An Analysis of the Implementation-Potential of the Threaded Engram Database Model

By

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ABSTRACT

The row-and-column orientation of the Relational Database Model is optimized for the storage of "data," but is not optimized for the storage of "information." This capstone project, researches the different human memory models, in-order to understand how memories are formed and how independent memories are linked together. The memory models explored include the Atkinson-Shiffrin memory model, Baddeley's model of working memory, and the Memory-Prediction model. The results of this investigation of human memory serve as a foundation for the design and implementation of a new database model, called the Threaded Engram Database (TED) model.

Keywords: Threaded Engram Database Model, Relation Database, Engram, Memory Models

TOPIC STATEMENT/HYPOTHESIS

The Relational Database Model was first introduced in 1969 by E.F. Codd in an IBM Research Report titled, "Derivability, Redundancy, and Consistency of Relations Stored in Large Data Banks." Over the past few decades, the model has become the de facto standard for data management and is generally used whenever an individual or organization needs to store a large amount of information in an efficient and organized manner. Today, there are numerous widely successful products in the marketplace, such as Oracle, IBM's DB2, and Microsoft SQL Server, all of which are based upon the relational database model. However, the explosive increase in web services and document types over the past decade has begun to highlight the limitations of this model.

The widespread use of the Internet has led to the advent of Web services like Hulu (http://www.hulu.com/), YouTube (http://www.youtube.com/), Flickr (http://www.flickr.com/), etc. which provide us with instant access to videos, music, and photos. Also, organizations are rapidly adopting the latest available computing technologies and are generating data in a variety of formats: Word documents, Web pages, emails, etc. All of this "unstructured data" is generally stored in relational databases despite the fact that the relational database model was not originally designed to store unstructured data. Although database vendors have definitely made great strides in trying to come-up with new data types like Large Objects (LOB), Character Large Objects (CLOB), and Binary Large Objects (BLOB), the storage and retrieval of unstructured objects from any relational database is far from efficient. Additionally, the definition of relationships in a relational database is limited to the foreign keys that have to be created and maintained by the database administrator. These foreign key relationships are generally insufficient to represent all the multifaceted relationships that exist amongst data in the real world. Furthermore, the simplistic, table-based structure utilized by relational databases makes it extremely difficult to represent relationships that span across multiple levels of a hierarchy (Bloor 5).

This capstone thesis will draw inspiration from human memory models for the design and implementation of a new database model called the Threaded Engram Database (TED) Model (Zilora).

Hypothesis Statement: Human memory models can serve as the basis for the design of a new database model. The implementation of this database model can be accomplished using a flexible logic programming language like Prolog, neural networks, or a combination of both.

MEMORY: A HISTORICAL PERSPECTIVE

The interest in, and study of, human memory is not of recent origin, rather there has been slow but gradual progress towards the understanding of human memory over the past few centuries. As such, it is important to review the basic concepts and ideas which are common across the memory models explored in this capstone.

The earliest available reference to the study of human memory dates back to the twentieth century when Aristotle (384 BC – 322 BC), in trying to understand memory, compared the human mind to a *tabula rasa* (Latin for blank slate), in his treatise titled "de Anima" (English translation: On the Soul [sic]) Aristotle postulated that a newborn child does not possess any innate ideas, or intellect, and only has the capacity to receive new ideas on the basis of his senses. Although numerous philosophers and thinkers weighed in either for or against Aristotle's treatise, little empirical progress was made in understanding the workings of human memory until the eighteenth century, when a German psychologist named Herman Ebbinghaus (1850 –

1909) designed and executed experiments to deduce the learning and forgetting curves associated with learning new information (Mastin; Rafed).

Ebbinghaus

Based upon prior experiments, Ebbinghaus knew that people can easily memorize long lists of words provided that the words are familiar to them and that they can form some sort of association between the words. For example given a list of words such as root, stem, branch, and leaf, a person can easily memorize the word list by associating these descriptive words with a "plant," thus defeating the purpose of the memory experiment. Therefore, Ebbinghaus created a list of two thousand three hundred nonsense syllables, such as NOG, BOL, BAF, etc., containing a consonant-vowel-consonant combination which would normally not be associated with any commonly used words. He then performed memory experiments on himself, wherein he memorized a subset of the nonsense syllables and recorded the number of syllables he was able to recall at specific time intervals, such as after twenty minutes, an hour, a day, etc. Based upon the results of his experiments, Ebbinghaus was able to generate an exponential learning curve showing that when we engage in repetitious learning to memorize new information, we learn the most during our initial attempts, but the incremental amount of information retained in our memory decreases with an increase in the number of repetitions. See Appendix A for a sample learning curve. Secondly, his experiment allowed him to generate an exponential forgetting curve that depicted the speed with which we forget newly learned information. He found that forgetting occurs most rapidly during the first twenty minutes after our learning the new information and then gradually levels off over a period of time. See Appendix B for Ebbinghaus's forgetting curve. Thirdly, he was able to empirically prove that an increase in the amount of new information that needs to be learned will cause a proportional increase in the amount of time it will take to learn the new information (Ebbinghaus 51; Plucker; Adams).

The research and experiments performed by Ebbinghaus greatly extended the scientific knowledge base. The empirical experimentation and methodological innovations used by Ebbinghaus in his experiments helped establish a de facto standard that was then followed by the rest of the scientific community. Additionally, the results of Ebbinghaus's experiments helped establish that while meaningful stimuli are fairly easily to memorize, due to the fact that they can be easily associated with preexisting knowledge or experiences, memorizing meaningless stimuli is far more difficult since no associations can be made prior knowledge. Thus, Ebbinghaus provided empirical proof for the widely held belief that it is much harder to learn information that has no relevance to a person. However, despite proving the importance of preexisting knowledge and experiences in learning new information, Ebbinghaus never postulated the mechanism which is used to store new experiences or form new associations with pre-existing knowledge (Plucker).

Semon

While Ebbinghaus's application of the scientific method in his studies was primarily responsible for ushering the study of human memory from the field of philosophy into the realm of science, it was the work of Richard Wolfgang Semon (1859 – 1918) that was responsible for providing the scientific community with a viable model for the storage and recall of memory in the nervous system. Semon first proposed the hypothetical concept of a "trace" or an "engram" in a book titled, "Die Mneme." He used it to describe the physical and chemical changes that occur in the nervous system, whenever we experience new stimuli (Semon). He postulated that the stored memory can be revived or recalled whenever a person is re-exposed to the same or similar stimuli. He introduced the concept of “ecphoric stimulus,” to describe the cue that can be used to trigger the recall of a specific memory. According to Semon, this ecphoric stimulus could be a partial section of the very same trace or another trace that is very similar to the trace that needs to be recovered.

Prior to the Semon’s introduction of the concepts of “trace” and “ecphoric stimulus,” researchers studying human memory were focused on trying to understand the processing that takes place when a memory is formed, by following the logical (stepwise) process that they thought led to the formation of memories. Semon adopted a markedly different approach when studying human memory by initially abandoning the study of the steps that lead to the physical encoding of memory; rather, he focused on the question of “How are memories actually stored?” Semon’s theory was well received by the scientific community, and he was responsible for starting extensive research to detect traces and discover the reasoning behind trace decay or forgetting ("Richard Semon: Define, Explore, Discuss").

There were a few key limitations in the work done by Semon. Firstly, Semon provided no empirical basis for his assertion that memories are stored as traces. While his proposed theory certainly doesn’t lack merit, the fact that is isn’t backed up by specific observations or experiments means that there is no way for scientists to either prove or disprove this theory. Secondly, building upon the previous limitation, since there is no way to prove the existence of a trace, there is essentially no viable way to test and see if the ecphoric stimuli do indeed work and cause us to recall or recover a trace (“Semon, Richard (1859-1918)”).

McGeoch

Up until 1932, trace decay was believed to occur primarily due to the spontaneous decay of the memory trace, over the time period during which it is disused (not accessed or retrieved), thus leading to a person forgetting the requisite information. However, in 1932, John A. McGeoch (1897 - 1942) challenged this assumption by questioning the validity of blaming an independent variable like time for trace decay, and he proposed that interference is what causes loss of retention. His argument against trace decay deserves special mention and is reproduced verbatim below:

> "Even were disuse and forgetting perfectly correlated, it would be fruitless to refer the forgetting to the disuse as such. Such reference is equivalent to the statement that the passage of time, in and of itself, produces loss, for disuse, literally interpreted, means only passivity of time. In scientific descriptions of nature time itself is not employed as a causative factor nor is passive decay with time ever found. In time iron, when unused, may rust, but oxidation, not time, is responsible." (McGeoch 539)

McGeoch's theory of interference for forgetting states that retention loss occurs primarily because of competing stimuli or responses that a person might have acquired or experienced either before the memory test, i.e. proactive inhibition, or during the time period between memorizing the list and being tested for recall, i.e. retention interval. Numerous experiments have been performed over the years to ascertain the cause and effect of different types of interference on human memory (McGeoch).

The classic format followed for the proactive interference experiments is that a test subject is provided with a sequence of letters, such as AC, AB, and asked to memorize the AC sequence before being asked to memorize the AB sequence. A memory test is performed after a specific retention period, during which the subject is presented with the prefix of the letter sequence, in this case A, and is asked to state the first suffix that comes to mind. The subjects are supposed to respond with the suffix C, but it was found that since the AB sequence constitutes sequential alphabets in the English Language, the subject's experience "proactive inhibition" and state AB, rather than AC as the answer. Similarly, in a retroactive inhibition interference experiment, a test subject is asked to memorize a sequence of letters, such as AB, but the subject is exposed to a conflicting sequence of letters, such as AC, during the retention period. Upon completion of the retention period, the test subject is tested by providing them with the prefix of the letter sequence and is asked to state the first suffix that comes to mind. If the subject responds with AC as the letter sequence, it proves that retroactive inhibition has taken place and caused a retention loss of the initial stimuli (Adams 69; McGeoch).

McGeoch is one of the most successful and recognized figures in the memory research area of verbal learning. His assertion that the passage of time cannot be used as a viable means to explain the occurrence of trace decay and his postulation that it is the activities that occurred during this passage of time that is responsible for trace decay were responsible for nudging the scientific community towards the study of "interference" and the numerous ways in which it can negatively influence the retention of given trace in our memory. A key limitation in McGeoch's work is that, although he did postulate that the passage of time cannot be used as the cause for the occurrence of trace decay, his discounting of time as a variable that had no effect on trace decay was erroneous. This is so because, time is generally used as an independent variable against which scientific processes are usually measured and all experiments generally revolve around it. As a result, the current belief is that time cannot entirely be discounted as a causative factor with regard to trace decay (Adams 69).

Peterson and Peterson

McGeoch's experiment inspired Lloyd R. Peterson and Margaret J. Peterson to design and execute a simple, but elegant, experiment that tested the retention interval of short-term memory (STM). In this experiment, the test subjects were asked to memorize a single three-unit consonant syllable, such as QFZ, followed by the backwards counting of numbers. This backwards counting of three digit number in threes (e.g. 333, 330, 327, etc.) defined the retention period and was used to ensure that the subjects did not get the chance to rehearse the assigned syllable during that time period. At the end of the retention period (the interval of which varied between three, six, nine, twelve, fifteen or eighteen seconds) the subject was asked to recall the consonant that they had memorized. The results of this test showed that the subjects experienced rapid forgetting as the retention interval increased from three to eighteen seconds. See Appendix C for a graph of these short-term retention interval results. This loss of retention over such a short period of time provided empirical proof of the existence of STM (Adams 107; L. Peterson and M. Peterson).

Prior to Peterson and Peterson's retention interval experiment, scientists were of the opinion that forgetting (or trace decay) generally takes place over a period of hours; however, by means of their landmark study, Peterson and Peterson were able to prove that that under the right conditions subjects could forget almost all of a learned stimulus in as little as eighteen seconds. Their experiments with the retention interval of short-term memory were responsible for reviving interest in the study of, and experimentation with, STM and exploration of the relationship between STM and Long-Term Memory (LTM) (Adams 109).

Jenkins and Dallenbach

Similar experiments were performed by John G. Jenkins and Karl M. Dallenbach (1895 - 1969) in 1924, to gain empirical evidence of the presence of long-term memory. In these experiments, the subjects were asked to memorize a list of ten nonsense syllables, until they were able to correctly repeat the list verbatim. The test subjects were then separated into two groups. The first group stayed awake, whereas the other group had to sleep in the lab for the duration of a "retention interval." The hypothesis in this experiment was that the test subjects that stayed awake would be exposed to much more interference than the group that spent the retention interval sleeping. The retention intervals that the scientists used were one, two, four and eight hours. At the end of each retention interval the subjects were asked to recite the nonsense lists from memory. See Appendix D for retention interval for long-term memory graph. The scientists found that the test subjects who spent the retention time sleeping in the lab retained almost twice the amount of nonsense syllables, as compared to the test subjects that spent the time awake, thus leading the authors to conclude that "forgetting is…the interference, inhibition, or obliteration of the old by the new" (Adams 183; Jenkins and Dallenback 612).

While the affect of interference on STM was extensively studied and was fairly well documented, it wasn't until Jenkins and Dallenback performed this landmark experiment that the effect of interference on LTM became evident. Their study was able to empirically establish that interference was not merely a STM phenomenon; rather, it tends to afflict both STM and LTM equally. Their findings were supported by the experimental results of the scientific community and were responsible for augmenting the understanding of the working of LTM, as well as, the causative factors of memory loss in LTM.

Permanent Memories

Although it is generally accepted that interference does indeed play a role in memory retention loss, it is important to note that the acceptance of the effects of interference on human memory does not discount the theory of memory trace. Rather, it can be argued that interference merely acts as an agent to inhibit the activation of a memory trace by means of a given stimulus. The proponents of this inhibition theory of human memory maintain that human memory is essentially permanent, and that forgetfulness only occurs because of inhibition of the underlying traces, which are essentially intact and can be accessed by removing the inhibitory barrier surrounding the trace (Adams 29). In his 1896 essay, "The Aetiology of Hysteria," Sigmund Freud (1856 - 1939) proposed the concept of repressed memories or motivated forgetting, wherein an individual either consciously or unconsciously tries to forget, or inhibit, unwanted, hurtful or traumatic memories. There are numerous real life examples wherein victims of traumatic events either don't remember anything, or only parts of the event, although they were conscious and alert throughout the occurrence of the event. However, when these victims are questioned under hypnosis, or by means of visualization; group therapy; or trance writing, they are able to retrieve their repressed memories (Carroll).

Penfield

While the theory of permanent memory provides some fairly interesting implications for memory research and its application potential, only the works of Wilder Penfield (1891 - 1976), a clinical surgeon, provide any empirical verification of the permanence of memory. In 1959, while conducting a craniotomy, Penfield stimulated a patient's temporal lobe and was able to recreate the patient's childhood experience which generally accompanied their epileptic attacks. One of the most interesting aspects of the patient's recall process, as reported by Penfield, was that:

> "It [the memory recalled by the patient] may produce the picture, but the picture is usually not static. It changes, as it did when it was originally seen and then the individual perhaps altered the direction of his gaze. It follows individual observed events of succeeding seconds or minutes…The thread of continuity, in evoked recollections, seems to be time. The original pattern was laid down in temporal succession. And it is the thread of temporal succession that later seems to hold the elements of evoked recollection together" (Penfield 24).

Penfield was able to perform the same experiment and replicate the results in more than 1000 craniotomies. He used his observations to propose a mechanism for the storage of human memory that incorporated the physical structures of brain (Penfield).

According to the Penfield's observations, the stimulation of the temporal lobes was the primary cause of a complete and realistic recall of childhood memories, including acute recall of all colors, sounds and emotions the test subject felt at that point in time. Based on this evidence, he labeled the temporal lobes as the "interpretive cortex," although he did realize that the memories evoked by the temporal cortex are not actually stored in the temporal cortex, since the complete removal of the temporal cortex didn't cause a person to lose his recall of the event in question (Penfield).

While numerous authors proposed various mechanisms and methodologies for the coding, storage and retrieval of memories – be it STM or LTM – no viable evidence has ever been found to support any of these hypotheses. Penfield's innovative and systematic study of the effects of electrical stimulation on the brain provides us with an empirically verified hypothesis that memories might actually be permanent. However, even though the hypothesis of permanent memories has always been a minor theme in psychological literature, it has never been pursued seriously as a viable alternative to the standard memory hypotheses that revolve around the existence of STM and LTM. One of the primary reasons for this sidelining of the permanent memory hypothesis is the change in the legal and ethical environment. While it was once acceptable to electrically stimulate the temporal lobes of a patient to see what response, if any, occurs, this very same act is now illegal. Additionally, since a disproportionately large proportion of the scientific community has been focused on research into short-term and long-term memory, the research into the permanent memory hypothesis has faded into obscurity (Adams 37).

Distinctions between Long-Term Memory (LTM) and Short-Term Memory (STM)

Throughout the history of psychology, exploration of human memory had been based on the assumption that our brain treats both immediate and past events equally, and that all memories are stored in the same way and in the same location. However, the interference experiments performed by Peterson and Peterson, as well as, Jenkins and Dallenbach proved that while we generally don't experience a difference in the way that we access and retrieve information from our memory, there really are two distinct memory stores, namely short-term memory and long-term memory. The following is the empirical and experimental evidence which helped confirm the dual-store memory hypothesis:

I. Physiological Evidence- There is empirical evidence of the distinctions between long-term and short-term memory. Numerous experiments have been performed on people who have experienced damage to the hippocampus through lesions or accidents, or whose hippocampus was removed to resolve life threatening seizures. These test subjects were found to have impaired learning of new information, when compared to the control subjects who didn't have any hippocampal damage.

In their paper titled, “Loss of recent memory after bilateral hippocampal lesions,” Brenda Milner (born 1918) and William B. Scoville (1906 – 1984) outline the case of a patient whose hippocampus was excised to treat his frequent severe seizures. A few months after the operation, the authors interviewed the patient and found that although he had retained his long-term memories, he wasn’t able to learn new information. So much so that, even though his parents had moved to a new home ten months prior to the authors interviewing the patient, he had still not learned the new address and could not be trusted to find his way home on his own. As such, there was a severe disconnect between his short-term and long-term memory. Though he retained his long-term memory, he wasn’t able to create new memories (Scoville and Milner 14; Adams 42).

II. Interference- Different types of interference tend to affect STM and LTM differently. Interference in the STM tends to occur primarily due to the acoustic similarity of items being learned, whereas interference in LTM tends to occur primarily due to the semantic similarity of two experiences or items in memory.

A prime example of acoustic similarity affecting STM memory occurs when a subject is asked to memorize letters that sound similar, such as B, C, P, T, V, F, M, N, S, and X (Conrad). Researchers found that test subjects frequently forgot, or got confused, when trying to remember these letters. This is markedly different from semantic-similarity-based interference in LTM in which conceptually similar words or pictures can lead to interference. Examples of semantic interference occurs when a subject is exposed to a picture of a cat titled as a “house,” a castle titled as a “house,” a picture of an actual house, and the word “house,” and is then tested to see how many variants of house the subject remembers (Van Maanen and Van Rijn 324). See Appendix E for pictorial example of semantic interference.

III. Capacity- Numerous experiments performed between 1910 and 1960 have determined that the STM can only store a few items, somewhere in the range of seven to ten items, whereas LTM's capacity is considered to be so large that it has yet to be quantified empirically. This large variation in memory capacities is commonly cited as the leading difference between LTM and STM (Adams).

