

Robust Sample Average Approximation

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Reference: D. Bertsimas, V. Gupta, N. Kallus, Robust Sample Average Approximation,
Mathematical Programming, 2018.

Stochastic optimization with unknown distribution

Given a decision space $\mathcal{X} \subseteq \mathbb{R}^{d_x}$ and an uncertain parameter $\xi \in \Xi \subseteq \mathbb{R}^d$ with unknown distribution F , we consider the stochastic optimization problem

$$\min_{x \in \mathcal{X}} \mathbb{E}_{\xi \sim F} [c(x; \xi)].$$

Here:

- ▶ x is the decision variable,
- ▶ $c(x; \xi)$ is the cost incurred when uncertainty ξ realizes,
- ▶ F is the **true but unknown** distribution of ξ .

Baseline: Sample Average Approximation (SAA)

- ▶ **Idea.** Replace the unknown distribution F by the empirical distribution constructed from observed samples ξ^1, \dots, ξ^N .
- ▶ **Empirical distribution.**

$$\hat{F} = \frac{1}{N} \sum_{j=1}^N \delta_{\xi^j}.$$

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- ▶ **SAA problem.**

$$\hat{z}_{\text{SAA}} = \min_{x \in \mathcal{X}} \mathbb{E}_{\hat{F}}[c(x; \xi)] = \min_{x \in \mathcal{X}} \frac{1}{N} \sum_{j=1}^N c(x; \xi^j).$$

Remark. SAA is asymptotically consistent under mild conditions [6], i.e., $\hat{z}_{\text{SAA}} \rightarrow z^*$ as $N \rightarrow \infty$.

Motivation

- ▶ **SAA is asymptotically correct.** As the sample size grows, the SAA solution converges to the true optimum.
- ▶ **The real issue is finite-sample instability.** With limited data, the SAA solution can be highly sensitive to small data perturbations, especially under heavy-tailed noise.
- ▶ **No reliable finite-sample performance guarantee.** In general, there is no clean, non-asymptotic upper bound on the true out-of-sample performance of the SAA solution.

A common workaround: two-sample SAA (2-SAA).

- ▶ Use one part of the data for optimization and the other for evaluation;
- ▶ Apply classical concentration results (e.g., Student- t).

Limitation. Data splitting increases variance and may fail under heavy-tailed distributions [3].

Distribution-first approach

- ▶ Construct a data-driven ambiguity set \mathcal{F}_N such that

$$\Pr(F \in \mathcal{F}_N) \geq 1 - \alpha.$$

- ▶ Define the robust objective

$$\hat{z}(x) := \sup_{F_0 \in \mathcal{F}_N} \mathbb{E}_{F_0}[c(x; \xi)].$$

Interpretation. Among all distributions that are statistically plausible given the data, evaluate the decision under the worst-case expected cost.

Key challenge: \mathcal{F}_N lives in the space of probability distributions, so the inner problem is **infinite-dimensional** in general.

Robust SAA: the core objective

Goal. Construct an upper bound $\widehat{z}(x)$ such that, for confidence $1 - \alpha$,

$$\Pr(\mathbb{E}_F[c(x; \xi)] \leq \widehat{z}(x), \forall x \in \mathcal{X}) \geq 1 - \alpha.$$

Key idea.

- ▶ Not to directly modify the objective;
- ▶ But to first construct a *confidence region* for the unknown distribution F .

General structure of the robust problem

- ▶ The decision variable in the inner problem is a *distribution*;
- ▶ A distribution is a function object (infinite-dimensional);
- ▶ The inner problem

$$\sup_{F_0 \in \mathcal{F}_N} \mathbb{E}_{F_0}[c(x; \xi)]$$

is therefore an infinite-dimensional optimization problem.

From GoF confidence regions to tractable formulations

General picture.

- ▶ goodness-of-fit (GoF) tests (KS, CvM, AD, χ^2 , etc.) induce confidence regions in the space of probability distributions [4, 7];
- ▶ These regions define the ambiguity set \mathcal{F}_N ;
- ▶ Under suitable structure, the worst-case expectation can be computed via convex optimization.

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Remark. Depending on the test and cost structure, the resulting formulation may be an LP, SOCP, or other convex program.

