Embedding contrastive unsupervised features to cluster in- and out-of-distribution noise in corrupted image datasets

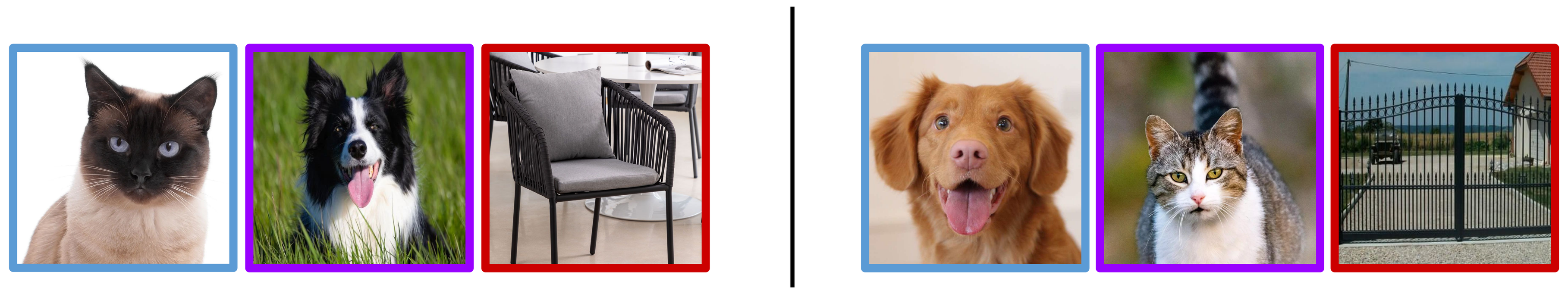
Paul Albert, Eric Arazo, Noel O'Connor, Kevin McGuinness (Dublin City University)

Insight
SFI RESEARCH CENTRE FOR DATA ANALYTICS

Motivations

→ Use web search engines to scrape large amounts of images from the web
→ The gathered data will either be clean, in- or out-of-distribution noisy (ID or OOD). The noisy nature of each sample is unknown

CAT vs DOG



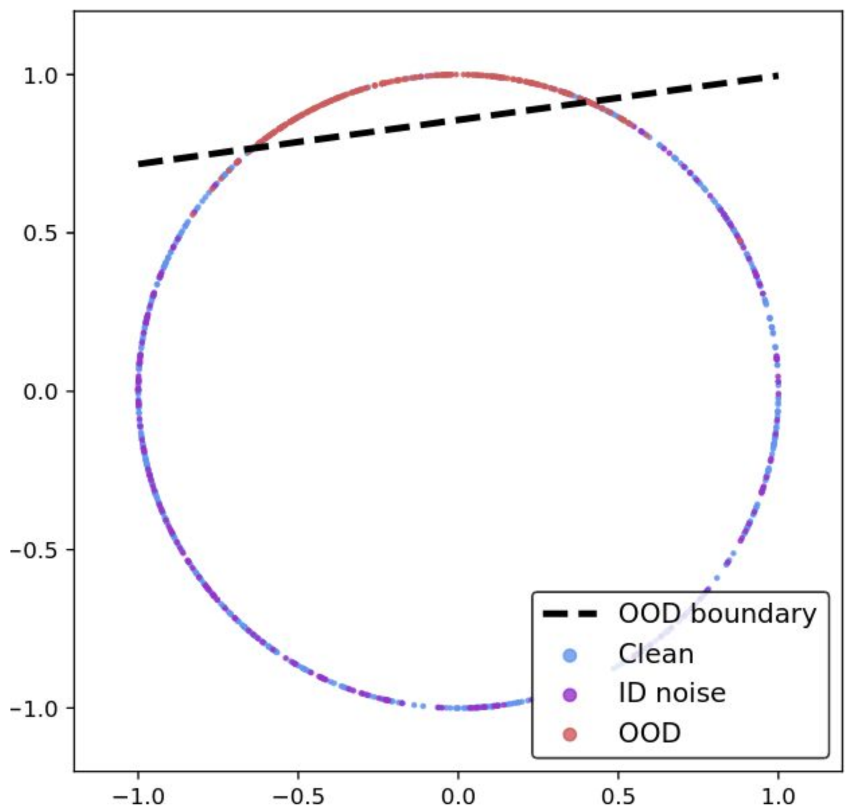
Clean ID noisy OOD noisy

How can noisy images be detected without the need for human annotators ?

