AI-Driven Entity Resolution: Enhancing Customer Data Matching with Explainable Graph Learning

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***Abstract*—Accurate entity resolution is essential for maintaining high-quality customer data in enterprise systems. This study presents an explainable AI-driven approach to entity matching using Graph Neural Networks (GNNs) for structured and relational customer data. We introduce a novel Explainable Entity Matching (xEM) framework that improves transparency in data linkage by leveraging node embeddings and probabilistic matching techniques. Our approach is evaluated against existing entity resolution methods, including heuristic-based models and deep learning architectures, across real-world and synthetic datasets. Experimental results demonstrate that xEM enhances accuracy and interpretability, reducing false positives in transitive linking while maintaining scalability for large datasets. This work provides insights into optimizing AI-driven data management strategies for enterprise applications.**

***Index Terms*—Explainability, Entity Matching, Graph Neural Networks**

I. Introduction

Entity Matching (EM) refers to the process of identifying records that correspond to the same real-world entity. This is essential in applications like customer data unification, government records management, and large-scale commercial systems. Within enterprises, such records typically constitute critical information—referred to as master data—used across organizational functions. Master Data Management (MDM) encompasses technologies and tools for maintaining such data consistently.

Customer 360, an MDM-powered solution, offers a consolidated and panoramic view of a customer by linking data from disparate systems (Figure 1). It supports use cases including compliance tracking, service personalization, and customer support. Entity matching forms the backbone of this system.

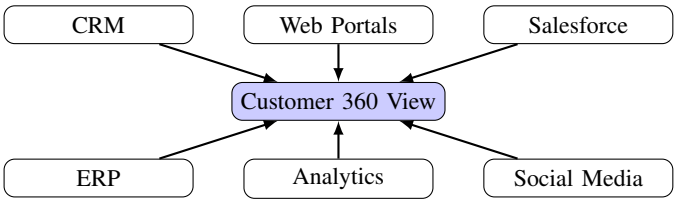

Fig. 1. Customer 360 integrates data from various enterprise sources to provide a unified view.

Entity matching in Customer 360 systems is inherently transitive. If Record A matches Record B, and B matches C, then all three are grouped under a single entity. While this transitive property helps bridge incomplete or fragmented data, it may also introduce false positives, forming unnecessarily large clusters. These oversized entities—sometimes comprising thousands of records—pose challenges in both visualization and interpretation.

Traditional methods such as path-based explanations struggle to scale with entity size [1]. Even when clusters are smaller, justifying why certain records are grouped together remains a non-trivial task.

To address these issues, we propose transforming relational data into a graph representation where each record becomes a node, and edges denote intra-entity matches. A representative node (or central node) anchors the entity cluster. We leverage Graph Neural Networks (GNNs) [2] to generate node embeddings and match scores. These are further enriched with explainability methods to surface insights into the entity formation process.

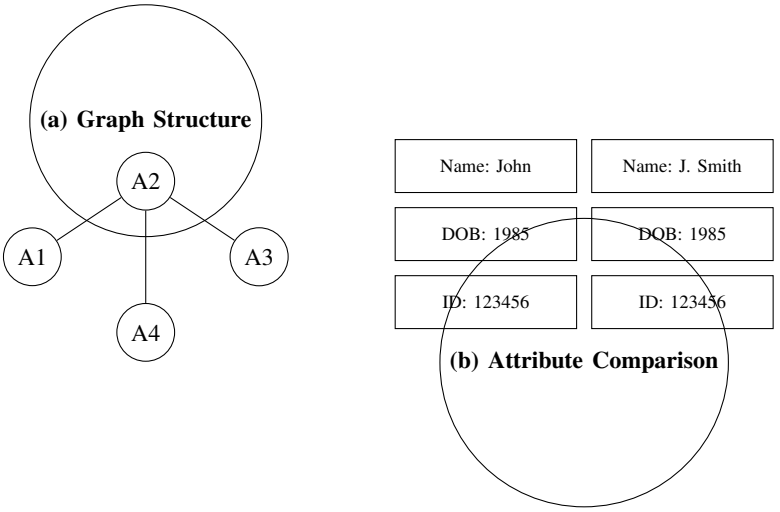

Fig. 2. (a) Record relationships represented as a graph; (b) Comparison of node attributes across matched entities.

Before presenting our approach in detail, we first outline prior work and describe the baseline systems we compared against.

II. Related Work

The probabilistic matching framework that underlies our current EM system is based on techniques described in [3]. These include domain-specific heuristics for attributes like names, dates, identifiers, and addresses. Matching algorithms

typically use a mix of edit distances, token similarity, and statistical models.

