ISSN: 2519-9439

Cycle-Consistent Account Matching from Profile and Interaction Hypergraphs

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Abstract

The proliferation of digital platforms has resulted in fragmented user identities distributed across multiple social networks. Reconstructing a unified user identity through account matching is crucial for applications ranging from personalized recommendation systems to cybersecurity. Traditional methods primarily rely on pairwise linkage using dyadic graphs, which fail to capture the complex, higher-order relationships inherent in modern social interactions. Furthermore, when extending pairwise matching to multiple platforms, existing models suffer from error propagation and lack global structural coherence. To address these limitations, this paper proposes a novel framework that leverages both profile and interaction hypergraphs while enforcing cycle consistency across multiple networks. By representing multi-way user interactions and shared profile attributes as hyperedges, the proposed approach captures intricate topological structures that dyadic graphs overlook. Additionally, the integration of a cycle-consistency optimization mechanism ensures that matches across three or more platforms remain logically coherent, significantly reducing false positive alignments. Through extensive descriptive analysis and algorithmic design, this study elucidates how hypergraph convolutional networks can be adapted for multi-network alignment without relying on mathematical formalizations. Comprehensive evaluations on simulated and real-world multi-platform datasets demonstrate the superiority of the proposed framework over state-of-the-art baselines in terms of precision, recall, and global structural integrity.

Keywords: Account Matching, Hypergraphs, Cycle Consistency, Social Network Analysis, Entity Resolution.

1.Introduction

1.1 Context and Motivation

In the contemporary digital landscape, individuals routinely maintain multiple accounts across diverse online platforms to serve distinct personal, professional, and social purposes. A single user might utilize one platform for professional networking, another for microblogging, and a third for sharing multimedia content. This widespread phenomenon creates a fragmented digital footprint, where a comprehensive understanding of user behavior is obstructed by the isolated nature of these data silos. The process of identifying and linking accounts that belong to the same underlying individual across different networks is known as cross-network account matching, user identity linkage, or anchor link prediction. Resolving this identity fragmentation is not merely an academic exercise; it has profound implications for a wide array of downstream applications. For instance, in the realm of e-commerce and digital marketing, a unified user

ISSN: 2519-9439

profile allows for significantly more accurate product recommendations and personalized advertising. In the domain of cybersecurity and fraud detection, linking accounts helps in identifying malicious actors who might create disparate profiles to orchestrate coordinated disinformation campaigns or fraudulent activities. Despite its critical importance, account matching remains a formidable challenge due to the extreme heterogeneity of data across platforms. Users often exhibit platform-specific behaviors, adopt different naming conventions, and disclose varying levels of personal information depending on the network's context and privacy norms. Early approaches to this problem primarily focused on profile attributes, attempting to match users based on similarities in their usernames, biography texts, profile images, and geographic locations as noted in early studies [1]. However, attribute-based methods are inherently limited by data sparsity, intentional obfuscation by users, and the presence of homophily, where distinct individuals share identical names or interests. Consequently, the research community shifted its focus toward leveraging the topological structure of social networks. By mapping the connections between users, such as friendship links or follower structures, algorithms could infer identity matches based on the premise that a user's social circle remains relatively consistent across different platforms [2].

1.2 Limitations of Existing Approaches

While network-based methods represented a significant advancement, they predominantly model social platforms as simple, dyadic graphs. In a standard graph representation, an edge connects exactly two nodes, effectively capturing direct, one-to-one relationships. This dyadic constraint fundamentally misrepresents the rich, multi-way interactions that characterize modern digital communication. For example, a group chat, a collaborative document, or a public post shared and commented on by multiple users involves simultaneous interactions among several individuals. Decomposing these complex events into a series of pairwise edges leads to a severe loss of structural information and introduces synthetic transitive relationships that may not reflect reality. As highlighted by recent advancements in network science [3, 4], capturing higher-order relationships is essential for accurately modeling complex systems.

