

Distributionally Robust Optimization

Stochastic Programming

- Consider the following stochastic program:

$$\underset{x \in \mathcal{X}}{\text{maximize}} \quad \mathbb{E} [g_0(x, Z)] \quad (8.1a)$$

$$\text{subject to} \quad \mathbb{E} [g_j(x, Z)] \leq b_j, \forall j = 1, \dots, J \quad (8.1b)$$

- This model is quite flexible: bounds on probability, expected utility models, risk measures, etc.
- DRO questions the assumption that the distribution of Z is known

Ellsberg's urn game

- Consider a game in which two urns are presented to you
 - Urn #1 has an equal amount of blue and red balls inside
 - Urn #2 also has red and blue balls but of unknown proportion
- You are asked to choose between urn #1 & #2.
- I will draw a ball from the chosen urn
 - If you chose urn #1 and a red ball is drawn, you win 1000\$
 - If you chose urn #2 and a red ball is drawn, you win 1100\$
- What would you choose?

A strict preference for urn #1 demonstrates ambiguity aversion

Distributionally Robust Optimization

- Assume that one only knows that $F \in \mathcal{D}$
 - E.g. 1: normal distrib. with mean and covariance in some confidence region
 - E.g. 2: distribution supported on some region with known mean
- Instead of maximizing expected value, maximize the worst-case expected value (similarly for constraints)

$$\underset{x \in \mathcal{X}}{\text{maximize}} \quad \inf_{F \in \mathcal{D}} \mathbb{E}_F[g_0(x, Z)] \quad (8.2a)$$

$$\text{subject to} \quad \mathbb{E}_F[g_j(x, Z)] \leq b_j, \quad \forall j = 1, \dots, J, \quad \forall F \in \mathcal{D}. \quad (8.2b)$$

- In this chapter, we focus on :

$$\underset{x \in \mathcal{X}}{\text{minimize}} \quad \sup_{F \in \mathcal{D}} \mathbb{E}_F[h(x, \xi)], \quad (8.3a)$$

Moment based
models

Mean and support models

- We would like to solve:

$$\underset{x \in \mathcal{X}}{\text{minimize}} \quad \sup_{F \in \mathcal{D}} \mathbb{E}_F[h(x, \xi)], \quad (8.3a)$$

where the distribution set takes the form

$$\mathcal{D}(\mathcal{Z}, \mu) = \left\{ F \in \mathcal{M} \mid \begin{array}{l} \mathbb{P}(\xi \in \mathcal{Z}) = 1 \\ \mathbb{E}[\xi] = \mu \end{array} \right\},$$

- E.g. : Markov inequality

$$P(\xi \geq a) \leq \sup_{F \in \mathcal{D}([0, \infty[, \mu)} E[\mathbf{1}\{\xi \geq a\}] = \begin{cases} 1 & \text{if } \mu \geq a \\ \mu/a & \text{otherwise.} \end{cases}$$

Semi-infinite linear programming duality

- The worst-case expected value problem looks like:

$$\underset{F \in \mathcal{M}}{\text{maximize}} \quad \int_{\mathcal{Z}} h(x, \xi) dF(\xi) \quad (8.4a)$$

$$\text{subject to} \quad \int_{\mathcal{Z}} dF(\xi) = 1 \quad (8.4b)$$

$$\int_{\mathcal{Z}} \xi dF(\xi) = \mu, \quad (8.4c)$$

- Duality theory for semi-infinite linear program states that if there exists a feasible distribution then dual problem is equivalent:

$$\underset{r,q}{\text{minimize}} \quad \mu^T q + r \quad (8.5a)$$

$$\text{subject to} \quad z^T q + r \geq h(x, z), \quad \forall z \in \mathcal{Z}, \quad (8.5b)$$

The main reformulation

Theorem 8.6. : Let $\mathcal{D}(\mathcal{Z}, \mu)$ be a distribution set for which there exists a feasible solution $F_0 \in \mathcal{D}(\mathcal{Z}, \mu)$, the DRO problem presented in (8.3) is equivalent to the following robust optimization problem:

$$\underset{x \in \mathcal{X}, q}{\text{minimize}} \quad \sup_{z \in \mathcal{Z}} h(x, z) + (\mu - z)^T q . \quad (8.11)$$

Moreover, the problem can be reformulated as follows when \mathcal{Z} is a convex set and $h(x, z) := \max_k h_k(x, z)$ where each $h_k(x, z)$ is a concave function of z :

$$\begin{aligned} & \underset{x \in \mathcal{X}, q, \{v_k\}_k, t}{\text{minimize}} \quad t + \mu^T q \\ & \text{subject to} \quad t \geq \delta^*(v_k | \mathcal{Z}) - h_*^k(x, v_k + q), \forall k , \end{aligned}$$

where for each k , $v_k \in \mathbb{R}^m$, while $\delta^*(v | \mathcal{Z})$ is the support function of \mathcal{Z} and $h_*^k(x, v)$ is the partial concave conjugate function of $h_k(x, z)$.

