eHealth Context Inference
A Review of Open Source Frameworks Initiatives

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Abstract: The collection of health and fitness longitudinal data can be used to model disease progression and shape new algorithms to diagnose and predict health hazards. Continuously tracking vital signs, in particular heart rate and skin temperature, can be very informative by using models and algorithms to predict and notify the user about when he might be falling ill. With the current wearable devices and the proper algorithms, the individual can be permanently monitored, which might be much more interesting than a one-off reading comparison with the population average, made by a doctor. It would be possible to intervene earlier and to prevent somebody from becoming seriously ill. From a broader perspective, the knowledge about a user's health can be considered as an element of that user's context and be used by context aware applications to provide higher value to the user. After the trivialization of the data acquisition sensors, wearable devices, and raw data, the next logical step is the development of contained software components that can infer and produce knowledge from the raw data. These components and the knowledge they produce can be used by all sorts of applications in order to further customize their usage by a specific user. Customization and context awareness, in regard to health, is a wide field for research and there are a multitude of proposals for models and algorithms. In this review work we searched for software components (frameworks, software libraries, etc.), freely available and that can be used as building blocks for other computer systems by software developers.

1 INTRODUCTION

In this work, we conduct a review of the currently available software systems, freely accessible to developers, which can be used as software building blocks, providing functionalities associated to information inference and knowledge production, related the user's health status.

There are currently multiple wearable devices, equipped with sensors, which can read vital signs from a user. Some of these devices are not very accurate, mainly developed and targeted for the low end recreational and fitness market, others have medical grade accuracy and are targeted for the high-performance sports and medical environments.

For a health-related solutions developer, the raw data must be interpreted according to the specific purpose of the desire solution. In that regard, data analysis and knowledge inference is a specific research domain from which can be produced software modules, encapsulating all the research and deep knowledge necessaries to create the inference functionalities. These modules can be used as building blocks for other software solutions than will then benefit from having knowledge regarding their user's health.

This work reviews and analyses the currently available software systems, designed to provide specific health knowledge and that can be used as building blocks for more general software solutions. In this document, we designate these systems as frameworks and middleware in same sense as the terms are used in software engineering, although not being very strict and using the framework term even when in fact the system doesn't have all the elements of a software framework according to the well-known concept of software framework.

A framework is a structure or conceptual guide to build an entity by expanding itself into something useful. In electronic systems a framework, generally, describes a layered structure of software programs and hardware devices and how they are built, interconnected, and interact, to provide a full system functionality. The framework is comprehensive and

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prescriptive. In computer programming, a software framework is an abstraction in which a software system, providing a generic functionality, can be extended to provide application specific functionality by building and changing specific elements of the framework, thus creating a specific solution from a generic set of elements. The software framework provides a standard way to build and deploy applications. It can provide a functionality, as part of a larger software platform, simplifying the development of software application and solutions in a universal and reusable environment, which may include several types of elements, e.g., programs, compilers, code libraries, tool sets, and application programming interfaces (APIs) that can be used for the development of a system.

Software frameworks have the following key features that distinguishes them from other software components. (1) inversion of control, in which is the framework that controls the overall program's flow and not the caller library or application; (2) extensibility, providing mechanisms for the user to extend the framework, by selective overriding or addition of specialized user code to provide a specific functionality; (3) non-modifiable framework code, meaning the users can't modify the framework's code but must extend it instead.

A software library is a collection of resources used to develop software and build computer programs. It includes configuration data, documentation, help data, message templates, pre-written code and subroutines, classes, values or type specifications, etc. Usually these resources have specific behaviors and are accesses by well-defined interfaces.

In software engineering, an Application Programming Interface (API) is a set of subroutine definitions, protocols, and tools for building application software. It clearly defines the methods of communication between various software components. An API provides the methods for the programmer to develop a computer program by assembling together different building blocks.

