



The median of an exponential family and the normal law

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ABSTRACT

Let P be a probability on the real line generating a natural exponential family $(P_t)_{t \in \mathbb{R}}$. We show that the property that t is a median of P_t for all t characterizes P as the standard Gaussian law $N(0, 1)$.

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1. Introduction

Let P be a probability on the real line and assume that

$$L(t) = \int_{-\infty}^{+\infty} e^{tx} P(dx) < \infty \quad \text{for } t \in \mathbb{R}. \quad (1)$$

Such a probability generates the natural exponential family

$$\mathcal{F}_P = \{P_t(dx) = \frac{e^{tx}}{L(t)} P(dx), t \in \mathbb{R}\}.$$

Then it might happen that the natural parameter t of \mathcal{F}_P is always a median of P_t , in the sense of

$$P_t((-\infty, t)) \leq \frac{1}{2} \leq P_t((-\infty, t]) \quad \text{for } t \in \mathbb{R}. \quad (2)$$

In the sequel we denote by \mathcal{P} the set of probabilities P such that (1) and (2) are fulfilled. A noteworthy example of an element of \mathcal{P} is the standard normal distribution $N(0, 1)$, for which $L(t) = e^{t^2/2}$ and $P_t = N(t, 1)$. It will turn out that it is the only one. The following preliminary lemmas simplify the study of \mathcal{P} .

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Lemma 1. If $P \in \mathcal{P}$, then P is absolutely continuous with respect to Lebesgue measure. As a consequence, we have equality throughout in (2).

Lemma 2. If $P \in \mathcal{P}$, then its distribution function is strictly increasing.

If $P \in \mathcal{P}$, then Lemma 1 allows us to write

$$P(dx) = g(x)\varphi(x)dx, \quad (3)$$

where g is some measurable non-negative function and $\varphi(x) = e^{-x^2/2}/\sqrt{2\pi}$ denotes the standard normal density, and we will show that then $g(x) = 1$ a.e. to get:

Theorem 1. $\mathcal{P} = \{N(0, 1)\}$.

The proofs of the above results are contained in Section 2, followed by a conjecture and a further theorem.

2. Proofs

Proof of Lemma 1. The next paragraph shows that the distribution function of P is locally Lipschitz, and this implies the claimed absolute continuity, even with a locally bounded density, compare for example Royden and Fitzpatrick (2010, pp. 120–124).

For $t \in \mathbb{R}$, multiplying in assumption (2) by $L(t)$ yields

$$h(t) := \int_{(-\infty, t]} e^{tx} P(dx) \geq \frac{1}{2} L(t) \geq \int_{(-\infty, t]} e^{tx} P(dx) = h(t-). \quad (4)$$

Hence, if $A > 0$ is given, then for s, t with $-A \leq s < t \leq A$, we get

$$\begin{aligned} P((s, t)) &= \int_{(s, t)} e^{-tx} e^{tx} P(dx) \leq e^{A^2} \int_{(s, t)} e^{tx} P(dx) \\ &= e^{A^2} \left(h(t-) - h(s) + \int_{(-\infty, s]} (e^{sx} - e^{tx}) P(dx) \right) \\ &\leq e^{A^2} \left(\frac{1}{2} (L(t) - L(s)) + (t - s) \int_{\mathbb{R}} |x| e^{A|x|} P(dx) \right) \\ &\leq c_A \cdot (t - s) \end{aligned}$$

for some finite constant c_A . We have been using (4) and $|e^u - e^v| \leq |u - v|e^w$ for $|u|, |v| \leq w$ at the penultimate step. Using assumption (1), we rely at the ultimate step on local Lipschitzness of L , due to its analyticity, and on finiteness of $\int_{\mathbb{R}} |x| e^{A|x|} P(dx)$. \square

Proof of Lemma 2. Assume to the contrary that there exist $a, b \in \mathbb{R}$ with $a < b$ and $P((a, b)) = 0$. Then, for $t \in (a, b)$, Lemma 1 and (2) yield

$$\int_{-\infty}^a e^{tx} P(dx) = \int_{-\infty}^t e^{tx} P(dx) = \int_t^{+\infty} e^{tx} P(dx) = \int_b^{+\infty} e^{tx} P(dx).$$

Thus the two measures $\mathbf{1}_{(-\infty, a]}(x)P(dx)$ and $\mathbf{1}_{[b, +\infty)}(x)P(dx)$ have finite and identical Laplace transforms on some non-empty interval. Hence the two measures coincide, and hence P must be the zero measure, which is absurd. \square

Proof of Theorem 1. With the representation (3) for $P \in \mathcal{P}$, assumption (2) is rewritten as

$$\int_{-\infty}^t e^{tx - \frac{x^2}{2}} \frac{1}{\sqrt{2\pi}} g(x) dx = \frac{1}{2} \int_{-\infty}^{+\infty} e^{tx - \frac{x^2}{2}} \frac{1}{\sqrt{2\pi}} g(x) dx. \quad (5)$$

We multiply both sides by $e^{-t^2/2}$:

$$\int_{-\infty}^t e^{-\frac{(t-x)^2}{2}} \frac{1}{\sqrt{2\pi}} g(x) dx = \frac{1}{2} \int_{-\infty}^{+\infty} e^{-\frac{(t-x)^2}{2}} \frac{1}{\sqrt{2\pi}} g(x) dx. \quad (6)$$

