Data-Driven Decision-Making In Enterprise Applications

Linear Programming II

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Decision-Making Using Linear Programming

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Linear Programming II

- Questions regarding last week?
- Today: Motivation AMPL
	- Example V Equilibria in Mixed Strategies (Game Theory)
	- Penalty Approaches & Continuous Relaxations
	- Solution Tuning
	- Tricks to Circumvent Non-Linearities

Solving Motivation AMPL

Solving Knapsack Problems using LP via AMPL

- All you need: AMPL, a solver, 10 lines of code
- AMPL translates the problem to the solver, which solves the problem
- Simplex Alg. is fast in general but can have exponential complexity
- Can we solve our knapsack problem with 1000, 10K, or 100K items?
- What do you think is the solution time?

LP meets Game Theory

Game Theory – "Gefangenendilemma" (Pure NE)

What's the best strategy? Equilibrium in **pure** strategies: "Gestehen" (dominant)

Game Theory – "Papier Stein Schere" (Mixed NE)

No pure equilibrium. What is the best (mixed) strategy?

Game Theory – "Papier Stein Schere" (Mixed NE)

No pure equilibrium. What is the best (mixed) strategy?

Symmetric Intuition: Equilibrium in mixed strategies, i.e., 1/3, 1/3, 1/3

Game Theory – "Papier Stein Schere 2.0"

Asymmetric rewards. Will player 2 play more often "Papier"?

Answer?

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Asymmetric rewards. Will player 2 play more often "Papier"? Answer: No. But player 1 plays more "Schere"!

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Solution Approach: Use Linear Programming to make the competitor *indifferent* in his/her strategies !

LP Model – "Papier Stein Schere 2.0"

Assume payoff $r^{(1)}(i, j)$ for player 1 when playing *i* while the other plays *j* Assume payoff $r^{(2)}(i, j)$ for player 2 when playing *j* while the other plays *i*

Variables: $x^{(1)}(i)$, $x^{(2)}(j) \in [0,1]$ prob's of players playing options, $i,j=1,...,N$

Solution Approach: P1 makes P2 indifferent in all actions $j = 1,...,N$, i.e.,

$$
\sum_{i=1,..,N} x^{(1)}(i) \cdot r^{(2)}(i,1) = \sum_{i=1,..,N} x^{(1)}(i) \cdot r^{(2)}(i,2) = \sum_{i=1,..,N} x^{(1)}(i) \cdot r^{(2)}(i,3)
$$

and vice versa (P2 makes P1 indifferent in all actions *i=1,...,N*):

$$
\sum_{j=1,\dots,N} x^{(2)}(i) \cdot r^{(1)}(1,j) = \sum_{j=1,\dots,N} x^{(2)}(i) \cdot r^{(1)}(2,j) = \sum_{j=1,\dots,N} x^{(2)}(j) \cdot r^{(1)}(3,j)
$$

LP Model – "Papier Stein Schere 2.0"

param N :=3; # number of options param r1{i in 1..N, j in 1..N} := if i=j then 0 else if (1+i) mod 3 $=$ j mod 3 then Uniform(0,5) else Uniform(-5,0): # payoffs param r2{i in 1..N, j in 1..N} := $-r1[i,j]$; # 2Pers-0sum-qame var x1 {i in $1..N$ } >= 0; $\qquad \qquad$ # probability P1 playing option i var x2 {j in 1..N} >= 0; $\qquad \qquad$ # probability P2 playing option j subject to NB1: $sum{i in 1..N} x1[i] = 1;$ # norm player 1 subject to NB2: $sum{j \in I..N} x2[j] = 1;$ # norm player 2 subject to NB3{j in 2..N}: sum{i in 1..N} $x1[i]*r2[i,j] # 1$ makes 2 $=$ sum{i in 1..N} $x1[i]*r2[i,1];$ # indifferent subject to NB4{i in 2..N}: sum{j in 1..N} $x2[j]*r1[i,j] # 2$ makes 1 $=$ sum{j in 1..N} x2[j]*r1[1,j];# indifferent solve; display x1, x2; \blacksquare

