In Silico Simulations and Analysis of Human Phonological Working Memory Maintenance and Learning Mechanisms with Behavior and Reasoning Description Language (BRDL)

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Abstract. Human memory systems are commonly divided into different types of store, the most basic distinction being between short-term memory (STM) and long-term memory (LTM). Phonological STM, as proposed in the working memory model is closely linked to semantic LTM. Nevertheless, the mechanisms of maintenance with STM, and transfer of information with LTM are poorly understood. Candidate mechanisms within phonological STM are rehearsal (either articulatory or elaborative), and refreshing. There is also evidence of long-term learning within STM.

In this paper we use the Behavior and Reasoning Descriptive Language (BRDL) to model human memory contents as well as the perceptions that allow humans to input information into STM. By using the Maude rewrite system to provide semantics to BRDL and dynamics to BRDL models, we can explore various cognitive theories about phonological STM maintenance and transfer of information for long-term retention, such as articulatory rehearsal, elaborative rehearsal, and refreshing. This approach has been implemented in a tool that allows cognitive scientists to carry out in silico the simulation of learning processes as well as the replication of experiments conducted with human beings in order to contrast alternative cognitive theories.

Keywords: Short-term memory · Working memory · Semantic memory · Behaviour and Reasoning Description Language (BRDL) · Formal methods

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1 Introduction

Most theories of human learning processes make a fundamental distinction between short-term memory (STM) and long-term memory (LTM). This distinction is supported by a wealth of evidence from neuropsychology, experimental psychology, and analysis of the different computational needs of short-term and long-term forms of information processing [30]. Although multiple models exist of the interactions between STM and LTM, predominant is the Multicomponent Working Memory Model proposed by Baddeley and Hitch [7].

In our paper, the expression working memory should thus be interpreted as referring broadly to the model proposed by Baddeley and colleagues, unless stated otherwise. In the most recent form of the Multicomponent Working Memory Model, the most basic feature distinguishing short-term processing is that it is essentially fluid, while LTM is essentially crystalized [3,4]. The concepts of fluid and crystalized processing originated in studies of intelligence within differential psychology [14].

Crystalized knowledge is viewed as stored information, and is thus highly dependent on experiences, culture and education. In contrast, fluid processing describes processes which work ‘online’ and are conducted to deal with novel, current demands and are basically independent of cultural influences and education. That working memory is fluid is almost tautological, as its very definition includes, in addition to short-term storage of information, it “supports human thought processes by providing an interface between perception, long-term memory and action” [4, p. 829]. Indeed, some argue that working memory is so involved with high-level, domain-general cognitive processing that it is virtually equivalent to general intelligence [21], and concordant with that, is a substantial predictor of performance in formal education [35].

The most recent version of the Multicomponent Working Memory Model proposes a singular top-down, executive, limited capacity processor, and two STM stores. Visuospatial storage in STM, also known as the visuospatial sketchpad, interacts with visual semantics stored in LTM, while an acoustic-based STM, known as the phonological loop interacts with semantic LTM [3,4].

In our paper we focus on the latter of these two, the phonological loop, and how information is maintained (i.e., how it acts as an STM store) and how information may be parsed with semantic LTM. In our own computational modelling, we refer to this phonological store as pSTM, but we consider it more or less equivalent to the phonological loop in the Multicomponent Working Memory Model of Baddeley and Hitch [7] or the basic acoustic-based STM store in the Atkinson and Shiffrin’s model [1].

Evidence that pSTM is closely linked to semantic LTM is known from various sources. One being that pSTM in the context of working memory ability is linked to normal vocabulary learning in children, and brain damage that impairs pSTM in adults effectively prevents new vocabulary learning, but not episodic LTM learning [6]. This suggests that pSTM is a crucial stage contributing to crystalized semantic LTM. In support of the opposite connections, from LTM to pSTM, the often quoted capacity of pSTM, seven plus or minus two items, is frequently disproven by prose recall [23] and chunking of verbal material [31]. Both of which suggest that semantic-lexical LTM can actively support pSTM, allowing much more information to be held ready for immediate use.

In fact, a recent conceptualization of the position of working memory in the greater memory system, proposes that while still basically separate, working memory operates between LTM and action/output systems [5].

