

Stochastic Programming Introduction

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Outline

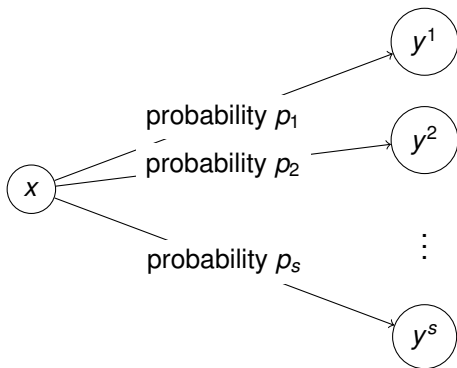
- 1 Introduction
- 2 A server location example
- 3 General formulation
- 4 Theoretical considerations
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Introduction

In a two-stage stochastic program:

- we make an initial decision x , then
- a random scenario ξ occurs with probability p , and
- we make another (*recourse*) decision y .

initial decision scenarios recourse

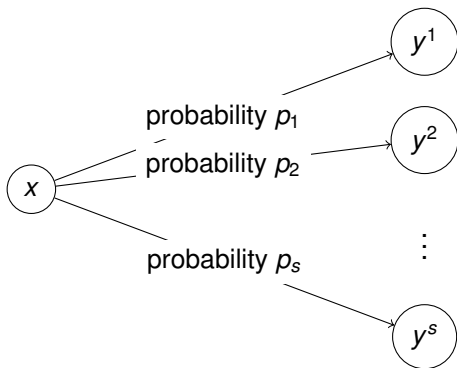


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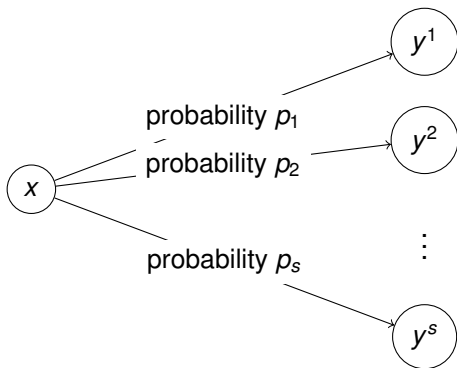


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Objective function

The standard objective is to **minimize the expected cost**.

Other objective functions can be used.

For example, in **robust optimization** we minimize the worst scenario.

In a **CVaR** approach we minimize the average cost of the worst few scenarios.

The scenario that is “worst” depends on the first stage decision x .

For recent surveys see [1, 2].

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Stochastic server location

We have n_1 possible server locations and m possible customers.

We pay a fixed cost c_i for choosing to open a server at location i .

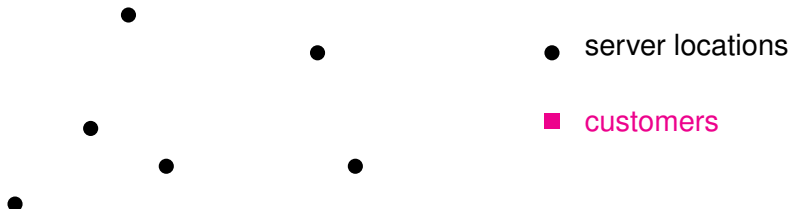
We must place at least one server, and no more than r servers.

We have to locate the servers before we know the integral demand $d_j(\xi)$ of the customers j .

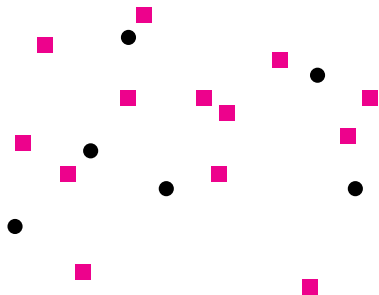
We assume any server can serve any customer, and the profit for each unit of demand of customer j met from server i is g_{ij} .

The servers have soft capacities w_i for each server i , in that we must pay a penalty g_{i0} per unit if the demand at server i is greater than its capacity w_i .

Server location



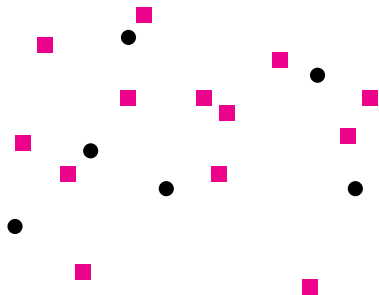
Server location



● server locations

■ customers

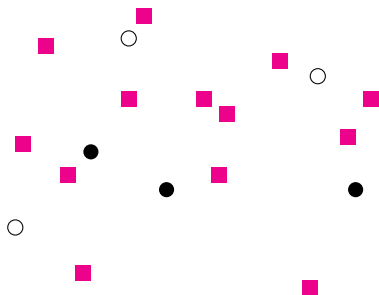
Server location



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Server location



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First stage model

Let x_i denote the binary variable indicating whether or not we place a server at location i for each i .

