

Study on the Planning and Forecasting of Urban Residents' Travel Modes: Application Based on Markov Chain

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Abstract: Urban residents' travel mode is an important part of urban traffic planning, which is often closely related to time series and spatial pattern. As an important part of traffic demand forecasting, the planning and forecasting of urban residents' travel modes plays an important role in traffic planning. In this paper, the Markov Chain, which is characterized by discrete time parameters and discrete state space, is used as an important quantitative tool. Based on the Markov Chain theory, the Markov Chain model is constructed after modifying and adjusting. The paper puts forward a theoretical application on the planning and forecasting of urban residents' travel mode, in order to provide a new theoretical perspective and approach for the early demonstration of urban traffic planning.

1. Introduction

Travel mode of urban residents is the main carrier of citizens' behavioral activities, and the manifestation of the diversified urban life. It is influenced by economic conditions, the regional environment, individual differences and other factors. ^[1] As the access to travel information becomes more and more convenient and the types of travel information become more and more abundant, residents' choices on travel modes are more frequently influenced by various traffic information. ^[2] In many cities, especially in small and medium-sized cities, residents also rely on private transport means apart from public transportation methods. Travelers' choices of trip mode have always been the core issue in the field of urban traffic management. Their choices can determine the structure of urban traffic mode to a large extent, and serve as the foundation for the formulation of traffic management measures and traffic policies. ^[3] As an important part of urban traffic demand forecasting, forecasting of travel mode selection plays an important role in urban traffic planning. The travel mode selection forecasting is a complex system and has a certain non-linear relationship with its influencing factors. ^[4]

Urban planning, as the forecast for the future development of urban space, is an important public policy. Residents' travel modes and travel behavior demands are important factors which determine the relationship between the space use efficiency and the self-development of the city. Through planning residents' travel modes, traffic demands and urban traffic situation can be predicted, which can provide important reference for space optimization and planning evaluation.

2. Theoretical Analysis of the Markov Chain

Markov Chain is a kind of Markov process with discrete time parameters and discrete state space. Among random processes, it has the longest history and is full of vitality. ^[5] It has profound theoretical foundations, such as topology, the function theory, functional analysis, modern algebra and geometry; it can be used in a wide range of applications, such as modern physics, random fractal, social public service system, as well as electronic information computing technology. This paper adjusts the Markov Chain theory, and constructs an applied model for the planning and forecasting of urban residents' travel modes.

Definition 1.1 $\{X_n, n=0,1,2,\dots\}$ is defined as a random sequence in probability space (Ω, F, P) ; its values are in a countable set E . For any nonnegative integers n and state $i_0, i_1, \dots, i_n, i_{n+1} \in E$,

there are

$$P\{X_{n+1} = i_{n+1} | X_0 = i_0, X_1 = i_1, \dots, X_n = i_n\} = P\{X_{n+1} = i_{n+1} | X_n = i_n\}, \quad (1)$$

The random sequence $\{X_n, n=0,1,2,\dots\}$ is called as a Markov Chain and is denoted as $\{X_n, n \geq 0\}$.

Definition 1.2 $\{X_n, n \geq 0\}$ is set as a Markov Chain, and called as conditional probability.

$$P_{ij}(m, m+k) = P\{X_{m+k} = j | X_m = i\} \quad (2)$$

The k step transition probability of the Markov Chain $\{X_n, n \geq 0\}$ at the moment of m is called as matrix.

$$P^{(k)}(m) = [p_{ij}(m, m+k)]_{i,j \in E} \quad (3)$$

It is the k step transition probability matrix of the Markov Chain $\{X_n, n \geq 0\}$ at the time of m .

In particular, when $k=1$, $P^{(1)}(m)$ is abbreviated as $P(m)$.

3. Construction of the Markov Transition Probability Matrix Model

The meaning of Markov's one-step transition probability, p_{ij} is the probability that the variable in now in the state i and will be in the state j afterwards. This probability is one-step transition probability, that is to say, the probability of random phenomena occurring in a certain direction. Considering all possible m state space transition probabilities p_{ij} of the Markov Chain, a one-step transition probability matrix is constructed in this paper.

$$p = \begin{pmatrix} p_{11} & \cdots & p_{1n} \\ \vdots & \cdots & \vdots \\ p_{n1} & \cdots & p_{nn} \end{pmatrix}$$

It satisfies $\sum_j p_{ij} = 1, p_{ij} \geq 0$, so we can get the relationship between the k step transition probability matrix and the one step transition probability matrix.

$$p^{(k)} = p^k$$

The proportion of variables in the initial stage is the initial distribution of the chain, which can be recorded as:

$$p^T(0) = (p_1, p_2, \dots, p_m)$$

If we know the one-step transition probability matrix and the initial distribution of the chain, then we can know the state of the chain after the n step transition. If the chain is an irreducible ergodic Markov Chain, then there is a stationary distribution in the chain. The stationary distribution is the limit distribution of the chain, that is, the probability distribution obtained based on the limit distribution of the chain is a stationary probability that almost invariant.

The k step transition matrix has the following properties:

$$(1) p^{(k)}(n) \geq 0, \quad p^{(k)}(n)1 = 1$$

$$(2) p^{(k+l)}(n) = p^{(k)}(n)p^{(l)}(n+k)$$

Among them, 0 represents zero matrix and 1 represents infinite dimensional column vectors with all elements of 1.

