

Turbo-CF: Matrix Decomposition-Free Graph Filtering for Fast Recommendation

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ABSTRACT

A series of *graph filtering* (GF)-based collaborative filtering (CF) showcases state-of-the-art performance on the recommendation accuracy by using a low-pass filter (LPF) without a training process. However, conventional GF-based CF approaches mostly perform *matrix decomposition* on the item-item similarity graph to realize the ideal LPF, which results in a non-trivial computational cost and thus makes them less practical in scenarios where rapid recommendations are essential. In this paper, we propose Turbo-CF, a GF-based CF method that is both *training-free* and *matrix decomposition-free*. Turbo-CF employs a *polynomial graph filter* to circumvent the issue of expensive matrix decompositions, enabling us to make full use of modern computer hardware components (*i.e.*, GPU). Specifically, Turbo-CF first constructs an item-item similarity graph whose edge weights are effectively regulated. Then, our own polynomial LPFs are designed to retain only low-frequency signals without explicit matrix decompositions. We demonstrate that Turbo-CF is *extremely fast yet accurate*, achieving a runtime of **less than 1 second** on real-world benchmark datasets while achieving recommendation accuracies comparable to best competitors.

KEYWORDS

Collaborative filtering; low-pass filter; matrix decomposition; polynomial graph filter; recommender system.

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1 INTRODUCTION

Recommender systems have significantly impacted various industries, including e-commerce (*e.g.*, Amazon [19]) and content streaming services (*e.g.*, YouTube [6] and Netflix [8]), enabling with personalized recommendations. Central to these systems is collaborative

filtering (CF), which predicts a user's preferences based on the historical user-item interactions [10, 12, 21, 31, 33, 34, 41]. Notably, CF techniques based on graph convolutional networks (GCNs) have been shown to achieve state-of-the-art recommendation performance by aggregating the information from high-order neighbors through message passing [1, 10, 16, 36].

On one hand, it is often the case where the speed at which recommender systems update their models becomes increasingly crucial, mainly due to two key factors. First, user preferences are not static; they tend to evolve rapidly due to various influences such as trends, personal circumstances, and exposure to new content [1, 17, 24, 35]. In this case, recommender systems must be agile enough to reflect such evolving preferences. Second, the influx of new data is often very high, with users constantly interacting with content and services [13, 35, 39]. For example, social media platforms such as Gowalla and Facebook may require quick model updates due to the fast pace of user interactions and content generation [24, 35]. Therefore, these factors result in the need to build an efficient and prompt system [7, 13, 17]. Such a fast adaptation ensures that the recommendations remain relevant and in sync with current user interests and behaviors, thereby enhancing user satisfaction and engagement with the underlying system [1, 7, 17, 24, 30, 35].

On the other hand, most of existing GCN-based CF methods [10, 31, 33, 34, 40, 41] have their inherent limitations, notably their reliance on extensive offline training [3, 15]. Recently, a series of graph filtering (GF) methods have emerged as another CF technique since they can naturally alleviate this problem with their training-free nature. However, conventional GF-based CF methods suffer from a high computational cost during matrix decomposition to realize the ideal low-pass filter (LPF), hindering their potential for real-time applications [4, 20, 27, 37].

To tackle these practical challenges, we introduce Turbo-CF, a novel GF-based CF method that is both *training-free* and *matrix decomposition-free*. By harnessing the computational efficiency of *polynomial graph filters*, Turbo-CF is composed solely of simple matrix operations (*i.e.*, matrix multiplications). Thanks to its computational simplicity, it becomes more straightforward for Turbo-CF to make full use of modern computer hardware components such as GPU. As shown in Figure 1, we demonstrate that our Turbo-CF is *extremely fast yet sufficiently accurate*, showing a runtime of **less than 1 second** on real-world benchmark datasets (*e.g.*, Gowalla and Yelp) while still showing competitive performance compared to other benchmark CF methods. For reproducibility, the source code is available at <https://github.com/jindeok/Turbo-CF>.

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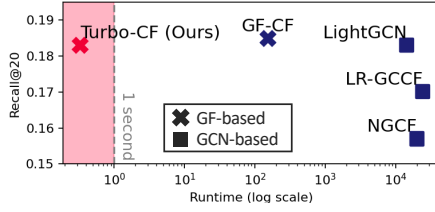


Figure 1: Accuracy versus runtime among Turbo-CF and other benchmark methods on the Gowalla dataset.

