A Gray Box Model for Characterizing Driver Behavior

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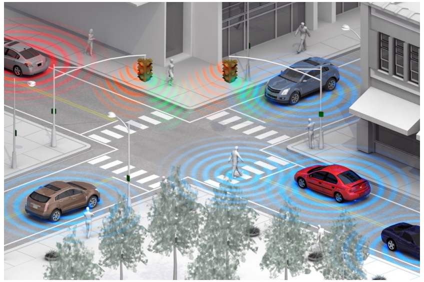
Autonomous driving

Safe integration

Human drivers

Autonomous vehicles



Autonomous driving

Validation through simulations

TransModeler

CARLA

Autonomous driving

Validation through simulations

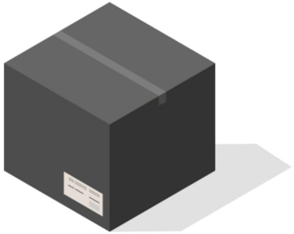
TransModeler

CARLA

Realistic driver models

Gray-box model

Black-box model



Zero knowledge

+ : High expressivity
− : Lack Interpretability

White-box (Rule-based) model

Full knowledge

+ : High Interpretability, simple
− : Cannot model stochasticity

Gray-box model

Rule-based driver models

- IDM (Intelligent Driver Model)
  - Car-following model that governs longitudinal acceleration
  - Collision-free

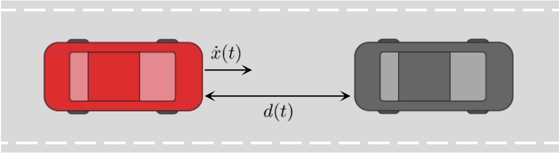
$$\ddot{x}_{\text{IDM}} = a_{\max}\left[1 - \left(\frac{\dot{x}(t)}{v_{\text{des}}}\right)^4 - \left(\frac{d_{\text{des}}}{d(t)}\right)^2\right]$$

$$d_{\text{des}} = d_{\min} + \tau\dot{x}(t) - \frac{\dot{x}(t)\Delta\dot{x}(t)}{2\sqrt{a_{\max}b}}$$

IDM parameter	Symbol
Desired speed (m/s)	v_{des}
Desired time gap (s)	τ
Minimum acceptable gap (m)	$d_{\min}$
Max acceleration (m/s^2)	$a_{\max}$
Desired deceleration (m/s^2)	b

- Stochastic IDM
  - Additional variance term to IDM

$$\ddot{x}_{\text{sIDM}} \sim \mathcal{N}(\ddot{x}_{\text{IDM}}, \sigma^2_{\text{IDM}})$$



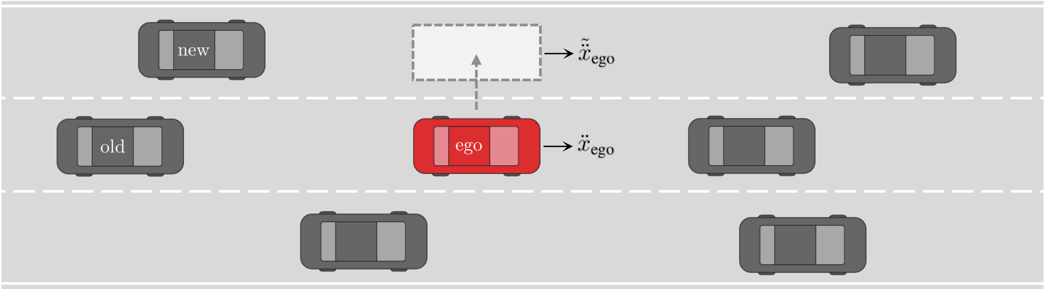
[1] Treiber, M.; Hennecke, A.; and Helbing, D. 2000. Congested traffic states in empirical observations and microscopic simulations. *Physical Review E*, 62(2): 1805.
[2] Treiber, M.; and Kesting, A. 2017. The intelligent driver model with stochasticity—new insights into traffic flow oscillations. *Transportation Research Procedia*, 23: 174–187.

