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Bayesian Learning for User Modeling

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Abstract. User modeling has been a focal point of numerous studies in the web domain. The World Wide Web serves as a widely utilized platform for delivering adaptive user interfaces. Various techniques have been explored to capture user preferences, with Bayesian Networks (BNs) emerging as an effective means of constructing probabilistic models. This paper introduces an adaptive user interface, specifically designed for web applications, focusing on a social network context. The construction of our Bayesian user model is detailed, involving a comparison of learning algorithms to train the Bayesian structure. Evidence in a Bayesian network serves as a pivotal point for inference methods, originating from information derived through variable observations. Subsequently, inference algorithms are employed to enable the user model to predict user preferences. The effectiveness of the Bayesian Network in predicting user preferences is affirmed by evaluating inferred results for essential variables across various scenarios. Ultimately, the adaptive user interface is validated as more user-friendly compared to a fixed user interface.

Keywords: Learning model, user modeling, Bayesian model.

1 Introduction

Numerous research endeavors are dedicated to exploring the ergonomics and information organization within an interface, along with adapting this information to align with user preferences. Central to issues of presentation and adaptive interfaces are the user's preferences and experience. Users possess diverse interests, knowledge, learning styles, and preferences, leading to a significant focus on designing interfaces capable of understanding user characteristics.

A crucial area of research involves determining how interfaces can be crafted to comprehend user attributes. To deliver personalized information, it becomes imperative to observe and generalize from user behavior, enabling predictions based on these observations. This collection of information about the user is commonly referred to as a user model [15, 33].

The objective of a user model may encompass predicting user behavior to acquire user knowledge or creating a comprehensive database of user profiles. To address these requirements, contemporary research on user modeling is shifting towards more comprehensive models that incorporate uncertain knowledge. Traditional models are deemed inadequate in capturing the intricacies of the human-machine interface.

Consequently, Bayesian Networks are gaining prominence as a means to handle uncertainty in user modeling [14, 40]. This trend is attributed to their lucid semantics and the opportunities they present for machine learning [42, 16]. In this study, the Bayesian networks approach was implemented within a web interface to infer user preferences. Our approach leveraged learning and inference algorithms, with the obtained results showcasing the effectiveness of Bayesian networks in user modeling.

Evidence forms the foundation for inference methods. In certain studies [39, 1, 6, 5, 13, 23, 28, 55], the term “soft evidence” is employed to denote probabilistic evidence [21]. However, in another study [7, 11], the use of the term “soft evidence” was abandoned. This literature review, coupled with an examination of Bayesian network software, reveals the inconsistent usage of the term “soft evidence,” leading to confusion.

Notably, Valtorta and co-authors [22, 41, 30, 29, 44, 43, 52, 37, 38, 4], along with [27, 51], refer to probabilistic evidence as “soft evidence”. The proposed methodology underwent evaluation, involving ten subjects performing tasks using both a fixed user interface and the proposed adaptive user interface. The remainder of this paper is structured as follows: Section 2 introduces the related work.

Bayesian Rules was defined in Section 2. Section 3 is dedicated to defining the construction of the Bayesian networks model, utilizing learning algorithms. Section 4 and 5 focuses on the update of a probabilistic evidence distribution within our Bayesian model. A comprehensive discussion of the experimental results is presented in Section 6 covering the prediction of user needs of our users interface. Finally, Section 7 concludes the paper.

2 Bayesian Networks for User Modeling

The exploration of user modeling has been a focal point in numerous studies, reflecting its intricate nature that spans various domains of information and human sciences, including psychology, education, artificial intelligence, and human-machine interface. This multifaceted field has yielded a mix of successes and failures. The surge in interest in the 1980s, particularly within the Intelligent Tutoring Systems (ITS) domain, marked a significant growth in user modeling research [3, 45].

Advancements in existing user models have aimed to enhance personalization capabilities by considering diverse user characteristics. A substantial body of research has concentrated on delivering personalized services across a range of web applications, such as e-commerce [53], books[36], films [17] and online research papers [34]. Notably, Jie and al [31] emphasized the integration of a hybrid fuzzy semantic recommendation approach into an intelligent recommendation system, enabling the personalized recommendation of relevant business partners to individual users.

