Reverse Distillation

for Visual Anomaly Detection

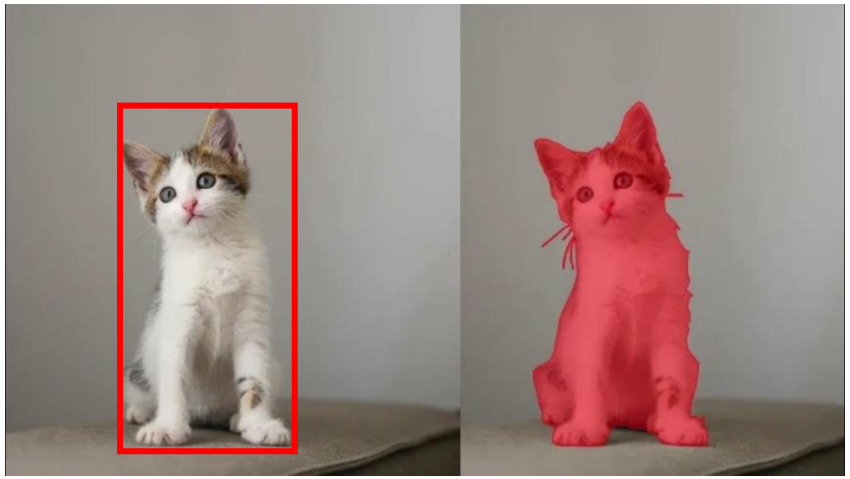
IT University Copenhagen

Spring Semester 2026

Visual Anomaly Detection

and why is it cool?

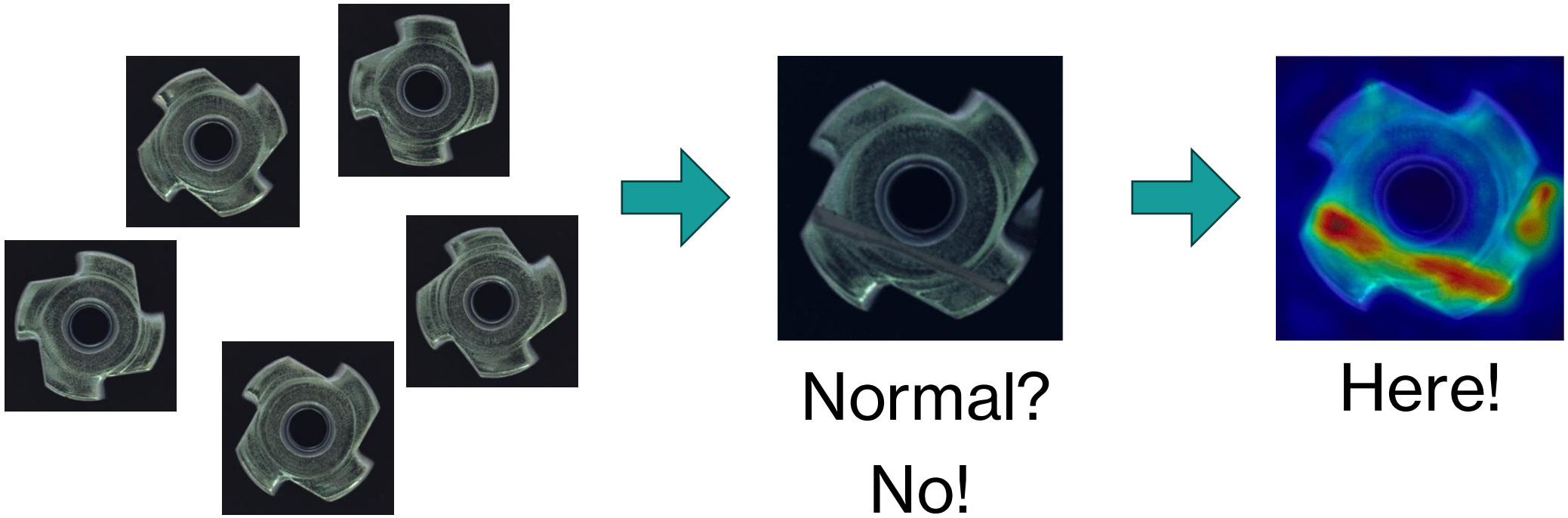
Detection / Segmentation
Where is the object?



Visual Anomaly Detection (VAD)
Where is the object **weird**?

