# Machine Learning for Predictive Maintenance Applications:
## Prognostics

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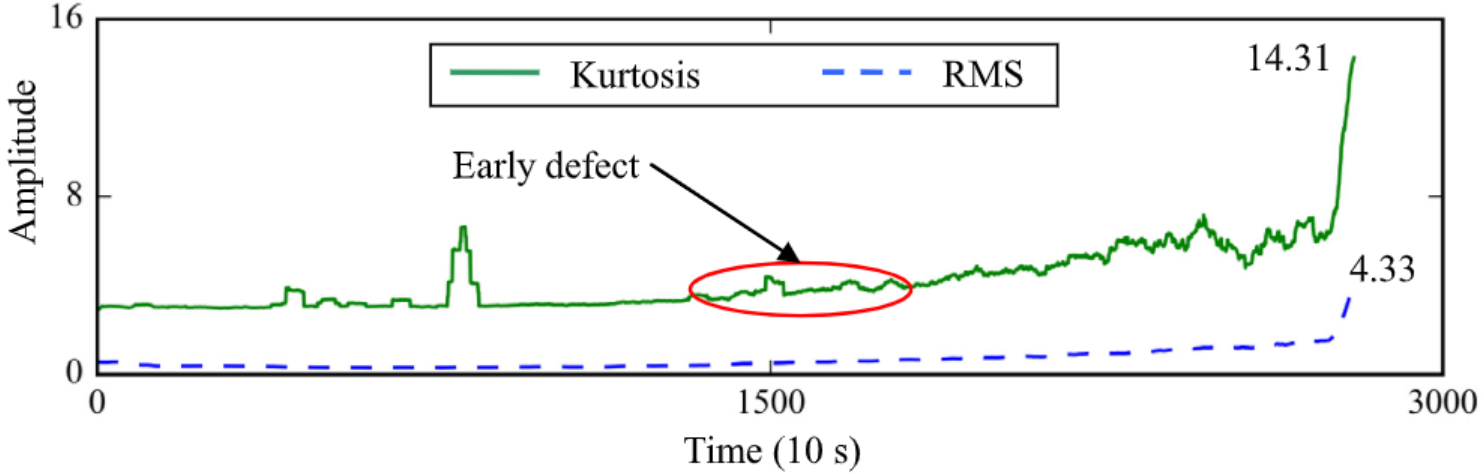
# Condition / Health indicators

# Condition indicators

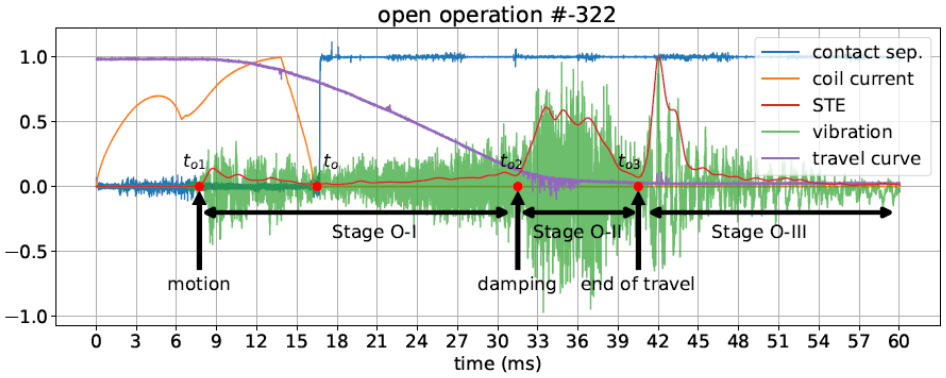
- A *condition indicator* is a feature of system data whose behavior changes in a predictable way as the system degrades or operates in different operational modes.
- A condition indicator can be any feature that is useful for distinguishing normal from faulty operation or for predicting remaining useful life.

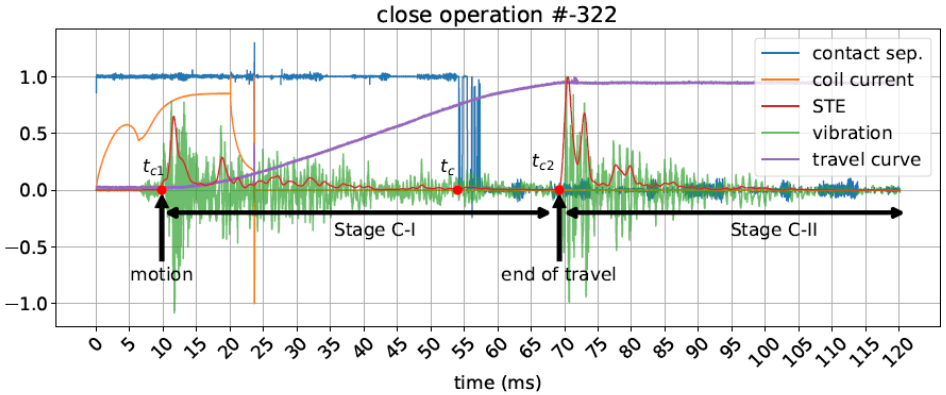
# Condition indicators: example




Source: Guo et. al 2017

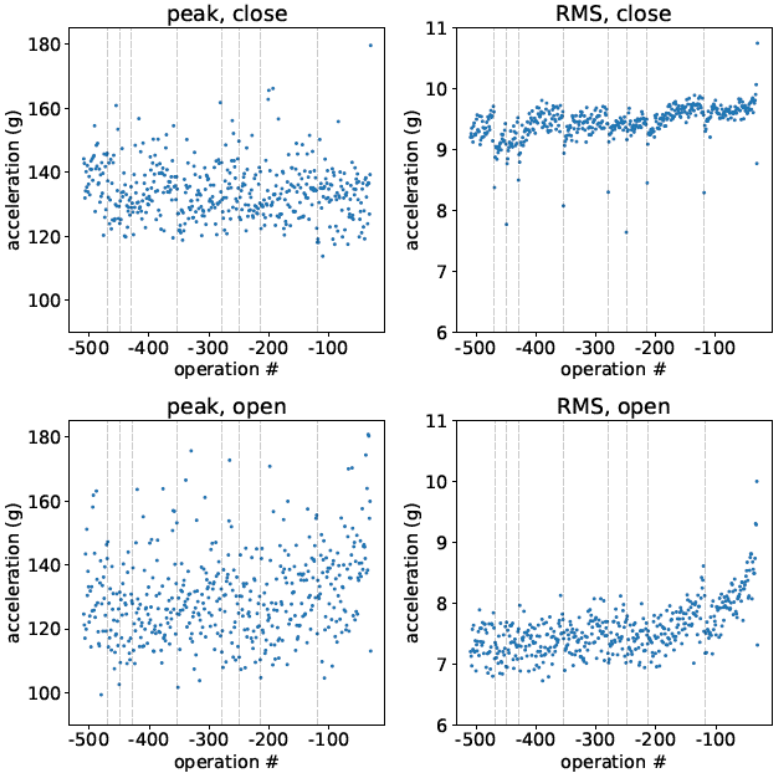
# Example signals (normalised) collected during open and close operation of a circuit breaker




C.-C. Hsu , G. Frusque , O. Fink , & C. M. Franck: Condition Monitoring on a High Voltage Gas Circuit Breaker using Vibration Signals in a Run-to-Failure Experiment

# Condition indicators of a circuit breaker

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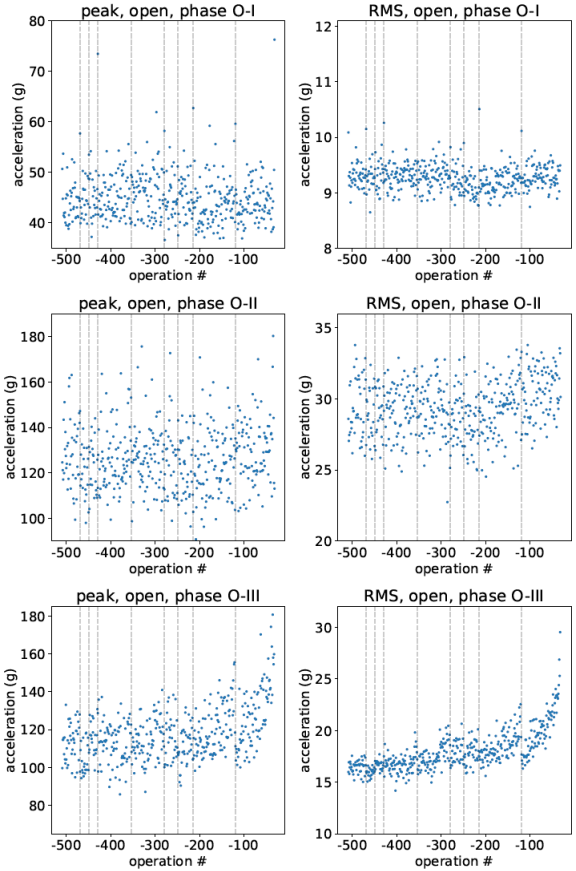



C.-C. Hsu , G. Frusque , O. Fink , & C. M. Franck: Condition Monitoring on a High Voltage Gas Circuit Breaker using Vibration Signals in a Run-to-Failure Experiment

# Condition vs. Health Indicators

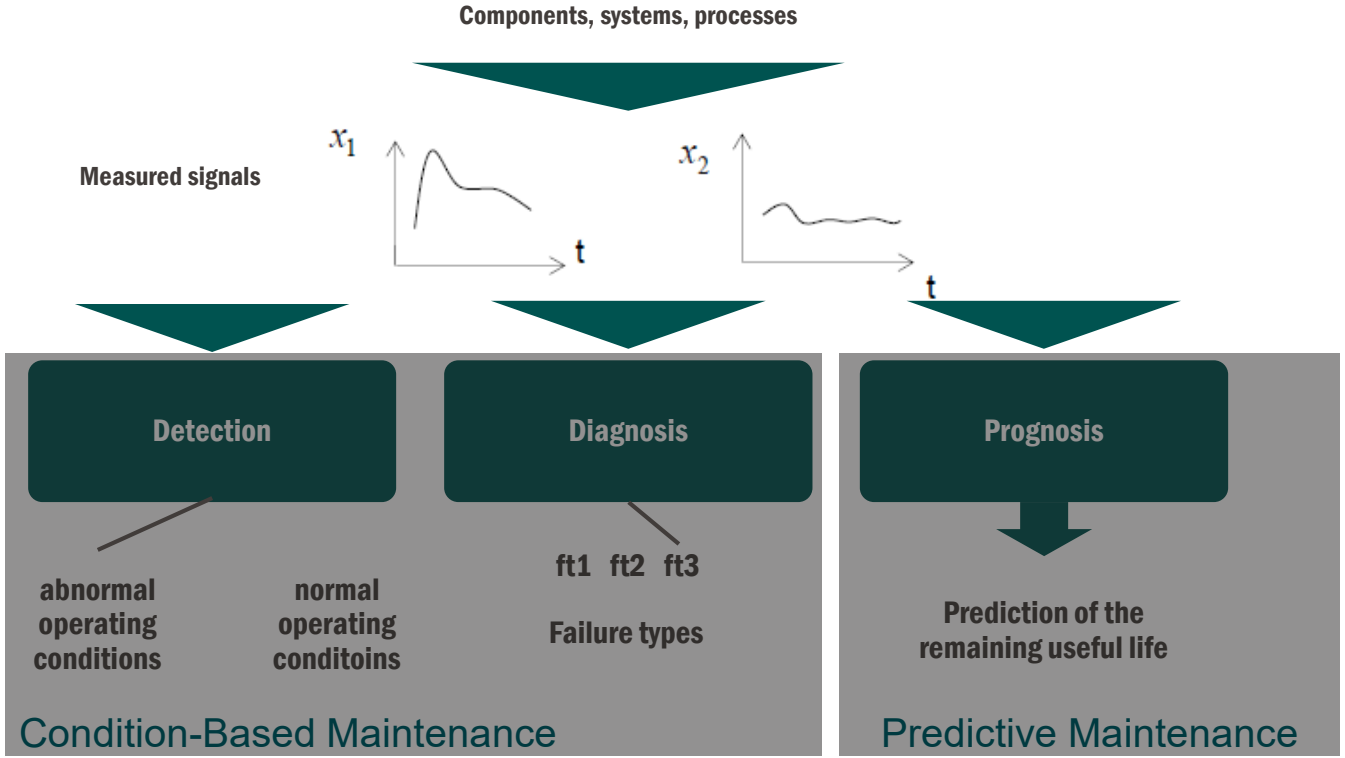
- Health indicators consist of the integration of **several condition indicators** into one value that provides the health status of the component to the end user.

# Desired characteristics of health / condition indicators

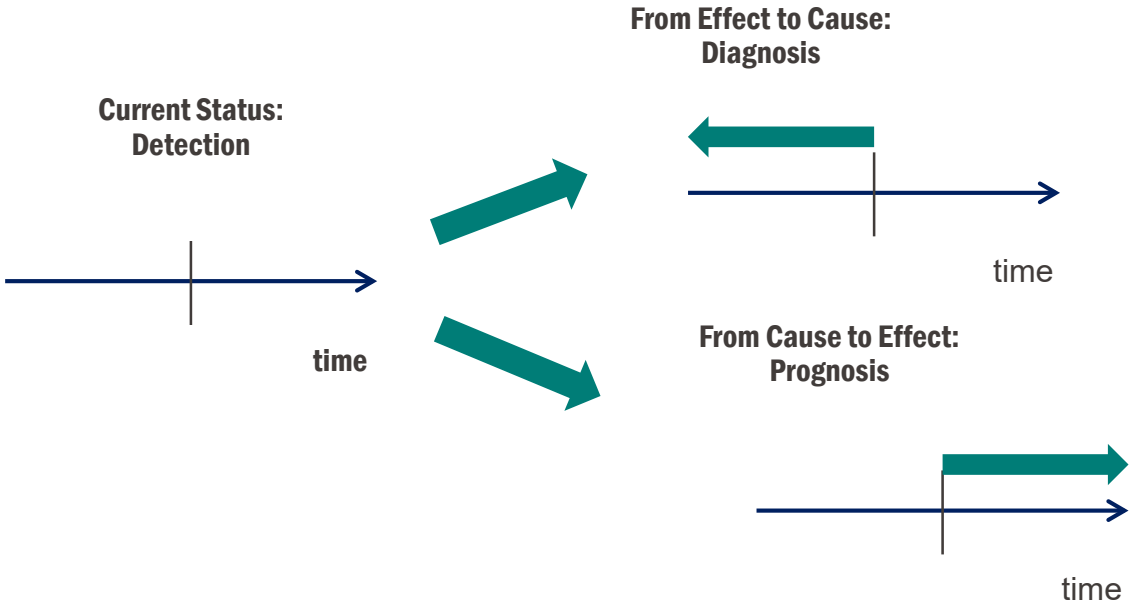
- Monotonicity
- Robusstness
- Adaptability

# Prognostics

# Prognostics and health management (PHM)

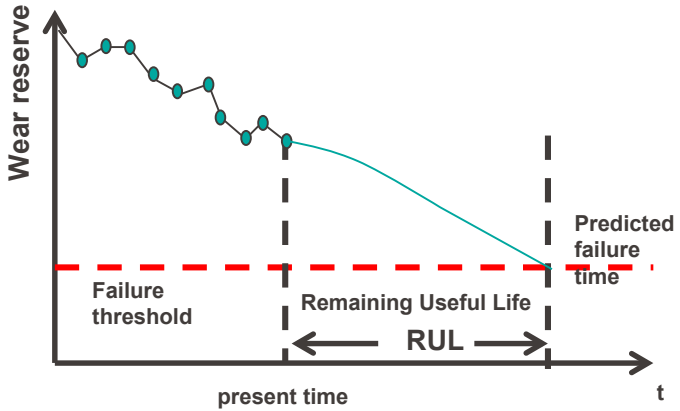


# Detection, Diagnosis, Prognosis



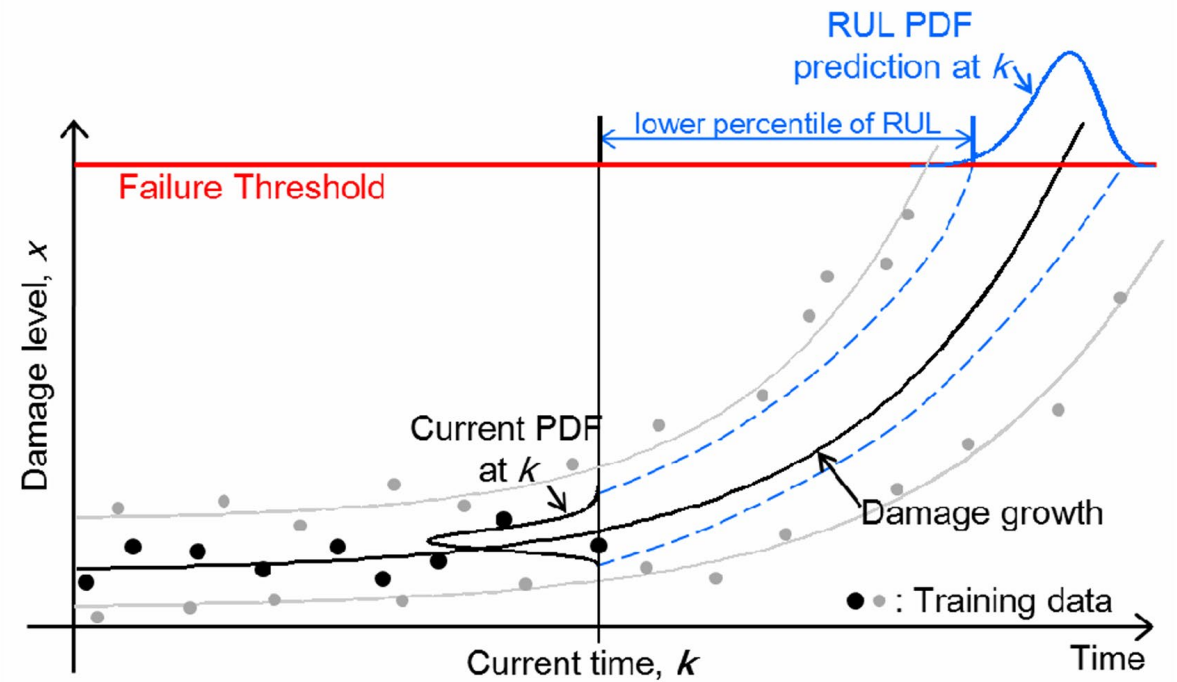
# Prognostic Term Definitions

- Remaining Useful Life (RUL): the amount of  time, in terms of operating hours, cycles, or other measures the component will continue to meet its design specification
- Time of Failure (ToF): the time a component  is expected to fail (no longer meet its design specifications).
- Probability of Failure (PoF): the failure  probability distribution of the component.
- End of Life (EoL) refers to a failure of the component as defined by its functional specifications




Source: Coble, 2016

# RUL prediction




An, D., Choi, J. H., & Kim, N. H. (2018). Prediction of remaining useful life under different conditions using accelerated life testing data. *Journal of Mechanical Science and Technology*, *32*, 2497-2507.

