A New Paradigm for AGI: A Cognitive Architecture with Sliding Function-Driven Attention Heads Operating on Knowledge Graphs and Integrated Endogenous Thinking Design

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Abstract

This study proposes a novel cognitive architecture inspired by human cognitive flow mechanisms, designed for high feasibility in achieving Artificial General Intelligence (AGI). The architecture integrates four core design principles: a dynamic attention mechanism driven by sliding functions, knowledge graph representations with multimodal embeddings, a perception selection mechanism guided by sensory entropy, and an endogenous thinking system with emotional regulation and subconscious association capabilities.

In this system, the sliding attention mechanism dynamically adjusts the attention trajectory on the knowledge graph based on multi-source factors such as semantic similarity, memory entropy, emotional weights, and rule-based associations, enabling human-like free association and nonlinear cognitive leaps. The knowledge graph incorporates multidimensional node attributes and semantic tensor fields, combining abstract logic with sensory experiences to construct a dynamic graph supporting inference leaps and knowledge evolution. The perception module employs sensory entropy to evaluate novelty and task relevance, driving attention focus and cognitive prioritization. The endogenous thinking module, through self-monitoring, emotional simulation, and subconscious generation mechanisms, enables the system to continuously generate hypotheses, expand the knowledge graph, and shape cognitive styles even in the absence of task-driven inputs.

The architecture holistically simulates human-like associativity, emotion-driven cognition, and task self-organization, incorporating multi-level attention coordination, inference-decision closed-loop control, and fuzzy semantic generation as engineerable modules. This provides a clear path and technical foundation for building AGI systems with autonomous goal generation, continuous learning, and innovative reasoning capabilities. Compared to traditional neural networks or symbolic logic systems, this architecture demonstrates significant advantages in cognitive consistency, multimodal integration, and personalized evolution, laying a scalable cognitive foundation for human-like intelligent systems.

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1 Introduction

Amid the rapid evolution of artificial intelligence technologies, deep neural networks, reinforcement learning, and large-scale pretrained language models have achieved breakthroughs in specific tasks. However, these systems reveal significant limitations in real-world applications, particularly in core general intelligence capabilities such as open-environment adaptability, complex goal coordination, cross-domain knowledge transfer, and autonomous innovative problem-solving, where they fall short of human intelligence levels.

This paper addresses these technical bottlenecks by exploring a novel cognitive architecture design that integrates cognitive science mechanisms, multimodal coupling control, and autonomous innovative thinking.

1.1 Current Research and Limitations

The dominant AI paradigms rely on deep neural networks, emphasizing pattern recognition through massive data training. These models excel in single-task scenarios such as image recognition, natural language processing, and strategy optimization in reinforcement learning. However, in real-world scenarios, intelligent agents must operate in complex, dynamic, and partially unknown environments, requiring cross-domain transfer, composite goal coordination, causal chain reasoning, and dynamic model self-correction.

Current deep learning systems depend on static large-scale data distribution assumptions, lacking active hypothesis generation and autonomous knowledge organization. Reinforcement learning models converge slowly in high-dimensional complex state spaces and incur high costs for adapting to new tasks. Large-scale pretrained language models, while excelling in language generation and comprehension, exhibit significant gaps in systematic knowledge integration, dynamic inference chain construction, and self-cognitive modeling. Particularly in open-ended exploration tasks and cross-temporal knowledge recombination, existing models lack intrinsic cognitive motivation and sustained autonomous learning drive, resulting in task-oriented but not truly world-oriented capabilities.

1.2 Insights from Cognitive Science and Psychology

Cognitive neuroscience and psychology research reveal that human intelligence does not stem from singular pattern recognition or logical reasoning but is built on a complex cognitive architecture with multi-system coordination. When individuals face complex real-world environments, perception, attention, emotion, memory, reasoning, and decision-making mechanisms are dynamically coupled in a feedback-regulated process.

The emotional system plays multiple roles in cognitive regulation: it modulates sensory intensity and attention distribution through hormone levels and neurotransmitters, influencing information encoding and memory weighting; it also reinforces learning paths through motivation and reward-punishment feedback, shaping personalized behavioral preferences and long-term personality styles. Psychological studies indicate that human thinking exhibits high leap-like associativity and endogenous thought generation, capable of reorganizing existing knowledge during rest, sleep, or free association, forming creative hypotheses and distant associative connections. These core characteristics are critical cognitive abilities absent in current AI systems.

