A APPENDIX

B LIMITATION OF EXISTING DATASETS

B.0.1 LIMITED COLLECTION OF PUBLIC REAL-WORLD DATASETS

For univariate time series datasets, KPI and Yahoo are the most popular ones with 58 and 367 curves, respectively. Although TSB-UAD (Paparrizos et al., 2022b) provides 13766 time series with labeled anomalies, 10828 of them are synthetic data where different strategies are used to increase detecting difficulty. However, one main concern is that, with data transformed, the labels usually remain unchanged which may result in wrong labels. What's worse, if data is created artificially, it is hard to say the data is natural and the performance of models on it may be manipulated through information given by generation rules/processing. That is also why real-world data matters in the TSAD tasks.

For multivariate time series datasets, although more public datasets are available, the number of samples is less as one point is contained with several dimensions. The size of multivariate time series datasets is even less. Performances of models vary among different datasets. It is urgent to collect more real data for MTSAD.

B.0.2 CONFUSING GROUND TRUTH LABELS

Another flaw of existing datasets is that mislabels happen in all these datasets. It may be mainly due to the difficulty for experts to check for every label. However, non-negligible mislabels do hurt the evaluation of models and even lead to wrong research directions.

B.0.3 LIMITED TYPES OF TIME SERIES ANOMALIES

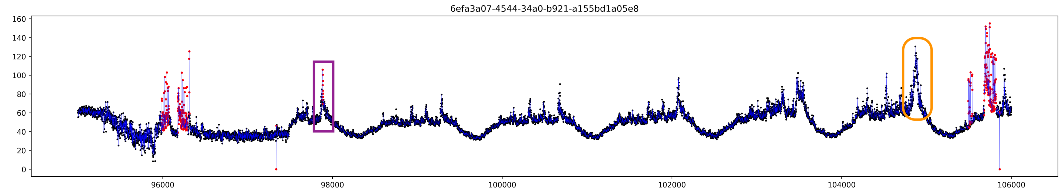
Time series anomalies can be roughly classified as point-wise anomalies and pattern-wise anomalies (Lai et al., 2021) where point-wise anomalies contain global and contextual outliers, pattern-wise anomalies contain shapelet outliers, seasonal outliers and trend outliers. However, most of the anomalies in public datasets are peaks or valleys. This is also part of the reason why random guesses can achieve an even better score than most of the well-designed anomaly detection models (Doshi et al., 2022; Kim et al., 2022). Lack of a good performance metric also causes such results which we will discuss in Section 3.3. Seasonal outliers and trend anomalies are rare which is also why many synthetic datasets, including the Yahoo dataset, datasets in TSB-UAD and UCR dataset, are generated for univariate TSAD.

Actually, the above types of outliers are also mainly set for single/univariate time series. When more than one time series is considered, it will be much more complicated as a change of relationships among different time series or channels may also lead to anomalies. Different from univariate time series, it is usually too difficult to generate synthetic MTSAD datasets as the types of anomalies in multivariate time series are hard to define and then there are few rules that can be followed for a generation. Thus, real-world large-scale multivariate time series datasets with reliable labels are in urgent need.

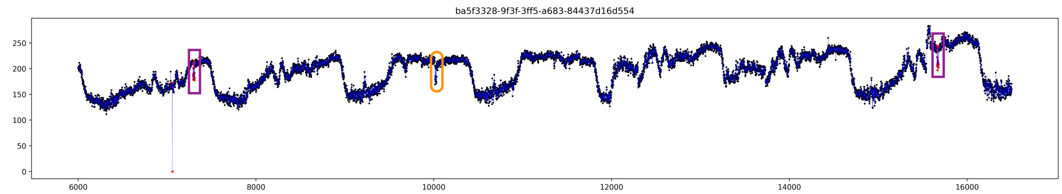
C CONFUSING LABELS IN EXISTING DATASET

Confusing Labels in KPI Figure 4(a) mainly shows peak-type anomalies in time series. However, it is confusing that the peak around index 97900 is labeled as abnormal, while a higher peak in around index 14850 is labeled as normal. A similar thing happens in valley-type anomalies. As shown in Figure 4(b), while valleys in indexes around 7300 and 15680 are both labeled as anomalies, a deeper valley in index 10020 is considered as normal.

Confusing Labels in Yahoo Figure 5 gives some examples where the labels of ground truth are confusing. The beginning points of A1_28, A1_38, and A1_55 are abnormal but the labels are not abnormal as shown in Figure 5(b), 5(c) respectively. In A1_38 (Figure 5(b)), the points around index 646 are too high to be normal but they are labeled as normal. In A1_55 (Figure 5(c)), only one point (whose index is 1206) is labeled as abnormal when a new pattern happens at around 1200. However, in A1_32 (Figure 5(a)), if the change in index around 1221 is a new pattern, further more than one point is labeled as abnormal which is different from A1_55. If all the points in this 'new pattern' are considered as abnormal, all of them should be labeled as anomalies. Such inconsistency makes the labels confusing.

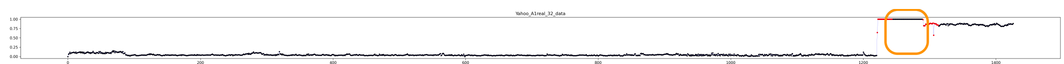


(a) Data with KPI id 6efa3a07-4544-34a0-b921-a155bd1a05e8.

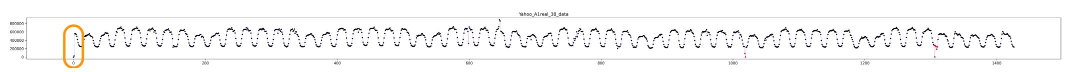


(b) Data with KPI id ba5f3328-9f3f-3ff5-a683-84437d16d554.

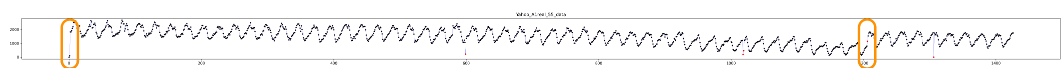
Figure 4: Confusing labels in KPI dataset. Normal points are black and abnormal points are red. The lines show changes among points are blue.



(a) Yahoo real data A1_32.



(b) Yahoo real data A1_38.



(c) Yahoo real data A1_55.

Figure 5: Confusing labels in Yahoo dataset. Normal points are black and abnormal points are red. The lines show changes among points are blue.

Confusing Labels in SMAP Figure 6 shows an example of anomalies in the NASA-SMAP test dataset from index 4600 to 4800. It is hard to understand why the points in the window from 4690 to 4770 are all abnormal. On the left of the window, no peaks appear which is just the same as the window from 4620 to 4650. However, the labels are not the same.

Other MTSAD datasets have similar flaws with labels. We will not show all of them here.

D Illustrations of Real-world AIOps Datasets.

Figure 7 shows the architecture of the real-time data warehouse where the real-world datasets are collected in this paper. Figure 8 shows a real-world case of multivariate time series anomaly detection from a data warehouse instance.

E Detailed Evaluation Metrics

F1-Score with Point Adjustment This metric is proposed by (Xu et al., 2018; Audibert et al., 2020). It works as follows: if one anomaly point is correctly detected in the ground truth anomaly segment, all the points in such segment will be considered as correctly detected. Then F1-score is calculated with such adjusted predictions. F1-PA is designed with the alert that one detected anomaly shows errors in the system sufficiently. However, such a metric has a high possibility of overestimating the performance of models and does not consider the information of anomaly events. Actually, with the F1-PA metric, even random guess gains SOTA performance (Kim et al., 2022; Doshi et al., 2022).

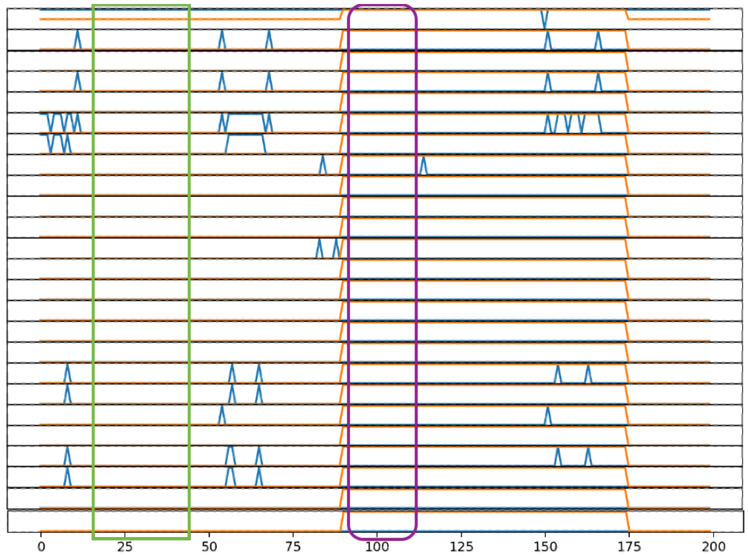


Figure 6: Confusing labels in SMAP dataset. In each dimension, the blue line is the original values and the orange line is the labels.

