

Leveraging generative AI approaches for small data settings in clinical research

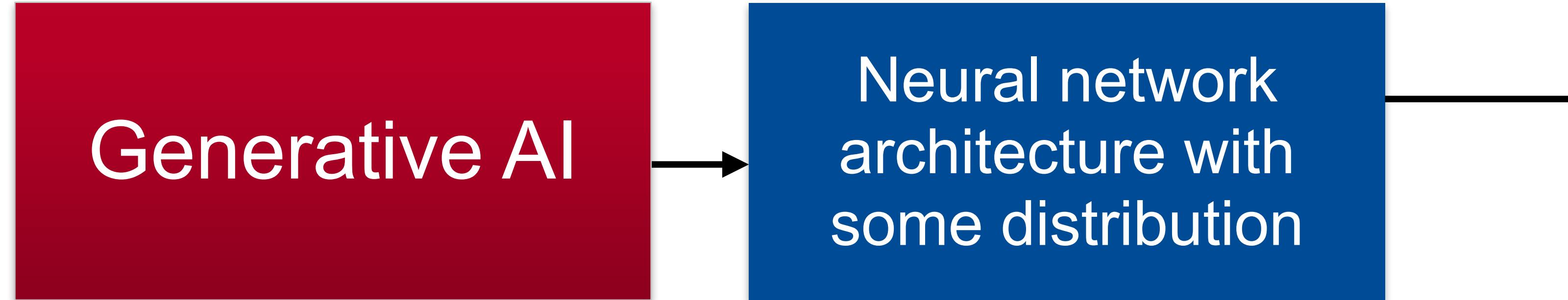
Harald Binder, Institute of Medical Biometry and Statistics (IMBI)

Generative AI

Generative AI

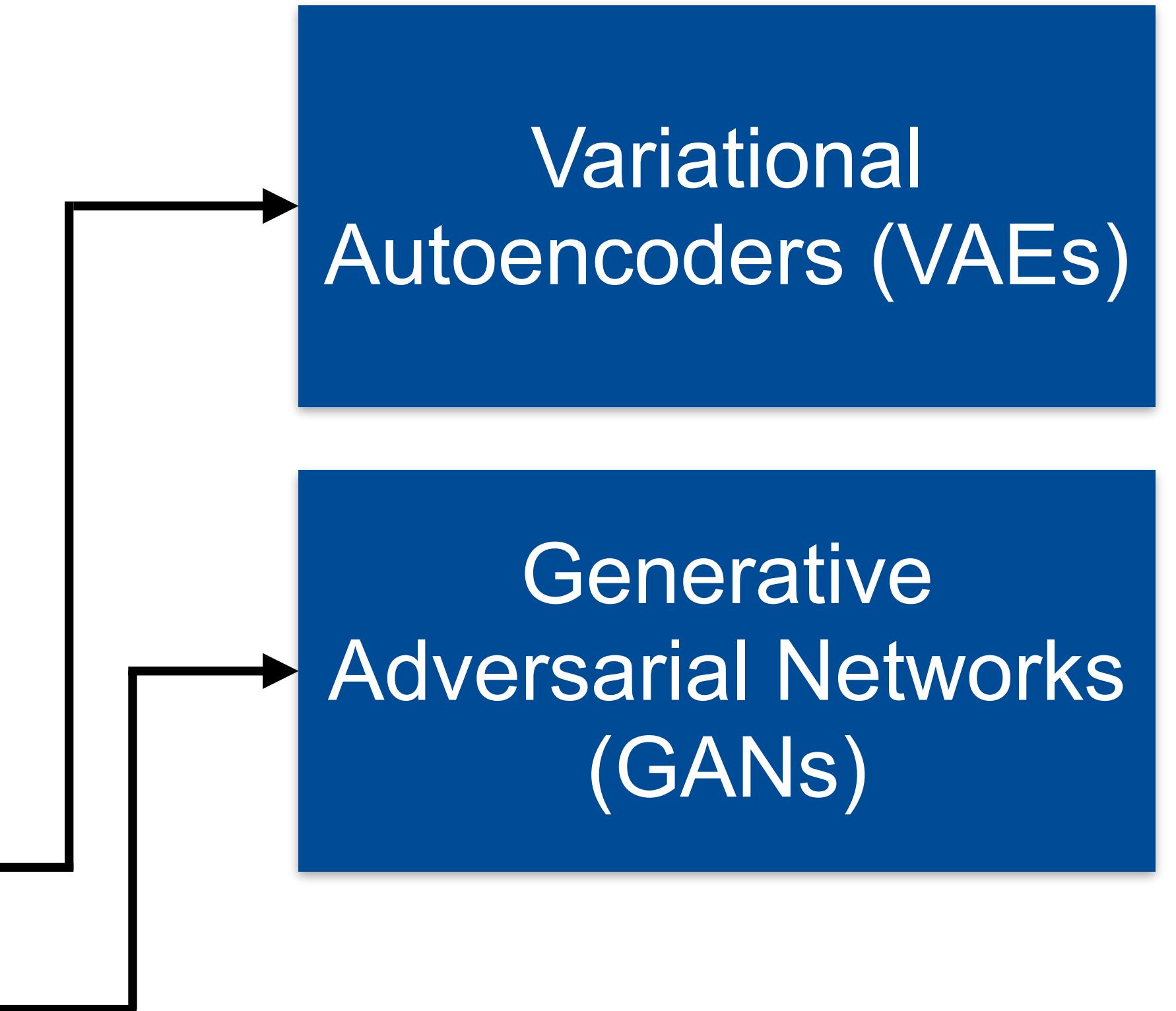


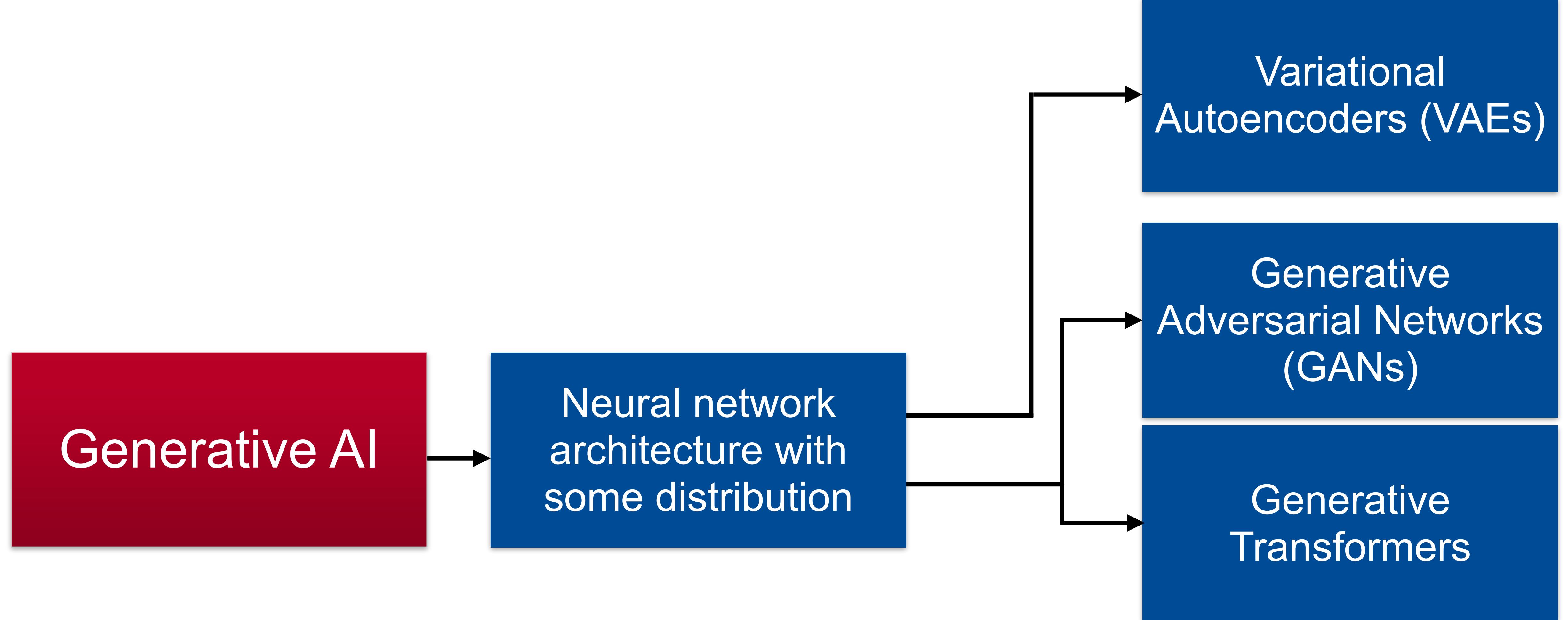
Neural network
architecture with
some distribution

