

A New Approach For Convert Multiply-Connected Trees in Bayesian networks

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Abstract- One of the purposes of the Bayesian networks is inference. There have different algorithms for this purpose. Message passing algorithms us one of the inference approaches on the junction trees. However all of the Bayesian networks are not singly-connected tree, but solution was presented for making junction tree from multiply-connected tree. This article presents a new approach for converting multiply-connected tree to junction tree by moor and meely machine concepts. This approach is based on edge labeling by conditional probability, then moral and triangulation steps transact based on five-step design.

I. INTRODUCTION

One of the exhibition relative between elements in our world is planning the variables and relation between them by directional and in directional graphs. Probability nature of phenomena and depended occurrence in real world, that is subject of conditional probability. Therefore many of researchers have concerned to solve uncertainty problems by combination graph models whit conditional probability. Each graph consist nodes, edge between to node that exhibit relation between them. In directional graph each edge connect from parent to childe and declare conditional relation between them.

In the most general case, the needed structure is a (directed acyclic) graph, rather than simply a tree. This means that at least two nodes are connected by more than one path in the underlying undirected graph. Such a network is multiply-connected and occurs when some variable can influence another through more than one causal mechanism.

It is always possible to transform a multiply-connected network into a polytree. one of converting methods is Clustering. Clustering algorithms transform the multiply-connected graph into a probabilistically equivalent polytree by merging nodes (removing the multiple paths between the two nodes). The junction tree algorithm [1] provides a methodical and efficient method of clustering, versions of which are implemented in the main BN software packages. In this article we suggested new method (MVC¹) for easier converting. The paper is organized as follows. In section II we will explain Bayesian network. Then in section III we discuss MVC method. And in the last section we will talk about method time cost.

II. BAYESIAN NETWORKS

The Bayesian networks constitute a reasoning method based on probability theory. A Bayesian network consists of a set of nodes and a set of arcs which together constitute a directed acyclic graph (DAG). The nodes represent random variables, all of which, in general, have a finite set of States. The arcs indicate the existence of direct causal connections between the linked variables, and the strengths of these connections are expressed in terms of conditional probabilities.

For determining the joint probability distribution $P(x_1, x_2, \dots, x_n)$ in a Bayesian network, it is Sufficient to know the conditional probabilities $P(x_i | \text{parent}(X_i))$, where $\text{parent}(X_i)$ is the parent set of variable X_i , i.e. the set of variables by which X_i is affected:

$$P(X_1, X_2, \dots, X_n) = \prod_{i=1}^n P(X_i | \text{parent}(X_i)) \quad (1)$$

Excellent introductions on Bayesian networks can be found in Pearl (1988)[2], Neapolitan (1990)[3] and Jensen (1995)[4]. In directional acyclic graph each node identifies one variable of real world and each edge declare relative between two nodes. For example in figure (1)

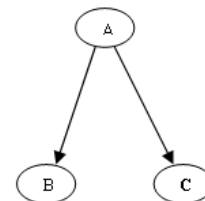


Figure (1): simple probability graph

B, C Dependent to variable A and calculate probability graph by relation (2)

$$P(A, B, C) = P(B | A) \cdot P(A) \cdot (C | A) \quad (2)$$

III. INFERENCE

Banyan model is mapping in real world that is whit having silage or multi observation gain to answer our query. In other word inference in banyan network is calculation posterior probability in network using the probability value from one or more observation. That is named conditional inference.

There are several algorithms to make exact and approximate inference. One of the most popular, and that is also an exact method, is the evidence propagation algorithm of Lauritzen and Spiegel halter[5] improved later by Jensen et al. [6][7] and another method is Kim and Pearl’s message passing algorithm is based on passing node probability by edge between two nodes. Those details can be found elsewhere [8, 9, 10] this algorithm calculate true answer in tree graph, but in some of the graph that pass or receive message from two or multi path is not applicable. This limitation is solved by junction tree method.

