Migration Letters

Volume: 21, No: S1(2024), pp. 162-182

ISSN: 1741-8984 (Print) ISSN: 1741-8992 (Online)
www.migrationletters.com

From Artificial Intelligence and Bayesian Statistics to Neuroanatomy: Connections, Analogies, and Applications

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Abstract

This study examines the interaction between artificial intelligence (AI), Bayesian statistics, and various key brain structures, such as the hippocampus, amygdala, and thalamic nuclei. The goal is to explore how Bayesian inference can contribute to the development of AI systems that simulate and optimize essential aspects of human cognition, such as decision-making, attention, learning, and memory. By analyzing the functions of these structures within the framework of Bayesian statistics, possible avenues are identified for improving the adaptability and efficiency of AI systems in problem-solving and decision-making. Additionally, the relevance of Brodmann areas in the context of AI and Bayesian statistics is considered. The knowledge gained from this study can provide a solid foundation for the design of increasingly advanced and human-centric AI systems, facilitating more effective and understandable interaction between humans and AI technologies.

Keywords: *artificial intelligence, neurology, statistics.*

Introduction

Artificial intelligence (AI) is a field that seeks to develop systems that can perform tasks that normally require human intelligence (1), such as learning, reasoning, and adaptation (2). Bayesian statistics is a branch of statistics that relies on Bayes' theorem to update the probability of a hypothesis based on observed data (3). Both fields, AI and Bayesian statistics, have been shown to have deep links to human brain functioning, especially in terms of information processing and decision-making(4).

Bayes' theorem states the following: $P(H|D) = (P(D|H) * P(H)) / P(D)$

Where: $P(H|D)$ is the posterior probability of hypothesis H given evidence D.

$P(D|H)$ is the probability of evidence D given that hypothesis H is true (likelihood). $P(H)$ is the a priori probability of the hypothesis H. $P(D)$ is the probability of evidence D (5).

In artificial intelligence, especially machine learning, Bayesian statistics is used to update beliefs about models and their parameters based on observed data. This allows AI algorithms to adapt and learn more efficiently.

Learning in the human brain is based on a highly adaptive and efficient system that processes information and makes decisions based on available evidence. Some AI algorithms, such as artificial neural networks, are inspired by the structure and function of

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the human brain. These algorithms mimic how neurons in the brain process and transmit information through synaptic connections.

In addition, the human brain appears to use principles similar to those of Bayesian statistics to process information and make decisions. Neuroscientists have found evidence that the brain updates the probabilities of different hypotheses based on observed evidence, suggesting that Bayesian statistics may be a theoretical framework for understanding how the brain processes information and makes decisions (4)

AI and the Bayesian Formula

The Bayes theorem formula can be applied in artificial intelligence systems by adapting and replacing the components of the formula depending on the context and the specific problem being addressed. Each element of the formula is described below and how they are integrated into how the AI works.

P(H|D): The subsequent probability of a hypothesis (H) given the evidence (D) represents the degree of belief actualized in a specific model or parameter after looking at new data. In AI, this term can be interpreted as the probability of a model or parameter given the training data. In supervised learning, for example, one could estimate the probability that a class label is correct given the input.

P(D|H): The plausibility, or probability of the evidence (D) given that hypothesis (H) is true, is used in AI to quantify how well a model or parameter explains the observed data. In machine learning, likelihood can be calculated as the probability of the training data given the model's predictions. In generative models, this term is used to measure the quality of the samples generated.

P(H): The a priori probability of hypothesis (H) reflects prior knowledge or initial beliefs about a model or parameter before looking at the data. In AI, prior knowledge can be incorporated into the initialization of model parameters, such as the weights of a neural network. A priori distributions can also be used to express initial beliefs about a model's parameters, such as in Bayesian machine learning models.

P(D): The probability of evidence (D) is a normalizing constant that ensures that subsequent probabilities add up to one. In AI, this term is often omitted or implicitly calculated, as the main focus is usually on maximizing the subsequent probability or finding the most likely values of the model parameters (3,5).

In summary, the Bayesian statistics formula can be applied in artificial intelligence by adapting its components to specific problems and contexts. This allows AI algorithms to learn efficiently, adapt to new data, and combine prior knowledge with observed evidence in decision-making.

Relationship Between Artificial Intelligence Components and Anatomical Brain Structures

Artificial intelligence (AI) takes inspiration from brain structures and functions in the development of algorithms and learning systems. In this section, we attempt to draw analogies between the components of AI and anatomical brain structures.

Artificial neural networks (ANNs) are a core component of AI, inspired by the organization and function of neurons and their connections in the human brain. Although direct analogies between the components of ANNs and specific anatomical brain structures are limited, it is possible to identify some general relationships.

Artificial neural networks are computational models inspired by the workings of the biological nervous system, in particular, how neurons connect and communicate with each other to process information. ANNs have been designed to mimic the way the human brain solves problems and learns from experience, making them an effective tool in many fields of artificial intelligence.

An artificial neural network is made up of processing units called "neurons" or "nodes," organized in layers. These layers include the input layer, one or more hidden layers, and the output layer. Each neuron in one layer is connected to all neurons in the next layer through weighted links, which represent the "strength" of the connection between two neurons.

Learning in an ANN occurs through a process of adjusting the weights of the connections between neurons. During training, the network receives examples of labeled data, i.e., inputs with their corresponding desired outputs. The network processes the inputs and calculates an output that is compared to the desired output. If there is a discrepancy, the network adjusts the connection weights to minimize the error (noise). This process is repeated over a large number of training examples until the network reaches an acceptable level of accuracy.

Artificial neural networks have proven successful in a wide variety of applications, including pattern recognition, classification, prediction, optimization, and control. Examples of applications include speech recognition, machine translation, sentiment analysis, fraud detection, and autonomous driving (6).

Artificial neural networks, particularly deep neural networks (RNPs), can also leverage Bayesian statistics to improve accuracy and robustness in learning and decision-making. Bayesian inference allows neural networks to handle uncertainty and update their beliefs systematically as new information becomes available, which can improve the network's ability to adapt to unfamiliar situations and make more accurate and reliable predictions (7).

Comparison between the complexity of neural responses in the human nervous system and artificial neural networks.

Comparison between the response of an artificial neural network and the reflex act of the spinal cord:

The spinal cord reflex act is a rapid and automatic response to a stimulus, involving the transmission of information through sensory and motor neurons bypassing the brain. In the context of an artificial neural network, this can be compared to a response generated by a single-layer network, where input is processed directly to produce an output without additional intervention (6).

Image 1

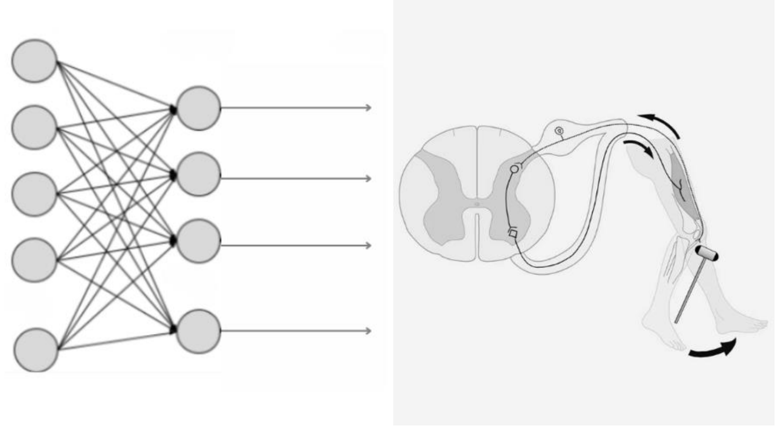


Image 1: In the image you can see a simple input and output of artificial neural networks, comparing their action with the reflex arc of the spinal cord.

Comparison between the response of an artificial neural network with a deep layer and the response of basal nuclei:

The basal nuclei, which are involved in motor control, cognition, and reward, generate more complex responses than the spinal cord reflex act. In an artificial neural network, this could be compared to a deep single-layer network, where intermediate neurons process the input information before it reaches the output layer. This level of complexity allows for more sophisticated responses than those generated by a single-layer network(8).