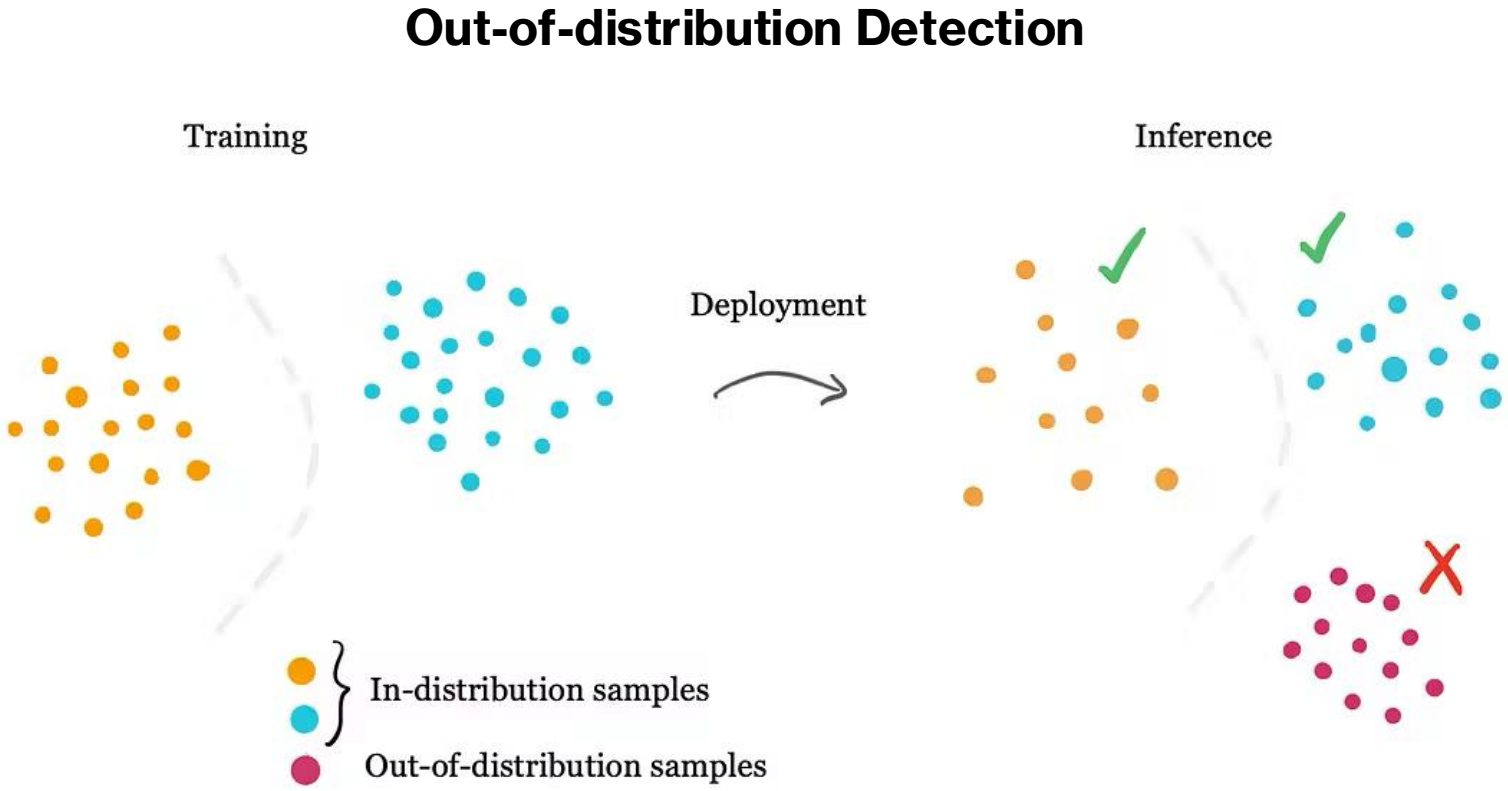
Visual Anomaly Detection

and why is it cool?



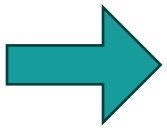
Visual Anomaly Detection

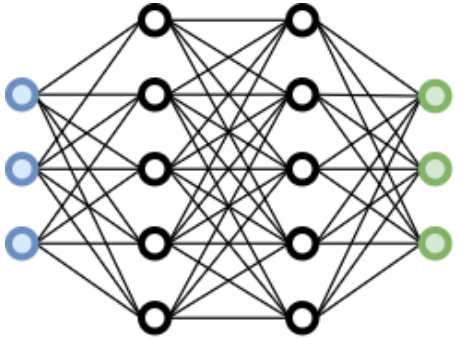
and why is it cool?

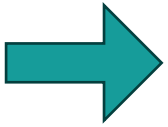


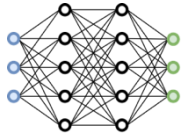
[https://encord.com/blog/what-is-out-of-distribution-ood-detection/]

Knowledge Distillation (2015)









