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Data-driven analysis of interactions between people with dementia and a tablet device

Abstract: In the project I-CARE a technical system for tablet devices is developed that captures the personal needs and skills of people with dementia. The system provides activation content such as music videos, biographical photographs and quizzes on various topics of interest to people with dementia, their families and professional caregivers. To adapt the system, the activation content is adjusted to the daily condition of individual users. For this purpose, emotions are automatically detected through facial expressions, motion, and voice. The daily interactions of the users with the tablet devices are documented in log files which can be merged into an event list. In this paper, we propose an advanced format for event lists and a data analysis strategy. A transformation scheme is developed in order to obtain datasets with features and time series for popular methods of data mining. The proposed methods are applied to analysing the interactions of people with dementia with the I-CARE tablet device. We show how the new format of event lists and the innovative transformation scheme can be used to compress the stored data, to identify groups of users, and to model changes of user behaviour. As the I-CARE user studies are still ongoing, simulated benchmark log files are applied to illustrate the data mining strategy. We discuss possible solutions to challenges that appear in the context of I-CARE and that are relevant to a broad range of applications.

Keywords: data mining, events, dementia, tablet device

https://doi.org/10.1515/cdbme-2017-0155

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1 Introduction

In the course of dementia, relatives and care professionals play an increasingly important role to achieve the best possible quality of life of those affected. In particular, activation and support of the remaining individual physical, mental and social resources of people with dementia are of crucial importance. Technical devices supporting people with dementia have a

Figure 1: Use case scenario of the I-CARE tablet device. Source: AWO Karlsruhe.

tremendous potential for optimizing therapies [2]. The adaptive and mobile I-CARE tablet system as one of these systems learns about individual needs and potentials of people with dementia. It offers e.g. image galleries, videos and games to activate the user, either in community settings or in one-on-one sessions with informal and professional carer (see Figure 1). I-CARE records the feedback of the user by interpreting facial expressions and by requesting short evaluations [3]. The feedback is used for online adapting a content recommendation system. All interactions like start or end of the engagement with a particular content (e.g. watching a particular video, listening to a music song) as well as results from interpreted facial expressions are documented in an event log. An event log is a regular file that is modified by continuously appending event messages [5]. Normally, the event messages are not sampled with some predefined frequency but are generated irregular and include a timestamp. Event logs are used for monitoring and analysing technical and IT systems [6, 7]. The most frequent methods are determining event correlations, i.e. finding a set of events that occur within a predefined time interval [8], clustering to find events belonging together [1] or to split the event log in homogeneous subsets [4].

In offline data analysis, data mining methods are used to visualize activation sessions, evaluate the online adaptation and identify groups of users. Methods of data mining require structured data like time series or features for clustering, classification or regression. The log files of user interactions do not provide such data in general. In this paper, we describe the implementation of a pre-processing chain of data transformation to achieve time series and features for data mining from log files as well as visualization routines to get insight in the interactions of user with the I-CARE tablet.

2 Materials and methods

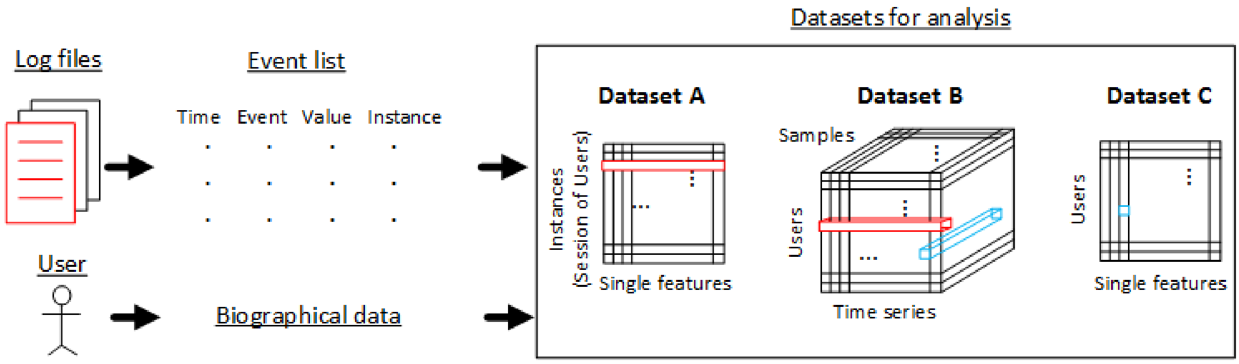
The data-driven analysis quantifies and visualizes single sessions of users as well as their development over time to demonstrate positive and negative trends or to discover even unforeseen effects of the I-CARE system. The datasets for the analysis are extracted from the log files. Figure 2 shows the transformation scheme from log files to datasets. Different tablet services document interactions of user with the tablet in the log file, e.g. the operating system orchestrator or the facial expression detection. Log file entries are converted to events containing a timestamp, a unique descriptor of the event type, a numerical value and the assignment to the corresponding user and session (instance). I.e. an event list can include different users and sessions, e.g. the data of an entire study. The meaning and the scale of the numerical value can be different between the event types, e.g. continuously in a range between 0 and 1 or nominal corresponding to discrete classes. Some event types even contain redundant information but are useful for further investigations. Table 1 shows an example for redundant events when starting and ending an activation content. There are events of the event types *activation started*, *activation ended*, *activation ID001*, *activation progress* and *activation tag sport*.

