Hard Disk Drive SMART Data Analysis using Apache Spark

ECE 590 – Big Data Technologies-Spring 2021

Team – 18

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Abstract

The enormous growth of data acquisition use cases in recent years has indeed demanded more storage resources, primarily hard disk drives (HDD) where data resides. Based on the organization's IT design choices these physical storage components could either be housed at Cloud storage or on-premises datacenters. Data availability from any of these storage implementations heavily depends on reliability characteristics of the underlying infrastructure. Apparently, of all the hardware components, hard disks experience high failure rates and in several cases its quite uncertain to accurately predict failures ahead of the impact, thereby losing service credibility and negatively influences financial prospects.

The scope of this project is primarily based on selected research papers[2][3][4] and data collected from Backblaze datasets. In this paper, we will leverage Big Data analytic concepts and characterize data, based on Hard Disks inherent feature called Self-Monitoring Analysis and Reporting Technology (SMART) attributes. Essentially, for the purpose of this study we obtained historical datasets from Backblaze[1] and considered SMART parameters that indicate abnormal hard disk behavior. Data analysis is performed by using Apache Spark implementation and finally established an analytical framework that will help to understand and determine co-relation between parameters (like temperature, capacity, manufacturer etc).

I. Introduction.

As demand for IT Infrastructure intensifies, deployments surged at an unprecedented rate and massively expanding at global scale. Reliability and availability being important factors, service providers and engineers focuses their attention to maintaining the ecosystem and aims to delivering uninterrupted service. Therefore, fault prevention requires advanced data analysis methods to early detection of failures analysis. Proactive detection and identification of abnormalities is the key to meeting the standards. Disks are among the most frequently failed components and observing abnormalities to predicting the impending failure of hard disks in the field can help systems at large organizations, datacenters and other crucial places to take corrective actions before the failure to avoid loss of data and performance degradation.

Data reliability, availability and low ownership costs are basic expectations from data users and it's essential for engineers to understanding the nature of failures and come up with predictive analysis mechanisms. With major advancements in machine learning, data mining etc, it has become possible to devise data analytic methods to proactively determine disk failure rates and preemptively solve large scale manufacturing concerns, thereby reducing the TCO and costs associated to HDD manufacturing and return merchandize processes.

The primary goal of this study is to implement Big Data analytics on HDD Smart attribute datasets and to understanding the relationship between various parameters that could negatively impact disk drive performance and premature failures. A significant size of 52 million records are considered towards the scope of this project and utilize Apache Spark as the analytics engine. The study will also demonstrate Big Data analytic Framework capabilities for various reporting and how we could derive value added solutions for Hard Disk Drive predictive failures.

II. Data Flow Architecture.

Fig(1) shows the schematic diagram of our analysis using Apache Spark. The data is collected from Backblaze, stored in our Local Machine. These are further analyzed using Apache Zeppelin notebook which triggers the spark jobs computation and visualize the results.

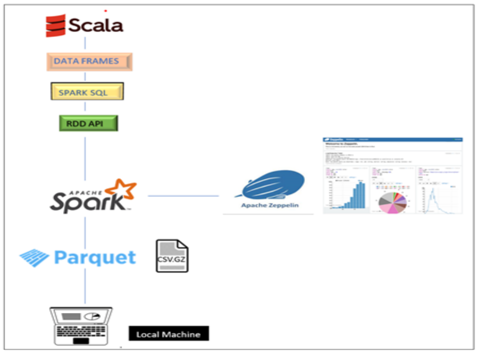


Fig (1) : Data Flow Architecture

For Analysis visualization we used open source software as listed below.

1. Apache Spark computation engine: version-2.4.7
2. Apache Zeppelin web notebook for querying and visualization: version-0.8.2
3. SCALA programming language : version-2.11.12

III. Implementation.

Data Collection:

The source of Data is collected from Backblaze which is primarily a Cloud Storage and Backup company[link1]. hard drive dataset. For the purpose of this project, we reviewed data files for year 2020 (Q1-Q4) that consisted 52286398 records **(approx. 52 million).**

Further breakdown of Data files specifics:

Total Files Size	16.37GB
Files Count	370 files
Drive Count	162,299
Drive Failures	1,302
Drive Days	51.2M
Drive Capacity Range	240GB – 18TB

The first row of each file contains the column names, the remaining rows are the actual data. The columns are as follows:

Date – The date of the file in yyyy-mm-dd format.
Serial Number – Mfg. assigned serial number of the drive.
Model – Mfg. assigned model number of the drive.
Capacity – The drive capacity in bytes.
Failure – Contains a "0" if the drive is OK. Contains a "1" if this is the last day the drive was operational before failing.
The remaining columns are Smart Attributes associated to Normalized and RAW values that ranges from 1 – 255 and each value signify a drive operating characteristic as reported by the drive built in smart function.

Hard Disk SMART Data Analysis:

The data consists of daily snapshots of the SMART statistics and a failure label for all operational hard drives in a data center in 2020. SMART stats are meant to be indicators of drive reliability and should, in theory, provide good input features to a predictive model of drive failure. The first step is to get all data in csv format arrangement and combine each month data and further archived those files for efficiency purposes. Data is converted to parquet format which allows compression schemes to be specified on a per-column basis. The data is then read via Spark and preview of most used column data is shown below in table[1].

