Fairer Recommendation Systems through Graph Neural Networks

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Overview

- In this thesis, we address fairness in recommendation systems from the user perspective
- We hypothesise that a certain class of recommendation algorithms (graph neural networks) can lead to fairer recommendations than traditional approaches (matrix factorisation)
- We will
  - Introduce recommendation systems
  - Review fairness in recommendation systems
  - Understand matrix factorisation approaches
  - Understand graph neural network approaches and why they can be more fair
  - Conduct experiments to address our hypothesis

Recommendation Systems

Recommendation Systems

A brief overview

- One of the most prolific applications of machine learning (ML) deployed today
- Powers many top internet sites' product offerings including YouTube [1], Spotify [2], Netflix [3] and TikTok [4].
- Retrieve and rank relevant items out of a large corpus of content

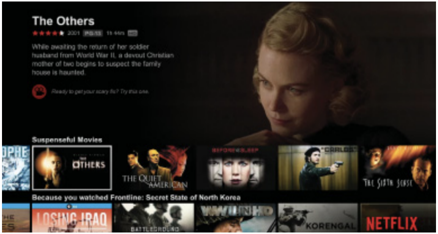


Figure: Netflix recommendations from [5]

Recommendation Systems

Data for Recommendation

- User-item interactions (explicit or implicit feedback)
- Explicit feedback
  - User gives true preference to an item
  - Rating data (out of 5)
  - Sparse
- Implicit feedback
  - Purchases, clicks, searches
  - More readily available
  - Assumed as a positive interaction
- Encoded into $\mathbf{A} \in \mathbb{R}^{M \times N}$ for M users and N items.
  $A_{ij} = 1$ if user i has interacted with item j, else 0

Recommendation Systems

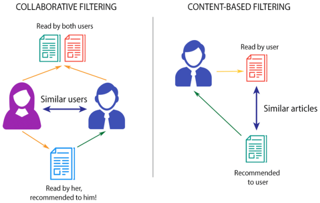
Mathematical Problem

- Sets
  - M users $\mathcal{U} = \{u_1, u_2, \ldots, u_M\}$
  - N items $\mathcal{V} = \{v_1, v_2, \ldots, v_N\}$
- Data
  - Encoded into $\mathbf{A} \in \mathbb{R}^{M \times N}$
  - Split into train and test set
- Objective
  - Predict preference scores for users to items $\{S_{ij} | i \in \mathcal{U}, j \in \mathcal{V}\}$.
  - Encoded into $\mathbf{S} \in \mathbb{R}^{M \times N}$
- Output
  - Produces a ranked top-K item list of recommendations for each user i
  - Achieved by sorting $\mathbf{s}_i \in \mathbb{R}^N$, the preference vector for user i

Recommendation Systems

Approaches

- Content based
  - Recommend similar items to the users preference
  - Considers each user in isolation
- Collaborative filtering (CF)
  - Assumes similar users will like similar items
  - Learn user embeddings $\mathbf{u}_i \in \mathbb{R}^{M\times d}$ and item embeddings $\mathbf{v}_j \in \mathbb{R}^{N\times d}$, in an inner product space to model preference
  - Modelled through shallow methods (matrix factorisation), deep neural networks or graph neural networks



Recommendation Systems

Evaluation Methods

- Traditionally analysed via accuracy metrics
  - Attempts to measure recommendation quality
  - Different metrics usually analysed together
  - May fail to capture essential recommendation system aspects
- Beyond accuracy metrics proposed to measure other qualities of a recommendation system (novelty, diversity, filter bubbles)
- Fairness is another way of evaluating a recommendation system to understand bias and recommendation quality compared across groups

- NDCG [6] emphasises more relevant items higher on a recommendation list:

$$NDCG@K(i) = \frac{DCG@K(i)}{IDCG@K(i)} \quad (1)$$

where

$$DCG@K(i) = \sum_{l \in rec_K(i)} \frac{2^{rating(i,l)} - 1}{log_2\left(rank\left(i, l\right) + 1\right)} \quad (2)$$

- Hit-rate [6] measures whether at least one item in the ranked list is relevant, defined as

$$HR@K(i) = \mathbb{1}\left[rel(i) \cap rec_K(i) > 0\right] \quad (3)$$

Recommendation Systems

Beyond Accuracy Metrics

- Diversity [7] measures the range of recommendations:

$$Diversity@K(i) = \frac{\sum_{l \in rec_K(i)} \sum_{j \in rec_K(i) \setminus l} v_l \cdot v_j}{K(K-1)} \tag{4}$$