Image 2

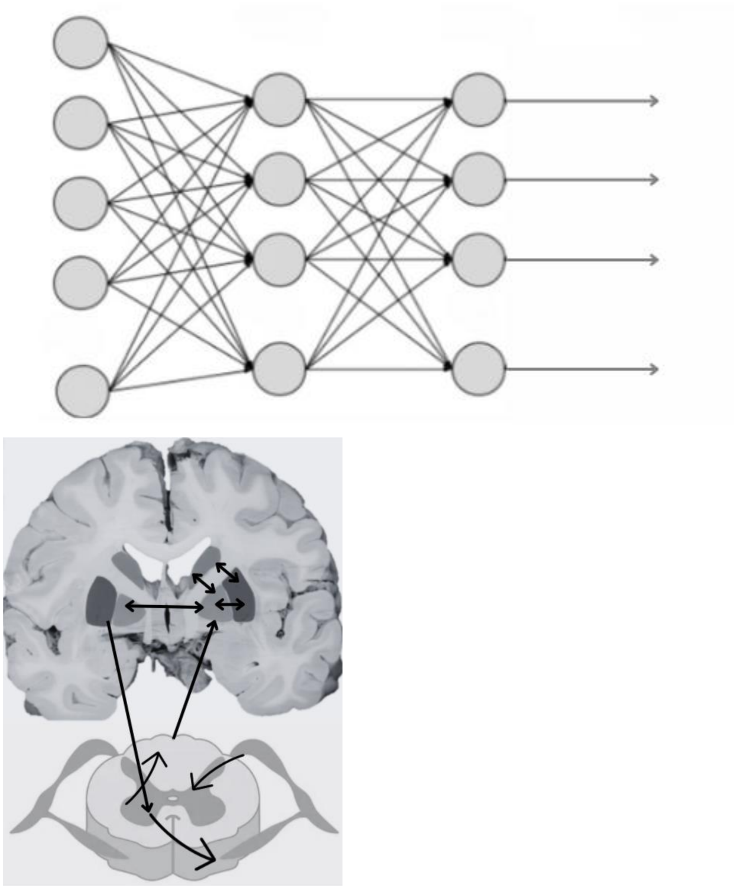


Image 2: This image shows a greater complexity in terms of the neural networks in Figure 1, so their action is compared with the input of information, the interconnection of the basal nuclei and their response.

Analogy between the response of a deep neural network of two or more layers and the response of the cerebral cortex:

The cerebral cortex, which is responsible for high-level functions such as perception, thinking, and decision-making, generates even more complex responses than those of the spinal cord and basal nuclei. In the context of artificial neural networks, this can be compared to a deep network of two or more layers, where information is processed through multiple layers of neurons before reaching the output layer. This architecture allows for detection and adaptation to more complex patterns, resulting in more complete and sophisticated responses (9).

In short, artificial neural networks can reflect different levels of complexity in the human nervous system, from the reflex act of the spinal cord to the more elaborate responses of the cerebral cortex. As the depth and complexity of neural networks increases, they become more capable of processing and adapting to complex patterns and contexts, allowing for more complete and efficient responses.

Image 3:

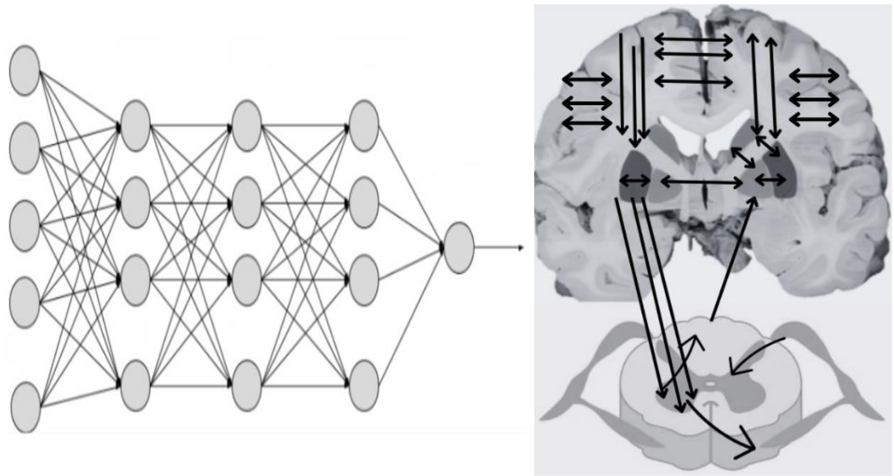


Figure 3: This image shows the greater complexity in terms of neural networks in the examples given. Where an input layer is shown, several deep layers and an output layer, so its action is compared with the input of information, the interconnection of the basal nuclei and their response.

Relationship between the components of artificial intelligence and the anatomical structures of the basal nuclei.

The basal nuclei (also called the basal ganglia) are a set of brain nuclei involved in regulating movement, decision-making, and forming habits. Possible correspondences between the components of artificial intelligence and the anatomical structures of the basal nuclei are described below.

A. Caudate and putamen core and reinforcement learning in AI

Reinforcement learning (RL) is a type of machine learning in which an agent learns to make decisions by interacting with its environment. The agent takes actions in an environment and receives feedback in the form of rewards or punishments. The agent's goal is to learn a policy that maximizes cumulative reward over time.

Q-learning and the Monte Carlo algorithm are two widely used reinforcement learning algorithms which are explained below.

Q-learning: It is a reinforcement learning algorithm based on the idea of learning the action value function Q, which estimates the expected value of taking an action in a specific state and then following an optimal policy. Q-learning is a method of learning based on temporal differences (TD), which means that it uses current estimates from the Q function to iteratively update its estimates. The Q-learning algorithm is a modelless learning approach, as it does not require a model of the environment to learn the optimal policy.

During the learning process, the agent scans its environment and updates the Q values using the following formula:

$$Q(s, a) \leftarrow Q(s, a) + \alpha [R(s, a, s') + \gamma \max_{a'} Q(s', a') - Q(s, a)]$$

Where s and a are the current state and the current action, s' is the next state, R(s, a, s') is the immediate reward, α is the learning rate, γ is the discount factor, and max_a' Q(s', a') is the maximum value of the function Q in the next state.

Monte Carlo algorithm: Monte Carlo methods are a class of reinforcement learning algorithms that use random sampling to estimate value functions and optimal policies. Unlike Q-learning, Monte Carlo methods are episodic-based learning algorithms, which means that value function updates are made at the end of each episode rather than at each step.

The Monte Carlo algorithm uses the average of the return rewards of entire episodes to estimate the value function. As more episodes are generated and different trajectories are sampled in the environment, value function estimates become more accurate. Through this process, the agent can learn an optimal policy based on value function estimates.

In summary, Q-learning and the Monte Carlo algorithm are two different approaches to solving reinforcement learning problems. Q-learning is a time-difference-based method that updates the Q values at each step, while the Monte Carlo algorithm uses random sampling and averages of complete episode returns to estimate the value function. Both algorithms have applications in various fields and have been successfully used in a wide variety of tasks and domains.

The caudate nucleus and putamen, collectively known as the striatum, are involved in reward-based learning and habit formation. In AI, reinforcement learning algorithms, such as Q-learning and the Monte Carlo algorithm, can be considered analogous to these structures, as they both seek to learn and optimize actions based on the rewards and consequences of the environment (10).

