ICONIP 2023

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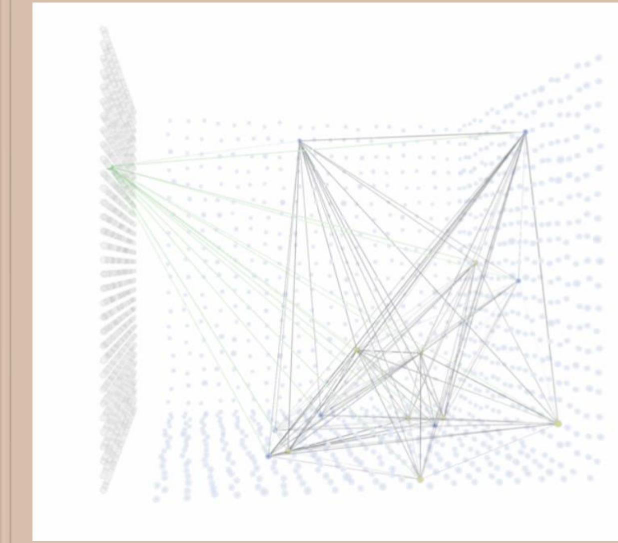
關聯知識圖的結構屬性

由許多代表相關物件的重疊場景組成



Structural Properties of Associative Knowledge Graphs

composed of many overlapping scenes representing associated objects

PAPER NO. 186

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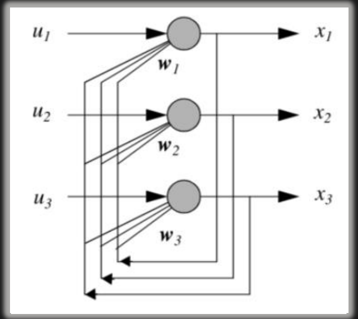
Introduction and Contribution

- ✓ Associative networks and memories store and retrieve scene information using contextual cues.

- ✓ Classic associative memories Hopfield Networks (HN) have linear memory capacity.



The significant **contribution of this work** is to demonstrate that a specific type of **associative knowledge graphs** can function as **semantic memories**, even when synaptic connections are constrained to **binary weights (0 or 1).**

Knowledge graphs represent objects and their relationships.

Graph Neural Networks (GNNs) are neural network models that operate on graphs.

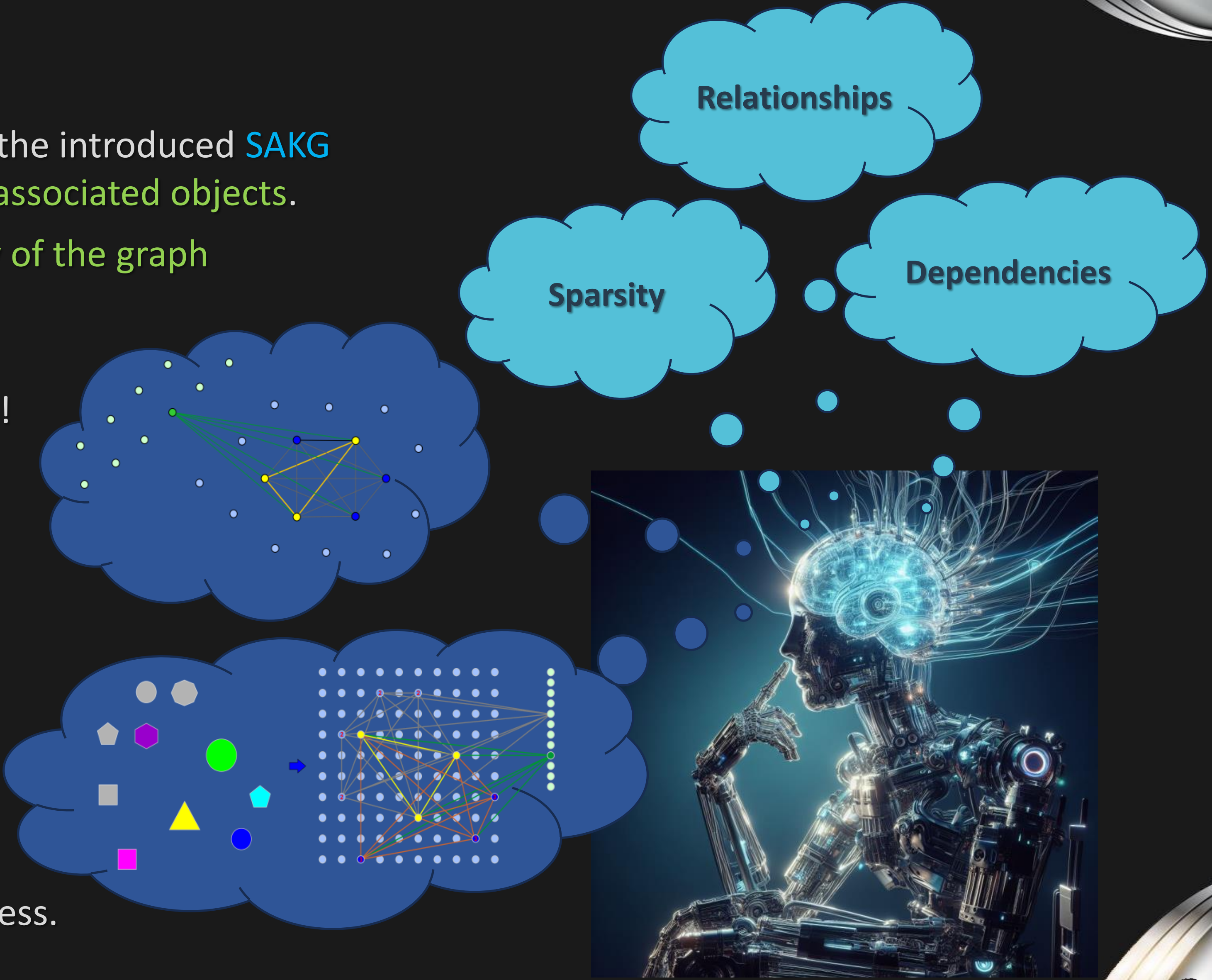
→

Active Neuro-Associative Knowledge Graph (ANAKG) is a form of neural, cognitive architecture that leverages an associative model of neurons.

Presentation Content and Contribution

Our paper, model, and this presentation:

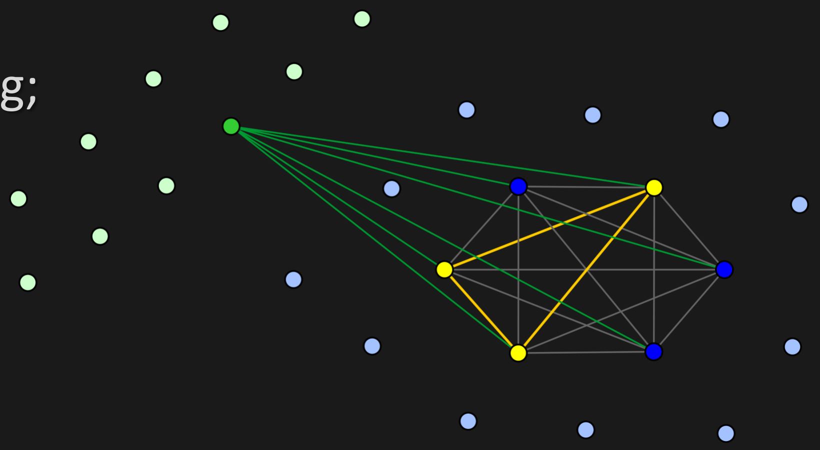
- ✓ Demonstrate that the mere sparse structure of the introduced SAKG can capture and restore information among its associated objects.
- ✓ Establish the relationships between the sparsity of the graph and the amount of stored information.
- ✓ Establish conditions that enable flawless recreation of the stored scenes (without errors)!
- ✓ Estimate critical dependencies between
  - ✓ the number of nodes in the graph,
  - ✓ the graph density,
  - ✓ the context size, and
  - ✓ the number of saved scenes.
- ✓ Show that the sparsity of the graph memory allows for a high memory capacity.
- ✓ Demonstrate how smart sparse associative structure can replace an extensive training process.



Structural Associative Knowledge Graphs

Structural Associative Knowledge Graphs (SAKGs)

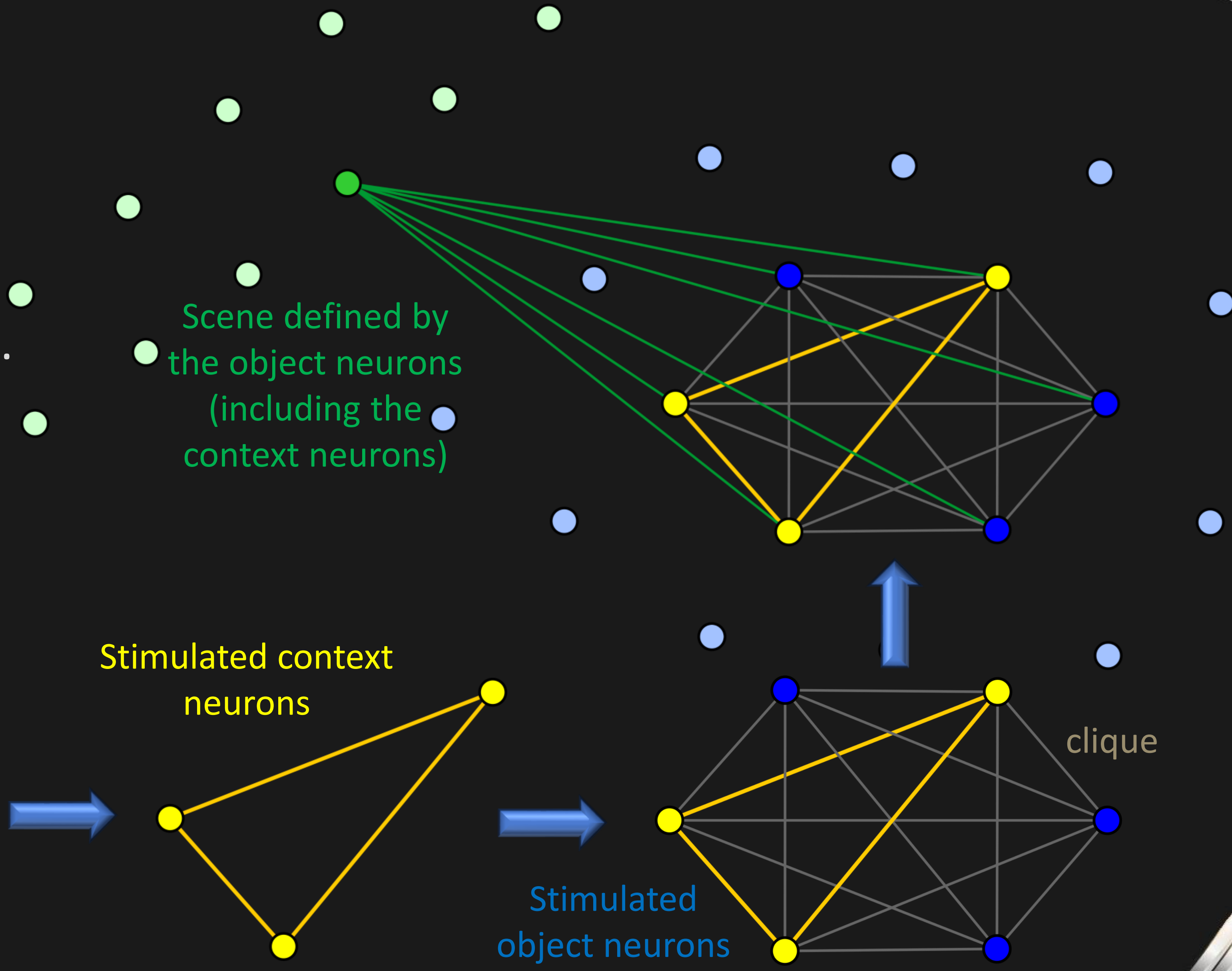
- are sparse, transparent, and explainable graphs where all synaptic connections have a weight value equal to 1 (strong structural attention);
- are a type of associative knowledge graph that relies solely on the graph structure itself, disregarding synaptic connection weights;
- can represent episodes consisting of intricate scenes featuring diverse objects;
- can be used to construct associative memories that store associations between the observed events, actions, objects, or their parts;
- can be updated with new scenes at any moment without retraining;
- SAKG density (measured by the ratio of the number of used synaptic connections to the total possible synaptic connections among the graph nodes) is a crucial factor influencing memory storage capacity.



[16] Horzyk, A., Starzyk, J. A., Graham, J.: Integration of Semantic and Episodic Memories, IEEE Transactions on Neural Networks and Learning Systems, vol. 28, no. 12, pp. 3084–3095 (2017). DOI: 10.1109/TNNLS.2017.2728203.

