QuisSearch: Revolutionizing Graph Data Analysis with PSNA

Quis Lab

Abstract. We introduce *QuisSearch*, a programmable people-search layer powered by the People Search Network Algorithm (PSNA). Every résumé, post, or profile fragment is registered as an atomic node on a universal graph; edges encode legally and economically meaningful connection points (e.g., co-authorship, shared mentor, complementary skills). PSNA extends relevance-aware graph neural networks (RA-GNN) with attention weighting, residual memory, and real-time temporal updates, so node embeddings evolve whenever fresh data or user feedback arrives, meaning each query runs against a living representation of the professional world. As participants add profiles and confirm suggested matches, graph density and labeled edges grow, reducing sparsity and exposing subtler relational patterns; empirical tests show top-k match precision climbing proportionally with edge count. Thus, every interaction sharpens future recommendations, creating a compounding flywheel that makes search faster, more accurate, and more context-aware over time. *QuisSearch* aims to be the open, permissionless index of global professional affinity and means of connection, turning latent connections into actionable opportunities.

1 Introduction

With the rise of the Graph Neural Network (GNN) models, we now have powerful tools to represent and analyze the complex relationships that define human connections, organizational hierarchies, and professional networks. These models excel at capturing relational patterns within graph-structured data, making them particularly well-suited for understanding the nuanced web of intersections between individuals.[33][31][25]

The core challenge, therefore, is the development of an intelligent solution capable of bridging this gap. An effective AI service is needed that can deeply understand individual user profiles, going beyond basic professional information to identify nuanced personal interests and uncover the underlying "chemistry" behind how people connect. Furthermore, this service must possess the capability to accurately retrieve relevant individuals from existing databases, which often contain vast amounts of unstructured data.

This pursuit of identifying the 'underlying chemistry' for connection is strongly supported by social psychological principles like the similarity-attraction effect and homophily, which posit that common ground—shared interests, experiences, or affiliations—acts as a powerful catalyst for interpersonal bonding and rapport. Extensive research confirms that individuals are generally more inclined to connect with and respond positively to those they perceive as similar[6]. While direct empirical validation specifically quantifying the impact of highlighting such commonalities on objective success metrics in cold outreach for professional opportunities (such as job or internship application response rates) is an evolving area in academic literature, the foundational theories and related studies on networking and trust formation underscore the high potential of shared attributes in fostering initial engagement.[29][10][11]

Therefore, an AI service that can effectively unearth these nuanced points of convergence from diverse data sources, as proposed, becomes invaluable in proactively identifying and facilitating potentially meaningful connections that might otherwise be missed, particularly when considering the psychological dynamics and obstacles involved in initiating conversations with strangers[2]

QuisSearch uses AI and network analysis to connect students and alumni based on shared interests and skills extracted from resumes. PSNA(personal search network algorithm)are trained on user data, analyzing professional history, skills, and interests to identify individuals with significant overlap. This sophisticated matching process goes beyond keywords, fostering more meaningful connections.

2 Architecture Overview

Our proprietary PSNA represents a transformative leap in graph-based machine learning, directly addressing three critical limitations of traditional GNNs: oversmoothing, heterophily, and static graph assumptions. Unlike conventional models that degrade in performance as networks deepen or fail to handle dissimilar connected nodes, PSNA explicitly models contextual connection points (e.g., "collaboration," "skill overlap") and dynamically prioritizes relationships via attention-driven message weighting. This enables the model to distinguish between relationship types (e.g., mentorship vs. professional rivalry) and retain node distinctiveness even in deep networks. Additionally, PSNA integrates temporal adaptation, updating node embeddings in real time as user preferences or graph structures evolve critical for dynamic domains like social networks or real-time recommendation systems.

