The Variational Autoencoder as a Scalable Alternative for Spatiotemporal Data in the Presence of Big Data: With an Application in Glaucoma

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R / Medicine Conference
Boston, MA

September 13, 2019

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HEALTH DATA IN ACTION

Presentation Outline

- Introduction to glaucoma progression and visual field data.
- Modeling concerns when analyzing high-dimensional spatiotemporal (ST) data.
- Defining the variational autoencoder (VAE) and adapting it to ST data.
- Verifying the VAE performance in simulation and real data analysis.

Glaucoma Disease Progression

- Glaucoma is the most common cause of irreversible vision loss worldwide.
- Once diagnosed, clinicians must balance the risks and expenses of advancing levels of medical and surgical intervention with the risks of further vision loss due to **disease progression**.
- Determining if the disease is progressing remains one of the most difficult tasks in the clinical setting, making **prediction** integral.

Functional Detection of Progression

Longitudinal monitoring through visual field examinations.

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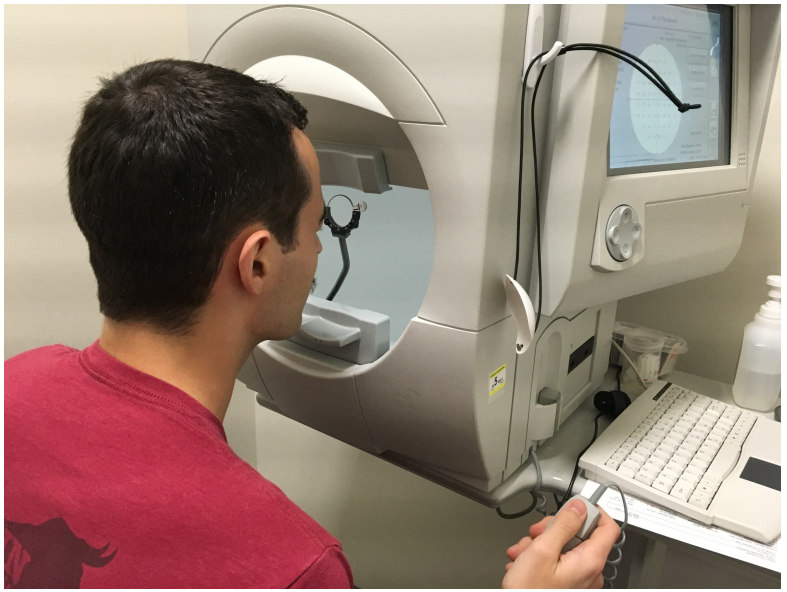

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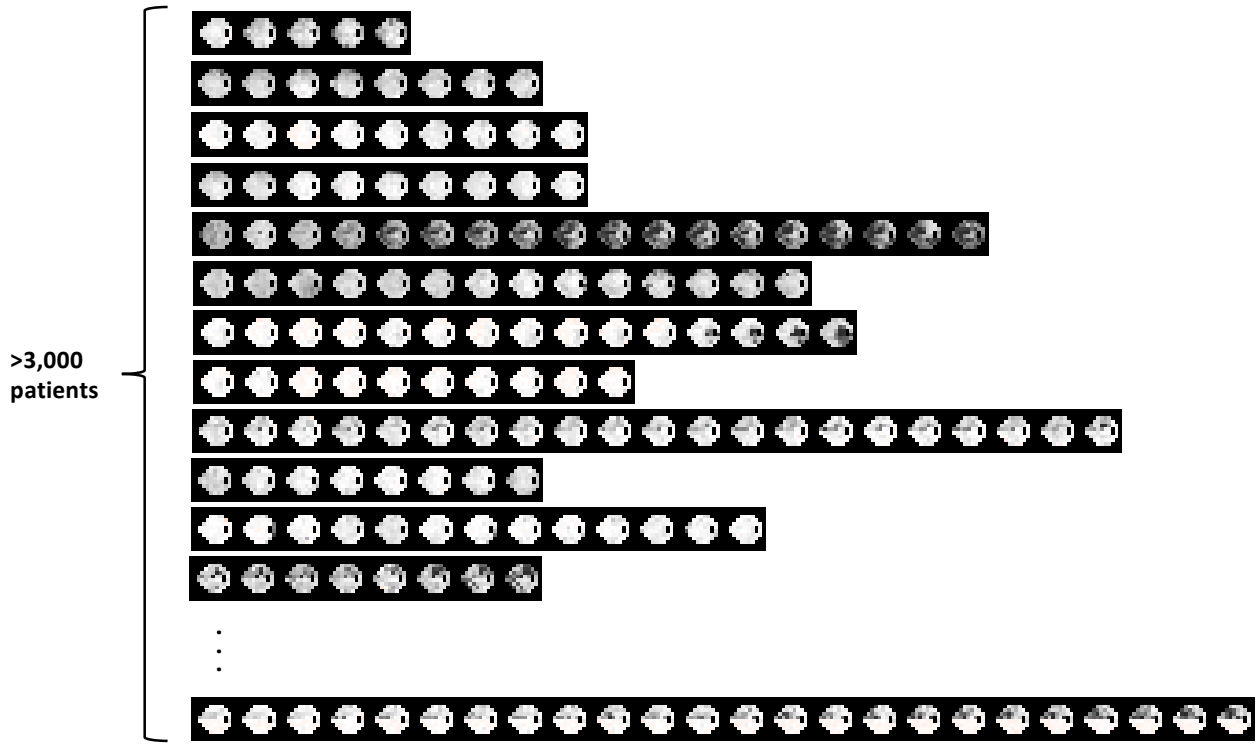
High-Dimensional Spatiotemporal Data



