Performance of Ensemble Classifier for Location Prediction Task: Emphasis on Markov Blanket Perspective

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Abstract

As the ubiquitous computing becomes popular, its applications come to real life as a form of a wide variety of ubiquitous decision support systems (UDSS). However, such ubiquity should be supported by prediction capability no matter which kind of contexts users are in. In this sense, context prediction capability, which is to predict future contexts users are going to enter sooner or later, becomes an extremely important part of ubiquitous decision support systems. This study proposes a new breed of context prediction mechanism using the Markov Blanket obtained from General Bayesian Network (GBN) as a main vehicle. To improve the prediction accuracy, ensemble of robust prediction classifiers is suggested on the basis of the GBN Markov Blanket. Three classifiers included in the ensemble mechanism are Bayesian networks, decision classifiers, and an SVM (Support Vector Machine). The proposed GBN Markov blanket-assisted ensemble classifier is applied to a real dataset of location prediction. Results were promising enough to conclude that the proposed ensemble classifier based on the GBN Markov Blanket is worthwhile for being adopted in developing a powerful context prediction purpose UDSS. Practical implications are also discussed with future research issues.

Keywords: *Context Prediction, Location Prediction, Ensemble Methods, General Bayesian Network, GBN Markov Blanket-Assisted Ensemble Classifier, ID3, C4.5, CART, SVM*

1. Introduction

Ubiquitous decision support systems [1] adapt to users' changing contexts to provide context-sensitive services that meet users' needs and preferences. Such adaptation requires the system to predict user's future context based on the current context data gathered from various sources, e.g., user's handheld devices, sensors embedded in the environment, and distributed databases. Context is defined as, "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 integration between a user and an application, including the user and the application themselves [2]." The collected (context) data are used as training and test data for building context prediction models, and the constructed models are used to infer user's future context. The success of context prediction depends on the degree of accuracy of related predictors.

Existing works have successfully employed Bayesian networks to predict future contexts: Patterson et al. [3] used dynamic Bayesian network for predicting likely travel destinations on a city map; Hwang and Cho [4] proposed a modular Bayesian network model to infer landmarks of users from mobile log data collected through smart phones; and Kasteren and Kröse [5] used naive Bayesian and dynamic Bayesian networks to infer daily activities of elderly people performed inside their houses; Sánchez et al. used discrete hidden Markov model to automatically estimate hospital-staffs' activities [6].

Other works have employed decision tree classifiers and Support Vector Machines (SVM) for context prediction: Byun and Cheverst [7] used decision tree to infer the preferences of the user in an intelligent office environment; Lum and Lau [8] proposed a negotiation algorithm based on decision trees to handle content adaptation for mobile devices; Matsuo et al. [9] used SVM to infer user's long-term properties such as gender, age, profession, and interests from location information; their system automatically learns patterns between users' locations and user properties. Decision tree algorithms have advantage over SVM or neural network in that they require less training time [10].

While individual prediction models perform well on many context prediction tasks, better performance may be achieved by harnessing the power of multiple models. Ensemble-based systems, also known as multiple classifier systems, committee of classifiers, or mixture of experts, combine individual classifiers that make errors on different parts of data to enhance prediction performance. This paper investigates yet another kind of context prediction using Bayesian Network (BN)-based ensemble system; we investigate the power of *GBN Markov blanket-assisted ensemble system* on location prediction.

A GBN Markov blanket-assisted ensemble system is defined as a multiple classifier system that uses those variables inside the Markov blanket of a GBN's class node (or target node) to build an ensemble system. A Markov blanket of a node X consists of the direct parent of X, the direct successors of X, and all direct parents of X's direct successors [11] in a given Bayesian network. The Markov blanket of node X may be thought of as the minimal set of nodes that isolates X from the rest of the graph [12]. If a node is absent from the target node's Markov blanket, its value is completely irrelevant to the prediction [13]. Hence, the Markov blanket can be used to select the core variables that affect the class variable. In this paper, we first create a GBN to identify the variables inside the Markov blanket of GBN's class node, and then use those selected variables to create GBN Markov blanket-assisted ensemble system by merging Bayesian network (BN), decision tree, and/or SVM using voting and stacking combination strategies. Location prediction experiments are conducted using real-world data to evaluate the prediction accuracies of GBN Markov blanket-assisted 2-classifier and 3-classifier ensemble systems.

