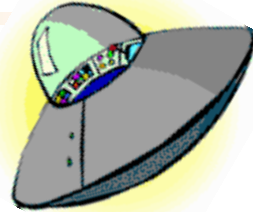

UFO



Uncertainty Feature Optimization, an Implicit Paradigm for Problems with Noisy Data

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CTW2008

Schedule

- Motivations
- The UFO framework
- Existing Methods seen as UFO
- Example: Problem with **M**ultiple **K**napsack

Constraints (MKC)

- Preliminary Simulation Results for MKC
- Future Work and Conclusions

Motivation

- Uncertainty should not be neglected
- Uncertainty is hard to characterize exactly
- Problems under uncertainty are hard to solve in general
- Few guarantees on real solution

Four Approaches

1. Neglect and solve deterministic problem

- Not realistic (Herroelen 2005, Sahinidis 2004)

Four Approaches

1. Neglect and solve deterministic problem
2. On-line Optimization
 - Data-driven
 - Not feasible for some problems (e.g. airline schedules)

Four Approaches

1. Neglect and solve deterministic problem
2. On-line Optimization
3. Characterize the Uncertainty and solve robust or stochastic problems
 - Need explicit Uncertainty characterization
 - Hard to characterize/model in general
 - Leads to difficult problems
 - Solutions tend to “simple” properties

Examples from Airline Scheduling

- Increase plane's idle time (Al-Fawzana & Haouari 2005)
- Decrease plane rotation length (Rosenberger et al. 2004)
- Departure de-peaking (Jiang 2006, Frank et al. 2005)
- More plane crossings (Bian et al. 2004, Klabjan et al. 2002)
- ...

Four Approaches

1. Neglect and solve deterministic problem
2. On-line Scheduling
3. Characterize the Uncertainty
4. Model Uncertainty Implicitly => Uncertainty Features

Uncertainty Feature Optimization

- I. Increase **robustness**/stability (e.g. idle time)

- II. Increase **recoverability** (e.g. plane crossings)

How to Derive an UF ?

Know **WHAT** changes, not **HOW**

- UF is problem dependent
- use practitioner's experience/intuition

If **recovery strategy** is known

- seek UF improving recovery's performance
⇒ **RECOVERABILITY**

General Optimization Problem

$$\text{MIN } f(x)$$

$$\text{s. t. } a(x) \leq b$$

$$x \in X$$

UFO: Multi-Objective Problem

$$OPT [f(x), \mu(x)]$$

$$s. t. \quad a(x) \leq b$$

$$x \in X$$

UF and Optimality Budget

$\mu(\mathbf{x})$ Uncertainty Feature

f^* Original Optimum

ρ Maximal Optimality Gap

UFO with Budget Relaxation

$$\text{MAX } \mu(x)$$

$$\text{s. t. } a(x) \leq b$$

$$f(x) \leq (1 + \rho)f^*$$

$$x \in X$$

UFO Properties

- I. Complexity not changed if $\mu(x)$ similar to $f(x)$
- II. Implicit modeling of uncertainty
- III. Differentiate solutions on optimal facet
- IV. “Plug” tool for any existing method
- V. Can use UF based on explicit uncertainty set
- VI. Generalizes existing methods

Stochastic Problem as an **UFO**

Given an Uncertainty Set \mathbf{U} with a probability measure on it

$$\begin{aligned} \min \quad & E_{\mathbf{U}}\{f(\mathbf{x})\} \\ \text{s. t.} \quad & a(\mathbf{x}) \leq b \\ & \mathbf{x} \in X \end{aligned}$$

Stochastic problem as an **UFO**

$$\text{MAX } \mu(x) = -E_U\{f(x)\}$$

$$\text{s. t. } a(x) \leq b$$

$$f(x) \leq (1 + \infty)f^*$$

$$x \in X$$

Robust problem as an UFO

Original LP Problem

$$\text{MAX } \mathbf{c}^T \mathbf{x}$$

$$\text{s. t. } \mathbf{Ax} \leq \mathbf{b}$$

$$\mathbf{x} \in X$$

Robust problem as an UFO

Formulation of Bertsimas and Sim (2004)

$$\text{MAX } \mathbf{c}^T \mathbf{x}$$

$$\text{s. t. } \quad \mathbf{Ax} + \boldsymbol{\beta}(\mathbf{x}, \Gamma) \leq \mathbf{b}$$

$$\mathbf{x} \in X$$

$$\tilde{a}_{ij} \in [a_{ij} - \hat{a}_{ij}; a_{ij} + \hat{a}_{ij}] \quad \forall j \in J_i$$

$$\beta_i(x, \Gamma_i) = \max_{\{S_i \cup \{t_i\} \mid S_i \in J_i, |S_i| = \lfloor \Gamma_i \rfloor, t_i \in J_i \setminus S_i\}}$$

$$\left\{ \sum_{j \in S_i} \hat{a}_{ij} |x_j| + (\Gamma_i - \lfloor \Gamma_i \rfloor) \hat{a}_{it_i} |x_{t_i}| \right\}$$