B. Pale Globe and Motor Control in AI

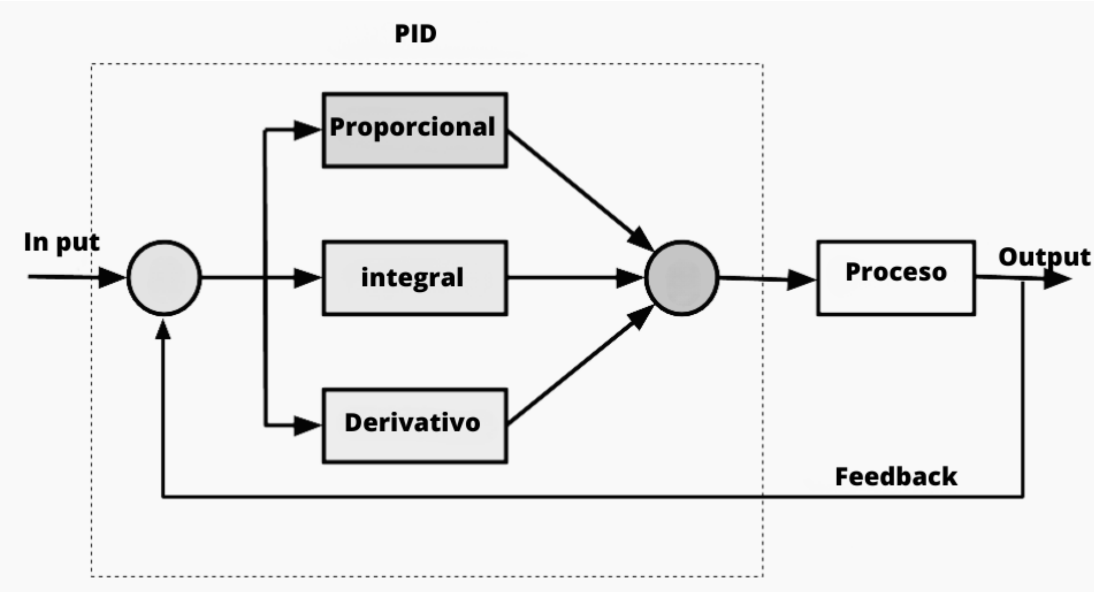
In the context of artificial intelligence, a PID (Proportional, Integral, Derivative) controller can be used to regulate and optimize the behavior of an intelligent agent or algorithm. The PID controller can be applied in machine learning control and adaptation systems, robotics and other areas where a quick and accurate response to changes in environmental conditions is required.

In artificial intelligence, the PID controller can be used to dynamically adjust the parameters of an algorithm or the behavior of an intelligent agent based on its performance and environmental conditions. By combining the proportional, integral, and derivative components, the PID controller can improve the efficiency and stability of a machine learning system or intelligent agent, helping to minimize error and adapt to changes in real time.

Proportional (P): This component is based on the current error and adjusts the output proportionally to the present error. If the error is large, the correction will be more significant. However, there can be a constant residual error called steady-state error.

Integral (I): This component takes into account the accumulation of past errors and acts to eliminate the steady-state error. It adjusts the output based on the sum of errors accumulated over time, helping to improve system accuracy.

Derivative (D): This component is based on the rate of change of the error with respect to time and acts to predict the future behavior of the error. Provides anticipatory control action and improves system stability by reducing oscillation and over-oscillation (11).



For example, in robotics, a PID controller could be used to regulate the speed and direction of an autonomous vehicle or to adjust the movement of a robotic arm based on feedback received from sensors. In reinforcement learning, the PID controller could adjust an algorithm's parameters, such as learning and exploration rates, to improve agent performance and adaptability over time.

The globus pallidus, a structure of the human brain, plays an important role in regulating and coordinating movements and actions. Just as the globus pallidus modulates motor activity, so do certain algorithms and techniques in the field of artificial intelligence, such as the PID controller and optimal trajectory planning. Below are more specific examples of how these AI techniques relate to the functions of the globus pallidus (12):

PID controllers are used in robotics and prosthetics, autonomous navigation, and motor control in video games and simulations to improve the accuracy and stability of motion. These controllers make it possible to adapt to changing conditions in real time, ensuring smooth and precise movements in robotic arms, autonomous vehicles and video game characters, as well as in optimal trajectory planning and obstacle avoidance (13).

C. Substantia nigra and dopaminergic modulation in AI

The substantia nigra is a brain structure that produces dopamine, a neurotransmitter essential for reward-based learning and movement regulation. In AI, reward signal modulation and regulation mechanisms, such as adaptive learning rate and reward normalization schemes, can be considered analogous to this structure, as they both adjust and modulate the reward signal to enhance learning and adaptation to changing environmental conditions (14).

D. Subthalamic Nucleus and Decision Making in AI

The subthalamic nucleus is involved in decision-making and movement control, especially in the selection and execution of motor actions. In AI, decision-making and action selection algorithms, such as hierarchical planning and model-based optimization, can be considered analogous to this structure, as they both seek to select and coordinate the right actions to meet the goals and constraints of the environment (15).

Nuclei of the thalamus and their analogy with AI

A. Anterior nuclei of the thalamus and memory systems in AI

The anterior nuclei of the thalamus play a critical role in the formation and processing of memory in the human brain. In the context of artificial intelligence (AI), functional aspects of these thalamic nuclei can be extracted to inspire and improve algorithms and approaches related to the storage and retrieval of information in AI systems. Below are specific examples of how the function of the anterior nuclei of the thalamus could be emulated in AI:

Associative memory networks: The anterior nuclei of the thalamus are involved in forming associations between different pieces of information. The formation of associations between different pieces of information is a key process in the consolidation of memory and in the understanding of complex concepts and events. The anterior nuclei of the thalamus facilitate this process by receiving information from various areas of the brain, such as the prefrontal cortex, amygdala, and hippocampus, and then transmitting this information to other regions of the brain.

For example, when we learn something new, our brain needs to relate that information to previous knowledge and store it efficiently for later retrieval. The anterior nuclei of the thalamus act as a kind of "exchange center," where different types of information, such as sensory, emotional, and cognitive details, are combined and processed. This allows the brain to form connections between seemingly unrelated information, which ultimately helps enrich our understanding of the world and improve our ability to remember and access this information in the future (16,17).

In AI, this could be implemented through the use of associative memory networks, such as Hopfield networks or self-associative memory networks, which allow for the storage and retrieval of associated information patterns based on the similarity and relationship between them.

Hopfield networks are a type of recurrent artificial neural network that is primarily used to solve optimization problems and to store and retrieve associative memory patterns.

A Hopfield network consists of interconnected neurons, where each neuron is connected to all other neurons (except itself) with a synaptic weight. Neurons can have a binary state, i.e. be on (+1) or off (-1).

The Hopfield network works iteratively, updating the state of neurons based on the states of the connected neurons and synaptic weights. The network eventually converges to a steady state, called an "attractor," which may represent a solution to the optimization problem or a pattern stored in memory (18).

Basic example:

A Hopfield network stores and retrieves a simple pattern, such as a letter "T" on a 3x3 grid. The pattern of the letter "T" would look like this:

diff Copy code

```diff
+1 +1 +1
-1 +1 -1
-1 +1 -1
```

Here, "+1" represents an activated neuron (white) and "-1" represents an activated neuron (black).

To store this pattern in the Hopfield network, we first initialized the synaptic weights between neurons using the "Hebb learning rule." Then, to retrieve the stored pattern, we provide a partially correct or noisy input pattern to the network. For example, we could provide the following pattern with noise:

```diff
+1 -1 +1
-1 +1 -1
-1 +1 -1
```

The Hopfield network will iteratively update the state of the neurons until it converges to a steady state, which in this case, will be the original pattern of the letter "T." In this way, the Hopfield network can store and retrieve associative memory patterns despite noise or partial inputs.

Short-term and long-term memory: The anterior nuclei of the thalamus also play a role in consolidating and transferring information between short-term memory and long-term memory. In AI, this can be addressed using dual-level memory structures, such as LSTM (Long Short-Term Memory) networks or GRU (Gated Recurrent Unit) networks, which allow AI systems to retain temporally relevant information in short-term memory and consolidate important information into long-term memory.

LSTM (Long Short-Term Memory) networks and GRU (Gated Recurrent Unit) networks are recurrent neural network (RNN) architectures designed to address the problem of short-term forgetting and gradient fading in traditional RNNs. These architectures allow networks to learn how to capture long-range temporal dependencies on data streams.

LSTM:

LSTM networks introduce a structure called a "memory unit" that contains three "gates" (in, forget, and out). These gateways allow the network to decide when to add new information to short-term memory, when to remove irrelevant information, and when to allow stored information to influence the current output. By regulating the flow of information through these gateways, LSTMs can learn long-range temporal dependencies more effectively than simple RNNs.

