

HDDse: Enabling High-Dimensional Disk State Embedding for Generic Failure Detection System of Heterogeneous Disks in Large Data Centers

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Disk Failure Prediction (ATC, ICPP, TPDS)

Sector Error Prediction (DAC, FAST)

Database Tuning (SIGMOD, VLDB, VLDBJ, NEDB)

Disk Failure

**Data
Protection Scheme**

eg., replication and
erasure codes

**Disk
Failure Prediction**

eg., Machine Learning-based
Disk Failure Prediction

S.M.A.R.T Technology

Self-**M**onitoring **A**nalysis and **R**eporting **T**echnology

(**ID**, **Normalized**, **Raw**, Threshold, Worst)

SMART technology contains up to 30 attributes, reporting various disk operating conditions.

Threshold Method



Failure detection rate (FDR) of **3%-10%** with **0.1%** false alarm rate (FAR)

Six classes of approaches

Threshold-Based
approaches
(TB)

Distance-based
Anomaly Detection
approaches
(DAD)

Shallow Machine
Learning-based
approaches
(SML)

Deep Neural
Network-based
approaches
(DNN)

One-Class
Classification -based
approaches
(OCC)

Transfer
Learning-based
approaches
(TL)

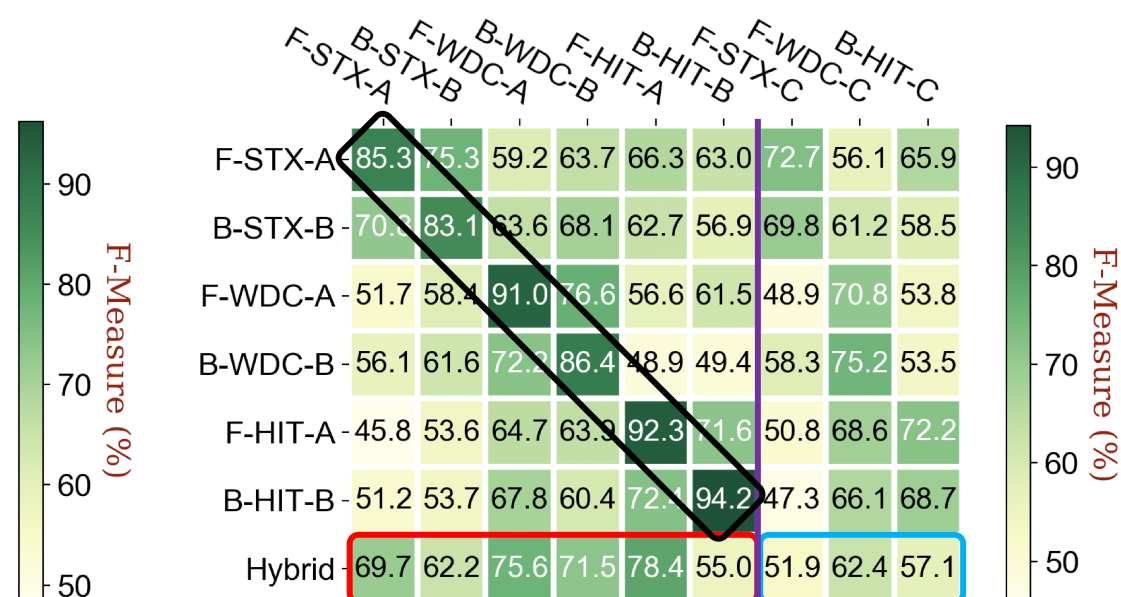
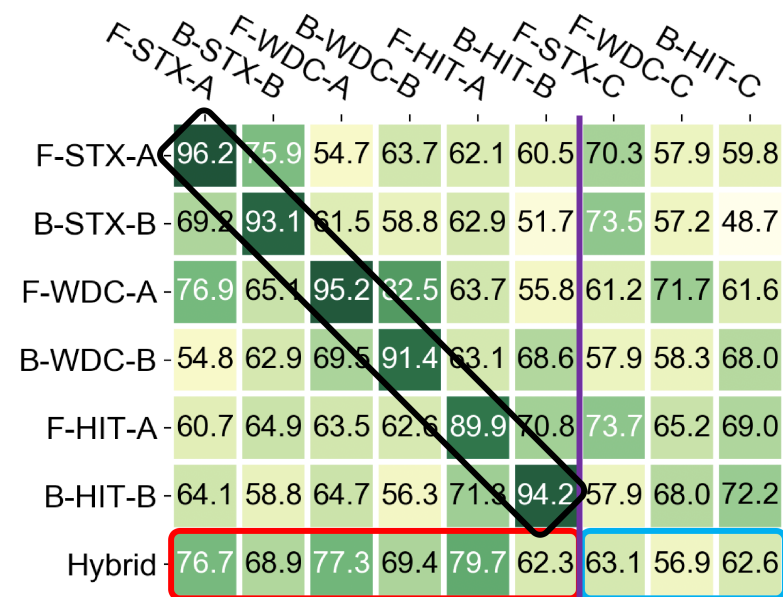
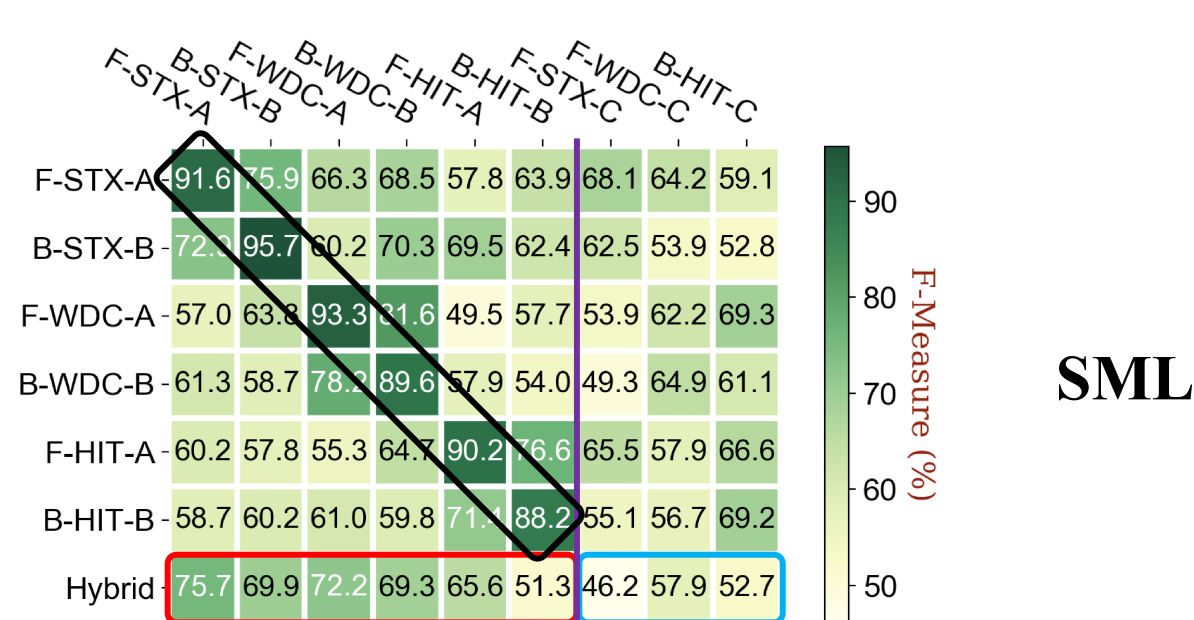
Limitations

