

Topology-Aware Popularity Debiasing via Simplicial Complexes

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ABSTRACT

Recommender systems (RS) play a critical role in delivering personalized content across various online platforms, leveraging collaborative filtering (CF) as a key technique to generate recommendations based on users' historical interaction data. Recent advancements in CF have been driven by the adoption of Graph Neural Networks (GNNs), which model user-item interactions as bipartite graphs, enabling the capture of high-order collaborative signals. Despite their success, GNN-based methods face significant challenges due to the inherent popularity bias in the user-item interaction graph's topology, leading to skewed recommendations that favor popular items over less-known ones.

To address this challenge, we propose a novel topology-aware popularity debiasing framework, Test-time Simplicial Propagation (TSP), which incorporates simplicial complexes (SCs) to enhance the expressiveness of GNNs. Unlike traditional methods that focus on pairwise relationships, our approach captures multi-order relationships through SCs, providing a more comprehensive representation of user-item interactions. By enriching the neighborhoods of tail items and leveraging SCs for feature smoothing, TSP enables the propagation of multi-order collaborative signals and effectively mitigates biased propagation. Our TSP module is designed as a plug-and-play solution, allowing for seamless integration into pre-trained GNN-based models without the need for fine-tuning additional parameters. Extensive experiments on five real-world datasets demonstrate the superior performance of our method, particularly in long-tail recommendation tasks. Visualization results further confirm that TSP produces more uniform distributions of item representations, leading to fairer and more accurate recommendations. Code and data will be made available.

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CCS CONCEPTS

• Information systems → Recommender systems.

KEYWORDS

Simplicial Complex, Popularity Bias, Collaborative Filtering

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1 INTRODUCTION

Recommender systems (RS) are essential for delivering personalized content across various online platforms. They have been widely applied in areas such as e-commerce, social media, news portals, app stores, and digital libraries [48]. Collaborative filtering (CF) is the most crucial technique in the field of RS, employing algorithms that generate item recommendations based on the analysis of users' historical interaction data. Recent advancements of CF have been driven by the adoption of Graph Neural Networks (GNNs) [7, 21, 33]. By representing user-item interactions as a bipartite graph, GNNs are capable of capturing high-order collaborative signals between users and items through message passing and aggregation mechanisms [42]. This unique advantage makes GNNs achieve state-of-the-art performance in recommendation tasks.

Although GNN-based collaborative filtering has achieved significant success, a critical issue has emerged concerning the popularity bias inherent in the user-item interaction graph's topology and the approaches used to mitigate this bias. The bias issue poses a significant challenge in RS, arising from various factors such as user behavior, item popularity, and system design. Biases are categorized based on their underlying causes, including exposure bias, selection bias, popularity bias, and others [8]. Among these, popularity bias is one of the most prevalent and difficult to address in RS. It refers to the tendency of RS to recommend popular items over more relevant ones. Popularity bias occurs because, in real-world datasets, a small number of items are typically highly popular, while the majority are less well-known or niche [16]. As a result, the model's learned representations will exhibit a bias towards popular items.

There is a growing body of research focused on developing techniques to alleviate popularity bias, including regularization [1], adversarial learning [27], and causal learning [55] methods. While these approaches have shown promise in alleviating popularity bias, they often fail to explicitly address the inherent biases embedded in the graph topology itself. GNN-based recommendation methods rely on message passing and aggregation mechanisms to learn representations of users and item. A recent study [9] notes that popular items exert a dominant influence on the information propagation among neighboring users in GNNs. This dominance results in a representation space where users are drawn closer to popular items, regardless of their actual preferences. Figure 1 provides an intuitive example. We select two typical GNN-based recommendation methods, LightGCN [21] and SimGCL [26] trained on the Gowalla dataset, project the representations of the top 500 popular items, as well as the top 500 long-tail items, into a two-dimensional space. It shows that user representations tend to cluster closer to popular items while remaining more distant from long-tail items, resulting in a lower recommendation probability for long-tail items in GNN-based models.

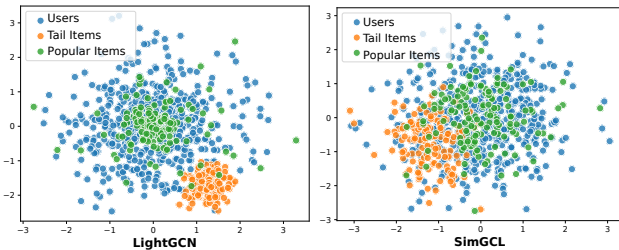


Figure 1: Representation distribution of users, popular items and tail items on Gowalla dataset.

A line of research [29, 30, 54] attempts to bridge the gap between popular and tail items by applying topological graph augmentations, directly addressing the root cause of popularity bias from the perspective of graph topology. However, augmentation-based methods still rely on pairwise relationships, and predominantly focus on message passing over the augmented graphs, overlooking the rich higher-order relationships embedded within them. As a result, the significant disparity between the degrees of popular and tail items persists during the message passing process. Recognizing these shortcomings, researchers have started exploring methods that explicitly model higher-order relationships in RS. Hypergraph-based approaches, such as HCCF [50], represent a significant advancement in this direction. By employing hyperedges, these methods can capture complex interactions involving multiple users and items simultaneously. This enhanced expressiveness enables a more nuanced representation of user-item relationships, potentially leading to more accurate and less biased recommendations. However, while hypergraphs offer greater expressiveness, they also introduce scalability challenges due to their ability to connect an arbitrary number of nodes, resulting in significant computational overhead, particularly in large-scale RS [22].

To address the challenging issue of popularity bias in GNN-based methods and overcome the shortcomings of existing mainstream approaches, we propose a novel topology-aware popularity debiasing

framework called Test-time Simplicial Propagation (TSP). Our core idea is to construct simplicial complexes (SCs) for nodes, enhancing their representations through hierarchical multi-order connections. Figure 2 illustrates the difference in message passing between augmented graph, hypergraph, and simplicial complexes. Simplicial complexes extend beyond pairwise connections by capturing multi-order relationships, offering a more nuanced and comprehensive representation of user-item interactions.