GRU:

GRU networks are a simplified variant of LSTMs that also address the problem of short-term forgetting and gradient fading. Instead of using three gates like LSTMs, GRUs have only two gates: the upgrade gate and the reset gate. The refresh gate determines which information from the previous memory is retained and which is discarded, while the reset gateway controls how past information is combined with current information. Although GRUs are less flexible than LSTMs, they generally have fewer parameters and are therefore faster and more computationally efficient.

Main differences:

LSTMs have three gates (in, forget, and out), while GRUs have only two (update and reset).

LSTMs are typically more flexible and can capture more complex temporal dependencies, but they are computationally more expensive due to the greater number of parameters.

GRUs are a simplified version of LSTMs with fewer parameters, making them faster and more computationally efficient, although they might be less able to capture very complex time dependencies.

The anterior nuclei of the thalamus are involved in the selection and retrieval of relevant information, as well as in the adaptability and plasticity of memory. In AI, these processes can be implemented using attention and focus mechanisms, such as softmax or local attention, and learning algorithms that dynamically adjust their weights and connections, such as Hebbian learning or backpropagation error learning. These techniques allow AI systems to select relevant information and adapt to new situations (19).

B. Lateral nuclei of the thalamus and sensory processing in AI

The lateral nuclei of the thalamus are involved in the processing of sensory information, especially in the visual modality. In AI, convolutional neural networks (CNNs) and recurrent neural networks (RNNs) that process visual and temporal signals could be related to these cores, as both structures are designed to process sensory information and extract relevant features.

The lateral nuclei of the thalamus are essential in sensory processing and in the transmission of sensory information to the human brain. These anatomical structures are involved in the processing of sensory information from the visual, auditory, and somatosensory systems. In the context of artificial intelligence (AI), functional aspects can be extracted from the lateral nuclei of the thalamus to improve and design algorithms and approaches related to the processing and interpretation of sensory information in AI systems. Below are specific examples of how the function of the lateral nuclei of the thalamus could be emulated in AI using convolutional neural networks (CNNs) and recurrent neural networks (RNNs):

The lateral nuclei of the thalamus are involved in the filtering and processing of sensory signals, the integration and fusion of sensory information, sensory attention and focus, and sensory adaptability and learning. In AI, CNNs can detect and extract relevant features from sensory data, while the combination of CNNs and RNNs allows information from different modalities to be integrated. Attention mechanisms improve selection and concentration on relevant sensory information, and learning algorithms allow AI systems to adapt to changes in the environment and improve their interpretation of sensory information (19,20).

C. Medial nuclei of the thalamus and decision-making in AI

The medial nuclei of the thalamus are involved in decision-making and action planning. In AI, reinforcement and planning learning algorithms, such as Q-learning and the Monte Carlo algorithm, can be considered analogous to these cores, as they both seek to optimize actions and decisions based on goals and rewards (21).

D. Intralaminar nuclei of the thalamus and synchronization in AI

The intralaminar nuclei of the thalamus are involved in the synchronization and modulation of neuronal activity throughout the brain. In AI, attention mechanisms, such as auto-regressive attention and softmax attention (22).

In AI, auto-regressive attention and softmax attention are attention mechanisms used in deep learning models, such as neural networks, to improve the selection, processing, and interpretation of relevant information in complex, sequential data. These mechanisms are especially important in tasks such as natural language processing (NLP), computer vision, machine translation, and speech recognition, among others. The following is a brief description of both mechanisms in the context of AI:

Auto-regressive attention: In AI, auto-regressive attention is an approach that allows deep learning models, such as recurrent neural networks (RNNs) and Transformer models, to capture and model temporal and sequential dependencies on data. RNNs and Transformers models are two types of deep learning architectures widely used in the field of artificial intelligence (AI) to address problems involving sequential or temporal data, such as natural language processing (NLP). This mechanism allows the model to take into account the history of the sequence to improve the prediction of future elements, which is essential in tasks such as text generation, machine translation, and sentiment analysis, where dependencies between words and phrases play a crucial role in understanding and generating semantically coherent content(23).

Softmax attention: Softmax attention is another attention mechanism used in AI to allow deep learning models to selectively weight and focus on relevant information based on its importance. Instead of treating all information equally, softmax attention allows models to assign attention weights to different parts of the input information, allowing them to focus on the most relevant parts and discard the less relevant ones. This approach is useful in tasks such as natural language processing, computer vision, and speech recognition, where relevant information may be scattered and not contiguous in the input data.

The intralaminar nuclei of the thalamus are a set of nuclei found within the thalamus, a brain structure that plays an important role in the integration and processing of information. These intralaminar nuclei are involved in various brain functions, including the synchronization of neuronal activity and the modulation of consciousness and attention. In the context of artificial intelligence (AI), the functional aspects of the intralaminar nuclei of the thalamus can inspire algorithms and approaches related to the synchronization and coordination of processes and tasks in AI systems, involving auto-regressive attention, softmax attention, and recurrent neural networks (RNNs). Below are specific examples of how the function of the intralaminar nuclei of the thalamus could be emulated in AI:

The intralaminar nuclei of the thalamus are involved in neuronal synchronization, task coordination, and modulation of attention and consciousness. In AI, RNNs with auto-regressive attention mechanisms and softmax can be used to model the interaction between areas, selectively focus relevant information, and adapt resource allocation according to the demands of the task. These mechanisms improve the efficiency of the system and allow for better adaptability in changing situations and noisy environments (24).

E. Median nuclei of the thalamus and emotional information processing in AI

The median nuclei of the thalamus, also known as the medial dorsal nuclei of the thalamus, play a crucial role in the processing and integration of emotional information in the human brain. These thalamic structures are closely interconnected with several areas of the brain involved in emotion, such as the amygdala, hippocampus, cingulate cortex, and prefrontal cortex. Together, these brain regions are involved in modulating emotions, emotional memory, and making emotionally relevant decisions (25).

In the context of artificial intelligence (AI), the processing of emotional information can be critical to the development of more advanced and human-like systems. Current techniques in AI, such as deep learning and neural networks, have allowed AI systems to begin to address aspects of emotion in their processing and response generation. For example, detecting emotions in text, images, or voice signals can be used to create more empathetic and adaptive chatbots or recommendation systems that are sensitive to the user's emotional state.

To address the complexity of emotional information processing, artificial neural networks can use different architectures, such as convolutional neural networks (CNNs) for image analysis and facial expression, and recurrent neural networks (RNNs) and Transformer models for text and emotion analysis in language. Auto-regressive attention and softmax attention, which are key features in Transformer models, can improve the ability of these networks to capture the emotional and semantic relationships between words and sentences (26,27).

Analogous to the role of the median nuclei of the thalamus in the human brain, AI architectures can integrate emotional information from various sources, allowing AI systems to interact and respond in more humane and personalized ways. Importantly, however, despite these advances, today's AI is still far from matching the complexity and richness of human emotional processing.