- Coverage [7] measures the percentage of items recommended:

$$Coverage@K = \frac{|\cup_{i \in \mathcal{U}} rec_K(i)|}{|\mathcal{V}|} \tag{5}$$

- Novelty [7] measures the uniqueness of a set of recommendations:

$$Novelty@K(i) = \frac{\sum_{j \in rec_K(i)} - \log_2 p(j)}{K} \tag{6}$$

where $p(j)$ is the popularity of item j:

$$p(j) = \frac{|\{i \in \mathcal{U}, rating(i,j) = 1\}|}{|\mathcal{U}|} \tag{7}$$

Fairness in Recommendation Systems

Fairness in Recommendation Systems

Fairness in Machine Learning

- "A fair and ethical machine learning system should be inclusive and accessible, and should not involve or result in unfair discrimination against individuals, communities or groups" [8].
- Fairness issues arise from bias in the data (unrepresentative data, minority groups) and can be propagated via ML algorithms
- General ML fairness solutions involve:
  - pre-processing (data augmentation to reduce bias)
  - in-processing (regularisation or constrained optimisation)
  - post-processing (re-ranking of results)

Fairness in Recommendation Systems

Bias in Recommendation Systems

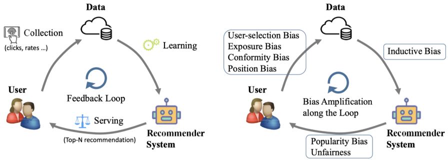


Figure: Recommendation system feedback loop from [9]

- Like ML, fairness arises from biases, although propagated through an explicit feedback loop

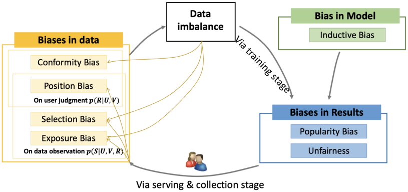


Figure: Bias feedback loop in RS from [9]

Fairness in Recommendation Systems

Types of Fairness

- ML fairness methods don't easily extend to RS due to multi-sided nature (users and items)
- Fairness in recommendation system can generally be split into user, item and multi-sided
- Item fairness aims for fair exposure, lots of research on popularity bias [10–12].
- Multi-sided fairness trades off user and item fairness together [13–15].

User Fairness in Recommendation Systems I

- Aims for minority groups to receive similar recommendations to other non-protected groups.
- Measured via a comparison of a metric between groups:

$$Fairness(G_1, G_2, M) \tag{8}$$

where G_1 is one group of users, G_2 is the other group of users such that $G_1 \cap G_2 = \emptyset$ and M is any recommendation metric

User Fairness in Recommendation Systems II

- [16] splits users into high activity and low activity. Low activity users receive poorer recommendations than the active users via NDCG. Propose a heuristic re-ranking technique to improve fairness.
- They show fairness improves post-heuristic according to

$$Fairness(G_1, G_2, M) = \left| \frac{1}{G_1} \sum_{i \in G_1} M(i) - \frac{1}{G_2} \sum_{i \in G_2} M(i) \right| \quad (9)$$

User Fairness in Recommendation Systems III

- [17] similarly groups users into advantaged and disadvantaged based on interactions, price and consumption. Advantaged users receive better recommendations, apply a similar re-ranking approach to improve fairness, using the same metric.
- [18] generalises [17], repeating the approach for multiple algorithms and multiple datasets.
- [19] split users into groups based on personality traits and compare recommendation performance
- [20] split users into groups based on age and gender, comparing recommendation performance via NDCG
- One paper [21] considered user fairness from a beyond-accuracy perspective, although metrics were drawn from survey questions

Gaps in the research

- No explicit research on out of the box algorithms
  - Graph neural networks can learn higher order structure in the data $\rightarrow$ could lead to fairer outcomes for disadvantaged users
- Beyond accuracy and accuracy: a lack of research together in fairness to get a holistic overview
  - Just because a RS is fair for accuracy, doesn't mean it's the case for beyond-accuracy (and vice versa)

Matrix Factorisation for Recommendation Systems

Matrix Factorisation for Recommendation Systems

Overview

- Matrix factorisation [22] is a CF method that decomposes $\mathbf{A}$ into embedding matrices $\mathbf{U} \in \mathbb{R}^{M \times d}$ and $\mathbf{V} \in \mathbb{R}^{N \times d}$:

$$\mathbf{A} \approx \mathbf{S} = \mathbf{U}\mathbf{V}^T \tag{10}$$

- The preference score for user i to item j, $\mathbf{S}_{ij}$ is expressed via the inner product of their embeddings:

$$\mathbf{S}_{ij} = \mathbf{u}_i \cdot \mathbf{v}_j^T \tag{11}$$

Matrix Factorisation for Recommendation Systems

Example

- Consider a toy example with 3 users and 3 items (movies).

