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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.

`myClass`

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

This chapter introduces

2.1 Digital Revolution, Knowledge Management and the Knowledge Worker

General Purpose Machine

In the digital revolution, society experiences a shift by having computers as main tools for work and free time. The acceleration of communication influences all sectors of public life like politics, science, economy and sports. According to Bühl [1997] the indicator for an epoch change is the all-purpose character of a Turing Machine. A computer fulfills the following functionalities:

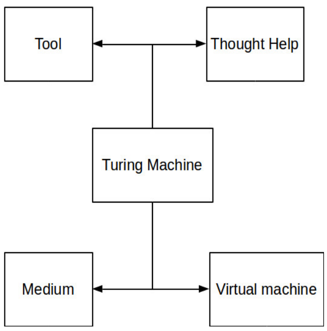

Abbildung 2.1: The All-Purpose-Machine

The difference from a computer to a conventional machine is its faculty to applicable not only to a single domain like for example a double ram press that stamps the autobodies of a new car models. Its purpose gets clear not by the hardware but by the software and the human being that is operating the computer. Following Turing, all computers are equivalent when they have to solve computable tasks. For this reason, a computer has the potential to simulate all other machines (given the software for simulation is properly written). This lets Bühl [1997] state the following: computers are a new entity a so-called non-machine, as they simulate processes that were formerly run with specialized machines. Second they are used as "implants" for specialized machines in order to fulfill a set of tasks, including communication.

Virtual Space

As society gets more interconnected with the help of computers and the internet, they form a new space - the cyberspace or virtual space. Humans communicate with machines and map information in new ways (Dodge and Kitchin [2001]). Machines become portable and support the workers in different situations and different contexts. But machines not only provides solutions for computable problems or communication, they also help to gather and aggregate information. The information shall become knowledge by the effort of human beings and machines that start to interpret available information.

Knowledge Management

The management of this knowledge is an issue (Knowledge Management (KM)) for organizations. The goal for companies is to foster human capital and make resources available. "To compete effectively, firms must leverage their existing knowledge and create new knowledge that favorably positions them in their chosen markets .... KM must be present in order to store, transform and transport knowledge throughout the organization" (Gold et al. [2001]). This happens in a mutual agreement - as according to Taylor, the founder of Scientific Management, states: The employes are interested in the profit of their employers(Taylor [2013], p.10).

Knowledge Worker

According to Drucker [1999] the challenge for companies is to make knowledge-workers productive. Six factors determine his productivity:

1. Productivity demands the answer to the question: *What is the task?*
2. Knowledge workers take the responsibility for their actions, they have to decide and manage themselves
3. Continuous innovations is part of the knowledge workers' job
4. Quantity and quality of a knowledge workers' output are equally important
5. A Knowledge worker is an asset and not a cost factor for the company
6. Knowledge worker undergo a continuous process of learning and teaching

The enlisted factors hint to the fact that knowledge workers do not have a clear plan or task description but many obligations: They manage multiple tasks, collaborate effectively among their colleagues and clients, and manipulate and find the information that is most relevant to them (Voida et al. [2002]). From a point of view of organizations, the interconnection of organizational departments and the fluid character of working in projects are the main characteristics of knowledge workers. But what are knowledge workers in concrete?

Knowledge Work in Organizations

According to Späth and Kelter [2009] the productivity of the production sector is always improved and rationalized, whereas office routine did not take the same development. But in Germany 17 mio people work in the office. Paper as the basic medium for information has become obsolete. An estimated 41.2% of German companies already digitalized their relevant information. Because of the tightly coupled interconnection between departments, knowledge work seems to be arranged on a continuum. On the low end, typcial office tasks as book keeping, finances and controlling are included in knowledge work. On the high end, scientist, managers and departmental heads need new tools and information to make their decisions. So three factors: organizational structure, IT and workplace design influence the performance of knowledge workers - but companies seem not to be able to find out how to handle the new type of work. Some companies put great emphasis on IT solutions, creating the so-called software Swiss army knife that integrates communication, collaboration, knowledge management and virtual teaming. On the other hand, many employees are overwhelmed by the amount of new tools and calculations they shall do (Davenport et al. [2012]). As a last resort, emails seem to be the mainly used knowledge management tool.

