LLM Reconstructions of the Text Narrative With and Without the Time Markers

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Annotation

Traditional narrative structure is often based on a linear time sequence of events. However, there are many books in which the time axis is replaced by a system of cause-and-effect and associative relationships between events. Examples of this approach include works such as *Cloud Atlas* (Cloud Atlas) by David Mitchell, The Torah and *The Master and Margarita* by Mikhail Bulgakov or the Hebrew Tora. This article presents a model for text reconstruction based on a network structure, in which cause-and-effect and associative relationships act as the main coordinates. The presented model uses large language models (LLMs). The methodology involves the creation of a semantic network using LLM and subsequent text reconstruction, which is illustrated by the example of the reconstruction of a short story consisting of two plots. We consider how plots can be modeled through such networks without regard to traditional chronological time. The article presents a mathematical model that describes the process of reconstruction and the paradoxes of time that arise as a result of the mixing of associative and causal connections, which leads to the creation of new spaces of meaning. This model allows us to reconstruct a complete narrative without the need to take into account chronological time, which opens up new opportunities for analysis, reconstruction, modification and interpretation of texts.

Keywords: Text reconstruction, hypergraphs, cause-and-effect relationships, associative connections, time paradoxes, nonlinear storytelling, world reconstruction, LLM.

1. Introduction

Literature has evolved over the centuries in the context of time, where storylines unfold sequentially in chronological order. However, many works exhibit a non-linear structure in which time frames play a secondary role or are ignored altogether. In such a structure, following the logic of causality and associations becomes most important. Texts that challenge the linear flow of time and offer associative connections instead of temporal ones have become the object of deep literary and philosophical study today, in the postmodern era. In modern literature, works continue this tradition, offering texts with non-linear structures, where associative connections between events play a crucial role. One striking example is the novel by David Mitchell *Cloud Atlas*, where multiple storylines intertwine and time seems to disappear, leaving the reader to explore the causal and associative connections between the storylines. The main emphasis in such works is on the connections between individual events, and not on their temporal sequence. In fact, a causal-associative event is created, where cause and effect can change places in the reader's perception. Instead of traditional time, plots are organized based on cause-and-effect and associative chains, which can be modeled using hypergraphs.

This paper proposes a mathematical model that makes it possible to reconstruct texts based on such networks. In one of the author's works, [Lande, 2024], it is shown how LLMs are used to create semantic maps from short texts, after which these texts are reconstructed following slight modifications to these maps for marketing purposes. We will consider how such networks of connections can be used to reconstruct texts and create new “worlds” of storytelling, where time as a concept disappears, and its place is taken by the structure of cause-and-effect and associative connections. It is known that cause-and-effect (causal) relationships play an important role in structuring the text. Works [Runge, 2018], [Egami, 2022] about causation offer a mathematical apparatus for analyzing such connections, which has become the basis for many studies in the field of cognitive sciences.

In this paper, we propose an approach based on hypergraphs and large language models for extracting and analyzing the concepts and relationships that form the structure of text, where time loses its traditional role. Recall that hypergraphs are a generalization of traditional graphs, where one hyperedge can connect many nodes. This makes them suitable for analyzing complex relationships such as symbolic and associative connections in literary texts. The works of [Dhanya, 2023] and [Criado-Alonso, 2022] show how hypergraphs can be applied to literary analysis by modeling connections between characters and events. These works highlight the advantages of hypergraphs over traditional graphs, especially in the context of multilayer and associative structures.

The idea of using hypergraphs in text reconstruction is the ability to model complex relationships between concepts. Hypergraphs can represent many relationships between text elements, and the use of LLM allows us to automatically extract these relationships from text. This is especially true in the context of analyzing large volumes of data, where traditional methods may not be effective enough.

We will also consider the paradoxes that arise when associative and causal connections are mixed, and suggest ways to interpret these paradoxes.

In the era of information technology and artificial intelligence, the reconstruction of text and related structures is becoming an urgent task in various fields, including literature, biology, cybernetics, and artificial intelligence. In this context, hypergraphs are a powerful tool for modeling complex relationships between concepts and events, which, unlike conventional graphs, allow us to take into account multiple connections between nodes, which is critical when analyzing multi-layered texts.

