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Research on the Economic Data Model of Hidden Markov Chain

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Abstract:
Markov chain is widely used in the fields of natural science and engineering technology because of its no aftereffect. The classic Markov chain does not reflect the uncertainty of the object state, and when the state division boundary is too clear, the state transition is unstable. In order to maintain the stability of the state transition and be able to effectively represent and deal with the uncertainty of the object state for sex, this paper proposes a reliability Markov model. The new model introduces the Dempster-Shafer (DS) evidence theory to describe the uncertainty of the object state, classifies all the object states into an identification framework, establishes a basic probability assignment function, and then generates a proposition transition probability matrix, and finally according to the object The current state gets the future state. The reliability Markov model proposed in this paper is a generalization of the classic Markov chain, which is backward compatible with its properties. The example shows that the new model overcomes the above-mentioned shortcomings, and obtains more reasonable and accurate results than the classic Markov chain, and has higher effectiveness and practicability.

Keywords: Hidden Markov Chain; Dempster-Shafer Evidence Theory; Forecast; Transition Probability; Sensitivity Model; Internet Finance

1.INTRODUCTION

In many fields of natural society, there are many uncertain phenomena that follow a special evolutionary rule: from the state of the system or process at time t_0, the state of the system or process at time $t > t_0$ can be determined, without resorting to the historical data of its state before time t_0. This kind of special random process is Markov process [1−2]. Markov property process when the state of the process at time t_0 is known, the conditional distribution of the state of the process at time $t > t_0$ has nothing to do with the state of the process before time t_0.

Markov chain is widely used in the fields of natural science and engineering technology [3-10], especially in the prediction technology, which has in-depth applications, such as forecasting rainfall trends [11], evaluating economic operation conditions [12-13], analysis Protein types and cross-modal regions [14-15], etc. However, when the state space is approximately continuous values, the prediction results may vary. In addition, when the state transitions, it may not be possible to determine the unique state, that is, the description of the state cannot be accurately given. The essence of these problems is Markov. The process sequence of cove chain is uncertain, which is mainly manifested in that the status of the research object cannot be clearly divided. At present, regarding this aspect of research, most researchers introduce fuzzy concepts into the Markov chain to establish a Fuzzy Markov prediction model based on fuzzy division of state [16−19]. Fuzzy Markov prediction model requires the establishment of a certain membership function between the sequence value of the chain and the language variable representing the state of the object. However, reality it is possible that such a definite membership function cannot be established under circumstances. For example, at certain sequence value points, it is completely unknown that it belongs to the membership of each state, but only that it may belong to certain states, but the specific the situation is uncertain. Faced with such a situation, the fuzzy Markov forecasting model cannot be represented and processed.

In response to these shortcomings and existing problems, this paper proposes a new model that combines the Dempster-Shafer (DS) evidence theory [20−22] with the Markov chain to obtain a reliability Markov model. It uses the basic probability assignment defined in the process sequence to represent the uncertainty of the state, which not only avoids the phenomenon of jumping in the predicted state, but also overcomes the shortcomings of the fuzzy Markov model. The new model is an extension of the classic Markov chain, it is backward compatible with the nature of the Markov chain, and can effectively deal with the uncertainty of the state in the Markov chain.

Data in 2017 showed that they are the main participants in my country's market economy. However, enterprises have been facing serious financing difficulties, and the financial resources they obtain are often difficult to support the normal development of enterprises. At present, there are more and more discussions about the relationship between Internet finance and SME financing, which has aroused widespread concern in the society.

