# Designing a Ubiquitous Decision Support Engine for Context Prediction: General Bayesian Network Approach

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***Abstract***

*Ubiquitous decision support systems have remained an imaginary and almost useless system for decades since its first introduction in early 1990's. However, it came out of lab into real world as ubiquitous computing became tangible in the form of mobile devices, pervasive mechanisms, and various mobile Internet technologies. Typically, context-aware systems had received acclaims from both researchers and practitioners as an alternative to making ubiquitous systems touch-and-feel electronics to the users. Nevertheless, context-aware systems lack predictive power which is essential for any ubiquitous systems to suggest timely and effective information for users. Poorly predicted information is likely to degrade the ubiquitous systems seriously. In this respect, context prediction mechanism emerges as a reliable vehicle for making ubiquitous systems more sustainable decision support tool for users. Despite the potentials of context prediction mechanism, few reliable mechanisms exist in literature which shows robust performance against changes in user's contexts. For this reason, we propose a new type of ubiquitous decision support system that is powered by General Bayesian Network (GBN) capable of organizing causal relationships among a set of related variables. Drawing on the GBN's strengths, this study proposes U-BASE (Ubiquitous Bayesian network-Assisted Support Engine) to suggest more reliable solution for the context prediction tasks. Performance of U-BASE was tested against real contextual data set, garnering very robust results. The practical implications are fully discussed with some future research issues.*

***Keywords:*** *Context Prediction, General Bayesian Network, U-BASE*

## 1. Introduction

As ubiquitous computing steps into our life as reality, the related context-awareness concept which has been discussed only in an experimental level in labs has started to receive attention in many application domains [1]. Users working in the ubiquitous computing environment are always in need of timely decision support with regard to their domain-related tasks using, for example, the mobile devices they bring with themselves. The contexts that users face tend to change and decision support systems must adapt intelligently to the changes in users' contexts. For this reason, context-aware systems are usually engaged in more efficient interaction with users, enabling ubiquitous computing devices to be aware of changes in the environment and to intelligently adapt themselves to provide more meaningful and timely decision support to the decision makers [2]. Context-aware systems tend to malfunction, however, when the current context changes go beyond its ability to recognize the contextual characteristics. That is why context-aware systems must improve to the extent of predicting the future context and adapting itself to the changes in context in the future. Accordingly, we need to consider the task of context prediction in order to proactively offer high-quality services to users in ubiquitous computing environments. In other words, enabling ubiquitous decision support systems to be embedded with such proactiveness requires information about users' future needs, which must be inferred from users' future contexts. Predicting users' future context, which is called context prediction (CP), requires highly sophisticated inference methods capable of analyzing the given contextual data and finding meaningful patterns from them to predict future changes in user contexts.

Existing researches on CP have utilized Bayesian networks [3, 4], Markov models [5, 6], and neural networks [4] to predict future context; many concentrate on the problem of location prediction [4, 7, 8, 9] and action prediction [6, 10, 11, 12]. When future locations that users are likely to visit soon (e.g., one hour later) are predicted accurately, a ubiquitous decision support system (UDSS) [13] can provide timely and adequate decision support. Likewise, the UDSS will be accepted very favorably when the types of actions that decision makers take in the future are accurately forecasted. Existing literature has introduced various approaches to CP methods. For example, Mozer et al. [14] use neural networks to predict how long a user will stay home and whether a particular zone will become occupied. Kaowthumrong et al. [15] use Markovian models to predict which remote-control interfaces a user will likely use next. Patterson et al. [16] use a dynamic Bayesian network to predict likely travel destinations on a city map. Laasonen et al. [9] define a hierarchy of locations and describe various methods that use statistics to predict a user's future locations. Petzold et al. [17] use global and local state predictors to predict the next room that a user will likely enter in an office environment. A more extensive methodological comparison was conducted by Mayrhofer [18], who compared the performances of different methods such as neural networks, Markov models, autoregressive moving average model (ARMA) forecasting, and support vector regression.

