



Public Travel Mode Choice Model

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Abstract: Under the policy background of accelerating the urban integration construction in China, the development of urban transportation is facing new challenges. Because there are many serious traffic jams on the road, reasonable planning of road construction is an urgent problem for our country. This paper first sorted out the relevant common travel choice prediction models. On this basis, MATLAB, SPSS and other software were used to model the travel choice prediction model, intending to obtain the relevant analysis of public transport travel mode selection. After improving the parameters of the probabilistic neural network model, it is concluded that the improvement of parameter calibration is beneficial to the accuracy of the model. The results of probabilistic neural network classification of traffic models are compared with other traffic prediction models, and it is concluded that the probabilistic neural network classification of traffic models has smaller measurement errors, and the results are better.

Keywords: travel mode; Public transportation; Mathematical software; Probability and statistics; Improved parameter proofing

1. Introduction

As China's urbanization accelerates, the development of urban transport is facing new challenges. A document issued by The State Council in 2013 put forward: "The development of public transport is a necessary condition for reducing traffic congestion, transforming urban traffic, improving citizens' quality of life and improving the level of basic public services provided by the government."

At the same time, due to social progress and economic development, traffic jams on the road has become more serious, and traffic has become one of the problems urgently needed to be solved in our country. Many experts and researchers are studying this problem. Most experts believe that simply increasing the number of roads can not solve the urban traffic problem from the root cause, the available land in the city is limited, the road can not be unlimited increase, and the urban public transport problem has become a common phenomenon in various cities at home and abroad. With the reform and progress of science and technology, the city's public transportation structure can be further developed and gradually form a three-dimensional urban transportation structure composed of bus, walking, subway and other public transportation modes.

The purpose of prioritizing public transport is to improve its competitiveness compared with private transport, encourage greater use of public transport and increase the share of public transport in urban travel. Therefore, in order to improve the structure of the urban transportation system, it is very useful to analyze the behavior of residents when choosing public transportation in detail. In addition, the improvement of the traffic structure helps to improve the traffic environment, such as traffic congestion or traffic road construction.

The way people travel is usually to choose from all the available means of transportation to reach the destination in an acceptable time. There are many combinations of travel modes, so travelers are faced with a variety of transportation mode choices, in addition, under the uncertainty and randomness of road conditions and external environment changes, travelers' choice will have greater fluctuations. This paper will conduct a quantitative analysis of the factors that affect the traveler's travel mode and make assumptions and infer the possibility of the



traveler's travel mode through data statistics and probability analysis of these factors. In this paper, only walking, bus and subway are considered as public transportation modes. According to the analysis of the survey data, the residents' travel modes can be divided into three types: normal work travel mode, mixed travel mode and leisure travel mode. The three types of public transportation modes are analyzed and compared. A model between the results of public transport travel mode selection and the influencing factors of travel mode selection was established to describe the Logistic regression model of travel characteristics of residents in Wujiang area.

Therefore, with the continuous progress of society, the accelerated development of economy and people's demand for a good traffic environment proposed by the government, it is urgent to optimize the structure of urban public transport on this basis. It is what researchers have been doing to predict how to improve the structure of urban public transport by analyzing the choice of public transport modes.

A large number of scholars have conducted research on travel modes, Basciftci and Van Hentenryck study how to integrate rider mode preferences into the design of on-demand multimodal transit systems [1]. Bhat's research shows that An individual's intrinsic mode preference and responsiveness to level-of-service variables affects her or his travel mode choice for a trip [2]. Bhat study an Endogenous Segmentation Mode Choice Model with an Application to Intercity Travel [3]. Ettema et al. study the Travel mode use, travel mode shift and subjective well-being [4]. Verplanken et al. study the Habit, information acquisition, and the process of making travel mode choices [5]. Baslington study A social theory of travel mode behavior [6]. De Vos et al. study the Travel mode choice and travel satisfaction [7]. Hagenauer and Helbich study A comparative of machine learning classifiers for modeling travel mode choice [8]. Hoffmann et al. study What cognitive mechanisms predict travel mode choice? [9]. Vij et al. study the influence of latent modal preferences on travel mode choice behavior [10]. Since travel mode selection uses different basic units, mode segmentation models are mainly divided into aggregated model (taking traffic area as a unit to jointly analyze people's travel choices) and non-aggregated model (taking individuals as a unit to identify different mode choices). Then these individual probability sets are combined to predict the travel sharing rate.

