Towards Intention Aware Systems: A Critical Evaluation

Dissertation

Zur Erlangung des Grades

Doktor der Psychologie (Dr. phil.)

des Fachbereiches Psychologie der Universität Trier

Inhaltsverzeichnis

Kapitel 1

Introduction

After a long working day, Michael opens his apartment door. Or better, his door is opened for him. He has no key. Cameras at different positions in the corridor have registered his movement and his attitude. After entering his pin on a console, the DNA and the retina were scanned by another camera. An intelligent system has already approved him. As Michael enters the kitchen, his intelligent friend also sees that he is tired today. The light is dimmed, the blinds are shut down. Michael's behavior indicates that he does not want to be disturbed for the next hour. The phones and doorbell are switched to mute.

When Michael wakes up an hour later, he feels refreshed. The blinds open slightly. Michael now decides to do something for work as he often does, because he feels more relaxed there. He boots up his computer and opens the first working documents. The system is connected to the operating system of its job. It recognizes Michael's current and rapidly changing work processes. All other relevant and required information is provided discreetly while Michael starts listening to soft jazz and soul music. Michael begins to devote himself to his work.

The above scenario outlines a future working and private environment based on a networked intelligent system. It evokes reminiscences of *HAL 9000*, the intelligent computer of Stanley Kubrick's Space Odysee 2001. *HAL* is really intelligent, doing complex navigational computations for the spaceship and solving other computable problems. *HAL* is sensitive, shows emotional reactions and bondings towards crew members, he is socialized and very human. Moreover, he is able to guess the intentions of the astronauts, knows their habits and has a strong drive for self-preservation. An emotional conflict forces him to draw his own conclusions, which lead to his deconstruction. As his neuronal circuits are slowly withdrawn from his artificial brain, *HAL* suffers terribly.

It is quite clear that intelligent machines will not be like this, but assistance and location based information systems are increasingly finding their way into everyday life. From a personal point of view, this development can be called either good or bad. Fact is, many representatives of Artificial Intelligence (AI) announce a quantum leap of intelligent agents in the next decades, and more: Ray Kurzweil, Rodney Brooks, and Jeff Hawkins are of the opinion that the future of this development will be located in the so-called "intelligent biological systems", i.e. systems that replicate basic working principles of the brain. These will complement the previous learning-based inferential models for machine intelligence (Kurzweil [2013],Hawkins and Blakeslee [2007] and Brooks et al. [2012]). But will these approaches be able to interpret emotions and guess about intentions? This is conceivable, if one thinks of the many sensors, which are described in the introductory example: A lower heart rate and blood pressure can indicate fatigue, facial expression can confirm this, etc. But without the physical sensors, this task gets difficult. Nevertheless, this is studied in computer science and slowly in psychology as well: How can we make sense of the "actions" of persons in the digital world, i.e. the websites searched, the documents read and the friends that were contacted? And moreover: Is this important at all?

Yes it is, and not just for the reason that social platforms and search engines like *Facebook* and *Google* gather and analyze a lot of personal data (it is always good to know, what others can do with private data). The main driving factor is the paradigm of the *knowledge worker* that has become true for most of the western society and that proclaims a new working model: The knowledge worker completes his tasks by non-routine problem-solving approaches with the help of a computer applications, the internet and social media (Drucker [1999]). As his work is fairly non-linear and complex, companies depend on these specialists (Foss [2006]). In recent years the management boards of many companies became aware of this shift and established the position of a Chief Information Officers (CIO) whose work focus is information management. The objectives of this practical knowledge management go well beyond the mere supply of employes with relevant information: Employes are wanted to develop learning skills and abilities that provide added value for the company. The classification of knowledge is expressed on two poles: on the one hand the so-called explicit knowledge, which can be described and is therefore suitable to be kept in documents and on the other hand, implicit knowledge, which that can not be brought easily into tangible form.

Getting implicit knowledge is studied in computer science under the term "knowledge- and task mining". Its aim is to extract knowledge from elementary actions, i.e. operations on programs and documents, websites and social activities.

This work tries to answer the question in what form knowledge can be extracted from interaction of users with the virtual environment. The concrete research questions are:

1. Is it possible to extract user tasks and intentions from state-of-art computer science approaches?
2. What theoretical concepts of task analysis, goals and intentions are applied? What are the psychological foundations?
3. If knowledge from elementary tasks can be extracted, how to handle that information?

