

AM 121: Intro to Optimization Models and Methods Fall 2016

Lecture 20: Stochastic Optimization



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SEAS

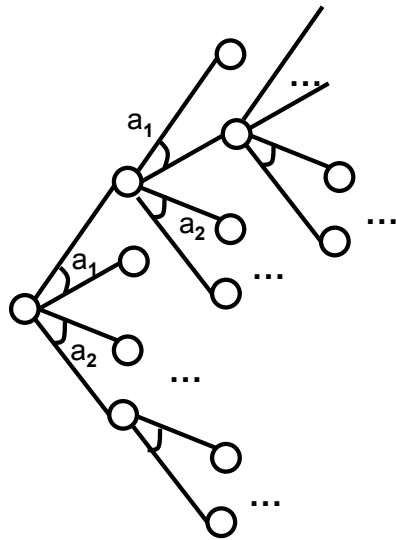


Lesson Plan

- Two-stage stochastic optimization
 - Stage one; stage two (recourse)
- Example: the Farmer's problem, the Contractor's problem
- Optimal stochastic solution
- EVPI and VSS
- Analytic solution method, Sample Average Approximation method

Reading: "A tutorial on stochastic programming," Schapiro and Philpott, March 2007 (sections 1 and 2)

Stochastic Optimization



MDP: $M=(S,A,P,R)$
m states, n actions

Decision variables in the LP are $\pi(s,a)$. Can only solve if $m*n$ is small.

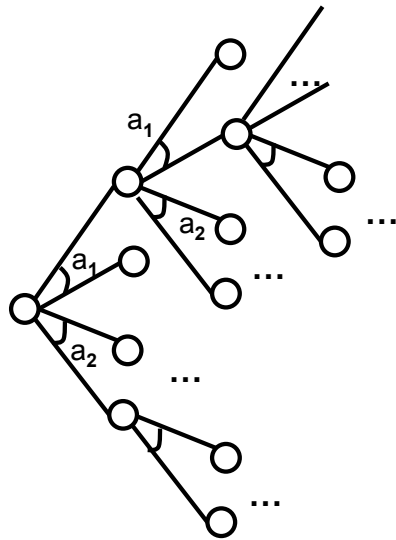
But n may be large.

Two-stage stochastic optimization is special case for two periods.

Example: Contractor's problem

- Accept some projects at time 1. Gain revenue.
- #actions = # subsets of projects
- Exponentially large!
- At **time 2**, know the labor needed to complete each project. Can **recruit additional workers**.

Stochastic Optimization

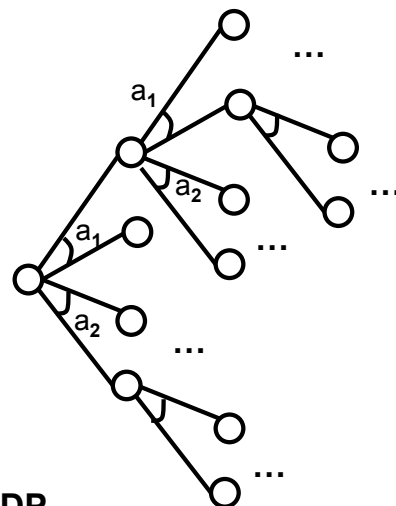


MDP: $M=(S,A,P,R)$
 m states, n actions

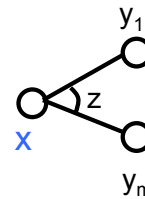
Decision variables in the LP are $\pi(s,a)$. Can only solve if $m*n$ is small.

But n may be large (e.g., subsets of projects.)

m may also be large (e.g. all things that can go wrong with a project!)



