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Evaluation of Factors Affecting Driver's Behaviors Using Association Rule

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Abstract

In this paper, association rule mining algorithm is utilized to analyze the correlations of various factors of causing traffic accidents, from which the relationship model of dangerous driving behaviors is established. In this model, the factors and their correlations include: ability of risk control, ability of driving self-confidence, individual characteristics, and incorrect driving operations. By selecting the drivers in the city of Chengdu to be the objects of investigation, a group of valid sample data is obtained. Based on these data, the Support and Confidence for association rules are analyzed. In the analysis, the two stage computing of Apriori algorithm programming is simulated, and from which some important rules are obtained. With these rules, departments of traffic administration can focus on these key factors in their processing of traffic transactions. By the training of drivers' skills and their physical and mental behaviors, the incorrect driving operations can be greatly reduced and the traffic safety can be effectively guaranteed.

Keywords: Driving Technique; Traffic Safety; Big Data; Association Rules; Apriori Algorithm

1 INTRODUCTION

Traffic accidents have become "the world's largest harm to human beings", while China is one of the counties with the world's largest number of deaths in traffic accidents [1]. In the end of the 80's of the 20th century, it is the first time of that the traffic accidents in China killed more than 50,000 people. From that time to now, 500 thousand traffic accidents happened in China each year with deaths of more than 100 thousand people which continuously being the No. 1 in the world in the recent ten more years. While most of these tragic accidents originated in the improper operations of the drivers. In general, drivers in China have poor understanding to driving safety knowledge. According to the statistics of traffic accidents in China in 2011, among the 97000 road traffic accidents, 91.85% of them were caused by the driving behavior related factors, which indicated that road traffic accidents had a high correlation with the driving behaviors. The theoretical study also confirmed that, in the traffic conflict model induced by various risk factors (road, vehicle and environment), the dangerous driving behaviors were the main cause of traffic accident [2]-[7]. Therefore, starting from the dangerous driving behaviors, the exploring of the causes of traffic accidents will be possible to handle the main aspects of the formation of traffic accidents. To find the factors that affect the dangerous driving behavior, analyzing of the internal association is the key of the problems, and it is also the problem that we need to further study. It is necessary to establish a set of suitable tools to measure the dangerous driving behaviors in China, which can be used to explore the effect and correlations of dangerous driving behavior factors for Chinese road transportation. The research results in this paper will provide important solutions for decision-making in traffic accident prevention and management.

The key function of association rules is to find the regularity of the transaction from the big data, so that the important correlation of specific events in transactions can be found. If we can get amount of certain types of transaction data, then with this method, we can find the degree of association of the data that latently related. The most important thing is that it helps to find the intrinsic correlations of data which are not easily observed in daily life and traditional statistic correlation analysis [9]-[13]. So, this method has more important applications than the previous methods we used. Traditional correlation analysis can be only used for the data which we believe that they are related. That is, from the related statistical formula, the degree of correlations of these data that we expect can be calculated. Using association rules, however, we can find potential rules from large scale data, only if we have the appropriate data in database, then, with the help of techniques of data mining, the association rules of hiding in large scale data can be easily discovered. Thus, it is a very interesting exploration to apply this method in the analysis of driving behaviors. The condition is that we should set up the model of association rule mining for these data. In fact, in the department of traffic accident processing, they need to investigate the causes of every traffic accident. In this process, large scale data about the related drivers' personal characteristics and behaviors can be recorded into the database. If the investigated results can be structuralized to the form of transaction items, these data will be very interesting for the association rule mining. In our research, we expect to design a form which can include all the factors affecting drivers' driving operation and at the same time these factors and the results can be easily obtained in the traffic accident investigating and processing. Thus, large scale data can be available for the future data mining of association rules and more potential regularities for traffic safety can be discovered.

