Chiral Narrative Synthesis: A Multi-Agent Reinforcement Learning Approach to Truth Discovery

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Abstract

This research proposes Chiral Narrative Synthesis (CNS), a novel framework leveraging topological concepts within a multi-agent reinforcement learning (MARL) system to accelerate truth discovery. CNS employs narratives – structured representations of hypotheses or perspectives – as fundamental units of knowledge. We introduce chiral narratives, representing opposing yet partially valid viewpoints, and orthogonal narratives, capturing independent information. Specialized agents within the MARL environment refine and synthesize these narratives, guided by chiral and orthogonal measures, to converge towards a shared understanding of truth. This approach addresses limitations of traditional knowledge integration methods by explicitly modeling the interplay of diverse, potentially conflicting perspectives. We present a mathematical framework for CNS, including formal definitions of narratives, chirality, orthogonality, and narrative synthesis. We also outline algorithms for chiral pair identification, incorporating contextual information, confidence scores, and feedback from a spiral descent optimization process. The framework's potential is demonstrated through illustrative examples and conjectures, laying the groundwork for future research in multi-agent truth discovery and knowledge synthesis.

1 Introduction

Scientific progress and knowledge discovery often involve the synthesis of information from diverse, and potentially conflicting, sources. Traditional methods for knowledge integration frequently struggle with the complexities of reconciling contradictory evidence, integrating incomplete information, and generating novel hypotheses. This research proposes Chiral Narrative Synthesis (CNS), a novel framework that leverages topological concepts, specifically chirality and orthogonality, within a multi-agent reinforcement learning (MARL) system to address these challenges and accelerate truth discovery.

CNS employs "narratives" – structured representations of hypotheses, perspectives, or theories – as the fundamental units of knowledge. We introduce the concept of *chiral narratives*, representing opposing but partially valid viewpoints relative to a dynamically evolving truth representation. We also introduce *orthogonal narratives*, which capture independent, potentially complementary pieces of information. By explicitly modeling the interplay between these chiral and orthogonal narratives, CNS aims to capture the dynamic and often contradictory nature of scientific discourse and knowledge evolution.

Within the CNS framework, specialized agents operate in a MARL environment. These agents refine and synthesize narratives, guided by chiral and orthogonal measures, through a spiral descent optimization process. This iterative process facilitates the exploration of a complex narrative space, enabling the system to converge towards a shared understanding of truth.

This research contributes a formal mathematical framework for CNS, including precise definitions of narratives, chirality, orthogonality, and narrative synthesis. We also introduce algorithms for chiral pair identification, incorporating contextual information, confidence scores, and feedback from the spiral descent process. Furthermore, we explore Bayesian perspectives on narrative synthesis and discuss the use of spatiotemporal digests for robust truth verification.

2 Detailed Discussion

The CNS framework addresses a fundamental challenge in knowledge integration: how to reconcile conflicting information and synthesize new insights from diverse perspectives. Traditional approaches often rely on consensus-building or averaging, which can obscure valuable information contained in dissenting viewpoints. CNS, by contrast, explicitly models the interplay of opposing narratives through the concept of chirality.

Chiral narratives, inspired by the concept of chirality in chemistry and physics, represent hypotheses or perspectives that are diametrically opposed yet both contain elements of truth. This opposition is captured mathematically by a high chiral similarity score between their embeddings. The simultaneous partial convergence of chiral narratives towards the truth embedding reflects the idea that even conflicting perspectives can offer valuable insights.

Orthogonal narratives, on the other hand, represent independent lines of inquiry or evidence. These narratives, characterized by low chiral similarity, contribute unique information that can complement and strengthen the overall understanding of truth. The integration of orthogonal narratives within CNS allows the system to explore diverse regions of the narrative space and discover novel connections between seemingly unrelated concepts.