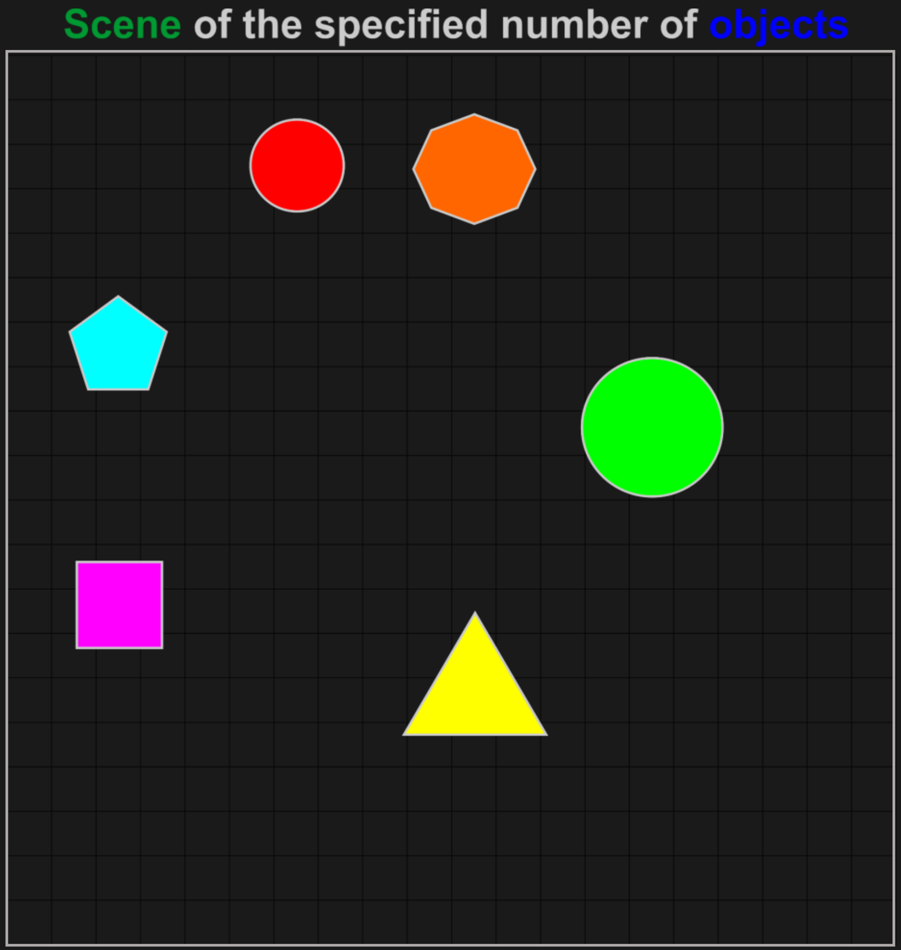
SAKG Structure

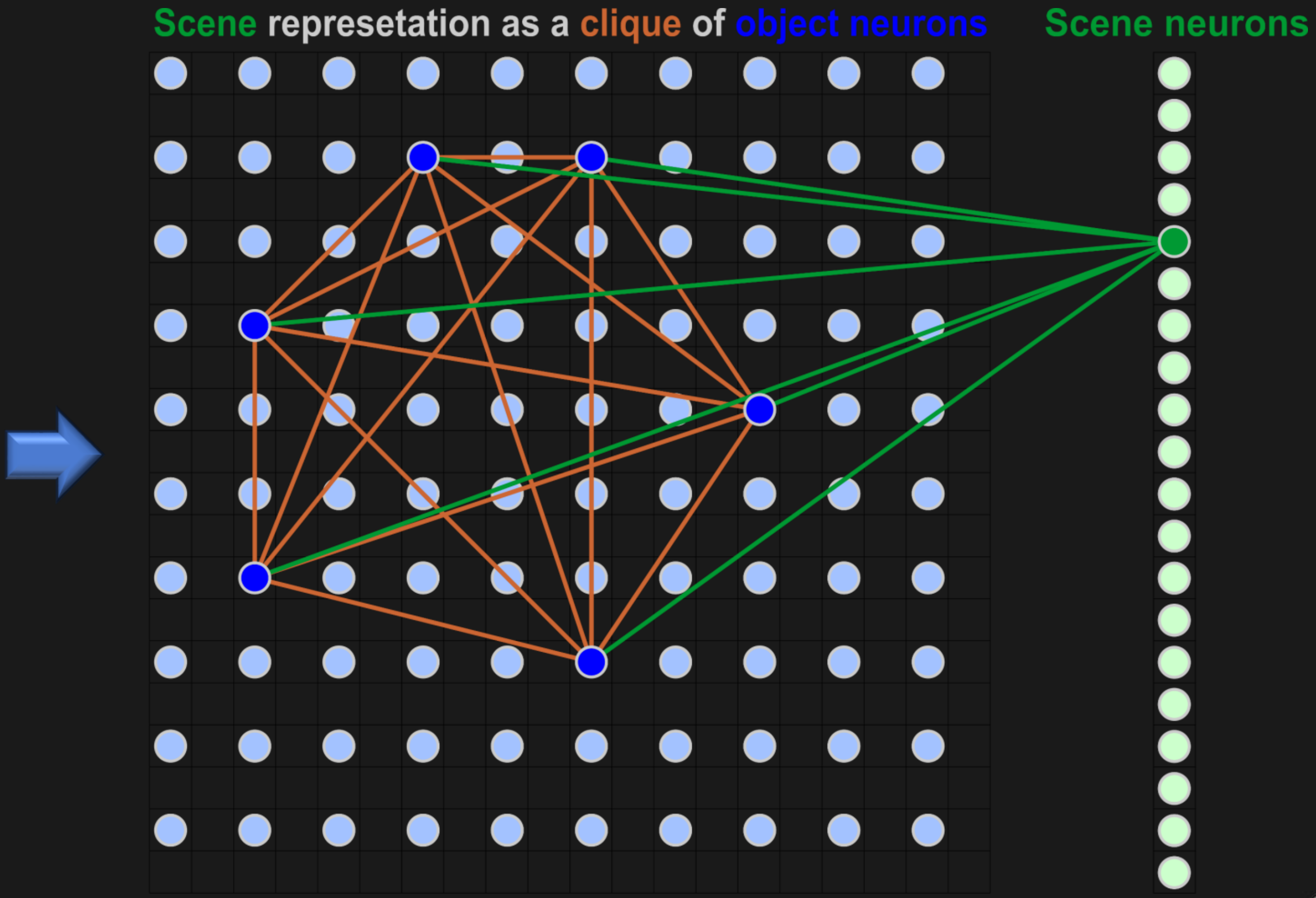
- SAKG is a graph containing many scenes represented by cliques consisting of a specified number of objects.
- Objects are represented by the object neurons that are connected to each other in every clique.
- If some object neurons are activated, we call them context neurons.



SAKG Structure Construction

SAKG is constructed from the scenes represented by several objects (here 6):





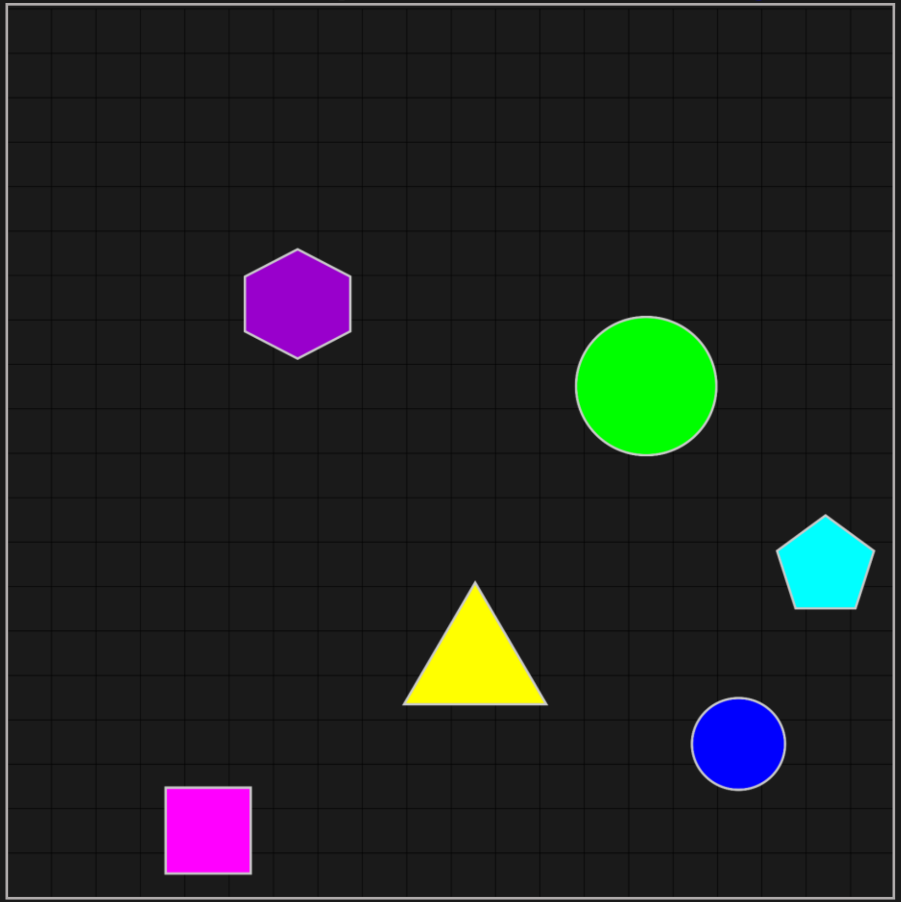
SAKG after adding the representation (connected neurons in a clique) of scene 1.

SAKG graph density grows with each added scene!

SAKG Structure Construction

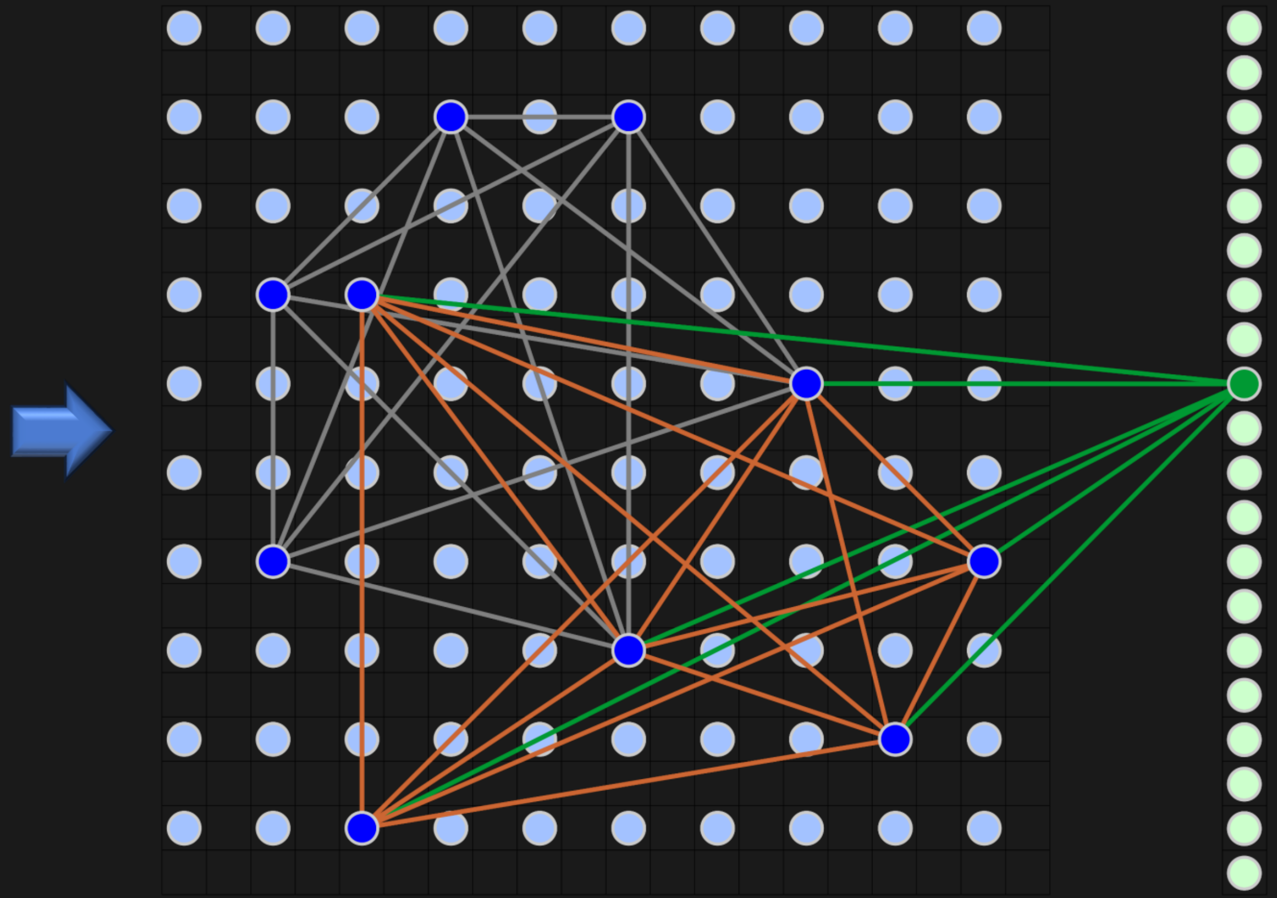
SAKG is constructed from the scenes represented by several objects (here 6):

Scene of the specified number of objects



Scene represetation as a clique of object neurons

Scene neurons

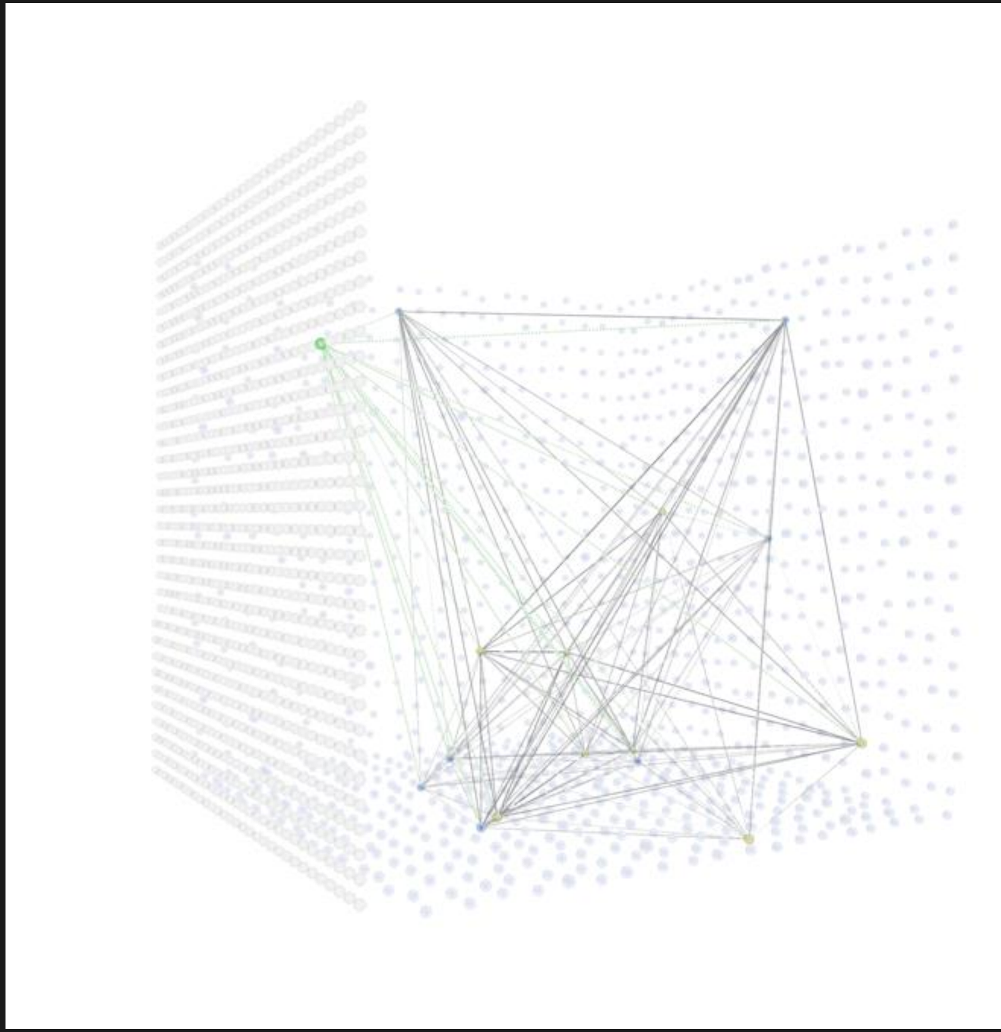


SAKG after adding the representation (connected neurons in a clique) of scene 2.

SAKG graph density grows with each added scene!

SAKG Structure and Graph Density

- SAKG graph is developed by adding scene information and recording synaptic connections.
- Nodes in the graph represent objects, words, or concepts.
- A large amount of information increases density of synaptic connections.
- Performed analysis of a SAKG density demonstrated the ability of a SAKG to capture and restore information.
- Investigated relationship between SAKG sparsity and amount of stored information.



Establishing of memory density is essential to calculate the size of the context for unequivocal scene recovery!

Memory Storage Capacity and Critical Graph Density

Def: Knowledge graph memory storage capacity is the maximum number of scenes that can be uniquely recalled without errors.

This will be demonstrated by:

- Criteria for error-free and unique scene recall.
- Dependency of storage capacity on graph density, node count, and scene and context size.
- Identifying the critical graph density that defines memory capacity.
- Addressing situations with insufficient unique objects generating virtual objects.
- Methods for creating virtual objects (color, position, reflectivity, size, motion, etc.).

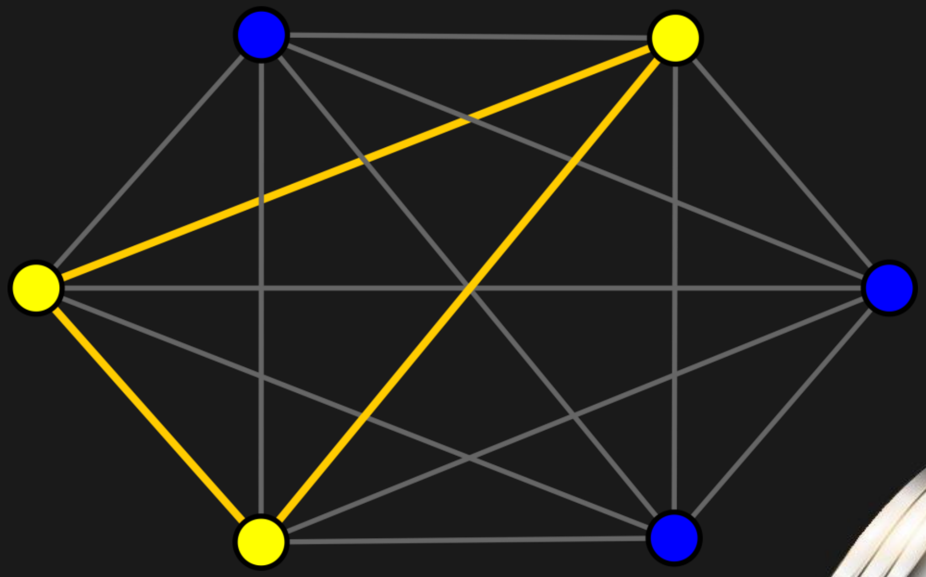
Knowledge Graph Density in Scene Associative Memory

- There is a relationship between knowledge graph density and the number of stored scenes.

