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IoT Recommender System: A Recommender System based on Sensors from the Internet of Things for points of interest

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Abstract. The Internet of things is a great source of knowledge. Its strength is based on the use of sensors that can provide information in real time on multitude of variables in any part of the world connected to an internet connection. At the same time, social networks increasingly encourage users to create comments on points of interest they visit or could visit, giving valuable feedback for other users or even for recommender systems that could use that information to anticipate user tastes in the future. In this work, we present an overview of a novel recommendation system to generate recommendations for users based on both the information gathered from sensors and the opinions explicitly indicated by users about places or recommendations previously made by the system.

Keywords. Recommender Systems; Internet of Things; Smart Objects; Sensors; Artificial Intelligence;

1. Introduction

Currently, different services use in their background Recommender Systems to give a specific and custom-made recommendation for each user. This is the case of AliExpress, Amazon, HBO, Netflix, or even Google and Facebook when showing us advertisements. This is possible due to the use of a specific Recommender System that analyzes all the data that we produce or the data from people that have similar tastes to us. Using these data, Recommender Systems can suggest us customized contents.

Nevertheless, there are different types of Recommender Systems [1]. Some of them need specific content by users, like reviews or scored items to create the personalized recommendations. Other times, they use metadata, like the things that were searched, visited or read. Notwithstanding, the former is something that users do not usually do. Then, when we need to recommend different points of interest (POIs), we need this information and in this case, this creates a lack of data to do the customized recommendations. However, with the Internet of Things (IoT) [2–4], this situation could change drastically because of the heterogeneous and ubiquitous sensors that could be dispersed around the world [5,6], allowing us to use any object to do anything [7–9].

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To solve this situation, in this article we propose a hybrid system where the information is retrieved through explicit feedback. This Recommender Systems will use the feedback from users and from sensors to give different recommendations for the user who does a query to the system, as Cha et al. demonstrate [10]. However, in our case, we want to extend all the work to any area, not only tourism, and including personal data about similar users to improve the system.

Using the idea that we present here, it will be possible to obtain feedback from similar users that have been in places and have been given a "like" to those places; the different sensors that are distributed in different places allows us to gather data from the exact POI that we want to evaluate. Clearly, in these cases, sensors will have to be registered under the same POI or to be placed closely, inside or around the POI, which will be evaluated to use the exact valid sensor to create good recommendations.

Notwithstanding, the major problem in this case is how to analyse all the amount of data, what method or methods use to do that, and how to create correct recommendations. This proposal presents the main idea of IoT Recommend Systems and how the problems could be solved with different solutions to create a Recommend System that uses the sensors of the IoT.

The remainder of this work is structured as follows: Section 2 presents the state of the art, which contains the related work and what technologies will be used in this proposal. Section 3 shows the proposal and the general ideas and solutions to fit and solve our goals. Section 4 contains the conclusions. Finally, section 5 presents future work to be done.

2. State of the Art

In this section, we introduce some of the most important concepts to understand the proposal. We start with the Internet of Things.

2.1. Internet of Things

The Internet of Thins (IoT) is one of the most important topics in research and business [2,3,11,12]. Its goal is the interconnection between heterogeneous and ubiquitous objects between themselves. It was considered as one of the six technologies with more interest to the EEUU until 2025 by the United States National Intelligence Agency [13].

As we already said, the aim of IoT is the interconnection of heterogeneous and ubiquitous objects and different systems between each other. A requirement to achieve that interconnection is the capacity of the objects and system to connect to the Internet [14], so, IoT exists to extend the Internet to things [15].

The term 'Internet of Things' emerged in a presentation of Kevin Ashton for Procter & Gamble (P&G) about the use of the technology RFID in supply chains [16] in 1999. He introduced the word Internet because it was a trending topic and he wanted to attract attention. However, he never defined this term, and of course, he did not expect its future impact.