Questions 1. and 2. are answered in chapter 2. It will be argued that by the common approaches, so-called "Intention-Aware Systems" are not yet feasible. The theoretical shortcomings of the current concepts are revealed. As intentions are not extractable, there are two ways left to go. First, take existing approaches of computer science and see, how they can be integrated into organizations. Second try out a new approach and test, if the returned results are valuable and helpful on the way towards "Intention-Aware Systems". The second way is handled by applying a new form of bio-inspired computing, called Hierarchical Temporal Memory (HTM), that will be explained in chapter XXX. Results will be compared to the findings of re-implemented traditional ways of knowledge-mining.

The findings of either two approaches shall be evaluated and brought into organizational context to see, whether the extracted information is useful to a company. The evaluation and discussion are the last parts of this work.

Kapitel 2

Related work

This chapter is voluminous. It starts with with an explanation of how knowledge work arose by the increasing use of computers. Knowledge work influences the organizational structures of companies and raise the question of how to best integrate and organize this new way of working. Notwithstanding the fact that companies are unable to handle the fast changes in work, research has set its own development in motion. The next section therefore explains how knowledge and task-mining have developed from a scientific perspective and which theoretical constructs they use. As these constructs are mainly unclear or elliptic in their usage, a psychological analysis follows. This analysis discloses the shortcomings in the existing scientific approaches. This fact will be further highlighted by demonstrating two examples of knowledge mining that make use of machine learning technologies. By the juxtaposition of the findings of the theoretical analysis and the state-of-the-art approaches in Information and Communication Technology (ICT), the further research agenda is derived.

2.1 Digital Revolution, Knowledge Management and the Knowledge Worker

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 (see figure 2.1):

General Purpose Machine

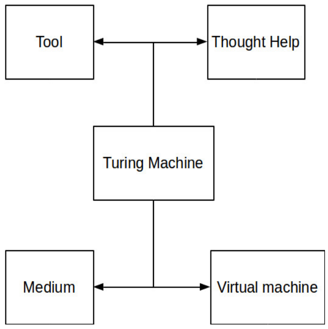

Abbildung 2.1: The All-Purpose-Machine

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

Consequently, as work is facilitated by this general purpose machine, humans can solve and work on many new and diverse problems with only one computer: 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 provide 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 .... Knowledge Management (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).

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

Knowledge Worker

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 employes 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.

As organizational structures are not ready and the new processes not yet defined, innovative tools and artificial intelligence can have no success. It seems that the digital revolution is countered by a passive strategy of companies. In contrast to the economic reality, science forged ahead on its own: The term “knowledge worker“ is not new, and ways were researched 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 2.2.

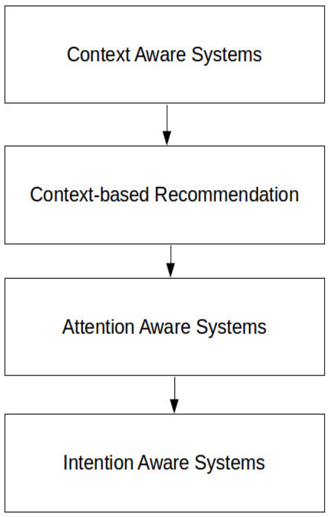

Abbildung 2.2: HCI approaches towards contextual user support

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

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

users' actions (clicks, search terms, documents downloaded etc.) 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 historic process is explained.

Physical Context-Aware Systems

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 is the "Active Badge Location System" developed in 1992 that 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. [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). Context-Based Recommender Systems (CBRS) and their related techniques like user-based collaborative filtering are applied in search engines like Amazon [2].

Attention-aware systems

Attention-Aware Systems (AAS) at last have different focus: The guiding principle of Attention-Aware Systems (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. They seek to detect the current state of the attention of a users in order to provide support. The Attention-Aware Systems (AAS) 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 of IAS. IAS combines CAS and AAS. This new approach reasons about implicit intentions and plans of users'. Explicated task models, so the idea, could help to increase the chances in proactive support. The term "intention" is faced in the following way (Cohen and Levesque [1990]):

[2] www.amazon.com

> 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.

What is Intention?

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.

