



# Using AI to Predict Server **Hard Drive Failure**

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# What's the Problem?

- A datacenter contains servers which contain hard drives, used to store application data

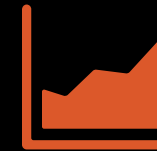
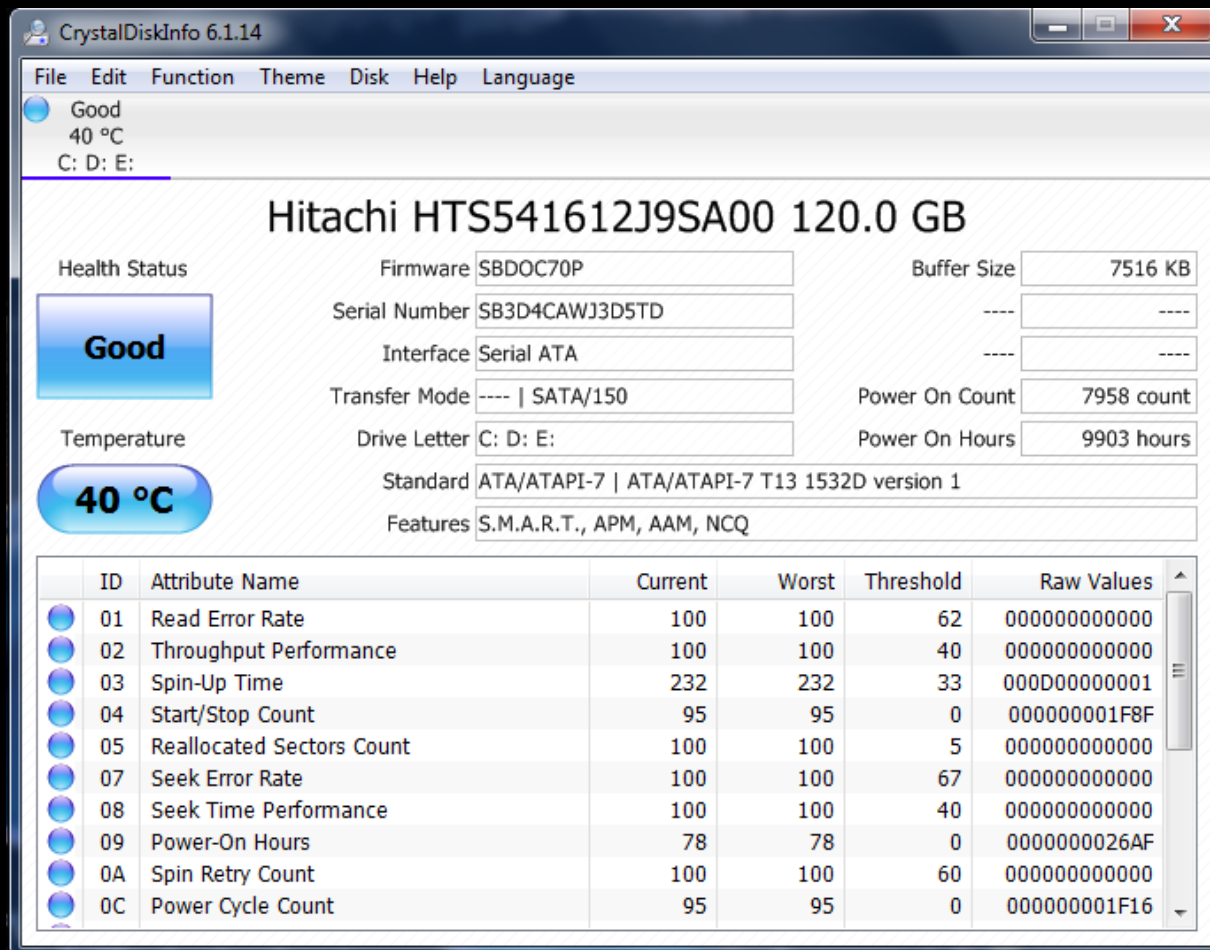
- For 98% of companies, one hour of downtime costs **over \$150,000**

Source: ITIC 2017-2018 Global Server Hardware, Server OS Reliability Survey

- Server operators rely on arbitrary rules or wait for failure to replace drives
- **What if we could predict hard drive failures?**



# A S.M.A.R.T.er Solution



Modern hard  
drives provide  
S.M.A.R.T.  
stats  
Self-monitoring



Train and test  
predictive  
models

# So Many Questions...

- 1 What are the most important features to consider?
- 2 How accurate can classifiers get?
- 3 Can models be ported to other drives?



