Predicting Hard disk failure at the Delta center in the Netherlands

1 Introduction

From centuries, Dutch people have pumped the water of the lakes and the sea in order to build big cities on the new dry land. That is why around of sixty percent of the surface area of the Netherlands is bellow the sea level, with a high risk of flooding. In order to prevent an overflow that could destroy the western part of the country, artificial beaches, sand dunes and dikes were built to absorb the forces of a rising sea. However, the Dutch hydraulic system was not built and maintained properly until the 50's. Proof of that were the effects of the most devastating flood in the Netherlands' history, where 1800 people and 200000 animals died as a result of the collapse of the dikes' structure.
The delta project started in 1953, twenty days after the flooding. The aim of the Delta project was to build a complex system of automatic dikes, barriers and dams that control the sea level and drain off the excess of water coming from the large rivers. Currently, the Netherlands has 700 km of dikes, which are divided in 53 dike areas. The dikes and damns are controlled with supercomputers, which monitor the status of these structures 24 hours per day. A damage in the supercomputer; for instance, a failure in some of its hard disks, would produce devastating effects that would result in another flood.
The aim of this project is to predict the hard disks that fail during the first week of 2016 at the Delta center in the Netherlands. To make this prediction, I will use the data provided by the Backblaze center, which contains the information of the year of 2015 of the status of approx. 62800 hard drive disks. The data can be downloaded from this website:

https://www.backblaze.com/b2/hard-drive-test-data.html

Every day, the Backblaze center takes a snapshot of each hard disk. This snapshot includes basic drive information along with the S.M.A.R.T. (Self Monitoring Analysis and Reporting Technology) statistics reported by that drive. The daily snapshot of one drive is one record or row of data. All of the drive snapshots for a given day are collected into a file consisting of a row for each active hard drive. The format of this file is a CSV (Comma Separated Values) file. Each day this file is named in the format YYYY-MM-DD.csv, for example, 2015-04-10.csv.

The data contains the following information (listed by columns):

- *Date*: The date of the file in yyyy-mm-dd format.
- *Serial Number* : The manufacturer-assigned serial number of the drive.
- *Model*: The manufacturer-assigned model number of the drive.
- *Capacity*: The drive capacity in bytes.
- *Failure*: Reports two values: '0' if the drive is OK; '1' if this is the last day the Hard disk was operational before failing.
- *2015 SMART Stats*: 90 columns of data, that are the Raw and Normalized values for 45 different SMART stats as reported by the given drive. Each value is the number reported by the drive.

From the 90 columns corresponding to different S.M.A.R.T. attributes of the disk, I will restrict my analysis to only six attributes namely:

- *Read Error Rate* (S.M.A.R.T. 1): Stores data related to the rate of hardware read errors that occurred when reading data from a disk surface.
- *Spin-up time* (S.M.A.R.T. 3): Time that spends the spin disk to be at the operational velocity (milliseconds).
- *Reallocated Sectors Count* (S.M.A.R.T. 5): Count of the bad sectors that have been found and remapped. The higher the attribute value, the more sectors the drive has had to reallocate.
- *Running time* (S.M.A.R.T. 9): Number of hours a drive has been in service up that point. The raw value is measured in hours.
- *Power cycle count* (S.M.A.R.T. 12): The count of full hard disk power on/off cycles.
- *Internal temperature* (S.M.A.R.T. 194): Internal Temperature of the disk in Celsius.

This report is organized as follows: In Sect. 2 I explain the procedure to clean the data. In Sect. 3 I present the Exploratory Data Analysis (EDA) carried out. In Sect. 4 I explained the techniques and the machine learning algorithms that were used to predict the failed hard drives at the delta center in the Netherlands. Finally, in Sects. 5 and 6 I summarize and discuss the steps that can be done in the future.

