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ForgetIT

Concise Preservation by Combining Managed Forgetting
and Contextualized Remembering

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Executive summary

In human memory, forgetting plays a crucial role for focusing on important things and neglecting irrelevant details. In digital memories, the idea of systematic forgetting has found little attention, so far. At first glance, forgetting seems to contradict the purpose of archival and preservation and of digital memory in more general. However, we are currently facing a tremendous growth in volumes of digital content in the public, organizational and personal context. Thus, it becomes ever more important to focus, on the relevant and important content, while forgetting irrelevant details, redundancies and noise. This holds true for better organizing the information space as well as, in preservation management, for making and revisiting decisions on what to keep. Therefore, the ForgetIT project introduces a concept of *managed forgetting* as part of a joint information management and preservation management process in digital memories.

Although inspired by human memory, managed forgetting is meant to complement rather than copy human remembering and forgetting. It can be regarded as functions of attention and significance dynamics relying on multi-faceted information assessment: managed forgetting models resource selection as a function of attention and significance dynamics. Based on dynamic, multidimensional information value assessment managed forgetting identifies information objects, e.g., documents or images of decreasing importance and/or topicality and triggers *forgetting actions*. Those actions include a variety of options, namely, aggregation and summarization, revised search and ranking behavior, elimination of redundancy, decisions about transitions to the archive and finally, also deletion.

The objective of WP3 is to develop models, methods and strategies for managed forgetting. This first deliverable of WP3 focuses on the foundations of managed forgetting. In particular, we present main research questions and outline the state of the art in human and digital remembering and forgetting. In addition, we discuss our first ideas on "complementing human memory", as well as introduce our vision for managed forgetting, including the proposed conceptual model and computational framework. To this end, we present a case study for further strengthening the need for systematic forgetting support, and planned research activities for the next months.

1 Introduction

While preservation of digital content is now well established in memory institutions, such as national libraries and archives, it is still in its infancy in most other organizations, and even more so for personal content. There are several obstacles for the wider adoption of preservation technology in organizational and personal information management: There is a considerable gap between active information use and preservation activities. Active information use refers to dealing with information objects for everyday private or professional activities, typically supported by some information management environment, such as a content management system in an organization or a desktop environment in the context of personal information management. In addition, especially in personal information management, there is typically little awareness for preservation. Although the need for personal preservation has been recognized in theory [34, 50], this did not propagate to more practical settings and solutions yet. As a consequence, readiness for investing considerable resources in terms of time and money for preservation is low. Finally, establishing effective preservation and concise and usable archives still requires a lot of manual work for selecting content that is relevant for preservation and for keeping the archives accessible and meaningful in the long run, thus entailing expenses much larger than just the storage costs. This is further aggravated by the fact that no benefits are seen for moving from more or less systematic backup to systematic preservation.

In order to overcome some of the above obstacles, the ForgetIT project proposes the introduction of the novel concept of *managed forgetting* as part of a joint information and preservation management process. Managed forgetting is inspired by the understanding of principles of human brain, where forgetting enables us to focus on the things that are relevant instead of drowning by meticulous details. Managed forgetting does not mean to simulate human forgetting processes, but rather to *complement* the human memory through intelligent use of the computational and storage powers of digital technologies.

1.1 Managed Forgetting

The idea of managed forgetting is to systematically deal with information that progressively ceases in importance and becomes redundant in order to enable the user to focus on the things that are important. At first glance, forgetting seems to contradict the idea of preservation, which is about keeping things, not about throwing them away. However, if no special actions are taken for long-term preservation, we already face a rather random digital forgetting process in the digital world today in the private as well as in the professional information management context. This is triggered, e.g., by changing hardware, hard-disk crashes, or changes in employment. Furthermore, on a more global level there is a growing understanding that *forgetting* has to be considered as an alternative to the dominating keep it all paradigms, especially for information about individuals available in the Web [52].

We aim to replace such random forgetting processes with managed forgetting where users are optimally supported in their explicit decisions about what information to keep, and how such information should be organized and preserved. In particular, we envision an idea of *gradual forgetting*, where complete digital forgetting is just the extreme and a wide range of forgetting actions including different levels of condensation for preservation is foreseen. This concept is expected to help in preservation decisions and to create direct benefits for active information use. The aim is to strike a balance between preservation and managed forgetting, also taking into account constraints for digital forgetting (e.g. legal regulations). Furthermore, managed forgetting offers an immediate benefit from adopting preservation by helping to keep the active information spaces more focused.

1.2 Complementing Human Memory

Managed forgetting improves the management of digital memories (storage devices, personal digital spaces such as blogs, etc.) by learning from human forgetting and remembering process. However, it does not make sense to just simulate human memory, because it should be the role of the digital memory to support human activities and human memory. This goal can be better achieved, if the digital memory complements the human memory process, i.e. supports its weaknesses rather than copying its strengths.

Translating the high-level goal of “complementing” human memory into concrete methods and research questions is not trivial. On the one hand, there is a large number of processes and effects in human memory in the context of forgetting and remembering, which interact and serve different purposes. These will imply different notions of complementing them via digital memories. On the other hand, we expect that to just do the opposite of what the human brain does (e.g. just remember everything digitally, which the human would and possibly wants to forget) would neither lead to a satisfying user experience nor fully exploit the potential of combining human and digital memory. This means that a careful analysis of possible ways of “complementing” is required. In addition, it has to be considered that the way a digital memory supports remembering and forgetting will - on the long run - also influences what the human keeps in memory.

1.3 Deliverable Organization

This first deliverable of WP3 focuses on the foundations of managed forgetting. In particular, we discuss our first ideas for “complementing human memory”, as well as introduce our vision for managed forgetting, including our proposed conceptual model and computational framework. The detailed organization of the deliverable is outlined below.

- Section 2 present research questions providing details on key challenges to be carefully investigated as well as propose our anticipated methodological insights.
- Section 3 summarizes our literature study on the state of the art in human and digital remembering and forgetting, as well as existing approaches to assist human

memory in digital preservation context.

- Section 4 reports our first ideas on “complementing human memory”, which are the results from interdisciplinary discussions within the ForgetIT Consortium. This section does not aim to be a thorough study in cognitive foundations of human remembering process, but rather to focus on aspects of human memory where “complementing” is needed or desirable.
- Section 5 presents our initial approach for managed forgetting, including the proposed conceptual model and computational framework, as well as the first learning models of human remembering in different scenarios.
- Section 6 outlines our research plan for the next months in WP3 and reports on a case study for further highlighting the need for systematic deletion support, which will be published in the proceedings of the 10th International Conference on Preservation of Digital Objects (iPres2013).
- Section 7 summarizes and concludes the deliverable.

2 Research Questions

In this section, we present research questions providing details on key challenges to be carefully investigated, as well as propose our anticipated methodological insights.

2.1 How Can Managed Forgetting Complement the Human Memory?

Supporting managed forgetting in a digital memory is a novel concept, for which no former experience and best practices exist. It is therefore important to thoroughly analyze the human expectation for this process in order to increase the chances of acceptance. An interdisciplinary approach is followed for this purpose in ForgetIT. The idea is to investigate what we can learn from the way a human memory forgets and remembers for the design of processes of forgetting, remembering and preservation in a digital memory. Humans are, for example, very effective in (a) rapidly extracting the general gist of an experience, while forgetting many details, (b) extracting common features of similar experiences avoiding the "storage" of repeated features, and (c) identifying data that are only temporally required and can be forgotten after task completion. Those and additional characteristics of human forgetting will be further investigated. Selected characteristics will flow into a model for managed forgetting. The goal is, however, to complement rather than to copy or replace human memory. This perspective will create the highest benefit in the interaction of humans with digital memory. A first discussion of how to complement human memory can be found in Section 4 of this deliverable.

2.2 What Are Flexible Methods for Dynamic Information Assessment?

To support proper preserve-or-forget decisions, it is essential to evaluate the information resources with respect to their importance and "preservation-worthiness" in the long term. Furthermore, any assessment methods need to be flexible enough to cope with the inherent heterogeneity and temporal dynamics of resources over time. In the ForgetIT project, we define two complementing parameters to assess information values of resources. The first parameter, *memory buoyancy*, is inspired by the metaphor of information objects sinking down in the digital memory with decreasing importance, usage, etc. increasing their distance to the user. This type of information value is highly associated to **short-term** interests [69], which is influenced by a variety of factors that can be roughly grouped in the following categories: usage parameters (such as frequency and recency of use, user ratings, recurrent pattern), type and provenance parameters (information object type, source/creator), context parameters (such as relevance of resources as background information, general importance of topic, external constraints), and temporal parameters (age, lifetime specifications). In this activity various factors influencing memory buoyancy will be investigated as well as approaches for learning most effective factor combinations. Furthermore, approaches for enabling the user to explicitly and implicitly influence the values for memory buoyancy will be developed e.g. explicit expiry dates and lifetime specifications or tagging objects as non-forgettable. The second information assessment value to be investigated is *preservation value* used for making a decision on whether the resource under consideration should be preserved. The preservation value will use an overlapping but slightly different set of parameters for its computation, compared to memory buoyancy. The preservation value is more related to long-term interests and to a more objective assessment e.g. diversity and coverage.

