Dynamic Scrutable User Modeling utilizing Machine Learning

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Abstract— **Personalization generally attempts to offer information and services that are delivered to meet user's individual preferences. It helps by providing the appropriate services in a dynamic and automatic manner. Involving the user in this process may enhance how tailored information and services are delivered. However, there is a challenge in engaging users in the user modeling process. Building user models in a manner that engages the user in a feedback cycle may improve the quality of the model and the user's control over the personalization. Allowing such user control over machine learning-derived user models is a significant research challenge as such models are often difficult to scrutinize. This is the main challenge addressed in this early stage research. This work proposes using ontology-based domain models to provide a means for users to engage with ML-derived models. Moreover, such an approach may enable the user model scope to grow as a user's preferences grow.**

Keywords-Personalization; User Modeling; Machine Learning; Scrutability.

I. INTRODUCTION

Personalization has the potential to play an important role in supporting the tailoring of system behavior in ways that fit each individual user's preferences. Personalization reduces information overload and facilitating targeted access to relevant information objects in an information system [1]. However, it depends on creating and maintaining an adequate set of information about the user's preferences [2].

Generally, personalization is achieved whenever the behavior of a system is adjusted by information about the user [3]. Postma and Brokke defined personalization as "a segmented form of communication that sends (groups of) different recipients different messages tailored to their individual preferences" [4] and this is the definition adopted in this work. A key challenge lies in delivering the right information at any time, at any place, while respecting the user interests [5]. These interests are continuously evolving and changing, generally at a rate that is faster than most implicit approaches, which create a user model from observed behavior in a system, can keep pace with.

Capturing the right information about the user at the right time in the right way is the main concept of user modeling [5][6]. A user model is the collection of personal information associated with a specific user. So, it is the fundamental basis for any personalization changes to a system. It is also potentially a key instrument through which the user can adjust and control how a personalization system works for them.

Machine learning has recently attracted much attention and has been employed for user modeling [7]. Much research is concerned with utilizing machine learning for building intelligent user models [8]. Generally, the internet evolution was the motivating force underlying the recent surge of research in this field [9]. However, the user is not engaged in most of these studies leading to models which are difficult to represent to a user and nearly impossible for users to control. M. E. Muller summarized the idea in one sentence: "machine learning in user modeling tries to mimic a user's behavior, but it does not model a user" [8]. We believe that modeling the user, while providing them with control over the model, is the main contribution in the work proposed in this paper.

The research outlined in this paper is concerned with developing an approach that incorporates dynamic machine learning with user scrutability to facilitate effective user modeling. The ML processes will operate over a large corpus of email messages that will enable the modeling of a variety of dimensions of the users in the corpus. There are three main aspects under consideration in this study: user preferences, actionable items and machine learning techniques. This combination is responsible for building the user model, taking into consideration the user's control over the user model.

This paper is structured as follows: Section II discusses the background and related work. Section III states the research question and the intended contribution. After that, the design of the proposed solution is outlined and the final section will state the progress of this work so far.

II. BACKGROUND AND RELATED WORK

This section discusses personalization and user modeling in more detail. It then illustrates the relationship between them.

A. Personalization and User Modeling

A fundamental objective of research in personalization and adaptation is to make systems more usable, more useful, and to provide users with experiences fitting their specific background knowledge and objectives [10]. What is really challenging in a world loaded with a large volume of information, is not only to make information available at anytime, anywhere and in any form, but to precisely specify the "right" thing, at the "right" time and in the "right" way.

Personalization has become of major concern across all industries and interest in tailoring customer/user experiences has increased significantly [11]. In general, it is hard to have

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a broader definition of personalization [3]. It is mainly the concept of using a user profile that may include personal information and sometimes their preferences. Accordingly, this has received significant consideration both as a way for offering appealing services and locking these users into the appropriate services [12].

Once information is collected about a certain user, the system can evaluate that data by a preset analytical algorithm and then personalize it to meet the user's needs [13]. This adaptation considers every feature of the system's behavior. The user profile affects how information and functions are displayed. In the case of [13], profiles highlight only relevant aspects and hide knowledge that is not needed by the user; this is in addition to providing offers and proposals [14].

There are three main mechanisms for handling system personalization. To date, personalization and profile modeling have mainly fallen into two categories: explicit and implicit techniques [15]. However, the hybrid approach was added and followed afterward [2][16].

