DCdetector: Dual Attention Contrastive Representation Learning for Time Series Anomaly Detection

(KDD 2023 research track)

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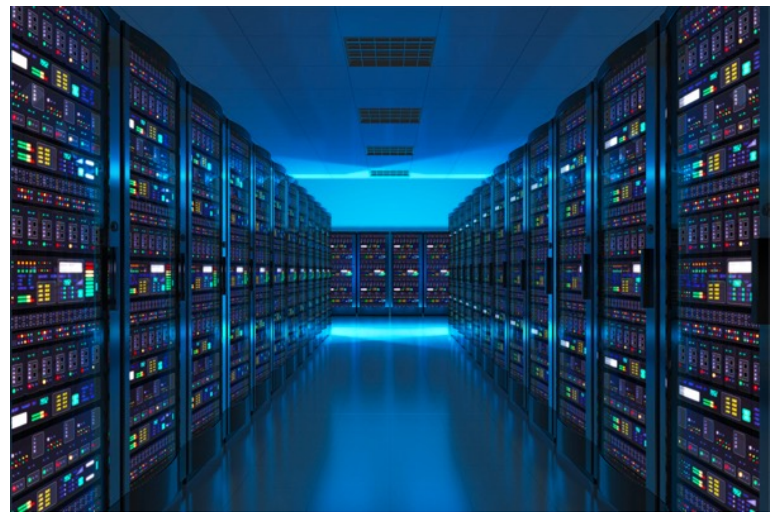
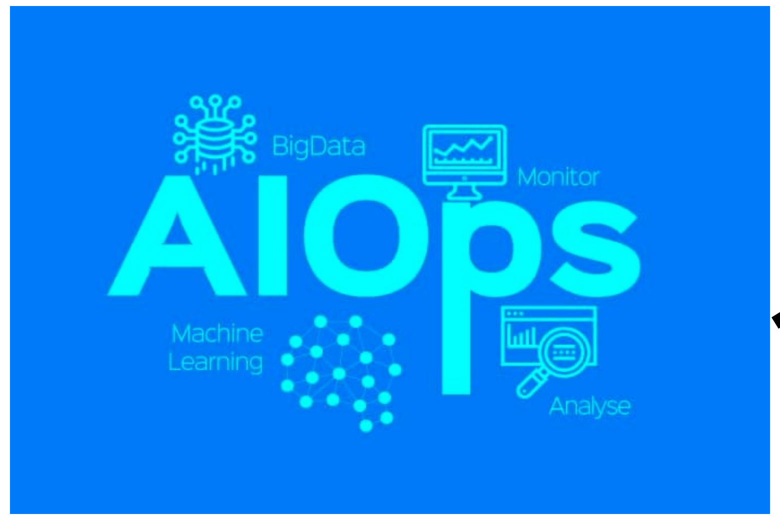
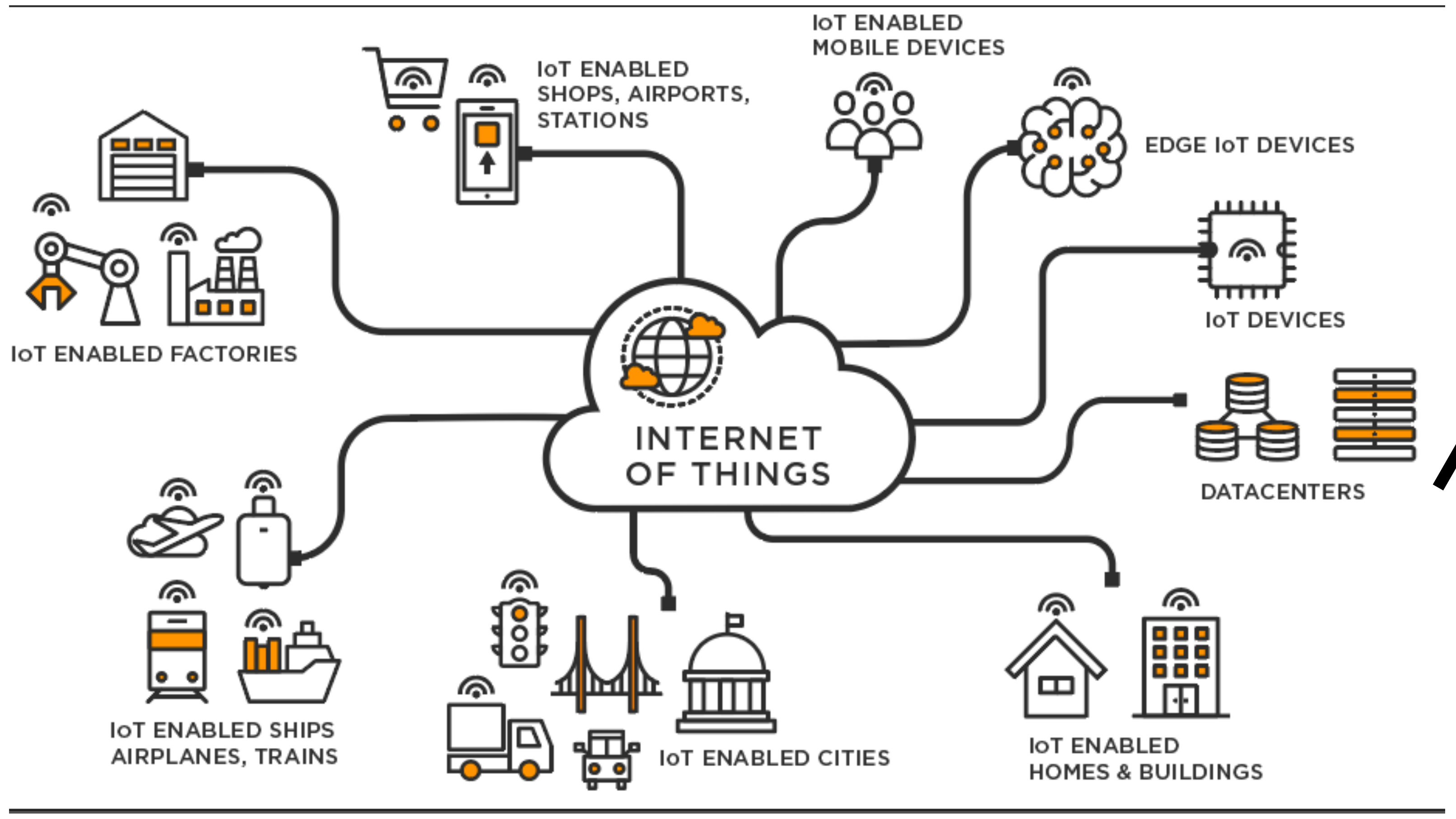
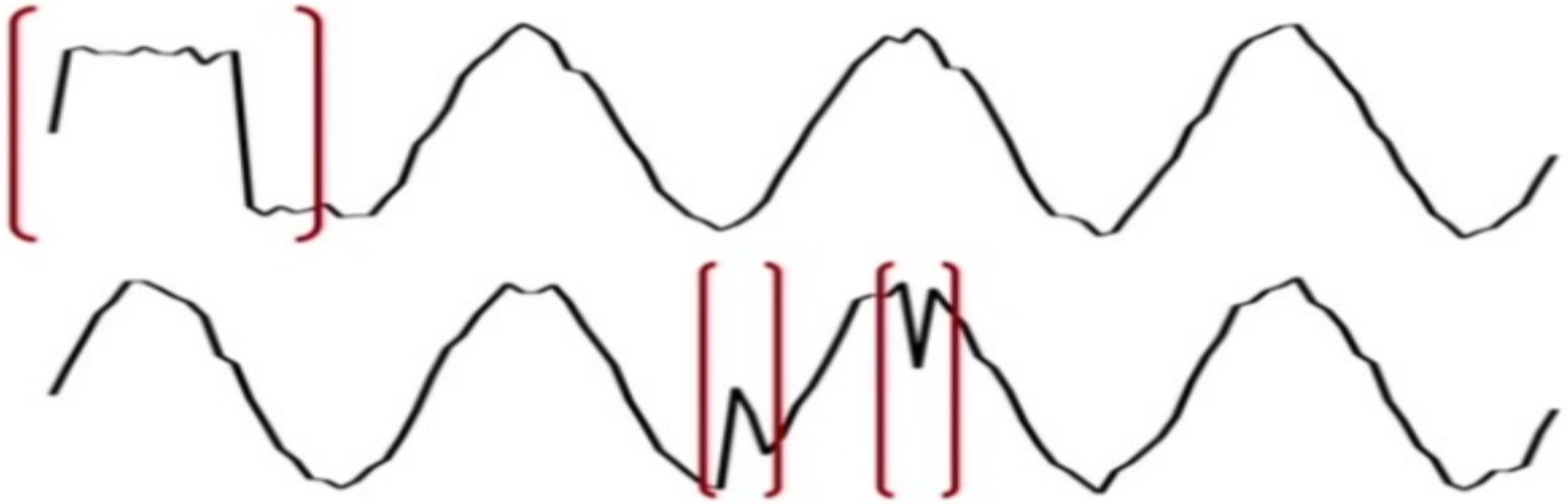
✓ Background: Time Series Anomaly Detection









