

EXERCISE : Value of information calculations for a Gaussian example

Part I:

Assume the profit of a project has a **univariate Gaussian** pdf,

$$p(x) = \frac{1}{\sqrt{2\pi}} \frac{1}{\sigma} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right), \quad -\infty < x < \infty.$$

A decision maker will invest in a project which has positive expected value.

- Use a transformation of variables: $z = g(x) = \frac{x-\mu}{\sigma}$, $x = g^{-1}(z) = \mu + \sigma z$, and the transformation formula $p(z) = \left| \frac{dg^{-1}}{dz} \right| p(g^{-1}(z))$ to show that the variable z is standard normal distributed.
- Use integration by parts; i.e. $\left(\int u \cdot v' = u \cdot v - \int u' \cdot v \right)$ to show that $\int_a^b z \phi(z) dz = \int_a^b 1 \cdot z \phi(z) dz = \phi(a) - \phi(b)$, where the standard normal pdf is $\phi(z) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{z^2}{2}\right)$.
- Suppose a decision maker is considering getting perfect information about the profit. The posterior value of perfect information is $PoV(x) = \int \max\{0, x\} p(x) dx = \int_0^{\infty} x p(x) dx$. Use the results from a. and b. along with symmetry properties of the standard normal pdf $\phi(z)$ and its cumulative distribution $\Phi(z)$ to show that $PoV(x) = \mu \Phi\left(\frac{\mu}{\sigma}\right) + \sigma \phi\left(\frac{\mu}{\sigma}\right)$.
- Plot the analytical VOI as i) a function of the mean in the range $\mu \in (-2, 2)$ and ii) as a function of standard deviation $\sigma \in (0.1, 2)$. Interpret results.

Part II:

Consider the **bivariate Gaussian pdf** $p(\mathbf{x}) = N(\mathbf{0}, \Sigma)$ for profits $\mathbf{x} = (x_1, x_2)$ at two projects. Assume variance 1 for both projects, and correlation $-1 < \rho < 1$.

The decision maker selects a project (alternative $a_i = 1, i = 1, 2$) if its expected profit is positive, otherwise avoids investment (alternative $a_i = 0, i = 1, 2$). We consider a decision situation with a free selection of projects, without constraints. Assume the decision maker can purchase total imperfect information, $y_j = x_j + N(0, \tau^2)$, $j = 1, 2$, i.e. conditional model for

the data is then $p(\mathbf{y} | \mathbf{x}) = N(\mathbf{x}, \mathbf{T})$, $\mathbf{T} = \tau^2 \mathbf{I}$. It can be shown that the posterior model for project profits, conditional on observations \mathbf{y} , is $p(\mathbf{x} | \mathbf{y}) \propto p(\mathbf{x}) p(\mathbf{y} | \mathbf{x}) = N(\boldsymbol{\mu}_{x|y}, \boldsymbol{\Sigma}_{x|y})$, where $\boldsymbol{\mu}_{x|y} = \boldsymbol{\Sigma}(\boldsymbol{\Sigma} + \mathbf{T})^{-1} \mathbf{y}$ and $\boldsymbol{\Sigma}_{x|y} = \boldsymbol{\Sigma} - \boldsymbol{\Sigma}(\boldsymbol{\Sigma} + \mathbf{T})^{-1} \boldsymbol{\Sigma}$.

- a. Use the formula for linear combinations of Gaussian variables to show that $p(\mathbf{y}) = N(\mathbf{0}, \boldsymbol{\Sigma} + \mathbf{T})$ and $p(\boldsymbol{\mu}_{x|y}) = N(\mathbf{0}, \boldsymbol{\Sigma}(\boldsymbol{\Sigma} + \mathbf{T})^{-1} \boldsymbol{\Sigma})$.
- b. Use the result from a. and from Part I to compute the posterior value of total imperfect information: $PoV(\mathbf{y}) = \sum_{j=1}^2 \int \max\{0, \mu_{x|y,j}\} p(\mathbf{y}) d\mathbf{y}$. (Note: the only part of the data which is informative of the decision is $\boldsymbol{\mu}_{x|y}$, so the expression simplifies to: $PoV(\mathbf{y}) = \sum_{j=1}^2 \int \max\{0, \mu_{x|y,j}\} p(\mu_{x|y,j}) d\mu_{x|y,j}$.)
- c. Cross-plot the VOI results as a function of the correlation ρ and for standard deviation $\tau = 0.5$ and $\tau = 1$ of the imperfect test. Interpret results.
- d. Assume next that the decision maker can gather information about only one of the projects (partial testing), say $y_1 = x_1 + N(0, \tau^2) = \mathbf{F}\mathbf{x} + N(0, \tau^2)$, where $\mathbf{F} = (1, 0)$. Calculate the posterior value of this partial test. Note that the conditional mean now becomes $\boldsymbol{\mu}_{x|y} = \boldsymbol{\Sigma}\mathbf{F}'(\mathbf{F}\boldsymbol{\Sigma}\mathbf{F}' + \tau^2)^{-1} y_1$. Plot results as in c. and interpret and compare results.