

iCoLoc: An Interactive System for Spatial Co-location Pattern Mining via LLM-Guided Intent and Contrastive Preference Learning

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Abstract. Traditional interactive spatial co-location pattern mining (SCPM) systems require users to possess domain expertise and manually select relevant patterns at the initial stage. Moreover, they rely on fixed parameter settings, often generating numerous irrelevant patterns, and cannot adapt to dynamically changing user requirements. This demonstration presents iCoLoc, an end-to-end workbench for non-expert analysts whose core mechanism is contrastive preference learning with re-ranking-without-re-mining. On a Beijing POI benchmark (4,592 instances, 16 categories), users issue natural-language queries; a local LLM cold-start a user vector from fuzzy intent, a PI-based miner generates candidates once, and binary feedback iteratively refines the user representation to re-rank the top-20 results without regenerating the candidate set. In a 10-round simulated interaction study, we compare three ranking variants on the same data and mining settings; the contrastive configuration reaches 0.98 ranking accuracy after feedback accumulates compared with 0.80 (baseline) and 0.86 (feature-weighted) at the final round. This demo shows how non-experts can mine spatial patterns via natural language, without domain expertise.

Keywords: SCPM, spatial data mining, LLMs, contrastive preference learning, intent understanding

1 Introduction

Traditional SCPM [1] focuses on mining frequently co-occurring spatial features (e.g., nearby POIs) but ignores user behavior and preferences. Subsequent studies incorporate high-utility mining [2], graph-based modeling [3], interactive systems [4], and preference-aware filtering [5] to involve users. However, they still rely on fixed parameters and domain expertise, adapt poorly to evolving preferences, and rarely link fuzzy intent or binary feedback to ranking in one session—limiting use by non-expert analysts (e.g., retail screening, urban POI review). To address these gaps, this demonstration presents iCoLoc, whose central mechanism is contrastive preference learning with re-ranking-without-re-mining: a local LLM cold-starts a user vector from fuzzy intent; a PI-based

miner generates candidates once; binary feedback then iteratively refines the user vector to re-rank the top-20 results without regenerating the candidate set. Rather than returning a static set of patterns, iCoLoc iteratively engages with the user, employing contrastive learning to capture implicit, evolving preferences and LLMs to handle cold-start semantic parsing and initialize the user vector. The demo targets non-experts who explore patterns via language and feedback, without hand-tuning mining parameters.

2 System Overview

iCoLoc is an interactive SCPM system that supports fuzzy natural-language queries as well as human-in-the-loop refinement. The overall system workflow is illustrated in Fig. 1. At runtime, the system loads the POI dataset and model configurations, and then processes user requests through an intent-driven pipeline: (i) LLMs interpret natural language to extract user preferences, which are then used to initialize potentially interesting patterns and a corresponding user vector, (ii) Using a Join-Base algorithm, frequent candidate itemsets are derived, sorted by cosine similarity to the user vector, and the top-20 patterns are offered for user selection, (iii) Users select patterns as either interesting or uninteresting, and the system uses the selected patterns to train a contrastive learning model, thereby refining the user vector to better align with the user’s preferences.

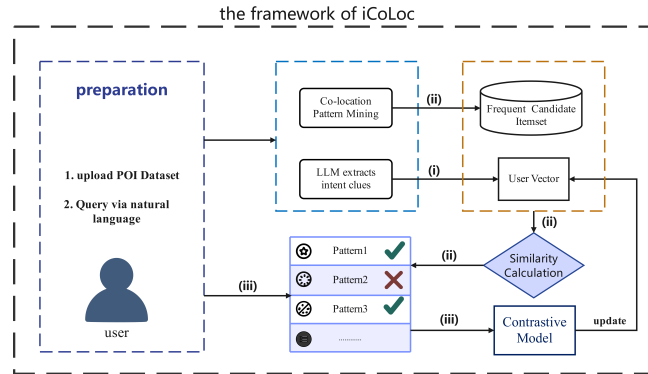


Fig. 1. architecture of the iCoLoc system

3 DEMONSTRATION

The demonstration uses a Beijing POI dataset derived from open geographic features and converted to a uniform JSON schema: 4,592 instances and 16 categories (e.g., Restaurant, Cafe, Supermarket, Cinema, Hospital), each record containing id, type, and planar coordinates (x, y) in a local projected space. The same schema is used for the preloaded demo and for user uploads via the Web UI. For more demonstrations, please refer to <https://youtu.be/19WxxZbObKc>.