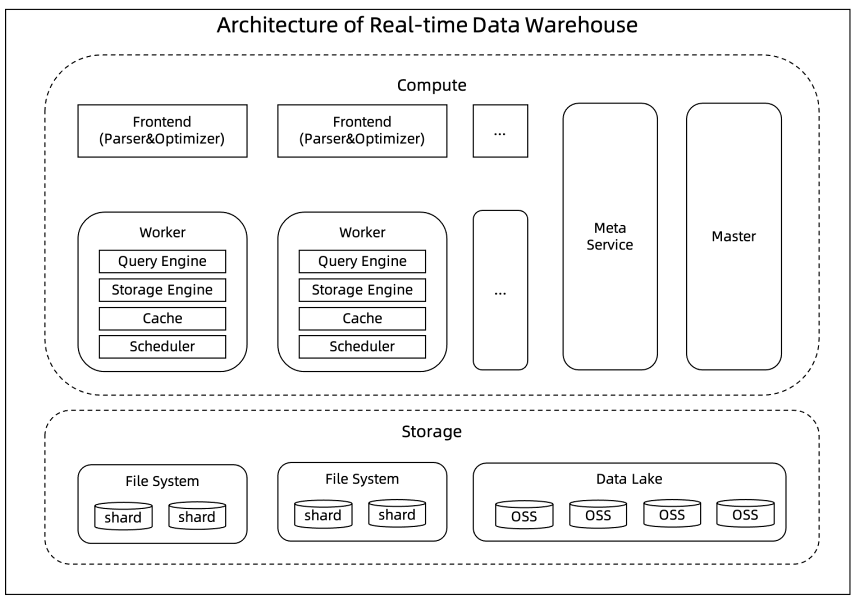


Figure 7: Architecture of the real-time data warehouse.

Besides the original F1-score with point adjustment, there are also several variants of F1-PA. For example, F1-PA%K (Kim et al., 2022) applies point adjustment only when the ratio of the number of correctly detected points is larger than the %K of anomaly length. K is a threshold. It indeed helps relieve over-optimistic in F1-PA but does not solve the problem of F1-PA. The gut issue of F1-PA is that it considers anomalies from a point-wise view. However, in the time series field, it is hard to say reasonable to consider a single point as a sample. A more natural way is to define something like anomaly events to gain information.

Composite F1-score It is a metric taking event-wise anomaly into account (Garg et al., 2021) but still keeps the main design of point adjustment. Specially, it takes a point-wise precision with point adjustment and an event-wise recall. The formalization is shown as follows.

$$Pr_t = \frac{TP_t}{TP_t + FP_t} \quad \text{and} \quad Rec_e = \frac{TP_e}{TP_e + FN_e}, \tag{2}$$

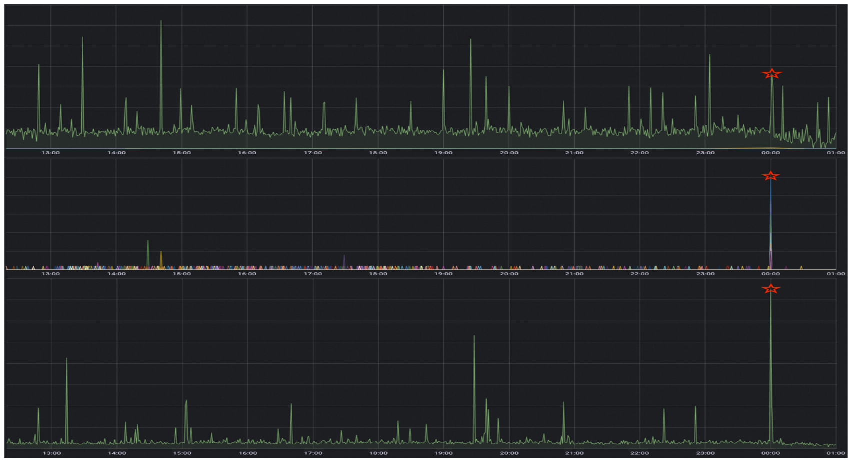


Figure 8: Real-world case of multivariate time series anomaly detection from a data warehouse instance.

where TP_t and FP_t are the numbers of TP and FP points respectively, TP_e and FN_e are the number of TP and FN events respectively. TP_e is the number of true events for which at least one point is detected rightly. The other true events are counted under FN_e. This metric doesn't differentiate the locations of false positive events and over punish missing detection of single point events. What's more, it is not very persuasive that precision and recall should be defined in different views. Actually, there are metrics taking the position of results into consideration, like NAB score (Lavin & Ahmad, 2015), SPD score (Doshi et al., 2022). Recently, affiliation metric is proposed with pure event-view to deal with the above challenges.

Affiliation Score Affiliation (Huet et al., 2022) is a metric with an intuitive interpretation where both precision and recall are calculated based on the distance between ground truth and prediction events. Event distance is defined through point sets by Hausdorff distance (Dubuisson & Jain, 1994) and precision/recall is set by individual probability based on event distance normalized by affiliation zone. Affiliation is proven to be robust against adversary strategies. It is novel to measure event distance by Hausdorff distance and exquisite to draw individual probability into precision and recall. However, the affiliation zone has a huge influence on the final score. With little improvement in precision, the bigger size of the zone results in a higher score in a non-negligible degree. What's more, all the prediction events in the zone contribute to the final score even when they are false positives. Actually, if a prediction event is far from the ground truth, it should be punished. Another phenomenon caused by zone splitation is with a high tolerance for false positives but a tolerance low for false negative points.

Volume Under the Surface (VUS) Metric Besides the above metrics based on the F1-score, there are also metrics based on the receiver operator characteristic (ROC) curve and the area under the curve (AUC). The original ROC and AUC are based on point-wise detection. However, as discussed above, such point-wise type metrics introduce unavoidable shortcomings in range-based anomalies by mapping discrete labels into continuous data. That is why the event-based F1-score appears. VUS metric extends the AUC-based measures to account for range-based anomalies. The key designs are the label transformation technique and volume under the surface metric. For label transformation, with a buffer length, the binary label is extended into a continuous value. Given buffer length l, the positions $s, e \in [0, |label|]$ the beginning and end indexes of a labeled (range) anomaly, the formalization of the continuous $label_r$ is set as follows:

$$\forall i \in [0,\ |label|], \quad label_{li} = \begin{cases} (1 - \dfrac{|s-i|}{l})^{\frac{1}{2}} & \text{if: } s - \dfrac{l}{2} \leq i < s \\ 1 & \text{if: } s \leq i < e \\ (1 - \dfrac{|e-i|}{l})^{\frac{1}{2}} & \text{if: } e \leq i < e + \dfrac{l}{2} \\ 0 & \text{if: } i < s \text{ or } e < i \end{cases}.$$

The surface is comprised of ROC curves with different buffer lengths. Thus, l doesn't need to be set as a hyperparameter. The main concern of VUS is with label transformation, the false positive points are overestimated than the false negative points. It is not sure if it is better for specific situations.

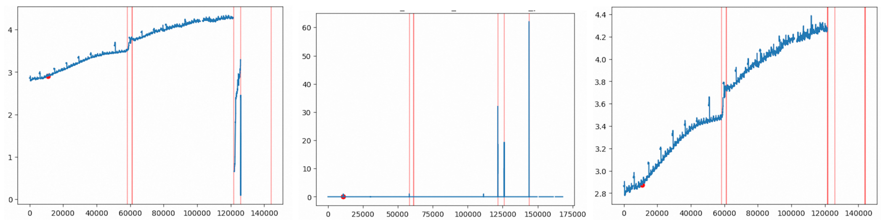


Figure 9: Visualization of part of metrics of Instance 18 where the red line instructs anomalies happening and the vertical axis is normalized.

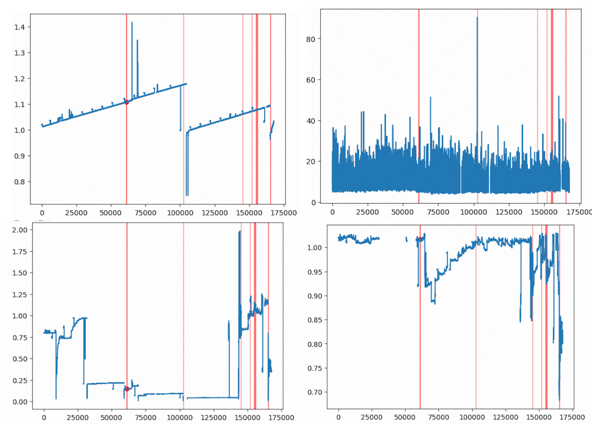


Figure 10: Visualization of part of metrics of Instance 23 where the red line instructs anomalies happening and the vertical axis is normalized.

