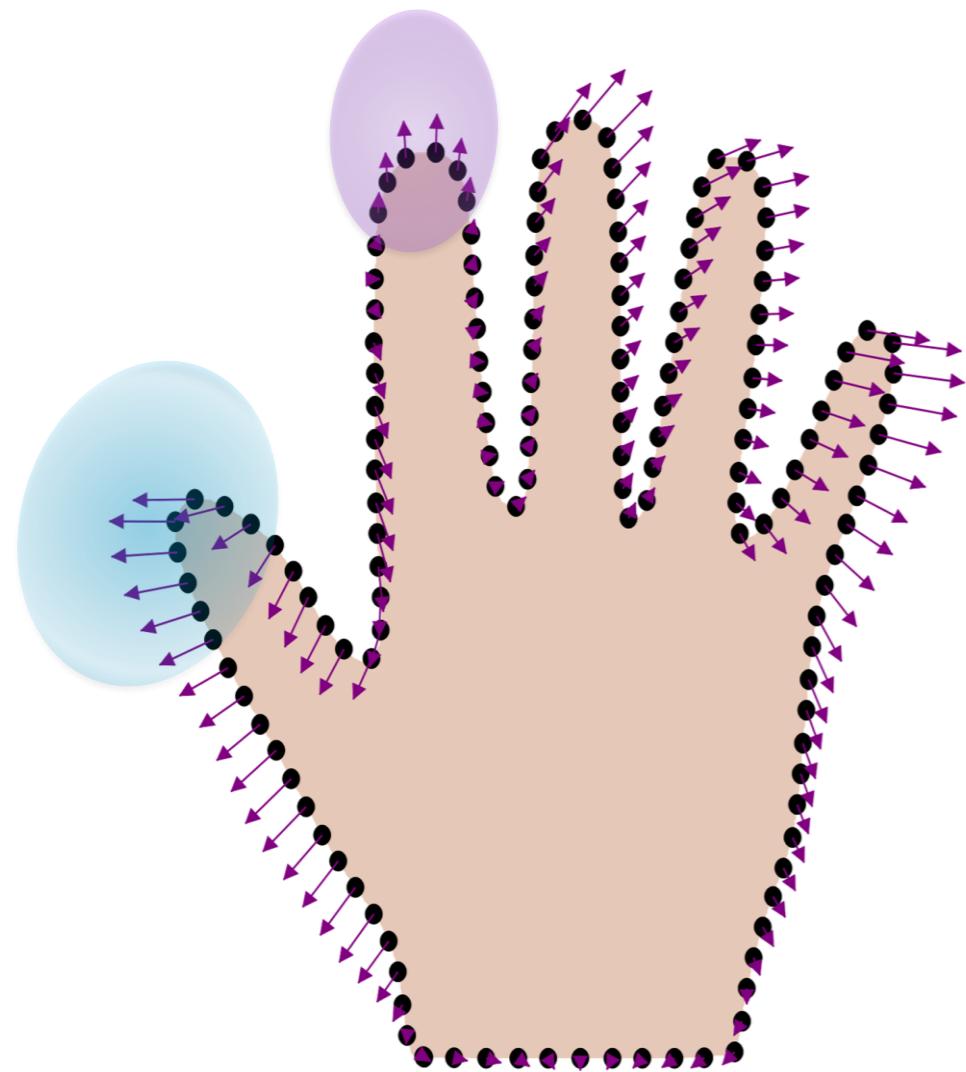


**University
of Basel**

The marginalization property

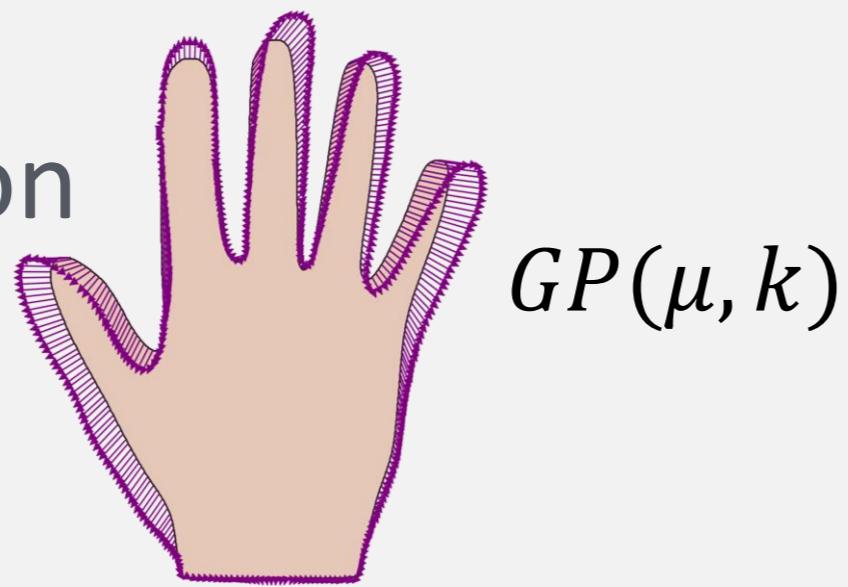
Constructing Gaussian processes



$$N \left(\begin{pmatrix} \mu_1(x_1) \\ \mu_2(x_1) \\ \vdots \\ \mu_1(x_n) \\ \mu_2(x_n) \end{pmatrix}, \begin{pmatrix} k_{11}(x_1, x_1) & k_{12}(x_1, x_1) & \dots & k_{11}(x_1, x_n) & k_{12}(x_1, x_n) \\ k_{21}(x_1, x_1) & k_{22}(x_1, x_1) & \ddots & k_{21}(x_1, x_n) & k_{22}(x_1, x_n) \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ k_{11}(x_n, x_1) & k_{12}(x_n, x_1) & \dots & k_{11}(x_n, x_n) & k_{12}(x_n, x_n) \\ k_{21}(x_n, x_1) & k_{22}(x_n, x_1) & \dots & k_{21}(x_n, x_n) & k_{22}(x_n, x_n) \end{pmatrix} \right)$$

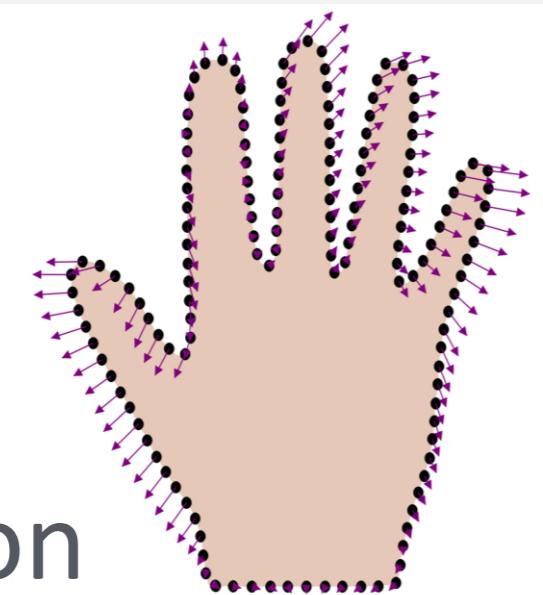
Constructing Gaussian processes

Continuous
representation



$$\begin{aligned}\mu: \Gamma_R &\rightarrow \mathbb{R}^2 \\ k: \Gamma_R \times \Gamma_R &\rightarrow \mathbb{R}^{2 \times 2}\end{aligned}$$