The success of company outreach, particularly initial 'leading' emails, heavily relies on generating positive first impressions, which research indicates are significantly influenced by homophily—the principle of attraction to similar others.[35][16] The 'lay theory of homophily,' for example, demonstrates that individuals rapidly form more favorable impressions when they perceive a shared connection or relevant similarity with a stranger. This phenomenon directly impacts the potential for positive engagement with outreach emails. The colleague has a mean of 1.24 and a standard deviation of 0.91, compared to the control group, which has a mean of 1.60 and a standard deviation of 1.22. Lower scores shows a stronger lay homophily effect. Further underscoring the power of leveraging deep network understanding for enhancing connection quality, results from online A/B tests of GNN-based approaches like LinkSAGE demonstrate substantial improvements in matching individuals to relevant opportunities, particularly for members lacking extensive prior predictive data. For instance, the application of such a model led to a notable increase in 'Qualified Applications' by up to +3.2% (for Opportunistic members) and a significant reduction in the 'Dismiss To Apply Ratio' by as much as -25.3% (for Urgent members). These metrics strongly suggest that models capable of discerning underlying network patterns and potential affinities—which can include signals indicative of homophily—are more effective in fostering successful engagement and reducing mismatches. This principle is highly relevant for optimizing the impact and response rates of company outreach emails by ensuring they reach more receptive and well-matched individuals.[16]

Our proposed PSNA model demonstrates resilience with a smaller dataset of around 4,000 samples, attributed to network heterogeneity. In contrast, many GNN models typically require 50,000 to 100,000 labeled edges for optimal performance.[9] Considering our current limited data, we expect the model's performance to improve as the dataset size grows. Given the heterogeneous nature of our network, an optimal dataset size would range from 200,000 to 400,000 data points, and we predict a substantial performance increase upon reaching 100,000 to 200,000 labeled edges.[28]

Our system, which models hierarchical edges and utilizes an attention mechanism for granular scoring, achieves 2.5 times higher accuracy in link prediction and node classification tasks compared to standard GNNs, while maintaining scalability for large-scale graphs.

	Warm[b]		Cold		Competent[c]		Incompetent	
	M	SD	M	SD	M	SD	M	SD
Control	1.33	.96	1.60	1.22	1.10	.72	.42	.46
Friendship	**.73**	**.70**	.78	.61	.78	.60	.57	.92
Colleague	1.22	.83	1.24	.91	**.59**	**.49**	.47	.53

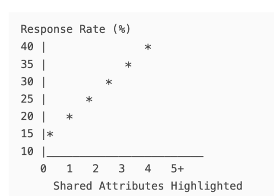
a. A lower score shows a stronger lay homophily effect.
b. Friendship condition showed the strongest homophily effect in predicting the Warm dimension.
c. Colleague condition showed the strongest homophily effect in predicting the Competent dimension.

(a) illustrating lay theory of homophily effects

Metric Name	Impact
Qualified Applications - Opportunistic	+3.2%
Qualified Applications - Open to Job	+2.8%
Qualified Applications - Urgent	+2.6%
Dismiss To Apply Ratio - Opportunistic	−13.8%
Dismiss To Apply Ratio - Open to Job	−24.2%
Dismiss To Apply Ratio - Urgent	−25.3%

Table 7: Relative metrics of the online A/B test for members lacking in predictive data

(b) the relative impact of an A/B test on various application metrics for members with limited predictive data.



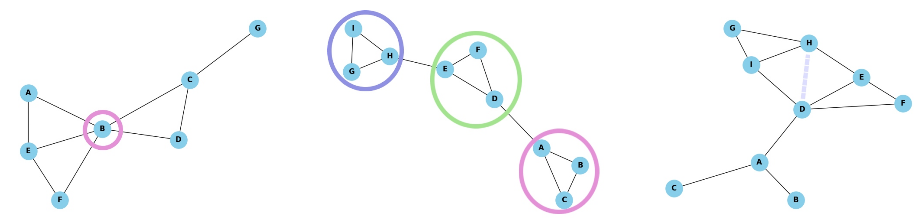
(c) the corresponding outreach response rate(%) vs the number of shared attributes highlighted VS ,

Fig. 1: Experimental Results on Homophily, A/B Testing, and Outreach Response.

