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CALIPS: DESIGN OF UBIQUITOUS DECISION SUPPORT MECHANISM FOR THE CAMPUS LIFE PLANNING FROM THE VIEW OF INTEGRATING GENERAL BAYESIAN NETWORKS AND CONTEXT PREDICTION

Lee Jae Sung
London School of Economics, London, leejs1@lse.ac.uk

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Research in Progress

Lee, Jae Sung, London School of Economics, London, UK, leejs1@lse.ac.uk

Abstract

Recently, ubiquitous decision support systems become more popular in many applications. However, the campus life planning area has remained untouched in the decision support literature. Moreover, the potentials of context prediction in lieu of context awareness systems were rarely explored in previous studies of the ubiquitous decision support systems. In this sense, this study proposes the systematic usage of General Bayesian Networks (GBNs) to organize high quality of causal knowledge base to be used for the sake of campus life planning. The prototype named CALIPS was designed on the smartphone. Two research questions that were never investigated in literature were raised- (1) suggestion of the ubiquitous decision support mechanism for the campus life planning, named CALIPS, and (2) integrating GBN and context prediction into the CALIPS. Experiment results proved to support the validity of the CALIPS.

Keywords: Ubiquitous decision support, Context prediction, Campus life planning, Bayesian networks, General Bayesian network

1 Introduction

It is well known that we are living in a world of ubiquity. The ubiquitous devices like smartphone and other mobile devices we are enjoying at home and offices are defining most parts of our daily lives. Such ubiquity facilitated by various kinds of ubiquitous devices has been sinking in ubiquitous decision support systems (Kwon et al. 2005; Muntermann 2009). Recently, the ubiquitous decision support system becomes advanced very fast thanks to the dazzling development of smartphone techniques. Among plentiful applications of the ubiquitous decision support systems (Seo et al. 2013; Hosack et al. 2012), campus life planning has remained void in the ubiquitous decision support literature. There were some studies about the campus life planning, but most of them are focused on giving advice to young college students and emphasizing the importance of college educations (Horowitz 1987). Considering the fact that modern campus life is dominated by colourful types of cutting-edge ubiquitous technologies, it is necessary to investigate the usability of ubiquitous decision support system for the campus life planning.

Good usage of ubiquitous technologies has been regarded as crucial part of college students' satisfaction (Valenzuela et al. 2009). Nevertheless, how to systematically enhance the quality of college students' campus life from the perspective of providing an ubiquitous decision system has been neglected to some extents in the IS literature. In this sense, as a first research question, this paper proposes designing the ubiquitous decision support system aiming to help college students plan their campus life more intelligently. The prototype named CALIPS (CAmpus LIfe Planning Support system) is suggested.

By the way, main directions of the ubiquitous decision support systems are context awareness and context prediction. Concepts of "context" emerge as one of crucial factors framing our lives, which are defined as situations under which people work and move. Context awareness plays an important role in enabling ubiquitous systems to act as intelligent decision support systems (Cook et al. 2009). Context awareness is based on interpreting context to understand the user situation. Context is any information that can be used to characterize the situation of an entity, where an entity is a person, place, or object that is considered relevant to the interaction between a user and an application (Dey and Abowd 1999). When combined with ubiquitous computing systems (Weiser 1995), context awareness allows for novel applications and services that adapt according to the user situation. However, simple context awareness does not guarantee proactiveness, which attempts to reduce a user's required efforts by predicting future changes in relevant contexts (Tennenhouse 2000; Mayrhofer et al., 2003). In other words, enabling ubiquitous decision support systems to be embedded with such proactiveness requires information about the users' future needs acquired through inferences about the users' future contexts. Predicting users' future context, known as context prediction, requires highly sophisticated inference methods that can analyze the given contextual data and identify meaningful patterns to predict future changes in user contexts.

Most context prediction problems pertain to location prediction (Petzold et al. 2005) or action prediction (Singla et al. 2010). When future probable user locations likely to be visited in the near future (e.g., one hour later) are predicted precisely, the ubiquitous decision support system can provide timely and accurate decision support. Likewise, users will accept the ubiquitous decision support system when the types of actions in which decision makers will engage are forecasted accurately. Various works have introduced context prediction methods. Patterson et al. (2003) use a dynamic Bayesian network to predict likely travel destinations on a city map; however, this algorithm requires a city map and is thus restricted to a particular area. Petzold et al. (2004) use global and local state predictors to predict the room a user is likely to enter in an office environment. Mayrhofer (2004) conducted a more extensive methodological comparison of the performances of different methods such as neural networks, Markov models, autoregressive moving average model (ARMA) forecasting, and support vector regression. However, the tests were performed on a specific data set, and thus the results cannot be fully generalized.