Innovative tools and artificial intelligence had no effect, because organizational structures were not prepared to include them in their processes. It seems that the digital revolution is countered by a passive strategy of companies. As the term "knowledge worker" is not new, science already suggested ways to tackle the problem of transparency and help in knowledge work. Typical approaches in information science and psychology are elaborated in the following sections.

2.2 Knowledge and Task Mining

With the availability of more elaborate computing devices and more information, information sciences began to develop solutions to support daily work. From a historic point of view the phases can roughly be brought into a chronological order with rising complexity as seen in figure 2.10.

The first approaches called Context-Aware Systems (CAS) had the agenda to support users with specific information in different physical locations. With the support of Natural Language Processing (NLP)[1] methods, the term context was widened to be usable in virtual space as well. In the virtual space a users' actions determine what is his context. Not only is it necessary to get information from a user's activities in the form of semantics: a psychological and explaining model is also necessary. For example, if a user is working on a lot of data with the keyword "NLP", what documents and information is needed in a specific situation? What tools are best to be used next? At this stage, the terms Attention-Aware Systems (AAS) and Intention-Aware Systems (IAS) were created and the field of research became more complex. In the following the scientific process is explained and figure 2.11 depicts the chronological development.

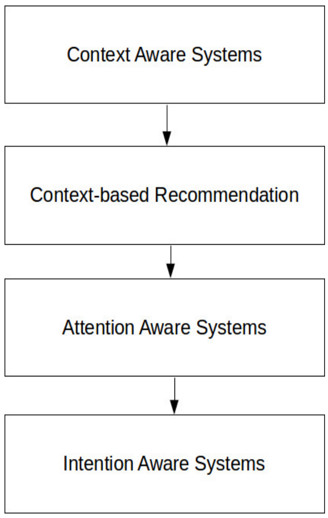

Abbildung 2.2: HCI approaches towards contextual user support

Physical Context-Aware Systems

With the rise of mobile computing devices the term 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 is the "Active Badge Location System" developed in 1992 was able to detect the whereabouts of a person and forwarded phone calls to phone cells close by (Want et al. [1992]). Systems like these adapt not only to the location but also to other relevant and changing parameters in the surroundings (Schilit et al.

[1]NLP is a field of computer science, artificial intelligence, and linguistics analyzing the interactions between computers and human languages.

[1994]).

Internal Context Parameters

This definition was widened in 1998, where context also implied the emotional state, focus of attention, date and time as well as people in the environment (Dey [1998]). These new aspects led 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]).

Proactive User Support

An example of the use of internal parameters for extracting context is the *Watson Project* Budzik and Hammond [2000] . In this project the goal was to proactively support the user in daily and complex work. 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.

Natural Language Processing and Context Based Recommender Systems

This approach had further implications, as gathering information from the user interaction with his computer requires techniques from information retrieval and computer linguistics. For example, the documents a user works with were analyzed in order to store keywords. The keywords then help to narrow the topical context a user is working on. The topical context is then used 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, a frequency matrix of search terms, that is compared to those of other users to identify related topics. If keywords are matching, documents of those others users are recommended (Anand and Mobasher [2007]). This approach is called Context-Based Recommender Systems (CBRS). CBRS and their related techniques like user-based collaborative filtering are applied in search engines like Amazon [2].

AAS at last have different focus: The guiding principle of AAS is that users

[2] www.amazon.com

Attention-aware systems

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 not only seek to detect the current state of the attention of a users, but also want provide support. Therefore not only the attentional state has to be tracked, but the system needs to find out about the users' goals and current tasks and also the happenings in the environment (Roda and Thomas [2006]).

Intention-Aware Systems

Consequently this lead to the proclamation IAS. IAS 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]):

What is Intention?

> 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 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 exploited with a Turing Machine.

Modeling User and Intention

The following approach is an example from Schmidt et al. [2011]. Here intention is externalized in task models.

