Control improvisation in vehicle modeling and control

Jin Ge[1], Richard M. Murray[1], Bastian Schürmann[2], and Matthias Althoff[2]

1. Department of Computing and Mathematical Sciences, California Institute of Technology. 2. Department of Informatics, Technische Universität München.

Control improvisation

Given a finite alphabet Σ, find a distribution D: $\Sigma^* \to [0,1]$:

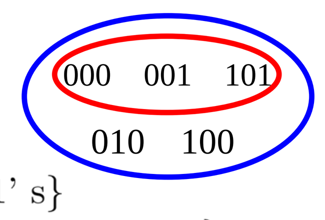
- **Hard constraint H** $\mathbf{P}[\omega \in L(H) | \omega \leftarrow D] = 1$
- **Soft constraint S** $\mathbf{P}[\omega \in L(S) | \omega \leftarrow D] \geq 1 - \xi$
- **Randomness** $\forall \omega \in L(H), \quad D(\omega) \leq \rho$

Example:

$\Sigma = \{0,1\}$, $\xi = \frac{1}{4}$, $\rho = \frac{1}{4}$

$H = \{$Strings of length 3 that have no consecutive 1' s$\}$

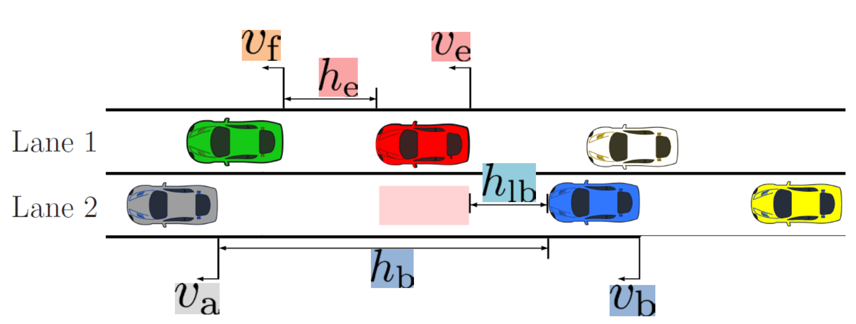
$S = \{$Strings with Hamming distance no larger than 1 from 001$\}$