Events of the event type *activation started* and *activation ended* only occur with value 1. The frequencies of these events contain the information how often activation content was started and ended at all (there are also event types for pausing, resuming and aborting activation content). The *activation ID001* event occurs with value 1 when this specific activation content (e.g. an image gallery of the latest World Cup) starts and occurs with value 0 when it ends. *Activation progress* events do the same by any activation content and *activation tag sport* events for any activation content that is labelled by the tag “sport”. Such events can be used to learn something about how long (specific) activation content is used.

Table 1: Examples for events when starting activation content

Timestamp	Event type	Value	Instance
12:01:00	Activation started	1	1
12:01:00	Activation ID001	1	1
12:01:00	Activation progress	1	1
12:01:00	Activation tag sport	1	1
12:04:00	Activation ended	1	1
12:04:00	Activation ID001	0	1
12:04:00	Activation progress	0	1
12:04:00	Activation tag sport	0	1

Figure 2: Scheme of data transformation (from left to right). (1) Log files contain information about one session of one or maybe more users. (2) One event list is created by merging all log files. Next step is the aggregation and compression of potential useful information to features of sessions of users. (3) Dataset A results from single session of users. (4) Dataset B describes trends of users over all sessions with time series. (5) Dataset C displays users by summarising all sessions. Additionally biographical data is used for data analysis.



Features and time series are extracted from the event list, e.g. representing the most frequent emotions in a session of a user during activation content, rating of activation content or frequencies of activation content. Extracting appropriate features lead to datasets where a data point (row of a dataset) corresponds to

– one session of a user that is described by single features (Dataset A),
– one user (with all of its sessions) that is described by time series, the sample points correspond to the sessions of a user (Dataset B) or
– one user (with all of its sessions) that is described by single features summarising all sessions (Dataset C).

Since the duration of activation sessions and activation content are not equal, appropriate normalizations are required. Visualization routines are developed to give insight in occurrences and numerical values of single event types, emotions detected during activation content is active, frequencies of using activation content, numerical ratings of activation content and free text ratings of activation content. For a detailed analysis, every activation content is labelled by tags that represent its topic. When activation content is started, all its labels are documented in the log file. In this way, the relationships between rating values or emotions and content labels can be modelled. Based on such features, hypotheses of studies can be statistically evaluated in future clinical studies.

3 Results

In this section, we show some visualizations and discuss their value. Since there are no log files from real studies yet, simulated benchmark log files are created to develop the transformation and visualization routines. The benchmark log files describe three sessions of nine users with different preferences concerning type and topic of activation content. Beside starting and ending activation content, the benchmark log files contain events of emotion detection and numerical ratings. With numerical ratings (1: good, 0.5: neutral, 0: bad), the recommendation system as well as the emotion detection can be evaluated. In the following, possible visualizations and investigations are discussed. Figure 3 shows the mean rating values for activation contents over user and content label from the simulated benchmark log files. The blank field represents a missing value i.e. User 1005 never rated activation content that is labelled with "swimming". Therefore, no mean rating is available. It must be pointed out that using more different tags to describe activation content will result in more missing values.

