Stanford University

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Multimodal Probabilistic Model-Based Planning for Human-Robot Interaction

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Human-Robot Interaction

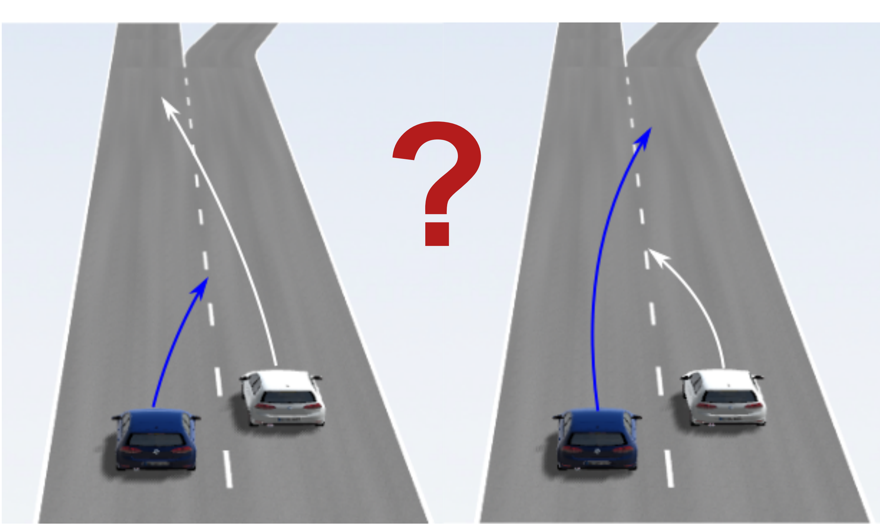
Human behavior is inconsistent across populations, settings, and even different instants, with all other factors equal. Addressing this inherent uncertainty is one of the fundamental challenges in human-robot interaction (HRI). Even when a human's broader intent is known, there are often **multiple distinct courses of action** they may pursue to accomplish their goals.

Research Goals

It is important to take into account the full breadth of possibilities in how a human may respond to a robot's actions to allow for **proactive and anticipatory** robot interaction policies.

- Model-based planning: multimodal probability distribution over human actions.
- Robot policy that accounts for interaction/ response dynamics.

Traffic Weaving Case Study

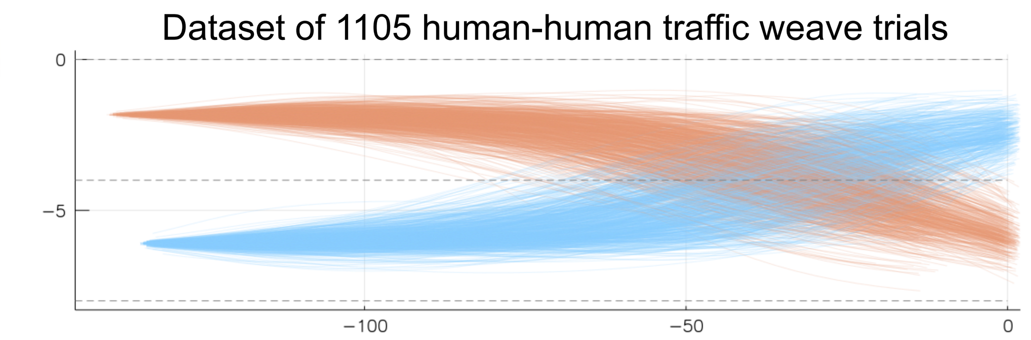


The cars must swap lanes in a limited amount of time; similar to an onramp and offramp merge on a highway. It is not clear who shall pass whom. This is even sometimes tricky for us humans!

Why is this interesting?

