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# COMET: Codebook-based Online-adaptive Multi-scale Embedding for Time-series Anomaly Detection

Jinwoo Park, Hyeongwon Kang, Seung Hun Han, Pilsung Kang
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**DSBA Lab, Seoul National University**

**Presenter: Jinwoo Park**



# Three Problems Addressed by COMET

Challenges that arise from multivariate time series and from the anomaly detection task itself

### EMBEDDING

**What should be represented?**

An embedding that captures temporal dependency and multivariate correlation

### ANOMALY TYPE

**How should we score?**

A scoring unit that does not miss contextual and collective anomalies

### DISTRIBUTION SHIFT

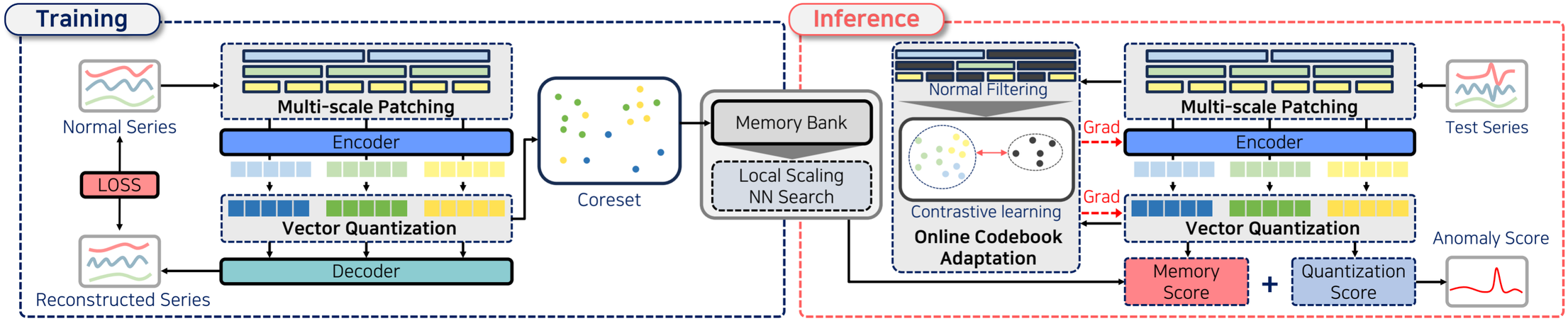
**What if the distribution shifts?**

Safe adaptation to distribution shifts between training and inference

- The three problems are interdependent
- Good embeddings make patch-level scores meaningful, and reliable prototypes make normal sample selection possible

# Overall architecture: Training → Scoring → Adaptation

Normal prototypes learned during training are reused for both scoring and adaptation at inference




