Quantum Computing Model for Human Semantic Memory

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ABSTRACT: Understanding the structures of human semantic memory search has been a critical initiative in cognitive science. One testing method is the semantic memory task, which asks patients to recall as many words as possible within a specific category, often to test for neurological disorders. Recent studies have shown that classical computers can simulate brain mechanisms using random behaviors. But unlike classical models, which assume that semantic activation spreads along a single probabilistic pathway at a time, quantum random walks allow for simultaneous exploration of multiple conceptual associations, reflecting the parallel and context-dependent retrieval mechanisms observed in cognition through the use of superposition and interference. To address this, we introduce a quantum random walk computation approach for more detailed modeling to address this. By developing the first quantum computing procedure for classical INVITE random walks using quantum random walks, we provide the maximum probabilities of generating semantically related word categories pertinent to the semantic fluency task in assessing a patient's potential semantic memory recall for cognitive diseases. Thus, this method promises the potential for various quantum search algorithms and offers greater scalability in statistical analysis.

KEYWORDS: Physics, Quantum Physics, Quantum Computing, Semantic Memory, Quantum Random Walks.

Introduction

Memory retrieval, the process of accessing and bringing into consciousness information previously encoded and stored in memory, is essential to cognitive science and psychology. One of the different types of memory retrieval is semantic memory, a type of long-term memory that involves storing and retrieving general knowledge about the world, facts, concepts, meanings, and the understanding of language. One of the core motivations for understanding semantic memory stems from its applications in neuropsychology and rehabilitation. The diagnosing and treatment of memory-related disorders like Alzheimer's disease, semantic dementia, and other forms of cognitive impairment use semantic memory as a measure widely. Further understanding of its mechanisms can aid in developing targeted therapies and interventions.[1] While significant progress was made in identifying brain regions involved in semantic memory retrieval, the precise neural mechanisms and pathways still need to be fully understood.[2] But even more, while encoding specificity and transfer-appropriate processing are well-established concepts, the exact nature of these interactions and how they affect retrieval success remain areas of active research.[3]

Such attempts to model semantic retrieval were made through classical computation methods, one being the concept of random walks. As a mathematical representation of the random movement of an entity through a space consisting of discrete or continuous steps, random walks are practical markers in the simulation and analysis of computer algorithms in studying the behavior of complex systems and predictions of future states. Random walks are also further aided by their Markov property, which describes how the system's future behavior depends only on its current state and is independent of its history beyond the current state. In the context of semantic memory retrieval, they provide a flexible and intuitive framework for modeling the associative nature of semantic networks, where concepts are connected based on semantic relationships. Such random walks on the networks offer a computational approach to simulate the spreading activation process of memory retrieval.[4]

One example of an application of random walks in semantic networks can be that of optimal foraging, a behavioral ecology model that explains how animals maximize their energy intake while minimizing the time and effort spent searching for and consuming food, predicting that organisms will adopt foraging strategies that provide the highest net energy gain, balancing factors like food availability, handling time, and travel distance. A classic method for studying memory retrieval involves asking people to retrieve as many members of a category as possible in a limited amount of time, known as the semantic fluency task. Despite the simple task, its results have been used in clinical settings to study memory deficits in patients with different forms of dementia.[5] However, more profound research on semantic fluency tasks has revealed that retrieval from semantic memory occurs in bursts of semantically related words, with pauses between bursts. Inspired by this pattern, recent work compared memory search via random walks to animal foraging theory from biology, which suggests that animals switch foraging patches when the marginal value of staying in the current patch is lower than the overall rate of return.[6] Later, predictions have shown to be consistent with those results by utilizing random walks on semantic networks in which items that belong to the same cluster are close together in the network.[7] A deeper delve into the direct mental structures and processes underlying human semantic memory search is continued using the semantic fluency task. A new random walk created for this approach is the INVITE random walk, where the random walk is on a

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set of states (words) with transition probabilities to indicate memory associations. These words are only generated when first visited. This model, a method to compute the maximum likelihood of generating words from the semantic fluency task and an estimation of the transition matrix, comes directly from the semantic fluency lists.[8]