Using LLM to extract semantic connections opens up new horizons for text analysis and reconstruction. Large language models (LLMs) such as GPT and BERT have shown significant success in the task of extracting concepts and their relationships from texts. The work [Minaee, 2024] provides an overview of transformers, which formed the basis of modern LLMs and have become the main tool for extracting semantic relationships from texts. The works of [Mekrache, 2024], [Tsaneva, 2024], [Lande, 2023] show how such models can be used to analyze semantic relationships between words, concepts, and events, which opens up new opportunities for automatic text reconstruction.

2. Methodology

2.1. Formation of a hypergraph of concepts and connections in the source text via LLM

Let's assume that each concept from the text, be it an event, a character, or another entity, can be represented as a node (vertex) in a graph. The connections between these nodes can be of two types:

1. Cause-and-effect relationships – a relationship in which one event causes another.
2. Associative connections – less formal relationships based on shared ideas, themes or concepts.

Thus, the text can be represented as a network (hypergraph) with two types of edges:

— Edges are connecting concepts along cause-and-effect chains.

— Edges that connect nodes based on associations (such as common keywords, geographic locations, or ideas).

The process of creating a semantic network begins with the extraction of concepts and relationships using LLM. In the first stage, the text is divided into sentences, and for each sentence, the LLM identifies key concepts and their relationships. These concepts become nodes of the hypergraph, and the connections between them become hyperedges.

The following steps are expected to be taken to create a semantic network:

1. Extracting sentences: using LLM, the text is broken down into individual sentences for further analysis.
2. Definition of concepts: for each sentence, LLM highlights key concepts.
3. Defining Relationships: LLM determines associative and cause-and-effect relationships between selected concepts.
4. Construction of a hypergraph: a hypergraph is created where nodes represent concepts and hyperedges represent connections between them.

Network structure

Let the text consist of many events that can be denoted as $E_1, E_2, \ldots, E_n$, where E_i is an event or part of a text that can be connected with others through cause-and-effect and associative relationships.

Every event E_i appears as a node v_i in the column $G = (V, C, A)$, Where:

— $V = \{v_1, v_2, \ldots, v_n\}$ – a set of nodes (events).

— $C \subseteq V \times VC$ – a set of oriented edges (cause-and-effect relationships). If there is a cause-and-effect relationship between two events, then it is represented as an oriented edge $(v_i, v_j) \in C$, Where v_i – is the reason, and v_j – is consequence.

— $A \subseteq V \times VA$ – a set of unoriented edges (associative connections). If events v_i and v_j are connected by associative logic, then an edge is added $(v_i, v_j) \in A$.

Thus, a network structure is defined in which the vertices are connected by two types of connections: cause-and-effect and associative. To model such a network, you can use hypergraphs, since some events can participate in several connections at once (both cause-and-effect and associative). A hyperedge can connect more than two concepts, allowing for complex intersections of storylines and themes.

2.2 Hypergraphs for modeling concepts and relationships

Unlike simple graphs, where connections exist between two elements, hypergraphs allow you to model complex connections between many elements, which is especially important when analyzing works such as "The Torah" or "The Master and Margarita", where several events can be simultaneously connected. through associations or cause-and-effect relationships.

Hypergraph $H = (V, E)$ consists of many nodes $V = \{v_1, v_2, \ldots, v_n\}$, representing text concepts, and hyperedges $E = \{e_1, e_2, \ldots, e_m\}$, where each hyperedge $e_i \in V$ connects one or more concepts at the same time.

Each hyperedge e_i can represent two types of connections:

— Associative connections $A \subseteq V \times VA$, which form semantic or thematic relationships between concepts.

— Cause-and-effect relationships $C \subseteq V \times VC$, which express dynamic relationships between events or concepts.

For each hyperedge $e_i \in V$ let's determine the weight coefficients $w_A(e_i)$ and $w_C(e_i)$, representing the degree of associative and causal connections between nodes.

2.3 Combining two types of links

Now, to model the process of text reconstruction, we need to take into account both associative and cause-and-effect relationships. Consider the combined weight $w(e_i)$, which can be expressed as a weighted sum of two types of connections:

$$w(e_i) = \alpha w_A(e_i) + \beta w_C(e_i),$$

where α and β are parameters that control the contribution of associative and causal connections. It is important that when $\alpha = \beta$ we achieve equality between associative and causal relationships, which can lead to the paradoxes described below.

