KARE: A Hybrid Reasoning Approach for Promoting Active Lifestyle

Rahman Ali
Dept. of Comp. Engineering, Kyung Hee University
Seocheon-dong, Korea
rahmanali@oslab.khu.ac.kr

Muhammad Hameed Siddiqi
Dept. of Comp. Engineering, Kyung Hee University
Seocheon-dong, Korea
siddiqi@oslab.khu.ac.kr

Byeong Ho Kang
Dept. of Computing and Information Systems, University of Tasmania, Australia
byeong.kang@utas.edu.au

Sungyoung Lee*
Dept. of Comp. Engineering, Kyung Hee University,
Seocheon-dong, Korea
sylee@oslab.khu.ac.kr

ABSTRACT
Healthcare systems provide suitable services in different domains to help people in fitting themselves into their best pattern of life. This study is focused on the development of a hybrid reasoning engine called KARE (knowledge acquisition and reasoning engine) which is the core reasoning module of ATHENA (activity-awareness for human-engaged wellness applications) platform[1], carried out at UCLab[2] as a project for promoting active lifestyle. This engine recommends food, mental and physical therapy to the ATHENA users that are based on their personal preferences, historical physical, mental and social health information. In KARE, a hybrid approach is used for reasoning which internally combines the predictions of multiple parallel reasoners into a collective decision. Random Forest, Naïve Bayes and IB1 algorithms are used in parallel in each of the reasoner to generate personalized recommendations for the specified service. The predictions of all the individual reasoners are combined using majority voting scheme to enhance the predictive accuracy of the individual reasoner. The proposed hybrid reasoning approach is tested on real world dataset of weight management, collected under the ATHENA project. The accuracy of correct recommendations for food, physical and mental therapies is 98.7%.

Categories and Subject Descriptors
Algorithms.

General Terms
Algorithms, Experimentation.

Keywords
Reasoning; hybrid reasoning; learning; KARE; healthcare; recommendations; active lifestyle.

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IMCOM (ICUIMC)'15, January 8–10, 2015, Bali, Indonesia.
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*Corresponding author

[1] http://uclab.khu.ac.kr/ATHENA/

[2] http://uclab.khu.ac.kr/

1. INTRODUCTION
A person's health is defined in terms of a number of attributes, but few of them are considered as more promising, such as physical, mental, and social primitives[1]. These attributes are highly correlated and vastly contributed in healthy lifestyle [3; 24]. In a real clinical environment, physiotherapists prescribe exercise and other physical activities to patients to promote their active lifestyle[25]. According to the survey [21], physiotherapists in United States of America have indicated that physical activity is the most focused activity for promoting health behavior. A physically inactive person is highly exposed to chronic, cardiovascular, obesity, type 2 diabetes mellitus, several forms of cancer, and depression diseases[4; 17]. Similarly, mental health is also a fundamental factor that provides significant benefits for improving health and quality of life. Mental health provides elasticity, health assets, capabilities and positive adaptation that enables people to cope, to flourish and to experience good health and social outcomes[12]. Apart from physical and mental factors, balanced diet and healthy eating plan are key factors to healthier lifestyle.

To promote active life style, in UCLab, at Kyung Hee University, we are conducting a research project with the name ATHENA aimed to elevate active lifestyle and wellbeing by identifying the underline connections between the physical, mental and social health primitives of users [11]. The prototype version of ATHENA is implemented which provides personalized dietary, physical and mental therapy recommendations to its users. The reasoning part of ATHENA is performed by KARE that generates personalized recommendations. In this paper, we present KARE, which uses a hybrid reasoning approach for generating personalized recommendations for users wellbeing.

