Modeling mode choice preference in a Mexican university with discrete choice models

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Abstract

The study of the mode choice for urban regions has increased, with a growing set of recent works using joint methodologies of data gathering and modeling with machine learning models. This work details the design and application of a mobility survey to a private urban university in the north of Mexico. Decision tree based, machine learning models for multiclass classification, are shown to be effective with datasets in which categorical data predominates, having a better performance than the widely applied econometric models covered in literature. The interpretability of decision trees helps to identify relevant variables that influence modal choice. It can be concluded that, for the studied sample, people's awareness of their access to collective modes is the most decisive factor, and thus the efforts of institutions to promote investments and availability of better modes will determine the mode's adoption rate.

Keywords
Discrete choice model, Transportation, Mode choice study, Machine learning

1. Introduction
The Monterrey Metropolitan Area in the state of Nuevo León is the second most important metropolis in Mexico. Its economic and territorial growth in the last years has caused externalities with a considerable impact on the health of its population. Along with this growth, the number of vehicles in Nuevo Leon has increased. The National Institute of Statistics and Geography reported, in 1980, around 180,000 automotive vehicles. In 2019, the number increased to 1,800,00 vehicles (INEGI, 2019). UDEM is a university located at the west of the MMA., With more than 12,000 affiliates (students, professors, and staff) is one of the main universities of the region, attracting students from around the state, therefore becoming an important attractor and generator of mobility and influencing the externalities of traffic in the region.

To understand the mobility characteristics and patterns of the region, the Sustainable Urban Mobility Integral Program (PIMUS ZMM) gathered origin-destination surveys to the Monterrey Metropolitan Area (MMA) and modelled the travel behavior of the population to develop public policies to reduce greenhouse effect gases emissions (Transconsult, 2020).

The elaboration of robust models is difficult without experiments to observe the behavior of the system under a wide range of conditions; this is the reason why mobility studies are needed (Ortúzar & Willumsen, 2011). These studies provide basic and necessary information to elaborate models that are implemented in system simulation and to understand the characteristics of the population (Portilla et al., 2007a).

This work aims to identify the factors that influence the choice of mode of transport of the community of UDEM. In this specific case study and through a literature review, it is believed the most relevant factors to be the stage of life (Whalen et al., 2013), the access to modes of transport (Danaf et al., 2014), and the travel time of the mode (Rybarczyk & Shaker, 2021).

In the rest of this paper, a review of similar works in the available literature will be shown. Then, showing the implemented methods in this work to study the modal preference and then to model the choice of mode of UDEM's members. Then, the results from the application of said methods will be presented. Lastly, a discussion of the results and further possibilities of the work will be covered.

2. Literature review

Understanding mode choice has been widely covered in literature mainly as study cases of population around the world. Regularly studied populations are university communities worldwide. These areas and their related populations are subject of testing for mobility studies since they can be analyzed as small-scale cities from which these works can be scaled to larger populations easily. The location of the reviewed studies is predominantly North American (Akar et al., 2012; Rybarczyk & Shaker, 2021; Sweet & Ferguson, 2019; Whalen et al., 2013), European (Eboli et al., 2013; Rotaris et al., 2019; Sprumont et al., 2017a) and South American (Galdames et al., 2011; Gutiérrez et al., 2020; Márquez et al., 2019) universities. To the best of the authors' knowledge this work is the only one implemented in Mexico that will have applied both a mobility survey and predictive models of modal choice.

Other types of populations have been studied as well, for example, users of different passenger transportation companies to understand if their choice of mode differs (Richter & Keuchel, 2012), due to a specific interest as they might represent a source of mobility externalities or represent one of the predominant modes in the region. Other populations could be more specific, such as the case of citizens who use private car to go to work at the center of Theran, Iran, as they could be offered a collective mode that could reduce their externalities (Habibian & Rezaei, 2017). The selected scope of the study is UDEM's community since that population size is smaller. Making the case study replicable and scalable for future works as to the best of the authors' knowledge, it is the first one of its kind in the region.