Each CP method has a unique advantage over the others, but all the methods have many drawbacks. The primary disadvantage is that most CP methods cannot establish causal relationships among the target variable and related explanatory variables. If such a causal relationship is extracted from the target contextual data, it can be used to conduct a wide variety of what-if analyses. What-if analysis allows decision makers to see the possible results by varying the input conditions. In this way, the causal relationships obtained from the training dataset can be used as an inference engine that can perform various what-if analyses given the scenarios under consideration.

To take advantage of the what-if analysis capability, we propose using a General Bayesian Network (GBN) in CP so that the causal relationships are induced from the training dataset, and future contexts can be inferred via what-if analyses for various scenarios. To illustrate the usefulness of the GBN-powered CP, a system called Ubiquitous Bayesian network-Assisted Support Engine (U-BASE) is proposed; in the system, a GBN structure is used as a knowledge base to store a number of causal relationships among interested variables, and an inference engine is based on the what-if functions assisted by the GBN inference mechanism.

Hereafter, we explain the U-BASE design and usage scenarios in Section 2. A prediction performance evaluation of the GBN-powered CP is conducted using real contextual dataset in Section 3. Section 4 discusses the implications of the GBN-powered CP, and Section 5 delivers concluding remarks and suggestions for future research issues.

## 2. U-BASE

The U-BASE system collects user transaction data to construct BN models and predicts a user's future contexts using the GBN models to provide context-sensitive recommendations to users. Fig. 1 shows the U-BASE system architecture.

### 2.1. Design

The U-BASE system consists of five components (a data collection component, a BN model learning component, a GBN model registration component, a context prediction component, and a recommendation component), a GBN model base, and a set of databases that store both context and the factual data (Fig. 1). The key component of the U-BASE system is the context prediction (CP) component. The CP component consists of (1) a context data handler, (2) a GBN model selector, and (3) a GBN inference engine. The context data handler passes user context data to the GBN model selector, and the GBN model selector selects an appropriate GBN model from the GBN model base on the basis of user context data. The GBN inference engine then performs context prediction on the basis of the selected GBN model and the context data and passes the predicted results back to the context data handler. The context data handler then passes the results to the recommendation component.