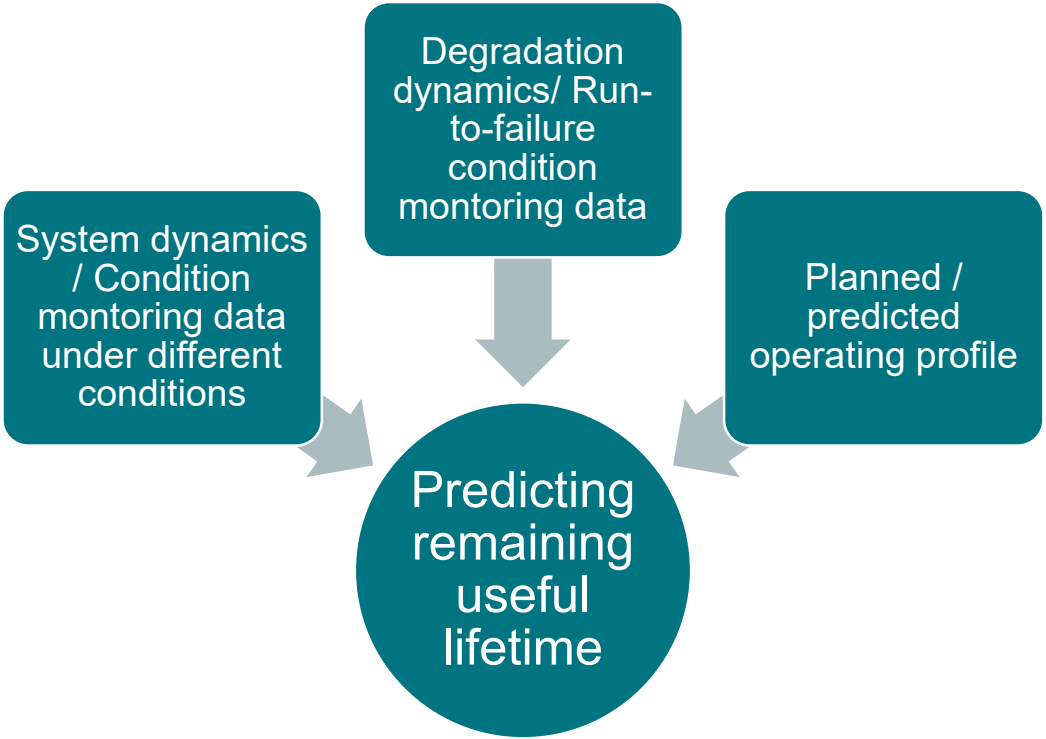
# Types of failures (End of Life)

- Soft failures:
  - Soft failures refer to conditions where a system or component experiences performance degradation or intermittent issues without complete loss of functionality. These failures often manifest as a gradual decline in performance, reliability, or efficiency.
  - Intermittent Performance Issues: Systems may function sporadically, with performance fluctuating between optimal and suboptimal states.
  - Degradation Over Time: Gradual wear and tear lead to diminishing performance metrics.
  - Early Warning Signs: Often preceded by detectable anomalies or deviations in health indicators.
  - Non-Catastrophic: Do not cause immediate or severe damage but can lead to significant issues if unaddressed.
- Hard Failures
  - Hard failures occur when a system or component ceases to function entirely or experiences a catastrophic breakdown. These failures result in the immediate and complete loss of functionality, often requiring significant repairs or replacements.
  - Sudden and Complete Failure: Systems stop working abruptly without prior warning.
  - Catastrophic Impact: Can cause extensive damage to equipment, infrastructure, or even pose safety hazards.
  - High Severity: Often lead to significant operational disruptions and financial losses.
  - Immediate Action Required: Necessitate prompt intervention to restore functionality and prevent further damage.
- Other terms used in the context of system failures:
  - Warning
  - Alarm

# Definition prognostics

- *Predict progression of the system health state based on current and future operational and environmental conditions to estimate the time at which a system no longer fulfils its function within desired specifications ("Remaining Useful Life")*

# Required ingredients for successful prefiction of remaining useful lifetime (RUL)



# Prognostics vs Trending vs Predictive Diagnostics

- **Prognostics:** Predict the remaining useful life or time to failure of a failing component/system
- **Trending:** Trend or linearly project/regress a current measurement until it reaches a predefined threshold
- **Predictive Diagnostics**: Find precursors to failure

# Algorithm selection

## End-of-Life predictions

Event predictions → RUL prediction

Decay /degradation prediction → trajectory prediction

No/little history data → mainly model-based

History data –> data-driven methods can be applied

Nominal data only

Nominal and failure data

# Prognostic Algorithm Categories

- Type I: Reliability Data-based
  - Use population based statistical model
  - These methods consider historical time to failure data which are used to model the failure distribution. They estimate the life of a typical component under nominal usage conditions.
  - Example: Weibull Analysis

- Type II: Stress-based
  - Use population based fault growth model – learned from accumulated knowledge
  - These methods also consider the environmental stresses (temperature, load, vibration, etc.) on the component. They estimate the life of an average component under specific usage conditions.
  - Example: Proportional Hazards Model

- Type III: Condition-based
  - Individual component based data-driven model
  - These methods also consider the measured or inferred component degradation. They estimate the life of a specific component under specific usage and degradation conditions.
  - Example: Cumulative Damage Model, Filtering and State Estimation

Source: Goebel, 2012

# Reliability and Prognostics

- Reliability analysis gives us information about the failure of a population of similar systems or components
- Prognostics extends this to a specific system or component
- When will it fail?
- What's the probability that it will fail in the next 5 minutes?
- What's the probability that we can complete the mission before something fails?

Source: Coble, 2016

# Type III – Degradation-based Prediction

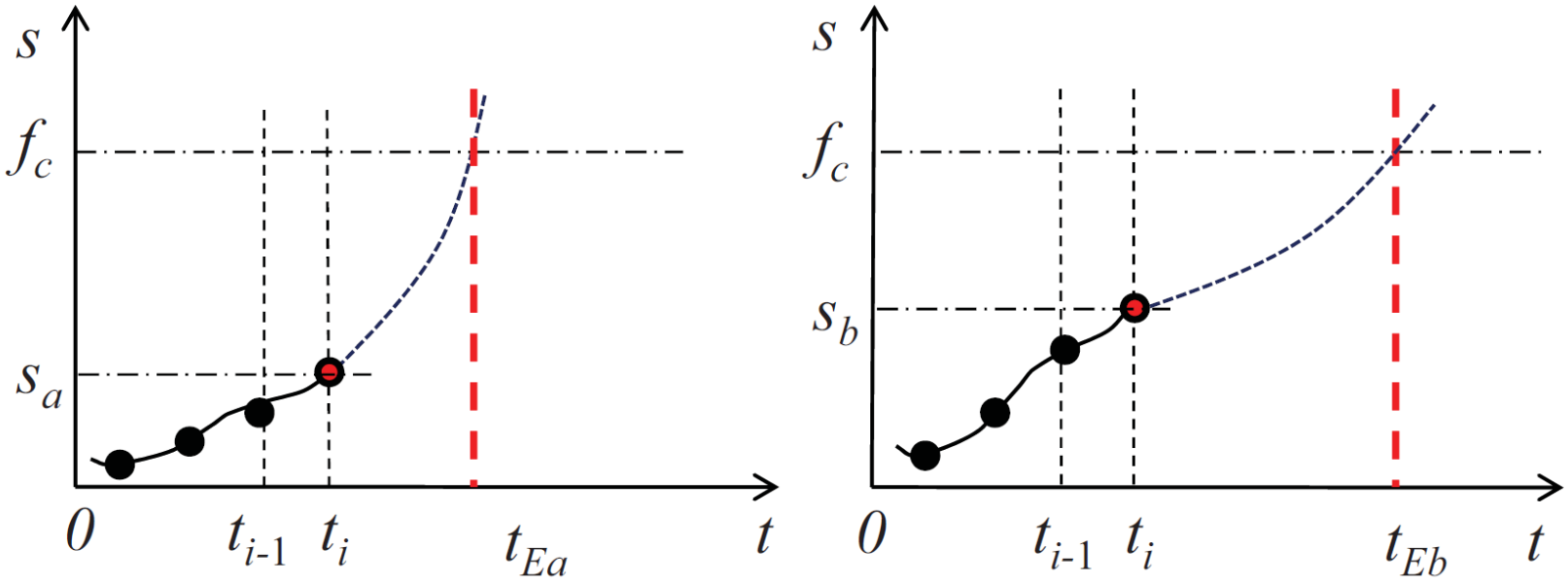
- Type III prognostics estimate the lifetime of the specific component in its specific operating environment
- Type III algorithms track the degradation (damage) as a function of time and predict when the total damage will exceed a predefined threshold that defines failure
- Damage is generally assumed to be cumulative (irreversible)

# Degradation-Based Prognostics

- A degradation measure is a scalar or vector quantity that numerically reflects the current ability of the system to perform its designated functions properly. It is a quantity that is correlated with the probability of failure at a given moment.
- A degradation path is a trajectory along which the degradation measure is evolving in time towards the critical level corresponding to a failure event.

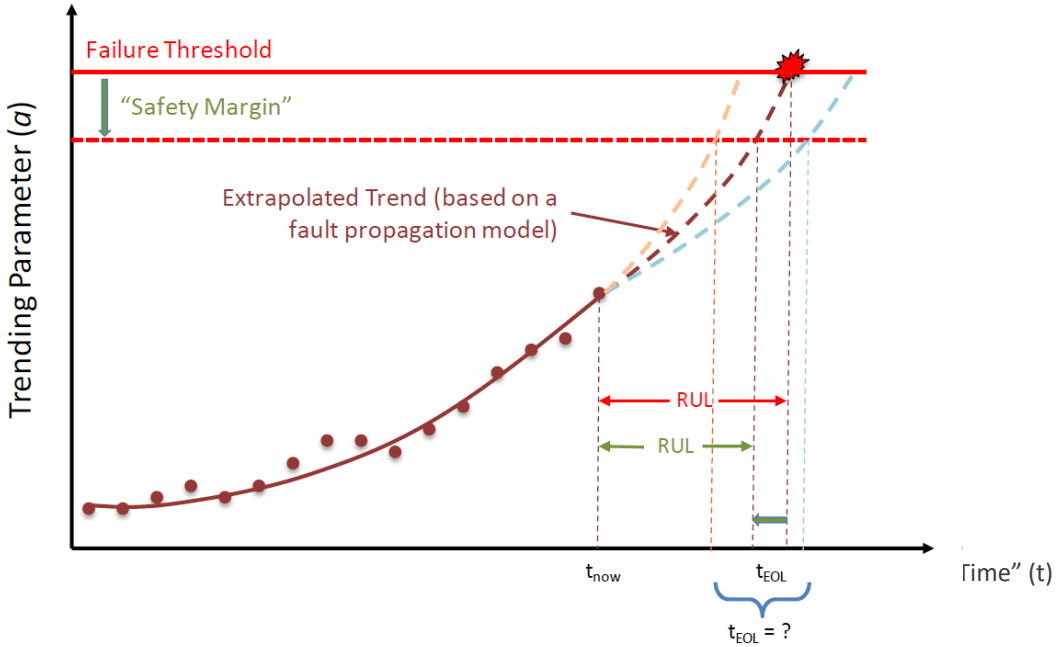
Source: Coble, 2016

# Health indicator vs. RUL



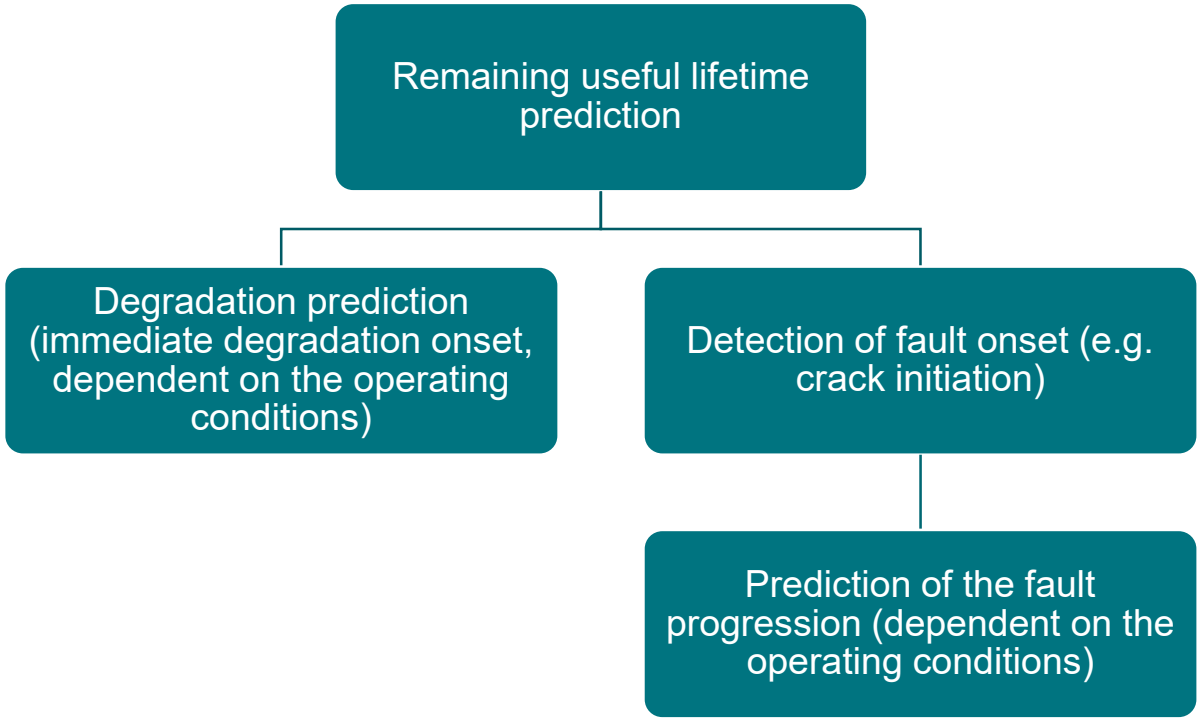

Wang, T., Trajectory Similarity Based Prediction for Remaining Useful Life Estimation, 2010

