fKPISelect: Fault-Injection Based Automated KPI Selection for Practical Multivariate Anomaly Detection

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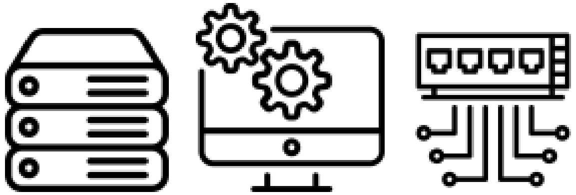
Outline

- Studying the problem of KPI selection for practical KPI-based multivariate anomaly detection in cloud systems
  - KPI-based Multivariate Time Series Anomaly Detection
  - There are a larger number of KPIs in practice than those in datasets and the SOTA model has a detection accuracy loss when the number of KPIs is large
- Proposing fKPISelect, a fault-injection-based automated KPI selection mechanism.

KPI Anomaly Detection

Components on cloud systems

- Software Programs
- Virtual Machines
- Physical Servers
- Network Devices
- …

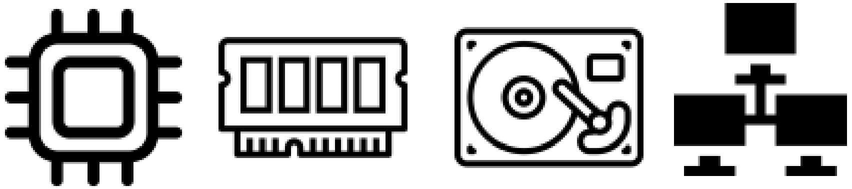


Error Causes Anomaly

Anomaly Indicates Error

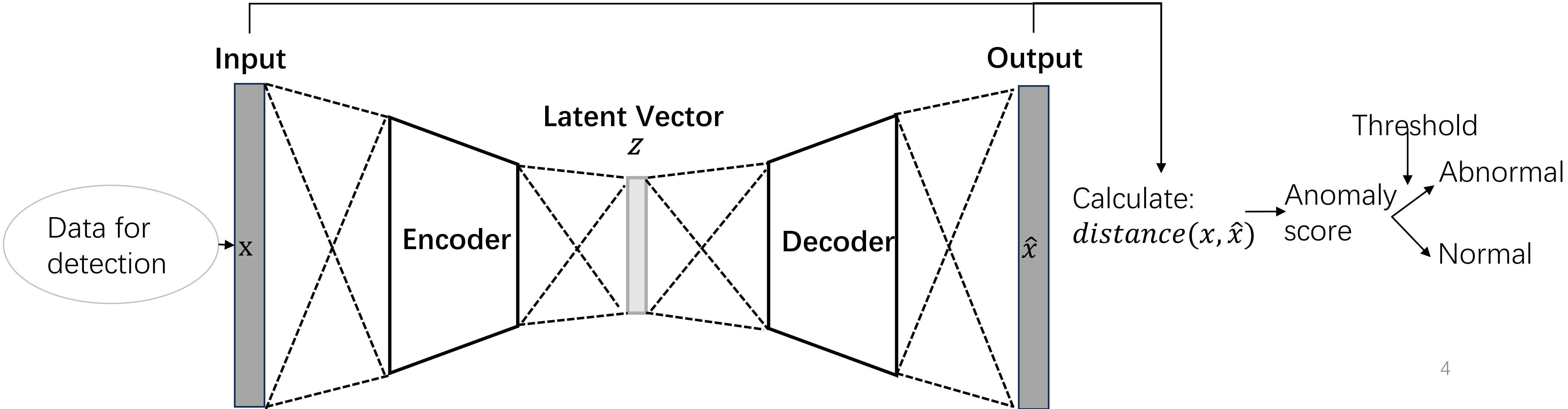
Key Performance Indicators (KPIs) of components

- CPU Utilization
- Memory Utilization
- Disk usage
- Network latency, bandwidth
- Service response time, throughput
- …



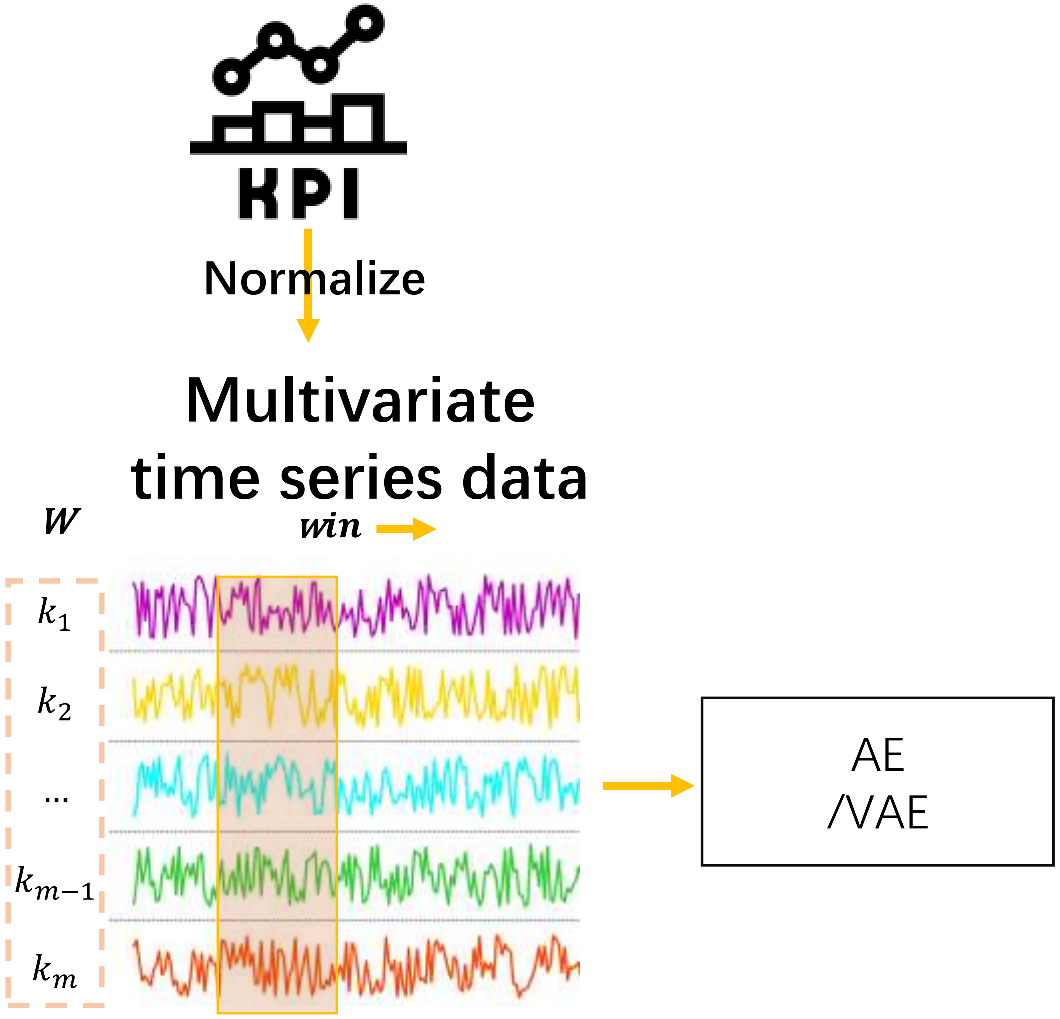
AI-based Anomaly Detection

- Based on Autoencoder (AE)
- Learn representations of normal data patterns
- Encountered data patterns ➡️ Reconstruct well
- Anomalous data patterns ➡️ Reconstruct poorly

