

ETH ZURICH

READING COURSE

Contiguity

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1 Introduction and Notation

Image Probability Measure Let $(\Omega, \mathcal{F}, \mathbb{P})$ be a probability space with a random vector $X : \Omega \rightarrow \mathbb{R}^n$, then define the *image probability measure* or *pushforward probability measure* as

$$(X)_*\mathbb{P} : \begin{cases} \mathcal{B}(\mathbb{R}^n) & \rightarrow [0, 1] \\ B & \mapsto \mathbb{P}(X^{-1}(B)) \end{cases}$$

Absolute Continuity Let \mathbb{P} and \mathbb{Q} be two given probability measures on a measurable space (Ω, \mathcal{A}) . The measure \mathbb{Q} is said to be *absolutely continuous* with respect to the measure \mathbb{P} if $\mathbb{P}[A] = 0$ implies $\mathbb{Q}[A] = 0$ for all $A \in \mathcal{A}$. This will be denoted by $\mathbb{Q} \ll \mathbb{P}$. The measures \mathbb{P} and \mathbb{Q} are said to be *mutually orthogonal* if there exists a partition $\Omega = \Omega_{\mathbb{P}} \cup \Omega_{\mathbb{Q}}$ such that $\Omega_{\mathbb{P}}$ and $\Omega_{\mathbb{Q}}$ are disjoint and measurable and $\mathbb{P}(\Omega_{\mathbb{Q}}) = 0 = \mathbb{Q}(\Omega_{\mathbb{P}})$. This will be denoted by $\mathbb{P} \perp \mathbb{Q}$.

By the Radon-Nikodym theorem, we can extract a density $\frac{d\mathbb{Q}}{d\mathbb{P}}$ if $\mathbb{Q} \ll \mathbb{P}$. In particular we can define

$$p := \frac{d\mathbb{P}}{d(\frac{1}{2}\mathbb{P} + \frac{1}{2}\mathbb{Q})} \quad q := \frac{d\mathbb{Q}}{d(\frac{1}{2}\mathbb{P} + \frac{1}{2}\mathbb{Q})}$$

Then we can define the measures

$$\mathbb{Q}^a : \begin{cases} \mathcal{A} & \rightarrow [0, 1] \\ A & \mapsto \mathbb{Q}(A \cap \{p > 0\}) \end{cases} \quad \mathbb{Q}^\perp : \begin{cases} \mathcal{A} & \rightarrow [0, 1] \\ A & \mapsto \mathbb{Q}(A \cap \{p = 0\}) \end{cases}$$

It is easy to see that the following holds:

- $\mathbb{Q}^a \ll \mathbb{P}$ (If $\mathbb{P}(A) = 0$ then $\int_{\Omega} \mathbb{1}_A p \, d(\frac{1}{2}\mathbb{P} + \frac{1}{2}\mathbb{Q})$ then $\mathbb{1}_A \cdot p = 0$ \mathbb{Q} -a.s.)
- $\mathbb{Q}^\perp \perp \mathbb{P}$ (take $\Omega_{\mathbb{Q}^\perp} = \{p = 0\}$ and $\Omega_{\mathbb{P}} = \{p > 0\}$)
- $\mathbb{Q} = \mathbb{Q}^a + \mathbb{Q}^\perp$
- since $\int_{\Omega} \mathbb{1}_A \cdot \frac{q}{p} d\mathbb{P} = \int_{\Omega} \mathbb{1}_A \cdot q \cdot \mathbb{1}_{\{p > 0\}} \, d(\frac{1}{2}\mathbb{P} + \frac{1}{2}\mathbb{Q})$

$$\forall A \in \mathcal{A} : \mathbb{Q}^a(A) = \int_{\Omega} \mathbb{1}_A \cdot \frac{q}{p} d\mathbb{P} \tag{1}$$

- For the next section, it is of special interest that

$$\mathbb{Q} \ll \mathbb{P} \iff \mathbb{Q}^\perp = 0 \iff \mathbb{Q}^a = \mathbb{Q},$$

in other words

$$\mathbb{Q} \ll \mathbb{P} \iff \mathbb{Q}(\{p = 0\}) = 0 \iff \int_{\Omega} \frac{q}{p} d\mathbb{P} = 1. \tag{2}$$

Important Remark On Notation Even if $\mathbb{Q} \ll \mathbb{P}$ doesn't hold, we will use the notation

$$\frac{d\mathbb{Q}}{d\mathbb{P}} := \frac{d\mathbb{Q}^a}{d\mathbb{P}}.$$

From (1), it follows that

$$\frac{d\mathbb{Q}}{d\mathbb{P}} = \frac{q}{p} \quad \mathbb{P}\text{-almost surely.}$$