Training

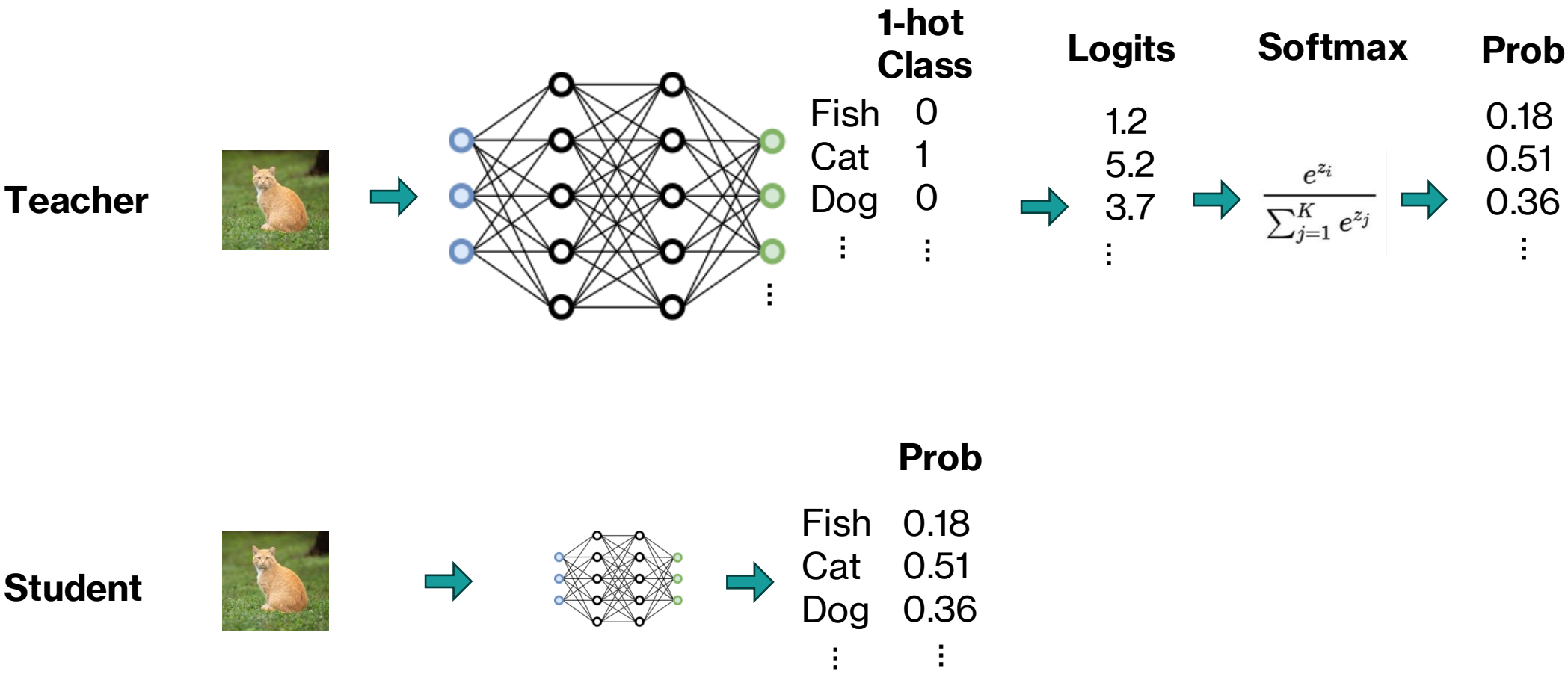
Teacher

Deployment

Student

[Hinton, Geoffrey, Oriol Vinyals, and Jeff Dean. 'Distilling the Knowledge in a Neural Network'. arXiv:1503.02531. Preprint, arXiv, 9 March 2015. https://doi.org/10.48550/arXiv.1503.02531]

