DATA MINING TECHNOLOGY
IN PREDICTING THE CULTIVATED LAND DEMAND

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ABSTRACT:

Although data mining is relative young technique, it has been used in a wide range of problem domains over the past few decades. In this paper, the authors present a new model to forecast the cultivated land demand adopts the technique of data mining. The new model which is called fuzzy Markov Chain model with weights ameliorate the traditional Time Homogeneous Finite Markov chain model to predict the future value of cultivated land demand in land use planning. The new model applied data mining technique to extract useful information from enormous historical data and then applied fuzzy sequential cluster method to set up the dissimilitude fuzzy clustering sections. The new model regards the standardized self-correlative coefficients as weights based on the special characteristics of correlation among the historical stochastic variables. The transition probabilities matrix of new model was obtained by using fuzzy logic theory and statistical analysis method. The experimental results shown that the ameliorative model combined with technique of data mining is more scientific and practical than traditional predictive models.

1. INTRODUCTION

Data mining is the nontrivial extraction of implicit, previously unknown, and potentially useful information from the mass, incomplete, fuzzy, uncertain and stochastic data. Data mining is the important step of Knowledge Discovery in Database (KDD) (Li, 2001). It has three major components such as clustering or classification, association rules and sequence analysis. The tasks of data mining are mainly such as association analysis, clustering, classification, prediction, time-series pattern, and deviation analysis etc. Data mining encompass a number of different technical approaches such as statistical methods, artificial neural network, decision trees, genetic algorithms, nearest neighbour method, rough set theory, and fuzzy logic theory etc.

At present time, data mining mainly applied to the trade territories such as banking, telecom, insurance, transportation, and retailing. It solved the behaviours of marketable analysis such as database marketing, customer segmentation & classification, credit scoring, and fraud detection etc.

Geo-spatial data mining, a subfield of data mining, is a process to discover interesting and potentially useful spatial patterns embedded in spatial databases. Efficient tools to extract information from massive geo-spatial datasets are crucial for organizations own, generate, and manage geo-spatial datasets. These organizations are spread across many domains including ecology and environmental management, public safety, transportation, public health, tourism (Hinzle, 2004).

Technique of data mining is relative young research field. New models and theories appeared every year. Many problems and challenges were presented for data mining such as enhancing the efficiency of model, data mining from dynamic sets, data mining on web, fuzzy spatial association rules mining etc.

As a new kind of data analysis technique data mining developed fast. Many kinds of datasets can be the objects of data mining. Because time series data are very common in datasets, Time Series Data Mining (TSDM) has been one of the focuses of current data mining research (Murray, 1998). The cultivated land demand data are time series data but researches on how to apply the technique of data mining to predict cultivated land use are not discovered at current time. In this paper, the authors present a new model adopt data mining technique to predict the cultivated land demand in land use planning.

2. DATA MINING AND PREDICTION OF CULTIVATED LAND DEMAND

Prediction is one of tasks of data mining technique. It is a process to find the mutative rule from mass, fuzzy, stochastic data and then construct predictive model to forecast the trend, category, and character of future value.

Prediction of cultivated land demand is an important stage of land use planning. The result of prediction accurate or not relate directly with the quality of land use planning. Linear regression prediction model and trend prediction model were traditional methods which only used mathematical method to analyzed the time series data and not considered the “fuzzy and uncertain” effect of natural and social factors. Traditional methods on prediction of cultivated land demand applied the technique of data mining un-sufficiently.

The fuzzy logic theory is one of technical approaches of data mining. It is an un-classical mathematics theory for uncertain problems. It makes available a convenient and meaningful tool to the practicing engineers to incorporate these seemingly vague but practically powerful factors in the several phases of a project life cycle.

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Markov chain model can predict a good many problems, but it exist shortages. The traditional Time Homogeneous Finite Markov Chain model transact the time series data with pure algebra method and not consider the effect of fuzzy, uncertain information embedded in data. This paper presents new Markov chain model combined with fuzzy logic theory.

