Fuzzy Bayesian Belief Network for Analyzing Medical Track Record

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Abstract. Bayesian Belief Network (BBN), one of the data mining classification methods, is used in this research for mining and analyzing medical track record from a relational data table. In this paper, the BBN concept is extended with meaningful fuzzy labels for mining fuzzy association rules. Meaningful fuzzy labels can be defined for each domain data. For example, fuzzy labels *secondary disease* and *complication disease* are defined for disease classification. We extend the concept of *Mutual Information* dealing with fuzzy labels for determining the relation between two fuzzy nodes. The highest fuzzy information gain is used for mining association among nodes. A brief algorithm is introduced to develop the proposed concept. Experimental results of the algorithm show processing time in the relation to the number of records and the number of nodes. The designed application gives a significant contribution to assist decision maker for analyzing and anticipating disease epidemic in a certain area.

Keywords: Bayesian Belief Network, Classification Data, Data Mining, Fuzzy Association Rules.

1 Introduction

Bayesian Belief Network (BBN) is a powerful knowledge representation and reasoning tool under conditions of uncertainty. A Bayesian network is a Directed Acyclic Graph (DAG) with a probability table for each node. The nodes in a Bayesian network represent propositional variables in a domain, and the arcs between nodes represent the dependency relationship among the variables.

There are several BBN researches. Integrating fuzzy theory into Bayesian networks by introducing conditional Gaussian models to make a fuzzy procedure was conducted by [1]. Integrating fuzzy logic into Bayesian networks were also proposed by [2, 3]. Learning Bayesian network structures using information theoretic approach was proposed in [5]. The last research is very close related with our proposed concept. In this paper, we extend the concept of *Mutual Information* (MI) dealing with meaningful fuzzy values in constructing Fuzzy Bayesian Belief Network (FBBN). The result of MI is used to determine whether there is a relation between two fuzzy nodes. Direction of arc between two nodes depends on

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comparison between asymmetric results of their conditional probability. Conditional probability table can be provided during the process of generating FBBN. Fuzzy association rules are directly achieved from the networks in which every weight of relationship between two nodes might be considered as a confidence factor of the rule. A brief algorithm is given to develop the proposed concept. The experimental results show processing time in the relation to the number of records and the number of nodes.

The paper is organized as follows. Section 2 as a main contribution of this paper discusses our proposed concept and algorithm for generating FBBN. Section 3 demonstrates the concept and algorithm with an illustrative example. Experimental result expressing processing time is also provided in this section. Finally a conclusion is given in Section 4.

2 Fuzzy Bayesian Belief Network (FBBN)

Bayesian Belief Network specifies joint conditional probability distributions. It allows class conditional independencies to be defined between subsets of domains. It provides a graphical model of causal relationships, on which learning can be performed. BBN is defined by two components, i.e. Directed Acyclic Graph (DAG) and Conditional Probability Table (CPT) [6]. In this section, a concept of FBBN is proposed and generated from a relational data table. Every node in the FBBN is considered as a fuzzy set over a given domain in the relation. Formally, let a relation schema [7] R consists of a set of tuples, where t_i represents the i-th tuple and if there are n domain attributes D, then $t_i = \langle d_{i1}, d_{i2}, \cdots, d_{in} \rangle$. Here, d_{ij} is an atomic value of tuple t_i with the restriction to the domain D_j, where $d_{ij} \in D_j$. A relation schema R is defined as a subset of the set of cross product $D_1 \times D_2 \times \cdots \times D_n$, where $D = \{D_1, D_2, \cdots, D_n\}$. Tuple t (with respect to R) is an element of R. In general, R can be shown in Table 1.

Table 1. A schema of relational data table

Tuples	D_1	D_2	$\dots$	D_n
t_1	d_{11}	d_{12}	$\dots$	d_{1n}
t_2	d_{21}	d_{22}	$\dots$	d_{2n}
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
t_s	d_{s1}	d_{s2}	$\dots$	d_{sn}

Now, we consider A and B as two fuzzy subsets over D_j and D_i as defined by $A: D_j \to [0,1]$ and $B: D_i \to [0,1]$ so that $A \in \Gamma(D_j)$ and $B \in \Gamma(D_i)$, where $\Gamma(D_j)$ and $\Gamma(D_i)$ are fuzzy power set over domain D_j and D_i, respectively. As defined in [4, 8], some basic operations of fuzzy sets are given by:

Complement: $\sim A(x) = 1 - A(x)$ for all $x \in D_j$

Intersection: $A \cap B(x) = \min(A(x), B(x))$ for all $x \in D_j$

Union: $A \cup B(x) = \max(A(x), B(x))$ for all $x \in D_j$

In probability theory and information theory, the MI of two random variables is a quantity that measures the mutual dependence of the two variables. The MI value between two fuzzy sets *A* and *B* can be defined by a function in (1).

$$MI(A,B) = P(A,B)\log_2\left(\frac{P(A,B)}{P(A)\times P(B)}\right) \quad (1)$$

where $P(A) \neq 0$ and $P(B) \neq 0$.

Here, $P(A,B)$ is probability of fuzzy sets *A and B* or intersection between *A* and *B*. Therefore, $P(A,B)$ can be also denoted by $P(A \cap B)$ as given by the following definition:

$$P(A,B) = P(A \cap B) = \frac{\sum_{k=1}^{|R|} \min\left(A(d_{kj}), B(d_{ki})\right)}{|R|} \quad (2)$$

where $A(d_{kj}), B(d_{ki}) \in [0,1]$ are membership degrees of d_{kj} and d_{ki} in fuzzy sets *A* and *B*, respectively. |*R*| is the number of tuples/ records in the relation *R*. *P*(*A*) and *P*(*B*) are defined as probability of fuzzy set A and B, respectively as follow.

$$P(A) = \frac{\sum_{k=1}^{|R|} A(d_{kj})}{|R|} \quad \text{and} \quad P(B) = \frac{\sum_{k=1}^{|R|} B(d_{ki})}{|R|}, \quad (3)$$

It can be verified from (1), MI(*A*,*B*) is a symmetric function (MI(*A*,*B*)=MI(*B*,*A*)). The relationship between *A* and *B* strongly depend on the following equation.

$$\frac{P(A,B)}{P(A)\times P(B)}$$

The above equation represents a correlation measure as one of important measures in determining interestingness of an association rule. There are three possible results given by the correlation measure, namely *positive correlation* (if the result of calculation is greater than 1), *independent correlation* (if the result of calculation is equal to 1) and *negative correlation* (if the result of calculation is less than 1). It can be verified that MI(*A*,*B*) might be greater than 0 (MI(*A*,*B*)>0)), equal to 0 (MI(*A*,*B*)=0) and less than 0 (MI(*A*,*B*)<0). Fuzzy sets *A* and *B* are assumed to have a relationship in constructing a network if and only if *A* and *B* have a positive correlation so that the value of MI(*A*,*B*) is greater than 0. If A and B have a relation in the network then direction of relationship between A and B is determine by comparing values of conditional probability. Conditional probability of fuzzy event A given B denoted by $P(A|B)$ is defined as follows [14].

$$P(A \mid B)=\frac{P(A,B)}{P(B)}=\frac{\sum_{k=1}^{|R|}\min(A(d_{kj}),B(d_{ki}))}{\sum_{k=1}^{|R|}B(d_{ki})} \tag{4}$$

Similarly, conditional probability of fuzzy event B given A is given by $P(B|A)$ as defined by

$$P(B \mid A)=\frac{P(A,B)}{P(B)}=\frac{\sum_{k=1}^{|R|}\min(A(d_{kj}),B(d_{ki}))}{\sum_{k=1}^{|R|}A(d_{kj})} \tag{5}$$

A comparison between $P(A|B)$ and $P(B|A)$ is used to decide a relationship direction between two nodes represented by two fuzzy sets in constructing a Bayesian Belief Network. Here, if $P(A|B) > P(B|A)$, then relationship direction from B to A as shown in Figure 1(a). If $P(A|B) < P(B|A)$, then relationship direction from A to B as shown in Figure 1(b). Suppose in a particular case $P(A|B) = P(B|A)$, the direction might be either from A to B or from B to A. However, it is necessary to make sure that the chosen direction does not cause any cyclic in the network.