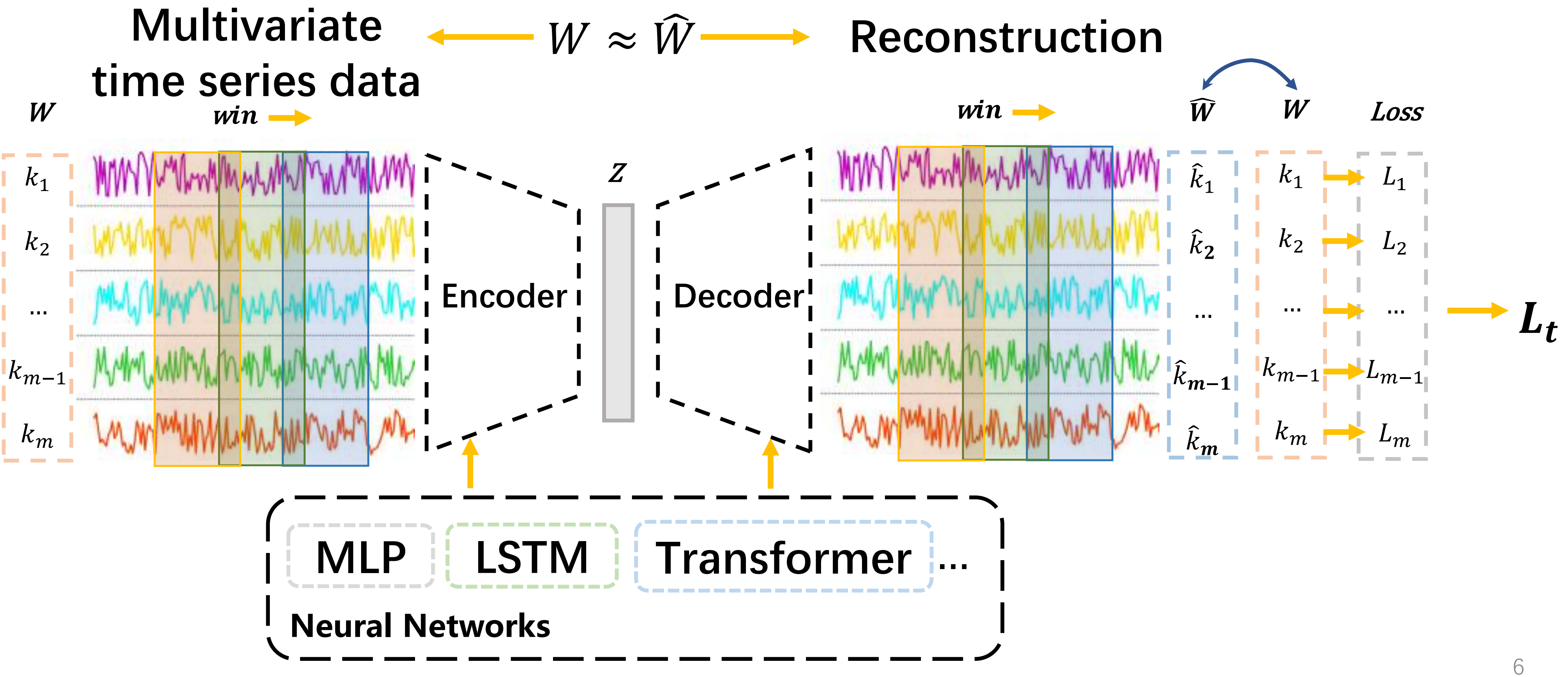


Multivariate Time Series Anomaly Detection

- Sliding windows are used to cut part of the data
- The multiple time series are treated equally with the same weight.
- Anomaly score can be seen as the average reconstruction loss of each time series: $L_t = \frac{1}{m}\sum_{i=1}^{m}\left\|k_{i,t} - \widehat{k_{i,t}}\right\|_2^2$
- Previous models:
  - OmniAnomaly (KDD’19), USAD(KDD’20), AnomalyTransformer(ICLR’22), Uni-AD(ISSRE’22)……



AI-based Multivariate Time Series Anomaly Detection



From experiments to real-world systems

- Models directly applied to real-world systems does not perform as well as reported in experimental datasets.
- There's a gap between existing datasets and data in practice.
- Experimental Datasets
  - Well-preprocessed
  - Limited KPI numbers
  - Lack KPI metadata

Data	KPI Number	KPI Description in Dataset
SMD (KDD'19)	38	CPU, network and memory usage, etc.
CTF_data (INFOCOM'21)	49	CPU, memory, sockets, UDP, TCP
TC_data (ISSRE'22)	11	CPU usage, memory usage, and network speed, etc
FluxRank (ISSRE'19)	47	CPU, Disk, Memory, Network, and OS kernel

Gap Between Existing Datasets and Data in Practice

- Data in Practice
  - Complex & Diverse
- Example: Node Exporter Data
  - Collected by Prometheus
  - Visualized by Grafana

Data	KPI Number	KPI Description in Dataset
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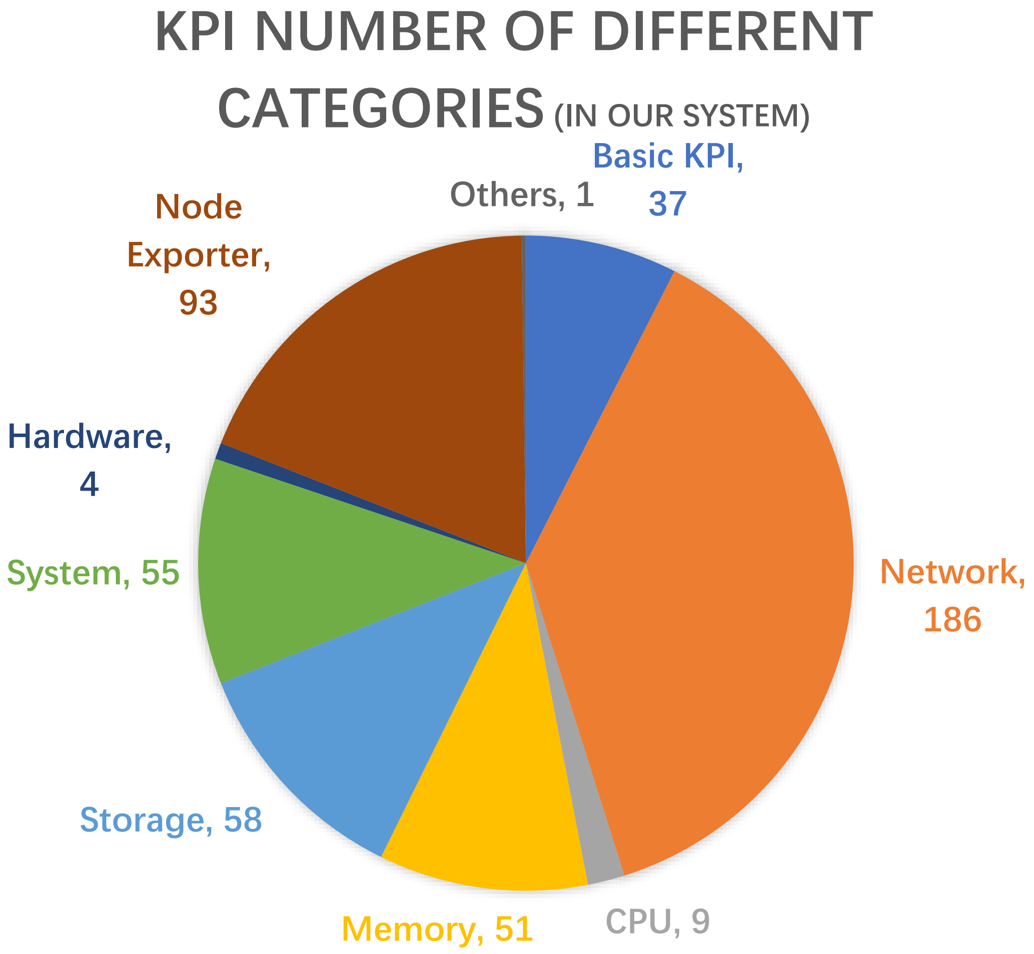
Node Exporter	**493**	**All KPIs provided by node exporter**