2.3 How and When to Perform Different Forgetting Actions?

In the managed forgetting process "forgetting" does not mean deletion. Rather, forgetting actions are required that are able to meet various settings, requirements and preferences. Therfore, several forms of forgetting will be supported by managed forgetting. This includes methods for quality-aware consolidation and concentration for textual and multimedia content such as summarization, aggregation, detection of redundancy, and consideration of diversity. Furthermore, this might also comprise changing the ranking of the "forgotten" object in a result list or not showing it as a result at all, replacing object(s) by a summary object, marking the object as a deletion candidate etc. As an extreme the process will also support deletion as a forgetting option.

As part of our approach a set of "forgetting" options will be defined in close collaboration with the activity on assessing human acceptance for managed forgetting. Clearly there will be no one-size-fits-all for managed forgetting, either. The challenge here is the definition of a flexible forgetting process that can implement adaptable forms of forgetting depending upon the needs and properties of the respective setting.

It is planned to define an adaptable framework for the managed forgetting process, which fixes the principle mechanisms of the process and can be customized along different dimensions: the parameters that are used for information assessment, the threshold used for memory buoyancy and preservation value for triggering forgetting actions and the options of forgetting considered. We will also investigate the use of a policy framework that supports the definition of different forgetting policies. Policies have been shown to be an intuitive and powerful tool in the area of security management, e.g., for specification of access rights. In the preservation context, besides customizing the forgetting process, policies also can capture external constraints, such as legal preservation requirements or business requirements (e.g., to make sure that information pertinent to obsolete product versions is preserved). Furthermore, we will also investigate into methods for detecting redundancies as well as for condensating textual and multimedia information objects (see WP4).

Evaluation Methodology. Research evaluation will be subjective assessments by human volunteers of (a) how they currently use data systems for retrieval of information at home and in work/organisational settings, (b) the extent to which the volume of digital information stored hinders/facilitates retrieval, and (c) expectations of managed forgetting in digital systems. We aim at conducting questionnaires and studying interaction between human and managed digital forgetting, e.g., experimental studies with human volunteers to collect objective data on human forgetting of personal details, and ease of retrieving those details from personal digital storage systems.

3 State of the Art in Digital Memories

In this section, we outline the state of the art in relevant interdisciplinary research areas. Since managed forgetting is a novel concept with no prior research work, we identify the four main interdisciplinary areas that are close to work in WP3.

3.1 Human Memory-Assisted Digital Mementos

In [64], a recent study has shown that a search technology, such as Google, effects on human memory. Similarly, shared retrieval-induced forgetting in a social network can reshape the memories of speakers and listeners involved in a conversation, so-called collective memories [16]. Typically, such studies shed a light on understanding how humans remember or forget information. This understanding can benefit methods that aim at complementing the human ability to remember or forget, such as managed forgetting. When it comes to organizational and societal memory (and forgetting), we face difficult challenges to deal with - whether in the case of state archives detailing a dictatorial past, or sensational media reports that are subsequently shown to be false, and the unending digital memories they create [52]. In recent years, there have been several works addressing digital preservation from the Human-Computer Interaction (HCI) perspective, e.g., focus on the system design to support human memories [8, 19, 20, 37, 55]. An interdisciplinary model and approach for flexible and gradual managed forgetting in a digital memory has to be developed that meets human expectations and is driven by the goal of the digital memory complementing human memory.

3.2 Personal Information Management

Personal Information Management (PIM) is about finding, keeping, organizing, and maintaining information [35], both in a personal and organizational context. PIM is a vivid research area trying to understand the best practice of users in storing, retrieving, and (re-)using information and to develop new methods and tools to overcome their problems (e.g., personal information retrieval [23], a temporal perspective in PIM [36, 41]). In [50], the author identifies several issues in PIM with personal digital archives which start to pile lots of information over the years. Challenges for users include deciding for deletion, because it is a cognitive demand; assessing the value of information in advance, because it is difficult to judge; and finally, “a full chronological and contextual record is essential for using one’s archives as a memory prosthesis”. A promising direction to support users in organizing personal information is the Semantic Desktop [61], which introduces a knowledge representation layer to describe the information elements on the desktop (such as, emails, webpages, documents, pictures) with a personalized vocabulary. This approach has been further extended to activity-based desktop search [12], semantic search and ontology-based information extraction [28], trend detection in the PIMO [42], personal task management [51], personal image collections [40], or bootstrapping from individual email [62].

3.3 Multifaceted Information Value Assessment

Methods for multi-faceted and dynamic information value assessment are required in support of managed forgetting for long-term information access. Several valuation methods have been proposed, employing a rich variety of criteria. Many approaches take observed usage in the past as the main indication for information value, i.e., probability of future use [11, 54]. From the cognitive science community, forgetting process in human brain is typically studied in two approaches. Decay theory suggests that time has the highest effects on the fading of human memory strength over time [25, 31, 59]. Some decay models, for instance Ebbinghaus Saving Functions [71], have found applications in the field of data streams [14, 56] and information retrieval [44, 57]. The second approach, inference theory, suggests that forgetting in human brain occurs mainly due to the interfering of related or correlated happenings [70]. In [4], the temporal dynamics of forgetting were studied in terms of either temporal decay or event-based interference. However, there is little work on information value assessment incorporating human forgetting factors, to the best of our knowledge.

3.4 Quality-Aware Consolidation

Relevant research areas to forgetting actions for quality-aware consolidation include document summarization, duplicate detection, and diversity analysis. Automatic document summarization [63] is aimed at extracting the semantic content from a document in order to produce a well-formed and grammatical summary of what the document or document set is about and what its broad content is. A recent work [26] considers the time dimension for automatically generating temporal summarization of events from Wikipedia updates. Aforementioned works on detecting duplicate or near-duplicate documents have been mainly focused on different similarity metrics [9, 13, 66]. In the area of information retrieval, there is an interplay between redundancy, diversity and interdependent document relevance [7, 58]. Condensation ans summarization is considered in more detail in WP4.

4 Complementing Human Memory

In the ForgetIT project we expect to learn from human forgetting and remembering[1] for an improved management of digital memories. In psychology, memory is the process in which information is encoded, stored, and retrieved [65]. Forgetting, on the other hand, refers to apparent loss of information already encoded and stored in individual's memory [30]. There has been extensive study in cognitive science on principles of why humans remember and forget things for more than a century, with several models and theories proposed [70, 68]. However, it is of our particular interest in understanding how to complement the processes in human memory instead of simulating them. Therefore, we only discuss here cognitive models of human memory where complementing is relevant and needed.

There are numerous types of human memory and each is classified based on particular dimensions and categorization systems; for example, in time dimension, we have five categories: sensory memory, working memory, short-term memory, intermediate-term memory, and long-term memory. However, in the beginning phases of WP3, we will focus on two types of memory, namely *episodic memory* (fall under long-term memory category, see Section 4.1 and D2.1 for more details), and *working memory* (see Section 4.4) due to their high relevance to the preservation scenarios studied in WP9 and WP10. In addition, what is "complementing" these two human memory types will also depend on the purpose or task, which the digital memory is used for. In ForgetIT, we are interested both in short-term benefits (for information support in everyday human activities) and in long-term effects (for fostering the adoption of preservation solutions). Therefore, we focus in WP3 onto the following settings (use cases) for our initial analysis of "complementing human memory":

- **Supporting (long-term) reminiscence**, especially, focusing on new opportunities that are opened by the richness of personal digital content available[2].
- **Better focus in current information use**, e.g. de-cluttering personal information spaces

In the following, we discuss known characteristics of human cognition that are fundamental to managed forgetting methods. For each of these characteristics, we start with basic principles as widely agreed in human memory studies, then envision possible and desirable ways of complementing human memory, which are expected to lead to a positive user experience. Of course these are just first envisioned ideas, and considerable work in WP3 will need to be invested into refining, validating and revising those ideas, in order to create an effective solution for managed forgetting. This process will be integrated with the work on WP2 on human memory and forgetting function and human expectations.

[1] See more detailed reviews of human memory and forgetting in D2.1
[2] See also the description of the Reminiscence use case in D9.1.