In Sect. 2 we review experimental studies on the pSTM processes (articulatory rehearsal, elaborative rehearsal, and refreshing) that enable information to persist in the short-term storage and, possibly, move to LTM (Sects. 2.1 and 2.2), and we introduce fast and slow learning mechanisms (Sect. 2.3). In Sect. 3 we briefly recall the Behavior and Reasoning Descriptive Language (BRDL), which was introduced in the first author's previous work [15], and we describe how to use it to model maintenance and learning mechanisms (Sect. 3.1). In Sect. 4 we first review modelling approaches to the in silico simulation of working memory, and then describe our own approach and tool, which are based on our previous work [16–18], in which Real-Time Maude [34] is used to provide semantics to BRDL and dynamics to BRDL models. In particular, Sect. 4.1 describes the tool implementation and Sect. 4.2 illustrates the use of the tool for the in silico replication of the 1969 Collins and Quillian's experiment [20] on time retrieval from LTM and the 2017 Souza and Oberauer's experiment [37] comparing fast and slow learning mechanisms. Finally, in Sect. 5 we draw conclusions and discuss future work.

2 Maintenance in pSTM and Transfer to LTM

Despite wide-spread support for the concept of the Multicomponent Working Memory Model, the mechanism by which material is maintained in STM (e.g., the phonological loop), is poorly understood. Furthermore, based on experimental evidence, it is argued that whatever the mechanisms are, they also seem to contribute to information retention in LTM [26]. Thus, working memory maintenance and LTM trace formation or strengthening are intertwined. Two main mechanisms have been proposed for how information is maintained in pSTM, given that it is supposedly of short duration, with memory traces decaying in perhaps less than 3 seconds [13]. These are rehearsal and refreshing. Both have also been proposed as mechanisms of how information transfers from STM to LTM.

2.1 Rehearsal

As the phonological loop component of the Working Memory Model developed from the earlier Modal Model of memory [1,2], it inherited from that the concept of rehearsal. This suggests that information decays rapidly within phonological STM, unless it undergoes some form of repetition, hence the name, phonological loop. This appears to take the form of sub-vocal articulation. As it is proposed as a trace enhancing mechanism, it is often called articulatory rehearsal. Nevertheless, such rehearsal is also proposed as a principal mechanism by which information moves from STM to LTM storage [2]. These are thus quite closely related concepts, as information that is articulatory rehearsed (presumably increasing the probability of transfer to LTM) also remains available in STM for longer.

This has led to the suggestion that the length of time that information spends in phonological STM determines its likelihood of transfer to LTM [1]. However, experimental support for this, at least as caused by articulatory rehearsal, has proven to be quite limited [38]. One suggestion is that the intentional act of initiating articulatory rehearsal and the associated processes, such as preparing the articulatory code, are the mechanism that causes some transfer to LTM, with subsequent rehearsal loops maintaining information in STM, but not inducing further transfer [29]. Recent evidence suggests that the amount of time that information spends in phonological STM does indeed greatly influence whether or not it will become available for later recall from LTM, but this may be due to reasons other than greater opportunity for articulatory rehearsal, such as elaboration [37].

As articulatory rehearsal appears to not explain much LTM learning, an alternative version, elaborative rehearsal, has been proposed [28]. The expression is something of a misnomer, as it refers to processing of the meaning of information with phonological STM. However it is interpreted, it is clear that accessing meaning of material and making connections of meaning is a potent mechanism of LTM learning. This is demonstrated in the classical experiments used to form the Levels of Processing approach to human memory [22]. It is now widely accepted that elaborative semantic rehearsal of information that is held in phonological STM substantially increases the chance that the material will be available from LTM when tested later, particularly if this is for linguistic material [8].

2.2 Refreshing

An alternative mechanism for delaying trace decay in phonological STM is refreshing, which has become particularly popular within cognitive psychology over the past two decades. It is defined in general terms as "a domain-general maintenance mechanism that relies on attention to keep mental representations active" [11, p. 19]. This is core to the Time-Based Resource-Sharing (TBRS) model of working memory, which suggests that attention is a limited resource which can maintain representations, but they will decay if attention is moved to other tasks, unless it momentarily returns to refresh the traces [9]. This emphasizes the difference between the older Modal Model of STM and the more current working memory models, in which some form of resource limited executive control is required, such as to sporadically refresh memory traces. This executive resource produces a bottleneck as it is argued to work sequentially, and thus must be switched frequently to maintain not only STM traces but also various task goals, and other task-relevant information.