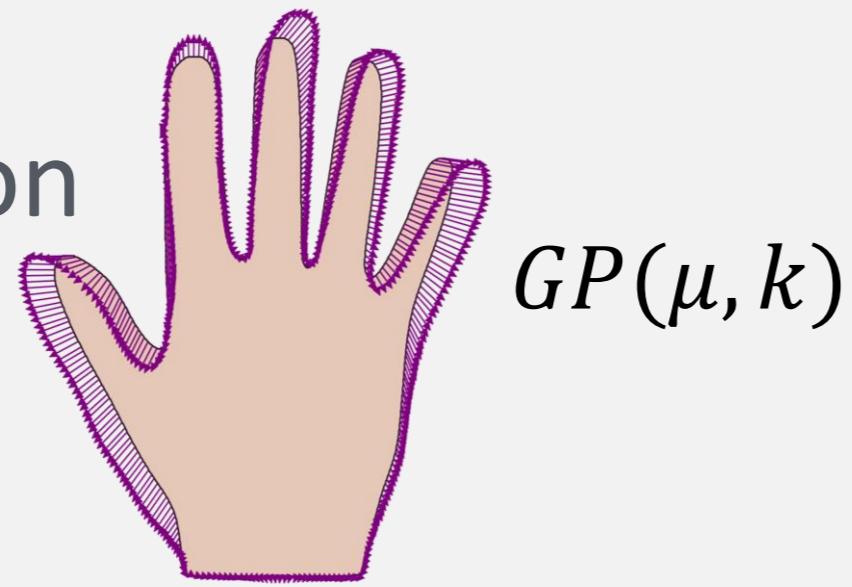
Discrete
representation



$$N \left(\begin{pmatrix} \mu_1(x_1) \\ \mu_2(x_1) \\ \vdots \\ \mu_1(x_n) \\ \mu_2(x_n) \end{pmatrix}, \begin{pmatrix} k_{11}(x_1, x_1) & k_{12}(x_1, x_1) & \dots & k_{11}(x_1, x_n) & k_{12}(x_1, x_n) \\ k_{21}(x_1, x_1) & k_{22}(x_1, x_1) & \ddots & k_{21}(x_1, x_n) & k_{22}(x_1, x_n) \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ k_{11}(x_n, x_1) & k_{12}(x_n, x_1) & \dots & k_{11}(x_n, x_n) & k_{12}(x_n, x_n) \\ k_{21}(x_n, x_1) & k_{22}(x_n, x_1) & \dots & k_{21}(x_n, x_n) & k_{22}(x_n, x_n) \end{pmatrix} \right)$$

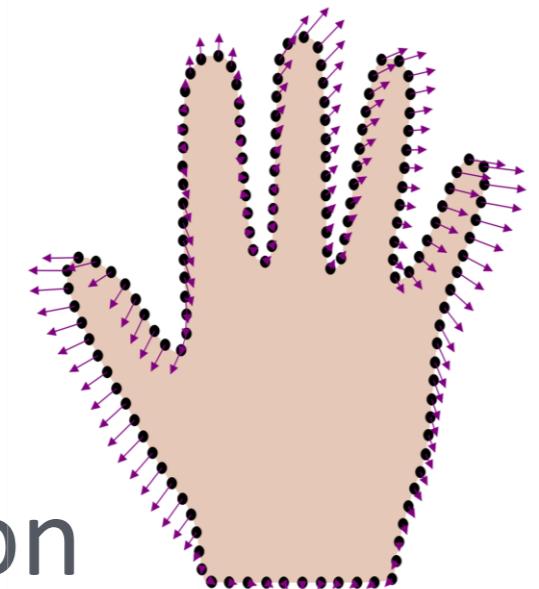
Constructing Gaussian processes

Continuous representation



$$\begin{aligned}\mu: \Gamma_R &\rightarrow \mathbb{R}^2 \\ k: \Gamma_R \times \Gamma_R &\rightarrow \mathbb{R}^{2 \times 2}\end{aligned}$$

