

Sparse Multi-Channel Variational Autoencoder for the Joint Analysis of Heterogeneous Data

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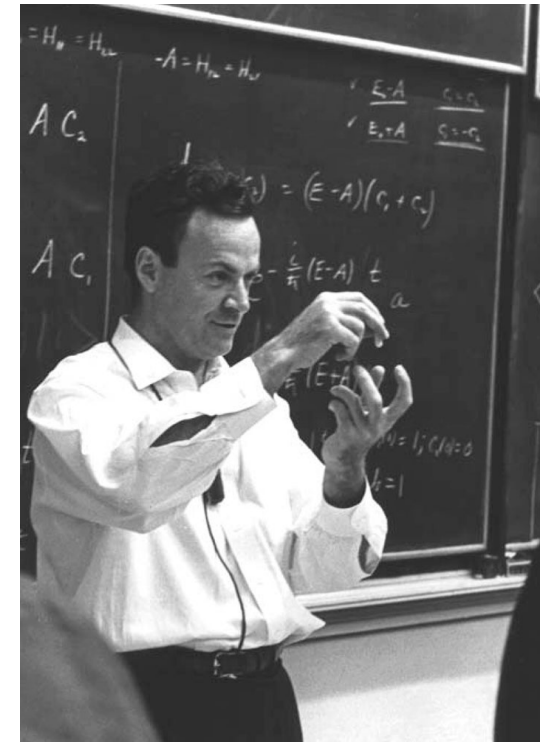
ICML 2019, Long Beach, June 12th 2019

Session: *Generative Models*

Why I like Generative Models

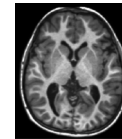
“What I cannot create, I do not understand”

R. P. Feynman



The Generative Multi-Channel Model

For C channels ...



\mathbf{x}_1



\mathbf{x}_2

.

.

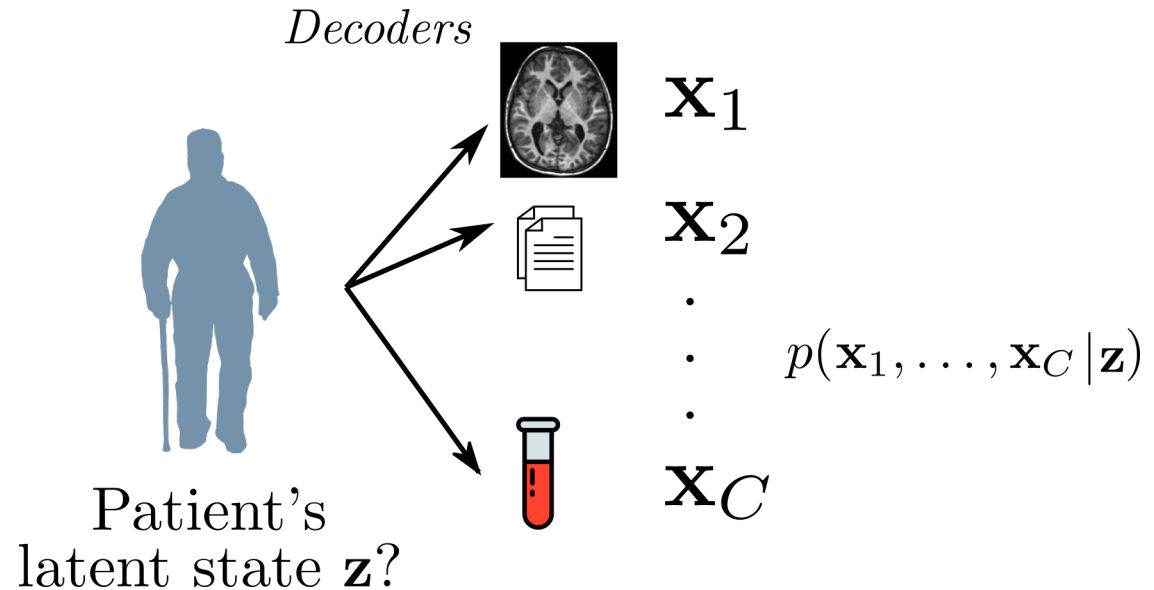
.