Campus life planning support system must be embedded with various simulation capabilities so that its users, individuals or institutes, can take advantage of it in order to investigate location prediction, mobility prediction with the possibility of planning new development of personal life, services and building on campus. For example, in the case of individual usage, depending on personal preferences and profiles such as leisure preferences, favourite transportation, major, age, and grade, college students show different preferences about locations and leisure activities, etc. When the campus life planning support system is used by the institutes (or departments) affiliated with the university, college students' future movements into specific locations and activities can be predicted with reasonable accuracy, which plays into designing new services and buildings for all the people working on campus. Therefore, success of campus life planning, a target problem of this study, is heavily dependent on the quality of causal relationships capable of providing various simulation options such as what-if analysis and goal-seeking analysis.

However, traditional context prediction methods cannot provide such causal relationships between the target variable and related explanatory variables. If such a causal relationship is extracted from target contextual data, it can be used to conduct a wide variety of what-if and goal-seeking analyses. A what-if analysis is one in which decision makers analyze the possible results by changing input conditions in various ways. Goal-seeking analysis is closely related to such simulation activities in which a certain goal is suggested, and decision makers attempt to observe what kind of input conditions are necessary to obtain such a goal. In this way, the causal relationships obtained from the training dataset can be used as an inference engine of the ubiquitous decision support system, which can be combined with the what-if and goal-seeking analyses, given the scenarios under consideration.

Therefore, a more robust and promising method for the context prediction task is necessary in order to design the CALIPS more intelligently. The context prediction method should be capable of extracting meaningful patterns hidden in contextual data, formulating them into causal relationships, and providing relevant what-if and goal-seeking analysis power. To this end, as a second research question, we suggest embedding Bayesian Network (BN) into the proposed CALIPS, which is capable of formulating causal relationships based on a training dataset and of making inferences about various types of scenario. Among three types of BN like NBN (Naïve BN), TAN (Tree Augmented NBN), GBN (General BN), GBNs are most flexible in formulating causal relationships in a formal structure composed of target nodes and related nodes. A detailed explanation about BN and GBN is addressed in the next theoretical background section. For the sake of performing the context prediction task more effectively, a prototype called CALIPS is proposed, in which the GBN structure is used as a knowledge base that stores several causal relationships among the interested variables and in which an inference engine based on what-if and goal-seeking functions is used with assistance from a GBN inference mechanism.

In a nutshell, this study aims to answer two research questions that were never investigated in literature-(1) suggestion of the ubiquitous decision support mechanism for the campus life planning, named CALIPS, and (2) integrating GBN and context prediction into the CALIPS. This study is organized as follows. The theoretical background is described in section 2, where details about context prediction are summarized from the recent literature and an introduction to BN is outlined with reference to relevant studies. Besides, design procedures of the CALIPS are explained. In section 3, experiments with a real contextual dataset collected from college students are described, along with the associated results and implications. Finally, this paper is concluded with some remarks and issues for future study.

2 Theoretical Backgrounds

2.1 Context Prediction in the Ubiquitous Decision Support

The proposed ubiquitous decision support mechanism CALIPS is fundamentally based on the capability of context prediction. In recent years, ubiquitous decision support systems have been the subject of growing attention (Cook et al., 2009; Kwon et al., 2005). With the promise of proactive and intelligent decision-making alternatives for users, which utilize their contextual information, ubiquitous decision support systems hold great potential for entertainment, education, and various mobile applications (Shim et al., 2002). For example, an application deployed on a mobile device may track user movements, actions, or preferences and provide personalized services most appropriate for a given context. Despite recent advances in ubiquitous computing technologies, ubiquitous decision support systems lack important functionality that could significantly increase their abilities to automatically generate decision alternatives. They cannot quickly predict which contexts users will likely enter as users interact with ubiquitous computing environments. Providing ubiquitous decision support systems with the ability to accurately predict user context would enable decision support systems to consider users' future contexts when generating decision alternatives and to ensure that they adapt to changes in user context.