At a certain stage of network research, it is possible to “equalize” associative and causal connections, considering them as equivalent. Equalizing connections can lead to a situation where associative transitions will be equal to or even exceed the significance of cause-and-effect transitions, which will cause paradoxes in reconstruction.

2.4 Construction of a network based on a hypergraph

The hypergraph is translated into a regular network (graph), where each hyperedge is transformed into a set of edges between its nodes. If a hyperedge connects more than two nodes, it is split into several edges and the weights are recalculated. This allows us to form a network $G=(V,E')$, Where $E'\in V\times V$ — a set of edges between concepts with their weighted connections $w(e_i)$.

Errors in the construction of primary networks can occur when there is excessive mixing of associative and cause-and-effect relationships. For example, if LLM misclassifies associative connections as causal when extracting concepts and relationships, this can distort the network structure and lead to temporal paradoxes in text reconstruction.

2.5. Application example

Suppose the following key events are present in the text E_1, E_2, E_3, E_4, where:

— E_1 – reason for E_2,

— E_2 is associated with E_3,

— E_4 – consequence E_3.

The network representation of this fragment of the work will be as follows:

— Nodes: v_1, v_2, v_3, v_4.

— Cause-and-effect relationships: $(v_1 \to v_2)$, $(v_3 \to v_4)$.

— Associative connections: $(v_2 \leftrightarrow v_3)$.

Thus, text reconstruction can rely on transitions through nodes $v_1 \to v_2 \leftrightarrow v_3 \to v_4$.

2.6. Cause-and-effect relationships at the micro level

To study the network more deeply, we can analyze the micro transitions that occur within each link. Let every event E_i can be broken into small pieces $f_{i1}, f_{i2}, \ldots, f_{im}$, each of which may have its own micro-causal connections.

So, between fragments of two events E_i and E_j there may be micro-causal connections:

$$f_{i1} \to f_{j2}.$$

These micro transitions allow you to trace in detail the chain of events, including cause-and-effect dependencies at the level of concepts and symbols within one event.

3. Paradoxes of time and their influence

To analyze time paradoxes, it is necessary to take into account that causal connections must support the axiom of causality, but associative connections must not. In case of violation of this axiom, it is possible to identify nodes involved in cyclic dependencies.

3.1. The Paradox of Associative Over-validity

Let's say we have two events:

— E_1 (for example, a key event leading to a revolution),

— E_2 (event resulting from this revolution).

Events are arranged in time so that E_1 happen earlier E_2. However, in the narrative between these events, there is an associative connection with the third event E_3, which by its nature is associated with E_2 (for example, through general themes or symbolism).

If the associative connection $(E_1 \leftrightarrow E_3)$ turns out to be quite strong, then the reconstruction of the text can lead to the fact that E_3, associated associatively with E_1, will be interpreted earlier in the network than E_2, although in real-time E_2 it should be earlier.

Thus, the associative connection seems to "displace" the consequence E_2 to a later position, resulting in time inversion. It is important to note that when reconstructing a text using a network of associative connections, the reader may perceive the result as the reverse of the causal chain.

A model for resolving the Paradox of Associative Over-validity

The paradox of associative super significance occurs when the associative connection between events is so strong that it disrupts the chronological sequence of the narrative. To resolve this paradox, it is necessary to take into account the weight of both causal and associative links, but to introduce a mechanism that ensures that chronological structure is preserved when it is relevant to the context.

Let $G=(V,E)$ — hypergraph of events, where:

— $V=\{v_1,v_2,v_3\}$ — a set of event nodes representing a key event v_1, event-result v_2, and associative event v_3,

— $E=\{C,A\}$ — set of hyperedges:

- $C(v_1 \rightarrow v_2)$ — causal connection between v_1 and v_2,
- $A(v_2 \leftrightarrow v_3)$ — associative connection between v_2 and v_3.

Weight of connection between events:

— Causal connection $w_C(v_1,v_2)$ — reflects the influence of one event on another.

— Associative connection $w_A(v_2,v_3)$ — reflects the thematic or symbolic similarity of events.

Enter an additional parameter $h(v_i,v_j)$, representing the chronological importance of the connection, which is enhanced if the order of events is critical to the narrative. This parameter can be binary: $h(v_i, v_j) = 1$, if chronology is important, and $h(v_i, v_j) = 0$, if the order of events is not critical.