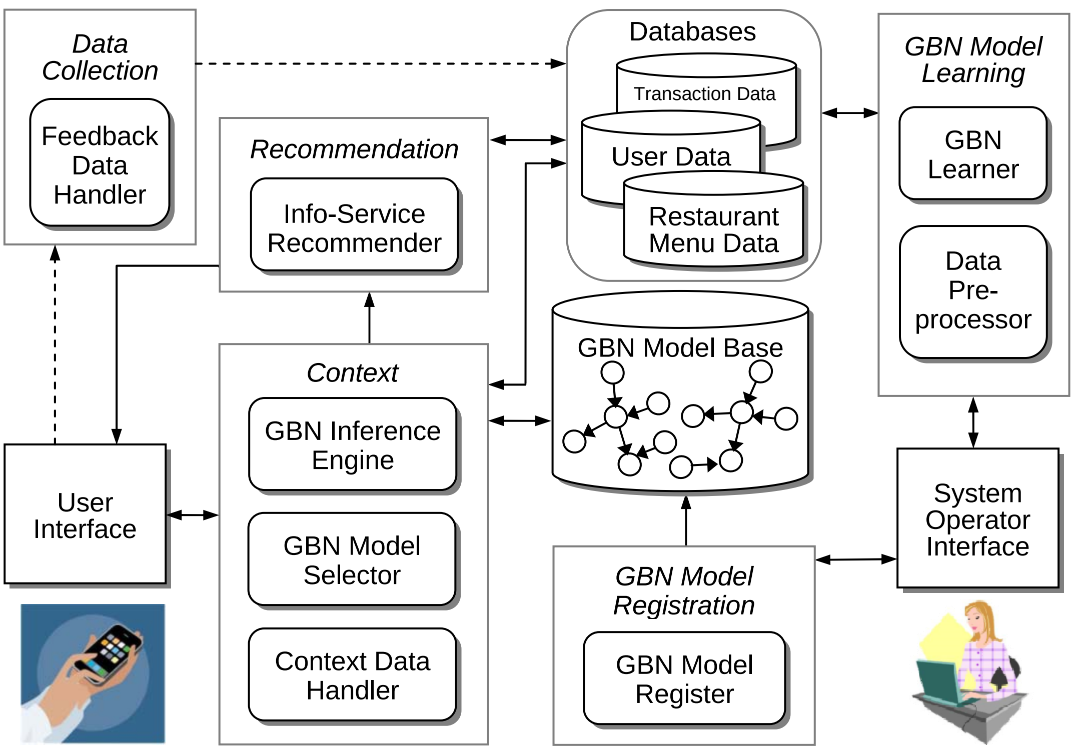



**Figure 1.** U-BASE system architecture.

**(1) Context Data Handler:** The context data handler receives user context data from user applications in two ways: it can receive context data that are deliberately sent by the user (user-initiated), or it can receive data by proactively requesting the user application for context data (system-initiated). In some cases, not all context data will be available via user applications. In such cases, additional context data may be obtained from the databases. For example, the user application may pass only the user ID to the context data handler, and the rest of the user data may be retrieved from the user database.

**(2) GBN Model Selector:** The GBN model selector selects an appropriate GBN model from the GBN model base on the basis of the user context data, and then passes the selected GBN model and user context data to the GBN inference engine for context prediction.

**(3) GBN Inference Engine:** The GBN inference engine performs what-if simulation on the selected GBN model using the user context data. The target variable's entries' posterior probabilities are calculated by instantiating the explanatory variables; the entry with the greatest probability is returned as the predicted result.

### 2.2. Usage scenario

We present three scenarios to demonstrate how a GBN is used to predict contexts in a ubiquitous decision support system. Consider a smart-phone service targeted toward college students to assist their daily activities on campus. This campus information service provides three kinds of information services: (1) a room occupancy verification service, (2) a food menu recommendation service, and (3) a leisure activity recommendation service. To initiate the service, the student logs on to the service (Fig. 2, left) and sets up his/her profile (Fig. 2, right). The student can also set the auto-collect feature to 'on' or 'off' to enable or disable system's automatic data collection feature. The main screen of the service (Fig. 2, middle) displays three activity buttons, 'STUDY,' 'EAT,' and 'PLAY,' which correspond to the three information services described above. By clicking one of the activity buttons, the user either receives the final information or is asked to provide additional data necessary for predicting future context depending on the auto-collect setting. Hereafter, we describe the scenarios of each information service and explain how the U-BASE system operates in the background to predict user's future context and to provide context-sensitive recommendation to the user.