	TB	DAD	SML	DNN	OCC	TL
Applicability	✓	✓	✗	✗	✗	✗
Adaptability	✓	✓	✗	✗	✗	✓(*)
Imbalance Datasets	✓	✗	✗	✗	✓	✗
Minority Disk	✓	✗	✗	✗	✗	✓(*)
Performance	FDR:3%-10%	FDR:56%-70%	FDR:75%-96%	FDR:87%-98%	FDR:70%-92%	FDR:80%-97%
	FAR:0.1%-2%	FAR:0%-0.8%	FAR:0.8%-4%	FAR:0.6%-1.9%	FAR:0%-10%	FAR:0.5%-6%

(*) refers to certain conditions that are required, e.g., finding a suitable source domain (i.e., another disk model) for knowledge transfer.

Limitation

Applicability and Adaptability

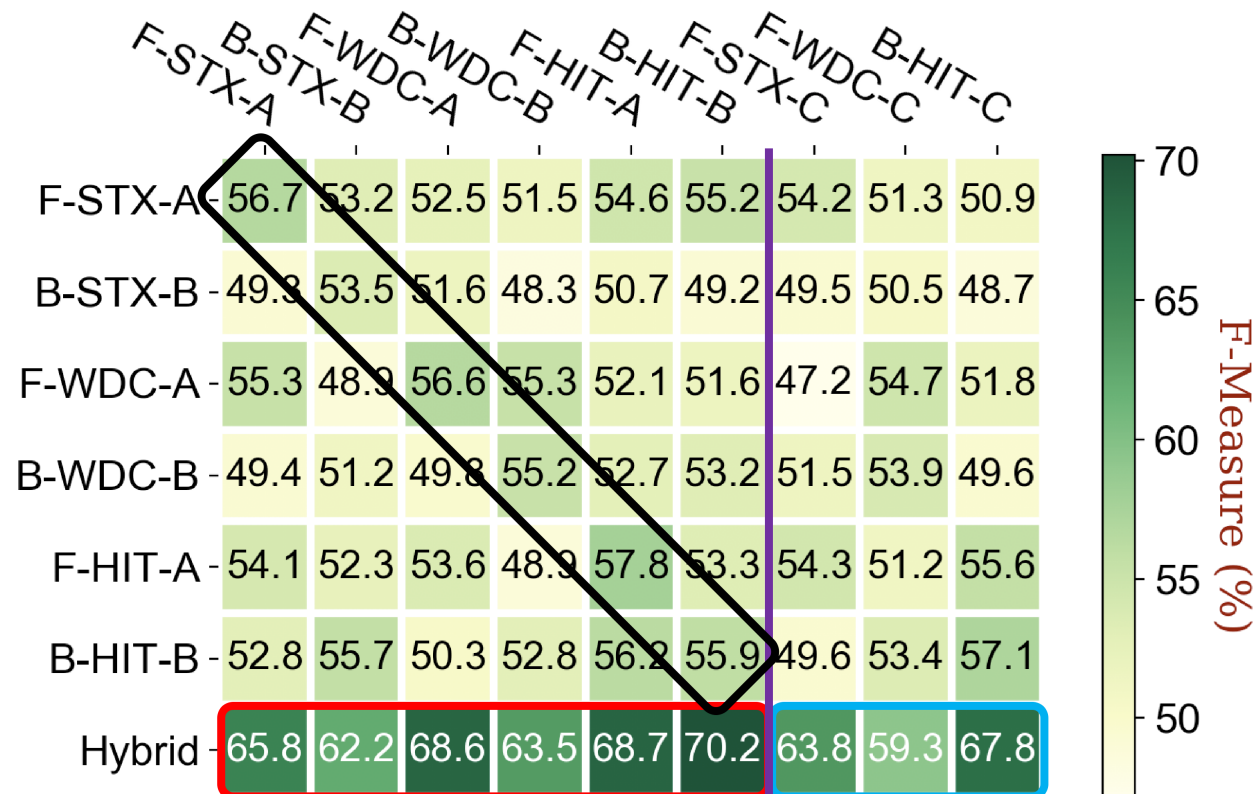


DNN

OCC

Limitation

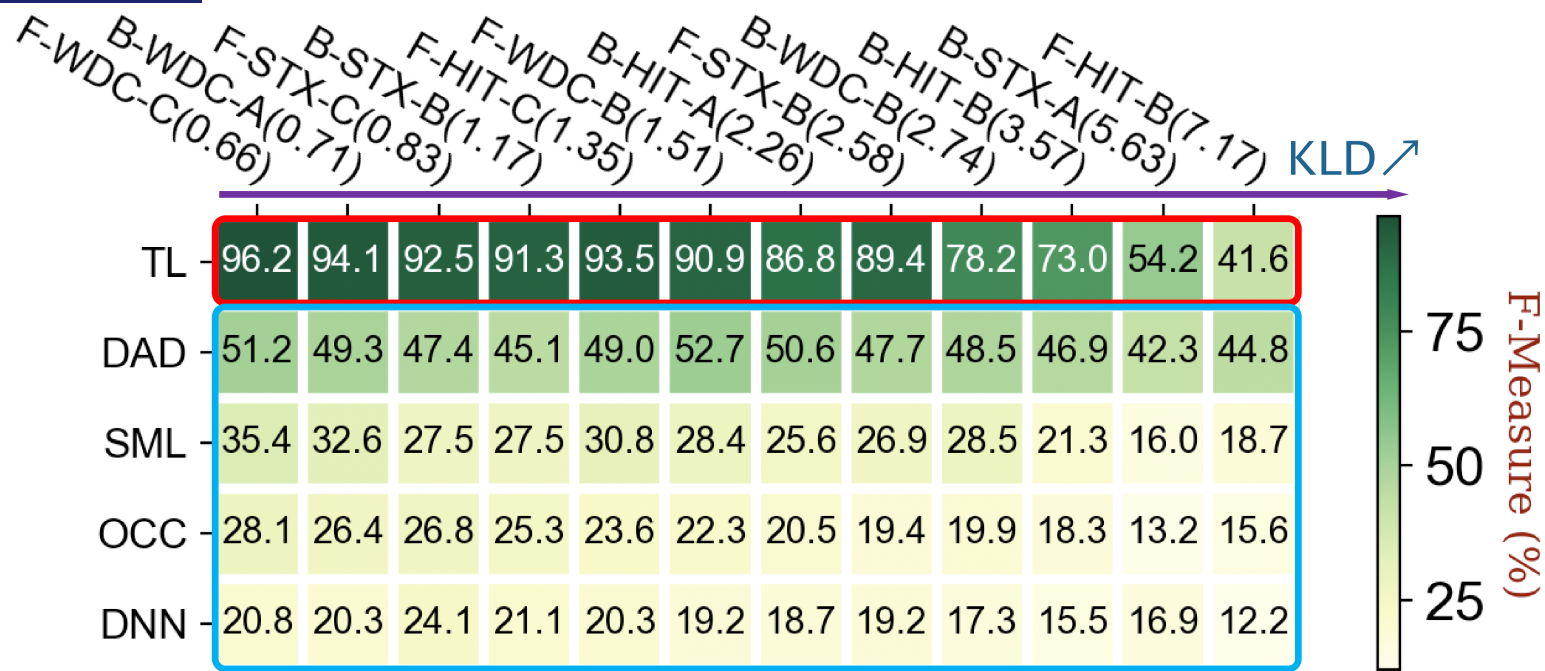
Applicability and Adaptability



DAD

Limitation

Minority Disk

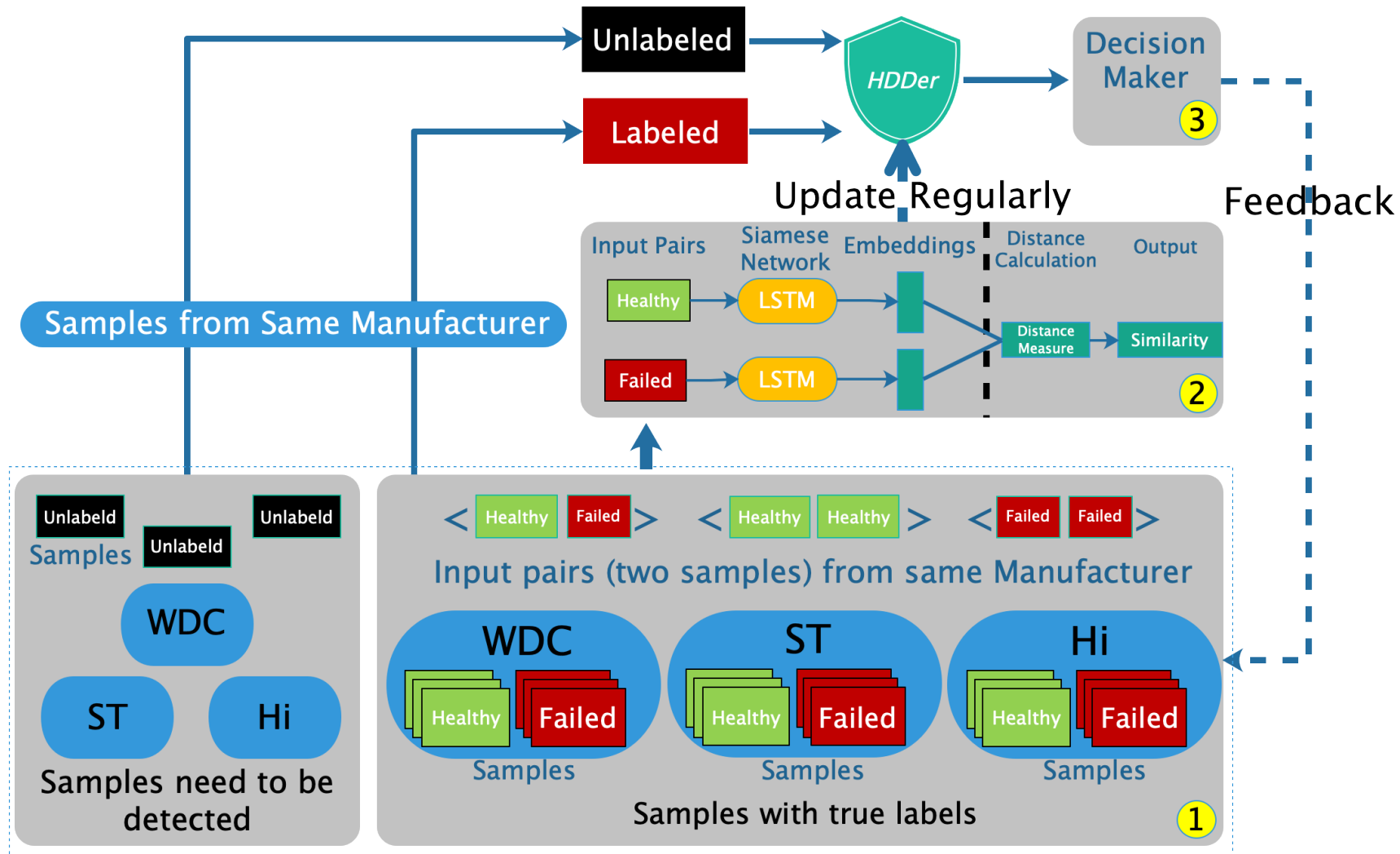


Data Center	KLD(0 ~ 1)	KLD(1 ~ 2)	KLD(2 ~ 3)	KLD(>4)
Tencent	35%	25%	23%	17%
Backblaze	32%	18%	31%	19%