- Factors affecting knowledge graph density are:
  1. Average scene size
  2. Number of scenes stored in associative memory
  3. Graph size (number of vertices)

- The total number of synaptic connections in a dense graph (n-clique) can be calculated after:

$$e_0 = \frac{n*(n-1)}{2} \qquad (1)$$



Knowledge Graph Density in Scene Associative Memory

Accumulation of Subgraphs (after adding next scenes):

- The new graph density after adding the next complete subgraph (n – subgraph size, n_f - number of scene objects):

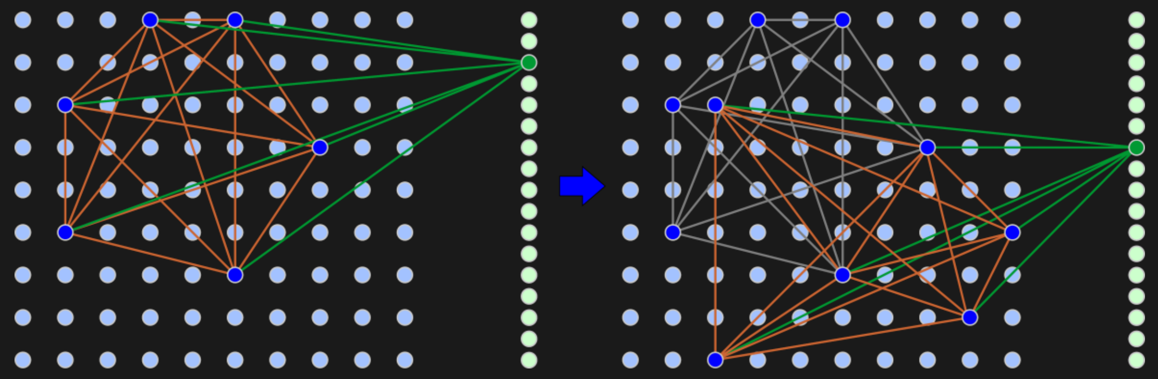
$$d_{i+1} = \frac{d_i * \frac{n*(n-1)}{2} + (1-d_i) * \frac{n_f*(n_f-1)}{2}}{\frac{n*(n-1)}{2}}$$

- After simplification, the graph density changes with each step in the following way:

$$d_{i+1} = d_i * (1-\xi) + \xi$$

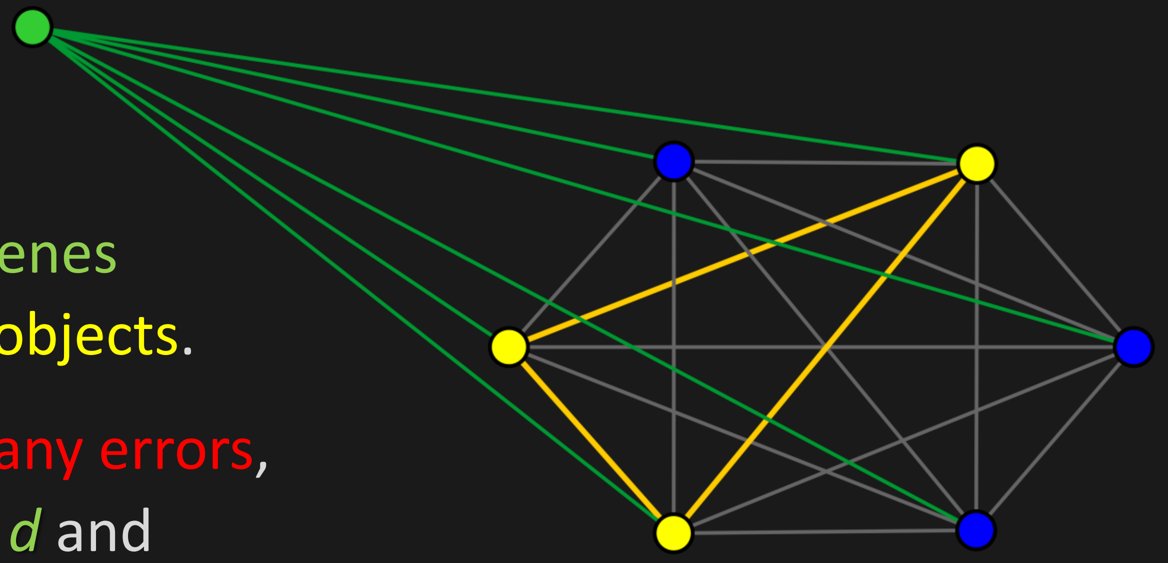
- ξ is a crucial parameter in this equation:

$$\xi = \frac{n_f*(n_f-1)}{n*(n-1)}$$



Dependence on the Size of the Context

- The associative knowledge graph (SAKG) serves as context-addressable memory, allowing for the retrieval of scene memories based on a specific (given) context.



- The memory capacity of the SAKG graph depends not only on the size of the stored scenes but also on the number of observed context objects.
- The probability of memory retrieval without any errors, can be calculated for the given graph density *d* and the size of the retrieval context n_c.
- To retrieve the desired scenes uniquely and accurately without any errors, the probability of success must be greater than $1\text{-}\varepsilon$ for a given small positive ε.

Critical graph density

- **DEF: The critical graph density is the maximum graph density that allows for all scenes in the SAKG graph to be retrieved with an error smaller than any small positive number ε.**
- The critical graph density can be estimated iteratively using:

$$d_{i+1} \cong \left(-\frac{\xi * \varepsilon}{log(1-d_i)}\right)^{\frac{1}{\zeta}} \quad i \in [0, \infty) \text{ , where } d_0=0.5 \qquad (8)$$

where:

$$\zeta = \frac{n_c * (n_c - 1)}{2}$$

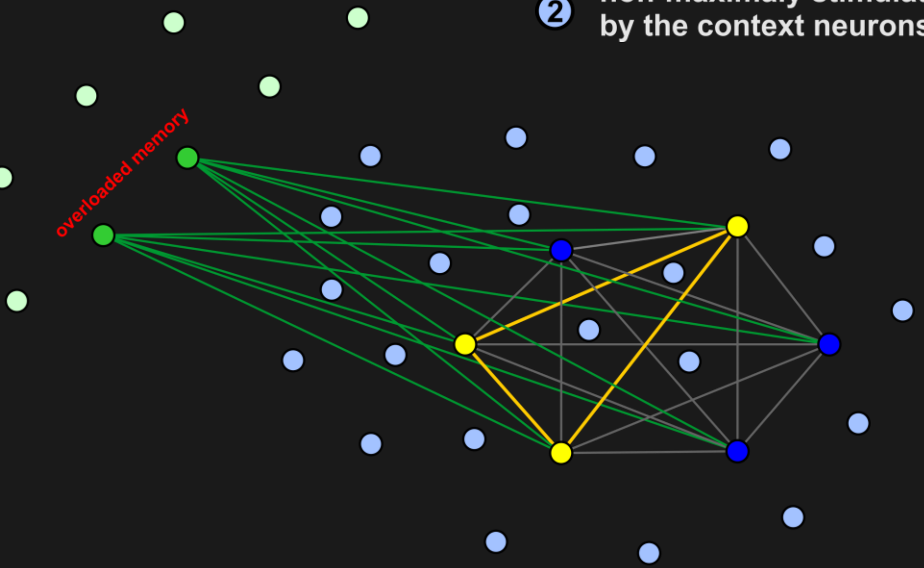
and

$$\xi = \frac{n_f * (n_f - 1)}{n * (n - 1)}$$

n_c - number of the context objects

n_f - number of the scene objects

- activated scene neuron stimulated by the maximally stimulated object neurons
- unactivated scene neurons (unstimulated)
- stimulated context neuron representing a subset of scene objects
- activated object neuron forming a clique with context neurons
- 3 maximaly stimulated object neurons stimulating the scene neuron (here 3)
- unactivated object neuron (unstimulated by the context neurons)
- 2 non-maximaly stimulated object neurons by the context neurons (here 2)



We got iterative estimation of critical graph density with fast iteration convergence.

Maximum Memory Capacity

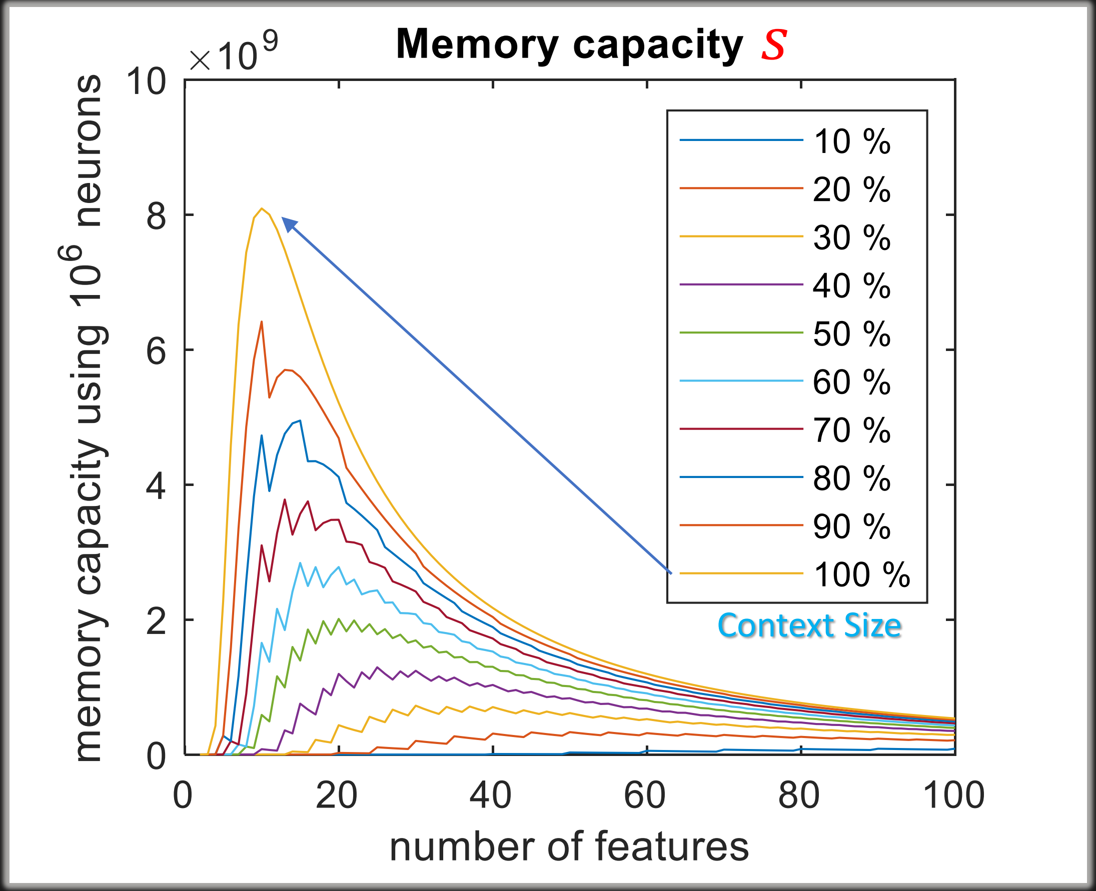
Thesis 1: For the critical graph density *d* and a given context, assuming that ξ is small, the memory capacity *s* can be determined by equation (13):

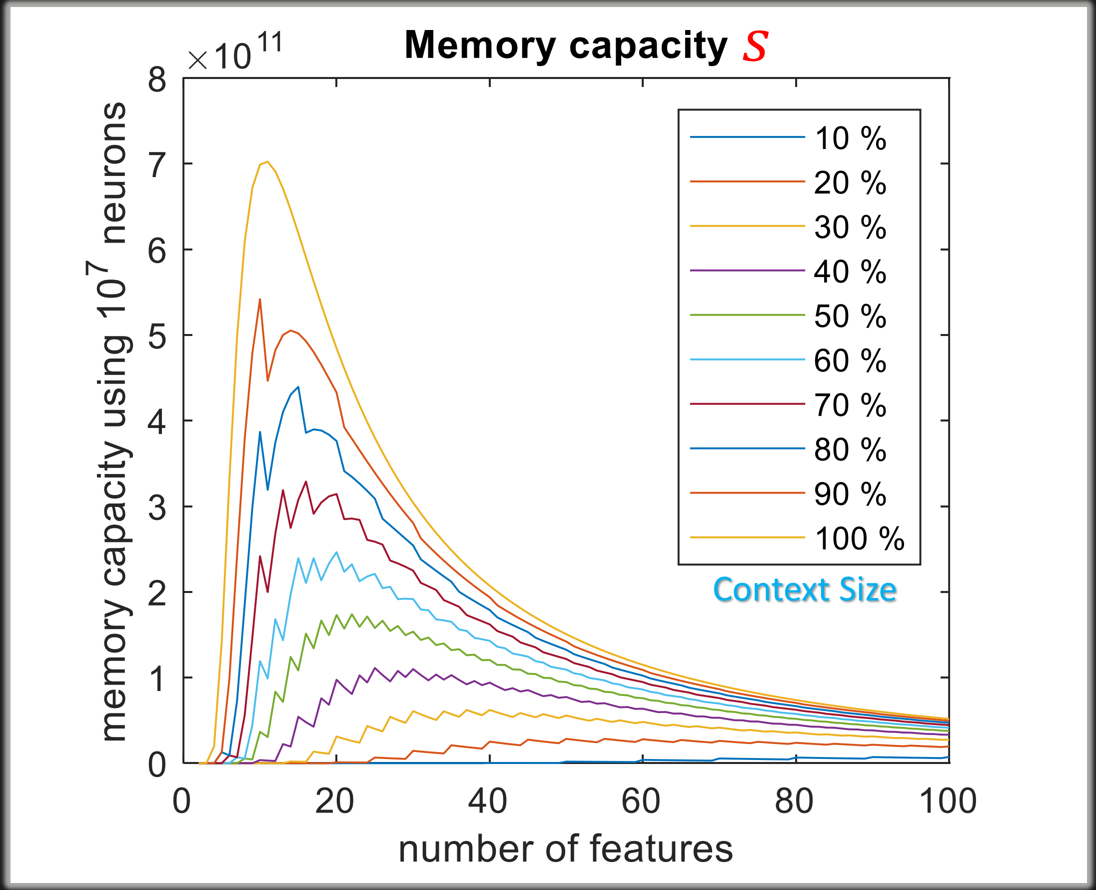
$$s = \frac{\log(1-d)}{\log(1-\xi)} = \frac{\log(1-d)}{-\xi} = \frac{\log(1-d)*n*(n-1)}{-n_f*(n_f-1)} \qquad (13)$$

Factors that influence the memory capacity:

- d - Critical Graph Density,
- n_f - Average Scene Size (no of objects in the scene), and
- n - the number of Graph Nodes

