Exploratory Modeling with Collaborative Design Spaces

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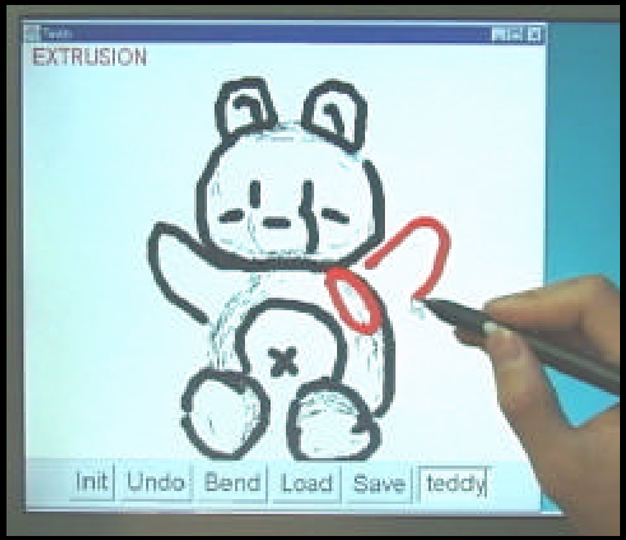
The Big Picture

Growing demand for *user-created* 3D content:

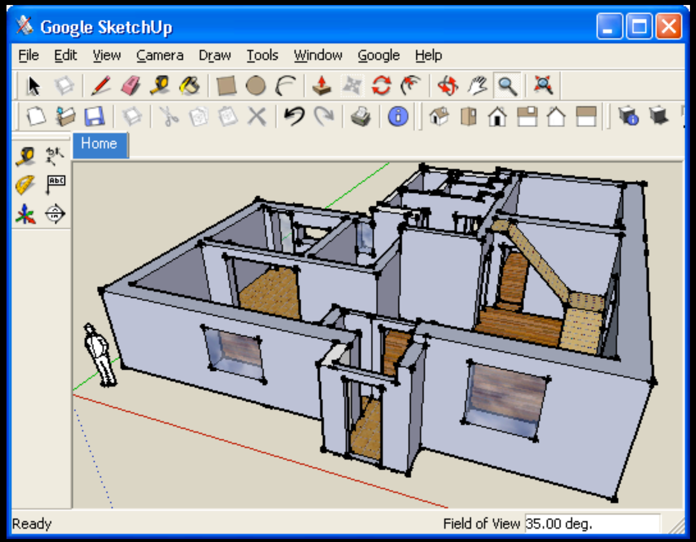
- Spore [Maxis ’08]
- LittleBigPlanet [Media Molecule ’08]
- The Sims 3 [Electronic Arts ’09]
- Second Life [Linden Labs ’03]

Previous Work

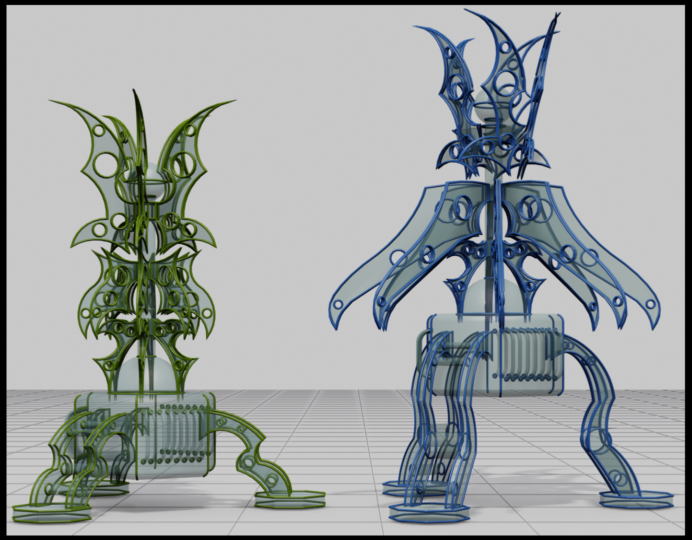


Teddy ’99

Modeling by Example ’04



SketchUp ’07



iWIRES ’09

Motivation

Professional design:

- Formalized processes [Navinchandra ’91]
- Extensive previsualization [Brown ’89]

Casual design:

- Looser constraints [Gero ’90]
- Serendipitous/opportunistic [Tweedie ’96]

Exploration

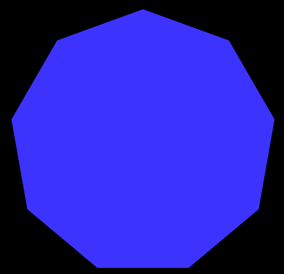
Suggest new, high-quality designs to users

Collaboration

Leverage models created by user community

Parametric Models

$$\begin{bmatrix} \text{red} \\ \text{green} \\ \text{blue} \\ \text{sides} \end{bmatrix} \in \mathbb{R}^n \longrightarrow$$



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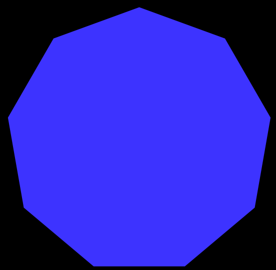
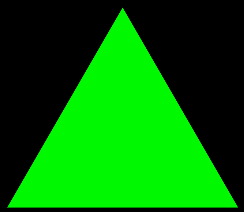
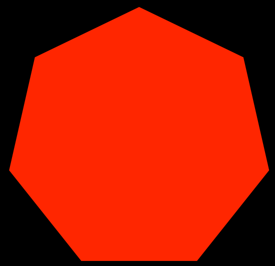




$$\begin{bmatrix} 0 \\ 1 \\ 0 \\ 3 \end{bmatrix}$$



$$\begin{bmatrix} 1 \\ 0 \\ 0 \\ 7 \end{bmatrix}$$

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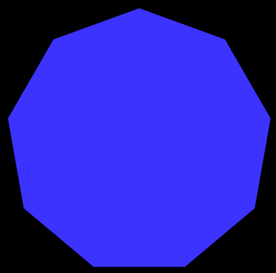

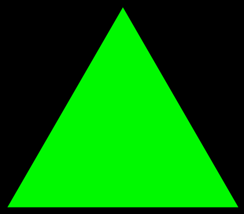

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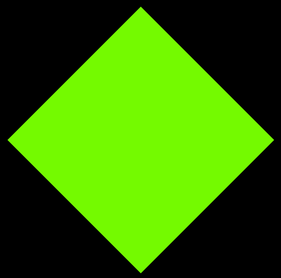
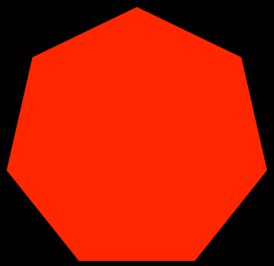


$$\begin{bmatrix} 0.25 \\ 0.75 \\ 0 \\ 4 \end{bmatrix}$$



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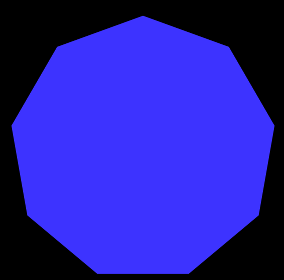

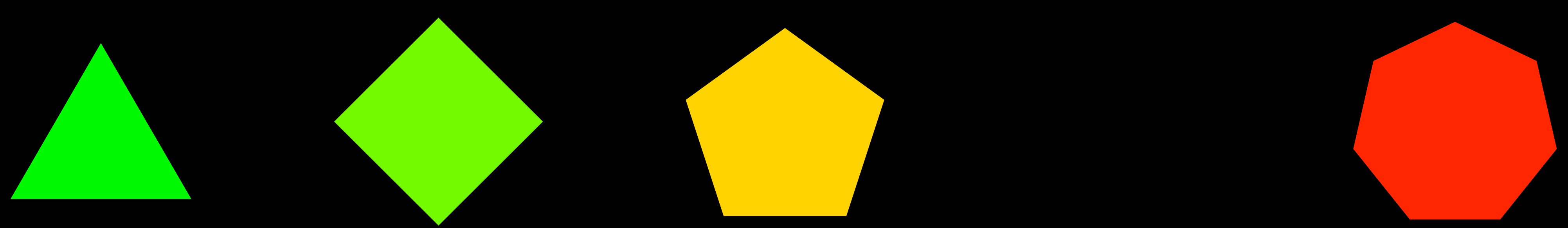

$$\begin{bmatrix} 0 \\ 1 \\ 0 \\ 3 \end{bmatrix} \quad \begin{bmatrix} 0.25 \\ 0.75 \\ 0 \\ 4 \end{bmatrix} \quad \begin{bmatrix} 0.5 \\ 0.5 \\ 0 \\ 5 \end{bmatrix} \quad \begin{bmatrix} 1 \\ 0 \\ 0 \\ 7 \end{bmatrix}$$

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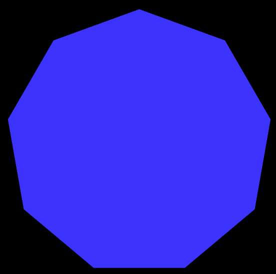

