User Profile-aware Daily Activity Prediction

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Abstract— **Human activity Prediction mechanisms are a challenging issue discussed within literature. Daily human activities are complex and are constituted of multiple actions, where each one provides important information about a person's lifetime and routine. These mechanisms use this information as a baseline for the prediction of humans' next activity, by decomposing and examining the sequences of all the activities a person has performed using information that has been collected by sensors. This paper proposes a Human Activity Prediction module based on a Recurrent Neural Networks (RNN) - Long Short-Term Memory (LSTM) network, for predicting the next activity of a user based on the information included in the user's personalized activity profile. The activity profile is constituted of sequences of historical activities performed by an individual along with their demographic characteristics. Aside from the method, this paper presents also its three points evaluations, by comparing (a) its results with a Markov Chain model, (b) the effect that the number of activities included in a sequence has on the accuracy of prediction and (c) by evaluating the introduction of characteristics as input to the network alongside with the insertion of historical sequences or not.**

I. Introduction

The vast amount of information available nowadays from different sources can be leveraged by several technological applications, including Human activity Prediction mechanisms. Such mechanisms deal with the collection and analysis of the individuals' routines, including the activities they perform daily, so as to predict their upcoming activities. An individual's daily routine is composed of a sequence of activities performed by the individual throughout a day, and includes information about the types of activities performed, their location, and duration. A sequence of activities shows both regularity and randomness simultaneously [1]. From the analysis of the individual's regular activities, existing patterns can be identified, allowing the Human activity Prediction mechanisms to predict an upcoming activity.

By leveraging the information provided by users daily, this paper presents a personalized Activity Prediction module that provides personalized predictions on user's upcoming activity within a day. The prediction module presented is based on an RNN - LSTM network [6]. This type of network was selected due to the nature of the task since long-term dependencies on current and prior activities should be considered when predicting a user's upcoming activity.

Prior activities of a user included in the user's activity profile, during a certain time period in the past, can help the prediction mechanisms infer about its activity profile and subsequently form a notion about their potential upcoming activity. That information constitutes the user's activity profile used as input in the presented Activity Prediction module aiming to provide personalized predictions for each user. In addition, based on the assumption that the previous element in a sequence affects the future elements of this sequence [1], a method supporting sequential processing of the user's daily activities alongside with use of user attributes (i.e gender, age, occupation, marital status) should be followed.

Within the main scope of this paper, a comparative analysis of the RNN-LSTM network and the Markov Chain model on the same task and dataset is described. Both methods are presented in the literature in prediction mechanisms and therefore comparing them on a common dataset was a springboard for exploring the possibilities and limitations of each method. In addition, this study presents how the use of user's characteristics, the number of activities, and the intervals in which the activities are distributed within the day affect a method's outcome. More specifically, the contribution of this paper is:

- Evaluating and comparing an RNN-LSTM network and a Markov Chain model on the activity prediction task.
- Experimenting with the optimum attributes included in the user's activity profile
- Experimenting with the time intervals between activities included in the user's activity profile

The rest of the paper is organized as follows: Section II includes the related work of the paper. Section III presents the information included in the users' activity profiles. The next section presents the Activity Prediction module, while section V presents the experimental setup. The evaluation results are demonstrated in section VI. Lastly, the main conclusions are summarized.

II. Related work

In literature there is an extensive number of papers that deal with the issue of predicting a user's next activity based on historical activity data [2], [15]. In paper [3] the authors propose another approach for predicting both user's next activity and location based on both the individual's activity pattern and the common activity pattern, using a 1st order Markov Chain model.

In [4] an approach for predicting long-duration complex activity by discovering the causal relationships between constituent actions and predictable characteristics of the activities is proposed. The models tested include K-order Markov model, variable order and hidden Markov model.

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In study [5] a deep learning system is proposed to predict human activities. Given a sequence of past activities with their durations, the described system provides as output the probabilities for future activities and their duration. In this method, two distinct LSTM network architectures encode long-term dependencies on historical activities. Alongside in this study, it was shown that the next activities for a completely new person given the observed days of other people who belong to her population segment can be predicted.

III. Activity Profiles

Predicting a user's anticipated activity is a process requiring specific knowledge of the user's status (including prior activities, etc.). The activity profiles are personalized user profiles containing demographic information about the user, information about the activities performed daily, and additional information (i.e. date of prediction and whether the day of prediction is a weekend or not) required as input from the activity prediction module. The data included in the user's activity profile are formed in sequences of activities performed by a user in the past, presenting a certain behavior or routine.