Specifically, we begin by enriching the neighborhoods of tail items using graph augmentation to achieve a more balanced topological structure. We then introduce SCs to model complex and multi-dimensional relationships between nodes, capturing interactions such as shared user preferences or co-consumption patterns. Subsequently, we employ message passing on these SCs to generate embeddings that integrate information from various levels of relationships, further mitigating biased propagation. Finally, these representations, functioning as a plug-and-play module, are integrated with the original learned representations to serve as fair representations of users and items for recommendation.

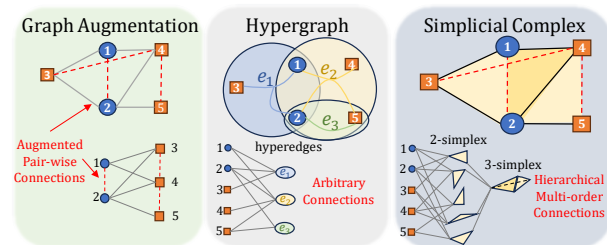


Figure 2: Differences in message passing between graph augmentation, hypergraph, and simplicial complex.

We summarize our contributions as follows:

- We propose a novel topology-aware debiasing method by incorporating simplicial complexes. Our method addresses the bias propagation issue in existing GNN-based recommendation methods, which arises from popularity-induced biases in the user-item network topology during message passing and aggregation. By leveraging simplicial complexes for feature smoothing, our method enables the propagation of multi-order collaborative signals and effectively achieves feature debiasing.
- Our proposed Test-time Simplicial Propagation (TSP) module is designed as a plug-and-play solution, enabling seamless integration into pre-trained GNN-based models for inference without the need for fine-tuning additional parameters, thereby demonstrating its superior extensibility.
- We conduct extensive experiments on five real-world datasets, varying in size, domain, and sparsity. The proposed method exhibits remarkable performance, particularly in long-tail recommendation tasks. Visualization results indicate that our approach produces more uniform distributions of user and item representations, confirming its ability to produce fairer representations.

2 RELATED WORKS

2.1 GNNs for Recommendation

GNNs [13, 14, 38] have achieved significant success in various downstream tasks involving graph data. Many works [28, 37, 49, 53] have applied GNNs to recommender systems. For example, NGCF [42] models user-item interactions as a bipartite graph and utilizes graph convolutional layers to learn embeddings for users and items. Although GNNs are effective in capturing collaborative filtering signals, their core message passing and aggregation mechanisms may introduce unnecessary redundancy. Subsequent research works propose several improvements. Methods like LightGCN [21], UltraGCN [31] and SVD-GCN [33] primarily focus on simplifying GNNs to improve efficiency and scalability while preserving performance.

Recently, contrastive learning has been integrated into GNNs, demonstrating strong potential for enhancing graph representation learning in recommender systems [26, 39, 47, 52]. SGL [47] proposes a self-supervised learning framework to learn the node embeddings by maximizing the similarity between the embeddings of the same node under different views. LightGCL [7] and SimGCL [26] further simplify the graph augmentation process, achieving improvements both in efficiency and performance.

2.2 Simplicial Neural Networks

Despite the success of GNNs in various areas, they are constrained to capturing only pairwise relationships between nodes in the graph, which limits the expressiveness of the learned node representations. Xu et al. [43] propose a GNN with the expressive power equivalent to that of the 1-Weisfeiler-Lehman graph isomorphism test (1-WL test). While some higher-order GNN methods theoretically possess the expressive power to surpass the 1-WL test, they are hindered by extremely high computational complexity and suboptimal performance on downstream tasks [2, 32]. Chen et al. [11] further show that GNNs have difficulty in detecting substructures like triangles and cliques. To address these limitations, some research works begin to explore the use of simplicial complexes to enhance GNNs. Simplicial complexes are first explored from a signal processing perspective [3]. Recent works [4, 19, 20] propose to conduct message passing on simplicial complexes. Simplicial Neural Network (SNN) [15] extends graph convolution to higher orders by utilizing Hodge Laplacians. BSCNet [10], a representative model that enables message passing across arbitrary rank, integrates node- and edge-level shifting mechanisms to predict linkages among nodes using a pseudo Hodge Laplacian. Subsequent works [17, 18, 24] draw inspiration from the graph attention mechanism introduced in GAT [38] and incorporate a simplicial attention mechanism to enhance message passing between simplices.

2.3 Popularity Debiasing

To mitigate the influence of popularity in recommender systems, numerous methods have been proposed. One straightforward approach is to apply regularizations [1, 12, 40, 44] to balance the influence of popular items. For instance, Sam-Reg [6] introduces a regularization term aims at minimizing the biased correlation between user-item relevance and item popularity. Adversarial learning is also a widely adopted method in popularity debiasing [8, 23, 27, 51].

The main idea is to co-train another adversarial network to improve the fairness of the recommendation. Another perspective is to model the popularity bias using casual graph [41, 45, 55, 56]. Counterfactual reasoning is then applied to causal graphs to mitigate the bias. MACR [45], for example, models the effect of popular items on the recommendation process and removes their influence in the final inference. Some recent works [29, 30, 54] have also explored the cause of popularity bias from the topology perspective. GALORE [30] uses graph augmentations, such as edge addition, edge dropping, and synthesized nodes, to bridge the gap between the neighborhoods of popular and tail items. Although topological graph augmentations can effectively alleviate the impact of popular items, they are still limited to pairwise relationships in graphs. Higher order relationships between nodes remain underutilized.

