

# Probability Distributions on the Torus with Applications to Bioinformatics

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# Motivation

There are many problems in applied statistics where it is beneficial to use probabilistic methods for angles. This is part of **directional statistics**.

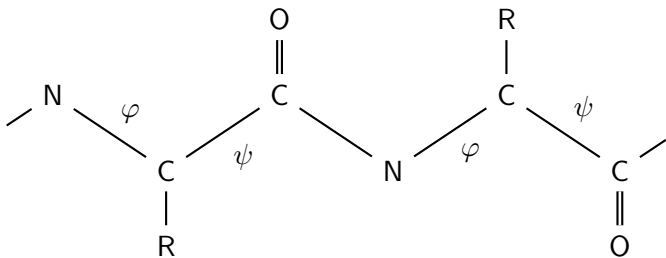
- ▶ distribution of a single angle = distribution on a circle
- ▶ joint distribution of several angles = distribution on a torus  $\mathbb{T}^d$

Application areas include

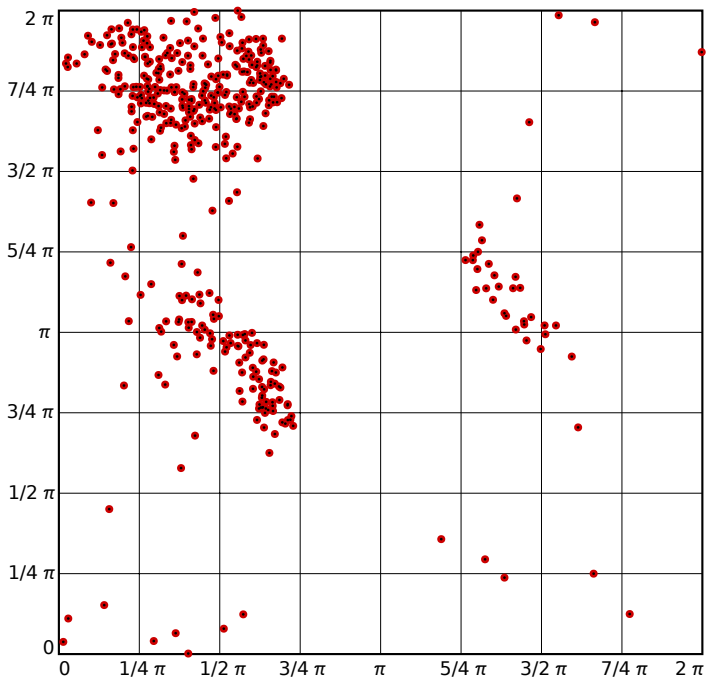
- ▶ astronomy
- ▶ geology
- ▶ biochemistry

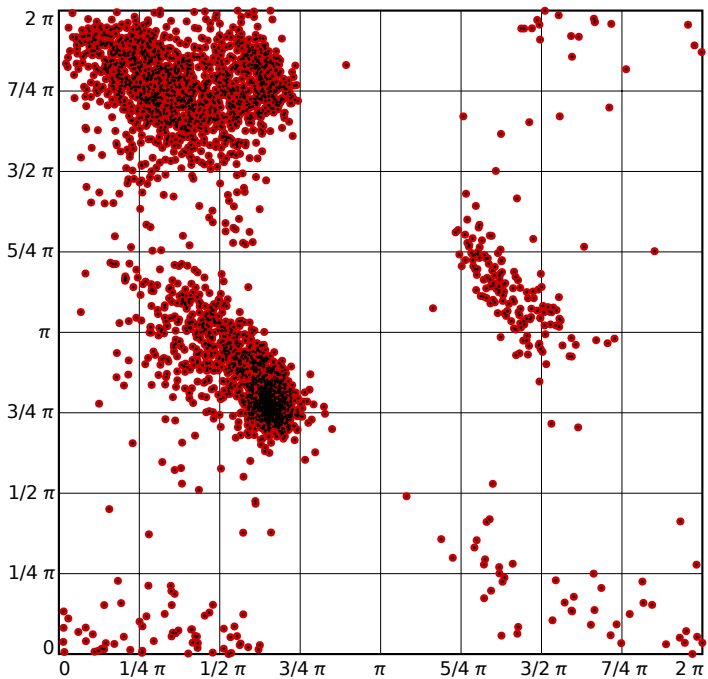
In this talk I'll briefly consider some examples from biochemistry, and in particular distributions of angles describing the conformation of proteins or RNA molecules.

