Real-time changepoint detection in the steel industry using Python

Case Study

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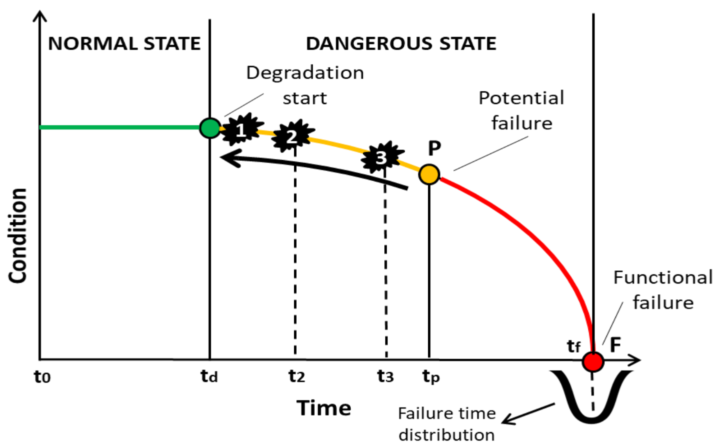
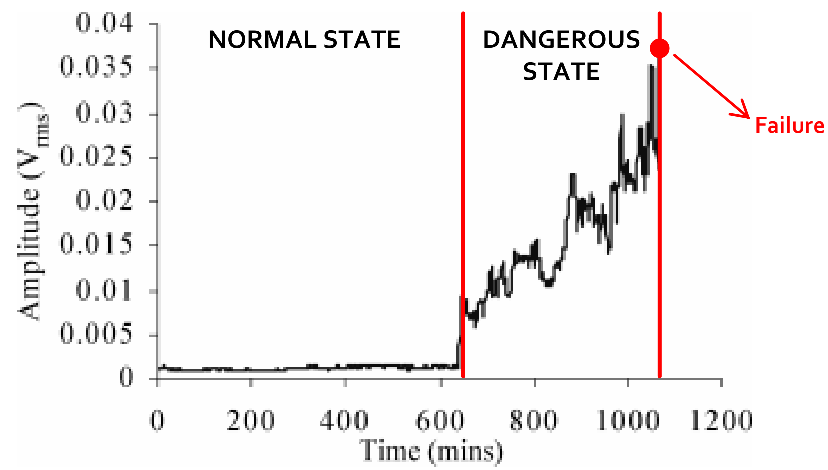
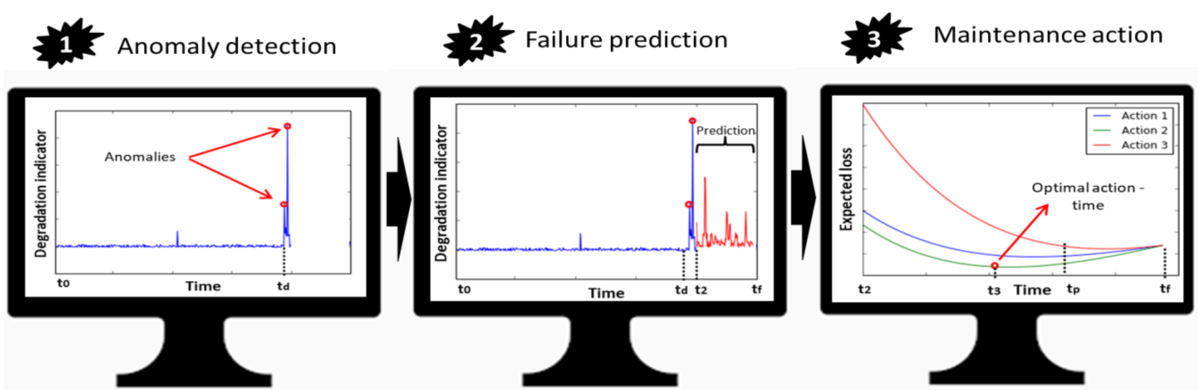
Background

Predictive maintenance

- **Predictive maintenance** uses condition monitoring equipment (e.g. sensors) in order to track the performance of equipment, to detect abnormal behaviour, to predict future failures and to support decision making about proactive actions.