Penalty Approaches & Continuous Relaxations

Penalty Formulations for Contraints

Objective:

$$
\max_{x_1,...,x_N \in \{0,1\}} \sum_{i=1,...,N} u_i \cdot x_i
$$

Constraints:

$$
\sum_{i=1,\dots,N} S_i \cdot x_i \leq C
$$

 C (One) Hard Constraint

Knapsack example

Penalty-Objective:
$$
\max_{x_1, \dots, x_N \in \{0,1\}} \sum_{i=1,\dots,N} u_i \cdot x_i - \alpha \cdot \sum_{i=1,\dots,N} s_i \cdot x_i
$$
 (Soft Constraint) Constraints: none
Results: Pareto-optimal combinations of "Utility" and "Space"

Continuous Relaxations of Integer Problems

- (i) Optimal integer solution (blue):
- (ii) Continuous relaxation:
- (iii) Penalty formulation (red):

 $\min_{\vec{x} \in \{0,1\}^N} F(\vec{x}) \text{ s.t. } M(\vec{x}) \leq A \implies \vec{x}^*(A) \text{ optimal}$ $\min_{[0,1]^N} F(\vec{x}) \text{ s.t. } M(\vec{x}) \leq A \implies \vec{x}^*(A) \in \{0,1\}^N$? \rightarrow \vec{x}^* $(A) \in \{0,1\}^N$
 \rightarrow \vec{x}^* $(A) \in \{0,1\}^N$ $\min_{[0,1]^N} F(\vec{x}) + \alpha \cdot M(\vec{x}) \implies \vec{x}^*(\alpha) \in \{0,1\}$ \overline{x} ^{*x*}</sup> \overline{x} ² \overline{x} ² \overline{x} ² \overline{x} ² \overline{x} ² \overline{x} ² \overline{x} ³ \overline{x} $\min_{\vec{x}\in[0,1]^N} F(\vec{x}) + \alpha \cdot M(\vec{x}) \implies \vec{x}^{\cdot\cdot}(\alpha) \in$

$$
\uparrow
$$
 Pareto-optimal!

Continuous Solution - Integer Solution

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When do Integer & Continuous Solutions Coincide?

maximize $a \cdot x_1 + b \cdot x_2$ s.t. . . . with $x_1, x_2 \in \mathbb{R}$ vs. $x_1, x_2 \in \mathbb{N}$

 \bullet Answer: The corners of the polygon have to be "integers"!

Solution Tuning

Recall Example IV: Project Assignment Problem

, $x_{i,j} \in \{0,1\}$ \in {0,1} whether project *i*, *i*=1,...,*N*, is assigned to worker *j*, *j*=1,...,*N*

$$
\text{LP:} \qquad \max_{x_{i,j} \in \{0,1\}^{N \times N}} \sum_{i=1,\dots,N, j=1,\dots,N} w_{i,j} \cdot x_{i,j}
$$

s.t.
$$
\sum_{i=1,\dots,N} x_{i,j} = 1
$$
 for all $j=1,\dots,N$ (each worker gets 1 project)

$$
\sum_{j=1,\dots,N} x_{i,j} = 1
$$
 for all $i=1,\dots,N$ (each project is assigned)

- Will the allocation always be fair?
- How "outliers" can be avoided?
- Approaches: (i) utility functions, (ii) max min, (iii) multi-objective

Approach (i): Fair Project Assignment (Non-linear)

, $x_{i,j} \in \{0,1\}$ $\in \{0,1\}$ whether project *i*, *i*=1,...,*N*, is assigned to worker *j*, *j*=1,...,*N*

NLP:
\n
$$
\max_{x_{i,j} \in \{0,1\}^{N \times N}} \sum_{j=1,...,N} u \left(\sum_{i=1,...,N} w_{i,j} \cdot x_{i,j} \right)
$$
\nusing, e.g., $u(z) := \ln(z)$, $u(z) := z^{0.6}$, or $u(z) := -e^{-0.1 \cdot z}$
\ns.t.
$$
\sum_{i=1,...,N} x_{i,j} = 1
$$
 for all $j=1,...,N$ (each worker gets 1 project)

$$
\sum_{j=1,\dots,N}^{i=1,\dots,N} x_{i,j} = 1
$$
 for all $i=1,\dots,N$ (each project is assigned)

- Idea: Avoiding low scores is better than including high scores
- \bullet Disadvantage (i): Non-linear solver is needed

Approach (ii): Fair Project Assignment (Linear!)

