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by
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Abstract

Überblick

Acknowledgements

Thank you!

Conventions

Throughout this thesis we use the following conventions.

Text conventions

Definitions of technical terms or short excursus are set off in coloured boxes.

EXCURSUS:
Excursus are detailed discussions of a particular point in a book, usually in an appendix, or digressions in a written text.

Definition: *Excursus*

Source code and implementation symbols are written in typewriter-style text.

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The whole thesis is written in Canadian English.

Download links are set off in coloured boxes.

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Kapitel 1

Introduction

Michael öffnet nach einem längeren Arbeitstag zuhause seine Wohnungstüre. Er hat keinen Schlüssel. Kameras an verschiedenen Positionen im Flur haben seinen Bewegungsablauf und seine Haltung registiert. Nach der Eingabe seiner Pin auf einer Konsole wurde die DNA sowie die Retina über eine weitere Kamera gescannt. Ein intelligentes System hat Michael bereits erkannt. Als er die Küche betritt erkennt sein intelligentes Apartment, dass Michael heute müde ist. Das Licht wird verdunkelt, die Jalousien werden heruntergefahren. Michaels Verhalten signalisiert dem System, dass er in der nächsten Stunde nicht gestört werden möchte. Die Telefone und Haustürklingel werden auf stumm geschalten.

Als Michael nach einer Stunde wieder aufwacht, ist er erholt. Die Jalousien öffnen sich wieder etwas. Michael muss jetzt noch etwas für die Arbeit tun, da er oftmals besser von zuhause arbeiten kann. Er geht an seinen Rechner und öffnet die ersten Arbeitsdokumente. Das System ist gekoppelt mit dem Arbeitssystem seiner Arbeitsstelle. Es erkennt Michaels aktuellen und sich schnell ändernden Arbeitsprozess. Alle relevanten weiteren benötigten Informationen werden Michael unauffällig zur Vergügung gestellt. Michael beginnt sich seiner Arbeit zu widmen.

Das obige Zukunftsszenario skizziert eine Arbeitsumgebung und Privatumgebung, die auf einem vernetzten intelligenten System basiert. Assistenz- und ortssensitive Informationssysteme halten zunehmend Einzug in den Alltag. Diese Entwicklung kann vom persönlichen Standpunkt aus gut oder schlecht geheißen werden. Tatsache ist, dass die Entwicklung intelligenter Systeme zu einem sprunghaften Fortschritt ansetzt. Bekannte Wissenschaftler im Bereich der Artificial Intelligence wie Ray Kurzweil, Rodney Brooks und Jeff Hawkins sind der Meinung, dass die Zukunft dieser Entwicklung im Bereich der sog. „biologischen intelligenten Systeme“ angesiedelt sein wird. Diese ergänzen die auf der Inferenzstatistik beruhenden bisherigen Lernmodelle maschineller Intelligenz um zusammen neuartige intelligente System zu bilden. The Intelligent systems that are mentioned in the example above rely on certain architecture: lots of data (so-called "Big Data") is collected via a sensoric layer. For example sensors collecting information about engergy consumption within a building or sensors that recognizes the surroundings of a building in order to detect moving persons. The accumlated raw data then has to be transferred to information and fed into a machine learning algorithm that condenses the information and is able to predict future events and deduce patterns in the flow of information. In the above example this means that that the actual energy usage is send to the computing layer. In the according model future energy values are predicted. The final part of the architecture is the feedback of the analyzed data to an output system: as in the energy example, energy peaks could be predicted and as such it is ensured that energy commming from solar heaters is supplemented by traditional energy resources. This is a typical input-computation-output approach. As machines do not depend on ears, eyes and smells, sensors can be applied to other areas as well.

A disputed field of research is the "movement“ of persons in the digital world. The paradigm of the *knowledge worker* that has become true for most of the western society proclaims a new working model: The knowledge worker achieves his tasks by non-routine problem-solving approaches encompassing a usually non-linear sequence of steps like problem definition, information seeking, planning of solutions approach with the help of a Personcal Computer and the internet. As his work is fairly non-linear, workflows are of interest for companies to keep the knowledge as an essential good. Extracting workflows from elementary actions, i.e. operations on programs and documents, is difficult. The same documents and programs can be used in different contexts, users act in automated ways to achieve their goals, but orders of higher level activities (searching for information, elaborating presentations ...) are permutated. This work tries to answer the question, if it is possible to extract meaningful workflows ("Process Mining") from sensoric data ("Protocol Data") by applying a new form of Biological Intelligence, called Hierarchical Temporal Memory (HTM). In analogy to the former example, the sensoric data is transmitted to the HTM algorithm, that is able not only to model behaviour but also predict next steps. The results are abstracted to information in terms of knowledge work in order to get a workflow model. The results are fed back to the user and serve as basic for a knowledge management system.

