Weight Influence in Cognitive Graph Construction Based on Activation Diffusion Models

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Date: 2023-07-28T00:00:00+00:00

Abstract

[Purpose/Significance] To address the issues of current cognitive graphs lacking a universal weight assignment mechanism, insufficient explanatory power in retrieval or inference processes, and excessive cognitive load due to graph redundancy, this paper proposes a cognitive graph construction method based on the activation diffusion model to optimize weight allocation and further enhance cognitive intelligence. [Method/Process] First, we analyze the current limitations of cognitive graphs and propose corresponding solutions. Second, based on these solutions, we design a cognitive graph construction process grounded in the activation diffusion model, integrating calculation formulas for energy acquisition, allocation, and decay, activation state determination, and activation scope limitation from the activation diffusion model, thereby establishing the activation diffusion model-based cognitive graph construction method. [Results/Conclusion] Comparative experiments between the proposed activation diffusion model and traditional frequency statistics-based weight calculation methods for cognitive graph construction demonstrate that the activation diffusion model-based cognitive graph exhibits stronger detail revelation capabilities and certain flexibility, can present multi-level weight distributions, features reliable weight assignment, and can verify the causal asymmetry of construction results. The activation diffusion model-based weight calculation method for cognitive graph construction significantly enhances the cognitive intelligence of cognitive graphs and enables the formation of cognitive graphs with cognitive preferences and differences.

Full Text

Preamble

Research on Weight Influence in Cognitive Graph Construction Based on Spreading Activation Model

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This work is supported by the National Social Science Fund of China (Education) General Project "Research on Construction Methods and Application Models of Knowledge Graphs for Basic Education" (Project No. BCA190087).

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Abstract

[**Objective/Significance**] To address the current issues of cognitive graphs lacking a universal weight assignment mechanism, insufficient explanatory power in retrieval or reasoning processes, and excessive cognitive load caused by graph redundancy, this paper proposes a cognitive graph construction method based on the spreading activation model to optimize weight allocation in cognitive graphs and further enhance cognitive intelligence. [**Method/Process**] First, we analyze the limitations of current cognitive graphs and propose solutions. Second, based on these solutions, we design a cognitive graph construction process grounded in the spreading activation model and integrate calculation formulas for energy acquisition and distribution, energy decay, activation state judgment, and activation range limitation from the spreading activation model, thereby proposing a cognitive graph construction method based on the spreading activation model. [**Results/Conclusion**] Comparative experiments between the proposed spreading activation model and traditional frequency-based weight calculation methods for cognitive graph construction demonstrate that the spreading activation-based cognitive graph exhibits stronger detail revelation capability, certain flexibility, and can present more hierarchical weight distributions with reliable weight assignments, while also proving the causal asymmetry of the construction results. The weight calculation method based on the spreading activation model for cognitive graph construction has a significant effect on improving the cognitive intelligence of cognitive graphs and can form cognitive graphs with cognitive preferences and differences.

Keywords: Cognitive Graph; Spreading Activation Model; Weight Calculation; Cognitive Intelligence; Activation Energy
Classification Number: G250

With the rapid development of artificial intelligence research, numerous problems in humanity's objective world can be solved through AI-related applications. However, even in today' s era of intelligence, the "intelligence" of artificial intelligence remains questioned by many scholars. This is because most current AI systems are driven by big data, and their task completion typically requires complex multi-layer computations, a process considered a "black box" due to the lack of explanatory mechanisms. Regarding the understanding of "intelligence" in AI, although scholars hold different views, most agree with the notion of "simulating, extending, and expanding human intelligence." Artificial intelligence originally took humans as a reference to simulate human cognition, thinking, and decision-making. Some scholars have also divided AI intelligence into three developmental stages: computational intelligence, perceptual intelligence, and cognitive intelligence. Computational intelligence establishes functional models through means based on data, perceptual intelligence involves large-scale collection and structural processing of data, while cognitive intelligence requires machines to have active thinking and understanding capabilities to achieve self-learning. To realize cognitive intelligence, scholars have recognized the important position of "language" in AI learning, leading to significant development in natural language processing technology and the emergence of knowledge graphs on the AI stage. Knowledge graphs have further opened new paths for cognitive intelligence because they possess sufficient advantages in data description capability, can improve retrieval quality from the semantic level, describe various entities and their relationships in the objective world, and effectively organize and manage large amounts of data information.