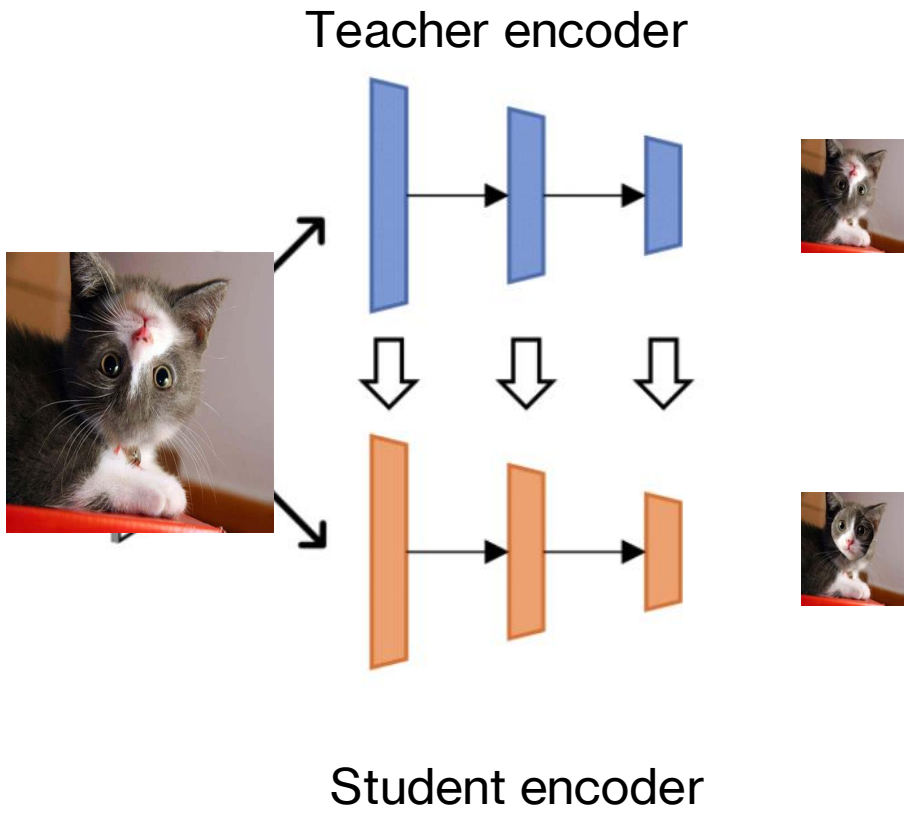
Knowledge Distillation



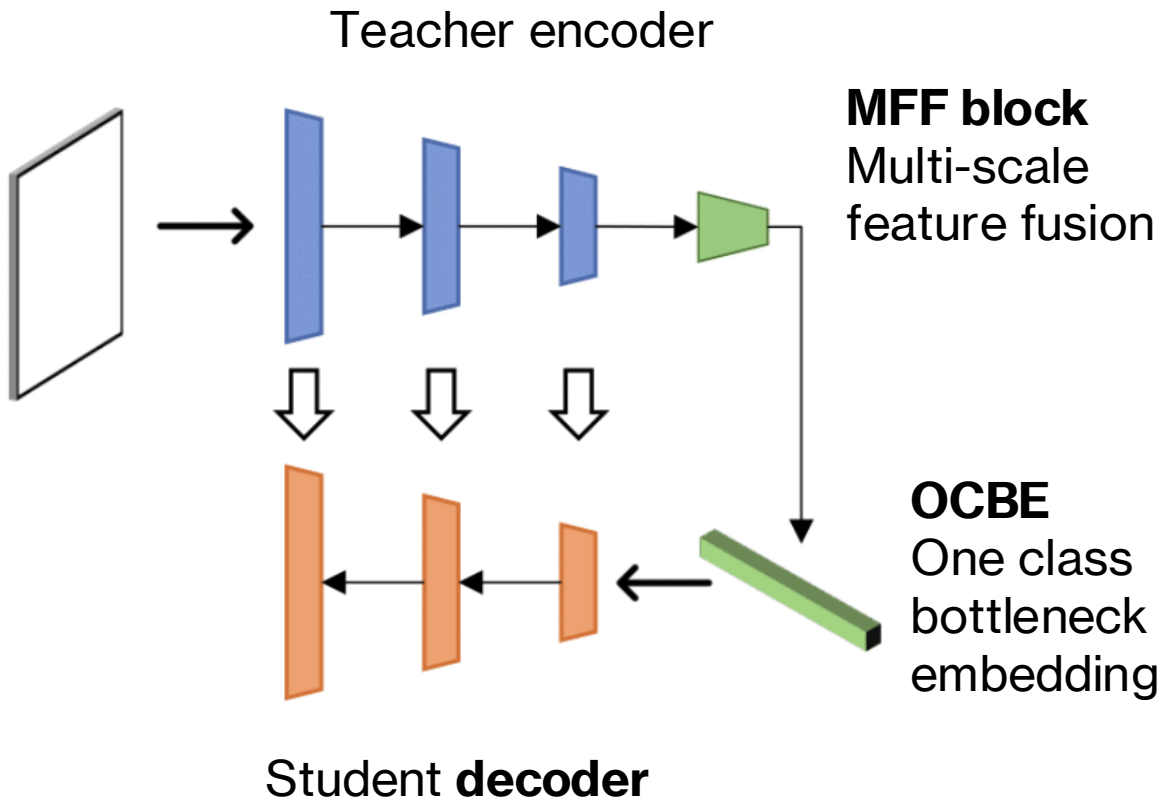
[Hinton, Geoffrey, Oriol Vinyals, and Jeff Dean. 'Distilling the Knowledge in a Neural Network'. arXiv:1503.02531. Preprint, arXiv, 9 March 2015. https://doi.org/10.48550/arXiv.1503.02531]