MDP
 (state transition depends on action)



Two-stage stochastic optimization:

Decision $x \in X$ at time step 1

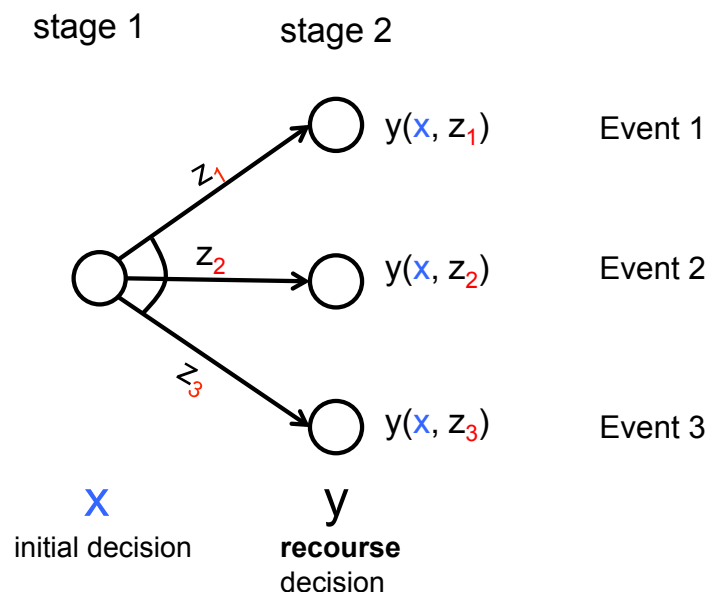
Random event z : models *all* uncertainty (e.g., what could go wrong with every possible set of projects!)

Decision y at time step 2.

Examples

- **T-shirt problem.** Buy x t-shirts at time 1, cost c . At time 2, uncertain demand z realized and need to either back-order or hold excess inventory.
- **Farmer's problem.** Plant x crops at time 1, incur cost. At time 2, uncertain weather z realized. Buy/sell crops to ensure enough feed for animals, maximize profit.
- **Contractor's problem.** Accept projects x at time 1, get payments. At time 2, realize amount of labor z needed for each project, recruit workers as necessary.

Two-stage stochastic optimization



Example: Farmer's problem

(Birge & Louveaux' 97)

- A farmer has 500 acres to plant wheat, grain and sugar beets. Needs min amount of wheat/corn to feed animals. Can also buy/sell in period 2.
- Without uncertainty about yield:

	Wheat	Corn	Beets
Yield (T/acre)	2.5	3	20
Cost (\$/acre)	150	230	260
Sell price (\$/T)	170	150	36 (under 6000 T) 10 (above 6000 T)
Purchase price (\$/T)	238	210	-
Min requirement (T)	200	240	-

Formulation without Uncertainty

- Stage 1: x_1, x_2, x_3 = acres to plant for each crop
- Stage 2:
 - y_1^b, y_1^s = amount to buy, sell of crop 1 (w)
 - y_2^b, y_2^s = amount to buy, sell of crop 2 (c)
 - y_3^{s1}, y_3^{s2} = amount to sell of crop 3 at high, low price

$$\begin{aligned}
 & \bullet \max -150x_1 - 230x_2 - 260x_3 \\
 & \quad - 238y_1^b + 170y_1^s - 210y_2^b + 150y_2^s + 36y_3^{s1} + 10y_3^{s2} \\
 & \text{s.t.} \quad x_1 + x_2 + x_3 \leq 500 \quad \text{(land)} \\
 & \quad 2.5x_1 + y_1^b - y_1^s \geq 200 \quad \left. \begin{array}{l} \\ \\ \end{array} \right\} \text{(quotas)} \\
 & \quad 3x_2 + y_2^b - y_2^s \geq 240 \\
 & \quad y_3^{s1} + y_3^{s2} \leq 20x_3 \quad \left. \begin{array}{l} \\ \end{array} \right\} \text{(beets)} \\
 & \quad y_3^{s1} \leq 6000 \\
 & \quad x_1, x_2, \dots, y_1^b, \dots, y_3^{s2} \geq 0
 \end{aligned}$$

Optimal solution (No uncertainty)

	Wheat	Corn	Beets
acres	120	80	300
yield (T)	300	240	6000
sales	100	-	6000
purchase	-	-	-

