

# Stochastic Optimization

## IDA PhD course 2011ht

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2. Lecture: Uncertainties in objective  
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## 1 Randomness occurs in the objective function

- Expected value objective function
- Probability of shortfall
- Minimize Variance
- Value at risk

## 2 One more SP example

- Machine Scheduling

## 3 A bit of History



# Outline

- 1 Randomness occurs in the objective function
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Deterministic Opt. Model  $\rightarrow$  Stochastic Programming Model

$$\begin{array}{ll} \min_{x \in X} & f(x) \\ \text{s.t.} & g(x) \leq 0 \end{array} \quad \rightarrow \quad \begin{array}{ll} \min_{x \in X} & f(x, \chi) \\ \text{s.t.} & g(x, \chi) \leq 0 \end{array}$$

$\chi \in \Omega \subseteq \mathbb{R}^s$ : vector with random variable as entries



- └ Randomness occurs in the objective function
- └ Expected value objective function

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## Minimize an expected value function

$$\begin{aligned} \min_{x \in X} \quad & \mathbb{E}[f(x, \chi)] \\ \text{s.t.} \quad & g(x) \leq 0 \end{aligned}$$

## Examples

- Expected cost / Expected gain
- Expected machine working time
- Expected transportation time
- Expected customer waiting times
- Expected damage on target



## Advantages

- Good result "on average"
- Objective function can often be reformulated deterministically
- Convex objective if  $f(\cdot, \chi)$  is convex (for all possible  $\chi$ )
- Lower bound using Jensen's inequality:

## Theorem (Jensen, 1906)

Let  $f$  be a convex function and  $X$  a random variable. Then

$$\mathbb{E}[f(X)] \geq f(\mathbb{E}[X])$$

## Disadvantages

- We might encounter very "bad cases" ("Risk")
- Expectation can only be computed as multidimensional integral

# Linear Programming Problem

## Stochastic Programming Problem

$$\begin{aligned} \min_{\substack{x \in \mathbb{R}^n \\ x \geq 0}} \quad & \mathbb{E} [c(\chi)^T x] \\ \text{s.t.} \quad & Ax \leq b \end{aligned}$$

$\chi \in \mathbb{R}^s$ : random vector

## Deterministically Reformulated Programming Problem

$$\begin{aligned} \min_{\substack{x \in \mathbb{R}^n \\ x \geq 0}} \quad & \mu^T x \\ \text{s.t.} \quad & Ax \leq b \end{aligned}$$

$\mu \in \mathbb{R}^n$ : (deterministic) vector of means



- └ Randomness occurs in the objective function
- └ Expected value objective function

# Discrete Finite Distribution

## Stochastic Programming Problem

$$\begin{aligned} \min_{x \in X} \quad & \mathbb{E}[f(x, \chi)] \\ \text{s.t.} \quad & g(x) \leq 0 \end{aligned}$$

$\chi \in \mathbb{R}^s$ : random vector

## Deterministically Reformulated Programming Problem

$$\begin{aligned} \min_{x \in X} \quad & \sum_{k=1}^K p^k f(x, \chi^k) \\ \text{s.t.} \quad & g(x) \leq 0 \end{aligned}$$

$\chi^1, \dots, \chi^K \in \mathbb{R}^s$ : scenarios  
 $\mathbb{P}\{\chi = \chi^k\} := p^k$ : probabilities

# General problem with discrete finite distributions

## Exponential number of scenarios

Assume:

- Discretely distributed random variables
- Independently distributed random variables
- (Linear) Dependence:  $\#$  dec. variables  $\leftrightarrow$   $\#$  rand. variables

$\implies$  Exponential number of scenarios



# General problem with discrete finite distributions

## Exponential number of scenarios

Assume:

- Discretely distributed random variables
- Independently distributed random variables
- (Linear) Dependency:  $\#$  dec. variables  $\leftrightarrow$   $\#$  rand. variables

$\implies$  Exponential number of scenarios

## Example

- $n$  decision variables
- $n$  random variables
- 2 possible outcomes for each random variable (e.g. Bernoulli distribution)

Independent random variables  $\implies 2^n$  scenarios

- └ Randomness occurs in the objective function
- └ Expected value objective function

# Discrete Finite Distribution

## Stochastic Programming Problem

$$\begin{aligned} \min_{x \in X} \quad & \mathbb{E}[f(x, \chi)] \\ \text{s.t.} \quad & g(x) \leq 0 \end{aligned}$$

