Predicting Hard Drive Failure - A Juul Labs Case Study

February 18, 2020

0.1 Predicting Hard Drive Failures Using SMART Metrics

0.1.1 - A Juul Labs Case Study

`- by Harshvardhan Pandey | Jan 09 2019`

0.1.2 What are SMART systems ?

SMART features or *S.M.A.R.T. (Self-Monitoring, Analysis and Reporting Technology)* is a software monitoring system for hard drives. It is a widely used industry practice around data center management and disk heavy resources. SMART generates a collection different metrics related to help evaluate the overall health of a Hard Drive. These metrics can be specific to a certain number of manufacturers or be more general, sometimes.

A single metrics may not always determine the exact failure prediction but are commonly accepted to help identify any imminent failure and help handle the backup and restore, in time.

0.1.3 About this case study :

This case study relies on a given data stream provided for this purpose. The goal of this case study is to try and analyze given data and find out meaningful information that can help determine drives failure trends and different factors that may idicate if a drive would fail, and attempt to propose a more data driven answer to future failures based on SMART metrics.

The study concludes with discussing possible opportunities and challenges with existing model and features that can help design a better predictive model for future.

Here's a quick look of how this problem has been approached:

0.1.4 Extraction and Load

1. Connect to the postgres server.
2. Download the dataset offline

0.1.5 Transform

3. Wrangle and explore
4. Change Dimentions, clean and slice and dice

0.1.6 Analyze

5. Analyze dataset, plot most significant trends

0.1.7 Predict:

6. Feature Selection
7. Model and predict

0.1.8 Conclusion and Improvement Ideas:

8. Conclude
9. Challenges with the current dataset and ways to improve it

Extraction and Load 1. Connect to the postgres server

- I'll begin by importing libraries to connect to postgres and download the dataset offline.
- I will create a few database utility funtion get the table data and columns
- next up, I will use pandas to join columns and dataset and transform incoming data into a pandas dataframe.
- Lastly I will save the data locally in a csv format.

Next up, I will beging wrangling and exploring the data to understand different attributes that will be used later on in analysis.

In [72]:
```
import psycopg2
import matplotlib.pyplot as plt
%matplotlib inline
import pandas as pd
from sklearn import ensemble, metrics
```

In [10]:
```
#### postgres database utility functions
####

# db connection object generator
def postgres_db_connection():
    # postgresql://35.230.114.237", "postgres", "luuj"
    conn = psycopg2.connect(host="35.230.114.237", dbname="postgres",
    user="candidate", password="luuj")
    print('Connecting to postgresql server...')
    cur = conn.cursor()
    print('Successfully connected to the host\n')
    return cur
```

```
def get_all_tables(cur):
        print('Extracting list of tables:')
        cur.execute("SELECT * FROM pg_catalog.pg_tables where schemaname NOT IN ('pg_
        tables = cur.fetchall()
        t = [i[1] for i in tables]
        return t


def lookup_a_table(cur, tablename):
        # get data from a given table: tablename
        print("\nReading table: "+tablename+"...")
    # cur.execute('SELECT * from '+tablename+' limit 10')

        # get table_data
        cur.execute("SELECT * from "+tablename+' limit 10')
        table_data = cur.fetchall()
        return table_data


def get_table_columns(cur, tablename):

        # get column_names
        print('Fetching columns in: ', tablename)
        try:
                cur.execute("SELECT table_name, column_name from information_schema.c
                column_names = cur.fetchall()
                column_names = [j[1] for j in column_names]
        except:
                print('Column fetch failed')

        return column_names


# transform data in pandas and save table locally for offline analysis
def clean_response(table, data, column_names):
        # inp: table data and column_names
        # out: pandas dataframe

        data = pd.DataFrame(data)
        data.columns = [column_names]
        out_file = 'out_data_from_tablename_'+table+'.csv'
        print('Saving data from table: {}, to file: {}'.format(table, out_file))
#         data.to_csv(out_file, index=False, encoding='utf-8')


# Etracting all tables at the host in a list and finally,
# extracting the table we want i.e. 'hard_drive_stats
```

```
db_conn_obj = postgres_db_connection()
tables = get_all_tables(db_conn_obj)

table = 'hard_drive_stats'
data = lookup_a_table(db_conn_obj, table)
table_data = lookup_a_table(db_conn_obj, table)
table_column_names = get_table_columns(db_conn_obj, table)

# transform data in pandas
clean_response(table, table_data, table_column_names)
```

```
Connecting to postgresql server...
Successfully connected to the host

Extracting list of tables:

Reading table: hard_drive_stats...

Reading table: hard_drive_stats...
Fetching columns in:  hard_drive_stats
Saving data from table: hard_drive_stats, to file: out_data_from_tablename_hard_drive_stats.csv
```

