Forgetful Digital Memory: Towards Brain-Inspired Long-Term Data and Information Management

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ABSTRACT

With the growing volumes of and reliance on digital content, there is a clear need for better information management approaches that keep *relevant* information accessible and usable in long-term encapsulated together with the evolving context information that is needed for its interpretation. Inspired by the role of forgetting in the human brain, in this paper, we envision a concept of *managed forgetting* for systematically dealing with information that progressively ceases in importance and also with redundant information - leading to a form of *Forgetful Digital 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. Its goal is to introduce an alternative to the dominating "keep-it-all" strategy for digital content, which ensures that the important content is kept safe, useful, and understandable over time.

1. INTRODUCTION

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. At first glance, forgetting seems to contradict the purpose of digital memories. However, we are currently facing a tremendous growth in volumes of digital content in the public, organizational and personal context [4]. Thus, it becomes more important to focus on relevant and important content, while forgetting irrelevant details, redundancies and noise.

This also holds true for the survival of content; Let's consider the large quantities of photos that we typically bring back from a holiday trip as an example. Although safely stored (with a backup), they might become inaccessible over time due to digital format changes or failures of technology such as hard disk crashes. The automated selection of important content as it is supported by managed forgetting thus, does not only make an image collection more enjoyable. It also helps in deciding about where to invest in making the important content more future-proof, e.g., by relying on preservation management methods.

We envision the notion of *managed forgetting* that is aimed at improving the management of digital memories (organizational or personal collections). Managed forgetting is related to the idea of data rotting presented in *Big Data Space Fungus* [8]. However, we aim to learn from human forgetting and remembering processes. Thereby, it does not make sense to just simulate human memory, but to support human activities and human memory. This goal can be better achieved if the digital memory complements the human memory process.

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 complex processes and effects in human memory; thus implying different notions of complementing. On the other hand, we expect that to just do the opposite of what the human brain does (for example, just remember everything digitally, when the human possibly wants to forget) would neither lead to a satisfying user experience nor fully exploit the potential of combining human and digital memory. For the above example of a holiday trip, it would be preferable, if the system could "forget" about the boarding pass after the flight in the same way as the human does. However, it might make sense to keep photos of all subevents of the trip for reminiscing, even if some of the subevents will be quickly forgotten by the human. It is noteworthy that the way a digital memory supports the human will - on the long run - also influence what the human keeps in memory.

An interdisciplinary model for flexible and gradual managed forgetting has to be developed that meets human expectations. As a core contribution, in this paper, we present such a brain-inspired conceptual model for a virtual digital memory that embraces human and digital memory and relies on managed forgetting. To this end, we present the Preserve-or-Forget (PoF) framework as a basis for the development of long-term information management systems based on our model.

2. RELATED WORK

In psychology, memory is the process in which information is encoded, stored, and retrieved. For complementing human memory, episodic and working memory are most relevant.

Episodic memory is the memory of autobiographical events (times, places, associated emotions, and other contextual knowledge). A characteristic of episodic memory is that details are lost very rapidly and that it is subject to interference [18]. Digital items such as photos and videos can play an important role in verifying (or falsifying [7]) the reconstructed memory of an event, thus having high potential for complementing human memory.

Human working memory [9] refers to the moment to moment activation and use of information in daily life. It activates a small amount of information just long enough to complete a task. This allows to focus on the current task while minimizing irrelevant information from the environment and from episodic and semantic memory.

There is general agreement among human memory researchers as to the basic principles of memory and forgetting, but there are several different conceptual and computational models of human memory and forgetting, e.g. [18]. On a global level, societies face difficult situations for societal memory, 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 created. This results in a growing understanding that *forgetting* also should be considered there, especially for information about individuals in the Web [10].

A search technology, such as Google, has shown effects on human memory [15]. Similarly, shared, retrieval-induced conversations in a social network can reshape the memories of people who are involved forming so-called collective memories [3]. In recent years, there have been several works addressing long-term information management, e.g., focus on the system design to support human memories [1], and personal information retrieval [6].

In the area of multifaceted information value assessment, several valuation methods have been proposed by 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]. This type of information value is highly associated to short-term interests [17]. Existing works on time decay models can, for example, be found in the field of processing data streams [12] and time-aware information retrieval [13, 16].

3. FOUNDATIONS

In this section, we present a conceptual model of the forgetful approach to information management. Particularly, we identify five main characteristics for a forgetful digital memory: value-driven, forgetful, brain-inspired, evolution-aware, and integrative.

