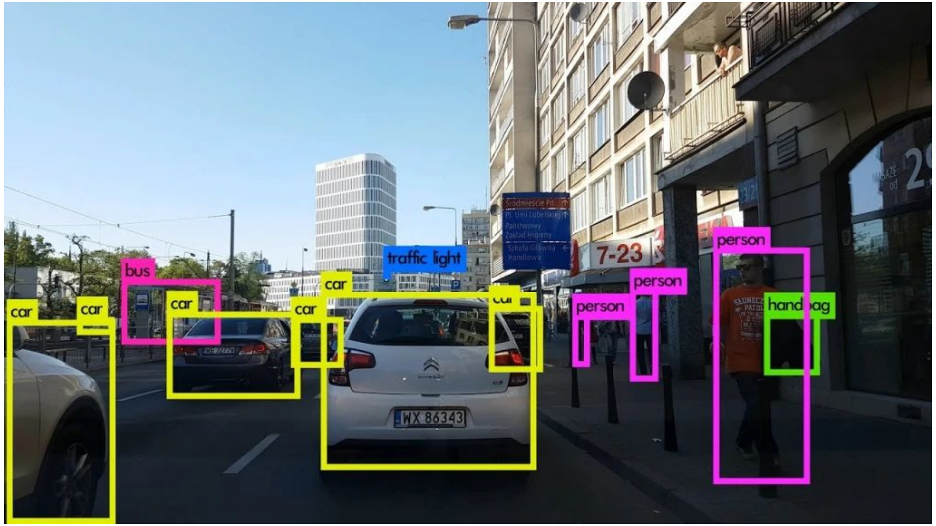
ReAct: OOD Detection with Rectified Activations

Yiyou Sun, Chuan Guo, Yixuan Li (Neurips 2021)

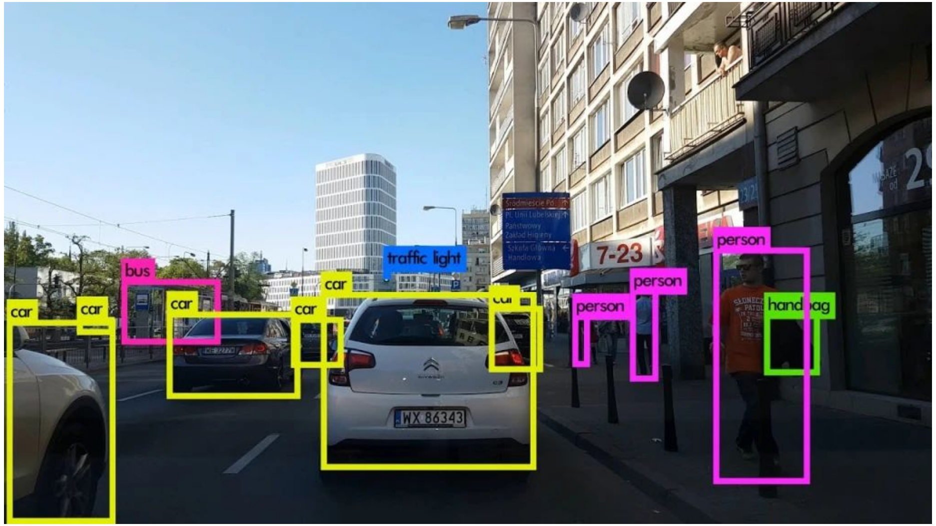
Presented by: **Group 4**
{Logan Crowl, Abishek Sridhar, Deying Song, Prince Wang, Shuaiqi Wang}

ML-715 (Fall 2022)

Carnegie Mellon University



Autonomous driving



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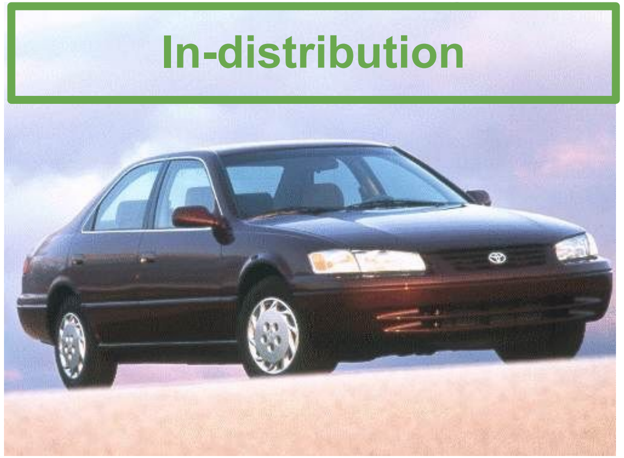