Discrete representation

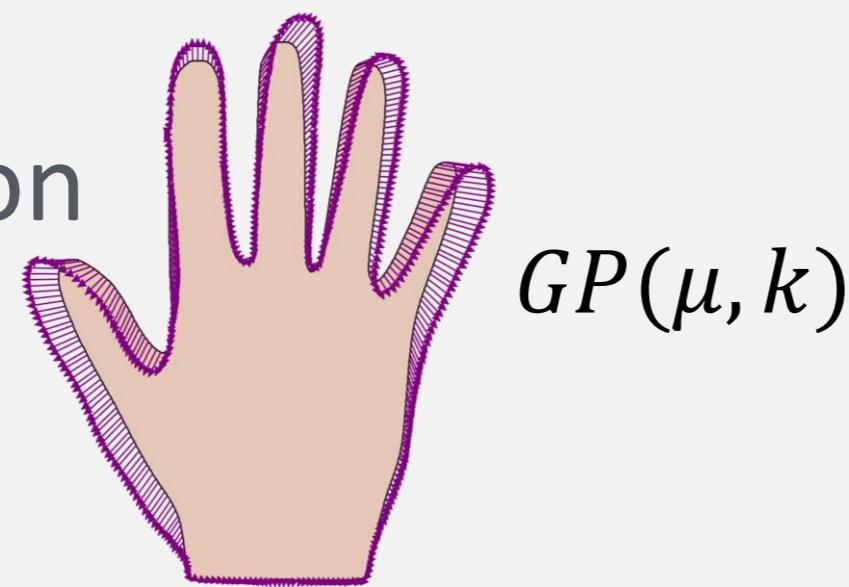


$$N \left(\begin{pmatrix} \mu_1(x_1) \\ \mu_2(x_1) \\ \vdots \\ \mu_1(x_n) \\ \mu_2(x_n) \end{pmatrix}, \begin{pmatrix} k_{11}(x_1, x_1) & k_{12}(x_1, x_1) & \dots & k_{11}(x_1, x_n) & k_{12}(x_1, x_n) \\ k_{21}(x_1, x_1) & k_{22}(x_1, x_1) & \ddots & k_{21}(x_1, x_n) & k_{22}(x_1, x_n) \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ k_{11}(x_n, x_1) & k_{12}(x_n, x_1) & \dots & k_{11}(x_n, x_n) & k_{12}(x_n, x_n) \\ k_{21}(x_n, x_1) & k_{22}(x_n, x_1) & \dots & k_{21}(x_n, x_n) & k_{22}(x_n, x_n) \end{pmatrix} \right)$$

- + Simple and compact definition
- + Can be infinite dimensional
- + Independent of discretization

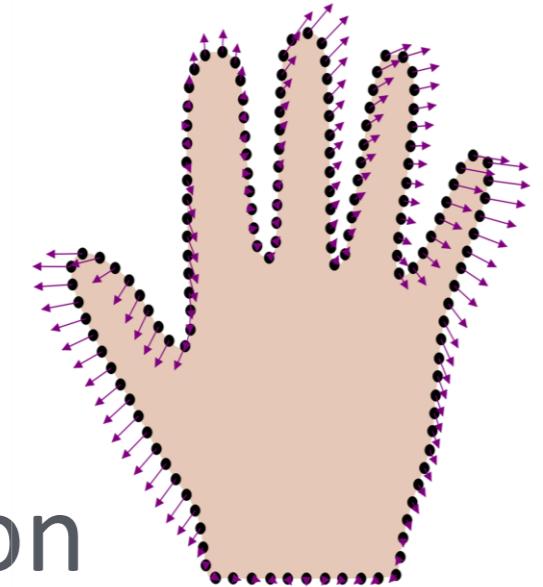
Constructing Gaussian processes

Continuous representation



$$\begin{aligned}\mu: \Gamma_R &\rightarrow \mathbb{R}^2 \\ k: \Gamma_R \times \Gamma_R &\rightarrow \mathbb{R}^{2 \times 2}\end{aligned}$$

Discrete representation



- + Simple and compact definition
- + Can be infinite dimensional
- + Independent of discretization

?

Computer implementation

$$N \left(\begin{pmatrix} \mu_1(x_1) \\ \mu_2(x_1) \\ \vdots \\ \mu_1(x_n) \\ \mu_2(x_n) \end{pmatrix}, \begin{pmatrix} k_{11}(x_1, x_1) & k_{12}(x_1, x_1) & \dots & k_{11}(x_1, x_n) & k_{12}(x_1, x_n) \\ k_{21}(x_1, x_1) & k_{22}(x_1, x_1) & \ddots & k_{21}(x_1, x_n) & k_{22}(x_1, x_n) \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ k_{11}(x_n, x_1) & k_{12}(x_n, x_1) & \dots & k_{11}(x_n, x_n) & k_{12}(x_n, x_n) \\ k_{21}(x_n, x_1) & k_{22}(x_n, x_1) & \dots & k_{21}(x_n, x_n) & k_{22}(x_n, x_n) \end{pmatrix} \right)$$

Marginalization property

Let $X = (x_1, \dots, x_n)$ and $Y = (y_1, \dots, y_m)$

be jointly normal distributed random variables

$$p(X, Y) = N\left(\begin{pmatrix} \mu_X \\ \mu_Y \end{pmatrix}, \begin{pmatrix} \Sigma_{XX} & \Sigma_{XY} \\ \Sigma_{YX} & \Sigma_{YY} \end{pmatrix}\right)$$

The marginal distribution $p(X) = \int p(X, Y) dY$

is given by $p(X) = N(\mu_X, \Sigma_{XX})$.

