

#### SPECTRAL REPRESENTATION OF ROBUSTNESS MEASURES

#### FOR OPTIMIZATION UNDER INPUT UNCERTAINTY

Jixiang Qing, Tom Dhaene, Ivo Couckuyt



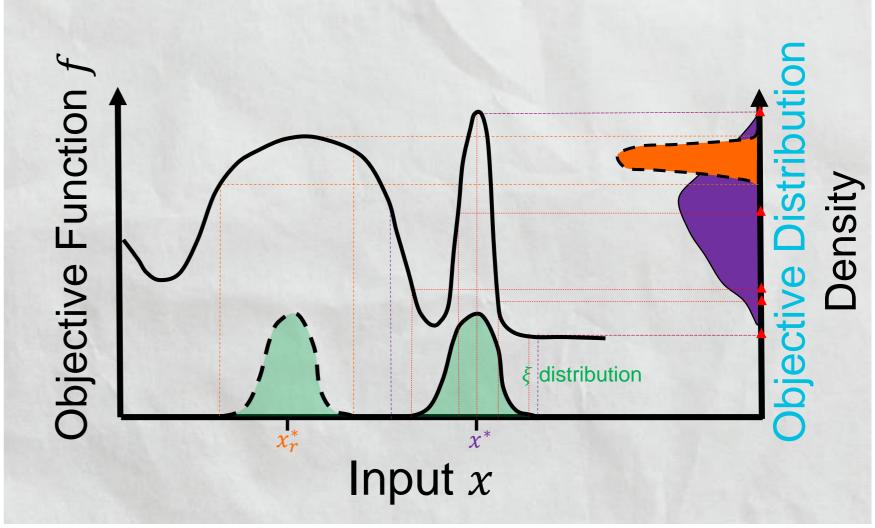






### PROBLEM FORMULATION

- Robust optimization
  - Optimize black box function *f*
  - Consider Input Uncertainty
- What is a robust solution?
  - First moment:  $\mathbb{J}_{\xi}(f) = \mathbb{E}_{\xi}[f(x+\xi)]$
  - Second moment:  $\mathbb{V}_{\xi}(f) = \mathbb{V}_{\xi}[f(x+\xi)]$



"Solution  $\chi_r^*$  is more robust than  $\chi^*$ "

Mean:  $\mathbb{E}_{\xi}[f(x_r^* + \xi)] \ge \mathbb{E}_{\xi}[f(x^* + \xi)]$ 

Variance:  $\mathbb{V}_{\xi}[f(x_r^* + \xi)] \leq \mathbb{V}_{\xi}[f(x^* + \xi)]$ 