2 METHODS FOR THE ANALYSIS OF FACTORS AFFECTING DRIVER'S BEHAVIORS

Using traditional correlation analysis, factors and their relationship of driving behaviors can be computed. However, with this type of algorithms, research results show that we cannot discover those regularities hiding in the large-scale data. We need to have more effective algorithms for the data analysis since computer science and technologies are so extensively applied today. In 1993, Agrawal et al. first proposed the concept of association rules, and gave the corresponding mining algorithms at the same time, but the algorithm was poor in performance. In 1994, they established a project named Lattice Space Theory. Based on two theorems, they developed the famous Apriori algorithm [8]. As a classical data mining algorithm, Apriori algorithm has been widely discussed by many later researchers. Up to now, many researchers are studying association rules mining algorithms and applying them to different engineering areas [11]-[13].

Association rules are defined as follows:

I = {I_1, I_2, …, Im} is a set of transaction items. For a transaction set of specific items, given a transaction data set D in a database, in which each transaction T is a non-empty subset of I, a unique identifier TID (transaction ID) is defined for each transaction T. Assuming X and Y are two different item sets in D, the support degree (Support) of association rules of X and Y in D is the X=>Y correlation express, which is the percentage of all the items in X and at the same time in Y in the transaction set D. The result is expressed by a probability. The confidence degree (Confidence) is the percentage of that in the transaction set D, under the condition of containing all the items in X, at the same time items contained in Y, that is, the result is a conditional probability. By scanning all the transaction items and statistic calculation, for some items in sets X and Y, if the thresholds of minimum Support and the minimum Confidence are satisfied, then we consider that the association rules for these items are significant. These thresholds are set according to the need for mining. The item sets X and Y are also called the frequent itemsets.

1) Support:

Support(X=>Y)

=P(XUY)=Support_Count(XUY)/Support_Count (D);

2) Confidence:

Confidence(X=>Y)

=P(Y/X)=Support_Count(XUY)/Support_Count (X).

All these counts in the Support and Confidence can be obtained by scanning the database. After that, association rule mining process have two stages: the first stage, pick out all the high frequent itemsets from a data set, and the second stage, from the high-frequent itemsets, association rules are generated.

By modelling the survey data of traffic safety factors, the association rules can be used to analyze the correlation of the factors of driving behaviors and traffic safety, so that we can find out the correlation degree between each factor and provide a basis for traffic safety education and safety early warning, so as to avoid the occurrence of traffic accidents.

To analyze the latent correlation between these factors accurately, since these results are based on the results of probability, large scale data is required. To do this, the departments of traffic administration can make the questionnaire survey in the driving training school or traffic accident processing center to every related driver, from which large data can be saved to database for conducting the analysis in-depth.

3 THE MODELLING OF TRAFFIC SAFETY FACTOR ANALYSIS

Choose technological level (or driving self-confidence), personal characteristics, ability of risk control of drivers and incorrect driving operations, totally four kinds of possible factors to study the association of driver's behaviors. Each factor is divided into different specific expressions, illegal or incorrect driving behaviors may result in these factors, and may also be not caused by either of the above factors. On the other hand, each factor may be affected by one factor, but may also be two or more affected. Due to the limitations of time and expenses, we only carry out a general questionnaire survey.

3.1 Questionnaire Design

To apply data mining techniques for big data analysis, we need valid and available data sources. Currently in China, from the departments of traffic administration, these data are unavailable. We expect that in the future, institutes of driving training or departments of traffic accident processing can obtain large scale data from their daily transactions. Based on the research model in [2], we specifically designed questionnaire survey form in Table 5-1 ～ 5-4. In general, it seems that they have too many factors in forms. Traffic accident processing may not have time to investigate these factors in their daily work. In fact, we try to design a scheme which includes all the factors and data available from the department of traffic administration.

