

# Jump-Starting Multivariate Time Series Anomaly Detection for Online Service Systems

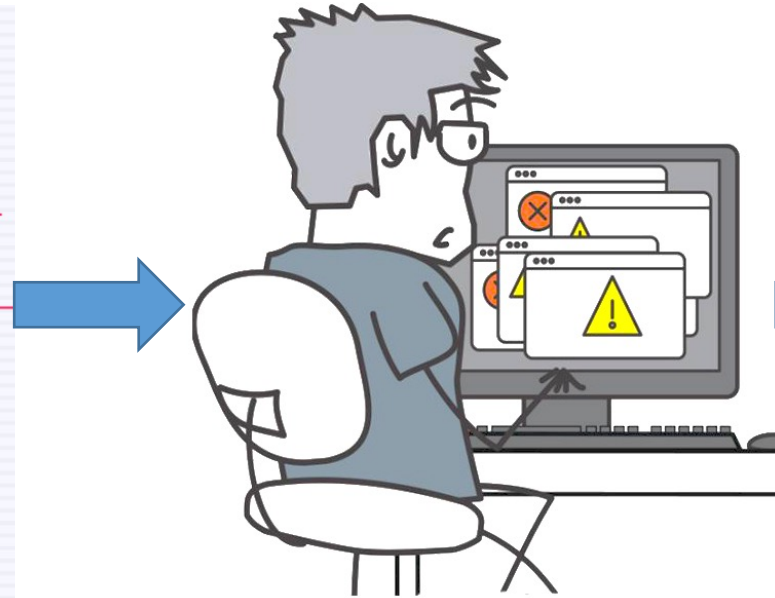
Minghua Ma, Shenglin Zhang, Junjie Chen, Jun Xu, Dan Pei, et. al.



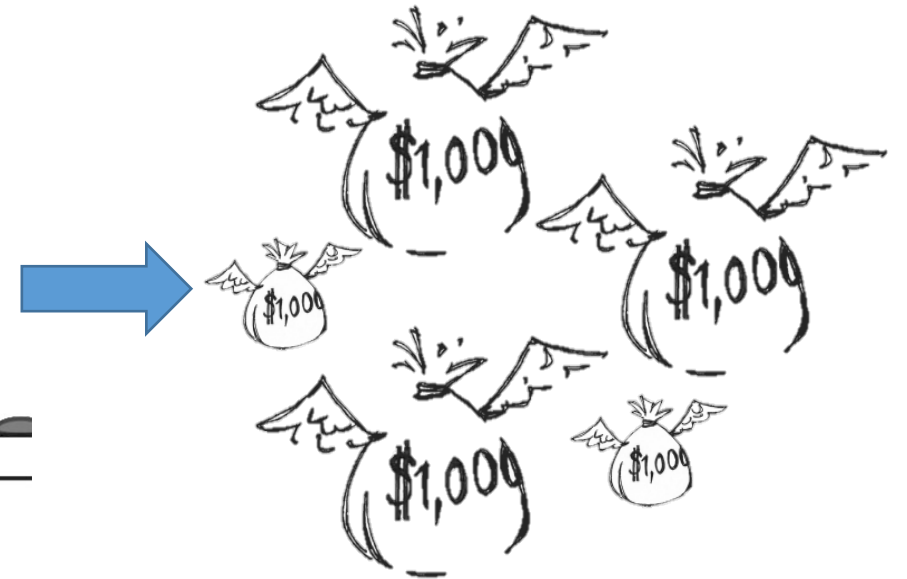
# Service Reliability is Important



Users



Operators



Companies

# Real-World Revenue Loss

A study of 584 U.S. based data center professionals found that

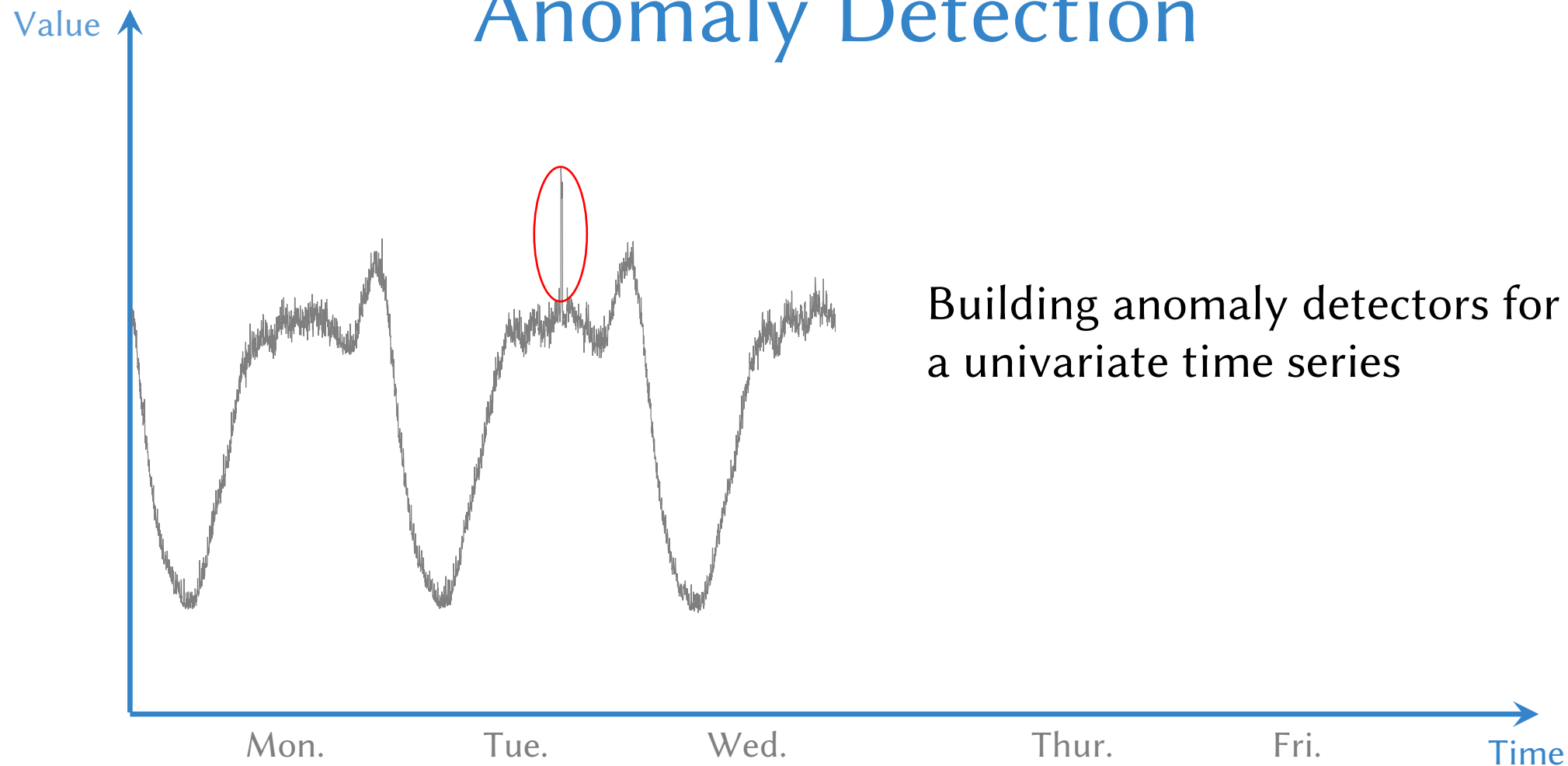
**91%** of data centers have experienced an **unplanned data center outage** in the past 24 months.<sup>2</sup>



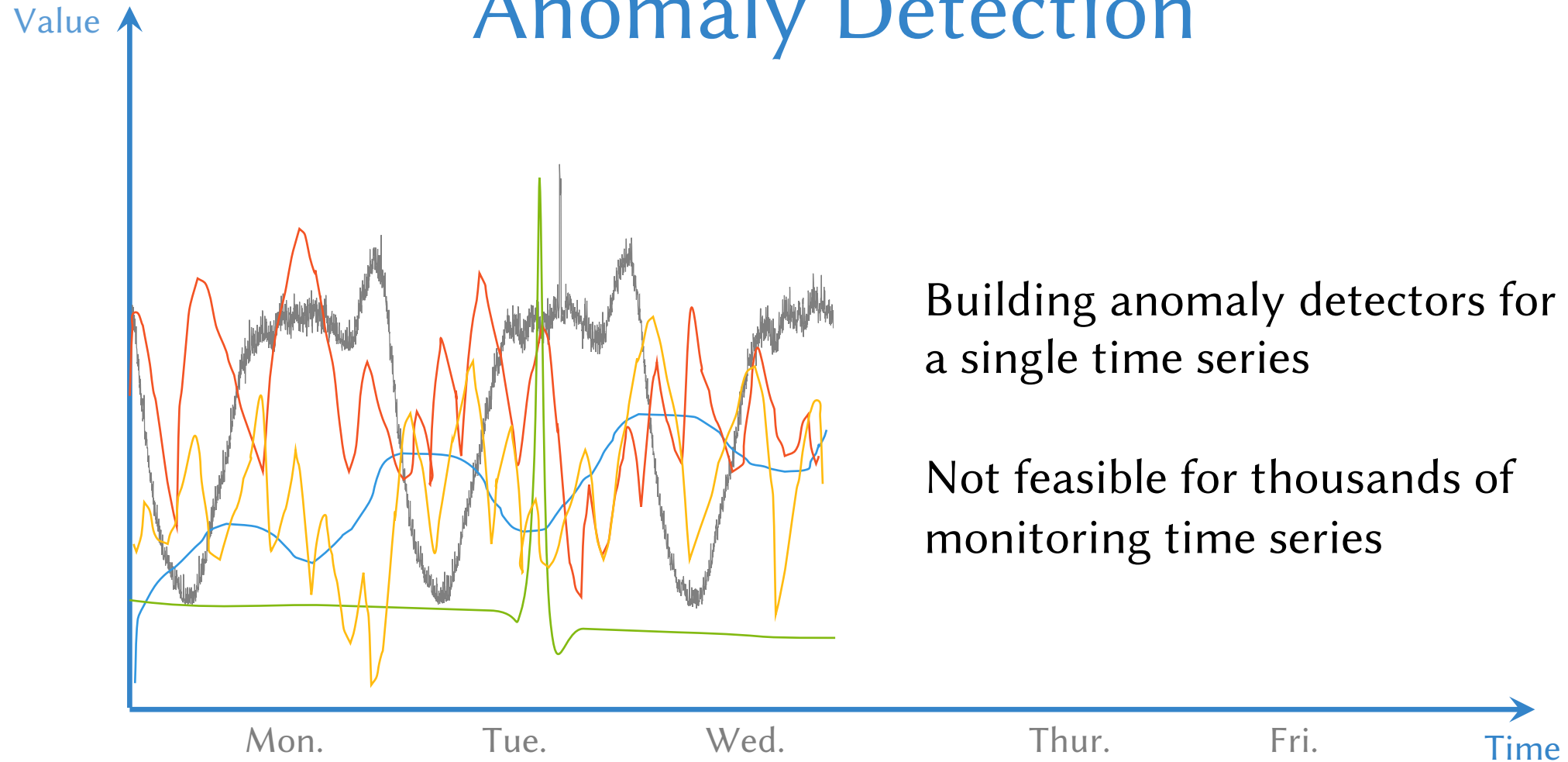
[Evolven: GAD COHEN]

VMware Joins Cloud Outage Party  
With Cloud Foundry Blackout  
Intuit Service Outages Leave Frustrated  
Verizon Customers In Their Wake  
RIM outage costs could top \$100 million  
Online Banking Upgrade contributed to Bank of America Outage  
Yahoo Mail suffers outage; users react