Distillation

in VAD

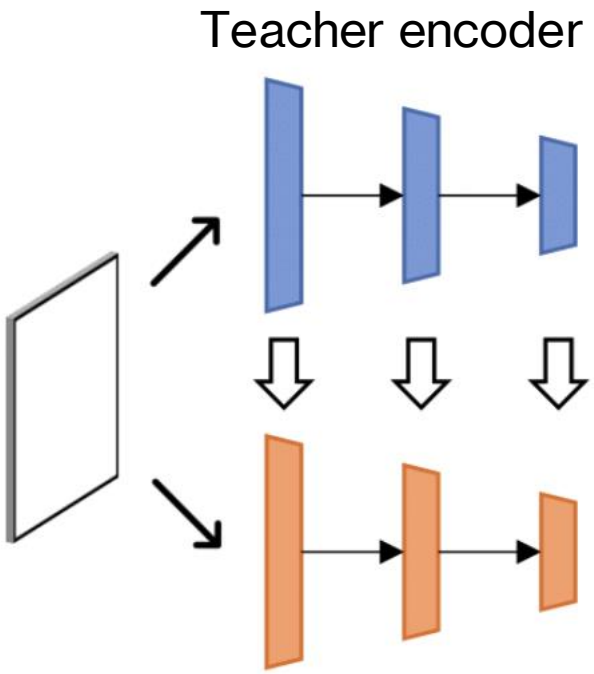


Reverse Distillation

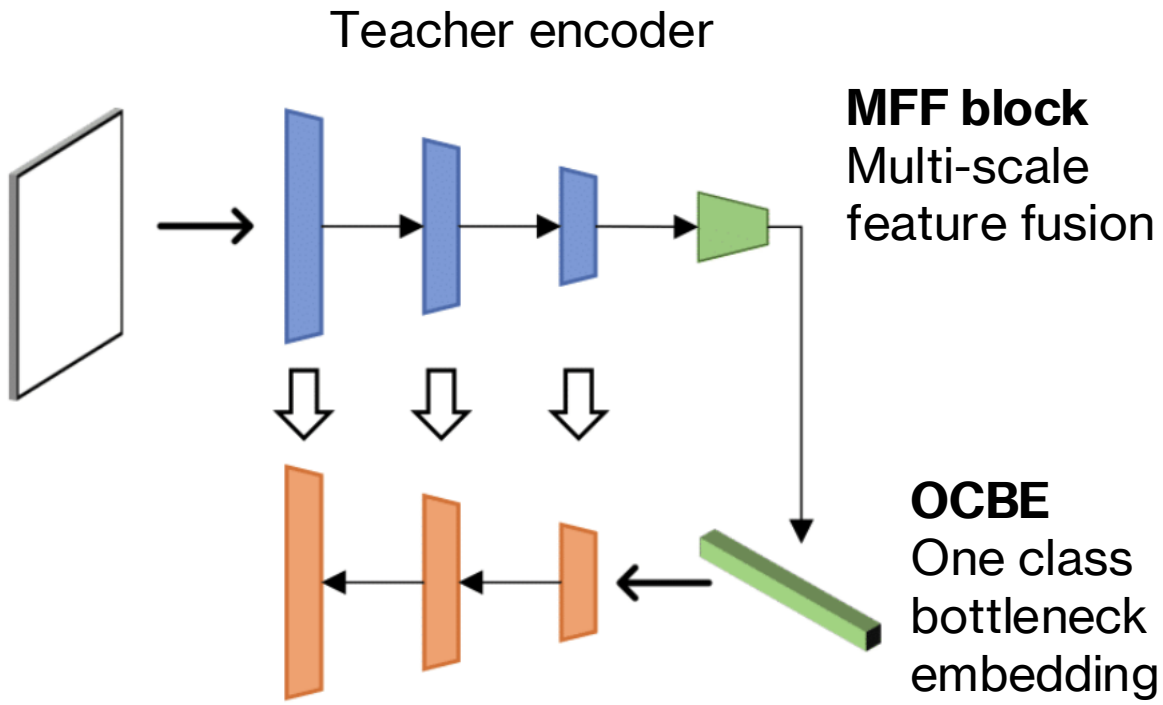


Assumption: Student generalizes differently in feature maps when shown anomalous images

