

## 1 Outline

In this lecture, we cover

- modeling with VaR,
- comparing risk measures,
- the newsvendor problem with various risk measures.

## 2 Modeling with VaR

Assume that we can model any constraint of the form  $g(x, \xi_i) \leq b_i$ . Based on this, let us try to model

$$\text{VaR}_\alpha \left( g(x, \xi); \hat{P}_N \right) \leq 0.$$

This is equivalent to

$$\min \left\{ t : \mathbb{P}_{\xi \sim \hat{P}_N} [g(x, \xi) \leq t] > \alpha \right\} \leq 0.$$

We may rewrite this as

$$\begin{aligned} t &\leq 0 \\ \mathbb{P}_{\xi \sim \hat{P}_N} [g(x, \xi) \leq t] &> \alpha \end{aligned}$$

Without loss of generality, we can take  $t = 0$  and just consider

$$\mathbb{P}_{\xi \sim \hat{P}_N} [g(x, \xi) \leq 0] > \alpha.$$

This is because  $\mathbb{P}_{\xi \sim \hat{P}_N} [g(x, \xi) \leq 0]$  never decreases as  $t$  increases.

Therefore,  $\text{VaR}_\alpha \left( g(x, \xi); \hat{P}_N \right) \leq 0$  is equivalent to a **chance constraint**.

$$\mathbb{P}_{\xi \sim \hat{P}_N} [g(x, \xi) \leq 0] > \alpha \quad \Leftrightarrow \quad \mathbb{P}_{\xi \sim \hat{P}_N} [g(x, \xi) > 0] \leq 1 - \alpha.$$

To model this, we introduce binary variables  $z_i \in \{0, 1\}$  for  $i \in [N]$  for scenarios.

$$z_i = \begin{cases} 1, & \text{if } g(x, \xi_i) > 0 \\ 0, & \text{otherwise.} \end{cases}.$$

Basically, we add implications

$$z_i = 0 \quad \Rightarrow \quad g(x, \xi_i) \leq 0, \quad i \in [N]$$

This can be modelled with the big-M technique:

$$g(x, \xi_i) \leq M z_i, \quad i \in [N].$$

We need to ensure that the probability  $g(x, \xi) > 0$  is no greater than  $1 - \alpha$ :

$$\sum_{i \in [N]} p_i z_i \leq 1 - \alpha.$$

In summary,

$$\begin{aligned} \min \quad & f(x) \\ \text{s.t.} \quad & \text{VaR}_\alpha(g(x, \xi); \hat{P}_N) \leq 0 \\ & x \in \mathcal{X} \end{aligned}$$

is equivalent to

$$\begin{aligned} \min \quad & f(x) \\ \text{s.t.} \quad & g(x, \xi_i) \leq M z_i, \quad i \in [N] \\ & \sum_{i \in [N]} p_i z_i \leq 1 - \alpha \\ & x \in \mathcal{X}, \quad z \in \{0, 1\}^N \end{aligned}$$

### 3 Which risk measure should we use?

#### 3.1 Modeling aspects

Value at Risk (VaR) and Conditional Value at Risk (CVaR) can adjust the **degree of risk aversion** by adjusting the parameter  $\alpha$ . The higher the value of  $\alpha$ , the greater the risk aversion of the decision  $x$ . Note that

$$\begin{aligned} \lim_{\alpha \rightarrow 1} \text{VaR}_\alpha(g(x, \xi); \hat{P}_N) &= \max_{i \in [N]} g(x, \xi_i) \\ \lim_{\alpha \rightarrow 1} \text{CVaR}_\alpha(g(x, \xi); \hat{P}_N) &= \max_{i \in [N]} g(x, \xi_i). \end{aligned}$$

Therefore,

$$\begin{aligned} \lim_{\alpha \rightarrow 1} \text{VaR}_\alpha(g(x, \xi); \hat{P}_N) \leq 0 &\Leftrightarrow g(x, \xi_i) \leq 0 \quad \forall i \in [N] \\ \lim_{\alpha \rightarrow 1} \text{CVaR}_\alpha(g(x, \xi); \hat{P}_N) \leq 0 &\Leftrightarrow g(x, \xi_i) \leq 0 \quad \forall i \in [N] \end{aligned}$$

In contrast,

$$\begin{aligned} \lim_{\alpha \rightarrow 0} \text{VaR}_\alpha(g(x, \xi); \hat{P}_N) &= \min_{i \in [N]} g(x, \xi_i) \\ \lim_{\alpha \rightarrow 0} \text{CVaR}_\alpha(g(x, \xi); \hat{P}_N) &= \mathbb{E}_{\xi \sim \hat{P}_N} [g(x, \xi)]. \end{aligned}$$

Moreover, we always have

$$\text{CVaR}_\alpha(g(x, \xi); \hat{P}_N) \geq \text{VaR}_\alpha(g(x, \xi); \hat{P}_N).$$

The Conditional Value at Risk takes into account the **tail risk/tail probability** whereas the Value at Risk does not. Considering the tail risk is important for some applications, but it leads to more conservative solutions.