# Trending the degradation parameter

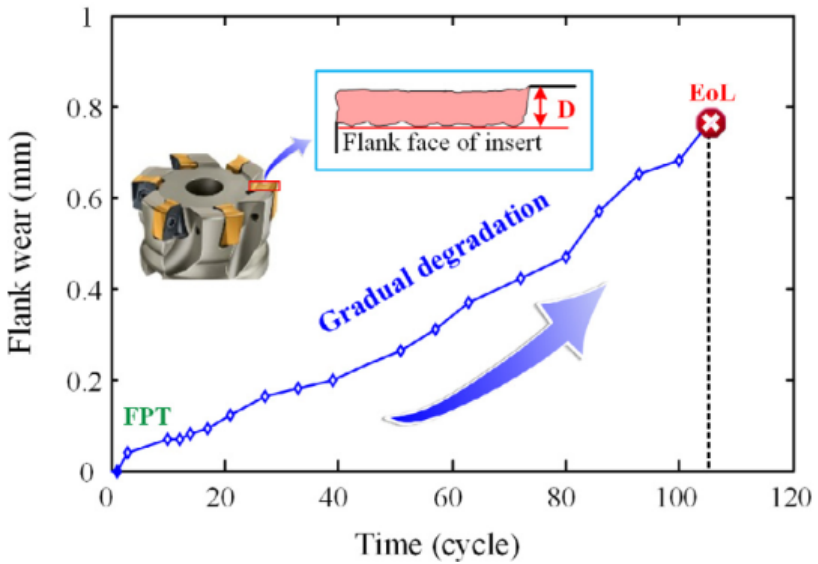


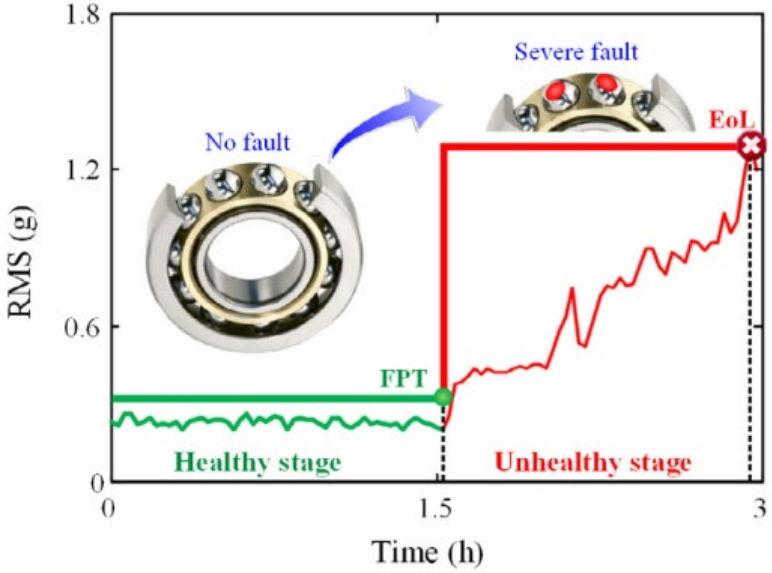

Source: Goebel, 2012

# Prognostics: degradation and fault progression



# Different degradation trajectories




Source: Lei et al, 2018

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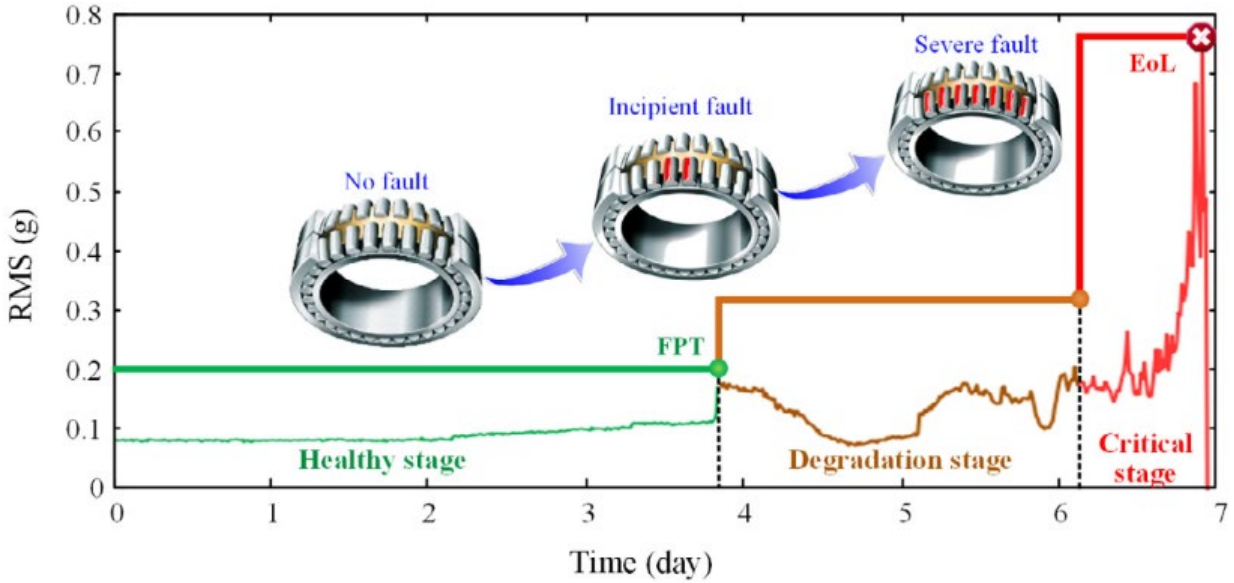
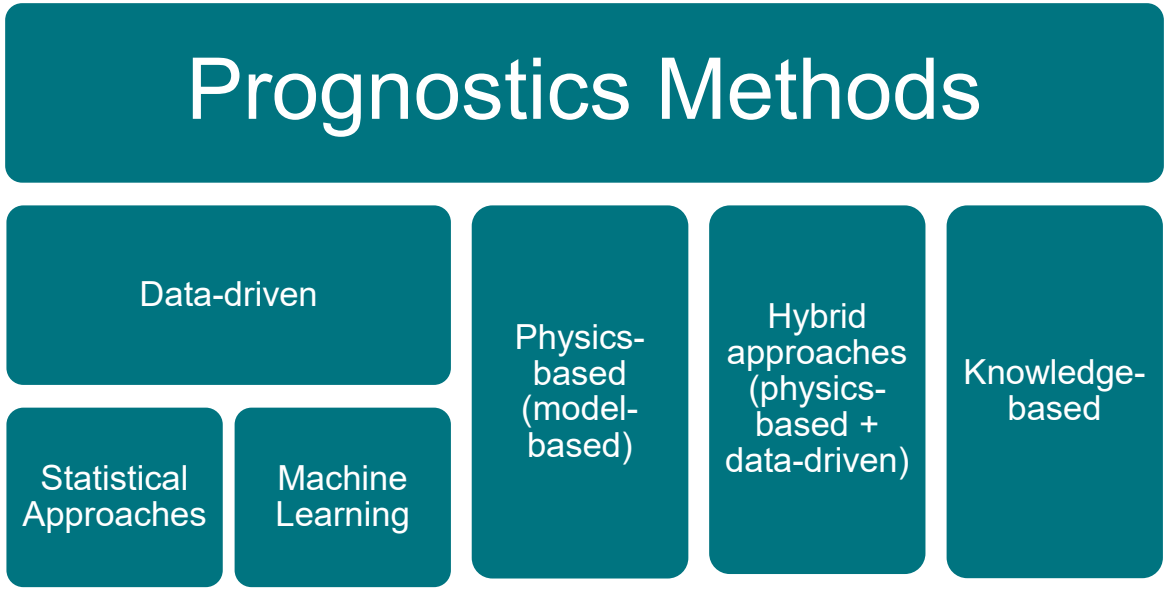
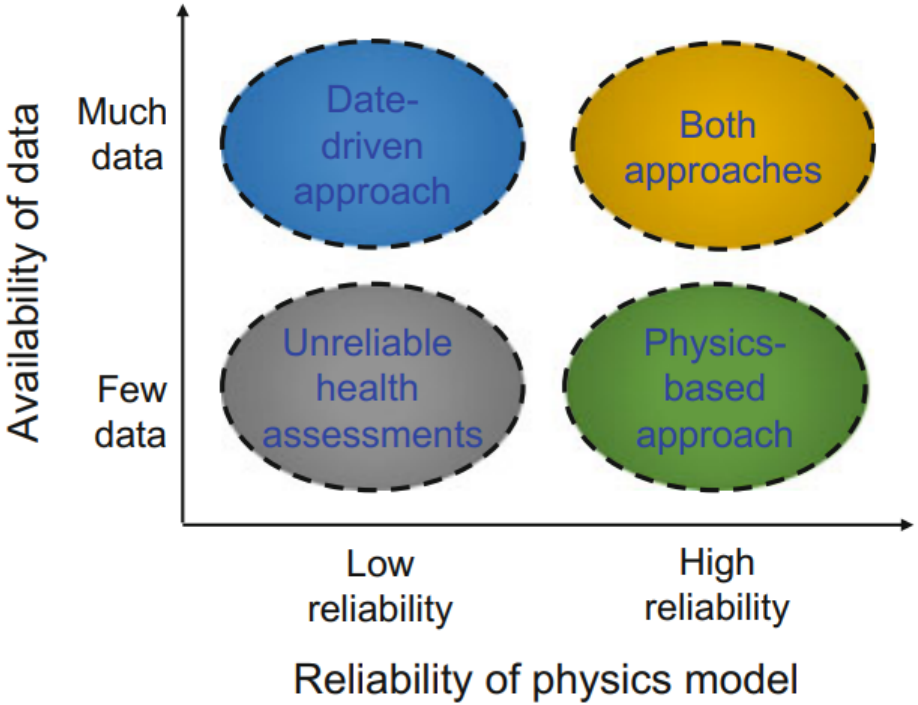



Source: Lei et al, 2018

# Prognostics Methods

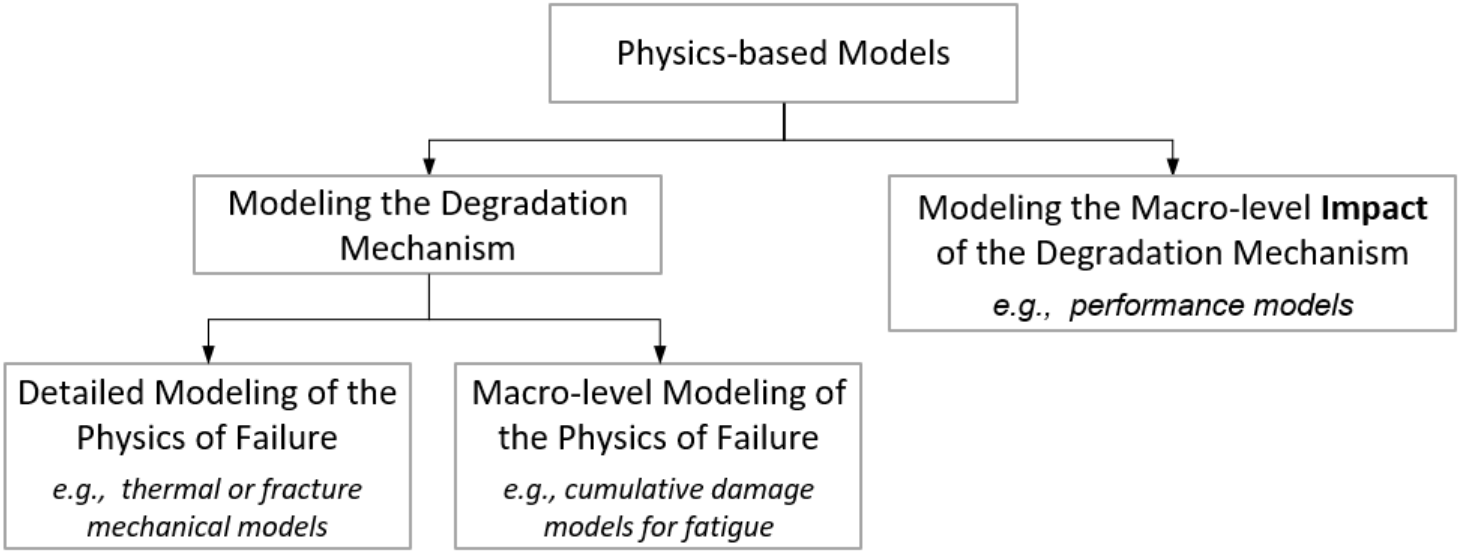


# Choice of Methods




Source: Prognostics and Health Management of Engineering Systems

# Physics-based models




M. Arias, Algorithm for Fleet Diagnostics and Prognostics Combining Deep Learning and Physics-based Performance Models (2021)

# Physics-Based Methods

- Description of a system's underlying physics using suitable representation
- Some examples:
  - Model derived from "First Principles"
    - Encapsulate fundamental laws of physics
      - partial differential equations (PDEs)
      - Euler-Lagrange Equations
  - Empirical model chosen based on an understanding of the dynamics of a system
    - Lumped Parameter Model
    - Classical 1st (or higher) order response curves
  - Mappings of stressors onto damage accumulation
    - Finite Element Model
    - High-fidelity Simulation Model
- Something in the model correlates to the failure mode(s) of interest

Source: Goebel, 2012

# Steps for physics-based prognostics

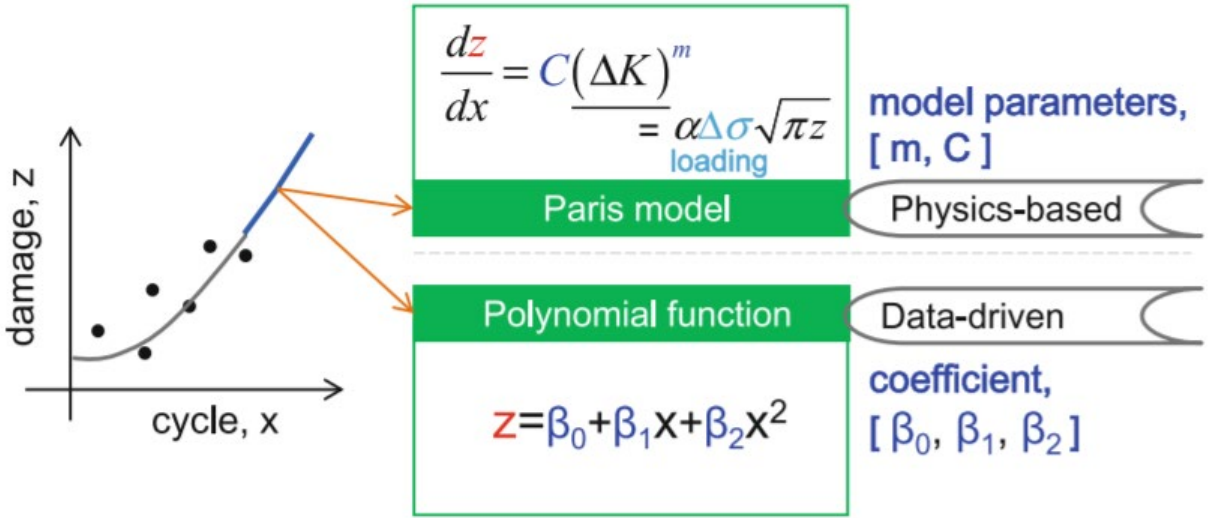
- Model underlying physics of a component/subsystem
- Model physics of damage propagation mechanisms
- Determine criteria for End-of-Life threshold
- Develop algorithms to  propagate damage into future
- Deal with uncertainty

# Data-Driven Methods

- Model is based solely on data collected from the system
- Some system knowledge may still be handy:
  - What the system ‘is’
  - What the failure modes are
  - What sensor information is available
  - Which sensors may contain indicators of fault progression (and how those signals may ‘grow’)
- *General* steps:
  - Gather what information you can (if any)
  - Determine which sensors give good trends
  - Process the data to “clean it up” – try to get nice, monotonic trends
  - Determine threshold(s) either from experience (data) or requirements
  - Use the model to predict RUL
    - Regression / trending
    - Mapping (e.g., using a neural network)
    - Statistics

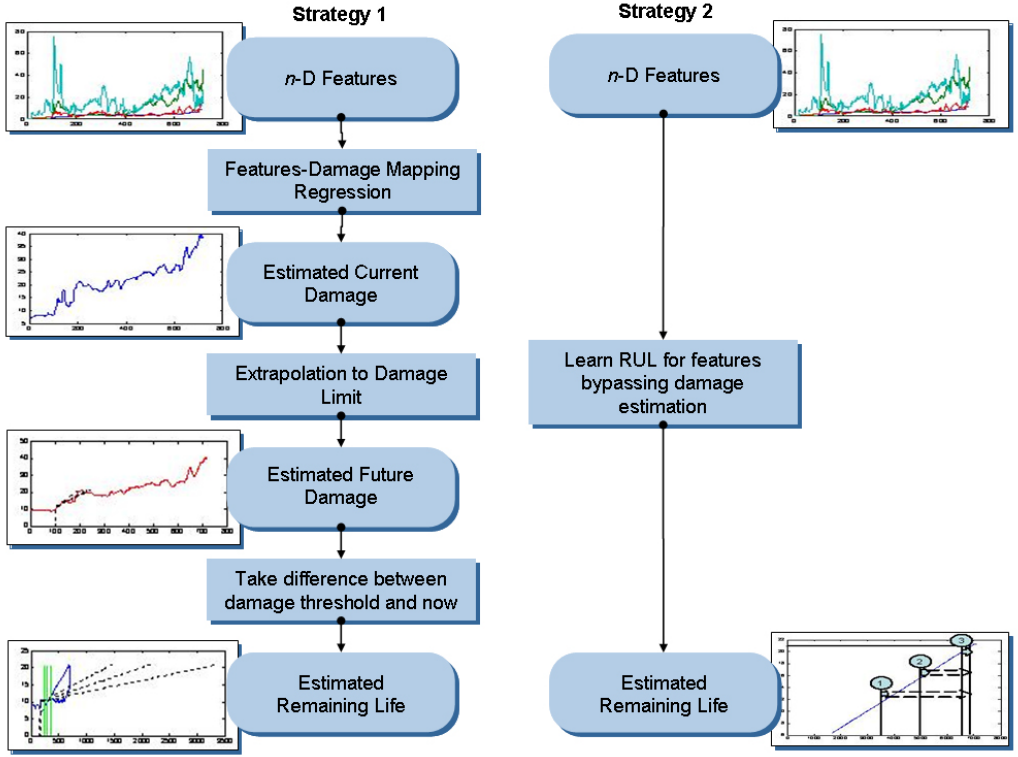
Source: Goebel, 2012

# Simple example of data-driven vs. physics-based (crack growth model)




Source: Integrated Vehicle Health Management

# Different approaches to data-driven RUL prediction




Source: NASA

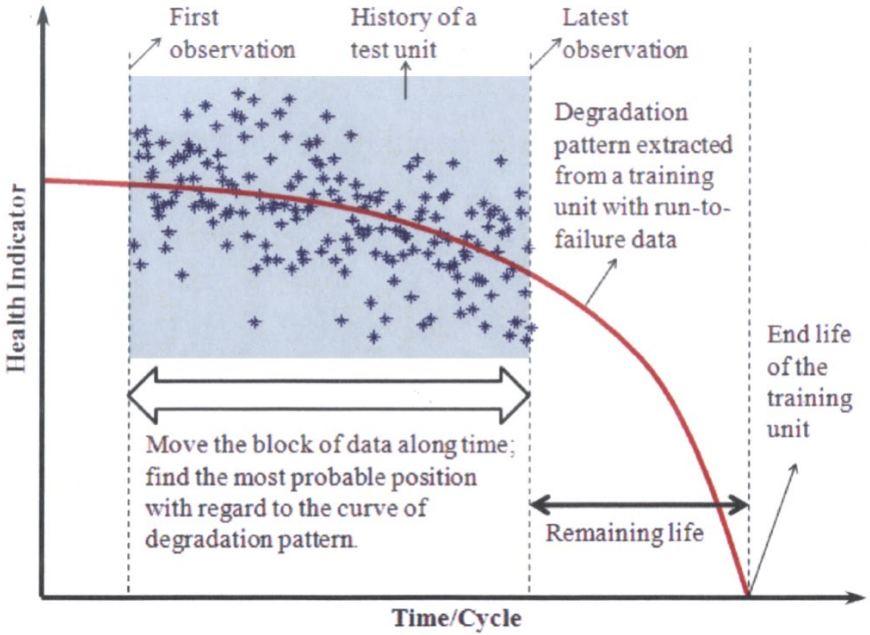
# Similarity-based RUL prediction

- Leverages the concept of comparing the current state of a system with historical data to estimate the remaining useful life.
- Underlying assumption is that systems with similar degradation patterns will exhibit similar RUL trajectories.
- Similarity-based approaches generally involve the following steps:
- Data Collection and Preprocessing:
  - Historical Data: Gather comprehensive historical operational and failure data.
  - Feature Extraction: Identify and extract relevant health indicators or features that represent the system's state.
  - Normalization: Standardize data to ensure consistency across different datasets.
- Similarity Measurement:
  - Distance Metrics: Utilize metrics such as Euclidean distance, Dynamic Time Warping (DTW), or Mahalanobis distance to quantify similarity between current and historical states.
  - Feature Space Comparison: Assess similarity in a multidimensional feature space where each dimension corresponds to a health indicator.
- RUL Estimation:
  - Weighted Averaging: Compute RUL based on the weighted average of RULs from the most similar historical instances.
  - Nearest Neighbors: Identify the 'k' most similar historical cases and use their RULs to predict the current RUL.