With the widespread development and application of knowledge graphs, the concept of "cognitive graph" has gradually emerged. A cognitive graph is essentially still a semantic network but demonstrates stronger reasoning capability than knowledge graphs. Zhang Yuliu and Zhao Bo also emphasize that "cognitive" technology is an unavoidable key technology in AI research and development, and cognitive graphs are precisely the combination of knowledge graphs and cognitive intelligence [1]. While there is still no complete consensus on the definition of cognitive graphs domestically and internationally, it can be summarized as focusing on imitating human cognition, being related to cognitive psychology and brain science, spanning technologies such as domain knowledge graphs, causal reasoning, and continuous learning, constructing effective mechanisms for stably acquiring and expressing knowledge, enabling knowledge to be understood and utilized by machines to achieve breakthroughs in cognitive intelligence. Cognitive graphs are often based on the "dual-process theory" in psychology and possess more powerful and flexible reasoning capabilities. Dual-process theory posits that human reasoning systems consist of an implicit subconscious system that retrieves relevant information (System 1) and an explicit, conscious, controllable reasoning process that infers based on collected information (System 2) [2]. System 1 completes simple, intuitive thinking for humans, while System 2 completes complex, experience-based logical reasoning [3]. These two systems are associative and symbolic respectively; the former's computation reflects similarity and temporary structures, responsible for encoding and processing statistical rules of associations, frequency, and connections among multiple features, while the latter's computation reflects rule-based structures with computational principles based on rule reasoning. From the papers of Elizabeth R. Chrastil and William H. Warren [4] and Michael Peer et al. [5], we can also find that cognitive graph can be understood as an abstracted topological structure stored in the human brain that differs from Euclidean spatial distance, also belonging to a markable representation method of spatial knowledge. Zhao Guoqing, Li Xinyuan, Lu Tong et al. consider cognitive graphs as the terminological expression in the computer field of the interdisciplinary concept "cognitive map" [6]; therefore, cognitive graphs in computers can draw on research about cognitive maps from various fields. As tools for knowledge organization and visualization, cognitive maps are internal representations of the external environment established based on past experiences. Similar terms have appeared in psychology such as "schema," "knowledge structure," etc., which can all be unified under the term "cognitive structure" [7]. Psychologist Sternberg proposed in 1985 three components of individual cognitive structure: metacomponents, operation components, and knowledge acquisition components [8]. The knowledge acquisition component involves screening and selecting information in situations and matching new information with existing knowledge, characterized by selectivity. Metacomponents regulate other components in specific cognitive processes, which is an important foundation for cognitive development. Operation components solve problems, including encoding, reasoning, association, and application. Thus, the construction of cognitive graphs should reflect information selectivity, regulation of cognitive structure, and facilitate problem-solving.

However, current cognitive graph construction often employs the same methods as knowledge graph construction, with many scholars achieving higher-order "cognitive intelligence" in cognitive graphs by combining machine learning and knowledge graph construction. It is evident that current cognitive graph construction lacks a method that aligns with human cognitive processes and enhances the cognitive intelligence of cognitive graphs. Moreover, domestic research rarely uses the weight attribute as information for entities and relationships in cognitive graphs, whereas there are cases in the knowledge graph domain where weighted knowledge graphs are constructed. Graphs carrying weight information demonstrate superior performance in both knowledge visualization display and knowledge reasoning. If nodes and edges in cognitive graphs carry weights, the magnitude of weights can represent the reliability or strength of nodes and edges in cognitive graphs, which basically aligns with psychology's fundamental assumptions about human cognition. Therefore, this study proposes a method for constructing cognitive graphs based on the psychological cognitive model—the spreading activation model—and dynamically assigns weight values to cognitive graphs through a designed spreading activation process to optimize the cognitive intelligence of cognitive graphs.

2 Analysis of Problems in Existing Cognitive Graph Construction Methods

Existing cognitive graph construction methods primarily focus on satisfying both intuition-based and rule-based reasoning approaches, thereby enabling cognitive graphs to achieve specific retrieval or reasoning functions. DING M et al. proposed a new CogQA framework to implement multi-hop question answering at web scale, simulating both implicit extraction modules and explicit reasoning modules based on BERT and graph neural networks [9]. DU Z X et al. implemented a cognitive graph for one-shot knowledge reasoning, which divides the graph into a summary module and a reasoning module. The summary module summarizes basic relationships of given instances, and the reasoning module infers correct answers accordingly. To supplement prior knowledge in the retrieval space, the summary module uses neural networks to infer relationships between entity pairs based on vector representations of entity pairs generated by graph neural networks. The reasoning module contains System 1 for retrieving information from knowledge graphs and System 2 for reasoning based on collected information, where System 2 uses deep learning for relationship reasoning [2]. However, these methods and technologies for constructing cognitive graphs are essentially no different from knowledge graph construction and still suffer from problems such as cognitive graphs lacking a universal weighting mechanism, cognitive graph retrieval or reasoning results lacking explanatory power, and cognitive graph redundancy leading to excessive cognitive load.

2.1 Cognitive Graphs Lack a Universal Weighting Mechanism

Current cognitive graph construction suffers from excessive mechanization and lack of a universal weighting mechanism. This is because the construction results of cognitive graphs completely depend on input data, while general knowledge graph weighting often employs frequency statistics or semantic distance calculation methods to assign weights, making it difficult for cognitive graph weighting results to change. Although such cognitive graphs increase reliability, they lack flexibility, and this construction method does not meet the requirements of cognitive intelligence. Flexible cognitive graph construction results should have both certain reliability and allow construction results to vary according to different input data orders. Wang Zhongqun, Ye Anjie, Huang Subin et al. extended knowledge graphs with weighting and then constructed an online product review semantic network to calculate and rank product credibility [10]. Sun Haotian and Yang Liangbin implemented a new weighted knowledge graph construction for current political microblogs based on intimacy as the relationship, using co-occurrence frequency statistics [11]. It is evident that there are cases of weight calculation and assignment for knowledge graphs and semantic networks, but currently, no universal method exists for weight calculation in cognitive graphs.

2.2 Cognitive Graph Retrieval or Reasoning Processes Lack Explanatory Power

Existing cognitive graphs often focus on constructing dual-process reasoning mechanisms, mostly using machine learning methods to implement complex reasoning functions. Chu Runfu used cognitive graphs to design a downhole operation knowledge recommendation system, employing a context-based graph neural network recommendation model in the simulated cognitive reasoning module [12]. Yuan Man, Zhang Weigang, and Li Mingxuan proposed an intelligent question-answering reasoning model based on cognitive graphs using BERT+CRF and GCN [3]. Although these cognitive graphs can achieve good application results, they often lack strong explanatory power due to their black-box mechanisms.

