CASE STUDY - DISK FAILURE PREDICTION

WEI REN

Abstract. The motivation of this report is to show a case study of disk failure prediction as a coding test/supporting material for the application of an AIOps position of Alibaba Group. In this report, the detailed illustration of data preprocessing and feature engineering, model choosing and parameter tuning, results evaluation and insights from this task are included.

1. Brief Introduction

1.1. **Introduction.** Various disk failures are not rare in large-scale IDCs and cloud computing environments, fortunately, we have S.M.A.R.T. (Self-Monitoring, Analysis, and Reporting Technology; often written as SMART) logs collected from computer hard disk drives (HDDs), solid-state drives (SSDs) and eMMC drives that detects and reports on various indicators of drive reliability, with the intent of enabling the anticipation of hardware failures.

In data center environments, hard disk drive (HDD) failures are a rare but costly occurrence. Therefore, HDD vendors are highly motivated to reduce the rate of failures as a cost saving measure. But currently, HDD manufacturers use Self-Monitoring and Reporting Technology (SMART) attributes collected during normal operations to predict failures. SMART attributes represent HDD health statistics such as the number of scan errors, reallocation counts and probational counts of a HDD. If a certain attribute considered critical to HDD health goes above its threshold value, the HDD is marked as likely to fail [P inheiro] . Our project focuses on applying machine learning to improve prediction accuracy over baseline heuristics in hard disk drives. The goal of our project is twofold: 1) to achieve a higher recall, precision and accuracy than our baseline implementation modeled off of current enterprise failure detection models. 2) to analyze which of our subset of machine learning models is best suited towards predicting failure of HDDs. We analyze three different algorithms: Logistic Regression, Naive Bayes and Random Forest, to see which has the highest accuracy, recall and precision when predicting HDD failures.

1.2. **Literature Review.** Pinheiro et al analyzed failure trends in a large disk drive population of over one hundred thousand enterprise HDDs at a Google data center. They found that specific SMART parameters (scan errors, reallocation counts, offline reallocation counts, and probational counts) had a large impact on failure probability. Most importantly, a large fraction of failed drives showed no signs of failure in all of its monitored SMART features, making it unlikely to achieve an accurate predictive failure model that can be built based on SMART signals alone [Pinheiro]. Similarly, BackBlaze analyzed the correlation rates between its HDD failures and SMART attributes and found that SMART 5, 187, 188, 197, and 198 had the highest rates of correlation to HDD failure. These SMART attributes are also related to scan error, reallocation count and probational counts [Klein]. Pitakrat et al evaluated 21 machine learning (ML) algorithms for predicting HDD failure. Pitakrat et al found that of the 21 ML algorithms tested, a Random Forest algorithm produced the highest area under a ROC Curve (AUC), while a Nearest Neighbor classifier had the highest F1-score. Hughes et al also studied machine learning methods for predicting failures in HDDs. They analyzed the performance of

Date: March 19, 2018.

Key words and phrases. Machine Learning, SMART, Disk Failure.

Support Vector Machines (SVM), rank-sum and multi instance Naive Bayes. SVMs achieved the highest performance with a 50.6% detection and 0% false alarm rate [Hughes et al].

2. Data Preprocessing and Feature Engineering

Data sources from `https://www.backblaze.com/b2/hard-drive-test-data.html`

As of the end of 2017, there are about 88 million entries totaling 23 GB of data. Each entry consists of the date, manufacturer, model, serial number, status (operational or failed), and all of the SMART attributes reported by that drive.

There are some critical questions to be answered if one needs to complete this case study:

- Define the amount of data, and which columns should be counted; Data inputs. Data of the year of 2017.
- Define the features; Some feature selection methods.
- Define the training data sets and test data sets; Cross-validation for model selection.
- Define model, cost/loss function, parameters, training methods. Machine Learning. Scikit-Learn
- Train the models and tune parameters.
- Conduct prediction for other data sets and evaluate results. Confusion Matrix.

2.1. **Data Preprocessing.**

(1) Choose raw over normalized SMART Data points
(2) Failure status smoothing/backtracking
(3) Filter out all HDD models besides Seagate models
(4) Balance out the data set

2.2. **Feature Engineering.**

Feature Selection.

- Filter
- Wrapper
- Embedded

Ninety variables and millions of data points not only take an extensive amount of time to train and test on, but can also lead to overfitting. To reduce the computational workload and improve the performance of our models, we chose to select only the most relevant features and avoid features with a large amount of unfilled data points.