Main focus of context prediction lies in making inference on the user context by analyzing the observed contextual history of the user. The observed contextual history is a collection of contextual information that shows how users are moving around in a certain ubiquitous computing environment. Context can be defined in various ways (Schmidt et al. 1998; Dey and Abowd 1999), but it usually represents a certain kind of environment in which users exist and perform their actions. The general definition of context is as follows: "Any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves" (Dey and Abowd, 1999). The purpose of context prediction is therefore to predict the subsequent user context that users will likely to face sooner or later (if the contexts are locations or situations) or take (if the contexts are actions) on the basis of contextual database. Context prediction examples include location prediction (Anagnostopoulos et al. 2009), movement prediction (Perl, 2004), action prediction (Singla et al. 2010), and daily routine prediction (Huýnh et al 2008; Kim et al. 2010). The task of context prediction is basically challenging because it targets predicting a user's future context, whereas context-aware systems focus on recognizing the current user context. In other words, predicting contextual changes in the future requires more intensive treatment and analysis of all the relevant data and information regarding the contexts that people will go into soon.

In the context prediction literature, various types of context prediction techniques were proposed. Petzold et al. (2005) investigated BNs, neural networks, and Markov and state predictors to predict the next location of an office owner in an office building and route phone calls to the predicted location. Singla et al. (2010) proposed a Hidden Markov Model (HMM) approach to recognize activities performed by multiple residents in a single smart-home environment. Hwang and Cho (2009) proposed a modular BN model to infer landmarks using mobile log data such as GPS logs, call logs, SMS logs, picture logs, music-playing logs, and weather logs. Huýnh et al. (2008) adopted a topic model to predict a user's daily routine (such as office work, commuting, or lunch routine) based on the user's activity patterns. Huýnh et al. first identified the user's activity patterns based on the low-level sensor data using various classifiers such as Support Vector Machines (SVM), Hidden Markov Models (HMM), and a Naïve Bayesian network (NBN).

From the literature review so far, we can conclude that potentials of GBNs are not fully explored for the task of context prediction. Especially, we will take advantage of the fact that GBNs are able to formulate the appropriate causal relationships among decision variables. Therefore, we exploit GBNs to design the CALIPS.

2.2 Bayesian Networks

A Bayesian Network (BN) is a probabilistic model in the form of directed acyclic graphs (Pearl, 2000). Nodes in a BN represent random variables or propositions (e.g., the occurrence of an event or a feature of an object) and provide a compact representation of full joint probability distributions. Likewise, links represent causal or informational dependencies among variables, and each node is associated with a probability distribution. If a node does not have parents, it is associated with a prior probability. If a

node does have parents, it is associated with a conditional probability, given its parents. Since BNs represent causal or informational dependencies among variables, variables that are not influenced by other variables but that do exert influences on other variables are positioned at the top layer of the network. Similarly, variables that are influenced by some variables and also influence other variables are positioned in the middle layers of a network, and variables that are influenced by some variables but that do not influence other variables are positioned at the bottom layer. In such a representation, it is possible to infer the probability of any combination of variables without having to represent the joint probabilities of the variables.

The structure of a BN can be either manually constructed by domain experts or learned from data. Learning the structure is difficult; however, this structure is essential because of its enormous usefulness in various application areas. For the sake of the structure learning, two families of approaches can be taken: conditional independence (CI)-based algorithms or search-and-scoring-based algorithms (Heckerman, 1995). The CI-based algorithms conduct several conditional independence tests on the data and construct a Bayesian network that agrees with the test results. Search-and-scoring approaches start with an edgeless graph, and then a search algorithm is used to add an edge to the graph. Once the structure is constructed, a conditional probability table for each variable must be specified through a technique called parameter learning. Learning structure and parameters from data enable BN-based decision support mechanisms to dynamically modify their behaviors to better support users by generating the most appropriate decision alternatives according to users' current and future contexts.

There are three types of BNs such as NBN (Naïve BN), TAN (Tree Augmented NBN), and GBN (Generalized BN). NBN has the simplest structure among BNs, where a target node is linked directly with other explanatory nodes and there exist no causal relationships among explanatory nodes. Therefore, since NBN structure is fixed, no computational needs are necessary to learn the structure. Unlike NBN, TAN allows causal relationships among explanatory nodes. According to Friedman et al. (1997), TAN outperforms NBN, while maintaining computational simplicity on learning. GBN is very flexible in its structure among nodes, on the basis of data and learning algorithms. Basically, GBN is an unrestricted BN which deals with the target node (i.e., class node) as an ordinary node that can be free to become a child node or parent node for some nodes (Cheng and Greiner, 2001; Choi et al., 2013).

