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.

This prediction problem is addressed as classification problem, in which the positive samples are failure disks and the negative sample are non-failure disks. As there are usually far more normal disks than the failure disks, this problem is obviously an unbalanced classification problem. Thus prediction accuracy is not enough for evaluating the prediction model. Instead, 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).

As is stated in the previous section, the inputs are failure label(1 indicates failure, and 0 means normal disk.), daily SMART attributes, and basic HDD information including the snapshot date, serial number and model. Note that there are 45 SMART attributes in the data set input features with raw value and normalized value for each SMART attribute. As we can see there are lots of features, so it may not be a good idea to use all of them to train a classifier, but we can train one with all the features to obtain a baseline model.

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 one column of label, several columns of 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 data set is believed to be helpful for disk failure prediction. The basic HDD information contains the disk model types of different vendors, which may help build several model specific classifiers to gain better overall performance. Note that the failure disks are positive samples, so they are labeled as 1 and the others are labeled as 0.

As is stated in section 2, the HDD failure prediction problem is by nature a very unbalanced classification problem. From the input data set, it is observed that there are 65993 disks and more than 3,000,000 daily records, however there are only 215 daily records labeled as 1. Consequently it will definitely not work if we naively throw all the data records into the classifiers for training. The unbalance gives credits on the selectio of the metrics which includes both recall and FAR.

Usually the data set is split into 60% training set, 20% validation set and 20% test set, nevertheless the split is not based on the original set because the daily records are not our direct inputs. Instead the data set will be reproduced in such a way: group all the same disk serial numbers; for all records of the same disk, sort them in ascending date order; select a window and mark all the records of the failure disk within the window as failure records as well; split the normal disk data and failure disk data respectively with each disk in only one set to form the training set, validation set and test set, all of which mix normals and failures. Even though the failure sample data set can be augmented, they are still much fewer than the normal samples. Some kind of down sampling method could be applied to balance the data set or some other mechanism, say mixture of experts, may be employed to get better results for the limited number of positive samples.

In the training and validation stages, there are just records with binary labels and the date sequentiality doesn't matter. In the test stage, we need to simulate the daily predicting behavior so as to obtain the Time_To_Failure. Additional description may be found in section 4 and section 7, but in this proposal, it can not reach the extreme details.

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. In the test procedure, the records of each disk will be tested in the order of ascending date so that the real scenario of predicting job on each day can be simulated. 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. One thing to note is that there are different strategies regarding how to determine the failure disk is successfully predicted. One is to accept only the failure prediction within a certain period before the actual failure date; the other is to deem all failure prediction with respect to the actual failure disk as valid hits. The latter would be used in this project for the threshold date range in the former approach is closely related to the practical requirements, and there is no standard on this range. Thus in the case of this project, in the test stage only the label of the disk matters and that of each record doesn't.

5 Benchmark Model

After the data set is reproduced, a naive classifier can be trained based on the reproduced data set with all features included. It is certain that this predictor won't perform well because of the large number of features. However, it can be our first baseline model to be compared to our final predictor.

On the other hand, 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. Nevertheless 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 secondary 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, this step could be redone many times, and for the first time no feature reduction, transformation and creation would be performed in order to have the first benchmark model. Then domain knowledge and other technique could be utilized to obtain a new set of features, which may bring benefits to our predictor.

No matter what is done with the features, as is described in section 3, the data set has to be reproduced to boost positive samples and make the data set more balanced. 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 20% samples about respectively. The data set will be split based on the disk serial numbers to have all the records of the same disk stay in the same data set, and in the test set the label of each record is not important because as is stated in section 4 only the label of the disk is cared about. 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 section 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.