Simulation based uncertainty handling with polyhedral clouds

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Motivation

Challenges in many real-life applications:

- handling of uncertain parameters
  - $\longrightarrow$ incomplete information
  - $\longrightarrow$ high-dimensional uncertainties
- robust optimization
  - $\longrightarrow$ bilevel formulation
  - $\longrightarrow$ extra effort to account for robustness
  - $\longrightarrow$ black box objective functions

Potential clouds

- n-dimensional random vector ε
- potential function $V : \mathbb{R}^n \to \mathbb{R}$

Construct

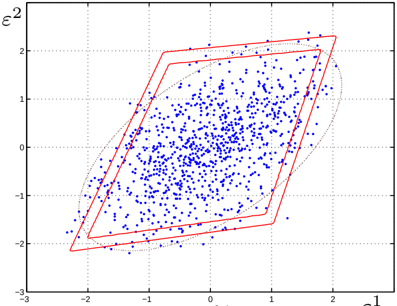
- lower α-cut $\underline{C}_\alpha := \{x \in \mathbb{R}^n \mid V(x) \leq \underline{V}_\alpha\}$
  contains at most a fraction of α of all possible scenarios
- upper α-cut $\overline{C}_\alpha := \{x \in \mathbb{R}^n \mid V(x) \leq \overline{V}_\alpha\}$
  contains at least a fraction of α of all possible scenarios

$\Rightarrow$ nested regions defining a **potential cloud**

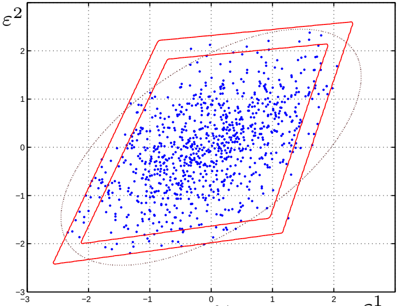
How?

- regard $V(\varepsilon)$ as a 1-dimensional random variable
- find an enclosure of the CDF of $V(\varepsilon)$

Example



90%



95%

- level sets of V chosen polyhedral shaped
- α-cuts reasonably approximate the confidence regions linearly

Problem formulation

$$\min_{\theta\in\mathbf{T}} \max_{\varepsilon\in\mathcal{C}} g(\theta,\varepsilon) \tag{1}$$

- bilevel problem
- nonlinear or black box objective function $g : \mathbf{T} \times \mathcal{C} \to \mathbb{R}$
- possibly mixed integer programming (depending on $\mathbf{T}$)
- $\varepsilon \in \mathcal{C}$ represents the uncertainties

Worst-case search

The inner level represents the **worst-case search**, i.e., for fixed $\theta \in \mathbf{T}$,

$$\max_{\varepsilon \in \mathcal{C}} \; g(\theta, \varepsilon). \tag{2}$$

- replaces nominal objective function

$\longrightarrow$ produces overhead of treating uncertainties

- g can be computationally expensive, ε can be high-dimensional

$\longrightarrow$ worst-case search can be prohibitively expensive

$\Rightarrow$ speed-up required

Polyhedral uncertainty

- $f(\varepsilon) := g(\theta, \varepsilon)$ for fixed θ
- $\mathcal{C} := \{\varepsilon \mid A(\varepsilon - m) \leq b\}$, a polyhedral α-cut

$\Rightarrow$ worst-case search becomes

$$\max_{\varepsilon} \; f(\varepsilon) \quad \text{s.t.} \; A(\varepsilon - m) \leq b. \tag{3}$$

- classical approach: linearize f and solve LP
- simulation based approach for bound constraints $\varepsilon \in b_0$ and linear f: **Cauchy deviates method**

$$[\min_{\varepsilon} f(\varepsilon), \max_{\varepsilon} f(\varepsilon)] \quad \text{s.t.} \; \varepsilon \in b_0. \tag{4}$$

Modified Cauchy deviates method

1. evaluation at center
   - compute $f(m)$
2. sample $\mathcal{C}$ uniformly
   - rejection step
3. transformation to Cauchy distribution via inverse Cauchy CDF
   - sample point x_i possibly outside $\{\mathcal{C} - m\}$
4. normalization step
   - $K = \left\| \frac{Ax_i}{b} \right\|_\infty \Rightarrow \frac{x_i}{K} \in \{\mathcal{C} - m\}$
5. simulated deviation
   - $\delta_i = K(f_i - f(m))$, with $f_i := f\left(\frac{x_i}{K} + m\right)$
6. thus generate N sample points $\delta_1, \ldots, \delta_N$

Modified Cauchy deviates method ctd.

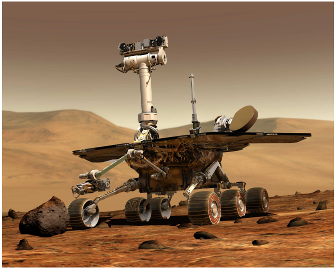
$\longrightarrow$ estimate the deviation Δ of f in $\mathcal{C}$ via max-likelihood from $\delta_1, \ldots, \delta_N$

$\longrightarrow$ approximate solution

$$\max_{\varepsilon \in \mathcal{C}} f(\varepsilon) \approx f(m) + \Delta \tag{5}$$

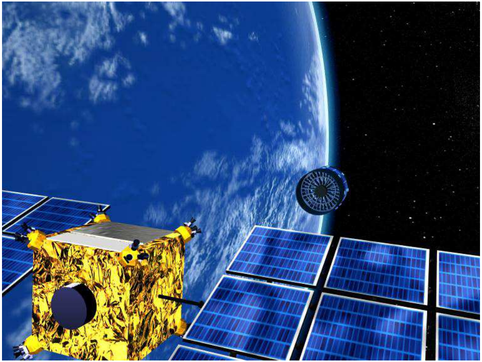
- tractable estimation error even for very small N
- can be easily parallelized

Mars Exploration Rover (MER) – ADCS Subsystem



- **A**ttitude **D**etermination and **C**ontrol **S**ystem (**ADCS**)
- 1-dimensional design problem, 30 choices
- complex uncertainty info, 34 dimensions

XEUS mission – permanent space-borne X-ray observatory



- complex design problem, 10 dimensions, $4 \times 14 \times 6 \times 8 \times 5 \times 20 \times 9 \times 44 \times 30 \geq 3 \cdot 10^9$ discrete choices, 1 continuous choice variable
- box uncertainty, 24 dimensions

Results

Number of simulation based worst-case estimations within close range (40% error) of linearization based worst-case searches:

	number of estimations	**close results**	**percentage**
MER	400	384	96.0%
XEUS	5340	5154	96.5%

Number of simulation based solutions within close range of solutions from linearization based robust optimization:

	number of optimizations	**same results**	5% **close results**	40% **close results**	**average error**
MER	10	2	6	10	7.3%
XEUS	10	0	0	9	22%

Summary

- polyhedral clouds capture and processes incomplete and unformalized information
- we embed clouds as the worst-case search in robust optimization
- high-dimensional worst-case search benefits from simulation based speed-up

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