Therefore, a set of user sequences of activities included in a user's activity profile can be represented in L = l_1, l_2, . . . , l_n, where each sequence l_i = r_1, r_2 . . . r_m consists of a series of $m \geq 1$ activities. Each activity r is a tuple in the form of $r = \{uid, starttime, duration, location, category, age, gender, occupationstatus, maritalstatus\}$ where uid is the user id, $starttime$ is the time the activity starts (in timestamp), $duration$ refers to the total duration of the activity, $location$ is where the activity was performed, e.g., home, office, etc. (in one-hot encoding) and $category$ is a label describing the type of the activity.

This type of format of the input data may lead to information redundancy due to the repetition of user profile data, however, efficiency was not the main scope of this work and can be considered as future work.

These sequences of activities are first processed and then transformed into a vector in order to be used as input on the Activity Prediction module.

IV. Activity prediction module's architecture

For the prediction of the next activity on a certain time interval, a LSTM [6], has been used. The RNN-LSTM network receives as input the user's profile and thus the sequences of activities a user has performed daily as well as different attributes of the user as presented in the previous section (Fig. 1). The columns of the vector are related to the attributes included in the user's activity profile, the number of activity types supported by the prediction model since each activity type is represented in one-hot encoding, and the categories of the location. All other values are first normalized and then included in the vector.

This vector has 25 rows, where each row represents a certain time interval (a 60-minute interval is selected). The first row of the vector represents "stage 0", indicating that no daily activities were stored in the past. The parameters in rows that correspond to future intervals are filled with zeros. Any new prediction is stored on the corresponding interval, aiming to be used further for training and inference predictions. For the inference, the network uses as input the sequence of daily activities performed by the day of the prediction.

The RNN-LSTM network is composed of one layer of 20 units determined through a number of experiments with different settings. The RNN-LSTM is a continuous model; therefore, a softmax activation function is adopted at the output layer, aiming to convert the continuous type of output into the discrete class of output.

The described Activity Prediction module has been evaluated in multiple aspects. The evaluation results are discussed in the following section.

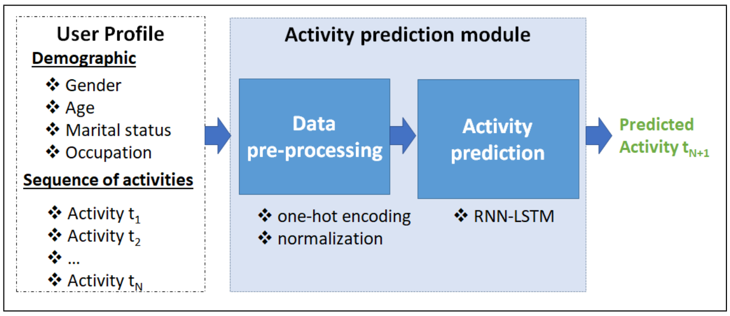

Fig. 1. Activity Prediction module's pipeline

V. Experimental Setup

The evaluation of the proposed personalized Activity Prediction module has been conducted in three steps, a) concerning the comparison of a Markov Chain model and the presented architecture of the RNN-LSTM b) the evaluation of time intervals in a sequence of activities in RNN-LSTM, and c) the evaluation of the RNN-LSTM with the use of both sequence of activities and user attributes as input. The aim of this 3-step evaluation is to find the best combination of variables, input data, and method for accurate predictions.

A. *Dataset pre-processing*

For the evaluation of the implemented RNN-LSTM model, the ATUS dataset [8] was used. The ATUS dataset was selected, version 2008, to be used for both training and evaluation. This dataset contains about 200.000 activity episodes collected from over 10.000 different users and is composed of 17 categories of activities for evaluation, it was spilt into training (70%) and testing (30%) according to the results provided in [17].

The initial version of the ATUS dataset was filtered, aiming to select users whose number of activities performed in a day was less than 30. The age and gender of users included in their demographic characteristics in the ATUS dataset were grouped initially and then normalized. In addition, variables concerning the day and month of the prediction were also normalized in terms of days of the week (7) and months of the year (12), respectively.