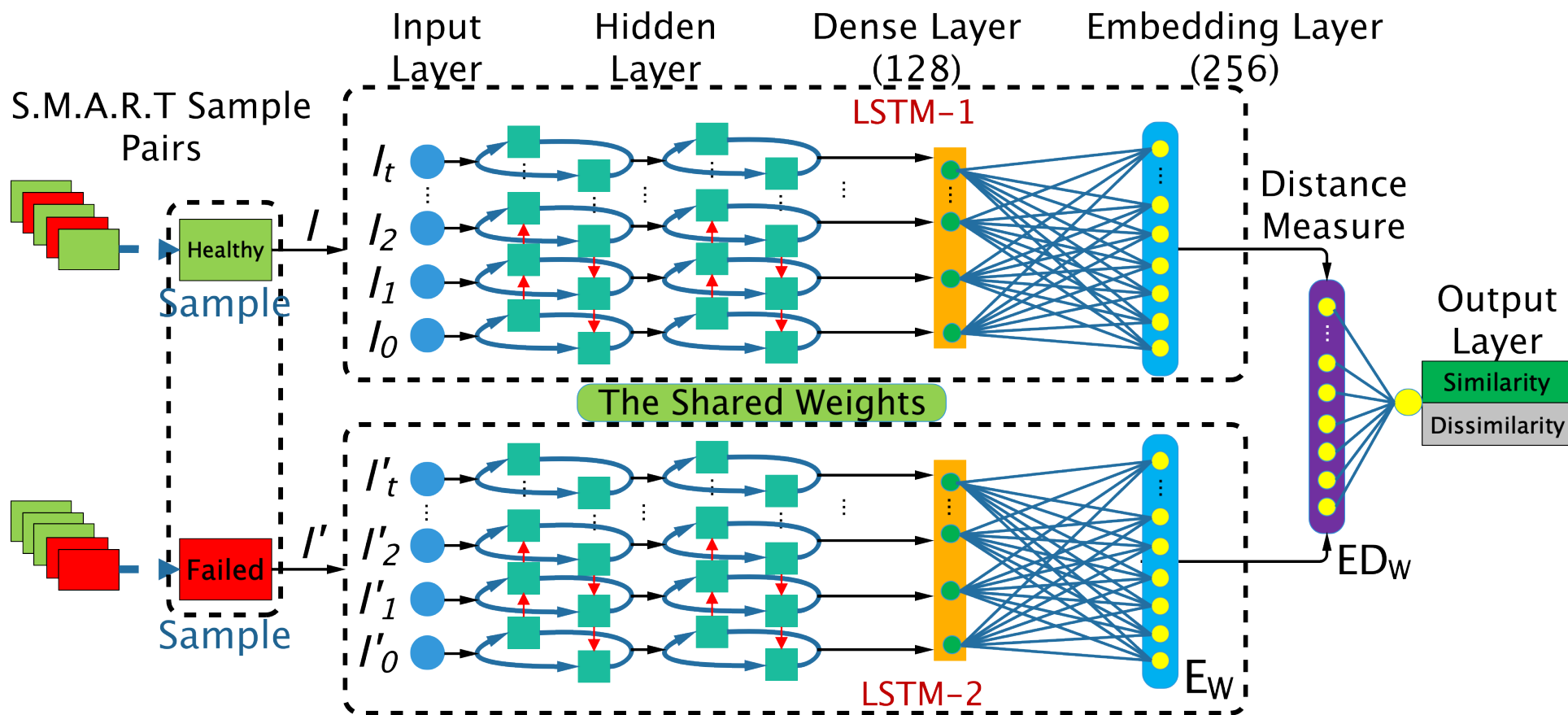
Motivation

- **Why the DAD approaches have good applicability and high adaptability while DNN does not?**
 - A commonality and not sensitive to the disk models.
- **Why the overall detective performance of the DAD method is not as good as other approaches?**
 - Transformation and computation in low-dimensional space.
- **Why the DNN approach achieves the best performance among other candidates**
 - Good expression and fitting ability.

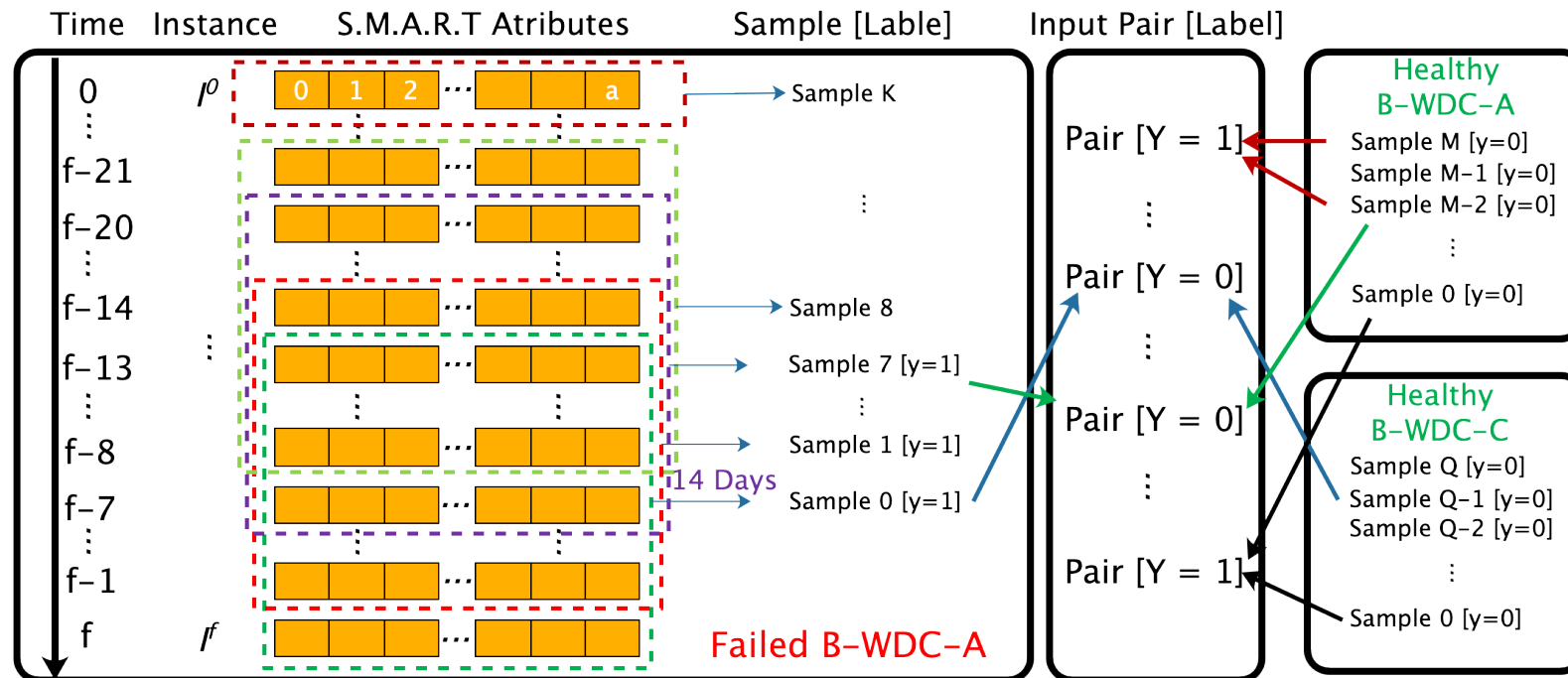
Overview of *HDDse*



LSTM-based Siamese Network in *HDDse*



The relationship between instances, samples and the input pairs in *HDDse*



Benefits

Imbalance degree (IDE).

For an imbalanced dataset containing a minority class sample with size A and the IDE is α , the majority class sample size is αA .

- Better with imbalanced datasets

The new imbalance degree $IDE' = \frac{n_1}{n_0} = \frac{\alpha}{2} - \frac{1+\alpha-A}{2A\alpha}$ since $A, \alpha > 1$, which effectively alleviates the original data imbalance by a factor of two.