A representative case: discrete / scenario-based formulation

Remark. To illustrate tractability, we consider a discrete (or discretized) formulation, which yields a representative finite-dimensional model.

Scenario representation. Let $\{\xi^1, \dots, \xi^m\}$ be a finite set of scenarios. Any distribution is represented by a probability vector $p \in \Delta_m := \{p \geq 0 : \mathbf{1}^\top p = 1\}$.

Polyhedral ambiguity set (discrete case)

From SAA to Robust SAA. Recall that SAA replaces the true distribution by the empirical distribution constructed from data.

Empirical distribution. Let \hat{p}_i denote the empirical frequency of scenario i .

Robustification via confidence bounds. Instead of trusting the empirical distribution exactly, we construct componentwise confidence bounds

$$\ell_i \leq p_i \leq u_i$$

such that

$$\Pr(\ell_i \leq p_i \leq u_i, \forall i) \geq 1 - \alpha.$$

Resulting ambiguity set.

$$\mathcal{F}_N = \{p \in \mathbb{R}^m : \ell \leq p \leq u, \mathbf{1}^\top p = 1\}.$$

Robust SAA: min–sup formulation

For a decision $x \in \mathcal{X}$, define scenario costs

$$c_i(x) := c(x; \xi^i), \quad c(x) := (c_1(x), \dots, c_m(x))^\top.$$

$$\widehat{z}(x) = \sup_{p \in \mathcal{F}_N} c(x)^\top p, \quad \widehat{z}^* = \min_{x \in \mathcal{X}} \widehat{z}(x).$$

Structure.

- ▶ Inner problem: worst-case expectation;
- ▶ Outer problem: decision optimization.

Inner problem: a linear program (discrete case)

Fix x . The inner problem is

$$\max_{p \in \mathbb{R}^m} c(x)^\top p \quad \text{s.t.} \quad \ell \leq p \leq u, \quad \mathbf{1}^\top p = 1.$$

This is an LP:

- ▶ Linear objective;
- ▶ Linear constraints.

Interpretation. Find the statistically plausible distribution that maximizes expected cost.

Single-level reformulation via strong duality

By strong duality of linear programming [1], for each fixed x ,

$$\sup_{p \in \mathcal{F}_N} c(x)^\top p = \min_{\lambda, \mu \geq 0, \nu \in \mathbb{R}} \nu + u^\top \lambda - \ell^\top \mu \quad \text{s.t.} \quad \lambda - \mu + \nu \mathbf{1} \geq c(x).$$

Thus the robust SAA problem becomes a single convex optimization problem.

If \mathcal{X} is polyhedral and $c_i(x)$ is linear or piecewise-linear, this formulation reduces to an LP.

Finite-sample validity of robust SAA

Theorem. Finite-sample validity (uniform upper bound)

Let $\xi^1, \dots, \xi^N \sim F$ be IID samples and let $\mathcal{F}_N = \mathcal{F}_N(\xi^1, \dots, \xi^N)$ be a (random) ambiguity set constructed from the data such that

$$\Pr(F \in \mathcal{F}_N) \geq 1 - \alpha.$$

Define the robust SAA objective for any $x \in \mathcal{X}$ by

$$\hat{z}(x) := \sup_{F_0 \in \mathcal{F}_N} \mathbb{E}_{F_0}[c(x; \xi)].$$

Then, with probability at least $1 - \alpha$,

$$\sup_{x \in \mathcal{X}} (\mathbb{E}_F[c(x; \xi)] - \hat{z}(x)) \leq 0.$$

Implication. The optimal value of robust SAA is a high-confidence upper bound on the true optimal value of the stochastic program, without data splitting.