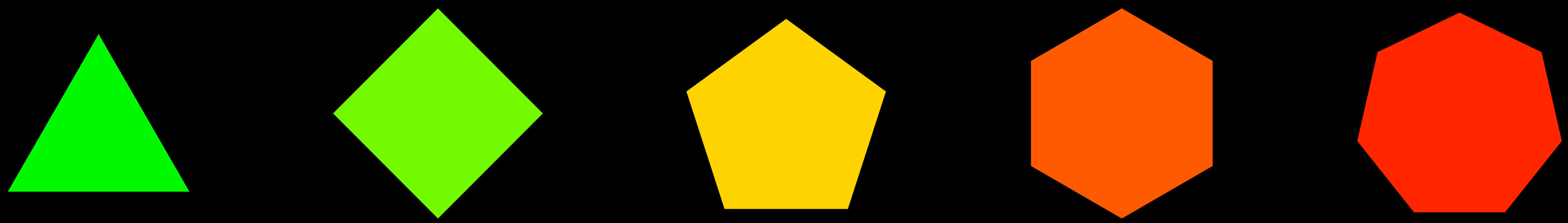

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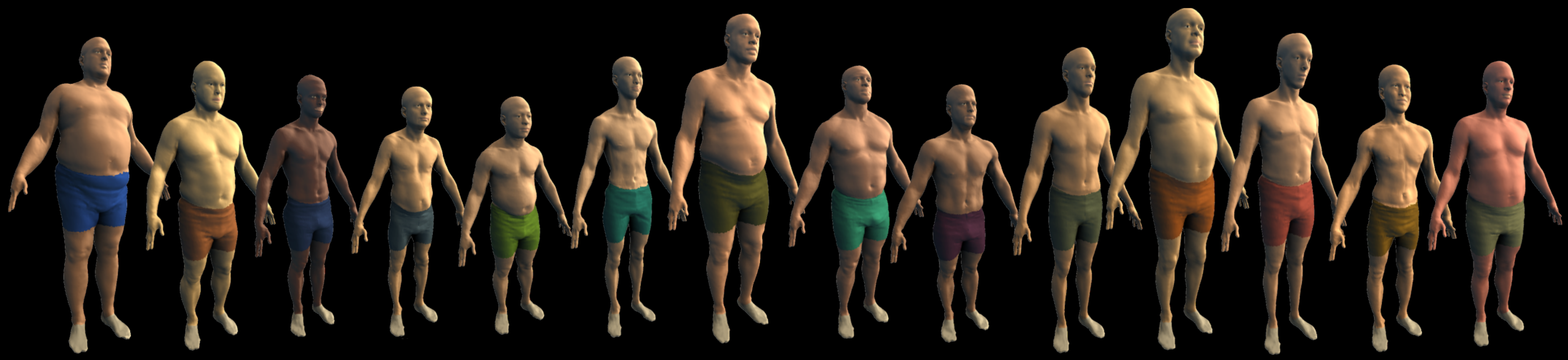
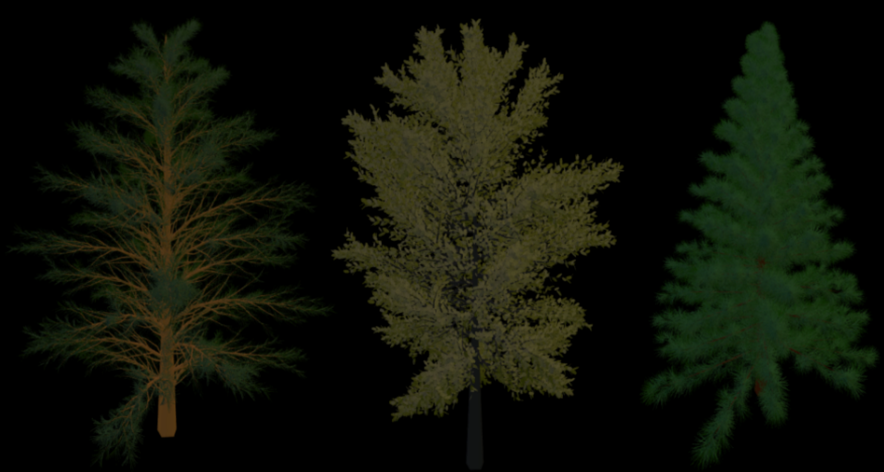
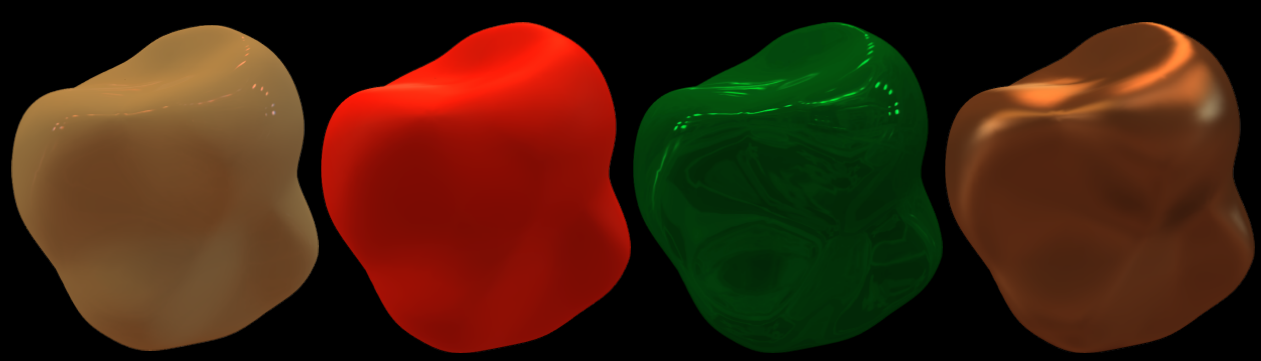
Parametric Models



[Allen et al. '03]



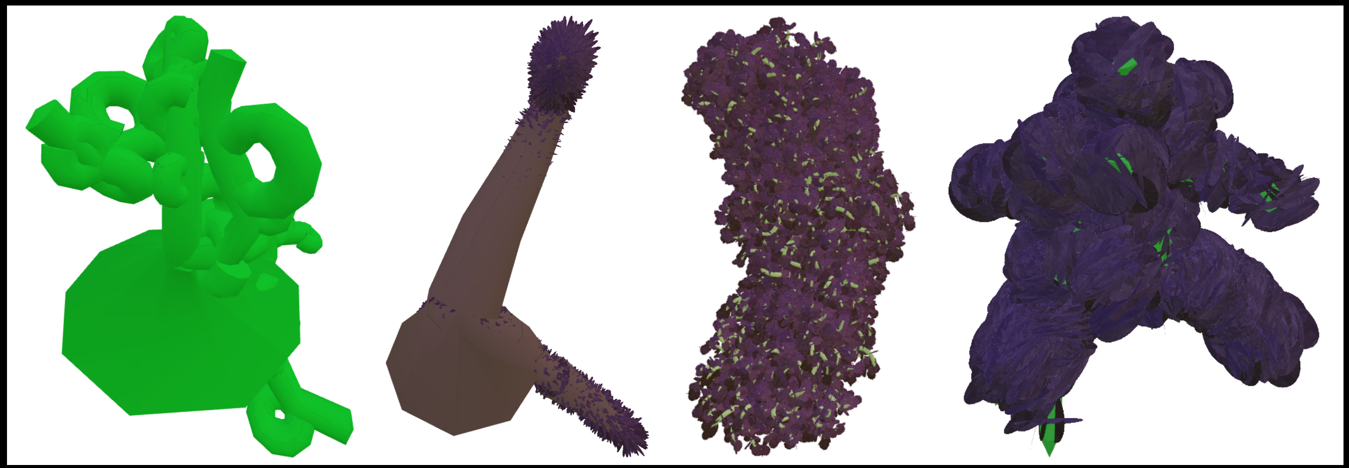
[Weber & Penn '95]