## 1 TRAINING

- Patching → Encoder → VQ → Decoder
- Store activated entries as the coreset

## 2 SCORING

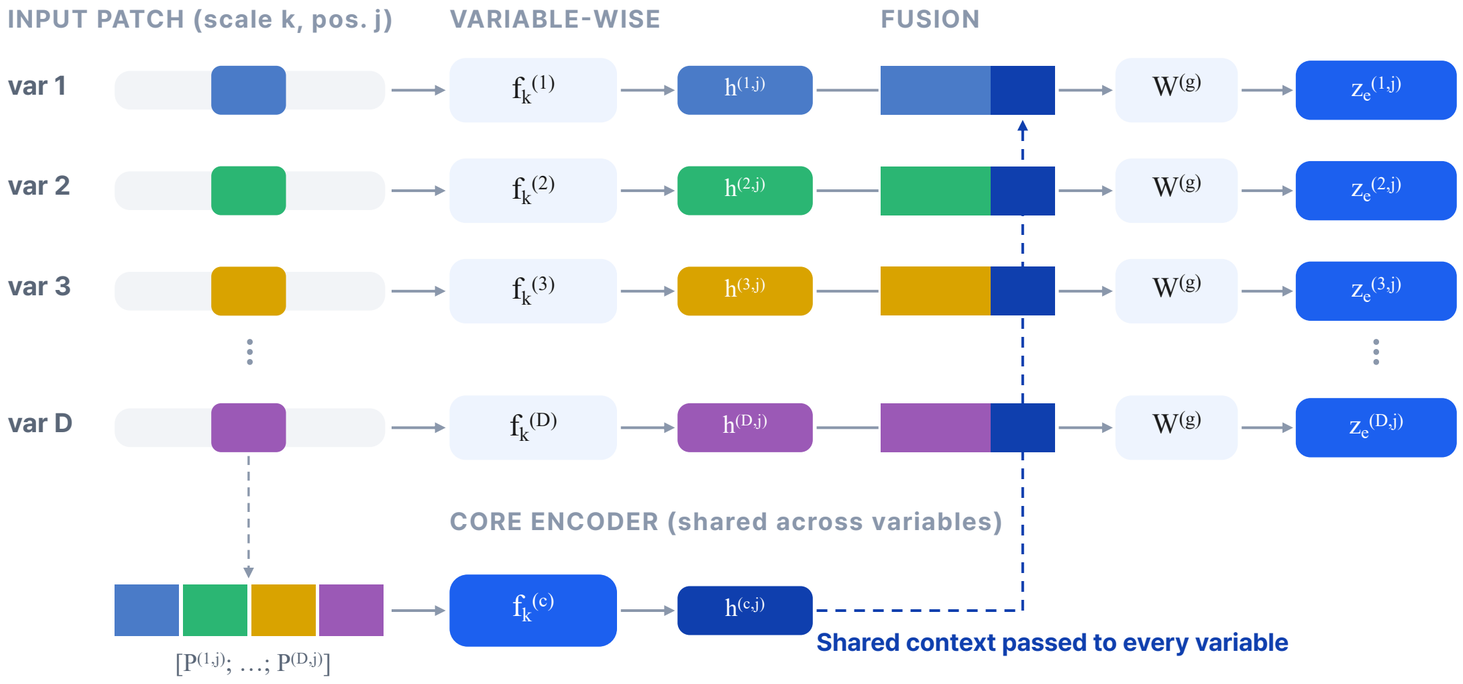
- Memory score + Quantization score
- Normalized and combined by a weighted sum

## 3 ADAPTATION

- Normal filtering based on activated entries
- Contrastive learning

# Multi-scale Patch Encoder

Patches at position j are encoded by variable-wise encoders and a shared core encoder, and then fused




### Variable-wise encoder

- Each variable has its own encoder to learn its distinct patterns

### Core encoder

- Concatenates all variables at one position to extract system-wide context

### Fusion

- Concatenates both features into a d-dim patch embedding

➢ **Each variable embedding = its own pattern + system context at the same position**
➢ **Models variable-specific patterns and inter-variable interactions**

# Vector-Quantized Coreset

Codebook entries activated by the training data serve as the normal prototypes of each scale

## COMET: ACTIVATION-BASED CORESET

**① Codebook $C_k$ (M entries)**

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
| 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 |

**② Pass the training data once more → indices selected at least once = Ak**

↓

**③ Memory bank $M_k$**

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 4 | 5 | 6 | 7 | 9 | 10 | 11 | 12 | 14 | 15 | 16 | 17 | 18 | 21 | 23 |

Activated entry (normal prototype)  Inactive entry

$$M_k = \{ c_{k,m} \mid m \in A_k \}, \quad |M_k| \leq M$$

Stored indices allow direct updates after adaptation, and local scales are precomputed

## WHY ACTIVATION-BASED?

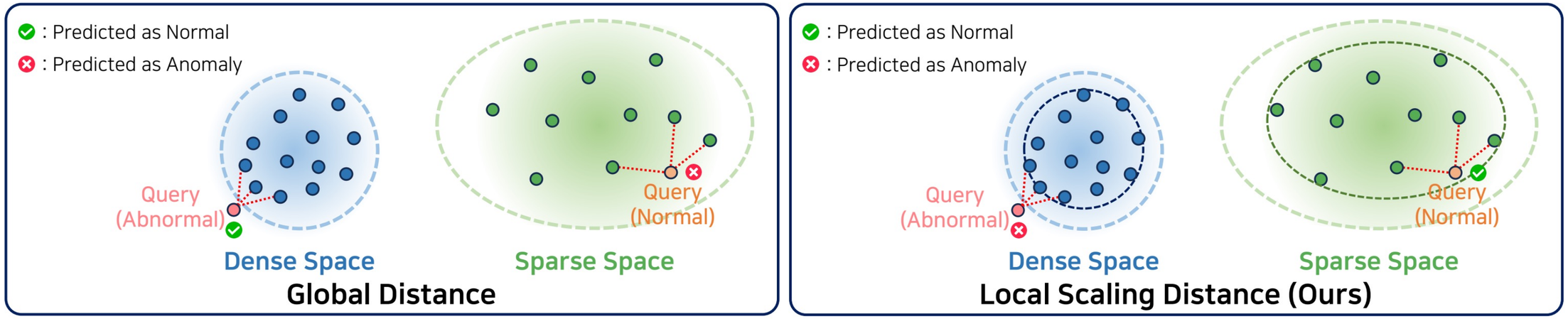
**No extra sampling**
Activated entries are collected in a single pass, without clustering all training embeddings afterwards

