Model documentation

Personality Estimator

1. Prospect Theory Utility

Given:

- G: potential gain
- L: potential loss
- $p_{\text{win}}, p_{\text{loss}}$: probabilities of gain/loss
- θ: ambiguity preference
- Λ: loss aversion
- α, β: risk sensitivity
- γ: probability distortion

a. Effective probabilities (with ambiguity):

$$\eta_{\text{gain}} = \text{clip}(p_{\text{win}} + (1 - p_{\text{win}} - p_{\text{loss}}) \cdot \theta, 0, 1)$$

$$\eta_{\text{loss}} = \text{clip}(p_{\text{loss}} + (1 - p_{\text{win}} - p_{\text{loss}}) \cdot (1 - \theta), 0, 1)$$

b. Subjective probability transformation:

$$\pi(p) = \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{1/\gamma}}$$

c. Subjective value transformation:

$$v(x) = \begin{cases} x^\alpha & \text{if } x \geq 0 \\ -\Lambda(-x)^\beta & \text{if } x < 0 \end{cases}$$

d. Utility of gamble:

$$U = v(G) \cdot \pi(\eta_{\text{gain}}) + v(-L) \cdot \pi(\eta_{\text{loss}})$$

2. Investment Decision Model

Given a binary decision $y \in \{0, 1\}$ (invest or not):

a. Decision probability (logistic):

$$P(y = 1|U) = \frac{1}{1 + \exp(-\tau(U - \epsilon))}$$

$$P(y = 0|U) = 1 - P(y = 1|U)$$

Where:

- τ: sensitivity (steepness of sigmoid)
- ϵ: decision noise

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3. Log-Likelihood Function

Observed data D includes investments and gamble attributes. For parameters $\Theta = [\theta, \Lambda, \tau, \alpha, \gamma, \epsilon]$, and log-normal priors over parameters:

$$\mathcal{L}(\Theta|D) = -\left(\sum_i \log P(y_i|x_i, \Theta) + \sum_{p \in \Theta \setminus \{\epsilon\}} \log \mathrm{LogNorm}(p) + \log \mathrm{Norm}(\epsilon)\right)$$

This is minimized via `scipy.optimize.minimize(method='nelder-mead')`.