Mode choice studies have a wide range of possible objectives, for example, determining the possibility of change of mode from a private mode to a collective and less polluting option (Becker & Carmi, 2019; Guo et al., 2021; Gutiérrez et al., 2020; Rotaris et al., 2019), or the characteristics of the decision making of users of certain modes of transport as they could potentially become the market for new modes offered in the region (Akar et al., 2012; Basbas et al., 2017; Bhaduri et al., 2020; Galdames et al., 2011; Gonzalo-Orden et al., 2012; Habib, 2019; Yang et al., 2018). When initial studies in a region take place, the works are more focused on building initial databases as platforms for future works to take place (Choudhury et al., 2018; Gao & Sun, 2018). This work is the first one in the region, and thus will aim to generate the first base of mode preference.

The development of predictive models requires extensive and specific information that is normally not readily available. Therefore, we find that modeling studies usually follow a previous stage of data gathering. For example, designing an online survey answered by students, professors, and staff to gather preference data to use different degrees of collective modes (Dell'Olio et al., 2017). Additionally, the data gathering stage could be physically delivered and use margin of error criterions to establish the sample size and gathering stage objectives (Gonzalo-Orden et al., 2012). Due to the lack of previous data that could be used to carry out the modeling stage, this work presents the design of a survey to gather mode choice preferences for the population of UDEM's campus. Due to the COVID-19 pandemic online surveying is used and estimation of margin of errors are used for sample size calculation.

3. Methods

3.1 Survey

A mobility survey was designed and applied based on the questionnaires of reviewed mobility studies (Portilla et al., 2007b) to obtain information about the factors that influence how the UDEM community chooses their transport mode. The population of study was the UDEM community which has a population around 14,000 people related in the undergraduate campus.

The survey was implemented during one month with diffusion through social media, e-mail, and promotion in courses. 779 responses were collected, after the removal of invalid responses, and were processed to be used in the modeling stage. **Table 1** shows the sample size and actual number of responses.

Table 1. Statistical significance of survey.

Disaggregated results analysis		
Parameter	**Students**	**Teachers and workers**
Population size	12,000	2,000
Goal	373	180
Actual responses	612	214
Final responses	568	211
Confidence level	95%	95%
Margin of error	4%	6%

The survey design was based on different studies in which surveys were conducted to collect data for discrete choice models. The UDEM community was asked about relevant sociodemographic data (gender, age, socioeconomic status, where they live, with whom they live, etc.) and information about their role in UDEM, such as their current semester (Bhaduri et al., 2020).

Other questions included the characteristics regarding trips to UDEM's campus, such as the travel modes used for the UDEM community to travel to campus, the reason they choose this travel mode, the usual time of the day in which they leave to UDEM, and the duration of the trip (Bhaduri et al., 2020; Sanko, 2020). Additionally, mobility habits were gathered, such as how much money is spent traveling to UDEM, and which factors are the most and least relevant when choosing a transport mode (Sanko, 2020).

Access to different modes of transport was additionally asked as a crucial variable. A person will have a certain mode of transport as an alternative mode choice only if they have access to it. Therefore, these questions are useful to know which are the collective modes of transport with more accessibility, and which can easily be an alternative to cars.

3.2 Econometric models

Random utility maximization models are one of the most used techniques for modeling transport mode choice. These models work as optimization problems where travelers choose the transportation mode that maximizes its utility. This utility is defined as a combination of different attributes that relate to a specific decision. In this case, which mode of transport to use (Sprumont et al., 2017b).

When a decision maker i chooses an option, they consider m_i alternatives that are mutually exclusive and make up the choice set. They assign a perceived utility U_{ij} to each alternative j from the choice set and chooses the alternative that maximizes the utility. Each alternative's utility depends on several attributes X_{ij} of the alternative and/or of the decision maker (Sprumont et al., 2017a).

Logit and probit models are found among these models. The difference between them is the way in which they specify the probability density function of the non-observed values, this being the stochastic residual.

3.3 Machine learning models

For machine learning models, classification models are considered. The modeling process was divided into 2 steps. First, the independent variables of mode choice for each individual were classified into 2 classes: private and collective vehicles. Private vehicles are gas cars and hybrid vehicles. Collective vehicles are public transport, on demand services, Directo UDEM and Urbvan. Directo UDEM is a bus service specifically for the UDEM community which has different routes and a semestral fee, while Urbvan is a free van service which has routes only near UDEM.