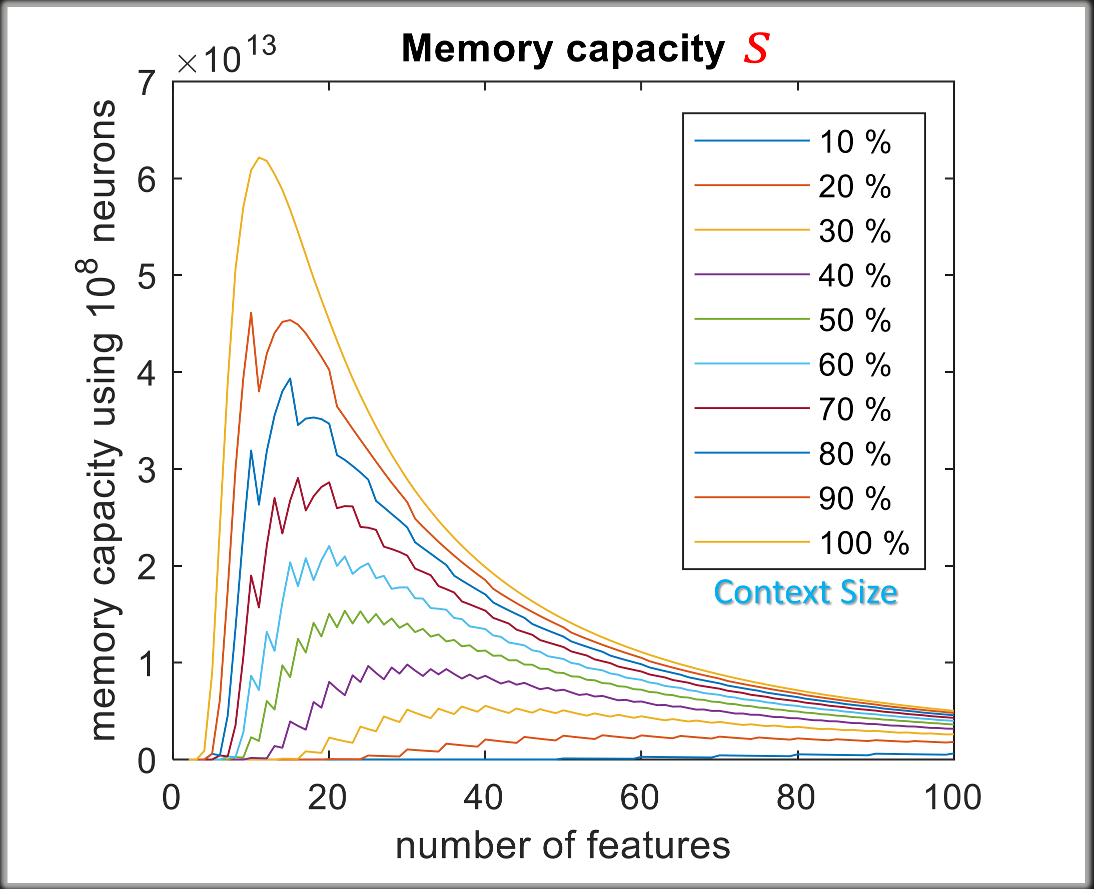
Maximum Memory Capacity

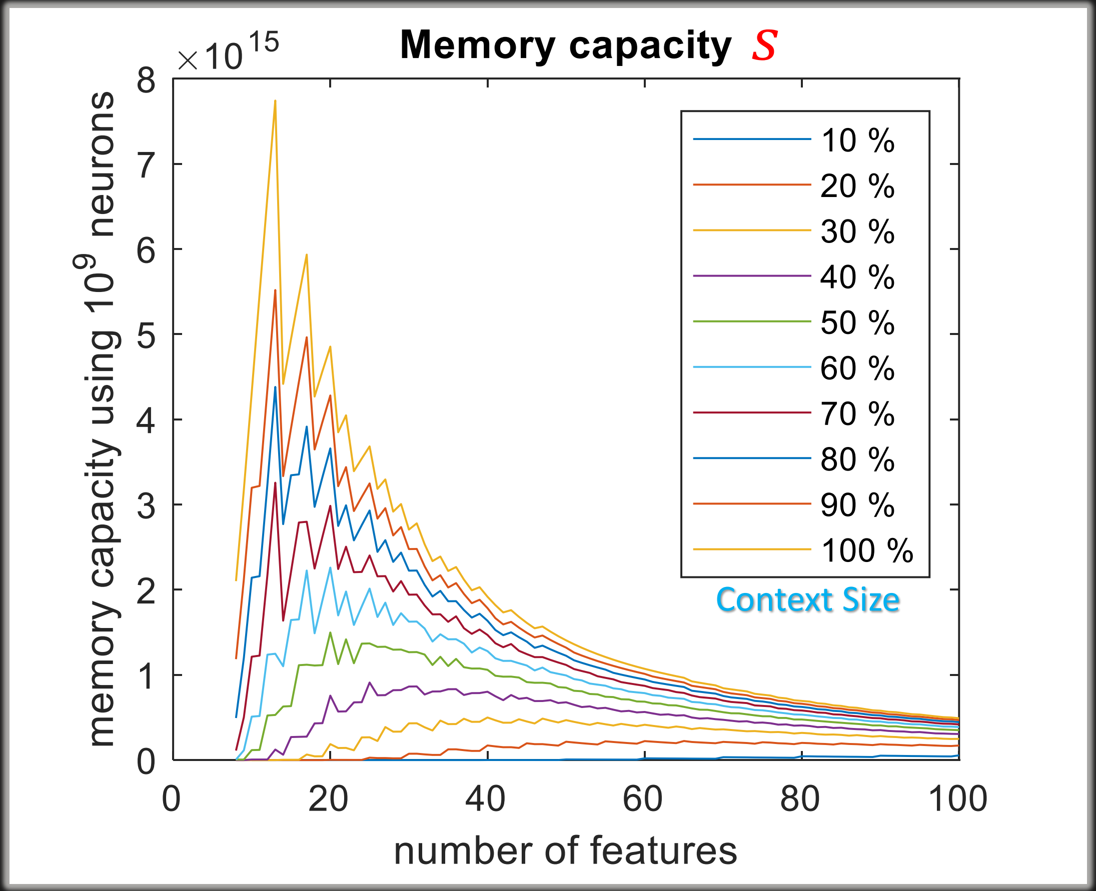




- Memory Capacity vs. Number of Features for n = 10^6, 10^7
- Context Size as Percentage of Scene Size
  (calculated as ratio of context size and the number of scene objects)

Maximum Memory Capacity





- Memory Capacity vs. Number of Features for n = 10^8, 10^9
- Context Size as Percentage of Scene Size
  (calculated as ratio of context size and the number of scene objects)

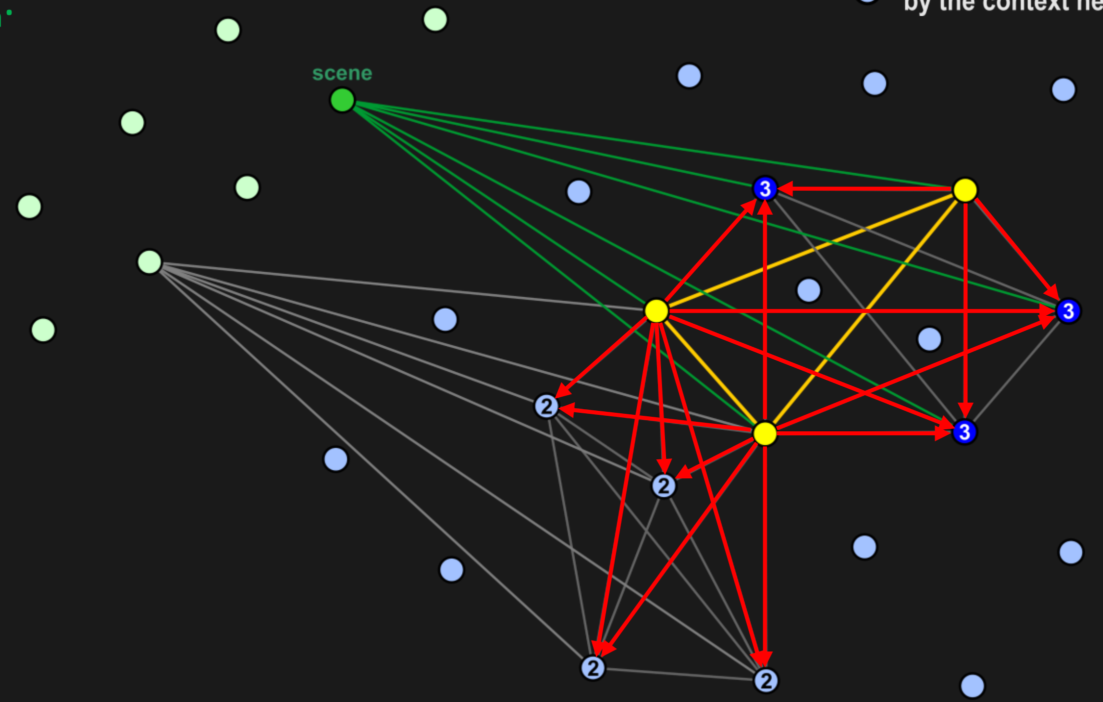
Scene Recovery Algorithm

Steps for successful scene recovery and recognition:

1. Randomly select a context o_c from each scene o_s stored in the SAKG graph and stimulate connected object neurons by these selected context neurons.
2. Determine the set o_m of maximally stimulated neurons, which are the neurons in the SAKG graph that are connected to all context neurons o_c.
3. The sum of the context neurons and the maximally stimulated neurons recreates the desired scene $o = o_c \cup o_m$.
4. If the recreated desired scene $o \neq o_s$, then the scene recovery error is increased by one.

The scene retrieval error rate is determined by dividing the scene recovery error by the number of tested scenes.

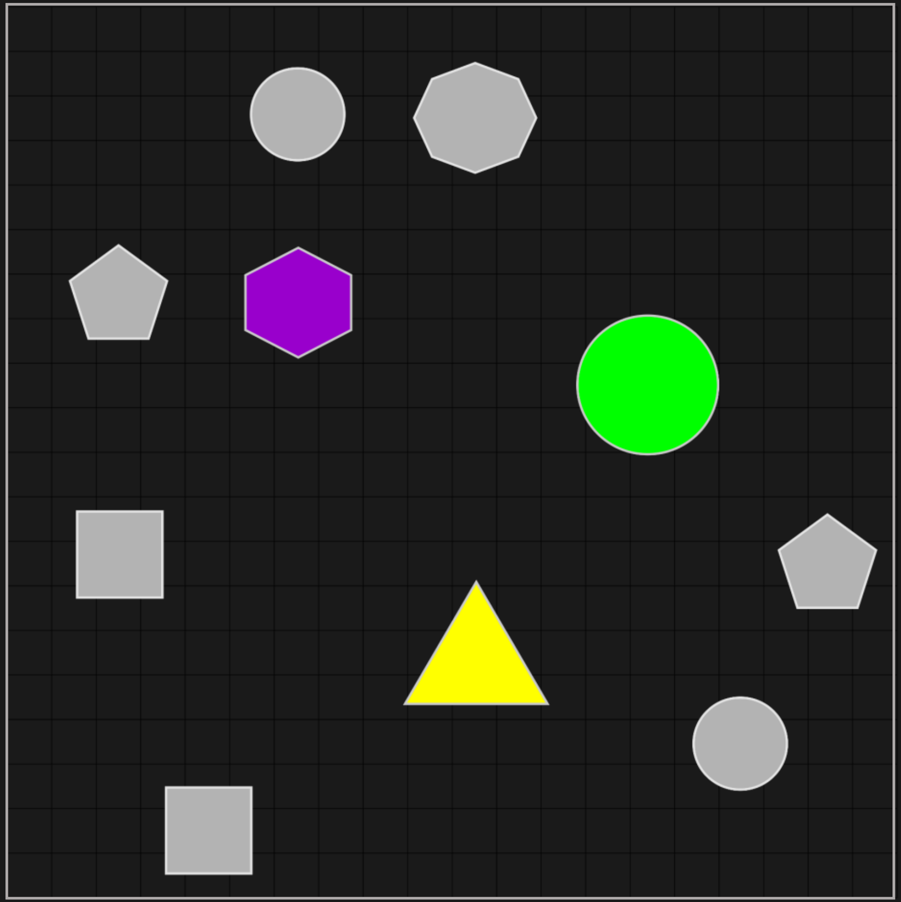
- activated scene neuron stimulated by the maximally stimulated object neurons
- unactivated scene neurons (unstimulated)
- stimulated context neuron representing a subset of scene objects
- activated object neuron forming a clique with context neurons
- maximaly stimulated object neurons stimulating the scene neuron (here 3)
- unactivated object neuron (unstimulated by the context neurons)
- non-maximaly stimulated object neurons by the context neurons (here 2)



Scene Recovery Example

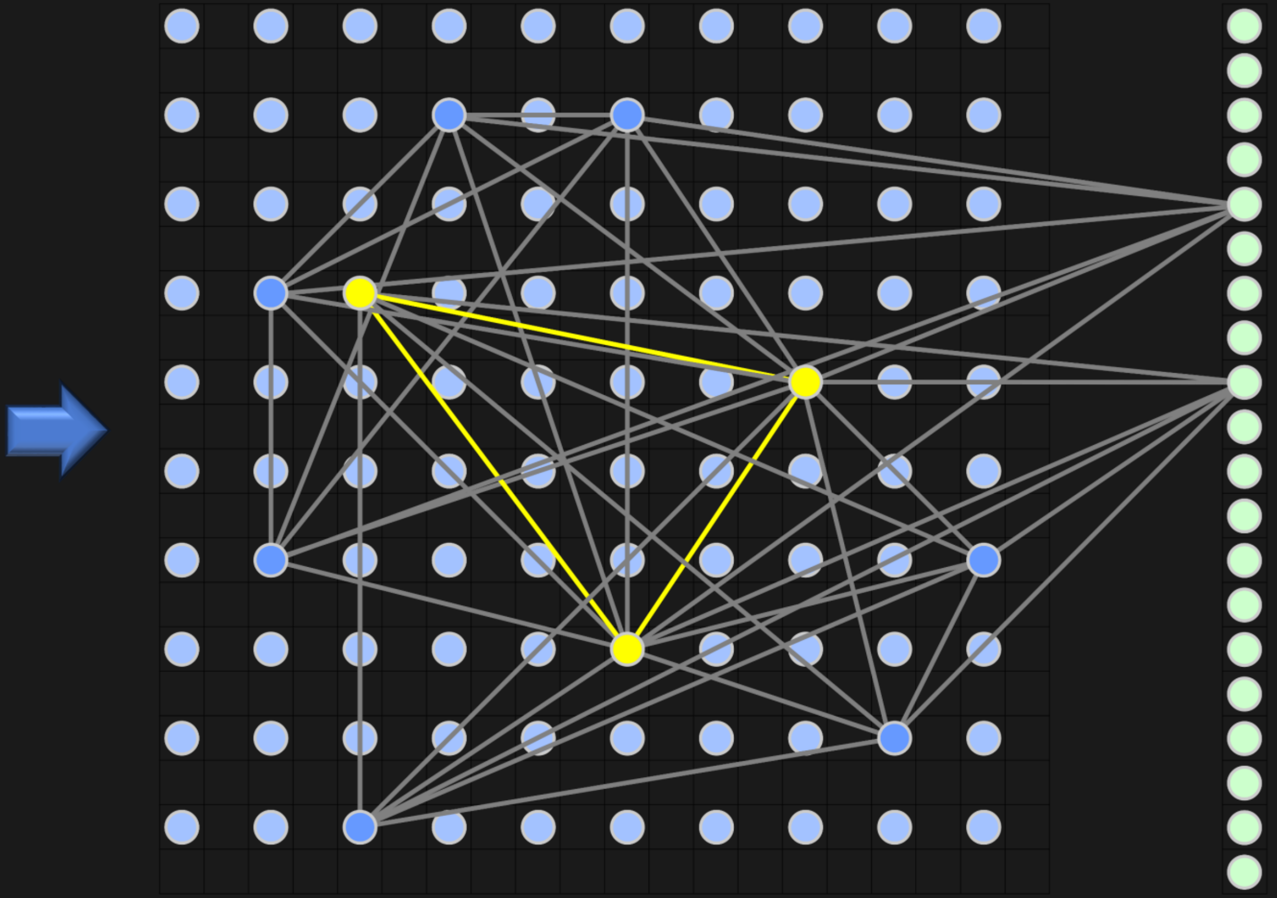
SAKG recovers scenes correctly and unequivocally
if associative memory capacity is large enough for a given context size:

Scene of the specified number of objects



Stimulation of 3 context neurons to recover a scene

Scene neurons



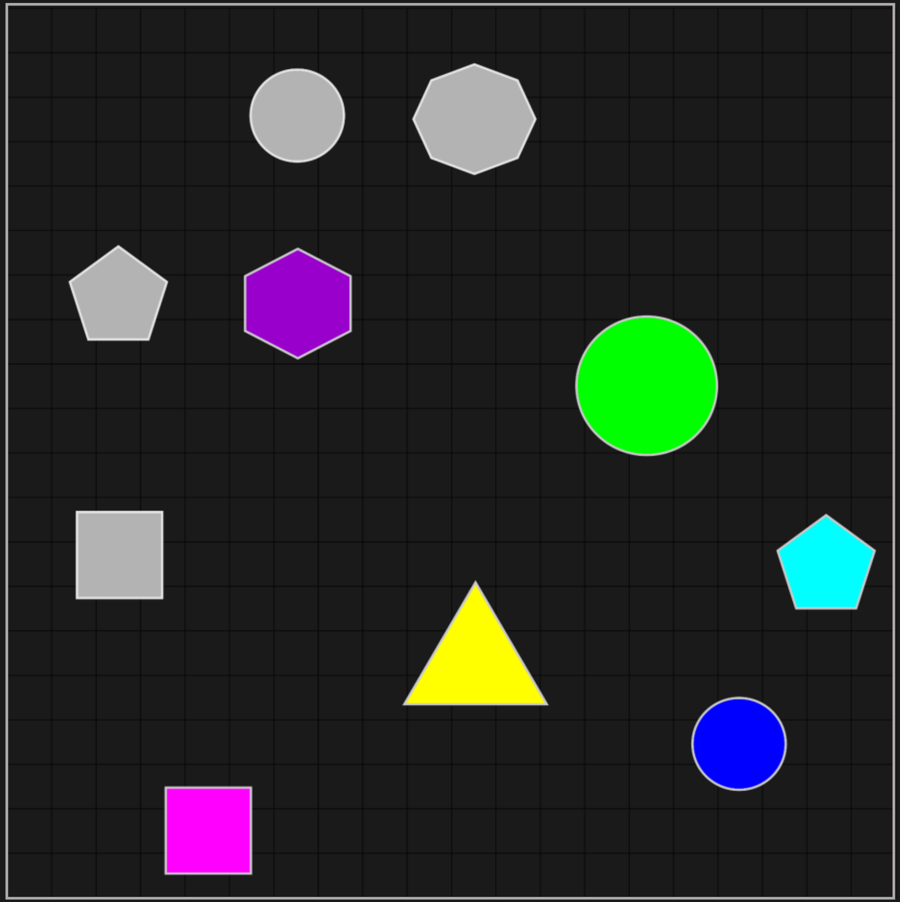
Here, 3 activated context neurons stimulate all connected object neurons to recover the strongest associated scene of all stored in the SAKG associative memory.