1.3 Comparison with Existing AGI Frameworks

Several research frameworks for AGI aim to transcend single neural network models. For example, OpenCog Hyperon combines symbolic logic, heterogeneous graphs, and control systems for complex reasoning (1); LeCun's autonomous world model emphasizes self-constructed models and causal learning (2); and recent embodied AI research integrates multimodal sensing and physical interaction to enhance knowledge abstraction.

Despite their innovations, these frameworks face common challenges: knowledge graphs and symbolic logic, while strong in structured expression, lack cognitive fluidity in inference chain expansion and dynamic knowledge leaps; pure neural network models lack stable long-term self-modeling and interpretability; and emotional regulation, personality formation, and endogenous hypothesis generation remain largely unmodeled. Thus, a comprehensive architecture is needed to integrate the rigor of symbolic expression, the adaptability of neural models, and the motivational drive of emotional systems, providing a unified solution for cognitive fluidity, autonomous learning, and personalized development in AGI.

1.4 Innovative Contributions of This Study

Addressing the limitations of existing AGI frameworks in open-environment adaptability, complex goal coordination, and autonomous innovative reasoning, this study integrates insights from cognitive science and psychology to propose a novel cognitive architecture driven by sliding functions. The architecture introduces the following five key innovations:

1. **Dynamic Sliding Attention Mechanism**: Utilizes sliding functions to dynamically adjust attention trajectories in the knowledge graph embedding space, integrating semantic similarity, memory entropy, emotional weights, and rule-based associations to emulate human-like cross-node associative leaps, enabling recall, divergent thinking, and nonlinear cognitive flow.

2. **Multidimensional Knowledge Graph with Memory Entropy**: Incorporates a memory entropy mechanism within knowledge graph embeddings, combining knowledge richness, recency, and sensory interest to enable dynamic knowledge activation and interest-driven reorganization, supporting inference leaps and continuous knowledge evolution.

3. **Sensory Entropy-Guided Perception Design**: Employs sensory entropy to assess the novelty and task relevance of input signals in real time, prioritizing cognitive focus and facilitating efficient perception-cognition integration for dynamic cognitive flow.

4. **Autonomous Endogenous Thinking System**: Combines autonomous goal modeling, self-monitoring, and subconscious association generation to support hypothesis generation, knowledge graph expansion, and cognitive style development without external task inputs, fostering long-term cognitive growth and creative reasoning.

5. **Human-like Emotional Simulation System**: Simulates physiological hormone models (e.g., dopamine, cortisol) to dynamically regulate sensory entropy distribution and decision path preferences, shaping stable cognitive styles and risk assessment tendencies, enhancing personalized and adaptive intelligence.

These innovations collectively establish a fluid, autonomous, and scalable cognitive framework, integrating symbolic logic, neural adaptability, and emotional motivation to provide a robust technical foundation for AGI systems with autonomous goal generation, continuous learning, and innovative reasoning capabilities.

2 Overall System Architecture Design

2.1 Sliding Attention Head Inference Mechanism Design

In this AGI architecture, Sliding Attention Heads serve as the core control unit for cognitive flow, managing internal association control, cognitive flow regulation, and dynamic exploration drive. Inspired by the natural attention shift mechanism in human thinking, they integrate hypothesis generation, associative leaps, and emotional drive to achieve self-generated cognition and cognitive leaps. Essentially, the sliding attention head operates as a dynamic focusing and activation process on a node or local subgraph in the knowledge graph, with its focus range sliding continuously in the graph space based on internal states, emotional tension, and sensory entropy changes, driving natural cognitive focus transitions.

The sliding attention head's control mechanism relies on a sliding function that dynamically adjusts attention trajectories in the knowledge graph embedding space, constructing flexible, cross-level inference paths. The sliding function ensures that attention focuses on the most relevant cognitive nodes while activating distant association mechanisms to expand cognitive breadth. Its construction involves three stages:

- **Semantic Candidate Selection**: The system centers on the semantic vector of the current focus node, computes semantic similarities (e.g., cosine similarity) with all nodes in the graph based on contextual semantic information, and selects a set of candidate nodes as potential directions for attention sliding, ensuring semantic coherence.

- **Cognitive Consistency Evaluation**: Candidate nodes are evaluated based on their memory entropy weights (reflecting knowledge richness and reliability) and semantic relevance to the active regions of the self-cognitive graph, dynamically adjusting their sliding weights. This ensures attention allocation reflects both current inputs and the system's long-term experience and subjectivity.

- **Rule-Based Constraints**: In task-driven or directed inference scenarios, the system incorporates rule-based constraints encoded in certain graph edge relationships, which can be explicit (e.g., "screwdriver $\rightarrow$ turn $\rightarrow$ screw") or flexibly guided by rule-like nodes, enabling keyword identification and semantic generalization for task-driven structural guidance.

