Quantifying uncertainty in probability dynamics of production processes, using physics-informed artificial intelligence

Marcus J. Neuer

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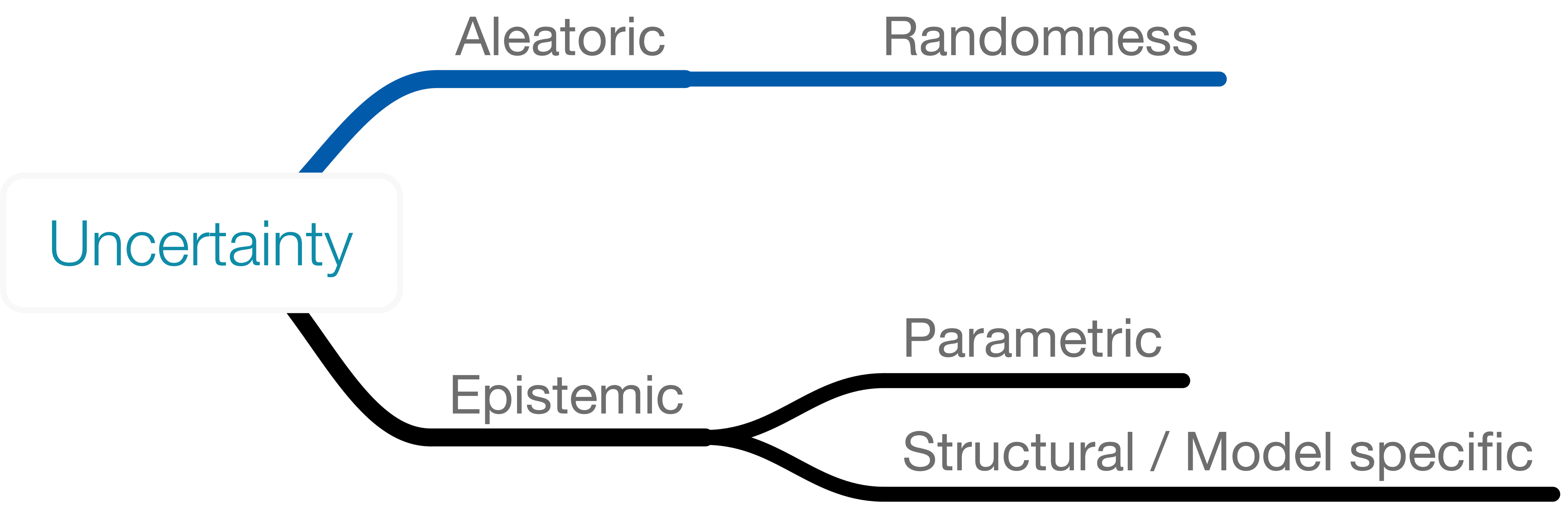
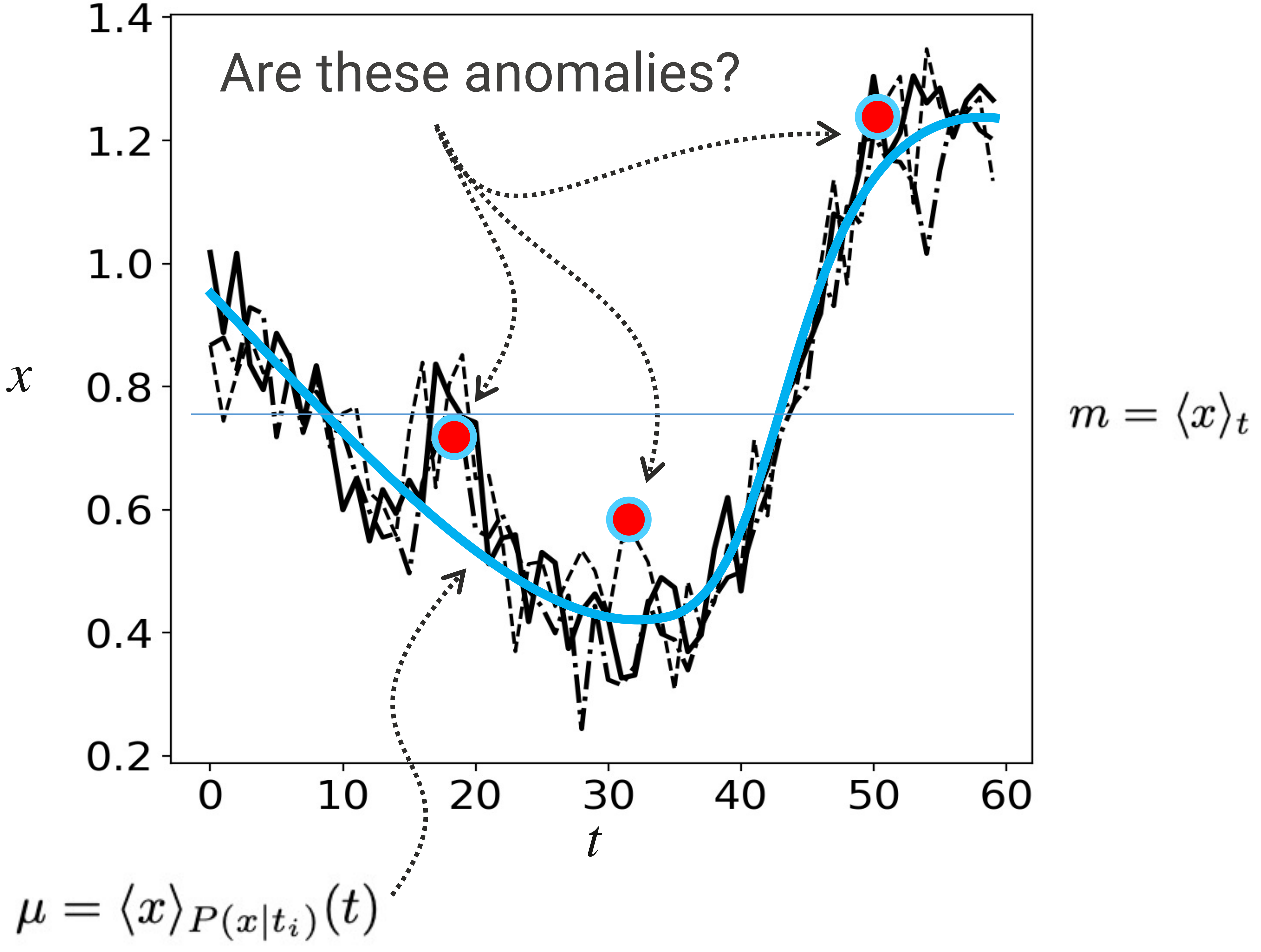
1.

Uncertainties in process data of automation systems

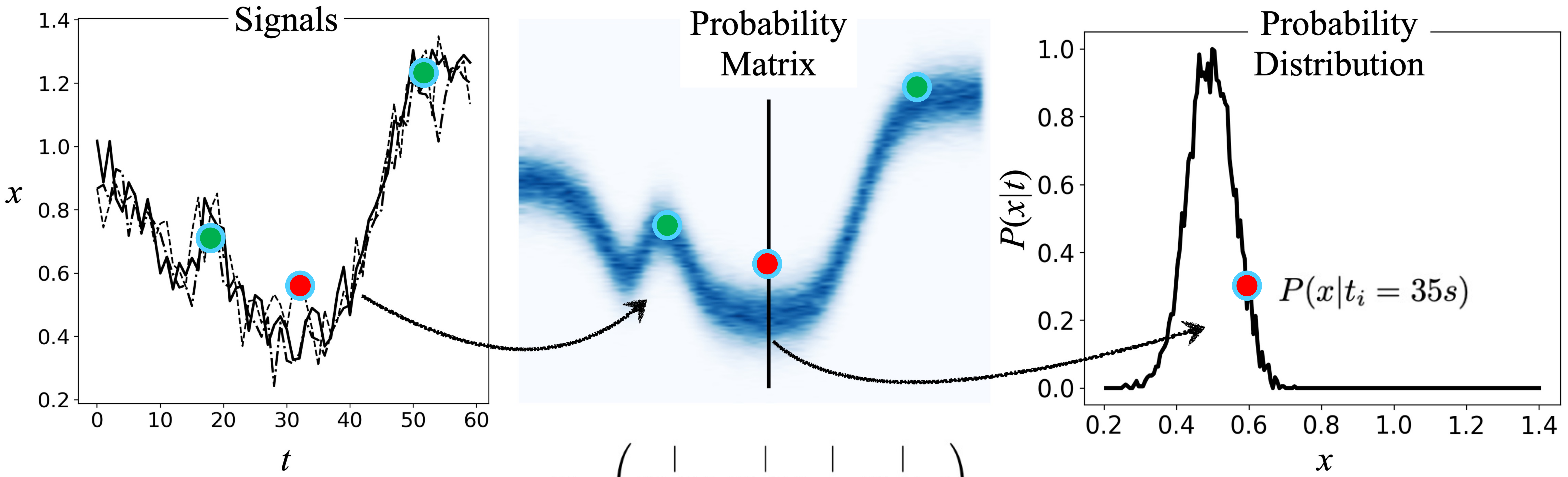


Uncertainty in process variables

- Simple demo signal: normalized, Hall effect test curve in Helmholtz coils
- Use case: detection of anomalies
  - Primary question: how to distinguish the anomalous behaviour and statistics?
- Important information about the aleatoric uncertainty can be extracted from process data



