

## Optimization with application in finance – exercises

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**HW:** Examples 4.3, 4.6.

### 4 Chance constrained programming

Chance constrained problem

$$\begin{aligned} \min_{x \in X} f(x) \\ \text{s.t. } P(g_1(x, \xi) \leq 0, \dots, g_r(x, \xi) \leq 0) \geq p, \end{aligned}$$

where  $p \in [0, 1]$  is given level,  $X \subseteq \mathbb{R}^n$  is a set of (deterministic) constraints,  $\xi$  is a real random vector on probability space  $(\Omega, \mathcal{F}, P)$ . If  $r > 1$ , then we speak about joint chance constraint, whereas  $r = 1$  corresponds to individual chance constraint.

For a given  $x \in X$ , the probability of  $\xi$  for which the random constraint is fulfilled must be at least  $p$ :

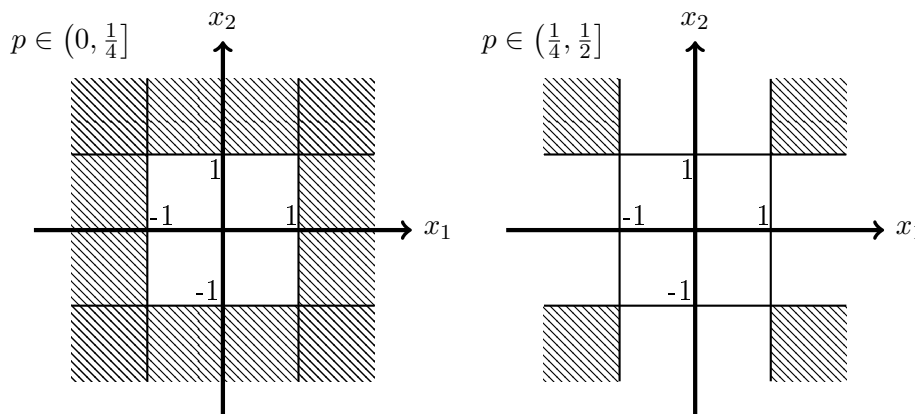
$$P(g_1(x, \xi) \leq 0, \dots, g_r(x, \xi) \leq 0) = P(\{\xi : g_1(x, \xi) \leq 0, \dots, g_r(x, \xi) \leq 0\}) \geq p.$$

**Example 4.1** Consider  $\xi = (\xi_1, \xi_2, \xi_3)$  with equiprobable realizations  $p_i = 1/4$ :  $(-1, 0, -1)$ ,  $(0, -1, -1)$ ,  $(1, 0, -1)$ ,  $(0, 1, -1)$ . For  $p \in [0, 1]$ , derive the set of feasible given by chance constraint:

$$X(p) = \{(x_1, x_2) \in \mathbb{R}^2 : P(\xi_1 x_1 + \xi_2 x_2 \leq \xi_3) \geq p\}.$$

Discuss the convexity of the set.

**Solution:** Realize that  $p \in (0, \frac{1}{4}]$  means that the random constraint is fulfilled for at least one realization of random vector  $\xi$ , whereas  $p \in (\frac{1}{4}, \frac{1}{2}]$  requires that the constraint is fulfilled for at least two realizations at the same time. This leads to these sets:



For  $p \in (0, \frac{1}{4}]$ , we have

$$X(p) = \{x_1 \geq 1\} \text{ or } \{x_2 \geq 1\} \text{ or } \{x_1 \leq -1\} \text{ or } \{x_2 \leq -1\},$$

whereas for  $p \in (\frac{1}{4}, \frac{1}{2}]$

$$X(p) = \{x_1 \geq 1, x_2 \geq 1\} \text{ or } \{x_1 \geq 1, x_2 \leq -1\} \\ \text{or } \{x_1 \leq -1, x_2 \geq 1\} \text{ or } \{x_1 \leq -1, x_2 \leq -1\}.$$

