

STOCHASTIC PROGRAMMING

December 7, 2023

Today:

- More on stochastic programming with recourse (metrics of interest, multi-stage)
- Beyond expected value: risk measures

① Assessing the value of stochastic programming

↳ Illustrated using two-stage stochastic programming

$$\text{minimize}_{x \in \mathbb{R}^n} \left\{ f(x) + \mathbb{E}_{\xi} [Q(x, \xi)] \right\} \text{ s.t. } x \in \mathcal{X}$$

$$\text{where } Q(x, \xi) = \min_{y \in \mathbb{R}^{m_2}} \left\{ g(y, \xi) \text{ s.t. } y \in \mathcal{Y}(x, \xi) \right\}$$

↳ Originally, the problem was

$$\text{minimize}_{x \in \mathbb{R}^n} \left\{ f(x) + Q(x, \xi) \right\} \text{ s.t. } x \in \mathcal{X} \quad \text{with } \xi \text{ being uncertain}$$

↳ Could we have considered

$$\text{minimize}_{x \in \mathbb{R}^n} \left\{ f(x) + Q(x, \mathbb{E}_{\xi}[\xi]) \right\} \text{ s.t. } x \in \mathcal{X} ?$$

$$\text{↳ How does } \mathbb{E}_{\xi} \left[\min_{x \in \mathbb{R}^n} \left\{ f(x) + Q(x, \xi) \right\} \text{ s.t. } x \in \mathcal{X} \right]$$

$$\text{Compare to } \min_{x \in \mathbb{R}^n} \left\{ f(x) + \mathbb{E}_{\xi} [Q(x, \xi)] \right\} \text{ s.t. } x \in \mathcal{X} ?$$

a) Expected value of perfect information (EVPI)

• Define the value of the recourse problem as

$$\text{VRP} = \min_{x \in \mathbb{R}^n} \left\{ f(x) + \mathbb{E}_{\xi} [Q(x, \xi)] \right\} \text{ s.t. } x \in \mathcal{X}$$

(optimal value of the two-stage stochastic program)

→ Deciding x before observing ξ

• We want to compare VRP with the value that one can get on average by waiting until ξ is observed

⇒ We define the expected wait-and-see cost as

$$EWS = \mathbb{E}_{\xi} \left[\min_{x \in \mathbb{R}^n} \{ f(x) + Q(x, \xi) \} \text{ s.t. } x \in X \right]$$

→ We wait until ξ is revealed to decide x

→ EWS is the average performance/cost of that approach

Def. The expected value of information (or EVPI) for the problem is given by $EVPI = VRP - EWS$

→ $EVPI \geq 0$ by property of the expected value

→ $EVPI = 0$: no interest in making the decision before observing ξ

→ $EVPI > 0$: represents the price one would pay to know the distribution of ξ in advance

b) Value of the stochastic solution

↳ An expected value decision for the problem is defined as

$$\bar{x} \in \operatorname{argmin}_{x \in \mathbb{R}^n} \{ f(x) + Q(x, \mathbb{E}_{\xi}[\xi]) \} \text{ s.t. } x \in X$$

Example

$$\text{minimize } x_1 + 4x_2 + Q(x, \xi) \\ x \in \mathbb{R}^2$$

$$\text{s.t. } \begin{aligned} x_1 + x_2 &= 1 \\ x_1, x_2 &\geq 0 \end{aligned}$$

$$Q(x, \xi) = \min_{y \in \mathbb{R}^3} \left\{ \begin{aligned} &y_1 + 10y_2 + 10y_3 \quad \text{s.t.} \quad y_1 + y_2 - y_3 = \xi + x_1 - 2x_2 \\ &y_1 \leq 2 \\ &y_1, y_2, y_3 \geq 0 \end{aligned} \right\}$$

- Suppose that ξ is uniformly distributed in $[1, 3]$

$$\text{Then } \text{EVPi} = 0 \text{ and } \text{VSS} = \frac{11}{4} > 0$$

$$\rightarrow x^* = \begin{bmatrix} 1/3 \\ 2/3 \end{bmatrix} \text{ is a solution of the problem for any } \xi \in [1, 3] \\ \Rightarrow \text{EVPi} = 0$$