# Examples of possible approaches

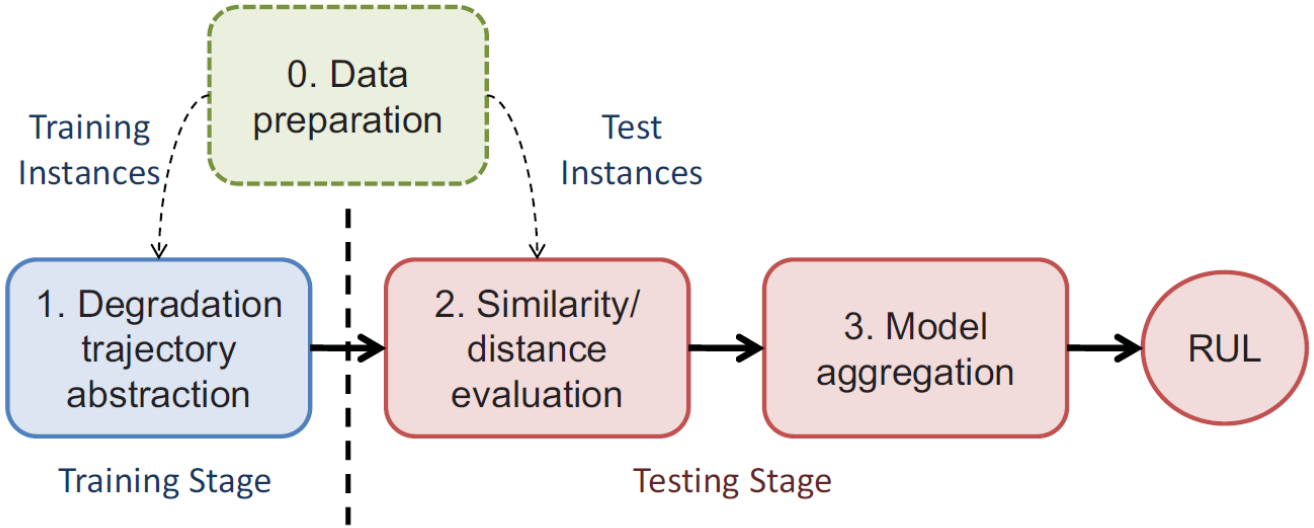
- **K-Nearest Neighbors (K-NN):**
  - Description: Identifies the 'k' most similar historical instances to the current state and averages their RULs.
  - Advantages: Simple to implement and interpret.
  - Limitations: Sensitive to the choice of 'k' and distance metrics; may not capture complex degradation patterns.
- **Pattern Matching and Template Matching:**
  - Description: Compares current degradation patterns with predefined templates representing typical failure modes.
  - Advantages: Can effectively recognize known failure patterns.
  - Limitations: Limited to detecting only those failure modes represented by templates; lacks flexibility for novel failures.
- **Cluster-Based Similarity:**
  - Description: Groups historical data into clusters and predicts RUL based on the cluster membership of the current state.
  - Advantages: Reduces computational complexity by limiting comparisons within relevant clusters.
  - Limitations: Requires effective clustering algorithms; may not handle overlapping or dynamic clusters well.

# Similarity based RUL prediction




Source: T. Wang, et al. 2008

# Similarity based RUL predictions

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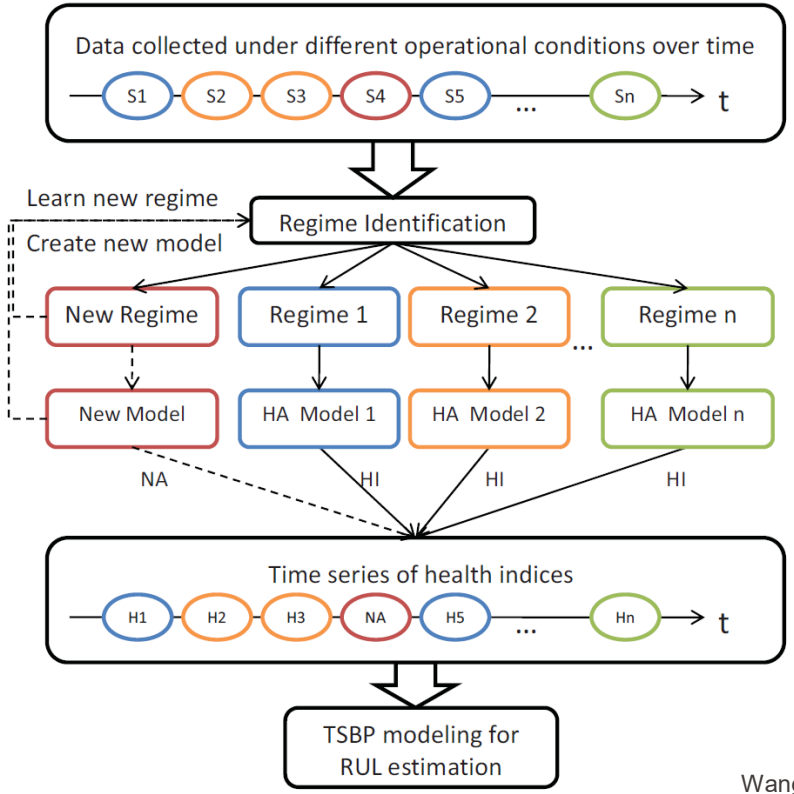


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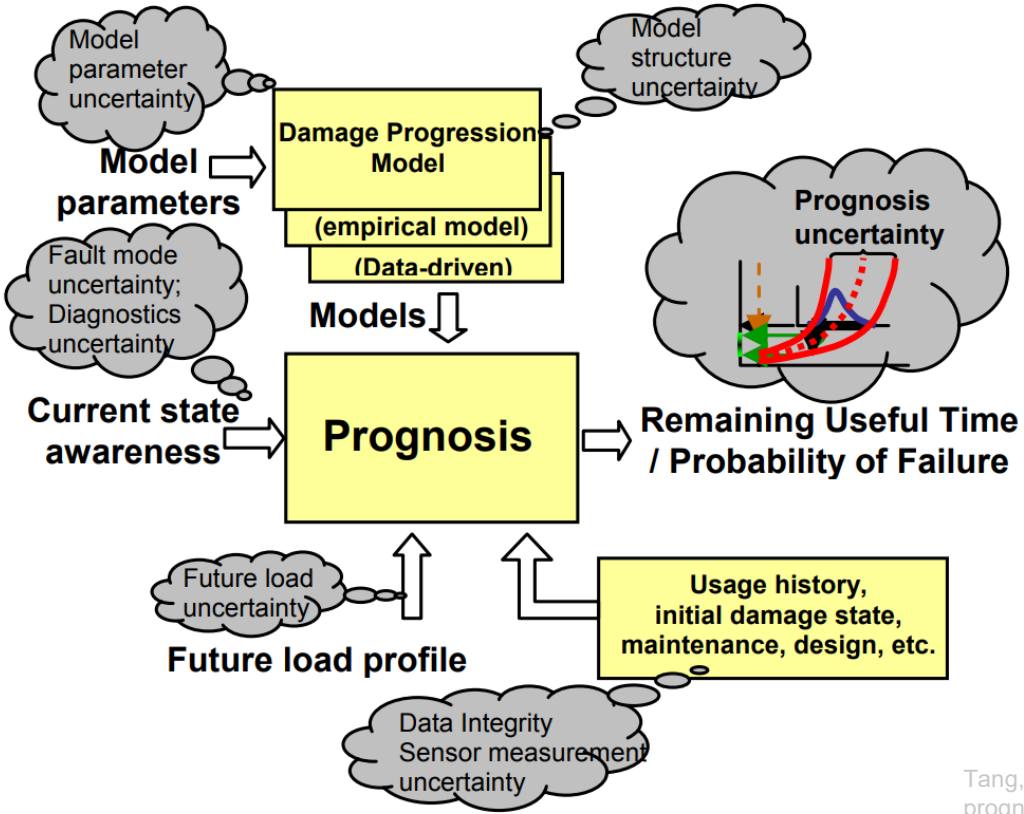
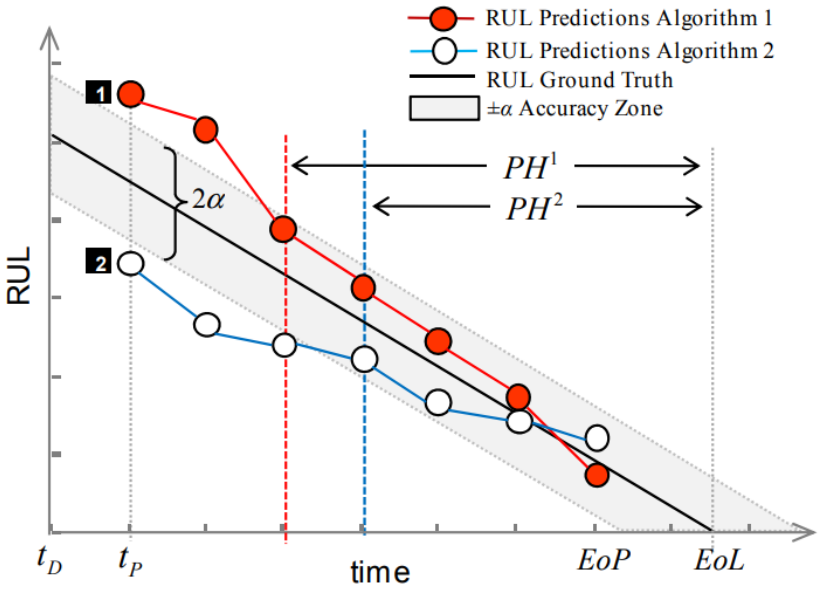
# Sources of uncertainty in prognostics




Tang, Liang, et al. "Methodologies for uncertainty management in prognostics." *2009 IEEE Aerospace conference*. IEEE, 2009.

# Prognostic Horizon




$$PH = EoL - i$$

where:

$i = \min\{j \mid (j \in \ell) \wedge (r_* - EoL^*\alpha) \le r^l(j) \le r_* + EoL^*\alpha)\}$ is the first time index when predictions satisfy $\alpha$-bounds

$\ell$ is the set of all time indexes when a prediction is made

$l$ is the index for $l^{th}$ unit under test (UUT)

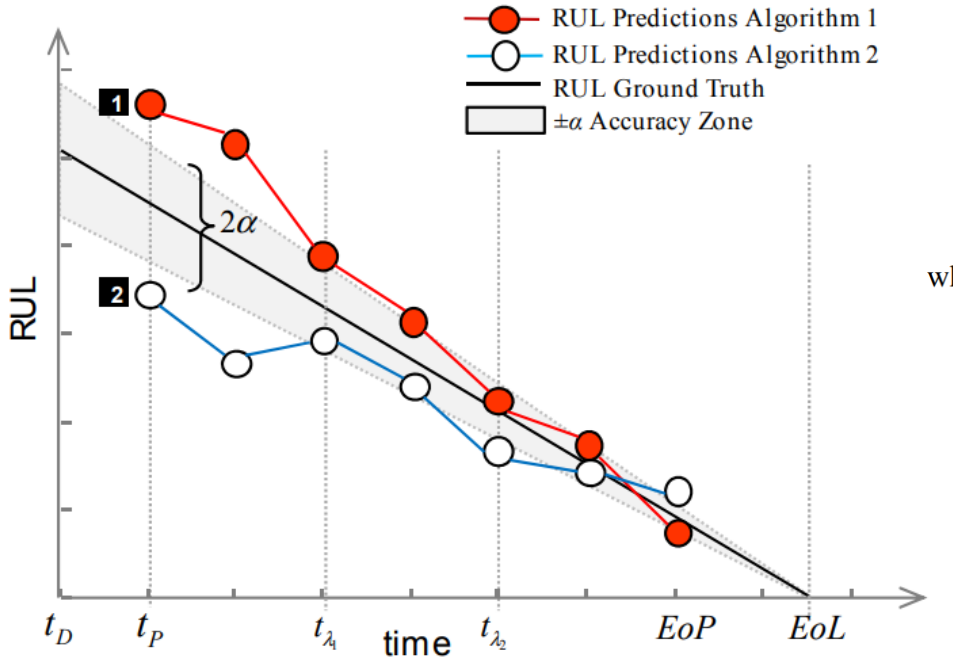
$r_*$ is the ground truth RUL

$r(j)$ is the predicted RUL at time $j$

EoL is the ground truth End-of-Life (actual failure)

Saxena, A., Celaya, J., Saha, B., Saha, S. and Goebel, K., 2009. On applying the prognostic performance metrics. In *Annual Conference of the PHM Society* (Vol. 1, No. 1).

# α- λ Accuracy




$$(1-\alpha)\cdot r_*(t) \le r^l(t_\lambda) \le (1+\alpha)\cdot r_*(t)$$

where:

$\alpha$ is the accuracy modifier

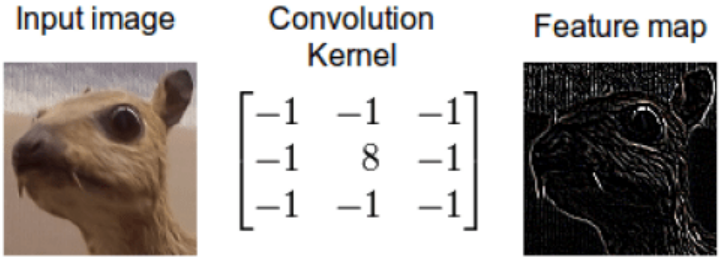
$\lambda$ is a time window modifier such that $t_\lambda = t_P + \lambda(EoL - t_P)$

Saxena, A., Celaya, J., Saha, B., Saha, S. and Goebel, K., 2009. On applying the prognostic performance metrics. In *Annual Conference of the PHM Society* (Vol. 1, No. 1).

# Recap: Convolutional neural networks

# General intuition behind unsing convolutional filters

- Image filters can enhance  image attributes
- Convolutional neural networks  are similar to conventional  image filtering
- Filter kernels are learnt




Source: UIO, 2017

# Filters

| | | | | | | |
|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 2 | 4 | 9 | 1 | 4 | 0 |
| 0 | 2 | 1 | 4 | 4 | 6 | 0 |
| 0 | 1 | 1 | 2 | 9 | 2 | 0 |
| 0 | 7 | 3 | 5 | 1 | 3 | 0 |
| 0 | 2 | 3 | 4 | 8 | 5 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Image

X

| | | |
|---|---|---|
| 1 | 2 | 3 |
| -4 | 7 | 4 |
| 2 | -5 | 1 |

Filter / Kernel

=

| | | | | |
|---|---|---|---|---|
| 21 | 59 | 37 | -19 | 2 |
| 30 | 51 | 66 | 20 | 43 |
| -14 | 31 | 49 | 101 | -19 |
| 59 | 15 | 53 | -2 | 21 |
| 49 | 57 | 64 | 76 | 10 |

Feature

$$O = \frac{n - f + 2p}{s} + 1$$

Where O is the output height/length, n is input height / length, f is filter size, p is the padding, and s is the stride

# Pooling

| | | | | | |
|---|---|---|---|---|---|
| 6 | 8 | 6 | 3 | 1 | 0 |
| 9 | 13 | 10 | 5 | 2 | 0 |
| 9 | 14 | 11 | 6 | 3 | 0 |
| 9 | 13 | 11 | 6 | 2 | 0 |
| 8 | 13 | 10 | 5 | 3 | 0 |
| 6 | 7 | 5 | 3 | 1 | 0 |

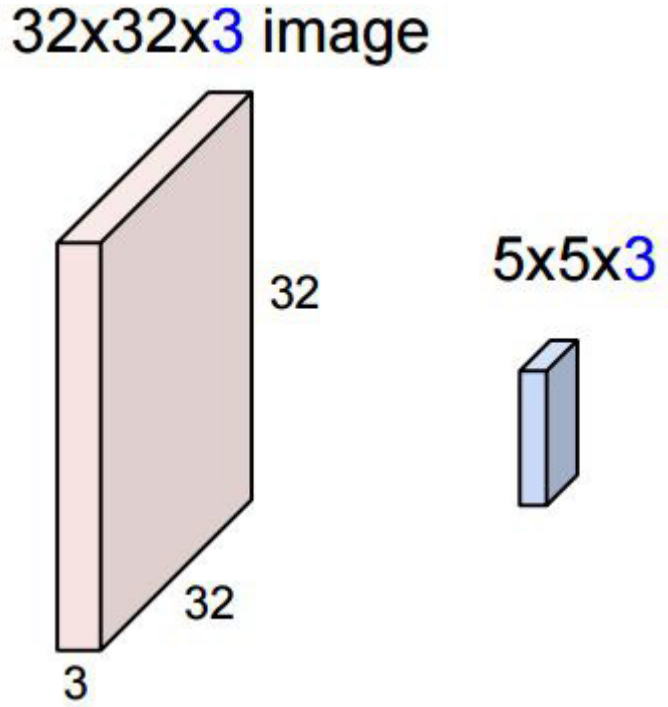
Feature map

| | | |
|---|---|---|
| 13 | 10 | 2 |
| 14 | 11 | 3 |
| 13 | 10 | 3 |

Max pooling

# Filters and channels (Standard method)

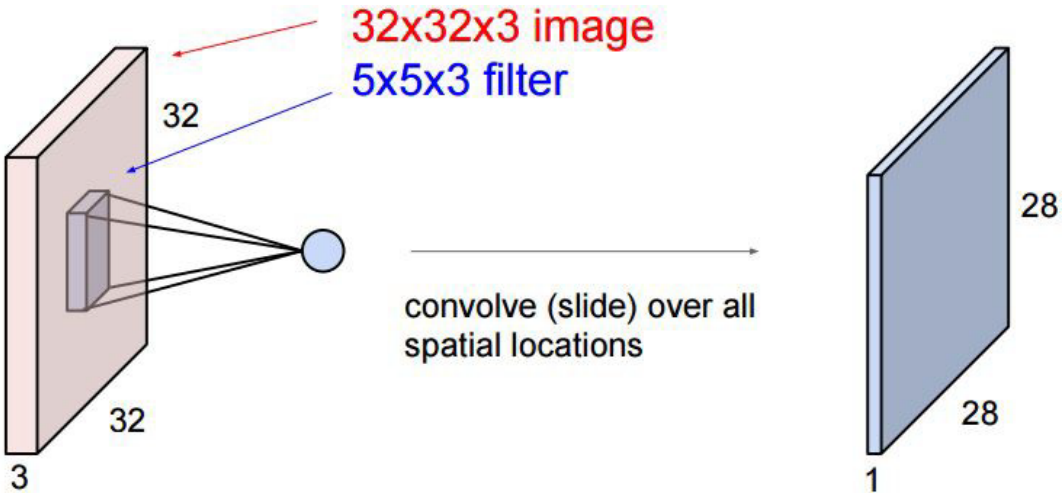
- An input image has a third dimension (say RGB)
- A filter/kernel always has the same third dimension