Cultivated land demand data are stochastic time series data, so Markov chain model can be employed to forecast the future data according to historical data. Generally time series data can be divided into a continuous real number zone. In order to use Markov chain model, the continuous real number zone should be divided into finite number unambiguous state sets. But states during the process of prediction of cultivated land demand were not unambiguous but fuzzy. According to the instance, the authors present that using the fuzzy state sets describe the classified states will be closely to the actual status. Factors were diverse, complicated, and uncertain which affected cultivated land demand, so the authors indicate that the new model should adopt the technique of data mining. In this paper, the authors combine the fuzzy logic theory and data mining technique with traditional Markov chain model to enhance the precision of prediction of cultivated land demand. In order to effectively employ the historical data, new model also calculated the weights according the correlations among historical data series.

3. CONSTRUCTION OF NEW MODEL

Calculation of transition probabilities is the important step of Markov chain model process. Transition probabilities were calculated based on the unambiguous sate sets. The authors solved this problem by extending the transition probabilities matrix from unambiguous state sets to fuzzy state sets. Fuzzy sequential cluster model is one of useful method to classify time series data. In this paper, the authors apply fuzzy sequential cluster model to divide the historical data of cultivated land demand into fuzzy state zones and then construct the transition probabilities matrix of Markov chain model by using fuzzy logic theory and data mining technique.

3.1 Fuzzy Sequential Cluster Model

In order to make the divided zones reasonable, the new model apply fuzzy sequential cluster model to divide the cultivated land demand data into several fuzzy mutative zones based on the analysis of data structure. Fisher algorithm was the traditional algorithm of fuzzy sequential cluster model (HU, 1990). The fundamental of Fisher algorithm can be described as following equation:

$$\overline{X_{ij}} = \frac{1}{j-i+1}\sum_{l=i}^{j} x_l \tag{1}$$

where $\overline{X_{ij}}$ = average vector

$\{x_i \cdots x_j\}, j \geq i$ = one possible fuzzy sequential clustering zone of stochastic variables series $x_1 \cdots x_n$.

The correlation among time series data meets the following equation:

$$D(i,j) = \sum_{l=i}^{j}\left(x_l - \overline{x_{ij}}\right)'\left(x_l - \overline{x_{ij}}\right) \tag{2}$$

where $D(i,j)$ = the diameter of $\{x_i \cdots x_j\}, j \geq i$.

It denotes the discrepant degree among variables locate at one and the same clustering zone. And it shows that when $D(i,j)$ smaller indicates discrepancy among data series smaller and the correlation more adjacent, contrariwise the discrepancy larger and correlation is dispersive. In order to compare the effect among different possible clustering, Fisher algorithm defined the error function described as following:

$$e[P(n,K)] = \sum_{j=1}^{k} D(i_j, i_{j+1}-1) \tag{3}$$

where $e[P(n,K)]$ = the error numerical value

K = the number of clustering zones, $D(i_j, i_{j+1}-1)$ is obtained from Eq2, $P(n,K)$ is one possible clustering be expressed as following:

$$P(n,K):\{i_i = 1,\cdots,i_2-1\};\{i_2,\cdots,i_3-1\};\cdots;\{i_k,\cdots,n\} \tag{4}$$

From Eq 3 we can see that when $e[P(n,K)]$ get minimal value the best fuzzy clustering division will be obtained. At the same time, the number K can be obtained at the inflexion of correlation graph between $e[P(n,K)]$ and K.

3.2 Time Homogeneous Finite Markov Chain Model

A Time Homogeneous Finite Markov Chain model was a stochastic process with finite sets $S = \{1,2,\cdots,n\}$ of state (Breikin, 1997). How to calculate these transition probabilities is the important step of Markov chain model. The transition probability only depended on the state in the previous step. It can be described as following:

$$p\{x_n = j | x_{n-1} = i\} \tag{5}$$

where j = the series number of state among state sets

n and $n-1$ = time.