\rightarrow When ξ is fixed to $\mathbb{E}_\xi[\xi] = 2$, there are multiple solutions to

$$\text{minimize } \left\{ \begin{aligned} &x_1 + 4x_2 + Q(x, 2) \quad \text{s.t.} \quad x_1 + x_2 = 1 \\ &x \in \mathbb{R}^2 \\ &x_1, x_2 \geq 0 \end{aligned} \right\}$$

that do not give the same value of

$$x_1 + 4x_2 + \mathbb{E}_\xi[Q(x, \xi)]$$

- Suppose now that $\xi \in \langle 0, \frac{3}{2}, 3 \rangle$ with $P(\xi=0) = P(\xi=3/2) = P(\xi=3) = 1/3$

$$\text{Then } \text{EVPi} = 3 > 0 \text{ and } \text{VSS} = 0$$

→ $\mathbb{E}_\xi[\xi] = 3/2$ and the fact that $(\frac{2}{3}, \frac{1}{3})$ is a solution for every possible value give $VSS = 0$

→ The solution sets for $\xi \in \{0, \frac{3}{2}, 3\}$ are not identical.

⇒ By picking different values $\bar{x}(0)$, $\bar{x}(\frac{3}{2})$ and $\bar{x}(3)$, we can show that

$$\begin{aligned} EWS &= \mathbb{E}_\xi \left[f(\bar{x}(\xi)) + Q(\bar{x}(\xi), \xi) \right] \\ &= \frac{1}{3} \times (f(\bar{x}(0)) + Q(\bar{x}(0), 0)) + \frac{1}{3} \times (f(\bar{x}(\frac{3}{2})) + Q(\bar{x}(\frac{3}{2}), \frac{3}{2})) \\ &\quad + \frac{1}{3} \times (f(\bar{x}(3)) + Q(\bar{x}(3), 3)) \end{aligned}$$

$$< f(x^*) + \frac{1}{3} (Q(x^*, 0) + Q(x^*, \frac{3}{2}) + Q(x^*, 3))$$

where x^* solves the two-stage recourse problem

Exercise: Consider
 minimize $\{ 2x + \mathbb{E}_\xi [Q(x, \xi)] \}$ s.t. $x \geq 0$
 $x \in \mathbb{R}$

where $Q(x, \xi) = \min_{y \in \mathbb{R}} \{ \xi \cdot y \}$ s.t. $y \geq 1-x, y \geq 0$

a) Give a closed-form expression for $Q(x, \xi)$

b) Suppose that $\xi \in \{1, 3\}$ with $P(\xi=1) = \frac{3}{4}$ and $P(\xi=3) = \frac{1}{4}$
 show that $EWS < CEV$

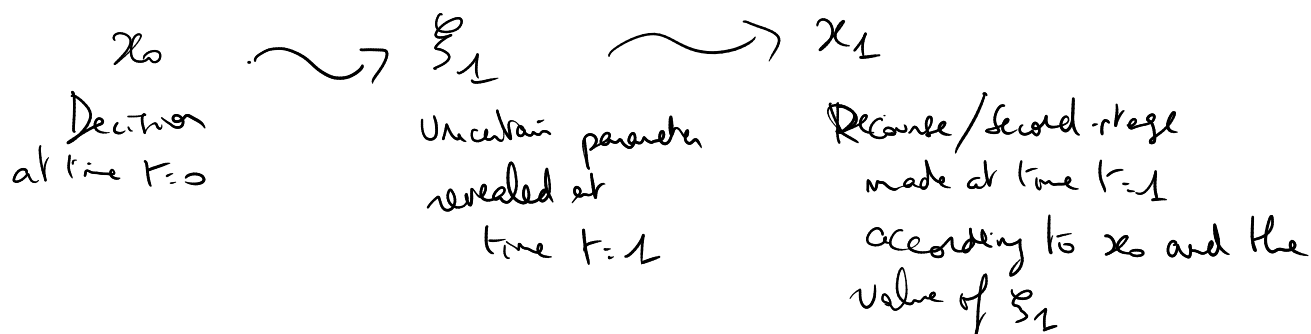
(2) From two-stage to multi-stage stochastic programs