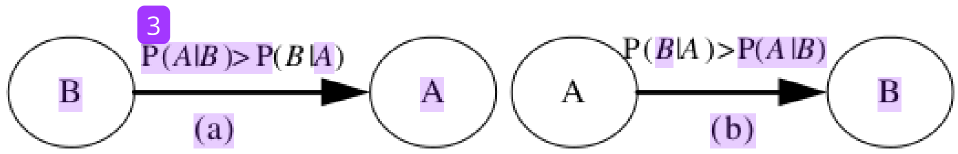

Fig. 1. Determining direction between A and B

The algorithm to calculate conditional probability, mutual information, and direct arc between two nodes is given by the following algorithm.

```
1. Prepare data using relational algebra (e.g. select,
   project, Cartesian product).

2. Select domains and define node types as a fuzzy set
   for every domain (e.g. value, group of value, or
   fuzzy set) to be analyzed.

3. Generate a temporary relation from the selected
   domains. Name the domains with defined labels
   sequentially and the default value is 0. Fill a
   value of new domain with a weight depend on the
   defined node type in the selected domains
   sequentially. In case value and group of value node
   type is selected for the domain, set weight 1 for
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   every selected value and set weight 0 for unselected
   value. Another case, fuzzy set is selected for the
   domain, set weight with defined alphanumeric fuzzy
   set weight. Set weight with function fuzzy set for
   numeric fuzzy set. Set weight 0 for undefined
   values.

4. Calculate total weight for every domain into dynamic
   array respectively.

5. Check relationship and decide arc direction
   Max=number of domains
   First=2 {the first node}
   For First to Max-7
    Second=First + 1 {the second node}
    For Second to Max
     Calculate P(First) using equation (3)
     Calculate P(Second) using equation (3)
     Calculate P(First, Second) using equation (2)
     Calculate MI(First, Second) using equation (1)
     If MI(First, Second) > 0 Then
      Calculate P(First| Second) using equation (4)
      Calculate P(Second| First) using equation (5)
      If P(First| Second)> P(Second| First) Then
       Save Second, First, P(First| Second)into FBBN
       {arc direction Second→First}
      Else
       Save First, Second, P(Second| First) into FBBN
       {arc direction First→Second}
      End If
     End If
    End For
   End For

6. Draw the network base on FBBN.

7. Generate a conditional probability table for each
   node for the value node with each possible
   combination from parent nodes value.
```

3 Illustrative Example

To make our proposed FBBN method clearly understandable, we demonstrate an illustrative example. A relational data table of patient medical record is given in Table 2. The data table consists of 10 records with several domains, such as *Patient Id*, *Diagnose*, *Another Diagnose*, *Age*, and *Education*. *Diagnose* and *Another Diagnose* use ICD-10 identifier [14].

First of all, we need to define every node that will be used in constructing FBBN. Here, every node is subjectively defined by users as a meaningful fuzzy

Table 2. A medical record example

Patient Id	*Diagnose*	*Another Diagnose*	*Age*	*Education*
806931	A09.X	D50	20	Bachelor
806932	Z51.1	A15.9	36	Master
806933	Z51.1	D50	35	Master
806934	S02.1	K56.6	59	Master
806935	Z51.1	C79.8	19	Bachelor
806936	Z51.1	A41.9	49	Bachelor
806937	Z51.1	D64.9	36	Master
806938	A09.X	K56.6	27	Master
806939	E14.9	A16.9	52	Bachelor
806940	A16.2	K74.6	56	Master

set over a given domain. *Secondary* and *Complication* nodes are arbitrarily defined as fuzzy sets on *Another Diagnose* domain as follows.

$$Secondary = \left\{ \frac{0.85}{\text{A15.9}}, \frac{0.2}{\text{A41.9}}, \frac{0.5}{\text{D50}}, \frac{0.2}{\text{D64.9}} \right\},$$

$$Complication = \left\{ \frac{0.85}{\text{C79.8}}, \frac{0.3}{\text{D50}}, \frac{0.6}{\text{D64.9}}, \frac{0.5}{\text{K56.6}} \right\}.$$

The above expressions mean that *Secondary*(A15.9)=0.85, *Secondary*(A41.9)=0.2, *Complication*(C79.8)=0.85, *Complication*(D50)=0.3, etc. *Chemo-Neo* node has only one data value defined on the domain *Diagnose* as given by *Chemo-Neo* = {Z51.1}. Similarly, Node *Master* is defined on the domain *Education* by *Master* = {Master}. Three nodes, *Young*, *Middle*, *Old* are defined on domain *Age* as numerical fuzzy sets as given by the following equations. Their fuzzy sets graph is shown in Fig. 2.