Gap Between Existing Datasets and Data in Practice

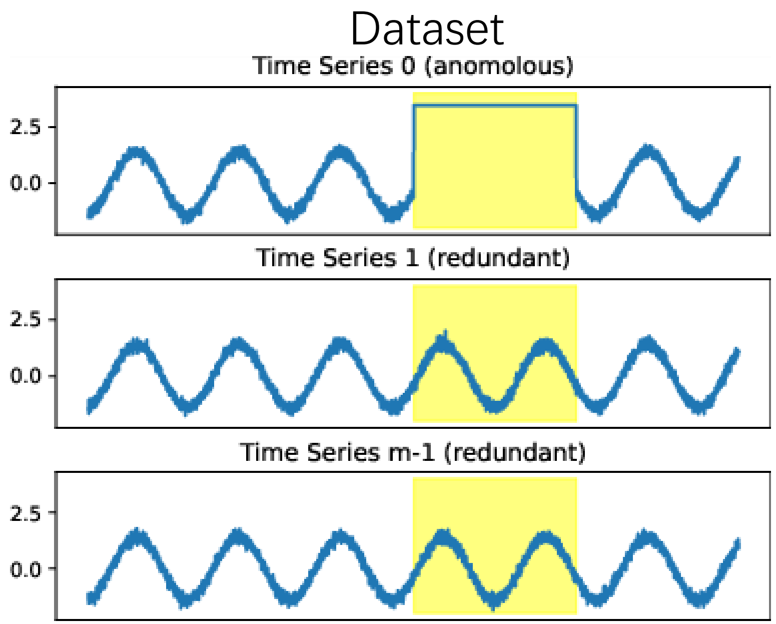


The figure is from Grafana

Accuracy loss of TSAD: Experiment

Phenomenon: Current multivariate TSAD models have a detection accuracy loss when there are a huge number of KPIs.

- Synthetic datasets
  - With various KPI numbers
  - Partial KPIs are affected by errors, other KPIs remain normal
- SOTA Model: AnomalyTransformer (ICLR’22)

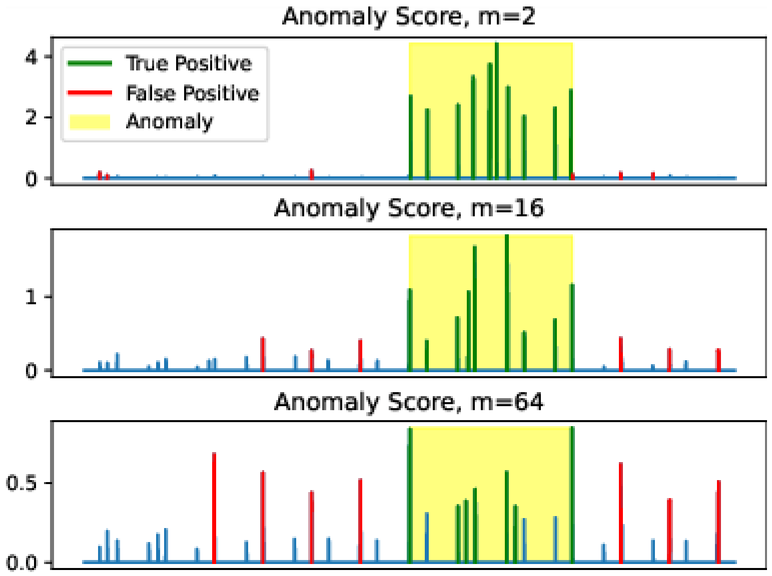


Performance loss of TSAD: Experiment

Phenomenon: Current multivariate TSAD models have a detection accuracy loss when there are a huge number of KPIs.

- Result
  - When the number of KPIs increases, the anomaly scores during the error-present period become not so outstanding, causing more false positives.

Anomaly score & Prediction Results



KPI number is m

Performance loss of TSAD: Explanation

Phenomenon: Current multivariate TSAD models have a detection accuracy loss when there are a huge number of KPIs.

Unsupervised learning: Anomaly scores can only be calculated as the averages of the reconstruction loss values of all KPIs.

$$L_t = \frac{1}{m} L_{i,t}$$

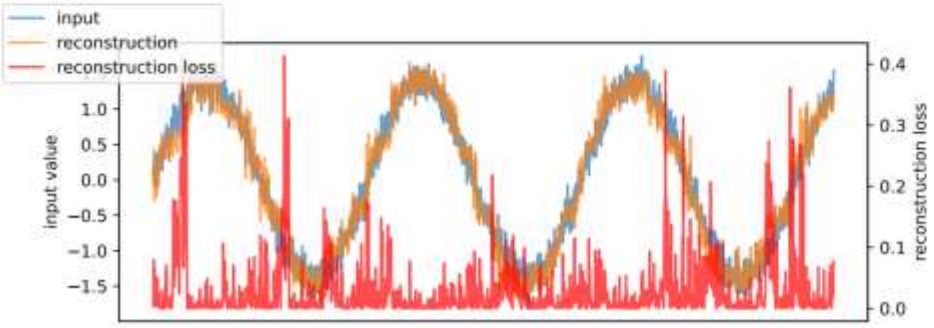
Imprecise Reconstruction: Deviation exists in the reconstruction loss of each KPI due to noises.

$$n_i \sim N(\mu_i, \sigma_i)$$

Deviation accumulates:

$$n = \sum_{i=0}^{m} n_i \sim N\left(\sum_{i=0}^{m} \mu_i, \sum_{i=0}^{m} \sigma_i^2\right)$$