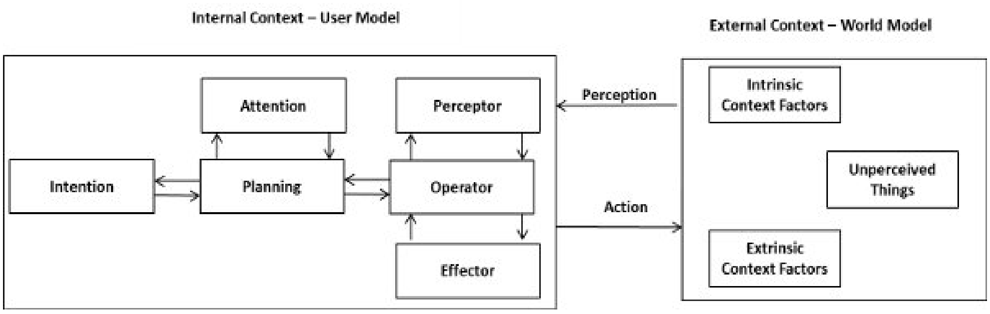

Abbildung 2.3: K-Model

The basis for this approach is a simple cognitive Human-Interaction-Model (*K-System-Model*) as shown in figure 2.12. The human being is composed of a perceptor, operator, and an effector. The components: attention, planning and intention are seen as a 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.

Task and Task Models

This first model does not answer the question of how intention can be operationalized. Therefore the authors introduce the terms "task" and "task models". If task objectives are described including further information about the task execution processes, they lead to a plan that operationalizes intentions. In this line of thought, humans are seens as operands and their behavior is analyzed according to a clear set of measures. This mechanic like definition is also visible in the model above (figure 2.12). 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 behavioral 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 behavioral 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 order (Eder and Liebhart [1995]). If actions and tasks are not described in advance, they usually do not have a predefined order or structure. In this case b., the 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 modeling of tasks is usually a very tedious assignment. Well-defined task descriptions 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: Analise, 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]).

Task Extraction and Machine Learning

It is obvious from these descriptions that there are many terms that require explanation. Not the least, how typical behavioral traces like "click a document X at time Z" can be aggregated to a higher level event. The following section tries to tackle these questions from a psychological perspective.

2.3 Psychological Theories

As was described in chapter 2.2, ICT was forced to find methods to group and define fuzzy terms like intention and tasks. In the following the theoretical approaches behind the concepts shall be elaborated. The first models tended to be observational, analyzing tasks in normal jobs with given goals (Scientific Management). This model was transmitted to the field of ICT(MHP and GOMS). The results there are to fine grained and constrained, as explicit task models and process description are necessary. A need for a broader model was pronounced. This was achieved with the approaches of Activity Theory (AT), Actor Network Theory (ANT) and DC. These models are very fruitful in Human Computer Interaction (HCI) but treat the results as artifacts, i.e. tools used and tasks discovered are useful when they are fed back to the users and the organization. They are not helpful in discovering intentions or tasks from user observation, but show a way to integrate findings in organizational processes. To find out more about tasks, a psychological approach is proposed that connects habits and intentions. The conclusion is, that intentions can not be extracted from user observations alone but it is worthwhile to elaborate and research habits in connection with CAS.

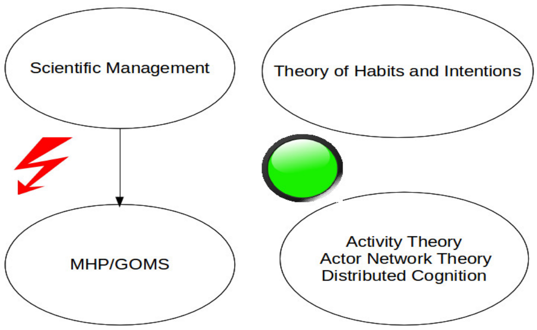

Abbildung 2.4: Psychological Approaches

2.3.1 Scientific Management

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 production with assembly lines and finding ways to support veterans from the first world war. The idea was to analyze working tasks in order to find solutions that are efficient 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].

2.3.2 MHP und GOMS

The MHP is a cognitive approach that helps to determine the time needed to complete a task in HCI. This is in resemblance to the approaches described above by Taylor and Gilbreth but with basics from cognitive psychology and psychophysics: the human is seen as an information processing system in accordance with a machine. The different parts of that machine: The Perceptual Processor, Working Memory with Visual and Auditory Image Store, a Cognitive Processor and Motor Processor as well as a Long-Term Memory have a Storage Capacity μ, a Decay Constant δ, a Cycle Time τ and a Main Code Type κ. The time needed to fulfill a task is constrained by the speed of the separate faculties. An example is the experiment of drawing a line back and forth between two parallel lines. The motor processor can issue commands about once every $\tau = 70$ msec. This leads to a certain number of pen reversals within a defined time period. The perceptual system can see whether the strokes are correctly drawn between the two lines. The percption has $\tau = 100$ msec and sends the information to the cognitive system with a decision time of $\tau = 70$ msec. The correction then takes again $\tau = 70$ msec. Total correction time therefor is 240 msec. As a conclusion, if a test person draws as rapidly as he can, corrections occur at a different frequency as the simple drawing of lines (Card et al. [1986]). It can be seen that this way of measuring task time needs a well-defined task description as proposed by Annett and Duncan [1967] and even on a granular level. The same holds to be true for the extension of the MHP to HCI, called GOMS: GOMS is a framework the maps the different steps in MHP to the processes in HCI. GOMS assumes that routine cognitive skills can be described as a serial sequence of of cognitive operations and motor activities within the a computer session (Olson and Olson [1990]):

