Online Data Drift Detection for Anomaly Detection Services based on Deep Learning towards Multivariate Time Series

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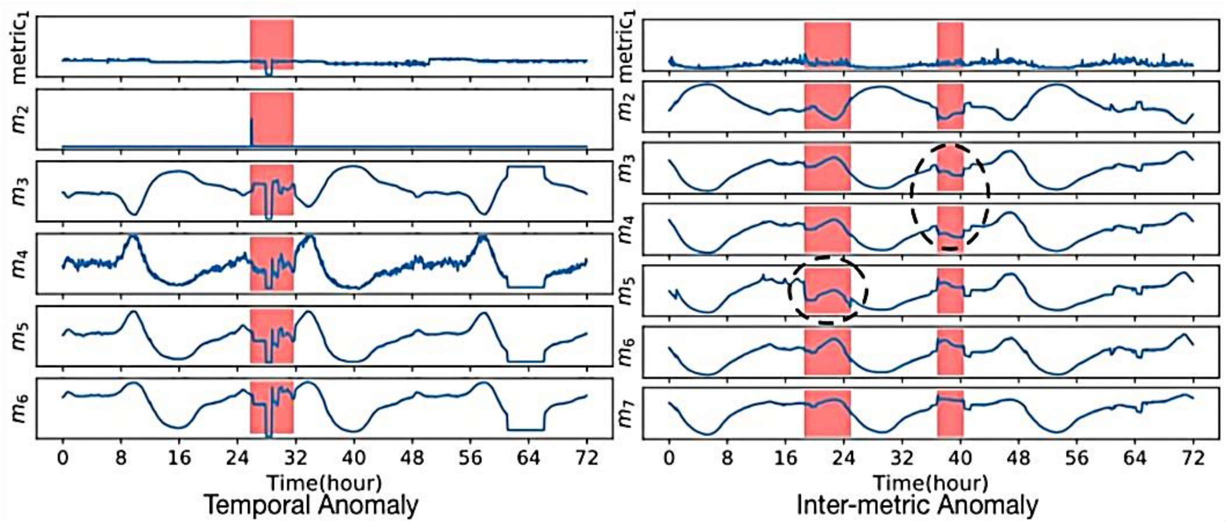
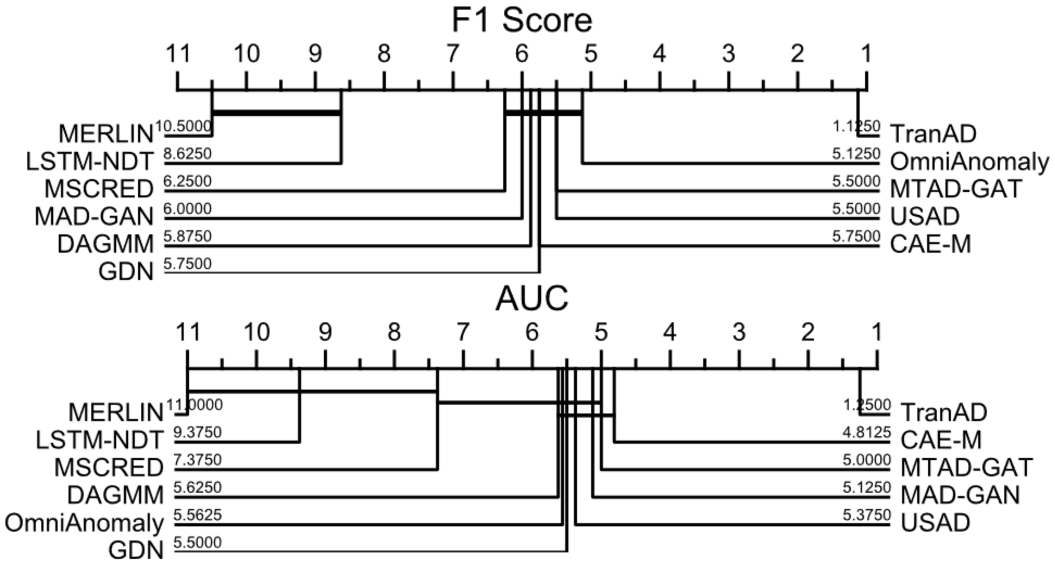
Background

- Deep learning models have been applied in anomaly detection for multivariate time series.



Two types of anomalies [1]

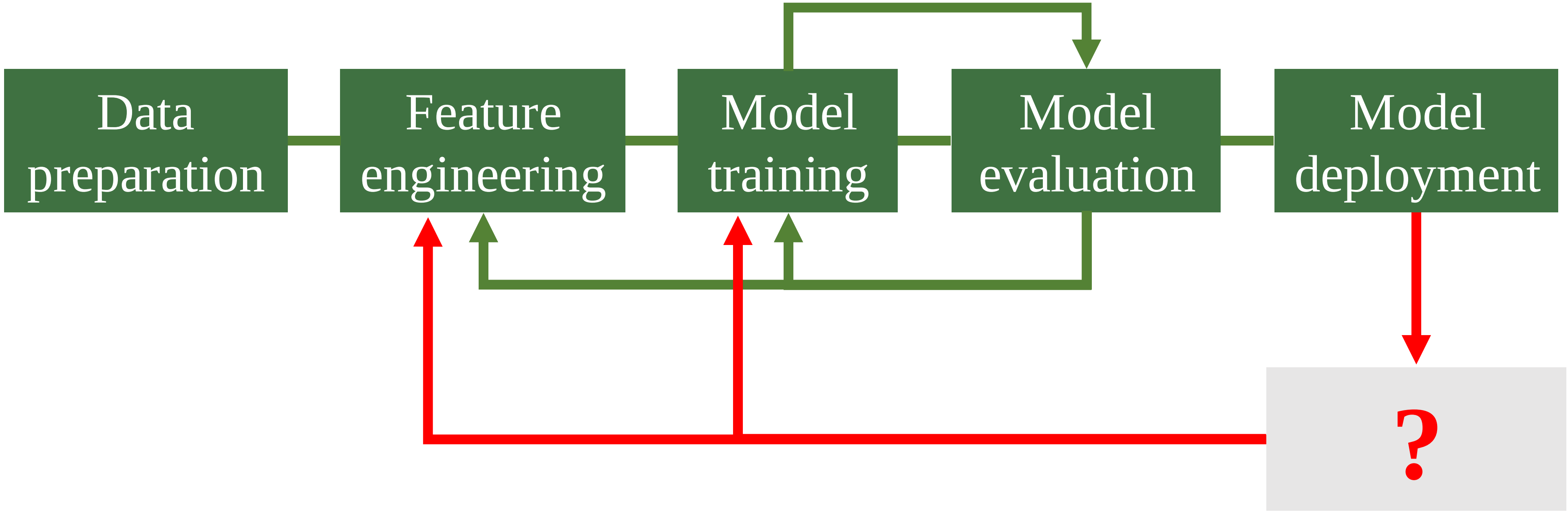


Critical difference diagrams [2]

