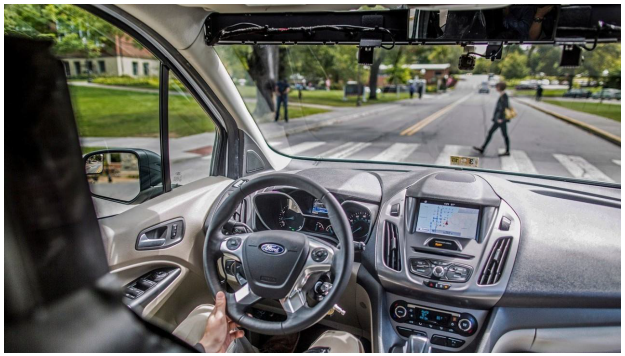
CRIPAC
智能感知与计算研究中心
Center for Research on Intelligent Perception and Computing

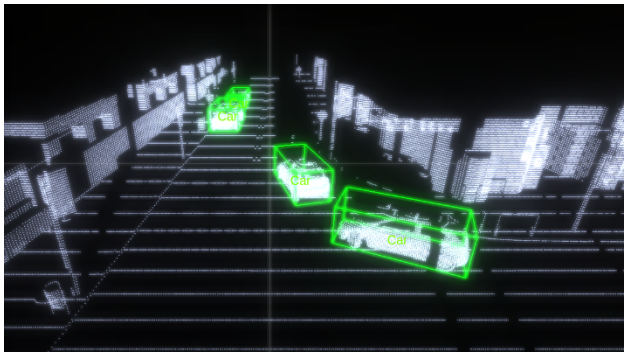
Manual-Label Free 3D Detection via An Open-Source Simulator

Zhen Yang

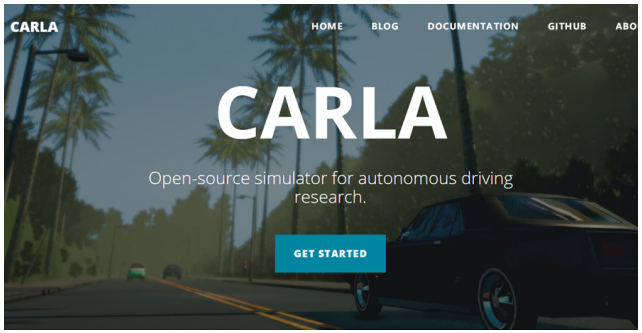
Contents

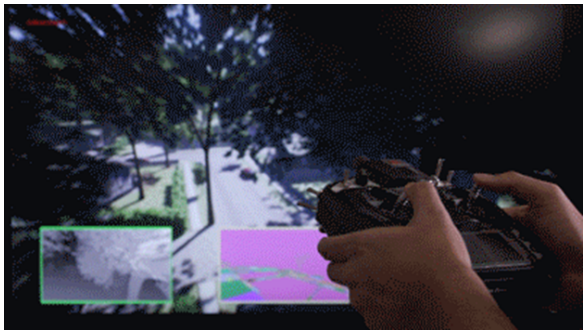
Background





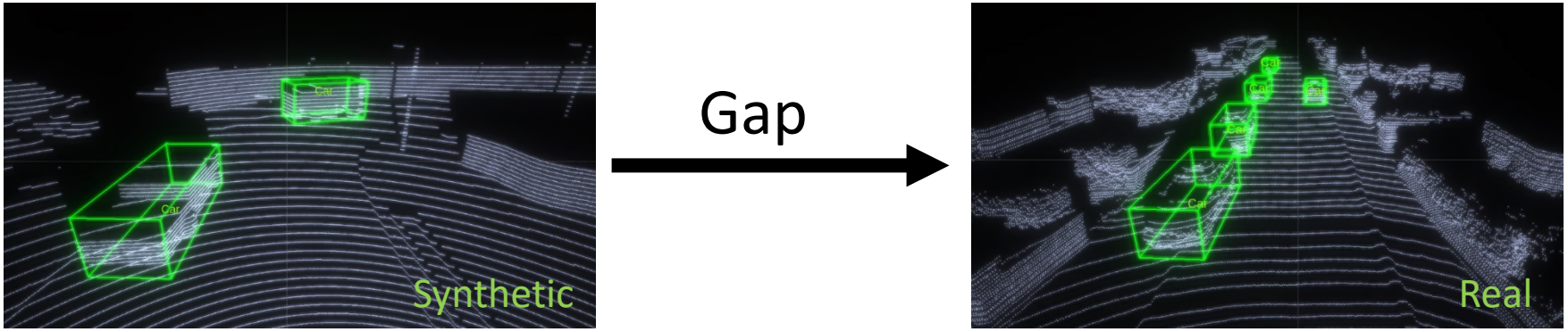
Manual labeled point cloud data is scarce and expensive.





