Robust Optimization & Network Design Lecture 7

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Recoverable Robustness

- 1.1 Mathematical Descriptions
- 1.2 Complexity
- 1.3 Polyhedral Study
- 1.4 Cover Inequalities
- 1.5 Computational Results

Conclusions



Recall: In many problems, all decisions have to be made in advance.

Discrete Scenarios

- limited number of scenario vectors
- solution should be valid for all scenarios

Γ Scenarios (Bertsimas & Sim 03/04)

- demand $d^k \in [\bar{d}^k, \bar{d}^k + \hat{d}^k]$ with nominal demand \bar{d}^k and deviation \hat{d}^k
- due to statistical multiplexing only few simultaneous peaks
- assume at most Γ peaks at same time
- solution should be valid for all scenarios

In both cases: optimize worst-case

Drawback: "almost always" good solutions might be infeasible



Two-Stage RO: some decisions are only taken at 2nd stage Recoverable robustness: repair 1st stage decisions

uncertainty as two-stage process:

1st stage: a-priori decision 2nd stage: recovery: limited change of first-stage decision after realization of uncertainty is known

- optimize worst-case w. r. t. recovery
- In this lecture: Recoverable Robust Knapsack problem (RRKP) with
- Discrete Scenarios¹
- Γ Scenarios²

¹C. Büsing, A. M. C. A. Koster, and M. Kutschka. Recoverable robust knapsacks: the discrete scenario case. *Optimization Letters*, 5(3):379–392, 2011

²C. Büsing, A. M. C. A. Koster, and M. Kutschka. Recoverable robust knapsacks: *gamma*-scenarios. In *Proceedings of INOC 2011*, volume 6701 of *Lecture Notes on Computer Science*, pages 583–588, 2011



(k, ℓ) -RRKP with Discrete Scenarios

Given items $N = \{1, \ldots, n\},\$ first stage: profits p^0 , weight w^0 , capacity c^0 , • scenarios $S \in S_D$ with profits p^S , weight w^S , capacity c^S , recovery set $\mathcal{X}(X)$: delete $\leq k$ items, add $\leq \ell$ items Find subset $X \subseteq N$ Such that $\blacksquare w^0(X) \leq c^0$, • for all $S \in S_D$ there exists $X^S \in \mathcal{X}(X)$ with $w^S(X^S) < c^S$. total profit $p_{\mathcal{T}}(X) = p^{0}(X) + \min_{\substack{S \in S_{D} \\ X^{S}}} \max_{X^{S}} p^{S}(X^{S})$ is maximized. First S 1 S 2



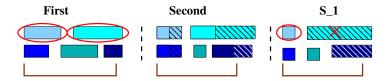
RRKP with Discrete Scenarios - ILP

$\max \sum_{i \in N} p_i^0 x_i + \omega$			first stage	
s. t. $\sum_{i \in N} w_i^0 x_i$	$\leq c^0$		second stage removal of $\leq k$ items	
$\sum_{i \in \mathbf{N}} w_i^S x_i^S$	$\leq c^{S}$	$\forall S \in \mathcal{S}_D$	addition of $\leq \ell$ items	
$x_i - x_i^S - y_i^S$	\leq 0	$\forall S \in \mathcal{S}_D, i \in N$		
$\sum_{i=1}^{n} y_{i}^{S}$	$\leq k$	$\forall \boldsymbol{S} \in \mathcal{S}_{D}$		
$x_i^S - x_i - z_i^S$	\leq 0	$\forall S \in S_D, i \in N$		
$\sum_{i=1}^{n} z_i^S$	$\leq \ell$	$\forall S \in \mathcal{S}_D$		
$\omega - \sum_{i=1}^n p_i^{\mathcal{S}} x_i^{\mathcal{S}}$	≤ 0	$\forall S \in \mathcal{S}_D$		
$x_i, \boldsymbol{x_i^S}, \boldsymbol{y_i^S}, \boldsymbol{z_i^S} \in \{0,1\}$				



k-RRKP with Γ Scenarios

Given Items $N = \{1, ..., n\}$, If irst stage: profits p^0 , weights w^0 , capacity c^0 , F-scenarios: weights $[\bar{w}, \bar{w} + \hat{w}]$, capacity $c, \Gamma \in \mathbb{N}$, recovery set $\mathcal{X}(X)$: delete $\leq k$ items from $X \subseteq N$ Find subset $X \subseteq N$, Such that $w^0(X) \leq c^0$, for all $S \in S_{\Gamma}$ there exists $X^S \in \mathcal{X}(X)$ with $w^S(X^S) \leq c$, total profit $p^0(X)$ is maximized