\mathbf{x}_C

The Generative Multi-Channel Model

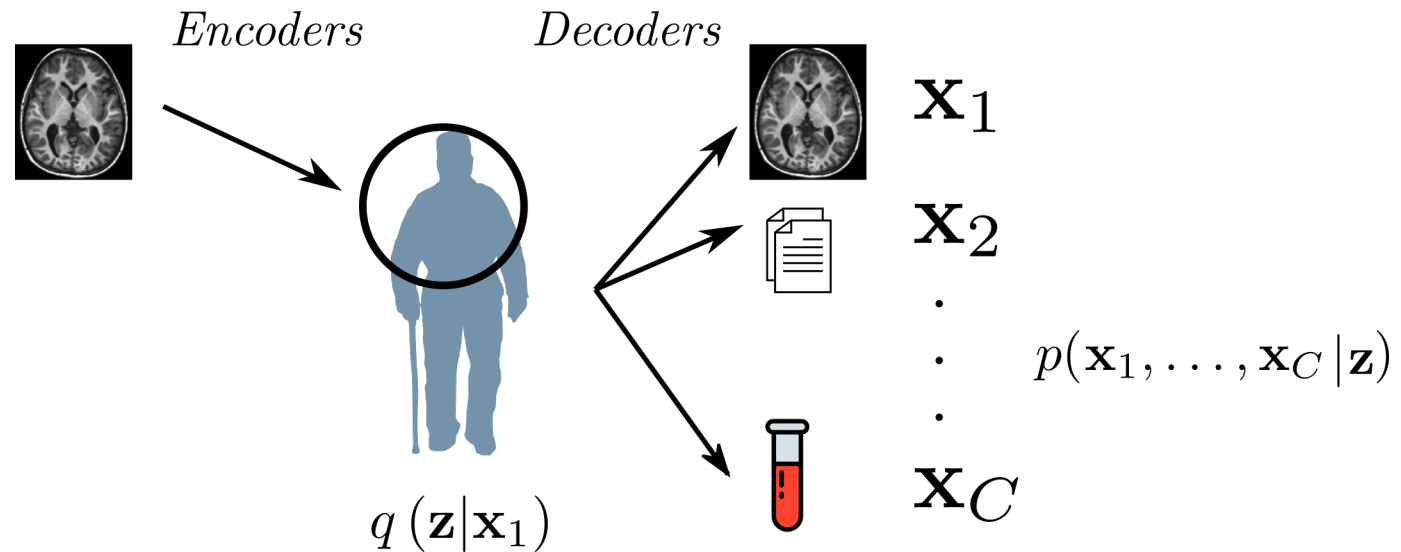
For C channels we assume the following generative process:



Decoders: reconstruction of data from the latent space \mathbf{z}

The Generative Multi-Channel Model

For C channels we assume the following generative process:

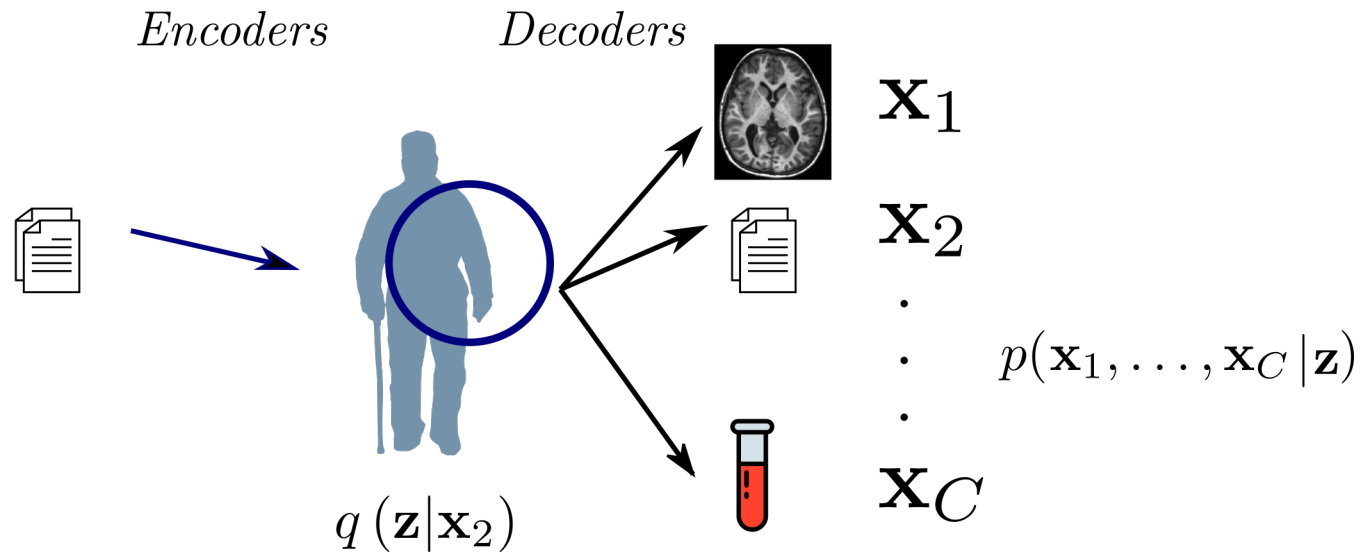


Decoders: reconstruction of data from the latent space \mathbf{z}

Encoders: inference of the latent space \mathbf{z} from the data

The Generative Multi-Channel Model

For C channels we assume the following generative process:

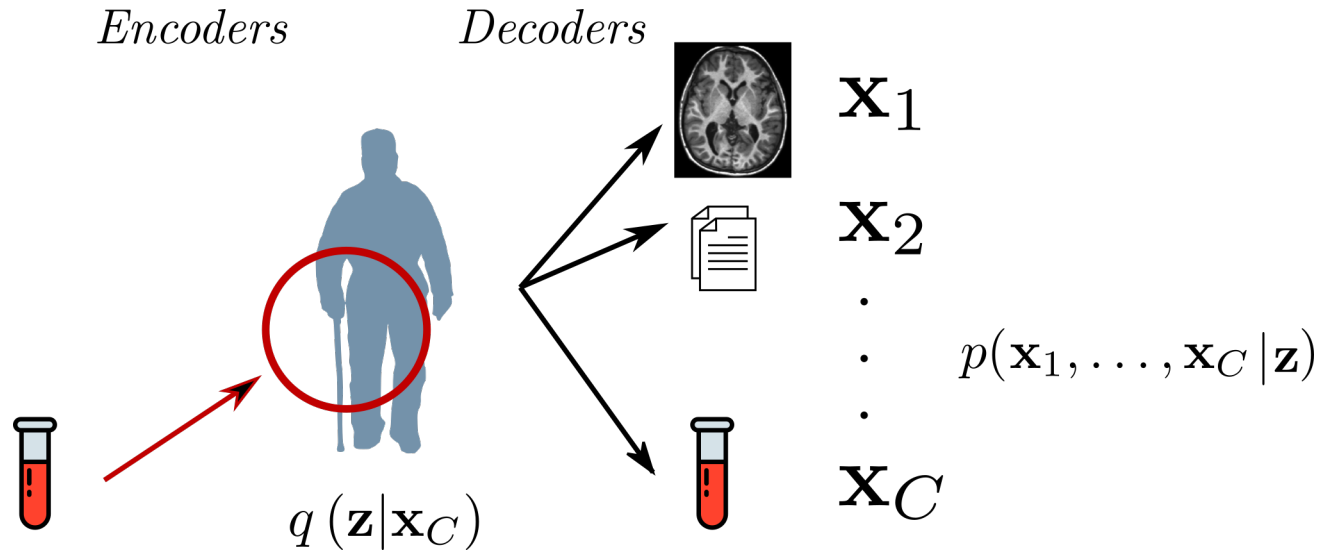


Decoders: reconstruction of data from the latent space z

Encoders: inference of the latent space z from the data

The Generative Multi-Channel Model

For C channels we assume the following generative process:

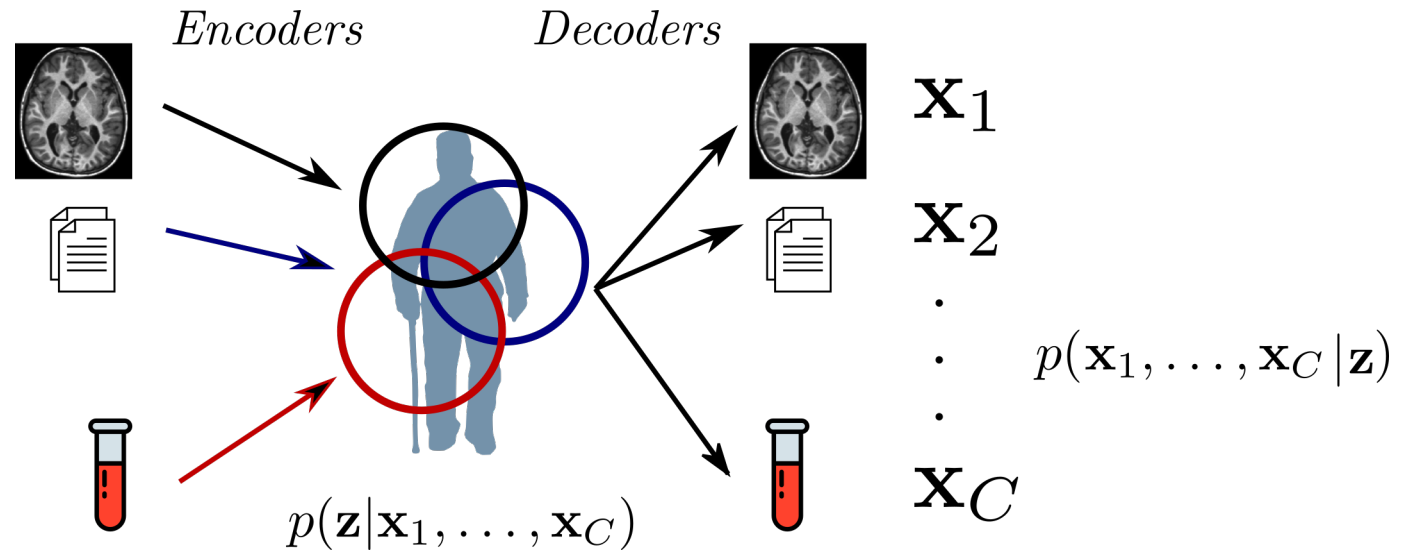


Decoders: reconstruction of data from the latent space \mathbf{z}

Encoders: inference of the latent space \mathbf{z} from the data

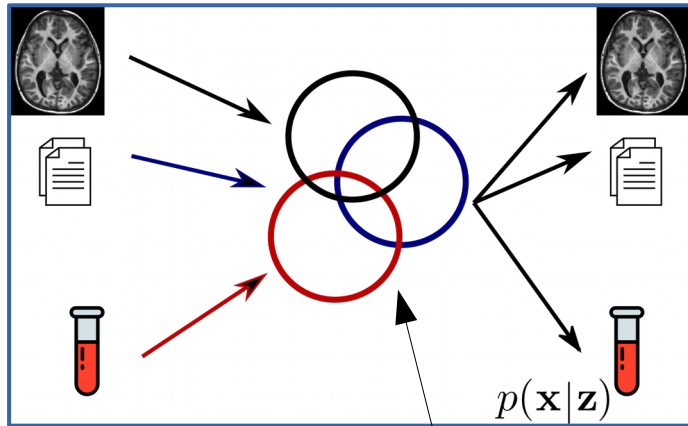
The Generative Multi-Channel Model

Every channel is informative



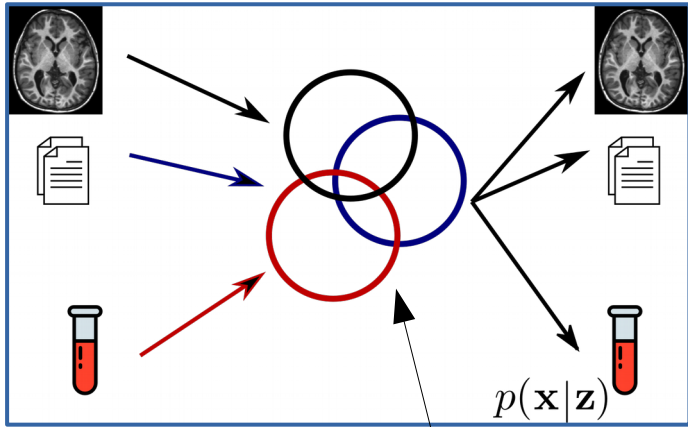
Decoders: reconstruction of data from the latent space z
Encoders: inference of the latent space z from the data

The Generative Multi-Channel Model



$$\arg \min_{q \in \mathcal{Q}} \mathbb{E}_c \mathcal{D}_{\text{KL}} (q(\mathbf{z}|\mathbf{x}_c) \| p(\mathbf{z}|\mathbf{x}_1, \dots, \mathbf{x}_C))$$

The Generative Multi-Channel Model

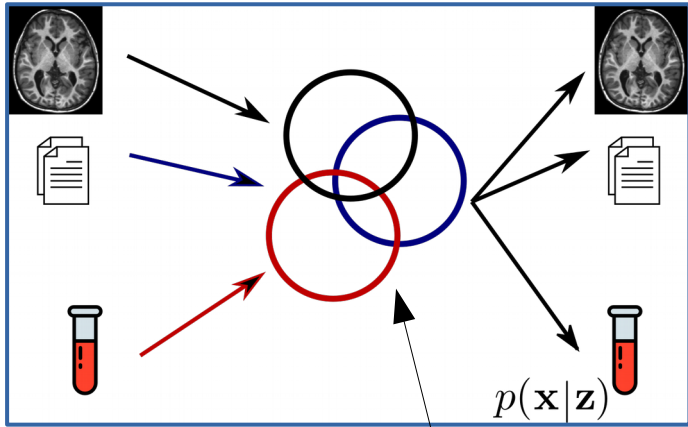


Evidence Lower Bound

$$\frac{1}{C} \sum_{c=1}^C \mathbb{E}_{q(\mathbf{z}|\mathbf{x}_c)} [\sum_{i=1}^C \ln p(\mathbf{x}_i|\mathbf{z})] - \mathcal{D}_{\text{KL}} (q(\mathbf{z}|\mathbf{x}_c) \| p(\mathbf{z}))$$

$$\arg \min_{q \in \mathcal{Q}} \mathbb{E}_c \mathcal{D}_{\text{KL}} (q(\mathbf{z}|\mathbf{x}_c) \| p(\mathbf{z}|\mathbf{x}_1, \dots, \mathbf{x}_C))$$

The Generative Multi-Channel Model



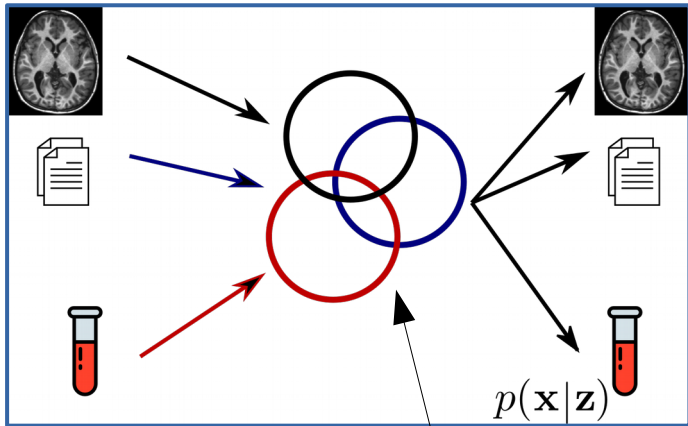
Evidence Lower Bound

$$\frac{1}{C} \sum_{c=1}^C \mathbb{E}_{q(\mathbf{z}|\mathbf{x}_c)} [\sum_{i=1}^C \ln p(\mathbf{x}_i|\mathbf{z})] - \mathcal{D}_{\text{KL}} (q(\mathbf{z}|\mathbf{x}_c) \| p(\mathbf{z}))$$

Encoding from a given channel

$$\underset{q \in \mathcal{Q}}{\operatorname{arg\,min}} \mathbb{E}_c \mathcal{D}_{\text{KL}} (q(\mathbf{z}|\mathbf{x}_c) \| p(\mathbf{z}|\mathbf{x}_1, \dots, \mathbf{x}_C))$$

