A scheme for proving Mill's ratio inequalities

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September 22, 2016

Abstract

We prove Mill's ratio inequalities via a scheme that provides increasingly sharper bounds and unlike other proofs is easy to remember!

1 Introduction

Mill's ratio for a distribution F with density f is inverse of the hazard rate/survival function, i.e. $\overline{F}(x)/f(x)$, where $\overline{F} = 1 - F$. For the Gaussian distribution a well-known and often used bound for the Mill's ratio (due to Gordon (1941)) is

$$\frac{x}{1+x^2} \cdot \phi(x) < \bar{\Phi}(x) < \frac{1}{x} \cdot \phi(x).$$
(1)

Another variant of this inequality is

$$\left(\frac{1}{x} - \frac{1}{x^3}\right)\phi(x) < \bar{\Phi}(x) < \frac{1}{x}\phi(x).$$
(2)

In this note we show that inequalities (1) is part of a series of increasingly sharper inequalities. The proof is very easy to remember unlike the standard proofs. To get the upper bound in (1) just integrate the inequality $\bar{\Phi}(t) > 0$ from x to ∞ :

$$0 < \int_x^\infty \bar{\Phi}(t) dt$$

= $t\bar{\Phi}(t)|_x^\infty - \int_x^\infty t(-\phi(t)) dt$
= $-x\bar{\Phi}(x) + \phi(x).$

To get the lower bound, we just integrate the above inequality to get

$$\begin{split} 0 &< \int_x^\infty [-t\bar{\Phi}(t) + \phi(t)] \, dt \\ &= -\frac{t^2}{2}\bar{\Phi}(t)|_x^\infty - \int_x^\infty \frac{t^2}{2}\phi(t) \, dt + \Phi(x) \\ &= \frac{x^2}{2}\bar{\Phi}(x) - \frac{t}{2}(-\phi(t))|_x^\infty + \int_x^\infty \frac{1}{2}(-\phi(t)) \, dt + \bar{\Phi}(x) \\ &= \frac{x^2}{2}\bar{\Phi}(x) - \frac{x}{2}\phi(x) - \frac{\bar{\Phi}(x)}{2} + \bar{\Phi}(x) \\ &= \frac{1}{2}[(1+x^2)\bar{\Phi}(x) - x\phi(x)]. \end{split}$$

You see the structure, right? We can integrate the above inequality to obtain a sharper upper bound

$$\bar{\Phi}(x) < \frac{1}{x} \cdot \frac{2+x^2}{3+x^2} \cdot \phi(x),$$
(3)

and so on. This repeated integration trick is quite easy to remember although it is somewhat cumbersome to integrate after a few steps. Below we give a systematic approach.

Proposition 1.1. Let X be a random variable (with distribution function F) and set $m_k(x) = \mathbb{E}[X^k \mathbf{1}_{X>x}]$. Assume that $\mathbb{E}|X|^N < \infty$. Then for all $0 \le n \le N$ we have

$$\sum_{k=0}^{n} \binom{n}{k} m_k(x) (-x)^{n-k} \ge 0.$$

Proof. Note that the left hand side is just $\mathbb{E}(X - x)^n_+ \ge 0$:

$$\mathbb{E}(X-x)_{+}^{n} = \mathbb{E}\sum_{k=0}^{n} \binom{n}{k} X^{k} (-x)^{n-k} \mathbf{1}_{X>x}$$
$$= \mathbb{E}\sum_{k=0}^{n} \binom{n}{k} \mathbb{E}[X^{k} \mathbf{1}_{X>x}] (-x)^{n-k}$$
$$= \sum_{k=0}^{n} \binom{n}{k} m_{k}(x) (-x)^{n-k}.$$

To fecilitate calculating $m_k(x)$ we have the following recursion. **Proposition 1.2.** Suppose $E|X|^{k+1} < \infty$. Then

$$m_{k+1}(x) = xm_k(x) + \int_x^\infty m_k(u) \, du.$$

Proof. Note that

$$\int_{x}^{\infty} m_{k}(u) du = \int_{x}^{\infty} \mathbb{E}(X^{k} \mathbf{1}_{X>u}) du$$
$$= \mathbb{E}\left[X^{k} \int_{x}^{\infty} \mathbf{1}_{X>u} du\right]$$
$$= \mathbb{E}[X^{k}(X-x)\mathbf{1}_{X>x}]$$
$$= m_{k+1}(x) - xm_{k}(x).$$

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Now let's compute using Proposition 1.2 for the Gaussian. If $X \sim N(0, 1)$, then

$$m_{0}(x) = \Phi(x) m_{1}(x) = \phi(x) m_{2}(x) = x\phi(x) + \bar{\Phi}(x) m_{3}(x) = x^{2}\phi(x) + 2\phi(x) m_{4}(x) = x^{3}\phi(x) + 3x\phi(x) + 3\bar{\Phi}(x) \vdots$$

Now n = 1 in Proposition 1.1 gives

$$m_1(x) - xm_0(x) > 0,$$

i.e.

$$\phi(x) - x\bar{\Phi}(x) > 0,$$

which is the upper bound in (1). Taking n = 2 we have

$$m_2(x) - 2xm_1(x) + x^2m_0(x) > 0,$$

the LHS is

$$x\phi(x) + \bar{\Phi}(x) - 2x\phi(x) + x^2\bar{\Phi}(x) = (1+x^2)\bar{\Phi}(x) - x\phi(x).$$

So we get the lower bound in (1). Taking n = 3 gives (3), while n = 4 gives

$$\bar{\Phi}(x) \ge x \cdot \frac{1}{1+x^2} \cdot \frac{5+6x+x^2}{3+6x+x^2} \cdot \phi(x)$$

and so on.

References

Gordon, R. D. (1941). Values of mills' ratio of area to bounding ordinate and of the normal probability integral for large values of the argument. *The Annals of Mathematical Statistics*, 12(3):364–366.