**Compact memory**
At most M entries per scale. On WADI, 96 codewords of about 25 KB replace roughly 124 GB of embeddings

**Ready for adaptation**
Stored indices refresh the bank right after adaptation, and inactive entries flag anomaly candidates

# Vector-Quantized Coreset

Since the coreset has non-uniform density, the memory score relies on a density-aware distance




Left: global distance, Right: local scaling distance

× **Global distance:**
sparse normal → false positive, dense anomaly → false negative

✓ **Local scaling:**
accounts for both distance and local density

- Nearest-neighbor distance as a proxy for local density (Zelnik-Manor & Perona, NeurIPS 2004)

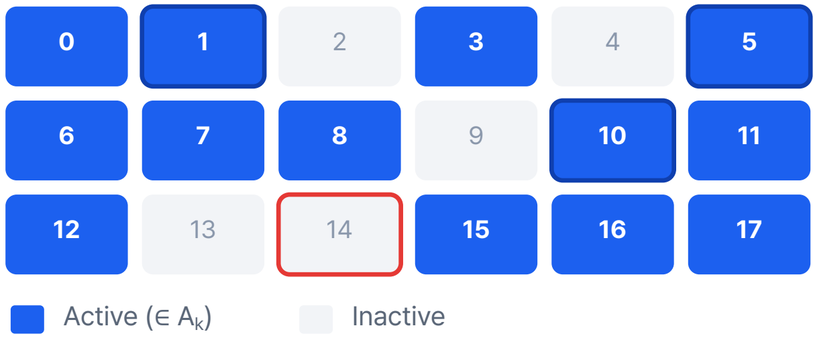
# Online Codebook Adaptation

A test patch is treated as a normal candidate only if its entry was activated during training

## TEST PATCH → INDEX → PSEUDO-LABEL

| | | | | |
|---|---|---|---|---|
| Patch 1 | → | $\hat{q} = 1 \in A$ | → Normal ($\tilde{y} = 0$) | Used for adaptation |
| Patch 2 | → | $\hat{q} = 10 \in A$ | → Normal ($\tilde{y} = 0$) | Used for adaptation |
| Patch 3 | → | $\hat{q} = 14 \notin A$ | → Abnormal ($\tilde{y} = 1$) | Excluded |
| Patch 4 | → | $\hat{q} = 5 \in A$ | → Normal ($\tilde{y} = 0$) | Used for adaptation |

## CODEBOOK $C_k$: ACTIVE SET $A_k$




$$\tilde{y} = 0 \text{ if } \hat{q} \in A_k, \quad 1 \text{ otherwise}$$

× **Prior work**: anomaly score ≤ threshold → normal
➢ Sensitive to the threshold choice

✓ **COMET: $\hat{q} \in A_k$ → normal, no threshold needed**

- $C_{seen} = \cup_k M_k$: entries activated during training. Inactive entries serve as a natural safeguard