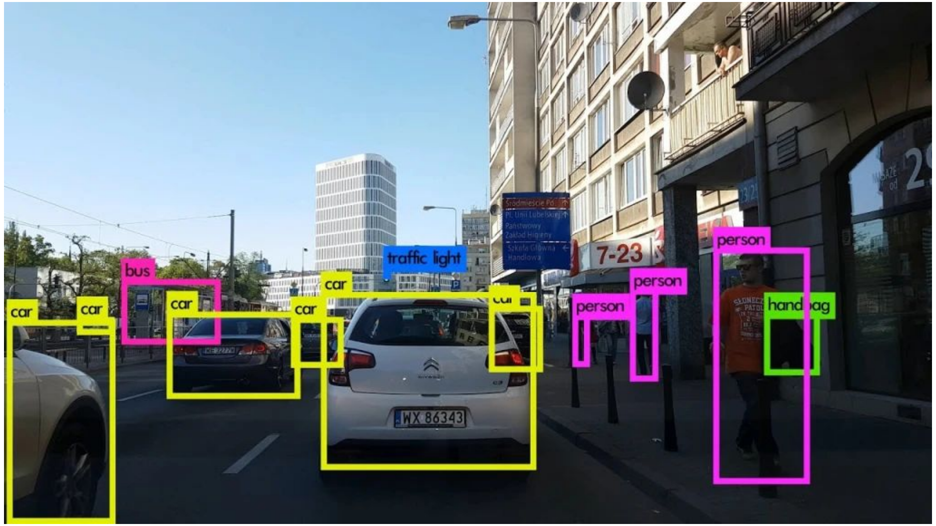

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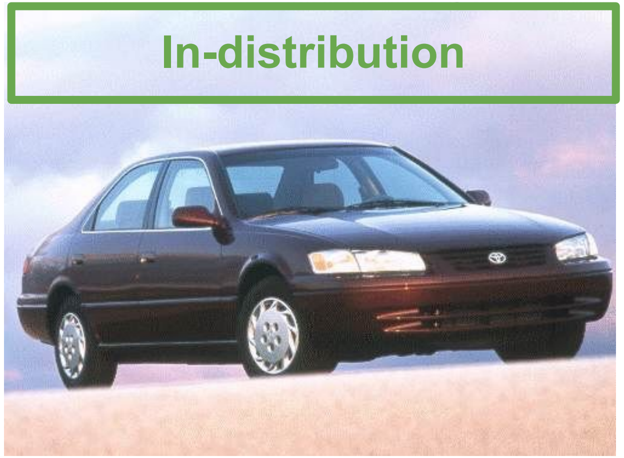
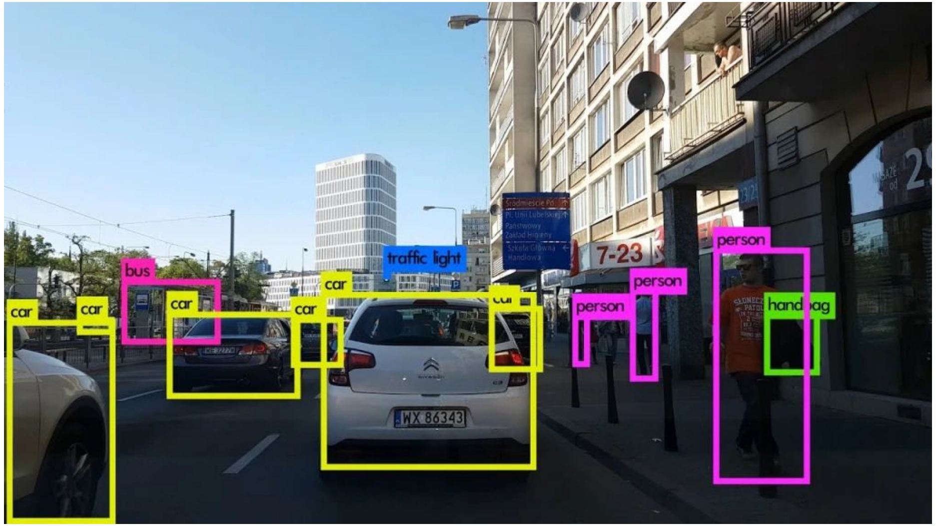


How can we detect these OOD inputs at test time?