The total weight of the connection between events is defined as:

$$w(v_i, v_j) = \alpha w_C(v_i, v_j) + \beta w_A(v_i, v_j) + \gamma \cdot h(v_i, v_j) w(v_i, v_j),$$

where α, β, and γ are coefficients reflecting the priority of causal, associative and chronological connections, respectively. When chronology is important, γ increases, which prevents associative displacement of events.

Moreover, if the chronological connection is important ($h(v_1, v_2) = 1$), then even if $w_A(v_2, v_3) > w_C(v_1, v_2)$, then the order of events must be maintained according to the causal connection.

Consider the example of Alice and Bob:

1. Initial events:
   - v_1: Alice is looking for the key (key event associated with the revolution),
   - v_2: Bob finds the key (result of the revolution),
   - v_3: Alice meets a cat (an associative event associated with the symbolism of the key).
2. Link weight:
   - $w_C(v_1, v_2) = 0.7$ (causal connection: searching for the key leads to finding it),
   - $w_A(v_2, v_3) = 0.8$ (associative connection: the cat is symbolically connected with the key),
   - $h(v_1, v_2) = 1$ (chronology is critical: finding the key must follow the search for it).
3. Total link weight: We use a model with α=0.5, β=0.4, and γ=0.6:

   $$w(v_1, v_2) = 0.5 \times 0.7 + 0.6 \times 1 = 0.95$$

   $$w(v_2, v_3) = 0.4 \times 0.8 = 0.32$$

4. Reconstruction: Despite the strong associative connection between the events v_2 and v_3, the order of events is maintained due to the chronological importance of the connection $v_1 \to v_2$:
   - Alice first looks for the key in the forest,
   - Bob finds a key in the city
   - Alice then meets a cat associated with the symbolism of the key.

As a result of the final reconstruction using, we get the text:

Alice wandered through the forest, looking for a long-lost key. Meanwhile, Bob, after much effort, finally found the key in the bustling city. After the key was found, Alice met a strange cat who seemed to know something about her quest.

3.2. The paradox of inversion of logic

One of the paradoxes is the inversion of logic (or inversion of causality), when associative connections dominate over causal ones (that is, $\alpha \gg \beta$), events can be reconstructed in reverse order, leading to an inversion of causality. For example, if the concept v_1 is associated with the concept v_2, but v_2 is a consequence v_1, strong associative connections can lead to v_2 will be reconstructed earlier v_1:

$$w_A\left(v_1,v_2\right) > w_C\left(v.,v_2\right) \Rightarrow v_2 \rightarrow v_1.$$

This paradox can be described mathematically through a change in the direction of the edges with a predominance of associative connections.

A paradox arises when associative connections are given more weight than causal ones, despite their less obvious causal role.

Paradox resolution model

To resolve the paradox, a mixed model is proposed, where each connection receives a common weight $w\left(v_i,v_j\right)$, depending on both causal and associative factors. Let us remind you where α and β — these are coefficients reflecting the priority of causal and associative connections, respectively. Values α and β are chosen in such a way as to resolve the conflict: if the inversion of logic is not acceptable, the value is strengthened α; if associations are important, increases β.

Thus, the inversion paradox is resolved by finding a balance between causation and association.

Let's look at the Alice and Bob example again:

1. Initial data:
   - Alice is looking for a key in the forest (v_1),
   - Bob loses his key in the city (v_2),
   - Associative link: key (the link between Alice and Bob events through an object),
   - Causal connections: Alice searches for the key → finds the key → meets the cat; Bob loses his key → meets a dog.
2. Definition of weights:
   - Causal connection: $w_c(v_1 \rightarrow v_3) = 0.7$ (searching for the key leads to finding and meeting the cat),
   - Associative connection: $w_A(v_1 \leftrightarrow v_2) = 0.8$ (the key is the associative connection between the plots of Alice and Bob).
3. Weight of the final connection:

   We use a model with α=0.5 and β=0.5:

   $w(v_1,v_3) = 0.5 \times 0.7 + 0.5 \times 0.8 = 0.75.$

Events are associated associatively through a key, which somewhat inverts the cause-and-effect dependencies.