B. Evaluation Metrics

As far as the evaluation metrics concerns, for the evaluation of both the Markov Chain model and the RNN-LSTM network the accuracy with the Top-N approach was used, and more specifically Top-1 and Top-3. Top-1 is the conventional accuracy where the model's output (the one with the highest probability) must be exactly the expected answer. Alongside, Top-3 accuracy means that any of the model's 3 highest probability answers must match the expected answer.

VI. Evaluation Results

This section describes the evaluation results of the Activity Prediction module using the pre-processed ATUS dataset as it was presented in the previous section.

A. Performance comparison between Markov Chain and RNN-LSTM

In a sequence of activities, the activity performed at a certain time interval is correlated with the previous activities performed by a user. Therefore, the methodologies developed and evaluated should take into consideration the past activities performed by a user as a sequence. Apart from RNN-LSTM models, the Markov Chain model is a baseline method used for prediction mechanisms that receive as input sequences of data. A Markov Chain and has been extensively used in the literature to model and predict human behavior in collaborative tasks [9] [13]. For the prediction of the user's next activity, the 1st to the 6th orders of the Markov Chain have been used. Each order corresponds to a previous state (aka previous activity) of the dataset, used as input in the Markov Chain model. In order to predict the next activity of a user, the probabilities for moving from one state to another must be calculated, the calculation of which is based on the sequence of activities of all users.

Alongside, two architectures of an RNN-LSTM network have been evaluated, having the best result among others after conducting several experiments, in order to find the optimal one with the optimal hyper-parameters. The first one is the one described in section IV. The second architecture of the RNN-LSTM network tested is composed of two layers, using different numbers of units in each layer respectively, as presented in Fig. 2. The activation function used is the Exponential Linear Unit (ELU) [10] [11]. The selection of the ELU activation function resulted after executing several tests and evaluations among other activation functions. The output layer is a fully connected layer using the softmax activation function to convert the continuous type of output into a discrete class of output. For this case of evaluation, the RNN-LSTM network used as input the sequence including the daily activities performed by the day of the prediction.

According to the results provided in Fig. 2, the RNN-LSTM achieves better accuracy on both Top-1 and Top-3 metrics. The results of the Markov Chain model could be enhanced if other attributes, such as user characteristics, were included. From this evaluation phase, the resulting percentages present that the usage of a sequence of activities as input provides more accurate predictions, instead of only providing a certain number of previous activities to the model, as in the case of Markov Chain.

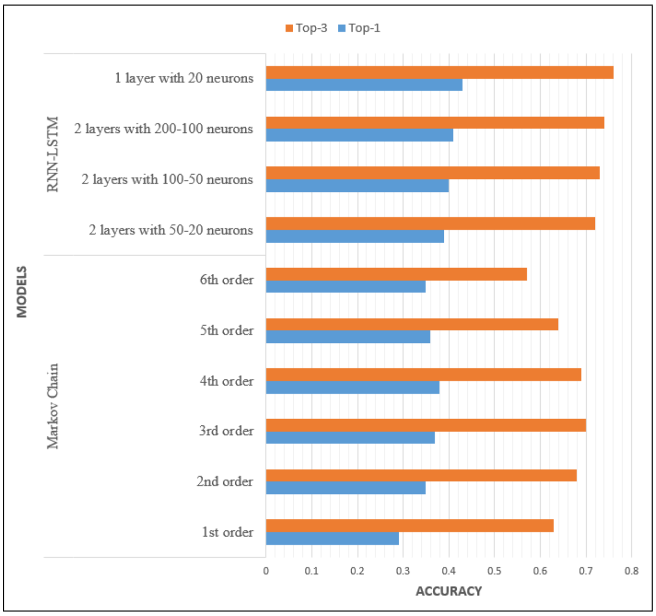

Fig. 2. Evaluation results of Markov Chain model and RNN-LSTM

B. RNN-LSTM performance evaluation of time intervals in a sequence of activities

The second evaluation is related with the performance of the RNN-LSTM network and how it is affected by the varying number of activities in a sequence of activities for one day. In order to examine this, the ATUS dataset has been processed and split into different time intervals.