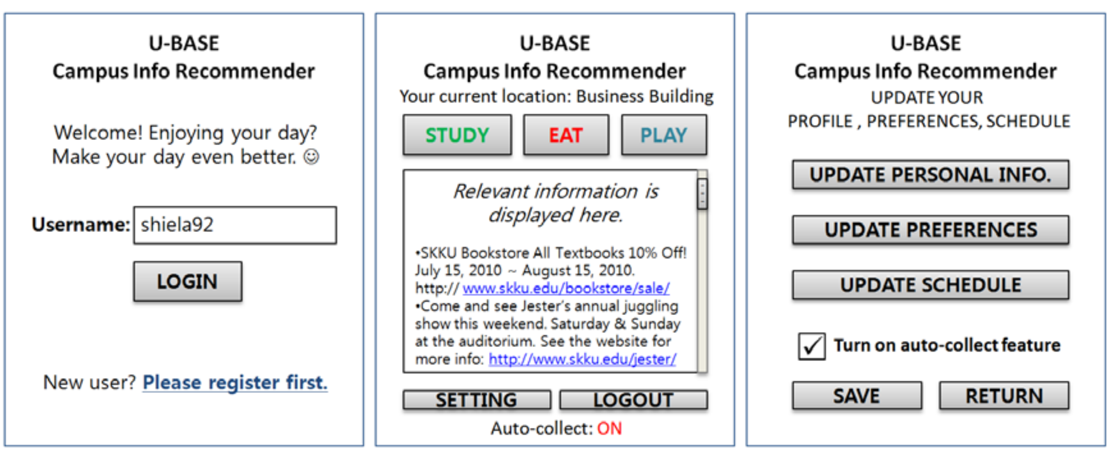



**Figure 2.** User interfaces of campus information recommendation service.

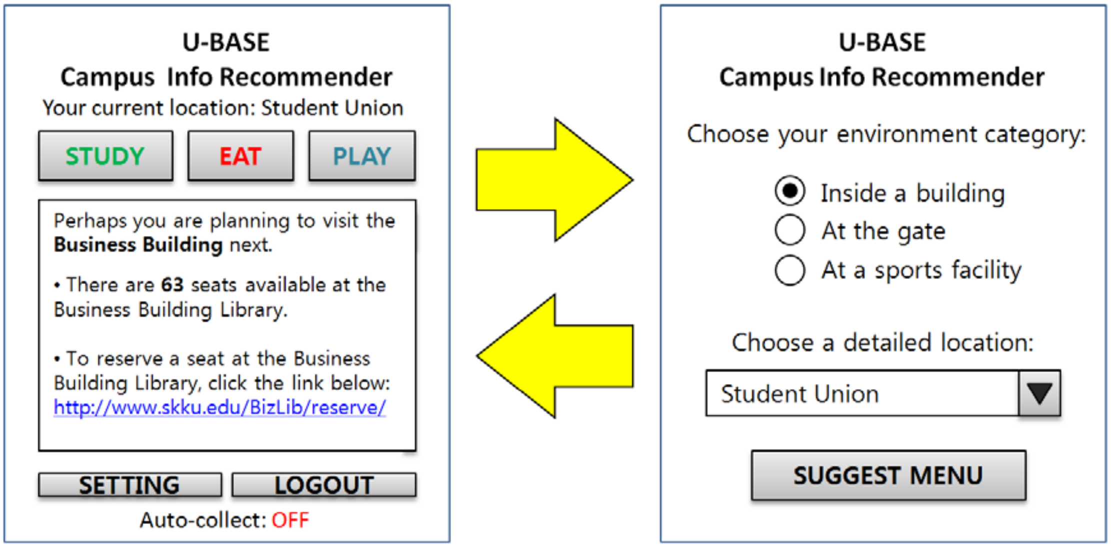



**Figure 3.** Current location input screen (right) and recommended result (left).

**(1) Room occupancy verification service:** The room occupancy verification service predicts the user's future location (i.e., the place a user will visit next) and informs the user about the availabilities of meeting rooms and study seats at the facility which the user will visit next. It is three in the afternoon, and Sheila, a senior majoring in liberal arts, is thinking of working on her English Literature assignment. She logs onto the campus information service and clicks the 'STUDY' button. The U-BASE system then asks her for her current location. Sheila sends her current location ('Student Union', Fig. 3 right) to the system, and the context data handler inside the context prediction component (Fig. 1) receives the current location information and retrieves additional user data such as her major ('Liberal Arts') and student year ('Senior') from the user's database using her user ID. The user context data (major, student year, current location, and future activity which in this case is 'Study') are then sent to the GBN model selector and the GBN model selector picks out a relevant GBN model from the GBN model base according to the user context data (Fig. 1). In this scenario, the GBN model selector picks out a GBN model that predicts the user's next location (Fig. 4).

