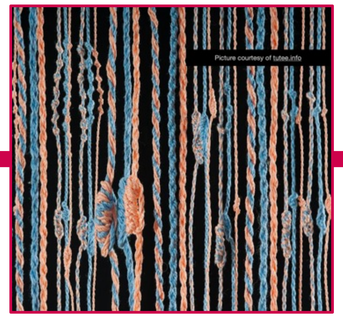
CONTROL IN STEEL



(3-Fold) Digitalisation as Key Driver for Steel Industry

M. J. Neuer, N. Holzknecht, N. Link, M. Feldges, A. Dunayvitser, M. Loos, A. Wolff and R. Lathe

2022-06-28, Digitalisation as key driver for steel industry: Cases from some RFCS projects

BFI Excellence in Applied Research

Research Fund for Coal & Steel

About the project

CONTROL IN STEEL

- ControlInSteel is a dissemination activity focusing **advanced automation and control**
  - We selected around **45(+5) former RFCS research projects** for a scientific analysis
  - Mission goals were
    - 1. Analyze and understand **dynamics** of the **problem-**, **solution-** and **impact space** which also includes **barriers** and **issues**, as well as **physical interaction channels**
    - 2. Perform **dissemination events**, e.g. conference sessions and workshops to effectively distribute knowledge from and about these former projects
    - 3. Provide a **roadmap for future research**

Part 1. Digitalisation & Digital Data

Part 2. The Relation between Physical Information and Reliable Secondary Digitalisation

Part 3. Assorted Application Examples in Steel Production

Part 1. Digitalisation & Digital Data

Data was never a new concept

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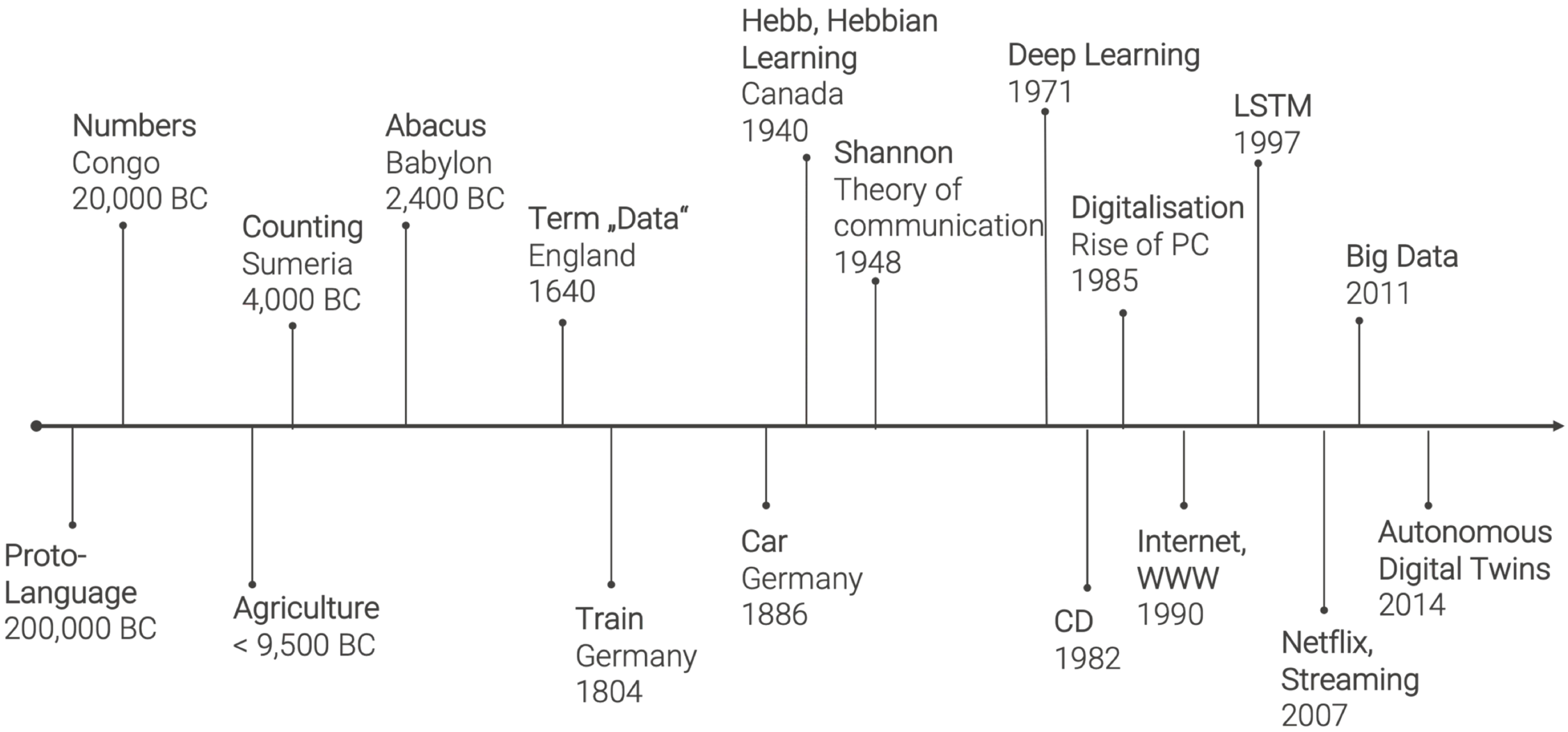

Relevance of data storage

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Picture taken from Wikipedia under Creative Commons, photo reproduction prior to 1926

Innovation arises from the **methodology we use to evaluate data**.

Even digital data is not new...

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- Inca Quipu
- Simple, **digital** instructions
- Fully functional information storage and transfer

