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Probabilistic Asthma Case Finding – A Pilot Study using the CHICA System

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Abstract
Identifying and prioritizing decision support messages can be a challenge. We use Bayesian Belief Networks as a strategy for modeling patients' clinical status with the goal of case finding in childhood asthma. ***Methods:*** *We compared two Belief networks, one developed by a domain expert and one mined using data from a retrospective cohort consisting of 16,187 children having wheezing. Data were used to derive a directed acyclic graph (DAG) for a Bayesian Belief network. We evaluated this mined network with a domain expert's belief network using two test datasets- (a) 1/3 of the data (5000 cases) from the 16,187 case training cohort (b) data from 2000 children collected prospectively from the clinic. We used Area under the receiver operating curves (AUC) to compare the ability of the networks to predict asthma.* ***Results:*** *For the retrospective test data (a) the expert's network had AUC=0.697, mined network = 0.708. For the prospective test data (b) the expert's network AUC = 0.637, mined network = 0.603.* ***Conclusion:*** *The mined Bayesian Belief network was able to detect asthma cases comparably to the expert's network in both test scenarios suggesting that this technique can be used for asthma case finding and dynamically prioritizing alerts in a decision support system.*

Keywords:

computer decision support, rule based systems, alerts and reminders, guidelines, pediatric, asthma, prevention, Arden Syntax, belief network, Bayesian Network

Introduction

Computer alert and reminder systems improve rates of preventive services [1-3]. However the number of services recommended by authoritative bodies exceeds what can be addressed in a typical clinic visit [4-6]. Providers are often overwhelmed with competing demands, [7] leaving little or no time to address patient specific services. Reminder systems should prioritize alerts to maximize the benefit to patients. Expected value decision making provides an attractive model for prioritization of these services [8]. In Nov. 2004 we developed and deployed a decision support system -Child Health Improvement through Computer Automation (CHICA) for pediatric preventive services and disease management in a busy Primary Care Clinic. [9-13]. CHICA has a static, global prioritization scheme that limits the flexibility of the system - The Arden Syntax Medical Logic Modules (MLMs) [14] that encode the CHICA knowledge are prioritized using a global priority scheme to address the most relevant questions and reminders. [8, 11, 15].

We are experimenting with Bayesian Belief networks (BN) as a strategy for modeling a patient's clinical status with the idea of calculating the expected value of making alternative recommendations to physicians, tailoring prioritization to the patient.[8] BNs are appealing because they can be derived from clinical experts or empirically from data. In this paper we compare BNs derived in two ways: 1) using a clinical expert to define the nodes and arcs in the BN and training the resulting BN using data or 2) using data mining techniques to derive the BN from data. We compare these approaches in the domain of childhood asthma.

Methods

CHICA Overview – CHICA provides decision support by collecting data from families before a clinic visit, using a prescreener form (PSF) and reminders to physicians on a Provider Worksheet (PWS). CHICA now has records of over 11,000 patients, with an average of 3 visits per patient. The question in Figure 1 is asked on the PSF to find children who may have asthma. If answered "yes," the physician is asked to consider the diagnosis of asthma. Such a question appears on the PSF because it is assigned a high global priority among the questions that could be asked. Potentially, for a given patient when other questions are relevant that have higher global priority the asthma question may not appear on the questionnaire. It has the same global priority regardless of data in the medical record that may indicate higher or lower risk of asthma. Therefore, a patient specific prioritization would be very desirable which takes into account the evidence and the expected value of decision making.

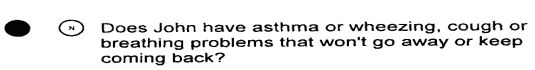

Figure 1 – Asthma question on Prescreen Form (PSF)

Model – Belief Networks (BN) and Influence Diagrams (ID) have been shown to represent domain knowledge with natural perception of causal influences [16]. They have been used widely in medical diagnoses because of their concise representation and ability for belief propagation [17]. We used Netica software [18] to construct a BN designed by our expert and the WinMine toolkit [19] software from Microsoft Corporation for mining a directed acyclic graph (DAG) directly from data. Netica was used for parameter learning from data in both BN models.

