# Part IB — Statistics Example Sheet 1

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If  $X \sim \text{Exp}(\lambda), Y \sim \text{Exp}(\mu), X, Y$  independent, we have

$$\mathbb{P}(\min[X,Y] < t) = 1 - \mathbb{P}(\min[X,Y] \ge n)$$

$$= 1 - \int_0^\infty \int_0^\infty I(\lambda e^{-\lambda x_1} \ge t, \mu e^{-\mu x_2} \ge t) \, \mathrm{d}x_2 \mathrm{d}x_1$$

$$= 1 - \int_t^\infty \lambda e^{-\lambda x_1} \, \mathrm{d}x_1 \int_t^\infty \mu e^{-\mu x_2} \, \mathrm{d}x_2$$

$$= 1 - e^{-(\lambda + \mu)t}, \text{ i.e. } \min[X,Y] \sim \mathrm{Exp}(\lambda + \mu)$$

Next, suppose  $X \sim \Gamma(\alpha, \lambda)$ ,  $Y \sim \Gamma(\beta, \lambda)$ . We want to find the joint PDF of

$$U = X + Y$$
, and  $V = X/(X + Y)$ 

Consider the map

$$T:(x,y)\mapsto (u,v), \text{ where } u=x+y,\ v=rac{x}{x+y}$$

where  $x, y, u \ge 0, 0 \le v \le 1$  The inverse map  $T^{-1}$  acts by

$$T^{-1}: (u, v) \mapsto (x, y)$$
, where  $x = uv$ ,  $y = u(1 - v)$ 

and has the Jacobian

$$J(u,v) = \det \begin{pmatrix} v & u \\ 1-v & -u \end{pmatrix}$$
$$= -u$$

Then the joint PDF

$$f_{U,V}(u,v) = f_{X,Y}(uv, u(1-v)) |-u|$$

Substituting in  $f_{X,Y}(x,y) = \frac{\lambda^{\alpha} x^{\alpha-1} e^{-\lambda x}}{\Gamma(\alpha)} \frac{\lambda^{\beta} y^{\beta-1} e^{-\lambda y}}{\Gamma(\beta)}, x, y \ge 0$ , yields

$$f_{U,V}(u,v) = \frac{\lambda^{\alpha+\beta}}{\Gamma(\alpha)\Gamma(\beta)} (uv)^{\alpha-1} (u(1-v))^{\beta-1} u e^{-\lambda u}, \ u \ge 0, \ 0 \le v \le 1$$

$$= \frac{\lambda^{\alpha+\beta}}{\Gamma(\alpha)\Gamma(\beta)} u^{\alpha+\beta-1} v^{\alpha-1} (1-v)^{\beta-1} e^{-\lambda u}$$

$$= \text{Beta}(v;\alpha,\beta) \frac{\lambda^{\alpha+\beta}}{\Gamma(a+b)} u^{\alpha+\beta-1} e^{-\lambda u}$$

$$= \text{Beta}(v;\alpha,\beta) \text{Gamma}(u;\alpha+\beta)$$

This factorises, so the respective marginal PDFs are

$$f_U(u) = \text{Gamma}(u; \alpha + \beta), \quad f_V(v) = \text{Beta}(v; \alpha, \beta)$$

The factorization criterion states that a statistic  $T = t(\mathbf{x})$  is sufficient for  $\theta$  iff

$$f_{\mathbf{X}}(\mathbf{x};\theta) = g(t(\mathbf{x}),\theta)h(\mathbf{x})$$

We have proved the discrete case in lectures. The continuous case is similar:

*Proof.* Suppose we are given the factorization  $f_{\mathbf{X}}(\mathbf{x};\theta) = g(t(\mathbf{x}),\theta)h(\mathbf{x})$ . If T = u, then

$$f_{\mathbf{X}|T=u}(\mathbf{x}; u) = \frac{g(t(\mathbf{x}), \theta)h(\mathbf{x})}{\int_{\mathbf{y};T(\mathbf{y})=u} g(t(\mathbf{y}), \theta)h(\mathbf{y}) \, d\mathbf{y}}$$
$$= \frac{g(u, \theta)h(\mathbf{x})}{g(u, \theta) \int_{\mathbf{y};T(\mathbf{y})=u} h(\mathbf{y}) \, d\mathbf{y}}$$
$$= \frac{h(\mathbf{x})}{\int_{\mathbf{y}} h(\mathbf{y}) \, d\mathbf{y}}$$

which does not depend on  $\theta$ ; thus T is sufficient for  $\theta$ .

The other direction is the same as the discrete case: Suppose T is sufficient for  $\theta$ , ie. the conditional distribution of  $\mathbf{X} \mid T = u$  does not depend on  $\theta$ . Then

$$\mathbb{P}_{\theta}(\mathbf{X} = \mathbf{x}) = \mathbb{P}_{\theta}(\mathbf{X} = \mathbf{x}, T = T(\mathbf{x})) = \mathbb{P}_{\theta}(\mathbf{X} = \mathbf{x} \mid T = T(\mathbf{x}))\mathbb{P}_{\theta}(T = T(\mathbf{x}))$$

The first factor does not depend on  $\theta$  by assumption; call it  $h(\mathbf{x})$ . Let the second factor be  $g(t, \theta)$ , and so we have the required factorisation.

(a) Let  $X_1, \dots, X_n$  be independent  $\operatorname{Po}(i\theta)$ . So

$$f_{\mathbf{X}}(\mathbf{x} \mid \theta) = \prod_{i=1}^{n} \frac{e^{-i\theta}(i\theta)^{x_i}}{x_i!}$$

$$= \exp\left(-\frac{n(n+1)}{2}\theta\right)\theta^{\sum x_i} \cdot \underbrace{\frac{1^{x_1} \cdot 2^{x_2} \cdot \dots \cdot n^{x_n}}{x_1!x_2! \cdot \dots \cdot x_n!}}_{h(\mathbf{x})}$$

Using the factorization criterion,  $t(\mathbf{x}) = \sum_{i=1}^{n} x_i$  is a sufficient statistic, with distribution:

The maximum likelihood estimator  $\hat{\theta}$  is given by

(b) Let  $X_1, \dots, X_n$  be independent  $\text{Exp}(\theta)$ . So

$$f_{\mathbf{X}}(\mathbf{x} \mid \theta) = \prod_{i=1}^{n} \lambda e^{-\lambda x_i}$$
$$= \lambda^n e^{-\lambda \sum x_i}$$

Choosing  $t(\mathbf{x}) = \sum_{i=1}^{n} x_i$ , we can use the factorization criterion with  $g(t(\mathbf{x}), \lambda) = \lambda^n e^{-\lambda \sum x_i}$ ,  $h(\mathbf{x}) = 1$ , to show that  $t(\mathbf{x})$  is a sufficient statistic for  $\lambda$ .

(a) Let  $X_1, \dots, X_n$  be  $\sim$  iid Bin(1, p). (this is Ber(p))

$$f_{\mathbf{X}}(\mathbf{x} \mid p) = \prod_{i=1}^{n} p^{x_i} (1-p)^{1-x_i}$$
  
=  $p^{\sum x_i} (1-p)^{n-\sum x_i}$