Generic form of a two-stage program

$$\text{minimize}_{x_0 \in \mathbb{R}^{m_0}} \left\{ f_0(x_0) + \mathbb{E}_{\xi_1} [Q_1(x_0, \xi_1)] \right\} \text{ s.t. } x_0 \in X_0$$

$$\text{where } Q_1(x_0, \xi_1) = \min_{x_1 \in \mathbb{R}^{m_1}} \left\{ f_1(x_1, \xi_1) \text{ s.t. } x_1 \in X_1(x_0, \xi_1) \right\}$$

Models a two-step decision process



Multi-stage stochastic programming

$T+1$ stages where $T \geq 1$ (here T is finite)

$$x_0 \rightsquigarrow \xi_1 \rightsquigarrow x_1 \rightsquigarrow \xi_2 \rightsquigarrow \dots \rightsquigarrow \xi_T \rightsquigarrow x_T$$

Short notation

$$\text{minimize}_{x_0 \in X_0} \left\{ f_0(x_0) + \mathbb{E}_{\xi_1} \left[\min_{x_1 \in X_1(x_0, \xi_1)} f_1(x_1, \xi_1) + \mathbb{E}_{\xi_2} \left[\dots + \mathbb{E}_{\xi_T} \left[\min_{x_T \in X_T(x_{T-1}, \xi_T)} f_T(x_T, \xi_T) \right] \dots \right] \right] \right\}$$

Log version

$$\text{minimize}_{x_0 \in \mathbb{R}^{m_0}} f_0(x_0) + \mathbb{E}_{\xi_1} [Q(x_0, \xi_1)] \quad \text{s.t. } x_0 \in X_0$$

where

$$Q_1(x_0, \xi_1) = \min_{x_1 \in \mathbb{R}^{m_1}} \left\{ f_1(x_1, \xi_1) + \mathbb{E}_{\xi_2} [Q_2(x_1, \xi_2)] \quad \text{s.t. } x_1 \in X_1(x_0, \xi_1) \right\}$$

$$Q_t(x_{t-1}, \xi_t) = \min_{x_t \in \mathbb{R}^{m_t}} \left\{ f_t(x_t, \xi_t) + \mathbb{E}_{\xi_{t+1}} [Q_{t+1}(x_t, \xi_{t+1})] \quad \text{s.t. } x_t \in X_t(x_{t-1}, \xi_t) \right\}$$
$$\forall t = 1, \dots, T-1$$

$$Q_T(x_{T-1}, \xi_T) = \min_{x_T \in \mathbb{R}^{m_T}} \left\{ f_T(x_T, \xi_T) \quad \text{s.t. } x_T \in X_T(x_{T-1}, \xi_T) \right\}$$

- ↳ Two main approaches to multistage stochastic programming
- Scenario approach, essentially for linear multistage stochastic programs
 - Dynamic programming

a) Scenarios and linear multistage programming

Linear multistage stochastic program

$$f_t(x_t, \xi_t) = c_t^T x_t$$

$$X_t(x_{t-1}, \xi_t) = \left\{ x_t \mid B_t x_{t-1} + A_t x_t = b_t, x_t \geq 0 \right\}$$