2 PRELIMINARY

Given a weighted graph $G = (V, E)$, the Laplacian matrix L of G is $L = D - A$, where $D = \text{diag}(A\mathbf{1})$ is the degree matrix for the all-one vector $\mathbf{1} \in \mathbb{R}^{|V|}$ and A is the adjacency matrix. A graph signal is represented as $\mathbf{x} \in \mathbb{R}^{|V|}$, where x_i represents the signal strength of node i in \mathbf{x} . The smoothness of \mathbf{x} on G is quantified as $S(\mathbf{x}) = \sum_{i,j} A_{i,j} (x_i - x_j)^2 = \mathbf{x}^T L \mathbf{x}$, where $A_{i,j}$ is the (i, j) -th element of A . By the eigen-decomposition $L = U\Lambda U^T$, we can formally define the graph Fourier transform for a graph signal \mathbf{x} as $\hat{\mathbf{x}} = U^T \mathbf{x}$, where $U \in \mathbb{R}^{|V| \times |V|}$ is the matrix whose columns correspond to a set of eigenvectors of L . Now, we are ready to formally define the graph filter and graph convolution as follows:

Definition 2.1. (Graph filter) [22, 27, 28, 37] Given a graph Laplacian matrix L , a graph filter $H(L) \in \mathbb{R}^{|V| \times |V|}$ is defined as

$$H(L) = U \text{diag}(h(\lambda_1), \dots, h(\lambda_{|V|})) U^T, \quad (1)$$

where $h : \mathbb{C} \rightarrow \mathbb{R}$ is the frequency response function that maps eigenvalues $\{\lambda_1, \dots, \lambda_{|V|}\}$ of L to $\{h(\lambda_1), \dots, h(\lambda_{|V|})\}$.

Definition 2.2. (Graph convolution) [27, 28, 37] The convolution of a graph signal \mathbf{x} and a graph filter $H(L)$ is given by

$$H(L)\mathbf{x} = U \text{diag}(h(\lambda_1), \dots, h(\lambda_{|V|})) U^T \mathbf{x}. \quad (2)$$

3 METHODOLOGY

3.1 Motivation and Challenge

Suppose that \mathcal{U} and \mathcal{I} are the sets of all users and all items, respectively, in recommender systems dealing with user-item ratings. Then, conventional GF-based CF methods [20, 27, 37] initially construct an item-item similarity graph as

$$\tilde{P} = \tilde{R}^T \tilde{R}; \tilde{R} = D_U^{-1/2} R D_I^{-1/2}. \quad (3)$$

Here, $R \in \mathbb{R}^{|\mathcal{U}| \times |\mathcal{I}|}$ is the rating matrix; \tilde{R} is the normalized rating matrix; $D_U = \text{diag}(R\mathbf{1})$ and $D_I = \text{diag}(\mathbf{1}^T R)$; and \tilde{P} is the adjacency matrix of the item-item similarity graph. GF-based CF methods [20, 27, 37] typically employ both linear and ideal LPFs. As the representative work, GF-CF [27] performs graph convolution as $\mathbf{s}_u = \mathbf{r}_u (\tilde{P} + \alpha D_U^{-1/2} \tilde{U} \tilde{U}^T D_I^{-1/2})$, where $\mathbf{s}_u \in \mathbb{R}^{|\mathcal{I}|}$ is the predicted preferences for user u ; $\mathbf{r}_u \in \mathbb{R}^{|\mathcal{I}|}$ is the ratings of u , serving as graph signals to be smoothed; $\tilde{U} \in \mathbb{R}^{|\mathcal{I}| \times k}$ is the top- k singular vectors of \tilde{R} ; \tilde{P} is the linear LPF; $D_U^{-1/2} \tilde{U} \tilde{U}^T D_I^{-1/2}$ is the ideal LPF of \tilde{P} ; and α is a hyperparameter balancing between these two filters.