Distillation

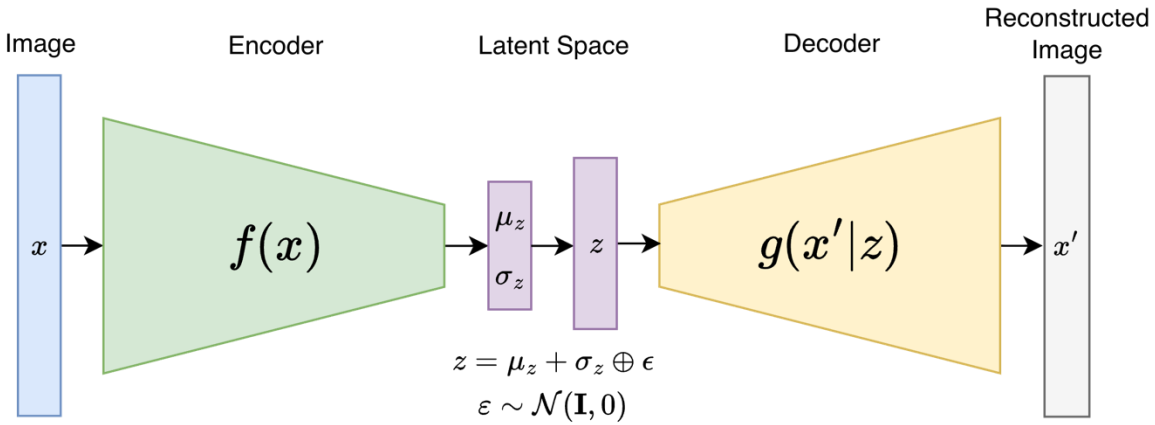


Reverse Distillation

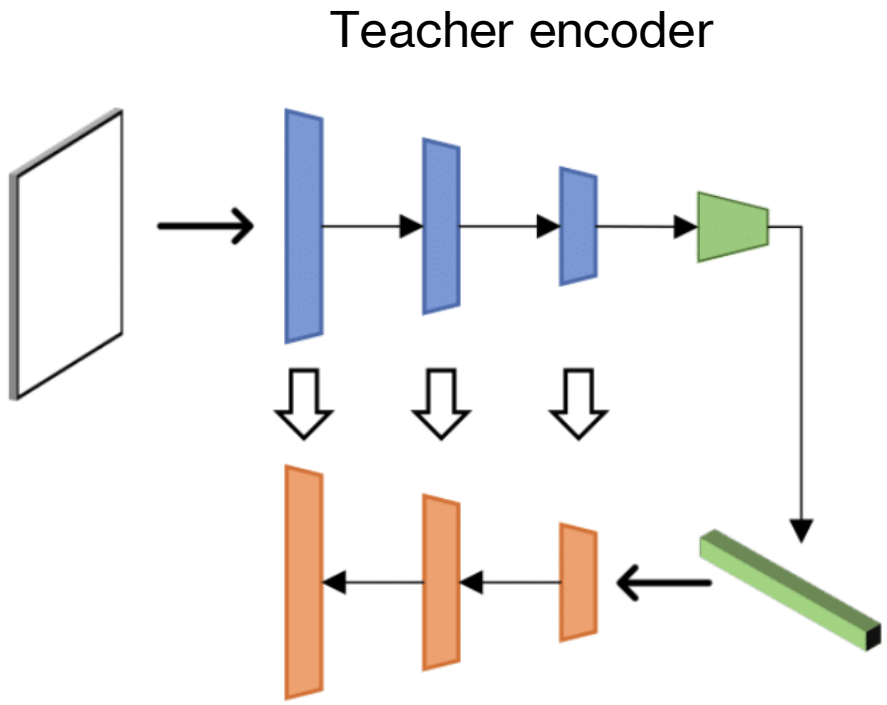


BUT HANG ON!
Isn’t this just an encoder-decoder VAE type thing?