1. At the end of the above code snippet, data is downloaded and saved locally to current directory.
2. Name: out_data_from_tablename_hard_drive_stats.csv

0.2 Transform

1. Now, the dataset is downloaded.
2. Filename is: out_data_from_tablename_hard_drive_stats.csv
3. We shall be be using this file going forward, in order to avoid calling the postgres again and again.

In [73]:
```
# loading dataset from local machine
df = pd.read_csv('out_data_from_tablename_hard_drive_stats.csv')
df.head(5)
```

Out[73]:
```
   row.names        date   serial_number                model  \
0    1865121  2018-01-20        ZA11RRZY           ST8000DM002
1    1865122  2018-01-20  PL1331LAHD3Y7H  HGST HMS5C4040BLE640
2    1865123  2018-01-20        ZA174A42          ST8000NM0055
3    1865124  2018-01-20  PL1331LAHGB3VH  HGST HMS5C4040ALE640
4    1865125  2018-01-20        ZA14ELXG          ST8000NM0055

   capacity_bytes  failure  read_error_rate  throughput_performance  \
0   8001563222016        0      209151808.0                     NaN
```

```
1   4000787030016        0          0.0                 106.0
2   8001563222016        0    28504744.0                  NaN
3   4000787030016        0          0.0                 104.0
4   8001563222016        0    77116864.0                  NaN

   spin_up_time  start_stop_count  reallocated_sector  seek_time_performance  \
0           0.0               3.0                 0.0                    NaN
1           0.0               4.0                 0.0                   42.0
2           0.0               4.0                 0.0                    NaN
3         431.0               5.0                 0.0                   42.0
4           0.0               3.0                 0.0                    NaN

   power_on_hours  power_cycle_count  reported_uncorrect  command_timeout  \
0         13874.0                3.0                 0.0              0.0
1         14041.0                4.0                 NaN              NaN
2          4726.0                4.0                 0.0              0.0
3          8475.0                5.0                 NaN              NaN
4          7309.0                3.0                 0.0              0.0

   high_fly_writes  airflow_temprature  load_cycle_count  total_lbas_written
0              0.0                29.0            3888.0        5.189666e+10
1              NaN                 NaN             143.0                 NaN
2              0.0                35.0             716.0        2.152110e+10
3              NaN                 NaN              11.0                 NaN
4              0.0                34.0            2380.0        3.561304e+10
```

Get basic look of the dataset

In [12]:
```python
# number of rows
rows = df.shape[0]
columns = df.shape[1]

print('Number of rows are: {} and number of columns: {}\n'.format(rows, columns))
print(df.dtypes)
```

```
Number of rows are: 8949492 and number of columns: 20

row.names                  int64
date                      object
serial_number             object
model                     object
capacity_bytes             int64
failure                    int64
read_error_rate          float64
throughput_performance   float64
spin_up_time             float64
start_stop_count         float64
reallocated_sector       float64
```

```
seek_time_performance     float64
power_on_hours            float64
power_cycle_count         float64
reported_uncorrect        float64
command_timeout           float64
high_fly_writes           float64
airflow_temprature        float64
load_cycle_count          float64
total_lbas_written        float64
dtype: object
```

More wrangling of the data First up, I get rid of some irrelevant columns and then indentify the top 10 hard drives.

