Spectral Collaborative Filtering

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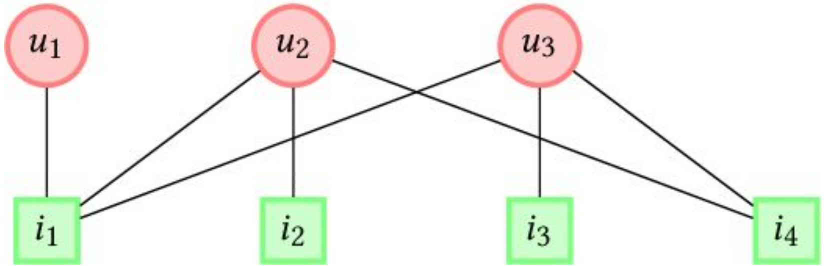
Motivation

Collaborative Filtering(CF) based methods suffer from cold start problems, which negatively impacts the user experience in Recommender Systems.



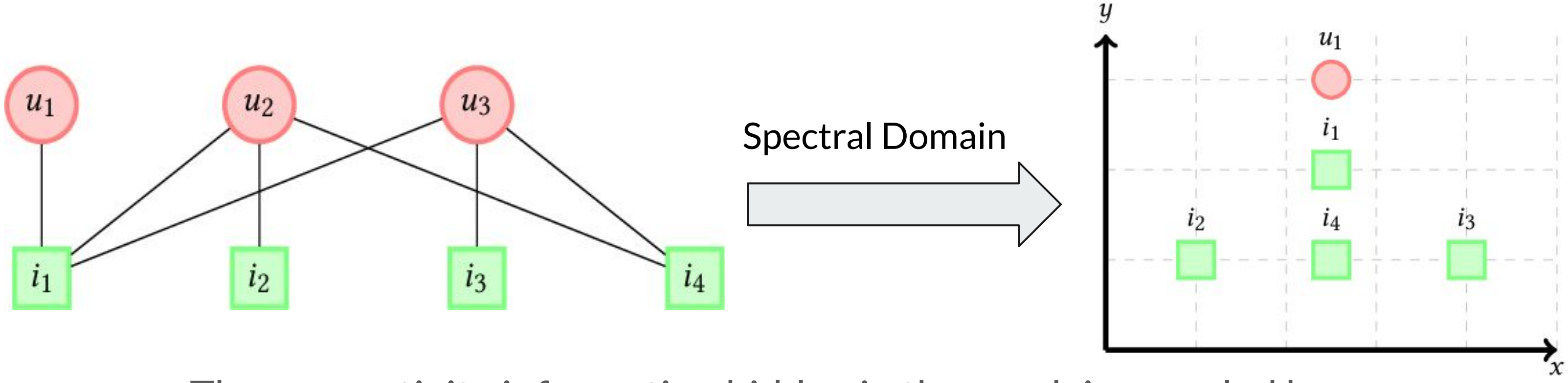
Which items to Recommend user u1 ???

Figure 1: A toy example of a user-item bipartite graph B **with edges representing observed user-item interactions. Red circles and green rectangles denote users and items, respectively.**

Motivation

- Using CF-based i2, i3 and i4 are recommended. But Which one of the 3 recommendations are most reliable to u1?
- The key to the answer lies in user-item connectivity information.
- If we take a look at the graph, we can see that there is one path between u1 and i2(or i3), while there are 2 paths from u1 to i4. So i4 is a reliable recommendation for u1.
- Existing CF-based methods fails to model this connectivity information.

Motivation



- The connectivity information hidden in the graph is revealed by spectral domain.
- This paper implements a CF-based method which is learnt from the spectral domain of user-item bipartite graphs.

Main technical contributions

- **Novelty** : This work claims to be the first CF based method that directly learns from spectral domains of user-item bipartite graph.
- **A deep recommendation model** : The paper proposes a new spectral convolution operation for the spectral domain. Multiple such spectral convolution layers are stacked to form a model named Spectral Collaborative Filtering(SpectralCF)
- **Strong Performance** : SpectralCF effectively utilizes both proximity and connectivity information of spectral domain to ease the cold start problem.

Main technical contributions

- The relationship between the user and item is formalated as a bipartite graph.
- Spectral graph theory is used to leverage the rich information present in the Spectral domain of the user-item bipartite graph.
- This paper focuses on the recommendation problem for implicit feedbacks.
- SpectralCF finds the deep connections between users and items which alleviates the cold start problem.

Main technical contributions

To solve the difficulty of learning from spectral domain, a new spectral convolution operation to dynamically amplify and attenuate each frequency domain in introduced.

The new spectral convolution,

- Uses polynomial approximation for the filter to make its number of parameters independent from the number of vertices.
- Generalizes the user and item nodes to C channels to learn C dimensional embeddings for each user and item nodes.

Main technical contributions

- Spectral Convolution is then generalized to C channels and F filters using classic convolution methods.
- The Spectral Convolution operation learns an embedding for each user and item node using the information from the spectral domain of the user-item bipartite graph.
- A deep model is create by stacking these spectral convolution layers, and embeddings from each layers are concatenated.

Experimental results

Quality of Recommendations for cold-start Users

- Dataset : MovieLens-1M
- Training dataset was built to contain different degrees of sparsity, by varying the number of items associated with each user denoted as P(from 1 to 5).
- All the remaining items associated with users are used as test set.
- SpectralCF is compared with a strong performer BPR.

Experimental results

In Table, we see that due to cold start problem the performance of BPR and SpectralCF inevitably degrade.

	P	1	2	3	4	5
Recall @20	BPR	0.021 (0.003)	0.029 (0.004)	0.031 (0.003)	0.034 (0.004)	0.038 (0.003)
	SpectralCF	**0.031** (0.003)	**0.039** (0.003)	**0.042** (0.002)	**0.045** (0.003)	**0.051** (0.003)
	Improvement	47.6%	34.5%	35.5%	32.4%	34.2%
MAP @20	BPR	0.014 (0.002)	0.017 (0.002)	0.021 (0.002)	0.024 (0.003)	0.027 (0.003)
	SpectralCF	**0.019** (0.002)	**0.024** (0.002)	**0.028** (0.003)	**0.031** (0.003)	**0.035** (0.002)
	Improvement	35.7%	41.2%	33.3%	29.2%	29.6%

Experimental results

- Regardless of the number of items(P) associated with users, SpectralCF consistently outperforms BPR in terms of Recall@20 and MAP@20.
- On average, SpectralCF improves BPR by 36.8% and 33.8% in Recall@20 and MAP@20 respectively.
- Hence, the paper shows that compared with BPR, SpectralCF can better handle cold-start users and provide more reliable recommendations.

Limitations

- Eigen decomposition is a main operation in this paper.
- It is to convert the user-item bipartite graph into spatial domain. This is very time consuming as in practice the Recommendation matrix is very huge.
- Hence the Eigenvectors and Eigenvalues were precomputed by the author. This makes the system hard to scale.

My thoughts

- This work could be tested on only non cold-start users to see if the results are consistent as mentioned in paper. (The paper however tests the implementation on cold-start+non cold-start users)
- This work could be extended to explicit dataset by changing the initial binary matrix to rating matrix.