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

Modeling User and Intention

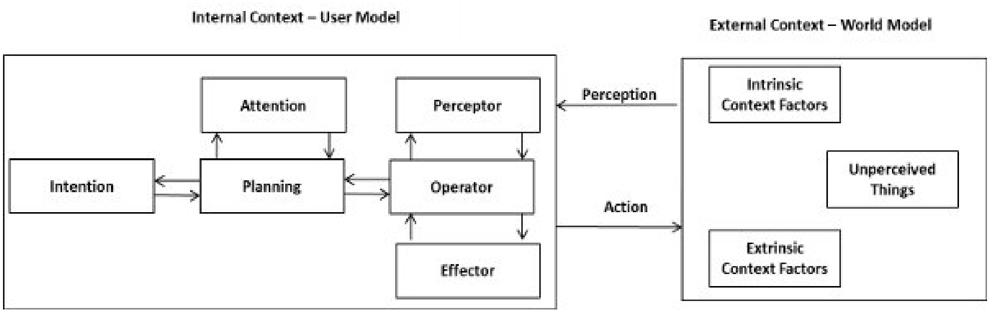

Abbildung 2.3: K-Model

The basis for this approach is a simple cognitive Human-Interaction-Model (*K-System-Model*) as shown in figure 2.3. 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 human is confronted with the external world: The environment provides 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 mechanic line of thought, humans are seens as operands and their behavior shall be analyzed according to a clear set of measures. But is this so easy? 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.

Task Extraction and Machine Learning

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 knowledge at hand, typical classification of knowledge workers' roles shall be made possible: Learners, linkers, networkers etc. can be identified (Reinhardt et al. [2011]).

It is obvious from these descriptions that there are many terms that require explanation. 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. At first the basic method of task analysis at the beginning of the last century is explained (Scientific Management). The elaborated procedures were valuable and transmitted to the field of ICT (MHP and GOMS). GOMS produces fine grained results that need explicit task models and process description. A need for a broader model was pronounced. This was achieved with the approaches of Activity Theory (AT), Actor Network Theory (ANT) and Distributed Cognition (DC). These models are very fruitful in 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 Context-Aware Systems (CAS) (see figure 2.4).

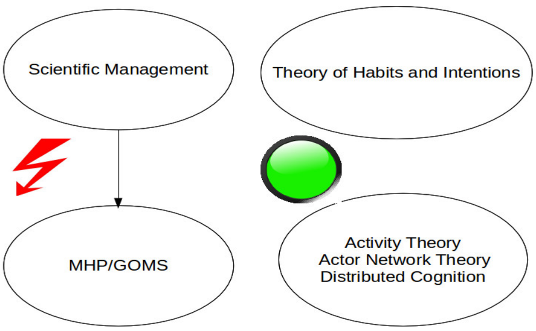

Abbildung 2.4: Psychological Approaches

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 handicapped veterans from the first world war. The idea was to analyze work processes in order to find solutions that are efficient and not exhausting for the worker. To this end every single working step on a predefined task was analyzed 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 Model Human Processor (MHP) und GOMS

The MHP is a cognitive approach that helps to determine the time needed to complete a task in Human Computer Interaction (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 (see figure 2.5).

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 therefore 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 computer session (Olson and Olson [1990], see figure **?**):

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:

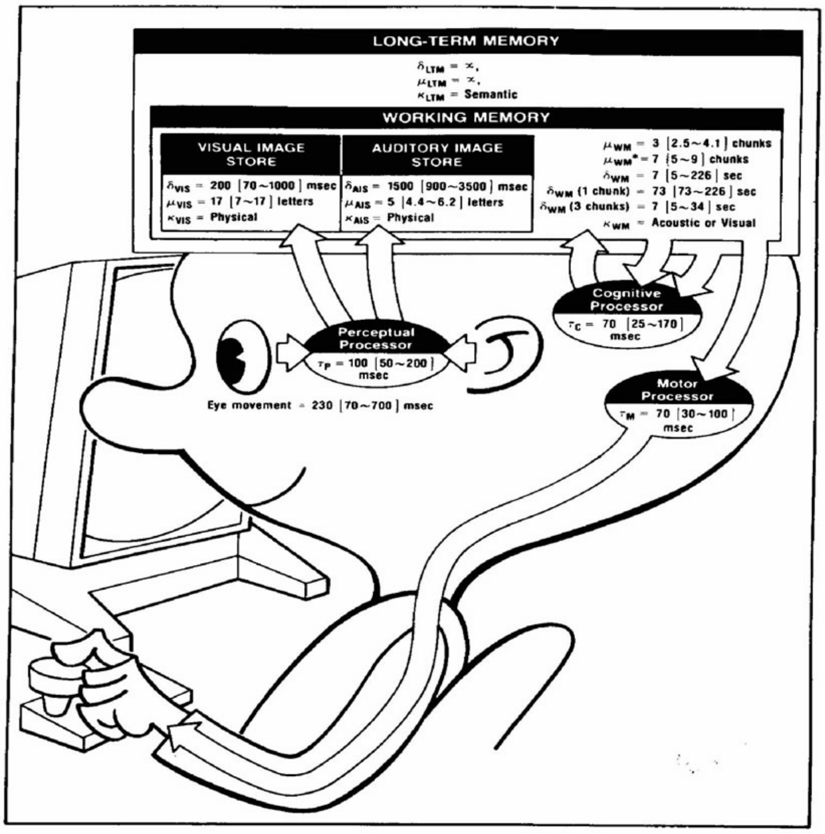

Abbildung 2.5: Model Human Processor

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.

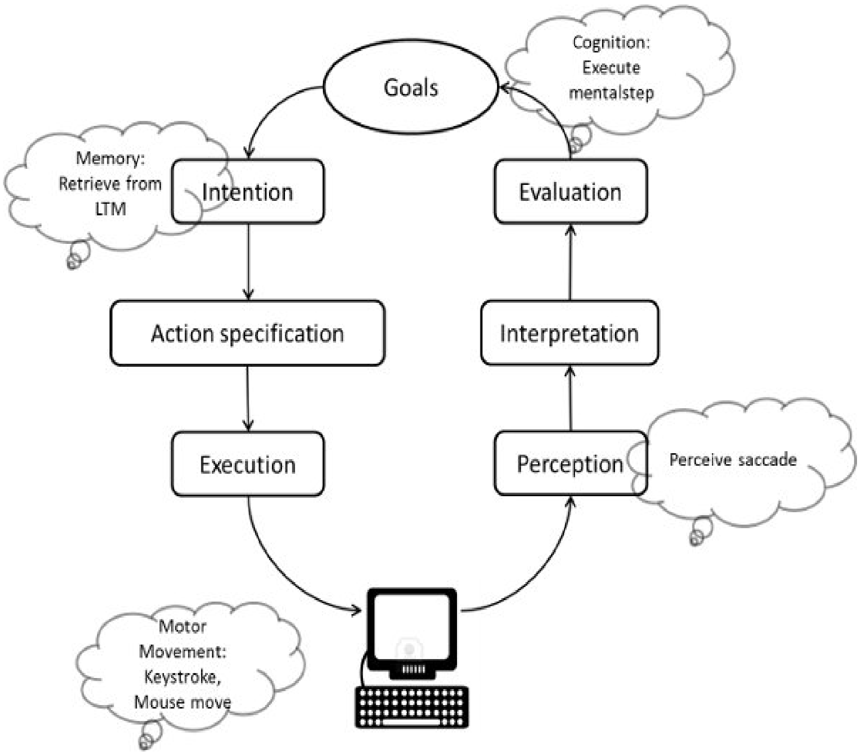

Abbildung 2.6: GOMS

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 Activity Theory (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 2.7):

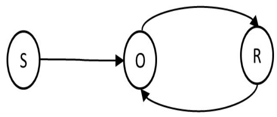

Abbildung 2.7: Feedback of SOR

But the feedback mechanism in AT is more complex: The "persona" (the whole set of attitudes, believes and behaviour) becomes only visible in its 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 2.8 (Bryant et al. [2005]).

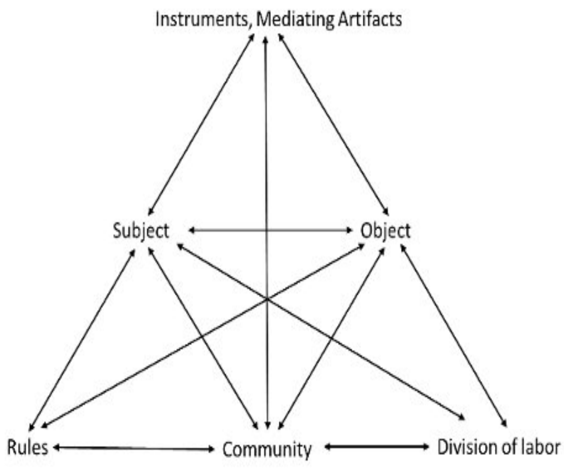

Abbildung 2.8: Components of Activity Theory

2.3.4 Actor Network Theory and Distributed Cognition

Actor Network Theory

The Actor Network Theory (ANT) is related to the AT as it takes a similar analytical position: Humans and their behaviour 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 blocks 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 Distributed Cognition (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 to the front. 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