Formal definition

A Gaussian process $p(u) = GP(\mu, k)$

is a probability distribution over functions

$$u : \mathcal{X} \rightarrow \mathbb{R}^d$$

such that every finite restriction to function values

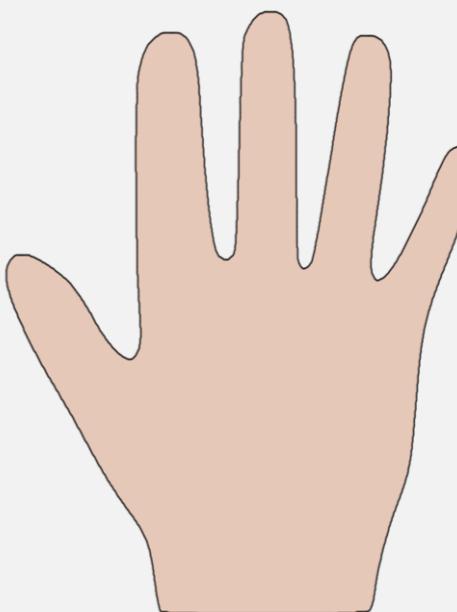
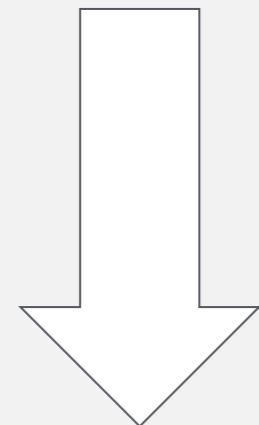
$$u_X = (u(x_1), \dots, u(x_n))$$

