Imitating Driving Behavior in an Urban Environment

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Summary

Introduction

- Autonomous vehicles need to adapt to a wide range of situations, even unlikely
- Modern approaches imitate human drivers by fitting a control model using Behavioral Cloning or Reinforcement Learning
- They fail to generalize to unseen situations
- GAIL is a new framework that incorporates Imitation Learning into a Generative Adversarial model

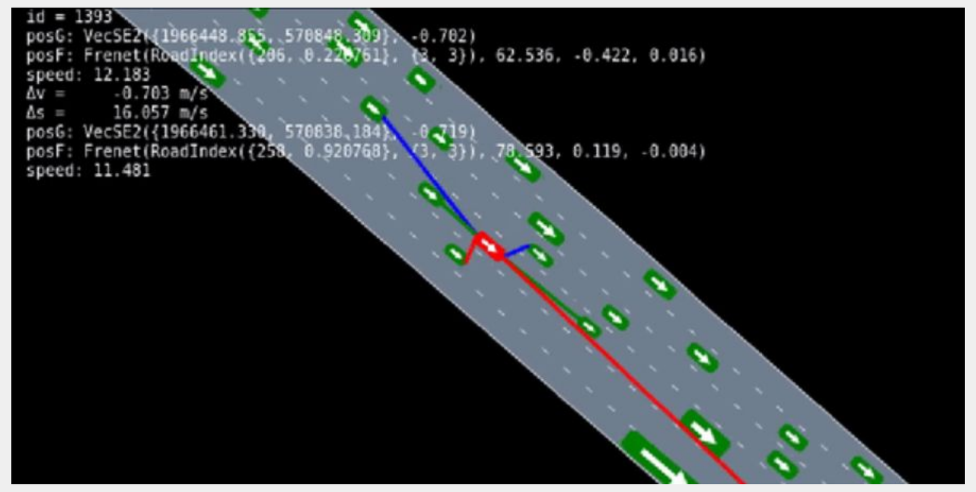
Contributions

- We tested GAIL's on an urban dataset (only tested on highways so far)
- We show we can obtain good performances with simpler policy architectures

Background

- State s = set of a vehicle's features
- Action a = acceleration and turn rate
- Policy π = neural network with input s and output distribution over a

  $$a \sim \pi(a|s;\theta)$$
- Rolled-out in a simulation environment to get next state



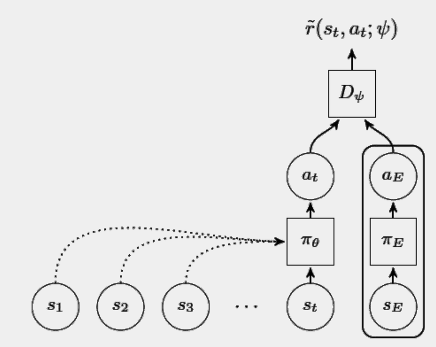
- **Training process**
  - Discriminator ψ = neural network trying to distinguish generated trajectories from expert trajectories
  - θ and ψ are optimized in a GAN fashion:

$$\boxed{\max_{\psi}\min_{\theta} V(\theta,\psi) = \mathop{\mathbb{E}}_{(s,a)\sim\mathcal{X}_E}[\log D_\psi(s,a)] + \mathop{\mathbb{E}}_{(s,a)\sim\mathcal{X}_\theta}[\log(1-D_\psi(s,a))].}$$

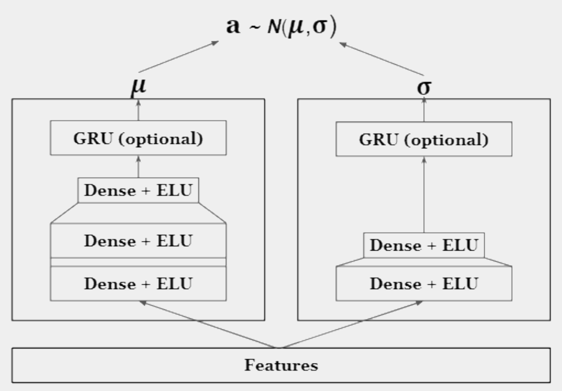
Model

Overall Architecture

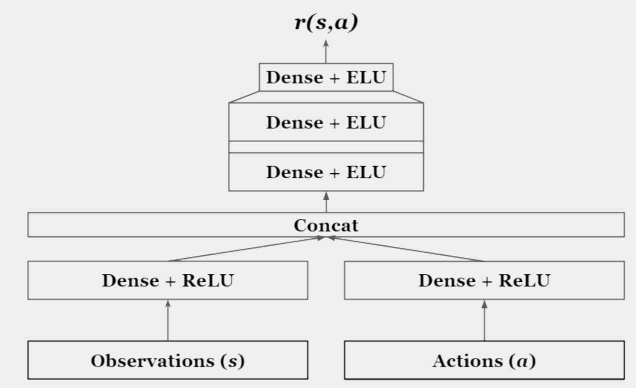
- π_Θ and D_ψ competing
- π_Θ can be **recurrent**