Experimental evidence supports the existence of attentional refreshing as an independent mechanism of maintenance of verbal material within STM. Furthermore, that it operates in addition to articulatory rehearsal, and that the two may have an additive effect [12]. Several studies have suggested that in addition to extending traces in STM, refreshing leads to better delayed recall, indicating it promotes learning in LTM. For example, Loaiza and McCabe [27] used a word learning task and found that articulatory rehearsal had no impact on later recall from LTM, but opportunities for refreshing did. Nevertheless, a recent experimental study that compared elaborative rehearsal and refreshing side-by-side, found evidence that word learning in LTM is improved by the former, but not by the latter [36]. The experimental evidence for LTM trace formation being enhanced by refreshing in phonological STM is therefore unclear, as is whether rehearsal can fulfil that function.

2.3 Fast and Slow Learning Mechanisms

It has been suggested that learning may take place within pSTM. This is implied by the Hebb repetition effect [32] in which lists that are surreptitiously repeated in immediate recall tasks are better recalled than novel lists, suggesting an incidental STM learning mechanism. Burgess and Hitch [10], in their neural network model of pSTM, implement a 'fast mechanism' responsible for storage of items with pSTM for active use, and a 'slow mechanism' (e.g. long-term potentiation) responsible for long-term learning that would form the LTM traces.

3 Behavioral and Reasoning Descriptive Language (BRDL)

BRDL [15] is a modelling language to describe human reasoning and human automatic and deliberate behavior. A BRDL model consists of a set of mental representations of facts, inference rules and behavior patterns, classified as one of the following types:

fact representation which is part of our knowledge, such as 'An animal can move';

inference rule which is acquired through our lives and applied deliberately; for example, when we are driving a car, we know that if we are approaching a zebra crossing and we see pedestrians ready to walk across the road, then we must give way to the pedestrians;

deliberate basic activity which is driven by a goal; for example the activity of grasping an object is driven by the goal of moving it to a specific place;

automatic basic activity which occurs as a reaction to perception from the environment in combination with some mental state; for example the activity of pushing the car brake may occur as a reaction to a red light while I am in a driving mental state.

The first three types of representation refer to information stored in the declarative part of LTM. The use of this information by working memory processing is driven by specific goals. Namely, we may retrieve a fact as the answer to a question [16] or because we need to use it in the achievement of a goal [17]. The retrieval of facts is modeled as an internal process of LTM. It operates through a pattern matching between elements of some information stored in pSTM (i.e., a question or some information stored by the goal-driven task execution) and elements of fact representations in LTM, possibly in combination with the identification of a semantic connection between the two matched elements of the two information items. For example, if pSTM contains the question ‘Can a dog bark?’, a full pattern matching with the fact ‘A dog can bark’ is directly identified in LTM (both ‘dog’ and ‘bark’ match). Instead, if the question is ‘Can a dog move?’, two partial pattern matches with the facts ‘A dog is an animal’ (match on ‘dog’) and ‘An animal can move’ (match on ‘move’) are identified in combination with the semantic connection between ‘dog’ and ‘animal’, which expresses generalization.

An alternative possibility is that one of the information items involved in the matching is actually stored in pSTM as a consequence of some working memory activity. In this case, the semantic connection may be identified between a fact in LTM and a fact in pSTM or even between two facts in pSTM. Representations of automatic activities are stored in the procedural part of LTM and are not driven by goals. For example, the behavior of an experienced car driver is mostly automatic: the driver is aware of the high-level tasks that are carried out, but is not aware of low-level activities such as changing gear, using the indicator and reacting to the presence of a traffic light or a zebra crossing. These low-level activities are performed automatically as a direct response to specific perceptions whose selection is controlled by the information stored in STM, with no involvement of actual reasoning activities. Thus, in this approach, attention is modeled as an STM/working memory process [17].

3.1 Modelling Maintenance and Learning Mechanisms

Inspired by Burgess and Hitch’s ‘fast’ and ‘slow’ short-term learning processes [10], we model articulatory rehearsal by associating each information item (or chunk) stored in pSTM with a decay time and lifetime. The former is the remaining time after which the information item would be removed from STM for natural decay, in the absence of any form of maintenance or reinforcement. The latter is the entire lifetime of the item from the moment it is stored to the moment it is removed.

The ‘fast’short-term learning process is controlled by the decay time, while the parallel ‘slow’ learning mechanism is represented by an increase in the information lifetime. Such an increase can be set in a way that can accommodate a specific hypothesis or theory by using appropriate equations to define operator maintenance-effect. For example, we can model a small, constant increase at each rehearsal loop or we may implement the suggestion by Naveh-Benjamin and Jonides [29] that the first rehearsal is the most important, because it involves producing the articulatory plan, with subsequent loops of that plan within pSTM adding little to the transfer to LTM.

