Integrating discrete choice models in mixed integer linear programming to capture the interactions between supply and demand

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Outline



- 2 Demand-based benefit maximization problem
- 3 Lagrangian relaxation
- 4 Conclusions and future work







Introduction

Demand-based benefit maximization problem

3 Lagrangian relaxation

4 Conclusions and future work







Discrete choice models and optimization





- Disaggregate demand modeling
- Behavioral realism
- Complex formulations



- Linearity and/or convexity
- MILP models





Bridging the gap



- Linear characterization of a discrete choice model
- Simulation to address stochasticity
- Demand-based benefit maximization problem







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Linearization of the choice model (1)











Linearization of the choice model (2)



$$w_{inr} = \begin{cases} 1 & \text{if } U_{inr} \ge U_{jnr}, \forall j \in \mathcal{C}_n, j \neq i \\ 0 & \text{otherwise} \end{cases} \qquad D_i = \frac{1}{R} \sum_r \sum_n w_{inr}$$

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Benefit maximization problem (1)





- Set of services \mathscr{C} (i > 0)
- Opt-out option *i* = 0
- Population $N (n \ge 1)$

- Price $a_i \le p_{in} \le b_{in}$
- Capacity levels c_{iq} (fixed f_{iq} and variable v_{iq} costs)





MPP, BG, VL, SSA, MB

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Benefit maximization problem (2)

obj. fun.	$\sum_{i>0} \text{Revenue}_i - \text{Cost}_i$		
availability	operator level and scenario level		
disc. utility	variable capturing availability and utility		
choice	linearization of the highest utility		
price	linearization of the vari	able η_{iqnr} (revenue)	
capacity	relation with the availab	ility at scenario level	
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Computational results



- Parking choices: mixtures of logit model
- Distributed parameters (and correlated)
- R = 50 draws and N = 50 customers
- $|\mathscr{C}| = 3$: PSP, PUP and FSP (opt-out)





Computational times up to 34 hours!





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Motivation



- Maximization of own utility
- Objective function and capacity constraints



- Behavioral scenario
- Objective function





Uncapacitated case and revenue maximization



Lagrangian decomposition

$\mathsf{Relax} \text{ complicating constraints} \Rightarrow \mathsf{subproblems \ easier \ to \ solve}$

 $\cancel{!} Price p_{in} \text{ is the same across draws} \Rightarrow \mathbf{no} \text{ decomposition by } n \text{ and } r$

$$p_{in1} = p_{in2} = \cdots = p_{inR} = p_{in1}$$

 $p_{inr} - p_{in(r-1)} = 0 \Rightarrow$ Lagrangian multipliers $\alpha_{inr} \Rightarrow$ decomposition by n and r



Subgradient method

```
Input: UB: Z(\overline{\alpha}) with \overline{\alpha} starting values, LB: Z^* (from a feasible solution)
 1 while k < K or Z(\alpha(k)) has not improved in \omega_3 iterations do
        for r = 1 \dots R do
 2
             for n = 1 \dots N do
 3
                 Lagrangian subproblem Z_{nr}(\alpha(k)) (MILP);
 4
                 Obtain p_{inr}, w_{inr} and Z_{nr}(\alpha(k));
 5
 6
             end
        end
 7
        Compute Z(\alpha(k)) = \sum_{r} \sum_{n} Z_{nr}(\alpha(k));
 8
        k \leftarrow k + 1:
 9
        Obtain \omega(k) (step) and d_{inr}(k) (direction);
10
        Update the Lagrangian multipliers: \alpha_{inr}(k) = \alpha_{inr}(k-1) - \omega(k)d_{inr}(k)
11
12 end
```



Preliminary results (1)



- N = 20 and R = 100
- $\lambda(0) = 0.5, \ \theta = 0.5, \ \omega_3 = 30$
- Number of iterations: K = 1000

Computational time:

- Exact method: 33.7 min
- Subgradient method: 21.4 min





Preliminary results (2)



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Conclusions and future work



- Efficient method to obtain lower and upper bounds
- Calibrate the parameters of the subgradient method
- Changes in the formulation (tighter LP relaxation)
- Gradually include the complexity back (capacity, availability...)





Questions?



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Subgradient method: step size and direction

$$\alpha_{inr}(k) = \alpha_{inr}(k-1) - \omega(k)d_{inr}(k)$$

Step:

•
$$\omega(k) = \lambda(k) \frac{Z(\alpha(k-1)) - Z^*}{\|\gamma(k)\|^2}$$

•
$$\lambda(0) \in [0,2)$$

•
$$\gamma_{inr}(k) = p_{inr}(k) - p_{in(r-1)}(k)$$
 (subgradients)

• $\lambda(k)$ divided by ω_1 if $Z(\alpha(k))$ has not improved in ω_2 iterations

Direction:

•
$$d(k) = \gamma(k) + \theta d(k-1)$$

• $\theta \in [0,1)$

$$\theta \in [0,1)$$

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