- Quipus even store semantic context information in different coloring

Digital Data originates from Digital Sampling

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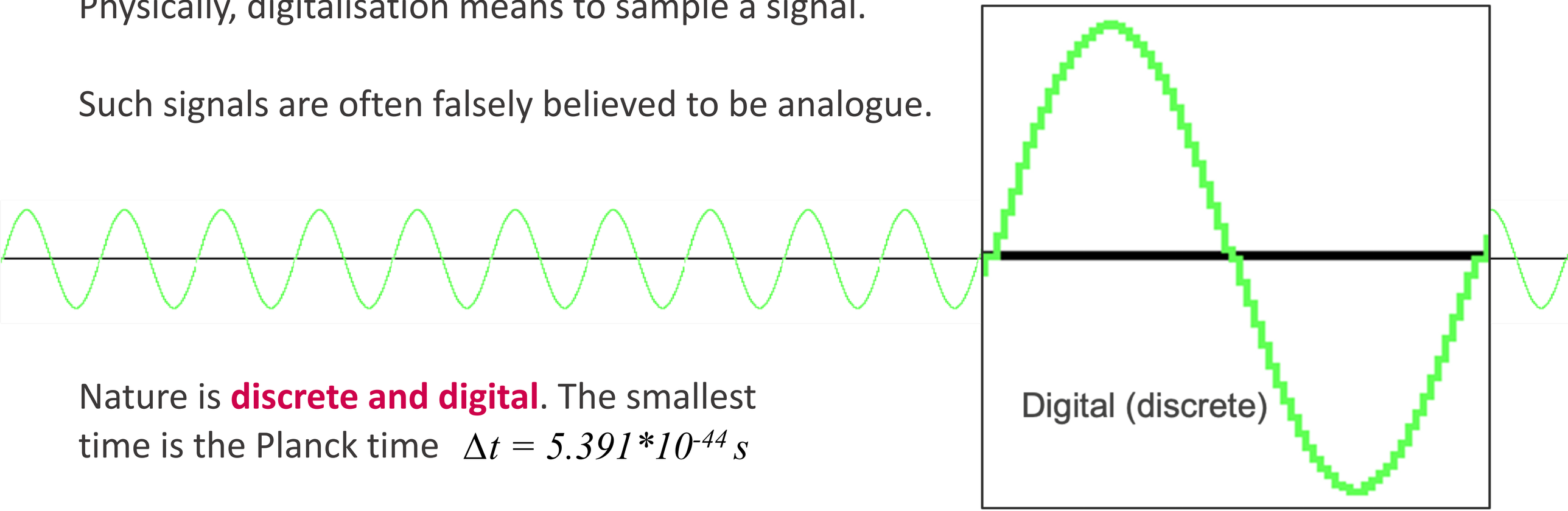
Physically, digitalisation means to sample a signal.

Such signals are often falsely believed to be analogue.



Nature is **discrete and digital**. The smallest time is the Planck time $\Delta t = 5.391 * 10^{-44}\, s$

Digitalisation in Industry (and in Steel Industry)

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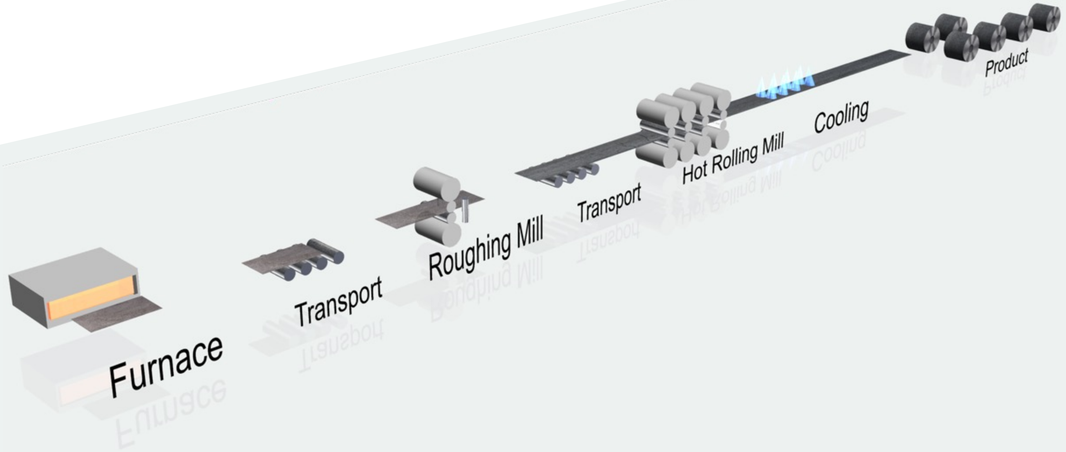
- Primary digitalisation
  - Sampling of **time series** (length series)
  - Sampling of parameters and variables

- Secondary digitalisation
  - Factory wide **automatic availability of digital information**
  - **Computer models** that represent process chains
  - Enabling or improving the flow of data across chain aggregates (horizontal integration, I4.0)
  - Application of **semantic tools**



Part 2. The Relation between Physical Information and Reliable Secondary Digitalisation

How can we formalize digitalisation...

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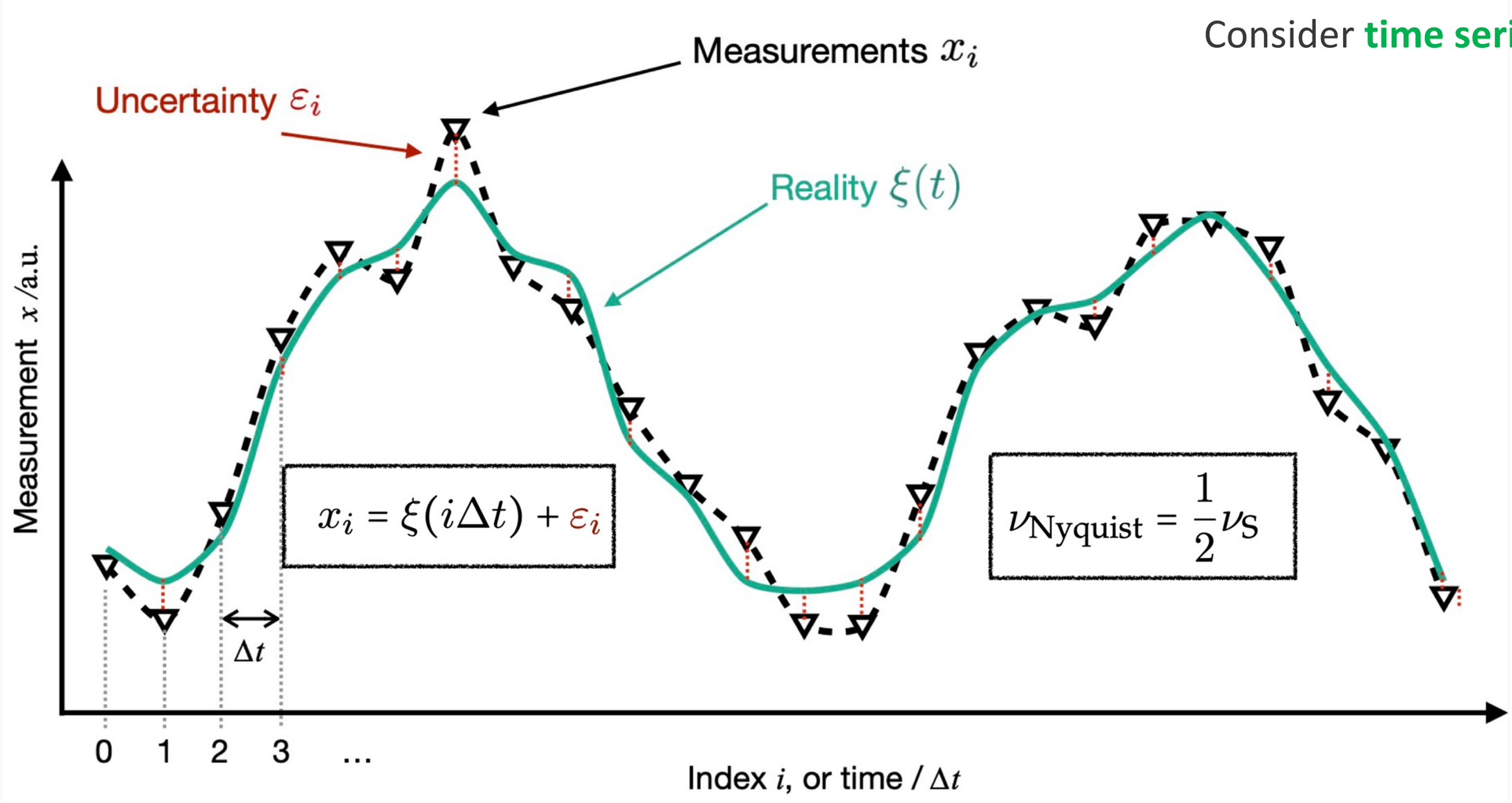
Consider **time series data**



