Large-Scale Allocation of Personalized Incentives

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Introduction

Motivation

- Standard transportation policies are **non-personalized**: subsidies and taxes are equal for everyone or they differ according to objective and observable characteristics.
- Example: In several countries, public-transit services are subsidized. The subsidy is equal for everyone or vary by population group (e.g., poor households, students).
- Nowadays, decision makers have access to more information so **economic policies can be personalized**, by accounting for individual's preferences.

Introduction

Example: No Policy

		Car	Walk
Alice	Indiv. value	**3**	2
	CO_2 emissions	**1**	0
Bob	Indiv. value	**4**	2
	CO_2 emissions	**2**	0

- **Without policy**, Alice and Bob choose the alternative with the largest individual value (Car for both).
- To minimize CO_2 emissions, they should both choose to walk.
- Public expenses: 0; CO_2 emissions: 3.

Introduction

Example: Flat Subsidy

		Car	Walk
Alice	Indiv. value	3	**2** + **2**
	CO_2 emissions	1	**0**
Bob	Indiv. value	4	**2** + **2**
	CO_2 emissions	2	**0**

- With a **flat subsidy** of 2 € for walking, both Alice and Bob switch to walking.
- Public expenses: 4; CO_2 emissions: 0.

Introduction

Example: Personalized Incentives

		Car	Walk
Alice	Indiv. value	3	**2** + **1**
	CO_2 emissions	1	**0**
Bob	Indiv. value	4	**2** + **2**
	CO_2 emissions	2	**0**

- With a **personalized incentive policy** (1 € for Alice and 2 € for Bob), they both switch to walking.
- The CO_2 emissions are the same than with a flat subsidy but the expenses decreased by 1 €.
- Public expenses: 3; CO_2 emissions: 0.

Introduction

Contributions

- We show that the problem of finding an **optimal personalized incentive policy**, in a discrete-choice framework, is a Multiple-Choice Knapsack Problem **(MCKP)**.
- We propose a **polynomial-time greedy algorithm** to find a near-optimal policy and we analyze its analytical and economic **properties**.
- Numerical application to mode choice for Lyon (France).

Introduction

Literature

Personalized policy in transportation:

- Araldo, Andrea, et al. "System-level optimization of multi-modal transportation networks for energy efficiency using personalized incentives: Formulation, implementation, and performance." *Transportation Research Record* 2673.12 (2019): 425-438.
- Zhu, Xi, et al. "Personalized incentives for promoting sustainable travel behaviors." *Transportation Research Part C: Emerging Technologies* 113 (2020): 314-331.

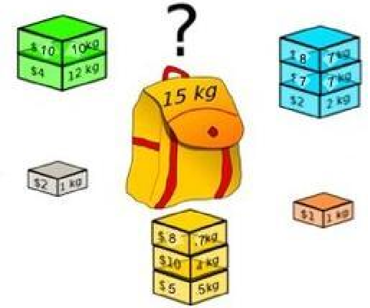
Application of Multiple-Choice Knapsack Problem to economics:

- Colorni, Alberto, et al. "Rethinking feasibility analysis for urban development: A multidimensional decision support tool." *International Conference on Computational Science and Its Applications.* Springer, Cham, 2017.

Incentive Policy

Multiple-Choice Knapsack Problem

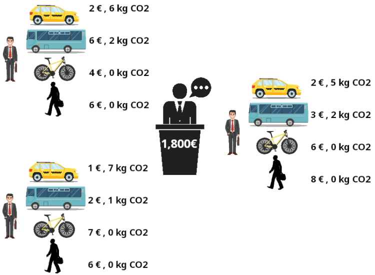
- Input: **set of items**, with a **weight** and a **value**, that are classified in different **classes**; **knapsack** with a given **weight limit**.
- **One item from each class** is in the knapsack.
- Goal: **maximize the value** of the items in the knapsack, subject to the **weight constraint**.



Incentive Policy

Personalized Incentive Policy

- Input: **set of transportation modes**, with an **individual value** and **CO_2 emissions**, for different **individuals**; **regulator** with a given **budget limit**.
- The regulator uses incentives to induce individuals to choose **one transportation mode**.
- Goal: **minimize the CO_2 emissions** of the modes chosen, subject to the **budget constraint**.



Incentive Policy

Assumptions

- **Fixed congestion:** the individual values are independent from the transportation mode chosen by the other individuals.
- **Independent CO_2 emissions:** the CO_2 emissions are independent from the transportation mode chosen by the other individuals.
- **Perfect information:** the regulator knows perfectly the individual values and the CO_2 emissions for any available transportation mode.

Algorithm

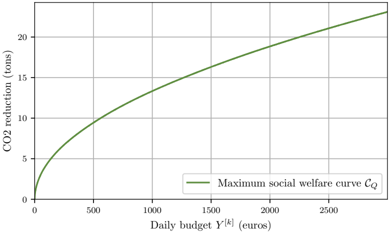
Greedy Algorithm

- We propose a **polynomial-time greedy algorithm**, extending Kellerer et al. (2004)'s algorithm.
- The algorithm returns the **individual incentives** and the **CO_2 emissions reduction**, **given a budget**.
- It also computes the **Maximum Social Welfare Curve** (CO_2 reduction achievable for a range of budgets).

Algorithm

Algorithm Properties

- **Upper bound:** solution is boundedly close to the optimum.
- **Anytime algorithm:** solution is optimal for the budget spent at any iteration.
- **Diminishing returns:** social welfare is concave with the expenses of the regulator.



Application to Mode Choice

Data

- Census data for **220k individuals** in Lyon's area (France): home, workplace, transportation mode for commuting, socio-demographic variables.
- Analysis of the transportation mode chosen for **home-work trips**.
- Travel times data: OpenStreetMap and HERE.
- **5 transportation modes:** car, public transit, walking, cycling and motorcycle.

Application to Mode Choice

Intrinsic Utilities and Social Indicators

- Individual values are estimated from a **Multinomial Logit model**.
- CO_2 emissions are computed with ADEME data.

Daily CO_2 emissions	595.26 tons of CO_2
Yearly CO_2 emissions (200 days)	119050 tons of CO_2
Average yearly individual CO_2 emissions	0.54 tons of CO_2

Application to Mode Choice

Results

- Budget is set to 1800 € (per day).
- Only **1.57 % of individuals receive incentives**.
- CO_2 reduction: 18 tons per day (3 % of total emissions).
- Average regulator's cost of CO_2: 100 € per ton.

Application to Mode Choice

Results

- 1.163 % of individuals are switching from car to public transit.
- The car share decreases from 57.326 % to 55.843 %.

Mode choice after the policy (columns) / Mode choice before the policy (rows)

	car	public transit	walking	cycling	motorcycle	total
car	55.839%	1.163%	0.099%	0.128%	0.097%	57.326%
public transit	0.005%	27.29%	0.037%	0.032%	0.005%	27.368%
walking	0%	0%	9.481%	0%	0%	9.481%
cycling	0%	0%	0%	4.339%	0%	4.339%
motorcycle	0%	0.005%	0.001%	0.001%	1.479%	1.486%
total	55.843%	28.458%	9.618%	4.5%	1.581%	100%

Conclusion

Summary

- Personalized-incentive policy boundedly close to optimum can be computed with **MCKP algorithms**.
- The policy shows **diminishing returns** behavior.
- Decrease of 3 % of the CO_2 emissions, by impacting only 1.57 % of individuals.

Conclusion

Future Works

- Extend the model to **imperfect information** on the individual values, by computing **switching probabilities**.
- Account for **congestion** with an iterative procedure.

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