Performance of econometric and Machine Learning models for the economic study of discrete consumer choices

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Abstract

This works is a cross-disciplinary study of Econometrics and machine learning (ML) models applied to consumer choice data analysis. The problematic arises from the insufficient points of contact among users (economists and engineers) and data scientists, who pursue different objectives, although using closely related techniques. First of all, as an interdisciplinary research project, the PhD work aims to define a common ground for analysis and performance comparison of different *modelling procedures* used in Econometrics and ML in application to individual decision making process. A second objective is to incorporate the recent developments in the decision making theory into the general *procedure comparison* framework. A third objective is to comprehensively illustrate the performance differences of several broadly used modelling procedures in presence of specific behavioural bias through applications to circular economics. To bridge the interdisciplinary gap a simulation and theory-testing framework is proposed. It incorporates all essential steps from hypothetical setting generation to the comparison of key performance metrics.

***K*eywords** Econometrics · Discrete Choice Analysis · Consumer choice · Data science · Machine Learning · Simulation · Circular Economics

1 Introduction

The advances in statistical learning (Hastie, Tibshirani, and Friedman 2009), data analysis (Zielesny 2011) and data science (Donoho 2017) of the past decades have resulted in propagation of Machine Learning (ML) techniques. Nowadays, it is impossible to imagine a field of science that is not benefiting from the fruits of statistical learning. In economics, consumer choices data are mainly studied through classification tools from machine learning techniques or regression tools like discrete choice models from econometric techniques. These two practices illustrate two distinct approaches to applying statistical learning. As described by Breiman et al. (2001) and later by Athey et al. (2019), the Machine Learning (ML) focus on the predictive qualities and Econometrics, in its turn, attempts to decipher the underlying properties of the data. Engineering sciences and Computer sciences focus mainly on ML techniques, whereas in Economics and other applied Social sciences, the scientific community prefers to implement the traditional Econometrics techniques to explore hidden patterns (Athey 2018).

But how the scientists working on the applied problems, such as modelling discrete individual choices, can correctly select the appropriate tools given the confusions between the fields and disciplines? Some pluri-disciplinary scientists make attempts to breach this wall between ML and Econometrics on a high level: Athey et al. (2019), Mullainathan and Spiess (2017), Varian (2014). Their advances are mostly focused on the general interdisciplinary question, without entering into the application specific details. There exist some recent advanced in the field-specific literature as well. In the Discrete Choice Analysis (DCA) domain we can cite the works of Aboutaleb et al. (2021), Lederrey et al. (2021), Ortelli et al. (2021) and Wang et al. (2021). Most of those focus on specific use-cases, attempting to adapt the advanced ML tools for DCA. In contrast, we strive to offer the users a comprehensive methodology for discipline agnostic *modelling procedure* performance comparison for toolset selection.

2 Objectives

Initially, the aim of this work was to explore and compare performance of the different econometric and ML *models*, focusing on the consumer discrete choice analysis applications. This was because in Econometrics, as well as in domain of data science in general, there exists a confusion on what modelling techniques should be used in which situation. However, as the projects' scope was focused on the *model* as the main subject of the research we have faced a number of inconsistencies.

To be more precise, it was the term *model*, which caused the most complications in its definition. We have faced the appearance of both *inter*- and *intra*-discipline terminology inconsistency. The *intra*-discipline inconsistency appears when inside the single domain of Econometrics we encounter several different terms containing the noun *model*. The first one, *theoretical model* refers to an *a priori* selected *model*, which is assumed to correctly describe the *behaviour* of agents in the observed system. The second one, *econometric model* defines the statistical translation of the previously assumed *behavioural model*. Another inconsistency, the *inter*-disciplinary one, accentuates the differences in the understanding of the same terms among the disciplines. For example, between Econometrics and ML. As previously described, the disciplines have different aims and objectives, which induce the different understanding of the terminology.

After this years' progress we have discovered that it was apparently incorrect to speak only about the models, when performing performance comparison. The initial framework had already incorporated some conceptual elements related to the scientific choices englobing modelling procedure, but it was not enough. Consequently, it was decided to switch towards the *procedural approach*. This new methodology assumes that the data analysis task can be perceived as a single *procedure*, which encompasses all the eventual scientific choice starting from the research question and target metrics identification to the answer to this same question. Such change in the study scope perception has somewhat shifted our objectives.

To be more precise the need of knowledge systematisation and vocabulary unifications diminishes because of the flexibility of the *procedural approach*. Contrary to the construction of a taxonomy of the estimation techniques, a taxonomy for the *procedural approach* can not exist. The immense number of possible combinations multiplied by the number of potential applications makes this task literally impossible. The only solution is the knowledge systematisation in a format of relational database, which may never be fully exhaustive.