Source: UIO, 2017

# Filters and channels

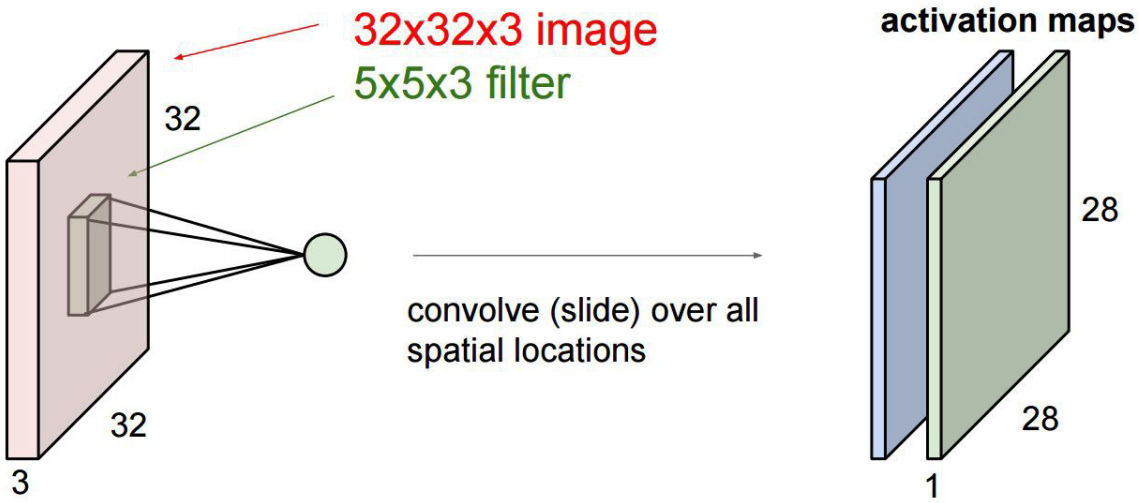
- Overlapping area is multiplied then summed (dot product)
- With sliding you get 28x28x1 output




Source: UIO, 2017

# Usually we use multiple filters per layer

- A new kernel/filter slides over the same image
- Create a new filtered image

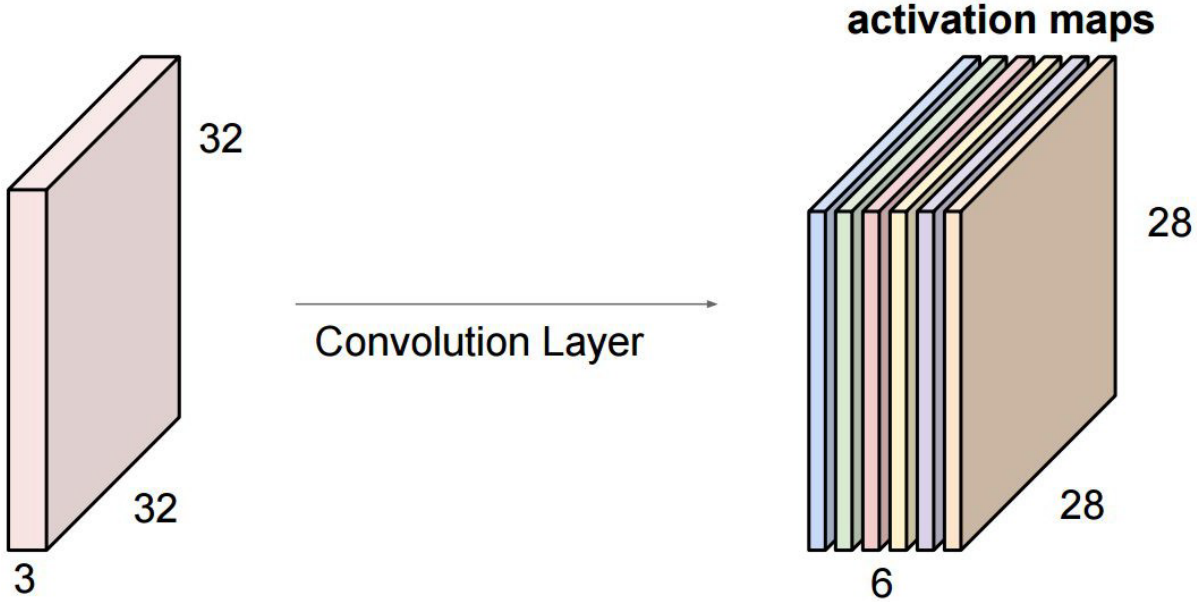



Source: UIO, 2017

# Applying filters

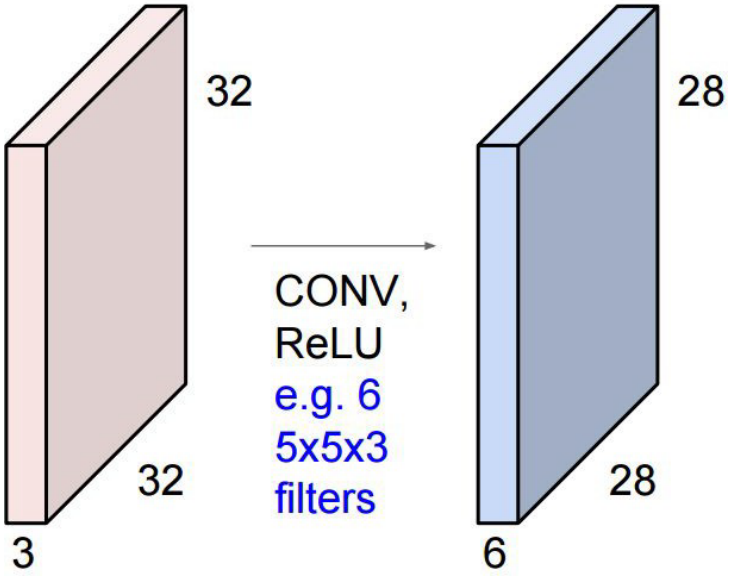
## Many activation maps create a new “image”

If we filter the image 6 times, we get a new image with 6 channels.



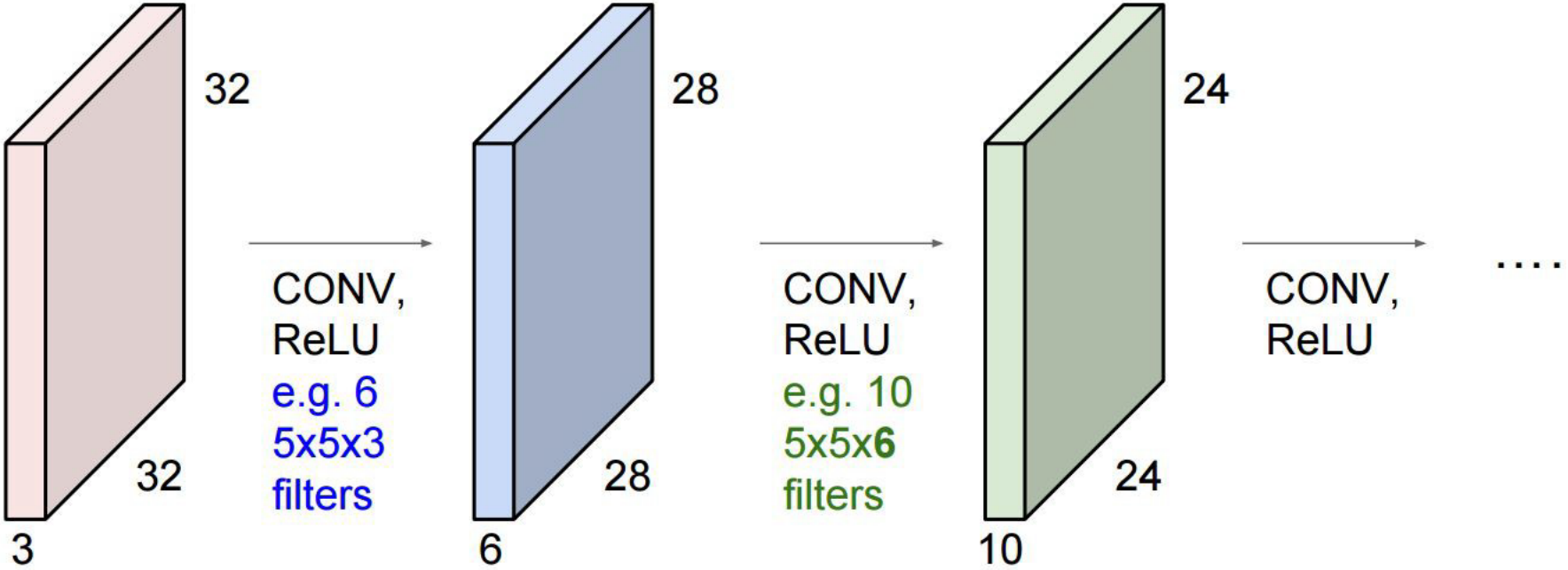

Source: UIO, 2017

# Convolutional neural network consist of multiple layers



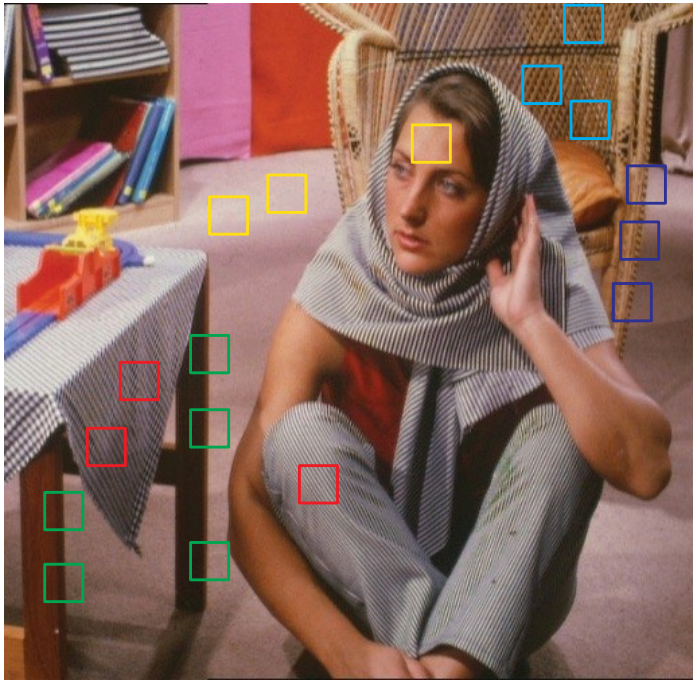

Source: UIO, 2017

# Convolutional neural network consist of multiple layers




Source: UIO, 2017

# Stationarity and Self-similarity



Data is self-similar across the domain

# Translation invariance (image classification tasks)

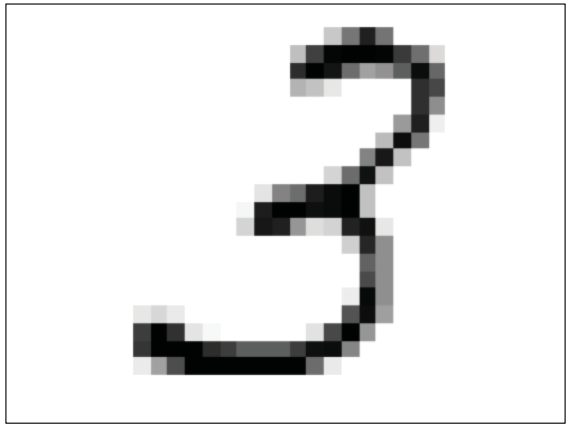
$$f(\mathcal{T}_{\mathbf{v}}x) = f(x) \quad \forall x, \mathbf{v}$$

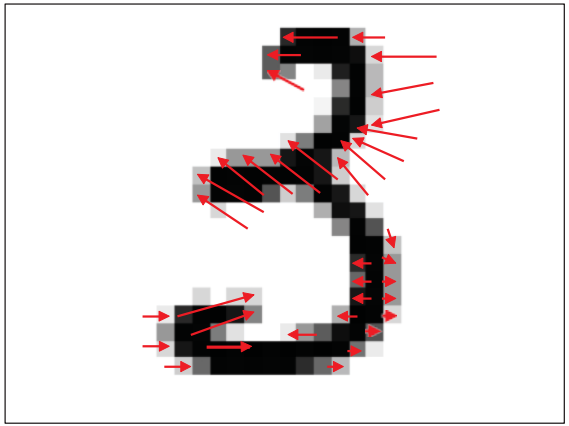
where

- image is modeled as a function $x \in L^2([0,1]^2)$
- $\mathcal{T}_{\mathbf{v}}x(\mathbf{u}) = x(\mathbf{u} - \mathbf{v})$ is a translation operator
- $\mathbf{v} \in [0,1]^2$ is a translation vector
- $f : L^2([0,1]^2) \to \{1, \ldots, L\}$ is a classification functional

Bruna, Mallat 2012

# Deformation invariance (image classification tasks)





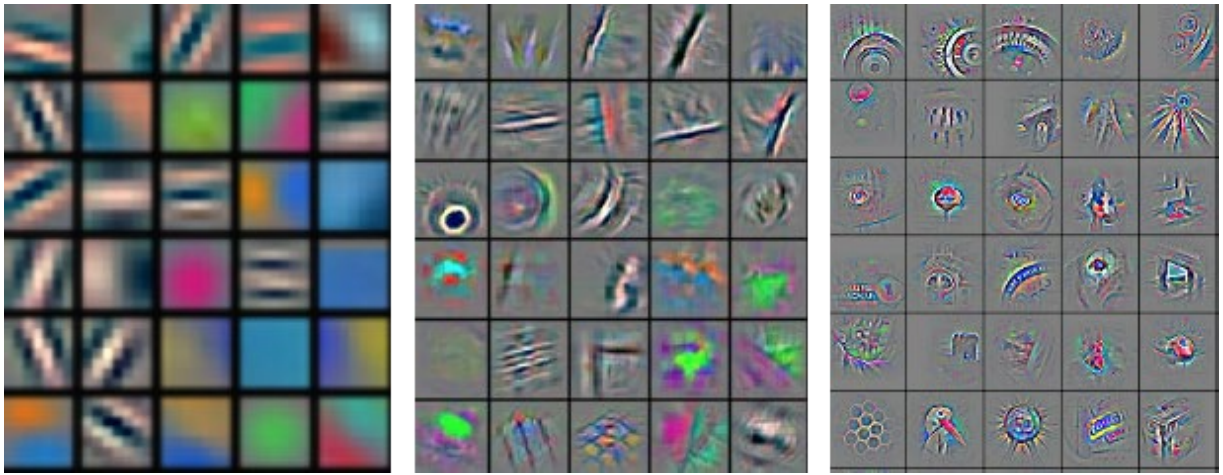
$$|f(\mathcal{L}_\tau x) - f(x)| \approx \|\nabla \tau\| \quad \forall f, \tau$$

where

- image is modeled as a function $x \in L^2([0,1]^2)$
- $\mathcal{L}_\tau x(\mathbf{u}) = x(\mathbf{u} - \tau(\mathbf{u}))$ is a warping operator
- $\tau : [0,1]^2 \to [0,1]^2$ is a smooth deformation field
- $f : L^2([0,1]^2) \to \{1, \dots, L\}$ is a classification functional

Bruna, Mallat 2012

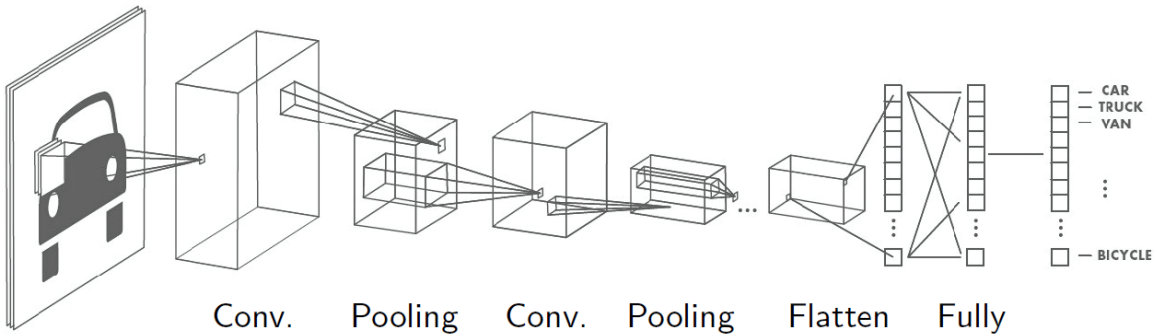
# Hierarchy and Compositionality



Typical features learned by a CNN becoming increasingly complex at deeper layers

Zeiler, Fergus 2013

# Convolutional Neural Networks (CNN)




Conv. layer $$x_{\ell'}^{(l+1)}(\mathbf{u}) = \xi\left(\sum_{\ell=1}^{d^{(l)}}(w_{\ell'\ell}^{(l+1)} \star x_{\ell}^{(l)})(\mathbf{u})\right)$$

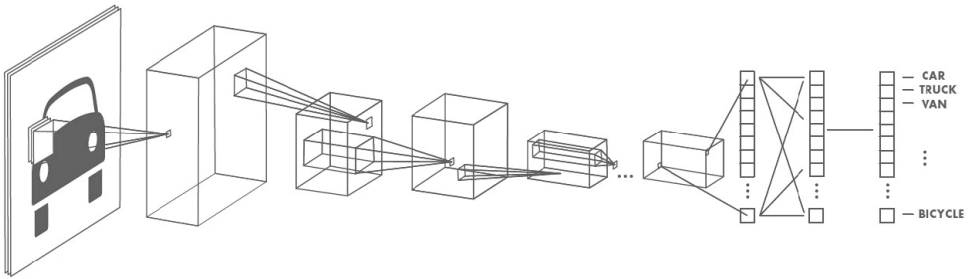
Activation, e.g. $\xi(x) = \max\{x, 0\}$ rectified linear unit (ReLU)

Parameters filters $W^{(1)}, \ldots, W^{(L)}$

Pooling $x_{\ell}^{(l+1)}(\mathbf{u}) = \|x_{\ell}^{(l)}(\mathbf{u}') : \mathbf{u}' \in \mathcal{N}(\mathbf{u})\|_p \quad p = 1, 2, \text{ or } \infty$

LeCun et al. 1989 (Image: Debarko De)