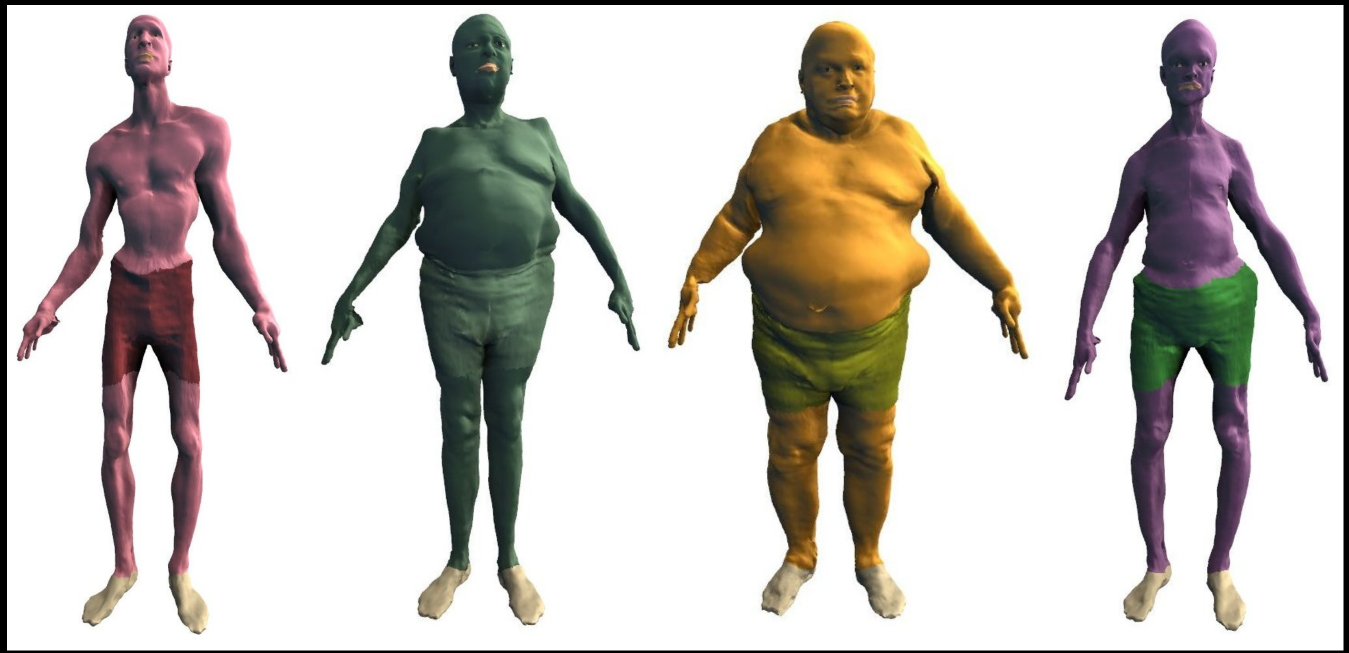
[Ashikhmin & Shirley '00]

High-Dimensional Spaces

Uniform Random Samples



Tree Space
$n = 91$



Human Body Space
$n = 124$

Mapping Spaces

$$f : \mathbb{R}^n \rightarrow [0, 1]$$

"Quality" of a model

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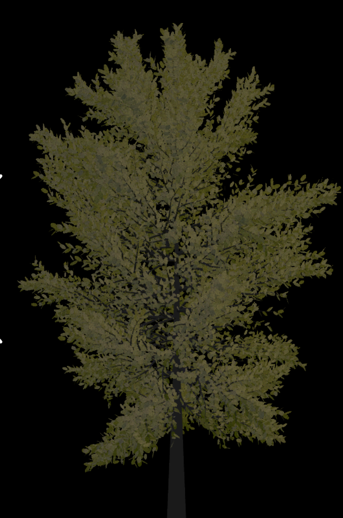
$f($  $) \gg f($  $)$

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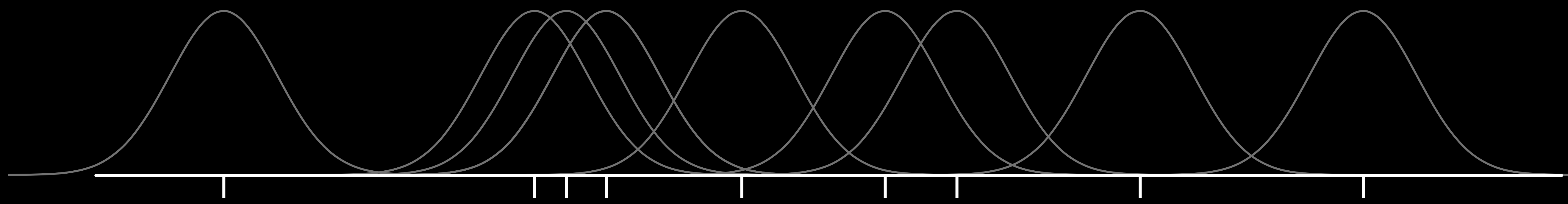