Furthermore, it then holds for nonnegative measurable f that

$$\int_{\Omega} f d\mathbb{Q} \geq \int_{\Omega} f d\mathbb{Q}^a = \int_{\Omega} f \frac{d\mathbb{Q}}{d\mathbb{P}} d\mathbb{P} \quad (3)$$

and in this notation, (2) can be written as

$$\mathbb{Q} \ll \mathbb{P} \iff \mathbb{Q}(\{\frac{d\mathbb{P}}{d\mathbb{Q}} = 0\}) = 0 \iff \int_{\Omega} \frac{d\mathbb{Q}}{d\mathbb{P}} d\mathbb{P} = 1. \quad (4)$$

Change of measure If $\mathbb{Q} \ll \mathbb{P}$, then for each random vector $X : \Omega \rightarrow \mathbb{R}^k$ the \mathbb{Q} -law of X can be obtained by the \mathbb{P} -law of $(X, \frac{d\mathbb{Q}}{d\mathbb{P}})$:

$$\begin{aligned} \forall A \in \mathcal{B}(\mathbb{R}^k) : \quad (X_*\mathbb{Q})(A) &= \int_{\Omega} \mathbb{1}_A(X(\omega)) d\mathbb{Q}(\omega) = \int_{\Omega} \mathbb{1}_A(X(\omega)) \frac{d\mathbb{Q}}{d\mathbb{P}}(\omega) d\mathbb{P}(\omega) \\ &= \int_{\mathbb{R}^k \times \mathbb{R}} \mathbb{1}_A(x)v d(X, \frac{d\mathbb{Q}}{d\mathbb{P}})_*\mathbb{P}(x, v) \end{aligned} \quad (5)$$

2 Contiguity

Definition 1 (Contiguity). Let $(\Omega_n, \mathcal{A}_n)_{n \in \mathbb{N}}$ be a sequence of measurable spaces. For each $n \in \mathbb{N}$ assume there are two probability measures \mathbb{Q}_n and \mathbb{P}_n on $(\Omega_n, \mathcal{A}_n)$. The sequence $(\mathbb{Q}_n)_{n \in \mathbb{N}}$ is *contiguous* with respect to the sequence $(\mathbb{P}_n)_{n \in \mathbb{N}}$ if

$$\forall (A_n)_{n \in \mathbb{N}} \in \prod_{n \in \mathbb{N}} \mathcal{A}_n : \quad \lim_{n \rightarrow \infty} \mathbb{P}_n(A_n) = 0 \implies \lim_{n \rightarrow \infty} \mathbb{Q}_n(A_n) = 0.$$

This will be denoted by $(\mathbb{Q}_n)_{n \in \mathbb{N}} \triangleleft (\mathbb{P}_n)_{n \in \mathbb{N}}$. If $(\mathbb{Q}_n)_{n \in \mathbb{N}} \triangleleft (\mathbb{P}_n)_{n \in \mathbb{N}}$ and $(\mathbb{P}_n)_{n \in \mathbb{N}} \triangleleft (\mathbb{Q}_n)_{n \in \mathbb{N}}$ then $(\mathbb{P}_n)_{n \in \mathbb{N}}$ and $(\mathbb{Q}_n)_{n \in \mathbb{N}}$ are *mutually contiguous*, which will be denoted by

$$(\mathbb{P}_n)_{n \in \mathbb{N}} \triangleleft \triangleright (\mathbb{Q}_n)_{n \in \mathbb{N}}.$$

Theorem 2. *The sets of measures $((\frac{d\mathbb{Q}_n}{d\mathbb{P}_n})_* d\mathbb{P}_n)_{n \in \mathbb{N}}$ and $((\frac{d\mathbb{P}_n}{d\mathbb{Q}_n})_* \mathbb{Q}_n)_{n \in \mathbb{N}}$ are tight.*

Proof. The densities are nonnegative and their expectations are bounded by 1. Tightness follows from

$$(\frac{d\mathbb{Q}_n}{d\mathbb{P}_n})_* \mathbb{P}_n [[M, \infty]] \leq \frac{1}{M} \int_{\mathbb{R}} \frac{d\mathbb{Q}_n}{d\mathbb{P}_n} d\mathbb{P}_n \leq \frac{1}{M}, \quad (\frac{d\mathbb{P}_n}{d\mathbb{Q}_n})_* \mathbb{Q}_n [[M, \infty]] \leq \frac{1}{M} \int_{\mathbb{R}} \frac{d\mathbb{P}_n}{d\mathbb{Q}_n} d\mathbb{Q}_n \leq \frac{1}{M},$$

using the fact that for a probability measure μ on (Ω, \mathcal{A}) and a nonnegative random variable $X : \Omega \rightarrow \mathbb{R}$ it holds

$$\forall M \geq 0 : \quad M\mu(\{X \geq M\}) \leq \int_{\Omega} X d\mu.$$

□

The following theorem is often called Le Cam's first lemma. It gives two additional characterizations when there is contiguity. It can be seen as an asymptotic version of (4).

