

# FlowCon Supplementary

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## 1 Far-OOD (Individual Dataset)

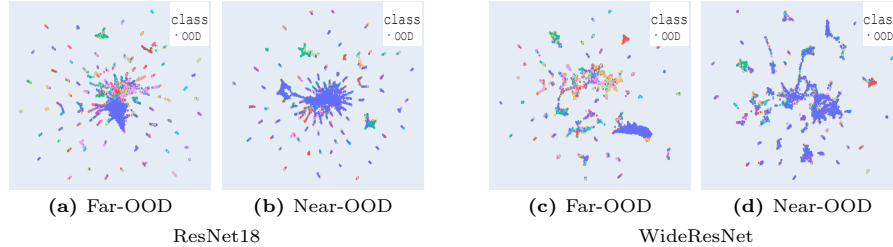
Table 1 reports the performance of *FlowCon* on each of the six OOD Dataset - LSUN-Resize [5], LSUN-Crop [5], iSUN [3], SVHN [2], Textures [1], and Places365 [6]. We observe a decline in performance for both CIFAR-10 and CIFAR-100 when they are evaluated on Places365. This can potentially be due to the OOD instances within the dataset that also contains hidden ID semantics, as shown by Yang *et al.* [4].

**Table 1:** *Far-OOD*: Individual dataset-wise OOD detection performance during only semantic shift using *FlowCon*.

$D_{in}$ (model)	Method	AUROC	↑AUPR-S	↑AUPR-E	↑FPR-95 ↓
CIFAR-10 (ResNet)	lsun-r	98.37	99.68	90.30	6.75
	lsun-c	96.12	99.24	78.82	25.05
	isun	98.07	99.63	89.25	9.5
	svhn	98.07	99.49	85.31	16.4
	textures	97.94	99.58	91.06	11.6
	Places365	95.22	99.00	79.22	28.3
CIFAR-10 (WideResNet)	lsun-r	98.86	99.76	95.19	5.8
	lsun-c	92.15	97.87	80.80	29.95
	isun	98.67	99.71	95.01	6.35
	svhn	97.86	99.53	92.61	11.15
	textures	96.97	99.31	90.60	15.15
	Places365	87.99	96.87	67.22	46.25
CIFAR-100 (ResNet)	lsun-r	96.82	99.32	87.20	16.9
	lsun-c	75.07	93.46	36.05	78.65
	isun	95.80	99.09	84.13	21.55
	svhn	87.71	97.21	56.40	59.0
	textures	97.99	99.55	93.24	10.1
	Places365	75.93	92.47	50.44	64.95
CIFAR-100 (WideResNet)	lsun-r	88.53	97.53	53.89	61.05
	lsun-c	76.68	93.01	43.17	69.15
	isun	88.99	97.58	55.48	59.45
	svhn	89.59	97.44	66.78	45.3
	textures	87.15	96.48	67.26	46.40
	Places365	70.81	91.55	33.48	80.35

## 2 UMAP embeddings for CIFAR-100

Fig 1 shows the UMAP embeddings for CIFAR-100 dataset trained using *FlowCon*. We observe a similar pattern as with CIFAR-10 dataset wherein there was increased overlap between semantically similar classes in the latent space.



**Fig. 1:** UMAP embeddings of  $z_{flow}$  trained on CIFAR-100 using *FlowCon*

## References

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