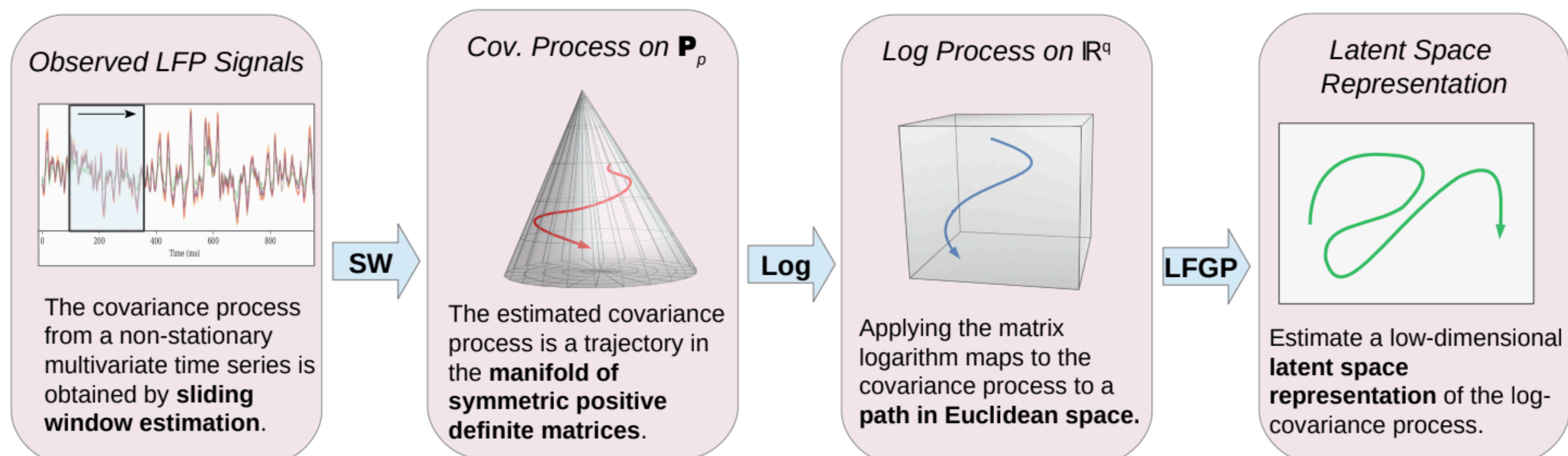


Modeling Dynamic Functional Connectivity with Latent Factor Gaussian Processes

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LFGP Model

- Dynamic functional connectivity (DFC), as measured by the time-varying covariance of neurological signals, is important for cognition.
- Stochastic process $X_i(t)$ with covariance $K_i(t)$; log-covariance $Y_i(t)$ as a linear combination of latent factors $F_i(t)$.

$$X_i(t) \sim \mathcal{D}(0, K_i(t)) \text{ where } K_i(t) = \exp(\bar{\mathbf{u}}(Y_i(t)))$$

$$Y_i(t) = F_i(t) \cdot B + \epsilon_i \text{ where } \epsilon_i \sim \mathcal{N}(0, I\sigma^2)$$

$$F_i(t) \sim \mathcal{GP}(0, \kappa(t; \theta))$$

$$B \sim p_1, \sigma^2 \sim p_2, \theta \sim p_3$$

- Naturally allows for inference of scientific hypotheses, inclusion of prior information, and visualization of connectivity dynamics.

Simulation Study

- Data generated with latent covariance dynamics: square waves, piecewise linear, and cubic splines.
- Compare with sliding window and principal component analysis, hidden Markov model, and latent factor stochastic volatility model.