Based on fuzzy sets definition on every node, we transform Table 2 into a temporary relation as shown in Table 3. For instance, values {0.30, 0.00, 0.30, 0.50, 0.85, 0.00, 0.60, 0.50, 0.00, 0.00} in the column *Complication* in Table 3 is related to the *Another Diagnose* values {D50, A15.9, D50, K56.6, C79.8, A41.9, D64.9, K56.6, A16.9, K74.6} in Table 2, where *Complication*(D50)=0.30, *Complication*(A15.9)= 0.00, *Complication*(D64.9)=0.60, etc. Total weight of *Chemo-Neo*, *Complication*, *Secondary*, *Young*, *Middle*, *Old*, and *Master* are calculated as given by: 5, 3.05, 2.25, 2.53, 5.07, 2.40, and 6, respectively.

Mutual information relation between two nodes are calculated in order to decide whether there is a relationship or not between them. In addition, to decide the arc direction between two nodes, we use conditional probability as described in Section 2. For example, mutual information between node *Chemo-Neo* and *Complication* is calculated by MI(*Chemo-Neo*, *Complication*) as given by (1). *P*(*Chemo-Neo*) is calculated by equation (3), i.e.

$$Young(x)=\begin{cases}1 & ,x<20\\ \dfrac{35-x}{15} & ,20\le x\le 35\\ 0 & ,x>35\end{cases},\qquad Middle(x)=\begin{cases}0 & ,x\ge 20\\ \dfrac{x-20}{15} & ,20\le x\le 35\\ 1 & ,35\le x\le 45\\ \dfrac{60-x}{15} & ,45\le x\le 60\\ 0 & ,x>60\end{cases},$$

$$Old(x)=\begin{cases}0 & ,x<45\\ \dfrac{x-45}{15} & ,45\le x\le 60\\ 1 & ,x>60\end{cases}.$$

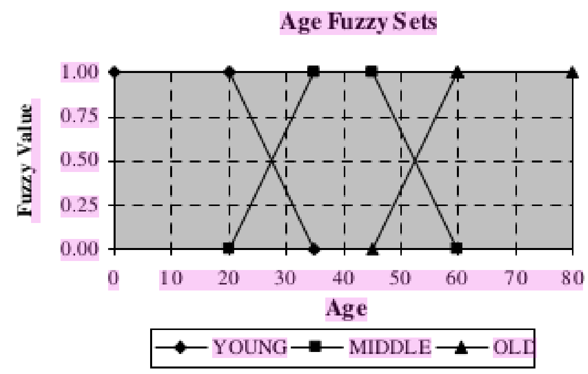

Fig. 2. Age fuzzy sets

$P(Chemo\text{-}Neo)$ = Total weight of *Chemo-Neo*/Total Records
= 5/10 = 0.5

$P(Complication)$ = Total weight of *Complication*/Total Records
= 3.05/10 = 0.305

Furthermore, $P(Chemo\text{-}Neo, Complication)$ is calculated by equation (2) as follows.

$$P(Chemo\text{-}Neo, Complication) = 1.75/10 = 0.175.$$

Since MI(*Chemo-Neo*, *Complication*) is greater than zero, we can conclude that there is a relationship between *Chemo-Neo* and *Complication* nodes. Similarly, other MI relationship between two nodes can be calculated by equation (1) as shown in Table 4.

Arc direction between two nodes can be determined by comparing the results of P(Node1| Node2) and P(Node2| Node1) as given by equation (4) and (5). For example, since P(Chemo-Neo| Complication) = 0.574 is greater than P(Complication| Chemo-Neo) = 0.35, the direction of arc is from Complication to Chemo-Neo with conditional probability 0.574. Other directed arcs are calculated in the same way as given in Table 5. Finally, FBBN is generated as shown in Fig. 3.

Table 3. The weighted medical record example

Patient Id	*Chemo-Neo*	*Complication*	*Secondary*	*Young*	*Middle*	*Old*	*Master*
806931	0	0.30	0.50	1.00	0.00	0.00	0
806932	1	0.00	0.85	0.00	1.00	0.00	1
806933	1	0.30	0.50	0.00	1.00	0.00	1
806934	0	0.50	0.00	0.00	0.07	0.93	1
806935	1	0.85	0.00	1.00	0.00	0.00	0
806936	1	0.00	0.20	0.00	0.73	0.27	0
806937	1	0.60	0.20	0.00	1.00	0.00	1
806938	0	0.50	0.00	0.53	0.47	0.00	1
806939	0	0.00	0.00	0.00	0.53	0.47	0
806940	0	0.00	0.00	0.00	0.27	0.73	1
Total	**5**	**3.05**	**2.25**	**2.53**	**5.07**	**2.40**	**6**