$$\mathbf{A} = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 1 & 1 \end{bmatrix}$$

- The embedding matrices $\mathbf{U}, \mathbf{V}$ and also $\mathbf{S}$ are learned as

$$\mathbf{U} = \begin{bmatrix} 1 & 0.1 \\ -1 & 0 \\ 0.2 & -1 \end{bmatrix}, \mathbf{V} = \begin{bmatrix} 0.9 & -0.2 \\ -1 & -0.8 \\ 1 & -1 \end{bmatrix}, \mathbf{S} = \begin{bmatrix} 0.88 & -1.08 & 0.9 \\ -0.9 & 1 & -1 \\ 0.38 & 0.6 & 1.2 \end{bmatrix}$$

$$S_{11} = u_1 \cdot v_1^T = \begin{bmatrix} 1 & 0.1 \end{bmatrix} \cdot \begin{bmatrix} 0.9 \\ -0.2 \end{bmatrix} = 0.88$$

- User 1's ordered recommendations are items $3, 1, 2$.

- Singular value decomposition [23] decomposes $\mathbf{A}$ into

$$\mathbf{A} = \mathbf{U}\Sigma\mathbf{V}^T \tag{12}$$

  $\mathbf{U} \in \mathbb{R}^{M\times M}$, $\mathbf{V} \in \mathbb{R}^{N\times N}$ are orthogonal matrices and $\Sigma \in \mathbb{R}^{M\times N}$ is diagonal.

- While the above is computationally heavy, a low-rank approximation can be found:

$$\mathbf{A} = \mathbf{U}_k\Sigma_k\mathbf{V}_k^T \tag{13}$$

  with $\mathbf{U}_k\Sigma_k^{1/2}$ user embeddings and $\mathbf{V}_k\Sigma_k^{1/2}$ item embeddings, and preference score $\mathbf{S}_{ij}$:

$$\mathbf{S}_{ij} = \left(\mathbf{U}_k\Sigma_k^{1/2}\right)_i \left(\mathbf{V}_k\Sigma_k^{1/2}\right)_j \tag{14}$$

Matrix Factorisation for Recommendation Systems

Classical Matrix Factorisation

- Classical matrix factorisation rose to prominence during the Netflix Prize [24], with a winning solution proposed in [22].
- Embeddings are learned that minimise the sum of squared errors across all positive (the set P) user, item pairs i, j:

$$\min \sum_{i,j \in P} \left(\mathbf{A}_{ij} - \mathbf{u}_i \mathbf{v}_j^T \right)^2 + \lambda \left|\left|\mathbf{u}_i\right|\right|^2 + \left|\left|\mathbf{v}_j\right|\right|^2 \tag{15}$$

- Stochastic gradient descent used to update embeddings:

$$\mathbf{u}_i = \mathbf{u}_i + \alpha \left(e_{ij} \mathbf{v}_j - \lambda \mathbf{u}_i \right) \tag{16}$$

$$\mathbf{v}_j = \mathbf{v}_j + \alpha \left(e_{ij} \mathbf{u}_i - \lambda \mathbf{v}_j \right) \tag{17}$$

with e_{ij} as the error from prediction:

$$e_{ij} = \mathbf{A}_{ij} - \mathbf{u}_i \mathbf{v}_j^T \tag{18}$$

Matrix Factorisation for Recommendation Systems

Alternating Least Squares

- Alternating least squares [22]: fix $\mathbf{U}$ or $\mathbf{V}$ and a quadratic form can be obtained.
- Take v_j constant, solving the loss function yields for $\mathbf{u}_i$:

$$\mathbf{u}_i = \mathbf{A}_i \mathbf{V} \left(\mathbf{V}^T \mathbf{V} + \lambda \mathbf{I} \right)^{-1} \tag{19}$$

  In a similar fashion, taking u_i constant, solving for $\mathbf{v}_j$ yields

$$\mathbf{v}_j = \mathbf{A}_j \mathbf{U} \left(\mathbf{U}^T \mathbf{U} + \lambda \mathbf{I} \right)^{-1} \tag{20}$$

- Repeat in a two-step process until convergence.