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2 LITERATURE REVIEW

Research on financing theory is relatively early in foreign countries, and the development of theories related to financing constraints is relatively mature. When there are no transaction costs and taxes, there is no difference between the cost of internal financing and external financing[23]. The capital structure of the company has nothing to do with the company's total cost of capital and company value, and there is no financing constraint at this time. Myers and Majluf (1984) proposed the financing priority theory based on information asymmetry and transaction costs. Equity financing will convey negative information about business operations[24]. Fazzari et al. (1988) proposed the investment-cash sensitivity model (FHP model) and the concept of financing constraints, and believed that the severity of financing constraints was positively correlated with investment-cash sensitivity[25]. Bernanke and Gentler (1989) believe that the principal-agent problem will cause the cost of external financing of a company to be higher than the cost of internal financing[26]. Therefore, the difficulty of external financing is one of the reasons why corporate financing is restricted. Since then, most scholars have conducted empirical analysis or perfected the model conclusions on the basis of the FHP model. Due to the Tobin's Q measurement error in the FHP model, Almei-da et al. (2004) will reserve some cash. The greater the financing constraint, the greater the cash-cash flow sensitivity of the company[27].

Chinese scholars started relatively late in the study of corporate financing constraints. Existing studies mostly focus on the analysis of the influencing factors of financing constraints, which can be divided into two aspects: on the one hand, study the reasons for the existence of financing constraints from external factors such as financial development, credit environment, and banking competition; on the other hand, from the SMEs themselves Set out to study the reasons. Guo Lihong and Xu Xiaoping (2012) empirically study the relationship between corporate characteristics. The research shows that corporate characteristics are important influencing factors[28]. Small and micro enterprises, non-listed companies, and non-group affiliated companies face more serious problems. Financial constraints. Ma Lianfu (2015) found through empirical research that investor relationship management can reduce the investment constraints faced by small and medium-sized enterprises through network communication, communication guarantee, and on-site communication[29]. Xiao Jing and Su Qin (2016) used the Ordered Probit model to conduct empirical analysis. The results emphasize the important role of small and medium banks in alleviating financing constraints[30].

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From the existing literature, relevant researches are mostly based on theoretical perspectives, and empirical studies are rare. Xiao Ping (2015) provides suggestions for constructing financing paths for SMEs by analyzing three typical models of Internet finance[17]. He Qizhi and Peng Mingsheng (2017) used the SVAR model to point out that Internet financial platforms have not effectively promoted the development of SME financing[15]. Feng Jianben (2018) combined specific cases to give financing Path suggestion[17].

3 PRELIMINARIES

3.1 The basic principles and problems of Markov chain

This section mainly introduces the basic concepts and properties of Markov chain, and uses a specific case analysis to illustrate the defects and reasons of Markov chain.

Definition 1 Let $\{X_n : n > 0\}$ be a random sequence defined in a probability space (Ω, F, P). P represents the probability measure, which is a function from the set F to the real number domain R. Each event in F is assigned a probability value from 0 to 1 by this function. For any $n \in N^+$ and state $i_1, i_2, \ldots,$ when $P\{X_n = i_n, X_{n-1} = i_{n-1}, \ldots, X_1 = i_1\} > 0$, if there is

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

then the random sequence $\{X_n : n > 0\}$ is called a Markov chain. Formula (1) is called Markovian or no aftereffect.

Definition 2 Markov chain $\{X_n : n > 0\}$ is called homogeneous. If for any m, n and state i, j, as long as $P\{X_n = i\} > 0, P\{X_m = i\} > 0$, there is:

$$P\{X_{n+1} = j | X_n = i\} = P\{X_{m+1} = j | X_m = i\} \quad (2)$$

Definition 3 For a homogeneous Markov chain, the conditional probability

$$P\{X_{n+1} = j | X_n = i\} = P\{X_{m+1} = j | X_m = i\} \quad (3)$$

defined by the following formula is called the transition probability that the Markov chain is in the state i at the time m and transitions to the state j at the time $m+n$.

The transition probability is the most important feature of a homogeneous Markov chain. The transition probability defined by equation (3) which is recorded as $P_{ij}(n)$. When $n=1$, the equation (3) define the one-step transition probability of Markov chain, namely

$$P_{ij} = P_{ij}\left(1\right) = P\left\{X_{m+1} = j \middle| X_m = i\right\} \quad (4)$$

Let E be the state space, and $p_{ij}^{(k)}$ represent probability of state i transitioning to state j through k steps.