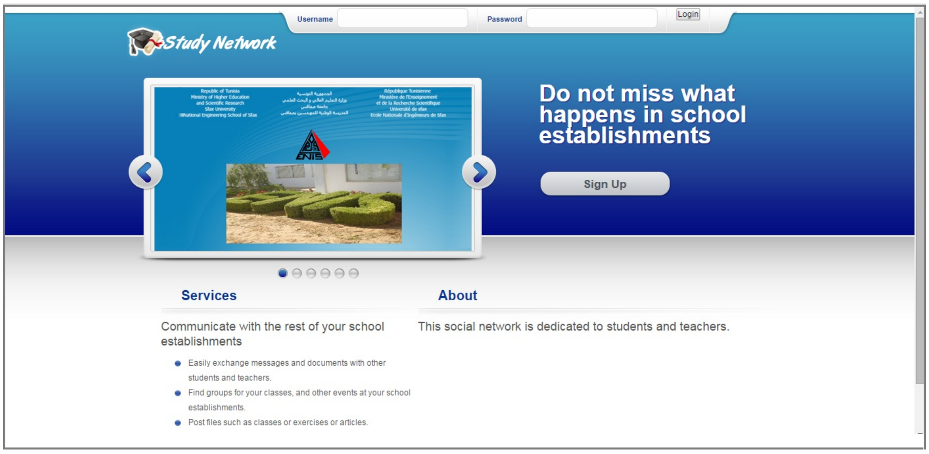

Fig. 1. The web interface.

Probabilistic models have been instrumental in addressing the uncertainty associated with modeling user needs and characteristics, making them well-suited for the challenges inherent in user modeling [52, 2]. In particular, Bayesian user modeling has emerged as an effective method for understanding a user's objectives [3, 9, 10]. They have been applied in various systems to anticipate user preferences and objectives [19, 48, 50]. Horvitz and al [19] employed Bayesian networks to deduce users' objectives and needs based on their interactions and conditional probability models.

In Horvitz's study, a Bayesian model was initially constructed by psychologists through observations of users in different situations. In another research endeavor [20], Horvitz and al introduced a system designed to forecast a user's intention within an uncertain environment. Various approaches have been explored in the domain of student modeling [3, 8]. Notably, Bayesian networks have garnered significant attention from theorists due to their robust mathematical foundations and their natural representation of uncertainty through probability models [8].

Andes [9], a tutorial employed in e-learning for addressing problems related to Newtonian mechanics, assesses the student's level of knowledge. Millàn and al [35] have equipped education practitioners with the necessary background to comprehend Bayesian networks and applied them to construct student models. Nguyen and Do [40] introduced an approach that combines Bayesian networks and the overlay model, enabling the inference of a user's knowledge from evidence gathered during the learning process. [32] presented various systems employing Bayesian networks to choose the next teaching activity for students based on their knowledge level.

Moreover, Bayesian networks have proven to be a straightforward and effective method for managing uncertainty in context awareness [12]. Korpipaa and al [26] characterized a user's context using the naive Bayes classifier. Hong and al [18] suggested a context-sensitive messenger that autonomously deduces the user's context. In a recent study [49], In-Jee Song and al proposed a model for the ubiquitous family environment to implement a context-adaptive user interface. They employed a Bayesian network to allocate necessary devices in each location.

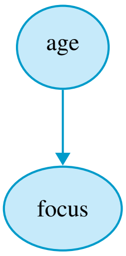

Fig. 2. Representation of two nodes.

The knowledge models outlined earlier may not attribute reasons for failures in the knowledge domain. Conversely, preference models solely furnish information about users' preferences without accounting for the evolution of these preferences. This paper introduces an effective approach that tackles the challenging task of detecting user preferences using probabilistic models. Specifically, we developed a Bayesian user model capable of automatically discerning users' preferences.

Our approach considers the evolution of preferences, resulting in a more accurate alignment between a user's preferences and the provided information. Despite the constrained probability of interaction through a web application due to service quality, we successfully gathered user preferences from our adaptive user interface (Figure 1). Subsequently, we created specific models to recommend web interfaces with the most suitable content and format for each user.

