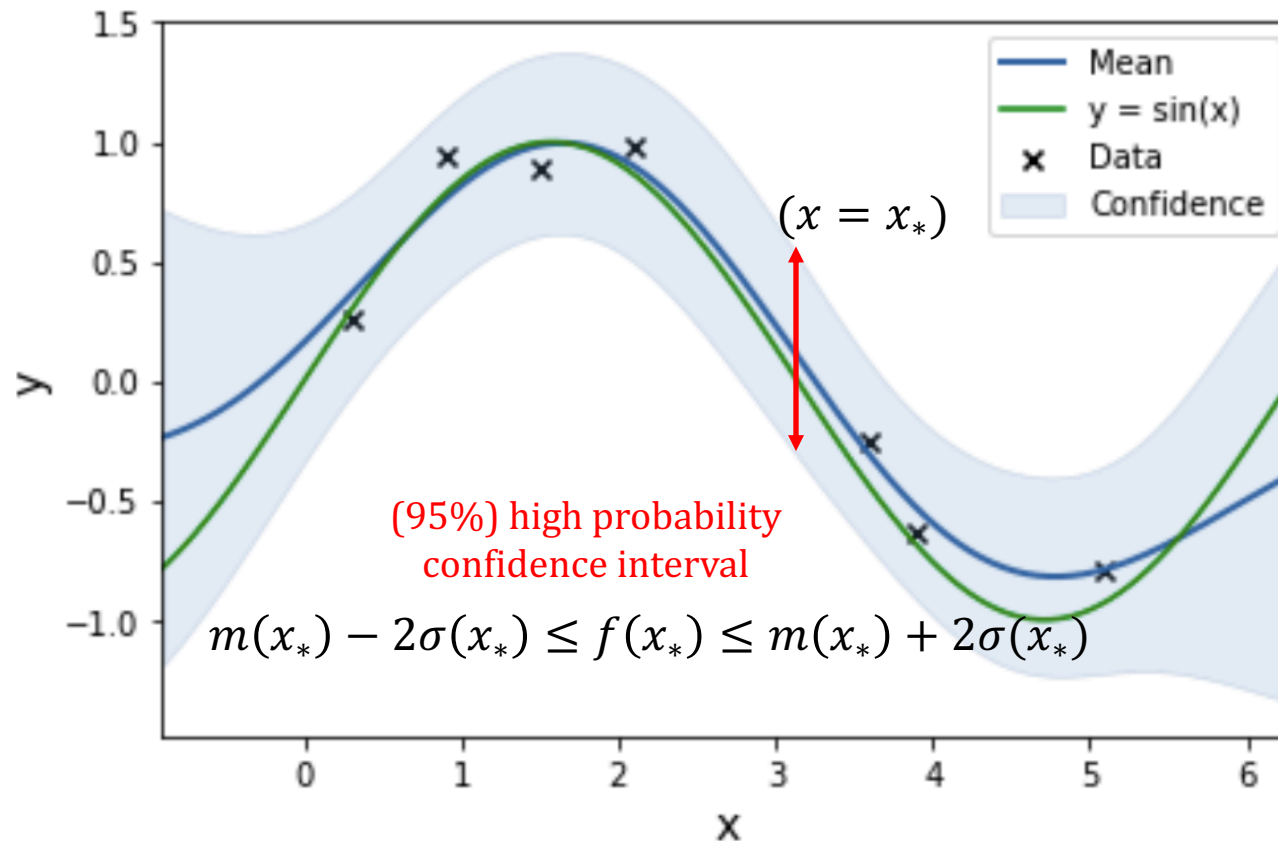


- GP regression of single output function $f(x)$

$$f(x_*) \sim \mathcal{N}(m(x_*), \sigma^2(x_*))$$



- In [1], they use GP regression of multi output function
 - Nominal control affine model

$$s_{t+1} = f(s_t) + g(s_t)a_t + d(s_t)$$

where f, g are **known** and d is **uncertain** → **GPR!**

In this case

$d(s)$ is **n** – dimensional function : $\mathbb{R}^n \rightarrow \mathbb{R}^n$
How should we express the variance...?

- GP for each factor of $d_i(s): \mathbb{R}^n \rightarrow \mathbb{R}$

$$\underbrace{\begin{pmatrix} m_1(s) \\ \vdots \\ m_n(s) \end{pmatrix}}_{\mathbf{m}(s)} - 2 \underbrace{\begin{pmatrix} \sigma_1(s) \\ \vdots \\ \sigma_n(s) \end{pmatrix}}_{\boldsymbol{\sigma}(s)} \leq \begin{pmatrix} d_1(s) \\ \vdots \\ d_n(s) \end{pmatrix} \leq \underbrace{\begin{pmatrix} m_1(s) \\ \vdots \\ m_n(s) \end{pmatrix}}_{\mathbf{m}(s)} + 2 \underbrace{\begin{pmatrix} \sigma_1(s) \\ \vdots \\ \sigma_n(s) \end{pmatrix}}_{\boldsymbol{\sigma}(s)}$$

[1] : R. Cheng, G. Orosz, R. M. Murray, and J. W. Burdick. "End-to-end safe reinforcement learning through barrier functions for safety-critical continuous control tasks." *Thirty-Third AAAI Conference on Artificial Intelligence (AAAI-19)*, 2019.

- What is proved ①
 - If there exists a solution to (*) for all $s \in C$ (set of safe states) with $\varepsilon = 0$, the set C will be **forward invariant** w.p. $1 - \delta$.
 - If there exists a state $s \in C$ such that (*) has solution with $\varepsilon = \varepsilon_{max} > 0$. If for all $s \in C$, the solution to (*) satisfies $\varepsilon < \varepsilon_{max}$, then set C_ε (larger set to C) will be **forward invariant** w.p. $1 - \delta$.

(*)

$$(a_t, \varepsilon) = \operatorname{argmin}_{a_t, \varepsilon} \|a_t\|_2 + K_\varepsilon \varepsilon$$

$$\text{s.t.} \quad p^\top f(s_t) + p^\top g(s_t) (u_{\theta_k}^{RL}(s) + a_t) + p^\top \mu_d(s_t) \\ - k_\delta |p|^\top \sigma_d(s_t) + q \geq (1 - \eta) h(s_t) - \varepsilon$$

$$a_{low}^i \leq u_{\theta_k}^{RL(i)}(s) + a_t \leq a_{high}^i \text{ for } i = 1, \dots, M$$

- What is proved ②
 - If we use TRPO for RL, the algorithm achieve performance guarantee

$$J(\pi_k^{prop}) \geq J(\pi_{k-1}) - \frac{2\lambda\gamma}{(1-\gamma)^2} \delta_\pi$$

$$J(\pi) = \mathbb{E}_{a \sim \pi} \left[\sum_{t=0}^{\infty} \gamma^t r(s_t) \right]$$