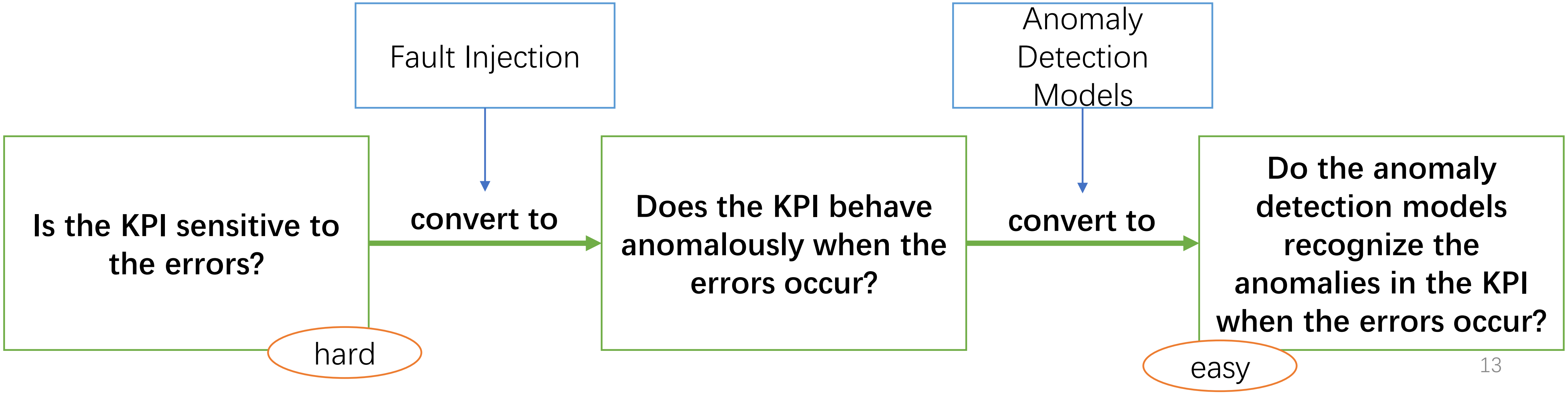
(assume the deviations are in normal distribution)



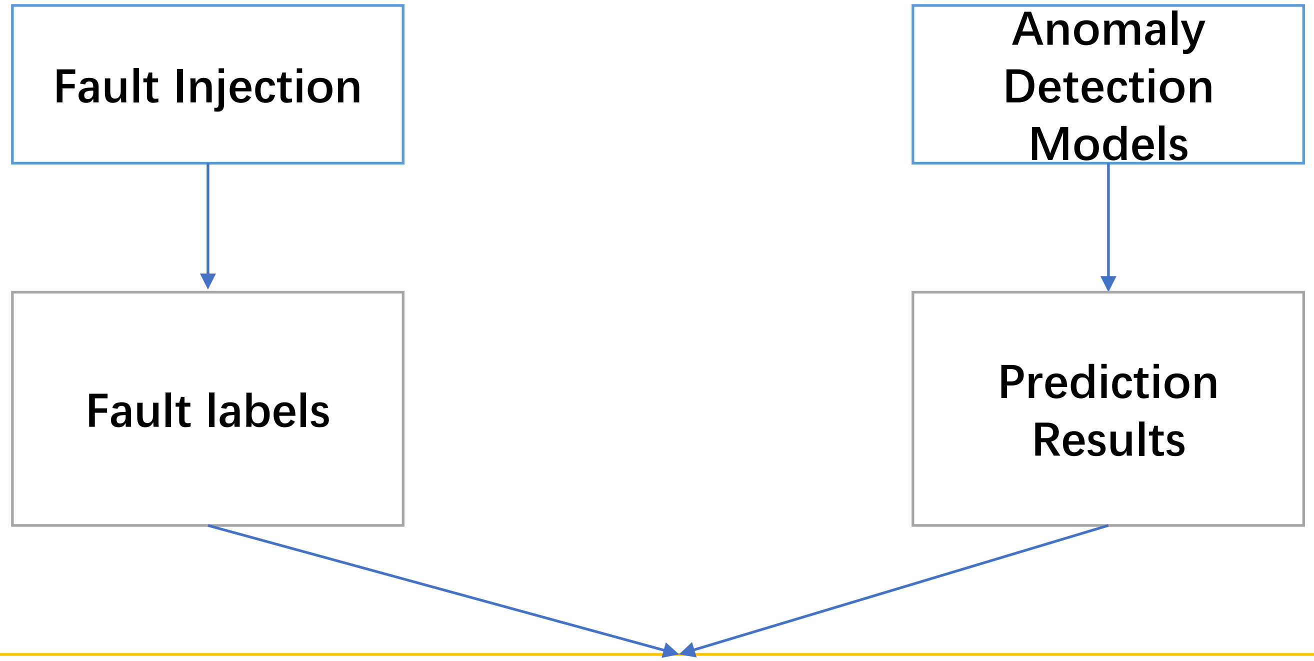
fKPISelect: Fault Injection-Based KPI Selection

- **Problem: KPI selection for practical KPI-based multivariate anomaly detection in cloud systems**
- Solution:

For each KPI, consider:



fKPISelect: Fault Injection-Based KPI Selection

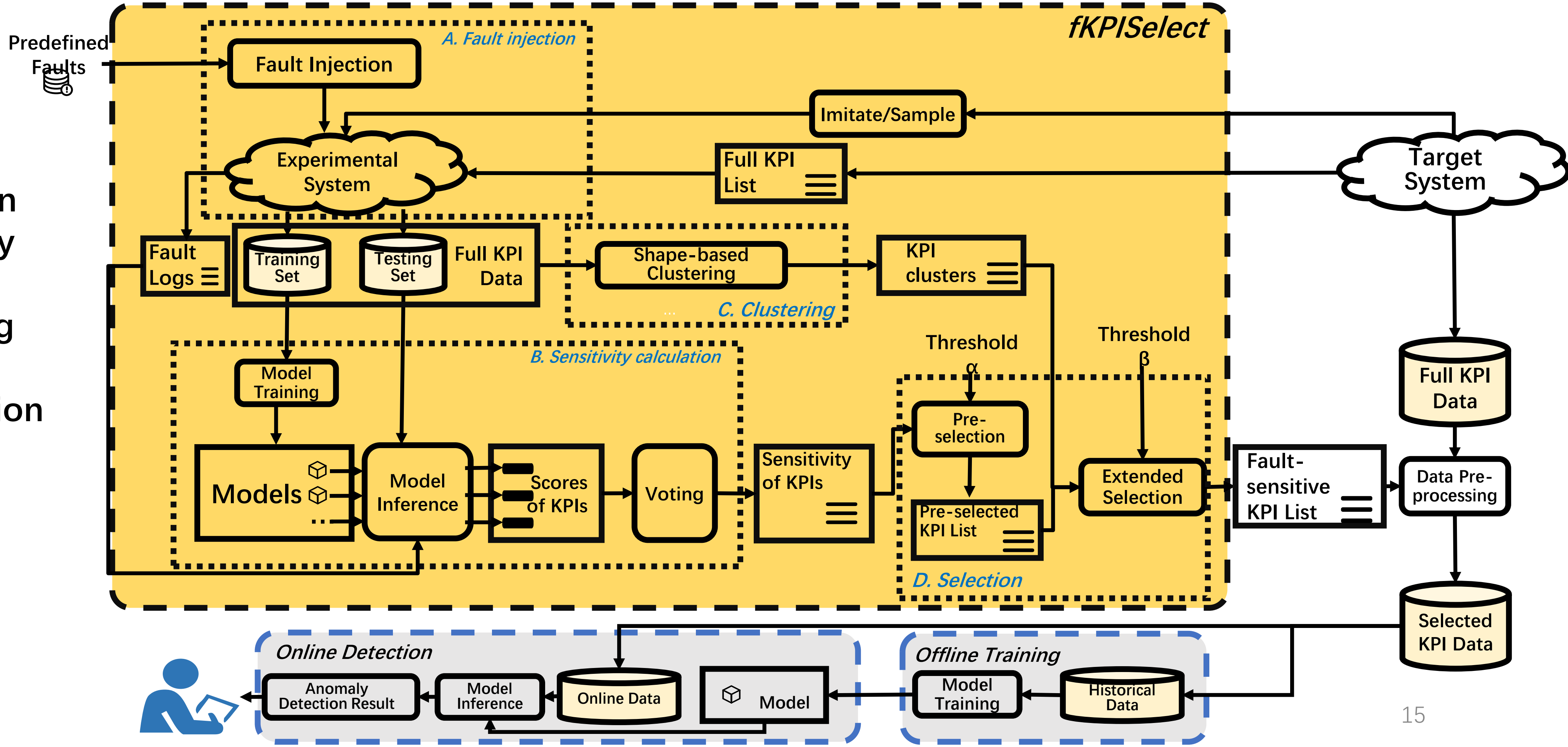


quantitative criterion of KPI's Sensitivity to Errors:

$$\text{sensitivity of KPI i} = \frac{\textit{The number of errors correcly predicted by the model with KPI i}}{\textit{The total number of injected errors}}$$

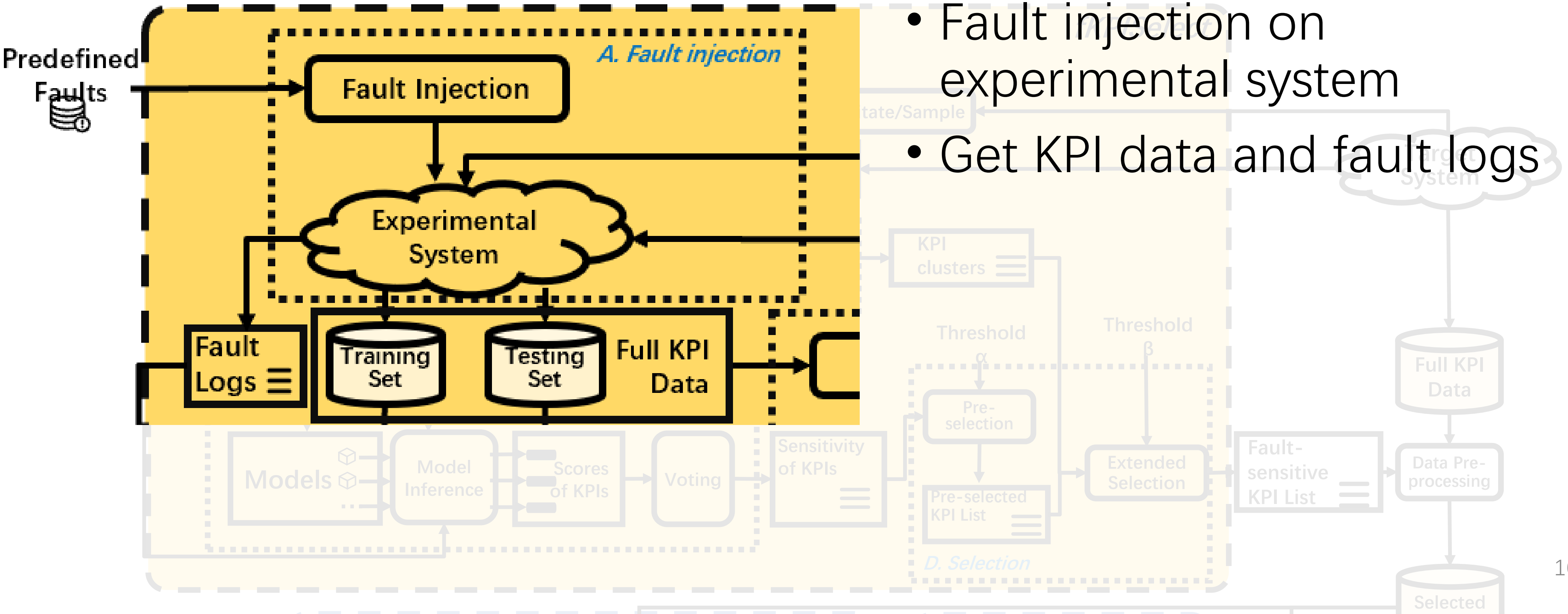
fKPISelect: Fault Injection-Based KPI Selection

(1) Fault Injection
(2) KPI Sensitivity Calculation
(3) KPI Clustering
(4) KPI Selection
Anomaly Detection



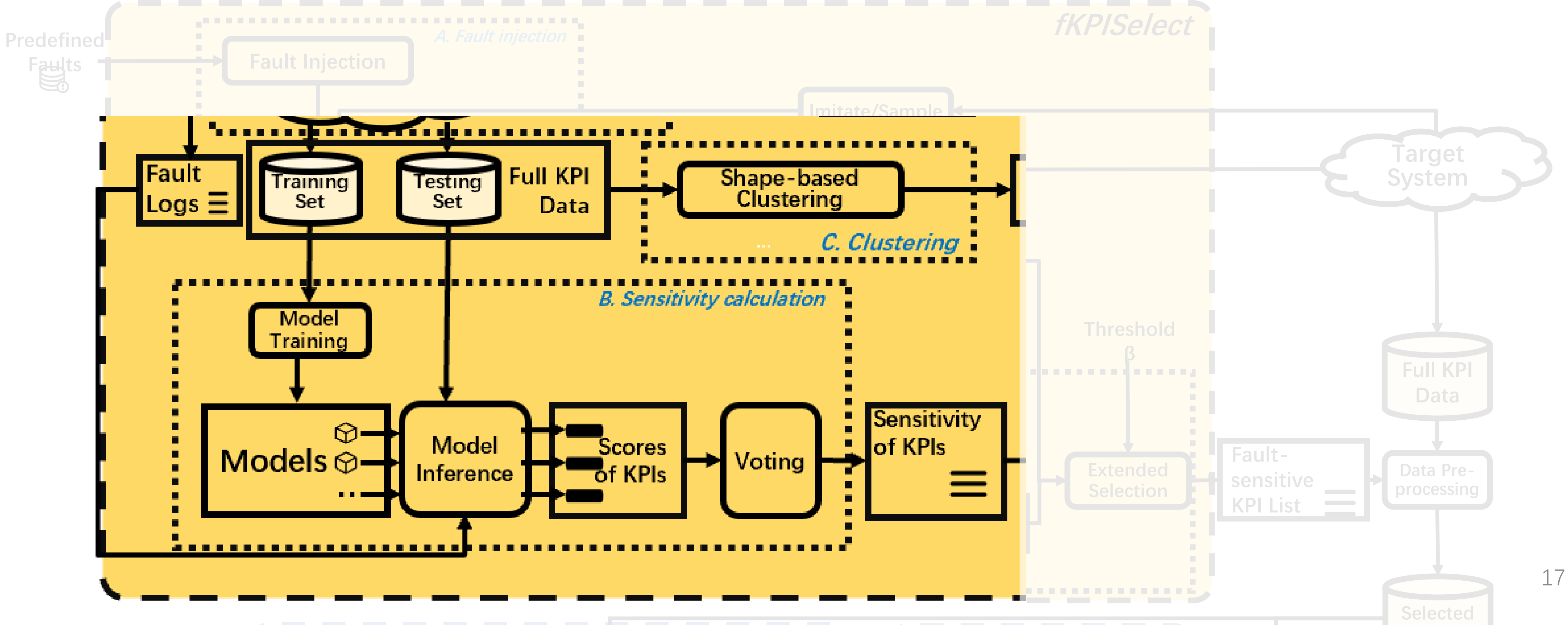
fKPISelect: (1) Fault Injection

- Define fault types and plan fault injection configurations in detail
- Fault injection on experimental system
- Get KPI data and fault logs