TABLE 5-1 FORM OF QUESTIONNAIRE SURVEY I

Investigation Item Categories and Factors TI	Select Element (Mark √)
Ability of Risk Control Class T1 Element 1: Risk Control of Serious Violations E1 A1 Intensely slow down when going downhill A2 Always follow the traffic signs when riding A3 Never chase each other on driving way Element 2: Incorrect Behavior Control E2 A4 Never chat to back seat riders when riding bikes A5 Stop to answer the phone A6 Ride bike on non-motorized vehicle's way Element 3: General Illegal Behavior Control E3 A7 Wait for traffic lights on the intersection patiently A8 Keep away from vehicles when riding bike A9 Slow down and observe	

TABLE 5-2 FORM OF QUESTIONNAIRE SURVEY II

Investigation Item Categories and Factors TI	Select Element (Mark √)
Ability of Driving Self-Confidence Class T2 Element 4: Technical Level E4 B1 Have right skills to pass other vehicles. B2 Deal with emergence case properly B4 Change lanes correctly and safely Element 5: Safety Awareness E5 B5 Always drive carefully B6 Keep distance with other vehicles when in driving Element 6: Self-Controlling E6 B7 Can tolerate the mistakes of other drivers B8 Can slow down according to road situation B9 Never take speed competition with other drivers	

TABLE 5-3 FORM OF QUESTIONNAIRE SURVEY III

Investigation Item Categories and Factors TI	Select Element (Mark √)
Personal Characteristics Class T3 Element 7: Irritability E7 C1 Don't like to communicate with some ones when I thought they are boring C2 Will be angry with other people's behaviors C3 Will be disappointed when annoying Element 8: Anxiety E8 C4 Usually do not feel feared and anxious C5 Generally do not feel nervous Element 9: Disobeying Rules E9 C6 In case of without trouble, I will choose the road to go through C7 Usually I will not violate the traffic rules directly	

TABLE 5-4 FORM OF QUESTIONNAIRE SURVEY IV

Investigation Item Categories and Factors TI	Select Element (Mark √)
Incorrect Driving Behavior Class T4 Factor 1: Serious Violations E10 R1 Reversely drive on the one-way traffic lane R3 Even the prohibiting right turn red light is on, turn right directly R4 Go through the intersection without observing and accelerating when yellow traffic light is on R5 Quickly goes on a non-motorized vehicle lane R6 Do not stop but accelerate at the stop line of intersection Factor 2: General Illegal Behaviors E11 R8 Compete with parallel vehicles without yielding. R9 Is not going within the lane of the road R10 Change lanes continuously Factor 3: Mistakes E12 R11 Goes through an intersection without slowing down and carefully observing the vehicles at both sides. R12 Turn to left or right without observing pedestrians who are crossing the zebra lines R13 Change lanes without observing the rear and side vehicles Factor 4: Incorrect Driving Behaviors E13 R14 Talk to riders while driving R15 Answer the phone while driving on road C7 Usually I will not violate the traffic rules directly	

To test our scheme, the survey is conducted in a number of libraries in different universities in Chengdu for two months. 500 questionnaires were distributed and 372 valid questionnaires were received. In the forms, driver's personality characteristics, ability of risk control, ability of driving self-confidence, and incorrect or illegal driving behaviors related specific issues are designed for the testing. If these factors in this model can be merged into the transaction data of departments of traffic administration or partly available from the departments in the future, we will no longer need to design the questionnaire, but only use the database for the analysis; thus, a wider range of potential data variation regularity can be available by the analysis.