There are a number of advantages when GBNs are used for the design of the ubiquitous decision support systems. First, because BNs are quantified by probabilities that represent a decision support system's knowledge about user context, the decision support system can determine the confidence of its knowledge about a user. Confidence about user context is important because a decision support system can provide different types of assistance on the basis of its confidence level. Second, GBN provides a natural way to quantify prior beliefs about the propositions of users that are modelled in the network. If we have prior knowledge about a user, we can incorporate this knowledge into the decision support system, which can thereby be effectively adapted to the user. Third, GBN provides a natural way in which to model "explaining away," which is difficult in rule-based systems (Pearl and Russell, 1998). If there is more than one possible cause for a problem and it is known that one cause is more probable than the other, then the likelihoods of the other causes decrease. The "explaining away" by GBN provides a great potential to the users-centric design of the ubiquitous decision support mechanism.

2.3 Design

The CALIPS is now being developed on smartphone. Its prototype consists of main components as in the below, which was used for the experiment.

Contextual Database

Contextual database of the CALIPS is updated on a periodical basis in which the university is planning to renew its database regarding the college students' behaviours and activities on the campus. Now the CALIPS is being connected to the cloud computing system of the university to update its contextual database on a real-time basis whenever college students register and record their preferences and contexts. In this way, CALIPS can maintain its recency regarding the college students' campus life trends. Privacy issue is circumvented by not only soliciting agreement from respondents before collecting contextual database, but also suggesting non-disclosure agreement to them.

Inference Engine

Inference engine of the CALIPS is based on the causal inference capability suggested by the GBNs that were extracted from the contextual database. The CALIPS inference engine is supported by causal knowledge base which is being maintained by the GBNs. Especially, what-if and goal-seeking functions of the GBNs provide main components for the CALIPS inference engine.

Model Base

Model base of the CALIPS is composed of a GBN which is updated on a periodical basis at the present time with its contextual database being used by the BN modeller. A number of multiple APIs (application programming interface) available from reliable BN engine like WEKA (Witten et al. 2011) is used nicely as an alternative source for building model base which is to be used for the CALIPS.

3 Experiments

3.1 Contextual Dataset

Contextual dataset describing college students' campus activity data were collected from a total of 335 students who registered a private university in Seoul, South Korea. Participants were invited on an incentive basis to fill in a list of their activity codes containing information of their travel routes between 23 buildings during two weeks of day time when they were on the campus. The college students were shown a campus map with building and route information, and were asked to document their one-day activities on campus for any two days of their choice. They documented the locations they visited via what route at what time for how long and in what activity they engaged at the location by explicitly filling out the following items: day of week, time they arrived at the specific location, time they departed that location, route they took to arrive at the location (a list of letters was specified to describe a sequence of paths), which location they visited (both the building/gate/facility number and the location name were specified), in which room they stayed, if applicable, and what activity they performed at the location

In addition to campus activity data, students were asked to complete a questionnaire consisting of questions about their gender, major, student year, weekday leisure activities, lunch-time leisure activities, monthly allowance, student ID, age, military service status, religion, smoking status, weekend leisure, vacation leisure, leisure utility, leisure satisfaction, housing, campus arrival transportation, campus departure transportation, daily study time, monthly mobile phone fee, and whether they were dating someone (boyfriend/girlfriend status). As a result, we collected a total of over 6000 datasets with 40 attributes : StudentId, DayOfWeek, MovingTime, ArrivalTime, ArrivalHour, ArrivalMinute, Arrival15Min, Arrival10Min, Arrival5Min, DepartTime, DepartHour, DepartMinute, Depart15Min, Depart10Min, Depart5Min, PathWay, StartPath, BuildingDeparted, BuildingArrived, Gender, Age, Major, Grade, MilitaryService, Religion, MonthlyAllowance, Smoking, Lover, WeekdayLeisure, WeekendLeisure, VacationLeisure, LunchLeisure, LeisureUtility, LeisureSatisfaction, Housing, ArrivalTransportation DepartureTransportation, AverageStudyTime.

