

A Deep Variational Approach to Clustering Survival Data

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1 Survival Cluster Analysis

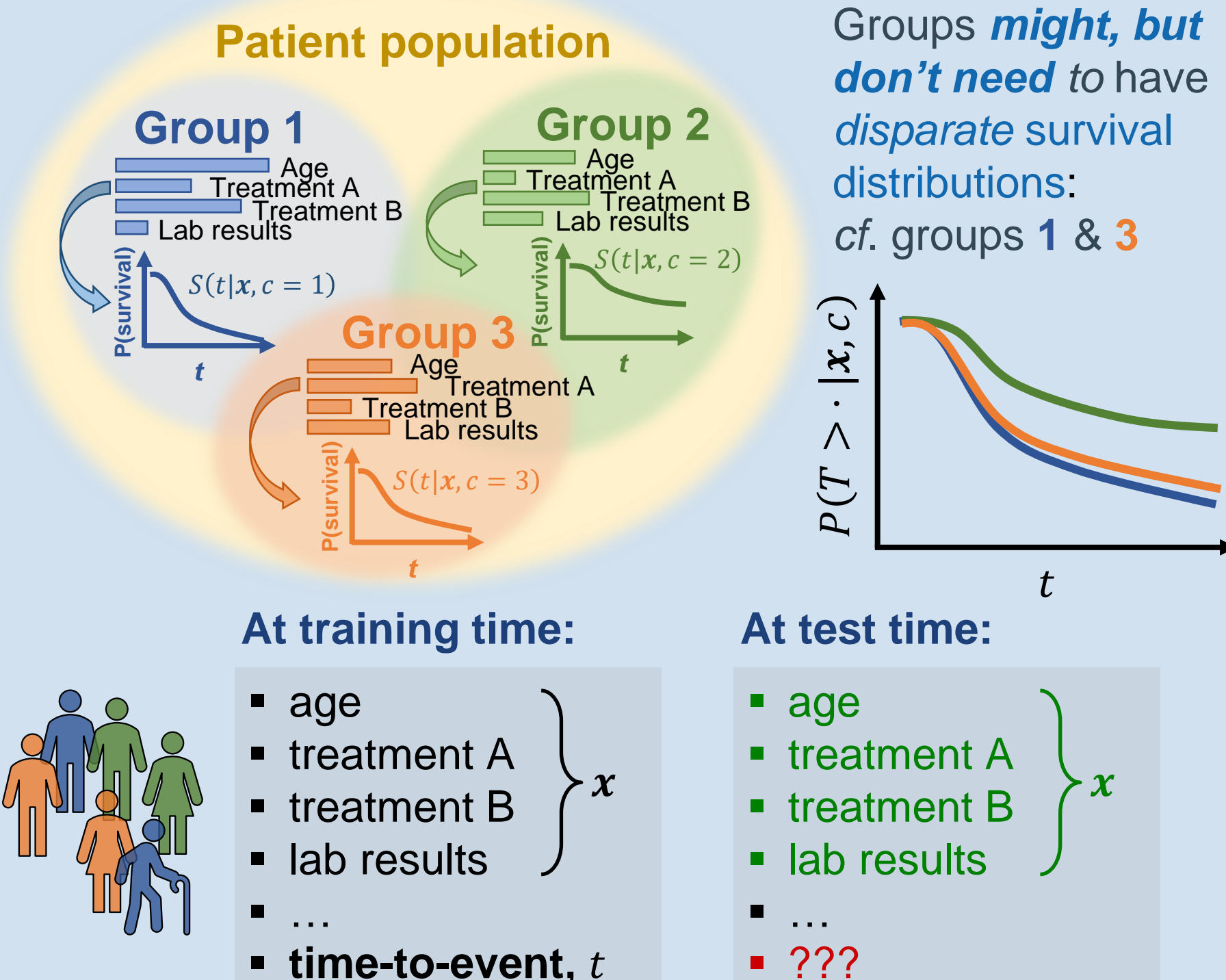
Given:

- data $\mathcal{D} = \{x_i, t_i, \delta_i\}_{i=1}^N$
- x_i is a vector of *explanatory variables*
- t_i is the *time to a certain event*
- t_i is *censored* ($\delta_i = 0$) when its value is only partially known

Goal: discover **cluster-specific** relationships between *explanatory variables* x and *time-to-event* t , that is:

- discover the unobserved *cluster assignment* c
- model the *survival distribution*: $S(t|x, c) = P(T > t|x, c)$

Example: patient population consists of **three clusters** with different disease subtypes. Each group features **different associations** between the covariates x and survival time t