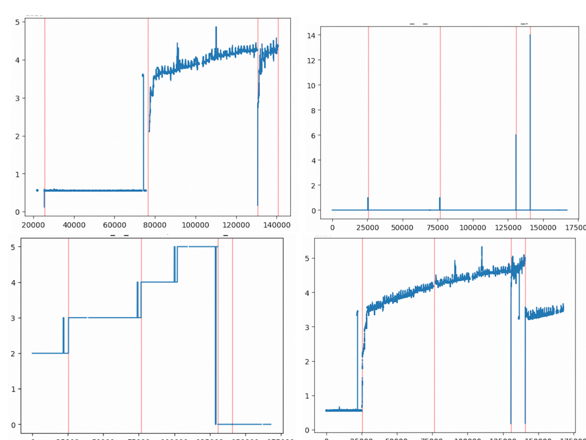


Figure 11: Visualization of part of metrics of Instance 28 where the red line instructs anomalies happening and the vertical axis is normalized.

Here, we show the full results of different methods on 8 datasets with various metrics in Table 5 and Table 6.

F VISUALIZATION OF REAL-WORLD AIOPS DATASET

We have proposed real-world multivariate time series datasets from the AIOps system of the real-time data warehouse. In this section, we would like to show some visualization of the instances to make it more intuitive to the users. Figure 9, Figure 10, and Figure 11 show some of the metrics of Instance 18, Instance 23, and Instance 28, respectively, where the red line represents anomalies. We visualize these different instances to demonstrate the complexity of anomalies in multivariate time series.

G Detailed Experiment Results and Discussion

In this section, we summarize more experiment results of those instances in the AIOps datasets. To compare the performance of different methods, we evaluate different methods with hyperparameter selection and summarize the results in Table 7. For the processing of missing data, Table 8 shows the experiment results on part of the instances with filling mean for missing data, where the abbreviations of the evaluation metrics are accuracy, precision, recall, F1-score, affiliation precision, affiliation recall (Huet et al., 2022), Range_AUC_ROC, Range_AUC_PR, VUS_ROC, VUS_PR, AUC_PR, and AUC_ROC (Paparrizos et al., 2022a) in order. Besides, we also evaluate other methods for filling missing data with zero interpolation and linear interpolation as shown in Table 9 and Table 10, respectively.

From the results, we have discovered some interesting phenomena.

- Different models achieve rather different metric results even in the same instance. What's more, the order of the performance on different metrics is also inconsistent. For example, although the state-of-the-art deep models Anomaly-Transformer and DCdetector do not gain a good performance on F1 with point adjustment, they achieve the best ones in V_ROC and V_PR. This may be mainly because the V_ROC and V_PR metrics are more sensitive for detection in the recall direction and take the recall and the precision balanced. The ECOD model performs almost the best in Precision with point adjustment (P metric) and almost worst with Recall with point adjustment (R metric). At the same time, it also gains almost the worst score in V_PR. Such inconsistency among metrics also indicates the importance of the choice of the proper metric for a certain situation.
- Among all the metrics, the variances of R_A_P and R_A_R are the least. For instance, in the results of instance 38, the variances of different models on metric R and metric R are extremely large. However, we do not see a huge gap among models on the A_PR and A_R metrics. We are not sure which is expected in a general case. Is it reasonable to have such a large gap among the models? Actually, the detection differences among the models may just be a few points. However, is A_PR or A_R a good one? If the detection purpose is to choose the best method, such a "robust" metric may not be a good choice. We will leave this as an interesting future work.
- The classical methods, such as KNN, seem to perform more robustly among different instances. For example, with filling the mean for missing data, the P metric does not show a large variance among instances (most ranging from 0.09 2.19). However, the deep method, such as Anomaly-Transformer, can range from 0 to 60.28. Part of the reason is that we do not make parameter adjustments for each instance which has an influence on deep models, while classical methods are more robust with hyperparameters.
- As real-world data always suffers from missing data, we evaluate different data-filling methods. The results are rather different among different instances. We take instance14 and instance44 as examples. To clarify the discussion, we first consider the "robust" A_R metric. The results of instance14 are similar with different filling methods. That is, different models show similar performances with different filling methods. However, the thing is very different for instance 44. With the filling mean method, USAD and KNN achieve 89.04 and 92.66, respectively. While, with the filling linear interpolation method, they achieve only 32.54 and 40.40, respectively. What's more, BeatGAN gains 89.01 score with filling mean and only 34.48 with filling linear interpolation.
- The models show rather different performances on Recall and Precision. For example, with filling zero, KNN and LOF both gain 100 (100 percent) recall for instance 14 but with only 1.75 for precision. It is also common in reality that in different situations, we take different views into consideration. Sometimes, recall is important as a missing anomaly may lead to a huge loss. In other situations, precision is more important as too many anomaly alarms are not acceptable. However, how to choose or design a metric to apply in real situations is extremely important and challenging.

There are still many works for time series anomaly detection in the real world. And the gap between public datasets/metrics and real-world application evaluations is still large. We hope our work can inspire more interest in exploring real-world applications.

Table 5: MTSAD comparisons on all public datasets - part 1.