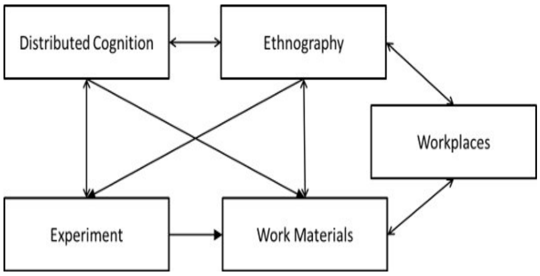

Abbildung 2.9: Research areas in DC

Figure 2.9 resembles figure 2.2. But DC extends the approach of AT as it specifies how experiments should be done: taking the aspects of figure 2.9 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 and 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 Hull (Ouellette 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

In this context, intentions are defined in accordance with chapter 2.2: 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]).

Intention Action Plan

An example for an action flow with intentions is figure 2.10: 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:

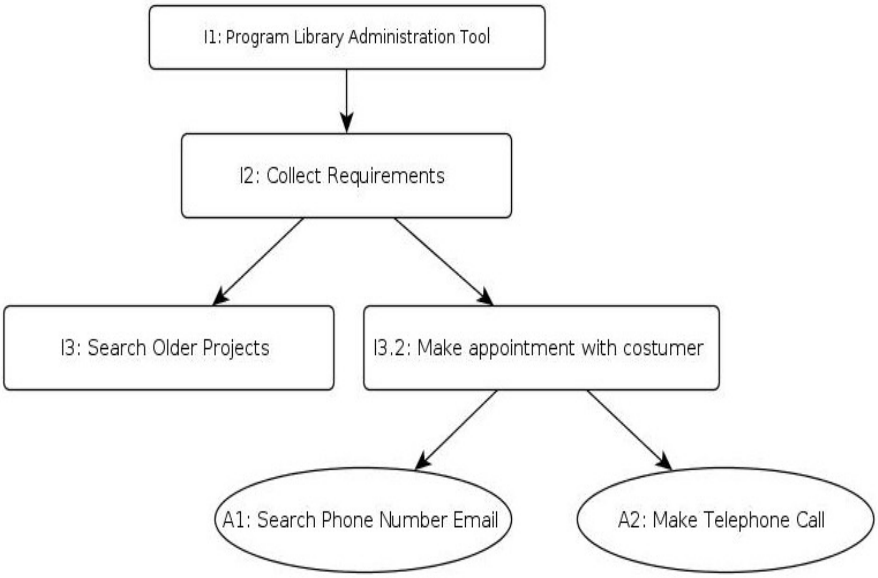

Abbildung 2.10: Action Flow with Intentions

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]), but all in all, the approaches were not very successful.

2.3.6 Discussion of the psychological theories

The examination of the psychological approaches usable and partly used in Information and Communication Technology (ICT) paints an ambiguous picture: Either the approaches are too fine grained as explained in GOMS or very broad as depicted with Activity Theory (AT) and subsequent approaches. Nevertheless, AT,Actor Network Theory (ANT) and Distributed Cognition (DC) show a way how to use results in experiments that try to discover tasks: The results are only usable, when they are transmitted to the employes and the employers in the organization. The question here is, whether the results are usefull and how they are interpreted. The discussion of intentions revealed that granular actions are not sufficient to deduce plans, goals or tasks. It seems that IAS are not realizable at the current state. Possible solutions would be to concentrate on CAS and the deduction of habits. Habits are not yet researched in ICT, and the question is, if they could be useful.

In the next chapter, typical approaches of context and task extraction in ICT will be demonstrated. It shall become visible that they follow a very pragmatic agenda. The following discussion shall juxtapose the pragmatic approaches with the results from the consolidated findings of this chapter.

2.4 Machine Learning and Knowledge Management

Most Knowledge Management (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]).

It is obvious that computer algorithms need definitions of what to do, and therefore the approaches are pragmatic. The following question have to be answered, if results are to be expected:

1. What is an action or an event when interacting with the computer?
2. If answered, how can chains of events be treated? What separates one chain from the next?
3. Are there permutations in the execution of tasks or events? How does a machine treat that?
4. Does the machine acquire knowledge in order to be more flexible?