If the sliding weights of candidate nodes are generally low, the system triggers distant associations or external memory retrieval, jumping to non-neighbor nodes or generating temporary fuzzy memory nodes to fill knowledge gaps, adjusting exploration divergence, depth, and leap amplitude based on context to enhance divergence and adaptability.

The sliding function is further modulated by multi-source factors, including emotional states (e.g., joy, anxiety, curiosity), simulated hormone parameters (e.g., dopamine, cortisol), and implicit subconscious drives. For instance, in positive emotional states, the system favors novel nodes; in stressed or anxious states, attention converges to more certain knowledge areas, enhancing cognitive stability. The subconscious module influences sliding leap size and fuzzy association window, supporting dream-like nonlinear leaps.

The endogenous thinking module imbues the system with metacognitive capabilities, enabling real-time evaluation of inference path attributes and structures, matching them against psychological models (e.g., Monty Hall paradox, anchoring effect). This allows flexible cognitive adjustments in complex scenarios, simulating human decision biases and psychological traps.

Task urgency, logical demands, and social factors (e.g., compliance/rebellion tendencies, anticipated attitudes of others) further modulate the sliding function, affecting leap depth and cognitive restructuring scope. Historical memories similar to the current scenario are assigned higher activation, promoting experience transfer and analogical reasoning. The sliding function also integrates composite nodes and hierarchical parent-child structures in the knowledge graph, enabling controlled inference chain growth, ensuring self-organization, directionality, and cognitive resilience in open-ended problems.

Multiple independent but interacting sliding attention heads operate concurrently for different cognitive tasks, such as hypothesis generation, future scenario prediction, fuzzy association, contradiction detection, and potential path generation. During inference, multiple nodes may be activated in parallel, requiring the system to compute sliding values for each node's neighbors to determine the next inference direction. To balance divergent exploration and convergent progress, the architecture introduces a Primary-Auxiliary Sliding Strategy. The system constructs a weighted sliding score function based on memory entropy, emotional regulation factors, and task relevance, selecting the highest-scoring neighbor as the "primary sliding node" to advance the main cognitive path. Suboptimal nodes with memory entropy above a threshold are retained as "auxiliary paths" for lightweight parallel exploration, assessing their potential value. If the main path hits an inference bottleneck (e.g., declining sliding values, loops, or goal deviation), auxiliary paths can take over or provide cognitive pivots for nonlinear leaps and restructuring. If no neighbor shows significant advantage, each node defaults to its highest-scoring neighbor, maintaining inference channel diversity and independence. This mechanism ensures efficient parallel inference, enhancing attention scheduling flexibility and contextual adaptability, significantly improving human-like creativity and intuitive reasoning in complex tasks.

To support hierarchical organization and parallel processing of complex cognitive tasks, the architecture introduces Hierarchical Sliding Attention Heads. Attention heads are structured into multiple levels, from top-down main thinking flow (meta-attention layer) to layered task-specific flows. The main thinking flow maintains the core theme or goal, such as "music composition," coordinating and driving sub-tasks. First-level task heads, like "composing" and "lyric writing," control key sub-tasks, while second-level heads handle specific operations like "melody structure selection" or "timbre style choice," and third-level heads focus on micro-operations like "note selection" or "rhythm distribution." This hierarchical structure enables simultaneous global control and local fine-grained inference, mimicking human brain-like layered cognition. Dynamic information flow between levels ensures upper layers set cognitive goals and abstract expectations, while lower layers provide feedback on execution states and deviations, enabling cross-level cognitive consistency and adaptive adjustment.

Inference and decision-making form a dynamic, mutually reinforcing cognitive closed-loop, breaking the traditional linear "inference-then-decision" assumption. In the inference-to-decision path, the system extends associations and logic along attention chains in the knowledge graph. When reaching actionable nodes, it evaluates expected value and risk-reward ratios based on context, multimodal inputs, emotional states, hormone parameters, and historical experience, pushing candidates into a decision queue. Semantic expansion in word vector spaces parses task instructions at a conceptual level, activating related nodes (e.g., "evaluation," "criteria," "priority") to construct and select action paths.

Multiple action schemes may be discovered and evaluated in parallel cognitive channels, forming dynamic competition and complementarity. After inference, the system selects the highest-value, contextually adaptive scheme as the final output, ensuring logical and multi-factor balanced decisions. The reverse decision-to-inference path regulates inference by adjusting sliding function biases and attention strategies based on task urgency and goal weights, focusing on goal-relevant semantic regions or triggering cross-domain associations. Continuous feedback monitoring adjusts goal expectations, influencing subsequent inference directions.