As an extension of cognitive intelligence, cognitive graphs need to have cognitively explainable features in retrieval and reasoning mechanisms. This requires cognitive graphs to explain retrieval or reasoning results—that is, why the retrieval and reasoning result for a question is A rather than

2.3 Cognitive Graph Redundancy Leads to Excessive Cognitive Load

In existing cognitive graph construction processes, merging identical entities does not affect links between entities, meaning that links in cognitive graphs only have relationship type distinctions without link strength representation. This is not conducive to judging the importance of links in cognitive graphs, leading to overly redundant visualization results from which it is difficult to harvest important information. Link strength can be interpreted as reliability and importance. In knowledge graph research, some have proposed that complete knowledge graph presentation will bring excessive extraneous cognitive load to learners. Zhao Guoqing et al. believe that in the future, based on cognitive load theory and drawing on ideas from concept map research in educational psychology, constructing macro, meso, and micro maps respectively can reduce learners' cognitive load when using diagrams [6]. Therefore, distinguishing node hierarchies in cognitive graphs has important value in reducing cognitive load for cognitive graph users. Entities in cognitive graphs should also be distinguished and marked through different strengths to reflect the different statuses of entities in cognitive graphs.

3 Solutions Based on Existing Cognitive Graph Limitations

To address the above problems, this paper proposes a weight-carrying, flexibly changeable cognitive graph construction method based on the psychological cognitive theory of the spreading activation model, aiming to improve the explanatory power and cognitive intelligence of cognitive graphs.

3.1 Promoting Dynamic Cognitive Construction Through Iterative Methods

The iterative method is a process in computational mathematics that continuously uses old values of variables to derive new values, and it is also a fundamental method for solving problems with computers. In psychology, the continuous change of "cognitive structure" relies on the interaction between existing knowledge and external information, thereby promoting the adjustment and change of cognitive structure. The iterative method is an effective means to integrate new knowledge into existing knowledge structures. Using iterative methods to construct cognitive graphs makes each iteration' s results closely related to the previous iteration' s cognitive graph results. The existing cognitive structure and new cognitive structure continuously undergo iterative processes of assimilation and accommodation, which is the process of acquiring new knowledge in their development [13]. Currently, there are applications of iterative methods in cognitive graph construction. Ding M et al. proposed a cognitive graph-based question-answering system that gradually constructs cognitive graphs by iterating System 1 and System 2 [9]. Du Z X et al. proposed a cognitive graph model for one-shot knowledge graph reasoning that also iteratively performs expansion and reasoning on cognitive graphs to imitate human reasoning processes [2]. It is evident that using iterative methods to construct cognitive graphs has its necessity and rationality, as it imitates the evolution process of human cognitive structure and makes cognitive graphs have stronger explanatory power.

3.2 Using the Spreading Activation Model as the Weight Calculation Mechanism

The essence of cognitive graphs is still a semantic network. To give different strengths to nodes and links in the network, a weight calculation mechanism needs to be determined. For example, domestically, Liu Lu et al. constructed a citation network based on lexical semantic weighting to improve the accuracy of community division in citation networks [14]. Wang Xianchen proposed two weighted bipartite network prediction algorithms from the perspective of semantic features to address the problem of personalized requirement prediction in intelligence analysis [15]. Xiong Huixiang et al. achieved academic information recommendation by weighting heterogeneous information networks [16]. There are also weighted knowledge graph constructions in knowledge graph research. Sun Haotian and Yang Liangbin proposed a method for constructing current political microblog knowledge graphs based on weighted triadic closure [11]. Wang Zhongqun et al. extended knowledge graphs with weighting, using domain common sense, product reviews, and domain experts as information sources to construct weighted knowledge graphs [10]. Comprehensive research shows that for weight extension and assignment, rules set by domain experts are often used as the basis for weighting, and weight distribution depends more on specific problem contexts. There is no unified weight distribution method. Such weighted networks and knowledge graphs with expert-defined rules have been proven to have better effects on problem-solving. However, they still lack explanation for this mechanism, or the emergence of weighted networks and weighted knowledge graphs initially aimed not at improving cognitive intelligence but at better solving application problems. Therefore, to improve the cognitive intelligence of cognitive graphs, this study selects the psychological cognitive theory—the spreading activation model—as the weight distribution mechanism in weighted cognitive graphs, aiming to make cognitive graphs have strongly explanatory cognitive intelligence and play a role in regulating cognitive structure.

The Spreading Activation Model is a semantic network model proposed by Collins and Loftus in 1975. Based on Quillian' s research, Collins and Loftus proposed that the preparation effect (or priming) in semantic memory is interpreted as the spread of activation from primed concept nodes. This is a theory designed to demonstrate how human semantic structures and processes can be built in computers, rather than a theory to explain data. Spreading activation theory can explain why different combinations of nodes in experiments lead to different reaction times, which Collins and Loftus described as: the amount by which the first concept primes the second concept determines reaction time. According to Yorick Wilks, "spreading activation is a procedural theory on networks that can achieve a series of phenomena and has done so." Ashcraft believes that the spreading processes of activation and priming are interrelated—these phenomena enable people to access semantic information, and he considers that the spreading activation mechanism causes attributes highly associated with concepts (dominant) to be better primed [5]. Spreading activation is also a method for searching associative networks, biological and artificial neural networks, or semantic networks. In most cases, these "weights" are real values that decay as activation spreads through the network. When weights are discrete, this process is often called marker passing. Activation may originate from alternate paths, identified by different markers, and terminate when two alternate paths reach the same node. The search process begins by given a set of source nodes (e.g., concepts in a semantic network) and labeling weights or "activation," then iteratively propagating or "spreading" to other nodes connected to the source nodes.