Refreshing of an item in pSTM may be activated by questions which involve the identification of semantic connections between facts in pSTM and facts in LTM. For example, if we have just read the fact that ‘a dog is an animal’, which we were unaware of, this fact is stored in pSTM but is not present in LTM. In pSTM, the fact is associated with an initial decay time that equals the lifetime. If we are then asked to answer the question 'Can a dog move?', we may actually use the new fact to access the LTM fact that 'an animal can move' and find out that also 'a dog can move'. In our model this usage of the newly read fact in pSTM increases its lifetime and resets its decay time to the value of the lifetime. Such a process promotes learning by expanding the lifetime of facts in pSTM that are used to access information in LTM. We also consider a lifetime threshold for the transfer of information from pSTM to LTM, so that the repetition of the refreshing process will eventually lead to a transfer of the fact from pSTM to LTM, where it is finally stored permanently, thus completing the knowledge acquisition process.

4 A Tool for Simulating Learning Processes and Performing In Silico Experiments

Although the experimental evidence described in Sect. 2 has been greatly informative on elucidating the overall human memory system, other approaches are available. One of these is producing various forms of in silico simulations, which can then be tested in different circumstances, using hypotheses derived from the experimental cognitive literature. For example, Oberauer and Lewandowsky [33] have used a neural network approach to model their Time-Based Resource-Sharing (TBRS) model approach to working memory, showing that it can produce many of the phenomena associated with human performance on experimental tasks designed to assess working memory. In fact, a basic version of the TBRS neural network implementation has been used to compare articulatory rehearsal and refreshing mechanisms directly in pSTM, and reported that the former performed substantially below the level of the latter as an STM trace maintenance mechanism [25].

In this section we describe how to carry out in silico experiments by using our own formal-modelling approach, which we have implemented using the real-time extension of Maude [34]. Our approach supports the modeling of experiments in terms of sequences of perceptions present in the environment with which the human memory model interacts. Each perception is associated with a starting time and a duration. When the starting time is reached the perception may be transferred to pSTM, depending on the attentional mechanism controlled by the content of pSTM.

We use in silico experiments to compare alternative hypotheses and theories that describe the transfer of information from pSTM to LTM through rehearsal and refreshing. One way to carry out such a comparison is to determine and test alternative quantitative implementations of conceptual hypotheses or theories, as we proposed for the parallel learning mechanisms within pSTM proposed by Burgess and Hitch [10] and for the Naveh-Benjamin and Jonides hypothesis [29] about the initial articulatory plan for a rehearsal loop being the most important factor contributing to retention within LTM. Another approach is the direct comparison of alternative estimates from cognitive psychology or neuroscience. This is the case for pSTM decay time, and for inclusion of the time to read a sentence, i.e., the initial conversion of the orthographical format into the phonological format, estimated at about 100 msecs by Kolers [24].

Furthermore, the results of in silico experiments may also be compared with real datasets to evince which model best mimics reality. In addition to a manual comparison, we can use the methodology defined in our previous work [19] in order to formally validate hypothesis, automatically converting a dataset into a formal representation that can be composed in parallel with our human memory model. Finally, from a computer science perspective, the human memory model of a user can be combined with the model of the computer system or application in order to analyze properties of the interaction, such as usability, learnability and safety.

4.1 Tool Implementation

The purpose of our tool is to perform in silico experiments that allow researchers to compare and analyse hypothesis and theories related to human memory. Users of the tool are able to automatically generate a formal model of the human component and analyse the overall system by performing simulation and checking properties.

The tool can be downloaded from a GitHub repository[1]. It is equipped with a simple and concise interface which was implemented using the Python GUI framework, an MySQL database, and the Maude rewrite system. The tool interface allows the researcher to model human memory in a BRDL-like fashion and the resultant model is automatically translated into a formal model expressed using Real-Time Maude. The tool allows for the adjustment of memory parameters before running experiments. The results of the in silico experiments are then visualised by the tool by appropriately changing the content of the human memory model.

The tool supports project and version control to make the user's experience friendly, reliable and maintainable. The user can create a project with a number of versions to compare the results of different in silico experiments, using various combinations of the parameters of the memory. The project page (Fig. 1) represents a simplified simulation of human memory.

This main project page allows the researcher to define a model of human memory by entering the contents in the various memory components. Episodic memory and sensory memory are not implemented in the current version of the tool. However, sensory memory is implicitly given by the presence of timed perceptions in the environment. The timing may be actually used to characterise the duration of the perception in sensory memory. BRDL fact representations, inference rules and deliberate basic activities are stored in semantic memory, while automatic basic activities are stored in procedural memory. Normally, the short-term memory is initially empty, but several parameters can be set by the

[1] https://github.com/nuraynab/interactive-system-modelling.

