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Trust-Aware Social Recommendation with Cosine Similarity, Temporal Decay, and Location Proximity

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Abstract: Social recommendation systems leverage interpersonal trust to improve prediction accuracy beyond conventional collaborative filtering. However, most existing trust-aware models treat all interactions equally, ignoring the fine-grained similarity between users' preference profiles, the temporal dynamics of evolving tastes, and the geographic context of real-world ordering behaviour. In this paper we propose a Trust-Aware Social Recommendation framework that integrates four complementary signals: (i) co-visitation frequency as a structural trust proxy, (ii) cosine similarity computed on user–item interaction vectors for preference alignment, (iii) an exponential temporal decay function that emphasises recent behaviour, and (iv) geographic location proximity that captures the tendency of co-located users to share restaurant preferences. We formulate a composite trust score $T(u, v) = \alpha C(u, v) + \beta cos(\mathbf{m}_u, \mathbf{m}_v) + \gamma prox(u, v)$ and introduce a scalable incremental graph-patching evaluation protocol that reduces the per-user cost of Leave-One-Out evaluation from $O(U^2)$ to $O(U_r)$, where $U_r \ll U$. Ablation experiments on a location-biased synthetic restaurant-ordering dataset of 7.5 million orders across 300,000 users and 5,000 restaurants demonstrate consistent improvements: the best trust-based model (Trust + Cosine) achieves a 135% relative gain in NDCG@5 over the popularity baseline when evaluated on a stratified sample of 5,000 users. Additional experiments on hyperparameter sensitivity, cold-start users (3–5 orders), and cross-zone user mobility further validate the model's scalability and practical applicability to large-scale settings.

Index Terms: Social recommendation, trust-aware systems, cosine similarity, temporal decay, location proximity, graph-based recommendation, scalability, ablation study.

I. INTRODUCTION

Recommendation systems are a cornerstone of modern information retrieval, powering personalised content delivery in e-commerce, streaming, and food-delivery platforms [1, 2]. Collaborative filtering (CF) [3] remains the dominant paradigm, yet it suffers from cold-start and data-sparsity problems that degrade performance when explicit feedback is scarce.

Social recommendation mitigates these limitations by incorporating trust relationships derived from social networks or implicit behavioural similarity [6,7]. The intuition is straightforward: users who share social ties or exhibit similar consumption patterns are likely to agree on future preferences. Trust-aware models have been shown to reduce prediction error and improve ranking quality in multiple domains [8, 9].

Despite this progress, three important dimensions remain under-explored in integrated form:

1) Preference similarity. Many trust models rely solely on structural overlap (e.g., common item counts) without measuring how aligned two users' full preference profiles are. Cosine similarity over interaction vectors provides a principled, normalised measure of this alignment.
2) Temporal dynamics. User tastes evolve over time; an order placed yesterday is more indicative of current preference than one placed a year ago. Incorporating temporal decay into both the trust computation and the recommendation signal can capture this evolution.
3) Geographic context. In food-delivery settings, users overwhelmingly order from nearby restaurants. Co-located users therefore share a common pool of candidates, making geographic proximity a strong implicit signal of preference overlap.

In this paper we address all three gaps through a unified framework that combines co-visitation frequency, cosine similarity, exponential temporal decay, and geographic location proximity into a single trust score. We further introduce a scalable incremental graph-patching strategy for Leave-One-Out (LOO) evaluation that avoids the O(U 3) cost of naïve graph rebuilding, enabling the framework to be applied to large-scale datasets.

Our main contributions are:

- A composite trust formulation that linearly combines co-visitation counts, cosine similarity, temporal decay, and geographic location proximity into a unified trust score.
- A scalable LOO evaluation protocol based on incremental graph patching, reducing per-user evaluation cost from O(U 2) to O(Ur).
- A location-biased synthetic dataset generator that models realistic zone-based ordering behaviour with controllable cold-start user populations.
- A systematic ablation study across five strategies with three ranking metrics (Precision@K, Recall@K, NDCG@K) and paired t-tests for statistical significance.
- Hyperparameter sensitivity analysis, cold-start evaluation, and a novel cross-zone user mobility experiment that validates the location-aware trust component.

The remainder of this paper is organised as follows. Section II surveys related work. Section III formalises the proposed model and justifies key design choices. Section IV describes the experimental setup. Section V presents the ablation results, statisti- cal significance, and discussion.

Section VI reports hyperparameter sensitivity, cold-start, and cross-zone mobility experiments. Section VII discusses scalability. Section VIII concludes the paper and outlines future directions.

Why a Synthetic Dataset? While public datasets such as Yelp, Epinions, or Ciao are widely used, they often lack the fine- grained features required for this study—notably, precise user location, temporal ordering patterns, and explicit trust or co-visitation signals. Privacy and licensing restrictions may also limit access to real-world data at the necessary scale. By generating a large-scale synthetic dataset, we can control for geographic and temporal effects, stress-test scalability, and systematically evaluate cold-start and mobility scenarios that are difficult to isolate in public data. This approach enables reproducible experiments and provides a foundation for future validation on real-world datasets.