In cognitive psychology, spreading activation is a theory about how the brain extracts specific information through associated networks [18]. The spreading activation model implies that people organize their world knowledge based on personal experience, meaning that personal experiences form networks of thought, which constitute the person' s knowledge of the world [19]. Different from other semantic network models in psychology, the spreading activation model abandons hierarchical structures of concepts and chooses to connect concepts through semantic associations and semantic similarity relationships. The connections between concepts can represent their relationships, and the length of connections can represent the closeness between concepts. When a concept is stimulated, the concept node generates activation, which then spreads simultaneously along the node' s connections to the surroundings. Nodes more closely connected to this node receive activation faster and with greater intensity. Due to limited activation amount, as time passes and distance increases, the spread of activation in the network gradually weakens. When activation spreading along different connections crosses at a node and its total obtained activation reaches the threshold, the network pathway producing this crossing is evaluated, and based on the evaluation results, the network makes a decision to extract certain information. The spreading activation model belongs to pre-storage models but requires two processing stages: search and decision. In the retrieval process, spreading activation originates from nodes stimulated by external information and performs path retrieval according to the closeness of units in the semantic network.

Through analysis of the spreading activation model, we can find that it is a psychological theoretical model with a network structure that conforms to human cognitive flexibility, sufficient to achieve retrieval functions and weight calculation. This model perfectly matches the structure, attributes, and data processing methods of cognitive graphs. This paper attempts to use the spreading activation model as the weight increase mechanism in cognitive graphs, treating weight changes in cognitive graphs as weight adjustments of edges and nodes in the cognitive model network, thereby obtaining rules for cognitive graph weight allocation.

3.3 Simultaneous Data Input and Graph Construction

In traditional knowledge graph and cognitive graph construction, two construction methods are typically adopted—top-down and bottom-up approaches. The difference lies in whether ontology definition or entity addition comes first. The top-down approach requires defining ontology and data patterns first, then adding entities to the knowledge base, while the bottom-up approach extracts entities from some open linked data to add to the knowledge base before constructing the top-level ontology pattern. In terms of knowledge graph construction technology, the knowledge graph technical framework proposed by Liu Qiao et al. includes processes of information extraction, knowledge fusion, and knowledge processing [20]. Xu Zenglin et al. believe that the key technologies for knowledge graph construction mainly include four categories: knowledge extraction, knowledge representation, knowledge fusion, and knowledge reasoning [21]. Comprehensive research by most scholars shows that the main steps for constructing cognitive graphs include information extraction, ontology construction, knowledge fusion, and knowledge representation, meaning that the knowledge for constructing cognitive graphs is determined and processed before construction. The advantage is that the constructed graphs have good structure, and each entity has high value, but the disadvantage is the lack of influence between entities and insufficient flexibility.

Based on the above research, to enable dynamic construction of cognitive graphs that can change with information, this paper uses the top-down construction approach, first defining the ontology of cognitive graphs, then continuously adding entities based on information, and simultaneously constructing and visualizing the cognitive graph during entity addition. That is, the steps of information extraction, knowledge fusion, and knowledge representation will occur simultaneously.

4 Cognitive Graph Construction Based on Spreading Activation Model

In this study, we assume that concepts are entities in cognitive graphs, represented as nodes in the network. Therefore, under the spreading activation mechanism, we use weights in cognitive graphs to represent the association attributes between concepts and update the weights of cognitive graphs using the calculation mechanism from the spreading activation model. These new weights serve as the basis for judging the next spreading activation behavior. During the spreading activation process, nodes traversed by retrieval paths undergo varying degrees of memory enhancement, which is manifested numerically as weight increases. [Figure 1: see original paper] shows the complete process of the cognitive graph construction method based on the spreading activation model.

First, information is extracted from text data according to dependency syntax, including entity extraction, relationship extraction, and attribute extraction. Entities formed after information extraction participate in graph construction based on the defined ontology. After entities enter the graph, spreading activation calculations are performed, and participating entities are assigned weight values and stored in an updated database.

The spreading activation process in this paper includes four stages: activation energy acquisition and distribution, activation energy value decay, activation state judgment, and activation range limitation. In the continuous iteration of spreading activation, these four stages alternate, as shown below:

[Figure 2: see original paper] illustrates the steps of the spreading activation model. In the figure, we use A to represent node energy in spreading activation, subscripts to denote corresponding nodes, T to represent activation threshold, and a to represent the energy value transmitted by nodes or edges.

4.1 Activation Energy Acquisition and Distribution

During the activation phase, numerous activation channels exist between a node and other connected nodes. At a simple unit level, the input calculation of the pure spreading activation model follows formula (1):

$$net_j = \sum_i w_{ij} \cdot out_i$$

Formula (1) represents the total input of node j; out_i represents the output of unit i linked to node j; w_{ij} represents the link weight connecting node i and node j [22].