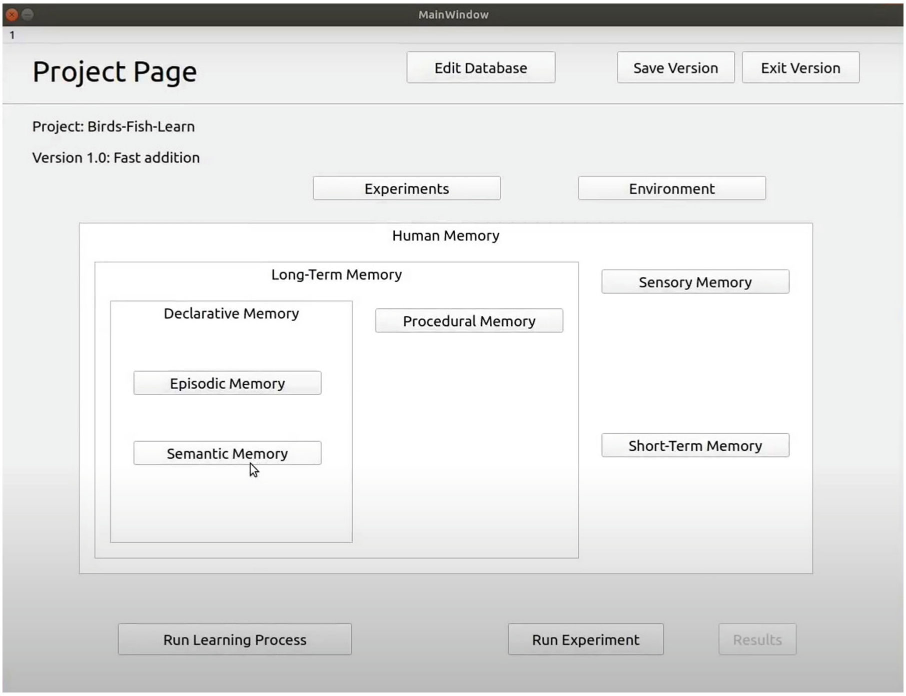


Fig. 1. Project main page.

experimenter: STM capacity and cognitive load (a load due to other tasks, which are not explicitly modeled) as well as information initial lifetime and its increase due to the information persistence in pSTM.

Experiments are timed sequences of facts and/or questions, which in a real experimental setting with human subjects may appear on a screen for a given duration at given time intervals. These timings are set by the user before running the experiment. As can be seen from the buttons in Fig. 1, the tool can run two kinds of experiments, that is, two functionalities: a 'proper' experiment or a learning process.

A 'proper' experiment may be a timed sequence of questions that are generated in the environment, are perceived and then enable a memory process that retrieves information from the semantic memory in order to produce the answer in STM and then transfer it to the environment. Another form of 'proper' experiment may be a timed sequence of generic perceptions that the 'virtual' subject has to rehearse. The experiment functionality can be used to study information retrieval from semantic memory and maintenance rehearsal in pSTM.

A learning process normally occurs over a long period of time, which can seldom be incorporated within any real experiment with human subjects. Here the 'experiment' is a timed sequence of facts and questions that are generated in the environment, are perceived, and then enable a number of memory processes, including retrieval of information from the semantic memory, inferences, automatic action performance, deliberate action planning and performance, and transfer of information from short-term memory to semantic memory. The learning process functionality allows users to investigate various forms of rehearsal, such as elaborative rehearsal and refreshing.

4.2 Illustrative In Silico Experiments

In order to illustrate the use of our tool, we consider two experiments from the cognitive science literature.

Collins and Quillian's Experiment. The first experiment is a classic in cognitive science. It was carried out by Collins and Quillian [20] in 1969 to show that the time to retrieve information from LTM is proportional to how far we need to navigate the LTM network to find the requested information. In fact, the results of this experiment supported the definition of the hierarchically organised memory model, still largely accepted nowadays.