[1] Z. Li et al,. Multivariate time series anomaly detection and interpretation using hierarchical inter-metric and temporal embedding. SIGKDD, 2021.
[2] Tuli S et al,. Tranad: Deep transformer networks for anomaly detection in multivariate time series data. 2022.

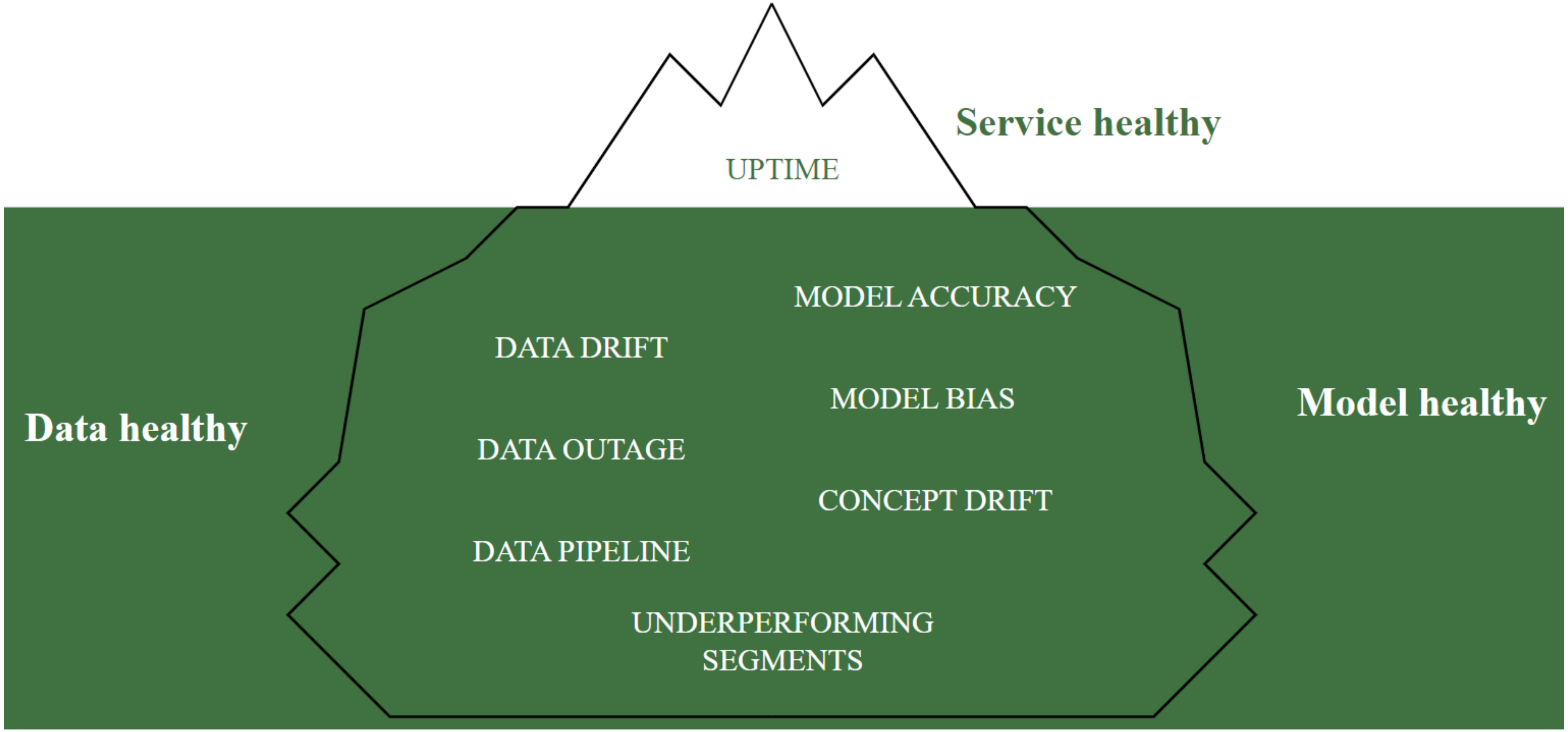
Background

- Is deploying the high-performing models as a service the last step?



Background

- What do we need to monitor? & Can we monitor them?