In pure spreading activation, there is no distinction between a unit's "activation" and its "output," and the unit' s activation level is considered its output value

[22]. Therefore, the output value is calculated as a function of the input value, expressed as formula (2):

$$out_j = f(net_j)$$

Anderson, in his spreading activation theory of memory, proposed that the activation amount emitted by activation sources is a function of their strength. If node n__y receives activation a__{1y} to a__{iy} from n__1 to n__i, its activation level is determined accordingly. The activation sent from node n__x to nodes n__1 to n__y depends on the strength s__1 to s__j of each node and the activation level of node n__x. If the activation level of this node is a__x, the activation amount it sends to node n__k is determined by the relative weight from node n__x to n__k. For all nodes j connected to n__x, setting it to 0 yields formula (3) [18]:

$$a_y = c_y + \sum_x a_x \cdot s_x \cdot w_{xy}$$

where c__y is the activation amount from the activation source, and c__y = 0 when y is not an activation source.

Based on the above, this paper' s calculation formula for energy distribution in the spreading activation model and the relative weight calculation formula can be expressed as formula (4) when distributing activation energy from node x:

$$A_y(t) = A_x(t-1) \cdot \frac{w_{xy}}{\sum_k w_{xk}}$$

Formula (4) represents the energy distribution formula from node x to node y, calculated using edge weights, where w__{xy}/Σ__k w__{xk} is the relative weight. A__x(t-1) is the activation energy output by node x, A__y(t) is the activation energy received by node y, w__{xy} is the weight of the activation pathway from node x to node y (i.e., edge weight), and Σ__k w__{xk} is the sum of all edge weights around and connecting node x, which constitutes the node weight of node x.

Additionally, for activation source energy acquisition, since its energy is not obtained through reception, the system needs to assign it an initial value. Activation sources in the spreading activation model are the nodes activated first, also called focused units in some papers. Here we use activation sources as the origin of activation. The energy of activation sources is the energy they possess before spreading activation as the origin. Anderson believed that the activation amount emitted by activation sources is a function of their strength [18]; therefore, during spreading activation, node weights should be considered as factors when assigning energy to activation sources.

In summary, since logarithmic functions have the characteristic of increasing first fast then slow, and can map values selected from different orders of magnitude to a relatively low-level range, we select the logarithmic function y = ln(x) to map node weight values, with the mapping result serving as activation source energy. Let the activation source energy be A_i and the activation source node weight be W_{e_i}, then formula (5) applies:

$$A_i = \ln(W_{e_i})$$

4.2 Activation Energy Value Decay

In heuristic principles, the relationship strength between two nodes decreases as their semantic distance increases. Therefore, it can be considered that distance-limited spreading activation models need to adopt breadth-first spreading, i.e., considering first-order relationships first, then second-order relationships. Relationships between directly connected two nodes are called first-order relationships. Relationships between two nodes connected through an intermediate node are called second-order relationships, and this diffusion-related condition can be flexibly set according to specific applications. Correspondingly, in terms of activation energy values, this manifests as activation energy value decay. Decay refers to the decline of activation energy values over time, which can be understood here as energy decay with increasing node distance. Therefore, some scholars have proposed calculation methods for decay. For example, Sheng Ke used the output of the previous moment multiplied by edge connection and then multiplied by (1-α) as the input for the next moment in defining principles followed by the spreading activation process, which can be expressed as formula (6) [23]:

$$input_y(t) = output_x(t-1) \cdot link_{xy} \cdot (1-\alpha)$$

where output_x(t-1) is the output of node x at time t-1, input_y(t) is the input of node y at time t, link_{xy} is the connection between node x and y, and α is the decay factor representing energy decay in the spreading activation process, generally valued at 0.2.

Anderson also considered activation loss in his spreading activation theory of memory. If a node' s activation level is a_x, the activation amount it sends to node n_k is a_x s_x w_{xk} d, where d is the loss in activation. It can be found that in formula (3), the energy transmitted from node x to node y along an edge is the product of energy loss, relative weight between the two nodes, and the energy of node x.

Similarly, Hong Kunhui [24] proposed a formula for psychological information activation, expressing the formula for a single state variable of mental state as formula (7):

$$d(x,t-1) = d(x,t-2) + e(x,t-1) \cdot d(x,t-1)$$

where d(x, t-1) represents the existence degree of object x at time t-1, which equals the existence degree of object x at time t-2 plus the product of e(x, t-1) (the activation priming effect received by object x at time t-1) and d(x, t-1) (the decay amount of simultaneous priming effect). The simultaneous priming effect decay amount can be expressed as formula (8):

$$d(x,t) = ae^{-kt}$$

This paper adopts the linear decay method in formula (6) as the decay function and expresses it as formula (9):

$$Loss(x) = (1-0.2) \cdot A_x$$

where Loss(x) represents the loss function during node x' s energy reception process, and A__x represents the original unlost energy of x.

4.3 Activation State Judgment

In evaluating outputs, functions are often used for assessment, among which the most widely used is the threshold function, commonly used to determine whether a node is activated. Its principle is to set a threshold; when node j' s input value exceeds the set threshold, node j is considered activated; otherwise, node j is considered inactive. Threshold setting can be determined according to specific applications, either as a globally unified threshold or as a threshold that varies according to different nodes [22]. Here we set the activation threshold T as a fixed value of 0.2. This is because we have already set the activation source energy value to be related to node weight; if the activation threshold were also set to vary with node weight, nodes with higher weights in the knowledge graph would be more easily activated than nodes with lower weights, and the network weights would tend to favor higher-weight nodes. This mechanism would be unfair to nodes with lower weights but more connections to other nodes.