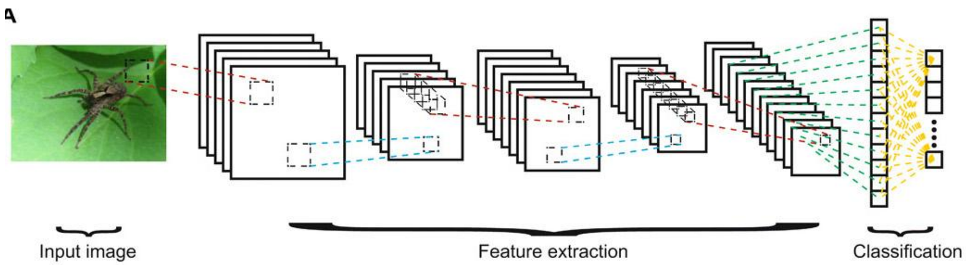


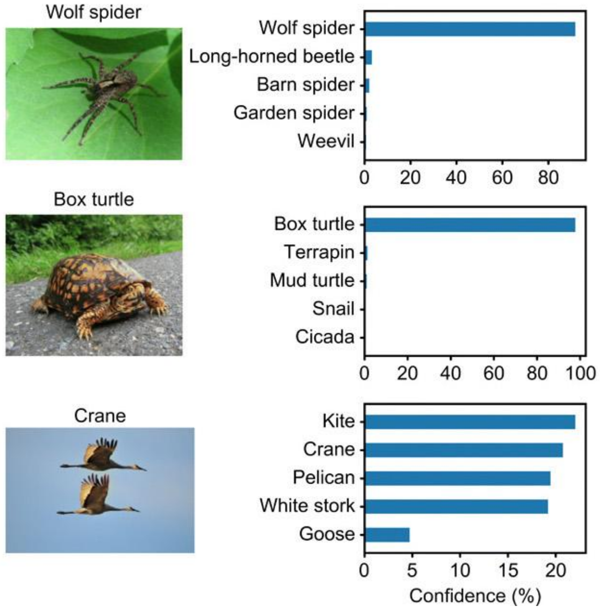
Autonomous driving

In-distribution

Out-of-distribution

Typical approach: interpret magnitude of logits as “confidence”





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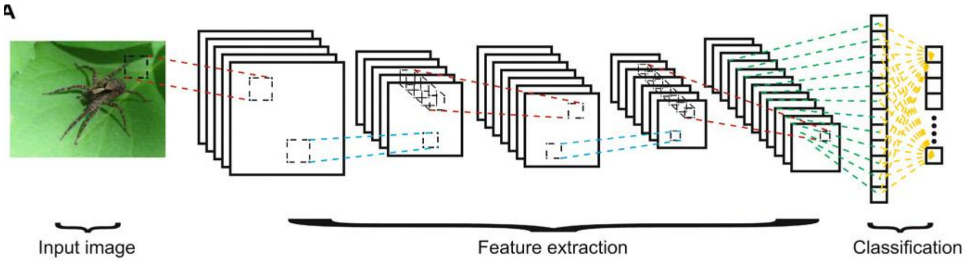
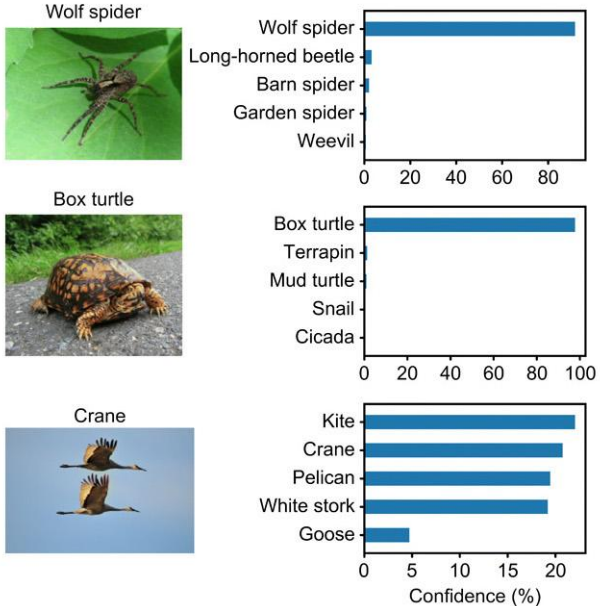


$$S_{\mathrm{MSP}}(\mathbf{x}; f) := \max_k \mathrm{Softmax}(Wh(\mathbf{x}) + \mathbf{b})_k$$

$$S_{\mathrm{Energy}}(\mathbf{x}; f) = -\log \sum_{k=1}^{K} \exp(\mathbf{w}_i^\top h(\mathbf{x}) + b_i)$$



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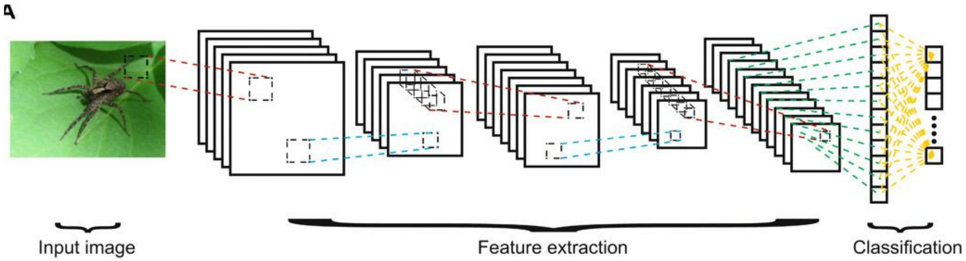