4. Reconstruction: Because associative links have more impact, the story starts with Alice, but quickly switches to Bob via an associative link (key):
   - Alice is looking for the key in the forest, but instead of immediately finding it and meeting the cat, it switches to the story of Bob, who loses the key in the city.
   - Then, through Bob the dog, the story switches back to Alice, who meets the cat in the forest.

As a result of the reconstruction we get a short text:

Alice was walking through the forest, looking for her lost key, when at the same time in the city Bob lost his key and became upset. Bob decided to look for the key and unexpectedly came across a dog who helped him. Meanwhile, in the forest, Alice finally found her key, and then a cat approached her, holding in its paws the shiny key that she had lost.

3.3. The chicken-egg paradox

Another paradox is the situation when cause and effect can change places in different parts of the text. If the weights of associative and causal connections are close:

$$w_A(v_1,v_2) \approx w_C(v_\cdot,v_2),$$

then a situation may arise when two events change places: the effect becomes the cause, and the cause becomes the effect. This leads to cyclical dependencies in the reconstructed text, which violates the traditional understanding of causality:

$$w_A(v_1,v_2) \approx w_C(v_2,v_1) => v_1 \leftrightarrow v_2.$$

An example of a solution to the chicken-egg paradox

Let v_A — an event in which Alice looks for a key, and v_B is the event in which Bob loses the key. If both events can be interconnected through causal and associative connections, but one event depends on the other, a paradox arises: $v_A \leftrightarrow v_B$ $v_B \leftrightarrow v_A$ — two possible communication options.

To resolve the paradox, we consider the hyperedges with the largest weight:

$$\operatorname*{argmax}_{e_i}\{w(e_i)\}$$

We select the hyperedge with the highest probability of influence (either associative or causal) and build a reconstruction based on this edge.

If the weights of the edges are equal or close, an additional criterion can be used, for example, the associative strength of the context (connection with higher level nodes). In general, when we have a cyclical causality then we could look for or imply the higher entity that created both entities in question.

An example solution with heroes Alice and Bob

1. Initial data:
   - — Alice is looking for a key in the forest (v_1),
   - — Bob loses his key in the city (v_2),
   - — Associative connections: key, animals (Alice's cat, Bob's dog),
   - — Causal connections: finding the key leads to Alice meeting a cat, and losing the key leads to Bob meeting a dog.
2. Hypergraph:
   - — Nodes: v_1= Alice is looking for the key, v_2= Bob loses his key, v_3= Alice meets a cat, v_4= Bob meets a dog.
   - — Hyperribs: $e_1=\{v_1,v_3\},e_2=\{v_2,v_4\},e_3=\{v_1,v_2\}$ (associative connection through a key).
   3. Hyperedge scales:
   - — $w(e_1)=0.7$ (Alice meets the cat after searching),
   - — $w(e_2)=0.8$ (Bob meets the dog after losing his key)
   - — $w(e_3)=0.6$ (associative connection through a key).
4. Resolution of the paradox:
   - — Because $w(e_2)>w(e_1)$, Bob's event comes first (he loses his key and meets a dog).
   - — Then, using the associative link through e_3, we switch to Alice's story, where she finds the key and meets the cat.

A short example of the reconstructed text:

Bob was walking through the city when he suddenly noticed that he had lost his key. He was upset, but on the way he met a dog who came up in a friendly manner and brought something shiny. At the same time, Alice, walking through the forest, was looking for the key that she had lost. She suddenly saw a cat sitting on a branch and holding a key in its paws, exactly the one she was looking for.

3.4. The paradox of information noise

Equalization of connections can lead to the emergence of information noise, when associative connections begin to dominate, thereby "eroding" the causal structure. As a result, the text may end up being reconstructed in a more abstract form, where the logic loses its obviousness and the plot becomes less coherent.

3.5. Modeling Paradoxes

To model paradoxes when equalizing connections, you can consider the network as a stochastic process, where each connection (v_i, v_j) activates with a probability depending on its weight:

$$P(v_i, v_j) = \frac{w(v_i, v_j)}{\sum_k w(v_i, v_k)}$$

In this case, the activation of associative connections will lead to the "blurring" of causal paths and the inversion of some transitions, which can be assessed through a change in the probability of chains.