Another extension of random walks is the quantum random walk, which utilizes quantum superposition and entanglement instead of nodes and one-way links. In a quantum random walk, multiple nodes (quantum states) can become entangled and simultaneously exist in a superposition of various locations. In a superposition state, a qubit exists in a combination of both $|0\rangle$ and $|1\rangle$ states simultaneously, each with a complex coefficient whose squared magnitude represents the probability of measuring that outcome. When this superposition is measured, it collapses to either the $|0\rangle$ state—representing an unsuccessful generation of a word—or the $|1\rangle$ state, indicating a successful generation. In this way, a semantic network modeled by qubits can reflect the probabilistic nature of word recall through the superposition of these basis states. At each step, the particle's state evolves through a unitary transformation, which in quantum mechanics corresponds to a rotation of axes in the Hilbert space that does not alter the normalization of the state vector but a change in different components. These transformations are facilitated through quantum operators, where the probabilities of transitioning to neighboring nodes combine constructively or destructively for different quantum paths.[9]

In contrast to classical random walks, quantum random walks exhibit some advantages. First, quantum random walks can exhibit faster spreading or localization than classical random walks. Since classical random walks don't contain superpositions of the different possibilities of generating words, they may only follow a singular path between the nodes to produce an outcome.[10]

Secondly, quantum random walks can provide efficiency in specific algorithms and search problems, such as the Ambainis algorithm, spatial search on grids, hitting time problems, and Grover's algorithm via enhanced exploration, accelerated search, and exponential speedups.[11] Ambainis (2003) highlights how quantum random walks provide computational advantages by enabling faster exploration of solution spaces, particularly in search and decision problems. For example, quantum walks on the hypercube demonstrate an exponential speedup over classical random walks in finding marked elements, as quantum interference guides probability amplitudes toward optimal paths while canceling out non-optimal ones. Additionally, in graph-based search algorithms, quantum walks outperform their classical counterparts by achieving quadratic speedups, mirroring Grover's search algorithm in improving efficiency over brute-force classical methods. One pattern of quantum random walk's natural ability to spread and localize is its slight tendency to have higher probabilities in having a measurement or outcome of basis states that return unanimous measurements.[12] Since the observations of such states may indicate groups of qubits with unanimous measurements, one can represent a semantic network of words through a quantum random walk to detail its behaviors and showcase whether words are released in bursts of categories of words. A novel method of determining the maximum likelihood of producing a specific category, given a semantic corpus, is created to do this. The maximum likelihood estimate (MLE) is a statistical approach used to find the set of parameters that maximizes the probability of observing the given data—in this case, the likelihood of generating certain words from a category. The MLE is defined as

$$(1) \quad \hat{\theta}_{MLE} = \arg\max_{\theta} \mathrm{P}(data \mid \theta)$$

where θ represents the model parameters (e.g., probabilities of word recall), and $\mathrm{P}(data \mid \theta)$ is the likelihood function. The first advantage relates to how quantum walks spread across semantic memory networks, while the second highlights their computational power in efficiently solving complex search and decision problems. Being able to use quantum computation to analyze semantic behavior in semantic fluency tasks can offer new ways of studying cognitive science.

It is important to note, however, that while quantum random walks offer significant advantages in exploring complex networks and enabling faster search algorithms, they also come with notable drawbacks. One major limitation is their sensitivity to decoherence, where interactions with the environment can collapse superposition and entanglement, reducing the quantum advantage and making the system behave more classically. Additionally, designing and implementing appropriate quantum circuits for specific semantic tasks can be complex and may require a high number of qubits and gates, which poses scalability challenges on current noisy intermediate-scale quantum (NISQ) hardware. Furthermore, interpreting the results of quantum walks—especially when applied to abstract cognitive models like semantic memory—can be less intuitive, requiring careful mapping between physical qubit behavior and conceptual representation. These challenges highlight the need for further development in both hardware stability and algorithmic design to fully harness the potential of quantum walks.[13]

In this study, we show how quantum superposition, entanglement, correlation between particles where the state of one instantly influences the state of another, quantum random walks, and auto-differentiation can be used to build a new model of semantic memory that finds the maximum likelihood of generating a given category of words. We demonstrate this using quantum circuits applied to two different examples of semantic word groups. Although each example involves a different task, the model helps reveal patterns in how semantic memory works based on simulated data.