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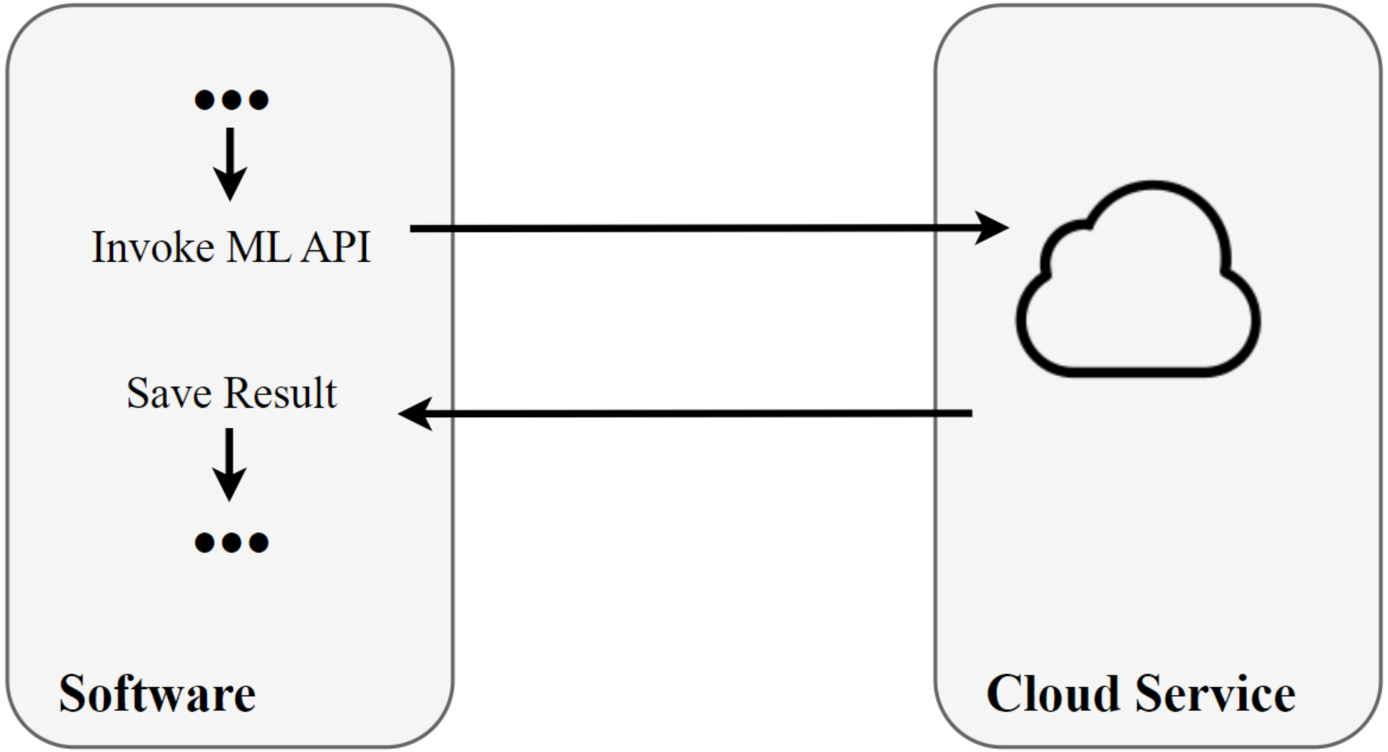
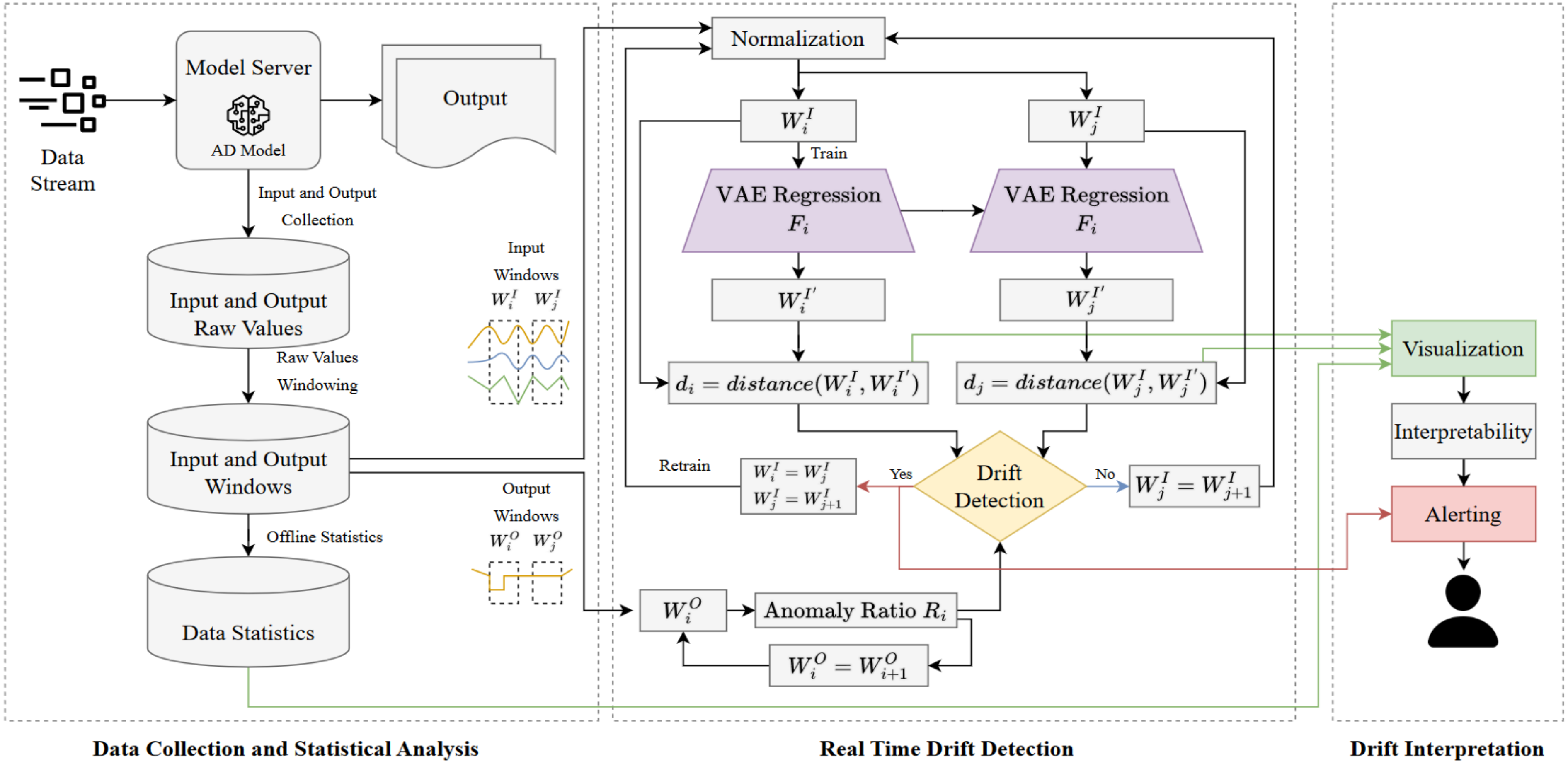


Background

- Challenges
  - The Quality of Model Services Lacks Standards.
  - Lack of Data Drift Labels.
  - The Detection Method Needs to be Updated in Time.
  - Interpretability.