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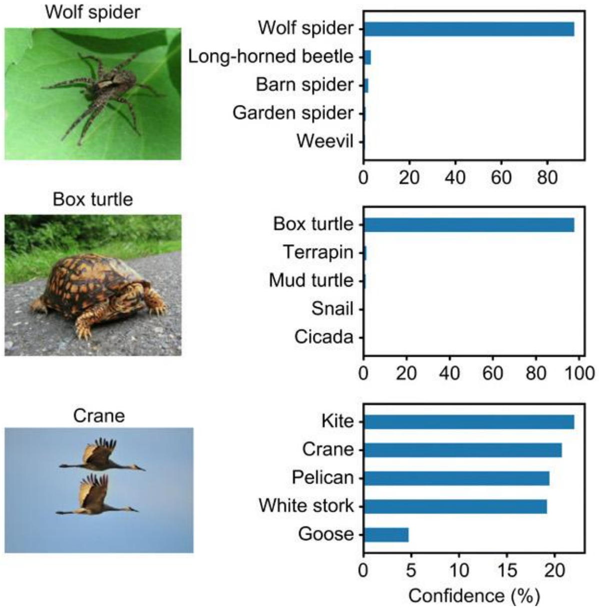
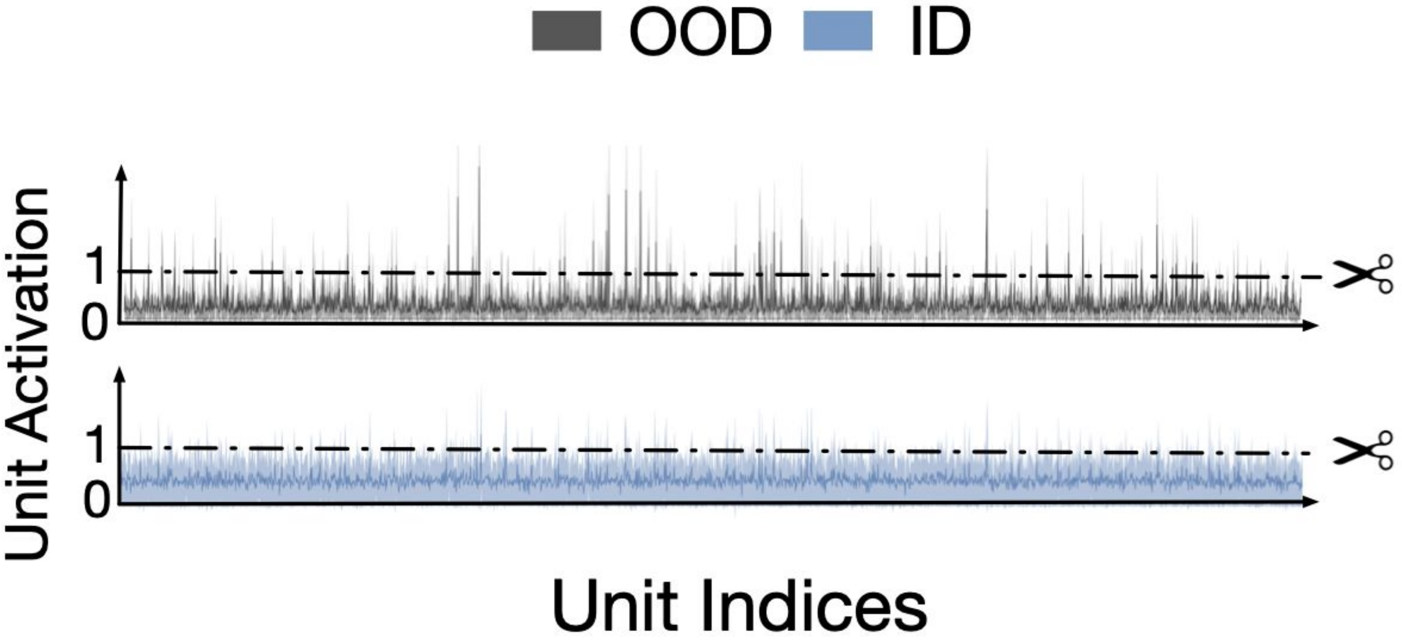
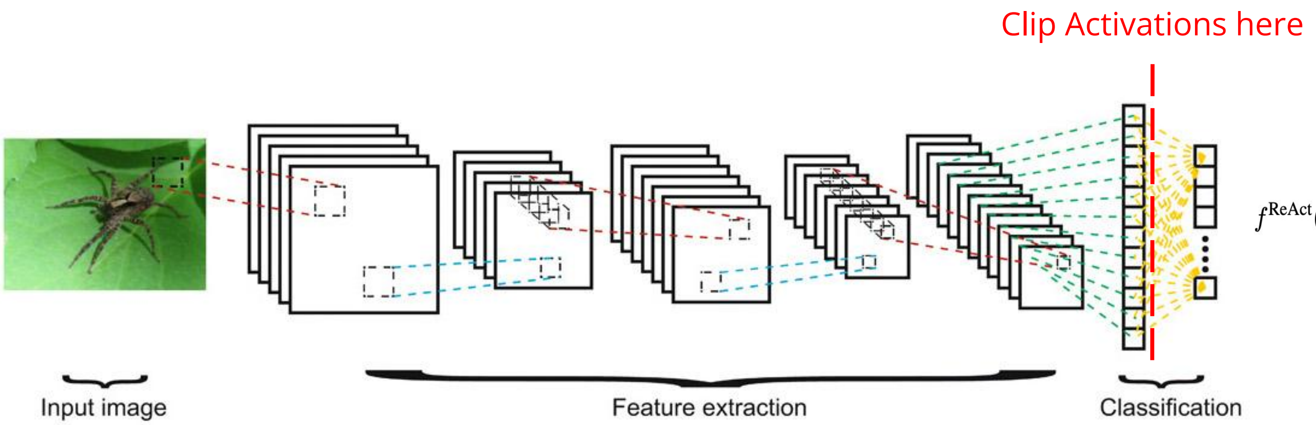


