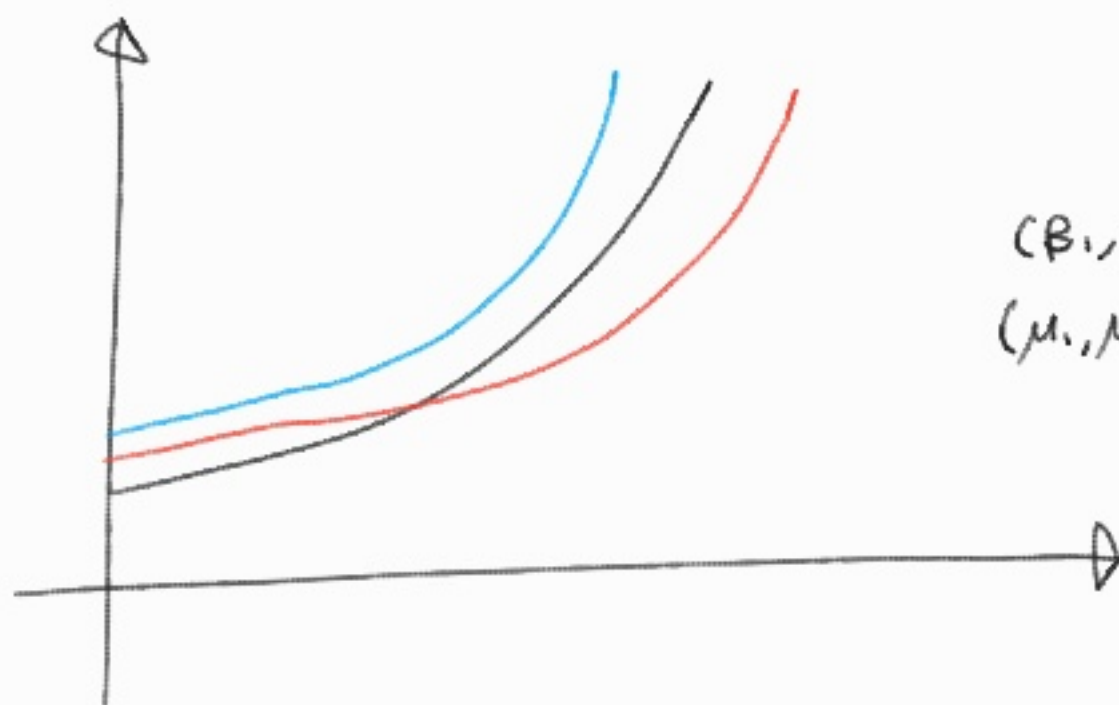
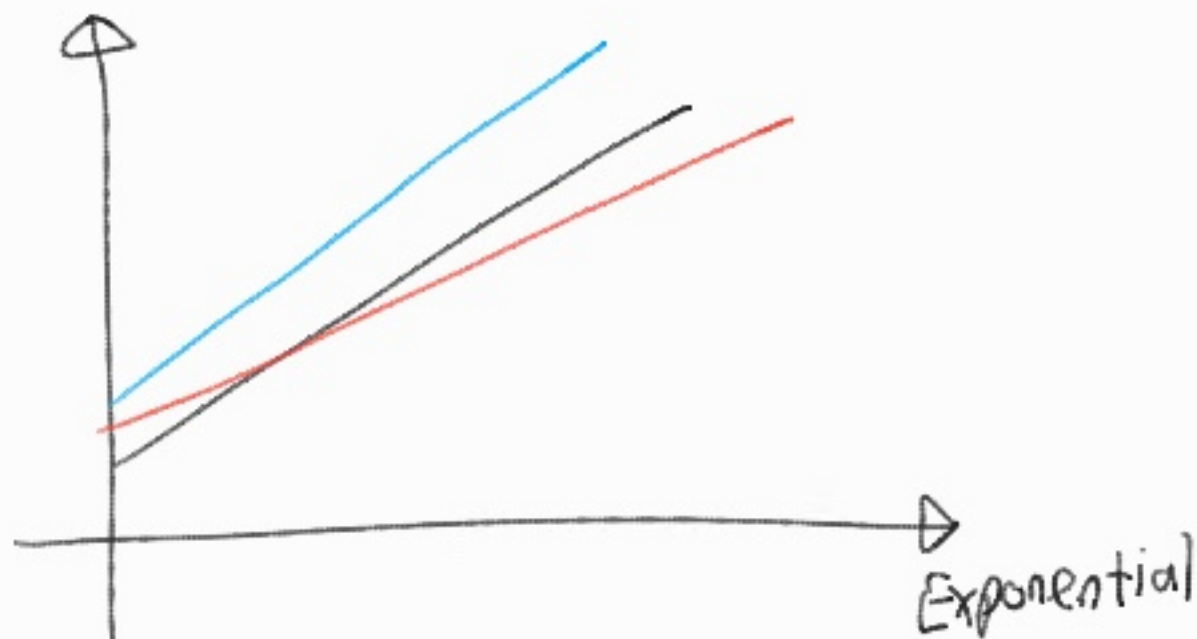