# Univariate Time Series (UTS) Anomaly Detection



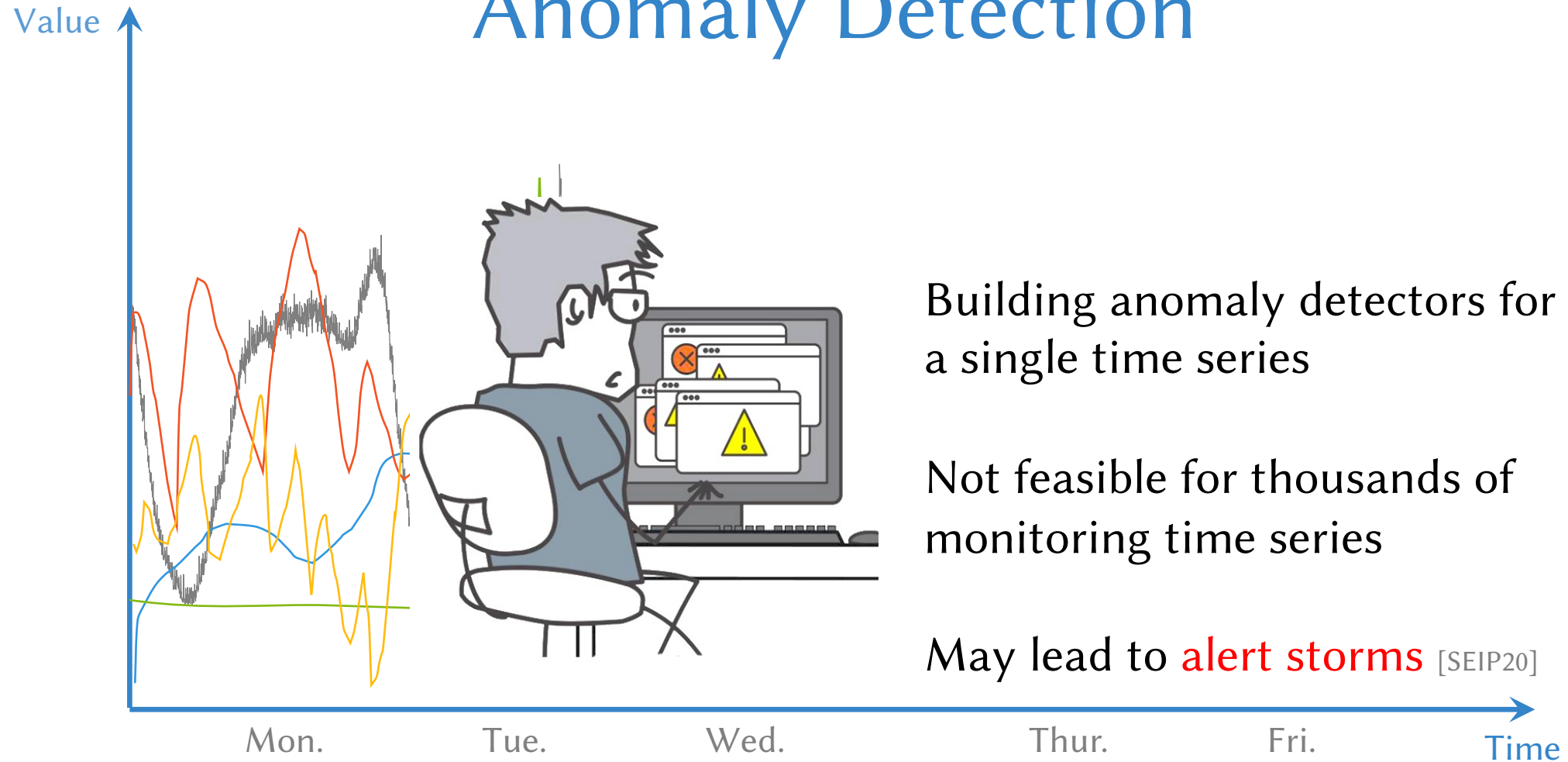
# Univariate Time Series (UTS) Anomaly Detection



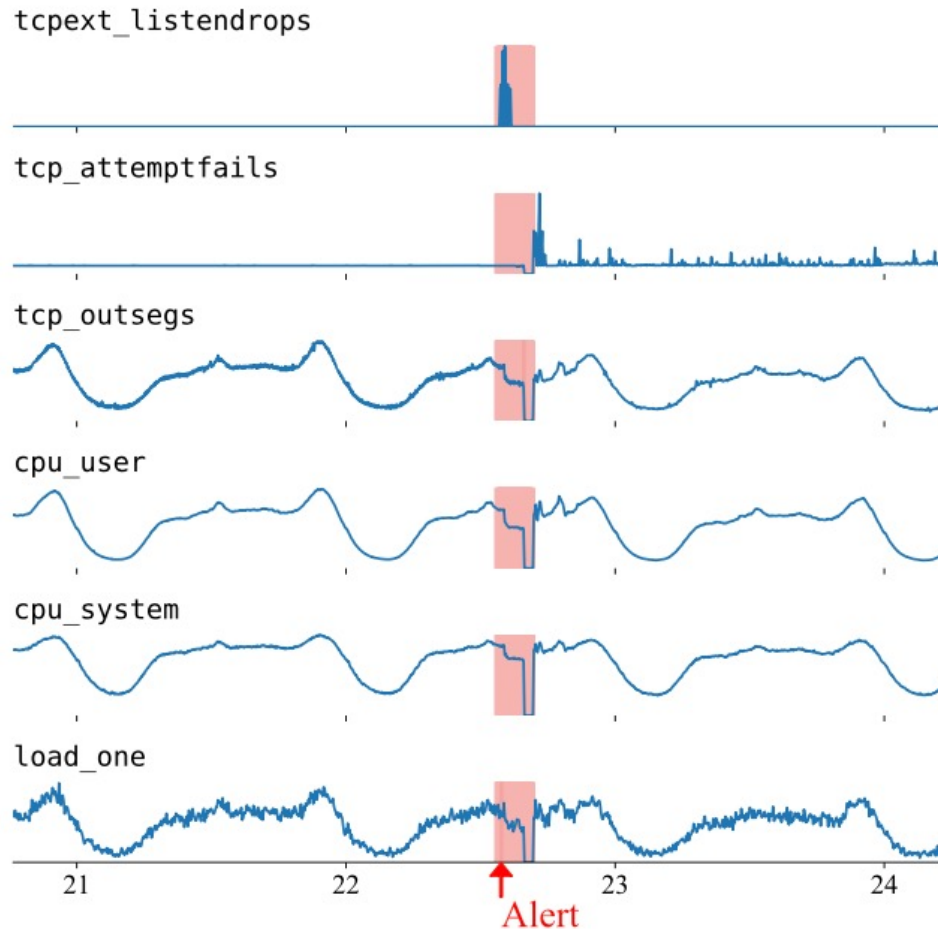
Building anomaly detectors for  
a single time series

Not feasible for thousands of  
monitoring time series

# Univariate Time Series (UTS) Anomaly Detection



# Multivariate Time Series (MTS) Anomaly Detection

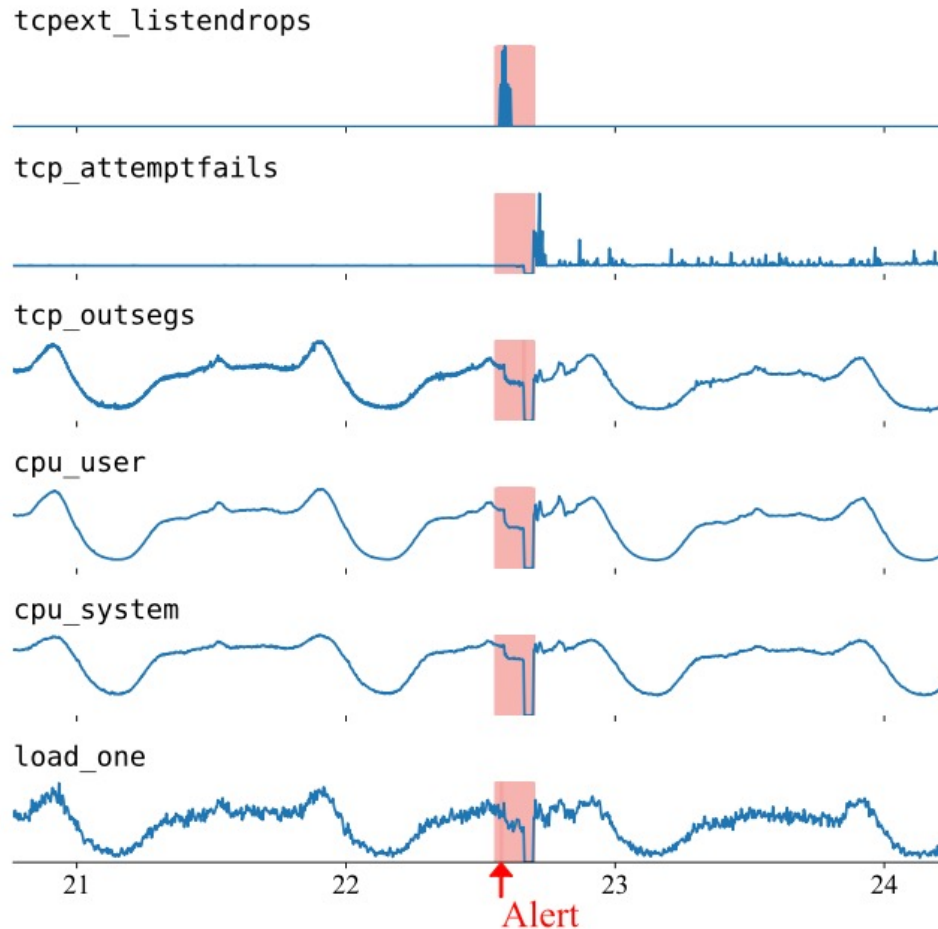


Capture status of the overall  
service system

Intuitive & effective & efficient

[KDD18, KDD19, KDD20, KDD21, AAAI19, AAAI21, NeurIPS20]

# Multivariate Time Series (MTS) Anomaly Detection



Capture status of the overall  
service system

Intuitive & effective & efficient

[KDD18, KDD19, KDD20, KDD21, AAAI19, AAAI21, NeurIPS20]

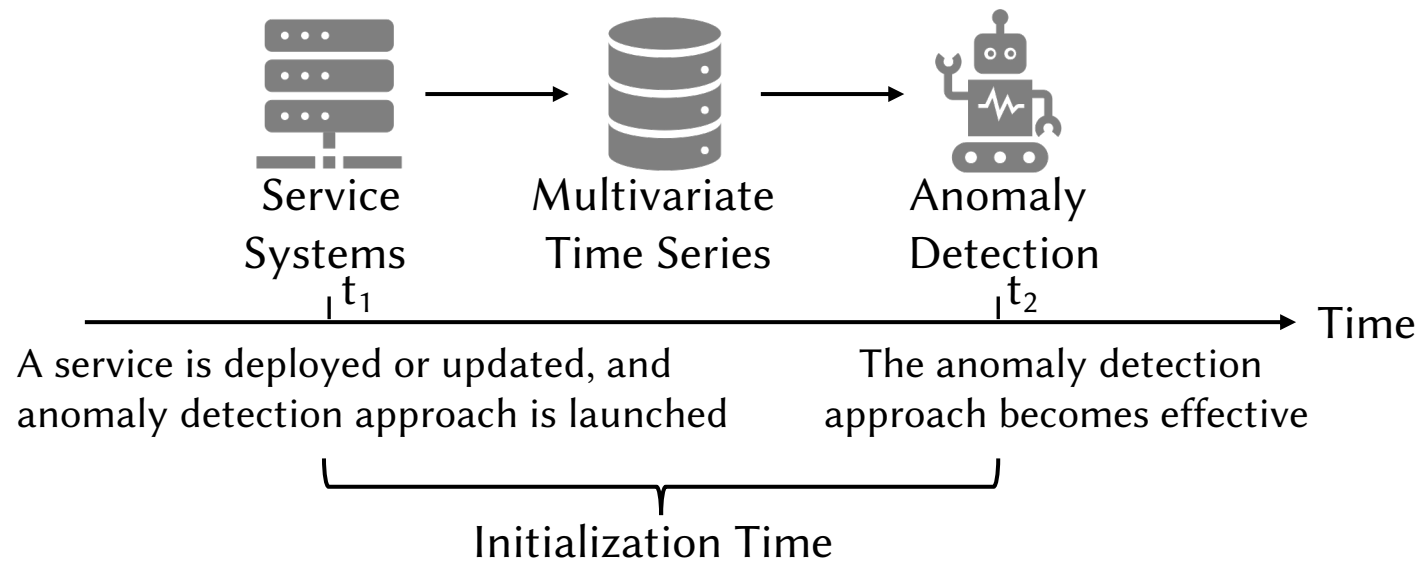


Deep learning based approaches  
(LSTM, LSTM-VAE, ConvLSTM...)