Role of Natural Language Mediators

Although the experiments and observations outlined in previous sections empirically prove that interference plays a role in retention loss, it is important to remember that these experiments only test retention loss with regard to rote memorization, whereas most of what we learn on a daily basis occurs by means of Natural Language Mediators (NLM). Experiments performed by Underwood and Schulz, Clark, Lansford and Dallenbach, and Bugelski provide ample evidence of the use of NLMs when assimilating new information into memory. NLMs occur whenever a test subject is asked to memorize something, be it an alphabetic sequence, a word, or a sentence. The subject automatically tries to mediate, or form associations, between the stimulus and response, thus helping them remember any new information (Adams). We frequently use various forms of NLM in our daily lives, but rarely ever notice doing so because they are second nature to us. The use of mnemonics such as "My Very Easy Method Just Sped Up Naming Planets" to learn the names of the nine planets in our solar system, the use of a sing-along rhyme to learn the multiplication tables, or memorizing the list of groceries by associating the required items with the fridge, bedroom, or bathroom are all forms of NLMs that we utilize on a daily basis. Depending on the amount of time we spend developing these NLMs and the frequency of their use; these NLMs might reside temporarily in our STM or may be stored permanently in our LTM, where they may be recalled when required.

NLMs play a very important role in helping us expand the capacity of STM and store more information in it. Additionally, NLMs might play a very important role in helping us not only link new information to preexisting knowledge, but they (NLMs) might also serve to tear down the barriers that are created by interference and renew the information that is stored in our LTM.

Underwood

Numerous "free recall" experiments have been performed to observe the effects of NLM on STM and LTM. In these experiments, the test subjects are provided a scrambled list of words that belong to the same conceptual categories or contain associations among each other. The subjects are allowed to read the list to commit it to memory, and are then asked to recall the contents of the list in whatever order they want. The scientists observed that the test subjects would rearrange the contents of the list into clusters of words based upon the conceptual categories or associations (Adams 153). A key experiment illustrating this concept was performed by Benton J. Underwood (1915 – 1994) in 1964, when he presented his test subject with four lists of words. Two of these word lists contained words that were of the same conceptual category and had strong associations among each other, whereas the other two lists contained words that were completely unrelated to one another. The following is an excerpt of the list of words that were utilized by Underwood in his experiment:

Word List 1	Word List 2	Word List 3	Word List 4
Apple	Bob	France	Daisy
Football	Bill	England	Wall
Emerald	Joe	Russia	Bee
Trout	John	Germany	Second
Copper	Rabbi	Blue Jay	Knife

Theft	Priest	Canary	Bus
Hat	Bishop	Sparrow	Geology
Table	Minister	Robin	Maple
Cruiser	Cow	Measles	Arm
Trumpet	Horse	Mumps	Hammer
Doctor	Dog	Polio	Salt
Head	Cat	Cancer	Tent
Wine	Rumba	Nitrogen	Cobra
Blue	Fox-trot	Oxygen	Mountain
Gasoline	Tango	Hydrogen	Window
Cotton	Waltz	Sulphur*	Rain

* This is the British spelling of Sulfur.

Table 1: Lists of words used by Underwood in his free recall experiment in 1964

Underwood found that thirty-eight percent of his test subjects were able to perfectly recall Word Lists 2 and 3, whereas only three percent of his test subjects were able to perfectly recall Word Lists 1 and 4. None of the test subjects were informed that Word Lists 2 and 3 had four categories of four words each, but all subjects were able to deduce the same and none of them provided more than four words per category during the recall test.

Based on the results of the experiment, Underwood concluded that the test subjects utilized category clustering and used a category as the smallest unit or "chunk" in their memory to learn the word lists. Since Underwood did not explicitly tell the test subjects that there were four items for each concept and a total of sixteen items in the experiment, he postulated that the test subjects utilized an editing process, which he called a "selector mechanism," to separate words from the list into multiple categories.

Underwood's proposal that a central editing process was responsible for the sorting and clustering of words from the wordlist was highly controversial and was immediately challenged by multiple scientists who argued that what was being called an "editing process" under the influence of a "selector mechanism" was nothing more than simple word association. An example helps explain this. If we present the word “table” to a test subject and asking him to verbalize the first word that comes to mind, the test subject may reply with “table-top” or “table-cloth” or “dining table.” This response is commonly known as the primary response of a stimulus and is the product of the test subject’s lifetime of learning which led to the creation of the given stimulus-response associations in LTM. According to Underwood’s opponents, the instantaneous word association formed by the test subjects in his experiment had little to do with the use of a selector mechanism or a complicated editing process, rather, they categorized their wordlists based upon simple word association.

Hellyer

Overt practice is another factor that plays an important role in helping us remember new information. While the use of NLMs is one way that we can remember a shopping list, the continuous verbal or visual repetition of the shopping list will also accomplish the same goal. In 1962, Hellyer performed a comprehensive study of the effect of the number of overt repetitions on the memory of test subjects. In the study, Heller presented the subjects with a three-unit consonant syllable, and asked them to repeat the syllable one, two, four, or eight times, so as to ensure sufficient overt practice. During the retention period of three, nine, eighteen, or twenty nine seconds, the subjects indulged in digit naming to ensure that they weren’t able to spend additional time reciting or memorizing the new information. Hellyer found that an increase in the number of repetitions was directly proportional to the decrease in forgetfulness.

Prior to Hellyer’s experiment, the scientific community was not in agreement on whether the amount that a subject practices a stimulus influences the associative strength of the item and increases its resistance to forgetting. The commonly held belief was that rehearsal only stalls the decay of a memory trace and that different amounts of practice would not affect the retention of information, since once the last repetition is complete, the decay process will continue on as before. However, by means of his experiments, Hellyer was able to conclusively prove that practice definitely slows down the rate of forgetting and his experiments paved the way for further research into the affect of repetition on STM and LTM.

Relationship between short-term and long-term memory

While it is fairly easy to classify STM and LTM as two different memory structures that operate on different principals, it is critical to realize that these distinctions of the workings of memory are done solely to simplify the study and understanding of memory. In actuality, LTM and STM are irrevocably interlinked and neither can exist independently without the other. The recognition of a picture, a word, or even a fragment of a song, all require extensive interaction between STM and LTM. The recognition of the fact that the word lists presented in the Underwood study contained words that belonged to specific categories requires the interaction of STM with LTM to ascertain whether the words relate to any overall concepts or categories which can actually be used to memorize the word list.

The preceding sections outline the research performed by various scientists that have provided a comprehensive understanding of the basics of human memory and played a critical role in designing the memory component of the TED model in this capstone. The following section outlines another paper that played a critical role in understanding the implementation potential and methodologies that can be utilized to implement the concepts learned from human memory into a computationally relevant TED model.

K. Joy and S. Dattatri

The Association for Computing Machinery paper, "Implementing a fuzzy relational database using community defined membership values" by K. Joy and S. Dattatri, explores the limitations of using the relational database model. According to the authors, the data stored in a relational database is extremely precise, or "grounded in black-and-white," whereas data in the real world is never really precise. In this paper, Joy et al. designed and executed a research project that implemented a fuzzy relational database which allowed the authors to represent imprecise data, such as the description of a picture or a person, using imprecise attributes based upon the feedback of the users. They did this by incorporating a "membership value" that would represent the truthfulness of the different image descriptions (Joy and Dattatri 268). This innovative use of fuzzy relations to describe imprecise or incomplete data in a database helped provide the initial stimulus for using a neural network, or a logic based language, to define the threads that connect the engrams in the TED Model.

HUMAN MEMORY MODELS

Numerous memory models have been proposed by scientists over the years. The following memory models were extensively studied for the purposes of this capstone: Atkinson-Shiffrin memory model (Atkinson and Shiffrin), Baddeley's model of working memory (Baddeley and Hitch) and the Memory-prediction model (Hawkins and Blakeslee).

Atkinson-Shiffrin memory model

In 1968, Richard C. Atkinson and Richard M. Shiffrin proposed a model for human memory in a paper titled, "Human Memory: A proposed system and its control processes." A graphic representation of Atkinson and Shiffrin's proposed structure of human memory and its inner workings, reproduced from the "Human Memory" article, by Atkinson and Shiffrin (93), can be seen below in Figure 1.

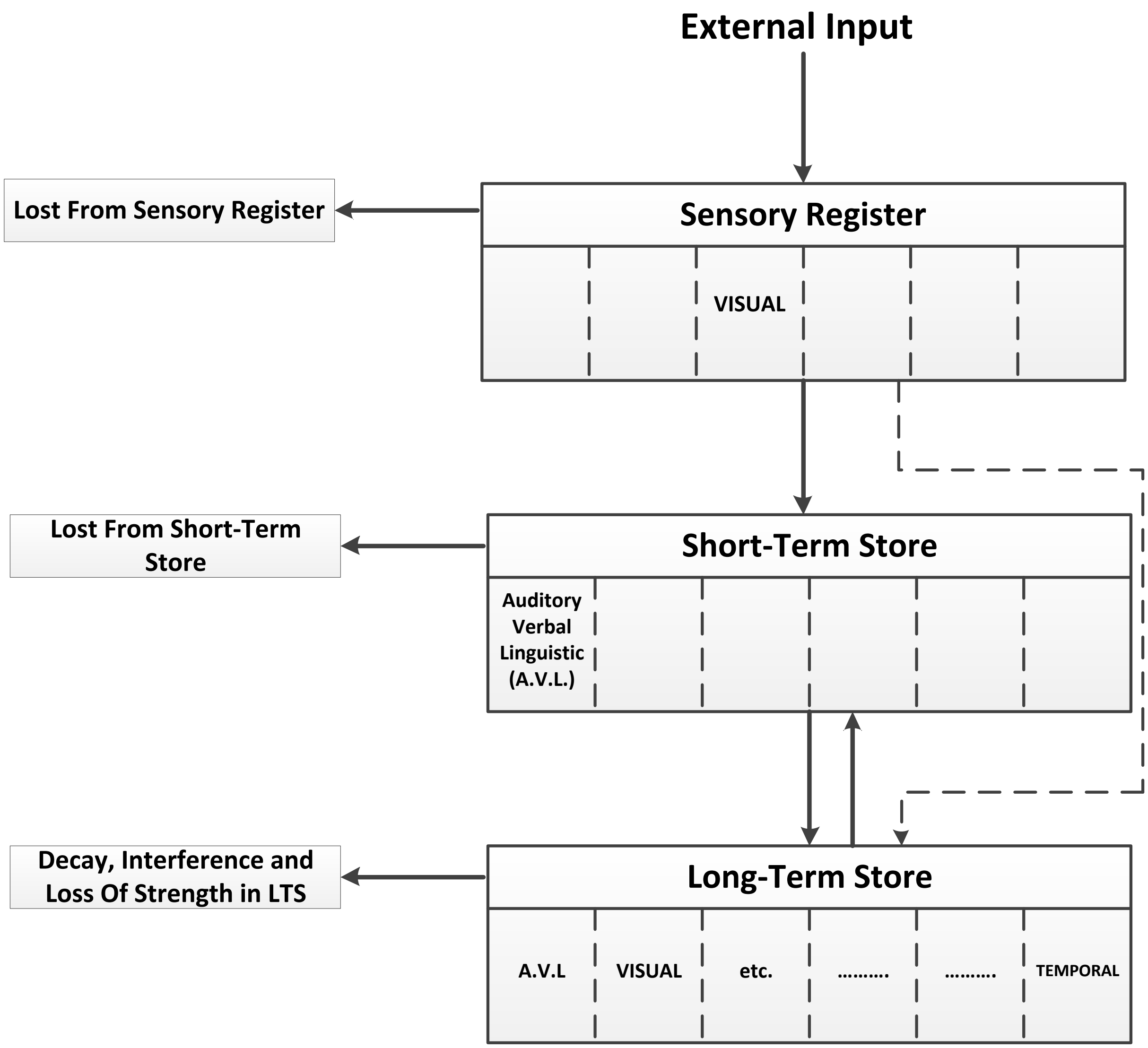

Figure 1: The Atkinson and Shiffrin Memory Model

Atkinson and Shiffrin postulated that memory can be divided into three different components:

I. Sensory Register- We are exposed to thousands of new stimuli on a daily basis. At any given time, each of our five senses, namely sight, hearing, taste, touch and smell, are assimilating a plethora of information around us, but we generally pay attention to only a small section or segment of these inputs and ignore the rest. Our senses generally store this assimilated information for a very short period of time in the sensory register, before any cognitive processing is undertaken by our brain, thus allowing us to be aware of our surroundings while focusing on a given task (Atkinson and Shiffrin 94). Each of our senses has its own sensory register, which are described briefly below:

A. Echoic Memory or Store- Auditory sensory memory is generally referred to as echoic memory, and is believed to last for three or four seconds. A key example that illustrates the working of echoic memory occurs when we are in a crowded room and overhear someone talking about us. We can generally recall the whole sentence in which our name was used, despite the fact that we were not actually paying attention to that conversation a second or so ago ("Sensory Memory").

B. Iconic Memory or Store- Visual sensory memory is generally referred to as iconic memory, and is believed to last for approximately 250ms. We can easily experience the effects of iconic memory if we stare at any given picture or even our immediate surroundings for a few seconds, and then close our eyes. We'll find that, even after closing our eyes, we can still see the picture for a fleeting second before it fades away into oblivion ("Psychology Glossary").

C. Haptic Memory or Store- The sensory memory of touch is generally referred to as the haptic store. The capacity of the haptic store can vary depending upon the stimuli and can vary from between two to ten seconds. A classic example that illustrates the working of the haptic store occurs whenever we sit on a couch for a while and then get up suddenly. Part of our body still feels the impressions of the couch for at least a few seconds before gradually fading away. This post-activity tactile sensation is caused by the haptic store.

II. Short-Term Memory – The small section of sensory input that we pay attention to, or focus on, arrives into the Short-Term Memory (STM). As discussed in the previous sections, the STM's capacity to store information is fairly limited. In 1956, George A. Miller, a cognitive psychologist at the Princeton University, published a paper titled, "The Magical Number Seven, Plus or Minus Two: Some Limits on Our Capacity for Processing Information," in which he postulated that our STM is capable of storing seven, plus or minus two, chunks of information in it. In his paper, Miller acknowledged that there isn't a specific definition of "chunk." A chunk could be a single alphabet, a word, a phrase or even a sentence. The following is an excerpt from the paper, wherein he explains the ever changing nature of a chunk in STM:

> "A man just beginning to learn radio-telegraphic code hears each *dit* and *dah* as a separate chunk. Soon he is able to organize these sounds into letters and then he can deal with the letters as chunks. Then the letters organize themselves as words, which are still larger chunks, and he begins to hear whole phrases…I am simply pointing to the obvious fact that the dits and dahs are organized by learning into patterns and that as these larger chunks emerge the amount of message that the operator can remember increases correspondingly. In the terms I am proposing to use, the operator learns to increase the bits per chunk" (Miller 91).

This chunking of information for ease of learning was also seen in the experiments performed by Underwood in 1964, wherein he observed that the test subjects rearranged the contents of the word lists provided to them into clusters of words based upon conceptual categories, or associations. Although mentioned previously, it is important to reiterate the fact that STM is not only limited in terms of capacity, but also in terms of the duration of time that it can store new information. As shown by Peterson and Peterson in 1959, we can only retain information in our STM for eighteen to twenty seconds, after which we experience rapid forgetting, unless we verbally or visually rehearse the information. This rehearsal generally takes place in the rehearsal buffer of our STM. An image, reproduced from the "Human Memory" paper (Atkinson and Shiffrin 113), outlining the role of the rehearsal buffer, as well as its position in the memory system can be seen below in Figure 2.

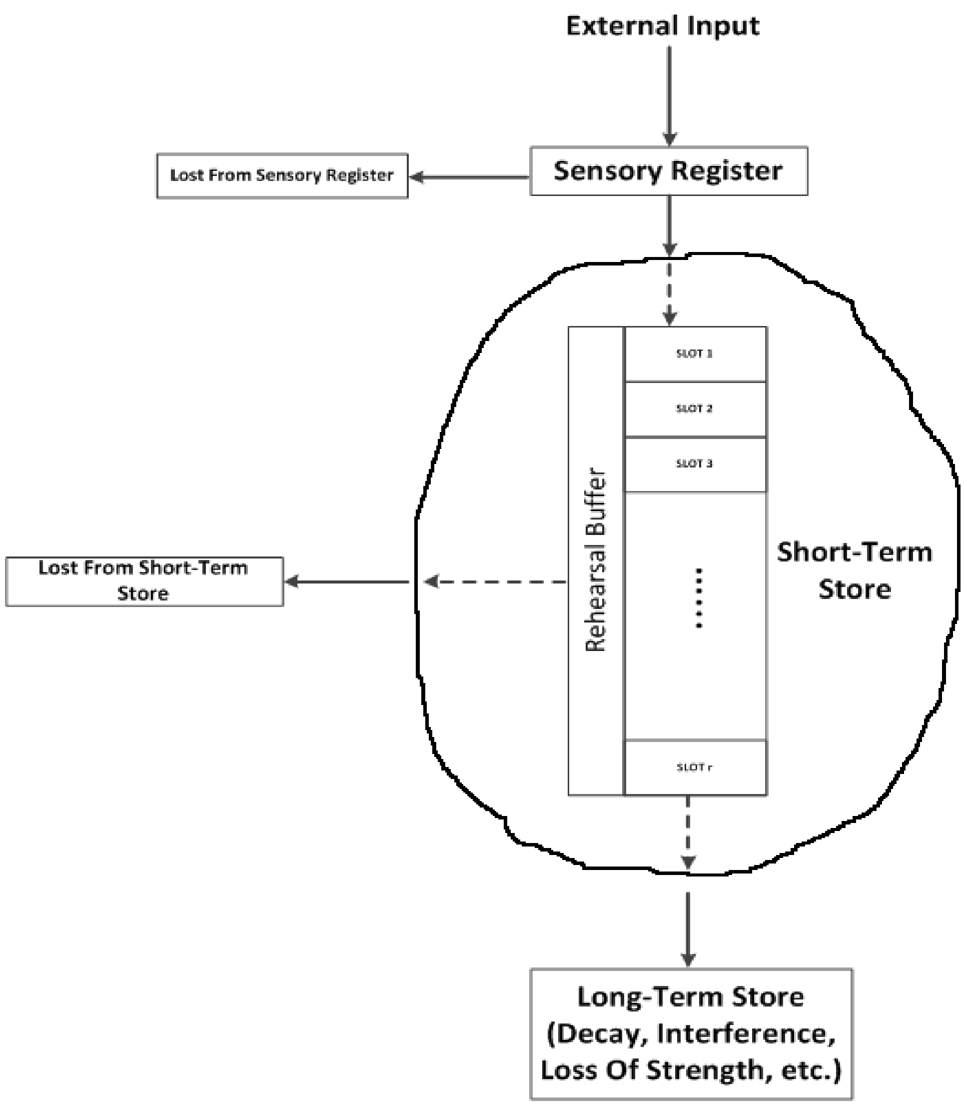

Figure 2: Role and position of the rehearsal buffer

As seen in the Figure 2 above, input from the sensory register, as well as LTM, enters the STM where it is stored in the rehearsal buffer. The rehearsal buffer contains a set number of slots, wherein the incoming information can be stored. The number of slots available, as well as the size of the slots, depends primarily upon the type of information being stored. Based upon the experimental results of Wickelgren, Atkinson and Shiffrin believe that the lower limit on the capacity of the rehearsal buffer is usually in the range of five to eight slots. This is in keeping with Milner's experimental results, wherein he found that STM's capacity was generally limited to seven, plus or minus two, chunks of information. Once this capacity is reached, and the buffer is full, the rehearsal buffer utilizes the First-In-First-Out (FIFO) methodology to add new information. As such, the oldest chunk of information is discarded, before a new chunk of information is incorporated into the rehearsal buffer. The use of this process ensures that every new chunk of information spends as much time as possible in the rehearsal store, thus resulting in a long-term trace being built for that chunk of information in the LTM. A key example that can be used to illustrate this fact is that whenever we try to memorize a new phone number, we repeat the number several times. This repetition of the telephone number helps it remain in the rehearsal buffer of the STM for a longer period of time, and ensures that its trace is not only built, but also strengthened in LTM (Atkinson and Shiffrin 114).