Theorem 3 (Le Cam's first lemma). *Let $(\mathbb{P}_n)_{n \in \mathbb{N}}$ and $(\mathbb{Q}_n)_{n \in \mathbb{N}}$ be sequences of probability measures on measurable spaces $(\Omega_n, \mathcal{A}_n)_{n \in \mathbb{N}}$. The following are equivalent.*

1. $(\mathbb{Q}_n)_{n \in \mathbb{N}} \triangleleft (\mathbb{P}_n)_{n \in \mathbb{N}}$
2. If $(d\mathbb{P}_n/d\mathbb{Q}_n)_* \mathbb{Q}_n \rightarrow \mathbb{U}$ in distribution along a subsequence for some probability measure \mathbb{U} on \mathbb{R} then

$$\mathbb{U}((0, \infty)) = 1$$

3. If $(d\mathbb{Q}_n/d\mathbb{P}_n)_* \mathbb{P}_n \rightarrow \mathbb{V}$ in distribution along a subsequence for some probability measure \mathbb{V} on \mathbb{R} , then

$$\int_{\mathbb{R}} x d\mathbb{V}(x) = 1$$

Proof.

1. implies 2. Assume that there is some subsequence along which

$$\left(\frac{d\mathbb{P}_{n_k}}{d\mathbb{Q}_{n_k}}\right)_* \mathbb{Q}_{n_k} \rightarrow \mathbb{U} \text{ in distribution as } k \rightarrow \infty.$$

Then it follows by the Portmanteau Theorem 9

$$\forall \varepsilon > 0 : \liminf_{k \rightarrow \infty} \left(\frac{d\mathbb{P}_{n_k}}{d\mathbb{Q}_{n_k}}\right)_* \mathbb{Q}_{n_k} ((-\infty, \varepsilon)) - \mathbb{U}((-\infty, \varepsilon)) \geq 0.$$

For a sequence $(\varepsilon_n)_{n \in \mathbb{N}}$ of positive numbers converging to 0 sufficiently slowly, this implies

$$\liminf_{k \rightarrow \infty} \left(\frac{d\mathbb{P}_{n_k}}{d\mathbb{Q}_{n_k}}\right)_* \mathbb{Q}_{n_k} ((-\infty, \varepsilon_{n_k})) - \mathbb{U}((-\infty, \varepsilon_{n_k})) \geq 0$$

or equivalently

$$\mathbb{U}((-\infty, 0]) \leq \liminf_{k \rightarrow \infty} \left(\frac{d\mathbb{P}_{n_k}}{d\mathbb{Q}_{n_k}}\right)_* \mathbb{Q}_{n_k} ((-\infty, \varepsilon_{n_k})). \quad (6)$$

It also holds¹

$$\mathbb{P}_n \left(\left\{ \left(\frac{d\mathbb{P}_n}{d\mathbb{Q}_n}\right) < \varepsilon_n \wedge q_n > 0 \right\} \right) = \int_{\frac{d\mathbb{P}_n}{d\mathbb{Q}_n} < \varepsilon_n} \frac{d\mathbb{P}_n}{d\mathbb{Q}_n} d\mathbb{Q}_n \leq \int_{\Omega_n} \varepsilon_n d\mathbb{Q}_n \rightarrow 0 \text{ as } n \rightarrow \infty$$

and now the contiguity assumption 1. implies that

$$\mathbb{Q}_n \left(\left\{ \left(\frac{d\mathbb{P}_n}{d\mathbb{Q}_n}\right) < \varepsilon_n \right\} \right) = \mathbb{Q}_n \left(\left\{ \left(\frac{d\mathbb{P}_n}{d\mathbb{Q}_n}\right) < \varepsilon_n \wedge q_n > 0 \right\} \right) \rightarrow 0 \text{ as } n \rightarrow \infty.$$

Combined with (6), this implies $\mathbb{U}((0, \infty)) = 1$.

2. implies 3. Assume now that 2. holds and let some subsequence $(n_k)_{k \in \mathbb{N}}$ be given such that

$$\left(\frac{d\mathbb{Q}_{n_k}}{d\mathbb{P}_{n_k}}\right)_* \mathbb{P}_{n_k} \rightarrow \mathbb{V} \text{ in distribution as } k \rightarrow \infty$$

for some probability measure \mathbb{V} on \mathbb{R} . Define the probability measures

$$\mu_n = \frac{1}{2}(\mathbb{P}_n + \mathbb{Q}_n) \text{ for } n \in \mathbb{N}.$$

Then for all $n \in \mathbb{N}$ we have $\mathbb{P}_n \ll \mu_n$ and $\mathbb{Q}_n \ll \mu_n$ and the densities $W_n = \frac{d\mathbb{P}_n}{d\mu_n}$ and $R_n = \frac{d\mathbb{Q}_n}{d\mu_n}$ satisfy

$$\forall n \in \mathbb{N} : R_n + W_n = 2 \text{ } \mu_n\text{-almost surely.}$$

¹Let $q_n = \frac{d\mathbb{Q}_n}{d(\frac{1}{2}\mathbb{Q}_n + \frac{1}{2}\mathbb{P}_n)}$, see first Section 1.

