

## Appendix A

### Prerequisites

#### A.1 Generating functions

Since generating functions of distributions on  $\bar{\mathbb{N}}_0 = \mathbb{N}_0 \cup \{\infty\}$  play a central role in this text, we collect some of their most important properties in this appendix. We begin with the definition for the case of proper distributions on  $\mathbb{N}_0$ .

**Definition A.1.** Given a random variable  $X$  taking values in  $\mathbb{N}_0$  and with distribution  $Q = (p_n)_{n \geq 0}$ , the *generating function (gf) of  $X$  or  $Q$*  is defined as

$$f(s) := \mathbb{E}s^X = \sum_{n \geq 0} p_n s^n \quad \text{for } |s| \leq R_Q,$$

where  $R_Q \geq 1$  denotes the radius of convergence of the right-hand power series.

Although formulated for distributions on  $\mathbb{N}_0$ , which are our main concern here, the same definition holds for the gf of any finite, or even  $\sigma$ -finite measure  $Q$  on this set. Since  $f(1) = \sum_{n \geq 0} p_n = Q(\mathbb{N}_0)$ , we see that  $R_Q \geq 1$  if  $Q(\mathbb{N}_0)$  is finite, whereas even  $R_Q = 0$  may hold if  $Q(\mathbb{N}_0) = \infty$ .

If  $\varphi(t) = \mathbb{E}e^{-tX}$  for  $t > \sigma_Q := \inf\{s \leq 0 : \mathbb{E}e^{-sX} < \infty\}$  denotes the Laplace transform (LT) of  $X$ , then the gf  $f$  can be directly derived from it by a logarithmic transform of its argument, viz.  $f(s) = \varphi(-\log s)$  for  $|s| < R_Q = e^{-\sigma_Q}$ . Furthermore,  $f$  is actually defined on the whole complex disc  $\mathbb{D}_{R_Q} = \{z \in \mathbb{C} : |z| \leq R_Q\}$ , where it constitutes a continuous function [E<sup>3</sup> Prop. A.4]. On the interior of  $\mathbb{D}_{R_Q}$  it is even analytic (holomorphic). On the other hand, our analysis will mostly deal with  $f$  only on the subdomain  $[0, 1]$  in which case the definition of gf's may easily be extended to random variables on  $\bar{\mathbb{N}}_0$  under the usual convention that  $s^\infty := 0$  for  $s \in [0, 1)$  and  $s^\infty := 1$  if  $s = 1$ .

**Definition A.2.** Given a random variable  $X$  taking values in  $\overline{\mathbb{N}}_0$  and with distribution  $Q = (p_n)_{n \in \overline{\mathbb{N}}_0}$ , the *generating function (gf)* of  $X$  or  $Q$  is defined as

$$f(s) := \mathbb{E}s^X = \sum_{n \geq 0} p_n s^n \quad \text{for } s \in [0, 1].$$

Notice that  $f$ , when restricted to  $[0, 1)$ , coincides with the gf  $f^*$ , say, of the defective distribution  $Q^* = (p_n)_{n \geq 0}$  on  $\mathbb{N}_0$ . However, we have  $f^*(1) = \sum_{n \geq 0} p_n = Q^*(\mathbb{N}_0)$ , while  $f(1) = 1 > f^*(1) = f(1-)$  whenever  $p_\infty > 0$ . This shows that  $f^*$  is continuous at 1 while  $f$  is so only if  $p_\infty = 0$ .

It is a well-known fact in complex analysis that an analytic function is uniquely determined by its values on a set  $\{s_n : n \geq 0\}$  with accumulation point in the interior of its domain. Therefore, the following uniqueness theorem is immediate.

**Theorem A.3. [Uniqueness theorem]** *Let  $f_1, f_2$  be the gf's of distributions  $Q_1, Q_2$  on  $\overline{\mathbb{N}}_0$ . Then the following assertions are equivalent:*

- (a)  $f_1 = f_2$ .
- (b)  $f_1(s) = f_2(s)$  for all  $s \in I$ , where  $I$  is a subset of  $[0, 1)$  with accumulation point in  $[0, 1)$ .
- (c)  $Q_1 = Q_2$ .

The most important analytic properties of gf's are listed in the following proposition.