Scene Recovery Example

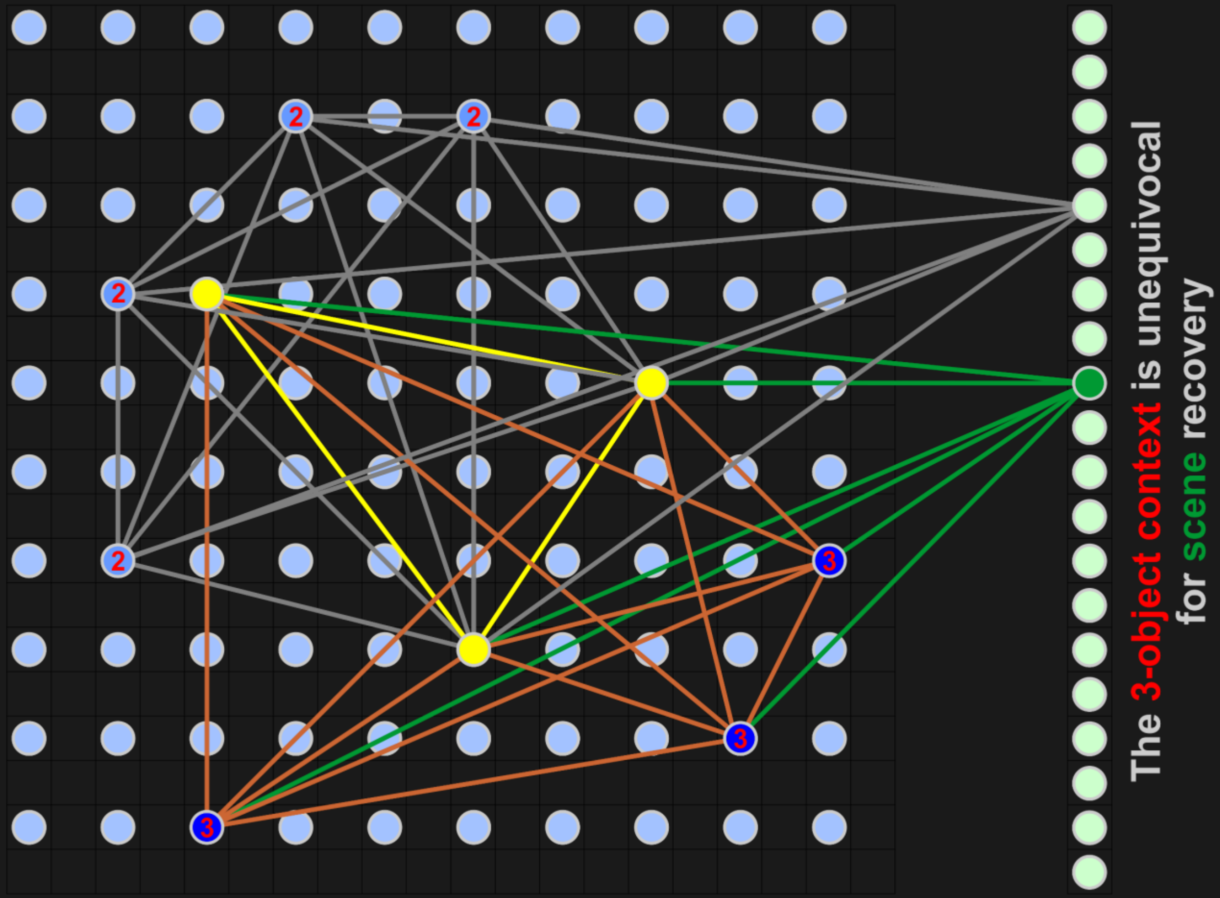
SAKG recovers scenes correctly and unequivocally

if associative memory capacity is large enough for a given context size (here 3):

Scene of the specified number of objects



Scene represetation as a clique of object neurons **Scene recovery**

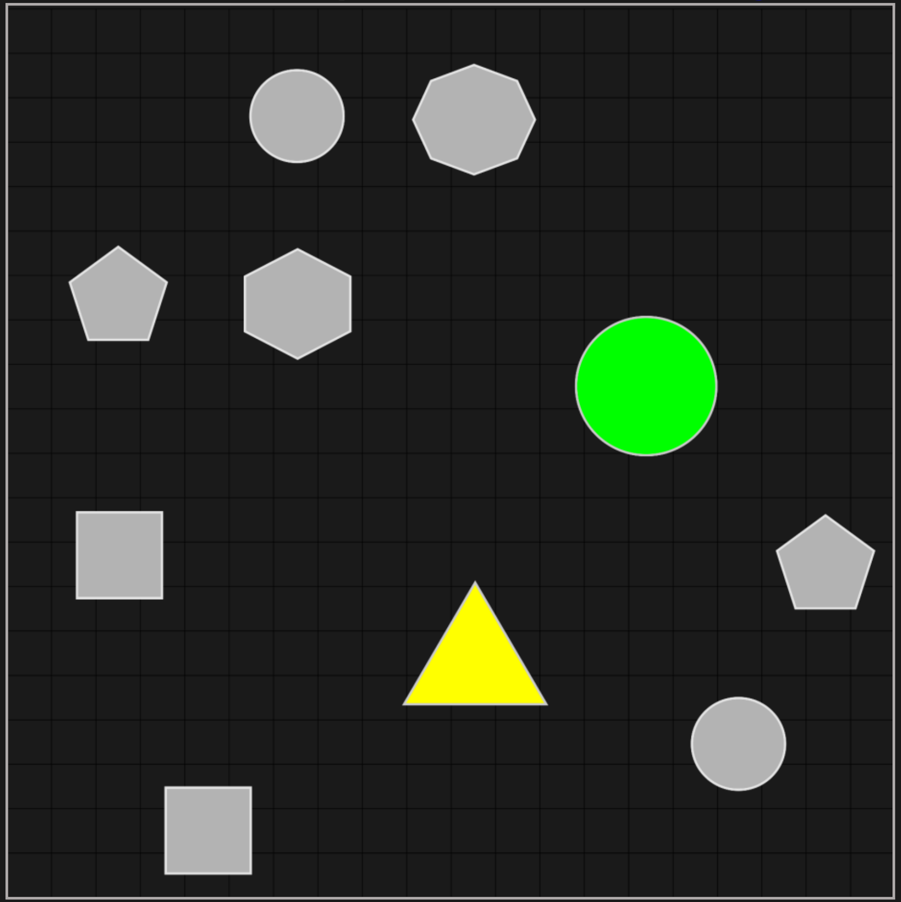


One scene was recovered because the context was large enough (3) for this SAKG memory capacity.

Scene Recovery Example

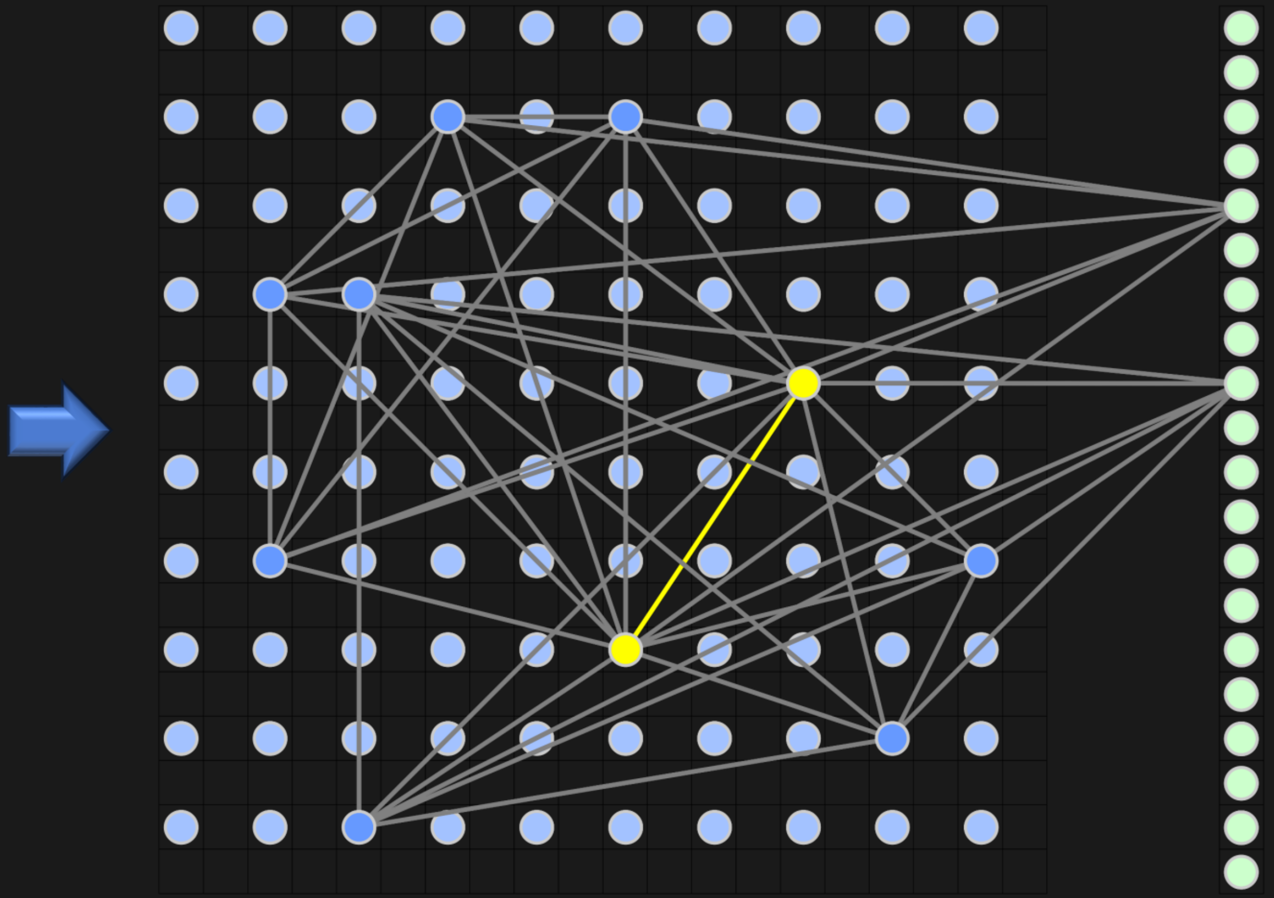
SAKG recovers scenes correctly and unequivocally
if associative memory capacity is large enough for a given context size:

Scene of the specified number of objects



Stimulation of 2 context neurons to recover a scene

Scene neurons



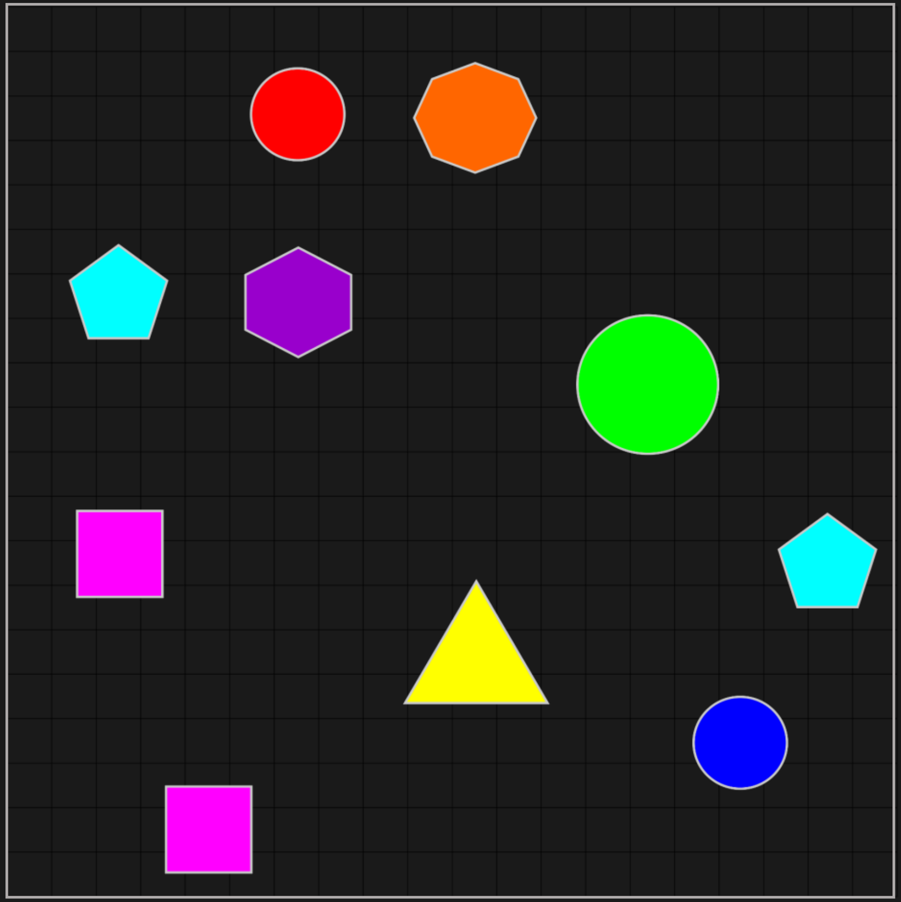
Here, 2 activated context neurons stimulate all connected object neurons to recover the strongest associated scene of all stored in the SAKG associative memory.