Classical Random Walk:

A classical random walk is a mathematical model that describes a path consisting of a succession of random steps in some mathematical space, such as the integers, the plane, or higher dimensions. Within memory retrieval, classical random walks are versatile tools that can model the randomness of nature. Each step in a random walk is typically governed by a probabilistic rule, with the direction and distance of each step

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being independent of previous steps.[14] In its simplest form, a one-dimensional integer lattice allows a random walker to move one step to the right with probability p and one step to the left with probability 1 – p. This model is used to represent various real-world processes in fields such as physics, economics, and biology, exemplifying phenomena like particle diffusion, stock market fluctuations, and population genetics. The random walk is characterized by examples like the mean squared displacement, and the average squared distance traveled from the starting point over linear time, indicating that the path taken spreads out over time in a predictable manner despite the inherent randomness of each step. A schematic illustrating this concept could show a particle on a one-dimensional line, starting at position zero. As time progresses (t = 1, 2, 3...), the probability distribution spreads outward symmetrically, with peaks flattening and extending toward farther positions. This visual demonstrates how the mean squared displacement increases linearly with time, indicating that, although each individual step is random, the overall spread of the particle's position follows a predictable pattern.

In semantic memory retrieval, a classical random walk can model the process by which concepts and associations are accessed within the network of stored knowledge. Semantic memory encompasses our understanding of facts and general knowledge about the world.[15] It is often represented as a network of interconnected nodes, where each node represents a concept and edges represent associations between them. For example, a network of circles (nodes) labeled with words like "cat," "dog," and "animal," connected by lines (edges) that represent associations—for example, "cat" and "dog" linked to "animal", illustrating how concepts are organized and related within semantic memory. During semantic memory retrieval, the mind can be thought of as performing a random walk through this network: starting from an initial concept, it moves to a connected concept with a certain probability, and this process continues iteratively. The random walk captures the probabilistic and often unpredictable nature of memory retrieval, where the next concept accessed is influenced by the strength and number of associations (edges) leading to it. This model helps explain how people can arrive at seemingly unrelated ideas or memories through associative steps, illustrating semantic memory's flexible and dynamic nature.

Quantum Random Walk:

Classical computing utilizes the binary bits of 0 and 1. In quantum computing, however, quantum bits are denoted as such:

$$(2) \quad |0\rangle = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$(3) \quad |1\rangle = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$|0\rangle$ and $|1\rangle$ are represented as column vectors because of the standard basis states of a two-dimensional complex vector space called a Hilbert space. As mentioned before, the $|0\rangle$ will represent the unsuccessful generation of a word, while $|1\rangle$ will represent the successful generation of a word. Within quantum random walk, a quantum coin (a metaphorical term) guides the evolution of the quantum walker through the generation of words. This coin represents a quantum system that can be prepared in a superposition of basis states. The evolution of the walker involves two main steps: the coin operation and the conditional shift operation. The coin operation applies a unitary transformation to the coin degree of freedom, while the conditional shift operation modifies the walker's position based on the coin state. In a standard quantum random walk with a quantum coin on a line graph, the Hadamard gate (H), an operation that manipulates the state of one or more qubits, similar to the function of logic gates in classical computing. The Hadamard gate specifically puts a qubit into an equal probability superposition, and is often used as a coin operation.[16] The Hadamard gate's mathematical representation is as such:

$$(4) \quad H = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

This gate allows for equal probability distribution within the superposition of words. The Hadamard gate is applied to the coin qubit to create a superposition of the basis states, leading to an equally balanced exploration of both $|0\rangle$ and $|1\rangle$ in subsequent steps of the walk, known as a plus state:

$$(5) \quad |+\rangle = \frac{|0\rangle + |1\rangle}{\sqrt{2}}$$

Quantum Entanglement:

Quantum entanglement is a fundamental concept in quantum computing, where the states of two or more qubits become deeply linked such that the state of one qubit cannot be described independently of the others, even if they are physically separated. This entanglement forms the basis for many quantum algorithms and information-processing tasks. In the context of this study, we use entangled states to represent groups of semantically related words in a memory network. Understanding how these entangled states behave when quantum gates are applied and measured helps us explore how semantic information is stored, recalled, and spread through a quantum-inspired model of memory.