In our proposal, we want to connect distributed sensors around different places with users to get recommendations relative to their preferences and the data collected by sensors in real-time. These sensors are objects in the Internet of Things. In the next subsection, we are going to introduce the Objects of Internet of Things, the Smart Objects, and, the Not-Smart Objects.

2.2. Smart Objects, Sensors and Actuators

An important piece of the Internet of Things is the Smart Objects and the Not-Smart Objects. Smart Objects or Intelligent Products [17] are physical elements capable of interact with everything around them, the environment and other objects. Their behaviour depends on the data that they process and it can be automatic or semi-automatic. They are usually capable of reacting according to interactions with other Objects [3,18]. We can consider Smart TVs, smartphones, tablets, some cars, etc. as examples of this type of objects. Smart Object can be classified in three dimensions [6] which represent qualities of their intelligence: **Level of Intelligence**, how much intelligence an object can have, **Location of Intelligence**, where the intelligence is located, and **Aggregation level of Intelligence**.

However, Not-Smart Objects also exist. These objects lack intelligence [6]. They usually compose other objects or Smart Objects. Whereas Smart Objects can work without any dependency, Not-Smart Objects are devices that need another device to work. Sensors and Actuators are two examples of Not-Smart Objects. They need another object that can process the data that sensors measure, like temperature, or, in the case of actuators, they need another object that can order them the actions to do according to certain conditions.

2.3. Recommender Systems

Recommender Systems are intelligent systems that use mechanisms and techniques applied to information retrieval. These systems are very important tools that help users to reduce the search time of content on the web that can be of interest for them, efficiently and effortlessly. These systems help users to find any kind of content, such as books, movies, electronic products, websites, songs, hotels, insurance, etc. in a relatively easy way for users [19].

Recommender Systems tries to solve the information overload problem on the web and facilitate the retrieval of information, through the implementation of algorithms and information classification mechanisms [20–22].

According to the information-filtering paradigm that is used, in general, Recommender Systems can be classified in several approaches that are: **Collaborative filtering, Content-based and Hybrid Approach**. Other authors also propose other classifications of Recommender Systems, such as **Utility based recommendation, Knowledge-based recommendation and Demographic recommendation** [23].

Recommender Systems collect information related to user's profiles using **Explicit or Implicit feedback techniques**. This information is used to provide a valid information to users. For example, in Donovan and Smyth [19], the authors present an approach where a Recommender System can help users in finding electronic books in a social network using a mixed feedback techniques (explicit and implicit). This mixed approach represents another paradigm for recommender systems.

Many eCommerce webs and Online Social Networks like Amazon store, AliExpress, Facebook, LinkedIn and other types of websites as Film affinity, Netflix and HBO have a recommender system to offer interesting content to its users.

Finally, on the Internet of Thing world, this kind of intelligent systems can help discover points of interest (beaches, hotels, parks, etc.) using sensor networks available on the Internet. The integration of Recommender Systems with a real-time sensor network can help minimize travel time and costs, and increase users' satisfaction.

2.4. Artificial Intelligence

Artificial Intelligence (AI) is a concept that refers to the intelligence exhibited by machines or intelligent agents, i.e., any device that perceives its environment and performs actions that maximize its chance of success from the point of view of some specific goal [24]. AI is a huge and interdisciplinary field founded on the claim that human intelligence can be so precisely described that a machine could be created to mimic it [25]. Thus, AI is based on a range of different disciplines such as computer science, biology, psychology, linguistics, mathematics or sociology.

To achieve its goal, AI usually relies on different approaches. For example, search and optimization algorithms are important for reasoning and leading from premises to conclusions. Fuzzy Logic is a version of first-order logic which allows the truth of a statement to be represented as a value between 0 and 1, rather than just 1 or 0. Probabilistic methods (e.g., Bayesian networks, Hidden Markov model, etc.) are very interesting for uncertain reasoning. Classifiers and statistical learning methods such as machine learning give computers the ability to learn without being explicitly programmed. Neural networks are computational models used to solve problems in the same way that the human brain would do.