The techniques used are decision trees, random forest, gradient boosting, and extreme gradient boosting. D trees are used to represent decision analysis visually and explicitly. They are conformed by internal nodes where the tree splits into branches. The end of the branch is called a leaf, where the prediction is shown. For classification, the function used by the decision trees is the Gini index, which is the proportion of the samples that belong to a certain class for each node (Gupta, 2017).

Decision trees are the base of models like Random Forest, Gradient Boosting, and XGBoost. Random Forest is a technique that consists of a great number of decision trees that result in predictions of classes. The class that has the highest number of votes becomes the model's prediction. Random Forest uses bagging, which is an ensemble meta-algorithm that combines predictions made by different decision trees through voting. Gradient Boosting models are created through boosting, in which models are created minimizing the errors of previous models and increasing the efficiency of the new ones (Chen & Guestrin, 2016).

The last and best type of models related to decision trees are XGBoost, which is an optimized Gradient Boosting model, but uses advanced regularization to prevent overfitting. In XGBoost models an initial prediction is made and residuals are calculated through the difference between the predictions and data. The main objective is to lower the residuals, for which the model calculates a similarity score in each node. With the residuals and similarity score, a gain for each split is calculated. Each split has a variable selected at random to determine the condition. The model keeps the splits with the highest gains. For each leaf, an output is calculated. This output is used to calculate the final predictions (Chen & Guestrin, 2016).

Another method tried out was Support Vector Machine (SVM) for classification, in which each data item is plotted in n-dimensional space, and n is the number of features. The goal is to find the hyper-plane that best differentiates the classes (Cortes & Vapnik, 1995). Logistic regression was also implemented, which is a model based on probability that uses the Sigmoid Function to map predicted values to probabilities (Sperandei, 2014). Finally, we also worked with Naive Bayes, which is based on the Bayes theorem: $P(y|X) = P(X|y)P(y) = P(X)$ where y is the class and X are the features (Friedman et al., 1997).

4. Results

Econometric models were developed but didn't have a good outcome, their classification scores was 0. This was probably because most of the variables collected from the survey were categorical (76%), and just 24% were numerical. Therefore, the use of a utility function might not be compatible with the variables. This caused the econometric models that were carried out to not adjust properly to the variables.

For machine learning models, classification models were implemented. The modeling process was divided into two steps. First, the independent variables of mode choice for each individual were classified into two classes: private and collective vehicles. Private vehicles are gas and hybrid cars, while collective vehicles are public transport, on demand services, Directo UDEM and Urbvan. After this, private and collective modes enter each one into another classification process using different models. The compared techniques are decision trees, random forest, gradient boosting, support vector machine, and extreme gradient boosting, **Table 2** shows the results for every phase. Models based on decision trees-based algorithms had the best results.

Table 2. Machine learning model's performance for both phases

			First Stage		Second Stage	
Model	**Accuracy train set**	**Accuracy test set**	**Geometric mean test set**	**Accuracy train set**	**Accuracy test set**	**Geometric mean test set**
Random Forest	1.00	0.93	0.91	1.00	1.00	1.00
XGBoost	1.00	0.92	0.90	1.00	1.00	1.00
Gradient Boosting	1.00	0.89	0.88	1.00	1.00	1.00
Naïve Bayes	0.88	0.86	0.87	1.00	0.99	0.99
Support Vector Machines Polynomial Kernel	1.00	0.91	0.85	1.00	0.99	0.99
Logistic Regression	0.95	0.89	0.84	1.00	0.98	0.98
Decision Trees	1.00	0.85	0.81	0.99	0.98	0.98
Support Vector Machines Radial Basis Function Kernel	0.88	0.87	0.78	0.99	0.97	0.97

Feature importance analysis was performed and obtained on each modelling stage. Feature importance is a measure that represents the relative gain score of each feature to the full model. A higher percentage means a more important predictive feature (Iguyon & Elisseeff, 2003). **Table 3** shows the most relevant variables for first stage. Comfort is evidently the most important one as it affects mode choice to a large extent since private modes are considered as more comfortable. The risk of infection is higher in collective modes, so people who are most aware of the COVID-19 virus will most likely choose a private mode. Also, access to hybrid cars is a feature that marks an important division since hybrid car owners will make use of it to travel.

