

# CS-E5885 Modeling biological networks

Exam, February 23, 2023

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You are NOT allowed to use calculators or any other additional equipments/material in the exam. Please write your answers in English. Please write carefully. Use **mathematical notation and equations in your answers whenever possible and reasonable**. The use of diagrams and drawings is also encouraged.

Questions:

- Consider random variables  $\mathbf{x} = (x_1, \dots, x_6)$ .
  - Write the joint probability distribution for  $\mathbf{x}$  in product-form in two different ways: such that it factorizes according to the undirected graphical model (also known as Markov random field) shown in Figure 1 a), and such that it factorizes according to the directed graphical model (also known as Bayesian network) shown in Figure 1 b). Explain all the mathematical notations used in your answer. (5 points)
  - Convert the static directed graphical model in Figure 1 b) to a dynamic Bayesian network for  $\mathbf{x}(t) = (x_1(t), \dots, x_6(t))$ ,  $t = 0, 1, 2, \dots$ , by “unrolling” the static network over one time step, from time  $t - 1$  to  $t$ . Draw the resulting dynamic Bayesian network model as a directed graph for one time step, from time  $t - 1$  to  $t$ . Also write the joint distribution over a finite length time-series  $\mathbf{x}(0), \mathbf{x}(1), \dots, \mathbf{x}(T)$  in a product form such that the product involves conditional probabilities only for univariate variables. You can assume that the initial state  $\mathbf{x}(0)$  is fixed, i.e.,  $\mathbf{x}(0)$  does not have any uncertainty. (5 points)

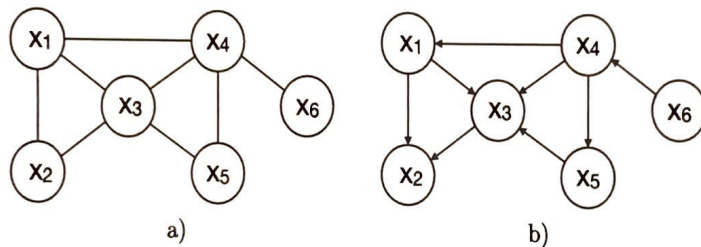
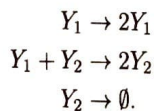


Figure 1: a) Undirected and b) directed graphical model for random variables  $\mathbf{x} = (x_1, \dots, x_6)$ .

- The reaction equations for the well-known Lotka-Volterra can be written as



Write the ODE version of the Lotka-Volterra model for concentrations  $[Y_1]$  and  $[Y_2]$  assuming the mass-action kinetics with deterministic reaction rates  $k_1$ ,  $k_2$  and  $k_3$  for the three reactions. (5 points)

- Consider modeling continuous-time dynamics for  $n$  variables,  $\mathbf{x}(t) = (x_1(t), \dots, x_n(t))$ , using ODEs, where the model for the  $i$ th variable can be written in a general form as

$$\frac{dx_i(t)}{dt} = f_i(\mathbf{x}(t)|\theta_i), \quad i = \{1, \dots, n\}.$$

Assume you have  $N + 1$  measurements  $\mathbf{y}(t_0), \mathbf{y}(t_1), \dots, \mathbf{y}(t_N)$  from a single time-series trajectory that are measured at arbitrary time points  $t_0, t_1, \dots, t_N$ . Each measurement

$\mathbf{y}(t) = (y_1(t), \dots, y_n(t))$  contains a measurement for all  $n$  variables, where  $y_i(t) = x_i(t) + \epsilon_i(t)$ , where  $\epsilon_i(t)$  denotes measurement error. Describe the gradient matching method for learning the parameters  $\theta_i$  separately for each variable  $x_i$ . (5 points)

4. **Background:** Recall the Poisson timestep method for approximative simulation of coupled chemical reaction networks. Briefly, time is discretized into small time increments  $\Delta t$ . For each time increment we need to simulate a  $v$ -dimensional reaction vector  $r$  such that  $r_i \sim \text{Po}(h_i(x, c_i)\Delta t)$  and then the updated state  $x$  and time  $t$  are obtained by  $x := x + Sr$  and  $t := t + \Delta t$ , where  $S$  is the stoichiometric matrix.

**Question:** Describe how you can obtain the chemical Langevin equation (CLE) as a further approximation of the Poisson timestep method, and write down a general equation for CLE in terms of a stochastic differential equation (SDE) model (or the corresponding Euler-Maruyama simulation algorithm). In your answer, remember to describe the statistical aspects and motivations for deriving the CLE. (10 points total)