The Generative Multi-Channel Model



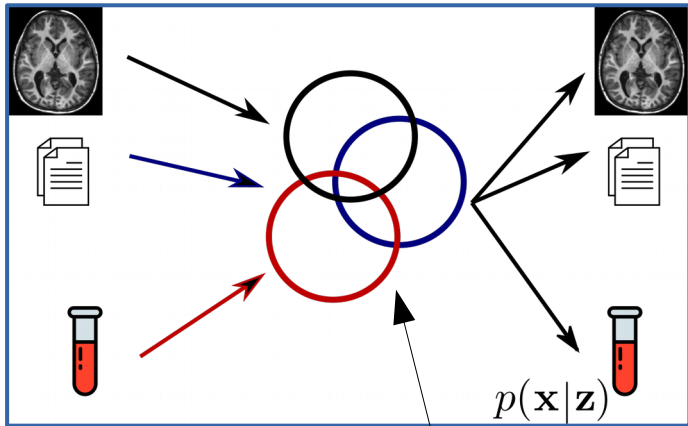
Evidence Lower Bound

$$\frac{1}{C} \sum_{c=1}^C \mathbb{E}_{q(\mathbf{z}|\mathbf{x}_c)} [\sum_{i=1}^C \ln p(\mathbf{x}_i|\mathbf{z})] - \mathcal{D}_{\text{KL}}(q(\mathbf{z}|\mathbf{x}_c) \| p(\mathbf{z}))$$

Encoding from a given channel
Reconstruction of all the channels

$$\arg \min_{q \in \mathcal{Q}} \mathbb{E}_c \mathcal{D}_{\text{KL}}(q(\mathbf{z}|\mathbf{x}_c) \| p(\mathbf{z}|\mathbf{x}_1, \dots, \mathbf{x}_C))$$

The Generative Multi-Channel Model



Evidence Lower Bound

$$\frac{1}{C} \sum_{c=1}^C \mathbb{E}_{q(\mathbf{z}|\mathbf{x}_c)} \left[\sum_{i=1}^C \ln p(\mathbf{x}_i|\mathbf{z}) \right] - \mathcal{D}_{\text{KL}} (q(\mathbf{z}|\mathbf{x}_c) \| p(\mathbf{z}))$$

Encoding from a given channel
 Reconstruction of all the channels
 Regularization inducing sparsity:

- variational dropout on \mathbf{z}
- model selection
- interpretability
- pruning factor $\sim 50\%$

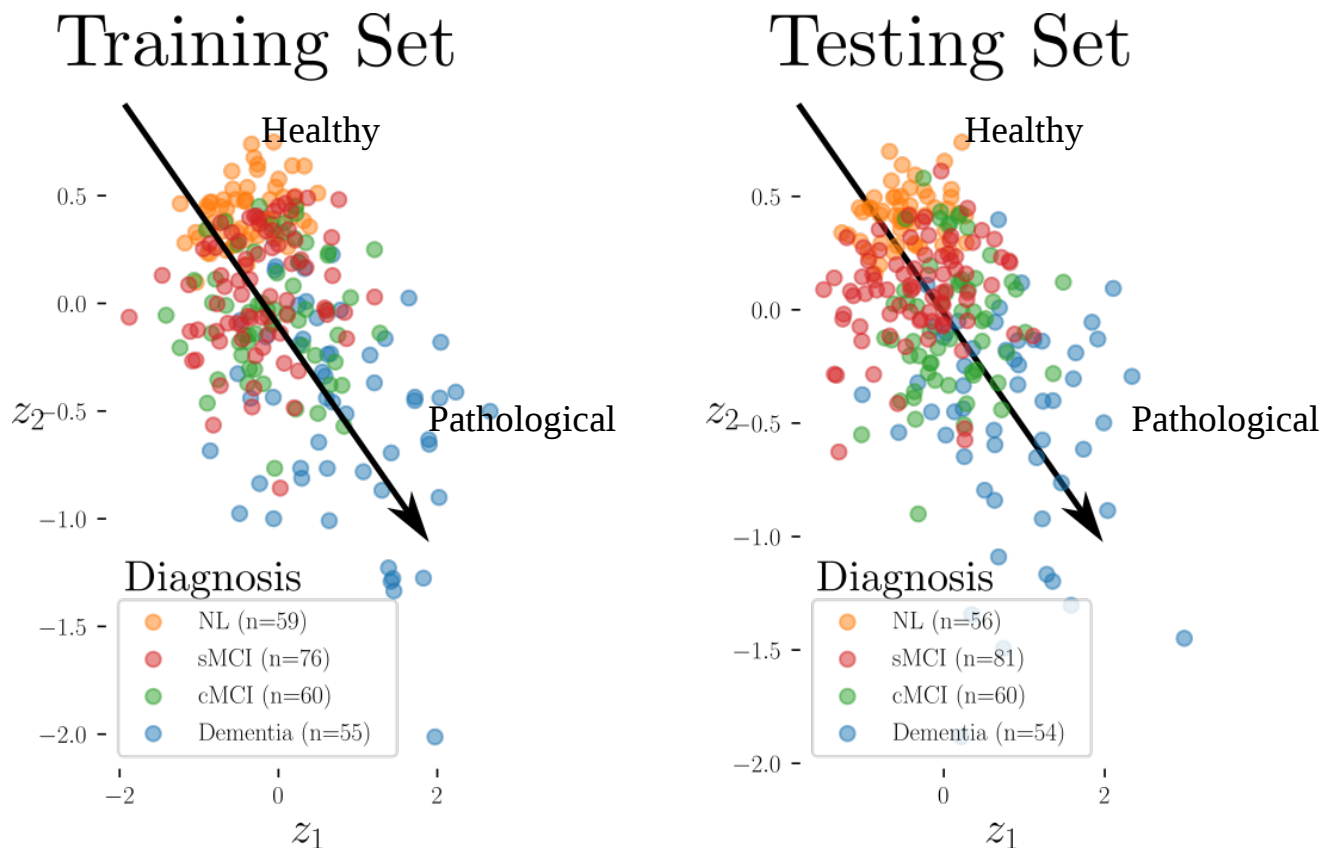
$$\arg \min_{q \in \mathcal{Q}} \mathbb{E}_c \mathcal{D}_{\text{KL}} (q(\mathbf{z}|\mathbf{x}_c) \| p(\mathbf{z}|\mathbf{x}_1, \dots, \mathbf{x}_C))$$

Variational Dropout bibliography: Wang et al., ICML 2013; Kingma et al., NIPS 2015; Molchanov et al., ICML 2017.

