Towards Learning Relations between User Daily Routines and Mood

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Abstract. The main aim of our research is to investigate whether it is possible to find a relation between the user's mood and daily routines. To this aim we developed an application, Smart Calendar, that, thanks to its nature, allows collecting annotated datasets of mobile data, learning user daily routines and relating activities and pattern of sensor data to the user mood. Results of this preliminary phase of the research have shown that it is possible to learn routines and, if present, to find relations with the user mood.

1 Introduction

Pervasive computing applications to be successful should proactively support users in their tasks according to their situation [1]. To this aim, the application should reason on the user and on the context for making prevision about the user's needs and for personalizing the task accordingly. In particular, given data that can be captured by mobile phones over long durations of time, it is possible to discover the emerging behavior of people (including habits and routines) over a long period [2,3]. Examples of applications that could exploit models of the user's daily routines are context-aware reminders, personal assistants, contexts-aware recommender systems, life diaries and lifelogging systems. In a previous stage of our research we focused our effort on learning the daily routines of the user both from sensors present in smart environments and from mobile data [4]. In particular, our approach exploits the WoMan (acronym for 'Workflow Management') system to incrementally learn and refine users routines represented in First-Order Logic (FOL) [5]. The WoMan system is able to deal with non-sequential activities and repeated-tasks, and therefore the approach is suited to represent models of user's routines for predicting the user needs. At the current phase of research we investigate whether it is possible to use our approach to relate patterns of daily routines to affective factors, mood in particular. Mood is an affective state that plays a significant role in our lives. It is more general and less intense than emotion, and depends on broader factors and not necessarily on stimuli [6]. Mood influences our behavior, decisions, communication and preferences. Therefore, we consider the possibility to learn possible relations between mood, activities and routines both in the physical world (activities located in a place such as shopping, driving, and so on) and in the digital world (activities like email, listening to music, posting on facebook, and so on). Starting from the consideration that smartphones have rich information about their owner and that they can help us in collecting a lot of traces (sensor data), many applications have been developed with the purpose of mapping mood to recurrent patterns of sensors data [7,8,9,10]. In our work we aim at discovering the relation between the user's daily location-driven routines and mood states and changes starting from an annotated real life human dataset collected by mobile phones. To this aim we developed an application (SmartCalendar) that allows to incrementally learn contextual models of the user routines and associate them with certain moods. The purpose of SmartCalendar is twofold: on one side it provides to the user a calendar and a ToDoList manager and a context-aware reminder, on the other side it allows gathering annotated dataset of mobile usage data, to learn the daily routines and relate activities to mood that is supplied by the user on request. This phase is necessary in order to collect a dataset that relates variations in the user mood to activities, places, changes in the routine. Results of a first analysis showed that a relation exists and it is possible with our approach to learn such a relation and then use the learned model to predict variations.

2 Incremental Learning of Daily Routines

As far as learning the lifestyle of the user by building models of his daily routines is concerned, it can be seen as a set of processes. Therefore, modeling such routines can then be cast as a process-mining task. A *workflow* model is a formal specification of how a set of tasks can be composed to result in valid processes, allowing compositional schemes such as sequence, parallel, conditional, or iteration. So, in WoMan we decided to learn models that are represented as workflows. In order to understand the example in this paper, we provide here a short description of the employed formalism. In WoMan, a trace element is represented as a 6-tuple **(T,E,W,P,A,O)** where **T** is the time/date the event occurred, **E** is the type of the event (begin of process, end of process, begin of activity, end of activity), **W** is the name of the workflow the process refers to, **P** is a unique identifier for each process execution, **A** is the name of the activity, and **O** is the progressive number of occurrence of *A* in *P*. This is a standard formalism that allows describing explicitly the flow of activities (both sequential and parallel). An example is provided in the following:

```
entry(20121001073047,begin_of_process, monday,rl1,none,none).
entry(20121001073048,context_description, monday,rl1,[mood_valence_neg,
mood_arousal_low, meteo_rain, temp(19.5)],none).
entry(20121001073049,begin_of_activity,monday,rl1,act_Wakeup,1).
entry(20121001073523,end_of_activity,monday,rl1,act_Wakeup,1).
entry(20121001080940,begin_of_activity,monday,rl1,act_KidsToSchool,1).
entry(20121001083002,end_of_activity,monday,rl1,act_KidsToSchool,1).
entry(20121001083010,context_description, monday,rl1,[mood_valence_neutral,
mood_arousal_low, meteo_cloud, temp(20.5)],none).
entry(20121001093028,begin_of_activity,monday,rl1,act_GoToWork,1).
entry(20121001093028,begin_of_activity,monday,rl1,act_Eat,1).
entry(20121001150033,end_of_activity,monday,rl1,act_Eat,1).
```

```
entry(20121001150033,end_of_activity,monday,rl1,act_GoToWork,1).
entry(20121001150036,begin_of_activity,monday,rl1,act_KidsFromSchool,1).
entry(20121001153007,end_of_activity,monday,rl1,act_KidsFromSchool,1).
…
entry(20121002073524,end_of_process,monday,rl1,none,none).
```