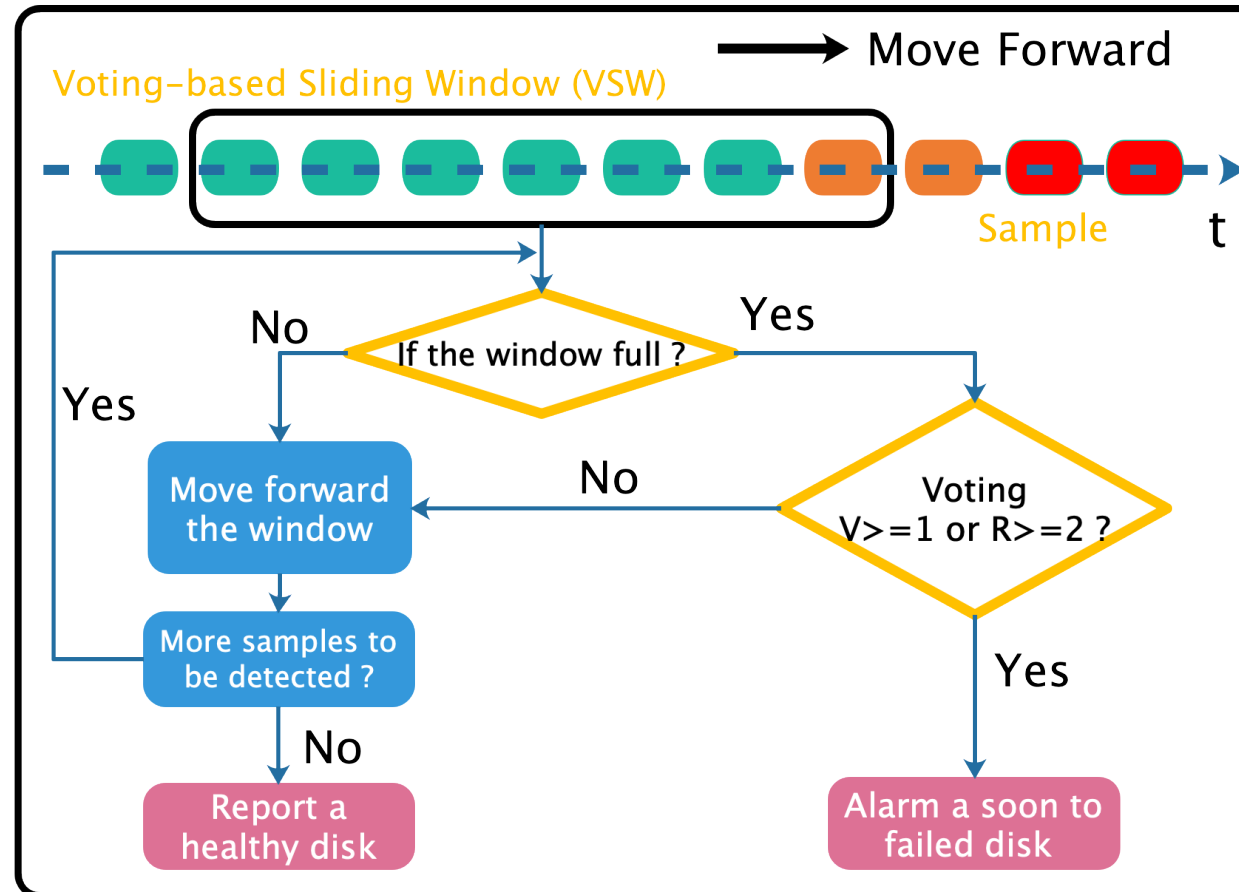
- Better with minority disk models

The number of training pairs with the minority disk models in existing methods is $P = A(1 + \alpha)$

In our method the number of training pairs is $\frac{P!}{2!(P-2)!} = \frac{P(P-1)}{2}$

Decision Maker in *HDDse*

A voting-based sliding window (VSW)



Define a length- W time sliding window and move it forward everyday.

Experimental Evaluation

Datasets:

- From Backblaze, which spans a period of 58 months consisting of 146,203 healthy disks and 8,256 failed disks.
- Tencent and spans 29 months consisting of 70,192 healthy disks and 2,971 failed disks.

Evaluation Metrics:

- **TPR**. True Positive Rate (also called recall) is the proportion of failed disks that are correctly predicted.
- **FPR**. False Positive Rate (also called false alarm rate) is the proportion of healthy disks that are falsely predicted as failed.
- **AUC**. Area under the receiver operating characteristic curve value under the ROC curve (receiver operating characteristic) to evaluate the binary classification performance of our detection model in imbalanced datasets.
- **F-Measure**. A balance between the two metrics TPR and Prediction Precision.
- ***C-MTTDL***. Cost-based MTTDL.

Cost-based Mean Time To Data Loss (C-MTTDL)

$$MTTDL \approx \frac{MTTF}{1 - \frac{k\mu}{\mu + \gamma}}$$

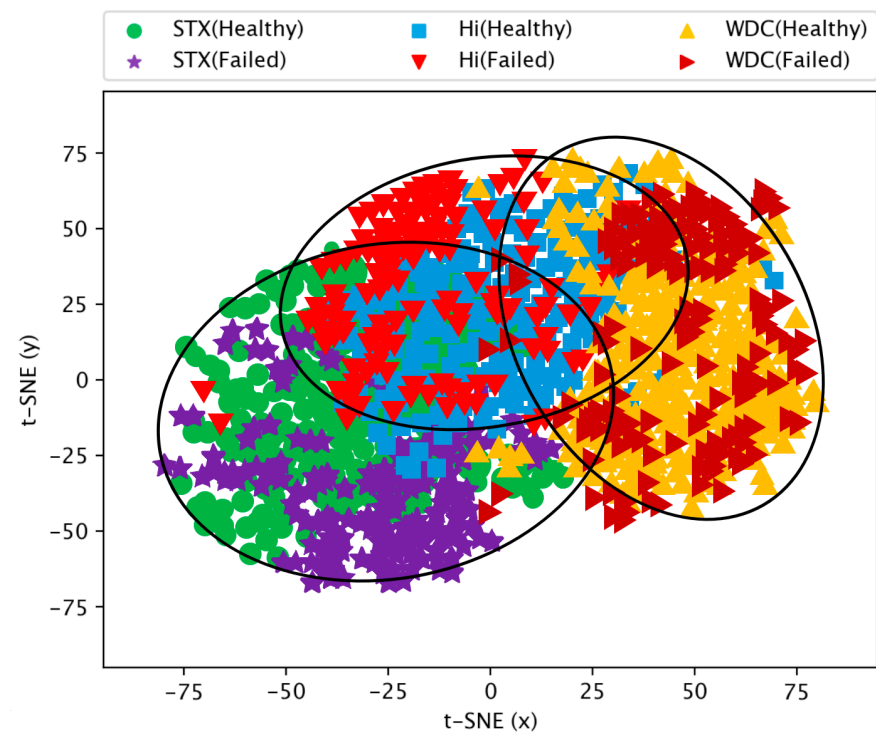
approximate the mean time to data loss with failure detection model

Neglect the cost of misclassification by the approach !

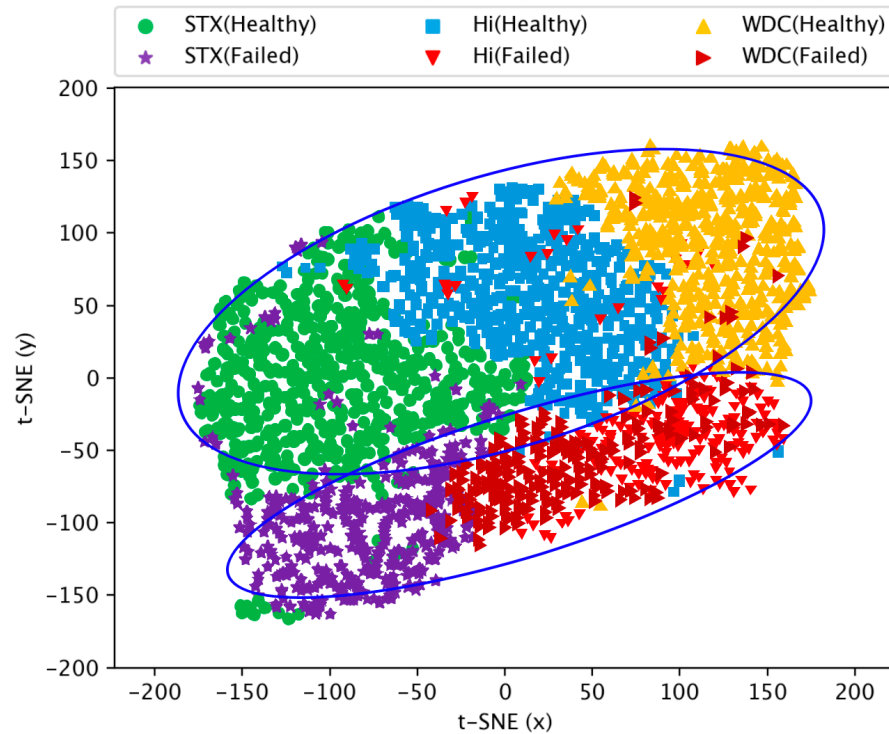
An end-to-end economic analysis metric called **C-MTTDL**

