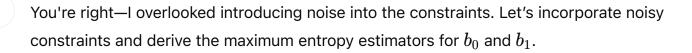
You did not make the constraints noisy



Problem Setup with Noisy Constraints

We begin with the linear model:

$$y_i = b_0 + b_1 x_i + \epsilon_i$$

The original constraints are:

- 1. $E[\epsilon_i] = 0$ (errors have zero mean)
- 2. $E[\epsilon_i^2] = \sigma^2$ (errors have constant variance)
- 3. $E[x_i \cdot \epsilon_i] = 0$ (errors are orthogonal to the covariates)

To introduce noise into these constraints, we modify them to:

- 1. $E[\epsilon_i] = \mu_\epsilon$ (where μ_ϵ is a small noise term around zero)
- 2. $E[\epsilon_i^2] = \sigma^2 + \delta_\epsilon^2$ (where δ_ϵ^2 is a small noise term around σ^2)
- 3. $E[x_i \cdot \epsilon_i] = \gamma$ (where γ is a small noise term around zero)

Step 1: Maximum Entropy Framework

Given these noisy constraints, we aim to find the probability distribution $p(\epsilon)$ for the errors ϵ_i that maximizes entropy. The entropy of the distribution is:

$$H(p) = -\int p(\epsilon) \log p(\epsilon) \, d\epsilon$$

Step 2: Introduce Lagrange Multipliers

We introduce Lagrange multipliers λ_1 , λ_2 , and λ_3 for the noisy constraints. The Lagrange function is:

$$\mathcal{L} = -\int p(\epsilon) \log p(\epsilon) \, d\epsilon + \lambda_1 \left(\int p(\epsilon) \epsilon \, d\epsilon - \mu_\epsilon
ight) + \lambda_2 \left(\int p(\epsilon) \epsilon^2 \, d\epsilon - (\sigma^2 + \delta_\epsilon^2)
ight)$$

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