Stages of this method are the following:

1. **Moralize:** Connect all parents and remove arrows; this produces a so-called **moral graph**.
2. **Triangulate:** Add arcs so that every cycle of length > 3 has a chord (i.e., so there is a sub cycle composed of exactly three of its nodes); this produces a **triangulated graph**.
3. **Create new structure:** Identify maximal cliques in the triangulated graph to become new compound nodes, then connect to form the so-called **junction tree**.
4. **Create separators:** Each arc on the junction tree has an attached **separator**, which consists of the intersection of adjacent nodes.
5. **Compute new parameters:** Each node and separator in the junction tree has an associated table over the configurations of its constituent variables. These are all a table of ones to start with.

For each node X in the original network,

(a) Choose one node Y in the junction tree that contains X and all of X’s parents,

(b) Multiply $P(X_i | \text{parent}(X_i))$ on Y’s table.

6. **Belief updating:** Evidence is added and propagated using a message passing Algorithm.

Now in this tree may inference with passing message.

III. SUGGESTED METHOD (MVC)

The idea of the suggested method is implementation steps by mind when we solve similar problem. Mind searches nodes with unconnected parents after understanding graph projection. Edge labeling transact with idea in moor and meely machine in suggested method. the first advantages of the suggested method is effort of the approach for implementation subjective method i.e. this method is implement by perceptual and visual method with contracted rules and symbols.

The relational connectivity of the nodes with unconnected parents (moralize) is implemented by labeling identification with same prefix and using permutation. Then mind identify loops with length more than three, then transact triangulation with drawing new edge. Suggested method doesn’t need to find loops. This method eliminates loops with length more than three by using conditions for prevention of the mistake connection like connection between two leaf-nodes. The next steps of the suggested method transact elimination of the loops with length more than three that doesn’t need these stages in majority of the graphs.

This method combiner two stages of mention method by moor and meely machine idea, then conditional phrase was produced by each condition and following steps. We can transact moral and triangulation

Step one: each conditional phrase is explained by consideration to direction of connection. Figure (2) display phrase $A | B$ and figure (3) display phrase value $B | A$ in other word each connection is labeled only by conditional phrase, then calculate it.



Figure (2)

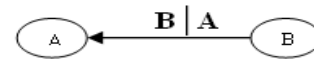


Figure (3)

Step two: after labeling all of the graph’s edge, moral is needed. By probe in labeling in figure (4) we can understand label of two edges whit same prefix node, then for graph moralization in step two, all labels select that have same prefix node, and we draw edge between two nodes after condition (|).

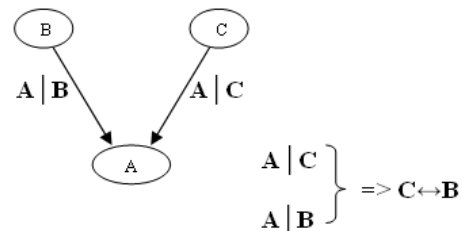


Figure (4) moralization of graph

Note: if more than two of the edge labels have same prefix node, we should determine permutation of the second side of edge label and draw edge between them according to permutation.