Graph Neural Networks for Recommendation Systems

- Graph neural networks (GNN's) are a general framework for defining deep learning algorithms over graph-structured data
- Graph structured data consists of nodes and edges
- At each layer in a GNN, the embedding of a node is refined based on the neighbors, through three steps:
  - Messaging: Neighbours pass their embeddings as messages
  - Aggregation: Messages are aggregated for the layer
  - Updating: Combine previous layer embeddings with current layer neighbour embeddings to update

Graph Neural Networks for Recommendation Systems

Applying to Recommendation Systems

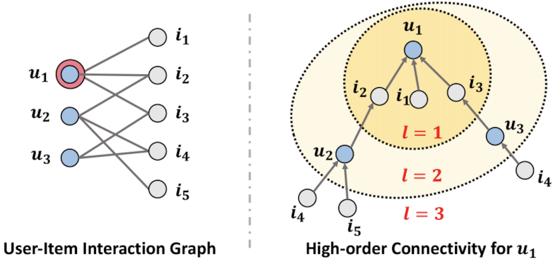


Figure: User-item interactions as a graph from [25]

- To apply graph neural networks to recommendation system, represent user-item interactions as a graph.
- Embeddings can be propagated and stacked to access higher order information in the interaction data

Graph Neural Networks for Recommendation Systems

Neural Graph Collaborative Filtering [25]

- Define a message embedding for a user-item pair (i, j) as

$$\mathbf{m}_{i \leftarrow j} = \frac{1}{\sqrt{|\mathcal{N}_i||\mathcal{N}_j|}} \left(\mathbf{W}_1 \mathbf{v}_j + \mathbf{W}_2 \left(\mathbf{v}_j \odot \mathbf{u}_i\right)\right) \tag{21}$$

  where $\mathbf{W}_1, \mathbf{W}_2 \in R^{d' \times d}$ are learnable weight matrices and $\mathcal{N}_i$ and $\mathcal{N}_j$ represent the first-hop neighbours of user i and item j.
- Messages can be aggregated from neighbours to refine the embedding after one layer:

$$\mathbf{u}_i^{(1)} = f\left(\mathbf{m}_{i \leftarrow i} + \sum_{k \in \mathcal{N}_i} \mathbf{m}_{i \leftarrow k}\right) \tag{22}$$

  including self-connection $(\mathbf{m}_{i \leftarrow i} = \mathbf{W}_1 \mathbf{u}_i)$

Graph Neural Networks for Recommendation Systems

Neural Graph Collaborative Filtering [25]

- To include higher order structure and improve CF, propagate embeddings across multiple layers to refine further:

$$\mathbf{u}_i^{(l)} = f\left(\mathbf{m}_{i\leftarrow i}^{(l)} + \sum_{k\in\mathcal{N}_i} \mathbf{m}_{i\leftarrow k}^{(l)}\right) \tag{23}$$

with the message propagation functions defined as

$$\mathbf{m}_{i\leftarrow j}^{(l)} = p_{ij}\left(\mathbf{W}_1^{(l)}\mathbf{v}_j^{(l-1)} + \mathbf{W}_2^{(l)}\left(\mathbf{v}_j^{(l-1)} \odot \mathbf{u}_i^{(l-1)}\right)\right) \tag{24}$$

$$\mathbf{m}_{i\leftarrow i}^{(l)} = \mathbf{W}_1^{(l)}\mathbf{u}_i^{(l-1)} \tag{25}$$

where $\mathbf{W}_1, \mathbf{W}_2 \in R^{d_l\times d_{l-1}}$ are different weight matrices for that layer, and $\mathbf{u}_i^{(l-1)}$ and $\mathbf{v}_j^{(l-1)}$ are aggregated embedding representations from previous layers.

Graph Neural Networks for Recommendation Systems

Neural Graph Collaborative Filtering [25]

- The l layers encode different levels of information, for users as $\{\mathbf{u}_i^{(1)}, \ldots, \mathbf{u}_i^{(L)}\}$ and items as $\{\mathbf{v}_j^{(1)} || \ldots || \mathbf{v}_j^{(L)}\}$.
- Embeddings are combined by concatenation to yield a final user and item embedding:

$$\mathbf{u}_i^* = \mathbf{u}_i^{(0)} || \ldots || \mathbf{u}_i^{(L)} \tag{26}$$

$$\mathbf{v}_j^* = \mathbf{v}_j^{(0)} || \ldots || \mathbf{v}_j^{(L)} \tag{27}$$

The inner product is used to calculate similarity between a user i and item j as in (11),

$$\mathbf{S}_{ij} = \mathbf{u}_i^* \cdot \mathbf{v}_j^{*T} \tag{28}$$

Graph Neural Networks for Recommendation Systems

LightGCN [26]