Problem: model is often too "confident" on OOD data (Nguyen et al.)

Key insight: OOD data have a distinctive activation pattern



Proposed solution: clip activations in the penultimate layer



$$f^{\text{ReAct}}(\mathbf{x};\theta) = \mathbf{W}^\top \bar{h}(\mathbf{x}) + \mathbf{b},$$

$$\texttt{ReAct}(x;c) = \min(x,c)$$

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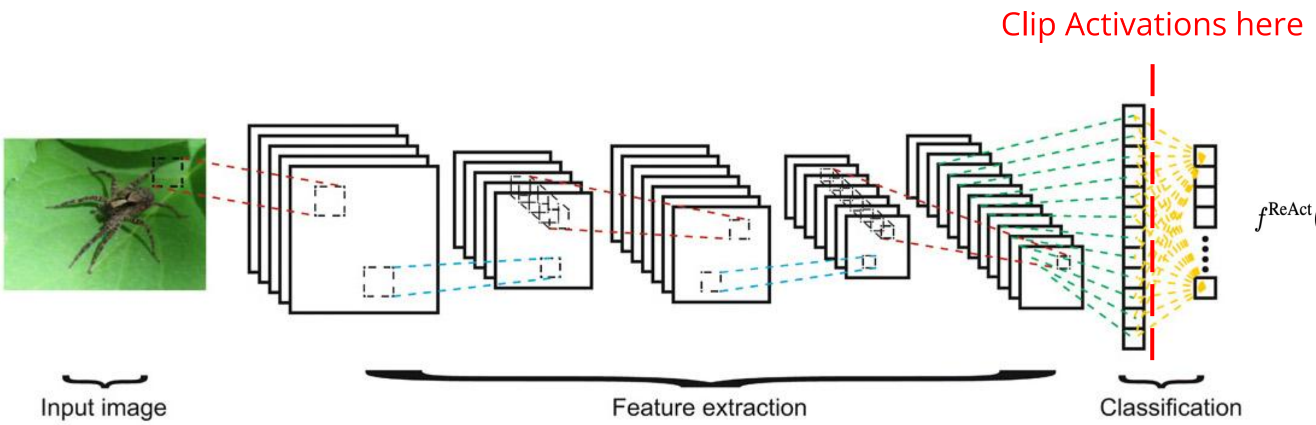

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$$G_\lambda(\mathbf{x}; f^{\text{ReAct}}) = \begin{cases} \text{in} & S(\mathbf{x}; f^{\text{ReAct}}) \geq \lambda \\ \text{out} & S(\mathbf{x}; f^{\text{ReAct}}) < \lambda \end{cases},$$