3 PRELIMINARIES

GNN-based Collaborative Filtering. Let $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ represents a graph, where \mathcal{V} is the set of nodes and \mathcal{E} is the set of edges. In the context of GNN-based RS, the user-item interaction data is modeled as a bipartite graph. Each edge $e_{i,j} \in \mathcal{E}$ signifies an interaction between user i and item j . For each node, the GNN iteratively gathers feature information from its neighbors and then aggregates it. The propagation process is formulated as follows:

$$\mathbf{x}_i^{(l)} = \text{UPDATE}\left(\mathbf{x}_i^{(l-1)}, \text{AGGREGATE}(\{\mathbf{x}_j^{(l-1)}, \forall j \in \mathcal{N}_i\})\right), \quad (1)$$

where \mathbf{x}_i denotes the feature embedding of node i , with the superscript l indicating the l -th layer. The set of neighbors of node i is represented by \mathcal{N}_i . The functions UPDATE and AGGREGATE correspond to the update and aggregation processes, respectively. Taking the representative LightGCN [21] method as an example, the propagation process is formulated as follows:

$$\mathbf{x}_i^{(l+1)} = \sum_{j \in \mathcal{N}(i)} \frac{1}{\sqrt{|\mathcal{N}(i)||\mathcal{N}(j)|}} \mathbf{x}_j^{(l)}. \quad (2)$$

The user's preference for an uninteracted item is typically modeled using the inner product of their feature vectors, i.e., $\hat{y}_{i,j} = \mathbf{x}_i^T \mathbf{x}_j$. The Bayesian Personalized Ranking (BPR) loss [34] is commonly employed for optimization:

$$\mathcal{L}_{\text{BPR}} = \sum_{(i,j^+,j^-) \in \mathcal{V}} \log(\text{sigmoid}(y_{i,j^+} - \hat{y}_{i,j^-})) \quad (3)$$

where j^+ denotes the positive item that user i has interacted, and j^- is a randomly sampled negative item that has not been interacted by i .

Simplicial Complexes. Given the set of vertices \mathcal{V} , a k -simplex $\sigma \subseteq \mathcal{V}$ is a subset containing $k+1$ elements, where any two distinct elements in the subset are connected by an edge. For example, a 0-simplex is a vertex, a 1-simplex is an edge, and a 2-simplex is a triangle. A simplicial complex \mathcal{X}^k is a collection of simplices with the property that if a simplex σ belongs to \mathcal{X}^k , then any subset of σ is also an element of \mathcal{X}^k . The order k of a simplicial complex represents the maximum dimension among its simplices.

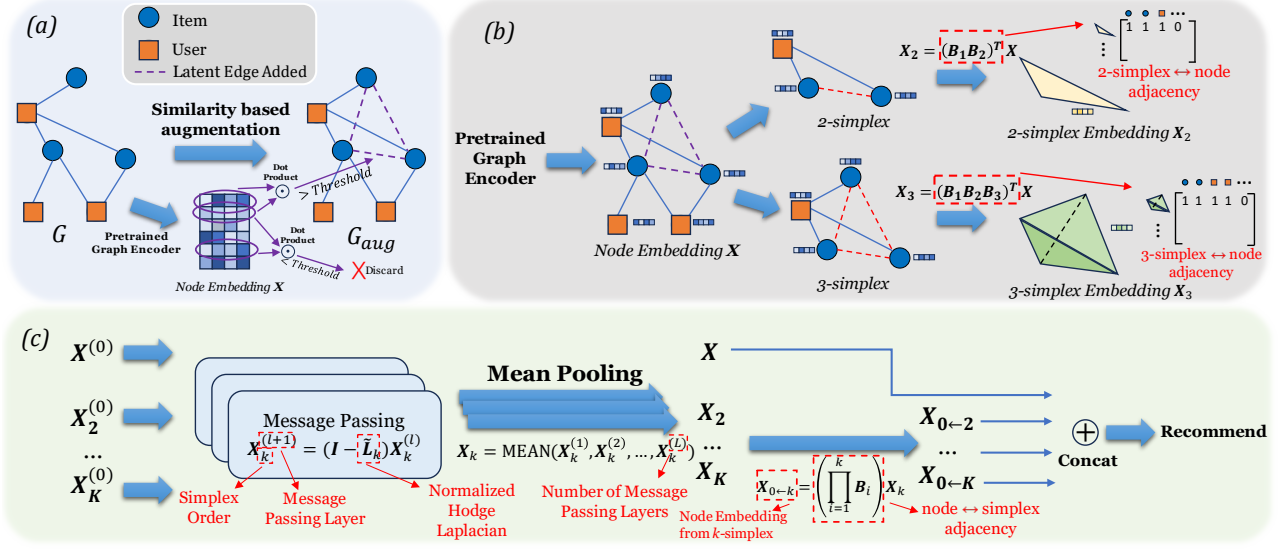


Figure 3: The proposed Test-time Simplicial Propagation (TSP) framework comprises three components: (a) Tail Enhancement that augments the original graph based on node similarity. (b) Embedding Converter that calculates embeddings for all simplices in augmented graph G_{aug} based on pre-trained node embedding. (c) Simplicial Propagation that performs parallel message passing for each order of simplicial complexes and concatenates multi-order embeddings for recommendation.

4 METHODOLOGY

Figure 3 depicts the pipeline of our proposed Test-time Simplicial Propagation (TSP) framework, which is designed around three core modules: **Tail Enhancement**, **Embedding Converter**, and **Simplicial Propagation**. In the following sections, we provide a detailed description of each part.

4.1 Tail Enhancement

To promote a balanced graph topology and improve the adjacency of tail items, we begin by expanding the original graph G to enhanced graph G_{aug} through the incorporation of latent edges between nodes, determined by similarity metrics:

$$S = X^T X, \quad (4)$$

where S represents the similarity matrix and X is the node embedding matrix. The newly added edges are identified by applying a threshold to S :

$$\mathcal{E}_{add} = \{(i, j) \mid (i, j) \notin \mathcal{E}_{ori} \text{ and } S(i, j) > \text{Threshold}(\theta)\}. \quad (5)$$

Here, \mathcal{E}_{add} and \mathcal{E}_{ori} denote the sets of added latent edges and the original graph's edges, respectively. θ is the manually set hyperparameter determined by the ratio of the desired number of new edges to the total number of edges in the original graph, e.g., 1e-3. $\text{Threshold}(\theta)$ means choosing a threshold that selects $\theta|\mathcal{E}_{ori}|$ new edges.