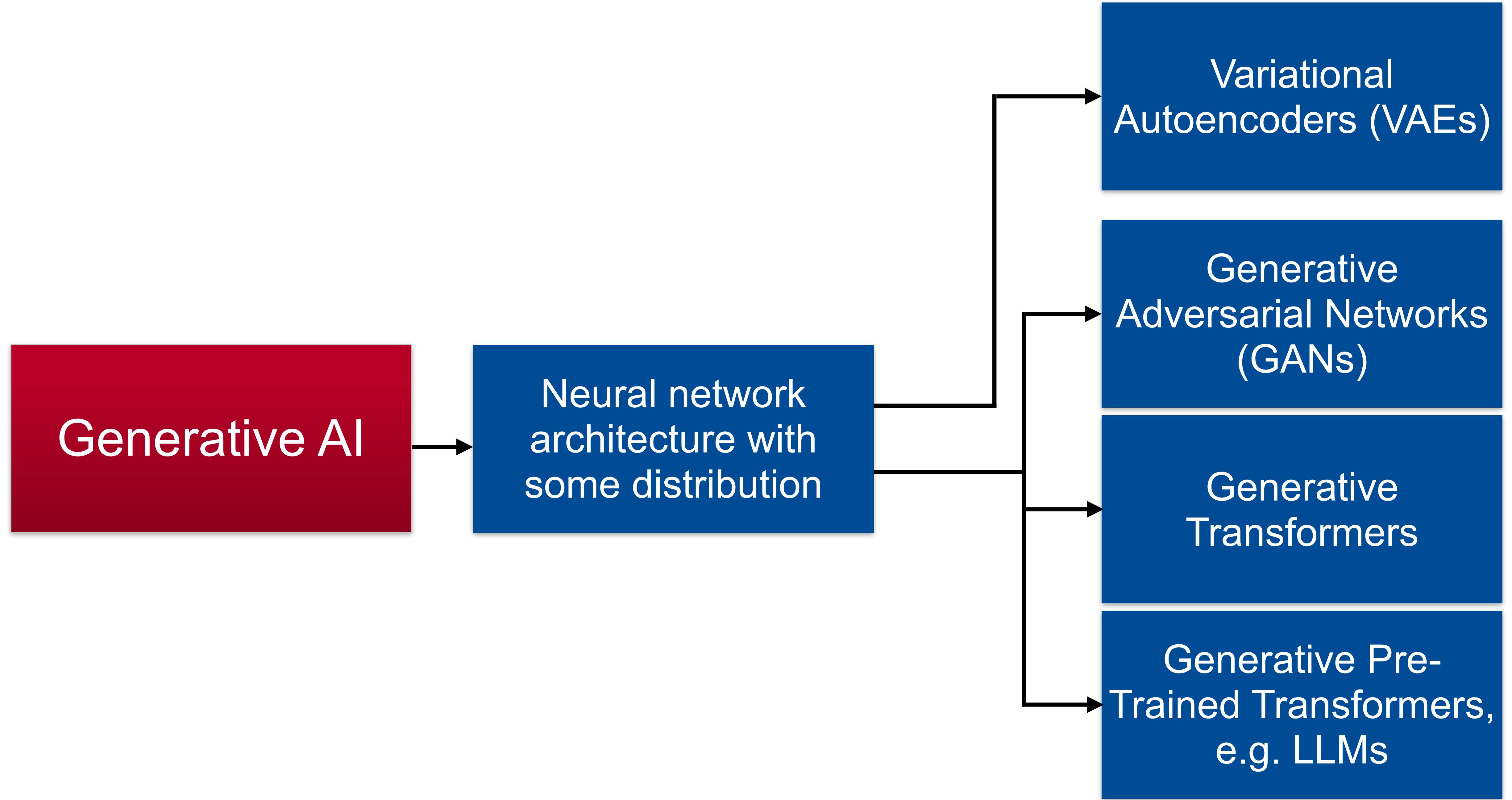


Generative AI

Neural network
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Longitudinal rare disease registries

Pechmann *et al.* *Orphanet Journal of Rare Diseases*
<https://doi.org/10.1186/s13023-019-0998-4>

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Orphanet Journal of
Rare Diseases

RESEARCH

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CrossMark

SMArtCARE - A platform to collect real-life outcome data of patients with spinal muscular atrophy

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Abstract

Background: Survival and quality of life for patients affected by spinal muscular atrophy (SMA) are thought to have improved over the last decade due to changes in care. In addition, targeted treatments for SMA have been developed based on a better understanding of the molecular pathology. In 2016 and 2017, nusinersen was the first drug to be approved for treatment of all types of SMA in the United States and in Europe based on well-controlled clinical trials in a small subgroup of pediatric SMA patients. Systems are required to monitor treated and untreated SMA patients in a real-life environment to optimize treatment and care, and to provide outcome data to regulators, payers, and the SMA community.

Methods: Within SMArtCARE, we conduct a prospective, multicenter non-randomized registration and outcome study. SMArtCARE collects longitudinal data on all available SMA patients independent of their actual treatment regime as disease-specific SMA registry. For this purpose, we provide an online platform for SMA patients

Dimension reduction with VAEs

Items from motor function assessment in SMA

Test items

Q1: Can the patient stand?

Unable: True →

With support: False →

Without support: False →

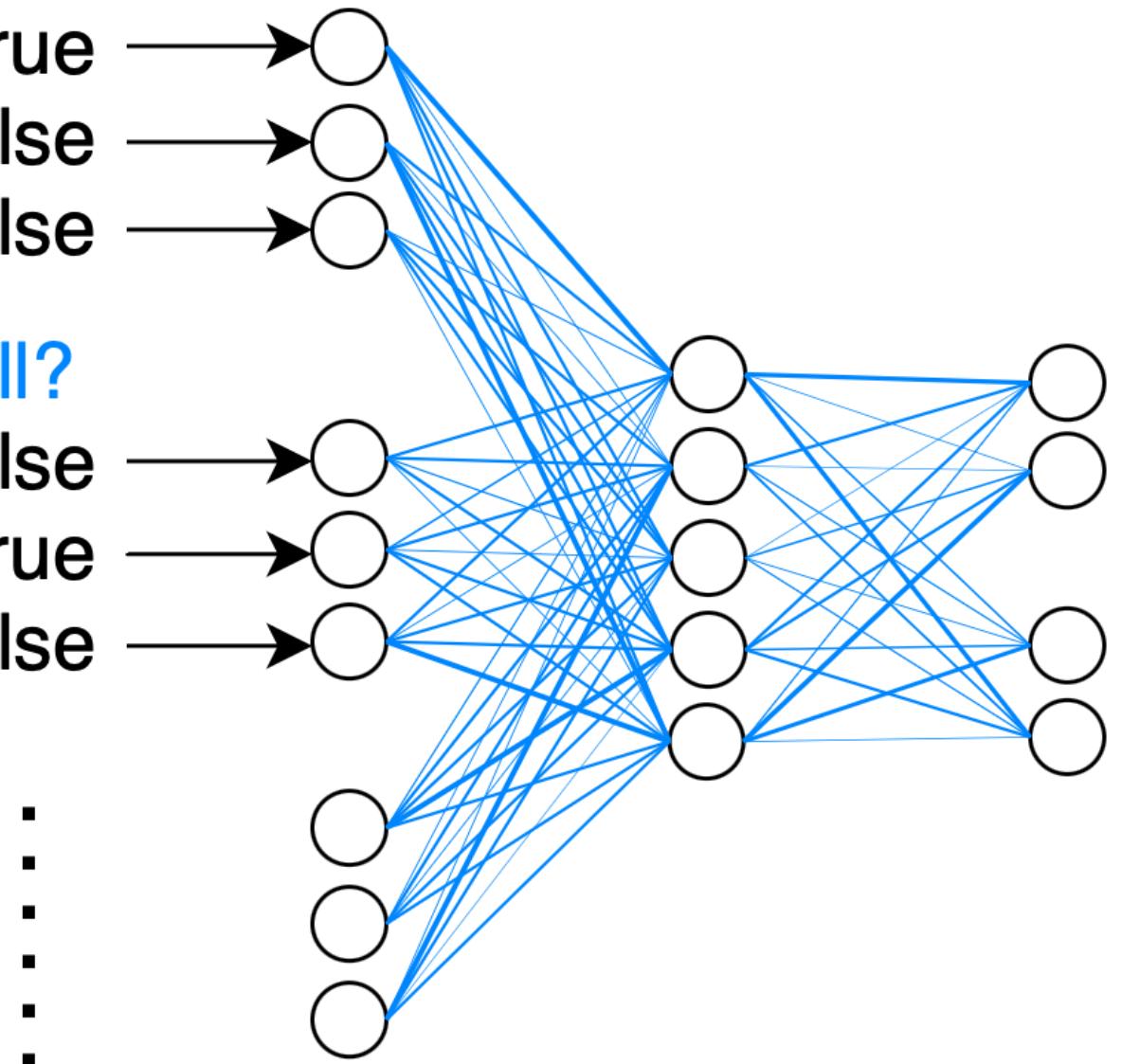
Q2: Can the patient grab a ball?