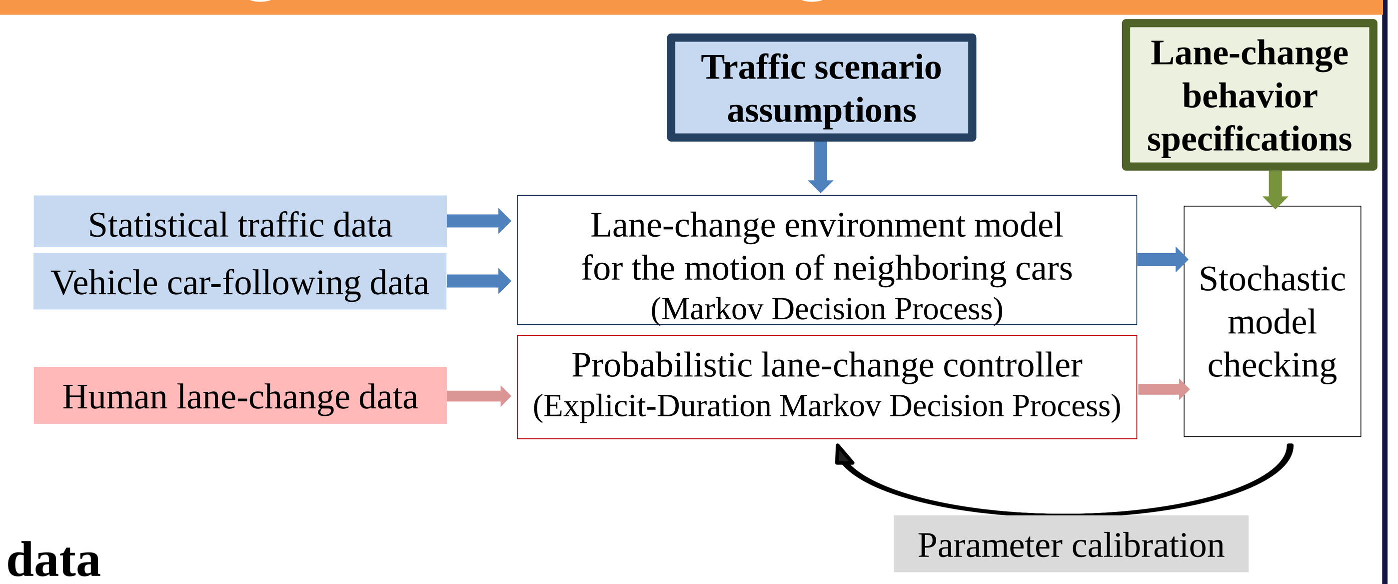


Applications:

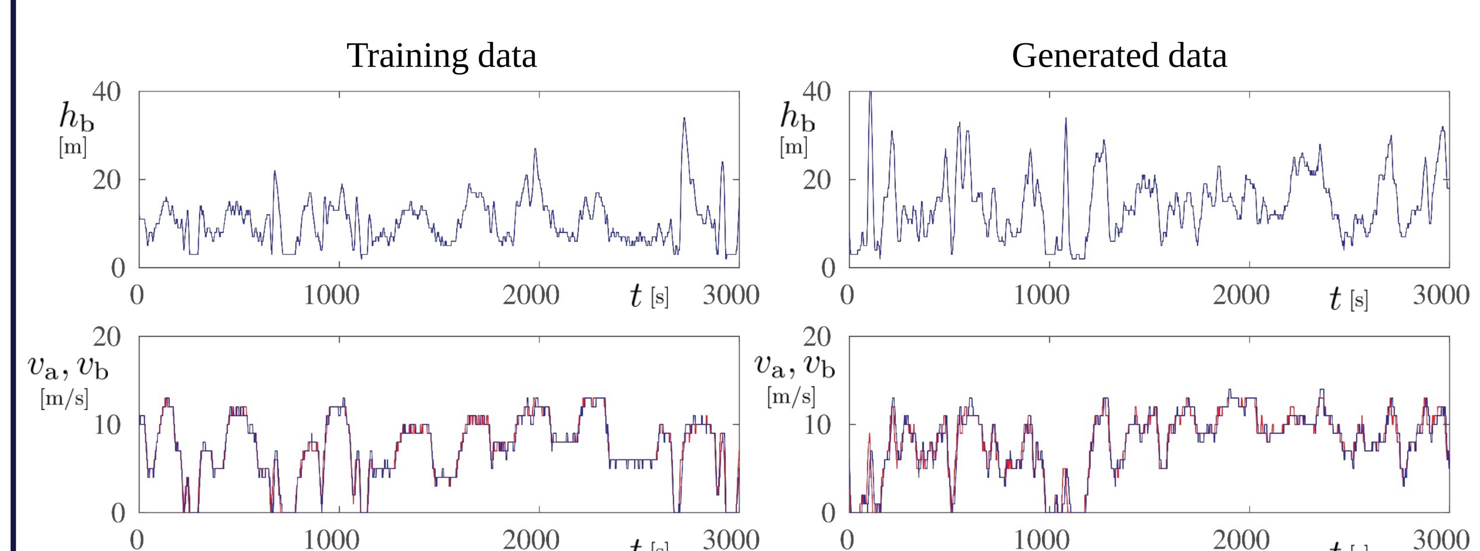
- Composing music
- Lighting control mimicking human behavior
- Robot surveillance
- Human driving behavior
- …