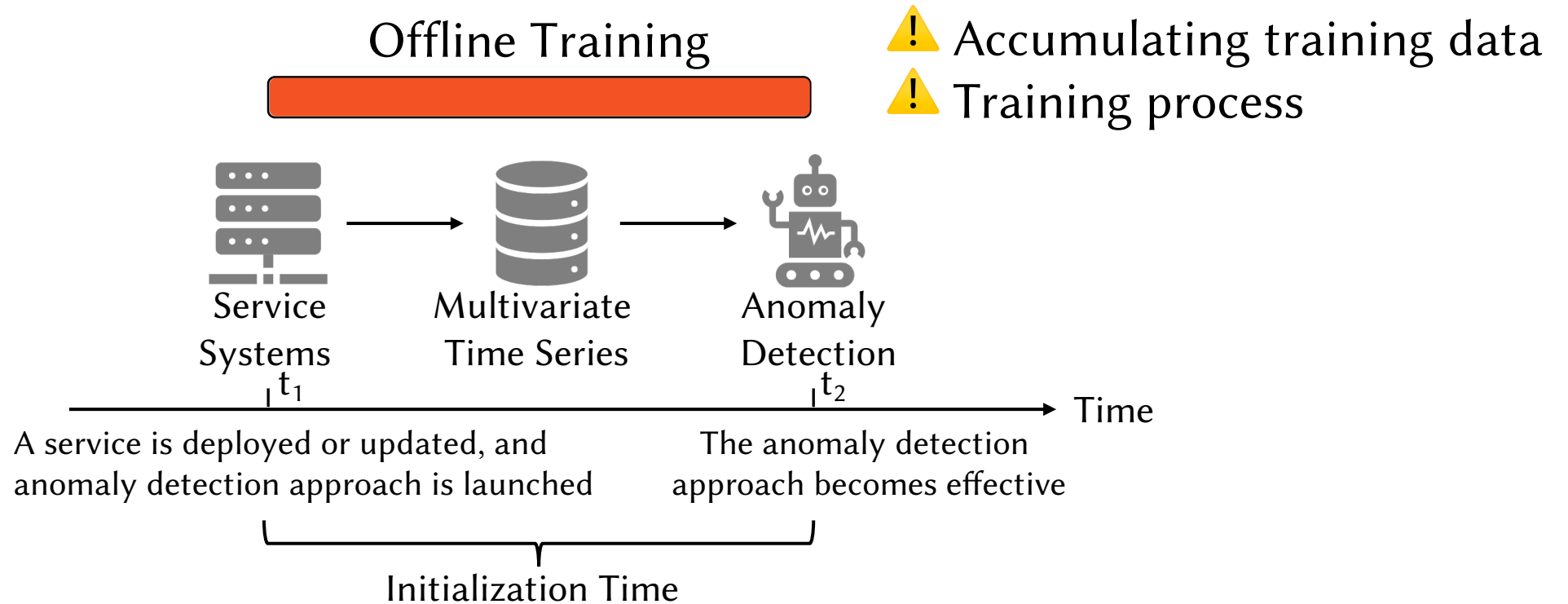


# Initialization Time

Software change (concept drift) -> Anomaly detection -> Initialize



# Deep Learning Based Approaches: Long Initialization Time



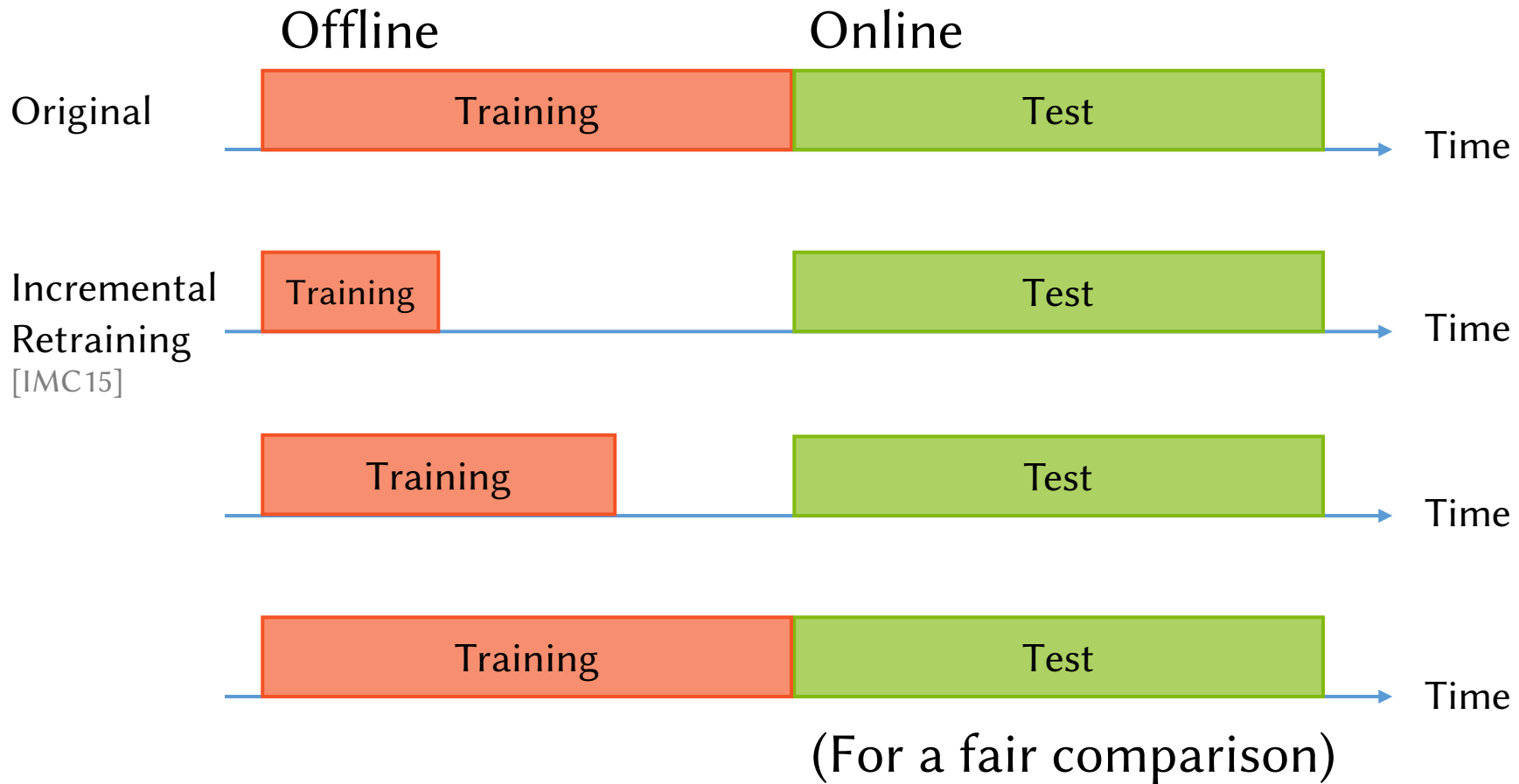
# Deep Learning Based Approaches: Long Initialization Time

Approach	S1	S2	S3	Avg.	Days!
MSCRED [AAAI19]	7	13	-	10	
OmniAnomaly [KDD19]	17	15	17	16.3	
LSTM-NDT [KDD18]	69	36	-	52.5	
Donut* [WWW18]	102	110	99	103.6	

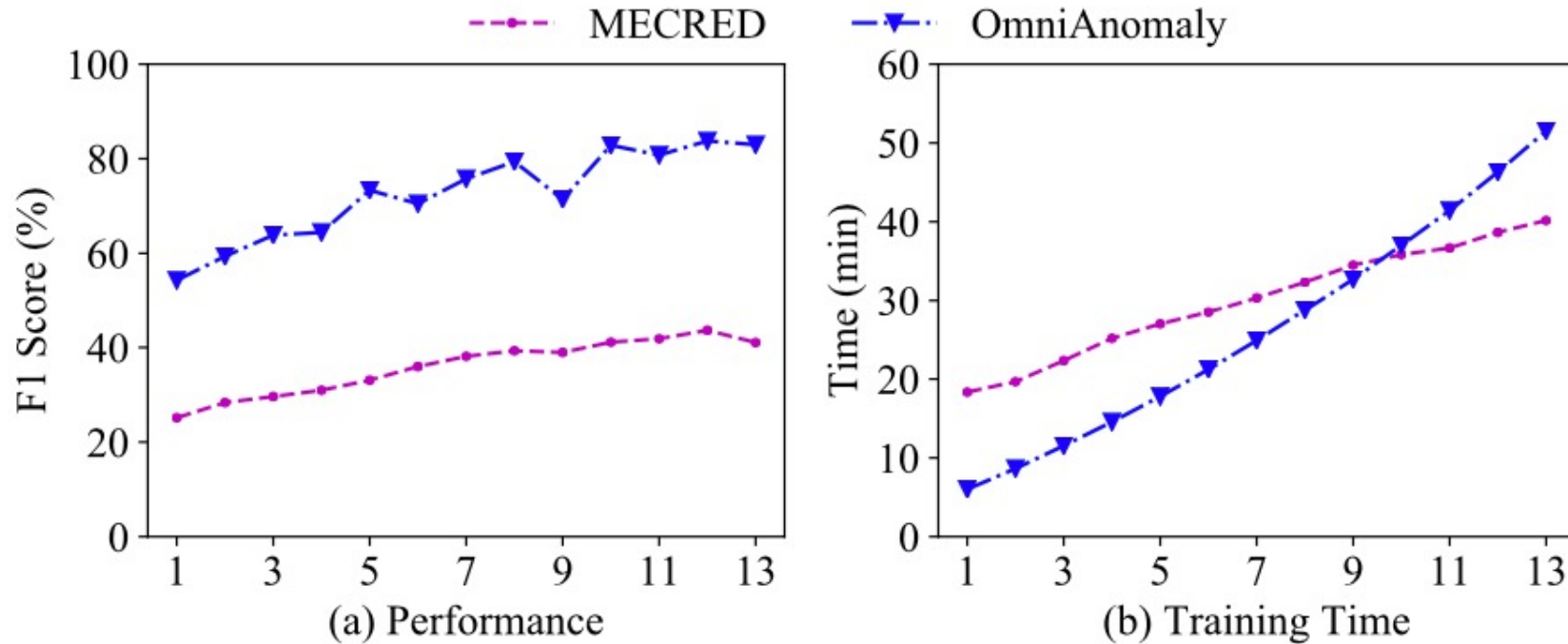
\* denotes UTS anomaly detector, which can be used for MTS by combining it with majority vote

Inappropriate for newly deployed or updated systems

# Incremental Retraining



# Incremental Retraining Cannot Ensure Satisfactory Performance



Non-robustness and considerable training cost

# Outline

The drawback of deep learning based approaches

➔ Long initialization time

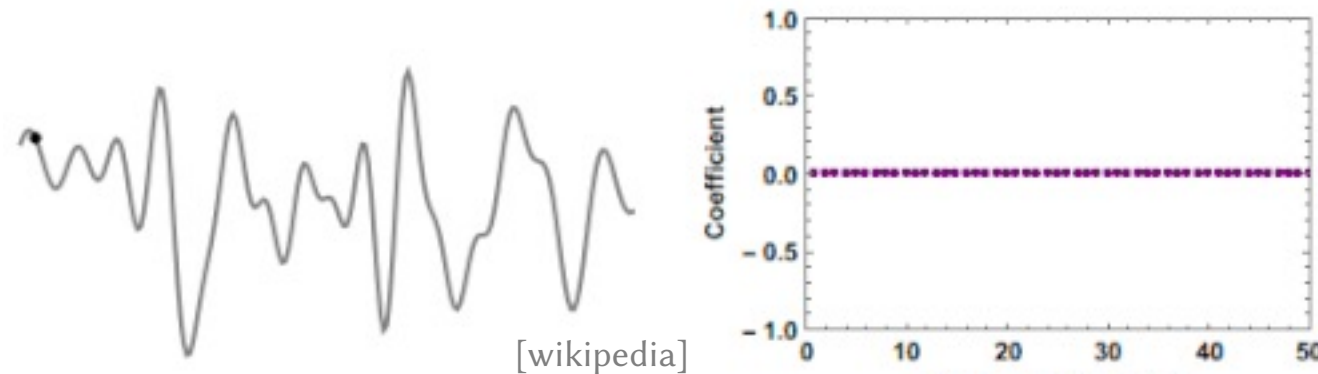
**Our key idea of compressed sensing and its challenges**

JumpStarter approach

Evaluation

# Key Idea: Compressed Sensing (CS)

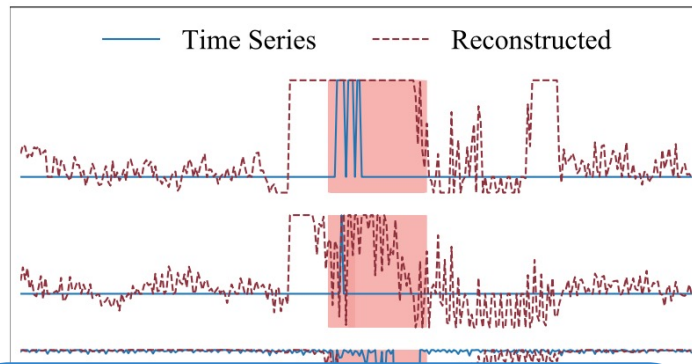
- CS can reconstruct time series with low energy components.
- Anomalies are always high energy components.
- CS uses a fixed-length window to initialize.