Hybrid reasoning is a widely used and acceptable research area in the reasoning community due to its high predictive accuracy. It provides appropriate technology for computer-based solution of complex, real-life problems, like those encountered in medical domain[8]. In healthcare, a pervasive system, called Context-Aware Real-time Assistant (CARA) [27] has been designed for providing personalized healthcare services for elderly, so that to fit them into their normal activities of life. In CARA, contextual sensory data of elderly's activities are collected, fused, analyzed and reasoned to generate timely appropriate alerts using rule-based and case-based reasoning. Similarly, to promote and maintain healthy lifestyle, HealthyLife [9] system is developed for recognizing users activities and generating appropriate alerts, suggestions and recommendations. HealthyLife uses answer set programming-based stream reasoning (ASR) and artificial neural network (ANN) to generate alerts and suggestions. Similarly, WebDIET [20] is a web-based healthcare system that recommends suitable food to its users on the web using menu plans and users preferences. This system uses case-based reasoning for providing recommendations either directly to its users or to the dieticians who serve as administrators. Health cloud[15] is another system used to recommend better food to its users using ontological reasoning which exploits knowledge reasoning model. Thismodel gives a reasonable way of getting a better food choice from original food information and personal profile of the users. The food information consumed by this system includes food types, names and ingredients while the profile information includes physical, health and habit information.

Apart from healthcare, a number of systems and studies can be found in clinical setup which exploit hybrid reasoning models. For example, in end-of-life cancer care, nurse clinicians attempt to deliver care to the patients to minimize their pain, and improve their quality of life using case-based reasoning [10]. Similarly, a web-based health self-checkup system [23] is developed which helps the users to monitor their healthy lifestyle through their daily checkups. This system takes key physiological parameters of its users and their lifestyle information as input, performs analysis and generates report. The users adopt themselves according to the recommendations, mentioned in the report, for promoting their lifestyle. Likewise, the hybrid of rule-based and case-based reasoning can also be found in literature for acute bacterial meningitis [7] and domain independent clinical decision support in ICU[16]. Case-based reasoning and cluster analysis have been tried for health monitoring of elderly people in remotely way[2]. A hybrid case-based reasoning, rule-based reasoning and fuzzy theory reasoning has been applied for the treatment planning of adolescent early intervention of mental healthcare [26]. Similarly, a hybrid neural network (NN) and case-based reasoning (CBR) model is used for the diagnosis of congenital heart diseases [22]. In the same way, to classify the types of liver diseases, a hybrid diagnosis model of CBR, AHP (analytic hierarchy process) and ANN is used [18]. For the diabetes type 1, a decision support tool is designed using rule-based, case-based and model-based reasoning [19].

The existing work on reasoning is limited to classical approaches with single learning and reasoning algorithm for recommendations. Similarly, if some approaches use multiple learning and reasoning approaches, they only focus single objective function. To overcome the problem of generating recommendations for multiple services using multiple learning and reasoning algorithms, this paper presents a hybrid approach with parallel design for learning and reasoning. The outputs of the parallel reasoners are combined using majority voting scheme. The algorithms used are random forest, naïve Bayes and IB1 and the services targeted are diet, physical and mental therapy. The main contributions and uniqueness's of the paper includes:

- The development of a novel hybrid reasoning engine with a parallel design to generate personalized healthcare recommendations for promoting active lifestyle.
- The generation of personalized cross-domain recommendations for food, physical and mental therapies.
- The development of a stable reasoning approach for providing highly stable and accurate recommendations even with small data.
- The development of an integrated environment for data preprocessing learning and reasoning without degrading the system performance.

The rest of paper is structured as follows. Section 2 discusses the overview of ATHENA. Section 3 discusses the architecture and methodology of the proposed KARE system. Section 4 describes the implementation and results while section 5 concludes the work done with future directions. Section 6 acknowledges the funding agencies and section 7 presents the references used in the paper.

2. ATHENA OVERVIEW

ATHENA (a project taken as a research at UCLab) is a platform designed to integrate relationship between the basic health primitives of the users and estimates their lifestyle to generate real-time recommendations for their wellbeing. The purpose of ATHENA was to develop a system in order to promote the active lifestyle for individuals as shown in Figure 1. The platform presented personalized recommendations to its users by analyzing their past history data and personal preferences. This system used sensory data, collected through smart devices and processed using ingeniously developed tools. It exploited big data infrastructure for the massive sensory data storage and fast retrieval.