This bidirectional mechanism integrates inference, decision-making, and goal regulation, forming a human-like closed-loop cognitive process combining logical evolution and motivational drive. Subconscious and emotional simulation modules provide internal regulation, enhancing flexibility and self-adaptation in uncertain environments.

In summary, the sliding attention head achieves a balance of divergence and convergence in cognitive association, supporting complex hypothesis generation, scenario simulation, and stable logical chains while coordinating emotion, logic, and subconscious influences. It integrates with multimodal knowledge graphs to support dynamic graph construction and inference chain formation, providing robust support for AGI cognitive growth and intelligent evolution.

2.2 Perception Module Design

The perception module employs neural networks for image, speech, and text perception. For touch, it senses pressure, texture, and temperature, distinguishing softness/hardness and smoothness/roughness, simulating pressure sensors to enhance object interaction. For vision, a dynamic coordinate system based on the visual center processes object location information, shifting during agent movement to maintain spatial consistency. The visual sub-module recognizes objects, colors, optical flow, and motion trajectories, decomposing complex objects into parts (e.g., shape, texture) using structured object recognition (3) and point cloud technology for 3D scene perception and multimodal fusion. For audition, it processes sound signals, distinguishing human voices, instruments, or environmental noise, recognizing emotions (e.g., joyful laughter) or intentions (e.g., warnings), and supporting music preference learning and emotion-memory linkage. For taste, it analyzes chemical components, distinguishing sweet, sour, bitter tastes to support food evaluation and preference learning. For smell, it detects odor molecules, classifying types (e.g., floral, foul) to aid environmental assessment.

Sensory entropy is the core metric for evaluating the importance of individual perceptual inputs, measuring salience and attention priority without directly intervening in inference or decision-making. Sensory entropy calculation integrates sensory salience, memory entropy (preference), environmental features (rarity, high-value targets), emotional hormone levels (high dopamine increases entropy growth, promoting novelty exploration; high cortisol lowers entropy thresholds, favoring caution), and task context. High-entropy inputs are prioritized for attention and cognitive processing, while low-entropy inputs may be delayed or discarded.

Sensory and memory entropy form a bidirectional feedback mechanism. High memory entropy nodes enhance related perceptual modes' sensory entropy, increasing sensitivity to high-value or high-attention memories. Sustained high sensory entropy inputs may generate new high memory entropy segments, enriching memory and knowledge structures. The emotional module modulates entropy weights, shaping personality differences. For example, high dopamine levels increase sensory entropy growth, promoting exploration, while high cortisol lowers thresholds, favoring conservative attention patterns.

After multimodal data collection, the perception module feeds continuous perceptual streams into a large language model (LLM) for semantic modeling and structured conversion, generating knowledge graph node sequences for inference. This bridges unstructured perceptual signals to unified symbolic knowledge representations, enabling all perceptual content (linguistic and non-linguistic) to integrate into the cognitive system's knowledge network.

For non-linguistic modalities like vision and audition, the LLM performs object recognition, attribute extraction, temporal integration, event summarization, and causal pattern recognition. Beyond recognizing "seeing a knife" or "hearing a crash," it constructs "action-consequence-context" chains (e.g., "person moves forward $\rightarrow$ object enters view $\rightarrow$ potential danger"). These high-level semantic units are encoded as knowledge graph nodes and edges, representing state transitions, event logic, and causal links, enabling analogical reasoning and predictive inference.

Natural language processing is more complex. The natural language understanding (NLU) module, powered by the LLM, parses syntactic structures and semantic roles, extracting subjects, predicates, objects, modifiers, and temporal markers. Using a "sliding understanding" strategy, it dynamically focuses on different linguistic components to interpret metaphors, implications, ambiguities, and omissions accurately.

In the structuring phase, the NLU module generates fact-based nodes and high-level semantic nodes, including:

- Intent nodes: revealing behavioral motivations, inference directions, or needs;
- Emotion nodes: modulating virtual hormone systems via linguistic emotional cues, influencing attention and judgment;
- Symbolic and semantic density nodes: representing cultural metaphors, symbolic abstractions, and implicit cognitive cues;
- Context-dependent nodes: parsing spatiotemporal contexts, dialogue flows, and knowledge assumption spaces.