- Explicit modeling: In the beginning, the user was the main item in the personalization process. It depends completely on them to set their personal information and manage their interests. Explicit personalization may reduce somehow the effort of resource management, as well as assuring the data precision However, managing an entire preference set manually means putting a burden on the user to carry out the profile management responsibilities [17]. In other words, the user has the mission to update their profile whenever a new service is encountered in order to refine and update interests in their profile.
  This approach fundamentally engages the user in the whole task and places the onus on the user. They set their profile manually in order to keep their interests up to date (maybe through an appropriate GUI). Although in this technique, the user is in charge of the whole management process, the responsibility of maintaining such potentially large profile is a burden. This can often lead to a sparse preference set and hence inaccurate personalization [2]. In fact, this is the main shortcoming of this mechanism as this undermines the strength of personalization.
- Implicit modeling: This approach is considered the other extreme in the personalization process. It primarily uses various techniques for monitoring and learning the user's preferences without engaging the user directly. The system tends to maintain the user profile and the preferences set on behalf of the user. This depends mainly on the intelligence level of the system. This may affect the information accuracy and accordingly the environment personalization [18].
- Hybrid implicit and explicit modeling: The learning approaches employed by such systems often fall under two types: rule-based learning algorithms (which store preferences as rules) and network algorithms (which store preferences in some network structure). Rule-based learning algorithms have the advantage that their output is easily translated into a human-readable form allowing their knowledge to be understood [16].

The benefit of the hybrid approach is the minimal burden on the user, however, care must be taken to provide some method of user control. Without such functionality, the user cannot alter system behavior to reflect new situations or behaviors in a rapid way. Therefore, for more successful systems, hybrid personalization providing implicit personalization must be employed where possible, but also providing a GUI through which the user can manually manipulate their preferences and take final control.

B. User Models

Capturing the right thing at the right time in the right way is the main concept of user modeling [5][6]. A user model is the collection of personal information associated with a specific user. So, it is the basis for any personalized changes made by a system.

This research is concerned mainly with saying the "right" thing. Selecting which data is used and employed in the model depends on the goal of the application and the output required. It can include personal information [19] such as users' names, ages, their interests, their skills and knowledge, their goals and plans, their preferences and their dislikes, or data about their behavior and their interactions with the system. There are different design patterns for user models, though often a mixture of them is used.

- Static user models: Static models are the primary type of user models. As the name indicates, the model does not change; once data is collected they are normally not changed again. Changes in user's information do not affect the model and no learning algorithms are used to alter the model [5][20].
- Dynamic user models: Dynamic models allow a more active representation of users' preferences. The model can dynamically adapt to the different shifts in users' interests or their interactions with the model. This adaptation helps meeting the different needs of the users [5][20][21].
- Static and Dynamic (SaD) User Models: We can easily imagine that SaD as a hybrid modeling technique. It can be more common to allow the modeler to move from just using a one level standard static user model that uses static unchangeable information to a more thorough two-level model. This combines a static with a dynamic user model thus containing user preferences alters and various interactions with the system [20].

Since user modeling is fundamentally based on personal information, user control over the model may bring value, particularly when pertinent information about the user may not be implicitly observed by the system. Such a model with user control mechanisms is described as scrutable model [22]. It is designed so that a person has the option, but not an obligation, to determine what is modeled about them and how it is used.

Personalization generally aims to unburden the user of profile and preferences management tasks, adjusting the system to meet the user interests, thus leaning more towards implicit modeling with no user control. Also, in order to enhance the interaction between the user and a personalized environment, information systems must be capable of dynamically personalizing the system content [23]. For this reason, many pervasive and ubiquitous systems include machine learning techniques coupled with user behavior monitoring systems to provide the implicit personalization part, where preferences can be created and managed which may be coupled with user control (explicit engagement) for better results [1][2].

III. Research Question and Intended Main Contributions

The ultimate goal of this research is building a dynamic scrutable user model while utilizing machine learning. The key idea of this work is to merge the three aspects: dynamic user modeling, scrutable user modeling, and machine learning. We believe that this combination would provide the optimum balance between implicit modelling, dynamic model growth towards new domains of interest and user control. The target is defining an approach to facilitate this balance.

The strategy of this study will start by building a case study as shown in Figure 1 - which is discussed in detail later - that demonstrates the idea as a proof of concept. Then the next step is the evaluation of the approach and presenting the results and comparing the results with and without the user control and discussing how far the user control over the user model affects the results.

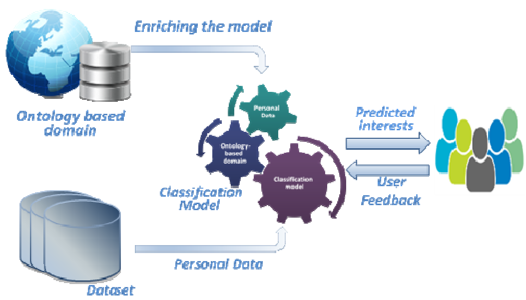

Figure 1. Classification model design

The case study has been designed to provide and promote to users services that suit their interests with taking in consideration the user feedback. We are working on this target by exploring large set of user data [24]. This data contains important and unimportant information for these participants. This work needs to process a very large number of facts and capture the vital chunks from it. This selected important data indicates each user's likes and dislikes. This information then goes through the learning phase in order to build a customized user model. The model will be capable of selecting the appropriate service for each user. These promotions should suit each user preferences.

