

Modelling competition in demand-based optimization models

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Outline

- 1 Motivation
- 2 Modelling the problem
- 3 Future work

1 Motivation

2 Modelling the problem

3 Future work

Competition

- In many markets competition is present in the form of oligopolies (regulations, barriers to entry, mergers, acquisitions, alliances).
- In transportation, deregulation often led to oligopolistic markets.
 - Airlines
 - Railways
 - Buses
 - Multi-modal networks

How to study competitive transport markets?

- Modelling demand
- Modelling supply
- Modelling competition

Demand

- Each customer chooses the alternative that maximizes his/her utility.
- Customers have different tastes and socioeconomic characteristics that influence their choice.



Supply

- Operators take decisions that optimize their objective function (e.g. revenue maximization).
- Decisions can be related to pricing, capacity, frequency, availability ...
- Decisions are influenced by:
 - The preferences of the customers
 - The decisions of the competitors



Competition

- We consider non-cooperative games.
- We aim at understanding the Nash equilibrium solutions of such games, i.e. stationary states of the system in which no competitor has an incentive to change its decisions.



1 Motivation

2 Modelling the problem

3 Future work

The framework

Three elements to be modelled: customers, operators and market.

- 1 **Customers:** discrete choice models take into account preference heterogeneity and model individual decisions.

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Three elements to be modelled: customers, operators and market.

- 1 **Customers:** discrete choice models take into account preference heterogeneity and model individual decisions.
- 2 **Operators:** a mixed integer program can maximize any relevant objective function.
- 3 **Market:** Nash equilibrium solutions are found by enforcing best response constraints.

The framework: customer level

Non-linear formulation:

- The probability of customer $n \in N$ choosing alternative $i \in I$ depends on the discrete choice model specification.
- For the logit model, there exists a closed-form expression:

$$P_{in} = \frac{\exp(V_{in})}{\sum_{j \in I} \exp(V_{jn})}$$

- For other discrete choice models, there is no closed-form expression.

The framework: customer level

Linear formulation:

- A linear formulation can be obtained by relying on simulation to draw from the distribution of the error term of the utility function.
- For all customers and all alternatives, R draws of are extracted from the error term distribution. Each ξ_{inr} corresponds to a different behavioral scenario.

$$U_{inr} = \beta_{in} p_{in} + q_{in} + \xi_{inr}$$

- In each scenario, customers choose the alternative with the highest utility:

$$w_{inr} = 1 \text{ if } U_{inr} = \max_{j \in I} U_{jnr}, \text{ and } w_{inr} = 0 \text{ otherwise}$$

- Over multiple scenarios, the probability of customer n choosing alternative i is given by

$$P_{in} = \frac{\sum_{r \in R} w_{inr}}{R}.$$

The framework: operators level

- We assume that an operator $k \in K$ can decide on the price p_{in} of each alternative $i \in I$ for all customers $n \in N$.
- Stackelberg game: the operator (the leader) knows the best response of the customers ("collective" follower) to all strategies.
- Objective function to be maximized by operator k :

$$V_k = \sum_{i \in I} \sum_{n \in N} p_{in} P_{in}$$

Non-linear optimization model for a single operator

$$\max V = \sum_{i \in I} \sum_{n \in N} p_{in} P_{in}$$

$$\text{s. t. } P_{in} = \frac{\exp(U_{in})}{\sum_{j \in I} \exp(U_{jn})}$$

$$U_{in} = \beta_{in} p_{in} + q_{in}$$

$$\forall i \in I, \forall n \in N$$

$$\forall i \in I, \forall n \in N$$

Linear optimization model for a single operator

$$\begin{aligned}
 \max \quad & V = \sum_{i \in I} \sum_{n \in N} p_{in} P_{in} \\
 \text{s.t.} \quad & P_{in} = \frac{\sum_{r \in R} w_{inr}}{R} && \forall i \in I, \forall n \in N \\
 & U_{inr} = \beta_{in} p_{in} + q_{in} + \xi_{inr} && \forall i \in I, \forall n \in N, \forall r \in R \\
 & U_{inr} \leq U_{nr} && \forall i \in I, \forall n \in N, \forall r \in R \\
 & U_{nr} \leq U_{inr} + M_{U_{nr}}(1 - w_{inr}) && \forall i \in I, \forall n \in N, \forall r \in R \\
 & \sum_{i \in I} w_{inr} = 1 && \forall n \in N, \forall r \in R \\
 & w_{inr} \in \{0, 1\} && \forall i \in I, \forall n \in N, \forall r \in R
 \end{aligned}$$

The framework: market level

- The payoff of an operator also depends on the strategies of the competitors.
- Let's define as X_k the set of strategies that can be played by operator $k \in K$.
- Condition for Nash equilibrium (best response constraints):

$$V_k = V_k^* = \max_{x_k \in X_k} V_k(x_k, x_{K \setminus \{k\}}) \quad \forall k \in K$$

- Nash (1951): finite games have at least one mixed strategy equilibrium solution.
- Finite/infinite strategy sets; pure/mixed strategies; continuous/discrete payoff function.

A fixed-point iteration method

- Sequential algorithm to find Nash equilibrium solutions of a k -player game:
 - Initialization: players select an initial feasible strategy.
 - Iterative phase: players take turns and each plays its best response pure strategy to the current solution.
 - Termination criterion: either a Nash equilibrium or a cyclic equilibrium is reached.