Although such GF-based CF methods often employ an ideal LPF, they pose a critical challenge: they necessitate matrix decomposition to acquire \tilde{U} , incurring substantial computational costs whose

complexity is typically $O(|\mathcal{I}|^3)$. This leads to a natural question: "how can we bypass the problem of matrix decomposition without losing the recommendation accuracy in GF-based CF?". To answer this question, we propose Turbo-CF, which effectively solves this challenge using *polynomial graph filters*.

3.2 Proposed Method: Turbo-CF

3.2.1 Graph construction. We describe how to construct an item-item similarity graph with R for GF. Unlike conventional GF-based CF methods that symmetrically normalize R along the user/item axis [20, 27, 37], we adopt *asymmetric* normalization on R to regularize the popularity of users/items before calculating \tilde{P} , which is formulated as

$$\tilde{P} = \tilde{R}^T \tilde{R}; \tilde{R} = D_U^{-\alpha} R D_I^{\alpha-1}. \quad (4)$$

Here, $\alpha \in [0, 1]$ is the hyperparameter to control the normalization along users/items. Increasing α weakens the effect of popular users (*i.e.*, high-degree users) while strengthening the effect of popular items. Next, according to the type of graph filter we use based on \tilde{P} , the corresponding filtered signals may be over-smoothed or under-smoothed, depending on the intensity of connections between nodes in \tilde{P} . Thus, we aim to adjust the edge weights differently depending on the graph filter. To this end, we present an additional adjustment process for the graph \tilde{P} by using the Hadamard power. Finally, the adjusted graph \tilde{P} is calculated as

$$\tilde{P} = \tilde{P}^{os}, \quad (5)$$

where s is the adjustment parameter that can be tuned based on the validation set. We empirically show that properly adjusting the edge weights in the two graphs (\tilde{R} and \tilde{P}) substantially improves the recommendation accuracy even without the costly matrix decomposition, which will be verified in Section 4.5.

3.2.2 Polynomial GF. We now specify how to perform GF based on \tilde{P} . To bypass the high computation overhead of matrix decompositions in GF, we make use of *polynomial* graph filters. We denote the normalized Laplacian matrix of \tilde{P} as $\tilde{L} = I - \tilde{P}$. Then, since \tilde{L} is a symmetric positive semi-definite matrix, there exists orthogonal eigen-decomposition $\tilde{L} = \tilde{U} \tilde{\Lambda} \tilde{U}^T$, where $\tilde{U} \tilde{U}^T = \tilde{U}^T \tilde{U} = I$. Thanks to \tilde{U} being an orthogonal matrix, we can still manipulate the eigenvalues by the matrix polynomial of \tilde{L} (*e.g.*, $\tilde{L}^2 = \tilde{U} \tilde{\Lambda}^2 \tilde{U}^T$) without the need for costly matrix decomposition. The *matrix decomposition-free* polynomial graph filter can be expressed as

$$\sum_{k=1}^K a_k \tilde{P}^k, \quad (6)$$

where a_k is the coefficient of a matrix polynomial and K is the maximum order of the matrix polynomial bases. We establish the following theorem, which provides a closed-form solution to the frequency response function of a polynomial graph filter.

THEOREM 3.1. *The matrix polynomial $\sum_{k=1}^K a_k \tilde{P}^k$ is a graph filter for graph \tilde{P} with the frequency response function of $h(\lambda) = \sum_{k=1}^K a_k (1 - \lambda)^k$.*

The proof of Theorem 3.1 is omitted due to page limitations. Interestingly, Theorem 3.1 implies that we can design arbitrary LPFs by deciding proper coefficients of polynomials, depending on the

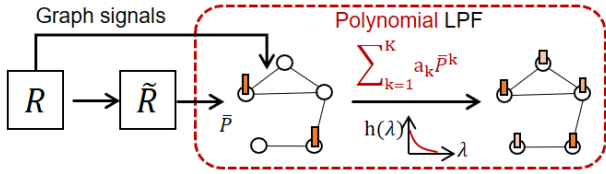


Figure 2: The schematic overview of Turbo-CF. The graph signals are smoothed by using polynomial LPFs in Turbo-CF.