Variational Autoencoder

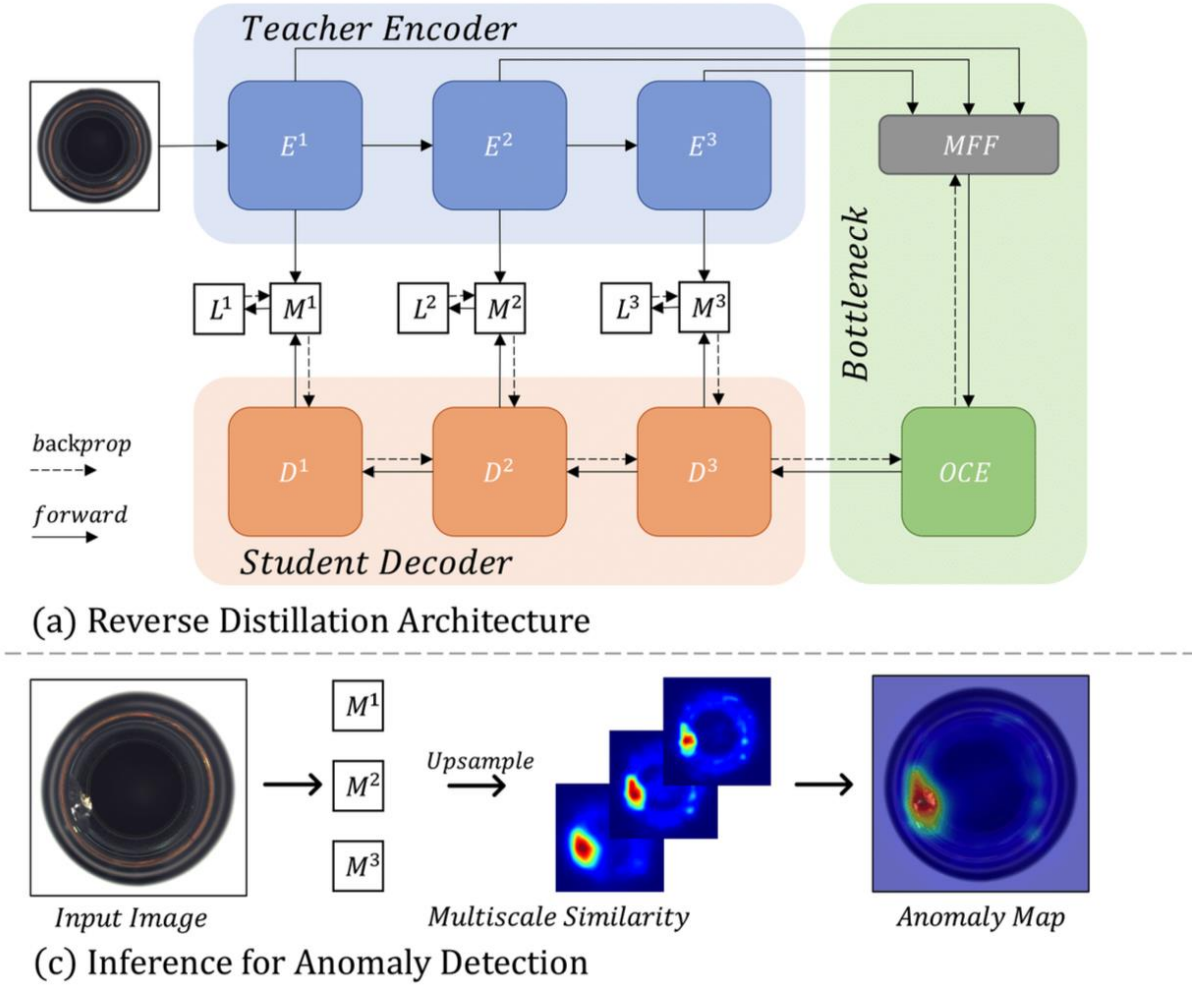


Reverse Distillation



No ☺

Reverse Distillation



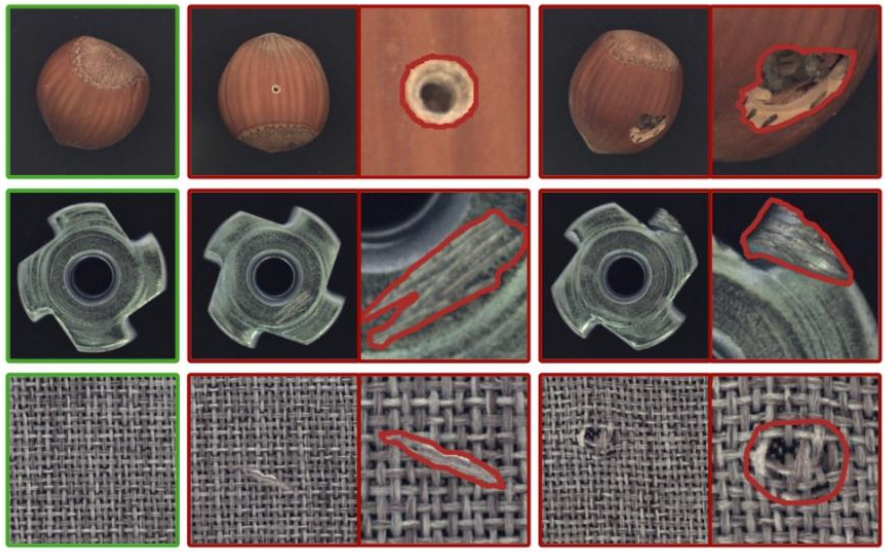
Anomaly score

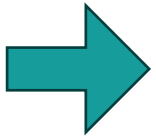
=

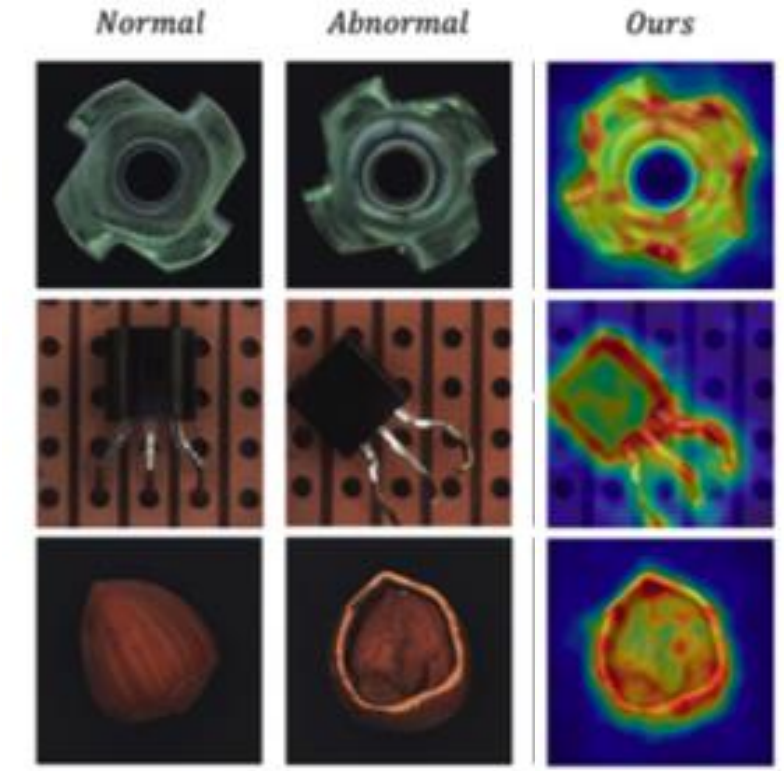
MaxVal(Anomaly Map)