Unsupervised contrastive learning linearly separates in- from out-of-distribution images on the hypersphere !

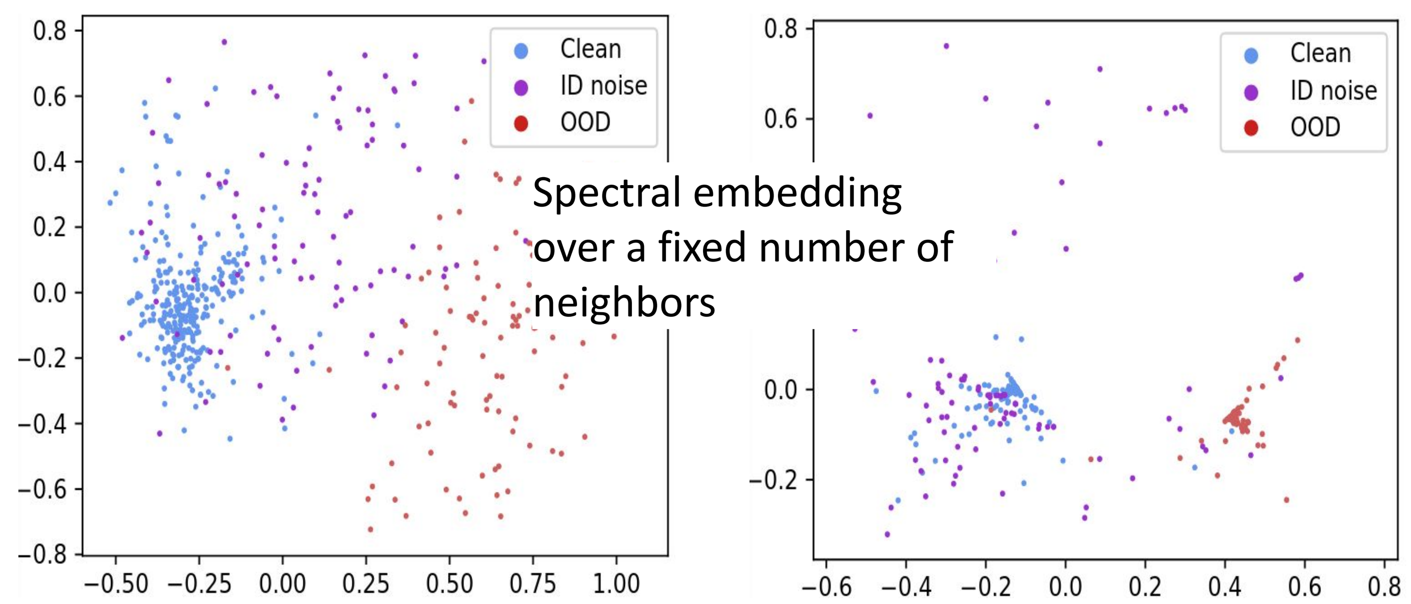
Dataset	Cifar-100		miniImageNet	
Corruption dataset	INet32	P365	Web	Web
r_{out}	0.2	0.2	0.2	0.6
Linear classifier score	98.21	95.95	99.66	99.54

Linear separation accuracy for ID and OOD noise in corrupted datasets



Linear separation on the 2D hypersphere. CIFAR10 corrupted with 20% OOD and ID noise