Data as Signal Matrix

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$$x_i = \xi(i\Delta t) + \varepsilon_i$$

$$\boldsymbol{X} = \begin{pmatrix} \boldsymbol{x}_0 \\ \boldsymbol{x}_1 \\ \cdots \\ \boldsymbol{x}_{M-1} \end{pmatrix} = \begin{pmatrix} x_{0,0} & x_{1,0} & \cdots & x_{M-1,0} \\ x_{0,1} & x_{1,1} & \cdots & x_{M-1,1} \\ \cdots & \cdots & \cdots & \cdots \\ x_{0,N-1} & x_{M-1,1} & \cdots & x_{M-1,N-1} \end{pmatrix}$$

$$\mu = \langle \boldsymbol{x} \rangle = E(x) = \sum_{i=0}^{M} x_i P(x_i) \rightarrow \mu = \langle \boldsymbol{x} \rangle = \frac{1}{M} \sum_{i=0}^{M} x_i$$

$$\mathrm{Var}(\boldsymbol{x}) = \sigma^2 = \langle (\boldsymbol{x} - \langle \boldsymbol{x} \rangle)^2 \rangle$$

Inductive Statistics

Machine Learning

Famous Principal Component Analysis (PCA)

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$$\boldsymbol{X} = \begin{pmatrix} x_{0,0} & x_{0,1} & \dots & x_{0,M-1} \\ x_{1,0} & x_{1,1} & \dots & x_{1,M-1} \\ \dots & \dots & \dots & \dots \\ x_{N-1,0} & x_{N,1} & \dots & x_{N-1,M-1} \end{pmatrix}$$

$$\boldsymbol{C} = \mathrm{Cov}(\boldsymbol{X}) = \begin{pmatrix} \mathrm{Var}(\boldsymbol{x}_0) & \mathrm{Cov}(\boldsymbol{x}_0, \boldsymbol{x}_1) & \dots & \mathrm{Cov}(\boldsymbol{x}_0, \boldsymbol{x}_{N-1}) \\ \mathrm{Cov}(\boldsymbol{x}_1, \boldsymbol{x}_0) & \mathrm{Var}(\boldsymbol{x}_1) & \dots & \mathrm{Cov}(\boldsymbol{x}_1, \boldsymbol{x}_{N-1}) \\ \dots & \dots & \dots & \dots \\ \mathrm{Cov}(\boldsymbol{x}_{N-1}, \boldsymbol{x}_0) & \mathrm{Cov}(\boldsymbol{x}_{N-1}, \boldsymbol{x}_1) & \dots & \mathrm{Var}(\boldsymbol{x}_{N-1}) \end{pmatrix}$$

$$\boldsymbol{\Lambda} = \boldsymbol{S}^T \boldsymbol{C} \boldsymbol{S}$$

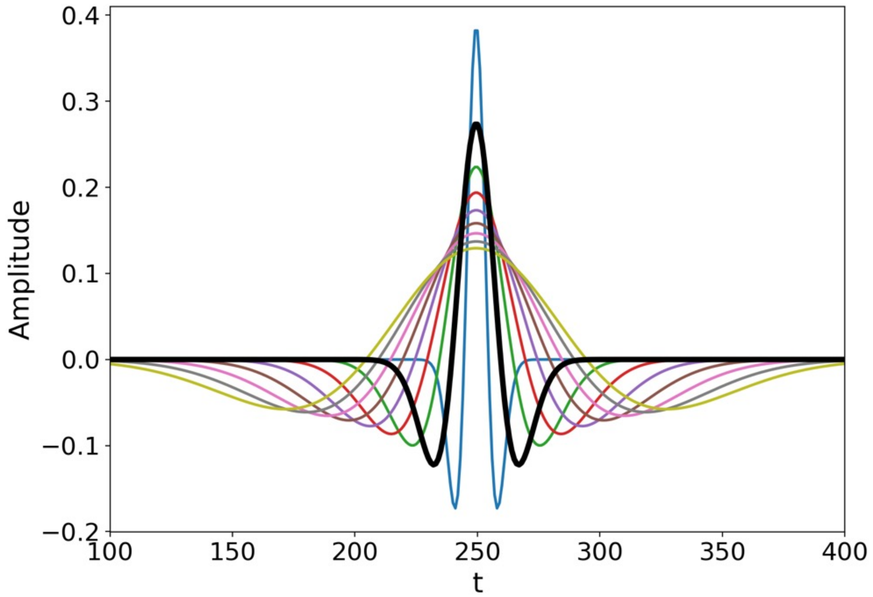
$$\boldsymbol{\Lambda} = \begin{pmatrix} \lambda_0 & 0 & \dots & 0 \\ 0 & \lambda_1 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & \dots & 0 & \lambda_{L-1} \end{pmatrix}$$

