Social Behavior Estimation For Autonomous Vehicles

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Motivation

The Problem: Human-driven cars introduce great uncertainty in autonomous-human driving interactions. The biggest challenge of social behavior systems is to estimate human drivers' intentions.

Existing Models are not trained with real data in previous research. The Probabilistic Graphical Model has restrictions in defining relationship among nodes.

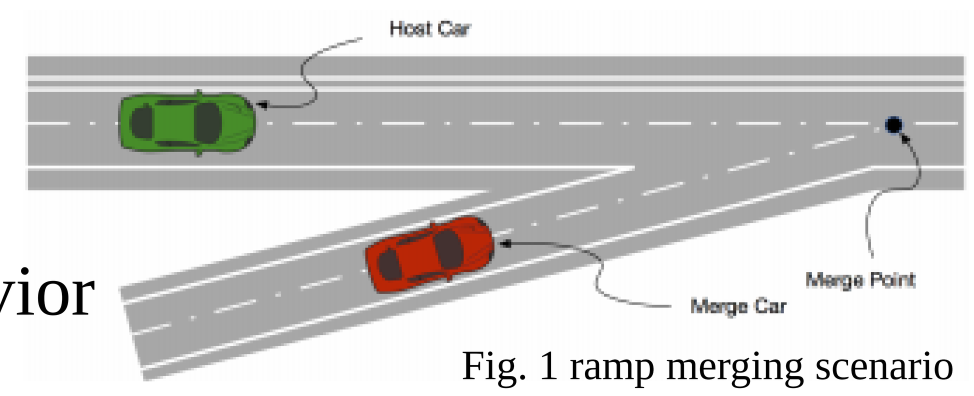


Fig. 1 ramp merging scenario

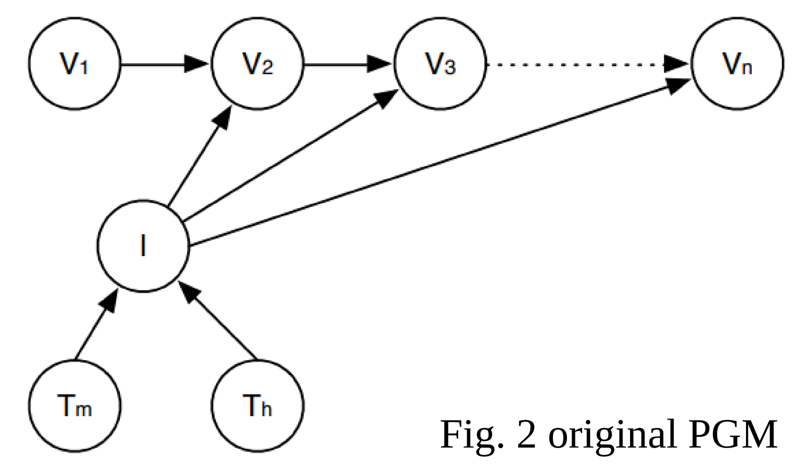


Fig. 2 original PGM

Method

Factor Graph Design

* Intention I is a continuous random variable with a range of [0,1].

$$P(I_{t+1}|I_t, V_{t-n}, \dots V_t) \qquad I_{t+1} = argmax_I f(I_{t+1}, I_t, V_{t-n}, \dots V_t)$$

Factor nodes take velocity observation, and timestamp

$g(S_t) = \prod \omega(i) f(V_i, V_{i-1})$

Where forgetting factor is included.

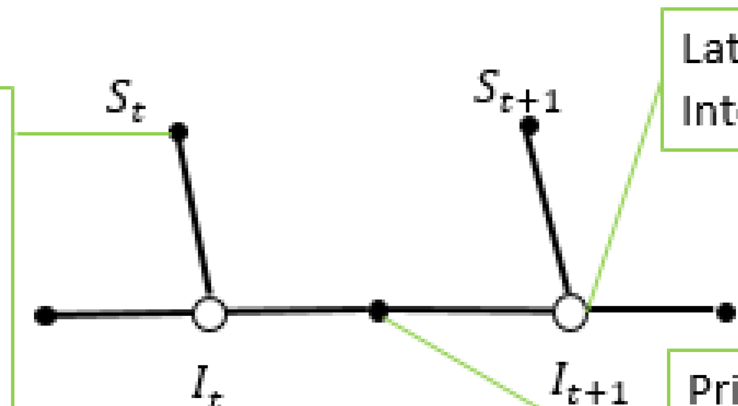


Fig. 3 Factor Graph

Latent variable: Intention over time.

