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A STUDY OF COMPUTATIONAL LONG-TERM MEMORY ARCHITECTURE FOR MIMIC HUMAN BEHAVIOUR

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ABSTRACT

Computational Long Term Memory Architecture is the suggested model's module name. Each of the three modules in the Architecture represents one of the three main categories of human long-term memory: computational semantics, episodic memory, and procedural memory. In order to aid the episodic and procedural modules and to make cognitive judgments, the semantic module is programmed to acquire knowledge about the semantics of various sensory domains. This component learns the semantics of phrases in natural language and translates them into episodic experiences that may serve as a prompt for conversation. A computational mechanism based on a grid and the place neuron is presented, enabling an artificial agent to localize itself in a known environment; this paves the way for the agent to navigate to complex tasks that necessitate learning the spatial semantics of objects for handling. The capabilities of episodic memory are mirrored in the proposed episodic module. This section utilizes the abstract event information, such as event activities and other contextual elements necessary for event encoding and episode generation that has been pre-processed. To save on storage, the episodic module uses a remembering process similar to the forgetting mechanism. By carefully crafting the forgetting decay function, we were able to reduce the rate of event miss relative to state-of-the-art methods like EM ART. The suggested model's third component is a procedural module meant to teach the user how to carry out certain actions. Together, it and the semantic module teach the meaning of actions. This component was developed to learn tasks via the sequential manipulation of object bodies. This module uses deep neural networks to learn the motor level activities that occur in the body in response to interactions with objects.

KEYWORDS: Computational, Long-Term Memory Architecture, Mimic Human Behaviour

Introduction

In this study, we look at a Computational Long Term Memory Architecture (CLTMA) that implements some of the fundamental computational components of human intelligence. Figure 1 depicts this architectural setup. The architecture's modules are each specified in terms of the role they play. To attain human intelligence, all modules coordinate their efforts and share the results of their processing with one another. One of the model's three components, the Semantic Module (SM), is designed to mimic the human mind's semantic memory. The second part, the Episodic Module (EM), is specifically designed to store human episodic memories. Third, there is a

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specific section of your brain devoted to procedural memory, known as a Procedural module (PM).

COMPUTATIONAL SEMANTIC MODULE (CSM)

In order to understand the semantics of language, space, bodily motions, and events, the computational Semantic Module processes all sensory information. The module is broken down even further into four sub-parts, each of which is responsible for a distinct task. Each building block's purpose is outlined below.

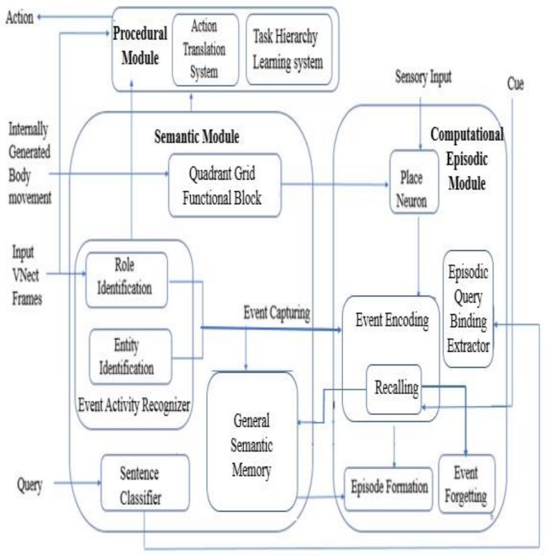

Figure 1: Proposed Computational Long-Term Memory Architecture

a. Event Activity Recognizer (EAR)

This block's job is to figure out what those people in the background are doing. The Vnect model's preprocessed visual output is sent into the functional block, where it is further processed in order to accomplish the role identification task. After determining what has occurred, block notifies the episode module of the roles or tasks involved in the event. In order to understand the broad strokes of real-world occurrences, it also passes the recognized actions on to the semantic module's general semantic memory. In addition, the EAR cooperates with the procedural module by transmitting motor-level semantics to procedural memory in order to instruct behavior.

b. Sentence Classifier

The classifier's task is to determine which of the stored sentences the input sentence most closely resembles. The agent may make use of the relevant interaction module for the input phrase by routing it to the correct module using categorization. For instance, the phrase classifier will forward event-related queries to the episodic model so that the agent may provide appropriate responses.

c. General Semantic Memory

So that the agent can anticipate what will happen next, the block studies the patterns and timing of actual occurrences. The EFFB receives the block's forecast. Concepts and their hierarchies may be learned by the memory.

d. Quadrant Grid Functional Block (QGFB)

Learning the spatial semantics of various 2D settings and objects is the job of the functional block. Using quadrants, the module has constructed a hexagonal pattern with varying spacing and rotations, all dependent on the generated motion of internal body components. The environment is broken down into a grid code by a network of neurons. To learn how places are laid up in a given area, the module transmits a grid code to the place neuron block of the episodic memory module.