The time of generation of the aggregate model is earlier than that of the non-aggregate model, and the operation is relatively simple, but it has advantages and disadvantages, and the aggregate model cannot be accurate for calculation. Hence the research on disaggregated models initiated in the early 1960s.

As early as 1955, Puget Sound used extensive survey statistics to build classification prediction models through classification studies. However, this model is difficult to calculate once there is more data, and the calculated results have great uncertainty and relatively large unit error, so this model is not suitable for the traffic prediction of large and medium-sized cities and is not suitable for the situation that cities need to make huge adjustments.

Logit model is the most representative of non-set models. Its form is relatively simple, it is more pragmatic, and it is closer to reality. However, Logit model has a fatal defect, that is, its random utility term is assumed separately, which means that Logit model will have relatively large prediction errors.

The Logit model does not take this mechanism into account but instead considers the efficiency of each mode separately. This uncertainty in the Logit model's mode choice in describing resident passengers weakens the model's overall description of traffic conditions.

As a result, the Logit model has been improved and generalized Logit models have been developed, but these models do not significantly overcome the shortcomings of the Logit model, whereas the Probit model, while overcoming these shortcomings, tends to rely on extremely complex Monte-Carl simulation algorithms or polynomial Clark solution approximation algorithms. In view of these inconsistencies, it is necessary to study and improve the feasibility of traffic choice prediction models in traffic prediction. Only in this way can the model be more realistic and practical.

2. Travel Mode Prediction Model

Prediction model of common travel mode selection

The aggregate method usually takes the traffic area as the research unit, analyzes the flow of residents in the statistical block, and establishes the prediction model in four stages: the generation and attraction of trips, the distribution of trips, the distribution of patterns and the distribution of traffic flows. For this model, the first step is to estimate the total number of trips; In the second step, these total trips are calculated using rules of thumb,



such as method traffic zones, traffic patterns, and route intervals; Finally, the data is predicted by traffic cell to cell. This prediction method is part of the set-count model modeling process and is called set-count analysis. For example, in the first step of establishing the model, the population and population density of the traffic community are analyzed (expressed by a function), so as to express the amount of travel in the traffic community. In the analysis process of the traffic community, the original sample of the traffic community will become a vector. The above method is called the set-count method, and the model obtained by the method is called the set-count model. At present, the traffic generation and distribution in the four-stage model is one of the aggregated models. Of all the aggregated models, the simplest is to classify travel choices using the mode of transportation.

When studying the frequency distribution of a group of aggregated traffic modes, the frequency of a group of traffic modes can be considered separately, or the traffic mode, the generation of traffic, the distribution of traffic and the distribution of traffic can be analyzed together. The time of traffic distribution is considered less, and the main consideration is the space in which the traffic mode is divided. According to the traffic space, the model can be divided into: the division combination model at the beginning of the trip, the division combination model at the distribution of the trip, the division combination model after the start of the trip, the division combination model after the distribution of the trip, and the mode division combination model. Here are some practical models for dividing the modes of transportation.

Regression model method

The model takes the traffic distribution rate as the dependent variable and various traffic related factors as the independent variables and studies the specific dependence relationship and law of the dependent variable to the independent variable by regression analysis. Regression models can be used as models to predict transportation modes.

$$G_{im} = \alpha_m + \beta_{1m}X_1 + \beta_{2m}X_2 + \dots + \beta_{mm}X_m \quad (1)$$

Among, G_{im} — The traffic production volume of traffic area i and traffic mode m ;

X_1 、 X_2 、 X_m — Relevant factors such as population, land use, indicators of living standards, etc.;

α_m 、 β_{1m} 、 β_{2m} 、 β_{mm} — Regression coefficient

The results of using regression model as prediction mode for transportation choice prediction are relatively rough, and the establishment of this model is based on the premise of making a huge investigation of the current situation. At the same time, the inherent law of traffic mode sharing rate and some factors related to traffic travel choice cannot be expressed by linear regression analysis, while for nonlinear analysis, this analysis can only represent the inherent law between traffic mode travel choice and a single traffic-related factor, and the relationship between traffic-related factors and traffic sharing rate cannot be simply dealt with. It is also necessary to understand the internal laws between traffic-related factors and analyze them. However, it is difficult for this nonlinear regression model to undertake such complicated work. Therefore, for the forecasting model, the regression model method still has defects that cannot be solved at present, and at the same time, the application of the model is extremely limited.