Asymptotic behavior of robust SAA

Theorem. Asymptotic consistency

Let $\{\xi^1, \dots, \xi^N\}$ be IID samples drawn from the true distribution F . Assume that the ambiguity set $\mathcal{F}_N = \mathcal{F}_N(\xi^1, \dots, \xi^N)$ is constructed such that

$$\Pr(F \in \mathcal{F}_N) \rightarrow 1 \quad \text{as } N \rightarrow \infty,$$

and that \mathcal{F}_N shrinks to $\{F\}$ in the sense that

$$\sup_{F_0 \in \mathcal{F}_N} |\mathbb{E}_{F_0}[c(x; \xi)] - \mathbb{E}_F[c(x; \xi)]| \rightarrow 0 \quad \text{for each fixed } x \in \mathcal{X}.$$

Then, for any fixed $x \in \mathcal{X}$, the robust SAA objective

$$\hat{z}(x) := \sup_{F_0 \in \mathcal{F}_N} \mathbb{E}_{F_0}[c(x; \xi)]$$

converges to the true expected cost:

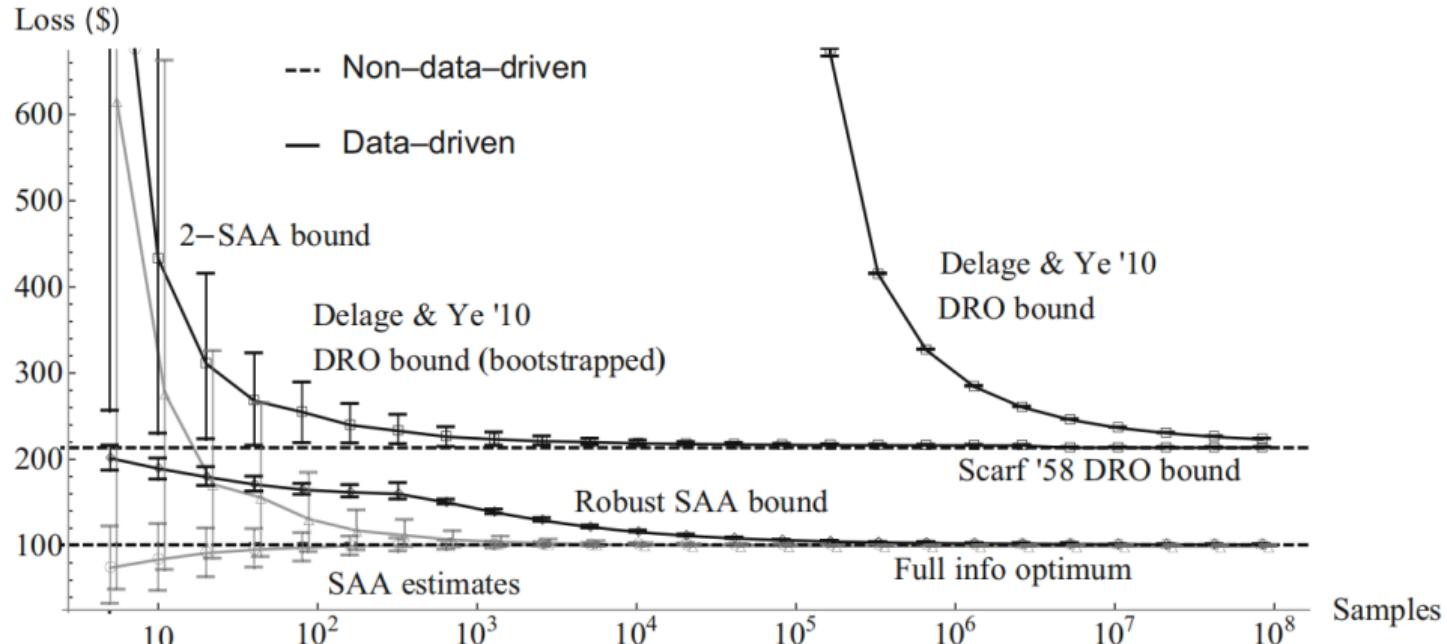
$$\hat{z}(x) \rightarrow \mathbb{E}_F[c(x; \xi)] \quad \text{as } N \rightarrow \infty.$$