ReAct beats other post-hoc OOD detection methods

Model	Methods	OOD Datasets								Average	
		iNaturalist		SUN		Places		Textures			
		FPR95 ↓	AUROC ↑	FPR95 ↓	AUROC ↑	FPR95 ↓	AUROC ↑	FPR95 ↓	AUROC ↑	FPR95 ↓	AUROC ↑
ResNet	MSP [15]	54.99	87.74	70.83	80.86	73.99	79.76	68.00	79.61	66.95	81.99
	ODIN [31]	47.66	89.66	60.15	84.59	67.89	81.78	50.23	85.62	56.48	85.41
	Mahalanobis [29]	97.00	52.65	98.50	42.41	98.40	41.79	55.80	85.01	87.43	55.47
	Energy [33]	55.72	89.95	59.26	85.89	64.92	82.86	53.72	85.99	58.41	86.17
	ReAct (Ours)	**20.38**	**96.22**	**24.20**	**94.20**	**33.85**	**91.58**	**47.30**	**89.80**	**31.43**	**92.95**
MobileNet	MSP [15]	64.29	85.32	77.02	77.10	79.23	76.27	73.51	77.30	73.51	79.00
	ODIN [31]	55.39	87.62	54.07	85.88	57.36	84.71	49.96	85.03	54.20	85.81
	Mahalanobis [29]	62.11	81.00	47.82	86.33	52.09	83.63	92.38	33.06	63.60	71.01
	Energy [33]	59.50	88.91	62.65	84.50	69.37	81.19	58.05	85.03	62.39	84.91
	ReAct (Ours)	**42.40**	**91.53**	**47.69**	**88.16**	**51.56**	**86.64**	**38.42**	**91.53**	**45.02**	**89.47**

Table 1: **Main results.** Comparison with competitive *post hoc* out-of-distribution detection methods. All methods are based on a model trained on **ID data only** (ImageNet-1k), without using any auxiliary outlier data. ↑ indicates larger values are better and ↓ indicates smaller values are better. All values are percentages.

Our Dissection

Activation functions matter!

ReAct fails to improve metrics with tanh activation:

- Theoretical analysis and even the idea of upper clipping seem to rely on ReLU
- Effect of activation function not studied
- No comments about generalization to other activation functions and architectures

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With tanh activation

Without ReAct	FPR95	AUROC
	89.51	70.99

Became Worse!

With ReAct	FPR95	AUROC
	91.69	64.01

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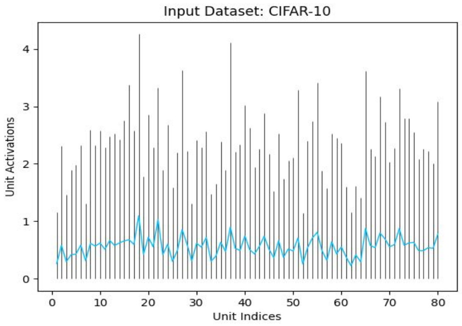
Going Ahead:

- Analyze ReAct for bounded activation functions
- Explore upper and lower clipping for symmetrical, zero-centered activations

Batchnorm isn't the only reason ReAct works; so what is?



Model With BatchNorm

AUROC 46.86 → 79.36

FPR95 95.34 → 78.10

ReAct improves metrics without BatchNorm for a smaller model:

- Unexplained by paper's BatchNorm reasoning

- The variation in ID activations' mean not constant without BatchNorm => Theoretical analysis breaks

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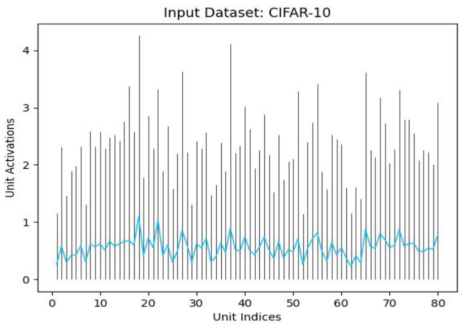

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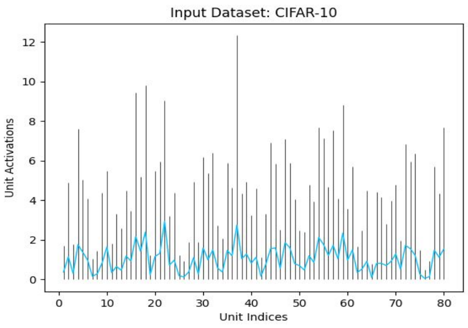

Model Without BatchNorm

AUROC	38.74	→	54.70
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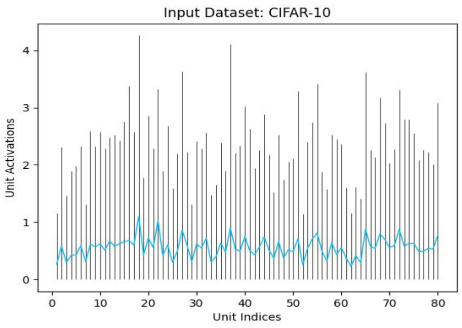