The thesis is has strong psychological implications, that will become clear in the following chapters: For one, the HTM-CLA (Cortical Learning Algorithm) was designed in analogy to the working principles of the human brain. This will the touch the areas of intention research in psychology as knowledge and knowledge acquistion are tied to intention. Second, data acquisition and analysis gained from user interaction with digital devices will become more important in the future. This work gives a hint at how this could work.

The work is structured as follows: In the Related Work 2 the existing approaches for knowledge mining are introduced and the problems are defined. The the HTM is elaborated and distinguished from known classical AI approaches. Its psychological relevance is emphasized and compared to the psychological research of intention. In the the chapter Own Work 3 the implementation of the HTM is elaborated. Experiments and results are shown. The work concludes with an outlook.

Kapitel 2

Related work

2.1 Knowledge and Task Mining

Context-Aware Systems

In the computer scientific field of knowledge and task mining is no new subject. With the rise of mobile computing devices the term Context-Aware Systems (CAS) was created. The meaning and definition are disputed. First publications referred to a user's location: in different places usually different contextual parameters are relevant. For example a diver that is ascending from deep water has to be made aware of resting times before emerging to the surface.Another example was the *Active Badge Location System* in 1992 that detected the whereabouts of a person and in order to forward relevant phone calls to telephones close targeted person (Want et al. [1992]). Such systems adapt not only to the location but also to other relevant and changing parameters in the surroundings (Schilit et al. [1994]). This definition was widened in 1998 where context was referred to not only the computer accessible parameters of the surroundings but also the emotional state, focus of attention, date and time as well as people in the environment (Dey [1998]). The new aspect of internal parameters like focus of attention was then referred to a further elaboration of the definition: the internal (logical) and external context: Internal context parameters are specified by the user in interaction with the computer like goals, tasks, work context, business processes and emotional state. External parameters are usually measured by hardware sensors, i.e. location, light, sound, movement, temperature, pressure etc. (Hofer et al. [2003]). The contextual parameters can be grouped into four categories: identity (marked by a unique identifier), the location (an entity's position), activity (status, meaning the intrinsic properties of an entity, e.g., temperature and lightning for a room, processes running currently on a device etc.) and time (timestamps, Dey et al. [2001]). An example of the use of internal data for extracting context is the *Watson Project* Budzik and Hammond [2000]. Here the focus is shifted for collecting contextual information from user interaction with the computer in order to proactively support the user. Proactivity is a term that originates in organizational psychology and describes the ability of workers to not react to situations, but sense upcoming situational changes in advance and take control (Grant and Ashford [2008]). As work gets more dependent of the retrieval and analysis of information, a proactive support system shall help the user in his various tasks by providing him with relevant information. This approach had further implications as gathering information from the user interaction with his computer requires techniques from information retrieval and computer linguistics. In this case the documents a user works with are analyzed and keywords are stored as vectors or a bag of words. The relevant keywords shall help to narrow the topical context a user is working on. Keywords than help to start searches with relevant search terms and provide the user with the information he needs (Budzik and Hammond [2000]). As a single user is often not able to find the needed information, his typical search patterns are compared with those of other users. In these cases as *user model* is created, and his search terms are compared to those of other users' and the documents they found. If keywords are matching, documents of those others users are recommended (Anand and Mobasher [2007]). This approach is called Context-Based Recommender Systems (CBRS) recommendation and their related techniques like user-collaborative filtering are applied in search engines like Amazon [1].Attention-Aware Systems (AAS) at last have different focus: The guiding principle of AAS is that users have limited cognitive resources and are distracted easily . They suffer from an *information overload* as they jump quickly from one resource to the next in the same and different workings tasks. Whilst it is beneficial to be able to change foci in certain situations, in others it is exhausting. Therefore systems capable of supporting and guiding user attention have to assess the current user focus, and calculate the cost/benefits of attention shifts (interruptions). As this explanation shows, AAS have a foundation in cognitive psychology, i.e. how attention is elicited, distracted and shifting over time. Experimental setups include multiple sensor arrays like gaze-tracking-, gesture-tracking, speech-detection and systems that measure the physiological cues (Roda and Thomas [2006]). But there are also non-sensory based approaches that record users' interaction with software (Horvitz et al. [2003], Schmitz et al. [2011]). Attention management architectures expand the agenda of context-based systems, as they want not only to detect the current state of the attention of users, but also want provide support. Therefore not only the attentional state has to be tracked but the system needs to establish the users' goals and current tasks and also the happenings in the environment (Roda and Thomas [2006]). Consequently