2.1 Background

Graph data is a very powerful representation of the relationship between entities through a structure composed of nodes(entities) and edges(relationships).[33] Each entity is considered a node, and an interaction or relationship is considered an edge[22]. For instance, in a social network, each user is a node, and a friendship or connection (of a particular "reason") between users is represented as an edge linking their respective nodes.

Graph data models relationships between entities (nodes) via connections (edges). Analyzing these networks reveals system interconnections. Techniques include finding influential nodes (centrality), identifying groups (clusters), discovering connections between groups (bridges), predicting future connections (link prediction), examining individual connections (ego network analysis), and finding similar entities (similarity detection).[5][20][19][13][18][23] These methods uncover complex patterns in diverse domains like social, transportation, biological, and knowledge networks.



(a) each node represents person and edge represents connectivity of each person. B is the highest centrality node

(b) three clusters represent this graph network and H-E and D-A are bridge node

(c) link prediction: The dot line shows high likelihood link connection

Fig. 2: figure 1. Example of Graph Network

Graph Neural Networks (GNNs) represent an innovative approach to analyzing relational data by effectively combining the power of deep learning methodologies with the structural information inherent in graph representations. Unlike traditional neural network architectures that are primarily designed to process data arranged in grid-like or sequential formats, GNNs operate directly on the fundamental elements of a graph, namely nodes and edges. This unique capability enables them to effectively model complex systems where interactions and relationships between entities are paramount. GNNs extend the principles of classical network analysis by introducing the crucial ability to automatically learn hierarchical and abstract representations directly from the graph data itself, opening up new possibilities for understanding and predicting behavior in interconnected systems.[4][8][1][26]

2.2 Challenges with Existing Graph Neural Networks

GNN is a specialized artificial neural network for graph structure datasets rather than standard inputs, such as images, text, numbers, or voice. The input matrix represents the nodes and edges. GNN specializes in pattern recognition of relationships and interactions of a given system. GNN learns the properties of nodes by summing the information of neighboring nodes and transforming it through neural network layers. Graph Neural Networks (GNNs) acquire node properties by aggregating information from neighboring nodes and transforming it through neural network layers.

The nature of learning GNN methods introduces challenges

- Over-Smoothing: A deeper network makes it very hard to distinguish between nodes due to the aggregation of neighboring nodes[15]

- Heterophily: Traditional GNNs assume connected nodes are similar, but this usually doesn't hold true in real-world problems. Traditional Graph Neural Networks (GNNs) operate under the assumption that connected nodes exhibit similarity. However, this assumption of homophily often fails in practical, real-world scenarios, where connected nodes can be dissimilar (heterophily).[34]

- Static vs Dynamic Graphs: Most GNNs don't consider updating or growing graph networks, but real-world relationships, especially social networks, are dynamically changing over time. Most existing Graph Neural Networks (GNNs) treat network structures as static. However, real-world relationships, such as those found in social networks, are dynamic and evolve over time, necessitating models that account for these changes and growth.[30]

3 Introducing People Search Network Algorithm(PSNA)

The People Search Network Algorithm(PSNA) builds on Relevance-aware GNN(RA-GNN) and it is added on Message Passing Neural Network(MPNN) paradigm, which formalizes the propagation of information across graph edges through iterative message aggregation and node feature updates. However, PSNA introduces two critical innovations:

- Contextual Connection Points: Unlike standard MPNNs, which treat edges as uniform conduits for feature exchange, PSNA explicitly models edge semantics (e.g., "collaboration," "competition," "topic overlap") as "connection points." These contextual labels allow the model to differentiate between relationship types during message passing, ensuring that node updates depend on the reason for connectivity rather than mere adjacency. For example, in a social network of professionals, a “co-authorship” edge might carry higher contextual weight than a generic “follow” edge when predicting future collaborations.