3.2 Computational Episodic Module (CEM)

The Episodic component successfully replicated all the key features of human episodic memory. The module's functionality is broken down into separate but related sections. Each cognitive module is a computer model that replicates a particular aspect of episodic memory. Each building block is described as follows:

a. Place Neuron Functional Block (PNFB)

The job of the functional block is to link a grid code (received from the QGFB) with the sensory input (sight or touch) that will be obtained via engagement with the physical world. Associative learning allows the block to produce a grid code that is in sync with the user's sight and touch. The grid code may be useful for entering a mental map of a location and for encoding a sense of location in a remembered event.

b. Event Encoding Functional Block (EEFB)

The block's job is to record the happenings of an event, keep track of them, and play them back at the drop of a hat. Additionally, the block supplies the generalized functional block for event consolidations with the remembered output.

c. Event Forgetting Functional Block (EFFB)

The purpose of the functional block is to prevent the agent from remembering irrelevant experiences (those with low emotional significance and low recall frequency).

d. Episode Formation Functional Block (EFFB)

The GSM's forecasts inform how the functional block groups the occurrences.

e. Episodic Query Binding Extractor Functional Block (EQBEFB)

This section should be used for inquiries about the past. A functional block's job is to take an episodic query and convert it into a binding that can be processed by the episodic module.

COMPUTATIONAL PROCEDURAL MODULE (CPM)

The component is analogous to people's procedural memory. There are two distinct functional units that make up the module.

a. Task Hierarchy Learning System

This computational module's responsibility is to acquire knowledge about task hierarchies. It creates a hierarchical structure for jobs by breaking them down into smaller and smaller pieces, until the lowest-level work is reduced to its atomic components.

b. Action Translation System

An implicit motor procedural memory that uses deep learning to learn tasks in terms of the movement of bodily joints

PRELIMINARIES OF GRID AND THE PLACE NEURON

To appreciate the suggested computational work on the grid and the place neuron, it is necessary to be familiar with certain hypotheses, scientific research findings, and architectural particulars pertaining to both.

During experiments on the rat brain conducted by John O'Keefe et.al in 1971, the place cell was discovered in the CA3 region of the hippocampus. The neuron only gives a spike when the rat comes in a particular area of the environment, hence the name "Place Neurons". When a person's Place neurons fire, they are alerted to their current place. The place field describes the extent and form of the field in which a place neuron may become active, which may be affected by the dimensions of the surrounding space. Researchers didn't know where the neuron got its position information from until the discovery of grid neurons. The fact that the place neuron is able to foresee their impending locations, as shown by its activity in an earlier phase of theta rhythm during traversal towards the site corresponding to the place neuron, further added to the enigma. It has been postulated that the location neuron acquires a cognitive map of an environment, i.e. an internal representation of the world, since it generates the same activity even in the dark (without any visual input). The picture becomes clearer, however, with the discovery of grid neurons in the entorhinal cortex of rodents and humans; these neurons are one of the main sources of input to the place neurons, and they generate the hexagonal gridlike periodic activation pattern during navigation in an environment (i.e., activation derives from the self-motion). When the agent enters the hexagonal grid's firing range, the grid neuron lights up like a bulb whose brightness varies with the distance between the agent and the closest grid point. Our article describes a circular shooting range around each grid point, which we call the grid ring, with the grid point at its center. If the agent is not inside the grid ring of a given grid point, that point's bulb or grid is deactivated; also, the intensity of the bulb, i.e. the grid neuron, is greater when the distance between the agent and the center is less, and vice versa. As a grid neuron's activation depends on where the agent is located; at time t = 2, a red grid neuron indicates that the agent is at any grid point of the hexagonal grid, while at time t = 0, a blue grid neuron indicates that the neuron is inactive because the agent is outside the firing range of any grid point.

A grid neuron's grid pattern might differ in spacing and orientation from neighbouring grid neurons depicts three distinct grid neurons with varying spacing and orientation. When these patterns are stacked, they form a unique compact code called a grid code (grid neuron activation) that corresponds to the current sensory input or the agent location. This code can be associated with the current sensory input, in this case the visual input of place, and used to create a cognitive map of the environment. Since grid activation is periodic, integrating one's movement (self-motion) with the present activation state of grid neurons yields prediction activation of each grid neuron. Grid code prediction means that associated information can be gleaned from self-motion input, aiding in localization within the working environment. As a result, both rodents and humans can find their way to their destination in the dark (where visual input is unavailable).

CONCLUSION

The semantic module is equipped with an LSTM-based natural language classifier, a computational mechanism that enables it to communicate with people. Our research has led us to classify natural language sentences as either order, information, or a question. Since each sentence category requires its own dedicated memory module, LSTM is used for classification to determine the sentence's category and then direct the sentence to the appropriate memory module. The LSTM neural network is used to do the classification, and a 91% accuracy rate is attained. The computational event encoding, forgetting, episode construction, query response, and hierarchical event storage method are all made available to the episodic module so that specific data about events may be kept in memory storage. The suggested encoding technique stores information about real-world events in a form that allows them to be remembered in response to an episodic question. The inquiry is in plain language, thus the episodic module proposes a binding extractor to translate it into a form that may be understood as a trigger in episodic memory. In terms of binding extraction, we reach a precision of 91%. The method is more abstract since it does not use sensory data or motor skill use in its suggested model. This method works well in simulated situations if the agent is only given high-level, abstract knowledge rather than sensory data. The model has an event encoding mechanism, which, in contrast to prior models, allows forgetting of just certain event activities rather than the whole event itself. The model's space efficiency is superior than that of any other episodic memory model because of a cardinality element included to the forgetting process. In addition, we provide a novel unified process for creating the knowledge graph that is based on remembering and repeating experiences. In addition, a goal-directed inference is performed on the constructed knowledge graph. The effectiveness of the model is evaluated by sending it into a simulated battlefield.

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