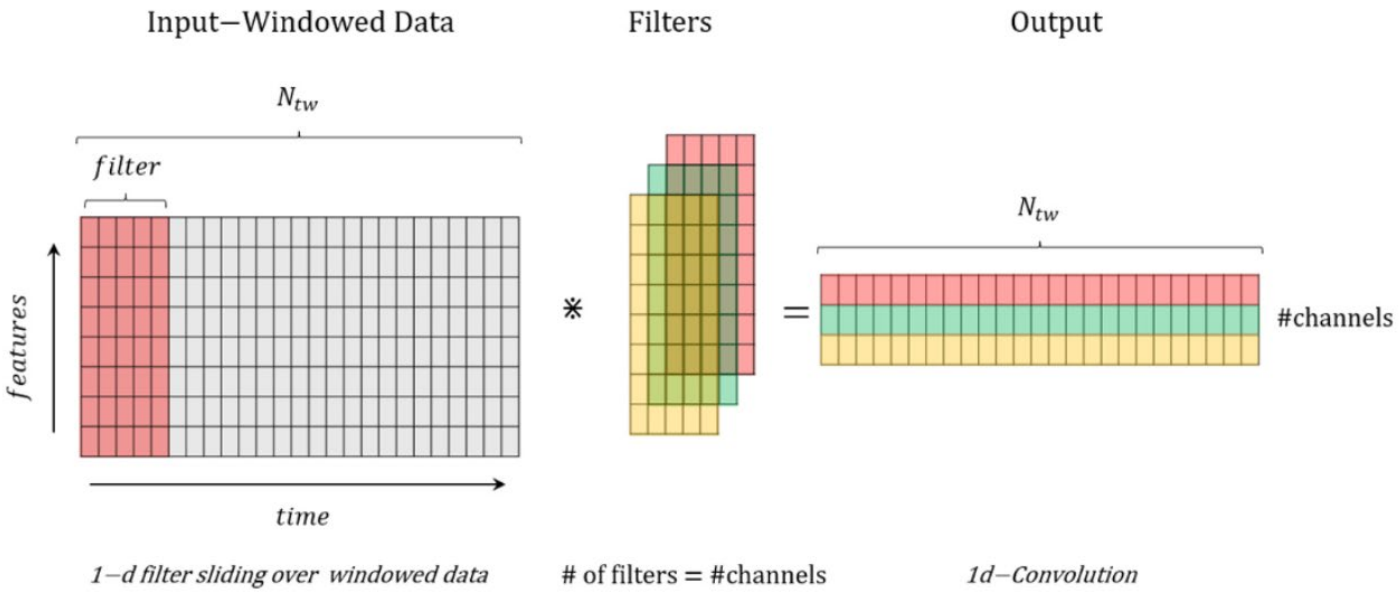
# Key properties of CNNs




- ☺ Convolutional filters **(Translation invariance+Self-similarity)**
- ☺ Multiple layers **(Compositionality)**
- ☺ Filters localized in space **(Locality)**
- ☺ $\mathcal{O}(1)$ parameters per filter (independent of input image size $n$)
- ☺ $\mathcal{O}(n)$ complexity per layer (filtering done in the spatial domain)
- ☺ $\mathcal{O}(\log n)$ layers in classification tasks

LeCun et al. 1989

# 1D CNN


Input—Windowed Data
Filters
Output
$N_{tw}$
filter
features
time
*
=
$N_{tw}$
#channels
1−d filter sliding over windowed data
# of filters = #channels
1d−Convolution

# Hyperparameter search

# Hyperparameter Tuning in Machine Learning

- **Definition**: Hyperparameter tuning involves adjusting the parameters of a machine learning model that are set prior to the start of the learning process. These parameters influence model training and can significantly affect performance.

## Why It's Important

- Hyperparameters control the learning process and directly impact the effectiveness and efficiency of the model.
- Proper tuning can prevent overfitting, underfitting, and can improve model accuracy.

# Formalizing hyperparameter tuning

- In a general sense, tuning involves these components:
  - a learning algorithm A, parameterized by hyperparameters $\lambda$
  - training and validation data $\mathbf{X}^{(tr)}$, $\mathbf{X}^{(vl)}$
  - a model $\mathcal{M} = \mathcal{A}(\mathbf{X}^{(tr)} \mid \lambda)$
  - loss function $\mathcal{L}$ to assess quality of $\mathcal{M}$, typically using $\mathbf{X}^{(vl)}$:

$$\mathcal{L}(\mathcal{M} \mid \mathbf{X}^{(te)})$$

- In optimization terms, we aim to find $\lambda^*$ (assuming minimization):

$$\lambda^* = \arg\min_{\lambda} \mathcal{L}\left(\mathcal{A}(\mathbf{X}^{(tr)} \mid \lambda) \mid \mathbf{X}^{(vl)}\right) = \arg\min_{\lambda} \underbrace{\mathcal{F}(\lambda \mid \mathcal{A}, \mathbf{X}^{(tr)}, \mathbf{X}^{(vl)}, \mathcal{L})}_{\textit{objective function}}$$

Source: Claesen, de Moor 2015

# Tuning in practice

- Most often done using a combination of grid and manual search:
  - grid search suffers from the curse of dimensionality
  - manual tuning leads to poor reproducibility

# Abstraction of hyperparameter tuning

- We need to define the hyperparameters we want to optimize:
  - Architecture (#layers, #kernels, stride, kernel size)
  - Learning rate, optimizer (momentum)
  - Regularizations (weight decay rate, dropout probability)
  - Batchnorm / no batchnorm
  - Number of epochs: The number of times the learning algorithm will work through the entire training dataset.
  - Batch size: The number of training examples utilized in one iteration.
- Our diagnostic statistics:
  - Loss curves
  - Gradient norms
  - Accuracy / Visual output (generative models)
  - Performance on training vs validation set
  - Other abnormal behaviors

Source: Li, Johnson, Yeung, 2018

# Example Hyperparameters SVM

$$\min_{\alpha,\xi,b} \frac{1}{2} \sum_{i \in SV} \sum_{j \in SV} \alpha_i \alpha_j y_i y_j \kappa(\mathbf{x}_i, \mathbf{x}_j) + C \sum_{i=1}^{n} \xi_i,$$

$$\text{subject to } y_i \Big( \sum_{j \in SV} \alpha_i \alpha_j y_i y_j \kappa(\mathbf{x}_i, \mathbf{x}_j) + b \Big) \geq 1 - \xi_i, \quad \xi_i \geq 0, \quad \forall i.$$

# Tuning Techniques

- Grid Search: Exhaustive search over a specified parameter range.
- Random Search: Randomly samples the search space and evaluates sets from a specified probability distribution.
- Bayesian Optimization: Uses a probabilistic model to predict which hyperparameters might lead to better performances.
- Gradient-based Optimization: Adjusts hyperparameters using gradient descent to minimize a predefined loss function.
- Evolutionary Algorithms: Uses mechanisms inspired by biological evolution: reproduction, mutation, recombination, and selection.

# Fast iteration

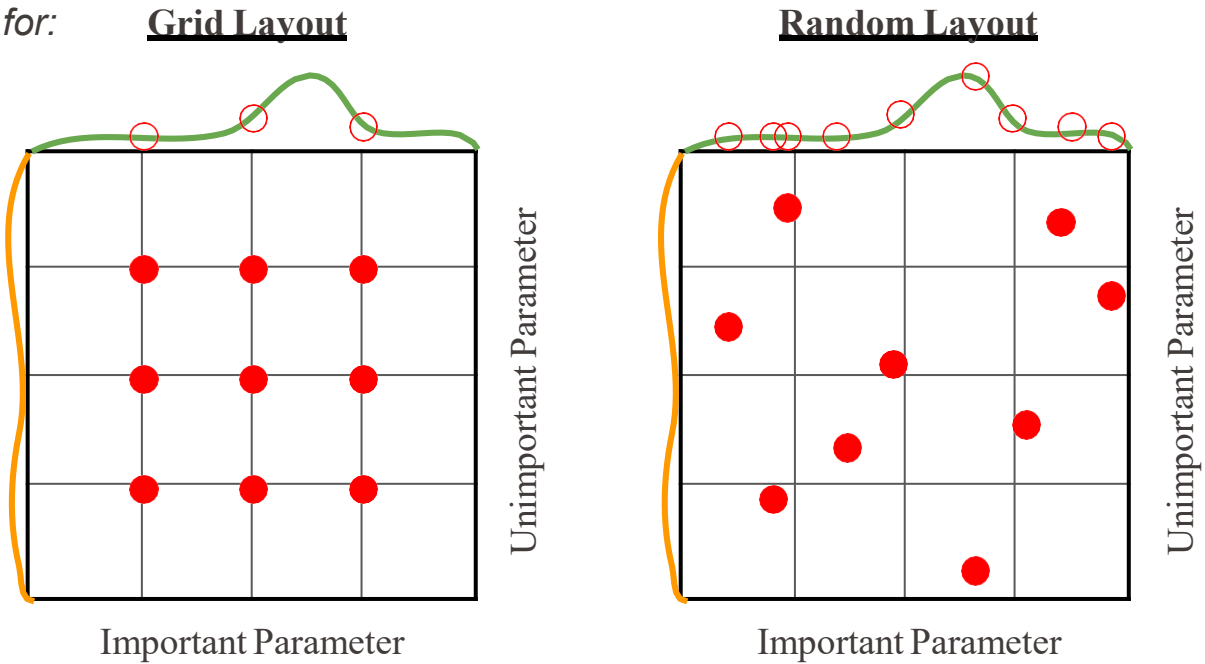
- When tuning parameters, only use a small portion of the dataset for fast iteration.
- Start from a larger learning rate for fast prototyping.

- Cross-validation strategy:
  - coarse → fine: cross-validation in stages
  - First stage: only a few epochs to get rough idea of what parameters work
  - Second stage: longer running time, finer search
  - … (repeat as necessary)

Source: Li, Johnson, Yeung, 2018

# Random Search vs. Grid Search

*Random Search for:*




Hyper-Parameter Optimization
Bergstra and Bengio, 2012

# Can we use Machine Learning instead?

- To predict regions of the hyperparameter space that might give better results.

- To predict how well a new combination of hyperparameters will do and also model the uncertainty of that prediction

Source: Snoek et. al., 2012

# Can We Do Better? Bayesian Optimization

- Build a probabilistic model for the objective.
- Include hierarchical structure about units, etc.
- Compute the posterior predictive distribution.
- Integrate out all the possible true functions.
- Gaussian process regression is often used.
- Optimize a cheap proxy function instead.
- The model is much cheaper than the true objective.
- The main insight:
  - Make the proxy function exploit uncertainty to balance exploration against exploitation.

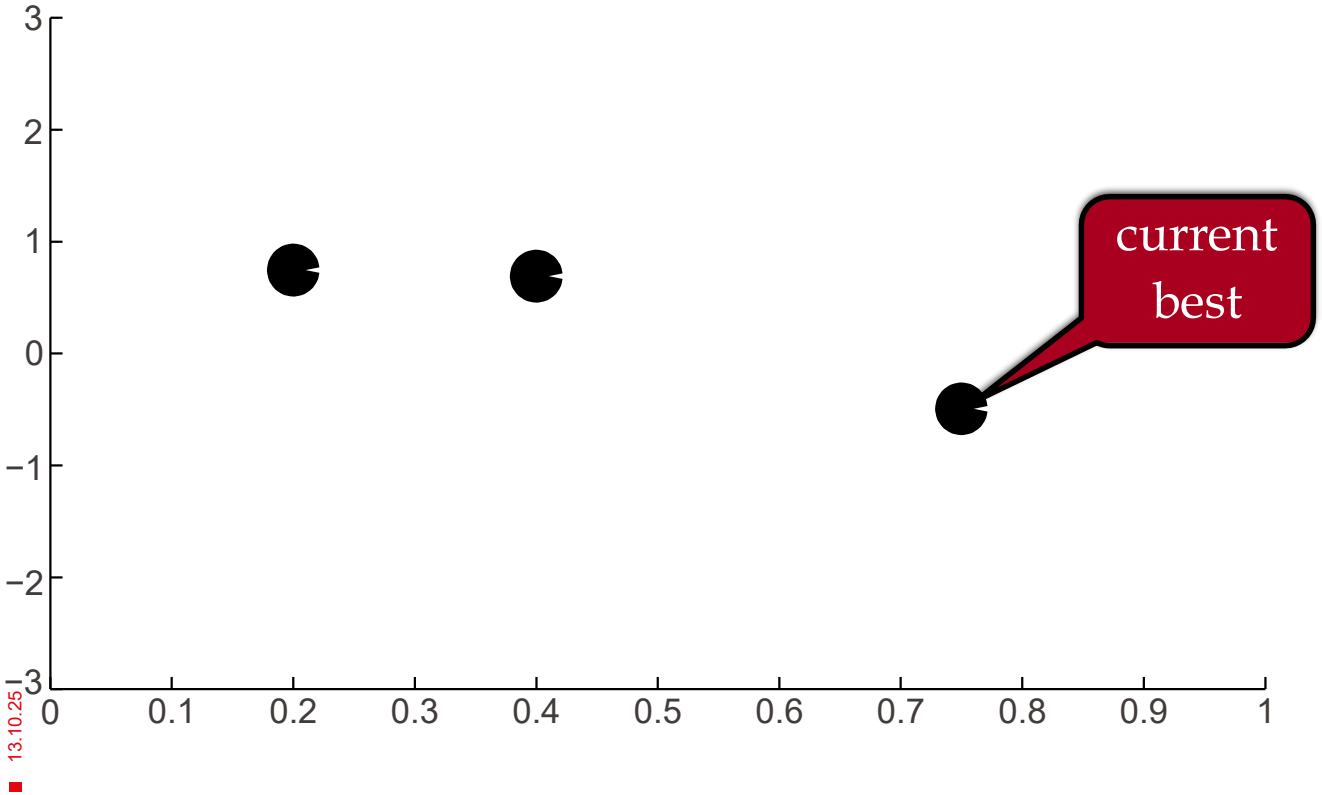
Source: R. Adams, 2017

# Bayesian Optimization

- Frame Hyperparameter Search as an Optimization Problem
- Model the estimation of the function from hyperparameters to the error metric as a regression problem
- Use Gaussian Process Prior: “Similar inputs have similar outputs” to build a statistical model of the function. Prior is weak but general and effective.
- Use statistics to tell us:
  - Location of expected minimum of the function
  - Expected Improvement of trying other parameters

