Oblivion Tracking: Towards a Probabilistic Working Memory Model for the Adaptation of Systems to Alzheimer Patients

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ABSTRACT

We introduce a new probabilistic working memory (WM) model that we intend to use to automatically personalize user interfaces with respect to Alzheimer patients' declining WM capacity. WM is the part of the human memory responsible for the conscious short-term storing and manipulation of information. It is known to be extremely limited and to be one of the strongest factors that impact individual differences in cognitive abilities. In particular, individuals suffering from Alzheimer's disease have significantly impaired WM capacities that worsen as the disease progresses. As a use case for our model, we describe a system that is designed to help patients with Alzheimer's disease choose the music track they would like to listen to from a given playlist. We discuss how our WM model could be used to adapt this system to each patient's disease progression in time and the consequent deterioration of her WM capacity.

CCS CONCEPTS

•**Human-centered computing** →**User models;** •**Mathematics of computing** →*Bayesian networks;*

KEYWORDS

Alzheimer's disease; working memory; Bayesian network

1 INTRODUCTION

The world is in the midst of a major demographic shift, with the proportion of people over the age of 65 becoming increasingly significant. While a part of this population segment does remain healthy and functional, they are more susceptible to dementia than younger people. Dementia is characterized by the deterioration of a person's memory and cognitive functions. The most common form of dementia is Alzheimer's Disease (AD). The World Health Organization predicts that, in 2050, there will be over 100 million people suffering with AD [12]. This prediction, when put in perspective with the growing shortage of caregivers, creates an alarming situation, presenting many challenges and opportunities for technological development.

There is a great effort from the scientific community to create technologies that enable the older part of the population to cope with the difficulties linked to cognitive impairment [14][5]. As cognitive diseases progress, mental faculties such as decision making, language and judgment are affected, resulting in a gradual loss of autonomy. AD causes thus a lot of stress to the patient, his family and caregivers. Luckily, there are systems developed that intend to give back some of the autonomy lost through the progress of the disease and release the burden on caregivers and family. For instance, systems such as Smart homes [15] try to compensate the patient's loss of autonomy through advanced technologies.

However, there are not many studies concerned with the adaptation of assistive systems to the patient's cognitive capability over time. Since AD is a progressive disease in which the symptoms usually worsen over time, a system designed for patient care must be able to adapt to the user's current state. For instance, as the disease progresses, patients may have trouble communicating or even understanding lengthy requests [1]. Therefore, caregivers are required to speak slower or use short sentences with simple words. However, if we design an assistive system that communicates through verbal cues, a one-for-all solution that uses only slow and short sentences might be seen as boring and unattractive to patients with higher cognitive capabilities. Depending on the progress of the disease, some patients may also need some extra time to process uttered questions before answering a request [1]. Therefore, if an assistive system does not consider the patient-dependent response time and keeps asking the same query over and over again, assuming that the person just did not understand, then any kind of useful interaction with the patient becomes impossible. Adapting the assistive device technology to the patient's cognitive capacities may be a way to render these systems more receptive for Alzheimer patients.

We introduce in this paper a new probabilistic working memory (WM) model that we intend to use to automatically personalize user interfaces with respect to Alzheimer patients' declining WM capacity. WM is the part of the human memory responsible for the conscious short-term storing and manipulation of information. It is known to be extremely limited and to be one of the strongest factors that impact individual differences in cognitive abilities. In particular, individuals suffering from AD have significantly impaired WM capacities that worsen as the disease progresses.

To handle the specifics of AD with respect to WM, we propose to model WM via a probabilistic model that tracks the probability of memory retention. We discuss how such a model can be used to adapt to the disease-related deterioration of WM. Moreover, to take into account the time dependence of AD, we propose to adapt over time the patient-specific probability distributions of this model, thus tracking the oblivion-generation traits of each user. This advanced WM model is intended to be a central feature of any assistive technology that targets AD patients. To illustrate how our new concept can be used in practice, we introduce a simple entertainment system that is designed to help AD patients choose from a given playlist the music track they would like to listen to. This assistive system would use an artificial WM-based embodied

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conversational agent to interact with the patients. We discuss how our WM model helps adapting such a system to the disease progression over time, with the deterioration of the patients' WM capacity.

