Connecting the dots:

A probabilistic model for biomolecular latent space trajectories

Mittelerde Meeting 2025

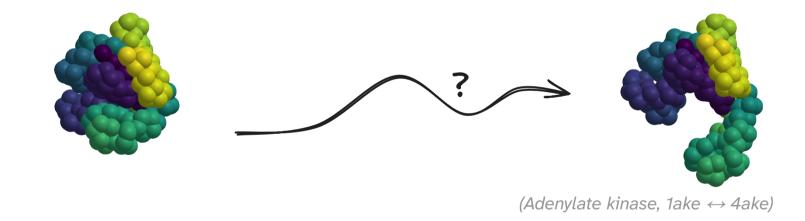
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Conformational Dynamics of Biomolecules

- want to understand molecular machines
- can observe individual conformations



 want to find continuous dynamic of conformational change (in some latent space)

Mathematical abstraction

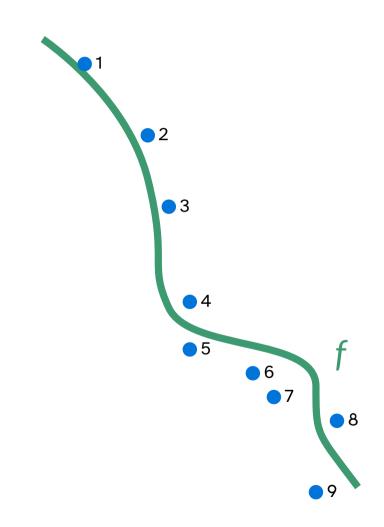
we have

observations
$$\mathcal{Y} = \{y_1, ..., y_m\} \subset \mathbb{R}^d$$

and want to explain them with a

curve $f:[0,1] \to \mathbb{R}^d$

by the magic of 🔑 Bayes 🔆



Mathematical abstraction

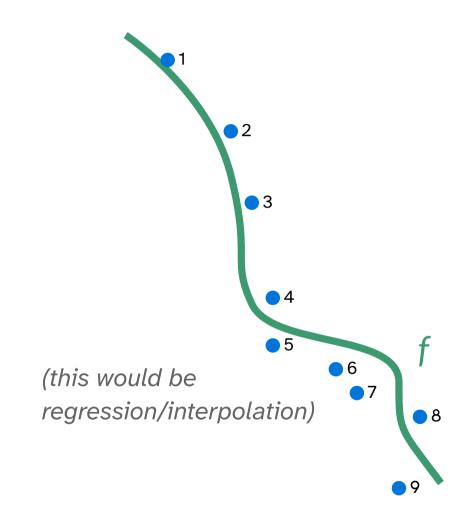
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Mathematical abstraction

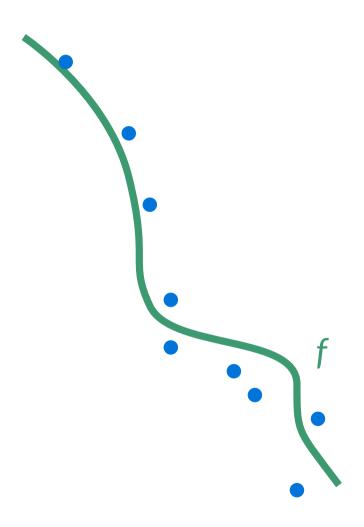
we have

unordered observations $\mathcal{Y} = \{y_1, ..., y_m\} \subset \mathbb{R}^d$

and want to explain them with a

curve $f:[0,1] \to \mathbb{R}^d$

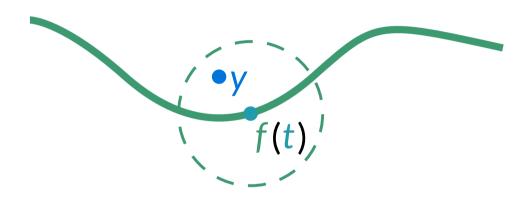
by the magic of 🔑 Bayes 🔆



Data generating process: Curve Mixture

Curve mixture \mathcal{M} consists of curve f and observation noise σ . Observation y is generated from \mathcal{M} like this:

- 1. draw $t \sim \mathcal{U}[0, 1]$
- 2. draw $y \sim \mathcal{N}(f(t), \sigma^2 I)$



likelihood:
$$p(y \mid \mathcal{M}) = \frac{1}{Z(\sigma)} \int_0^1 \exp\left(-\frac{\|y - f(t)\|^2}{2\sigma^2}\right) dt$$

Smooth curves



... corresponding to preferring a low bending energy.

prior:
$$p(\mathcal{M}) = \exp\left(-\tau \left(\int_0^1 \|f''(t)\|^2 dt\right) / \left(\int_0^1 \|f'(t)\| dt\right)^2\right)$$

Posterior: Likelihood and Prior combined

Bayes' theorem:

$$\underbrace{p(\mathcal{M} \mid \mathcal{Y})}_{\text{posterior}} = \prod_{\mathbf{y} \in \mathcal{Y}} \underbrace{p(\mathbf{y} \mid \mathcal{M})}_{\text{likelihood}} \cdot \underbrace{p(\mathcal{M})}_{\text{prior}}$$

posterior: How much do we believe \mathcal{M} given \mathcal{Y} ?

likelihood: from the data generating process

prior: for the smoothness

Discrete approximation

Instead of arbitrary curves f, consider concatenations of **line segments**:



Model \mathcal{M} now consists of

- ▶ observation noise $\sigma > 0$
- ▶ nodes $x_1, ..., x_n \in \mathbb{R}^d$
- connectivity information (which two nodes form a segment?)

Properties of discrete model



- ▶ clear what the parameters are: $x_1, ..., x_n \in \mathbb{R}^d$ and $\sigma \in \mathbb{R}$
- can compute integrals in likelihood and prior exactly

$$p(| \mathcal{Y}) = p(| \mathcal{Y})$$

easily generalizable to arbitrary topologies (mixture of curve mixtures)



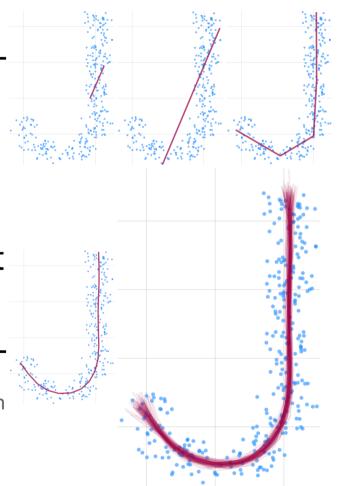


have to think about number of segments

Estimating a Curve Mixture

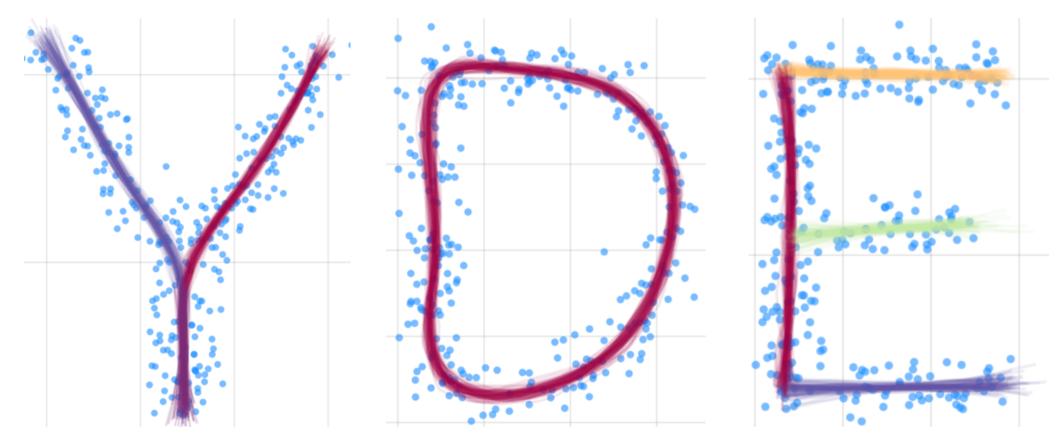
- 1 $\mathcal{M} \leftarrow$ single segment
- 2 until satisfied
- 3 maximize posterior density (ADAM)
- 4 \lfloor finegrain \mathcal{M} , i.e. split every segment
- 5 sample *M* from posterior (NUTS)