Recently, the simulators are being increasingly used to remedy the shortage of labeled data.

Challenges

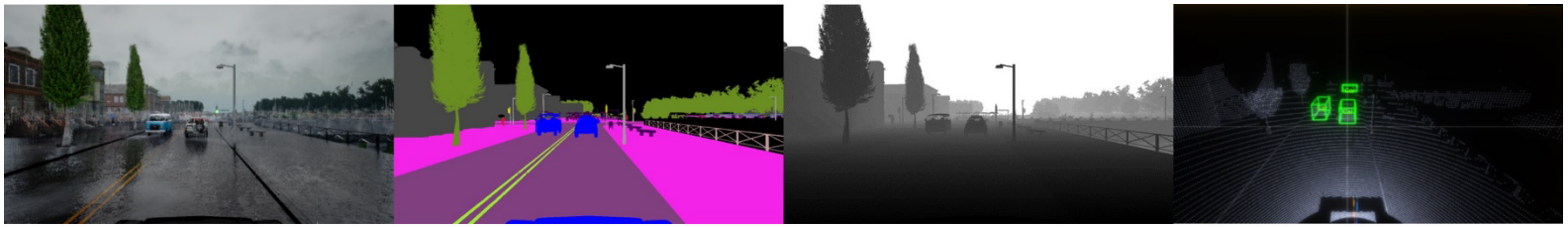


The synthetic data is severely distorted, and such discrepancies would cause significant performance drop.