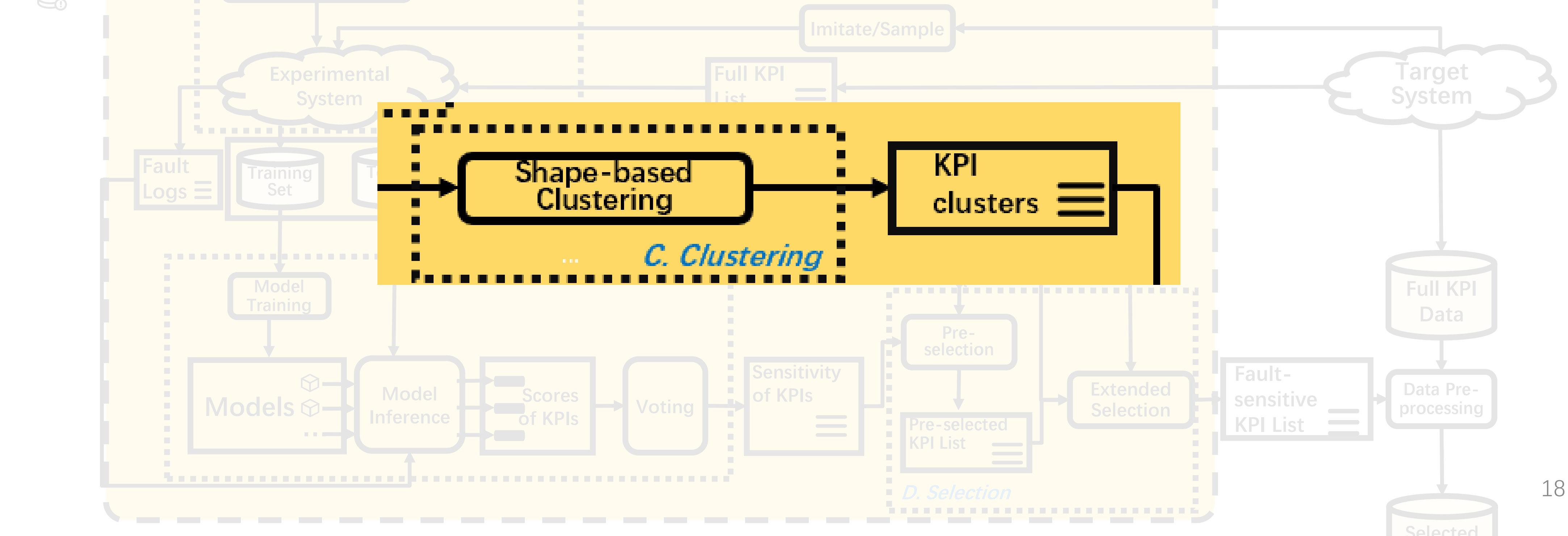
fKPISelect: (2) KPI Sensitivity Calculation

- Use the detection results for injected faults to calculate sensitivity
- Voting mechanism by multiple models to improve accuracy



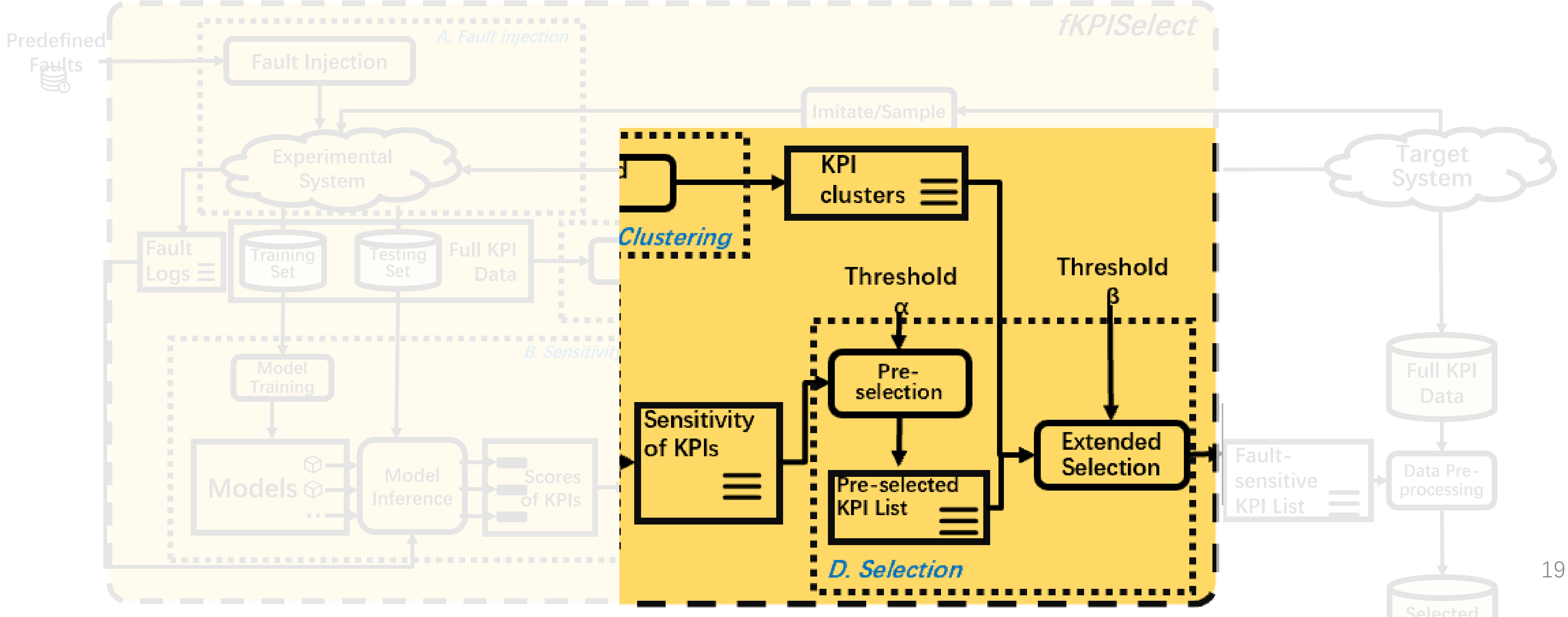
fKPISelect: (3) KPI Clustering

- Solve the problem of the false ignorance of error-sensitive KPIs due to the limitation of fault injections
- Cluster the KPIs with similar properties for extended KPI selection