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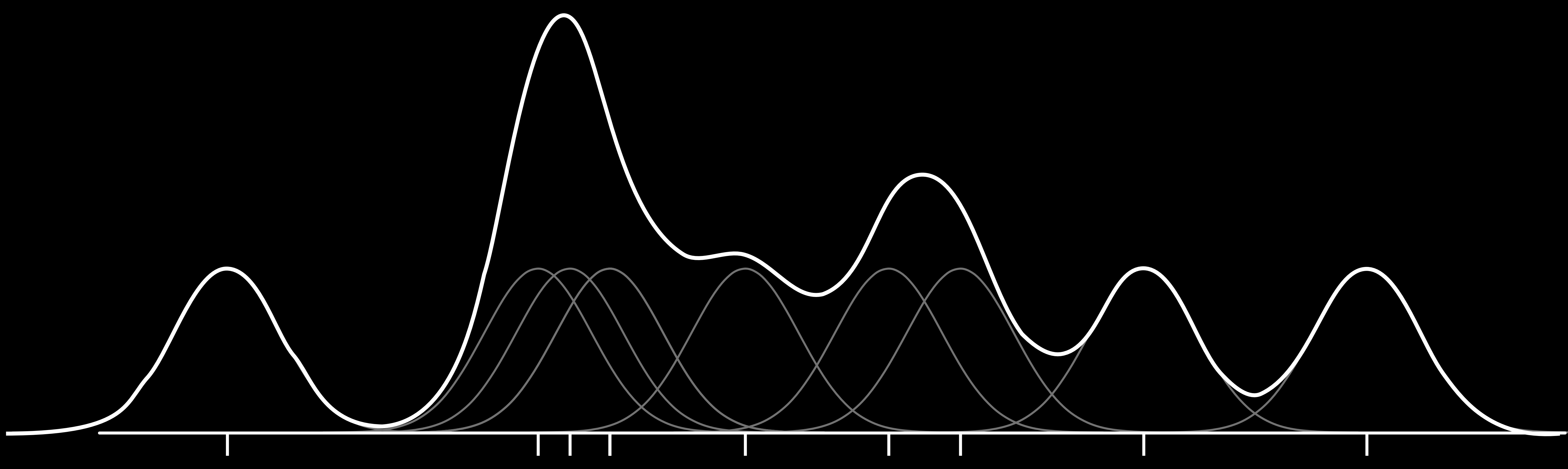
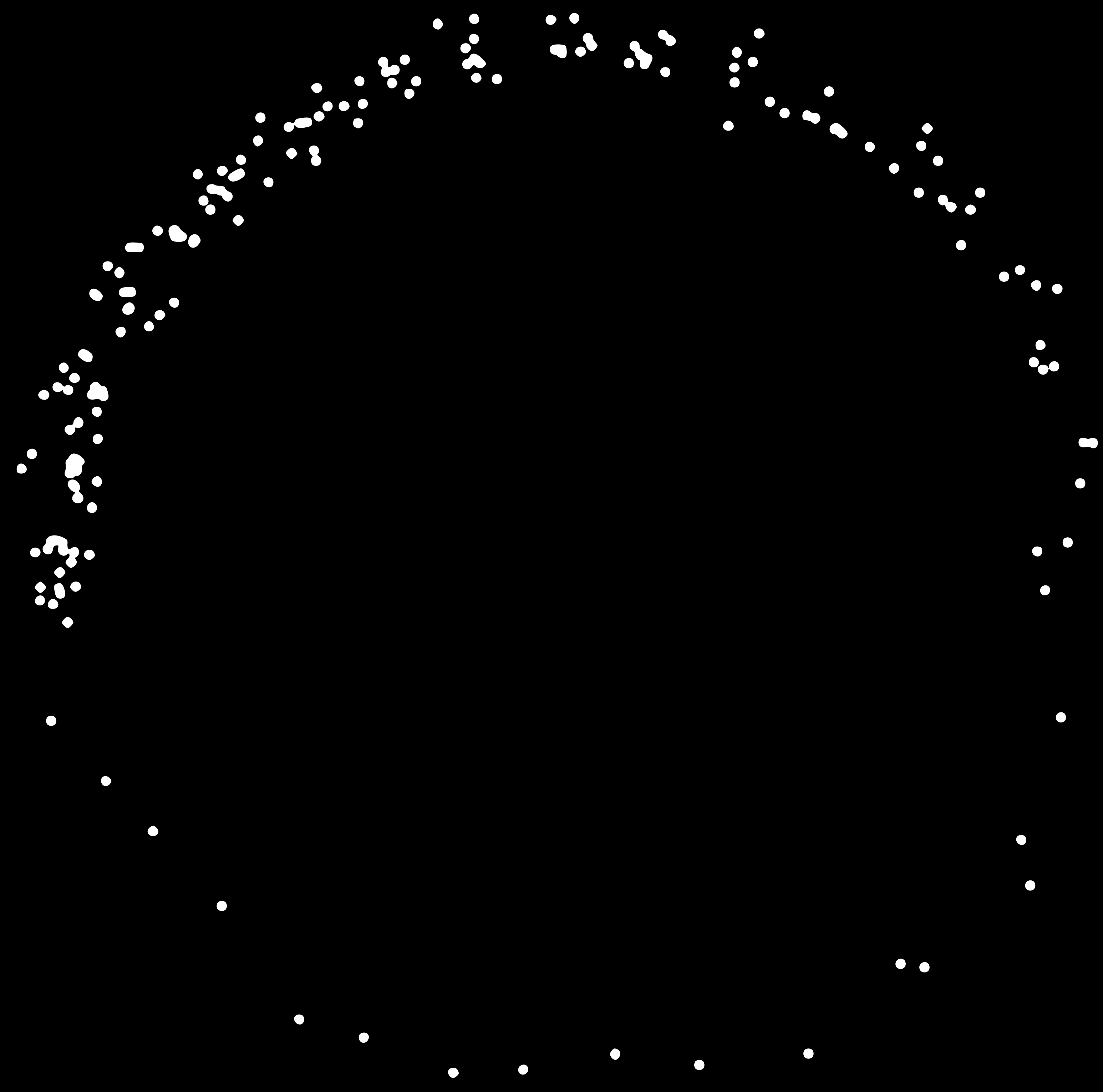
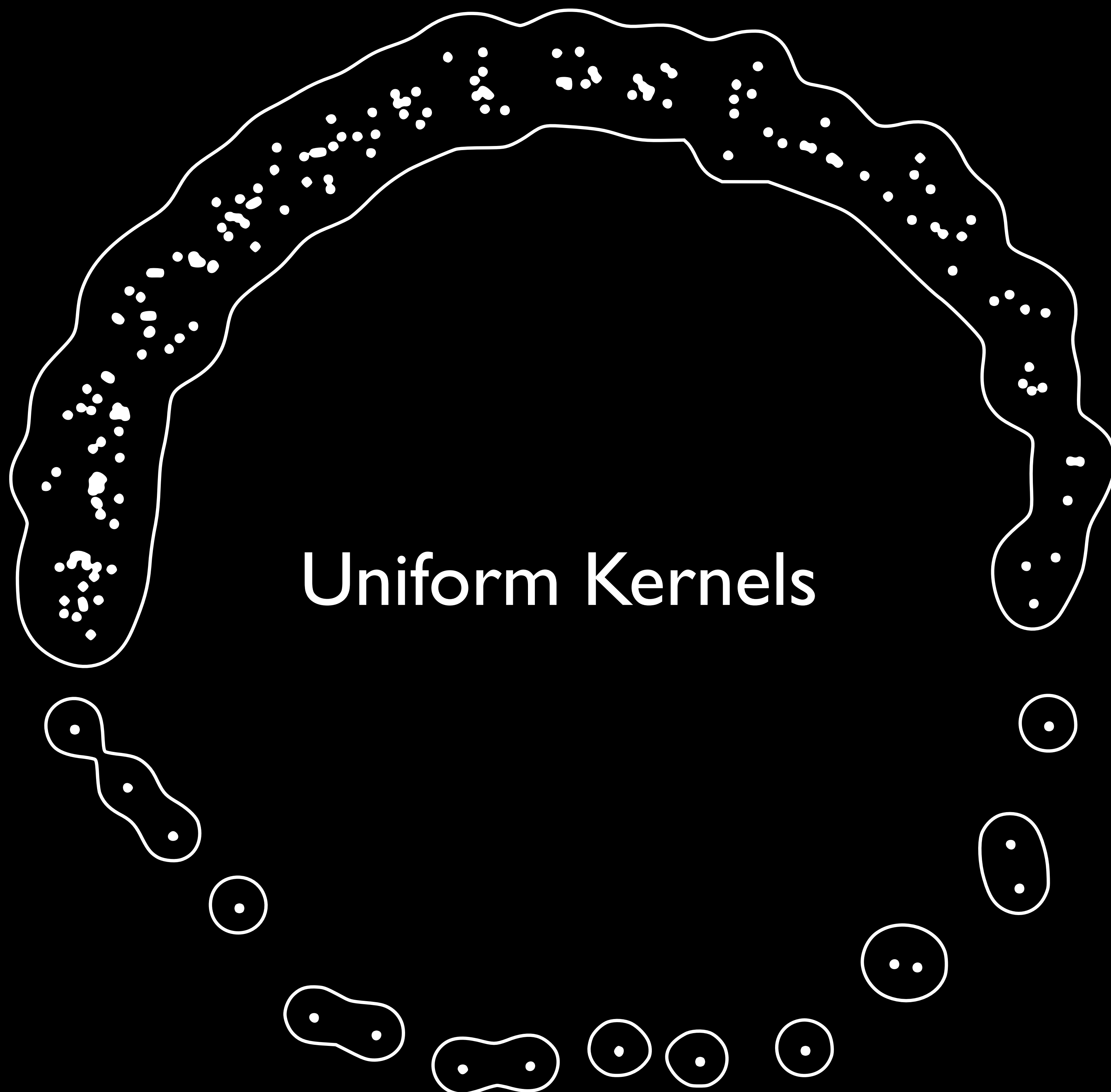
- Sum kernels to estimate $\hat{f}(\mathbf{x}) \approx f(\mathbf{x})$







Uniform Kernels

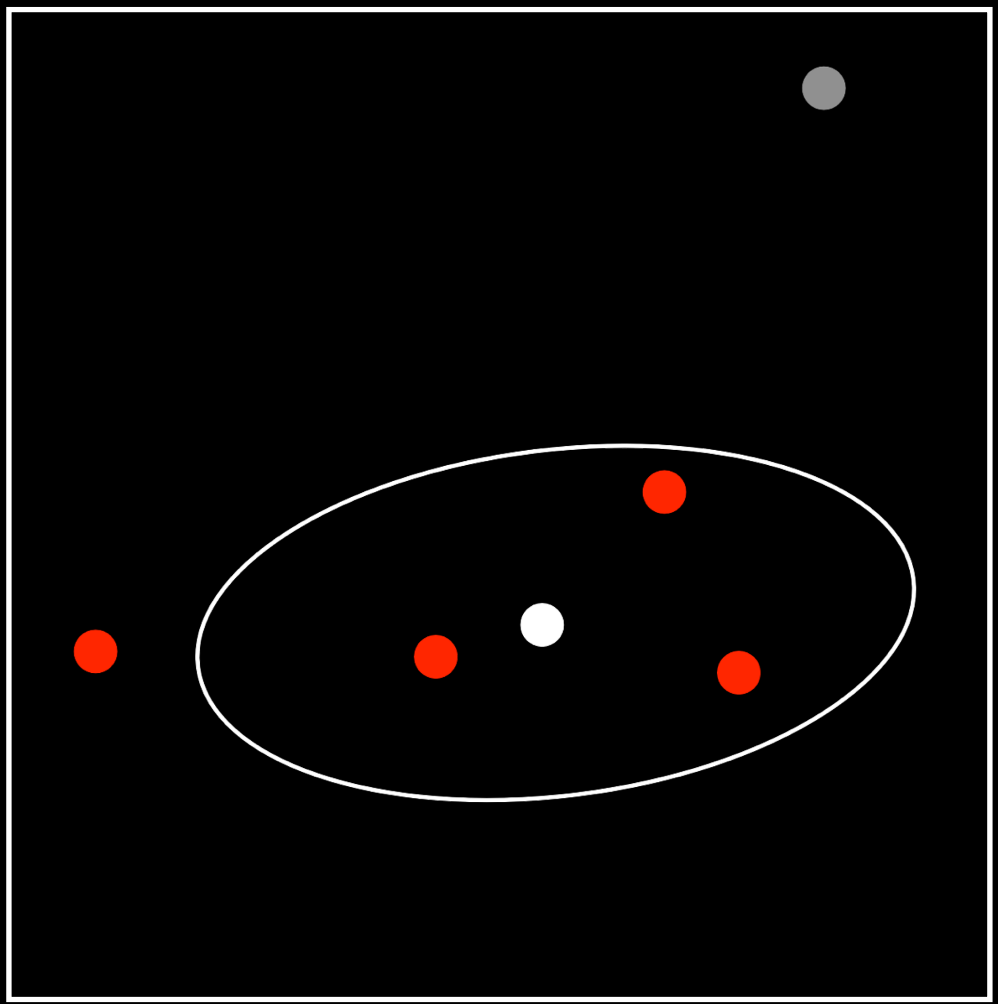
Kernel Estimation

Must choose size/shape *carefully*:

- No analytic solutions for $n \geq 3$
- Iterative cross-validation expensive
- k^{th} nearest neighbors more promising...

k^{th} Nearest Neighbors

- Find k^{th} nearest neighbors for each $\mathbf{x}_i$
- Use computed covariance matrix as $\mathbf{\Sigma}_i$