Mathematical Programming formulation:

$$\max \sum_{i \in N} p_i^0 x_i$$

$$s. t. \sum_{i \in N} w_i^0 x_i \leq c^0$$

$$\sum_{i \in N} \bar{w}_i x_i + \max_{\substack{X \subseteq N \\ |X| \leq \Gamma}} (\sum_{i \in X} \hat{w}_i x_i - \max_{\substack{Y \subseteq N \\ |Y| \leq k}} (\sum_{i \in Y} \bar{w}_i x_i + \sum_{i \in X \cap Y} \hat{w}_i x_i)) \leq c$$

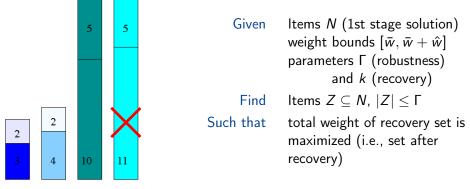
$$x_i \in \{0, 1\}$$

Question: Compact Linear reformulation? Answer: LP duality and enumeration of solution values!



Max Weight Set Problem

Example:



- $\Gamma = 2, \ k = 1, \ Opt = 21$
- Choice of Z for $\Gamma = 2$ does not include choice for $\Gamma = 1!$
- Reformulation by LP duality!



Let $U := \{0\} \cup \{\overline{w}_i : i \in N\} \cup \{\overline{w}_i + \hat{w}_i : i \in N\}$ Then, a compact reformulation is:

$$\max \sum_{i \in N} p_i^0 x_i$$

$$s. t. \sum_{i \in N} w_i^0 x_i \leq c^0$$

$$\sum_{\substack{i \in N: \\ \overline{w_i} < u}} \overline{w_i} x_i + \sum_{\substack{i \in N: \\ \overline{w_i} \geq u}} u x_i + \Gamma \xi^u + \sum_{i \in N} \theta_i^u \leq c + ku \quad \forall u \in U$$

$$\min \{ -\overline{w_i} + u, \hat{w_i} \} x_i - \xi^u - \theta_i^u \leq 0 \qquad \forall u \in U$$

$$\xi^u, \theta_i^u \geq 0 \qquad \forall u \in U, i \in N$$

$$x_i \in \{0, 1\} \qquad \forall u \in U, i \in N$$

Resulting compact model contains $O(n^2)$ variables and constraints



Theorem 1 (Karp 72, Bellman 57)

The knapsack problem is weakly NP-hard, i.e., it can be solved in O(nc) time.

Theorem 2 (Yu 96, Kalai & Vanderpooten 06)

The robust knapsack problem with bounded number of scenarios can be solved in pseudo-polynomial time.

Theorem 3 (Yu 96, Aissi et al. 07)

The robust knapsack problem with discrete scenarios is strongly NP-hard and not approximable, unless P = NP.

Theorem 4 (Bertsimas & Sim 03/04, Klopfenstein & Nace 08)

The Γ -robust knapsack problem can be solved in pseudo-polynomial time.

Theorem 5

The (k, ℓ) -rrKP is strongly NP-hard for unbounded sets of discrete scenarios even if either $p^0 = 0$ or $p^S = 0$ for all $S \in S_D$ holds.

Reductions from 3SAT.

Corollary 6

The (k, ℓ) -rrKP cannot be approximated within $\frac{\ell+1}{\ell}$, unless P = NP. In particular, for $\ell = 0$, the problem cannot be approximated.