Lemma 1.

$$p_{ij}^{(k)} \geq 0, \forall i, j \in E, k \geq 0 \quad (5)$$

Lemma 2.

$$\sum_{j \in E} p_{ij}^{(k)} = 1, \forall i \in E, k \geq 0 \quad (6)$$

Lemma 3.

$$p_{ij}^{(m+k)} = \sum_{r \in E} p_{ir}^{(m)} p_{rj}^{(k)}, \forall i, j \in E, m, k \geq 0 \quad (7)$$

Equation (7) is called C-K equation for short, which is the basis for calculating the n-step transition probability in a homogeneous Markov chain.

3.2 Dempster-Shafer evidence theory

DS evidence theory (Dempster-Shafer theory of evidence, hereinafter referred to as evidence theory) is an imprecise reasoning theory established and developed by Dempster and Shafer. It can deal with the uncertainty caused by the unknown prior probability and is more satisfying than probability theory. Weak axiom system[20-21]. The theory extends the basic event space to the power set of the basic event (also known as the identification framework), and assigns probability according to the basic probability assignment function BPA on the subset of the identification framework (proposition), and obtains the basic probability of each subset (proposition) Number to form a piece of evidence. At present, as an important tool for information fusion, evidence theory has a wide range of applications in target recognition[25-26], clustering combination[27-28], decision analysis[29-32], image processing[33] and so on.

The following are some basic concepts in evidence theory.

Definition 4 Suppose U is an exhaustive set of all possible values of random variable X, and each element in U is mutually exclusive, then U is called an identification frame of X. The power set 2^U of U is called the power set of the identification frame. Each element in the power set corresponds to a proposition (subset) about the value of X.

Definition 5 Let U be the identification frame, and the power set of U 2^U constitutes the set of propositions 2^U. For any subset A (proposition) of U, if the function m: $2^U \to [0,1]$ satisfies:

$$\sum_{A \subseteq U} m\left(A\right) = 1 \quad (8)$$

$$m\left(\phi\right) = 0 \quad (9)$$

Then m is the basic probability assignment function BPA on 2^U, and $m\left(A\right)$ is the base probability number of A. BPA reflects the degree of evidence supporting the proposition in the identification framework. If $m\left(A\right) > 0$, then Call A Jiao Yuan.

Since evidence theory assigns probability on a subset of the identification framework, the obtained BPA is usually not only about the probability of a single basic event, but involves the probability assignment of multiple sets of states. It is in this way that it can reflect the differences in the real world. Certainty. However, it is inconvenient to directly use BPA to make decisions. A typical method is the Pignistic probability conversion in the Semits transitive reliability model[34−35].

Definition 6 Suppose $(U,\Re)$ is a proposition space, m is the basic reliability assignment on $\Re$, and $|A|$ is the number of atoms of $\Re$ in A. For any atom x of $\Re$:

$$BetP(x)=\sum_{x\subseteq A\in\Re}\frac{m(A)}{|A|} \tag{10}$$

4 RELIABILITY MARKOV MODEL AND ITS PROPERTIES

4.1 Reliability Markov Model

Information in the real world often has various uncertainties such as randomness and ambiguity. Probability theory mainly deals with randomness and uses probability to measure the possibility of random events. DS evidence theory expresses uncertain information It is better than probability theory in that it can not only integrate empirical and conditional information, but also random information and fuzzy information can be converted into the framework of evidence theory through different means for processing. Throughout the development of evidence theory, Dempster takes BPA represents uncertain information[20], Shafer systematically discussed the reliability function and likelihood function as the upper limit function and lower limit function of the proposition in his book[21]. It can be seen that, as a concept different from probability, reliability represents uncertainty in evidence theory. One layer of meaning is support and confidence. The model to be established in this article is to combine evidence theory with Markov chain, or it can be regarded as a combination of reliability and Markov chain. Therefore, the new model is called Reliability Markov model. The specific approach is

Step 1. Determine the state space according to the situation of the sample. If necessary, classify the data into several large states to reduce the number of states. These states form an identification framework U.

Step 2. According to the needs of the application, a basic probability assignment function is established on the power set 2^U of the identification framework, so as to obtain the basic probability assignment (BPA) of each sample data about 2^U.

