User-Centered Recommendation Services in Internet of Things Era

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ABSTRACT

In the Internet of Things era, we need to face increased masses of data, across all domains. Current researches have long been working to develop methods that help users to identify, extract, visualize and understand useful information from these huge masses of high dimensional and often weakly structured and/or non-standardized data. Our goal is to propose a solution for supporting users to interactively analyze such data flow and to visualize their most relevant parts through proper interaction style, without getting overwhelmed. In the paper, we describe a multi-level recommendation system (RS) by providing users with a decision-making process interactively accessible and by integrating it with social and crowdsourcing analysis, and interpretations that can lead to a new and meaningful use and presentation of data. to provide users with a decision-making process interactively accessible and enriched with social and crowdsourcing analysis tools, and interpretations that can lead to a new and meaningful use and presentation of data. The challenge is to enable effective human control over powerful machine algorithms based on a set of recommendation services used to filter data and choose proper data visualization and interaction style for supporting user's insight, discoveries and decision making.

Author Keywords

Social Networks; Recommendation System; User-centered design; Internet of Things.

INTRODUCTION

The emerging concept of the Internet of Things (IoT) [1] offers the capabilities to uniquely identify, locate, and connect people, machines, devices, equipment and other resources available in the living environments. Putting the human at the center of informative systems, ambient and personal sensors, communicative tools, mobile and ubiquitous computing devices, offers unprecedented opportunities to achieve deeper, meaningful and faster insights. Research in Human-Computer Interaction (HCI) and Knowledge Discovery in Databases and Data Mining (KDD) has long been working to develop methods that help users to identify, extract, visualize and understand useful information from these huge masses of high dimensional and often weakly structured and/or non-standardized data [11][5]. Our goal is to combine those efforts to support users to interactively analyze information properties and to visualize the most relevant parts without getting overwhelmed. Current researches focus on studying solution based on two main approaches: Context Awareness and Content Adaption. Context Awareness deals with the fact that systems are able to recognize the situation the user of the device is in at the moment [2]. Content Adaption mainly deals with how to present a user-friendly visualization of the results of information requests [8]. These approaches need to face the problem to manage huge amounts of heterogeneous data as very often happens in IoT contexts. This paper aims to present a context awareness solution based on an active participation of users in solving problems that are personally meaningfully to them when they interact with big-data in IoT contexts. Our point is that only the end-users have the proper knowledge to face a set of drawbacks, such as accumulation of irrelevant information, the need to adapt huge amount of data according to the context of use and their visual preferences. Specifically we present a solution based on a multi-level recommendation system (RS) based on a set of services able to suggest relevant information according to the user's profile and context of use, and to trigger an iterative process that involves users in the decision-making activities devoted to filter data and choose their final visualization and the interaction style to adopt. Moreover, it is of paramount relevance to consider the human not as single individual but as member of social communities of interest [4]. Exploiting information coming from the user's social networks (SNs), the idea is to integrate our recommendation services with social and crowdsourcing analysis, and interpretations that can lead to a new and meaningful use and presentation of data.

The paper is organized as following. The first section provides an overview of drawbacks characterizing current intelligent systems used in IoT context. Then, the second section describes the multi-level RS that we propose for placing the user in the center of the recommendation process. The third section provides details on the recommendation services for helping the user in filtering data and in choosing the final data visualization and interaction style, whereas the fourth section presents two ancillary services used by our RS. Concluding remarks are finally presented.