The selected model (Fig. 4) and the user context data are then passed to the GBN inference engine, and a what-if simulation is performed by setting the 'Activity' node's evidence to 'Study', the 'Major' node to 'Liberal Arts', the '(Student) Year' node to 'Senior', and the 'Location Departed' node to 'Student Union' (Fig. 4). Consequently, the target node ('Location Arrived') entries are influenced by these instantiations and the inference engine calculates 'Business Building' to have the largest posterior probability (0.6882). Based on this inference, the 'Business Building' is determined as the next location value (i.e., the next location the user is likely visit next). The context data handler, then, receives this next-location value ('Business Building') from the GBN inference engine and passes the next-location value and the user context data to the recommendation component (Fig. 1). As a result, the study seat availability at the 'Business Building Library' is displayed ("There are 63 seats available at the Business Building Library.") to the user along with the link to the seat reservation system (Fig. 3 left).

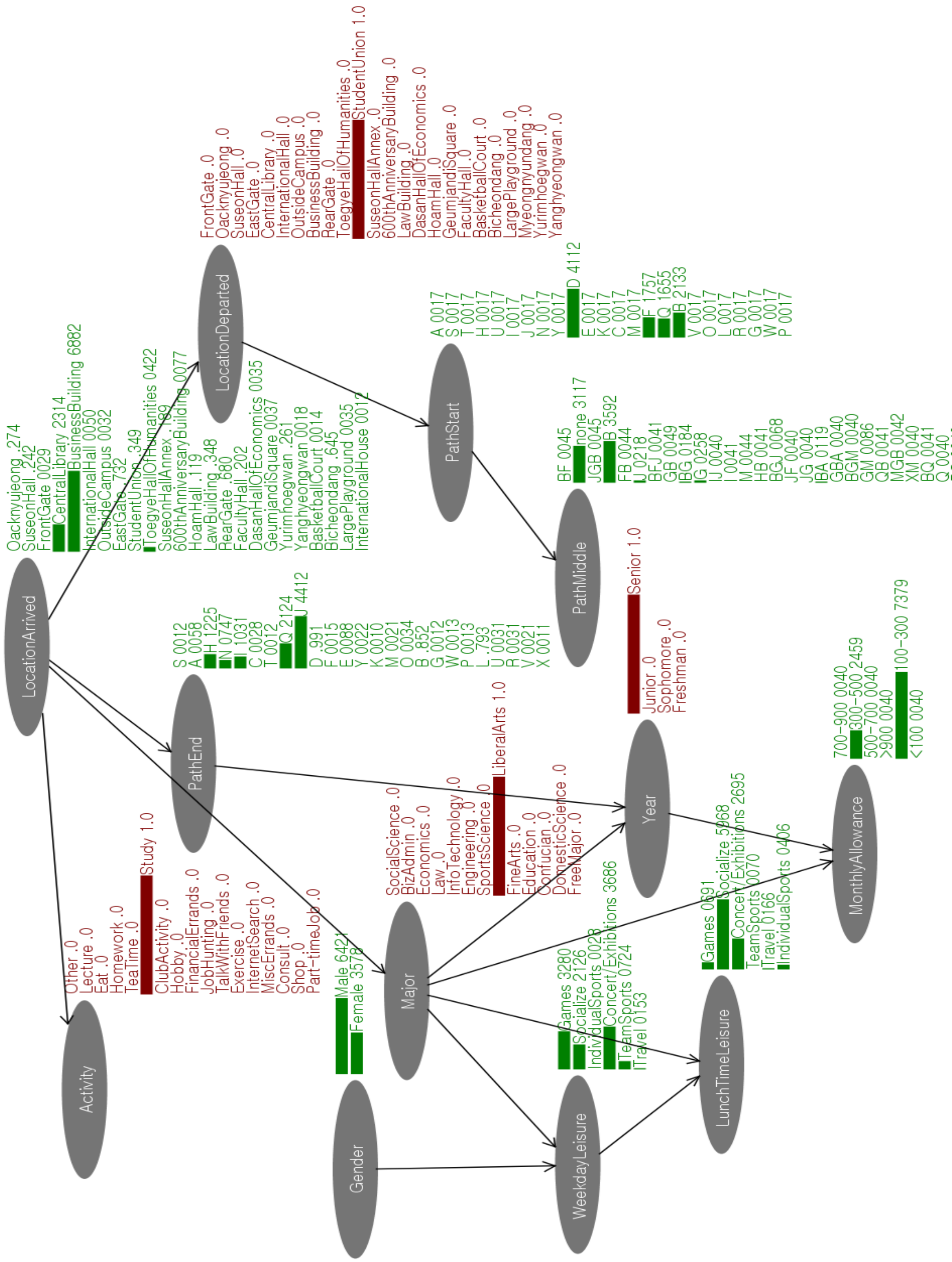



**Figure 4.** A GBN for next-location prediction with ‘Location Arrived’ (top) as the target node.

**(2) Food menu recommendation service:** The food menu recommendation service is similar to the room occupancy verification service in that it predicts the future location a user is likely to visit next. After predicting user's future location, the service suggests menus from restaurants located near the future location. The same GBN model for next-location prediction is used for this service. It is eleven in the morning, and as Peter, a junior majoring in law is contemplating what to eat for lunch, he receives a message from the U-BASE system asking for his current location. The student sends his current location information ('Hoam Hall') to the