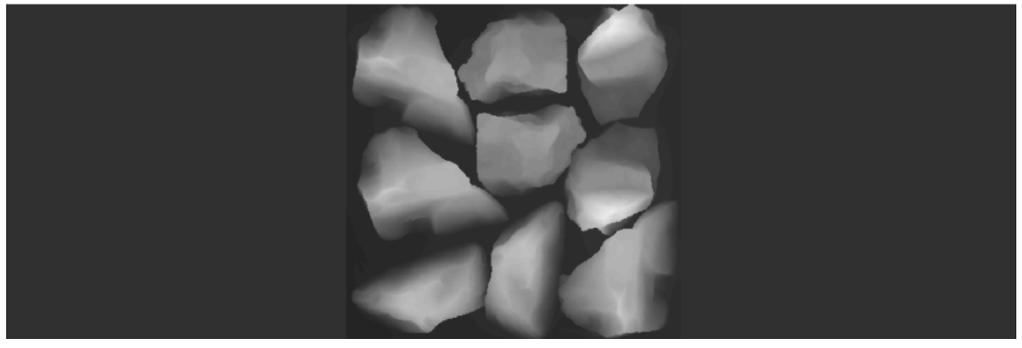
Hierarchical max margin [Kolter, Abbeel & Ng, 2008]

# Experimental setup

- Demonstrate path across the “training terrain”



- Run the apprenticeship learning algorithm to find the reward function
- Receive “testing terrain”---height map.

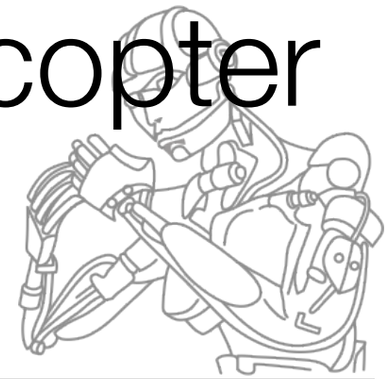


- Find the optimal policy with respect to the learned reward function for crossing the testing terrain.

# Little Dog: CMU Team

Ratliff + al, 2007

# Remainder of lecture: extreme helicopter flight

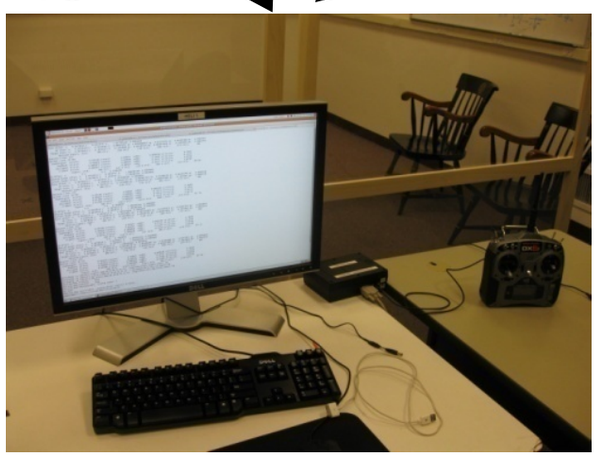


- How does helicopter dynamics work
- Autonomous helicopter setup
- Application of inverse RL to autonomous helicopter flight

# Autonomous helicopter setup

On-Board Inertial Measurements Unit (IMU) data

Position data



1.Kalman filter

2.Feedback controller

Send out controls to helicopter

# Helicopter dynamics

- 4 control inputs:
  - Main rotor collective pitch
  - Main rotor cyclic pitch (roll and pitch)
  - Tail rotor collective pitch

# Experimental setup for the helicopter

1. Our expert pilot demonstrates the airshow several times.

2. Learn (by solving a joint optimization problem):
   - Reward function---trajectory.
   - Dynamics model---trajectory-specific local model.
3. Fly autonomously:
   - Inertial sensing + vision-based position sensing → (extended) Kalman filter
   - Receding horizon differential dynamic programming (DDP) feedback controller (20Hz)
   - **Learning to fly new aerobatics takes < 1 hour**

# Results!

# Summary

What you should know:

- Why is inverse RL useful / better than direct imitation learning?
- Algorithmic Challenges in IRL
- Different methods that use IRL, all are linear in features
- Why maximum margin?
- Why max. entropy?