WEEKLY REPORT 7

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1. Paper: 'Predicting Disk Replacement towards Reliable Data

Centers'

Main work: Refer to Rui Zhe's code and fixed bugs in my code.

1) Dataset: Blackblaze 2015 Q1-Q4

Model name: ST4000DM000 Total number of disks: 29670 Total number of failed disks: 586

2) ML result:

stat

| | GBDT | SVM | DT | LR | RF | RGF |
|----|-------|-------|-------|-------|-------|-------|
| P | 0.912 | 0.334 | 0.875 | 0.723 | 0.905 | 0.934 |
| R | 0.911 | 1.000 | 0.891 | 0.688 | 0.887 | 0.906 |
| F | 0.911 | 0.500 | 0.883 | 0.699 | 0.896 | 0.919 |
| Sd | 0.060 | 0.001 | 0.045 | 0.087 | 0.058 | 0.050 |

SVM still has the problem of low precision and high recall.

2. Paper: 'Hard Drive Failure Prediction Using Classification and Regression Trees'

1) Vary different number of voters and apply a voting rule: 'When detecting a drive, we check the last N consecutive samples (voters) before a time point, and predict the drive is going to fail if more than N/2 samples are classified as failed, and the next time point is tested otherwise.'

Result in paper:

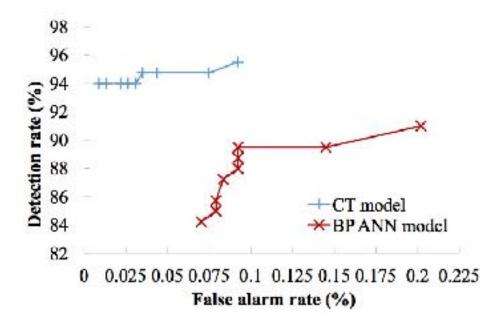
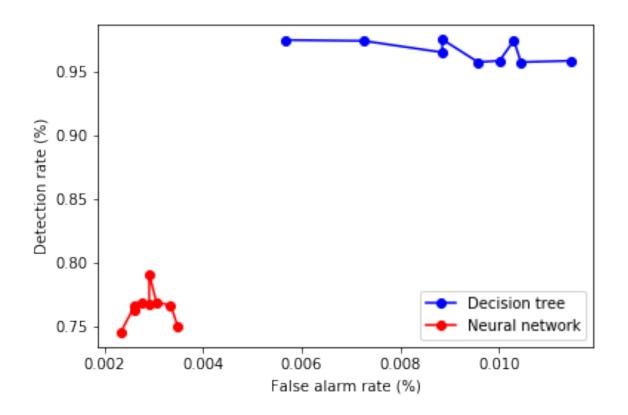


Figure 2. Impact of voting-based detection method on prediction performance. The points on each curve are obtained by the number of voters N = 1, 3, 5, 7, 9, 11, 15, 17, and 27 from right to left.

My result:



2) Calculate 'time in advance': Result in paper:

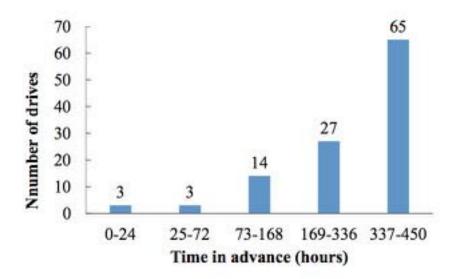


Figure 3. Distribution of time in advance of BP ANN model.

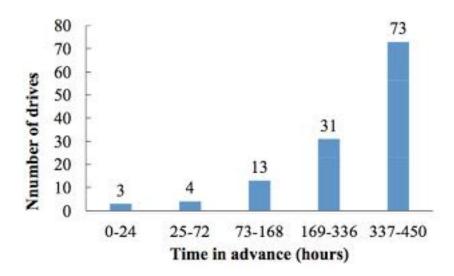
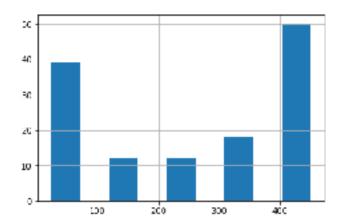
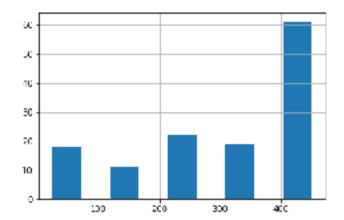


Figure 4. Distribution of time in advance of CT model.





Distribution of time in advance of BP ANN model.

Distribution of time in advance of CT model.

3) predict on smaller dataset: 10%, 25%, 50% and 75% Result in the paper:

| Model | Dataset | FAR (%) | FDR (%) |
|--------|---------|---------|---------|
| | A | 2.93 | 88.24 |
| DD ANN | В | 1.10 | 90.63 |
| BPANN | С | 0.16 | 84.38 |
| | D | 0.03 | 81.82 |
| | A | 0.22 | 82.35 |
| CT | В | 0.07 | 90.63 |
| CT | С | 0.11 | 90.63 |
| | D | 0.09 | 91.82 |

My result:

| Model | Dataset | FAR (%) | FDR (%) |
|--------|---------|---------|---------|
| | A | 0.377 | 57.627 |
| DD ANN | В | 0.232 | 76.271 |
| BP ANN | С | 0.015 | 66.949 |
| | D | 0.421 | 72.034 |
| | A | 0.842 | 84.034 |
| CT | В | 0.290 | 82.353 |
| CT | С | 0.682 | 89.076 |
| | D | 0.624 | 91.597 |

3. 'Improving Service Availability of Cloud Systems by Predicting Disk Error'

1) Dataset overview:

Dataset: Blackblaze 2017 Q4 Model name: ST4000DM000

2) Data preprocessing:

[1] create labels: use SMART 5 'Reallocated Sectors Count' as the error indicator. Labels are 'the number of days between the data is collected and the first error is detected'.

My question: How to handle those disks without any error?

[2]Dataset statistics:

Total number of disks that have SMART 5 error: 232

Total number of samples: 17284

[3] Feature identification:

All SMART attribute(46 features) + 3 kinds of statistical features:

Diff, Sigma and Bin

Totally 135 features

My questions: Should we consider the difference between cumulative features and noncumulative features?

[4] Feature selection:

An iterative algorithm to prune away non-predictive features.

Issue: zero accuracy, since it uses labels of higher range to predict labels of lower range.