Prior factor: Encourage the stability of the Intention over time.

Factorization: $F = f(I_{t+1}, I_t, V_{t-n}, \dots V_t)$

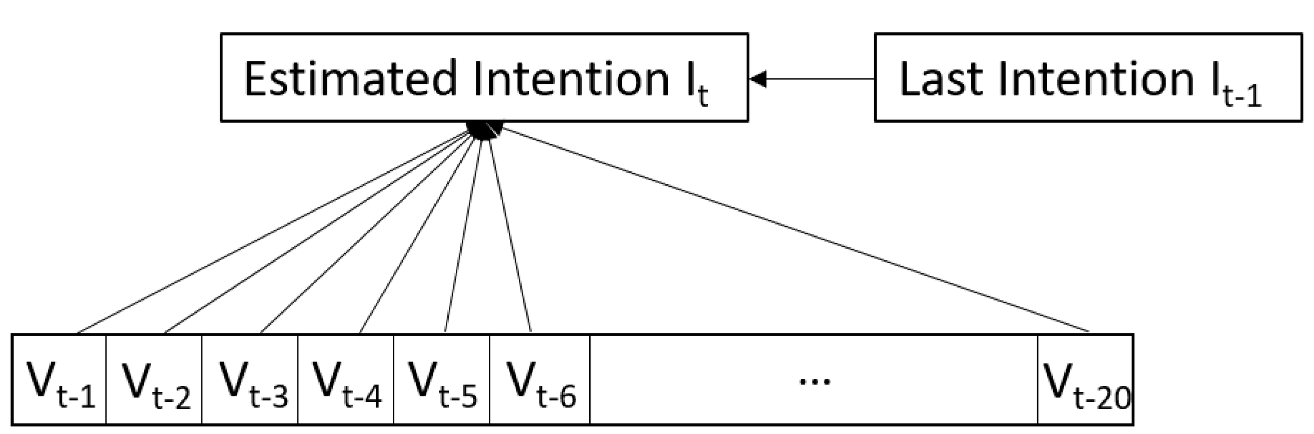


Fig. 4 States and last intention effects on estimated intention

Forgetting Factor: assign self-defined weight to historical data

State (speed) effects: $g'(S_{t+1}) = \prod \omega(i) f(V_i, V_{i-1})$

Last Intention effect: $m(I_t) = \exp(-\frac{||b(I_{t+1}) - b(I_t)||^2}{\sigma})$

"Blurring function", make the discrete intention as a continuous value ranging from 0 to 1