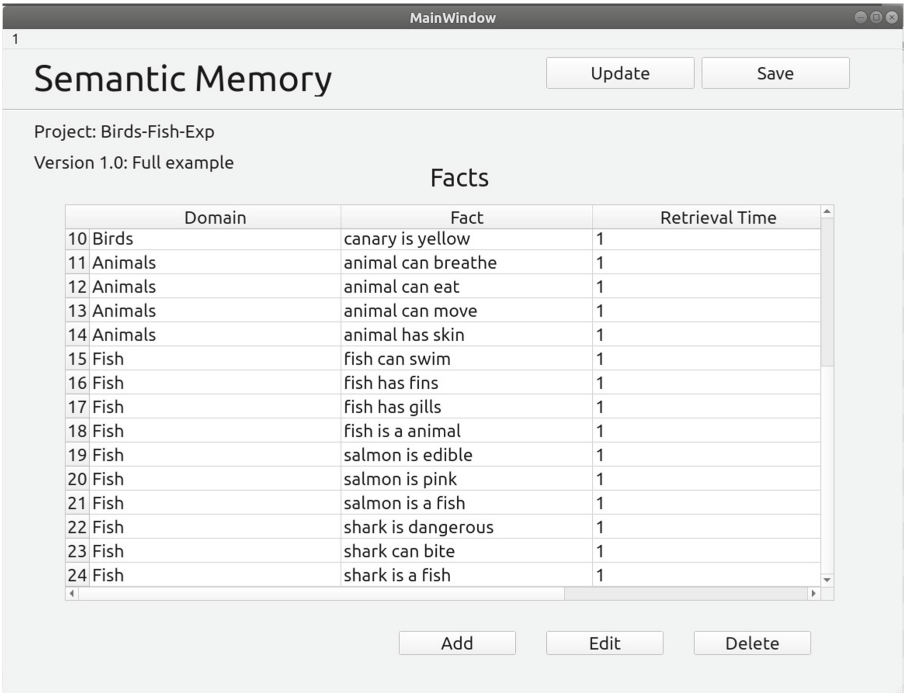
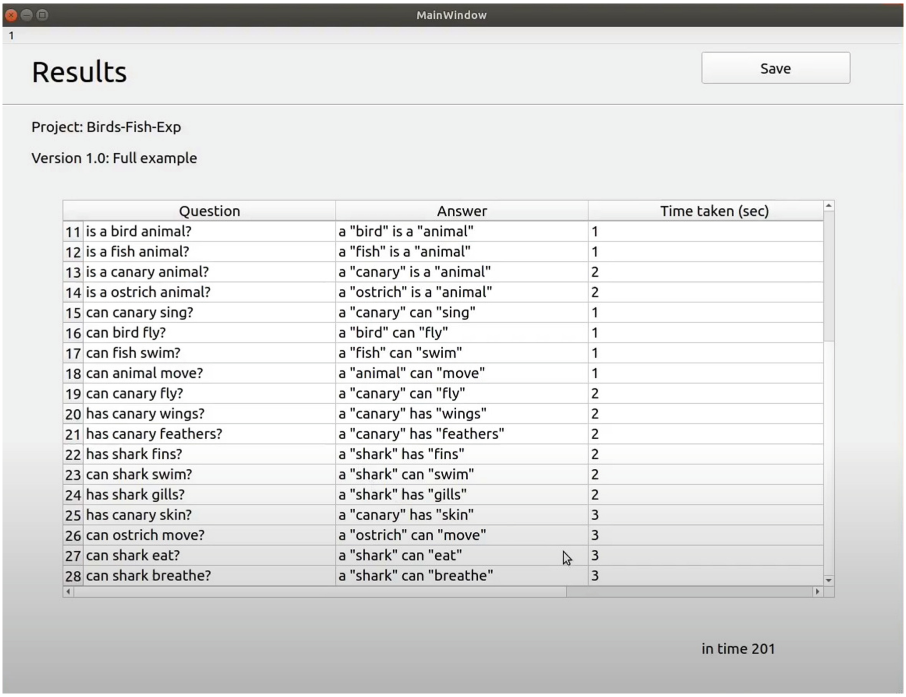


Fig. 2. Initial setting in the in silico replication of Collins and Quillian's experiment.

In this experiment, the semantic memory model consists of three domains "Animals", "Birds", and "Fish". Collins and Quillian's hypothesis was that instead of saving the fact “Shark can swim” in the model it is more memory efficient to retrieve this data from the category relation, in particular from the facts that shark is a fish and a fish can swim. However, in this way, the time to retrieve the fact from the hierarchical model will be longer than if it had stored and retrieved it directly from semantic memory. Therefore, they concluded that the deeper the information in semantic memory the longer it will take time to retrieve it. This works under the assumption that it takes an equal amount of time to get the fact from a single node regardless of its level. Collins and Quillian’s experiments produced results in accordance with their hypothesis.