Probability corridor, classical approach



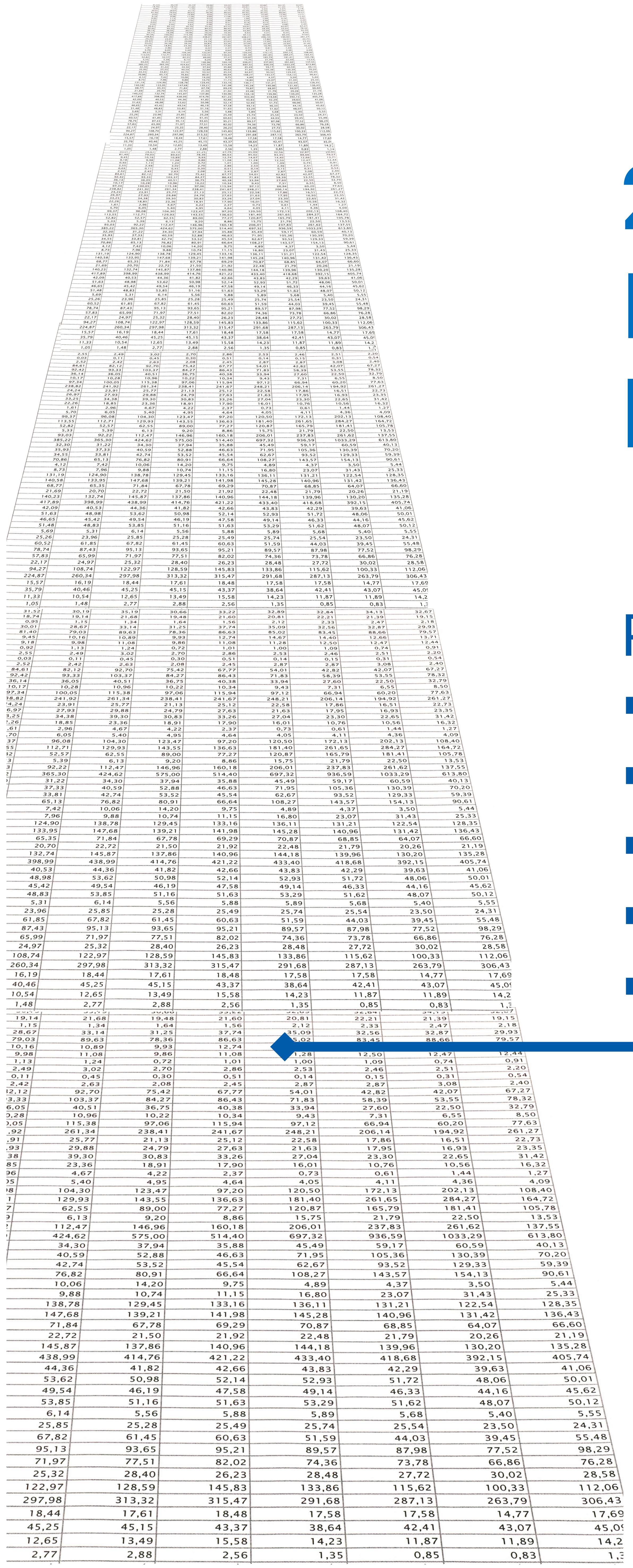
$$\mathbf{P} = \begin{pmatrix} | & | & | & | \\ P(x|t_0) & P(x|t_1) & \dots & P(x|t_N) \\ | & | & | & | \end{pmatrix}$$

Generation of moments:

$$\mu_k(t_i) = \int_{-\infty}^{\infty} x^k P(x|t_i) dx$$

$$\mu_k(t_i) = \sum_k^{\infty} x^k P(x|t_i)$$

- Now, we do not only have the mean curve, but also all moments, including the 2nd moment, the variance and higher moments

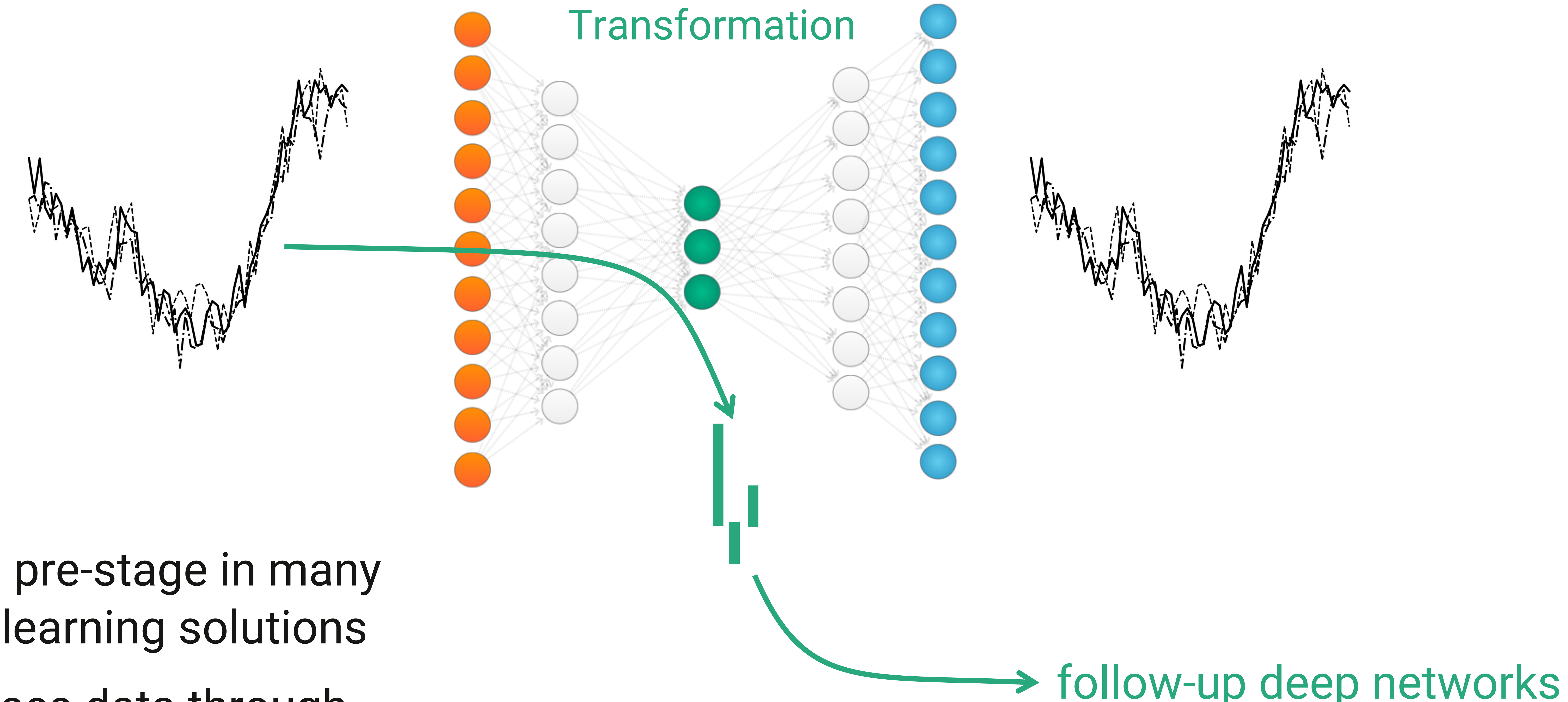


2.
Physics-informed, variational autoencoder & latent space probability distributions

Process data
- Streams
- Telegrams
- Tabular
- Machine oriented
- Time-series

Object data
- Per run, per product
- Prepared time-series
- All relevant data
- Ideally labelled
- Timestamped

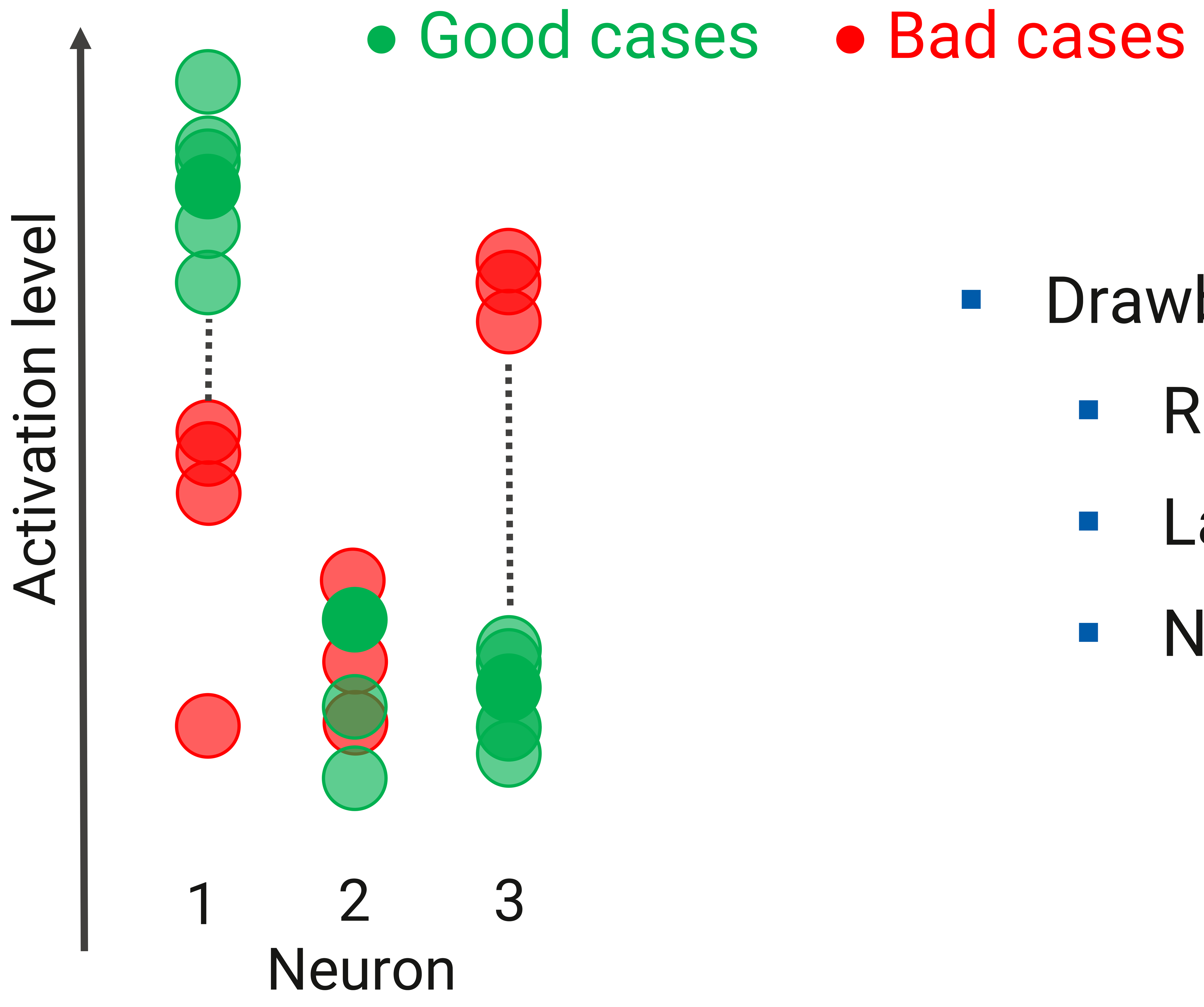
Unsupervised machine learning via autoencoder