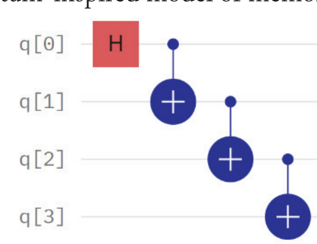

Figure 1: The quantum circuit configuration uses quantum bits (qubits). A three-qubit-entangled state is shown here, with a Hadamard gate at the first qubit and successive CNOT gates (a two-qubit gate that flips the target qubit only if the control qubit is in the |1> state.) placed in numerical order.

There are two different types of entangled states: Greenberger-Horne-Zeilinger states (maximally-entangled states produced by the Hadamard gate through

$$(6) \quad |GHZ\rangle = \frac{|0\rangle^{\otimes n} + |1\rangle^{\otimes n}}{\sqrt{2}}$$

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where an n-qubit GHZ state has the basis states $|0\rangle^{\otimes n}$ and $|1\rangle^{\otimes n}$, denoted as tensor products ($\otimes$)).[17] To produce the GHZ state in quantum computing, we use the Hadamard and CNOT gates successively, as shown in **Figure 1**. By having the measurements of GHZ states entirely collapse to a single state, $|0\rangle$ or $|1\rangle$, the GHZ state measurements exhibit nonlocal correlations and contextuality, meaning that their outcomes depend on the choice of measurement basis in a way that cannot be reproduced by classical probabilistic models. Unlike classical statistics, which rely on independent probability distributions, quantum interference and entanglement ensure that the system's state collapses in a globally coherent manner, allowing for the simultaneous encoding and retrieval of multiple semantic associations in ways that classical models, limited by local probabilities, cannot replicate.

However, in partially entangled states, the measurement does not necessarily destroy the entangled state of others. An example of such a partially-entangled state is

$$\frac{|110\rangle+|101\rangle+|011\rangle}{\sqrt{3}}. \tag{7}$$

If the first qubit of this state (where the first to third qubit is represented from left to right for each basis state) is measured and collapsed to $|1\rangle$, the result is $|1\rangle \otimes (|10\rangle + |01\rangle)$. The measurement can be represented as a tensor product of two or more states, with one being a particular entangled state for two qubits (called a Bell state), $|10\rangle + |01\rangle$. Thus, after measurements of partially entangled states, the result only partially collapses all the basis states.

Methods

Semantic Memory Model:

For this study, we assume that categories are denoted as maximally entangled states for semantically related words. For example, the category "animal" may include "cat," "dog," "horse," etc., which may be modeled as Figure 2A. To signify a semantically related category in quantum computing, we use the formation of the GHZ state to create a superposition and a GHZ state between two or more qubits in Figure 2B. A qubit is shared by one circle, which represents a GHZ state between multiple qubits. Thus, a qubit must not share more than one semantic category.

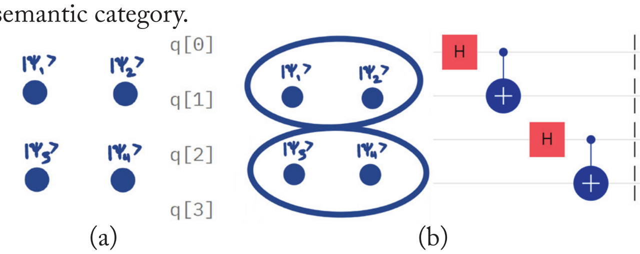

Figure 2: Each of the four qubits represents a word with a state $|\psi\rangle$ that represents a superposition of the word generated and not generated (A). In this example, $|\psi1\rangle$ and $|\psi2\rangle$ belong to one category, while $|\psi3\rangle$ and $|\psi4\rangle$ belong to a second category. Within semantic memory, one can think of simultaneously having the words in both the $|0\rangle$ and $|1\rangle$ state as a probability of recalling or not recalling the word successfully. When making categories with words, we consider separate Hadamard gates to indicate the entanglement of an individual group (B).