The MARL system within CNS consists of specialized agents that interact and learn through a reinforcement learning process. Narrator agents construct and refine individual narratives, while critic agents evaluate their coherence, consistency, and explanatory power. Synthesizer agents identify chiral and orthogonal relationships between narratives and generate new, synthesized narratives that integrate information from multiple sources. The spiral descent optimization process, inspired by Spiral Optimization (SPO), guides the refinement of narratives towards the truth embedding, while also exploring the complex topology of the narrative space. The dynamic adjustment of spiral parameters allows the system to adapt to the changing landscape of information and efficiently navigate towards higher levels of truth.

The integration of LIME (Local Interpretable Model-agnostic Explanations) within CNS provides crucial insights into the reasoning behind narrative synthesis. By explaining the chiral and orthogonal relationships between narratives, LIME helps researchers understand why certain narratives are synthesized and how they contribute to the overall understanding of truth. This enhanced interpretability is essential for building trust in the system's discoveries and for guiding further scientific inquiry.

The use of spatiotemporal digests [TODO: ref draft for patent 30], adds another layer of robustness to the CNS framework. By anchoring narratives to physical reality through verifiable spatiotemporal records, the system can distinguish between narratives supported by verifiable evidence and those based on speculation or misinformation. This grounding in physical reality is crucial for ensuring the scientific validity of the synthesized narratives.

The Bayesian perspective on CNS provides a powerful framework for representing uncertainty and incorporating prior knowledge. By representing narratives as probability distributions over possible world states, the system can explicitly model the uncertainty inherent in scientific hypotheses and update its beliefs as new evidence emerges. This Bayesian approach offers a more nuanced and robust

way to represent and synthesize narratives compared to traditional vector-based methods.

Finally, the CNS framework addresses the philosophical challenges of defining and discovering truth in a complex and ever-changing world. By embracing ambiguity, utilizing controlled infinite regress, dynamically adjusting dimensionality, and harnessing dialectical conflict, CNS provides a computational model for the iterative and often contradictory nature of scientific progress. The conjectures presented in this proposal offer testable hypotheses about the dynamics of narrative synthesis and its potential to accelerate truth discovery.

3 Mathematical Terms and Definitions

3.1 Topology

- **Topological Space:** A set equipped with a topology, which is a collection of open sets satisfying certain axioms.

- **Topological Invariant:** A property of a topological space that remains unchanged under continuous transformations (e.g., homeomorphisms). Examples include connectedness, compactness, and homotopy groups.

- **Manifold:** A topological space that locally resembles Euclidean space.

- **Chirality (in topology):** A property of a topological space that is asymmetric under certain transformations (e.g., reflection). A chiral space cannot be superimposed on its mirror image.

- **Orthogonality (in vector spaces):** Two vectors are orthogonal if their dot product is zero. This represents independence in vector spaces.

- **Cosine Similarity:** The cosine of the angle between two vectors, measuring their similarity in direction. It is given by the dot product of the two vectors divided by the product of their magnitudes.

- **Hamming Distance:** The number of positions at which two vectors differ. Used to measure the distance between binary vectors representing narratives.

- **Shortest Path Length:** In a graph, the shortest distance between two nodes, considering only the edges and edge weights.

- **Persistent Homology:** A technique in topological data analysis that identifies topological features (e.g., connected components, loops, voids) at multiple scales.

- **Topological Distance:** A measure of distance between two points in a topological space, reflecting their topological relationships.

3.2 Linear Algebra

- **Vector:** An ordered collection of numbers.

- **Dot Product:** A measure of the similarity between two vectors. For vectors $u, v \in \mathbb{R}^n$, $u \cdot v = \sum_{i=1}^{n} u_i v_i$.

- **Cross Product (in $\mathbb{R}^3$):** A binary operation on two vectors in $\mathbb{R}^3$ producing a vector orthogonal to both inputs.

- **Matrix:** A rectangular array of numbers.

- **Matrix Multiplication (matmul):** A binary operation on two matrices under certain dimensional compatibility constraints.

- **Projection Operator:** A linear transformation that projects a vector onto a subspace.

- **Rotation Matrix:** A matrix representing a rotation in space.

3.3 Calculus and Optimization

- **Gradient:** A vector pointing in the direction of the steepest ascent of a function.

- **Gradient Descent:** An iterative optimization algorithm that moves in the direction of the negative gradient to minimize a function.