Modeling assumptions for large samples of ST data

1. Observations across patients are independent.
2. Images have a low-dimensional representation that can be modeled in place of the original image (predict on the latent level).

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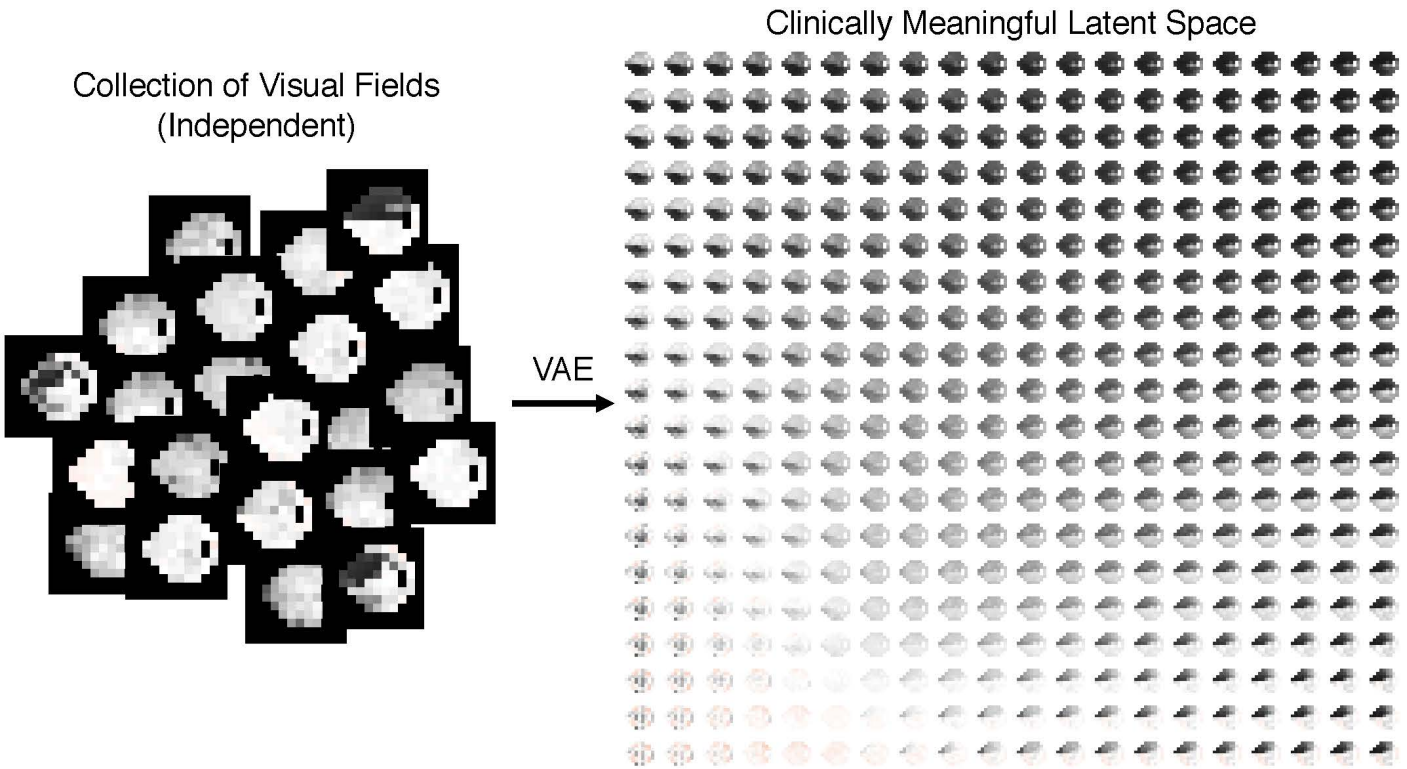
Two-Stage Variational Autoencoder