Voluntary lane-change decision-making





Train Markov traffic models using traffic data



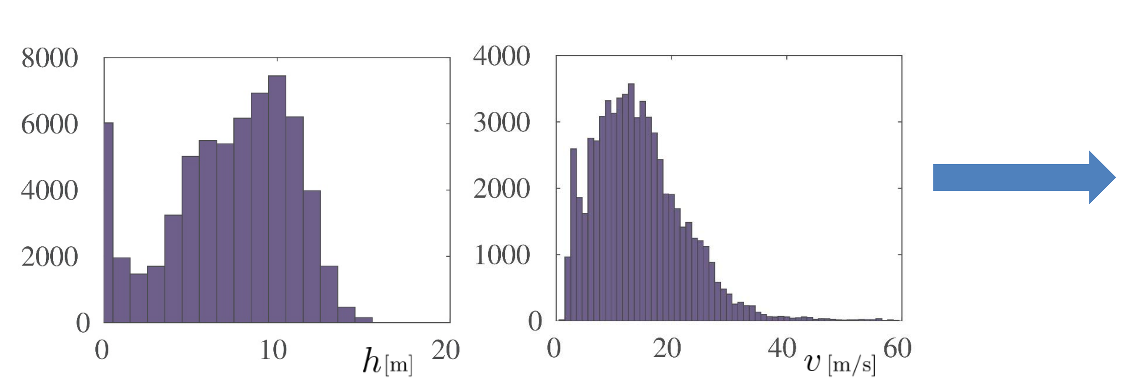
Traffic scenario assumptions:

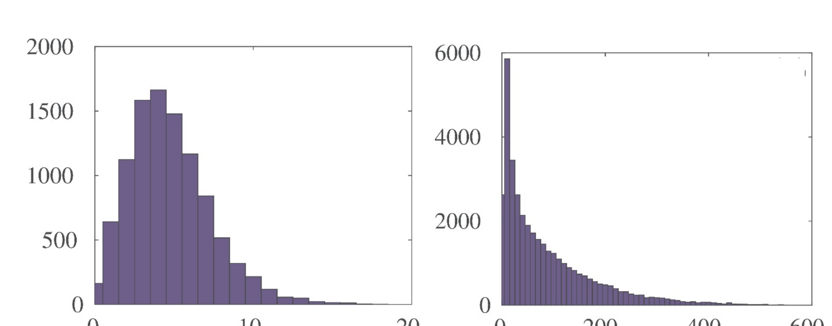
- Hard constraints $v \geq 0,\ h > 0$
- Soft constraints

$$\mathbb{P}\Big[|v(t+1) - v(t)| < \Delta^{a}\Big] \geq 1 - \xi^{a}$$
$$\mathbb{P}\Big[|v(t) - v^*| < \Delta^{v}\Big] \geq 1 - \xi^{v}$$
$$\mathbb{P}\Big[|h(t) - h^*| < \Delta^{h}\Big] \geq 1 - \xi^{h}$$

- Randomness

Histogram for lane-change opportunities during stop-and-go traffic





Number of lane-change opportunities

Time interval between two lane-change opportunities [s]

Lane change behavior specifications:

- Hard constraints
  Satisfy safety & incentive conditions
- Soft constraints
  Number of lane changes during a period of time
  $$P\Big[|n_\phi - N_\phi| < \Delta^N\Big] > 1 - \xi_N$$
  Time between two consecutive lane changes
  $$P\Big[\theta_\phi > \Theta_\phi\Big] > 1 - \xi_\theta$$
- Randomness

Safety

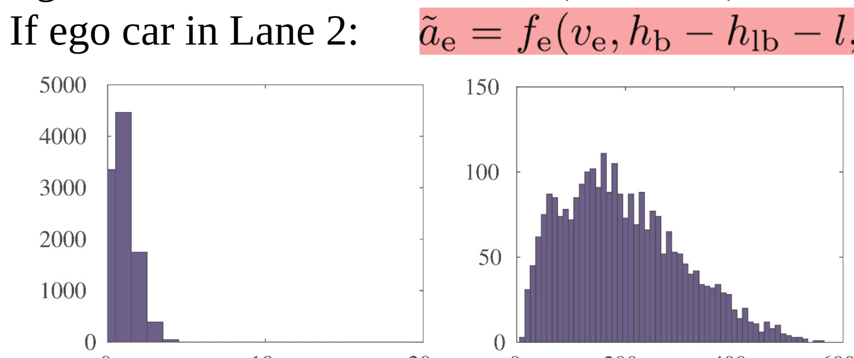
Car b's acceleration: $a_b = f_b(v_b, h_b, v_a)$