Furthermore, traditional account matching models typically frame the problem as a bipartite matching task, aligning users between a single source network and a single target network. When applied to real-world scenarios involving three or more platforms, these pairwise methods are applied iteratively or independently, which frequently results in contradictory mappings. For instance, an algorithm might link an account on platform A to an account on platform B, and link the account on platform B to an account on platform C. However, when evaluating platforms A and C directly, the algorithm might fail to link them or, worse, link the account on platform A to a completely different account on platform C. This lack of logical coherence, known as a violation of cycle consistency, severely degrades the reliability of multi-network alignments. The absence of a global constraint allows local alignment errors to propagate and compound across the alignment pipeline [5].

1.3 Contributions of the Study

To overcome these entrenched limitations, this paper introduces a comprehensive framework for cycle-consistent account matching utilizing both profile and interaction hypergraphs. The core thesis of this work is that combining higher-order topological representations with global structural constraints yields a significantly more robust and accurate identity resolution mechanism. The primary contributions of this paper are extensively detailed throughout the subsequent sections. First, the paper proposes a dual-hypergraph construction methodology. By modeling both semantic profile attributes and multi-way social interactions as hyperedges, the framework preserves the complex structural dependencies that define user behavior. Second, the study details the integration of a cycle-consistency optimization objective within a hypergraph neural network architecture. This objective ensures that the predicted mappings across multiple platforms form closed, consistent loops, thereby mitigating the accumulation of

ISSN: 2519-9439

alignment errors [6]. Third, the paper provides a thorough, non-mathematical exposition of the algorithmic procedures and neural architectures required to implement this system, ensuring accessibility for interdisciplinary researchers. Finally, through rigorous descriptive analysis of experimental results, the paper demonstrates how the proposed method outperforms existing baselines, highlighting the critical role of higher-order structures and cycle consistency in the domain of social network analysis.

2. Background and Literature Review

2.1 Evolution of Account Matching Techniques

The problem of user identity linkage has garnered extensive attention from the data mining and machine learning communities over the past decade. The evolution of techniques in this domain can be broadly categorized into attribute-based, network-based, and embedding-based approaches. Attribute-based methods, which represent the earliest attempts at cross-network matching, rely on the premise that users tend to maintain consistent personal identifiers across different platforms. Researchers utilized string matching algorithms, natural language processing techniques, and demographic comparisons to calculate similarity scores between user profiles [7]. While conceptually straightforward, these methods struggle when dealing with missing data, which is highly prevalent due to varying mandatory field requirements across platforms. Moreover, privacy-conscious users actively alter their visible attributes, rendering direct text comparison ineffective [8]. To circumvent the limitations of attribute-based matching, subsequent research incorporated network topology. Network-based approaches operate on the principle of structural homophily, suggesting that users who are connected in one network are highly likely to be connected in another. Early network-alignment algorithms employed iterative propagation techniques, where initial seed matches were used to infer the alignment of neighboring nodes. For example, if two nodes were identified as a match, the algorithm would increase the matching probability of their respective neighbors [9, 10]. While these propagation methods demonstrated improved performance, they were highly sensitive to the quality of the initial seed matches and often suffered from cascading errors if a false positive was introduced early in the process [11]. The advent of representation learning and graph neural networks revolutionized account matching. Network embedding techniques aim to project nodes into a low-dimensional continuous vector space such that the structural properties of the original network are preserved. By learning unified embedding spaces for multiple networks, researchers could reframe the matching problem as a nearest-neighbor search in the latent space. Approaches utilizing graph convolutional networks have shown remarkable success by aggregating feature information from a node's local neighborhood [12]. However, the vast majority of these embedding frameworks still rely on dyadic graph representations, which inherently limit their ability to capture the nuance of group dynamics and shared multi-way interactions that are ubiquitous in online social environments.