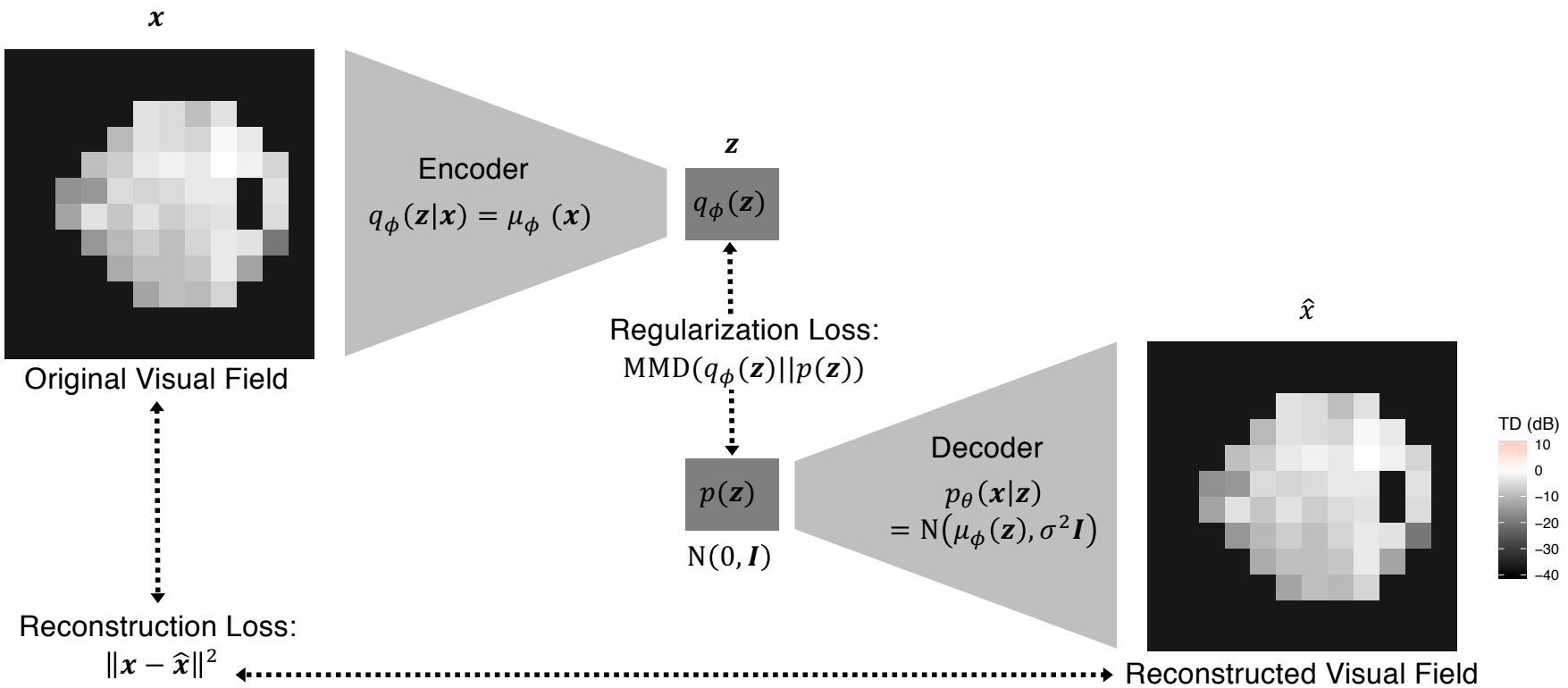
- Joint model across eyes (prediction at the observed data level).
- **Stage 1:** Apply VAE (treats visual fields as independent).
- **Stage 2:** Incorporate longitudinal information by regressing through latent space.