When the activation threshold T is 0.2, a node will be activated if the energy it receives reaches 0.2; if the energy received is less than 0.2, the node will not be activated. If node x finally receives energy A__x, then:

$$activation = \begin{cases} activated, & A_x \geq 0.2 \\ not\ activated, & A_x < 0.2 \end{cases}$$

4.4 Activation Range Limitation

To limit spreading activation within a specified range, it is necessary to restrict the depth of spreading activation. Depth represents the maximum number of paths spreading downward from an activation source node x. When node x transmits to the next-level node (i.e., node x' s first-level node), the diffusion depth is 1; when transmitted to second-level nodes, the diffusion depth is 2. The diffusion range is controlled through depth. For example, in [Figure 3: see original paper], when the depth is 3, node x has a maximum diffusion path number of 3, and node x can transmit activation energy through three paths: x->a->b->c, x->d, and x->e->f->g. Node h is not in the diffusion range because reaching h from x involves four paths, meaning node h has a depth of 4 relative to node x, and therefore is outside the activation diffusion range.

[Figure 3: see original paper] Activation Diffusion Depth Control

5 Application Effect Analysis of Cognitive Graphs Constructed Based on Spreading Activation Model

To compare the visualization effects of cognitive graphs constructed using the method proposed in this paper with those constructed using traditional weighted knowledge graph methods, we selected Chinese mythological stories as experimental materials for comparative experiments. Here, the traditional weighted knowledge graph method selected was frequency statistics-based weighted knowledge graphs.

5.1 Visualization Evolution Process of Cognitive Graphs

This study compares the differences between the spreading activation model-based cognitive graph construction method and the frequency statistics-based weighting method (where weights are assigned as three times the frequency) by selecting texts of different sample sizes as experimental materials, as shown in , to demonstrate the evolution process of cognitive graphs as the number of texts increases.

Experimental Corpus

Text & Number	Text Name
1	Chang' e Flying to the Moon
2	Gonggong Striking the Sky
3	Houyi Shooting the Suns
4	Jingwei Filling the Sea
5	Kuafu Chasing the Sun
6	Carp Leaping Over the Dragon Gate
7	Meng Jiangnu Crying at the Great Wall
8	The Origin of the Nian Beast
9	Nüwa Mending the Sky

Text & Number	Text Name
10	Iron Crutch Li and the Ducks
11	The Origin of Five Finger Mountain
12	Yu Gong Moving the Mountains
13	Drilling Wood to Make Fire
14	The Eight Immortals Crossing the Sea
15	Cangjie Creating Characters
16	Yu the Great Controlling Floods
17	The Peacock Princess
18	Longbo Fishing for Turtles
19	Dragon Girl Worshipping Guanyin
20	The Cowherd and Weaver Girl
21	Nüwa Ascending to Heaven
22	Nüwa Creating Humans
23	Pangu Creating the World
24	Shennong Tasting Herbs
25	Heavenly Generals Saving Humanity

Group	Experimental Corpus Number Assignment
Group 1	1-5
Group 2	1-10
Group 3	1-15
Group 4	1-20
Group 5	1-25

By inputting experimental materials of different scales (by group) and using both frequency statistics-based and spreading activation-based cognitive graph construction methods, two cognitive graphs of different scales were formed. The evolution process of both cognitive graphs as the scale expands can be observed in [Figure 4: see original paper]. Node size in the graphs represents node weight magnitude, edge thickness represents edge weight magnitude, and color mapping shows different weight levels of nodes in cognitive graphs, with more vivid colors indicating higher node weight levels in the cognitive graph. Graphs labeled "Fre" use frequency statistics-based construction, while those labeled "ACT" use spreading activation model-based construction.

Overall, as the scale expands, both graphs exhibit the emergence of some high-weight-level nodes. However, frequency statistics-based cognitive graphs have fewer overall weight distribution levels and generally lower weight values compared to spreading activation-based cognitive graphs. Observing the spreading activation model-based cognitive graphs reveals that as the graph scope increases, the weight level distribution of cognitive graphs presents multi-layered characteristics, manifested in the appearance of representative nodes with different colors and weight levels, all having relatively high but different node weights. From the overall graph perspective, the visualization of cognitive graphs constructed using the spreading activation model method, compared to those using frequency statistics weighting, shows more multi-layered node weights, with a few local node weight values being strengthened. Therefore, after visualization, it can better highlight important nodes in cognitive graphs, which to some extent reduces the cognitive load of cognitive graph audiences.

From a local graph perspective, the spreading activation process gives different weight growth to various nodes in the graph. For example, in Group 1, the node "Sun," which has the highest and most prominent weight in the frequency statistics cognitive graph (see [Figure 5: see original paper]), is not the node with the highest weight value in the spreading activation model-based cognitive graph. This indicates that after the spreading activation process, the weight values of various nodes have changed in status throughout the entire graph, and node weights are not determined by simple frequency superposition but are increased in small amounts multiple times through a series of complex and precise calculations after the spreading activation process. From [Figure 5: see original paper], we can see that in the frequency statistics-based knowledge graph, the weight of the "Sun" node is contributed by its connected edges and nodes, but we lack the basis to identify which node or edge contributes more to the "Sun" node' s weight. In contrast, from the spreading activation-based cognitive graph, we can clearly see that nodes "appear," "one," and "in the sky" contribute more to the "Sun" node' s weight than other nodes. Thus, compared to frequency statistics-based weighted cognitive graphs, spreading activation model-based weighted cognitive graphs have certain flexibility, stronger detail revelation capability, and strong explanatory power.