INTELLIGENT SYSTEMS IN THE IOT DOMAIN

Although context awareness is not a novelty at this point [2], its maturity, in the context of the big data research field, is still far away to be solved. Relevant problems concern the need to connect SNs, personal and ambient sensors, devices, equipment and other resources in human-centered solutions. In IoT domain, current systems are not able to manage in real time and in a satisfactory way huge amounts of heterogeneous data (including structured, unstructured and semi-structured data) for a user-centered standpoint. Recent proposals [7][12][10] move toward smart systems able to extrapolate relevant information for the user or the community in which he/she acts according to the proper context of use. These solutions based on the use of RS techniques appear to be very interesting. Nevertheless in the IoT context, the amount of data to handle is so relevant that these RSs need to find proper solutions for placing the user at the center of the recommendation process. Such suggestions should be delineated in order to control the informative flow generated by sensors and machines. In turn, the RSs need to recommend proper data visualizations and interaction strategies according to the context of use, the adopted device, and the user's profile and goals, exploiting a range of possible multichannel, multimodal and multimedia solutions. With the advancement of computational techniques, we have the unprecedented ability to allow machines to assist users or groups of users in completing their tasks. Relying on only automatic suggestions may not be entirely appreciated by the active user, which risks to get frustrated in using the RS platform whenever its recommendations prove to be erroneous. To solve this problem, the main challenges that we have to face are:

- The need of a recommendation model and, as a consequence, of a recommendation policy understandable by the user.
- The need to define how the user can be part of the recommendation process.
- The need to exploit the social relationships between users. User-centered recommendation can be enriched in considering SNs where each user will certainly appreciate receiving recommendations from those considered "closest" to her/him.
- The need to take into account the uncertainty of both the ratings/suggestions proposed by the SN members. In fact, judgments collected from a plethora of users with different habits and cultures may produce contradictions which in turn result in data having a high degree of ambiguity. This calls for a granular interpretation of the information provided by such crisp attributes, for instance in terms of fuzzy sets, rough and interval sets, and so on.

MULTI-LEVEL RECOMMENDATION SYSTEM

Starting from the problems outlined in the previous section, our idea is to design multi-level recommendation system centered around the users in order to involve them in tailoring the informative flow generated by sensors and machines and in delivering and visualizing right information at the right time, in the right place, in the right way, to the right person according to his context of use, preferences, goals, profile and the used devices. In order to face drawbacks of current RS, our RS is designed for providing users with a set of services to intelligently control the final data to visualize and what interaction modality to adopt. Specifically, these services follow an user-centered approach able:

- To associate each user to a user model able to offer a representation of his explicit and implicit preferences. Explicit preferences concern the user's registry data instead the implicit ones are defined automatically by the system by analyzing user behavior and preferences.
- By exploiting the user model, to offer a recommendation model designed around a dynamic decision tree based on fuzzy rules for supporting the user to interactively participate in the development of the final recommendation both for filtering data and for choosing the final data visualization and interaction style.
- To integrate the recommendation with SNs analysis techniques to capture social relationships among users.

Motivating example

Consider a household scenario where user Francesco wishes to taste something new for dinner and so he asks suggestions to our system about possible recipes. These recipes need to be compliant to Francesco's preferences, what there is in the cupboard and in the fridge, the diet provided by his nutritionist, what Francesco has eaten in the last days, suggestions of his friends or of the community of cooking experts. Moreover, in preparing the food, our system needs to take into account how long the meal will be ready before dinner, the energy consumption by the other Francesco's household appliances (to avoid overcharges) and the weather (if it is cold Francesco prefers something warm otherwise fresh food is desired).

USER-CENTERED RECOMMENDATION SERVICES

User Model Service

A user model is a sort of stereotype able to offer an aggregated and balanced profile of a group of users. A function is defined in order to take a profile and return a stereotype: each profile falls in exactly one stereotype according to his registry data and behavior. If two people have the same stereotype, then they belong to the same group and they behave similarly and have similar interests. In the architecture depicted at Figure 1, the explicit and implicit data of all users are analyzed and clustered (grouped) into stereotypes through a service named User Model (UM) service. Some of the challenges of designing and implementing stereotypes concerns their dynamics and extensive review requirements. The dynamicity of stereotypes is caused by the dynamic nature of user's interests and behaviors. To generalize the user behavior we could assume that the user matches a set of stereotypes