Context-based Recommender Systems

Attention-aware systems

[1] www.amazon.com

this lead to the proclamation Intention-Aware Systems (IAS). This approach combines CAS and AAS by explicating individual and implicit intentions and plans of users' to reason about attention and context information. Dealing with context and attention means dealing with uncertainty . Explicated task models, so the idea, could help to increase the chances in proactive support. The term "intention" is approached in the following way(Cohen and Levesque [1990]):

Intention-Aware Systems

> Intention has often been analyzed differently from other mental states such as belief and knowledge. First, whereas the content of beliefs and knowledge is usually considered to be in the form of propositions, the content of an intention is typically regarded as an action. For example, Castefiada treats the content of an intention as a „practition" similar to an action description .... It is claimed that by doing so, and by strictly separating the logic of propositions from the logic of practitions, one avoids undesirable properties in the logic of intention, such as the fact that if one intends to do an action a one must also intend to do a or b. However, it has also been argued that needed connections between propositions and practitions may not be derivable.

The authors further argue that intention is directed towards the future actions and according plans. Intention thus shall be modeled as "a composite concept of what an agent has chosen and how the agent is committed to that choice". The choice can be a desire or goal. Intention therefore can be described as a persisting goal. If intention is defined in a formal theory, then beliefs, goals and desires must be expressed in the same way. As the theory may be correct, the deductions fall short for real world problems. On the other hand, if those terms are used in a very abstract way, they can not be used for a touring machine. The following approach is an example In Schmidt et al. [2011] intention is externalized in task models.

