Jensen's Inequality

Intuition and Proof

January 20, 2023

Goals

- 1. Formally state Jensen's inequality.
- 2. Provide intuition on the direction of the inequality.
- 3. Show how to prove it by representing an arbitrary convex function in terms of linear functions.

Theorem (Jensen's Inequality)

Let g be a convex function from I to \mathbb{R} , where I is an open interval of reals. Let X be random variable on (Ω, \mathcal{F}, P) , with $X(\omega) \in I$ for all ω . Assume E[X] to be finite. If \mathcal{H} is a sub σ -field of \mathcal{F} , then

$$\mathbb{E}[g(X) \mid \mathcal{H}] \ge g(\mathbb{E}[X \mid \mathcal{H}])$$
 a.e. (2)

In particular, $\mathbb{E}[g(X)] \geq g(\mathbb{E}[X])$.

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$$\mathbb{E}[g(X) \mid \mathcal{H}] \ge g(\mathbb{E}[X \mid \mathcal{H}]) \quad a.e. \tag{2}$$

For example:

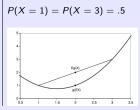
In particular, $\mathbb{E}[g(X)] \geq g(\mathbb{E}[X])$.

How to recall the direction of the inequality [Durrett, 2010]

Take
$$P(X = x) = \lambda$$
, $P(X = y) = 1 - \lambda$.

$$\mathbb{E}[g(X)] = \lambda \, g(x) + (1-\lambda) \, g(y)$$
 Lotus $\geq g \, (\lambda x + (1-\lambda) y)$ def. convexity

$$=g\left(\mathbb{E}[X]
ight) .$$
 def. expectation



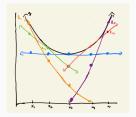
Line of Support Theorem.

Let $g: I \to \mathbb{R}$, where I is an open interval of reals, bounded or unbounded. Assume g is convex, that is,

$$\underbrace{g\left(\alpha x + (1-\alpha)y\right)}_{\text{graph}} \leq \underbrace{\alpha g(x) + (1-\alpha)g(y)}_{\text{chord}}$$

for all $x, y \in I$ and all $\alpha \in [0, 1]$. Then there are sequences $\{a_n\}, \{b_n\}$ of real numbers such that for all $x \in I$,

$$g(x) = \sup_{n} (a_n x + b_n)$$



Proof (partial)

Here we show that Jensen's inequality (Eq. (1)) holds.

$$g(X) = \sup_n a_n X + b_n$$
 Line of Support Theorem (Theorem 3)
$$\implies g(X) \geq a_n X + b_n$$
 supremum is an upper bound
$$\implies \mathbb{E}[g(X) \mid \mathcal{H}] \geq \mathbb{E}[a_n X + b_n \mid \mathcal{H}] \quad \text{a.e.} \quad \text{monotonicity}$$

$$\implies \mathbb{E}[g(X) \mid \mathcal{H}] \geq a_n \, \mathbb{E}[X \mid \mathcal{H}] + b_n \quad \text{a.e.} \quad \text{linearity}$$

$$\implies \mathbb{E}[g(X) \mid \mathcal{H}] \geq \sup_{g(\mathbb{E}[X \mid \mathcal{H}]) \text{ by LoS Thm.}} \quad \text{a.e.} \quad \text{supremum is least upper bound}$$

The Line of Support Theorem allows us to take an arbitrary convex function and represent it in terms of linear functions (and therefore apply properties that hold under linearity).