2 Data wrangling and cleaning

The following figure shows the commands used to clean the data provided by the Blackbaze center:

```
import numpy as np
import pandas as pd
import glob

column_names=['date', 'serial_number', 'model', 'capacity_bytes',
'failure', 'smart_1_normalized', 'smart_1_raw','smart_3_normalized',
'smart_3_raw', 'smart_5_normalized', 'smart_5_raw','smart_9_normalized',
'smart_9_raw', 'smart_12_normalized', 'smart_12_raw',
'smart_194_normalized', 'smart_194_raw' ]

files= glob.glob('2015*.csv')
data= pd.concat([pd.read_csv(i, usecols= column_names) for i in files],
ignore_index=True)

# data cleaning
data= data[data.capacity_bytes>0]
data['date']= pd.to_datetime(data['date'], errors= 'coerce')
data.to_csv('hard_drive_data_2015.csv')
```

The original dataset is stored in 365 files corresponding to the year of 2015. I gather all these data into a single, big file with the aim of making a better management and analysis of the data. For this task, I used the Python's module `glob` which searches for the files belonging to the hard drive's dataset. I also filtered the columns of interest; that is, those that contains the date, serial number, model, capacity, failure and the raw and normalized values of the six S.M.A.R.T. attributes listed in the previous section.
Once all the information is stored in a single data frame, I removed the data points with unphysical sense. These data correspond to hard disks that have negative capacity bytes. Additionally, I converted the *date* column into a type that is manageable by Pandas.
The data frame is finally written into a file called `hard_drive_data_2015.csv`, which will be used to make the data analysis.
The Python's script that makes the data wrangling and cleaning can be found in this link:

https://github.com/anamabo/Predicting_failure_hard_disks/blob/master/data_reading_and_wrangling.ipynb