I will apply some cleaning on the columns, changing dtypes and more. Next, I discard/drop columns based on: 1. high number of Nan 2. irrelevance 3. top 10 models

```
In [13]: # drop everything where 10 or more rows are Nan
         df = df.dropna(thresh=10, axis=0)


         # drop column row.names
         df = df.drop(['row.names'], axis=1)


         # change data type
         new_date = pd.to_datetime(df['date'])
         df['date'] = new_date
```

Data types now look like this:

```
In [14]: df.shape

Out[14]: (8949141, 19)
```

0.2.1 Top 10 most common hard drives

- After getting rid of some of the duplicates.
- Now based the dataset, I am making the following assumptions:

1. Hard drives with number of datapoints are the most common hard drives.
2. Since there are multiple serial_numbers that belong to the same Hard Drive model, I am taking a unique count only.

```
In [15]: # getting a list of the msot common drives
         most_common_models = df.groupby(['model'], as_index=True)['model', 'date']. size()
         most_common_models = most_common_models.sort_values(ascending=False)
```

Most Common Models in descending order are:

```
In [16]: # number of different models
         print("There are 53 models: ", len(most_common_models))
```

```
There are 53 models:  53
```

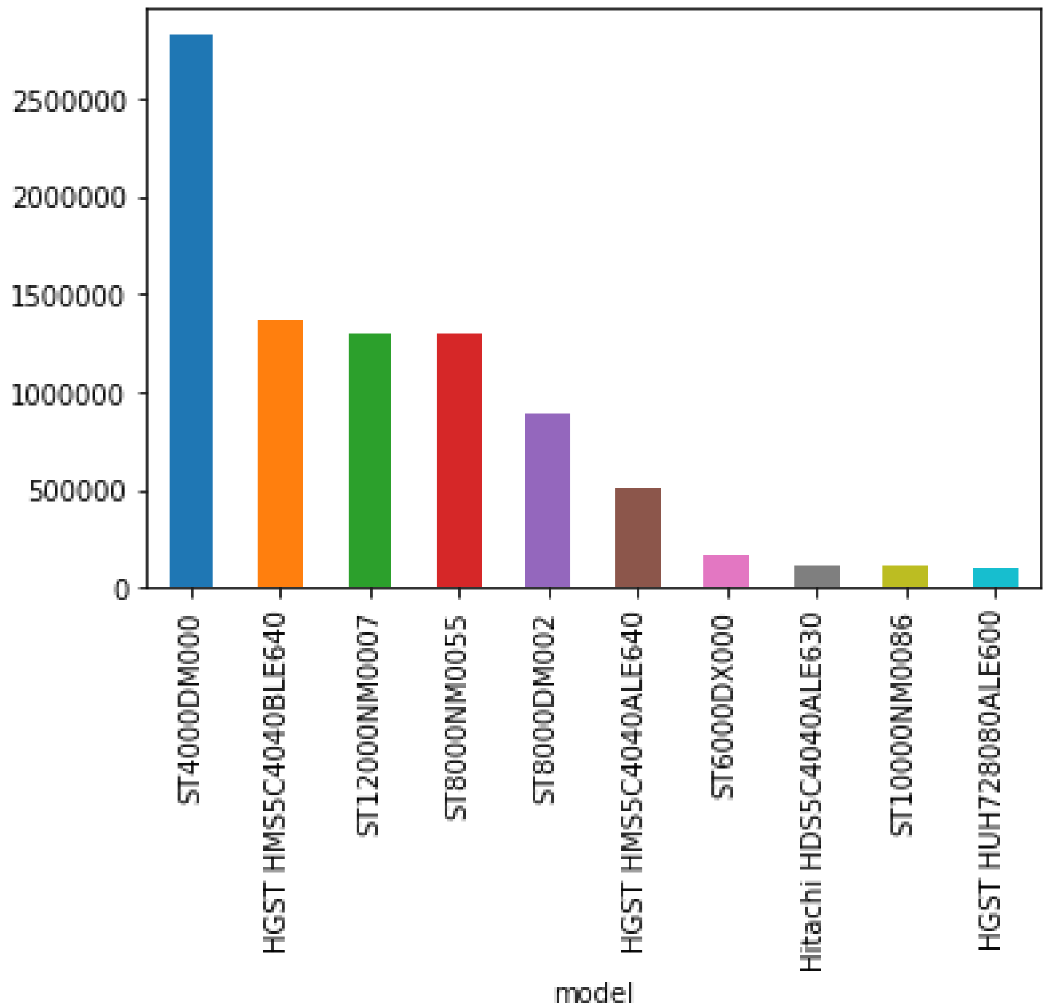
Top 10 Models based on most number of Hard Drives are

```
In [17]: top10_models = most_common_models[:10]
         top10_models
```

```
Out[17]: model
         ST4000DM000               2822270
         HGST HMS5C4040BLE640      1363173
         ST12000NM0007             1296241
         ST8000NM0055              1293502
         ST8000DM002                888733
         HGST HMS5C4040ALE640       505026
         ST6000DX000                169017
         Hitachi HDS5C4040ALE630    115984
         ST10000NM0086              109738
         HGST HUH728080ALE600        94024
         dtype: int64
```

```
In [61]: top10_models.plot(kind='bar', legend= False)
         print('Top 10 common models and the number of hard Drives in each:')
```

```
Top 10 common models and the number of hard Drives in each:
```