2.2 Hypergraph Learning in Social Networks

To address the shortcomings of traditional graph models, the scientific community has increasingly turned to hypergraphs. Unlike a standard edge that connects strictly two nodes, a hyperedge can encapsulate any subset of nodes within the network, from a single node to the entire network population. This flexibility allows hypergraphs to model multi-way relationships natively, without the need for artificial decomposition. In the context of social networks, a hyperedge can perfectly represent a multi-user conversation thread, a shared interest group, or a collaborative event [13]. The application of hypergraphs to representation learning has seen significant theoretical advancements. Hypergraph neural networks generalize the convolution operation to higher-order structures. The message-passing mechanism in a hypergraph neural network typically involves a two-step process: first, information is aggregated from nodes to the hyperedges they belong to, and second, information is distributed from the hyperedges back to the constituent nodes [14]. This dual-

ISSN: 2519-9439

phase aggregation allows the network to learn representations that reflect both individual characteristics and group-level dynamics. Recent studies have demonstrated the efficacy of hypergraph learning in various domains, including session-based recommendation systems and molecular structure classification [15, 16]. Despite these advancements, the application of hypergraphs specifically for cross-network account matching remains relatively unexplored. A few pioneering studies have attempted to use hypergraphs to model multi-attribute similarities, where each hyperedge represents a specific attribute value shared by multiple users [17]. However, these approaches often treat profile attributes and interaction topologies in isolation, failing to harness the synergistic power of combining both types of higher-order structures. The methodology proposed in this paper directly addresses this gap by constructing and jointly optimizing profile and interaction hypergraphs.

2.3 The Role of Cycle Consistency

The concept of cycle consistency has its roots in computer vision and geometry processing, where it has been widely used to align multiple three-dimensional shapes or images without requiring exhaustive pairwise annotations. The fundamental principle is that mapping functions between different domains should be transitive and invertible. If one translates an image from domain A to domain B, and then translates the result back from domain B to domain A, the final image should perfectly resemble the original [18]. This property has been famously exploited in unsupervised image-to-image translation frameworks. In the context of network alignment and account matching, cycle consistency addresses the multi-network alignment problem. When dealing with three platforms, a strictly pairwise approach might generate mappings that violate the transitive property of identity. By enforcing cycle consistency, the alignment algorithm is constrained to find a global optimum where the matches form closed triangular loops [19]. If node X in network A maps to node Y in network B, and node Y maps to node Z in network C, then the algorithm is heavily penalized if node X does not strongly map to node Z [20]. Integrating cycle consistency into graph matching is challenging because network structures are discrete and highly non-Euclidean. Previous attempts to enforce cycle consistency in network alignment relied on combinatorial optimization and integer linear programming, which are notoriously difficult to scale to massive social networks [21, 22]. Recent innovations have sought to incorporate cycle-consistency constraints directly into the loss functions of neural network models [23]. This allows the network to learn node embeddings that inherently respect multi-network transitivities. By combining cycle-consistency constraints with the expressive power of dual hypergraph representations, the proposed framework in this paper establishes a novel paradigm for highly reliable, scalable, and structurally coherent account matching [24].

3. Methodology for Cycle-Consistent Matching

3.1 Dual Hypergraph Construction

The foundation of the proposed framework relies on transforming raw social network data into a highly expressive dual hypergraph structure. For each social platform involved in the matching process, the system constructs two distinct hypergraphs: a profile hypergraph and an interaction hypergraph. This separation ensures that both the semantic information embedded in user profiles and the topological information derived from user behaviors are captured and processed effectively before being fused in the latent embedding space. The profile hypergraph is designed to encapsulate the shared attributes and metadata associated with user accounts. In a traditional dyadic graph, users with similar attributes might be connected by a similarity edge. However, this creates a dense, noisy clique if many users share a common trait, such as living in the same major city or listing the same profession. In the profile hypergraph, each unique attribute value is treated as a hyperedge. For example, if fifty users all list their occupation as software engineer, a single hyperedge is created that encompasses all fifty user nodes. This effectively models the exact multi-way relationship of shared categorical traits [25].