To sum up, the main contributions of this paper are: (1) a new time- and attention-dependent Bayesian model of the Working Memory, (2) its adaptation to Alzheimer patients' WM capacity and (3) a simple music-selection use case.

In Section 2, we briefly introduce the notion of WM and its relation with AD. Section 3 is dedicated to the description of our new probabilistic WM model. We put it into play in Section 4, where we propose the overall design of a WM-based application for AD patients: an assistive music player. We discuss future work and conclude in Section 5.

2 WORKING MEMORY

Working memory is the part of the human memory responsible for conscious short-term storage and recall of information. It is essential to successfully perform complex cognitive functions, such as driving in heavy traffic, cooking or reading. Acquisition of new information, such as a list-learning task, is also an example of a complex cognitive activity that requires the resources of WM [7].

A simple example of how WM works is when we are having a group discussion and we have something to say; the information of what we are about to say is stored in our memory while we wait for our turn to speak. But, at the same time, we are focusing our attention on what is being said by the others so that, if someone says what we were about to utter, we can modify it or even decide it's not worth saying it again.

Baddeley and Hitch proposed a multi-component working memory model [2] that is now widely accepted. This model includes two slave systems that hold information: the phonological loop, for verbal information, and the visuospatial sketchpad, for visual images. A third component, the central executive, acts as an attentional controller that (1) processes information, (2) focuses, switches and divides attention and (3) links with long-term memory. A revised version of this model [3] introduces an additional subsystem, the episodic buffer, which provides additional memory to manage linked knowledge and relation to long-term memory.

2.1 Capacity

The capacity of WM is known to be extremely limited and is one of the strongest factors that impact individual differences in cognitive abilities [11]. There are a number of models of WM capacity. One of the proposed models describes WM as having a limited number of slots (or chunks) where information is stored [6] and, if there are more information than available slots, it will be lost. Miller [9] estimated the human capacity as being about 7 ± 2 items at a time, while Cowan [6] estimated that value to be about 4 items.

There are mostly two classes of WM: item-based and resource-based models [11].

- Item-based models ignore the structure of items and their respective parameters and treat each one as a "unit of memory"; the same amount of memory space is allocated to every item, and partial storage does not occur.
- Resource-based models consider the number of properties, called resources or features, of an item. In fact, properties such as the number of parameters are primary to such models. Complex items may take on more memory space than simple items, and partial storage may occur.

In this article, we will consider WM as an item-based model. In future work, we may have to consider a more complex model of WM depending on our results.

Following an item-based approach, Pashler [13] suggested a probabilistic way to estimate a person's WM capacity. In an experiment where n items are presented to the subject, if the person's WM capacity k is such that $k \geq n$, then the person will remember all the items and the probability D that one item remains stored into the WM is 1. However, if $k < n$, Pashler assumes a uniform distribution, and $D = \frac{k}{n}$. As a whole, the subject stores an item in his WM with probability $D = \min(\frac{k}{n}, 1)$. This is the most common method of estimating working memory capacity.

The behavior of WM varies along various factors. Besides the capacity, time is an important factor; the data present in the WM storage areas [4] can be recovered during a finite amount of time with little loss in either quantity or quality [17]. But, after this time, the probability that an item remains in memory declines. Another key important ingredient is attention; if one directs patients' attention away from the stimuli at the time of their presentation, one clearly observes its impact on the WM capacity [6].

2.2 AD Impact

Memory span tasks, i.e., giving several words or numbers for a subject to remember, can be used to investigate WM. As the span length increases, the ability to recall the words decreases, the largest length representing the subject's memory span. This kind of test is used to show that WM is limited. In [8], a series of studies are presented that compare the performance of AD patients in these kinds of tasks with a healthy elderly control group. The obtained results seem contradictory. Indeed, several studies have found that the memory span of AD subjects was reduced when compared to the elderly control, while finding no difference between the elderly and a young control group. However, some of the studies presented in [8] found normal performance of subjects with early or mild stages of AD. This difference may be explained by different degrees of the disease severity and patient-specific conditions. There is evidence that spans for lists of digits are preserved in mild cognitive impairment (MCI) pathologies and minimal AD, but become increasingly impaired through the progression of the disease, across mild and moderate groups [8].

