

# Stochastic Optimization

## IDA PhD course 2011ht

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2. Lecture: Uncertainties in objective  
06. October 2011



Linköping University

- 1 Randomness occurs in the objective function
  - Expected value objective function
  - Probability of shortfall
  - Minimize Variance
  - Value at risk



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  - Machine Scheduling



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## 3 A bit of History



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- 3 A bit of History



Deterministic Opt. Model  $\rightarrow$  Stochastic Programming Model

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



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



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## Minimize an expected value function



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



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## Advantages

- Good result "on average"



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- Convex objective if  $f(\cdot, \chi)$  is convex (for all possible  $\chi$ )



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## Theorem (Jensen, 1906)

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

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



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- We might encounter very "bad cases" ("Risk")

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## Disadvantages

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

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# Linear Programming Problem

## Stochastic Programming Problem



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



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

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# General problem with discrete finite distributions



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# General problem with discrete finite distributions

Exponential number of scenarios



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## Exponential number of scenarios

Assume:

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- $n$  decision variables

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

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Independent random variables  $\implies 2^n$  scenarios

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Minimize probability of shortfall



## Minimize probability of shortfall

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



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## Examples

- Investment strategies



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Probability of "Target" achievement



## Advantages

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



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

## Disadvantages

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



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Stochastic Programming Problem



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$$\text{s.t. } g(x) \leq 0$$

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Basic idea:

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- Probability that one of these arises minimized

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- Introduce one binary decision variable  $z^k$  per scenario

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- $z^k = 1$ : shortfall in scenario  $k$

# Discrete Finite Distribution II

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min

s.t.  $g(x) \leq 0$

$x \in X$

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s.t.  $g(x) \leq 0$

$$f(x, \chi^k) \leq T + Mz^k$$

$$x \in X, \quad z^k \in \{0, 1\} \quad \forall k = 1, \dots, K$$

M: some "big" constant

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

## Deterministically reformulated problem

min

$$\text{s.t. } g(x) \leq 0$$

$$f(x, \chi^k) \leq T + Mz^k$$

$$x \in X, \quad z^k \in \{0, 1\} \quad \forall k = 1, \dots, K$$

**M**: some "big" constant

# Discrete Finite Distribution II

## Reformulate Problem Deterministically

Basic idea:

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

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

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- └ Randomness occurs in the objective function
- └ Probability of shortfall

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Problems



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- Deterministic reformulation hard

# $f$ linear / Normal Distribution

## Stochastic Programming Problem



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$$\min_{x \in X} \mathbb{P}\{\chi^T x > T\}$$

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

$$x^* \neq 0$$

# Outline

- 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**



## Minimize variance



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Disadvantages:

- Makes not much sense without benchmark for expected costs



# Simple Mean-Variance Models

Minimize convex combination of variance and expectation



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



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## Problems when variance in objective

- Loss of linearity



## Problems when variance in objective

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- Hardness of problem (e.g. quadratic objective)



## Problems when variance in objective

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



# Outline

- 1** Randomness occurs in the objective function
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## Question





## Question

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



- └ Randomness occurs in the objective function
- └ Value at risk

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## Examples



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## Examples

- What is the probability that my stock portfolio will fall in value by more than \$ 100 million in one week?



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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  $T$



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





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### Interpretation (Philippe Jorion)



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### 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



## Value at Risk in Stochastic Programming

- Risk measure
- Objective: Minimize value at risk



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# Deterministic Problem

(Possible) Parameters





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## (Possible) Parameters

- # of (different) machines / parts



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- # of (different) machines / parts
- Processing times



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- # of (different) machines / parts
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- # of (different) machines / parts
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- # of jobs to be completed
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- Maximize # of completed jobs

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- # of (different) machines / parts
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# Stochastic Problem

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- # of (different) available machines



# Stochastic Problem

## (Possible) Uncertain Parameters

- # of (different) available machines ← break downs



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# Stochastic Problem

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- # of (different) available machines ← break downs
- # of (different) parts ← customization



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- # of (different) parts ← customization
- Processing times ← manual operations



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- # of employees available



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- # of (different) available machines ← break downs
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- Processing times ← manual operations
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- Due dates ← uncertainty in processing times



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# Stochastic Problem

(Possible) Objective



# Stochastic Problem

(Possible) Objective

- minimize expected...



# Stochastic Problem

## (Possible) Objective

- minimize expected... total processing time



# Stochastic Problem

## (Possible) Objective

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



# Stochastic Problem

## (Possible) Objective

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





# Stochastic Problem

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- minimize expected... total processing time
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## Stochastic Settings



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- minimize expected... total processing time
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## Stochastic Settings

- Single stage decision



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## Stochastic Settings

- Single stage decision
- Multi-Stage decision



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- Single stage decision
- Multi-Stage decision ← Discretization of processing time



# Stochastic Problem

## (Possible) Objective

- minimize expected... total processing time
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- Single stage decision
- Multi-Stage decision ← Discretization of processing time
- Online Programming



# 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



# Outline

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# The beginning



George Dantzig

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

*Management Science* 1:197–206



Linköping University



# The beginning



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- Two-Stage and Simple recourse problems



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- Deterministic Reformulation



# The beginning



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- 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





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- Solution method that makes use of special problem structures





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- 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







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András Prékopa

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

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- Main contributions to understanding of chance-constraint programming





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





Maarten H. van der Vlerk

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

*PhD thesis, University of Groningen, The Netherlands*





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- Main contributions to understanding of Integer Programming with Recourse





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- 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





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- Stochastic Programming via Monte Carlo Sampling: Sample Average Approach







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- Stochastic Programming via Monte Carlo Sampling: Sample Average Approach
- Much work on convergence properties





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- 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



# Next lecture

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



# QUESTIONS?

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