Start with Feasibility Problem

$$f^* = \text{MIN } f(\mathbf{x})$$

$$= \text{MIN } [A\mathbf{x} + \boldsymbol{\beta}(\mathbf{x}, \mathbf{J})] - \mathbf{b}$$

$$\text{s. t. } \quad \mathbf{x} \in X$$

Define **UF** and budget

$$\mu(\mathbf{x}) = \mathbf{c}^T \mathbf{x} \quad \rho = \max_i \left\{ \frac{\rho_i f_i(\mathbf{x}^*)}{f^*} - 1 \right\}$$

Where

$$\rho_i = \begin{cases} \frac{\bar{\beta}_i(\mathbf{x}, \Gamma_i)}{f_i(\mathbf{x}^*)} \\ 0 \text{ if } f_i(\mathbf{x}^*) = 0 \end{cases} \quad \text{and} \quad \beta(\mathbf{x}, \mathbf{J}) = \beta(\mathbf{x}, \mathbf{\Gamma}) + \bar{\beta}(\mathbf{x}, \mathbf{\Gamma})$$

UFO formulation

$$\text{MAX } \mu(x) = \mathbf{c}^T \mathbf{x}$$

$$\text{s. t. } [\mathbf{A}\mathbf{x} + \boldsymbol{\beta}(x, \mathbf{J})] - \mathbf{b} \leq (1 + \rho)\mathbf{f}^*$$

$$\mathbf{x} \in X$$

Replace Elements in Constraint

$$[Ax + \beta(x, J)] - b \leq (1 + \rho)f^*$$
$$=$$

$$[Ax + \beta(x, J)] - b \leq \bar{\beta}(x, \Gamma)$$

Which is equivalent to

$$Ax + \beta(x, J) - \bar{\beta}(x, \Gamma) \leq b$$
$$=$$

$$Ax + \beta(x, \Gamma) \leq b$$

Retrieve Robust Formulation

$$\text{MAX } \mu(x) = c^T x$$

$$\text{s. t. } Ax + \beta(x, \Gamma) \leq b$$

$$x \in X$$

Q.E.D.

BONUS

Gives methodology to compute maximal values of Γ to ensure a robust solution exists.

Multiple Knapsack Constraints

$$\begin{aligned} & \max \sum_{i=1}^N c_i x_i \\ \text{s. t. } & \sum_{j=1}^N a_{ij} x_i \leq b_i \quad \forall i = 1, \dots, M \\ & \mathbf{x} \in \mathbb{Z}_+^N \end{aligned}$$

MKC with Max Taken Object **UFO**

$$\min \left\{ \mu(\mathbf{x}) = \max_{i=1, \dots, N} \{x_i\} \right\}$$

$$s. t. \quad A\mathbf{x} \leq \mathbf{b}$$

$$\mathbf{c}^T \mathbf{x} \geq (1 - \rho) \mathbf{c}^*$$

$$\mathbf{x} \in \mathbb{Z}_+^N$$

Other derived UF

- Max Taken (MTk): $\mu(\mathbf{x}) = \max_{i=1,\dots,N} \{x_i\}$
- Diversification (Div): $\mu(\mathbf{x}) = \sum(\min \{1, x_i\})$
- Impact Ratio (IR): $\mu(\mathbf{x}) = -\max_i \frac{a_{ij}x_j}{b_i}$
- 2Sum: $\mu(\mathbf{x}) = -\max_{i,j \neq k} \frac{a_{ij}x_j + a_{ik}x_k}{b_i}$

MKC Simulator

- Generation of problems
- Solve Models inc. Robust (combining possible)
- Simulation with user-defined parameters

Simulation Results

- Partial results on 8 of 24 classes
- Classes according to
 - i. Cost-correlated A matrix
 - ii. Granularity
 - iii. Number of Constraints
 - iv. Number of varying coefficients

Simulation Results

- Simulations according to
 - a. Exact variability matrix \hat{A}
 - b. Variability matrix based on A
 - c. Random Variability Matrix
 - d. High or Low variances

	ROBUST \hat{A}	ROBUST 0.1*A	IR rho = 10%	$_{-}MTk + 2Sum$ rho = 10%	Div rho = 10%
Nbr Unfeasible	21470	25763	40680	40841	50212
% of unfeasible	25.56	30.67	48.43	48.62	59.78
Avg Optimality Gap (%)	18.07	11.66	9.25	9.23	7.94
Max Optimality Gap (%)	98.13	96.89	96.4	96.4	96.89

Used Model	ROBUST \hat{A}			_MTk rho = 10%		
	\hat{A}	0.2*A	RANDOM	\hat{A}	0.2*A	RANDOM
Nbr Unfeasible	2	15	761	47	117	1186
% of unfeasible	<0.01	1.00	50.73	3.13	7.8	79.07
Avg Optimality Gap (%)	3.95	4.10	9.59	9.67	9.45	6.57
Max Optimality Gap (%)	37.43	33.55	90.01	24.97	24.98	89.22

Future Work

- Extended Tests on MKC
- Application of UFO to Airline Transportation
- Find an UF generator ?

Conclusions

- UFO allows to cope with uncertainty **IMPLICITLY**
- Use explicit uncertainty model is still possible
- UFO can be combined with any already existing method
- It is NOT an alien method !

THANKS for your attention

Any Questions?