The second aspect that plays the main role in this research is the system re-learning. In other words, how is user control exerted and maintained over the model? How to blend the machine learning and user control is envisaged a key outcome of this work.

The other dimension in this research is what these services are and how we can feed the model with different alternatives for the same subject. We are proposing to use an ontology-based domain, which uses terms from a domain model to indicate a user's relationship to different concepts. The Domain Model describes how concepts are connected to each other defining a semantic relationship between them [25][26]. We believe that using this ontology-based approach will enrich the system with various substitution potentials. This is discussed in detail later in the design section.

The main data source for this case study was selected to enable user profiles to be built from users' email messages. This is used to construct the initial user models. These emails are rich with personal information: inbox messages, sent messages, folders messages, outgoing messages, email subject, and time stamps are all used. The privacy of this personal data is an important aspect in this context; however, this is out of scope as we are using a publicly published dataset in this study.

The crucial research questions here are:

1) How far can we support the user in controlling and improving their user model?

2) How will we use the user feedback loop for improving the model?

3) How can we prioritize this data in order to get the best results of the model?

4) What is the level of detail in the model that we should consider?

We can observe that our proposed model is founded on three dimensions: 1) user modeling using machine learning, 2) user control, and 3) ontology-based domains as input for the model.

The overarching research question is: How far can we merge these three dimensions in order to construct a dynamic and controllable user model?

IV. Methodology and Design of the System

This section discusses the methodology approached in this research. Then, it mentions the technologies used in the case study.

A. Methodology

Generally, building predictive data analytics solutions for this kind of problems involves a lot more than choosing the right machine learning algorithm. One of the most frequently used methodologies for this is the CRoss Industry Standard Process for Data Mining (CRISP-DM) [27]. The six key steps of the predictive analytics project lifecycle that are defined by the CRISP-DM are; problem understanding, data understanding, data preparation, Modeling, evaluation, and deployment. These steps are expanded in the context of this work below.

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Step 1: Problem Understanding

The target is to build a personalized predictive data analytics model that provides services to number of users according to their general interests. These preferences are collected from their email messages. The system can read the email documents, build and train a model, and hence decide whether this person is interested in a certain topic.

The emails of participants are explored and scanned in order to find topics of interest for a person from his email history. Then, email messages are then classified using the appropriate machine learning technique.

Step 2: Data Understanding

It is critical to find the right data in order to be able to solve the problem in hand. In this research, we are working on Enron email dataset [24], which will be described later in detail. It is a huge dataset that contains about 0.5M messages. This step is concerned with selecting the subset of all available data that we will be working with.

There is always a strong desire for including all data that is available, that the maxim “more is better” will hold. We need to consider what data we really need to address the problem in hand. We have to be more disciplined in our data selection then handling to achieve more consistent and accurate results that are likely to attain.

Step 3: Data Preparation

After selecting the data, we needed to study how we are going to use the data. This preprocessing phase is mainly about getting the selected data into a form that we can work. The data preprocessing is divided into three stages; formatting, cleaning, and sampling:

- Formatting: We have selected a format that is suitable to work with. All the mail messages are now in comma separated file format.
- Cleaning: Quality data is a prerequisite for quality predictive models. So, to avoid "garbage in, garbage out" and improve data quality, we have to work this crucial step carefully. Sometimes we find some data instances that are incomplete and do not carry the data there should be. So, we removed all the records of incomplete, noisy, or inconsistent data. In our research, there is a mandatory task which is text preparation. Text cleaning phase includes stripping whitespace, removing stop words, numbers, punctuation, URLs, and links.
- Sampling: In working on this huge data dataset (Enron emails dataset), sampling is an important factor that we have to take into consideration at least in the early learning stages. We have to experience the performance before deciding whether we need to carry on this step. We think that we can start with working on the whole dataset. If we found out that this is inefficient, then we could use a smaller representative sample of the selected data. The target of this step is to be much faster in exploring and prototyping solutions instead of considering the whole dataset.
- Data Transformation: This step is also referred to as feature engineering. As per the problem we are targeting, we are concerned mainly with the text included in the data. we are principally working on analytics for the text data in the users' email messages. Data transformation here is mainly text normalization which means converting it to a more convenient and standard form. For example, most of what we are going to do with language rely on first separating out or tokenizing words from running tokenization text, the task of tokenization. Another part of text normalization is Stemming which refers to a simpler version of lemmatization, in which we mainly strip suffixes from the end of the word.