But, how does the VAE work?

Stage 1: The Variational Autoencoder

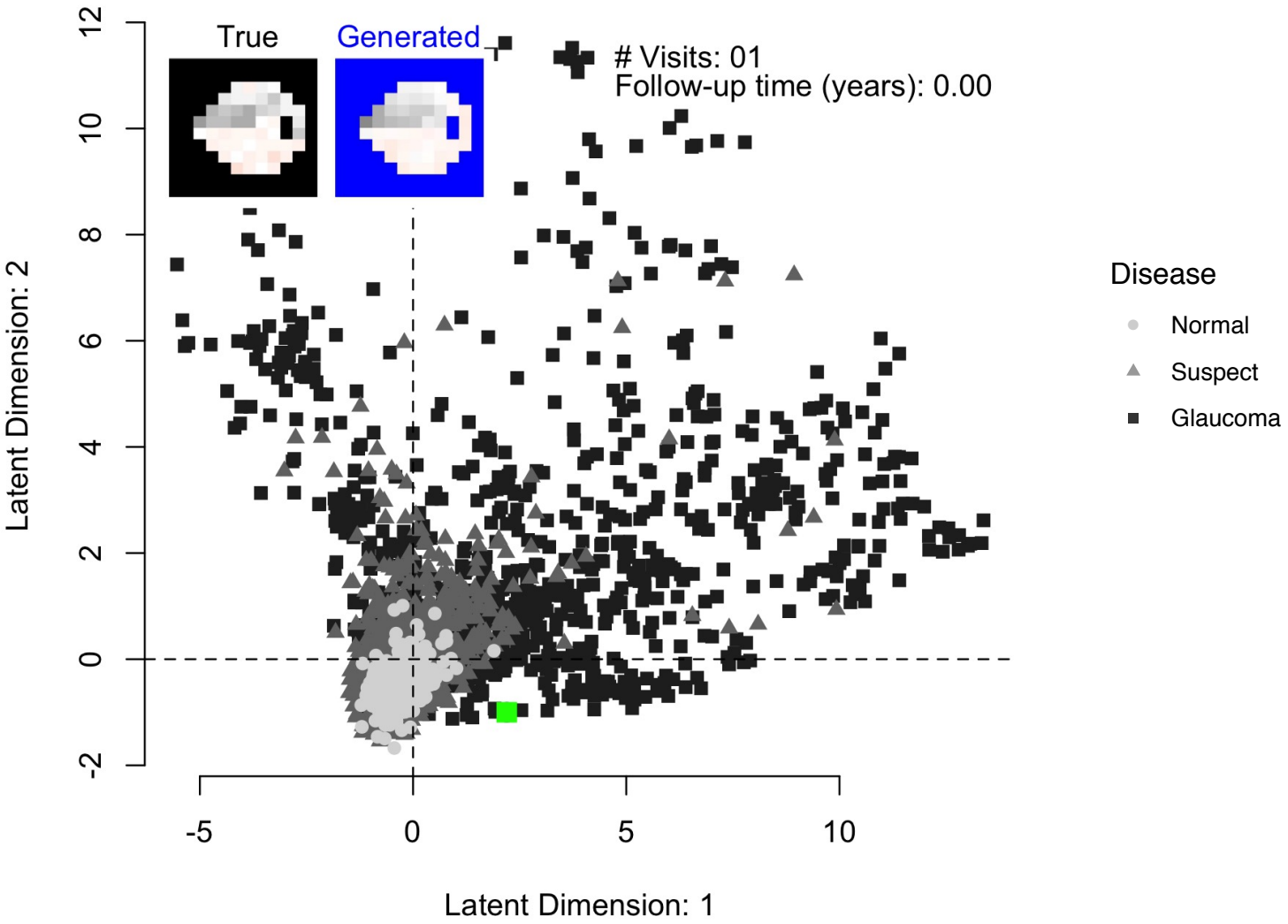
The VAE is an unsupervised, generative model that learns a latent space representation for large samples of high-dimensional spatial data [1].