- Common pre-stage in many machine learning solutions
- Compresses data through bottleknecking

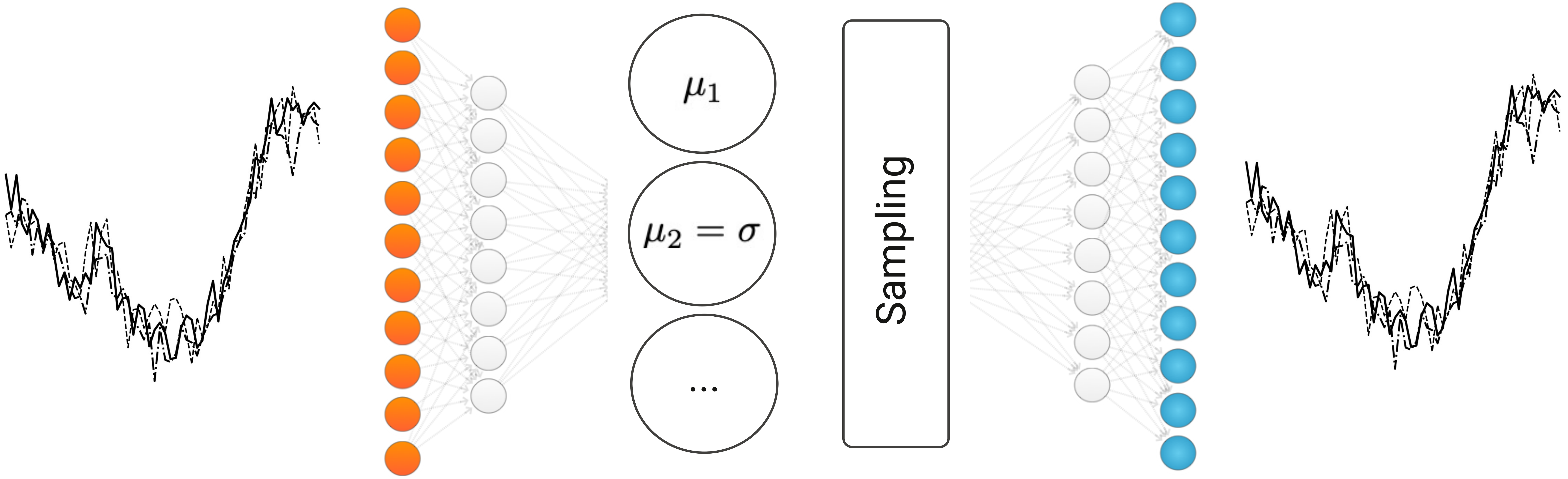
Interpreting latent layer transformation neurons

- How can we visualize the transformation so that we can study the behaviour of such algorithms?



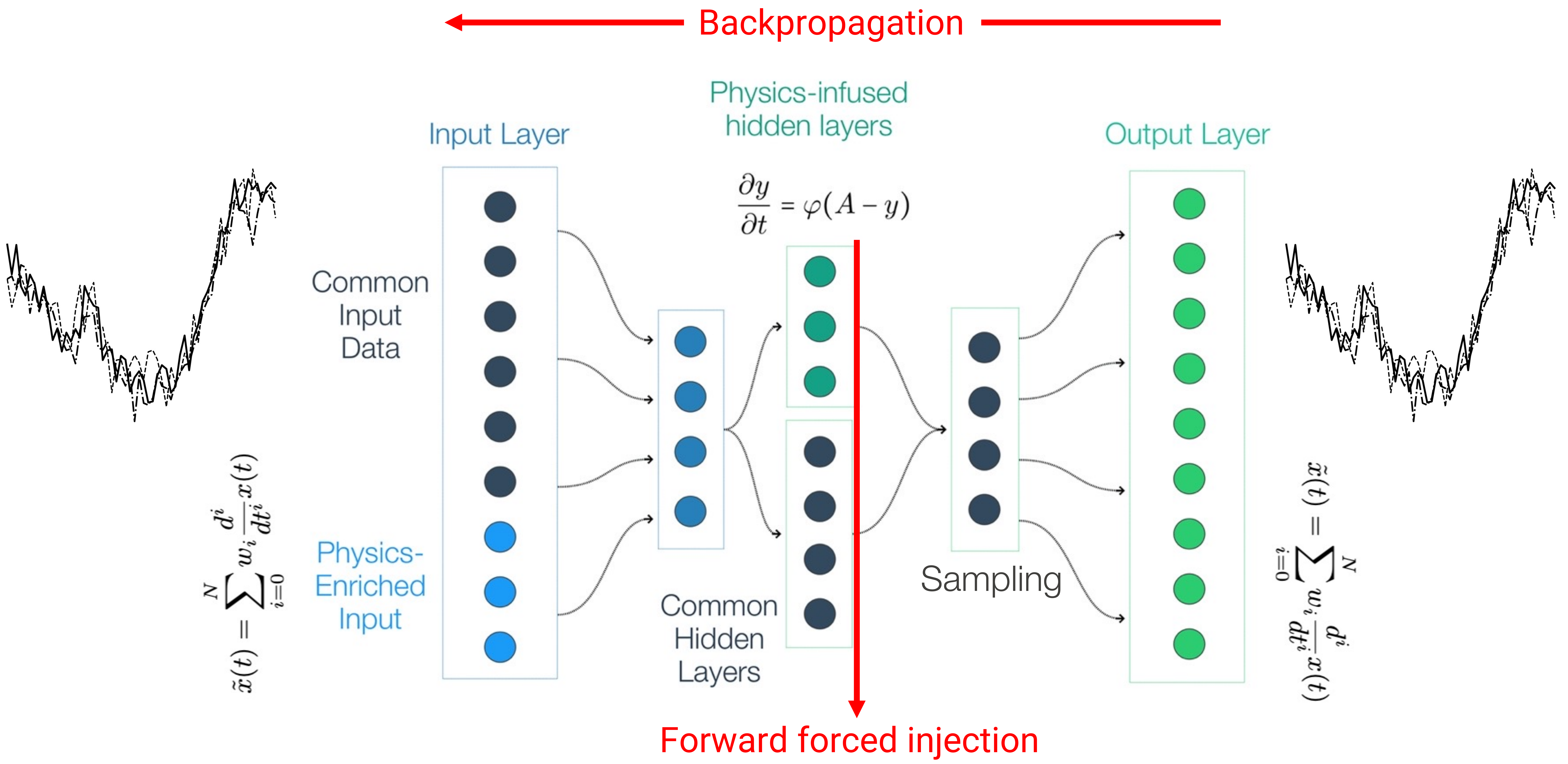
- Drawbacks
  - Random assignment to neurons
  - Latent space (the middle neurons) is irregular
  - Not easy to interpret