The contributions of this paper are twofold: (1) the finding that GBN Markov blanket-assisted ensemble systems are comparable to BN-based ensemble systems, but with less computational costs; (2) what practical implications the GBN Markov blanket-assisted ensemble system has for location prediction. Section 2 addresses two kinds of classifier combination strategies, voting and stacking, used for building ensemble classifiers for the location prediction experiment. Section 3 describes the data, experimental setup, and experimental results. Practical implications of GBN Markov blanket-assisted ensemble approach are discussed in Section 4, and conclusion and future research issues are given in Section 5.

2. Ensemble methods: Voting and stacking

Many studies have shown that fusing a set of different classifiers (or ensemble of classifiers) with different misclassified instances (i.e. ones that do not overlap) will yield better classification performance over an individual classifier, which makes up the ensemble system, having the best performance [14]. The intuition is that if different classifiers make errors on different instances, the strategic combination of these classifiers can reduce the overall error to improve the performance of the ensemble system [15].

The success of ensemble system depends on achieving diversity among individual classifiers with respect to misclassified instances. There are four ways to achieve this diversity [15]: (1) use different training examples to train individual classifiers; (2) use different training parameters; (3) use different features to train classifier; or (4) combine entirely different type of classifiers. The first approach deals with incorporating various resampling techniques; bagging (or bootstrap aggregating) [16] and boosting [17] are two well known techniques. The second approach deals with using different parameter values such as weights, nodes, or layers (depending on the classifier to be trained) to train the individual classifier. The third approach deals with using different features to train the classifier; random subspace method [18] is one such method. Finally, the last approach deals with combining entirely different type of classifiers; an example would be combining decision trees, SVMs, and nearest neighbor classifiers.

In this paper, we focus on the last approach of combining entirely different type of classifiers to construct ensemble systems for location prediction experiment. We select three types of individual classifiers – decision trees, Bayesian classifiers, and SVM – and integrate them using two different combination strategies – voting and stacking. Note that prior to the ensemble system creation, we first create a GBN to identify the variables inside the Markov blanket of the class node; these variables, which parsimoniously describe the class node, are selected to create the GBN Markov blanket-assisted ensemble systems. We now briefly introduce each combination strategy.

Voting. Voting or majority voting has been used for centuries by humans to make decisions. The same methodology is employed to determine the final outcome of multiple classifier system. Three versions of majority voting exist [19]: unanimous voting in which all agree to the final decision, simple majority voting in which the final decision exceeds 50% + 1 votes, and plurality voting in which one with the most votes becomes the final decision. While these approaches cast entire vote to a single class that each classifier considers most likely, voting can also combine classifiers by averaging each classifier’s probability estimates. We average each classifier’s probability estimates when using voting strategy in our experiment.

Stacking. Stacking or stacked generalization [20] uses a high-level method (called level-1 generalizer or meta-learner) to combine lower-level methods (called level-0 models or base classifiers); predictions of the lower-level methods are used as training data for high-level method. The ensemble learning proceeds in two steps: first, the predictions of level-0 models are calculated; then, the predictions are used as training data for training level-1 generalizer. The class labels of the original data are retained for level-1 learner's training data. In essence, stacking provides the meta-learner indirect feedback about the correctness of its base classifiers [21].

Existing researches have mainly applied ensemble-based system to credit scoring analysis [22-25], bankruptcy prediction [26], heart disease diagnosis [27-28], and traffic incident detection [29]. Some have focused on location prediction [30]. We also apply our GBN Markov blanket-assisted ensemble approach to the problem of location prediction.

3. Empirical evaluation

To investigate the location prediction performance of GBN Markov blanket-assisted ensemble system, we collected real-world data from undergraduate students to construct and evaluate 2-classifier and 3-classifier ensemble systems. Hereafter, we indicate ensemble systems as ensembles or ensemble classifiers.