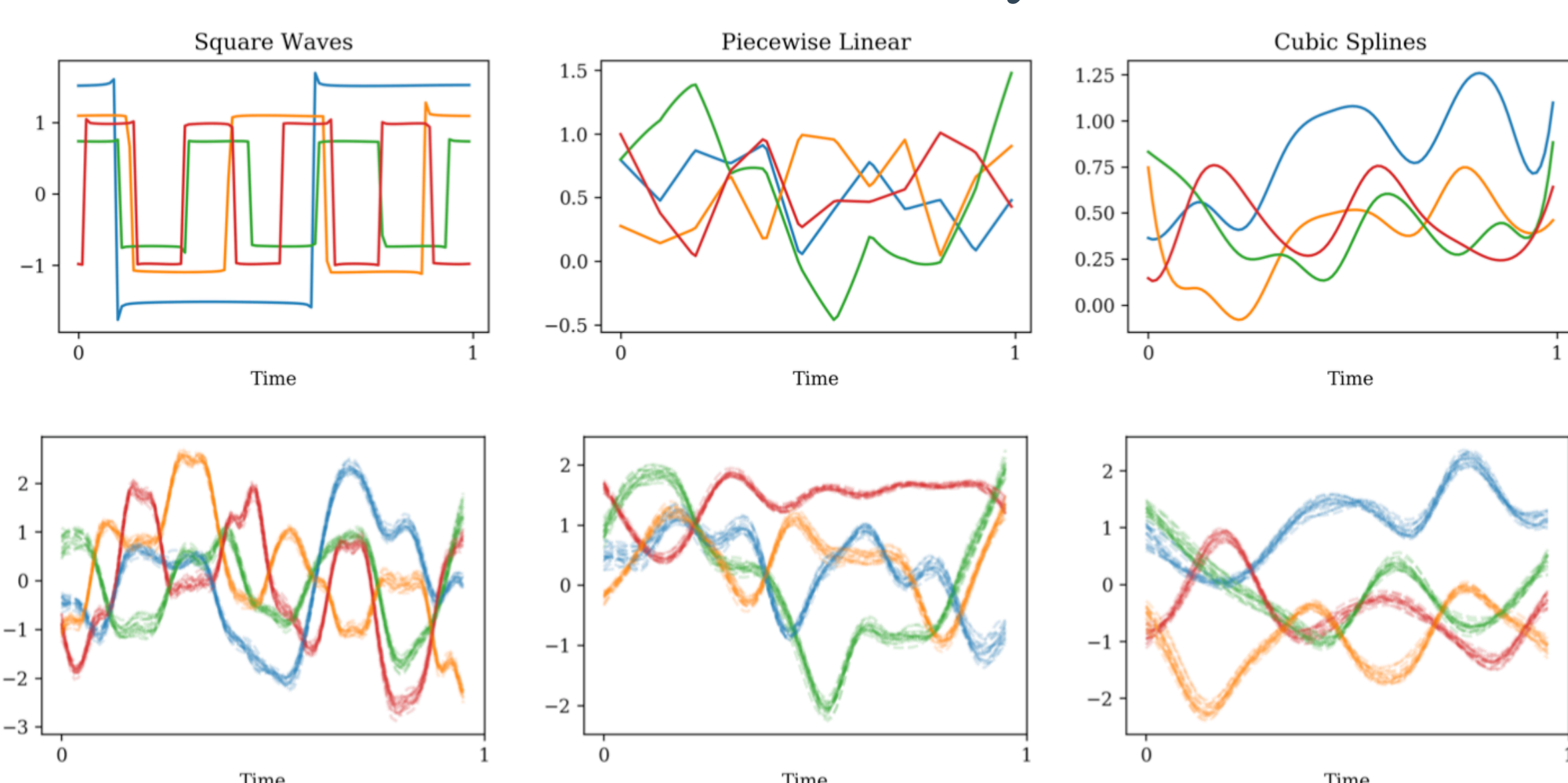