The visual or verbal rehearsal of information is not the only means by which information can be transferred from STM to LTM. Atkinson and Shiffrin put forth the proposal that information transfer from the STM to LTM is an "unvarying feature of the system." They cited the studies of incidental learning as reported by Hebb and Melton, wherein test subjects were required to repeat sequences of digits. They found that if a given sequence was presented to the test subjects every few trials, it was gradually learned (stored in LTM), despite the fact that the test subjects could easily perform the given task by rehearsing the sequences in their STM. As such, any and all information that is attended to when stored in the STM is also transferred to LTM (Atkinson and Shiffrin).

While the previously described sections on STM explain what happens whenever we are exposed to new stimuli or information through any of our senses, exposure to familiar stimuli leads to a very different response. For example, when we are exposed to the picture of a cat, a definite sequence of events is set into motion. Firstly, the image of the cat is registered in the iconic store (the sensory register of our eyes), following which, the sensory register tries matching the image of the cat with the contents of the short-term memory. If the exact or even a similar pattern is found in our short-term memory, we recognize that this is the image of a cat. However, if the sensory register doesn't find any pattern match in the STM, it conducts a similar search in the LTM. If a match for the "cat" pattern is found in the LTM, the pattern will be immediately copied over to the STM and we will simultaneously recognize that we are seeing the image of a cat. It is important to note that in the case that the pattern of the cat is found in LTM, the original pattern of the cat is not moved or removed from the LTM to STM; rather, the pattern is copied over from our LTM to our STM. Alternatively, if a pattern match is not found in the LTM, then the unknown pattern is copied over from our sensory register to the STM where it continues to reside temporarily until we learn what the unknown pattern is, or until it decays from the STM.

III. Long-Term Memory- Information that we rehearse, concentrate on, or are repeatedly exposed to is transferred from the STM into the Long Term Memory (LTM). Contrary to the sensory register and the STM, wherein the capacity and length of information storage is restricted, the LTM has a virtually limitless capacity (Adams). Whenever new information is introduced in the STM, we generally relate this new information to some preexisting concepts, words, phrases or items that already exist in our memory. This can be explained further by expanding upon the example of the exposure to a picture of a cat from the previous section. Assuming that a person has never heard of or seen a cat, but has actually seen a dog, he may react to form a tentative association between a cat and dog using the following logic:

> "I see a furry animal that is a pet, just like a dog. Both dogs and cats are furry, have four legs and a tail. Dogs bark, but cats meow. Cats eat mice, but dogs don't. Dogs are generally larger than cats."

Although the above described description is highly subjective, and could vary from person to person, it would definitely help categorize the cat using a variety of key concepts. Thus, the next time the same person sees a cat, his sensory register would initiate a search in LTM and find that the furry animal in front of him meets the characteristics of a cat, and as such all the cat-related information would be transferred from his LTM to STM. This use of Natural Language Mediation (NLM) for learning of new information is well documented and has been verified empirically in experiments performed by Underwood and Schulz, Clark, Lansford and Dallenbach, and Bugelski.

The Atkinson and Shiffrin memory model was one of the first viable memory models that attempted to explain the workings of human memory and was responsible for directing or redirecting the attention of the scientific community towards the exploration of a holistic memory model that would account for most, if not all, of the experimental results and observations accumulated over a period of decades by numerous scientists and philosophers. Although the memory model proposed by Atkinson and Shiffrin was certainly a viable model, the critics were quick to point out that it was primarily a theoretical model and did not address the issue of which parts of the brain were responsible for the existence and functioning of each of the proposed memory components. Additionally, critics such as Alan D. Baddeley and Graham Hitch argued that the short-term memory component proposed by Atkinson and Shiffrin was primarily a storage area that did not perform any processing of the information that it holds, whereas a multitude of experiments have shown that we continuously process and manipulate information in both our STM and LTM. However, despite these and other limitations, the Atkinson and Shiffrin model deserves special recognition primarily because it attempted to explain the complete workings of the human memory at a time when most of the scientists were focused on the study of the individual components of human memory.

Baddeley and Hitch- Working memory

In 1974, Alan D. Baddeley and Graham Hitch, both professors of psychology at the University of Stirling, Scotland, proposed that the Short Term Memory (STM) component of the Atkinson-Shiffrin memory model be replaced by a much more complex system titled “Working Memory.”

The following observations and experiments led the authors to propose a modification of the existing memory model:

I. Atkinson and Shiffrin's memory model stipulated that learning generally occurs whenever an item is held in STM, and that the longer an item stays in STM the greater the chance that it will be transferred from STM to LTM. However, the experimental results provided evidence that was contrary to Atkinson and Shiffrin's model. Scientists found that the key feature that decided whether an item transitioned from STM to LTM was the depth to which the item was processed. Therefore, if a person merely glanced at a sentence and noticed that the first alphabet of a word was in upper case, he wouldn't spend a lot of time processing this information, and as such it was unlikely that the item would be transferred to LTM. But if the person reads the word, notices that the first alphabet is capitalized and that it rhymes with some other word in his vocabulary, then it becomes increasingly likely that this word association will be transferred to his LTM, and that he would be able to recall or recognize it in the future (Baddeley).

II. According to Atkinson and Shiffrin's memory model, STM is crucial for long term learning of new concepts, ideas and experiences. Baddeley and Hitch found that patients that suffered from STM issues were still able to form LTMs despite the fact that they weren't able to calculate the change while shopping, and faced other cognitive problems on a daily basis. Baddeley and Hitch conducted further research in this realm to accurately ascertain the relationship between STM and LTM. For their experiments, they had their test subjects learn new material, and conducted reasoning or comprehension tests while simultaneously reciting gradually increasing digit sequences to block or occupy their STM. The results showed that although the blocking of the test subjects' STM did bring about

> some decrement in learning, especially as the length of the digit sequences increased, it was not as significant as it should have been if LTM was as dependent upon STM as the Atkinson-Shiffrin model suggested (Baddeley; Baddeley and Hitch).

The working memory model, as proposed by Baddeley and Hitch, uses STM as an active information processor wherein information is not only stored, but is also manipulated to make the most use of it. This stands in stark contrast to the Atkinson-Shiffrin memory model, in which the STM is merely a passive store where information is stored, but is never manipulated or worked with (Neezes). An example that can illustrate this difference would be that of a person shopping for furniture in a store. In the Atkinson-Shiffrin model, if the person sees a couch, he will simply be temporarily storing the couch as a “chunk” in his STM; whereas in the working memory model, the person would use his visuospatial memory to move the furniture around in his apartment and figure out the best location to place the couch.

The structure of working memory is markedly different than that of the Atkinson-Shiffrin model’s STM. Baddeley and Hitch’s working memory model contains a central controlling mechanism, called the “Central Executive,” which manages the attention of a person. The central executive has three subsidiary systems namely the phonological loop, the visuospatial sketchpad, and the episodic buffer. An image of the working memory model, reproduced from Alan Baddeley’s paper titled “The episodic buffer: a new component of working memory?” can be seen below in Figure 3:

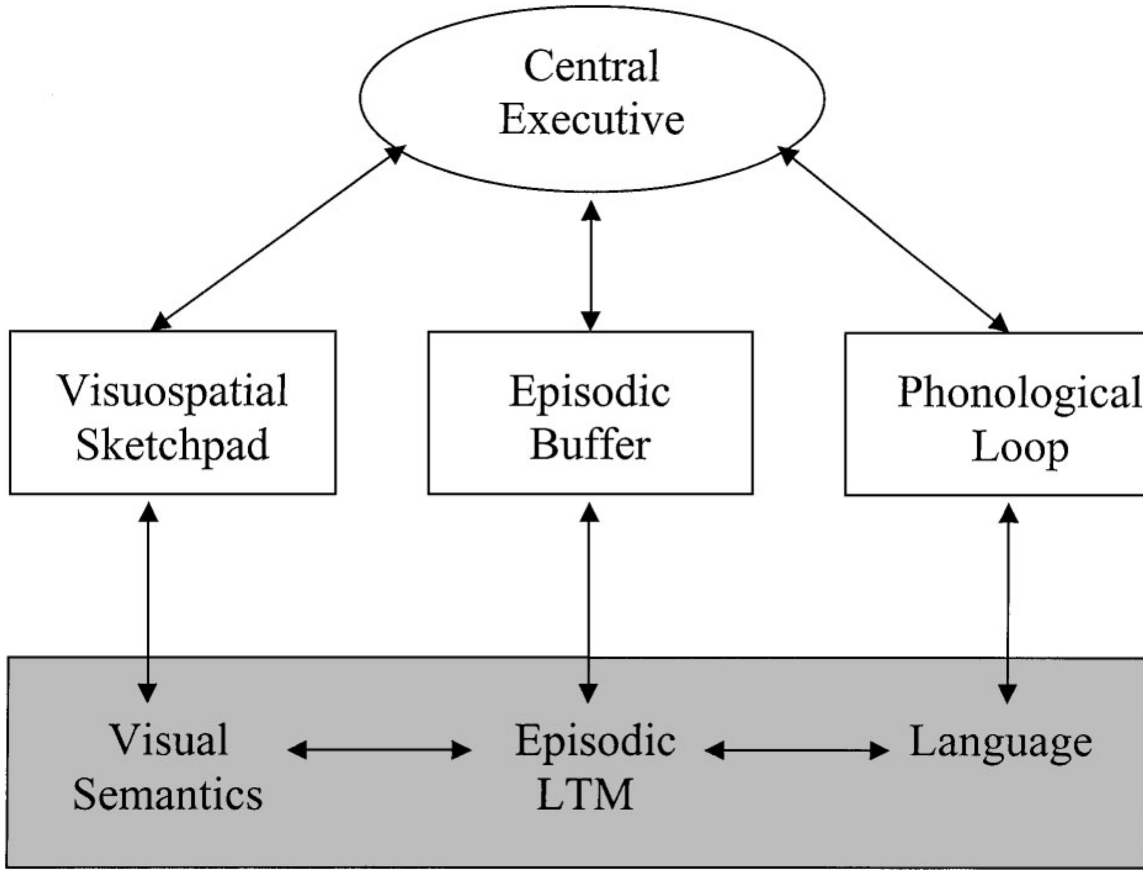

Figure 3: Working Memory Model (Baddeley)

Initially, in their paper titled "Working Memory," Baddeley and Hitch had only included three components in their working model, namely the "central executive," the "phonological loop," and the "visuospatial sketchpad." However, subsequent research and experiments by the authors revealed an important weakness in the model: it didn't provide for a means to integrate the information gathered through the phonological loop and the visuospatial sketchpad. As such, a new component termed the "episodic buffer" was added to the working memory model (Baddeley). The following is a detailed description of each of the components of the working memory model and their respective functions:

I. The Central Executive- This component forms the most important part of the working memory model as it is responsible for controlling the attention of a person, as well as, the flow of information to and from the phonological loop and visuospatial sketchpad. It is speculated that the central executive is also responsible for all reasoning and decision making activities that are undertaken by us (Narayanan).

According to Baddeley, the proposed workings of the central executive are identical to that of the Supervisory Attentional System (SAS) that was proposed by Norman and Shallice (6). Also per Norman and Shallice, most of our daily activities, such as driving a car, riding a bike, walking, etc., are governed by habitual processes which are guided by environmental clues. However, the occurrence of any unexpected or novel situations, which we haven't experienced before and are not a part of our habitual processes, requires the use of SAS (Norman and Shallice 6). An example of the SAS in action during a novel occurrence would be the actions we take when our car skids in the snow. When we drive our car on a daily basis, we depend on our habitual processes which allow us to drive home without paying too much attention to the minute details of our surroundings. But if we are driving home and our car skids, our attention to our surroundings is heightened and we begin maneuvering our car with as much precision as possible to recover from the skid. These emergency actions are generally not a part and parcel of our habitual process and are governed by SAS.

II. Phonological Loop- The phonological loop uses a rehearsal mechanism to maintain acoustic or spoken information, so as to prevent the trace from decaying (Pezzulo). A reproduction of the phonological loop, as depicted by Susan E. Gathercole in her paper titled, “The structure and functioning of phonological short-term memory,” can be seen below in Figure 4.

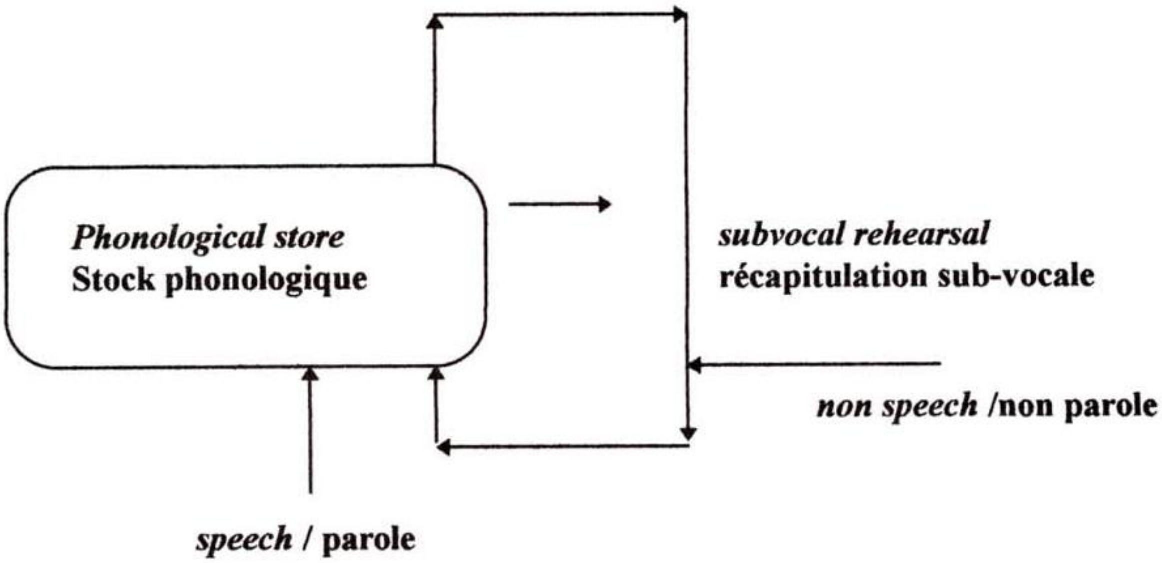

Figure 4: Structure and functioning of the phonological loop

As seen in Figure 4 above, the phonological loop is comprised of the following two parts.

A. The Phonological Store- The phonological store receives input from two main sources. Firstly, thorough auditory input, i.e. by means of our ears. Any and all spoken language that we hear is directly stored in the phonological store. Secondly, by means of our long term memory. Anytime we feel that a piece of music is stuck in our head, we are generally listening to it by means of the phonological store (Baddeley and Hitch). Any information that enters the phonological store generally decays after a period of about two seconds, unless it is rehearsed by means of the Articulatory Control System (Walsh).

B. Subvocal rehearsal or Articulatory Control System- The articulatory control system serves two critical functions. Firstly, it helps prevent the decay of information in the phonological store. This is done by means of subvocal rehearsal, or silently repeating the information in our minds, without actually verbally reciting the information. An example for the same would be that of a person repeating a list of grocery items to himself, to ensure he doesn't forget it. Secondly, it enables us to convert visual information into phonetic information that can be transferred into the phonological store. A good example of the conversion of visual information to phonetic information would be a test subject reading the letter "A." Although the alphabet is essentially just a simple shape, the test subject would convert this shape to the phonetic pronunciation of the letter 'A,' which will then be store in his phonetic store (Walsh; Gupta and MacWhinney 510).

III. Visuospatial Sketchpad- The visuospatial sketchpad is used for the storage, as well as the manipulation, of visual and spatial information. It receives input from both the eyes and long-term memory. According to Logie, the visuospatial sketchpad can be divided into the following two subcomponents.

A. Visual cache- The visual cache is used for the storage of information such as visual form and color of images that a person is exposed to (Eysenck and Keane 199).

B. Inner Scribe- The inner scribe is the visuospatial component that deals with spatial information that a person is exposed to. Its function is similar to that of the Articulatory Control System, in that it rehearses the information in the visual cache, and is responsible for the transfer of information from the cache to the central executive (Eysenck and Keane 199). Additionally, it has been theorized that the inner scribe is responsible for the planning and execution of our body and limb movements too (Logie).

IV. Episodic Buffer- The episodic buffer was the fourth component that was added to the working memory model (Baddeley). It is called the episodic buffer because it is primarily responsible for the integration of information over space and time. It is a temporary storage system that can be accessed and controlled by the central executive through the medium of conscious awareness. The central executive uses the episodic buffer to integrate information from the phonological loop and the visuospatial sketchpad with LTMs. As such, it is theorized to play a very important role in the feeding and retrieving of information from LTM. Additionally, the episodic buffer is also speculated to be responsible for the chunking of information in STM (Miller).

Baddeley proposed that the episodic buffer uses a common multi-dimensional code, to enable it to interface with the visuospatial sketchpad and the phonological loop, both of which utilize different sets of codes to process the incoming information (Baddeley). Although the exact size of the buffer hasn't been established, it has been theorized that the buffer size should be fairly limited, so as to reduce the amount of resources that would be utilized to process the different sets of codes retrieved from the different components of the working memory model.

Although the Working Memory model represents a marked improvement over the Atkinson and Shiffrin model in representing human memory components and their associated processes, it (the Working Memory Model) shares some of the same limitations as that of the Atkinson and Shiffrin Memory model. Firstly, the Working Memory model postulates that the STM can be divided into various specialized components, however, no physical evidence is provided to validate these claims. Neither the original "Working Memory" article by Baddeley and Hitch, nor any of the subsequent research by the proponents of this memory model have postulated or attempted to explain which sections of the brain are used for the specialized processing activities that are proposed by this model. Secondly, the Working Memory model only focuses on the functionality of the STM, while steadfastly ignoring the LTM. No attempt is made to explain the functioning of LTM nor is there any explanation as to how information is transferred from the various components of Working Memory into LTM and vice-versa. Thirdly, when proposing the Working Memory model in 1974, Baddeley believed that there were further subsystems that have yet to be identified and he believed that these subsystems would be discovered as further research was conducted, however these subsystems have yet to be identified despite the model being in existence for over 40 years. As such, although the Working Memory model serves as a marked improvement over the Atkinson and Shiffrin model and is generally accepted as a better model, it has some serious limitations which will have to be addressed before it can achieve broader recognition amongst the scientific community.

Memory-prediction model

Jeff Hawkins's book, "On Intelligence: How a New Understanding of the Brain will Lead to the Creation of Truly Intelligent Machines," explains why we need to understand the workings of the human brain, to build truly intelligent machines. Hawkins delves deeply into the physiology of the human brain and explains, by means of his "Memory-Prediction Framework," how our brain combines our thoughts with sensory perceptions to form predictions about future events.

According to Hawkins, there are three essential criteria that have to be met to ensure a proper understanding of the brain.

