

# Combinatorial and Algebraic Statistics

## Problem Set 2

Due Date: 31 May 2021

1. (a) For  $\lambda > 0$ , a random variable  $X$  has a Poisson distribution with parameter  $\lambda > 0$  if its state space is  $\mathbb{Z}_{\geq 0}$  and

$$P_\lambda(X = k) = \frac{\lambda^k}{k!} e^{-\lambda} \quad \text{for } k \in \mathbb{Z}_{\geq 0}.$$

Show that the family of Poisson random variables is a regular exponential family. What is its natural parameter space?

- (b) Let  $G = ([m], E)$  be a graph with  $m$  nodes and edge set  $E \subset [m] \times [m]$ . We denote the adjacency matrix of  $G$  by  $A = [a_{i,j}] \in \mathbb{R}^{m \times m}$  where  $a_{i,j} = 1$  if  $(i, j) \in E$  and  $a_{i,j} = 0$  if  $(i, j) \notin E$ . The *Erdős-Renyi graph model* is the one parameter model with state space  $\mathbb{G}_m$  consisting of all graphs  $G$  on  $m$  nodes where the probability

$$P_\theta(G) = \prod_{i \in [m]} \prod_{j \in [m]} \theta^{a_{i,j}} (1 - \theta)^{1 - a_{i,j}} \quad \text{where } \theta \in (0, 1).$$

Show that the Erdős-Renyi graph model is an exponential family. What is its natural parameter space?

2. Consider the vector  $h = (1, 1, 1, 2, 2, 2)$  and the matrix

$$A = \begin{pmatrix} 2 & 0 & 0 & 1 & 1 & 0 \\ 0 & 2 & 0 & 1 & 0 & 1 \\ 0 & 0 & 2 & 0 & 1 & 1 \end{pmatrix}$$

- (a) What are the generators of  $I_A$  and  $I_{A,h}$ ?
- (b) What familiar statistical model is the discrete exponential family  $\mathcal{M}_{A,h}$ ?
3. Suppose we have three particles  $P_1, P_2, P_3$  that each can be in one of two states  $+1$  or  $-1$ . The state space of our model is pairs of particles and states  $\{(P_i, \pm 1) : i \in [3]\}$  (at any one moment a particle appears and we can measure its state), and our data-generating distribution is assumed to be an exponential family with canonical sufficient statistic

$$T(P_i, \pm 1) = (\pm e_i, 1)^t \in \mathbb{R}^4,$$

where  $e_1, e_2, e_3$  denote the standard basis vectors in  $\mathbb{R}^3$ . Suppose we observe the data

$$\mathbb{D} = \{(P_3, 1), (P_1, -1), (P_2, -1), (P_2, 1), (P_2, -1), (P_1, -1), (P_2, 1), (P_2, 1), (P_2, 1), (P_1, 1), \\ (P_2, -1), (P_1, -1), (P_2, 1), (P_3, 1), (P_2, 1), (P_3, 1), (P_3, 1), (P_1, -1), (P_2, -1), (P_3, -1)\}.$$

Does the MLE of this data exist? If so, what is it?

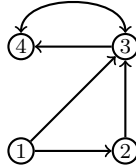
4. Let  $(X_1, \dots, X_m)$  be jointly distributed discrete random variables, and let  $G = ([m], E)$  be a DAG in which we assign to each edge  $(i, j) \in E$  a subset  $\ell(i, j)$  of the outcomes of  $X_{\text{pa}_G(j) \setminus \{i\}}$ . Given  $S \subset [m]$  and an outcome  $x_S$  of  $X_S$ , we define the DAG  $G_{x_S}$  to be the DAG in which we delete all edges  $(i, j)$  of  $G$  whose label contains an outcome  $y_{S \cap \text{pa}_G(j) \setminus \{i\}}$  of  $X_{S \cap \text{pa}_G(j) \setminus \{i\}}$  all of whose entries coincide with the corresponding entries in  $x_S$ . For disjoint subsets  $A, B, C, S \subset [m]$  and  $x_S$  an outcome of  $X_S$ , we say that  $A$  and  $B$  are *c-separated* in  $G$  given  $C$  and  $x_S$  whenever  $A$  and  $B$  are d-separated given  $C \cup S$  in  $G_{x_S}$ . A distribution  $\mathbb{P}$  is *Markov* to  $G$  if it entails  $X_A \perp\!\!\!\perp X_B | X_C, X_S = x_S$  whenever  $A$  and  $B$  are c-separated given  $C$  and  $x_S$  in  $G$ . Note here that a distribution  $P(X_1, \dots, X_m)$  entailing the relation  $X_A \perp\!\!\!\perp X_B | X_C, X_S = x_S$  is equivalent to the condition that

$$P(x_A, x_B | x_C, x_S) = P(x_A | x_C, x_S)P(x_B | x_C, x_S),$$

for all outcomes  $x_A, x_B$ , and  $x_C$ .

Show that c-separation is not complete: Show there exist DAGs  $G$  with edge assignments  $\ell(i, j)$  for which any positive distribution Markov to  $G$  must entail a relation  $X_A \perp\!\!\!\perp X_B | X_C, X_S = x_S$ , but  $A$  and  $B$  are not c-separated given  $C$  and  $x_S$  in  $G$ .

5. Let  $G$  be the following mixed graph, and let  $\mathcal{M}(G) \subseteq PD_4$  denote its linear structural equation model.

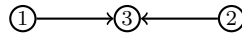


- (a) The definition of d-separation can be extended directly to mixed graphs from DAGs. Show that the mixed graph  $G$  encodes no d-separation statements, and hence, d-separation captures no constraining equations on the model  $\mathcal{M}(G)$ .
- (b) Show that any  $\Sigma = [\sigma_{i,j}] \in \mathcal{M}(G)$  satisfies the constraint

$$\det(\Sigma_{12,34}) = 0,$$

where  $\Sigma_{12,34}$  is the submatrix of  $\Sigma$  given by the rows  $\{1, 2\}$  and the columns  $\{3, 4\}$ . What do these two results combine to say?

6. Consider the multivariate normal model associated to the DAG



Given the data  $\mathbb{D} = \{(1, 1, 0), (0, 0, 1)\}$ , find all MLEs.