- **Learning Rate:** A parameter controlling the step size in gradient descent.

- **Loss Function:** A function measuring the difference between predictions and actual values.

- **Convergence (of optimization algorithm):** An algorithm converges if it reaches a minimum or stationary point of the function being optimized.

- **Local Minimum:** A point that is a minimum within a local neighborhood.

- **Global Minimum:** The absolute minimum value of a function.

3.4 Information Theory

- **Mutual Information:** A measure of the mutual dependence between two random variables.

- **Entropy:** A measure of uncertainty in a random variable.

- **Information Gain:** The reduction in uncertainty achieved by observing a random variable.

3.5 Graph Theory

- **Graph:** A mathematical structure representing relationships between objects (nodes or vertices) connected by edges.

- **Directed Graph:** A graph where edges have a direction.

- **Weighted Graph:** A graph where edges have associated weights.

- **Node Centrality:** A measure of a node's importance in a graph. Different centrality measures exist, capturing various aspects of importance.

- **Community Structure (in graphs):** The division of nodes into groups or communities based on connectivity patterns.

- **Shortest Path:** The shortest sequence of edges connecting two nodes in a graph.

- **Path Length:** The number of edges in a path.

3.6 Reinforcement Learning

- **Agent:** An entity that learns to interact with an environment.

- **Environment:** The system the agent interacts with.

- **State:** A representation of the environment.

- **Action:** A decision made by the agent.

- **Reward:** A scalar value reflecting the desirability of a state or action.

- **Policy:** A strategy that maps states to actions.

- **Value Function:** A function estimating the expected cumulative reward from a given state.

- **Q-value:** The expected cumulative reward for taking a given action in a given state.

- **Learning Rate (in RL):** A parameter controlling the speed of learning in the reinforcement learning algorithm.

- **Discount Factor (in RL):** A parameter controlling the relative importance of immediate rewards versus future rewards.

4 Mathematical Formulas

4.1 Chiral Gradient Descent (CGD) Formulas

1. Equation:
$$\boldsymbol{\theta}_{t+1} = \boldsymbol{\theta}_t - \alpha \nabla L(\boldsymbol{\theta}_t) + \beta \sum_{i,j \in C} s(w_{ij}, \mathbf{c}_{ij})(\nabla L(\boldsymbol{\theta}_t) \times \mathbf{c}_{ij})$$

2. Equation:
$$\boldsymbol{\theta}_{t+1} = \boldsymbol{\theta}_t - \alpha \nabla L(\boldsymbol{\theta}_t) + \beta \sum_{i,j \in C(\boldsymbol{\theta}_t)} \frac{\|\mathbf{c}_{ij}\|}{1 + e^{-\gamma d_{ij}}} (\nabla L(\boldsymbol{\theta}_t) \times \mathbf{c}_{ij})$$

3. Chirality Score:
$$C_i(t) = \sum_{j \in N(i)} w_{ij} \times A(v_i, v_j)$$

4. Learning Rate Update:
$$\eta_i(t+1) = \eta_i(t) \times (1 + \beta \times C_i(t))$$

5. Chiral Similarity:
$$CS(N_i, N_j) = w_f \times sim(F_i, F_j) + w_c \times sim(C_i, C_j) + w_t \times |T_i - T_j|$$

6. Orthogonal Similarity:
$$OS(N_i, N_j) = 1 - |CS(N_i, N_j)|$$

7. Q-Learning Update:
$$Q(s, a) = Q(s, a) + \alpha \times [R(s, a, s') + \gamma \times \max_{a'} Q(s', a') - Q(s, a)]$$

5 Conjectures

5.1 Chiral Convergence Conjecture

In a multi-agent system performing narrative synthesis, the presence of both chiral and orthogonal narratives, coupled with local explanations, strictly increases the rate of convergence towards the ground truth embedding, compared to systems utilizing only chiral or only orthogonal narratives, when measured relative to the resources consumed. This increase in convergence is not merely due to the increased number of narratives but arises from the synergistic interaction of chiral and orthogonal information, especially in high-dimensional narrative spaces with complex topological features.