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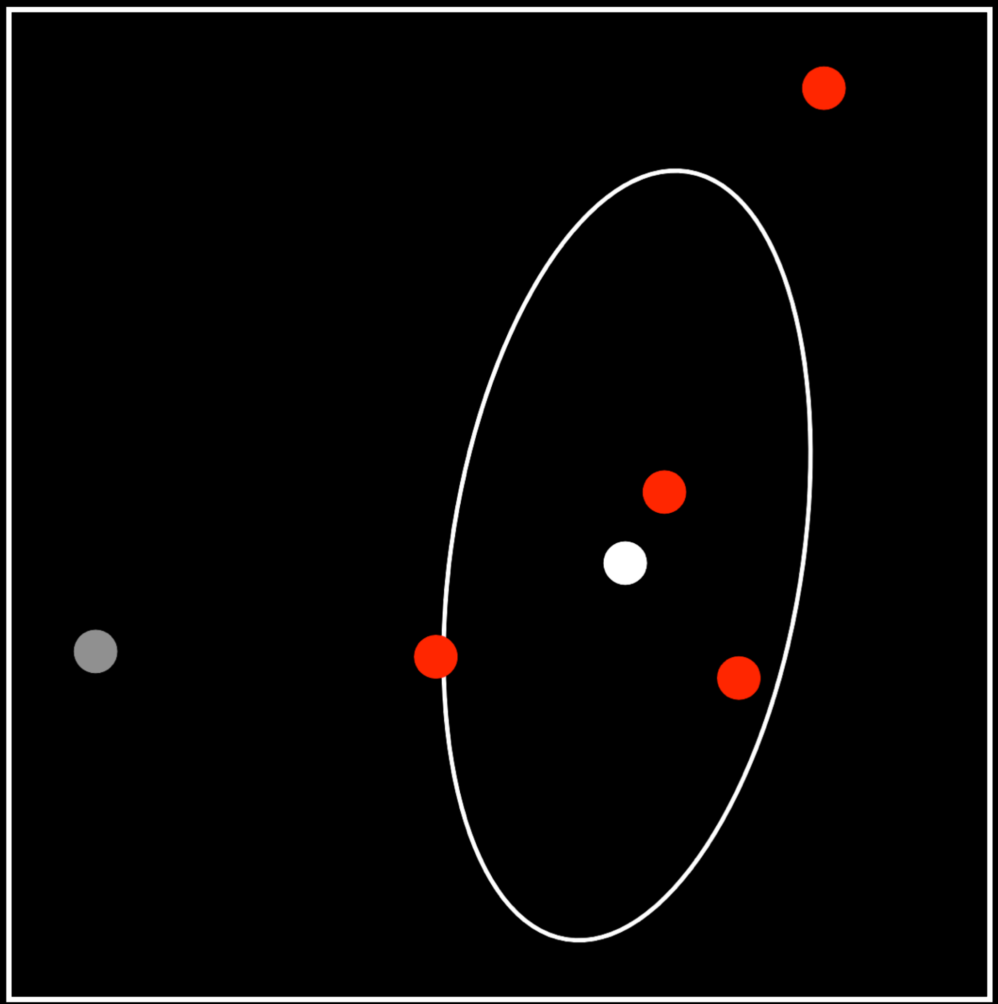
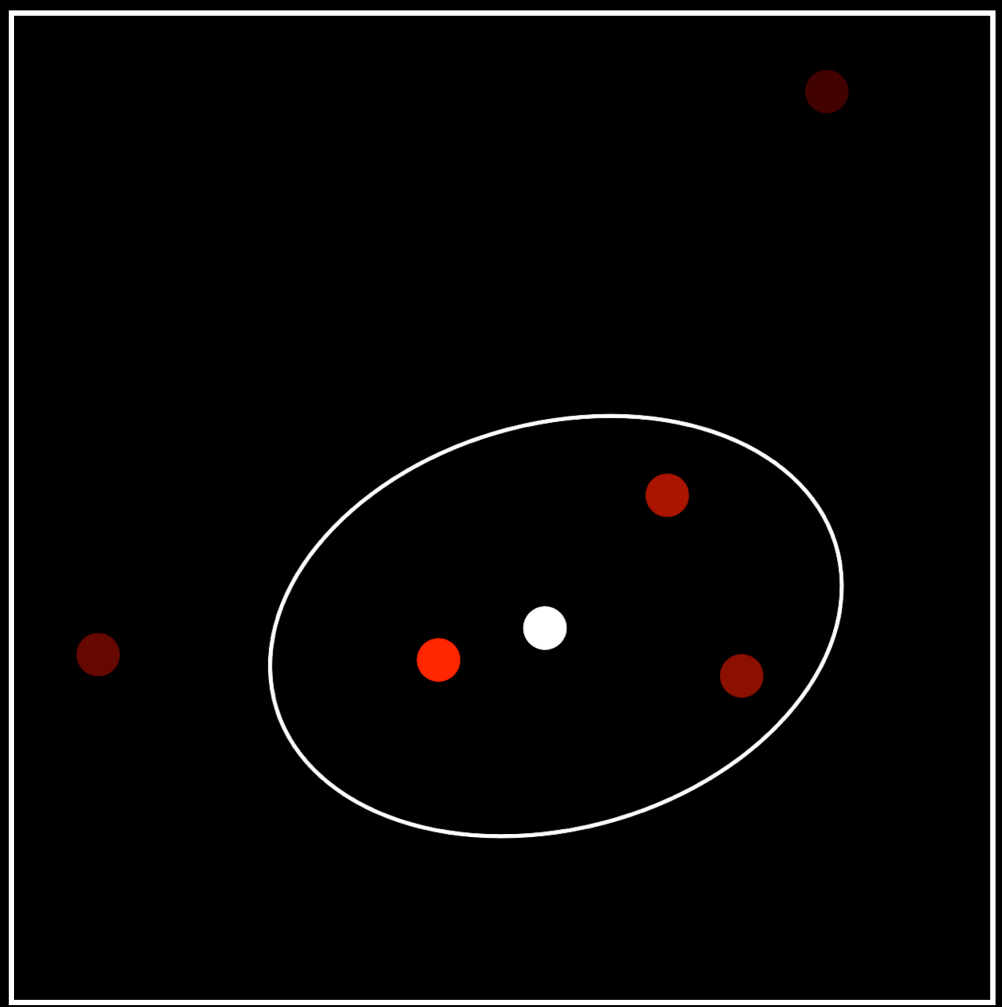


Soft Kernels

Distance-weighted matrix [Bengio & Vincent '04]:

$$\mathbf{\Sigma}_{s,t} = \sum_{i=1}^{N} \omega_i \left[(\mathbf{x}_i)_s - (\mathbf{x})_s \right] \left[(\mathbf{x}_i)_t - (\mathbf{x})_t \right]$$



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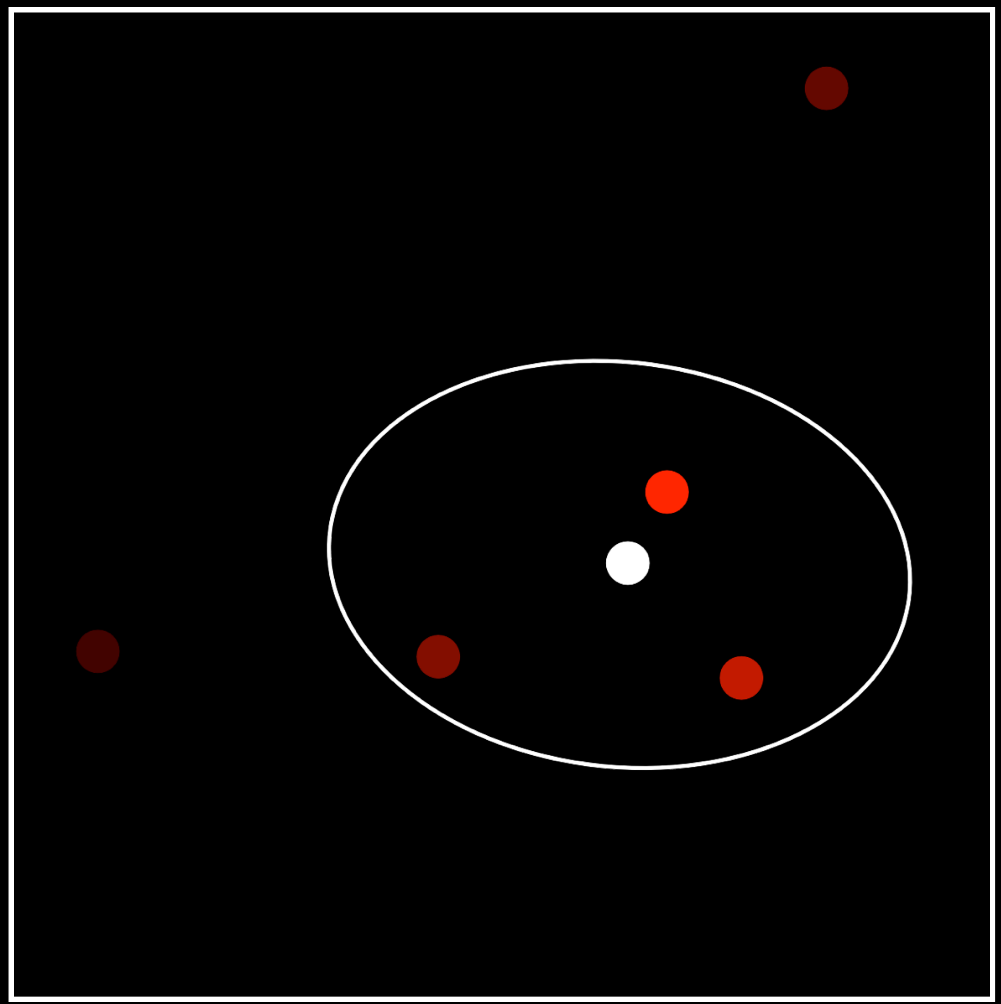