3 Bayesian Networks

Bayesian networks [25] are graphical models with both qualitative and quantitative components. The qualitative aspect involves the network's structure, represented by a directed acyclic graph where nodes correspond to variables, and arcs depict influences between these variables. On the quantitative side, conditional probability tables define the network settings. These networks serve as potent tools, leveraging algorithms for both inference and associated learning.

Inference relies on Bayes' theorem to disseminate knowledge within the network, while learning encompasses the determination of both the network structure and parameters. These parameters can be derived from either complete or incomplete data. To be more precise, a Bayesian Network constitutes a collection comprising a directed acyclic graph and n random variables $X = X_1, X_2, .., X_n$, establishing a bijection between the set of graph vertices and the set of random variables, ensuring that:

$$P(X_1, X_2, \cdots, X_n) = \prod_{i=1}^{n} P(X_i \mid \mathrm{pa}(X_i)), \tag{1}$$

where, $pa(X_i)$ denotes the collection of parents of variable X_i within the graph.

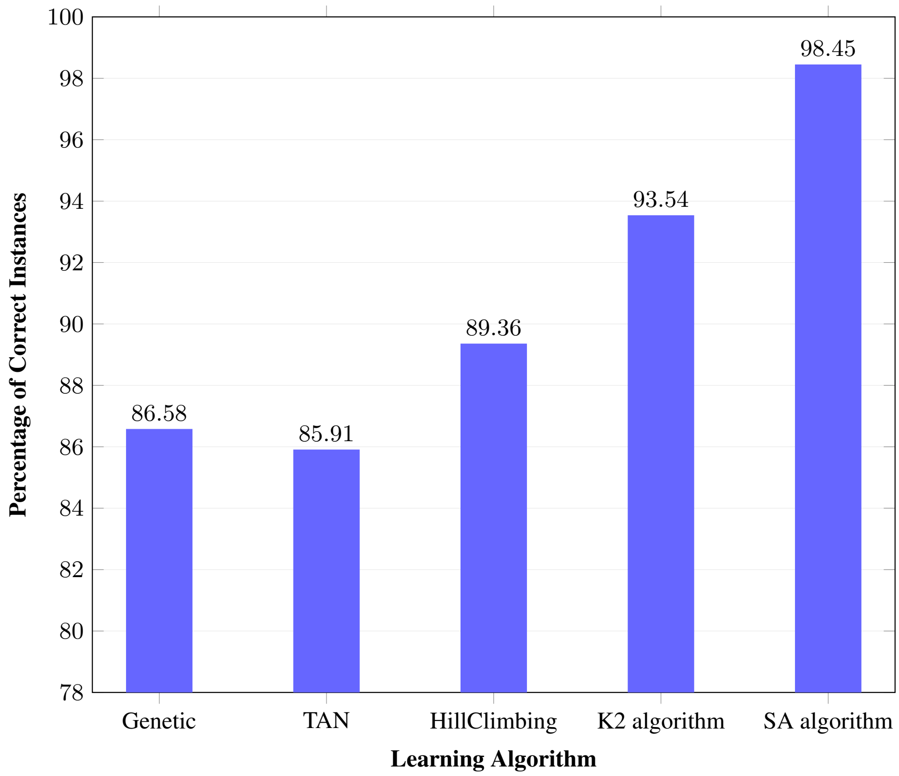

Fig. 3. A comparison between the learning algorithms.

4 Learning Structure in Bayesian Model

To capture a user's experience in an initial model, we utilized data from our web interface, which functions as a social study network. The user's interactions, stemming from their experiences, were employed to update the parameter set of their model. Depending on the ongoing observations within the Bayesian model, learning and inference algorithms were applied to enhance and refine the Bayesian user model.

Our goal was to identify the pivotal variables in a user model for creating a personalized model for a web interface. To achieve this, instead of treating items for the user as isolated variables, we endeavored to consolidate and represent them in a Bayesian Network model. Implementing rules were then incorporated to articulate these aspects. User preferences, in this context, may encompass: preferences for the presentation of information, selection of services, Determination of which advertisements to display, specification of graphic components to be omitted.