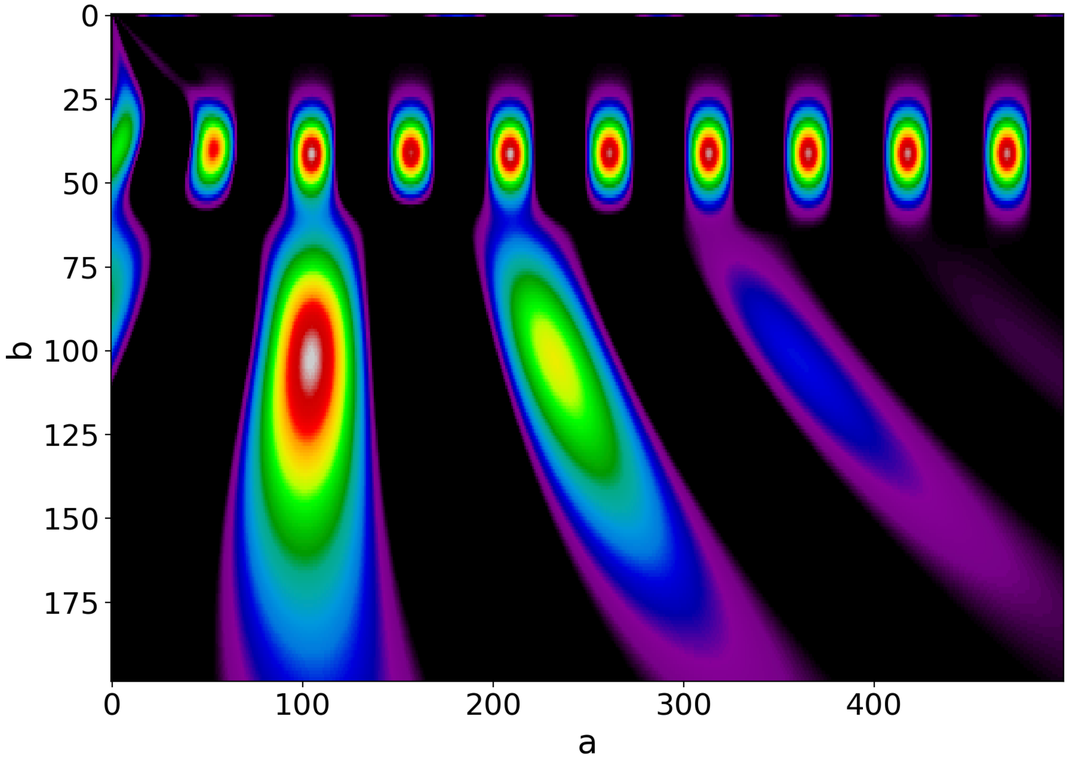
$$\boldsymbol{S} = \begin{pmatrix} s_{0,0} & s_{0,1} & \dots & s_{0,L-1} \\ s_{1,0} & s_{1,1} & \dots & s_{1,L-1} \\ \dots & \dots & \dots & \dots \\ s_{M-1,0} & s_{M-1,1} & \dots & s_{M-1,L-1} \end{pmatrix}$$

- Principal component analysis
- Unsupervised technique
- Eigenspace of covariance matrix

How can we use human rationalism and know-how to **improve this well-known method**?

Data preparation Example Wavelet Transformation





$$\mathrm{CWT}[x(t)](a,b) = \frac{1}{|a|^{\frac{1}{2}}} \int_{-\infty}^{\infty} x(t)\overline{\psi}\left(\frac{t-b}{a}\right) dt$$

Continuous wavelet transformation, as one example for describing oscillatory processes

Analytical Physics-Infusion on PCA

$$\mathrm{Cov}(\boldsymbol{X}) = \begin{pmatrix} \mathrm{Var}(\boldsymbol{x}_0) & \mathrm{Cov}(\boldsymbol{x}_0, \boldsymbol{x}_1) & \dots & \mathrm{Cov}(\boldsymbol{x}_0, \boldsymbol{x}_{N-1}) \\ \mathrm{Cov}(\boldsymbol{x}_1, \boldsymbol{x}_0) & \mathrm{Var}(\boldsymbol{x}_1) & \dots & \mathrm{Cov}(\boldsymbol{x}_1, \boldsymbol{x}_{N-1}) \\ \dots & \dots & \dots & \dots \\ \mathrm{Cov}(\boldsymbol{x}_{N-1}, \boldsymbol{x}_0) & \mathrm{Cov}(\boldsymbol{x}_{N-1}, \boldsymbol{x}_1) & \dots & \mathrm{Var}(\boldsymbol{x}_{N-1}) \end{pmatrix}$$

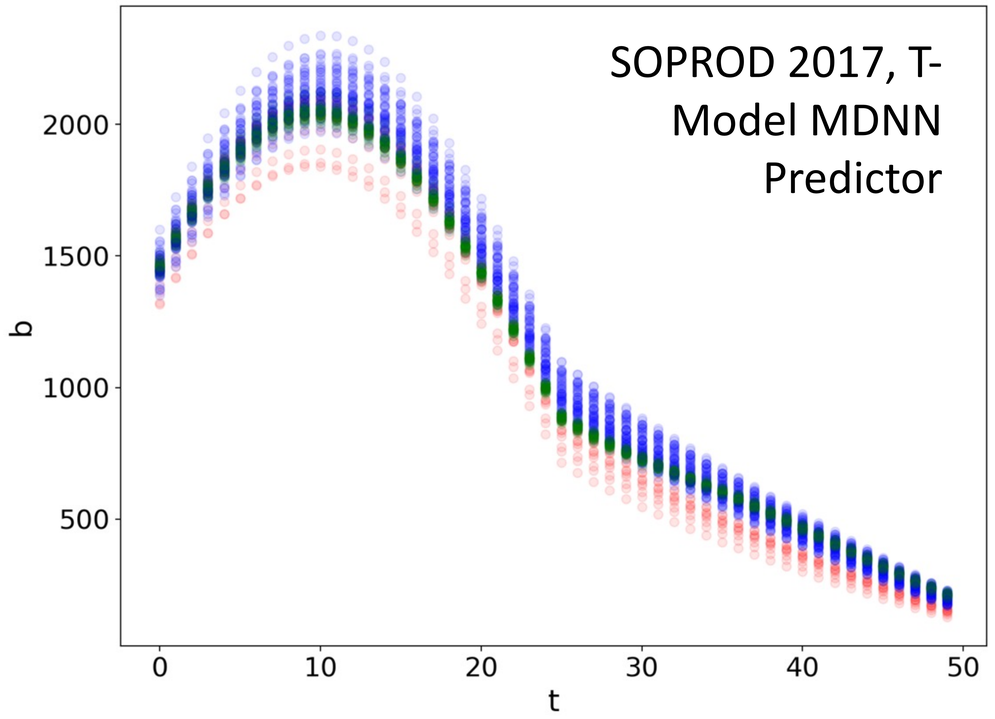
- **Now, we mix both methods**, if (and only if) Ricker wavelets are useful here

$$\mathrm{CWT}[x(t)](a,b) = \frac{1}{|a|^{\frac{1}{2}}} \int_{-\infty}^{\infty} x(t)\overline{\psi}\left(\frac{t-b}{a}\right) dt$$

$$C = \mathrm{Cov}\{\mathrm{CWT}[x(t)](a,b)\}$$

- Now... Eigenspace of the Wavelet covariance matrix

$$\boldsymbol{\Lambda} = \boldsymbol{S}^T \boldsymbol{C} \boldsymbol{S}$$



Digitalisation in Industry (and in Steel Industry)

