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cases	authors	Yujia Huang Dai Sihui Tan N. Nguyen	authors	Yujia Huang Sihui Dai Tan Nguyen Richard G. Baraniuk Anima Anandkumar	
		Richard G. BaraniukAnimashree Anandkumar	title	Out-of-Distribution Detection Using Neural Rendering Generative Models	
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	id	id-542026754148321189		models assign higher likelihood to images from SVHN when trained on CIFAR-10 images. We use a recently proposed generative model known as neural rendering model	
	abstract			(NRM) and derive metrics for OoD. We show that NRM unifies both approaches since it provides a likelihood estimate and also carries out reconstruction in each layer of the	
	versions			neural network. Among various measures, we found the joint likelihood of latent variables to be the most effective one for OoD detection. Our results show that when trained on CIFAR-10, lower likelihood (of latent variables) is assigned to SVHN images. Additionally, we show that this metric is consistent across other OoD datasets. To the best of our knowledge, this is the first work to show consistently lower likelihood for OoD data with smaller variance with deep generative models.	ined linest
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