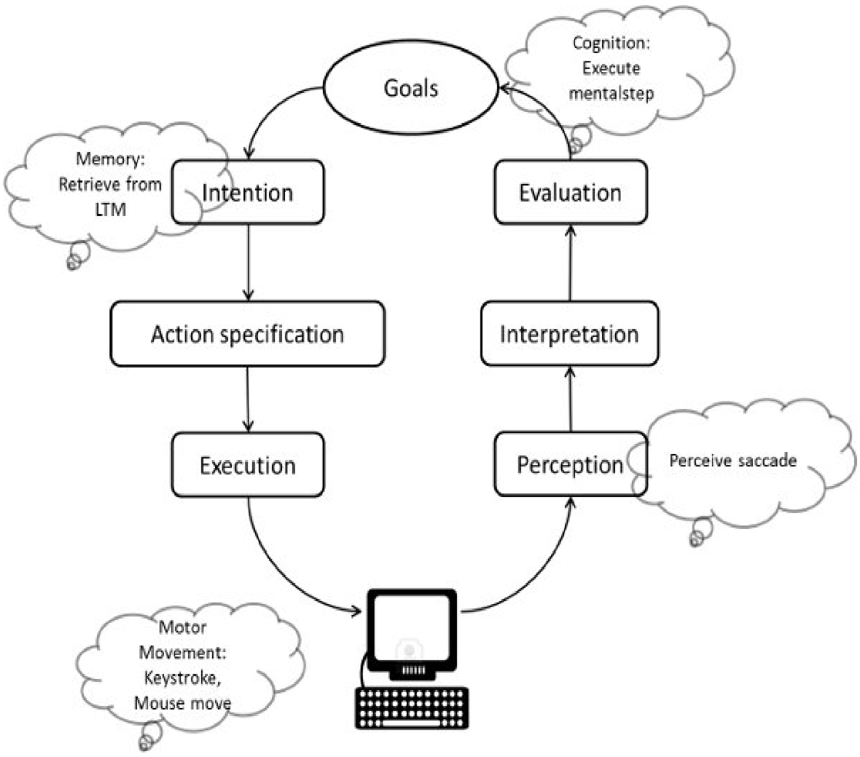

Abbildung 2.5: GOMS

An example of a typical study is the following: a user has several ways of entering digits into a spreadsheet application: with a mouse or by using the keyboard. The mouse method takes 4.19 sec in average, the keyboard 2.46

sec. The mouse method is calculated in the following way:

Moving the hand to the mouse	360 msec
Clicking the mouse	230 msec
Moving the hand to the keyboard	360 msec
Retrieving two digits	1200 msec
Typing two digits (each)	460 msec
Retrieving the end action	1200 msec
Typing the <ret> key	230 msec
_Total	4040 msec

As GOMS is very exact for a well-defined task, its usefulness declines when a task is not clearly described, when there are too many choices for users, too much parallel work and cognitive load.

2.3.3 Activity Theory

Besides the behavioristic approaches mentioned in chapter 2.2, task analysis had another impact in the field of HCI in the form of the AT. AT is a psychological metatheory developed in Russia with its main protagonists being Vygotsky, Rubinshtein, Leont'ev, Zeigarnik, Ovsiankina and, in its original ideas, Lewin. Activity theorists, although developing a meta theoretic terminology, were interested in solving practical problems like helping mentally or physically handicapped children, solving problems in educational testing and ergonomics etc. AT is a powerful and clarifying descriptive tool rather than a strongly predictive theory, with a general criticism of the subject and its interpretation in psychology (Nardi [1996], Leont'ev [1974]): Psychology separates object and subject in order to get a direct relation in the form of, f.ex. *S*timulus-*R*esponse 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. For example, a person is treated by a doctor with a needle for the first time. It hurts. As the patient sees the needle again the next time, he denies treatment (see figure 2.9):

But the feedback mechanism in AT is more complex: The "persona" (the whole set of attitudes, believes and behaviour) becomes only visible in its

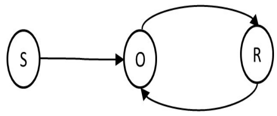

Abbildung 2.6: Feedback of SOR

daily activities. These activities are influenced, motivated and guided by cultural and internalized "artifacts" (cultural and personal conventions). 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.