First attempt to use CS for multivariate time series anomaly detection

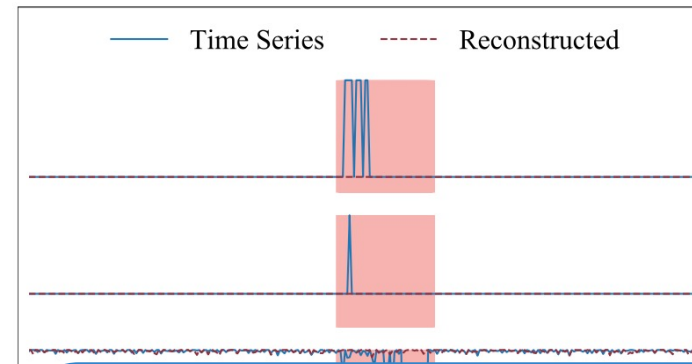
# Two Strawman Solutions Using CS

Examples of CS-based anomaly detection when the MTS is reconstructed as a whole matrix (a) or as separate UTS (b)



(a) Inaccurate reconstruction leads to many false alarms

(a) As a Whole



(b) Low efficiency, cannot capture the complex relationships

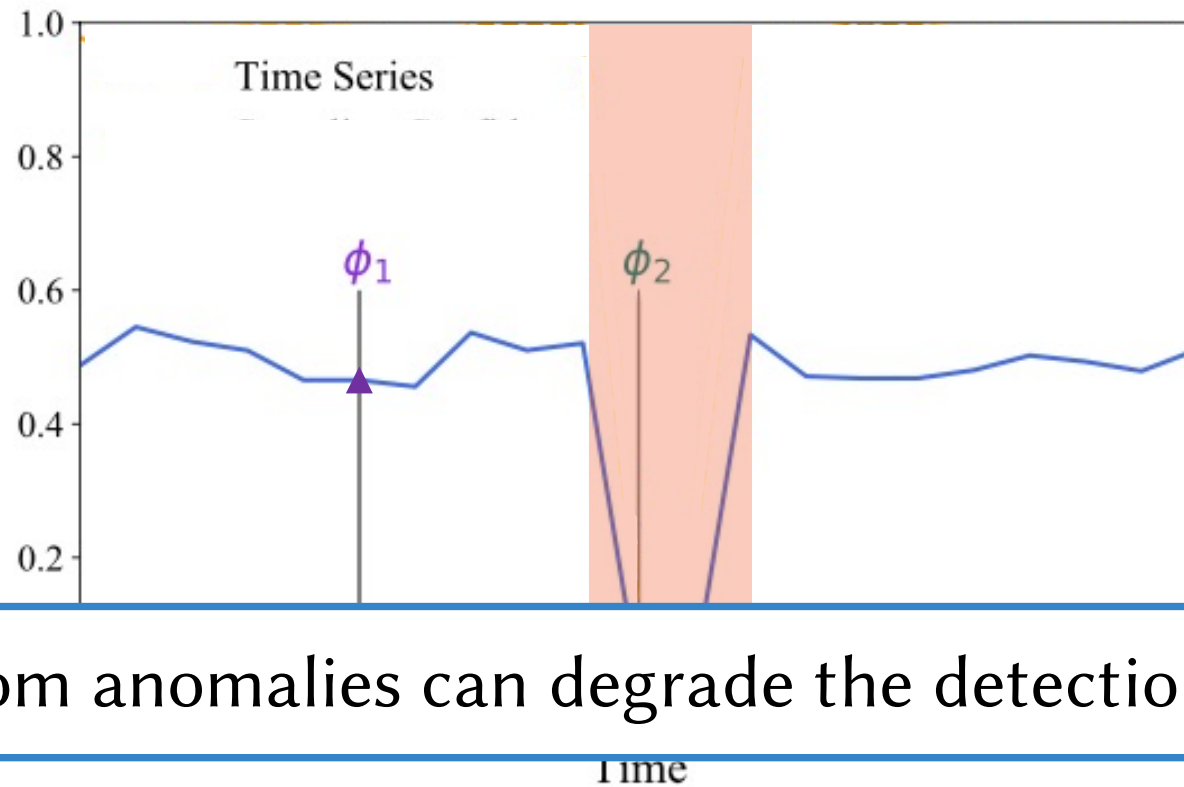
(b) Separately



# Problem of Random Gaussian Sampling

- The sampled matrix: guarantee Restricted Isometry Property (RIP)

[Information Theory 15]