In Eq5 $x_n = j$ express the Markov chain process locate at j state at n time and $x_{n-1} = i$ express the process locate at i state at $n-1$ time. Define $p_{ij}(n)$ denotes the transition probability from j state to i state at n time. These transition probabilities form the transition probability matrix expressed as $P = (P_{ij})_{ij=1,2,\cdots,n}$. It is an $n \times n$ non-negative matrix (such a matrix is called stochastic). The transition probabilities matrix can be described as following:

$$P = (P_{ij}) = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ P_{n1} & P_{n2} & \cdots & P_{nn} \end{bmatrix} \quad (6)$$

4. FUZZY MARKOV CHAIN MODEL WITH WEIGHTS BASED ON DATA MINING

As above sections analyze, the authors present a new model adopt the technique of data mining. The new model is summarized as the following steps:

1. Calculate the self-correlative coefficient of cultivated land demand data

The cultivated land demand data series are depended on each other. In order to describe the correlation, new model calculate the self-correlative coefficients among data. The equation of self-correlative coefficients calculation can be expressed as:

$$r_k = \sum_{t=1}^{n-k}(x_t - \bar{x})(x_{t+k} - \bar{x}) \Big/ \sqrt{\sum_{t=1}^{n-k}(x_t - \bar{x})^2 . \sum_{t=1}^{n-k}(x_{t+k} - \bar{x})^2} \quad (7)$$

where r_k = the self-correlative coefficients of k grade (step is k),
x_t = the cultivated land demand data at t time
$\bar{x}$ = the average value of all cultivated land demand data series
n = the data number of cultivated land demand data series

2. Standardizing self-correlative coefficients data as weights

Different fuzzy clustering zone has different effect on predictive value. In order to describe this difference, the new model takes the standardized self-correlative coefficient data as weight. The weight can be calculated by following equation:

$$\varpi_k = |r_k| \Big/ \sum_{k=1}^{m} |r_k| \quad (8)$$

where ϖ_k =weight, r_k can be obtained with Eq7.

3. Calculate the cultivated land use trend coefficients

The cultivated land use trend coefficient (LUTC) is an important parameter to express the utilized degree of cultivated land during one unit time. The coefficient can be calculated by following equation:

$$S = ds/s_i \times 100 \times (1/t) \times 100/100 \quad (9)$$

where s_i = the cultivated land area at the beginning time of supervision
ds = the reductive amount of calculate land during time of supervision
t = the time's length of supervision
S = the cultivated land use trend coefficient which was scaled up to 100 in order to make research conveniently

4. Divide the fuzzy clustering zones

With step3 the data of cultivated land use trend coefficients were obtained. New model applies the fuzzy sequential cluster model to divide these coefficients data series into several fuzzy clustering zones. Thus, the fuzzy clustering zone state for each historical cultivated land demand data located at can be confirmed.

5. Calculate the transition probability

Calculation of transition probabilities is the main step of new model. In this paper, the authors calculate the transition probability for each different step by using fuzzy logic theory. The process of calculation can be described as following:

Assume $X_t : x_1 \cdots x_n$ is the stochastic time series data of cultivated land demand, $E_k : e_1 \cdots e_k$ is one fuzzy clustering set for X_t. The new model obtains the transition probability by following equations:

$$M_i^{(m)} = \sum_{l=1}^{n-m} \mu_{e_i}(x_l), i = 1,2 \cdots k \quad (10)$$

and,

$$M_{ij}^{(m)} = \sum_{l=1}^{n-m} \mu_{e_i}(x_l) \cdot \mu_{e_j}(x_{l+m}) \quad (11)$$

where M_i =the number of data which locate at the fuzzy clustering state e_i ($e_i \subset E_k$) among X_t
$M_{ij}^{(m)}$ =the data number transitioned from e_i fuzzy clustering state to e_j state through m steps,
m = the step number of transition
$\mu_{e_i}(x_l)$ = the fuzzy membership function which denotes the degree of x_l belongs to e_i fuzzy state.
From Eq10 and Eq11, The authors obtain the transition probability from e_i fuzzy clustering state to e_j state by the following equation:

$$P_{ij}^{(m)} = \frac{M_{ij}^{(m)}}{M_i^{(m)}} \quad (12)$$

6. Construct the new transition probabilities matrix. Each line vector is the different step transition probabilities of historical data calculated with Eq12.
7. Calculate the predictive value