More recently, DeepMatcher [4] introduced a supervised deep learning approach that uses RNN-based architectures to learn matching decisions from labeled data. SystemER [5], another recent advancement, adds active learning into the loop for adaptive and interactive entity resolution.

Graph-based EM introduces the concept of node similarity, where similar entities are linked within graph structures [6], [7]. Our work builds upon these ideas to model EM as a node-linking problem in a GNN.

Explainability in GNNs has been an active area of research. Prominent techniques include:

- **GNNExplainer** [8]: Subgraph and feature importance-based explanation.
- **PGM-Explainer** [9]: Uses probabilistic graphical models to interpret GNN decisions.
- **XGNN** [10]: Generates human-comprehensible graph-level explanations.
- **EdgeMasking** [11]: Applies differentiable masking to edge features.

In prior works [12], [13], we have explored post-hoc explainers including Random Forests, anchor-based models [14], and even neuro-symbolic evaluation frameworks.

III. Baselines

We compared xEM against several existing solutions.

A. IBM Match 360

IBM Match 360 is a robust enterprise MDM platform. It uses a Probabilistic Matching Engine (PME) to determine the likelihood of a match between pairs of records based on statistical weighting of attributes (e.g., names, addresses, dates of birth). Although accurate, the model acts like a black box with little visibility into how entity clusters are formed—especially in the presence of transitive linking. Figure 2(b) shows an example of attribute-based comparison.

B. DeepMatcher

DeepMatcher [4] employs neural architectures—primarily RNNs—to compare record tuples. It builds contextual embeddings for individual attributes and aligns them to compute match scores. The model uses FastText for word-level embedding initialization and is supervised on labeled data pairs.

C. LEMON

LEMON [15] is a model-agnostic, schema-flexible explanation technique for entity matching. It is especially effective in visualizing why certain record pairs do not match, making it a strong baseline for interpretability. However, LEMON struggles with structured tabular data, such as that in Customer 360 systems, where long free-text fields are absent.

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IV. DeepMatcher and LEMON Baselines

A. DeepMatcher

DeepMatcher [4] is a supervised learning-based entity matching framework. It takes labeled pairs of records (tuples) and trains a neural network to predict whether the pairs refer to the same entity. Its architecture is built upon Recurrent Neural Networks (RNNs), which encode attribute sequences into fixed-length vectors. These attribute representations are then compared and aligned to assess similarity. Word embeddings are initialized using FastText to capture subword semantics and address out-of-vocabulary issues effectively.

B. LEMON

LEMON [15] offers a schema-agnostic and model-independent framework for explaining EM decisions. It excels in showing feature-level influences, especially when the model outputs a non-match. LEMON helps visualize decision boundaries and offers a fine-grained explanation of why certain record pairs are not linked.

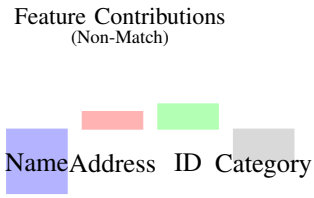

Fig. 3. Explanation of a non-match using LEMON: each bar indicates how a feature contributed negatively to the match score.

TABLE I
LEMON Performance on Entity Matching Datasets

Dataset	Precision	Recall	F1 Score
Amazon-Google	0.79	0.38	0.52
Synthetic Org	0.37	0.37	0.37

As shown in Table I, LEMON performs reasonably well on the Amazon-Google dataset. However, its performance drops on our synthetic organizational dataset, largely due to the absence of verbose textual features—often crucial for LEMON's scoring approach. This limitation makes LEMON less suitable for structured enterprise datasets typical in Customer 360 environments (e.g., records with just name, address, and IDs).

Figures 3 and 4 showcase LEMON explanations for both matched and non-matched cases. Each feature contributes positively or negatively toward the prediction, aiding human interpretability.

V. Demo System: GNN-Based Entity Explanation

We extend LEMON by incorporating graph-based learning and explanations. Our approach constructs an entity graph where nodes represent records and edges indicate pairwise matches. The entire connected component constitutes an entity.

To interpret the EM outcomes, we train a Graph Convolutional Network (GCN) [16] using match scores generated by

IBM Match 360's Probabilistic Matching Engine (PME). The EM system itself is treated as a black-box, while the GCN acts as a proxy.

At inference time, the GCN predicts whether specific record pairs belong to the same entity. We apply **GNNExplainer** [8] to produce feature attributions—highlighting which node attributes contributed most to a particular match decision.