Transfer curved model

One type of travel mode division model is to express the travel sharing rate of a certain mode of transportation through multiple groups of curves, mainly related to the relationship between several modes of transportation (two or three) and some factors affecting the choice of travel mode.

Similar to regression models, the transfer curve is based on a large survey of the current situation, and the transfer curve is used to visually show the share rate of each mode of transportation.

Transfer curve is the most widely used method to predict traffic patterns abroad. While they are simpler and easier to use than other models, the construction of these curves is not simple because they are based on a lot of research into the status quo followed by a lot of statistical analysis. In addition, because it is based on a large number of current situation studies, the model is only meaningful when it includes a small number of important influences, and in the scenario of numerous vehicles and huge factors for transportation choice in our country, it is unrealistic to use the transfer graph to show the internal law between different transportation modes, which requires a lot of human resources. Therefore, transfer curve models are not very suitable for our country.

Disaggregated method is a four-step assignment method used to predict the choice of traffic trip. Disaggregated method takes individuals as research objects, uses the direct original data of individuals in the model, studies the



original data of individuals with probability, and describes the behavior of individuals. This type of model is called disaggregated model. Compared with the limitations of the set-counting method, the non-set-counting method requires fewer samples, but its prediction accuracy is higher. Therefore, it has a larger error range for the traffic frequency prediction model.

Since this paper is based on the analysis of disaggregated model, the disaggregated model is mainly discussed below. So far, several types of disaggregated models have been developed, including Logit models, Probit models, and improved models of Logit models. The following analysis focuses on the theoretical basis, structural and functional forms of the disaggregated model, and a series of results of the model.

1. Stochastic utility theory

The theory of random utility has become the basic theory for the public to use disaggregated models. Disaggregated model is a choice prediction model, in which the factors that affect the choice of travel mode are inconsistent with each other, but generally consistent.

The alternative modes of transportation are called choice branches, and each choice branch has its own utility function, which is used to measure the probability of the transportation choice. The utility function is determined by the individual's own characteristics and the characteristics of the transportation mode. If it is assumed that the maximum travel selection mode of the utility function is the selected choice, then it is impossible to measure all the influencing factors because there are many influencing factors on the utility function. Therefore, in summary, the utility function acts as a random variable in this model.

Let $U_{iq} = V_{iq} + \varepsilon_{iq}$, The measurable or representable part of the system is V_{iq} , It is a function of the measurable property x ; Random part ε_{iq} , It belongs to the characteristic preference and other errors of residents' travel choice, and also includes the rules established by modeling and the errors generated by the model.

In the above utility model, two points should be paid attention to: First, the individual can make a decision regardless of other factors except random variables, and the default plan selects the most appropriate scheme; Second, the modeler only needs to observe part of the factors of traffic trip selection, instead of all the factors, and the unreasonable behavior of factors that are not considered is explained by the residual value ε .

Individual q chooses the scheme with the maximum utility, that is, individual choice A_j , if and only if $U_{jq} \geq U_{iq}$, $\forall A_j$, $V_{jq} - V_{iq} \geq \varepsilon_{iq} - \varepsilon_{jq}$. However, since the analyst has ignored the value of ε , it is not certain that this is true. To choose A_j probability for $P\{\varepsilon_{jq} \leq (V_{jq} - V_{iq}), \forall A_j \in A\}$.

We know that the residual value ε is a random variable with a certain distribution. Here $f(\varepsilon) = f(\varepsilon_1, \dots, \varepsilon_N)$ its distribution, Use $f(u)$ said u distribution, and its distribution and ε are the same, but different mean value (namely the mean V , ε average 0).

Therefore, the above formula can be expressed more simply as: $P_{jq} = \int_{R_N} f(\varepsilon) d\varepsilon$, among:

$$R_N = \begin{cases} \varepsilon_{iq} \leq \varepsilon_{jq} + (V_{jq} - V_{iq}), \forall A_i \in A(q) \\ V_{jq} + \varepsilon_{jq} \geq 0 \end{cases} \quad (2)$$

Thus, different model forms can be derived by using the residual values of different distributions ε .

