

cases	doc_1		doc_2		decision	id
	authors	<ul style="list-style-type: none">Chen, YaowuChen, YueFengLi, XiaodanTian, XiangXie, ChuanlongXue, HuiZhang, Rongzheng, bolunZhu, Yao	authors	<ul style="list-style-type: none">Yaowu ChenBolun ZhengXiang TianHui XueRong ZhangXiaodan LiChuanlong XieYuefeng ChenYao Zhu	DUPLICATES	7
	title	Boosting Out-of-distribution Detection with Typical Features	title	Boosting Out-of-distribution Detection with Typical Features		
	publication_date	2022-10-09 00:00:00	publication_date	2022-10-09 00:00:00		
	source	SupportedSources.CORE	source	SupportedSources.PAPERS_WITH_CODE		
	journal		journal			
	volume		volume			
	doi	None	doi			
	urls	<ul style="list-style-type: none">http://arxiv.org/abs/2210.04200	urls	<ul style="list-style-type: none">https://arxiv.org/pdf/2210.04200v1.pdfhttps://github.com/alibaba/easyrobust		
	id	id-4801139237736908866	id	id815553996111564609		
	abstract	Out-of-distribution (OOD) detection is a critical task for ensuring the reliability and safety of deep neural networks in real-world scenarios. Different from most previous OOD detection methods that focus on designing OOD scores or introducing diverse outlier examples to retrain the model, we delve into the obstacle factors in OOD detection from the perspective of typicality and regard the feature's high-probability region of the deep model as the feature's typical set. We propose to rectify the feature into its typical set and calculate the OOD score with the typical features to achieve reliable uncertainty estimation. The feature rectification can be conducted as a {plug-and-play} module with various OOD scores. We evaluate the superiority of our method on both the commonly used benchmark (CIFAR) and the more challenging high-resolution benchmark with large label space (ImageNet). Notably, our approach outperforms state-of-the-art methods by up to 5.11\$%%\$ in the average FPR95 on the ImageNet benchmark	abstract	Out-of-distribution (OOD) detection is a critical task for ensuring the reliability and safety of deep neural networks in real-world scenarios. Different from most previous OOD detection methods that focus on designing OOD scores or introducing diverse outlier examples to retrain the model, we delve into the obstacle factors in OOD detection from the perspective of typicality and regard the feature's high-probability region of the deep model as the feature's typical set. We propose to rectify the feature into its typical set and calculate the OOD score with the typical features to achieve reliable uncertainty estimation. The feature rectification can be conducted as a {plug-and-play} module with various OOD scores. We evaluate the superiority of our method on both the commonly used benchmark (CIFAR) and the more challenging high-resolution benchmark with large label space (ImageNet). Notably, our approach outperforms state-of-the-art methods by up to 5.11\$%%\$ in the average FPR95 on the ImageNet benchmark.		
	versions		versions			