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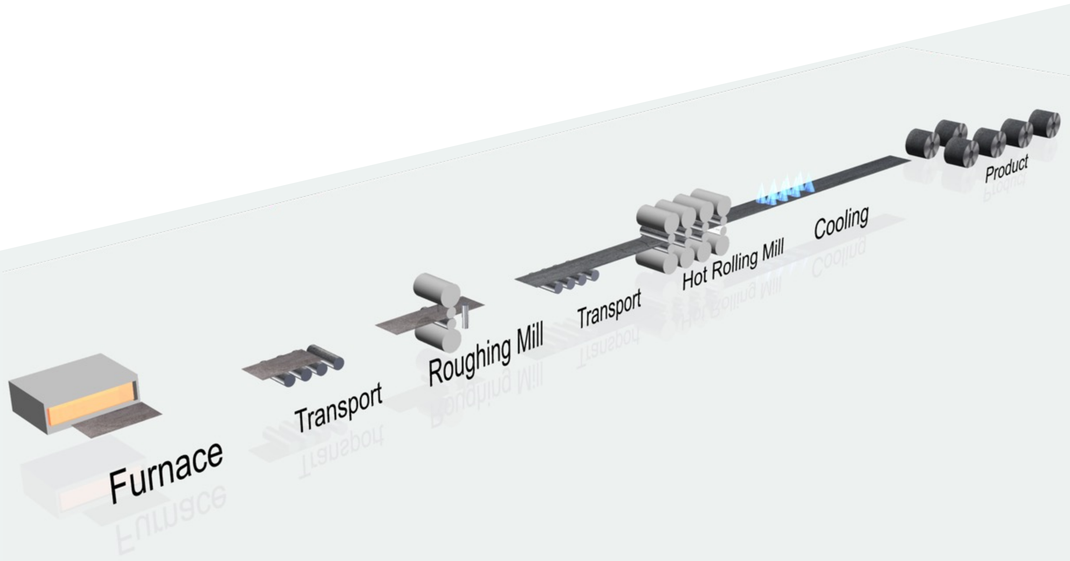
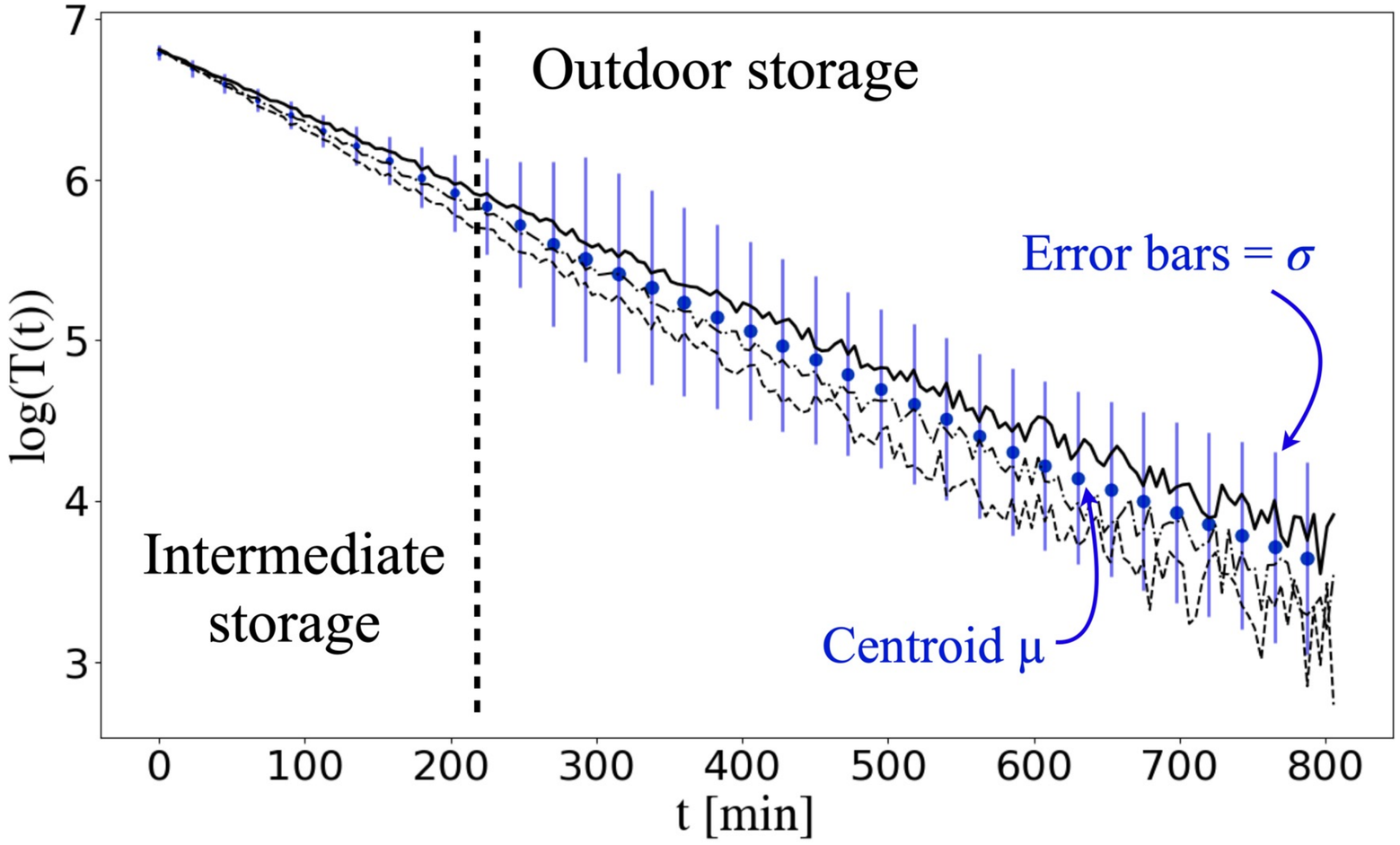
- Tertiary digitalisation
  - Semantic layer which **integrates optimized analysis techniques** (algorithmic integration)
  - Include a digital repository of methodology
    - **If** the process requires a **wavelet preparation**, this can be automatically received from a **semantic database**
  - In specific cases, PCA or other procedures perform better if a suited **physics-informed preprocessing** is applied



Part 3. Assorted Application Examples in Steel Production

Physics-Informed MDNN Temperature Predictor



Ricker Wavelet based temperature prediction mixture density network, for estimating also the uncertainty of the prediction.