Summing the data of each row vector belongs to one and the same state with the corresponding weight in the new transition probabilities matrix by the following equation:

$$P_i = \sum_{k=1}^{m} \varpi_k P_i^{(k)} \quad (13)$$

where $P_i^{(k)}$ = the transition probability of k step

i = the serial number of fuzzy clustering zone

ϖ_k = weight obtained with Eq8.

In this paper, the fuzzy clustering state of predictive value is obtained according to the maximum subordination principle, that is: $\max\{P_i, i \in I\}$. The predictive value can be calculated with the following equation:

$$\widehat{Y}_{(k)} = \frac{Q_{1d} + Q_{2d}}{2} \quad (14)$$

where $\widehat{Y}_{(k)}$ = the predictive value

Q_{1d} = the left value of fuzzy clustering value zone

Q_{2d} = the right value of fuzzy clustering value zone

8. Quality assessment of the new model

Relative error between predictive value and factual value is taken as the quality assessment parameter of new model. Relative error can be calculated by the following equation:

$$\sigma = \left(\widehat{Y}_{(k)} - Y_{(k)}\right) / Y_{(k)} \times 100/100 \quad (15)$$

where σ = the relative error

$\widehat{Y}_{(k)}$ = predictive value obtained with Eq14

$Y_{(k)}$ = factual value obtained from statistical yearbook

5. EXPERIMENTAL RESULTS AND ANALYSES

The historical cultivated land demand data of one county in the province of Hubei (Table 1) during 1950~2003 periods were obtained from Hubei Province Statistical Yearbook.

- Calculate the self-correlative coefficient of cultivated land demand data of research area, that is: r_1 = 0.980, r_2 = 0.941, r_3 = 0.905, r_4 = 0.871.
- Standardizing self-correlative coefficients data as weights, that is: ϖ_1 = 0.266, ϖ_2 = 0.255, ϖ_3 = 0.245, ϖ_4 = 0.236.
- Applying fuzzy sequential cluster model to divide the cultivated land demand data which be arranged from low to high order into fuzzy clustering zones. Figure 2 shows the correlation between error and the number of category.

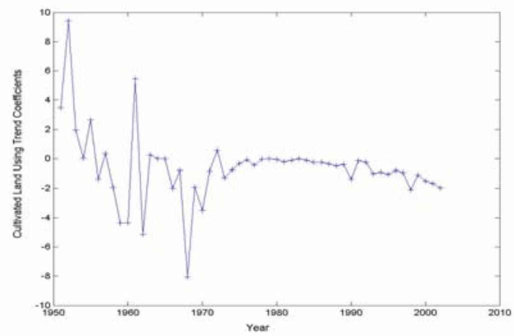

Figure 1. Cultivated land used trend degree

Figure 1 is the graph of cultivated land used trend degree. In the graph, negative value express that the area of cultivated land was increased, contrariwise positive value express that the area of cultivated land was decreased. As figure1 shown, the change of cultivated land area was great before 1979 and the change was slow after 1979.

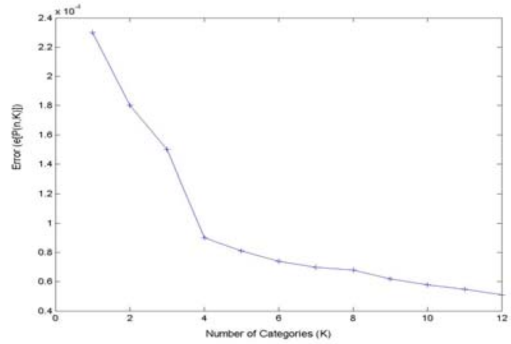

Figure 2. Correlation graph of error ($e\left[P\left(n, K\right)\right]$) and number of categories (K)

As figure 2 shown, 4 is the number of best division category. Table 2 shows the result of fuzzy clustering zones using the method of fuzzy sequential clustering.