Overview design

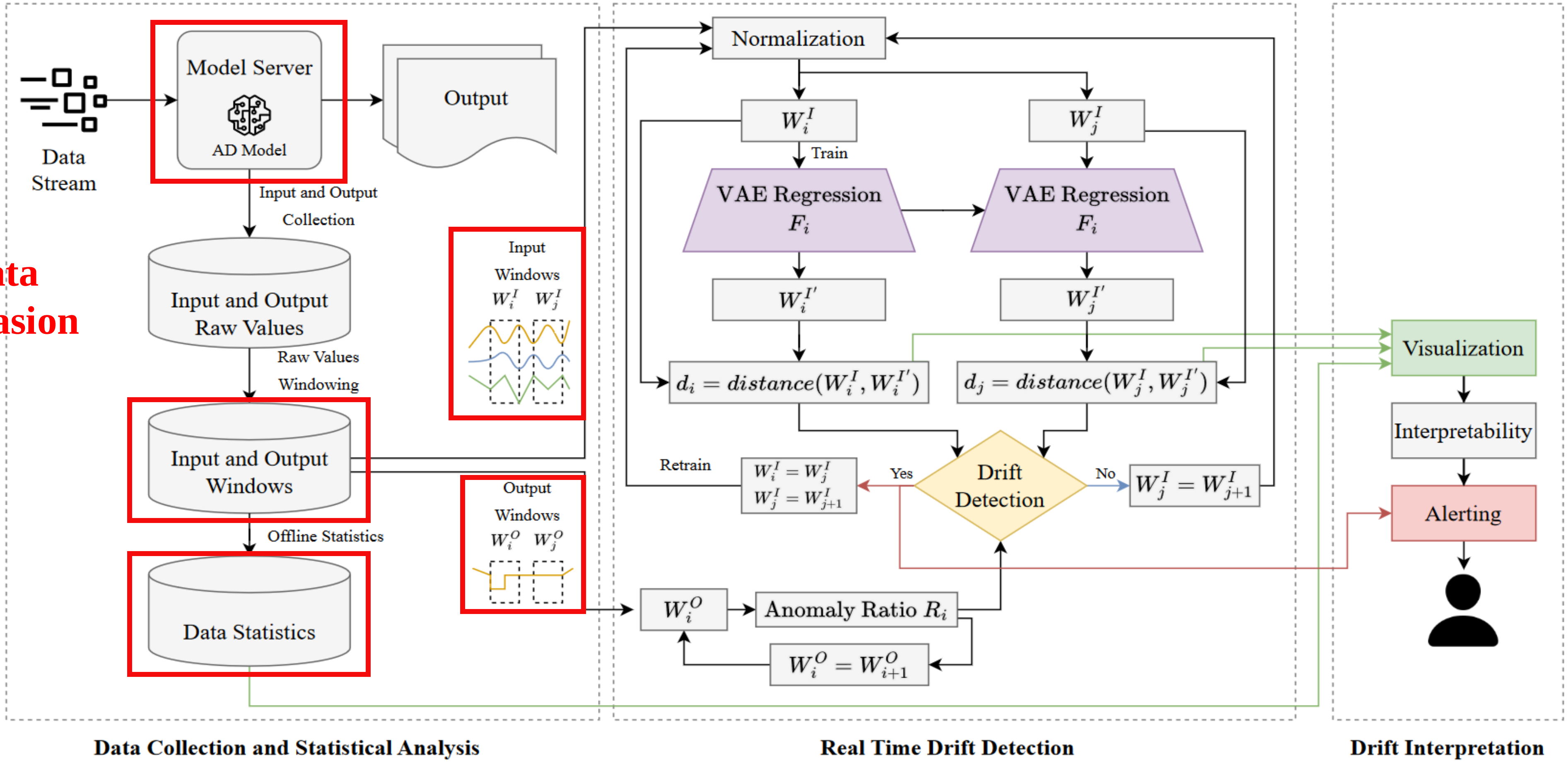
- End-to-end Monitoring Approach



Overview design

- Data Collection and Statistical Analysis

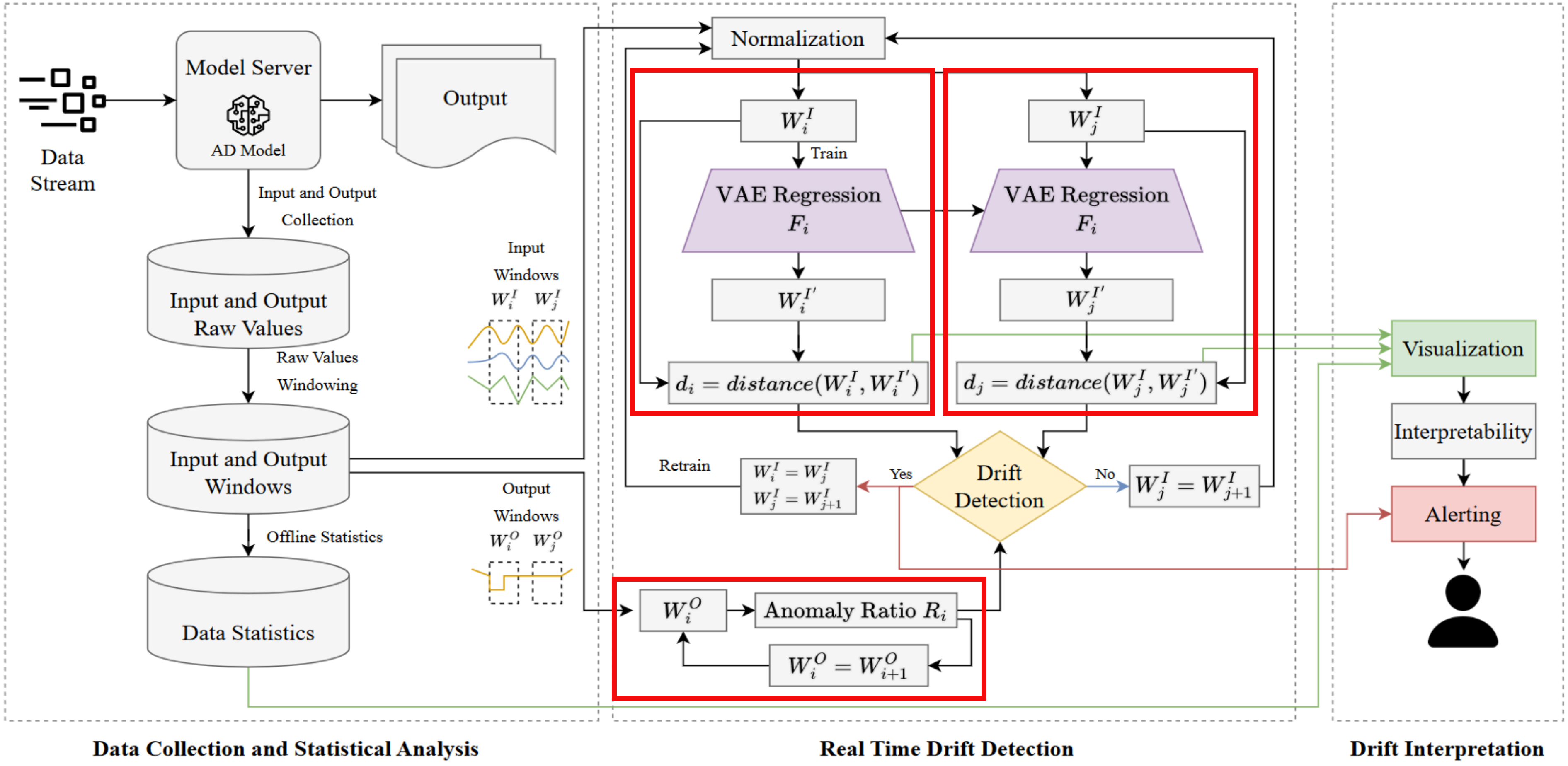