AT 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]). The complex arrangement can be seen in figure 2.7 (Bryant et al. [2005]).

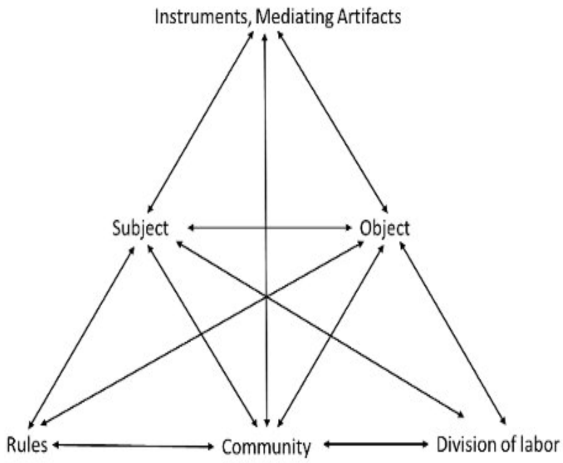

Abbildung 2.7: Components of Activity Theory

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 derives 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.

It can be seen, that AT is misunderstood: Although it is correct, that tools are used and goals are followed, the approach separates the different actions from the whole context. In order to gain insight, it would be necessary to mirror the findings to the employes and the organization as a whole.

2.3.4 Actor Network Theory and Distributed Cognition

Actor Network Theory

The ANT is related to the AT as it takes a similar analytical position: Human and their functionality can not be described independently of the tools they are working with. For example a scientist would not be a scientist anymore if he was deprived of his desk, his journals, books and computer. The scientist in his function as a scientist is working and interacting with a *heterogenous network* (Law [1992]). This network and the interactions are the basic building block for understanding the organization as whole, may it be a company, a state or another kind of union. In this view, machines and humans are not separated, they are part of a bigger system. Humans usually don't interact without tools, may this be a blackboard or a beamer. Interaction is *mediated*.

> ...what counts as a person is an effect generated by a network of heterogenous, interaction materials. ...people are who they are because they are a patterned network of heterogeneous materials. ...So when ANT explores the character of an organization, it

treats this as an effect or a consequence - the effect of interaction between materials and strategies of the organization (Law [1992]).

Distributed Cognition

The theory of DC uses the ANT as a foundation and elaborates it to be usable in the sens of the AT. At first the term *cognition* is pushed forward again. Cognition can be thought of as the inner representation of a "heterogeneous" interaction (Hutchins [2000]). A process here is not cognitive because it happens in the brain. It is enclosed in the relationship among the elements that participate. The guidelines are (Hollan et al. [2000]):

1. Cognitive processes are distributed across the members of a social group, including emerging phenomena of social interactions
2. Cognitive processes involve coordination between internal and external (material or environmental) structure
3. Cognitive processes are mediated by culture

As the cognitive processes are brought to light by activities the main focus of observation are *events*. But events are not isolated or a mere collections of observational data, they have to be brought into the context of the situation and require different observational technologies (Interviews, Audio, Video). They show how information is arranged by interaction. The complex arrangement of the DC approach can be seen in figure