Our Methods

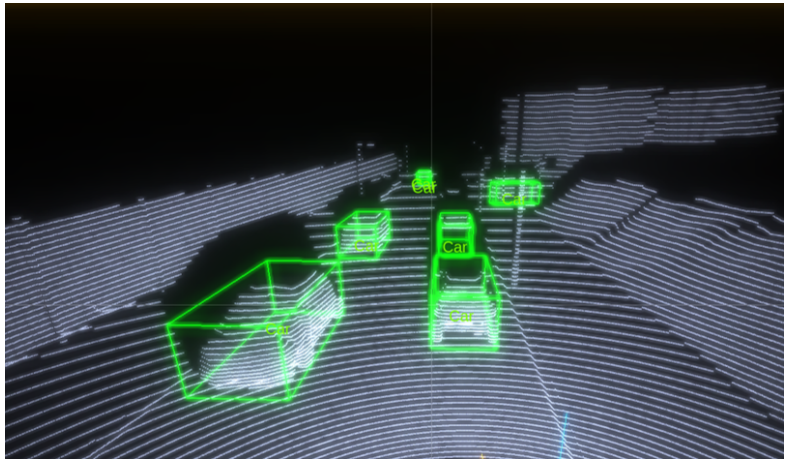
Original 3D Models in CARLA Simulator

Embedded High Quality 3D Models

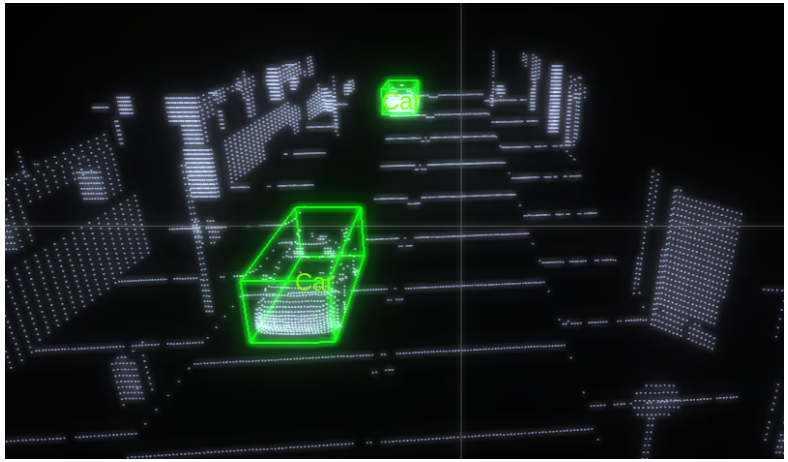


RGB Semantic Depth LiDAR