On the other side, the *procedural approach* allows us to fully focus our attention on the performance comparison task. This will allow the researchers to pretest and perform the model selection based on relevant performance criteria on their own, setting their own limits on the available techniques and methods. To achieve this goal we focus now on the framework development, which aims to lay foundation for a comprehensive and reproducible model comparison. The **comprehensiveness** means that the procedure should be sufficiently documented to avoid any ambiguity in understanding and errors in implementation. It should be expected that whomever uses the framework for model performance assessment should be able to provide results that can be reused in further studies. Nowadays, many of the existing studies use different datasets and models, as well as the modelling algorithms and model specification strategies. All this, alongside with distinct use-case scenarios, performance metrics and research objectives. The **reproducibility** is another key property of such framework it is expected that models *perform identically* under *identical circumstances*. Quite a lot of most advanced model rely on simulation or have some random components in their estimation procedures. Moreover, many of models, techniques and algorithms incorporate multiple *hyperparameters*, which should be defined by the end-user. Such elements are often overlooked in typical performance comparison benchmarks.

In terms of immediate results the final work will propose a field-tested version of such performance comparison framework. This methodological approach should be easily extensible and flexible enough to bring benefits to average economist/data analyst. The valuable insights into model performance in the context of discrete individual choice, as well as underlying behavioural theories influences on the results are expected to be obtained. A detailed study will allow for future researchers to choose the appropriate method for a specific application in relation with cognitive and behavioural studies.

3 Advances

As one can deduce from the slight changes brought to the problematic and objectives of this research work, several major advances were achieved during this year. Those advances affect both the theoretical and applied parts of the PhD project.

3.1 From models to procedural approach

First of all, comes the previously mentioned switch towards the *procedural approach* in scientific research. To bypass the limitations imposed by all the differences in the *model* term definition it was decided to use the entire data analysis *procedure* as subject of this work. Nevertheless the term *model* will still appear in our discussion, because the various types of *models* make part of the entire *procedure*. It is typically assumed, that readers are familiar with such terminology and already understand the sense commonly attributed to the term depending on the context. The most vast definitions of the *model* term are:

- "a set of ideas and numbers that describe the past, present, or future state of something (such as an economy or a business)" ("Model Definition & Meaning | Britannica Dictionary" n.d.)
- "a theoretical description that can help you understand how the system or process works, or how it might work" ("Model Definition and Meaning | Collins English Dictionary" n.d.)

At this point it is equally important to ensure the general understanding of the *procedural approach* to data analysis. For references in the (scientific) *procedure* description we take such fundamental works as Wooldridge (2012) and Baltagi (2008), as well as field specific literature (ex: Agresti (2013), De Palma et al. (2011), Durlauf and Blume (2010)). Not all of those works make a direct accent on the *procedural* view, but one can identify the common patterns across those works. With slight differences in those works the *procedure* may be in general divided into several major steps. First of all, every research starts with a *problematic* identification and *research question* definition. Every study begins with a particular need - a problematic to be addressed. The first step reflects the transition of the real world problem to be treated into the more restricted context of a research specific question. The next stage in the research requires the scientist to make some assumptions about the nature of the data and the underlying processes. Typically it's during this stage that *hypothetical (interaction) model* is defined based on the theoretical assumptions or the preliminary analysis of the available (if available) data. Thus the second step is a further extension of the *problematic* narrowing and translation into numerical terms: target *metrics* identification. Once the target defined, the research may proceed differently, depending on the available information. Without loss of generality this step may be summarised as *data collection and analysis* process. Either the actors already have access to some data and build the model using available information. Or the model is pre-built and drives the data collection step. Finally, the data analysis provides the actor with information on the target *metrics* (*estimates*). Those allow to answer the initial question and offer a *solution* to the initial problematic.

We propose to understand the entire *procedure* composed of all the steps to be a single subject of our research. Because nearly all the steps of such *procedure* affect the obtained results we assume that the comparison of performances should be performed on the *procedural* level instead of being limited to only the *modelling technique*. The choice of data collection procedure, all the eventual transformations and hyperparameter definitions should be taken into account while comparing performance of two alternative *modelling techniques*, which makes it far easier to operate on the *procedural* level.

3.2 Framework modifications

The changes in the subject of our research entailed the inevitable modifications within the proposed performance comparison framework. The framework retraces in its structure the previously described data analysis *procedure*, incorporating at the same time additional blocks devised for *hypothesis testing* and *performance analysis*.

The *performance analysis* and target performance metrics in procedure comparison may drastically vary depending on the study's objective and searched target. This fact pushes us to extend our framework to incorporate the *research problematic* and *the research question*. Because some tools are simply not devised to answer some questions or there are no known or established practices of their usage, the definition of the research question should therefore be considered as the first step in the proposed framework. It will provide the researcher with particular metrics to consider while performing the model comparison.