Detecting the abnormal time-step from the original time-series.

Extracting useful information from the time-series to ensure security, avoid financial loss and so on.

✓ Challenges: Time Series Anomaly Detection

- **Lack of Labeled Data**: Anomalies are usually rare without many labels. Systems are in steady state in majority of cases.
- **Imbalance**: The number of anomalies is much smaller than the normal one. For example, in the financial system.
- **Noise Interference**: Time-series data may be affected by noise that may mask the true anomaly signal.
- **Complex Patterns**: Typical anomalies are often complex (e.g., wind turbines operate in different modes and conditions).
- **Multi-dimensional Features**: Models should consider temporal, multidimensional and non-stationary characteristics.
- **Explanatory and Interpretable**: In some application scenarios, explanatory and interpretable results for anomaly detection are needed to better understand why an anomaly was flagged and to be able to take action accordingly.

Anomaly detection based on unsupervised learning (learning without labeled data)

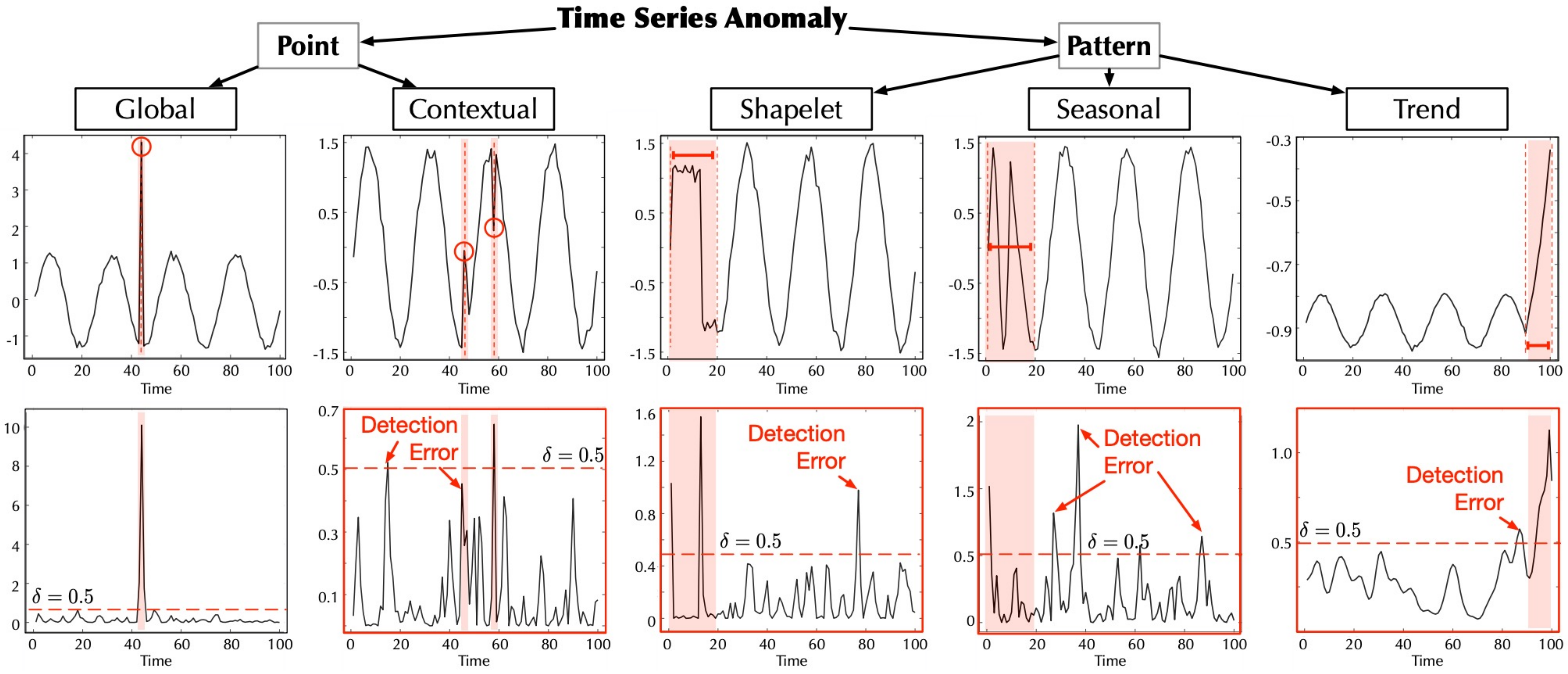
time series data → Per timestamp feature mining → Anomaly detection, evaluation at each timestamp

✓ Challenges of time series anomaly detection

Illustration of the challenges: 1, Numerous complex patterns in time series; 2 Different types of anomalies