F. Reticular nucleus of the thalamus and control of neuronal activity in AI

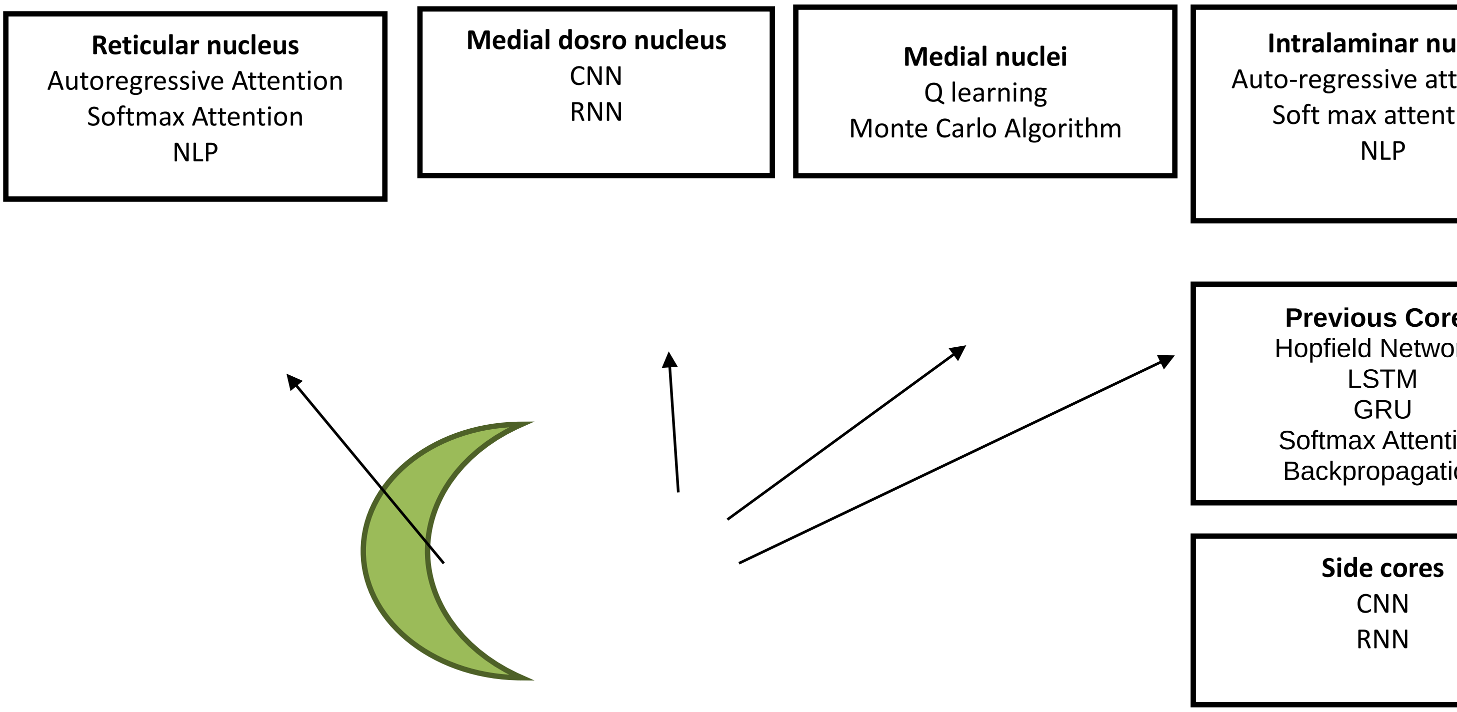
The reticular nucleus of the thalamus (NRT) is a sheet-like structure that surrounds the thalamus and plays an essential role in regulating and controlling thalamic neuronal activity in the human brain. The NRT is the main modulator of information passing through the thalamus and is closely involved in functions such as selective attention, control of the sleep-wake cycle, and the generation of neural rhythms, such as the teat and gamma oscillations (28).

In the context of artificial intelligence (AI), controlling neural activity and regulating the flow of information are also key aspects of ensuring the efficiency and effectiveness of AI systems. At the level of AI architectures, auto-regressive attention and softmax attention in Transformer models are techniques that, in a sense, emulate the information selection and filtering function performed by NRT in the human brain.

In terms of controlling neural activity, AI can use algorithms that mimic some of the functions of NRT, such as regulating activity in artificial neural networks to ensure stability and avoid saturation of processing units. For example, recurrent neural networks (RNNs) and long-term and short-term memory networks (LSTMs) can learn to regulate their own neural activity over time in response to data inputs.

In terms of generating neural rhythms, techniques such as reinforcement learning, in particular algorithms such as Q-learning and Monte Carlo, can allow artificial neural networks to generate more efficient and adaptable activity patterns. These algorithms can help adjust neural network weights and connections based on feedback and results obtained during training (6)

Image 5



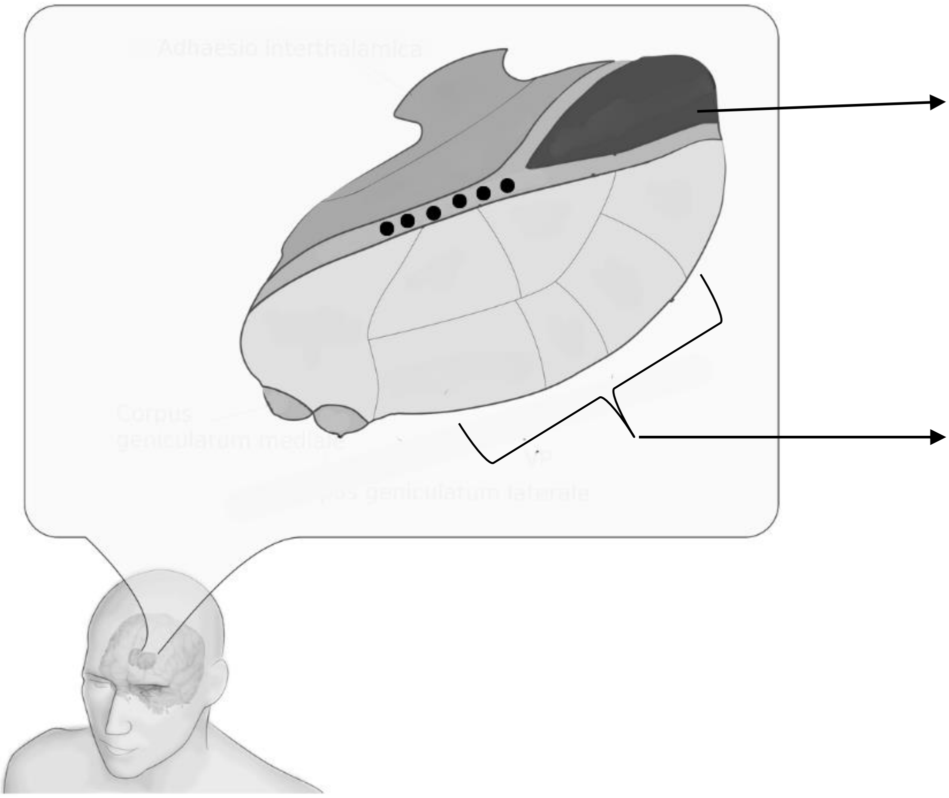


Figure 5: Analogies of the functions of the thalamus nucleus as represented by the functions of different components of AI: CNN (Convolutional Neural Networks), RNN (Recurrent Neural Networks), LSTM (Long Short Memory), GRU (Gated Recurrent Unit), NLP (Natural Language Processing)

The amygdala, emotions, and AI.

The amygdala is an almond-shaped structure located in the human brain, which plays a crucial role in processing emotional information, forming emotional memories, and making emotion-based decisions. The amygdala is also involved in functions related to detecting threats and regulating fear and anxiety responses (29).

In the context of artificial intelligence (AI), incorporating emotional aspects into decision-making and behavior can provide a more humane and realistic approach to AI systems. Although machines don't experience emotions in the human sense, AI systems can be designed and programmed to recognize and process emotional signals in input data and adapt their behavior accordingly.

One of the ways this can be achieved is by using artificial neural networks, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to process emotional data and generate emotional representations in the machine. These networks can be trained on datasets labeled with emotional information to learn to recognize emotional patterns and adapt their behavior accordingly (26).

In addition, AI systems can also use reinforcement learning algorithms, such as Q-learning and the Monte Carlo algorithm, to adjust their actions based on emotionally relevant feedback. These algorithms allow AI to learn through trial and error, maximizing emotional reward (such as user satisfaction) and minimizing emotional penalties (such as user frustration or disappointment).

Another focus in AI that relates to the function of the amygdala is the development of artificial emotional agents that can interact with humans and express emotions more naturally and realistically. These agents can be useful in applications such as AI-assisted therapy, personalized learning, and online social interaction.

Relationship between the hippocampus and AI: Memory and spatial learning.

The hippocampus is a seahorse-shaped structure located in the human brain, and it plays a critical role in memory formation, learning, and spatial navigation. Neuroscience research has shown that the hippocampus is involved in the consolidation of short-term memory into long-term memory and in the formation of cognitive maps of the environment (30,31).