An API usually describes and prescribes the expected behavior of a software library, while the library is an actual implementation of the functionalities. The separation of the API from the implementation allows programs written in one language to use a library written in a different one (Robillard et al., 2012).

Middleware is a software that stands in between two software layers (in the middle), usually providing value added services to software applications, on top of those available from the operating system.

A framework can include a software library, accessible by means of an API, and freely available to the programming community as middleware software, as represented in Figure 1.

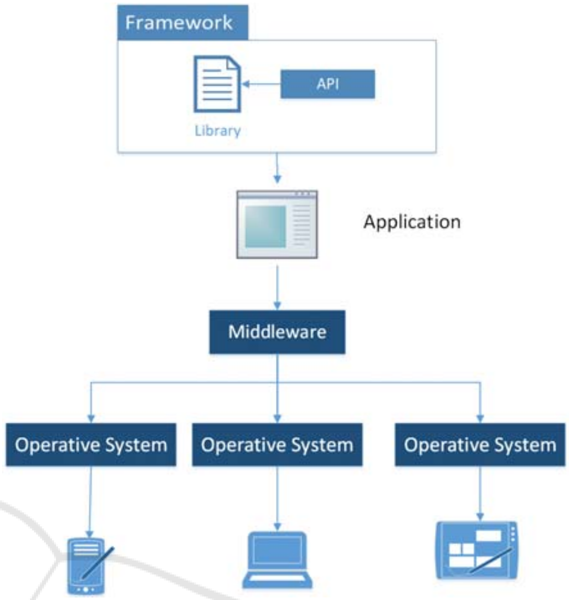

Figure 1: Overview of the connections between framework, middleware and API.

In the context of the software development elements previously described (frameworks, libraries and APIs), we are interested in those that can use health related data, e.g., vital signs and others, and produce health related knowledge, that can be used as building blocks by user developed applications.

2 HEALTH DATA AND PROGNOSTIC MODELS

Currently there are several consumer wearables and portal services that can monitor some basic vital signs, e.g., heart rate and skin temperature, allowing the user to register and view their evolution over time.

Based on this data, models and algorithms can be developed that will be able to predict the user's health status and evolution by computing the longitudinal data of the basic vital signs. The recent consumer grade wearables are not really expensive (some hundred euros per device) and some have good quality sensors, mainly developed for the fitness market. These devices have, mostly, an informative usage. They provide monitoring information to the users. To have a real impact on the users' health management and on the health care system usage, besides to provide information about the user's vital signs, this devices must also be able to analyze and draw conclusions about the user's health on his behalf. It is then necessary to collect data and create models and algorithms for the interpretation of the vital signs data.

The abundance of wearable devices, together with the Internet of Things (IoT) connectivity paradigm, are very strong drives for the acquisition of real-time data, particularly, data collection from individuals in their daily lives, as well as in specific sportive activities, such as the data of simple vital signs, e.g, heart rate and skin temperature, as well as, more complex data, regarding the individual health evolution, e.g., ECG, surveys (Paulino et al, 2017; Felisberto et al, 2015). The basic data can be used as parameters to model specific health phenomena and the complex data can be used to assess the correlation of basic data patterns with the health phenomena. It is then possible to create inference algorithms to predict the user's health evolution.

To create health related prediction models, several techniques can be used, e.g, decision rules, score systems, Markov processes, decision trees, neural networks and Baysian networks. To model the evolution of health phenomena over time, the Baysian approach is one the most suitable solutions. However, the adoption of a specific technique must be considered according to the available data, specific phenomena, and objective.

There are several techniques currently used to create prognostic models. The simplest are the decision rules, which are based on a prognostic score, classifying the patient in a specific risk category (Knaus et al., 1991). Also, in decision analysis, the Markov decision processes, which is a stochastic process that evolve over time, can be used as basis for prognostic models (Sonnenberg et al., 1993). More sophisticated techniques, with support from the artificial intelligence community, are becoming popular as prognostic models, including: decision-trees, neural networks, support vector machines, and Bayesian networks (Cruz et al., 2006; Ohno-Machado, 1997). These techniques have much better performance but require substantial amounts of quality data.