Theorem 7

The (k, ℓ) -rrKP can be solved in pseudo-polynomial time for a bounded number of scenarios.

Generalization of dynamic programming for robust knapsack (Yu, 1996).



Theorem 8

The RRKP with Γ scenarios is at least weakly NP-hard.

Open Problem

Is the RRKP with Γ scenarios strongly NP-hard or does there exist a pseudo-polynomial time algorithm?



Projection of Discrete Scenarios

Let $p^S \equiv 0$ for all $S \in S_D$.

 \Rightarrow The number ℓ of items added do not play a role

Definition 9 (RRK Polyhedron)

$$\mathcal{K}_{D}(k) := \operatorname{conv} \left\{ x \in \{0,1\}^{n} : \sum_{i \in N} w_{i}^{0} x_{i} \leq c^{0} \text{ and} \\ \min_{\substack{T \subseteq N \\ |T| \leq k}} \sum_{i \in N \setminus T} w_{i}^{S} x_{i} \leq c^{S} \ \forall S \in \mathcal{S}_{D} \right\}$$

Projection on original variables

If $p^S \equiv 0$, the (k, ℓ) -RRKP with discrete scenarios can be formulated as

$$\max\left\{\sum_{i\in N}p_i^0x_i:x\in \mathcal{K}_D(k)\right\}$$

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Definition 10 (Γ-RRK Polyhedron)

$$\mathcal{K}_{\Gamma}(k) := \operatorname{conv} \left\{ x \in \{0,1\}^n : \sum_{i \in N} w_i^0 x_i \le c^0 \text{ and} \\ \min_{\substack{T \subseteq N \\ |T| \le k}} \sum_{i \in N \setminus T} w_i^S x_i \le c \; \forall S \in \mathcal{S}_{\Gamma} \right\}$$

Projection on original variables

The Γ-RRKP can be formulated as

$$\max\left\{\sum_{i\in N}p_i^0x_i:x\in \mathcal{K}_{\Gamma}(k)\right\}$$

How do \mathcal{K}_D and \mathcal{K}_Γ look like?

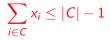


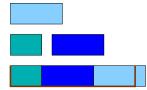
Non-robust Knapsack Polytope:

$$\mathcal{K} := \operatorname{conv} \{ x \in \{0,1\}^n : \sum_{i=1}^n w_i^0 x_i \le c^0 \}$$

• Cover
$$C$$
 : $\sum_{i \in C} w_i^0 \ge c^0 + 1$

Cover inequality :







Cover Inequalities for \mathcal{K}_D

Non-robust cover: If
$$\sum_{i \in C} w_i^0 \ge c^0 + 1$$
, then $\sum_{i \in C} x_i \le |\mathcal{C}| - 1$.

Definition 11

A set $C \subseteq N$ is called an *rrKP cover* if first stage cover: $w^0(C) \ge c^0 + 1$ or scenario cover: $w^S(C) - w^S(\max, C, k) \ge c^S + 1$, where $w^S(\max, C, k) := \max_{\substack{B \subseteq C \\ |B| \le k}} w^S(B)$.

Theorem 12

Given a rrKP cover C, the rrKP cover inequality

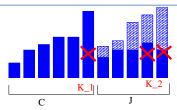
$$\sum_{i\in C} x_i \le |C| - 1$$

is valid for \mathcal{K}_D .



Cover Inequalities for \mathcal{K}_{Γ}

- $C \subseteq N$ nominal items $(w_i = \bar{w}_i)$
- $J \subseteq N$ peak items $(w_i = \bar{w}_i + \hat{w}_i)$
- $K_1 \subseteq C$ recovered(=removed) nominal items
- $K_2 \subseteq J$ recovered(=removed) peak items



Definition 13 (A quadruple (C, J, K_1, K_2) is a Γ -*rrKP cover* if)