As context and activities are detected or entered by the user, the corresponding entries are provided to the WoMan system that, applying the algorithm described in [5], learns activities and relations among them. The task flow of a case is internally expressed in WoMan as a conjunction of ground atoms built on the following predicates:

- **activity(S,T)** : at step *S* task *T* is executed
- **next(S',S")** : step *S"* follows step *S'*

Argument *T* of the *activity/2* predicate is taken from a (fixed and context-dependent) set of constants representing the allowed tasks. Steps are denoted by unique identifiers. Steps are associated to events, and can be implemented as timestamps denoting the associated events. The *next/2* predicate allows to explicit represent parallel executions in the task flow. This avoids the need to infer/guess the parallelism by means of statistical considerations, which may of course be wrong and thus mislead the workflow learning process. Any trace represented in the 6-tuple format previously introduced can be automatically translated into this internal format. For instance, the previous sample trace for the 'monday' would be expressed as:

activity(s0,act_Wakeup), mood_valence_neg(s0), mood_arousal_low(s0), meteo_rain(s0), temp(s0,19.5), next(s0,s1), activity(s1,act_KidsToSchool), mood_valence_neg(s1), mood_arousal_low(s1), meteo_rain(s1), temp(s1,19.5), next(s1,s2), activity(s2,act_GoToWork), mood_valence_neutral(s2), mood_arousal_low(s2), meteo_cloud(s2), temp(s2,20.5), next(s2,s3), activity(s3,act_Eat), mood_valence_neutral(s3), mood_arousal_low(s3), meteo_cloud(s3), temp(s3,20.5), …

The first activity ('Wakeup') is associated to step s0. At that time, the last detected context says that the actor has a negative mood valence and low arousal, it is raining and the temperature is 19.5°C. Activity 'KidsToSchool' is associated to step s1, and has a 'next' relationship to 'Wakeup' as the (only) most recently closed activity. At this time, no changes in the context have been notified to the system, and hence it assumes that at step s1 the context is the same as for the previous step, and so on.

In the WoMan system a workflow structure is described as a conjunction of atoms built on the following predicates:

- **task(t,C)** : task *t* occurs in cases *C*;
- **transition(I,O,p,C)** : transition *p*, that occurs in cases *C*, consists in ending all tasks in *I* (that must be running), and starting the execution of new instances of all tasks in *O*.

Argument *C* represents a history of those tasks/transitions, and thus can be exploited for computing statistics on their use.

WoMan may run in 3 modes. The *learning* mode allows to learn a process model from logs of activities. The *supervision* mode allows to apply a learned model to new cases of the process in order to check that they are compliant with the model. The *prediction* mode allows to apply a learned model to new cases of the process in order to foresee the most likely subsequent activities that the user will perform at a given moment of the execution.

Models are built by WoMan according to the procedure reported in Algorithm 1.