Unable: False →

With great effort: True →

Without effort: False →

Encoder



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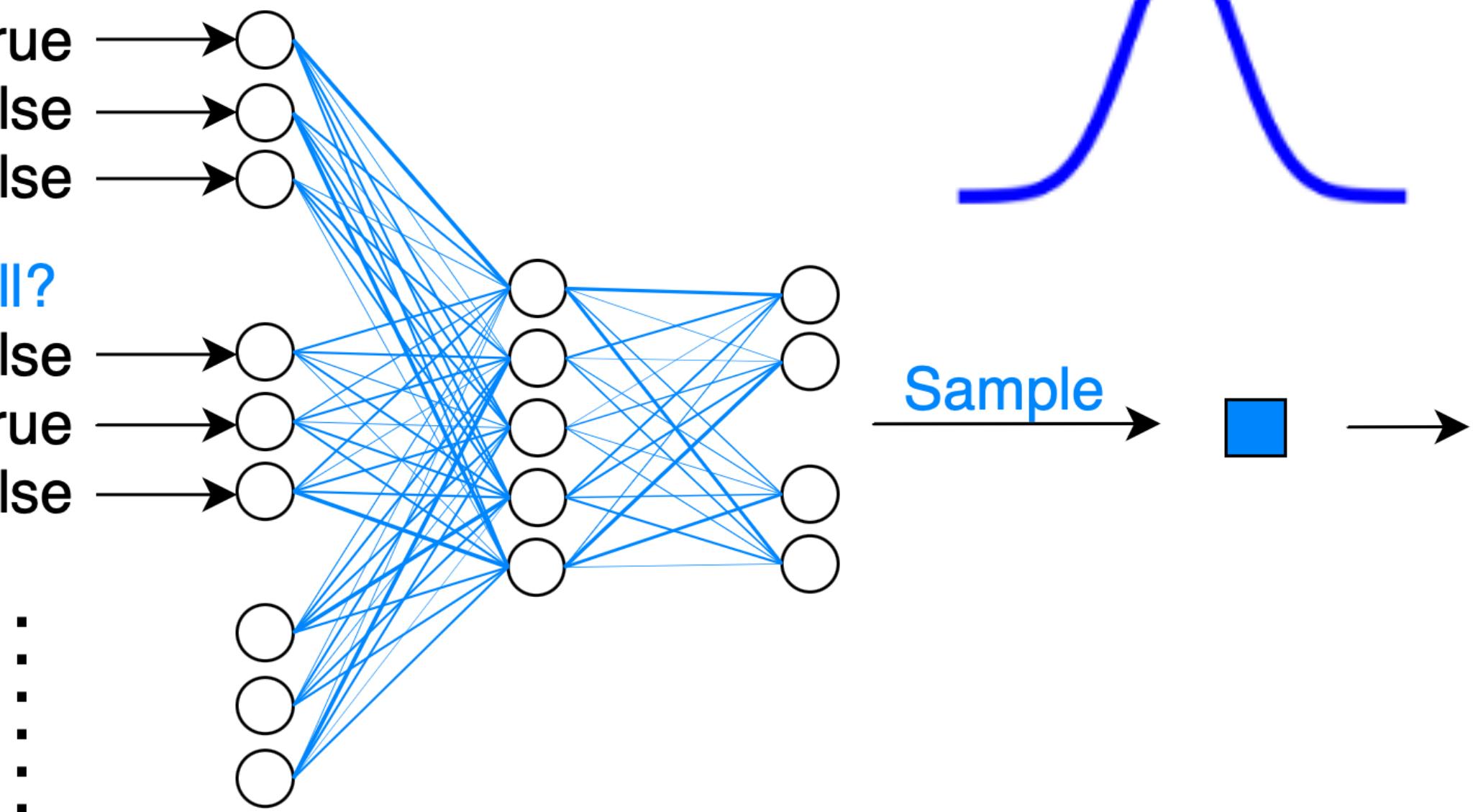
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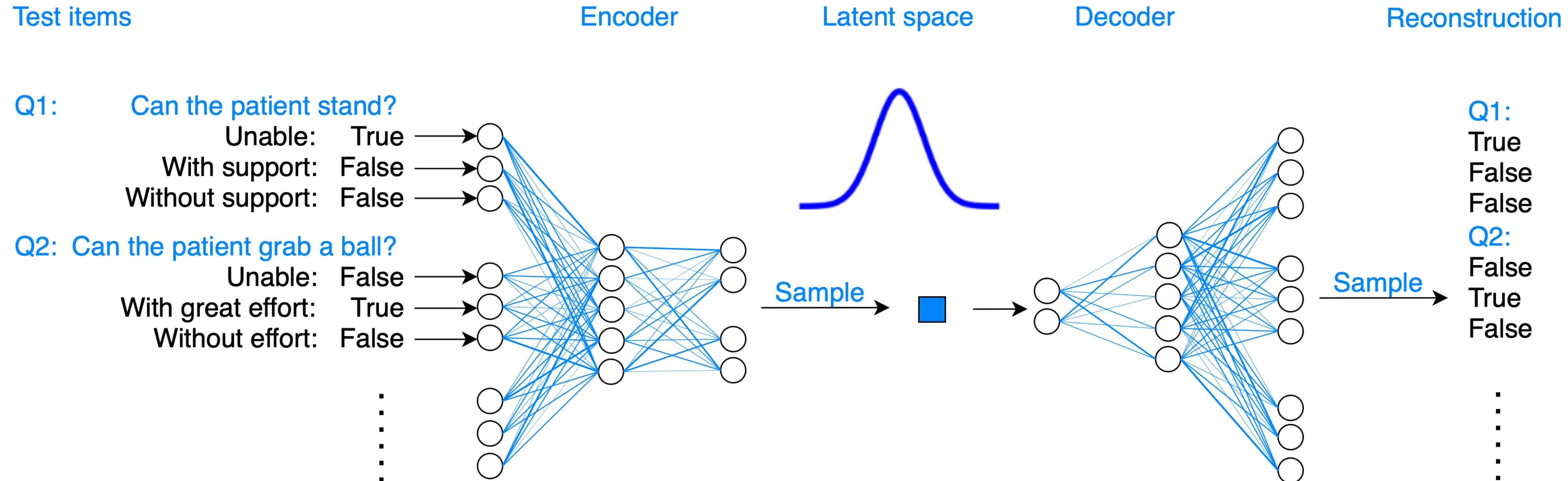
Encoder