Presuming that our adaptive interface can deduce user preferences, gleaned from observations such as age, interests, gender, and profession, the concept revolves around assigning a profile to each user. We initiate this process by establishing certain nodes of random variables that serve as representations for these profiles.

Algorithm 1 A pseudocode for the simulated annealing algorithm used to create the structure of a Bayesian model.

procedure SIMULATED ANNEALING()
    D. ▷ A DataSet.
    B_{current}. ▷ Create initial network.
    T_0, T_{final}: integer. ▷ Set the initial temperature.
    N. ▷ Make N attempts for the given temperature T.
    $t = 1$.
    repeat
        repeat
            Create new network B_{new} from B_{current}.
            Evaluate $E(B_{\text{current}}, D)$, $E(B_{\text{New}}, D)$.
            if $E(B_{\text{New}}, D) \leq E(B_{\text{current}}, D)$ **then**
                $B_{\text{current}} = B_{\text{New}}$.
            else
                $X = \dfrac{E(B_{\text{New}}, D) - E(B_{\text{current}}, D)}{T(t)}$.
                Select a number, denoted as p, uniformly at random from the interval [0, 1].
                if $(e^{-x} > p)$ **then**
                    $B_{\text{current}} = B_{\text{New}}$.
                end if
            end if
            $N = N - 1$.
        until $N = 0$.
        $T_{t+1} = \tau(T_t)$.
        $t = t + 1$.
    until $T_{t+1} \geq T_{\text{final}}$.
    $B_{\text{final}} = B_{\text{current}}$. ▷ Final Network.
end procedure

As an illustration, we depict the node “focus” with a marginal probability vector that signifies the likelihood of the user having a specific center of interest: As an illustration, we depict the node “age” with a marginal probability vector that signifies the age of the user:

$$P(\text{age} = a_1),\ \cdots,\ P(\text{age} = a_n) \tag{2}$$

Subsequently, we delineate the array of potential focus $f_1; ...; f_k$. This can be represented by introducing another random variable named “focus”. In this case, we obtain a matrix of conditional probabilities for all possible scenarios:

$$\begin{gathered} P(\text{focus} = f_1|\text{age} = a_1);\ \cdots;\ P(\text{focus} = f_1|\text{age} = a_n) \\ \vdots \\ P(\text{focus} = f_k|\text{age} = a_1);\ \cdots;\ P(\text{focus} = f_k|\text{age} = a_n) \end{gathered} \tag{3}$$

The decision regarding which focus to present is contingent on the user’s age, prompting us to establish a causal relationship between the two nodes (see Figure 2). Initially, the Bayesian network was constructed based on expert knowledge, even in the absence of training data.

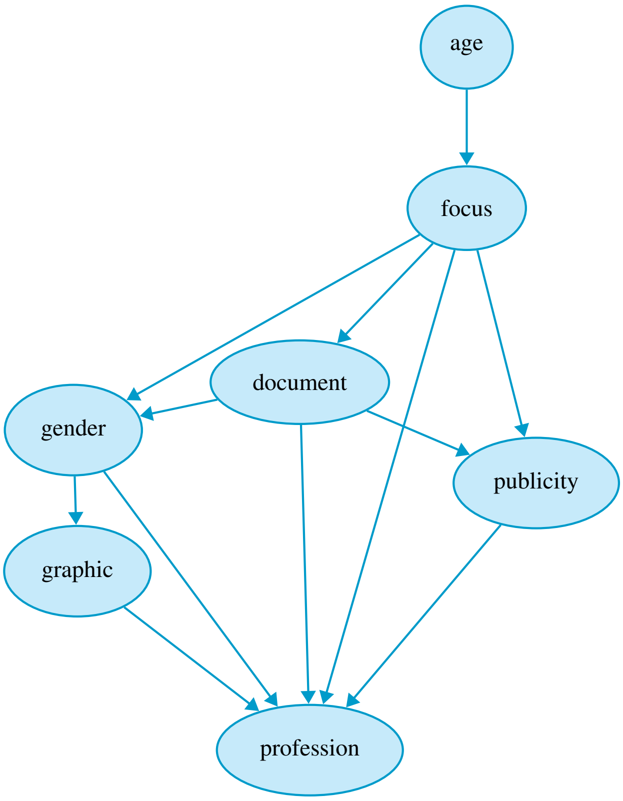

Fig. 4. The structure of the Bayesian network.

