

# Stochastic Programming Introduction

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# Outline

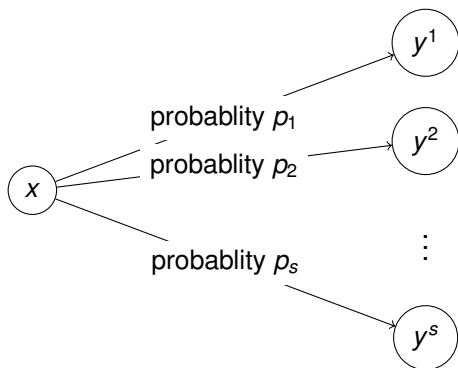
- 1 Introduction
- 2 A server location example
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# Introduction

In a two-stage stochastic program:

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

initial decision      scenarios      recourse

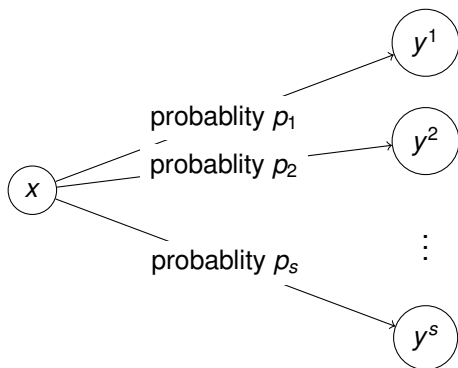


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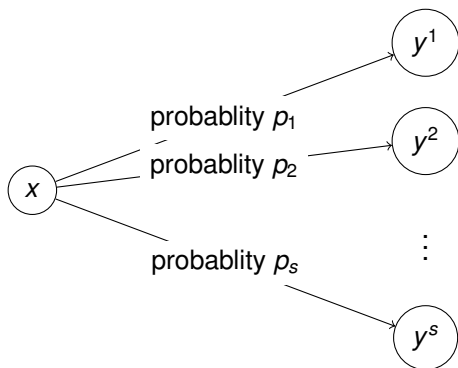


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# Objective function

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.

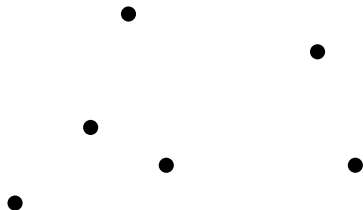
We have to locate the servers before we know the integral demand  $d_j(\xi)$  of the customers  $j$ .

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  $w_i$ .



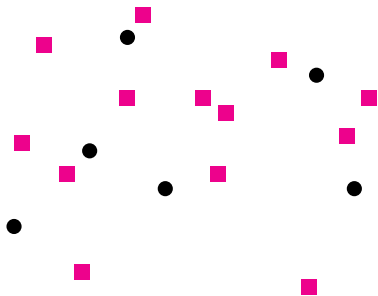
# Server location



● server locations

■ customers

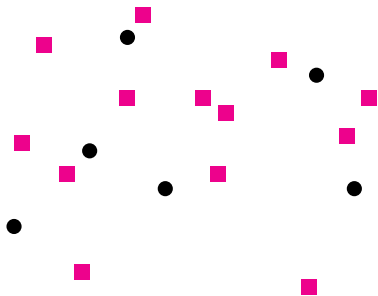
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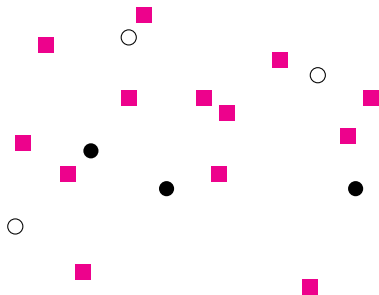
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# First stage model

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:

$$\begin{array}{ll}
 \min_x & c^T x + \mathbb{E}(x, \xi) \\
 \text{subject to} & e^T x \leq r \\
 & e^T x \geq 1 \\
 & x \in \mathbb{B}^{n_1}
 \end{array}
 \quad = \quad
 \sum_s p_s x \left( \begin{array}{l} \text{value of} \\ \text{scenario} \end{array} \right)$$

$\downarrow$   
 prob of scenario

where  $e$  denotes the vector of ones.

## Second stage model

For a given realization  $\xi$ , 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

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

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# General formulation

*mixed integer*

We will focus on **stochastic two stage ~~linear~~ 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,  $\xi$  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  $\xi$ .

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



## Second stage cost

The second stage cost

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

subject to

$$Wy = h(\xi) - T(\xi)x$$

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

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  $\xi$ , and the  $m_2 \times n_2$  technology matrix  $T(\xi)$  also depends on  $\xi$ .

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 ~~linear~~ *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

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

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

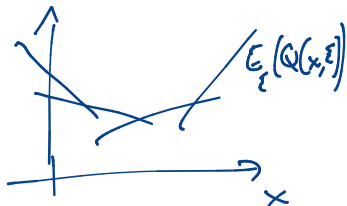
The second stage subproblems are separable, with a different subproblem for each scenario.

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

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

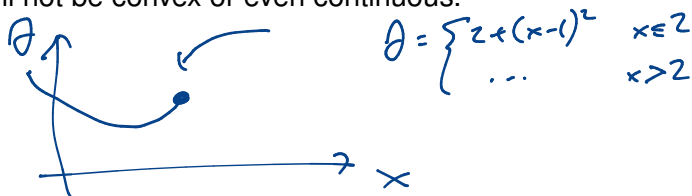
The feasible solutions require  $x$  be even.

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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