Artificial intelligence (AI) can benefit from understanding how the hippocampus works and applying similar principles in the design of machine learning and navigation systems. Some areas of interest in AI that relate to hippocampal functions include:

Memory and learning: Artificial neural networks, such as recurrent neural networks (RNNs) and long-term memory networks (LSTMs), can be inspired by the structure and function of the hippocampus to improve its ability to learn and retain information over time. These networks are designed to address short-term memory problems and can store information temporarily in a stream of data (27).

Spatial learning and navigation: AI systems that require navigating physical environments, such as mobile robots or autonomous vehicles, can benefit from algorithms and techniques inspired by the spatial navigation function of the hippocampus. Convolutional neural networks (CNNs) play an important role in spatial learning and navigation, as they can process visual information and recognize relevant features of the environment. By extracting and learning spatial patterns and features from input data, CNNs make it easier to understand and represent the environment in which the agent moves (26).

Reinforcement learning algorithms, such as Q-learning and the Monte Carlo algorithm, and PID (Proportional, Integral, Derivative) controllers can be used to develop navigation systems that learn to move and plan routes efficiently in unfamiliar environments. The PID controller can adjust and optimize agent actions in real-time, enabling more accurate and stable navigation by addressing issues such as trajectory tracking and speed control. Together, these techniques, including CNNs, enable AI systems to learn and adapt to dynamic and complex environments (13).

Cognitive models of the environment: Neuroscience research has identified specific cells in the hippocampus, such as place cells and grid cells, that are involved in the representation and mapping of space. AI can use techniques such as simultaneous localization and mapping (SLAM) and deep learning to develop internal models of the environment that allow AI systems to navigate and understand their environment in a similar way to how humans do (32,33).

Reticular training and AI

Reticular formation is a complex network of neurons located in the brainstem that plays a crucial role in regulating functions such as attention, awareness, and brain activation (34). In the context of artificial intelligence (AI), lattice training can be relevant in a number of ways:

Attention: Reticular formation modulates attention and filters irrelevant information, allowing organisms to focus on relevant stimuli. In AI, similar attention mechanisms, such as auto-regressive attention and softmax attention, can be used to focus processing on relevant information and optimize performance on specific tasks (35,36).

Arousal and activation: Reticular formation regulates levels of arousal and awareness depending on the situation and the demands of the environment. AI could incorporate similar triggering mechanisms to dynamically adapt to different contexts and operational states, adjusting the intensity of its computational resources according to the needs of the task (37,38).

Multisensory integration: Reticular formation also contributes to the integration of sensory information from different sensory modalities. AI systems can apply multisensory fusion techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to process and integrate information from various sources in a coherent and efficient manner (26,39).

Relationship between the structure of artificial intelligence and Brodmann's brain areas.

Brodmann areas are regions of the brain defined by their cellular organization and are related to specific brain functions. Possible correspondences between the structure of artificial intelligence and several areas of Brodmann are described below.

A. Brodmann's Area 4 (Primary Motor Cortex) and Motor Control in AI

Brodmann's area 4 is involved in motor control and the execution of movements. In AI, motor control and motion planning algorithms, such as PID controller and optimal trajectory planning, can relate to this area, as they both seek to regulate and coordinate the movements and actions of AI systems (11,40).

B. Brodmann's Area 17 (Primary Visual Cortex) and Visual Processing in AI

Brodmann's area 17 is involved in visual processing and the detection of basic visual features. In AI, convolutional neural networks (CNNs) that process visual signals and extract relevant features can relate to this area, as they are both designed to process visual information and detect important features (26,41).

C. Brodmann's Areas 44 and 45 (Broca's Areas) and Language Processing in AI

Brodmann's areas 44 and 45, also known as Broca's areas, are involved in language processing and speech production. In AI, natural language processing models, such as recurrent neural networks (RNNs) and transformer networks, can relate to these areas, as they both seek to understand and generate human language. Auto-regressive attention, a technique used in some transformer models, allows AI systems to focus on relevant parts of the text during processing, improving language understanding and generation by considering the context in which each word or linguistic element is located. Thus, auto-regressive attention enriches the analysis and generation of language in AI models, establishing a closer connection with the functions of the human brain associated with Broca's areas (6,7,42).

D. Brodmann's Area 24 (anterior cingulate cortex) and decision making in AI

Brodmann's area 24, located in the anterior cingulate cortex, is involved in decision-making and emotional regulation. In AI, reinforcement learning algorithms and emotional agents can relate to this area, as they both seek to make optimal decisions based on goals, rewards, and emotions (42,43).

E. Brodmann's Area 41 (Primary Auditory Cortex) and Auditory Processing in AI

Brodmann's Area 41 is involved in auditory processing and the detection of basic auditory features. In AI, convolutional and recurrent neural networks that process auditory signals and extract relevant features can relate to this area, as they are both designed to process auditory information and detect important features (38,44).

These analogies between Brodmann's areas and the structure of artificial intelligence suggest that AI systems can draw inspiration from the organization and functioning of these brain areas to improve their ability to learn, adapt, and function in various domains and tasks.

Bayesian statistics and the brain.

Relationship between Bayesian statistics and the anatomical structures of the basal ganglia.

Bayesian statistics is an inference approach that uses probability to update beliefs about uncertain events. In relation to the anatomical structures of the basal ganglia, several correspondences can be established between the components of Bayesian statistics and these structures. First, the caudate nucleus and putamen, involved in reward-based learning and habit formation, resemble a priori probability insofar as they store prior information about events and actions that have been rewarded in the past. Second, the globus pallidus, involved in the regulation of movement and the inhibition of unwanted motor actions, can be considered analogous to the likelihood of plausibility, insofar as it helps to assess whether or not a specific action is appropriate based on the sensory information received and contextual demands. Third, the substantia nigra, which produces dopamine, plays a key role in reward-based learning and updating our expectations about actions, thus resembling probability after the fact. Finally, the subthalamic nucleus, involved in decision-making and movement control, resembles Bayes' theorem insofar as it integrates previous information (stored in the caudate nucleus and putamen) and new sensory information (processed by the globus pallidus) to make informed decisions about what actions to take. In summary, Bayesian statistics and the anatomical structures of the basal ganglia are interconnected and offer possibilities for improving motor control and coordination, especially in artificial intelligence systems that involve physical actions such as robots and autonomous vehicles (12,45).

Bayesian Statistics and the Anatomical Structures of the Thalamus

Possible correspondences between the components of Bayesian statistics and the anatomical structures of the thalamus are described below:

The anterior, lateral, medial, intralaminar, and median nuclei of the thalamus can be related to the fundamental concepts of Bayesian statistics, such as a priori probability, likelihood probability, and a posteriori probability, as well as Bayes' theorem. The anterior nuclei of the thalamus can be considered analogous to a priori probability, as they store prior information about events and expectations. Lateral nuclei could be analogous to likelihood of plausibility, as they assess the correspondence between the sensory information received and our expectations based on previous events. Medial nuclei could be analogous to a posteriori probability, as they update our expectations and beliefs based on the sensory and cognitive information available. Intralaminar and median nuclei could relate to Bayes' theorem, as they combine previous and new information to update our beliefs and expectations. In addition, the reticular nucleus of the thalamus and geniculate nuclei modulate sensory information, adjusting it based on our expectations and attention before sending it to higher cortical areas for more accurate processing. The integration of these cores and concepts of Bayesian statistics into artificial intelligence may lead to more sophisticated and adaptive systems, which process and act on information in a similar way to how biological organisms do (46,47).

Bayesian Statistics and Reticular Formation

The relationship between Bayesian statistics and lattice formation could be established based on how both processes contribute to adaptability and adjustment in decision-making and information processing.

The relationship between lattice formation and Bayesian statistics can be established in the context of artificial intelligence and human brain modeling. AI systems could use Bayesian statistics to simulate the workings of the lattice formation, adjusting its level of arousal and attention according to incoming information and context. In this way, AI systems could dynamically adapt and focus on relevant tasks in a similar way to how humans do (34,36,39,45,48).

Relationship between Bayesian statistics and Brodmann areas.

A priori probability represents our initial beliefs about an event before we look at new data. Brodmann's area 46, located in the dorsolateral prefrontal cortex, is involved in working memory and decision-making, and stores prior information about events and expectations that guide our decisions and actions.