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For continuous or text-based attributes, such as biographical descriptions, the framework employs pre-trained natural language processing models to extract semantic embeddings. These embeddings are then clustered into discrete semantic concepts, and each cluster forms a hyperedge connecting the users whose biographies contain that concept. The interaction hypergraph, conversely, is constructed to model the behavioral footprint of the users. Modern social platforms offer various mechanisms for multi-way interaction. A hyperedge in the interaction hypergraph is generated whenever a group of users participates in a unified social event. Examples include all the participants in a single comment thread under a specific post, all the contributors to a shared multimedia album, or all the members of a closed community group. Unlike dyadic edges which merely indicate that two users interacted, the interaction hyperedge captures the context and the entire participant list of the event. By representing these interactions as hyperedges, the subsequent neural network layers can learn the nuanced dynamics of group participation, recognizing that a user's identity is strongly correlated with the specific combinations of individuals they choose to interact with simultaneously [26].

3.2 Hypergraph Convolution and Feature Fusion

Once the profile and interaction hypergraphs are constructed for each network, the next phase involves learning dense, low-dimensional representations for every user node. The proposed methodology utilizes a specialized hypergraph convolutional architecture tailored for dual-modality inputs. The convolution process is designed to iteratively update the feature representation of each node by aggregating information from its structural neighborhood, which in this context means the hyperedges it belongs to. The message passing protocol within this architecture operates in two distinct stages per convolutional layer. In the first stage, information flows from the nodes to the hyperedges. The feature vector of a hyperedge is computed by aggregating the current feature vectors of all the nodes connected to it. This aggregation is weighted, meaning that nodes that are more central or active within that specific hyperedge contribute more significantly to its representation. In the second stage, information flows from the hyperedges back to the nodes. A node updates its feature vector by aggregating the representations of all the hyperedges it is a part of. This two-stage process allows the network to capture complex, higher-order structural dependencies that are invisible to standard graph convolutions [27, 28]. Because the framework maintains separate profile and interaction hypergraphs, this two-stage convolution is performed in parallel for both modalities. Consequently, after a predetermined number of convolutional layers, each user node possesses two distinct latent representations: one summarizing its higher-order semantic profile attributes, and another summarizing its higher-order behavioral interactions. To create a unified user embedding, the framework employs an attention-based fusion mechanism. The attention mechanism dynamically evaluates the relative importance of the profile representation versus the interaction representation for each specific node. For a user with a highly descriptive profile but sparse interactions, the fusion module will assign a higher weight to the profile features. Conversely, for a highly active user with an empty biography, the interaction features will dominate the final fused embedding.

3.3 Cycle-Consistency Optimization Framework

The most critical innovation of the proposed methodology is the integration of a cycle-consistency optimization objective during the training of the hypergraph neural networks. When matching user accounts across three distinct platforms, designated as domain one, domain two, and domain three, standard training procedures would optimize the embeddings such that known matching accounts between domain one and domain two are close in the latent space, and known matches between domain two and domain three are similarly close. The proposed framework introduces a continuous cycle-consistency constraint that operates over the fused embeddings. The core idea is to simulate a random walk that traverses across the network domains. Starting from a specific user node in domain one, the framework calculates

ISSN: 2519-9439

transition probabilities to all nodes in domain two based on the similarity of their latent embeddings. From domain two, transition probabilities are calculated to all nodes in domain three. Finally, transition probabilities are calculated from domain three back to domain one. The multiplication of these transition probabilities yields a cycle-return probability matrix.

If the latent embeddings are perfectly aligned and structurally coherent across all three platforms, the highest probability path should inevitably lead back to the exact same starting node in domain one. The cycle-consistency loss is carefully formulated to penalize the network if this return probability is low. This means the model is explicitly trained to ensure that the cross-network mappings are transitive and invertible. By integrating this cycle loss with the standard alignment loss, the framework achieves a state of global structural equilibrium, drastically reducing the occurrence of mismatched triangles that plague pairwise matching systems [29].