Step 4: Modeling

The Modeling phase of the CRISP-DM process is when the machine learning work occurs. Different machine learning algorithms are used to build a range of prediction models from which the best model will be selected. The knowledge of the problem domain will influence this step and we will very likely have to be revisited to achieve the optimal solution for the problem in hand.

Step 5: Evaluation

This stage covers all the evaluation tasks required to show that a prediction model will be able to make accurate predictions after being used and that it does not suffer from overfitting or underfitting. This step would be clearer through different experiments in this research journey as this is vague in this stage of study.

Step 6: Deployment

Eventually, the last phase of CRISP-DM covers the work done to successfully integrate a machine learning model into the process within an organization. This phase is not applicable in our research.

The second part of this research is to feed the user model with a wide range of words that enriches it and help it for better understanding the user. This enhancement will improve the prediction accuracy of the model and get better results.

B. Technologies

- *Enron Email Dataset*

Enron email dataset was primarily gathered and prepared by the CALO Project (Cognitive Assistant that Learns and Organizes) [28]. It was formerly posted to the web and made public by the Federal Energy Regulatory Commission [24]. It includes a huge amount of data. It is corpus for about 150 persons, which mostly senior managements of Enron. The dataset contains a total of about 0.5M messages that are organized into folders.

There are some modifications done on the original data collected. All attachments were removed. Some messages have been deleted. The deletion was part of a reduction effort that was requested by some employees. There were some invalid email addresses converted to something different. For example, when no recipient was specified, user@enron.com is converted to no_address@enron.com [24].

- *Development*

  In this work, we tended to find integrated machine learning tools and programming languages. R and Python were primarily popped up in our search space due to the availability of multiple open source machine learning libraries. Python is selected as the core programming language including NumPy, SciPy, and Python visualization tools.

  SciKitLearn API is a free software machine learning library. It provides an implementation of a wide range of machine learning algorithms and data preparation methods. SciKitLearn is a simple and efficient tool for data mining and data analysis. It is built on NumPy, SciPy, and matplotlib. This is in addition to that it is open source and commercially usable (BSD license) [29].

V. Progress to Date and Plan of Further Research

To build the target user predictive model and to be able to evaluate it, we applied the model in a usecase, then we divided the journey to number of phases.

Phase 1: One user only

This is the current experiment we are working on. The target of this part of research is to work on the email dataset for one user only and build a model that can predict the points of interest for this user. And at an incoming message, the model can predict whether the user would be interested in this message or the message needs an action from them. And then, it takes the user's feedback and retrains the model to enhance its prediction accuracy. The early results of this experiment show promising prediction accuracy results; however, it still needs more work in the evaluation phase to ensure reliable results.

Phase 2: Classifying the whole dataset

The next phase is to build a model on the whole dataset, the model should be trained on the whole data, and then it can classify the users according to their preferences. At an incoming message for any of the users, the model could predict whether it would be interesting to the user. And then, the users' feedback is gathered and employed to retrain the classification model. This feedback should enhance the model prediction accuracy.

Phase 3: Providing services from Ontology-based domain

The last stage of this study will work on the model built in the previous step. And then we will try to feed the model in a certain domain with words that describe this domain (vocabulary alternatives, different subject, etc.). For example, if we are concerned with football, we have to search for the words football, David Beckham, Manchester United, etc. In such case, we will take these words from an Ontology concerned with football (DBPedia for example). Then, this will feed the model with a big range of words that helps it to understand more about the users and hence improve the results of the model.

VI. Conclusion

Generally, the main goal of personalizing a system is to provide the right information and services to meet user's individual preferences. Recently, it has become increasingly important to deliver not just the right information, but to do so in a highly dynamic way. This makes the environment more reliable and tailored to the change in the user preferences. The other important feature that this work is trying to offer is to incorporate user control in the feedback cycle in machine learning-derived user modeling. This has an advantage over some classical interpretations of personalization.

In this study, we are employing machine learning techniques to achieve this goal. Enabling the user control over a machine learning-derived model is a significant research challenge. This is the main challenge addressed in this early stage of this research. In this paper, we discussed this research idea, current plan, and progress to date.

At this stage of the research there are three core concerns. First, to what extent can we support the user in controlling and improving the model? Future work will require examining user intervention in building a dynamic user model using machine learning.

Secondly, where should the user feedback dimension be placed in the modeling cycle? This will involve identifying a balance between the model intelligence whilst maintaining the scrutability in a machine learning-derived user model.

The third challenge is concerned with the model evaluation and how to evaluate the efficacy, efficiency and reliability of the proposed system.

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