Results

MVTec







Results

Image Size		128		256								
Category/Method		MKD [33]	Ours	GT [10]	GN [2]	US [4]	PSVDD [43]	DAAD [16]	MF [40]	PaDiM [8]	CutPaste [23]	Ours
Textures	Carpet	79.3	99.2	43.7	69.9	91.6	92.9	86.6	94.0	**99.8**	93.9	**98.9**
	Grid	78.0	95.7	61.9	70.8	81.0	94.6	95.7	85.9	96.7	**100**	**100**
	Leather	95.1	100	84.1	84.2	88.2	90.9	86.2	**99.2**	**100**	**100**	**100**
	Tile	91.6	99.4	41.7	79.4	**99.1**	97.8	88.2	99.0	98.1	94.6	**99.3**
	Wood	94.3	98.8	61.1	83.4	97.7	96.5	98.2	**99.2**	**99.2**	**99.1**	**99.2**
	Average	*87.7*	*98.6*	*58.5*	*77.5*	*91.5*	*94.5*	*91.0*	*95.5*	*98.8*	*97.5*	***99.5***
Objects	Bottle	99.4	100	74.4	89.2	99.0	98.6	97.6	99.1	**99.9**	98.2	**100**
	Cable	89.2	97.1	78.3	75.7	86.2	90.3	84.4	**97.1**	92.7	81.2	**95.0**
	Capsule	80.5	89.5	67.0	73.2	86.1	76.7	76.7	87.5	91.3	**98.2**	**96.3**
	Hazelnut	98.4	99.8	35.9	78.5	93.1	92.0	92.1	**99.4**	92.0	98.3	**99.9**
	Metal Nut	73.6	99.2	81.3	70.0	82.0	94.0	75.8	96.2	98.7	**99.9**	**100**
	Pill	82.7	93.3	63.0	74.3	87.9	86.1	90.0	90.1	93.3	**94.9**	**96.6**
	Screw	83.3	91.1	50.0	74.6	54.9	81.3	**98.7**	**97.5**	85.8	88.7	97.0
	Toothbrush	92.2	90.3	97.2	65.3	95.3	**100**	99.2	**100**	96.1	99.4	**99.5**
	Transistor	85.6	99.5	86.9	79.2	81.8	91.5	87.6	94.4	**97.4**	96.1	**96.7**
	Zipper	93.2	94.3	82.0	74.5	91.9	97.9	85.9	**98.6**	90.3	**99.9**	98.5
	Average	*87.8*	*95.4*	*71.6*	*75.5*	*85.8*	*90.8*	*88.8*	*96.0*	*93.8*	*95.5*	***98.0***
Total Average		*87.8*	*96.5*	*67.2*	*76.2*	*87.7*	*92.1*	*89.5*	*95.8*	*95.5*	*96.1*	***98.5***

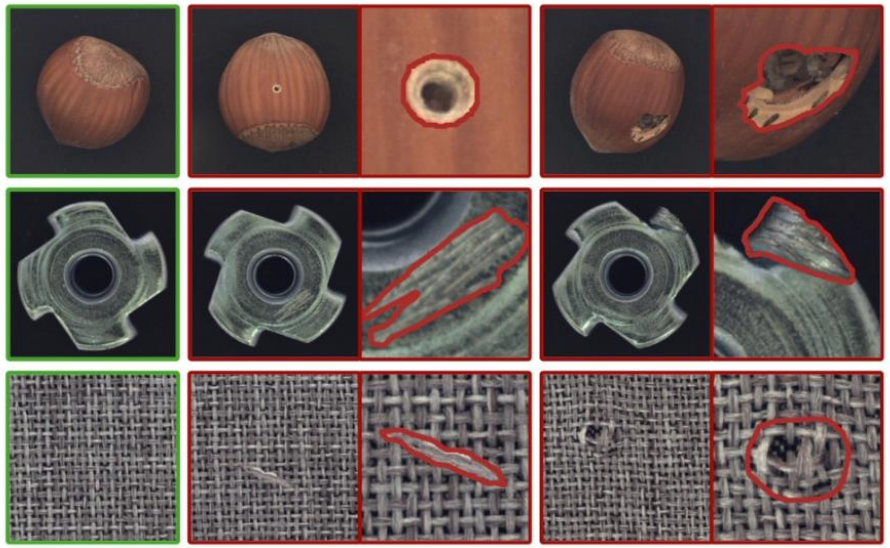
Table 1. *Anomaly Detection* results on MVTec [3]. For each category with images of 256 × 256 resolution, methods achieved for the top two AUROC (%) are highlighted in bold. Our method ranks first according to the average scores of **textures**, **objects** and overall.

What about underwater!?

Underwater Scenes

are extremely weird

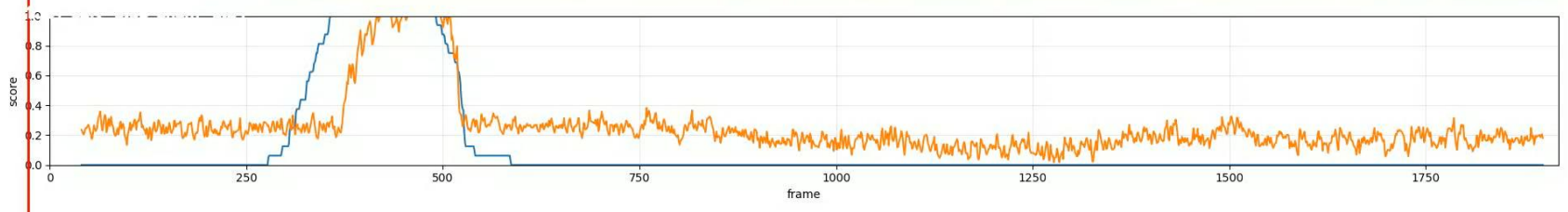
MVTec



Perfect conditions

Difficult conditions

Underwater Example



Underwater Example

Split	Model	**Scene A** (v00- MAE (Mean ± Std)
Split 1	EfficientAD	0.420 ± 0.071
Split 1	GANomaly	0.526 ± 0.139
Split 1	Stfpm	0.432 ± 0.078
Split 1	Reverse Distillation	**0.354** ± 0.153
Split 2	EfficientAD	0.393 ± 0.101
Split 2	GANomaly	0.425 ± 0.127
Split 2	Stfpm	0.465 ± 0.107
Split 2	Reverse Distillation	**0.271** ± 0.151

Thanks!

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