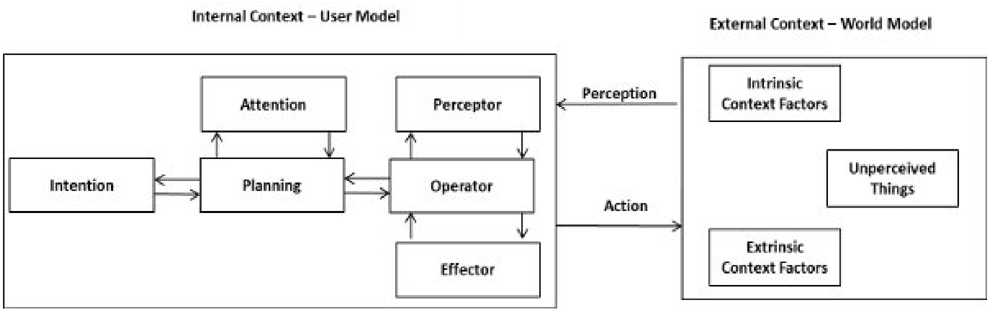

Abbildung 2.1: K-Model

The basis for this approach is a simple cognitive Human-Interaction-Model (*K-System-Model*) as shown in figure 2.1. The human being is composed of a perceptor, operator, and an effector. The components: attention, planning and intention are seen as motivator according the definition of intention mentioned above. The environment is seen as context divided into three components: things directly related to human intention (intrinsic context), unrelated external context and things that are not perceived. Context-aware and attention-aware systems are included in this model if user attention can be guided: i) intrinsic context features are provided in a user-friendly manner, ii) deficits of selections of intrinsic and extrinsic context features are corrected by shifting irrelevant features to the extrinsic context and vice versa and iii) unperceived things a are brought to user awareness. This first model does not answer the question how intention can be operationalized. Therefore they introduce the term *task* and *task models*. If task objectives are described including further information about task execution processes they lead to a plan that operationalizes intentions. Task analysis is no new invention: famous task analysis were done by Taylor (Scientific Management) and Gilbreth (Taylor [2013], Gilbreth [1911]). The approach was connected to the new ways of industrialization and assembly lines. Their goal was to analyize working tasks in order to find solutions that are performant and not exhausting for the worker, analyzing every single working step for optimization. Gilbreth outlined the steps in analyzing a task as follows: 1. Reduce practice to writing (i.e. stop work and write down). 2. Enumerate motions used. 3. Enumerate variables which affect each motion. Three categories of variables were considered in a motion study: characteristics of the worker (e.g., physical build, experience, temperament), characteristics of the surroundings (e.g., lighting, tools), and characteristics of the motion (e.g., direction, length, speed) Creighton [1992]. In this line of thought, humans are seens as operands and their behaviour is analyzed according to a clear set of measures. This mechanic like definition is also visible in the model above (figure 2.1). Existing task models in Information and Communication Technology (ICT) apply different modeling methods but the same approach towards the analysis of behavioural traces. It is obvious, that the behavioural patterns must in some way be connected to tasks or goals. The way to do this is by a. the means of describing the tasks, b. the methods for culstering the behavioural traces and connecting them to the tasks. In general there are two approaches to describe tasks: a. model the tasks and goals in advance. This can be achieved by describing tasks hierarchically (Newell et al. [1972]), or as a sequence of actions with a defined (Eder and Liebhart [1995]) order. If actions and tasks are not described in advance, they usually do not have a pre-defined order or structure. In this case, machine-learning technologies are used to extract regularities that can be named as tasks (Schmitz et al. [2011]). The second approach is eligible as the modelling of tasks is usually a very tedious assignment and then well-defined description do not match working processes in the real world. If task or coherent sequences of actions are found and named, the next job is to cluster them according to so-called activity schemes, that match the higher level descriptions of intentions as typical tasks of knowledge workers: Anyalse, acquire, disseminate, search and communicate information. With this again, typical classification of knowledge workers' roles shall be made possible: Learners, linkers, networkers etc. can be identified (Reinhardt et al. [2011]). The machine-learning approaches will be explained in more detail in the next chapter.

As a whole, the efforts explained belong to the research field of Knowledge Management (KM) and as such have the goal, in accordance with Taylor, to foster human capital and make resources available for companies . As described in "To compete effectively, firms must leverage their existing knowledge and create new knowledge that favorably positions them in their chosen markets .... (*Knowledge Management*) must be present in order to store, transform and transport knowledge throughout the organization" (Gold et al. [2001]). This happens, as according to Taylor, in a mutual agreement (Taylor [2013], p.10):

Knowledge Management

> Scientific management ... has for its very foundation the firm conviction that the true interests of the two (*employé and employer*) are the one and the same; that prosperity for the employer cannot exist through a long term of years unless it is accompanied by prosperity for the employé, and vice versa.

2.2 Psychological Theories

2.2.1 Activity Theory

Besides the behavioristic approaches mentioned in chapter 2.1, task analysis had another impact in the field of Human Compter Interaction (HCI) in the form of the Activity Theory (AT). AT is a psychological metatheory developed in Russia with its main protagonists being Vygotsky, Rubinshtein, Leont'ev, Zeigarnik and Ovsiankina and in its original ideas inspired by Lewin. Activity theorists, although developing a meta theoretic terminology, were interested in solving practical problems like helping mentally or physically handicapped children, educational testing and ergonomics etc. Activity theory is a powerful and clarifying descriptive tool rather than a strongly predictive theory (Nardi [1996]). Activity theory begins with a general criticism of the subject and interpretation in psychology (Leont'ev [1974]): Psychology separates object and subject in order to get a direct relation in the form of, f.ex. $S - R$ approaches, whether they are cognitively mediated or not. Another example is a typical experimental setup that artificially creates an environment (a so-called *standardized* environment as a *ceterus paribus* condition), that does not fit the socio-economical surroundings of the human being. Nevertheless it generalizes its findings to that extent. Like in cybernetics it seems to postulate a cyclic feedback between an actor and its surroundings:

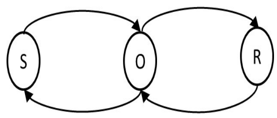

Abbildung 2.2: Feedback of SOR

But the feedback mechanism is more complex, as the *persona* becomes visible in its activity that is influenced, motivated and guided by cultural and internalized artifacts. The person thus is acting upon the world and changing it, changing culture and thus changing himself again. To understand its motivation, external activity must be observed and brought in relation with the other factors. Activity therefore theorists argue that consciousness is not a set of discrete isolated cognitive acts (decision making, classification, remembering, reasoning), and certainly it is not the brain: consciousness is located in everyday practice. Doing is firmly embedded in the social matrix of which every person is an organic part. The social matrix is composed of people and artifacts. Artifacts may be physical tools or sign systems such as human language. Understanding the interaction of the individual, other people, and artifacts in everyday activity is the challenge activity theory has set for itself (Nardi [1996]).