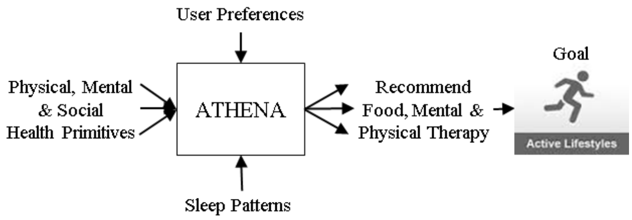

Figure 1. Abstract View of ATHENA.

In ATHENA, physical health (i.e., activities), mental and social health (i.e., feelings and emotions) were linked to sleep patterns, food habits, and users preferences to recommend food, physical and mental therapies to its users (Figure 1). All these parameters were measured through the activity recognition, emotion recognition, and sleep monitoring systems developed by our lab. Users profile and preferences were also taken into account, while recommending services for active lifestyle. In the first phase of ATHENA, data is collected from social network and sensory data sources and stored into the big data storage. This data is then loaded into the low-level data processing layer for extracting low-level and high-level activates using different modules, such as social media interactor, wearable device-based activity recognizer, smart-phone based activity recognizer and emotion recognizer, developed by our lab. These recognized activities and emotions were stored into the personalized intermediate data and also forwarded to the human behavior analyzer and context-aware recognizer for higher level decision making. This personalized intermediate data was passed into the personal service processing and reasoner layer. In this layer, personal profile information were collected from the users and stored them into the personalized intermediate data store. The inference and reasoner modules of this layer took personalized intermediate data, performed automatic learning, and stored the learned models into the personalized intermediate knowledge base. The learned models were retrieved for generating personalized healthcare recommendations for an input request when the reasoning process is activated for an input request. The scope of this study is only limited to the hybrid reasoning for the ATHENA platform.

3. ARCHITECTURE & METHODOLOGY

3.1 Architecture

The proposed architecture of KARE, implemented in ATHENA is shown in Figure 2.

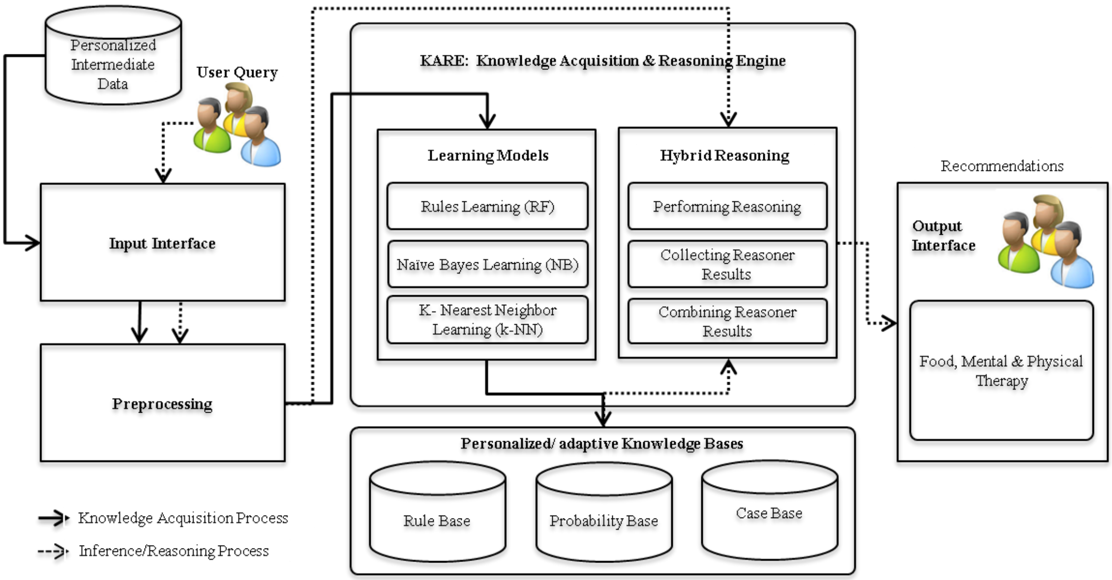

Figure 2. Architecture of Knowledge Acquisition and Reasoning Engine.