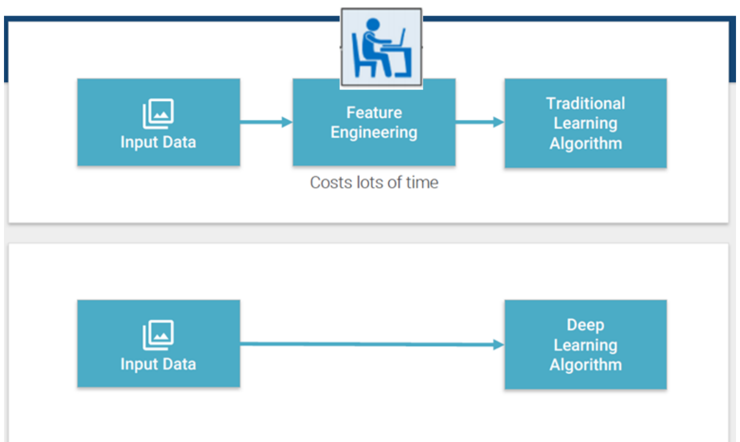




Real-time anomaly detection

Facts

Machine learning requires feature extraction



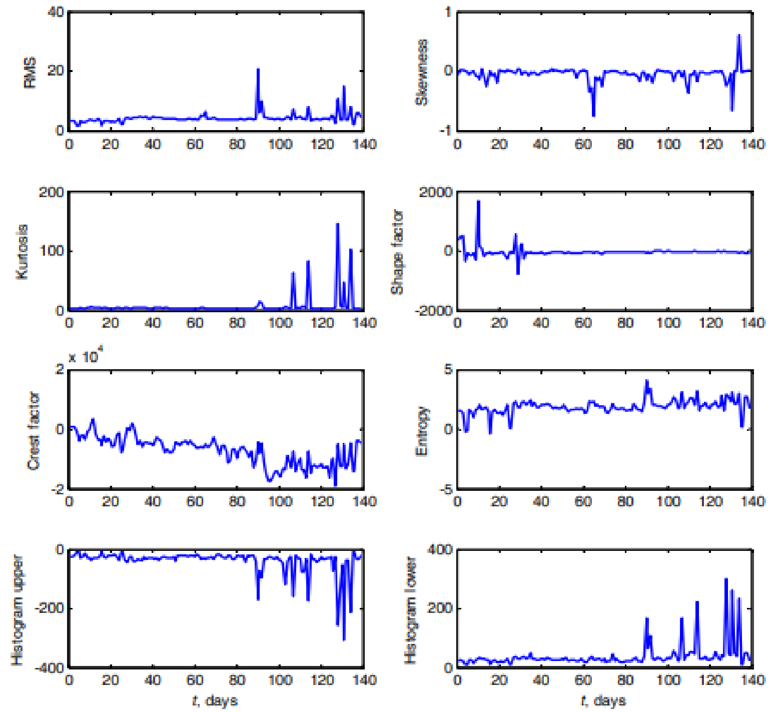
80% of all available data are uncertain

Method of the case study

Extract **time-domain features** → Implement **Bayesian Online Changepoint Detection**

Time-domain features (1/2)

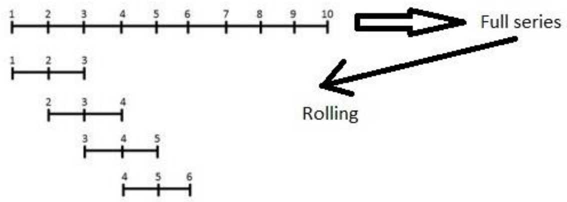
Feature Name	Description	
	Brief Definition	**Formula**
RMS	The RMS value increase gradually as fault developed. However, RMS is unable to provide the information of incipient fault stage while it increases with the fault development [11].	$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$
Variance	Variance measures the dispersion of a signal around their reference mean value.	$\mathrm{Var} = \frac{\sum_{i=1}^{N}(x_i - m)^2}{(N-1)\sigma^2}$
Skewness	Skewness quantifies the asymmetry behavior of vibration signal through its probability density function (PDF).	$\mathrm{Sk} = \frac{\sum_{i=1}^{N}(x_i - m)^3}{(N-1)\sigma^3}$
Kurtosis	Kurtosis quantifies the peak value of the PDF. The kurtosis value for normal rolling element bearing is well-recognized as 3.	$\mathrm{Ku} = \frac{\sum_{i=1}^{N}(x_i - m)^4}{(N-1)\sigma^4}$
Shape factor	Shape factor is a value that is affected by an object's shape but is independent of its dimensions [12].	$\mathrm{SF} = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}}{\frac{1}{N}\sum_{i=1}^{N}\lvert x_i\rvert}$
Crest factor	Crest factor (CF) calculates how much impact occur during the rolling element and raceway contact. CF is appropriate for "spiky signals" [12].	$\mathrm{CF} = \frac{\max\lvert x_i\rvert}{\sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}}$
Entropy	Entropy, $e(p)$, is a calculation of the uncertainty and randomness of a sampled vibration data. Given a set of probabilities, $(p_1, p_2, \ldots, p_n)$, the entropy can be calculated using the formulas as shown in the right column.	$e(p) = -\sum_{i=1}^{n} p(z_i)\log_2 p(z_i)$



