# Learning Driving Styles for Autonomous Vehicles from Demonstration [1]

**Markus Kuderer, Shilpa Gulati, Wolfram Burgard**

## Reinforcement Learning

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**17/12/2020**

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# Introduction and paper presentation

# Introduction


Figure 1: Pony.ai’s self-driving car in Guangzhou [2]

> Autonomous Vehicles or self-driving car contains thousands of sensors, and the way the vehicle is driven is strictly based on algorithms that analyse the inputs from sensors with little or no human intervention. [3]

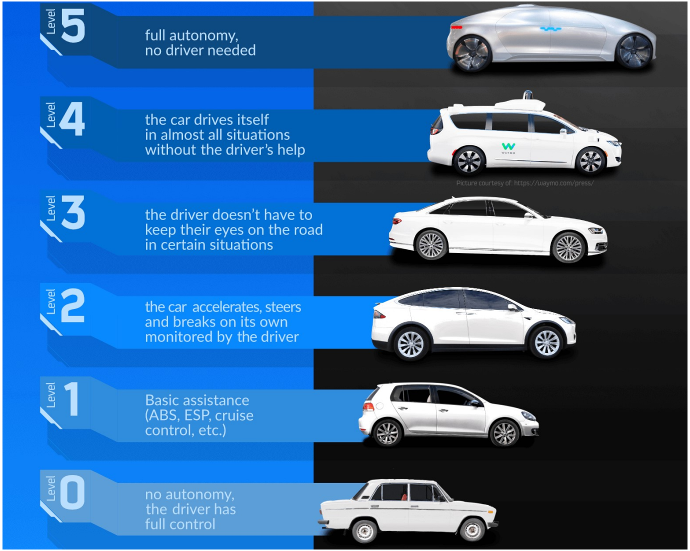


Figure 2: Levels of Vehicle Autonomy *SAE*

# Paper presentation

**Problem**

The authors affirm that in order to ensure comfort and acceptance by passengers, the self-driving car must use a driving style similar to that of the car's passengers.

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**Proposed Solution**

Learn the driving style of human drivers (Imitation Learning)

# Paper presentation



### Problem

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### Proposed Solution

Learn the driving style of human drivers (Imitation Learning)

### Methodology

Feature-based inverse reinforcement learning to create a continues reliable trajectory

# Reinforcement Learning Approach

# Forward Vs Inverse reinforcement learning

**"forward" reinforcement learning**
given:
states $\mathbf{s} \in \mathcal{S}$, actions $\mathbf{a} \in \mathcal{A}$
(sometimes) transitions $p(\mathbf{s}' \mid \mathbf{s}, \mathbf{a})$
reward function $r(\mathbf{s}, \mathbf{a})$
$\text{learn } \pi^{\star}(\mathbf{a} \mid \mathbf{s})$

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given:
states $\mathbf{s} \in \mathcal{S}$, actions $\mathbf{a} \in \mathcal{A}$
(sometimes) transitions $p(\mathbf{s}' \mid \mathbf{s}, \mathbf{a})$
samples $\{\tau_i\}$ sampled from $\pi^\star(\tau)$
$\text{learn } r_\theta(\mathbf{s}, \mathbf{a})$
Then use it to learn $\pi^\star(\mathbf{a} \mid \mathbf{s})$

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$\theta$ reward parameters

linear reward function: $r_{\theta}(\mathbf{s}, \mathbf{a}) = \sum_i \theta_i f_i(\mathbf{s}, \mathbf{a}) = \theta^T \mathbf{f}(\mathbf{s}, \mathbf{a})$

# Trajectory

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is a path that a vehicle should follow with a given velocity profile.

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**Trajectory Representation**
Use quintic (5th order) spline $s_j : [t_j, t_{j+1}] \to \mathbb{R}^2$.

$$\mathbf{r}(t) = \mathbf{s}_j(t) \quad \text{for} \quad t \quad \in \quad [t_j, t_{j+1}]$$

# The features of driving styles

The author defines driving style and the similarity between trajectories by:

- **Velocity Selections:** $f_v = \int_t \|\mathbf{v}_{\text{des}} - \dot{\mathbf{r}}(t)\| \, dt$

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- **Jerk:** $f_{\mathrm{j}} = \int_t \|\dddot{\mathrm{r}}(t)\|^2 dt$
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- **Curvature of path** $f_\kappa = \int_t \|\kappa(t)\|^2 dt$
- **Lane keeping** $f_1 = \int_t \|\mathbf{l}(t) - \mathbf{r}(t)\| dt$
- **Collision avoidance with other vehicles:** $f_{\text{d}} = \sum_c \int_t \frac{1}{\|\mathbf{r}(t) - \mathbf{o}_c(t)\|^2} dt$
- **Following distance** $f_{\text{ft}} = \int \max(0, \hat{d} - d(t)) dt$

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All features are then merged into a single feature vector.