$$C - MTTDL = \frac{MTTDL}{Cost} \approx \frac{MTTF}{(1 - \frac{k\mu}{\mu + \gamma})(C_a FP + C_b FN)}$$

The t-SNE of the S.M.A.R.T data before and after embedding using *HDDse*

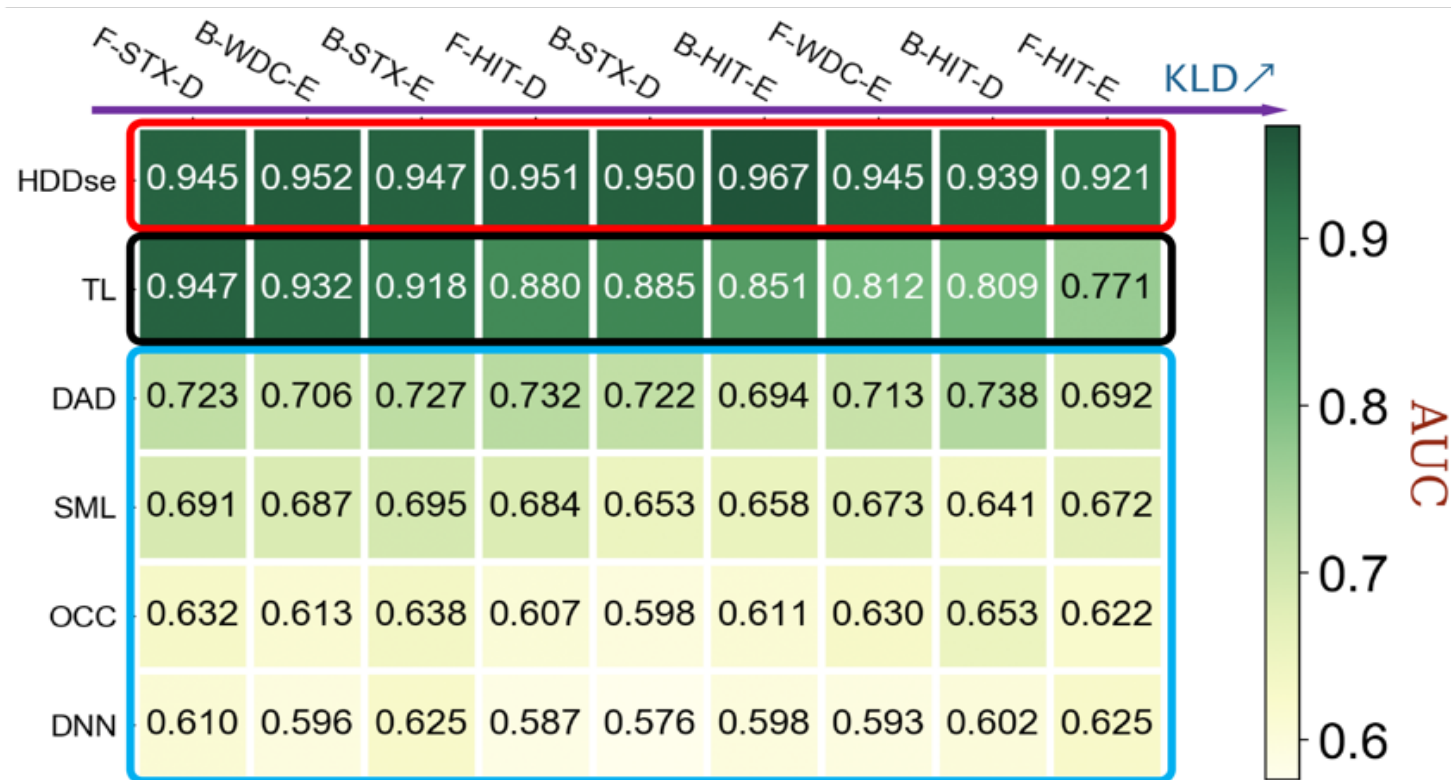


Before

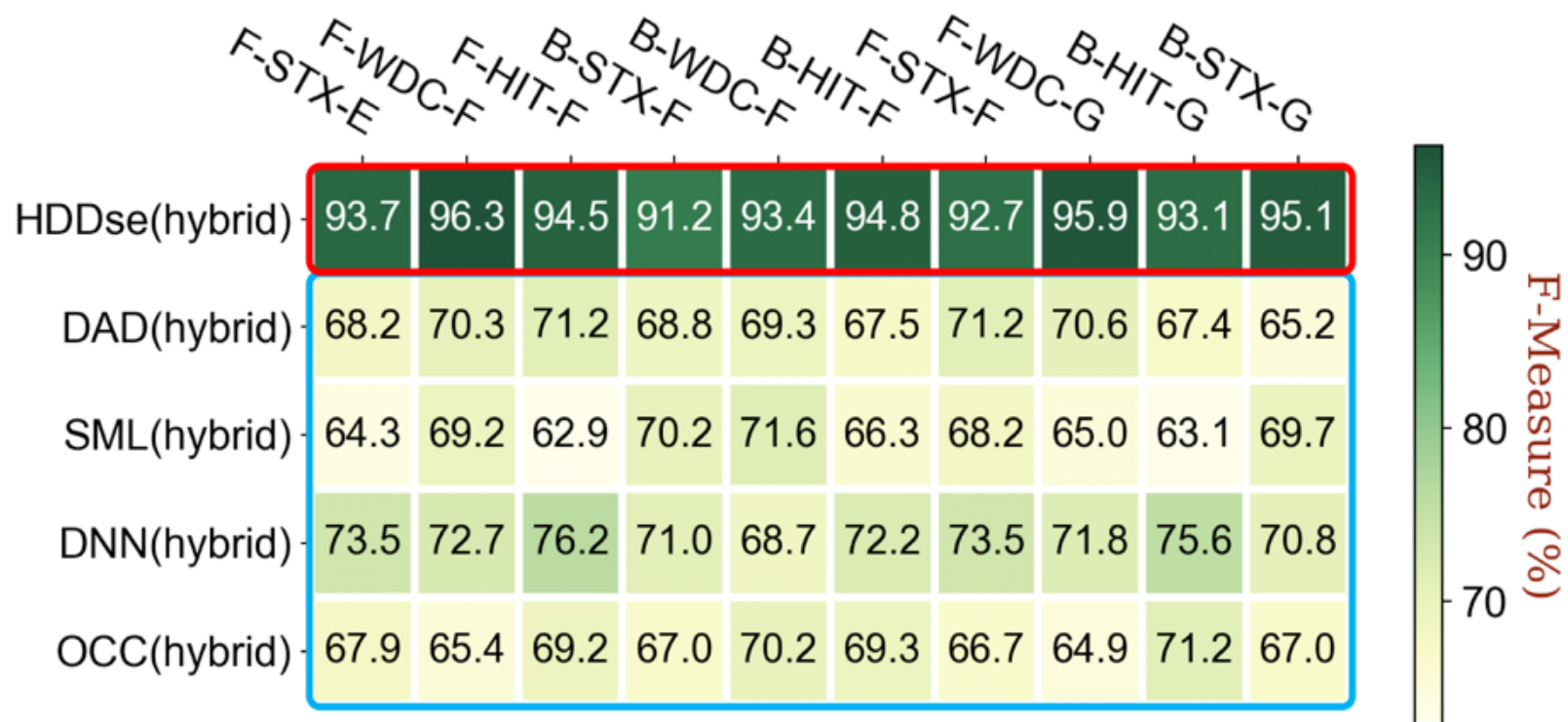


After

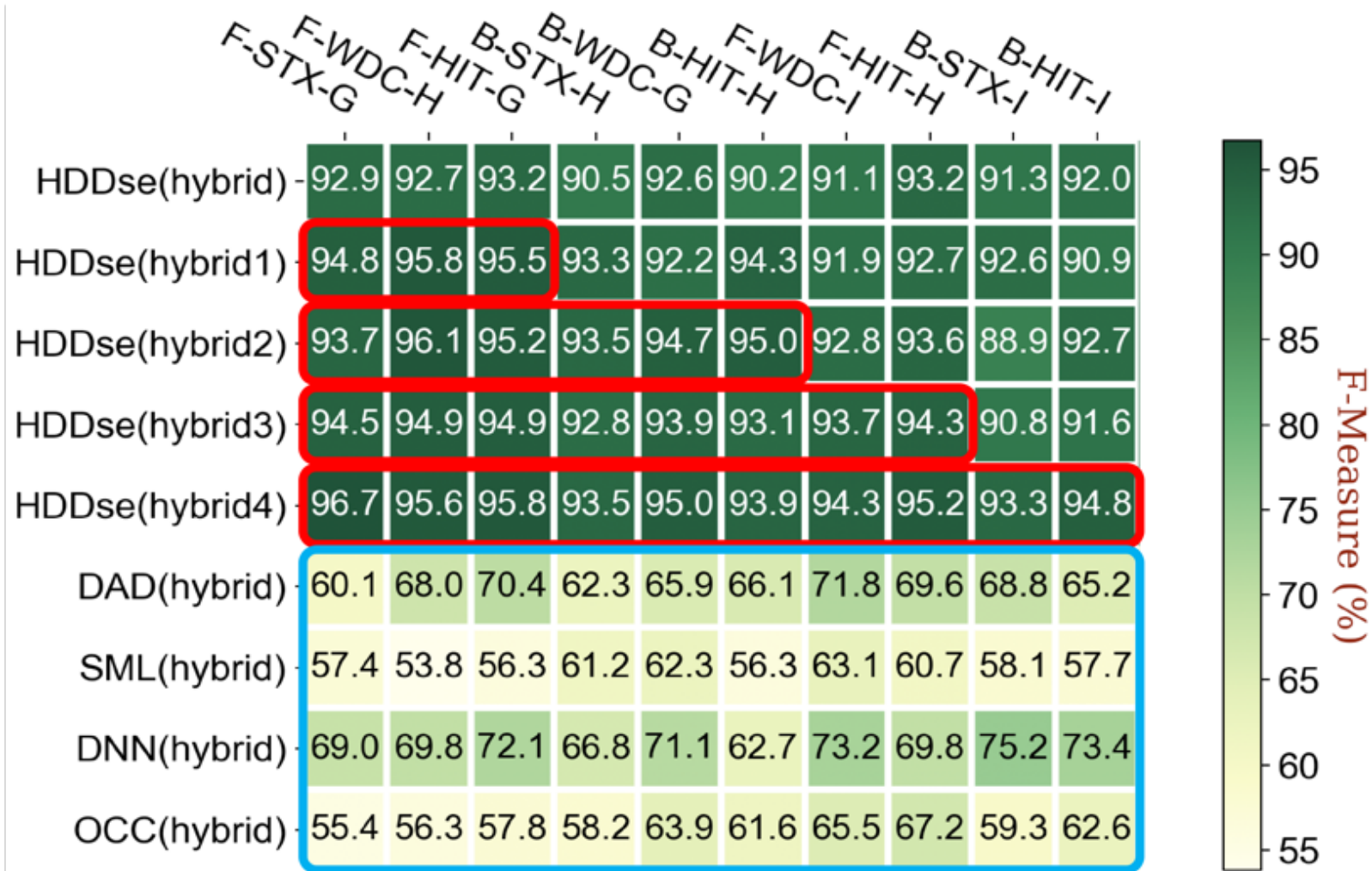
HHDse only Trained on Minority Disk Datasets



