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Monthly Rainfall Forecasting Using Bayesian Belief Networks

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ABSTRACT: Bayesian Belief Networks (BBNs) provide an effective graphical model for factoring joint probability distributions under uncertainty. In this paper we introduce application of BBNs in weather forecasting. We work with a database of observations (monthly rainfall) in a network of 20 stations in Khorasan provinces (Iran), measured for the years 1985-2011 on a grid of approximately 600km resolution. Firstly, we analyze the efficiency of Tabu search algorithm to structural learning of BBN. In this step, a directed acyclic graph shows dependencies among weather stations in the area of study; we also use Netica software for parametric learning of BBNs. The comparisons show usefulness of proposed method as a probabilistic rainfall forecasting model.

Keywords: Rainfall, Forecasting, Bayesian Belief Network, Tabu Algorithm, Netica

INTRODUCTION

Basically, weather factors prediction such as wind speed, rainfall and atmospher pressure is difficult and complex. Firstly, we should pay attend to weather patterns, including Great weather systems, long-term climatic models and also atmospheric circulation phenomenon. Secondly, we must supply computational requirements of algorithms and training data sets. In recent decade, Most of climatic issues are solved with Acyclic Circulation Methods or ACM. Generally, these methods are most effective at low resolution and for production of climatic patterns use descriptive models on short-term time scales. But today, the increasing availability of climate data Such as observational records, radar maps, satellite maps and approximate data, led to the development of statistical techniques and intelligent data mining in meteorology sciences. ACMs are based on objective observations but intelligent tools use inferential observations. Today, many attempts have been performed to integrate classical ACMs with regression and machine learning techniques. Basically, these hybrid methods are designed based on the discovery of relationships between stored observations in the meteorological databases. In this paper we introduce Bayesian Belief Networks or BBNs as probabilistic graphical model in rainfall forecasting process. BBN is a popular descriptive modeling technique for available data by giving an easily understandable way to see relationships between attributes of a set of records. It is employed to reason under uncertainty, with wide varying applications in the field of medicine, meteorology, finance, and military planning. Computationally, BBN provides an efficient way to represent relationships between attributes and allow reasonably fast inference of probabilities.

In the next section, the characteristics of experimental data set are briefly reviewed. The Bayesian Belief Networks will be introduced in the section 3. Section 4 describes the proposed method with full details. Finally, Section 5 summarizes the main results and conclusions.

area of study and available data

In this work we consider the Khorasan provinces including North Khorasan, South Khorasan and Razavi Khorasan in Islamic Republic Iran as the geographical area of study, and use monthly data (rainfall) from a 20 weather synoptic stations network on a grid of approximately 600km resolution (see Figure. 1) published by the Iran weather services. Synoptic stations are responsible to measurement (is done in two ways: Synop (Every three hours) and Metar (Hourly)) and the atmospheric parameters production and send them in telecommunication networks according to the rules and regulations of the World Meteorological Organization. The data set covers the period from 1985 to 2011. Before any processing on our data set, Continuous variables should be converted into discrete variables using a classification method. For rainfall variables, four different classes are considered. 1= no rainfall (rain < 6mm), 2 = Low rain (6mm<rain<30mm), 3 = moderate rainfall (30mm<rain<60mm), 4 = high rainfall (rain>60mm).

Figure 1. Indicating 20 Stations In The Khorasan Provinces.

Bayesian belief networks

A Bayesian belief network encodes the joint probability distribution of a set of v variables $\{x_1, \ldots, x_v\}$ as a directed acyclic graph (DAG) and a set of conditional probability tables (CPTs). Each node corresponds to a variable, and the CPT associated with it contains the probability of each state of the variable given every possible combination of states of its parents. The set of parents of x_i, denoted π_i, is the set of nodes with an arc to x_i in the graph. The structure of the network encodes the assertion that each node is conditionally independent of its non-descendants given its parents. Thus the probability of an arbitrary event $X = (x_1, \ldots, x_v)$ can be computed as:

$$P(x_1, \ldots, x_v) = \prod_{i=1}^{v} P(x_i | \pi_i) \qquad (1)$$

Equation 1 shows that the joint probability distribution for node X in DAG is product of the probability of each X_i of node Y given the parents of X_i .

In general, encoding the joint distribution of a set of v discrete variables requires space exponential in v. Consider the following simple example that indicates some of the properties of BBNs by DAG and with CPTs for each node when the variables are discrete (consists of three random variables).