TABLE 5-5 DRIVER'S BEHAVIORS AND THE QUESTIONNAIRE RESULTS

Respondents (NO.)	List of Survey selection results
N001	E2, E5, E9, E11, E12
N002	E1, E3 E4, E6, E7, E10, E11, E12
N003	E2, E4, F7, E8, E9, E10, E11
N004	E2, E3, E5, E10, E11, E12
N005	E4, E5, E6, E7, E8, E9
N006	E1, E2, E3, E4, E5, E6, E7, E8, E9, E10, E11, E12, E13
N007	E2, E3, E8, E10, E12, E13
N008	E3, E4, E6, E8, E10
N009	E1, E2, E4, E6, E7, E10, E11, E13

N010	E4, E5, E6, E7, E8, E9, E10, E11, E12, E13
N011	E2, E3, E9, E10, E11, E12
N012	E1, E2, E3, E4, E5, E6, E7, E11, E12, E13
N013	E4, E5, E6, E7, E8, E9
N014	E1, E4, E8, E10, E11, E12
N015	E4, E5, E6, E7, E8, E9, E10, E11, E13
…	…
N368	E1, E2, E3, E4, E5, E6, E7, E8, E9
N369	E5, E6, E7, E8, E9, E10, E11, E12, E13
N370	E6, E7, E8, E9, E10, E11, E12, E13
N371	E4, E5, E6, E7, E8, E9, E10
N372	E1, E2, E3, E10, E11, E12, E13

TABLE 5-6 STATISTICAL RESULTS OF DRIVER'S BEHAVIORS AND THEIR CORRELATIONS

Survey of frequent item sets (PID)	Frequent results of statistical support
T1 (Risk control)	228
T2 (Driving self-confidence)	204
T3 (Personal characteristics)	210
T4 (Incorrect driving behaviors)	181
{T1, T2}	120
{T2, T3}	67
{T3, T4}	116
{T1, T3}	65
{T1, T4}	84
{T2, T4}	77
{T1, T2, T3}	39
{T2, T3, T4}	37
{T1, T3, T4}	34
{T1, T2, T4}	32
{T1, T2, T3, T4}	19

From the selected results in the above survey data forms, we can use association rules for correlation analysis of driving behavior related factors. To do this, we must standardize these factors and their selected results to be the transactions of association rules. We need to consider each choice of the investigation results as an item, selected factors as transactions. Since everyone's technology, behavior and mental state is certainly associated to his/her driving operations, so the standardization is reasonable.

3.2 Title Computation of Frequent Items

Because we have hundreds of survey results and each item has multiple choices, we are not going to list all the selected results here. We will input data in Table 5-5 into a database for long-term preservation and further calculation.

According to Table 5-1～5-4, we know that factors E1～ E3 belong to T1, E4～E6 belong to T2, E7～E9 belong to the third class T3, and E10 ～ E13 belongs to class T4. If some FE is selected, then in this class, a transaction is created. If more than two different factors Ei and Ej are selected, then we will input only one transaction to database. The results in Table 5 and Table 6 provide the basic data for the calculation of Confidence and Support degree.

3.3 Analysis of Association Rules

If we consider that the support level is greater than 10% (some related events have happened frequently) and confidence level is greater than 50% to be the minimum thresholds of strongly association. We have the following analysis results of association rules for the investigated factors.

(1) The correlation between personal characteristics and incorrect driving operations.

The support of personal characteristics and incorrect driving operations is

$$\text{Support } (X{=}{>}Y) = P\ (X \cup Y) = 121/372 = 33\%.$$

The confidence of personal characteristics and incorrect driving operations is

$$\text{Confidence } (X \Rightarrow Y) = \text{Support\_Count } (X \cup Y) \,/\, \text{Support\_Count } (X) = 121/210 = 58\%.$$

The results show that personal characteristics and incorrect driving operations are significantly associated, which indicate that personal characteristics is strong, the rate of incorrect driving operations is high. Statistics also show that Chinese drivers have big number in disobeying rules and less anxiety, so that the number of strong personal traits is big.

(2) The correlation between the ability of self-confidence and incorrect driving operations.

The support of self-confidence and incorrect driving operations is

$$\text{Support } (X \Rightarrow Y) = P\,(X \cup Y) = 77/372 = 21\%.$$

The confidence of self-confidence and incorrect driving operations is

$$\text{Confidence } (X \Rightarrow Y) = \text{Support\_Count } (X \cup Y) \,/\text{Support\_Count } (X) = 77/204 = 38\%.$$

The results show that the ability of self-confidence and incorrect driving operations have no significant strong association, that is, if the ability of self-confidence is strong, the frequency of dangerous driving operations will be small.