0.2.2 Filtering - Limiting the dataset by only top 10 models

```
In [62]: # top 10 models
         list_top10_models = [i for i in top10_models.index]

         # this is the new dataframe based on the top 10 models
         new_df = df[df['model'].isin(list_top10_models)]

         new_df.shape

Out[62]: (8657708, 19)
```

Using the new dataframe from here on

```
In [63]: # Changing datatypes
         new_df['failure'] = new_df['failure'].astype('bool')

         # saving top10 models data to csv
         # new_df.to_csv('top10_models.csv', index=False)
```

```
/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
```

0.3 Analysis

Keeping in mind that the resources available *do not* accurately describe this particular dataset. It is crucial to proceed with caution.

I researched online and read a number of articles. I settled one the ones I found most relevant. I have used this information to help me understand the schema and it's various attributes.

0.3.1 Resources:

These are some of the resources I found helpful.

1. Understanding differet SMART stats: https://www.backblaze.com/blog/what-smart-stats-indicate-hard-drive-failures/
2. SMART schema on WIKI: https://en.wikipedia.org/wiki/S.M.A.R.T.#ATA_S.M.A.R.T._attributes
3. Research Paper: http://cs229.stanford.edu/proj2017/final-reports/5242080.pdf

0.3.2 Tools:

1. I have utilized scikit library for prediction.
2. Partly used pandas and Google Big Query for faster analysis in SQL, and
3. matplotlib + Google Data Studio for plotting charts.

Let's check the cardinality of each columns

```
In [21]: # find unique values per columns
         for cols in new_df.columns:
             print("{} has: {} unique values".format(cols, len(new_df[cols].unique())))
```

```
date has: 90 unique values
serial_number has: 101310 unique values
model has: 10 unique values
capacity_bytes has: 5 unique values
failure has: 2 unique values
```

```
read_error_rate has: 5938125 unique values
throughput_performance has: 67 unique values
spin_up_time has: 288 unique values
start_stop_count has: 187 unique values
reallocated_sector has: 1023 unique values
seek_time_performance has: 11 unique values
power_on_hours has: 43903 unique values
power_cycle_count has: 123 unique values
reported_uncorrect has: 70 unique values
command_timeout has: 161 unique values
high_fly_writes has: 1175 unique values
airflow_temprature has: 45 unique values
load_cycle_count has: 190691 unique values
total_lbas_written has: 6562030 unique values
```

0.4 ### Plotting graphs to get a visual look and analyze

Using Google Data Studio and Big Query:

- Google Data Studio provides for a much more robust and interactive reporting system.
- I loaded the dataset into Big Query and used Google Data Studio because of it's SQL support, interactive platform and robustness with doing exploratory analysis on a large dataset.
- There are some key charts provided below.