$\chi \in \mathbb{R}^s$ : random vector

## Deterministically Reformulated Programming Problem

$$\begin{aligned} \min_{x \in X} \quad & \sum_{k=1}^K p^k f(x, \chi^k) \\ \text{s.t.} \quad & g(x) \leq 0 \end{aligned}$$

$\chi^1, \dots, \chi^K \in \mathbb{R}^s$ : scenarios  
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- └ Randomness occurs in the objective function
- └ Probability of shortfall

# Outline

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## Minimize probability of shortfall

$$\begin{aligned} \min_{x \in X} \quad & \mathbb{P}\{f(x, \chi) > T\} \\ \text{s.t.} \quad & g(x) \leq 0 \end{aligned}$$

## Examples

- Investment strategies
- Project cost management ( $T = 0$ )

Probability of "Target" achievement



## Advantages

- If probability of shortfall too high actions can be taken.

## Disadvantages

- We might still encounter very "bad cases"
- No influence on average cost



# Discrete Finite Distribution

## Stochastic Programming Problem

$$\begin{aligned} \min_{x \in X} \quad & \mathbb{P}\{f(x, \chi) > T\} \\ \text{s.t.} \quad & g(x) \leq 0 \end{aligned}$$

$\chi \in \mathbb{R}^s$ : random vector

$\chi^1, \dots, \chi^K \in \mathbb{R}^s$ : scenarios

$\mathbb{P}\{\chi = \chi^k\} := p^k$ : probabilities

## Reformulate Problem Deterministically

Basic idea:

- "Choose" scenarios with shortfall
- Probability that one of these arises minimized

Realization:

- Introduce one binary decision variable  $z^k$  per scenario
- $z^k = 1$ : shortfall in scenario  $k$



# Discrete Finite Distribution II

## Reformulate Problem Deterministically

Basic idea:

- "Choose" scenarios with shortfall
- Probability that one of these arises minimized

Realization:

- Introduce one binary decision variable  $z^k$  per scenario
- $z^k = 1$ : shortfall in scenario  $k$

## Deterministically reformulated problem

$$\begin{aligned} \min \quad & \sum_{k=1}^K p^k z^k \\ \text{s.t.} \quad & g(x) \leq 0 \\ & f(x, \chi^k) \leq T + Mz^k \quad \forall k = 1, \dots, K \\ & x \in X, \quad z^k \in \{0, 1\} \quad \forall k = 1, \dots, K \end{aligned}$$

**M**: some "big" constant

# Discrete Finite Distribution III

## Deterministically reformulated problem

$$\begin{aligned} \min \quad & \sum_{k=1}^K p^k z^k \\ \text{s.t.} \quad & g(x) \leq 0 \\ & f(x, \chi^k) \leq T + Mz^k \quad \forall k = 1, \dots, K \\ & x \in X, \quad z^k \in \{0, 1\} \quad \forall k = 1, \dots, K \end{aligned}$$

$M$ : some "big" constant

## Problems

- Numerical instability due to big  $M$  possible
- $K$  additional constraints
- $K$  additional **binary** decision variables
- Deterministic reformulation hard

# $f$ linear / Normal Distribution

## Stochastic Programming Problem

$$\begin{aligned} \min_{x \in X} \quad & \mathbb{P}\{\chi^T x > T\} \\ \text{s.t.} \quad & g(x) \leq 0 \end{aligned}$$

$\chi \in \mathbb{R}^n$ : random vector with normally distr. entries

$\chi \sim \mathcal{N}(\mu, \Sigma)$

$\Sigma$ : Covariance Matrix of  $\chi$

## Deterministically reformulated problem

$$\begin{aligned} \max_{x \in X} \quad & \frac{T - \mu^T x}{\sqrt{x^T \Sigma x}} \\ \text{s.t.} \quad & g(x) \leq 0 \end{aligned}$$

$$x^* \neq 0$$

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## Minimize variance ?

$$\begin{aligned} \min_{x \in X} \quad & \text{Var} [f(x, \chi)] \\ \text{s.t.} \quad & g(x) \leq 0 \end{aligned}$$

Advantages:

- Outcome more concentrated around mean
- Possibility to reduce risk

Disadvantages:

- Makes not much sense without benchmark for expected costs



# Simple Mean-Variance Models

Minimize convex combination of variance and expectation

$$\begin{aligned} \min_{x \in X} \quad & \lambda \text{Var} [f(x, \chi)] + (1 - \lambda) \mathbb{E} [f(x, \chi)] \quad (\lambda \in (0, 1)) \\ \text{s.t.} \quad & g(x) \leq 0 \end{aligned}$$