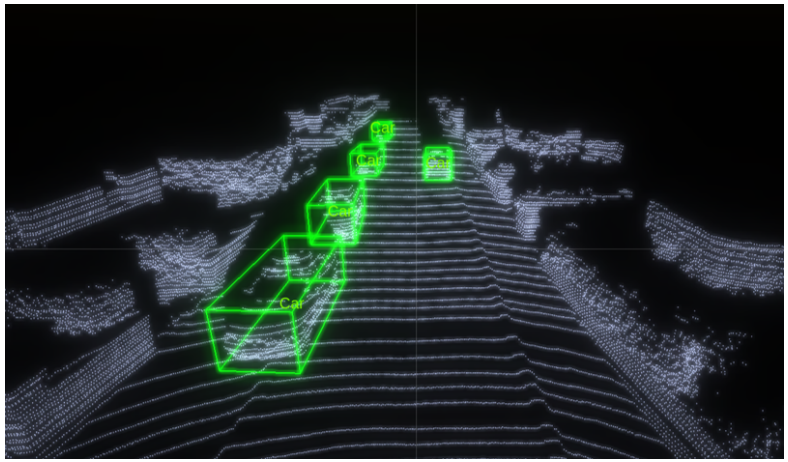
Our Methods



CARLA-origin

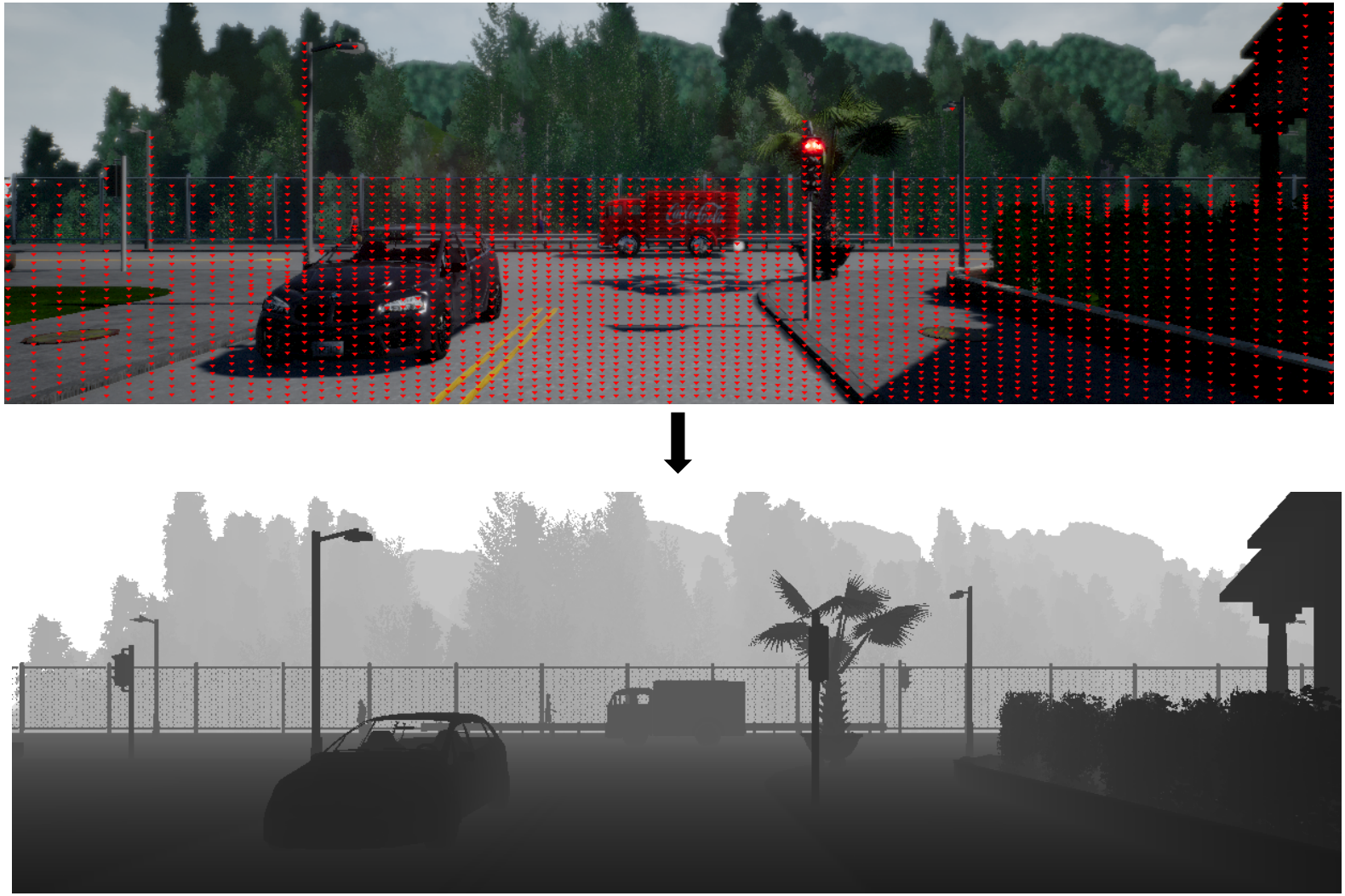


Depth-bp

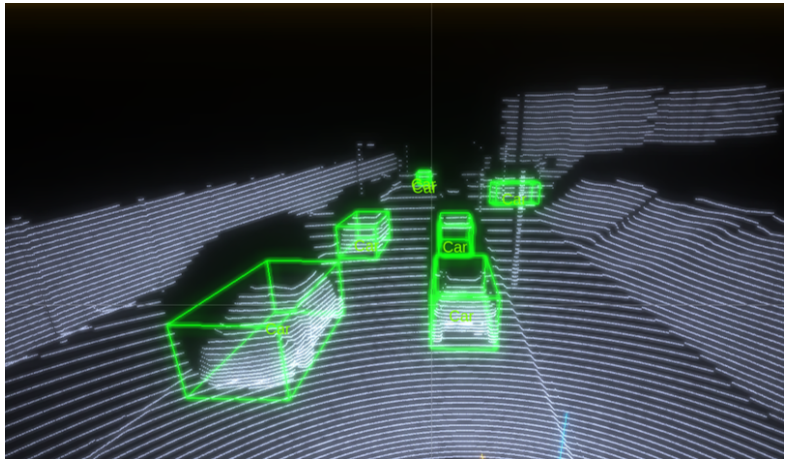


KITTI(real scene)