Table 3. Variables with higher importance for first stage

Variable	**Importance (Gain score)**
Comfort of the mode	0.10
Risk of infection	0.052
Access to hybrid vehicle	0.040
Using same mode for departure and return	0.045
Use of Urbvan for other trips	0.044
Access to gas car	0.035
Economic impact of mode	0.03

Access to hybrid auto and infection prevention results are relevant features on the first stage decision and the second stage, specifically in the private modes decision (Iguyon & Elisseeff, 2003). For the second stage, the common use of Bus or Urbvan result important features at mode choice, as can be seen in **Table 4**.

Table 4. Most relevant variables per stage

<table>
<tr><td></td><td colspan="7">Important factors per stage</td></tr>
<tr><td rowspan="2">First stage</td><td colspan="3">Private mode</td><td colspan="4">Collective mode</td></tr>
<tr><td colspan="3">Mode comfort</td><td colspan="2">Infection prevention</td><td colspan="2">Hybrid auto access</td></tr>
<tr><td rowspan="2">Second stage</td><td>Gas auto</td><td colspan="2">Hybrid auto</td><td>Public transport</td><td>On demand service</td><td>Directo UDEM</td><td>Urbvan</td></tr>
<tr><td>Hybrid auto access</td><td>Schedule flexibility</td><td>Environmental awareness</td><td>Bus common use</td><td colspan="2">Urbvan common use</td><td>Mode comfort</td></tr>
</table>

On the other hand, it can be inferred that value of time would change in order of the students' stage of life and that the most substitutable modes to Urbvan would be gas auto and on demand service.

Value of time calculation was performed according to the weekly cost and travel time reported by each person on the survey and made use of Minitab to run ANOVA 1 factor analysis, which divides people in the categories presented in different demographic variables and reports if there exist statistically significant difference between means. **Figure 1** group shows the variables in which at least one level resulted statistically different.