5.2 Weight Distribution Differences in Cognitive Graphs

By using both methods to construct graphs from Group 5 materials and plotting scatter diagrams of the relationship between node weight values and quantities in the constructed graphs, we can compare the weight distribution differences between graphs constructed by the two methods, as shown in [Figure 6: see original paper] (where red scatter points "x" represent weight distribution of graphs constructed by the frequency statistics method, and blue scatter points "o" represent weight distribution of graphs constructed by the spreading activation model method proposed in this study).

[Figure 6: see original paper] Weight Distribution Comparison of Group 5

The left side of [Figure 6: see original paper] shows the weight distribution in cognitive graphs, with the horizontal axis representing node weight and the vertical axis representing node quantity. Points on the graph represent the number of nodes with corresponding node weights. The right side shows the weight proportion distribution in cognitive graphs, with the horizontal axis representing the proportion of node weight in total node weight and the vertical axis representing the proportion of node quantity in total nodes. Points on the graph represent the proportion of node quantity corresponding to node weight proportion.

From [Figure 6: see original paper], we can find that the number of scatter points using the spreading activation model-based cognitive graph construction method is greater than that of frequency statistics-based cognitive graphs, and the weight values of spreading activation model-based cognitive graphs are distributed over a larger range. This again confirms that weight values in spreading activation model-based cognitive graphs are at different weight hierarchy levels. The result of multi-level weight values is that the vertical coordinate of each scatter point—the number of nodes at that weight value—decreases. However, careful observation reveals that the initial trend of the scatter plot still shows a slightly declining triangle.

Moreover, the weight distributions of both graphs show characteristics of being dense first and then sparse, indicating that the weight value distribution of graphs is concentrated at lower weight proportion levels, and the number of nodes with weight values generally decreases as weight value proportion increases. To further observe the characteristics of weight distribution in spreading activation model-based cognitive graphs and explore the reasons for the triangular region formation in the weight distribution graph, we plotted the weight proportion and node number proportion images for Groups 1 to 5 based on spreading activation model-based cognitive graph construction, as shown in [Figure 7: see original paper].

[Figure 7: see original paper] Weight Distribution of Cognitive Graphs Constructed Based on Spreading Activation Model

From [Figure 7: see original paper], as the scale of spreading activation model-based cognitive graphs gradually expands, the quantity distribution on the vertical axis gradually changes from layered scatters to continuous scatters. Meanwhile, except for the lowest layer of scatters in images with lower quantity proportions, the range on the horizontal axis for scatter points at each level shortens significantly as graph scale expands, corresponding to the increase in scatter point layers.

From [Figure 7: see original paper], we can find that scatters with higher weight proportions are at lower quantity proportion positions, while scatters with higher quantity proportions are at lower weight proportion positions. This is consistent with the pattern formed by frequency statistics-based cognitive graph construction methods and also conforms to the pattern of scale-free networks. However, the difference is that there exists an “area”composed of multiple scatter plots in the weight distribution graph of spreading activation model-based cognitive graphs (see [Figure 8: see original paper]), which is related to the wider distribution of weight values in cognitive graphs.

[Figure 8: see original paper] Comparison of Weight Distribution Graphs of Two

Cognitive Graph Construction Methods (2219 nodes)

By plotting weight distribution scatter diagrams for cognitive graphs constructed by both methods, we can find that compared to frequency statistics-based cognitive graphs, the image decline trend of spreading activation model-based cognitive graphs is consistent: as node weight proportion increases, node quantity proportion decreases. That is, nodes with higher weights in cognitive graphs are in the minority, while nodes with lower weights are in the majority.

5.3 Proof of Causal Asymmetry in Cognitive Graphs

Human cognition is often progressive layer by layer, meaning that different learning sequences produce different learning results. Physicists and information theorists believe that "causal asymmetry" exists in universal systems. In classical computer science, computer software can more easily predict the future development direction of a complex system but finds it difficult to infer the system's past activities. That is, moving forward along one direction of time requires more information and more complex calculations than the other direction. Rong Mei once introduced causal asymmetry into the field of conceptual cognitive learning and visualized causal asymmetry through concept trees [25]. The cognitive graph construction method proposed in this study also has the function of visualizing cognitive processes. To demonstrate causal asymmetry, we constructed spreading activation model-based cognitive graphs by inputting five texts and twenty-five texts in both sequential and reverse order, comparing the final visualization results of different weight allocations. The experimental materials and input sequences for each group are shown in :

Experimental Corpus

Text & Number	Text Name
1	Chang'e Flying to the Moon
2	Gonggong Striking the Sky
3	Houyi Shooting the Suns
4	Jingwei Filling the Sea
5	Kuafu Chasing the Sun
6	Carp Leaping Over the Dragon Gate
7	Meng Jiangnu Crying at the Great Wall
8	The Origin of the Nian Beast
9	Nüwa Mending the Sky
10	Iron Crutch Li and the Ducks
11	The Origin of Five Finger Mountain
12	Yu Gong Moving the Mountains
13	Drilling Wood to Make Fire
14	The Eight Immortals Crossing the Sea
15	Cangjie Creating Characters