BAYESIAN NETWORKS LEARNING METHODS

Two major categories of methods for learning Bayesian networks are parametric learning and structure learning. Parameters in a BBN are the probabilistic values in the CPTs. Basically, The aim of parameter learning is Calculation of the elements in each CPT. But the main objective of the structural learning is finding the best structure for BBNs that is compatible with existing data and is optimal in terms of complexity. This approach includes two methods of constraint based learning and score based learning. In constraint based learning the network structure is achieved using conditional independence relations between nodes. Score base learning algorithms assign a score to each possible BBN and try to maximize it with some heuristic algorithm. Although Bayesian networks can be used to predict the weather but determine of network structure is a problem NP – Hard, because there are many scenarios to connect the weather stations. To solve this problem, Greedy search algorithms (such as K2 search, hill-climbing or tabu search) are a common choice. Basically, score based learning algorithms offer scale or metric solutions. These methods evaluate all of possible relationships between nodes in general space and determine a instance with the maximum ranking.

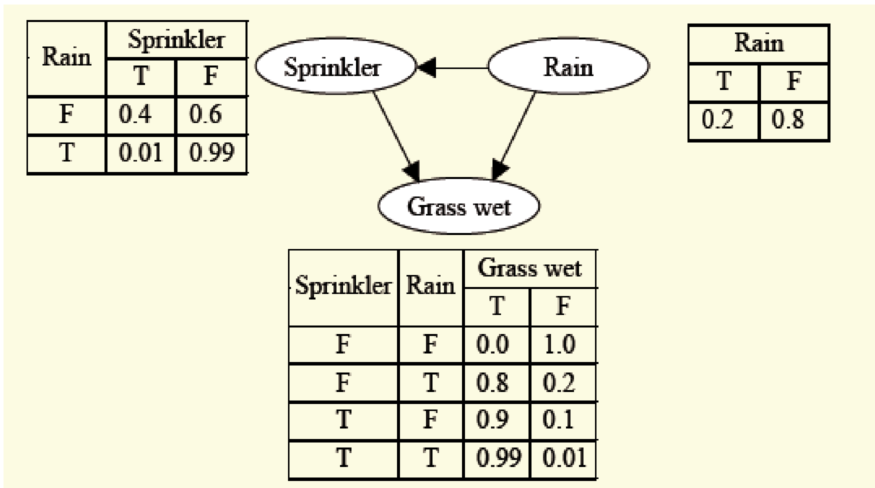

Figure 2. Inference Method of Bayesian

RESULTS AND DISCUSSION

In this paper, Tabu search algorithm applied as a structure learning method. Tabu search (See Figure. 3) is a heuristic algorithm that obtains the best structure through a local search process among all variables. Before the execution of Tabu search, the variables must to be ordered. Usually in specific applications such as weather forecasting, the experts of field determine order of nodes and amount of parents for each node. Pseudo-code of algorithm is shown as follows:

```
Tabu Search Pseudo-Code
s ← s0
sBest ← s
List ← null
while (not stoppingCondition())
   candidateList ← null
   for(sCandidate in sNeighborhood)
        if(not containsTabuElements(sCandidate, List))
              candidateList ← candidateList + sCandidate
        end
   end
   sCandidate ← LocateBestCandidate(candidateList)
   if(fitness(sCandidate) > fitness(sBest))
        sBest ← sCandidate
        tabuList ← featureDifferences(sCandidate, sBest)
        while(size(List) > maxTabuListSize)
             ExpireFeatures(List)
        end
   end
end
return(sBest)
```

Figure 3. Pseudo Code of Tabu Search Algorithm

In this section, the nodes of DAG are weather synoptic stations (See Figuer. 2) that record rainfall of each region. Each node of DAG represens a geographic area. Four states are defined for each node that was fully expressed in the second section. With Considering a maximum of 3 parents for each node, Tabu algorithm produces the network shown in figure 4.