Moreover  $X(0) = \mathbb{R}^2$  and  $X(p) = \emptyset$  for  $p \in (\frac{1}{2}, 1]$ . Obviously the set is convex only in the trivial case for  $p = 0$ . Please realize that even though we used very simple chance constraint, the set is already nonconvex.  $\square$

**Example 4.2** Let  $\xi$  have a uniform distribution on interval  $[-1, 1]$ . Derive the reformulation of chance constraint

$$P\left(\xi(x_1 - x_2) \geq \frac{1}{2}\right) \geq \frac{1}{4}.$$

**Solution:** We can use the explicit formula for the distribution function of  $\xi$ , i.e.

$$F(x) = \begin{cases} 0, & x \leq -1, \\ \frac{x+1}{2}, & x \in [-1, 1], \\ 1, & x \geq 1. \end{cases}$$

Assume that  $x_1 \neq x_2$ . If  $x_1 > x_2$ ,

$$P\left(\xi(x_1 - x_2) \geq \frac{1}{2}\right) = 1 - P\left(\xi \leq \frac{1}{2(x_1 - x_2)}\right) = 1 - \frac{\frac{1}{2(x_1 - x_2)} + 1}{2} = \frac{2(x_1 - x_2) - 1}{4(x_1 - x_2)} \geq \frac{1}{4},$$

which holds if

$$x_1 - x_2 \geq 1.$$

If  $x_1 < x_2$ ,

$$P\left(\xi(x_1 - x_2) \geq \frac{1}{2}\right) = P\left(\xi \leq \frac{1}{2(x_1 - x_2)}\right) = \frac{\frac{1}{2(x_1 - x_2)} + 1}{2} = \frac{2(x_1 - x_2) + 1}{4(x_1 - x_2)} \geq \frac{1}{4},$$

which holds if

$$x_1 - x_2 \leq -1.$$

Other cases lead to empty set, so the chance constrain is equivalent to

$$x_1 - x_2 \geq 1 \text{ or } x_1 - x_2 \leq -1.$$

Realize that it is a *union* of two disjunctive half-spaces.  $\square$

**Example 4.3** Let  $\xi_1$  have a uniform distribution on interval  $[1, 4]$ ,  $\xi_2 \sim U[1/3, 1]$  and  $\xi_1, \xi_2$  be independent. Derive the explicit form of the chance constrained problem

$$\begin{aligned} \min_{x_1, 2} \quad & x_1 + x_2 \\ \text{s.t.} \quad & P(\xi_1 x_1 + x_2 \geq 7, \xi_2 x_1 + x_2 \geq 4) \geq p, \\ & x_{1,2} \geq 0. \end{aligned}$$

**Solution:** Use the independence and explicit formula for cdf of the uniform distribution. Be careful with the bounds where some of the probabilities is equal to 0 or 1.

**Example 4.4** Consider chance constrained problem

$$\begin{aligned} \max_{x_1, 2, 3} \quad & x_3 \\ \text{s.t.} \quad & P(\xi_1 x_1 + \xi_2 x_2 \leq x_3) = 0.37, \\ & P(3x_1 + 2x_2 \leq \xi_3) = 0.8, \\ & P(-x_1 + 4x_2 \leq \xi_4) = 0.9, \\ & x_{1,2} \geq 0. \end{aligned}$$

and assume that

$$\begin{pmatrix} \xi_1 \\ \xi_2 \end{pmatrix} \sim \mathcal{N}_2\left(\begin{pmatrix} -1 \\ 2 \end{pmatrix}, \begin{pmatrix} 10 & 7 \\ 7 & 20 \end{pmatrix}\right), \quad \begin{pmatrix} \xi_3 \\ \xi_4 \end{pmatrix} \sim \mathcal{N}_2\left(\begin{pmatrix} 3 \\ 3 \end{pmatrix}, \begin{pmatrix} 2 & 0.4 \\ 0.4 & 1 \end{pmatrix}\right).$$

Find a nonlinear programming reformulation.

