ETA: Energy-based Test-time Adaptation for Depth Completion

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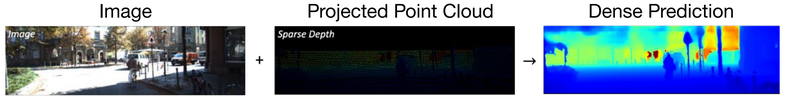
Preliminaries



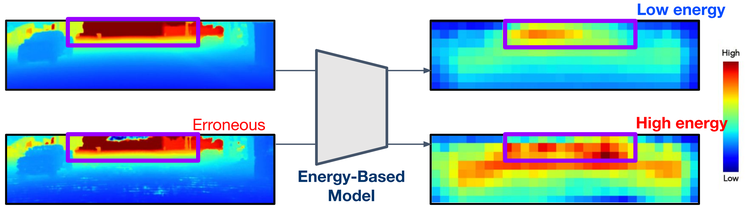
Depth Completion is the egocentric task of **reconstructing** 3D scenes in the form of dense depth maps

Test-Time Adaptation is the task of adapting a pretrained source model to the target domain, using only a **single epoch**, in an **unsupervised** manner, i.e., without accessing the source data.

Motivation: Energy-Based Model (EBM)

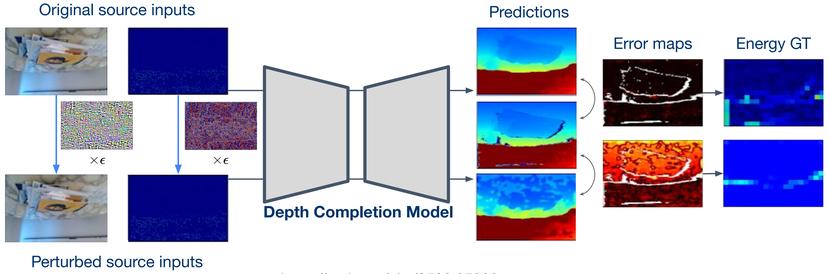
Q: How can we *quantify* distributional (mis)alignment during test-time in an unsupervised way?
Q: How can we *utilize* the quantified distributional shift to perform test-time adaptation?

A: We train **energy-based models (EBMs)** that assign a value called **energy** to each input sample, where lower values indicate higher likelihood that it belongs to the source distribution.

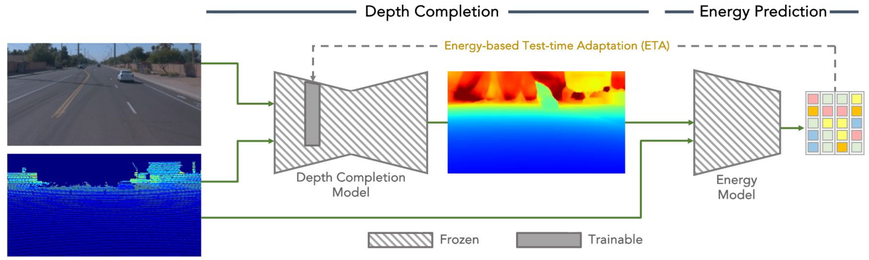


$$E_\phi : (\hat{d}; z) \to e, \quad e : \Omega \to [0, 1]$$

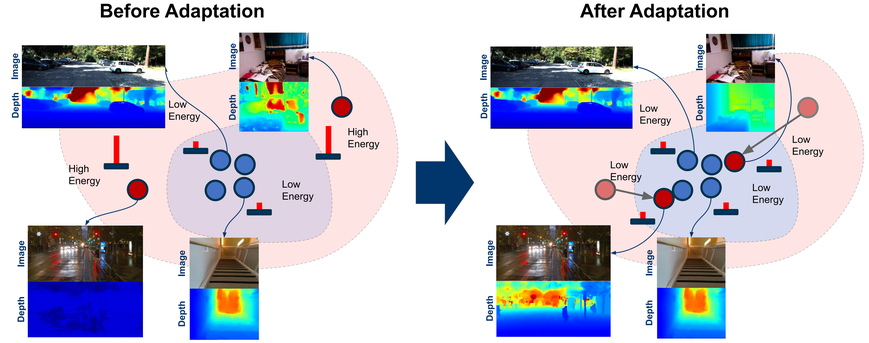
To explore samples in OOD regions of the input data space, to which we assign high energy values, we apply adversarial perturbations using the Fast Gradient Sign Method (FGSM).



Method Formulation

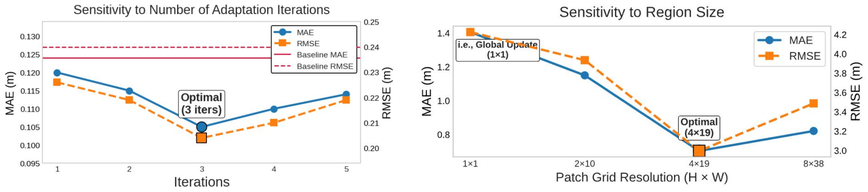


Using an energy model, we can quantify and *maximize* distributional alignment, i.e., *minimize* energy. To do so, we update a layer of the depth completion model in an end-to-end differentiable manner.