States	Levels	Distinguished Standards
1	Increase Quickly	X ≥ 0.591
2	Increase Slowly	0 ≤ x< 0.591
3	Decrease Slowly	-1.349≤x<0
4	Decrease Quickly	x<-1.349

Table 2. Fuzzy clustering zones of cultivated land data

Year	1950	1951	1952	1953	1954	1955	1956	1957	1958	1959
Area /hm^2	63646.57	65866.61	72073.33	73480.01	73493.30	75440.02	74406.67	74673.43	73226.68	70020.02
LUTC		3.488	9.423	1.951	0.018	2.649	-1.370	0.359	-1.937	-4.379
States		1	1	1	2	1	4	2	4	4
Year	1960	1961	1962	1963	1964	1965	1966	1967	1968	1969
Area /hm^2	66973.33	70626.61	67006.59	67180.01	67179.80	67179.80	65846.67	65333.33	60073.38	58926.61
LUTC	-4.351	5.455	-5.126	0.259	0.000	0.000	-1.984	-0.780	-8.051	-1.909
States	4	1	4	2	2	2	4	3	4	4
Year	1970	1971	1972	1973	1974	1975	1976	1977	1978	1979
Area /hm^2	56866.69	56400.06	56720.08	55986.67	55566.39	55380.07	55333.33	55086.59	55073.33	55073.33
LUTC	-3.496	-0.821	0.567	-1.293	-0.751	-0.335	-0.084	-0.446	-0.024	0.000
States	4	3	2	3	3	3	3	3	3	2
Year	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989
Area /hm^2	55046.68	54933.31	54866.55	54906.60	54806.58	54739.51	54553.33	54366.62	54086.57	53906.48
LUTC	-0.048	-0.206	-0.122	0.073	-0.182	-0.122	-0.340	-0.342	-0.515	-0.333
States	3	3	3	2	3	3	3	3	3	3
Year	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999
Area /hm^2	53146.37	53059.21	52986.37	52419.11	51939.02	51233.13	50805.66	50453.31	49500.02	48952.89
LUTC	-1.410	-0.164	-0.137	-1.071	-0.916	-1.359	-0.834	-0.694	-1.889	-1.105
States	4	3	3	3	3	4	3	3	4	3
Year	2000	2001	2002	2003						
Area /hm^2	48259.91	47606.62	46959.82	46327.01						
LUTC	-1.416	-1.354	-1.359	-1.347						
States	4	4	4	3						

Table 1. Cultivated land demand data and states during 1950~2003 period

- Confirming the fuzzy state of each historical data locate at based on the standard of table 2. The result is described in table 1.
- Calculate the transition probability matrix of each transition step. That is following:

$$P_1 = \begin{bmatrix} 2/5 & 1/5 & 0/5 & 2/5 \\ 1/8 & 2/8 & 3/8 & 2/8 \\ 0/24 & 3/24 & 16/24 & 5/24 \\ 1/14 & 2/14 & 5/14 & 5/14 \end{bmatrix}$$

$$P_2 = \begin{bmatrix} 2/5 & 3/5 & 0/5 & 0/5 \\ 0/8 & 1/8 & 4/8 & 3/8 \\ 0/24 & 2/24 & 17/24 & 5/24 \\ 1/13 & 2/13 & 3/13 & 5/13 \end{bmatrix}$$

$$P_3 = \begin{bmatrix} 1/5 & 2/5 & 0/5 & 2/5 \\ 0/8 & 1/8 & 4/8 & 3/8 \\ 0/24 & 2/24 & 17/24 & 3/24 \\ 1/12 & 3/12 & 3/12 & 3/12 \end{bmatrix}$$

$$P_4 = \begin{bmatrix} 1/5 & 2/5 & 0/5 & 2/5 \\ 1/8 & 1/8 & 3/8 & 3/8 \\ 0/23 & 1/23 & 17/23 & 3/23 \\ 0/12 & 3/12 & 4/12 & 4/12 \end{bmatrix}$$