I. Inclusion of time in brain function- Our brains are constantly processing rapidly changing streams of information that are sent to it by our senses and our LTM. Whenever we experience an event or process any information, we generally remember at least part of the information and can always refer back to it in the future. This time based storage of information helps us associate new information with preexisting knowledge and learn new concepts. As such, it is imperative that a time component be included when trying to understand the workings of the brain (Hawkins 25).

II. Feedback- Researchers have found that for every connection feeding information forward from our senses into the neocortex, there are roughly ten connections feeding backwards into our senses. While we generally expect that we are mostly feeding information from our senses into the brain, this really isn't the case. We receive ten times the amount of feedback from our brain to our senses. Hawkins postulated that this feedback mechanism must be extremely important to the brain and should definitely be explored (25).

III. Physical Structure of the Brain- Most memory models, and research into the workings of the human brain, ignore the actual structure of the brain and try to compare its workings to a preexisting object or tool (for e.g. a computer). According to Hawkins, a proper understanding of the workings of memory and the brain is only possible by taking into account the physical architecture of the brain (25).

Our neocortex is divided into multiple functional regions. Each functional area serves as a semi-independent unit that specializes in certain aspects of perception or thought. These functional areas are arranged in a functional hierarchy. It is important to note that a functional hierarchy does not imply that one functional area is physically above or below another, rather it merely refers to the connections that exist between one functional area and another. Thus, although two functional areas might be on the same level physically, the hierarchically lower functional area will feed information to the functional area that is at a higher level (Hawkins 44).

Whenever we are exposed to any external stimuli, the sensory information enters the primary sensory area of the cortex. The primary sensory area forms the lowest functional area of the neocortical hierarchy, and it is here that raw sensory information is initially processed, before being passed up the hierarchy. Hawkins provided an example of our sense of vision to illustrate this fact. Every time we see anything, our eyes pass-on the visual information to our cortex through the primary visual area, V1. The V1 area is responsible for the processing of the visual information's low level features, such as the presence of edges, binocular disparity (the difference in the image seen by the left and right eye which helps in ascertaining information about depth), basic color and contrast information. Once this basic processing of visual information is completed, V1 feeds the information into the next hierarchical area, such as V2, V3, V4, V5, etc. where additional processing of the visual information takes place. As we go higher up the visual cortex, we reach the functional areas that have visual memories of familiar objects such as faces, animals, furniture, etc (Hawkins 45).

Each of our senses has its own cortical hierarchy, wherein the sense specific information is processed. All of our senses then pass on the processed information to the "association areas," which are higher up in the cortical hierarchy. The association areas are primarily responsible for combining the input from the different senses and forming a single experience. For example, when we watch TV we are receiving multiple inputs through our senses. We see visual images on the TV screen, hear the audio associated with the visual images, and assuming that we are sitting on a couch, our somatosensory system senses the touch, temperature and pressure of our body on the couch. All three of these senses pass on this information to the association area, via millions of axons, which integrates the disparate streams of information into a single unit. As such, we experience that the audio and video images are in-sync and that we are sitting comfortably on the couch (Hawkins 46).

According to Hawkins, the associative area is easily able to integrate the wide variety of inputs provided to it from all of our senses primarily because the neocortex uses a single underlying algorithm for all its functions. This theory of a single underlying algorithm is based upon Vernon Mountcastle's observation that despite the wide variety of functional areas and operations performed by the neocortex, the overall structure of the cortex is remarkably similar. The auditory region of the cortex is similar to the motor region of the cortex, which is again similar to visual region of the cortex. Thus, the specialization of the cortex is dependent upon which of the five senses it is actually connected to. This is the reason why the human neocortex is considered to be very flexible. A prime example of its flexibility occurs in individuals who are born deaf. Scientists have found that people who are born deaf generally have superior peripheral vision and motion detection as they utilize the auditory regions, in addition to the visual areas, of the brain to process visual information (Sanders). This flexibility proves that each functional area of the neocortex doesn't use different algorithms to process information in different areas. Also, no matter which one of our senses are being used, be it auditory, vision, touch, etc., all of our sensory inputs are received by our neocortex in the form of neural signals through the axons. As such, all our brain sees is a pattern of neural signals, wherein certain axons are firing while others are at rest. Each pattern of neural signals uniquely identifies a given object, sound, smell, etc. Whenever we see a car driving by our house, a specific pattern of neural signals will fire up all the way from our optic nerve to the visual area of the cortex. If the driver honks, then a different pattern will travel down from our auditory nerve into the auditory area of our cortex. The cortex doesn't process the patterns differently, no matter where they originated, be it through vision, hearing or any of our other senses. Additionally, our cortex doesn't necessarily need a complete or uncorrupted stimulus to recreate a previously seen pattern. Our cortex is auto-associative by nature and can easily fill in an incomplete or distorted pattern (Hawkins 54). The following image serves as a classic example of our cortex using auto associative memories to fill in the gaps.

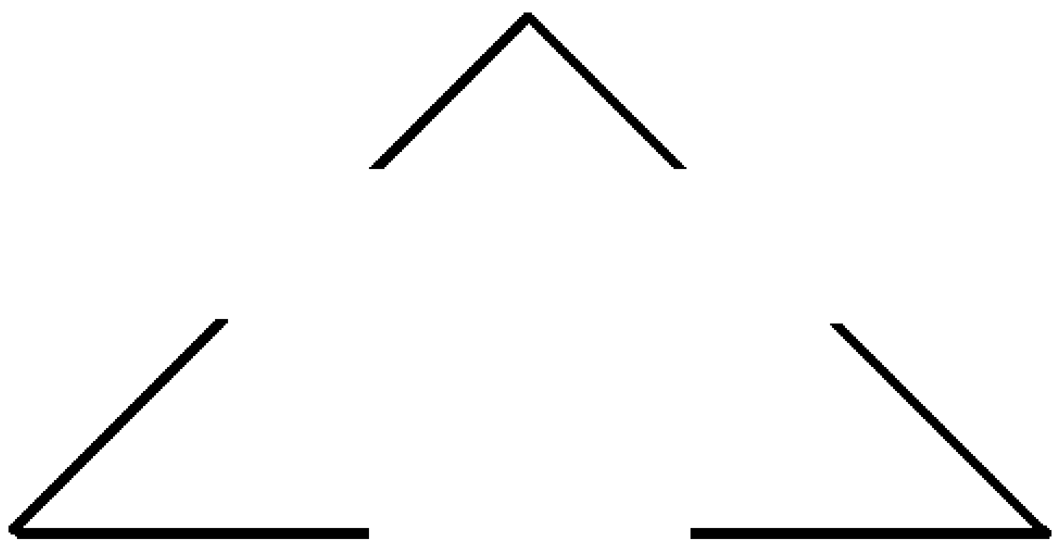

Figure 5: An image of three angled lines

Although we are consciously aware that the diagram in Figure 5 above is incomplete, with three missing sections, we can easily discern that this is an image of a triangle. We are able to reach such a conclusion primarily because of our auto-associative memory of a triangle. Another example of our auto associative memory in action occurs when we hear a part of a song be it just the music, part of the lyrics, or someone humming a tune of a song. In each case, although we are receiving different types of auditory signals, the upper echelons of our functional area are able to recognize the underlying pattern and help us recall the name or the complete lyrics of the song. According to Hawkins, the reason we are able to recall the song, no matter what the input pattern, is because our neocortex doesn't really store the song, or anything else, exactly as we see, hear, feel or experience, rather, it only stores the "invariant representation," or the important characteristics, of our experiences. For example, in the previously mentioned case, where we can recall a song no matter the format of the input pattern, our cortex doesn't store the notes of the song; rather, it probably stores the relative pitch of the notes. This is the reason why we can recognize the song in any format. Similarly, we can always recognize the face of a friend even in a crowd, no matter the distance, angle, or lighting. It is quite an impressive feat especially when we take into account the fact that when the friend is standing closer to us, they occupy a larger area of our retina, and when they are standing far from us, they occupy a much smaller area of our retina. When in a crowd, there are other faces too that are crowding our retina, but we recognize the friend nevertheless. Again, this occurs due to the fact that our cortex stores the "invariant representation" of our friend's face, and not the exact image. As such, an invariant representation could be defined as the cortical storage of the critical or defining elements of a pattern such that even if the pattern is modified and presented in a different form, our cortex can instantly match the critical or defining elements and recognize the pattern. Thus, we are able to recognize the face of a friend in any surroundings because our cortex stores the critical or defining elements such as the relative dimensions and proportions of the friend's face: the distance between their eyes, the size and shape of their nose, the color and shape of their eyes and hair, etc. It is by means of these relative proportions that we compensate for the lighting, distance, angle, or other environmental variations, and still recognize the friend.

Our cortex is continuously making predictions about everything around us, but we are never consciously aware of it unless or until one of the predictions fails, or is not completely fulfilled

(Hawkins 77). In his book, Hawkins uses the example of a person climbing down a flight of stairs to illustrate the role of cortical prediction. Whenever we descend down a flight of stairs, we usually have an inherent expectation, each time we put our foot down, that the next step will be present after a given distance. If our foot passes beyond that anticipated point where the next step is supposed to be present, we get alarmed and immediately make an effort to stop ourselves from tripping or falling down. However, if we stop to analyze this situation, our foot didn't really feel anything when it missed the step, but our cortex made a prediction that was not met and we realize that there is something wrong (Hawkins 91). Similarly, if one of our friends dyes her hair from black to electric blue and we happen to pass by them, we tend to stare, and generally complement their choice of hair color. But again, the reason our attention is instantaneously drawn to her hair is because our cortex made the prediction that her hair will be black, but that prediction was not met.

The previous sections outline the role of the neocortex in predicting future events, based upon the learning that occurred from prior events. The cortex stores each event or stimuli as an invariant representation or pattern, and anytime we undertake an activity or experience an event, it checks the newly generated pattern against the past patterns to see if there are any similarities. The fact that the patterns are stored in an invariant form ensures that the past patterns can actually be applied to new situations, which are similar, but not necessarily the same (Hawkins 77). An example should illustrate this concept clearly. If we listen to someone playing a piano rendition of "Let It Snow," and then a guitar rendition of the same song, we can easily recognize that both renditions are of the same song. This is despite the fact that the newly generated pattern of guitar notes is similar to, but not the same as, the piano notes. Our cortex recognizes this because of the fact that it stores an invariant representation of the song. To understand how these patterns are stored in the cortex, we will have to delve into a little bit of anatomy. A diagram of the structure of a neuron can be seen below in Figure 6.

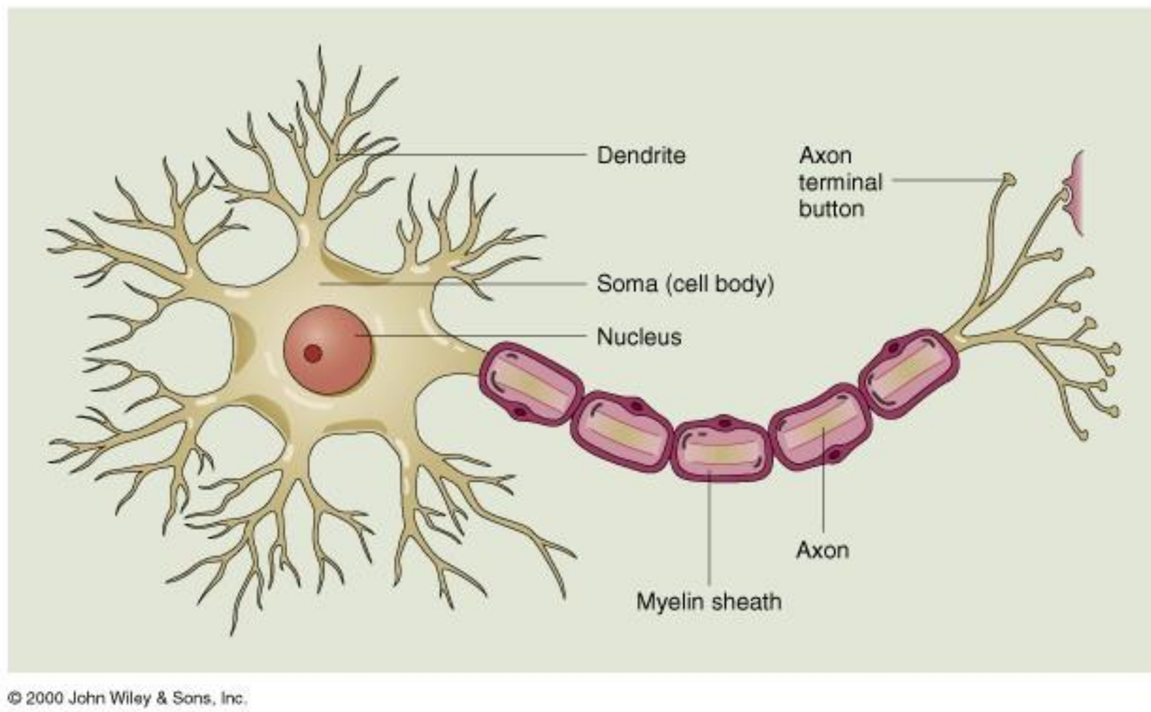

Figure 6: Diagram of a neuron (Jrious)

Anytime we experience external stimuli, an electrochemical signal travels down a neural pathway from the bottom of the cortical hierarchy all the way to the top of the hierarchy. All neurons along this path have the same structure and conduct the electrochemical current similarly. Once our senses receive an input, the cells in the lowest layer begin firing and the current travels down from the dendrite through the axon towards the axon terminal button. The axon terminal button contains a synapse that emits electrochemical signals through the synaptic cleft to the next neuron down the path. The structure of a synapse can be seen below in Figure 7.

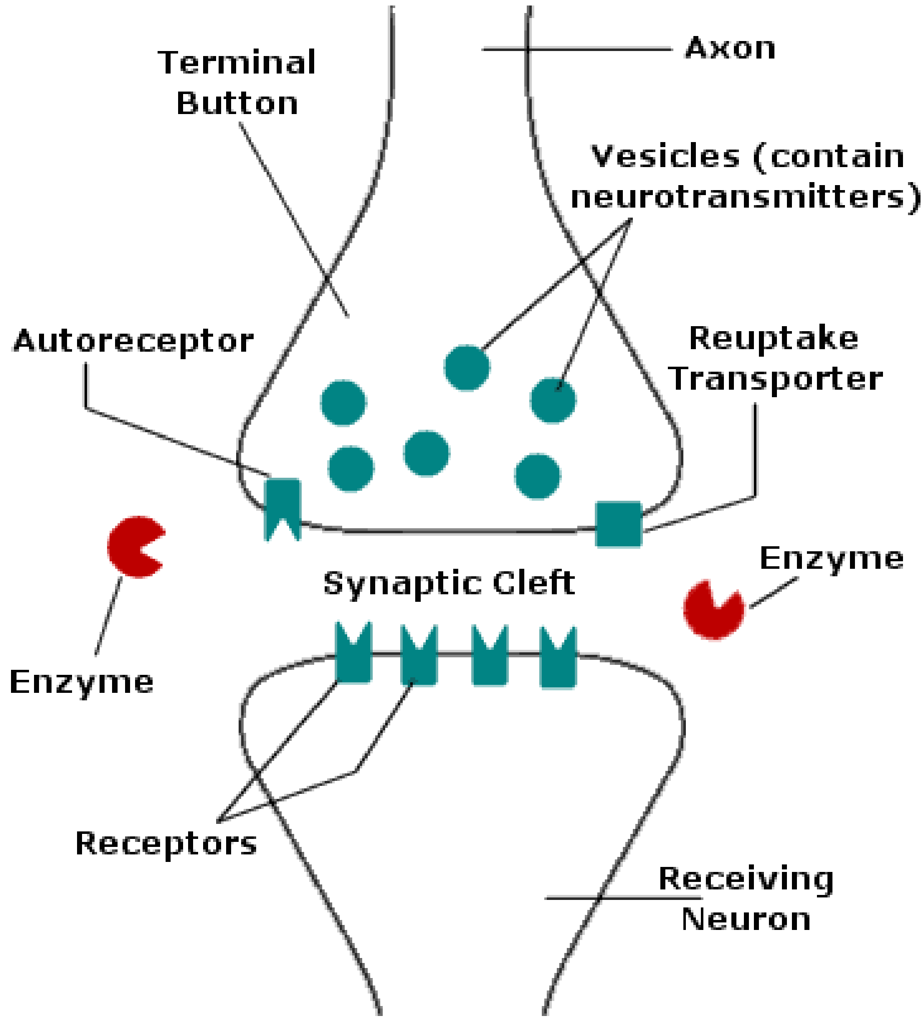

Figure 7: Structure of a synapse (Purse)

Each time an electrical signal travels down a specific neural path, it strengthens the connection between the synapses of the neurons that lie along the path. This synaptic plasticity, wherein the strength of the synapse varies according to the frequency of use of that particular synaptic pathway, is known as Hebbian Learning. If we experience the same stimuli multiple times, the synaptic strength, or the amount of neurotransmitters, between the two neurons increases sufficiently that the cells in the highest layers of the cortical hierarchy can fire automatically whenever the cells at the lowest layer of the hierarchy fire, without the firing of cells in the intermediate layers. As such, whenever the cells in the lowest layer of the cortical hierarchy are exposed to a previously experienced pattern, the cells in the upper layers of the cortical hierarchy begin firing in anticipation, without actually being “told” or driven to begin firing by the cells lower in the cortical hierarchy (Hebb). Over time, these repeated exposures to the same, or similar, stimuli ensure that we indulge in repeated learning, which causes our cortex to reform the memory representations for the stimuli at the lower levels of the cortical hierarchy. Hawkins illustrates this concept by using the example of a child who is learning to read for the first time. Initially, the child learns to recognize the shapes of the letters and differentiate amongst them. Then they learn to combine letters to form small three letter words, like cat, bat, rat, etc. Then they learn multi-syllable words, followed by entire phrases or sentences. There is a general progression in the learning process. At the outset, the child requires the use of the complete visual cortex just to recognize the individual letters, but as learning takes place, the recognition of the letters moves down the cortical hierarchy and closer to the sensory input, thus, freeing up the upper echelons of the cortical hierarchy to work on learning more complex material, such as words and phrases (Hawkins 166). This is the reason why when reading a complete sentence, we don’t really read the individual letters of every word, rather, we tend to read the word as a whole, unless and until we come across a word that is spelled incorrectly and doesn’t meet the patterns stored in our cortex. Alternatively, we could make the argument that at each step in the learning process of the child represents the evolution of the size and definition of a “chunk.” Initially, each individual letter forms a chunk, and the child has to learn each alphabet or letter individually. As the learning process continues, the size of the chunk evolves and increases in size from individual letters to words, and eventually complete sentences.

While the previous sections outline the role that the neocortex plays in the formation and utilization of memories, it is important to understand that the cortex is not the only brain structure that helps to form new memories. According to Hawkins, whenever we are exposed to completely new or novel stimuli that we have never experienced before, each functional region of our neocortex tries to match the new pattern to a pre-existing one. If a pattern match is not found, it escalates the pattern onto the next step in the cortical hierarchy. This process continues until the pattern reaches the hippocampus, the top most level of the cortical hierarchy, where it is stored temporarily. If we experience the novel input repeatedly then the pattern is moved down into the lower levels of the cortex. However, if we don't access that pattern in the near future then it is eventually lost (or forgotten). Although Hawkins has merely speculated about the role, as well as the process, that is utilized by the hippocampus to transfer novel patterns to the neocortex, the previous sections of this capstone have outlined experiments that have empirically proved that no new long-term memories can be formed if a patient has a damaged hippocampus. As such, it is not only feasible, but also highly probable that the memory prediction framework outlined by Hawkins does indeed help us form and utilize our memories.