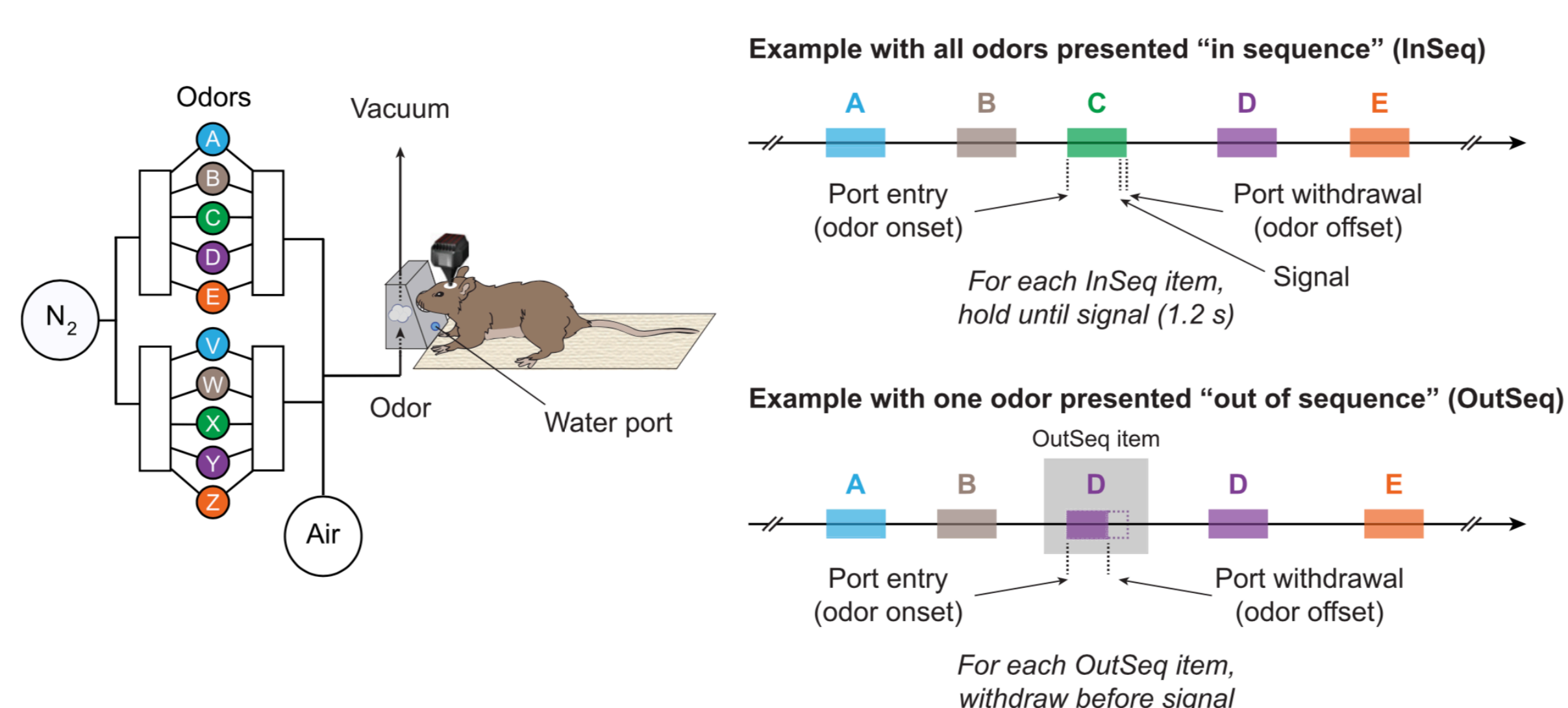