Time-domain features (2/2)

- A rolling feature extraction algorithm on the sensor data set creates another time-series data set including the feature values (instead of the raw data).

- Rolling window:

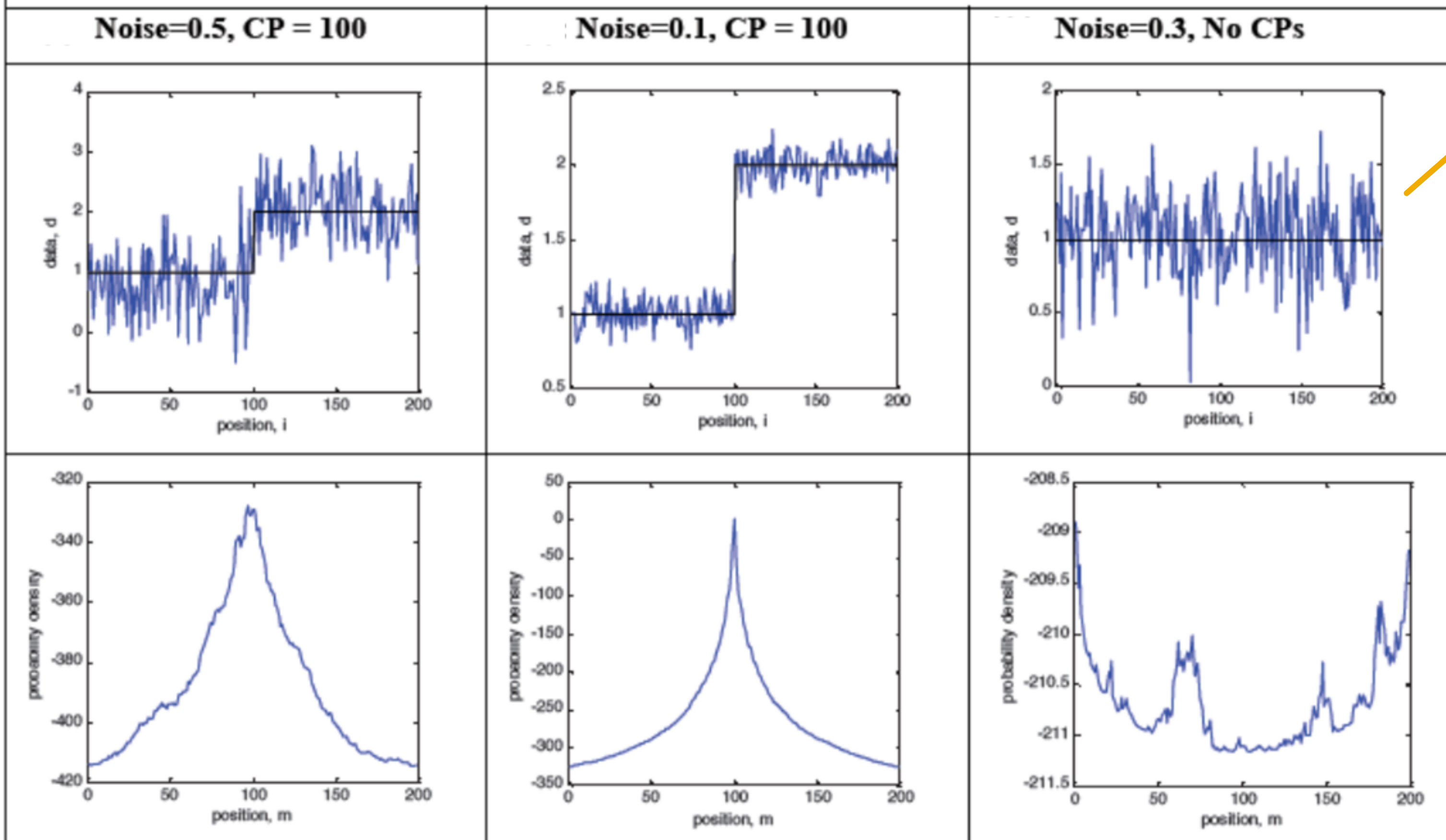


Longer rolling window sizes tend to yield smoother estimates.

Shorter rolling window sizes are more computationally efficient.

Bayesian Online Changepoint Detection (2/2)

CP = Changepoint location(s), Noise= S.D. of noise component. Log posterior probability plots from the single changepoint algorithm are shown below each simulated data plot.



The most common case in manufacturing

http://gregorygundersen.com/blog/2019/08/13/bocd/

https://arxiv.org/abs/0710.3742