This memory prediction framework proposed is quite unlike any of the memory models explored previously in this capstone. First, all of the previous memory models were generally theoretical models that didn't attempt to explore or explain the physical basis of the theoretical memory structures proposed in them. The Hawkins memory model stands in stark contrast to them, primarily because the entire theoretical framework is based on the study of the physical structure of the brain. Second, although the other memory models purport to explain how human memory works, none of them attempt to explain how memories are formed, encoded or retrieved, whereas Hawkins's memory prediction framework explores these and other concepts, such as the predictive ability of the human brain and the reasoning behind the flexibility of the various functional areas of the brain, comprehensively and provides ample empirical evidence to back it up. However, one of the key limitations, at least currently, of Hawkins memory prediction framework happens to be the numerous leaps of faith that he had to make in order to create a cohesive memory framework. These leaps of faith, wherein he postulates the existence of physical structures that have yet to be researched, discovered, and empirically proved, form a critical part of his theory, and as such, despite the fact that most of the memory prediction framework theory makes sense and is entirely believable, the model will not gain a strong foothold in the scientific community until it is empirically verified.

Analysis of the Memory Models

Work on this capstone had begun with the naïve assumption that a single memory model could easily serve as the basis for the design of the Threaded Engram Database (TED) Model, and that all that would be required was the selection of the "appropriate" model from the leading human memory models proposed by scientists. However, this assumption turned out to be erroneous because the results of the study of human memory over the past few decades are far from definitive. While there are various models and proposed methodologies of the workings of human memory, there is no agreement in the scientific circles on the following questions:

I. How are memories formed?
II. Where are memories actually stored?
III. Are memories transient or permanent?
IV. How or why do we forget things once they are stored in our memory?
V. What architecture in our brain helps us store memories?

As such, an efficient TED model could only be designed by borrowing and incorporating the salient features of each of the memory models studied for the purposes of this capstone, namely the Atkinson-Shiffrin memory model (Atkinson and Shiffrin), Baddeley's model of working memory (Baddeley and Hitch) and the Memory-prediction model (Hawkins and Blakeslee). The following are the components that should be incorporated into the TED model:

I. **The Central Executive (Baddeley's model of working memory) –** The Central Executive (CE) component played a critical role in Baddeley and Hitch's model of working memory. It was believed to be responsible for the management, or control, of our attention span and ensuring seamless flow of information between the various components of the working memory model. It could be argued that the role of the CE in managing human memory is remarkably similar to that of a database engine, as a database engine is generally responsible for the storage, retrieval and management of access to the data that is stored in a database.

   The addition of a CE like entity into the TED model will help simplify the storage and management of all of the TED model components. While the functionality of the CE and, to a certain extent most database engines, is limited to the management of data storage, the CE component of the TED model will perform additional processing tasks, such as the interfacing of the TED model with relational sources, abstraction of relational data into TED components, pattern recognition or generation, pattern matching, access monitoring, and pattern migration of patterns amongst the various storage units.

II. The Short-Term Store (Atkinson-Shiffrin Memory Model)- The Atkinson-Shiffrin memory model postulated that anything that we focus on or pay attention to resides for a temporary period of time in our short-term memory. While the Atkinson-Shiffrin model depicted the STM as being a passive store where the storage capacity is limited, both in size and in content, without the conscious knowledge or control of humans, the short-term store component of the TED model as a temporary storage area for TED components with user configurable capacity and decay periods. The inclusion of this component in the TED model will help provide a temporary staging area where patterns may be held until the CE component ascertains whether they should be deleted or moved to the long-term store. Thus, limiting the total size of the long-term store and ensuring that only the important or relevant patterns are migrated into the long-term store.

III. The Long-Term Store (Atkinson-Shiffrin Memory model) – The long-term memory component of the Atkinson-Shiffrin model is believed to have potentially unlimited capacity to store new information and is believed to be utilized whenever we are exposed to the same stimuli repeatedly or when we try to memorize a new piece of information by relating it to our preexisting knowledge. The inclusion of a LTM-like component in the TED model will enable it to store TED components or patterns for a much longer period of time than the short-term store. However, contrary to the LTM component of human memory which has potentially unlimited capacity and an uncertain decay period, the Long-Term Store (LTS) should have a user configurable capacity and decay period. The addition of these user modifiable parameters will help organizations plan for the resource usage and growth of the LTS, which would not be possible if it (the LTS) is configured for unlimited growth.

IV. Invariant representation (Hawkins Memory model) – The Hawkins Memory model proposed that the brain tends to store invariant representations of all experiences we encounter in our daily life. Anytime we experience something new, our brain tries to relate the pattern generated from the new experience with the previously stored invariant representations and form new associations based upon those representations. The incorporation of the concept of invariant representations in the TED model would enable it perform similar tasks. While the current RDBMs limit our understanding of data and its underlying relations to those that are specifically setup by the user by means of foreign keys or defined relationships, the use of invariant representations in the TED model would enable us to perform a multifaceted analysis of the data by not only viewing data that is directly related, but also data that is similar or potentially relevant to the data that is being analyzed.

The incorporation of the above described components from the assorted memory models should enable the TED model to function similar to human memory and form new correlations between both preexisting and newly entered data.

TED Model Terminology

The implementation of the TED model is dependent upon two key concepts, a "thread" and an "engram." However, although both key concepts are commonly used in the field of neuropsychology, they have not been defined in a computational context. Therefore, the following definitions are proposed for them:

I. Engram- The term "chunk" has been used numerous times by multiple scientists to define the smallest unit of storage in human memory. The size and definition of a "chunk" was found to vary widely, depending upon a subject's familiarity with a given subject, as well as level of categorization of information. As such, it was found that a chunk could vary in size from a single alphabet, to a single word, to multiple sentences.

   In the TED model, the term "engram" will be used as the computational equivalent of a "chunk," and will represent any database object(s) that can be related to, or can form relationships with, another object(s). As such, an engram could be a single record/image/LOB/CLOB/BLOB or any other object in a database. Also, it could be a grouping of multiple records/images/LOBs/CLOBs/BLOBs or any other similar objects in a database. Since these definitions might sound exceedingly vague, a few examples might help illustrate the concept of an engram much better. The “FAMILY VIDEOS” table, as seen in the table below, contains a unique identifier, the name of the video and the title of the family members of the Adams, James and Smith families who star in the video.

Unique Identifier	Name	Title
1	Jane Adams Video	Mother
2	John Adams Video	Father
3	Judy Adams Video	Sister
4	Jesse Adams Video	Brother
5	Jane James Video	Mother
6	John James Video	Father
7	Judy James Video	Sister
8	Jesse James Video	Brother
9	Jane Smith Video	Mother
10	John Smith Video	Father
11	Judy Smith Video	Sister
12	Jesse Smith Video	Brother

Table 2: FAMILY VIDEOS table

Based upon the information contained in the FAMILY VIDEOS table, we could form the following engrams:

A. Engrams of videos created by the family members of each family.

Unique Identifier	Name	Title	
1	Jane Adams Video	Mother	Engram 1
2	John Adams Video	Father	Engram 2
3	Judy Adams Video	Sister	Engram 3
4	Jesse Adams Video	Brother	Engram 4
5	Jane James Video	Mother	Engram 5
6	John James Video	Father	Engram 6
7	Judy James Video	Sister	Engram 7
8	Jesse James Video	Brother	Engram 8
9	Jane Smith Video	Mother	Engram 9
10	John Smith Video	Father	Engram 10
11	Judy Smith Video	Sister	Engram 11
12	Jesse Smith Video	Brother	Engram 12

B. Engrams of videos based on families with the same surnames.

Unique Identifier	Name	Title	
1	Jane Adams Video	Mother	Engram 1
2	John Adams Video	Father	
3	Judy Adams Video	Sister	
4	Jesse Adams Video	Brother	
5	Jane James Video	Mother	Engram 2
6	John James Video	Father	
7	Judy James Video	Sister	
8	Jesse James Video	Brother	
9	Jane Smith Video	Mother	Engram 3
10	John Smith Video	Father	
11	Judy Smith Video	Sister	
12	Jesse Smith Video	Brother	

C. Engrams of videos based on title of the family members.

Unique Identifier	Name	Title	
1	Jane Adams Video	Mother	Engram 1
5	Jane James Video	Mother	
9	Jane Smith Video	Mother	
2	John Adams Video	Father	Engram 2
6	John James Video	Father	
10	John Smith Video	Father	
3	Judy Adams Video	Sister	Engram 3
7	Judy James Video	Sister	
11	Judy Smith Video	Sister	
8	Jesse James Video	Brother	Engram 4
4	Jesse Adams Video	Brother	
12	Jesse Smith Video	Brother	

D. A single engram of all videos contained in the FAMILY VIDEOS table, as seen in the table below:

Unique Identifier	Name	Title
1	Jane Adams Video	Mother
2	John Adams Video	Father
3	Judy Adams Video	Sister
4	Jesse Adams Video	Brother
5	Jane James Video	Mother
6	John James Video	Father
7	Judy James Video	Sister
8	Jesse James Video	Brother
9	Jane Smith Video	Mother
10	John Smith Video	Father
11	Judy Smith Video	Sister
12	Jesse Smith Video	Brother

Engram

Similarly, we could group multiple images, LOBs, CLOBs, BLOBs and other objects together into individual engrams based upon their categorical or conceptual similarities. The key defining factor of these engrams would be that they should help provide context for the data stored in the database. This context could be provided by means of the answers to the information gathering questions of “who, what, when and where” (Zilora, Ackoff).

The information gathering questions were first introduced in 1988 by Russell Ackoff in a paper titled, “From Data to Wisdom,” where he defined the hierarchical relationships between: Data, Information, Knowledge and Wisdom (DIKW). The following are the definitions of the different levels of the DIKW hierarchy:

i) Data- Data forms the first and the lowest level of the DIKW hierarchy and represents raw and unprocessed signs, symbols and signals that have no inherent meaning (WEBO).

ii) Information- Information forms the second level of the hierarchy and is composed of data that has been processed and can provide useful answers to the information gathering questions of "who, what, when and where." The conversion of data from its raw and unusable form into information occurs because the application of context enables us to perform complex analysis and draw logical conclusions (Nitasha).

iii) Knowledge- Knowledge forms the third level of the hierarchy and can be defined as the application of data and information to answer the question of "how." The answers provided to the question of "how" are believed to be subjective, as each person views, perceives and analyzes information differently (Bellinger).

iv) Wisdom- Wisdom forms the fourth and the highest level of the hierarchy and is believed to occur when people begin to question "why" a particular task or event occurs (Bellinger). While the answers to the lower levels of the hierarchy may be fairly simple and definitive, there may be no answer to the question of "why."

The previous sections outlined the key differences between data, information, knowledge and wisdom. It is important to note that while the attainment of wisdom is generally considered to be the essential goal in human development, the goal of the TED model is limited to that of applying context to the data and converting it into information. To this effect, the threads that will be used to link engrams together will be formed on the basis of the answers to the information gathering questions of "who, what, when and where." Also, since the answers to the "how" and "why" questions are generally subjective and open to interpretation, excluding them from the information gathering questions will help ensure that the context TED threads provide to the data is objective and accurate.

II. Threads- Threads are the standard bidirectional connections that are used to link, or relate, one engram to another. Each thread connecting one engram to another is formed on the basis of the answers to the information gathering questions, and can easily change or be modified anytime the answer to a question changes. Additionally, engrams could be connected using a single, all or just some of the information gathering questions. As such, it isn't necessary that every engram will have the complete combination of the "who, what, when and where" threads that link it to other engrams (Zilora, Ackoff). A continuation of the "FAMILY VIDEOS" table example, as seen in the image below, illustrates and clarifies the concept of a thread, as well as the constantly evolving nature of the threads. Assuming that each individual video created by members of the Adams family forms an engram, we could establish the following threads:

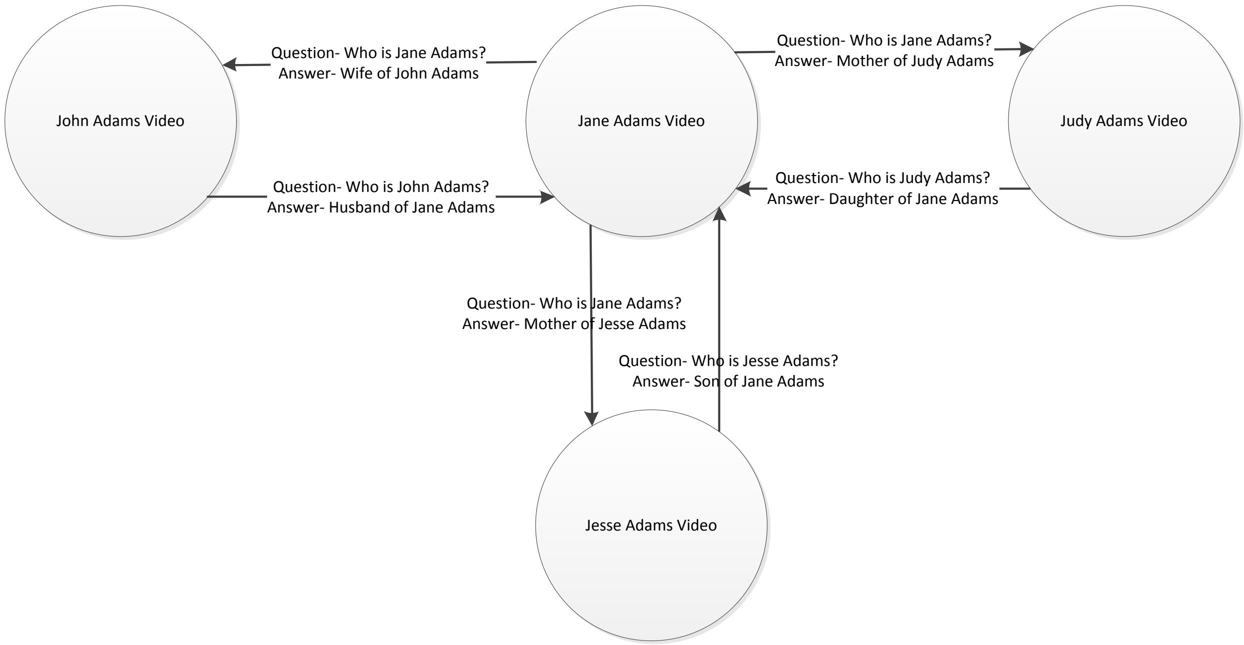

Figure 8: TED illustration of the Adams family videos with Jane Adams as the focal point

As seen in Figure 8 above, there are six threads that link the “Jane Adams Video” engram to the rest of the family. Since the TED threads are bidirectional, we could traverse from the “Jane Adams Video” engram to the “John Adams Video” engram by asking “Who is Jane Adams?” Similarly we may traverse from the “John Adams Video” engram to the “Jane Adams Video” engram by asking the question “Who is John Adams?” The directionality of the TED thread combined with the information gathering question being determines the relationship between any given engrams in the TED model. For the sake of simplicity, the only information gathering question that was used to establish the threads in the example above was “who.” Also, “Jane Adams Video” was used as the focus or the central engram around which the remaining engrams and threads were aggregated. If all of the Adams family relationships were shown, there wouldn’t be a single central engram, rather, we could choose any individual engram as the central engram, and could traverse on to the other engrams using the linking threads. Now, in case a new member, say someone named Michael, joins the Adams family and adds a new video to the FAMILY VIDEOS table, the TED model would automatically create a new engram called "Michael Adams Video" and connect it to the "Jane Adams Video" engram by means of new threads that answer the information gathering question of "who." Figure 9 is a graphical illustration of this change.

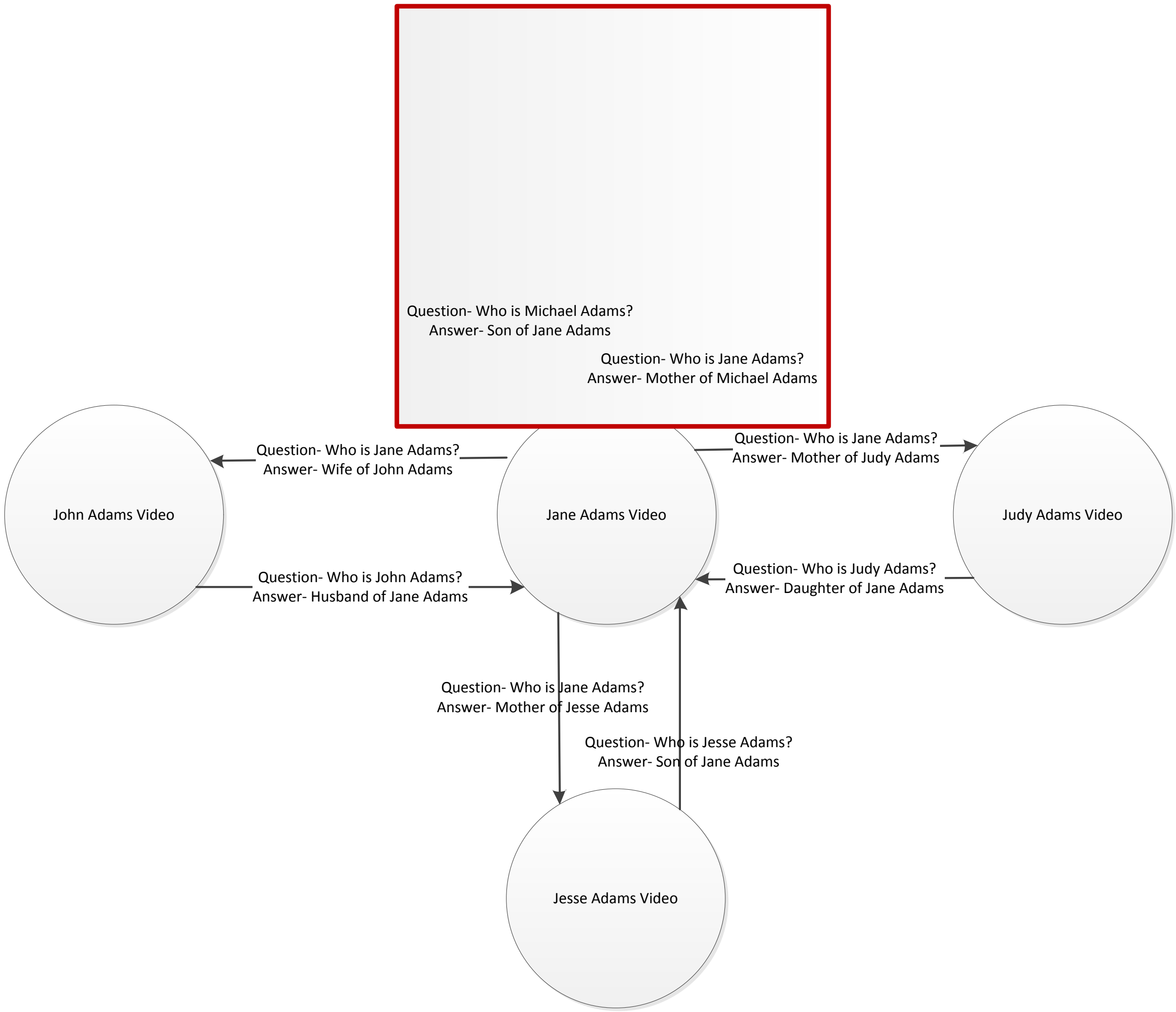

Figure 9: TED illustration of the addition of a new video to the FAMILY VIDEOS table

As shown in Figure 9, the threads, as well as the engrams that are connected by means of the threads, are dynamic in nature and constantly in a state of evolution. The highlighted section of the TED model shows the "Michael Adam Video" engram that is now connected to the "Jane Adams Video" engram by means of the information gathering question "who." Another example, that illustrates the linking of various individual engrams using all of the information gathering questions, can be seen in the following figure.

