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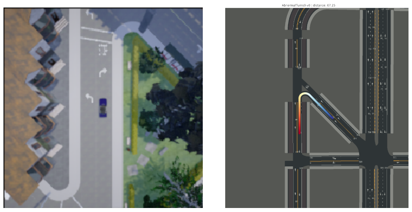
A. CARNOVEL: Suite of Tasks Under Distribution Shift



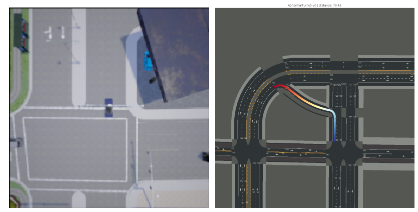
(a) AbnormalTurns0-v0

(b) AbnormalTurns1-v0

(c) AbnormalTurns2-v0

(d) AbnormalTurns3-v0

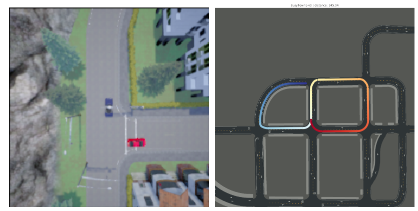
(e) AbnormalTurns4-v0



(f) AbnormalTurns5-v0

(g) AbnormalTurns6-v0

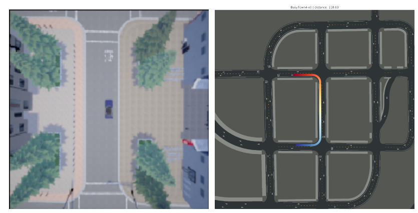
(h) BusyTown0-v0



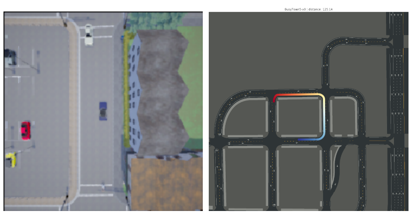
(i) BusyTown1-v0

(j) BusyTown2-v0

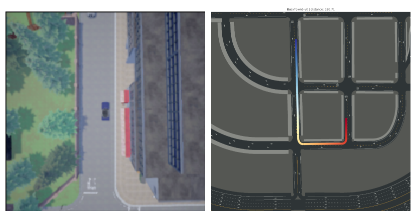
(k) BusyTown3-v0



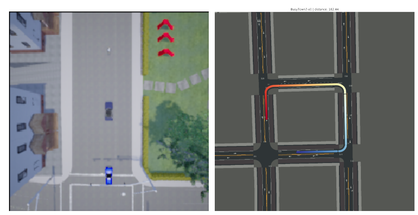
(l) BusyTown4-v0



(m) BusyTown5-v0

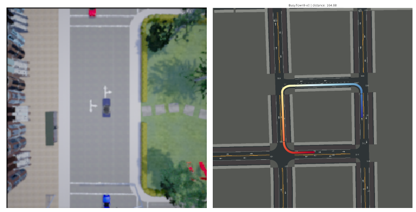


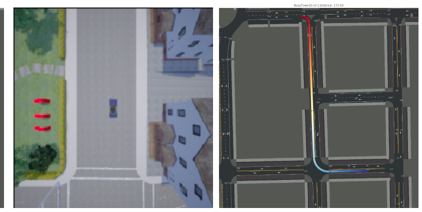
(n) BusyTown6-v0

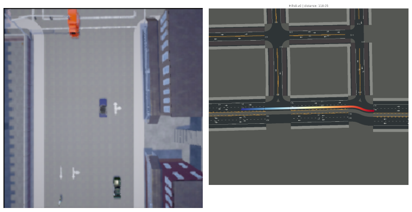


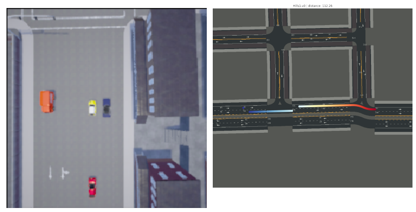
(o) BusyTown7-v0

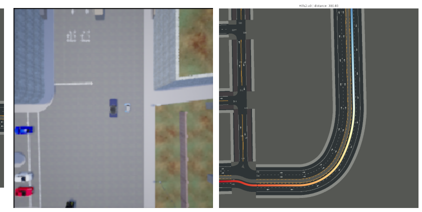

(p) BusyTown8-v0


(q) BusyTown9-v0


(r) BusyTown10-v0


(s) Hills0-v0

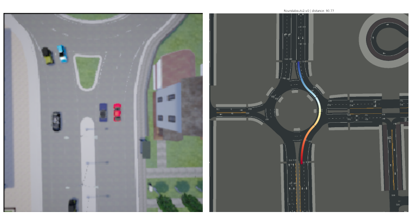

(t) Hills1-v0


(u) Hills2-v0

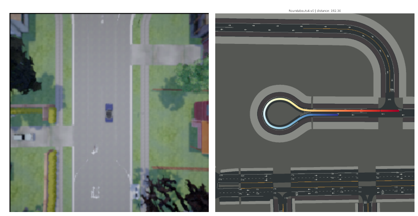

(v) Hills3-v0


(w) Roundabouts0-v0


(x) Roundabouts1-v0


(y) Roundabouts2-v0


(z) Roundabouts3-v0


(aa) Roundabouts4-v0

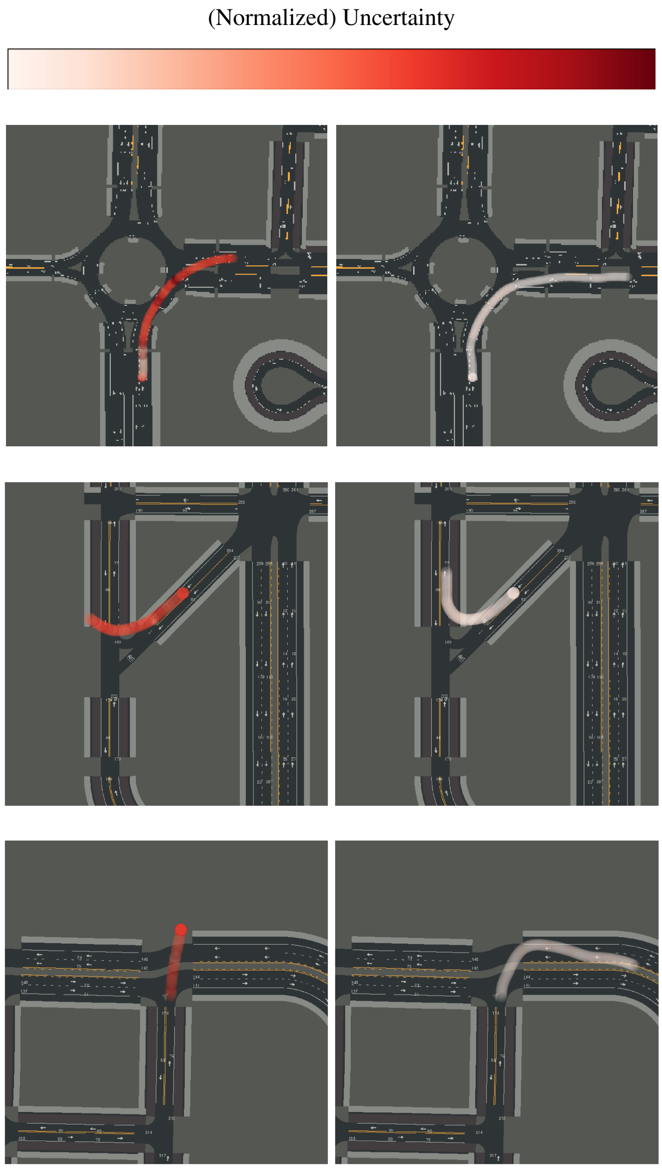
B. Experimental Results on CARNOVEL

Table 4. We evaluate different autonomous driving methods in terms of their robustness to distribution shifts, in our new benchmark, CARNOVEL. All methods are trained on CARLA Town01 using imitation learning on expert demonstrations from the autopilot (Dosovitskiy