As this approach is complex it is strongly simplified in task analysis. As f.ex. described in an experiment by Rattenburry (Rattenbury and Canny [2007]) using an unsupervised system called CAAD to detect tasks:

> We draw primarily from Activity Theory (AT). Activities are the key structure in AT. They are composed of a subject, tools and an objective. The subject is the person, or persons, motivated to carry out and achieve the objective of the activity. The actions performed in an activity are mediated by tools. Tools include everything from found objects like sticks to manufactured objects like hammers to abstract, non-physical objects like words and ideas. In terms of CAAD, users are subjects and documents, folders, applications, and email addresses are tools. In the next section, we discuss how CAAD finds, represents, and uses context structures. Activities are generally long-term structures whose stability de-

rives from their motivating objective. In working on an activity, however, people tend to focus on shorter-term goals. These goals organize the actions that people perform e.g. sending an email, writing a section of a paper, or painting a room. Both actions and the activities they service involve a fairly stable set of subjects (i.e. people) and tools. This stable set of people and tools constitutes the context structure of the user's action and activity. CAAD searches for these stable sets in the event logs it gathers.

2.3 Machine Learning and Knowledge Management

Most KM and Data Mining (DM) techniques involve learning patterns from existing data or information, and are therefore built upon the foundation of machine learning and artificial intelligence. The primary techniques that can be used by the organizations usually are statistical analysis, pattern discovery and outcome prediction. A variety of non-typical data can be similarly monitored. Before the advent of DM and KM techniques, the organizations relied almost exclusively on human expertise (Tsai [2012]). In the following the general approaches in DM for KM are discussed.

2.3.1 Supervised Machine Learning

A typical example for supervised task learning is an approach called 'bag of words'-modeling. In the 'bag of words'-model a text is represented as an unordered collection of words, where the frequency of each word is used as a feature for training a classifier. Granitzer et al. [2008] use this basic method with the Term Frequency Inverse Document Frequency (TF-IDF) measure from the field of Information Retrieval (IR) as the input for their classifiers which is the final step of their processing pipeline. On the first level, the so-called *data acquisition*, raw event data from the operating system is collected. These are keystrokes, mouse clicks and used applications as well as file names, file authors, document structure etc. User actions and operating system reactions are called *events* (see fig. 2.3).

In this case, subsequent events are aggregated to so-called *event blocks*. The rule for creating these blocks can be 'time': events that take place within a small time period, or semantic characteristics defined by applications like *editing* a text file. An example for this mapping would be: A user opens a text file with his text processing application, navigates to a certain paragraph, be-

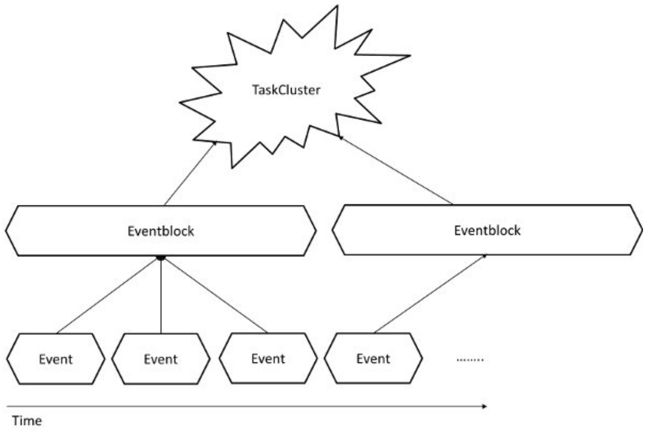

Abbildung 2.3: Classifying events

gins reading and then writing (as reading is usually recognized by scrolling within the application). These would map to an event block with a corresponding semantic meaning (see below) that could be called: *edit a word document*. Event blocks have *features or attributes* that are part of the event log format. The features used by the authors were: Application name, window title, content and semantic type. Of these, the semantic type is the prevalent feature described above for building event blocks, if the application provides according detailed information. If this is not the case, data is furthermore preprocessed to be used as a 'bag-of-words' for each event block. To this ends the features are summarized in word vector, stopwords are removed and then the words are *stemmed* which means the words are reduced to their root. An example for this is the stem 'dog' that is extracted from words like: doggy, doglike, dogs etc. To get the meaningful terms the TF-IDF-measure is computed, that extracts meaningful words from the event-block. The result then is used as a classifier for the machine-learning algorithms. Classifying hereby is done with a supervised approach where users train the algorithms with task labels given to the found event-block clusters. Classifiers used were K-Nearest Neighbor (KNN), Naive Bayes (NB) and Support Vector Machine (SVM). The authors report an accuracy rate for this approach with an average of $\hat{A} = 74.1$ with a standard-deviation of $\sigma = 8.2$.

