

cases	doc_1		doc_2		decision	id
	authors	<ul style="list-style-type: none"><li>Jarrod Haas</li><li>William Yolland</li><li>Bernhard Rabus</li></ul>	authors	<ul style="list-style-type: none"><li>Bernhard Rabus</li><li>William Yolland</li><li>Jarrod Haas</li></ul>	DUPLICATES	2
	title	Linking Neural Collapse and L2 Normalization with Improved Out-of-Distribution Detection in Deep Neural Networks	title	Linking Neural Collapse and L2 Normalization with Improved Out-of-Distribution Detection in Deep Neural Networks		
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	urls	<ul style="list-style-type: none"><li>https://web.archive.org/web/20230115170908/https://arxiv.org/pdf/2209.08378v3.pdf</li></ul>	urls	<ul style="list-style-type: none"><li>https://arxiv.org/pdf/2209.08378v3.pdf</li></ul>		
	id	id1331377022105942906	id	id-9027556613701719447		
	abstract	We propose a simple modification to standard ResNet architectures--L2 normalization over feature space--that substantially improves out-of-distribution (OoD) performance on the previously proposed Deep Deterministic Uncertainty (DDU) benchmark. We show that this change also induces early Neural Collapse (NC), an effect linked to better OoD performance. Our method achieves comparable or superior OoD detection scores and classification accuracy in a small fraction of the training time of the benchmark. Additionally, it substantially improves worst case OoD performance over multiple, randomly initialized models. Though we do not suggest that NC is the sole mechanism or a comprehensive explanation for OoD behaviour in deep neural networks (DNN), we believe NC's simple mathematical and geometric structure can provide a framework for analysis of this complex phenomenon in future work.	abstract	We propose a simple modification to standard ResNet architectures--L2 normalization over feature space--that substantially improves out-of-distribution (OoD) performance on the previously proposed Deep Deterministic Uncertainty (DDU) benchmark. We show that this change also induces early Neural Collapse (NC), an effect linked to better OoD performance. Our method achieves comparable or superior OoD detection scores and classification accuracy in a small fraction of the training time of the benchmark. Additionally, it substantially improves worst case OoD performance over multiple, randomly initialized models. Though we do not suggest that NC is the sole mechanism or a comprehensive explanation for OoD behaviour in deep neural networks (DNN), we believe NC's simple mathematical and geometric structure can provide a framework for analysis of this complex phenomenon in future work.		
	versions		versions			