https://www.slideshare.net/FrankKelly3/changepoint-detection-with-bayesian-inference

Case study in the steel industry

Test cases

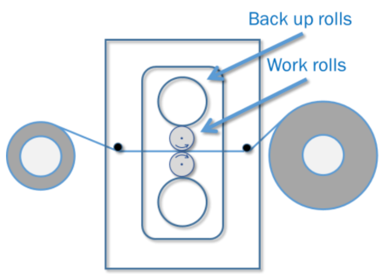
Datasets with sensor measurements during the whole lifetime of the equipment, i.e. from installation until a failure mode or time-based replacement.

1. Bayesian Online Changepoint Detection on **raw sensor data**

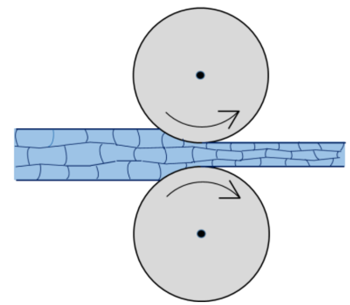
2. Bayesian Online Changepoint Detection on **features**

Steel industry

Roll Mill Stand



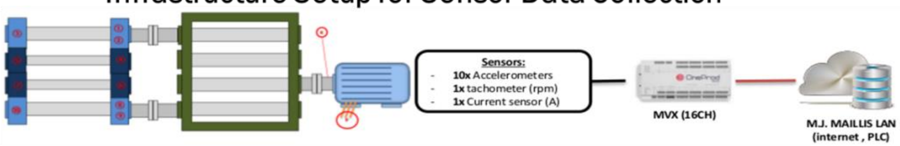
Deforming and Reducing the Grain Size



Raw material

Cold rolling mill

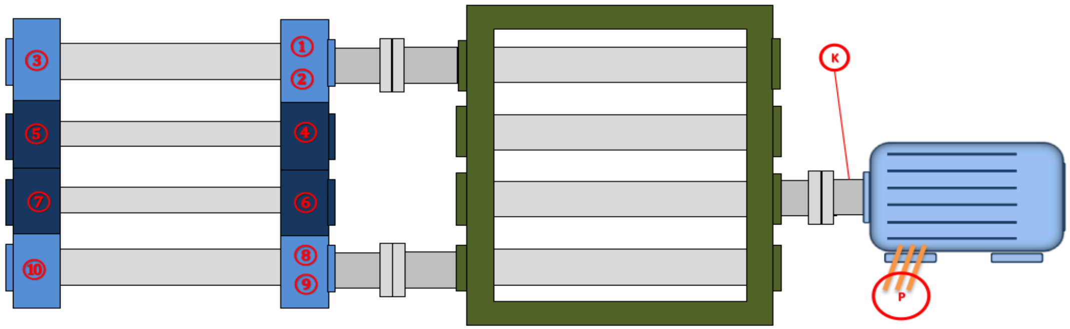
Infrastructure Setup for Sensor Data Collection



