Paper Review

Neural Graph Collaborative Filtering
(NGCF)

Xiang Wanf, Xiangnan Han, Meng Wang, Feli Feng, Tat-Seng Chua

2019 (SIGIR)

Simplifying and Powering Graph Convolution Network for Recommendation
(LightGCN)

Xiangnan He, Kuan Deng, Xiang Wang, Yan Li, Yongdong Zhang, Meng Wang

2020 (SIGIR)

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- **Part II**
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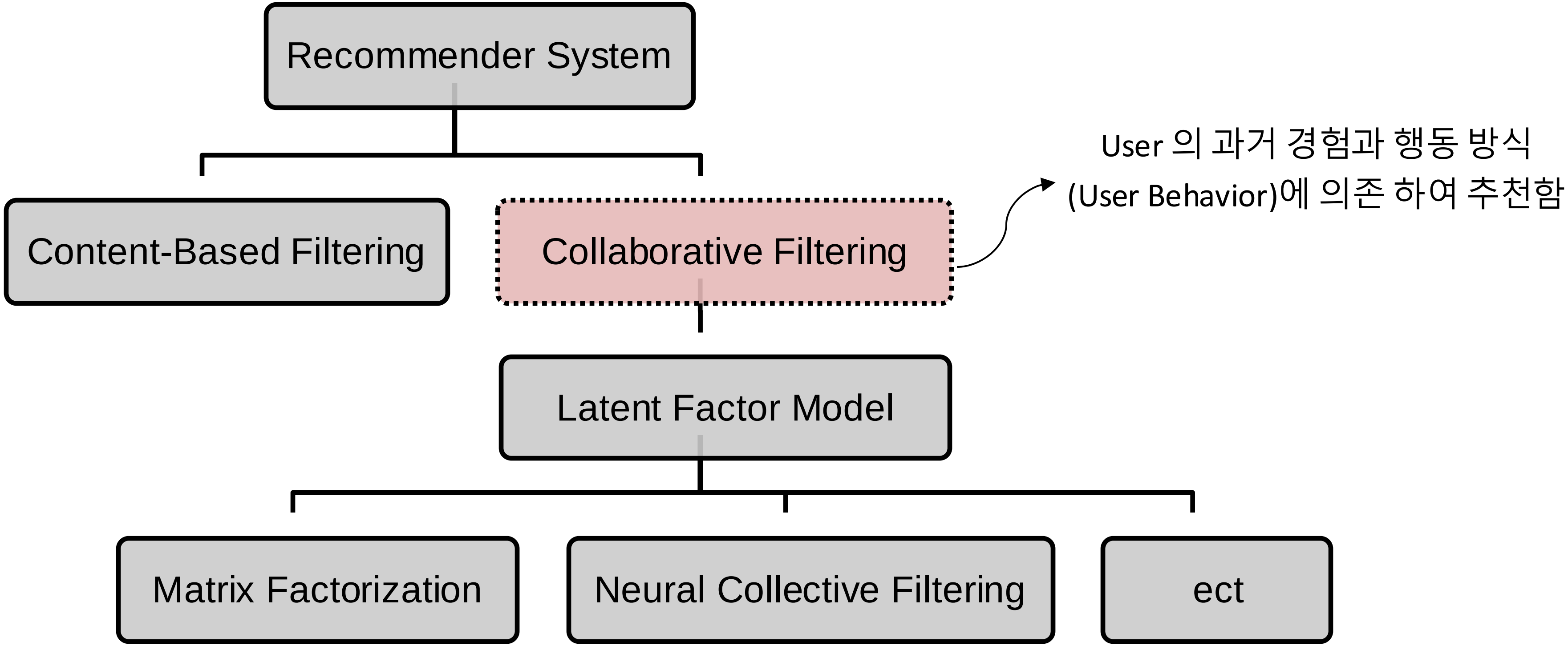
Introduction



Introduction

□ What is Collaborative Filtering (협업 필터링)?