3.1. Data

User context data were collected from 335 college students in Seoul, Korea to create training and test data for location prediction experiment. The students were asked to complete a demographic survey which asked gender, major, student year, weekday leisure activity, lunch-time leisure activity, monthly allowance, and student ID; then, they were instructed to document their whole-day activity on campus for any two days; in particular, where they visited via what route and what activity they engaged in at the visited location. A list of campus location codes, route codes (a list of letters was specified to describe a sequence of paths), and activity codes were provided to help them record their activities. They were given extra credits for their work.

After the two types of data (i.e., demographic data and campus activity data) were cleaned, they were merged using student IDs to create a campus activity-demographic data. The merged data contained 12 variables: 'Location Arrived', 'Path Start', 'Path Middle', 'Path End', 'Location Departed', 'Activity', 'Gender', 'Major', 'Year', 'Weekday Leisure', 'Lunch Time Leisure', and 'Monthly Allowance'. Table 1 lists the 12 variables and the values of each variable. A total of 3,150 records of campus activity-demographic data were used in the experiment. The 'Location Arrived' variable was selected as the class variable in the experiment.

3.2. Experimental setup

WEKA [31], an open source data-mining tool, was used to construct and evaluate BN-based ensembles and GBN Markov blanket-assisted ensembles. BN-based ensembles were built using all 12 variables of the campus activity-demographic data whereas GBN Markov blanket-assisted ensembles used only 5 ('Location Arrived', 'Path End', 'Location Departed', 'Activity', and 'Major'); these 5 variables were selected on the basis of the Markov blanket of GBN's class node. That is, prior to creating GBN Markov blanket-assisted ensembles, a GBN was created using 12-variable data to identify the variables that parsimoniously describe the class variable. Note that the class variable is included in both the 12-variable and 5-variable dataset.

Three types of decision trees (ID3 [32], C4.5 [33] or J48 in WEKA, and CART [34]), four types of Bayesian network classifiers (GBN-K2 [35], GBN-Hill Climb, hereafter GBN-HC, Naïve Bayesian Network, hereafter NBN, and Tree-Augmented Naïve Bayesian Network [36], hereafter TAN), and one SVM (SMO algorithm [37]) were mixed to create 2-classifier (BN+DT, BN+SVM and GBN+DT, GBN+SVM) and 3-classifier (BN+DT+SVM and GBN+DT+SVM) ensemble classifiers. Each ensemble classifier employed voting and stacking strategy. All in all, 32 two-classifier (Table 3) and 24 three-classifier (Table 4) were created for both the BN-based ensembles and GBN Markov blanket-assisted ensembles in the experiment.

Table 1. Variables, values, and number of values in the location prediction dataset.

Variable	Variable Value (No. 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	ChatWithFriends, 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, FreeMajor, InfoTechnology, Law, LiberalArts, SocialScience, SportsScience (13)
Student Year	Freshman, Sophomore, Junior, Senior (4)
Gender	Male, Female (2)
Weekday Leisure	Concert/Exhibitions, Games, IndividualSports, Socialize, TeamSports, Travel (6)
Lunch Time Leisure	
Monthly Allowance	<100, 100-300, 300-500, 500-700, 700-900, >900 (6)

All algorithms needed to create individual and ensemble classifiers were already available in WEKA version 3.6.2. For the GBN-K2 and GBN-HC classifier construction, the maximum number of parent node was set to two. To construct the NBN, TAN, decision trees (ID3, J48, CART) and SVM, the default settings in WEKA were used. In all cases of the GBN-K2, GBN-HC, and TAN, the BAYES scoring metric was used. As for the two combination strategies, the averaging of the probability estimates was used to combine classifiers for voting, and multi-response linear regression was used for level-1 generalizer (or meta-classifier) for stacking following [38].

We performed 10 runs of 10-fold cross-validation on each ensemble classifier to obtain its prediction accuracy, and then conducted corrected resampled t-tests [39] at the 0.1% and 1% significance level to compare each ensemble classifier with the baseline GBN-K2 individual classifier.