service, and the GBN model is instantiated using the user context data (Student Year = 'Junior', Major = 'BizAdmin', Location Departed = 'Hoam Hall', and Activity = 'Eat'). As a result, the next location is predicted as the 'Law Building', and today's menu served at the 'Law Building' cafeteria is retrieved from the restaurant menu database and sent to the user application as the final output.

**(3) Leisure activity recommendation service**: The leisure activity recommendation service predicts appropriate weekday leisure activity information of the user. The user logs onto the campus information service and clicks the 'PLAY' button; then, the service asks the user to choose one of the six lunch-time leisure activities, such as 'Games', 'Socialize', 'Concert/Exhibitions', 'Team Sports', 'Travel', and 'Individual Sports' (refer to the 'Lunch Time Leisure' node values displayed in Fig. 4). The user selects one activity and sends it to the U-BASE system, and the system predicts the weekday leisure activity of the user using a new GBN model which contains 'Weekday Leisure Activity' as the target node. The student data, such as his/her gender, major, student year, and monthly allowance, as well as the lunch-time leisure activity value is used to instantiate the GBN to predict user's weekday leisure activity.

For instance, a junior male student majoring in law, whose monthly allowance is between 300,000 to 500,000 won, has chosen socialization (i.e., 'Socialize') as his lunch-time leisure activity. From the instantiation, the GBN inference engine outputs 'Individual Sports' as the predicted weekday leisure activity for this user. The system then sends school swimming pool discount coupons and information about a free horse-riding event to the user application. The predicted weekday leisure activity will change as the user's lunch-time leisure activity changes, reflecting the changes in the leisure context of the user.