Collect data without invasion



Overview design

- Real Time Drift Detection

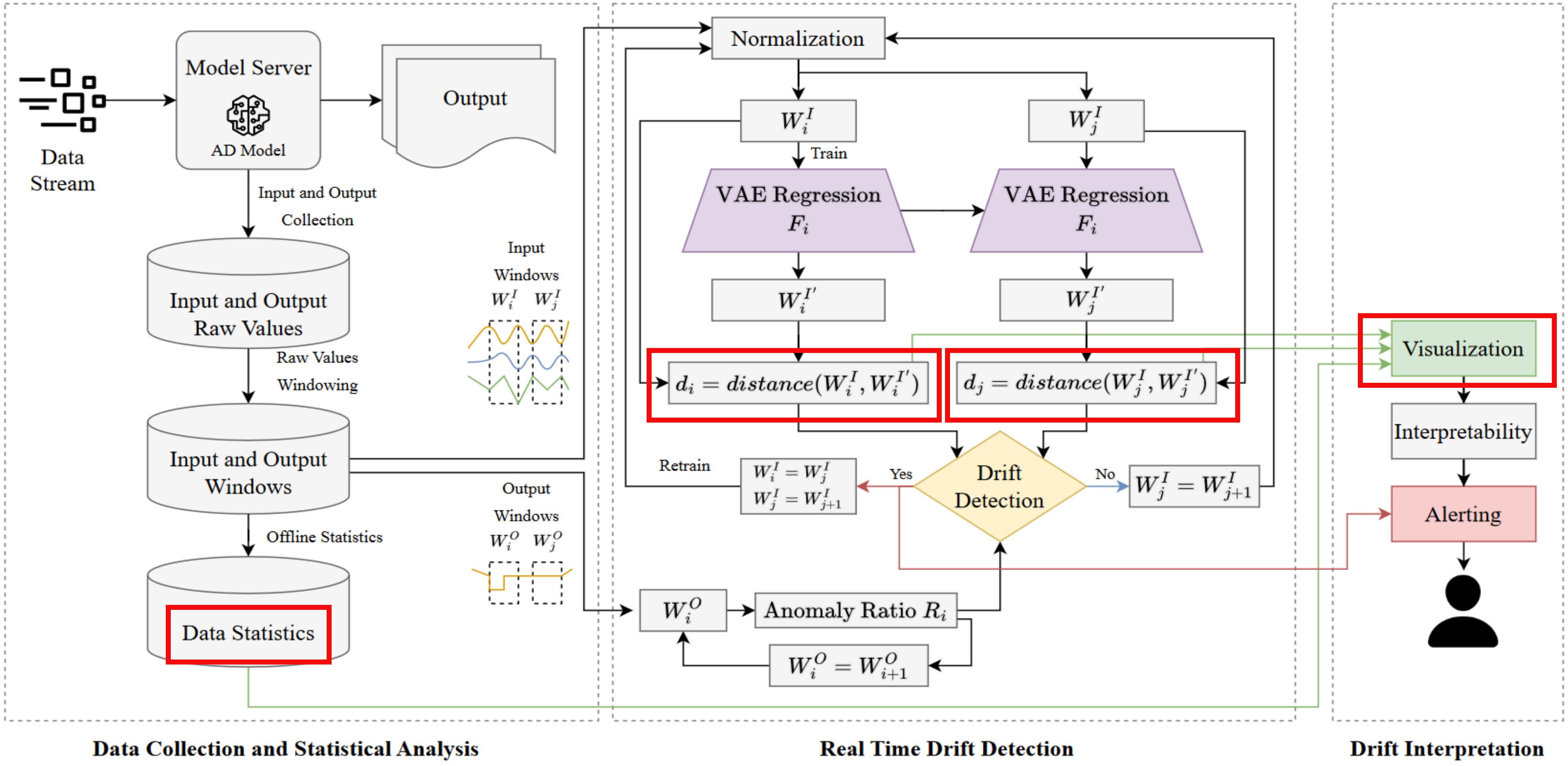
Apply deep learning drift detection algorithm