Datafiles in consists of both "normalized" and "raw" columns for each of the SMART attribute. "Normalized" columns are ignored for the purpose of this analysis as standardized RAW data would suffice the need and provide detailed information required to determining drive statistics. Manufacturer-specific normalizations would be applicable to partial datasets due to transformations and therefore creates discrepancies. Hence, for the scope of this analysis we considered denormalized Raw values to establishing a model across all manufacturers drives.

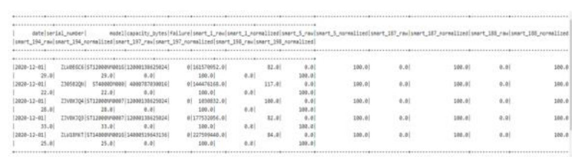


Table (1): most used columns in our data

Drive count of each manufacturer:

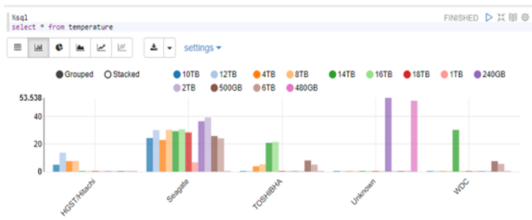
The count of drives for each manufacturer is shown below in table(2)

manufacturer	count
Unknown	160
HGST/Hitachi	33170
TOSHIBHA	23356
WDC	6278
Seagate	118197

Table 2: Drive count

Analysis of Temperature on hard drives:

We analyzed the Smart_194_raw value which represent the temperature of the drive for various manufacturers. Through the visualization below, the distribution of drive temperatures for our four most popular drives. Depicted in bar graph below Fig(2), all drives were well operated between 0° (or 5°) to 60° as specified by manufacturers and within threshold. However, typical operating temperature range of Hard Disk drives could potentially vary by specific disk design characteristics.



Fig(2) : Bar chart on MFG vs TEMP(avg)

Computing Annual Failure Rate:

Considering a given group of drives (i.e. model, manufacturer, etc.) an attempt is made to compute the AFR for a period of observation as follows:

AFR = (Drive Failures / (Drive Days / 366) * 100

where:
Drive Failures are the number of drives that failed during the period of observation.
Drive Days is number of days all of the observed drives were operational during the period of observation.
There are 366 days in 2020, obviously in non-leap years we would consider 365.

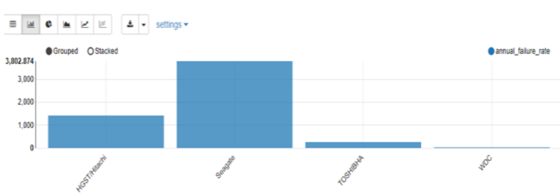


Fig (3) : Annual Failure Rate 2020 stats

manufacturer	model	capacity_bytes	drivedays	failures	temperature	annual_failure_rate
HGST/Hitachi	HGST HDS5C4040ALE630	4TB	9276	1	0	3.945666
HGST/Hitachi	HGST HMS5C4040ALE640	4TB	1083641	8	19.5	0.2702
HGST/Hitachi	HGST HMS5C4040BLE640	4TB	4662611	34	200.1470588	0.266889
HGST/Hitachi	HGST HUH721212ALE600	12TB	820272	7	11.42857143	0.312335
HGST/Hitachi	HGST HUH721212ALE604	12TB	275036	9	24.11111111	1.197661
HGST/Hitachi	HGST HUH721212ALN604	12TB	3968303	50	3.84	0.461154
HGST/Hitachi	HGST HUH728080ALE600	8TB	371930	3	13.33333333	0.295217
Seagate	ST10000NM0086	10TB	110451	7	28.57142857	2.319581
Seagate	ST12000NM0007	12TB	2314237	66	28.3030303	1.0438
Seagate	ST12000NM0008	12TB	1740779	49	32.85714286	1.030228
Seagate	ST12000NM001G	12TB	610091	12	33.83333333	0.719893
Seagate	ST14000NM001G	14TB	431057	13	32.53846154	1.103798
Seagate	ST18000NM000J	18TB	5491	2	30	13.330905
Seagate	ST4000DM000	4TB	1745899	83	23.79518072	1.739963
Seagate	ST500LM012 HN	500GB	170910	34	5.352941176	7.281025
Seagate	ST8000DM002	8TB	900304	28	33.28571429	1.138282
Seagate	ST8000NM0055	8TB	1325815	47	36.9787234	1.297466
Seagate	Seagate SSD	240GB	9902	1	38	3.696223
TOSHIBHA	TOSHIBA MG07ACA14TA	14TB	4100116	102	12.56862745	0.910511
TOSHIBHA	TOSHIBA MQ01ABF050	500GB	143891	96	7.625	24.418483
TOSHIBHA	TOSHIBA MQ01ABF050M	500GB	145672	32	10.3125	8.03998
WDC	WDC WD5000LPCX	500GB	19476	1	0	1.879236
WDC	WDC WD5000LPVX	500GB	73535	10	0	4.977222
WDC	WDC WUH721414ALE6L4	14TB	226848	1	40	0.161342