Second, the collected events need to have some semantic information. This simply means that the events have some human-readable connotation: a click on a rectangle in position $(x, y) = 110, 220$ translates to a click in an application called *Windows Word* with name *Open....* As mentioned in chapter 3.1, this is necessary to find the right level of abstraction for observation in order to be able to interpret events.

In the following the general approaches in DM for KM are discussed with regard to the questions mentioned above.

2.4.1 Supervised Machine Learning

Bag of Words

A typical example for supervised task learning is an approach called "bag of words"-modeling. In general, a "bag of words"-model captures text as an unordered collection of words, where the frequency of the most characteristic 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). In short, the authors collected semantic information from events or basic actions. Then they combined subsequent events to blocks that can be characterized by a "bag-of-words". Blocks that share a significant amount of the same characteristic words have a high probability to end up in the same cluster (algorithms were "KNN" and "SVM"). The resulting clusters were validated and named by the participants of the experiment and became "task-descriptions" and hence the ground-truth for the lazy learning that should be able to deduce the task from basic event-blocks (see figure 2.11). The ques-

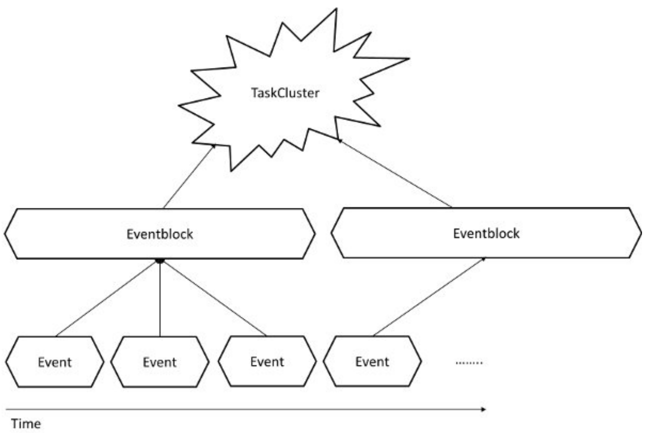

Abbildung 2.11: Classifying events

tions from above are enlisted to see how the authors addressed the pragmatic problems:

What is an action?

On the first level, the so-called *data acquisition*, raw event data from the operating system is collected. The keystrokes, mouse clicks and are enriched with semantic informations called *features or attributes*. The features used by the authors were: Application name, window title, content (file name, file authors, document structure), file name, file authors and semantic type which is a special type of event from the operating system and the programs used (like pushing an "Open"-Button).

What is a chain or cluster of actions?

Event - Eventblocks

User actions and operating system reactions are called *events* (see fig. 2.11). 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 above) that could be called: *edit a word document*.

Eventblocks - Task Clusters

Event blocks have *features or attributes* that are part of the event log format. The features were 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 $\sigma = 8.2$.

What separates on chain or cluster from the next?

In this example, the rules for building event-blocks were static. One rule was time, the other were semantic features from the applications: If "WinWord" was used, the attributes were available like "Opening", or "Scrolling" that did help in building event-blocks. The task clusters were then build by nonparametric classifiers.

Was the ordered sequence of events important?

No, ordering was not important as all the calculations based on semantic features.

What is the outcome of the algorithm?

The outcome is a classifier that maps basic events to user-defined tasks.

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.

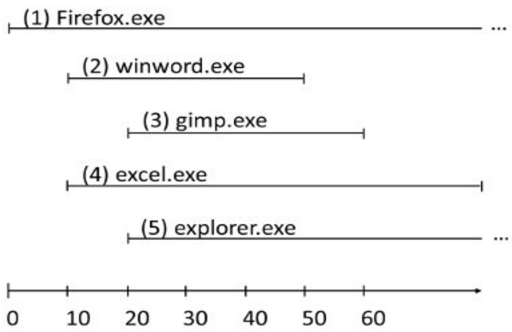

Abbildung 2.12: Classifying events

Figure 2.12 shows the timeline of activated applications (firefox, winword, gimp, excel, explorer).

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

If the logger checks for activated applications or documents 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.

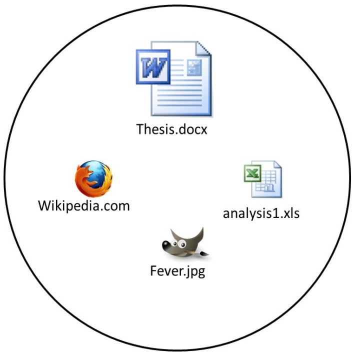

Abbildung 2.13: Context cloud

What is an action?

