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Transportation Mode Choice Analysis Based on Classification Methods

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***Abstract* – Mode choice analysis has received the most attention among discrete choice problems in travel behavior literature. Most traditional mode choice models are based on the principle of random utility maximization derived from econometric theory. This paper investigates performance of mode choice analysis with classification methods - decision trees, discriminant analysis and multinomial logit. Experimental results have demonstrated satisfactory quality of classification.**

***Keywords* – Decision trees, discriminant analysis, multinomial logit, transportation mode**

I. Introduction

Transportation mode is one of the major components (system user, mode, infrastructure, intermodal connections and stakeholders) of the transportation system that estimates the level of usage for different transportation modes (e.g., walking, public transport, bicycle, and vehicle) and given the performance characteristics of each available mode and characteristics of the individual user. [12].

Travel mode choice has received the most attention among discrete choice problems in travel behavior literature. Mode choice analysis and prediction are closely related to transportation system policies and congestion mitigation strategies. The most of mode choice models are based on random utility maximization principle derived from econometric theory. Since the multinomial logit (MNL) model was developed in the 1970, the parametric models with different structures have become the most common used tools for mode choice analysis. Several recent studies in the field of decision trees and neural networks [14], [15] have showed better performance indicators compared to discrete choice models.

Up to now, variety of neural network models have been operated in traffic flow management for driver behavior modeling, vehicle detection on the road and vehicle scheduling and routing. In the study (Chi Xie, Jinyang Lu, Emily Parkany, 2003) two data mining methods were considered: learning tree (algorithm C4.5) and neural networks (backpropagation) to improve performance of mode choice forecast. Two data mining models were compared with traditional multinomial logit (MNL). Comparative evaluation has showed that the two data mining models have comparable but slightly better prediction capability than the MNL model on work travel mode choice modeling. Decision trees have problems with processing continuous data; data have to first be grouped into ranges manually or automatically with software tool [14].

The approach proposed in Matthew G Karlaftis study (2001) was focused on the recursive partitioning methodology development for individual mode choice prediction. The methodology is based on tree-structured nonparametric classification technique (Breiman, 1984), as a result, a set of decision rules represented in the form of a binary decision tree was produced. This methodology allows using any combination of categorical and discrete variables compared to multinomial logit [15].

In the V.C.Tatineni, M.J. Demetsky study the supply chain methodology based on modeling methodology for regional freight transportation planning was investigated. The mode choice model was developed using four different classification methods: binary logit model, linear discriminant analysis, quadratic discriminant analysis and tree classification. The quadratic discriminant and classification trees have provided the most accurate modal split among the four empirical choice models (model accuracy 87% - 92% for test set). Logit models have provided the most interpretable results among the four empirical choice models [7].

The purpose of this study is to classify transportation mode choice based on classification methods: discriminant analysis, decision trees and multinomial logit. The capabilities of each classification method for the transportation mode choice analysis were evaluated.

II. Input Data

The data were collected from July 19 to August 05, 2005. A total of 7 171 personal interviews were conducted. All respondents were 16 years old or older and data collection was organised at four places: hotel, office, shopping center and home.

The survey collected information on: (a) socioeconomic and demographic variables; (b) travel characteristics; (c) travel influence conditions. Some of these variables were qualitative and others were quantitative. The following variables have been collected and used to determine the best fit model under study:

• Data. This variable has been used to determine the impact of the week day in the trip maker mode choice.

• Place or Trip purpose. The distinction among trip purposes is an important step in mode choice analysis because different trip maker behaviors are expected in selecting a mode for different trip purposes [8]. In order to distinguish between trip purposes, this information should be available to the model builder. Four trip purposes (hotel, office, shopping center and home) are reviewed in this study.

- Direction. This variable has been used to determine the visitor's direction to/from data collection points (for example, a visitor is going to or from a shopping centre).
- Part of City. The city was divided into four districts to get more accurate results and to determine the impact of the city part on the trip maker's mode choice.
- Transportation Mode. This variable is used to determine whether the trip maker owns a car or is captive to other modes such as public transport, taxi, bicycle and walking.
- Travel time. This is the time in minutes spent in the mode for a one-way trip including the access time, egress time and waiting time.
- Age. This variable has been used to determine if age has an impact on intercity mode choice for the trip maker or his family.
- Temperature. This variable is used to determine the average temperature during data collection.
- Wind Speed. This variable is used to determine the wind speed during data collection
- Conditions. This variable is used to determine the conditions (cloudy, rainy, sunny or thunder) during data collection.