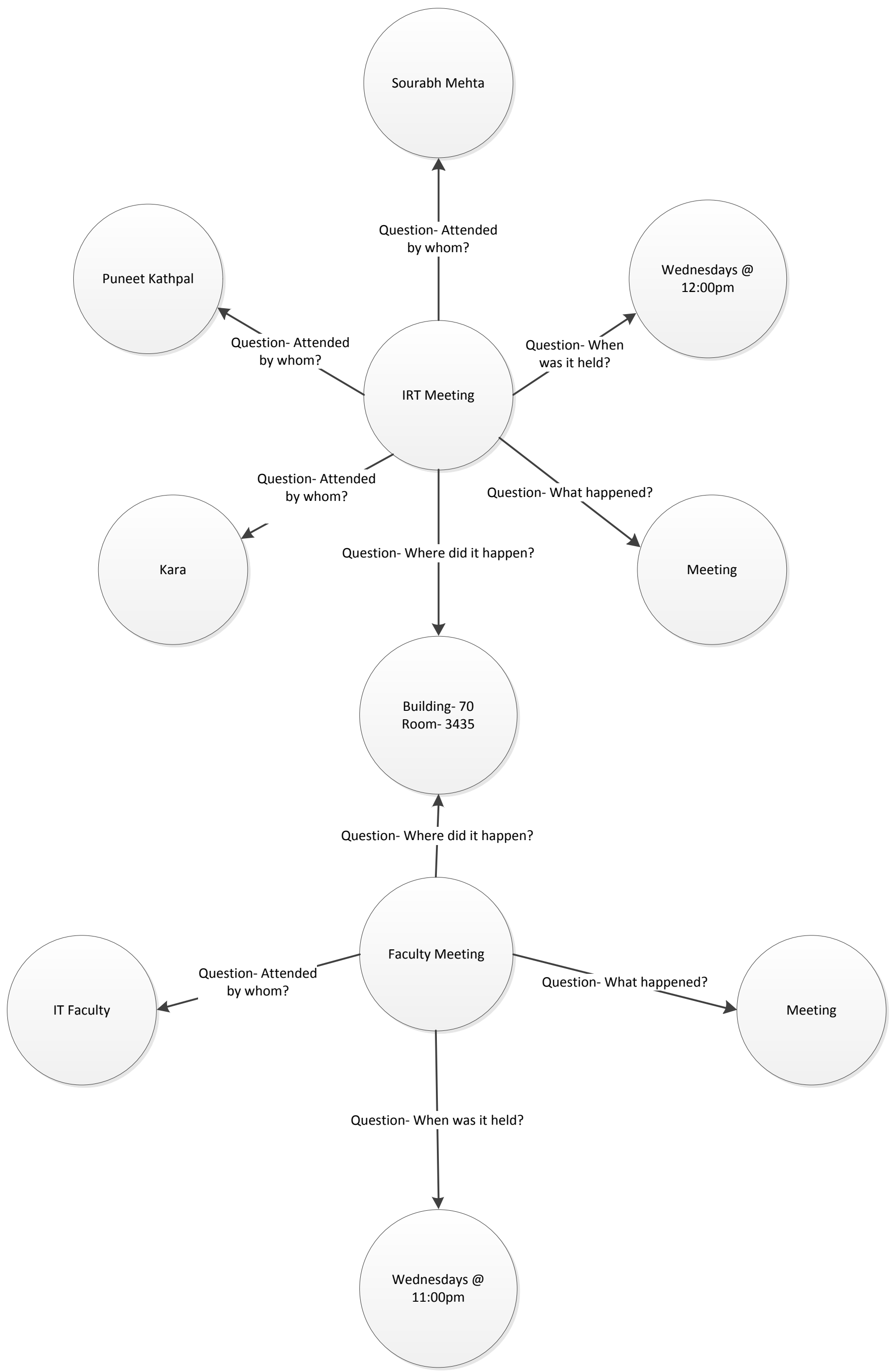

Figure 10: A TED representation of two clustered engrams linked by the "where" thread (Zilora- IRT).

As seen in Figure 10 above, two clustered engrams can easily be linked by traversing the "where" thread of one cluster to the other. This traversal of threads from one cluster of engrams to another would be the computational equivalent of the human brain relating new information to preexisting concepts, words, phrases, or items that already exist in memory. As such, it would theoretically be possible to link each and every new engram of information to a preexisting engram, or cluster of engrams, using at least one of the information gathering questions. This comprehensive network of threads connecting all the engrams of information together would enable analysis of preexisting relationships, the creation of new relations, and – ideally – the derivation of new insights.

Proposed Implementation Methodology

The Threaded Engram Database (TED) model represents a marked deviation from the relational models and methodologies. Most of the current database and data storage models tend to focus on the storage of "data" in an optimal fashion, while essentially ignoring or sidelining the fact that the sole reason for data storage is to allow for the derivation of information from the data. The TED model is designed to support the extraction of multiple relationships from unstructured data stored relationally and store the information using the TED components of threads and engrams.

The TED model proposed in this capstone is intentionally designed to be implemented as an application layer on-top-of a relational database, rather than as an independent standalone installation with its own underlying database. There are two main reasons for this, first, because most organizations, both in the US and worldwide, rely on relational databases to store and access data on a daily basis. By implementing the TED model on a relational database, we can facilitate the implementation process for businesses. They wouldn't have to drastically alter their database and data storage methodologies, rather, they could simply have to implement a TED layer on-top-of their relational database which would allow them to use both the TED model, as well as SQL queries to view their data. Secondly, implementing the TED model as an application layer, as opposed to an independent system, ensures that it will not be relegated to a niche market, wherein only a few institutions or organizations would use the model to meet a set of highly specialized requirements. This has been the case with Object Databases which were introduced in the early 1980s and were predicted to "supplant relational database management systems" (Leavitt). However, these predictions did not come true primarily because adoption of an alternative to the relational model would require a transfer out of the relational database which could lead to a loss of relations in the data. Additionally, the adoption of any alternative to the relational model generally translates to loss of the ability to use SQL as the language with which to query to data stores. SQL is generally the only data querying language in which organizations have in-house expertise. As such, the TED implementation as an application layer, on-top-of any relational database, provides organizations the freedom to continue using SQL to query the relational database, while simultaneously building a gradual expertise in TED. This would allow organizations to gradually adopt the TED model rather than making an unwelcome and abrupt shift from one data storage model to another.

Proposed Architecture of the TED Model

Based upon the study of human memory and numerous memory models, the author proposes that the architecture of the TED model be implemented as shown below in Figure 11.

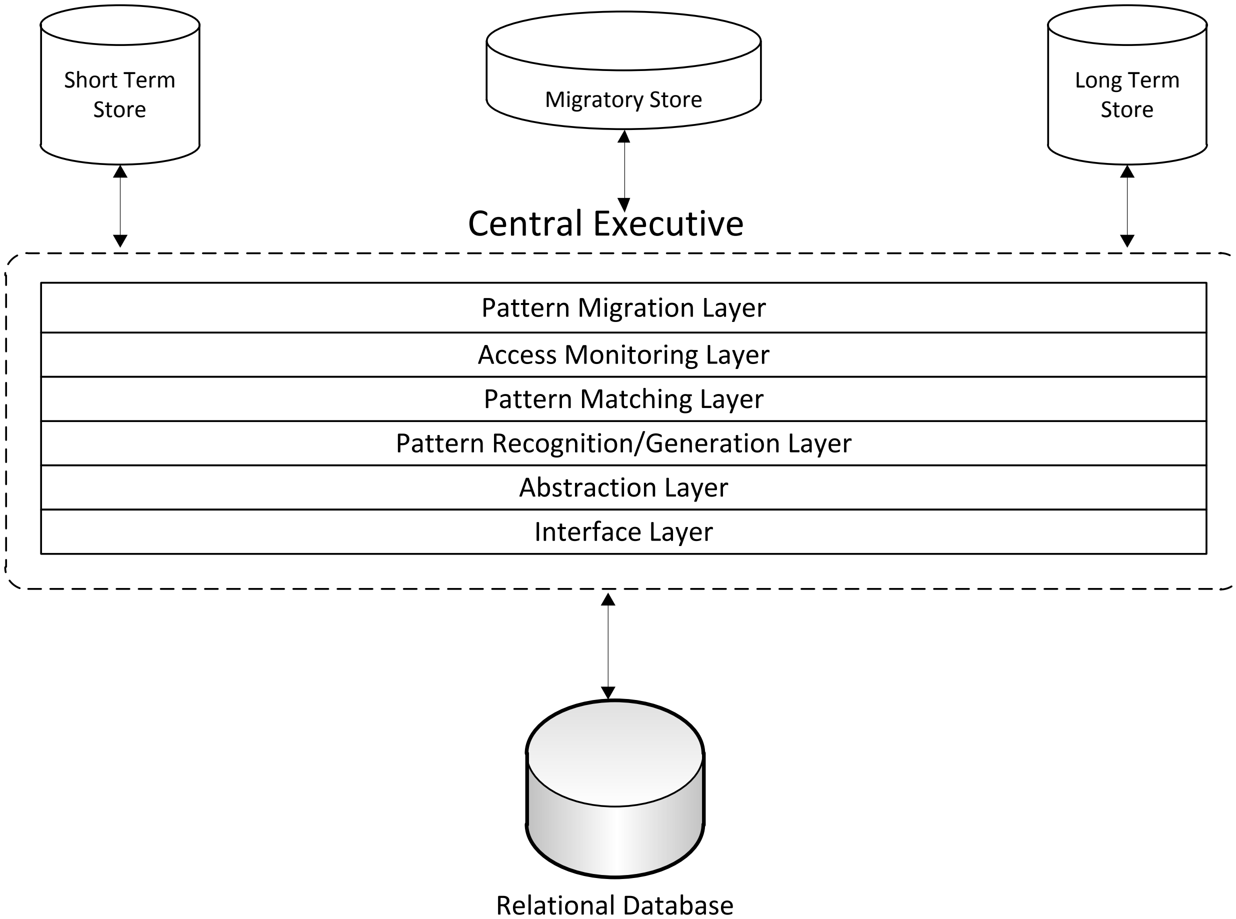

Figure 11: The TED model Architecture

The following will be the functions that will be performed by the different components of the TED model:

I. Migratory Store- The migratory store is the area wherein any newly created or derived engrams and their associated threads are stored once they have been processed by the pattern generation layer. The following are the key features and functionality of migratory store.

   A. Capacity- The capacity of the migratory store would depend greatly upon the implementation strategy employed for the TED model. If the TED model is implemented on a preexisting relational database, the TED model will have to convert all the components and relations stored in the relational database into TED components. This would mean that all of the newly derived engram clusters would be stored in the migratory store immediately, and would as such require a migratory store capacity that is greater than or equal to that of the relational database. The storage capacity requirements of the migratory store would not remain as high over time because once the pattern generation layer completes its conversion process, the pattern recognition layer will be activated and will begin monitoring the user queries and object access trends. This weighing of the contextual patterns will help ensure that the patterns that are accessed are moved from the migratory store to the short-term store, whereas patterns that are never accessed over a user defined period will eventually be decayed or deleted from the migratory store. Alternatively, if the TED model is implemented on a newly created relational database with little to no preexisting data, the migratory store will not be used and the size of the migratory store can be kept to a minimum, as there won't be many TED model components that will need to be stored.

B. Decay Period- The decay period is a user-defined time period after which any given engram cluster would be deleted or erased due to lack of access or usage. In the case of the migratory store, this decay period could be counteracted if the user accesses the engram cluster, as this would cause the weighing matrix layer to add weight units to the engram cluster, and move it from the migratory store to the short-term store. The decay period of the migratory store will generally be much longer than that of the short-term store, but smaller than that of the long-term store.

II. **Short-Term Store-** The short-term store is the TED model storage area that is based upon the short-term memory component of human memory, and as the name suggests, it serves as a short duration store for TED components, before they are actually transferred into the long-term store. The following are the key characteristics of the short-term store.

   A. **Capacity-** The capacity of the short-term store is designed to be relatively smaller than the long-term store, but is user-configurable, and as such can vary depending upon user requirements. If the TED model is implemented in a large organization where hundreds of transactions occur on a daily basis, the size of the short-term store would be much larger since each new SQL query or transaction would be converted into TED components and stored in the short-term store, at-least for the duration of the decay period. However, if the TED model is implemented in a smaller organization, the size of the short-term store would be much smaller since fewer engram clusters will be stored in the short-term store. The short-term store will also serve as a storage area for frequently accessed TED patterns. These contextual patterns or engram clusters will be pinned to the short-term store so as to speed-up the retrieval process for the engrams. The access monitoring layer will be responsible for adding weights to contextual patterns and ensuring that the engrams that are pinned to the short-term store meet the user defined weight constraint that enables them to remain pinned in the short-term store.

   B. **Decay Period-** The decay period in the short term store will be a user-configurable value, but will be relatively smaller than the long-term term store. Contextual patterns or engrams that do not meet the minimum user defined weight unit parameters, called “basal weight units,” in the short-term store will be erased after the end of the decay period. The length of the decay period, as well as the basal weight unit requirement of the short-term store will depend upon the activity level of a business. For example, the short-term store of a large scale business might have a weight unit limitation of say ten units and a decay period of a day, whereas a smaller business would require the basal weight unit to be five units and may setup a decay period of a month. The configuration of these parameters will be based upon getting an accurate feel of the business activity and requirements. As such, TED administrators might find it to their advantage to begin with a smaller basal weight unit requirement and a larger decay period.

III. Long-Term Store- Any engram or engram clusters that are accessed multiple times in the short-term store gradually build up sufficient weight to be moved into the long-term store. The long-term store serves as the TED model equivalent of long-term memory, and as such, stores engram clusters for a much longer period of time than the short-term store. The following are the key features and functionality of the long-term store.

A. Capacity- If the TED model is implemented on a newly created relational database, with no preexisting data, the storage requirements of the long-term store would be very reasonable, as it would have the opportunity to grow at a rate that is proportional to that of the relational database's storage. This is so because, the abstraction layer would transfer any newly created engram or engram cluster directly into short-term store, where they would reside until they are accessed again and, depending upon the user-defined weight parameters, are moved to long-term store or they decay based again upon a user-defined decay period. However, if the TED model is implemented on a preexisting database, the capacity of the long-term store would be much harder to predict as its growth would depend primarily on the user's access of specific datasets. As such, in this case the initial capacity of the long-term store might have to be setup to be of about the same size as the underlying relational database.

B. Decay Period- Although the long-term store is based upon the long-term memory component of human memory, it doesn't share all the features of long-term memory. A key difference between the long-term store and long-term memory is that unlike long-term memory, the long-term store doesn't store engram clusters indefinitely. Rather, engram clusters are stored in the long-term memory only as long as they meet the weight unit limits during the user specified decay period. This decay period could be offset if the user accesses the engram cluster, as this would cause the access monitoring layer to add weight units to the engram cluster, and preventing it from falling below the deletion threshold. The decay period of the long-term store will generally be much longer than that of the short-term store, but can vary widely depending upon the specific requirements of the business. For example, assuming that the TED model is implemented on a very active On-Line Transaction Processing (OLTP) system where hundreds of transactions occur on a daily basis, the TED administrators might decide to specify a decay time of a week to limit the total size of the long-term store. However, if the TED model is implemented in a much smaller business, where the total number of transaction are to the order of a hundred transactions per month, the TED administrator might decide to specify a decay period of three to six months.

Since the decay period is a variable parameter in the TED model, there would be a learning curve associated with setting the optimal length of time for every organization. As such, it would behoove every organization to begin with a larger decay period and then scale-back the time period as and when required. This would help ensure that the organization doesn't lose any previously created engram clusters that might be of potential use in the future.

IV. **The Central Executive-** The central executive is one of the most critical, as well as the most complicated, elements of the TED model. It is responsible for the integration of the TED model with the relational database. The central executive can be broken down into the following six functional components:

A. **Interface Layer-** The interface layer is responsible for establishing and maintaining a connection with the underlying relational database. While the initial design and implementations of the TED model might only be setup to connect to a single platform's relational database, the interface layer would ideally be designed to be platform agnostic or independent. This is to ensure that the central executive, and by extension the TED model, is able to connect to and work with any relational database platform, independent of the type, size or design.

B. **Abstraction Layer-** The abstraction layer is responsible for ensuring the efficient conversion of the relational database objects into TED components, while factoring out the details of the conversion, so as to reduce the observed complexity for the users. As such, the abstraction layer may receive database tables as input, and might output multiple engrams that are linked to each other by means of threads that answer the information-gathering questions. The conversion of the tables into engrams would be done by means of background processes. This will ensure that the users are able to access the preexisting TED components without having to wait for the new TED components or patterns to be processed by the abstraction layer.

C. Pattern Recognition or Generation Layer- The pattern recognition or generation layer, as the name suggests, is responsible for recognizing patterns in both preexisting, as well as newly entered information. In case the TED model is implemented on-top of a preexisting relational database, the pattern generation layer will be responsible for analyzing the existing table structure, data and other objects and generating a TED model based structure. Once the pattern generation layer has completed analyzing the existing data, it will begin monitoring all queries, as well as newly created database structures, such as tables, view, etc., to glean new information and generate new information and generate new patterns. These patterns will be linked to the preexisting engram clusters by means of invariant representation and auto-association. As discussed previously, our brain generally stores only the important parts or aspects of our daily experiences, and uses auto-association to fill in the missing blanks when we try to remember a particular experience or event. Similarly, the TED model also stores invariant patterns, composed of a set sequence of threads and engrams, of the information contained in the relational database and uses auto-association to match incomplete or partial patterns. An example illustrates this point. The following are partial reproductions of the previously shown TED diagram of the IRT meeting.

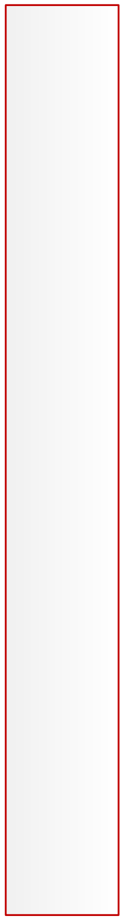

Figure 12: A TED model representation of the IRT meeting with a highlighted pattern.

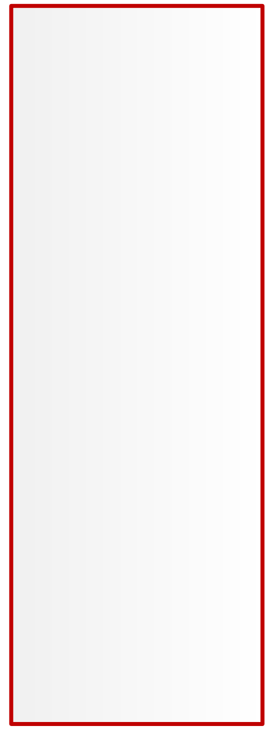

Figure 13: A partial pattern excised from the TED model representation in Figure 12.