Table 1 – Data Variables for Model

Variable	Values
Race	White, Black, Hispanic, Other, Unknown
Sex	Male, Female
Eczema	True, False
Wheeze	ICD9 or clinic billing diagnosis before age 2 (True, False)
Asthma	ICD9 (493.*) or any clinic billing diagnosis after age 5 or at least 3 drugs from a specified list within 12 months after age 5 (True, False)
X-ray	Chest x-ray before age 2 (True, False)
Drug	Drugs from a specified list before (True, False)
Wz_hosp	Inpatient admission with hospital ICD9 as wheezing (True, False)
Wz_er	Any ER visit with billing ICD9 as wheezing (True, False)
Ins_cat	Insurance category - first available insurance in the same year of the first wheezing diagnosis (True, False)

Data – We compared the performance of the BNs on two datasets – (1) data from 16,187 cases from Regenstrief Medical Record Systems (RMRS) previously identified for a large retrospective cohort study of asthma predictors and split randomly into 2/3 of cases for a training set and 1/3 for a test set. (2) Clinical observations collected prospectively from children aged 5 and above collected by CHICA from the RMRS database for every patient visit. Data were filtered and preprocessed to extract the data variables listed in Table 1. At the time of the writing, the CHICA system had prospective data for about 2000 cases.

Expert's Design of BN with training using Netica: Using the predictor data variables in Table 1 as nodes and the domain knowledge for joining them with arcs, the domain expert (SMD) created a BN. This BN was trained with the training set and compiled using Netica. The BN showed prior probabilities of each node and an asthma prior probability of 18.6%.

BN Derived using Data Mining Techniques: The training set from RMRS data was used to derive the directed acyclic graph (DAG) for this approach. The software from WinMine toolkit was used to preprocess the data and to instruct the learning algorithm to derive the DAG. Using the structure from the data-mined DAG, we created the BN in Netica software. This BN was also trained and compiled using the same training set as the expert BN to get the prior probabilities. The asthma prior probability in this model was 13.9%.

Testing the Two Models - The two BN models were evaluated, first, using 1/3 of the retrospective data from our test set removed before data mining or network training; and, second, using the data set derived from CHICA database. Asthma, our outcome of interest was treated as an "unobserved node" in Netica. We derived the sensitivity, specificity, positive predictive value and negative predictive value. We compared BNs using Receiver Operating Characteristics (ROC) curves [20]. The area under the curve was used as a measure of overall test performance. The ROC curve was obtained by plotting pairs of true positive rate (sensitivity) and false positive rate (1-specificity).

Results

We had 5188 cases in our RMRS test set and 2000 cases in the CHICA test set. Both the Expert and the Mined BN were tested using these sets, the results of which are shown below.

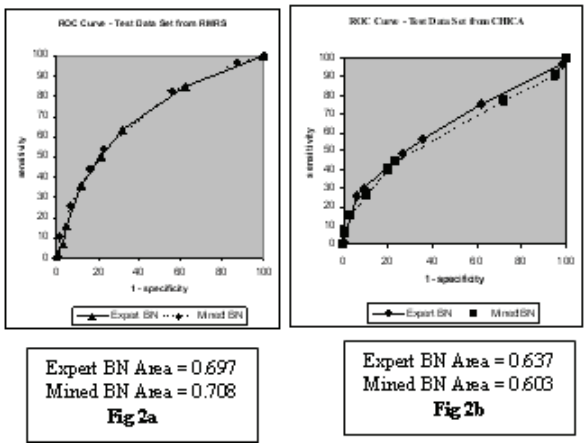

Figure 2a – ROC curves using test data from RMRS
Figure 2b – ROC curves using test data from CHICA

Discussion

The results of area under the ROC curve for both networks using the same test set are comparable. Both the expert BN and the mined BN performed better with the test data set from RMRS (for large retrospective study) when compared with the CHICA test data set. We attribute degraded performance when testing with CHICA test data set to less stringent inclusion criteria in the CHICA test set. For example, any chest x-ray observation will satisfy the inclusion criteria for CHICA data, where as X-ray finding before age 2 will satisfy the inclusion criteria for the RMRS test set.

Conclusion

Similar performance of each BN in each test scenario goes to suggest that the mined BN has a predictive value similar to an expert and hence can be used for case finding. We acknowledge that the performance of a BN would vary on the quality of data and the predictor variables used to model it however, we believe there is a value in the data mined approach. We can attach utility nodes for each of the desired outcomes in our model to drive the prioritization scores of prompts in the CHICA system using the expected values of case finding decision.

Our future work will involve developing a framework to mine the DAGs from data with in our system for many more preventive services such as lead screening and evaluating TB risk and utilizing the mined BNs with CHICA programmatically.

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