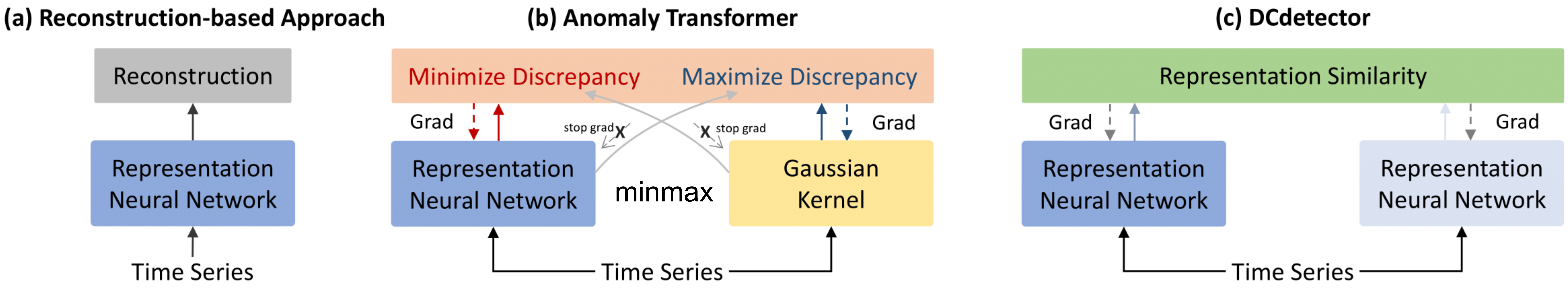
Input time series

Anomaly score



Xu J, Wu H, Wang J, Long M. Anomaly transformer: Time series anomaly detection with association discrepancy. ICLR'22

✓ Related work: previous SOTA methods vs. DCdetector



$$L_{rec} = \left\| x - \hat{x} \right\|_2^2$$

$$L_{AT} = \left\| x - \hat{x} \right\|_2^2 - \lambda \times \| AssDis(P, S; x) \|_1$$

$$\boldsymbol{L_{DCdetector} = Distance(R_1(x), R_2(x))}$$

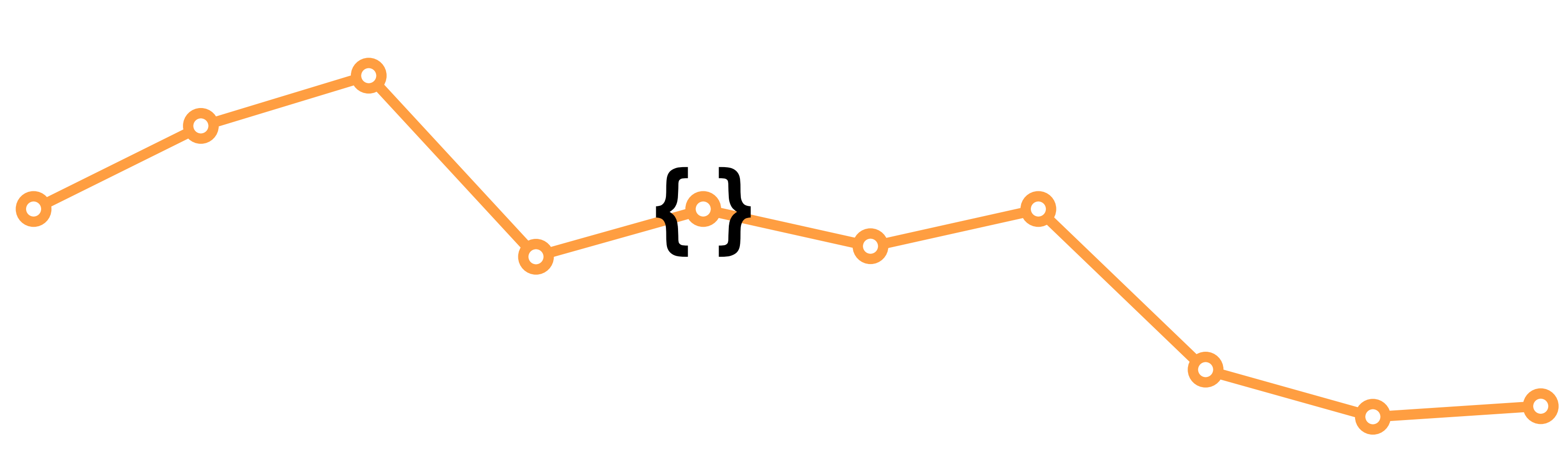
Reconstructed-based problem: The raw time series has a mixture of normalities and anomalies with noise. So it is difficult to train a high quality encoder for reconstruction based models.

Highlight: DCdetector is concise with pure contrastive structure without reconstruction and minmax learning

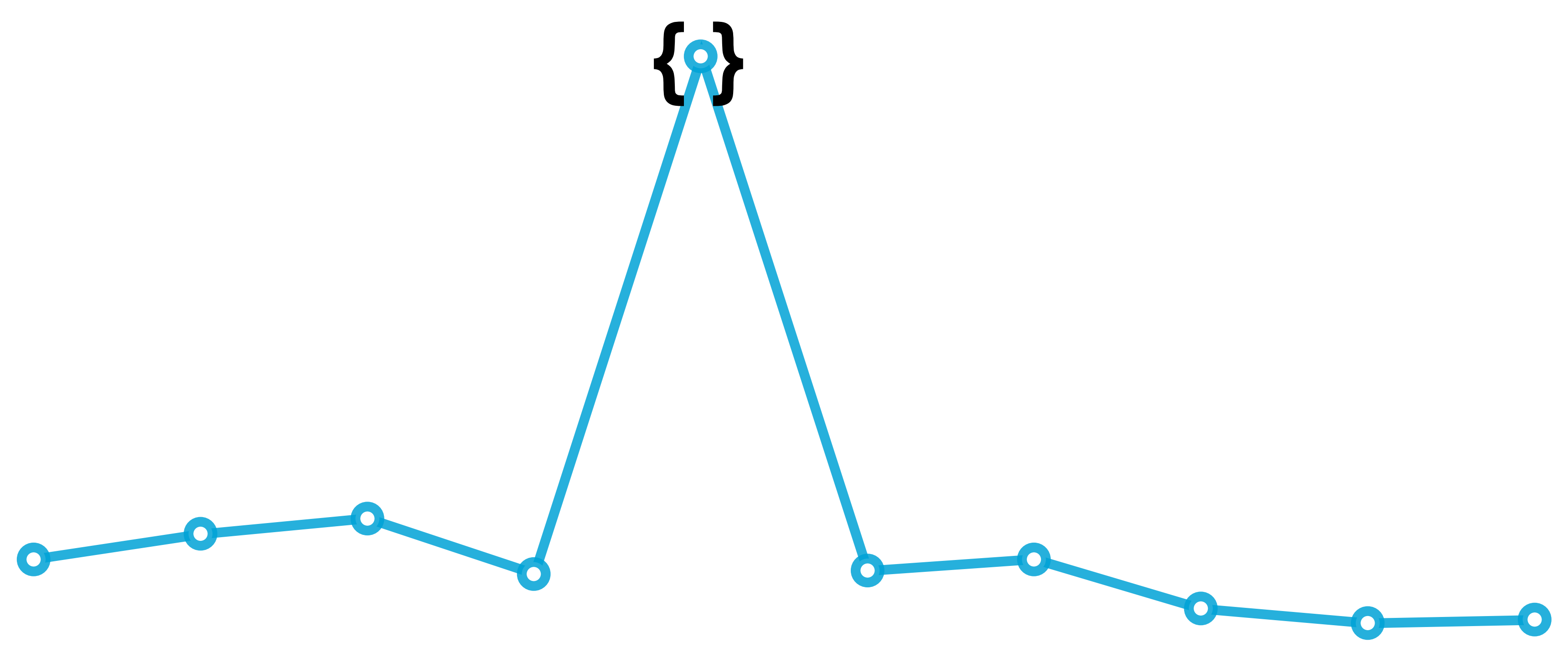
✓ Method: DCdetector’s Intuition

An intuition:

- Observation: normal points are closely related to other adjacent sample points, while abnormal points are discrete from others.
- Design Principle: by constructing different representations (patch-wise and in-patch) between the sample points, if the similarity of the different representations is high, it means that they are normal points.