To replicate this experiment in silico, we create a semantic memory with 24 facts about animals, birds and fish, using, for sake of simplicity, the same retrieval time of one unit. The initial setting of the experiment is shown in Fig. 2. The experiment component includes 34 questions, each available for 2 seconds. After running the experiments, 28 questions resulted answered, as shown in Fig. 3. Not all the questions were answered due to pSTM limited capacity and information decay time.



	Question	Answer	Time taken (sec)
11	is a bird animal?	a "bird" is a "animal"	1
12	is a fish animal?	a "fish" is a "animal"	1
13	is a canary animal?	a "canary" is a "animal"	2
14	is a ostrich animal?	a "ostrich" is a "animal"	2
15	can canary sing?	a "canary" can "sing"	1
16	can bird fly?	a "bird" can "fly"	1
17	can fish swim?	a "fish" can "swim"	1
18	can animal move?	a "animal" can "move"	1
19	can canary fly?	a "canary" can "fly"	2
20	has canary wings?	a "canary" has "wings"	2
21	has canary feathers?	a "canary" has "feathers"	2
22	has shark fins?	a "shark" has "fins"	2
23	can shark swim?	a "shark" can "swim"	2
24	has shark gills?	a "shark" has "gills"	2
25	has canary skin?	a "canary" has "skin"	3
26	can ostrich move?	a "ostrich" can "move"	3
27	can shark eat?	a "shark" can "eat"	3
28	can shark breathe?	a "shark" can "breathe"	3

Fig. 3. Results for the in silico replication of Collins and Quillian’s experiment.

Answers that could fully match the questions could be retrieved directly, thus requiring only one time units. For example, fact 18 “A fish is an animal” in Fig. 2 fully matches question 12 “Is a fish an animal?” in Fig. 3.

Instead, question 28 “Can a shark breathe?” in Fig. 3 is not fully matched by any fact representation. Answering the questions requires claiming the fact hierarchy in semantic memory (refer to the fact numbers in Fig. 2):

1. first by matching “shark” from the question with fact 24 “A shark is a fish”;
2. then by matching “fish” from fact 24 with fact 18 “A fish is an animal”;
3. finally by matching “animal” from fact 18 and “breathe” from the question with fact 11 “An animal can breathe”.

For this reason answer 28 in Fig. 3 is retrieved in 3 time units.

Souza and Oberauer’s Experiment. The second experiment was carried out by Souza and Oberauer [37] in 2017 to show that it is the total time duration that information spends in pSTM that influences whether or not it becomes represented in LTM. In their experiments, they used slower versus faster presentation of information. Slower presentation allows information to stay in STM for longer periods. In fact, slower presented information was found to be more likely to transfer to LTM.

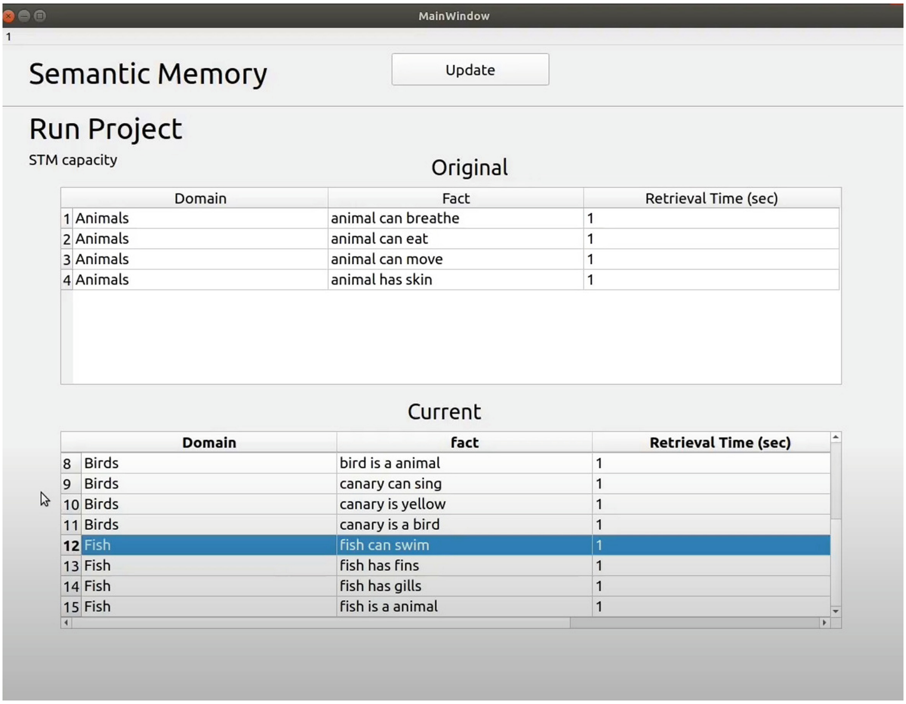


Fig. 4. Original and Final (Current) content of semantic memory for the in silico replication of Souza and Oberauer’s experiment.