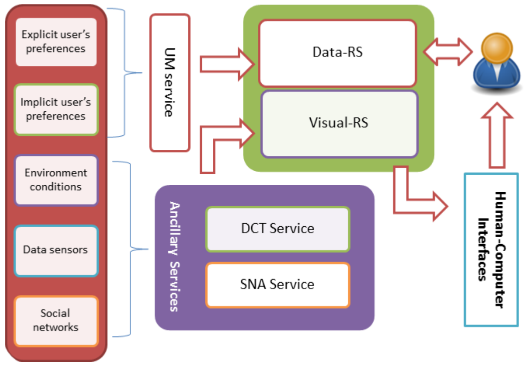

Figure 1. Architecture of the RS in which the user is involved in an iterative recommendation process by a set of services used for feeding the human-computer interfaces.

to some degree of affiliation. To do it, the UM service is based on user-centered similarity rings that are initiated by the registry data, preferences and log files representing the behavior of a single user. The similarity ring solution relies on the Nearest Neighborhood approach [9], where "the distance between the target user and every other user is computed and the closest-k users are chosen as the neighbors". The stereotypes of the identified users can be used to select the stereotypes, properly weighted into a degree of affiliation, of the target user. According to our scenario, the UM service is used to define a user model for Francesco. For example it can assign Francesco with a given degree of affiliation to the vegetarian group because he prefers to eat vegetable (or in the past he has predominantly ate vegetables) even if he is not a vegetarian. Francesco is also assigned to the group of forty-year-old males coming from north Italy and so having some specific food orientations. Finally, according to the Francesco's nutritionist notes, the UM service can assign him to a group that needs to follow specific food restrictions or a diet.

Data-RS and Visual-RS

As soon as the user's activity starts producing and requiring data for a specific task, our system triggers two recommendation services to cluster and to aggregate data coming from sensors and other informative resources according to the characteristics of the user stereotypes and to identify the better solution for data visualization and interaction. To suggest possible resources, our system triggers a first recommendation service named Data-RS that aims to provide the most valuable suggestions satisfying the (explicit and implicit) preferences characterizing the user stereotypes and a set of rules related to the context of use (e.g. environment conditions, location, data sensors). This enables a dynamical decision tree procedure where, depending on the current choice of the user, the service proposes branches of decision trees that may lead to a satisfactory classification of data items by posing a series of questions about features associated with the input data. Through these questions the user can modify, on run-time, his/her preferences and rest the rule set on the basis of the user inputs.

In turn, the system provides a second recommendation service named Visual-RS that aims to visualize data and to choose the better interaction strategy according to the user's device, context of use and preferences. This service is not triggered anytime a user wishes to have suggestions but only the first time or when he wants to change the interaction modality. As for the Data-RS, also the Visual-RS proposes branches of the decision tree related to possible usage strategies for visualizing and interacting with data through a dynamic procedure based on the current choice of the user and on features associated with the UM data. According to our scenario, the Data-RS is used to provide Francesco with a decision support queries based on a tree-like graph. Starting from the Francesco's UM and a set of rules related to the time, location, weather, energy consumption of household appliances, food in the cupboard and the fridge , Francesco's diet, and so on, the system retrieves a huge variety of recipes, that Francesco can further filter. To do it, the decision tree is generated for enabling Francesco to select further preferences covering his wishes, narrowing at most his choice basin. For example he might desire an Asian-based dinner. The tree provides Francesco with a set of iterative queries, the selection of the preferences of utmost importance in the evaluation of the best recipe through the use of machine learning techniques. Instead, by using the Visual-RS, Francesco could choose to visualize the queries for branching the decision tree or to visualize the recipes using a mobile phone or a tablet. He can choose to interact using animations or video or by means of touch-screen interaction or voice input control.

ANCILLARY SERVICES

How depicted in Figure 1, the Data-RS and Visual-RS rely on another two ancillary services, named Decision-Tree Creator (DTC) and Social Network Analysis (SNA) services. The first one aims to create the decision tree algorithm, exploiting the one-to-one correspondence between decision trees and the set of rules related to the context of use, whereas the second one aims to integrate the recommendation with SNA techniques.

