

Figure 1: Directed graphical model.

- 1. Given the graphical model in Figure 1, which of the following conditional independence statements are correct?
  - (a) *a* ⊥ *f*
  - (b) *a* ⊥⊥ *g*
  - (c) *b* ⊥⊥ *i*|*f*
  - (d)  $d \perp j | g, h$
  - (e)  $i \perp b | h$
  - (f) *j* ⊥⊥ *d*
  - (g)  $i \perp c | h, f$
- 2. Consider two random variables x, y with joint distribution p(x, y). Show that:

$$\mathbb{E}_{x}[x] = \mathbb{E}_{y}\Big[\mathbb{E}_{x}[x|y]\Big]$$

Here,  $\mathbb{E}_x[x|y]$  denotes the expected value of *x* under the conditional distribution p(x|y), with a similar notation for the conditional variance.

3. Consider a Gaussian random variable  $x \sim \mathcal{N}(x | \mu_x, \Sigma_x)$ , where  $x \in \mathbb{R}^D$ .

The random variable x is transformed according to

$$y = Ax + b + w, \qquad (1)$$

where  $y \in \mathbb{R}^E$ ,  $A \in \mathbb{R}^{E \times D}$ ,  $b \in \mathbb{R}^E$ , and  $w \sim \mathcal{N}(w | 0, Q)$  is independent Gaussian noise. "Independent" means that x and w are independent random variables.

(a) Write down p(y|x).

- (b)  $p(y) = \int p(y|x)p(x)dx$  is Gaussian.<sup>1</sup> Compute the mean  $\mu_y$  and the covariance  $\Sigma_y$ . Derive your result in detail.
- (c) Now, a value  $\hat{y}$  is measured. Compute the posterior distribution  $p(x|\hat{y})$ .<sup>2</sup> *Hint for solution:* Start by explicitly computing the joint Gaussian p(x,y). This also requires to compute the cross-covariances  $Cov_{x,y}[x,y]$  and  $Cov_{y,x}[y,x]$ . Then, apply the rules for Gaussian conditioning.

<sup>&</sup>lt;sup>1</sup>affine transformation of the Gaussian random variable x

<sup>&</sup>lt;sup>2</sup>This posterior is also Gaussian, i.e., we need to determine only its mean and covariance matrix.