Click Here for a full report: https://datastudio.google.com/open/1vzmbcHsLQ-OMZZsfXUnECJbIteK_kdF7

Looking at the trends displayed below, we can derive the following (refer to the Studio Report below) :

1. Number of positive Hard drives failure trend are going down. This trend is proportional to the power cycle of the hard drives. This means that as the hard drives get old over time, they are more likely to fail. This is also verified by external sources, a typical life of a hard drive is around 5 years. This can help find out the likelyhood of a drive failing.

2. Reported uncorrectable errors tend to go down as the failure count goes down over time. On the other hand, the reallocated sectors a going up. Both of these features should ideally be of a lower value for a healthy hard drive. There are higher chances of failure if both of these factors go up in the future.

3. Hard Drives have to reallocated sectors at a much higher rate in the event of a failure. This happens becase hard drives need to remap the data to a different sector in order to avoid data loss. Frequent remapping like this is not a good sign of a healthy hard drive.

4. High fly rates decrease with decrease in failure. This may indicate that a lower high fly rate is a potential sign of healthier hard drives.

There are more exploratory analysis performed on google data studio report, link is provided below.

```
In [67]: # rendering google data studio report
         from IPython.display import IFrame
         IFrame('https://datastudio.google.com/embed/reporting/1vzmbcHsLQ-OMZZsfXUnECJbIteK_kdl
```

```
Out[67]: <IPython.lib.display.IFrame at 0x10bc9af98>
```

0.5 #### Assumptions made and references drawn, in performing the analysis:

Since there isn't enough detail about the dataset in this case study, some external researching is required to get an understanding.

There are exponetial values in some of SMART metrics. The provided data stream is raw and there isn't much information available online about different expoential values. I couldn't find a meaningful method to normalize the raw data to a 100 point scale in order to make a better correlation.

0.6 #### Analysis Conclusion

In conclusion, the metrics in SMART systems are most often high uncorrelated. It wouldn't be recommended to rely on one of them to make a decision about a possible drive failure.

(This is Optional) *In case the above embeded code for Data Studio report failed, I am including local PNG import of some of the charts.*

1. Number Hard Drives per model

    2. Number of positive failures by model

```
<tr>
    <td>3. Failure Trend over time
        <img src="graphs/failure-trend-timeseries.png" width="600"></td>
```

4. Daily Failure Trend to determine missing failure data pattern

---

0.7 Machine learning to Predict Possible Failures based

0.7.1 Feature selection:

Based on my findings and research on SMART attributes, I have found the following variables to be the most significant out of the total available dataset. The variables are highly non correlated, I made the selection based on what works as a industry standard for SMART predictions.

```
In [23]: # get all columns and the number of NaN in them
         new_df.isna().sum()
```

```
Out[23]: date                             0
         serial_number                    0
         model                            0
         capacity_bytes                   0
```

```
failure                          0
read_error_rate                  0
throughput_performance     6579501
spin_up_time                     0
start_stop_count                 0
reallocated_sector               0
seek_time_performance      6579501
power_on_hours                   0
power_cycle_count                0
reported_uncorrect         2078207
command_timeout            2078207
high_fly_writes            3374448
airflow_temprature         2078207
load_cycle_count                 0
total_lbas_written         2078207
dtype: int64
```

In [24]:
```python
# new_df.groupby(['model'], as_index=True)['failure'].head()
# failure_by_model = new_df.groupby('failure').agg('model').head()
new_df.shape
```

Out[24]:
```
(8657708, 19)
```

In [25]:
```python
# featured selection
# -----------------

# selecting dataframe slice with no nan values.
# first doing a row wise check to see if dropping rows will solve this
featured_df = new_df.dropna(axis=0, how='any', thresh=15)
featured_df.isna().sum()

# there are still three metrics with very high number of nan
# dropping more columns
featured_df = featured_df.drop(['throughput_performance', 'seek_time_performance', 'hi

# final dataframe is ready for any predictive usage
# verify nan in featured_df
featured_df.isna().sum()
```