Dataset	Method	Acc	P	R	F1	Aff-P	Aff-R	R_A_R	R_A_P	V_ROC	V_PR
MSL	KNN	93.94	47.33	90.97	62.27	70.77	9.95	55.11	37.29	55.12	37.21
	LOF	91.86	26.42	87.69	40.61	61.83	9.78	52.15	23.60	52.08	23.40
	IForest	91.21	17.32	95.73	29.33	60.65	16.71	54.76	19.26	53.97	18.47
	COPOD	93.27	36.69	98.51	53.46	62.43	34.28	61.89	36.08	61.73	35.83
	ECOD	93.73	40.93	98.82	57.89	67.32	33.71	63.45	39.59	63.85	39.84
	DeepSVDD	96.92	76.20	93.39	83.92	59.33	8.40	59.85	59.30	59.52	58.39
	LSTM	95.86	61.35	99.17	75.81	69.34	30.46	61.56	47.96	61.38	47.73
	LSTM-AE	89.92	4.56	100.00	8.72	48.91	100.00	85.26	42.67	85.83	43.24
	LSTM-VAE	89.92	4.56	100.00	8.72	48.91	100.00	85.26	42.67	85.83	43.24
	DAGMM	92.91	95.22	34.37	50.51	60.87	42.35	58.42	18.64	57.52	18.45
	USAD	89.89	94.86	4.28	8.18	99.54	5.56	52.42	14.22	51.86	14.28
	BeatGAN	89.75	74.11	4.28	8.09	97.01	5.56	66.16	21.79	65.66	21.66
	Anomaly-Transformer	98.69	91.92	96.03	93.93	51.76	95.98	90.04	87.87	88.2	86.26
	DCdetector	99.06	93.69	99.69	96.6	51.84	97.39	93.17	91.64	93.15	91.66
NIPS_TS_Ccard	KNN	99.67	39.01	21.01	27.32	74.96	28.40	55.57	37.74	55.51	37.20
	LOF	99.64	0.00	0.00	0.00	48.34	18.17	54.08	12.16	54.01	12.48
	IForest	99.81	13.45	26.55	17.86	60.38	52.84	51.44	15.39	51.51	14.78
	COPOD	99.82	17.49	35.14	23.35	62.52	57.23	51.32	14.80	51.46	14.49
	ECOD	99.83	17.04	39.58	23.82	64.79	62.22	51.13	13.61	51.33	13.48
	DeepSVDD	99.74	0.45	0.65	0.53	54.28	32.41	52.22	8.29	52.20	8.38
	LSTM	99.85	22.97	55.43	32.48	69.08	73.53	51.05	14.26	51.53	14.95
	LSTM-AE	99.72	7.42	8.54	7.94	56.39	67.03	50.87	12.80	50.91	12.25
	LSTM-VAE	99.79	21.34	33.54	26.09	59.77	84.66	51.66	18.08	52.45	18.71
	DAGMM	99.73	0.59	0.45	0.51	52.39	23.8	76.5	10.02	76.16	9.71
	Anomaly-Transformer	99.66	0	0	0	50.76	37.14	52.51	11.91	52.46	11.65
	DCdetector	99.73	0.65	0.45	0.53	46.51	23.30	52.52	9.93	52.46	9.08
	USAD	99.78	22.50	16.14	18.80	62.13	9.71	86.97	23.26	86.73	22.08
	BeatGAN	99.85	53.54	23.77	32.92	74.02	24.17	81.83	14.42	82.31	13.90
NIPS_TS_Swan	KNN	88.16	64.87	98.38	78.18	85.80	88.02	78.40	75.07	79.04	75.40
	LOF	67.38	0.00	0.00	0.00	44.84	98.67	47.40	14.20	47.26	14.06
	IForest	86.55	58.76	99.95	74.01	66.09	93.02	89.98	78.54	88.28	77.17
	COPOD	86.47	58.50	100.00	73.82	76.24	100.00	91.63	79.27	91.62	79.26
	ECOD	86.44	58.50	99.83	73.77	48.12	80.20	69.73	61.93	72.23	63.92
	DeepSVDD	86.49	58.60	99.97	73.89	53.87	97.44	90.99	78.97	90.52	78.59
	LSTM	87.78	63.22	98.90	77.14	82.21	89.60	80.05	74.48	81.13	75.10
	LSTM-AE	86.48	58.58	99.98	73.88	56.05	98.37	78.97	69.22	78.95	69.20
	LSTM-VAE	86.47	58.50	100.00	73.82	76.24	100.00	91.63	79.27	91.62	79.26
	DAGMM	86.37	99.09	58.71	73.74	54.64	1.06	91.88	91.05	91.32	90.01
	USAD	86.45	99.39	58.78	73.87	68.00	0.66	93.64	93.46	91.24	91.41
NIPS_TS_Syn_Mulvar	KNN	79.92	8.55	100.00	15.75	55.95	100.00	67.73	40.33	69.91	42.20
	LOF	79.43	6.32	99.82	11.89	53.56	99.29	65.86	36.17	67.94	37.97
	IForest	79.55	6.88	100.00	12.87	64.89	100.00	64.28	35.35	65.74	36.25
	COPOD	78.42	1.91	90.32	3.75	53.24	95.51	62.80	29.26	63.00	29.29
	ECOD	78.56	2.53	94.28	4.93	51.53	98.29	63.76	30.65	64.52	31.15
	DeepSVDD	79.08	4.74	100.00	9.05	53.23	100.00	67.32	34.26	69.33	36.22
	LSTM	79.13	4.94	100.00	9.42	52.70	100.00	68.66	35.73	70.32	37.26
	LSTM-AE	78.43	2.14	87.85	4.18	50.26	99.07	65.50	32.16	65.93	32.41
	LSTM-VAE	78.25	1.40	79.10	2.75	50.08	99.12	65.21	31.98	65.26	31.89
	DAGMM	78.31	90.94	1.37	2.70	74.05	0.59	99.99	99.98	97.33	95.7
	USAD	78.04	48.8	7.88	13.61	50.49	8.31	99.98	99.98	96.53	95.23
NIPS_TS_Water	KNN	96.48	99.25	94.39	96.76	89.39	2.61	68.44	87.01	66.51	86.10
	LOF	53.65	100.00	49.56	66.28	100.00	2.52	82.24	99.08	79.35	98.81
	IForest	99.28	32.05	100.00	48.55	84.66	100.00	86.31	52.76	87.30	53.75
	COPOD	99.28	32.05	98.32	48.35	90.84	74.86	68.98	35.55	68.81	35.42
	ECOD	99.05	10.55	97.47	19.04	84.47	99.73	61.30	17.14	63.77	19.65
	DeepSVDD	58.14	73.70	4.29	8.10	94.52	1.31	53.88	63.30	53.60	62.88
	LSTM	99.29	35.47	92.53	51.28	76.58	28.04	55.43	26.27	54.82	25.10
	LSTM-AE	99.28	32.05	97.91	48.30	85.86	66.67	81.97	48.45	78.15	44.65
	LSTM-VAE	99.28	32.05	97.91	48.30	85.86	66.67	81.97	48.45	78.15	44.65
	DAGMM	98.86	36.32	10.55	16.35	75.05	10.40	71.02	5.06	71.38	5.10
	USAD	99.29	93.80	35.21	51.20	99.45	13.64	29.55	4.23	28.74	4.31
	BeatGAN	99.30	95.54	35.21	51.45	98.89	13.64	48.93	3.65	48.20	3.67
	Anomaly-Transformer	98.26	29.96	48.63	37.08	55.65	89.12	60.74	28.17	60.48	28.02
	DCdetector	98.23	33.46	39.05	36.04	51.67	88.96	59.12	28.84	58.50	28.25
PSM	KNN	94.84	95.31	91.98	93.62	93.33	6.38	73.90	84.71	70.89	82.86
	LOF	85.64	99.96	77.41	87.25	89.22	1.69	76.08	93.79	74.49	92.97
	IForest	78.36	22.04	100.00	36.12	55.22	100.00	87.32	59.95	87.33	59.97
	COPOD	78.36	22.04	100.00	36.12	55.22	100.00	87.32	59.95	87.33	59.97
	ECOD	78.36	22.04	100.00	36.12	55.22	100.00	87.32	59.95	87.33	59.97
	DeepSVDD	93.14	92.93	88.12	90.46	86.52	7.43	73.99	82.53	71.55	80.93
	LSTM	95.25	82.93	99.96	90.65	79.89	89.90	90.54	86.74	89.98	86.30
	LSTM-AE	92.84	79.39	99.72	88.40	77.36	43.84	81.79	80.16	83.03	81.03
	LSTM-VAE	97.10	92.83	99.80	96.19	85.35	65.86	96.82	95.86	95.73	95.17
	Anomaly-Transformer	98.68	96.94	97.81	97.37	55.35	80.28	91.83	93.03	88.71	90.71
	DCdetector	98.95	97.14	98.74	97.94	54.71	82.93	91.55	92.93	88.41	90.58

Table 6: MTSAD comparisons on all public datasets - part 2.

Dataset	Method	Acc	P	R	F1	Aff-P	Aff-R	R_A_R	R_A_P	V_ROC	V_PR
SMAP	KNN	93.89	52.98	98.60	68.93	58.42	10.35	51.14	35.64	51.05	35.52
	LOF	90.94	29.77	97.98	45.67	59.95	10.12	48.91	21.59	48.74	21.37
	IForest	93.62	50.57	99.05	66.95	58.55	15.50	51.33	34.14	51.39	34.15
	COPOD	94.02	53.80	99.03	69.72	59.52	14.42	51.51	35.94	51.57	35.94
	ECOD	94.02	53.80	99.05	69.73	59.52	14.69	51.51	35.94	51.57	35.94
	DeepSVDD	92.37	40.49	99.73	57.59	74.44	37.60	59.33	35.77	58.30	34.79
	LSTM	94.00	53.73	98.88	69.62	61.55	12.01	51.35	36.11	51.36	36.06
	LSTM-AE	94.04	54.23	98.47	69.94	63.92	13.90	51.92	36.60	51.98	36.60
	LSTM-VAE	93.14	47.24	98.16	63.79	65.03	21.49	52.47	33.19	52.52	33.20
	DAGMM	93.86	98.95	52.53	68.63	58.42	58.67	45.03	12.22	45	12.25
	USAD	88.23	95.24	8.42	15.47	52.82	24.90	37.89	10.83	37.82	10.85
	BeatGAN	94.00	98.37	53.98	69.71	74.03	62.24	44.91	12.03	44.80	12.04
	Anomaly-Transformer	99.05	93.59	99.41	96.41	51.39	98.68	96.32	94.07	95.52	93.37
	DCdetector	99.15	94.44	99.14	96.73	51.46	98.64	96.03	94.18	95.19	93.46
SMD	KNN	91.95	90.88	41.40	56.89	92.23	3.83	58.59	62.47	57.98	61.76
	LOF	79.36	96.94	27.57	42.93	88.19	1.68	60.69	74.76	60.04	73.95
	IForest	97.49	42.35	93.97	58.39	64.30	13.65	59.92	33.61	58.99	32.65
	COPOD	96.78	24.70	91.95	38.94	61.03	26.13	68.55	32.91	67.67	32.05
	ECOD	96.81	24.29	95.50	38.73	62.58	25.26	72.43	36.52	72.17	36.26
	DeepSVDD	97.36	50.57	78.37	61.47	72.99	10.66	61.33	39.38	60.88	38.92
	LSTM	98.84	76.10	94.99	84.50	83.84	15.66	59.06	50.90	58.74	50.48
	LSTM-AE	97.16	65.83	68.27	67.03	80.45	15.63	64.10	49.97	63.68	49.56
	LSTM-VAE	96.96	82.35	63.50	71.71	87.07	16.18	63.98	58.57	63.03	57.65
	DAGMM	96.86	88.78	28.05	42.63	69.55	16.4	63.69	9.67	63.06	9.62
	Anomaly-Transformer	99.16	88.47	92.28	90.33	58.94	91.79	76.57	72.76	76.67	72.88
	DCdetector	98.86	83.59	91.1	87.18	52.72	93.8	78.04	71.96	75.15	69.23
	USAD	96.45	89.42	16.51	27.87	85.03	3.81	57.98	10.12	57.34	10.09
	BeatGAN	97.44	80.77	50.36	62.04	90.00	28.30	76.83	14.59	76.28	14.47
Ave.	KNN	95.19	65.89	69.27	62.43	77.15	11.03	57.77	52.03	57.23	51.56
	LOF	83.09	50.63	52.56	39.10	71.66	8.45	59.61	46.24	58.84	46.00
	IForest	96.28	31.15	83.06	44.22	65.71	39.74	60.75	31.03	60.63	30.76
	COPOD	96.63	32.95	84.59	46.76	67.27	41.38	60.45	31.06	60.25	30.75
	ECOD	96.69	29.32	86.08	41.84	67.74	47.12	59.96	28.56	60.54	29.03
	DeepSVDD	88.91	48.28	55.29	42.32	71.11	18.08	57.32	41.21	56.90	40.67
	LSTM	97.57	49.92	88.20	62.74	72.08	31.94	55.69	35.10	55.57	34.86
	LSTM-AE	96.02	32.82	74.64	40.39	67.11	52.65	66.82	38.10	66.11	37.26
	LSTM-VAE	95.82	37.51	78.62	43.72	69.33	57.80	67.07	40.19	66.40	39.49
	DAGMM	94.89	53.31	20.99	29.77	59.03	25.35	65.60	18.68	65.26	18.44
	USAD	94.72	79.16	16.11	24.30	79.79	11.52	52.96	12.53	52.49	12.32
	BeatGAN	96.06	80.46	33.52	44.84	86.79	26.78	63.73	13.29	63.45	13.14

Table 7: Evaluation results with hyper-parameter selection. The LSTM performs better than other methods in most instances.

