A Bayesian Model about Relationship between Weather and Sales of Medicine for Cold

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Abstract—**Weather factors affecting the oscillation of the sales of cold medicine, may be various, uncertain and intermittent. A Bayesian model is built in this paper, to analyze the relationship between the weather factors and the sales of cold medicine, and BDE(Bayesian Dirichlet equivalent) score function is applied for learning Bayesian network structure so that the predominant weather factors could be identified. Some evaluation indicators are used to evaluate a reliable predictive model. Numerical examples confirm the feasibility and the reliability of the derived Bayesian model.**

Keywords—Bayesian network; probabilistic prediction; BDE score function

I. Introduction

Sales of some medicine such as cold medicine might be affected by many factors like weather conditions. Some research has been done on exploring the relationship between weather conditions and medicine sales, and some methods including linear regression analysis[1], grey prediction[2], artificial neural network[3-5], genetic algorithm[6], etc , have been applied to predict the sales. However, most of the above-mentioned methods are not applicable for problems of uncertainty, such as the relationship problem between the cold medicine sales and the weather factors including a variety of uncertain factors. As Bayesian Network is an efficient tool for dealing with uncertain problems by combining graph and probability to express probability reasoning, in this paper, structures of multiple Bayesian networks for exploring the relationship between the cold medicine sales and weather conditions are studied and built with BDE score function for prediction of cold medicine sales.

II. Bayesian Model

A. Analysis of Weather Factors Influencing Sales of Cold Drugs

Preliminary study of data of cold medicine sales and temperature from January to March shows that the temperature difference plays an important role .Temperature difference is a factor influencing the sale of medicine for cold in the Bayesian structure. The study shows that if temperature difference is greater than or equal to two, it is possible that at least one day's sale is above the monthly average sale. Other possible factors to affect the cold medicine sales include wind direction, transforming into bad weather (for instance, from sunny/cloudy to rain / rainstorm etc).

In this paper, 2 Bayesian networks are built: one is for predicting the sales of next five days based on the data of weather variations of the day, and the other is for predicating the sales of one day based on the data of the last five days. BDE score function is used to select the optimal structure for these two networks.

B. BDE Score Function

To determine the optimal network structure matching sample data, the BDE score function is used to evaluate the network structure. For a given sample data, its BDE score function is as follows:

$$P(D \mid G) = \prod_{i=1}^{n} \prod_{j=1}^{qi} \frac{\Gamma(a_{ij})}{\Gamma(a_{ij} + N_{ij})} \prod_{k=1}^{ri} \frac{\Gamma(a_{ijk} + N_{ijk})}{\Gamma(a_{ijk})} \tag{2}$$

Wherein, G is a network n is the number of variables, qi is the number of configurations of the parent set, ri is the number of states of discrete state variable x_i, N_{ijk} is the number of times took on the value k given the parent configuration j. $N_{ij} = \sum_{k=1}^{ri} N_{ijk}$, α_{ijk} is the Dirichlet hyper-parameter in Bayesian network. $\alpha_{ij} = \sum_{k=1}^{ri} \alpha_{ijk}$. $\Gamma(n)$ is the gamma function, for any $n(n \in \mathbf{N})$, $\Gamma(n) = (n-1)!$.

C. The Establishment of Bayesian Network Structure in the First Case

According to the analysis in section 2.2, temperature difference which plays an important role in affecting the sales of cold medicine, would be certain to be a node variable of the Bayesian network, and other variables including weather change, wind direction, would be candidate node variables of the Bayesian network.