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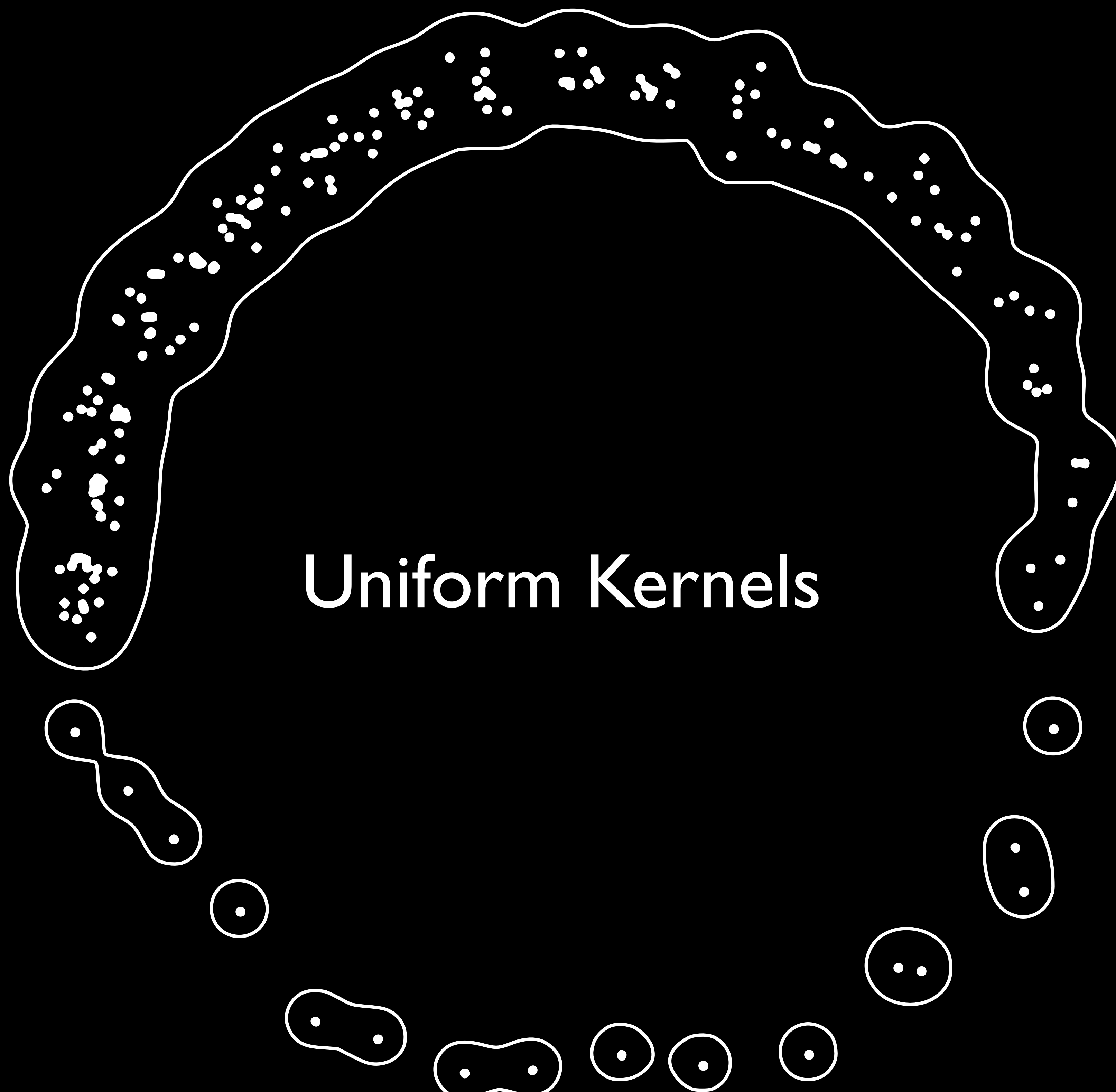
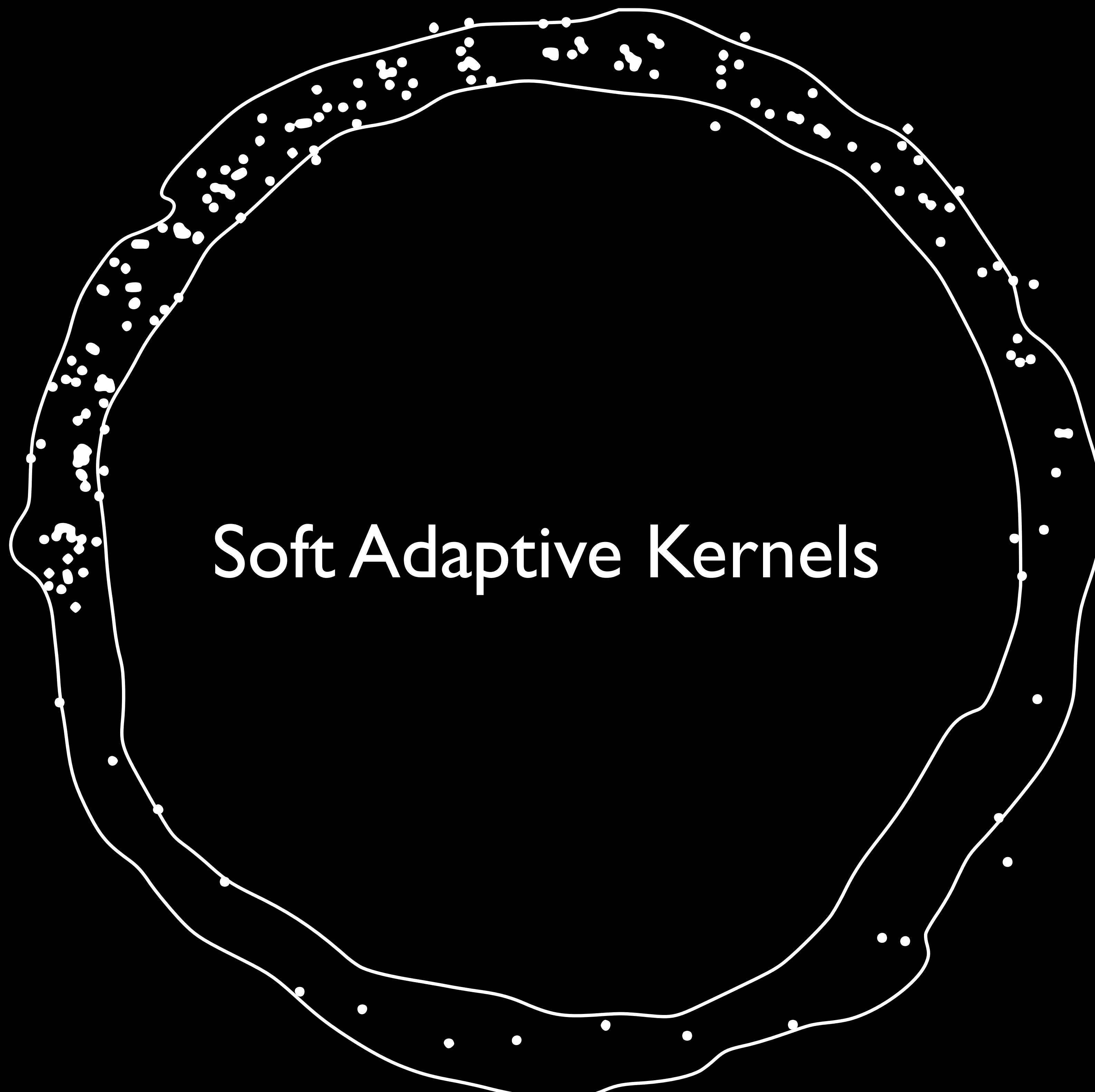


Soft Adaptive Kernels



Kernel Degeneracies

With covariance-based estimators:

- Unless $N \gg n$, $\boldsymbol{\Sigma}$ is ill-conditioned
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Need 1000 models to bootstrap
100-dimensional space

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$$\mathbf{\Sigma}^{\star} = \lambda \mathbf{diag}(\mathbf{\Sigma}) + (1-\lambda)\mathbf{\Sigma}$$