3.3. Results

Table 2 compares the prediction accuracies of individual classifiers created using the 12 variables (first row) and 5 variables (second row). SVM shows the best individual classifier prediction accuracy in both cases; TAN and ID3 shows the worst performance for 12-variable and 5-variable data respectively. Compared to the GBN-K2 individual classifier (84.12), none of the other individual classifiers show significantly better performance at the 5% significance level. GBN-HC (81.23), NBN (81.90), TAN (78.87), and ID3 (80.74) classifier created with the 12-variable data and ID3 (79.29) classifier created with the 5-variable data showed significantly worse performance at the 0.1% significance level; TAN (82.41) also showed worse performance at the 1% significance level compared to the GBN-K2 individual classifier. Hereafter, the prediction accuracies showing a statistical difference to the GBN-K2 individual classifier are marked in bold for better performance and in italic for worse performance.

Table 2. Prediction accuracies of 12-variable and 5-variable individual classifiers compared to GBN-K2 individual classifier.

No. of Variable	GBN -K2	GBN -HC	NBN	TAN	ID3	J48	CART	SVM
12-var	84.12	*81.23*	*81.90*	*78.87*	*80.74*	84.82	84.20	85.26
5-var	84.12	84.75	84.12	*82.41*	*79.29*	83.21	83.86	85.23

Table 3 compares the prediction accuracies of BN-based (ensembles created using the 12 variables) versus GBN Markov blanket (GBN MB)-assisted (ensembles created using the 5 variables inside the Markov blanket of the GBN's class node) 2-classifier ensembles. Compared to the GBN-K2 individual classifier, GBN-K2+ID3 (86.00 & 85.43), GBN-HC+ID3 (85.94 & 85.54), NBN+ID3 (85.91 & 85.43) voted-ensembles for both the BN-based and GBN MB-assisted approaches show significantly better performance at the 1% significance level; in the case of the stacked-ensembles, GBN-K2+J48 (86.11) and NBN+ID3 (85.84) using the BN-based approach and GBN-HC+J48 (85.44) using the GBN MB-assisted approach show significantly better performance at the 1% significance level; last but not least, GBN-K2+ID3 (86.19) stacked-ensemble using the BN-based approach show significantly better performance at the 0.1% significance level.

Table 3. Prediction accuracies of BN-based and GBN MB-assisted 2-classifier ensembles compared to GBN-K2 individual classifier. (** p<0.01, *** p<0.001)

2-Classifier Ensemble		Voting		Stacking		Average	
		BN-based (12-var)	GBN MB-assisted (5-var)	BN-based (12-var)	GBN MB-assisted (5-var)	BN-based (12-var)	GBN MB-assisted (5-var)
GBN-K2	ID3	**86.00****	**85.43****	**86.19*****	85.15	86.10	85.29
	J48	85.67	84.49	**86.11****	85.16	85.89	84.83
	Cart	84.94	84.54	85.53	84.76	85.24	84.65
	SVM	84.16	84.19	84.20	84.26	84.18	84.23
GBN-HC	ID3	**85.94****	**85.54****	85.57	85.23	85.76	85.39
	J48	84.79	84.22	85.05	**85.44****	84.92	84.83
	Cart	84.71	84.57	84.67	84.97	84.69	84.77
	SVM	*81.32*	84.79	*81.73*	84.75	81.53	84.77
NBN	ID3	**85.91****	**85.43****	**85.84****	85.15	85.88	85.29
	J48	85.25	84.49	85.73	85.16	85.49	84.83
	Cart	84.88	84.54	84.83	84.76	84.86	84.65
	SVM	*81.94*	84.19	*82.37*	84.26	82.16	84.23
TAN	ID3	85.31	84.80	84.85	84.81	85.08	84.81
	J48	85.46	84.59	85.75	85.13	85.61	84.86
	Cart	85.13	84.59	84.66	84.74	84.90	84.67
	SVM	*79.02*	*82.63*	*80.23*	84.00	79.63	83.32
Average		84.40	84.56	84.58	84.86	84.49	84.71

Table 4. Prediction accuracies of BN-based and GBN MB-assisted 3-classifier ensembles compared to GBN-K2 individual classifier. (** p<0.01, *** p<0.001)