1. 내가 좋아하는 감독, 장르, 키워드의 영화를 찾아본다

↓

Content-Based Filtering

2. 나랑 성향이 비슷한 친구들이 본 영화를 찾아본다

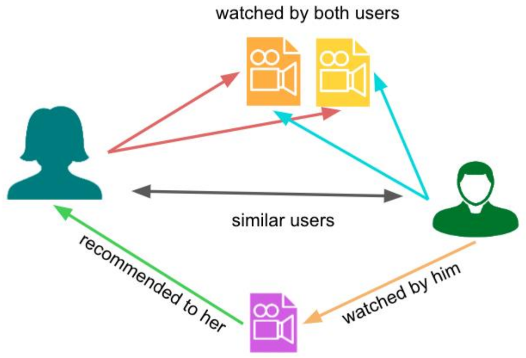
↓

Collaborative Filtering

Introduction

□ Characteristics of Collaborative Filtering

- **가정** : 나와 비슷한 취향의 사람들이 좋아하는 것은 나도 좋아할 가능성이 높다
- **핵심 포인트** : "**많은 사용자들**"로부터 얻은 취향 정보를 활용
  - 사용자의 취향 정보 = 집단 지성
  - 축적된 사용자들의 집단 지성을 기반으로 추천



Introduction

- **Types of Collaborative Filtering**
  - Memory Based Approach
  - Model Based Approach
    - Non-Parametric Approach
    - Matrix Factorization (행렬 분해) based Algorithm
    - Deep Learning

Introduction

□ Matrix Factorization

- 유저-아이템 상호작용의 잠재 요인(latent Factor)을 고려하여 유저에게 적합한 아이템을 추천
- Collaborative Signal 을 latent factor 간의 곱셈을 선형으로 결합하는 내적(저차원 공간)을 통해 나타남
- 복잡한 구조를 알아내기 어려움
- 새로운 User 가 나타나면 저차원 공간에 이를 표현하기가 어려움

Neural Collaborative Filtering

Collaborative Signal : patterns and information derived from the collective behavior and interactions of a group of users

Introduction

□ Neural Collaborative Filtering

- Deep Neural Network 를 사용해 user-item interaction 을 학습
- Non-linear 한 요소를 표현할 수 있음
- User-Item interaction 을 나타내기에 아직 부족함

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Neural **Graph** Collaborative Filtering

Introduction

☐ Why?

- 일반적으로 Collaborative Filtering Model 은 두 개의 주요 요소로 구성
  - Embedding : 유저와 아이템을 벡터로 변환하는 과정
  - Interaction Modeling : Embedding 을 기반으로 historical interaction(구매 혹은 클릭)을 재구성

- 기존의 CF 모델들은 user-item interaction 을 명시적으로 사용하지 않았음
  - 유저와 아이템 각각의 descriptive feature만을 embedding에 사용

Proposed Method

□ Neural Graph Collaborative Filtering - NGCF

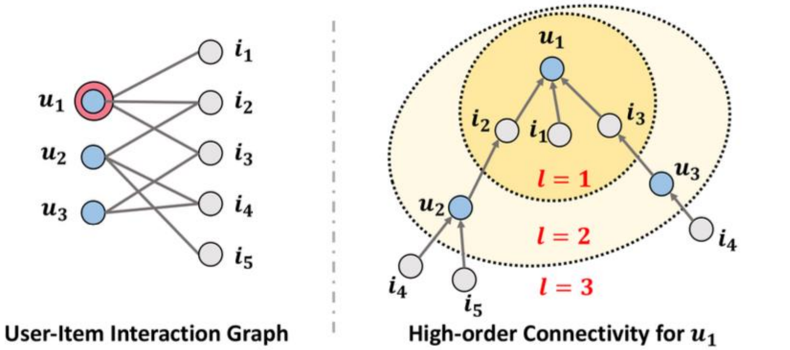


Figure 1: An illustration of the user-item interaction graph and the high-order connectivity. The node u_1 is the target user to provide recommendations for.