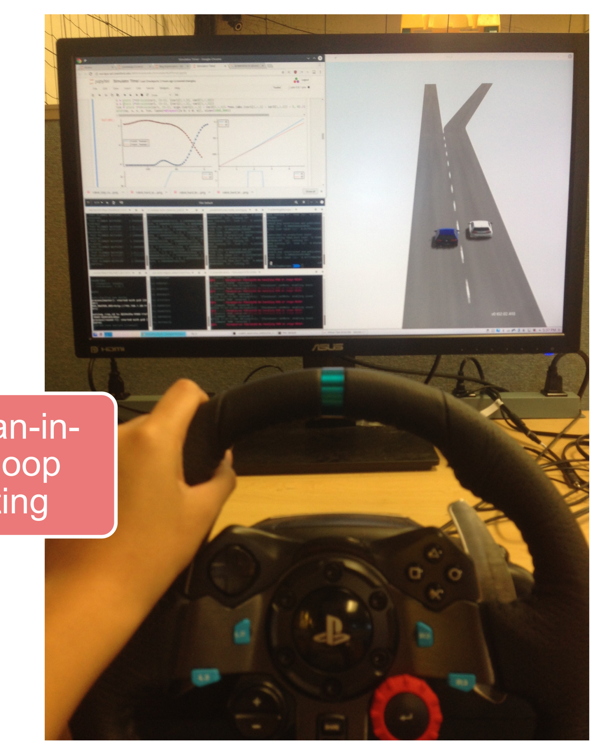
- Motivations are not obvious – is the other human cooperative? Adversarial? Indifferent?
  - We make no assumptions on human motivations/reasoning processes ➔ learn explicit action distributions from data
- Characteristic action and response time scales on the order of ~1 second.
  - Need to model sharp, multimodal behavior in response to (conditioned on) candidate robot actions

From Data Collection to Human-in-the-Loop Testing



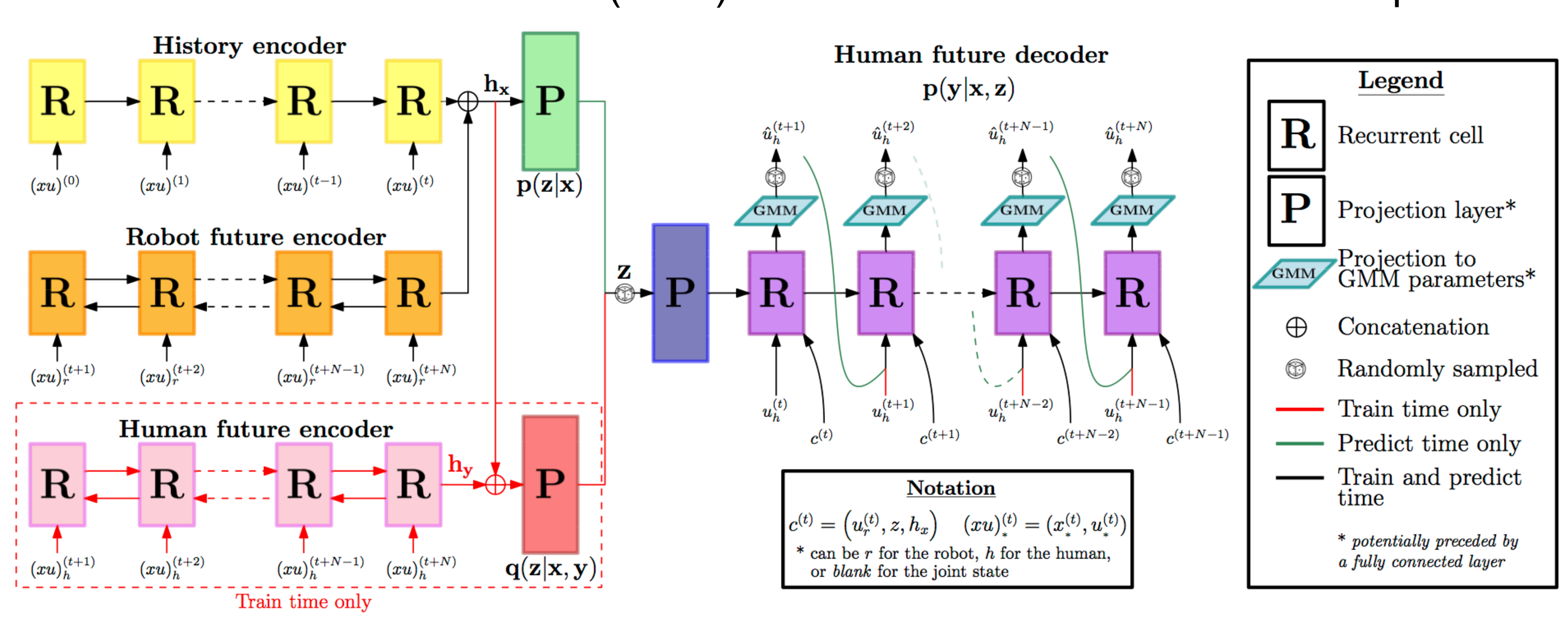
Data Collection ➔ Human action modeling ➔ Robot policy construction ➔ Human-in-the-loop testing