The collected data were cleaned by removing invalid data and by correcting typos. Some campus activity data with invalid route information were removed. After the activity data were cleaned, the route information with the alphabet path list (or attributes 'Path1' through 'Path5') was mapped onto a common path format consisting of three attributes, 'Path Start,' 'Path Middle,' and 'Path End. This conversion was performed to ensure that the route information would have no missing values. The sequence of paths the students travelled varied according to students and locations travelled, and using the path variable as is would have produced too many missing values. To avoid producing a large number of missing values, five path attributes were converted to three path attributes. After all data were cleaned, the campus activity data and personal data were integrated to create merged campus activity-demographic data. Student IDs were used as the primary key to combine the two kinds of data. The merged data contained 30 attributes, 12 of which ('Location Arrived,' 'Path Start,' 'Path Middle,' 'Path End,' 'Location Departed,' 'Activity,' 'Gender,' 'Major,' 'Year,' 'Weekday Leisure,' 'Lunch Leisure,' and 'Monthly Allowance') were selected to construct GBNs to be used in the CALIPS. This selection of variables was based on the discussion with experts of the campus life planning task force team working at the private university where the contextual dataset collection was arranged. Table 1 organizes the 12 variables and available fields used for building GBNs for the CALIPS. In all, 3,150 records of campus activity-demographic data were used to construct GBNs.

Variable	Available values (number of values)
Location Departed	{600thAnniversaryBuilding, BasketballCourt, Bicheondang, BusinessBuilding, CentralLibrary, DasanHallOfEconomics, EastGate, FacultyHall, FrontGate, GeumjandiSquare, HoamHall, InternationalHall, LargePlayground, LawBuilding, Myeongnyundang, Oacknyujeong, OutsideCampus, RearGate, StudentUnion, SuseonHall, SuseonHallAnnex, ToegyeHallOfHumanities, Yanghyeongwan, Yurimhoegwan}(24)
Path Start	{A, B, C, D, E, F, G, H, I, J, K, L, M, N, O, P, Q, R, S, T, U, V, W, Y} (24)
Path Middle	{A, AB, ABG, B, BA, BC, BE, BF, BFJ, BG, BGI, BGJ, BGM, BH, BHI, BQ, BQJ, C, CB, CBG, D, E, EBG, F, FB, G, GB, GBA, GJ, GM, H, HB, I, IJ, IM, J, JF, JFB, JG, JGB, JI, JK, JQB, K, M, MGB, MJ, N, NJ, none, Q, QB, QBA, SGB, T, X, XM} (57)
Path End	{A, B, C, D, E, F, G, H, I, J, K, L, M, N, O, P, Q, R, S, T, U, V, W, X, Y} (25)
Location Arrived	{600thAnniversaryBuilding, BasketballCourt, Bicheondang, BusinessBuilding, CentralLibrary, DasanHallOfEconomics, EastGate, FacultyHall, FrontGate, GeumjandiSquare, HoamHall, InternationalHall, InternationalHouse, LargePlayground, LawBuilding, Oacknyujeong, OutsideCampus, RearGate, StudentUnion, SuseonHall, SuseonHallAnnex, ToegyeHallOfHumanities, Yanghyeongwan, Yurimhoegwan} (24)
Activity	{TalkWithFriends, ClubActivity, Consult, Eat, Exercise, FinancialErrands, Hobby, Homework, InternetSearch, JobHunting, Lecture, MiscErrands, Other, Part-timeJob, Shop, Study, TeaTime} (17)
Major	{BizAdmin, Confucianism, DomesticScience, Economics, Education, Engineering, FineArts,

<table>
<tr><td></td><td>FreeMajor, InfoTechnology, Law, LiberalArts, SocialScience, SportsScience} (13)</td></tr>
<tr><td>Year</td><td>{Freshman, Sophomore, Junior, Senior} (4)</td></tr>
<tr><td>Gender</td><td>{Male, Female} (2)</td></tr>
<tr><td>Weekday Leisure</td><td rowspan="2">{Concert/Exhibitions, Games,IndividualSports, Socialize, TeamSports, Travel} (6)</td></tr>
<tr><td>Lunch Time Leisure</td></tr>
<tr><td>Monthly Allowance</td><td>{<100, 100-300, 300-500, 500-700, 700-900, >900} (6)</td></tr>
</table>