Variational autoencoder, latent layer regularization

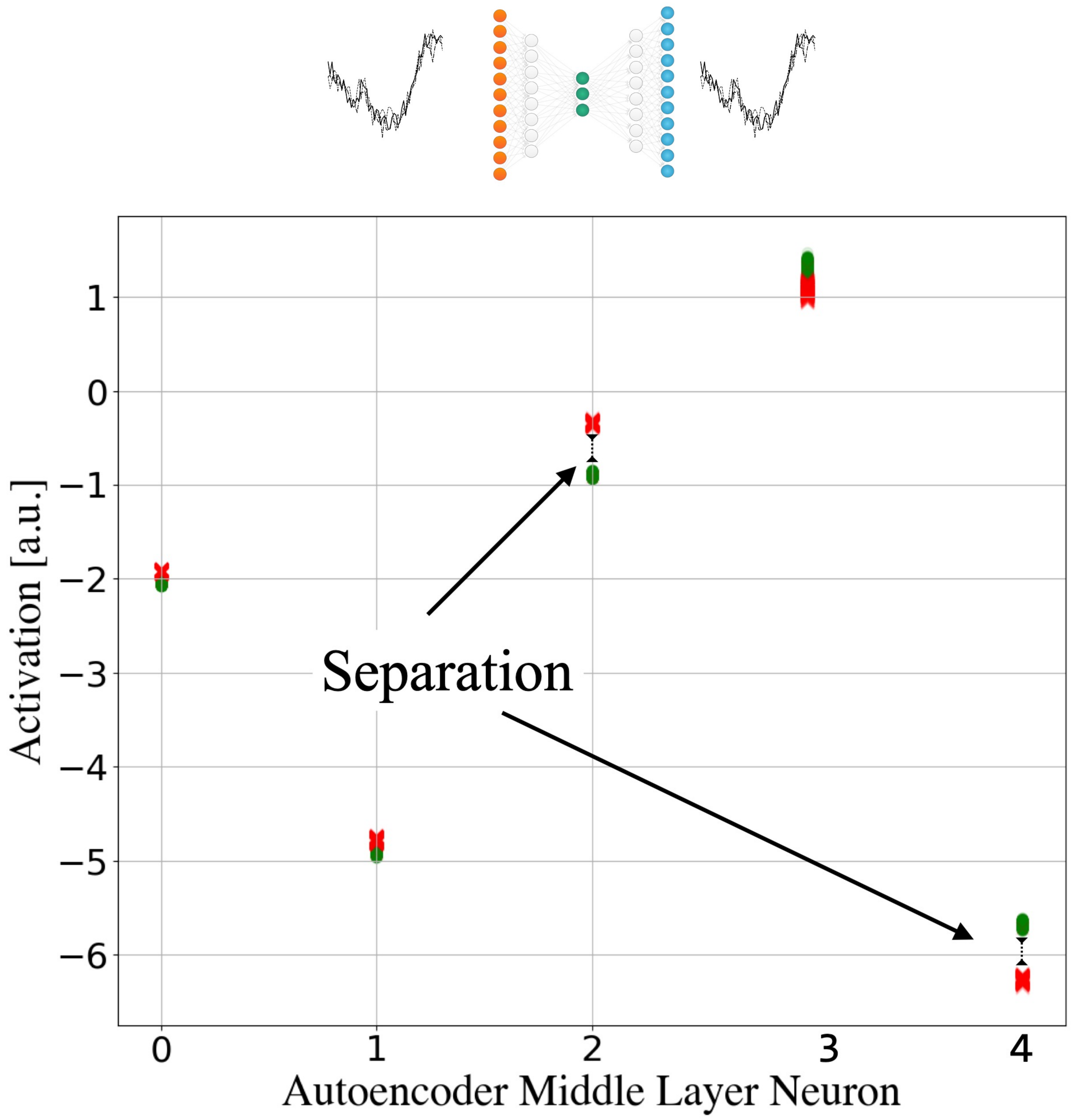


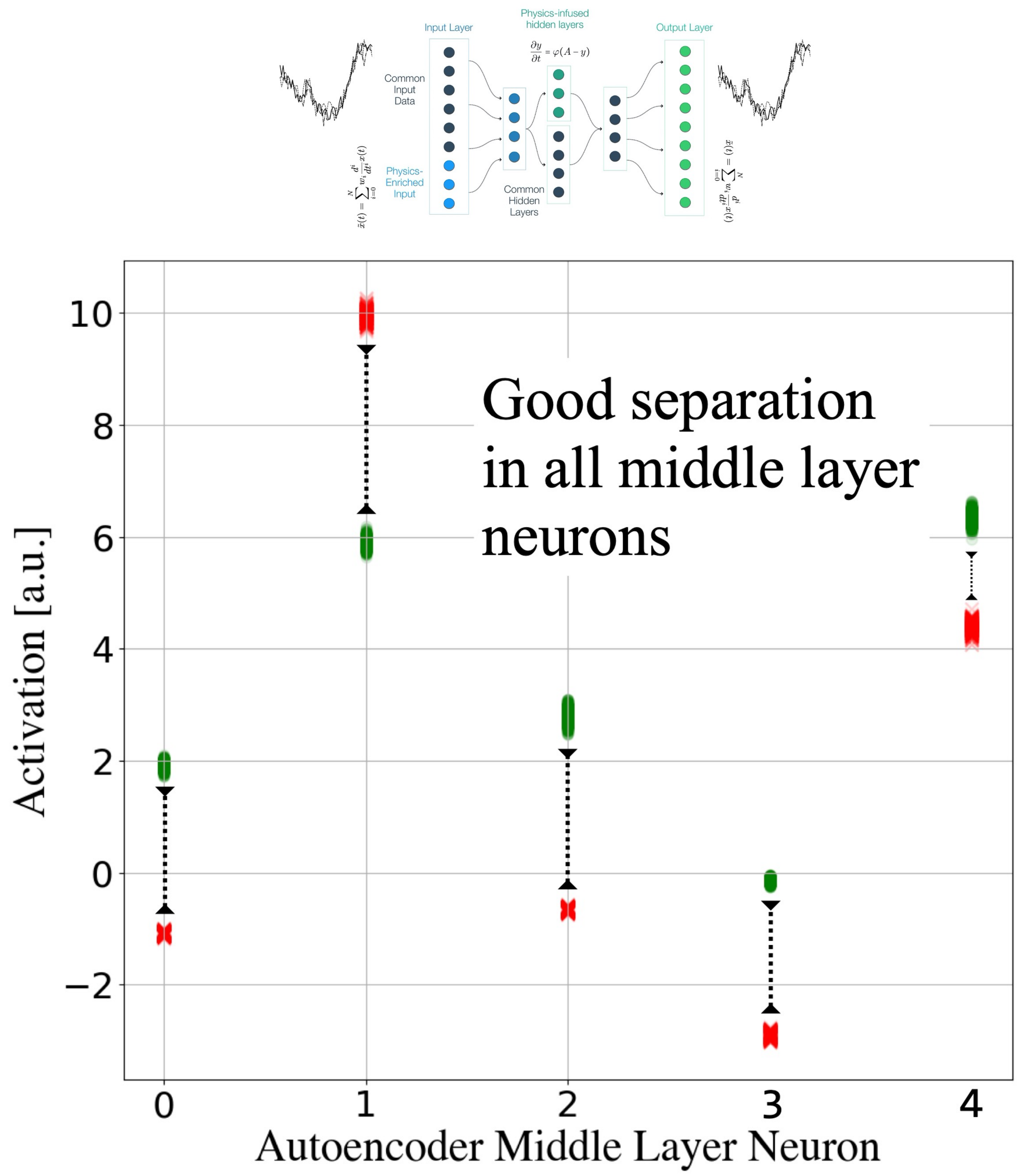
- Solution: force middle layer into regular structure
- Variational autoencoders train probability distributions into the middle layer
  - (1) encode inputs not as single numbers, but as distributions
  - (2) regularize covariance and mean of the distributions (!)

Physics-infused, stochastic autoencoder (shallow)



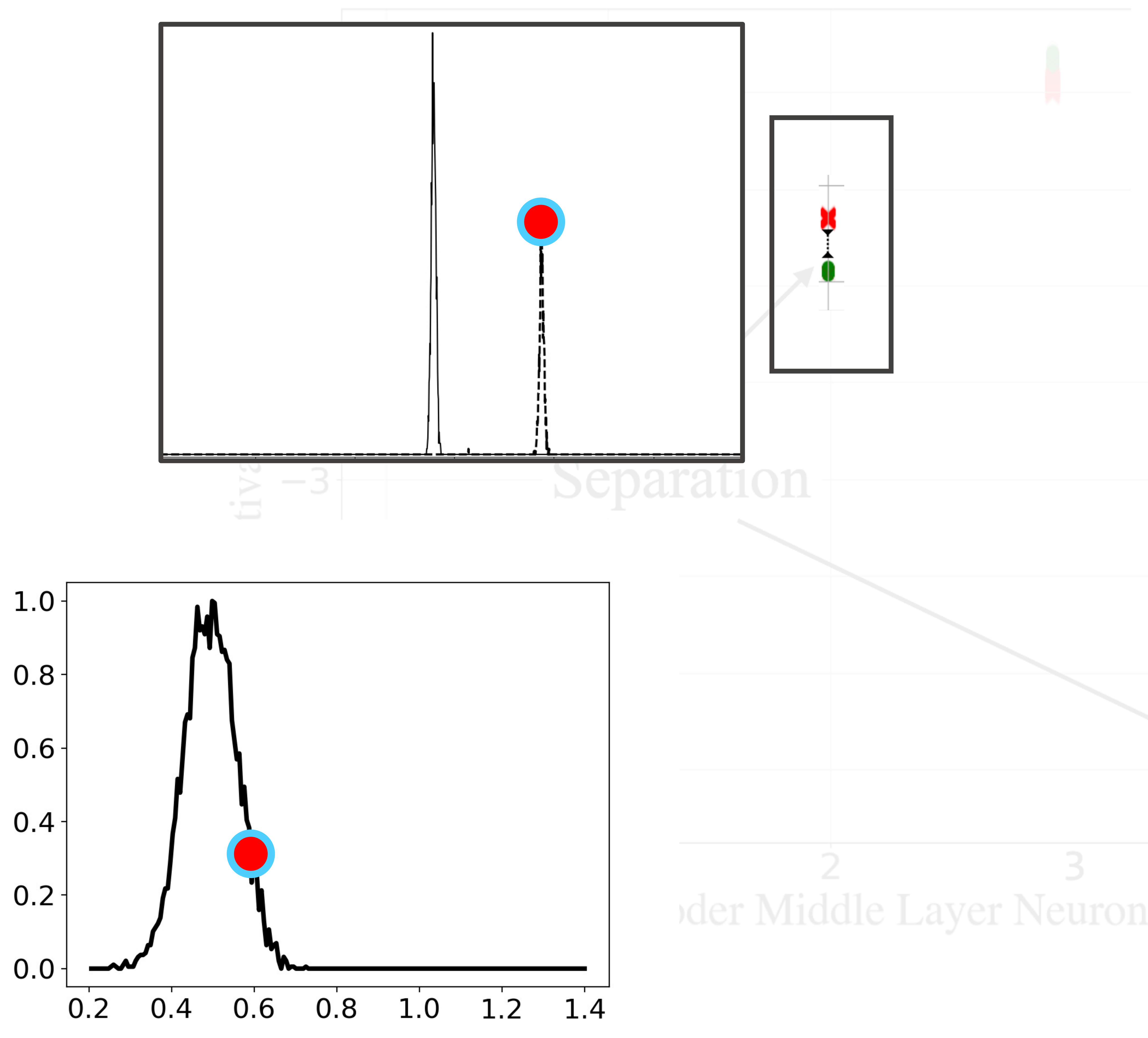
Result: comparison of AE anomaly detection