(3) The correlation between the ability of risk control and incorrect driving operations.

The support of the ability of risk control and incorrect driving operations is

$$\text{Support } (X \Rightarrow Y) = P\,(X \cup Y) = 84/372 = 23\%.$$

The confidence of the ability of risk control and incorrect driving operations is

$$\text{Confidence } (X \Rightarrow Y) = \text{Support\_Count } (X \cup Y) \,/\, \text{Support\_Count } (X) = 420/1140 = 37\%.$$

The results show the ability of risk control and incorrect driving operations have no significant strong association, that is, if the ability of risk control is strong, the frequency of incorrect driving operations will be small.

(4) The correlation between the personal characteristics and the ability of risk control.

The support of the personal characteristics and the ability of risk control is

$$\text{Support } (X \Rightarrow Y) = P\,(X \cup Y) = 132/372 = 35\%.$$

The confidence of the personal characteristics and the ability of risk control is

$$\text{Confidence } (X \Rightarrow Y) = \text{Support\_Count } (X \cup Y) \,/\, \text{Support\_Count } (X) = 132/276 = 47\%.$$

The results show that d the individual characteristics and the ability of risk control have significant weak association, that is, if the personality feature is strong, the ability of risk control will be weak.

(5) The correlation of ability of self-confidence and ability of risk control.

Support of ability of self-confidence and ability of risk control is

$$\text{Support } (X \Rightarrow Y) = P\,(X \cup Y) = 120/372 = 32\%.$$

The confidence of ability of self-confidence and ability of risk control is

$$\text{Confidence } (X \Rightarrow Y) = \text{Support\_Count } (X \cup Y) \,/\, \text{Support\_Count } (X) = 120/204 = 58.8\%.$$

The computation results show that driver’s ability of self-confidence and ability of risk control are significantly strong associated, that is, if ability of self-confidence is strong, the ability to control risks is the strong too.

(6) The correlation of risk controls, personal characteristics, and incorrect driving operation.

The support of these factors is

$$\text{Support } (X \cup Y \Rightarrow Z) = P\,(X \cup Y \cup Z) = 34/372 = 9\%.$$

The confidence of these factors is:

$$\text{Confidence } (X \cup Y \Rightarrow Z) = \text{Support\_Count } (X \cup Y \cup Z) / \text{Support\_Count } (X \cup Y) = 34/65 = 52\%.$$

The computation results show that risk controls, personal characteristics and incorrect driving operation have strong association, that is, if the abilities of risk controls, personal character traits are strong, the frequency of incorrect driving operation will be large.

(7) The correlation of risk control, self-confidence and the incorrect driving operations-The support of risk control, self-confidence and the incorrect driving operation is

$$\text{Support } (X \cup Y \Rightarrow Z) = P\ (X \cup Y \cup Z) = 32 / 372 = 8.6\%.$$

The ability of risk control, self-confidence and the incorrect driving operations is

$$\text{Confidence } (X \cup Y \Rightarrow Z) = \text{Support\_Count } (X \cup Y \cup Z) / \text{Support\_Count } (X \cup Y) = 32/120 = 26.7\%.$$

The results show that risk control, and the incorrect driving operations are significantly weak associated, that is, if both risk control, ability of self-confidence are strong, the occurrence of incorrect driving operation frequency will be small.

(8) The correlation of individual characteristics, self-confidence, and incorrect driving operations.