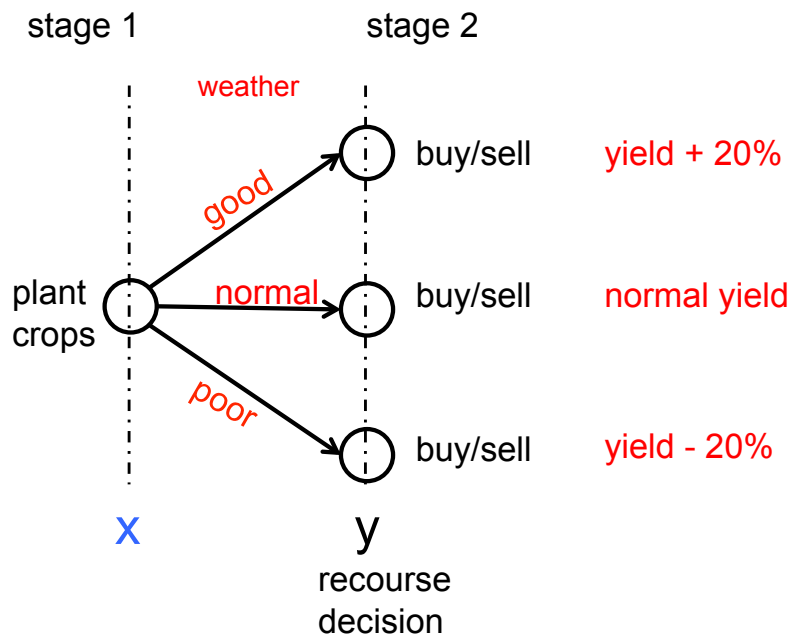
High profit on sales

High profit up to 6000T

Feed animals

Introducing uncertainty

- **Weather** may be “good”, “normal” or “poor.”
This affects the yield on each crop
- Given this **uncertainty**, what is optimal **decision in stage one** about which crops to plant?



Warm-up: An omniscient farmer

Suppose the farmer can predict the weather...

Optimal decision
if **weather** good

	Wheat	Corn	Beets
acres	183.3	66.7	250
yield (T)	550	240	6000
sales	350	-	6000
purchase	-	-	-

Optimal decision
if **weather** normal

	Wheat	Corn	Beets
acres	120	80	300
yield (T)	300	240	6000
sales	100	-	6000
purchase	-	-	-

Optimal decision
if **weather** poor

	Wheat	Corn	Beets
acres	100	25	375
yield (T)	200	60	6000
sales	-	-	6000
purchase	-	180	-

Comparing the Omniscient solutions

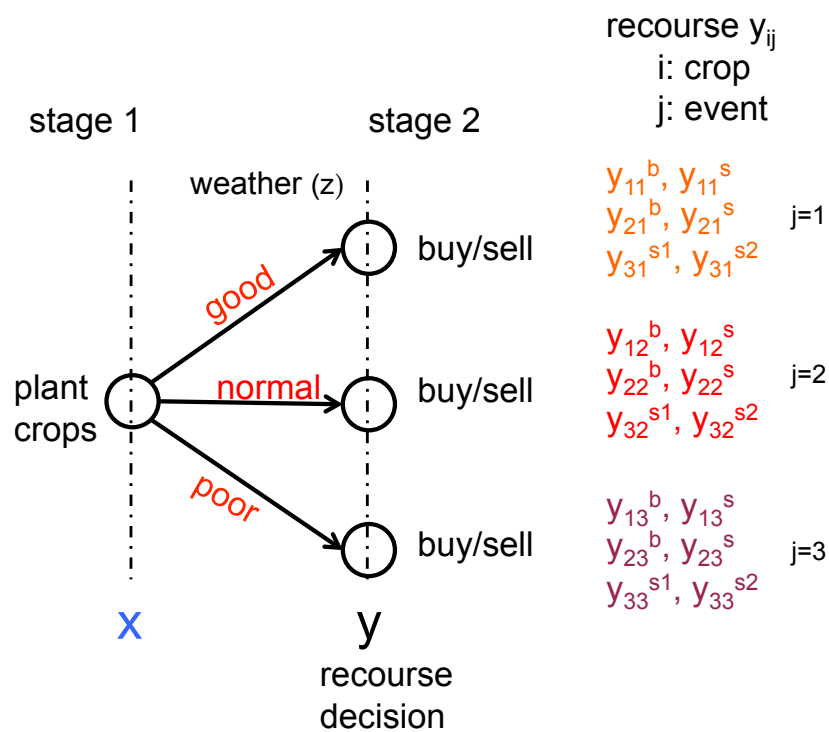
	good	normal	poor
wheat (acres)	183.3	120	100
corn (acres)	66.7	80	25
beets (acres)	250	300	375

A lot of variation: best to plant between 183 and 100 acres of wheat, depending on the weather.