- □ **User-Item Interaction Graph**
  - 유자가 아이템을 선택 => 끝
- □ **High-order Connectivity**
  - 유저와 아이템간 관계를 그래프적으로 표현
  - Sequential 한 관계 (High-order)

Proposed Method

☐ Neural Graph Collaborative Filtering - NGCF

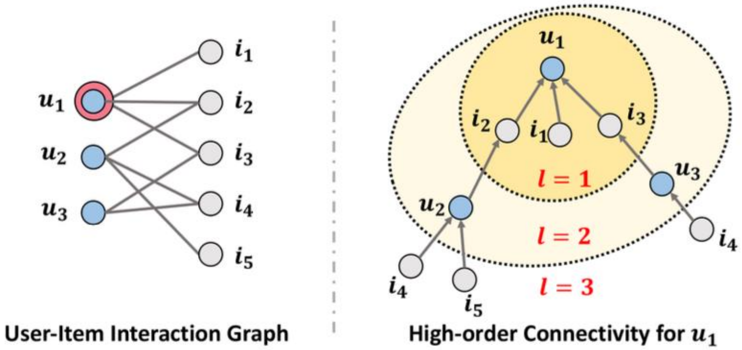


Figure 1: An illustration of the user-item interaction graph and the high-order connectivity. The node u_1 is the target user to provide recommendations for.

Collaborative signal 을 포착 가능

☐ **User-Item Interaction Graph**

- 유자가 아이템을 선택 => 끝

☐ **High-order Connectivity**

- $u_1 <= i_2 <= u_2$

  (u_1 과 u_2 간 유사성 존재)

- $u_1 <= i_2 <= u_2 <= i_4$

  (u_1 은 을 i_4 사용할 가능성 존재)

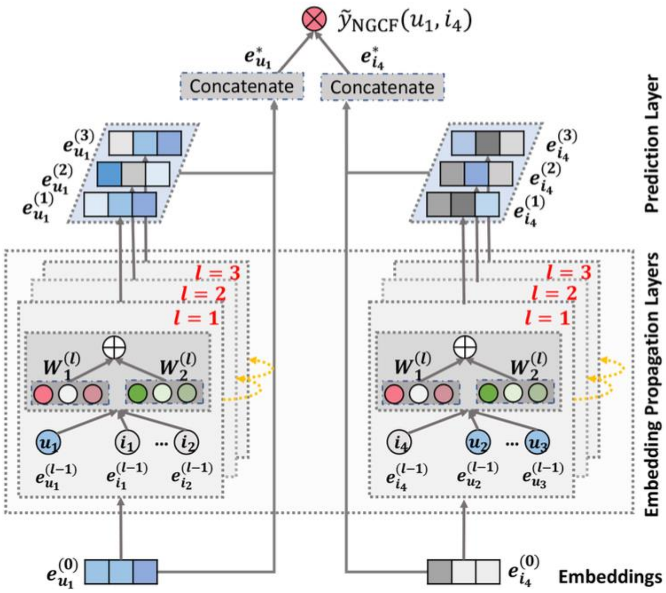
- u_1은 i_5보다 i_4 를 선호할 것

  u_1 와 유사한 또 다른 유저 $u3$도 i_4 를 사용

NGCF – Methodology

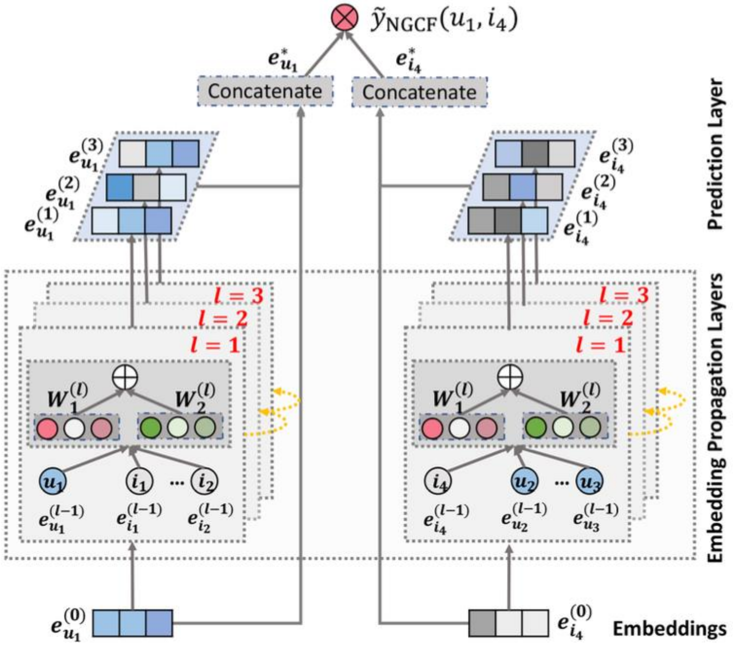
☐ High-order Connectivity

- ■ GNN (Graph Neural Network) 착용
  - ☐ Graph 로 Embedding 을 전파할 수 있음
  - ☐ 정보의 흐름을 embedding space 에 명시적으로 반영
  - ☐ Embedding propagation layer 를 이용
  - ☐ Collaborative signal 을 포착 가능