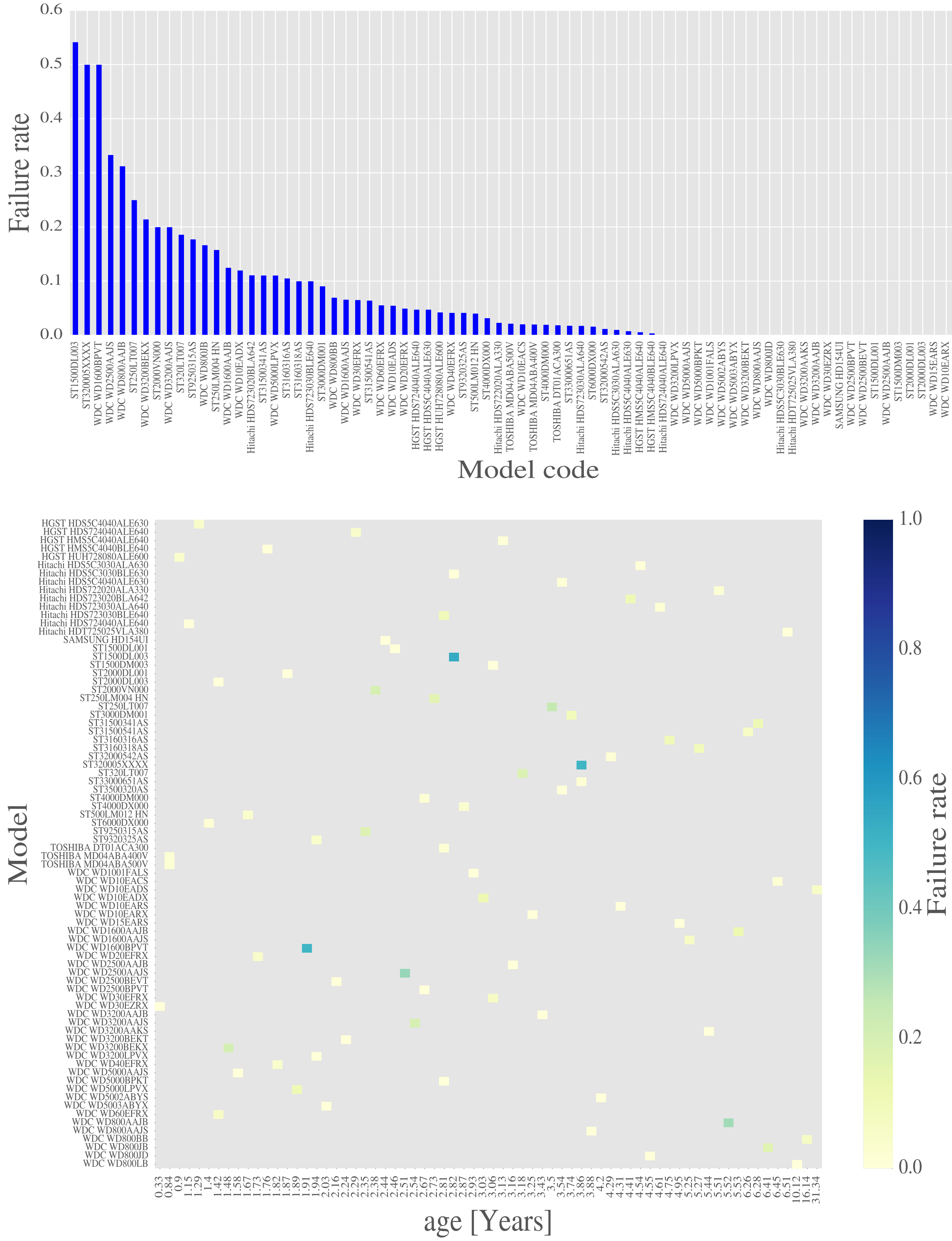

Figure 1: Failure rate as a function of: *Top:* the model of the disks. *Bottom:* the model and age of the disks.

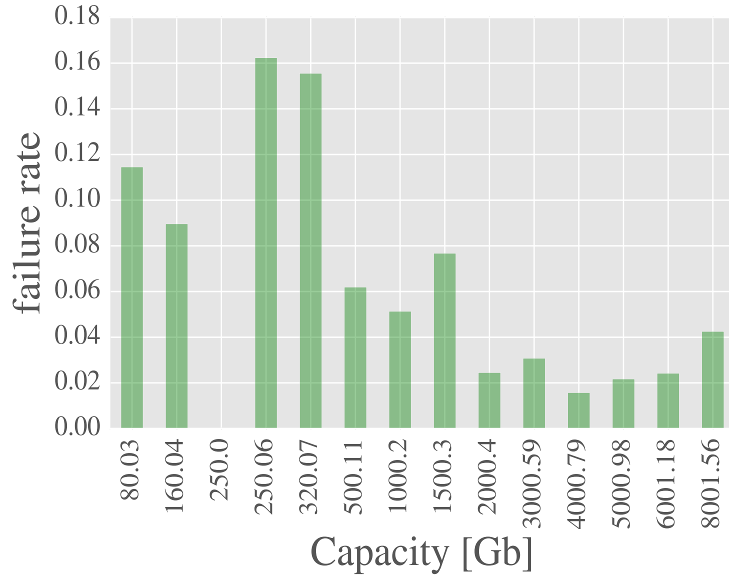

Figure 2: Failure rate as a function of the capacity bytes.

3 Exploratory Data Analysis

A preliminar exploration of the file `hard_drive_data_2015.csv` suggests that this dataset contains 62898 hard drive disks which are classified in 78 models and have 14 different capacity bytes.

I started the analysis of the dataset by computing the failure rate of the hard disks. The failure rate (FR) is defined as the ratio between the disks that fail over the total number of disks, given a certain property such as disk model, capacity or running time. The failure rate as a function of disk model is shown at the top panel of Fig. 1. We can see that in general, the failure rate is smaller than 0.4 for the majority of the models; however, the FR is around of 0.5 for the models: `ST1500DL003`; `ST320005XXXX` and `WDC WD1600BPVT`. This means that at least 50% of the disks belonging to these models, fail. Yet, the failure rate itself is not a determinant factor to make conclusions about the quality of these models. To achieve this, It is necessary to add the age of the disks in the analysis.

In the bottom panel of Fig. 1 I show the failure rate in terms of the disk model and age; that is, the maximum value of the disks' running time. We can observe that the three models mentioned previously have ages of 1.9, 2.8 and 3.8 years. According to this figure, the model `WDC WD1600BPVT` is the worst one, since roughly 50% of its hard drives fail when they have an age that is less than 2 years. This results suggest that the Delta center should not purchase hard disks of this model.

The plot in the bottom panel of Fig. 1 also gives us the better models of hard disks. According to the figure, around of 28 models have a FR$<$ 0.2 and ages larger than 5 years. The delta center in the Netherlands should buy one of those hard drive disks.