If ego car in Lane 2: $\tilde{a}_b = f_b(v_b, h_{lb}, v_a) > a^{\min}$

Incentive

Ego car's acceleration: $a_e = f_e(v_e, h_e, v_f)$

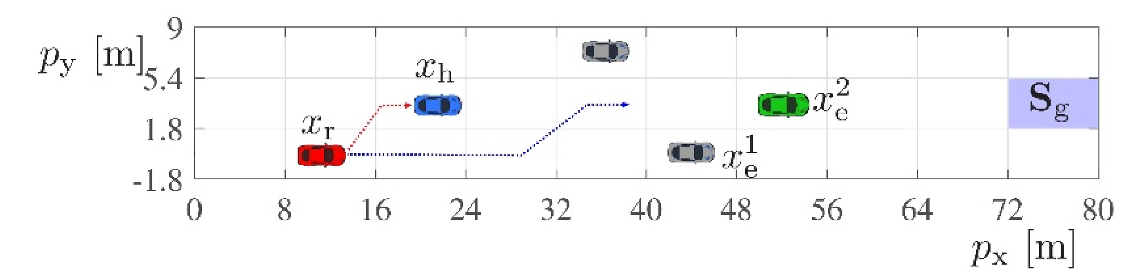
If ego car in Lane 2: $\tilde{a}_e = f_e(v_e, h_b - h_{lb} - l, v_a) > a_e + a^{th}$



Number of lane-change maneuvers

Time interval between two lane-change maneuvers [s]

Risk-aware motion planning



Automated vehicle (robot) x_r

Non-interactive vehicles (environment) x_e

Interactive vehicles (humans) x_h

Kinematic model

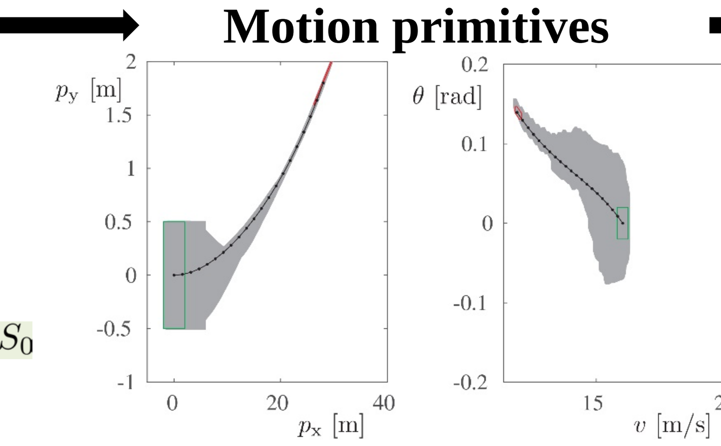
$$\dot{p}_x = v\cos(\theta)$$
$$\dot{p}_y = v\sin(\theta)$$
$$\dot{v} = u_1 + w_1$$
$$\dot{\theta} = u_2 + w_2$$

initial set $[p_x(0), p_y(0), v(0), \theta(0)] \in S_0$

input $[u_1, u_2] \in U$

disturbance $[w_1, w_2] \in W$

Motion primitives



Maneuver automata

Robot $\mathbb{M}_r = \{\mathbb{X}_r, x_r[0], \mathbb{A}_r, C_r, T_r, S_g\}$

cost $C_r[i] = f_{r1}\big(\mathcal{O}_r[i], \mathcal{O}_h[i]\big) + f_{r2}\big(\mathcal{O}_e[i], \mathcal{O}_r[i]\big) + d\big(\mathcal{O}_r[i], S_g\big) + \gamma_4 ||a_r[i]||^2$