Latent space



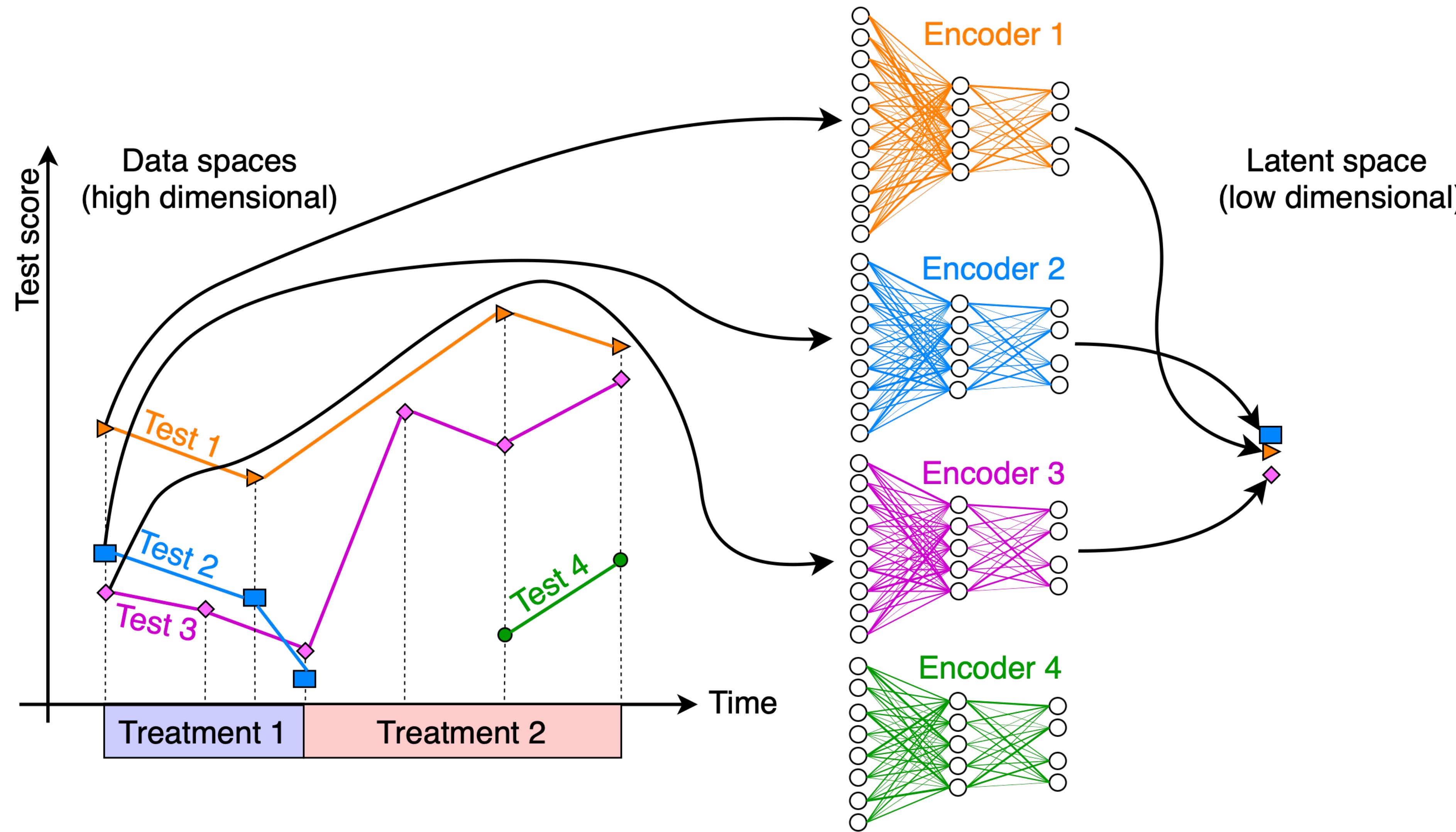
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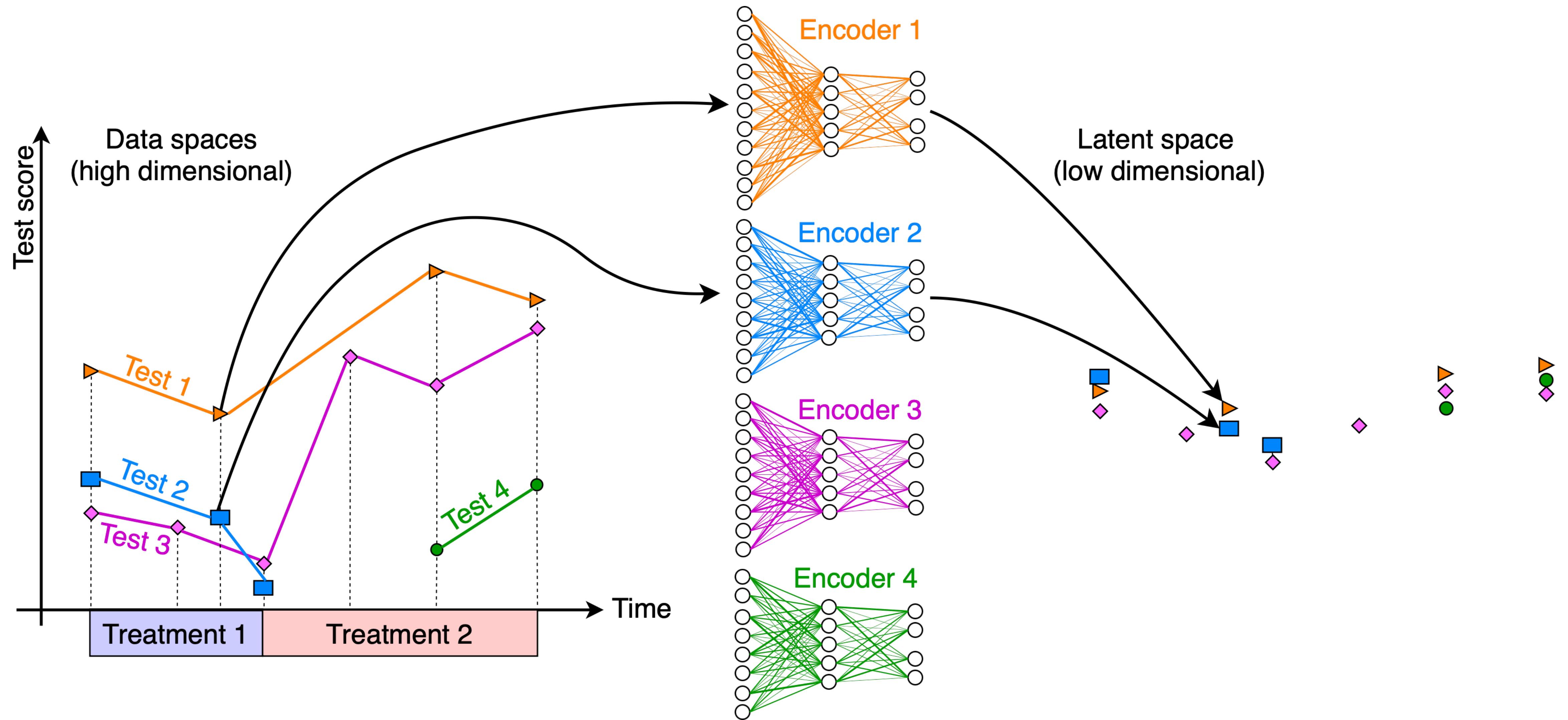
Incorporating several measurement instruments