Linear



$$(B_1, B_2) \sim BN$$
$$(\mu_1, \mu_2, \sigma_1^2, \sigma_2^2, \rho_{12})$$

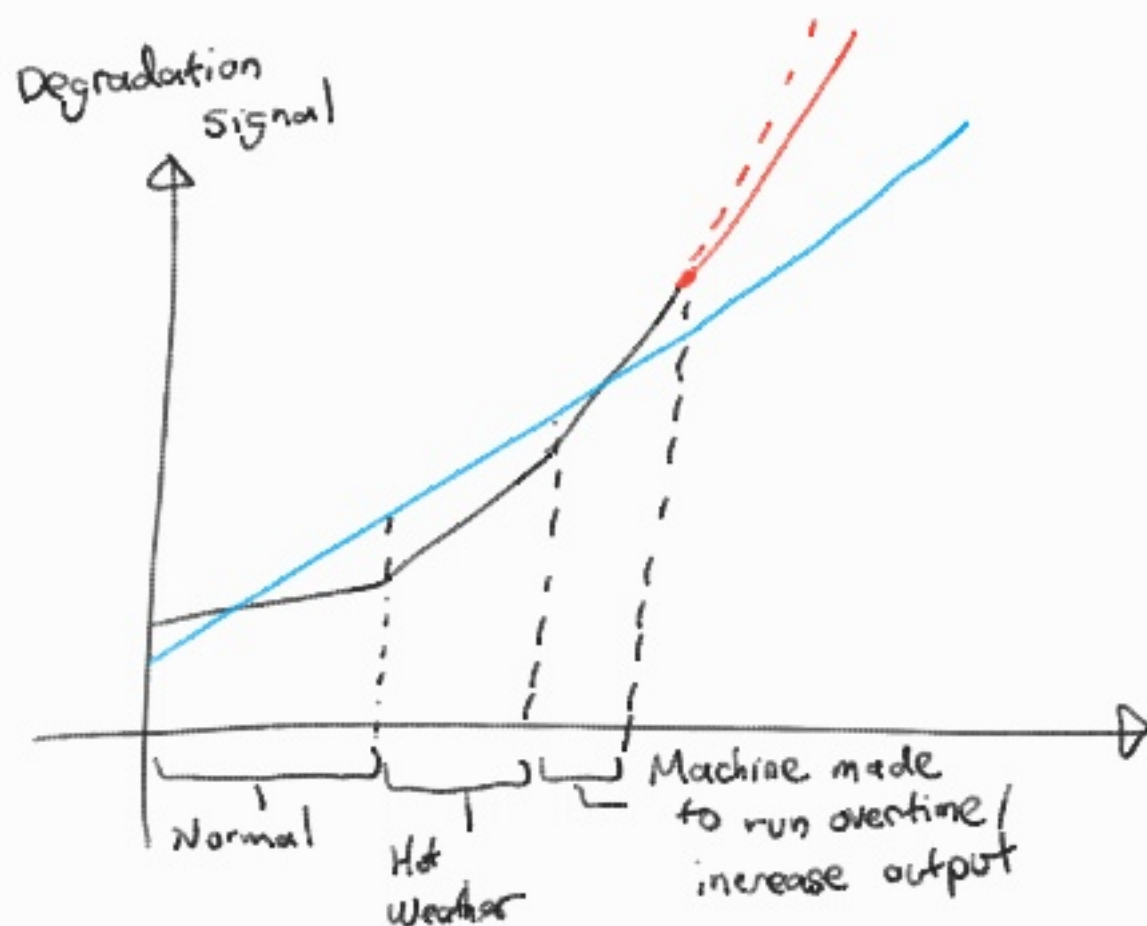
### Key Assumptions:

- Although "identical" components, slight manufacturing variations and/or differences in usage environments for each component results in different degradation patterns.

↓  
same type of underlying distribution, but different parameters for each component

- usage condition and degradation model for an individual is constant/unchanged for its lifetime/duration

# Adaptive Degradation Modelling



• traditional

• momentum

→ Bayesian updating

→ 1<sup>st</sup> & 2<sup>nd</sup> derivative momentum

→ Moving average

→ Online learning / batch learning

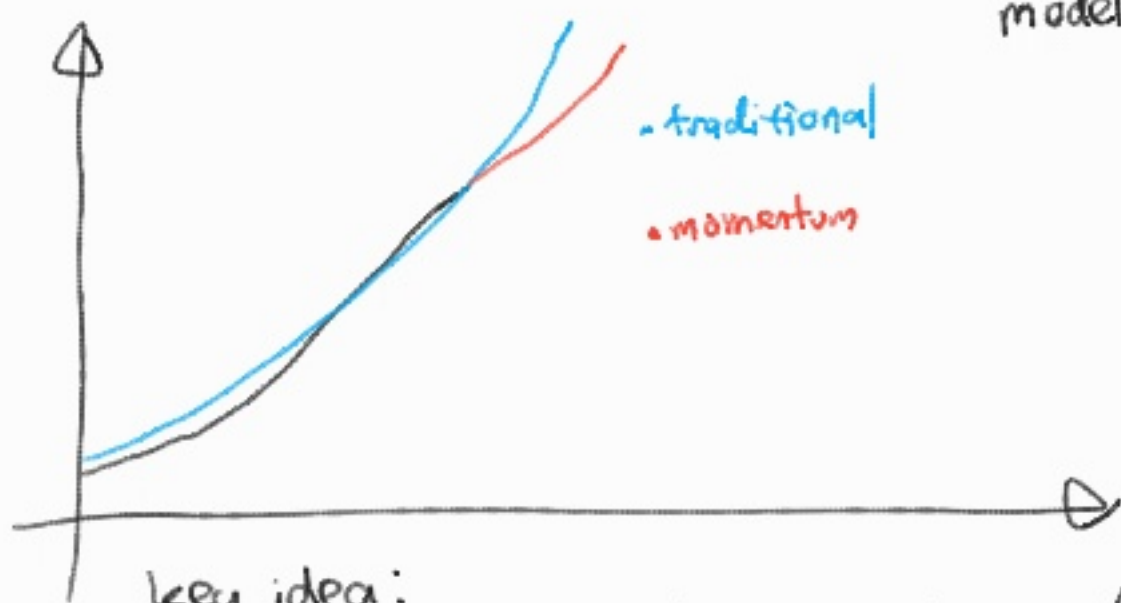
degradation model

or

- the rate of degradation for a single unit/realization might not constant throughout its lifespan

model

1. current state of degradation
2. current rate of degradation



key idea:

The nature/parameters of the degradation of a single component's degradation might not be constant, and might change over time.  
Need a framework for updating that gives more weight to recent data, and possibly ignore old data.

### Advantages:

- Allows model to react/adapt to systemic changes to the nature/use/operation of a machine that would fundamentally change/disrupt the rate of its degradation.

### Disadvantages:

- Highly overreactive & unstable in the presence of noise.
- Tuning hyperparameters is complicated.