These nodes are organized into a unified knowledge graph, enabling composable linkage with existing knowledge for cross-modal, cross-level knowledge expression. The system supports multi-level causal reasoning, judging action-consequence relationships and inducing new causal and semantic structures, promoting knowledge graph self-expansion and restructuring.

Combined with sliding attention and graph neural networks, the AGI system models current perceptions, predicts unobserved environmental states and emotional trends, and enhances behavioral foresight, emotional adaptability, and strategy generation in complex environments.

As an exploratory direction, the architecture proposes multi-level feature-guided training combined with meta-learning. Perception modules integrate MAML-based meta-learners in each sensory channel (e.g., vision, audition, touch) for rapid adaptation to new tasks and features. Meta-learners extract low-level features (e.g., color, shape, texture, motion, sound frequency), generating preference vectors based on frequency, confidence, and historical associations. Feature-guided neural networks adjust sample attention and learning rates, prioritizing high-frequency, high-value features to improve efficiency and generalization.

Meta-learners across channels integrate into higher-level meta-meta-learners, abstracting commonalities (e.g., shared object attributes in vision and touch, emotional-auditory associations), enhancing cross-modal transfer and joint representation learning. This design overcomes rigid convolutional templates and static training bottlenecks, enabling open-ended, real-time adaptive, cross-modal continuous learning for sustained perceptual evolution and cognitive expansion.

2.3 Knowledge Graph and Node Representation

Component	Function	Input/Output
Sliding Attention Head	Dynamic focus and path generation	Semantic vectors/Inference chains
Knowledge Graph	Multimodal knowledge representation	Nodes and edges/Inference results
Perception Module	Multimodal signal processing	Sensory data/Structured nodes
Endogenous Thinking	Autonomous cognition and hypothesis generation	Internal states/Cognitive paths

Table 1: Overview of core components in the proposed AGI architecture.

The knowledge graph comprises an axiom library and a personalized memory library, forming a dual-core architecture for AGI knowledge expression and experience accumulation. The axiom library includes entity nodes for simple relationships and rule nodes for social norms and complex logical structures. The personalized memory system captures dynamic, individualized, emotionally tagged temporal experiences, recording external perceptions, internal physiological states, emotional fluctuations, actions, and feedback as continuous time-series memory flows. Each memory includes high-precision timestamps and multi-channel sensor data, enabling event scene reconstruction and psychological state recall, mimicking human nostalgic experiences. Personalized memories, with their temporal nature, are encoded using recurrent neural networks (RNNs) or Transformers for dynamic activation and decay management. The axiom and memory libraries interweave, with the axiom library storing objective facts and rules while carrying individualized experiences (e.g., item preferences and related experiences), fostering knowledge-experience integration for cognitive growth and intelligent evolution.

To meet AGI's complex information processing needs, the knowledge graph employs multimodal joint encoding and semantic tensor fields, building a node-centric dynamic attribute set model with parent-child structures, interface-based generalization, and graph-based edge design. It internalizes physical environment simulation rules, supporting objective world reasoning. Each node, as a multidimensional attribute set, integrates sensory data (vision, audition, smell, taste, touch), linguistic descriptions, abstract semantics, emotional states, and physiological parameters. For example, an "apple" node includes color, texture, sweetness, hardness, bite sound, and emotional tags (e.g., pleasure), inheriting "food" class attributes (e.g., "edible") and linking to "softness" tensors, storing related entities' physical data for dynamic semantic-physical coupling.

Semantic tensor fields construct high-dimensional tensors for each attribute concept, integrating multimodal sensor data and linguistic semantics, supporting dynamic updates and lifelong learning. Word meanings are encoded via high-dimensional semantic vectors, covering single meanings, multi-sense associations (hyponyms, synonyms, metaphors), and context-adaptive disambiguation. Graph edges, beyond semantic links, express structured relationships with sub-graphs detailing context, conditions, inference chains, and dynamic evolution, enhancing relational inference depth and flexibility.

The node-relationship network includes causal, comparative, similarity, parallel, and metaphorical connections, forming hierarchical and interface-based generalization structures. Temporal updates and memory entropy metrics adjust node importance dynamically, focusing on task-relevant information. The graph internalizes physical simulation rules, supporting structured environmental cognition and self-adaptive evolution. This node-attribute and edge-graph architecture, combined with multimodal perception, semantic tensors, complex networks, and physical rules, ensures depth, breadth, and connectivity for robust contextual understanding, autonomous learning, and innovative reasoning.