Example 2: Mixture Density Network for Scale Prediction

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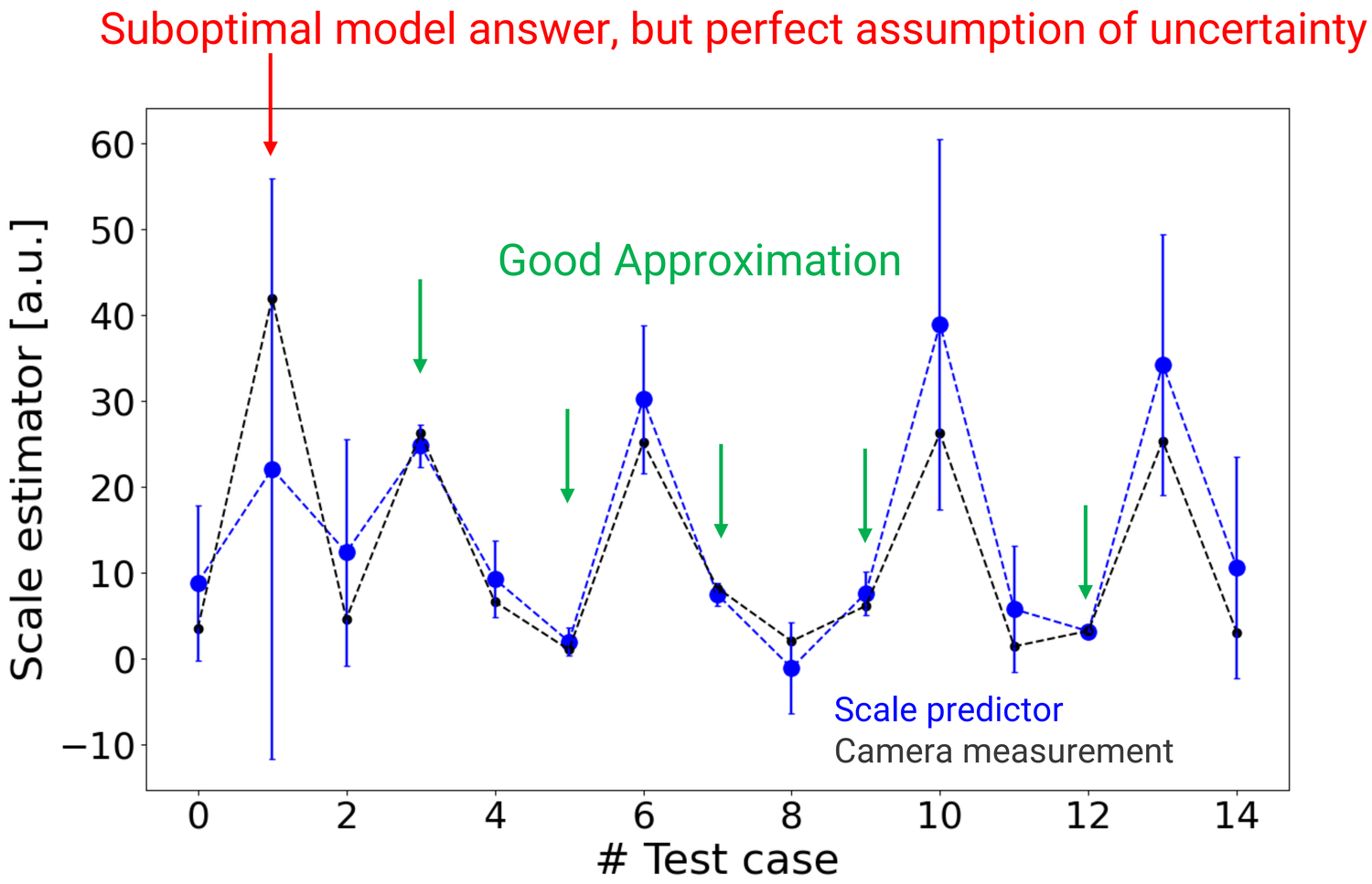
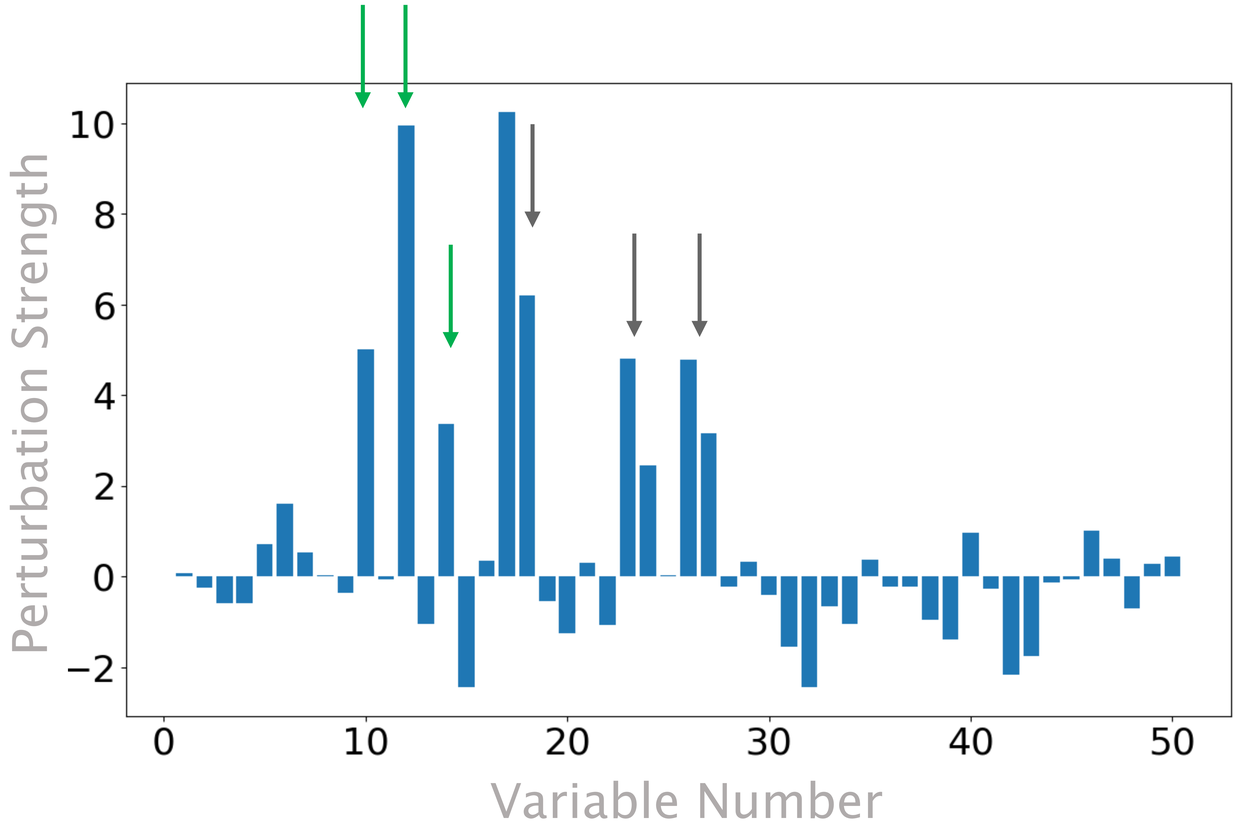
Different example: Scale predictor with MDNN

Scale is estimated together with the **uncertainty** of this prediction



Example 2: Testing for Sensitive Variables



Perturbation theory opened new understand about what variables essentially impacted the scale.