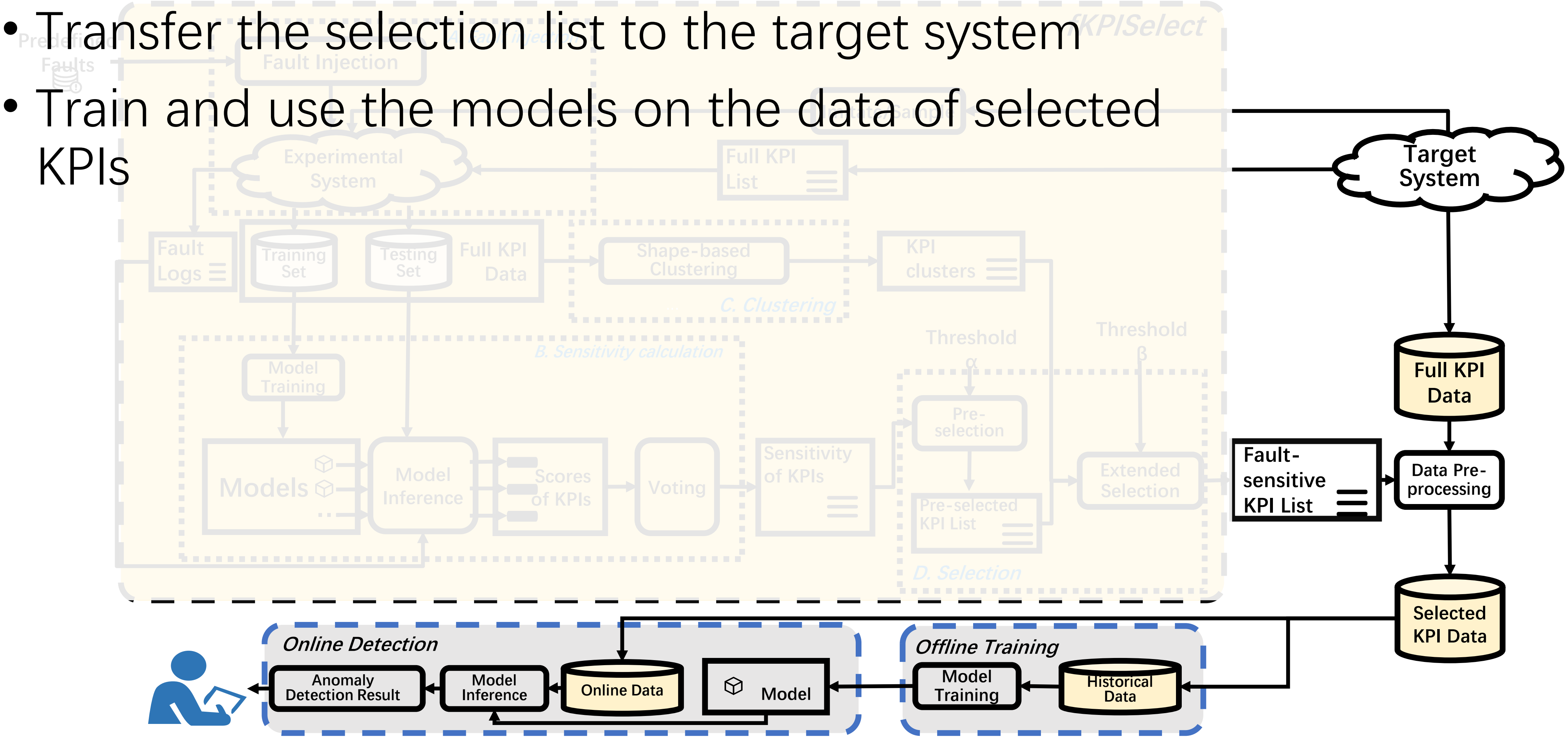
fKPISelect: (4) KPI Selection

- Threshold of KPI sensitivity (step 2)
- Threshold of cluster selecting ratio (step 3)



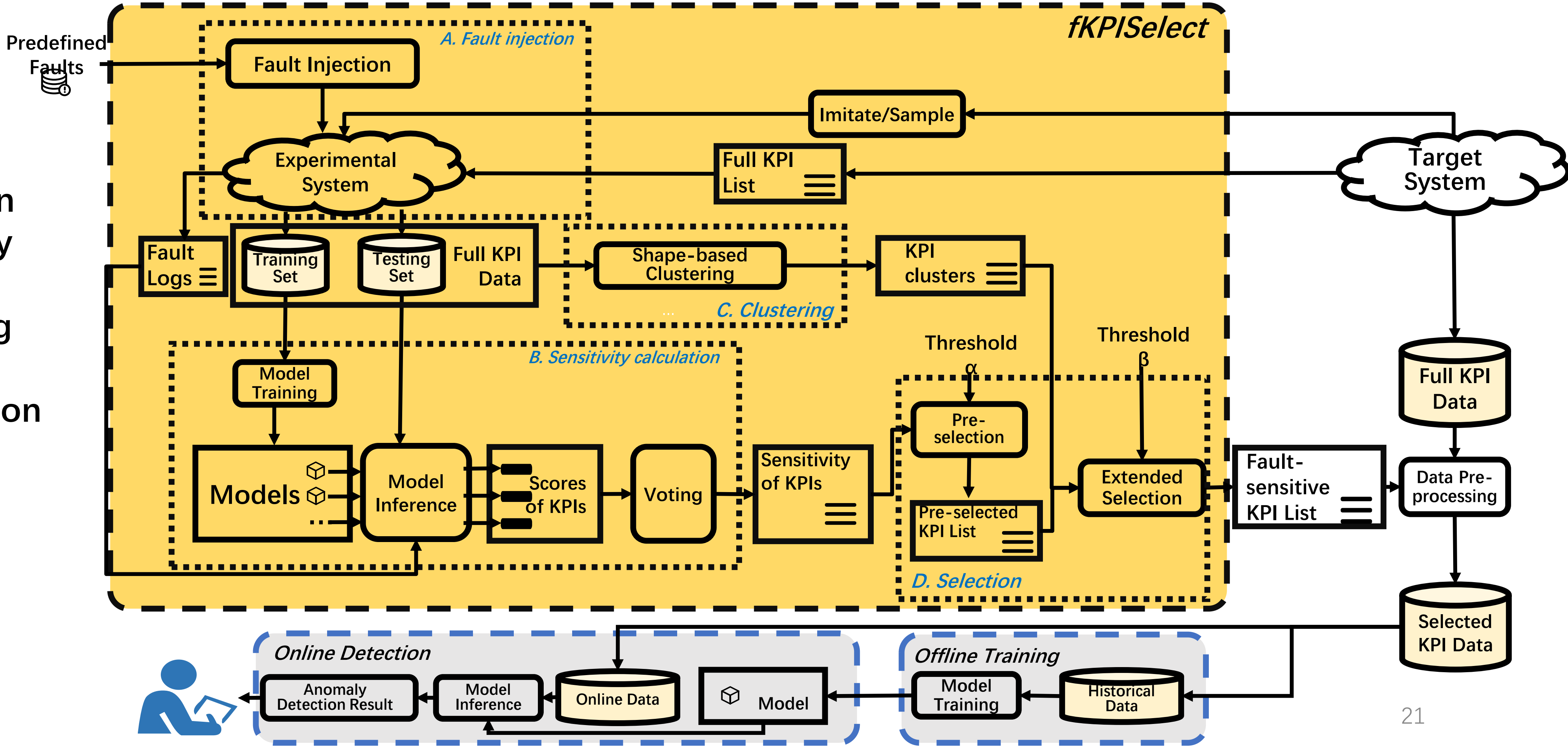
fKPISelect: Anomaly Detection on Target System