In the first case, several Bayesian networks are built: for analyzing the relationship between the sales of next five days and the weather variations of the day, and four Bayesian networks with different structures are shown in Figure. 1 with relevant formulas as shown in Eq. 3-6.
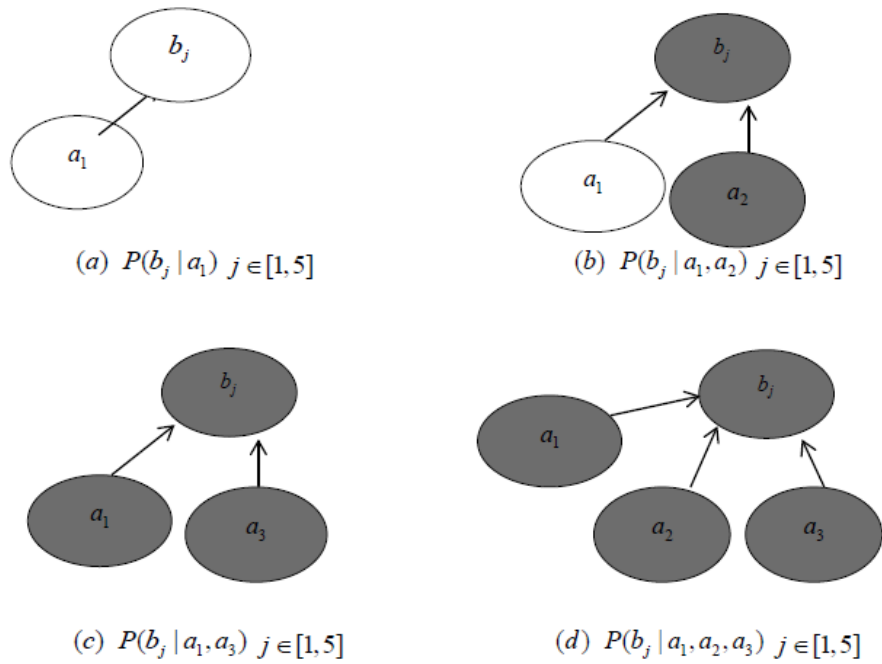
(a) $P(b_j \mid a_1)$ $j \in [1,5]$

(b) $P(b_j \mid a_1, a_2)$ $j \in [1,5]$

(c) $P(b_j \mid a_1, a_3)$ $j \in [1,5]$

(d) $P(b_j \mid a_1, a_2, a_3)$ $j \in [1,5]$

FIGURE I. FOUR HYPOTHETICAL BAYESIAN NETWORK DIAGRAMS IN THE SECOND CASE

$$G_1 = P(b_j \mid a_1) \quad j \in [1,5] \tag{3}$$

$$G_2 = P(b_j \mid a_1, a_2) \quad j \in [1,5] \tag{4}$$

$$G_3 = P(b_j \mid a_1, a_3) \quad j \in [1,5] \tag{5}$$

$$G_4 = P(b_j \mid a_1, a_2, a_3) \quad j \in [1,5] \tag{6}$$

Using BDE score function to evaluate the structures of the four Bayesian networks, and G1 is the optimal structure.

D. The Establishment of Bayesian Network Structure in the Second Case

In the second case, several Bayesian networks are built: for analyzing the relationship between the sales of one day and the weather variations among the last five days, and four Bayesian networks with different structures are shown in Figure. 2 with relevant formulas as shown in Eq. 7-10.
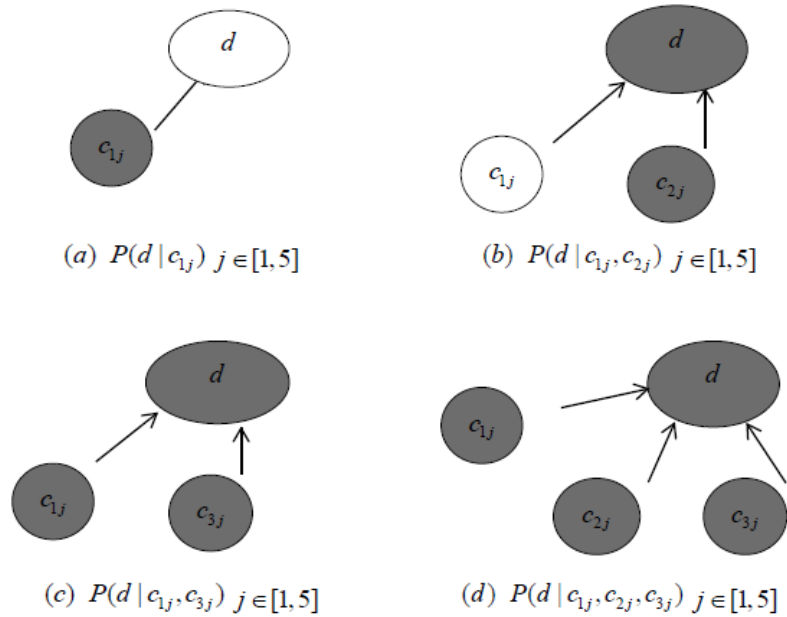