Method	dataset	Acc	P	R	F1	Aff-P	Aff-R	R_A_R	R_A_P	V_ROC	V_PR
DAGMM	instance38	0.9768	0.0048	0.1139	0.0072	0.7389	0.9781	0.8328	0.0237	0.8081	0.0231
	instance44	0.9575	0.0607	0.654	0.1095	0.6958	0.8153	0.8626	0.0527	0.8498	0.0505
	instance15	0.9978	0.6265	0.8983	0.7386	0.7785	0.988	0.8982	0.0541	0.89	0.0554
	instance23	0.96	0.0056	0.5938	0.01	0.6746	0.9365	0.9417	0.0198	0.9374	0.0199
	instance14	0.4969	0.0323	0.9566	0.0624	0.4818	0.9962	0.5948	0.0269	0.5821	0.0271
	instance39	0.9861	0.0649	0.7054	0.1154	0.5774	0.7579	0.7423	0.0309	0.7426	0.0297
USAD	instance38	0.9976	0.078	0.1392	0.0762	0.6332	0.4486	0.8598	0.1467	0.8185	0.1275
	instance44	0.9877	0.1596	0.4751	0.2342	0.9136	0.5858	0.9409	0.1776	0.9357	0.166
	instance15	0.9892	0.2264	0.861	0.3526	0.8189	0.9302	0.992	0.5171	0.9779	0.4764
	instance14	0.9956	0.8983	0.8452	0.8724	0.9452	0.3239	0.7723	0.1763	0.7161	0.154
	instance23	0.9463	0.0057	0.8125	0.0101	0.6717	0.6	0.9292	0.2404	0.9263	0.2234
	instance39	0.9948	0.1649	0.7054	0.2625	0.963	0.3333	0.6144	0.0783	0.6349	0.0827
iForest	instance38	0.9994	0.6778	0.7722	0.7453	0.6102	0.7163	0.9385	0.1116	0.923	0.1082
	instance44	0.9959	0	0	0	nan	0	0.7977	0.0369	0.7622	0.0347
	instance15	0.9974	0.5894	0.8172	0.7011	0.8367	0.8832	0.9627	0.2142	0.9663	0.2055
	instance14	0.9982	0.9853	0.9097	0.9473	0.9552	0.4801	0.9486	0.1809	0.9074	0.1745
	instance23	0.9653	0.0065	0.5938	0.0115	0.7742	0.5933	0.9522	0.0376	0.9321	0.0379
	instance39	0.9996	0.9634	0.7054	0.8352	0.9986	0.3333	0.8994	0.1219	0.8982	0.1226
LSTM	instance38	0.9832	0.0488	0.9114	0.0882	0.5984	0.9988	0.8839	0.1291	0.8697	0.1047
	instance44	0.9723	0.1262	0.9824	0.2196	0.8736	0.9918	0.9368	0.2201	0.9296	0.2032
	instance15	0.9989	0.8885	0.7831	0.8355	0.9034	0.8604	0.9721	0.2806	0.9646	0.2731
	instance14	0.9959	0.8628	0.9097	0.8867	0.8093	0.9874	0.9503	0.1775	0.9179	0.1726
	instance23	0.9984	0.1699	0.8125	0.2599	0.7281	0.9464	0.9967	0.4576	0.9924	0.3873
	instance39	0.9828	0.0659	0.9018	0.1177	0.6709	0.8525	0.9143	0.1524	0.9178	0.1625
ATrans	instance38	0.9876	0.061	0.8481	0.1138	0.489	0.8426	0.6126	0.1524	0.5922	0.1323
	instance44	0.989	0.5797	0.9898	0.7312	0.4965	0.4969	0.9464	0.7437	0.9066	0.7044
	instance15	0.9866	0.1635	0.6814	0.2638	0.4913	0.9719	0.6662	0.2595	0.651	0.2442
	instance23	0.9863	0	0	0	0.4967	0.9808	0.4991	0.0081	0.5006	0.0099
	instance14	0.9878	0.5907	0.9952	0.7413	0.5109	0.9958	0.9242	0.7276	0.9231	0.727
	instance39	0.9882	0.0788	0.7321	0.1422	0.5104	0.9879	0.59	0.1403	0.5892	0.1397
DCdetector	instance38	0.9891	0.0712	0.8632	0.1368	0.4923	0.8562	0.649	0.1749	0.6172	0.1536
	instance44	0.9902	0.6293	0.9898	0.7694	0.6016	0.5706	0.9466	0.768	0.8993	0.7213
	instance15	0.9891	0.2236	0.7458	0.344	0.514	0.9711	0.6827	0.3056	0.658	0.2811
	instance23	0.9901	0.0636	0.8524	0.1079	0.5123	0.9646	0.6245	0.1786	0.6034	0.1546
	instance14	0.9893	0.6342	0.9469	0.7596	0.5058	0.9958	0.9179	0.7426	0.885	0.7102
	instance39	0.9898	0.0998	0.8326	0.2043	0.6035	0.9895	0.6836	0.1834	0.645	0.2478

Table 8: Experimental results on part of the instances with filling mean for missing data.