**Solution:** Realize that under our distributional assumption it holds

$$\xi_1 x_1 + \xi_2 x_2 \sim \mathcal{N}(-x_1 + 2x_2, 10x_1^2 + 14x_1x_2 + 20x_2^2) =: \mathcal{N}(\mu(x), \sigma^2(x)).$$

Then we have

$$\begin{aligned} P(\xi_1 x_1 + \xi_2 x_2 \leq x_3) &= P\left(\frac{\xi_1 x_1 + \xi_2 x_2 - \mu(x)}{\sigma(x)} \leq \frac{x_3 - \mu(x)}{\sigma(x)}\right) \\ &= \Phi\left(\frac{x_3 - \mu(x)}{\sigma(x)}\right), \end{aligned}$$

where  $\Phi$  is cdf of  $\mathcal{N}(0, 1)$ . Then

$$\begin{aligned} \Phi\left(\frac{x_3 - \mu(x)}{\sigma(x)}\right) = 0.38 &\Leftrightarrow x_3 = \mu(x) + u_{0.38} \cdot \sigma(x) \\ &\Leftrightarrow x_3 = -x_1 + 2x_2 + u_{0.38} \cdot \sqrt{10x_1^2 + 14x_1x_2 + 20x_2^2}, \end{aligned}$$

where  $u_{0.38} = \Phi^{-1}(0.38)$ . We can use similar approach to the second chance constraint.

$$\begin{aligned} P(3x_1 + 2x_2 \leq \xi_3) &= P\left(\frac{3x_1 + 2x_2 - 3}{\sqrt{2}} \leq \frac{\xi_3 - 3}{\sqrt{2}}\right) \\ &= 1 - \Phi\left(\frac{3x_1 + 2x_2 - 3}{\sqrt{2}}\right) = 0.8 \\ &\Leftrightarrow 3x_1 + 2x_2 = 3 + u_{0.2} \cdot \sqrt{2}. \end{aligned}$$

The reformulation of the last constraint is analogous. Note that the dependence between  $\xi_3$  and  $\xi_4$  will not effect anything.  $\square$

**Example 4.5** Let  $f, g(\cdot, \xi) : \mathbb{R}^n \rightarrow \mathbb{R}$  be real functions,  $X \subseteq \mathbb{R}^n$ ,  $\xi$  be a real random vector,  $p \in (0, 1)$ :

$$\begin{aligned} \min_{x \in X} f(x) \\ \text{s.t. } P(g(x, \xi) \leq 0) \geq p. \end{aligned}$$

Let  $\xi$  has a finite discrete distribution with realizations  $\xi^1, \dots, \xi^S$  and probabilities  $p_s > 0$ ,  $\sum_{s=1}^S p_s = 1$ . Find a mixed-integer programming reformulation.

**Solution:** We can use  $S$  binary variables  $y_s$ .

$$\begin{aligned} \min_{x, y} f(x) \\ \text{s.t.} \\ \sum_{s=1}^S p_s y_s \geq p, \\ g(x, \xi_s) \leq M(1 - y_s), \quad s = 1, \dots, S \\ y_s \in \{0, 1\}, \quad s = 1, \dots, S, \\ x \in X, \end{aligned} \tag{1}$$

where  $M \geq \max_{s=1, \dots, S} \sup_{x \in X} g(x, \xi_s)$  is so called big-M constant. Realize that if  $y_s = 1$ , then the corresponding constraint  $g(x, \xi_s) \leq 0$  must be fulfilled and probability  $p_s$  contributes to fulfill the chance constraint, i.e. to reach the probability  $p$ . On the other hand, if the constraint is not fulfilled, i.e.  $g(x, \xi_s) > 0$ , then corresponding  $y_s = 0$ .  $\square$

**Example 4.6** Find reformulations of the Value at Risk portfolio optimization problem

$$\begin{aligned} \min_{z, x} z \\ \text{s.t. } P\left(-\sum_{i=1}^n R_i x_i \leq z\right) \geq p, \\ \sum_{i=1}^n \mathbb{E}[R_i] \cdot x_i \geq r_0, \\ \sum_{i=1}^n x_i = 1, \quad x_i \geq 0, \end{aligned}$$

where  $R_i$  is random rate of return of  $i$ -th asset and minimal expected return  $r_0$  is selected in such way that the problem is feasible. Assume that the distribution of returns is

1. discrete with realizations  $r_{is}$ ,  $s = 1, \dots, S$ , and probabilities  $p_s = 1/S$ ,
2. multivariate normal with mean  $\mu$  and variance matrix  $\Sigma$ .