2 Motivation

- Exploratory analysis** for survival data
- Discovery of **heterogeneity** in the relation between x and t
 - better understanding of the disease and its progression
 - personalised* disease management
- Patient **stratification by risk**

3 Variational Deep Survival Clustering (VaDeSC)

Model Overview:

- VAE with a **Gaussian mixture** prior
- cluster-specific Weibull* survival distributions in the latent space
- maximise the joint likelihood of $\{x_i, t_i\}_{i=1}^N$

Generative process:

- Cluster assignment* sampled from a categorical distribution:
 $c \sim p(c; \pi) = \pi_c.$
- Latent embedding* sampled from a cluster-specific Gaussian distribution:
 $z \sim p(z|c) = \mathcal{N}(z; \mu_c, \Sigma_c).$
- Inputs* generated from a distribution parameterised by a neural net (the decoder)
 $x \sim p(x|z; \gamma).$
- Time-to-event* sampled from a cluster-specific Weibull distribution:
 $t \sim p(t|z, c; \{\beta_1, \dots, \beta_K\}, k).$

Evidence Lower Bound:

The likelihood is intractable! We maximise the evidence lower bound (ELBO):

$$\mathbb{E}_{q(z, c|x, t)} [\underbrace{\log p(x|z; \gamma)}_{\text{reconstruction}} + \underbrace{\log p(t|z, c; \beta, k)}_{\text{survival}}] + \underbrace{D_{KL}(q(z, c|x, t) || p(z, c; \mu, \Sigma, \pi))}_{\text{clustering}}$$

The **variational distribution** factorises as follows

$$q(z, c|x, t) = \underbrace{q(z|x)}_{\text{encoder parameterised by an NN}} \underbrace{q(c|z, t)}_{\text{soft cluster assignments}}$$

4 Experimental Setup

An aggregated **computed tomography** (CT) dataset from non-small cell lung cancer patients:

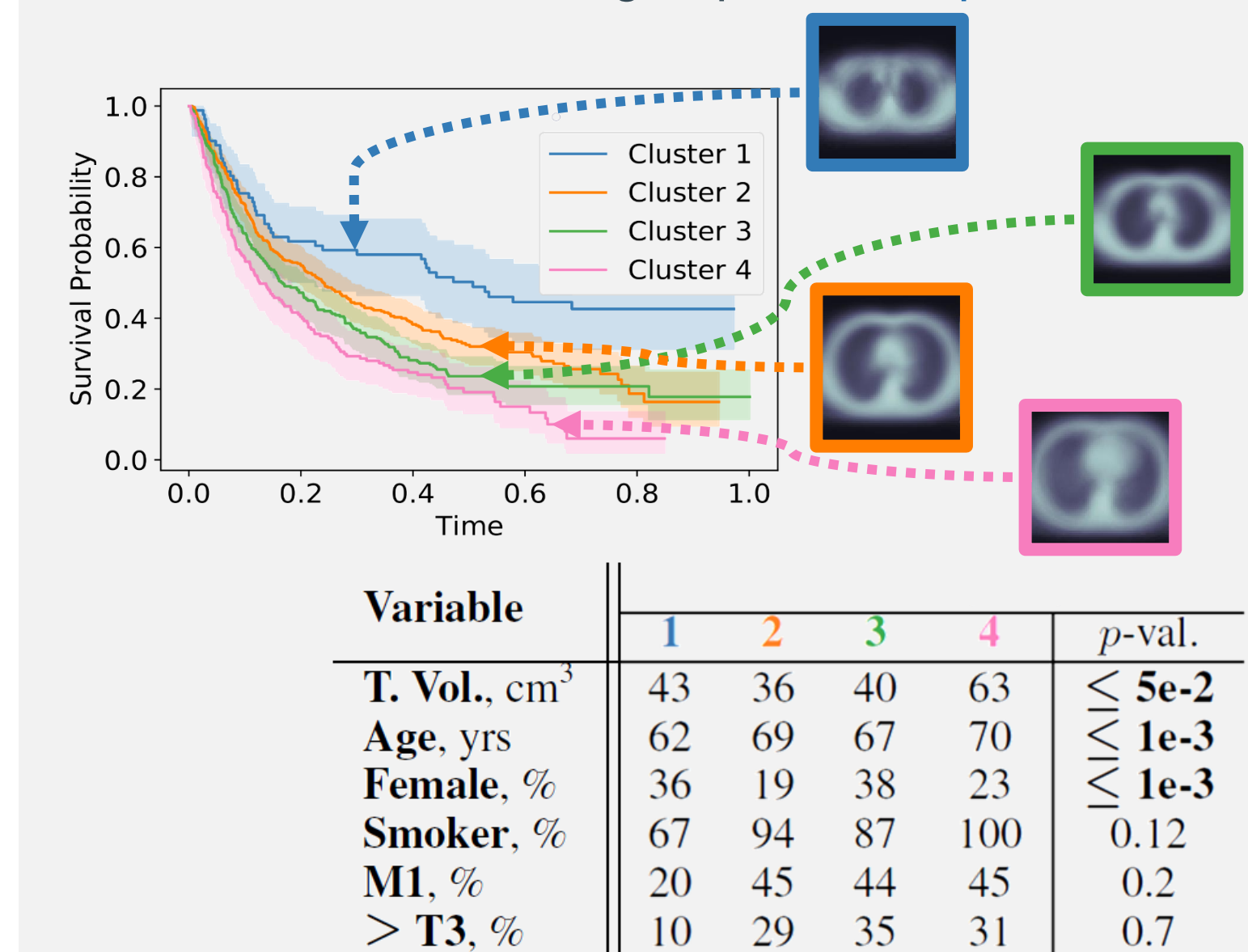
- Basel:** 392 patients, University Hospital Basel, CH
- Lung1:** 422 patients, Maastric clinic, NL
- Lung3:** 89 patients, Maastric clinic, NL
- NSCLC Radiogenomics:** 211 patients, Stanford University School of Medicine and Palo Alto Veterans Affairs Healthcare System, US