The Bayesian networks technique have been successfully used to model health phenomena, and other natural phenomena, e.g., genomics and ecology (Jansen et al., 2003), and has become a powerful tool for the analysis of real-world data, from health and the environment, leading to the shaping of novel algorithms (Gerven et al., 2007; Lucas et al., 1995; Murphy et al., 2002; Pearl et al., 2000). This tool and the collection of longitudinal data are creating research challenges for diagnosis and the modelling of disease progression (Abu-Hanna, 2001).

Wearable devices can be used to track the individual's vital signs and detect when he is about to get hill. In the follow-up of a recent research, by wearing sensors during a long period (over an year), Michael Snyder (Snyder, 2017) was able to detect abnormal readings, showing an increase in heart rate, when compared with his regular heart rate pattern, and a rise in skin temperature. On a recent interview, Snyder would confirm: "A mild fever soon followed, and Snyder asked a doctor for the antibiotic doxycycline, which can be used to treat Lyme disease. His symptoms cleared within a day". Subsequent tests confirmed his self-diagnosis. Snyder and his team are working with more than 40 volunteers, who wore smartwatch devices for up to two years and have demonstrated a solution to detect the first signs of illness by continuously monitoring their pulse and skin temperature (Li et al., 2017; Klein, 2017).

Several vital parameters can be continuously monitored using wearable devices. The most frequent is heart rate, as it is simple to monitor and has been widely studied, regarding several aspects, e.g., its levels, patterns, correlation with health, and death risk (Johansen et al., 2013). Skin temperature can also be monitor (Nakayama et al., 1977).

Heart rate variability (HRV) is a term that indicates the level of changes in HR. It was firstly used in 1846 when Carl Ludwing discovered Respiratory sinus arrhythmia, through which HR increases with inspiration and decreases during exhalation. HR is controlled via the two components of the autonomic nervous system (ANS): Sympathetic and parasympathetic indices (Makivic et al., 2013; Javorka et al., 2001). The sympathetic component is responsible for the HR acceleration during physical stress (i.e. exercise) whereas lower HR (example: Resting HR) is an impact of the vagal tone (parasympathetic tone) (Makivic et al., 2013). Consequently, the balance between the two components affects the time consistency between Heart beats, which is measured through HRV (Makivic et al., 2013).

Several studies have shown the correlation between heart rate data and particular health conditions. The analysis of heart rate variability (HRV) and its pattern can provide an insight into the health of the cardiovascular system (Javorka, 2001).

One of the simplest analysis, using heart rate data, is the interpretation of the resting pulse rate (RPR), which can provide useful information. RPR is a key vital sign measure in clinical practices with widely available reference data. Resting heart rate is independently associated with increased risks of all-cause and cardiovascular mortality, and, as shown by (Zhang et al., 2016), can be used as a mortality predictor. Beddhu et al, examined the association of resting heart rate with insulin resistance, cardiovascular events and mortality in the moderate chronic kidney disease (CKD) population and have demonstrated how higher resting heart is associated with increased mortality and possibly cardiovascular events in this population (Beddhu et al., 2009). There are several other authors using heart rate as a predictor for several health conditions, e.g., a tool for risk stratification in primary care (Leistner et al., 2012), osteoporotic fractures and mortality in older women (Kado et al., 2012), cardiovascular mortality in the general population (Hozawa et al, 2004), to sudden death and all-cause mortality in asymptomatic men (Adabag et al., 2008), coronary heart disease in the elderly (Legeai et al., 2011).

In the context of the sports practice, the exercise intensity assessment is important to inform the athlete of the correct training effort and prevent overtraining syndrome (OS) (Dressendorfer et al, 1985; Hedelin et al., 2000) or sudden cardiac death (SCD) (Savonen, 2006; Batty et al., 2010).