3.1 Value-driven: Acting upon Short-term and Long-term Information Value

One of our core ideas is to deviate from the dominating *keep-it-all* approach, which makes the implicit assumption that all information has the same value to be kept or preserved (invested into for long-term storage). In general the value of information is multifaceted and can be considered from different perspectives. An important distinction is between the short-term value for current activities and the long-term value of a resource.

The **short-term value** refers to the value of content for the current focus of activity, e.g., documents used for a task at hand are of high short-term value. Here, we will see a high dynamics in the information value (due to changing interests and tasks) and a high influence on interaction-based evidences on the information value. In terms of the human brain, this is roughly comparable to the working memory (see Section 3.3), although human working memory has a higher change frequency. Identifying the short-term value of a document is of high interest for creating immediate benefit in information management, e.g., by de-cluttering the desktop or re-ranking search results by preferring more important content. Our anticipated methodology is to give high priority or visibility to resources with high short-term value. For this purpose, we coin the term *Memory Buoyancy*, which is inspired by the idea of resources decreasing in importance and sinking away from the user.

The **long-term value** refers to the value that a resource has on the long run and it can be used to decide about the investment of preserving the respective resource. Long-term value is expected to be more difficult to compute, since it includes estimating future use of resources. Furthermore, long-term value is driven by (partially) different factors than short-term value. It is expected that more objective aspects, such as diversity, coverage and quality will play a more important role. In this case, we have coined the term *Preservation Value* for the long-term value of a resource.

3.2 Forgetful: Focus on Important Things

We introduce the idea of a forgetful approach to long-term data and information management as an alternative to the dominating *keep-it-all* approach. Forgetting enables humans to focus on the relevant things and to efficiently make decisions in their current life situations. The forgetful approach opts for conscious decisions about what is important and thus should be kept (and preserved) replacing a form of random forgetting (or losing) information, e.g., disk crashes, or obsolescence of formats and technology. Since preservation comes at a cost, it is important to make such conscious decisions about (1) what to preserve, (2) how much to invest in the preservation, and (3) of which part of the information space. For this purpose, our forgetful approach is a good fit.

A forgetful approach is based on *Information Value* assessment, i.e. computing and predicting the value of information resources (see also Section 3.1). Effective information value assessment, especially for long-term information value, is a complex task involving a variety of parameters and heuristics. Based on such value, preservation decisions can be taken. On a high level, these decisions could include choice of preservation service as well as decisions about the level of redundancy and investment into preservation processes such as format transformations.

3.3 Brain-inspired: What to Learn from Human Forgetting and Remembering?

The idea of complementing human memory suggests to take an embracing perspective on human and digital memory, which considers them as a joint system. Thus, the interactions and mutual influence of the two parts are taken into account as well. Figure 1 (a) shows such a joint system perspective. The human memory (on the left) and the digital memory (on the right) together contribute to a form of virtual memory a human can rely on. The underlying model of the human memory is based on the work presented in [9].

Working Memory (Short-term). Together with the currently activated episodic and semantic memory, the *verbal short term memory* (things just heard) and the *visual short term memory* (things just seen) form the working memory, which frames the current situation. Knowledge is activated on demand from the semantic and episodic memory according to current needs via the so-called *executive functions*.

Perception is one driver for such activation. It is worth noting that perceived signals do not directly become part of the verbal or visual short term memory, which are constantly updated, but they are rather filtered and interpreted by things already in the memory for making sense of them.

Similarly, we also foresee a working memory within the digital memory This is composed of the digital resources currently relevant, e.g., used or relevant for current tasks or activities. The idea here is to keep those resources as close as possible to the user and easily accessible. In an automated digital working memory signals from resource usage, pattern of usage and change as well as relationships between resources will be used to update the digital working memory. The introduced managed forgetting function controls the transitions between the different parts of the digital memory.

Together, the working memory and the digital working memory form the virtual working memory. Clearly, there is an influence between both of them. In the ideal case, the digital working memory would show to the user just all the information that the user needs in the current situation, but does not have in her working memory. Note, that it is also possible that there is an influence of the way the digital memory works on the human (working) memory. For example, with the easy storage of phone numbers in mobile phones, humans no longer bother to remember phone numbers.