Mapping to a joint latent space



Incorporating several measurement instruments

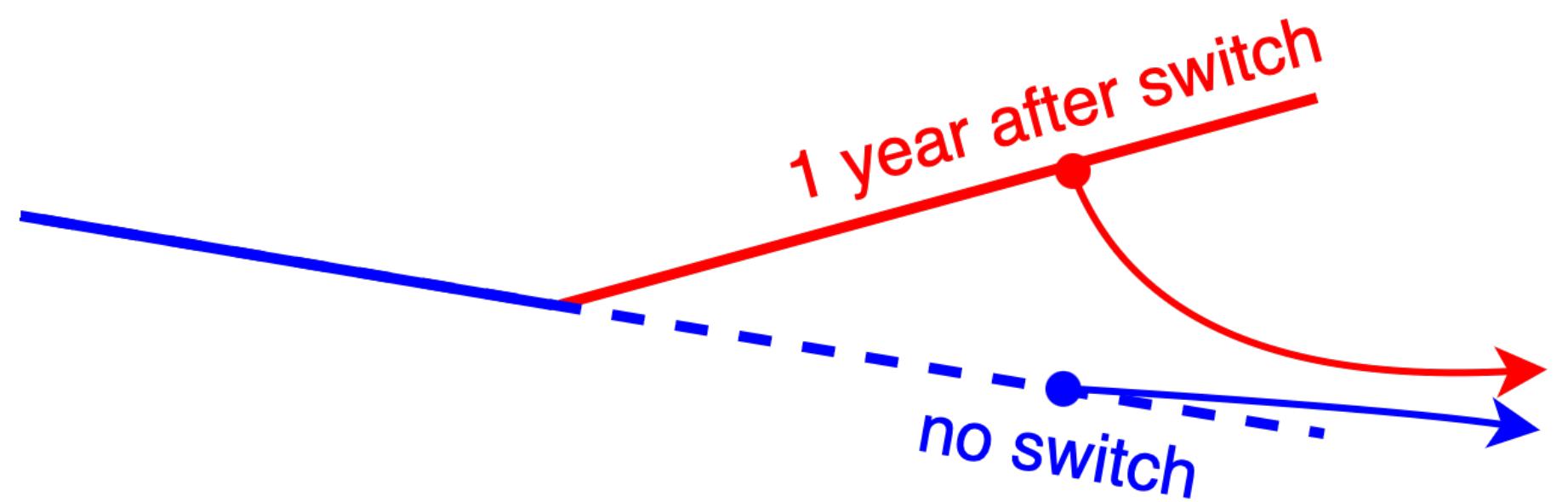
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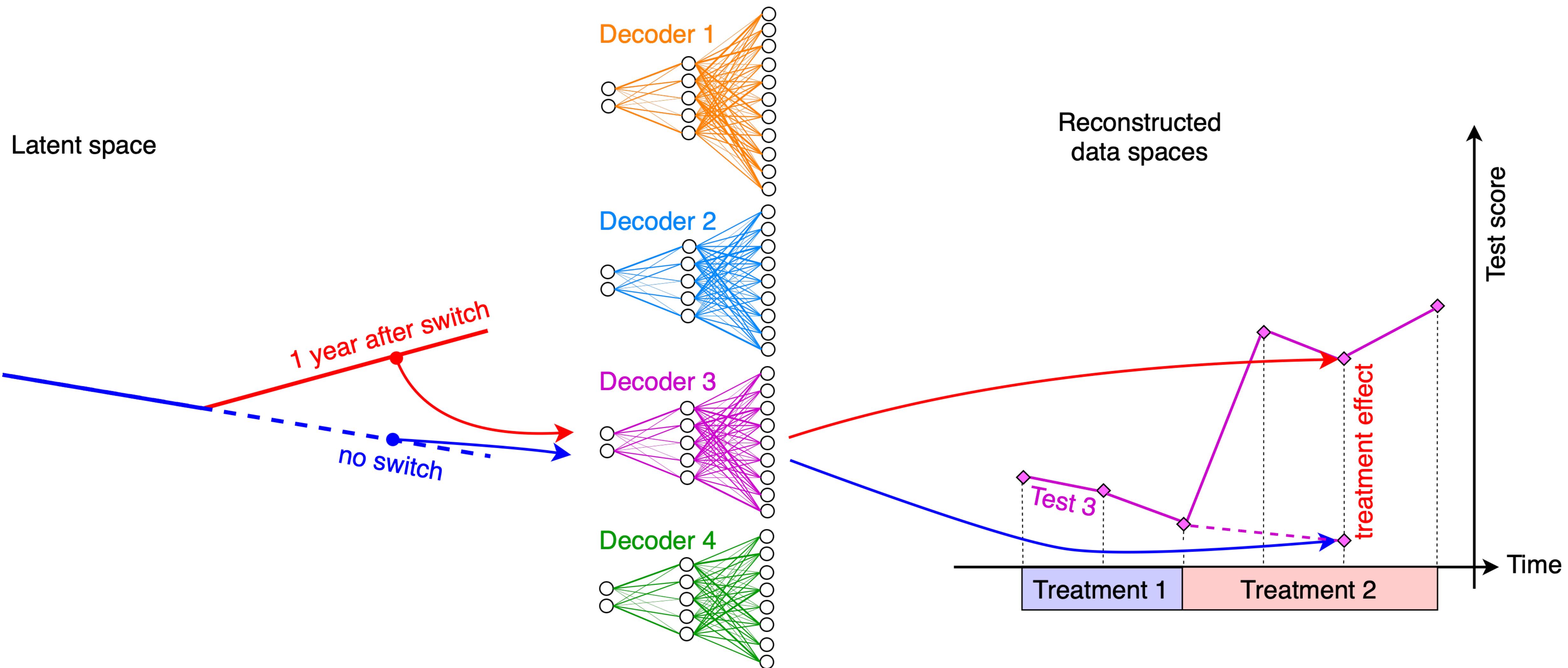
Modeling treatment switches

Latent space



Incorporating several measurement instruments

Modeling treatment switches



Calibrating ODEs with VAEs for synthetic data

Rare disease example: Epidermolysis bullosa (EB)

ODE system:

CRP:

$$\frac{dC}{dt} = (r_C + \delta) \cdot C \left(1 - \frac{C}{K_C}\right) - \alpha_{CB} \cdot \frac{B}{K_B}$$

Haemoglobin:

$$\frac{dH}{dt} = r_H \cdot H \left(1 - \frac{H}{K_H}\right) + \alpha_{HB} \cdot \frac{B}{K_B}$$

BMI:

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Albumin:

$$\frac{dA}{dt} = r_A \cdot A \left(1 - \frac{A}{K_A}\right) + \alpha_{AB} \cdot \frac{B}{K_B}$$

Iron:

$$\frac{dI}{dt} = r_I \cdot I \left(1 - \frac{I}{K_I}\right) + \alpha_{IB} \cdot \frac{B}{K_B}$$