## 4.1 Separated right-hand side

Let  $g : \mathbb{R}^n \rightarrow \mathbb{R}$  and  $\xi$  be a random variable with distribution function  $F$ ,  $p \in [0, 1]$ . Then the individual chance constraint with separated right-hand side is

$$P(g(x) \geq \xi) \geq p,$$

and it can be reformulated using the quantile function as

$$g(x) \geq F^{-1}(p).$$

Using so called  $p$ -level efficient points (pLEPs), this approach can be generalized to the joint chance constrained case, i.e. to reformulate

$$P(g_1(x) \geq \xi_1, \dots, g_r(x) \geq \xi_r) \geq p.$$

**Definition 4.7** Let  $\mathbf{X}$  be a  $r$ -dimensional random vector with distribution function  $F : \mathbb{R}^r \rightarrow [0, 1]$  and  $p \in [0, 1]$ . We say that  $z \in \mathbb{R}^r$  is a  $p$ -level efficient point (pLEP) if  $F(z) \geq p$  and there is no other  $y \in \mathbb{R}^r$  for which  $F(y) \geq p$  and  $y \leq z$ ,  $y \neq z$ .

Let  $\{z_1, \dots, z_n\} \subset \mathbb{R}^r$  be the set of pLEPs and  $\mathbf{g}(x) = (g_1(x), \dots, g_r(x))^T$ . Then the joint chance constraint is equivalent to

$$\mathbf{g}(x) \geq z \text{ for at least one } z \in \{z_1, \dots, z_n\}.$$

Sometimes it is written in the *disjunctive programming* form

$$\mathbf{g}(x) \in \bigcup_{i=1}^n \{z_i + \mathbb{R}_+^r\}.$$

**Example 4.8** Consider 6 equiprobable realizations of random vector:

$$\begin{pmatrix} 1 \\ 1 \end{pmatrix}, \begin{pmatrix} 1 \\ 2 \end{pmatrix}, \begin{pmatrix} 1 \\ 3 \end{pmatrix}, \begin{pmatrix} 2 \\ 1 \end{pmatrix}, \begin{pmatrix} 2 \\ 2 \end{pmatrix}, \begin{pmatrix} 2 \\ 3 \end{pmatrix}.$$

Find pLEPs for arbitrary  $p \in (0, 1]$ . Derive a deterministic reformulation for the chance constrained problem

$$\begin{aligned} & \min_{x \in X} f(x) \\ & \text{s.t. } P(g_1(x) \geq \xi_1, g_2(x) \geq \xi_2) \geq p. \end{aligned}$$

**Solution:** Compute the value of distribution function  $F$  in each point (in order):

$$\frac{1}{6}, \frac{1}{3}, \frac{1}{2}, \frac{1}{3}, \frac{2}{3}, 1.$$

Then, we can derive from the definition

$$\begin{aligned}
\text{pLEPs} &= \left\{ \begin{pmatrix} 2 \\ 3 \end{pmatrix} \right\}, p \in (2/3, 1], \\
&= \left\{ \begin{pmatrix} 2 \\ 2 \end{pmatrix} \right\}, p \in (1/2, 2/3], \\
&= \left\{ \begin{pmatrix} 1 \\ 3 \end{pmatrix}, \begin{pmatrix} 2 \\ 2 \end{pmatrix} \right\}, p \in (1/3, 1/2], \\
&= \left\{ \begin{pmatrix} 1 \\ 2 \end{pmatrix}, \begin{pmatrix} 2 \\ 1 \end{pmatrix} \right\}, p \in (1/6, 1/3], \\
&= \left\{ \begin{pmatrix} 1 \\ 1 \end{pmatrix} \right\}, p \in (0, 1/6].
\end{aligned}$$

Note that finding the set of pLEPs is in general highly demanding task and requires special algorithms. It is a serious research topic.