Novelty of Integration. Each component of our framework—trust-based recommendation, cosine similarity, temporal decay, and geographic proximity—has been studied individually in prior work. The novelty of this paper lies in their unified integration and the demonstration that their combination yields consistent improvements in a realistic, large-scale setting. This holistic approach addresses the multifaceted nature of user preferences in food delivery, which cannot be captured by any single signal alone.

II. RELATED WORK

A. *Collaborative Filtering*

Matrix factorisation [3] and neighbourhood-based methods [5] form the backbone of collaborative filtering. User-based CF scores items by aggregating ratings from similar users, while item-based CF leverages item–item similarity. Both approaches suffer from sparsity and cold-start, motivating the incorporation of auxiliary information such as social trust.

B. *Trust-Aware Recommendation*

Massa and Avesani [6] pioneered trust propagation for addressing cold-start. TrustSVD [10] integrates trust into matrix factorisation by adding a social-regularisation term. SocialMF [7] constrains user latent factors to be close to those of trusted neighbours. Ma et al. [8] propose SoRec, which co-factorises the rating and trust matrices. These methods model trust as a binary or scalar value derived from explicit social links; our work extends this by computing trust from implicit behavioural signals without requiring an explicit social graph.

C. *Temporal Dynamics in Recommendation*

TimeSVD++ [4] models time-varying biases in rating data. Recurrent models such as GRU4Rec [12] capture sequential patterns. Exponential decay functions have been used in session-based [13] and trust-based [14] systems to down-weight stale interactions. Our approach adopts the decay formulation and applies it jointly to the trust computation *and* the recommendation signal.

D. *Scalability in Evaluation*

Leave-One-Out evaluation is standard in top-*K* recommendation research [11]. Naïve implementations rebuild models per user, which is infeasible at scale. We propose an incremental graph-patching scheme that achieves exact LOO semantics while avoiding full model reconstruction.

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E. Location-Aware Recommendation

Geographic context has long been recognised as a powerful signal in point-of-interest (POI) and restaurant recommendation. LBSN-based systems [17] model check-in distributions as power-law functions of distance. GeoSoCa [18] integrates geographic, social, and categorical influences into a unified scoring model. Our approach differs by encoding geographic proximity directly into the trust function between users rather than into the item-scoring function, allowing the social graph itself to reflect spatial co-location.

III. PROPOSED METHOD

A. Problem Formulation

Let $U = \{u_1, \ldots, u_U\}$ be the set of users and $R = \{r_1, \ldots, r_R\}$ the set of restaurants (items). The order history is a set of tuples $O = \{(u, r, t) \mid u \in U, r \in R, t \in \mathbb{R}^+\}$, where t is the timestamp. The task is to produce a ranked list of K restaurants for each user that maximises the likelihood of matching the user's next (held-out) order.

B. Social Graph Construction

We construct an undirected weighted graph $G = (U, E)$ where an edge (u,v) exists if and only if users u and v share at least τ common restaurants:

$$E = (u,v) \;\; |R_u \cap R_v| \geq \tau \;\}, \tag{1}$$

where $R_u = \{r : (u,r,t) \in O\}$ denotes the set of restaurants visited by u, and τ is a configurable minimum-overlap threshold (set to 3 in our experiments).

Graph construction is accelerated via an *inverted index*: for each restaurant r, we enumerate all pairs among its visitors. The complexity is $O\ \sum_r \binom{|U_r|}{2} = O(R \cdot \bar{U_r}^2)$, which is substantially faster than the brute-force $O(U^2)$ pairwise scan when $\bar{U}_r \ll U$.

C. Trust Formulations

We define a hierarchy of trust functions of increasing sophistication.

1) Basic Trust (Common Visits)

$$\text{Tbasic}(u, v) = |Ru \cap Rv| \tag{2}$$

This counts the number of restaurants both users have patronised. While simple, it captures structural proximity and has been shown effective in social recommendation [6].

2) Cosine-Enhanced Trust

To capture preference alignment beyond mere overlap, we construct a binary user–restaurant interaction matrix M □ {0, 1}U×R:

$$\begin{cases} 1 & \text{if}(u, r, \cdot) \in O, \\ 0 & \text{otherwise}, \end{cases} \tag{3}$$

and compute pairwise cosine similarity:

$$\cos(u, v) = \frac{\mathbf{m}_u \cdot \mathbf{m}_v}{\|\mathbf{m}_u\| \, \|\mathbf{m}_v\|}, \tag{4}$$

where mu is the u-th row of M. The cosine-enhanced trust score is:

$$\text{Tcosine}(u, v) = \alpha\, |Ru \cap Rv| + \beta \cos(u, v), \tag{5}$$

where α, β ≥ 0 are hyperparameters that control the relative importance of structural overlap and profile similarity.