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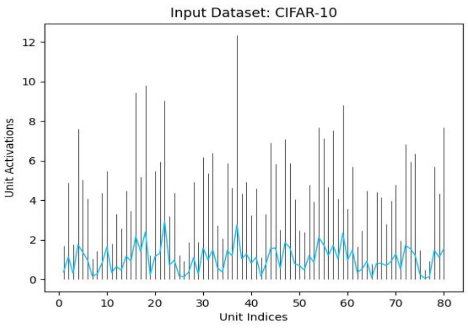

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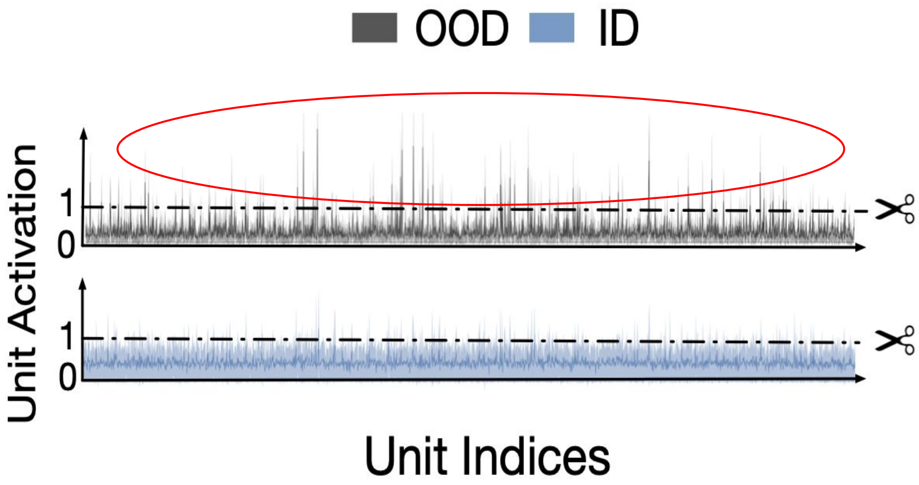
Going Ahead:

- Relax assumption about constant mean in theoretical analysis
- Run experiments on models without BatchNorm layers

If OOD activations look different, why not use that directly?

- ReAct relies on out-of-distribution activations being clipped more often



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- New proposed metric:
  Proportion of final layer activations below the clipping threshold

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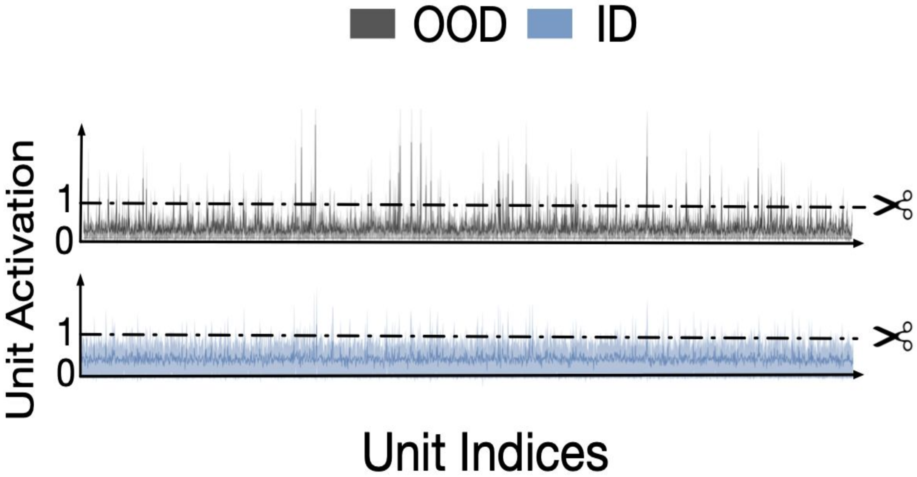

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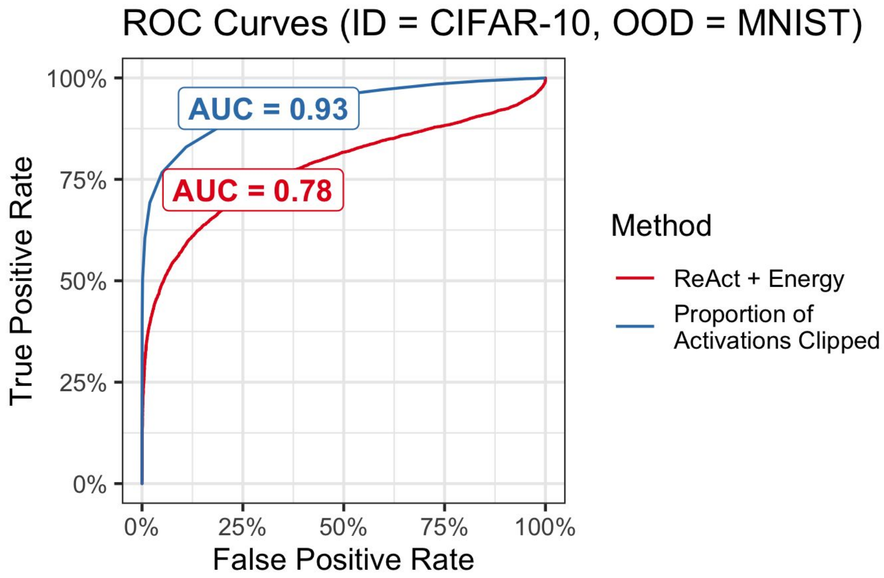
- Future research could use the activation patterns more thoughtfully