In other terms the unknown function g satisfies

$$\int_{-\infty}^{+\infty} \text{sign}(t - x) \varphi(t - x) g(x) dx = 0 \quad (7)$$

for all $t \in \mathbb{R}$. A formal derivation of (7) in t , using the product rule under the integral, and with one derivative being twice a delta function, leads to the equation

$$g(t) = \int_{-\infty}^{+\infty} q(t - x) g(x) dx \quad (8)$$

a.e. in t , where $q(y) := \frac{1}{2}|y|e^{-\frac{y^2}{2}}$ is a probability density, but instead of justifying this formal differentiation, it seems easier to start by computing the derivative of

$$h(t) := \int_{-\infty}^t e^{tx} P(dx).$$

By Lemma 2 the distribution function F of P has a continuous inverse F^{-1} . Using the quantile transform we have

$$h(t) = \int_0^1 \mathbf{1}_{\{F^{-1} \leq t\}}(u) e^{tF^{-1}(u)} du = \int_0^{F(t)} e^{tF^{-1}(u)} du = H(F(t), t)$$

with $H(s, t) := \int_0^s e^{tF^{-1}(u)} du$ for $s \in (0, 1)$ and $t \in \mathbb{R}$. Now H has continuous partial derivatives $H_1(s, t) = e^{tF^{-1}(s)}$ and $H_2(s, t) = \int_0^s F^{-1}(u) e^{tF^{-1}(u)} du$, due to the continuity of F^{-1} , and hence H is differentiable. Let f be a Lebesgue density of P . Then, at every t where $F'(t) = f(t)$, and hence at Lebesgue-a.e. t , the chain rule yields

$$\begin{aligned} h'(t) &= H_1(F(t), t)f(t) + H_2(F(t), t) = e^{t^2}f(t) + \int_0^{F(t)} F^{-1}(u) e^{tF^{-1}(u)} du \\ &= e^{t^2}f(t) + \int_{-\infty}^t x e^{tx} f(x) dx. \end{aligned}$$

Thus differentiating the identity (5) and observing that $f(x) = g(x)\varphi(x)$ we obtain the following a.e.-identity

$$\frac{1}{\sqrt{2\pi}} e^{t^2/2} g(t) + \int_{-\infty}^t x e^{tx - \frac{x^2}{2}} \frac{1}{\sqrt{2\pi}} g(x) dx = \frac{1}{2} \int_{-\infty}^{+\infty} x e^{tx - \frac{x^2}{2}} \frac{1}{\sqrt{2\pi}} g(x) dx,$$

and multiplying the latter by $\sqrt{2\pi} e^{-t^2/2}$ gives

$$g(t) = \frac{1}{2} \left(\int_t^{+\infty} x e^{-(t-x)^2/2} g(x) dx - \int_{-\infty}^t x e^{-(t-x)^2/2} g(x) dx \right).$$

Adding to the right hand side above the quantity

$$0 = \frac{t}{2} \left(\int_{-\infty}^t e^{-(t-x)^2/2} g(x) dx - \int_t^{+\infty} e^{-(t-x)^2/2} g(x) dx \right)$$

(recall (6)) yields the desired (8).

Next, with the (positive) Radon measures $\mu(dx) := g(x)dx$ and $\sigma(dx) := \varphi(x)dx$, Eq. (8) can be rewritten as the so-called Choquet–Deny equation $\mu = \mu * \sigma$. Observe that $t \mapsto \int_{-\infty}^{+\infty} e^{tx} \sigma(dx)$ is even and strictly convex, and is therefore equal to 1 only at $t = 0$. We can now use the results in section 6 of Deny (1960), where “ $n > 1$ ” is evidently a misprint for “ $n \geq 1$ ”, to conclude that μ has to be a positive scalar multiple of the Lebesgue measure. Since g is a probability density with respect to a probability measure, we have $g = 1$ a.e., and the theorem is proved. \square

A trivial characterization of the standard normal exponential family is to say that the mean is equal to the parameter t . But it is worthwhile to mention a natural conjecture about exponential families which seems harder to establish:

Conjecture. Suppose that the probability P satisfies (1), and denote $m(t) := \int_{\mathbb{R}} x P_t(dx)$. If for all t real $m(t)$ is a median of P_t , then $P = N(m, \sigma^2)$ for some m and σ .

This conjecture, which is probably more meaningful from a methodological point of view than the result established in the paper, does not translate in a neat harmonic analysis statement as (7) and (8) and as such it seems harder to establish. The next simple result offers some support to the conjecture. A probability Q on \mathbb{R}^n is said to be symmetric if there exists some $m \in \mathbb{R}^n$ such that $X - m \sim m - X$ when $X \sim Q$.

Theorem 2. Let P be a probability on \mathbb{R}^n such that

$$L(t) = \int_{\mathbb{R}^n} e^{(t,x)} P(dx)$$

is finite for all $t \in \mathbb{R}^n$. Assume that for all $t \in \mathbb{R}^n$ the probability $P_t(dx) = e^{(t,x)} P(dx) / L(t)$ is symmetric. Then P is normal.

Proof. Clearly $m(t) = \int_{\mathbb{R}^n} x P_t(dx) = L'(t) / L(t)$ exists and, since P_t is symmetric, $X_t - m(t) \sim m(t) - X_t$ when $X_t \sim P_t$. Therefore its Laplace transform

$$s \mapsto \mathbb{E}(e^{(s, X_t - m(t))}) = e^{-(s, m(t))} \frac{L(t + s)}{L(t)}$$

does not change when we replace s by $-s$. Considering the logarithm and taking the derivative in s we get $2m(t) = m(t + s) + m(t - s)$. Taking again the derivative in s we get $m'(t + s) = m'(t - s)$ for all $t, s \in \mathbb{R}^n$, which means that m' is constant, hence $\log L$ is polynomial of degree at most 2, and hence P is normal. \square

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