

NEW SHINY APP FORMULAE

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1. CURRENT METHOD

We assume that we have a model with input \mathbf{x} and scalar output $Y(\mathbf{x})$. We assume that $Y(\mathbf{x})$ is modelled as a (Deep Gaussian Process). We also know that $Y(\mathbf{x}) \geq 0; \forall \mathbf{x}$. Given a target \mathcal{T} , we want to estimate: $P(Y(\mathbf{x}) \geq \mathcal{T})$. If we make the assumption that $\mathcal{T} \geq E[Y(\mathbf{x})]$, we can use Cantelli's inequality to derive an upper bound on this probability.

$$P((Y(\mathbf{x}) - E[Y(\mathbf{x})]) \geq (\mathcal{T} - E[Y(\mathbf{x})]) | \mathcal{T} \geq E[Y(\mathbf{x})]) \leq \frac{Var[Y(\mathbf{x})]}{Var[Y(\mathbf{x})] + (\mathcal{T} - E[Y(\mathbf{x})])^2}$$

writing the Implausibility as:

$$I(\mathbf{x}) = \frac{\mathcal{T} - E[Y(\mathbf{x})]}{\sqrt{Var[Y(\mathbf{x})]}}$$

and replacing, we obtain:

$$P(Y(\mathbf{x}) \geq \mathcal{T} | \mathcal{T} \geq E[Y(\mathbf{x})]) = P\left(\frac{(Y(\mathbf{x}) - E[Y(\mathbf{x})])}{\sqrt{Var[Y(\mathbf{x})]}} \geq I(\mathbf{x}) | I(\mathbf{x}) \geq 0\right) \leq \frac{1}{1 + I(\mathbf{x})^2} \quad (1)$$

Similary, for cases where $\mathcal{T} \leq E[Y(\mathbf{x})]$, we can apply the negative side Cantelli's inequality:

$$\begin{aligned} P(Y(\mathbf{x}) \leq \mathcal{T} | \mathcal{T} \leq E[Y(\mathbf{x})]) &= P((Y(\mathbf{x}) - E[Y(\mathbf{x})]) \leq (\mathcal{T} - E[Y(\mathbf{x})]) | \mathcal{T} \leq E[Y(\mathbf{x})]) \\ &\leq \frac{Var[Y(\mathbf{x})]}{Var[Y(\mathbf{x})] + (\mathcal{T} - E[Y(\mathbf{x})])^2} \end{aligned}$$

replacing by $I(\mathbf{x})$, we obtain:

$$P(Y(\mathbf{x}) \leq \mathcal{T} | \mathcal{T} \leq E[Y(\mathbf{x})]) = P\left(\frac{(Y(\mathbf{x}) - E[Y(\mathbf{x})])}{\sqrt{Var[Y(\mathbf{x})]}} \leq -|I(\mathbf{x})| | I(\mathbf{x}) \leq 0\right) \leq \frac{1}{1 + I(\mathbf{x})^2} \quad (2)$$

We then have:

$$P(Y(\mathbf{x}) > \mathcal{T} | \mathcal{T} \leq E[Y(\mathbf{x})]) = 1 - P(Y(\mathbf{x}) \leq \mathcal{T} | \mathcal{T} \leq E[Y(\mathbf{x})]) \geq 1 - \frac{1}{1 + I(\mathbf{x})^2} \geq \frac{I(\mathbf{x})^2}{1 + I(\mathbf{x})^2} \quad (3)$$

The issue is that for the app, we must have the possibility to have both $\mathcal{T} \leq E[Y(\mathbf{x})]$ and $\mathcal{T} \geq E[Y(\mathbf{x})]$ and we see that first one bound obtained is an upper bound whilst the second bound is a lower bound. Second, the bounds are not continuous in 0 as we have: $\lim_{I(\mathbf{x}) \rightarrow 0^-} \frac{I(\mathbf{x})^2}{1 + I(\mathbf{x})^2} = 0$ and $\lim_{I(\mathbf{x}) \rightarrow 0^+} \frac{1}{1 + I(\mathbf{x})^2} = 1$ so we cannot use these 2 bounds in the app, otherwise there would be inconsistencies if the user crosses a threshold by moving the target above or below $E[Y(\mathbf{x})]$. We also note that if \mathcal{T} is near $E[Y(\mathbf{x})]$ the 2 thresholds are simply implying that the probability is between 0 and 1 that are not sufficiently tight bounds to be used. We propose instead to make the stronger assumption that $Y(\mathbf{x})$ follows a Gaussian truncated at 0.

2. TRUNCATED GAUSSIAN

We first standardize $Y(\mathbf{x})$:

$$\bar{Y}(\mathbf{x}) = \frac{Y(\mathbf{x}) - E[Y(\mathbf{x})]}{\sqrt{Var[Y(\mathbf{x})]}}$$

We then note that:

$$P(Y(\mathbf{x}) \geq \mathcal{T}) = P(\bar{Y}(\mathbf{x}) \geq \mathcal{I}(\mathbf{x}))$$

If we assume that $Y(\mathbf{x})$ is Normally distributed, we could assume that $\bar{Y}(\mathbf{x})$ is a standard Gaussian (mean=0, var=1). However, we also know that we must have $Y(\mathbf{x}) \geq 0; \forall \mathbf{x}$. We therefore assume that

$$\bar{Y}(\mathbf{x}) | \mathbf{x} \sim \mathcal{N}_{[a, \infty)}(0, 1)$$

To determine a , we simply use the positivity of $Y(\mathbf{x})$:

$$Y(\mathbf{x}) \geq 0 \Leftrightarrow \bar{Y}(\mathbf{x}) \geq \frac{-E[Y(\mathbf{x})]}{\sqrt{Var[Y(\mathbf{x})]}}$$