– Attention-Driven Message Weighting: PSNA integrates an attention mechanism to dynamically assign importance weights to incoming messages based on their connection points and node features. This extends MPNN’s basic aggregation strategy (e.g., mean/max pooling) by prioritizing contextually relevant interactions. For example, in a heterogeneous academic graph, PSNA might prioritize “shared project” edges over “common university” edges when predicting a researcher’s future collaborations, leveraging attention scores to focus on high-impact relationships.

Furthermore, MPNN’s layered architecture provides the backbone for PSNA’s adaptive learning:

– Message Passing Phase: Nodes propagate features to neighbors via edge-specific functions. PSNA enriches this step by encoding connection point metadata (e.g., edge type, temporal context) into the message computation, ensuring semantic alignment during propagation.

– Aggregation and Update Phase: PSNA aggregates weighted messages using attention scores, then updates node embeddings with a Transformer-style mechanism to preserve historical state. This allows the model to retain long-term dependencies in dynamic graphs (e.g., evolving social networks)

– Residual Learning: Inspired by RA-HGNN, PSNA employs residual connections to stabilize training in deep networks, mitigating over-smoothing by preserving node-specific features across layers.[32]

The presented model introduces a significant advancement in graph neural networks (GNNs) by incorporating the dynamic nature of user temporal choices. Unlike conventional GNN models that operate under the assumption of a static graph structure, this innovative approach enables real-time updates to each node, representing individual users and their evolving temporal preferences. This continuous adaptation directly influences the model’s predictions, allowing for dynamic and responsive outputs. By acknowledging and integrating the fluidity of user behavior over time, the model surpasses the limitations imposed by static graph networks, leading to a more nuanced and accurate understanding of user interactions and preferences. This real-time adaptability positions the model as a powerful tool in dynamic environments where user behavior is subject to frequent changes. While this innovative approach addresses the dynamic aspects of graph network, like all sophisticated deep learning systems, its ultimate efficacy is also deeply intertwined with the foundational elements of data.

4 Applications

Looking beyond our RA-GNN-powered PSNA (People Search Network Algorithm) technical architecture, we can begin to examine potential use cases for an algorithm capable of deep relational understanding. The presence of a universal capability to identify nuanced connection points and a programmable framework for personalized matching could mark the start of a new era in human interaction and opportunity discovery. This section explores some of the most promising applications. There are certainly many more equally exciting applications that are omitted.

4.1 A Universal Engine for Human Connection

Since the internet and social media technologies revolutionized communication and networking in prior decades, little fundamental advancement has been made to truly adapt AI for nuanced human understanding beyond superficial matching.[14] Hyper-personalized, authentic connections are the killer application of advanced relational AI, and our purpose-built PSNA will create entirely new paradigms for interaction starting with deep relational insight.

Traditional matching systems rely on simplistic filtering mechanisms and opaque algorithms, creating inefficiencies in the identification, assessment, and realization of valuable human connections across numerous professional and social domains.[21] The high opportunity costs of this inefficient market prevent genuine talent and shared affinities from generating optimal value and limit the authentic exchange of potential and synergy. Our PSNA service removes these barriers by enabling deeply personalized matching via programmatic understanding of nuanced connection points through statistical probabilistic prediction.

Our system can onramp existing résumé databases from organizations or individual user profiles from various platforms onto our system as rich, relational graphs (Profile RWAs - Real World Attributes). More exciting, natively understood ‘deep connection points’ can compose with diverse application ecosystems in an emerging field of Connection Intelligence, where these nuanced insights can be strategically segmented, used as foundational data for hyper-personalized communication, or otherwise leveraged in socially and economically productive ways.