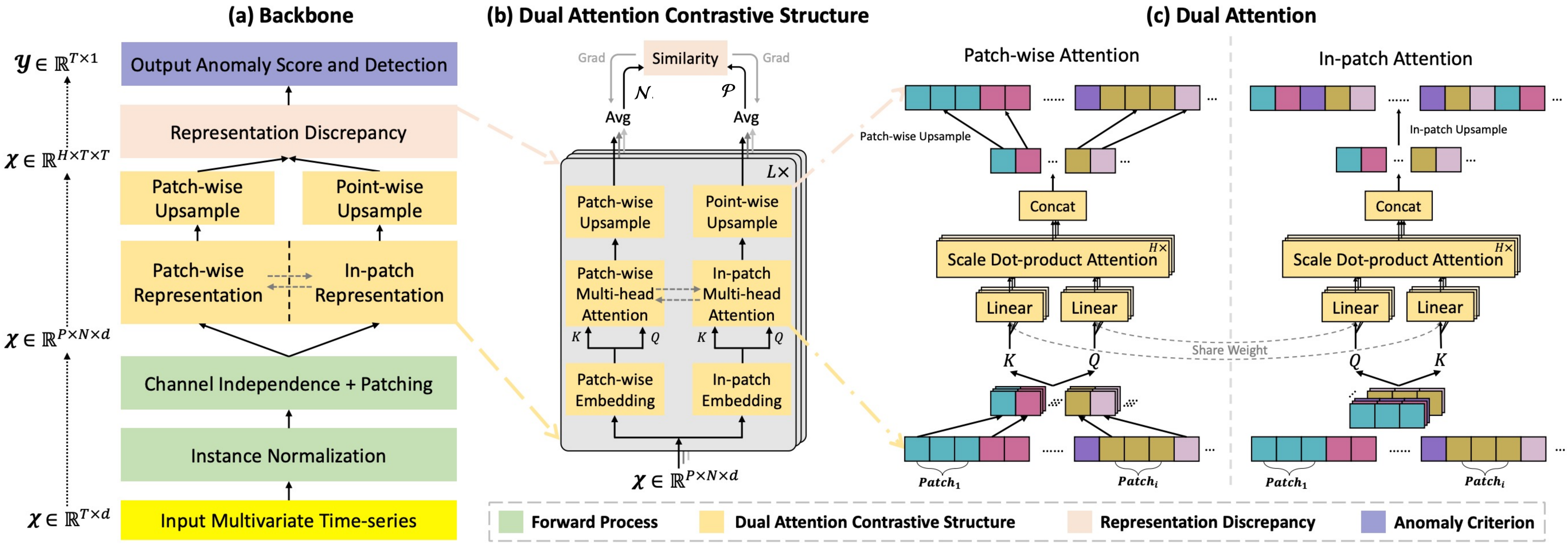
Normal point: Strong relation between adjacent data



Anomaly: Weak relation between adjacent data

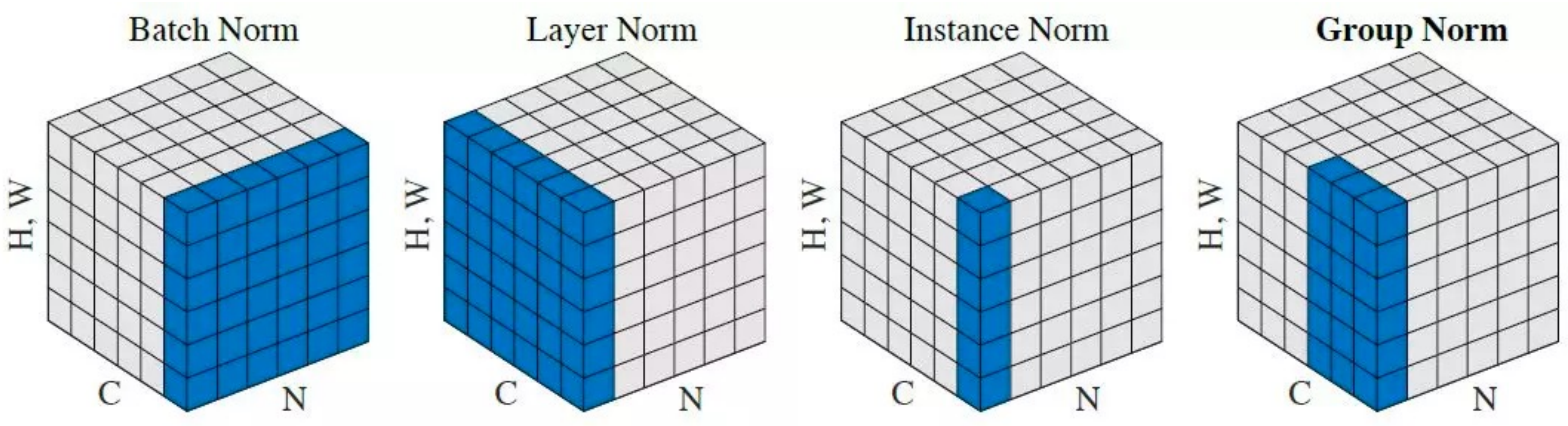
Differentiation by similarity of the different representations

✓ Method: DCdetector's Framework: 4 components

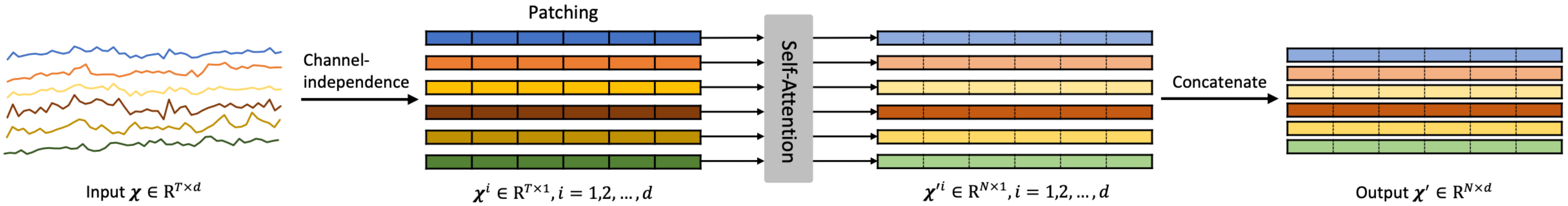


✓ Method: DCdetector's Framework - Forward Process (1/4)