Minimize weighted product of variance and expectation

$$\begin{aligned} \min_{x \in X} \quad & \text{Var} [f(x, \chi)]^\lambda \cdot \mathbb{E} [f(x, \chi)] \\ \text{s.t.} \quad & g(x) \leq 0 \end{aligned}$$

Minimize variance with expectation threshold

$$\begin{aligned} \min_{x \in X} \quad & \text{Var} [f(x, \chi)] \\ \text{s.t.} \quad & g(x) \leq 0 \\ & \mathbb{E} [f(x, \chi)] \leq T \end{aligned}$$

## Problems when variance in objective

- Loss of linearity
- Loss of convexity
- Hardness of problem (e.g. quadratic objective)
- Compute variance / Evaluate objective function



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## Question

What is the probability that my total loss during a fixed time interval does not exceed a certain limit?

## Examples

- What is the probability that my stock portfolio will fall in value by more than \$ 100 million in one week?
- If I invest \$ 1 million today, how much can I loose till tomorrow?



### Definition (Value-at-Risk)

$X$ : random variable describing the loss over time horizon  $T$

$\Phi_X$ : Cumulative distribution function of  $X$

**Value at risk over time horizon  $T$  at confidence level  $\alpha$ :**

$$\text{VAR}_\alpha(X) = \inf\{c \mid \Phi_X(c) \geq \alpha\}$$

### Interpretation (Philippe Jorion)

"Value at Risk measures the worst expected loss over a given horizon under normal market conditions at a given level of confidence."



## Value at Risk in Stochastic Programming

- Risk measure
- Objective: Minimize value at risk

## Critics

- Lack of subadditivity
- Lack of convexity
- Difficult to compute from scenarios

## Alternatives

- Conditional value at risk
- Tail value at risk
- ...

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# Deterministic Problem

## (Possible) Parameters

- # of (different) machines / parts
- Processing times
- # of jobs to be completed
- # of employees available
- Due dates
- Precedence relations

## (Possible) Objectives

- Minimize total completion time
- Maximize # of completed jobs
- Minimize maximum/sum of tardiness
- Minimize idle times

# Stochastic Problem

## (Possible) Uncertain Parameters

- # of (different) available machines ← break downs
- # of (different) parts ← customization
- Processing times ← manual operations
- # of jobs to be completed ← demand
- # of employees available ← sickness, vacations
- Due dates ← uncertainty in processing times
- Precedence relations



# Stochastic Problem

## (Possible) Objective

- minimize expected... total processing time
- Given # of jobs, maximize probability that... processing "in time"

## Stochastic Settings

- Single stage decision
- Multi-Stage decision ← Discretization of processing time
- Online Programming ← New information arrives over time





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# The beginning



George Dantzig

**Linear programming under uncertainty.** (1955)

*Management Science* 1:197–206

- Two-Stage and Simple recourse problems
- Finite number of scenarios
- Deterministic Reformulation
- No use of special structure





Richard Van Slyke and Roger J-B. Wets

**L-shaped linear programs with applications to optimal control and stochastic programming.** (1969)

*MSIAM Journal on Applied Mathematics* 17(4):638–663, 1969

- Solution method that makes use of special problem structures
- Reduced computing time





András Prékopa

**On probabilistic constrained programming.** (1970)

*Proceedings of the Princeton Symposium on Mathematical Programming* 113–1383



András Prékopa

**A class of stochastic programming decision problems.** (1972)

*Mathematische Operationsforschung und Statistik* 3(5):349–354

- Main contributions to understanding of chance-constraint programming
- Convex cases
- Joint constraints





Maarten H. van der Vlerk

**Stochastic Programming with Integer Recourse.** (1995)

*PhD thesis, University of Groningen, The Netherlands*

- Main contributions to understanding of Integer Programming with Recourse
- with Leen Stougie, Rüdiger Schultz





Alexander Shapiro and Tito Homem-de-Mello

**A simulation-based approach to two-stage stochastic programming with recourse.** (1998)

*Mathematical Programming* 81(3):301-325

- Stochastic Programming via Monte Carlo Sampling: Sample Average Approach
- Much work on convergence properties
- Realization: Often good approximations possible with "relatively" few samples



# Next lecture

- Chance-Constrained Programming and related problems
- (Simple Recourse Problems)



# QUESTIONS?

What about ~~next-week~~ in 2 weeks?