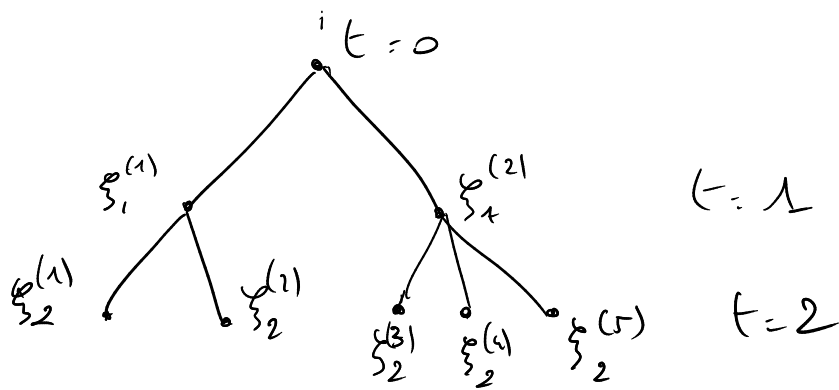
$$\xi_t = (A_t, B_t, b_t, c_t)$$

In that case, the problem can be reformulated as a linear program

$$\begin{aligned}
 & \text{minimize} && C_0^T x_0 + E_{S_1}[C_1^T x_1] + \dots + E_{S_T}[C_T^T x_T] \\
 & x_0 \in \mathbb{R}^{n_0} \\
 & \vdots \\
 & x_T \in \mathbb{R}^{n_T} \\
 & \text{s.t.} && A_0 x_0 &= b_0 \\
 & && B_1 x_0 + A_1 x_1 &= b_1 \\
 & && B_2 x_1 + A_2 x_2 &= b_2 \\
 & && \vdots \\
 & && B_T x_{T-1} + A_T x_T &= b_T \\
 & && x_0, x_1, \dots, x_T \geq 0
 \end{aligned}$$

→ We approximate this linear program using scenarios

⇒ We build a scenario tree



⇒ 5 Scenarios, each defining $(A_1, B_1, b_1, C_1, A_2, B_2, b_2, C_2)$

⇒ Can formulate the scenario problem by considering all scenarios with probabilities (p^1, \dots, p^5) such that

$$\sum_{k=1}^5 p^k = 1$$

$$\text{e.g. } E[C_1^T x_1] \Rightarrow \sum_{k=1}^5 p^k (C_1^k)^T x_1$$

$$A_1 x_0 + B_1 x_1 = b_1$$

⇓

$$\begin{cases} A_1^1 x_0 + B_1^1 x_1^1 = b_1^1 \\ \vdots \\ A_1^5 x_0 + B_1^5 x_1^5 = b_1^5 \end{cases}$$

Every scenario k has its own variables

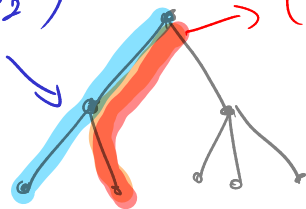
$$x_1^k, \dots, x_T^k$$

⇒ To guarantee consistency between the scenarios, we add non-anticipativity constraints

$$\forall t=1..T, \quad x_t^k = x_t^l \quad \text{for every pair } (k,l)$$

such that $(\xi_1^{(k)}, \dots, \xi_t^{(k)}) = (\xi_1^{(l)}, \dots, \xi_t^{(l)})$

$$(\xi_1^{(1)} = \xi_1, \xi_2^{(1)})$$



$$(\xi_1^{(2)} = \xi_1, \xi_2^{(2)})$$

NB: Not needed for two-stage stochastic program

Overall, the scenario approach gives a (very large) linear program, that we can decompose using variants of the L-shaped method (most common because it only requires a linear programming solver) or progressive hedging (requires a nonlinear programming solver)

Ex (J. Gordzic et al, 2005)

Linear six-stage stochastic program, scenario tree has 13 branches
 ⇒ Asset management problem for finance

\Rightarrow 4 million scenarios, 24 million variables,
12 million constraints

\Rightarrow Every iteration of the L-shaped required to solve
 ~ 2000 linear programs in parallel, each involving
 ~ 2000 variables

b) Dynamic programming

\rightarrow Idea: Break the multi-stage program into several
two-stages, solve it "backwards"

\rightarrow Problem formulation (from control theory)