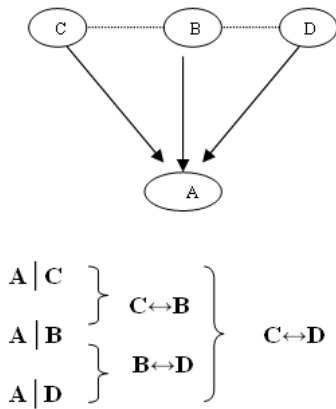


Figure (5) same prefix node

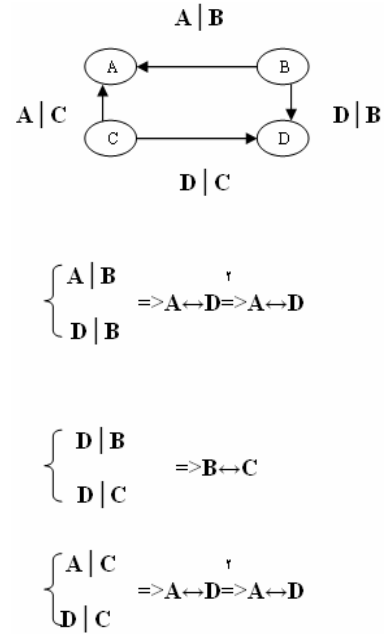
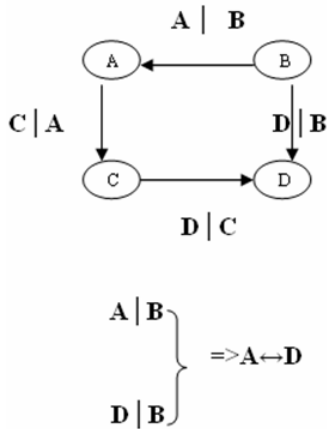


Figure (7)

Step tree: we should triangulation of the graph now and probe labeling is not participated in moral and with consideration to flowing condition connects two prefix nodes that suffixes are equal



Figure(6)

Step four: if there is chain from nodes after step 2 and step 3, we connect from initial node of the chain to second node after initial node and transact edge connection to final node of the chain.

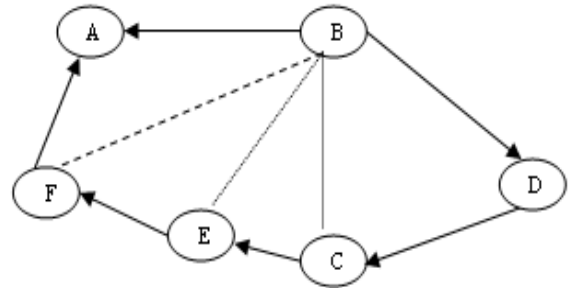


Figure (8)

Conditions:

- 1- If two prefix nodes are leave, they are not connecting between them.
- 2- If in second step node exist in prefix section and moral is transacted by it, there is not connection to this node in triangulation step
- 3- If node is leave and another node participate in triangulation previously, there is not connection between them

After first step attain one chain in graph similar to $B \rightarrow D \rightarrow C \rightarrow E$. That is overt, second node after initial node B is C then we connect them from B to C and continue this connection until node E that is final before F

Step five: if there is loop whit length more than tree whit new edges after four above steps we transact step four whit consideration following note

Note: if there are edges in produced sub graph whit equal suffix, connection preference is between that prefix

III.I ILLUSTRATED EXAMPLE

Now we obtain junction tree from Asia graph by mentioned method

1- figure (9) illustrate edge labeling

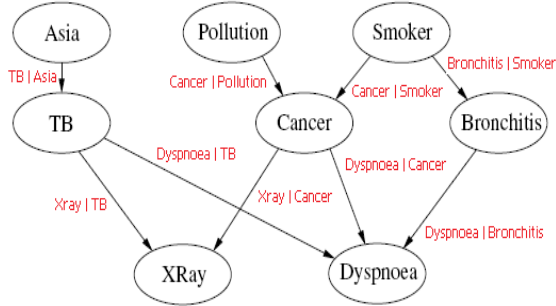


Figure (9): labeling

2- edges connect with same prefix

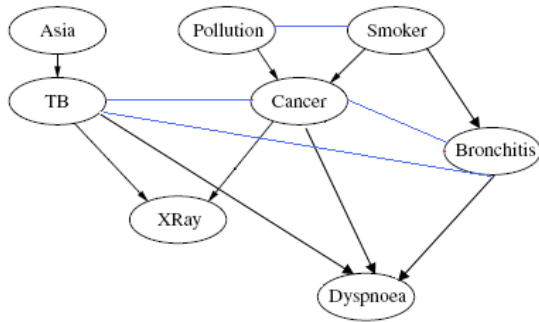


Figure (10): moralization

3- Consideration to third step condition, because of X-Ray and Dystopia nodes are leaves, and then we should not connection between them. And produced graph dose not need fourth and fifth steps.