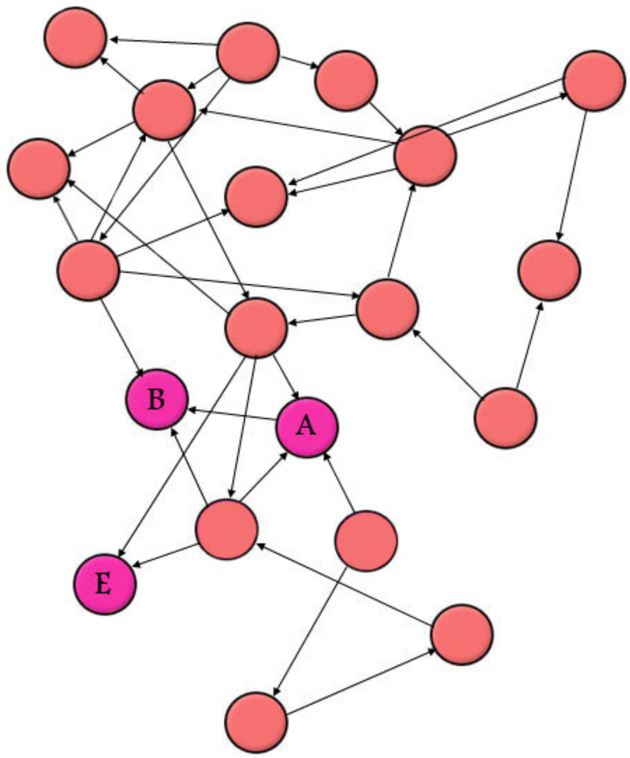

Figure 4. Proposed BBN for Connecting Weather Stations in Area of Study. The Nodes Shown With Red Color Correspond to the Following Cities: A=Gonabad, B=Bejestan, E= Ferdows

The obtained Bayesian network structure in the structural learning step is given to Netica[1] software for parametric learning. The Netica software makes CPTs based on the type of variables, number of states and obtained structure. And then using reduce the gradient technique as a parametric learning method, computes values of CPTs. The obtained Values at the nodes of final level are considered as predicted resultes. Exprimental data set for learning process cover the period from 1985 to 2010. Figure 5 shows the output of Netica software for proposed BBN.

CONCLUSION

In this paper, a Bayesian Belief Network (BBN) for rainfall forecasting is presented. Proposed BBN uses K2 algorithm (for structural learning) and uses Netica software (for parametric learning). As a case study, we considered the rainfall forecasting of the Khorasan provinces in Iran. Analysis and Comparison of the actual values with estimated values for three different stations-cities (Bejestan, Gonabad, Ferdows) in 2011 is shown in the following diagrams (see figure 6,7,8), that reflects acceptable accuracy of proposed method. We believe that the Bayesian Belief Networks can be used more often for many application of meteorology and weather forecasting. As future works, we are interested to investigate the use of other greedy based algorithms for searching the state space in structural learning.

Netica Software is a Bayesian Simulator [1]

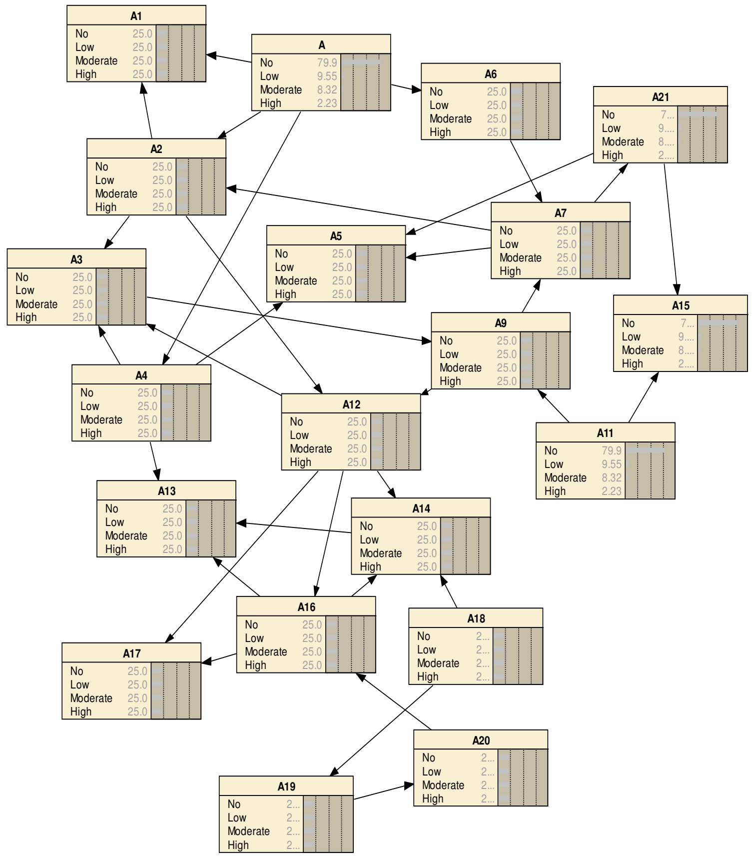

Figure 5. output of Netica software for proposed BBN.