Step 3. Calculate the single-step proposition transition probability matrix $[P_{ij}]$, $i,j\in 2^U$ of the Markov chain based on the BPA of all samples. P_{ij} represents the transition from proposition i to proposition j in the reliability Markov model Probability.

$$P_{ij}=\frac{\sum_{t=1}^{n-1}\left(m(i)_t\square m(j)_{t+1}\right)}{\sum_{j\in 2^U}\sum_{t=1}^{n-1}\left(m(i)_t\square m(j)_{t+1}\right)},i\in 2^U \tag{11}$$

Among them, $m(i)_t$ represents the base probability of proposition i at time t, and n is the length of the Markov chain.

Step 4. Suppose the basic probability assignment of the data in the last period of the sample is $m=\left[m(i)\right]$, $i\in 2^U$. Then the next period fee distribution $m^{'}$ can be obtained by the following formula:

$$m^{'} = m\square[P_{ij}] \tag{12}$$

Step 5. Use the PPT equal probability conversion method to convert the basic probability assignment $m^{'}$ obtained in the previous step into the probability distribution of the basic state $\left[p(i)\right]$, $i \in U$, and get the final result.

Note 1. In step 2 of the establishment of the reliability Markov model, no specific basic probability assignment function design plan is given. The user can flexibly design the BPA function according to the specific environment to obtain the calculation result suitable for the application environment. It will not reduce the versatility of the new model.

The reliability Markov model can represent and deal with uncertainty. When the description of the object state can be accurately given, the reliability Markov model degenerates into a classic Markov chain. Cove chain. Reliability Markov model has the following properties.

Suppose U is the identification frame, 2^{U} is the power set of the identification frame, and $p_{ij}^{(k)}$ represents the probability that the proposition transfers to proposition i through k steps.

Lemma 4.

Let $\{X_n : n > 0\}$ be the reliability Markov chain, assign $m_1, m_2, \ldots,$ to any positive integer n and the basic probability, there are:

$$P\left\{X_{n+1} = m_{n+1} \middle| X_n = m_n, X_{n-1} = m_{n-1}, \ldots, X_1 = m_1\right\} = P\left\{X_{n+1} = m_{n+1} \middle| X_n = m_n\right\} \tag{13}$$

4.2 Case Analysis

Table 1 is a company's inventory demand statistics for the 20 consecutive periods of product E15. Now it is necessary to use the Markov chain to predict and analyze its inventory in the 21st period based on these data. Generally speaking, use Markov the prediction of the Cove chain is by discovering the transition probability matrix of one step, and then calculating the probability of the next transition to each state from the initial state probability distribution. The greater the probability of the state, the greater the possibility, so as to get the next possible position state.

First determine the state space of the Markov chain. It will result in the number of states Too many states, and many states do not appear, it is difficult to count state transitions. Therefore, the states need to be reclassified. The classification results are shown in Table 2.

Table 1 Inventory requirements for product E15 for 20 consecutive periods

Time t (period)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Inventory quantity (pieces)	143	152	161	139	137	174	142	141	162	180	164	171	206	193	207	218	229	225	204	200

Assuming N_{ij} represents the frequency of transition from state i to state j, it is easy to get

$$N_{11} = 2, N_{12} = 3, N_{13} = 0$$
$$N_{21} = 2, N_{22} = 4, N_{23} = 2$$
$$N_{31} = 0, N_{32} = 2, N_{33} = 4$$

The transition probability matrix calculated from $P_{ij} = \frac{N_{ij}}{\sum_{j \in E} N_{ij}}$ is

$$P = \begin{bmatrix} 0.400 & 0.600 & 0.000 \\ 0.250 & 0.500 & 0.250 \\ 0.000 & 0.333 & 0.667 \end{bmatrix}$$

Table 2 The results of state classification

Inventory quantity (pieces)	[0,150)	[150,200]	(200,+∞)
State	Low（L）	middle（M）	high（L）
Serial number	1	2	3

Since the inventory in the last period is 200 pieces, it belongs to the loading "Middle". Therefore, the state probability distribution of the next quarter is: $(L, M, H) = (0.250, 0.500, 0.250)$. It can be seen that the most likely state of the 21st period is "Middle".

$$P = \begin{bmatrix} 0.400 & 0.600 & 0.000 \\ 0.250 & 0.500 & 0.250 \\ 0.000 & 0.167 & 0.833 \end{bmatrix}$$

The probability distribution of the state in the next period becomes: $(L, M, H) = (0.000, 0.167, 0.833)$. At this time, the possibility of the state "high" becomes the greatest.