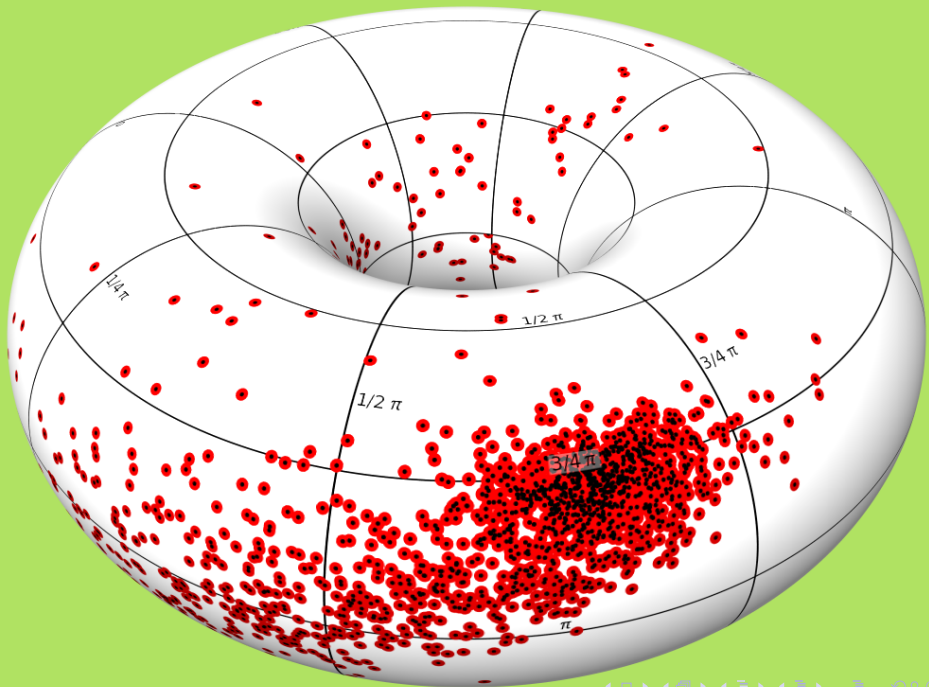
## Example: backbone angles of proteins



- ▶ Most of the geometric structure of the protein backbone is described by the sequence of dihedral angles  $\varphi_1, \psi_1, \varphi_2, \psi_2, \dots$
- ▶ By creating a scatter-plot of  $(\varphi, \psi)$  (Ramachandran plot) for naturally occurring proteins, one can see that  $(\varphi, \psi)$  have a non-trivial joint distribution on the torus  $\mathbb{T}^2$ .
- ▶ This forms the basis for probabilistic models of protein structure.









# Angular Distributions

Commonly used distributions of one angle include:

- ▶ uniform:  $\theta \sim \mathcal{U}[0, 2\pi]$
- ▶ von Mises distribution: density  $\varphi(\theta) = \frac{1}{Z(\kappa)} \exp(\kappa \cos(\theta - \mu))$
- ▶ Bingham distribution
- ▶ wrapped normal distribution:  
 $\theta = X \bmod 2\pi$  where  $X \sim \mathcal{N}(\mu, \sigma^2)$
- ▶ wrapped Cauchy distribution:  
 $\theta = X \bmod 2\pi$  where  $X$  is Cauchy distributed on  $\mathbb{R}$

Differences to probability distributions on  $\mathbb{R}$ :

- ▶ The usual definitions of “expectation”, “variance” etc. fail.  
(What is the mean of a uniform distributions on angles?)
- ▶ There are no “tails”.

Commonly used distributions of several angles include:

- ▶ the “full” bivariate von Mises distribution
- ▶ the multi-variate von Mises distribution (see next slide)
- ▶ wrapped multivariate normal distribution  $\mathcal{N}(\mu, \Sigma)$

Such distributions can be used as building blocks to model distributions like in the Ramachandran plot (e.g. as a mixture of several von Mises distributions).

