Performance comparison of the discrete choice models of consumer choice

Exploration of the Econometrics and Machine Learning model performances in the presence of heterogeneous preferences and random effects utilities

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Introduction

Introduction

History (Hensher, Rose, and Greene 2015)

In economics and econometrics of the individual choice modelling the traditional scientific procedure includes:

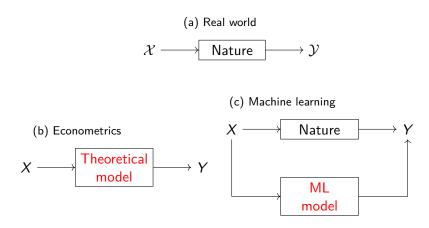
- 1. Economics question to resolve
- 2. Theoretical modelling of the underlying processus
- 3. Data collection (potentially through a controlled experiment)
- Econometrics model estimation based on the theoretical counterpart

Scientific question of the study

"How can we assess and compare the performances of different models applied to discrete consumer choice modelling?"

This question becomes extremely complex when extended to the general comparison of *Econometrics* and *Machine Learning (ML)* models.

Econometrics against ML (Breiman and others 2001)



Objectives

Theoretical:

- Offer a comprehensive methodology for consumer choice models comparison
- Devise a framework which will allow to test hypotheses affecting modelling and model performances
- ► Test the proposed framework on a real world problematic

Applied:

Study the effects of heterogeneous preferences in population on the estimation results

Scientific procedure

In this study we:

- 1. Propose a theory-testing framework
- Explore the different models' performances in the presence of heterogeneous preferences for attributes in population using the designed framework

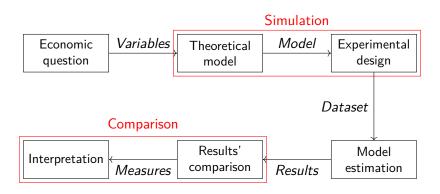
Which involves:

- Construction of two artificial datasets controlling for the presence of heterogeneous and homogeneous preferences in population
- ► Estimation of a selection of three models, issued from *econometrics* and *ML*, over the generated datasets
- ► Evaluation of the performances of the models over multiple criterias

└ Methodology

Methodology

Proposed framework



Consumer choice modelling (McFadden 1974)

Alternatives' set, from which only one alternative may be chosen

$$\{\omega_1,\ldots,\omega_r\}\in\Omega\tag{1}$$

Utility definition incorporating fixed and random terms, with $i \in \{1,...,N\}$ and $j \in \Omega$

$$U_{ij} = V_{ij} + \eta_{ij} \text{ where } V_{ij} = f(X_i, Z_j)$$
 (2)

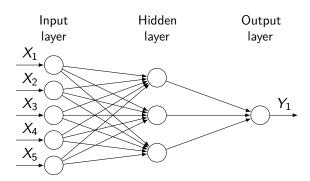
Random utility specification

$$\eta_{ij} \sim \textit{Gumble}(0,1)$$
(3)

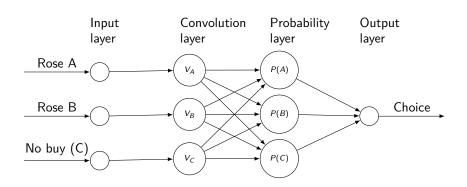
Models implemented

Model	Characteristics
MMNL	Advanced model used to estimate complex relationships
	Ex: random effects modelling
MNL	One of the most popular models in economics for treatment of multiple choice situations
	This leads to potential biases in many contemporary studies
CNN	Model with flexible architecture specifically adjusted for the studied case
	The computational efficiency offered by Big data techniques makes it particularly interesting

Traditional NN design



Chosen CNN design



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Performance comparison

- Precision in derivation of the economics values
 - Underlying parameters of the utility function
 - ► Case specific economic targets (WTP, Premiums, ...)
- Overall fit performance metrics
 - ► Absolute measures (Accuracy, . . .)
 - ► Probabilistic measures (KLD, ...)
- ► Alternative-specific performance metrics
 - ► Simple measures (TPR, TNR, ...)
 - ▶ Derived measures (F-measure, Geometric means, . . .)
- Technical efficiency and ressources consumption
 - Fstimation time

The starting point

We would like to demonstrate the advantages of our framework studying how heterogeneous preferences in population affect the results

Using an existing application (Michaud, Llerena, and Joly 2012), which incorporates all the elements of the framework:

- Economics question individual preferences for environmental attributes in presence of heterogenous preferences
- Behavioural assumptions random utility maximisation theory
- Experimental design complex factorial design with random price allocation
- Advanced model implemented to model individual choices mixed logit
- Economics target values willingness to pay for environmental attributes