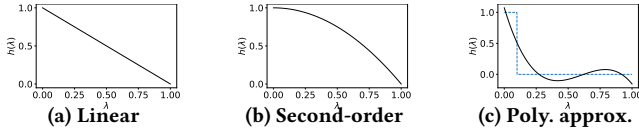


Figure 3: Frequency response functions of three polynomial LPFs. In Figure 3(c), the dotted blue line corresponds to the ideal LPF $h(\lambda) = 1_{\lambda \leq 0.1}$.

characteristics of a given task or dataset. Based on the polynomial graph filter in Eq. (6), Turbo-CF can be formalized as follows:

$$\mathbf{s}_u = \mathbf{r}_u \sum_{k=1}^K a_k \bar{P}^k, \quad (7)$$

where \mathbf{r}_u is the u -th row of R , which will be used as graph signals of user u ; and $\sum_{k=1}^K a_k \bar{P}^k$ is the polynomial graph filter for graph \bar{P} . Figure 2 illustrates how the graph signals are smoothed through the polynomial graph filter in Turbo-CF.

3.2.3 Filter design. We note that discovering the optimal polynomial low-pass graph filter in Eq. (7) involves an extensive search for coefficients $\{a_k\}_{k=1}^K$ using a validation set. This process is not ideal as it requires costly recalibration with varying datasets. Additionally, since GF-based CF methods necessitate loading the high-dimensional matrix \bar{P} into memory, handling high-order polynomials (e.g., $K > 3$) can cause additional space complexity issues. To this end, as an alternative, we design three polynomial LPFs up to the third order (i.e., $K = 3$) for GF. Figure 3 displays the frequency response functions of the three polynomial LPFs. The explicit forms of the three LPFs derived from Theorem 3.1 are expressed as follows.

- **(Linear LPF)** This filter employs the first-order matrix polynomial \bar{P} as a low-pass graph filter. Its frequency response function is $h(\lambda) = 1 - \lambda$.
- **(Second-order LPF)** This filter employs the second-order matrix polynomial $2\bar{P} - \bar{P}^2$ as a low-pass graph filter. Its frequency response function is $h(\lambda) = 1 - \lambda^2$.
- **(Polynomial approximation to ideal LPF)** Previous studies [20, 27, 37] have proven that utilizing an ideal LPF (i.e., $h(\lambda) = 1_{\lambda \leq \tau}$ with cutoff frequency τ) alongside a linear LPF is indeed beneficial in improving the recommendation accuracy. In this context, we aim to gain a similar effect to the case of using such an ideal LPF while avoiding the computational demands of matrix decomposition. To this end, we numerically approximate the ideal LPF using a polynomial function. Precisely, a linear LPF combined with the ideal LPF can be formulated as $\bar{P} + \beta \hat{f}_\tau(\bar{P})$, where β is a hyperparameter and $\hat{f}_\tau(\bar{P})$ is the approximated ideal LPF with cutoff

Table 1: The statistics of three datasets.

Dataset	# of users	# of items	# of interactions	Density
Gowalla	29,858	40,981	1,027,370	0.084%
Yelp	31,668	38,048	1,561,406	0.130%
Amazon-book	52,643	91,599	2,984,108	0.062%

frequency τ . In our study, we employ the third-order polynomial function to balance the approximation quality and computational burden. We numerically solve a non-linear least squares problem to find the coefficients $\{a_k\}_{k=1}^3$ in Eq. (6) for the approximation of $h(\lambda) = 1_{\lambda \leq \tau}$. For instance, as shown in Figure 3(c), we can pre-compute the coefficients of polynomials as $\hat{f}_\tau(\bar{P}) = -\bar{P}^3 + 10\bar{P}^2 - 29\bar{P}$ for the ideal LPF with $\tau = 0.1$.

We note that, besides the aforementioned three LPFs, one can design any LPFs by setting $\{a_k\}_{k=1}^K$ based on one’s own design choice. It is also worth noting that, as shown in Eq. (7), the polynomial low-pass graph filters can be implemented through simple matrix calculations, which allows us to more effectively leverage well-optimized machine learning and computation frameworks such as PyTorch [23] and CUDA [26] via parallel computation. Thanks to such rapid computation of polynomial low-pass graph filters via our Turbo-CF method, the optimal filter for a given dataset can also be readily found using the validation set.

4 EXPERIMENTAL RESULTS AND ANALYSES

4.1 Experimental Settings

Datasets. We carry out experiments on three datasets: Gowalla, Yelp, and Amazon-book. Statistics of the three datasets are summarized in Table 1.