**Proposition A.4.** *Let  $X$  be a random variable taking values in  $\overline{\mathbb{N}}_0$  and with distribution  $Q = (p_n)_{n \in \overline{\mathbb{N}}_0}$ . The the following assertions hold true for its gf  $f(s) = \mathbb{E}s^X$ :*

- (a) *For any  $R < R_Q$ ,  $f$  is uniformly continuous on  $\mathbb{D}_R$  with  $|f(z)| \leq f(R)$ .*
- (b) *For any  $R \leq R_Q$ ,  $f$  is analytic (holomorphic) on the interior of  $\mathbb{D}_R$  with  $n^{\text{th}}$  derivative*

$$f^{(n)}(z) = n! \sum_{k \geq n} \binom{k}{n} p_k z^{k-n} = n! \mathbb{E} \left[ \binom{X}{n} z^{X-n} \right].$$

- (c)  $f^{(n)}(1-) = \lim_{s \uparrow 1} f^{(n)}(s)$  exists for all  $n \in \mathbb{N}_0$  and is given by the  $n^{\text{th}}$  factorial moment of  $X$ , viz.

$$f^{(n)}(1-) = \mathbb{E}X(X-1) \cdots (X-n+1) = n! \mathbb{E} \binom{X}{n},$$

where  $f^{(0)} := f$  and  $\binom{k}{n} := 0$  if  $k < n$ . In particular,  $\mathbb{E}X = f'(1-)$ ,  $\mathbb{E}X^2 = f''(1-) + f'(1-)$  and  $\text{Var} X = f''(1-) + f'(1-)(1 - f'(1-))$ . If  $p_\infty = \mathbb{P}(X = \infty) = 0$ , then  $f^{(n)}(1-) = f^{(n)}(1)$  for all  $n \in \mathbb{N}_0$ .

- (d) For each  $n \in \mathbb{N}_0$ ,  $f^{(n)}$  is nondecreasing and convex on  $[0, R_Q)$ , and it is increasing if  $\mathbb{P}(X > n) > 0$ , and strictly convex if  $\mathbb{P}(X > n+1) > 0$ .

Finally, we want to present a continuity theorem for gf's that provides the connection between the vague ( $\xrightarrow{v}$ ) or weak ( $\xrightarrow{w}$ ) convergence of distributions on  $\mathbb{N}_0$  and the pointwise convergence of their gf's.

**Theorem A.5.** Let  $Q_1, Q_2, \dots$  be distributions on  $\mathbb{N}_0$  with gf's  $f_1, f_2, \dots$

- (a) If  $Q_n \xrightarrow{v} Q$  for a possibly defective distribution  $Q$  with gf  $f$ , then  $\lim_{n \rightarrow \infty} f_n(s) = f(s)$  for all  $s \in [0, 1)$ .
- (b) If  $Q_n \xrightarrow{w} Q$  for a distribution  $Q$  with gf  $f$ , then  $\lim_{n \rightarrow \infty} f_n(s) = f(s)$  for all  $s \in [0, 1]$ , and the convergence is uniform.
- (c) Conversely, if  $f(s) := \lim_{n \rightarrow \infty} f_n(s)$  exists for all  $s \in [0, 1]$ , then  $f$  is the gf of a possibly defective distribution  $Q$  and  $Q_n \xrightarrow{v} Q$ . If  $f$  is continuous at 1, i.e.  $f(1-) = f(1)$ , then  $Q(\mathbb{N}_0) = 1$  and the convergence holds true in the weak sense, i.e.  $Q_n \xrightarrow{w} Q$ .

## A.2 Total variation distance and coupling

Let  $\mathcal{M}_\pm = \mathcal{M}_\pm(\mathfrak{X}, \mathcal{A})$  denote the space of finite signed measures on a given a measurable space  $(\mathfrak{X}, \mathcal{A})$ , i.e. the vector space of all differences  $\lambda - \mu$  of finite measures  $\lambda, \mu$  on this space. Endowed with the supremum norm  $\|\cdot\|$ , that is

$$\|\lambda\| := \sup_{A \in \mathcal{A}} |\lambda(A)|,$$

$(\mathcal{M}_\pm, \|\cdot\|)$  becomes a complete normed space (Banach space). The induced metric  $d_{TV}$  is called *total variation distance*. Clearly, convergence in total variation of  $\lambda_n$  to  $\lambda$  means uniform convergence, that is

$$\lim_{n \rightarrow \infty} \sup_{A \in \mathcal{A}} |\lambda_n(A) - \lambda(A)| = 0.$$

By a standard extension argument the latter condition is further equivalent to

$$\lim_{n \rightarrow \infty} \sup_{g \in b\mathcal{A}: \|g\|_\infty \leq 1} \left| \int g d\lambda_n - \int g d\lambda \right|, \quad (\text{A.1})$$

where  $b\mathcal{A}$  denotes the space of bounded  $\mathcal{A}$ -measurable functions  $g : \mathfrak{X} \rightarrow \mathbb{R}$ .