Table 1 Variables and available values

3.2 Results and Implications

Results from the CALIPS were promising, although it is not fully developed on the smartphone yet. First of all, the CALIPS could provide what-if/goal-seeking capabilities to users by using the GBN models registered in its model base. Assume that we are board members at the college marketing club trying to recruit freshmen majoring in business administration. Moreover, to better persuade them, we would like to meet each student face-to-face. To do so, we must determine where these business-major freshmen hang out on campus. Using the what-if analyses capability, we can predict the next location of business-major freshmen by instantiating the GBN model for next-location prediction. Conversely, by setting the target node of a given GBN model to a certain value, we can determine the conditions required for achieving the target node value. This function is an example of the goal-seeking capability of the CALIPS system. For example, setting the 'Location Arrived' variable to 'Central Library' provides information about the composition of student majors, activities, and information about where the students were before coming to the central library. The current version of the CALIPS prototype displays an example of GBN model instantiation in which a senior student majoring in business administration staying at the 'Business Building' clicks the 'STUDY' button to determine the seating availability of the facility to be visited next; the BN model is instantiated using user context data (Year = 'Senior,' Major = 'BizAdmin', Location Departed = 'Business Building', and Activity = 'Study'). As a result, the next location is predicted as 'Central Library', and the room availability at the 'Central Library' is displayed to the user as the output information. Implications obtained from experimenting the CALIPS are plentiful. First, CALIPS can be adopted by the university itself in order to make the user-centric campus design. Regular update of the contextual database of the CALIPS will enable the campus designer to be aware of the college students' needs and wants, and then accommodate any changes of the students' preferences about specific activities, locations, and others. Second, college students tend to be excited about using the ubiquitous decision support system like CALIPS on their own mobile devices when they are on the campus. Such mobile and ubiquitous availability of the CALIPS capabilities will be a great fun for those young and brilliant college students, which is surely a success factor of the CALIPS. Third, when the CALIPS is integrated with existing start-up venture companies, more innovative types of business models will emerge, promoting active birth of various start-ups targeting the analysis of the college students' behaviours in various contexts.

4 Concluding Remarks

Campus is an important place for all the scholarly thoughts and innovative activities, some of which will become game changers in our society. That is why the campus has always been protected and revered by society. However, it is also true that the campus itself had been neglected by IS researchers. Especially, the potentials of the ubiquitous decision support mechanisms had been rarely applied to the campus, from the view of integrating GBNs and context prediction. In this sense, we proposed design of the ubiquitous decision support mechanism named CALIPS. Two research questions raised in this study are- (1) suggestion of the ubiquitous decision support mechanism for the campus life planning, named CALIPS, and (2) integrating GBN and context prediction into the CALIPS. To answer these research questions, we garnered a total of over 6000 contextual dataset with 40 attributes from 335 college students. A number of GBNs were built from these contextual dataset, and analysed accordingly to see how what-if/goal-seeking capabilities by using the GBNs work well to answer real questions. Results were promising and robust. Future studies still remain to be done further, though. First, we need to finish developing the full-fledged version of the CALIPS on the smartphones. Java language is used. Second, empirical analysis of the usability of CALIPS must be investigated by inviting real users. Third, the CALIPS can be used as a test bed for the purpose of developing more innovative business models targeting young consumers like college students.

References

Anagnostopoulos, T., Anagnostopoulos, C., Hadjiefthymiades, S., Kyriakakos, M., and Kalousis, A. 2009. "Predicting the Location of Mobile Users: A Machine Learning Approach," Proceedings of International Conference on Pervasive Services, London, England, pp. 65-72.

Cheng, J. and Greiner, R. 2001. "Learning Bayesian Belief Network Classifiers: Algorithms and System," Proceedings of 14th Canadian Conference on Artificial Intelligence, pp. 141-151.

Choi, D.Y., Lee, K.C., and Seo, Y.W. 2013. "Scenario-Based Management of Team Creativity in Sensitivity Contexts: An Approach with a General Bayesian Network," in Digital Creativity: Individuals, Groups, and Organizations, Kun Chang Lee (ed)., Springer, pp. 99-113.

Cook, D.J., Augusto, J.C. and Jakkula, V. R. 2009. "Ambient Intelligence: Technologies, Applications, and Opportunities," Pervasive and Mobile Computing (5:4), pp.277-298.