In the semantic fluency task, patients are asked to generate a specific category of words within a certain time frame. The expected correct combinations of words are represented through the ideal state, which contains the possible correct combinations of basis states. For example, a generation of the category of subjects would be expected to include "math," "science," "history," etc. After creating the semantic network representing the collection of words by their semantic meanings, we run a quantum random walk by adding an extra qubit to the system. By applying an H gate in **Figure 3**, the superposition either collapses to a $|0\rangle$ (an unsuccessful recall of a word) or a $|1\rangle$ (a successful recall of a word). The CNOT gates are then ordered so that the control is on the extra qubit, while the NOT part of the CNOT gates is on the qubits themselves in a zig-zag consecutive order to model the walker's next "steps."

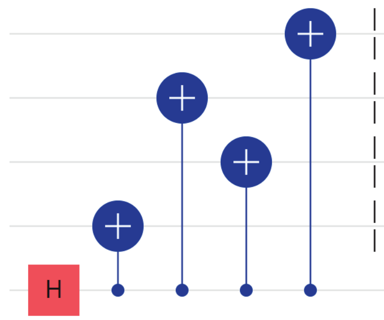

Figure 3: If we consider the system to have four qubits, a fifth qubit (extraneous) is added to apply the quantum coin, the Hadamard gate. The collapse of this equal-probabilistic superposition then induces the CNOT gates where the control is applied to the fifth qubit instead, creating the "random walk behavior."

Like the maximum likelihood function,[8] I created the quantum analog of this version. Instead of manually differentiating the likelihood function, we use a computer-based approach via automatic differentiation, a computational technique for computing derivatives of functions through a numerical approach in machine learning, optimization, and scientific computing.[14]

Then, I applied automatic differentiation on the quantum random walk through the specific RX and RZ gates with different rotations (Θ) on the Bloch sphere, a representation of a single qubit's quantum state as a point on a 3D sphere, in Figure 4A. Finally, we measure all of the qubits in Figure 4B that are only within the semantic network and record their results, where each qubit or word has either collapsed to a $|0\rangle$ or a $|1\rangle$. The resulting state from this measurement is called the measurement state.

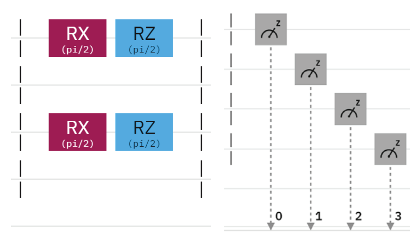

Figure 4: The input Θ for both the RX and RZ gates is $\pi/2$ (A). These gates are applied to the first and third qubits from Figure 2B. All the qubits (excluding the extraneous qubits) are then measured along the Z axis on the Bloch sphere (B).

We take the inner product of the ideal and measured state to calculate the likelihood of generating the prompted category after differentiation. This process is repeated through different Θ's that represent the angle between the ideal state and the measured state on the Bloch sphere. The value of Θ that brings the two-state vectors closest together on the Bloch sphere corresponds to the maximum absolute value of their inner product, representing the highest likelihood of generating the desired state. Thus, the differentiation on the quantum computer produces different values of the likelihood value, each associated with a different Θ. Through repeated-calculated likelihood values (By running each quantum circuit configuration on the Quantum Composer Software, 1,000 shots/trials of the circuit were completed), we find the estimated optimal Θ that leads to the most significant absolute value of the maximum likelihood that can be found.

While traditional statistical models rely on independent probabilities and associative strength between words, these approaches don't necessarily capture the idea that multiple concepts can be activated simultaneously and influence one another non-linearly, like how semantic memory does. By leveraging quantum random walks, we introduce context-dependent retrieval dynamics, where word associations emerge through quantum interference rather than fixed probability distributions. This allows for a more flexible and parallel exploration of semantic categories. Moreover, automatic differentiation on quantum gates (RX and RZ) enables adaptive learning within the quantum model, optimizing category associations based on empirical recall patterns, a feature that classical approaches cannot easily replicate.