For this experiment, which is the in silico emulation of a learning process occurring over a long time, the semantic memory only contains the four facts in the table labelled "Original" in both Fig. 4 and Fig. 5. The same human memory model underwent two experiments. Also the facts and questions in the experiment setup were the same. However, the persistence time of the perceptions were different.

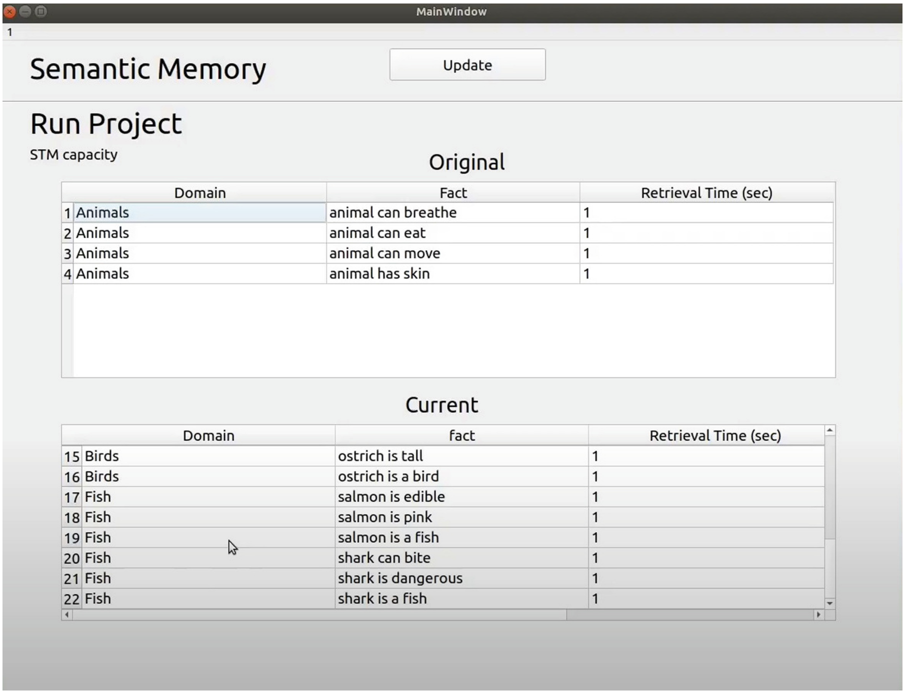


Fig. 5. Original and Final (Current) content of semantic memory for the in silico replication of Souza and Oberauer's experiment.

To simulate fast learning facts and questions were presented every 2 time units, whereas to simulate slow learning they were presented every 10 time units. As shown in the tables labelled "Current" in Fig. 4 and 5, semantic memory contains 15 facts in the case of fast learning (Fig. 4) and 22 facts in the case of slow learning (Fig. 5), which is consistent with Souza and Oberauer's experimental results [37] and Burgess and Hitch's neural network model [10] where slow learning is more effective than fast learning.

5 Conclusion and Future Work

In this paper we presented an approach and tool for the simulations and analysis of memory processes and learning mechanisms underlying pSTM maintenance and transfer of information to LTM. We built up on our previous work by using BRDL [15] to model the human memory content, and its Real-Time Maude implementation [16–18] to provide dynamics to BRDL models. With respect to our previous work we extended the Maude implementation with the timing infrastructure to support the modelling of fast and slow learning mechanisms. We tested our approach by comparing the outcome of our in silico simulation with Souza and Oberauer's experimental results [37].

Moreover, the tool addresses cognitive scientists, who are obviously not familiar with formal methods and would have difficulty in using Maude directly as the modelling language. By using the tool interface they can replicate in silico their experiments with human subjects and compare their experimental results with various human memory models. This approach can provide a form of empirical validation for a number of cognitive models.

In our future work, we are planning to generalise the scope of the tool by combining the human memory component with the model of an interacting computer/physical system. Such an overall model could be formally verified using Real-time Maude model-checking features. Furthermore, we plan to have a web-based version of this generalised tool and equip it with features for supporting remote collaboration among research teams.

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