Scene Recovery Example

SAKG recovers scenes correctly and unequivocally

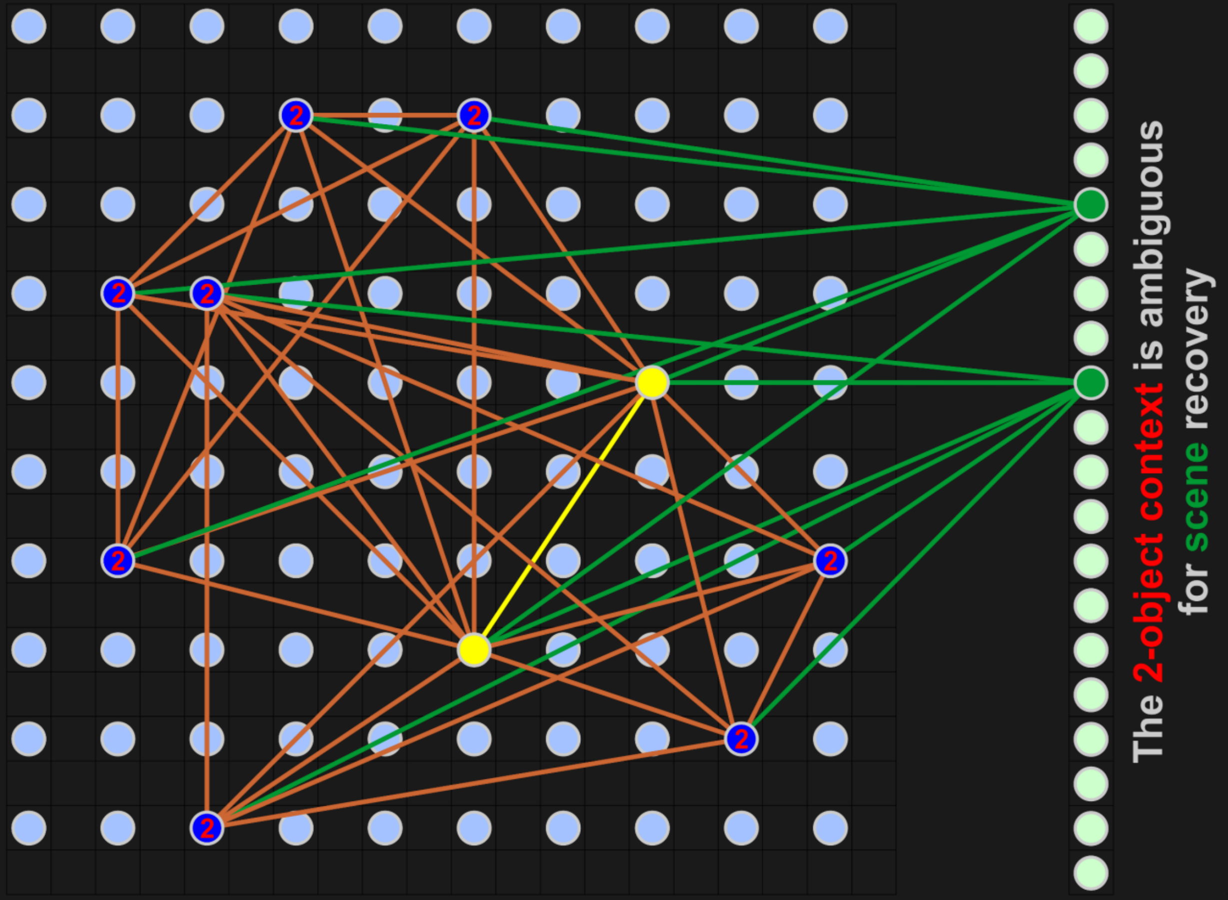
if associative memory capacity is large enough for a given context size (here 2):

Scene of the specified number of objects



Scene represetation as a clique of object neurons

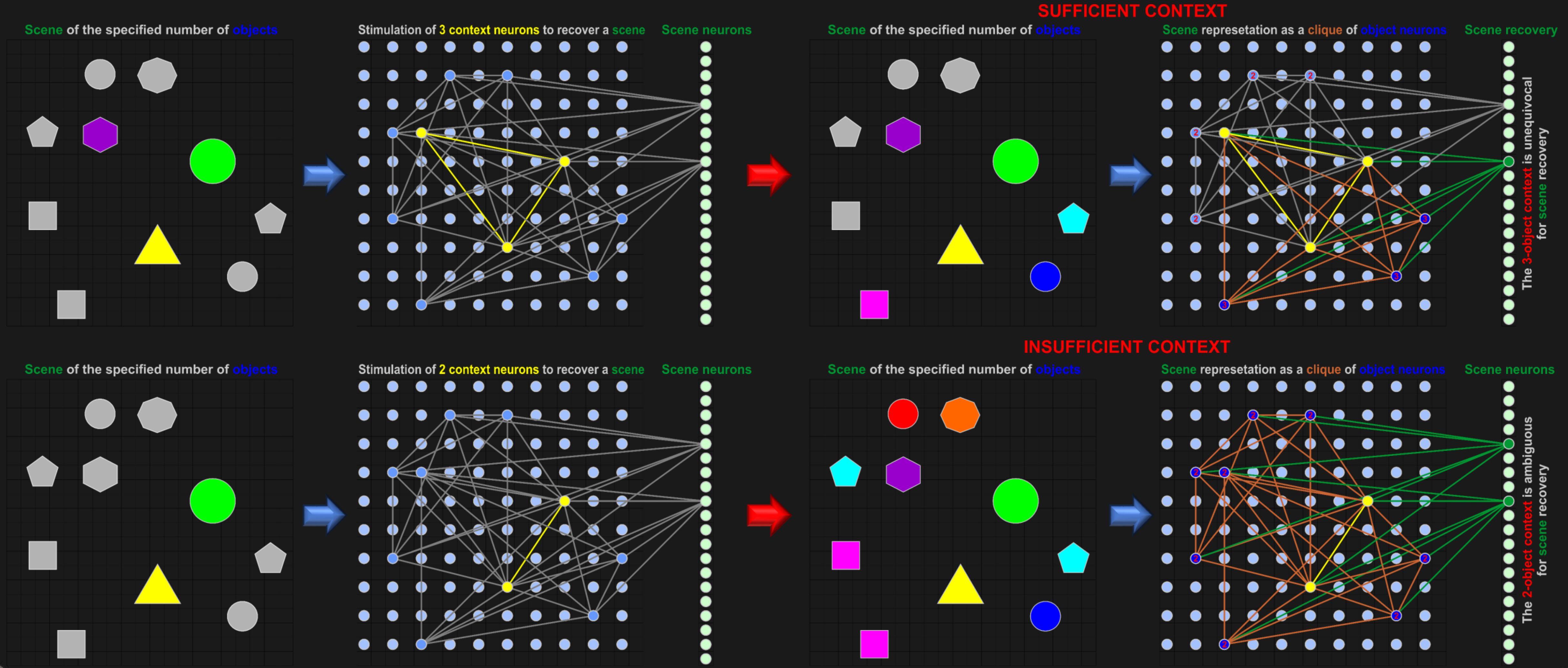
Scene neurons



Two scenes were recovered because the context was not enough large (2) (memory overloaded).

Scene Recovery Example Comparison

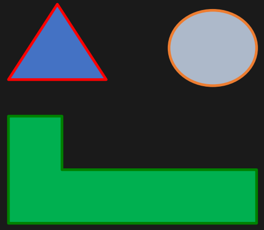
SAKG scene recovery process is determined by memory capacity and contexts size:



For this SAKG associative memory context size 2 is not enough to recover scenes unequivocally.
We need to use context size 3 or enlarge memory capacity to recovers scene correctly.

Experiment Overview Results

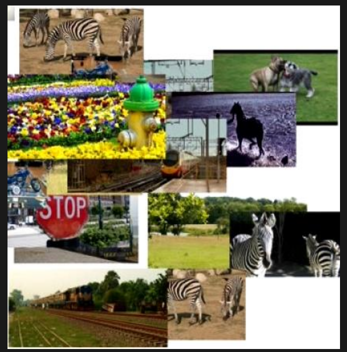
Three different datasets were used to evaluate the performance of the SAKG graph for scene retrieval:

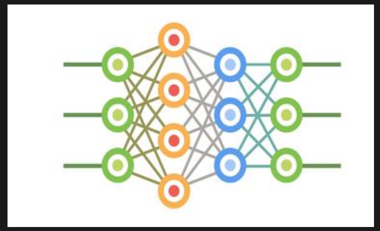


1. **Randomly generated scenes (symbolic representation)** with a specified number of objects drawn from a specified set of objects.

2. The well-known **Iris data set**, which specifies the length and width of sepals and petals in centimeters for three different species of Irises.

3. **A dataset of 1,000 scenes each consisting of 25 objects (graphical representation)**, generated and tested using a deep neural network to detect and recognize objects in video signals.





Overview Results of Experiment 1

Randomly Generated Scenes (symbolic representation) of defined objects

- Various sizes of the stored scene set, scene numbers, context sizes, and resulting graph densities were tested to validate the theoretical results.
- We stored and used respectively 1200 and 2400 scenes consisting of 15 objects each, where each scene was randomly drawn from a population of 1000 graphical objects.
- Theory predicted required context sizes were 5 for 1200 scenes and 7 for 2400 scenes.
- We tested the scene retrieval error level with various contexts provided for retrieval using an average of 20 simulations, comparing Context Size vs. Scene Recognition Error:

1200

Number of observed objects	7	6	5	4	3	2
Scene recognition error in %	0	0	0	0.008	0.446	12.30
Testing time in sec	31.0	30.7	31.8	35.0	50.0	120

2400

Number of observed objects	7	6	5	4	3	2
Scene recognition error in %	0	0.002	0.002	0.079	1.89	31.8
Testing time in sec	130	135	174	287	534	1102

The simulation results that confirm minimum context for error free retrieval fully agree with the theory! ☺

Errors for various numbers of observed context objects for 1200 and 2400 scenes.

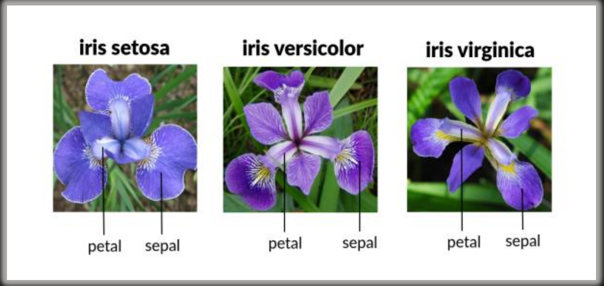
Overview Results of Experiment 2

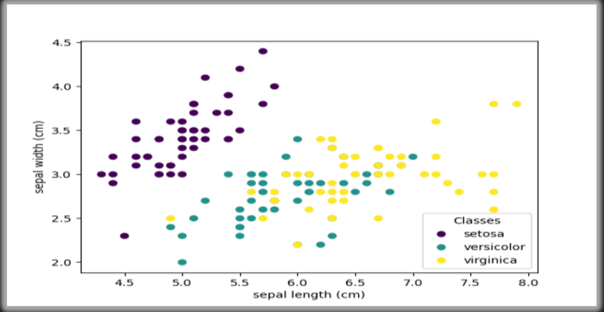
Iris Data (150 objects with 50 for each of 3 species):

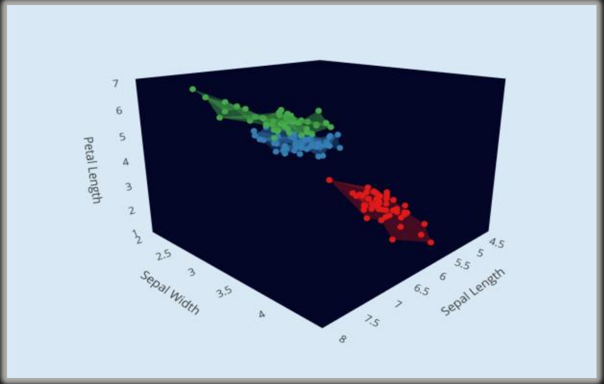
- Scenes were created using the numerical feature values of different Iris examples, along with the Iris species classes, as distinct object names.
- All the scenes (all Iris data) were tested using $n_c = 4$, $n_f = 5$, and $n = 126$.
- The theory predicted maximum memory capacity with 0.1% error rate was

$$s = \frac{\log(1-d)}{\log(1-\xi)} = 92.26\ (scenes).$$

- Since we stored 150 scenes the memory capacity was exceeded (above calculated maximum memory capacity 92.26), the average memory retrieval error was 9.8% after 20 simulations.
- When Iris data were tested using $n_c = 5$, $n_f = 5$, and $n = 126$, the error was 0% as expected by theory.







Iris Dataset 3D Animation
https://chart-studio.plotly.com/~amilworks/80.embed

虹膜資料（150 個對象，其中 3 個物種各 50 個）：
使用不同鳶尾花範例的數字特徵值以及鳶尾花物種類別作為不同的物件名稱來建立場景。
所有場景（所有 Iris 資料）均使用 nc = 4、nf = 5 和 n = 126 進行測試。
理論預測的最大記憶體容量為 0.1% 錯誤率
由於我們儲存了150個場景，超出了記憶體容量（上面計算出的最大記憶體容量92.26），
20次模擬後平均記憶體檢索錯誤為9.8%。
當使用 nc = 5、nf = 5 和 n = 126 測試 Iris 資料時，依照理論預期，誤差為 0%。

Overview Results of Experiment 3

Recognition of COCO Scenes with Deep Neural Networks:

- In this experiment we used 1097 unique virtual objects to construct 1000 different scenes constructed from 25 objects.
- A deep neural network was used to detect objects.
- The dataset was generated using the COCO data format.
- The maximum capacity of the SAKG scene memory using 6 context objects was calculated as 998 scenes based on the presented theory.
- Therefore, after storing 1000 scenes in the memory, it was expected that some of these scenes will not be recognized correctly due to the memory overload.

Fig. One of the scenes was used to define 6 context objects.
'cat 6', 'cat 13', 'cell phone 10', 'toilet 11’, 'zebra 15', and 'zebra 15’.

用深度神經網路辨識COCO場景：
該實驗涉及使用深度神經網路來識別 1,000 個場景，每個場景包含 25 個檢測到的物體。
1097個獨特的虛擬物件被用來建構不同的場景。
資料集是使用 COCO 資料格式產生的。
使用 6 個上下文物件的場景記憶體的最大容量經計算為 998 個場景。
因此，在記憶體中儲存了 1000 個場景後，預計其中一些場景將無法正確識別。

圖：其中一個場景用於定義 6 個上下文物件。
「類別 6」、「類別 13」、「手機 10」、「廁所 11」、「斑馬 15」和「斑馬 15」。

Overview Results of Experiment 3

Recognition of Scenes with Deep Neural Networks: 使用深度神經網路辨識場景：

Retrieval of 2 scenes as the result of overloading the maximum memory capacity:

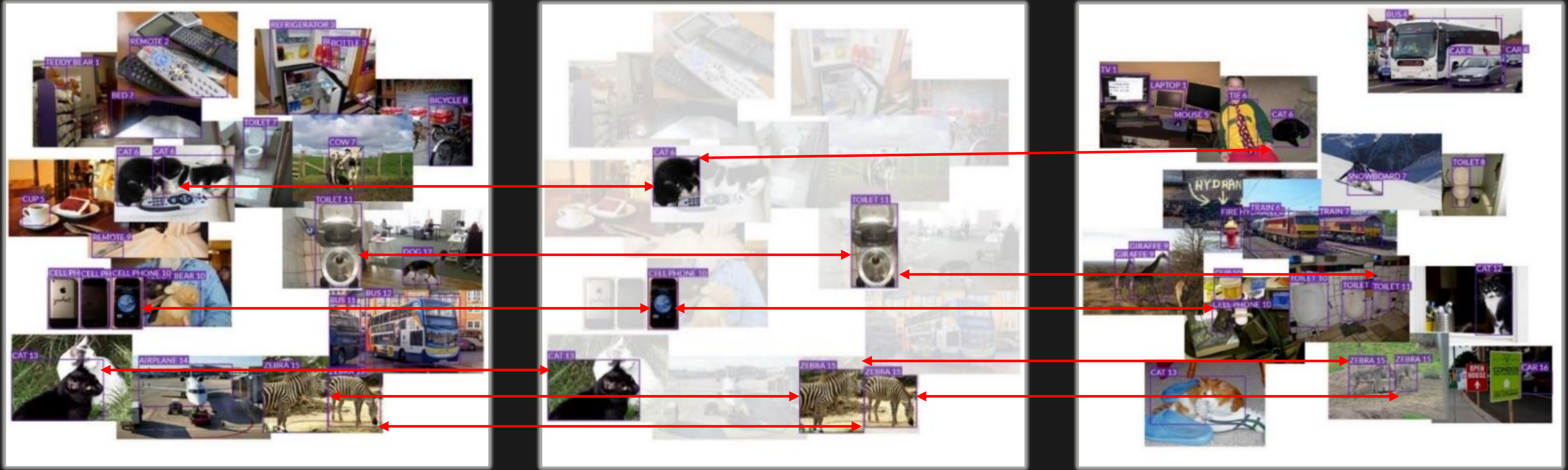


Fig. The context provided led to retrieval of two different scenes, having the same context of 6 virtual objects (context) located in similar locations.