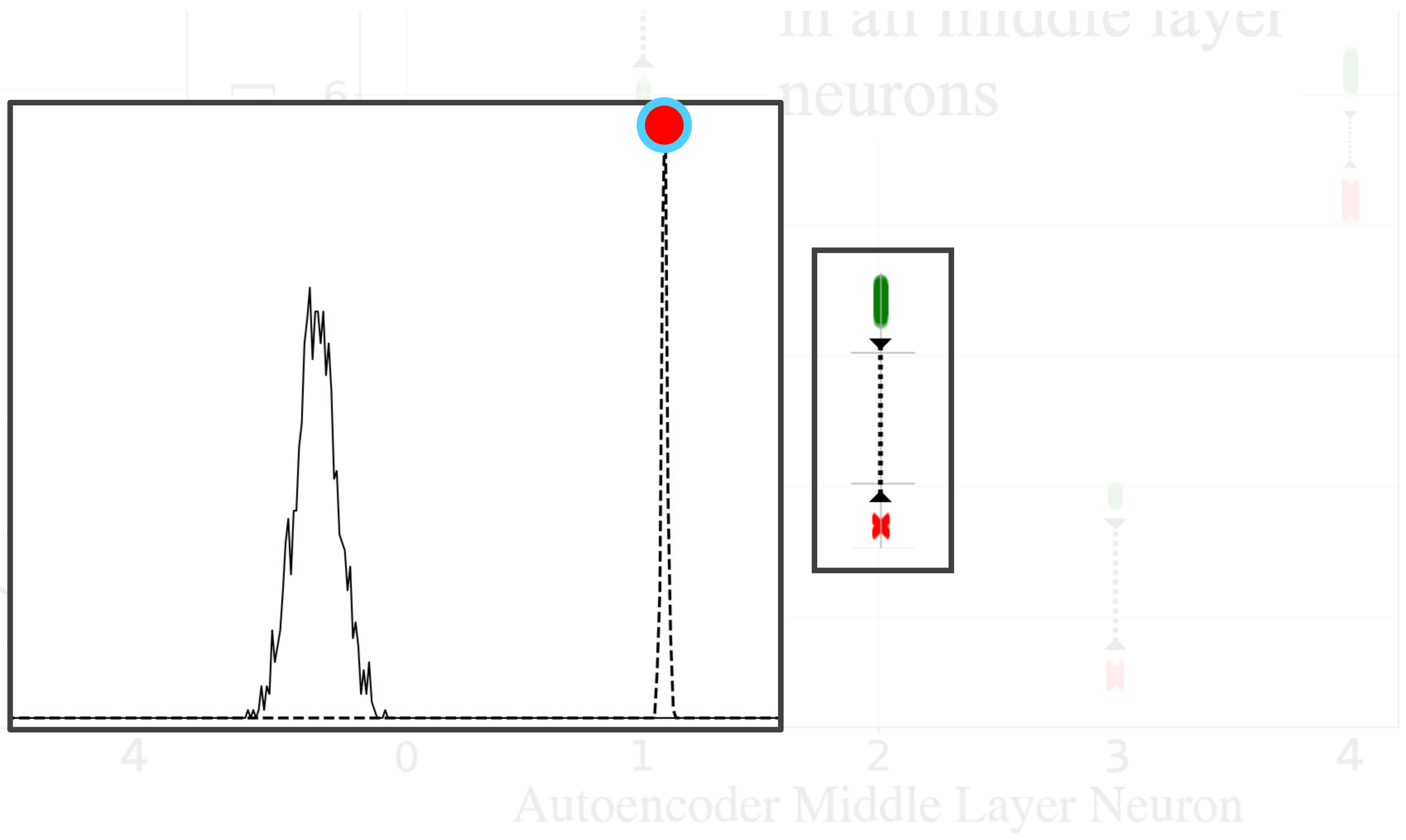




Analysis of the uncertainties propagated within the AE

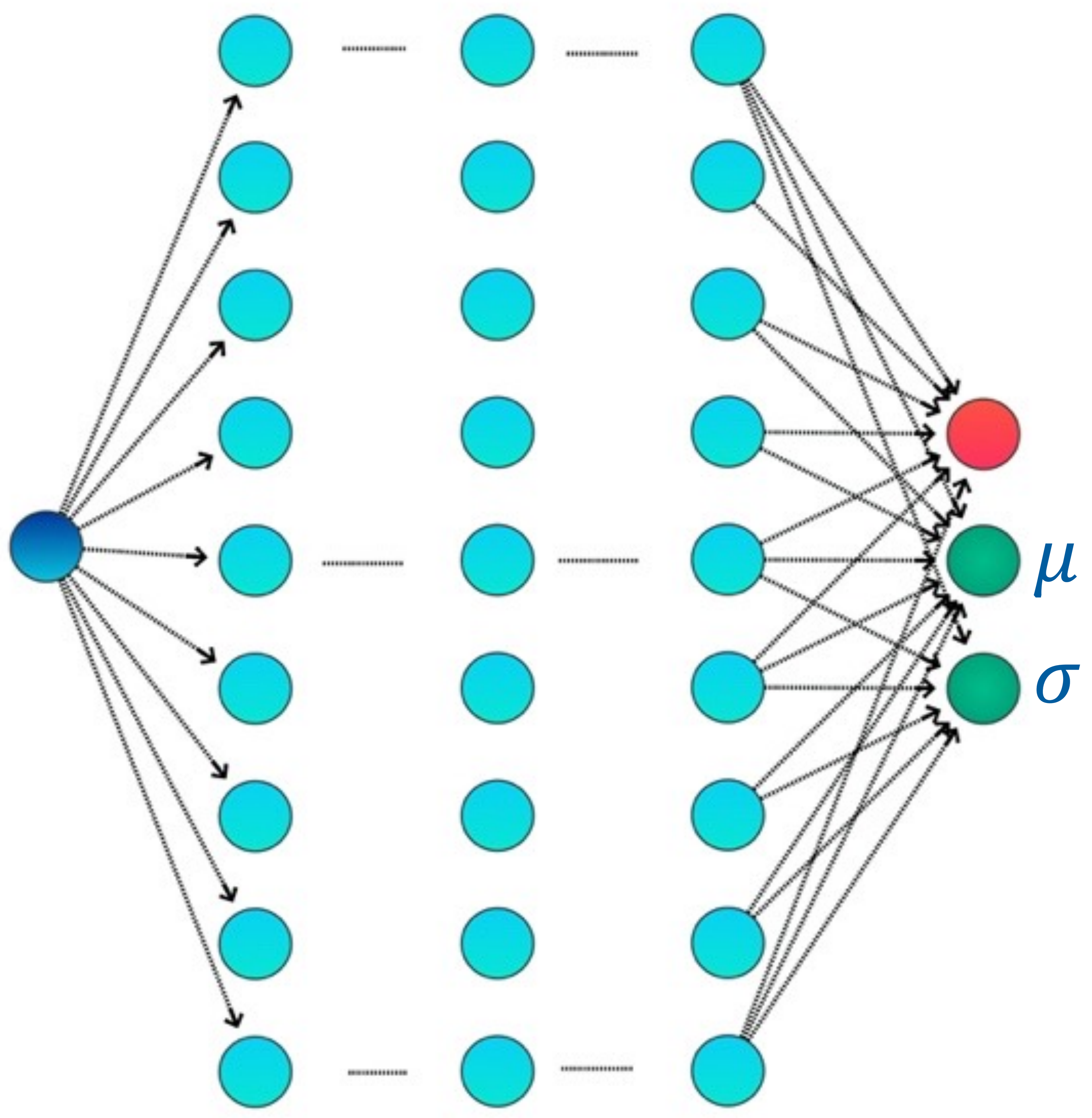
- In the encoded middle layer, we can also determine the probability distribution
- Nonlinear mapping increases visibility of anomaly significantly