A mixed integer model for the fixed-point problem

- We can write a model that minimizes the distance between two consecutive fixed-point iterations.
- A solution for a two-operator problem: (x_1^b, x_2^b)
- Optimization problems for the operators:

$$x_1^* = \arg \max_{x_1 \in X_1} V_1(x_1, x_2^b)$$

$$x_2^* = \arg \max_{x_2 \in X_2} V_2(x_1^b, x_2)$$

- Fixed-point problem:

$$\min_{x_1, x_2, x_1^*, x_2^*} \|x_1^* - x_1^b\| + \|x_2^* - x_2^b\|$$

Initial configuration

- No optimization at operator level: any feasible strategy could be selected.
- Constraints:
 - Customer choice
 - Continuous (MINLP), or
 - Binary (MILP)
 - Customer utility maximization

$$\sum_{i \in I} w_{inr}^b = 1 \quad \forall n \in N, \forall r \in R$$

$$U_{inr}^b = \beta_{in} p_{in}^b + q_{in} + \xi_{inr} \quad \forall i \in I, \forall n \in N, \forall r \in R$$

$$U_{inr}^b \leq U_{nr}^b \quad \forall i \in I, \forall n \in N, \forall r \in R$$

$$U_{nr}^b \leq z_{inr}^b + M(1 - w_{inr}^b) \quad \forall i \in I, \forall n \in N, \forall r \in R$$

Best response configurations

- Each operator solves an optimization problem having the following constraints:
 - Customer choice
 - Continuous (MINLP), or
 - Binary (MILP)
 - Customer utility maximization
 - Best response

Best response configurations

Best response constraints:

$$V_{ks} = \frac{1}{R} \sum_{i \in I_k} \sum_{n \in N} \sum_{r \in R} p_{ins} w_{inrs}^a \quad \forall k \in K, \forall s \in S_k$$

$$V_{ks} \leq V_{ks}^{max} \quad \forall s \in S_k$$

$$V_{ks}^{max} \leq V_{ks} + M(1 - x_{ks}) \quad \forall s \in S_k$$

$$\sum_{s \in S} x_{ks} = 1$$

Customer constraints:

$$U_{inrs}^a = \beta_{in} p_{ins} + q_{in} + \xi_{inr} \quad \forall i \in I_k, \forall n \in N, \forall r \in R, \forall s \in S_k$$

$$U_{inrs}^a = U_{inr}^b \quad \forall i \in I \setminus I_k, \forall n \in N, \forall r \in R, \forall s \in S_k$$

$$\sum_{i \in I} w_{inrs}^a = 1 \quad \forall n \in N, \forall r \in R, \forall s \in S_k$$

$$U_{inrs}^a \leq U_{nrs}^a \quad \forall i \in I, \forall n \in N, \forall r \in R, \forall s \in S_k$$

$$U_{nrs}^a \leq z_{inrs}^a + M(1 - w_{inrs}^a) \quad \forall i \in I, \forall n \in N, \forall r \in R, \forall s \in S_k$$

Objective function

- Minimization problem:

$$z^* = \min_{x_1, x_2, x_1^*, x_2^*} \|x_1^* - x_1^b\| + \|x_2^* - x_2^b\|$$

- If $z^* = 0$, we have an equilibrium. What can we say about this equilibrium?
If $z^* > 0$, can we conclude something? Are we in an equilibrium region?

Numerical experiments

- Case study: 3 parking choices. 2 owned by 2 different operators and 1 opt-out option. Parameter estimation available in the literature.
- Tests: non-linear and linear formulations with logit and mixed logit specifications.

	Non-linear	Linear
Logit	-	ξ
Mixed logit	β	β, ξ

Figure: Random draws needed in the different sets of experiments

Numerical experiments

- Model specification: drawing from the error term distribution ($R = 50, 100, 200$) gives good approximation of the choice probabilities found with the logit formula.
- Preliminary results: equilibrium solutions are found for all tested instances with the MILP formulation.
- Computational times:
 - Logit:
 - The non-linear model is faster (no need for simulation).
 - The time required by the linear model increases with the number of draws.
 - Mixed logit:
 - The non-linear model (highly non convex) does not converge for larger instances.
 - The linear model outperforms the non-linear model on larger instances.

1 Motivation

2 Modelling the problem

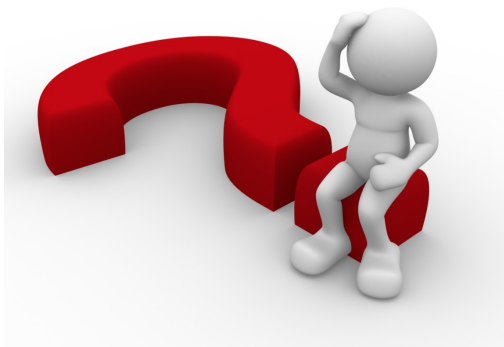
3 Future work

Open questions and future work

- The current model uses finite strategy sets (i.e. price discretization). Is it possible to reformulate the problem with the help of complementarity?
- How can the structure of the problem be exploited to efficiently search for equilibria in the solution space?
- Is it possible to compare different equilibrium solution or to prove uniqueness within a region of the solution space?



Questions?



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