4.1 Forgetting in Episodic Memory

In cognitive science, different types of long-term memory are distinguished including episodic memory and semantic memory, which are both parts of the declarative memory. Episodic memory is the memory of autobiographical events (times, places, associated emotions, and other contextual knowledge). Episodic memory includes a subjective sense of time (or mental time travel), a connection to the self, and is often represented in the form of (visual) images [67]. One of the characteristics of episodic memory is that details are lost very rapidly. This enables humans to focus on relevant and current information, while not being drowned by detail. One of the ideas of the ForgetIT project is to apply the mechanisms that drive the rapid process of forgetting unnecessary detail to achieve greater focus and less redundant information in digital memory. This especially serves the use case of “better focusing in active information use” (see above). A rapid forgetting function is therefore a good starting point for managed forgetting in digital memories.

One mechanism that drives the initial forgetting of detail from human episodic memory is the rapid matching of details in the current experience that are common to similar previous experiences. This allows contextualisation of the event for it to be stored as, for example, “a picnic”, “a beach scene”, “a restaurant”, or “a sad scene”, “a celebration”, etc. without the need to store details that appear in most or all picnics, beach scenes and restaurants, or in scenes associated with particular emotions. Only the details that are specific to particular episodes need to be stored. So, as more episodes of a similar kind are experienced, they tend to be incorporated into a more semantic form over time (less detail, less context information, i.e. location, time, emotions). In addition, similar experiences (e.g. similar types of events) blur into each other and details of one event interfere with memory for details of similar events. This is helpful when remembering later, because some details of an event can be reconstructed from knowledge of the context without any requirement for the repeated details to be stored for each individual event. However, this process makes it more difficult to assign facts to a specific event/experience. In addition, the details of the most recent experience of a given type tend to be remembered better than details of previous similar experience. So, the most recent experience of a given type (e.g. the last time we visited a restaurant) is remembered with more detail than previous similar experiences, and the interference is greater, the more similar the experiences are (e.g. previous visits to the same restaurant). This is schematically depicted in Figure 1, which depicts the loss of details over multiple experiences (smaller bars) as well as the increasing interference between the remembered events (bars come closer together).

This set of processes in human memory and forgetting leads to high efficiency and minimal redundancy in storage, so it is highly adaptive. However, it is also vulnerable to loss of details that might be important to remember, and the reconstruction process has been shown to lead to “false memories” for what the context would suggest is likely to have happened but did not actually happen for a specific event. The general idea for a digital memory with managed forgetting here is for digital memory to store details that differ between similar kinds of events, and that might be forgotten from human memory. The

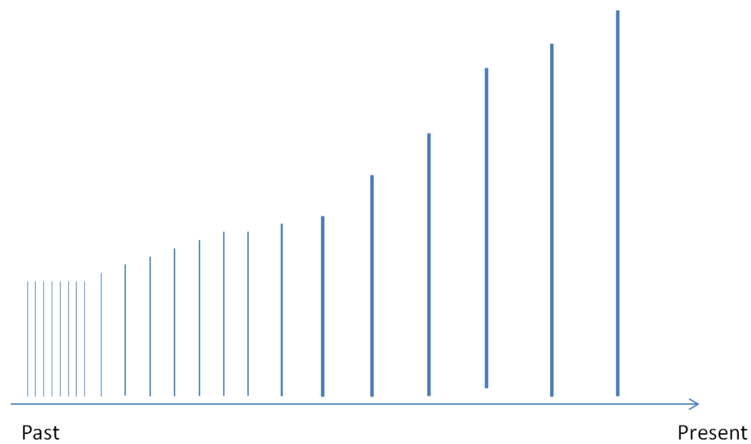

Figure 1: Lost of detail from Episodic Memory across similar experiences

digital memory then can support human memory when specific events are being retrieved and reconstructed. Event-centric organization of digital items will surely play an important role here. Furthermore - speaking in terms of the graphics above - a digital memory with managed forgetting could help to keep the bars of similar experiences from blurring into each other (or to re-establish a distance between them). In addition, it could prevent the bars from becoming too small; it could stabilize or re-vitalize them to a certain level of detail.

Interdisciplinary Research Questions. From the digital preservation perspective, complementing the human forgetting of episodic memory raises several interesting questions:

- What should a function for managed forgetting look like? On which parameters should it depend?
- How can digital memory be used in more detail to enrich or re-vitalize autobiographical memory? (This includes aspects of which content to use as well as of the way in which it is presented to the user.)
- How to balance between designing the digital system to detect similarities between events (as it serves structuring and establishing the parameters of context) and to store specific details that differ between individual event instances thereby helping humans to distinguishing between similar events?
- What is a reasonable level of detail to memorize for the individual events (middle size of bars)?
- How to decide, which content to keep for helping to re-vitalize episodic memory via managed forgetting?

4.2 Reconstruction in Human Memory

Retrieval from human memory involves reconstruction as well as retrieval of some detail. This reconstructive process is often automatic, and people can be unaware that they are reconstructing rather than recalling an event (e.g. [46, 48]). This means that memories as we experience them are not completely stored, but we construct our memory from a combination of what we have actually memorized and what we know. This makes the processes in human memory very effective, because memory can rely, in many cases, on common patterns rather than on storing information redundantly. For example, we can report many details about a visit to a restaurant - finding a table, reading the menu, choosing food, conversation, eating, paying the bill etc. - from our knowledge of the common features of restaurant experiences and without recalling any details about a specific visit. However, this reconstruction process may also lead to “false” memories, for example incorrectly recalling which food led to the experience of food poisoning (e.g. [6]), accusing someone who was an innocent bystander of having committed a witnessed robbery (e.g. [29, 47]), or details of a public event (e.g. [27]).

Digital items such as photos and videos can play an important role in verifying (or falsifying) the reconstructed memory of an event, thus complementing human memory. In one sense, we are in the fortunate position that there is an abundance of digital items of all kinds produced about everyday life situations as well as about personal and public events of all types (photos, videos, blogs, and microblogs). This provides a good foundation for verifying and complementing our memories, and can even detect the memory errors of a president [27]. What would be required from the managed forgetting process for complementing human memory in this respect is to create a diversified and as complete as possible representation of events. At the same time the “digital image” of each event should also be sufficiently compact and contextualised to support reconstruction in human memory rather than overload it with unnecessary detail.

Interdisciplinary Research Questions.

- Which parts of memorizing are especially subject to false memories and how can the likelihood of false memories best be reduced through use of digital memory systems?
- What are adequate managed forgetting methods to create a diversified but at the same time compact “digital image" of a situation or event from the available digital material?

4.3 Slowing Human Forgetting and Supporting Lifetime Episodic Memory

Although episodic memory is in general subject to fast forgetting, the memory of an event can be refreshed by recalling the event very soon after it occurs or being reminded of the

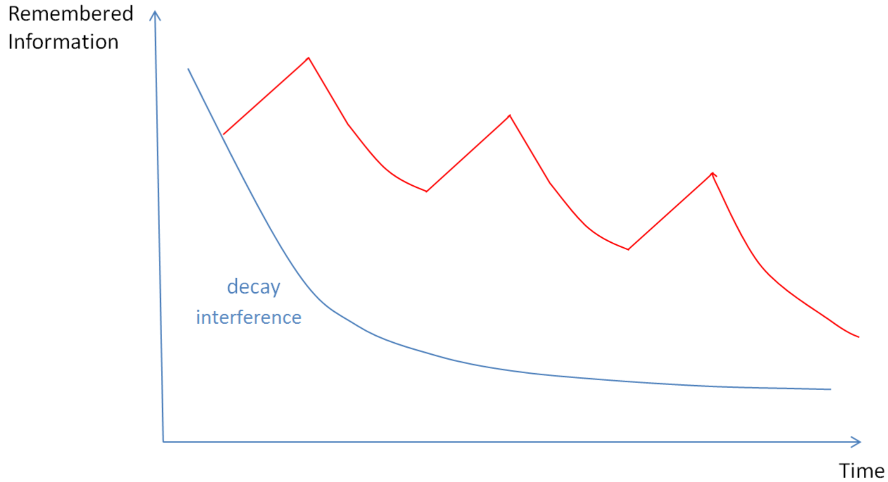

Figure 2: Triggering memories

event by a physical object (e.g. a printed photograph) or a digital memory system. This recall leads to a peak in the forgetting function as depicted in Figure 2. The immediate recall or reminder serves as a trigger for bringing up the original memory before many of the original details have been forgotten through decay or because of interference from different subsequent events. This then reinforces the details of the event, thereby slowing the rate of forgetting, allowing the details to be retained for longer before an additional recall or reminder which slows the rate of forgetting even more, and so on.