What to do?!

Two-stage Stochastic Optimization

- Uncertain event. Weather is {good, normal, poor}
- Probability 1/3 on each
- What to do in period one, and in period two (recourse)?



- $$\max -150x_1 - 230x_2 - 260x_3$$

$$+ 1/3 (-238y_{11}^b + 170y_{11}^s - 210y_{21}^b + 150y_{21}^s + 36y_{31}^{s1} + 10y_{31}^{s2})$$

$$+ 1/3 (-238y_{12}^b + 170y_{12}^s - 210y_{22}^b + 150y_{22}^s + 36y_{32}^{s1} + 10y_{32}^{s2})$$

$$+ 1/3 (-238y_{13}^b + 170y_{13}^s - 210y_{23}^b + 150y_{23}^s + 36y_{33}^{s1} + 10y_{33}^{s2})$$
- $$\text{s.t. } x_1 + x_2 + x_3 \leq 500$$
- stage 1

$$\boxed{3}x_1 + y_{11}^b - y_{11}^s \geq 200$$

$$\boxed{3.6}x_2 + y_{21}^b - y_{21}^s \geq 240$$

$$y_{31}^{s1} + y_{31}^{s2} \leq \boxed{24}x_3$$

$$y_{31}^{s1} \leq 6000$$
- stage 2:
good weather
- $$\boxed{2.5}x_1 + y_{12}^b - y_{12}^s \geq 200$$

$$\boxed{3}x_2 + y_{22}^b - y_{22}^s \geq 240$$

$$y_{32}^{s1} + y_{32}^{s2} \leq \boxed{20}x_3$$

$$y_{32}^{s1} \leq 6000$$
- stage 2:
normal weather
- $$\boxed{2}x_1 + y_{13}^b - y_{13}^s \geq 200$$

$$\boxed{2.4}x_2 + y_{23}^b - y_{23}^s \geq 240$$

$$y_{33}^{s1} + y_{33}^{s2} \leq \boxed{16}x_3$$

$$y_{33}^{s1} \leq 6000$$
- stage 2:
bad weather
- $$x_1, x_2, \dots, y_{11}^b, \dots, y_{33}^{s2} \geq 0$$

Optimal solution with Uncertainty

	Wheat	Corn	Beets
Acres	170	80	250
Yield (T)	510	288	6000
Sales (T)	310	48	6000
Purchase (T)	-	-	-
Yield (T)	425	240	5000
Sales (T)	225	-	5000
Purchase (T)	-	-	-
Yield (T)	340	192	4000
Sales (T)	140	-	4000
Purchase (T)	-	48	-

Profit: \$108,390

“omniscient solution” (if knew weather) would bring expected value $\frac{1}{3} (167+118+59) \approx \$114,667$

	stochastic	good	normal	poor
wheat (acres)	170	183.3	120	100
corn (acres)	80	66.7	80	25
beets (acres)	250	250	300	375
profits	\$108,390	\$167,000	\$118,000	\$59,000

“in expectation solution”

(Assume yield = expected yield. Has **expected value** \$107,240).