For assembling each quantum circuit, we follow Figure 2, the user initializes qubits to represent individual words, then applies the Hadamard and CNOT gates to entangle semantically related words into GHZ states, forming category-based semantic clusters. Next, as shown in Figure 3, an additional qubit (quantum coin) is introduced, and a Hadamard gate is applied to place it in superposition. This extra qubit then controls a series of CNOT gates in a zig-zag pattern, simulating a quantum random walk across the semantic network. Finally, drawing from Figure 4, RX and RZ gates are applied to selected qubits to implement parameterized transformations, and all relevant qubits are measured along the Z-axis to observe final states. By analyzing these measurement outcomes and computing the inner product between the ideal and measured states, users can evaluate the likelihood of successful category generation, completing a fully integrated quantum semantic memory circuit.

Result and Discussion

Corpus Setup:

For this experiment, simulated corpora of words were created to test the semantic memory model. Each corpus contains 5 and 6 words. Since the categories are assumed to be maximally entangled, we also think the words within the category do not correlate with extraneous categories. For example, the first corpus may be divided into an "animal" category with the first, second, and third qubits in Figure 5A that each represents "cat," "dog," and "bird," respectively. The second category may be "subject," where the latter two qubits each represent "math" and "science." If you suppose that one remembers only "cat" and "math," the successfully generated words would collapse the second and fifth qubits to a $|1\rangle$. Thus, the represented quantum state would be $|10010\rangle$, where the 1's and 0's are read from left to right.

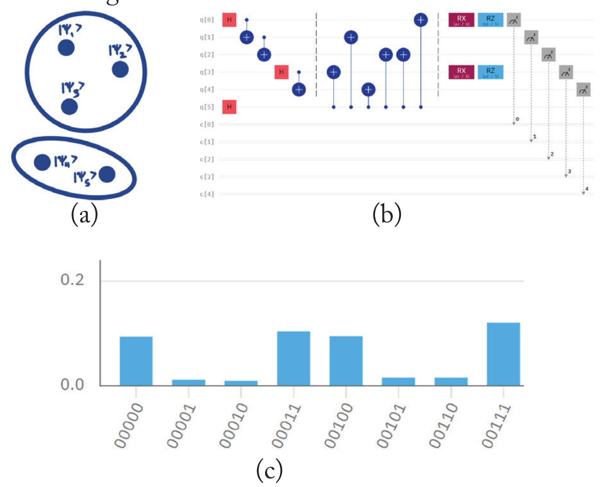

Figure 5: The first example involves two categories: "animal" and "subject" (A). $|\psi_1\rangle$ = "cat", $|\psi_2\rangle$ = "dog" and $|\psi_3\rangle$ = "bird" belongs to the "animal" category, while $|\psi_4\rangle$ = "math" and $|\psi_5\rangle$ = "neuroscience" belongs to the "subject" category. The quantum circuit configuration shows the category formation, quantum random walk, auto-differentiation, and measurement (B). The orange squares represent the Hadamard gates, the dark blue gates with a white cross represent the CNOT gates, the crimson gates represent the RX gate, the light-blue gate represents the RZ gate, and the gray squares represent measurements of each qubit in B. The probability of receiving each basis state from running the quantum circuit 1,000 shots is also shown, where each basis state is read from top to bottom (C). Basis states that contained a variation of 1's and 0's in $|\psi_1\rangle \ldots |\psi_3\rangle$ and only 0's in $|\psi_4\rangle$ and $|\psi_5\rangle$ were analyzed since the semantic fluency task in this example was only concerned with generating words from the "animal" category ($|\psi_1\rangle \ldots |\psi_3\rangle$).

Quantum Circuit:

Now, if we suppose that the given semantic fluency task is to generate only "animals," any possible memory retrieval of words from the "animal" category is acceptable. The ideal state that represents these combinations is

$$\frac{|11100\rangle+|11000\rangle+|01100\rangle+|10100\rangle+|10000\rangle+|01000\rangle+|00100\rangle}{\sqrt{7}}. \quad (8)$$

Figure 5B shows the associated quantum circuit: The Hadamard and CNOT gates of the first three qubits and the last two qubits represent their categories; an extra Hadamard gate is applied to the sixth qubit to create the quantum coin for the random walk. Next, the RX and RZ gates are placed on the first and fourth qubits (where the Hadamard gate was placed), which, in this case, has an input rotation of $\pi/5$; Lastly, we measure each qubit except the sixth qubit and repeat this process for 1,000 shots. By testing various angles via automatic differentiation, Figure 5C shows the distribution of outcome basis states using the $\pi/5$ angles yielded the highest probability of generating "animal"-based words.