We envision to use this mechanism as an inspiration in the design of the managed forgetting process. The idea is to propagate increased interest in an event, entity or location to other related events (e.g. same persons, same type of event, same location) increasing their relevance level or memory buoyancy. This propagation mechanism could complement and reduce the impact of a general human forgetting function in managed forgetting. It is especially useful in the use case of "better focusing in active information use" helping in identifying things that are currently of interest or are about to become of interest again. It might also contribute to the reminiscence use case, e.g. for implying a way to navigate or explore the available content (pushing up related things to look at) or for adapting the preservation value over time, such as providing a reminder on the anniversary of an event or when revisiting a location or meeting a person for a second time.

Related observations from cognitive science have been that certain events are remembered particularly well (e.g. [10, 18, 17]). These tend to be major public events such as the Olympic Games, major tsunami and earthquakes, resignation or assassination of a political leader, landing on the moon etc., or major personal events such as first day at school, wedding day, death of a close relative or friend, starting a new job or moving home. Memories for events in adolescence and early adulthood are also remembered well (e.g. [33]). This leaves an imbalance with many details forgotten about other events in life such as holidays, theatre visits, and work-related events or former colleagues. Again, just copying this behavior of human memory, e.g., by storing more digital items such as photos referring to events that are remembered well in any case will not be the best choice. What could be envisioned here is that the digital memory with managed forgetting rather tries to store more details across the lifespan for events that are less likely to be remembered, allowing for supported reminiscence in later life phases, and for reminders about previous meetings (e.g. a person's name and background). This could be done pro-actively by pointing to other life time events, which are related to the material currently under inspection. As a precondition for this form of managed forgetting, it is necessary that the underlying memory keeps a sufficient coverage of digital items from different phases of the life and that the material from different phases of the life is also interlinked in a meaningful way.

Interdisciplinary Research Questions.

- How could a propagation function for increasing memory buoyancy based on related events, entities and locations be developed and implemented?
- Does it fit users, if the digital memory (pro-actively) tries to store more details for events that are remembered poorly? Is there a difference between users depending on the age ?
- How can a good coverage of life-time with digital items be achieved? What to keep (managed forgetting) ?

4.4 Working Memory

Human working memory refers to the moment to moment storage and use of information in daily life. It stores a small amount of information just long enough to complete a task and this information is then forgotten to make room for the next task. This avoids there being too much information readily available at any one time allowing a focus on the current task while minimising irrelevant information from the environment and from episodic and semantic memory (e.g. [3, 43, 49]). However, if the crucial information is not readily available from memory or in the environment this can cause problems such as getting the wrong flight or gate number, misremembering the time of a train or the platform number, typing in the wrong bank card number, retrieving the currently required digital password from the 40 or more different passwords that we are required to use across our daily activities, or forgetting to turn up for an important appointment. Even if details are correctly retrieved and used at the time, there will be a requirement for long-term preservation as well as occasional updating of some of those details (e.g. bank numbers, passwords, the name of the person just met), whereas other details can be forgotten after task completion (e.g. flight numbers and station platforms).

A digital system with managed forgetting could complement human memory by making available e.g. on a mobile device details that are currently required but are difficult to retrieve from human memory. Details that need not be retained (e.g. after boarding the flight or the train) can most likely be deleted. Details such as passwords, bank numbers, and names of people could be archived and reactivated when a future situation requires them.

This support of working memory clearly adds additional requirements to the managed forgetting process and the computation of MB. The managed forgetting system has to be able to select information that is relevant to current activities and make them readily available (this is imoprtant for MB). It also has to be able to distinguish information that is required only once and information, which is revisited (this is especoally imoprtant for PV).

Technically, this information should be available locally (e.g. on a mobile device) also for periods when Internet access is not available (e.g. on an aeroplane, or walking in the mountains). This would require to download the information from an archive server in advance of an activity. This imoprtant feature for using a preservation and managed forgetting system could be implemented through development of a mobile device linked with a PIMO server (see D9.1).

Interdisciplinary Research Questions.

- How to contextualise and select information currently in use for immediate forgetting or for preservation and subsequent updating?
- How to determine which information can be easily retrieved and held in human working memory and which information should be made readily available on a mobile digital preservation device?
- How to reflect the needs of the working memory in the computation of MB?
- How to ensure that all key information is downloaded from the PIMO server to the mobile device in advance of planned events and activities, plus security of sensitive information (e,g. bank numbers and passwords)?
- What are the effects on the functioning of human working memory if there is increased dependence on a mobile preservation device? What arrangements for backup access would be needed if the mobile device is damaged, lost or stole?

5 ForgetIT Approach to Managed Forgetting

Based on the systematic review of existing practices in human-assisted digital mementos, as well as on cognitive aspects of complementing human memory discussed thus far, we envision and propose a general framework of managed forgetting in digital systems, and how to integrate them to personal information management. We believe that successful personal information management systems [21] need to combine the aspects of long-term technical availability of information (with “long-term” meaning at least a lifetime, if not across generations) with suitable accessibility of the information, which asks for sustainable structures and situation-specific information retrieval and delivery [39, 45]. As an ever-growing information space tends to clutter with information which is irrelevant in given situations and thus is in danger to become un-manageable and useless both for technical reasons (e.g., resource limits on smart phones) and for cognitive reasons (information overload), *time-aware information access* solutions will form a crucial part of a sustainable strategy for accessing the personal information space. In addition, a successful information value assessment should take into consideration the *context* surrounding the information space, in order to exploit as much as possible data to support “forgetting” (i.e. preservation) decisions.

In this first deliverable, we present a initial conceptual framework for managed forgetting and contextualized remembering in digital systems. While we are aware of the importance of contextualization in the framework, in WP3 we focus on the aspects of contexts that are relevant and useful to learn the human forgetting process, especially those that are in the temporal dimensions. More detailed discussion of several aspects and methods in information contextualization can be found in D6.1.

5.1 Conceptual Model

Our proposed conceptual framework is inspired by an integrated and contextual perspective on IR presented in [32]. As illustrated in Figure 3, the conceptual framework consists of three main parts:

- An *information space* which composes of and represents seamlessly human and digital memory;
- A *context* which defines a social, societal and organizational environment into which the information space is embedded;
- A *human actor* accessing the information space.

We decided to conceptually split the human actor from his/her memory and to rather consider the human and the digital memory as an integral system. There are two reasons for this: (a) we are especially interested in what we can learn from human memory for creating effectively accessible digital memories (time-aware information access) and (b) the boundaries between human and digital memory are in flux due to an increased delegation to digital memory (see below).

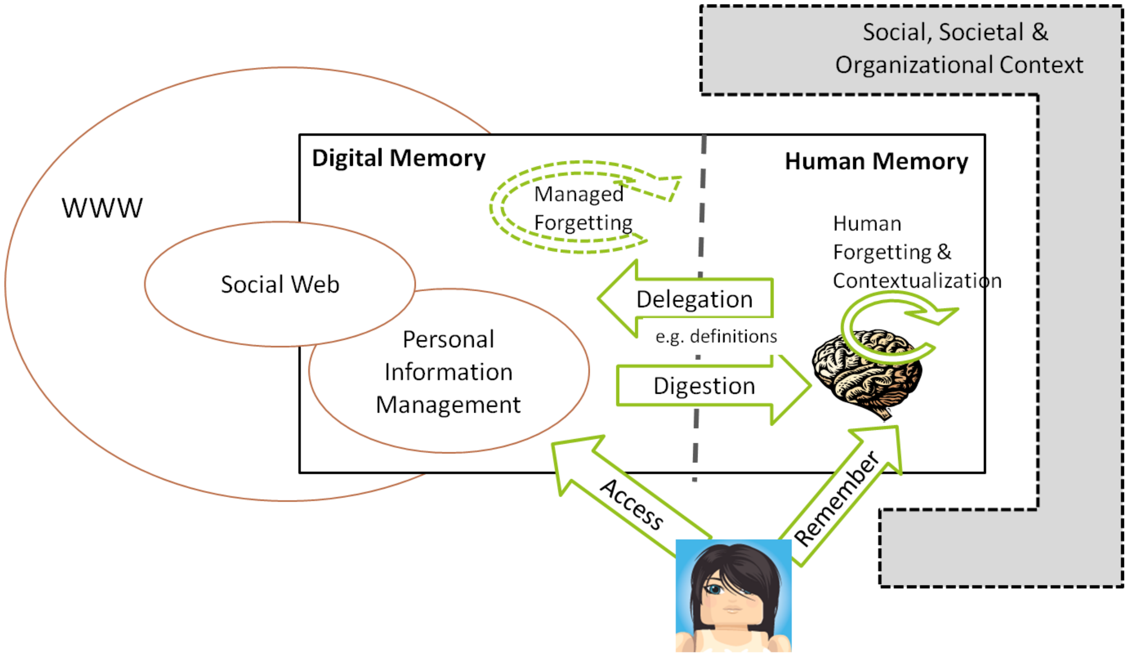

Figure 3: Conceptual Framework for Managed Forgetting Integration in Personal Information Management

For conceptually modeling the problems discussed in Section 2, we introduce the three main concepts: *resources*, *interactions*, and *human actors*.