NGCF – Methodology

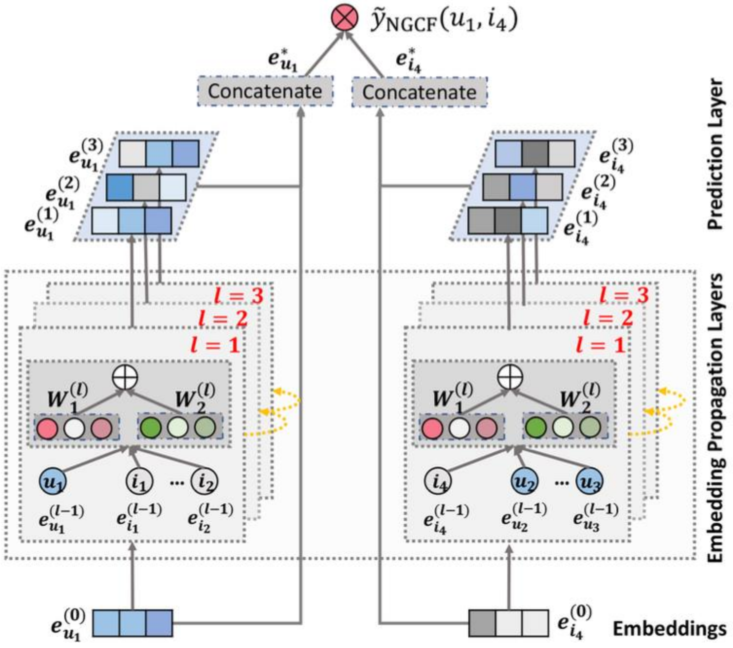
☐ **Architecture**



1. Embedding Layer
2. Embedding Propagation Layer
3. Prediction Layer

NGCF – Methodology

☐ Architecture



1. Embedding Layer

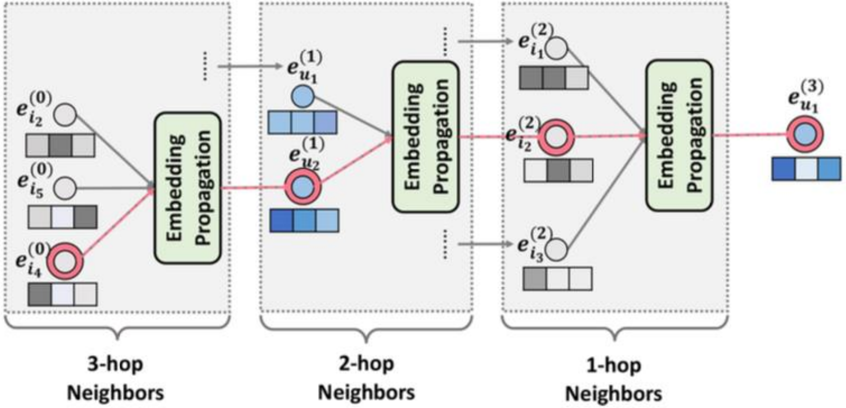
☐ User-Item Interaction 반영되지 않은 유저, 아이템 각각의 Embedding

$$\mathbf{E} = [\ \underbrace{\mathbf{e}_{u_1}, \cdots, \mathbf{e}_{u_N}}_{\text{users embeddings}}\ ,\ \underbrace{\mathbf{e}_{i_1}, \cdots, \mathbf{e}_{i_M}}_{\text{item embeddings}}\ ]$$

$\mathbf{e}_u \in \mathbb{R}^d$ ($\mathbf{e}_i \in \mathbb{R}^d$) where d denotes the embedding size