# Main results

Comparison with seven baselines on five benchmarks using nine point-wise and range-based metrics

| Dataset | Method | Metric | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | F1(K=0) | F1(K=100) | Aff-F1 | AUC-ROC | AUC-PR | R-AUC-ROC | R-AUC-PR | VUS-ROC | VUS-PR |
| PSM | CATCH | **97.70** | 42.38 | 60.77 | 62.07 | 41.13 | 70.46 | 53.01 | 69.50 | 51.74 |
| | D3R | 93.67 | 44.99 | 57.39 | 69.17 | 48.97 | 69.49 | 50.59 | 69.18 | 50.36 |
| | VTT | 92.81 | 48.35 | 56.13 | 76.94 | 49.93 | 76.23 | 52.95 | 76.01 | 52.69 |
| | AT | 97.43 | 2.20 | 65.19 | 50.48 | 27.88 | 52.33 | 34.81 | 52.13 | 34.61 |
| | LSTM-AE | 93.41 | 45.54 | 53.37 | 69.70 | 50.76 | 70.26 | 51.35 | 69.94 | 51.15 |
| | LSTM-VAE | 93.12 | 44.72 | 59.38 | 66.14 | 47.28 | 66.16 | 48.46 | 65.95 | 48.27 |
| | USAD | 91.78 | 43.44 | 56.04 | 64.84 | 44.18 | 65.71 | 46.43 | 65.40 | 46.21 |
| | **COMET (w/ TTA)** | 95.30 | **60.26** | **72.00** | **79.54** | **60.01** | **79.56** | **62.21** | **77.92** | **61.20** |
| | **COMET (w/o TTA)** | 95.37 | 60.13 | 71.80 | 79.15 | 59.10 | 79.18 | 61.45 | 77.50 | 60.42 |
| SWaT | CATCH | 91.35 | 10.11 | 69.12 | 23.78 | 8.66 | 27.34 | 9.95 | 27.17 | 9.86 |
| | D3R | 87.10 | 76.65 | 71.74 | 83.16 | 72.95 | 65.27 | 47.41 | 65.35 | 47.57 |
| | VTT | 86.13 | **77.05** | 60.11 | 81.42 | 71.08 | 58.43 | 43.62 | 58.48 | 43.74 |
| | AT | **95.98** | 3.91 | 61.05 | 49.29 | 13.06 | 49.63 | 12.35 | 49.63 | 12.36 |
| | LSTM-AE | 85.39 | 76.73 | 72.46 | 81.95 | 72.56 | 63.95 | 46.72 | 64.01 | 46.75 |
| | LSTM-VAE | 85.35 | 76.57 | 71.84 | 81.97 | 72.73 | 62.02 | 45.54 | 62.30 | 45.97 |
| | USAD | 85.36 | 76.57 | 71.78 | 81.98 | 72.74 | 62.16 | 45.65 | 62.42 | 46.08 |
| | **COMET (w/ TTA)** | 91.62 | 75.24 | **74.14** | **85.50** | **74.48** | **85.09** | **66.42** | **85.06** | **66.48** |
| | **COMET (w/o TTA)** | 91.38 | 75.06 | 72.93 | 85.48 | 74.33 | 84.85 | 65.46 | 84.82 | 65.50 |
| SMAP | CATCH | 70.44 | 12.05 | 50.85 | 43.09 | 11.90 | 44.65 | 12.88 | 44.42 | 12.83 |
| | D3R | 69.65 | 10.29 | 53.55 | 47.21 | 11.85 | 50.04 | 13.15 | 49.97 | 13.15 |
| | VTT | 70.99 | 10.96 | 50.78 | 46.59 | 11.73 | 49.39 | 12.81 | 49.27 | 12.82 |
| | AT | **96.42** | 2.21 | 67.54 | 50.03 | 12.89 | 50.44 | 14.16 | 50.43 | 14.20 |
| | LSTM-AE | 69.87 | 8.56 | 53.55 | 39.10 | 10.31 | 42.22 | 11.38 | 42.15 | 11.40 |
| | LSTM-VAE | 69.71 | 6.91 | 53.55 | 41.46 | 10.63 | 44.34 | 11.76 | 44.19 | 11.76 |
| | USAD | 69.18 | 7.01 | 53.55 | 38.82 | 10.25 | 41.79 | 11.36 | 41.69 | 11.36 |
| | **COMET (w/ TTA)** | 82.30 | 25.28 | **68.24** | **59.17** | **16.20** | **59.43** | **17.59** | **59.20** | **17.54** |
| | **COMET (w/o TTA)** | 82.46 | **25.40** | 68.01 | 59.06 | 16.17 | 58.69 | 17.51 | 58.52 | 17.46 |
| MSL | CATCH | 81.79 | 18.08 | 55.95 | 60.41 | 14.38 | 67.78 | 20.78 | 67.05 | 20.48 |
| | D3R | 87.81 | 18.37 | 62.56 | 53.88 | 14.75 | 61.91 | 19.97 | 61.42 | 19.72 |
| | VTT | 89.01 | 13.47 | 59.55 | 59.01 | 15.01 | 66.03 | 20.51 | 65.38 | 20.25 |
| | AT | **93.84** | 2.88 | 66.49 | 50.65 | 10.62 | 52.24 | 14.87 | 52.23 | 14.99 |
| | LSTM-AE | 88.30 | 17.62 | 62.60 | 53.61 | 14.05 | 60.18 | 18.33 | 59.77 | 18.20 |
| | LSTM-VAE | 88.27 | 17.62 | 62.60 | 53.22 | 13.97 | 59.83 | 18.18 | 59.44 | 18.06 |
| | USAD | 88.27 | 17.62 | 62.60 | 55.93 | 14.41 | 62.67 | 18.80 | 62.13 | 18.64 |
| | **COMET (w/ TTA)** | 87.44 | 26.28 | **71.04** | 65.40 | 16.56 | **69.90** | **22.67** | **68.87** | 22.25 |
| | **COMET (w/o TTA)** | 87.27 | **26.44** | 69.40 | **65.49** | **16.63** | 69.27 | **22.67** | 68.39 | **22.27** |
| WADI | CATCH | 45.28 | 9.46 | 3.74 | 47.03 | 5.36 | 50.44 | 6.24 | 50.29 | 6.24 |
| | D3R | 37.87 | 6.80 | 52.79 | 47.93 | 5.16 | 45.98 | 5.91 | 45.72 | 5.91 |
| | VTT | 49.52 | 7.03 | 52.72 | 50.10 | 5.30 | 47.46 | 6.14 | 47.22 | 6.14 |
| | AT | **91.10** | 2.53 | 53.81 | 50.93 | 5.77 | 51.02 | 6.69 | 51.07 | 6.72 |
| | LSTM-AE | 33.34 | 7.06 | 52.72 | 47.19 | 4.96 | 45.47 | 5.76 | 45.24 | 5.77 |
| | LSTM-VAE | 31.81 | 7.07 | 52.72 | 49.51 | 5.12 | 46.62 | 5.93 | 46.42 | 5.93 |
| | USAD | 31.81 | 7.07 | 52.72 | 48.92 | 5.07 | 46.27 | 5.86 | 46.04 | 5.86 |
| | **COMET (w/ TTA)** | 74.07 | 18.92 | 72.43 | **61.79** | **9.23** | **64.17** | **10.18** | **64.13** | **10.20** |
| | **COMET (w/o TTA)** | 73.81 | **18.98** | **72.63** | 61.19 | 9.14 | 63.64 | 10.10 | 63.57 | 10.11 |