Overview design

- Drift Interpretation

Interpret drift through multiple data sources



Experiment

- Research Questions
  - RQ1. The Effectiveness of Drift Detection
  - RQ2. The Effectiveness of Monitoring Anomaly Detection Models
  - RQ3. The Interpretability of the Model Performance

Experiment

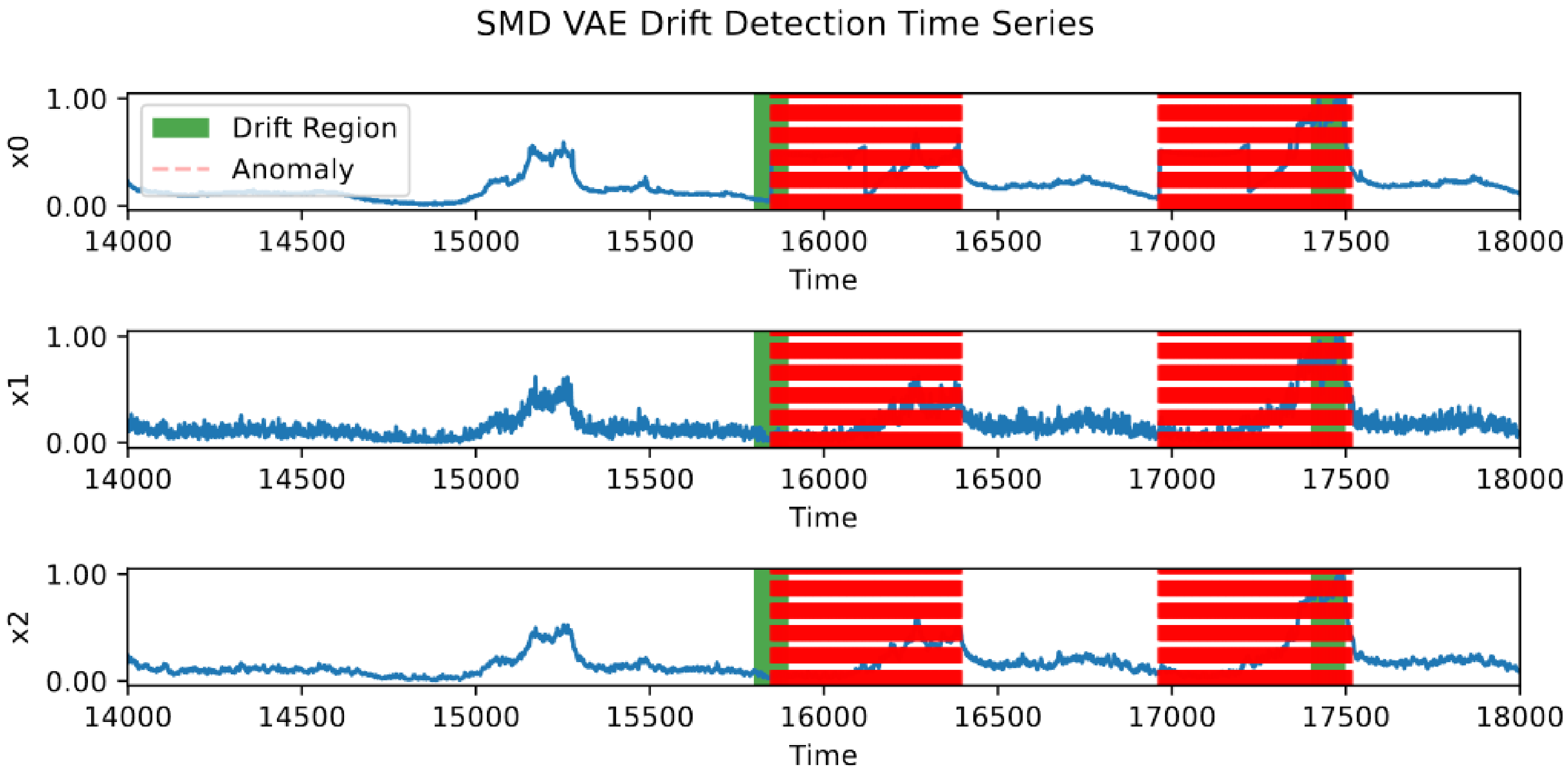
- RQ1. The Effectiveness of Drift Detection

Dataset	Train	Test	Dimensions	Anomalies(%)
SMD	28479	28479	38	9.46
MSL	58317	73729	55	10.72
SWaT	99000	89984	51	12.17

	Number of drifts			
	VAE(3σ)	VAE(2σ)	VAE(σ)	HDDDM
SMD	2	19	142	46
MSL	6	13	368	82
SWaT	8	25	449	65