Speed Transition Model

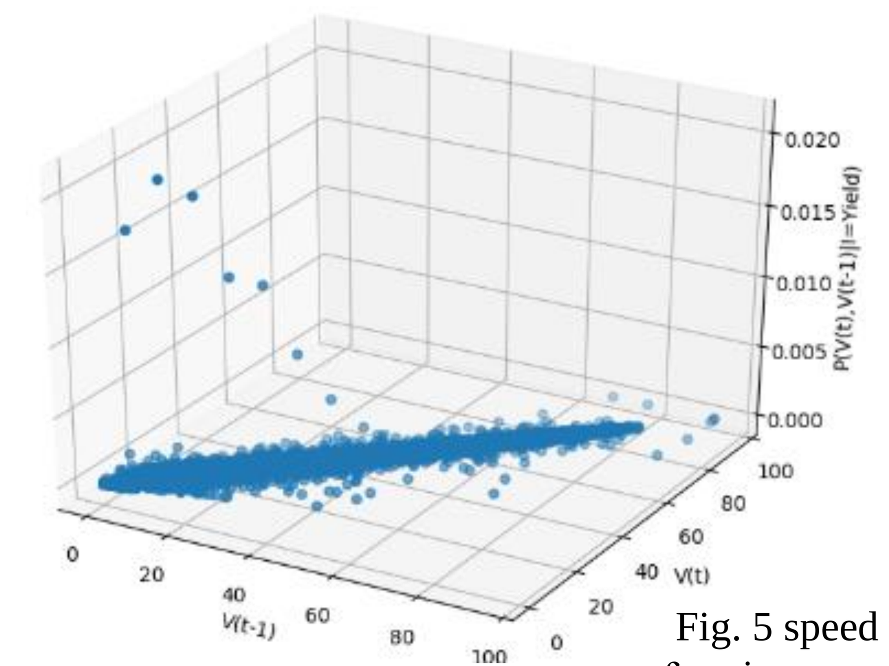


Fig. 5 speed transition distribution for given speed and 'Yield' intention

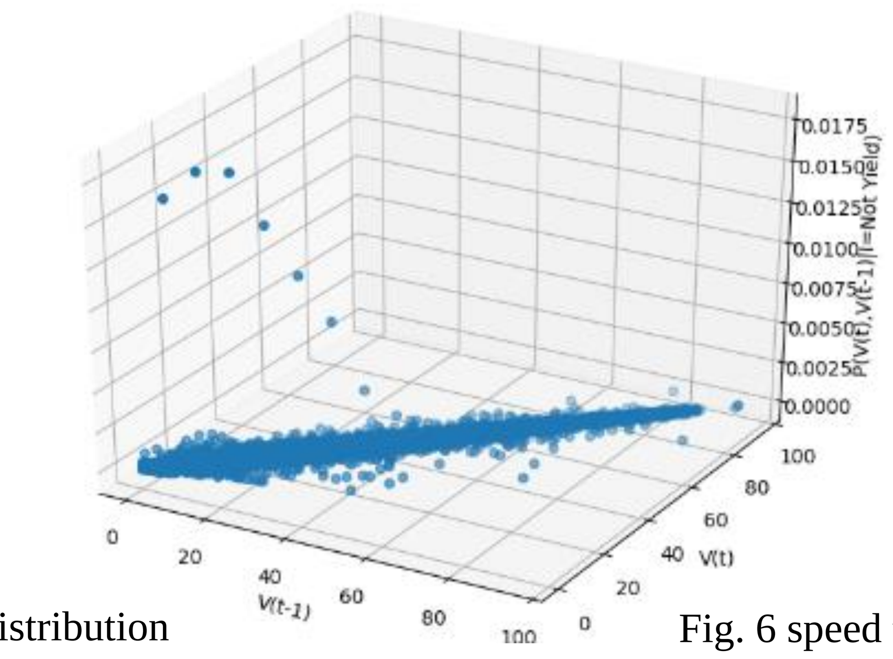


Fig. 6 speed transition distribution for given speed and 'Not Yield' intention

Gaussian Mixture Model

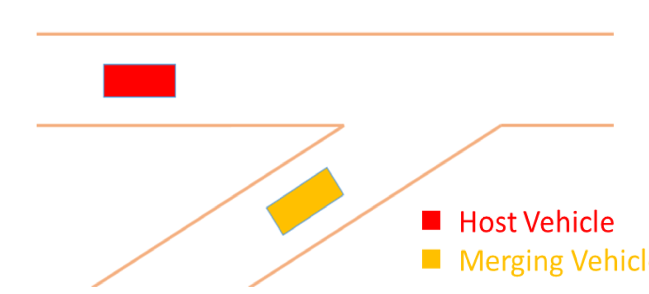
2-components

	Not Yield		Yield
Means	[[17.59 17.58][43.51 43.50]]	Means	[[44.03 44.02][17.87 17.87]]
Covariance	[[64.04 64.01][106.53 106.77]]	Covariance	[[106.96 107.21][66.25 66.20]]
Weights	[0.57 0.42]	Weights	[0.43 0.56]

3-components

	Not Yield		Yield
Means	[[13.30 13.31] [49.63 49.62] [29.94 29.93]]	Means	[[30.03 30.01] [13.36 13.35] [49.69 49.68]]
Covariance	[[33.83 33.84] [70.65 70.84] [25.16 25.11]]	Covariance	[[24.97 24.91] [34.43 34.45] [73.35 73.55]]
Weights	[0.38 0.25 0.35]	Weights	[0.35 0.37 0.27]

Experiment & Result



Dataset	Time Period	Tested Pairs	Collision Rate w/out GMM&FF	Collision Rate w/out GMM	Collision Rate w/ GMM (2-comp)
I80	05:15-05:30	100	23%	19%	9%

Conclusion

- Forgetting Factor decreases the collision rate
- Gaussian Mixture Model greatly improves the accuracy of intention estimation
- Gaussian Mixture Model helps reduce the computation time

Future Work

- More tests on I80, US101 and other datasets
- Well-tuned parameter and better-designed forgetting function

Reference:

[1] D. Marinescu and J.Curn, "On-ramp traffic merging using cooperativeintelligent vehicles: A slot-based approach,". . . Systems (ITSC), 2012. . ., 2012.

[2] J. Wei, J. Dolan, and B. Litkouhi, "A prediction-and cost function-based algorithm for robust autonomous freeway driving," inIntelligentVehicles Symposium, 2010.

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