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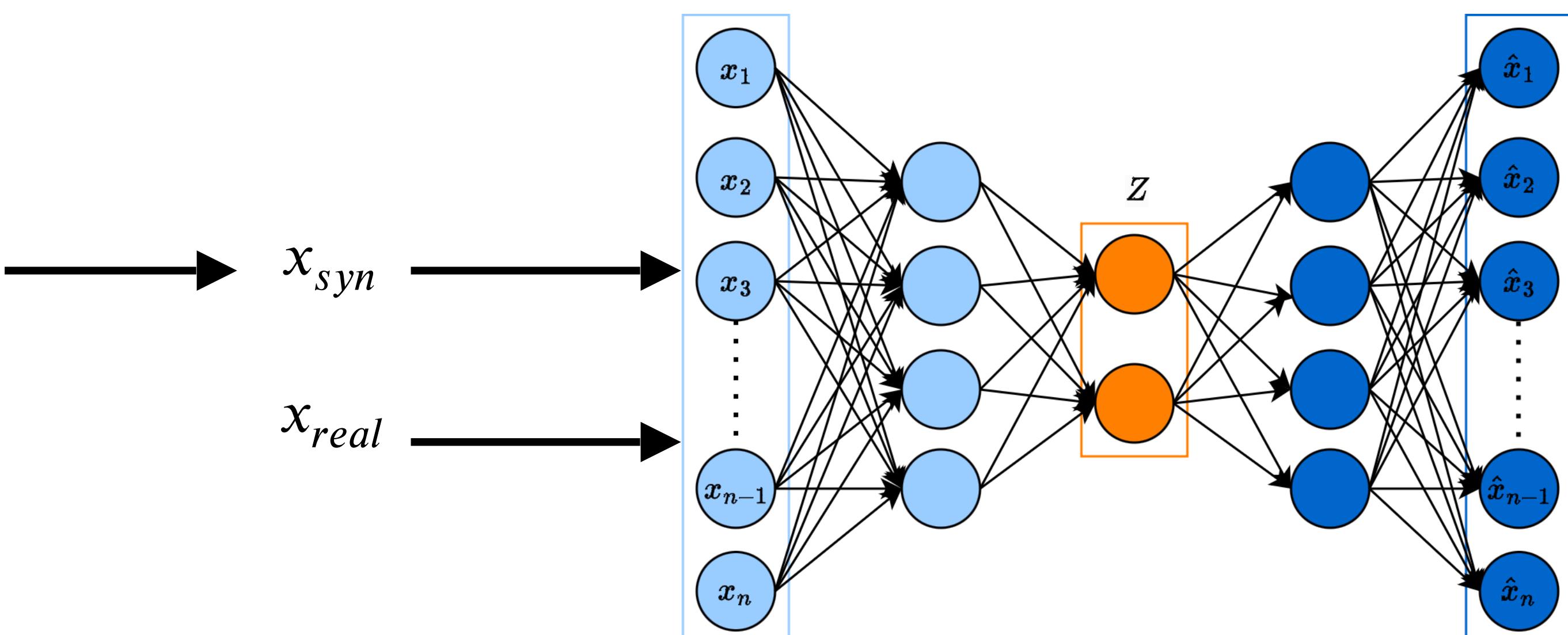
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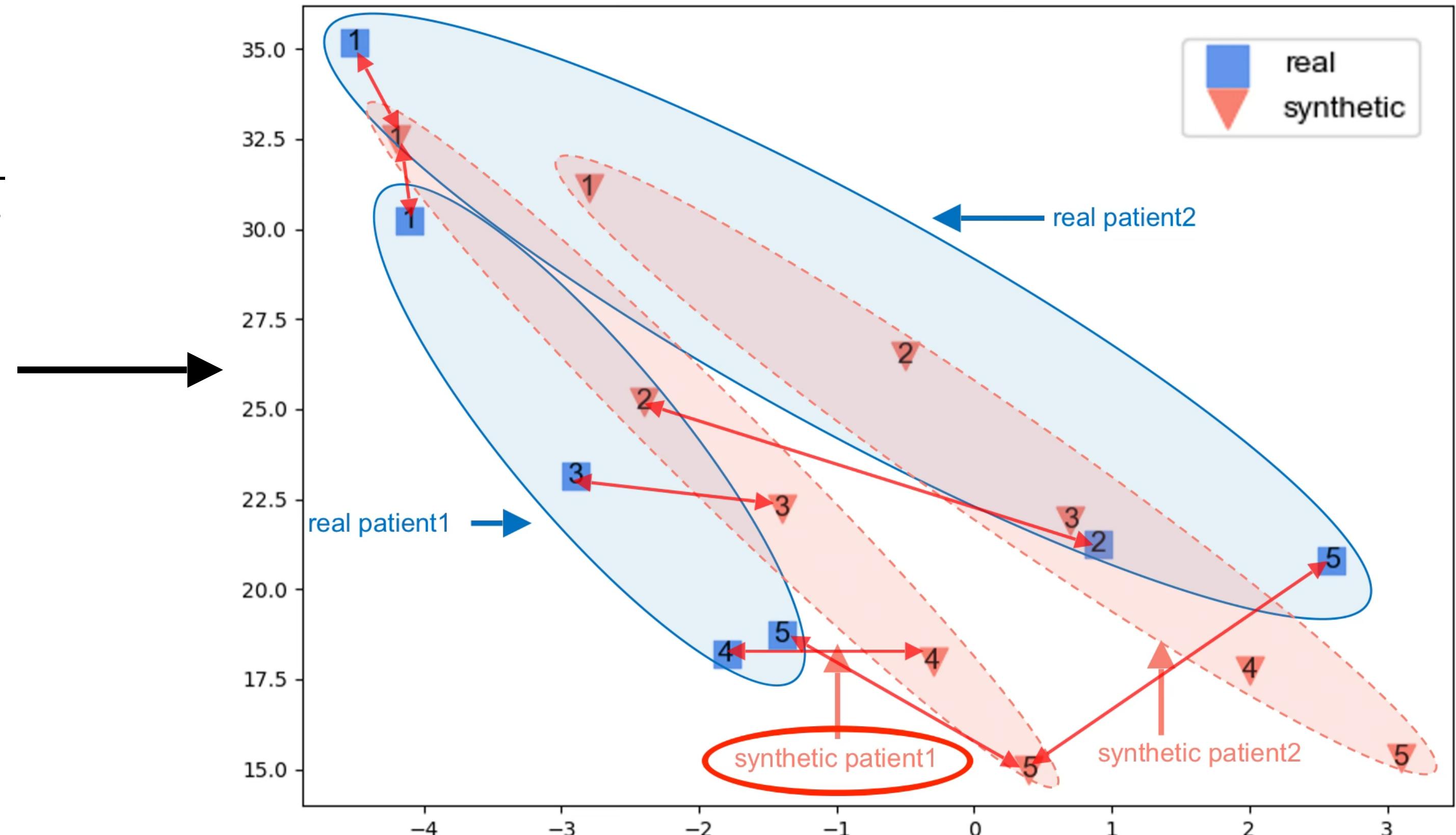
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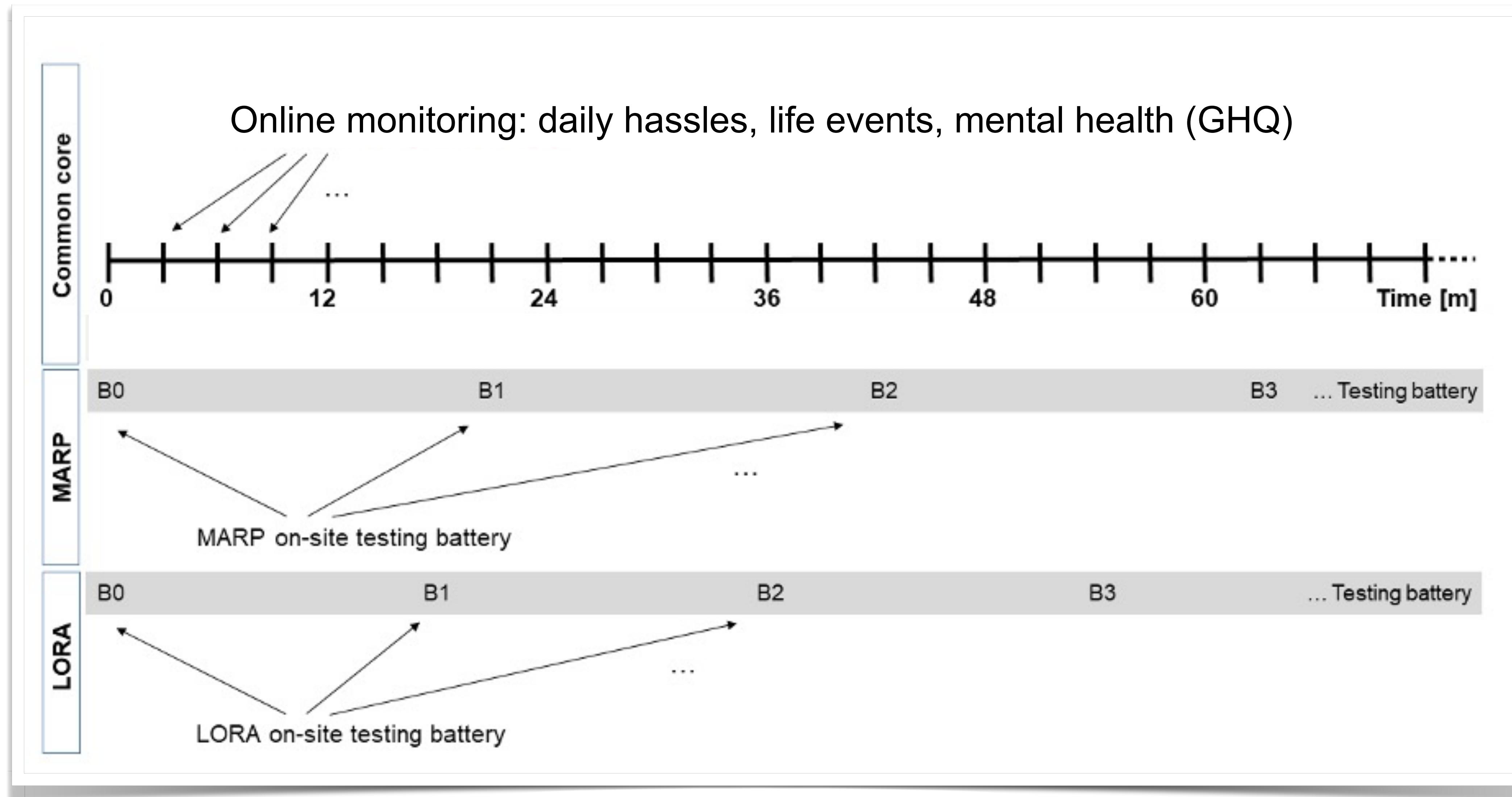
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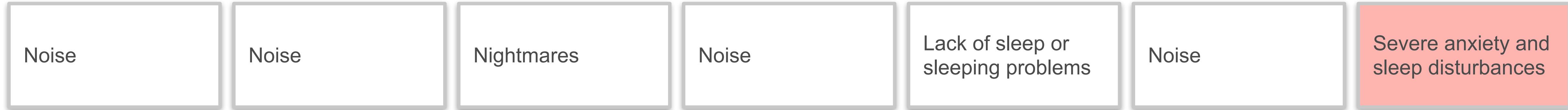
Application: Psychological resilience