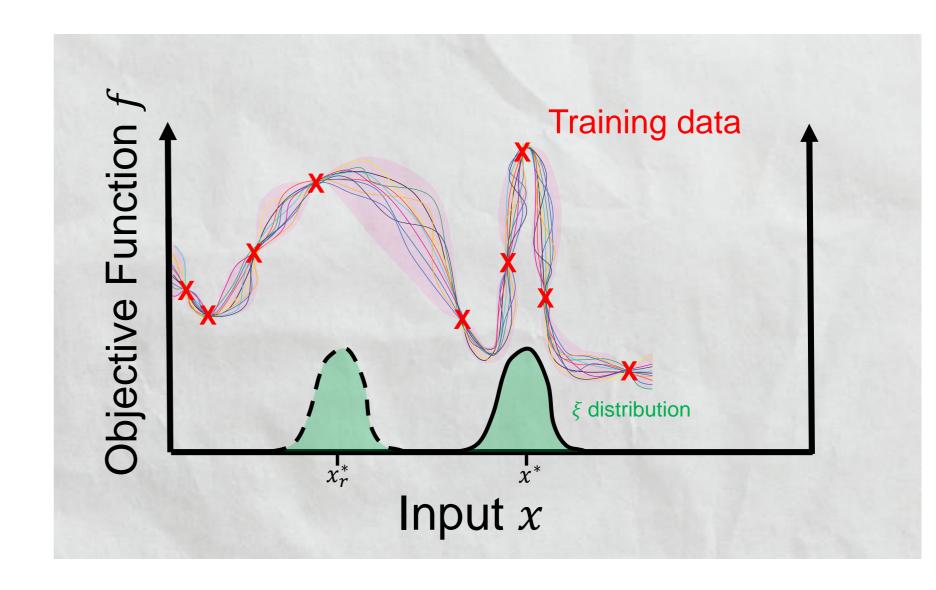






### PROBLEM FORMULATION

- Robust optimization
  - Optimize black box function *f*
  - Consider Input Uncertainty
- What is a robust solution?
  - First moment:  $\mathbb{J}_{\xi}(f) = \mathbb{E}_{\xi}[f(x+\xi)]$
  - Second moment:  $\mathbb{V}_{\xi}(f) = \mathbb{V}_{\xi}[f(x+\xi)]$
- Bayesian approach:
  - Gaussian Process  $f \sim GP$
  - Bayesian Treatment of the above moments
    - $\mathbb{J}_{\xi}[\mathcal{GP}(f)] = \mathbb{E}_{\xi}[\mathcal{GP}(x+\xi)]$
    - $\mathbb{V}_{\xi}[\mathcal{GP}(f)] = \mathbb{V}_{\xi}[\mathcal{GP}(x+\xi)]$



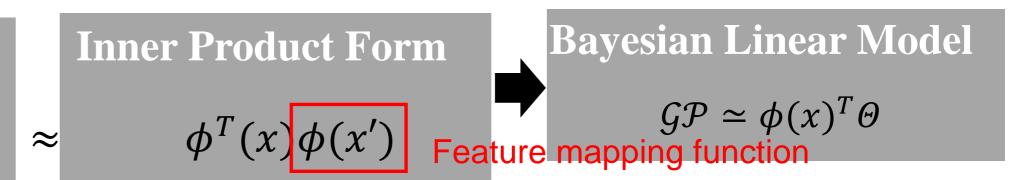








$$k(x, x')$$
 Bochner's Theorem
$$= \sigma^2 \int p(\omega) \cos(\omega^T L(x - x')) d\omega \approx$$











k(x, x') Bochner's Theorem

**Inner Product Form** 

Bayesian Linear Model

$$= \sigma^2 \int p(\omega) \cos(\omega^T L(x - x')) d\omega \approx$$

$$\phi^T(x)\phi(x')$$

 $\mathcal{GP} \simeq \phi(x)^T \Theta$ Feature mapping function

**Random Fourier Features** 

Monte Carlo









k(x, x') Bochner's Theorem

**Inner Product Form** 

Bayesian Linear Model

$$= \sigma^2 \int p(\omega) \cos(\omega^T L(x - x')) d\omega \approx$$

$$\phi^T(x)\phi(x')$$

 $\mathcal{GP} \simeq \phi(x)^T \Theta$ Feature mapping function

**Quadrature Fourier Features** 

**Numerical Quadrature** 

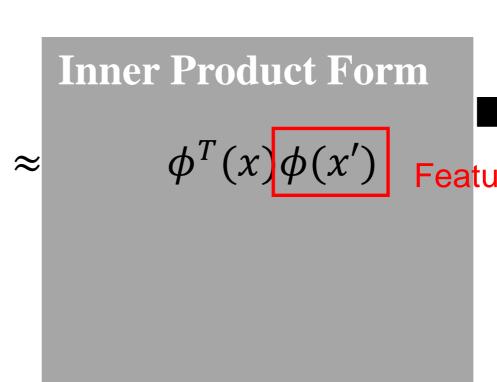








$$k(x, x')$$
 Bochner's Theorem
$$= \sigma^2 \int p(\omega) \cos(\omega^T L(x - x')) d\omega \approx$$



Bayesian Linear Model

$$\mathcal{GP} \simeq \phi(x)^T \Theta$$
Feature mapping function

- $\mathbb{J}_{\xi}[\mathcal{GP}(f)] \simeq \mathbb{E}_{\xi}[\phi(x+\xi)^T]\Theta^T$
- $\mathbb{V}_{\varepsilon}[\mathcal{GP}(f)]$  $\simeq \Theta^T \mathbb{E}_{\varepsilon}[\phi(x+\xi)^T]\Theta - [\mathbb{E}_{\varepsilon}[\phi(x+\xi)^T]\Theta]^2$