The last three variables were taken from *Internet resourses*.

III. Data Preprocessing

Data preprocessing is an important step in the data mining process, and it has a huge impact on the success of a data mining project. The purpose of data preprocessing is to clean the noise data, extract and merge them from different sources, and then transform and convert the data into a proper format. Data preprocessing was divided into three parts: sampling, entropy and information gain calculation for the attribute selection.

A. Sampling

The number of items was reduced from 7171 to approximately 500 to make the data more suitable for data mining. Sampling without replacement (if item is selected once, then it's removed from the set) was used to distribute uniformly all items for the instance "Mode". Table I shows distribution of items before and after preprocessing.

TABLE I
Items Distribution for the Attribute "Transportation Mode"

Attribute value	Before Preprocessing		After Preprocessing	
	Number of Items	% of Items	Number of Items	% of Items
Bicycle	105	1%	83	17%
Public transport	1460	20%	110	22%
Taxi	86	1%	86	17%
Vehicle	3394	47%	109	22%
Walking	2126	30%	110	22%
Total:	7171	100%	498	100%

B. Entropy and Information Gain

As the next step, information gain was calculated for each attribute by using data after preprocessing (approximately 500 items). To calculate information gain, entropy for each attribute was calculated. Entropy is a measure of variability in a random variable (1).

$$Gain(A,Q) = H(A,S) - \sum_{i=1}^{q} \frac{|A_i|}{|A|} H(A_i,S). \qquad (1)$$

where A_i – subset of *A* for which attribute *Q* has value *i*.
The calculated and sorted information gain from the biggest to the smallest for all attributes is given in Table II.

TABLE II
Information Gain for Attribute

Attribute	Information Gain
Direction	0,81
Age	0,76
Travel time	0,70
Part of city	0,65
Conditions	0,64
Date	0,63
Wind speed	0,38
Place	0,36

From received data the attributes „Direction" and „Age" have the maximum information gain; in turn attributes „Date", „Wind Speed" and „Place" have the minimum information gain values. To understand how information gains influence the classification task, the attribute „Mode" was classified without attributes with a small value of information gain.

C. Weka Filter Application (Supervised and Unsupervised)

To improve classification task for attribute "Mode", *Weka 3-6-0* filters were used. All filters in *Weka* are divided into two categories: supervised and unsupervised. Each category includes a filter on the attributes and instances. The supervised filters take class information into account and try to maintain the class distinctions in the grouped instances, while the unsupervised filters do not. All filters were used to classify attribute "mode" and then three of the filters with the best classification results are chosen for further analysis:

- *Resample* - Produces a random subsample of a dataset using sampling with replacement (items are not removed from the population as they are selected for the sample),
- *Remove Misclassified* - A filter that removes instances which are incorrectly classified. Useful for removing outliers and
- *Remove Folds* - This filter takes a dataset and outputs a specified fold for cross validation.

Using the Resample filter the number of instances remained unchanged – 498 instances, however some of instances did not get to the set, whereas some of the instances are chosen repeatedly. In the new data set the number of correctly classified instances has grown about by 10-15% in comparison with the other Weka filters (the classification results are shown in paragraph „Learning tree").

Using the Remove Misclassified filter the number of instances was reduced from 498 instances to the 253 and the percentage of correctly classified instances was 71%. However, by using this filter the distribution of the instances has changed; it did not correspond to the initial distribution (see Table 1, column – After Preprocessing).

Using the Remove Folds filter the number of instances is reduced to 50. The initial distribution has also changed and, as a result, only three instances corresponded to the values “Vehicle”, “Bicycle” and “Taxi” for attribute “Mode”.

IV. Learning Tree

After the data preprocessing has been finished, the classification was made to evaluate correctly and incorrectly classified number of instances. The classification was made with the *Weka 6-0-1* software using two algorithms C4.5 and CART (Classification and regression tree). CART method is nonparametric technique (binary) that can select important patterns from a large number of variables.

After the first part of the preprocessing – sampling and total pattern reduction to the 500 instances both algorithms have shown similar results – 65% of the correctly classified instances and 35% incorrectly. As a result, the confusion matrix was received; it showed the number of confused instances for classified attribute “Mode”. The confusion matrix for algorithm C4.5 with the sampling is shown in Table III.