Resource is the abstraction of information artifacts in the information space. A resource can refer to data objects stored in the digital systems, but it can also refer to the image of such objects as encoded and stored in the human brain, or as shared by human actors in three overlapping spheres of digital memory - personal information management (organizing resources on local devices such as mobiles or personal computers), the Social Web (online storage and sharing) and the Web in more general, see Figure 3.

Interaction refers to actions within the information space that resemble or are relevant to human memory processes (i.e. information encoding, storing and recalling [1]). We consider three main types of interaction: (a) delegation and digestion, (b) forgetting and contextualization, and (c) access and remembering. By *delegation* information is moved into outer spheres (e.g. from human memory to things that can be looked up, or from personal information management to the social web). This happens increasingly, triggered by improved access strategies and increased availability of information via the Web (e.g. via Smart phones). An example is looking up definitions instead of learning them. *Digestion* is the counterpart to delegation at the boundary between human and digital memory. *Forgetting* and *contextualization* are important processes in human memory which enable humans to focus on the relevant things, while “forgetting” about a large number of irrelevant details. The idea here is to complement human forgetting by introducing a process of managed forgetting into digital memory.

Human Actor can *access* his/her information space through access interfaces and such *direct interactions* can be, for instance, search, look-up or exploration of data objects. There also exist *indirect interactions* between actors and external contexts, for example, relevance of resources as background information, topic and general importance of topic, and external constraints, which also play an importance role in the proposed framework. *Remembering* can be (roughly) considered as counterpart of access for human memory. It is typically triggered by external events, which are experienced by the human actor.

The key difference between our proposed model and the previous work [32] is to explicitly introduce *managed forgetting* into the framework. Managed forgetting has a twofold purpose: (a) it creates immediate benefit by focusing on relevant content in a time-aware fashion, "forgetting" (unfocusing) things that are no longer important and (b) replacing random forgetting of information (e.g. by hardware crash) with managed forgetting, where users are optimally supported in their explicit decisions about what information to keep, and how such information should be organized and preserved.

5.2 Computational Framework

Figure 4 sketches our initial ideas for integrating forgetting functionality into a next-generation of digital memory system or in more detail into the Preserve-or-Forget System of ForgetIT. From this view, the core functionalities of managed forgetting are included in the *Forgettor* component, which resides in the Preserve-or-Forget Middlelayer and interacts with human actors through the information management system. The information management system is the abstraction of a computing system that is associated with a human actor, or with multiple human actors, and that gets human inputs directly or indirectly within particular tasks. For instance, content management systems of organizations and desktop management systems like the Semantic Desktop, or even web-based platforms such as social media sites, bookmarking systems, etc. can be example of information management system. Note that in our notion of information management system, human actors and tasks play an important role: they help distinguish our system from any arbitrary information systems. For example, a general blogosphere will not be considered for managed forgetting development (i.e. we do not target preserving general web blogs). For supporting managed forgetting, the information management system has to collect and exchange data with the Forgettor component. This includes meta-data (e.g. size, tags) for human-generated data (e.g. photos), but also contextual and usage information of the resources (authors, timestamps, usage activities such as usage frequency and recency of use, user ratings, recurrent usage pattern, social context data from other sources such as the Web, etc.). Every resource will be equipped with a unique ID, to facilitate the data exchange, management and analysis across different components.

The Forgettor component accesses the resources in the information management system through different strategies, depending on the different types of resources and preservation use cases. As an illustrative example, in organizational workspace scenarios (company intranet websites, collaborative places, such as SVN repository), a forgettor com-

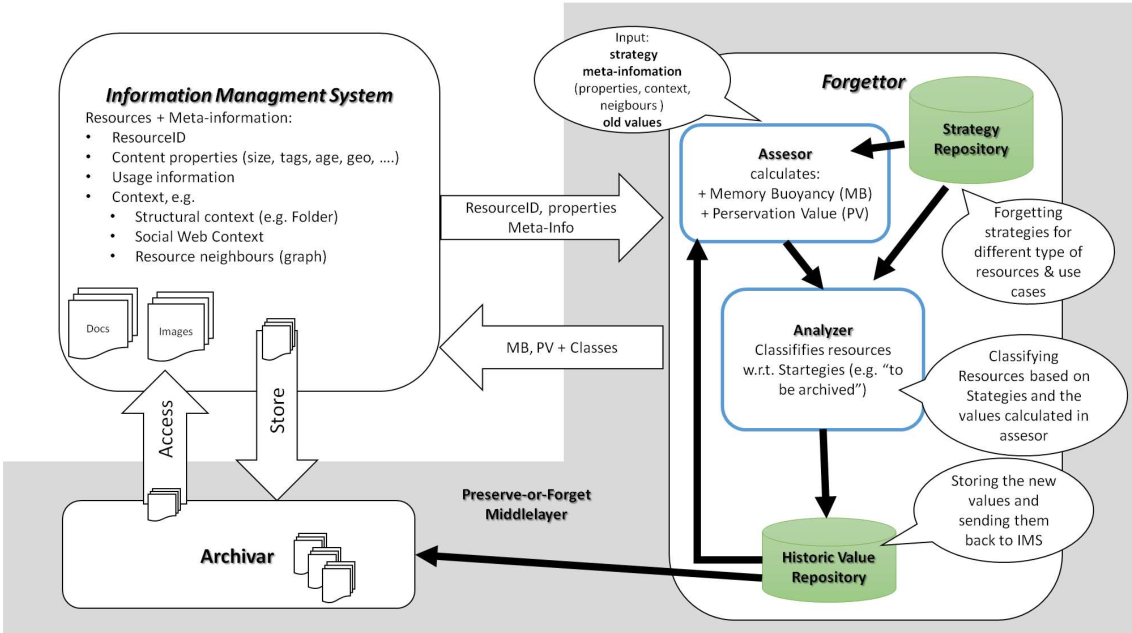

Figure 4: Managed Forgetting as a Computing Component in ForgetIT

ponent can be triggered periodically (e.g. every month), or when a working project goes through one big milestone. The knowledge of such strategies is stored in a *Strategy Repository*, which can be specified by human actors, or can also be learned from usage history of resources.

Inside the Forgettor, the *Assessor*, which is the core component of the Forgettor, is responsible for evaluating resources with respect to their current importance, as well as their intrinsic preservation worthiness at the moment or in the future. In the ForgetIT project, we define two complementing quantitative measures for the resource evaluation: **memory buoyancy** and **preservation value**. *Memory buoyancy* is inspired by the metaphor of resources sinking down in the digital memory with decreasing importance, usage, etc. (decreasing memory buoyancy) increasing their distance to the user. Memory buoyancy (MB) is influenced by a variety of factors that can be roughly grouped in the following categories: usage parameters (collected by the information management system), type and provenance parameters (resource type, source/creator), background information, topic and general importance of topic, and temporal parameters (age, lifetime specifications). The *preservation value* (PV) reflects the importance that the considered resource gets preserved and will be used to decide if and when to move a resource to the preservation archive. Partly, the preservation value is influenced by similar values as memory buoyancy, but it serves a different purpose: A resource with a high MB value might already be moved to the archive (as a copy), because it has a very high PV value, while staying still in direct uncondensed access to the user; on the contrary, a resource with both low MB and PV values might be preserved only in its condensed version or it might be decided not to preserve it at all. First ideas on how these two measures can be computed will be discussed in Section 5.3. One more thing worth noting here is that to evaluate the mem-

Table 1: Key features in two main settings.

	Person	Organization
Scenario	personal events (e.g., holidays, weddings)	work-related events (e.g., business travels)
Data Type	photos, mobile contacts, user-generated content	textual documents web pages or clouds
Feature	contents, behaviors, societal contexts	contents, user roles, organization policies
Interaction	search, explore, reminiscence, re-find, organize, preserve	
Action	summarize, aggregate, delete, diversify	

ory buoyancy and preservation value properly, it is often necessary to have knowledge of previously computed MB and PV values (e.g. statistics for the method development), therefore the Assessor component can have access to the *Historic Value Repository*, as illustrated in Figure 4.