The probability of likelihood in Bayesian statistics reflects the probability of looking at the given data for a particular event. Brodmann's area 17, located in the primary visual cortex, is involved in the initial processing of visual information and evaluates the correspondence between the received visual information and our expectations based on previous events.

A posteriori probability in Bayesian statistics is the actualization of our beliefs after looking at new data. Brodmann's area 10, located in the anterior prefrontal cortex, is involved in higher cognitive functions, such as planning and decision-making, and updates our expectations and beliefs based on available sensory and cognitive information.

Bayes' theorem describes how to combine a priori probability and likelihood to obtain a posteriori probability. Brodmann's area 7, located in the posterior parietal cortex, is involved in the integration of sensory and cognitive information and the formation of internal representations of space, and could be considered analogous to Bayes' theorem insofar as it integrates prior information and new sensory information to actualize our beliefs and expectations (5,42).

Bayesian Statistics and the Amygdalar Nucleus

By combining Bayesian statistics with the amygdala core, we can develop AI systems that are capable of learning and adapting to varying emotional situations and contexts. These systems could be used in a wide variety of applications, from detecting and analyzing emotions in human interactions to adapting AI systems to respond appropriately to people's emotional needs.

For example, AI systems based on the Bayesian approach could be developed that are capable of recognizing and analyzing people's facial expressions and emotions. These systems could progressively learn and adapt to new emotional contexts as they receive feedback and new data samples.

Likewise, artificial intelligence systems that incorporate Bayesian statistics and are inspired by the amygdala core can improve the empathy and adaptability of conversational agents or chatbots, allowing a more human and personalized interaction with users (43,49).

Bayesian statistics and the hippocampus.

By relating Bayesian statistics to the hippocampus, we can develop AI systems that are capable of learning and adapting to new situations and contexts in a similar way to how humans do. These systems could benefit from the Bayesian approach's ability to adapt their beliefs and knowledge based on available information and previous experiences.

For example, AI systems using Bayesian statistics could be applied in the field of navigation and trajectory planning. Inspired by the role of the hippocampus in spatial orientation, these systems could update their cognitive maps and position estimates based on new sensory data and previous experiences.

In addition, artificial intelligence systems based on the Bayesian approach could be used to model memory and learning in applications such as pattern recognition, classification, and prediction. These systems could learn incrementally and adapt to new contexts and situations as they receive feedback and new data (43,50,51).

Information Processing in the Human Brain and Its Relationship to Bayesian Statistics and AI

Artificial intelligence (AI), Bayesian statistics, and anatomical brain structures share fundamental principles and mechanisms in terms of information processing, belief actualization, and decision-making based on observed evidence. Below is a synthesis of how these three elements relate and interact in the framework of decision-making and learning.

A. Artificial Intelligence and Data-Driven Learning

AI, particularly machine learning and artificial neural networks (ANNs), uses algorithms inspired by the human brain to learn patterns and relationships in data. Learning is based on adapting and optimizing model parameters to maximize its ability to represent and predict information based on observed evidence (3,19,52).

B. Bayesian Statistics and Evidence-Based Decision Making

Bayesian statistics provides a formal framework for updating beliefs and making evidence-based decisions. The Bayesian formula combines a priori probability (prior knowledge) with likelihood (fit to data) to derive posterior probability, which represents the updated belief about a hypothesis based on the evidence (3,29).

C. Anatomical Brain Structures and Information Processing

Brodmann's brain areas, the basal ganglia (including the caudate nucleus, putamen, globus pallidus, substantia nigra, and subthalamic nucleus), and thalamus nuclei are involved in the processing and integration of sensory, motor, and cognitive information in the human brain. These structures are involved in the formation and storage of prior knowledge, the updating of beliefs based on observed evidence, and the making of decisions based on integrated information (5,28,42,47).

D. Integration and analogies

AI and Bayesian statistics can be thought of as computational and mathematical models that attempt to emulate aspects of information processing and decision-making in the human brain. Although there are no direct correspondences between ANNs, the Bayesian formula, and anatomical brain structures, there are analogies and similarities in terms of the underlying principles and mechanisms (18,19,45).

In summary, AI, Bayesian statistics, and anatomical brain structures share fundamental concepts related to information processing, belief actualization, and decision-making based on observed evidence. These analogies and similarities can be useful for understanding and designing more efficient and robust AI systems, as well as gaining deeper insight into the workings and organization of the human brain.

Conclusion.

In conclusion, the interrelationship between artificial intelligence (AI), Bayesian statistics, and brain structures provides a fascinating perspective on how AI technologies can simulate and improve certain aspects of human cognition. The ability of Bayesian statistics to update and adapt beliefs as new information is acquired is essential in the development of more efficient and adaptable AI systems, capable of learning and adjusting to different contexts and situations.

Throughout the text, the relevance of different brain structures in the context of AI and Bayesian statistics has been explored, showing how decision-making, attention, learning, memory and emotions can be linked to different areas of the brain. AI can benefit from simulating some of the functions of these structures, allowing for greater adaptability and efficiency in problem-solving and decision-making.

The knowledge gained by relating these elements can guide the design and implementation of AI systems that are increasingly advanced and closer to the way humans acquire, process, and update information. This is critical for the development of AI systems that can interact effectively and understandably with humans, enabling an increasingly seamless integration of AI into our daily lives and offering more advanced solutions to complex problems in various fields, from medicine to robotics.

References

1. Shimizu H, Nakayama KI. Artificial intelligence in oncology. Cancer Sci. May 2020; 111(5):1452-60.
2. Salvagno M, Taccone FS, Gerli AG. Can artificial intelligence help for scientific writing? Crit Care. February 25, 2023; 27(1):75.
3. Graham S, Depp C, Lee EE, Nebeker C, Tu X, Kim HC, et al. Artificial Intelligence for Mental Health and Mental Illnesses: an Overview. Curr Psychiatry Rep. November 2019; 21(11):116.
4. Jiang J, Heller K, Egner T. Bayesian modeling of flexible cognitive control. Neurosci Biobehav Rev. 2014 Oct;46:30-43.
5. Kording KP. Bayesian statistics: relevant for the brain? Curr Opin Neurobiol. 2014 Apr;25:130-3.
6. Luo L. Architectures of neuronal circuits. Science. September 3, 2021; 373(6559):EABG7285.
7. Malhotra P, Gupta S, Koundal D, Zaguia A, Enbeyle W. Deep Neural Networks for Medical Image Segmentation. Chakraborty C, editor. J Healthc Eng. 2022 Mar 10;2022:1-15.
8. Licen T, Rakusa M, Bohnen NI, Manganotti P, Marusic U. Brain Dynamics Underlying Preserved Cycling Ability in Patients With Parkinson's Disease and Freezing of Gait. Front Psychol. 2022 Jun 16;1:847703 PM.
9. Ganguly J, Kulshreshtha D, Almotiri M, Jog M. Muscle Tone Physiology and Abnormalities. Toxins. April 16, 2021; 13(4):282.
10. Bostan AC, Strick PL. The basal ganglia and the cerebellum: nodes in an integrated network. Nat Rev Neurosci. June 2018; 19(6):338-50.
11. Joseph SB, Dada EG, Abidemi A, Oyewola DO, Khammas BM. Metaheuristic algorithms for PID controller parameters tuning: review, approaches and open problems. Heliyon. May 2022; 8(5):E09399.
12. Fazl A, Fleisher J. Anatomy, Physiology, and Clinical Syndromes of the Basal Ganglia: A Brief Review. Semin Pediatr Neurol. 2018 Apr;25:2-9.
13. Kashyap AK, Parhi DR. Particle Swarm Optimization aided PID gait controller design for a humanoid robot. ISA Trans. 2021 Aug;114:306-30.
14. Liu C, Kaeser PS. Mechanisms and regulation of dopamine release. Curr Opin Neurobiol. 2019 Aug;57:46-53.
15. Bonnevie T, Zaghloul KA. The Subthalamic Nucleus: Unravelling New Roles and Mechanisms in the Control of Action. The Neuroscientist. February 2019; 25(1):48-64.
16. Geier KT, Buchsbaum BR, Parimoo S, Olsen RK. The role of anterior and medial dorsal thalamus in associative memory encoding and retrieval. Neuropsychology. 2020 Nov;148:107623.
17. Aggleton JP, O'Mara SM. The anterior thalamic nuclei: core components of a tripartite episodic memory system. Nat Rev Neurosci. August 2022; 23(8):505-16.
18. Millidge B, Salvatori T, Song Y, Lukasiewicz T, Bogacz R. Universal Hopfield Networks: A General Framework for Single-Shot Associative Memory Models. Proc Mach Learn Res. 2022 Jul;162:15561-83.