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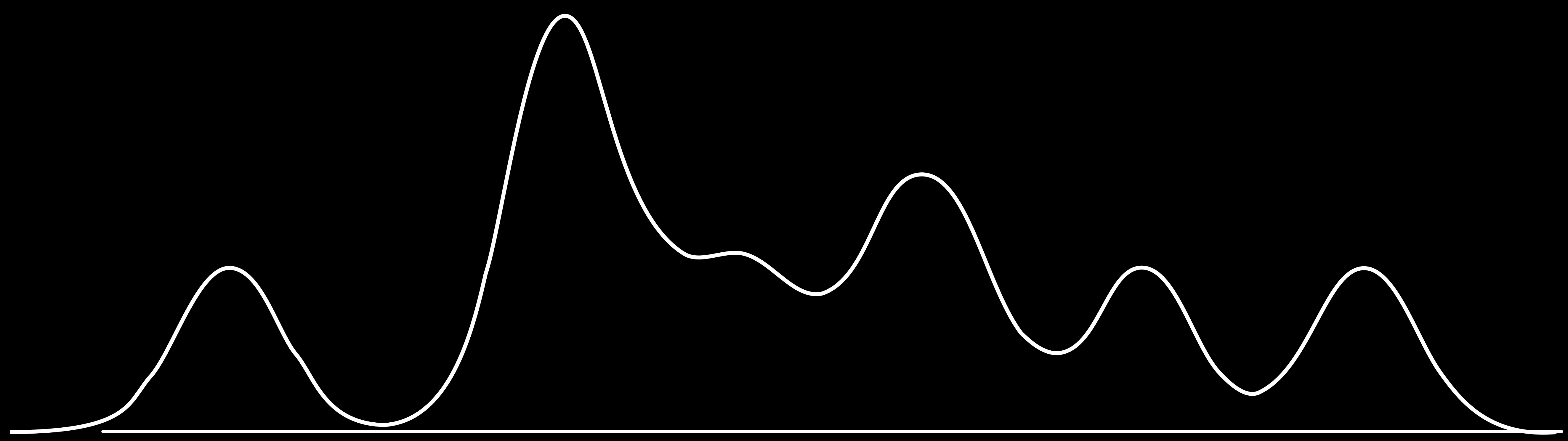
See the paper for details

Sampling



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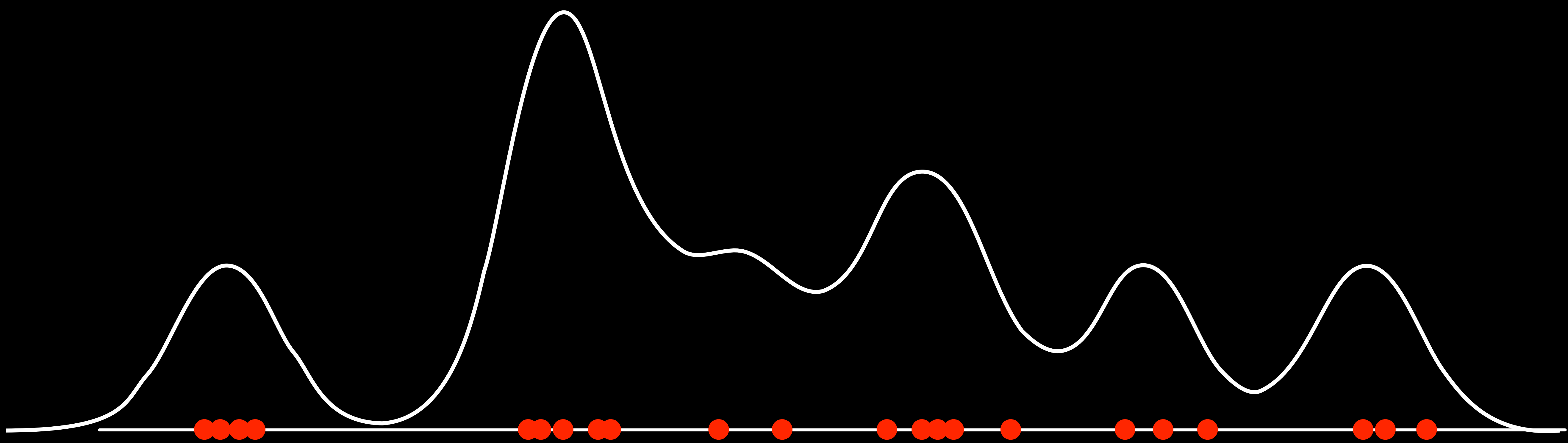
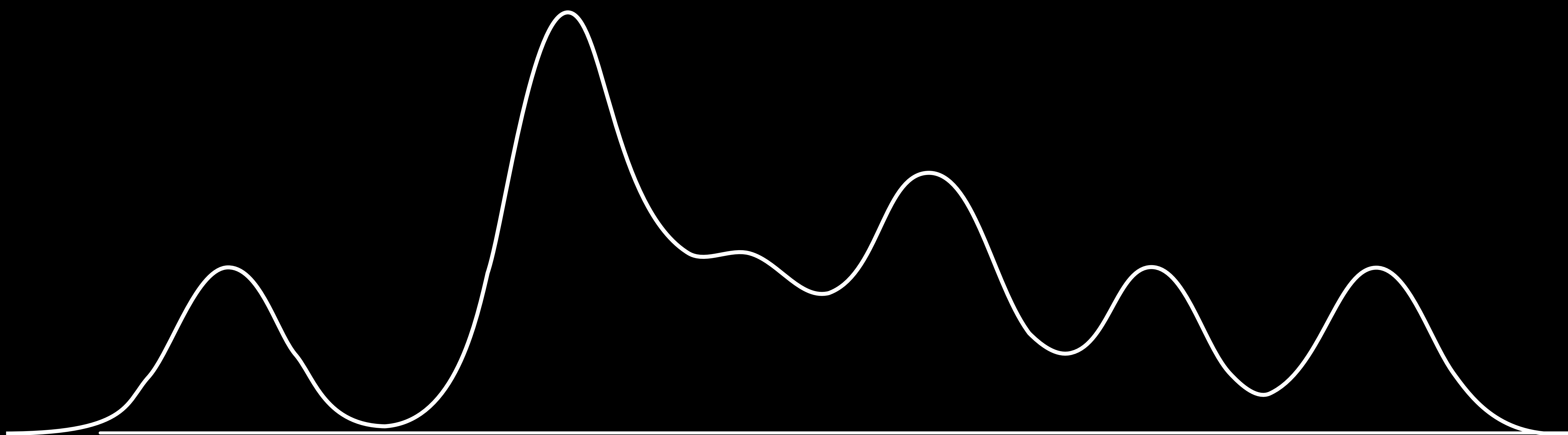


Local Sampling



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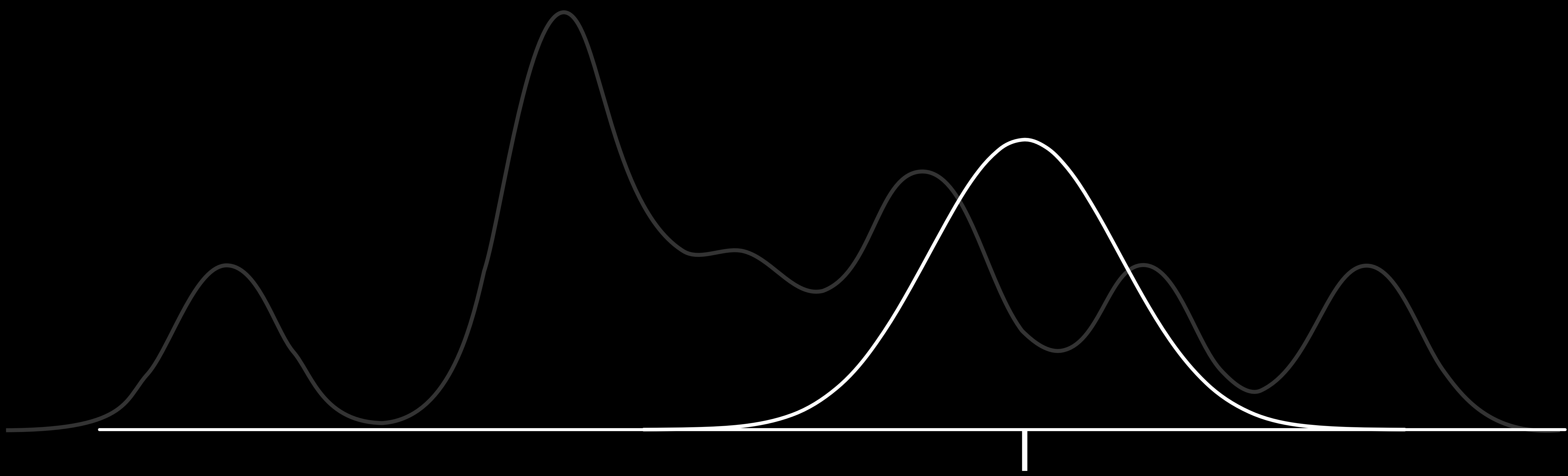