Instance	Method	Acc	P	R	F1	A-P	A-R	R_A_R	R_A_P	V_ROC	V_PR	A_PR	A_R
	DAGMM	44.47	2.94	95.66	5.7	48	99.62	54.15	2.09	53.1	2.13	53.67	46.98
	USAD	99.35	79.6	84.52	81.99	88.63	46.39	42.86	4.14	39.91	4.05	62.66	27.56
	KNN	24.66	2.19	96.13	4.28	51.65	99.65	81.89	6.99	78.56	6.8	82.51	66.67
	LOF	14.89	1.94	96.13	3.81	51.56	99.65	87.05	7.87	83.26	7.61	83.75	69.66
	IForest	99.69	91.47	90.97	91.22	80.46	87.96	89.25	14.92	85.44	14.44	84.86	71.39
	COPOD	98.24	0	0	0	95.9	33.3	94.02	16.66	90.59	15.91	91.24	78.69
	ECOD	98.35	90.48	6.45	12.04	96.42	49.97	86.03	7.77	82.4	7.41	83.89	70.07
instance14	DeepSVDD	47.58	3.11	95.66	6.02	55.16	99.63	91.63	29.66	86.93	27.29	93.18	64.8
	LSTM	99.35	79.45	84.52	81.91	88.87	47.25	44.49	4.16	41.92	4.08	63.21	28.1
	LSTM-AE	99.34	79.3	84.52	81.83	88.75	47.22	44.13	4.17	41.82	4.1	63.43	28.44
	LSTM-VAE	99.34	79.3	84.52	81.83	88.75	47.22	44.13	4.17	41.82	4.1	63.43	28.44
	Anomaly-Transformer	98.81	60.28	95.11	73.8	51.03	99.52	90.65	71.65	89.65	70.67	80.1	50.73
	DCdetector	98.93	63.57	94.69	76.07	50.52	99.59	91.8	74.34	89.53	72.11	81.74	50.66
	BeatGAN	99.32	78.25	84.52	81.27	88.76	47.34	44.45	4.16	41.86	4.08	63.17	28.05
	DAGMM	99.72	56.87	89.83	69.65	76.89	99.3	89.82	5.41	89	5.54	80.57	81.97
	USAD	0	0	0	0	0	0	0	0	0	0	0	0
	KNN	97.49	5.8	40.34	10.14	79	82	74.47	8.38	70.1	8.19	42.31	41.29
	LOF	99.37	0	0	0	30.89	10.1	66.79	2.58	63.54	2.55	43.85	43.67
	IForest	98.53	19.16	99.32	32.13	80.9	99.08	96.89	43.58	97.6	42.15	97.41	95.7
	COPOD	99.86	87.5	68.81	77.04	96.52	64.82	98.48	41.36	98.45	40.54	97.78	95.84
	ECOD	99.89	93.16	73.9	82.42	94	74.7	98.75	38.02	98.54	35.77	96.83	96.48
instance15	DeepSVDD	98.45	14.4	69.15	23.83	71.98	75.75	89.94	4.57	87.27	4.76	67.1	64.4
	LSTM	94.74	2.42	35.59	4.54	61.94	75.81	81.94	9.23	80.89	8.64	88.39	80.51
	LSTM-AE	94.17	2.18	35.59	4.11	71.06	73.19	81.78	6.39	80.77	6.34	88.51	80.87
	LSTM-VAE	94.17	2.18	35.59	4.11	71.06	73.19	81.78	6.39	80.77	6.34	88.51	80.87
	Anomaly-Transformer	98.66	16.35	68.14	26.38	49.13	97.19	66.62	25.95	65.1	24.42	58.12	50.68
	DCdetector	98.91	22.36	74.58	34.4	51.4	97.11	68.27	30.56	65.8	28.11	61.13	50.64
	BeatGAN	93.25	4.48	89.49	8.54	60.21	88.41	81.93	9.23	80.88	8.64	88.37	80.5
	DAGMM	95.36	0.49	59.38	0.97	65.48	96.57	94.17	1.98	93.74	1.99	91.72	89.77
	USAD	94.64	0.42	59.38	0.84	66.32	59.2	93.62	22.45	83.34	20.56	67.08	49.51
	KNN	55.33	0.09	100	0.17	59.44	100	99.25	31.13	97.9	25.37	91.77	91.11
	LOF	98.24	0	0	0	57.78	57.33	67.19	0.45	66.1	0.43	57.76	56.24
	IForest	95.34	0.48	59.38	0.96	69.08	59.33	95.81	5.17	94.96	5.31	92.84	90.37
	COPOD	99.97	59.38	59.38	59.38	99.84	40	95.44	23.4	92.94	21.43	85.41	81.31
	ECOD	99.97	67.86	59.38	63.33	99.85	40	95.85	23.63	93.91	21.67	85.9	84.47
instance23	DeepSVDD	0.04	0.04	100	0.08	50	100	66.25	1.06	63.92	1.01	52.73	52.07
	LSTM	97.58	0.93	59.38	1.84	76.8	59.33	94.03	23.09	85.28	21.47	67.21	51.31
	LSTM-AE	97.53	0.91	59.38	1.8	77.01	59.35	94.13	23.55	85.6	21.14	66.7	49.55
	LSTM-VAE	97.53	0.91	59.38	1.8	77.01	59.35	94.13	23.55	85.6	21.14	66.7	49.55
	Anomaly-Transformer	98.63	0	0	0	49.67	98.08	49.91	0.81	50.06	0.99	49.98	50.72
	DCdetector	99.01	1.97	48.39	3.79	50.22	98.65	55.38	7.05	55.42	7.08	50.98	50.63
	BeatGAN	95.07	0.46	59.38	0.91	66.74	59.33	94.03	23.12	85.28	21.5	67.22	51.32
	DAGMM	83.02	0.06	11.39	0.13	61.5	74.65	72	0.86	70.72	0.76	62.42	57.64
	USAD	98.69	0.48	6.33	0.9	63.48	89.33	77.49	11.5	76.51	9.84	79.76	73.69
	KNN	72.93	0.32	93.67	0.65	56.32	99.99	89.54	20.09	89.29	18.1	92.29	91.32
	LOF	96.26	0	0	0	55.98	39.96	85.6	1.38	83.83	1.31	74.83	70.86
	IForest	99.9	0	0	0	68.3	29.28	93.45	8.99	92.45	8.17	90.37	91.22
	COPOD	99.9	40	7.59	12.77	40.43	19.68	95.34	14.72	94.85	13.26	91.96	93.94
	ECOD	99.87	20	11.39	14.52	71.33	83.68	93.85	20.77	93.09	18.59	92.08	93.46
instance38	DeepSVDD	69.49	0.29	94.94	0.58	61.73	99.89	78.69	1.39	78.05	1.46	66.27	69.37
	LSTM	99.72	3.07	6.33	4.13	67.55	93.95	83.39	3.11	82.02	2.72	79.39	74.58
	LSTM-AE	99.27	1.1	7.59	1.92	60.46	84.28	79.7	12.39	79.01	10.99	83.92	78.9
	LSTM-VAE	99.27	1.1	7.59	1.92	60.46	84.28	79.7	12.39	79.01	10.99	83.92	78.9
	Anomaly-Transformer	98.8	0.64	7.59	1.18	50.8	84.09	51.04	2.36	50.9	2.21	50.28	50.63
	DCdetector	98.88	0	0	0	52.16	83.93	50.86	2.14	50.36	1.5	49.95	50.43
	BeatGAN	98.56	5.36	86.08	10.1	63.55	97.73	83.36	3.12	81.99	2.73	79.37	74.62
	DAGMM	98.82	3.87	33.04	6.92	64.78	69.75	73.32	3.31	73.84	3.17	83.31	72.58
	USAD	86.66	0.05	5.36	0.11	58.91	64.57	77.18	4.64	69.11	3.98	16	15.89
	KNN	26.72	0.18	100	0.36	56.63	100	59.38	4.09	61.57	4.29	91.74	70.32
	LOF	0.13	0.13	100	0.27	50.01	100	36.25	0.58	35.56	0.57	34.46	29.13
	IForest	99.95	87.78	70.54	78.22	99.69	33.33	91.29	12.87	90.82	12.89	93.6	86.93
	COPOD	99.89	81.25	23.21	36.11	99.98	22.22	77.68	10.96	78.38	11.31	92.1	81.42
	ECOD	99.88	66.67	23.21	34.44	98.6	33.02	86.23	19.71	86.19	19.02	92.4	85.76
instance39	DeepSVDD	67.17	0.37	90.18	0.73	60.62	73.95	54.61	1.23	55.05	1.25	77.48	57.5
	LSTM	99.77	0	0	0	62.42	61.9	79.48	5.14	73.01	4.56	19.78	23.91
	LSTM-AE	99.69	13.81	25.89	18.01	63.12	59.21	79.5	5.73	73.41	5.24	25.68	28.26
	LSTM-VAE	99.69	13.81	25.89	18.01	63.12	59.21	79.5	5.73	73.41	5.24	25.68	28.26
	Anomaly-Transformer	98.82	7.88	73.21	14.22	51.04	98.79	59	14.03	58.92	13.97	53.92	50.69
	DCdetector	98.94	7.41	54.46	13.05	50.4	97.62	56.97	11.87	57.32	12.21	53.67	50.61
	BeatGAN	99.65	8.14	16.07	10.81	63.35	70.83	79.48	5.13	73.01	4.56	19.78	23.91
	DAGMM	91.47	15	99.29	26.06	66.38	91.57	78.28	4.31	78	4.27	75	73.68
	USAD	81.05	7.4	100	13.77	61.62	100	91.13	8.67	90.88	8.69	90.43	89.04
	KNN	97.23	35.27	99.45	52.07	61.48	97.18	98.99	54.28	98.57	52.58	98.09	92.66
	LOF	97.63	0	0	0	57.82	10.02	97.78	28.53	97.25	26.89	96.7	90.37
	IForest	93.7	19.31	99.53	32.34	68.95	86.43	92.27	8.93	92.18	9.01	91.49	90.93
	COPOD	99.92	95.96	98.98	97.44	93.49	33.21	93.23	10.42	93.13	10.41	92.59	91.9
	ECOD	99.94	96.99	98.98	97.98	93.54	33.21	93.39	10.74	93.3	10.72	92.63	92.11
instance44	DeepSVDD	98.24	46.27	98.98	63.06	48.1	33.1	95.29	14.26	95.2	14.62	95.13	94.21
	LSTM	95.46	24.93	99.53	39.87	68.96	84.66	90.79	7.66	90.68	7.67	89.78	89.07
	LSTM-AE	88.22	11.38	99.84	20.42	65.51	99.59	91.32	8.28	91.2	8.33	90.63	89.43
	LSTM-VAE	88.22	11.38	99.84	20.42	65.51	99.59	91.32	8.28	91.2	8.33	90.63	89.43
	Anomaly-Transformer	98.93	58.73	98.98	73.72	58.86	56.06	94.54	74.57	90.44	70.53	79.36	50.7
	DCdetector	98.97	61.88	98.98	76.15	52.89	43.56	94.74	76.44	83.64	65.49	80.93	50.51
	BeatGAN	93.18	18.13	99.53	30.67	59.83	86.43	90.78	7.65	90.66	7.66	89.76	89.01

Table 9: Experimental results on part of the instances with filling zero for missing data.