Instance normalization (tackle non-stationarity problem)

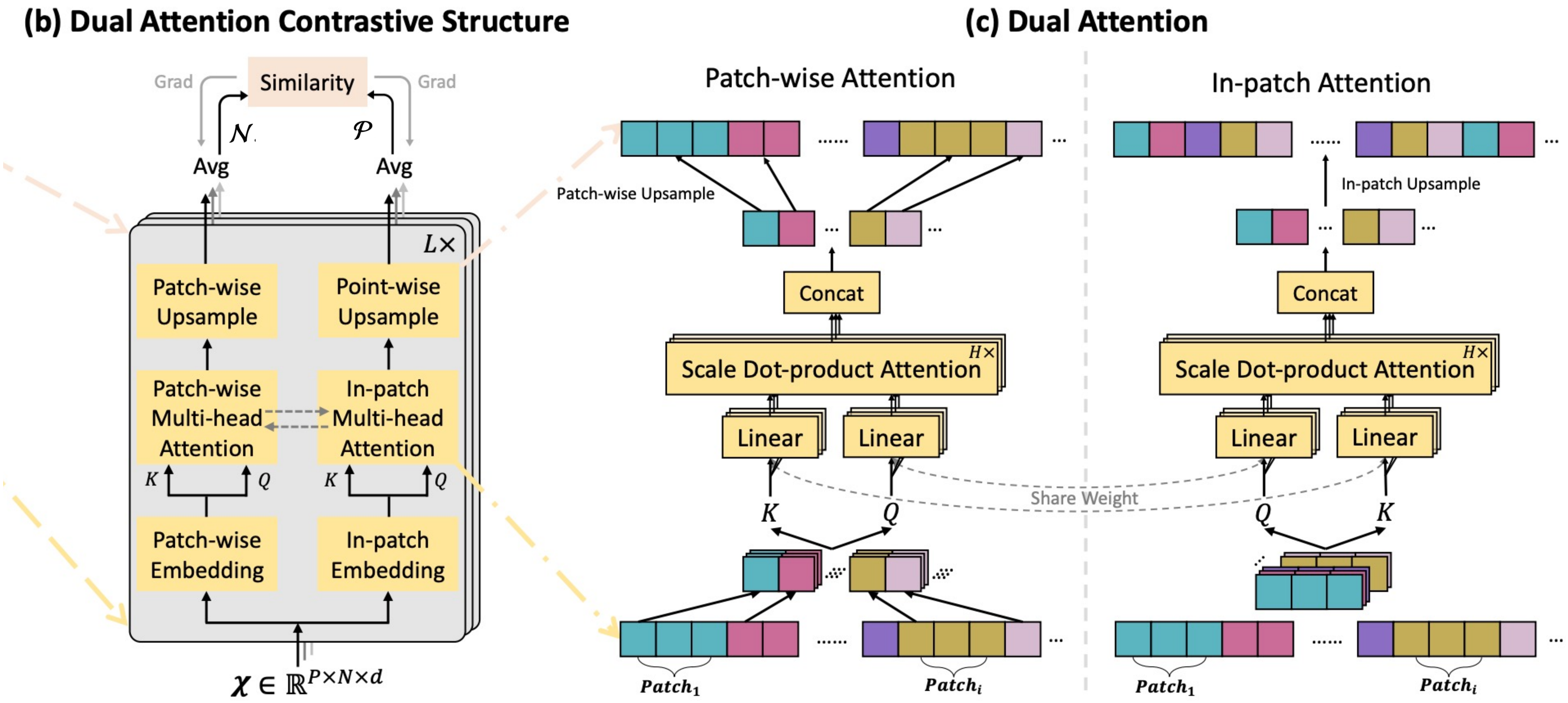


Patching and channel independence (tackle temporal dependency and multidimensional problems)

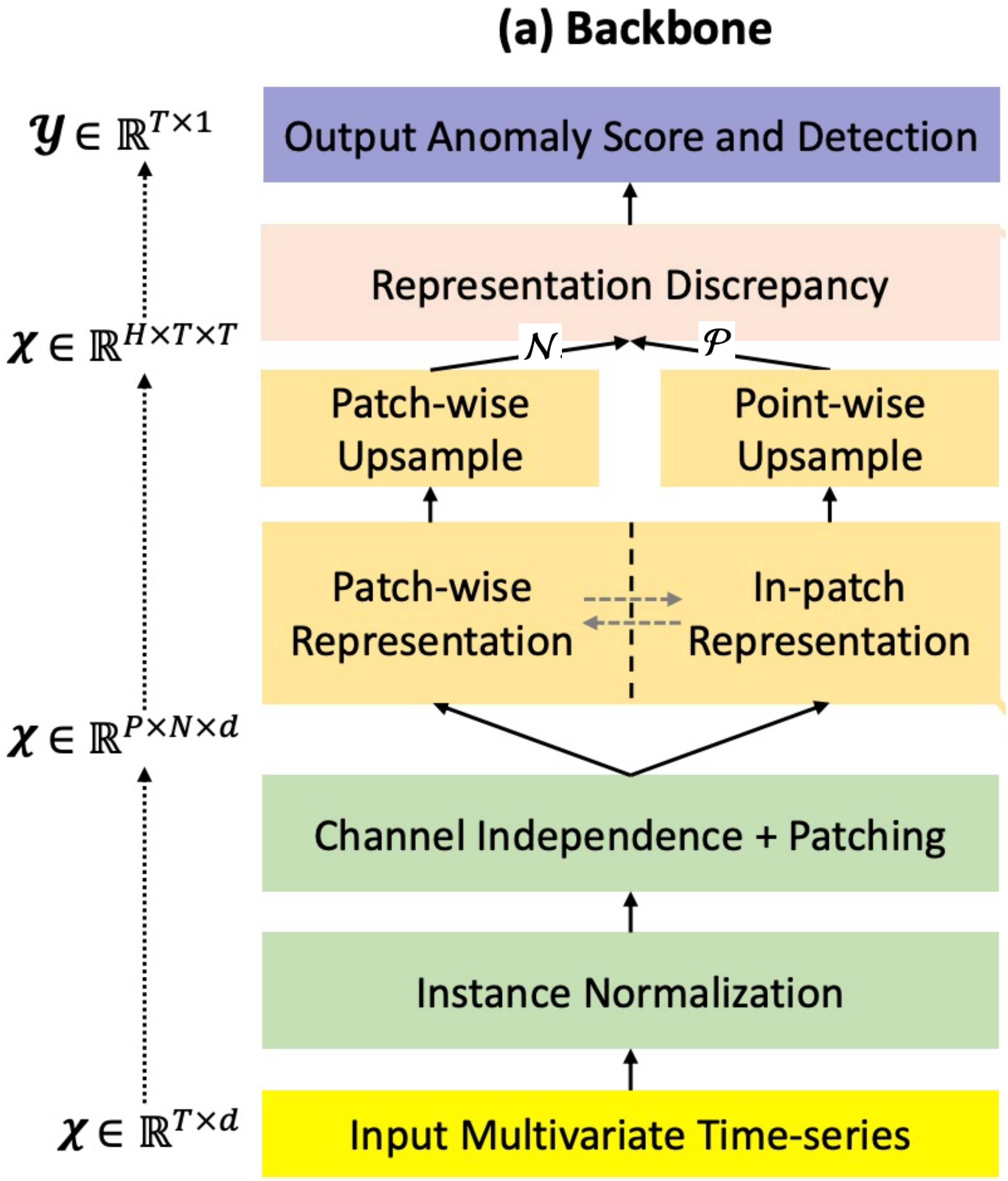


✓ Method: DCdetector's Framework – Dual Attention Contrastive Structure (2/4)