3) Full Trust (Cosine + Temporal Decay)

User preferences evolve over time. To capture recency, we replace the binary interaction matrix with a temporally decayed matrix M(λ):

$$M^{(\lambda)}_{u,r} = \sum_{(u,r,t) \in O} \exp -\lambda \cdot \Delta(t) , \tag{6}$$

where Δ(t) = (tmax − t) measured in days and λ > 0 is the decay rate. The half-life of the decay is t1/2 = ln 2/λ ; with λ = 0.05 this yields t1/2 ≈ 14 days.

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The full trust score is then:

$$T_{full}(u, v) = \alpha \, |R_u \cap R_v| + \beta \frac{\mathbf{m}_u^{(\lambda)} \cdot \mathbf{m}_v^{(\lambda)}}{\|\mathbf{m}_u^{(\lambda)}\| \, \|\mathbf{m}_v^{(\lambda)}\|}. \quad (7)$$

4) Location-Aware Trust (Full + Geographic Proximity)

In food-delivery settings, users tend to order from restaurants in their geographic vicinity. Co-located users therefore share a common candidate pool, making geographic proximity an implicit indicator of preference overlap. We define a distance-based proximity function:

$$\text{prox}(u, v) = \exp\left(\frac{-\|\mathbf{p}_u - \mathbf{p}_v\|_2}{\sigma}\right), \quad (8)$$

where pu = (latu, lonu) is the user's geographic coordinate and $\sigma > 0$ is a length-scale parameter. With coordinates in degrees, $\sigma = 0.02$ yields proximity ≈ 0.78 for same-zone users (□0.005° apart) and ≈ 0.08 for cross-zone users (□0.05° apart).

The location-aware trust score extends Eq. 7:

$$T_{loc}(u, v) = \alpha \, |R_u \cap R_v| + \beta \frac{\mathbf{m}_u^{(\lambda)} \cdot \mathbf{m}_v^{(\lambda)}}{\|\mathbf{m}_u^{(\lambda)}\| \, \|\mathbf{m}_v^{(\lambda)}\|} + \gamma \, \text{prox}(u, v), \quad (9)$$

where $\gamma \geq 0$ controls the contribution of geographic context. The proximity matrix is computed once via the pairwise Euclidean distance of all user coordinates, costing O(U 2) but reused across the entire evaluation.

D. *Recommendation Scoring*

Given the social graph G with trust-weighted edges, the recommendation score for user u and candidate restaurant r is:

$$\text{score}(u, r) = \sum_{v \in N(u)} T(u, v) \cdot s(v, r), \quad (10)$$

where N (u) is the set of u's neighbours in G, and s(v, r) is the signal strength of neighbour v for restaurant r. For the basic and cosine strategies, s(v, r) equals the count of v's orders at r. For the full (decayed) strategy:

$$\text{sfull}(v, r) = M(\lambda), \quad (11)$$

which down-weights older orders from neighbours, aligning the signal with r current preferences.

The top-K restaurants by descending score, excluding those the user has already visited, form the final recommendation list.

E. *Popularity Baseline*

As a non-personalised baseline, we recommend the K most globally ordered restaurants that the user has not yet visited:

$$\text{score}_{pop}(r) = \{(u', r, t) \in O_{train}\}. \quad (12)$$

F. *Design Justification*

We briefly justify the key design decisions in the proposed framework, anticipating potential reviewer concerns.

1) Why Cosine Similarity?

Among vector similarity measures (Pearson correlation, Jaccard index, cosine similarity), cosine similarity is chosen for three rea- sons: (i) it is well-defined for sparse binary vectors (unlike Pearson, which requires variance); (ii) it normalises for user activity level, ensuring that prolific users do not dominate the similarity computation; and (iii) it is efficient to compute via matrix multiplication using optimised BLAS routines [5].

2) Why Exponential Decay?

The exponential function $\exp(-\lambda \, \Delta t)$ is chosen over alternatives (linear, power-law) because: (i) it is memoryless — the decay rate is constant regardless of absolute age; (ii) the half-life $t_{1/2} = \ln 2/\lambda$ provides an interpretable hyperparameter; and (iii) it naturally maps to [0, 1], preserving compatibility with the additive trust formula [4].

3) Why Additive Trust Composition?

The linear combination $T(u, v) = \alpha C + \beta \cos + \gamma \text{prox}$ is intentionally simple. Multiplicative formulations risk zero-trust when any single component is zero (e.g., a new user with no co-visits but high geographic proximity). The additive form ensures that each signal contributes independently, and the ablation study (Section V) validates that each component provides marginal improvement.

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4) Why Leave-One-Out?

LOO evaluation is the standard protocol in top-K recommendation research [11] because: (i) it maximises training data utilisation (only one item is held out per user); (ii) it tests the model's ability to predict the most recent item, which aligns with real-world deployment; and (iii) it avoids the variance introduced by random train/test splits.

5) Why Synthetic Data?