4.2 Embedding Converter

The relationships between neighboring simplices are described using the boundary operator $\partial_k : \mathcal{X}^k \rightarrow \mathcal{X}^{k-1}$, which maps a k -dimensional simplex to its $(k-1)$ -dimensional boundary simplex.

This operator is mathematically represented by a boundary matrix $B_k \in \{0, 1\}^{|\mathcal{X}^{k-1}| \times |\mathcal{X}^k|}$, defined as follows:

$$B_k(i, j) = \begin{cases} 1, & \text{if } \sigma_i \subset \sigma_j, \text{ for } (k-1)\text{-simplex } \sigma_i \text{ and } k\text{-simplex } \sigma_j \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

This schema is extended to capture the relationships between simplices of different orders:

$$B_{m,n} = \prod_{i=m+1}^n B_i, \quad (7)$$

where $B_{m,n}$ describes the adjacency between simplices of order m and n . Adjacency relations form the basis for embedding conversion in TSP. Initial embeddings for various orders of simplices are derived from node embeddings obtained using pretrained graph neural networks. For example, each k -dimensional simplex σ_k is represented as the aggregation of the embeddings of its constituent elements:

$$\mathbf{x}_{\sigma_k} = \sum_{i \in \sigma_k} \mathbf{x}_i. \quad (8)$$

The equivalent matrix form is:

$$X_k = \left(\prod_{i=1}^k B_i \right)^T X, \quad (9)$$

where X_k and X are the embedding matrices for k -simplices and nodes, respectively. Specially for $k=0$, $X_0 = X$. Accordingly, the embedding for each node contained within k -order simplicial complexes (SCs) is:

$$X_{0 \leftarrow k} = \left(\prod_{i=1}^k B_i \right) X_k \quad (10)$$

4.3 Simplicial Propagation

Boundary matrices form the foundation for defining Hodge Laplacians, which extend graph Laplacians to accommodate simplicial complexes:

$$\begin{aligned} \mathbf{L}_0 &= \mathbf{B}_1 \mathbf{B}_1^T, \\ \mathbf{L}_k &= \mathbf{B}_{k+1} \mathbf{B}_{k+1}^T + \mathbf{B}_k^T \mathbf{B}_k, \quad \text{where } k = 1, 2, \dots, K-1. \\ \mathbf{L}_K &= \mathbf{B}_K^T \mathbf{B}_K. \end{aligned}$$

Each Hodge Laplacian \mathbf{L}_k comprises an upper Laplacian $\mathbf{L}_{k,u} = \mathbf{B}_{k+1} \mathbf{B}_{k+1}^T$ and a lower Laplacian $\mathbf{L}_{k,l} = \mathbf{B}_k^T \mathbf{B}_k$, aside from \mathbf{L}_0 and \mathbf{L}_K , which is specifically the case for \mathbf{L}_0 aligned with the graph Laplacian [35]. Figure 4 exhibits an example of boundary matrices and Hodge Laplacians for simplicial complexes. The diagonal degree matrix for Hodge Laplacian is defined as follows:

$$\mathbf{D}_k(i, i) = \sum_j \mathbf{L}_k(i, j). \quad (11)$$

Similar to normalized graph Laplacian, the normalized Hodge Laplacian is expressed by:

$$\tilde{\mathbf{L}}_k = \mathbf{D}_k^{-\frac{1}{2}} \mathbf{L}_k \mathbf{D}_k^{-\frac{1}{2}}. \quad (12)$$

Our approach integrates both node and multi-order simplicial complex propagation. We formulate an efficient propagation scheme using Hodge Laplacians, drawing inspiration from graph propagation techniques. The message-passing rule for k -order simplicial complexes (SCs) is established as follows:

$$\mathbf{X}_k^{(l+1)} = (\mathbf{I} - \tilde{\mathbf{L}}_k) \mathbf{X}_k^{(l)}, \quad (13)$$

where \mathbf{I} represents the identity matrix, and $\mathbf{X}_k^{(l)}$ denotes the embeddings of k -simplices at layer l . Equation 13 illustrates a generalized form of Laplacian smoothing, similar to graph convolution [25]. When $k = 0$, this process corresponds to conventional node message passing on graphs. The embedding for each simplicial order is computed as the mean of embeddings across each message passing layer:

$$\mathbf{X}_k = \text{MEAN}(\mathbf{X}_k^{(0)}, \mathbf{X}_k^{(1)}, \dots, \mathbf{X}_k^{(L)}), \quad (14)$$

where L represents the maximum message-passing layer. Subsequently, embeddings from all orders are concatenated for recommendation tasks:

$$\mathbf{X}_{rec} = \text{CONCAT}(\mathbf{X}_0, \mathbf{X}_{0 \leftarrow 2}, \mathbf{X}_{0 \leftarrow 3}, \dots, \mathbf{X}_{0 \leftarrow K}), \quad (15)$$

where \mathbf{X}_{rec} denotes the output embedding for recommendation, K is the highest order of simplices, and $\mathbf{X}_{0 \leftarrow k}$ is derived using Equation 10. Algorithm 1 provides a detailed description of TSP.

5 EXPERIMENTS

In this section, we evaluate the performance of our proposed method. We aim to answer the following research questions:

- **RQ1:** How does our proposed method compare to existing debiasing methods in terms of performance?
- **RQ2:** Can our proposed method generate fairer item embeddings?
- **RQ3:** How do the different modules of TSP impact recommendation performance?