3.
Outlook towards robust machine learning control

Mixed-density networks for uncertainty forecasts



$$\mu_k(t_i) = \sum_k^{\infty} x^k P(x|t_i)$$

- Bishop, 1994
- Maximize the probability of sampling the output values (the labels y):

$$C = -\log\{P(y;\mu,\sigma,\dots\}$$

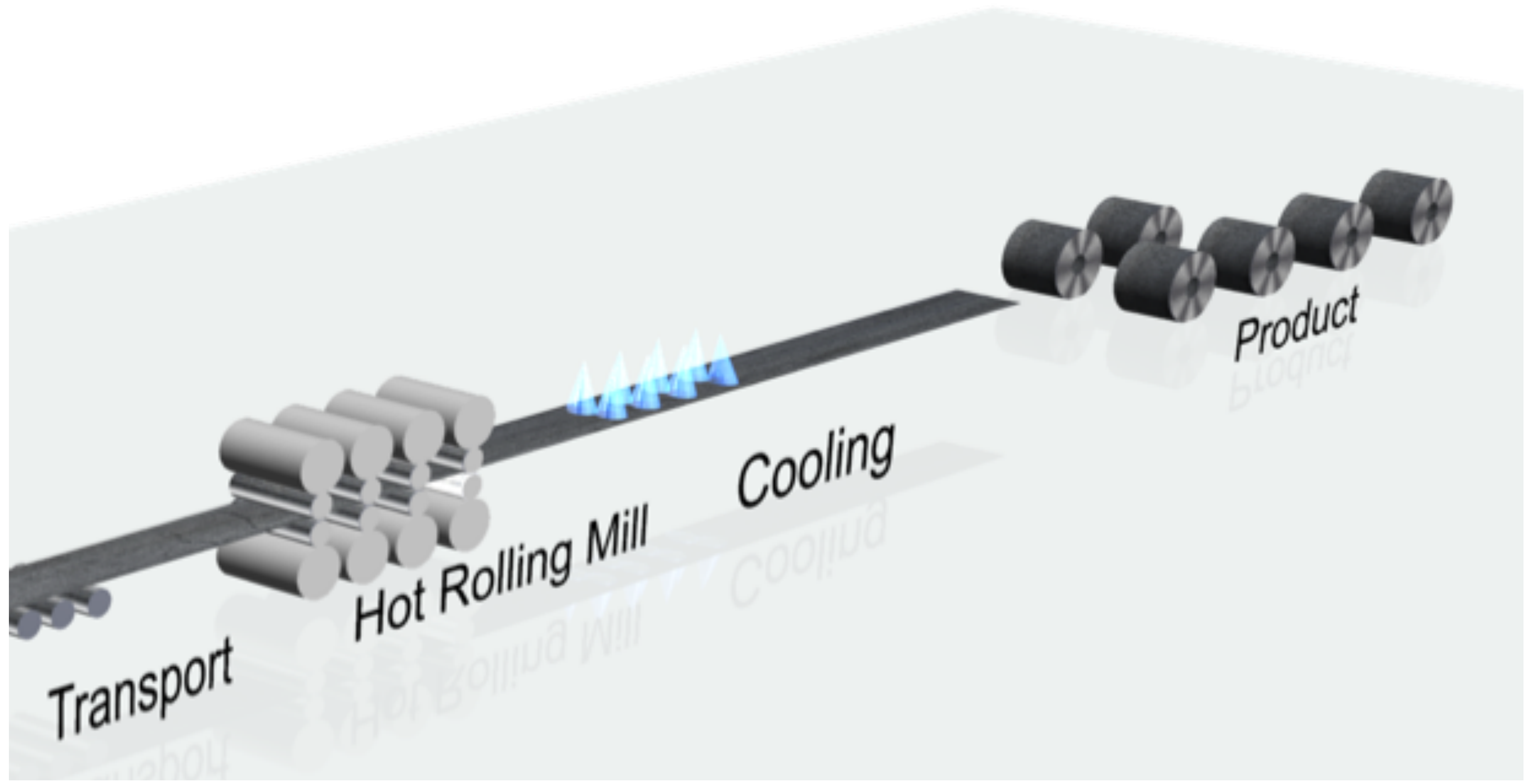
- Moments of probability distributions are not allowed to be negative so activation must ensure an non-negative value: Exponential-Linear-Unit (ELU)

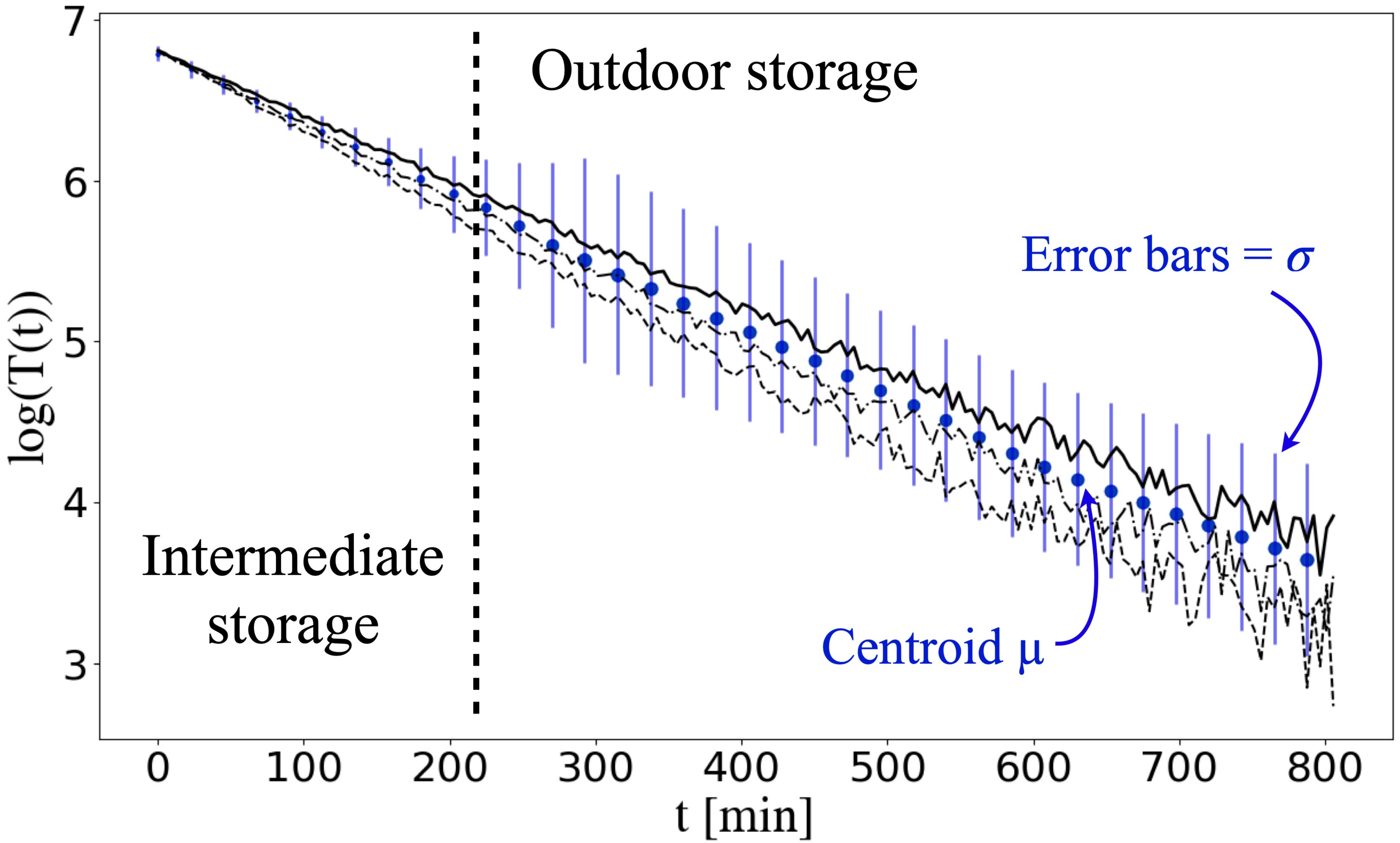
$$\mathrm{ELU}(x) = \begin{cases} \exp(x) - 1 & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$$