Example : Generalized Markov Inequality

- Consider trying to bound the following probability with respect to probabilities supported in the non-negative orthant with a mean of μ with \mathcal{U} as a convex set:

$$\mathbb{P}(\xi \in \mathcal{U})$$

- Based on Theorem 8.6, this can be measured using:

$$\begin{array}{ll} \text{minimize} & t \\ t, q, w & \end{array}$$

$$\text{subject to} \quad t \geq q^\top \mu + \delta^*(w|\mathcal{U}) + 1$$

$$t \geq q^\top \mu$$

$$q \geq -w$$

$$q \geq 0$$

Some intuition about the worst-case distribution

- We showed that the worst-case expected value problem is equivalent to:

$$\underset{r,q}{\text{minimize}} \quad \mu^T q + r \tag{8.5a}$$

$$\text{subject to} \quad z^T q + r \geq h(x, z), \forall z \in \mathcal{Z}, \tag{8.5b}$$

- For finite dimensional LP, it is well known that only $m+1$ constraints are needed to get an optimal solution
- There should therefore exist a set $\mathcal{Z}^* := \{z_1^*, z_2^*, \dots, z_{m+1}^*\}$ for which 8.5 becomes equivalent to

$$\underset{r,q}{\text{minimize}} \quad \mu^T q + r \tag{8.7a}$$

$$\text{subject to} \quad \xi^T q + r \geq h(x, z), \forall z \in \mathcal{Z}^*, \tag{8.7b}$$

Some intuition about the worst-case distribution

- The finite dimensional LP

$$\underset{r,q}{\text{minimize}} \quad \mu^T q + r \tag{8.7a}$$

$$\text{subject to} \quad \xi^T q + r \geq h(x, z), \forall z \in \mathcal{Z}^*, \tag{8.7b}$$

is equivalent to

$$\underset{p \in \mathbb{R}^{m+1}}{\text{maximize}} \quad \sum_{i=1}^{m+1} p_i h(x, z_i^*) \tag{8.8a}$$

$$\text{subject to} \quad \sum_i p_i = 1 \tag{8.8b}$$

$$\sum_{i=1}^{m+1} p_i z_i^* = \mu. \tag{8.8c}$$

Some intuition about the worst-case distribution

Theorem 8.2. : Let $\mathcal{Z} \in \mathbb{R}^m$ be a Borel set, and F_0 be some feasible distribution according to $\mathcal{D}(\mathcal{Z}, \mu)$, then problem (8.4) is equivalent to the following finite dimensional optimization problem

$$\underset{p, \{z_i\}_{i=1}^{m+1}}{\text{maximize}} \quad \sum_{i=1}^{m+1} p_i h(x, z_i) \quad (8.9a)$$

subject to
$$\sum_{i=1}^{m+1} p_i = 1 \quad \& \quad p \geq 0 \quad (8.9b)$$

$$\sum_{i=1}^{m+1} p_i z_i = \mu \quad (8.9c)$$

$$z_i \in \mathcal{Z}, \forall i = 1, \dots, m+1, \quad (8.9d)$$

where $p \in \mathbb{R}^{m+1}$ and each $z_i \in \mathbb{R}^m$.

Example : Mean-variance models

Example 8.7. : Consider that ξ is a random variable known to have a mean μ , and a variance of $\mathbb{E}[(\xi - \mu)^2] = \sigma^2$. This gives rise to the following DRO problem :

$$\underset{x \in \mathcal{X}}{\text{minimize}} \quad \sup_{F \in \mathcal{D}(\mu, \sigma^2)} \mathbb{E}_F[h(x, \xi)] ,$$

where

$$\mathcal{D}(\mu, \sigma^2) := \{F \mid \mathbb{P}(\xi \in \mathbb{R}) = 1, \mathbb{E}[\xi] = \mu, \mathbb{E}[(\xi - \mu)^2] = \sigma^2\} .$$