Mid-term and Long-term Memory. Managed forgetting functions are also used to identify content that is of long-term value (see Section 3.1) and should, therefore, be preserved. In Figure 1 (a), we distinguish between 1) information management for re-use, as it is, e.g., done on a desktop computer or a server, and 2) the system for archival

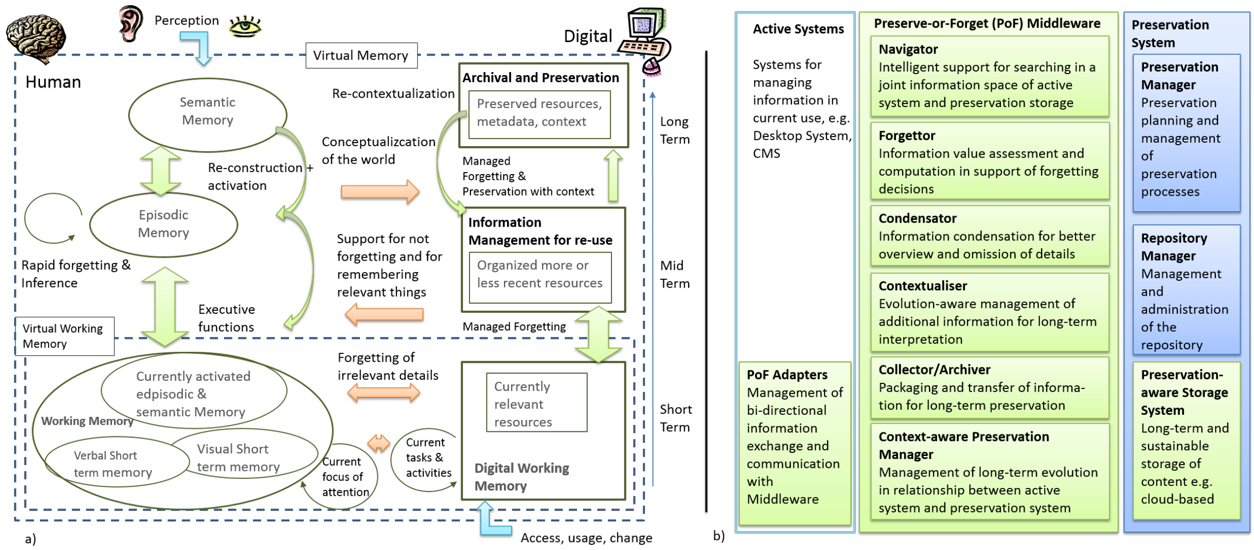

Figure 1: (a) Joint Perspective on Forgetful, Interacting Human and Digital Memory, and (b) Core Components of the Preserve-or-Forget (PoF) Framework.

and preservation. When content is transferred to *Archival and Preservation*, it makes sense to add context information to it (*contextualization*). This prepares the content for re-contextualization, which is required, when preserved content is brought back at a (much) later time. Re-contextualization is aimed to connect the re-activated content with the current environment, or at least, to make it understandable. The idea of re-contextualization as an active situation-dependent process is again inspired from human memory: when we as humans remember things this is also a re-construction process, which depends upon the current situation.

Episodic memory is mainly a detailed storage of events. It is typically subject to fast forgetting as well as blurring between the memory of similar events due to interference. Here, complementing human memory, e.g. via photos, can serve as a reminder of things that are forgotten, but that one might want to remember or refresh in a later point in time, e.g., reminiscing about past events.

Semantic memory is a more conceptual storage of memory, which stresses on patterns, abstractions and lessons learned. Here, the strongest interaction between human memory and digital memory is that the organization of digital resources does or should reflect the conceptualization of the world of the user, which is linked to the user's semantic memory. A more explicit modeling of the conceptualization of the world and a richer annotation of resource with this knowledge in *Information Management for Re-use* and in *Archival and Preservation*, such as, the Semantic Desktop approach proposed in [14], can ease navigation and search of the user and thus re-finding things in the digital memory.

3.4 Evolution-aware: The Long-term Perspective

Since we are targeting long-term integrated management systems, we are operating in a long-lived context, covering a time perspective up to several decades. Even things that are considered relatively stable in the current setting of an information system will change over time. For being prepared for sustainable operation it is important to be prepared for such changes. For this purpose, several types of evolution with different impacts have to be considered. This refers to the active system (which is the system used for active information management such as a desktop system or a CMS) as well as to the Preservation System, which is responsible for the long-term storage of the information.

Changes in conceptual model of the Active System can be due, for example, to changes in the organizational ontology underlying the content structuring as well as processes described in the content. This creates a semantic gap between the archived content (relying on the old implicit or explicit ontology) and the active content (structure by new ontology). This gap has to bridged, at latest when preserved content is brought back into the active environment, in order to enable correct interpretation of the re-activated content.