Since the densities R_n and W_n are thus in $[0, 2]$ μ_n -almost surely for every $n \in \mathbb{N}$, the sequence of Probability measure $(W_n)_* \mu_n$ are tight and Prohorov's Theorem 8 can be used together with Theorem 2 to find a further subsequence $(n_{k_j})_{j \in \mathbb{N}}$ such that

$$\left(\frac{dQ_{n_{k_j}}}{dP_{n_{k_j}}}\right)_* \mathbb{P}_{n_{k_j}} \rightarrow \mathbb{V}, \quad \left(\frac{dP_{n_{k_j}}}{dQ_{n_{k_j}}}\right)_* \mathbb{Q}_{n_{k_j}} \rightarrow \mathbb{U}, \quad (W_{n_{k_j}})_* \mu_{n_{k_j}} \rightarrow \mathbb{W}$$

as $j \rightarrow \infty$ for some probability measures $\mathbb{U}, \mathbb{W} : \mathcal{B}(\mathbb{R}) \rightarrow [0, 1]$. Since the densities $(W_n)_{n \in \mathbb{N}}$ take values in $[0, 2]$ μ_n -almost surely, the probability measures $((W_n)_* \mu_n)_{n \in \mathbb{N}}$ are asymptotically uniformly bounded and Theorem 12 implies the convergence of moments:

$$\int_{\mathbb{R}} x d\mathbb{W}(x) = \lim_{n \rightarrow \infty} \int_{\mathbb{R}} \frac{dP_n}{d\mu_n}(x) d\mu_n(x) = 1 \quad (7)$$

For a given function $f : \mathbb{R} \rightarrow \mathbb{R}$ define the functions g_f and h_f by

$$g_f : \begin{cases} \mathbb{R} & \rightarrow \mathbb{R} \\ x & \mapsto \begin{cases} 2f(0) & \text{if } x < 0 \\ f\left(\frac{x}{2-x}\right)(2-x) & \text{if } x \in [0, 2) \\ 0 & \text{if } x \geq 2 \end{cases} \end{cases}$$

$$h_f : \begin{cases} \mathbb{R} & \rightarrow \mathbb{R} \\ x & \mapsto \begin{cases} 0 & \text{if } x \leq 0 \\ f\left(\frac{2-x}{x}\right)x & \text{if } x \in (0, 2] \\ 2f(0) & \text{if } x > 2 \end{cases} \end{cases}$$

It is useful to collect some facts:

- If $|f|$ is bounded by $c < \infty$ then $|g_f|$ and $|h_f|$ are bounded by $2c$.
- If f is bounded and continuous then g_f and h_f are bounded and continuous
- If $f \geq 0$ then $g_f \geq 0$ and $h_f \geq 0$.
- If a sequence $(f_n)_{n \in \mathbb{N}}$ of functions converges pointwise to a function f then g_{f_n} and h_{f_n} converge pointwise to g_f and h_f respectively.

These facts will be used to apply the monotone and dominated convergence theorems. Now let $f : \mathbb{R} \rightarrow \mathbb{R}$ be a bounded continuous function, so the same holds for g_f and h_f . From the definition of μ_n , it follows that

$$\frac{dP_n}{dQ_n} = \frac{W_n}{2-W_n} \quad \mathbb{Q}_n\text{-a.s.}, \quad \frac{dQ_n}{dP_n} = \frac{2-W_n}{W_n} \quad \mathbb{P}_n\text{-a.s.}$$

and μ_n -almost surely

$$\frac{dQ_n}{d\mu_n} = 2 - W_n, \quad \frac{dP_n}{d\mu_n} = W_n.$$

Therefore, it holds

$$\begin{aligned}
\int_{\mathbb{R}} f(x) d\left(\frac{d\mathbb{P}_n}{d\mathbb{Q}_n}\right)_* \mathbb{Q}_n(x) &= \int_{\mathbb{R}} f\left(\frac{d\mathbb{P}_n}{d\mathbb{Q}_n}(x)\right) d\mathbb{Q}_n(x) \\
&= \int_{\mathbb{R}} f\left(\frac{d\mathbb{P}_n}{d\mathbb{Q}_n}(x)\right) \frac{d\mathbb{Q}_n}{d\mu_n}(x) d\mu_n(x) \\
&= \int_{\mathbb{R}} g_f(W_n) d\mu_n(x) \\
\int_{\mathbb{R}} f(x) d\left(\frac{d\mathbb{Q}_n}{d\mathbb{P}_n}\right)_* \mathbb{P}_n(x) &= \int_{\mathbb{R}} f\left(\frac{d\mathbb{Q}_n}{d\mathbb{P}_n}(x)\right) d\mathbb{P}_n(x) \\
&= \int_{\mathbb{R}} f\left(\frac{d\mathbb{Q}_n}{d\mathbb{P}_n}(x)\right) \frac{d\mathbb{P}_n}{d\mu_n}(x) d\mu_n(x) \\
&= \int_{\mathbb{R}} h_f(W_n(x)) d\mu_n(x).
\end{aligned}$$