In the version of the ATUS dataset used, each user has provided a sequence including various activities daily, along with the actual time the activity was performed. The majority of the users included in the dataset were not having the same number of activities reported daily and not in a certain time interval. According to the following surveys [1] [12] in order to achieve more accurate prediction results, the sequences of activities used should include one activity type per hour (equals to 24 activity types for a daily sequence). Therefore, the dataset had to be processed in order to create daily sequences of activities for each user and provide them as input to the Activity Prediction module [1]. The processing of the dataset was based on the timestamp provided in the initial information of the ATUS dataset. Initially, the timestamp was split into 60 minutes intervals aiming to create 24 activity types within a day. Through a matching process, each interval was matched with the activity type provided in the initial ATUS dataset. In cases where more than one activity type corresponded to one-time interval, the activity type that was finally set to this interval was the one with the greater duration among the others.

The evaluation of the Activity Prediction module was based not only on this dataset, where each sequence of activities includes 60-minute intervals and one activity type has been set for each time interval, but also in processing the dataset further aiming to create accordingly datasets with 30 minutes (equals to 48 activity types per day) and 15-minute intervals (equals to 96 activity types per day). The aim of this process was to evaluate the RNN-LSTM network by using the ATUS dataset rescaled in time, aiming to recognize the optimal internal between two activities in a sequence. The RNN-LSTM receives as input each rescaled dataset, using the same settings. As an evaluation metric, accuracy with Top-N approach was used. The results are presented in Fig. 3(a).

According to the results, the optimal interval between two activities in a sequence is 15 minutes. However, it is difficult to obtain information about the type of activity a user performs in such a short period of time. Therefore, the 60 minutes interval, which has a fairly good accuracy value, was chosen for the third part of the evaluation.

C. Performance of the RNN-LSTM network when using user attributes as input

The third step of the evaluation concerns the use of multiple attributes as input in an RNN-LSTM network aiming to review the behavior of the RNN-LSTM network by using the user attributes as input and at the same time to find the best input type for each one of these attributes. Additionally, the attributes that have the higher score in both Top-1 and Top-3 metrics will be used for further evaluation, where they will be inserted as input on the RNN-LSTM network with the sequence of activities the user's have performed. Thus, all possible inputs on an Activity Prediction module will be evaluated. The user attributes used for this step of evaluation are the ones included in user's activity profile described in section III. The architecture used for this evaluation step is the one described in section IV, since from the first evaluation step VI-A this one had the best results.

For the evaluation of the user attributes and their correlation with the number of activities included in each sequence, two versions of the ATUS dataset used were created. The first version, called version A, is the 2008 ATUS dataset without processing, meaning that the activities defined on the ATUS dataset were used without adding any other activities. This dataset was used to evaluate the effect that every user attribute included in the RNN-LSTM has. Nine cases (Table I) were tested and in every case, different user attributes were inserted as input in the RNN-LSTM. The results of each case are presented in Fig. 3(b). Some attributes have been used as input either normalized or in logarithmic scale, in order to evaluate all possible variations. The gender attribute has been considered as one (1) for males and zero (0) for females. The occupation's status attribute has been considered as one (1) for not employed and zero (0) for employed. The activity's location parameter was either inserted as one-hot-encoding or normalized. All the other parameters, such as the age attribute and the day and month of prediction were normalized.

According to the results displayed in Fig. 3 (b), the attributes with the higher accuracy in both Top-1 and Top-3 were taken into consideration for the third step of the

TABLE I

EXPERIMENTS CONDUCTED USING DIFFERENT USER ATTRIBUTES AS INPUT (# 9 CASES) ON ATUS DATASET WITHOUT PRE-PROCESSING (VERSION A)

Attributes	#1	#2	#3	#4	#5	#6	#7	#8	#9
Location (normalized)		X	X						
Location (one-hot-encoding	X			X	X	X	X	X	X
Start time (normalized)	X	X	X	X	X	X	X	X	X
Duration (normalized)			X	X	X	X	X	X	X
Day of prediction is weekend or not (normalized)				X		X	X	X	X
Gender					X	X	X	X	X
Marital status					X	X	X	X	X
Day of prediction							X	X	X
Month of prediction (normalized)							X	X	X
Occupation status							X	X	X
Index of activity							X	X	X
Age (normalized)								X	
Age (log)									X

TABLE II

EXPERIMENTS CONDUCTED USING DIFFERENT USER ATTRIBUTES AS INPUT (# 3 CASES) ON THE PRE-PROCESSED ATUS DATASET (VERSION B)