2.3 Application to Assistive Technologies

The very characteristics of AD call for assistive technologies that can adapt and be personalized in various ways. First, since WM performance decreases with the progression of AD, time adaptation of assistive systems for such patients is paramount to ensure, as much as possible, that common tasks that are properly handled at one point can be managed as well later on. Furthermore, the acquisition of new information calls for even more system adaptation. Indeed, suppose an AD patient needs to follow a new schedule (say he or she moved to a new house, or must take a new set of drugs); if this new information is presented without considering the person's WM capacity, some information may get lost and the patient might take more time to adapt to the new schedule. Our probabilistic memory model and its time evolution intend to deal with such issues (see Section 4 for a use case scenario that takes advantage of our approach).

3 A PROBABILISTIC WM MODEL

We introduce a new probabilistic WM model based on three characteristics of WM: capacity, time and attention.

3.1 Definition

Our probabilistic WM model, which tracks the probability of retention of items in WM, is specified as a Bayesian Network (see Figure 1). It is designed to be compatible with the hypotheses that (1) the recall-versus-word-number curve follows the "U" shape discovered by Murdock [10], i.e., that the items in the beginning of a presented list (primacy) and at the end of this list (recency) are more likely to be recalled than those in the middle of the list, and (2) all items in the WM have the same lifetime t_l before oblivion.

Our network has a node T, valued with the elapsed time (in seconds) from an application-dependent initial time (e.g., the presentation of information related to a choice to be made, as illustrated in Section 4). This node is parent to n information nodes $S_1, S_2, \ldots, S_n$. Each node S_i represents an item in the user's WM and its value assesses if the corresponding information is present there (1) or not (0). These values depend upon attention variables A_i that correspond to the estimated attention (between 0.0 and 1.0) the person was paying when the i-th information was presented. The attention estimation will be performed by a system similar to the one proposed in [16], where attention is assessed from the user's gaze or face orientation.

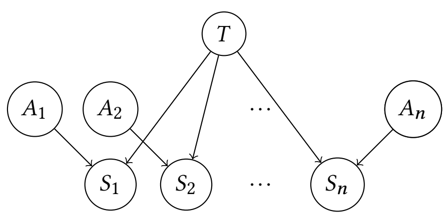

Figure 1: Probabilistic WM Model.

The conditional probability of a subject remembering the i-th item in a list of n presented items at instant t with attention a is thus denoted by

$$P(S_i = 1 | T = t, A_i = a) \ .$$

Assume that k is the estimated WM memory capacity; note that this parameter and t_l are user- and disease-dependent. In the case of a user fully attentive for the i-th item ($a = 1.0$), then, following Pashler's WM capacity model (see Section 2), one has

$$P(S_i = 1 | T = t, A_i = 1.0) = \min(\frac{k}{n}, 1), \text{ whenever } t \leq t_l \ ,$$

and

$$P(S_i = 1 | T = t, A_i = 1.0) = 0, \text{ whenever } t > t_l \ .$$

These are just examples of the conditional probabilities that could appear in our probabilistic approach to WM modeling; a complete set will have to be provided, either formally as above or via data from calibration experiments, to properly specify the model for a given user. In particular, we posit that the U-shaped curve will be encoded in the probabilities, giving higher primacy and recency probabilities of being remembered. Eventually, with a fully specified model, at each moment, we can compute the probability that one item is currently in the subject's WM. This information, properly updated according to each patient's capabilities, will enable the user interface of assistive systems to be finely tuned to each AD patient, as illustrated in Section 4.

3.2 Time-Dependent Model Fitting

To fit our model to the subject's WM, we intend to perform a calibration step. The calibration step will consist of a simple game, analog to memory span tasks. During this game, while estimating the person's attention, we will ask the subject to store a few items in his memory and then ask questions to see if the information is present in the subject's memory. Through this game, we intend to build a database corresponding to each subject. With the collected data, we will learn the probabilities that are going to link our network together, therefore building a model personalized for each subject.