(Vires VTD – Virtual Test Drive Simulator)
Dataset can be found at:
https://github.com/StanfordASL/TrafficWeavingCVAE



Human Action Sequence Modeling

We learn a **generative model** of human action sequences conditioned on **joint interaction history** and **candidate robot future action sequence**. We use a **Conditional Variational Autoencoder** (CVAE) with **Recurrent Neural Networks** (RNN) in the encoder and decoder for sequence-to-sequence prediction.

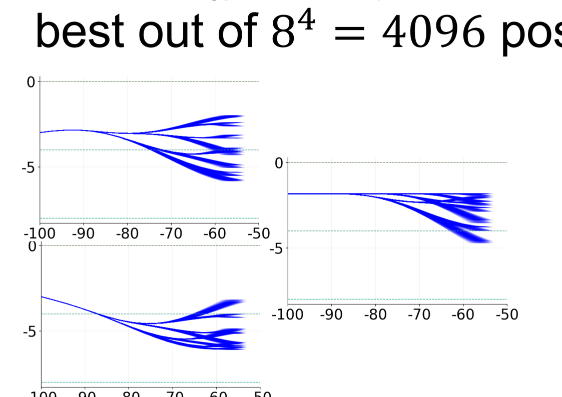


A **discrete latent space** enables the CVAE model to automatically capture **structure in multimodal human behaviors**.

A **Gaussian Mixture Model (GMM)** at each future time step models human **decision-making at each instant**.

Limited-Lookahead Robot Policy Construction

We consider a discrete set of robot candidate futures over the 1.5s prediction horizon with a replanning rate of 0.3s. The prediction horizon is broken in five 0.3s segments (first window is fixed from the previous planning step). The robot may choose one of four longitudinal actions $\{0, 4, -3, -6\} m/s^2$ and two lateral actions $\{go\ to\ left\ lane,\ go\ to\ right\ lane\}$. Given a cost function, we do an **exhaustive search** for the best out of $8^4 = 4096$ possible action sequences.



Different starting points in the lane result in different candidate robot future trajectories.

Cost function

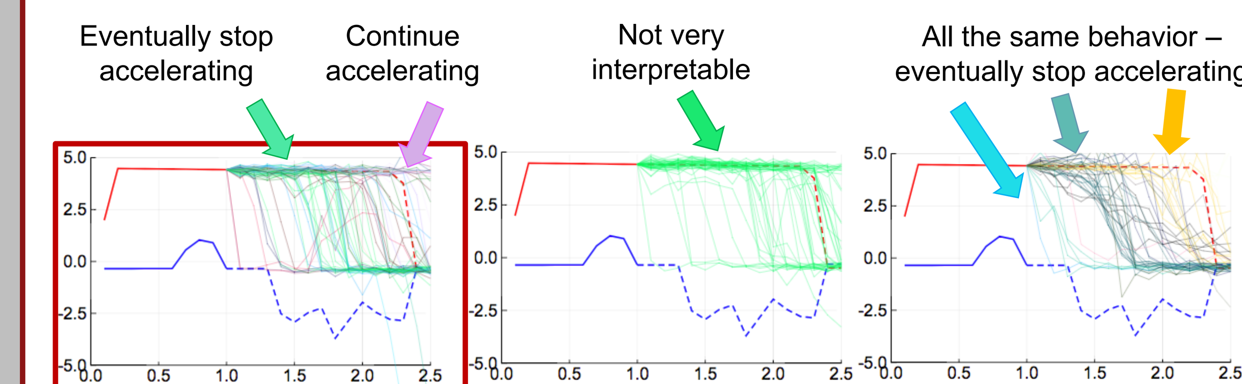
We aim to minimize expected cost. Our cost function considers:

- Collision avoidance
- Control effort
- Lane change incentive
- Longitudinal disambiguation incentive

4096 candidate robot action sequence
➔ (16 samples of future human action sequence)
Top 32 candidate robot action sequence
➔ (1024 samples of future human action sequence)
Best candidate robot action sequence