Once a substantial amount of user data became available, the Bayesian network was trainable. The typical process of training Bayesian networks from data involves two fundamental aspects: training the structure and training the parameter set. The structural training entails searching for the network structure that most closely aligns with the provided data. To identify the optimal structure, learning algorithms leveraging score metrics can be employed. Our database comprised 256 users, indicating its relatively modest size. Consequently, for the testing phase, we opted for the cross-validation process.

This method was employed to assess the predictive efficacy of Bayesian models using a single database. In the cross-validation test, we conducted a comparative analysis of various learning algorithms including simulated annealing algorithm (SA), the K2 algorithm, Tree Augmented Naive Bayes algorithm (TAN), genetic algorithm and Hill Climbing algorithm.

The structure of our Bayesian user model was developed using Weka [54]. The results, detailed in 3, revealed that the predictive performance of the network is contingent on the algorithm employed. Notably, the simulated annealing algorithm exhibited a high accuracy of approximately 98%, while the K2 algorithm performed slightly lower at about 94% correct values.

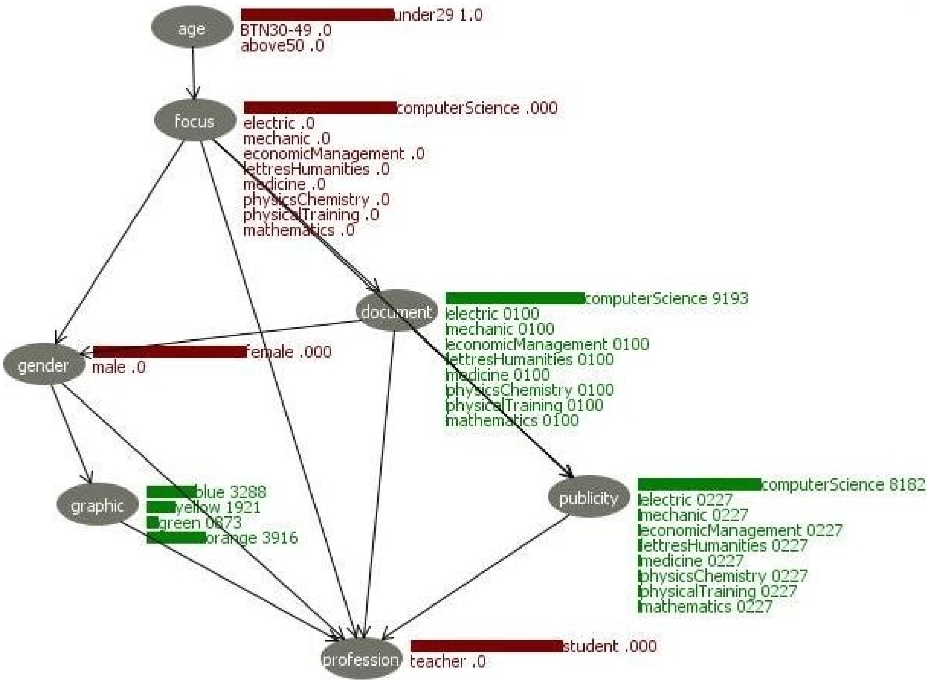

Fig. 5. Bayesian model.

The Hill Climbing algorithm yielded around 89% accuracy, and both the genetic and TAN algorithms showed an accuracy of approximately 86%. Therefore, we employed the simulated annealing algorithm to train the structure of our model. Simulated annealing (SA) is a global optimization technique crucial for enabling the current solution to transition to less optimal states based on a probability function.

This feature prevents the algorithm from being confined to a local optimum. Algorithm 1 outlines the simulated annealing algorithm, which draws analogies between the network (E represented in the structure as the function to be minimized), the configuration of the network structure (B, where E is a function of B), and the temperature (T, an annealing schedule controlling the convergence of the algorithm to a final configuration).

Figure 4 illustrates the structure of the Bayesian network. The selection of variables constituting the Bayesian network is based on what we found relevant for the user. These variables encapsulate various states, such as “the member’s profession” (profession), “the gender of the member” (gender), “the preferences of a member regarding the displayed documents” (documents), and “the preferences of a member regarding the displayed graphic components” (graphic), among others. The data collected earlier and the established structure of the Bayesian model are employed in the inference algorithm.