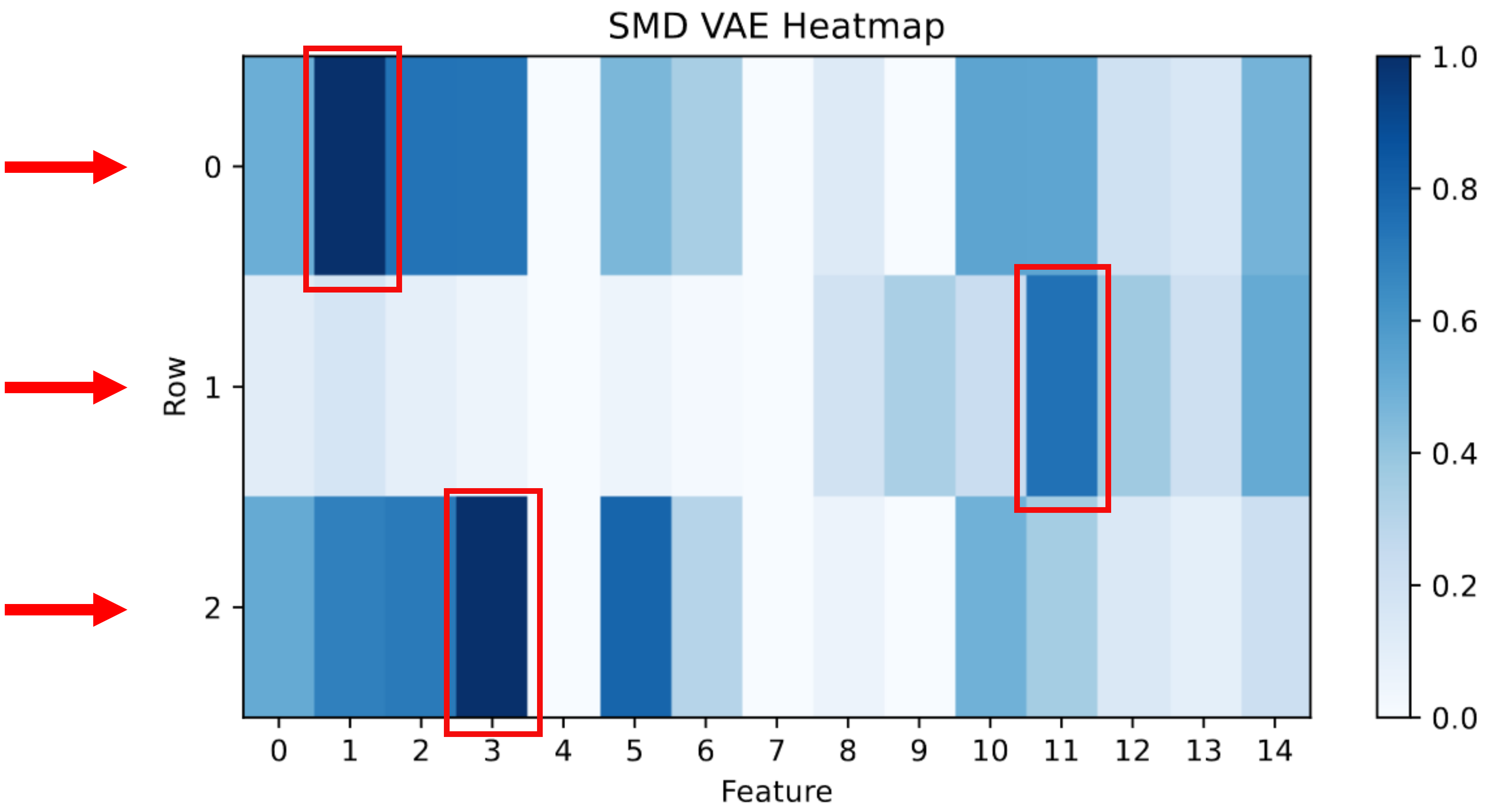
Experiment

- RQ1. The Effectiveness of Drift Detection



Experiment

- RQ1. The Effectiveness of Drift Detection



Experiment

- RQ2. The Effectiveness of Monitoring Anomaly Detection Models

Dataset	Segment	Segment Anomalies(%)
SMD	15001-20000(5000)	43.8
MSL	5001-10000(5000)	23.3
SWaT	10001-15000(5000)	15.9