3.1 Analysis of iCoLoc system

Fig. 2.(a) shows the complete query process from fuzzy query to result generation. Fig. 2.(b) visualizes dataset spatial distribution to reveal geographic data layout and feature spatial correlations. Fig. 2.(c) illustrates the parameter input and dataset import interface.

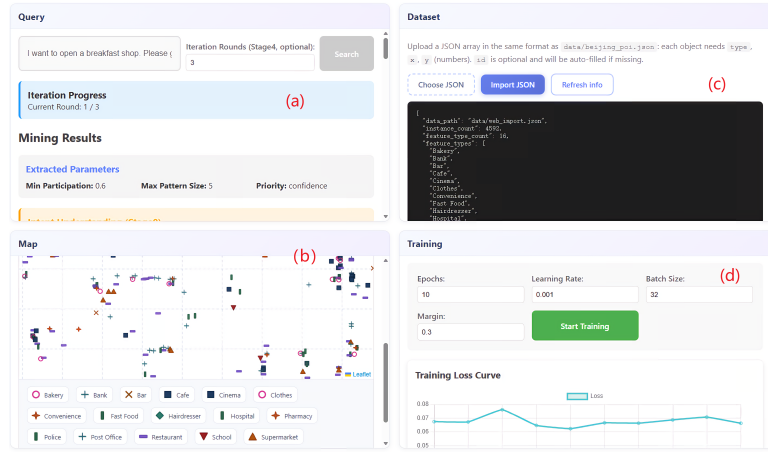


Fig. 2. iCoLoc system overview

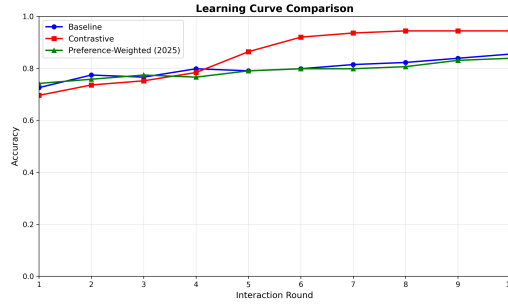


Fig. 3. efficiency evaluation result

We evaluated iCoLoc against conventional methods in terms of accuracy, comparing it with a baseline approach (iCoLoc without contrastive learning part) and the personalized region-of-interest recommendation method proposed in 2025 [6]. Evaluation uses a synthetic user who prefers patterns containing Restaurant, where the ground truth labels a pattern as relevant if and only if it includes a liked POI type and excludes all disliked types. After a single PI mining pass (participation index 0.6, maximum pattern size 5), one fixed query drives 10 feedback rounds, with five patterns labeled per round. Each round updates the ranker, and accuracy is computed as the fraction of all mined patterns

correctly classified at a decision threshold of 0.7. As shown in the 10-round interaction curves in Fig. 3, the contrastive approach exhibits clear “feedback-driven iterative improvement”: its metrics start low but, as contrastive learning time accumulates, the model progressively learns more stable user preference boundaries, leading to rapid accuracy gains in later rounds. In contrast, the baseline lacks a learnable projection layer. The preference-weighted method enhances ranking via explicit preference rules, yet its ability to model complex semantic preferences remains inferior to the contrastive preference approach.

4 Conclusion

In this work, we present iCoLoc, an interactive co-location mining system designed for spatial co-location pattern mining. It integrates LLMs with contrastive preference learning to effectively capture user preferences and identify relevant spatial patterns. Unlike traditional systems that require prior user profiles or structured queries, iCoLoc allows non-expert users to express their intent through fuzzy natural-language inputs. Users can also provide simple like/dislike feedback. The system initializes user preference vectors via LLM-based intent parsing and iteratively refines them through contrastive learning, continuously improving the quality of subsequent pattern ranking. Experimental results demonstrate that this human-in-the-loop design achieves superior performance in preference-aware pattern filtering, validating its practical utility in real-world spatial data mining tasks.

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