# Backblaze's Dataset

Backup company provides S.M.A.R.T. and failure stats for its hard drives, from Q1 2019 to Q3 2021

Daily snapshots of >175,000 disks' stats, 131 columns of data

date	serial_number	model	capacity_bytes	failure	smart_1_normalized	smart_1_raw	...
2021-04-01	ZHZ65F2W	ST1200NM0008	12,000,138,625,024	0	82	159,565,280	...
2021-04-01	ZLW0EGC7	ST12000NM001G	12,000,138,625,024	0	74	22,618,672	...
2021-04-01	ZA1FLE1P	ST8000NM0055	8,001,563,222,016	0	82	167,665,584	...
...	...	...	...	...	...	...	...

# The **Stuff** We Used



12-core Intel Core  
i7-9750H, 2.60GHz  
16 GB RAM  
Pop\_OS! 21.04



Anaconda 4.10.3  
Python 3.8.12  
NumPy, Pandas, Ruptures,  
Scikit-learn, Multiprocessing



Visual Studio Code  
Jupyter Notebook

# Which Models Should We Study?

Q1 2020 Dataset

	count	unique	fail_count	failure_rate	missing_stats
ST8000DM004	209	2	1	0.4785%	4
TOSHIBA MQ01ABF050	39,102	413	39	0.0997%	9
...	...	...	...	...	...
<b>ST4000DM000</b>	1,744,529	19,142	68	0.0039%	5
ST12000NM0008	750,681	10,876	29	0.0039%	6
<b>ST12000NM0007</b>	3,368,588	36,997	126	0.0037%	6



# ST4000DM000 It Is!

- One of the **most used drives**
- **High failure rate**
- Reports **nearly all S.M.A.R.T. stats**





# No Stats For You!

```
df.isnull().sum().sort_values(ascending=False).head(72)
```

smart_255_raw	132,339
smart_250_normalized	132,339
smart_15_raw	132,339
smart_15_normalized	132,339
...	...
smart_183_raw	112,270
smart_8_raw	94,583
smart_8_normalized	94,583



Q1\_2020 Dataset (132,339 rows)