3-Classifier Ensemble		Voting		Stacking		Average	
		BN-based (12-var)	GBN MB-assisted (5-var)	BN-based (12-var)	GBN MB-assisted (5-var)	BN-based (12-var)	GBN MB-assisted (5-var)
GBN-K2 + SVM	ID3	**86.04****	**85.46****	**86.28*****	**85.30****	86.16	85.38
	J48	85.69	84.50	**86.17*****	85.17	85.93	84.84
	Cart	84.95	84.54	85.51	84.71	85.23	84.63
GBN-HC + SVM	ID3	**85.97****	**85.56****	**85.73****	**85.44****	85.85	85.50
	J48	84.80	84.29	85.06	**85.53****	84.93	84.91
	Cart	84.72	84.60	84.67	84.90	84.70	84.75
NBN + SVM	ID3	**85.98****	**85.46****	**85.98****	**85.30****	85.98	85.38
	J48	85.26	84.50	85.80	85.17	85.53	84.84
	Cart	84.91	84.54	84.87	84.71	84.89	84.63
TAN + SVM	ID3	85.38	84.90	85.33	85.13	85.36	85.02
	J48	85.49	84.62	85.75	85.20	85.62	84.91
	Cart	85.15	84.59	84.65	84.73	84.90	84.66
Average		85.36	84.80	85.48	85.11	85.42	84.95

Overall, the BN+ID3 voted-ensembles and BN+ID3 and BN+J48 stacked-ensembles show good performances. It is interesting that the BN classifiers can benefit from one of the lowest-performing ID3 individual classifier; conversely, a good-performing SVM classifier may do little good in improving the performance of a BN classifier regardless of the voting/stacking combination or the BN-based/GBN MB-assisted approaches as shown in GBN-K2+SVM, GBN-HC+SVM, NBN+SVM, and TAN+SVM ensembles.

Table 4 shows the prediction accuracies of the GBN-based versus GBN MB-assisted 3-classifier ensembles. Even though the SVM classifier did not do much good in improving the performance of individual BN classifier (i.e., BN+SVM 2-classifier ensembles), the SVM pushes the prediction accuracy of the BN+DT 2-classifier ensembles up a little bit in most cases when the SVM classifier is added to the BN+DT 2-classifier ensemble. Compared to the GBN-K2 individual classifier, the GBN-K2+ID3+SVM (Voting: 86.04 & 85.46, Stacking: 85.30), GBN-HC+ID3+SVM (Voting: 85.97 & 85.56, Stacking: 85.73 & 85.44), and NBN+ID3+SVM (Voting: 85.98 & 85.46, Stacking: 85.98 & 85.30) ensembles show significantly better prediction performance at the 1% significance level regardless of the voting/stacking combination strategy or the BN-based/GBN MB-assisted approaches [1]. Moreover, the BN-based GBN-K2+J48+SVM (86.17) and the GBN MB-assisted GBN-HC+J48+ SVM (85.53) stacked-ensembles performed significantly better at the 0.1% and 1% significance level respectively.

To summarize, the combination of BN+ID3 worked favorably in most 2-classifier and 3-classifier ensembles regardless of the BN-based or the GBN MB-assisted approaches or voting/stacking combination strategies. In some cases, the GBN-(K2/HC)+J48 was a favorable classifier combination. A total of 24 ensemble classifiers performed better than the GBN-K2 baseline individual classifier; of these (1) 10 were 2-classifier ensembles and 14 were 3-classifier ensembles; (2) 12 employed voting strategy and 12 employed stacking strategy; (3) 13 used BN-based approach and 11 used GBN MB-assisted approach.