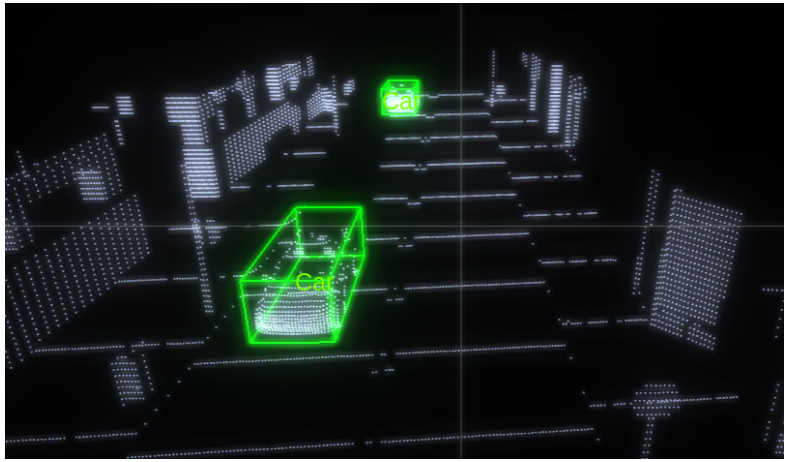
Our Methods



Our Methods



CARLA-origin



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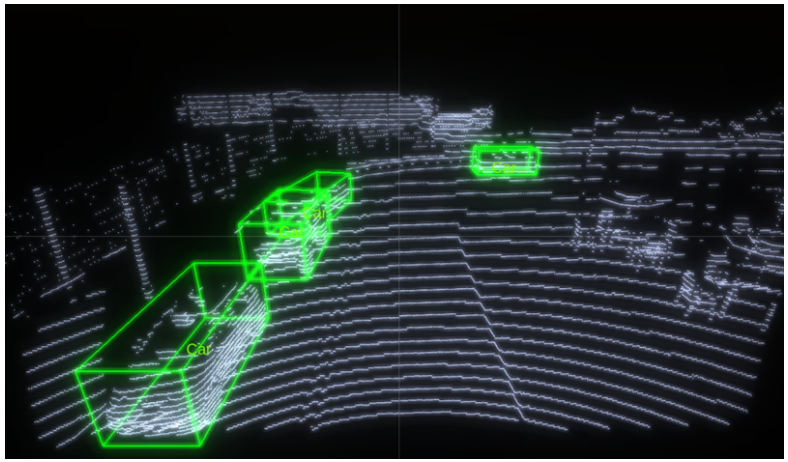
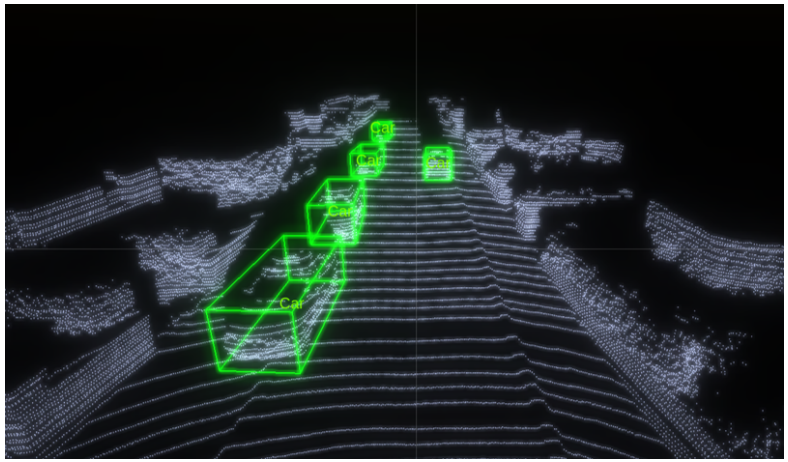
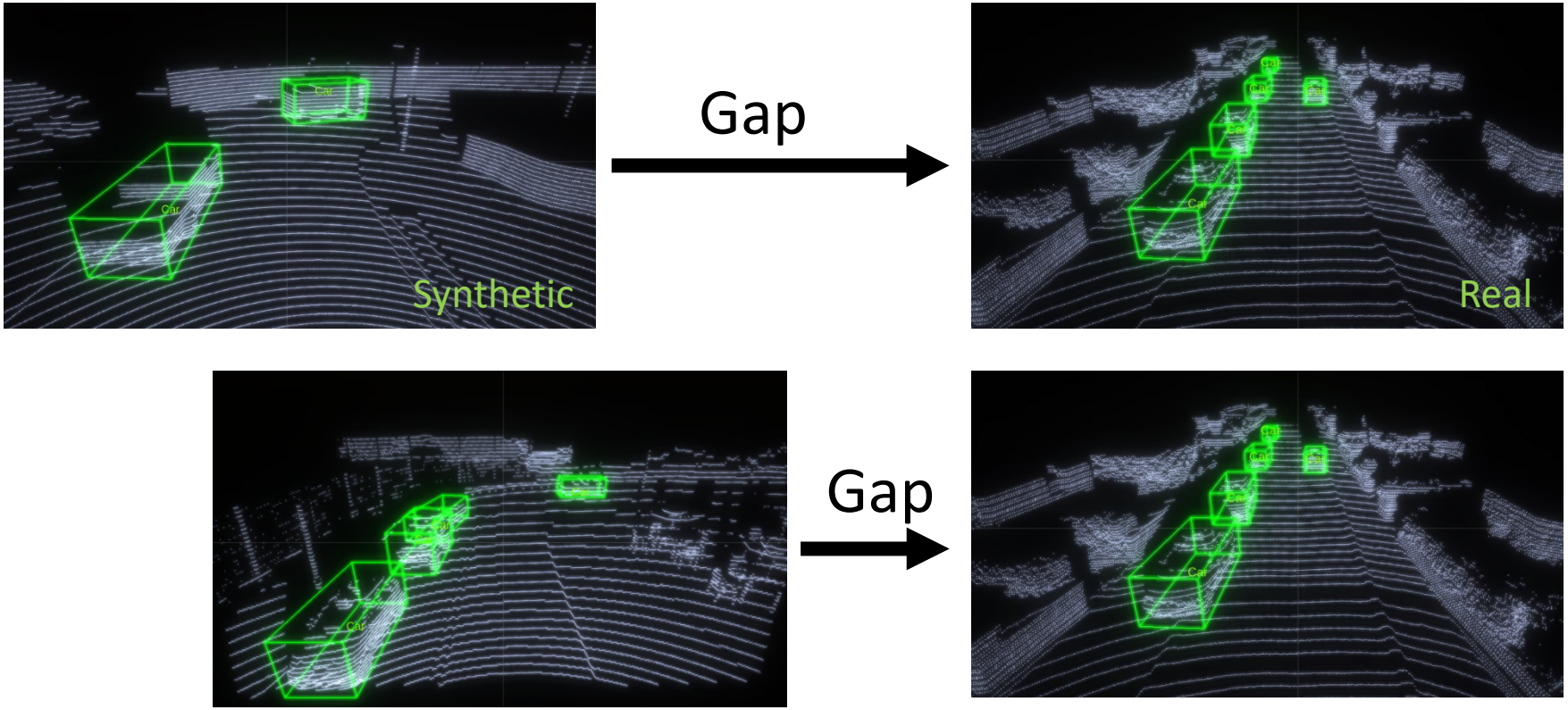