Prove: Apparently in (1), due to

$$\sum_{j \in E} p_{ij}^{(k)}(n) = \sum_{j \in E} p\{x(n+k) = j | x(n) = i\} = 1$$

Therefore, the second mode is established. And,

$$p_{ij}^{(k+1)}(n) = p\{x(n+k+l) = j | x(n) = i\}$$

$$= \frac{\sum_{r \in E} p\{x(n+k+l) = j, x(n+k) = r, x(n) = i\}}{p\{x(n) = i\}}$$

$$\begin{aligned}
&= \frac{\sum_{r \in E} p\{x(n+k+l) = j, x(n+k) = r, x(n) = i\}}{p\{x(n+k) = r, x(n) = i\}} \cdot \frac{p\{x(n+k) = r, x(n) = i\}}{p\{x(n) = i\}} \\
&= \sum_{r \in E} p\{x(n+k+l) = j | x(n+k) = r, x(n) = i\} \cdot p\{x(n+k) = r | x(n) = i\}
\end{aligned}$$

The Markov property condition is applied,

$$p^{(k+l)}_{ij}(n) = \sum_{r \in E} p^{(k)}_{ir}(n) p^{(l)}_{rj}(n+k)$$

Then,

$$p^{(k+l)}(n) = p^{(k)}(n) p^{(l)}(n+k)$$

Therefore, the k step transition matrix is determined by one step transition matrix.

4. Planning and Forecasting of Urban Residents' Travel Modes

This paper takes A city as the study case. According to the survey and statistics of relevant transportation departments, in 2013, the market shares of four kinds of private transportation means (assumed as bicycles, electric bicycles, motorcycles and cars) were 33.2%, 34.8%, 15.3% and 16.7 % respectively. From the survey data following facts are found.

(1) 67.2% bicycle users of 2013 continued to use bicycles in 2014; 22.7% turned to use electric bicycles, 2.5% to motorcycles, and 7.6% to cars.

(2) 79.3% of electric bicycles users in 2014 still used electric bicycles in 2015; 6.1% turned to use bicycles, 0.4% to motorcycles and 14.2% to cars.

(3) 46.8% motorcycle users of 2015 still used motorcycle in 2016, 7.3% turned to use bicycle, 31.2% to electric bicycles and 14.7% to cars.

(4) 63.3% car users of 2016 still used cars in 2017, 23.9% used bicycles, 12.1% used electric cars and 0.7% used motorcycles.

We use 1, 2, 3 and 4 to represent bicycles, electric bicycles, motorcycles and cars respectively. X_n represent the choice of residents in city A on the four modes of transportation in the month n . Then we can get the conclusion that $\{X_n, n \geq 0\}$ is a homogeneous Markov Chain with the state space of $\{1, 2, 3, 4\}$. That is, the initial distribution of the chain is:

$$p\{X_0 = 1\} = 0.332, p\{X_0 = 2\} = 0.348, p\{X_0 = 3\} = 0.153, p\{X_0 = 4\} = 0.167$$

Its transition probability matrix is calculated as follows:

$$P = \begin{pmatrix} 0.672 & 0.227 & 0.025 & 0.076 \\ 0.061 & 0.793 & 0.004 & 0.012 \\ 0.073 & 0.312 & 0.468 & 0.147 \\ 0.239 & 0.121 & 0.007 & 0.173 \end{pmatrix}$$

According to $p^{(k)} = p^k$, the relation between one-step transition probability matrix and n step transition probability matrix as well as the formula of total probability,

$$p_j(n) = \sum_{i=1}^4 p\{X_n = j, X_0 = i\} j = 1, 2, 3$$

Then

$$(p_1(2), p_2(2), p_3(2)) = (p_1(0), p_2(0), p_3(0)) p^2$$

After calculation, we can get the market shares of vehicles in 2018 are 29.2%, 45.4%, 4.3% and 21.2%.

From the one-step transition probability matrix, we can conclude that this chain is an irreducible ergodic Markov Chain, so the stationary distribution exists. Its stationary distribution is the limit distribution of the chain. That is to say, through the limit distribution, we can get fixed values for market share after a period of time. From stationary equation

$$(\Pi_1, \Pi_2, \Pi_3, \Pi_4) = (\Pi_1, \Pi_2, \Pi_3, \Pi_4) p \text{ and equation } \sum_{i=1}^4 \Pi_i = 1$$

Then

$$\Pi = (\Pi_1, \Pi_2, \Pi_3, \Pi_4) = (0.271, 0.467, 0.017, 0.245)$$

It can be seen that after a long period of time, the market shares of vehicles tend to be in a balanced state. Bicycles, electric vehicles and cars will have large market shares in the long run, while motorcycles will no longer be valued.

5. Conclusion

At present, China is in the stage of accelerated urbanization. In the urban traffic market, traffic demand is still greater than traffic supply capacity; competition on residents' traffic demands dominates the market. But there are great differences among different cities. From mega-cities to small towns, the market shares of vehicles vary in different cities. It is necessary to effectively guide the traffic demands of diversified cities based on their own characteristics. In particular, the comprehensive forecasting should be provided to reasonably and effectively guide urban traffic demands. Residents should also be led to form the traffic mode which is determined by public transportation, which is the development trend of urban transportation.

Through the research in this paper, we can see that the Markov Chain is reliable and feasible in predicting the occupancy of a certain vehicle in urban traffic planning, and it will be used more and more widely. It also reflects to a certain extent that the Markov Chain is an important stochastic process in stochastic systems.

It should be pointed out that the Markov Chain model established in this paper is simple and only involves matrix operation. This method has wide applicability. The above conclusions are derived under the assumption that the state of transition probability p_{ij} is "stable". Therefore, as long as the environmental conditions of economic development are relatively stable or change slightly, these conclusions will still have some practical significance in a relatively long period (several years or more than ten years later). Currently, big data research and application have been carried out to analyze the travel modes of large city residents. But the Markov Chain still has a high value in planning and forecasting the travel modes of residents who live in small cities, which are represented by the large number of county towns.

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