According to (Link and Estes, 2012), SCD rates in the US reaches 150 cases annually. Such cardiac complications occur either due to the medical history of the athlete or because of unmonitored exercising. If a trainee exercised without exceeding the endurance limit, then it is said he is in the functional over-reaching (FO) where the safety is highly assured and normal stamina can be obtained after hours/day of recovery. However, ignoring the OR region might lead to developing Overtraining syndrome (OS), which is a precursor of SCDs.

The pattern associated with how the heart rate recovers, after exercising, is a parameter that represents how fast the heart returns to the normal state after exercising. Typically, a drop of 12 bpm or less in the first minute of recovery is considered abnormal, and greater drop during this period signifies that the person is fit (Cole et al., 2000; Reis et al., 2016a).

With the vital signs collected data, e.g., HR and skin temperature, and with the support of meta data, it can be created longitudinal models and algorithms, correlating the health hazards (e.g., physical exhaustion, developing flu) and the HR patterns. These models will represent the time progression of the hazard and the algorithms will position the individual in a specific time of the model, by interpreting the patterns on the HR time line.

Although there are, currently available, devices that can continuously monitor the basic vital signs, the research, by Bloss et al., suggests: “there are not large short-term increases or decreases in health care costs or usage associated with monitoring chronic health conditions using mobile health or digital medicine technologies.” (Bloss et al., 2016; Reis et al., 2016b). That is a disappointing conclusion, and calls for further work to intelligently analyze the data and deliver truly valuable information to the user, as well as make the health-related inference and knowledge production features available to the general community of software solutions developers.

Context aware applications should then be able to use the knowledge about the user’s health as part of the user’s context. In a very simple example, a context aware groceries store shopping application, besides knowing the items that the user needs to buy, could also know the items the users should avoid buying due to its health status. Other applications have proposed the usage of electronic assistants to interact and accompany elderly people (Reis et al., 2017a; Marceline et al., 2009; Reis et al., 2017b).

3 METHODOLOGY

For this review we defined the following methodology in order to identify the software frameworks to consider and study:

1. An internet search using the terms “software”, “healthcare”, “health”, “inference”, “system”, “middleware”, “framework”. The search was conducted using the “publish or perish” software, using the google scholar engine data. The search was limited to 1,000 item and 980 items were returned.
2. A filter, excluding surveys and literature reviews. It returned 892 items.
3. A filter, excluding those without the term “health” on their title. The return list was narrow down to 301 items.
4. A filter, by means of a comprehensive reading by a researcher, and exclusion of those not related to a software framework or middleware. The list was shortened to 45 items.
5. A filter, excluding those not related to this work theme or not having any bibliographic citation. This filtered the results to 7 items.

After all the searching and filtering, the items were carefully analyzed and described, namely regarding:

- The inference algorithms (machine learning, vector learning, deep learning, Bayesian, Rules, Markov, etc);
- The system's learning strategy;
- The types of data necessary for the inference to work;
- The pathologies for which the system can produce knowledge;

4 ANALYSIS AND RESULTS

The results are summarized in Table 1, in which are listed the framework's titles and their online information links.

Table 1: Review results.

"Context-aware hybrid reasoning framework for pervasive healthcare" (https://link.springer.com/article/10.1007/s00779-013-0696-5)
"Bdcam: Big data for context-aware monitoring-a personalized knowledge discovery framework for assisted healthcare" (http://ieeexplore.ieee.org/document/7117389/)
"MediAlly: A provenance-aware remote health monitoring middleware" (http://ieeexplore.ieee.org/document/5466985/)
"An integrated multi-sensing framework for pervasive healthcare monitoring" (http://ieeexplore.ieee.org/document/5191197/)
"A framework for context-aware home-health monitoring" (http://www.inderscienceonline.com/doi/abs/10.1504/IJAACS.2010.030313?journalCode=ijaacs)
"A Middleware Framework for Ambiguous Context Mediation in Smart Healthcare Application" (http://ieeexplore.ieee.org/abstract/document/4390866/)
"An Inference System Framework for Personal Sensor Devices in Mobile Health and Internet of Things Networks" http://dro.deakin.edu.au/view/DU:30092154)

The following list describes, in more detail, the analysis of the selected frameworks.

