



LINMA2491 Operational Research

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Definition and notation

- Given Ω , a sigma-algebra \mathcal{A} is a set of subsets of Ω , with the elements called events, such that:
 - $\Omega \in \mathcal{A}$
 - if $A \in \mathcal{A}$ then also $\Omega - A \in \mathcal{A}$
 - if $A_i \in \mathcal{A}$ for $i = 1, 2, \dots$ then also $\cup_{i=1}^{\infty} A_i \in \mathcal{A}$
 - if $A_i \in \mathcal{A}$ for $i = 1, 2, \dots$ then also $\cap_{i=1}^{\infty} A_i \in \mathcal{A}$
- Consider:



- The state space is the set of all values of the system at each stage.

$$S_0 = \{C\}, \quad S_1 = \{C_u, C_d\}, \quad S_2 = \{C_{uu}, C_{ud}, C_{dd}\} \quad (1.1)$$

- The sample space is the set of all possible combination of the system.

$$\Omega = S_0 \times S_1 \times S_2 = \{(C, C_u, C_{uu}), (C, C_u, C_{ud}), (C, C_u, C_{dd}), \dots\} \quad (1.2)$$

- The power set of Ω is the set of all of the subsets, denoted $\mathcal{B}(\Omega)$.
- The probability space is the triplet (Ω, \mathcal{A}, P) where P is a probability measure.
 - $P(\emptyset) = 0$
 - $P(\Omega) = 1$
 - $P(\cup_{i=1}^{\infty} A_i) = \sum_i P(A_i)$ if A_i are disjoint
- $\forall t, A_t$ is the set of events on which we have information at stage t . For example, $A_0 = \{C\}$, $A_1 = \{C, C_u, C_d\}$. Thus is it evident that $t_1 \leq t_2 \Rightarrow \mathcal{A}_{t_1} \subseteq \mathcal{A}_{t_2}$

- Consider the following problem with $x \in \mathbb{R}^n$ and domain \mathcal{D} :

$$\begin{aligned} \min f_0(x), \quad & \text{s.t.} \\ f_i(x) &\leq 0, i = 1, \dots, m \\ h_j(x) &= 0, j = 1, \dots, p \end{aligned} \quad (1.3)$$

Then the Lagrangian function is defined as $L : \mathbb{R}^n \times \mathbb{R}^m \times \mathbb{R}^p \rightarrow \mathbb{R}$:

$$L(x, \lambda, v) = f_0(x) + \sum_{i=1}^m \lambda_i f_i(x) + \sum_{j=1}^p v_j h_j(x) \quad (1.4)$$

- The Lagrange dual function is defined as $g : \mathbb{R}^m \times \mathbb{R}^p \rightarrow \mathbb{R}$:

$$g(\lambda, v) = \inf_{x \in \mathcal{D}} L(x, \lambda, v) \quad (1.5)$$

- The Lagrange dual problem is a lower bound on the optimal value of the primal problem
- Lagrange relaxation of Stochastic Programs, consider the two problems:

$$\begin{aligned} \min f_1(x) + \mathbb{E}_\omega[f_2(y(\omega), \omega)] & \quad \min f_1(x) + \mathbb{E}_\omega[f_2(y(\omega), \omega)] \\ \text{s.t. } h_{1i}(x) \leq 0, i = 1, \dots, m_1 & \quad \text{s.t. } h_{1i}(x) \leq 0, i = 1, \dots, m_1 \\ h_{2i}(x, y(\omega), \omega) \leq 0, i = 1, \dots, m_2 & \quad h_{2i}(x(\omega), y(\omega), \omega) \leq 0, i = 1, \dots, m_2 \\ & \quad \textcolor{red}{x(\omega) = x} \end{aligned} \quad (1.6)$$

The red constraint is the non-anticipativity constraint, it transforms the deterministic variable into a stochastic variable. **A VERIFIER**

- The dual of a stochastic program is:

$$\begin{aligned} g(v) &= g_1(v) + \mathbb{E}_\omega(g_2(v, \omega)) \\ \text{where} \\ g_1(v) &= \inf f_1(x) + \left(\sum_{\omega \in \Omega} v(\omega) \right)^T x \\ \text{s.t. } h_{1i}(x) &\leq 0, i = 1, \dots, m_1 \\ \text{and} \\ g_2(v, \omega) &= \inf f_2(y(\omega), \omega) - vx(\omega) \\ \text{s.t. } h_{2i}(x(\omega), y(\omega), \omega) &\leq 0, i = 1, \dots, m_2 \end{aligned} \quad (1.7)$$