Confining to probability distributions  $\lambda, \mu$ , we have

$$\|\lambda - \mu\| = \int_{\{f>g\}} (f-g) d\nu = \int_{\{f<g\}} (g-f) d\nu = \frac{1}{2} \int |f-g| d\nu, \quad (\text{A.2})$$

where  $f, g$  are the densities of  $\lambda, \mu$  with respect to an arbitrary dominating measure  $\nu$  (e.g.  $\lambda + \mu$ ). With the help of this fact, we immediately get the following result for the set  $\mathcal{P}(\mathfrak{X}, \mathcal{A})$  of probability measures on  $(\mathfrak{X}, \mathcal{A})$ .

**Theorem A.6.** *The metric space  $(\mathcal{P}(\mathfrak{X}, \mathcal{A}), d_{TV})$  is complete.*

*Proof.* Given a Cauchy sequence  $(\lambda_n)_{n \geq 1}$  in  $(\mathcal{P}(\mathfrak{X}, \mathcal{A}), d_{TV})$ , let  $\mu$  be a dominating probability measure, e.g.  $\mu = \sum_{n \geq 1} 2^{-n} \lambda_n$ , and  $f_n$  a  $\mu$ -density of  $\lambda_n$  for any  $n \geq 1$ . By (A.2),

$$\|\lambda_n - \lambda_m\| = \frac{1}{2} \|f_n - f_m\|_1 \rightarrow 0$$

as  $m, n \rightarrow \infty$ , where  $\|\cdot\|_1$  is the usual  $L^1$ -norm on the space  $L^1(\mu)$  of  $\mu$ -integrable functions (modulo  $\mu$ -a.s. equality). Since this space is a Banach space, we infer the existence of some (nonnegative)  $f \in L^1(\mu)$  such that  $\|f_n - f\|_1 \rightarrow 0$  and thus  $\|f\|_1 = 1$ . Putting  $\lambda := f\mu$ , we finally obtain

$$\|\lambda_n - \lambda\| = \frac{1}{2} \|f_n - f\|_1 \rightarrow 0$$

as  $n \rightarrow \infty$  and therefore  $d_{TV}(\lambda_n, \lambda) \rightarrow 0$ .  $\square$

In the discrete case, where  $\lambda, \mu$  are distributions on  $\mathbb{N}_0$  (or any countable  $\mathfrak{X}$ ), (A.2) becomes

$$\|\lambda - \mu\| = \frac{1}{2} \sum_{x \in \mathfrak{X}} |\lambda_x - \mu_x| \quad (\text{A.3})$$

when choosing  $f, g$  as counting densities and setting  $\lambda_x = \lambda(\{x\})$ . Note further that  $\lambda, \mu$  are mutually singular if, and only if,  $\|\lambda - \mu\| = 1$  or, equivalently,  $\lambda \wedge \mu = 0$ , where

$$\lambda \wedge \mu(dx) := (f \wedge g)(x) \nu(dx).$$

In general, we have by (A.2) that

$$\|\lambda - \mu\| = \int_{\{f>g\}} (f - f \wedge g) d\nu = \int (f - f \wedge g) d\nu = 1 - \|\lambda \wedge \mu\|. \quad (\text{A.4})$$

A pair  $(X, Y)$  of random variables, defined on a probability space  $(\Omega, \mathfrak{A}, \mathbb{P})$ , is called a *coupling for  $\lambda$  and  $\mu$*  if  $X \stackrel{d}{=} \lambda$  and  $Y \stackrel{d}{=} \mu$ . It satisfies the *coupling inequality*

$$\|\lambda - \mu\| \leq \mathbb{P}(X \neq Y), \quad (\text{A.5})$$

because, for all  $A \in \mathcal{A}$ ,

$$\begin{aligned} |\lambda(A) - \mu(A)| &= |\mathbb{P}(X \in A) - \mathbb{P}(Y \in A)| \\ &= |\mathbb{P}(X \in A, X \neq Y) - \mathbb{P}(Y \in A, X \neq Y)| \leq \mathbb{P}(X \neq Y). \end{aligned}$$

The following lemma shows that there is always a coupling that provides equality in (A.5).