5 Results

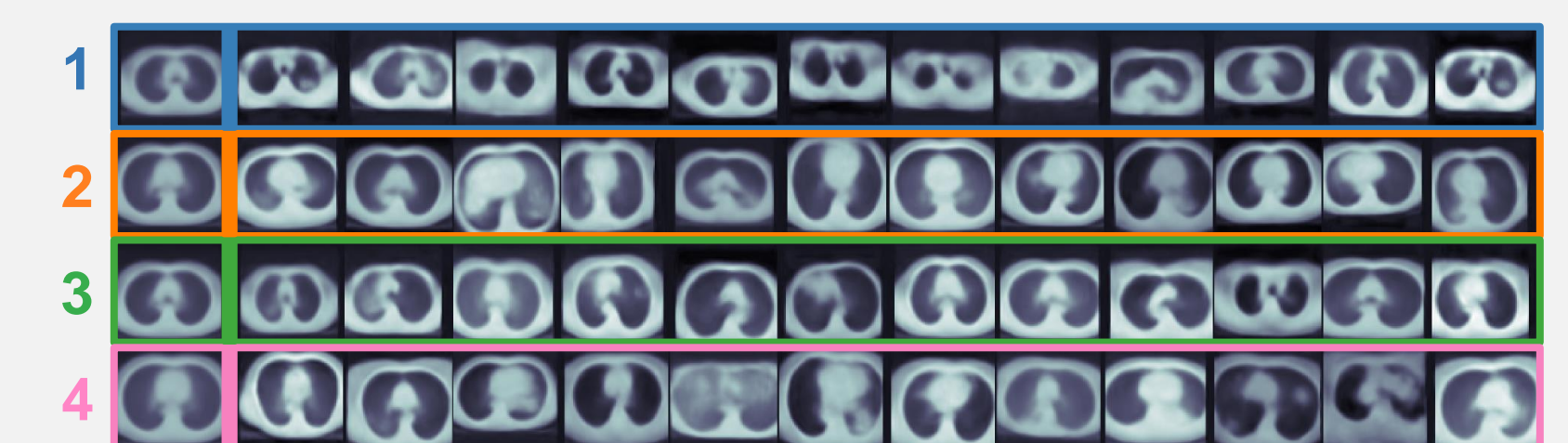
VaDeSC is competitive at predicting survival times:

Method	CI	RAE _{nc}	RAE _c	CAL
Radiomics + Cox PH	0.60±0.02	—	0.45±0.03	—
Radiomics + Weibull AFT	0.60±0.02	0.70±0.02	0.45±0.03	1.26±0.04
DSM	0.59±0.04	0.72±0.03	0.34±0.06	1.24±0.07
VaDeSC (ours)	0.60±0.02	0.71±0.03	0.35±0.05	1.21±0.05

VaDeSC discovers subgroups with **disparate** characteristics:



Clusters are associated with **tumour location**:



6 Summary

A **deep probabilistic model** for clustering survival data:

- novel generative assumptions
- improved clustering and competitive time-to-event prediction
- a holistic representation learning view of survival data

Future work:

- interpretability/explainability
- multimodal survival analysis