As mentioned before, the failure rate can also be measured in terms of other variables. In Fig. 2. I show the failure rate in terms of the capacity bytes. As we can observe, disks of 250 and 320 Giga Bytes (Gb) have a bigger failure rate; however, this is not higher than 0.2. We can also observe that there is a weak correlation among capacity bytes and failure rate.
The previous results lead us to conclude that the hard disk's dataset can be classified in two classes: the disks that still work after one year of measurements (working disks) and the disks that fail during this period of time (failed disks). To obtain the working and failed disks, I grouped the data by the `serial number` and I computed the sum of the attribute `failure` for each disk. If this sum is equals to 0, the disk is classified as a working disk; if the sum is equals to 1, the disk is classified as a failed disk.
An analysis of this classification shows that 97% of the disks in the dataset are working disks; while only 2% of the disks, fail. This is what is called an **unbalanced classification problem** and it has to be treated very carefully, specially when applying machine learning algorithms, since the predictions will be biased toward the larger class. I will tackle this issue in Sect. 4.

3.1 Possible correlations and trends

Once the classification is done in the dataset, I search for possible correlations among different S.M.A.R.T. attributes for the working and failed disk. The results are shown in Fig. 3. At a first glance, we observe that there is a weak correlation among S.M.A.R.T. attributes. Additionally, we can observe how the distributions of failed and working disks are almost overlapped, which means that they are hardly distinguishable. In order to make a better distinction between working and failed disks, I compare their corresponding distributions of the S.M.A.R.T. attributes and I made a further statistical analysis of these data. I show the results in the next section.

3.2 Statistical analysis of S.M.A.R.T. attributes

S.M.A.R.T. attr.	**d**	$\mathbf{P}_o$	$\mathbf{P}_s$	95% **CI**	**p-value**
Error rate	0.4	1.07	0.01	[0.3, 0.5]	< 0.001
Bad sectors count	0.26	1.10	0.005	[0.18, 0.35]	< 0.001
spin-up time	0.22	1.03	0.003	[0.15, 0.3]	< 0.001
Running time	0.09	1.05	0.01	[0.04, 0.15]	0.001
Internal temp.	0.05	0.96	0.01	[0.01, 0.1]	0.038
Power on-off cycle count	0.03	1.15	0.01	[0.02, 0.24]	0.075

Table 1. Statistics of the S.M.A.R.T. attributes. From left to right: S.M.A.R.T. attribute, Cohen's distance, overlap and superiority probabilities, confidence interval and p-value.

The scatter plots shown in Fig. 3 do not give us good information about the differences in the distributions of S.M.A.R.T. attributes for the working and failed disks. Instead,

