Set Features for Fine-grained Anomaly Detection

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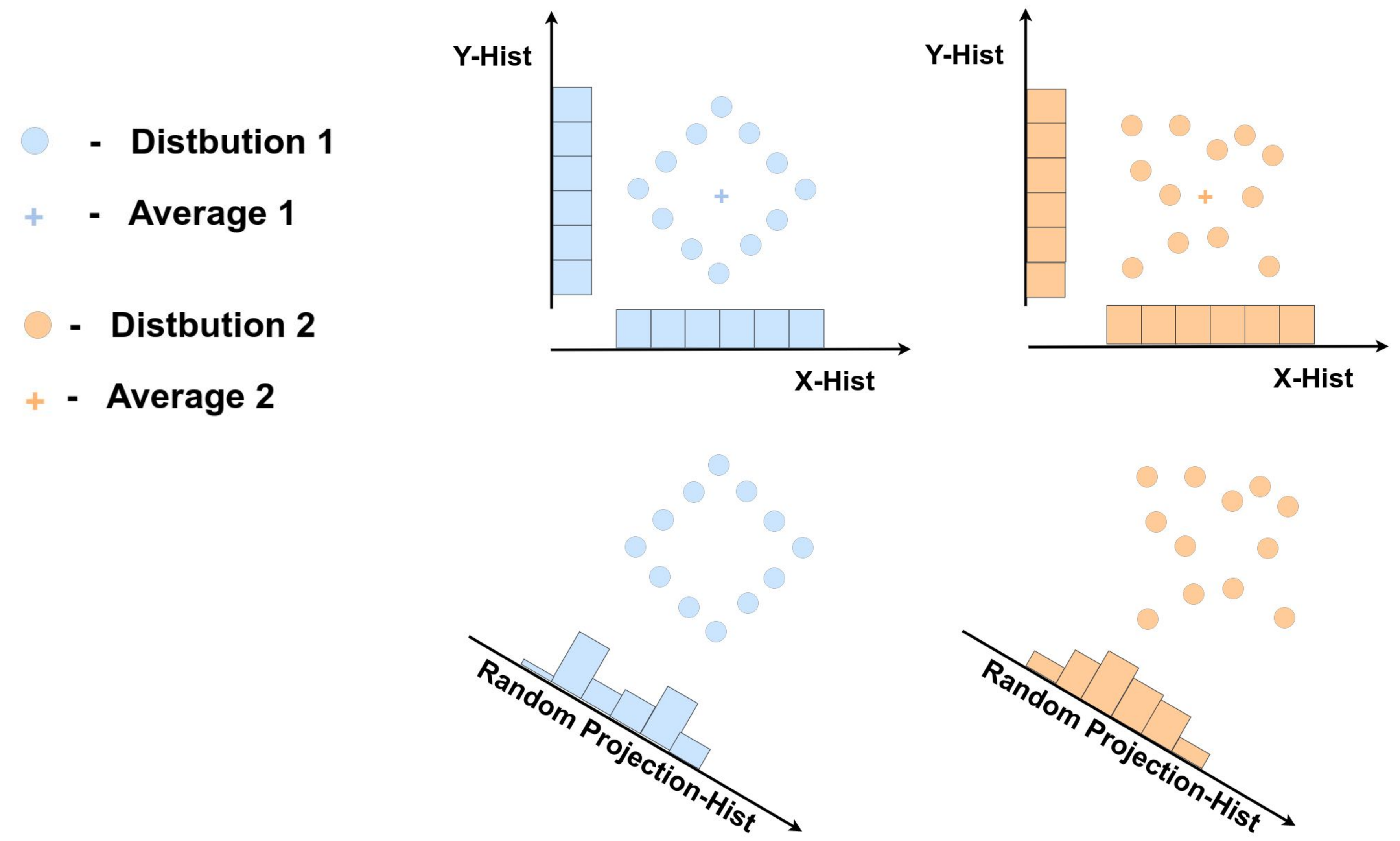
Introduction

- In logical anomalies, each image element (e.g., patch) may be normal even when their combination is anomalous.
- Similarly, time-series anomalies may results from an unseen combination of normal local elements
- We detect such anomalies, representing each sample as a *set* of its local elemets