TABLE III

Confusion Matrix for Algorithm C4.5

a	b	c	d	e	Classified as
77	8	10	11	3	a = Vehicle
0	77	15	0	18	b = Walking
0	12	86	0	12	c = Public transport
22	17	11	31	2	d = Bicycle
12	6	11	5	52	e = Taxi
a	b	c	d	e	Classified as
77	8	10	11	3	a = Vehicle
0	77	15	0	18	b = Walking

It can be seen from Table 3 that, for example, for instances value “Vehicle” 77 instances are classified correctly and others are confused with other instances value. The main reasons of the incorrect classification are poor quality input data with the noise, missing values, different types of attributes - the numeric and categorical, the significance of different attributes, as well as overfitting and underfitting (a situation where a large number of errors is observed when checking the classifier on the training set. This means that the specific patterns in the data were not detected and either they do not exist at all or it is necessary to choose another method of detection).

Entropy and information gain calculations were used to improve the classification results in the second part of the data preprocessing. After the information gain calculations the classification without attributes with the smallest information gain values has been made (Table IV).

The results obtained give evidence that the number of correctly classified instances slightly improved for the algorithm CART when seven attributes (excluding attributes “Place” and “Wind speed”) were used for class attribute classification “Mode”. On the other hand, the number of the correctly classified instances for the algorithm C4.5 is slightly worse (up to 5%) in comparison with the CART algorithm and with classification with sampling.

TABLE IV

Confusion Matrix for Algorithm C4.5

	The number of classified instances					
	Correctly	Incorrectly	Correctly	Incorrectly	Correctly	Incorrectly
	8 attributes [1]		7 attributes [2]		6 attributes [3]	
C4.5	65%	35%	63%	37%	63%	37%
SimpleCart	65%	35%	66%	34%	61%	39%

[1] 8 attributes – classification results without attribute “Place”;
[2] 7 attributes - classification results without attributes “Place” and “Wind speed”;
[3] 6 attributes - classification results without attributes “Place”, “Wind speed” and “Date”.

Using the information gain calculation the classification of the attribute “mode” is improved insignificantly. It was decided to use the *Weka* filters for classification to make the classification more accurate. The classification results are given in Table V.

TABLE V

Classification Results. Learning Tree

	Classified Instances			
Data preprocessing	Algorithm C4.5		Algorithm CART	
	Correctly	Incorrectly	Correctly	Incorrectly
Resample	67%	33%	67%	33%
Remove Misclassified	71%	29%	69%	31%
Remove Folds	78%	22%	77%	23%

The use of *Weka* filters produced various classification results. The number of correctly classified instances varies within 67% - 78% percent according to the chosen classification algorithm, C4.5 or CART. In addition, to increase classification accuracy, the filters are used in combination with each other. As a result, the correctly classified instances are 80% for the C4.5 algorithm and 92% for the CART algorithm.

V. Discriminant Analysis

Discriminant analysis is a statistical technique that classifies dependent variable between groups and calculates each respondent probability to get into one or another group. As a result of discriminant analysis, a discriminant function is obtained that is similar to regression function. In the discriminant analysis the initial group size and quantity are given and the main task is to determine how accurately it is possible to predict the object membership to groups with the given set of discriminant variables [2]. The main problems of discriminant analysis are the selection of discriminant variables and the choice of discriminant function. The multiple forward stepwise discriminant analysis was used to predict values of five categories (Table VI).

In general, all nine variables (see p. 2 “input data”) were discriminated well between the groups and are suitable for classification purposes. The correlation coefficient between the discriminant function values and an indication of belonging to a group have shown an average relationship for the first (correlation coefficient - 0.697) and second (0.65) functions, and the weak relationship of the third (0.436) and fourth (0.303) functions. That means that the third and fourth functions are not clearly divided into groups, and it has resulted in a small number of correctly classified observations. Forward stepwise analysis was carried out to improve the discriminant analysis results (Table VII).