DynaMORE project: The MARP and LORA studies

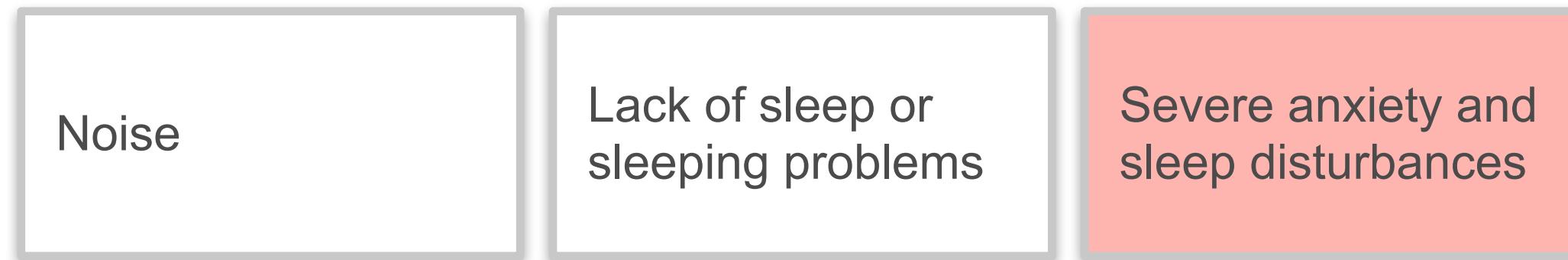


Turning the data into a sequence of tokens

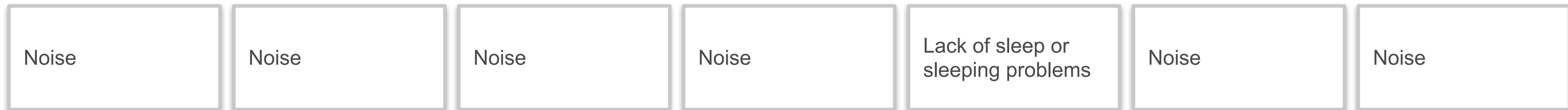
ID 1



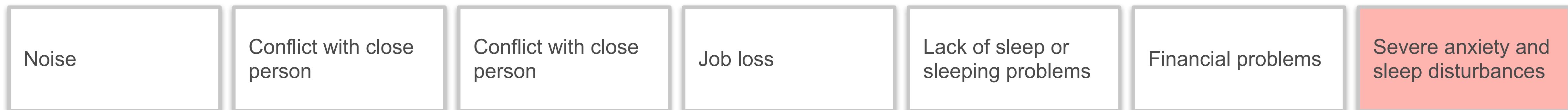
ID 2



ID 3



ID 4



The attention mechanism

- Starting point: sequence of embedding vectors $x_i, i = 1, \dots, n$
(maybe with position information added)

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$$v_i = W_v x_i \quad \text{value tokens}$$

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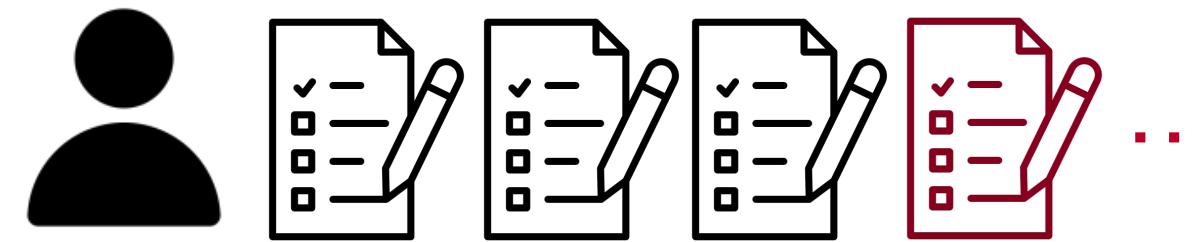
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- Updating the embedding vectors:

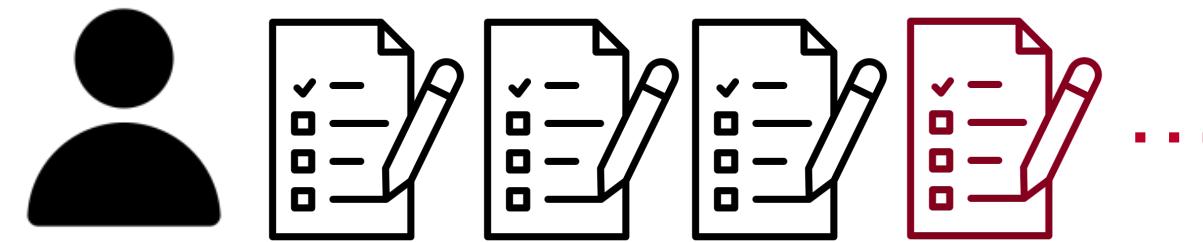
$$h_i = \sum_{j=1}^n \text{softmax}_j \left(g(q_i, k_j) \right) \cdot v_j$$

Generating synthetic data by continuing sequences



In the first visit, the participant reported, [conflict with a close person], [severe argument with partner,] [job loss,] [end.] In the next visit, the participant reported [looking for a new job,] [conflict with a close person,] [meeting,] [end.] In the next visit the participant reported [conflict with a close person,] [severe argument with partner,] [lack of sleep,] [end.]

Generating synthetic data by continuing sequences



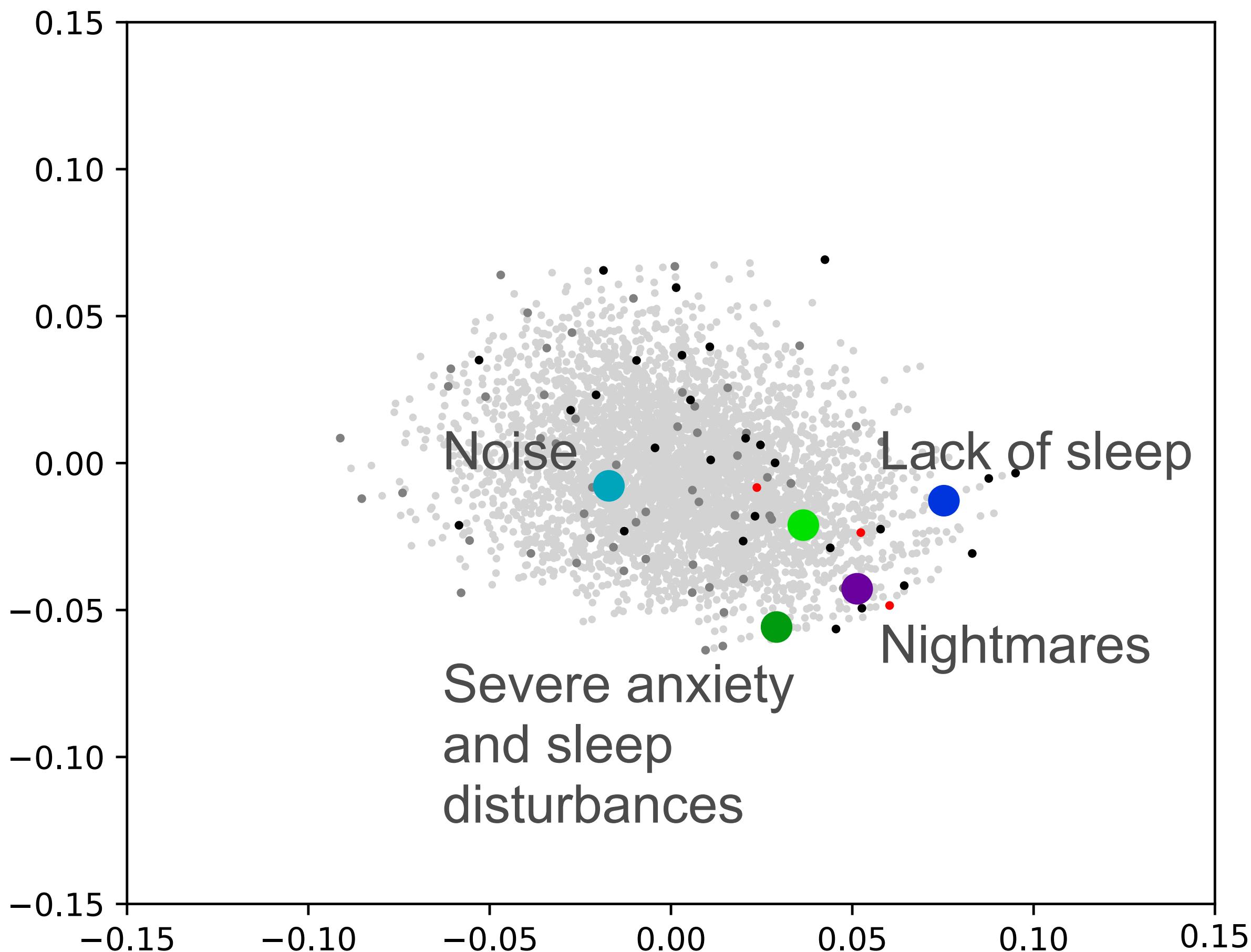
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In the next visit the participant reported [looking for a new job,][financial problems,]
[conflict with a close person,][time pressure,][end.]