## 3. Experiment

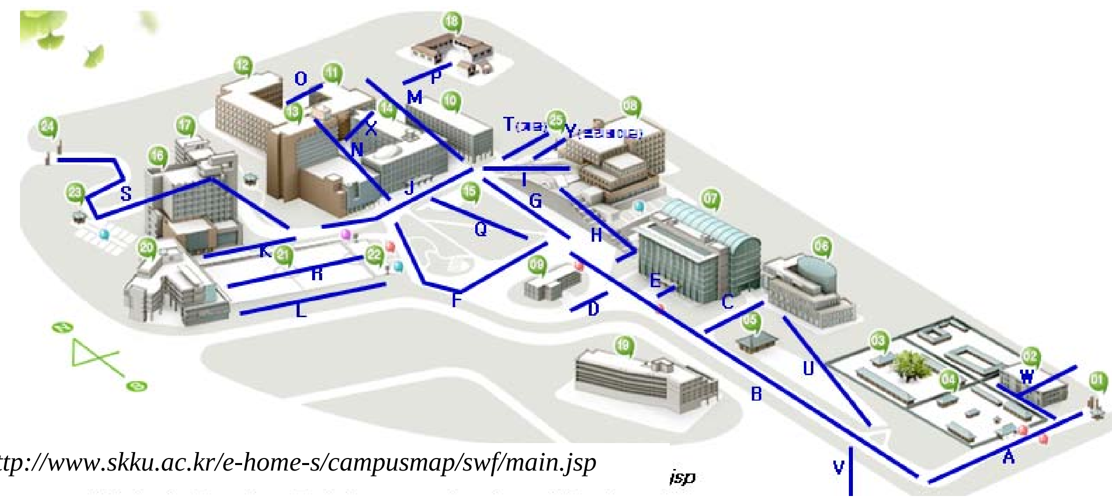
Since the heart of the U-BASE system lies in its context prediction component, the system would be far less useful if the accuracy of the predicted context was low. In this section, we investigate how effective the GBN is compared to the naïve Bayesian network classifier. We collect contextual data from undergraduate students, and construct two types of Bayesian networks (BN models): (1) General Bayesian Networks (GBNs) and (2) Naïve Bayesian Networks (NBNs). Note that the GBNs created for the experiment are the ones discussed in Section 2.2 (Fig. 4 included).

### 3.1. Data and variables

Campus activity data were collected from undergraduate students in Seoul, Korea to create user context data for the experiment. The college students were shown a campus map containing building and route information, as depicted in Fig. 5, and were asked to document their two days of activities on campus. They documented where they visited via what route (a list of letters in Fig. 5 was specified to describe a sequence of paths) and what activity they engaged in at that location. To describe the activity, they chose one of seventeen predefined activities listed in the 'Activity' node in Fig. 4.

In addition to the campus activity data, the students filled out a questionnaire that asked their gender, major, student year, weekday leisure activity, lunch-time leisure activity, monthly allowance, and student ID. The performance evaluation experiment used data from 335 students: among the students, 205 students were male and 130 students were female; 131 were freshmen, 38 were sophomores, 64 were juniors, and 102 were seniors.

After all data were cleaned, the campus activity data and questionnaire data were combined to create a merged campus activity-demographic data. The student ID was used to combine the two types of data. The combined data contained twelve attributes (‘Location Arrived’, ‘Path Start’, ‘Path Middle’, ‘Path End’, ‘Location Departed’, ‘Activity’, ‘Gender’, ‘Major’, ‘Year’, ‘Weekday Leisure’, ‘Lunch Leisure’, and ‘Monthly Allowance’). A total of 3,150 records of the campus activity-demographic data were used to construct two types of Bayesian networks, i.e., GBNs and NBNs.




*http://www.skku.ac.kr/e-home-s/campusmap/swf/main.jsp*

**Figure 5.** A campus map containing building and route information.

### 3.2. Structure learning

We used WEKA [19], an open-source data-mining tool with Bayesian network learning and inference capabilities, to construct the Bayesian networks and to perform the prediction accuracy evaluations. The 12-variable campus activity-demographic data were used to construct two networks containing two different target nodes (‘Location Arrived’ and ‘Weekday Leisure Activity’). The structure of the GBN was learned using two search algorithms, K2 [20] and Hill Climbing, with the maximum number of parent nodes limited to two or three. The parameter setting (the structure-learning algorithm and the maximum number of the parent node) with the better prediction accuracy was employed as the final GBN for the experiment. For the GBN with ‘Location Arrived’ as the target node, the K2 algorithm was used with the maximum number of the parent node set to two. For the GBN with ‘Weekday Leisure’ as the target node, the Hill Climbing algorithm was used with the maximum number of the parent node set to three. Both GBNs used the BAYES scoring metric. To create the NBN [21], the default setting in WEKA was used.