It is not difficult to find that just because of the slight changes in the last period of data, the prediction results have undergone drastic changes, and the prediction results have jumped from one state to another. Obviously, this is unreasonable. There is reason to believe that the 20th period is 200 or at 201, the prediction results should be similar. The reason for this phenomenon is that the state division boundary is too clear. In this way, prediction results are prone to occur on the state boundary The phenomenon of jumping. However, the actual situation is that at certain numerical points, such as 200, it is completely unknown that it belongs to a certain state. The probability of these states, but only knows that it is the state "medium" or "high", the specific situation is uncertain. The former situation can still be analyzed by methods such as probability theory and fuzzy sets, while the latter situation requires with the help of new processing methods. In-depth investigation of the latter found that this is precisely the probability assignment on a subset of basic events, which belongs to the research category of DS evidence theory. Therefore, it is natural to think of introducing DS evidence theory into Markov chain and establish Reliability Markov model.

This section also uses the data of Example 1 as an example to illustrate the application method and process of the reliability Markov model and its improvement effect on the Markov chain.

First, all values are still: Low (L), Medium (M), High (H). They form an identification frame $U = \{L, M, H\}$.

Then, create an identification frame based on the user's different perceptions . Here, a cognitive judgment is shown in Figure 1.

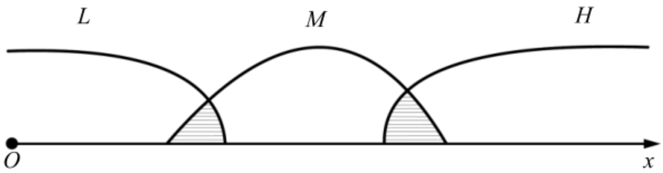

Fig.1. The distribution of three states on the axis

This article focuses on how to model data in order to analyze its future trends, which is essentially a method of classification and prediction. At present, there are a large number of classification and prediction algorithms, each with its own advantages and disadvantages. For example, support vector machines are the classification algorithm proposed based on the principle of structural risk minimization has very strong ability to model complex nonlinear decision boundaries, but when the number of samples is large, its training speed is slow, and classification problems with multiple categories still need to be explored a more effective processing method. Bayesian classification algorithms are a class of algorithms that use probability and statistics knowledge based on Bayes theorem for classification, such as naive Bayes, Bayesian belief networks, etc. Their advantages are higher the accuracy and speed of this type of algorithm. However, this type of algorithm relies on a strong assumption of independence, and this assumption is often invalid in actual situations, resulting in a decrease in the accuracy of its classification. Other classification and prediction algorithms, such as decision tree induction, sequential propagation of neural networks, and regression-based methods, etc., have good performance in some specific environments, but no algorithm is superior to other methods in all data types and fields. Compared with these classification algorithms in contrast, the reliability Markov model based on the DS evidence theory proposed in this paper effectively combines the advantages of the classic Markov model and the DS evidence theory. The determined prediction has a good advantage, showing better accuracy and stability.