The second main component of the Forgettor, the Analyzer, is used to classify the values computed for MB and PV based on the selected strategy (thresholds) and the evolution of the respective values. The idea here is to translate the numerical values for MP and PV into easy to interpret information such as “to be preserved” or “medium preservation need” for the consuming information management system also considering how MB and PV have developed in the past for the considered resource.

5.3 Learning to Assess Information in Preservation Scenarios

5.3.1 Use Case Focus

The core computation of managed forgetting is to find an intelligent and flexible way to compute MB and PV values of resources, taking into consideration various information such as the resource type, usage pattern, contextual data, previous computation values, etc. Clearly, there is no one-size-fit-all solution for any arbitrary information management system and task. During the course of the ForgetIT project, we will limit to particular preservation scenarios, in which the forgetting process of human episodic memory is more apparent. Furthermore, we target two main settings of information management system: personal and organizational. For each setting, we identify key features of complementing human forgetting and remembering that can be incorporated or adapted for implementation of managed forgetting, as shown in Table 1. This also includes a list of resource types to be considered. We anticipate taking into account different periods of life and types of personal events, such as years at school, holidays, social events, moving house, weddings, and periods of illness and funerals, birthdays, anniversaries, birth and early years of a child, Christmas and other festivals, visits to concerts. We will also consider personal memories of public events such as watching the Olympic Games, high profile weddings and celebrations, national elections, the trapped Chilean miners, attack on World Trade Center, Japanese Tsunami, or the shootings in Norway and Colorado. We anticipate selecting workplace settings from among individual work related periods and events, for example job interviews, period with a major responsibility, key meetings, business travel, arrival/departure of other staff, work-related periods of success and disappointment, completion of a major task, pleasant and unpleasant interactions with work colleagues. Examples will be drawn from private life, business, public service, and university settings.

5.3.2 Memory Buoyancy

Memory buoyancy quantifies the importance and required accessibility of resources to human actors, be they information objects in the information management system or the images of those objects in the human mind. In this first deliverable, we discuss one of the simplest models of memory buoyancy which follows early theory of human forgetting - decay theory [22]. We also discuss how to incorporate factors of human forgetting of episodic memory (Section 4.1) into the model to measure the MB values.

Forgetting Curve

Early studies in human memory attribute the nature of forgetting to the passage of time, i.e. when no external interference to the memory encoding and storage is observed, retrieval of information in human brain still decays over time. This decay theory was pioneered in Ebbinghaus' famous work on human forgetting curve, where he hypothesized that human forgetting follows an exponential function [24]. The rough form of this function (called *Ebbinghaus forgetting function*) is:

$$M = e^{-bt}$$

where M is the memory retention of information, b is the rate of forgetting, and t is the time (i.e., the retention interval). Ebbinghaus forgetting function was revisited and expanded in several works, including the recent version of Rubin, Hinton and Wenzel [59]:

$$M = (a - c)e^{-bt} + c$$

where a is the degree of learning, and c is the asymptote.

In personal settings, time decay model has been criticized for its limits in explaining various phenomena of learning and remembering in human brain (for example, shocking events tend to be imprinted in memory vividly [17, 27], or interference of similar events, see Section 4.1). In collaborative settings, however, recent work has shown that collaborative remembering of public events (e.g. recall of historical events in societies and different communities) tends to decay with similar forgetting curves [2, 38]. This inspires us to model the memory buoyancy of digital objects in information management system by time decays, with some adaptation to cope with other attributes (resource type, authorship, contextual information, etc.) for taking into account further driving factors.

Time Decay Model of Memory Buoyancy

The rough idea is that, at each time step t, each resource r is associated with a real value $MB(r,t) \in \mathbb{R}$. The range of $MB(r)$ will be dependent on the tasks and scenarios discussed above. Time decay model assumes that intrinsic importance and need for accessibility of the resource will decrease over time:

$$MB(r,t) \propto (a_r - c_r)e^{-f(r,t)} + c_r$$

where a_r, c_r are the degree of learning and asymptote parameter with respect to the resource r, and $f(r,t)$ is a function that measures the rate of forgetting r over time variable t. Note that a_r and c_r are static over time, and therefore are influenced by non-temporal parameters, for example provenance parameters (resource type and authorship, for example remembering photos of oneself is easier than remembering text documents written by others), task-related parameter (remembering faces in photos is easier than remembering details), etc.

To model the forgetting rate $f(r,t)$ is trickier, since it depends on both temporal and non-temporal parameters. Instead of devising a concrete mathematical formula, we believe that $f(r,t)$ can be better estimated through a machine learning method (for one example, regression techniques [15]) that takes into consideration different features of resources and context for each particular scenario and task listed in Table 1. To accommodate the effects of similar experiences on human episodic memory being lost (Section 4.1), we will investigate features that reflect the overlap of topics, contexts or contents of resources across the information management system. For example, to learn the MB value of a photo of a sightseeing place during one's holiday trip, features indicating duplicated photos of the same place (that pre-exist in the repository) should be included to train the model.

5.3.3 Preservation Value

As compared to Memory Buoyancy, Preservation Value relates more closely to human perception of the long-term importance of a resource supporting e.g. reminiscence. As already discussed in Sections 4 and 5.3.1, there are numerous cognitive aspects affecting this assessment, and in practice numerous features can play different roles depending on the settings and tasks of the information management system. To gain more insights into this assessing process, we plan to conduct human experiments on a particular preservation scenario and task, namely reminiscence of personal event-related photos. We discuss our experiment setting plan in more detail in Section 6.2.2.

6 Preliminary Study and Research Plans

In this section, we first present a case study in support of the motivation of managed forgetting. Then, we propose research plans with detailed descriptions of the next steps towards realizing the concept of managed forgetting.

6.1 Case Study: Deletion Behaviour in Social Bookmarking

To support our motivation of collaborative forgetting, we conducted a case study of analyzing deletion behavior in Online Social Bookmark and Publication Management System - BibSonomy [5]. This web-based system supports team-oriented publication management and social bookmark sharing. BibSonomy offers users an ability to categorize and archive two types of resources, i.e., *bookmarks* and *literature references*. In particular, a user can upload and share a resource, or label it with arbitrary words, so-called *tags*. In addition, an uploaded resource can also be deleted from the system by its owner when needed.

A formal model for BibSonomy is given as follows: U, T, and R are finite sets, whose elements are called users, tags and resources, respectively. Y is a ternary relation between them, i.e., $Y \subseteq U \times T \times R$, whose elements are called tag assignments, and the set P of all posts is defined as $P = \{(u, S, r)|u \in U, r \in R, S = T(u, r), S \neq \emptyset\}$ where, for all $u \in U$ and $r \in R$, $T(u, r) = \{t \in T|(u, t, r) \in Y\}$ denotes all tags the user u assigned to the resource r. The principal unit of our analysis is a post p, which is a transaction made when inserting a resource to the system. Based on the BibSonomy data model described in [5], there can be more than one transaction records associated to a resource uploaded. This is because a transaction record will be created for *each tag* assigned to the inserted resource. In this study, we do not leverage user tag information, and all transaction records belonging to the same resource ID will be regarded as one unit of study, or a *post* in our case. Thus, a post p is defined as a tuple $(u, r, time(r))$, where a user u is the owner of a resource r uploaded at *time(r)*.

In order to motivate the concept of managed forgetting, we investigate deletion processes manually performed by users over time, so-called *deletion behavior*. We obtained the publicly-available data dumps of BibSonomy consisting of 15 data snapshots, i.e., 2006-06-30, 2006-12-31,..., 2012-01-01, 2012-07-01, 2013-01-01, where the average time distance between any two snapshots is approximately 6 months. The dataset does not contain information about user names and demographics, thus our analysis was unobtrusive and based on compiling anonymised client based Web transaction logs. As of 1 January 2013, the number of active users in this study is 8,928 users, and basic statistics about distinct posts per user are shown in Table 2. The maximum numbers of bookmarks and bibtex entries posted per user are 58,144 and 119,678, respectively. On average, there is about 370 resources posted per user and the average of bookmarks and bibtex entries posted per user are 171 and 198, respectively.

Table 2: Statistics of distinct posts per user.

Type	Max	Avg	Std
All	119,678	370.87	2872.39
Bookmark	58,144	171.91	1292.09
Bibtex	119,678	198.96	2556.16

As mentioned in [5], there are non-human users that automatically insert posts, e.g., the DBLP computer science bibliography. Therefore, we ignored such users with more than 5,000 posts from the analysis. Thus, we included in the study in a total of 8,853 users. Figure 5 shows the distribution of the number of distinct resources (post counts) per user. We conducted a detailed analysis by dividing users with respect to the number of their resources posted in total, into three groups: Group1 (10-100 posts), Group2 (101-1,000 posts), and Group3 (> 1,000 posts). Our hypothesis is that different groups of users can shed light on the different characteristics of deletion behavior among users who share posts from very few to very many.