**Lemma A.7. (Maximal coupling lemma)** *Given two distributions  $\lambda, \mu$  on a measurable space  $(\mathfrak{X}, \mathcal{A})$  there exist random variables  $X, Y$  on a common probability space  $(\Omega, \mathfrak{A}, \mathbb{P})$  such that  $X \stackrel{d}{=} \lambda$ ,  $Y \stackrel{d}{=} \mu$  and*

$$\|\lambda - \mu\| = \mathbb{P}(X \neq Y).$$

*The pair  $(X, Y)$  is called a **maximal coupling of  $\lambda$  and  $\mu$** .*

*Proof.* Put  $\alpha := \|\lambda \wedge \mu\|$ ,  $\varphi := \alpha^{-1}(\lambda \wedge \mu) \in \mathcal{P}(\mathfrak{X})$  and observe that

$$\lambda = \alpha\varphi + (1 - \alpha)\lambda' \quad \text{and} \quad \mu = \alpha\varphi + (1 - \alpha)\mu'$$

with obviously defined  $\lambda', \mu' \in \mathcal{P}(\mathfrak{X})$ . Now let  $\eta, X', Y'$  and  $Z$  be independent random variables on a common probability space  $(\Omega, \mathfrak{A}, \mathbb{P})$  such that  $X' \stackrel{d}{=} \lambda'$ ,  $Y' \stackrel{d}{=} \mu'$ ,  $Z \stackrel{d}{=} \varphi$  and  $\mathbb{P}(\eta = 1) = 1 - \mathbb{P}(\eta = 0) = \alpha$ . Defining

$$X := \begin{cases} Z, & \text{if } \eta = 1, \\ X', & \text{if } \eta = 0 \end{cases} \quad \text{and} \quad Y := \begin{cases} Z, & \text{if } \eta = 1, \\ Y', & \text{if } \eta = 0 \end{cases}$$

it is easily seen that  $X \stackrel{d}{=} \lambda$ ,  $Y \stackrel{d}{=} \mu$ , and

$$\mathbb{P}(X \neq Y) = \mathbb{P}(\eta = 0) = 1 - \alpha = 1 - \|\lambda \wedge \mu\|$$

which, by (A.4), proves the assertion.  $\square$

Let us return to the special case of distributions on  $\mathbb{N}_0$  and finally point out that for those weak convergence and total variation convergence (i.e. uniform convergence) are actually equivalent.

**Theorem A.8.** *Let  $(\lambda_n)_{n \geq 0}$  be a sequence of distributions on  $\mathbb{N}_0$ . Then  $\lambda_n \xrightarrow{w} \lambda_0$  holds iff  $\|\lambda_n - \lambda_0\| \rightarrow 0$  as  $n \rightarrow \infty$ .*

*Proof.* We must only verify that  $\lambda_n \xrightarrow{w} \lambda_0$  implies  $\|\lambda_n - \lambda_0\| \rightarrow 0$ . Hence assume weak convergence, fix any  $\varepsilon \in (0, 1)$  and choose  $N$  so large that

$$\sup_{n \geq 0} \lambda_n([N+1, \infty)) = \sup_{n \geq 0} \sum_{k > N} \lambda_{n,k} < \varepsilon,$$

where  $\lambda_{n,k} = \lambda_n(\{k\})$ . This is possible by tightness of the  $\lambda_n$ . Using (A.3), we now infer that

$$\|\lambda_n - \lambda_0\| \leq \frac{\varepsilon}{2} + \frac{1}{2} \sum_{k=0}^N |\lambda_{n,k} - \lambda_{0,k}|.$$

But the last sum converges to 0, for weak convergence on  $\mathbb{N}_0$  clearly entails point-wise convergence of the counting densities. Hence  $\|\lambda_n - \lambda_0\| \rightarrow 0$ , for  $\varepsilon \in (0, 1)$  was chosen arbitrarily.  $\square$