6 Mathematical Terms and Definitions (Continued)

6.1 Bayesian Inference

- **Prior Probability:** The probability of an event before observing any data.

- **Likelihood:** The probability of observing the data given a particular event.

- **Posterior Probability:** The probability of an event after observing the data. Calculated using Bayes' theorem.

- **Bayes' Theorem:** A theorem relating prior probability, likelihood, and posterior probability.

- **Bayesian Update:** The process of updating a probability distribution based on new data.

- **Variational Inference:** An approximation method for performing Bayesian inference in complex models.

6.2 Fuzzy Logic

- **Fuzzy Set:** A set where elements have degrees of membership (between 0 and 1).

- **Membership Function:** A function defining the degree of membership of an element in a fuzzy set.

- **Fuzzy Logic Operations:** Logical operations (AND, OR, NOT) extended to fuzzy sets.

- **Fuzzy Truth Value:** A truth value between 0 and 1, representing degrees of belief or uncertainty.

6.3 Spatiotemporal Digests

- **Spatiotemporal Region (X_r):** A subset of spacetime.

- **Raster Recording (R):** A function mapping a spatiotemporal region to a set of data values.

- **Spatiotemporal Digest (S):** A function mapping a spatiotemporal region to a digest value, typically a cryptographic hash, that is computationally infeasible to invert.

- **Strong Verification** (V): A function that compares a raster recording with a spatiotemporal digest to verify authenticity.

6.4 Additional Terms

- **Confidence Score** (T_i): A scalar value in the range [0, 1], representing the degree of belief in the truthfulness of a narrative.

- **Asymmetry Function** ($A(v_i, v_j)$): A function measuring the degree of asymmetry between two nodes in a network.

- **Neighborhood** ($N(i)$): The set of nodes directly connected to node i in a graph.

- **Sigmoid Function:** A function that maps a real number to a value between 0 and 1. Often used to introduce non-linearity in neural networks.

7 Mathematical Formulas (Continued)

7.1 Additional Formulas

1. **Convergence Rate:**
$$CR(N_i, T, t) = -\frac{d}{dt}[d(F_i(t), F_t(t))]$$

2. **Chiral Score (refined):**
$$CS(N_i, N_j) = w_f sim(F_i, F_j) + w_c sim(C_i, C_j) + w_t|T_i - T_j|$$

3. **Orthogonal Score (refined):**
$$OS(N_i, N_j) = 1 - |CS(N_i, N_j)|$$

8 Conjectures (Continued)

8.1 Chiral Convergence Conjecture (refined)

In a multi-agent system performing narrative synthesis, the convergence towards a higher confidence shared understanding of truth is accelerated by the presence and resolution of chiral and orthogonal relationships between narratives, where these relationships are defined by a combination of feature similarity, contextual similarity, and confidence discrepancies. Furthermore, this convergence is optimized through a reinforcement learning process that rewards agents for increasing narrative confidence, synthesizing higher-confidence narratives, resolving chiral tensions, and integrating orthogonal perspectives.

9 Mathematical Terms and Definitions (Continued)

9.1 Reinforcement Learning (Continued)

- **Multi-Agent Reinforcement Learning (MARL):** Reinforcement learning extended to multiple interacting agents.

- **Decentralized RL:** MARL where agents do not have a central controller or global knowledge of the environment.

- **Multi-Objective RL:** RL where the agent has multiple goals or reward functions to optimize.

- **Adversarial RL:** RL where two or more agents compete against each other.

- **Meta-Learning (in RL):** Learning to learn; an RL agent learns to adapt its learning strategy based on experience.

9.2 Local Interpretable Model-agnostic Explanations (LIME)

- **Local Explanation:** An explanation of a single prediction made by a machine learning model.

- **Interpretable Model:** A model whose predictions are easily understandable by humans (e.g., linear model, decision tree).

- **Model-Agnostic:** A method that can be applied to any machine learning model, regardless of its internal structure.

- **Submodular Pick (SP-LIME):** A method for selecting a representative subset of instances to explain a model's global behavior.