Implementing the Variational Autoencoder in `RStudio`

- Machine learning, and particularly deep learning, are most commonly implemented in `Python`.
- In recent years, however, `R` has caught up with the introduction of the `tensorflow` and `keras` packages.
- A tutorial for implementing the two-stage VAE is available on `Github:` berchuck/vaeST.

Stage 2: Regression Through Latent Space

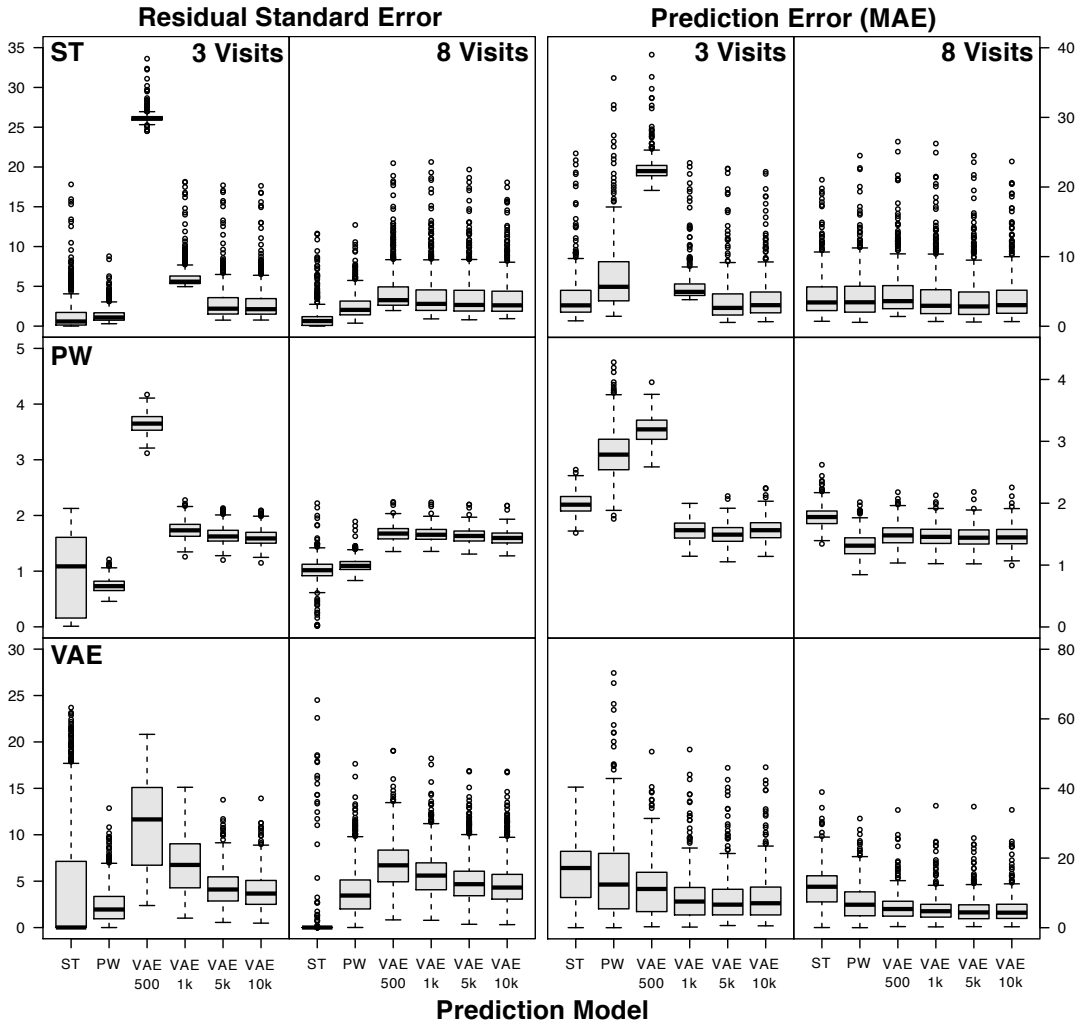


Visual Field Data

Table 1: Demographic and clinical characteristics of subjects included in the study across training, validation, and test data sets. MD = mean deviation; PSD = Pattern standard deviation. Values are presented as mean (standard deviation), unless otherwise noted.