2. Functional form

Utility functions can be expressed for various functions, but because of the ease of analysis and data calibration of linear functions, the linear form of utility functions is currently the most widely used. The following is the representation of a linear function:

$$V_{jq} = \sum_k^K Q_{kj} X_{jkq} \quad (3)$$

The Q_{kj} is unknown parameters, it is the same constant for all individuals, but varies with the scheme; $X_{jkq} = [X_{j1q} \cdots X_{jkq} \cdots X_{jKq}]$ is the individual q who chooses the j eigenvector, It is composed of the individual's social and economic characteristics and the characteristics of each selection branch.

3. A set of discrete choice models

The predictions of aggregate models usually reflect the overall market behavior. The classification models used to estimate the probability of individual travel mode choice often pay more attention to the loss of aggregate travel behavior.



When the prediction model is chosen to be linear, the set-counting process simply uses the mean of the explanatory variables in the non-set-counting equation, but when the prediction model is chosen to be non-linear, this method is often referred to as the simple set-counting method.

The discrete choice model is defined as follows:

$$P_{jq} = f_j(X_q) \quad (4)$$

P_{jq} is the probability that the individual q selects j ; X_q is the set of variables that affect an individual's decision; f_j is the selection function of the selection branch j .

For the population of Q individuals, the aggregate proportion of selected branches j according to this model is the expected value of the probabilities for each individual:

$$P_{jq} = \frac{1}{Q} \sum_{q=1}^Q f_j(X_q) = \frac{1}{Q} \sum_{q=1}^Q P_{jq} \quad (5)$$

For a medium-size selection dataset, this model is suitable for short-term prediction of the mode of transportation choice. In contrast, it does not have ideal prediction results for long-term prediction, so this model is not suitable for describing the situation where the data changes greatly from year to year.

Traffic mode division model based on probability statistics

Model principle: Probabilistic neural network is a branch of radial network and a type of feedforward network. Conceptually, PNN belongs to the category of radial networks. It is a four-layer feedforward network consisting of a certain number of Gaussian functions (or Parzen Windows). Some studies have shown that PNN can be used as an ideal classifier by evaluating homoscedasticity Gauss. Radial basis function network is a scalar function with radial symmetry. Learning such network is equivalent to finding the best fitting plane of training data in a multidimensional space. The neuronal transfer function of the adaptive level forms the input, implicit (indirect), summation, and output of each layer, thus forming the network.

The input layer, hidden layer, summation layer and output layer constitute a probabilistic neural network. The input layer is used to obtain data from the training sample and transfer the data to the hidden layer using the transfer function of the same number of neurons as the input vector. This layer has the same number of neurons as the previous input layer, and the same number of input samples.

The vector x is input to the hidden layer, where the input/output relationship determined by the j neuron of the i type pattern is defined by the following formula:

$$\phi_{ij}(x) = \frac{1}{(2\pi)^{\frac{1}{2}}} e^{-\frac{(x-x_{ij})(x-x_{ij})^T}{\sigma^2}} \quad (6)$$

To sum up: it can be known that the number of sample data received by the input layer, the number of neuron transfer functions and the length of the input vector are the same; In addition, the hidden layer is the radial base layer, and each neuron represents a center, which is set against the data of each sample. The input data is sorted into i because PNN is used for sorting. First, the sample is used to train the network, and then after the trained network is obtained, the trained network is used to calculate the data, and the calculation results are classified. On the type of x i j and RBF neural network is consistent, request samples of each input and Euclidean distance. The number of neuron transfer functions in the summation layer is the same as the number of data classification. The average value of each type of data in the upper layer is obtained in the summation layer, and the average value obtained is compared and analyzed, so that the data is classified.

Regarding the axiom that the summing layer weights the output of implicit neurons belonging to the same class:

$$V_i = \frac{\sum_{j=1}^L \phi_{ij}}{L} \quad (7)$$

V_i said categories of output, the first i L first i said the number of neurons in the class. The number of neurons in the summation layer is the same as the number of categories M .

Output layer The largest one in the summation layer as the output category:

$$y = \operatorname{argmax}(V_i) \quad (8)$$

In the actual operation, the vector in the input layer needs to be multiplied with the weighting coefficient, and then the data obtained from the operation is input into the radial basis function, and finally the radial basis function is used for calculation:

$$Z_i = x\omega_i \quad (9)$$



Assume that x and ω are normalized to unit lengths, and then perform the radial basis operation on the result $\exp\left(\frac{(z_i-1)}{\sigma^2}\right)$ be equivalent to:

$$\exp\left[-\frac{(\omega_i-x)^T(\omega_i-x)}{2\sigma^2}\right] \quad (10)$$

σ is the smoothness factor, which plays a crucial role in networking.