Taking limits yields by the Portmanteau Theorem 9

$$\int_{\mathbb{R}} f(x) d\mathbb{U}(x) = \int_{\mathbb{R}} g_f(x) d\mathbb{W}(x), \quad \int_{\mathbb{R}} f(x) d\mathbb{V}(x) = \int_{\mathbb{R}} h_f(x) d\mathbb{W}(x).$$

For a sequence $(f_n)_{n \in \mathbb{N}}$ of continuous functions converging pointwise to $\mathbb{1}_{\{0\}}$ with $|f_n| \leq 1$ for $n \in \mathbb{N}$, the facts above imply that $(g_{f_n})_{n \in \mathbb{N}}$ is a sequence of continuous functions converging pointwise to $2\mathbb{1}_{(-\infty, 0]}$ with $|g_{f_n}| \leq 2$ for $n \in \mathbb{N}$ and the dominated convergence theorem can be applied:

$$\mathbb{U}[\{0\}] = \lim_{n \rightarrow \infty} \int_{\mathbb{R}} f_n(x) d\mathbb{U}(x) = \lim_{n \rightarrow \infty} \int_{\mathbb{R}} g_{f_n}(x) d\mathbb{W}(x) = 2\mathbb{W}[(-\infty, 0]] = 2\mathbb{W}[\{0\}] \quad (8)$$

Similarly for an increasing sequence of continuous functions converging pointwise to $x \mapsto \mathbb{1}_{[0, \infty)}(x)x$ with $f_n \geq 0$ for $n \in \mathbb{N}$, the facts above imply that $(h_{f_n})_{n \in \mathbb{N}}$ is an increasing sequence of continuous functions converging pointwise to $x \mapsto \mathbb{1}_{(0, 2]}(x) \cdot (2-x)$ with $h_{f_n} \geq 0$ for $n \in \mathbb{N}$ and the monotone convergence Theorem can be applied:

$$\int_{\mathbb{R}} x d\mathbb{V}(x) = \lim_{n \rightarrow \infty} \int_{\mathbb{R}} f_n(x) d\mathbb{V}(x) = \lim_{n \rightarrow \infty} \int_{\mathbb{R}} h_{f_n}(x) d\mathbb{W}(x) = 2 - 2\mathbb{W}[\{0\}] - \int_{\mathbb{R}} x d\mathbb{W}(x)$$

Combining this with equations (7) and (8) completes the proof:

$$\mathbb{U}[\{0\}] + \int_{\mathbb{R}} x d\mathbb{V}(x) = 1$$

3. implies 1. Let $(A_n)_{n \in \mathbb{N}} \in \prod_{i \in \mathbb{N}} \mathcal{A}_n$ such that

$$\lim_{n \rightarrow \infty} \mathbb{P}_n(A_n) = 0$$

and assume by contradiction that

$$\limsup_{n \rightarrow \infty} \mathbb{Q}_n(A_n) > \varepsilon$$

for some $\varepsilon > 0$. By taking a subsequence, without loss of generality assume that

$$\forall n \in \mathbb{N}: \quad \mathbb{Q}_n(A_n) > \varepsilon.$$

Obviously $(\mathbb{1}_{\Omega_n \setminus A_n})_* \mathbb{P}_n \rightarrow \delta_1$ in distribution². Take a limit in distribution \mathbb{V} of a subsequence of $(\frac{d\mathbb{Q}_n}{d\mathbb{P}_n})_* \mathbb{P}_n$ (there exist such limits by Prohorov's Theorem 8 and Theorem 2).

$$\left(\frac{d\mathbb{Q}_{n_k}}{d\mathbb{P}_{n_k}}\right)_* \mathbb{P}_{n_k} \rightarrow \mathbb{V} \text{ in distribution as } k \rightarrow \infty.$$