- Two branches as permutated multi-view representations:
  - **Patch-wise representation**: Attention scores between different patches
  - **In-patch representation**: Attention scores of internal patch
  - **Asymmetric design:** avoid model collapse and trivial solution in
- Inductive bias: normal points can maintain their representation under permutations while the anomalies can not



✓ Method: DCdetector's Framework - Representation Discrepancy and Anomaly Detection (3/4, 4/4)



Loss: $$\mathcal{L}_{\mathcal{P}}\{\mathcal{P},\mathcal{N};\mathcal{X}\} = \sum KL(\mathcal{P}, \text{Stopgrad}(\mathcal{N})) + KL(\text{Stopgrad}(\mathcal{N}), \mathcal{P})$$

$$\mathcal{L}_{\mathcal{N}}\{\mathcal{P},\mathcal{N};\mathcal{X}\} = \sum KL(\mathcal{N}, \text{Stopgrad}(\mathcal{P})) + KL(\text{Stopgrad}(\mathcal{P}), \mathcal{N})$$

$$\mathcal{L} = \frac{\mathcal{L}_{\mathcal{N}} - \mathcal{L}_{\mathcal{P}}}{len(\mathcal{N})}$$

Stop-gradient is used to train two branches asynchronously to avoid model collapse

$$\mathcal{Y}_i = \begin{cases} 1\text{: anomaly} & \text{AnomalyScore}(\mathcal{X}_i) \geq \delta \\ 0\text{: normal} & \text{AnomalyScore}(\mathcal{X}_i) < \delta \end{cases}$$

$$\text{AnomalyScore}(\mathcal{X}) = \sum KL(\mathcal{P}, \text{Stopgrad}(\mathcal{N})) + KL(\mathcal{N}, \text{Stopgrad}(\mathcal{P}))$$

✓ Evaluation: Datasets and Implement (all open-sourced)

- Datasets & Baselines
  7+1 benchmarks, **26** baselines
- Evaluation Criteria
  10 metrics (F1, Affiliation, VUS)
- Performance on Parameter Sensitivity
- Visual Analysis
- Time-Cost and Memory Used

- One NVIDIA Tesla-V100 32GB GPU
- batch size to 128
- 3 epochs
- other hyper-parameters…
- Inference time less than 1s for all datasets
- All test scripts open source

Table 8: Details of benchmark datasets. AR (anomaly ratio) represents the abnormal proportion of the whole dataset.

Benchmark	Source	Dimension	Window	Patch Size	#Training	#Test (Labeled)	AR (%)
MSL	NASA Space Sensors	55	90	[3,5]	58,317	73,729	10.5
SMAP	NASA Space Sensors	25	105	[3,5,7]	135,183	427,617	12.8
PSM	eBay Server Machine	25	60	[1,3,5]	132,481	87,841	27.8
SMD	Internet Server Machine	38	105	[5,7]	708,405	708,420	4.2
SWaT	Infrastructure System	51	105	[3,5,7]	495,000	449,919	12.1
NIPS-TS-SWAN	Space (Solar) Weather	38	36	[1,3]	60,000	60,000	32.6
NIPS-TS-GECCO	Water Quality for IoT	9	90	[1,3,5]	69,260	69,261	1.1
UCR	Various Natural Sources	1	105	[3,5,7]	2,238,349	6,143,541	0.6

https://github.com/DAMO-DI-ML/KDD2023-DCdetector

✓ Evaluation: Multivariate Dataset Results

Dataset	SMD			MSL			SMAP			SWaT			PSM		
Metric	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1
LOF	56.34	39.86	46.68	47.72	85.25	61.18	58.93	56.33	57.60	72.15	65.43	68.62	57.89	90.49	70.61
OCSVM	44.34	76.72	56.19	59.78	86.87	70.82	53.85	59.07	56.34	45.39	49.22	47.23	62.75	80.89	70.67
U-Time	65.95	74.75	70.07	57.20	71.66	63.62	49.71	56.18	52.75	46.20	87.94	60.58	82.85	79.34	81.06
IForest	42.31	73.29	53.64	53.94	86.54	66.45	52.39	59.07	55.53	49.29	44.95	47.02	76.09	92.45	83.48
DAGMM	67.30	49.89	57.30	89.60	63.93	74.62	86.45	56.73	68.51	89.92	57.84	70.40	93.49	70.03	80.08
ITAD	86.22	73.71	79.48	69.44	84.09	76.07	82.42	66.89	73.85	63.13	52.08	57.08	72.80	64.02	68.13
VAR	78.35	70.26	74.08	74.68	81.42	77.90	81.38	53.88	64.83	81.59	60.29	69.34	90.71	83.82	87.13
MMPCACD	71.20	79.28	75.02	81.42	61.31	69.95	88.61	75.84	81.73	82.52	68.29	74.73	76.26	78.35	77.29
CL-MPPCA	82.36	76.07	79.09	73.71	88.54	80.44	86.13	63.16	72.88	76.78	81.50	79.07	56.02	**99.93**	71.80
TS-CP2	87.42	66.25	75.38	86.45	68.48	76.42	87.65	83.18	85.36	81.23	74.10	77.50	82.67	78.16	80.35
Deep-SVDD	78.54	79.67	79.10	91.92	76.63	83.58	89.93	56.02	69.04	80.42	84.45	82.39	95.41	86.49	90.73
BOCPD	70.9	82.04	76.07	80.32	87.20	83.62	84.65	85.85	85.24	89.46	70.75	79.01	80.22	75.33	77.70
LSTM-VAE	75.76	90.08	82.30	85.49	79.94	82.62	92.20	67.75	78.10	76.00	89.50	82.20	73.62	89.92	80.96
BeatGAN	72.90	84.09	78.10	89.75	85.42	87.53	92.38	55.85	69.61	64.01	87.46	73.92	90.30	93.84	92.04
LSTM	78.55	85.28	81.78	85.45	82.50	83.95	89.41	78.13	83.39	86.15	83.27	84.69	76.93	89.64	82.80
OmniAnomaly	83.68	86.82	85.22	89.02	86.37	87.67	92.49	81.99	86.92	81.42	84.30	82.83	88.39	74.46	80.83
InterFusion	87.02	85.43	86.22	81.28	92.70	86.62	89.77	88.52	89.14	80.59	85.58	83.01	83.61	83.45	83.52
THOC	79.76	90.95	84.99	88.45	90.97	89.69	92.06	89.34	90.68	83.94	86.36	85.13	88.14	90.99	89.54
AnomalyTrans	**88.47**	**92.28**	**90.33**	91.92	96.03	93.93	93.59	**99.41**	96.41	89.10	99.28	94.22	96.94	97.81	97.37
DCdetector	83.59	91.10	87.18	**93.69**	**99.69**	**96.60**	**95.63**	98.92	**97.02**	**93.11**	**99.77**	**96.33**	**97.14**	98.74	**97.94**

✓ Evaluation: Other Dataset and Evaluation Criteria Results

Table 4: Multi-metrics results on NIPS-TS datasets. All results are in %, and the best ones are in Bold.

