Hard Disk Drive Failure Prediction

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1 Domain Knowledge

Hard Disk Drive failure problems have become headaches for many storage equipment users and suppliers, and these problems are also drawing attention in datacenters, where they could lead to failures both in the servers and RAIDs. Nowadays, many companies, such as Baidu, Microsoft, IBM etc, are paying attention to how to predict the failures of HDD in order to schedule the replacement of disks so that the data migration can be done ahead. Disk providers such as Seagate are also researching how to predict HDD failures. Maybe Seagate is holding a different view from others and is probably taking a slightly different method to approach these problems, because they know HDD's internal mechanism better. However, these disk failure problems are valuable as we can see multiple companies are exerting efforts (perhaps there are still more companies and institutes). As far as I'm conerned, the prediction for HDD failures is important, for I work in the related field and I know how it hurts when the HDD failures cause the whole system to fail although it does have some dual safe mechanism. Sometimes one disk fails, and before we could take measures another disk also fails, so that the whole storage system breaks and some data is lost.

SMART(Self Monitoring, Analysis and Reporting Technology) attributes are important indicators telling if the disk is healthy or not from some point of view, for example if SMART 187(Reported Uncorrectable Errors) is much greater than zero, which indicates the number of reads that cannot be corrected by the hardware error correction code [1], there may be something wrong with the disk and we should investigate. Of course, other SMART attributes such as SMART 5, SMART 188, SMART 197 and SMART 198 are also helpful for failure prediction. Backblaze offers a discussion in [2] as well. There are still more related work in researching how to use SMART stats to predict failures. When the potential solutions are discussed, some of those work would be presented in order to justify the possibility of our solution.

2 Problem Statement

The aim is to predict the failures of HDDs ahead for some period. If a disk is removed at time Tr, our problem is to predict a disk is to fail at some time Tp, which is before Tr; for the data set of disks which only contains a small amount of failure disk samples, we want to identify the failure disks at some time before all the Tr for all the failure disks. Define Avg_Pred_Ahead(Time_To_Failure. These two can be used interchangeably in this context) = avg(Tp - Tr) for all identified failure disks), we hope Avg_Pred_Ahead is greater than or equal to 3, which is a value that may be influenced by the model hyper parameters. The recall and false alarm rate(FAR) are used to evaluate the prediction model. Note that FAR is defined as (the number of false positive) / (the total number of disk samples).

3 Datasets and Inputs

Backblaze offers many disk datasets, which are helpful for disk failure research, especially for SATA HDD. One of those datasets, which is the dataset for the Kaggle competition [3], will be used in this project. This dataset contains basic hard drive information, and there are 90 columns consisting of raw values and normalized values of 45 SMART attributes. Of course, the 5 important SMART attributes are included with both the raw values and the normalized values. As more statistics of SMART info are provided, the dataset is believed to be helpful for disk failure prediction.

Usually it is difficult to obtain many failure disks, even if a disk is removed, we don't know for sure whether it has failed, for in practice, there are too many occasions when the operation men remove active disks. From this point of view, these datasets provided by backblaze are valuable because they have checked and labeled the failure disks.

4 Solution Statement

As the problem is stated in the previous sections, the solution to it is now clear: it can be treated as a classification problem in which the model predicts a disk as a failure or not. In this classification problem, the postive samples are failure disks and the negative samples are the non-failure disks. Recall and FAR are mainly used as the metrics, besides the date when the model predicts a disk as failure is recorded as well so that the expectation of time to failure can be measured. As stated before, how long ahead the model can finds out the failure disks is not so important as the other two metrics.

5 Benchmark Model

In Table 5.11 of [4], performance of different algorithms were compared. As can be seen, when the recall hit 60%, False Positive Rate can be as low as 0.16% for XGBoost. It should be noted that there is a difference between FAR and FPR, because the latter only takes care of the actual negative samples. However in the context of this disk failure prediction problem, FPR is just a little bit higher than FAR as the amount of negative samples considerably surpasses that of the positive samples by several orders of magnitude.

Because the data set used in [4] is from Backblaze within a similar period, it should be much similar with the data set to be used in this project so that the performance result of XGBoost mentioned previously can be the benchmark for our model.

6 Evaluation Metrics

Because enough is discussed in section 2, just recap that recall and FAR are going to be used in this project to evaluate the performance of the models. 70% and 0.1% are expected in this project as the lowest performance metric combination. When the models are at a draw, the expectation of time to failure output by the models are then taken into account.

7 Project Design

In this section, the project design will thoroughly described to present how it will be implemented based on the data set and general working pipelines.

7.1 Data Peeking

First of all, we have to download the data set from [3], and then take a close look at the fields to gain understanding all the inputs. As is mentioned previously, SMART 187, SMART 188, SMART 197 etc should be carefully watched, however, other columns should be paid attention to.

The correlation between the attributes may be gained by scatter plot, which could also show which attribute influences the failure more. Pherhaps other figures could be plotted to help understand the failure of disks.

7.2 Data Preprocessing

Obviously all the features cannot be applied in the process of training, at the same time new features may be created to make the model perform better. For instance, should the normalized value of the SMART attribute or the original value be used? Can the delta of each atrribute per day impose large impact on the prediction, or maybe are there the delta values of some attributes that can make the model a better one? Different data preprocessing including feature creation, feature selection and feature transformation will directly influence how the model predicts. Thus this step is much important, which is worth lots of try.

Of course, the data split is necessary in this step as well. The data will be split into training, validation and test data sets, and the training data set will takes 60% percent of the whole as the other two have occupies 20% respectively. It should be noted that whether the training and validation data sets have to be pre-split is determined by the to-be-used APIs, because some API will take care of the cross-validation stage and ask for only the training data set.

7.3 Model Training

This is an easy step as the algorithms sit there in the library. XGBoost, Random Forest, Baysian Models are the primary ones to be considered. As usual, different algorithms with default hyper parameters are to be used to train the prediction models and the results are going to be compared so as to select the potential one.

7.4 Parameter Tuning

In this step, cross-validation (maybe K-Fold) will be employed to tune the parameters to gain best model performance. As probably neural nets are not going to be tried, for which grid search is not that valid, K-Fold with grid search is very appropriate for this tuning task.

7.5 Final Test and Conlusion

In the final step of the project, the tuned prediction model would be tested against the test data set or even an all new similar data set, for there are still other data sets on Backblaze's website. After the test, the recall and FAR will be presented, besides the Avg_Pred_Ahead in 2 will be shown to reflect the ability of forecasting the future.

All the test results constitute the conclusion on whether the failure of SATA HDD can be predicted and whether our approach is proper compared to the benchmark model or even other models if any.

Certainly this project, if successful per our defined evaluating metrics, may lay some basis for future study of SAS HDD failures, which I know is much trickier thanks to the SAS protocol.

References

[1] Lucas Mearian. *The 5 SMART stats that actually predict hard drive failure*. Computer World, NOV 12, 2014.

[2] Andy Klein. *What SMART Stats Tell Us About Hard Drives*. Backblaze, Oct 6, 2016.

[3] *Hard Drive Test Data*. Backblaze, 2016.

[4] Xiaohong Huang. *Hard Drive Failure Prediction for Large Scale Storage System*. UCLA Electronic Theses and Dissertation, University of California Los Angeles, 2017.