3. Model Selection and Parameters Tuning

How to choose machine learning models and tune the parameters?

Reduce to a classification problem.

Base Line. Our baseline analysis mimics what BackBlaze currently implements in its failure prediction system. We analyze five SMART attributes (SMART 5, 187, 188, 197, 198) and predict a HDD will fail if any of these critical raw SMART attributes are greater than 0. Our goal is therefore to maintain as high of a TPR with a maximum TPR equal to the baseline analysis, and to focus on reducing the FPR to 0.

Logistic Regression. Logistic Regression is one of the basic tools for performing binary classification. One of the assumptions made in order for Logistic Regression to potentially perform well is that the data is linear. This means that the score we obtain from Logistic Regression is affected proportionally to changes in the feature values in a linear fashion. The tool mainly served as a second baseline in some sense as it was our first attempt at the classification problem beyond implementing the simple baseline. We also employed L2 regularization.

TABLE 1. Confusion Matrix

	actual positive	actual negative	total
predicted positive	TP	FP	$TP+FP$
predicted negative	FN	TN	$FN+TN$
total	$TP+FN$	$TN+FP$	

Naive Bayes. The Naive Bayes classifier model makes the assumption that the value of a feature is conditionally independent of the value of another feature given some class label. Among the different techniques used for building Naive Bayes models, we chose Multinomial Naive Bayes, which assumes that the probability of a feature value given some class label is sampled from a multinomial distribution. For regularization, we use Laplace smoothing.

Random Forest. Random forest is an ensemble tool which takes a subset of observations and a subset of variables to build a group of decision trees. It builds multiple such decision trees and amalgamate them together to get a more accurate and stable prediction.

K-Nearest Neighbours.

Support Vector Machines.

Neural Network.

4. Results Evaluation

How to evaluate the results?

To evaluate the classifier's performance, we measure precision, recall and F-score as defined below.

- Precision: to measure the ability of the classifier to correctly identify disks at risk;
- Recall: to measure the classifier's sensitivity. A higher recall is equivalent to minimizing the number of false negatives;
- F-score: the combined score between precision and recall, or the weighted harmonic mean;
- ROC: Receiver Operating Characteristic, is the plot of TPR vs FPR. In usual, we can also draw the Precision-Recall Curve.

$$P = \frac{TP}{TP+FP} \qquad R = \frac{TP}{TP+FN} \qquad F_{score} = \frac{2PR}{P+R} \tag{1}$$

where TP refers to true positives, FP is false positives and FN denotes false negatives.

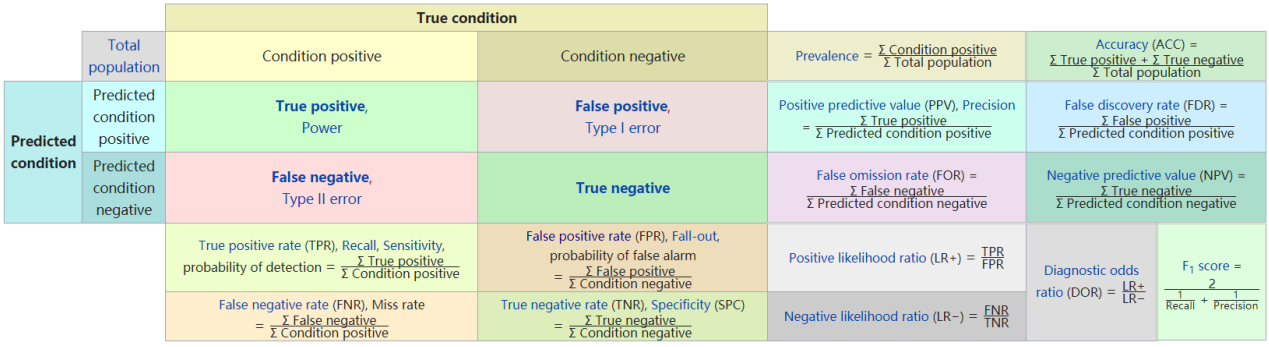

FIGURE 1. Confusion Matrix[2]

5. Conclusions

What insights or lessons learned from this task? [1]

References

1. Wei Ren, *This is a test book*, Oxford University Press, 2018.
2. Wikipedia, *Receiver operating characterisitc*.