Algorithm 1: Test-time Simplicial Propagation

Input: Pretrained node embedding $\mathbf{X}_0^{(0)}$
Boundary matrices \mathbf{B}_k
Hodge Laplacians $\tilde{\mathbf{L}}_k$
Number of propagation layers L
Maximum SC order K
Output: final node embeddings \mathbf{X}

```

1 for  $k = 1$  to  $K$  do
    /* Initialize multi-order simplex embeddings */
2    $\mathbf{X}_k^{(0)} \leftarrow (\prod_{i=1}^k \mathbf{B}_i)^T \mathbf{X}_0^{(0)}$ 
3   for  $k = 0$  to  $K$  do
    /* Propagate embeddings for each simplex order */
4     for  $l = 1$  to  $L$  do
5        $\mathbf{X}_k^{(l+1)} \leftarrow (\mathbf{I} - \tilde{\mathbf{L}}_k) \mathbf{X}_k^{(l)}$ 
6   for  $k = 0$  to  $K$  do
    /* Aggregate embeddings across layers */
7      $\mathbf{X}_k \leftarrow \text{MEAN}(\mathbf{X}_k^{(1)}, \mathbf{X}_k^{(2)}, \dots, \mathbf{X}_k^{(L)})$ 
8   for  $k = 1$  to  $K$  do
    /* Convert higher-order simplex embeddings to node embeddings */
9      $\mathbf{X}_{0 \leftarrow k} \leftarrow (\prod_{i=1}^k \mathbf{B}_i) \mathbf{X}_k$ 
10   $\mathbf{X} \leftarrow \text{CONCAT}(\mathbf{X}_0, \mathbf{X}_{0 \leftarrow 1}, \dots, \mathbf{X}_{0 \leftarrow K})$ 
11 return  $\mathbf{X}$ 

```

Table 1: Statistics of the datasets.

Dataset	Users	Items	Interactions	Sparsity
Adressa	13,485	744	116,321	0.011594
Globo	158,323	12,005	2,520,171	0.001326
ML10M	69,166	8,790	5,000,415	0.008225
Yelp2018	31,668	38,048	1,561,406	0.001300
Gowalla	29,858	40,981	1,027,370	0.000840

- **RQ4:** How do various hyperparameter settings influence the performance outcomes?
- **RQ5:** Are the overhead of introducing simplicial complexes acceptable?

5.1 Experimental Setup

Dataset. We use five real-world benchmark datasets in our experiments: Yelp2018¹ and Gowalla² are widely used datasets in the RS research. Adressa³ and Globo⁴ are two popular news recommendation datasets, ML10M⁵ contains movie ratings from MovieLens. We convert the explicit ratings to implicit feedback by assigning a value of 1 if the user rated the item, and 0 otherwise. The datasets exhibit a rich diversity in terms of size, domain, and sparsity. The statistics for these datasets are summarized in Table 1.

¹<https://www.yelp.com/dataset>

²<https://snap.stanford.edu/data/loc-gowalla.html>

³<https://reclab.idi.ntnu.no/dataset>

⁴<https://www.kaggle.com/gspmoreira/news-portal-user-interactions-by-globocom>

⁵<https://grouplens.org/datasets/movielens/10m>

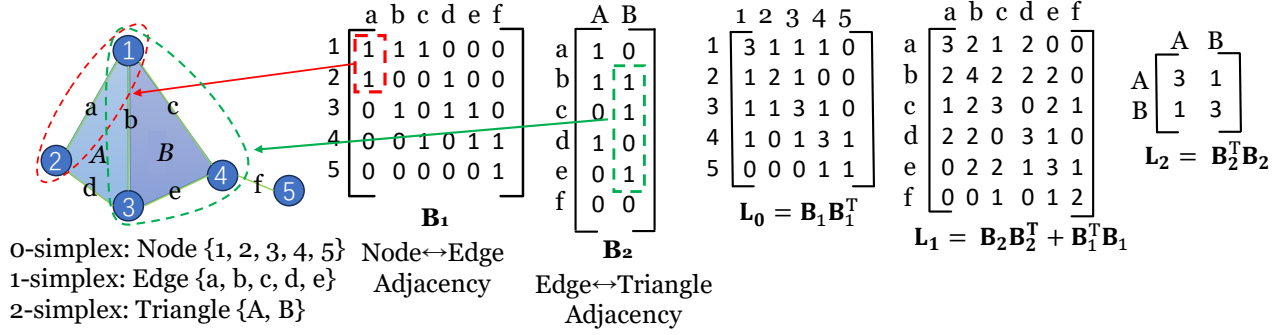


Figure 4: Boundary matrix and Hodge Laplacian in simplicial complexes.

Table 2: The performance of the bottom 20% of tail items. The best results are highlighted in bold and the second-best results are underlined. K is set to 20. %Improve represents the relative improvement of TSP over the second-best baseline.