Sampling from anomalies can degrade the detection performance

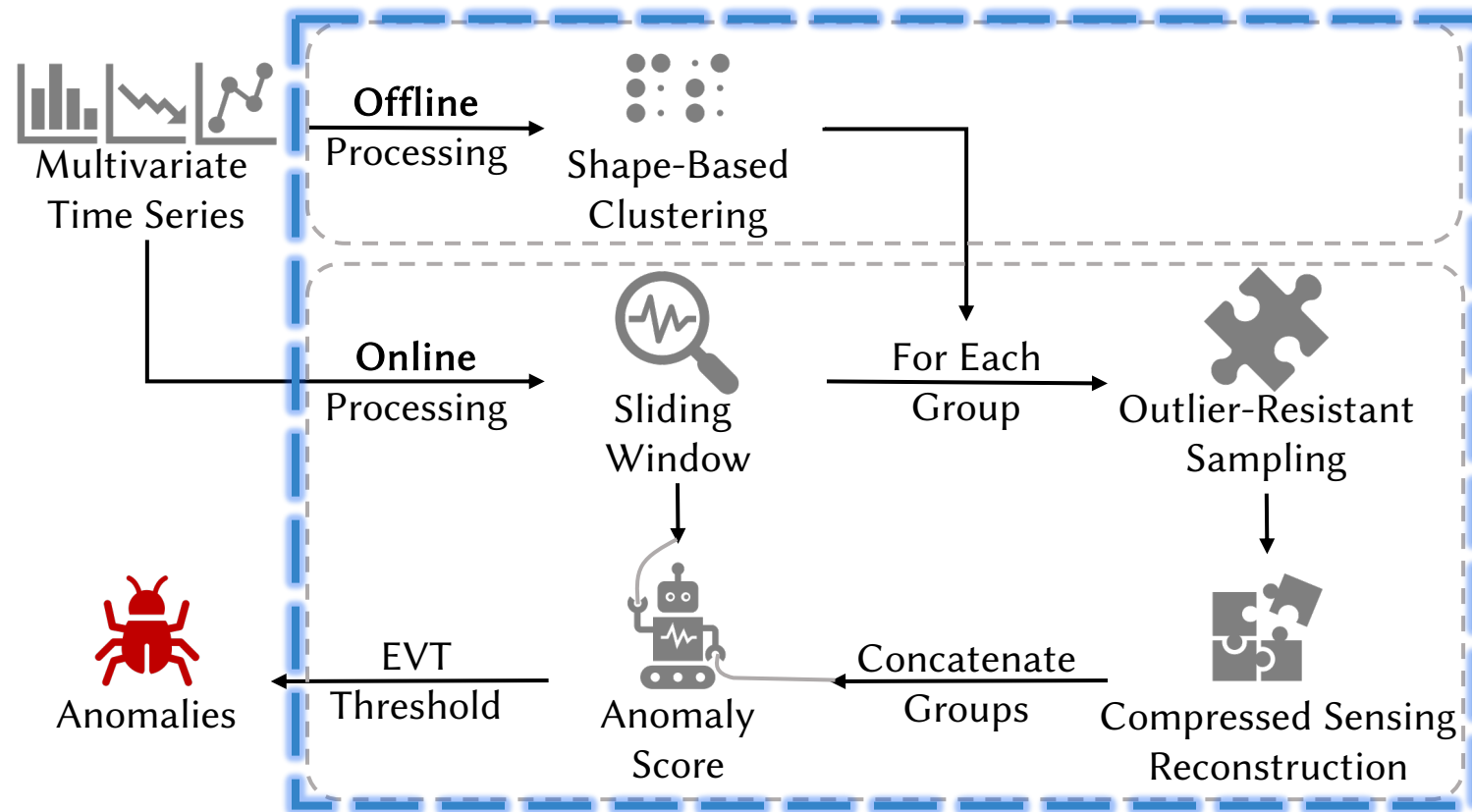
# JumpStarter

Jump-Starting Multivariate Time Series

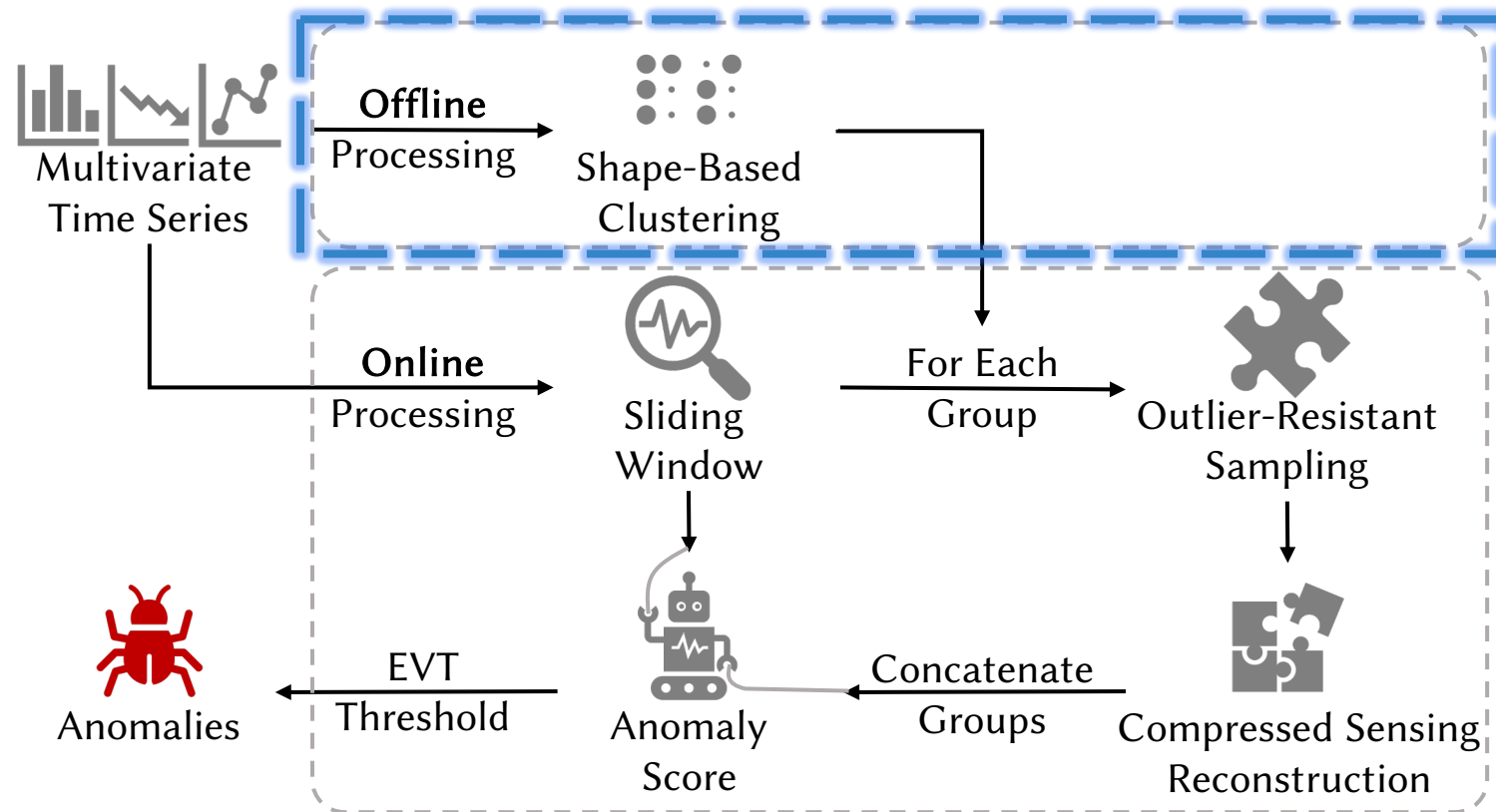
Anomaly Detection

for Online Service Systems

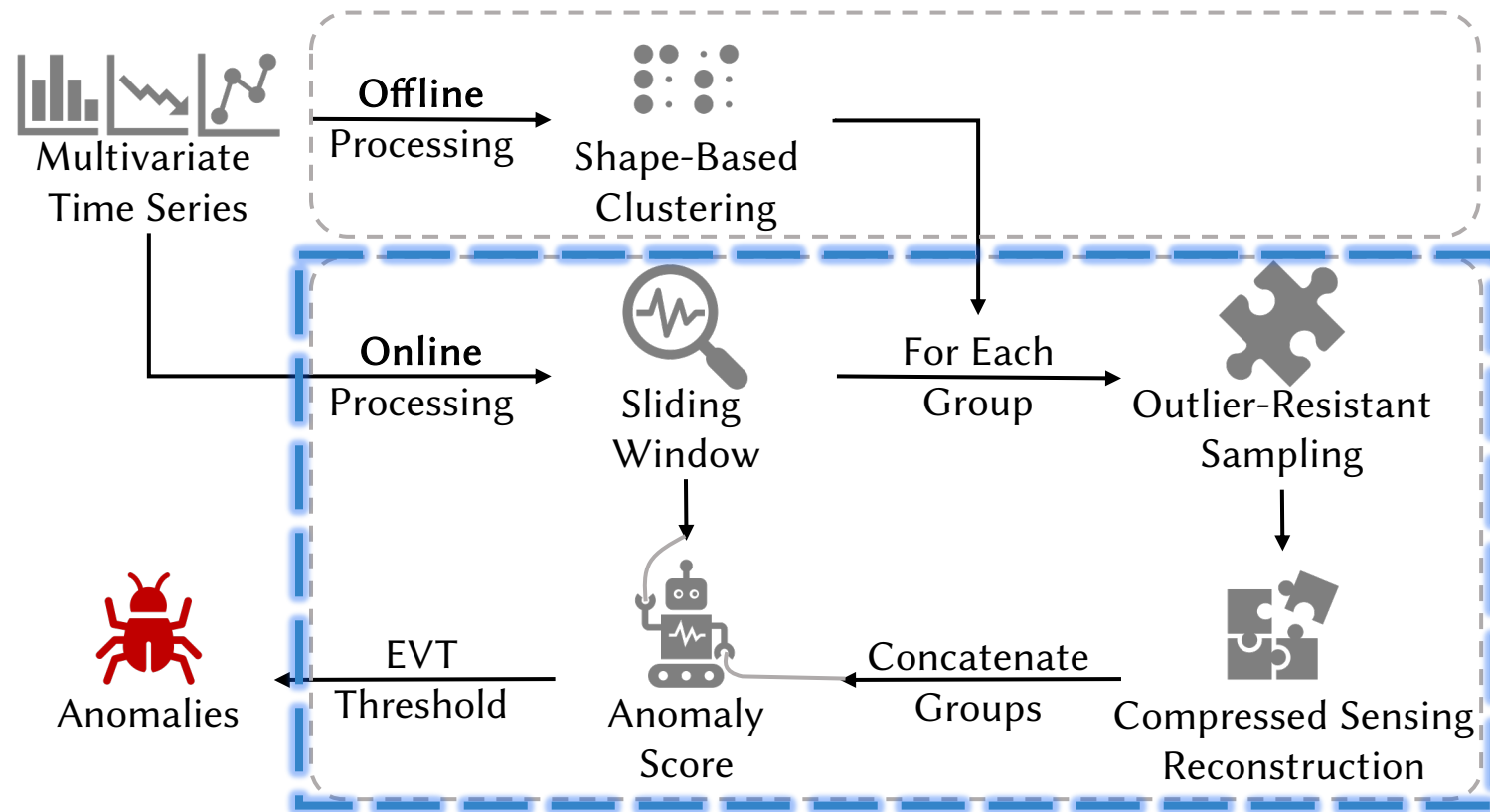
# JumpStarter Overview



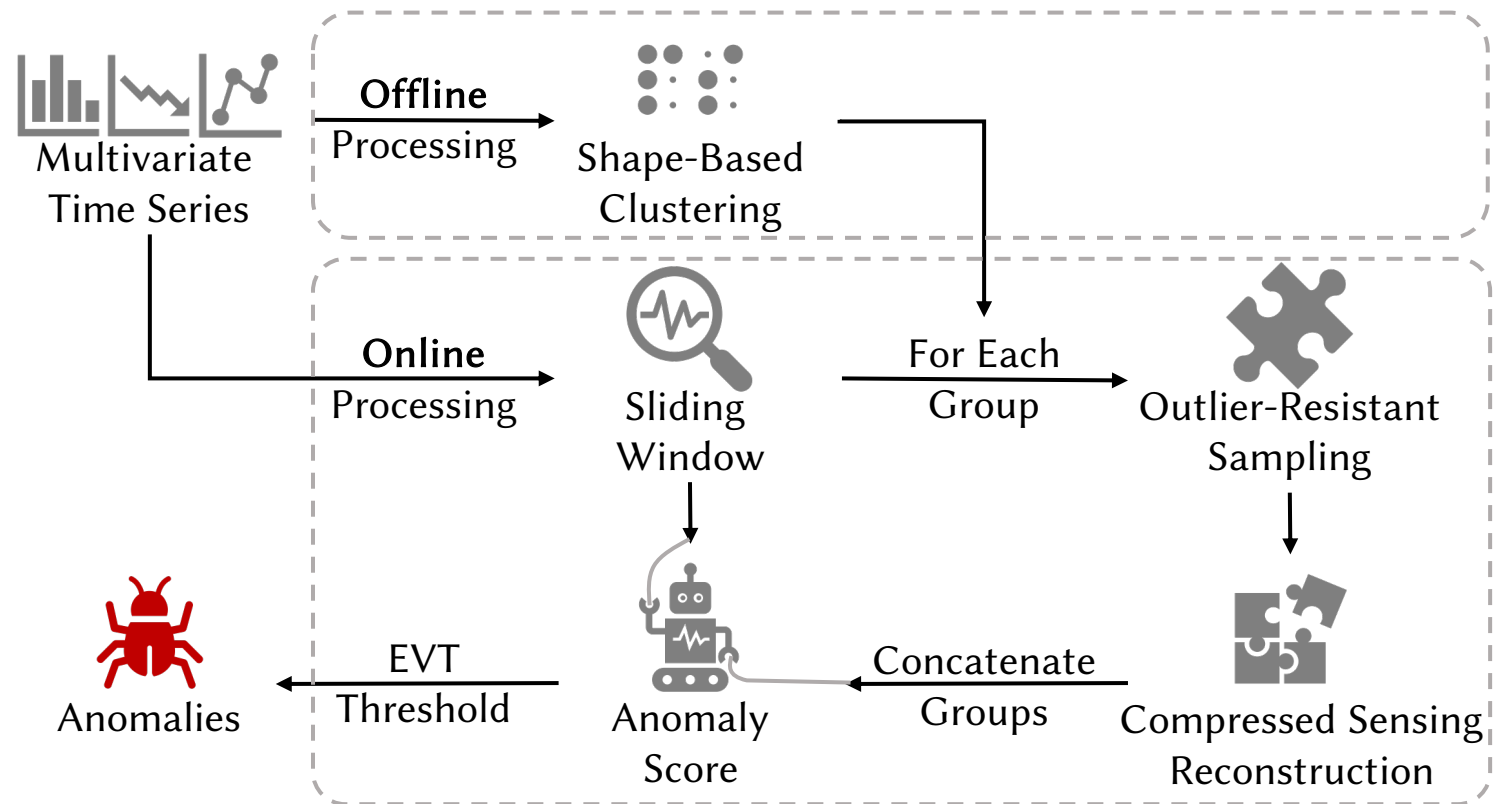
# JumpStarter Overview



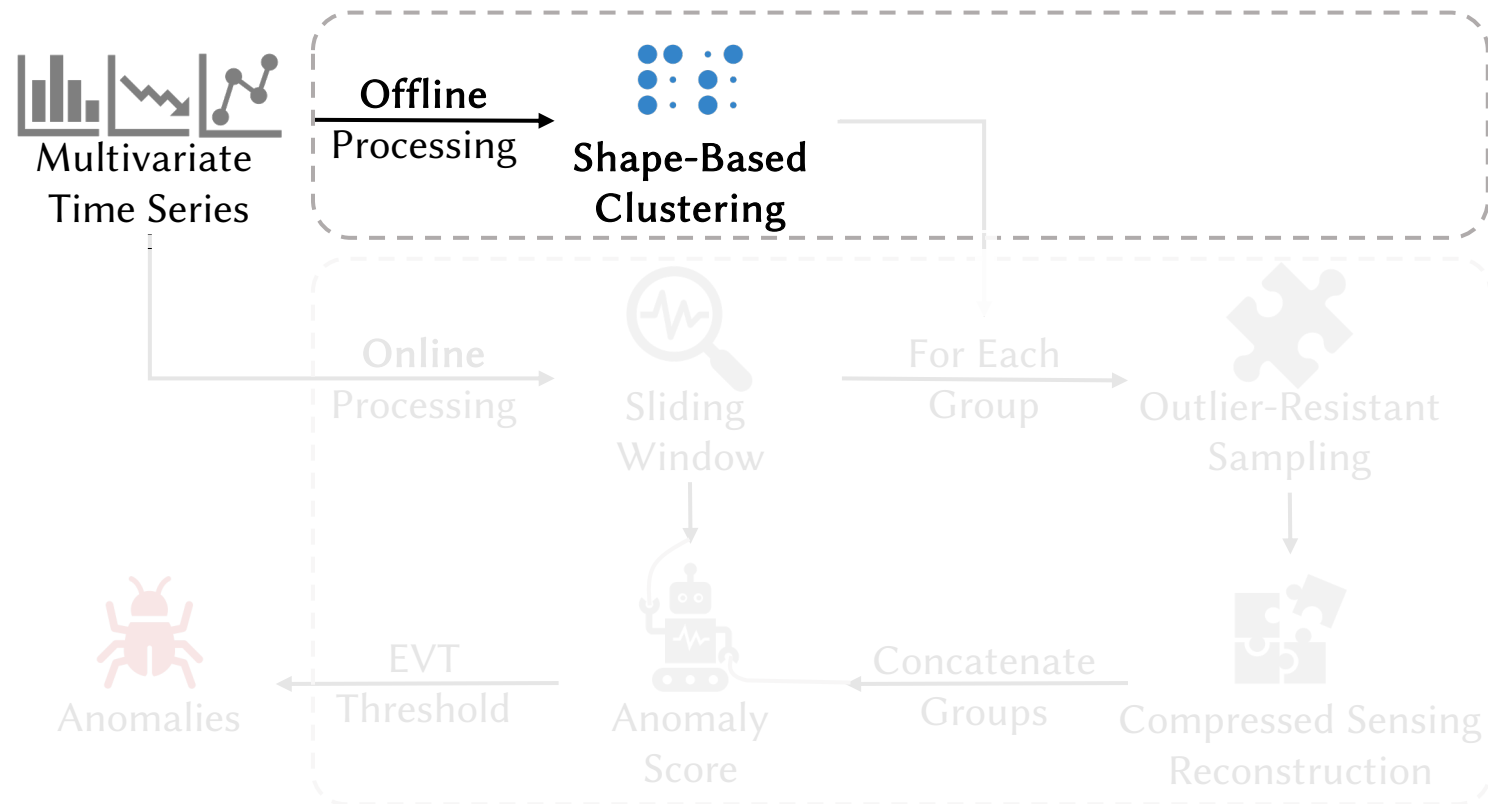
# JumpStarter Overview



# JumpStarter Overview

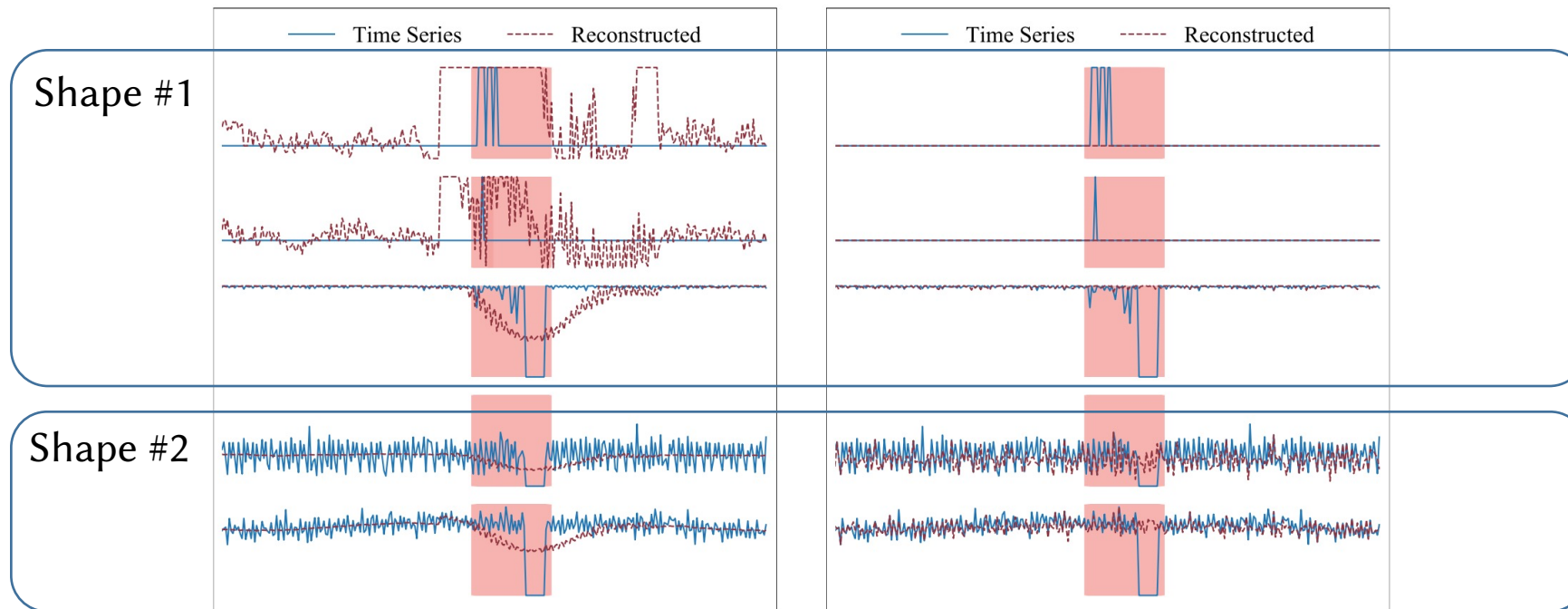


# JumpStarter Offline Processing



# Shape-Based Clustering

- Strawman (a) cannot deal with different shapes of time series