Figure 12 contains a TED contextual pattern pertaining to the “Building-70 Room-3435” engram. Traversing up from the central “Building-70 Room-3435” engram using the information gathering question of “where,” we see that it is linked to the “IRT Meeting” engram. Furthermore, traversing up from the “IRT Meeting” engram using the information gathering question of “whom,” we see that the “IRT Meeting” engram is linked to the “Sourabh Mehta” engram. Similarly, travelling down from the “Building-70 Room-3435” engram using the information gathering question “when,” we see that the “Building-70 Room-3435” engram is linked to the “Faculty Meeting” engram. Traveling down further, we see the “Wednesdays @ 11:00pm” engram linked to the “Faculty Meeting” engram using the information gathering question of “when.” Let’s assume that the pattern generation layer generated the pattern shown in Figure 12, based on the data stored in a given relational database, and that the pattern recognition layer is presented with the partial pattern shown in Figure 13. Since the TED model stores invariant representation of engrams, it would automatically recognize that although the “IRT meeting” engram, in Figure 13, is currently linked to the “Building-70, Room-3435” engram by means of the “where” thread, this is not a restrictive relationship where the “Building-70, Room-3435” cannot be linked to any other engram. The “IRT meeting” engram could also form relationships with other engrams stored in either the long-term or the short-term store. These relationships would have the “IRT meeting” engram common amongst them and would be based upon the context of the information question being asked. Such context based relationships between engrams are called “contextual relationships” in the TED model. The auto-associative functionality of the TED model would then be utilized to perform a pattern match search against the preexisting engram clusters. The sensitivity and number of engrams returned by the pattern match search will be user-configurable parameters. This will help ensure that the search domain remains limited and relevant to the task at hand. The user will also be able to broaden the search parameters so as to traverse the various engram clusters and derive new information from the preexisting data.

D. Pattern Matching Layer- The TED model replicates two key characteristics of human memory, that all components of human memory function in concert with each other and that each component has its own independent storage area. Anytime we recall the verses of a song that we heard a long time ago, we are essentially copying the memory trace of the song from our long-term memory to our short-term memory, and say we begin humming the tune of the song, we would copy the same memory trace from our short-term memory to our phonological loop. Here, it is important to point out again that the act of copying the memory trace from one memory source to another doesn't erase the trace from the originating memory source. Thus, at any given time, there might be multiple copies of any given experience or event throughout our memory system depending on how we recall it. Similarly, even though the long-term store is responsible for the storage of all engram clusters over a comparatively longer period of time than the short-term store, it isn't the only location that an engram cluster might reside at any given time. Depending on the frequency of user access to the engram cluster, the following three scenarios might play out.

(i) The whole engram cluster is found in the short-term store- Whenever a pattern is passed on to the pattern matching layer, by the pattern recognition layer, it first attempts to match the contextual pattern with the engram clusters found in short-term memory. If a complete match is found, the engram cluster is returned back to the user through the central executive component of the TED model.

(ii) No match is found in the short-term store- If the user has never accessed, or rarely ever accesses, the engram cluster then the pattern matching layer wouldn't find a pattern match and would have to resort to a search of the long-term store. If a pattern match is found in the long-term store, then the matching pattern would be transferred into the short-term store by means of the pattern migration layer, and returned back to the user through the central executive component of the TED model.

(iii) A partial match is found in the short-term store- Since the engram clusters of the TED model are composed of multiple engrams that are linked by numerous threads, it is quite possible that a search of the short-term store would return a contextual pattern that is a partial match to the pattern presented by the pattern matching layer. In this case, the pattern recognition layer would again revert back to searching the long-term memory for either a complete match to the partial contextual pattern using auto associative search, or it could use the contextual pattern presented by the pattern matching layer to search for a complete pattern match in the long-term store.

E. Access Monitoring Layer- Each time the pattern matching layer finds a partial or complete match to a given pattern in the short-term or long-term store the access monitoring layer adds a weight unit to the contextual pattern. This addition of weight units performs two functions as discussed below.

(i) Prevention of decay- Any engram cluster or contextual pattern that is not accessed for a user-defined period of time is generally subject to deletion from the short-term or long-term stores. The use of weight units enables the TED model to monitor the access level of every contextual pattern or engram cluster. If an engram cluster does not receive even a single weight unit within a given decay period, then the TED model would be able to safely delete the engram clusters.

(ii) Ease of retrieval of frequently retrieved items- The assigning of weight units to engram clusters enables the access monitoring layer to recognize which engrams are accessed more frequently than others. These frequently accessed engrams can then be pinned to the short-term store, so as to ensure that anytime the pattern matching layer searches for a pattern match, it finds the pinned pattern instantly in the short-term store, without having to check the long-term store and transfer the pattern from the long-term store to the short-term store.

F. Pattern Migration Layer- The pattern migration layer will be responsible for the movement of TED components between the abstraction layer, the short-term store, the migratory store and the long-term store. The following is a breakdown of its specific functions.

(i) Migration of data between abstraction layer and the short-term store, migratory-store, or long-term store- The pattern migration layer will be responsible for the migration of data from the abstraction layer to the migratory store, the short-term store or long term store. This activity will take place once the abstraction layer has completed converting the relational database objections into TED components. Since the communication between the TED layer and the relational database is a two-way street, the pattern migration layer will also be responsible for migrating data from the short or long term store to the interface layer which can then communicate with the relational database directly.

(ii) Migration of data between the short-term store and the long-term store- Although the short-term and long-term store of the TED model are shown as separate components without clear links between them, they actually function together as a cohesive unit, much like the short-term and long-term components of human memory. This cohesive functioning is possible primarily due to the pattern migration layer which will be responsible for the seamless migration of data between the short-term and long-term stores.

(iii) Migration of data between the migratory store and the short-term store- If the TED model is implemented on a preexisting database, the pattern generation layer, in collaboration with the abstraction layer, will convert all the relational data and relationships into TED components and place them into the migratory store. This will be done by means of the abstraction layer. Furthermore, if the users attempt to access the data in the migratory store, this data will be moved from the migratory store to the short-term store. This will be accomplished by means of the pattern migration layer.

(iv) Migration of data amongst the central executive components- The central executive is composed of multiple layers, each of which performs a predefined set of tasks that helps transform relational components into TED components and integrates the TED model with the underlying relational database. The pattern migration layer is responsible for the migration of the TED components amongst these layers, so as to ensure that they function as an integrated unit and can communicate efficiently.

Implementation Techniques

The four components of the TED model, namely, the central executive, short-term store, migratory store and long-term store, can be implemented using a variety of programming languages, techniques and methodologies. The following is a brief overview, and in some cases a critique, of some of the most promising implementation techniques for each of the components of the TED model.

I. Central Executive- As stated previously, the central executive forms one of the most complex parts of the TED model, and can be divided into multiple layers or components, each of which performs a specific task that allows for the conversion and integration of data from the relational database to the TED model. As such, the CE can be considered to be the TED equivalent of a database engine.

   Since the TED model is designed to be both database and operating system platform agnostic, the CE would have to be designed in a platform independent programming languages like C, C++, Ruby, Python or Java. Each of these language conforms to the "write once, run anywhere" principle of programming and will essentially run on every platform, albeit with minor tweaks to account for operating system specific nuances. Additionally it is critical to reiterate that no matter what language or combination of languages is used in implementing the CE component, the key factor that needs to be taken into account is that each of the individual layers will have to be implemented in a way that ensures that all layers of the CE are able to seamlessly communicate bi-directionally with all the other layers of the CE.

II. Long-term, short-term and migratory store- Although the long, short and migratory stores of the TED model perform different functions and store data for varied lengths of time, they will share the same infrastructure. The following are the most promising methodologies that can be used to implement these stores.

A. Artificial Neural Networks- Neural networks are the closest computational construct to the neurons in the human brain and reflect the proposed TED model components of threads and engrams perfectly (NeuroDimensions). An Artificial Neural Network (ANN) is composed of programmatic constructs that are designed to emulate the neurons, and the dendrites, that connect these neurons. Generally, the ANN can be used for pattern recognition by first training the network on a subset of the actual data. In this process, the users provide an input, say an addition problem, to the neural network and observe the output produced by the network. If the output is incorrect, they increase the weight associated with the path the neural network followed. This increase in the weight of a path is considered to be the equivalent to an increase in the cost for the neural network to follow the path. Since neural networks are designed to follow paths with the least associated costs, the addition of weights to a wrong path ensures that the neural network will avoid following that path if the same input is provided again. Thus, by means of this "training process," the neural network is able to learn different pathways, or patterns, and arrive at an optimal solution ("NeuroSolutions: What Is a Neural Network?").

In an ANN-based implementation of the TED model, the short-term, migratory and long-term stores would each have its own neural network. In the event that the TED model is presented with a partial contextual pattern, the pattern matching layer would be responsible for presenting the partial pattern, first to the short-term store and then to the long-term store. Additionally, the pattern recognition layer will be responsible for recognizing whether the partial pattern that was presented to each of the stores actually matches a preexisting engram cluster in either the short-term or the long-term store. If a match is found, then the pattern migration layer will return the matching contextual pattern to the user.

Although an ANN based implementation of the TED model seems as the most promising development path, it is important to point out some inherent limitations of this methodology.

(i) Hidden Nodes- Neural networks generally contain multiple layers of hidden nodes that obscure the path that was taken to travel from the input to the output. This could potentially be one of the biggest limitations of a neural network-based implementation, since the TED model inherently depends upon detection of the complete path, starting from the input all the way to the output, to actually recognize contextual patterns. As such, the use of a neural network could severely limit the TED model's ability to discover and traverse new and alternative paths ("NeuroSolutions: What Is a Neural Network?"). The following is an image that illustrates the architecture of a simple feed forward neural network with a single hidden layer. It is important to note that although the image shows just a single hidden layer, the number of hidden layers in a neural network is not limited to one, rather, the complexity, and as a result the number of hidden layers, is dependent primarily upon the potential usage of a neural network.

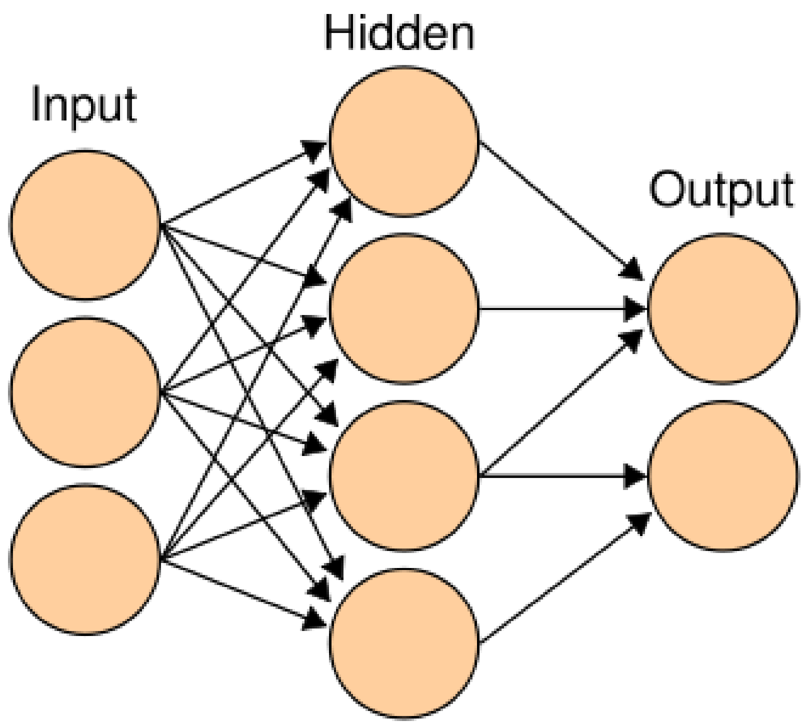

Figure 14: A simple feed forward neural network (NeuroDimensions)

(ii) Travel Paths- In the TED model each engram is connected to other engrams by means of the answers to the information gathering questions of "who, what, when and where" (Ackoff). These information gathering questions serve as the primary means by which a user can traverse not only from one engram to another, but also from one engram cluster to another. However, in the case of neural networks, although each node is connected to another node by means of edges, there is no way to establish multiple directed edges or label the edges with the information gathering questions, so as to ensure that the users travel down a contextual path based upon the question being asked, rather than aimlessly traversing from one node to another. This limitation of not being able to label and as a result travel down specific travel paths is another limitation of ANN.

B. Prolog- The logic-based language Prolog can serve as a viable alternative to neural networks when implementing the short-term, migratory and long-term stores of the TED model. This is because Prolog supports the storage of data in the form of a Prolog construct called a "fact," and links (or relates) these facts using "rules." Additionally, since Prolog is a declarative language, it does not require that the user specifically design a program that tells it how to solve a problem. Rather, it uses the rules and facts entered into the Prolog database to deduce an answer to any user given query (Endriss). An example illustrates this concept.

Unique Identifier	Name	Title
1	Jane Adams	Mother
2	John Adams	Father
3	Judy Adams	Sister
4	Jesse Adams	Brother
5	Jane James	Mother
6	John James	Father
7	Judy James	Sister
8	Jesse James	Brother
9	Jane Smith	Mother
10	John Smith	Father
11	Judy Smith	Sister
12	Jesse Smith	Brother

Table 3: FAMILY table

Table 3 contains a unique identifier, the name and relationship (based upon a specific question) of every person that resides in the Adams, James and Smith families. This very same information can be easily stored and correlated in a Prolog database. In fact, the Prolog Family tree is a classic training example that is often used to teach students the basic workings of the Prolog language. The Adams family data stored in the FAMILY table can be stored in a Prolog database using the following syntax.

Prolog Clauses	Explanation
male(JohnAdams). Male(JesseAdams). Female(JaneAdams). Female(JudyAdams).	The code on the left represents Prolog "facts." Facts are pieces of data in Prolog that can be connected or related using rules. The facts on the left specify the gender of Adams family members.
Mother_child(JaneAdams, JudyAdams). Mother_child(JaneAdams, JesseAdams).	The facts on the left can be read as follows: (i) Jane Adams is the mother of Judy Adams. (ii) Jane Adams is the mother of Jesse Adams.
Father_child(JohnAdams, JudyAdams). Father_child(JohnAdams, JesseAdams).	The facts on the left can be read as follows: (i) John Adams is the father of Judy Adams. (ii) John Adams is the father of Jesse Adams.
Siblings(A,B) :- parent_child(P,C), parent_child(P,D).	The code on the left represents a rule. The text before the ":-" represents the head, or the name of the relation, whereas the text after the ":-" sign represents the body, or the definition of the relation. The variables A and B are used to represent potential siblings, and the variables P and C are used to represent Parent and Child. This rule can be read as: A and B are siblings if both C and D share the same parent P.
parent_child(P,C) :- mother_child(M,C).	This rule can be read as: P and C are parent and child if M is the mother of C.
parent_child(P,C) :- father_child(F,C).	This rule can be read as: P and C are parent and child if F is the father of C.
?- siblings(JudyAdams, JesseAdams). Yes	The "?-" sign in the text on the left represents the Prolog prompt. In the text immediately following the prompt, we

	query Prolog to see if JudyAdams and JesseAdams are siblings. Prolog uses logical reasoning to infer the response to the query using the facts and rules specified previously. In this case, it responds with "Yes" and positively identifies Judy Adams and Jesse Adams as siblings.
?- father_child(JohnAdams, JaneAdams). No	The query on the left evaluates to "No," as it is in violation of the father_child facts stated previously.
?- mother_child(JaneAdams, X). X= JudyAdams X= JesseAdams	The query on the left uses the mother fact with the variable X to search for the child of JaneAdams. The Prolog compiler checks the facts and rules stored in the database and returns the two children of JaneAdams.

Table 4: Prolog Example

As seen in the examples in Table 4, Prolog is entirely capable of taking facts and rules as inputs and inferring conclusions from them. Contrary to the working methodology of neural networks wherein the ANN has to be specially trained on a dataset that is representative of the actual data, Prolog doesn't require any training on a dataset and can begin responding to queries as soon as all the relevant facts and rules are entered into the Prolog database (Endriss).

Based upon the discussion above, a Prolog based implementation of the short-term, long-term and migratory stores would be ideal because, unlike neural networks which have hidden nodes and travel paths, Prolog's logic based traversal of the facts can easily be structured by providing the appropriate rules which in the case of the TED model would be the information gathering questions of "who, what, when, and where" (Ackoff).

Conclusion

The Threaded Engram Database (TED) model introduced in this capstone is based upon extensive study of architecture and workings of numerous memory models, such as the Atkinson-Shiffrin memory model (Atkinson and Shiffrin), Baddeley's model of working memory (Baddeley and Hitch), Memory-prediction model (Hawkins and Blakeslee). It is designed to search, extract and store structured and unstructured data from relational databases, such that the context of the data is maintained by means of the answers to the information gathering questions of "who, what, when and where." Additionally, by means of features, such as invariant representation and auto-association, the TED model can easily and efficiently create and maintain relationships between new and preexisting information.

The efficient design and implementation of the TED model, as proposed in this capstone, should enable it overcome the key limitation of the relational database model, namely, the storage of data in a relational database leads to a loss of the context of the data. Furthermore, the addition of context by the TED model would enable administrators and users to perform new and improved analysis of their data by traversing diverse engram clusters that would be linked by the information gathering questions.

Future Work

In this capstone thesis, the author has attempted to explore, define and introduce the concept of the TED model and lay the groundwork for future research in this area. A lot of work remains to be done before the TED model can actually be successfully implemented as an independent layer on-top-of a relational database. The author recommends that a piecemeal approach be used when developing the numerous components of the TED model. As such, the first step would be the development of individual layers of the Central Executive component of the TED model.

Specifically, the development of an interface layer that is capable of interacting with multiple relational databases will help ensure that the TED model's proposed design of being database platform agnostic is indeed realistic or not. Given the current advancements in the JDBC and ODBC drivers in all programming languages, the author believes that this task should be relatively straightforward and wouldn't be a stumbling block in the development process. The next critical step would be the development of the abstraction layer, which would be much more complicated, as it would require the conversion of the data and relations, read-in from the relational database, into TED model components. Once the abstraction layer is successfully developed, the development of the other components of the CE could be done in parallel, as all the other layers perform specific tasks that are not completely dependent upon each other.

Depending upon the degree of success and acceptance of the TED model by the academic and business community, the author believes that the TED model could be further improved or expanded upon by implementing the following features:

I. Rank order of returned list of clusters- The architectural implementation proposed in this capstone outlines the minimal requirements that have to be met to ensure successful development of the TED model, however, once the model has been successfully implemented, one of the first developmental steps that should be undertaken would be to incorporate a rank ordering system for clusters that are returned by the pattern matching layer. As it stands currently, anytime the pattern matching layer finds a matching pattern, it will return the complete contextual path without really trying to sort the result to see if there is any segment of the path that actually meets the user's specific requirements. By implementing a rank ordering system, the TED model would be well positioned to evaluate the user requirements and return smaller segments of the contextual path in a rank order, such that the most likely result would be ranked first and would be followed by a list of the other possible results. This feature would be extremely beneficial to the user as they could easily scan through the result-set and choose the contextual path that best meets their needs or requirements.

II. Fuzzy logic- As mentioned previously, data stored in the real world is never really precise and can rarely ever be described in the absolute terms that are required when storing data in any format. The TED model tries to alleviate this issue by presenting, storing and retrieving data in a way that provides context to the data. However, even this context that is provided to the data is limited due to the level of precision that is required when linking engrams by means of the information gathering questions of "who, what, when and where." For example, whenever we ask the question "when," we expect a time based response, such as "At 10:00 am." However, the question "when" can also be answered as "repeatedly," "last summer," "a short while back," etc. Each of these responses is an imprecise answer to a very precise question. The current proposed design of the TED model does not take into account the imprecision of data or the information gathering questions. As such, this would form one of the most important aspects of the TED model that would need to be addressed in the near future.