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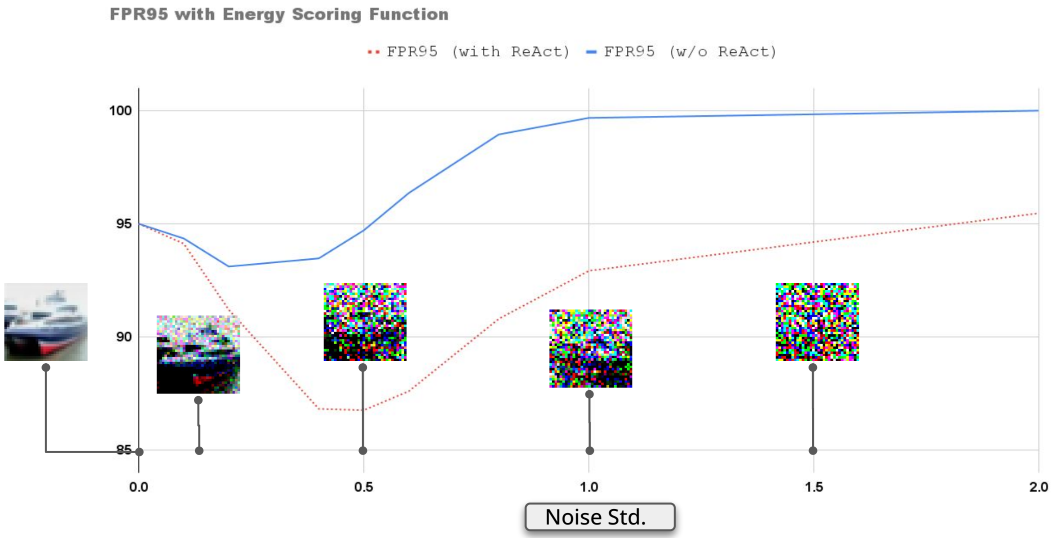

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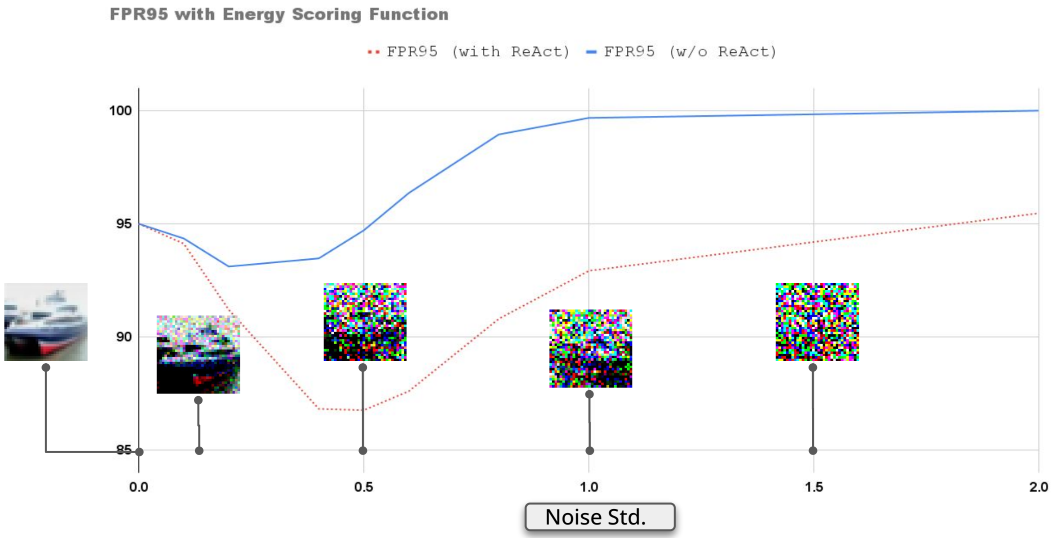

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Going Ahead:

- Verify and handle effect of OOD statistics on the metrics
- Prioritize scoring functions that don't scale with logit values - like softmax