There are plenty of areas in which AI can be applied. For example, Devedzic [26] worked on a survey of Web-based education applications in which adaptability and intelligence is important, through the use of semantic Web technologies. KL-ONE is a well-known system that has been used in both basic research and implemented knowledge-bases systems for representing knowledge [27]. Others, like Bennett and Hauser [28] worked on developing a general purpose framework to explore various healthcare policies, payment methodologies and to be the basis for clinical artificial intelligence.

One classic application of AI is to support recommendation systems. They are a clear example of intelligent systems. For example, Veena and Babu [29] propose a user-based recommendation system addressing challenges in collaborative filtering and scalability based on Apache Mahout. Lam et al. [30] addressed the cold-start problem in recommendation systems using hybrid approaches, with the analysis of two probabilistic aspect models that put together collaborative filtering and information from users. There are also many more general works that deal with issues related to machine learning [31].

Another current and rising use of AI is the Internet of Things. For example, Gubbi et al. [32] presents a cloud centric vision for worldwide implementation of Internet of Things. They discuss the key enabling technologies and application domains in which machine learning methods are an essential aspect. Among the many related works we can highlight some as Kahn et al. [33], that explain the architecture, applications and key challenges on the Internet of Things, in which machine-to-machine communication is also essential to embed some form of intelligence.

Internet of things, recommendation systems and AI can also work together. An interesting work is the one by Von Reischach et al. [34]. They present an idea to enable consumers to access and share product recommendations using their mobile phone by using RFID codes to receive and submit product rankings. Mashal et al. [35] work on a platform to recommend services in IoT (e.g., personal care, energy monitoring) by a graph-based formal model. There are some authors that work on topics more related to our proposal. One very interesting work is the one by Sun et al. [36]. They work on smart communities by connecting devices and smart sensors. They propose the use of personal sensors, open data, and sensing services in tourism and cultural heritage with a context-

aware recommendation system. Cha et al. [10] propose a platform for supporting a real-time recommendation system based on IoT smart connected devices. They show their approach with a prototype of a tourism-based application to demonstrate the entire process.

3. Proposal

In this section, we are going to introduce our proposal. Our goal is to give recommendations about POIs to users which will be based on data recollected by sensors from the IoT and previous users' experiences. Throughout this section, we will address how we will collect data from users and from sensors, how the system will access to a list of places to recommend, and the different solution to process the collected data. Our proposal focuses on the creation of a novel recommendation system that users will be able to use to know relevant places that fit a query made by them. For accomplish this goal, we propose the creation of a novel system that will gather relevant data to users' queries from sensors distributed around different places and it will allow users to give feedback about the given recommendations. Thus, we will have two sources of information: the users themselves and the distributed sensors. Throughout both sources of information, we will obtain a score per place according to users' preferences and sensors data. Moreover, we will give more recommendations based on similar preferences of other users. Hence, we are proposing a hybrid recommendation system (content-based and, also, based on collaborative filtering) where the information is retrieved through explicit feedback.

This section is composed by four different subsections: 1) obtaining information from the users themselves and from sensors; 2) the registration of places: 3) the interaction of users with the proposed system; and 4) the different possible implementations of the score calculator whose goal is to obtain a score by each place in an intelligent way.

3.1. Feedback of Information

Our proposal consists in the creation of a novel recommendation system that will suggest different POIs to users according to their preferences and conditions of the places through distributed sensors. Thus, we will have two different sources of feedback, the users and the sensors.

3.1.1. Feedback from Users

Our proposal is a hybrid recommendation system whose information is retrieved through explicit feedback. First, we are going to explain why the feedback will be explicit and after, why the recommendation system will be hybrid.