We can model the first stage problem:

$$\begin{aligned}
 \min_x \quad & c^T x + \mathbb{E}(x, \xi) \\
 \text{subject to} \quad & e^T x \leq r \\
 & e^T x \geq 1 \\
 & x \in \mathbb{B}^{n_1}
 \end{aligned}$$

where e denotes the vector of ones.

Second stage model

For a given realization ξ , we introduce second stage variables y_{ij} to represent the amount of demand of customer j that is met by server i , and z_i to denote the shortfall at server i .

The second stage problem can be written

$$\begin{aligned}
 \min_{y,z} \quad & \sum_i g_{i0} z_i - \sum_i \sum_j g_{ij} y_{ij} \\
 \text{subject to} \quad & -z_i + \sum_j y_{ij} \leq w_i x_i \text{ for each server } i \\
 & \sum_i y_{ij} = d_j \text{ for each customer } j \\
 & z, y \quad \text{integer, nonnegative}
 \end{aligned}$$

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General formulation

We will focus on **stochastic two stage mixed integer programs with recourse**. The general formulation can be written

$$\begin{array}{ll} \min_x & c^T x + \mathbb{E}_\xi [Q(x, \xi)] \\ \text{subject to} & Ax = b \\ & x \in \mathcal{X} \end{array}$$

where the first stage decisions are $x \in \mathcal{X} \subseteq \mathbf{R}^{n_1}$, the constraint matrix A is $m_1 \times n_1$, $b \in \mathbf{R}^{m_1}$, $c \in \mathbf{R}^{n_1}$.

Further, ξ is the uncertainty, and $Q(x, \xi)$ is the cost of the recourse decision when the first stage decision is x and the uncertainty is ξ .

Thus, $Q(x, \xi)$ is the second stage cost. We take the expectation of the second stage cost over all scenarios ξ .

Second stage cost

The second stage cost

$$Q(x, \xi) = \min_y \quad q^T y$$

$$\text{subject to} \quad Wy = h(\xi) - T(\xi)x$$

$$y \in \mathcal{Y}$$

where $y \in \mathcal{Y} \subseteq \mathbf{R}^{n_2}$, W is a fixed $m_2 \times n_2$ matrix, the right hand side $h(\xi) \in \mathbf{R}^{m_2}$ depends on the uncertainty ξ , and the $m_2 \times n_2$ technology matrix $T(\xi)$ also depends on ξ .

Note that the second stage optimization is over y , with x taken as a parameter.

Integrality

The sets \mathcal{X} and \mathcal{Y} impose nonnegativity, and discrete, binary, or continuous restrictions on the first and second-stage variables, respectively.

Explicit MIP formulation

Assume we have a finite number of scenarios $s = 1, \dots, S$, each with probability p_s .

We introduce **separate copies y^s of y for each scenario s** .

The complete problem can then be written as an explicit mixed integer program:

$$\begin{array}{ll}
 \min_{x,y} & c^T x + \sum_{s=1}^S p_s q^T y^s \\
 \text{subject to} & Ax = b \\
 & T(\xi^s)x + Wy^s = h(\xi^s) \quad s = 1, \dots, S \\
 & x \in \mathcal{X} \\
 & y^s \in \mathcal{Y}, \quad s = 1, \dots, S
 \end{array}$$

Constraint matrix structure

The primal constraint matrix has the structure

$$\begin{array}{ccc}
 \boxed{A} & & \\
 \boxed{T(\xi^1)} & \boxed{W} & \\
 \boxed{T(\xi^2)} & & \boxed{W} \\
 & \vdots & \ddots \\
 \boxed{T(\xi^S)} & & \boxed{W}
 \end{array}$$

If the first stage variables are integral and the second-stage variables are continuous, we can use Benders decomposition.

The second stage subproblems are separable, with a different subproblem for each scenario.

This is known as the *L-shaped* method in the stochastic programming literature.

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Theoretical considerations

When the second stage variables are all continuous, the expectation function $\mathbb{E}_\xi [Q(x, \xi)]$ is continuous and convex.

However, if some of the second stage variables are required to be integral, this function can be **discontinuous**.

Example

A simple example with just one scenario, with x and y being scalar variables:

$$\begin{array}{ll} \min_{x,y} & 3x + 4y \\ \text{subject to} & x \leq 6 \\ & x \geq 0, \text{ integer} \end{array}$$

where y solves the subproblem

$$\begin{array}{ll} \min_y & y \\ \text{subject to} & 2y = 6 - x \\ & y \geq 0, \text{ integer} \end{array}$$

The feasible solutions require x be even.

If x is odd then the subproblem is infeasible, so we can say that such a solution x has value $+\infty$.

Continuity

It is common to assume *complete recourse*:
the subproblem is feasible for any choice of first-stage variable that satisfies the first-stage constraints.

Under this assumption and some other assumptions, it can be shown that $\mathbb{E}_\xi [Q(x, \xi)]$ is well-defined, real valued, and lower semicontinuous, although it may still not be convex or even continuous.

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