Benchmark methods. We compare Turbo-CF with eight benchmark CF methods, including matrix factorization-based (MF-BPR [25] and NeuMF [11]), generative model-based (Multi-VAE [18] and DiffRec [32]), GCN-based (NGCF [33], LightGCN [10], LR-GCCF [2]), and GF-based (GF-CF [27]) methods.

Evaluation protocols. We randomly select 70/20/10% of the interactions for each user as the training/test/validation sets, where the validation set is used for hyperparameter tuning as well as LPF selection in Section 3.2.3. We use Recall@K and normalized discounted cumulative gain (NDCG@K) as our performance metrics, where K is set to 20 by default.

Implementation details. To ensure the optimal performance of the benchmark methods used for comparison, we directly quote the results reported [4, 10, 38], except DiffRec [32] where the results were not reported on the same datasets. All experiments are carried out on a machine with Intel (R) 12-Core (TM) i7-9700K CPUs @ 3.60 GHz and an NVIDIA GeForce RTX A6000 GPU.

4.2 Runtime Comparison

Table 2 summarizes the runtime of Turbo-CF using three different graph filters against some of the benchmark methods on the Gowalla dataset as other datasets exhibit similar tendencies. Here, runtime indicates the training time for GCN-based approaches (NGCF and LightGCN) while the processing time for GF-based approaches (GF-CF and Turbo-CF). Our findings are as follows:

Table 2: Runtime of baselines and Turbo-CF using the three different graph filters in Section 3.2.3 on the Gowalla dataset.

	NGCF	LightGCN	GF-CF	Turbo-CF
Runtime	6h34m15s	4h1m9s	2m33s	0.3s/5.6s/5.8s
Training	✓	✓	✗	✗

Table 3: Performance comparison among Turbo-CF and competitors. The best and second-best performers are highlighted in bold and underline, respectively.

Method	Gowalla		Yelp		Amazon-book	
	Recall	NDCG	Recall	NDCG	Recall	NDCG
MF-BPR	0.1291	0.1109	0.0433	0.0354	0.0250	0.0190
NeuMF	0.1399	0.1212	0.0451	0.0363	0.0258	0.0200
Multi-VAE	0.1641	0.1335	0.0584	0.0450	0.0407	0.0315
DiffRec	0.1653	0.1417	0.0656	0.0552	OOM	OOM
NGCF	0.1570	0.1327	0.0579	0.0477	0.0344	0.0263
LightGCN	0.1830	0.1554	0.0649	0.0530	0.0411	0.0315
LR-GCCF	0.1701	0.1452	0.0604	0.0498	0.0375	0.0296
GF-CF	0.1849	0.1518	0.0697	<u>0.0571</u>	<u>0.0710</u>	0.0584
Turbo-CF	<u>0.1835</u>	<u>0.1531</u>	<u>0.0693</u>	0.0574	0.0730	0.0611

- (i) In comparison with LightGCN using a lightweight architecture design, Turbo-CF significantly boosts the computational efficiency, achieving up to $\times 48,230$ faster runtime without costly model training.
- (ii) Even compared to GF-CF, Turbo-CF offers $\times 510$ faster runtime when the linear LPF is used. This is attributed to the design of Turbo-CF where matrix decomposition is unnecessary and rather much simpler polynomial GF, composed of simple matrix multiplications, is utilized.

4.3 Recommendation Accuracy

Table 3 compares the performance of Turbo-CF and eight competitors. Our findings are as follows:

- (i) Turbo-CF consistently achieves competitive performance compared to the state-of-the-art CF methods, while achieving the best performance in NDCG@20 on Yelp and in both metrics on Amazon-book. Specifically, Turbo-CF shows gains up to 4.6% in terms of NDCG, compared to the second-best performer on the Amazon-book dataset.
- (ii) The competitive performance of Turbo-CF demonstrates that the polynomial GF is still effective in guaranteeing satisfactory recommendation accuracies, even without using a matrix decomposition-aided ideal LPF in GF-CF.
- (iii) In short, Turbo-CF is extremely fast yet reliable, making it a strong benchmark for CF-based recommender systems.