An event or action is an activation of an application or document (semantic information).

What is a chain or cluster of actions?

Events chains are subsequent or coincidental events. Other used resources can be computed with a probability value.

Was the ordered sequence of events important?

No, ordering was not important as all the calculations were based on semantic features and coincidence probabilities.

What is the outcome of the algorithm?

Clusters of related timely related resources.

2.5 Discussion

The examination and analyses of both: Task Mining Systems in ICT and the theories regarding task analyses in psychology lead to the following conclusions:

1. Attention-Aware Systems (AAS) and Intention-Aware Systems (IAS) to date and with the standard repertoire of machine learning technologies are not realizable. CAS are deployable
2. Activity Theory (AT) and the related approaches recommend to feed scientific findings back to the target groups (employes and employers).
3. Habits in relation to computer usage have not yet been analyzed
4. Psychological concepts are misused in ICT

The last point of "misuse" can be emphasized by the example the CAAD-System that was introduced in the last chapter. Here AT was mentioned as basic theoretical foundation:

> 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.

The findings from all the related work determine the further research agenda:

1. A new approach of machine learning is introduced that promises to have the potential of a "really" intelligent system. The approach is introduced and tested. Shortcomings are depicted and explained
2. Established approaches like the two machine-learning algorithms mentioned above are reimplemented. Findings, if possible, will be compared to the new approach. Most important, the findings will be evaluated in an organizational context. This addresses the issue of problem 2. above
3. Habits will be researched. Are habits inferable in knowledge work? Are they helpful in predicting further actions?

Kapitel 3

Own work

As was elaborated in the last chapter, an important research question is the detection of habits. This is based on the following findings:

- Habits are stored as procedural knowledge structures in goal achievement. They are an indicator for expert knowledge as they free cognitive resources for more conscious intentional plans (Aarts and Dijksterhuis [2000])
- Habits can predict future behavior (Bentler and Speckart [1979])
- Most activities of the day have habitual character as they take place in the same context (social environment, people and preceding actions ((Townsend and Bever [2001], Wood and Neal [2007])
- Habits usually are learned when achieving intentional goals but later, by a slow learning progress, they become subordinate parts of many goal directed behaviors (Wood and Neal [2007]).

It is interesting that the detection of habits has not yet been researched in computers sciences and even in psychology it is a relatively new subject as habits are hard to measure. The usual means for detecting patterns are diaries, self-reports or questionnaires. But habits are clearly behavioristic. Computers are an interesting platform to detect patterns. The following hypotheses are formulated:

- Habits must be detectable by people who are involved with daily computer work

- Habits are an indicator for expert knowledge
- Habits can be predicted
- Habits indicate to relevant context parameters

The hypotheses rely on the ability to detect and measure habits. As chapter 2.3.2 introduced, the Model Human Processor (MHP) and Goals, Operators, Methods and Selection Rules (GOMS) are not feasible to detect tasks, but their methodical approaches can be used to analyze habits. This gets clearer as GOMS was developed to estimate the total amount of time a task will take based on the composite of elementary actions. Routine cognitive skills can be described as a serial sequence of cognitive operations and motor activities. Each action can be quantified independently from the actual context. Figure 2.6 shows the steps of a user by using his software: The user perceives activity on the screen, evaluates whether the activity is according to goals sets up the intention for the next step, retrieves the way to act accordingly on the system and executes his movements. The time for the activities is a compound empirical value of the MHP where all operations are calculated from the interconnections of a set of processors and memories based on a "recognize-act-cycle": the "perceptual processor" encodes information from the senses to be available in the visual image store (short-term memory). From there the encoded information is retrieved from the long-term memory that modifies the information in the short-term memory again (act of recognizing). After that, the decision to act is taken by the "cognitive processor" and executed by the "motor processor" (see chapter 2.3.2). As the feedback loop from action to perception is time-consuming, rapid acts are executed in bursts (Card et al. [1986]). The shortcomings of the GOMS approach in elaborating tasks make it therefore useful for analyzing habits:

1. The model applies only to very skilled users
2. Learning or recall after periods of non-use are not elaborated
3. The model focuses on errorless performance
4. The model was developed exclusively for tasks in which the principal modeled components were assumed to be serial in nature
5. The model does not address mental workload
6. The model does not address fatigue

Empirically derived values for typical actions were verified and are listed in table 3.1: As time can vary for expert and novice mid-skilled users there is individual variation: For example key-stroke time for an average typist as is listed below is about 230 msec. An expert writer is listed with 80 msec (Olson and Olson [1990]).

