Differentiable Constrained Imitation Learning for Robot Motion Planning and Control

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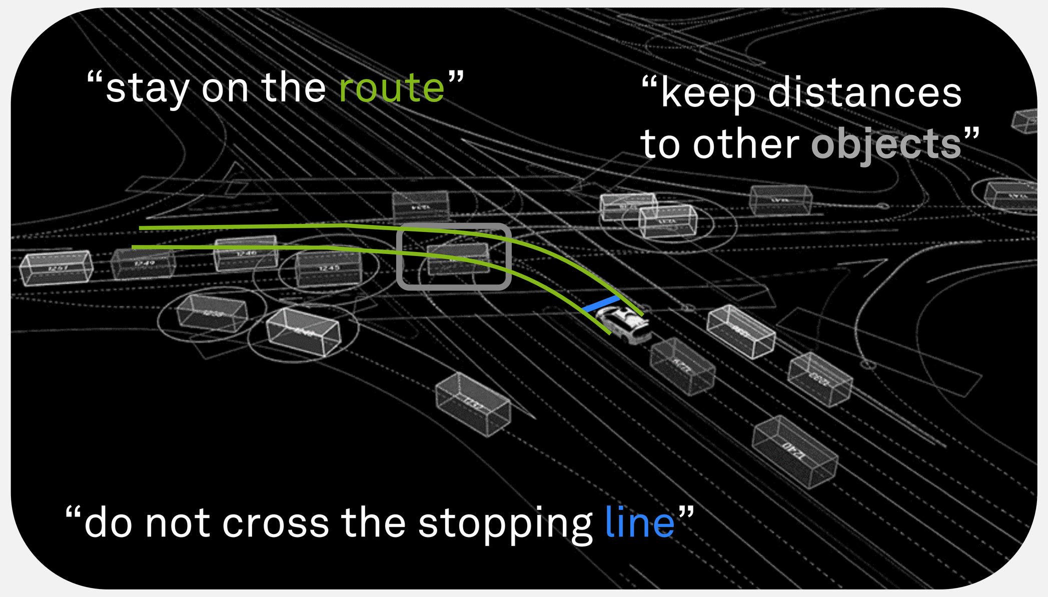
Motivation

Problem: Constrained motion planning and control

Imitation Learning (IL)
- simple design
- scales with data
- constraints implicit

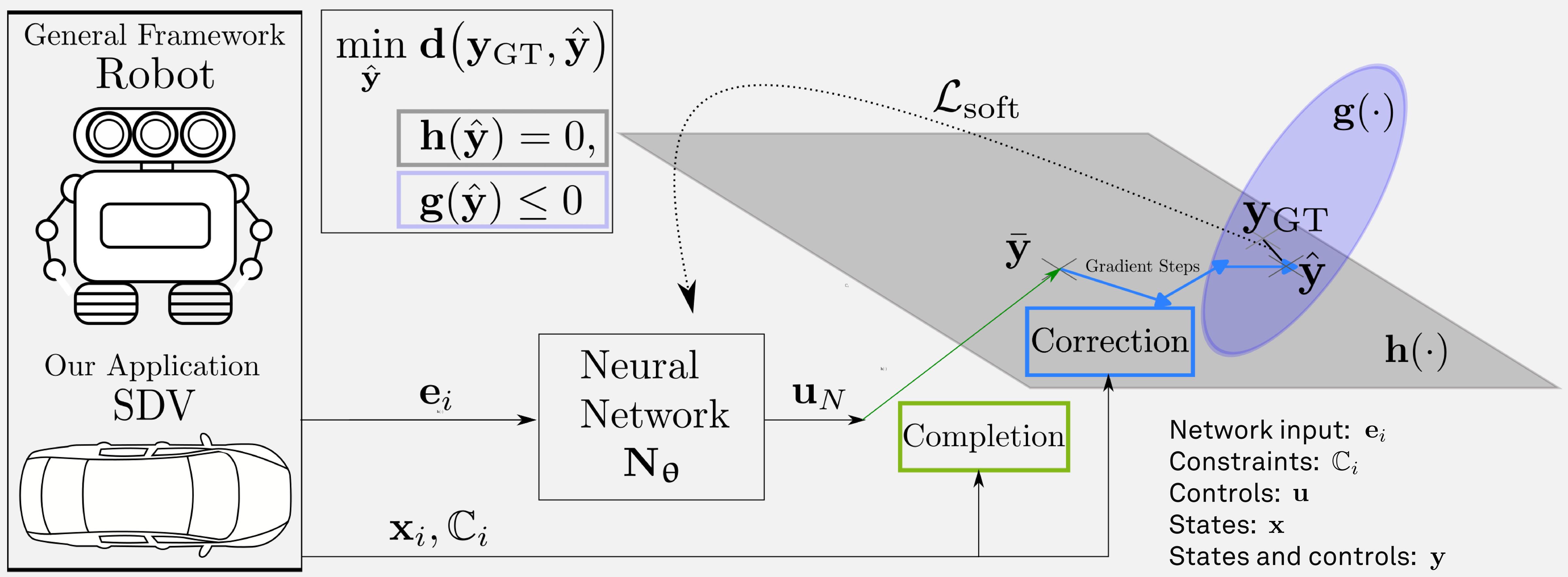
Optimal Control
- complex design
- explicit (hard) constraints



https://waymo.com/

How can we harvest the synergies of both groups of approaches?