Borrowing label embeddings from a large language model (LLM)

Dimension reduction using a variational autoencoder

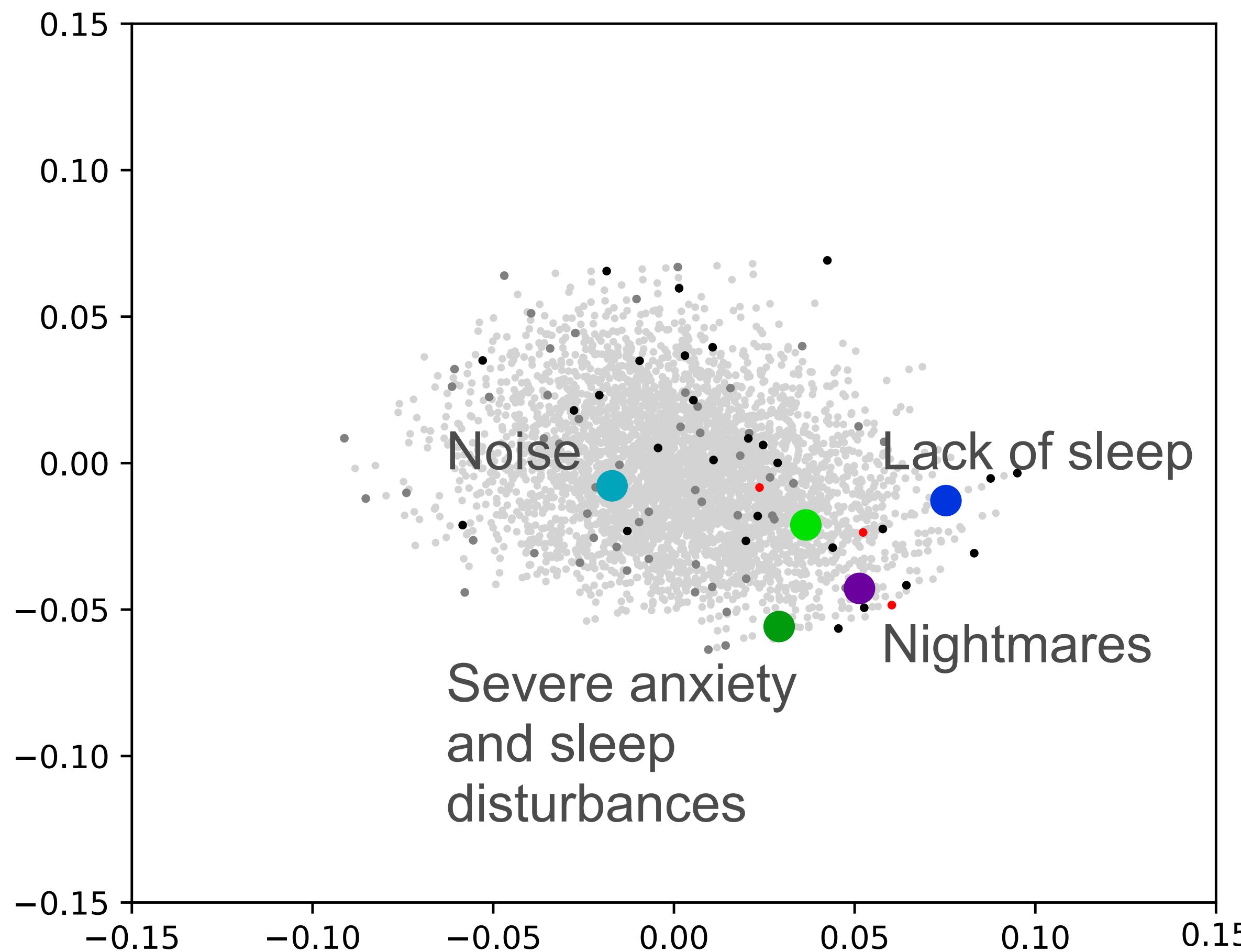
Averaging the embedding of “Nightmares”,
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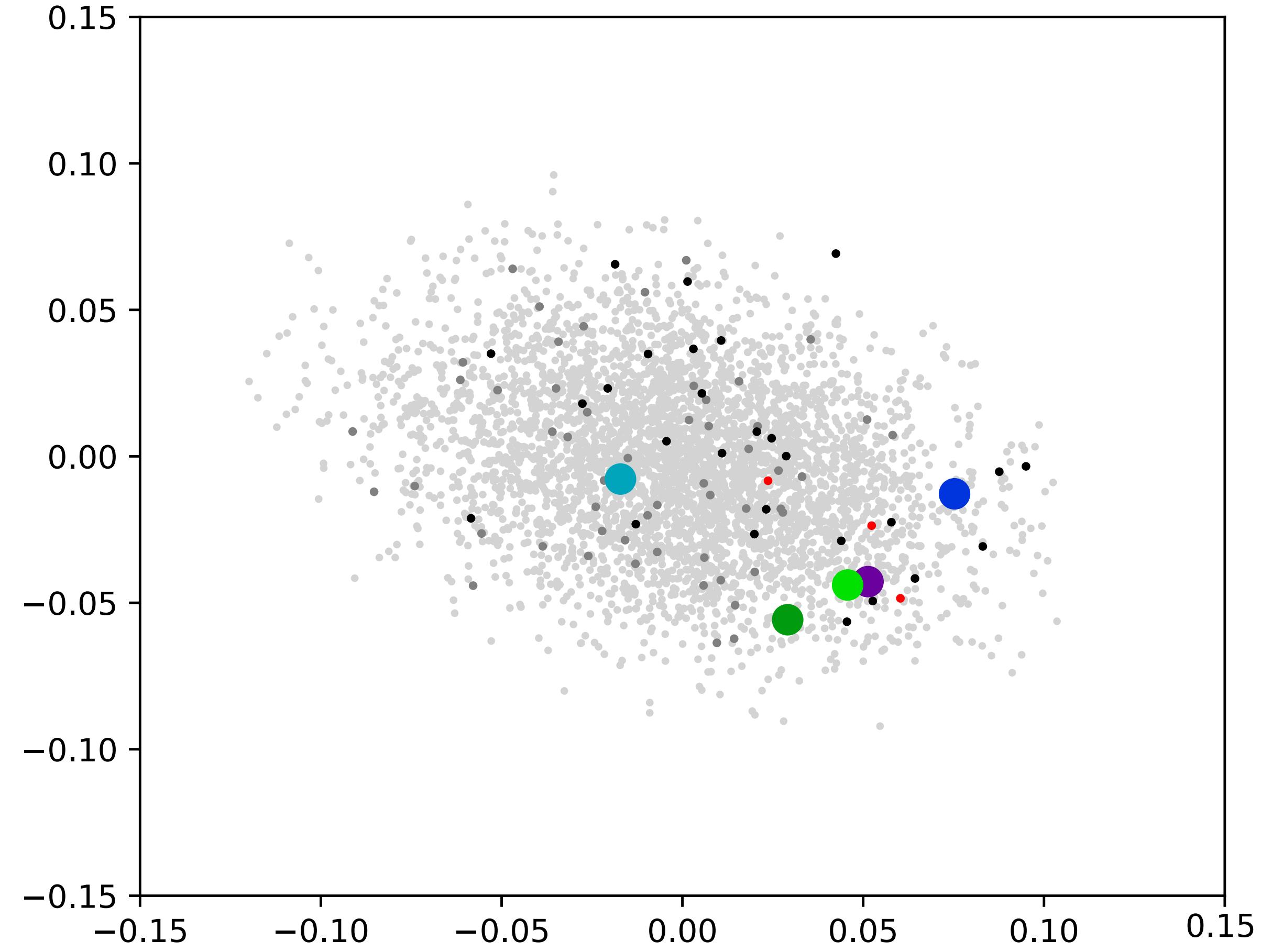
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Using “Nightmares” and “Lack of sleep” as a context for “Noise”



Thanks to ...

Members of my group who did the actual work:

Max Behrens, Kiana Farhadyar, Maren Hackenberg, Michelle Pfaffenlehner,
Clemens Schächter, Hanning Yang



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