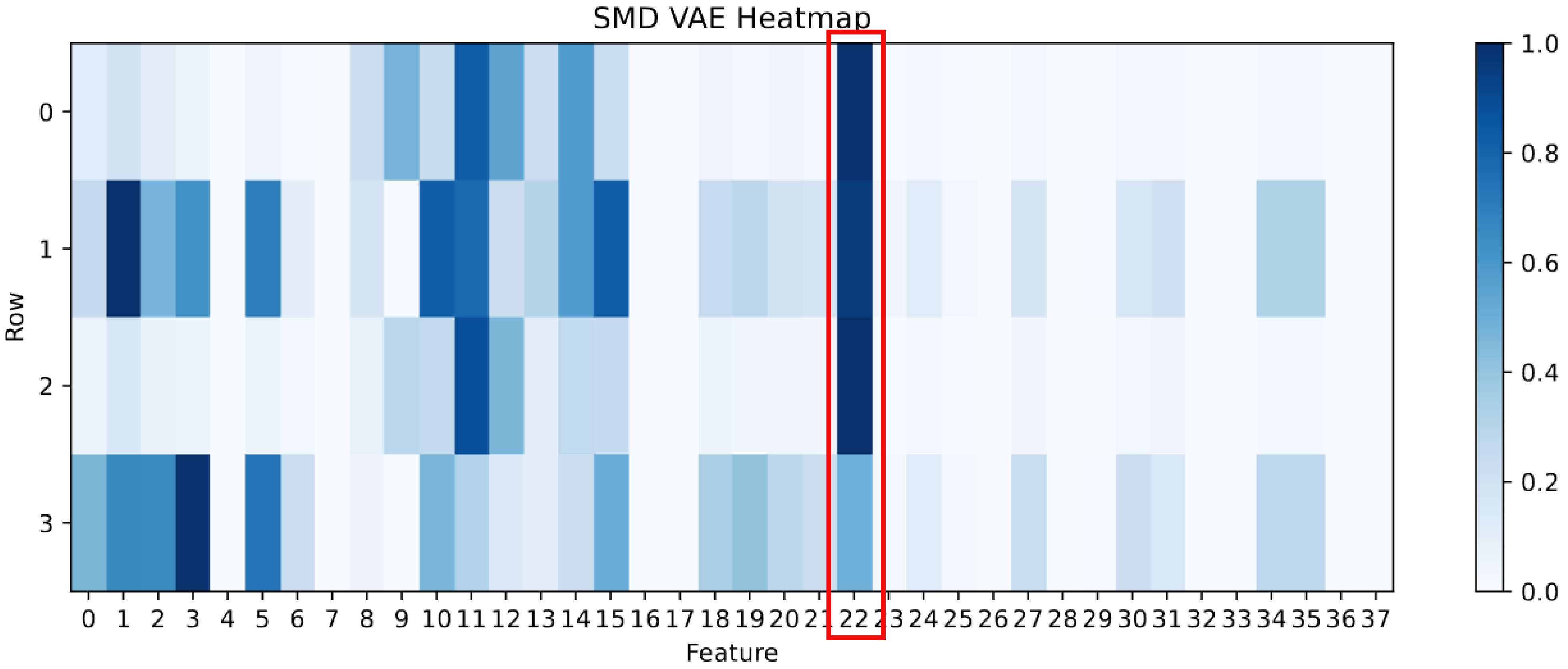
Experiment

- RQ2. The Effectiveness of Monitoring Anomaly Detection Models

Method	SMD							
	P	P'	R	R'	AUC	AUC'	F1	F1'
USAD	0.6808	0.4050	0.9973	0.8915	0.8929	0.7745	**0.8092**	0.5570
LSTM_AD	0.7731	0.8644	0.9820	0.9844	0.9102	0.9406	0.8651	**0.9205**
GDN	0.2648	0.4233	0.9983	0.9298	0.8083	0.7988	0.4186	**0.5817**
MAD_GAN	0.6169	0.2954	0.6127	0.5312	0.6447	0.5502	**0.6148**	0.3797
	MSL							
	P	P'	R	R'	AUC	AUC'	F1	F1'
USAD	0.9039	0.9047	0.6610	0.7350	0.8130	0.8510	0.7636	**0.8111**
LSTM_AD	0.9056	0.9056	0.7404	0.8460	0.8539	0.9075	0.8147	**0.8748**
GDN	0.9923	0.9888	0.5862	0.7042	0.7915	0.8500	0.7370	**0.8226**
MAD_GAN	0.9099	0.9082	0.5400	0.4008	0.7515	0.6756	**0.6777**	0.5561
	SWaT							
	P	P'	R	R'	AUC	AUC'	F1	F1'
USAD	0.1613	0.1613	0.6332	0.7967	0.7341	0.8167	0.2571	**0.2683**
LSTM_AD	0.1613	0.3226	0.6360	0.1618	0.7355	0.4797	**0.2573**	0.2155
GDN	0.1613	0.3226	0.6170	0.3062	0.7259	0.5741	0.2557	**0.3142**
MAD_GAN	0.1613	0.3226	0.6277	0.2871	0.7313	0.5632	0.2566	**0.3038**

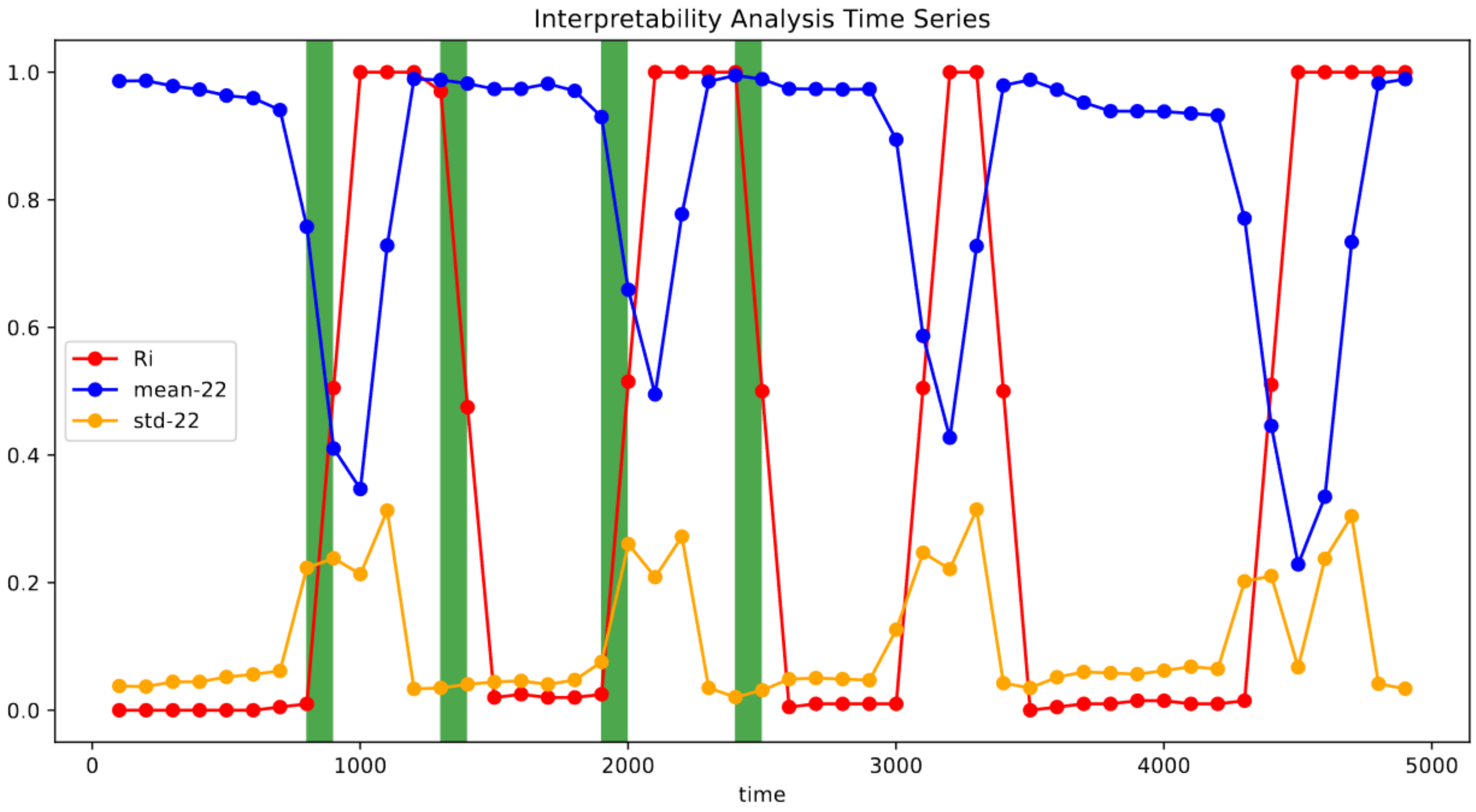
Experiment

- RQ3. The Interpretability of the Model Performance



Experiment

- RQ3. The Interpretability of the Model Performance



Summary

- Key Contributions
  - A novel data-driven monitoring scheme for MTS anomaly detection services.
  - One of the earliest attempts to apply deep learning-based drift detection algorithms to MLOps monitoring.
  - A method that accurately detects data drift in services based on deep learning and provides reasonable interpretations.

Thank You For Listening!

Q & A

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