LiDAR-guided



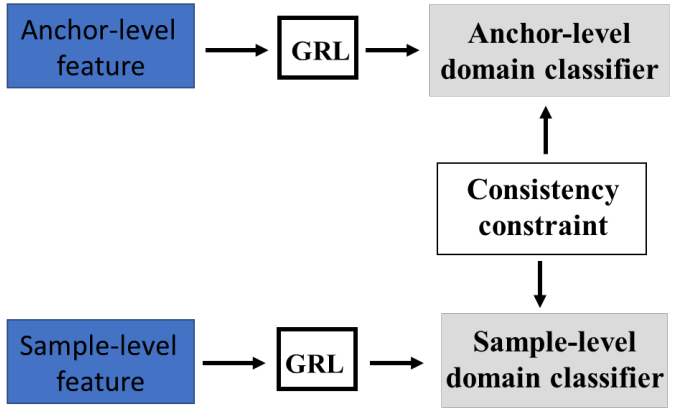
KITTI(real scene)

Challenges

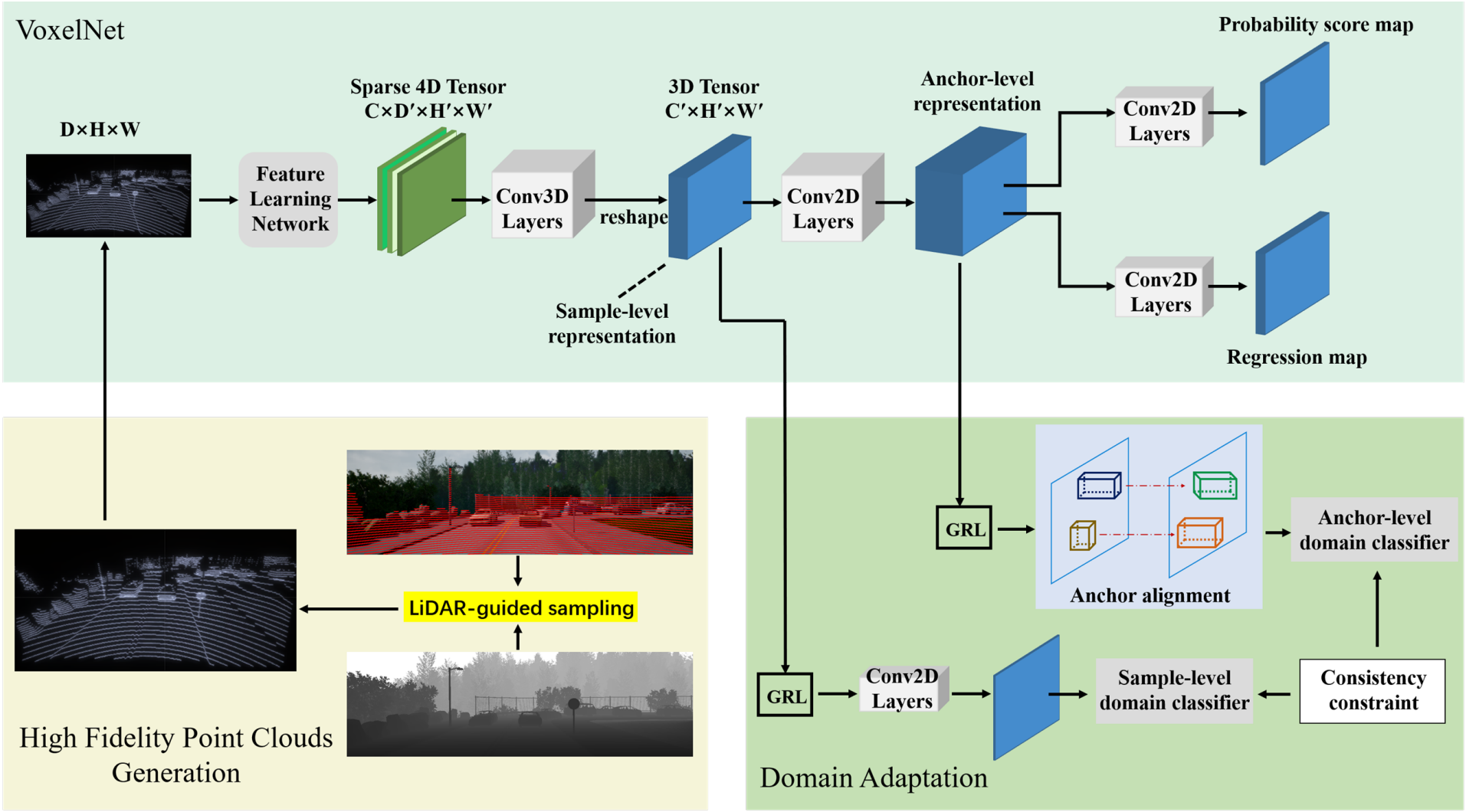


Our Methods

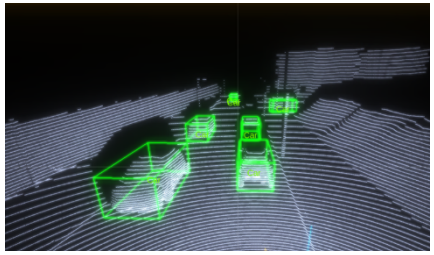
Domain adaptation: Feature alignment helps reduce the impact of the discrepancy between the synthetic data and the real data on model performance.



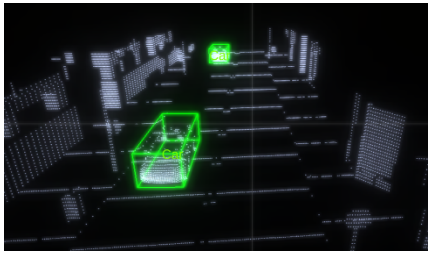
Framework


VoxelNet
D×H×W
Feature Learning Network
Sparse 4D Tensor C×D′×H′×W′
Conv3D Layers
reshape
3D Tensor C′×H′×W′
Conv2D Layers
Anchor-level representation
Conv2D Layers
Conv2D Layers
Probability score map
Regression map
Sample-level representation
LiDAR-guided sampling
High Fidelity Point Clouds Generation
GRL
Anchor alignment
Anchor-level domain classifier