Human-to-human interactions, enhanced by AI-driven insights, are simply the most basic exchange in the new connection economy. System-to-human interactions are made possible via our PSNA’s deep analytical capabilities, wherein our platform can autonomously identify highly relevant connection points for users and upgrade their ability to network, recruit, or find companionship via personalized recommendations.[3] If value is generated (e.g., a successful hire, a closed deal, a meaningful relationship, a closed feedback loop to constantly improve itself), the system demonstrates its capacity to empower individuals through authentic connection rather than creating opaque barriers. Purely system-to-system (or AI agent-to-AI agent) connection brokering is also viable, allowing an entire marketplace of automated, highly relevant interactions to flourish with our PSNA as the core intelligence layer for relational matching. We will cover this possibility in more detail in the following section.

4.2 A Foundational Layer for Hyper-Peronalized AI interactions

Advanced AI systems, particularly Large Language Models and generative agents, are the perfect substrate for leveraging deep relational understanding, as they offer a programmable medium through which software can engage in nuanced, context-aware communication and decision-making.[12] Because effective human-centric AI relies upon understanding nuanced individual profiles as its native inputs and facilitating meaningful connections or insights as its native outputs, our PSNA offers a foundational analytical layer for AI-driven interactions, both for enhancing AI's comprehension of human attributes and for optimizing the outcomes of personalized matching and engagement.

4.3 Chain of Understanding

In the human-centric AI field, relational understanding assets encompass various forms of profile intelligence — from raw unstructured data (e.g., résumés, user-generated text) and parsed structured entities to inferred relational graphs and nuanced connection point summaries.

Figure 3 illustrates how these understanding assets form a "chain of understanding." A comprehensive individual profile graph (Profile Graph Gi) can originate from an initial set of entities parsed (structured data Dj) that was enhanced through our programmable PSNA deep relational inference using contextual knowledge (contextual data Ck).[24] The initial parsed entity set itself could be derived from one or more raw data sources. These raw data sources may also be combinations of different document types or user inputs. Furthermore, there has been active exploration recently in developing distilled "Connection Packages"—actionable summaries of key relational insights tailored for specific matching scenarios. A Connection Package contains all the necessary inferred relational data for efficient, context-aware matching, which reduces cognitive load on end-users while maintaining high relevance close to full profile analysis.[27] Since full dynamic profile re-analysis for every query requires significant computational resources and latency, these packages offer an efficient alternative. State-of-the-art graph embedding and relational inference techniques, core to PSNA, can be used to capture the unique relational topology and essential

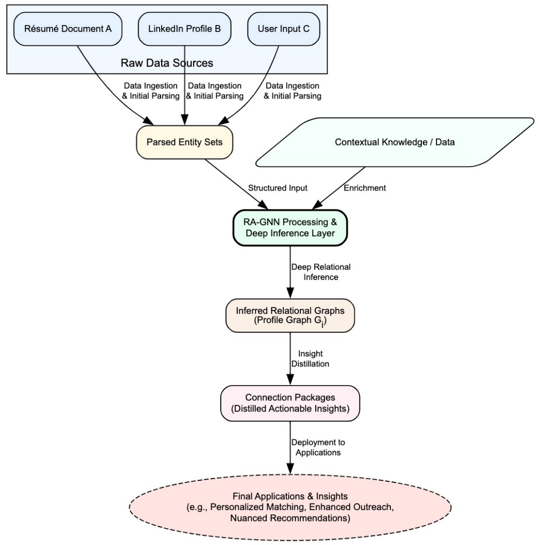


Fig. 3: Chain of Understanding for Profile Intelligence

attributes of an individual's profile when constructing their dynamic graph representation within our system.