Utility function specification (Michaud, Llerena, and Joly 2012)

Deterministic utility of the "Buy" option is

$$V_{ij} = \\ \alpha_{i,Buy} + \\ \beta_{Buy,Sex} Sex_i + \beta_{Buy,Age} Age_i + \\ \beta_{Buy,Income} Income_i + \beta_{Buy,Habit} Habit_i + \\ \gamma_{Price} Price_{ij} + \gamma_{i,Label} Label_{ij} + \\ \gamma_{i,Carbon} Carbon_{ij} + \gamma_{i,Label \times Carbon} Label_{ij} \times Carbon_{ij}$$

$$(4)$$

Where $i \in \{1, ..., N\}$, $j \in \{\text{"Buy A"}, \text{"Buy B"}, \text{"No buy"}\}$ and $Buy = I(j \in \{\text{"Buy A"}, \text{"Buy B"}\})$.

Target values from Michaud, Llerena, and Joly (2012)

	Effects
	Means
Individual characteristics (β)	
Sex $\beta_{Buy,Sex}$	1.420
Age $eta_{ extit{Buy}, Age}$	0.009
Salary $\beta_{Buy,Income}$	0.057
Habit $\beta_{Buy,Habit}$	1.027
Alternatives' attributes (γ, α)	
Price γ_{Price}	-1.631
Label $\gamma_{i,Label}$	2.824
Carbon $\gamma_{i,Carbon}$	6.665
LC $\gamma_{i,Label \times Carbon}$	-2.785
Buy $\alpha_{i,Buy}$	2.285
• •	

	E	ffects
	Fixed	Random
Buy	0	3.202
Label	0	2.654
Carbon	0	3.535
LC	0	2.711
Covariance		
Buy:Label	0	-0.54
Buy:Carbon	0	-4.39
Buy:LC	0	6.17
Label:Carbon	0	8.77
Label:LC	0	-2.33
Carbon:LC	0	-4.82

Results

Results

Simulated datasets: Individuals

	Fixed Effects (N=1000)	Random Effects (N=1000)	Target (N=102)	p value
Sex				0.851
Mean (SD)	0.506 (0.500)	0.515 (0.500)	0.490 (0.502)	
Range	0.000 - 1.000	0.000 - 1.000	0.000 - 1.00Ó	
Habit				0.182
N-Miss	0	0	1	
Mean (SD)	0.683 (0.466)	0.657 (0.475)	0.604 (0.492)	
Range	0.000 - 1.000	0.000 - 1.000	0.000 - 1.000	
Salary				< 0.001
Mean (SD)	2.750 (1.476)	2.671 (1.438)	2.147 (1.222)	
Range	1.000 - 6.000	1.000 - 6.000	1.000 - 6.000	
Age				0.255
Mean (SD)	41.862 (13.685)	42.161 (13.820)	39.755 (18.895)	
Range	18.000 - 84.000	18.000 - 84.000	18.000 - 85.000	

Simulated datasets: Alternatives

Table 2: Alternatives' descriptive statistics by dataset

	Fixed Effects (N=320000)	Random Effects (N=320000)	Target (N=2372)	p value
Price				0.002
Mean (SD)	2.936 (0.958)	2.936 (0.958)	3.005 (0.887)	
Range	1.500 - 4.500	1.500 - 4.500	1.500 - 4.500	
Carbon				0.999
Mean (SD)	0.500 (0.500)	0.500 (0.500)	0.500 (0.500)	
Range	0.000 - 1.000	0.000 - 1.000	0.000 - 1.000	
Label				0.999
Mean (SD)	0.500 (0.500)	0.500 (0.500)	0.500 (0.500)	
Range	0.000 - 1.000	0.000 - 1.000	0.000 - 1.000	