Out[25]:
```
date                  0
serial_number         0
model                 0
capacity_bytes        0
failure               0
read_error_rate       0
spin_up_time          0
start_stop_count      0
reallocated_sector    0
power_on_hours        0
```

```
power_cycle_count      0
reported_uncorrect     0
command_timeout        0
airflow_temprature     0
load_cycle_count       0
total_lbas_written     0
dtype: int64
```

In [26]:
```python
# quick look at the featured_df
featured_df.shape

# find unique models per columns
len(featured_df['model'].unique())
```

Out[26]: 6

In [27]:
```python
# number of dates in featured_df
len(featured_df['date'].unique())
```

Out[27]: 90

In [28]:
```python
# number of dates in featured_df
len(featured_df['serial_number'].unique())
```

Out[28]: 76355

In [29]:
```python
# saving feature_df to csv, this is optional.
# ----------------
# using this to ocassionally push data to Big Query

# this is optional for re-runs
# featured_df.to_csv('featured_hard_drive_dataset.csv', index=False)
```

In [57]:
```python
import psycopg2
import matplotlib.pyplot as plt
%matplotlib inline
import pandas as pd
from sklearn import ensemble, metrics
```

In [31]:
```python
# load featured hard drive dataset
hdd = pd.read_csv('featured_hard_drive_dataset.csv')
```

In [32]:
```python
hdd.shape
```

Out[32]: (6579501, 16)

In [33]:
```python
# number of unique hard drives
hdd['serial_number'].value_counts().shape

# since hard drives serial number is unique across, we use this as the index
```

Out[33]: (76355,)

In [34]: # there are 6 models now left in the featured dataset

```
hdd['model'].value_counts().shape
```

Out[34]: (6,)

I've used Big Query in parts where I found it easy to do analysis using SQL. Below is the sql script to get % of failure per model #### SQL to get % of failure per model:

```
SELECT
  model,
  COUNT(DISTINCT serial_number) number_of_hdd,
  SUM(IF(failure IS TRUE,
      1,
      0)) fails,
  ROUND(SUM(IF(failure IS TRUE,
        1,
        0))/COUNT(DISTINCT serial_number),3) percentage_of_fails
FROM

  `orbital-linker-226700.pandey.hard_drive_stats_top10_models`
GROUP BY
  model order by number_of_hdd desc
```

In [69]: # exported sql output and reading in pandas

```
sql_output = pd.read_csv('reports/failure_percentage_by_model.csv')
sql_output.head(10)

# This shows that the data is highly imbalanced and the model with most fails is only
```

Out[69]:

	model	number_of_hdd	fails	percentage_of_fails
0	ST4000DM000	32091	178	0.006
1	ST12000NM0007	16833	32	0.002
2	HGST HMS5C4040BLE640	15374	16	0.001
3	ST8000NM0055	14418	28	0.002
4	ST8000DM002	9912	21	0.002
5	HGST HMS5C4040ALE640	6237	8	0.001
6	Hitachi HDS5C4040ALE630	2296	0	0.000
7	ST6000DX000	1882	1	0.001
8	ST10000NM0086	1220	0	0.000
9	HGST HUH728080ALE600	1048	3	0.003

Above: Full list of model their % of failure

In [70]: # using ST4000DM000   model

```
hdd_st4000 = hdd.query('model == "ST4000DM000"')
hdd_st4000.shape
```

```
        hdd_st4000['serial_number'].value_counts().shape

        # number of failures in this hard drive model
        hdd_st4000['failure'].value_counts()
```

```
Out[70]: False    2822092
         True         178
         Name: failure, dtype: int64
```