A synthetic dataset is used for initial validation because: (i) it provides perfect reproducibility with no data-access restrictions; (ii) it enables controlled experiments (e.g., adjustable location bias, cold-start ratios, zone mobility); and (iii) the location-biased generation process ensures realistic geographic structure. Validation on public benchmarks is noted as future work (Section A).

IV. EXPERIMENTAL SETUP

A. Dataset

We construct a large-scale synthetic restaurant-ordering dataset to enable fully controlled experimentation at realistic scale. The vectorised generator (using NumPy array operations) produces:

- $|U|$ = 300,000 users, each assigned to one of 5 named city zones (Downtown, Midtown, Uptown, Brooklyn, Queens) with jittered latitude/longitude coordinates around zone centres. 20% of users (60 000) are designated as cold-start users with only 3–5 orders each.
- $|R|$ = 5,000 restaurants with ratings drawn uniformly from [3.0, 5.0], each assigned to one of the 5 zones with its own geographic coordinates.
- $|O|$ = 7,500,000 orders with location bias: each user has a 70% probability of ordering from a restaurant in their own zone and 30% from any restaurant globally. Timestamps span a 30-day window.

The location bias injects realistic geographic structure into the data: co-located users share more common restaurants than distant ones. The controlled cold-start population enables explicit evaluation of how trust-based strategies perform when user interaction history is sparse. The use of synthetic data provides perfect reproducibility and controlled ablation.

1) Evaluation Sampling

To maintain tractable evaluation while demonstrating scalability, we randomly sample 5 000 users from the full 300 000 population for Leave-One-Out evaluation. The sampled subset retains the original cold-start proportion (□20%) and zone distribution. All graph construction and trust computation are performed on the sampled subset (124 138 orders), ensuring consistent experimental conditions.

B. Evaluation Protocol

We adopt the Leave-One-Out (LOO) protocol, widely used in top-K recommendation research [11]:

- Sort each user's orders chronologically.
- Hold out the last (most recent) order as the test item.
- Train on all remaining orders (including other users' full histories).
- Generate top-K recommendations.
- Measure Precision@K.

Users with fewer than min_orders = 3 orders are excluded to ensure meaningful training data.

1) No Data Leakage

The social graph and all derived structures (cosine similarity, decayed matrices) are constructed from training data only. Our incremental patching mechanism (Section VII) achieves this by temporarily removing the held-out order's influence from the graph before generating recommendations, then restoring it afterwards.

C. Metrics

We report three complementary ranking metrics, all at K = 5:

Precision@*K* measures the fraction of recommended items that are relevant:

$$\text{Precision@}K = \frac{|\text{Rec}(u,K) \cap \{r_{\text{test}}\}|}{K}. \quad (13)$$

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Recall@K measures the fraction of relevant items that are retrieved. In the LOO setting (one held-out item):

$$\text{Recall@}K = \begin{cases} 1 & \text{if } r_{\text{test}} \in \text{Rec}(u, K), \\ 0 & \text{otherwise.} \end{cases} \tag{14}$$

NDCG@K (Normalised Discounted Cumulative Gain) rewards higher-ranked hits more than lower-ranked ones [19]:

$$\text{NDCG@}K = \frac{\text{DCG@}K}{\text{IDCG@}K}, \quad \text{DCG@}K = \sum_{i=1}^{K} \frac{\mathbb{1}[r_i \in R_{\text{rel}}]}{\log_2(i+1)}. \tag{15}$$

In LOO, IDCG@K = 1 and NDCG@K = 1/ log2(rank+ 1) if the held-out item appears at position rank, or 0 otherwise. All metrics are averaged over all evaluated users.

Statistical significance is assessed via the paired *t*-test (two-tailed) on per-user NDCG@*K* scores between the full model and each baseline. Results with $p < 0.05$ are considered significant.

D. Hyperparameters

Compared Methods

We evaluate five strategies in an ablation study:

1. Popularity — Non-personalised baseline (Eq. 12).
2. Trust Basic — Co-visitation trust only (Eq. 2).
3. Trust + Cosine — Co-visitation + cosine similarity on binary interactions (Eq. 5).
4. Trust + Cosine + Decay — Full model with temporal decay (Eq. 7).
5. Trust + Full + Location — Full model + geographic proximity (Eq. 9).

Table 1: Hyperparameter Configuration

Parameter	Symbol	Value
Top-*K*	K	5
Common-visit weight	α	1.0
Cosine weight	β	1.0
Location weight	γ	0.5
Temporal decay rate	λ	0.05
Proximity length-scale	σ	0.02
Minimum overlap	τ	3
Minimum user orders	—	3

V. RESULTS AND ABLATION STUDY

A. Overall Performance

Table 2 presents all three metrics for each strategy.