**Remark.** These are distributions on the torus. Distributions on the sphere are different!

# The Sine Model

The *multivariate von Mises distribution* on the  $d$ -dimensional torus  $\mathbb{T}^d$  has density

$$\varphi(\theta; \mu, \kappa, \Lambda) = \frac{1}{Z(\kappa, \Lambda)} \exp(\kappa^\top c(\theta) + \frac{1}{2} s(\theta)^\top \Lambda s(\theta))$$

where

- ▶  $c_i(\theta) = \cos(\theta_i - \mu_i)$  and  $s_i(\theta) = \sin(\theta_i - \mu_i)$  for  $i = 1, \dots, d$ ,
- ▶  $\mu \in \mathbb{T}^d$  is the location parameter,
- ▶  $\kappa \in \mathbb{R}_+^d$  determines “concentration”,
- ▶  $\Lambda = (\lambda_{ij}) \in \mathbb{R}^{d \times d}$  with  $\Lambda^\top = \Lambda$  and  $\lambda_{ii} = 0$  for  $i = 1, \dots, d$ , and
- ▶  $Z(\kappa, \Lambda)$  is the normalisation constant.

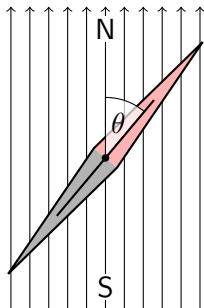
**Remark.** For  $d = 1$  one has  $Z(\kappa, \Lambda) = 2\pi I_0(\kappa)$  where  $I_0$  is the modified Bessel function of order 0. For  $d > 1$  there is no closed-form expression for the normalising constant  $Z$ .

**Example.** The motion of a compass needle in a magnetic field under the influence of white noise is described by the following stochastic differential equation:

$$d\theta(t) = -\alpha \sin(\theta(t)) dt + \sigma dB(t)$$

where

- ▶  $B$ : a Brownian motion
- ▶  $\alpha > 0$ : strength of the magnetic field
- ▶  $\sigma > 0$ : strength of noise



It is easy to check that the equilibrium distribution of  $\theta(t)$  is a one-dimensional von Mises distribution with  $\kappa = 2\alpha/\sigma^2$  and  $\mu = 0$ .

**Normal Approximation.** By Taylor-approximation we have  $\cos(\theta) \approx 1 - \frac{1}{2}\theta^2$  and  $\sin(\theta) \approx \theta$ . Thus

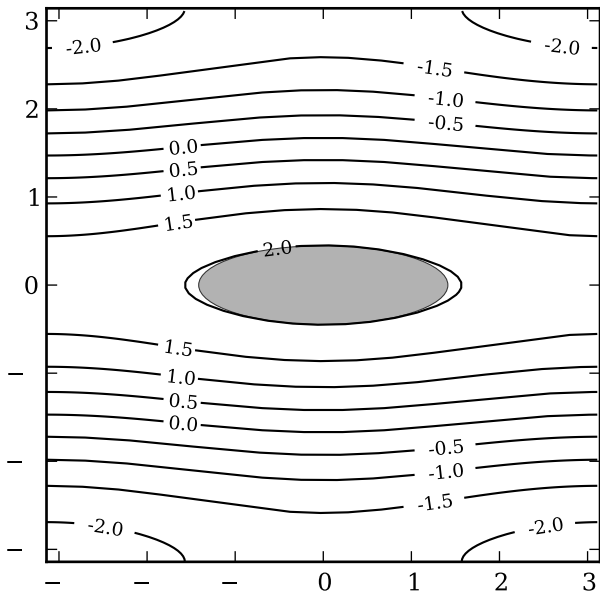
$$\begin{aligned}\kappa^\top c(\theta) + \frac{1}{2}s(\theta)^\top \Lambda s(\theta) &\approx \sum_{i=1}^d \kappa_i \left(1 - \frac{1}{2}\theta_i^2\right) + \frac{1}{2} \sum_{i,j=1}^d \theta_i \lambda_{ij} \theta_j \\ &= -\frac{1}{2}\theta^\top \Sigma^{-1} \theta + \text{const.}\end{aligned}$$

where

$$\Sigma^{-1} = \text{diag}(\kappa) - \Lambda.$$

Result: For “big”  $\kappa$ , the multivariate von Mises distribution “converges” to the wrapped  $\mathcal{N}(\mu, \Sigma)$  distribution.