It is easy to see that this implies

$$\left(\frac{d\mathbb{Q}_{n_k}}{d\mathbb{P}_{n_k}}, \mathbb{1}_{\Omega_{n_k} \setminus A_{n_k}}\right)_* \mathbb{P}_{n_k} \rightarrow \mathbb{V} \otimes \delta_1 \text{ in distribution as } k \rightarrow \infty,$$

where $\mathbb{V} \otimes \delta_1$ denotes the product measure of \mathbb{V} and δ_1 . Since $\mathbb{R}^2 \rightarrow \mathbb{R}, (s, t) \mapsto s \cdot t \cdot \mathbb{1}_{[0, \infty) \times [0, \infty)}(s, t)$ is a continuous nonnegative function, the Portmanteau Theorem 9 implies the second to last step in the following calculation:

$$\begin{aligned} 1 - \varepsilon &\geq 1 - \limsup_{k \rightarrow \infty} \mathbb{Q}_{n_k}(A_{n_k}) \\ &\geq \liminf_{k \rightarrow \infty} \mathbb{Q}_{n_k}(\Omega_{n_k} \setminus A_{n_k}) \\ &\geq \liminf_{k \rightarrow \infty} \int_{\Omega_{n_k}} \mathbb{1}_{\Omega_{n_k} \setminus A_{n_k}} \frac{d\mathbb{Q}_{n_k}}{d\mathbb{P}_{n_k}} d\mathbb{P}_{n_k} \\ &= \liminf_{k \rightarrow \infty} \int_{\mathbb{R}^2} s \cdot t \cdot \mathbb{1}_{[0, \infty) \times [0, \infty)}(s, t) d\left(\frac{d\mathbb{Q}_{n_k}}{d\mathbb{P}_{n_k}}, \mathbb{1}_{\Omega_{n_k} \setminus A_{n_k}}\right)_* \mathbb{P}_{n_k}(s, t) \\ &\geq \int_{\mathbb{R}^2} s \cdot t d\mathbb{V} \otimes \delta_1(s, t) = \int_{\mathbb{R}} s d\mathbb{V}(s) = 1, \end{aligned}$$

which is a contradiction to $\varepsilon > 0$. □

Example 4. Let $(\mathbb{P}_n)_{n \in \mathbb{N}}$ and $(\mathbb{Q}_n)_{n \in \mathbb{N}}$ be probability measures on measurable spaces $(\Omega_n, \mathcal{F}_n)_{n \in \mathbb{N}}$ such that³

$$\left(\frac{d\mathbb{P}_n}{d\mathbb{Q}_n}\right)_* \mathbb{Q}_n \rightarrow e^{\mathcal{N}(\mu, \sigma^2)} \text{ in distribution as } n \rightarrow \infty$$

Then Le Cam's first lemma allows us to conclude

- $(\mathbb{Q}_n)_{n \in \mathbb{N}} \triangleleft (\mathbb{P}_n)_{n \in \mathbb{N}}$ because $e^{\mathcal{N}(\mu, \sigma^2)}[(0, \infty)] = 1$.
- If $\mu = -\frac{1}{s}\sigma^2$ then $(\mathbb{P}_n)_{n \in \mathbb{N}} \triangleleft (\mathbb{Q}_n)_{n \in \mathbb{N}}$ because $\int_{\mathbb{R}} x d e^{\mathcal{N}(\mu, \sigma^2)}(x) = e^{\mu + \frac{1}{2}\sigma^2} = 1$. Thus, in this case $(\mathbb{P}_n)_{n \in \mathbb{N}}$ and $(\mathbb{Q}_n)_{n \in \mathbb{N}}$ are mutually contiguous.

The following theorem shows how a \mathbb{Q}_n limit law can be obtained from a \mathbb{P}_n limit law. This is analogous to the non asymptotic case in equation (5).

Theorem 5 (Le Cam's third lemma). Let $(\mathbb{P}_n)_{n \in \mathbb{N}}$ and $(\mathbb{Q}_n)_{n \in \mathbb{N}}$ be probability measures on measurable spaces $(\Omega_n, \mathcal{A}_n)_{n \in \mathbb{N}}$ with random vectors $(X_n : \Omega_n \rightarrow \mathbb{R}^k)_{n \in \mathbb{N}}$. Assume that $(\mathbb{Q}_n)_{n \in \mathbb{N}} \triangleleft (\mathbb{P}_n)_{n \in \mathbb{N}}$ and

$$\left(X_n, \frac{d\mathbb{Q}_n}{d\mathbb{P}_n}\right)_* \mathbb{P}_n \rightarrow (X, V)_* \mu \text{ in distribution as } n \rightarrow \infty$$

²Let $\delta_1 : \begin{cases} \mathcal{B}(\mathbb{R}) & \rightarrow [0, 1] \\ B & \mapsto \mathbb{1}_B(1) \end{cases}$

³Let $e^{\mathcal{N}(\mu, \sigma^2)}$ denote the image probability measure of a $\mathcal{N}(\mu, \sigma^2)$ distribution under the map $x \mapsto e^x$ (log-normal distribution)

for some probability measure μ on some measurable space (Ω, \mathcal{A}) with random variables $X : \Omega \rightarrow \mathbb{R}^k$ and $V : \Omega \rightarrow \mathbb{R}$. Then

$$\mathbb{L} : \begin{cases} \mathcal{B}(\mathbb{R})^k & \rightarrow [0, 1] \\ B & \mapsto \int_{\Omega} \mathbf{1}_B(X(\omega))V(\omega)d\mu(\omega) \end{cases}$$

is a probability measure and satisfies that

$$(X_n)_*\mathbb{Q}_n \rightarrow \mathbb{L} \text{ in distribution as } n \rightarrow \infty.$$