4. Discussion

In the experiment, we were able to confirm that the prediction accuracies of 24 ensemble classifiers (Tables 3 and 4, ** p<0.01 & *** p<0.001, numbers in bold) were statistically better than the baseline GBN-K2 individual classifier. But how do they compare to one another? To see whether any of these superior ensemble classifiers perform significantly better than the other, we conducted a one-way ANOVA using a significance level of $\alpha = 0.01$ to check the statistical differences in prediction accuracy. The result showed that the differences among the prediction accuracies of 24 ensemble classifiers were statistically significant ($F(23, 2376) = 4.02$, $p<.001$). To find out which classifier means are significantly different, we performed post hoc analyses using the Tukey's HSD post hoc criterion for significance; as a result, there was a significance mean difference between 3 stacked-ensemble classifiers, in particular, between (1) BN-based (12-variable) GBN-K2+ID3+SVM (86.28) ensemble and GBN MB-assisted (5-variable) GBN-K2+ID3+SVM (85.30) ensemble (p<.002), and between (2) the same BN-based GBN-K2+ID3+SVM ensemble in (1) and GBN MB-assisted (5-variable) NBN+ID3+SVM ensemble (p<.002). However, there were no

[1] In the case of GBN-K2+ID3+SVM (86.28) stacked ensemble using the BN-base approach, the prediction accuracy was significantly better at the 0.1% significance level.

significant mean differences among the 21 ensemble classifiers or between the 21 ensembles and the 3 stacked-ensembles mentioned above.

Based on what we know so far, choosing a 2-classifier ensemble (Table 3, ones in bold) over a 3-classifier ensemble (Table 4, ones in bold) could be one rational choice since the 2-classifier ensembles require lower computational cost while maintaining comparable prediction performance to the 3-classifier ensembles. Voting strategy may be preferred over the more computationally expensive stacking strategy for the same reason. Similar rationale could be applied to the BN-based (12-variable) versus GBN MB-assisted (5-variable) ensemble approaches; with less number of features (variables) to work on, choosing the GBN Markov blanket-assisted approach could save on computational cost without hurting prediction performance; but this is not the only advantage of the GBN MB-assisted approach.

Because GBN MB-assisted ensemble approach exploits the Markov blanket of the target node, context prediction can be performed efficiently by focusing on the truly relevant explanatory variable(s); the GBN MB-assisted ensemble approach can be said to encapsulate a natural feature selection capability that picks out the features that parsimoniously describe the target variable. Such feature selection (or reduction) capability is beneficial both to humans and machines; for example, when designing a context prediction system, data gathering strategy for context prediction must be coordinated; if the prediction model inside the system requires too many context data to predict future context, both the users and the system may need to make much effort in supplying and handling these data; keeping the model simple with the features kept to a minimum allows low data-handling cost for both the users and machines.

A GBN expresses the relationship between a target variable and explanatory variables using nodes and links; thus, humans can easily interpret how variables influence each other through this graph model. Since humans can understand which explanatory variables directly influence the target variable, GBN can be used in what-if and goal-seeking analyses. A what-if analysis is one in which decision makers analyze the possible results by considering intended changes to input conditions. A 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. Although ensemble systems sacrifice model interpretability over performance, both the *GBN-based* (whether it uses K2, Hill Climbing, or other algorithms for building GBN) and *GBN Markov blanket-assisted* ensemble approaches have the advantage of acquiring basic understanding of variable relationship of the models.

5. Concluding remarks

A GBN Markov blanket-assisted ensemble system exploits the Markov blanket of the GBN's target node to parsimoniously identify the relevant features needed to create an ensemble system. We compared the prediction performance of BN-based and GBN MB-assisted ensemble systems and found that the performance of the two approaches were comparable to each other despite the fact that GBN MB-assisted approach handled fewer features. In this sense, we can view the GBN MB-assisted ensemble approach to have computational edge over the BN-based approach. Ensemble systems generally output improved prediction accuracy, but instead sacrifice interpretability; using the BN-based or the GBN MB-assisted ensemble approach may complement interpretability if humans construct Bayesian networks to obtain some basic understanding of the variable relationship prior to the construction of ensemble system. In the future, we plan to work on a context prediction system which can handle multiple prediction models suited to the individual user; here, the GBN MB-assisted voted-ensemble will be a suitable approach for constructing multiple prediction models for its computational efficiency.

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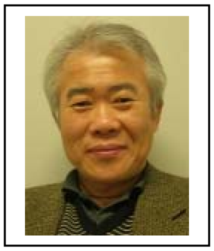

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