- $|J| \leq \Gamma$, $C \cap J = \emptyset$, and $|K_1| + |K_2| = k$ and
- $w^0(C \cup J) \ge c^0 + 1$ (first stage cover)
- or (C, K_1, J, K_2) is a second stage cover:

$$\sum_{i \in C \setminus \mathcal{K}_{\mathbf{1}}} \bar{w}_i + \sum_{i \in J \setminus \mathcal{K}_{\mathbf{2}}} (\bar{w}_i + \hat{w}_i) \geq c + 1$$

Theorem 14

Given a Γ -rrKP cover (C, K₁, J, K₂), the Γ -rrKP cover inequality

$$\sum_{\in C \cup J} x_i \le |C \cup J| - 1$$



Theorem 15

Let $x \in \{0,1\}^n$. Then $x \in \mathcal{K}_D$ ($x \in \mathcal{K}_{\Gamma}$) if and only if x satisfies all minimal (Γ -)rrKP cover inequalities.

I.e., the minimal cover inequalities provide a formulation of the problem.

But, they do not provide a complete description of the convex hull of binary solutions.



Extended Cover Inequalities

Non-robust knapsack: Let
$$E(C) := \left\{ j \in N : w_j^0 \ge \max_{i \in C} w_i^0 \right\} \cup C$$
. Then

the Extended Cover inequality for non-robust knapsack reads:

i

$$\sum_{\in E(C)} x_i \le |C| - 1$$

rrKP with discrete scenarios: A cover C w.r.t. scenario S can be extended with items whose weights exceed (canonical extension) the weight of the k + 1 highest-weight-item in C (advanced extension)

- 1. the residual capacity according to the weights of the first
 - |C| k 1 lowest-weight-items
- 2. the weight of the k + 2 highest-weight-item in C

Theorem 16

Let S be a cover w.r.t scenario S and $E^{S}(C)$ its extension. Then



rrKP with Γ scenarios:

$$E(C, \mathcal{K}_1, J, \mathcal{K}_2) := \left\{ j \in \mathcal{N} : \bar{w}_j \ge \max_{i \in C \setminus \mathcal{K}_1} \bar{w}_i \text{ and } \bar{w}_j + \hat{w}_j \ge \max_{i \in J \setminus \mathcal{K}_2} \bar{w}_i + \hat{w}_i \right\}$$
$$\cup \{C \cup J\}$$

Theorem 17

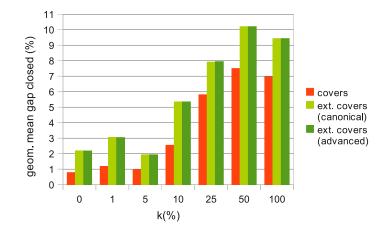
Let (C, K_1, J, K_2) be a Γ cover and $E(C, K_1, J, K_2)$ its extension. Then

$$\sum_{i\in E(C,\mathcal{K}_1,J,\mathcal{K}_2)} x_i \leq |C\cup J| - 1$$

is valid for \mathcal{K}_{Γ} .



Gap closed by cover inequalities:

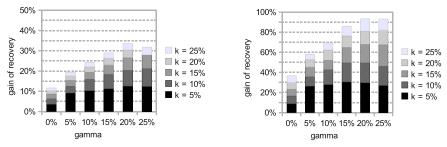


Note: the complete ILP formulation is used



exact separation by ILP

Gain of Recovery:



geometric mean

observed maximum

For each instance, Γ , and k, the gain of recovery is determined by the objective value normalized to the corresponding case with k = 0 %.



Recoverable Robustness

- 1.1 Mathematical Descriptions
- 1.2 Complexity
- 1.3 Polyhedral Study
- 1.4 Cover Inequalities
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Conclusions



- Light Robustness: bound price of robustness of budget uncertainty and minimize weighted sum of constraint violations
- Distributionally Robust Optimization: given historical data, find solutions that are robust whatever probability distribution the data follows. Marriage between stochastic and robust optimization
- Minimax Regret Optimization or Robust deviation: Minimize largest possible difference between observed objective value of robust solution and optimal solution value (knowing uncertain parameters in advance)
- Relative robust deviation: Minimize largest possible ratio of robust deviation to the optimal objective value

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