The proposal will give several recommendations to users according to their queries, allowing them to visualise the information and indicate whether they like such recommendations. By this way, we obtain what their theoretical preferences are. Moreover, users will have the possibility of rating the place when they are there. Due to that, we will obtain a rate about a place with specific conditions in real time. So, we will collect feedback before the user goes to the place and when the user is there. By this way, we will know the preferences of each user and their level of satisfaction with each recommendation taking into consideration the real conditions which will be obtained through the sensors.

3.1.2. Feedback from Sensors

Our proposal will collect data from sensors distributed around the available places. These set of sensors will be sensors registered in our system by the users themselves or public sensors available in other services through public Application Programming Interfaces (APIs). Our goal is the creation of a recommendation system for places, hence, we will collect data only from some type of sensors.

The registration of sensors in our system is an important issue to address. Our system will be able to use sensors from third services and sensors registered by our users. Thus, we will have to enable users to register their sensors and make the system compatible with third services.

How users will able to register their sensors will be addressed in a next section when we will address how users will be able to interact with the proposed system. How to use sensors from third services is also so important. We propose the creation of different categories of sensors related to environment conditions like temperature, humidity, air quality, wind speed, and so on. These conditions will be used to classify each place according to the different values. Thus, each place will have a temperature, a humidity, etc.

When a user makes a query like the best beaches of the north of Spain, the system will collect all registered places and it will retrieve the actual status though the sensors registered in the system and making requests to the registered third services through their APIs. Therefore, the system will have a list of places with their actual conditions. To make good recommendations, the system will consult the preferences of the users and the POIs they liked, since they should have given a good value from previous visits. From this information, the system will select a set of POIs and calculate a score per place to give suggestion to users.

3.2. Registration of Places

Our proposal will need a list of POIs which will be recommended to users. To make this list, we identified three possibilities to register places: 1) manually; 2) automatically on demand; and 3) predictive and automated way.

- Manually

With the purpose of registering POIs that our proposal can use, we propose that users could register places manually through a form in the web application. The principal advantage of this approach is that places will be already registered in our system when a user makes a query. Nevertheless, the number of registered places would be too limited to satisfy any query of every user. Moreover, it could appear errors related with the introduction of wrong information during the manual registration.

- Automatically on demand

On the other side, the information on POIs would be collected from external services without the need of manual interaction, hence, the registration of places could be automatic. An external service could be Google Places, nevertheless, we cannot process all places available in this service. Therefore, the process of collecting information would begin when users make queries, on demand. A case of use could be the following: a user makes a query about beaches in the north of Spain, then, the system will search all beaches in the north of Spain in Google Places and compare the results with the places stored in our proposal. Nevertheless, if these places were not register in the system, they would be registered to future queries.

- Predictive and automated way

Finally, the last approach that we suggest could be a predictive and automated one. Although we are introducing this approach as another option, it would be complementary to the automatic one because it is based on automatically collecting places that users will search through Google Places. The principal issue is the identification of possible future searches. An example of how to address it could be the following: if users made many queries about places of the same location, the system would identify this location as a potential one for future queries, hence, the system would register automatically more places of this location from Google Places.

3.3. Users Interface

In this paper, we propose the creation of a novel recommendation system that suggests places according to a query made by users and their personal preferences. These preferences will be registered in the system through valuing the recommendations. When the system recommends several places, users will be able to choose what recommendations they like, and moreover, when users will be in a recommended place, they will be able to rate this place. However, the first time that users will use our proposal they will not have any previous interaction that enables the system to know their preferences. Therefore, when users will be registered, they will have to fill in a form with their preferences to help the system to make the first recommendations.

To make queries, users will have to use a web application with a form designed for this purpose. Throughout this form, the system will know what users will want. The queries would be composed of a location, a distance, type of place, and other filters that will enable the system to do accurate recommendations.

After making the query, users will be able to choose the recommendations that they like to save it and consult them later because they will be able to value these recommendations before going to the places and after being there. In this way, the system will know where users were and make more recommendations according to users that usually go to same places with similar conditions.

