Incorporating behavioral model into transport optimization

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Outline



Disaggregate demand models A simple example 4 A generic framework5 MILP6 Conclusion



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Mobility as a service



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Mobility as a service

Demand orientation [Jittrapirom et al., 2017]

- User-centric paradigm
- Best from customer's perspective
- Demand responsive

Personalization

- Every user has different needs
- Tailor-made solutions
- Social network

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Mobility as a service

Key challenges [Jittrapirom et al., 2017]

- Demand-side modeling
- Supply-side modeling
- Governance and business model to match supply and demand

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Outline



Demand and supply

Disaggregate demand models

A simple example

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Choice models



Behavioral models

- Demand = sequence of choices
- Choosing means trade-offs
- In practice: derive trade-offs from choice models



Choice models

Theoretical foundations

- Random utility theory
- Choice set: C_n
- $y_{in} = 1$ if $i \in C_n$, 0 if not

 $P(i|\mathcal{C}_n) = \frac{y_{in}e^{v_{in}}}{\sum_{i\in\mathcal{C}}y_{jn}e^{V_{jn}}}$

• Logit model:





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Logit model

Utility

$$U_{in} = V_{in} + \varepsilon_{in}$$

Choice probability
$$P_n(i|\mathcal{C}_n) = \frac{y_{in}e^{V_{in}}}{\sum_{j\in\mathcal{C}}y_{jn}e^{V_{jn}}}.$$

- Decision-maker n
- Alternative $i \in C_n$



Variables: $x_{in} = (p_{in}, z_{in}, s_n)$

Attributes of alternative *i*: *z*_{in}

- Cost / price (p_{in})
- Travel time
- Waiting time
- Level of comfort
- Number of transfers
- Late/early arrival
- etc.

Characteristics of decision-maker n: s_n

- Income
- Age
- Sex
- Trip purpose
- Car ownership
- Education
- Profession
- etc.

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Demand curve

Price



Outline



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Example

Choice set: Jupiler

- 't Klooster i = 0
- Belvédère i = 1

Utility functions

$$V_{0n} = -2.2p_0 - 1.3$$

 $V_{1n} = -2.2p_1$



Prices

- 't Klooster: [0 6€]
- Belvédère: 1.8€

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Demand and revenues



Heterogeneous population



Two groups in the population

$$V_{0n} = -\beta_n p_0 + c_0$$

Mathematics:25%Business:75% $\beta_1 = -4.5$, $\beta_2 = -0.25$, $c_2 = -1.3$



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Demand per market segment



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Demand and revenues



Optimization

Pricing

- Non linear optimization problem.
- Non convex objective function.
- Multimodal function.
- May feature many local optima.
- In practice, the groups are many, and interdependent.
- Optimizing each group separately is not feasible.



Optimization

Pricing

- Non linear optimization problem.
- Non convex objective function.
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- Optimizing each group separately is not feasible.

Assortment

What about assortment?



Heterogeneous population, two products



Utility functions: math

$$\begin{split} V_{\text{K,Jupiler},m} &= -4.5 p_{\text{K,Jupiler}} - 1.3 \\ V_{\text{K,Orval},m} &= -4.5 p_{\text{K,Orval}} - 1.3 + 3 \\ V_{\text{B,Jupiler},m} &= -4.5 p_{\text{B,Jupiler}} \\ V_{\text{B,Orval},m} &= -4.5 p_{\text{B,Orval}} + 3 \end{split}$$

Utility functions: HEC

K: Price Orval = $1.5 \times \text{price}$ Jupiler B: Price Orval = $2 \times \text{price}$ Jupiler

$$\begin{split} V_{\text{K},\text{Jupiler},b} &= -0.25 p_{\text{K},\text{Jupiler}} - 1.3 \\ V_{\text{K},\text{Orval},b} &= -0.25 p_{\text{K},\text{Orval}} - 1.3 + 1 \\ V_{\text{B},\text{Jupiler},b} &= -0.25 p_{\text{B},\text{Jupiler}} \\ V_{\text{B},\text{Orval},b} &= -0.25 p_{\text{B},\text{Orval}} + 1 \end{split}$$

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Total revenues



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In transportation

Assortment and pricing

- Airlines
- Deregulated railways
- Mobility as a service



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Optimization

Assortment and pricing

- Combinatorial problem
- For each potential assortment, solve a pricing problem
- Select the assortment corresponding to the highest revenues
- MINLP
- Non convex relaxation



Disaggregate demand models

Advantages

- Theoretical foundations
- Market segmentation
- Taste heterogeneity
- Many variables
- Estimated from data

Disadvantages

- Complex mathematical formulation
- Not suited for optimization
- Literature: heuristics





Research objectives

Observations

- Revenues is not the only indicator to optimize,
- e.g. customer satisfaction.
- Many transportation applications need a demand representation

Goal

- Generic mathematical representation of choice models,
- designed to be included in MILP,
- linear in the decision variables.