Hence we assume that:

$$\bar{Y}(\mathbf{x}) | \mathbf{x} \sim \mathcal{N}_{\left[\frac{-E[Y(\mathbf{x})]}{\sqrt{Var[Y(\mathbf{x})]}}, \infty\right)}(0, 1)$$

$$P(Y(\mathbf{x}) \geq \mathcal{T}) = 1 - P(\bar{Y}(\mathbf{x}) \leq \mathcal{I}(\mathbf{x})) = 1 - \int_{\frac{-E[Y(\mathbf{x})]}{\sqrt{Var[Y(\mathbf{x})]}}}^{\mathcal{I}(\mathbf{x})} \phi(x) dx = 1 - \Phi\left[\frac{-E[Y(\mathbf{x})]}{\sqrt{Var[Y(\mathbf{x})]}}, \infty\right](\mathcal{I}(\mathbf{x})) \quad (4)$$

A tolerance (for model error,...) ‘be added to the variance at the denominator for the calculation of the Implausibility. The tolerance can be added to denominator of the lower bound $a = -\frac{E[Y(\mathbf{x})]}{\sqrt{(Var(Y(\mathbf{x})))}}$.

This avoids infinite values for $|I(\mathbf{x})|$ and $-a$ if the variance of $Y(\mathbf{x})$ is 0.

2.1. Max Target Initialization. Let’s now assume that we have a known confidence level α that we want to achieve:

$$P(Y(\mathbf{x}) \geq \mathcal{T}) \geq \alpha$$

and we want to determine the maximum possible value allowed for \mathcal{T} such that if the parcels are all planted, then the Target is met with a probability at least α :

$$P(Y(\mathbf{x}_{all}) \geq \mathcal{T}) \geq \alpha \Leftrightarrow 1 - \Phi\left[\frac{-E[Y(\mathbf{x}_{all})]}{\sqrt{Var[Y(\mathbf{x}_{all})] + tol}}, \infty\right]\left(\frac{\mathcal{T}_{max} - E[Y(\mathbf{x}_{all})]}{\sqrt{Var[Y(\mathbf{x}_{all})] + tol}}\right) \geq \alpha$$

$$\left(\sqrt{Var[Y(\mathbf{x}_{all})] + tol}\right) \times \left(\Phi^{-1}\left[\frac{-E[Y(\mathbf{x}_{all})]}{\sqrt{Var[Y(\mathbf{x}_{all})] + tol}}, \infty\right](1 - \alpha) + E[Y(\mathbf{x}_{all})]\right) \geq \mathcal{T}_{max} \quad (5)$$

2.2. Formulae for \leq . We have:

$$P(Y(\mathbf{x}) \leq \mathcal{T}) = P(\bar{Y}(\mathbf{x}) \leq \mathcal{I}(\mathbf{x})) = \int_{-\frac{E[Y(\mathbf{x})]}{\sqrt{var[Y(\mathbf{x})]}}}^{\mathcal{I}(\mathbf{x})} \phi(u) du = \Phi\left[-\frac{E[Y(\mathbf{x})]}{\sqrt{var[Y(\mathbf{x})]}}, \infty\right](\mathcal{I}(\mathbf{x}))$$

$$P(Y(\mathbf{x}_{min}) \leq \mathcal{T}) \geq \alpha \Leftrightarrow P(\bar{Y}(\mathbf{x}_{min}) \leq \mathcal{I}(\mathbf{x}_{min})) \geq \alpha \Leftrightarrow \Phi\left[-\frac{E[Y(\mathbf{x}_{min})]}{\sqrt{var[Y(\mathbf{x}_{min})]}}, \infty\right]\left(\frac{\mathcal{T}_{min} - E[Y(\mathbf{x}_{min})]}{\sqrt{var[Y(\mathbf{x}_{min})]}}\right) \geq \alpha$$

$$\mathcal{T}_{min} \geq E[Y(\mathbf{x}_{min})] + \sqrt{var[Y(\mathbf{x}_{min})]}\left(\Phi^{-1}\left[-\frac{E[Y(\mathbf{x}_{min})]}{\sqrt{var[Y(\mathbf{x}_{min})]}}, \infty\right](\alpha)\right)$$

In the case x is the planting area, \mathbf{x}_{min} consists in no planting and the area is zero. In this case $E[Y(x_{min})] = 0$. In practice, we add a tolerance to the variance. Hence even if $var[Y(x_{min})] = 0$, we still have a tolerance in the square root of the second argument. Hence:

$$\mathcal{T}_{min}^{area} \geq \sqrt{tol_{area}} \left(\Phi_{[0,\infty]}^{-1}(\alpha) \right)$$

We also need to have:

$$P(Y(\mathbf{x}_{max}) \leq \mathcal{T}_{max}) \geq \alpha \Leftrightarrow P\left(\bar{Y}(\mathbf{x}_{max}) \leq \mathcal{I}(\mathbf{x}_{max})\right) \geq \alpha \Leftrightarrow \Phi\left[-\frac{E[Y(\mathbf{x}_{max})]}{\sqrt{var[Y(\mathbf{x}_{max})]}}, \infty\right] \left(\frac{\mathcal{T}_{max} - E[Y(\mathbf{x}_{max})]}{\sqrt{var[Y(\mathbf{x}_{max})]}}\right) \geq \alpha$$

$$\mathcal{T}_{max} \geq \sqrt{var[Y(\mathbf{x}_{max})]} \left(\Phi_{\left[-\frac{E[Y(\mathbf{x}_{max})]}{\sqrt{var[Y(\mathbf{x}_{max})]}}, \infty\right]}^{-1}(\alpha) \right) + E[Y(\mathbf{x}_{max})]$$