Prediction Results

Our human action sequence model can **identify distinct behavior** modes in an **unsupervised** manner. Our model is interpretable – different latent variable instantiations correspond to different behavior modes

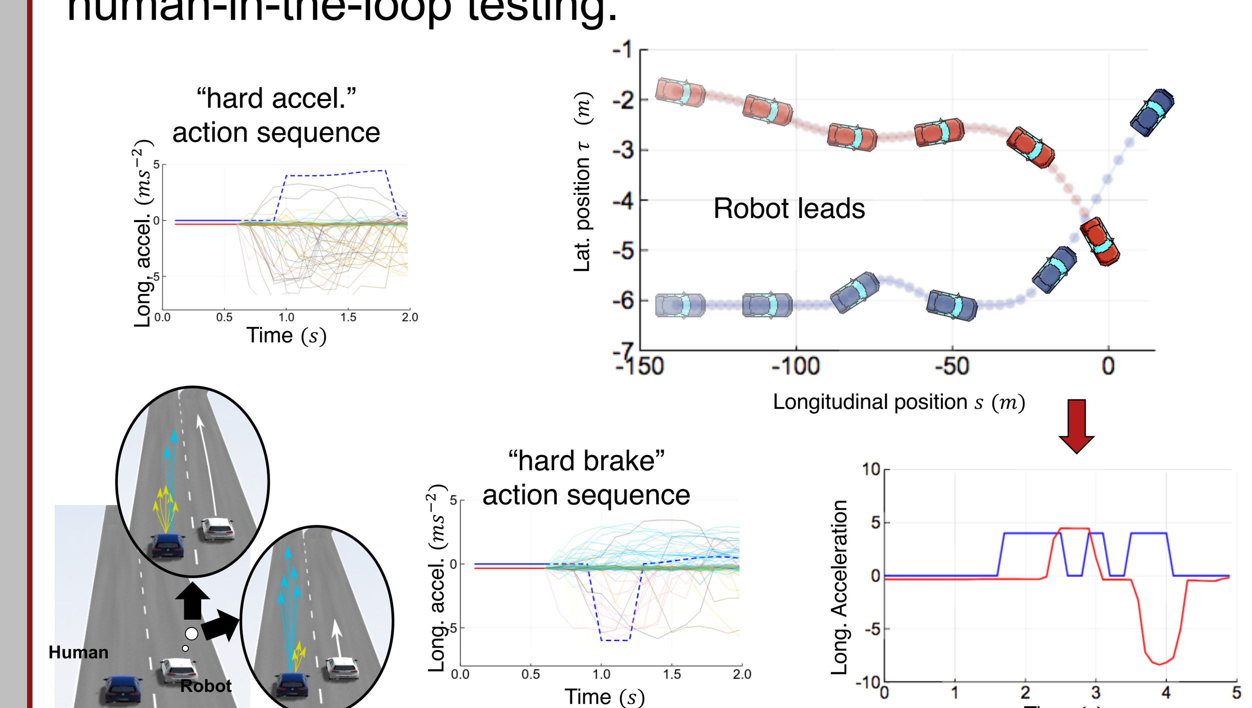


$N_z = 25, N_{GMM} = 16$	$N_z = 1, N_{GMM} = 16$	$N_z = 25, N_{GMM} = 1$
Eval. NLL = -27.07	Eval. NLL = -26.2	Eval. NLL = -18.96

Sequence prediction of longitudinal acceleration on unseen test data.
N_z = size of latent space N_{GMM} = GMM components NLL = Negative log-likelihood

Human-in-the-Loop Results

We test and validate the unified action sequence modeling and policy construction frameworks with human-in-the-loop testing.



Conclusions

Human action sequence modeling

- Our recurrent CVAE architecture enables us to learn a multimodal action distribution that has interpretable human behavioral modes
  - Conditioned on robot action ➔ anticipatory!

Traffic weaving policy construction

- Massively parallel search covers all interaction modes in real-time operation

Ongoing and Future Work

- Human-in-the-loop track testing (X1 research platform + additional car) ➔ incorporate real-world features

Paper: http://stanford.edu/~schmrlng/Schmerling.Leung.Vollprecht.Pavone.ICRA18.pdf