$$\mathrm{ELU}(x) + 1 \geq 0$$

Mixed-density networks for uncertainty forecasts

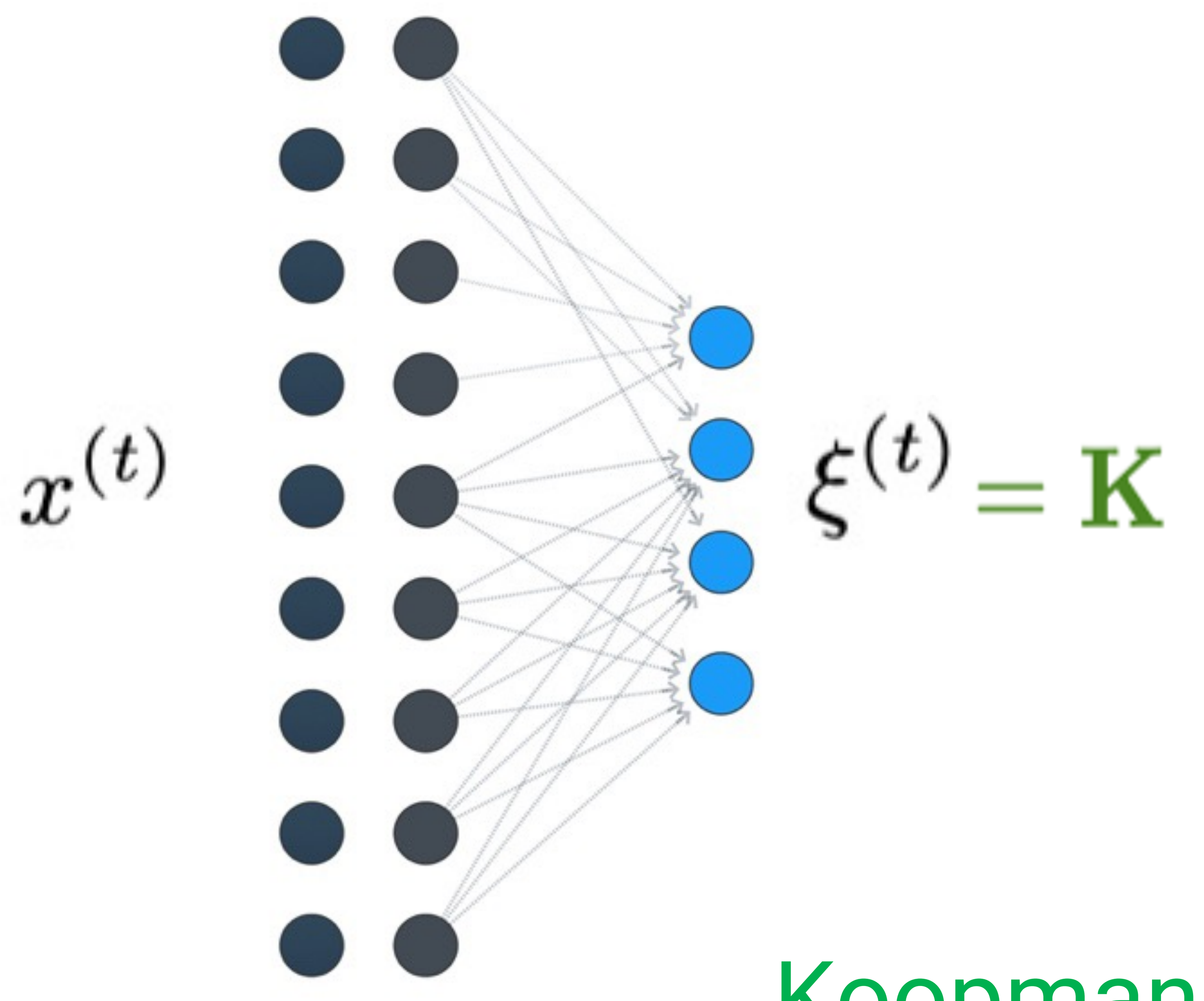
- Hot rolled coils
- Two storage locations





Dynamic mode decomposition

Highly nonlinear
system dynamics



Koopman space
Linear dynamics of
observables

Highly nonlinear
system dynamics

Summary

- Enrichment of autoencoding to include process stochastics and physical a priori information
- Probability distributions can be determined in encoded space
- Importance of integrating probabilistic information into network evaluation
- Outlook towards the dynamic mode decomposition, being a upcoming tool for controller development

- Methodological work was supported by following funded research projects
  - iba AG, MeDeLe German Research Project within ZIM programme
  - Use cases and methodology will be reviewed further in the RFCS dissemination project ControlInSteel, which revisits nearly 46 European research projects funded by RFCS
  - Results were based upon funded projects RFCS FlexGap, RFCS CyberMan4.0, RFCS CyberPOS

Thanks for your patience

Marcus J. Neuer

Head of Department
Automation Downstream
Marcus.Neuer@bfi.de
+49 175 2064672
Please visit also
www.bfi.de

Machine learning control

- Autoencoder variants built from scratch
  - Prototype in Tensorflow 1.9, used for training and hyperparameter selection
  - Deployable C++ code which runs on embedded Linux platform

  - Training details
    - 288 epochs, 50x iterations on ca. 9000 data sets with 98 anomalies, mainly leaky_relu activation
    - ADAM optimizer