Front view of rollers

Rear view of rollers

Sensor infrastructure



Front view of rollers

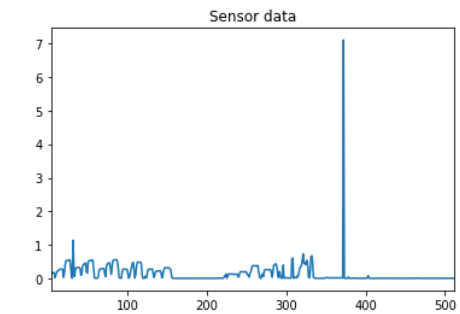
Rear view of rollers

Sensor ID	Measurement point	Sensor direction	Sensor Type
1	Upper backup roll – DE side	Vertical	Accelerometer
2	Upper backup roll – DE side	Axial	Accelerometer
3	Upper backup roll – NDE side	Vertical	Accelerometer
4	Upper working roll – DE side	Reverse horizontal	Accelerometer
5	Upper working roll – NDE side	Horizontal	Accelerometer
6	Down working roll – DE side	Reverse horizontal	Accelerometer
7	Down working roll – NDE side	Horizontal	Accelerometer
8	Down backup roll – DE side	Vertical	Accelerometer
9	Down backup roll – DE side	Axial	Accelerometer
10	Down backup roll – NDE side	Vertical	Accelerometer

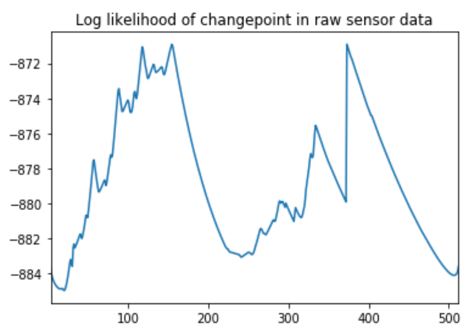
Example

Bayesian Online Changepoint Detection on <u>raw sensor data</u>

Raw sensor data

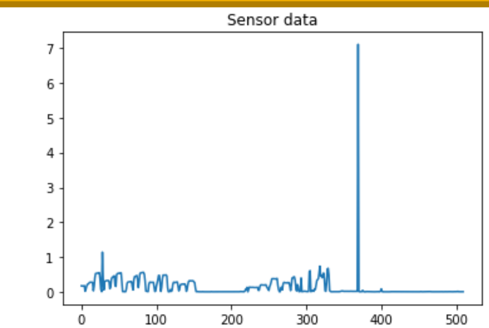


Changepoint detection

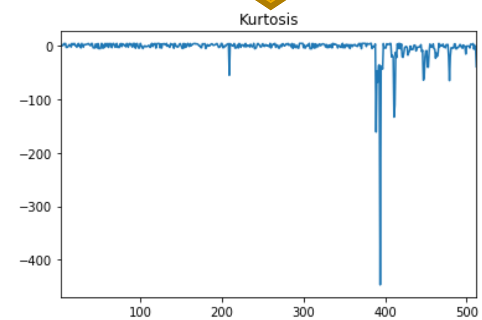


Bayesian Online Changepoint Detection on the <u>Kurtosis feature</u>

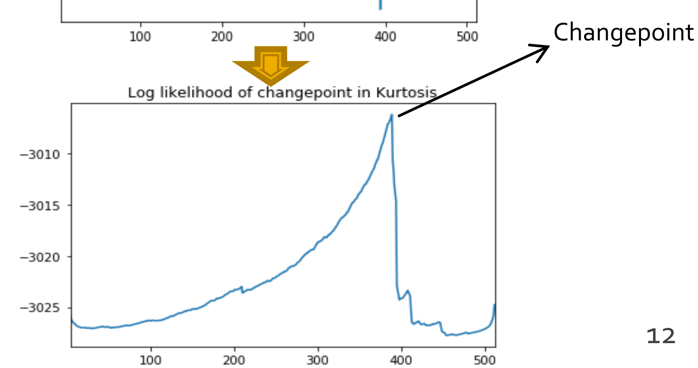
Raw sensor data



Kurtosis extraction



Changepoint detection



Thank you