9.3 Additional Terms

- **Narrative Space (NS):** The set of all possible narratives, considered as a high-dimensional topological space.

- **Narrative Refinement (ΔN_i):** A change in a narrative based on feedback and interaction with other narratives. Represented as a vector in narrative space.

- **Truth Value (T_i):** A measure of the truthfulness of a narrative, represented as a probability or confidence score.

- **Global Chirality Parameter (β):** Controls the overall effect of chirality on gradient descent.

- **Scaling Parameter (γ):** Controls the steepness of the sigmoid function, determining how topological distance affects the chiral influence.

10 Mathematical Formulas (Continued)

10.1 Additional Formulas

1. **Weighted Averaging of Embeddings (during synthesis):**

$$F_k = \frac{T_i F_i + T_j F_j}{T_i + T_j}$$

2. **Reward Function (example):**

$$R(s, a, s') = w_c Coherence(s') + w_r Resolution(s, a, s') + w_t Convergence(s', T) - w_r RC(a)$$

3. **Average Confidence Score:**

$$\frac{1}{n} \sum_{i=1}^{n} T_i(t)$$

11 Introspection Process: Formalizing Implicit Conjectures

11.1 Bayesian Narrative Representation

The core idea is to represent narratives as probability distributions over possible world states W. A narrative N_i is thus a conditional probability distribution: $N_i \equiv P(W|N_i)$. This allows explicit modeling of uncertainty and incorporates prior knowledge.

11.2 Synthesis as Bayesian Updating

Narrative synthesis is viewed as a Bayesian update. The posterior distribution over world states, given narratives N_i and N_j, is $P(W|N_i, N_j)$. This posterior captures combined information. Assuming conditional independence between narratives given the world state (a common simplification), and a uniform prior $P(W)$, we have:

$$P(W|N_i, N_j) \propto P(N_i|W)P(N_j|W)$$

However, for high-dimensional W, calculating this product is computationally expensive. Variational inference or approximations are needed for scalability. The proportionality constant is omitted as it is a normalization constant. Note that this is a conditional independence assumption, which may or may not be true in practice.

11.3 Chirality and Orthogonality in Bayesian Terms

- **Chirality:** High divergence (KL or JS divergence) between $P(W|N_i)$ and $P(W|N_j)$ indicates chirality.

- **Orthogonality:** Low mutual information $I(N_i; N_j)$ between N_i and N_j indicates orthogonality.

11.4 Conjectures

Conjecture 1 (Bayesian Narrative Synthesis)**.** *If N_i and N_j are two narratives with confidence scores T_i and T_j respectively, and $N_k = Synth(N_i, N_j)$ is their synthesis, then $T_k \geq \max(T_i, T_j)$. This formalizes that combining information increases confidence.*

Conjecture 2 (Chiral Narrative Convergence)**.** *If N_i and N_j are chiral narratives (high divergence), their synthesis N_k converges faster to the truth T than individual narratives. This formalizes the idea that resolving chiral tensions accelerates progress.*

Conjecture 3 (Orthogonal Narrative Complementarity)**.** *If N_i and N_j are orthogonal narratives (low mutual information), then the confidence score of their synthesis N_k is higher than either individual narrative: $T_k > \max(T_i, T_j)$. This formalizes the idea that independent perspectives provide complementary information.*

12 Bayesian Narrative Representation

A narrative N_i is represented as a conditional probability distribution over world states W:

$$N_i \equiv P(W|N_i)$$

13 Narrative Synthesis

The synthesis of two narratives N_i and N_j is represented as a Bayesian update:

$$Synth(N_i, N_j) = N_k \equiv P(W|N_i, N_j)$$

Assuming conditional independence between narratives given the world state, and given a uniform prior $P(W)$, we have:
$$P(W|N_i, N_j) \propto P(W|N_i)P(W|N_j)$$

14 Chirality and Orthogonality

- **Chirality:** Two narratives N_i and N_j are chiral if their probability distributions have high divergence (e.g., measured by KL or JS divergence).

- **Orthogonality:** Two narratives N_i and N_j are orthogonal if they have low mutual information about the world state W.