DCT Service

By using an interactive machine learning algorithm of the well-known tool C5.0[1], the DCT service creates the decision tree algorithm, with particular emphasis on the entropic criteria at the basis of its construction. The service is endowed with a set of granular computing techniques, which are essentially used to handle non crisp judgments. By fuzzifying the sets constituting antecedents and consequents of the set of rules, these techniques are used to introduce a fuzzy reasoning based on fuzzy entropic criteria and expressed in terms of fuzzy decision trees. To avoid injecting inconsistencies in the final rule set, the tree construction carried out by the DTC service, is compliant with the multivalued attributes characterizing informative contents of our repository or that come from sensors. In this way, the service will be able to extend the decision tree based on the DTC service to handle non crisp data for instance in terms of fuzzy sets, rough sets, interval sets so on. For example in our scenario, such fuzzy conditions could be expressed by Francesco using queries such as:

[1]freely downloadable from http://www.rulequest.com/see5-info.html

I prefer food less fat or I want to have a dinner between 7 and 8 P.M.

SNA Service

SNA service works on ad hoc clustering techniques for finding groups within the SN members. In detail, the service replaces the concept of proximity of a typical recommender system: the Collaborative Filtering System [10], with the corresponding Social Network Analysis [6][3] one, introducing weights on the preferences of the users, so that well-reputed members of the SN will have a higher influence in the whole process. In our scenario, the idea is to provide Francesco with recipes also using the SNA service for reinforcing the suggestions on the basis of the feedback of his friends or suggestions of members belonging to communities of cooking experts. This last reinforcement uses weights on the users preferences by taking into account their role in each community, their competencies, and their level of participation. These users take the role of domain experts since they have a deep understanding of where the data come from, what audience will consume the data and how that audience will interpret the information. For example, in specific contexts of use such as traffic management systems, learning platforms, healthcare services it is important to properly weight the contribution of domain experts (police, teachers, physicians) in the evaluation and interpretation process of the data. In this way ,the user when accesses data can be helped to analyze them by people with a deep understanding of the data. The Visual-RS by using the SNAS service, reinforces the suggestions by means of existing visualization and interaction strategies on the basis of the users feedback. Since each user can set up and personalize interfaces of his device according to his preference, the Visual-RS can exploit such information for recognizing the minimal distance of the current visualization request from solutions adapted by members of the same community. The clustering and the identification of the most similar visualization solutions may profit of families of algorithms normally used in conventional SNs.

CONCLUDING REMARKS

Mobile, ubiquitous computing, sensors everywhere, social networks, are accelerating an avalanche of data and there will be definitely the danger of drowning in data, but starving for knowledge. From our standpoint, this increasing data flow requires sophisticated methods of handling that need to be placed under the human control for avoiding the risk to get frustrated in using the recommendation system platform whenever its recommendations prove to be erroneous. To this aim, the paper outlines some ideas and a possible architecture based on multi-level RS in order to place the user at the center of the decision-making process addressed to analyze and filter the data flow and visualize the most relevant parts of it through proper interaction style. To overcome all the limitations of current RSs, our approach presents the following aims.

- To define a recommendation policy based on explicit and implicit user's preferences and a set of fuzzy rules characterizing the data flow coming from sensors, equipment and other information sources.
- To drive users in filtering and tailoring the data flow by means a dynamic decision tree which branches on the base of users' wishes by posing a series of questions about features associated with the input data.
- To endow the decision tree with interactive machine learning and granular computing techniques to allow the user to interactively participate in the development of the final recommendation and to handle non crisp judgments.
- To integrate the recommendation with social networks analysis techniques to capture social relationships among users.

Important further implementation aspects include:

- A detailed study of the techniques in the field of machine learning, data mining, and granular computing, with the aim to deepening the theoretical notions at the base of our decision tree algorithm.
- A better definition and integration of SNA to graphically represent the social networks and the degree of centrality of each user.
- A study of suitable metrics and dimensionality reduction techniques as well as prerequisites to a robust and efficient clustering algorithm able to handle fuzzy, multi-value, and high dimensional attributes.
- A set of testings of our approach in real contexts of use for validating the theoretical analysis.

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