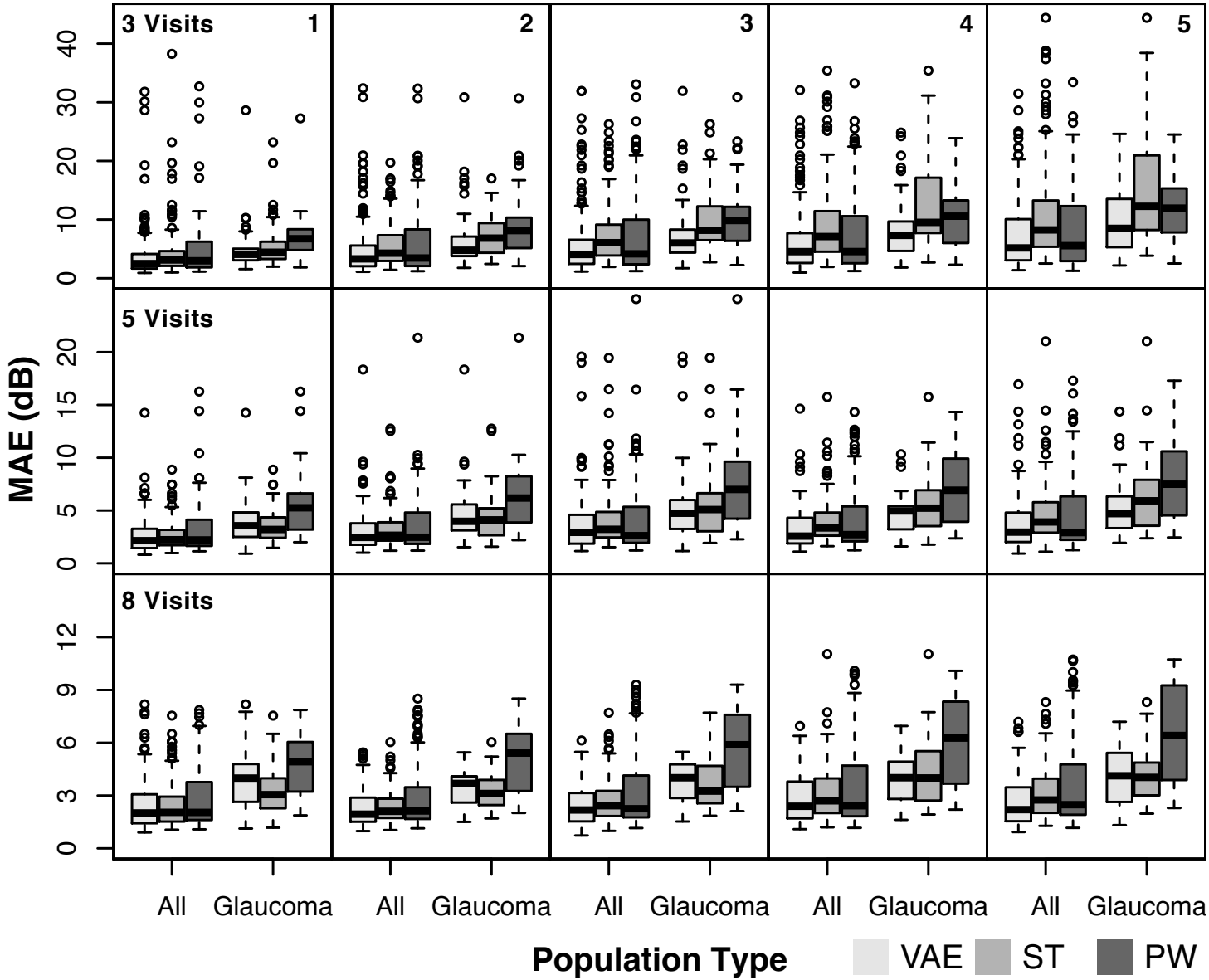
		Machine Learning Datasets		
	Total	Training	Validation	Test
Number of Visual Fields	29,161	23,744 (81%)	2,577 (9%)	2,840 (9%)
Number of Patients	3,832	3,108 (81%)	363 (9%)	361 (9%)
Normal (n, %)	667 (17%)	547 (18%)	58 (16%)	62 (17%)
Suspect (n, %)	2,221 (58%)	1,793 (58%)	222 (61%)	206 (57%)
Glaucoma (n, %)	944 (25%)	768 (25%)	83 (23%)	93 (26%)
Number of visits	7.61 (7.35)	7.64 (7.36)	7.10 (7.24)	7.87 (7.29)
Follow-up period (years)	4.95 (5.25)	4.94 (5.24)	4.67 (5.36)	5.33 (5.24)
Age (years)	60.94 (15.66)	61.04 (15.77)	60.38 (15.9)	60.67 (14.47)
Baseline MD (dB)	-3.55 (5.71)	-3.57 (5.72)	-3.76 (6.12)	-3.23 (5.17)
Baseline PSD (dB)	3.42 (3.29)	3.42 (3.27)	3.49 (3.41)	3.42 (3.34)