is a **multivariate normal distribution**

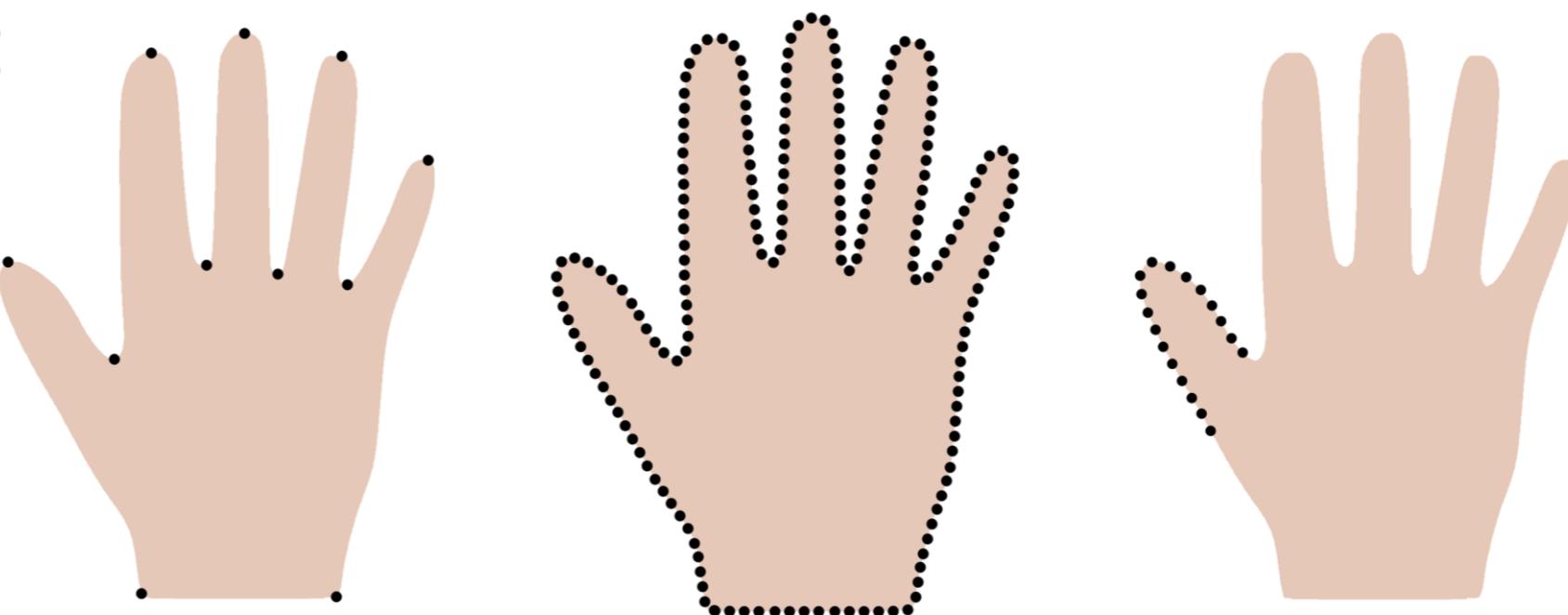
$$p(u_X) = N(\mu_X, k_{XX}).$$

Marginalization

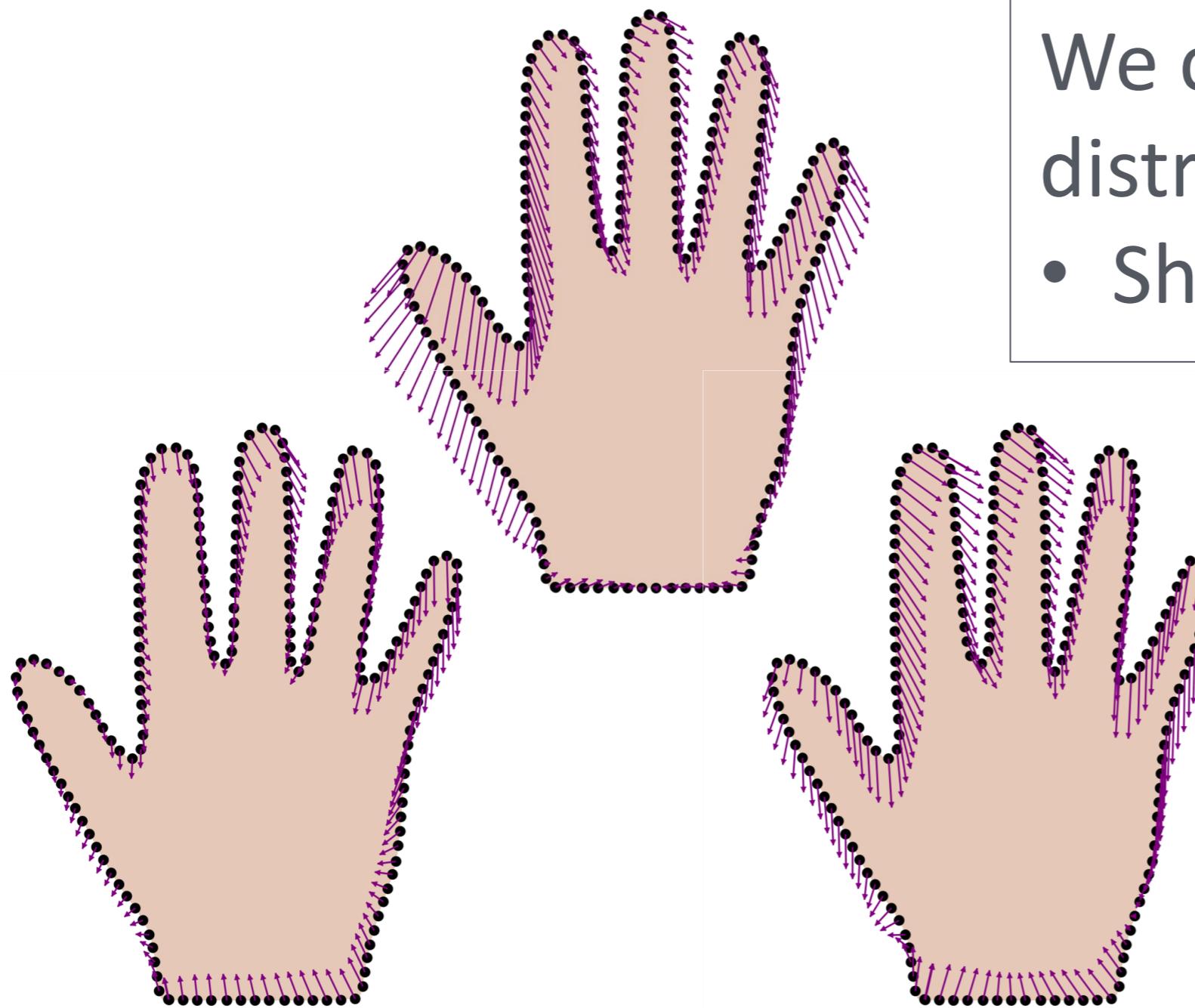
Continuous representation:
 $GP(\mu, k)$