Maximum-Likelihood Calculations:

With an output of -0.544, $\pi/5$ provides the highest absolute value of the maximum likelihood estimate. Thus, out of

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the 2^5 = 32 different possibilities, our maximum likelihood for generating "animal" words under the correct instance is 37.3%, and the combined probability of each of the ideal basis states: $|11100\rangle$, $|10100\rangle$, $|00100\rangle$, etc. However, out of the basis states produced, the highest probabilities were 0.095, 0.104, 0.095, and 0.12, each from the basis states $|00000\rangle$, $|11000\rangle$, $|11000\rangle$, and $|00100\rangle$, respectively. From this simulation, the random walk mostly resorted to remembering all the "animal" category words, no words, or an adjacent pairing of words based on the most probable basis states.

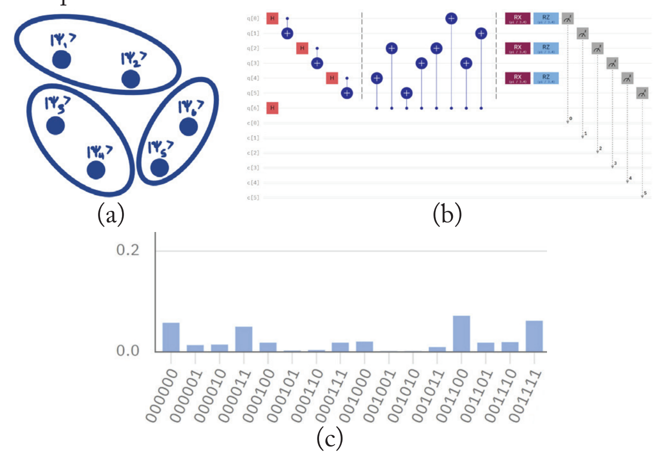

Figure 6: The second example involves three categories: "animal," "subject," and "instrument" (A). $|\psi_1\rangle$ = "panda" and $|\psi_2\rangle$ = "elephant" belongs to the "animal" category; $|\psi_3\rangle$ = "biology", $|\psi_4\rangle$ = "computer science" belong to the "subject" category; and $|\psi_5\rangle$ = "piano", $|\psi_6\rangle$ = "violin" belongs to the "instrument" category. The quantum circuit configuration shows the category formation, quantum random walk, auto-differentiation, and measurement (B). The probability of each basis state from running the quantum circuit 1,000 shots is also shown (C). Basis states that contained a variation of 1's and 0's in $|\psi_1\rangle \ldots |\psi_4\rangle$ and only 0's in $|\psi5>$ and $|\psi6>$ were analyzed since the semantic fluency taskin this example was only concerned with generating words from the "animal" and "subject" category ($|\psi_1\rangle \ldots |\psi_4\rangle$).

Similarly, we apply the model to a second example, where instead, there are two qubits each for three categories in Figure 6A (for example, "animal": "cat," "dog"; "subject": "math," "history"; and "instrument": "piano," "guitar"). This time, we can set an instance where the categories wanted from the semantic fluency task are now used to generate words from both the "animal" and "subject" categories but not the "instrument" category. According to Figure 6a, our ideal state is the highest probabilities equally distributed across basis states with a combination of 1's on the first four qubits.

After 1,000 shots of the quantum circuit in Figure 6b, the resulting angle that led to the maximum likelihood estimate was π/3.4, which yielded -0.592. Out of the 2^6 = 64 different possibilities, our maximum likelihood for generating "animal" and "subject" words under the correct instance is 33.1%, while the basis states that had the highest probabilities were 0.061, 0.056, 0.078, and 0.065, each from the basis states $000000\rangle$, $|110000\rangle$, $|001100\rangle$, and $|111100\rangle$, respectively. Thus, when running the quantum random walk on simulated corpora, we see that semantically-related words are likely to be remembered in pairs or groups of words.

