

Taking your data for a spin!

S.M.A.R.T ways of predicting hard drive failure

The Team



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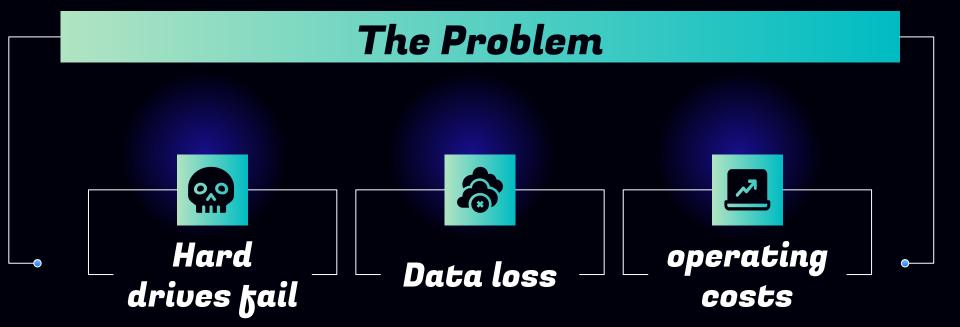
The Stakeholder

Backblaze

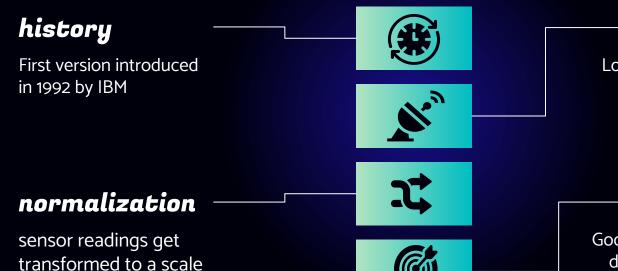


- Cloud storage for business and private use
- Regular release of their hard drive statistics





Self-Monitoring, Analysis and Reporting Technology (S.M.A.R.T)