- Applying Theorem 8.6 we get:

$$\underset{x \in \mathcal{X}, q \in \mathbb{R}^2}{\text{minimize}} \quad \sup_{z_1 \in \mathbb{R}} h(x, z_1) + (\mu - z_1)q_1 + (\sigma^2 - (z_1 - \mu)^2)q_2$$

- If $h(x, z)$ is bounded below this reduces to:

$$\underset{x \in \mathcal{X}, q_1, q_2 \geq 0}{\text{minimize}} \quad \sup_{z_1 \in \mathbb{R}} h(x, z_1) + (\mu - z_1)q_1 + (\sigma^2 - (z_1 - \mu)^2)q_2$$

concave in z_1

Example: Support-mean-bounded covariance model

Example 8.8. : Consider that one has information about the support \mathcal{Z} , the mean μ , and an upper bound on the second order moment matrix of the type $\mathbb{E}[\xi\xi^T] \preceq \Sigma$ where $A \preceq B$ refers to the fact that $B - A$ is positive semi-definite, i.e. $z^T(B - A)z \geq 0$ for all $z \in \mathbb{R}^m$. This gives rise to the following DRO problem :

$$\underset{x \in \mathcal{X}}{\text{minimize}} \quad \sup_{F \in \mathcal{D}(\mathcal{Z}, \mu, \Sigma)} \mathbb{E}_F[h(x, \xi)] ,$$

where

$$\mathcal{D}(\mathcal{Z}, \mu, \Sigma) := \{F \mid \mathbb{P}(\xi \in \mathcal{Z}) = 1, \mathbb{E}[\xi] = \mu, \mathbb{E}[\xi\xi^T] \preceq \Sigma\} .$$

- Solution:

$$\underset{x \in \mathcal{X}, q, Q \succeq 0}{\text{minimize}} \quad \sup_{z \in \mathcal{Z}} h(x, z) + (\mu - z)^T q + \Sigma \bullet Q - z^T Q z$$

- See Wiesemann et al. [42] for many more moment models

Accounting for moment uncertainty

- Data-driven moment estimation leads to moment uncertainty
- DRO problem might instead take the form:

$$\underset{x \in \mathcal{X}}{\text{minimize}} \quad \sup_{\mu \in \mathcal{U}, F \in \mathcal{D}(\mathcal{Z}, \mu)} \mathbb{E}_F[h(x, z)]. \quad (8.13a)$$

Corollary 8.9. : Let $\mathcal{D}(\mathcal{Z}, \mu)$ be a distribution set and $\mathcal{U} \subseteq \mathbb{R}^m$ be a bounded uncertainty set for the moment vector μ . Given that there exists a feasible pair (μ_0, F_0) for which $\mu_0 \in \mathcal{U}$ and $F_0 \in \mathcal{D}(\mathcal{Z}, \mu_0)$, the DRO problem presented in (8.13) is equivalent to the following robust optimization problem:

$$\underset{x \in \mathcal{X}, q}{\text{minimize}} \quad \sup_{z \in \mathcal{Z}} h(x, z) - z^T q + \delta^*(q | \mathcal{U}) \quad (8.14a)$$

Mean-Covariance Uncertainty

Example 8.10. : In [24], the authors explain how independently and identically distributed samples $\{\xi_i\}_{i=1}^M$ from F can be used to construct the following uncertainty set:

$$\mathcal{D}(\mathcal{Z}, \hat{\mu}, \hat{\Sigma}, \gamma_1, \gamma_2) = \left\{ F \in \mathcal{M} \middle| \begin{array}{l} \mathbb{P}(\xi \in \mathcal{Z}) = 1 \\ (\mathbb{E}[\xi] - \hat{\mu})^T \hat{\Sigma}^{-1} (\mathbb{E}[\xi] - \hat{\mu}) \leq \gamma_1 \\ \mathbb{E}[(\xi - \hat{\mu})(\xi - \hat{\mu})^T] \preceq (1 + \gamma_2)\hat{\Sigma} \end{array} \right\} ,$$

- The parameters can be chosen such that this set has high probability of containing the true distribution

$$\begin{aligned} \underset{x \in \mathcal{X}, q, Q \succeq 0}{\text{minimize}} \quad & \sup_{z \in \mathcal{Z}} h(x, z) - z^T q - z^T Q z \\ & + ((1 + \gamma_2)\hat{\Sigma} - \hat{\mu}\hat{\mu}^T) \bullet Q + \hat{\mu}^T q + \sqrt{\gamma_1} \|\hat{\Sigma}^{1/2}(q + 2Q\hat{\mu})\|_2 \end{aligned}$$