The *hypothesis testing* capability is another block which was extended in comparison with the previous framework's version.
This stage in the framework comprises the dataset choice or dataset generation procedure. At this point the opinions may vary as discussed by Japkowicz and Shah (2011). Even though in statistical modelling when speaking about model performance assessment and comparison the focus is typically made on the classification (prediction) accuracy (Andersson, Davidsson, and Lindén (1999), Hand (2012), Askin and Gokalp (2013)) this is not always the best option.

On the one hand, in model comparison, whatever is the research question, one will always have some target metrics or criteria in mind. It means, that for a complete comparison procedure one should be able to compare not only the models between themselves, but compare the results with some externally defined target as well. The best strategy in this case is to artificially generate the required dataset: either using simple Monte-Carlo simulation (Rubinstein and Kroese 2016) or some more complex simulation approach (ex: agent based simulation (Chan, Son, and Macal 2010)). Simulated datasets are often used to validate various theories (Garrow, Bodea, and Lee 2010) or assess the capabilities offered to the researcher (Munizaga and Alvarez-Daziano 2005). Synthetic datasets are equally often used for usability and statistical efficiency testing (Caron et al. 2021). Another objective of such test is the study of the requirements towards dataset sample size (Alwosheel, van Cranenburgh, and Chorus 2018). The effects of alternatives' sampling are equally explored (Nerella and Bhat 2004). There exist even studies focusing on the exploration of statistical properties and procedural implications in synthetic dataset usage (Bodea and Garrow 2006).

On the other hand, it's possible to use an existing real world dataset. Evidently, this approach limits the researcher in the performance metrics usage, but combined with analytical model exploration it may not be that limiting for the research. What is more, such approach is assumed to bring more external validity to the results, because of the similarities with other collected datasets. Such decision may be reasonable if we were to compare the model performances in terms of prediction, for example. The comparison of predictive power has more external validity in this case, compared to the simulation approach (Japkowicz and Shah 2011). Such strategy uses real world data, which approaches the modelled situation to the reality. Some researchers imply that this assures at least some degree of external validity, in contrast to simulated data, which assures identical results only under same theoretical assumptions.

3.3 Differences in procedures

Now, when we have presented the differences introduced into the methodological approach, we can discuss such changes as the *inter-* and *intra-* disciplinary differences in the implemented approaches. Those distinctions were brought in evidence through the interviews with the practising researchers, who use the DCA practices in their work. It appears that the procedural differences exist not only between the *Econometrics* and *ML* disciplines, but also within the Econometrics community.

The main procedural differences between the Econometrics and ML lie in the target indicators of interest. For example, while in Econometrics the focus is typically made on the *effects* and their magnitude, in the ML the typical tasks involve the focus on the predictive quality or pattern recognition. Another difference, which is not that omnipresent as the first one, resides in the interaction with the data. While in Econometrics the scientist may typically bring some critical *theory driven* opinion to the data collection, transformation and analysis, in the ML disciplines the approach is rather *data driven*.

Within the Econometrics community there also exists a separation in the analysis *procedure*. For instance, in the experimental economics the researchers have the possibility to mitigate many of the potential biases prior or during the data collection step. This means, that in such cases they can opt for a usage if simpler modelling techniques during latter stages of the analysis *procedure*. On the other hand, field studies rarely have such advantage. This means that the scientists in this case are pushed to address all the same biases through the usage of advanced *analysis techniques*.

3.4 Toolset development

This year was equally used to improve the existing toolset both as part of the *framework* and for the help in everyday tasks. First of all, the simulation package lying at the heart of the *framework* was reworked. This involved to completely switching the Object Oriented Programming (OOP) paradigm from representation of the Choice Experiment as an object to the *objectification* of the Discrete Choice Experiment (DCE) elements on a finer level. The new structure approaches by its logic the ones observed in `biogeme` and `apollo` packages. This package reconstruction has made it far more extensible and flexible, making it at the same time easier to use in the future applications.

Another toolset modification involved creation of a side-package uniting all the known to this day traditional performance metrics. This package represents another module of the *framework.* the resulting modular approach is expected to make the project results easier to adopt by other researchers.

Finally, another tool created during this year was the `R` package for interaction with *Web of Science* (WoS) API for bulk bibliography extraction. This toolset greatly facilitated and automated bibliography review generation using the *VOSviewer* software. The resulting bibliography review methodological notes have greatly helped in the exploration of the trends in DCA, as well as the biases understanding in the literature, target indicators usage and many more.

4 Future work

Once we have outlined all the major changes that have marked this year, we can switch our attention to the discussion of the planning for the next year. In this part of the report we are going to present the main directions for future work.

