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Research Article

Architectural Framework For Enhancing The Artificial Brain - Memory Segmentation Mechanism Using K- Mapping Algorithm

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Abstract: The concept of an "artificial intelligence brain" and "memory segmentation mechanism" can be approached from various angles, and it's important to clarify what you mean by these terms. However, I can provide a general overview of how these concepts might relate to artificial intelligence. The AI as a Brain Analogy of artificial intelligence, the term "AI brain" is often used metaphorically to describe the central processing unit or core logic of an AI system. This refers to the software and hardware components that enable an AI system to process information, make decisions, and perform tasks.

Key words: Artificial Intelligence, Memory, Segmentation, Brain and Segmentation

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1. INTRODUCTION

One of the most common techniques in AI, especially in deep learning, is the use of artificial neural networks. These networks are inspired by the structure and function of the human brain. They consist of interconnected nodes (neurons) that process and transmit information. In another aspect, the "Cognitive Computing" play a significant role in some AI systems aim to mimic cognitive functions like perception, learning, reasoning, and problem-solving, which are performed by the human brain. These systems use various algorithms and data structures to simulate cognitive processes. The AI Brain Research: In the field of AI research, there is an ongoing effort to understand and replicate the brain's functionality to create more efficient and capable AI systems [1][2][3]. This includes studying neuroscience to inform AI design. The Memory Segmentation Mechanism in AI typically refers to the ability of a machine to store and retrieve information. In AI, the memory can take various forms, such as short-term memory (used for immediate tasks) and long-term memory (used for retaining knowledge over time).

i) Segmentation in Memory: Memory segmentation can be seen as the process of organizing and storing information in a structured manner. This might involve categorizing information, indexing it, or separating it into different compartments based on relevance or context.
ii) Applications: In AI, memory segmentation mechanisms can be crucial for tasks like natural language understanding, where the AI system needs to

remember and categorize different aspects of the conversation to provide meaningful responses.

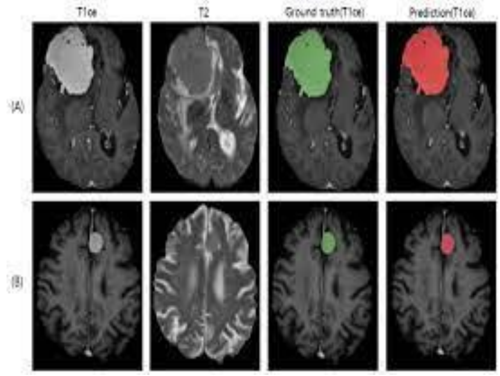

Figure 1.1 Brain-Memory segmentation sample in medical domain

In the context of machine learning, recurrent neural networks (RNNs) and attention mechanisms are used to manage memory and focus on specific parts of input sequences, effectively implementing a form of segmentation. The above figure 1.1 represents an sample image of artificial brain -memory segmentation in medical domain. The concept of an "artificial intelligence brain" is often used metaphorically to describe the core processing and decision-making components of AI systems.

Memory segmentation mechanisms refer to the ways AI systems organize and manage information, which is essential for various AI applications, including natural language processing and cognitive tasks. These concepts are part of the ongoing effort to make AI more intelligent and capable.

2. LITERATURE SURVEY: EXISTING ALGORITHMS

The "Artificial Brain Memory segmentation architecture" that is widely accepted and replicating the human brain's memory and cognitive processes in artificial systems is a complex and ongoing area of research in the fields of artificial intelligence and neuroscience. Researchers have explored various models and algorithms inspired by the brain, but there isn't a universally agreed-upon architecture for artificial memory segmentation [4][5][6]. However, I can provide you with an overview of some key concepts and approaches that have been explored in the field of neuromorphic computing, which aims to replicate certain aspects of the brain's functionality:

- **Spiking Neural Networks (SNNs):** SNNs are a type of artificial neural network that closely mimics the behaviour of biological neurons. In SNNs, information is transmitted through discrete spikes or pulses of activity. The segmentation of memory in SNNs can be inspired by the way the brain stores information in the form of synaptic weights and connectivity patterns [7].