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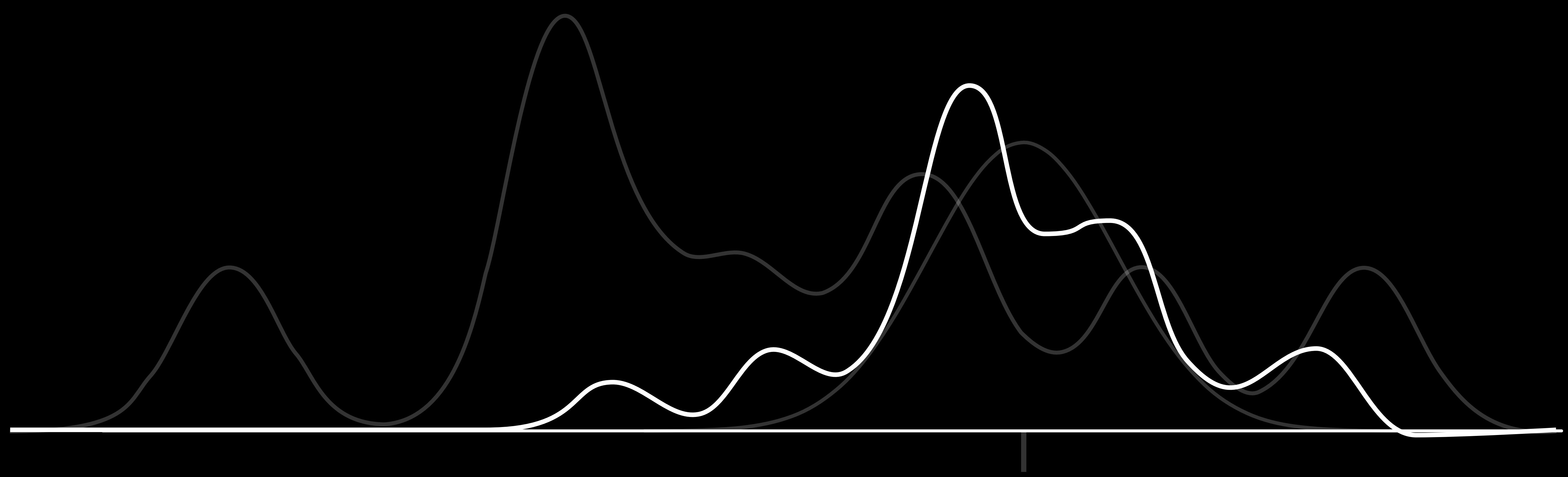

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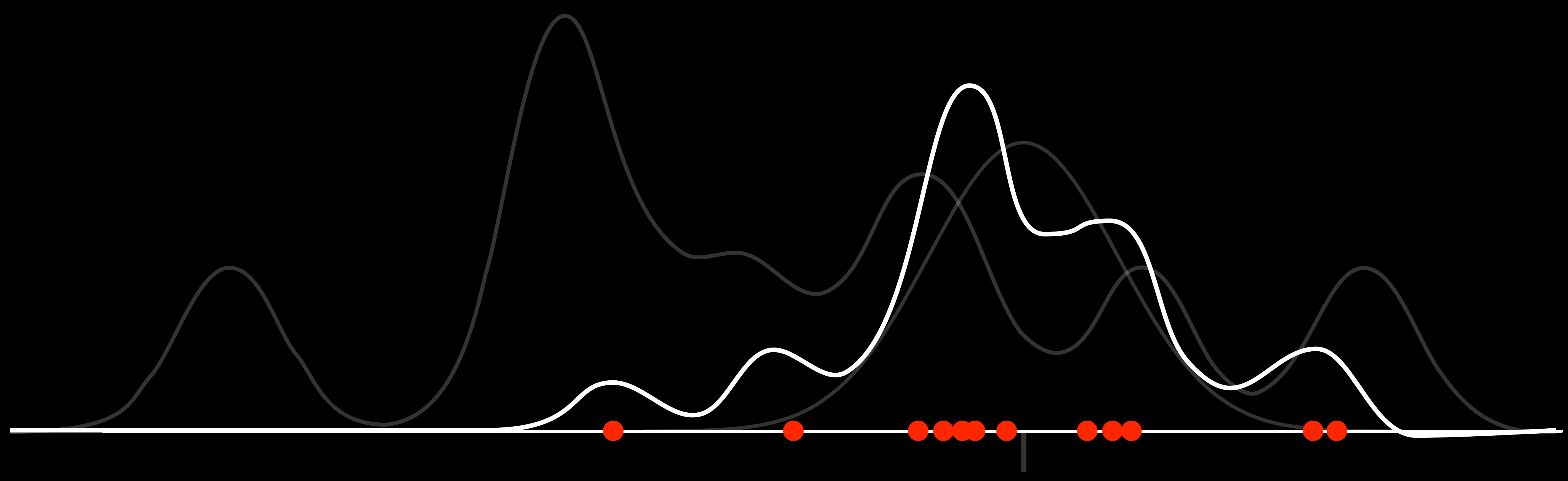
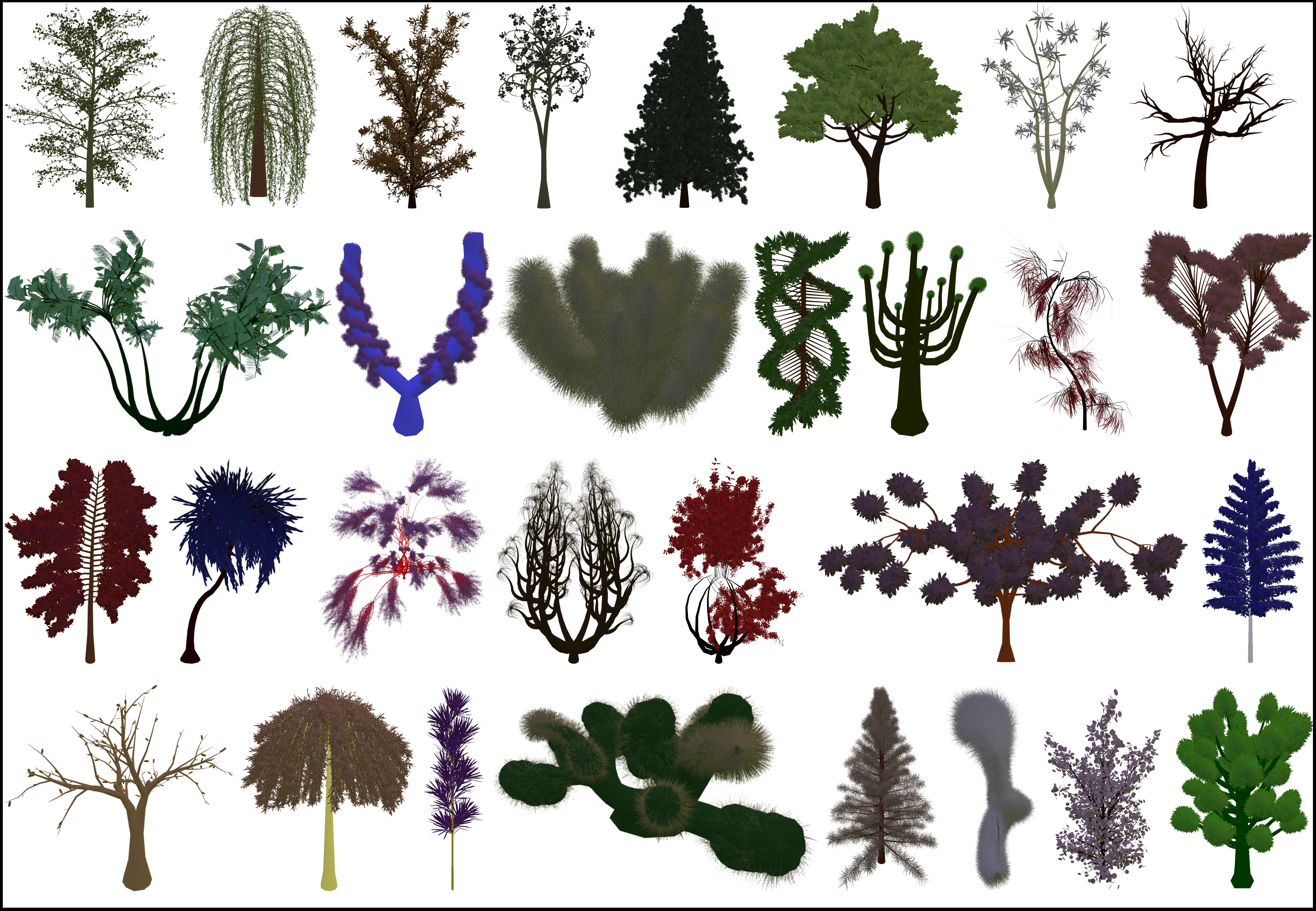



DRYAD

Results

- Released 12/07
- 20,000+ downloads in a year
- 19 initial models in the database
- 6,936 created trees
- Average modeling time 15.1 minutes
- 15% of users "fluent" in 3D modeling



Questions?