	Adressa			Gowalla			Yelp2018			ML10M			Globo		
	Recall	HR	NDCG	Recall	HR	NDCG	Recall	HR	NDCG	Recall	HR	NDCG	Recall	HR	NDCG
LightGCN	0.015	0.016	0.007	0.006	0.027	0.006	0.002	0.012	0.001	0.002	0.009	0.001	0.001	0.007	0.002
+ IPS	<u>0.040</u>	<u>0.050</u>	<u>0.020</u>	<u>0.030</u>	<u>0.097</u>	0.025	0.006	<u>0.040</u>	<u>0.007</u>	<u>0.011</u>	<u>0.035</u>	<u>0.005</u>	<u>0.022</u>	<u>0.057</u>	<u>0.012</u>
+ CausE	0.023	0.032	0.011	0.020	0.063	0.013	<u>0.007</u>	0.022	0.004	0.007	0.017	0.002	0.014	0.038	0.008
+ MACR	0.016	0.022	0.007	0.014	0.037	0.008	<u>0.005</u>	0.019	0.004	0.007	0.012	0.002	0.006	0.027	0.005
+ sDRO	0.014	0.019	0.007	0.012	0.032	0.007	0.005	0.017	0.003	0.007	0.016	0.002	0.003	0.018	0.004
+ Ours	0.055	0.066	0.024	0.038	0.115	<u>0.021</u>	0.009	0.056	0.008	0.013	0.050	0.008	0.024	0.070	0.013
%Improve	37.50	28.00	20.00	26.67	18.56	-	28.57	40.00	14.29	18.18	42.86	60.00	9.09	22.81	8.33
SimGCL	0.016	0.021	0.007	0.008	0.032	0.007	0.002	0.013	0.003	0.003	0.010	0.002	0.002	0.008	0.001
+ IPS	<u>0.052</u>	<u>0.063</u>	<u>0.027</u>	0.021	<u>0.080</u>	<u>0.018</u>	<u>0.008</u>	<u>0.042</u>	<u>0.006</u>	<u>0.013</u>	0.040	0.008	0.025	0.075	<u>0.011</u>
+ CausE	0.018	0.025	0.008	<u>0.028</u>	0.074	<u>0.018</u>	0.006	0.035	0.005	0.010	0.027	0.004	0.010	0.026	0.008
+ MACR	0.014	0.019	0.006	0.017	0.034	0.006	0.005	0.020	0.004	<u>0.013</u>	<u>0.048</u>	<u>0.009</u>	<u>0.012</u>	0.037	0.008
+ sDRO	0.016	0.021	0.007	0.014	0.031	0.007	0.006	0.030	0.003	0.008	0.025	0.003	0.007	0.022	0.006
+ Ours	0.085	0.103	0.046	0.055	0.125	0.047	0.015	0.087	0.014	0.016	0.073	0.012	0.025	<u>0.063</u>	0.017
%Improve	63.46	63.49	70.37	96.43	56.25	161.11	87.50	107.14	133.33	23.08	52.08	33.33	-	-	54.55
LightGCL	0.020	0.023	0.009	0.010	0.034	0.008	0.003	0.012	0.003	0.003	0.010	0.002	0.004	0.010	0.004
+ IPS	<u>0.045</u>	<u>0.058</u>	<u>0.022</u>	<u>0.040</u>	<u>0.120</u>	<u>0.030</u>	0.010	<u>0.060</u>	0.010	0.010	0.035	0.006	<u>0.024</u>	<u>0.068</u>	<u>0.016</u>
+ CausE	0.022	0.027	0.008	0.026	0.080	0.019	0.002	0.011	0.002	0.003	0.009	0.001	0.015	0.044	0.011
+ MACR	0.008	0.011	0.005	0.015	0.046	0.012	<u>0.011</u>	0.038	<u>0.012</u>	<u>0.011</u>	<u>0.045</u>	<u>0.007</u>	0.013	0.032	0.007
+ sDRO	0.015	0.019	0.007	0.013	0.032	0.007	0.010	0.038	0.003	0.007	0.019	0.002	0.007	0.027	0.005
+ Ours	0.075	0.115	0.047	0.050	0.160	0.032	0.020	0.095	0.019	0.014	0.065	0.010	0.032	0.079	0.018
%Improve	66.67	98.28	113.64	25.00	33.33	6.67	81.81	58.33	58.33	27.27	44.44	42.86	33.33	16.18	12.50

Evaluation Protocols. Conventional train-test split strategies are not suitable for evaluating the debiasing performance of recommender systems, as test sets created through random partitioning inevitably retain the same popularity biases present in the original data. To accurately assess a model’s ability to mitigate popularity bias and highlight relevant long-tail items, we need unbiased test sets with a balanced distribution across the popularity spectrum.

To this end, we adopt the unbiased data split method proposed by He et al. [45]. Specifically, we uniformly sample 10% of the user-item interactions for the test set, another 10% for the validation set, and the remaining 80% for the training set. Importantly, all items are sampled with equal probability during this process, regardless of their overall popularity in the original data. This stratified sampling

scheme ensures that the test and validation sets are well-balanced, covering the entire spectrum of item popularity. We evaluate the performance of our method on these unbiased test sets, using three widely adopted ranking metrics: Recall@K, Hit Ratio (HR@K), and Normalized Discounted Cumulative Gain (NDCG@K). The results are reported as the average across all users.

Backbones. We choose three recent advanced GNN-based methods as backbone models. **LightGCN** [21] employs lightweight graph convolutions for recommendation. **SimGCL** [26] represents a simplified approach to graph contrastive learning, utilizing noised embeddings rather than augmented graph views. **LightGCL** [7] is

the state-of-the-art contrastive learning-based model for collaborative filtering, which constructs a novel view of the original graph through an SVD approximation of the graph adjacency matrix.

Baselines. We compare our proposed model with following baselines for popularity debiasing: **IPS** [36] is a reweighting method based on an unbiased importance estimator, designed to convert biased data into an unbiased distribution. **CausE** [5] employs domain generalization techniques to learn from biased data and make predictions based on random exposure. **MACR** [45] models the causes of bias using causal graphs and mitigates the effect of popular items through counterfactual inference. **sDRO** [46] utilizes distributionally robust optimization to improve worst-case performance, aiming for fairer recommendations.

Implementation Details. For the backbone recommendation models, we implement LightGCN, SimGCL and LightGCL using a consistent architecture of 3 graph convolutional layers with an output embedding dimension of 64. In line with the original LightGCL paper, we set the temperature parameter τ to 0.5, and the weighting factor λ for the contrastive loss to $1e-2$. For SimGCL, the temperature parameter τ is set to 0.2, and the noise parameter ϵ is set to 0.1, as recommended by the authors. We employ the Adam optimizer with a learning rate of 0.001 and a weight decay regularization of $1e-4$ for all models. The batch size is fixed at 4096 across experiments. During training, we allow up to 500 epochs and implement an early stopping mechanism with a patience of 50 epochs to prevent overfitting.