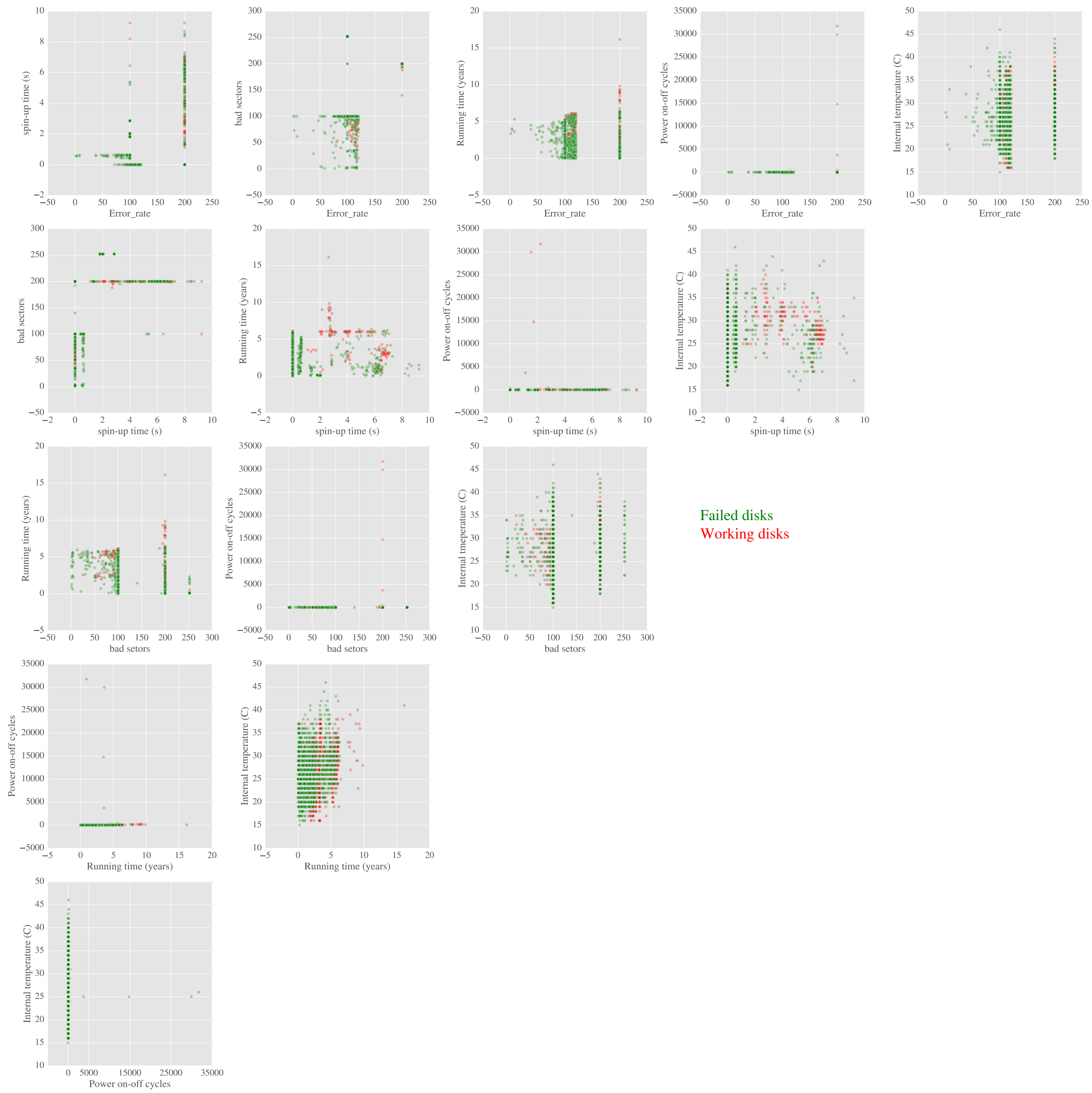

Figure 3: Distribution of failed and working disks in the space of the S.M.A.R.T. attributes