Convention
(equivalent
to a
minimization
problem)

$$\begin{aligned} & \rightarrow \text{maximize}_{x_0, \dots, x_T} \mathbb{E}_{\xi_0, \dots, \xi_T} \left[\sum_{t=0}^T f_t(s_t, x_t, \xi_t) + f_{T+1}(s_{T+1}) \right] \\ & \text{s.t.} \quad s_{t+1} = \varphi_t(s_t, x_t, \xi_t) \quad \forall t=0, \dots, T \end{aligned}$$

s_t : state at time t , that obeys some dynamics

\hookrightarrow Dynamic programming works by computing the best
 x_t given (x_{t+1}, \dots, x_T)

Motivation: Bellman's optimality principle

$$\begin{aligned} \text{Define } V(s_0) &= \max_{x_0, \dots, x_T} \mathbb{E} \left[\sum_{t=0}^T f_t(s_t, x_t, \xi_t) + f_{T+1}(s_{T+1}) \right] \\ \text{and } V_t(s_t) &= \max_{x_t, \dots, x_T} \mathbb{E} \left[\sum_{u=t}^T f_u(s_u, x_u, \xi_u) + f_{T+1}(s_{T+1}) \right] \end{aligned}$$

$$\forall t=1, \dots, T$$

Then

$$\forall t=0, \dots, T \quad V_t(s_t) = \max_{x_t} \left\{ \mathbb{E}_{\xi_t} \left[f_t(s_t, x_t, \xi_t) + V_{t+1}(\varphi_t(s_t, x_t, \xi_t)) \right] \right\}$$

Algorithmic framework:

• solve maximize x_T $\mathbb{E}_{\xi_T} [f_T(s_T, x_T, \xi_T) + V_{T+1}(s_{T+1})]$
s.t. $s_{T+1} = \varphi_T(s_T, x_T, \xi_T)$

as a function of s_T

• For $t=T-1, \dots, 0$

solve maximize x_t $\mathbb{E}_{\xi_t} [f_t(s_t, x_t, \xi_t) + V_{t+1}(\varphi_t(s_t, x_t, \xi_t))]$

Classical setup: f_t is quadratic in x_t , φ_t is linear in s_t and x_t

Main software/algorithm: SDDP (Stochastic Dual
Dynamic Programming)
↓
SDDP.jl

RISK - AVERSE STOCHASTIC PROGRAMMING

↳ Basic approach to stochastic programming

$$\underset{x \in \mathbb{R}^m}{\text{minimize}} \quad \mathbb{E}_{\xi} [F(x, \xi)] \quad \text{s.t. } x \in \mathcal{X}$$

⇒ risk-neutral model: does not account for the full distribution of $F(x, \xi)$

⇒ $\mathbb{E}_{\xi} [\cdot]$ can be replaced by other measures that are more risk-averse, i.e. they provide guarantees with respect to values of $F(x, \xi)$ far from the average

Motivation: Finance

→ Suppose that $x \in \mathbb{R}^m$ represents a portfolio of allocations among m assets

→ Suppose that $\xi \in \mathbb{R}^m$ is a random vector of returns on investment

$$\text{Invest } x \quad \Rightarrow \quad \text{Return } \xi^T x$$

Risk-neutral investment: obtained by solving

$$\underset{x \in \mathbb{R}^m}{\text{maximize}} \quad \mathbb{E}_{\xi} [\xi^T x] \quad \text{s.t. } x \in \mathcal{X}$$

$= \mathbb{E}_{\xi} [\xi] ^T x$

(typically $x \geq 0$)
 $\sum x_i = 1$
suitable constraints

→ One way to take risk into account: Find the portfolio that minimizes the variance/dispersion

$$\begin{array}{ll} \text{minimize} & \mathbb{E}_{\xi} \left[\left((\xi - \mathbb{E}_{\xi}[\xi])^T x \right)^2 \right] \\ x \in \mathbb{R}^n & \text{s.t. } x \in \mathcal{X} \end{array}$$

↙
"Minimum-risk portfolio"

$$= x^T V x$$

where

$$V = \mathbb{E}_{\xi} \left[(\xi - \mathbb{E}_{\xi}[\xi]) (\xi - \mathbb{E}_{\xi}[\xi])^T \right]$$

is the covariance matrix of ξ