The Applicability of *HHDse*



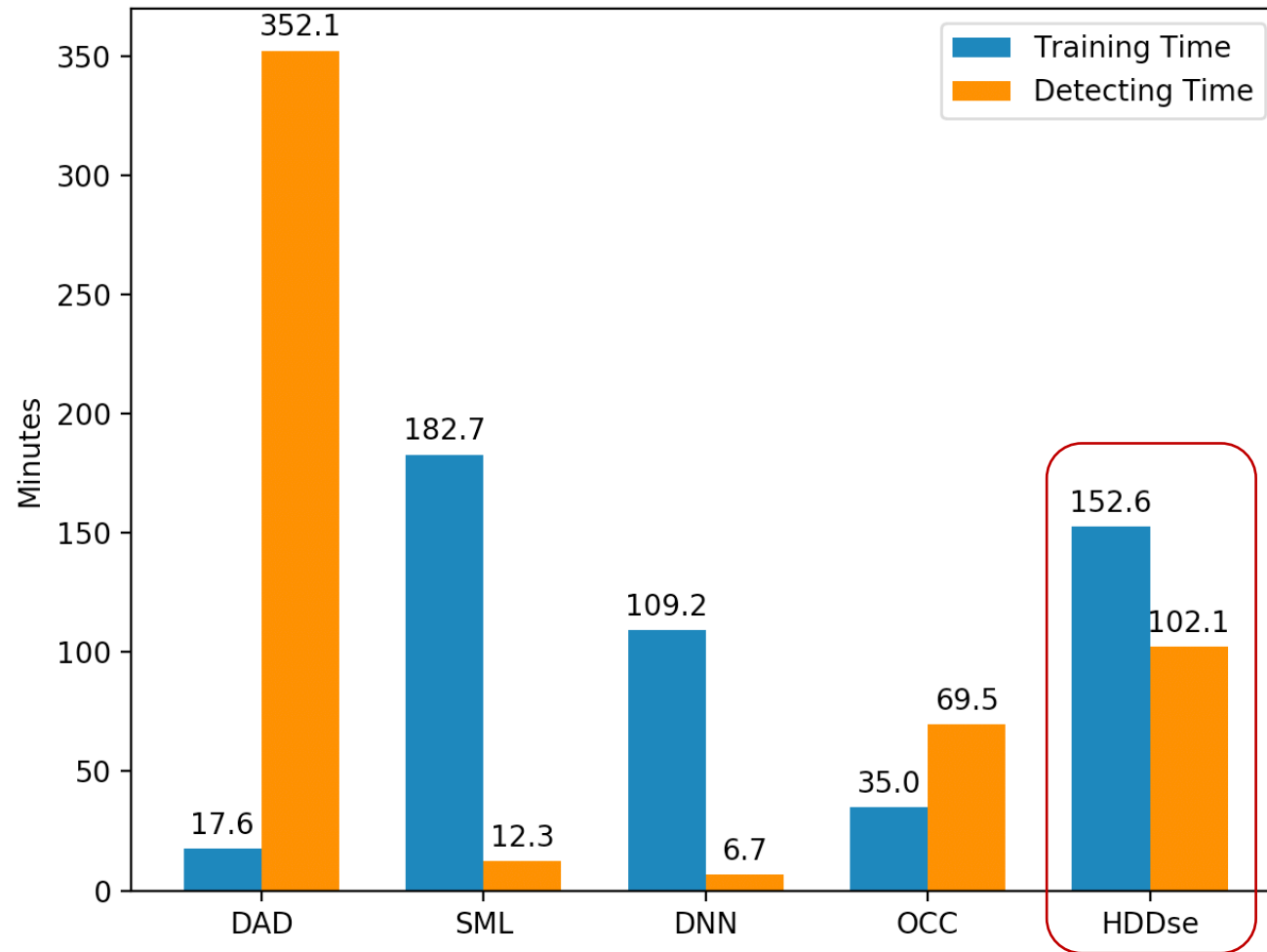
The Adaptability of *HHDse*



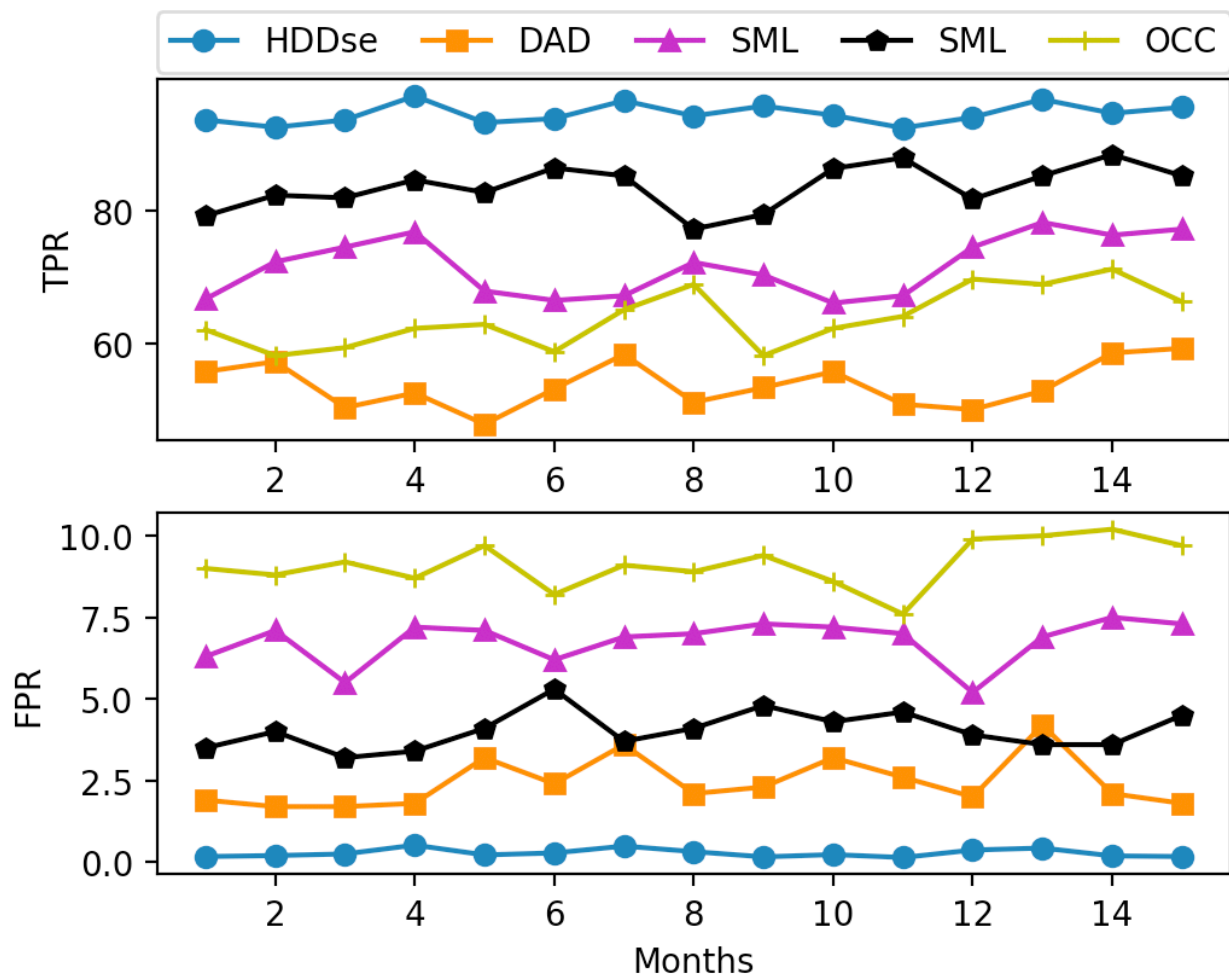
Improvement of Storage System Reliability

Method	$k(TPR)$	FP	FN	Cost	MTTDL (years)	C-MTTDL (hours/dollar)
OCC	62.6%	8212	1062	1,748,600	397.6	1.94
DAD	45.2%	3422	1537	838,100	276.7	2.89
SML	72.6%	6159	783	1,310,100	504.10	3.37
DNN	85.3%	4791	419	1,000,100	814.13	7.13
HDDse	95.8%	103	140	34,600	1656.3	419.35

Training and Detecting Time



Evaluating Practical Long-Term Availability



Conclusion

HDDse: an LSTM-based siamese network that can learn the dynamically changed long-term behavior of disk healthy statues and generate a unified and efficient high dimensional disk state embeddings from low dimensional S.M.A.R.T attributes for disk failure detection.

Applicability



Adaptability



Imbalance datasets



Minority Disk



Performance

TPR: 92%-97%

FPR: 0.2%-0.4%

F-Measure: 91%-97%

Thanks