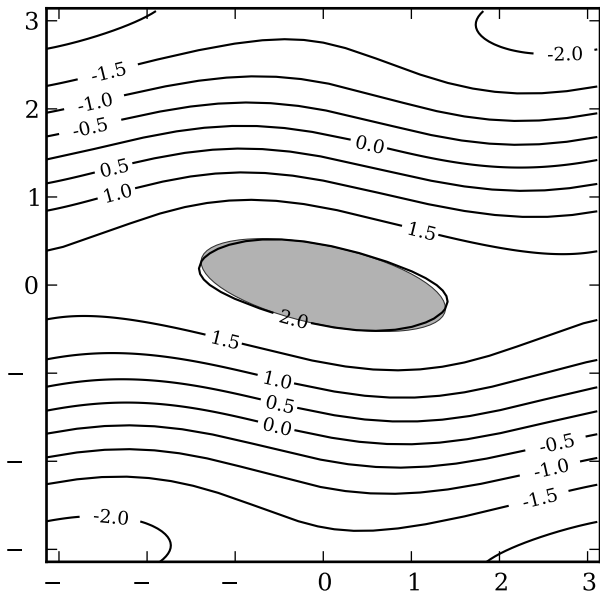
**Lemma.** Assume that the matrix  $\Sigma^{-1}$  is positive definite. Then the global maximum of the von Mises density  $\varphi$  is attained at  $\theta = \mu$  and  $\varphi$  has no other (local) maxima.



$$\kappa = \begin{pmatrix} 0.200 \\ 2.000 \end{pmatrix}$$

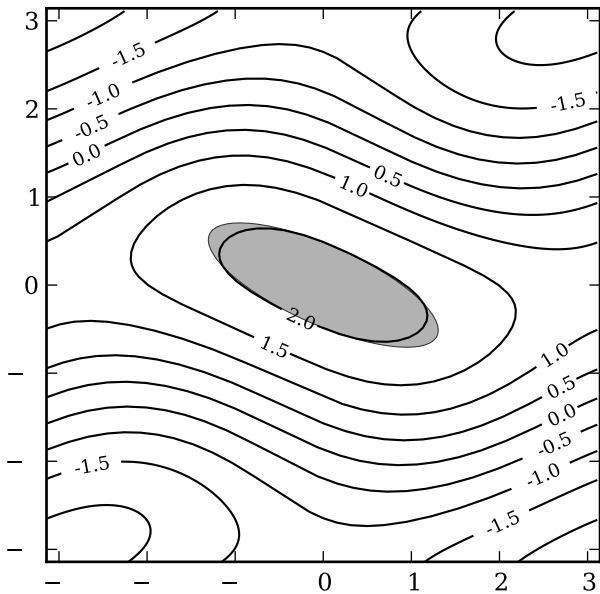
$$\Lambda = \begin{pmatrix} 0 & -0.000 \\ -0.000 & 0 \end{pmatrix}$$





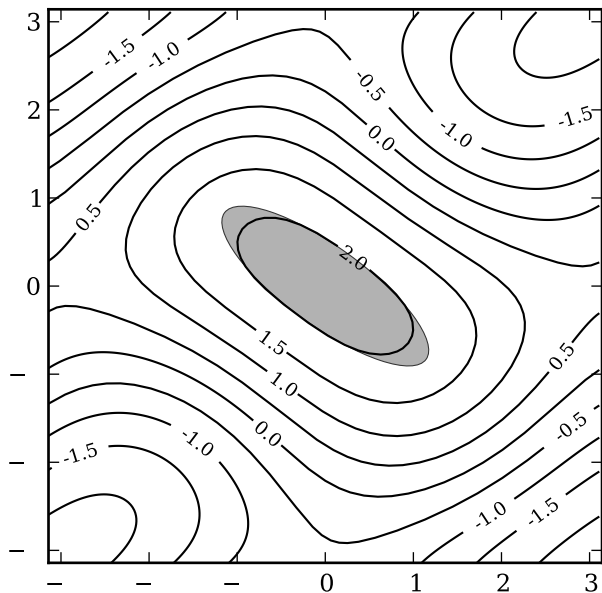
$$\kappa = \begin{pmatrix} 0.278 \\ 1.922 \end{pmatrix}$$