(obtain gradient for ADAM and NUTS via automatic differentiation with Mooncake.jl)



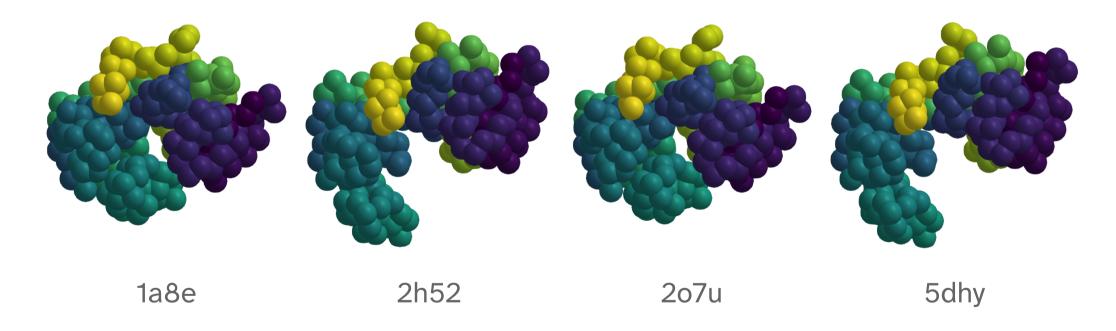
More letters!

(showcasing other topologies with a generalized model)



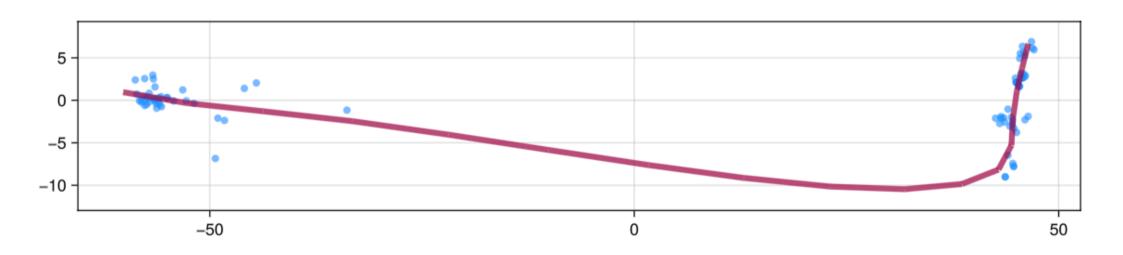
Demo: Human Serum Transferrin (1a8e)

84 AA-chains from PDB with sequence similarity ≥ 90 % to 1a8e



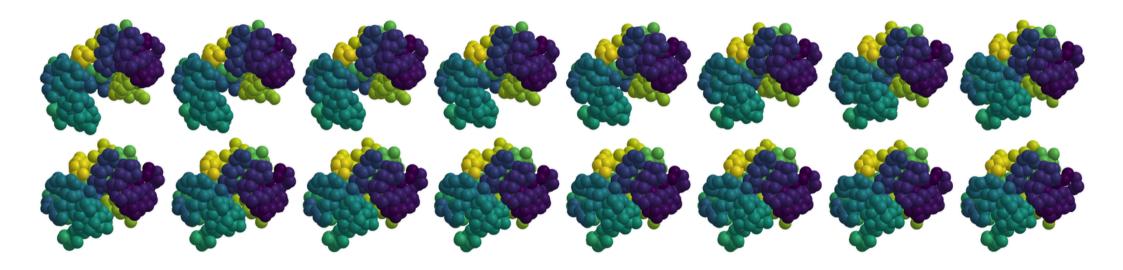
Demo: Human Serum Transferrin (1a8e)

Curve Mixture in 2D latent space (PCA)



Demo: Human Serum Transferrin (1a8e)

Traverse curve and project back into "structure space"





Summary and next steps

- curve mixtures are a nice tool to find trajectories in data points
 - predictions biologically meaningful?
 - design user interface
- works reasonably well for PCA-embedded protein structures
 - other latent embeddings?
 - apply to RNA-seq data
- implementation in Julia let me focus on domain problem and performance (gradient, sampling, and optimization "for free")

Let's discuss!



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Islides and code on Github