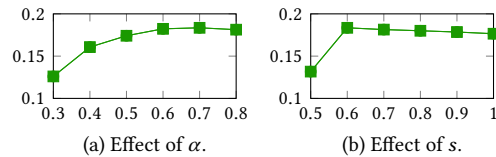
4.4 Effect of Polynomial Graph Filters

To discover a relationship between accuracy and runtime, Table 4 summarizes the runtime and recall according to three different polynomial graph filters in Turbo-CF. We present three variants of Turbo-CF, namely Turbo-CF-1, Turbo-CF-2, and Turbo-CF-3, which represent Turbo-CF using the linear LPF, second-order LPF, and polynomially approximated LPF to the ideal one, respectively.

- (i) The optimal polynomial graph filter in terms of Recall@20 is observed differently depending on each dataset. Turbo-CF-3, Turbo-CF-2, and Turbo-CF-1 achieve their best performance

Table 4: Runtime and recall according to three different polynomial graph filters in Turbo-CF.

	Gowalla		Yelp		Amazon-book	
	Runtime	Recall	Runtime	Recall	Runtime	Recall
Turbo-CF-1	0.32s	0.1823	0.31s	0.0689	27.9s	0.0730
Turbo-CF-2	5.59s	0.1740	4.80s	0.0693	OOM	OOM
Turbo-CF-3	5.79s	0.1835	4.82s	0.0689	OOM	OOM

**Figure 4: The effect of two hyperparameters on the Recall@20 for the Gowalla dataset.**

on Gowalla, Yelp, and Amazon-book, respectively. This indicates that higher-order polynomial LPFs do not always guarantee better performance and using a linear LPF is often sufficient to achieve satisfactory performance.

- (ii) As stated in Section 3.2.3, GF-based CF methods require loading the high-dimensional matrix \bar{P} into memory. Thus, the inclusion of high-order polynomials (Turbo-CF-2 and Turbo-CF-3) causes out-of-memory (OOM) issues on larger datasets such as Amazon-book. To relieve this, we can utilize efficient algorithms for matrix multiplication such as the Strassen algorithm [14, 29] or submatrix partitioning [5, 9]; this enables us to greatly reduce the memory complexity when large-scale matrix multiplication is involved.

4.5 Sensitivity Analysis

We analyze the impact of the key parameters in Turbo-CF, including two balancing parameters α and s for graph construction, on the recommendation accuracy for the Gowalla dataset as other datasets exhibit similar tendencies. Other parameters are set to the pivot values. First, Figure 4(a) shows that the optimal α is found at $\alpha = 0.7$, which confirms that symmetric normalization $\alpha = 0.5$ is not an optimal choice for ensuring accurate recommendations. Next, Figure 4(b) shows that the optimal s is found at $s = 0.6$, not at $s = 1$. The sensitivity analysis on α and s validates that properly adjusting the two balancing parameters α and s leads to sufficient gains.

5 CONCLUSIONS

In this paper, we proposed Turbo-CF, a GF-based CF method that is both *training-free* and *matrix decomposition-free*. Turbo-CF was built upon a computing hardware-friendly *polynomial graph filter* to circumvent the issue of expensive matrix decomposition. Extensive experiments demonstrated (a) the extraordinarily computational efficiency of Turbo-CF with a runtime of less than 1 second on Gowalla and Yelp datasets and (b) the competitive recommendation accuracy of Turbo-CF compared to other benchmark methods.