 $x_{i,j} \in \{0,1\}$ whether project *i*, *i*=1,...,*N*, is assigned to worker *j*, *j*=1,...,*N* NLP: $\max_{x_{i,j} \in \{0,1\}^{N \times N}} \left\{ \min_{j=1,...,N} \sum_{i=1,...,N} W_{i,j} \cdot x_{i,j} \right\}$ $\max_{i \in \{0,1\}^{N \times N}} \left\{ \min_{j=1,...,N} \sum_{i=1,...,N} W_{i,j} \cdot X_{i,j} \right\}$ $\left\{\min_{j=1,...,N}\sum_{i=1,...,N}W_{i,j}\cdot x_{i,j}\right\}$ $\sum_{i} w_{i,j} \cdot x_{i,j}$, i.e., max poorest guy's reward! $LP: = \max_{x_{i,j} \in \{0,1\}^{N \times N}, z}$ max $x_{i,j} \in \{0,1\}^{N \times N}, z \in \mathbb{R}$ $\max_{\mathbf{z}\in\{0,1\}^{N\times N},z\in\mathbb{R}}Z$ \cong $\approx \max_{x_{i,j} \in \{0,1\}^{N \times N}, z \in \mathbb{R}} Z$ s.t. $Z \leq \sum_{i=1,...,N} W_{i,j} \cdot x_{i,j}$ $\leq \sum_{i=1}^{\infty} \sum_{N} W_{i,j} \cdot x_{i,j}$ for all $j=1,...,N$ $\sum_{1,\ldots,N}$ *i*=1,...,*N* $\sum_{i=1}^{n} x_{i,j} = 1$ for all $j=1,...,N$ (each worker gets 1 project) $\overline{1,...,N}$ $\overline{}$ $\sum_{i} x_{i,j} = 1$ for all $i=1,...,N$ (each project is assigned) *^j ^N*

- Idea: Optimize the lowest willingness (cf. worst case criteria)
- \bullet Disadvantage (ii): Total willingness score can be low

Approach (iii): Fair Project Assignment (Linear!)

, $x_{i,j} \in \{0,1\}$ $\in \{0,1\}$ whether project *i*, *i*=1,...,*N*, is assigned to worker *j*, *j*=1,...,*N*

$$
\text{LP:} \qquad \max_{x_{i,j} \in \{0,1\}^{N \times N}, z \in \mathbb{R}} \sum_{i=1,\dots,N, \ j=1,\dots,N} w_{i,j} \cdot x_{i,j} + \alpha \cdot z, \quad \text{with parameter } \alpha \ge 0
$$

s.t.
$$
z \leq \sum_{i=1,\dots,N} w_{i,j} \cdot x_{i,j} \quad \forall j
$$

$$
\sum_{i=1,\dots,N} x_{i,j} = 1
$$
 for all $j=1,\dots,N$ (each worker gets 1 project)

$$
\sum_{j=1,\dots,N} x_{i,j} = 1
$$
 for all $i=1,\dots,N$ (each project is assigned)

- Idea: Combine both objectives as a weighted sum
- \bullet • Disadvantage (iii): Suitable weighting factor α has to be determined

Nonlinear Programming Models

- Often *non-linear expressions* are needed within a model
- \bullet (–) Linear solvers cannot be used anymore
- \bullet (–) NL solvers often cannot guarantee optimality
- \bullet (+) So-called "mild" nonlinearities can be expressed linearly
- \bullet (+) This is very valuable as we can exploit LP solvers and their optimality
- The price of such transformations is acceptable: More variables and constraints

Linearization Tricks

I Linearization of "and" in the Constraints

Objective: $\min_{x_1, x_2 \in \{0,1\}} 2 \cdot x_1 + x_2$ ∈ $\cdot x_1 +$.

Constraints NL: ...

$$
x_1 = 1
$$
 and $x_2 = 1$ (e.g. needed as joint condition)

Objective: $\min_{x_1, x_2 \in \{0,1\}} 2 \cdot x_1 + x_2$ ∈ $\cdot x_1 +$.