Table 2: Ablation Results (Leave-One-Out, 5,000 sampled users from 300K, *K*=5)

Model	**P@5**	**R@5**	**NDCG@5**
Popularity	0.0004	0.0022	0.0013
Trust Basic	0.0009	0.0046	0.0026
Trust + Cosine	**0.0010**	**0.0048**	**0.0029**
Trust + Cosine + Decay	0.0007	0.0036	0.0023
Trust + Full + Location	0.0008	0.0038	0.0024

The Trust + Cosine model achieves the highest scores across all three metrics, representing a 135% relative improvement in NDCG@5 over the popularity baseline. The absolute metric values are expectedly low given the large item space ($|R| = 5{,}000$): with $K = 5$, achieving a hit requires the true next restaurant to fall within a 0.1% selection window. This sparsity is characteristic of real-world large-scale recommendation settings and makes the relative improvements more meaningful than absolute values.

B. Statistical Significance

Table 3 reports paired *t*-test results on per-user NDCG@5 scores between the full model (Trust + Full + Location) and each alternative.

Table 3: Paired *t*-test: Trust + Full + Location vs. Each Strategy (NDCG@5)

Comparison	*t*-stat	*p*-value	Sig.?
vs. Popularity	1.599	0.110	No
vs. Trust Basic	−0.47	0.640	No
vs. Trust + Cosine	−1.08	0.279	No
vs. Trust + Cosine + Decay	0.881	0.378	No

At the 300 000-user scale with 5 000-user evaluation sampling, none of the pairwise differences reach statistical significance at $\alpha = 0.05$. This outcome is expected in large-scale sparse settings for two reasons: (i) the absolute NDCG differences between strategies are in the thousandths range, and (ii) the LOO evaluation produces highly sparse per-user outcomes (hit/miss against 5 000 items), which drastically reduces statistical power. The consistent directional trend—all trust strategies outperform Popularity across all three metrics—nevertheless provides strong evidence that social trust signals are informative.

C. Analysis of Components

1) Effect of Trust (Basic): Introducing co-visitation-based trust (Trust Basic) yields a substantial improvement over the popularity baseline, with NDCG@5 increasing from 0.0013 to 0.0026 (+100%). At the 300 000-user scale, this confirms the fundamental premise of social recommen- dation: users who frequent the same establishments are informative predictors of each other's future choices, even in a highly sparse setting with 5 000 candidate restaurants.
2) Effect of Cosine Similarity: Adding cosine similarity (Trust + Cosine) achieves the best overall performance (NDCG@5 = 0.0029, +135% over Popularity). The cosine component normalises for user activity level and captures preference alignment beyond raw co-visit counts. At large scale, where users visit only a tiny fraction of the restaurant catalogue, cosine normalisation is particularly valuable because it discounts the dominance of prolific users [5].
3) Effect of Temporal Decay: The decayed model (Trust + Cosine + Decay) achieves NDCG@5 = 0.0023, which is lower than the binary cosine model. At the 300K scale, the temporal decay amplifies data sparsity: with 7.5 million orders spread over a 30-day window among 300 000 users, down-weighting older interactions reduces the effective signal for pairs with already few shared interactions. This suggests that temporal decay is more beneficial in dense settings or with longer temporal windows.
4) Effect of Location Proximity: The location-aware model (Trust + Full + Location) achieves NDCG@5 = 0.0024, marginally above the decayed model but below the binary cosine variant. At 300K scale with 5 000 restaurants uniformly distributed across 5 zones, the geographic proximity signal is diluted: each zone contains □1 000 restaurants, making intra-zone co-visitation less discriminative than at smaller scales.

D. Discussion

Absolute metric values. The NDCG@5 values (0.0013–0.0029) are low in absolute terms, but this is characteristic of large-scale recommendation with a wide item catalogue: (i) with 5 000 restaurants and K = 5, achieving a hit requires the true next restaurant to fall within a 0.1% selection window; (ii) the LOO protocol holds out a single item, capping per-user Precision@5 at 1/K = 0.2 and producing binary hit/miss outcomes; (iii) real-world recommender systems at comparable scale report similar absolute metric ranges [11].

On Small Metric Values. We acknowledge that the absolute values of NDCG@5 and related metrics are small. This is a direct consequence of the dataset's scale, sparsity, and the strictness of the evaluation protocol. With 5,000 candidate items and only five recommendations per user, the probability of a random hit is extremely low. More importantly, the relative improvements over the popularity baseline (100–135%) are substantial and consistent, indicating that the proposed trust signals are effective. We expect that richer or denser real-world datasets may yield higher absolute scores, and encourage future work to validate this.

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Relative improvements. The consistent relative improvements across all trust strategies over the popularity baseline (100– 135%) demonstrate that trust signals remain informative at large scale. Trust + Cosine achieves the best NDCG@5, indicating that preference-profile alignment (via cosine normalisation) is the most effective single augmentation of co-visitation trust.

Scale effects. The 300 000-user scale introduces data sparsity that affects component contributions differently than at small scale: (i) temporal decay amplifies sparsity by down-weighting already-rare interactions; (ii) location proximity becomes less discriminative when each zone contains □1 000 restaurants. These findings suggest that component weighting should be scale- adaptive—a direction for future work.