III. Development towards an independent model- In this capstone, the author has proposed that the TED model be implemented as an application layer on-top-of a relational database model, rather than an independent database model with no links to a relational database. This was done to ensure that the general public has a chance to use and explore the additional benefits that the TED model has to offer over the use of just a relational database. However, this sort of relational database dependent implementation does not and never will resolve all of the limitations (outlined in the introduction) of the relational database model. As such, the author believes that the TED model should eventually evolve into an independent database model, which would support the import or transfer of data from a relational database, but would be free standing and wouldn't be inherently dependent upon the relational database model.

IV. Alternative Implementations- The database based implementation of the TED model proposed in this capstone forms just one of many potential paths that a maturing TED model might take. If the TED model receives a favorable reception, then this model could be expanded upon to improvise the storage of data in general. A prime example of such an application would be the organization and linking of documents stored on an operating system such as Microsoft Windows.

Whenever we store documents of any kind, be it word documents, text documents, photographs, etc. we generally store them in a centralized location, such as the "My Documents" folder or in separate folders organized by the type of content, such as My Music, My Pictures, etc. This storage format of materials is far from efficient as it requires us to either consciously arrange or classify the stored data in separate folders, or search for the data on-the-fly whenever we happen to need the data. Additionally, this storage methodology makes it extremely difficult to link related files even if they are stored in different locations. For example, if we store the image of a drill in the My Pictures folder, a document describing the parts and specifications of the drill in the My Documents folder, and say a video of the drill in action in the My Videos folder, there is currently no way to link the files without actually putting them all together in a single folder. However, by means of an extended TED model, we could easily manage the disparately stored data and link them using the threads of the TED model.

V. Storage of biological sequences- With the recent advent of new and improved gene mapping tools and algorithms, biology and bioinformatics scientists have been able to make rapid progress in deciphering and mapping the genomes of hundreds of species. As it stands currently, there is no efficient way of storing unstructured data, such as partial or complete genetic sequences of individual species, and comparing that to other species. The author believes that by adapting the TED model for the storage of gene information, scientists can easily slice and dice the genes to perform comparative analysis. For example, given a gene sequence of say 100 base pairs, the scientists can easily tag individual sections (chunks) of the sequence as relating to specific diseases like cancer, necrosis, etc. while keeping the overall sequence intact by means of the TED thread component. This will enable the scientists to compare individual sections of one biological sequence to another and detect matching patterns both within similar species and between seemingly disparate species.

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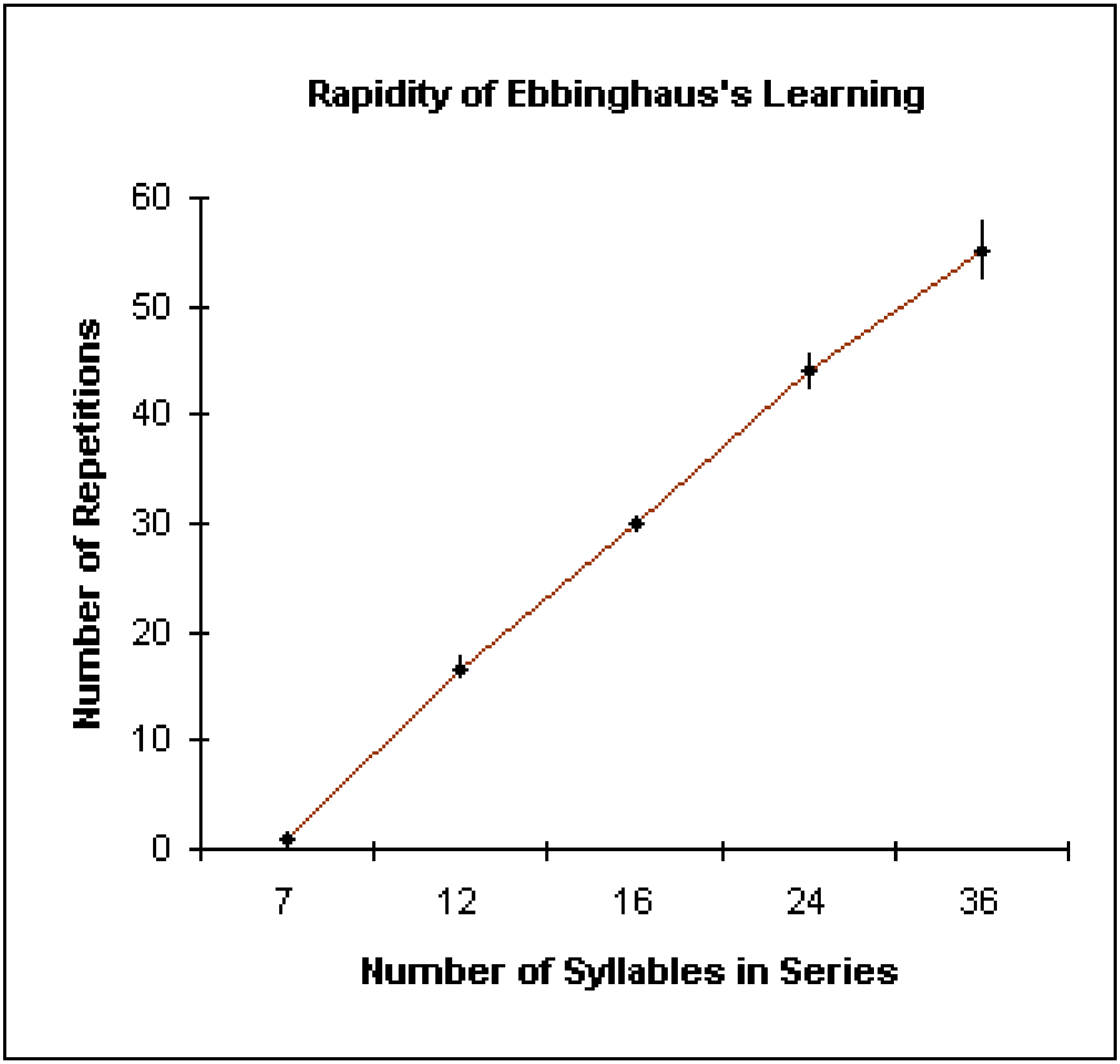
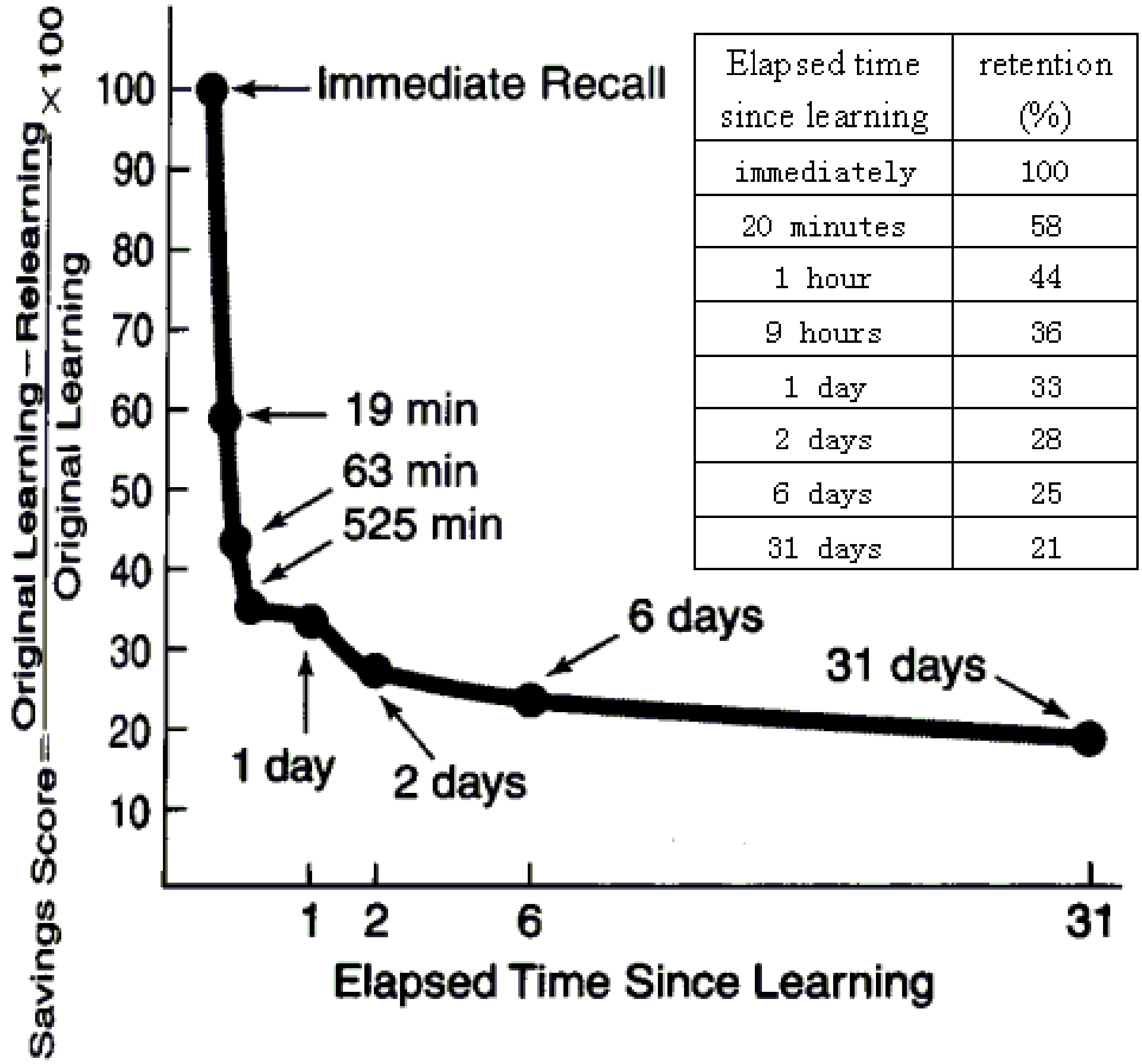
APPENDIX A- A Sample Learning Curve



Reference: Johnson

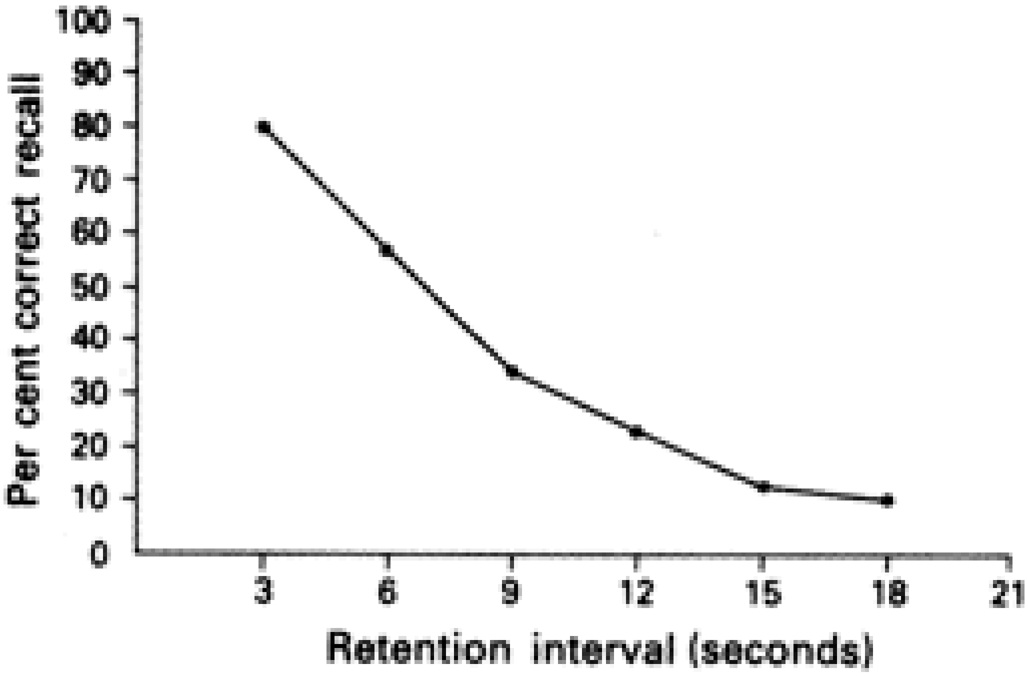
APPENDIX B- A Sample Forgetting Curve



Elapsed time since learning	retention (%)
immediately	100
20 minutes	58
1 hour	44
9 hours	36
1 day	33
2 days	28
6 days	25
31 days	21

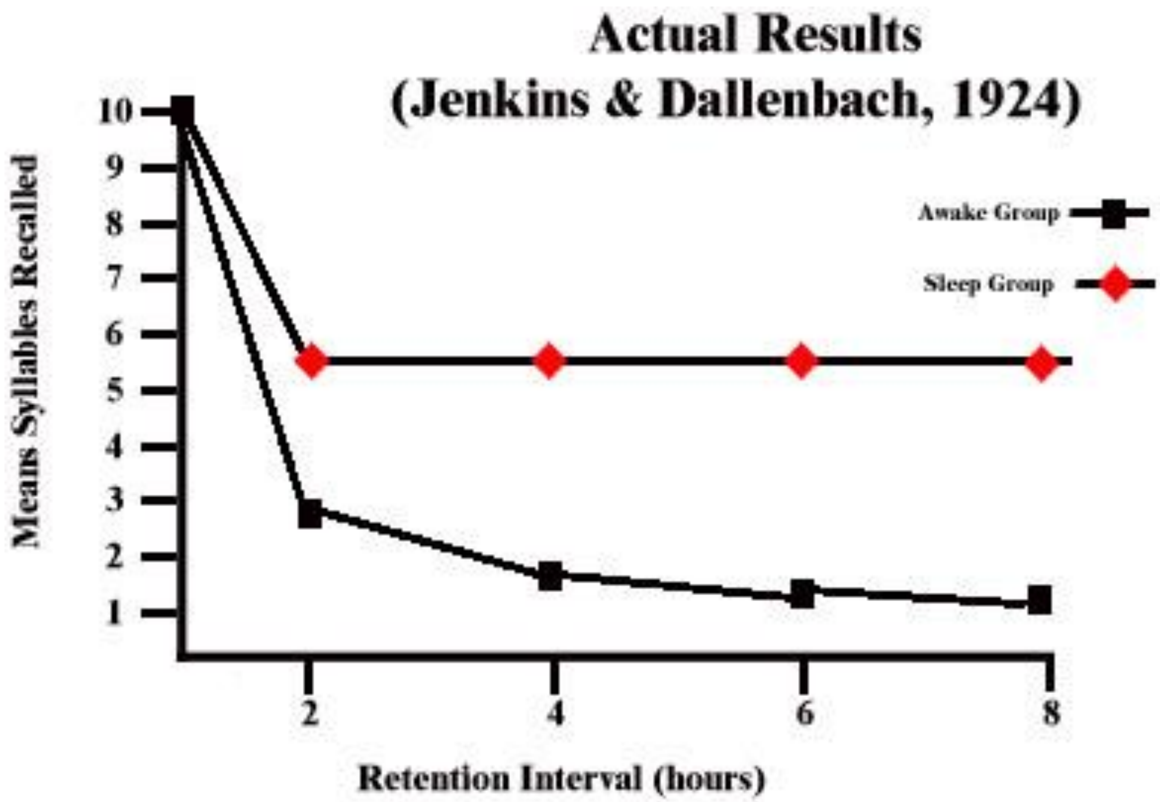
Reference: McCormick

APPENDIX C- Retention Interval for Short-Term Memory



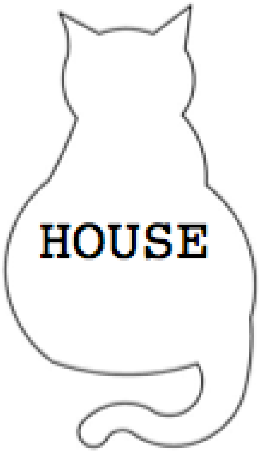
Reference: Gillet

APPENDIX D- Retention Interval for Long-Term Memory

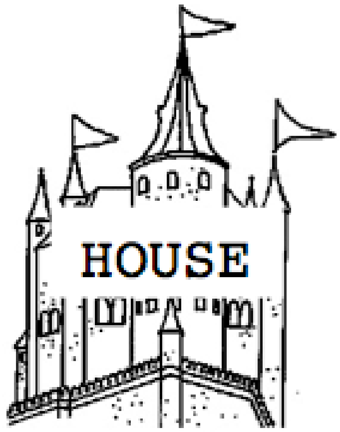


Reference: Eckerman

APPENDIX E- Pictorial Example of Semantic Interference



(a)



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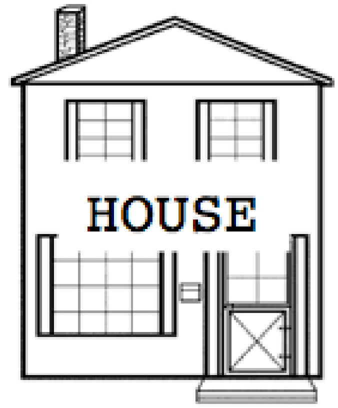
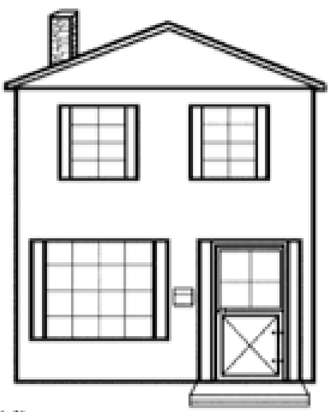


(c)



(d)

HOUSE

(e)

Reference: Van Maanen and Van Rijn

Glossary of Terms

1. **Auto-association-** Auto-association is a feature of both the human cortex and the TED model. It is used in the TED model to fill in the missing blocks of an incomplete or distorted pattern.
2. **Basal weight units-** The short-term, migratory and long-term stores of the TED model are designed to store contextual patterns or engrams only until they meet the minimum user defined weight unit parameter called "basal weight units." Each time the pattern matching layer finds a partial or complete match to a given pattern in the short-term or long-term store the access monitoring layer adds a weight unit to the contextual pattern. The contextual patterns that do not meet the basal weight units within a user defined period of time are generally erased from the short-term, migratory and long-term stores.
3. **Contextual pattern-** Each engram in the TED model is linked to multiple engrams using numerous threads. As such, a user may traverse from one engram to another using one or more specific information gathering questions which help them arrive at a result. This traversal of key engrams and threads to answer a predetermined question is called a contextual pattern.
4. **Contextual relationships-** Any two engrams can be related by means of the answer to one or more of the information gathering questions. Since the answer to the information gathering question depends upon the context of the question, the relationship between the engrams is called a contextual relationship.
5. **Decay period-** The decay period is a user-defined time period after which any given engram cluster would be deleted or erased due to lack of access or usage.
6. **Engram-** Any database object(s) that can be related to, or can form relationships with, another object(s).

7. Information gathering questions- The information gathering questions are composed of "who, what, when and where." The answers to these information gathering questions are used to link engrams together using threads.
8. Threads- Threads are the standard connections that are used to link, or relate, one engram to another. Each thread connecting one engram to another is formed on the basis of the answers to the information gathering questions of "who, what, when and where."
9. Engram cluster- A collection of threads and engrams is called an engram cluster.
10. Invariant representation- Invariant representation is a feature of both the human cortex and the TED model. It can be defined as the storage of the critical or defining elements of a pattern such that even if the pattern is modified and presented in a different form, the TED model or our cortex can instantly match these elements and recognize the pattern.