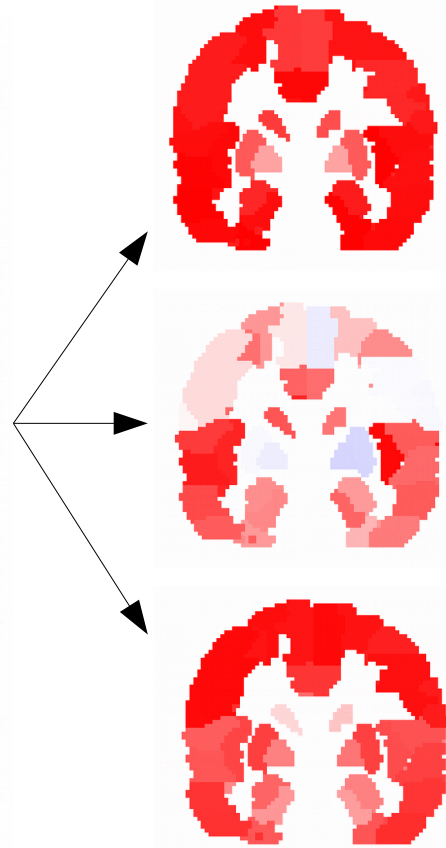
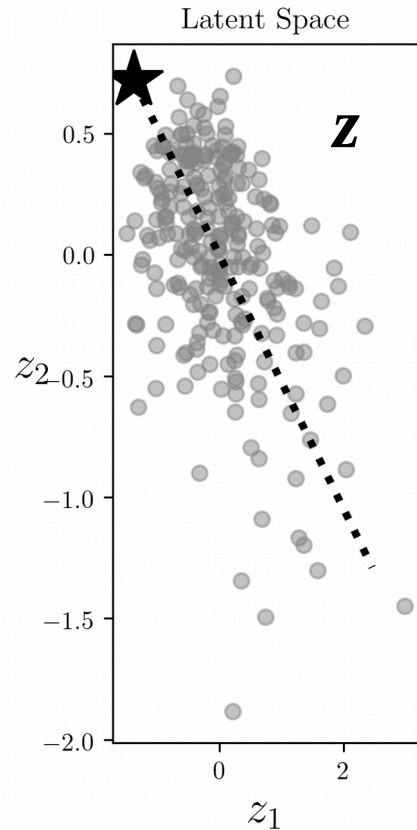
Unsupervised clustering in Alzheimers' Disease

Joint modeling of: **Clinical scores** + {Structural + Metabolic + Molecular} **Imaging**.

Diagnosis status **unknown** to the model



Generation from latent space

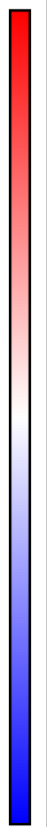


Structural Imaging (MRI)

Metabolic Imaging (FDG-PET)

Molecular Imaging (AV45-PET)