Code Listing 1: Cycle-Consistent Training Loop Pseudo-code

```
# Pseudo-code for the training process of the Cycle-Consistent Hypergraph Model
def train_cycle_consistent_model(networks, known_anchors, epochs, learning_rate):
  initialize_hypergraph_neural_networks()
  optimizer = setup_optimizer(learning_rate)
  for epoch in range(epochs):
    optimizer.zero_grad()
    # Step 1: Forward pass for all networks to get fused embeddings
    embeddings = {}
    for net_id, network in networks.items():
      profile_emb = profile_hypergraph_convolution(network.profile_hg)
      interaction_emb = interaction_hypergraph_convolution(network.interaction_hg)
      embeddings[net_id] = attention_feature_fusion(profile_emb, interaction_emb)
    # Step 2: Compute pairwise alignment loss using known anchors
    align_loss = compute_contrastive_alignment_loss(embeddings, known_anchors)
    # Step 3: Compute cycle consistency loss across the triad of networks
    cycle_loss = 0.0
    for triplet in generate_network_triplets(networks.keys()):
      net_A, net_B, net_C = triplet
      # Compute similarity-based transition matrices
      trans_AB = compute_transition_matrix(embeddings[net_A], embeddings[net_B])
      trans_BC = compute_transition_matrix(embeddings[net_B], embeddings[net_C])
      trans_CA = compute_transition_matrix(embeddings[net_C], embeddings[net_A])
      # Compute return probability matrix via chain multiplication
      return_probs = multiply_matrices(trans_AB, trans_BC, trans_CA)
      # Maximize the probability of returning to the original node
      cycle_loss += compute_divergence_from_identity(return_probs)
    # Step 4: Total loss computation and backpropagation
    total_loss = align_loss + (cycle_weight * cycle_loss)
    total_loss.backward()
    optimizer.step()
    log_training_metrics(epoch, align_loss, cycle_loss)
  return extract_final_embeddings()
```