5.2 Overall Performance (RQ1)

Table 2 shows the recommendation performance of the bottom 20% long-tail items. In contrast, the overall recommendation performance is depicted in Table 3. Both are evaluated in terms of Recall@20, HR@20 and NDCG@20. Our observations are as follows:

- The proposed method shows a remarkable improvement in recommendation performance for tail items, while also delivering a general enhancement in overall performance. These results collectively underscore the effectiveness of our approach.
- Compared to LightGCN, TSP demonstrates a more substantial improvement in recommendation performance for tail items when applied to graph contrastive learning-based methods SimGCL and LightGCL. This indicates that, despite being state-of-the-art, graph contrastive learning methods may produce imbalanced representations for popular and tail items. Our method effectively addresses this issue by learning fairer representations.

5.3 Distribution of Item Embeddings (RQ2)

To explore the impact of our proposed method on the distribution of learned embeddings, we project the item embeddings learned by LightGCN and LightGCL on the Gowalla dataset into a two-dimensional space using t-SNE visualization. We compare these results with other popularity debiasing methods, as shown in Figure 5. Our key observations are as follows:

- LightGCL exhibits a more balanced distribution of item embeddings compared to LightGCN, aligning with the expectation that

contrastive learning methods can learn more uniform representations by negative sampling.

- The incorporation of simplicial propagation in our method results in a more uniform distribution of item embeddings. This observation indicates that our approach can promote fairer recommendations by extending the message-passing process beyond pairwise relationships.

5.4 Ablation Study (RQ3)

To thoroughly assess the effectiveness of different components in our proposed TSP framework for tail items, we conduct an ablation study by using LightGCN as the backbone. Three variants are examined on two datasets, as shown in Table 4: 1) **TSP-Full**, the complete TSP framework, 2) **TSP-TE**, which performs message passing solely between nodes on the same enhanced graph, 3) **Base**, which is LightGCN without debiasing. The results indicate that while tail enhancement partially addresses the topology bias on the graph caused by popularity bias, message passing on simplicial complexes further smooths the representation of nodes, ultimately leading to fairer recommendations.

5.5 Impact of Different Hyperparameters (RQ4)

There are two pivot hyperparameters in our model: the threshold θ for latent connection sparsity and the number of layers L for simplicial propagation. Figure 6 shows the change of Recall@20 and number of faces (k -simplices)⁶ over different hyperparameters on the Gowalla dataset.

Effect of θ . The parameter θ critically impacts model performance by adjusting the complexity of the simplicial complex networks. An optimal θ between $1e-4$ and $1e-3$ yields consistent, near-optimal results, while θ exceeding $2e-3$ introduces noisy connections, distorting learned representations. Appropriately setting θ is essential to balance topological simplicity and noise mitigation for accurate recommendations.

Effect of L . Multiple simplicial propagation layers progressively capture higher-order relationships, but regulating layer depth (L) is crucial. Increasing L enhances encoding of complex dependencies, yet excessive layers may lead to oversmoothing, where node embeddings become indistinguishable. Optimal performance is typically achieved with 3 to 5 layers, beyond which the negative effects of oversmoothing outweigh the benefits.

5.6 Scalability (RQ5)

The scalability of our proposed TSP approach is evidenced by the time costs presented in Table 5. The lightweight one-time preprocessing and efficient inference compared to the backbone LightGCN suggests that our approach introduces minimal additional computational overhead. Notably, as the dataset size increases, the relative computational overhead introduced by TSP diminishes in comparison to the backbone model. This trend demonstrates TSP’s scalability suited for large-scale recommendation systems.

⁶The number of faces can be slightly different due to different training process between LightGCN and LightGCL. But the trend and magnitude are consistent. Thus we only demonstrate statistics from LightGCN.

Table 3: The overall performance of our proposed method compared to other baseline methods. The best results are highlighted in bold and the second-best results are underlined. The value of K is set to 20. %Improve is the relative improvement of TSP over second best baseline.

	Adressa			Gowalla			Yelp2018			ML10M			Globo		
	Recall	HR	NDCG	Recall	HR	NDCG	Recall	HR	NDCG	Recall	HR	NDCG	Recall	HR	NDCG
LightGCN	0.096	0.122	0.042	0.047	0.203	0.038	0.007	0.086	0.012	0.009	0.058	0.008	0.010	0.037	0.007
+ IPS	0.110	0.138	0.050	0.062	0.246	0.048	0.012	<u>0.120</u>	<u>0.017</u>	0.016	0.086	0.012	<u>0.023</u>	<u>0.071</u>	<u>0.015</u>
+ CausE	0.072	0.096	0.031	0.044	0.163	0.031	0.007	0.067	0.011	0.005	0.037	0.005	0.009	0.027	0.006
+ MACR	<u>0.124</u>	<u>0.149</u>	<u>0.052</u>	<u>0.077</u>	<u>0.254</u>	<u>0.051</u>	0.031	0.148	0.018	<u>0.024</u>	<u>0.088</u>	<u>0.014</u>	0.012	0.029	0.007
+ sDRO	0.113	0.143	0.051	0.029	0.130	0.025	0.003	0.053	0.007	0.015	0.047	0.008	0.010	0.028	0.005
+ Ours	0.132	0.160	0.059	0.082	0.264	0.058	<u>0.020</u>	0.116	0.018	0.027	0.110	0.018	0.027	0.073	0.019
%Improve	6.45	7.38	13.46	6.49	3.94	13.73	-	-	5.88	12.50	25.00	28.57	17.39	2.82	26.67
SimGCL	0.110	0.137	0.049	<u>0.062</u>	<u>0.230</u>	<u>0.046</u>	0.008	0.090	0.013	0.009	0.052	0.008	0.010	0.038	0.008
+ IPS	<u>0.122</u>	<u>0.148</u>	<u>0.061</u>	0.047	0.192	0.039	<u>0.012</u>	<u>0.103</u>	<u>0.015</u>	0.020	0.095	0.015	0.040	0.112	<u>0.025</u>
+ CausE	0.044	0.065	0.020	0.057	0.184	0.038	0.007	0.068	0.010	0.005	0.034	0.005	0.010	0.029	0.006
+ MACR	0.028	0.038	0.010	0.001	0.031	0.005	0.003	0.029	0.003	0.027	<u>0.097</u>	<u>0.016</u>	<u>0.013</u>	0.029	0.007
+ sDRO	0.114	0.140	0.052	0.026	0.119	0.022	0.002	0.038	0.006	0.015	0.054	0.009	0.007	0.027	0.004
+ Ours	0.128	0.156	0.067	0.094	0.300	0.070	0.024	0.154	0.024	<u>0.026</u>	0.108	0.017	0.040	<u>0.100</u>	0.026
%Improve	4.92	5.41	9.84	51.60	30.43	52.17	100.00	49.51	60.00	-	11.34	6.25	-	-	4.00
LightGCL	<u>0.145</u>	<u>0.174</u>	<u>0.062</u>	0.075	0.254	0.054	0.010	0.098	0.014	0.010	0.064	0.009	0.026	0.078	0.018
+ IPS	0.100	0.122	0.046	<u>0.087</u>	<u>0.276</u>	0.072	0.033	0.187	0.029	0.031	0.116	0.020	<u>0.039</u>	<u>0.103</u>	<u>0.025</u>
+ CausE	0.136	0.171	0.059	0.081	0.255	0.058	<u>0.010</u>	0.094	<u>0.014</u>	0.008	0.054	0.008	0.024	0.073	0.017
+ MACR	0.031	0.040	0.012	0.051	0.214	0.051	0.001	0.011	0.001	0.004	0.010	0.002	0.003	0.006	0.001
+ sDRO	0.125	0.152	0.057	0.029	0.131	0.024	0.003	0.053	0.007	0.013	0.051	0.008	0.009	0.029	0.005
+ Ours	0.152	0.181	0.070	0.092	0.292	<u>0.062</u>	0.033	<u>0.178</u>	0.029	<u>0.021</u>	<u>0.107</u>	<u>0.016</u>	0.046	0.115	0.029
%Improve	4.83	4.02	12.90	5.75	5.80	-	-	-	-	-	-	-	17.95	11.65	16.00