Type of action	Time
Enter a keystroke	230 msec
Point with a mouse	1500 msec
Move hands to mouse	360 msec
Perceive	100 msec
Retrieve from memory	1200 msec
Execute mental step	70 msec
Choose among methods	1250 msec

Tabelle 3.1: Cognitive engineering parameters

The sequences of burst actions can be described in the following manner: a skilled programmer is using an editor for writing code. He uses a many shortcuts (**sk**) and takes time to think (**M**) between busts of actions. A typical protocol of his text edits could look like the following

<M,sk,sk,sk,M,sk,sk,sk>

Now the idea is, the programmer is very experienced. Shortcuts for him take about 150 msec. Retrieval from memory takes about 1200 msec. Total time for the burst action would be $2Ms+6sks = 3200$ msec. The computer protocol on the other hand, would net detect the cognitive activities but the key presses. Therefore the protocol would exhibit 2 very quick bursts of action with a break of about one and a half seconds. Another example without using the keyboard: Imagine a knowledge worker clicking through menus in order to achieve his subtask like adding a table to a word document. He would have to move his mouse (**MM**) to the according main menu entry first: 'Insert' and click (**MC**), than he would choose the submenu entry: 'Table' and click (**MM,MC**). After that, a dialog pops up that lets the user choose the number of rows and columns. He moves his mouse to make to choose (**MM**) and then clicks to insert the table into his document (**MC**). The computer detected protocol could look like this:

<MM,MC,MM,MC,MM,MC>

The total time would include the movement of the hand to the mouse at first and the cognitive operations. These are not included. But we can estimate the mouse click and mouse move time with roughly 1500 msecs. The result would be 9000 msec for the whole operation.

With the help of the elaborated results by GOMS and MHP we can not predict tasks, but extract habits from user interaction protocols. Short bursts of actions indicate habits as the "recognize-act-cycle" is simplified. The examination of habits in the experiments therefore is straightforward and explorative: Extract from user interaction protocols short bursts of actions.

3.1 Examining Habits in Human Computer Interaction (HCI)

3.1.1 Description

The first experiment tests the hypothesis whether habits are deducible from user interaction protocols. To this end, the protocol has to fulfill the following constraints:

1. Time stamps for each action must be recorded in fined-grained manner, i.e. typical date in the format "**Day Monthy Year Time Milliseconds**". An Example for this is "**31.03.2013 14:30,06 769**"
2. Actions have to be annotated with the executed application like "**firefox**" or "**chrome**" and even more semantic information for later analyses.
3. Actions have to semantically categorized and only user actions have to be taken care of. User actions are typically executed by using the keyboard and the mouse. Therefore the action categories at least must be "**KeyPress**" and "**MouseClick**".
4. As expert actions are usually executed by *shortcuts* the value of the activated keys has to be recorded. Typical values for shortcuts are "**Shift**", "**Alt**", "**Tab**" combined with alpha numerical letters.

3.1.2 Method

In order to extract the user interactions a logger was installed by all participants. The logger is able to get all interaction of a user with the Windows Operating System (Windows Vista, Windows 7) and the installed applications. It is based on the UI Automation. Microsoft UI Automation is an accessibility framework that enables Windows applications to provide and consume programmatic information about user interfaces (UIs). It provides programmatic access to most UI elements on the desktop [1]. As the extracted data lacked some information, UI Automation was combined with hooks to Windows Procedures like "**user32.dll**" (a dynamic-link library) and Mouse and Keyboard listeners. The "**user32.dll**" implements the Windows user component that creates and manipulates the standard elements of the Windows user interface, such as the desktop, windows, and menus. Programs call functions from Windows to perform operations such as creating and managing windows, receiving window messages (which are mostly user input such as mouse and keyboard events, but also notifications from the operating system).

The UILogger is open source and can be downloaded from GitHub[2].

[1]http://msdn.microsoft.com/en-us/library/windows/desktop/ee684009.aspx
[2]www.github.com/ukirsche

Kapitel 4

Evaluation

Kapitel 5

Summary and future work

5.1 Summary and contributions

5.2 Future work

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 Goals, Operators, Methods and Selection Rules

NLP Natural Language Processing

SVM Support Vector Machine

AI Artificial Intelligence

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Typeset 10. Oktober 2013