Table 4. Mutual information between two nodes

Node1	Node2	*P*(Node1)	*P*(Node2)	*P*(Node1, Node2)	MI(Node1, Node2)
Chemo-Neo	Complication	0.500	0.305	0.175	0.035
Chemo-Neo	Secondary	0.500	0.225	0.175	0.112
Chemo-Neo	Young	0.500	0.253	0.100	-0.034
Chemo-Neo	Middle	0.500	0.507	0.373	0.208
Chemo-Neo	Old	0.500	0.240	0.027	-0.058
Chemo-Neo	Master	0.500	0.600	0.300	0.000
Complication	Secondary	0.305	0.225	0.080	0.018
Complication	Young	0.305	0.253	0.165	0.181
Complication	Middle	0.305	0.507	0.143	-0.016
Complication	Old	0.305	0.240	0.050	-0.027
Complication	Master	0.305	0.600	0.190	0.010
Secondary	Young	0.225	0.253	0.050	-0.009
Secondary	Middle	0.225	0.507	0.175	0.108
Secondary	Old	0.225	0.240	0.020	-0.029
Secondary	Master	0.225	0.600	0.155	0.031
Young	Middle	0.253	0.507	0.047	-0.068
Young	Old	0.253	0.240	0.000	$-\infty$
Young	Master	0.253	0.600	0.053	-0.081
Middle	Old	0.507	0.240	0.107	-0.020
Middle	Master	0.507	0.600	0.380	0.122
Old	Master	0.240	0.600	0.167	0.036

Table 5. Generated FBBN

Node1	Node2	P(Node1|Node2)	P(Node2|Node1)	Fuzzy Association Rules
Chemo-Neo	*Complication*	0.574	0.350	*Complication* → *Chemo-Neo*
Chemo-Neo	*Secondary*	0.778	0.350	*Secondary* → *Chemo-Neo*
Chemo-Neo	*Middle*	0.736	0.746	*Chemo-Neo* → *Middle*
Complication	*Secondary*	0.356	0.262	*Secondary* → *Complication*
Complication	*Young*	0.651	0.541	*Young* → *Complication*
Complication	*Master*	0.317	0.623	*Complication* → *Master*
Secondary	*Middle*	0.345	0.778	*Secondary* → *Middle*
Secondary	*Master*	0.258	0.689	*Secondary* → *Master*
Middle	*Master*	0.633	0.750	*Middle* → *Master*
Old	*Master*	0.278	0.696	*Old* → *Master*

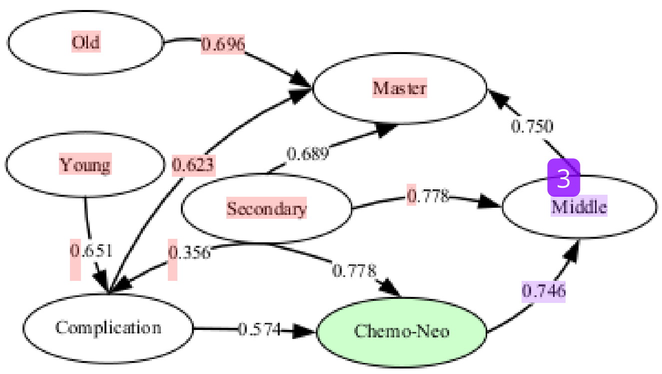

Fig. 3. The generated FBBN for analyzing medical track record

Finally, MI(Chemo-Neo, Complication) is given by

$$P(Chemo-Neo, Complication)\log_2\left(\frac{P(Chemo-Neo, Complication)}{P(Chemo-Neo)\times P(Complication)}\right) = 0.035.$$

The last step, we generate a CPT. For example, a conditional probability node of *Chemo-Neo* given *Complication* as parental node is *P*(*Chemo-Neo*| *Complication*) and *P*(~*Chemo-Neo*| *Complication*). Fig. 3 shows that *P*(*Chemo-Neo*| *Complication*) = 0.574. It can be verified that

$$P(\sim Chemo\text{-}Neo \mid Complication) = 1 - P(Chemo\text{-}Neo \mid Complication) = 1 - 0.574 = 0.426.$$