Perturbation theory

- Test vectors

$$T = \{\mathbf{t}^{(1)}, \mathbf{t}^{(2)}, \ldots, \mathbf{t}^{(N)}\}$$

$$\mathbf{t}^{(i)} = (t_1^{(i)}, t_2^{(i)}, \ldots, t_{50}^{(i)})$$

- Stochastic perturbation

$$\tilde{\mathbf{t}}(i,k) = \mathbf{t}^{(i)} + \sum_{\lambda} \delta_{\lambda,k} \mathbf{e}_\lambda \Delta t_k$$

- Tests the influence of specific variables

Summary

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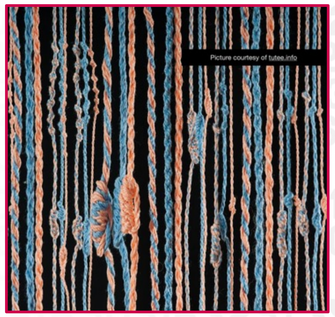
- **Digitalization** allows steel industry to get a full grasp of information about their processes
- **Digital data** can be gathered from the processes

- **Transformations** exists that help to project the data to a certain physically reasonable coordinate system
- Using the example of the well-known PCA, we showed how to apply PCA to a **different covariance space**

- Steel industry can use digitalisation to actually understand the **inherent uncertainties**
- The digital data then leads to tools for **predicting behaviour** or **detecting anomalies**

Thank you for your interest!



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Example 3. Uncertainty Distributions of Processes

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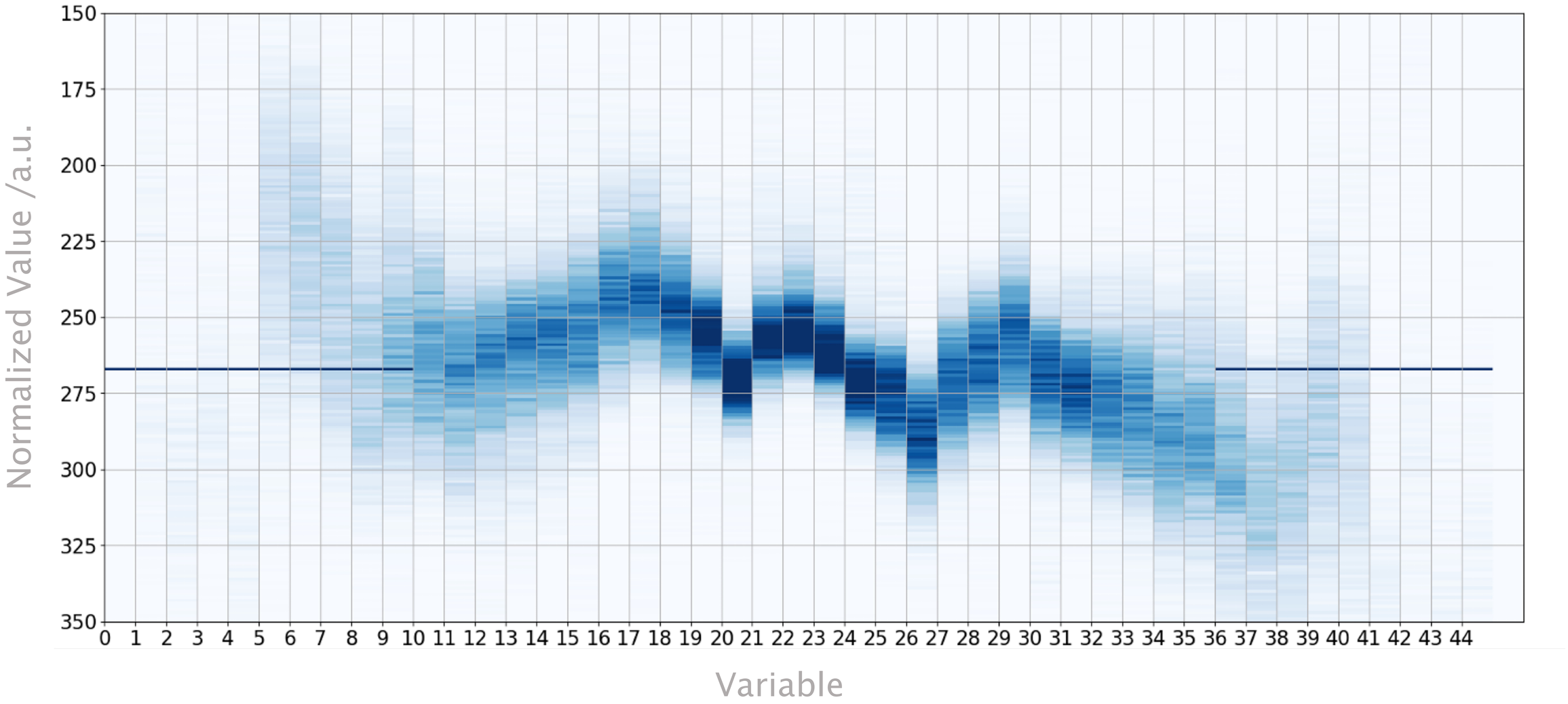
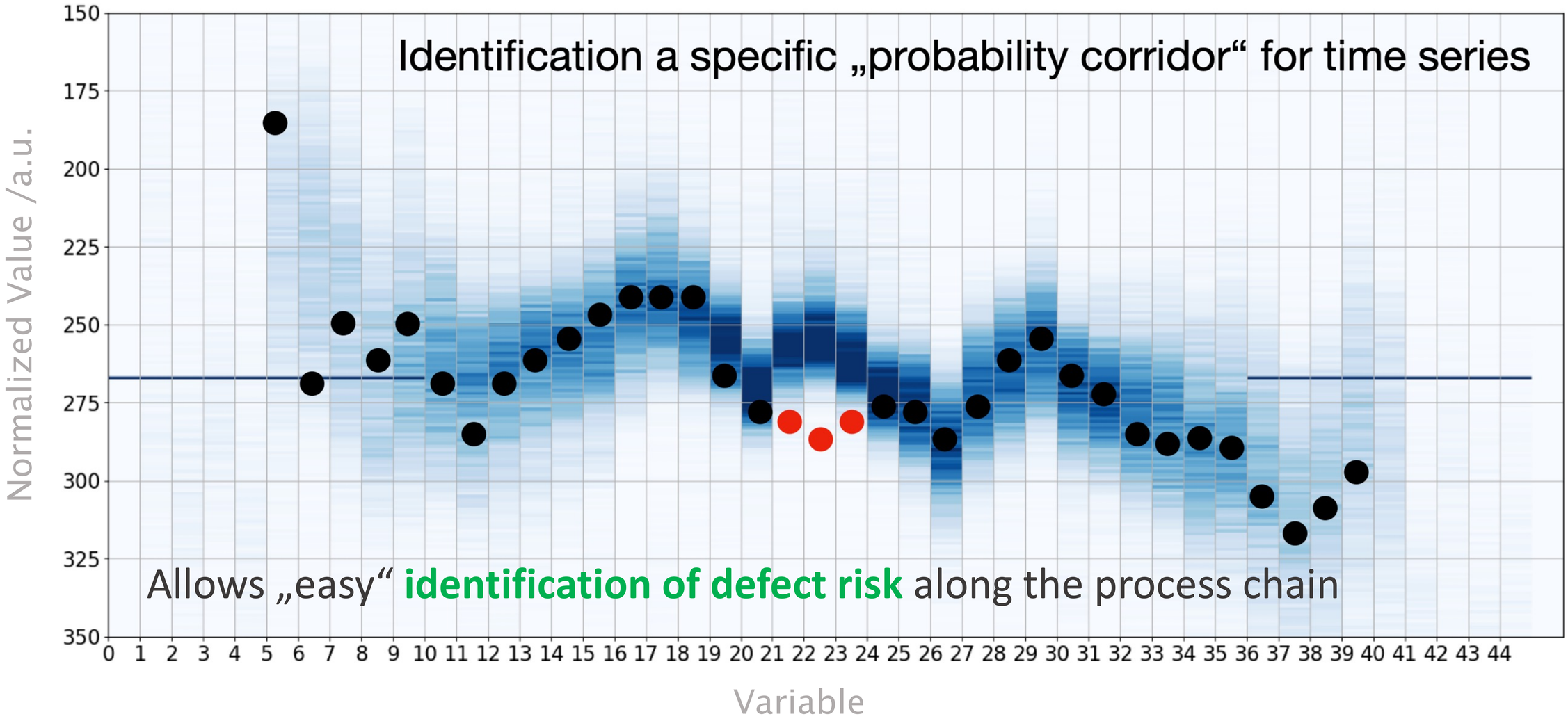