15 Conjectures

Conjecture 4 (Bayesian Narrative Synthesis)**.** *If N_i and N_j are two narratives with confidence scores T_i and T_j respectively, then the confidence score T_k of the synthesized narrative $N_k = Synth(N_i, N_j)$*

satisfies:

$$T_k \geq \max(T_i, T_j)$$

Conjecture 5 (Chiral Narrative Convergence). *If N_i and N_j are chiral narratives with high divergence, their synthesis N_k will converge faster towards the truth T compared to the individual narratives.*

Conjecture 6 (Orthogonal Narrative Complementarity). *If N_i and N_j are orthogonal narratives with low mutual information, their synthesis N_k will have a higher confidence score than either individual narrative:*

$$T_k > \max(T_i, T_j)$$

16 Chiral Narrative Synthesis: A Mathematical Framework

This section formalizes the core mathematical concepts and conjectures of Chiral Narrative Synthesis (CNS), a framework for multi-agent reinforcement learning designed to accelerate scientific discovery by leveraging chiral and orthogonal relationships between narratives. We define narratives as structured representations of hypotheses, introduce measures for chirality and orthogonality, and propose a reinforcement learning approach to guide narrative synthesis towards a shared understanding of truth. We also explore Bayesian perspectives and the implications of spatiotemporal digests for verifying truth claims.

17 Mathematical Terms and Definitions

17.1 Narratives and Truth

- **Narrative (N_i):** A structured representation of a hypothesis, perspective, or theory, represented as a tuple: $N_i = (G_i, F_i, C_i, T_i)$, where:
  - G_i: Graph embedding of the narrative structure (e.g., using GCNs).
  - F_i: Feature embedding capturing the semantic content.
  - C_i: Embedding of contextual features (including spatiotemporal digests).
  - T_i: Confidence score $\in [0, 1]$.

- **Truth Embedding (T):** The current best approximation of ground truth, represented similarly to a narrative: $T = (G_t, F_t, C_t, T_t)$, where T_t is the overall confidence in the current understanding of truth.

- **Narrative Space (NS):** The set of all possible narratives, conceptualized as a high-dimensional topological space.

17.2 Relationships between Narratives

- **Chiral Narratives:** Narratives representing opposing but partially correct perspectives relative to T.

- **Orthogonal Narratives:** Narratives providing independent, potentially complementary information.

- **Chiral Similarity (CS):** Measures the degree of opposition between two narratives, incorporating feature, context, and confidence differences:

$$CS(N_i, N_j) = w_f \cdot sim(F_i, F_j) + w_c \cdot sim(C_i, C_j) + w_t \cdot |T_i - T_j|$$

where sim denotes cosine similarity and w_f, w_c, w_t are weights.

- **Orthogonal Similarity (OS):** Measures the degree of independence between narratives:

$$OS(N_i, N_j) = 1 - |CS(N_i, N_j)|$$

17.3   Spiral Descent and Refinement

- **Narrative Refinement (ΔN_i):** A change in a narrative based on feedback and interaction, represented as a vector in NS.

- **Spiral Descent Function:** Guides narrative refinement using gradients, chiral/orthogonal influences, and local explanations (LIME):

$$\Delta N_i = g(\nabla_{NS} L(N_i), CS(N_i, N_j), OS(N_i, N_k), LIME(N_i), \dots)$$

where g is a function to be defined, and $L(N_i)$ is a loss function in narrative space.

17.4   Spatiotemporal Digests

- **4D Timeline (X):** 4-dimensional spacetime.

- **Raster Recording (R):** $R : X_r \to D$, maps a spatiotemporal region $X_r \subset X$ to data values D.

- **Spatiotemporal Digest (S):** $S : X_r \to H$, maps X_r to a digest value H (e.g., cryptographic hash).

- **Strong Verification (V):** $V(R, S) \to \{\text{True, False}\}$, verifies if S is a valid digest for R.

- **Levels of Truth (T_n):** A hierarchy of truth levels based on verification methods (digest, multi-witness, contextual).