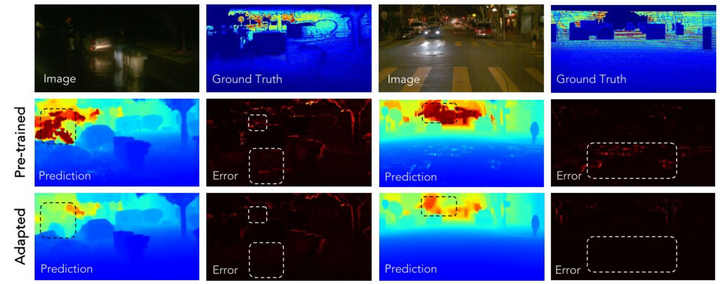


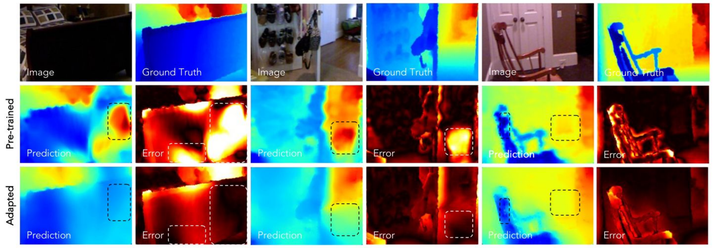
We propose to reformulate TTA as energy minimization, positing that minimizing energy of OOD predictions will improve their fidelity by aligning them back to those of the source data distribution.

Analysis



Results





Across indoor and outdoor adaptation settings, ETA improves over ProxyTTA by 7.75% and 6.15%, and over TEA by 41.6% and 23.1% in MAE and RMSE.

Model	Method	Outdoor (KITTI)						Indoor (VOID)					
		VKITTI-FOG		nuScenes		Waymo		NYUv2		SceneNet		ScanNet	
		MAE↓	RMSE↓	MAE↓	RMSE↓	MAE↓	RMSE↓	MAE↓	RMSE↓	MAE↓	RMSE↓	MAE↓	RMSE↓
MSG-CHN [41]	Pre-trained	2.842	6.557	3.331	6.449	1.107	2.962	1.040	1.528	0.281	0.645	0.687	1.201
	CoTTA [97]	0.730	3.330	3.157	6.434	0.655	2.213	0.876	1.148	0.223	0.498	0.619	1.141
	ProxyTTA-fast [61]	0.728	3.087	2.834	6.096	0.608	1.921	0.699	1.120	0.192	0.424	0.302	0.480
	ETA (Ours)	0.703	2.996	2.666	6.073	0.583	1.907	0.561	0.850	0.187	0.401	0.298	0.460
NLSPN [62]	Pre-trained	1.309	7.423	2.656	6.146	1.175	3.078	0.388	0.702	0.167	0.438	0.233	0.431
	BN Adapt [94]	0.775	3.465	2.928	8.209	0.494	1.921	0.147	0.271	0.120	0.345	0.082	0.181
	CoTTA [97]	0.767	3.799	2.650	6.242	0.933	2.763	0.390	0.704	0.205	0.540	0.234	0.496
	TEA [122]	0.735	3.417	2.841	6.667	1.055	2.942	0.256	0.411	0.206	0.415	0.132	0.226
	ProxyTTA [61]	0.686	2.666	2.589	6.006	0.477	1.598	0.124	0.240	0.113	0.333	0.074	0.166
	ETA (Ours)	0.545	2.617	2.359	5.927	0.472	1.568	0.105	0.204	0.109	0.311	0.067	0.154
BP-Net [86]	Pre-trained	0.893	3.926	2.787	6.500	0.692	2.534	0.234	0.405	0.271	0.488	0.123	0.196
	BN Adapt [94]	0.605	3.426	2.618	5.850	0.540	1.838	0.178	0.257	0.236	0.373	0.116	0.177
	CoTTA [97]	0.611	3.090	2.432	5.490	0.538	1.874	0.212	0.364	0.293	0.421	0.140	0.199
	TEA [122]	0.631	3.311	2.581	5.677	0.673	1.942	0.171	0.253	0.256	0.404	0.115	0.165
	ProxyTTA [61]	0.571	2.844	2.373	5.413	0.489	1.520	0.174	0.248	0.231	0.368	0.102	0.155
	ETA (Ours)	0.544	2.729	2.281	5.278	0.451	1.433	0.161	0.231	0.221	0.352	0.093	0.148

https://arxiv.org/abs/2508.05989

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