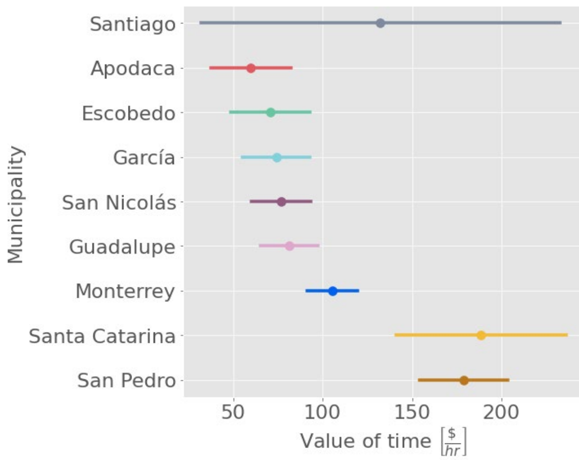

Figure 1a: Value of time by municipality

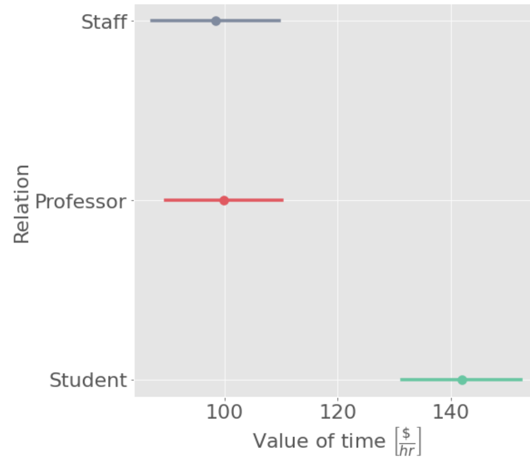

Figure 1b: Value of time by relation with UDEM

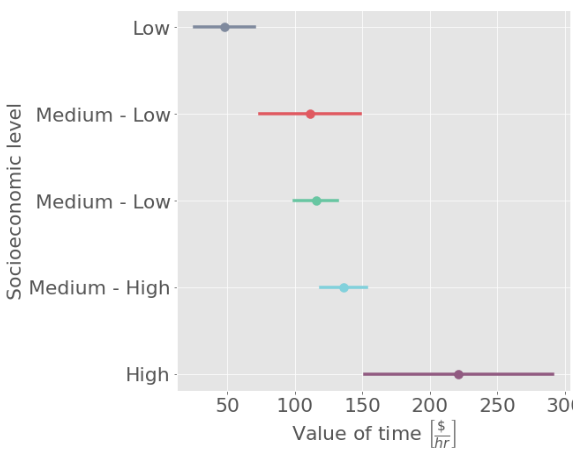

Figure 1c: Value of time by socioeconomic level

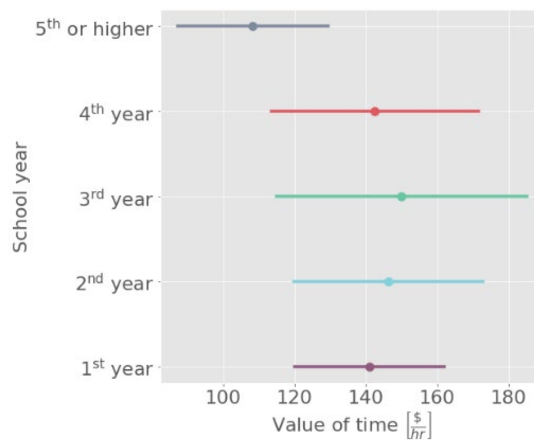

Figure 1d: Value of time by school year

Figure 1. Variables with categories statistically different for value of time.

The value of time shows differences between demographic variables. For example, people who live in municipalities closer to UDEM have a higher value of time than those that live farther. Also, students have a higher value of time, especially in their first semesters. This might be because the reason students go to the university is different from the reasons teachers and staff go. Additionally, it was also found that people with a higher socioeconomic level have a higher value of time. UDEM must develop different mobility strategies according to these characteristics.

At the same time, to prove the substitutability of modes, the impact of the most important features between pairs of modes was analyzed, choosing some individuals to change their values on those features and predict a new mode choice probability.

For On demand service vs Urbvan, common use of Urbvan and access to Urbvan resulted in the most important features. Because of this, people living nearby and reporting a medium or lower socioeconomic level using on demand service were filtered and recalculated their mode choice, considering they know about Urbvan routes and that can use it for daily and non-related UDEM trips. This exercise resulted in 100% of people with these characteristics changing their mode choice to Urbvan. The same exercise was made to calculate the percentage of people that would change from gas auto, and it resulted in 10% of people with these characteristics changing to Urbvan.

5. Conclusion

Every stage of a mobility study is interconnected. For example, an adjusted survey that considers the nature of its population of study and its current situation, along with adequate data processing, allows the development of effective choice models. Additionally, we note that machine learning models have a better performance than econometric models when using categorical variables that result from the perception of a surveyed community. Perhaps the econometric models would have a better outcome if working with quantitative data instead of focusing on categorical data.

It was also found that the municipality is the feature that mostly determines the UDEM community's value of time. People who live closer to UDEM have a higher value of time, which might be because they have the idea that they don't have to spend much time traveling to and from UDEM since they live close. Also, it is possible to change people's modal choice regardless of their socioeconomic level. The promotion of Urbvan, for example, would make more students know about the service and more would use it regularly. This would have an impact on the number of people who stop using cars to use Urbvan instead.

This work was large and has room to develop a wider range of analysis and solutions for any of the stages followed in its execution. This work creates opportunities to further develop any of the proposed stages in the methodology or to explore alternatives on some of the modeling or data gathering activities.

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Biographies

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Jenny Díaz-Ramírez is currently a professor of the Department of Engineering at the University of Monterrey. She has worked previously as professor at Tecnológico de Monterrey, Mexico and Pontificia Universidad Javeriana Cali, Colombia. She is an industrial engineer from Universidad del Valle, Colombia. She holds an MSc in industrial engineering from Universidad de Los Andes, Bogota, Colombia, an MSc in operations research from Georgia Tech, US, and a PhD in Industrial Engineering from Tecnológico de Monterrey. She is a member of the National System of Researchers of CONACYT, SNI Level I, since 2015 and recognized as an associated researcher by Colciencias, 2016. She is the author and co-author of scientific articles on topics such as applied optimization and statistics in health systems, air quality, energy efficiency, transport and logistics.