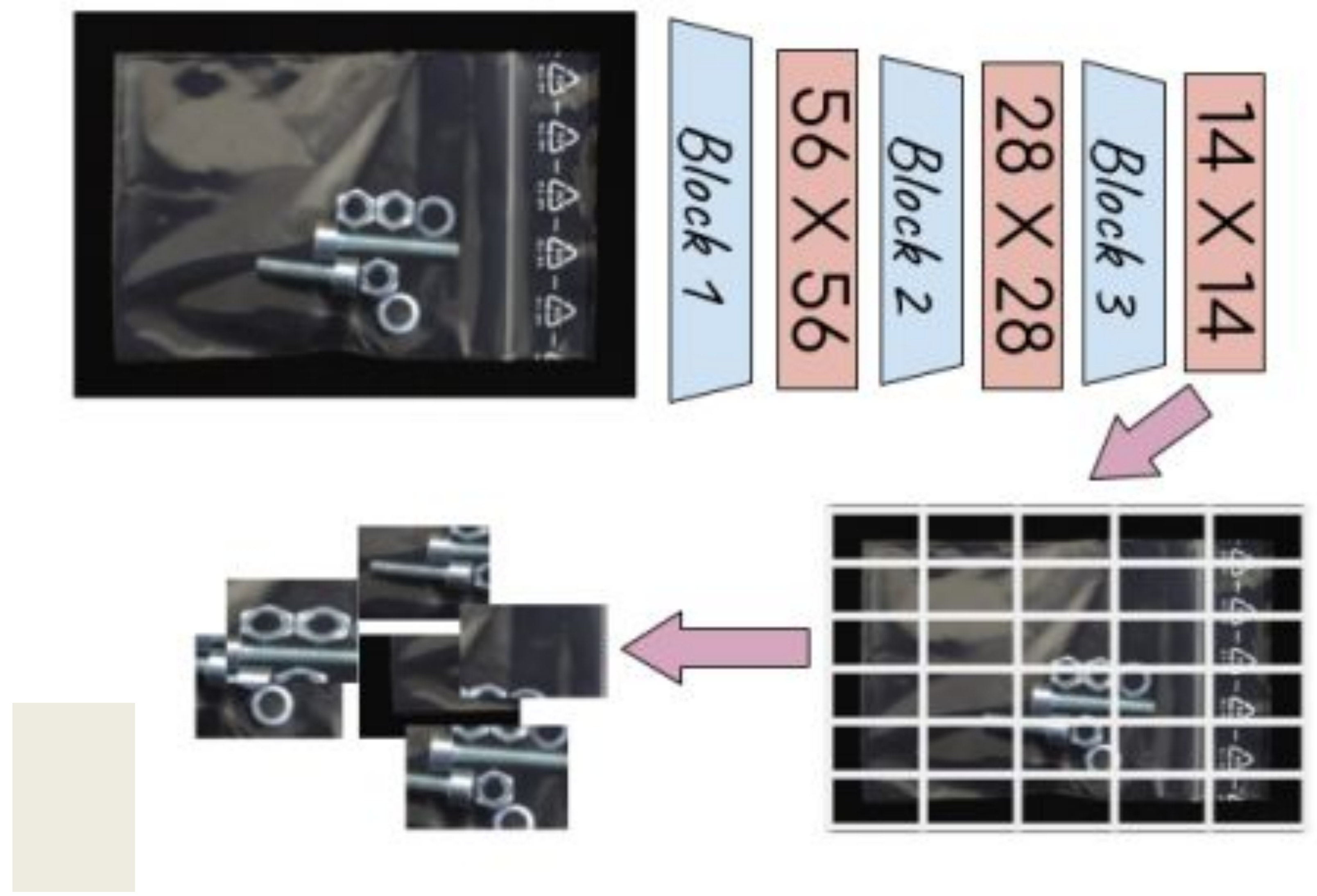
Using Sets: Beyond Average-Pooling



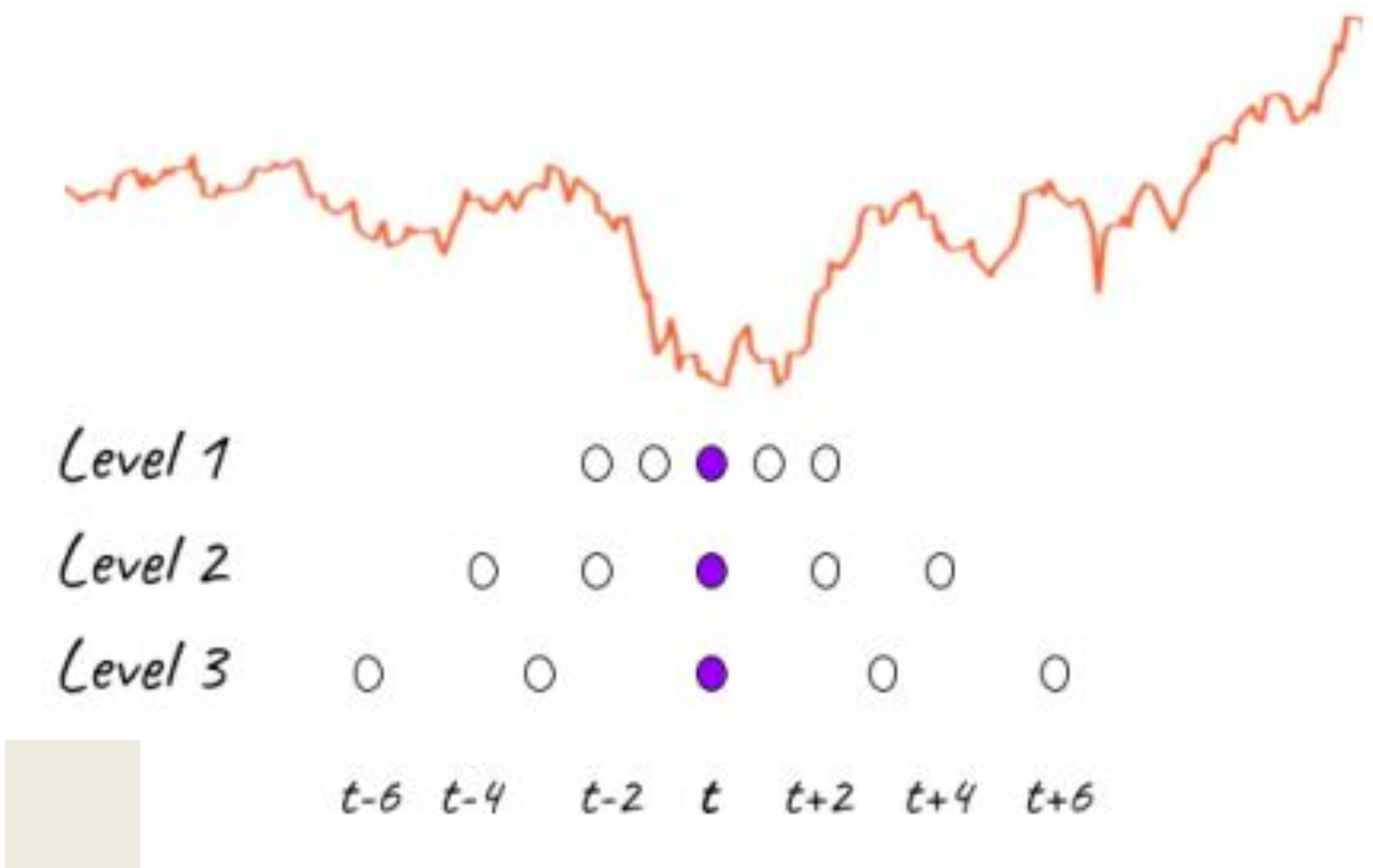
- **Histogram features:** We project the data to random axes, $f' = Pf$ and use histogram occupancy along these axes as our features
- **Anomaly scoring:** For each test image we use the mahalanobis distance from the test set of the kNN normal sets.

Describing Samples as Sets

- **Image Element Feature extractor:** A large ResNet pretrained on ImageNet for image patches