Instance	model	Acc	F1	P	R	A-P	A-R	R_A_P	R_A_R	V_P	V_R
	USAD	99.34	81.77	79.20	84.52	88.54	46.40	4.22	43.42	4.12	39.82
	KNN	1.75	3.45	1.75	100.00	50.26	100.00	6.46	80.87	6.29	77.59
	LOF	40.52	5.57	2.86	100.00	57.08	100.00	8.65	86.39	8.34	84.76
	IForest	98.23	16.99	48.10	10.32	50.21	33.80	14.54	92.25	14.41	92.19
	COPOD	98.24	0.00	0.00	0.00	47.66	16.08	20.40	95.37	20.24	95.32
	ECOD	99.70	90.94	98.42	84.52	89.27	45.60	12.24	92.52	12.15	92.46
instance14	DeepSVDD	74.24	11.55	6.14	95.86	64.38	99.64	22.50	91.24	21.09	89.41
	LSTM	99.34	81.85	79.35	84.52	88.87	47.25	4.25	45.18	4.17	42.19
	LSTM-AE	99.34	81.72	79.10	84.52	88.72	47.22	4.25	44.76	4.17	42.03
	LSTM-VAE	99.34	81.72	79.10	84.52	88.72	47.22	4.25	44.76	4.17	42.03
	Anomaly-Transformer	98.78	74.13	59.07	99.52	51.09	99.58	72.76	92.42	72.70	92.31
	DCdetector	98.93	75.96	63.42	94.69	50.58	99.58	74.26	91.79	71.02	88.50
	BeatGAN	99.31	81.21	78.15	84.52	88.73	47.34	4.25	45.12	4.16	42.10
	USAD	4.17	0.73	0.37	100.00	50.23	100.00	5.75	81.18	5.65	80.01
	KNN	94.31	5.04	2.68	43.05	60.18	88.90	8.06	74.41	7.91	70.03
	LOF	0.35	0.70	0.35	100.00	50.33	100.00	3.75	65.82	3.79	62.45
	IForest	99.74	70.31	58.94	87.12	81.67	96.03	19.47	95.48	18.82	95.30
	COPOD	99.86	75.47	98.90	61.02	94.43	52.48	39.52	96.77	38.32	97.12
	ECOD	99.67	13.29	100.00	7.12	100.00	22.22	38.36	98.02	37.18	98.07
instance15	DeepSVDD	99.62	57.90	47.60	73.90	75.54	96.72	25.10	94.95	22.57	92.99
	LSTM	94.74	4.54	2.42	35.59	61.94	75.81	9.24	82.52	8.64	81.50
	LSTM-AE	94.17	4.11	2.18	35.59	71.06	73.19	6.39	82.36	6.35	81.38
	LSTM-VAE	94.17	4.11	2.18	35.59	71.06	73.19	6.39	82.36	6.35	81.38
	Anomaly-Transformer	97.76	8.13	4.75	28.14	48.61	95.79	10.43	56.55	9.79	55.87
	DCdetector	98.91	34.46	22.40	74.58	49.49	97.25	30.59	68.28	28.18	65.85
	BeatGAN	93.25	8.54	4.88	89.49	60.21	88.41	9.24	82.45	8.64	81.45
	USAD	94.25	0.78	0.39	59.38	65.39	59.17	21.85	76.42	19.87	68.02
	KNN	50.36	0.06	0.03	40.63	64.11	79.61	2.01	66.95	1.66	64.68
	LOF	49.82	0.06	0.03	40.63	64.28	79.61	0.36	59.40	0.35	58.93
	IForest	99.90	0.00	0.00	0.00	86.04	35.45	0.71	75.36	0.69	74.26
	COPOD	99.97	63.33	67.86	59.38	99.85	40.00	34.65	98.68	29.05	97.84
	ECOD	99.97	63.33	67.86	59.38	99.85	40.00	23.71	96.49	21.72	94.05
instance23	DeepSVDD	38.76	0.12	0.06	100.00	54.20	100.00	1.39	84.83	1.21	82.34
	LSTM	97.15	1.56	0.79	59.38	72.08	59.33	22.05	77.58	20.50	70.16
	LSTM-AE	97.25	1.62	0.82	59.38	73.27	59.35	23.02	77.88	20.54	70.74
	LSTM-VAE	97.25	1.62	0.82	59.38	73.27	59.35	23.02	77.88	20.54	70.74
	Anomaly-Transformer	98.86	0.00	0.00	0.00	51.31	97.85	0.33	49.62	0.50	49.77
	DCdetector	98.96	3.62	1.88	48.39	49.71	98.89	7.03	55.38	7.31	55.66
	BeatGAN	95.05	0.91	0.46	59.38	65.77	59.33	22.10	77.47	20.54	70.04
	USAD	52.48	0.35	0.18	88.61	56.43	99.97	10.99	77.50	9.28	76.48
	KNN	15.30	0.22	0.11	100.00	54.76	100.00	1.51	72.75	1.36	71.29
	LOF	0.09	0.19	0.09	100.00	50.89	100.00	1.39	77.19	1.35	76.02
	IForest	99.03	13.01	7.10	77.22	60.63	82.78	1.98	89.64	1.81	88.07
	COPOD	99.90	0.00	0.00	0.00	13.97	2.00	5.01	93.77	4.40	93.12
	ECOD	99.82	3.82	3.85	3.80	67.63	87.30	12.54	91.75	12.08	89.82
instance38	DeepSVDD	18.51	0.23	0.12	100.00	51.77	100.00	1.94	76.79	1.92	76.89
	LSTM	99.78	5.13	4.31	6.33	67.87	93.95	10.52	80.59	8.39	79.76
	LSTM-AE	99.55	3.09	1.94	7.59	59.37	85.87	13.12	81.02	10.77	80.39
	LSTM-VAE	99.55	3.09	1.94	7.59	59.37	85.87	13.12	81.02	10.77	80.39
	Anomaly-Transformer	98.76	11.38	6.10	84.81	48.90	84.26	15.24	61.26	13.23	59.22
	DCdetector	98.91	0.00	0.00	0.00	49.35	83.86	1.59	50.54	1.31	50.30
	BeatGAN	98.65	10.73	5.72	86.08	64.80	98.15	10.53	80.57	8.40	79.73
	USAD	86.22	0.10	0.05	5.36	60.10	64.56	4.34	68.91	3.71	61.92
	KNN	35.76	0.39	0.20	94.64	56.66	96.09	2.02	54.33	2.06	56.10
	LOF	29.67	0.19	0.10	50.89	52.52	98.73	0.70	45.15	0.74	44.95
	IForest	99.87	0.00	0.00	0.00	95.53	10.63	3.05	67.03	2.99	68.02
	COPOD	99.87	35.37	55.77	25.89	78.04	27.83	7.13	86.62	6.72	86.59
	ECOD	99.88	35.80	58.00	25.89	78.09	27.83	5.97	83.96	5.62	83.05
instance39	DeepSVDD	85.14	1.13	0.57	63.39	84.94	77.32	0.86	65.64	0.86	63.95
	LSTM	99.76	0.00	0.00	0.00	64.06	64.81	5.23	72.07	4.60	65.36
	LSTM-AE	99.69	18.41	14.29	25.89	63.21	59.21	5.16	72.35	4.70	66.07
	LSTM-VAE	99.69	18.41	14.29	25.89	63.21	59.21	5.16	72.35	4.70	66.07
	Anomaly-Transformer	97.97	5.85	3.12	47.32	48.61	96.71	9.40	56.24	8.47	55.33
	DCdetector	98.93	11.41	6.49	47.32	51.01	97.48	10.89	56.33	10.51	56.00
	BeatGAN	99.66	11.25	8.65	16.07	62.48	70.65	5.23	72.05	4.60	65.31
	USAD	79.68	0.15	0.08	1.02	54.56	83.33	2.42	68.04	2.41	67.76
	KNN	98.26	63.20	46.42	98.98	78.92	26.68	62.86	98.27	69.13	98.19
	LOF	98.25	63.07	46.28	98.98	78.74	26.68	29.08	97.17	27.89	96.55
	IForest	91.71	26.55	15.33	98.98	76.90	32.68	1.20	31.97	1.22	32.26
	COPOD	99.90	96.92	94.94	98.98	93.88	33.27	13.64	94.82	13.67	94.71
	ECOD	99.93	97.71	96.47	98.98	93.69	33.27	11.47	93.80	11.42	93.72
instance44	DeepSVDD	99.97	98.98	98.98	98.98	67.92	33.10	35.06	50.71	43.77	61.55
	LSTM	93.90	0.27	0.18	0.55	62.75	67.99	2.42	68.16	2.41	67.87
	LSTM-AE	86.68	0.20	0.11	0.87	65.18	99.18	2.44	68.26	2.42	67.96
	LSTM-VAE	86.68	0.20	0.11	0.87	65.18	99.18	2.44	68.26	2.42	67.96
	Anomaly-Transformer	98.95	74.04	59.14	98.98	46.19	48.06	74.78	94.55	71.01	90.72
	DCdetector	99.00	76.61	62.49	98.98	59.10	56.36	76.58	94.65	70.38	88.36
	BeatGAN	91.60	0.20	0.12	0.55	52.22	69.76	2.41	68.10	2.40	67.81

Table 10: Experimental results on part of the instances with filling linear interpolation for missing data.