Discrete representation:
 $N(\mu, K)$



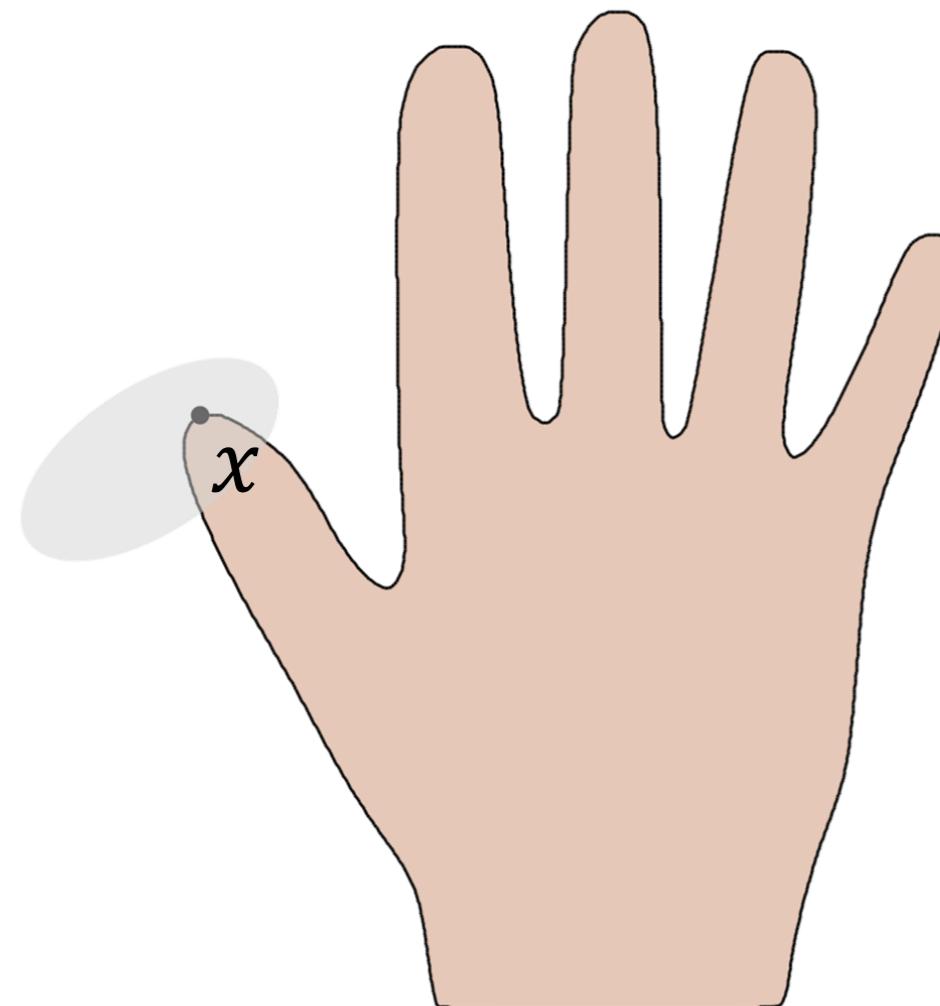
Sampling



We can sample from a normal distribution.