Then, the chance constrained problem is equivalent to

$$\begin{aligned}
&\min_{x \in X} f(x) \\
&\text{s.t. } g_1(x) \geq \xi_1, g_2(x) \geq \xi_2, \text{ for at least one } (\xi_1, \xi_2) \in \text{pLEPs.}
\end{aligned}$$

□

**Example 4.9** Consider compound Poisson distribution which characterizes the overall loss of a non-life insurance portfolio over 1 year period. Estimate the minimal level of portfolio premium such that the losses are covered with probability  $p$ .

**Solution:** Let  $\{X_i\}_{i=1}^{\infty}$  be iid positive random variables with finite second moment which model the claim severities and  $N \sim Po(\lambda)$  be independent on  $\{X_i\}$ . Then, our goal is to solve

$$\min_{x \in \mathbb{R}_+} x \text{ s.t. } P\left(\sum_{i=1}^N X_i \leq x\right) \geq p.$$

In fact, we would like to compute the quantile, or Value at Risk. However, this is a difficult task for any compound distribution even using modern mathematical software tools. An easy approach is to use a conservative approximation, in our case based on the *one-sided Chebyshev's inequality*<sup>1</sup>: for  $X \sim (\mu, \sigma^2)$ , and  $a > 0$ ,

$$P(X - \mu \geq a) \leq \frac{\sigma^2}{\sigma^2 + a^2}.$$

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<sup>1</sup>Its proof is not straightforward as for the traditional two-sided version. It is also known as Cantelli's inequality (under this name Wiki refers to several papers with a proof).

Now realize that for the moments of the compound Poisson distribution, it holds

$$\begin{aligned}\mu &:= \mathbb{E} \left( \sum_{i=1}^N X_i \right) = \mathbb{E}(N) \mathbb{E}(X_1) = \lambda \mathbb{E}(X_1), \\ \sigma^2 &:= \text{var} \left( \sum_{i=1}^N X_i \right) = \mathbb{E}(N) \text{var}(X_1) + (\mathbb{E}(X_1))^2 \text{var}(N) = \lambda \mathbb{E}(X_1^2).\end{aligned}$$

By applying the one-sided Chebyshev's inequality for  $x > \mu$ , we obtain

$$P \left( \sum_{i=1}^N X_i \geq x \right) = P \left( \sum_{i=1}^N X_i - \mu \geq x - \mu \right) \leq \frac{\sigma^2}{\sigma^2 + (x - \mu)^2} \leq 1 - p,$$

which is equivalent to

$$\begin{aligned}(x - \mu)^2 &\geq \frac{\sigma^2}{1 - p} - \sigma^2, \\ x &\geq \mu + \sqrt{\frac{p}{1 - p}} \sigma, \\ x &\geq \lambda \mathbb{E}(X_1) + \sqrt{\frac{p}{1 - p}} \sqrt{\lambda \mathbb{E}(X_1^2)}.\end{aligned}$$

To get the conservative estimate of safe premium, we can set  $x$  equal to the above expression. Realize that it is similar to the formula which we have obtained for the normal distribution, but instead of the normal quantile we are using  $\sqrt{\frac{p}{1-p}}$ . It can be shown that this is the most conservative (highest) value of quantile for the distribution with finite second moment.

Note that looking for new conservative tight approximations is still a serious research topic in stochastic optimization.  $\square$

**Summary:** You have seen several general approaches to deal with chance constraints:

- direct evaluation, Example 4.1
- reformulation using cumulative distribution function, Example 4.2, 4.3
- reformulation under Gaussian distribution using quantiles, Example 4.4
- mixed-integer reformulation using binary variables, Examples 4.5, 4.6
- generalized quantiles for separated random right-hand side, Example 4.8
- conservative approximation using probability inequalities, Example 4.9