(a) $P(d \mid c_{1j})$ $j \in [1,5]$

(b) $P(d \mid c_{1j}, c_{2j})$ $j \in [1,5]$

(c) $P(d \mid c_{1j}, c_{3j})$ $j \in [1,5]$

(d) $P(d \mid c_{1j}, c_{2j}, c_{3j})$ $j \in [1,5]$

FIGURE II. FOUR HYPOTHETICAL BAYESIAN NETWORK DIAGRAMS IN THE SECOND CASE

$$G_5 = P(d \mid c_{1j}) \quad j \in [1,5] \tag{7}$$

$$G_6 = P(d \mid c_{1j}, c_{2j}) \tag{8}$$

$$G_7 = P(d \mid c_{1j}, c_{3j}) \tag{9}$$

$$G_8 = P(d \mid c_{1j}, c_{2j}, c_{3j}) \tag{10}$$

According to the definition of formula (7 - 10), four types of Bayesian networks as shown in figs 2 (a), (b), (c), (d) may be formed.

Using BDE score function to evaluate the structures of the four Bayesian networks, and G5 is the optimal structure.

III. DISCUSSION

Using data among 91 days as training data, and data among 31 days as testing data, some metrics, which includes mean square error(MSE), mean absolute error(MAE), The mean absolute percentage error(MAPE) are employed to evaluate the performances of the two networks, and the results are listed in Table 1. Data among 91 days is used for training data, and data among 31 days is used for testing data. Equations of the four metrics are shown in Eq. (11-13).

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2 \tag{11}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |Y_i - \hat{Y}_i| \tag{12}$$

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} (|\frac{Y_i - \hat{Y}_i}{Y_i}|) \times 100 \tag{13}$$

According to the definition of formula (7 - 10), four types of Bayesian networks as shown in figs 2 (a), (b), (c), (d) may be formed.

In the first case, the symbol and are defined as follows:

$$Y_i = \begin{cases} 1 & P(b_j > S_{Mavg} \mid |a_1| \ge 2) > 0.5 \quad j \in [1,5] \\ 0 & P(b_j > S_{Mavg} \mid |a_1| \ge 2) \le 0.5 \quad j \in [1,5] \end{cases} \tag{14}$$

$$\hat{Y}_i = \begin{cases} 1 & b_j > S_{Mavg} \\ 0 & b_j \le S_{Mavg} \end{cases} \tag{15}$$

Where, $P(b_j > S_{Mavg} \mid |a_1| \ge 2)$ denotes the probability of b_j being greater than S_{Mavg} when the absolute value of the average temperature difference a_1 is greater than or equal to 2, Yi is the predicted value, and $\hat{Y}_i'$ is the real value.

$$Y_i' = \begin{cases} 1 & P(d > S_{Mavg} \mid |c_{1j}| \ge 2) > 0.5 \quad j \in [1,5] \\ 0 & P(d > S_{Mavg} \mid |c_{1j}| \ge 2) \le 0.5 \quad j \in [1,5] \end{cases} \tag{16}$$

$$\hat{Y}_i = \begin{cases} 1 & b_j > S_{Mavg} \\ 0 & b_j \le S_{Mavg} \end{cases} \tag{17}$$

Where, $P(d > S_{Mavg} \mid |c_{1j}| \ge 2)$ denotes the probability of d being greater than S_{Mavg} when the absolute value of the average temperature difference c_{1j} is greater than or equal to 2. Y_i' is the predicted value, and $\hat{Y}_i'$ is the real value.

The evaluation metrics are calculated for G_1 and G_5 respectively, and the results are shown in table 1..

TABLE I.   COMPARATIVE TABLE OF ASSESSMENT INDICATORS IN TWO CASES

Index	*MSE*	*MAE*	*MAPE*
$\arg\max\{BDE \mid G_i\} = G_1$ $G_i\,(i=1,2,3,4)$	0.1607	0.1607	16.0714
$\arg\max\{BDE \mid G_i\} = G_5$ $G_i\,(i=5,6,7,8)$	0.5714	0.5714	57.1429

As can be seen from table 1, G1 achieves a higher performance than G5. So the Bayesian network G1 for the first case is more reliable for predicting sales of cold medicine based on the weather data.

IV. CONCLUSIONS

There is a strong relationship between the sales of cold medicine and the weather variation, Several Bayesian networks are proposed in this paper to analyze such relationship, and BDE score function is applied to search for the optimal

structure in two cases, The obtained Bayesian network provides a reasonable prediction method to look for the relationship between weather and sales volume for pharmaceutical firms, so that inventory could be rationally arranged and profit could be improved accordingly. The numerical result shows that the proposed method is efficient.

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