Memory Retrieval Connections:

In the second example, the highest probable basis states also show that generating no words, all the words from the wanted categories, or pairing words is more probable. Specifically, the generation of pairings of words is evident in the first example with $|11000\rangle$ and $|00100\rangle$, along with $|110000\rangle$ and $|001100\rangle$, in the second example. Therefore, these results suggest that memory retrieval may be a direct reflection of being released in "bursts" of words. Additionally, since generating all of the words within the asked category was also most probable for both examples, recalling one "word" may most likely cause an extra word to be semantically recalled, but initiating the "burst" in the first place could be more difficult. Further, if one cannot generate a semantically related word in the first place, there will be no "bursts" and thus a high probability of the $|000000\rangle$, state, as shown in Figure 6B.

One note on the quasiprobabilities in Figure 6C is that the shape of the probability distribution of the basis states is symmetric. In other words, generating words in the incorrect category have similar probabilities to their correct counterparts. However, this may be expected since using the Hadamard gate as the quantum coin ensures an equal probability of collapsing to the $|0\rangle$ or the $|1\rangle$ state for each walk step.

Conclusion

The behavior of semantic memory was analyzed under simulated data of the semantic fluency task, using quantum random walks, instead of the usage of classical random walk models. The results of the semantic memory model used in this procedure may support the postulate that semantic words are recalled in groups, and pauses between those groups may be supported by the results of the semantic memory model used in this procedure. In particular, the outcome of high probabilities in generating correct words in pairs suggests that the postulate holds if memory retrieval is truly a random process.

In addition, the opposite is true for generating incorrect words. A successful interpretation (meaning that the words most semantically retrieved from the simulation model mirror those of the corpora) of the results showcases the possibility of using quantum computing to return the maximum likelihood estimates for semantic memory retrieval. The corpora were translated into quantum-entangled graphs using superposition and entanglement, where a quantum random walk was applied. The semantic memory model also utilized a new method that catered to the classical case's maximum-likelihood function by considering ideal and measured states. Based on the semantic memory model, the maximum likelihood was calculated to determine the ϴ that produces the maximum probability of generating correct categorical words under the semantic fluency task.

The frontier of quantum computing models for behavioral science also poses additional areas of exploration. The experiments used in the examples above are hypothetical, simulated scenarios of an equal probabilistic model of the brain's ability to generate a word. In this case, all the quantum circuits were created on IBM's Quantum Composer software, which allows

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you to design, simulate, and run quantum circuits on quantum simulators. Embedded within the software was Qiskit. To run the circuit, I utilized their gate features and measurement operations and submitted the job to their quantum simulator. However, the human brain is often more complex than flip-of-a-coin mechanics. Categories of words exhibit ambiguous distinctions between each other, and their semantic-relatedness can still be a subjective process. However, an attempt to account for possible words that may share more than just one category (for example, the color "red" may be associated with "car" and "color" at the same time) can invite more accurate predictions and understandings of semantic memory retrieval.

One way to control these confounding factors may be to use partially-entangled qubits instead of maximally-entangled qubits. A second proposed way is to use different quantum search algorithms exhibiting different Markovian probabilistic properties. Lastly, one can use the exponential speedup of quantum computation in applying larger datasets of corpora that actual patients have released. All of these future alternatives may be optimistic since partially-entangled qubits allow more flexible, context-sensitive relationships between words, reducing the rigidity of maximally-entangled states and better modeling real-world semantic variability. Using alternative quantum search algorithms with different probabilistic behaviors can tailor the exploration of semantic space to more accurately reflect how humans retrieve information. Additionally, leveraging the exponential speedup of quantum computation enables the analysis of larger, real-world corpora from patients, improving the model's scalability and applicability to actual cognitive data This demonstration was through simulated corpora, but accurate data may suggest different findings regarding semantic memory retrieval. Regardless, quantum computing reflects a prospective choice for individuals to analyze semantic memory in a novel way that could open new possibilities within cognitive psychology, in addition to current methods that utilize classical random walks.

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