Machine Learning for Storage System Reliability Prediction

Author: Ruizhe LI | **Supervisor:** Patrick P. C. Lee
Institution: The Chinese University of Hong Kong

Introduction

Disk failure in big data centers has been costing great loss for institutions. Many solutions are provided to enhance prediction accuracy and reduce institutions' cost. Three machine learning methods for disk failure prediction are tested in our experiment.

Expected Goals:

- Re-implement the algorithm of each paper.
- Identify the clarity and challenges presented in the paper.
- Test the validity and generality of the three methods.
- Analysis strengths and limitations of each method.

Papers to be tested:

- Predicting Disk Replacement towards Reliable Data Centers (ADF) [1]
- Hard Drive Failure Prediction Using Classification and Regression Trees (ATC17) [2]
- Improving Service Availability of Cloud Systems by Predicting Disk Error (ATC18) [3]

Paper 1: ADF

Title: Predicting Disk Replacement towards Reliable Data Centers [1]

Goal:

- Provide informative SMART attributes for disk replacement
- Apply machine learning method on the selected attributes to predict impending replacements with high accuracy (81-98%)

Dataset: Backblaze 2017 Q1 – 2018 Q1 | **Model:** ST4000DM000

- Label: Failure value recorded in the Backblaze dataset.
- Inputs: Selected and Compacted SMART attributes.

Method:

1. Feature Selection – Changepoint Detection
2. Timeseries compact – Exponentially Weighted Moving-Average (EWMA)
3. Classes Balancing – K-Means clustering
4. Classification – RGF dominates

Result:

a) Feature Selection:

SMART Number	Value in ADF	Value in experiment
S3	NA	13.5%
S4	NIP	30.8%
S9	NIP	50.6%
S12	NIP	30.7%
S183	0.5%	12.8%
S192	NIP	4.5%

Table 1. NIP stands for "not in paper". 6 features that selected in our experiment but not in ADF. They are either not available or not shown in the ADF, except for S183. This may due to the differences of the implementation procedures.

b) Classification:

Model	Precision	Recall	F1
RGF	0.990	0.986	0.988
GBDT	0.993	0.986	0.990
RF	0.980	0.992	0.986
SVM	1.0	0.980	0.990
LR	0.870	0.948	0.897
DT	0.989	0.993	0.991

Table 2. Similar to ADF, RGF has the highest accuracy in our experiment. However, it does not have an overwhelming advantage over other methods as in ADF.

Paper 2: ATC17

Title: Hard Drive Failure Prediction Using Classification and Regression Trees [2]

Goal:

- To predict whether a drive will have a sector error within a given time interval, based on its past behavior.

Dataset: Backblaze 2015 Q1 – 2015 Q4 | **Model:** ST3000DM000

- Label: 1 if SMART_5_raw (S5) increases in the next week, else 0.
- Inputs: SMART attributes and their increasement.

Method:

1. Data Preprocessing – Label and input features preparation
2. Classes Balancing – Random sample selection
3. Classification – RF dominates

Result:

a) Classification:

Metric	CART	SVM	NN	LR	RF
P	96.8%	99.1%	99.2%	90.1%	98.5%
R	86.5%	90.7%	93.1%	93.9%	97.5%
F	91.1%	94.6%	94.3%	91.5%	97.9%
Sd	9.0%	1.8%	5.2%	4.7%	1.3%

Table 3. Similar to ATC17,RF model has the best prediction performance. Despite the dataset contains only around 500 samples, the RF can reach a F-score as high as 97.9%.

b) Feature Importance:

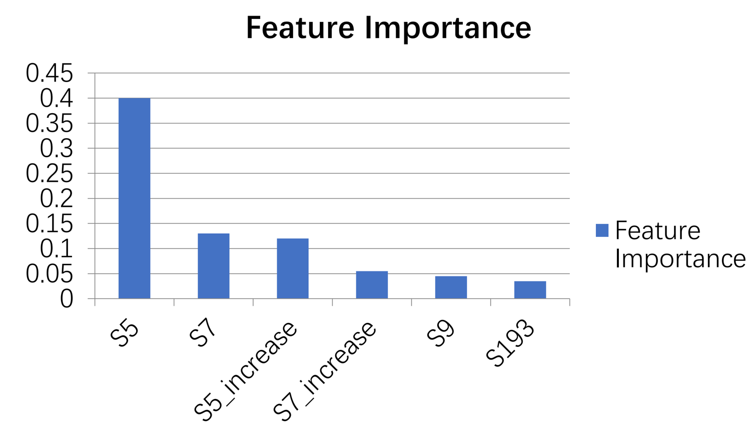

Chart 3. Feature Importance under RF model. S5, S7 and their increasements are the most important features to predict future sector errors. (S5 – Reallocated Sectors Count; S7 – Seek Error Rate)

Paper 3: ATC18

Title: Hard Drive Failure Prediction Using Classification and Regression Trees [3]

Goal:

- Provide a feature engineering method for selecting stable and predictive features.
- Construct a ranking model to increase the accuracy of cost-sensitive online prediction.

Dataset: Backblaze 2017 Q3 | **Model:** ST4000DM000

- Label: The number of days between the data is collected and the first error is detected.
- Inputs: Selected SMART attributes, and Diff, Sigma, and Bin of each selected attributes.

