

Verification of Gaussian Processes

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Motivation:

- Widely used in safety critical applications
- Need to incorporate the uncertainty of probabilistic models into safety analysis
- ⊛ No method exists for this yet (contribution)

Background:

Prior Distribution

$$f \sim \text{GP}$$

(distribution over function space)

Conditioned model

$$f \sim \text{GP} | \mathcal{X} \quad \left[\begin{array}{l} \text{We keep only the} \\ \text{functions from the} \\ \text{prior that justify} \\ \text{the data.} \end{array} \right]$$

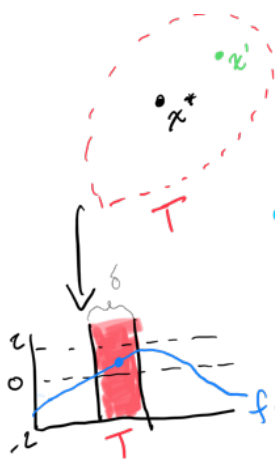
Important Note, the posterior can be done analytically, not the case in Bayesian Deep learning.

Problem Formulation:

Probabilistic Invariance
(local robustness)

$$\phi(x^*, T, \delta) :=$$

$$P(\exists x' \in T \text{ s.t. } \|z(x') - z(x^*)\| > \delta)$$



Does the change for x^* to x' induce a large change in the output of the GP?

Intuition for ϕ :
How many 'f' are scale according to the defined bounds

Method:

- Computing via sampling is not tractable so we want a formal way to get values for ϕ

[Note: you can do kind of formal things for intractable case.]

I have left the proof sketch for the slides

Experiments:

Because Neural Nets with single layer and infinite width gives a GP, we can use this method to gain some insights about how neural nets may behave with respect to ϕ

Main insight for Neural nets is that variance changes very slowly as the "depth" of

the neural network grows
[see last slide].