Policy Network π_θ



Discriminator D_ψ



GAIL Algorithm

Algorithm 1 Generative adversarial imitation learning

1: **Input:** Expert trajectories $\tau_E \sim \pi_E$, initial policy and discriminator parameters θ_0, w_0
2: **for** $i = 0, 1, 2, \ldots$ **do**
3: Sample trajectories $\tau_i \sim \pi_{\theta_i}$
4: Update the discriminator parameters from w_i to w_{i+1} with the gradient

$$\hat{\mathbb{E}}_{\tau_i}[\nabla_w \log(D_w(s,a))] + \hat{\mathbb{E}}_{\tau_E}[\nabla_w \log(1-D_w(s,a))] \tag{17}$$

5: Take a policy step from θ_i to θ_{i+1}, using the TRPO rule with cost function $\log(D_{w_{i+1}}(s,a))$. Specifically, take a KL-constrained natural gradient step with

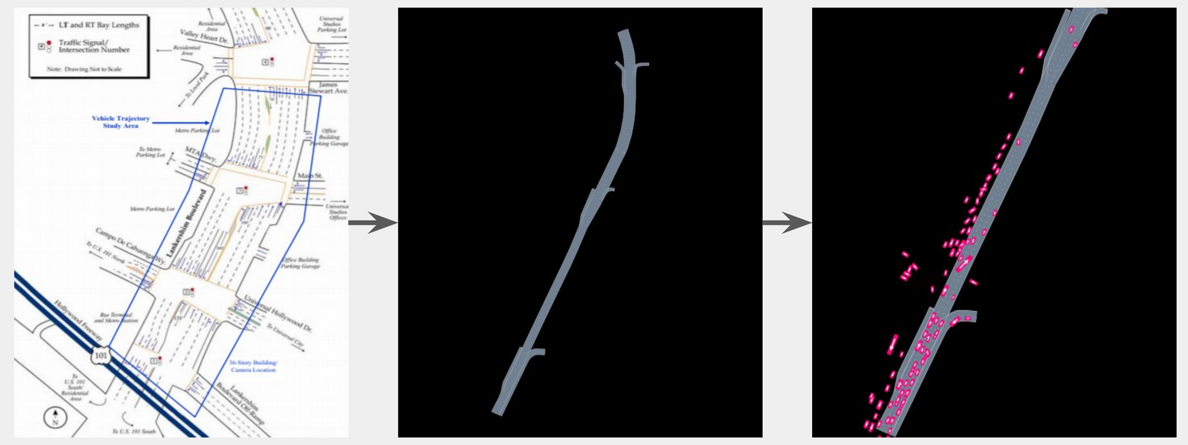
$$\begin{aligned}&\hat{\mathbb{E}}_{\tau_i}[\nabla_\theta \log \pi_\theta(a|s) Q(s,a)] - \lambda \nabla_\theta H(\pi_\theta),\\ &\text{where } Q(\bar{s},\bar{a}) = \hat{\mathbb{E}}_{\tau_i}[\log(D_{w_{i+1}}(s,a)) \mid s_0=\bar{s}, a_0=\bar{a}]\end{aligned} \tag{18}$$

6: **end for**

- Modified to use **Wasserstein-GAN** instead of GAN
- **Discriminator → Critic**: outputs trajectories rewards instead of probability

Data

- Data downloaded from the NGSIM database
- Lankershim Blvd, LA: intersections + traffic lights
- Processed using AutoCAD → roadway model + trajs



Experiments & Results

- **Input**: features extracted from trajectories:
  - Core features: speed, veh. length/width, lane offset/rel. heading/curvature, dist. to left/right markings
  - Simulated lidar features + Indicator features (collision, off-road, reverse)
- **Output:** Trained policy π_Θ : $s \rightarrow \mu, \sigma$. Action sampled from: $a \sim N(\mu, \sigma)$
- **Different architectures implemented**

Model	π_θ		D_ψ
	μ_θ	Σ_θ	
Baseline	(32,32)	(32,32)	
GAIL MLP	(128,128,64)	(128,64)	(128,128,64)
GAIL GRU	(128,128,64) + (64)	(128,64) + (64)	(128,128,64)
BC MLP	(256,128,64,64,32)		
BC GRU	(256,128,64,64,32) +(32)		