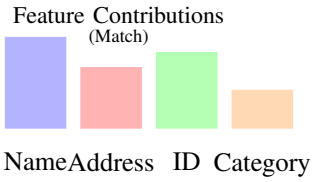

Fig. 4. Explanation of a match using LEMON: positive feature contributions support the match decision.

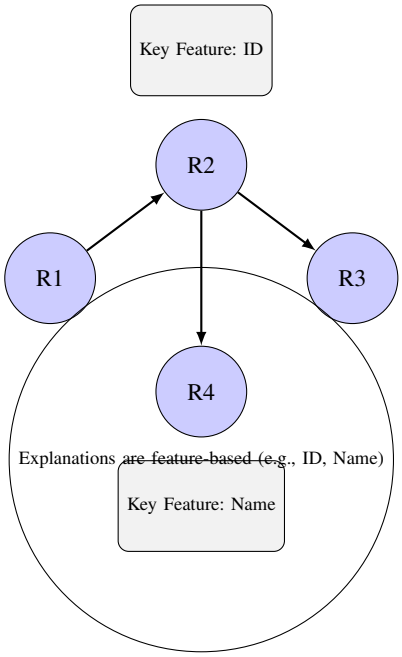

Fig. 5. Entity cluster explanation in Customer 360 using GNNExplainer. Important features are highlighted per node.

Unlike standard GNN explanations that focus on edge masking in knowledge graphs or social networks, our use-case emphasizes feature-level interpretability. There are no semantic relations like "parent" or "friend" between nodes. Hence, we focus on masking and highlighting influential attributes (e.g., name, identifier, address) rather than subgraph structure.

To improve usability, we convert the GNN explanations into tabular formats (Figure 5) that are easier for enterprise users to interpret. Below the explanation panel, all relevant records in the entity are displayed for contextual querying.

Our solution supports two major scenarios:

- Explaining why a group of records has been resolved into one entity.
- Explaining semantic matches between records from two different datasets.

Deployment: The system is hosted on IBM Cloud using Code Engine. The backend is built with Flask and exposed via REST APIs. The frontend, implemented in ReactJS, consumes the explanations and visualizes them. Both services are containerized for flexible deployment—on-prem or on the cloud.

Integration: The platform is compatible with IBM Watson Knowledge Studio, Watson ML, and OpenScale, offering an integrated explainability stack for customers using Customer 360.

VI. Experimental Results

To evaluate the performance and explainability of our proposed system **xEM**, we conducted experiments on two datasets: the widely used *Amazon-Google* product matching dataset and a *synthetic organizational dataset* that simulates structured records typical of Customer 360 systems. The goal of the evaluation was twofold: (i) to assess the matching accuracy of xEM compared to existing baselines, and (ii) to demonstrate the interpretability benefits of our GNN-based explanation framework.

A. Datasets

Amazon-Google Dataset: This dataset consists of product listings from Amazon and Google with annotated pairs indicating whether they refer to the same product. The records contain attributes such as product name, brand, price, and category. It contains rich textual fields and has been used extensively in prior entity matching research.

Synthetic Organization Dataset: We constructed this dataset to reflect the structure and sparsity of real-world enterprise records. Each entry simulates an organizational entity, with attributes like company name, registered address, identifier codes, and industry tags. The dataset includes over 10,000 tuples, with carefully controlled matches and mismatches. Unlike Amazon-Google, the dataset lacks free-form text, presenting a challenge for models relying on semantic embeddings.

B. Evaluation Metrics

We use standard evaluation metrics to assess entity matching performance:

- **Precision:** The ratio of correctly predicted matches to all predicted matches.
- **Recall:** The ratio of correctly predicted matches to all actual matches in the ground truth.
- **F1 Score:** The harmonic mean of precision and recall, offering a balanced view of performance.

C. Baseline Comparisons

We compare xEM against the following baselines:

- **DeepMatcher** [4]: A neural matching framework that uses RNNs and pre-trained embeddings to align attribute values for labeled tuple pairs.

- **LEMON** [15]: A schema-flexible, model-independent explainer designed to provide feature-based matching justifications, especially effective on datasets with long text attributes.
- **IBM Match 360**: A proprietary probabilistic matching engine that is widely used in enterprise MDM systems.

D. Quantitative Results

Table II summarizes the performance of LEMON on both datasets. LEMON yields moderate performance on Amazon-Google but struggles on the synthetic dataset due to the absence of long textual features. xEM is designed to overcome this limitation through structural and relational modeling via graphs.