NGCF – Methodology

☐ **Architecture**



2. Embedding Propagation Layer

$$\mathbf{e}_u^{(k+1)} = \sigma\Big(\mathbf{W}_1\mathbf{e}_u^{(k)} + \sum_{i\in\mathcal{N}_u}\frac{1}{\sqrt{|\mathcal{N}_u||\mathcal{N}_i|}}(\mathbf{W}_1\mathbf{e}_i^{(k)} + \mathbf{W}_2(\mathbf{e}_i^{(k)}\odot\mathbf{e}_u^{(k)}))\Big),$$

$$\mathbf{e}_i^{(k+1)} = \sigma\Big(\mathbf{W}_1\mathbf{e}_i^{(k)} + \sum_{u\in\mathcal{N}_i}\frac{1}{\sqrt{|\mathcal{N}_u||\mathcal{N}_i|}}(\mathbf{W}_1\mathbf{e}_u^{(k)} + \mathbf{W}_2(\mathbf{e}_u^{(k)}\odot\mathbf{e}_i^{(k)}))\Big),$$

☐ W_1, W_2 : feature transformation matrix

☐ σ(·) : nonlinear activation function

NGCF – Methodology

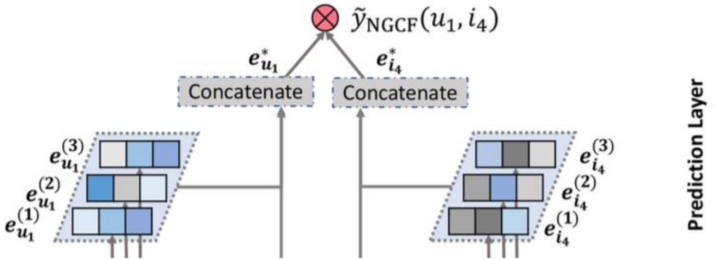
☐ Architecture

3. Prediction

- Embedding propagation output : $\{e_u^{(1)}, \ldots, e_u^{(L)}\}$
- 각기 다른 연결에서 전달 받은 메시지를 강조하므로, 유저 선호에 대해 각기 다른 부분을 반영
  - ☐ Concat 을 통해 최종 유저/아이템에 대한 임베딩 구성

$$\mathbf{e}_u^* = \mathbf{e}_u^{(0)} \| \cdots \| \mathbf{e}_u^{(L)}, \quad \mathbf{e}_i^* = \mathbf{e}_i^{(0)} \| \cdots \| \mathbf{e}_i^{(L)},$$

- 파라미타가 없어 연산이 단순
- Prediction Layer output : $\hat{y}_{\text{NGCF}}(u, i) = \mathbf{e}_u^{*\top} \mathbf{e}_i^*.$



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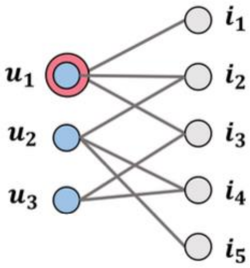
NGCF – Problem

- CF는 과거 유저-아이템 관계를 이용하여 예측
  - 그래프의 관점에서, 유저당 인접 노드만 고려하는 one-hop subgraph만을 이용한 것

- GNN key : performing multiple layers of nonlinear feature transformation 사용
  - 어떠한 이득도 가져와주지 않을 것



User-Item Interaction Graph

Solution

CAU

☐ Ablation Study 결과 두가지를 발견

- Feature transformation과 nonlinear activation이 NGCF의 효과에 기여하지 않음
- 제거 후 상당한 성능 향상