Simulation Experiment



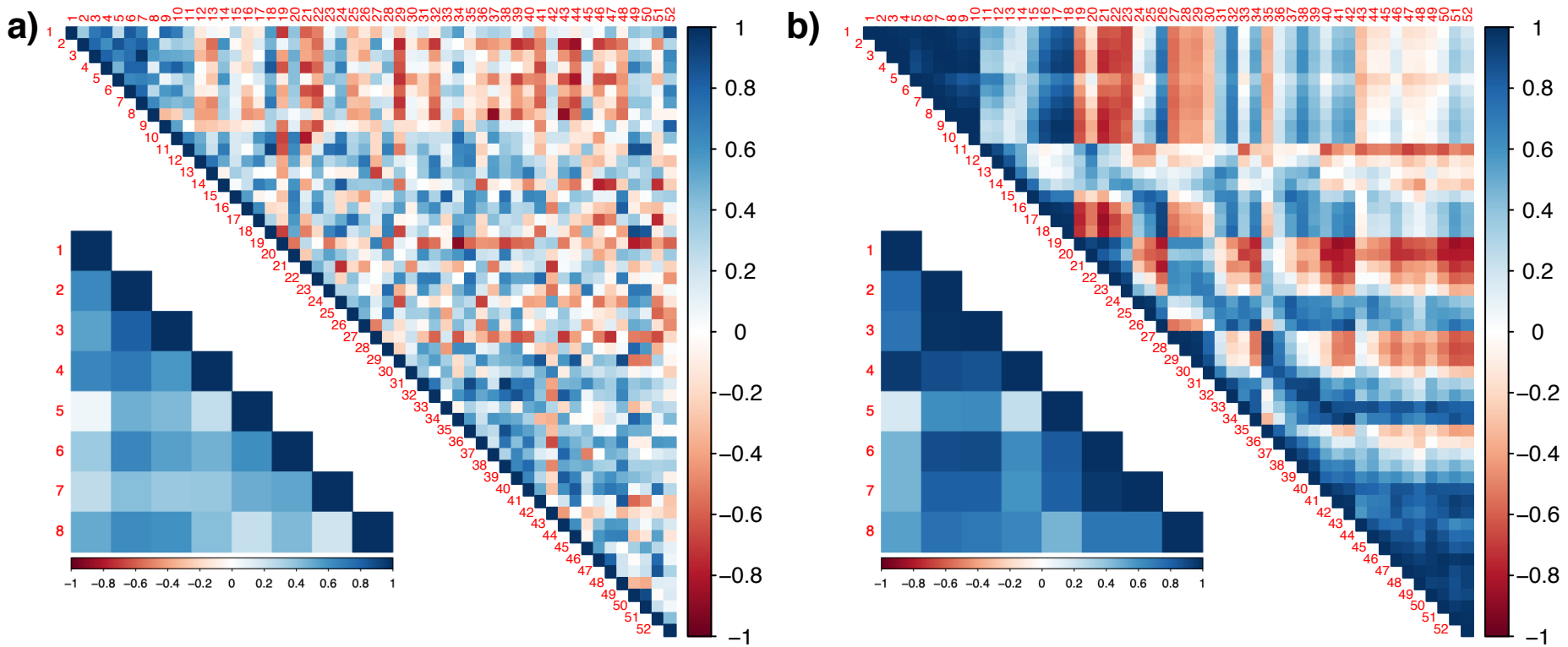
Boxplots are based on 500 simulated datasets. The ST model represents a fully parametric Bayesian hierarchical model [2].