圖：提供的上下文導致檢索兩個不同的場景，具有位於相似位置的 6 個虛擬物件的相同上下文。

The left scene includes only the context from the first scene (correctly). Upon observing the right scene, it becomes apparent that the context objects listed are positioned similarly to those in the left scene due to the maximum memory capacity overload.

左側場景僅包含第一個場景的上下文（正確）。觀察右側場景後，很明顯，由於最大記憶體容量過載，列出的上下文物件的位置與左側場景中的上下文物件類似。

Overview Results of Experiment 3

Recognition of Scenes with Deep Neural Networks:

- This example highlights the importance of the context size for scene retrieval, as the two scenes would be difficult to distinguish based on the context (consisting of 6 objects) alone.
- If we increase the context to include 7 objects for this dataset, the maximum capacity of this associative memory will rise to 1429 scenes based on the presented theory, and all the stored scenes are correctly recognized.
- A collection of 1000 scenes that were used in this experiment, along with a sample program that allows you to download any scene, is available at [21] of Paper #186.

使用深度神經網路辨識場景：

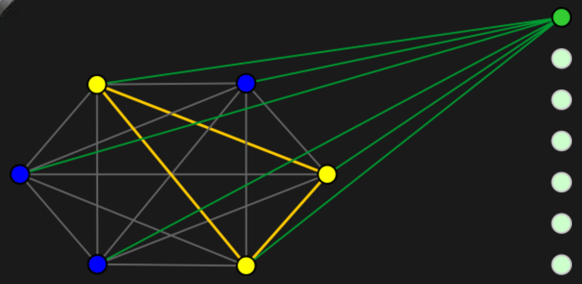
這個例子強調了上下文大小對於場景檢索的重要性，因為僅根據上下文很難區分兩個場景。

如果我們增加上下文以包含該資料集的 7 個對象，則根據所提出的理論，該關聯記憶體的最大容量將升至 1429 個場景。

根據統計，這使得同一組中的 1000 個場景的識別錯誤少於一個。

因此，在此場景中（使用 7 個物件上下文），所有儲存的場景都被正確識別。

本實驗中使用的 1000 個場景的集合以及允許您下載任何場景的範例程式可在論文 186 的 [21] 中找到。



Conclusions

- ✓ The paper presented a novel structural approach to constructing associative knowledge graphs SAKG that can be utilized to create associative memories.
- ✓ Experiments showed that the SAKG graphs can accurately retrieve stored scenes thanks to the context-sensitive structure based on associated cliques representing scenes.
- ✓ The results showed that the SAKG graph can store and retrieve all scenes without error up to the calculated critical graph density for a given context size.
- ✓ The critical graph density was validated experimentally using three different datasets.
- ✓ This approach enables the achievement of substantial scene-memory capacities by leveraging the sparsity of the knowledge graph and modest sizes of recorded scenes.
- ✓ Memory capacity is determined by the size of the graph and the density of its synaptic connections and grows quadratically with the number of SAKG neurons.
- ✓ Larger graphs have significantly larger scene memory capacity than smaller graphs.
- ✓ The use of contextual connections in a sparse SAKG graph makes them more effective than traditional associative Hopfield networks.

Thank you!

ICONIP 2023
November 20-23, 2023, Changsha, China

WedA1: Best Paper Award Competition Session (Chair: Zhanyu Ma)

Q&A?

Janusz A. Starzyk
University of Information Technology and Management in Rzeszow, Poland and Ohio University, Athens, USA

Przemysław Stokłosa
Institute of Management and Information Technology in Bielsko-Biala, Poland

Adrian Horzyk
AGH University of Krakow, Poland

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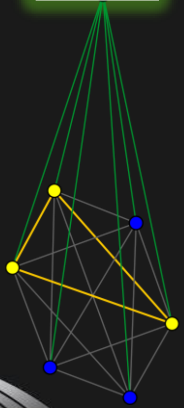

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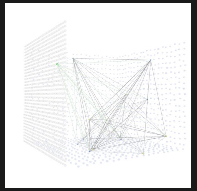


Thank you!

ICONIP 2023
November 20-23, 2023, Changsha, China

WedA1: Best Paper Award Competition Session (Chair: Zhanyu Ma)

Q&A?

2023 International Conference on Neural Information Processing (ICONIP2023)

Changsha, China, November 20–23, 2023

This is to certify that

Janusz A. Starzyk, Przemysław Stokłosa, Adrian Horzyk and Paweł Raif

was the best paper award finalist at the 2023 International Conference on Neural Information Processing for the paper entitled "Structural Properties of Associative Knowledge Graphs."

General Chairs:

Tingwen Huang, Chunhua Yang

Asia Pacific Neural Network Society

November 22, 2023

Thank you!

ICONIP 2023
November 20-23, 2023, Changsha, China

Q&A?

You are also invited to the second presentation…

16:00-18:00 Session ThuF4: Machine Learning 2

CHAIRS:

Zhong-Wei Jin and *Kosuke Yoshimura*

LOCATION: Changsha Ting (长沙厅)

17:45 *Adrian Horzyk*, *Jakub Kosno*, *Daniel Bulanda* and *Janusz A. Starzyk*

Explainable Sparse Associative Self-Optimizing Neural Networks for Classification

Overview Results of Experiment 3

Recognition of Scenes with Deep Neural Networks:

- This example highlights the importance of the context size for scene retrieval, as the two scenes would be difficult to distinguish based on the context alone.
- If we increase the context to include 7 objects for this dataset, the maximum capacity of this associative memory will rise to 1429 scenes based on the presented theory.
- Statistically, this allows for less than one recognition error for 1000 scenes from the same set.
- Accordingly, all the stored scenes were correctly recognized in this scenario using context of 7 objects.
- A collection of 1000 scenes that were used in this experiment, along with a sample program that allows you to download any scene, is available at [21] of Paper #186.

使用深度神經網路辨識場景：

這個例子強調了上下文大小對於場景檢索的重要性，因為僅根據上下文很難區分兩個場景。

如果我們增加上下文以包含該資料集的 7 個對象，則根據所提出的理論，該關聯記憶體的最大容量將升至 1429 個場景。

根據統計，這使得同一組中的 1000 個場景的識別錯誤少於一個。

因此，在此場景中（使用 7 個物件上下文），所有儲存的場景都被正確識別。

本實驗中使用的 1000 個場景的集合以及允許您下載任何場景的範例程式可在論文 186 的 [21] 中找到。

Experiments Overview Results

- ✓ The results of all experiments showed that the SAKG graph can accurately retrieve stored scenes thanks to the context-sensitive structure based on associated cliques representing scenes.
- ✓ Error rate is low, if the context size is large enough allowing for unambiguous recognition of scenes.
- ✓ The critical graph density was validated experimentally using three different datasets.
- ✓ The results showed that the SAKG graph can store and retrieve all scenes without error up to the calculated critical graph density.

所有實驗的結果表明，由於基於表示場景的關聯派系的上下文敏感結構，SAKG 圖可以準確地檢索儲存的場景。

如果上下文大小足夠大，允許明確識別場景，則錯誤率較低。

使用三個不同的資料集透過實驗驗證了臨界圖密度。

結果表明，SAKG 圖可以在計算出的臨界圖密度範圍內無錯誤地儲存和檢索所有場景。

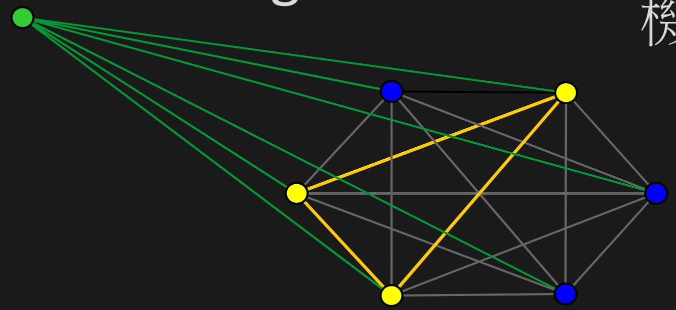
Exteded Conclusions

- ✓ The paper presented a novel structural approach to constructing associative knowledge graphs that can be utilized to create associative memories.
- ✓ Memory capacity is determined by the size of the graph and the density of its synaptic connections.
- ✓ Memory capacity grows quadratically with the number of neurons used to build the knowledge graph.
- ✓ Larger graphs have significantly larger scene memory capacity than smaller graphs.
- ✓ Memory tests conducted using both randomly generated synthetic data and real-world datasets confirmed the validity of the derived results.
- ✓ This approach enables the achievement of substantial scene-memory capacities by leveraging the sparsity of the knowledge graph and modest sizes of recorded scenes.
- ✓ In comparison to traditional associative Hopfield networks, this method proves to be more effective thanks to the use of contextual connections in a sparse SAKG graph.

- ✓ 該論文提出了一種新穎的結構方法來建立可用於創建聯想記憶的聯想知識圖。
- ✓ 記憶容量由圖的大小及其突觸連結的密度決定。
- ✓ 記憶容量隨著用於建構知識圖的神經元數量呈現二次方增長。
- ✓ 較大的圖形比較小的圖形具有更大的場景記憶體容量。
- ✓ 使用隨機產生的合成資料和真實世界資料集進行的記憶測試證實了派生結果的有效性。
- ✓ 這種方法透過利用知識圖的稀疏性和記錄場景的相對適中的大小，可以直接實現大量的場景儲存容量。
- ✓ 與傳統的關聯 Hopfield 網路相比，由於在稀疏 SAKG 圖中使用上下文連接，該方法更加有效。
- ✓ 未來的工作集中在將所提出的結構聯想記憶與現代 Hopfield 網路進行比較並使用微柱。

Key Findings and Contributions

- ✓ Developing Semantic Memories in SAKG Graphs
- ✓ Leveraging Sparse Binary Synaptic Connections
- ✓ Providing Rapid Construction and Increased Memory Capacities in comparison to other approaches.
- ✓ Examining Structural Properties of SAKG Graphs
- ✓ Examining Graph Density and Error-Free Scene Retrieval
- ✓ Establishing Associative Memory Limits
- ✓ Determining the Influence of Context on Memory Capacity in SAKG Graphs
- ✓ Conducting Experimental Validation on Diverse Datasets
- ✓ Implications for the Development of Motivated Learning in Robots and Artificial Intelligence



- ✓ 在 SAKG 圖中發展語義記憶
- ✓ 利用稀疏二元突觸連接
- ✓ 與其他方法相比，提供快速建置和增加的記憶體容量。
- ✓ 檢查 SAKG 圖的結構屬性
- ✓ 檢查圖密度和無錯誤情境檢索
- ✓ 建立關聯記憶體限制
- ✓ 確定 SAKG 圖中上下文對記憶體容量的影響
- ✓ 對不同資料集進行實驗驗證
- ✓ 對機器人和人工智慧發展動機學習的影響

Key Takeaways and Future Work

Overall, the paper presents a new and promising approach to associative memory that has the potential to be used in a variety of applications, such as scene retrieval, object recognition, and natural language processing.

總體而言，本文提出了一種新的、有前途的聯想記憶方法，該方法有潛力用於各種應用，例如場景檢索、物件識別和自然語言處理。

Future work encompasses:

- Comparative Analysis with Modern Hopfield Networks
- Incorporation of micro-columns
- Using of novel elements (objects)

未來的工作包括：

- 與現代 Hopfield 網路的比較分析
- 合併微柱
- 納入新穎的元素（對象）

Questions for Consideration

1. How can we apply these insights into **knowledge graph density** to enhance scene associative memory systems?
2. Are there specific scenarios in artificial intelligence or robotics where this **knowledge** could be particularly beneficial?
3. What further research avenues can be explored to refine our understanding of **knowledge graph density** in memory systems?

我們如何將這些見解應用於知識圖密度來增強場景聯想記憶系統？

在人工智慧或機器人技術中是否存在這些知識特別有用的特定場景？

可以探索哪些進一步的研究途徑來完善我們對儲存系統中知識圖密度的理解？

Fragment of a SAKG
with an activated single scene on the left plane

On the left plane, we have **scene neurons** corresponding to **scenes** composed of **objects** represented by **object neurons**.

Object neurons activate a **scene neuron** by the **green edges** when the stimulation **context** is activated.

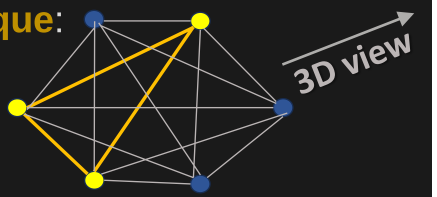
Object neurons are of two kinds:

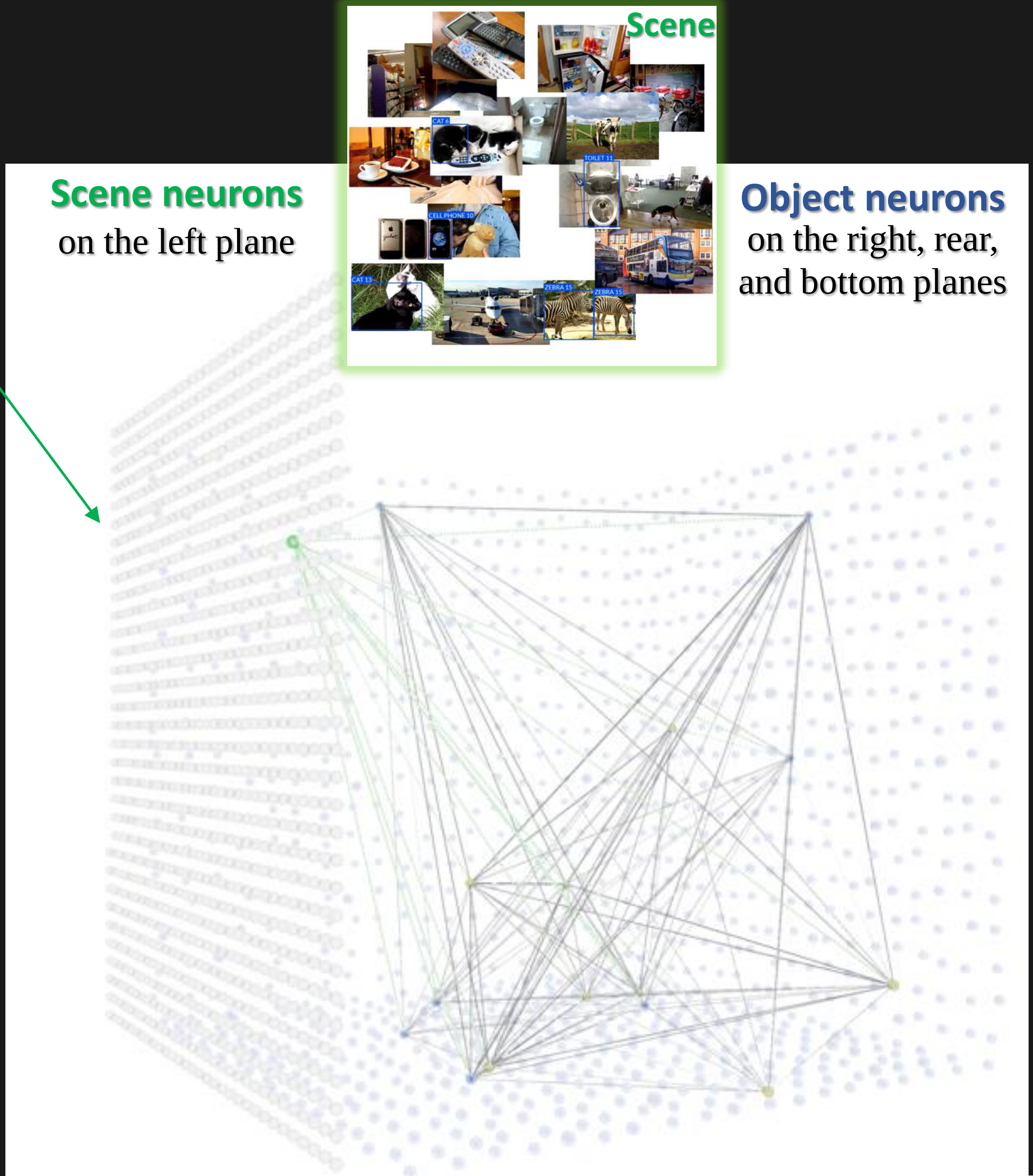
- **Yellow neurons** represent **context** that is a subset of **all objects** of the **scene**.
- **Blue neurons** represent remaining **objects** of the scene that were activated by the **context (context neurons)**.