We will exploit : $\delta^*([v_1^T \ v_2^T] \mid \mathcal{Z}_1 \times \mathcal{Z}_2) = \delta^*(v_1 \mid \mathcal{Z}_1) + \delta^*(v_2 \mid \mathcal{Z}_2)$

Exercise 8.1 + 8.2

Consider the following DRO problem:

$$\underset{x \in \mathcal{X}}{\text{minimize}} \quad \sup_{F \in \mathcal{D}_1} \mathbb{E}_F[\max(-\frac{1}{2}\xi^T Q(x)\xi, x^T C\xi)], \quad (8.17)$$

where $\mathcal{X} := \{x \in \mathbb{R}_+^n \mid Ax \leq b\}$ for some $A \in \mathbb{R}^{p \times n}$ and $b \in \mathbb{R}^p$, $Q(x) := \sum_{i=1}^n Q_i x_i$ with each $Q_i \in \mathbb{R}^{m \times m}$ such that $Q_i \succ 0$, and $C \in \mathbb{R}^{n \times m}$ such that each $C_{ij} \geq 0$.

Exercise 8.1. *Mean-support DRO problem*

Derive an explicit finite dimensional representation for the DRO problem (8.17) when

$$\mathcal{D}_1 := \{F \mid \mathbb{P}_F(\xi \in \mathcal{Z}) \geq 1, \mathbb{E}_F[\xi] = \bar{\mu}\},$$

where $\mathcal{Z} := \{z \in \mathbb{R}^m \mid Wz \leq v\}$, with $W \in \mathbb{R}^{p \times m}$, $v \in \mathbb{R}^p$, and $\bar{\mu} \in \mathbb{R}^n$.

Exercise 8.2. *DRO with moment uncertainty*

Derive an explicit finite dimensional representation for problem (8.17) when the distribution ambiguity set takes the form:

$$\mathcal{D}_2(\Gamma) := \{F \mid \mathbb{P}_F(\xi \in \mathcal{Z}) = 1, \mathbb{E}_F[\xi] \geq \bar{\mu}, \sum_i \mathbb{E}_F[\xi_i] - \bar{\mu}_i \leq \Gamma\}.$$

- Hint: Use Theorem 8.6 and Corollary 8.9

Theorem 8.6. : Let $\mathcal{D}(\mathcal{Z}, \mu)$ be a distribution set for which there exists a feasible solution $F_0 \in \mathcal{D}(\mathcal{Z}, \mu)$, the DRO problem presented in (8.3) is equivalent to the following robust optimization problem:

$$\underset{x \in \mathcal{X}, q}{\text{minimize}} \quad \sup_{z \in \mathcal{Z}} h(x, z) - z^T q + \mu^T q. \quad (8.11)$$

Moreover, the problem can be reformulated as follows when \mathcal{Z} is a convex set and $h(x, z) := \max_k h_k(x, z)$ where each $h_k(x, z)$ is a concave function of z :

$$\begin{aligned} & \underset{x \in \mathcal{X}, q, \{v_k\}_k, t}{\text{minimize}} \quad t + \mu^T q \\ & \text{subject to} \quad t \geq \delta^*(v_k | \mathcal{Z}) - h_*^k(x, v_k + q), \forall k, \end{aligned}$$

where for each k , $v_k \in \mathbb{R}^m$, while $\delta^*(v | \mathcal{Z})$ is the support function of \mathcal{Z} and $h_*^k(x, v)$ is the partial concave conjugate function of $h_k(x, z)$.

Corollary 8.9. : Let $\mathcal{D}(\mathcal{Z}, \mu)$ be a distribution set and $\mathcal{U} \in \mathbb{R}^m$ be a bounded and convex uncertainty set for the moment vector μ . Given that for all $\mu \in \mathcal{U}$, there exists an $F \in \mathcal{D}(\mathcal{Z}, \mu)$, the DRO problem presented in (8.14) is equivalent to the following robust optimization problem:

$$\underset{x \in \mathcal{X}, q}{\text{minimize}} \quad \sup_{z \in \mathcal{Z}} h(x, z) - z^T q + \delta^*(q | \mathcal{U}). \quad (8.15a)$$

Moreover, the problem can be reformulated as follows when \mathcal{Z} is a convex set and $h(x, z) := \max_k h_k(x, z)$ where each $h_k(x, z)$ is a concave function:

$$\begin{aligned} & \underset{x \in \mathcal{X}, q, \{v_k\}_k, t}{\text{minimize}} \quad t + \delta^*(q | \mathcal{U}) \\ & \text{subject to} \quad t \geq \delta^*(v_k | \mathcal{Z}) - h_*^k(x, v_k + q), \forall k, \end{aligned}$$

where for each k , $v_k \in \mathbb{R}^m$, while $\delta^*(v | \mathcal{Z})$ is the support function of \mathcal{Z} and $h_*^k(x, v)$ is the partial concave conjugate function of $h_k(x, z)$.