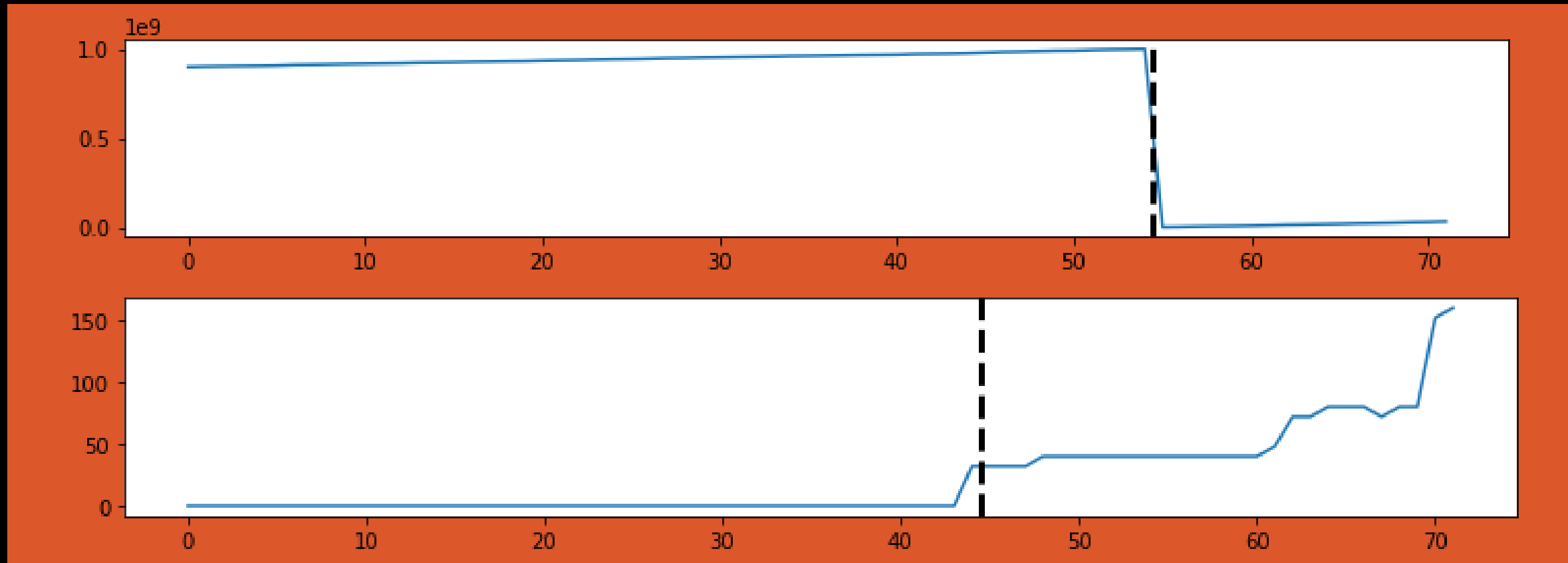
# The Quest for Relevancy

RQ1: Which S.M.A.R.T. stats must be considered?

- Dataset: Q1 2019 to Q4 2020
- 615 failed ST4000DM000 drives
- Up to 60 days of data before failure

# Change Is Now

*ruptures: change point detection in Python, Truong et al., 2018*



Seek Error Rate (SMART\_7\_RAW), Off-line Uncorrectable (SMART\_198\_RAW)

# The Results (Number 4 Will Shock You)

Analysis ran on 615 failed drives, from Q1 2019 to Q4 2020 (last 60 days)

Name	Description	Frequency
smart_242_raw	Total LBAs Read	43.74%
smart_9_normalized	Power-On Hours Count (Norm.)	42.44%
smart_241_raw	Total LBAs Written	42.28%
<b>smart_7_raw</b>	Seek Error Rate	33.66%
<b>smart_7_normalized</b>	Seek Error Rate (Norm.)	25.69%
smart_193_raw	Load/Unload Cycles	21.46%
<b>smart_187_{raw,normalized}</b>	Reported Uncorrectable Errors	15.12%
<b>smart_197_raw</b>	Current Pending Sectors	15.12%
<b>smart_198_raw</b>	Off-line Uncorrectable	15.12%
...and 19 more	including Reallocated Sectors	>1.00%

# Be Accur8 M8

RQ2: How accurate can models get?