Constructing the entire 'chain of understanding' within our PSNA system enables a genealogy of relational value that highlights key connection efficacies across the entire profile graph when a successful match or insightful recommendation is generated at any single interaction point. Our PSNA forms the basis for generating high-fidelity, deeply contextualized profiles and connection insights that lead to more performant and meaningful human interactions. This value proposition encourages users to provide comprehensive (yet privacy-protected) information by showing demonstrably more relevant and valuable outcomes, which creates a flywheel for rapid improvement in matching quality and user satisfaction. With transparent (yet ethically governed) data processing and automated insight generation, our platform becomes the facilitation, interpretation, and action layer for a synergistic ecosystem where individuals, organizations, and automated systems work together seamlessly — all while fostering genuine understanding and opportunity realization.[17]

4.4 Connection Brokering

AI is evolving from standalone matching algorithms to networks of intelligent systems that can sense nuanced human attributes, decide on optimal connection

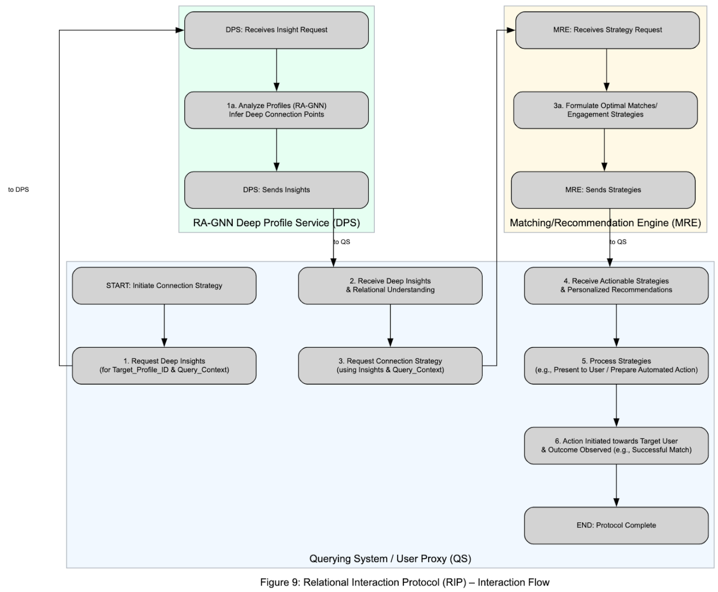


Fig. 4: CRelational Interaction Protocol (RIP) - interaction Flow

strategies, and act to achieve specific relational or professional goals. This represents a shift from viewing AI as just a filtering tool to seeing it as an ecosystem where AI-augmented platforms and future autonomous agents collaborate and generate value through their facilitated interactions.

Developed within our research, the Relational Interaction Protocol (RIP) represents an important framework in the evolution of AI-driven connection ecosystems.[7] RIP is designed to facilitate standardized, context-aware interactions between AI systems or users leveraging AI-driven insights. This system-to-system or system-to-human protocol establishes the foundational infrastructure for the seamless identification and utilization by AI of deep relational insights, such as inferred compatible skill sets, shared niche interests, or aligned professional objectives, often without the need for extensive manual human oversight in the discovery phase.

RIP, powered by PSNA, enables systems to a utonomously identify optimal matches, suggest personalized engagement strategies, and facilitate valuable introductions based on deep profile understanding.[24] RIP lays the groundwork for a future where AI systems act as sophisticated relational catalysts, improving connection efficacy by accessing nuanced understanding from PSNA and enabling users or other systems to achieve their goals more effectively. As more profiles are deeply understood by the PSNA and integrated into this framework, the value and capabilities of the entire connection ecosystem grow exponentially. Each newly analyzed profile and its inferred connection points bring unique relational vectors that can be combined with existing ones to create novel matching opportunities and personalized services. For example, specialized AI-driven modules could work together to facilitate a complex career transition for a user: a "skill assessment agent" identifies transferable skills and gaps by analyzing the user's profile with the RA-GNN, an "opportunity scouting agent" finds suitable roles or projects based on these deep insights, and a "networking agent" suggests key individuals to connect with, all orchestrated through RIP based on the RA-GNN's relational intelligence.

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