- **Memory Hierarchies:** Inspired by the hierarchical structure of the human brain, some artificial systems use memory hierarchies to segment and organize information. This can involve different levels of memory with varying capacities and access speeds [8].

- **Neuromorphic Hardware:** Some researchers have developed specialized hardware, known as neuromorphic chips, designed to simulate brain-like processing. These chips often have built-in memory structures that may implement segmentation in a manner inspired by the brain [9].

- **Long Short-Term Memory (LSTM) Networks:** While not directly replicating the brain, LSTM networks are a type of recurrent neural network (RNN) designed to capture longer-term dependencies in data. They are used in various applications, including natural language processing and speech recognition, and can be thought of as a form of memory segmentation [10].

- **Neuroscience-Inspired Memory Models:** Researchers have studied the brain's memory systems and have attempted to create artificial memory models based on these findings. For example, the hippocampus, which plays a critical role in memory formation and retrieval, has inspired some memory architectures [11].

- **Hybrid Approaches:** Many AI systems employ a combination of neural networks, symbolic reasoning, and memory structures to perform complex tasks. These hybrid models may use memory segmentation techniques as part of their overall architecture.

It's important to note that the field of AI and neuromorphic computing is rapidly evolving, and new research and models may have emerged since my last knowledge update [12][3][14]. Additionally, creating an "artificial brain" or replicating the brain's memory system in its entirety remains a formidable challenge, and no single algorithm or architecture has fully achieved this goal. The Spiking Neural Networks are computational models inspired by biological neural networks. They are primarily used for simulating and understanding the behaviour of neurons and neural networks [15][16]. SNNs are particularly suitable for modelling temporal information processing and are often used in neuromorphic computing applications. The Memory hierarchies are hardware and software structures designed to efficiently store and retrieve data in computing systems. They are used to manage the flow of data between different levels of memory (e.g., registers, cache, RAM, disk) to optimize access times. Among the existing algorithms, the proposed K-Mapping algorithm derive few features from SNN and Memory hierarchies.

3. PROPOSED WORK: K-MAPPING ALGORITHM

The logic behind K-mapping memory segmentation involves dividing a computer's memory into multiple segments, where each segment has its own base address and size. This technique is often used in operating systems and hardware architectures to organize memory for different purposes, such as code, data, and stack. Segmentation allows for better memory protection and isolation between different parts of a program or between multiple programs running concurrently. The key points related to memory segmentation:

- **Segments:** Memory is divided into segments, which are logical regions of memory. Each segment can represent a different aspect of a program, like code, data, stack, or heap.

- **Segment Descriptor:** Each segment is associated with a segment descriptor, which contains information about the segment, such as its base address, size, and access permissions.

- **Base Address:** The base address in the segment descriptor specifies where the segment starts in physical memory.

- **Size:** The size field in the segment descriptor determines the length of the segment.

- **Access Control:** Access permissions in the segment descriptor specify whether the segment is readable, writable, or executable, and who can access it.

- **Segmentation Registers:** Processors typically have segmentation registers to hold the segment descriptors. These registers are used to determine the actual physical address of memory locations based on the segment information.

K-mapping, on the other hand, is a technique used for simplifying Boolean expressions, usually in the context of digital circuit design. It is not directly related to memory segmentation. The Memory segmentation in the context of artificial intelligence and neuroscience typically refers to the organization and management of memory or storage in a way that is efficient and facilitates various cognitive processes, such as learning, recall, and decision-making. This can involve techniques like memory allocation, indexing, and data structure design, but it does not involve any other algorithms. In K-Mapping Artificial Brain-Memory segmentation working principle is in “segments" and "data stores “in the context of neural networks and data processing.

Segments in Neural Networks: Neural networks consist of layers of interconnected nodes (neurons). These connections are often organized into layers: input, hidden, and output layers. Each connection has a weight associated with it, which determines the strength of the connection. In some cases, people might refer to certain groups of connections or nodes within a layer as "segments" to represent specific patterns or features the network has learned. These segments could correspond to features like edges, shapes, or more complex patterns in image recognition, for example.