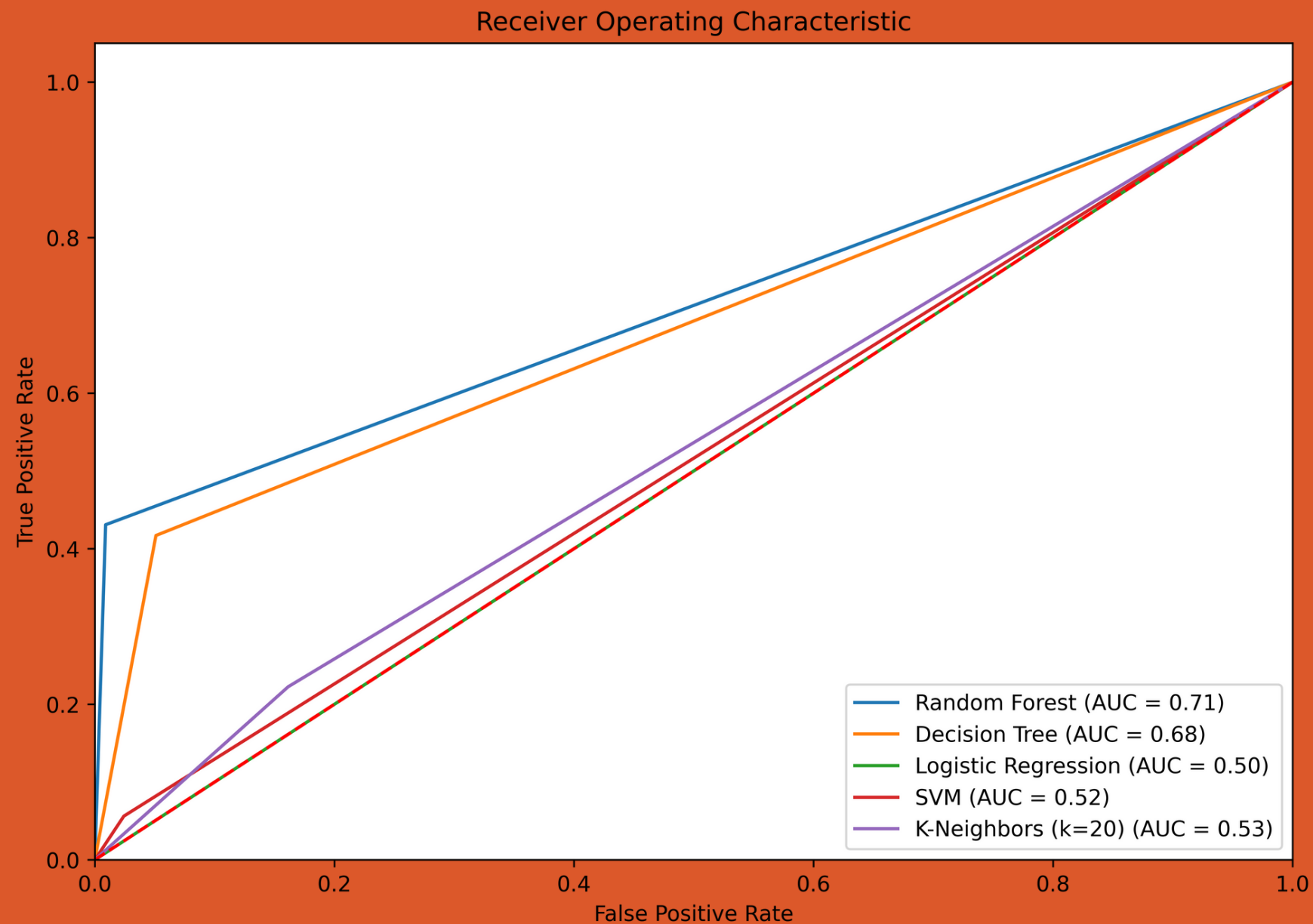
- Training set: Q1 2019 to Q4 2020
- Testing set: Q1 & Q2 2021
- Dataset processing: **backtracking**  
failure = 1 up to 15 days before actual failure
- Low failed drive count: **sampling**  
1/3 failed drives, 2/3 healthy drives

# The **Accuracy** of this... Classifier

RQ2: How accurate can models get?

	Accuracy	Recall	F1-Score
<b>Random Forest</b>	<b>0.8138</b>	<b>0.4309</b>	<b>0.5942</b>
Decision Tree	0.7807	0.4170	0.5461
Logistic Regression	0.6836	0.0000	0.0000
SVM	0.6848	0.0562	0.1014
K-Neighbors (k = 20)	0.6436	0.2225	0.2832
K-Neighbors (k = 2)	0.6513	0.1114	0.1682

# Dwayne “The **ROC**” Johnson





# Takeaways

Thank you for listening :)

## Discussions

- Possible to predict disk failures using common classifiers
- Many factors are at play
- Slight clustering of failed disks, as shown by K-Neighbors
- Low recall and F1-Score overall

## Limitations

- Analysis limited by chosen S.M.A.R.T. attributes
- Single drive model
- No real time-series approach

## Next steps

- Answer RQ3: how do these classifiers fare on other drives?
- Try more classifiers/models
- Try other drives
- Expand dataset to Q3 2021