0.7.2 Preparing training and testing datasets using dataframe 'hdd'

```
In [71]: # using data from all models
         # -----------------
         date = pd.to_datetime(hdd['date'])
         hdd['date'] = date

         # add day of year using date column
         hdd['day_of_year'] = hdd['date'].dt.dayofyear

         # grouping by getting all unique hard drives
         # indexing by serial number as every hard drive will have a unique serial number

         hdd_group = hdd.groupby('serial_number')

         # take the last row from each group
         hdd_last_day = hdd_group.nth(-1)


         len(hdd_last_day['date'].unique())
```

```
Out[71]: 29
```

```
In [40]: # total failure per model for one day
         hdd_last_day['failure'].value_counts()

         # number of drives in the dataset
         uniq_serial_numbers = pd.Series(hdd_last_day.index.unique())
         uniq_serial_numbers.shape
```

```
Out[40]: (76355,)
```

```
In [41]: hdd_last_day['failure'].value_counts()
```

```
Out[41]: False    76271
         True        84
         Name: failure, dtype: int64
```

```
In [42]: # slicing a copy of 25% of all unique hard drives for test
         test_ids = uniq_serial_numbers.sample(frac=0.25)
```

```
train = hdd_last_day.query('index not in @test_ids')
test = hdd_last_day.query('index in @test_ids')

# test data has now looks like this
test.shape
```

Out[42]: (19089, 16)

In [43]:
```
# test data
test['failure'].value_counts()
```

Out[43]:
```
False    19066
True        23
Name: failure, dtype: int64
```

In [44]:
```
train.shape
```

Out[44]: (57266, 16)

In [45]:
```
# train data has remaining 24029 data points
train['failure'].value_counts()
```

Out[45]:
```
False    57205
True        61
Name: failure, dtype: int64
```

In [46]:
```
# training and testing labels
train_labels = train['failure']
# failure is the final label we would like to predict
test_labels = test['failure']

# drop labels from train and test
train = train.drop('failure', axis=1)
test = test.drop('failure', axis=1)
```

In [47]:
```
train.shape
```

Out[47]: (57266, 15)

In [48]:
```
#drop date related features from tree model
train = train.drop(['day_of_year', 'date'], axis=1)
test = test.drop(['day_of_year', 'date'] , axis=1)

# removing other irrelevant or constant columns

# this is out final training and test dataset with all the right features
train = train.drop(['model', 'capacity_bytes', 'power_on_hours', 'total_lbas_written']
test = test.drop(['model', 'capacity_bytes', 'power_on_hours', 'total_lbas_written'],
```

In [49]:
```
train.shape
```

Out[49]: (57266, 9)

```
In [50]: # these are the training features
         train.columns
```

```
Out[50]: Index(['airflow_temprature', 'command_timeout', 'load_cycle_count',
                'power_cycle_count', 'read_error_rate', 'reallocated_sector',
                'reported_uncorrect', 'spin_up_time', 'start_stop_count'],
               dtype='object')
```

```
In [51]: # check first 10 training labels
         train_labels[:10]
```

```
Out[51]: serial_number
         S3000A9T    False
         S3000FZ5    False
         S3000NSV    False
         S3000QAP    False
         S30015PW    False
         S3001FPA    False
         S3001HBH    False
         S30034E6    False
         S3003A6V    False
         S3003GAB    False
         Name: failure, dtype: bool
```

0.7.3 Prediction using Random Forest Ensemble

For prediction, I tried a couple of options from logistic regression to Naive Bayes but finally settled on random forest classifier tree for following reasons: 1. Data is full of poorly correlated SMART features. 3. For regression, normalization of some of the attributes would be required. 4. Since there isn't much information available on how different large float values can be normalized, it's a better idea to stick with the absolute numbers only 5. Use raw values instead of normalization since normalization has no impact on performance of a tree. 6. Random forest classifiers are designed to reduce the overall error rate and work over raw data.