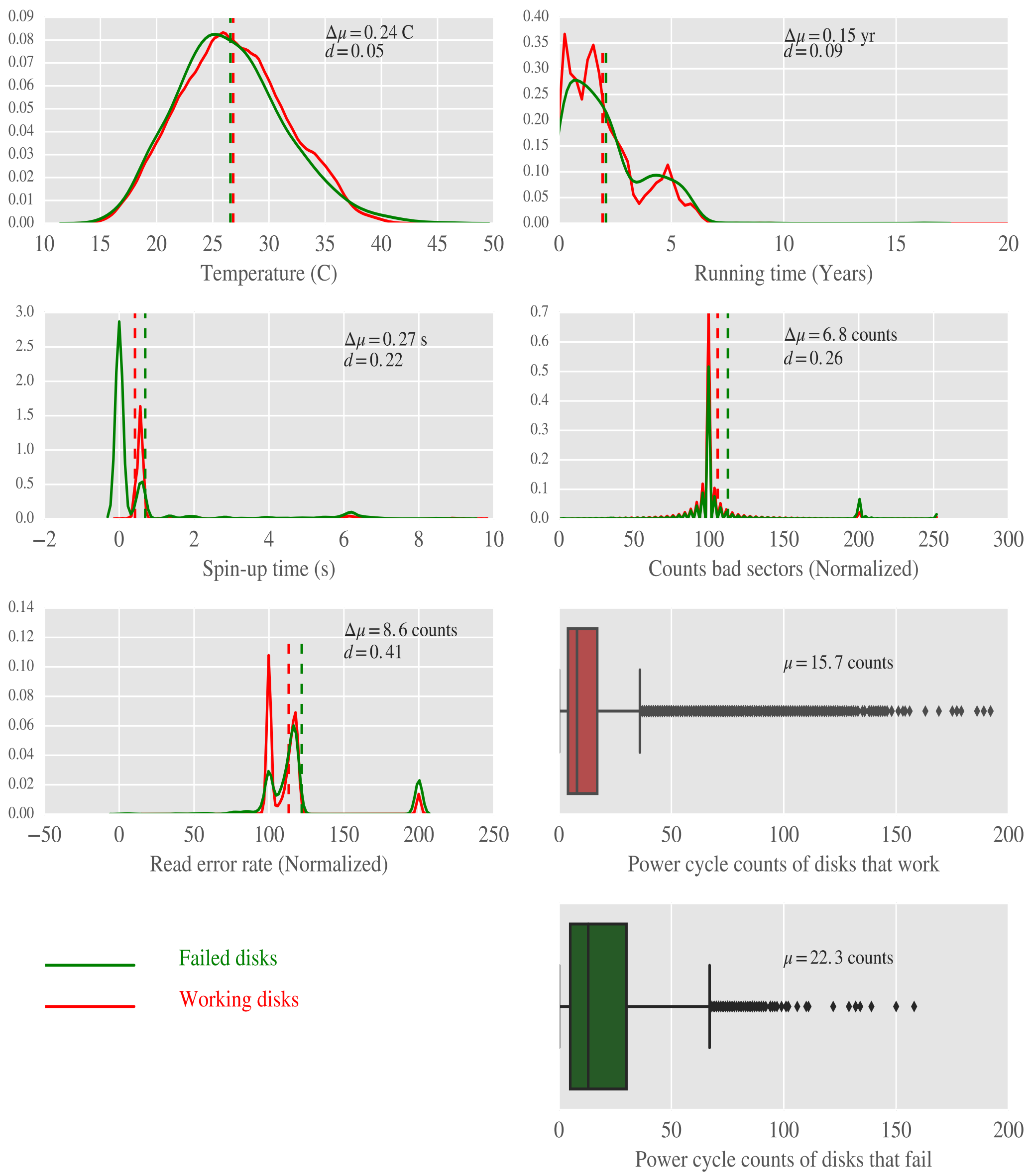

Figure 4: Distribution of S.M.A.R.T. attributes for failed and working disks. The dashed vertical lines show the mean values of these distributions. The quantity $\Delta\mu$ corresponds to the difference in the mean. The letter d represent the Cohen's distance.

it is better to visualize their respective density distribution functions (DFs). In Fig 4 I show the distribution functions of each of the S.M.A.R.T. attributes for the working and failed disks. The vertical dotted lines mark the position of the distribution's mean. For each S.M.A.R.T. attribute I show the difference in means ($\Delta\mu$), as well as the Cohen's distance (d). This last quantity is defined as the difference in means over the weighted average of the standard deviations of the distributions. The Cohen's distance is a better measurement of the difference of distributions (effect size), because it provides a standardized measurement. I made the statistical analysis of the data based on d; however, the results would be the same if the effect size taken is the difference in means.
From Fig. 4 we can observe that the distributions of the spin-up time, the counts of bad sectors and the read error rate for the working and failed disks seem to be different. On the other hand, the distributions of internal temperature, running time and power cycle counts of the working and failed disks, seem to be not so different at all.[1]. How precise are these measurements? Are these observed effects real? I answered these questions by carrying out a statistical analysis of the data.
In Table 1 I present the statistical analysis made to the difference in the distributions of S.M.A.R.T. attributes for the failed and working disks. The results are sorted in descending order by the Cohen's distance d. The third and fourth columns show the overlap and superiority probabilities respectively. These two quantities also serve to visualize the difference between the distributions. The fifth column lists the confidence interval of the estimate of d, with a significance level of 5%. The sixth column shows the p-value obtained after running a hypothesis test with a significance level of 1% ($\alpha = 0.001$). In this test, the null hypothesis states that for a given S.M.A.R.T. attribute, the distributions of fail and working disks are the same. From the p-value I obtain the following results:

- With a confidence of 99% I can reject the null hypothesis in the first three S.M.A.R.T. attributes listed in table 1. This means that **the distributions of the error rate, the spin-up time and the bad sector counts are different for the failed and working disks**.

- I can not reject the null hypothesis in the last two S.M.A.R.T. attributes listed in table 1. This means that **the distributions of the power cycle counts and the internal temperature might be the same for the failed and working disks.**

- Given that the p-value of the running time is the same as the established significance level, I can not conclude whether the distributions of the failed and working disks are the different or not.

These results suggest that there are some S.M.A.R.T. attributes that play an important role in establishing whether a hard disk might fail or not.

[1]For this last S.M.A.R.T. attribute the DFs have different amplitudes (scale difference of two orders of magnitude); therefore, it is better to visualize the distributions with a box plot.