It consists of five main components, such as input interface, preprocessing component, main KARE engine, knowledge base and output interface.

The input interface provides a user friendly and easy way for knowledge engineer to create knowledge and for end user to enter input request for recommendation services. It is used for loading personalized intermediate data for learning and entering input query for generating service recommendations. The second component is preprocessing which allows cleaning, transformation, and reduction of the loaded data. It converts data into the formats of the learning algorithms, i.e., random forest, naïve Bayes, and IB1 in this case.

Main KARE engine by itself consists of learning and reasoning modules. The learning module learns the preprocessed data using the specified learning algorithms and stores the knowledge into the knowledge base. The knowledge base keeps the learned models separately, that can easily be used during the hybrid reasoning process. The reasoning module is activated during the execution process when a service is requested by the user. Reasoning for an input request, for example food recommendation, is performed by all of the three, random forest, naïve Bayes, and IB1 models. The result from each of the reasoner is taken and combined using majority voting scheme to get the integrated output as a final personalized recommendation for appropriate food. Finally, the result of the KARE engine is directed to the output interface where it is presented to the ultimate user.

3.2 Methodology

KARE Methodology is divided into three parts: data preprocessing, learning, and reasoning. Preprocessing and learning are activated by knowledge engineer for building knowledge base. Knowledge engineer uses the input interface and preprocessing module to clean, transform, and reduce the personalized intermediate data. In the cleaning task, missing values that exist in the data are filled by adopting Grzymala-Busse [13] methodology. According to this method, holes in the dataset are filled with the most common values of the attributes if the attribute is of type nominal and the mean value if it is of type numeric. In transformation, the low level data in the dataset is replaced with the higher-level concepts, such as taking breakfast, lunch and dinner etc. In the reduction step, continuous values of the attributes, such as height, weight etc. are discretized using global discretization technique initially proposed by Polkowski et al. [5] implemented in the rough set exploration system [6].

After preprocessing, the knowledge acquisition (i.e., learning process starts). We are using one training dataset to be learn by three different approaches, such as rules generation method (i.e., random forest), probabilistic method (i.e., Naïve Bayes), and instance-based learning method (i.e., k-NN). The motivation for using multiple learners for one dataset is to learn the diverse data appropriately. Each learner learns the data differently and thus eliminates the shortcomings of the other learners. This way, the same dataset is learned three times with three learners, each time for the different service (i.e., food, mental therapy, and physical therapy). Total nine models are learned and stored separately into the knowledge base. The learning process is shown by the bold face line in the architecture (Figure 2).

Once the learning process is completed, execution process (i.e., inference or reasoning) is activated by the user query from the input interface. While requesting the service, user specifies his/her preferences in term of preferred activity, food, and music etc. The input interface transfers the user query to the preprocessing component for parsing and forwarding to the hybrid reasoning module of the KARE engine. During the reasoning process, if a request for food recommendation is made, knowledge base is activated and models are loaded for generating recommendations. The recommendations from all the three reasoners are collected and combined using majority voting schemes to get the integrated output. The final results of KARE are forwarded to the output interface, where it is presented to the users.

4. IMPLEMENTATION AND RESULTS

In this section, we focus on the case study and the results obtained (shown in Table 1) by simulating the weight management dataset in Weka environment [14].

4.1 Case study and dataset

KARE is simulated with a weight management scenario dataset in which the subject wants to maintain his normal body weight and adopt active life style. In this scenario, the subjects are interested in getting appropriate dietary, physical, and mental therapy recommendations. The attributes of the weight management dataset, collected as a result of ATHENA project, are divided into five groups (personal profile, physical activities, mental activities, food, and sleep), as shown in Figure 3. The dataset contains 116 records.