Memory entropy, a core node metric, quantifies cognitive importance and activation, integrating emotional intensity, sensory entropy accumulation, subjective preferences, and task relevance. It dynamically reflects node priority and emotional influence, with time decay and reinforcement ensuring high-weight retention for frequently used knowledge. Low-entropy nodes are abstracted into fuzzy semantic keyword representations, stored in a subconscious weight pool, activated in dream-like simulations, emotional triggers, and creative ideation, influencing attention focus and inference path generation via sliding functions.

Graph neural networks (GNNs) enhance graph construction and inference by aggregating neighbor information, predicting relationships, and refining fuzzy node classification. GNNs integrate multimodal features, learning high-dimensional node embeddings for semantic fusion and contextual perception. Combined with graph attention networks (GATs), sliding attention mechanisms enable dynamic inference path search based on topology, semantics, and emotional weights, promoting innovative cognition and efficient decision-making.

A dedicated neural network module supports tasks like speech and image generation and LLM-assisted inference, rapidly accessing relevant nodes for multimodal output, enhancing flexibility and efficiency in perception and interaction.

By integrating symbolic logic, personalized memory, GNNs, and sequence models, the AGI system forms a unified, dynamic cognitive architecture for knowledge storage, experience growth, logical reasoning, emotional regulation, and self-evolution, providing a robust foundation for general intelligence and personalization.

2.4 Endogenous Thinking

The endogenous thinking module is the core mechanism for autonomous cognition, reflection, and creative thinking, integrating self-monitoring, metacognition, emotional and hormonal regulation, sensory-driven perception, and subconscious association generation. It forms a continuous, dynamic, and highly autonomous cognitive kernel through multimodal, multi-level, and multi-path interactions, enabling human-like cognitive flow, flexible restructuring, and creative generation. The module comprises four core mechanisms:

2.4.1 Global Sliding Control Mechanism Based on Self-Cognitive Graph

The system maintains a dynamic self-cognitive graph representing internal states, including active inference chains, task goals, emotional states, personality traits, value preferences, and responsibility markers. This graph supports cognitive monitoring and self-modeling, serving as a basis for sliding control function scheduling.

High-frequency state sampling quantifies graph tension (e.g., conflict density, goal deviation, inference complexity), adjusting sliding function parameters like attention range, sampling rate, inference depth, and generation complexity. State changes (e.g., goal shifts, contradictions) trigger sliding function restructuring, enabling attention shifts, inference path updates, and cognitive style transitions (e.g., from conservative-deductive to exploratory-associative), supporting flexible resource allocation and cognitive elasticity.

2.4.2 Emotional Simulation and Hormonal Regulation

The self-cognitive graph embeds multidimensional emotional nodes, hormonal parameters, and personality factors, modulating behavior and cognitive strategies. Simulated neurotransmitters (e.g., dopamine, serotonin, cortisol) couple with task goals and feedback, forming an internal influence channel for sliding function computation.

Emotional states adjust sliding window range and focus tendencies: curiosity widens the window for exploratory inference, while anxiety narrows it to safe, familiar areas. Emotional intensity and direction map to attention weights, sampling depth, and generation complexity. Embedded in the self-cognitive graph, these parameters evolve with experience, feedback, and sliding history, forming stable personality and value sub-layers, ensuring consistent, stylized sliding regulation and human-like behavioral expression.

2.4.3 High-Entropy Signal-Driven Attention Sliding

The sliding function responds to high-entropy signals from memory and perception channels, maintaining cognitive activity in non-task states and introducing diversity in inference paths. It includes two independent but high-entropy-driven processes:

- **Spontaneous Thinking Activation**: In idle states, the system scans for high-entropy nodes (dense, multi-sense, frequently activated, or emotionally weighted) or high sensory entropy inputs (novel, complex, or emotionally resonant). Selected signals initiate non-goal-directed attention jumps, generating exploratory branches, activating problem chains, or entering associative states for subconscious, fuzzy, or novel concept generation.
- **Perturbation in Sliding Functions**: High-entropy signals modulate attention jump probabilities, window sizes, and path retracing, prioritizing high-information-density areas for efficient resource allocation. This nonlinear perturbation mimics human subconscious cognitive flow, enabling fuzzy transitions and cross-domain associations in weakly constrained states.