Expected value of Perfect Information (EVPI): $\$114,667 - \$108,390 = \$6,277$

Value of Stochastic Solution (VSS): $\$108,390 - \$107,240 = \$1,150$

EVPI and VSS

- $C(x)$: stage 1 value of stage 1 decision
- $Q(x,z)$: stage 2 value of opt recourse given (x,z)
- $V(z)$: total value of optimal stage 1 and 2 decisions given z
- EVPI: *expected value of perfect information*

$$\mathbf{E}_z[V(z)] - \max_x (C(x) + \mathbf{E}_z[Q(x,z)])$$
- VSS: *expected value of stochastic solution*

$$\max_x (C(x) + \mathbf{E}_z[Q(x,z)]) - (C(x^*) + \mathbf{E}_z[Q(x^*,z)])$$
 where x^* is opt “in expectation” stage 1 decision

Two-Stage Stochastic Programming

- First-stage decision $x \in \mathbb{R}^n$. Event $z=(q,T,W,h)$ defines second-stage problem.
- $y \in \mathbb{R}^m$ second-stage decision

$$\begin{aligned} \max_x \quad & c^T x + \mathbf{E}_z[Q(x,z)] \\ \text{s.t.} \quad & Ax \leq b \\ & x \geq 0 \end{aligned}$$

First-stage problem:
max the value of t=1 and expected value of t=2

where

$$\begin{aligned} Q(x,z) = \max_y \quad & q^T y \\ \text{s.t.} \quad & Tx + Wy \leq h \\ & y \geq 0 \end{aligned}$$

Second-stage problem:
given (x, z) , maximize value of t=2.

Example: Farmer's problem

- Only T matrix is uncertain in the farmer's problem
- Let t_i denote **yield** of crop i ; realized event $z=(t_1, t_2, t_3)$
- Second-stage decision problem:

$$\begin{aligned} Q(x, z) = \max & -238y_1^b + 170y_1^s - 210y_2^b + 150y_2^s + 36y_3^{s1} + 10y_3^{s2} \\ \text{s.t. } & t_1x_1 + y_1^b - y_1^s \geq 200 \\ & t_2x_2 + y_2^b - y_2^s \geq 240 \\ & y_3^{s1} + y_3^{s2} \leq t_3x_3 \\ & y_3^{s1} \leq 6000 \end{aligned}$$

Maximize period 2 value given (x, z) .

Computational approaches

- (1) **Small number of possible events**, can form a single LP and solve (e.g., Farmer's problem.)

(2) Event z is a continuous r.v., but can solve for $E_z[Q(x, z)]$ analytically and then solve for stage 1 analytically.

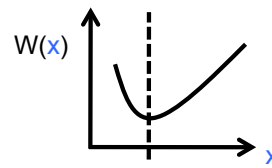
- (3) Cannot use approach (1) or (2). Use **sample average approximation (SAA)**.

Analytical approach: Example

- We're giving away Harvard-Yale T-shirts!
- Must decide how many to order x at cost $c=\$1$. Demand $z \sim U(0,100)$ uncertain
- Cost $b=\$1.5$ for "backorder cost" if $z > x$, holding cost $h=\$0.1$ if $x > z$.

- $\min cx + E_z[Q(x,z)]$

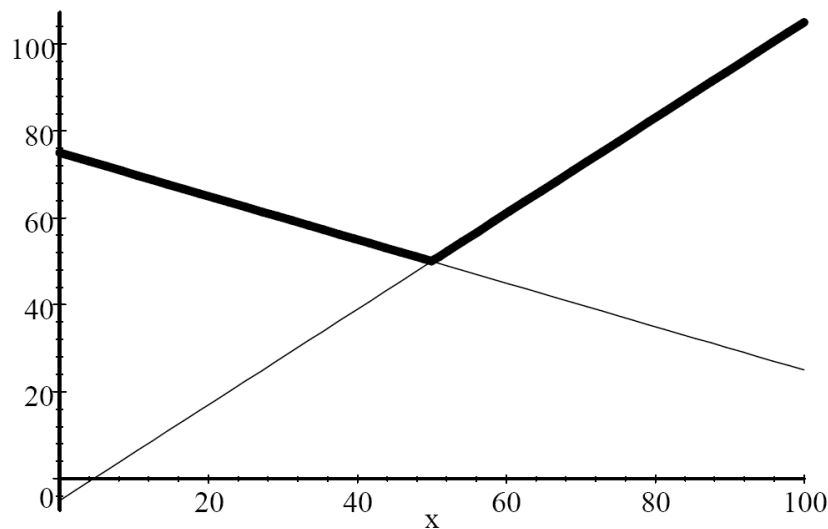
- $Q(x,z) = b \max(z-x,0) + h \max(x-z,0)$