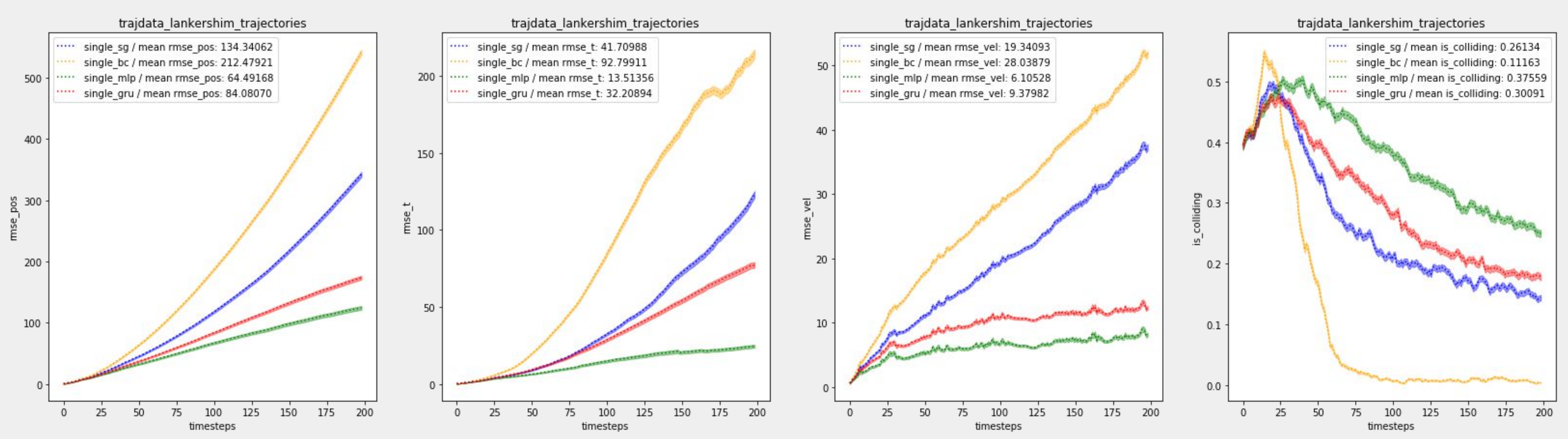
- **Training**
  - Different models trained for 1000 iterations (~4 days)
- **Evaluation**
  - Generate 10s trajectories in environment
  - Compute RMSE of position, lane offset and speed
  - Compute KL divergence KL ($p_\Theta(v)||p_{data}(v)$) for several variables v
- **RMSE**

$$RWSE(t) = \sqrt{\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(v_t^{(i)} - \hat{v}_t^{(i,j)})^2}$$

v : variable from expert traj

$\hat{v}$: variable from generated traj

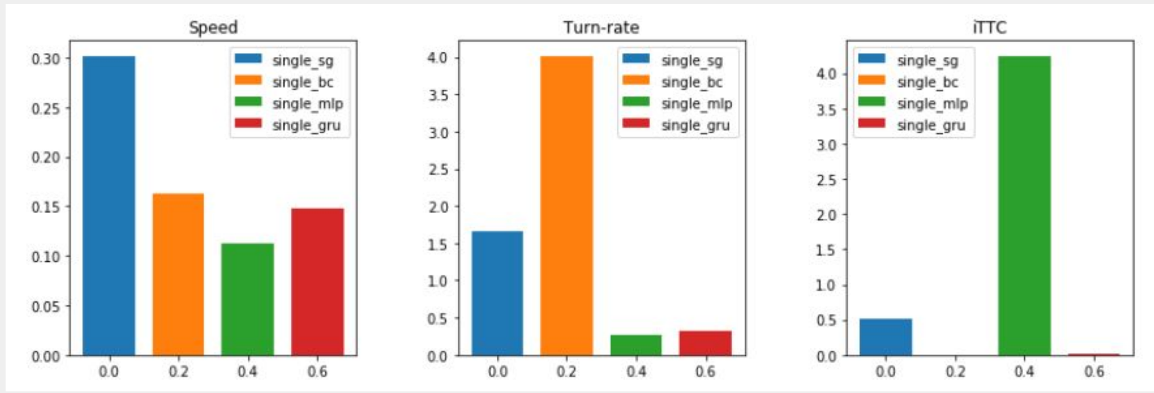
i , j : indices of traj



- **KL divergence**

Sample variable v and assume $p_{data}(v)$ and $p_{model}(v)$ are piecewise uniform (using B bins for both distributions)

$$D_{KL}(p_{data}||p_{model}) = \sum_{b=1}^{B} p_{b,data} log(\frac{p_{b,data}}{p_{b,model}})$$



Discussion

- GAIL improves realism of generated trajectories
- Deeper policies π_θ don't necessarily result in better performance
  - Initial paper : π_θ (256,128,64,64,32)
  - Baseline way simpler than BC MLP but works better
- In reality, other drivers are influenced by our behavior -> multi-agent
- Train models for longer (GAIL + GRU only trained for 50 it.)