# Maximum Entropy IRL

$$f : r \leftarrow (f1(r), ..., f_n(r)) \in \mathbb{R}_n \quad \text{- (1)}$$

$$\widetilde{f} = \frac{1}{N}\sum_{i=1}^{N} f(\widetilde{r_i}) \quad \text{- (2)}$$

$$\mathbb{E}_{p(r|\theta)}[f] = \widetilde{f} \quad \text{- (3)}$$

$$p(r|\theta) = exp(-\theta^T f(r)) \quad \text{- (4)}$$

$$\mathbb{E}_{p(r|\theta)}[f] - \widetilde{f} \quad \text{- (5)}$$

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## Maximum Likelihood estimation:

- Finding expectation is not possible using analytical methods, so we estimate the distribution and find it using MLE.

$$\mathbb{E}_p[f] \approx f(\arg\max_r p(r|\theta)) \quad \text{- (1)}$$

# Learning algorithm

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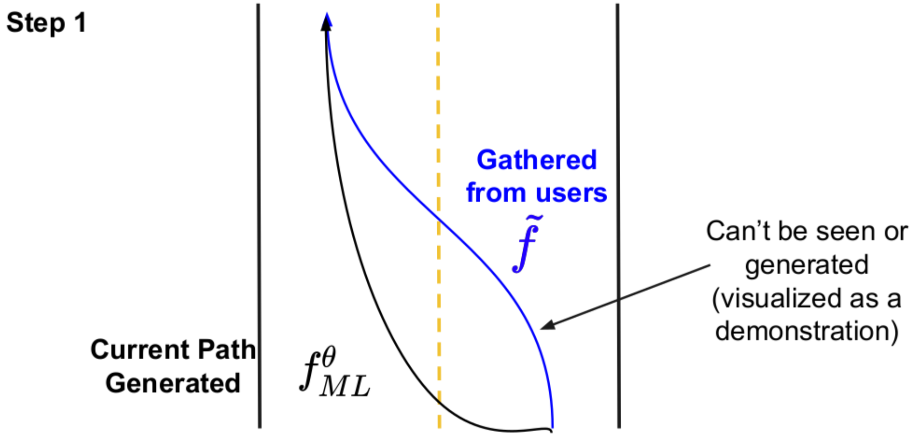
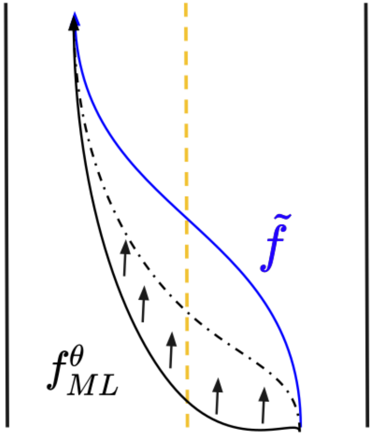
4. Calculate predicted feature vector and difference b/w predicted and observed feature vector $\mathbb{E}_{p(r|\theta)}[f] - \widetilde{f}$. Update the weights $\theta$ with this gradient.
5. Repeat from step 3 until convergence.