Proof. \mathbb{L} is a measure since sigma-additivity follows from the monotone convergence theorem. It is a probability measure since $\mathbb{L}(\mathbb{R}^k) = \int_{\mathbb{R}} x dV_*\mu(x) = 1$ because of Theorem 3 (Note that $(\frac{d\mathbb{Q}_n}{d\mathbb{P}_n})_*\mathbb{P}_n \rightarrow (V)_*\mu$ in distribution). For $f = \mathbf{1}_B$ with $B \in \mathcal{B}(\mathbb{R})^k$, it is clear that

$$\int_{\mathbb{R}} f d\mathbb{L} = \int_{\Omega} f(X(\omega))V(\omega)d\mu(\omega),$$

so this holds for step functions f , hence for positive measurable functions by monotone convergence, hence for integrable functions f by dominated convergence.

For a continuous nonnegative function $f : \mathbb{R}^k \rightarrow \mathbb{R}$, the function $(x, v) \mapsto f(x)v\mathbf{1}_{[0, \infty)}(v)$ is continuous and nonnegative. The Portmanteau Theorem 9 implies the third step in the following calculation.

$$\begin{aligned} \liminf_{n \rightarrow \infty} \int_{\mathbb{R}^k} f(x) d(X_n)_*\mathbb{Q}_n(x) &\geq \liminf_{n \rightarrow \infty} \int_{\Omega_n} f(X_n(\omega)) \frac{d\mathbb{Q}_n}{d\mathbb{P}_n}(\omega) d\mathbb{P}_n(\omega) \\ &= \liminf_{n \rightarrow \infty} \int_{\mathbb{R}^{k+1}} f(x)v d(X_n, \frac{d\mathbb{Q}_n}{d\mathbb{P}_n})_*\mathbb{P}_n(x, v) \\ &\geq \int_{\mathbb{R}^k} f(x)v d(X, V)_*\mu(x, v) \\ &= \int_{\mathbb{R}^k} f d\mathbb{L} \end{aligned}$$

This inequality holds for every continuous and nonnegative function $f : \mathbb{R}^k \rightarrow \mathbb{R}$ and hence the Portmanteau Theorem 9 implies that

$$(X_n)_*\mathbb{Q}_n \rightarrow \mathbb{L} \text{ in distribution as } n \rightarrow \infty.$$

□

The following result is a consequence of Le Cam's third lemma but often the term "Le Cam's third lemma" refers to this special case.

Example 6. Let $(\mathbb{P}_n)_{n \in \mathbb{N}}$ and $(\mathbb{Q}_n)_{n \in \mathbb{N}}$ be probability measures on measurable spaces $(\Omega_n, \mathcal{A}_n)_{n \in \mathbb{N}}$ with random vectors $(X_n : \Omega_n \rightarrow \mathbb{R}^k)_{n \in \mathbb{N}}$. Assume that

$$(X_n, \log(\frac{d\mathbb{Q}_n}{d\mathbb{P}_n}))_*\mathbb{P}_n \rightarrow \mathcal{N}\left(\left(\begin{matrix} m \\ -\frac{1}{2}\sigma^2 \end{matrix}\right), \left(\begin{matrix} \Sigma & \tau \\ \tau^T & \sigma^2 \end{matrix}\right)\right) =: \mu \text{ in distribution as } n \rightarrow \infty$$

For notational convenience define the maps

$$X : \begin{cases} \mathbb{R}^{k+1} & \rightarrow \mathbb{R}^k \\ (x_1, \dots, x_{k+1}) & \mapsto (x_1, \dots, x_k) \end{cases} \text{ and } W : \begin{cases} \mathbb{R}^{k+1} & \rightarrow \mathbb{R} \\ (x_1, \dots, x_{k+1}) & \mapsto x_{k+1} \end{cases}.$$

By the Continuous Mapping Theorem 10

$$(X_n, \frac{dQ_n}{dP_n}) \rightarrow (X, e^W)_* \mu \text{ in distribution as } n \rightarrow \infty.$$

By the last example, $(P_n)_{n \in \mathbb{N}} \triangleleft \triangleright (Q_n)_{n \in \mathbb{N}}$ and we can apply the theorem above. It states that

$$(X_n)_* Q_n \rightarrow \mathbb{L} \text{ in distribution as } n \rightarrow \infty,$$

where \mathbb{L} is defined as

$$\mathbb{L} : \begin{cases} \mathcal{B}(\mathbb{R})^k & \rightarrow [0, 1] \\ B & \mapsto \int_{\mathbb{R}^k \times \mathbb{R}} \mathbf{1}_B(X(x)) \cdot e^{W(x)} d\mu(x) \end{cases}$$