Furthermore, **evolution in the technology** of the active system and of the Preservation System as well as **exchange of those systems** have to be considered if we look at time frames of several decades. In spite of such changes the content should stay accessible and usable. In the case of exchange of the Preservation System, for example, This implies the migration of content into a new Preservation System. In the ideal case this should have as little impact on the Active System as possible.

Finally, for **change in best-practices and technology** such as technology or formats, which become obsolete, it is mainly possible to rely on preservation system functionality, which focus on such kinds of issues.

3.5 Integrative: Bridging the Gap

In the long run, it has to be foreseen that the Active System used as well as the employed Preservation System will change. Therefore, the idea is a flexible integration, which is prepared for major changes in the overall environment.

A core part of integration is to enable the smooth transition of content to be preserved into the Preservation System and the senseful reactivation of content back into the Active System after a -possibly very long - period. An integrative solution should also embrace the idea of a *joint information space*, where the information in the Preservation System stays conceptually accessible, e.g., visible in search results, even if the content is only available in the Preservation System.

4. COMPUTATIONAL FRAMEWORK

In the European project ForgetIT, we have developed the prototypical Preserve-or-Forget (PoF) Framework to validate the core ideas of a forgetful Digital Memory. Figure 1 (b) summarizes the core parts of the Framework, which consists of three layers: Active Systems, PoF Middleware and Preservation System. An Active System corresponds to the information management system (IMS) to manage the information actively used. The PoF Middleware implements the core concepts of the conceptual model. The Preservation System (archive) is responsible for the long-term storage.

In the following, we focus mainly on the role of the Forgettor, which includes the core functionality for managed forgetting. Concerning the other components in Figure 1 (b), it is worth mentioning that they mainly implement different functionalities associated to forgetful long-term information management, including bi-directional information exchange between the Active System and the archive, information condensation (Condensator), contextualization (Contextualizer), synergetic preservation (Context-aware Preservation Manager), and advanced forgetful search (Navigator). Many components of the PoF architecture have been omitted on purpose here, such as those responsible for process scheduling, work-flow management, data management and communication, because they are more related to the implementation.

The Preservation System leverages cloud technologies, with an innovative approach based on Storlets, which are components capable of running preservation processes in the storage.

For supporting managed forgetting, the Active System has to collect and exchange data with the Forgettor component. This includes content metadata (e.g. size, authors), but also context and usage information (timestamps, usage activities such as usage frequency and recency of use, user ratings, recurrent usage pattern, social context data). The Forgettor interacts with the Active System based on different strategies, depending on the application case. It can, for example, be triggered periodically or - for organizations - at major project milestones.

Inside the Forgettor, the *Assessor* is responsible for evaluating resources with respect to their current importance, as well as their intrinsic preservation worthiness for the future reflected by the quantitative measures for information value assessment, **Memory Buoyancy** (MB) and **Preservation Value** (PV), respectively. MB is influenced by a variety of factors that can be roughly grouped in the following categories: usage information, type and provenance information, relationship with other resources, and temporal parameters such as age and lifetime specifications. The PV reflects the expected value of a resource for the future and will be used to decide if and when to move a resource to the Preservation System. Partly, PV is influenced by similar values as MB, but it serves a different purpose: a resource with a high MB value might already be moved to the archive (as a copy) because of its high PV value 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. To assess the MB and PV 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 has access to a historic value repository.

5. ESTIMATING PRESERVATION VALUE

Information value assessment resulting in MB and PV values is in the core of our approach. For MB, the model for MB assessment basically embraces two aspects, namely, estimating the importance of digital objects and their retention in human brains by analyzing the observed activity logs (time-decay model) [12, 13], and associating them with their related objects, or with context information in the information space. In addition, we propagate the estimated MB scores along different connections to other digital objects (propagation model), or some of which might be unobserved by the activity logs.

Computation of PV is a much more demanding task, since it has to deal with usefulness expected in the future. Research is still required for understanding how the long-term value of information objects can be best estimated (using various kinds of evidences and features). However, first exploratory research in preservation value and its driving factors has already provided some insights to build further work upon. In experiments on expectation oriented photo selection for preservation with more than 18,000 photos [2], it has been shown that (automatically extracted) depicted concepts and the presence of persons are key features, while image quality is only of secondary importance. In addition, in contrast to other work in photo selection, it has been shown that the aspect of coverage (of all sub-events) is less dominating for the task of photo selection for preservation. In a second experiment [5], the retention preferences for Social Web content for the example of Facebook have been investigated. Here the level of social interaction (e.g., likes, comments), and the type of the content (e.g., images vs. status information) have a strong influence on retention decisions. The experiments also confirmed a general decay in the interest for older posts.