If the reader is interested in more detail about the scripts that I used to make the exploratory data analysis, you can go to the following links:

https://github.com/anamabo/Predicting_failure_hard_disks/blob/master/exploratory_data_analysis.ipynb
and
https://github.com/anamabo/Predicting_failure_hard_disks/blob/master/statistical_analysis.ipynb

4 Predicting the failed disks at the delta center in the Netherlands

In the last section I explored the S.M.A.R.T. attributes for which the working and failed disks can be better differentiated. This analysis, however, does not bring further constraints that can be applied in a machine learning code. Those constraints are related to the most important features that can make a prediction better and more robust. This approach is called **feature reduction** and it is a necessary step before applying any machine learning code.

The feature reduction has three main advantages:

1. It reduces overfitting by eliminating noise features.
2. It improves accuracy in the prediction.
3. It reduces training time.

There are several methods to compute the relative importance or 'weight' of each attribute. In this work I used ensembles of decision Trees (or Extra Trees), because these methods account for non-linear relations between the target variable and the features in the data. The ensembles of decision trees can be coupled with a Meta-transformer to select features based on their weights. In the Python's package scikit learn, this Meta-transformer uses the mean of the feature's weights as a threshold for feature selection. If the feature importance given by the decision tree is below that threshold, the feature is removed from the dataset.

In Fig. 5 I show the feature importance obtained with the Extra Trees classifier. By using the Meta-transformer in scikit learn, I obtain the most important features in the dataset, which are:

1. Reallocated sector counts (normalized values).
2. Reallocated sector counts (raw values).
3. Read error rate (normalized values).

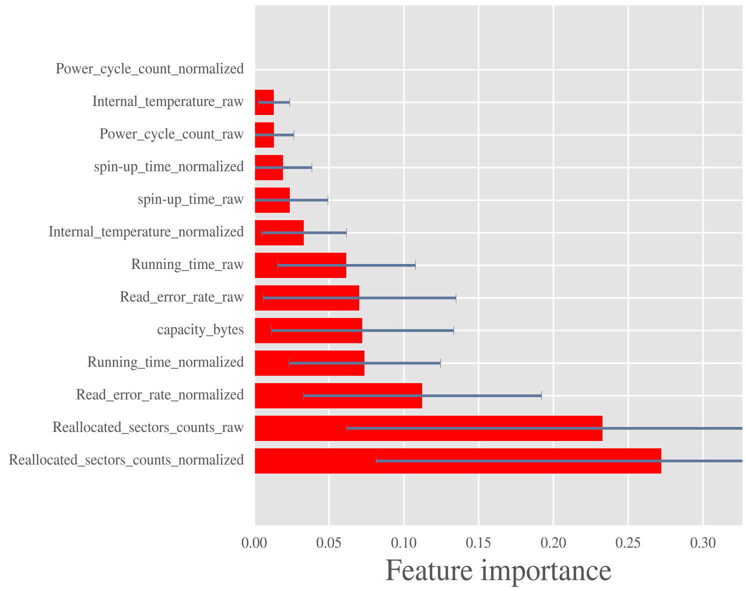

Figure 5: Feature importance in the dataset.

The dimensionality of the dataset is therefore, reduced by choosing these three features.

Once the most important features are selected, I split the dataset into a train and test sets. The train set is used to build the predictive model while the test set is used to evaluate the model. The train set contains 70% of the total data, which is around of 40000 hard drives. The test data contains 30% of the total data; which is approximately 18000 disks.

In Sect. 3 I mentioned that 97% of the disks are still working after one year, while only 2% of the disks, fail. This is one example of the so called **unbalanced classification problem**. Before running any machine learning code, it is necessary to balance the classes, to avoid biases towards the majority class in the final prediction. There are several methods to balance the classes; here I apply three methods namely:

- Oversampling: increase the minority class by creating new elements (sampling with replacement).
- Subsampling: decrease the majority class by deleting extra data points. This process can be done by selecting a number of random items from the majority class.
- Subsampling with bootstrap aggregating (bagging): subsampling the majority class multiple times and averaging the predictions of the machine learning code.