Brief Summary

This chapter mainly introduces the most commonly used traffic mode choice prediction models so far, which are roughly divided into two categories: aggregate model and non-aggregate model and rationally analyzes the models to clarify the drawbacks and defects of the models.

Aggregate models are easier to use than non-aggregate models but lack accuracy. The main disaggregated models are Logit model and Probit model. One drawback of the Logit model is that the random effects of each mode of transportation are assumed separately and separately. Although the Probit model overcomes this shortcoming, it relies on extremely complex Monte-Carl simulation algorithm or polynomial Clark solution approximation algorithm. As for the problems of lump-sum model and non-lump-sum model, probabilistic neural network is proposed to divide the traffic mode, and it is reasonable to explain that probabilistic neural network has a certain degree of implementation in the application of traffic mode division. At the same time, using the MATLAB probabilistic neural network toolbox function, the parameter calibration problem is realized conveniently and quickly.

3. Summary

The establishment of the transportation mode division model firstly calculates the sharing rate of transportation modes, which divides the transportation modes quickly and accurately by guessing the residents' transportation modes. This method is an effective way to understand how to improve the demand for public transportation. Because in essence, the division of the transportation mode problem is classification. Therefore, on the basis of the previous model of MATLAB function and probabilistic neural network to realize the division of traffic modes, the paper added the case analysis of Wujiang District residents and tested and verified the model through the sample data of Wujiang District. At the same time, the example of Wujiang District residents is brought into other models such as aggregate model and non-aggregate model to calculate the prediction, and the prediction results are compared horizontally. This paper explains the division of vehicle sharing rates by Down's predecessors using neural network and predicts it again by using data. With the support of the conclusion, it can be confirmed that the division of traffic model based on probabilistic neural network has smaller prediction error than other models. Therefore, the probabilistic neural traffic division model is a good model for dividing traffic mode selection.

Summary of research

Predecessors proposed the calibration of improved occupation parameters for the division of traffic modes in MATLAB probabilistic neural network and demonstrated through the data that the improvement of input parameters would indeed reduce the error of prediction results. In this paper, the sample data of Wujiang District was input, and the model was analyzed and compared, which once again confirmed that the improvement of occupation parameters would reduce the error of prediction results.

Before the transportation mode is divided, the main influencing factors of travel choice of residents in Wujiang region are determined first, and similar data are searched for each influencing factor, and typical samples are summarized. In the third chapter, the survey data of Wujiang District residents travel are analyzed statistically. The factors influencing the choice of travel mode of Wujiang District residents are established: occupation, age, gender, income, whether they have driver's license and means of transportation, etc., and the main transportation modes of Wujiang District residents: walking, bicycle, car, bus, motorcycle, etc. In the fourth chapter, the data modeling of Wujiang District residents' travel choice mode is carried out.

The sample data of the population travel survey in Wujiang area were input to monitor the prediction results of the model. By comparing the prediction results of the model before and after optimization, the prediction error of the model can be compared. From the comparison, it is concluded that better parameter calibration can reduce the prediction error of the model and achieve higher accuracy.



After comparing the prediction results of the probabilistic traffic distribution model with those of the lumped model and the non-lumped model, it can be concluded that the probabilistic neural network-based traffic mode model is superior to the lumped model and the non-lumped model in terms of accuracy and accuracy.

Insufficient aspect

In the analysis of residents' travel mode choice, residents' travel habits, psychological conditions, national policies on traffic road planning and the density of bus stops are not included in the influencing factors of residents' travel choice.

In addition, the means of transport owned by an individual is not necessarily a single, it is possible to own one or more means of transport. However, the calibration of data in the model only considers the case that the vehicle owned by an individual is the same, which is not in line with reality and is too idealized.

Therefore, in the future model building, consideration will be given to the density of buses, bus fares, and national policies on traffic road planning, so as to refine the traffic choice problem and provide a better solution to the traffic choice problem.

The division by means is to enable public transport to get better and more beneficial development. Municipal transportation planning needs to know the results of public transportation attendance, which plays an important role in whether the land can be fully utilized, and the environment can be protected to a greater extent. The most basic thing for the study of public transport mode selection is to consider the travel efficiency of residents and avoid traffic congestion, which determines how a country treats public transport.

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