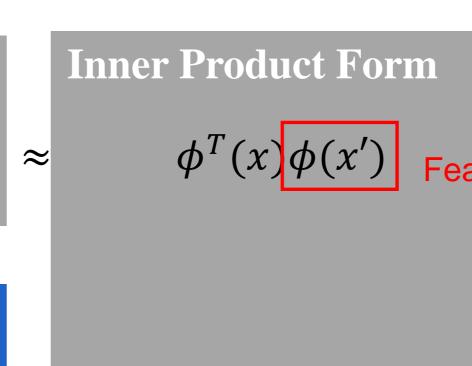




$$k(x, x')$$
 Bochner's Theorem
$$= \sigma^2 \int p(\omega) \cos(\omega^T L(x - x')) d\omega \approx$$

#### We derive expressions for

- ~ (multivariate) Normal distribution
- ~ Uniform distribution



Bayesian Linear Model

$$\mathcal{GP} \simeq \phi(x)^T \Theta$$
Feature mapping function

- $\mathbb{J}_{\varepsilon}[\mathcal{GP}(f)] \simeq \mathbb{E}_{\varepsilon}[\phi(x+\xi)^T]\Theta$
- $\mathbb{V}_{\varepsilon}[\mathcal{GP}(f)]$   $\simeq \Theta^T \mathbb{E}_{\varepsilon}[\phi(x+\xi)^T]\Theta \left[\mathbb{E}_{\varepsilon}[\phi(x+\xi)^T]\Theta\right]^2$





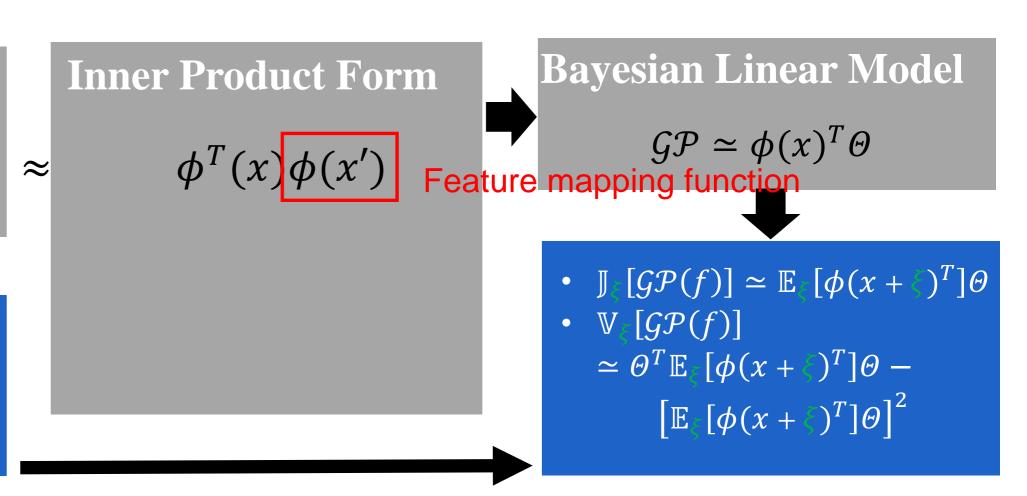




$$k(x, x')$$
 Bochner's Theorem
$$= \sigma^2 \int p(\omega) \cos(\omega^T L(x - x')) d\omega \approx$$

### We derive expressions for

- (multivariate) Normal distribution
- Uniform distribution



#### Fourier feature base robustness measures

A spectral representation (i.e., a parametric representation) of robustness measures that supports **sampling** continuous posterior trajectories