Nevertheless there are two subgroups observable: Those users who like sports and those who prefer content about nature, e.g. forests or hunting. Due to the fact that every activation content that is labelled with "hunting" is also labelled with "forest", the statement "users who like content about forests do also like content about hunting" is not valid.

Figure 3: Mean ratings of activation content labelled with different tags for the users of the simulated benchmark log files. User 1005 did not rate activation content labelled by “swimming”, so the field is blank. Entries belong to features of Dataset C.

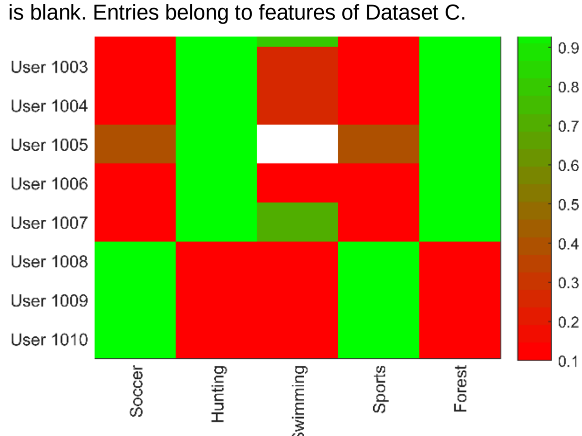


Table 2: Most frequent emotions of several users during activation content labelled with “sports”. Entries belong to Dataset A and Dataset B.

User	Session1	Session 2	Session 3
User 1002	-	Fear	-
User 1003	-	-	Neutral
User 1004	-	-	Neutral
User 1005	Happiness	Happiness	Fear
User 1006	Fear	Fear	Fear
User 1007	Fear	Fear	-
User 1008	Happiness	Happiness	Happiness
User 1009	Happiness	Happiness	Happiness
User 1010	-	-	Happiness

Table 2 shows the most frequent emotion of the users while activation content labelled with "sports" is active. Again, there are blank fields, e.g. for Session 1 and Session 3 of User 1002. In these sessions no emotions are detected or the emotion detection is not activated. Therefore, no most frequent emotion can be determined. Nevertheless, the emotions confirm the numerical rating. The most frequent emotion of the users 1008, 1009 and 1010 while activation content labelled with "sport" is active is happiness. That corresponds to their high ratings for this kind of activation content.

The most frequent emotion of User 1006 is fear for all three sessions. Regarding Figure 3, the user likes content about nature. By visualizing the frequencies over user and content label it can be evaluated if inappropriate activation content was started at most for User 1006. Such analyses results will be used to improve the recommendation system to adapt the system to new users. In addition, temporal preference changes can be detected and the system can react to changed user needs. In real studies the “neutral” emotion is probably the most frequent while the other emotions have a higher explanatory power. This leads to so-called imbalanced datasets and is taken account of when the data analysis is applied to real world data.

4 Discussion and conclusion

The aim of I-CARE is to support people with dementia, their relatives, friends and both, informal and professional carers. If and to what extend the I-CARE system is able to achieve this goal, is subject to several studies that will be carried out throughout the project. For this purpose, the tablet systems document the interactions in log files. In this paper, we introduced a transformation scheme to extract features and time series from the I-CARE log files. Furthermore, we showed how visualization routines are used to understand the activation sessions. The missing values are a major concern for clustering algorithms that are used to identify subgroups of users as well as for correlation calculations to model inference between content tags and ratings. In a next step, the proposed transformation scheme will be used to prepare datasets of real I-CARE studies for a data-driven analysis.

Author’s Statement

Research funding: The project I-CARE “Individuelle Aktivierung von Menschen mit Demenz” is funded by the Federal Ministry of Education and Research (BMBF) within the research programme “IKT 2020 – Forschung für Innovationen” as joint project under the reference number V4PID062. Conflict of interest: Authors state no conflict of interest. Informed consent: Informed consent has been obtained from all individuals included in this study. Ethical approval: The research related to human use complies with all the relevant national regulations, institutional policies and was performed in accordance with the tenets of the Helsinki Declaration, and has been approved by the authors' institutional review board or equivalent committee.

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