		doc_1		doc_2	decision	id
cases	authors	• Wenhu Chen • Yilin Shen • Hongxia Jin • William Wang	authors	• Wenhu Chen • Yilin Shen • Hongxia Jin • William Wang	DUPLICATES	26
	title	A Variational Dirichlet Framework for Out-of-Distribution Detection	title	A Variational Dirichlet Framework for Out-of-Distribution Detection		
	publication_date	2019-04-20 00:00:00	publication_date	2018-11-18 10:24:58+00:00		
	source	SupportedSources.INTERNET_ARCHIVE	source	SupportedSources.ARXIV		
	journal		journal	None		
	volume		volume			
	doi		doi			
	urls	• https://web.archive.org/web/20200914011139/https://arxiv.org/pdf/1811.07308v4.pdf	urls	• http://arxiv.org/pdf/1811.07308v4 • http://arxiv.org/abs/1811.07308v4 • http://arxiv.org/pdf/1811.07308v4		
	id	id2161930586672597012	id	id-8694912664018519311		
	abstract	With the recently rapid development in deep learning, deep neural networks have been widely adopted in many real-life applications. However, deep neural networks are also known to have very little control over its uncertainty for unseen examples, which potentially causes very harmful and annoying consequences in practical scenarios. In this paper, we are particularly interested in designing a higher-order uncertainty metric for deep neural networks and investigate its effectiveness under the out-of-distribution detection task proposed by hendrycks2016baseline. Our method first assumes there exists an underlying higher-order distribution P(z), which controls label-wise categorical distribution P(y) over classes on the K-dimension simplex, and then approximate such higher-order distribution via parameterized posterior function $p\_Î,(z|x)$ under variational inference framework, finally we use the entropy of learned posterior distribution $p\_Î,(z|x)$ as uncertainty measure to detect out-of-distribution examples. Further, we propose an auxiliary objective function to discriminate against synthesized adversarial examples to further increase the robustness of the proposed uncertainty measure. Through comprehensive experiments on various datasets, our proposed framework is demonstrated to consistently outperform competing algorithms.	abstract	With the recently rapid development in deep learning, deep neural networks have been widely adopted in many real-life applications. However, deep neural networks are also known to have very little control over its uncertainty for unseen examples, which potentially causes very harmful and annoying consequences in practical scenarios. In this paper, we are particularly interested in designing a higher-order uncertainty metric for deep neural networks and investigate its effectiveness under the out-of-distribution detection task proposed by~\cite{hendrycks2016baseline}. Our method first assumes there exists an underlying higher-order distribution $\mathbb{P}(z)$, which controls label-wise categorical distribution $\mathbb{P}(y)$ over classes on the K-dimension simplex, and then approximate such higher-order distribution via parameterized posterior function $p_{\theta}(z|x)$ under variational inference framework, finally we use the entropy of learned posterior distribution $p_{\theta}(z|x)$ as uncertainty measure to detect out-of-distribution examples. Further, we propose an auxiliary objective function to discriminate against synthesized adversarial examples to further increase the robustness of the proposed uncertainty measure. Through comprehensive experiments on various datasets, our proposed framework is demonstrated to consistently outperform competing algorithms.		
	versions		versions			