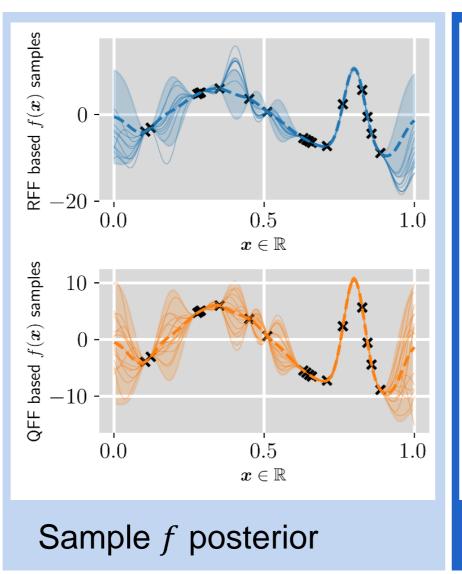
### MAIN CONTRIBUTION

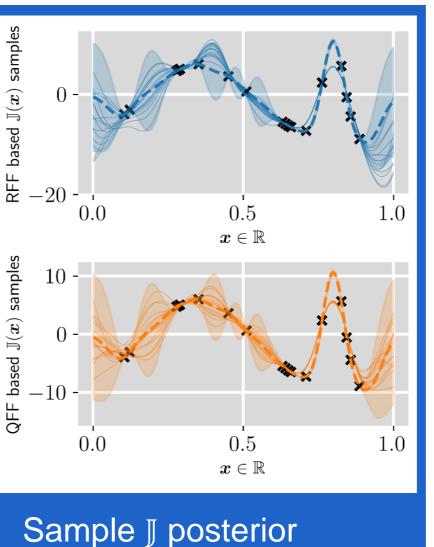
#### Fourier feature-based robustness measures

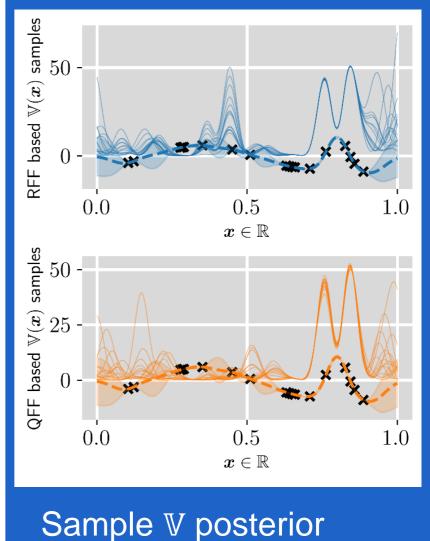
A spectral representation (i.e., a parametric representation) of robustness measures that supports sampling continuous posterior trajectories

# Application in Robust Bayesian Optimization

- Supports variousproblem formulations
- Supports variousacquisition functions















### MAIN CONTRIBUTION

**Function Value** 

Objective

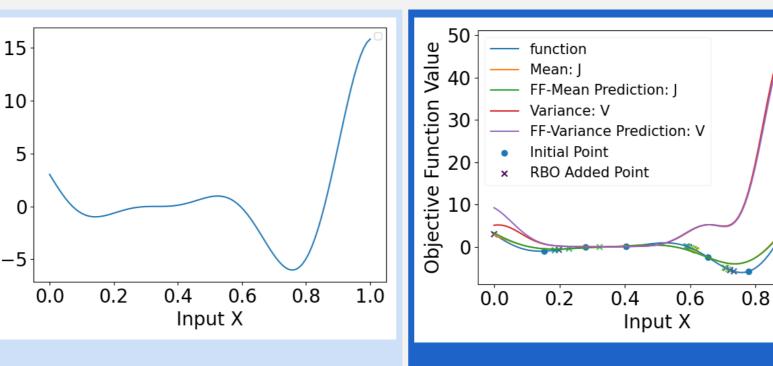
#### Fourier feature-based robustness measures

A spectral representation (i.e., a parametric representation) of robustness measures that supports sampling continuous posterior trajectories

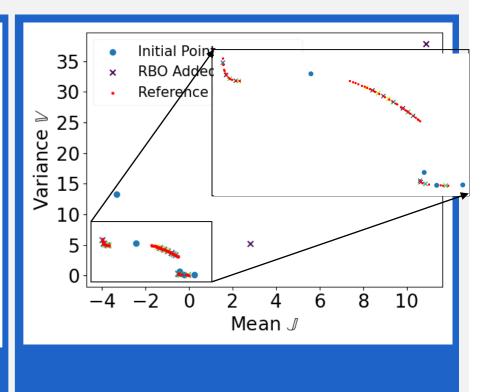
# Application in Robust Bayesian Optimization

- Supports variousproblem formulations
- Supports variousacquisition functions

### Proof of Concept







Pareto frontier

1.0







**Benchmark Function** 





### **Jixiang Qing**

Ph.D. Candidate at Ghent University

**IDLAB-IMEC** 

E Jixiang.Qing@ugent.be

M +32 486514628

W https://github.com/TsingQAQ

www.ugent.be

- f Universiteit Gent
- @ugent
- @ @ugent
- in Ghent University
  Code is available at:

https://github.com/TsingQAQ/gp\_mean\_var\_rbo