III.II CLIQUES ARE

Asia, TB

TB, Bronchitis, Cancer, Dyspnoea

Smoker, Bronchitis, Cancer

Pollution, Smoker, Cancer

TB, Cancer, Ray

III.III JUNCTION TREE IS

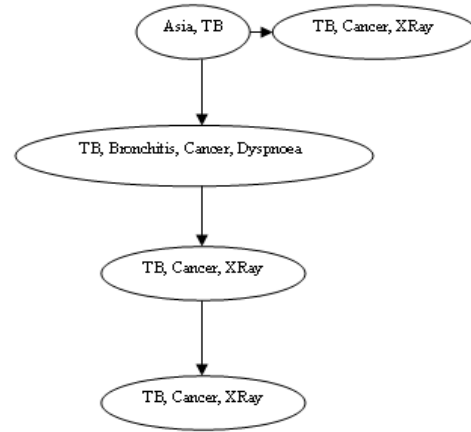


Figure (11): junction tree

IV. MVC TIME COST

Suggested algorithm has two part, moral and triangulation. Most of the consumed time for algorithm performance is, find of the nodes permutation with unconnected parents. At the continue cost of algorithm performance is investigated on three groups of graphs i.e. 1. Graph with a few number of edges 2. Graphs with numerous number of edges 3. Graph with numerous unconnected parents

1. Graph with a few number of edges:

Minimum of the consumed time for algorithm performance ($O(n^2)$) is occurring when suggested method is used on graph with a few number of edges

2. Graphs with numerous edges:

If graph includes perfect sub-graphs, cost of moral and triangulation are negligible, and we can say cost function is function of $O(n^2)$ and almost all of this cost consume for graph survey not for algorithm performance

3. Graph with numerous unconnected parents:

In this case the worst situation for suggested method occurs because that is require survey on unconnected parents permutation for each node then cost function is function of $O(n!)$ where n is number of unconnected parents.

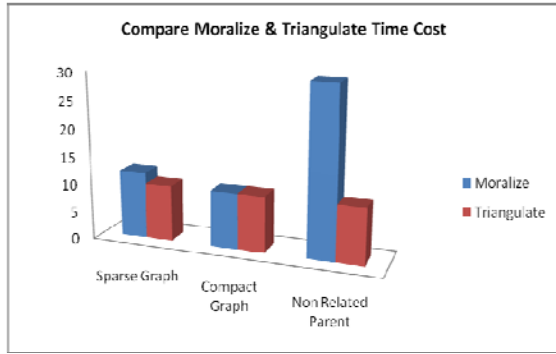


Figure (12) compare Moralize & Triangulate Tim cost

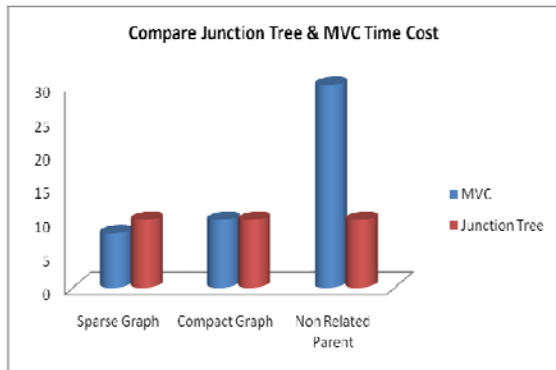


Figure (13) compare JT & MVC Tim cost

V. CONCLUSION

The purpose of the suggested method is, implementation of the steps is transacted by mind. Implemented method is visual with contracted rules and symbols without nodes ordering. Other privileges of the method are, converting graph to junction tree hasten in tree primary steps, and triangulation and relational connectivity of the graph using a pattern without severance them lead to modular-implementation. Cost of the processing for suggested method is not probed in very large graph with many edges and nodes but that seem, we can reduce cost of the performance of this method using divide and conquer algorithm and converting large graph to small sub graph.

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