Dey, A.K. and Abowd. G.D. 1999. "Towards a Better Understanding of Context and Context-Awareness," Proceedings of the 1st International Symposium on Handheld and Ubiquitous Computing (HUC), Karlsruhe, Germany, pp. 304-307.

Friedman, N., Geiger, D. , and Goldszmidt. M. 1997. "Bayesian Network Classifiers," Machine Learning (29:2), pp. 131-163.

Geiger, D., Heckerman, D., and Meek, C. 1999. "Asymptotic Model Selection for Directed Networks with Hidden Variables," Learning in graphical models, The MIT Press, Cambridge, MA, pp. 461-477.

Heckerman, D. 1995. "A Tutorial on Learning With Bayesian Networks," Microsoft Research, Technical Report MSR-TR-95-06. (available at http://research.microsoft.com/en-us/um/people/heckerman/tutorial.pdf

Horowitz, H.L. 1987. Campus Life: Undergraduate Cultures from the End of the Eighteenth Century to the Present, The University of Chicago Press. Chicago 60637.

Hosack, B., Hall, D., Paradice, D., and Courtney, J.F. 2012. "A Look Toward the Future: Decision Support Systems Research is Alive and Well", Journal of the Association for Information Systems (13), pp. 315-340.

Huýnh, T., Fritz, M., and Schiele, B. 2008. "Discovery of Activity Patterns Using Topic Models," Proceedings of 10th International Conference on Ubiquitous Computing (UbiComp), Seoul, Republic of Korea, pp.10-19.

Kwon, O., Yoo, K. and Seo, E. 2005. "UbiDSS: A Proactive Intelligent Decision Support System as an Expert System Deploying Ubiquitous Computing Technologies," Expert Systems with Applications (28:1), pp.149-161.

Mayrhofer, R. 2005. "Context Prediction Based on Context Histories: Expected Benefits, Issues and Current State-of-the-art," Cognitive Science Research Paper-University of Sussex CSRP, ISSU 577, pp.31-36.

Mayrhofer, R., Radi, H., and Ferscha, A. 2003. "Recognizing and Predicting Context by Learning from User Behavior," Radiomatics: Journal of Communication Engineering (1:1), pp. 30-42.

Muntermann, J. 2009. "Towards Ubiquitous Information Supply for Individual Investors: A Decision Support System Design," Decision Support Systems (47:2), pp.82-92.

Patterson, D.,Liao, L., Fox, D., and Kautz, H. 2003. "Inferring High-Level Behavior from Low-Level Sensors," Proceedings of 5th International Conference on Ubiquitous Computing (UBICOMP), Seattle, WA, pp.73-89.

Pearl, J. 2000. Causality: Models, Reasoning, and Inference, Cambridge University Press, New York, NY.

Perl, J. 2004. "A Neural Network Approach to Movement Pattern Analysis," Human Movement Science (23:5), pp. 605-620.

Petzold, J., Bagci, F., Trumler, W., and Ungerer, T. 2005. "Next Location Prediction Within a Smart Office Building," Proceedings of 1st International Workshop Exploiting Context Histories in Smart Environments (ECHISE), Munich, Germany.

Seo, Y.W., Lee, K.C., and Lee, D.S. 2013. "The Impact of Ubiquitous Decision Support Systems on Decision Quality through Individual Absorptive Capacity and Perceived Usefulness," Online Information Review (37:1), pp.101 - 113

Singla, G., Cook, D.J., and Schmitter-Edgecombe, M. 2010. "Recognizing Independent and Joint Activities among Multiple Residents in Smart Environments," Journal of Ambient Intelligence and Humanized Computing (1:1), pp.57-63.

Tennenhouse, D. 2000. "Proactive Computing," Communications of the ACM (43:5), pp. 43-50.

Valenzuela, S., Park, N., and Kee, K.F. 2009. "Is There Social Capital in a Social Network Site?: Facebook Use and College Students' Life Satisfaction, Trust, and Participation," Journal of Computer-Mediated Communication (14:4), pp. 875-901.

Weiser, M. 1995. "The Computer for the 21st Century," Scientific American (272:3), pp. 78-89.

Witten, I.H., Frank, E., and Hall, M.A. 2011. Data Mining: Practical Machine Learning Tools and Techniques, Morgan Kaufmann, 3rd Ed.