Data Stores: In artificial neural networks, the data store is essentially the dataset that the network is trained on. It contains the input data (e.g., images, text) and the corresponding labels (e.g., cat or dog for image classification). The neural network learns from this data store during the training process by adjusting the weights of its connections to minimize the difference between its predictions and the true labels in the data store. The link between segments and data stores would be in how the neural network learns to recognize patterns and features within the data store. During training, the network updates the weights of connections to optimize its ability to identify segments or patterns in the data that are relevant to making accurate predictions. For example, in image recognition, a neural network may learn to recognize segments of edges, corners, and textures in the images as it processes the data in the data store. Over time, these learned segments or features contribute to the network's ability to classify new, unseen images correctly. It's important to note that the terminology may vary depending on the specific neural network architecture and the field of study. Different neural network architectures might use different terms for similar concepts. Therefore, it's essential to consider the context and the specific neural network model when discussing segments and data stores in artificial brains. The efficiency of memory mapping after getting a segmented images is illustrated in the following table 1.1.

Algorithm	Access ability (KB)	Segmentation efficiency (%)	Time complexity (ms)	Space complexity (KB)
Spiking Neural Networks (SNNs)	250	67.35	17.3	145
Neuroscience-Inspired Memory Models	320	54.78	13.75	178
Neuroscience-Inspired Memory Models	240	71.05	12.01	164

Table 1.1 Performance analysis of Brain-segmentation memory access algorithm approaches

Pseudocode for random data segment generation:

```
N = 4000
x = np. random. Random(size=N) * 100
y = np. random. Random(size=N) * 100
radii = np. random. Random(size=N) * 1.5
colors = ["#%02x%02x%02x" % (r, g, 150) for r, g in zip (np. floor(50+2*x).as type(int), np. floor(30+2*y).as type(int))]
p = figure ()
p. circle (x, y, radius=radii, fill_color=colors, fill_alpha=0.6, line_color=None)
show(p)
```

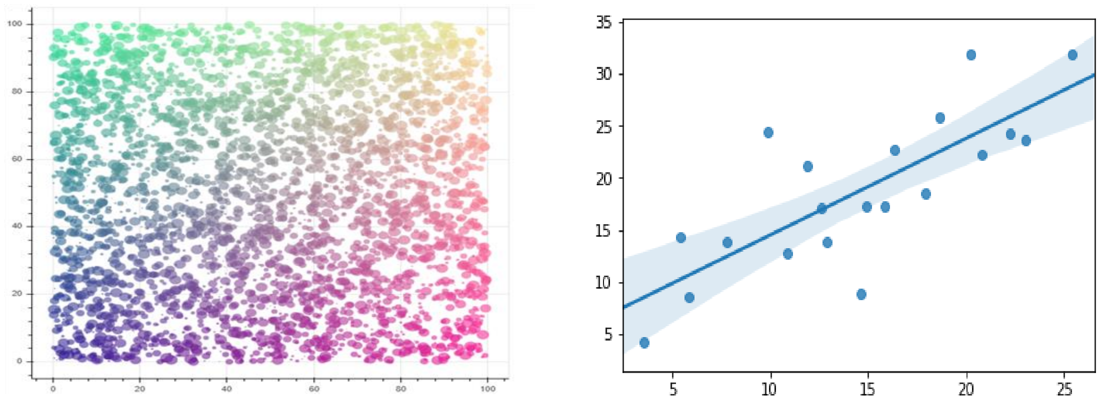

Figure 1.2 Random data segment generation

4. CONCLUSION AND FUTURE WORK:

The Artificial brain memory segmentation mechanisms continue to evolve, with ongoing research aimed at improving their efficiency, capacity, and ability to emulate the complexities of human memory with the help of different heuristic algorithms. In this proposed K-mapping algorithm is working with a principle of object segmentation and mapping mechanism with a constructive artificial brain architectural foundations and this mechanism play a crucial role in various applications, including machine learning, natural language processing, robotics, and AI systems. In future work will focus on the implementation aspect with the help of neural network logics and machine learning.

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