For the Oversampling and subsampling methods, I balance the classes such that the ratio between failed and working disks is 2/3 (40%/60%). For the bagging method, I

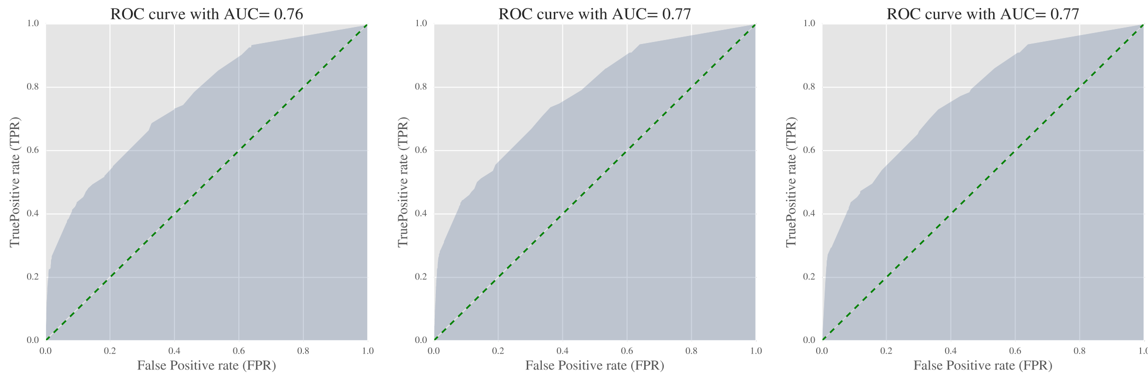

Figure 6: ROC curves for: *left:* Oversampling method. *Middle:* Subsampling method. *Right:* Bagging method.

additionally use 100 iterations. To be consistent with the method employed for the feature selection, I use a Random Forest classifier to predict the failed disks at the Delta center in the Netherlands. The parameters I use are: `n_estimators=200`; `min_samples_leaf= 5`; `max_depth= 10`. For the bagging method, I used a decision tree classifier with the same `max_depth` and `min_samples_leaf parameters`.

Metric	**Oversampling**	**Subsampling**	**Bagging**
Recall	0.41	0.43	0.43
Precision	0.10	0.10	0.10

Table 2. Accuracy metrics for several methods to balance unbalanced classes.

In Fig.6 I show the ROC curves obtained with the oversampling, subsampling and bagging methods. According to this figure, the Random forest and the decision tree (in the bagging method) are good models at predicting the failed disks (AUC$\sim$ 0.7 in each case). However, according to Table 2, the subsampling and the bagging methods make better predictions, the recall being 0.43 in both cases. This value is however low because only 43% of the total failed disks are predicted correctly. In order to improve the predictions, it is necessary to account for all the S.M.A.R.T. attributes present in the original dataset. In the feature selection process, the golden features would have the highest weight and they would make a better and more robust model.

The script that makes the feature selection and the prediction of the failed disks can be found in the following link:
https://github.com/anamabo/Predicting_failure_hard_disks/blob/master/machine_learning.ipynb

5 Conclusions

During this project I have selected, cleaned and analyzed a dataset of hard disks with the aim of provide a prediction of the number of hard drives that will fail at the Delta center in the Netherlands. In this process, I have found the following features in the data:

- From the sample of 62898 disks, only 2% of them fail during one year of measurements. This means that I have to pay special attention when working with machine learning techniques, since I am dealing with a unbalanced classification problem.

- The estimate of the failure rate as a function of the model and age gives information on the best and worst models for hard drives. I found that the models: `ST1500DL003`; `ST320005XXXX` and `WDC WD1600BPVT` have failure rates of around 0.5. From these, the model `WDC WD1600BPVT` is the worst one since the age of its hard disks is less than 2 years. On the other hand, I found that there are 28 models whose failure rate is less than 0.2 and have ages larger than 5 years. The Delta center in the Netherlands should buy those hard disks.

- The failure rate has a weak correlation with the capacity bytes of the hard disks.

- I am confident 99% that the distributions of the error rate, the spin-up time and the bad sector counts are different for the failed and working disks. On the other hand, the distributions of the power cycle counts and the internal temperature might be the same for the failed and working disks. I can not say anything from the distribution of the running time. These results suggest that there are some S.M.A.R.T. attributes that play an important role in establishing whether a hard disk might fail or not.

For the prediction of failed disks I used a Random Forest classifier over a balanced set. I found that the recall of this model is of 0.43 when subsampling. This means that only 43% of the failed disks are correctly predicted. In order to increase this estimate, it is necessary to account for more S.M.A.R.T. attributes in the analysis. In the feature reduction, only the golden features will have the highest weight, making the model better and more robust.

6 Next steps

The original dataset has 45 S.M.A.R.T. attributes. Future analysis must include all these attributes in the prediction of the failed hard disks at the Delta center in the Netherlands.