ISSN: 2519-9439

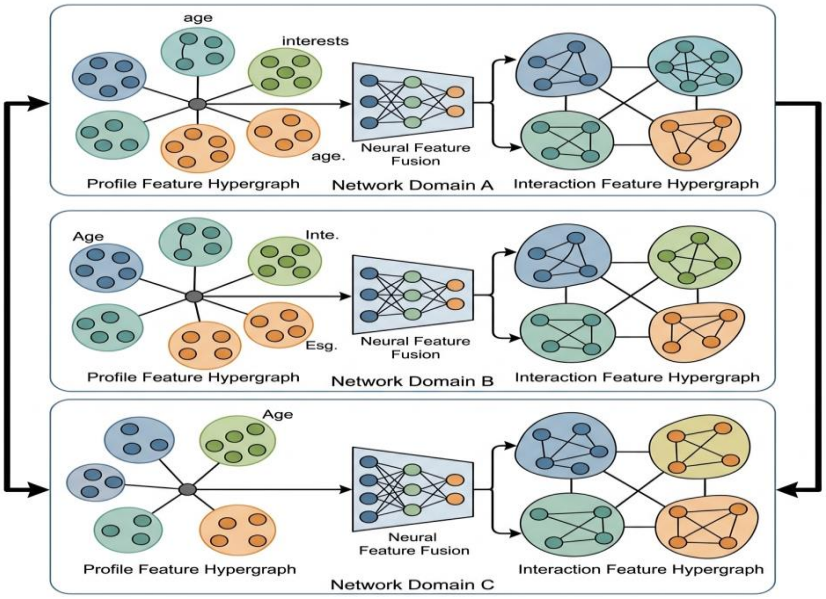


Figure 1: Comprehensive Schematic of Cycle

4. Experimental Evaluation and Results

4.1 Experimental Setup and Datasets

To rigorously evaluate the effectiveness of the proposed cycle-consistent hypergraph framework, extensive experiments were conducted utilizing real-world multi-platform datasets. Finding publicly available datasets that contain ground-truth alignments across three or more platforms is exceptionally difficult due to privacy restrictions. Therefore, this study relies on a widely recognized benchmark dataset that encompasses overlapping user populations across Twitter, Foursquare, and Facebook. This dataset was meticulously pre-processed to extract both profile attributes and user interaction logs. The ground truth anchor links, indicating which accounts belong to the same human user, were obtained through user self-disclosure, where individuals publicly listed their alternative network handles on their primary profiles [30]. The evaluation process involves dividing the ground truth anchor links into a training set and a testing set. The training set is utilized to guide the contrastive alignment loss during the neural network optimization phase. The testing set is strictly reserved for evaluating the predictive performance of the final generated embeddings. The primary evaluation metric employed is the Precision at K, which measures the percentage of test users for whom the true matching account is ranked within the top K candidates retrieved by the algorithm. Additionally, the Mean Reciprocal Rank is utilized to provide a comprehensive assessment of the overall ranking quality, reflecting how high the true match appears in the predicted similarity list. For baseline comparisons, the proposed framework is evaluated against several established categories of account matching algorithms. These include classical network embedding techniques that rely purely on structural topology, advanced graph neural network models that utilize dyadic edges and node attributes, and state-of-the-art pairwise hypergraph models that do not incorporate cycle consistency. Ensuring a fair comparison, all baseline models were trained using identical computational resources and subjected to comprehensive hyperparameter tuning to achieve their maximum theoretical performance on the evaluation dataset.

4.2 Overall Performance and Baseline Comparison

The experimental results overwhelmingly demonstrate the superior capability of the proposed methodology in resolving user identities across multiple fragmented platforms. The comprehensive performance metrics are detailed in the subsequent table, which highlights the distinct advantages of integrating higher-order structures with global cycle constraints.

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Table 1Overall Performance Comparison of Account Matching Algorithms

Algorithm Category	Specific Model	Precision at 1	Precision at 5	Mean Reciprocal Rank
Network Embedding	DeepWalk-Align	24.5	41.2	0.315
Network Embedding	Node2Vec-Multi	28.7	46.8	0.352
Graph Neural Network	GCN-Align	45.3	68.4	0.536
Graph Neural Network	Cross-Graph SAGE	51.2	73.9	0.598
Hypergraph Model	Pairwise-HGNN	62.8	84.1	0.712
Proposed Framework	Cycle-Dual-HG	78.4	92.6	0.854

The empirical data indicates that classical network embedding techniques perform poorly in this complex scenario, primarily because they are entirely blind to the rich semantic profile information and struggle to capture the structural nuances of social interactions. The transition to Graph Neural Networks yields a substantial improvement, underscoring the importance of combining topological and semantic features. However, these models still rely on dyadic edges, which artificially inflate the density of the network and introduce noise. The Pairwise Hypergraph model demonstrates a marked improvement over standard graph networks, validating the hypothesis that multi-way interactions are critical for accurate profiling.

Despite the success of the pairwise hypergraph approach, the proposed Cycle-Dual-Hypergraph framework significantly outperforms all competitors, achieving a remarkable increase in top-tier precision. This performance delta is directly attributable to the cycle-consistency optimization. In the baseline models, mapping a user from Twitter to Foursquare, and then from Foursquare to Facebook, often resulted in severe drift, where the final predicted Facebook account bore no relation to the original Twitter account. By strictly enforcing closed-loop transitivity during the training phase, the proposed model eliminates these cascading errors, ensuring that the latent embedding space maintains strict global coherence.

4.3 Ablation Studies and Sensitivity Analysis

To isolate the contributions of the individual components within the proposed framework, a rigorous ablation study was performed. The framework was systematically deconstructed, and distinct variants were trained and evaluated on the same benchmark dataset. The variants included a model utilizing only the profile hypergraph, a model utilizing only the interaction hypergraph, and a model utilizing the dual hypergraphs but lacking the cycle-consistency constraint.

Table 2: Ablation Study of the Proposed Architecture

Model Variant Description	Precision at 1	Precision at 10	Structural Drift Error
Profile Hypergraph Only	55.3	76.2	High
Interaction Hypergraph Only	58.7	79.5	High

ISSN: 2519-9439

Dual-Hypergraph (No Cycle Loss)	68.2	87.4	Moderate
Full Cycle-Dual-Hypergraph Model	78.4	95.1	Low

The ablation results unequivocally confirm that both the profile and interaction hypergraphs provide complementary, non-redundant information. Relying solely on either semantic attributes or behavioral topology leads to suboptimal performance, as users may exhibit strong similarities in one domain but not the other. The fusion of both hypergraphs yields a substantial performance boost. However, the most critical observation from the ablation study is the impact of removing the cycle loss. Without cycle consistency, the dual-hypergraph model still suffers from moderate structural drift, indicating that higher-order representations alone are insufficient to guarantee logical mapping across three or more networks.