- Without TTA, COMET outperforms all baselines on 39 of 45 metrics, and TTA further raises its own scores on 35 of the 45
- Five of the six remaining cases are point-adjusted F1(K=0), where AT drops to 2 to 4 once the adjustment is removed

# Conclusion

How the three components of COMET address the three problems

| | | |
|---|---|---|
| PROBLEM 1 **Embedding**<br>• Depending on the token unit, temporal or inter-variable structure is lost | → **Multi-scale Patch Encoder** → | • Combines variable-wise and shared core encoders across multiple patch scales |
| PROBLEM 2 **Anomaly type**<br>• Timestep-level scores miss contextual anomalies | → **Vector-Quantized Coreset** → | • Compresses normal patterns into prototypes and computes two patch-level scores |
| PROBLEM 3 **Distribution shift**<br>• Threshold-based adaptation is vulnerable to misclassification | → **Online Codebook Adaptation** → | • Selects normal candidates by activated indices and updates the codebook using only these samples |

## LIMITATIONS & FUTURE WORK

**Codebook size M**
Currently tuned per dataset, so a data-driven selection rule is needed

**Training-data contamination**
Heavy contamination may weaken activation-based pseudo-labeling

# COMET: Codebook-based Online-adaptive Multi-scale Embedding

Jinwoo Park, Hyeongwon Kang, Seung Hun Han, Pilsung Kang (NeurIPS 2026)

Code: github.com/JINU6497/COMET

# Thank you