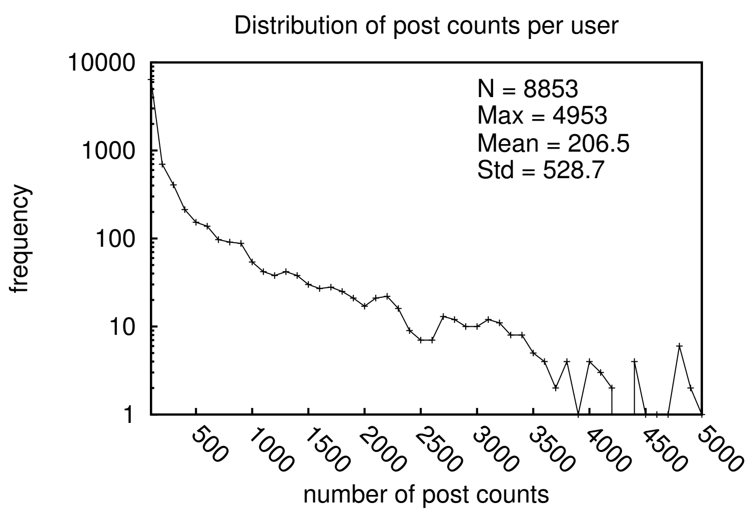

Figure 5: Distribution of post counts per user.

Deletion behavior was studied by computing the number of posts added or removed by each user at different time snapshots. For a given user u, the number of posts *added* at a particular time snapshot t_i can be computed as the *difference of two sets*, namely, the set of posts at current time t_i and the set of posts at the previous time snapshot t_{i-1}: *add*$(u, t_i) = P(u, t_i) - P(u, t_{i-1})$, where the type of post $p \in P$ can be either a bookmark, or a publication reference (denoted *bibtex*). On the contrary, the number of posts *removed* at a particular time snapshot t_i can be computed as the difference of the set of posts at the previous time snapshot t_{i-1} and the set of posts at current time t_i: *remove*$(u, t_i) = P(u, t_{i-1}) - P(u, t_i)$.

The trend over time of posts added or removed on average among three different groups is

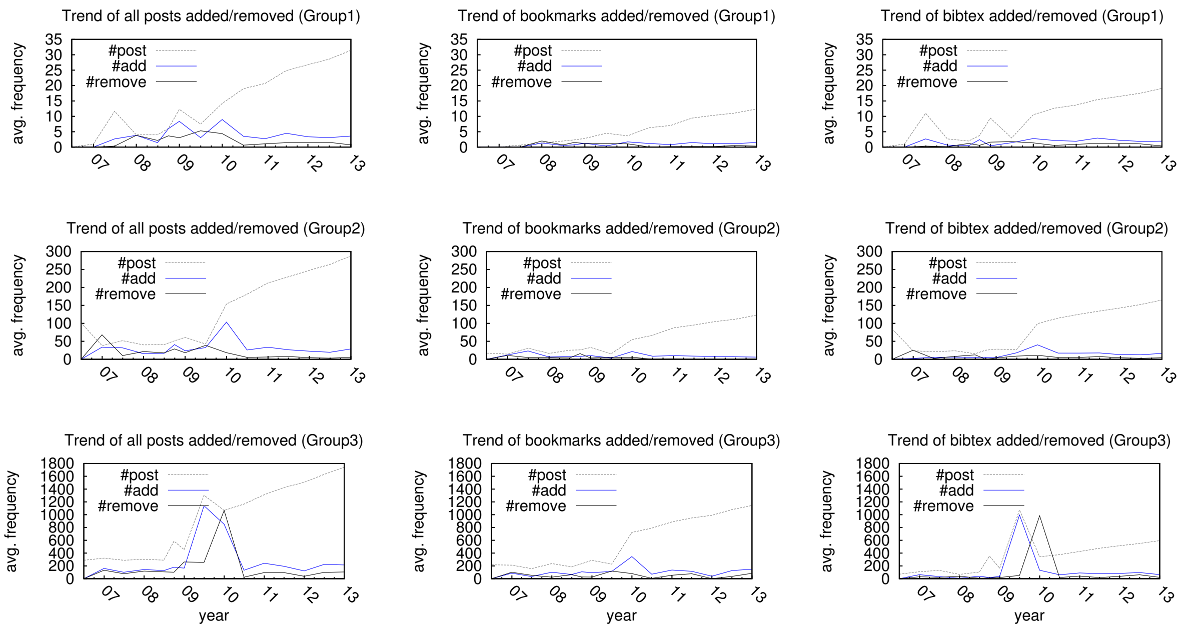

Figure 6: Trend over time of posts added/removed by user.

illustrated in Figure 6. In general, the results exhibit highly similar trends among different groups. Our observation is that, at each time snapshot, the number of added posts is greater than the number of posts removed in most cases, for all groups. This results in the increasing number of posts accumulated over time. For Group1 and Group2, the number of posts of the type *publication* is slightly higher than *bookmark*. It can suggest that users in the first two groups rather share publication references than bookmarks, whereas the number of bookmarks posted by Group3 users is significantly higher than publication references.

In addition to raw counts, we also computed *remove ratio* as a fraction of the number of time snapshots a user deleted at least one post. For example, a user u has been a member since 2006, and the user deletion activity is observed 10 times during 15 snapshots in time. Thus, *remove ratio*(u) equals to $0.67 = (10/15)$. Figure 7 illustrates the distribution of users' remove ratios among different groups. The results show that the group of users with fewer posts (Group1) has fewer deletion activities, while the group with more posts (Group3) tends to delete more often.

What triggers a deletion process? Does the number of current posts or that of newly added posts influence the deletion? We sought to answer such questions by performing a correlation analysis by correlating: 1) deletion activities with the total number of posts (or bookmarks or bibtex entries) and 2) deletion activities with the number of *added* posts (or bookmarks or bibtex entries). Note that, we only considered any user u with *remove ratio*$(u) \geq 0.5$. Table 3 shows the correlation results of deletion activities over time with the total number of posts (**Post**), the number of *added* posts (**Post+**), the total number of bookmarks (**Bookmark**), the number of *added* bookmarks (**Bookmark+**), the total

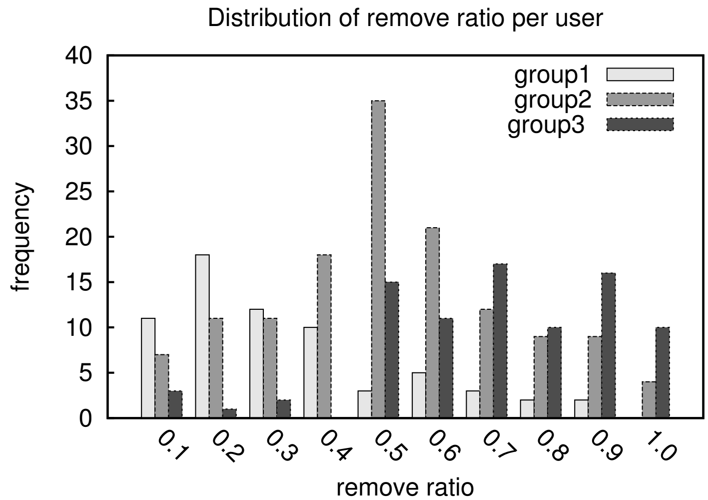

Figure 7: Remove ratios among different groups.

Table 3: Correlation of deletion behavior with the number of posts, bookmarks and bibtex entries.

	#Users	Post	Post+	Bookmark	Bookmark+	Bibtex	Bibtex+
Group1	13(66)	0.2632	0.5924	0.0875	0.3214	0.3413	0.6994
Group2	65(137)	0.2140	0.4247	0.1274	0.4195	0.3503	0.6249
Group3	73(85)	0.0918	0.3183	0.0845	0.3615	0.1591	0.4793

number of bibtex entries (**Bibtex**), and the number of *added* bibtex entries (**Bibtex+**), respectively. In general, it can be observed that deletion is highly correlated with the number of resources added, but not with the number of total resources users currently possess. Finally, Group1 shows highest correlation results between deletion and added resources in most cases.

Our final analysis is to determine whether the given resources are still accessible online. This is motivated by the recent study *Losing my revolution: how many resources shared on social media have been lost?* by SalahEldeen and Nelson [60]. That work has estimated that 27% of resources shared in social media are lost and not archived after 2.5 years. Table 4 shows the total numbers and percentage of resources that were accessible online using their URLs (retrieved on 28 April 2013). On average, there are less than 83% of bookmarks and less than 74% of publication references that were still accessible. This observation suggests that it is important to automatically identify unavailable resources and trigger a forgetting action, e.g., tagging objects as forgettable or performing deletion, in order to help users handle obsolete information.