2.4.4 Fuzzy Association and Knowledge Graph Self-Organization

Under self-cognitive graph and subconscious sliding regulation, the system supports cognitive expansion from blind spot identification to fuzzy concept creation and long-term task evolution. It autonomously constructs symbolic cognitive pathways via low-temperature random splicing, multi-path generalization, and semantic similarity screening, identifying missing concepts, logical gaps, or new hypotheses. Key processes include:

- **Knowledge Blind Spot Identification**: The system evaluates node density, causal chain completeness, and semantic connectivity to identify cognitive blind spots, generating fuzzy placeholder nodes to bridge inference gaps. Continuous contextual aggregation refines these nodes, forming a long-term mechanism for proactive blind spot detection and inference path construction.
- **Subconscious Fuzzy Generation**: In a human-like subconscious state, the system triggers nonlinear associations based on residual emotions, incomplete goals, or semantic paths, generating symbolic, metaphorical, or unnamed fuzzy structures as concept candidates. These stabilize through contextual learning, integrating into the knowledge graph to drive cross-domain leaps and creative cognition.
- **Dynamic Task Chain Generation**: The system monitors cognitive graphs, emotional states, and unsolved problems, evaluating resource occupancy and cognitive damping. Free resources activate historical tasks or derive new task chains, guided by long-term value signals (e.g., curiosity entropy, goal proximity, emotional reward).

This mechanism enables human-like growth, self-exploration, and structural innovation, supporting cognitive gap repair, autonomous concept generation, and knowledge system evolution without external inputs.

3 Task-Driven Application Examples

3.1 Problem Solving and Logical Reasoning

Example: Medical Diagnosis Reasoning The AGI receives patient symptom descriptions (fever, cough, shortness of breath), parsing inputs via the NLU module while linking to medical knowledge (diseases, symptoms, treatments) in the knowledge graph. It adjusts emotional hormone parameters (increased anxiety drives cautious inference) based on patient history and environmental factors.

Using disease-symptom causal chains, the system infers possible diagnoses (e.g., pneumonia, bronchitis), evaluates probabilities, and generates diagnostic suggestions. The subconscious module traverses similar past case memories to assess risks, producing a detailed diagnostic report with next-step recommendations.

3.2 Document Writing and Complex Task Decomposition

Example: Writing a Technical White Paper The AGI receives a task to write a technical white paper on quantum computing fundamentals. It decomposes the task using knowledge graph nodes to outline chapters (principles, quantum gates, algorithms, applications).

The NLU module identifies instruction details, and the emotional regulation module maintains a neutral, professional style. Multimodal text and image generation produce logically rigorous content. The cognitive simulation module reviews content for logical coherence, correcting conflicts to ensure document consistency.

3.3 Cross-Domain Knowledge Transfer

Example: Applying Population Dynamics Models to Economic Market Analysis Having mastered population growth and predator-prey models in ecology, the AGI identifies structural and causal similarities with economic market supply-demand and investor behavior dynamics via the knowledge graph.

It transfers ecological model frameworks to economics, adjusting parameters for market data. The hormonal module regulates exploration intensity, and the subconscious module generates hypothetical scenarios to validate model applicability, proposing innovative market prediction methods.

3.4 Creative Invention Simulation

Example: Designing a Novel Energy-Saving Smart Window System Tasked with designing an energy-saving smart window, the AGI integrates knowledge from architecture, materials science, meteorology, and sensor technology. Using high memory entropy nodes, it generates multiple design schemes via VAE and diffusion models, producing innovative structures and control strategies.

The subconscious module identifies potential flaws using environmental data and design experience, adjusting connection weights and hormone parameters to enhance scheme feasibility. The result is a detailed blueprint with material choices, sensor layouts, and adaptive algorithms.

4 Limitations and Future Research Directions

4.1 Perception Module Breakthroughs

Current convolutional neural networks (CNNs) excel in static image recognition but fall short in AGI-required visual free perception, adaptive learning, and deep semantic understanding. CNNs rely on closed labeled datasets and predefined feature patterns, lacking real-time adaptation to novel scenes, rare events, or unlabeled samples. Future work should incorporate efficient self-supervised learning, adaptive attention mechanisms, and cross-modal linkage to enhance autonomous learning and environmental adaptability.

4.2 Optimization Strategies for Large-Scale Graph Computation

As knowledge graph scale grows, node and edge complexity increase exponentially, escalating computation costs for queries, inference, and updates. Current dynamic graph expansion and real-time inference face performance limitations in large-scale scenarios. Future research should explore distributed graph storage, GNN acceleration, approximate inference algorithms, and graph compression/knowledge distillation to improve timeliness and scalability while maintaining inference accuracy.

4.3 Dynamic Regulation Complexity of Multidimensional Memory Entropy

Memory entropy, integrating emotional intensity, sensory entropy, subjective preferences, and time decay, faces challenges in balancing these factors to avoid overemphasizing certain nodes or ignoring critical information. Future work could use reinforcement learning and meta-learning to optimize entropy weight adjustments, enhancing adaptive memory management in complex environments.