Dataset	Method	Acc	P	R	F1	Aff-P	Aff-R	R_A_R	R_A_P	V_ROC	V_PR
NIPS-TS-SWAN	AnomalyTrans	84.57	90.71	47.43	62.29	**58.45**	**9.49**	86.42	93.26	84.81	92.00
	DCdetector	**85.94**	**95.48**	**59.55**	**73.35**	50.48	5.63	**88.06**	**94.71**	**86.25**	**93.50**
NIPS-TS-GECCO	AnomalyTrans	98.03	25.65	28.48	26.99	49.23	81.20	56.35	22.53	55.45	21.71
	DCdetector	**98.56**	**38.25**	**59.73**	**46.63**	**50.05**	**88.55**	**62.95**	**34.17**	**62.41**	**33.67**

Overall results on NIPS-TS datasets.

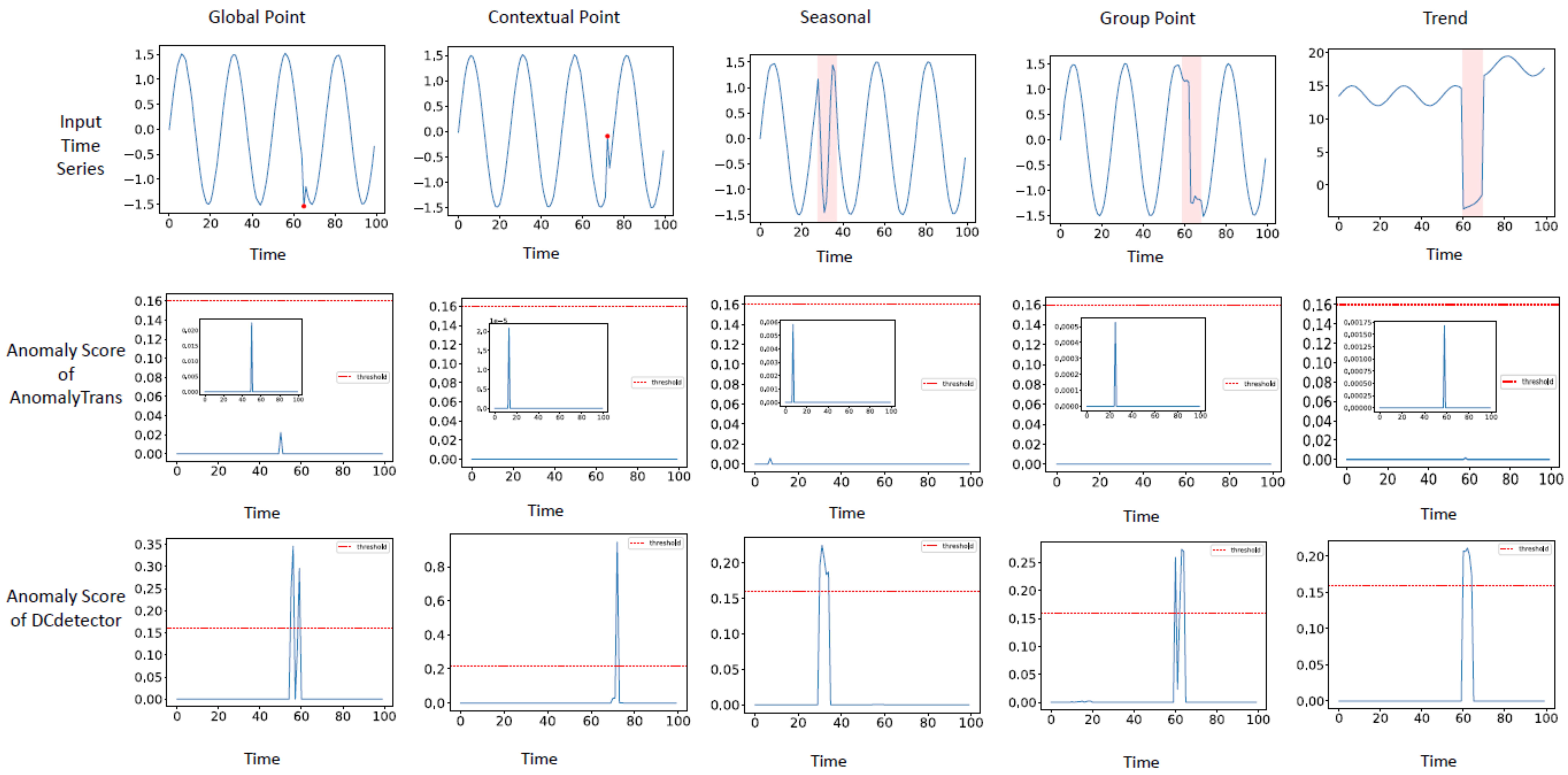
Dataset	NIPS-TS-GECCO			NIPS-TS-SWAN		
Metric	**P**	**R**	**F1**	**P**	**R**	**F1**
OCSVM*	2.1	34.1	4.0	19.3	0.1	0.1
MatrixProfile	4.6	18.5	7.4	16.7	17.5	17.1
GBRT	17.5	14.0	15.6	44.7	37.5	40.8
LSTM-RNN	34.3	27.5	30.5	52.7	22.1	31.2
Autoregression	39.2	31.4	34.9	42.1	35.4	38.5
OCSVM	18.5	**74.3**	29.6	47.4	49.8	48.5
IForest*	39.2	31.5	39.0	40.6	42.5	41.6
AutoEncoder	42.4	34.0	37.7	49.7	52.2	50.9
AnomalyTrans	25.7	28.5	27.0	90.7	47.4	62.3
IForest	**43.9**	35.3	39.1	56.9	**59.8**	58.3
DCdetector	38.3	59.7	**46.6**	**95.5**	59.6	**73.4**

Overall results on univariate dataset.