GRL
Conv2D Layers
Sample-level domain classifier
Consistency constraint
Domain Adaptation

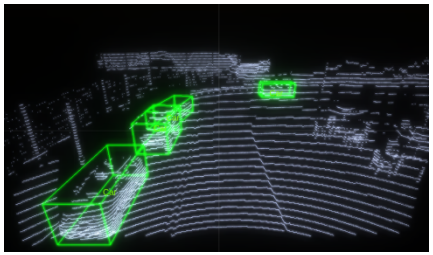
Experimental Results



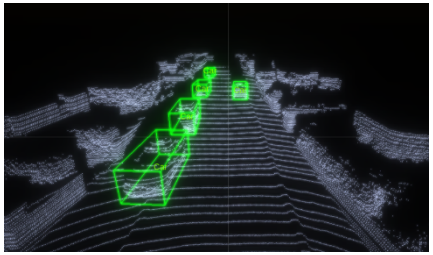
CARLA-origin



Depth-bp



LiDAR-guided



KITTI(real scene)

TABLE I: The average precision (AP) of Car on the KITTI validation set and nuScenes validation set respectively. The VoxelNet is trained using the training set of LIDAR dataset (L), DEPTH dataset (D), CARLA dataset (C), KITTI (K) and nuScenes (nuS) as the source domain respectively. Among them, L, D and C are synthetic dataset generated by the CARLA simulator, K and nuS are collected from the real scene. **Red** indicates the best and **Blue** the second best.