A guideline is as follows. CVaR is used when we have uncertain objectives or when computing VaR is too demanding. VaR is used when we have uncertain constraints.

### 3.2 Computational aspects

Expectation and worst-case value are relatively simple. Computing expectation requires a new function

$$\frac{1}{N} \sum_{i=1}^N g(x, \xi_i),$$

which is essentially the sum of functions  $g(x, \xi_1), \dots, g(x, \xi_N)$ . The worst-case value requires  $N$  constraints

$$g(x, \xi_i) \leq 0 \quad i \in [N].$$

CVaR requires adding new variables  $t, r_1, \dots, r_N$  that are all continuous and imposing  $2N + 1$  new constraints given by

$$\begin{aligned} t + \frac{1}{1 - \alpha} \sum_{i=1}^N p_i r_i &\leq 0 \\ r_i &\geq 0 \quad \forall i \in [N] \\ t + r_i &\geq g(x, \xi_i) \quad \forall i \in [N] \end{aligned}$$

VaR requires adding new binary variables  $z_1, \dots, z_N$  and  $N + 1$  new constraints given by

$$\begin{aligned} g(x, \xi_i) &\leq M z_i, \quad i \in [N] \\ \sum_{i \in [N]} p_i z_i &\leq 1 - \alpha \end{aligned}$$

Moreover, when using VaR and CVaR, we need to choose the parameter  $\alpha$ .

## 4 Newsvendor problem

Recall the newsvendor problem. The newsvendor must choose a quantity  $x \in \mathbb{Z}_+$  of newspapers to print on a particular day. The cost of printing a copy is  $c > 0$ . Each copy is sold at price  $p$ , and we assume that  $p > c$ . We also assume that each copy of unsold newspapers must be discarded at cost  $h > 0$ . The profit from printing  $x$  copies under customer demand  $\xi$  is given by

$$f(x, \xi) = p \cdot \min\{x, \xi\} - cx - h \cdot \max\{0, x - \xi\}.$$

The demand  $\xi$  is unknown, but we have historical data  $\xi_1, \dots, \xi_N$  that can be treated as scenarios. Note that

$$f(x, \xi) = \begin{cases} p\xi - cx - h(x - \xi), & \text{if } x \geq \xi, \\ px - cx & \text{if } x < \xi. \end{cases}$$

Moreover,  $p\xi - cx - h(x - \xi) \leq px - cx$  if and only if  $x \geq \xi$ . Hence, it follows that

$$f(x, \xi) = \min\{(p + h)\xi - (c + h)x, (p - c)x\}.$$

Here, we want to **maximize** the profit. Although the demand  $\xi$  is unknown, we define risk measures based on the data set  $\{\xi_1, \dots, \xi_N\}$ . Consider

$$\rho_f \left( x; \{\xi_i\}_{i \in [N]} \right).$$

Then we want to solve

$$\max_x \rho_f \left( x; \{\xi_i\}_{i \in [N]} \right).$$

Previously, we considered risk measures for the constraint function, with the goal of achieving a low value. However, for the newsvendor problem, we want to achieve a high profit. Nevertheless, the developments for the constraint function extend to the maximizing objective.

#### 4.1 Expectation

The expectation risk measure is given by

$$\rho_f \left( x; \{\xi_i\}_{i \in [N]} \right) = \frac{1}{N} \sum_{i=1}^N f(x, \xi_i).$$

Basically, we want to solve

$$\max \quad \frac{1}{N} \sum_{i=1}^N f(x, \xi_i).$$

This can be reformulated as

$$\begin{aligned} \max \quad & \frac{1}{N} \sum_{i=1}^N t_i \\ \text{s.t.} \quad & f(x, \xi_i) \geq t_i, \quad \forall i \in [N] \\ & x \in \mathbb{Z}_+ \end{aligned}$$