Unsupervised noise clustering using OPTICS & spectral embedding



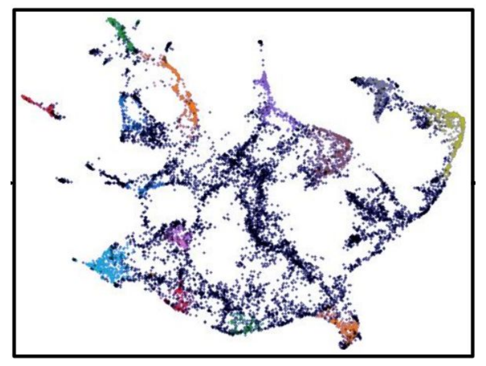
Spectral embedding evidences the OOD "cluster". OPTICS retrieves both clean ID and OOD clusters and detects ID noise as outliers to the clean cluster

ID noise correction and guided contrastive learning

The true label of ID noisy samples are guessed as the average of predictions p_i on weakly augmented views of the image (consistency regularization)

$$y_i = \left(\frac{p_{i,1}+p_{i,2}}{2}\right)^{\tau_1}$$

OPTICS applied on the OOD images to detect possible clusters. The guided contrastive learning loss is minimized



Detected OOD clusters

$$l_{cont} = -\frac{1}{N}\sum_{i=1}^{N}\frac{1}{B}\sum_{b=1}^{B} e_{i,b}\log\left(\frac{\exp\left(ip(r_b, r_i')/\tau_2\right)}{\sum_{k=1}^{B}\exp\left(ip(r_k, r_i')/\tau_2\right)}\right)$$

τ_1, τ_2 = temperature hyper-parameter
r_i, r_i' = contrastive representation of augmented and unaugmented images
$e_{i,b} = 1$ if sample i and b belong to the same cluster else 0

Results - Top 1 accuracy

Controlled web noisy label dataset (miniImageNet) - PreActResNet18

Noise level	CE	M	⋆DM	MM	FaMUS	⋆†SM	⋆†PM	Ours
20	47.36	49.10	50.96	51.02	51.42	59.06	61.24	**61.56**
40	42.70	46.40	46.72	47.14	48.03	54.54	56.22	**59.94**
60	37.30	40.58	43.14	43.80	45.10	52.36	52.84	**54.92**
80	29.76	33.58	34.50	33.46	35.50	40.00	43.42	**45.62**

Real world dataset - mini-Webvision - InceptionResNetV2

		100 epochs										150 epochs	
		M	MM	⋆DM	⋆ELR+	RRL	⋆DSOS	⋆†PM	⋆†SM	Ours	⋆Ours	FaMUS	⋆Ours
mini-WebVision	top-1	75.44	76.0	77.32	77.78	77.80	78.76	78.84	**80.04**	78.16	79.84	79.40	**80.24**
	top-5	90.12	90.2	91.64	91.68	91.30	92.32	90.56	93.04	92.60	**93.64**	92.80	**93.44**
ILSVRC12	top-1	71.44	72.9	75.20	70.29	74.40	75.88	−−	75.76	74.20	**76.64**	77.00	**77.12**
	top-5	89.40	91.10	90.84	89.76	90.90	92.36	−−	92.60	93.32	**94.20**	92.76	**94.32**

⋆ = network ensemble
† = unsupervised initialization

Conclusion

We use unsupervised features to detect both ID and OOD noise using spectral clustering and an unsupervised clustering algorithm OPTICS

The true label of ID noise is guessed in a consistency regularization approach while OOD is clustered using a guided contrastive objective

Paper link :

ECCV EUROPEAN CONFERENCE ON COMPUTER VISION TEL AVIV 2022 October 23-27, 2022, Tel Aviv

HOST INSTITUTIONS

PARTNER INSTITUTIONS

FUNDED BY:

Acknowledgements

Research conducted with the financial support of Science Foundation Ireland (SFI) under Grant Number [16/RC/3835] - VistaMilk and [12/RC/2289 P2] - Insight as well as the support of the Irish Centre for High End Computing (ICHEC)