1. "Context-aware hybrid reasoning framework for pervasive healthcare" (Yuan et al., 2014)

This article main objective is to describe the creation of a framework to manage the context monitoring of elderly people on their homes. The inference method is based on Fuzzy Rules (Wang et al., 1991) and the system learns by Case Based Reasoning (CBR) (Xu et al., 1995). The framework uses vital signs data and infers if the individual has a normal health condition.

2. "Bdcam: Big data for context-aware monitoring-a personalized knowledge discovery framework for assisted healthcare" (Forkan et al., 2015)

This framework is intended to build a system to monitor a person's vital signs, inferring the individual's current health status from that data. The system uses the MapReduce Apriori algorithm (Yahya et al., 2012) that can register the correlations between distinct variables of the acquired context, producing a set of rules. It uses data acquired from the blood pressure and the heart rate.

3. "MediAlly: A provenance-aware remote health monitoring middleware" (Chowdhury et al., 2010)

In this framework, the main purpose is to be a building block of a system based on mobile devices to monitor the user's physiological data, which is later sent to a middleware that infers the user's health status by applying a set of rules.

4. "An integrated multi-sensing framework for pervasive healthcare monitoring" (ElHelw et al., 2009)

This framework is intended for the implementation of a system to monitor a person's vital data as well as several specific personal activities, e.g., walking, eating, sleeping, etc. The system uses videos cameras and wearable devices to collect data. The inference determines the activity being executed by the person and is accomplished using Hidden Markov Models (HMM) (Eddy, 1996).

5. "A framework for context-aware home-health monitoring" (Esposito et al, 2010)

This article describes the construction of a framework and a context aware computational system, implemented in a home-care scenario. The vital data is collected and used for inference based on a predefined rule set.

6. "A Middleware Framework for Ambiguous Context Mediation in Smart Healthcare Application" (Roy et al., 2007)

In this article it is described the development of a middleware software system, tailored to deal with the context ambiguities in health data monitoring. In a Smart Home scenario it was used wireless sensors and RFID tags to acquired data, including: location, activities, and identification of the users. From this data, inferences are made using Dynamic Bayesian Networks, with the objective of measuring the context quality.

7. **“An Inference System Framework for Personal Sensor Devices in Mobile Health and Internet of Things Networks” (Kang, 2017)**

In this thesis the main objective is to create a framework to monitor vital signs. The framework can detect and alert when the user’s vital signs have abnormal readings. The inference is a simple method based on verification of rules and predefined thresholds applied to the vital signs data.

5 CONCLUSIONS

Although the health data monitoring subject is widely spread in the research community, there aren’t many proposals towards the development and implementation of health related inference systems frameworks. There is much more work related to the acquisition and presentation of vital signs data, which suggests a gap between the data and the inference and knowledge production. On that line of reasoning, knowledge inference is the next logic step to make sense from all the data.

Comparing the health knowledge inference with other research areas, (e.g., computer operating systems, computer vision, statistics analysis, content management, etc.) for which there are high quality and freely available frameworks (e.g. linux, android, java, openCV, R, wordpress, etc), we can’t find parallel frameworks for health knowledge inference. That might be because, although there are lots of high quality research regarding the models and algorithms, the technology hasn’t mature enough for the arising of a general software framework.

Unfortunately we did just a review work, but a deeper analysis, including actual tests would be very important to verify the quality of the inference provided by the systems. In a scenario on which the data acquisition and processing is trivial, it may be the models and algorithms to determine the quality of a complete solution.

Reading thought the documentation of the several frameworks it is clear that to apply some inference techniques and longitudinal analysis, it is necessary to have large amounts of data, which might explain the gap between the available analysis techniques and their actual usage in actual software frameworks.

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