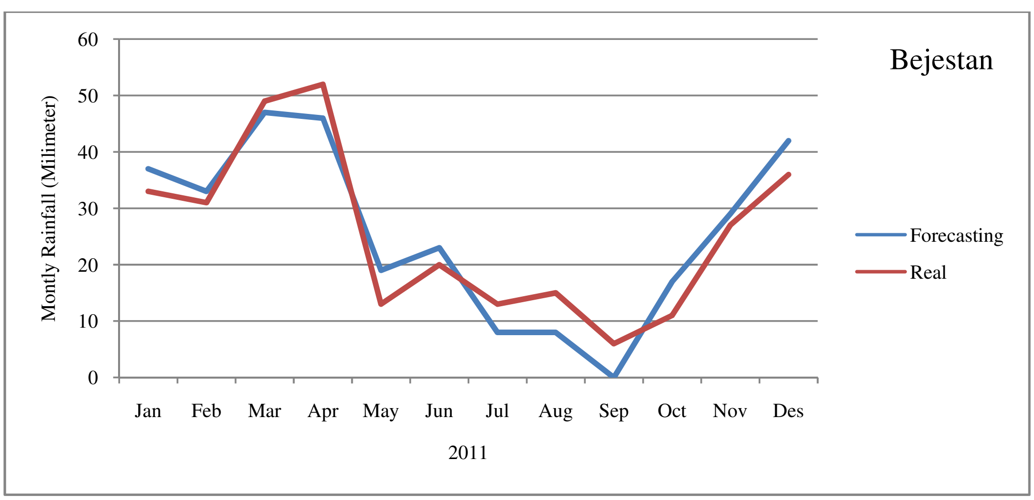

Figure 6. Comparison of predicted values with actual values – Bejestan City - 2011

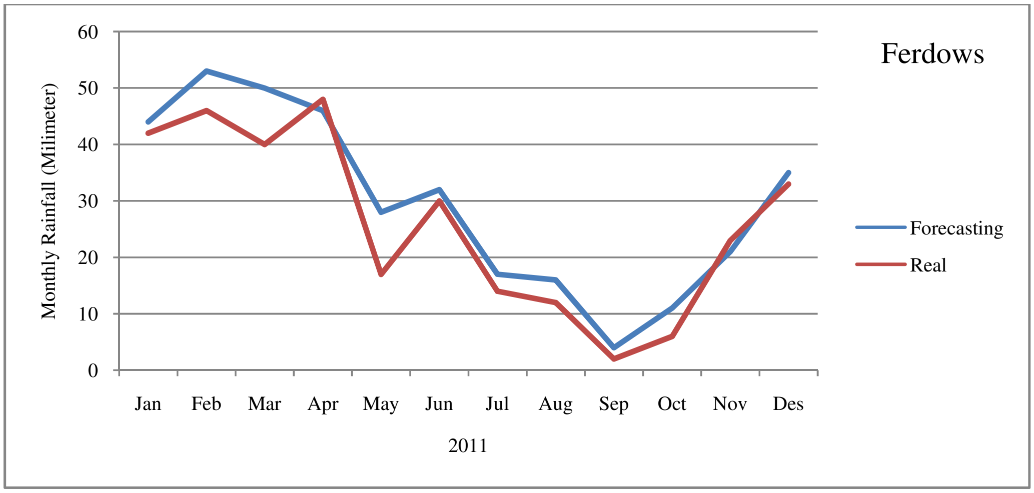

Figure 7. Comparison of predicted values with actual values – Ferdows City - 2011

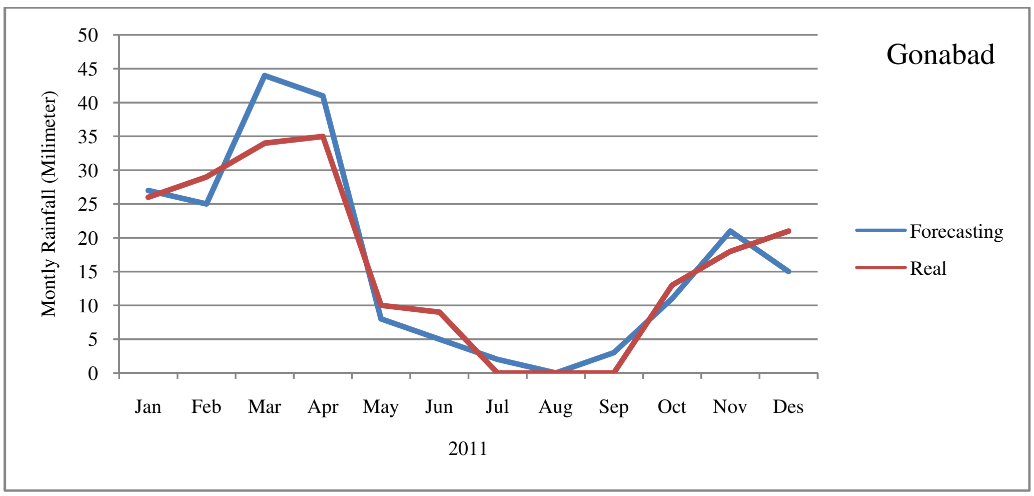

Figure 8. Comparison of predicted values with actual values – Gonabad Ciry – 2011

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