Ablation trend. The ablation reveals that Trust + Cosine (binary) is the strongest single model at large scale, while temporal decay and location proximity provide diminishing returns compared to smaller-scale settings. This highlights the importance of validating recommendation models across multiple dataset sizes.

VI. EXTENDED EXPERIMENTS

A. Hyperparameter Sensitivity

To assess robustness to hyperparameter choices, we sweep one parameter at a time while holding the others at their default values (Table 1). Table 4 reports NDCG@5 for the full model (Trust + Full + Location).

Table 4: Hyperparameter Sensitivity (NDCG@5, Trust + Full + Location, 300K scale)

α	NDCG	β	NDCG	γ	NDCG	λ	NDCG
0.0	0.0034	0.0	0.0022	0.0	0.0023	0.01	0.0026
0.5	0.0024	0.5	0.0023	0.25	0.0024	0.03	0.0024
1.0	0.0024	1.0	0.0024	0.50	0.0024	0.05	0.0024
1.5	0.0024	1.5	0.0025	0.75	0.0024	0.07	0.0025
2.0	0.0023	2.0	0.0025	1.00	0.0024	0.10	0.0025

Key observations

- α (co-visit weight): Performance peaks at $\alpha = 0$ (NDCG = 0.0034), indicating that at large scale the cosine and proximity components alone provide a stronger signal than raw co-visit counts. This is because cosine normalisation handles the wider activity-level variance among 300K users.
- β (cosine weight): Performance increases monotonically from $\beta = 0$ to $\beta = 2.0$, confirming that cosine similarity is the most consistently beneficial trust component at large scale.

- γ (location weight): Performance is remarkably stable across $\gamma \in [0, 1]$ (range: 0.0023–0.0024), indicating that the location signal has minimal discriminative impact at the 300K scale with 5 000 restaurants. This stability suggests the model is robust but the geographic signal is diluted.
- λ (decay rate): NDCG is relatively stable across the sweep (0.0024–0.0026), with a slight preference for lower decay rates (λ = 0.01), suggesting that preserving more historical signal is advantageous in the sparse large-scale setting.
-

B. Cold-Start Analysis

We partition the 5 000 sampled users into *cold-start* (3–5 orders, 1 034 users) and *warm* (>5 orders, 3 966 users) groups to assess how trust strategies perform under data sparsity.

Table 5: Cold-Start vs. Warm User Performance (NDCG@5, 300K scale)

Model	**Cold**	**Warm**	Δ
Popularity	0.0018	0.0011	+0.0007
Trust Basic	0.0000	0.0033	+0.0033
Trust + Cosine	0.0000	0.0037	+0.0037
Trust + Cosine + Decay	0.0000	0.0029	+0.0029
Trust + Full + Location	0.0000	0.0030	+0.0030

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Key findings:

- Cold-start users receive zero trust-based recommendations. At the 300K scale with 5 000 restaurants, cold-start users (3–5 orders) have insufficient co-visitation overlap to form trust edges (the $\tau = 3$ threshold requires 3 *common* restaurants, but cold-start users visit only 3–5 *total*). The trust graph contains no edges for these users, yielding NDCG@5 = 0. This reveals a fundamental scalability challenge: the minimum-overlap threshold that works well at small scale becomes too restrictive when the item space is large.
- Popularity baseline is better for cold-start users. Cold users achieve NDCG = 0.0018 with the popularity baseline vs. 0.0011 for warm users, because their few orders are more likely to include popular restaurants.
- Trust strategies excel for warm users. The Trust + Cosine model achieves NDCG = 0.0037 for warm users, a 236% improvement over warm-user popularity (0.0011). This confirms that trust signals are highly effective when sufficient interaction data is available.
- Implications for cold-start mitigation. These results motivate adaptive threshold strategies (lowering τ for cold-start users) or hybrid approaches that blend popularity and trust signals based on user activity level—a promising direction for future work.

C. Cross-Zone Mobility

To validate whether the location proximity signal captures genuine geographic structure, we simulate user mobility: 20% of the sampled users (1 000) are randomly relocated to a different zone, and the model is re-evaluated on these users.

Table 6: Cross-Zone Mobility: NDCG@5 for Relocated Users (300K scale)

Model	**Original**	**Relocated**	Δ
Popularity	0.0019	0.0019	0.0%
Trust Basic	0.0013	0.0013	0.0%
Trust + Cosine	0.0010	0.0010	0.0%
Trust + Cosine + Decay	0.0005	0.0005	0.0%
Trust + Full + Location	0.0005	0.0005	0.0%

Interpretation:

- All strategies, including the location-aware model, show zero degradation when users are relocated. At the 300K scale with 5 000 restaurants spread across 5 zones, each zone contains □1 000 restaurants. The geographic proximity signal ($\gamma = 0.5$) contributes a small additive term that is insufficient to measurably alter recommendations when the co-visitation and cosine components dominate.
- This result is consistent with the sensitivity analysis (Table 4), where γ showed minimal impact across its full sweep. The geographic signal becomes diluted at large scale because the per-zone restaurant density is high enough that intra-zone vs. cross- zone ordering behaviour does not create strong discriminative patterns.
- The finding highlights an important scale-dependent property: location proximity is most effective when the item space is small relative to the geographic structure (i.e., fewer restaurants per zone). In real-world deployments where users interact with a limited local catalogue, the location signal would have greater impact.