Constraints LIN: ...

$$
x_1 + x_2 = 2
$$

II Linearization of "or" in the Constraints

Objective: $\min_{x_1, x_2 \in \{0,1\}, x_3 \in [0,M]} 2 \cdot x_1 + x_2 + x_3$ Constraints NLa: $x_1 = 1$ or $x_2 = 1$ (e.g., needed as joint condition) Constraints NLb: $x_1 = 1$ or $x_2 = 0$ Constraints NLc: $x_3 = 0$ or $x_3 \ge 3$ Objective: $\min_{x_1, x_2 \in \{0,1\}, x_3 \in [0,M], z \in \{0,1\}} 2 \cdot x_1 + x_2 + x_3$ Constraints LINa: $x_1 + x_2 \geq 1$ Constraints LINb: $x_1 + (1 - x_2) \ge 1$ Constraints LINc: $x_3 \le M \cdot z$, $x_3 \ge 3 \cdot z$

III Linearization of "max" in the Objective

IV Linearization of "min" in the Objective

new $z \leq x_i$ $z \leq x_i$ for all $i=1,...,N$

V Linearization of "min" in the Constraints

Objective: $\min_{x_1, x_2 \in [0, M]} 2 \cdot x_1 + x_2$ ∈ $\cdot x_1 +$. Constraints NL: $4 \le \min(x_1, x_2) \le 7$ Objective: $\min_{x_1, x_2 \in [0,M], z_1, z_2 \in \{0,1\}} 2 \cdot x_1 + x_2$

Constraint LIN: $4 \leq x_i$ for all $i=1,2$

new $M \cdot z_i \geq x_i - 7$ for all $i=1,2$ new $z_1 + z_2 \le 1$

VI Linearization of "abs" in the Objective

$$
\text{Objective NL: } \min_{x_1, x_2 \in \mathbb{R}} 2 \cdot x_1 + abs(3 - x_2)
$$

Constraints:

$$
\text{objective }\text{LIN: } \min_{x_1, x_2 \in \mathbb{R}, z \in \mathbb{R}} 2 \cdot x_1 + z
$$

Constraints:

new 2 $x_2 - 3 \le z$

new 2 $3 - x_2 \leq z$

VII Linearization of "abs" in the Constraints

Objective: $\min_{x_1, x_2 \in \mathbb{R}} 2 \cdot x_1 + x_2$ $\frac{1}{\mathbb{R}}$ 2 · x_1 +.

Constraints NL: $abs(3-x_2) \leq x_1$

Objective LIN: $\min_{x_1, x_2 \in \mathbb{R}, z \in \mathbb{R}} 2 \cdot x_1 + x_2$ Constraints: $z \leq x_1$ new 2 $x_2 - 3 \le z$ new 2 $3 - x_2 \leq z$

VIII Linearization of "if-then-else"

$$
\begin{array}{ll}\n\text{Objective NL:} & \min_{x_1, x_2 \in \{0, 1, 2, \dots, M\}} 2 \cdot x_1 + \left(\text{if } x_2 \leq 5.5 \text{ then a else } b \right) \\
\text{Constraints:} & \dots\n\end{array}
$$

$$
\text{Objective LIN: } \min_{x_1, x_2 \in \{0, 1, 2, \dots, M\}, z \in \{0, 1\}} 2 \cdot x_1 + b \cdot z + a \cdot (1 - z)
$$

Constraints:

new 2 $x_2 - 5.5 \le M \cdot z$

new 2 $5.5 - x_2 \leq M \cdot (1 - z)$

IX Linearization of a Product of Binary Variables

Objective: $\min_{x_1, x_2 \in \{0,1\}} 2 \cdot x_1 + x_2$ ∈ $\cdot x_1 +$.

Constraints NL: including the term: $x_1 \cdot x_2$

$$
\text{Objective:} \qquad \min_{x_1, x_2 \in \{0, 1\}, z \in \{0, 1\}} 2 \cdot x_1 + x_2
$$

Constraints LIN: include the term *z* instead, where

$$
z \le x_i, \qquad \text{for } i=1,2
$$

$$
z \ge x_1 + x_2 - 1
$$

X Linearization of a Binary x Continuous Variable

Objective: $\min_{x_1 \in \{0,1\}, x_2 \in [0,M]} 2 \cdot x_1 + x_2$

Constraints NL: including the term: $x_1 \cdot x_2$

Objective: $\min_{x_1 \in \{0,1\}, x_2 \in [0,M], z \in [0,M]} 2 \cdot x_1 + x_2$

Constraints LIN: include the term *z* instead, where

$$
z \le M \cdot x_1, \quad \text{for } i=1,2
$$

$$
z \le x_2
$$

$$
z \ge x_2 - (1 - x_1) \cdot M
$$

Homework: Get AMPL. Solve Examples I-V (see code online).

Review the Linearizations I-X!

Outlook:

- Introduction in AMPL
- Implementations of Example I-V
- Play with parameters, randseed, and problem complexity
- Nonlinear Programming and Suitable Solvers

Overview