GCN 에 가장 필수적인 neighborhood aggregation만을 사용

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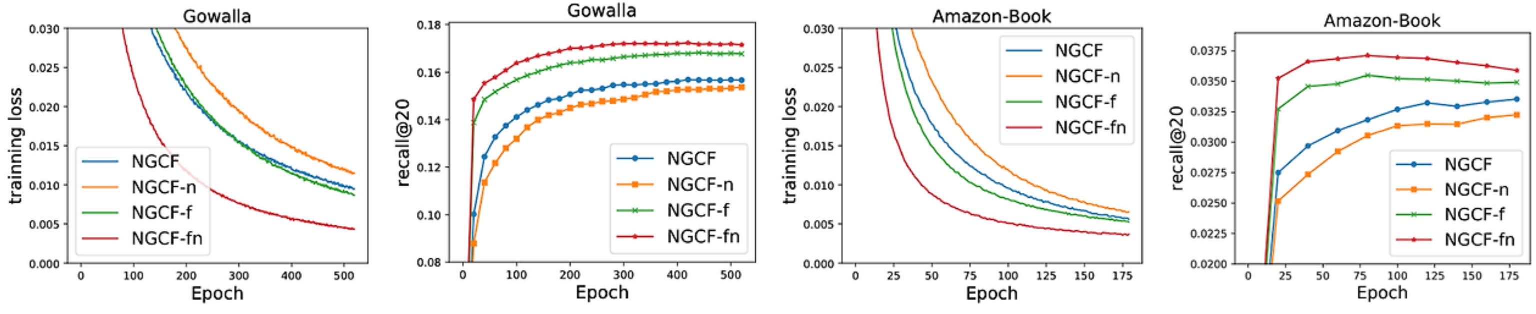
LightGCN

Ablation Study

- ☐ **NGCF-fn**
  - ■ Such lower training loss successfully transfers to better recommendation accuracy



(a) Training loss on Gowalla (b) Testing recall on Gowalla (c) Training loss on Amazon-Book (d) Testing recall on Amazon-Book

Figure 1: Training curves (training loss and testing recall) of NGCF and its three simplified variants.

- ☐ NGCF-f : removing the feature matrices, W_1 and W_2
- ☐ NGCF-n : removing nonlinear activation function, $\sigma(\cdot)$
- ☐ NGCF-fn : removing both

Proposed Method

□ LightGCN

- Feature transformations, nonlinear activation, self-connection을 제거함
- Layer Combination을 통해 유저와 아이템의 점수를 계산함
- 유저가 구매하지 않은 아이템 중 상위의 점수에 있는 k개의 아이템을 유저에게 추천

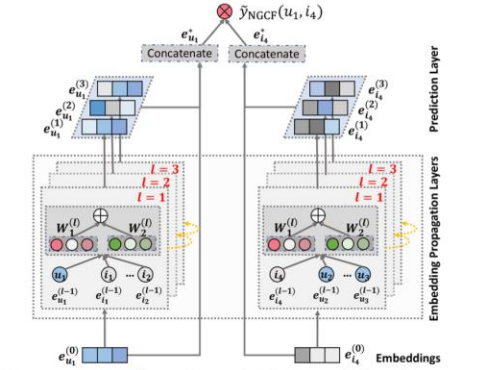
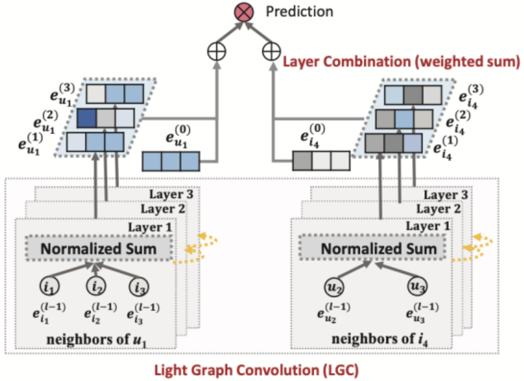


Figure 2: An illustration of NGCF model architecture



Proposed Method

LightGCN

- Performing two essential components
  - (1) Light graph convolution
    - Adopting simple weighted sum aggregator

$$\mathbf{e}_u^{(k+1)} = \sum_{i \in \mathcal{N}_u} \frac{1}{\sqrt{|\mathcal{N}_u|}\sqrt{|\mathcal{N}_i|}} \mathbf{e}_i^{(k)},$$
$$\mathbf{e}_i^{(k+1)} = \sum_{u \in \mathcal{N}_i} \frac{1}{\sqrt{|\mathcal{N}_i|}\sqrt{|\mathcal{N}_u|}} \mathbf{e}_u^{(k)}.$$