- With p^* the solution of the primal problem and d^* the solution of the dual problem, we have:

- Weak duality: $d^* \leq p^*$
- Strong duality: $d^* = p^*$

- The KKT conditions are necessary and sufficient for optimality in convex optimization, there aren't unique. They are:

- Primal constraint: $f_i(x) \leq 0, i = 1, \dots, m, h_j(x) = 0, j = 1, \dots, p$
- Dual constraint: $\lambda \geq 0$
- Complementarity slackness: $\lambda_i f_i(x) = 0, i = 1, \dots, m$
- Gradient of the Lagrangian: $\nabla_x L(x, \lambda, \nu) = 0$

Modelling

2.1 Introduction

- For a certain sequence of events: $x \rightarrow \omega \rightarrow y(\omega)$, where ω is the uncertainty:
 - A first-stage decision is a decision that is made before the uncertainty is revealed (in x)
 - A second-stage decision is a decision that is made after the uncertainty is revealed (in $y(\omega)$)
- We can have a mathematic formulation like this:

$$\begin{aligned}
 & \min c^T x + \mathbb{E}[\min q(\omega)^T y(\omega)] \\
 & Ax = b \\
 & T(\omega)x + W(\omega)y(\omega) = h(\omega) \\
 & x \geq 0, y(\omega) \geq 0
 \end{aligned} \tag{2.1}$$

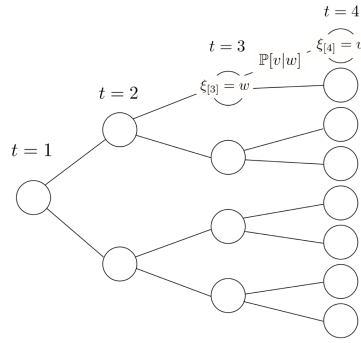
- First-stage decision: $x \in \mathbb{R}^{n_1}$
- First-stage parameter: $c \in \mathbb{R}^{n_1}$, $b \in \mathbb{R}^{m_1}$ and $A \in \mathbb{R}^{m_1 \times n_1}$
- Second-stage decision: $y(\omega) \in \mathbb{R}^{n_2}$
- Second-stage data: $q(\omega) \in \mathbb{R}^{n_2}$, $h(\omega) \in \mathbb{R}^{m_2}$ and $T(\omega) \in \mathbb{R}^{m_2 \times n_1}$, $W(\omega) \in \mathbb{R}^{m_2 \times n_2}$

2.2 Representations

2.2.1 Scenario Trees

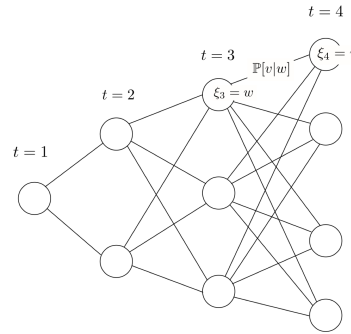
A scenario tree is a graphical representation of a Markov process $\{\xi_t\}_{t \in \mathbb{Z}}$, where the nodes are the histories of realizations ($\xi_{[t]} = (\xi_1, \dots, \xi_t)$), and the edges are the transitions from $\xi_{[t]}$ to $\xi_{[t+1]}$.

- We denote the root as $t = 1$;
- An ancestor of a node $\xi_{[t]}$, $A(\xi_{[t]})$ is a unique adjacent node which precedes $\xi_{[t]}$;
- The children of a node, $C(\xi_{[t]})$ are the nodes that are adjacent to $\xi_{[t]}$ and occur at stage $t + 1$.



2.2.2 Lattice

A lattice is a graphical representation of a Markov process $\{\xi_t\}_{t \in \mathbb{Z}}$, where the nodes are the realizations ξ_t and the edges correspond to the transitions from ξ_t to ξ_{t+1} .



2.2.3 Serial Independence

A process satisfies serial independence if, for every stage t , ξ_t has a probability distribution that does not depend on the history of the process. Thus, the probability measure is

$$\mathbb{P}[\xi_t(\omega) = i | \xi_{[t-1]}(\omega)] = p_t(i) \quad \forall \xi_{[t-1]} \in \Xi_{[t-1]}, i \in \Xi_t \quad (2.2)$$

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