2.3.2 Unsupervised Machine Learning

Unsupervised approaches also use clustering algorithms to group contextual artifacts. In Rattenbury and Canny [2007] the man-machine interaction was logged according to a pull approach: this means not operating system was triggering the events but a special program that checked for events every 2 seconds.

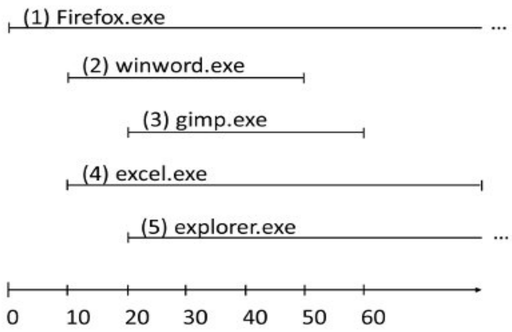

Abbildung 2.4: Classifying events

Figure 2.4 shows the timeline of activated applications (firefox, winword, gimp, excel, explorer).

$$D = \begin{array}{c} \begin{array}{ccccc} 1 & 2 & 3 & 4 & 5 \end{array} \\ \begin{pmatrix} 15 & 10 & 5 & 10 & 5 \\ 15 & 10 & 15 & 15 & 15 \end{pmatrix} \end{array}$$

If the logger checks for activated applications every to seconds, a frequency matrix composed of 30 second time intervals looks like the matrix depicted above. The first row marks the application numbers. The subsequent rows for each column show the activation frequency in the 30 second time interval if an activation check occurs every two seconds. *Firefox* was active for the whole shown 60 seconds thus the first column of the matrix has to entries with the value 15. *Winword* on the other hand, was active from second 10 to second 50 resulting in two entries of the value 10 etc. A single row shows the context structure with in the 60 second time period. The values show the probabilities of observing a certain artifact within the context. The non-negative matrices are then feed into an algorithm called Gamma-Poisson (GaP) being a subform of Latent Semantic Analysis (LSA) (Canny [2004]). As a result users get view of their task-related context-features in unobtrusive cloud tags.

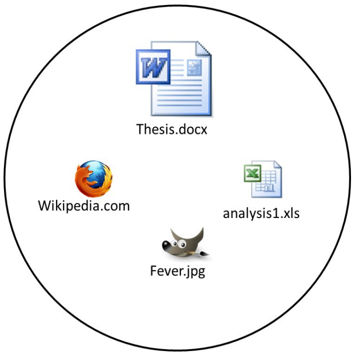

Abbildung 2.5: Context cloud

Kapitel 3

Own work

Kapitel 4

Evaluation

Kapitel 5

Summary and future work

5.1 Summary and contributions

5.2 Future work

Anhang A

TITLE OF THE FIRST APPENDIX

Anhang B

TITLE OF THE SECOND APPENDIX

CAS Context-Aware Systems

AAS Attention-Aware Systems

IAS Intention-Aware Systems

CBRS Context-Based Recommender Systems

ICT Information and Communication Technology

KM Knowledge Management

DM Data Mining

IR Information Retrieval

TF-IDF Term Frequency Inverse Document Frequency

KNN K-Nearest Neighbor

NB Naive Bayes

SVM Support Vector Machine

GaP Gamma-Poisson

LSA Latent Semantic Analysis

PCA Principal Component Analysis

HCI Human Compter Interaction

AT Activity Theory

Literaturverzeichnis

Sarabjot Singh Anand and Bamshad Mobasher. Contextual recommendation. In *From web to social web: Discovering and deploying user and content profiles*, pages 142–160. Springer, 2007.

Jay Budzik and Kristian J Hammond. User interactions with everyday applications as context for just-in-time information access. In *Proceedings of the 5th international conference on Intelligent user interfaces*, pages 44–51. ACM, 2000.