Estimates of mean effects

		Fixed effects		Random effects			Target
	MNL	MMNL	CNN	MNL	MMNL	CNN	
Characteristics							
Sex	1.401 ***	1.400***	1.369	0.712***	1.297***	0.719	1.420
	(0.031)	(0.031)		(0.016)	(0.024)		
Age	0.009***	0.009***	0.010	0.007***	0.010***	0.005	0.009
	(0.001)	(0.001)		(0.001)	(0.001)		
Salary	0.048***	0.048***	0.060	0.066***	0.120***	0.062	0.057
	(0.010)	(0.010)		(0.005)	(0.008)		
Habit	1.070***	1.071***	1.056	0.361***	0.641***	0.343	1.027
	(0.030)	(0.030)		(0.016)	(0.024)		
Attributes	, ,	, ,		,	, ,		
Price	-1.626***	-1.628***	-1.618	-0.886***	-1.586***	-0.886	-1.631
	(0.010)	(0.010)		(0.006)	(0.010)		
Buy	2.311***	2.313***	2.228	0.662***	2.180***	0.665	2.285
•	(0.065)	(0.066)		(0.036)	(0.054)		
Label	2.815***	2.817***	2.810	1.279***	1.922***	1.277	2.824
	(0.022)	(0.022)		(0.015)	(0.023)		
Carbon	6.654***	6.662***	6.634	3.259***	5.430***	3.250	6.665
	(0.032)	(0.033)		(0.016)	(0.030)		
LC	-2.781***	-2.782***	-2.765	-1.546***	-2.663***	-1.558	-2.785
	(0.028)	(0.028)		(0.019)	(0.030)		

Note:

p<0.1; p<0.05; p<0.05; p<0.01

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Note:

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Case specific metrics: WTP and Premiums

		Fixed	effects			Randon	n effects	
	MNL	MMNL	CNN	Target	MNL	MMNL	CNN	Target
WTP	1.421	1.416	1.377	1.401	0.747	1.360	0.751	1.401
		(0.058)				(1.887)		(1.973)
Label	1.731	1.732	1.737	1.731	1.445	1.243	1.442	`1.731
		(0.019)				(1.667)		(1.611)
Carbon	4.091	4.097	4.101	4.086	3.679	3.467	3.669	4.086
		(0.103)				(2.323)		(2.134)
LC	4.112	4.116	4.129	4.110	3.378	3.036	3.352	4.110
		(0.098)				(3.240)		(3.379)

General performance metrics

		Fixed effects		Random effects			
	MNL	MMNL	MMNL CNN		MMNL	CNN	
Overall measures							
Accuracy	0.863	0.863	0.723	0.725	0.863	0.721	
Probabilistic measures							
KLD	0.623	0.623	0.328	0.349	0.625	0.317	
CPU timing	s						
User	20.910	452.414	17.433	18.722	2066.934	16.806	

Positive and negative elements in modelling approaches

	Fixed effects			Random effects		
	MNL	MMNL	CNN	MNL	MMNL	CNN
Utility parameters	estimates					
Mean	+	+	-	-	+	-
Economics metrics						
WTP	_	+	+/-	_	+	+/-
Label premium	+	+/-	<u>-</u>	+	_	+/-
Carbon premium	+	+/-	-	+	_	+/-
LC premium	+	+/-	-	+	-	+/-
Overall measures						
Accuracy	+	+	-	+/-	+	-
Probabilistic measu	ires					
KLD	+	+	-	+/-	+	-
CPU timings				·		
User	+/-	_	+	+/-	_	+

Conclusion

Conclusion

Obtained results

- 1. Theoretical:
- ► We have proposed an integrated theory-testing framework
- Data simulation tool was created
- 2. Applied
- ► We have simulated the research procedure under different individual preferences specifications
- ► Three different models issued from different fields have been tested
 - ► Econometrics: MNL and MMNL
 - Machine Learning: CNN representation of MNL
- ► The application analysed the differences in performances of the models in various choice contexts

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Implications and future work

For experimental economics

- ▶ Possibility to test experimental designs
 - size of population to involve
 - the number of choice sets to consider
- Possibility to observe how the decision rules affect estimation results
 - Random Regret Minimisation
 - Random Utility Maximisation
 - Quantum Decision Theory
- Possibility to explore and choose models before study

Implications and future work

For econometrics

- Possibility to compare models issued from different disciplines
 - a further extended study of the ML techniques adoptation for economics
 - comparison of the advanced econometrics techniques
- Possibility to observe how different models perform in different environments
 - ▶ in field experiments
 - over the simulated data

Implications and future work

For the methodology of research in social sciences

▶ A hypothesis-testing framework has been proposed (it may be interesting to adjust the framework for other social science domains)

References

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Credits

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- ► Honors for the simulation tool implementation go to Amirreza Talebijamalabad, who worked under the supervision of Iragaël Joly and myself.
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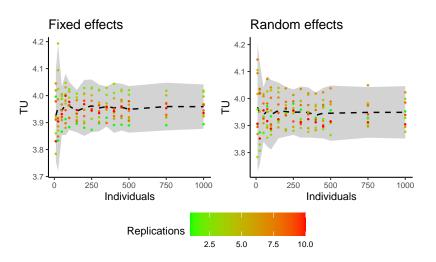
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Annexes

Annexes

Simulator robustness exploration



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