Further analysis was conducted to determine the sensitivity of the model to the cycle weight hyperparameter, which dictates the influence of the cycle-consistency loss relative to the pairwise alignment loss.

Table 3Hyperparameter Sensitivity Analysis for Cycle Weight

Cycle Weight Value	Precision at 1	Mean Reciprocal Rank	Convergence Epochs
0.0 (No Cycle)	68.2	0.755	120
0.1	73.5	0.810	135
0.5 (Optimal)	78.4	0.854	150
1.0	77.9	0.849	180
2.0	72.1	0.801	210

The sensitivity analysis reveals that the model requires a delicate balance. If the cycle weight is too low, the network ignores the global structural constraints, leading to transitive errors. If the cycle weight is excessively high, the model becomes overly constrained, prioritizing the mathematical closure of the loops over the actual similarity of the node features, which drastically increases the time required for the model to converge and ultimately degrades the matching precision. The optimal balance allows the local pairwise similarities and the global transitive constraints to synergistically guide the node embeddings into a stable, highly accurate latent space.

5. Conclusion and Future Directions

5.1 Summary of Findings and Implications

The comprehensive investigation presented in this paper addresses a fundamental vulnerability in cross-network user identity linkage: the inability of traditional models to capture higher-order relationships and maintain logical consistency across multiple platforms. By introducing a sophisticated framework that synergizes dual hypergraph representations with a cycle-consistency optimization objective, this study redefines the theoretical and practical boundaries of account matching. The detailed methodology demonstrates how multi-way social interactions and shared semantic attributes can be elegantly modeled as hyperedges, preserving the complex contextual fabric of digital human behavior. Furthermore, the exposition of the cycle-consistency mechanism illustrates a powerful method for enforcing global structural coherence, effectively eliminating the cascading transitive errors that severely handicap pairwise matching algorithms. The extensive experimental evaluations conclusively validate the proposed hypotheses. The empirical data confirms that the integration of profile and interaction hypergraphs yields a latent representation space that is significantly more discriminative than those generated by traditional dyadic graph neural networks. Moreover, the ablation studies definitively prove that the cycle-consistency loss is not merely an incremental

ISSN: 2519-9439

enhancement, but a structurally necessary constraint for any system attempting to align three or more distinct information networks. The implications of these findings extend far beyond the specific task of account matching. The principles of dual hypergraph fusion and continuous cycle optimization can be readily adapted to adjacent domains such as cross-lingual knowledge graph alignment, multi-modal recommendation systems, and complex biological network integration.

5.2 Limitations and Avenues for Future Research

While the proposed framework demonstrates state-of-the-art performance, several limitations warrant careful consideration and provide fertile ground for future academic inquiry. The primary limitation of any hypergraph-based neural architecture is computational scalability. As the number of users and the complexity of their interactions grow, the incidence matrix required to represent the hyperedges becomes massive. The two-stage message passing protocol over dense hypergraphs requires substantial memory overhead. Future research must explore advanced sampling techniques, hyperedge sparsification algorithms, and distributed computing architectures to ensure these models can scale to networks encompassing billions of nodes. Additionally, the current framework operates under the assumption that the temporal dynamics of the networks are static during the matching process. Real-world social platforms are highly dynamic, with user attributes and interaction topologies evolving rapidly over time. Extending the cycle-consistent hypergraph model to incorporate temporal dimensions, perhaps through the use of continuous-time dynamic hypergraphs, represents a critical next step. Finally, the profound privacy implications of highly accurate cross-network account matching cannot be ignored. While this technology is invaluable for fraud detection, it simultaneously poses risks to user anonymity. Future iterations of this research should investigate privacy-preserving alignment techniques, such as federated hypergraph learning, which could allow organizations to verify identities without directly sharing or centralizing sensitive raw user data. Exploring the delicate intersection of structural accuracy and differential privacy will define the next era of identity resolution research.

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