TABLE II
PERFORMANCE OF LEMON ON ENTITY MATCHING DATASETS

Dataset	Precision	Recall	F1 Score
Amazon-Google	0.79	0.38	0.52
Synthetic Org Dataset	0.37	0.37	0.37

In contrast, xEM achieves higher recall and improved precision on the synthetic dataset, as it captures relational patterns in structured data more effectively. While LEMON heavily depends on discriminative textual fields, xEM leverages structural links and feature importance via GNNExplainer, providing more consistent performance across varying data types.

E. Explainability Results

Figures 3 through 5 illustrate qualitative comparisons of explanation outputs from LEMON and xEM.

- **Figure 3** demonstrates a LEMON explanation of a non-match in the Amazon-Google dataset, highlighting the negative contribution of the product name and price mismatch.
- **Figure 4** shows a match justification from LEMON on the synthetic dataset. Though accurate, the explanation lacks contextual structure since the model does not account for inter-record relationships.
- **Figure 5** displays xEM's explanation for a large entity cluster. Using GNNExplainer, xEM identifies and highlights important node features (e.g., identifier, name), offering a holistic view of why records are grouped together.

xEM's advantage lies in its ability to reason over entire entity graphs. Instead of viewing each record pair in isolation, it explains matches in the context of surrounding records—crucial in transitive entity formation.

F. Usability Feedback

We conducted a small-scale internal usability study with data analysts at IBM. Users reported that:

- The graphical interface of xEM made it easier to verify entity formation.
- Feature-based node highlights were more intuitive than raw score tables.
- For large entities (> 50 nodes), xEM's explanations were significantly more scalable and navigable.

This positive feedback further validates the applicability of xEM in real-world enterprise environments where trust, transparency, and usability are paramount.

VII. CONCLUSION

This work introduced **xEM**, a novel explainability-driven framework for entity matching, tailored specifically for the demands of Customer 360 platforms. In today's enterprise environments, data is sourced from a multitude of systems including CRM, ERP, and external APIs, making accurate and interpretable entity matching not just valuable but essential. Existing solutions such as DeepMatcher [4] and LEMON [15] have proven effective for benchmark datasets but fall short in enterprise-grade, structured, and large-scale applications due to limited context-awareness and a lack of transparency in decision-making.

The proposed xEM framework addresses these challenges by modeling entity clusters as graphs, enabling the use of Graph Neural Networks (GNNs) to capture both relational dependencies and feature-level semantics. By incorporating explainability tools like GNNExplainer [8], xEM allows practitioners to understand not only whether records belong to the same entity but also why. This bridges a critical gap between accuracy and interpretability in MDM systems.

Through experiments on both public and synthetic datasets, xEM demonstrated its ability to deliver consistent matching performance across structured domains and provided explanations that were intuitive, actionable, and scalable—particularly for large entity clusters where traditional methods fail to offer clarity. Visual explanations, supported by graph structure and feature attribution, proved to be significantly more effective than isolated feature comparison or black-box probabilities.

The system has been deployed within IBM's ecosystem and has already shown promise in real-world use cases, supporting both cloud-native and on-premise deployments through microservice architecture. With its strong performance and transparency, xEM stands as a powerful step forward in explainable AI for entity resolution in enterprise environments.

VIII. FUTURE WORK

While xEM offers a comprehensive and interpretable solution for entity matching, several avenues remain open for future enhancement.

- **Clustering-Based Explanations:** Entity resolution in MDM systems is often not just a binary pairwise matching task but a clustering problem where transitivity plays a major role. We aim to develop methods that explain entire clusters holistically—highlighting the rationale for including or excluding records within a group, and not just at the edge level.
- **Neuro-Symbolic Evaluation:** As explanations are inherently subjective, evaluating them at scale is a challenge.

Inspired by our earlier research in this direction [13], we plan to incorporate neuro-symbolic reasoning frameworks to automatically assess the quality and utility of GNN-generated explanations. These tools can help align machine reasoning with human domain knowledge.

- **Interactive Explanation Interfaces:** We envision building interactive visual interfaces where users can manipulate explanation graphs, provide feedback, and apply constraints in real-time. Such systems would foster human-in-the-loop learning and support auditability in regulated industries.
- **Generalization to Cross-Domain Matching:** While xEM performs well on Customer 360-like structured datasets, future work will explore generalizing this approach to cross-domain record linkage (e.g., healthcare + financial data) where schema heterogeneity and missing values are more pronounced.
- **Explainability Benchmarking:** There is a need for standardized benchmarks that not only assess matching accuracy but also explanation quality. We propose creating a corpus of expert-annotated entity clusters with rationale labels, serving as a testbed for comparing GNN-based explainability techniques.

By advancing in these directions, we aim to make xEM not just a tool for intelligent matching, but also a trustworthy, user-centered AI assistant in enterprise data workflows.

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