Consistency properties across statistical tests

Table 1 Summary of convergence results

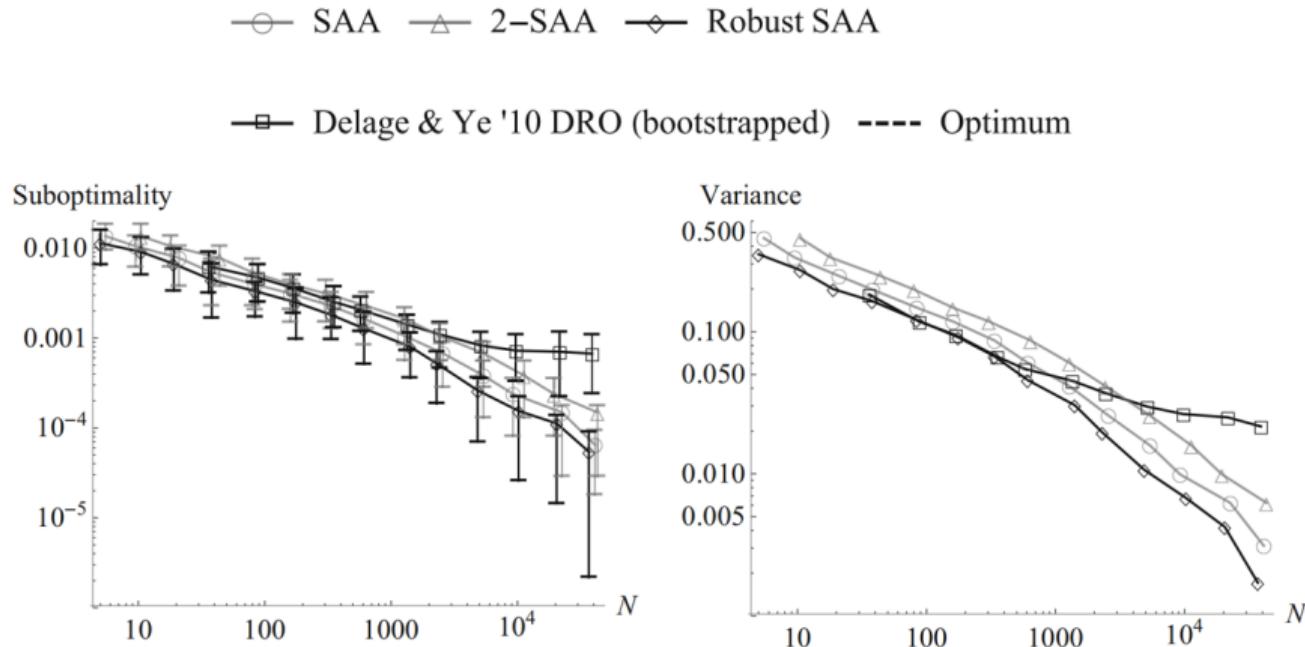
GoF test	Support	Consistent	Uniformly consistent
χ^2 and G-test	Finite	Yes	Yes
KS, Kuiper, CvM, Watson, and AD tests	Univariate	Yes	Yes
Test of marginals using the above tests	Multivariate	No	No
LCX-based test	Multivariate, bounded	Yes	Yes
LCX-based test	Multivariate, unbounded	Yes	?
Tests implied by DUSs of [13, 15]	Multivariate	No	No

Finite-sample behavior: comparison of upper bounds



Real-world application: portfolio allocation

- ▶ **Problem.** Portfolio allocation under distributional uncertainty, with a risk-sensitive objective (e.g., CVaR) [5].
- ▶ **Result.**



References

- [1] Stephen Boyd and Lieven Vandenberghe. *Convex Optimization*. Cambridge University Press, Cambridge, 2004.
- [2] Erick Delage and Yinyu Ye. Distributionally robust optimization under moment uncertainty with application to data-driven problems. *Operations Research*, 58(3):595–612, 2010.
- [3] Bradley Efron and Robert J. Tibshirani. *An Introduction to the Bootstrap*. Chapman and Hall/CRC, New York, 1993.
- [4] Erich L. Lehmann and Joseph P. Romano. *Testing Statistical Hypotheses*. Springer, New York, 3 edition, 2005.
- [5] R. Tyrrell Rockafellar and Stanislav Uryasev. Optimization of conditional value-at-risk. *Journal of Risk*, 2(3):21–42, 2000.
- [6] Alexander Shapiro, Darinka Dentcheva, and Andrzej Ruszczynski. *Lectures on Stochastic Programming: Modeling and Theory*. SIAM, Philadelphia, 2009.
- [7] Michael A. Stephens. Edf statistics for goodness of fit and some comparisons. *Journal of the American Statistical Association*, 69(347):730–737, 1974.