Real Data Application: Predicting Visual Fields



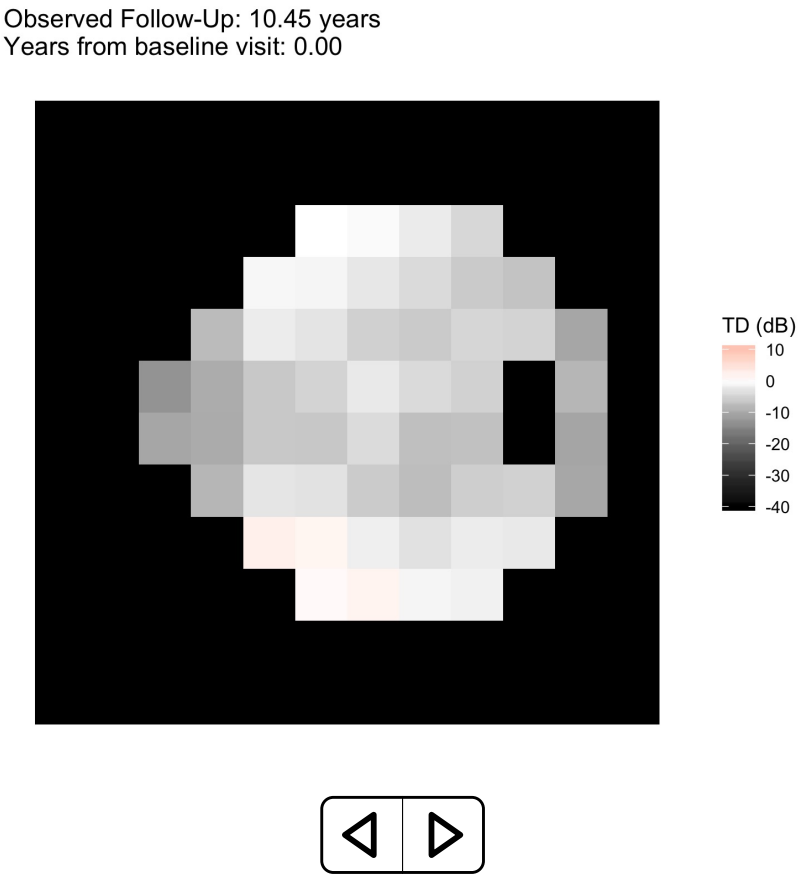
Intuition Behind the Two-Stage VAE

Figure: Demonstrating the spatial smoothing in the decoded visual fields. Presented are the **a)** raw and **b)** decoded empirical spatial (upper diagonal) and temporal (lower diagonal) correlations for an example patient.



Summary and Future Directions

- The VAE allows for scalable prediction in ST data, by jointly accounting for variability across patients.
- The latent space of the VAE allows for clinically meaningful inference.
- **Future Validation:** Duke Eye Center.
- **Clinically Actionable:** Through a `Shiny` app, communicating with Zeiss about incorporating into HFA software.
- Further Reading: [3, 4]



References

[1] Diederik P Kingma and Max Welling. Auto-encoding variational bayes. *arXiv preprint arXiv:1312.6114*, 2013.

[2] Alastair Rushworth, Duncan Lee, and Richard Mitchell. A spatio-temporal model for estimating the long-term effects of air pollution on respiratory hospital admissions in greater london. *Spatial and Spatio-temporal Epidemiology*, 10:29–38, 2014.

[3] Samuel I Berchuck, Sayan Mukherjee, and Felipe A Medeiros. Estimating rates of progression and predicting future visual fields in glaucoma using a deep variational autoencoder. *bioRxiv preprint bioRxiv:10.1101/652487*, 2019.

[4] Samuel I Berchuck, Felipe A Medeiros, and Sayan Mukherjee. Scalable modeling of spatiotemporal data using the variational autoencoder: an application in glaucoma. *arXiv preprint arXiv:1908.09195*, 2019.