Dataset	UCR				
Metric	**Acc**	**P**	**R**	**F1**	**Count**
AnomalyTrans	99.49	60.41	**100**	73.08	42
DCdetector	**99.51**	**61.62**	**100**	**74.05**	**46**

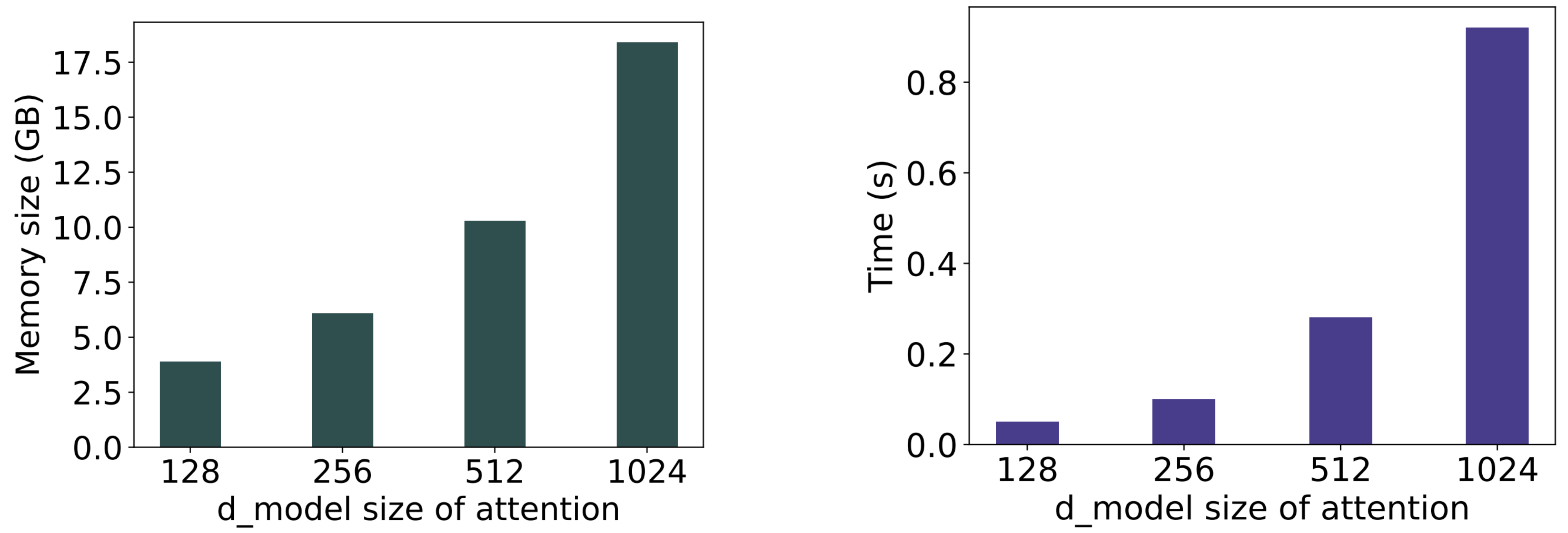
Alexis Huet, Jose Manuel Navarro, and Dario Rossi. Local Evaluation of Time Series Anomaly Detection Algorithms. KDD’22.
John Paparrizos, Paul Boniol, Themis Palpanas, Ruey S Tsay, Aaron Elmore, and Michael J Franklin. 2022. Volume under the surface: a new accuracy evaluation measure for time-series anomaly detection. VLDB’22

✓ Visualization: To Compare Anomaly Scores under Different Anomaly Types

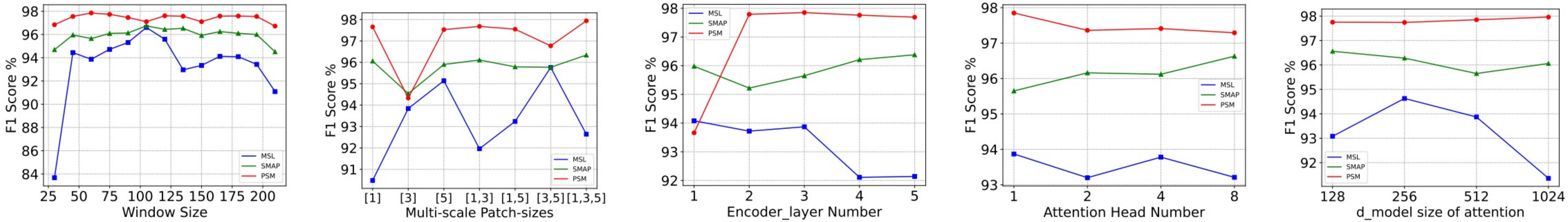


✓ Ablation Experiments and Parameter Sensitivity

- Window size
- Multi-scale size (patch size)
- Encoder layer number & Attention head number
- Two branches and single branch
- Anomaly threshold
- Loss function and Forward process
- Other model's parameter



(a) Memory used (b) Time cost



(a) Window size (b) Multi-scale size (c) Encoder layer number (d) Attention head number (e) d_{model} of attention

✓ Conclusion of DCdetector

❖ **Architecture**:

- A contrastive learning-based dual-branch attention structure

❖ **Optimization:**

- An effective loss function is designed based on the similarity of two branches
- Model is trained purely contrastively without reconstruction loss, reducing distractions from anomalies

❖ **Performance:**

- DCdetector achieves SOTA performance in 8 benchmarks with 10 metrics, compared with 26 baselines

✓ Open-sourced Codes

https://github.com/DAMO-DI-ML/KDD2023-DCdetector

Get Start

1. Install Python 3.6, PyTorch >= 1.4.0.
2. Download data. You can obtain all benchmarks from Google Cloud. All the datasets are well pre-processed.
3. Train and evaluate. We provide the experiment scripts of all benchmarks under the folder `./scripts`. You can reproduce the experiment results as follows:

```
bash ./scripts/SMD.sh
bash ./scripts/MSL.sh
bash ./scripts/SMAP.sh
bash ./scripts/PSM.sh
bash ./scripts/SWAT.sh
bash ./scripts/NIPS_TS_Swan.sh
bash ./scripts/NIPS_TS_Water.sh
bash ./scripts/UCR.sh
```

Also, some scripts of ablation experiments.

```
bash ./scripts/Ablation_attention_head.sh
bash ./scripts/Ablation_encoder_layer.sh
bash ./scripts/Ablation_Multiscale.sh
bash ./scripts/Ablation_Window_Size.sh
```

Code Description

There are ten files/folders in the source.

- data_factory: The preprocessing folder/file. All datasets preprocessing codes are here.
- dataset: The dataset folder, and you can download all datasets here.
- main.py: The main python file. You can adjustment all parameters in there.
- metrics: There is the evaluation metrics code folder, which includes VUC, affiliation precision/recall pair, and other common metrics. The details can be corresponding to paper's Section 4.2.
- model: DCdetector model folder. The details can be corresponding to paper's Section 3.
- result: In our code demo, we can automatically save the results and train processing log in this folder.
- scripts: All datasets and ablation experiments scripts. You can reproduce the experiment results as get start shown.
- solver.py: Another python file. The training, validation, and testing processing are all in there.
- utils: Other functions for data processing and model building.
- img: Images needed in readme.md.
- requirements.txt: Python packages needed to run this repo.

Thanks
Q&A

https://arxiv.org/abs/2306.10347

https://github.com/DAMO-DI-ML/KDD2023-DCdetector