Differentiable Constrained Imitation Learning (DCIL)



Method extends ideas from Donti et al. [ICLR 2021] to the IL domain

Completion step: Complete sequence of controls $\mathbf{u}_N$ to $\bar{\mathbf{y}}$ (controls and states) using a dynamics model (equality constraints)

Correction step: Corrects solution $\hat{\mathbf{y}}$ to also satisfy inequality constraints (e.g., lane boundaries, obstacles, traffic lights, control limits)

Loss:

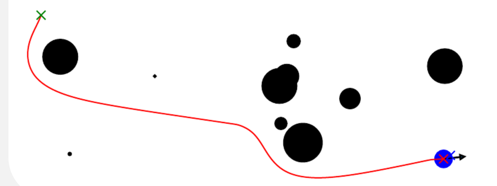
$$\mathcal{L}_{\text{soft}} = \underbrace{\mathbf{d}(\mathbf{y}_{GT}, \hat{\mathbf{y}})}_{\text{distance measure}} + \lambda_g \left\|\text{ReLU}\left(\boldsymbol{\alpha} \odot \mathbf{g}(\hat{\mathbf{y}})\right)\right\|_2 + \lambda_h \left\|\mathbf{h}(\hat{\mathbf{y}})\right\|_2$$

Evaluation

CARLA

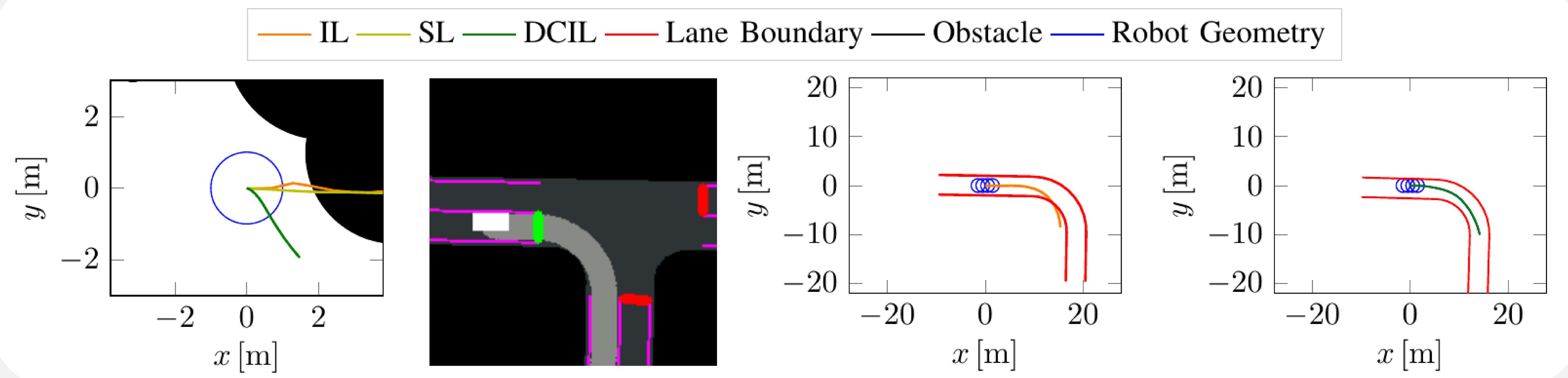
Methode	Sucess rate	Driving score	Route completion	Infraction penalty	Collision layout	Red light infraction	Agent blocked	Outside of lane	Wrong lane
	[%], ↑	[%], ↑	[%], ↑	[%], ↑	[#/Km], ↓	[#/Km], ↓	[#/Km], ↓	[#/Km], ↓	[#/Km], ↓
IL	36	50.18	44	95.65	1.44	0.42	525.00	0.06	5.73
IL++	52	62.33	80	98.84	5.70	0.27	94.28	3.39	9.41
DKM	76	76.69	92	98.94	1.40	0.11	6.90	**0.00**	8.85
DKM $\leq$	76	87,66	96	98.94	0.94	0.13	3.26	0.15	0.09
SL	92	96.09	**100**	**100.00**	0.35	**0.00**	**0.00**	**0.00**	0.21
DCIL	**96**	**97.40**	**100**	98.94	**0.22**	0.18	**0.00**	**0.00**	**0.00**

Mobile Robot Environment



Methode	GRR	CR	Time	KCV
	[%], ↑	[%], ↓	[%], ↓	[% (#)], ↓
IL	**100**	3.94	106	7.20 (4600)
SL	92	6.57	117	2.06 (1317)
DCIL	**100**	**0.00**	**105**	**0.12** (**89**)

IL: Imitation Learning
DKM: Deep Kinematic Models (Cui et al. [ICRA 2020])
DKM $\leq$: DKM + correction step only at test time (similar to SafetyNet, Vitelli et al. [ICRA 2022])
SL: IL + softloss (similar to ChaufferNet, M. Bansal etl al. [RSS2019])
GRR: goal-reaching rate, **CR:** collision rate, **KCV:** kinematic constraint violations, **SDV**: self-driving vehicle



DCIL has better constraint satisfaction during closed-loop control

Conclusion and Future Work

Conclusion: DCIL improves the closed-loop performance but has additional hyperparameters

Future work:
- hard-constraint methods with theoretical guarantees
- multi-agent formulation (Diehl et al. [ICML W., CoRL 2023])