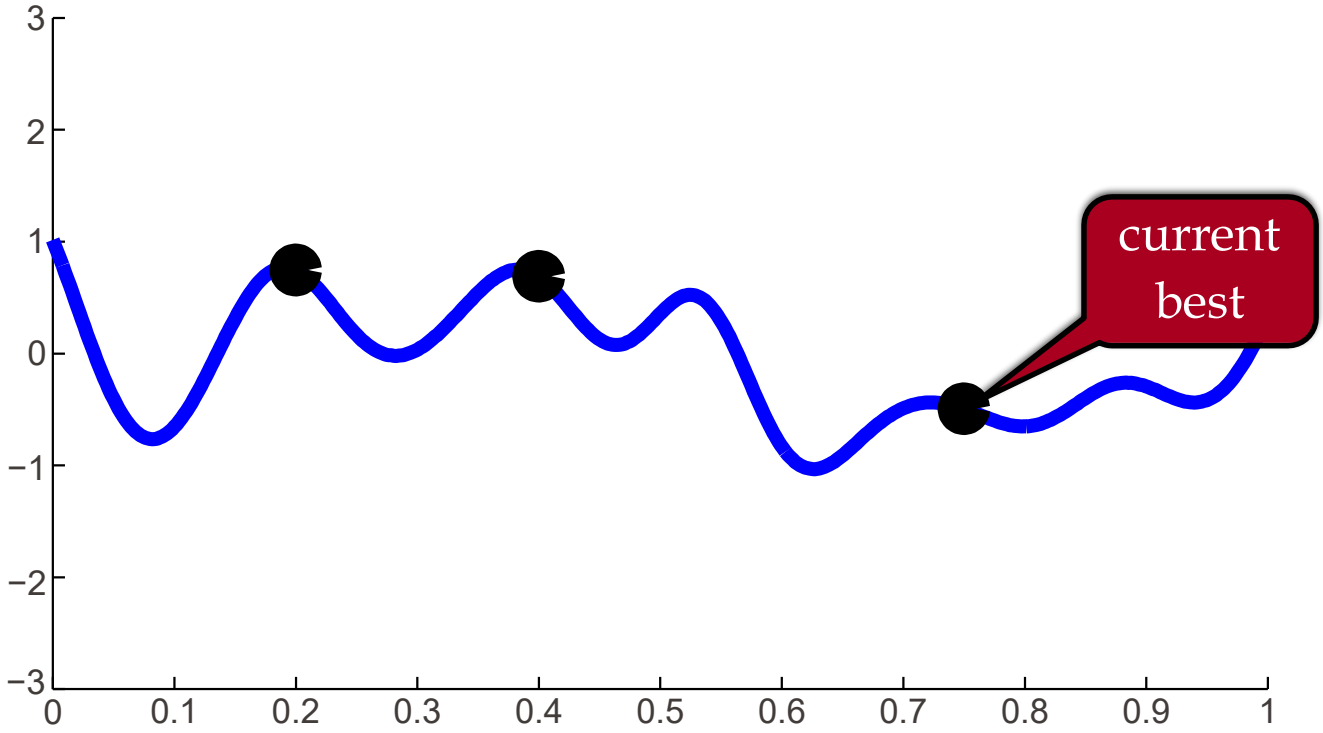
Source: Snoek et. al., 2012

# The Bayesian Optimization Idea



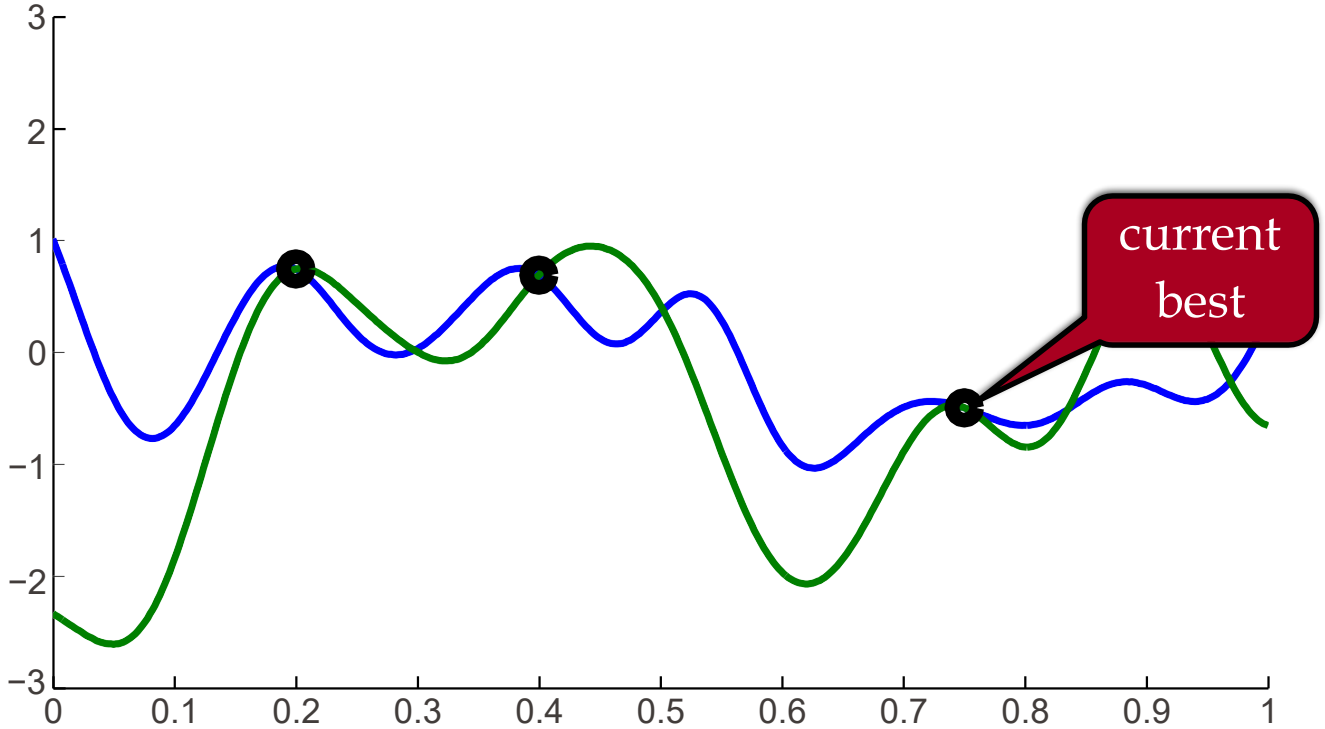

Source: R. Adams, 2017

# The Bayesian Optimization Idea



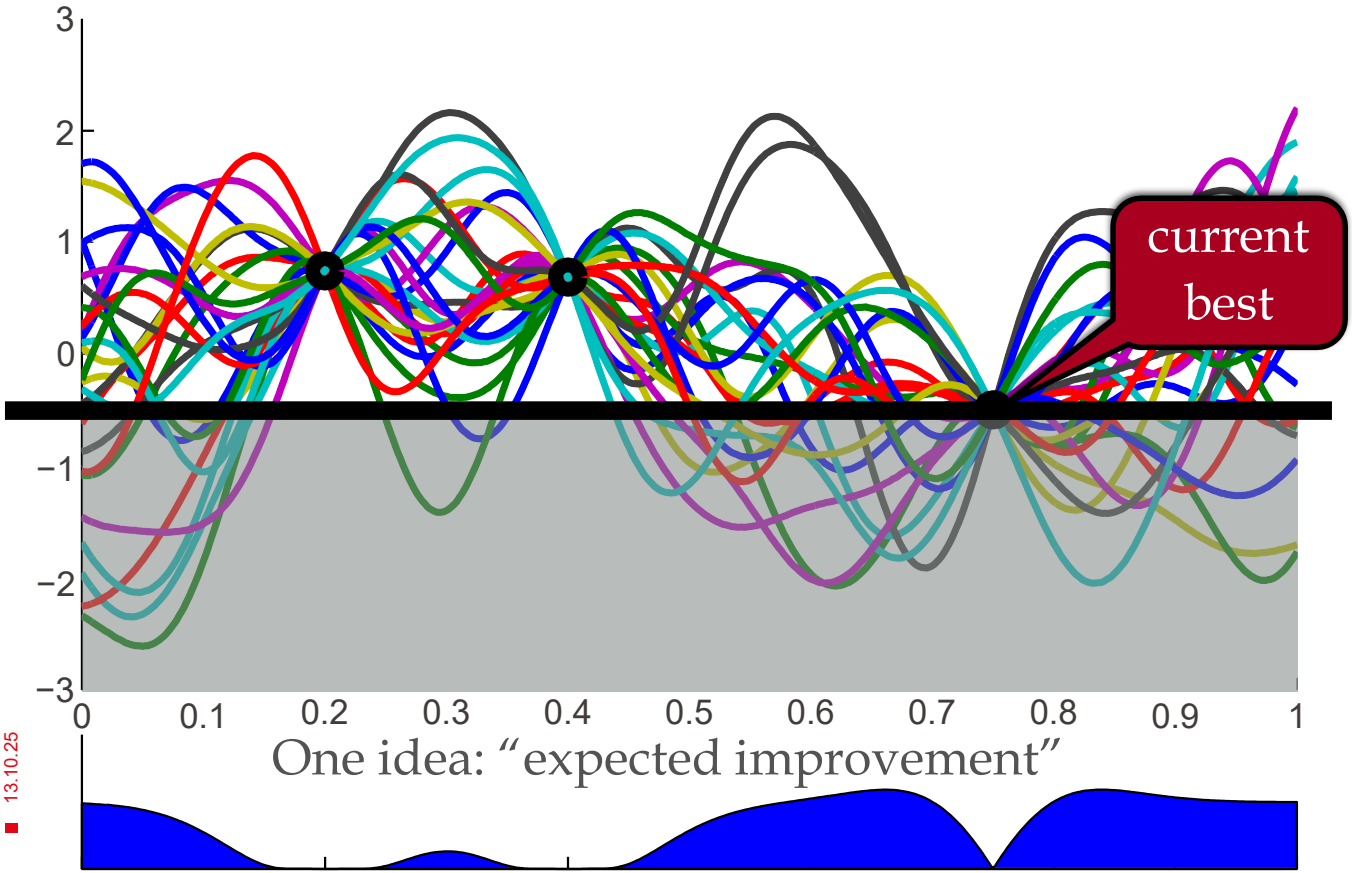

Source: R. Adams, 2017

# The Bayesian Optimization Idea




Source: R. Adams, 2017

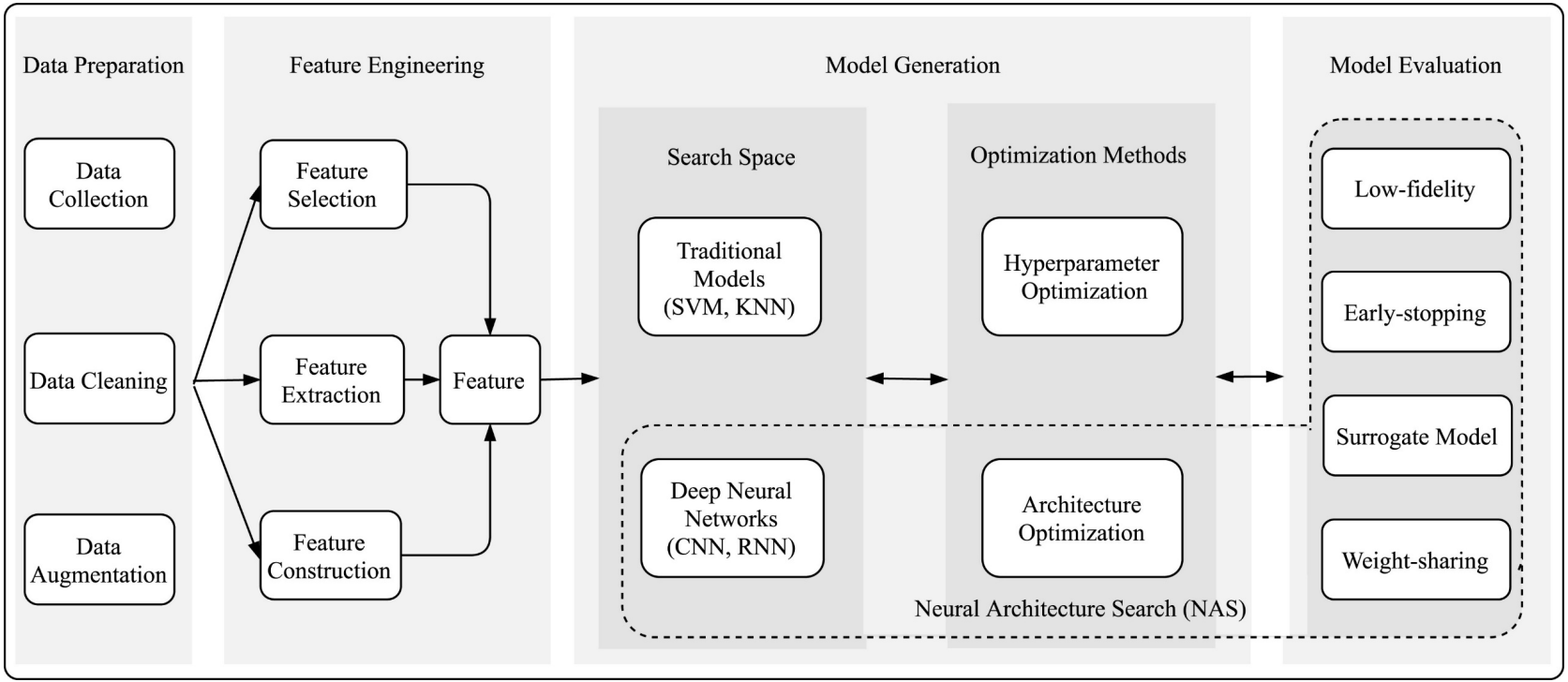
# The Bayesian Optimization Idea




Where should we evaluate next in order to improve the most?

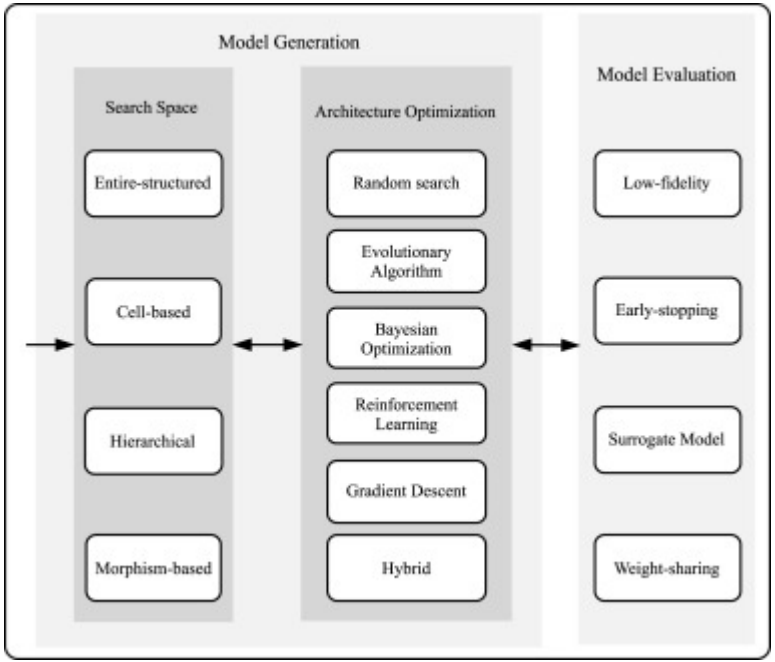
Source: R. Adams, 2017

# From hyperparameter search to Neural Architecture Search



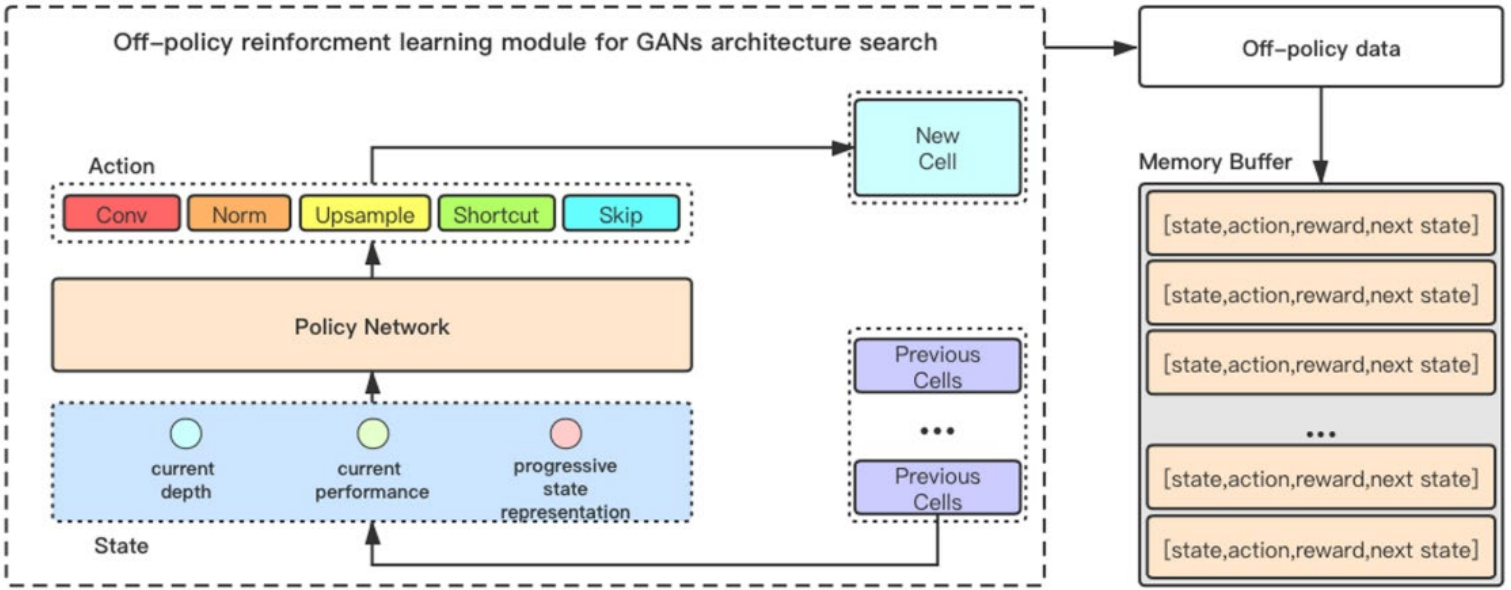

He, Xin, Kaiyong Zhao, and Xiaowen Chu. "AutoML: A Survey of the State-of-the-Art." *Knowledge-Based Systems* 212 (2021): 106622.

# An overview of neural architecture search pipeline




He, Xin, Kaiyong Zhao, and Xiaowen Chu. "AutoML: A Survey of the State-of-the-Art." *Knowledge-Based Systems* 212 (2021): 106622.

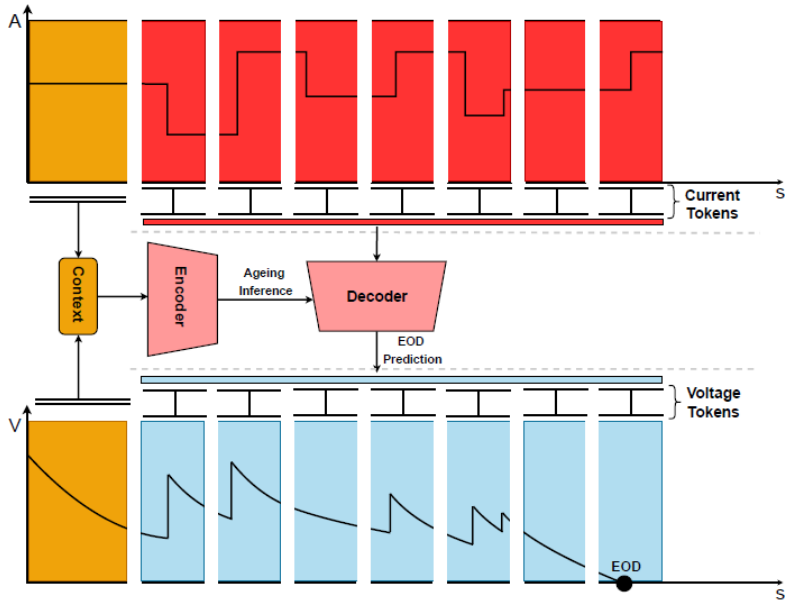
# Reinforcement learning for GAN architecture search




Tian, Y., Wang, Q., Huang, Z., Li, W., Dai, D., Yang, M., ... & Fink, O. (2020, August). Off-policy reinforcement learning for efficient and effective gan architecture search. In *European Conference on Computer Vision* (pp. 175-192). Springer, Cham.

# Tools and libraries

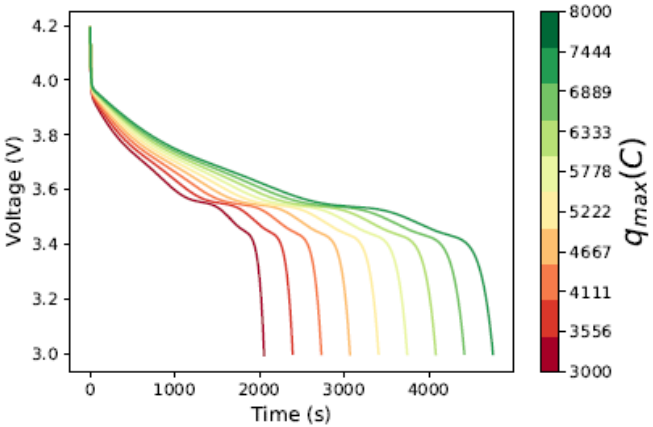
- **Scikit-learn**: Offers grid and random search capabilities.
- **Hyperopt**: Advanced optimization, including Bayesian and random.
- **Optuna**: Framework for automatic hyperparameter optimization, supporting sophisticated algorithms.