To handle the progression of AD over time, the WM model has to be updated periodically. One way to do this is to apply the previous process regularly, say once a month. A more appealing approach would be to extend our WM model to automatically adapt itself to the user's deteriorating cognitive abilities, for instance using a Dynamic Bayesian Network framework.

4 MUSIC PLAYLIST SELECTION: A USE CASE

We outline the design of a WM-based system that would help AD patients to choose a music track from a given playlist. This use case consists of an virtual assistant (embodied conversational agent, or ECA) equipped with a camera for attention estimation and capable of verbal communication (utterances and speech recognition).

4.1 WM-Based Music Assistant

This system takes our WM model in consideration to present the possible options in a way that does not cause information overload. Of course, this is simply one possible use case, as the basis of this system can be used later on to adapt to more complex tasks. While choosing a music track is not an everyday task at nursing homes, nor is it a critical activity in an Alzheimer patient's life, one can think of choosing meals, movies, television shows, or even deciding on medical treatment options, instead. Activities such as choosing one's lunch is a daily activity in nursing homes. Often, the staff does not have time to properly ask each person what he or she wants to eat; moreover, cognitively impaired patients may take a lot of time to make their choice.

This design for a system that helps patients avoid choice overload, i.e., too many options, when choosing a music track is a simple implementation that allows us to demonstrate how our WM model can be used to adapt a system to the users' abilities. The chosen system will, at the end of each task, reward the patient with the chosen music track, which would not have been a workable approach had we chosen the task of choosing a lunch menu (we would not be able to offer such a variety of dishes, nor would we be able to perform lots of choice interactions).

4.2 User Interface Adaptation

Our music-selection system can be adapted to our WM model according to three main characteristics: capacity, time and attention. The system uses the fitted WM model to make predictions of how the subject's WM will behave and takes actions to ensure the outcome will have the highest probability of success.

Capacity. Suppose we propose 15 different music tracks for the subject at a given time and her WM capacity is 5 tracks. This will cause a choice overload. Therefore, the subject won't be able to make her choice pondering each option, and may even end up with a random music track that was stored in her memory. Here we are talking about offering music tracks that the subject does not know a priori; if we propose some music tracks that the subject knows, she will probably just focus on those and most likely retain them in her memory. Proposing unknown music might be a way to eliminate such bias.

Again using Pashler's model of WM capacity as an example, for a 15-track inventory, the probability that each song is stored is 1/3. Therefore, if we are interested in having a high probability of memory retention (say 0.8), we can adapt the system by making a cut on the inventory length and propose a smaller range of tracks at a time (e.g., at most 6 tracks, for a probability of 0.83). Our adaptation system will also work in a similar fashion by cutting Murdock's U-curve below a given probability threshold in order to increase information retention. Being able to predict how the subject will store information will allow us to present it in user-specific way by making *cuts in the presented inventory*.

Time. Since WM decays with time, our model can tell at any given moment if an information item is likely still present in the subject's memory. This will allow us to command the user interface to *present again the needed information that has been lost*. While this is not critical when choosing music tracks, it can be a key point in learning systems.

Attention. By being able to infer how the subject's attention influences her performance, we can make sure to *request enough attention* from the subject by using the user interface to issue verbal prompts or repeat the name of the tracks. These actions ensure that the probability of memory retention stays high enough.

5 CONCLUSION

We introduced a new probabilistic WM model that we posit can be used to automatically personalize user interfaces with respect to AD patients' declining cognitive abilities. This probabilistic model is user- and time-dependent to better fit the user's cognitive capacity over time. As a use case for our model, we described a system for choosing music tracks from a given playlist. We discussed how our WM model can be used to adapt this system to the disease progression and the deterioration of the patients' WM capacity.

Future work will include the precise formalization of our WM model, the determination of a priori probabilities and the specification of an effective way to perform time adaptation as the system is utilized (to avoid periodical calibrations). There is also room for improvement to the model; for instance, we could take into account the bias of emotionally charged stimuli. Further down the road, a complete use case system will be implemented and tested in an ecological environment (we partner with the Broca hospital in Paris for this study). Our system will be tested with patients with different levels of cognitive impairment to simulate AD progression. Depending on how our WM model and adaptation strategy perform with such patients, our WM model may have to be updated, possibly requiring a more complex representation of WM.

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