- Transfer the selection list to the target system
- Train and use the models on the data of selected KPIs



fKPISelect: Fault Injection-Based KPI Selection

(1) Fault Injection
(2) KPI Sensitivity Calculation
(3) KPI Clustering
(4) KPI Selection
Anomaly Detection



Evaluation

- Compare performance with
  - All KPIs
  - Manual Selection
- Dataset replicating practical scenario: Node_data
  - Experimental System: 5-node Kubernetes cluster
  - Fault Injection on nodes
    - Network Anomalies
    - High CPU consumption
    - Memory Leaks
    - Anomalous number of disk access
- Also performed simplified experiments on public datasets

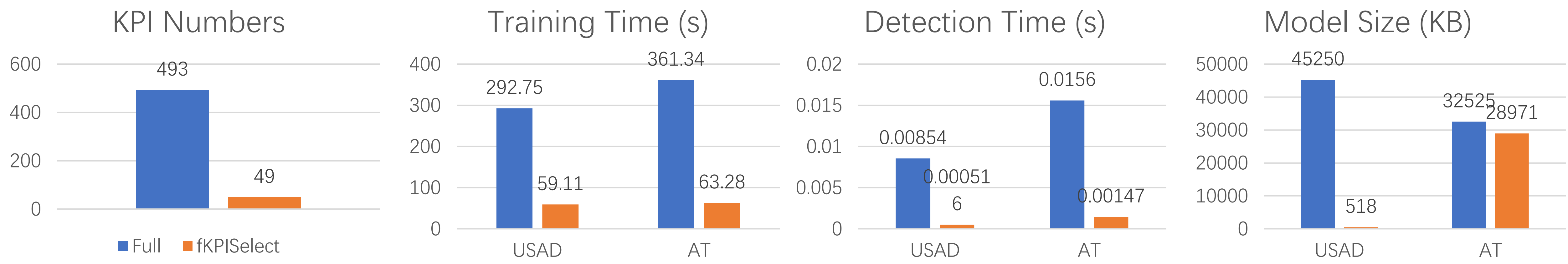
Evaluation

- The detection performance improved
  - F1 score increased from 0.68 to **0.91** (for AnomalyTransformer) in Node_data

Dataset	Preprocess	USAD Precision	USAD Recall	USAD F1 score	AnomalyTransformer Precision	AnomalyTransformer Recall	AnomalyTransformer F1 score
Node_data	Full	0.3847	0.4088	0.2756	0.5625	0.8571	0.6792
	Manual	0.4610	0.7976	0.5843	0.6296	0.9285	0.7504
	fKPISelect	**0.4702**	**0.8069**	**0.5942**	**0.8461**	**0.9897**	**0.9123**
SMD	Full	0.6509	0.6533	0.6521	0.9414	0.8901	0.9151
	Manual	**0.6800**	0.7100	0.6946	**0.9424**	0.8354	0.8856
	fKPISelect	0.6082	**0.8110**	**0.6951**	0.9421	**0.9247**	**0.9338**
CTF	Full	0.2976	0.3439	0.3190	0.9047	1.0000	0.9500
	Manual	0.2976	0.3440	0.3191	0.9051	1.0000	0.9502
	fKPISelect	**0.4534**	**0.5598**	**0.5010**	**0.9070**	**1.0000**	**0.9646**

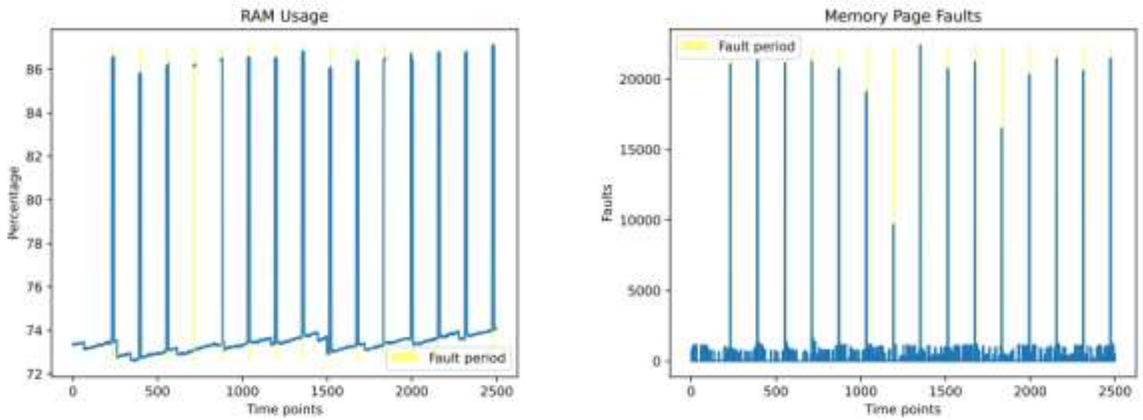
Evaluation

- Time & Space cost are reduced



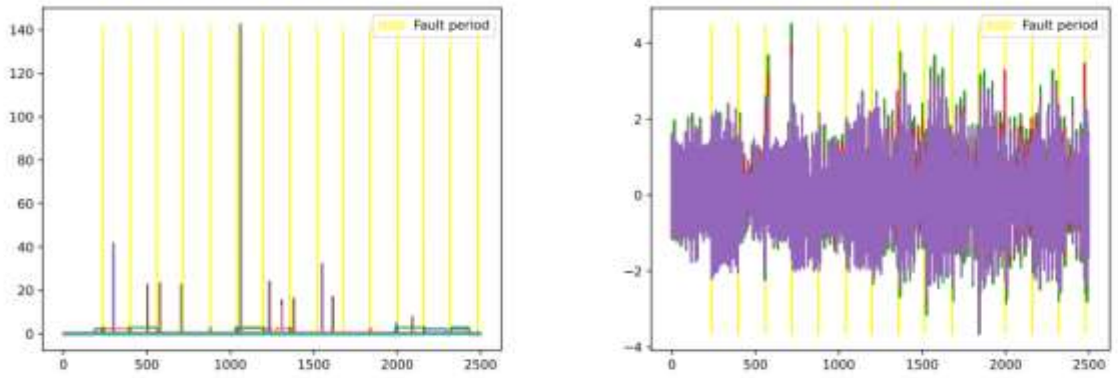
Evaluation

- Selected KPIs



RAM Usage & Memory Page Faults are sensitive to memory errors

- Unselected KPIs



2 groups of Unselected KPIs

Summary

- Focus on the issue of KPI selection in multivariate time series anomaly detection.
- Investigate the performance loss issue of multivariate TSAD models with experiments.
- Propose fKPISelect, a fault-injection-based automated KPI selection mechanism.
- Code and dataset are available at https://github.com/THUzxj/fKPISelect

References

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Thank you!