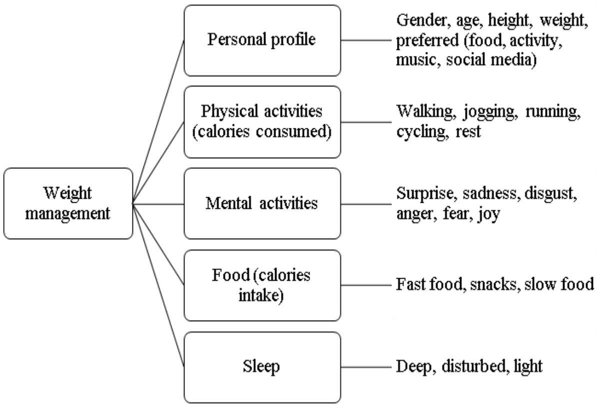

Figure 3. Characteristics of the Weight Management Dataset

The aim of this study is to generate food recommendations for the users and suggest them appropriate physical, mental therapy and food based on their body mass index (BMI), personal preferences, and sleep quality.

4.2 Experiments and results

We performed our experiments on the weight management dataset. For the first time, the whole dataset is taken for learning and the food attribute is selected as the target (label) attribute. The dataset is learned using random forest, naïve bays, and IB1 algorithms. For the second time, physical activity is selected as the label and the data is learned using the same algorithms. In the last, the mental therapy is taken as the label and the data is learned in the same way as the previously. For learning step, we used Weka [14] using an Intel Pentium Dual-CoreTM (2.5 GHz) with a RAM capacity of 4 GB. While conducting the experiments, we kept all the parameters of the learning algorithms as default in the Weka setup. Furthermore, 10−fold cross-validation scheme was chosen for splitting the data into training and testing sets.

The test set is provided to the hybrid reasoning system where all the learned models are utilized for generating predictions. All the results are collected and combined using majority voting scheme for the final predictions and recommendations. The detailed results are shown in Table 1.

Based on the results shown in Table 1, we observe that good results are generated by the hybrid reasoner where the individual results from all the three learners are combined together. As we know some learners produce good result when they are fed with small amount of dataset and bad result when the dataset is big. However, some other learners behave exactly opposite as produce good result when the dataset is big and bad result when the dataset is low. Hence, this hybrid reasoning consists of three different reasoners whose results are combined on the majority voting scheme, because its performance is always stable and good. We also noticed that naïve Bayes performance is not good compared to the other learners, such as Random Forest and IB1 because it is a weak classifier. On the other hand, 1-NN outperforms Random Forest by producing 99.1% accuracy, but when ensemble with the other classifiers, the final results produced is 98.7% accurate which is stable.

5. CONCLUSIONS AND FUTURE WORK

In this study, an easy to use automatic reasoning tool (KARE) is discussed which is an integral part of the ATHENA platform. Knowledge engineer can easily use the engine to automatically learn the data using multiple learning algorithms and store the models into the knowledge base. This knowledge base is used during the reasoning process of generating personalized recommendations using hybrid reasoning approach. The proposed approach achieves an accuracy of 98.7% for food, physical activity, and mental therapy recommendations.

Current work is focusing on weight management scenario and can be extended to other active lifestyle scenarios because this approach is independent of the domain but only needs formulation of the dataset. Furthermore, the complexity of the hybrid approach can be overcome by defining special techniques for the automatic selection of the learners for leaning the models.

6. ACKNOWLEDGMENTS

This work was supported by the National Research Foundation of Korea(NRF) grant funded by the Korea government(MSIP) NRF-2014R1A2A2A01003914 and by the Industrial Core Technology Development Program (10049079, Develop of mining core technology exploiting personal big data) funded by the Ministry of Trade, Industry and Energy (MOTIE, Korea).

Table 1. Percentage Accuracy and F-score of Individual Reasoners and Hybrid Reasoner

Personalized Recommendations	**Naïve Bayes**		**Random Forest**		**1-Nearest Neighbor**		**Hybrid Reasoning**	
	Accuracy	F-score	Accuracy	F-score	Accuracy	F-score	Accuracy	F-score
Mental (music) Therapy	87.931	0.873	87.931	0.878	87.069	0.87	87.069	0.87
Food Recommendation	98.2759	0.983	98.2759	0.983	96.5517	0.966	98.2759	0.983
Physical Therapy	83.6207	0.823	85.3448	0.851	88.7931	0.886	87.931	0.877

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