4.4 Physiological Plausibility and Computational Complexity of Emotional Models

The emotional regulation mechanism, relying on simulated hormones and neurotransmitters, enriches behavior but oversimplifies human emotional complexity. Complex interaction models increase computational burdens, limiting real-time responses. Future research should leverage neuroscience to design efficient, physiologically accurate emotional models and study multi-scale emotion-cognition coupling.

4.5 Deep Implementation of Self-Reflection and Metacognition

The “inner monologue” mechanism enables metacognition but requires deeper self-monitoring, correction, and optimization. Effective reflection needs integrated long/short-term memory, emotional states, and inference feedback for closed-loop improvement. Future directions include reinforcement learning-based self-supervision and cognitive science-inspired metacognitive models for human-like self-awareness.

4.6 Complexity and Performance Trade-offs in Sliding Function Design

The sliding function dynamically adjusts attention weights for input sequences but faces challenges in designing efficient, flexible windows. Window size, step length, and weight allocation must adapt to tasks and contexts to avoid information loss or redundancy. Long sequences increase computational complexity, impacting real-time performance. Future work should explore sparse attention, multi-scale window strategies, and hybrid sliding designs for expressiveness and efficiency.

4.7 Neural Logic Operators for Edge Relationship Modeling

Current edge modeling relies on static labels or weights, limiting complex logical structure expression. Future research could introduce neural-symbolic logic operators to learn propositional, first-order, or modal logic relationships end-to-end, enhancing differentiable inference and causal chain modeling, breaking bottlenecks in complex reasoning and fuzzy decision-making.

4.8 Lack of Spatial Perception and Imagination

The endogenous thinking module lacks deep spatial relationship modeling, limiting performance in spatial causal reasoning, scene construction, and embodied cognition. Future work should introduce spatial embedding and visual-semantic joint modeling to build spatial perception sub-modules, enhancing scene inference, task planning, and embodied interaction.

4.9 Neuralized Knowledge Graphs and Experience-Based Axiom Plasticity

Traditional knowledge graphs express static facts and rules, lacking dynamic restructuring based on subjective experience or context. Neuralized graphs with trainable memory strength, trust, and emotional weights enable adaptive restructuring, encoding subconscious content for flexible cognition. This enhances cognitive elasticity, mimicking human fuzzy emotion and non-logical association processing.

4.10 Language-Driven Human-like Cognitive Flow

While the architecture achieves attention regulation and emotion-driven thinking, it lacks a fully language-driven cognitive flow. Human thinking relies on language as a mediator for logic, emotion, memory, and goal-setting. Future work should integrate natural language generation into sliding attention, enabling language-based cognitive chains and style modulation for human-like cognition.

4.11 Deep Integration of Generative Models in Endogenous Thinking

Current endogenous thinking relies on heuristic strategies and graph-guided generation, limited in quality and structural coherence. Future work could integrate VAE, GAN, and diffusion models to enhance latent path construction, hypothesis generation, and fuzzy knowledge combination, improving goal-directed and emotionally consistent inference.

4.12 Complexity and Deepening of Subconscious Mechanisms

The current subconscious mechanism, relying on high-entropy node triggers and fuzzy path splicing, falls short of human subconscious complexity. Future research should incorporate recursive memory structures, emotion-driven metaphorical associations, cross-modal perception-semantic frameworks, and interaction paths with explicit cognition for deeper, controllable subconscious generation.

4.13 Vector Space-Based Endogenous Thinking Mechanisms

The current graph-based endogenous thinking, while flexible, faces efficiency and redundancy challenges in large-scale tasks. Vector space-based models could simplify design, enhance semantic transfer, and enable symbol-subsymbol synergy, improving cognitive continuity, generation flexibility, and understanding depth.

5 Conclusion

This paper proposes a novel cognitive architecture inspired by human cognition, integrating sliding function attention, multidimensional knowledge graph embeddings, perception-driven control, and endogenous thinking modules to build a fluid, autonomous, and stable inference system. It reconstructs associative thinking, nonlinear leaps, emotional regulation, and self-monitoring while emphasizing modular implementation feasibility, providing a foundation for AGI with continuous learning, contextual adaptation, and creative generation.

Future research will expand the architecture's expressiveness in multimodal alignment, long-term memory regulation, structural meta-reflection, and personality evolution, exploring applications in autonomous task construction, human-AI collaboration, and complex real-world reasoning. This cognitive structure offers a theoretical and engineering foundation for interpretable, scalable, and transferable general intelligence systems.

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