et al., 2017). A "†" indicates methods that use first-person camera view, as in (Chen et al., 2019), a "♣" methods that use LIDAR observation, as in (Rhinehart et al., 2020) and a "◇" methods that use the ground truth game engine state, as in (Chen et al., 2019). A "★" indicates that we used the reference implementation from the original paper, otherwise we used our implementation. For all the scenes we chose pairs of start-destination locations and ran 10 trials with randomized initial simulator state for each pair. Standard errors are in gray (via bootstrap sampling). The **outperforming** method is in bold.

	AbnormalTurns			BusyTown		
Methods	Success ↑ (7×10 scenes, %)	Infra/km ↓ ($\times 1e{-}3$)	Distance ↑ (m)	Success ↑ (11×10 scenes, %)	Infra/km ↓ ($\times 1e{-}3$)	Distance ↑ (m)
CIL$^{\clubsuit\star}$ (Codevilla et al., 2018)	65.71±07.37	07.04±05.07	128±020	05.45±06.35	11.49±03.66	217±033
LbC†* (Chen et al., 2019)	00.00±00.00	05.81±00.58	208±004	20.00±13.48	03.96±00.15	374±016
LbC-GT$^{\diamond\star}$ (Chen et al., 2019)	02.86±06.39	**03.68**±00.34	217±033	65.45±07.60	02.59±00.02	400±006
DIM$^{\clubsuit}$ (Rhinehart et al., 2020)	74.28±11.26	05.56±04.06	108±017	47.13±14.54	08.47±05.22	175±026
RIP-BCM$^{\clubsuit}$ (baseline, cf. Table 1)	68.57±09.03	07.93±03.73	096±017	50.90±20.64	03.74±05.52	175±031
RIP-MA$^{\clubsuit}$ (ours, cf. Section 3.3.2)	**84.28**±14.20	07.86±05.70	102±015	**64.54**±23.25	05.86±03.99	170±033
RIP-WCM$^{\clubsuit}$ (ours, cf. Section 3.3.1)	**87.14**±14.20	**04.91**±03.60	102±021	**62.72**±05.16	**03.17**±02.04	167±021