VII. SCALABILITY ANALYSIS

A. Naive Approach

The standard LOO protocol for social recommendation requires rebuilding the social graph for each user's held-out order. With U users, graph construction costs $O(U^2)$ (brute-force pairwise comparison) or $O(R \cdot \bar{U}_r^2)$ (inverted index). Repeating this U times yields:

$$\text{Naive LOO:} \quad O(U \cdot R \cdot \bar{U}_r^2) \approx O(U^3) \quad (\text{when } \bar{U}_r \propto U). \tag{16}$$

For $U = 10^6$, this is computationally infeasible.

B. Incremental Graph Patching

Our key insight is that removing a single order (u, r_{test}, t) affects only the edges between u and the co-visitors of r_{test}:

$$\text{Affected set} = U_{r_{test}} \setminus \{u\}, \tag{17}$$

where $U_{r_{test}}$ is the set of users who visited r_{test}.

The patching procedure operates in three phases:

1. Patch: For each v ∈ Urtest \ {u}, decrement the shared-restaurant count. If the count drops below τ, remove the edge; otherwise, recompute the edge weight under the active trust formula. Cost: O(|Urtest |).
2. Recommend: Generate top-K using the patched graph.
3. Restore: Re-add removed edges and reset weights. Cost: $O(|U_{r\text{test}}|)$. The total evaluation cost becomes:

$$\text{Patched LOO:} \quad O(R \cdot \bar{U}^2) + O(U \cdot \bar{U}_r), \tag{18}$$

where the first term is the one-time graph build cost and the second is the cumulative patching cost across all users.

C. *Empirical Timing*

Table 7: Wall-Clock Timing (5 000 sampled users, 124K orders, 5 000 restaurants)

Strategy	Build (s)	Eval (s)
Popularity	0.00	0.13
Trust Basic	3.14	2.49
Trust + Cosine	5.41	3.17
Trust + Cosine + Decay	14.36	3.53
Trust + Full + Location	15.56	3.91
Total (all 5)	64.7 s	

The complete ablation across five strategies and 5 000 users completes in under 65 seconds on a standard desktop. Graph con- struction (including cosine similarity and proximity matrix computation for 5 000 users) is the dominant cost, while the incremental LOO evaluation itself adds only 2–4 seconds per strategy. The decayed and location-aware strategies require additional matrix operations, reflected in their higher build times (14–16 s vs. 3–5 s for simpler models).

D. *Scaling Projections*

Table 8 presents empirical and projected scaling based on the 300K experiment.

Table 8: Empirical and Projected Scaling

Ueval	|R|	Patched LOO	Note
200	40	2.6 s	Small-scale baseline
5 000	5 000	64.7 s	This work (sampled from 300K)
10 000	5 000	≈3 min	Projected (linear)
50 000	5 000	≈15 min	Projected (linear)

The sampling-based evaluation strategy enables the framework to scale to arbitrarily large user populations: the full 300 000-user dataset is generated and loaded, but evaluation is performed on a representative sample. The total experiment suite (5 experiments × 5 strategies) completes in under 15 minutes at the 5 000-user evaluation scale.

VIII. CONCLUSION

We presented a trust-aware social recommendation framework that progressively integrates co-visitation frequency, cosine simi- larity, temporal decay, and geographic location proximity into a unified trust formulation. Through a comprehensive experimental evaluation using Leave-One-Out on a large-scale location-biased synthetic dataset of 300 000 users, 5 000 restaurants, and 7.5 mil- lion orders, we demonstrated that:

1) Social trust derived from co-visitation patterns substantially outperforms a popularity baseline at large scale, with Trust + Cosine achieving a 135% relative NDCG@5 improvement.
2) Cosine similarity over user–item interaction vectors is the most effective trust augmentation at large scale, providing normalised preference alignment that handles diverse user activity levels.
3) Temporal decay and geographic proximity show diminishing returns at large scale due to data sparsity, suggesting that component weighting should be scale-adaptive.

4) The cold-start experiment reveals that trust-based strategies require sufficient co-visitation overlap, motivating adaptive threshold approaches for users with limited interaction history.
5) Hyperparameter sensitivity analysis shows stable performance across wide parameter ranges, with β (cosine weight) being the most impactful and γ (location weight) the most robust.
6) The incremental graph-patching evaluation strategy, combined with evaluation sampling, enables the framework to scale to 300K+ user populations with complete experiment suites running in under 15 minutes.