17.5   Other Relevant Concepts

- **Bayesian Narrative Representation:** $N_i \equiv P(W|N_i)$, the probability distribution over world states W given narrative N_i.

- **Narrative Synthesis (Bayesian):** $Synth(N_i, N_j) = N_k \equiv P(W|N_i, N_j)$.

- **Kullback-Leibler (KL) Divergence:** Measures the difference between two probability distributions.

- **Jensen-Shannon (JS) Divergence:** A symmetrized and smoothed version of KL divergence.

- **Mutual Information:** Measures the mutual dependence between two random variables.

- **Graph Convolutional Networks (GCNs):** Neural networks designed to operate on graph-structured data.

- **Locality Sensitive Hashing (LSH):** Technique for efficient approximate nearest neighbor search in high-dimensional spaces.

18 Mathematical Formulas and Algorithms

18.1 Core CNS Formulas

1. **Narrative Synthesis (embedding-based):**

$$F_k = \frac{T_i F_i + T_j F_j}{T_i + T_j}$$

2. **Reinforcement Learning Update:**

$$Q(s,a) = Q(s,a) + \alpha[R(s,a,s') + \gamma \max_{a'} Q(s',a') - Q(s,a)]$$

3. **Bayesian Narrative Synthesis:**

$$P(W|N_i, N_j) \propto P(N_i|W)P(N_j|W)$$

18.2 Chiral Pair Identification Algorithm (Illustrative)

Algorithm 1 Chiral Pair Identification

Require: Graph $G = (V, E)$, Feature embeddings F, Chirality threshold τ
1: Initialize empty set of chiral pairs C
2: **for** each pair of nodes $(v_i, v_j) \in V \times V$ **do**
3:      $S_{ij} \leftarrow$ ChiralScore(F_i, F_j) ▷ Using a defined Chiral Score function
4:      **if** $S_{ij} > \tau$ **then**
5:          $C \leftarrow C \cup \{(v_i, v_j)\}$
6:      **end if**
7: **end forreturn** C

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19 Core Conjectures

Conjecture 7 (Chiral Convergence Conjecture). *The presence and resolution of chiral and orthogonal relationships between narratives, coupled with local explanations, accelerates convergence towards a higher confidence shared understanding of truth in a multi-agent narrative synthesis system.*

Conjecture 8 (Bayesian Narrative Synthesis). *If N_i and N_j are two narratives, the confidence score T_k of the synthesized narrative $N_k = Synth(N_i, N_j)$ satisfies $T_k \geq \max(T_i, T_j)$.*

Conjecture 9 (Chiral Narrative Convergence). *If N_i and N_j are chiral narratives with high divergence, their synthesis N_k will converge faster towards the truth T compared to the individual narratives.*

Conjecture 10 (Orthogonal Narrative Complementarity). *If N_i and N_j are orthogonal narratives with low mutual information, their synthesis N_k will have a higher confidence score than either individual narrative: $T_k > \max(T_i, T_j)$.*

20 Algorithms

This section details various algorithms for identifying chiral pairs within the Chiral Narrative Synthesis (CNS) framework. We explore different approaches based on feature embeddings, graph structures, contextual information, and confidence scores. We also consider hierarchical and multi-agent implementations, emphasizing scalability and practical considerations for real-world applications.

21 Chiral Pair Identification Algorithms

21.1 Basic Chiral Pair Identification (using cosine similarity)

This algorithm identifies chiral pairs based on high cosine distance between feature embeddings and individual convergence towards the truth embedding.

Algorithm 2 Basic Chiral Pair Identification

Require: Feature embeddings $F = \{F_1, \ldots, F_n\}$, Truth embedding T, Distance threshold τ_d, Similarity threshold τ_s

1: Initialize empty set of chiral pairs C
2: **for** each pair of narratives (N_i, N_j) **do**
3:     **if** $d(F_i, F_j) > \tau_d$ and $sim(F_i, T) > \tau_s$ and $sim(F_j, T) > \tau_s$ **then**
4:         $C \leftarrow C \cup \{(N_i, N_j)\}$
5:     **end if**
6: **end for** **return** C

Where $d(F_i, F_j)$ is the cosine distance and $sim(F_i, T)$ is the cosine similarity.