For the characteristic functions $\Phi_{\mathbb{L}} : \mathbb{R}^k \rightarrow \mathbb{C}$ and $\Phi_{\mu} : \mathbb{R}^{k+1} \rightarrow \mathbb{C}$ holds

$$\begin{aligned} \Phi_{\mathbb{L}}(t) &= \int_{\mathbb{R}^k} e^{it^T x} d\mathbb{L}(x) = \int_{\mathbb{R}^{k+1}} e^{it^T X(x)} e^{W(x)} d\mu(x) = \Phi_{\mu}((t, -i)) \\ &= \exp\left(it^T m - \frac{1}{2}\sigma^2 - \frac{1}{2}(t^T, -i) \begin{pmatrix} \Sigma & \tau \\ \tau^T & \sigma^2 \end{pmatrix} \begin{pmatrix} t \\ -i \end{pmatrix}\right) \\ &= \exp\left(it^T(m + \tau) - \frac{1}{2}t^T \Sigma t\right) \end{aligned}$$

This means that

$$(X_n)_* Q_n \rightarrow \mathbb{L} = \mathcal{N}((m + \tau), \Sigma) \text{ in distribution as } n \rightarrow \infty.$$

A Appendix

For the following theorems and definitions refer to [1]. In the sequel, let $d \in \mathbb{N}$.

Definition 7 (Tightness). A sequence of probability measures $(P_n)_{n \in \mathbb{N}}$ on \mathbb{R}^d is tight if

$$\lim_{M \rightarrow \infty} \sup_{n \in \mathbb{N}} P_n \left(\left\{ x \in \mathbb{R}^d \mid \|x\| \geq M \right\} \right) = 0$$

Theorem 8 (Prohorov). Let (μ_n) be a sequence of probability measures on \mathbb{R}^d .

1. If $\mu_n \rightarrow \mu$ in distribution for some probability measure μ , then $\{\mu_n \mid n \in \mathbb{N}\}$ is tight.
2. If $(\mu_n)_{n \in \mathbb{N}}$ is tight, then there exists a subsequence $(\mu_{n_j})_{j \in \mathbb{N}}$ with $\mu_{n_j} \rightarrow \mu$ as $j \rightarrow \infty$ for some probability measure μ on \mathbb{R}^d .

The following Theorem states parts of the Portmanteau Theorem.

Theorem 9 (Portmanteau). Let $(\mu_n)_{n \in \mathbb{N}}$ be a sequence of measures on \mathbb{R}^d . The following are equivalent

1. $\mu_n \rightarrow \mu$ in distribution
2. $\lim_{n \rightarrow \infty} \int_{\mathbb{R}^d} f d\mu_n = \int_{\mathbb{R}^d} f d\mu$ for all bounded continuous functions $f : \mathbb{R}^d \rightarrow \mathbb{R}$.
3. $\liminf_{n \rightarrow \infty} \int_{\mathbb{R}^d} f d\mu_n \geq \int_{\mathbb{R}^d} f d\mu$ for all nonnegative continuous functions $f : \mathbb{R}^d \rightarrow \mathbb{R}$.

4. $\liminf_{n \rightarrow \infty} \mu_n(U) \geq \mu(U)$ for every open set $U \subset \mathbb{R}^d$.

Theorem 10 (Continuous Mapping). *Let $(\mu_n)_{n \in \mathbb{N}}$ be a sequence of probability measures on \mathbb{R}^d converging in distribution to a probability measure μ and let $g : \mathbb{R}^d \rightarrow \mathbb{R}^m$ be continuous at every point of a set C such that $\mu[C] = 1$. Then*

$$g_*\mu_n \rightarrow g_*\mu \text{ in distribution as } n \rightarrow \infty.$$

Definition 11 (Asymptotic Uniform Integrability). A sequence $(\mu_n)_{n \in \mathbb{N}}$ of probability measures on \mathbb{R}^d is asymptotically uniformly integrable if

$$\lim_{M \rightarrow \infty} \limsup_{n \rightarrow \infty} \int_{\mathbb{R}^d} \|x\| \mathbb{1}_{\{x \in \mathbb{R}^d \mid \|x\|_2 > M\}} d\mu_n(x) = 0$$

Theorem 12 (Bounded Convergence). *Let $f : \mathbb{R}^d \rightarrow \mathbb{R}$ be measurable and continuous at every point in a set C . Let $(\mu_n)_{n \in \mathbb{N}}$ be a sequence of probability measures on \mathbb{R}^d converging in distribution to some measure μ on \mathbb{R}^d with total mass contained in C . If the sequence $((f)_*\mu_n)_{n \in \mathbb{N}}$ is asymptotically uniformly integrable, then*

$$\int_{\mathbb{R}^d} f(x) d\mu_n(x) \rightarrow \int_{\mathbb{R}^d} f(x) d\mu(x)$$

References

- [1] A.W. van der Vaart. Asymptotic Statistics. Cambridge University Press, 1998.