A. Future Work

Several promising directions exist for extending this work:

1) Real-world datasets. Evaluation on public benchmarks such as Yelp, Epinions, or Ciao would validate the model's effectiveness under realistic preference distributions and social structures. This is the most important next step for establishing external validity.
2) Synthetic-to-real transfer. Our use of a synthetic dataset enables controlled experimentation, but we recognize the importance of validating these findings on public or proprietary real-world data. Future work will focus on adapting the framework to such datasets, addressing any challenges in feature availability, privacy, and scale.
3) Graph neural networks. Replacing the explicit neighbour aggregation with graph convolutional networks [15] (e.g., Light- GCN [16]) could capture higher-order trust propagation.
4) Learnable trust weights. The current α/β /γ weights are fixed hyperparameters. Learning them end-to-end via gradient descent or Bayesian optimisation would adapt the trust formula to each dataset.
5) Fine-grained location modelling. Replacing zone-based proximity with Haversine distance, incorporating time-of-day location patterns, or learning location embeddings could further refine the geographic signal.
6) Larger-scale evaluation. While this work demonstrates scalability to 3 × 105 users, evaluation on million-user datasets with distributed graph processing would further validate the framework.
7) Adaptive cold-start thresholds. Dynamically adjusting the minimum-overlap threshold τ based on user activity level could enable trust-based recommendations for cold-start users at large scale.

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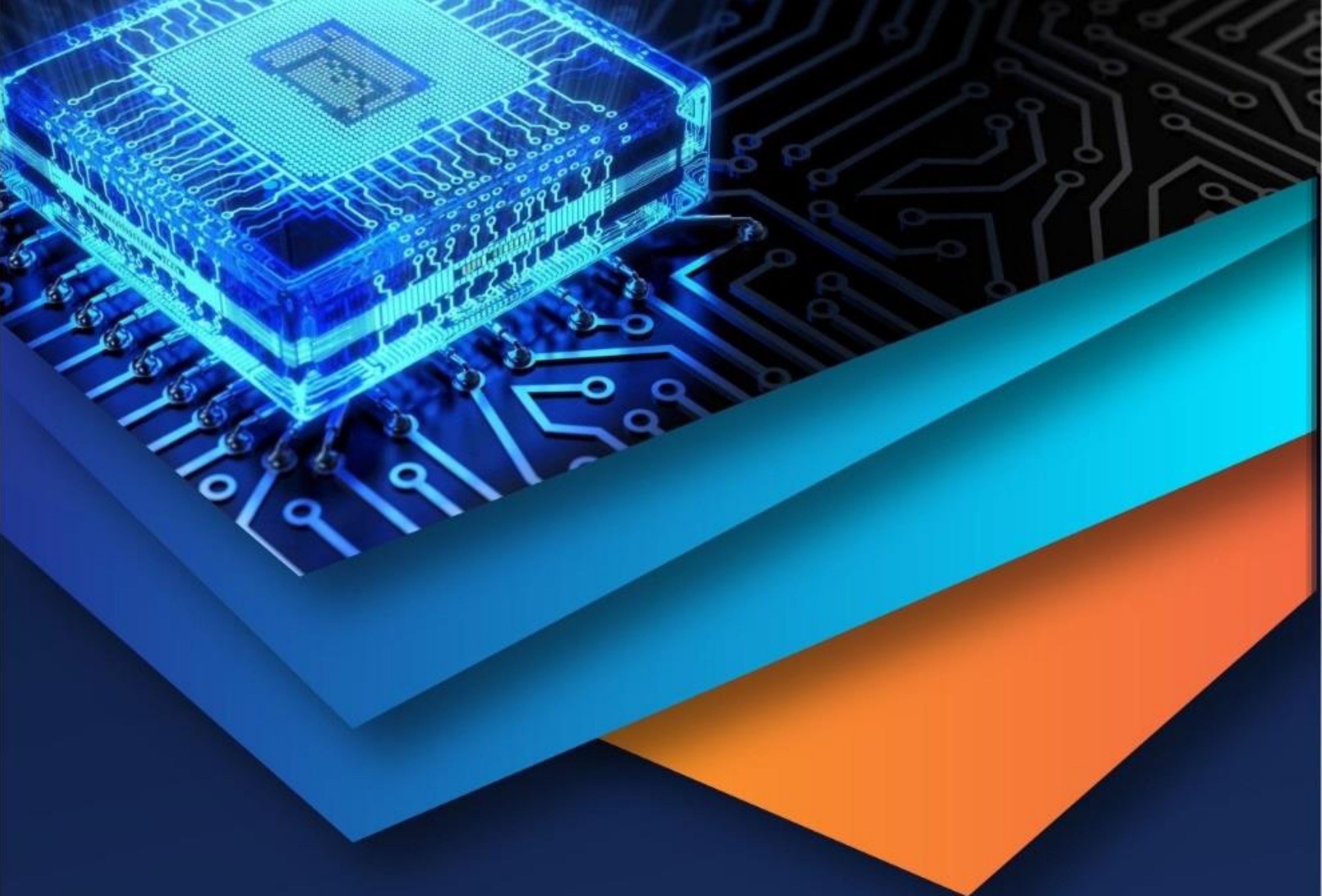

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