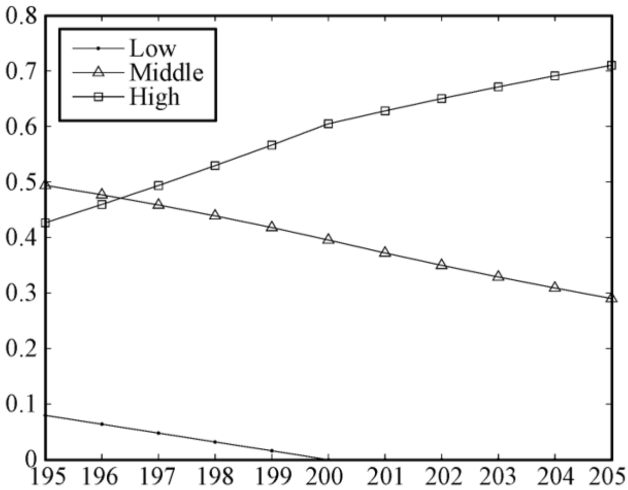

Fig.2. Predicted state probability distribution

5 CONCLUSION

This article first introduces the basic concepts and properties of the Markov chain, and then through a specific application of its prediction technology, it is found that the prediction result of the Markov chain may change slightly with the value, resulting in a jump at the boundary of the state division. Moreover, the classic Markov chain cannot reflect the uncertainty of the state description. In order to overcome this defect and the uncertainty of the state can be represented and processed, this paper introduces the DS evidence theory and combines it with the Markov chain, built a reliability Markov model. Examples show that the new model effectively overcomes the shortcomings of the classic Markov model, can represent and deal with the uncertainty of the state of the object, showing higher effectiveness and practicability. The Markov model is summarized as follows:

1) Overcoming the shortcomings of state jumping. For the reliability Markov model, small changes in the data in the "now" phase at the state boundary will not strongly affect the state of the "future" phase, and overcome the phenomenon of state jumping.

2) It can effectively represent and deal with the uncertainty of the state of the object. The adjacent stages of a random process jump between different states. There are often situations where the state of the object at a certain stage cannot be uniquely determined. Reliability Markov the model effectively represents and handles the uncertainty of the object state.

3) Stability. For the basic probability assignment function established under the same state classification standard, the new model will obtain realistic and consistent results at the state boundary, indicating that the calculation results of the reliability Markov model are stable.

4) Flexibility. Different basic probability assignment functions represent different state classification standards, resulting in different results. Users can flexibly design basic probability assignment functions according to the application environment and specific requirements, reflecting the flexibility of the new model. Moreover, when the new model is applied to a specific environment, a specific improvement plan that reduces the calculation of the algorithm can be flexibly designed according to the characteristics of the application environment, so as not to weaken the versatility of the new model.

5) Backward compatibility with the classic Markov model. The new model is a generalization of the classic Markov model. When the basic probability assignment function is only assigned on a single-element subset of the identification frame, the reliability Markov the model degenerates into a classic Markov model.

Since the reliability Markov model proposed in this paper is a general promotion of the classic Markov model and retains the basic properties of the classic model, the new model can be effectively applied to the application fields of the classic Markov model, for example Infectious disease prediction, speech recognition, time series analysis, discrete random system control, etc. In addition, Markov model also has a wide range of applications in bioinformatics, such as biological sequence analysis, gene recognition, etc. And, we have already carried out the study of using Hidden Markov model (HMM) to predict the structure of cell membrane proteins will expand the work in this area in the future, and extend the previous HMM membrane protein structure prediction model to be based on DS evidence The reliability of the theory HMM.

However, the new model also has shortcomings. First, the calculation results are affected by the basic probability assignment function, and the method for determining the basic probability assignment function is not clear. Different basic probability assignment functions will cause the data to form different basic probability assignments, and then Generate different proposition transition probability matrices, and finally get different results. This is the flexibility of the algorithm, but it still involves the generation method of BPA, which needs further research. Second, the computational complexity is high. It is easy to find, when calculating the proposition transition probability matrix, the amount of calculation increases exponentially with the increase in the number of basic states. But this is caused by the evidence theory itself. The DS evidence theory is precisely due to the probability assignment on the power set of basic events. In order to effectively reflect the uncertainty of the object state. Therefore, when calculating the state transition probability matrix, the amount of calculation due to the probability assignment of multiple subsets of the state is acceptable. Moreover, this is also the use of Markov chain Impossible Avoided, but can be improved and optimized in the specific application environment. Finally, the Markov model of reliability proposed in this paper has not yet involved the discussion of DS evidence theory combination rules, and a Markov should be established as much as possible Fusion rules in the process. The above deficiencies are exactly where this reliability Markov model needs to be improved next.

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