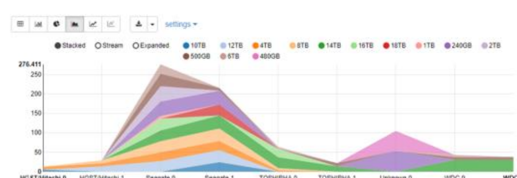
Table : Annual Failure Rate based on 2020 stats

After performing a comparative analysis, it's determined that on an average Seagate Drives shows highest rate of Annual failure and then followed by Hitachi as shown in Fig(3) and the table above.

IV. Results & Discussions.

Effect of Disk Temp on Predictive Failure Abnormalities:

Overall, there is no direct correlation between operating temperature and failure rates. However, from the observation, Seagate drives models from 2020 are generating more heat while experiencing predictive failure abnormalities and therefore disrupts thermal profiles in Datacenter Environments. This is an important metric as to understanding HDD behavior, which in this case Seagate generate elevated heat levels and contribute to thermal profile variations in storage deployments and thereby increasing Operating expenses. Refer Fig(4)



Fig(4) : Temperature vs Failure rate

Relationship between Predictive failure and 5 main SMART Parameters:

SMART readings presented by Hard Disks can be out-of-bounds, noisy, or inaccurate based on disk design and operating conditions, and therefore sometimes have quite a bit of missing data. One step to address these problems is to filter out columns where a lot of the entries are null.

The 5 Key SMART attributes for predictive errors:

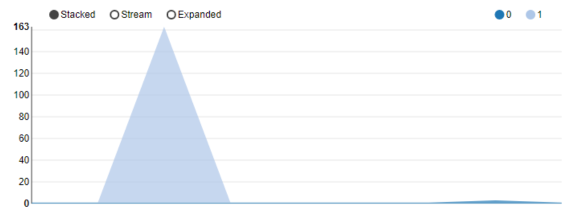
SMART 5 - Reallocated_Sector_Count.
SMART 187 - Reported_Uncorrectable_Errors.
SMART 188 - Command_Timeout.
SMART 197 - Current_Pending_Sector_Count.
SMART 198 - Offline_Uncorrectable

As stated by Backblaze, When RAW value for one of these five attributes is greater than zero, we have a clear indication to consider the value and investigate. Below graphs are to see whether there is a true relation between these SMART parameters and the failure.

Based on the observations, except for SMART 188, the definitions described above from Backblaze holds true for every other SMART value.

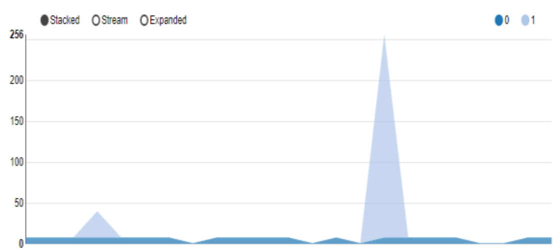
SMART 5

SMART 187

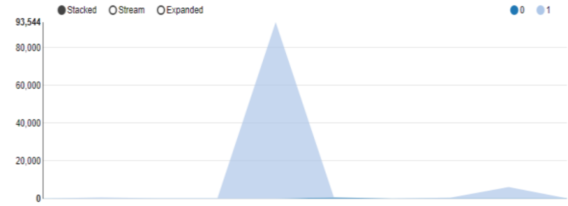


SMART 188

SMART 197



SMART 198



Considering the scope for next level analysis we have implemented **Linear Regression Model** with these smart parameters as features and failure column as label. However, the coefficients are sometimes visible as blank values and thus we cannot perform our analysis further to display predictions. Therefore, in the future scope we would like to investigate which regressions would best suit to predict the drive failure using machine learning training models.

V. Conclusion.

Proactive monitoring and management capabilities are the first steps towards improving current standards and modelling systems for gaining Infrastructure Insights. As summarized in each section, various methods and approaches are taken to demonstrate the powerful capabilities of Big Data concepts that included Spark and other supporting utilities. In this study, Hard Disks SMARTs were analyzed for measuring Hard Disk Drive Quality that essentially adds value to improving the availability and reliability of underlying storage. Primarily based upon engineering analysis, we considered the characteristics of each query, the type of data and size of data set were the main factors to optimally demonstrating the capabilities of Big Data Analytics and estimated the failure rates, therefore plotting information to minimizing the scope of impact to infrastructure. The methodologies described can provide proactive and valuable Insights to HDD Manufacturers and Customer Deployments. The paper also establishes relationship between various characteristics of the Hard Disks to understanding the operational overheads like thermals and discusses its impact.

VI. Future Scope.

In this paper, we proposed and established a solution that can be further extended to developing Telemetry & Transform Management system with advanced machine learning techniques. Applying deep data analytics to telemetry data to potentially enable Self Managing, Self-Healing and Self Optimizing features and improving the availability and performance of Storage infrastructure.

References:

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