TABLE VI
DISCRIMINANT ANALYSIS. CLASSIFICATION RESULTS

Discriminant analysis	Number of variables	Number of categories, transportation mode	True classified instances, % transportation mode
Stepwise analysis	9	5 (all include)	63,9%
	9	4 (exclude «bicycle»)	70,6%
	9	3 (exclude «bicycle», «taxi»)	79,6%
Forward stepwise analysis	6	5 (all include)	64,1%
	6	4 (exclude «bicycle»)	70,8%
	6	3 (exclude «bicycle», «taxi»)	79,6%

Comparative results of the stepwise and forward stepwise methods showed small difference of correctly classified instances, only 0.2%. In the case of forward stepwise discriminant analysis 64.1% instances were correctly identified and 63.9% of instances in the classification, taking into account all independent variables simultaneously. Low accuracy of classification was associated with "Taxi" and "Bicycle" categories of dependent variable "Transportation mode." Perhaps learning sets are closely located to each other, resulting in increased probability of erroneous classification of categories. The number of categories was reviewed to improve accuracy of the classification model.

Reduction of categories from five to four (excluding the category “Taxi”) and three (excluding the categories “Taxi” and “Bicycle”) has increased the classification accuracy by 10% and 25% (70.6% and 79.6%) for forward stepwise discriminant analysis and by 10% and 24% (70.8% and 79.6%) for stepwise discriminant analysis.

VI. MULTINOMIAL LOGIT

The multinomial logit model is a choice model between two or more alternatives, among several independent variables (also called predictors) and the dependent variable. Multinomial logit model (MNL) gives the choice probabilities of each alternative as a function of the systematic portion of the utility of all the alternatives.

The maximum likelihood method consists of finding model parameters that maximize the likelihood (posterior probability) of the observed choices conditional on the model. In this study the maximum likelihood method was used to calculate coefficient of logistic regression [18].

$$L(Y_1, Y_2, ... Y_k; \theta) = p(Y_1; \theta) \cdot ... \cdot p(Y_k, \theta). \qquad (2)$$

The multinomial logit classification results have showed that 88.6% of instances were correctly classified. High statistical significance of the model based on the method of maximum likelihood (Sig. <0,001) testifies to its quality and suitability for the task. The model explains 86.7% of the total variance (Pseudo R2 = 0,867 on the test Nagelkerke). Assessment of statistical significance of each of the dependent variable has indicated that three variables have little effect ("Place», Sig = 0.478; «Age», Sig = 0.728; and "Travel time», Sig = 0.263) on the model. As a result, these variables can be excluded from the model.

TABLE VII
CLASSIFICATION RESULTS. MULTINOMIAL LOGIT

Observed	Predicted categories			
	Vehicle	Public transport	Walking	Percent Correct
Vehicle	82	6	5	88,2%
Public transport	1	78	6	91,8%
Walking	2	9	66	85,7%
Overall percentage	33,3%	36,5%	30,2%	88,6%

VII. CONCLUSIONS

In this study the applications of learning tree, discriminant analysis and multinomial logit with different specifications in the context of mode choice analysis are presented. Socioeconomic and demographic data, travel characteristics and travel influence conditions were collected to estimate factor influence on individual’s choice of travel mode. Five available modes (vehicle, public transport, walking, bicycle and taxi) were taken into account for mode choice analysis according to survey data. All input data were cleaned from noise and were transformed into proper format for analysis.

Two algorithms C4.5 (Quinlan) and CART (Classification and regression tree) were chosen for building decision trees. C4.5 algorithm is one of the most well known algorithms with good combination of error rate and speed (Tjen-Sien Lim et al. 2000). CART algorithm is nonparametric and can easily handle outliers in travel characteristics data that are based on traveler perception. Both classification algorithms have shown roughly the same results 67% - 78% of correctly classified instances. After additional data preprocessing (first, a random dataset was produced using sampling with replacement and then incorrectly classified instances were removed from the dataset), the percentage of correctly classified instances was 80% for the C4.5 algorithm and 92% for the CART algorithm.

Discriminant analysis was chosen for transportation mode choice analysis because it deals with more individual than aggregate data, it may make fuller use of the data and more accurately reproduce structure inherent in the data (John A. Fiedler, 1996). Two methods of discriminant analysis were used: stepwise and forward stepwise. The stepwise method includes all variables simultaneously in a model and in the forward stepwise method a model of discrimination is built step by step. Comparative results of the stepwise and forward stepwise methods have shown that the percentage of correctly identified instances for depended variable “transportation mode” was 63.9% - 64.1% for five categories and 70.6% - 79.6% for three categories.