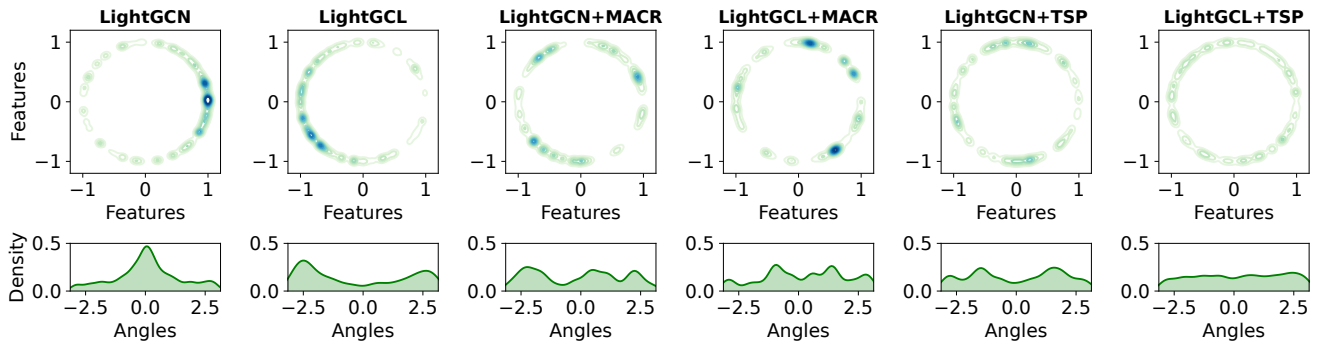


Figure 5: t-SNE visualization of item embeddings learned on Gowalla dataset. The top figures plot the Gaussian Kernel Density Estimation (KDE) of embeddings projected to \mathbb{R}^2 . The darker the color, the more items are in this region. The figures below show the KDE of angles (i.e. $\arctan2(y, x)$) for each point (x, y) .

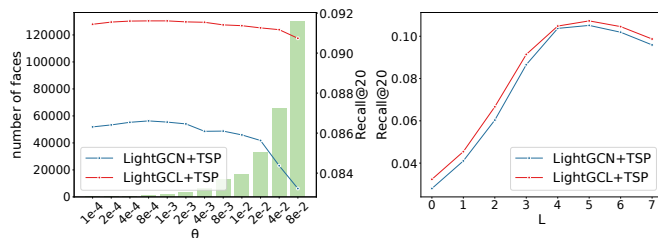


Figure 6: Effect of different θ and L on Gowalla dataset.

Table 4: Ablation study on Gowalla and Yelp 2018 datasets.

	Gowalla			Yelp2018		
	Recall	HR	NDCG	Recall	HR	NDCG
TSP-Full	0.082	0.264	0.058	0.020	0.116	0.018
TSP-TE	0.056	0.211	0.041	0.010	0.097	0.014
Base	0.047	0.203	0.038	0.007	0.086	0.012

Table 5: TSP preprocessing and inference time costs compared with LightGCN backbone.

	Adressa	Gowalla	Yelp2018	ML10M	Globo
LightGCN Training	10min	35min	1h40min	9h	3h
TSP Preprocessing	2.54s	15.97s	26.32s	91.34s	44.29s
LightGCN Inference	0.037s	0.080s	0.134s	0.575s	0.501s
TSP Inference	0.098s	0.130s	0.200s	0.650s	0.606s

6 CONCLUSION

In this work, we propose a novel Test-time Simplicial Propagation (TSP) method to address topology bias caused by item popularity in GNN-based recommendation. Our key contribution is the development of a plug-and-play module that employs a message-passing scheme over simplicial complexes for debiasing. Designed for test-time inference, our method is both efficient and highly scalable. Our promising results highlight the significant potential of simplicial complexes as a valuable inductive bias for debiasing and enhancing collaborative filtering with graph neural networks. We believe that our work opens up exciting avenues for future research in leveraging simplicial complexes for recommender systems.

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