Algorithm 1 Refinement of a workflow model according to a new case

Require: $\mathcal{W}$: workflow model
Require: c: case having FOL description D
for all $\texttt{activity}(s,t) \in c$ **do**
  if $\exists\ \texttt{task}(t,C) \in \mathcal{W}$ **then**
    $\mathcal{W} \leftarrow (\mathcal{W} \setminus \texttt{task}(t,C)) \cup \{\ \texttt{task}(t,C \cup \{c\})\ \}$ /* update statistics on task t */
  else
    $\mathcal{W} \leftarrow \mathcal{W} \cup \{\ \texttt{task}(t,\{c\}))\ \}$ /* insert new task and initialize statistics */
  end if
  refine_precondition($\mathcal{W}, t(s)$:- $D|_s$)
  refine_postcondition($\mathcal{W}, t(s)$:- D)
end for
for all $\texttt{next}(s',s'') \in c$ **do**
  $I \leftarrow \{t' |\ \texttt{activity}(s',t') \in c\}$
  $O \leftarrow \{t'' |\ \texttt{activity}(s',t'') \in c\}$
  if $\exists\ \texttt{transition}(I,O,p,C) \in \mathcal{W}$ **then**
    $\mathcal{W} \leftarrow (\mathcal{W} \setminus \texttt{transition}(I,O,t,C)) \cup \{\ \texttt{transition}(I,O,t,C \cup \{c\})\ \}$
    /* update statistics on transition p */
  else
    $p \leftarrow$ generate_fresh_transition_identifier()
    $\mathcal{W} \leftarrow \mathcal{W} \cup \{\ \texttt{transition}(I,O,p,\{c\}))\ \}$
    /* insert new transition and initialize statistics */
  end if
end for

The described approach is fully incremental: it can start with an empty model and learn from one case (while others need a large set of cases to draw significant statistics), and can refine an existing model according to new cases whenever they become available (introducing alternative routes, even adding new tasks if they were never seen in previous cases, and updating the statistics). This peculiarity is an advance to the state-of-the-art, because continuous adaptation of the learned model to the actual practice can be carried out efficiently, effectively and transparently to the users. A graphical representation of a portion of the learned model for the Monday workflow is shown in Figure 1.

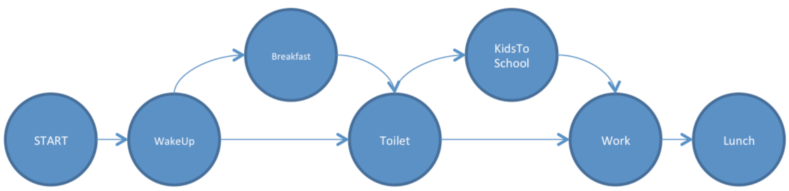

Fig. 1. A graphical representation of a portion of learned workflow for the "Monday" routine.

3 An overview on the SmartCalendar Application

In order to collect a dataset of entries containing annotated data about activities and mood, we implemented the Android application *Smart Calendar*. Besides providing the user with the functionalities of a Calendar, it is a ToDoList and a context-aware Reminder. It allows to learn the activities performed by the user according to two modalities: user-supplied information about performed activities and geo-localization. Each activity in the calendar is related to a place (voluntarily supplied by the user when inserting the activity or using a service that is activated on the bases of the GPS position and time of stay). For instance, if the user is in a supermarket at a certain time and this activity was not entered in the calendar, then the application will ask to the user what he is doing there and will insert the activity in the calendar. Indeed, if the user is in a place at the time expected for doing an activity present in the calendar and stays there for the expected amount of time, the application will consider that activity as done by the user. This is a strong assumption, but asking many information may annoy the user that could abandon using the calendar. However the user may always check the calendar and delete or insert activities. In both cases, SmartCalendar will send the entries about activities and the context to the WoMan system according to the formalism described previously. Figure 2 shows the interfaces for the main tasks of the application.