Table 2: Median reconstruction loss (standard deviation) across 100 data sets

	SW-PCA	HMM	LFSV	LFGP
Square wave	0.693 (0.499)	1.003 (1.299)	4.458 (2.416)	0.380 (0.420)
Piece-wise	0.034 (0.093)	0.130 (0.124)	0.660 (0.890)	0.027 (0.088)
Smooth spline	0.037 (0.016)	0.137 (0.113)	0.532 (0.400)	0.028 (0.123)

LFP Data Analysis



- Local field potentials from the rat hippocampus during non-spatial memory task.
- Latent factor posteriors show theta oscillation, non-stationary covariance of LFP, and separation of different stimuli.

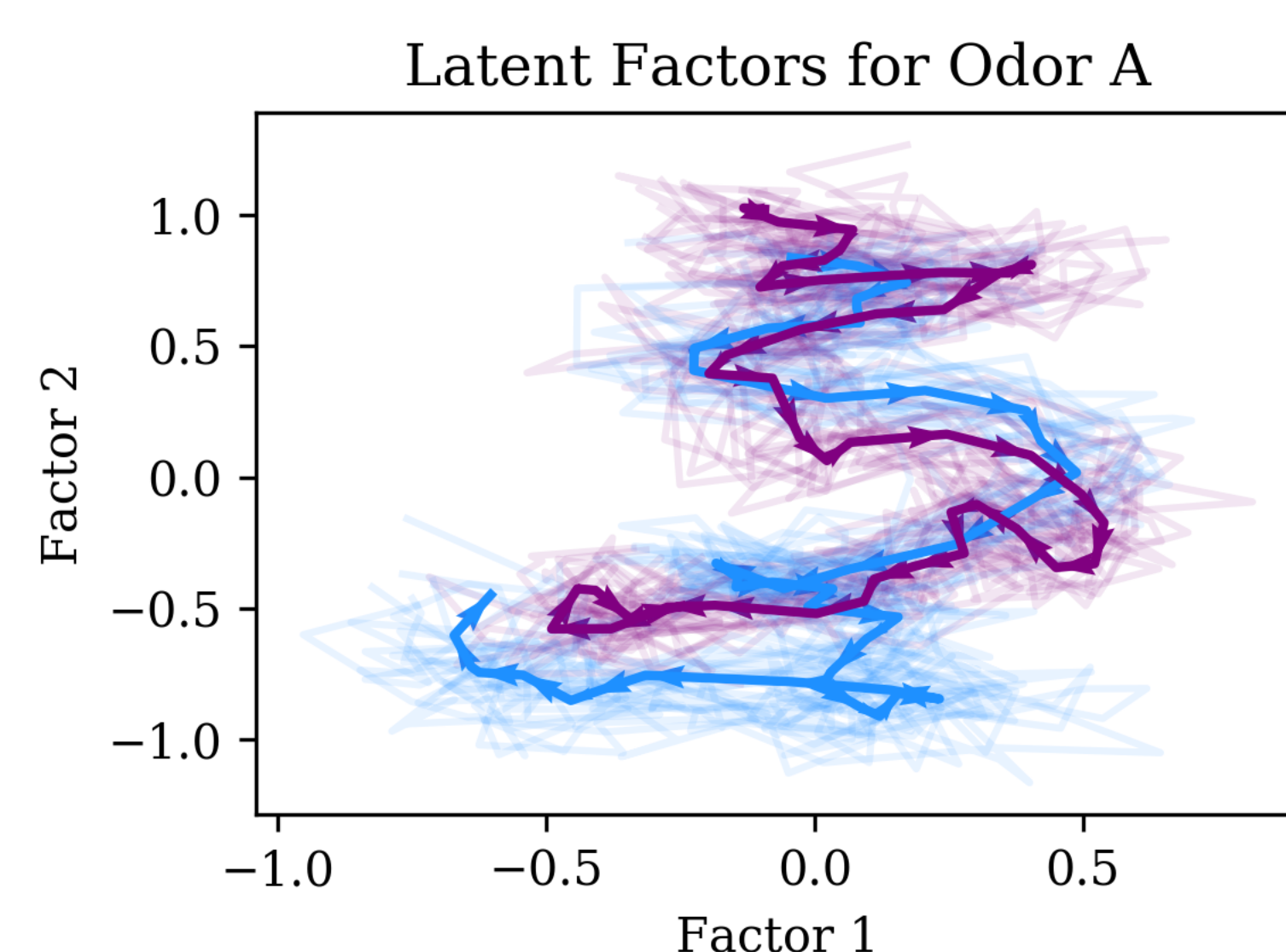
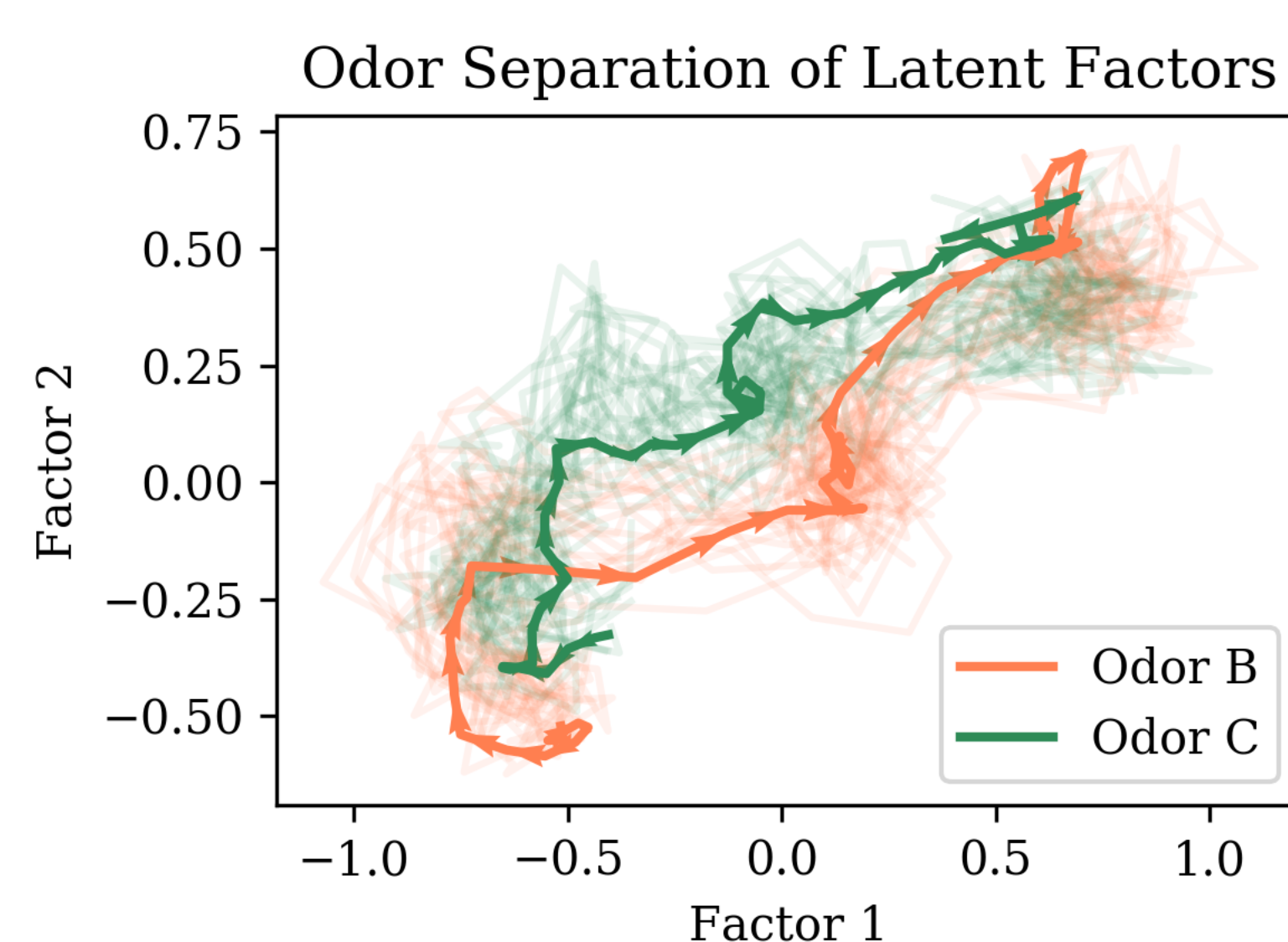


Table 3: Latent space classification accuracy (standard deviation)

	Different odors	Same odor
Logistic regression	69.97 (0.78)	63.10 (0.91)
k-NN	87.12 (0.33)	78.41 (0.65)
SVM	74.53 (0.67)	64.75 (1.21)