	Direction	Easy	Moderate	Hard	Direction	Easy	Moderate	Hard
BEV AP	C→K	61.09	53.13	49.30	C→nuS	37.11	31.27	14.41
	D→K	83.71	71.56	66.22	D→nuS	50.82	40.75	19.40
	L→K	**87.71**	**74.89**	**68.01**	L→nuS	**55.46**	**46.30**	**20.21**
	K→K	**89.97**	**87.85**	**86.84**	nuS→nuS	**74.82**	**65.99**	**31.67**
3D AP	C→K	26.64	21.98	20.56	C→nuS	2.08	1.79	1.30
	D→K	68.09	52.84	46.00	D→nuS	**25.51**	**20.12**	**10.53**
	L→K	**71.78**	**55.03**	**47.42**	L→nuS	23.78	18.32	9.75
	K→K	**88.41**	**78.37**	**77.33**	nuS→nuS	**49.82**	**42.24**	**20.54**

Experimental Results

TABLE II: Quantitative analysis of finetune result from synthetic data to real data. *Percentage* denotes the number of sampled data as a percentage of the target training set. If *Finetune*, we use the synthetic data to train the model and use the sampled data to finetune the model, else we use the sampled data to train the model directly.

	Percentage	Finetune	Direction	Easy	Moderate	Hard	Direction	Easy	Moderate	Hard
BEV AP	1%	×	K→K	29.12	23.61	18.08	nuS→nuS	34.52	27.54	13.96
	1%	✓	L→K	89.49	79.22	77.95	L→nuS	70.88	61.70	29.25
	5%	✓	L→K	89.75	85.68	79.33	L→nuS	72.80	63.78	29.79
	10%	✓	L→K	**90.24**	86.71	86.31	L→nuS	73.94	64.67	30.19
	100%	×	K→K	89.97	**87.85**	**86.84**	nuS→nuS	**74.82**	**65.99**	**31.67**
3D AP	1%	×	K→K	10.72	10.65	7.57	nuS→nuS	7.21	5.03	2.49
	1%	✓	L→K	83.82	72.25	66.00	L→nuS	39.04	29.98	15.35
	5%	✓	L→K	87.02	75.55	68.45	L→nuS	46.26	38.15	18.53
	10%	✓	L→K	87.51	76.40	74.45	L→nuS	49.44	41.27	19.60
	100%	×	K→K	**88.41**	**78.37**	**77.33**	nuS→nuS	**49.82**	**42.24**	**20.54**

Experimental Results

TABLE III: Results on adaptation from LIDAR to KITTI Dataset. Average precision (AP) of Car is evaluated on the KITTI validation set. *bs* is short for batch size.

	bs	method	Easy	Moderate	Hard
BEV AP	2	VoxelNet	79.27	66.72	63.33
		DA-VoxelNet	81.19	71.27	65.18
	8	VoxelNet	87.71	74.89	68.01
		DA-VoxelNet	**88.40**	**76.66**	**74.07**
3D AP	2	VoxelNet	57.04	43.02	40.62
		DA-VoxelNet	65.18	51.61	45.10
	8	VoxelNet	71.78	55.03	47.42
		DA-VoxelNet	**73.77**	**56.64**	**52.29**

TABLE IV: Ablation study: Quantitative results on the KITTI validation set for *Moderate* level, reported as mean and standard deviation over 3 rounds of training with batch size 2. Models are trained on the LIDAR training set. *an* is short for anchor-level adaptation, *sa* for sample-level adaptation and *cons* is short for our consistency constraint.

method	sa	an	cons	BEV AP (mean±std)	3D AP (mean±std)
VoxelNet				66.44±0.43	43.42±0.62
DA-VoxelNet	✓			69.49±1.70	48.12±1.16
		✓		70.50±0.20	50.30±0.42
	✓	✓		70.92±0.17	50.15±0.68
	✓	✓	✓	**71.15±0.33**	**50.57±1.61**

Conclusions

- LiDAR-guided sampling is helpful.
  - The high fidelity point cloud samples obtained by using LiDAR-guided sampling method can improve the detector's generalization ability on real scenes.
- DA-VoxelNet can relieve the domain gap.
  - DA-VoxelNet gain a large performance improvement compared to the VoxelNet, which reveals a promising perspective of training a LIDAR-based 3D detector without any hand-tagged label.

THANK YOU

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Suggestions Questions