Rule-based driver models

- MOBIL (Minimizing Overall Braking Induced by Lane change)
  - Lane-changing model that governs lateral motion
  - Initiates a lane change when these conditions are met:

$$\tilde{\ddot{x}}_{\text{ego}} - \ddot{x}_{\text{ego}} + p\left(\tilde{\ddot{x}}_{\text{new}} - \ddot{x}_{\text{new}} + \tilde{\ddot{x}}_{\text{old}} - \ddot{x}_{\text{old}}\right) > \Delta a_{\text{th}}$$
$$-\tilde{\ddot{x}}_{\text{new}} \leq b_{\text{safe}}$$

MOBIL parameter	Symbol
Politeness	p
Safe braking (m/s^2)	b_{safe}
Acceleration threshold (m/s^2)	a_{th}



[1] Kesting, A.; Treiber, M.; and Helbing, D. 2007. General lane-changing model MOBIL for car-following models. *Transportation Research Record*, 1999(1): 86–94.

Problem Formulation

- Known variables

$$\mathbf{x} = \{(x^{(i)}, y^{(i)})\}_{i=1}^{N}$$

  - x : longitudinal position measurements
  - y : lateral position measurements
  - i : vehicle index

- Latent variables

$$\mathbf{z} = \{v_{\text{des}}, \sigma_{\text{IDM}}, p, \lambda\}$$

  - v_{des} : desired speed
  - σ_{IDM} : stochasticity parameter
  - p : politeness
  - λ : lane-changing parameter

- Likelihood of the next observation
  - Probability of i-th vehicle changing lane at each timestep

$$f_{\text{lane}}^{(i)}(\mathbf{x}, \mathbf{z}) = \begin{cases} \frac{1}{1+e^{-\lambda^{(i)}\mathbf{C}}}, & \text{if (5) is met} \\ 0, & \text{otherwise} \end{cases}$$

where

$$\mathbf{C} = \tilde{\ddot{x}}_{\text{ego}}^{(i)} - \ddot{x}_{\text{ego}}^{(i)} + p^{(i)} \left(\tilde{\ddot{x}}_{\text{new}}^{(i)} - \ddot{x}_{\text{new}}^{(i)} + \tilde{\ddot{x}}_{\text{old}}^{(i)} - \ddot{x}_{\text{old}}^{(i)} \right) - \Delta a_{\text{th}}^{(i)}$$

  - Sum of lane-changing case and lane-following case

$$p(\mathbf{x}'^{(i)} \mid \mathbf{x}, \mathbf{z}) = p_{\text{change}}(\mathbf{x}'^{(i)} \mid \mathbf{x}, \mathbf{z}) f_{\text{lane}}^{(i)} + p_{\text{follow}}(\mathbf{x}'^{(i)} \mid \mathbf{x}, \mathbf{z}) \left(1 - f_{\text{lane}}^{(i)}\right)$$

Problem Formulation

- Parameter estimation using Expectation-maximization (EM) Algorithm

  - E-step

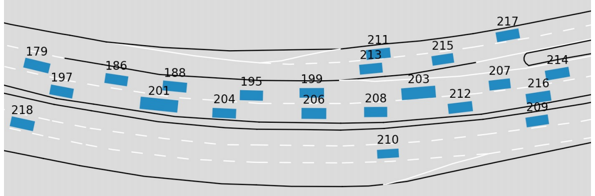
$$Q_t(\mathbf{z}_t^{(i)}) := p(\mathbf{z}_t^{(i)} \mid \mathbf{x}_t'^{(i)}, \mathbf{x}_t; \theta) = \frac{p(\mathbf{x}_t'^{(i)} \mid \mathbf{z}_t^{(i)}, \mathbf{x}_t) p(\mathbf{z}_t^{(i)}; \theta)}{\sum_{\mathbf{z}_t^{(i)}} p(\mathbf{x}_t'^{(i)} \mid \mathbf{z}_t^{(i)}, \mathbf{x}_t) p(\mathbf{z}_t^{(i)}; \theta)}$$