6. CONCLUSIONS

In this paper, we presented our vision of introducing *forgetting* into Digital Memory by following a brain-inspired approach. We proposed model and framework, which are promising steps for creating a new form of focused, long-term data and information management. However, a lot of research and experimentation are still required to ensure that such systems really complement human memory and also meet human expectations.

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7. REFERENCES

[1] S. Bowen and D. Petrelli. Remembering today tomorrow: Exploring the human-centred design of digital mementos. *International Journal of Human-Computer Studies*, 69(5):324–337, May 2011.

[2] A. Ceroni, V. Solachidis, C. Niederée, O. Papadopoulou, N. Kanhabua, and V. Mezaris. To keep or not to keep: An expectation–oriented photo selection method for personal photo collections. In *Proceedings of International Conference on Multimedia Retrieval*, ICMR '15, 2015.

[3] A. Coman and W. Hirst. Cognition through a social network: the propagation of induced forgetting and practice effects. *J Exp Psychol Gen*, 141(2):321–36, 2012.

[4] E. Cutrell, S. T. Dumais, and J. Teevan. Searching to eliminate personal information management. *Commun. ACM*, 49(1):58–64, 2006.

[5] K. Djafari Naini, R. Kawase, N. Kanhabua, and C. Niederee. Characterizing high-impact features for content retention in social web applications. In *Proceedings of International Conference on World Wide Web*, WWW Companion '14, 2014.

[6] S. Dumais, E. Cutrell, J. Cadiz, G. Jancke, R. Sarin, and D. C. Robbins. Stuff i've seen: a system for personal information retrieval and re-use. In *Proceedings of ACM SIGIR Conference on Research and Development in Informaion Retrieval*, SIGIR '03, 2003.

[7] D. L. Greenberg. President bush's false [flashbulb] memory of 9/11/01. *Applied Cognitive Psychology*, 18(3):363–370, 2004.

[8] M. Kersten. Big Data Space Fungus. In *Proceedings of the Conference on Innovative Data Systems Research*, CIDR '15, 2015.

[9] R. H. Logie. The functional organization and capacity limits of working memory. *Current Directions in Psychological Science*, 20(4):240–245, 2011.

[10] V. Mayer-Schönberger. *Delete - The Virtue of Forgetting in the Digital Age*. Morgan Kaufmann Publishers, 2009.

[11] S. Mitra, M. Winslett, and W. W. Hsu. Query-based partitioning of documents and indexes for information lifecycle management. In *Proceedings of ACM SIGMOD International Conference on Management of Data*, SIGMOD '08, 2008.

[12] T. Palpanas, M. Vlachos, E. Keogh, D. Gunopulos, and W. Truppel. Online amnesic approximation of streaming time series. In *Proceedings of International Conference on Data Engineering*, ICDE '04, 2004.

[13] M.-H. Peetz and M. de Rijke. Cognitive temporal document priors. In *Proceedings of the 35th European conference on Advances in Information Retrieval*, ECIR'13, 2013.

[14] L. Sauermann, A. Dengel, L. V. Elst, A. Lauer, and M. S. Schwarz. Personalization in the epos project. In *Proceedings of the International Workshop on Semantic Web Personalization at the ESWC 2006 Conference*, pages 42–52, 2006.

[15] B. Sparrow, J. Liu, and D. M. Wegner. Google effects on memory: Cognitive consequences of having information at our fingertips. *Science*, 333:776–778, 2011.

[16] N. K. Tran, A. Ceroni, N. Kanhabua, and C. Niederée. Back to the past: Supporting interpretations of forgotten stories by time-aware re-contextualization. In *Proceedings of International Conference on Web Search and Data Mining*, WSDM '15, 2015.

[17] R. W. White, P. N. Bennett, and S. T. Dumais. Predicting short-term interests using activity-based search context. In *Proceedings of International Conference on Information and Knowledge Management*, CIKM '10, 2010.

[18] J. T. Wixted. The psychology and neuroscience of forgetting. *Annu. Rev. Psychol.*, 55:235–269, 2004.