19. Tsantekidis A, Passalis N, Tefas A. Recurrent neural networks. In: Deep Learning for Robot Perception and Cognition [Internet]. Elsevier; 2022 [cited 2023 Apr 30]. p. 101-15. Available in: https://linkinghub.elsevier.com/retrieve/pii/B9780323857871000105
20. Matzeu A, Flores-Ramirez FJ, Martin-Fardon R. Thalamic circuits. In: Neurocircuitry of Addiction [Internet]. Elsevier; 2023 [cited 2023 Apr 30]. p. 209-46. Available in: https://linkinghub.elsevier.com/retrieve/pii/B9780128234532000126
21. Mitchell AS. The mediodorsal thalamus as a higher order thalamic relay nucleus important for learning and decision-making. Neurosci Biobehav Rev. 2015 Jul;54:76-88.
22. Morita K, Jitsev J, Morrison A. Corticostriatal circuit mechanisms of value-based action selection: Implementation of reinforcement learning algorithms and beyond. Behav Brain Res. 2016 Sep;311:110-21.
23. Bobba PS, Sailer A, Pruneski JA, Beck S, Mozayan A, Mozayan S, et al. Natural language processing in radiology: Clinical applications and future directions. Clin Imaging. 2023 May;97:55-61.
24. Saalmann YB. Intralaminar and medial thalamic influence on cortical synchrony, information transmission and cognition. Front Syst Neurosci [Internet]. 2014 May 9 [cited 2023 Apr 30];8. Available in: http://journal.frontiersin.org/article/10.3389/fnsys.2014.00083/abstract
25. Zhang FF, Peng W, Sweeney JA, Jia ZY, Gong QY. Brain structure alterations in depression: Psychoradiological evidence. CNS Neurosci Ther. November 2018; 24(11):994-1003.
26. Moutik O, Sekkat H, Tigani S, Chehri A, Saadane R, Tchakoucht TA, et al. Convolutional Neural Networks or Vision Transformers: Who Will Win the Race for Action Recognitions in Visual Data? Sensors. January 9, 2023; 23(2):734.
27. Zhang Y, Lin H, Yang Z, Wang J, Sun Y, Xu B, et al. Neural network-based approaches for biomedical relation classification: A review. J Biomed Inform. 2019 Nov;99:103294.
28. Cover KK, Mathur BN. Rostral Intralaminar Thalamus Engagement in Cognition and Behavior. Front Behav Neurosci. 2021;15:652764.
29. Šimić G, Tkalčić M, Vukić V, Mulc D, Španić E, Šagud M, et al. Understanding Emotions: Origins and Roles of the Amygdala. Biomolecules. May 31, 2021; 11(6):823.
30. Genon S, Bernhardt BC, La Joie R, Amunts K, Eickhoff SB. The many dimensions of human hippocampal organization and (dys)function. Trends Neurosci. December 2021; 44(12):977-89.
31. Gagliardo A, Colombo S, Pollonara E, Casini G, Rossino MG, Wikelski M, et al. GPS-profiling of retrograde navigational impairments associated with hippocampal lesion in homing pigeons. Behav Brain Res. 2021 Aug;412:113408.
32. Sun B, Gao S, Zi H, Wu Q. GAN based simultaneous localization and mapping framework in dynamic environment. J King Saud Univ - Sci. November 2022; 34(8):102298.
33. Debeunne C, Vivet D. A Review of Visual-LiDAR Fusion based Simultaneous Localization and Mapping. Sensors. April 7, 2020; 20(7):2068.
34. Robinson DA. Neurophysiology of the saccadic system: The reticular formation. In: Progress in Brain Research [Internet]. Elsevier; 2022 [cited 2023 May 1]. p. 355-78. Available in: https://linkinghub.elsevier.com/retrieve/pii/S0079612321002168
35. Clark CR, Geffen GM, Geffen LB. Catecholamines and attention I: Animal and clinical studies. Neurosci Biobehav Rev. December 1987; 11(4):341-52.
36. Ray CL, Mirsky AF, Pragay EB. Functional analysis of attention-related unit activity in the reticular formation of the monkey. Exp Neurol. September 1982; 77(3):544-62.
37. Routtenberg A. The two-arousal hypothesis: Reticular formation and limbic system. Psychol Rev. 1968; 75(1):51-80.
38. Salvi R, Radziwon K, Manohar S, Auerbach B, Ding D, Liu X, et al. Review: Neural Mechanisms of Tinnitus and Hyperacusis in Acute Drug-Induced Ototoxicity. Am J Audiol. October 11, 2021; 30(3S):901-15.

39. Martins I, Tavares I. Reticular Formation and Pain: The Past and the Future. Front Neuroanat. 2017;11:51.

40. Svoboda K, Li N. Neural mechanisms of movement planning: motor cortex and beyond. Curr Opin Neurobiol. 2018 Apr;49:33-41.

41. Chauhan P, Rathawa A, Jethwa K, Mehra S. The Anatomy of the Cerebral Cortex. In: Pluta R, editor. Cerebral Ischemia [Internet]. Brisbane (AU): Exon Publications; 2021 [cited 2023 May 1]. Available in: http://www.ncbi.nlm.nih.gov/books/NBK575742/

42. Geyer S, Dinse J. Brodmann's Areas ☆. In: Reference Module in Neuroscience and Biobehavioral Psychology [Internet]. Elsevier; 2017 [cited 2023 May 1]. p. B9780128093245039000. Available in: https://linkinghub.elsevier.com/retrieve/pii/B9780128093245038268

43. Rolls ET. The cingulate cortex and limbic systems for emotion, action, and memory. Brain Struct Funct. December 2019; 224(9):3001-18.

44. Pickles JO. Auditory pathways. In: Handbook of Clinical Neurology [Internet]. Elsevier; 2015 [cited 2023 May 1]. p. 3-25. Available in: https://linkinghub.elsevier.com/retrieve/pii/B9780444626301000019

45. Daunizeau J. The Bayesian Brain: An Evolutionary Approach to Cognition. In: Encyclopedia of Behavioral Neuroscience, 2nd edition [Internet]. Elsevier; 2022 [cited 2023 May 1]. p. 202-21. Available in: https://linkinghub.elsevier.com/retrieve/pii/B9780128196410001493

46. Huygelier H, Gillebert CR, Moors P. The Value of Bayesian Methods for Accurate and Efficient Neuropsychological Assessment. J Int Neuropsychol Soc. October 2022; 28(9):984-95.

47. Misulis KE, Zimmerman EE, Samuels MA. Basal Ganglia and Thalamus. In: Neurologic Localization and Diagnosis [Internet]. Elsevier; 2023 [cited 2023 May 1]. p. 81-4. Available in: https://linkinghub.elsevier.com/retrieve/pii/B9780323812801000147

48. Kording KP. Bayesian statistics: relevant for the brain? Curr Opin Neurobiol. 2014 Apr;25:130-3.

49. Kim MK, Kim M, Oh E, Kim SP. A Review on the Computational Methods for Emotional State Estimation from the Human EEG. Comput Math Methods Med. 2013;2013:1-13.

50. Tucker DM, Luu P. Motive control of unconscious inference: The limbic base of adaptive Bayes. Neurosci Biobehav Rev. 2021 Sep;128:328-45.

51. Shadmehr R, Holcomb HH. Neural correlates of motor memory consolidation. Science. 8 August 1997; 277(5327):821-5.

52. Montagnini A, Mamassian P, Perrinet L, Castet E, Masson GS. Bayesian modeling of dynamic motion integration. J Physiol-Paris. January 2007; 101(1-3):64-77.