MILP

Outline



Demand and supply Disaggregate demand models A simple example







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Linearization

- Hopeless to linearize the logit formula (we tried...)
- Anyway, we want to go beyond logit.





Linearization

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First principles

Each customer solves an optimization problem



Linearization

- Hopeless to linearize the logit formula (we tried...)
- Anyway, we want to go beyond logit.

First principles

Each customer solves an optimization problem

Solution

Use the utility and not the probability



MILP

A linear formulation

Utility function

$$U_{in} = V_{in} + \varepsilon_{in} = \sum_{k} \beta_k x_{ink} + f(z_{in}) + \varepsilon_{in}.$$

Simulation

- Assume a distribution for ε_{in}
- E.g. logit: i.i.d. extreme value
- Draw R realizations ξ_{inr} , $r = 1, \dots, R$
- The choice problem becomes deterministic



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MILP

Scenarios

Draws

- Draw R realizations ξ_{inr} , $r = 1, \ldots, R$
- We obtain R scenarios

$$U_{inr} = \sum_{k} \beta_k x_{ink} + f(z_{in}) + \xi_{inr}.$$

- For each scenario r, we can identify the largest utility.
- It corresponds to the chosen alternative.



MILP (in words)

MILP

max benefit subject to utility definition availability discounted utility choice capacity allocation price selection



MILP

A case study

Challenge

- Take a choice model from the literature.
- It cannot be logit.
- It must involve heterogeneity.
- Show that it can be integrated in a relevant MILP.



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MILP

A case study

Challenge

- Take a choice model from the literature.
- It cannot be logit.
- It must involve heterogeneity.
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Parking choice

• [lbeas et al., 2014]







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Parking choices [Ibeas et al., 2014]

Alternatives

- Paid on-street parking
- Paid underground parking
- Free street parking

Model

- N = 50 customers
- $C = \{PSP, PUP, FSP\}$
- $C_n = C \quad \forall n$
- $p_{in} = p_i \quad \forall n$
- Capacity of 20 spots
- Mixture of logit models

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General experiments

Uncapacitated vs Capacitated case

- Maximization of revenue
- Unlimited capacity
- Capacity of 20 spots for PSP and PUP

Price differentiation by population segmentation

- Reduced price for residents
- Two scenarios
 - Subsidy offered by the municipality
 - Operator is forced to offer a reduced price



MILP

Uncapacitated vs Capacitated case

Uncapacitated



MILP

Computational time

	Uncapacitated case				Capacitated case			
R	Sol time	PSP	PUP	Rev	Sol time	PSP	PUP	Rev
5	2.58 s	0.54	0.79	26.43	12.0 s	0.63	0.84	25.91
10	3.98 s	0.53	0.74	26.36	54.5 s	0.57	0.78	25.31
25	29.2 s	0.54	0.79	26.90	13.8 min	0.59	0.80	25.96
50	4.08 min	0.54	0.75	26.97	50.2 min	0.59	0.80	26.10
100	20.7 min	0.54	0.74	26.90	6.60 h	0.59	0.79	26.03
250	2.51 h	0.54	0.74	26.85	1.74 days	0.60	0.80	25.93



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Summary

Demand and supply

- Supply: prices and capacity
- Demand: choice of customers
- Interaction between the two

Discrete choice models

- Rich family of behavioral models
- Strong theoretical foundations
- Great deal of concrete applications
- Capture the heterogeneity of behavior
- Probabilistic models

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Optimization

Discrete choice models

- Non linear and non convex
- Idea: use utility instead of probability
- Rely on simulation to capture stochasticity

Proposed formulation

- Linear in the decision variables
- Large scale
- Fairly general



Ongoing research

- Decomposition methods.
- Competitive markets: several suppliers.



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