- Write $E_z[Q(x,z)] = W(x)$

- Solve for x^* by first-order optimality: $c+W'(x)=0$

Example: $cx + Q(x,z)$ for $z=50$



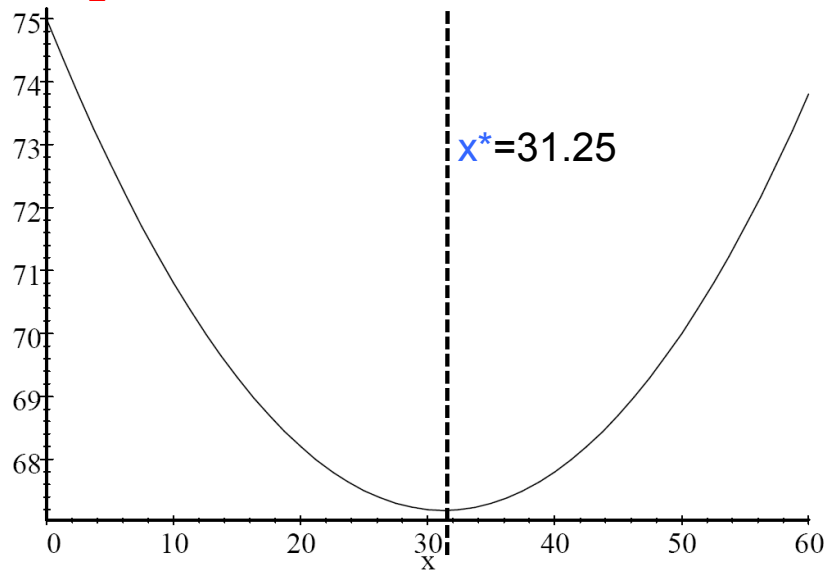
$$cx + Q(x,50) = 1x + 1.5 \max(50-x,0) + 0.1 \max(x-50,0)$$

- $$cx + E_z[Q(x,z)] = bE_z[z] + (c-b)x + (b+h) \int_0^x F(z) dz$$

$$= (1.5)(50) + (-0.5)x + 1.6 \int_0^x z/100 dz$$

$$= 75 - 0.5x + 0.008x^2$$

$cx + E_z[Q(x,z)]$



Computational approaches

- (1) **Small number of possible events**, can form a single LP and solve (e.g., Farmer's problem.)
- (2) Event z is a continuous r.v., but can solve for $E_z[Q(x,z)]$ analytically and then solve for stage 1 analytically.

(3) Cannot use approach (1) or (2). Use **sample average approximation (SAA)**.

Sample Average Approximation

(Kleywegt et al. 2001)

- **Approximate** $E_z[Q(x,z)]$ by sampling K possible events, with

$$E_z[Q(x, z)] \approx (1/K) \sum_{k=1}^K Q(x, z_k)$$

- Solve:

$$\begin{aligned} \min_{x, y} \quad & c^T x + (1/K) \sum_k q_k^T y_k \\ \text{s.t.} \quad & T_k x + W_k y_k \leq h_k \quad \text{for all } k \end{aligned}$$