- LightGCN [26] was proposed, eliminating the weight matrices and nonlinear activation function, surprisingly leading to faster and more accurate recommendation.
- The same message passing and aggregation principle applies.
- The embedding propagation step becomes (for user embedding i and item embedding j at layer l):

$$\mathbf{u}_i^{(l)} = \sum_{p \in N_i} \frac{1}{\sqrt{|N_i||N_p|}} \mathbf{u}_i^{(l-1)} \tag{29}$$

$$\mathbf{v}_j^{(l)} = \sum_{p \in N_j} \frac{1}{\sqrt{|N_p||N_j|}} \mathbf{v}_j^{(l-1)} \tag{30}$$

Graph Neural Networks for Recommendation Systems

LightGCN [26]

- The embeddings are then aggregated across the l layers via a sum,

$$\mathbf{u}_i^* = \sum_{m=0}^{l} \alpha_m \mathbf{u}_i^{(m)} \tag{31}$$

$$\mathbf{v}_j^* = \sum_{m=0}^{l} \alpha_m \mathbf{v}_j^{(m)} \tag{32}$$

  where α_m is the importance of the weights at each layer.

- The predicted preference is also the inner product,

$$\mathbf{S}_{ij} = \mathbf{u}_i^* \cdot {\mathbf{v}_j^*}^T \tag{33}$$

Evaluation and Experiments

Evaluation and Experiments

Motivation

- Gap 1: lack of investigation into which off-the-shelf algorithms are most effective at promoting fairness between users
- Gap 2: lack of research considering both accuracy and beyond-accuracy metrics in assessing fairness.
- This leads us to answer two research questions via experiments:
  RQ1 (Primary Research Question): Can graph neural networks lead to fairer outcomes in recommendation systems compared to matrix factorisation algorithms?
  RQ2 (Secondary Research Question): Does a different picture of fairness in recommendation systems emerge when we go beyond traditional accuracy metrics?

Evaluation and Experiments

Experimental Setup

- **User grouping**: Lowest 80% quantile of activity as the low activity (G_1) group, and the rest as high activity users (G_2), such that $G_1 \cap G_2 = \emptyset$.
- **Datasets**
  - **Last-FM** [27]: Music listening dataset
  - **MovieLens 100K** [28]: Movie review dataset
- **Algorithms**
  - **Alternating Least Squares (ALS)** Implemented using Apache Spark MLlib library in Python.
  - **LightGCN** Implemented using TensorFlow in Python.

Evaluation and Experiments

Metrics

- **Fairness**: define the fairness score under the generic framework (8)

$$Fairness(G_1, G_2, M) = \frac{1}{|G_2|}\sum_{i \in G_2} M(i) - \frac{1}{|G_1|}\sum_{i \in G_1} M(i) \quad (34)$$

- **Accuracy metrics**: NDCG@K (1) and HR@K (3)
- **Beyond-accuracy metrics**: Novelty@K (6) and Diversity@K (4)
- For all metrics, set $K = 10$
- Metrics are computed on a hold-out test set.
  - For the low activity users, compute metrics on the test set with only their interactions
  - Repeat for the high activity users

Results

MovieLens		NDCG@10	Hitrate@10	Diversity@10	Novelty@10
ALS	**All**	0.18	0.38	1.25	2.99
	Low	0.16	0.33	1.23	2.83
	High	0.26	0.56	1.33	3.58
	Fairness	0.10	0.23	**0.10**	0.75
LightGCN	**All**	0.18	0.42	2.19	2.27
	Low	0.18	0.40	2.23	2.32
	High	0.21	0.51	2.03	2.11
	Fairness	**0.03**	**0.11**	-0.20	**-0.21**
Last-FM		**NDCG@10**	**Hitrate@10**	**Diversity@10**	**Novelty@10**
ALS	**All**	0.11	0.21	0.39	6.66
	Low	0.09	0.18	0.39	6.64
	High	0.18	0.36	0.36	6.73
	Fairness	0.09	0.18	**-0.03**	**-0.09**
LightGCN	**All**	0.20	0.42	3.51	7.54
	Low	0.20	0.40	3.50	7.58
	High	0.22	0.50	3.55	7.38
	Fairness	**0.02**	**0.10**	0.05	0.20

- Results show LightGCN fairer on both datasets for accuracy metrics
- ALS fairer for both beyond-accuracy metrics on Last-FM, although un-normalised. LightGCN fairer by larger margin
- Speculate LightGCN fairer for accuracy due to high order information gained using a graph neural network
  - Through this, low activity users can have better recommendations, learning more from the data
- High activity users have more accurate recommendations for both datasets

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