  - M-step

$$\theta^* := \arg\max_{\theta'} \sum_{i=1}^{n} \sum_{t=0}^{T_i-1} \sum_{\mathbf{z}_t^{(i)}} Q_i(\mathbf{z}_t^{(i)}; \theta) \log \frac{p(\mathbf{x}_t'^{(i)} \mid \mathbf{z}_t^{(i)}, \mathbf{x}_t) p(\mathbf{z}_t^{(i)}; \theta')}{Q_i(\mathbf{z}_t^{(i)}; \theta)}$$

Experiments

- INTERnational, Adversarial and Cooperative moTION (INTERACTION) Dataset



- Baseline models
  - Default IDM+MOBIL parameter values
  - Parameters estimated using particle filtering

IDM parameter	Symbol	Value
Desired speed (m/s)	v_{des}	33.3
Desired time gap (s)	τ	1.5
Minimum acceptable gap (m)	d_{min}	2.0
Max acceleration (m/s^2)	a_{max}	1.4
Desired deceleration (m/s^2)	b	2.0
MOBIL parameter	Symbol	Value
Politeness	p	0.5
Safe braking (m/s^2)	b_{safe}	2.0
Acceleration threshold (m/s^2)	a_{th}	0.1

[1] W. Zhan et al., "INTERACTION Dataset: An INTERnational, Adversarial and Cooperative moTION Dataset in Interactive Driving Scenarios with Semantic Maps," arXiv:1910.03088 [cs, eess], 2019.

[2] Bhattacharyya, R.; Jung, S.; Kruse, L. A.; Senanayake, R.; and Kochenderfer, M. J. 2021. A Hybrid Rule-Based and Data-Driven Approach to Driver Modeling Through Particle Filtering. *IEEE Transactions on Intelligent Transportation Systems*.

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Results

- Prediction accuracy

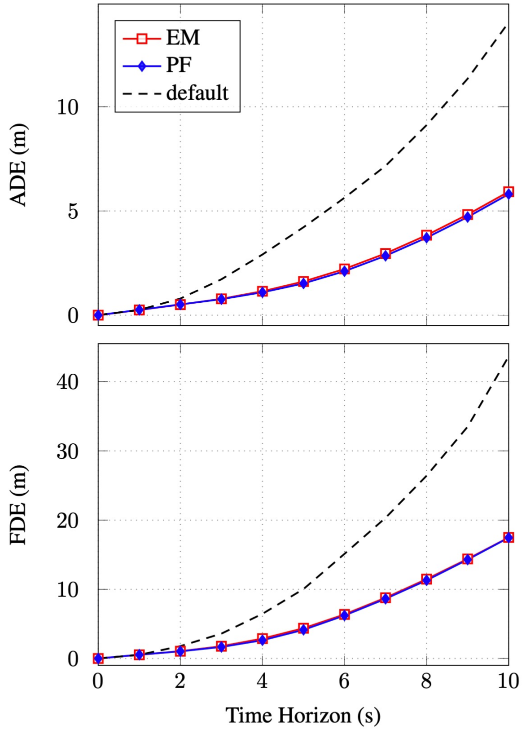
	ADE-5	ADE-10	FDE-5	FDE-10
Default	4.222	14.048	10.036	43.666
PF	1.527	5.809	4.144	17.459
EM	1.618	5.925	4.373	17.490

- Data efficiency

	small (10 data points)	medium (50 data points)	large (original)
Default	–	–	4.222
PF	4.113	3.381	1.527
EM	4.292	2.705	1.618

- Safety

Frequency	collisions	hard brakes
Default	0.0000	0
PF	0.0059	0
EM	0.0032	0



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Conclusions & Future work

- Conclusions
  - Developed a gray-box driver model to achieve both interpretability and variability.
  - Estimated distributions over IDM+MOBIL parameters using EM approach.
  - Achieved efficiency without sacrificing safety.

- Future Work
  - Use different distributions to define latent variables.
  - Analyze generalizability of proposed method using different scenarios and dataset.

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