4. Text reconstruction from a hypergraph

Text reconstruction is based on the sequential reconstruction of events based on a hypergraph of connections extracted using LLM. Using weights for associative and causal connections, we can determine the optimal order of events, which does not depend on linear time, but preserves the internal logic of the text. Based on the weights of the hyperedges, we can determine the optimal order of sentences and concepts, which allows us to create new text that reflects the original meaning. Based on the weights of connections, the program can rearrange storylines, avoiding the traditional chronological order and relying solely on cause-and-effect and associative relationships. Thus, the text will be reconstructed in accordance with the logic of interactions of concepts, and not time.

4.1. Formal model of text reconstruction

The essence of text reconstruction is to find paths in a network of concepts, relying on both cause-and-effect relationships and associative ones. To do this, we have already defined weighting functions that will control the recovery process — $w_C(v_i, v_j)$, $w_A(v_i, v_j)$ and $w(v_i, v_j)$.

The task of text reconstruction comes down to finding such a path in the graph G, which maximizes the sum of the weights w_C and w_A. To do this, you can use the dynamic programming method or a greedy algorithm, to find the strongest chains of connections.

4.2. Reconstruction with LLM

Reconstructing text from a hypergraph with multiple story threads can be done by following nodes (concepts) and hyperedges (links) in the hypergraph that represent different events, characters, and places. There are two types of connections in a hypergraph: causal (cause-and-effect) and associative (connections by meaning or context).

The process of text reconstruction from a hypergraph with several chains:

1. Initialization: We start from a certain vertex (concept) in the hypergraph. This could be a character, an event, or a location, depending on where one of the storylines begins.

2. Hyperedge selection: LLM evaluates connections between the current vertex and other vertices. If we encounter a causal hyperedge, we follow it, since it denotes the logical development of events. If an associative hyperedge is encountered, LLM evaluates the context and decides how appropriate the associative link is to proceed.
3. Path construction: Following the hyperedges with the largest weight, LLM constructs a sequence of concepts (storyline). The algorithm can switch between storylines if associative links lead to another character or location.
4. Completion of reconstruction: The process continues until all possible connections have been used or the ending of the plot has been reached.

Example story chain:

Storyline 1 (Alice):

— Character: Alice
— Events: Alice is looking for a key → Alice finds a key → Alice meets a cat.
— Locations: Forest, House

Storyline 2 (Bob):

— Character: Bob
— Events: Bob loses his key → Bob meets a dog.
— Locations: City, Park

Causal connections:

— Alice is looking for a key → Alice finds a key
— Alice finds the key → Alice meets the cat
— Bob loses his key → Bob meets a dog

Associative connections:

— Alice ↔ Forest
— Bob ↔ City

Example prompt for LLM:

Imagine a text consisting of two storylines. In the first line, the character Alice is looking for a key in the forest and meets a cat. In the second line, the character Bob loses his key in the city and meets a dog. Using a hypergraph with causal and associative connections, reconstruct this text, following the hyperedges with the largest weight. Start with Alice searching for the key and switch between storylines as associations lead to Bob or other events.

Follow these steps:

1. Start with Alice looking for a key in the forest.

2. Construct a chain of events for Alice, taking into account that she finds the key and meets the cat.

3. Switch to Bob when his association with the city or key becomes relevant.

4. Build a storyline for Bob who loses his key and meets a dog.

5. Complete the text when all connections have been exhausted.

Example of hyperedges:

- Causal: Alice is looking for a key → Alice finds a key → Alice meets a cat; Bob loses his key → Bob meets a dog.

- Associative: Alice ↔ Forest; Bob ↔ City.

Create your text following this structure, ignoring time frames and focusing on connections between events and characters.

As a result of processing the prompt, LLM reconstructs the text, starting with Alice looking for the key and following the causal connections. When associations emerge, for example between Bob and the city, LLM will switch to his storyline and continue it, alternating the events of both characters:

Alice walked through the forest, carefully examining every bush and every path. She knew that somewhere there must be the key that she had lost yesterday when she got lost on her way back home. The feeling that she was about to find him did not leave Alice.

Finally, a metallic sheen flashed among the fallen leaves. Alice bent down and happily picked up the old but beautiful key. Her heart filled with relief, but before she had time to hide the key in her pocket, a cat quietly appeared from the bushes. He walked up to Alice, his bright green eyes sparkling, and, as if understanding why she was there, he sat down in front of her, as if he was awaiting further instructions.