Instance	model	Acc	F1	P	R	A-P	A-R	R_A_P	R_A_R	V_P	V_R
instance14	USAD	99.34	81.77	79.20	84.52	88.54	46.40	5.57	50.08	5.26	47.33
	KNN	14.59	3.95	2.01	100.00	51.23	100.00	6.41	77.65	6.43	77.85
	LOF	1.75	3.45	1.75	100.00	50.26	100.00	9.11	84.82	9.01	84.79
	IForest	99.19	79.76	70.85	91.24	68.32	97.16	12.41	92.87	12.36	92.67
	COPOD	98.35	12.07	94.06	6.45	98.59	49.97	12.30	91.40	12.11	91.36
	ECOD	98.34	12.47	86.09	6.72	97.27	49.97	6.87	81.29	6.70	81.15
	DeepSVDD	1.75	3.45	1.75	100.00	50.26	100.00	15.29	87.50	14.92	86.75
	LSTM	99.34	81.85	79.35	84.52	88.87	47.25	5.58	51.32	5.17	48.74
	LSTM-AE	99.34	81.75	79.15	84.52	88.74	47.22	5.57	51.12	5.13	48.62
	LSTM-VAE	99.34	81.75	79.15	84.52	88.74	47.22	5.57	51.12	5.13	48.62
	Anomaly-Transformer	98.19	64.89	49.24	95.11	49.68	99.26	66.11	90.34	65.67	89.88
	DCdetector	98.91	75.65	62.99	94.69	49.57	99.53	74.05	91.78	71.93	89.69
	BeatGAN	99.31	81.21	78.15	84.52	88.73	47.34	5.57	51.27	5.17	48.67
instance15	KNN	89.78	3.03	1.57	45.42	51.20	92.95	5.69	69.48	5.24	65.50
	LOF	82.22	0.00	0.00	0.00	42.43	17.83	0.78	53.18	0.77	50.93
	IForest	98.92	39.22	24.44	99.32	76.12	99.98	24.14	96.67	24.20	97.28
	COPOD	99.88	80.16	96.65	68.47	99.91	44.44	40.92	98.10	40.90	98.32
	ECOD	99.67	13.04	77.78	7.12	99.85	22.22	37.59	98.86	36.01	98.62
	DeepSVDD	99.88	79.53	94.84	68.47	89.79	53.71	37.76	99.04	37.34	97.88
	LSTM	94.74	4.54	2.42	35.59	61.94	75.81	9.23	81.94	8.64	80.90
	LSTM-AE	94.17	4.11	2.18	35.59	71.06	73.19	6.39	81.78	6.34	80.78
	LSTM-VAE	94.17	4.11	2.18	35.59	71.06	73.19	6.39	81.78	6.34	80.78
	Anomaly-Transformer	98.78	29.92	18.73	74.24	50.59	97.56	28.46	68.03	26.77	66.34
	DCdetector	98.91	34.38	22.34	74.58	50.59	97.09	30.51	68.25	27.52	65.29
	BeatGAN	93.25	8.54	4.48	89.49	60.21	88.41	9.23	81.93	8.64	80.89
instance23	USAD	48.22	0.11	0.06	78.13	59.39	99.26	33.95	99.37	30.02	92.15
	KNN	43.45	0.13	0.07	100.00	59.00	100.00	3.06	78.39	2.60	80.07
	LOF	64.81	0.21	0.10	96.88	73.86	99.87	2.86	71.98	2.41	73.62
	IForest	85.73	0.53	0.27	100.00	61.15	100.00	3.10	96.33	2.87	95.05
	COPOD	99.97	59.38	59.38	59.38	99.78	40.00	42.48	99.57	37.02	98.33
	ECOD	99.97	59.38	59.38	59.38	99.78	40.00	44.27	99.63	38.87	98.89
	DeepSVDD	53.87	0.16	0.08	100.00	71.22	100.00	23.46	94.26	19.06	93.25
	LSTM	80.50	0.24	0.12	62.50	66.58	98.16	37.37	99.59	33.31	93.93
	LSTM-AE	80.07	0.24	0.12	62.50	66.83	98.18	35.38	99.49	31.51	93.90
	LSTM-VAE	80.07	0.24	0.12	62.50	66.83	98.18	35.38	99.49	31.51	93.90
	Anomaly-Transformer	98.84	0.00	0.00	0.00	50.74	97.92	0.33	49.61	0.66	48.97
	DCdetector	99.02	0.00	0.00	0.00	49.23	93.36	0.52	49.85	0.35	49.72
	BeatGAN	52.53	0.13	0.06	78.13	59.81	99.37	37.35	99.59	33.30	93.96
instance38	USAD	95.78	0.28	0.14	5.36	68.08	85.59	8.30	70.87	7.00	69.71
	KNN	21.30	0.24	0.12	100.00	57.88	100.00	13.72	82.31	13.84	82.31
	LOF	22.33	0.24	0.12	100.00	57.00	100.00	2.86	86.18	2.88	83.52
	IForest	99.89	0.00	0.00	0.00	53.38	44.24	5.02	92.04	5.12	90.86
	COPOD	99.90	17.31	36.00	11.39	61.59	40.21	19.24	95.81	17.99	95.39
	ECOD	99.82	10.53	9.78	11.39	69.46	87.37	15.72	93.60	15.36	92.60
	DeepSVDD	99.55	4.58	2.87	11.39	68.91	99.75	8.62	78.65	9.05	77.15
	LSTM	99.69	2.26	1.60	3.80	67.92	93.85	2.43	74.49	2.15	73.06
	LSTM-AE	97.79	6.73	3.50	84.81	58.62	82.66	11.02	71.61	9.74	70.47
	LSTM-VAE	97.79	6.73	3.50	84.81	58.62	82.66	11.02	71.61	9.74	70.47
	Anomaly-Transformer	98.00	0.00	0.00	0.00	49.46	84.06	1.25	50.25	1.06	50.08
	DCdetector	98.90	0.00	0.00	0.00	50.71	84.09	1.74	50.66	1.34	50.31
	BeatGAN	96.83	4.87	2.50	86.08	61.83	94.09	2.44	74.56	2.16	73.14
instance39	USAD	85.64	0.10	0.05	5.36	58.99	64.60	4.46	67.89	3.81	60.20
	KNN	20.65	0.34	0.17	100.00	54.25	100.00	3.87	63.48	3.96	65.24
	LOF	23.77	0.34	0.17	98.21	53.38	99.90	1.44	50.11	1.52	50.72
	IForest	99.89	27.48	94.74	16.07	99.93	22.21	15.51	82.18	15.15	82.10
	COPOD	99.89	27.48	94.74	16.07	99.93	22.21	17.29	82.42	16.98	82.53
	ECOD	99.87	25.00	56.25	16.07	81.24	36.33	31.29	89.30	29.04	88.96
	DeepSVDD	40.10	0.42	0.21	94.64	67.06	80.96	4.43	51.22	4.47	51.31
	LSTM	99.76	0.00	0.00	0.00	62.43	61.90	4.91	70.60	4.39	63.53
	LSTM-AE	99.69	18.12	13.94	25.89	60.77	54.08	5.61	70.64	5.12	64.18
	LSTM-VAE	99.69	18.12	13.94	25.89	60.77	54.08	5.61	70.64	5.12	64.18
	Anomaly-Transformer	98.66	8.62	4.74	47.32	47.10	96.61	9.10	55.41	9.42	55.71
	DCdetector	98.91	12.71	7.19	54.46	50.04	97.79	11.62	56.78	11.82	57.05
	BeatGAN	99.63	0.00	0.00	0.00	62.80	70.40	4.91	70.54	4.39	63.49
instance44	USAD	24.66	3.86	1.97	100.00	55.01	100.00	1.55	32.32	1.52	32.54
	KNN	37.28	4.58	2.34	99.45	53.16	97.18	3.14	39.99	3.60	40.40
	LOF	98.49	0.00	0.00	0.00	0.00	0.00	2.61	41.98	3.00	43.06
	IForest	77.86	11.94	6.35	99.13	48.02	81.26	2.58	62.72	2.57	61.92
	COPOD	99.97	98.86	98.74	98.98	93.15	32.31	9.38	90.52	9.59	90.38
	ECOD	99.95	98.51	98.05	98.98	92.80	32.31	7.07	88.31	7.03	88.20
	DeepSVDD	1.51	2.98	1.51	100.00	50.18	100.00	10.32	88.98	9.99	88.64
	LSTM	35.07	4.43	2.27	99.53	60.82	84.66	1.35	34.01	1.42	34.43
	LSTM-AE	27.55	4.00	2.04	99.69	57.06	98.70	1.44	32.68	1.41	32.97
	LSTM-VAE	27.55	4.00	2.04	99.69	57.06	98.70	1.44	32.68	1.41	32.97
	Anomaly-Transformer	98.90	73.12	57.97	98.98	49.65	49.69	74.37	94.64	70.44	90.66
	DCdetector	99.02	76.94	62.93	98.98	60.16	57.06	76.80	94.66	72.13	89.93
	BeatGAN	32.31	4.26	2.17	99.53	51.67	86.43	1.35	34.06	1.43	34.48