Example 3. Quantifying the process corridor



Physics-Informed Mixture Density Neural Network

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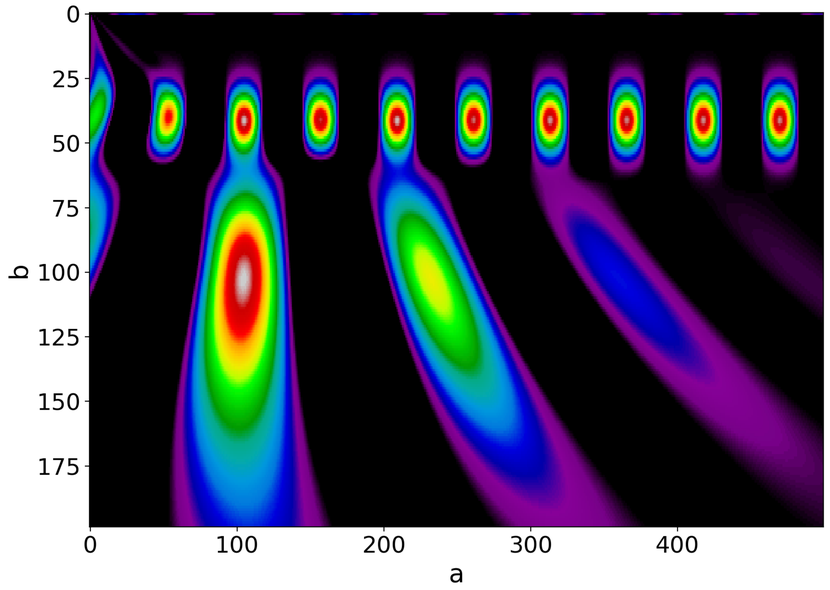
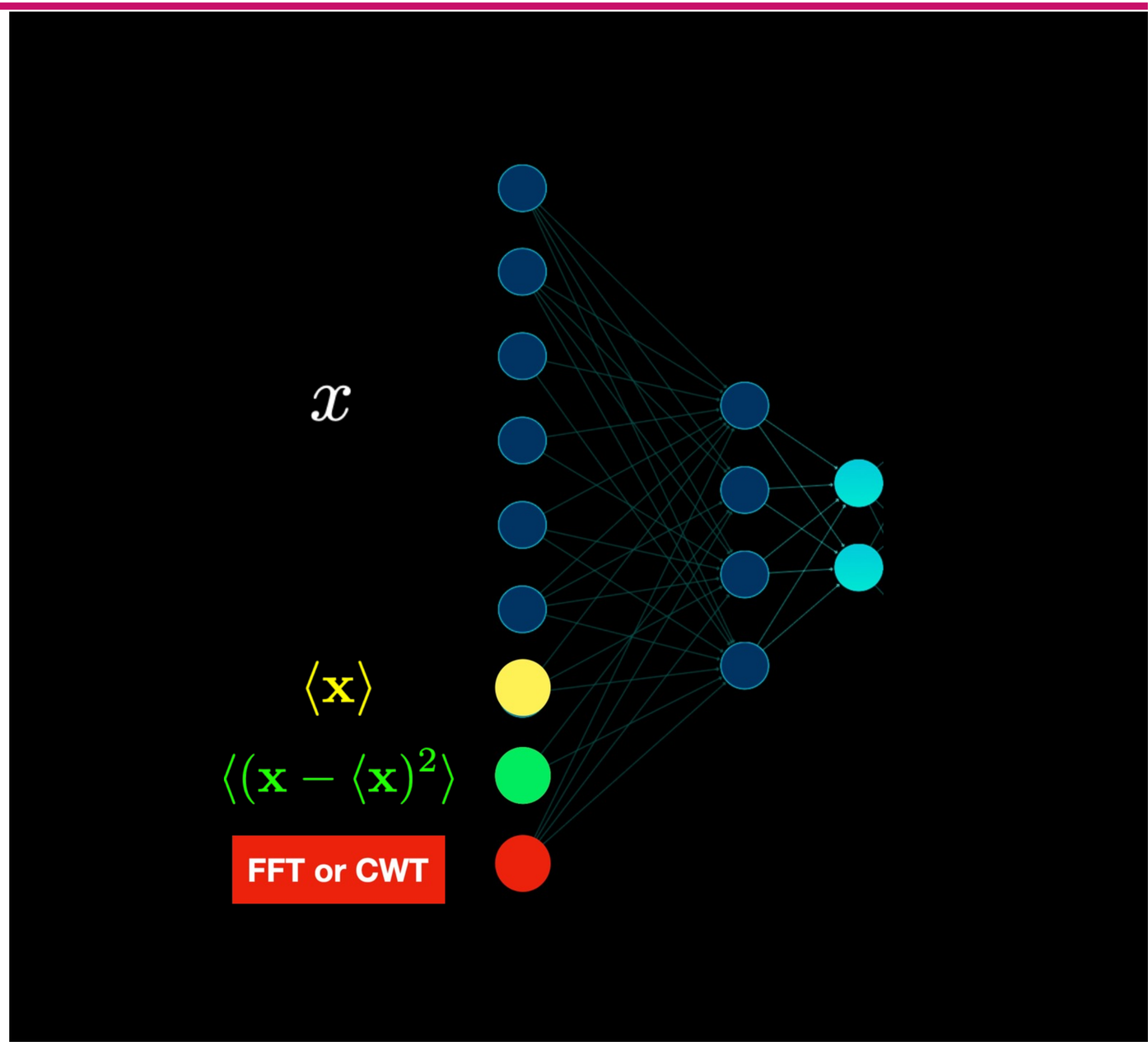
Physics-infusion means to enrich the input or output data of machine learning techniques with information that is based on **physical reasoning**.





Formalisation of data sampling

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