Healthy

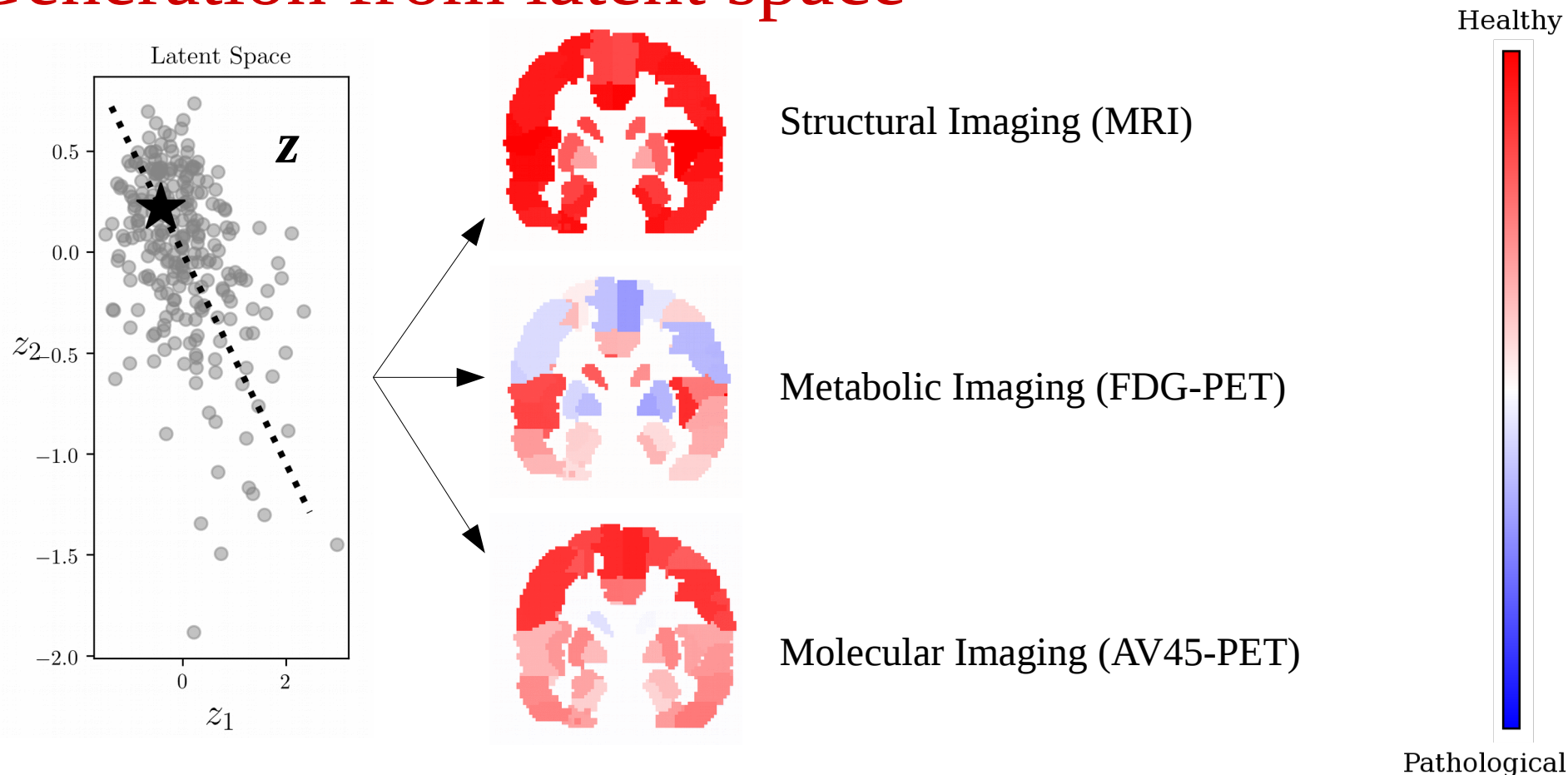


Pathological

- Improved interpretability
- Simulations for clinical trials

Adapted from: M. Lorenzi, Collège de France, 23/4/2019

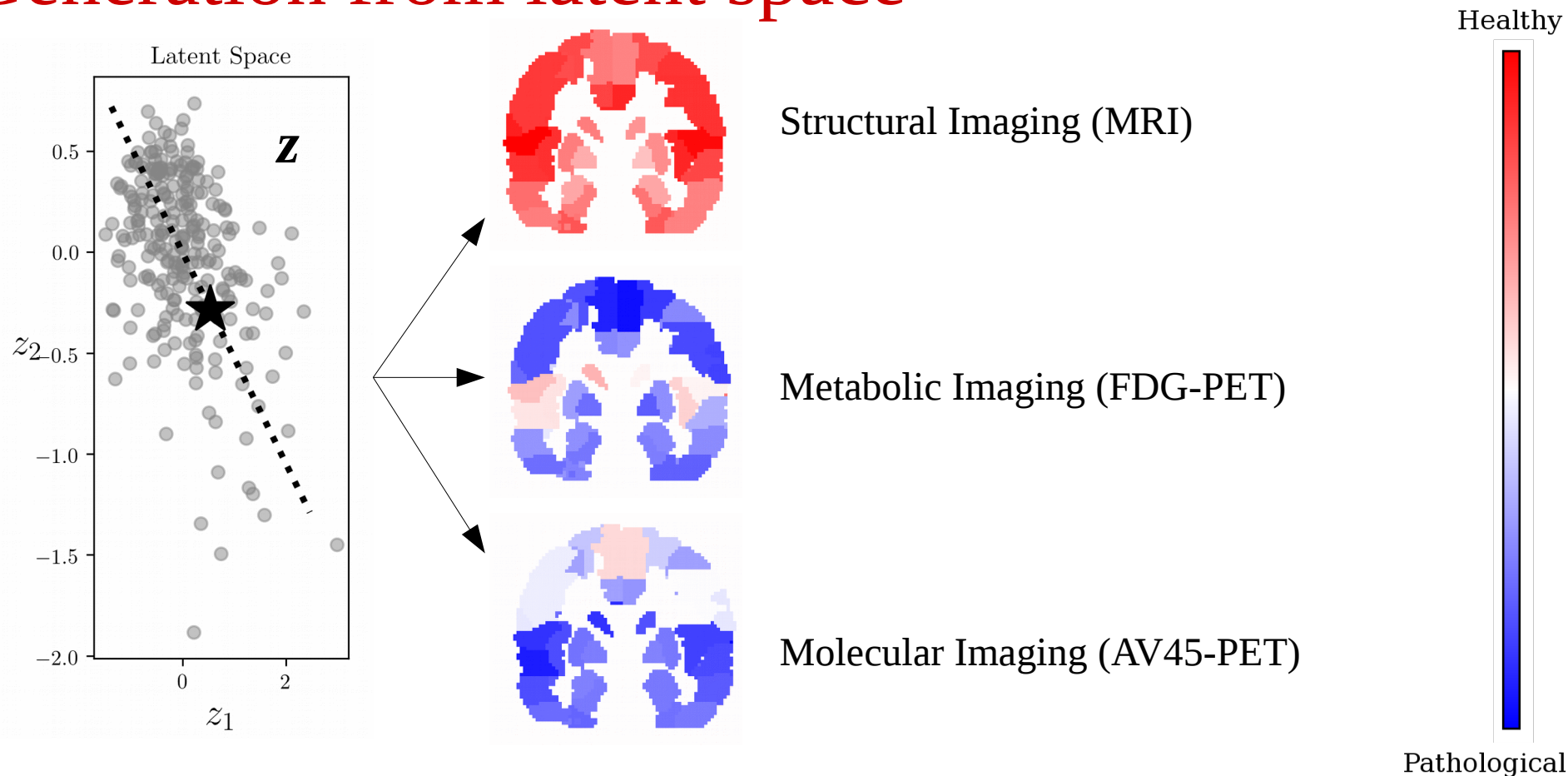
Generation from latent space



- Improved interpretability
- Simulations for clinical trials

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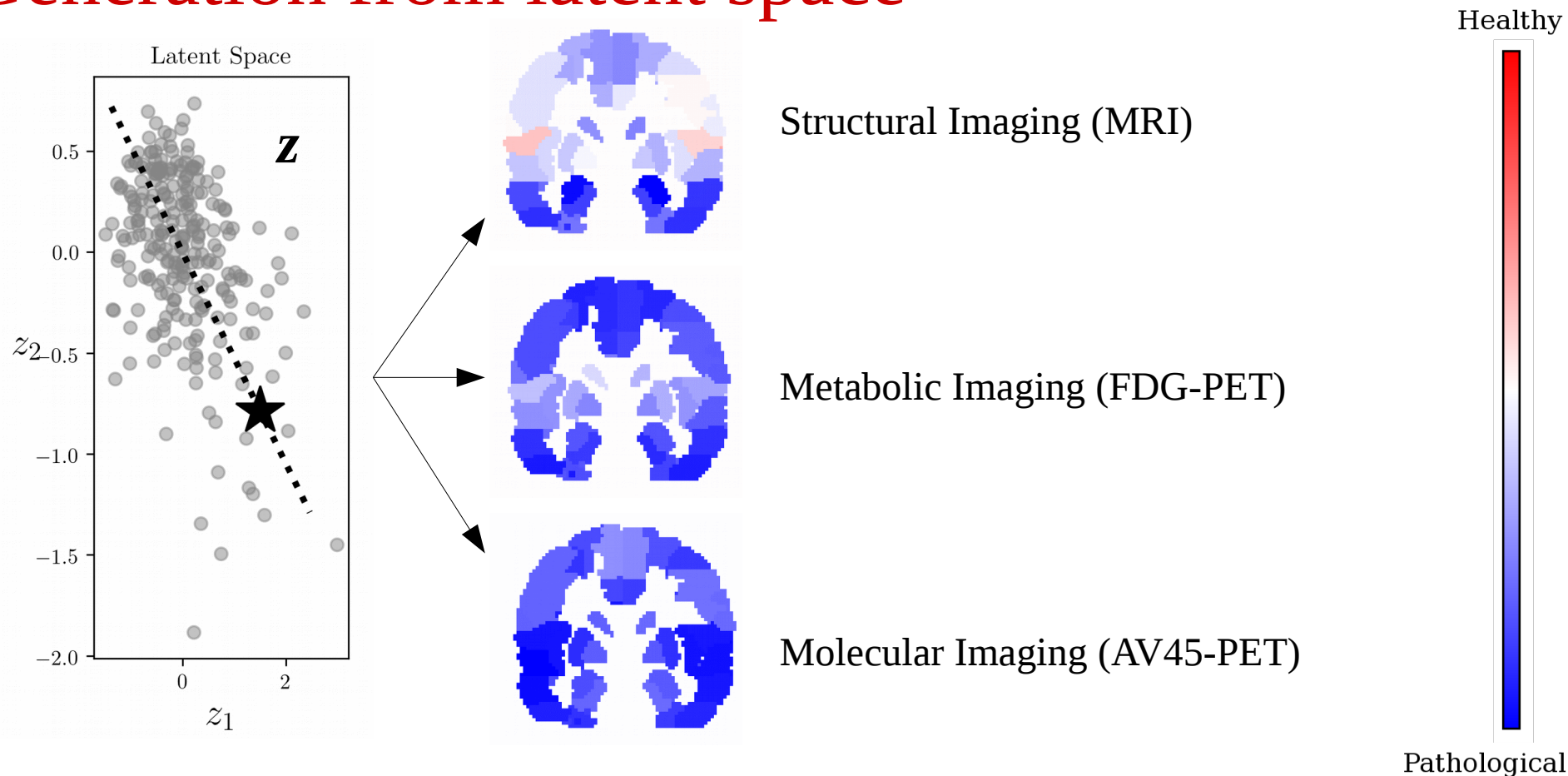
Generation from latent space



- Improved interpretability
- Simulations for clinical trials

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Generation from latent space



- Improved interpretability
- Simulations for clinical trials

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If you're interested in:

VAEs, Sparse Code, Interpretability, Prediction
of Missing Data, Medical Applications, ...

see you at Poster #57, Pacific Ballroom
06:30 pm - ...

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Thank you!