John Canny. Gap: a factor model for discrete data. In *Proceedings of the 27th annual international ACM SIGIR conference on Research and development in information retrieval*, pages 122–129. ACM, 2004.

Philip R Cohen and Hector J Levesque. Intention is choice with commitment. *Artificial intelligence*, 42(2):213–261, 1990.

Cynthia Creighton. The origin and evolution of activity analysis. *The American Journal of Occupational Therapy*, 46(1):45–48, 1992.

Anind K Dey. Context-aware computing: The cyberdesk project. In *Proceedings of the AAAI 1998 Spring Symposium on Intelligent Environments*, pages 51–54, 1998.

Anind K Dey, Gregory D Abowd, and Daniel Salber. A conceptual framework and a toolkit for supporting the rapid prototyping of context-aware applications. *Human-computer interaction*, 16(2):97–166, 2001.

Johann Eder and Walter Liebhart. The workflow activity model wamo. In *CoopIS*, volume 15, pages 87–98. Citeseer, 1995.

Frank Bunker Gilbreth. *Motion study: A method for increasing the efficiency of the workman*. D. Van Nostrand Company, 1911.

Andrew H Gold, Arvind Malhotra, and Albert H Segars. Knowledge management: an organizational capabilities perspective. *J. of Management Information Systems*, 18(1):185–214, 2001.

Michael Granitzer, M Kroll, Christin Seifert, Andreas S Rath, Nicolas Weber, Olivia Dietzel, and Stefanie Lindstaedt. Analysis of machine learning techniques for context extraction. In *Digital Information Management, 2008. ICDIM 2008. Third International Conference on*, pages 233–240. IEEE, 2008.

Adam M Grant and Susan J Ashford. The dynamics of proactivity at work. *Research in organizational behavior*, 28:3–34, 2008.

Thomas Hofer, Wieland Schwinger, Mario Pichler, Gerhard Leonhartsberger, Josef Altmann, and Werner Retschitzegger. Context-awareness on mobile devices-the hydrogen approach. In *System Sciences, 2003. Proceedings of the 36th Annual Hawaii International Conference on*, pages 10–pp. IEEE, 2003.

Eric Horvitz, Carl Kadie, Tim Paek, and David Hovel. Models of attention in computing and communication: from principles to applications. *Communications of the ACM*, 46(3):52–59, 2003.

Aleksei N Leont'ev. The problem of activity in psychology. *Journal of Russian and East European Psychology*, 13(2):4–33, 1974.

Bonnie A Nardi. Activity theory and human-computer interaction. *Context and consciousness: Activity theory and human-computer interaction*, pages 7–16, 1996.

Allen Newell, Herbert Alexander Simon, et al. *Human problem solving*, volume 14. Prentice-Hall Englewood Cliffs, NJ, 1972.

Tye Rattenbury and John Canny. Caad: an automatic task support system. In *Proceedings of the SIGCHI conference on Human factors in computing systems*, pages 687–696. ACM, 2007.

Wolfgang Reinhardt, Benedikt Schmidt, Peter Sloep, and Hendrik Drachsler. Knowledge worker roles and actions—results of two empirical studies. *Knowledge and Process Management*, 18(3):150–174, 2011.

Claudia Roda and Julie Thomas. Attention aware systems: Theories, applications, and research agenda. *Computers in Human Behavior*, 22(4):557–587, 2006.

Bill Schilit, Norman Adams, and Roy Want. Context-aware computing applications. In *Mobile Computing Systems and Applications, 1994. WMCSA 1994. First Workshop on*, pages 85–90. IEEE, 1994.

Benedikt Schmidt, Todor Stoitsev, and Max Mühlhäuser. Task models for intention-aware systems. *J. UCS*, 17(10):1511–1526, 2011.

Hans-Christian Schmitz, Uwe Kirschenmann, Katja Niemann, and Martin Wolpers. Contextualized attention metadata, in claudia roda (hrsg. 2011.

Frederick Winslow Taylor. *Scientific management*. Routledge, 2013.

Hsu-Hao Tsai. Knowledge management vs. data mining: Research trend, forecast and citation approach. *Expert Systems with Applications*, 2012.

Roy Want, Andy Hopper, Veronica Falcão, and Jonathan Gibbons. The active badge location system. *ACM Transactions on Information Systems (TOIS)*, 10 (1):91–102, 1992.

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