# Learning from Demonstration example



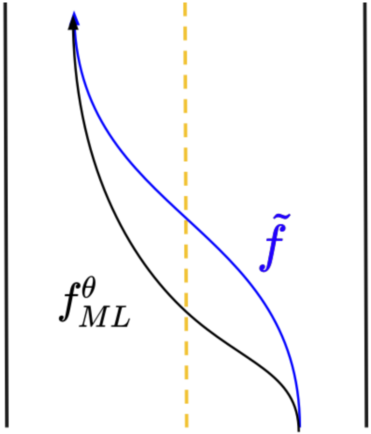
# Learning from Demonstration example

**Step 1**



# Learning from Demonstration example

**Step 2**



# Learning from Demonstration example

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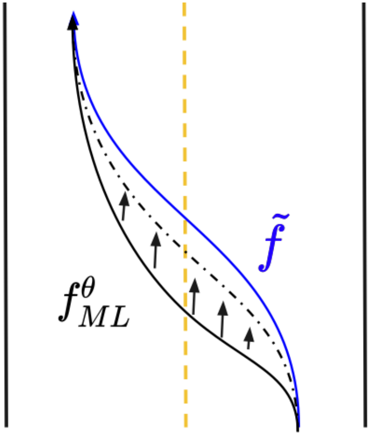
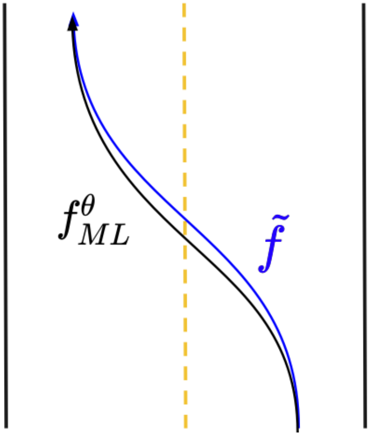


# Learning from Demonstration example

**Step N**



# Experiments and results

# Navigation

1. Divide navigation into planning cycles.
2. Fix position, velocity and acceleration, $p_0, v_0, a_0$ at beginning of each planning cycle according to the trajectory of previous planning cycle.
3. Determine the next spline control, $p_j, v_j, a_j$ for $j \in 1, ..., S$ points w.r.t. to cost function $\theta^T f(r)$

# Experiments

1. **Data Acquisition:** Recorded Driving styles of different drivers on US highways.
   1.1 Acceleration maneuvers (23 m/s   30 m/s) and lane change maneuvers.
   1.2 Each segment of 8 mins long.

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2. **Learning:** individual styles. Learn $\theta$ that yield policies which explain observed trajectory.
3. **Tested** in realistic simulation.

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# Results

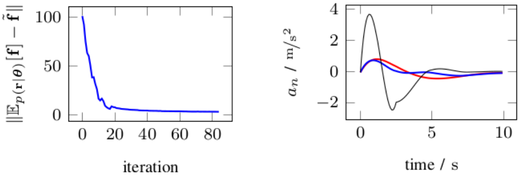


Figure 3: [1]

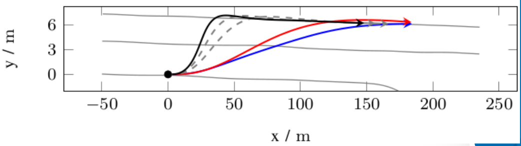


Figure 4: [1]

(Left) Norm of Expected and observed feature values. (Right) Normal acceleration during lane change. Initial Guess (black), Observed (blue), and Learned (red).

Trajectory during lane change. Initial Guess (black), Observed (blue), and Learned (red).

# Results

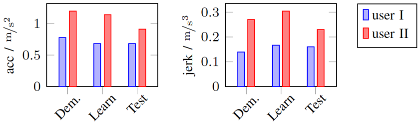


Figure 5: [1]

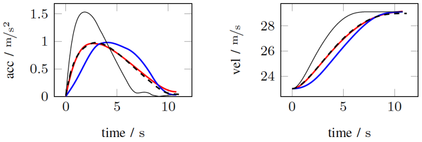


Figure 6: [1]

Comparison of mean observed and learned values for acc and jerk of driving style of two users.

Observed (blue), initial guess (black), learned (blue) and dotted (in realistic simulation) values for acceleration and velocity.

# Discussion and Related works

# Discussion

**Pros:**

- A novel approach. (Continuous domain, non MDP)
- Explainable features
- Simple to implement

**Cons:**

- Not enough info about experimental setup.
- No numerical quantification of "goodness". No benchmark is given.
- Tested only in simulation -> reality gap
- Risky: If a person drives badly, the algorithm will learn to drive badly
- 5 Hz is a concerningly slow planner to deal with all situations and speeds

# Related Works

- IRL for driving styles -> Abbeel and Ng[4], Ziebart et al.[5], Choi and Kim[6]
- New in this paper: Use IRL in continuous state spaces (can consider higher order properties such as latent jerk) and do not model dynamics as MDP in context of highway driving.
- Inspiration: learning pedestrian behavior. [7] [8]
- Inspired:
    - Cited by 257
    - [9] takes into account the response of other cars
    - [10] uses GANs for imitation learning from Human Driver (comparison with rule based and MLE).
    - [11] proposes algorithm for learning from humans in dynamical systems.

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# Thank you for your attention
# questions ?

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