Meanwhile, at the other end of town, Bob was looking for his key. He clearly remembered that he had lost it on the street next to the park, but now the whole park seemed the same to him. He had already walked around several benches and looked under the trees, but the key was nowhere to be found. Bob began to panic — without the key, he would not be able to get home. He looked back when he heard barking behind him and saw a dog running towards him. She wagged her tail cheerfully, holding something small and shiny in her teeth. Bob knelt on one knee and the dog brought him... his key. Bob laughed with relief and patted the dog on the head, and she wagged her tail happily as if knowing how much she had helped him.

At this time, Alice, a little confused by the unexpected meeting with the cat, decided that this was a sign. She decided to follow the cat, and he led her through the forest to an old house that she had not noticed before. It seemed that this meeting was her next step.

Thus, the stories of Alice and Bob, although they developed in parallel, are connected by thin associative threads: the loss and discovery of keys, an encounter with animals, and an unexpected solution to a problem.

Implications for Narrative Analysis and Beyond

The implications of this combined study extend beyond literature into fields like cognitive science, artificial intelligence, and cultural studies. By focusing on the interactions between associative and causal relationships, we can better understand how the human mind perceives time, causality, and narrative structure. Cognitive science can benefit from these models to explore how humans construct meaning from stories that defy linear progression.

In artificial intelligence, especially in the development of LLMs and narrative AI, the ability to reconstruct non-linear stories presents opportunities to create more dynamic and responsive storytelling agents. These agents could generate content that adapts not only to causal sequences but also to thematic and associative links, providing richer and more nuanced narrative experiences. This capability has significant potential for educational tools, where adaptive storytelling can be used to teach concepts through interactive narratives that adjust based on the learner's inputs and engagement level.

The semantic networks developed through LLMs also have practical implications for understanding the cognitive processes involved in storytelling and narrative comprehension. By representing narratives as semantic networks, we can better understand how associations and causalities form in the mind of the reader or listener, potentially informing educational practices and therapeutic storytelling techniques. In cultural studies, these methods can be leveraged to analyze cultural narratives and mythologies, which often feature non-linear timelines and complex interrelations, offering insights into the collective consciousness and cultural memory.

The literary analysis field can use these methods to revisit classical texts and explore alternative readings that focus on relationships between events beyond their chronological sequence. This approach encourages readers to think about narrative progression as a network of influences rather than a straightforward timeline, offering deeper insights into character motivations and thematic development. Moreover, these techniques can be leveraged to analyze cultural narratives and mythologies, which often feature non-linear timelines and complex interrelations.

Conclusions

Modeling texts using hypergraphs and extracting concepts and relationships using LLMs open new horizons in text mining, analyzing nonlinear narratives, and understanding complex relationships. The presented model of text reconstruction based on cause-and-effect and associative relationships, where associations play as important a role as causal saints, allows us to explore works that go beyond the traditional time narrative, demonstrates the possibility of creating a new space of meanings where time ceases to be a key parameter. Combining associative and causal connections opens up new opportunities for the analysis of literary texts and for further study of the paradoxes that arise when they are mixed. Paradoxes of time that arise when associative and causal connections are mixed create new problems and challenges for analysis but also offer ways to better understand the nonlinear structures of the text. In particular, inversion of causality and cyclic dependencies are an important problem in text reconstruction, which requires further research and development of new network analysis methods. Mathematical formalization allows the analysis of complex narrative structures and offers new approaches to the study of literature. The introduction of hypergraph tools into the model allows one to capture complex text structures. In addition, this methodology can be useful not only in literary studies but also in philosophy, cognitive sciences and artificial intelligence.

Paradoxes such as retroactive causality and logical inversion reveal the complexity of human perception when faced with non-linear narratives. The interaction between causal and associative links often leads to new, emergent meanings that are not apparent when considering time alone as the organizing principle. Future research may expand on these methods to explore other forms of narrative reconstruction and their potential applications in fields like cognitive science, artificial intelligence, and literary analysis.

Overall, this combined methodology represents a step towards a more holistic understanding of narrative structures, where time is no longer the sole determinant of sequence, and meaning is derived from the interplay of diverse relationships within the text. Furthermore, applying these methodologies to interactive storytelling and educational tools highlights the transformative potential of non-linear narrative reconstruction in creating engaging and adaptive experiences for readers and learners alike.

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