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REFERENCES

- [1] Jianxin Chang, Chen Gao, Yu Zheng, Yiqun Hui, Yanan Niu, Yang Song, Depeng Jin, and Yong Li. 2021. Sequential recommendation with graph neural networks. In *SIGIR*. 378–387.
- [2] Lei Chen, Le Wu, Richang Hong, Kun Zhang, and Meng Wang. 2020. Revisiting graph based collaborative filtering: A linear residual graph convolutional network approach. In *AAAI*. 27–34.
- [3] Huixuan Chi, Hao Xu, Hao Fu, Mengya Liu, Mengdi Zhang, Yuji Yang, Qinfen Hao, and Wei Wu. 2022. Long short-term preference modeling for continuous-time sequential recommendation. *arXiv preprint arXiv:2208.00593* (2022).
- [4] Jeongwhan Choi, Seoyoung Hong, Noseong Park, and Sung-Bae Cho. 2023. Blurring-sharpening process models for collaborative filtering. In *SIGIR*. 1096–1106.
- [5] Yea Rem Choi, Vsevolod Nikolskiy, and Vladimir Stegailov. 2020. Matrix-matrix multiplication using multiple GPUs connected by NVlink. In *GloSIC*. IEEE, 354–361.
- [6] Paul Covington, Jay Adams, and Emre Sargin. 2016. Deep neural networks for youtube recommendations. In *RecSys*. 191–198.
- [7] Ken Goldberg, Theresa Roeder, Dhruv Gupta, and Chris Perkins. 2001. Eigentaste: A constant time collaborative filtering algorithm. *Information Retrieval* 4 (2001), 133–151.
- [8] Carlos A Gomez-Uribe and Neil Hunt. 2015. The Netflix recommender system: Algorithms, business value, and innovation. *ACM Transactions on Management Information Systems* 6, 4 (2015), 1–19.
- [9] Kazushige Goto and Robert A van de Geijn. 2008. Anatomy of high-performance matrix multiplication. *ACM Transactions on Mathematical Software* 34, 3 (2008), 1–25.
- [10] Xiangnan He, Kuan Deng, Xiang Wang, Yan Li, Yongdong Zhang, and Meng Wang. 2020. LightGCN: Simplifying and powering graph convolution network for recommendation. In *SIGIR*. 639–648.
- [11] Xiangnan He, Lizi Liao, Hanwang Zhang, Liqiang Nie, Xia Hu, and Tat-Seng Chua. 2017. Neural collaborative filtering. In *WWW*. 173–182.
- [12] Xiangnan He, Hanwang Zhang, Min-Yen Kan, and Tat-Seng Chua. 2016. Fast matrix factorization for online recommendation with implicit feedback. In *SIGIR*. 549–558.
- [13] Chandima HewaNadungodage, Yuni Xia, and John Jaehwan Lee. 2017. A GPU-oriented online recommendation algorithm for efficient processing of time-varying continuous data streams. *Knowledge and Information Systems* 53 (2017), 637–670.
- [14] Steven Huss-Lederman, Elaine M Jacobson, Anna Tsao, Thomas Turnbull, and Jeremy R Johnson. 1996. Implementation of Strassen’s algorithm for matrix multiplication. In *SC*. 32–es.
- [15] Olivier Jeunen. 2019. Revisiting offline evaluation for implicit-feedback recommender systems. In *RecSys*. 596–600.
- [16] Bowen Jin, Chen Gao, Xiangnan He, Depeng Jin, and Yong Li. 2020. Multi-behavior recommendation with graph convolutional networks. In *SIGIR*. 659–668.
- [17] Bin Ju, Yuntao Qian, Minchao Ye, Rong Ni, and Chenxi Zhu. 2015. Using dynamic multi-task non-negative matrix factorization to detect the evolution of user preferences in collaborative filtering. *PLoS One* 10, 8 (2015), e0135090.
- [18] Dawen Liang, Rahul G Krishnan, Matthew D Hoffman, and Tony Jebara. 2018. Variational autoencoders for collaborative filtering. In *WWW*. 689–698.
- [19] Greg Linden, Brent Smith, and Jeremy York. 2003. Amazon.com recommendations: Item-to-item collaborative filtering. *IEEE Internet computing* 7, 1 (2003), 76–80.
- [20] Jiahao Liu, Dongsheng Li, Hansu Gu, Tun Lu, Peng Zhang, Li Shang, and Ning Gu. 2023. Personalized graph signal processing for collaborative filtering. In *WWW*. 1264–1272.