Industry 4.0 and its technological advances

Excellence in Applied Research

Production planning
Scheduling

Control theory

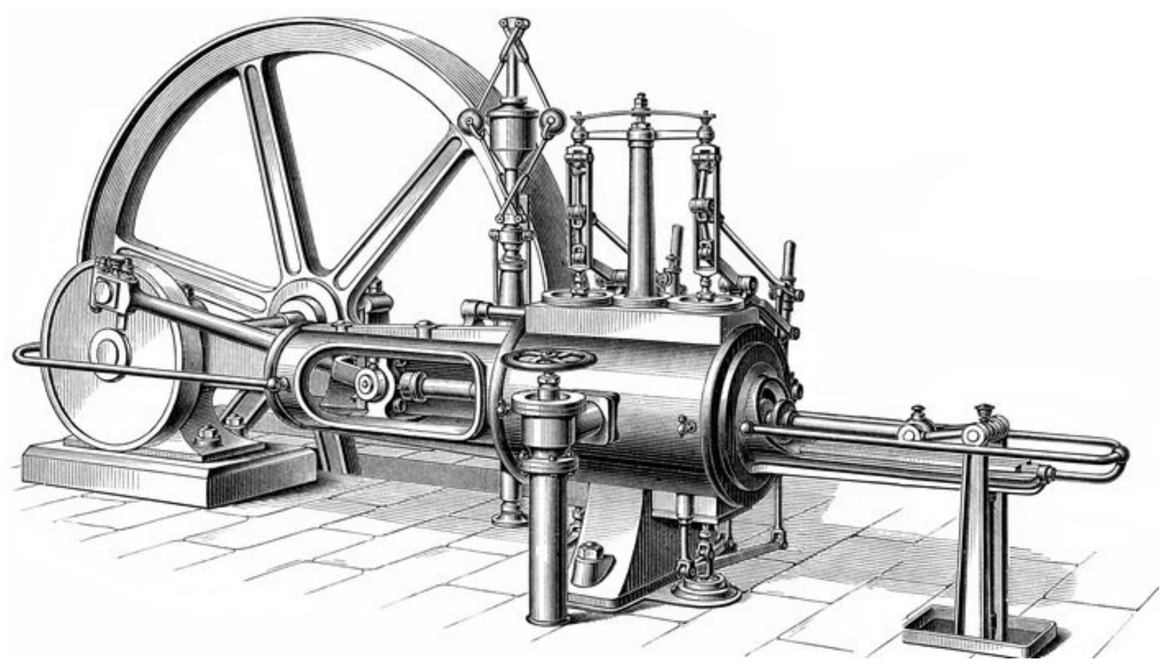
Decentral systems
Advanced algorithms

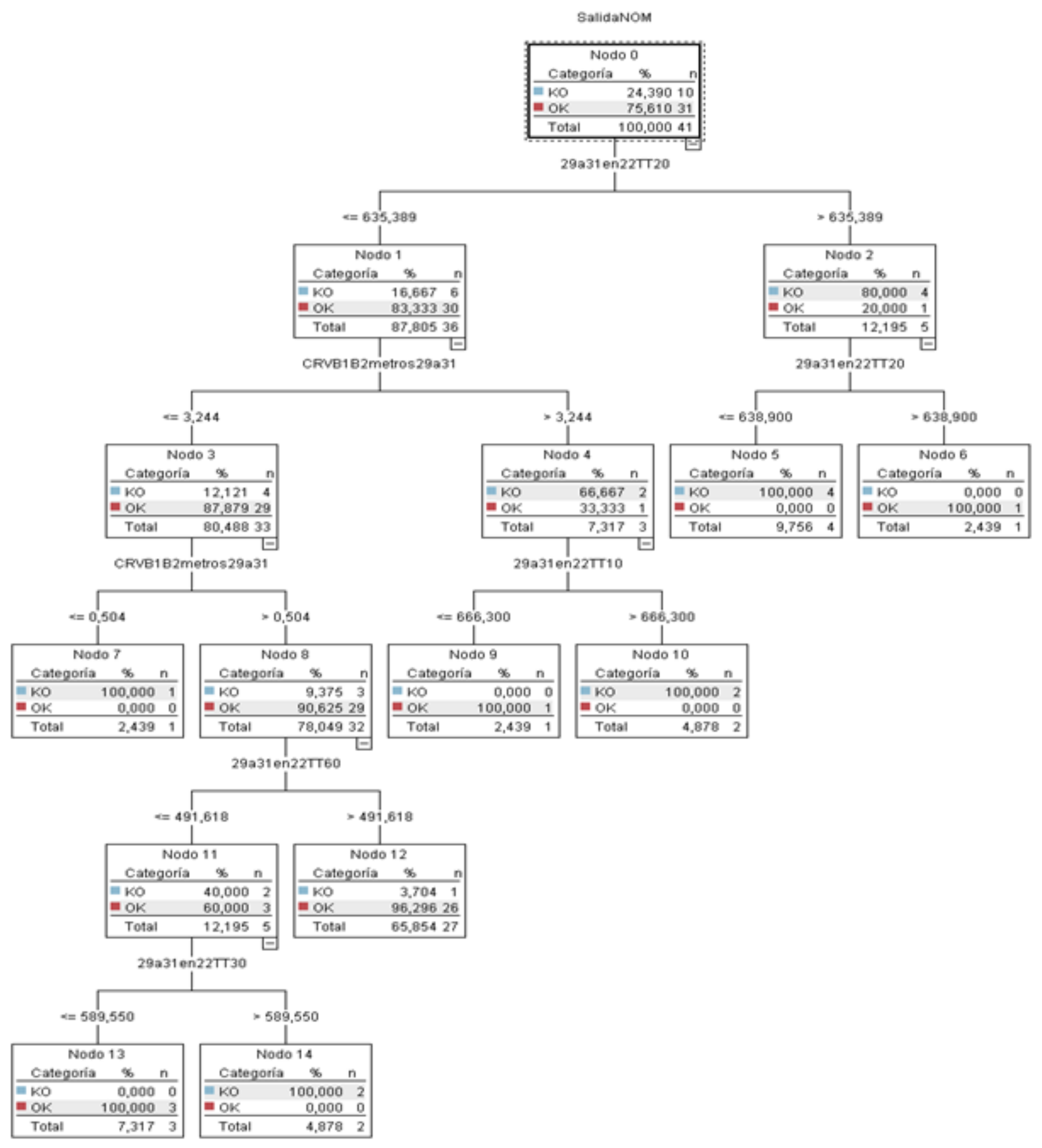
Industry 1.0
Machines

Industry 2.0
Assembly line
Mass production

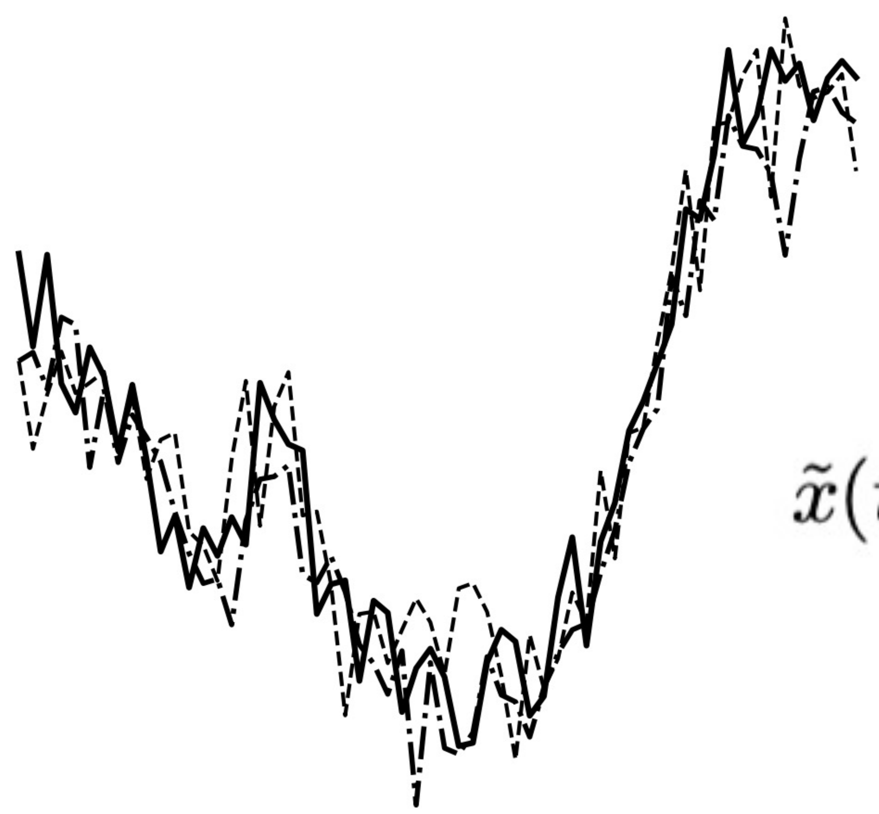
Industry 3.0
Computer
Automation

Industry 4.0
Networks
Communication
Integration

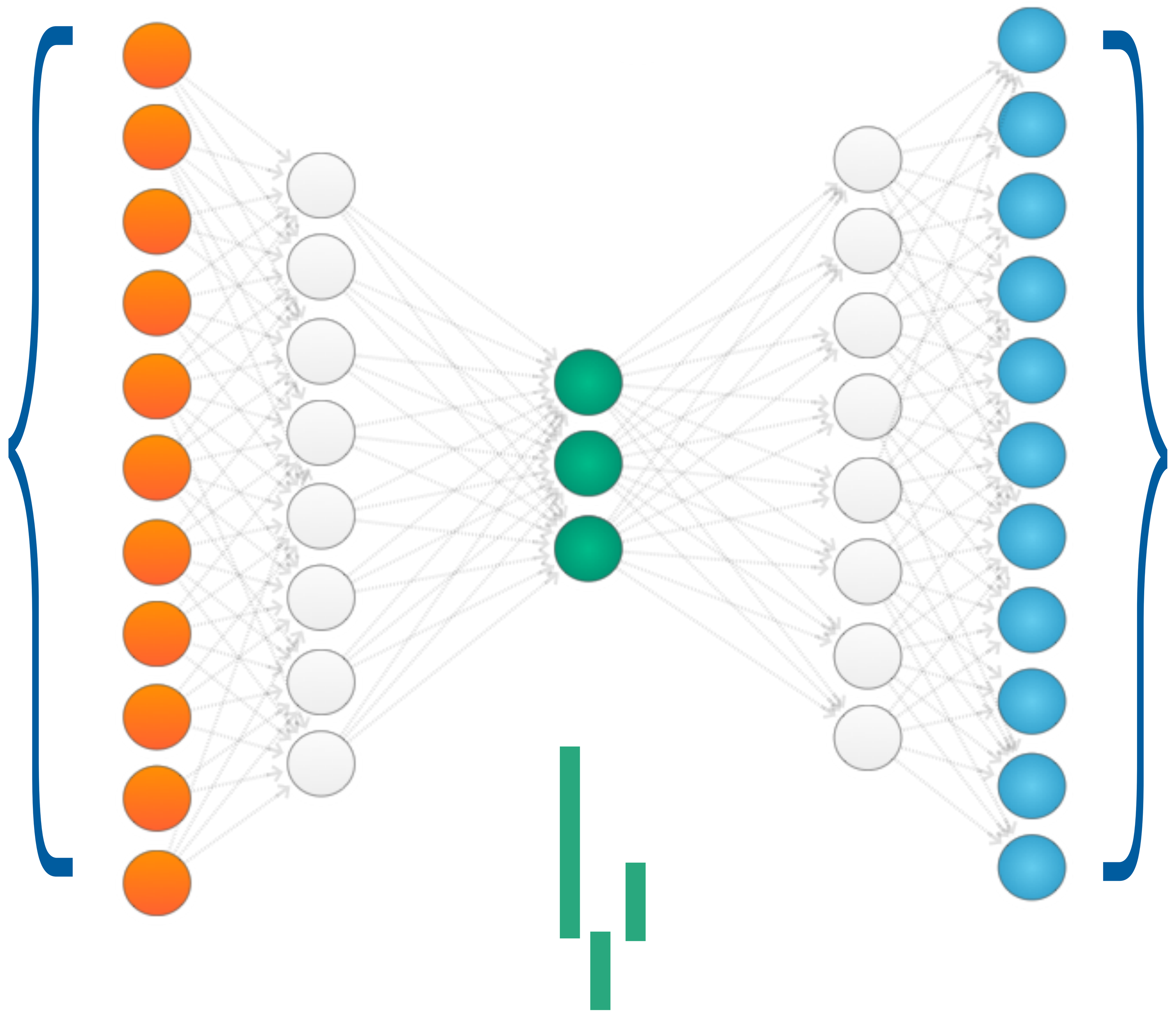




Enhancements of the autoencoder



$$\tilde{x}(t) = \sum_{i=0}^{N} w_i \frac{d^i}{dt^i} x(t)$$



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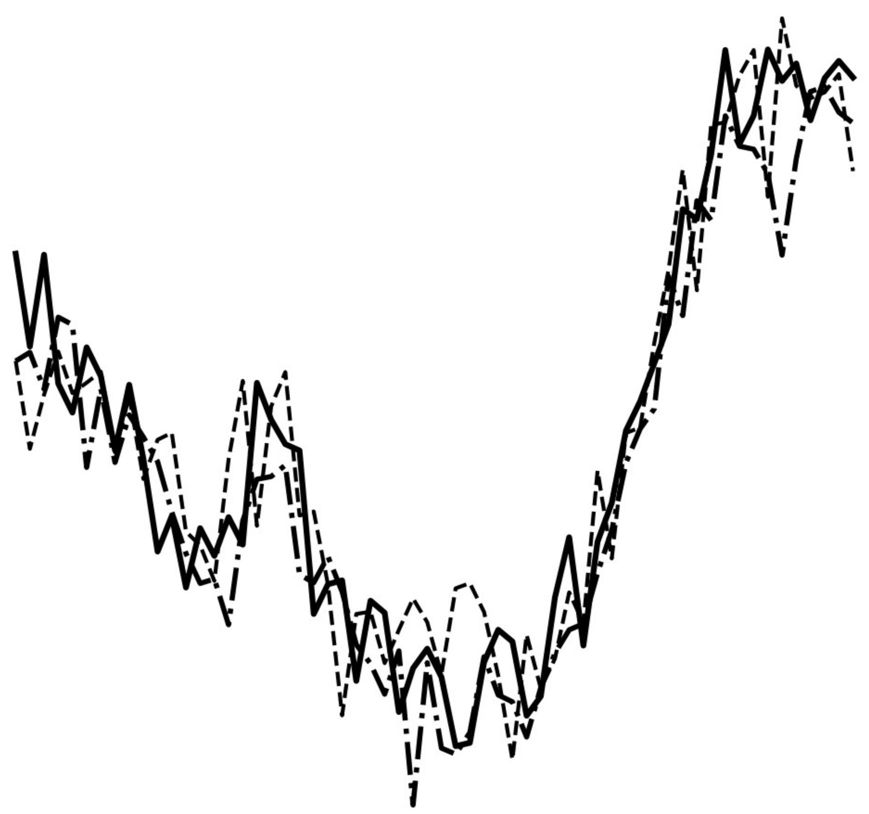

- Requires „knowledge“ about the process: physics-informed approach
- Disadvantage: Loss of the key property of machine learning to work without prior knowledge