- Shape-based distance [sigmoid15] + hierarchical clustering



(a) As a Whole

(b) Separately



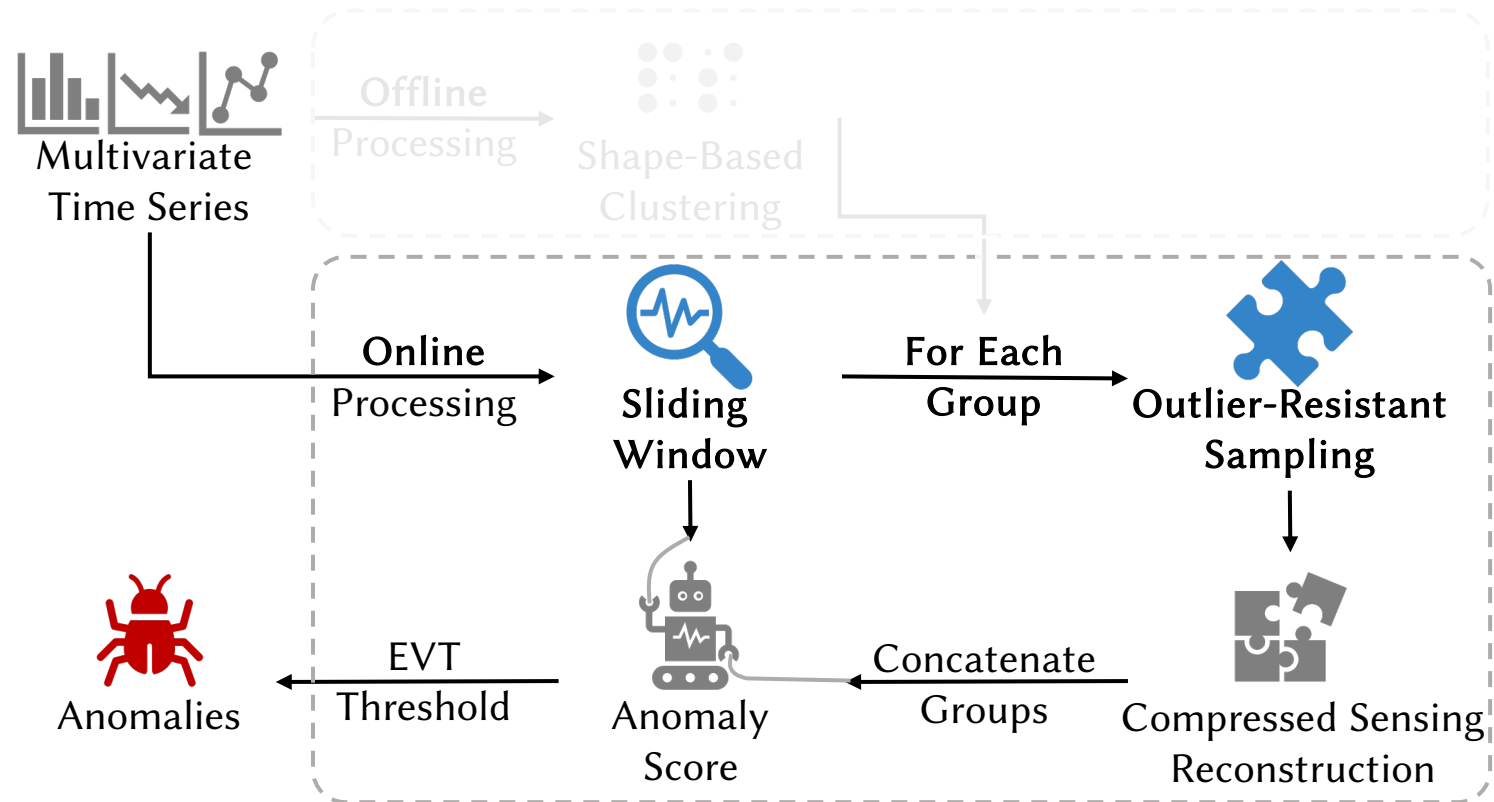
# Shape-Based Clustering

- Strawman (a) cannot deal with different shapes of time series
- Shape-based distance [sigmod15] + hierarchical clustering

An example of clustering the MTS into three clusters

#	Cluster of Univariate Time Series	Explanation
1	rx-pkts-eth0, rx-bytes-eth0	# received packets/bytes
2	tcp-insegs, tcp-outsegs, tx-pkts-eth0	TCP network metrics
3	cpu-ctxt, cpu-user, cpu-system, cpu-nice	CPU utilization metrics