- [21] Kelong Mao, Jieming Zhu, Xi Xiao, Biao Lu, Zhaowei Wang, and Xiuqiang He. 2021. UltraGCN: Ultra simplification of graph convolutional networks for recommendation. In *CIKM*. 1253–1262.
- [22] Antonio Ortega, Pascal Frossard, Jelena Kovačević, José MF Moura, and Pierre Vanderghenst. 2018. Graph signal processing: Overview, challenges, and applications. *Proceedings of the IEEE* 106, 5 (2018), 808–828.
- [23] Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, et al. 2019. PyTorch: An imperative style, high-performance deep learning library. (2019).
- [24] Fabíola SF Pereira, João Gama, Sandra de Amo, and Gina MB Oliveira. 2018. On analyzing user preference dynamics with temporal social networks. *Machine Learning* 107 (2018), 1745–1773.
- [25] Steffen Rendle, Christoph Freudenthaler, Zeno Gantner, and Lars Schmidt-Thieme. 2009. BPR: Bayesian personalized ranking from implicit feedback. In *UAI*. 452–461.
- [26] Jason Sanders and Edward Kandrot. 2010. *CUDA by example: An introduction to general-purpose GPU programming*. Addison-Wesley Professional.
- [27] Yifei Shen, Yongji Wu, Yao Zhang, Caihua Shan, Jun Zhang, B Khaled Letaief, and Dongsheng Li. 2021. How powerful is graph convolution for recommendation?. In *CIKM*. 1619–1629.
- [28] David I Shuman, Sunil K Narang, Pascal Frossard, Antonio Ortega, and Pierre Vanderghenst. 2013. The emerging field of signal processing on graphs: Extending high-dimensional data analysis to networks and other irregular domains. *IEEE Signal Processing Magazine* 30, 3 (2013), 83–98.
- [29] Mithuna Thottethodi, Siddhartha Chatterjee, and Alvin R Lebeck. 1998. Tuning Strassen’s matrix multiplication for memory efficiency. In *SC*. IEEE, 36–36.
- [30] Nguyen Thanh Toan, Phan Thanh Cong, Nguyen Thanh Tam, Nguyen Quoc Viet Hung, and Bela Stantic. 2018. Diversifying group recommendation. *IEEE Access* 6 (2018), 17776–17786.
- [31] Rianne van den Berg, Thomas N. Kipf, and Max Welling. 2017. Graph convolutional matrix completion. *CoRR* abs/1706.02263 (2017).
- [32] Wenjie Wang, Yiyang Xu, Fuli Feng, Xinyu Lin, Xiangnan He, and Tat-Seng Chua. 2023. Diffusion recommender model. In *SIGIR*. 832–841.
- [33] Xiang Wang, Xiangnan He, Meng Wang, Fuli Feng, and Tat-Seng Chua. 2019. Neural graph collaborative filtering. In *SIGIR*. 165–174.
- [34] Xiang Wang, Hongye Jin, An Zhang, Xiangnan He, Tong Xu, and Tat-Seng Chua. 2020. Disentangled graph collaborative filtering. In *SIGIR*. 1001–1010.
- [35] Le Wu, Yong Ge, Qi Liu, Enhong Chen, Richang Hong, Junping Du, and Meng Wang. 2017. Modeling the evolution of users’ preferences and social links in social networking services. *IEEE Transactions on Knowledge and Data Engineering* 29, 6 (2017), 1240–1253.
- [36] Shu Wu, Yuyuan Tang, Yanqiao Zhu, Liang Wang, Xing Xie, and Tieniu Tan. 2019. Session-based recommendation with graph neural networks. In *AAAI*. 346–353.
- [37] Jiafeng Xia, Dongsheng Li, Hansu Gu, Jiahao Liu, Tun Lu, and Ning Gu. 2022. FIRE: Fast incremental recommendation with graph signal processing. In *WWW*. 1808–1819.
- [38] Keyulu Xu, Weihua Hu, Jure Leskovec, and Stefanie Jegelka. 2019. How powerful are graph neural networks?. In *ICLR*. 1–17.
- [39] Xiujuan Xu, Jianyu Zhou, Yu Liu, Zhenzhen Xu, and Xiaowei Zhao. 2014. Taxi-RS: Taxi-hunting recommendation system based on taxi GPS data. *IEEE Transactions on Intelligent Transportation Systems* 16, 4 (2014), 1716–1727.
- [40] Rex Ying, Ruining He, Kaifeng Chen, Pong Eksombatchai, William L Hamilton, and Jure Leskovec. 2018. Graph convolutional neural networks for web-scale recommender systems. In *KDD*. 974–983.
- [41] Lei Zheng, Chun-Ta Lu, Fei Jiang, Jiawei Zhang, and Philip S Yu. 2018. Spectral collaborative filtering. In *RecSys*. 311–319.