	Hills			Roundabouts		
Methods	Success ↑ (4×10 scenes, %)	Infra/km ↓ ($\times 1e{-}3$)	Distance ↑ (m)	Success ↑ (5×10 scenes, %)	Infra/km ↓ ($\times 1e{-}3$)	Distance ↑ (m)
CIL$^{\clubsuit\star}$ (Codevilla et al., 2018)	60.00±29.34	04.74±03.02	219±034	20.00±00.00	**03.60**±03.23	269±021
LbC†* (Chen et al., 2019)	50.00±00.00	01.61±00.15	541±101	08.00±10.95	03.70±00.72	323±043
LbC-GT$^{\diamond\star}$ (Chen et al., 2019)	05.00±11.18	03.36±00.26	312±020	00.00±00.00	06.47±00.99	123±018
DIM$^{\clubsuit}$ (Rhinehart et al., 2020)	70.00±10.54	06.87±04.09	195±012	20.00±09.42	06.19±04.73	240±044
RIP-BCM$^{\clubsuit}$ (baseline, cf. Table 1)	75.00±00.00	05.49±04.03	191±013	06.00±09.66	06.78±07.05	251±027
RIP-MA$^{\clubsuit}$ (ours, cf. Section 3.3.2)	**97.50**±07.90	**00.26**±00.54	196±013	**38.00**±06.32	05.48±05.56	271±047
RIP-WCM$^{\clubsuit}$ (ours, cf. Section 3.3.1)	**87.50**±13.17	**01.83**±01.73	191±006	**42.00**±06.32	04.32±01.91	217±030

C. AdaRIP Examples



(a) RIP (b) AdaRIP

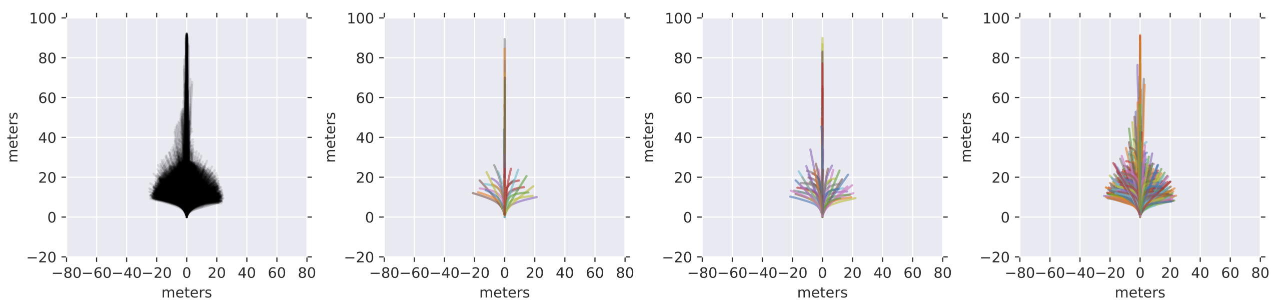
Figure 8. Examples where the non-adaptive method (a) fails to recover from a distribution shift, despite it being able to detect it. The adaptive method (b) queries the human driver when uncertain (dark red), then uses the online demonstrations for updating its model, resulting into confident (light red, white) and safe trajectories.

D. Online Planning with a Trajectory Library

In the absence of scalable global optimizers, we search the trajectory space in Eqn. (4) by restricting the search space to a trajectory library (Liu & Atkeson, 2009), $\mathcal{T}_{\mathbf{Y}}$, a finite set of fixed trajectories. In this work, we perform K-means clustering of the expert plan's from the training distribution and keep 64 of the centroids, as illustrated in Figure 9. Therefore we efficiently solve a search problem over a discrete space rather than an optimization problem of continuous variables. The modified objective is:

$$\mathbf{y}_{\text{RIP}}^{\mathcal{G}} \approx \underset{\mathbf{y} \in \mathcal{T}_{\mathbf{Y}}}{\arg\max} \bigoplus_{\boldsymbol{\theta} \in \text{supp}\left(p(\boldsymbol{\theta}|\mathcal{D})\right)} \log p(\mathbf{y}|\mathcal{G}, \mathbf{x}; \boldsymbol{\theta}) \tag{10}$$

Solving for Eqn. (10) results in $\times 20$ improvement in runtime compared to the gradient descent alternative. Although in in-distribution scenes solving Eqn. (10) over Eqn. (4) does not deteriorate perfomance, in out-of-distribution scenes the trajectory library, $\mathcal{T}_{\mathbf{Y}}$, is not useful. Therefore in the experiments (c.f. Section 4.2.3) we used online gradient-descent. Future work lies in developing a hybrid optimization method that takes advantage of the speedup the trajectory library provides without a decrease in performance in out-of-distribution scenarios.



(a) Trajectories (b) $K = 64$ (c) $K = 128$ (d) $K = 1024$

Figure 9. Our trajectory library from CARLA's autopilot demonstrations, 4 seconds.