

Simulation of random processes

Random variables.

Problem 1. Use `hist` to plot a histogram of the empirical distribution of a sample of 1000 numbers obtained with `randn`. Plot on the same picture the theoretical pdf $p(x) = 1/\sqrt{2\pi} \exp(-x^2/2)$.

Hint: If Z is the vector containing your sample, then the following matlab instructions give a normalized histogram of it:

```
[ns,xs]=hist(Z,20);  
ns=ns/length(Z)/(xs(2)-xs(1));  
bar(xs,nx); or plot(xs,nx);
```

The histogram is here normalized so that the total area is equal to one.

Gaussian vectors.

Algorithm to generate a realization of a Gaussian vector \mathbf{Y} with the distribution $\mathcal{N}(\mathbf{m}, \mathbf{R})$:

- compute a square root \mathbf{S} of \mathbf{R} .
- draw a random vector \mathbf{n} with the distribution $\mathcal{N}(\mathbf{0}, \mathbf{I})$ (use `randn`) and compute:

$$\mathbf{y} = \mathbf{m} + \mathbf{S}\mathbf{n}$$

The computationally expensive part is the computation of the square root of the covariance matrix (do it only once if you want to generate several realizations!). Use a Cholesky method for that. Here, use `sqrtn`.

Gaussian processes.

In order to generate realizations of a Gaussian process $\mu(\mathbf{x})$ with mean zero and covariance function $R(\mathbf{x}, \mathbf{x}') = \mathbb{E}[\mu(\mathbf{x})\mu(\mathbf{x}')]]$, the Cholesky method is suitable for an arbitrary grid $\{\mathbf{x}, \mathbf{x} \in \mathcal{D}\}$:

- evaluate the covariance matrix $\mathbf{R} = \{R(\mathbf{x}, \mathbf{x}'), \mathbf{x}, \mathbf{x}' \in \mathcal{D}\}$.
- compute a square root \mathbf{S} of \mathbf{R} .
- draw a random vector \mathbf{n} with the distribution $\mathcal{N}(\mathbf{0}, \mathbf{I})$ and compute:

$$\mathbf{y} = \mathbf{S}\mathbf{n}$$

Problem 2. Plot several realizations of a Brownian motion $(W_z)_{z \geq 0}$ over the regular grid $\{z_j = (j-1)h, j = 1, \dots, n\}$ with $n = 2^{10}$ and $h = 0.05$ (it is a Gaussian process with mean zero and covariance function $\mathbb{E}[W_z W_{z'}] = \inf(z, z')$). Use both the Cholesky method and the partial sum method (use `cumsum`).

Stationary Gaussian processes.

In order to generate realizations of a stationary Gaussian process $\mu(\mathbf{x})$ with mean zero and covariance function $C(\mathbf{x} - \mathbf{x}') = \mathbb{E}[\mu(\mathbf{x})\mu(\mathbf{x}')]]$, we can make use of the spectral representation of the random process $\mu(\mathbf{x})$:

$$\mu(\mathbf{x}) = \int_{-\infty}^{\infty} e^{i\mathbf{k} \cdot \mathbf{x}} \hat{C}(\mathbf{k})^{1/2} \hat{n}_{\mathbf{k}} d\mathbf{k}$$

where \hat{n}_k is a complex Gaussian white noise.

The Fourier algorithm makes use of the FFT and is suitable for a regular grid, say in 1D: $\{x_j = (j-1)h, j = 1, \dots, n\}$.

Problem 3. Plot several realizations of a zero-mean Gaussian process $\mu(x)$ with Gaussian covariance function $C(x) = \exp(-x^2)$ over the grid $x_j = (j-1)h$ with $n = 2^{10}$ and $h = 0.05$. Use both the Cholesky method and the Fourier method.

Plot the histogram of the empirical distribution $(\mu(x_j))_{j=1, \dots, n}$ and compare with the theoretical pdf $p(x) = 1/\sqrt{2\pi} \exp(-x^2/2)$.

Plot the empirical covariance function

$$C_e(x_j) = \frac{1}{n-j+1} \sum_{i=1}^{n-j+1} \mu(x_i) \mu(x_{i+j-1})$$

and compare with the theoretical function $C(x)$.

Repeat with a larger n , say $n = 2^{20}$, with the Fourier method.

Problem 4. Plot (with `imagesc` or `pcolor`) a realization of a zero-mean Gaussian process $\mu(\mathbf{x})$ with Gaussian covariance function $C(x) = \exp(-|\mathbf{x}|^2)$ over a 512×512 grid with step 0.05. Use the Fourier method with `fft2`.

Problem 5. Plot several realizations of a zero-mean Gaussian process $\mu(x)$ with Gaussian covariance function $C(x) = \exp(-x^2)$ over a grid covering $[0, 6]$, given the observations: $\mu(2) = 1$ and $\mu(4) = -1$. Compute the posterior mean and covariance matrix using the formula given below and use the Cholesky method (note: there exists a more efficient method called conditional kriging).

Remember (for problem 5): If

$$\begin{pmatrix} \mathbf{X}_1 \\ \mathbf{X}_2 \end{pmatrix} \sim \mathcal{N} \left(\begin{pmatrix} \mathbf{0} \\ \mathbf{0} \end{pmatrix}, \begin{pmatrix} \mathbf{R}_{11} & \mathbf{R}_{12} \\ \mathbf{R}_{21} & \mathbf{R}_{22} \end{pmatrix} \right)$$

then

$$\mathcal{L}(\mathbf{X}_1 | \mathbf{X}_2 = \mathbf{x}_2) = \mathcal{N}(\mathbf{R}_{12} \mathbf{R}_{22}^{-1} \mathbf{x}_2, \mathbf{R}_{11} - \mathbf{R}_{12} \mathbf{R}_{22}^{-1} \mathbf{R}_{21})$$