discrete state $x = [n_x, n_y, n_v]$

transition probability

$$[T]_{ijk} = P\big(x[l+1] = s_j \,\big|\, x[l] = s_i, a[l] = a_k\big)$$

Human $\mathbb{M}_h = \{\mathbb{X}_h, x_h[0], \mathbb{A}_h, C_h, T_h\}$

cost $C_h[k] = f_{h1}\big(\mathcal{O}_r[k], \mathcal{O}_h[k]\big) + f_{h2}\big(\mathcal{O}_e[k], \mathcal{O}_h[k]\big) + \gamma_a ||a_h[k]||^2$

Human driving model

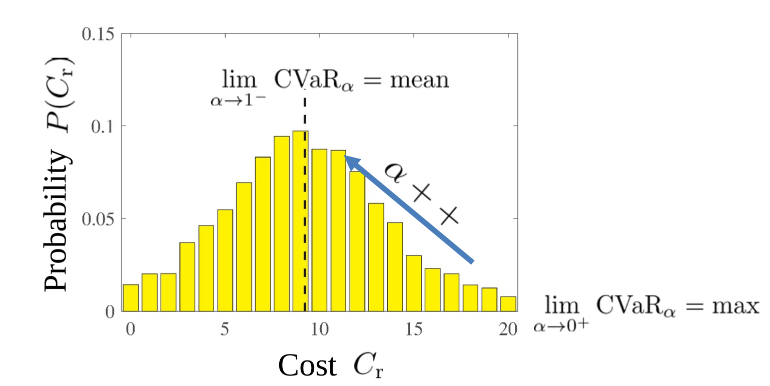
- Hard constraints (stay on the road, and drive forward)
  $x_h[k] \in \mathbb{X}_h,\ a_h[k] \in \mathbb{A}_h$
- Soft constraints (favor actions with "low enough" cost)
  $P\Big(C_h[k] < C^{th}\Big) \geq p^{th}$
- Randomness (action sequences are seldom repeated)

$$\Rightarrow P\big(a_h[k] \,\big|\, x_h[k], x_e[k], x_r[k], a_r^*[k]\big)$$

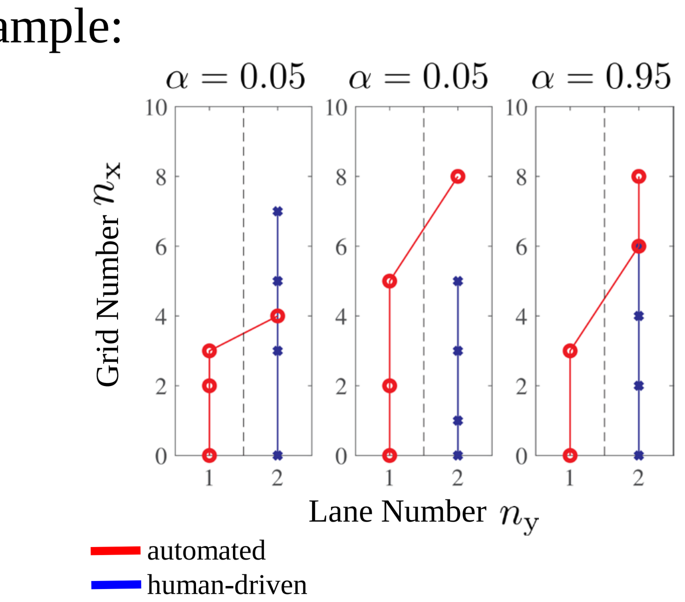
Optimal policy for the automated vehicle

$$a_r^* = \arg \min_{a_r \in (\mathbb{A}_r)^k} \boxed{\mathrm{CVaR}_\alpha}\Big(\sum_{i=0}^{k} C_r[i] \,\Big|\, X[0], a_r, \boxed{a_h}\Big)$$

conditional value-at-risk:
robustness against inaccuracy in the probabilistic human model



Example:



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