Object neurons are on the **right, rear, and bottom planes**.

All object neurons of each **scene** constitute a **clique** – a complete graph in which every two vertices are connected by an edge.

Grey edges connect **all object neurons** of the **clique**:





在左側平面上，我們有與由物件神經元表示的物件組成的場景相對應的場景神經元。

當刺激上下文被激活時，對像神經元會透過綠色邊緣激活場景神經元。

對像神經元有兩種：

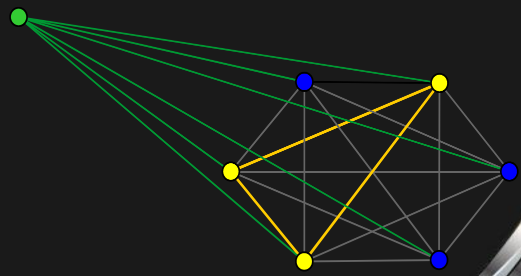
黃色神經元代表場景中所有物件的子集的上下文。

藍色神經元代表場景中被上下文活化的剩餘物件（上下文神經元）。

物體神經元位於右側、後方和底部平面。

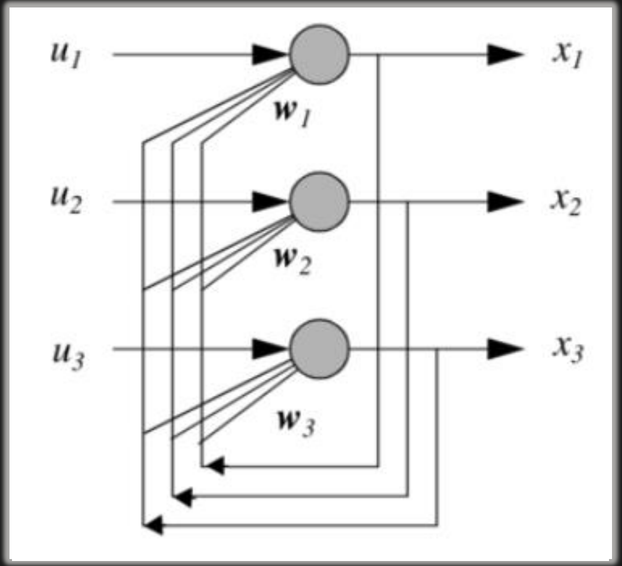
每個場景的所有物件神經元構成一個團——一個完整的圖，其中每兩個頂點由一條邊連接。

灰色邊連接團的所有物件神經元：



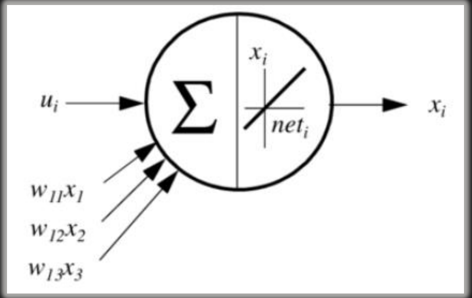
Classic Hopfield Networks

Hopfield網路的拓撲，以3個神經元為例。



Topology of Hopfield networks, with 3 neurons as an example.

其神經元的線性傳遞函數表徵了線性Hopfield 網路。

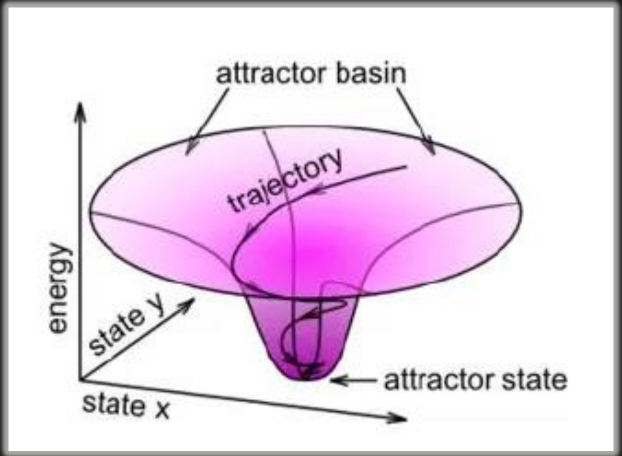


Linear transfer functions of its neurons characterize the linear Hopfield network.

Encoding a pattern in a Hopfield network requires to reduce the energy associated with this pattern, thereby turning it into an attractor state through the application of gradient descent.

要在 Hopfield 網路中對模式進行編碼，所需要做的就是減少與該模式相關的能量，從而透過應用梯度下降將其轉變為吸引子狀態。

這個過程涉及到能量相對於網路權重的偏導數，這個概念被稱為赫布學習規則。

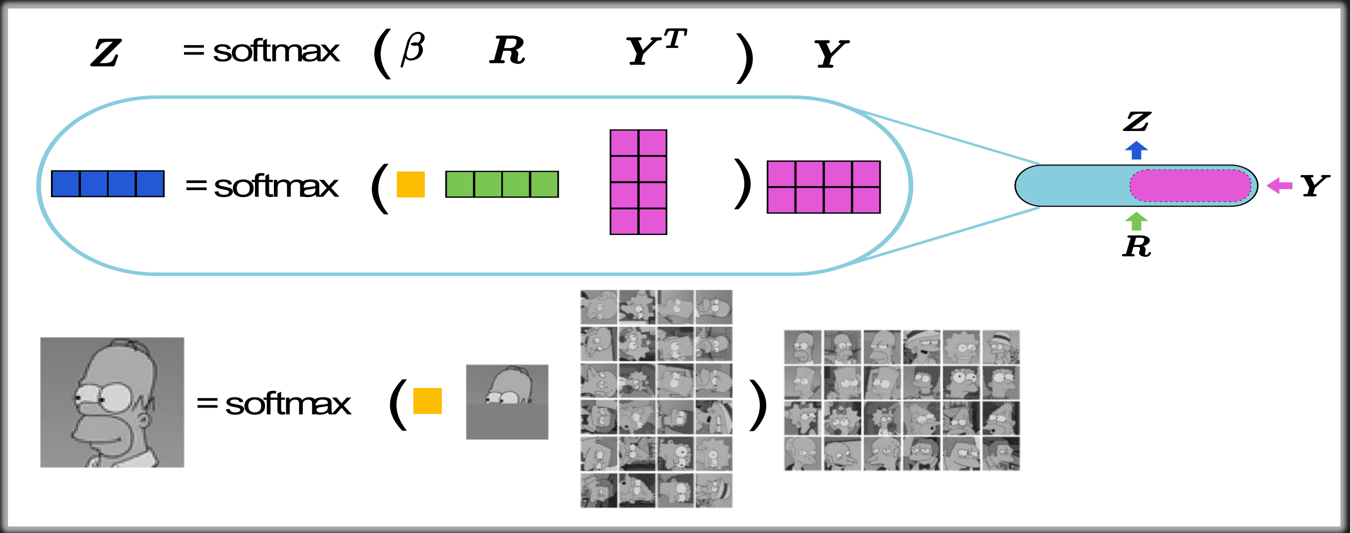


這個過程涉及到能量相對於網路權重的偏導數，這個概念被稱為赫布學習規則。

This process involves taking the partial derivative of the energy with respect to the network's weights, a concept referred to as the Hebbian learning rule.

Modern Hopfield Network (MHN) aka Dense Associative Memories

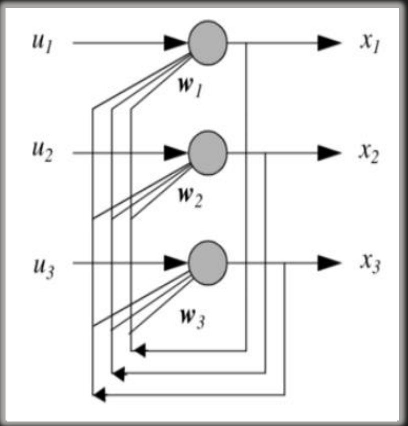
密集的聯想記憶



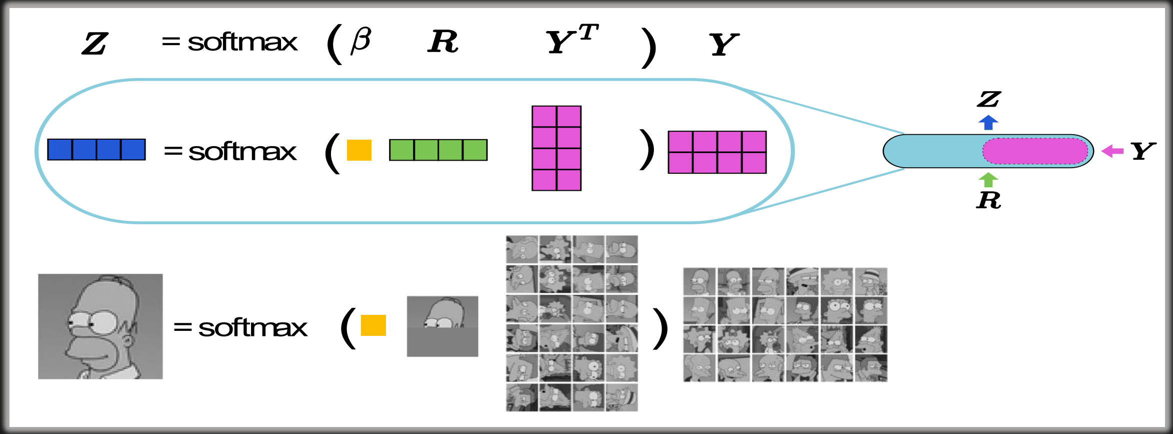
現代 Hopfield 網路 (MHN) 透過打破輸入特徵和儲存記憶之間的線性連結來改善經典 Hopfield 網路。
這是透過在能量函數或神經元激活函數中引入更強的非線性來實現的，導致記憶體儲存容量相對於特徵神經元的數量呈指數級增長。

Modern Hopfield networks (MHN)
improve classic Hopfield networks by breaking the linear link between input features and stored memories.
This is done by introducing stronger non-linearities in the energy function or neuron activation functions, leading to an exponential increase in memory storage capacity with respect to the number of feature neurons.

Comparison of Capacities of Classic and Modern Hopfield Networks



容量比較



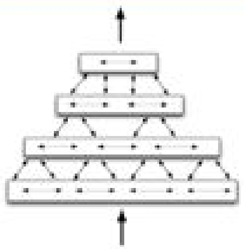
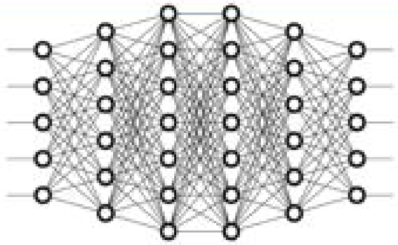
Storage capacity of classic Hopfield Networks (HN) trained to store multiple different patterns is:
C = ~ 0.14 d patterns (linear capacity),
where d is the number of neurons in the network.

經過訓練來儲存多種不同模式的經典 Hopfield 網路 (HN) 的儲存容量為：
C = ~ 0.14 d 模式（線性容量），
其中 d 是網路中神經元的數量。

Storage capacity of Modern Hopfield Networks (MHN) for retrieval of patterns free of errors is:
C = ~ $2^{d/2}$ patterns (exponential capacity),
where d is the dimension of the input,
while having extremely fast conference.

現代 Hopfield 網路 (MHN)
用於無錯誤模式檢索的儲存容量為：
C = ~ 2d/2 模式（指數容量），
其中 d 是輸入的維度，
同時擁有極快的會議速度。

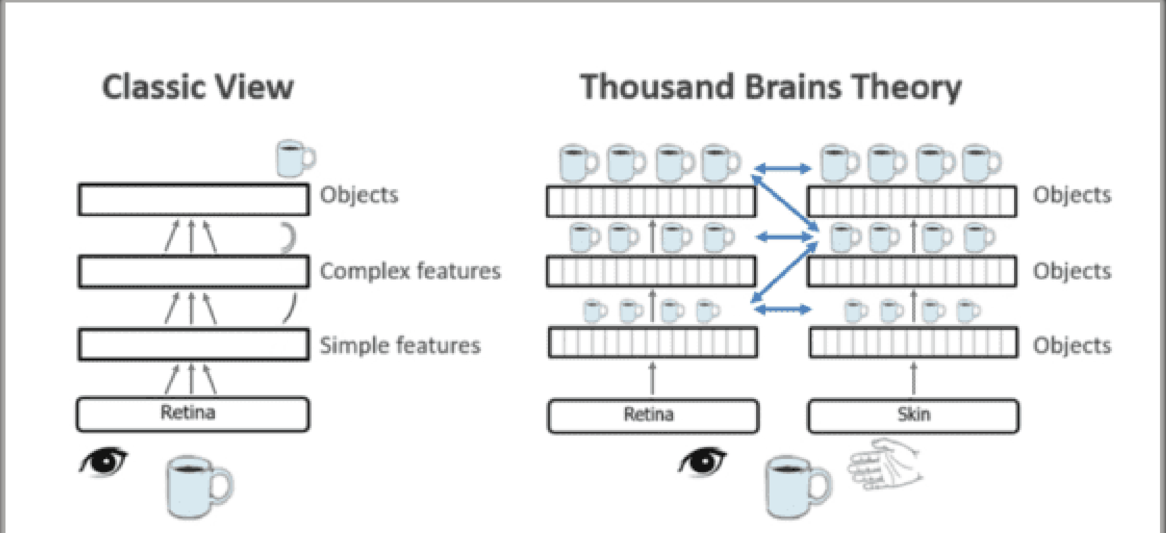
Comparison of Deep Learning and Hierarchical Temporal Memory (HTM)

Attribute 屬性	HTM (Hierarchical Temporal Memory) 分層時間記憶	Deep Learning 深度學習
		
Premise 前提	Biological 生物	Mathematical 數學
Learning Mechanism 學習機制	Hebbian Learning 希伯來文學習	Back Propagation 反向傳播
Learning type 學習類型	Unsupervised 無監督	Supervised 監督的
Learning batches 學習批次	Online learning 線上學習	Batch wise learning 大量學習
Neuron cell state 神經元細胞狀態	Active/Inactive/Predictive	Active/Inactive
Batch size need to learn 批量大小需要學習	Very small data is sufficient 非常小的數據就足夠了	Required huge data volume 訓練需要海量數據

In this presentation and accompanying paper, we will compare SAKG to classic associative Hopfield Networks. The presented method proves to be more effective thanks to the use of contextual connections in a sparse SAKG graph.

在本簡報和隨附論文中，我們將 SAKG 與經典關聯 Hopfield 網路進行比較。由於在稀疏 SAKG 圖中使用了上下文連接，所提出的方法被證明更有效。

Thousand Brains Theory of Intelligence and Hierarchical Temporal Memory



https://www.numenta.com/blog/2019/10/24/machine-learning-guide-to-htm/

千腦智力理論指出，新皮質的每個部分都學習物體和概念的完整模型，而不是學習世界的一個模型。
它使用分層臨時記憶體（HTM）進行儲存和學習。
新皮質中的長距離連接使模型能夠協同工作以創建對世界的感知。

The **Thousand Brains Theory of Intelligence** states that every part of the neocortex learns complete models of objects and concepts rather than learning one model of the world.
It uses **Hierarchical Temporal Memory (HTM)** for storage and learning.
Long range connections in the neocortex allow the models to work together to create perception of the world.