of 0-100

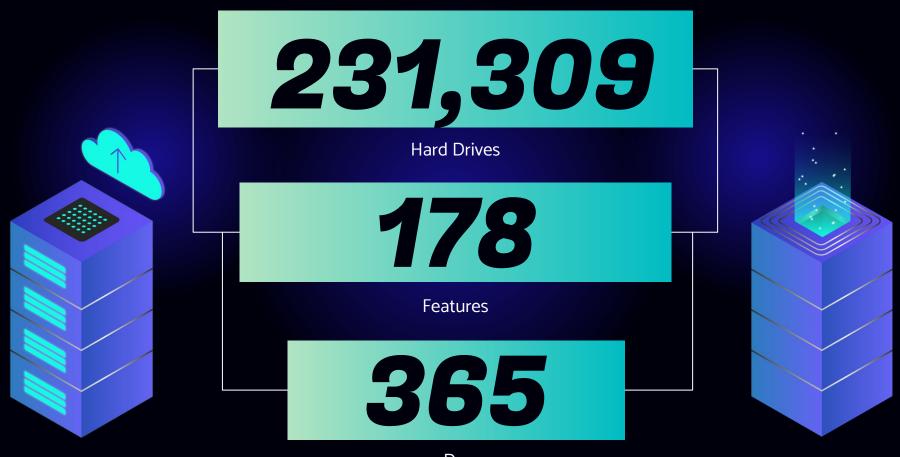
Sensor data

Log of various indicators of drive reliability

limitations

Google Study*: 36% of failed drives record no S.M.A.R.T. errors

*Pinheiro et al., 2007, Failure Trends in a Large Disk Drive Population

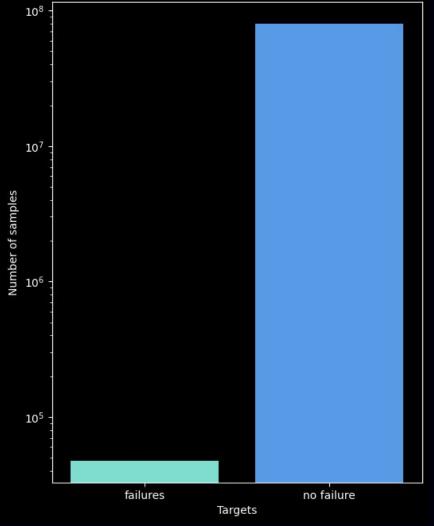


Days

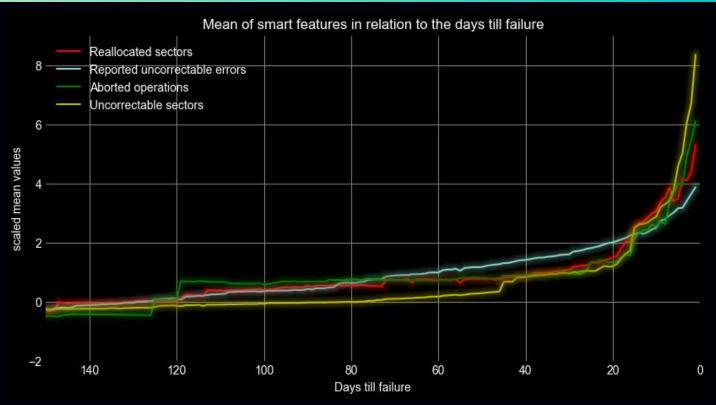
data is imbalanced!

80,357,762 observations

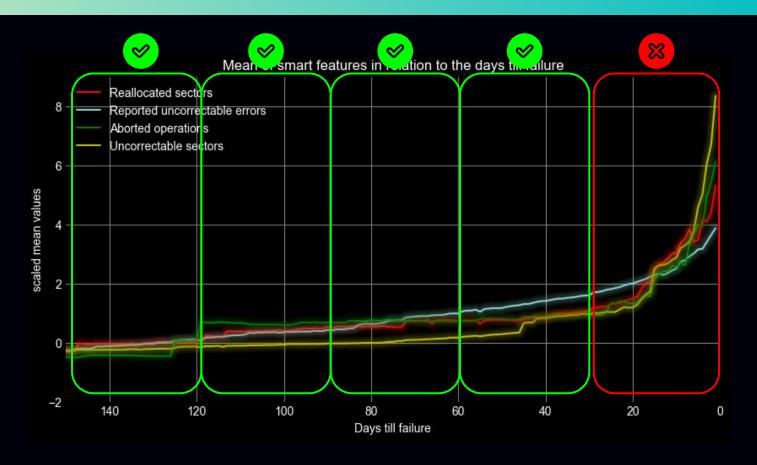
1.2% are failures and 98.8% are no failures



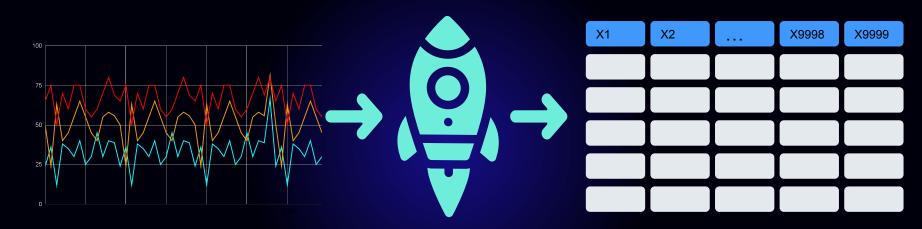
Certain smart features spike when failure is near



Split the time series into windows



How to transform time series data?



miniROCKET: A Very Fast (Almost) Deterministic Transform for Time Series Classification using convolutional kernels

Model results

Baseline model



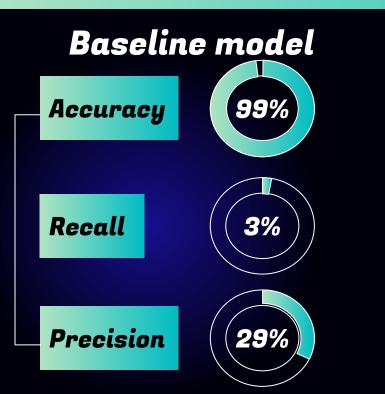
- Logistic regression
- Based on raw data
- Ignores time as a dimension

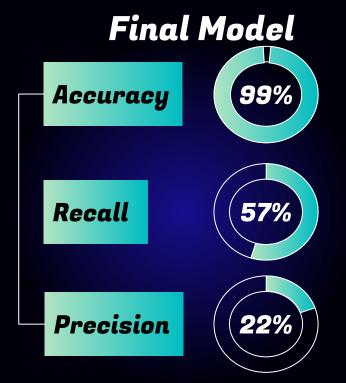
Final Model



- Random Forest
- Based on transformed data
- Time is used in creating features

Model results





Conclusions



Limitation of prediction

Imbalanced data Some failures show no signal



Long term trend

30 day window does not capture failure signs before the last 30 days



Detection rate of 57%

Compared to 52%* to 60%** in literature

Future Outlook

Anomaly detection



Neural Network as classifier

Increase scope



THANKS!

Do you have any questions? Join us in our breakoutroom! Github:

https://github.com/JRJWegener/hard_drive_ML capstone_project

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