- Predict the cultivated land demand data in 2003 based on the historical data and corresponding transition probabilities matrix during 1999-2002 periods. Table 3 shows the result of prediction using the proposed new model in this paper.

year	states	steps	weights	Transition Probabilities			
				1	2	3	4
1999	3	4	0.236	0/23	1/23	17/23	3/23
2000	4	3	0.245	1/12	3/12	3/12	3/12
2001	4	2	0.255	1/13	2/13	3/13	5/13
2002	4	1	0.266	1/14	2/14	5/14	5/14
The sum of P_i with weights				0.062	0.154	0.395	0.295

Table 3. Prediction of cultivated land demand data in 2003

year	states	steps	weights	Transition Probabilities			
				1	2	3	4
2000	4	4	0.236	0/12	3/12	4/12	4/12
2001	4	3	0.245	1/12	3/12	3/12	3/12
2002	4	2	0.255	1/13	2/13	3/13	5/13
2003	3	1	0.266	0/24	3/24	16/24	5/24
The sum of P_i with weights				0.04	0.21	0.42	0.31

Table 4. Prediction of cultivated land demand data in 2004

As table 3 shown, the $\max\{p_i\}=0.395$ and $i=3$. It shows that the predictive data locate at third fuzzy sequential clustering zone (decrease slowly). The fuzzy zone of predictive value can be calculated, that is: $[46326.33\,,\,46959.82]$. Thus, the predictive value $\widehat{Y}_{(k)}$ in 2003 is 46642.84 hm^2 while the factual value is 46327.01 hm^2 obtained from the statistical yearbook. It is easily to calculate the relative error only 0.68%. It indicates that applying the reformative model (fuzzy Markov chain model with weights) to predict the cultivated land demand data will effectively enhance the precision of prediction. At the same time new model can reduce the complexity of calculation.

With the same process, the authors predict the cultivated land demand data in 2004 based on the historical data and corresponding transition probabilities matrix during 2000-2003 periods. Table 4 shows the result of prediction using the proposed new model in this paper.

As table 4 shown, the $\max\{p_i\}=0.342$ and $i=3$. It shows that the predictive data locate at third fuzzy sequential clustering zone (decrease slowly). Fuzzy zone of predictive value can be calculated, that is: $[45702.06\,,46327.01]$. Thus, the predictive value in 2004 is 46014.53 hm^2.

6. CONCLUSIONS AND DISCUSSIONS

The traditional models for prediction of cultivated land demand were not effectively solved the fuzzy and uncertainty information. As a new kind of data analysis technique, data mining can extract the useful information from enormous historical data. Thus, the authors presented a new model to reform the general Time Homogeneous Finite Markov Chain model. The new model adopted the data mining technique such as fuzzy logic theory, weights, statistical analysis, and cultivated land use trend coefficients model.

As experimental results and analyses shown, the reformative model can divide the time series data more reasonable and effectively describe the distributing rule existed in the data series. New model take standardized self-correlative coefficient of each transition step as weight and be combined with correlation analysis. The physics concept of new model was clear and calculation was simply. The new model provided a groping method for enhancing the precision of prediction.

At the same time, the authors indicate that the influence of other fuzzy state zones besides the maximum subordination state zone should be considered when calculated the predictive value. The corresponding weight for each fuzzy clustering state zone should be defined and then calculate the predictive value with the average value of all weights. Adopt another theory and model into the calculation of weight for fuzzy clustering state zones is the research at next stage.

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