- Shape variations can be visualized

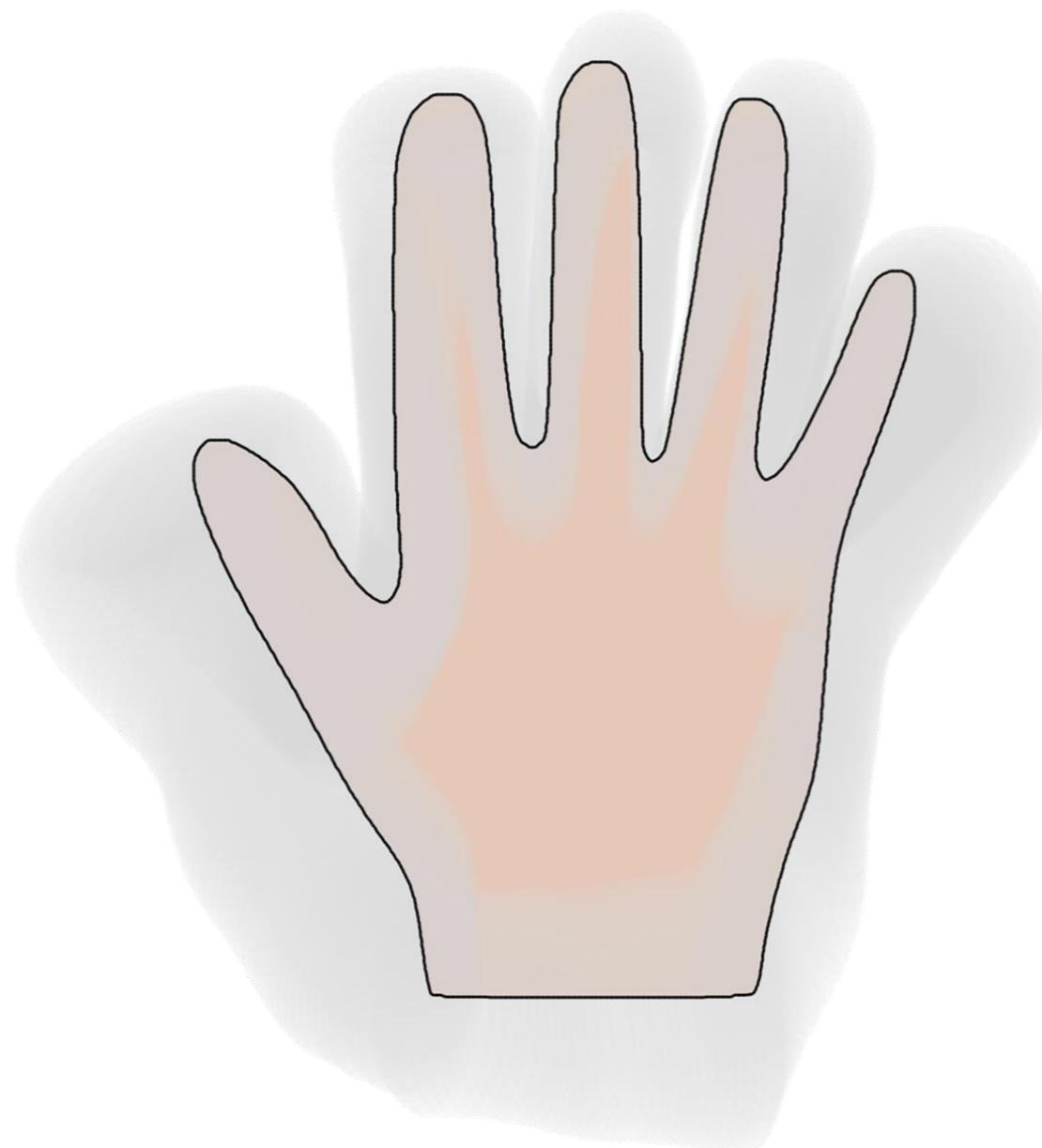
Computing probabilities



We can compute probabilities to answer questions like:

- What is the “normal” variation?
- Is a given variation still normal?

Computing probabilities



We can use the marginal distributions to compute confidence regions.