4.1 Applications and Circular Economics

Because of the shifts in the calendar due to the major alterations in the theoretical part of the work, it was decided to focus on the applied part during the third year of the work. The application should produce data, which will serve as the basis for several demonstrations of the modified framework potential. It was decided to participate in a collaboration with another PhD student at Grenoble INP (Maria-Victoria Hernandez-Marquina[1]) working on the Circular Economics adoption exploration. The resulting dataset should be collected through an online DCE survey, exploring the managerial preferences in Circular Supply Chain (CSC) adoption.

The survey was adapted from the supply chain literature to a CSC context. The main study strives to evaluate the impact of collaboration capacity elements on the quality of collaboration and overall performance in a supply chain. The principal part of the research focuses on the assessment of the impacts of collaboration within CSC on the CSC performance. The information on the supply chain is collected from the several firm representatives. Each of the participating firms is assumed to make part of some CSC. The individuals are assumed to occupy high hierarchical positions and be directly involved in the *strategic decision-making* processes (managers).

A Hybrid Choice Model (or Generalised Logit model as an extension) is expected to be used for the effect evaluation. Such choice of an advanced modelling technique ensures the large field for future experimentation and test of the framework.

4.2 Working papers

At this point in time it's expected to produce 3 working papers till the end of the PhD, by the end of 2023. Such objective is established because of the plans to present the final manuscript in the format of collection of the 3 working papers, united by a single theoretical and methodological background presenting the performance testing framework. The collected data on the CSC should serve as another baseline uniting the papers and the described applications. Such approach will make the contents easier for understanding through both common methodology and common dataset.

Unfortunately, such strategy implies extensive reworking of the first working paper, which was at its final stage of production by the end of the first year, but now has to undergo heavy modifications due to the

[1]Among the recent works we may cite: Hernandez Marquina et al. (2022)

methodology changes. It's equally assumed that the new dataset will replace the one previously used in the work.

The two new working papers will equally focus on the Circular Economics context. One of them (second working paper) should lay the foundation uniting other works, through the choice experiment presentation, data description and traditional *procedure* illustration. On the contrast, another paper (third working paper) will offer a more in-depth presentation of the *framework*. While the first working paper outlines the framework and should incorporate the basic notions relating the framework and the *procedural* approach, the third paper should extend the scope through contrast of the ideologically different *procedures*.

4.3 International experience

During the third year it is equally planned to experience an integration to the broader scientific community. Through the network of the Grenoble INP and UGA, and thanks to the financial support of MITACS fund it is experience an international mobility to the Polytechnique Montréal (*école Polytechnique de Montréal*). The visited team makes extensive usage of the different data analysis and ML techniques, which will allow us to further adjust and validate the proposed *procedural* approach to discrete data analysis. A series of interviews is planned to be performed with the laboratory members working with choice modelling or using classification toolset in broader context.

What is more, the inviting laboratory has tight relationships with many industrial partners, which may potentially allow us to collect better data for Circular Economics (CE) application. We expect to enter in contact with at least some of the industrial representatives for CE survey diffusion.

5 Supporting activities

The presentation of the current PhD work cannot bypass the numerous associated activities, among which: (1) various academic courses; as well as (2) teaching and improvement of the interpersonal skills. This report will not include all of the above activities, but only the most important ones[2].

5.1 Studies

The second year of PhD was marked by several major field-specific courses. During the first part of the year the focus was given to the ML field toolset exploration as a follow-up on the advances of the previous year. The participation in the 30h course on "*Outils statistiques pour Data Science*" (Statistical tools for Data Science) greatly helped us in the better understanding of the differences in the paradigms between the various scientific communities. It can be said that participation in this course has greatly impacted the transition towards the *procedural* vision of the performance comparison task.

The second part of the year was consecrated to the DCA and Choice Modelling community visions on the *modelling procedure*. The participation in the course on "*Discrete Choice Analysis: Predicting Individual Behaviour and Market Demand*" by M. Ben-Akiva and M. Bierlaire allowed to improve the understanding of the history of the DCA, as well as brought some corrections into the basic toolset taxonomy view. The usage of the `biogeme` package have also incited me to take a short course on the `Python` usage at UGA.

5.2 Teaching

The teaching responsibilities have been extended this year to the maximum amount possible, reaching the cap of 64 hours. Some courses were identical to the ones of the previous year: (1) *Statistics* (1A Génie Industriel) at Grenoble INP and (2) *Works of Study and Research* (Travaux d'Etude et Recherche, TER) projects supervision. Other new ones were added to the curriculum: (1) *Econometrics* (M2 BDA) at UGA, (2) *Advanced Econometrics* (M2 BDA) at UGA and (3) *Data Analysis for Génie Industriel* (2A Génie Industriel) at Grenoble INP.

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[2] For a complete list of the mentioned activities, please refer to the CSI form.

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