### 3.3. Results

Table 1 lists the accuracy and standard deviation of accuracy of the GBN and NBN classification algorithms as measured from 10 runs of 10-fold cross-validation. The better-performing classifier was determined using a corrected resampled t-test [22] at the 1% significance level based on the 10

X 10 fold cross-validation results. The results show that there are statistical differences between the GBN and the NBN, and that the GBN is significantly better. When we look at one specific run of the ten runs, we see that given 3,150 test instances, the GBN makes 492 false predictions whereas the NBN makes 566 false predictions.

**Table 1.** Prediction performance (accuracy ± standard deviation) of two BN algorithms.

| Target Node | GBN | NBN |
|---|---|---|
| Location Arrived | 84.12 ± 1.70 | 81.90 ±1.79 |
| Weekday Leisure | 70.95 ± 2.39 | 50.93 ± 2.86 |

## 4. Discussion

We confirmed the prediction accuracy of the GBNs to outperform NBNs, but better performance alone does not make GBN a good classifier for context prediction. The structure of GBN is much more flexible than the fixed structure of NBN, providing GBN with the capability to express cause and effect not only between the target variable and the explanatory variables, but also between the explanatory variables themselves. In contrast, NBN does not have any link between the explanatory variables.

Better prediction accuracy and greater representational power are both the strengths of GBN, but the greatest advantage of GBN is that fewer variables are required for context prediction. As demonstrated in Fig. 2, the target node is directly linked to fewer explanatory variables (four) compared to the NBN (eleven[1]). Hence, the selectiveness of the GBN allows humans to grasp which explanatory variables are crucial for the target variable prediction. Because obtaining data for instantiation sometimes can be costly and difficult, knowing which variables to be more important is advantageous, and this knowledge can be used to establish better data collection strategy for building an efficient and effective context prediction system.

Context prediction can improve human-computer interaction to provide better service that conforms to a user’s expectations. Needless to say, the prediction accuracy is crucial to the success of context prediction-based services. One way to achieve good context prediction accuracy is to use different GBN models as necessary. For example, a first-time user may not have enough personal transaction data, so it may be difficult to create a GBN model that adequately reflects the user. In such cases, the system can first construct a GBN model using the transaction data of a group of users sharing similar characteristics with the first-time user. Initially, the system can use the group-based GBN model to predict contexts for the first-time user. Over time, as the first-time user’s own transaction data gradually increases, the system can create a new GBN model that better reflects the user’s characteristics and use it for context prediction.

## 5. Concluding remarks

The main contributions of this paper are: (1) an evaluation of the performance of the U-BASE through the use of real-world contextual datasets to determine its effectiveness for resolving context prediction (CP) problems, and (2) a demonstration that the GBN-powered ubiquitous decision support for CP is efficient and robust in real-world situations.

[1] All eleven explanatory variables are directly linked to the target variable.

As to the first contribution, the results of the statistical test summarized in Table 1 show that the GBN-based U-BASE performs significantly better than the NBN-based U-BASE. At the 99% confidence level, the GBN-based U-BASE performed better for both of the two target nodes. As to the second contribution, the GBN-based inference mechanism for resolving CP problems was shown to be useful in a situation where there are many variables to be considered, and the target node seems to depend causally on many explanatory variables. Since GBN provides a set of causal relationships among the variables under consideration, the causal relationships given by a GBN can be stored into the knowledge base on the basis of which various types of what-if simulations can be performed to induce CP solutions for the target users.

Future research directions include a user evaluation of the U-BASE system and further comparison of the GBN-based inference mechanism with other inference methods such as neural networks and decision trees, among others. Moreover, the improvement of prediction performance through ensemble methods, which combine multiple classifiers such as neural network and decision trees, should be studied to produce more robust and more accurate context prediction.

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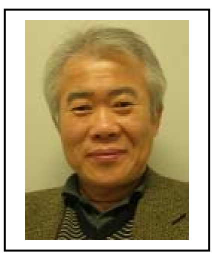

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