5 Bayesian Model

In the Bayesian framework, inference involves calculating the probability distribution for all variables based on the given evidence (or set of observations).

5.1 The Initial Bayesian Model

After constructing the Bayesian network, it becomes a valuable tool for reasoning about the model's state. Bayesian inference entails calculating the probability distribution across all variables, taking into account the set of observed variables. In the initial phases of our research, we conducted Bayesian inference utilizing the Weka software [54]. Initially, all observed variables in our Bayesian model, including "age," "gender," "focus," and "profession," were treated as hard evidence. Figure 5 depicts the results of Bayesian inference [46, 47].

The original Bayesian network is utilized to deduce user preferences, encompassing choices related to graphical components, advertising, and the selection of displayed documents. After establishing the values for all observed variables, Bayesian inference is employed to forecast user preferences in areas such as advertising and graphics. Variables with higher probabilities are anticipated to exert a more substantial influence on shaping the user interface compared to those with lower probabilities.

5.2 Bayesian Model Using Junction Tree Algorithm

The Junction Tree Algorithm is applicable to networks of different types, irrespective of whether they exhibit tree structures. Its core procedure includes transforming the graph into a junction tree. Following this, it initializes potentials, engages in message passing to propagate messages, and calculates posterior probabilities. The algorithm operates as outlined by [24]:

– Graph Transformation: The directed acyclic graph (DAG) of a belief network undergoes transformation into a join tree structure

– Global Propagation: A sequence of ordered local manipulations, referred to as message passes, is executed on the join tree potentials. These message passes restructure the join tree potentials to guarantee local consistency, yielding a consistent join tree.

– Marginalization: Utilizing the consistent join tree, the probability distribution for each variable is computed.

In conventional Bayesian networks, observations usually entail a singular state of the observed node. In simpler terms, when there is evidence in a node X, only one of its states is observed, assigned the value 1, while the remaining states are assigned the value 0. Nevertheless, this method falls short in representing scenarios where observations are uncertain. This uncertainty implies that the observation simultaneously relates to multiple states, each with well-defined percentages.

In our study, we utilize the Junction Tree algorithm to propagate evidence due to its precision and efficiency in handling a restricted number of nodes. Ultimately, the outcomes of this algorithm become apparent after undergoing the following steps: Moralization, Triangulation, and Marginalization.

6 Evidence for Bayesian Inference Model

Three types of non-deterministic evidence are identified. Likelihood evidence is defined by its imprecision, reflecting uncertainty and quantified through a likelihood ratio. It is then propagated using Pearl's method of virtual evidence. Probabilistic evidence places constraints on the state of specific variables following propagation in the Bayesian network (BN). Bayesian Networks offer a means to analyze the status of models upon their creation.

Inference algorithms play a crucial role in calculating posterior probability distributions for all variables. In our research, we utilized the Junction Tree algorithm [24], a versatile algorithmic framework that elucidates fundamental concepts in inference. Variables with higher probabilities are presumed to play a more significant role in generating an adaptive user interface compared to those with lower probabilities. Hence, the Bayesian user interface can be tailored based on these probabilities.

Consequently, the Bayesian user model is prepared for predicting user preferences, influencing the display of documents and advertisements based on heightened user preferences. Our web interface is adaptive, providing recommendations to guide users in selecting their preferences. For new members who haven't specified their preferences, the Bayesian user model is employed to establish default values

7 Conclusion

In this paper, we introduced our research and proposed an adaptive user interface utilizing the Bayesian network approach. Initially, we conducted a comparison of learning algorithms to train the Bayesian network structure and implemented Bayesian inference into our web interface. Our approach was further validated through an evaluation of the web interface.

Compared to the fixed user interface, our findings indicated that the proposed interface garnered higher user satisfaction than the fixed one. To enhance the model, we incorporated a more robust training approach by utilizing a log of users' activities to specify the Bayesian network. To further improve system evaluation, we plan to incorporate qualitative measures regarding user experience and satisfaction derived from verbal user feedback.

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