The calculations for multinomial logit model in Section VI have illustrated the manner in which different utility specifications and the estimated parameters associated with them are used to predict choice probabilities based on characteristics of the traveler and attributes of the alternatives. Overall experimental results have shown that 88.6% instances were classified correctly. Category “Public transport” of attribute “transportation mode” has shown the best result with 91.8% correctly classified instances.

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Nadežda Zeņina, Arkadijs Borisovs. Transportlīdzekļu pārvietošanās veidu analīze, pamatojoties uz klasifikācijas metodēm
Transportlīdzekļu veidu izvēle diskrēto uzdevumu vidē ir plaši atspoguļota literatūrā. Transportlīdzekļu veidu izvēle un prognoze ir cieši saistīti ar transporta sistēmas politiku, braucienu pieprasījuma vadību un ar sastrēgumu samazinājuma stratēģiju uz ceļiem. Darbā ir izskatīti lēmumu koki (algoritmi C4.5 un CART), diskriminantu analīze un daudzdimensiju logit regresija transportlīdzekļu veidu (mašīna, gājējs, sabiedriskais transports, taksometrs un riteņbraucējs) pārvietošanās analīzei. Lēmumu koku klasifikācijas rezultāti parādīja, ka 67% - 78% eksemplāru bija klasificēti pareizi. Papildus apstrādājot izejas datus, kombinējot vairākus filtrus, pareizi klasificēto eksemplāru skaits tika palielināts līdz 80% algoritmam C4.5 un līdz 92% algoritmam CART. Tiešā un soļu diskriminantu analīze parādīja nebūtisku atšķirību pareizi klasificēto eksemplāru skaitā. Soļu diskriminantu analīzes gadījumā pareizi tika identificēta piederība 64.1% novērojumu un 63.9% klasifikācijai ņemot vērā visus mainīgos vienlaicīgi. Klasifikācijas rezultātu ne sevišķi lielā precizitāte bija saistīta ar kategorijām „taksometrs” un „riteņbraucējs” atkarīgā mainīgā „transportlīdzekļu pārvietošanās veids”. Samazinot kategoriju skaitu līdz trim (bez kategorijām „taksometri” un „riteņbraucējs”) klasifikācijas precizitāte palielinājās līdz 79.6% soļu un tiešajai diskriminantu analīzei. Daudzdimensiju loģistiskās regresijas klasifikācijas rezultāti uzrādīja, ka 88.6% respondentu tika klasificēti pareizi. Uzbūvētā modeļa lielā statistiskā nozīme liecina par to augsto kvalitāti un piemērotību uzdevuma risināšanai.

Надежда Зенина, Аркадий Борисов. Анализ транспортных средств передвижения с помощью классификационных методов
Выбор вида перемещения (*mode choice*) среди дискретных задач выбора наиболее широко отражен в литературе. Выбор и прогнозирование вида передвижения тесно связаны с политикой транспортной системы, управлением спроса на поездки и стратегией уменьшения заторов на дорогах. В данной работе рассматриваются деревья решений (алгоритмы C4.5 и CART), дискриминантный анализ и множественная логит регрессия для анализа выбора средства передвижения (на машине, пешком, общественный транспорт, такси или на велосипеде). Результаты классификации с помощью деревьев решений показали 67% - 78% верно классифицированных экземпляров на тестируемом множестве. Дополнительно обработав исходные данные, комбинируя несколько фильтров, удалось повысить процент верно классифицируемых экземпляров до 80% для алгоритма C4.5 и до 92% для алгоритма CART. Сравнительные результаты прямого метода и пошагового дискриминантного анализа показали незначительную разницу верно классифицированных наблюдений. В случае пошагового дискриминантного анализа правильно определена принадлежность 64,1% наблюдений и 63,9% при классификации с учетом всех независимых переменных одновременно. Невысокая точность классификации связана с категориями «такси» и «велосипед» зависимой переменной «тип перемещения». Уменьшение категорий с пяти до трех (без категорий «такси» и «велосипед») увеличило точность классификации на 79,6% для пошагового дискриминантного анализа, и до 79,8% для классификации с учетом всех независимых переменных одновременно. Результаты множественной логистической регрессии показали, что 88,6% респондентов были классифицированы верно. Высокая статистическая значимость построенной модели, основанная на методе максимального правдоподобия (Sig. < 0,001), свидетельствует о ее высоком качестве и пригодности для решения поставленной задачи.