$$\Lambda = \begin{pmatrix} 0 & -0.366 \\ -0.366 & 0 \end{pmatrix}$$



$$\kappa = \begin{pmatrix} 0.498 \\ 1.702 \end{pmatrix}$$

$$\Lambda = \begin{pmatrix} 0 & -0.669 \\ -0.669 & 0 \end{pmatrix}$$



$$\kappa = \begin{pmatrix} 0.822 \\ 1.378 \end{pmatrix}$$

$$\Lambda = \begin{pmatrix} 0 & -0.856 \\ -0.856 & 0 \end{pmatrix}$$

**Small/vanishing concentration.** If  $\kappa$  is “small”, the von Mises distribution can have a surprising number of modes. Example: for

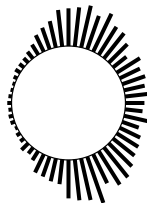
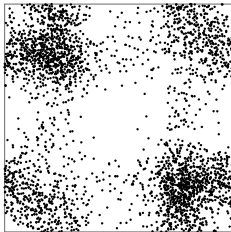
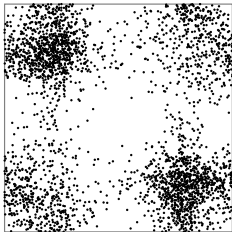
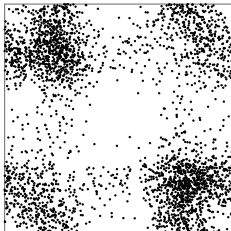
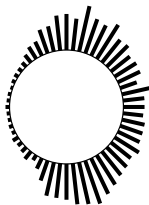
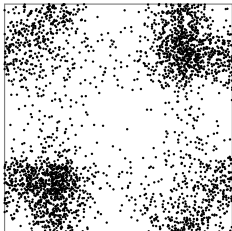
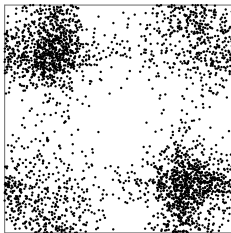
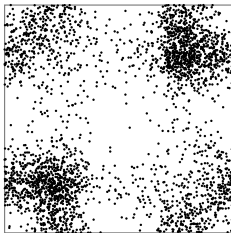
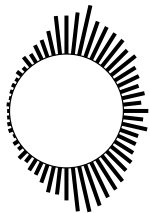
$$\kappa = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}, \quad \Lambda = \begin{pmatrix} 0 & -5 & 5 \\ -5 & 0 & 5 \\ 5 & 5 & 0 \end{pmatrix}$$

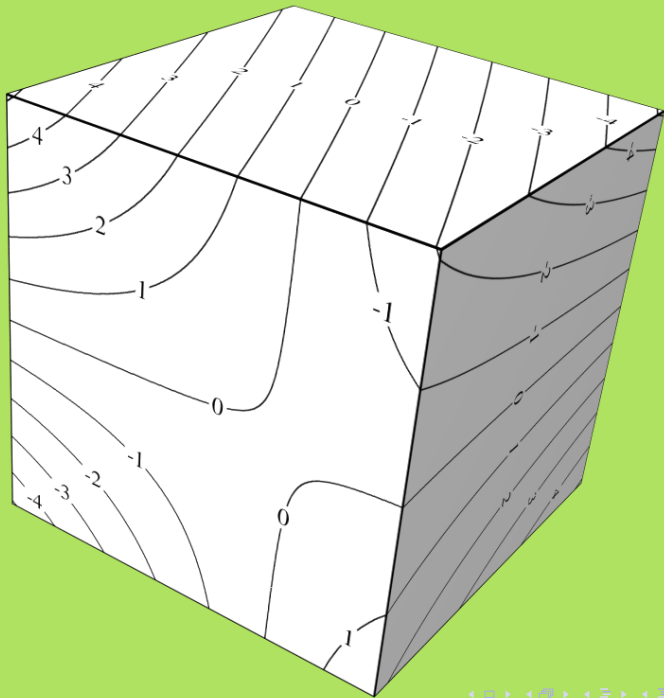
the distribution has 6 isolated modes. These cases will **not** be useful for modelling!