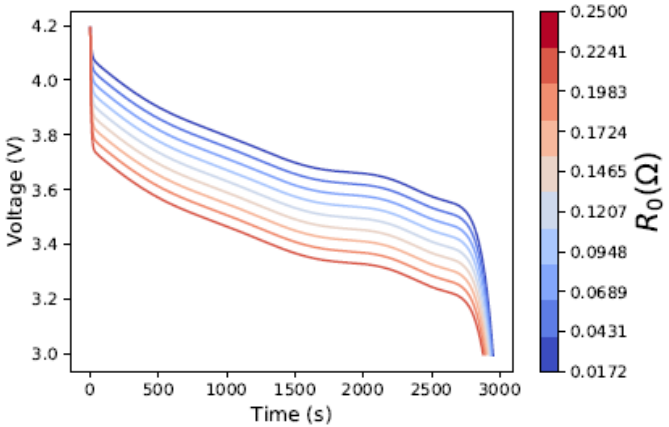



# Ageing-aware Battery Discharge Prediction

# Degradation of Li-Ion batteries → importance of precise planning

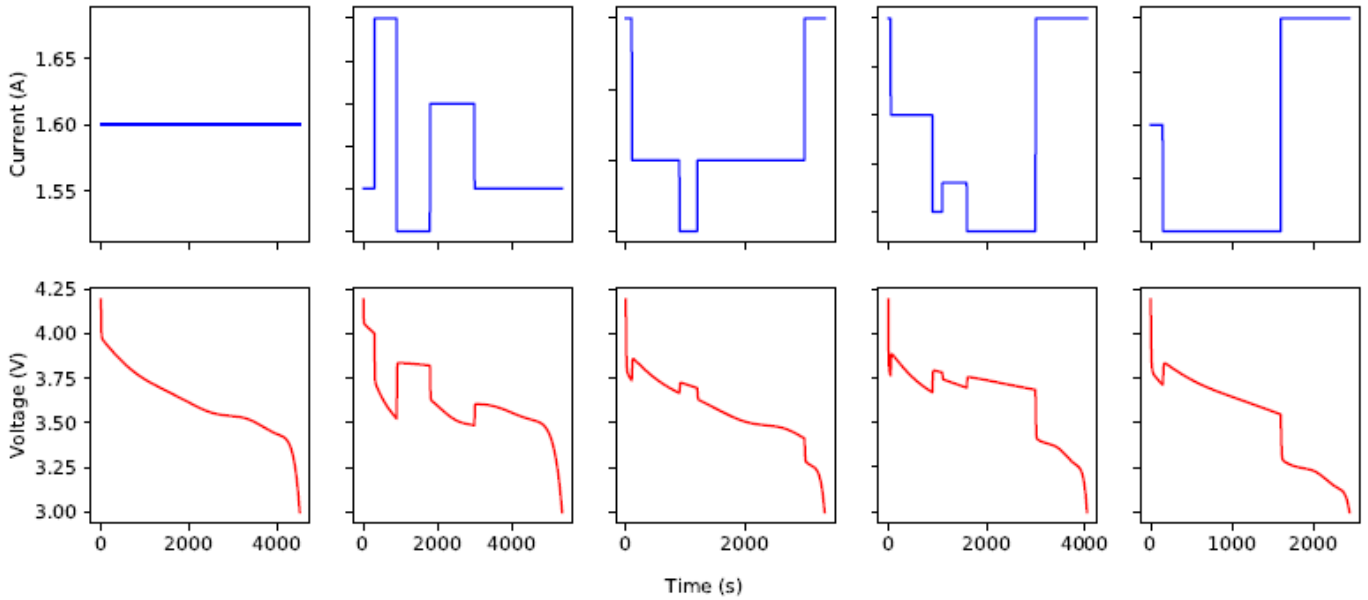
# Effect of varying the degradation parameters on the voltage discharge curve of a Li-ion battery



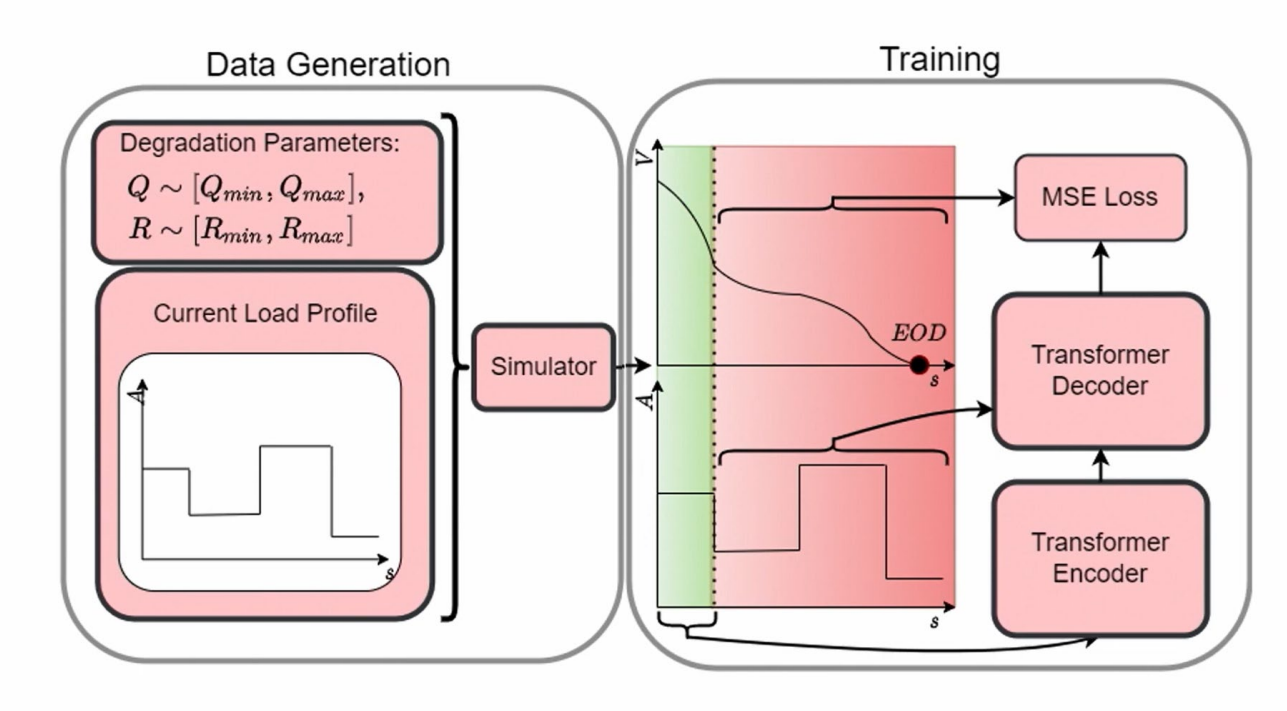

Biggio, L., Bendinelli, T., Kulkarni, C., & Fink, O. (2023). Ageing-aware battery discharge prediction with deep learning, Applied Energy

# Discharge behaviors with respect to the different load profiles



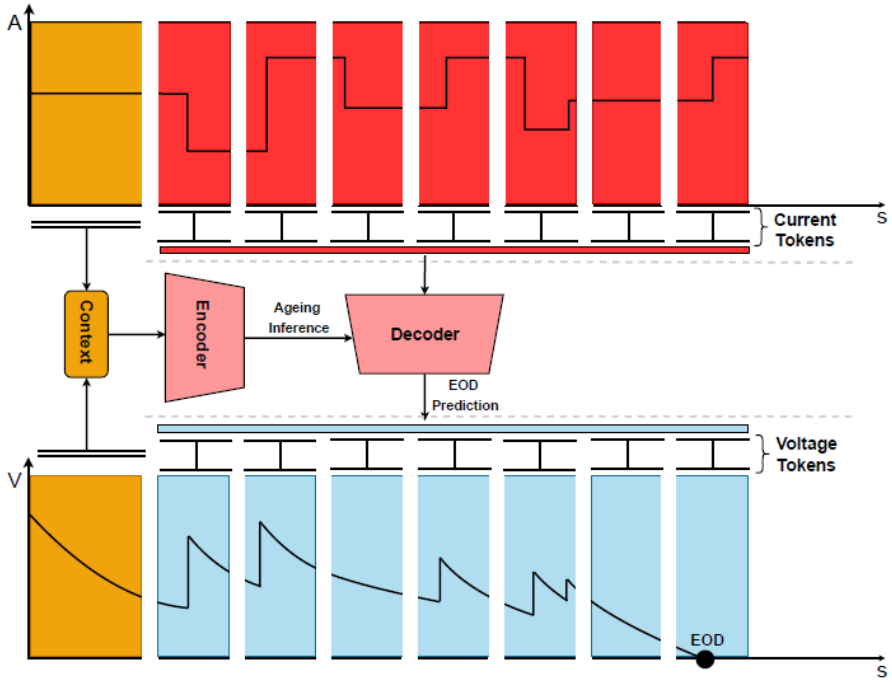

Biggio, L., Bendinelli, T., Kulkarni, C., & Fink, O. (2023). Ageing-aware battery discharge prediction with deep learning, Applied Energy

# Data generation + training



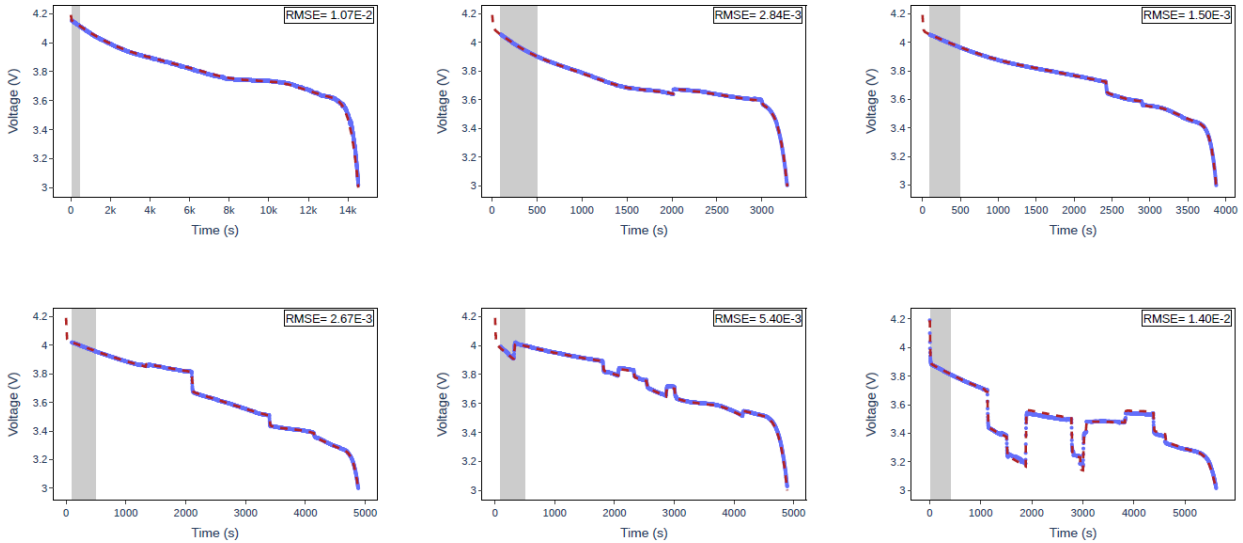

Biggio, L., Bendinelli, T., Kulkarni, C., & Fink, O. (2023). Ageing-aware battery discharge prediction with deep learning, Applied Energy

# Transformer-based long-term battery discharge prediction → Dynaformer



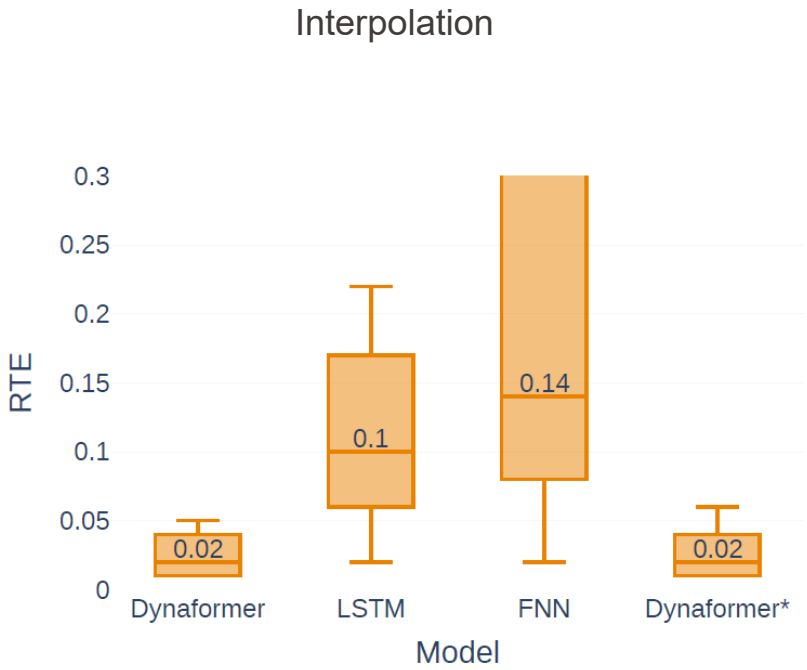

Biggio, L., Bendinelli, T., Kulkarni, C., & Fink, O. (2023). Ageing-aware battery discharge prediction with deep learning, Applied Energy

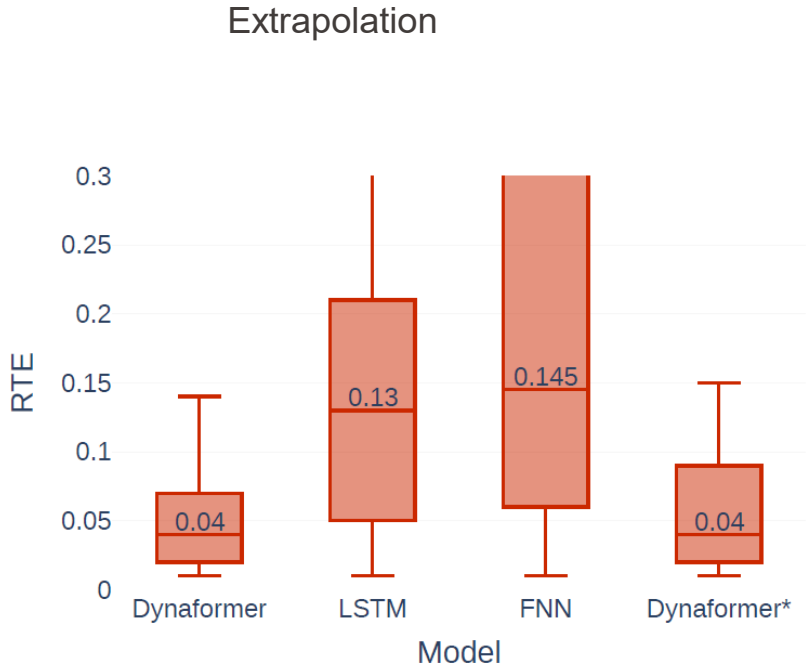
# Selected results




Biggio, L., Bendinelli, T., Kulkarni, C., & Fink, O. (2023). Ageing-aware battery discharge prediction with deep learning, Applied Energy

# Performance without fine-tuning



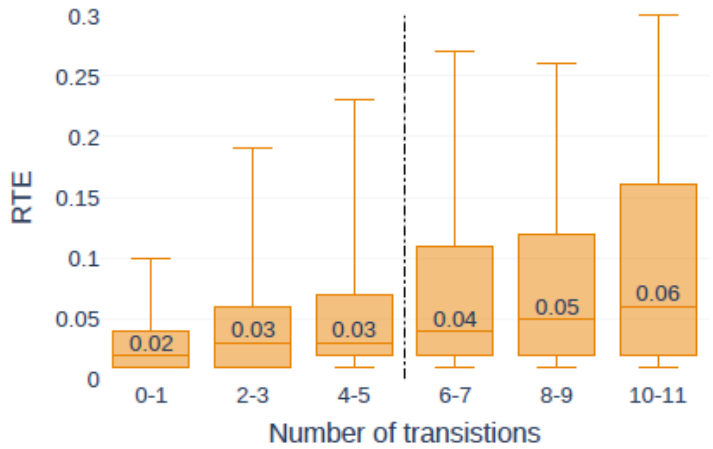




Dynaformer* → trained with variable current profiles

*RTE = relative temporal error

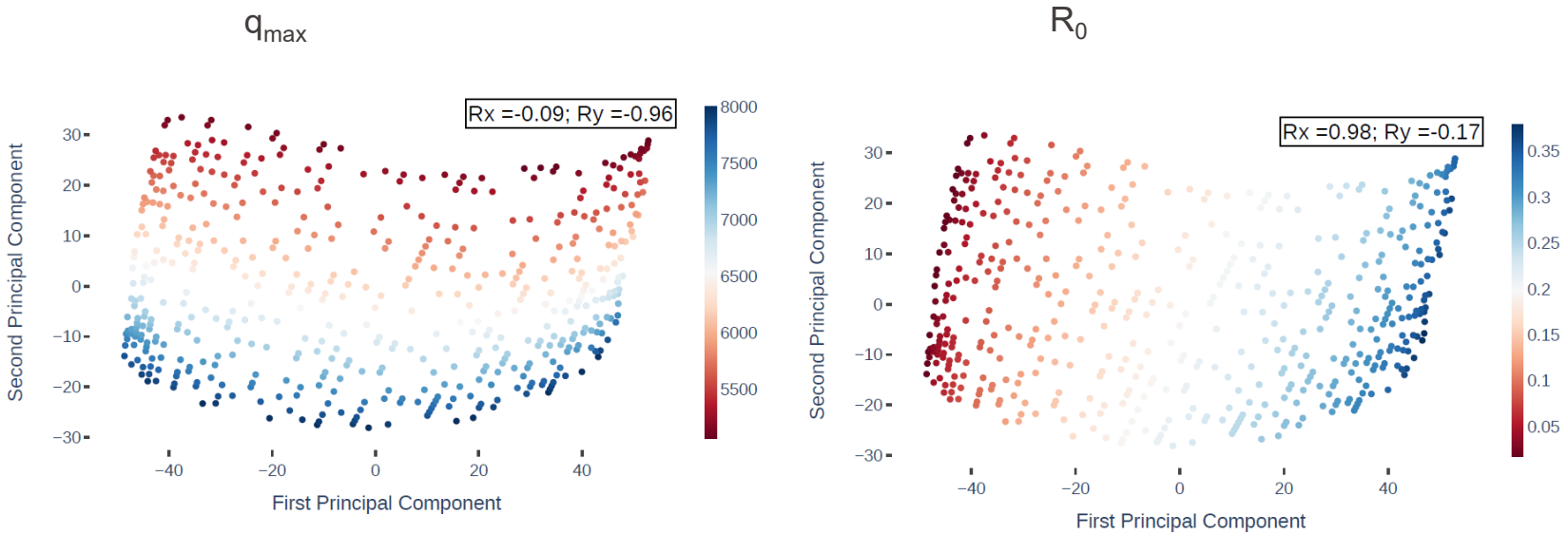
Biggio, L., Bendinelli, T., Kulkarni, C., & Fink, O. (2023). Ageing-aware battery discharge prediction with deep learning, Applied Energy

# Performance dependent on the complexity of the the load profiles




Biggio, L., Bendinelli, T., Kulkarni, C., & Fink, O. (2023). Ageing-aware battery discharge prediction with deep learning, Applied Energy

# Implicit learning of the degradation parameters in the latent space




Biggio, L., Bendinelli, T., Kulkarni, C., & Fink, O. (2023). Ageing-aware battery discharge prediction with deep learning, Applied Energy