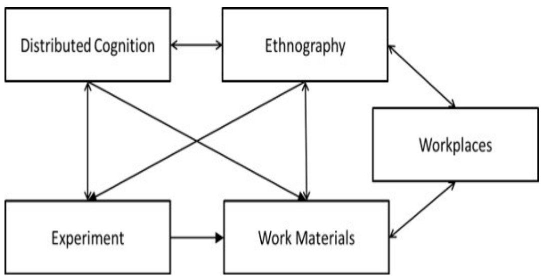

Abbildung 2.8: Research areas in DC

Figure 2.12 resembles figure 2.10. But DC extends the approach of AT as it specifies how experiments should be done: taking the aspects of figure 2.12 into account the experiments reveals the interactions between the components. As interaction includes the experiment itself, or the new tools, it becomes an artifact in itself. Experiments are seen as "settings in which people make use of variety of material ans social resources in order to produce socially acceptable behavior.". Experiments, if promising, are re-run in order to see changes in the distributed cognition. This iterative approach fits the change in the workflow as more organic. A typical example for a distributed designed experiment is a study done by Denef et al. [2008], where an orientation system in burning and smoking buildings for fire fighters was developed. The solutions proposed were tested in real world situations with fire fighters and strongly discussed afterwards. The aim was not only to find a technically performing platform but a new solutions that fit the operation plans of firefighters and even enhance their procedures in natural settings.

2.3.5 Habits and Intention

Habits

Habits play an important role in psychology, although research is not so well established. Early sociologists recognized the useful concept for social institutions(Weber et al. [1946], Mead [2007], Durkheim [1933]). William James suggested that habits have motivational properties, provide continuity to experience and behavior and uphold social structures (James [2011]). Of course, habits had an outstanding role in the psychological movement called 'behaviorism' in theories of Watson, Skinner and HullOuellette and Wood [1998]. In modern information-processing approaches habits are seen as automated responses to a stable context with high opportunity, emerging from response repetitions (Ronis et al. [1989]). As they are automated, the are usually executed subconsciously, leaving cognitive processing power for superordinate tasks.

Intentions

Intentions are defined in accordance with chapter . According to Heckhausen, intentions resemble plans about how to act when predetermined conditions occur. Once formed, they gradually become automatic operations or habits (Heckhausen and Beckmann [1990]). Intentions are also motivating because they become salient when the outcomes of an act can be predicted. They thus form attitudes towards behaviour (Ouellette and Wood [1998])

Habits and Intentions Integrated

Why are habits important? Because the help to predict future behavior. Or as outlined by Triandis: The frequency of past behavior is a standard indicator for habit strength (Triandis [1979]). And why are intentions important? Because they are also formed by attitudes, believes and habits, as habits are integrated into the self-concept (Ouellette and Wood [1998], Festinger [1962], Bem [1973]). First, habits differ from intentions and attitudes in scope. Intentions reach from the general to the specific, habits are always specific and limited in scope (Allport [1935]). Second, intentions play an important role in learning, when situations are encountered for the first time. Here intentions include details of how to handle the situations and the different aspects. They are formed and executed consciously. An example is a little child that learns to use the telephone, holding the receiver close to the ear, then listen and talk. With the practice in the constant context, intentions are represented in a broader and more efficient manner. They reflect more stable and long term strategies like: calling a friend to organize a party etc (Heckhausen and Beckmann [1990]). So intentions are chunked and packed into higher units that have automatic but as well controlled and conscious components. The typical flow of semiautomatic response patterns is a string of autonomous phases, where each phase is completed before the next will start. Between the phases, control acts are necessary, either to start the next process or to stop the flow of actions (Bargh [1989]).