# JumpStarter Online Processing

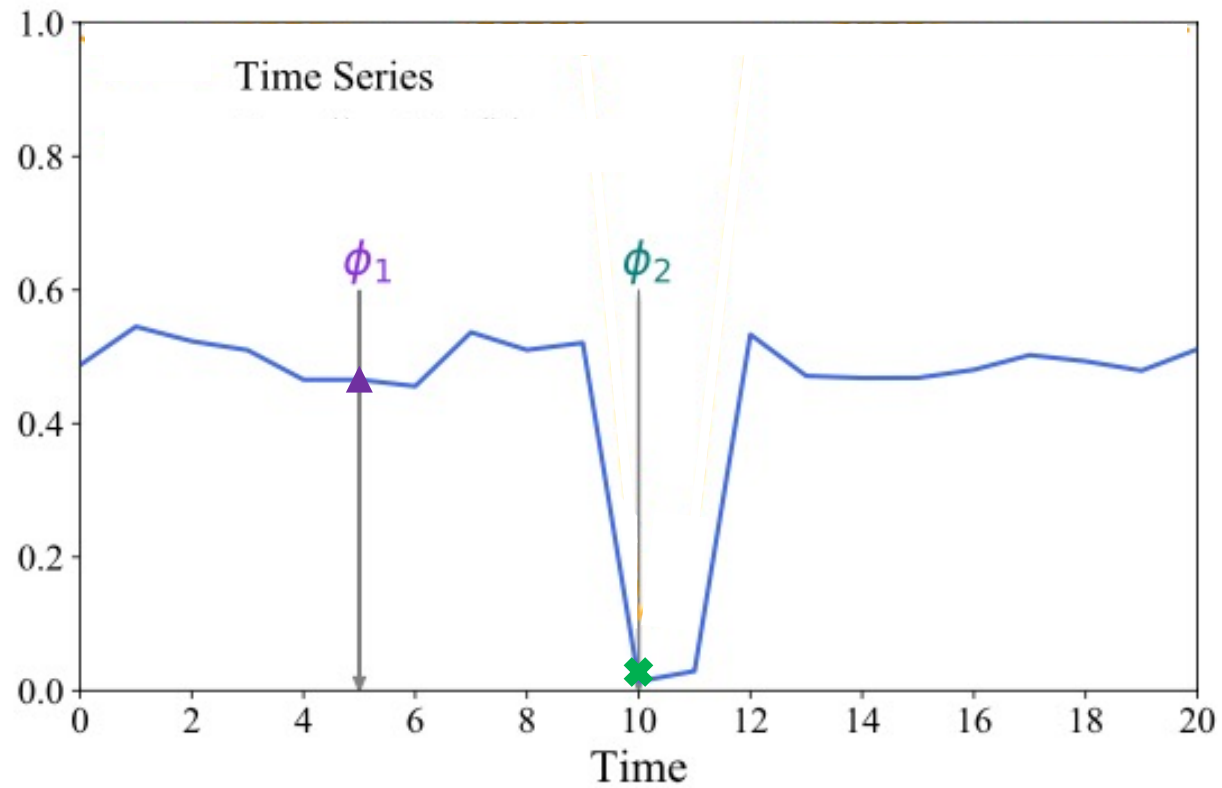


# Outlier-Resistant Sampling

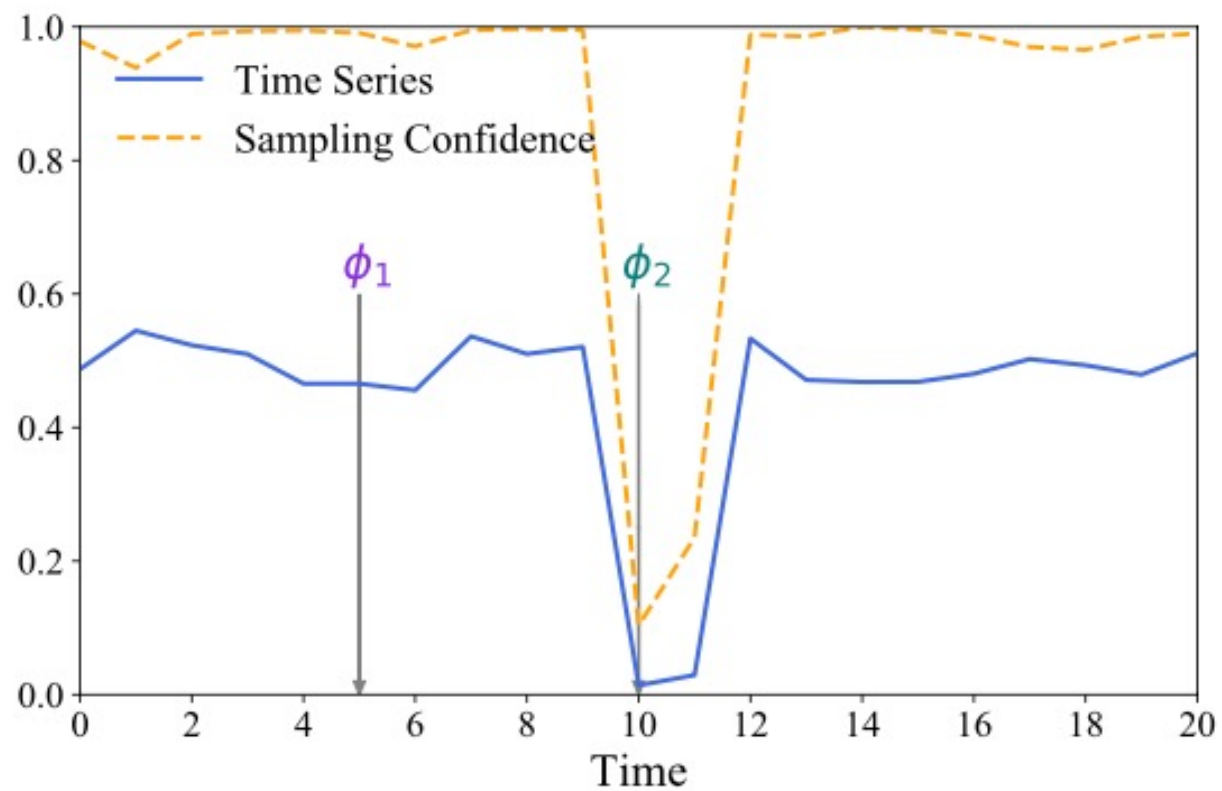
Domain-specific insights:

- Anomalies are usually outliers in an observation window.
- The value of time series has time locality.