Table 6.1: Table of reformulations for uncertainty sets (Table 1 in [8])

Uncertainty region \mathcal{Z}	Support function $\delta^*(v \mathcal{Z})$
Box	$\rho\ v\ _1$
Ball	$\rho\ v\ _2$
Polyhedral	$\inf_{w \geq 0: B^T w = v} b^T w$
Cone	$\inf_{w \in C^*: B^T w = v} b^T w$
KL-Divergence	$\inf_{u \geq 0} \sum_l z_l^0 u e^{(v_l/u)-1} + \rho u$
Geometric prog.	$\inf_{u \geq 0, w \geq 0: \sum_i d_i w_i = v} \sum_i \{w_i \ln \left(\frac{w_i}{\alpha_i u} \right) - w_i\} + \rho u$
Intersection	$\inf_{\{w_i\}: \sum_i w_i = v} \sum_i \delta^*(w^i \mathcal{Z}_i)$
Example	$\inf_{(w^1, w^2): w^1 + w^2 = v} \rho_1 \ w^1\ _\infty + \rho_2 \ w^2\ _2$
Minkowski sum	$\sum_i \delta^*(v \mathcal{Z}_i)$
Example	$\rho_\infty \ v\ _1 + \rho_2 \ v\ _2$
Convex hull	$\max_i \delta^*(v \mathcal{Z}_i)$
Example	$\max\{\rho_\infty \ v\ _1, (z^0)^T v + \rho_2 \ v\ _2\}$

Table 6.2: Table of reformulations for constraint functions (Table 2 in [8])

Constraint function	$g(x, z)$	Partial concave conjugate $g_*(x, v)$
Linear in z	$z^T g(x)$	$\begin{cases} 0 & \text{if } v = g(x) \\ -\infty & \text{otherwise} \end{cases}$
Concave in z , separable in z and x	$g(z)^T x$	$\sup_{\{s^i\}_{i=1}^n : \sum_{i=1}^n s^i = v} \sum_i x_i (g_i)_*(s^i/x_i)$
Example	$-\sum_i \frac{1}{2}(z^T Q_i z)x_i$	$\sup_{\{s^i\}_{i=1}^n : \sum_{i=1}^n s^i = v} -\frac{1}{2} \sum_{i=1}^n \frac{(s^i)^T Q_i^{-1} s^i}{x_i}$
Sum of functions	$\sum_i g_i(x, z)$	$\sup_{\{s^i\}_{i=1}^n : \sum_i s^i = v} \sum_i (g_i)_*(x, s^i)$
Sum of separable functions	$\sum_i g_i(x, z_i)$	$\sum_{i=1}^n (g_i)_*(x, v_i)$
Example	$-\sum_{i=1}^m x_i^{z_i},$ $x_i > 1, 0 \leq z \leq 1$	$\begin{cases} \sum_{i=1}^m \left(\frac{v_i}{\ln x_i} \ln \frac{-v_i}{\ln x_i} - \frac{v_i}{\ln x_i} \right) & \text{if } v \leq 0 \\ -\infty & \text{otherwise} \end{cases}$

Scenario based
models

Scenario based models

- An alternative to moment based models consists of using predefined scenarios:

$$\mathcal{Z} := \{z^1, z^2, \dots, z^K\}$$

- The DRO model takes the form:

$$\underset{x \in \mathcal{X}}{\text{minimize}} \quad \sup_{p \in \mathcal{U}} \sum_{k=1}^K p_k h(x, z^k)$$

- Pros : If all scenarios are covered, then DRO model can be asymptotically consistent in data-driven context (see Bayraksan & Love [5] for survey)

$$\sup_{p \in \mathcal{U}(\{\xi^i\}_{i=1}^M)} \sum_{k=1}^K p_k h(x, z^k) \xrightarrow[M \rightarrow \infty]{} E[h(x, \xi)]$$

- Cons: If some scenarios are missing, then there is no protection against them

Wasserstein distance based models
(see separate set of slides by D. Kuhn)
(see an example of implementation in
[RSOME](#) documentation)