Attributes	#1	#2	#3
Age (normalized)	X	X	X
Activity's location (one-hot-encoding)	X	X	X
Start time (normalized)	X	X	X
Gender	X	X	X
Marital status	X	X	X
Date of prediction (normalized)	X	X	X
Day of prediction is weekend or not (normalized)	X	X	X
Occupation status	X	X	X
Index of activity	X		X
Activity's duration (normalized)			X

evaluation. For this step, the ATUS dataset was preprocessed and created the second version used (version B) where the activities included in the dataset for each user were

For this step, the ATUS dataset was pre-processed and created the second version (version B) in which the activities of that dataset were distributed in order to create a sequence of user's daily activities in 60 minutes time intervals. Using the pre-processed dataset (version B), three cases (Table II) were tested and in every case, different user attributes were inserted as input in the RNN-LSTM. Fig. 3 (c) presents the results of this evaluation, ordered by top-1 metric.

Based on the provided evaluation results in all cases,

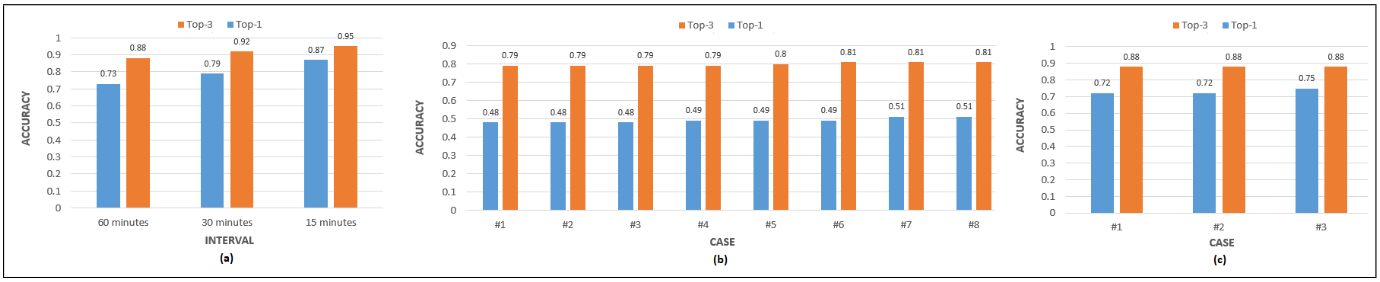

Fig. 3. Evaluation results of the second and third experiments conducted (a) Evaluation of multiple time intervals using RNN-LSTM (b) Evaluation results (#9 cases) using the ATUS dataset without pre-processing (version A) (c) Evaluation results (#3 cases) using the pre-processed ATUS dataset (version B)

the attributes providing higher accuracy on the RNN-LSTM model are the ones with the higher accuracy in both Top-1 and Top-3 from Table I. Comparing the results presented in Table I, including multiple user attributes as input in the RNN-LSTM, with the results provided in Fig. 2, where RNN-LSTM was evaluated only by receiving as input the sequences of user activities, it can be concluded that the use of demographic attributes and the use of activities with 60 minutes interval yield more accurate prediction results.

VII. Conclusions

The scope of this paper was to examine and experiment with the case of personalized user's next activity prediction, as this is proved to be an important asset and has an extensive application. Several experiments using RNN-LSTM model for the prediction of humans' next activity within a day have been provided and they are grouped in three categories. Initially, experiments were performed aiming at predicting next activity using RNN-LSTM models and Markov Chain models. All experiments were based on the ATUS dataset which is a detailed survey of the daily activities of more than 10.000 humans in America. The experiments showed that the RNN-LSTM performs better than Markov models in both Top-1 and Top-3 metrics.

In general, the predictions of the next activities based on a Markov Chain model are not that reliable, comparatively to the RNN-LSTMs, because the Markov Chain model's predictions are based on the training data and thus cases that are not included in the training set cannot be handled. On the other hand, Neural Networks (NN) can include several attributes as input, that could enhance the results of the prediction, as presented in the previous section. As a next step, the presented network can be further expanded with the use of attention mechanisms within the RNN-LSTM network and evaluated on the same scope.

Acknowledgment

This work is supported by the European Unions Horizon2020/Horizon Europe Research and Innovation Program through the SOCIO-BEE project (Grant Agreement No. 101037648). The opinions expressed in this paper are those of the authors and do not necessarily reflect the views of the European Commission.

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