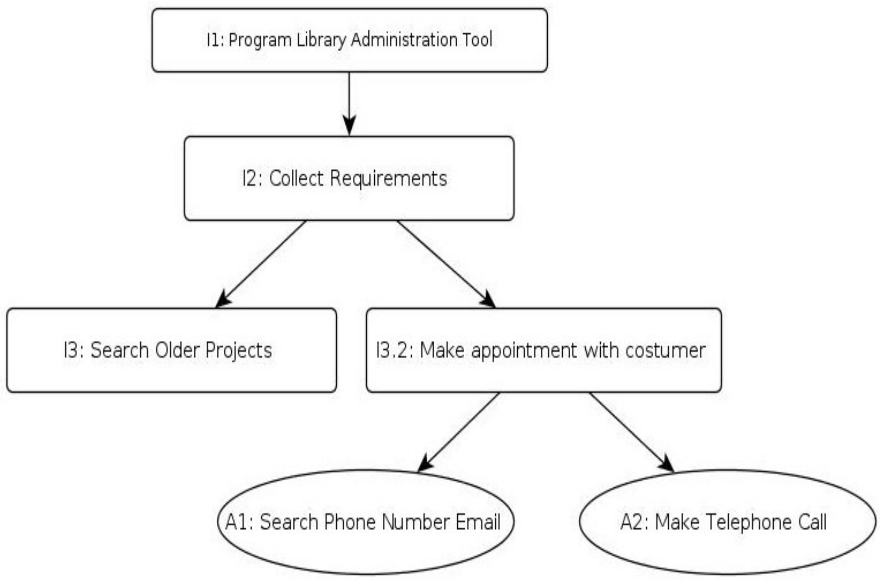

Abbildung 2.9: Action Flow with Intentions

Intention Action Plan

An example for an action flow with intentions is figure 2.9: The main intentions is to develop an administration tool for libraries. The next intention is to collect the necessary requirements. One important source for this is to call the costumer and see what he needs. This step for requirements engineering is executed. The example also clarifies a typical problem when researching intentions: if an intentional plan is executed, steps and their order can vary. For example the telephone call can be done after the phone number is found on the internet, rather than by searching older emails etc. Or emails are searched in another context, i.e. for another project. This leads to the conclusion that without further semantic information, simple actions can not be grouped to higher units of intentions as intentions are not only formed by former behavior but also by world knowledge (Baldwin and Baird [2001], Bandura and McClelland [1977]). So the question of interest is how intentions are acquired by children:

Baldwin and Baird [2001] argue that for understanding and chunking elementary actions to higher units, an understanding of the intentions of action performers is necessary. In the ongoing flow of actions, intentional cues give meaning to stream of activity. Cues can be physical and emotional, as for example a mother, explaining a child that it is dangerous to touch a hot plate by pointing to the plate, moving the hand over the plate and expressing signs of pain. This pattern of sensing environmental objects, moving towards them or showing other signs of recognition, are key patterns in detecting intentional acts. In accordance with this observation, children and grown-ups seem to have the ability of detecting statistical patterns in elementary actions: Siskind and Thibadeau argue, that these actions can be computationally modeled and used to make computers detect intentions (Thibadeau [1986], Siskind [1995]).

2.4 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.

2.4.1 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. 2.10).

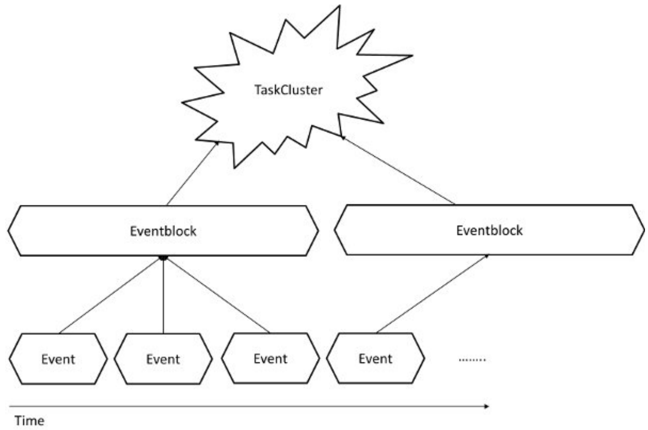

Abbildung 2.10: Classifying events

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, begins 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 $\sigma = 8.2$.

2.4.2 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.

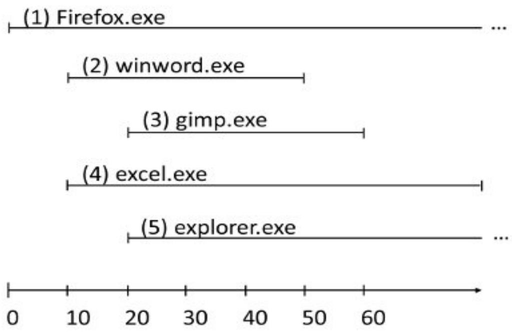

Abbildung 2.11: Classifying events

Figure 2.11 shows the timeline of activated applications (firefox, winword, gimp, excel, explorer).

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

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.

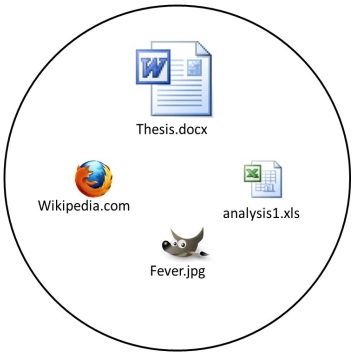

Abbildung 2.12: Context cloud

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 Computer Interaction

AT Activity Theory

ANT Actor Network Theory

DC Distributed Cognition

MHP Model Human Processor

GOMS GOMS

NLP Natural Language Processing

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