Overall There doesn't seem to be a lot of correlation between various SMART attributes, and this varies greatly over different models of hard drive. A decision tree model (random forest) that looks at more than one attribute in order to make a better guess at detecting any future failures.

```
In [64]: rf_clf = ensemble.RandomForestClassifier(n_jobs=1, max_depth=3)

         # here's how the random forest object looks
         rf_clf.fit(train, train_labels)
```

```
Out[64]: RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                     max_depth=3, max_features='auto', max_leaf_nodes=None,
                     min_impurity_decrease=0.0, min_impurity_split=None,
                     min_samples_leaf=1, min_samples_split=2,
```

```
                    min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=1,
                    oob_score=False, random_state=None, verbose=0,
                    warm_start=False)
```

```
In [53]: # Apply the Classifier we trained to the test data
         rf_clf.predict(test)
```

```
Out[53]: array([False, False, False, ..., False, False, False])
```

```
In [54]: # generating the predicted values of possible of features for test data using trained
         preds = rf_clf.predict_proba(test)

         # check predicted values of the first 10 observations
         preds[:10]
```

```
Out[54]: array([[9.98842063e-01, 1.15793746e-03],
                [9.98980480e-01, 1.01951991e-03],
                [9.99389243e-01, 6.10756587e-04],
                [9.98842063e-01, 1.15793746e-03],
                [9.98842063e-01, 1.15793746e-03],
                [9.98842063e-01, 1.15793746e-03],
                [9.98980480e-01, 1.01951991e-03],
                [9.99256057e-01, 7.43943123e-04],
                [9.98712833e-01, 1.28716695e-03],
                [9.98842063e-01, 1.15793746e-03]])
```

```
In [55]: # performing quick ROC and log loss functions to see how the the data looks

         print('ROC Area Under Curve', metrics.roc_auc_score(y_true=test_labels, y_score=preds
```

```
ROC Area Under Curve 0.7667108305702389
```

```
In [56]: # performing quick ROC and log loss functions to see how the the data

         metrics.roc_auc_score(y_true=test_labels, y_score=preds[:,1])
```

```
Out[56]: 0.7667108305702389
```

Since, above tell us that the area under curve is about 0.75, so that's a good enough

0.7.4 Challenges:

1. Highly critical features like throughput_performance', 'seek_time_performance', 'high_fly_writes and 'command_timeout' have a lot of missing data. This makes the training dataset unreliable.
2. A sound relationship between these uncorrelated metrics/features is needed to better understand things like:
    1. How command_timeout affects retry count or,

2. How reallocated sector changes over time as the drive gets old.
3. Different models are manufactured by different companies, and not all manufacturers have all SMART metrics, among other factors like usage, data-center wear and tear, climatic conditions. This makes it difficult to design a general training that would work across the board.
4. Data is not normalized and there isn't much information on how to normalize them: is the reallocated sector by bits or bytes? are all these drives magnetic tapes, hybrid or SSDs?

Normalization would make a much a better regression design, or at least present one such option to do so.

Our model accurately predicted about 77% of the time that a drive is likely to fail.

0.8 Business wide High Level Result

SMART systems widely used industry practice around data center management and disk heavy resources.

The above case study attempted to analyze and predict future hard drive failures based on the data that was provided. was to predict hard drive failures using available dataset.

We identified a few key metrics such as 'throughput_performance', 'reallocated sectors', age of the hard drive using 'power on hours' and a few more. We analyzed their effect over time as the failure rate goes down.

There was also some extensive researching done leading up to identifying other highly critical metrics but there seems to be missing data about those metrics. Since there isn't enough detail about the dataset in this case study, some external researching was required to get an understanding.

Using provided data, we predicted over 77% of possible failure, but this can be improved further.

Some recommended actions and improvements:

1. Realistically, since not all Hard Drives are manufactured and used under the same roof it's a good idea that for future predictions, we use the critical attributes, mentioned above to analyze their effect on per hard drive model instead of a general prediction.
2. Including more data source:

a. Using more than one source of information such as operating temperature, throughput, of reads and writes etc. can help build a more robust collection of data that can predict future.

3. Backing up drives that are showing critical changes.

0.9 Thanks!

Harsh