Plugging in the formula  $f(x, \xi) = \min\{(p+h)\xi - (c+h)x, (p-c)x\}$ , we obtain

$$\begin{aligned} \min \quad & \frac{1}{N} \sum_{i=1}^N t_i \\ \text{s.t.} \quad & (p+h)\xi_i - (c+h)x \geq t_i, \quad \forall i \in [N] \\ & (p-c)x \geq t_i, \quad \forall i \in [N] \\ & x \in \mathbb{Z}_+ \end{aligned}$$

#### 4.2 Worst-case value

Next, we consider

$$\rho_f \left( x; \{\xi_i\}_{i \in [N]} \right) = \min_{i \in [N]} f(x, \xi_i).$$

Here, the worst-case value is defined as the **minimum** of  $f(x, \xi_1), \dots, f(x, \xi_N)$ . Again, this is because we are trying to maximize the profit. Then we want to solve

$$\max_x \min_{i \in [N]} f(x, \xi_i).$$

This can be reformulated as

$$\begin{aligned} \max \quad & t \\ \text{s.t.} \quad & f(x, \xi_i) \geq t, \quad \forall i \in [N], \\ & x \in \mathbb{Z}_+ \end{aligned}$$

Plugging in the formula  $f(x, \xi) = \min\{(p + h)\xi - (c + h)x, (p - c)x\}$ , we obtain

$$\begin{aligned} \min \quad & t \\ \text{s.t.} \quad & (p + h)\xi_i - (c + h)x \geq t, \quad \forall i \in [N] \\ & (p - c)x \geq t, \quad \forall i \in [N] \\ & x \in \mathbb{Z}_+ \end{aligned}$$

### 4.3 Conditional Value at Risk

We may reformulate the problem  $\max_x f(x, \xi)$  as

$$\begin{aligned} \max \quad & v \\ \text{s.t.} \quad & f(x, \xi) \geq v. \end{aligned}$$

This is equivalent to

$$\begin{aligned} \max \quad & v \\ \text{s.t.} \quad & v - f(x, \xi) \leq 0. \end{aligned}$$

Then  $v - f(x, \xi)$  can be viewed as a constraint function. Here, the Conditional Value at Risk at level  $\alpha \in (0, 1)$  defined as

$$\begin{aligned} \text{CVaR}_\alpha \left( v - f(x, \xi); \hat{P}_N \right) &= \max \quad \frac{1}{1 - \alpha} \sum_{i=1}^N z_i \cdot (v - f(x, \xi_i)) \\ \text{s.t.} \quad & 0 \leq z_i \leq p_i \\ & \sum_{i=1}^N z_i = 1 - \alpha. \end{aligned}$$

By strong LP duality,

$$\begin{aligned} \text{CVaR}_\alpha \left( v - f(x, \xi); \hat{P}_N \right) &= \min \quad t + \frac{1}{1 - \alpha} \sum_{i=1}^N p_i r_i \\ \text{s.t.} \quad & r_i \geq 0, \quad i \in [N] \\ & t + r_i \geq v - f(x, \xi_i), \quad i \in [N]. \end{aligned}$$

Then

$$\text{CVaR}_\alpha \left( v - f(x, \xi); \hat{P}_N \right) \leq 0$$

can be written as

$$\begin{aligned} t + \frac{1}{1 - \alpha} \sum_{i=1}^N p_i r_i &\leq 0 \\ r_i &\geq 0, \quad i \in [N] \\ t + r_i &\geq v - f(x, \xi_i), \quad i \in [N]. \end{aligned}$$

Then we solve

$$\begin{aligned}
& \max \quad v \\
& \text{s.t.} \quad t + \frac{1}{1-\alpha} \sum_{i=1}^N p_i r_i \leq 0 \\
& \quad r_i \geq 0, \quad i \in [N] \\
& \quad v - t - r_i \leq f(x, \xi_i), \quad i \in [N] \\
& \quad x \in \mathbb{Z}_+.
\end{aligned}$$

Plugging in the formula  $f(x, \xi) = \min\{(p+h)\xi - (c+h)x, (p-c)x\}$ , we obtain

$$\begin{aligned}
& \max \quad v \\
& \text{s.t.} \quad t + \frac{1}{1-\alpha} \sum_{i=1}^N p_i r_i \leq 0 \\
& \quad r_i \geq 0, \quad i \in [N] \\
& \quad v - t - r_i \leq (p+h)\xi - (c+h)x, \quad i \in [N] \\
& \quad v - t - r_i \leq (p-c)x, \quad i \in [N] \\
& \quad x \in \mathbb{Z}_+.
\end{aligned}$$