3.4. Different Solutions for the Score Calculator

Here, we have different solutions to create the Score Calculator: two methods for the feedback from users, and two possibilities for the feedback from sensors. These methods are the following:

The first one is related to the **feedback from users**. Here, we can search similar users with a similar taste for the POI that the query user wants. This could be possible using a comparator between the profiles of each user to obtain the most similar users. In this way, the Recommender System could offer places that would maybe match the query made by the user based on similar users' tastes. Here, to give a score to each profile, we have two possibilities: One of these possibilities is using the old method of comparing one field with another field to obtain the profiles with more coincidences. Another possibility is applying Knowledge Discovery Databases (KDD) [37] to obtain valid patterns about what type of places usually likes one type of user, which must have been categorized previously in the same type of profile. For instance, a tanned-beach lover who likes the beach without wind, a very sunny day and without an opinion about the waves of the sea; a surfer-lover who likes the high waves but do not cares about the sun, or a seven-a-side football lover who probably likes cloudy days without wind, and so on.

In the second case, to obtain the **feedback from sensors**, we could create an algorithm, using Fuzzy Logic [38], to mix each linguistic variable and obtain a final score of that profile. In this case, we will have to create adaptive controllers [39], also known as expert systems [40], and membership functions [41]. These controllers have the rules that are used to process the linguistic variable in the fuzzification process [42]. After the whole process, we will obtain the final score after doing the defuzzification from the last fuzzy number to the final score that will have the POI interest for the query made by the user.

On the other hand, we can customize the adaptive controllers and the membership functions for each user in the case of using a mechanism to train, learn, and evolve in the time for each user. It could be possible to create it if we base the rules on different information to personalize the adaptive controllers and the membership functions for each user. This system will be an Adaptive Fuzzy Logic System [43]. In this case, we will have to use some machine learning technologies like Bayesian Networks, Artificial Neural Networks, Decision Trees, Association Rule Learning, Support Vector Machines, Clustering, Reinforcement Learning, Representation Learning, Genetic Algorithms or Deep Learning [37].

4. Conclusions

In this proposal, we have presented an idea that defines a new Recommender System, by improving the recommendations using the information of sensors of the IoT. This novel idea could give recommendations based on the exact weather conditions for the taste of each user. This is so because sometimes the same place has different weather conditions and not all of us like the same place when raining or being sunny. It depends on what type of place it is, like a beach.

Then, this IoT Recommender System could allow us to include in Recommend Systems a new external variable which is the weather conditions like the quantity of light, the speed of the wind, if it is raining or not and how much, the waves of the sea, the crowd, and so on. These data with the preferences of users could be able to give recommendations about different POIs according to the exact weather and the different tastes of people. Then, this idea is something that could improve the current recommendations.

Therefore, we could improve the Recommend Systems using personal tastes and the current condition of some POI. Nevertheless, the different possible solutions should be studied and compared in search of the best solution to fit well the system.

5. Future Work

In order to accomplish this Recommend System, we will need to apply different branches of the Computer Science fields, but it will not be totally finished due to the many different ways in which this work could be continued. We show some of these future ways as follows:

- **Big Data infrastructure**: to analyze in near-real time the different queries and to create good recommendations, as well as the storing of all the data, we will

have to research an optimal infrastructure which could use different Big Data tools to store, process, manage and execute all the data [37].

- **Comparison among the different Machine Learning methods**: as we have explained before, we could use different Machine Learning methods to create an Adaptive Fuzzy Logic System. Notwithstanding, we will not know what of these methods could produce the best results. This is why we will need to do a comparison between all of them.
- **Include more metadata to the recommendations**: the recommendations always could be improved. In this way, other metadata than could be included to improve the IoT Recommender System. For example, it could be different data from the smartphones in real-time, like the GPS or the places that the user is visiting to try to predict the next place they are going to visit based on the user route of that day.

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