Similarly, conditional probability node of *Chemo-Neo* given ~*Complication* as parental node is *P*(*Chemo-Neo*| ~*Complication*) and *P*(~*Chemo-Neo*| ~*Complication*). As defined in [8], ~*Complication* is given as follows.

$$\sim Complication(x) = 1 - Complication(x) \text{ for every } x \in Another\ Diagnose$$

Suppose the column *Complication* in Table 3 is changed to be ~*Complication*, values {0.30, 0.00, 0.30, 0.50, 0.85, 0.00, 0.60, 0.50, 0.00, 0.00} in the column *Complication* are recalculated by the above equation to be {0.70, 1.00, 0.70, 0.50, 0.15, 1.00, 0.40, 0.50, 1.00, 1.00}, where ~*Complication*(D50)=0.70, ~*Complication*(A15.9)=1.00, ~*Complication*(D64.9)=0.40, etc. It can be calculated *P*(*Chemo-Neo*,~*Complication*)= 3.25 and P(~*Complication*)=6.95. Finally, *P*(*Chemo-Neo*| ~*Complication*) and *P*(~*Chemo-Neo*| ~*Complication*) are given by

$$P(\textit{Chemo-Neo} \mid \sim\textit{Complication}) = 3.25/6.95 = 0.468,$$

$$P(\sim\textit{Chemo-Neo} \mid \sim\textit{Complication}) = 1 - 0.468 = 0.532.$$

All conditional probabilities node of *Chemo-Neo* in the relation to *Complication* and ~*Complication* is shown in Table 6.

Table 6. Conditional probability for node of *Chemo-Neo*

	Complication,	~*Complication*,
Chemo-Neo	0.574	0.468
~*Chemo-Neo*	0.426	0.532

The system has already been implemented in the real database stored in Oracle Database using *PC IBM/AT Compatible* with *AMD Turion X2 Processor*, *2 GB memory* and *320 GB Hard Disk* by [15]. Table 7 shows the experimental results of processing time required in the various number of processing records and nodes. In addition, Fig. 4 graphically shows processing time of the various number of nodes.

Table 7. Experimental results of processing time.

Number of Records	Number of Nodes	Time
12,000 records	2 nodes	3 seconds
	3 nodes	7 seconds
	4 nodes	12 seconds
	5 nodes	23 seconds
24,000 records	2 nodes	4 seconds
	3 nodes	11 seconds
	4 nodes	19 seconds
	5 nodes	28 seconds
36,000 records	2 nodes	6 seconds
	3 nodes	15 seconds
	4 nodes	25 seconds
	5 nodes	40 seconds
48,000 records	2 nodes	7 seconds
	3 nodes	22 seconds
	4 nodes	28 seconds
	5 nodes	54 seconds

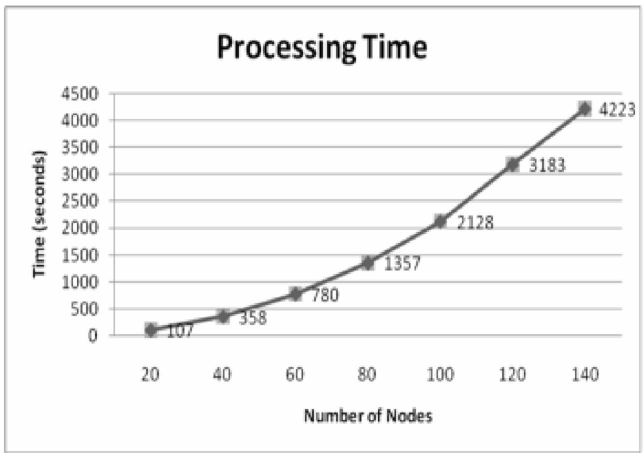

Fig. 4. The processing time of various number of nodes

4 Conclusion

In order to propose a concept of Fuzzy Bayesian Belief Network (FBBN), we extended the concept of mutual information gain induced by fuzzy labels. Relation between two fuzzy nodes was determined by the calculation of their MI. Comparison of conditional probability between two nodes was used to decide their arc direction. This paper also introduced an algorithm to implement the application of generating FBBN. An illustrated example was discussed to clearly understand the proposed concept. The generated FBBN can be applied to medical diagnosis tasks involving disease semantics by doctors or hospital staff.

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