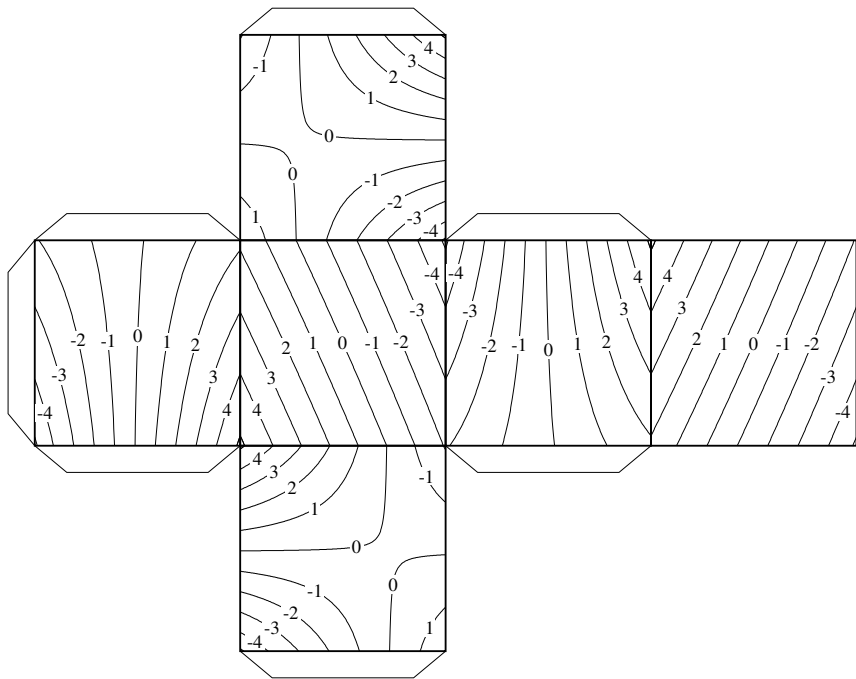
In the extreme case  $\kappa = 0$  the density of the von Mises distribution simplifies to

$$\varphi(\theta; \mu, 0, \Lambda) = \frac{1}{Z(0, \Lambda)} \exp\left(\frac{1}{2} s^\top \Lambda s\right) =: g(s)$$

where  $s = (\sin(\theta_1), \dots, \sin(\theta_d)) \in [-1, 1]^d$ . It transpires that at the maxima of the density,  $s$  is located in the corners of the cube  $[-1, 1]^d$ .







# Outlook

For “large”  $\kappa$  the multivariate von Mises distribution can be used as a building block for modelling distributions on the torus. Further questions include:

- ▶ How to sample from a multivariate von Mises distribution?
- ▶ How to perform statistical inference, e.g. fitting of parameters?

## References

- ▶ Kanti V. Mardia and Peter E. Jupp, *Directional statistics*. Wiley Series in Probability and Statistics, 2000
- ▶ Wouter Boomsma, Kanti V. Mardia, Charles C. Taylor, Jesper Ferkinghoff-Borg, Anders Krogh, Thomas Hamelryck, *A generative, probabilistic model of local protein structure*. PNAS, vol. 105 (26), pp. 1-6, 2008
- ▶ Kanti V. Mardia, Gareth Hughes, Charles C. Taylor, Harshinder Singh, *A multivariate von Mises distribution with applications to bioinformatics*. The Canadian Journal of Statistics, vol. 36 (1), pp. 99-109, 2008