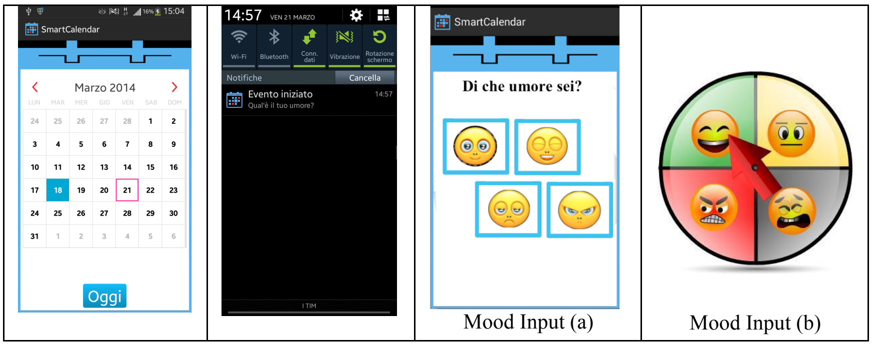

Fig. 2 Interfaces for the main tasks of the Smart Calendar Application

As in many similar applications [9,10], users are asked but not forced to input information about their mood at least three times a day: when the user starts using the telephone, when a not expected activity is performed by the user and after four hours after the last input. This is done using push notifications that are typically not very intrusive. In this way we can capture a user's self-reported mood in relation to activities and places. In deciding how to represent mood information we decided to adopt the two-dimensional approach (valence and arousal) described in the Circumplex model [11]. We developed two prototypes for testing which was a more intuitive and usable interface. In the former (Figure 2a) we used a gallery of faces expressing the set of moods that we considered relevant for our study. In the latter (Figure 2b) we used a circle divided in four quadrants representing the main moods associated to the combinations of the two dimensions of the model and an arrow that allows indicating also intermediate states. In order to avoid confusion and misunderstandings, we put representative faces in the quadrants. In both cases each selection corresponded to a combination of the valence and arousal dimensions. After a formative usability test we decided to use the second interface since it was preferred by 76% of the users. Besides collecting activities of the user related to places, we created a module for logging relevant information regarding application usage, phone calls, email, messages, compass data, and so on.

4 Analysis of the Collected Data

In order to explore the relations between changes in daily routines and the variation in people's mood, we used WoMan on the collected dataset. In total we collected data from 10 users (160 annotated days on average for each user) aged between 28 and 48. Then, first we learned the daily routine models for each working day (Monday-Friday) using WoMan in 'learning' mode (as described in Section 2). In order to have an insight of the learning system's performance, we tested the accuracy of the learned models using a 10-fold cross-validation procedure. For the considered dataset the system reached 85,63% average accuracy with a standard deviation of 10,84. After the learning step, we removed noisy (i.e., infrequent) pieces of the model, and specifically transitions and activities that were encountered in less than 4% of the training cases. Then, we ran WoMan in 'supervision' mode (see again Section 2) using the denoised models and the training cases, in order to collect for each day the warnings returned by WoMan, denoting deviations from the routines. After this, the cases were sorted in chronological order, and a histogram of the warnings in each day was drawn. The curves of mood variations, calculated as a function of valence and arousal, were finally superimposed to this histogram, normalizing the warning bars to their range [-1,1]. Specifically, for each day the average value of each parameter was plotted in these curves. This allowed to visually detect correlations between high or low valence and/or arousal and days with many warnings, which would confirm the influence of mood over routinary behavior (Figure 3).

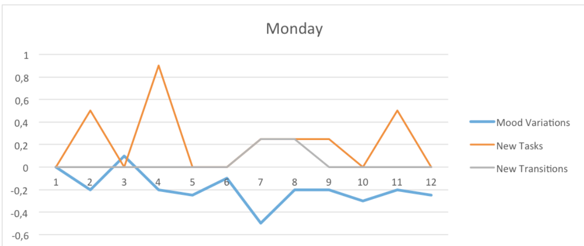

Fig. 3 Routine and mood variations

For sample days in which this correlation was noteworthy, it is possible to draw the plot of the mood parameters during the day, and to superimpose it to the curve of the warning occurrences during the same day, that would further confirm the relationship.

Moreover, we calculated on the dataset the percentage of mood variations in correlation with changes in the routine. In particular, a mood variation occurred in correspondence to a routine variation in 79% of the cases. At present we have not evaluated which factors affect the mood variation in terms of positivity or negativity (i.e. personality traits, type of events or activities, etc.) but this will be the goal of our future work.

5 Conclusions and Future Work

In this paper we reported the first results of the application of the WoMan system to the task of learning daily routines and their relation to mood variation. In order to do so, we developed an application, Smart Calendar, that, besides providing the typical functions of a smart calendar, allows to collect an annotated dataset of activities related to places and context features. In order to investigate on this, we used WoMan in supervision mode, checking the co-occurrence of significant changes in mood and deviations from the routine. Moreover we are combining data collected from mobile data with those that can be detected in indoor situations from indoor sensors of a smart environment [12]. We are aware that collecting personal sensors data may have a high impact on privacy issues. Most of the approaches present in the literature use cryptography, privacy-preserving data mining or store only inferred data from low-level sensors, that are discarded after this inference step. MoodMiner, for instance, hashes all the private user data [13]. At present our application informs the user that his data will be used only for research purposes and will be accessible only by the researchers working on the project. In the near future we plan to implement a stronger privacy policy and to develop a mood inference model that relates events, activities and other contextual factors that can be inferred by mobile data.

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