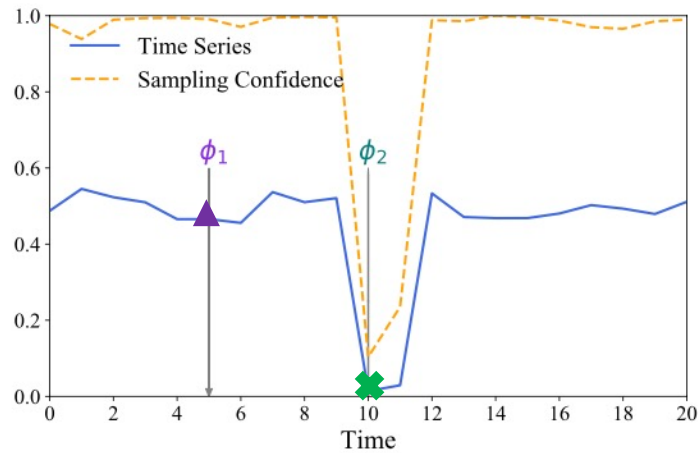
# Outlier-Resistant Sampling



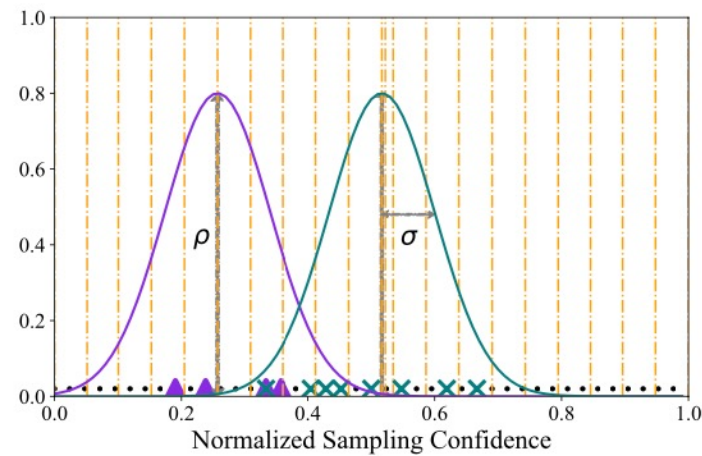
# Outlier-Resistant Sampling



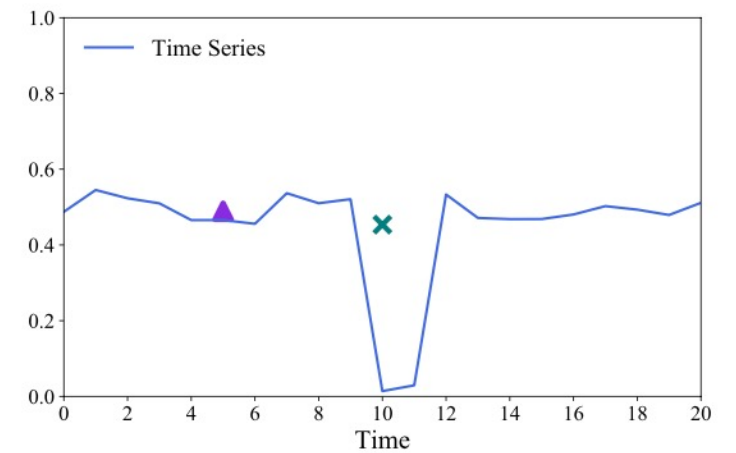
# Outlier-Resistant Sampling



(a) Initialize

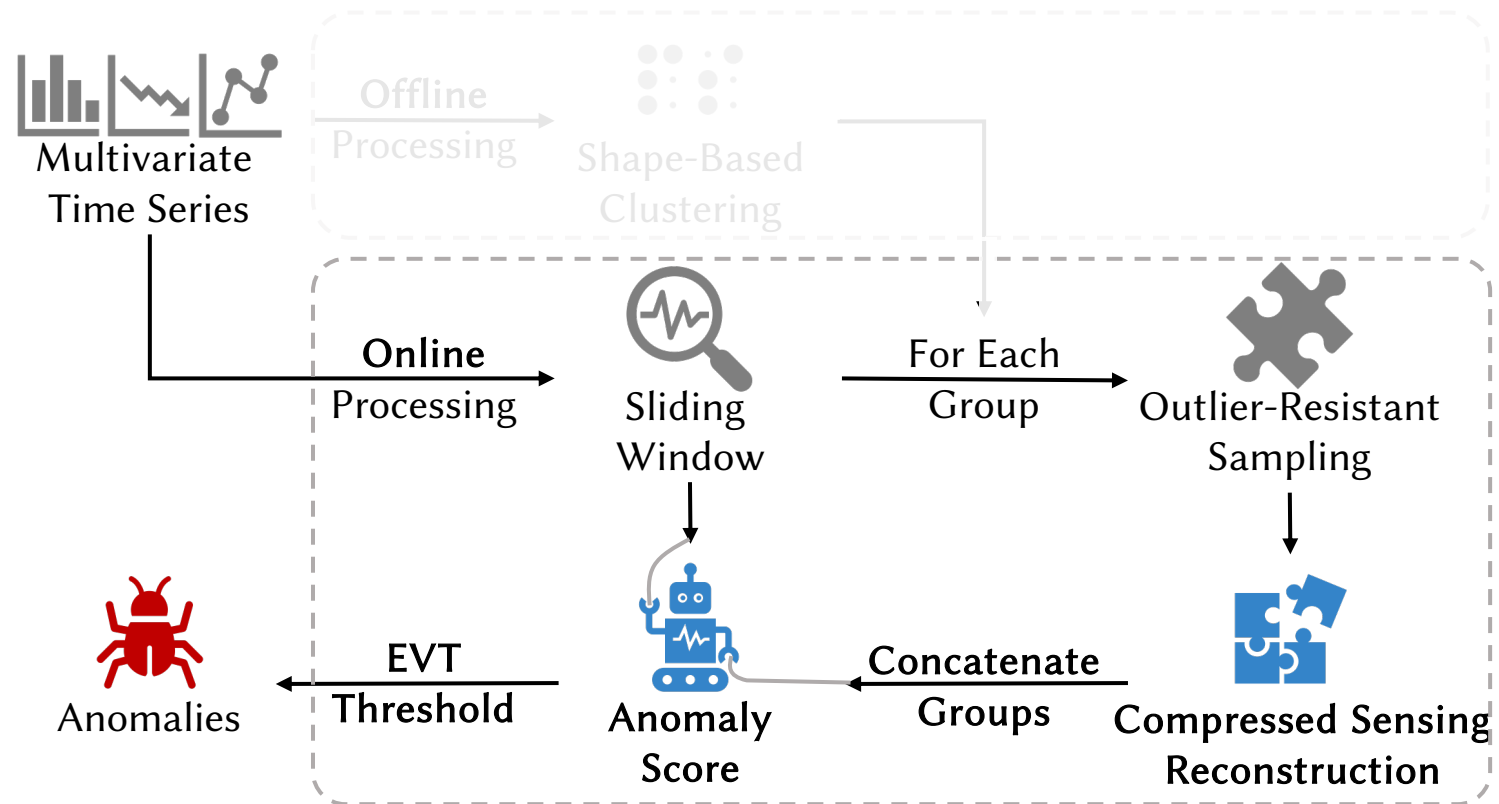


(b) Sampling



(c) Results

# JumpStarter Online Processing

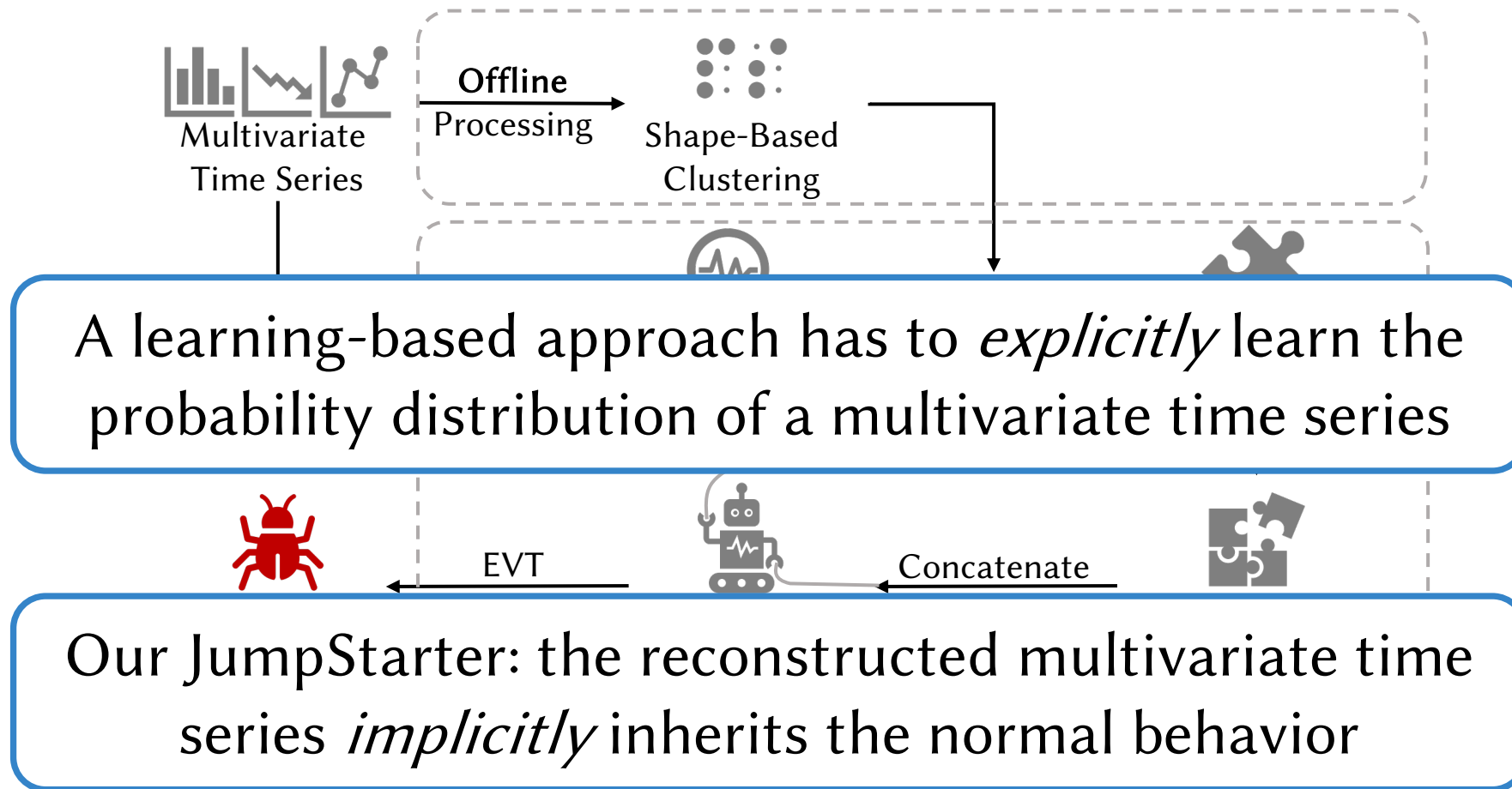


# Compressed Sensing Reconstruction

- Multivariate time series:  $\mathbf{X}_t = [\mathbf{x}_t^1, \mathbf{x}_t^2, \dots, \mathbf{x}_t^n]^T$
- Compressed sensing reconstruction:  $\mathbf{A}\mathbf{X}'_t = \mathbf{B}$  , calculating  $\mathbf{X}'_t$ 
  - A is calculated as:  $\mathbf{A} = \phi(\mathbf{D} \otimes \mathbf{D}^T)$ , D is the transform of  $\mathbf{X}_t$
  - B is the sampling result
- Calculation: CVXPY (convex optimization tool) [JMLR16]
- Anomaly score: measuring the differences between  $\mathbf{x}_t$  and  $\mathbf{x}'_t$
- Choosing threshold: Extreme Value Theory (EVT) [KDD17]



# JumpStarter Initialization Time: 20 mins



# Outline

The drawback of deep learning based approaches

→ Long initialization time

Our key idea of compressed sensing and its challenges

→ Reconstruction & Sampling

JumpStarter approach

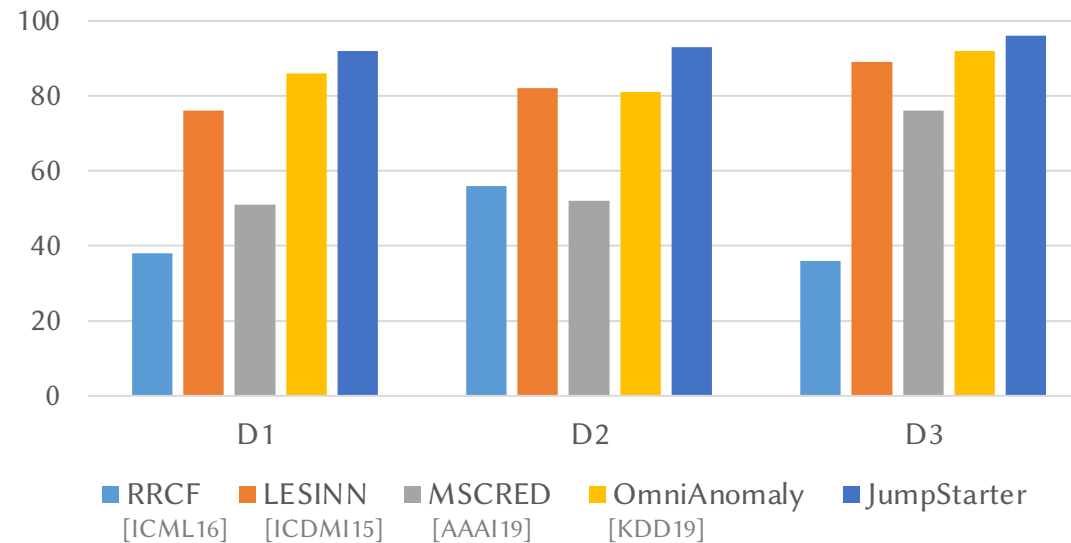
→ Shape-Based Clustering & Outlier-Resistant Sampling

**Evaluation**

→ Company A (28 service systems) & Company B (30 service systems)

# Evaluation: Accuracy

Average F1 Score of JumpStarter and baseline approaches

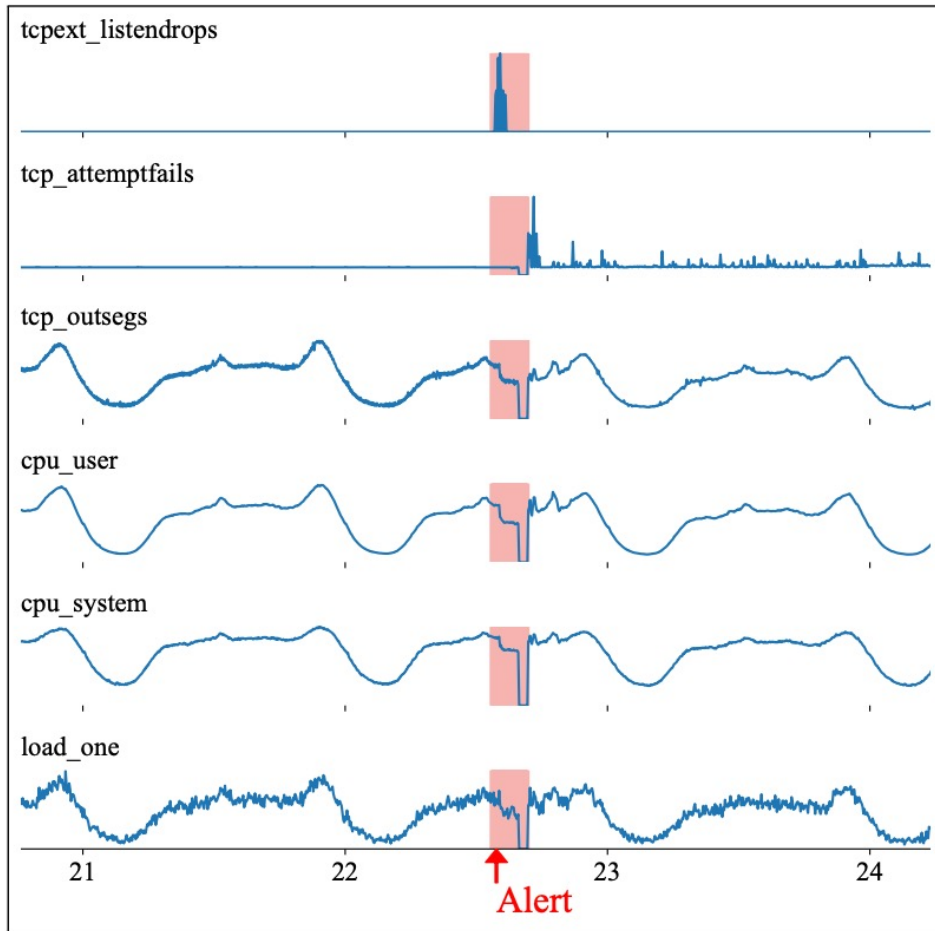


# Evaluation: Efficiency

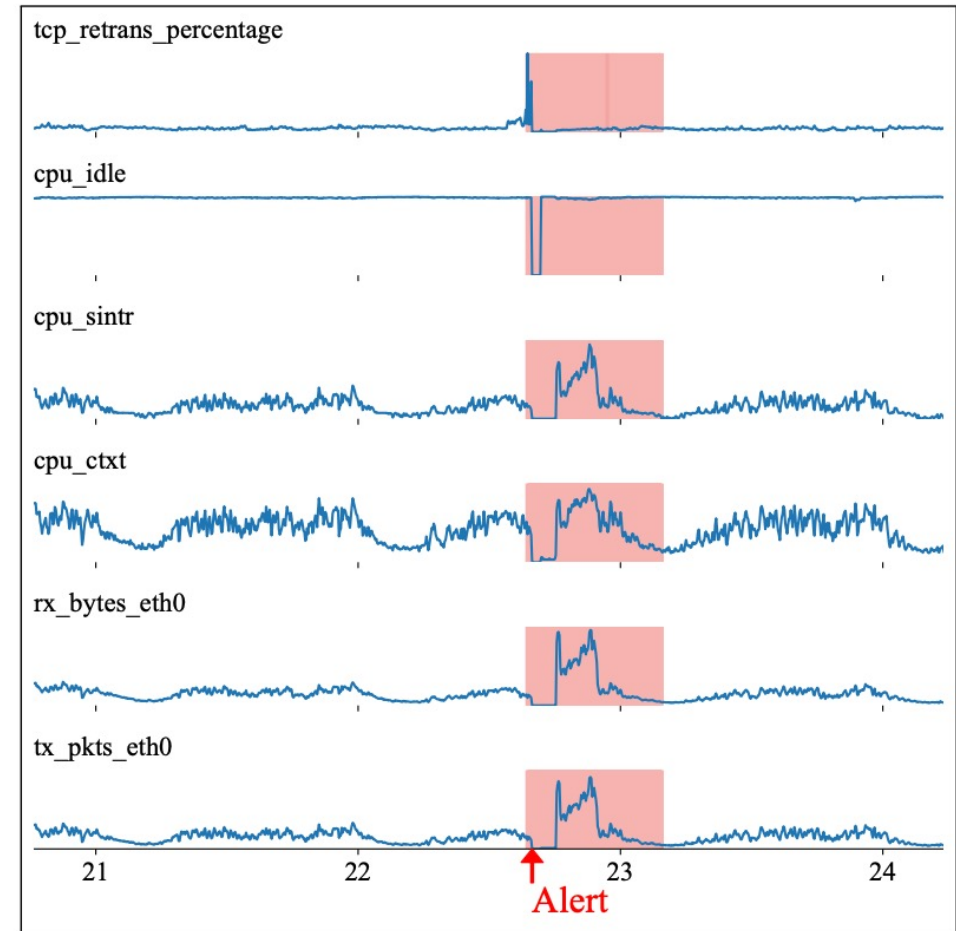
The initialization time (IT) and detection time (DT) comparison

Approach	RRCF	LESINN	MSCRED	Omni- Anomaly	<i>JumpStarter</i>
IT (min)	20	20	>86400	>86400	20
DT (ms)	41.24	118.63	122.82	191.86	127.13

# Case Study



(a) Network Issue



(b) Software Change

# Conclusion

To adapt to frequent changes in online service systems, multivariate time series, anomaly detection should be robust and can be **quickly initialized**.

JumpStarter adopts the **Compressed Sensing** technique

- Reconstruction challenge → **Shape-based clustering**
- Sampling challenge → **Outlier-resistant sampling**

## Evaluation

- Real-world online service systems of two Internet companies
- Achieving an average F1 score of 94.1%, initialization time 20 minutes
- <https://github.com/NetManAIOps/JumpStarter>

# Thanks

[mmh16@mails.tsinghua.edu.cn](mailto:mmh16@mails.tsinghua.edu.cn)