Example: T-shirt problem

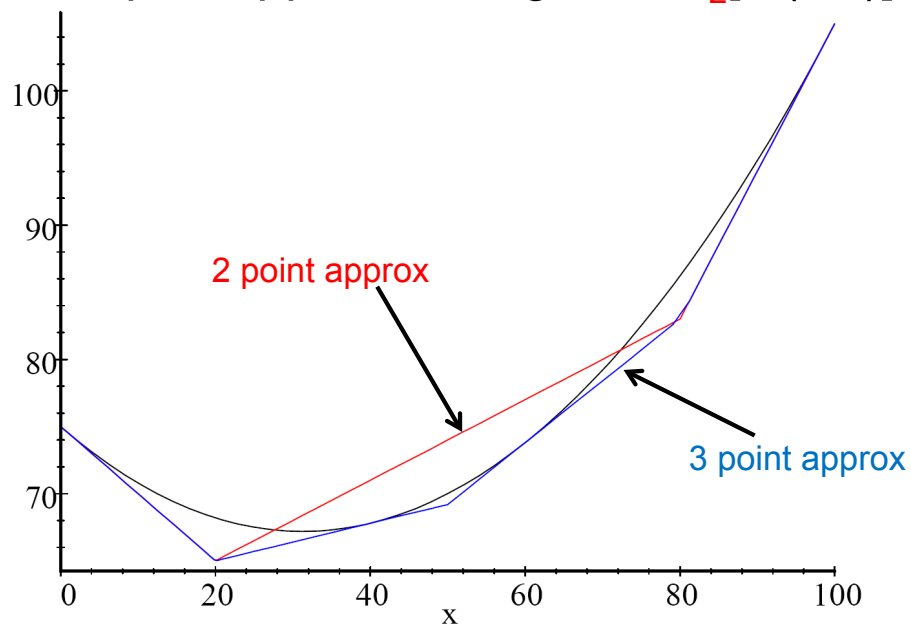
- Consider two realized (demand) events:

$$z_1 = 20, z_2 = 80$$

- Objective: $cx + \mathbf{E}_z[Q(x,z)] = cx + \frac{1}{2}Q(x,z_1) + \frac{1}{2}Q(x,z_2)$
- Have one set of period 2 decision variables per sampled event

- Can also consider three (or more!) scenarios...

Example: Approximating $cx + \mathbf{E}_z[Q(x,z)]$



Theoretical properties of SAA

(Kleywegt et al. 2001)

- V_K = exp. value of approx solution for K samples
- S_K^d = all solutions within distance d of approx soln
- V^* = exp value of optimal solution
- S^d = all solutions within distance d of optimal soln

Theorem:

(1) $\lim_{K \rightarrow \infty} V_K = V^*$.

(2) $S_K^d \subset S^d$ with probability 1 as $K \rightarrow \infty$, for any distance d.

Example Applications

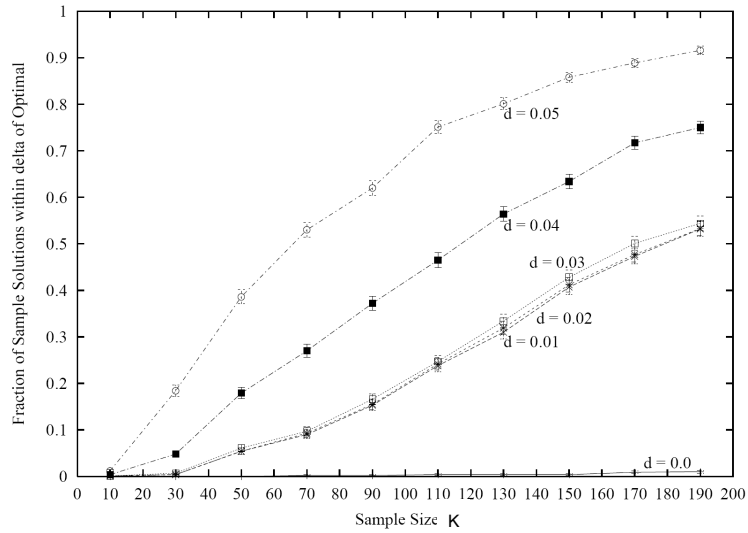
(Kleywegt et al. 01; van Hentenryck)

- Contractor's problem.
- Airline crew scheduling. Assign crew to routes, but each route takes an uncertain time. May need to pay over-time.
- Power restoration (schedule repair crews, schedule power restoration. Minimize overall size of blackout.)
- Scheduling evacuations (save as many lives as possible.)

Contractor's Problem

(Kleywegt et al. 01)

20 projects. Fraction of solutions within delta (d) of optimal:



Evacuation planning

(van Hentenryck 2015)

See additional slide deck.

K

Summary: Stochastic Optimization

- Scales up MDPs to settings with many decisions, many possible states
- Solve first-stage in anticipation of second-stage (recourse).
- Find value-maximizing first-stage decision
- “Optimal stochastic solution”
- Sample average approximation method