The support of personal characteristics, self-confidence and incorrect driving operations is:

$$\text{Support } (X \cup Y \Rightarrow Z) = P\ (X \cup Y \cup Z) = 37/372 = 9.9\%.$$

The confidence of personal characteristics, self-confidence and incorrect driving operations is

$$\text{Confidence } (X \cup Y \Rightarrow Z) = \text{Support\_Count}(X \cup Y \cup Z)/\text{Support\_Count } (X \cup Y) = 37/67 = 55.2\%.$$

The results show that individual characteristics, self-confidence, and incorrect driving operations have significant negative association, which indicates that if abilities of individual characteristics, self-confidence are strong, the frequency of dangerous driving operations will be great.

(9) The correlation of individual characteristics, risk control, self-confidence, and incorrect driving operations. The support of personal characteristics, self-confidence, risk control and incorrect driving operations is

$$\text{Support } (X \cup Y \cup Z \Rightarrow A) = P\ (X \cup Y \cup Z \cup A) = 19/372 = 5.2\%.$$

The confidence of personal characteristics, self-confidence, risk control, and incorrect driving operations is $\text{Confidence}(X \cup Y \cup Z \Rightarrow A)=\text{Support\_Count}(X \cup Y \cup Z \cup A)/\text{Support\_Count}(X \cup Y \cup Z)=19/39= 48.7\%$.

The computation results show that event items individual characteristics, self-confidence, driving risk control, and incorrect driving operations have strong association, that is, even individual characteristics, self-confidence, and driving risk control are strong, the possibility of incorrect driving operations is still large, probably because these drivers are over-confident. In general, by using association rule mining, we can compute the correlations of multiple factors, and at the same time, the correlations are intuitive since these related factors happened at a same event. Therefore, correlation mining will be more effective and extensively available than statistical analysis.

4 RESULTS ANALYSIS

Test results show that personal characteristics and incorrect driving operations have strong association since they have high Support (31%) and Confidence (55%). Another strong correlation is between the ability of self-confidence and the ability of risk control. They have the largest impact on drivers' driving behaviors. Strong individual characteristics will directly induce incorrect driving operations. On the other hand, the strong ability of driving self-confidence and the ability of risk control will obviously reduce the possibility of driver's incorrect driving operations. These correlations can also be easily calculated by traditional correlation analysis, but complicate correlations in (7)-(9) are hard to compute since we cannot see the correlations of condition and results between these factors from the statistical results. Only the association rule mining can discover the statistical results and driving self-confidence is also very important to driver's driving behaviors. If we want to reduce the frequency of driver's incorrect driving operations effectively, we need to improve the driver's technology, and take more care about their ability of risk control and self-confidence in their driving training and these correlations.

Personal character may determine the behaviours of someone's daily life, which indicates that, in driving training, the guidance of psychology and techniques are equally important.

Association rule mining is based on the database which contains a large number of data. By using a questionnaire survey to get mass data is difficult. Without the support of large-scale data, it seems impossible to obtain the potential data rule we want. However, from the discussion in this paper, an effective data analysis model can be established. Compared with the traditional correlation analysis model, the biggest advantage of our scheme is that it can build regular access to data automatically according to Apriori algorithm through which we can obtain potential information for data mining. Especially, from this method, it is possible to mine both unexpected and predictable regularities in data.

5 ISSUES FOR FURTHER STUDY

For drivers, many factors may affect their driving behavoirs, most easily accessible data in departments of traffic administration such as a driver's gender, age, driving age, location, level of education, the types of work, and the correlations of these attributes and driver's driving operations are easy to calculate. For the attributes proposed in this paper, the key is how to establish a more accessible data acquisition system. If the system can be developed, our method will inevitably play a crucial role for the road driving risk control. The design of questionnaire survey of for the association rule mining in this paper is only the first test of our research. In further work, we need to have in-depth research and improve the methods and database settings such that transaction data in departments of traffic administration can be directly available for the analysis. Thus, more complete and effective tools can be constructed for the analysis of traffic safety. These tools will provide important decision-making basis for the traffic safety control to departments of driving training and traffic safety administration.

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