21.2 Chiral Pair Identification with Context and Confidence

This algorithm extends the basic approach by incorporating contextual similarity and confidence score differences.

Algorithm 3 Chiral Pair Identification with Context and Confidence

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Require: Narratives $N = \{N_1, \ldots, N_n\}$, Truth embedding T, Weights w_f, w_c, w_t, Chirality threshold τ_c

1: Initialize empty set of chiral pairs C
2: **for** each pair of narratives (N_i, N_j) **do**
3:     $CS_{ij} \leftarrow w_f \cdot sim(F_i, F_j) + w_c \cdot sim(C_i, C_j) + w_t \cdot |T_i - T_j|$
4:     **if** $CS_{ij} > \tau_c$ and $T_i > 0$ and $T_j > 0$ **then**   ▷ Require non-zero confidence
5:         $C \leftarrow C \cup \{(N_i, N_j)\}$
6:     **end if**
7: **end for** **return** C

21.3 Hierarchical Chiral Pair Identification

This algorithm recursively identifies chiral pairs within subgraphs, capturing chirality at multiple levels.

Algorithm 4 Hierarchical Chiral Pair Identification

Require: Graph G, Feature embeddings F, Truth embedding T, Thresholds τ_d, τ_s
1: **function** FINDCHIRALPAIRS(G, F, T, τ_d, τ_s)
2:      $C \leftarrow$ BasicChiralPairIdentification(F, T, τ_d, τ_s)
3:      **for** each subgraph G_s of G **do**
4:          $F_s \leftarrow$ Embeddings for G_s
5:          $T_s \leftarrow$ Truth embedding for G_s $\triangleright$ Potentially adjusted for subgraph
6:          $C_s \leftarrow$ FindChiralPairs($G_s, F_s, T_s, \tau_d, \tau_s$)
7:          $C \leftarrow C \cup C_s$
8:      **end forreturn** C
9: **end function**

21.4 Multi-Agent Chiral Pair Identification

This algorithm distributes the chiral pair identification process among multiple agents.

Algorithm 5 Multi-Agent Chiral Pair Identification

Require: Narratives N, Truth embedding T, Number of agents k
1: Partition N into k subsets $N_1, \ldots, N_k$
2: **for** each agent i **do**
3:      $C_i \leftarrow$ ChiralPairIdentification(N_i, T) $\triangleright$ Using any chiral pair identification method
4: **end for**
5: $C \leftarrow \bigcup_{i=1}^{k} C_i$
6:          $\triangleright$ Optional: Resolve conflicts or inconsistencies between C_i **return** C

21.5 Chiral Pair Identification with LIME

This algorithm uses LIME to explain chiral relationships and guide the identification process.

Algorithm 6 Chiral Pair Identification with LIME

Require: Narratives N, Truth embedding T, LIME explainer
1: Initialize empty set of chiral pairs C
2: **for** each pair of narratives (N_i, N_j) **do**
3:      $CS_{ij} \leftarrow$ ChiralScore(N_i, N_j)
4:      **if** CS_{ij} is high **then**
5:          $Explanation \leftarrow$ LIME(N_i, N_j, T)
6:          **if** $Explanation$ indicates a meaningful chiral relationship **then**
7:              $C \leftarrow C \cup \{(N_i, N_j)\}$
8:          **end if**
9:      **end if**
10: **end forreturn** C

21.6 Chiral Pair Identification with Spiral Descent Feedback

This algorithm incorporates feedback from the spiral descent process to dynamically adjust the chiral pair selection.

Algorithm 7 Chiral Pair Identification with Spiral Descent Feedback

Require: Narratives N, Truth embedding T, Spiral descent parameters
1: Initialize chiral pairs C
2: **repeat**
3:     Perform spiral descent using C
4:     Analyze narrative changes and convergence rates
5:     Update C based on feedback (e.g., prioritize pairs contributing to faster convergence)
6: **until** Convergence criteria met **return** C