Table 4: Resources accessible on 28 April 2013.

	#Bookmark (%)	#Bibtex (%)
Group1	715 (87.73%)	546 (78.56%)
Group2	5,074 (81.34%)	4,396 (73.39%)
Group3	24,909 (78.21%)	3,984 (69.48%)

6.2 Research Plans

An overall high-level research plan as well as the goals for the research in managed forgetting has already been defined in the DoW (especially in the description of WP3). This section defines and highlights the research activities for the coming months of the project. The research plan will be frequently revisited and re-aligned with the activities in the rest of the project as well as with the requirements identified in collaboration with the two application pilots (WP9 and WP10) and the work in the architecture work package (WP8).

6.2.1 Systematic Work on Information Value Assessment and Managed Forgetting

Initial idea for modeling managed forgetting have been presented in section 5.3. Clearly, further conceptual work is still required for determining adequate functions for computing PV and MB guided by the idea of complementing human memory. In the next months we will work on progressing in this area, gathering further insights on human expectations, and defining methods for computing MB and PV in more detail.

This line of work will also include further work on the integration of the forgetting functionality into the overall framework in close collaboration with WP8.

6.2.2 Information Assessment in Photo Preservation Scenarios

Motivation. To further investigate the contribution of different factors in driving human episodic forgetting process in the two mentioned settings (personal and organizational), as well as to foster the design of MB and PV assessor models discussed in Section 5.2, we plan to conduct systematic experiments with human explicit and implicit feedback on photo preservation scenario (see Table 1). The idea is that we design a prototype that enables human to look at their photo collections stored in their computers, annotate and send the feedback to the system for the analysis in an anonymous way.

Methodology. For this study, we use the personal photo collections of volunteers and build a dataset of event-related photo albums of different ages (i.e. albums that were taken several years ago, as well as taken recently). To cope with the privacy issues, we design our dataset in a way that it does not require contributors either to share their photos to others, and the photos are kept in original place of the authors' choice without additional copies, e.g. in centralized databases or corpora. This characteristic means that the dataset does not reveal any sensitive information from the contributors, and thus enables them to share more of their photo albums and experiences.

In short, the dataset consists of two parts: *reference part* and *content part*. The reference part is a set of references to the location of personal photo albums. For instance, the location can be an absolute path of the directory where the photos are stored. The reference will be encoded and synchronized between the client device (e.g., cell phones and computers) and the server, so as to guarantee both the anonymity of the collections as well as to keep information up-to-date. The content part is a set of the physical location of photo albums, as stored in the user's own device. It contains user photos, plus one extra file named manifest.txt in the root of the location. The manifest file consists of human-annotated data, and is generated through a user interface runs in the contributor's local machines. The interface is designated to enable humans to quickly annotate their photo albums with some properties such as: age (when the albums were taken), location (where the albums were taken), privacy levels (private, or can shared with close friends, or can be exposed to acquaintances, or can be public), people tagged in the photos, keywords describing the concepts represent in the photos (household, picnic, etc.). To ensure the consistencies of tagging among annotators, we will utilize a standard taxonomy such as WordNet [53], as adopted in existing image annotated dataset such as ImageNet [3]

Once the dataset have been built, a different models will be built to learn the way humans justify the preservation values of their photos, taking into consideration the features and training labels that were obtained from the manifest files sent from annotators' local devices. Should the models require content features (e.g. photo visual features such as SIFT, histograms, etc.), a separate computing component will be deployed and run in annotator's local machine, and only extracted features (mostly in numerical formats) will be sent to the centralized learning system.

6.2.3 Temporal Summarization of Social Web Content

Motivation. In social networks like Facebook, Google+, and Twitter people share lots of different content about their personal life, interests and activities. The most of this shared information get a very short attention from the community and it gets forgotten. For a user it is almost impossible to get an overview about his activities and personal highlights over a long term in the past. Our idea is to provide a personalized summary from the social web content of the user from a particular time period. But the summary can also be helpful for other users to get a general overview of their contact's activity, e.g. by sharing the summary with family and close friends.

Methodology. For our study we use the Facebook profile of a user with all his different types of content like photos, videos, comments, likes and relations for creating a sum-

[3] `http://www.image-net.org/explore`

mary of a particular time period (e.g. monthly or yearly). One challenge is to select a representative subset of the different types of content and consider their connections and relevance in a context. This differs from the most of the summarization techniques in social web which use only one type of information like text, tweets, comments or tags. We finalize our research question as follows: 1) What are important types of content in the summary? 2) How to identify highly relevant content from the personal perspective of the user? 3) How to visualize the summary?

Evaluation. The first step of our evaluation is based on a questionnaire of Facebook users. We will ask general questions about user's Facebook activity and the content that should be captured in their summary. In the second part, users will have to evaluate their personal Facebook summary as well as the visualization of the summary.

6.2.4 Long-Term Analysis of Trending Topics in Microblog

Motivation. Microblogging sites such as Twitter are increasingly recognized as important channels for instant updates about real-world incidents. Many important events are initially posted (tweeted) by users on Twitter, and subsequently diffused in professional sources such as news portals or television services, as was the case in the Arab Spring Revolution of 2011. Unfortunately, such tweets are often highly mixed with noisy, mundane posts about daily routines which are only of local interest, thus making tracking influential messages a challenging task.

In this ongoing work, we conduct experiments to gain insights into several aspects affecting the influence of tweets in the long run. We believe that understanding the long term behaviour of trending topics in Twitter will shed light on the human perception of assessing the memorability of public events, because individuals on Twitter typically choose a small portion of events in Twitter to disseminate according to their judgments of the events' significance. While this judgment process can vary from person to person, the global view of which topics last longer than the other is somewhat relevant to the organisational preservation scenarios, where preservation decision is made by a common perception of the community.

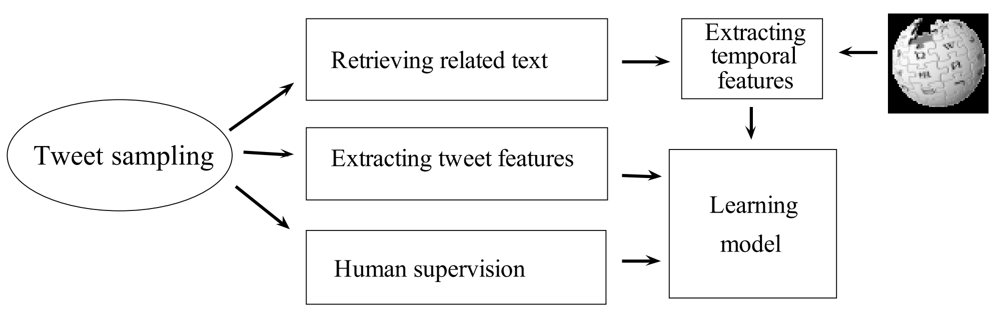

Figure 8: Workflow of Analysis Long-term Trending Topics in Twitter using Wikipedia.

Methodology. Our work distinguishes from the current state of the art in that we leverage the wisdom of the crowd from the Wikipedia encyclopedia, hypothesizing that information posted in Wikipedia and approved through the editing procedure contains a certain degree of significance as compared to other sources. The problem is that while Twitter exhibits immediate diffusion of information of all kinds, such information is often delayed by a considerable amount of time (hours to days) to become established in Wikipedia. To deal with this issue, we devise a model that leverages both Wikipedia and the linguistic characteristics of tweets. Figure 8 outlines the main components in our framework. It contains two components. The first component (extrinsic analyzer) links a tweet to a ranked list of relevant Wikipedia texts, using supervised machine learning techniques. From this, several features regarding recent updates on Wikipedia are scrutinized, providing indicators of whether the tweet contains influential information. The second component (intrinsic analyzer) extracts several features from the tweets (user-related features, orthographic features, corpus-wide statistical features). We then build a regression model to predict the significance of information encoded in the tweets. This is work in progress, that we plan to extend in the coming months.

7 Conclusions

In this report, we presented our vision for integrating the concept of managed forgetting into a joint information and preservation management process. This work is still in a very early phase. As a consequence there is still a rich set of future work ahead of us, including: foundations for the managed forgetting process building upon interdisciplinary work with cognitive psychology; a substantiated information value assessment model in support of the information value dimensions of memory buoyancy and preservation value. This also includes the identification of the set of measurable parameters best to be used for estimating those values; and experiments for better understanding the constituents and mechanisms of managed forgetting, e.g., interactions with photo collections, and revisiting behaviors for Web users as well as organizational information seekers.

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