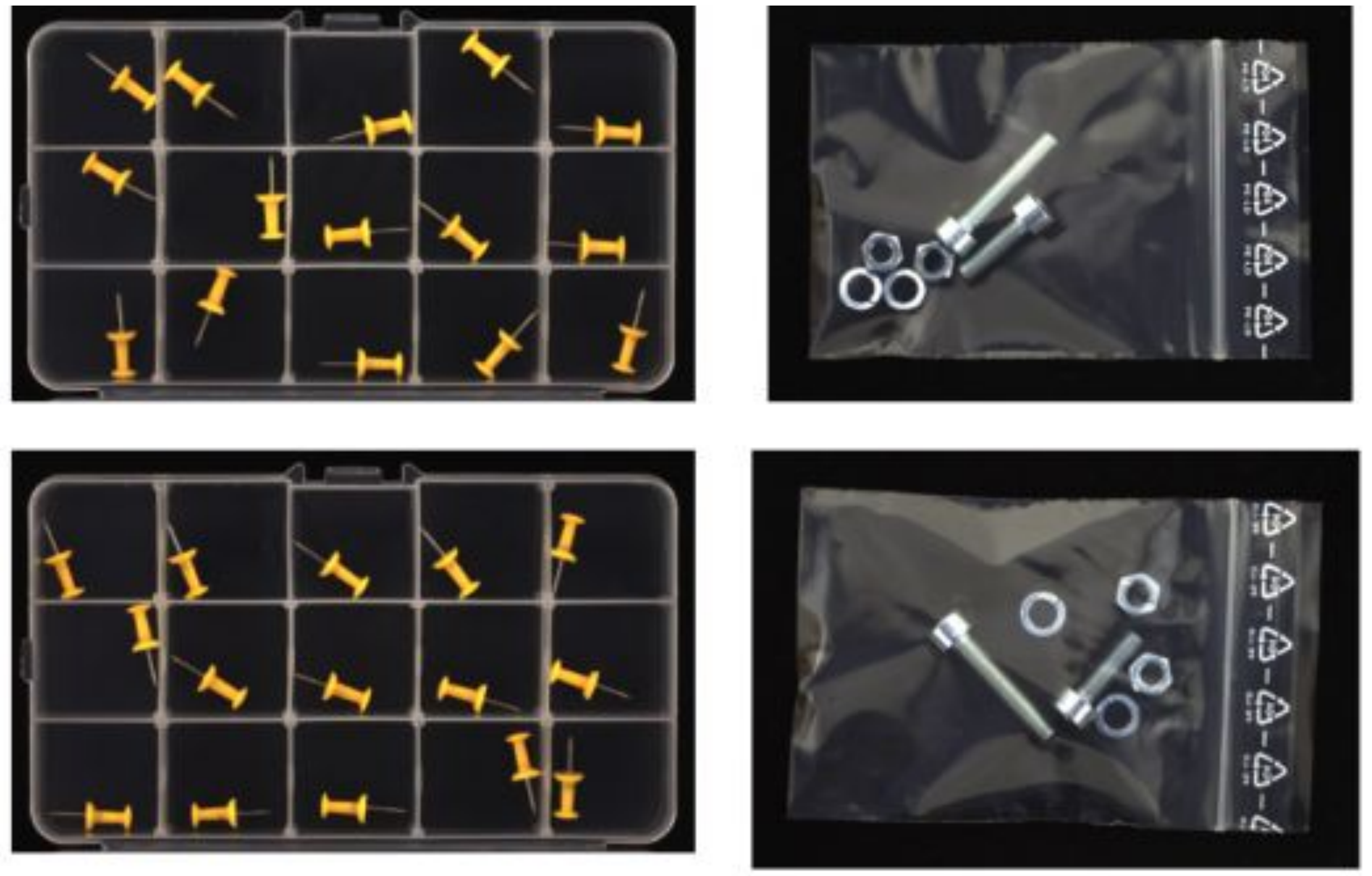


- **Time-Series Element Feature extractor:** we take pyramids of windows at different strides around each time ste



MVTec LOCO Results

		ST	SPADE	PCore	GCAD	SINBAD
Logical Anomalies	Breakfast box	68.9	81.8	77.7	87.0	**96.5** ± **0.1**
	Juice bottle	82.9	91.9	83.7	**100.0**	96.6 ± 0.1
	Pushpins	59.5	60.5	62.2	**97.5**	83.4 ± 3.0
	Screw bag	55.5	46.8	55.3	56.0	**78.6** ± **0.1**
	Splicing connectors	65.4	73.8	63.3	**89.7**	89.3 ± 0.2
	Avg. Logical	66.4	71.0	69.0	86.0	**88.9** ± **0.6**



Time-Series Results

	DAG	GOAD	DROCC	NeuTraL	Ours
EPSY	72.2	76.7	85.8	92.6	**98.1**
NAT	78.9	87.1	87.2	94.5	**96.1**
SAD	80.9	94.7	85.8	**98.9**	97.8
CT	89.8	97.7	95.3	99.3	**99.7**
RS	51.0	79.9	80.0	86.5	**92.3**
Avg.	74.6	87.2	86.8	94.4	**96.8**