Text & Number	Text Name
16	Yu the Great Controlling Floods
17	The Peacock Princess
18	Longbo Fishing for Turtles
19	Dragon Girl Worshipping Guanyin
20	The Cowherd and Weaver Girl
21	Nüwa Ascending to Heaven
22	Nüwa Creating Humans
23	Pangu Creating the World
24	Shennong Tasting Herbs
25	Heavenly Generals Saving Humanity

Experimental Corpus Number Assignment

Group	Sequence
Group 2	25, 24, 23, 22, 21, 20, 19, 18, 17, 16, 15, 14, 13, 12, 11, 10, 9, 8, 7, 6, 5, 4, 3, 2, 1

By constructing spreading activation model-based cognitive graphs through sequential and reverse input of the five texts and twenty-five texts in the above table, two groups of cognitive graph visualization results were obtained as follows:

[Figure 9: see original paper] Sequential vs. Reverse Order Comparison of Cognitive Graphs Constructed Based on Spreading Activation Model

From the first group experiment, we can find that the node "Chang' e" has a higher weight level in the sequential graph than in the reverse graph, possibly because "Chang'e Flying to the Moon"is the first text in the sequential graph but the last in the reverse graph. The node "Gonggong"also has a higher weight level in the sequential graph than in the reverse graph, which can also be explained by "Gonggong Striking the Sky" being the second text in the sequential graph and the fourth in the reverse graph. The weight level here does not completely represent the magnitude of weight value but the relative status of nodes in the graph network. There are cases where a node has a higher weight level but lower weight value compared to another graph, such as the "Gonggong" node, which has a weight value of 164.27 in the sequential graph and 168.65 in the reverse graph. However, through color mapping generated by comparison with the highest node weight in the entire graph, we can see that the weight level of node "Gonggong" in the sequential graph is higher than that in the reverse graph. Of course, this pattern does not cause absolute visualization results. Due to the flexibility of the spreading activation model, multiple possible outcomes still exist. A node's weight level in the graph depends not only on the node itself and other nodes connected to it but also on subsequently input text materials and, more importantly, the order of subsequently input text materials.

The second group, through sequential and reverse input of twenty-five texts, can more clearly reveal differences in weight distribution. As the number of texts increases, the weights of chapter theme nodes will not become high-weight-level nodes, mainly because as the number of chapters increases, some common concepts appear in different chapters and become hubs for more surrounding nodes, becoming nodes with higher frequency. These concepts are usually common words in sentences. By constructing spreading activation model-based cognitive graphs in sequential and reverse order and sorting node weight values, filtering out some meaningless function words, we can find the top 20 nodes as follows (25 texts formed 2219 nodes and 2225 edges):

Comparison of Top 20 Nodes by Weight in Sequential vs. Reverse Order

Through comparison, we can find that there are 8 common nodes within the top 20 nodes in both sequential and reverse orders: "become," "one," "girl," "self," "life," "Nüwa," "people," and "Pangu." These nodes are at relatively high weight levels in both sequential and reverse graphs, while other nodes within the range have undergone weight level changes to varying degrees due to the influence of input order. This demonstrates both the reliability of high-weight nodes highlighted by spreading activation model-based cognitive graph construction and the flexibility of this construction method. The same texts input in different sequences form cognitive graphs with different weight allocations because the spreading activation model itself conforms to this cognitive law: nodes incorporated into the graph earlier have more opportunities to be activated initially and thus gain more weight early on. This pattern also conforms to the Matthew effect phenomenon, where nodes placed in the network earlier have degree values that grow exponentially relative to later nodes—the earlier a node is placed in the network, the more edges it accumulates. This different visualization result caused by different sequences demonstrates that cognitive graphs constructed using this method can prove causal asymmetry.

This paper proposes a method for constructing cognitive graphs based on the spreading activation model to address the current dilemma of cognitive graphs lacking cognitive intelligence. By designing a spreading activation process to assign different strength weight values to cognitive graph nodes, this serves as a basis for cognitive graph retrieval and reasoning. Through comparative experiments between the spreading activation model-based cognitive graphs proposed in this paper and frequency statistics-based cognitive graphs, results show that the weight assignment mechanism for graph nodes proposed in this paper has strong explanatory power because it is superior to frequency statistics-based cognitive graphs in detail revelation capability. Its weight values are more multi-layered, can reduce cognitive load, simulate human cognitive structure, and have flexible characteristics. Additionally, the characteristic that the evolution results of this cognitive graph are related to input material order can also prove causal asymmetry.

The cognitive graph proposed in this paper can be applied to multiple scenarios, such as knowledge recommendation, knowledge retrieval, and knowledge question-answering. Assigning weights to cognitive graphs is an optimization of their cognitive intelligence. The most direct application is that the optimized cognitive graph visualization will carry weight information, thereby helping cognitive graphs perform cognitive reasoning and judgment.

The cognitive graph constructed in this study has the characteristic of being domain-unrestricted, especially the spreading activation process, which can be applied to cognitive graph construction in various fields because it conforms to cognitive laws. However, this also indicates that it has the problem of overly single weighting mechanism considerations. Since node types are not distinguished by importance, it has shortcomings when constructing cognitive graphs that require classified processing of nodes. In such cases, it is necessary to design a spreading activation process related to fan-out restrictions, which needs further discussion in future work.

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Note: Figure translations are in progress. See original paper for figures.