Method:

1. Feature Engineering – Label preparation, feature identification and selection
2. Cost-sensitive ranking model
   - FastTree dominate
   - Metric: Cost $= \text{Cost1} * FP_r + \text{Cost2} * FN_r$

Result:

a) Classification:

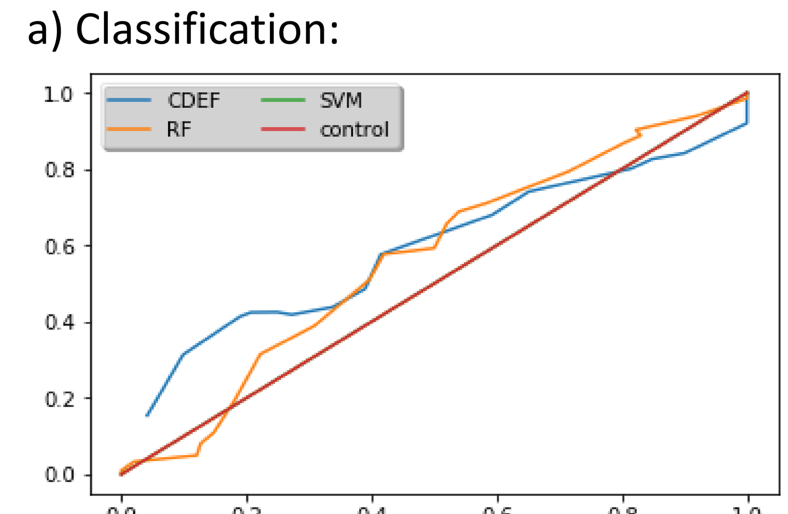

Chart 2. Performances of different machine learning method. The proposed method does not show any advantage.

b) Feature Selection:

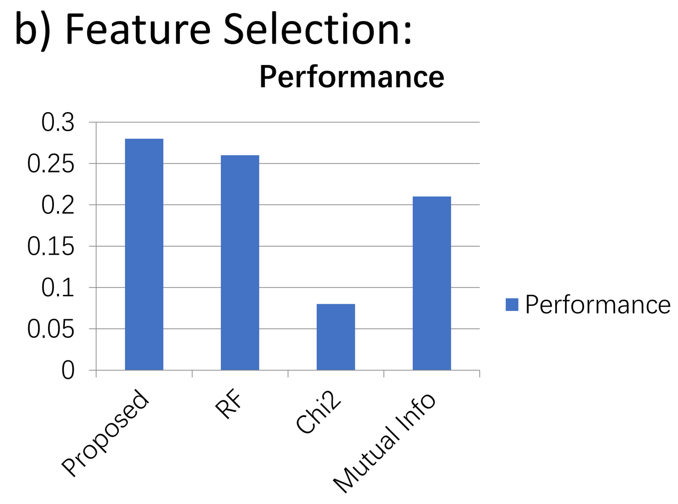

Chart 3. The accuracy of FastTree model under different feature selection method. The proposed method has the best performance.

Conclusions

For ADF, there are 6 more features selected in our experiment. All extra features except for S183 are not available in ADF, thus could not be selected in the original experiment. With the feature selection and K-Means down sampling, our results could reach an accuracy of 98%. Thus, the method in ADF is valid. However, the advantage of RGF over other models is not as significant as in ADF's results.

The re-implementation of ATC17 validates the efficiency of the sector error prediction method. Moreover, our feature importance analysis shows that the most foreboding factor is S5 (Sector Error Count) and S7 (Seek Error Rate). It means that a sector error occurred means more sector error are coming. Meanwhile, RF has achieved the best performance under small dataset, same as ATC17. Thus, forest algorithms are better.

The ATC18's reproduction has a very low accuracy. And although its proposed machine feature selection method has a better performance, it costs too much time. Meanwhile, FastTree's prediction power is not that remarkable in our experiment.

Acknowledgement

Special thanks to Prof. Patrick P. C. Lee and his PhD student Shujie Han.

Contact

Ruizhe, LI
The Chinese University of Hong Kong
Email: 1155076990@link.cuhk.edu.hk
Phone: (+852) 66134346

References

1. M. M. Botezatu, I. Giurgiu, J. Bogojeska, and D. Wiesmann, Predicting Disk Replacement towards Reliable Data Centers, Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining - KDD 16, 2016.
2. J. Li, X.P. Ji, Y.H. Jia, B.P. Zhu, G. Wang, Z.W. Li, X.G. Liu, Hard Drive Failure Prediction Using Classification and Regression Trees, 2014 44th Annual IEEE/IFIP International Conference on Dependable Systems and Networks, Atlanta, GA, 2014, pp. 383-394.
3. Y. Xu, K.X. Sui, R. Yao, H.Y. Zhang, Q.W. Lin, Y.N. Dang, P. Li, K.C. Jiang, W.C. Zhang, J.G. Lou, M. Chintalapati, D.M. Zhang, Improving Service Availability of Cloud Systems by Predicting Disk Error, in Proceedings of the 2018 USENIX Annual Technical Conference, 2018.