  - (2-1) Layer combination to get final representations

$$\mathbf{e}_u = \sum_{k=0}^{K} \alpha_k \mathbf{e}_u^{(k)}; \quad \mathbf{e}_i = \sum_{k=0}^{K} \alpha_k \mathbf{e}_i^{(k)},$$

    - $\alpha_k \geq 0$: hyper-parameter/ model parameter (here – setting uniformly : 1/(K + 1))

  - (2-1) Model Prediction -> $\hat{y}_{ui} = \mathbf{e}_u^T \mathbf{e}_i$ (used as ranking score)

LightGCN

- Layer combination한 결과를 사용하는 이유
  - 레이어 수가 늘어나면 임베딩들이 over-smoothed 됨
    - 마지막 layer만을 사용하는 것은 문제가 존재
  - 포괄적인(comprehensive) representation을 추출할 수 있음
    - 각각의 layer에서 서로 다른 semantic을 포착한
      - First layer – Smoothness on users and items that have interactions
      - Second layer – Smoothness on users(items) that have overlap on interacted items(user)
  - Self-connected의 효과를 포착할 수 있음
    - 서로 다른 layer의 embedding을 가중합(weighted sum)을 통해 결합함으로써

LightGCN

□ Matrix form of LightGCN

- user-item interaction matrix : $\mathbf{R} \in \mathbb{R}^{M \times N}$

- Adjacency matrix : $A = \begin{bmatrix} \mathbf{0} & \mathbf{R} \\ \mathbf{R}^T & \mathbf{0} \end{bmatrix}$

- $E^{(0)} \in \mathbb{R}^{(M+N) \times T}$ (T : embedding size)
- $\mathbf{E}^{(k+1)} = (\mathbf{D}^{-\frac{1}{2}}\mathbf{A}\mathbf{D}^{-\frac{1}{2}})\mathbf{E}^{(k)}$, **D** : *(M+N) x (M+N) Degree matrix*

- Final embedding matrix : $\mathbf{E} = \alpha_0\mathbf{E}^{(0)} + \alpha_1\mathbf{E}^{(1)} + \alpha_2\mathbf{E}^{(2)} + \ldots + \alpha_K\mathbf{E}^{(K)}$

$$= \alpha_0\mathbf{E}^{(0)} + \alpha_1\tilde{\mathbf{A}}\mathbf{E}^{(0)} + \alpha_2\tilde{\mathbf{A}}^2\mathbf{E}^{(0)} + \ldots + \alpha_K\tilde{\mathbf{A}}^K\mathbf{E}^{(0)}$$

  - □ $\tilde{\mathbf{A}} = \mathbf{D}^{-\frac{1}{2}}\mathbf{A}\mathbf{D}^{-\frac{1}{2}}$: Systematically normalized matrix

LightGCN

- **Self-connection in SGCN (Simplified GCN)**
  - By removing nonlinearities and collapsing the weight matrices to one weight matrix

$$\mathbf{E}^{(k+1)} = (\mathbf{D} + \mathbf{I})^{-\frac{1}{2}}(\mathbf{A} + \mathbf{I})(\mathbf{D} + \mathbf{I})^{-\frac{1}{2}}\mathbf{E}^{(k)}$$

    - $\mathbf{I} \in R^{(M+N)\times(M+N)}$: identity matrix *(added on A to include self-connections)*
    - $(D + I)^{-1/2}$ terms for simplicity, since they only re-scale embeddings.

$$\begin{aligned}\mathbf{E}^{(K)} &= (\mathbf{A} + \mathbf{I})\mathbf{E}^{(K-1)} = (\mathbf{A} + \mathbf{I})^K\mathbf{E}^{(0)} \\ &= \binom{K}{0}\mathbf{E}^{(0)} + \binom{K}{1}\mathbf{A}\mathbf{E}^{(0)} + \binom{K}{2}\mathbf{A}^2\mathbf{E}^{(0)} + \ldots + \binom{K}{K}\mathbf{A}^K\mathbf{E}^{(0)}\end{aligned}$$

- **LightGCN fully recovers the self-connection effect by layer combination**

LightGCN

- Alleviate Over-smoothing (APPNP)
  - Connecting GCN with personalized PageRank
  - Propagating long range with without the risk of over-smoothing

$$\mathbf{E}^{(k+1)} = \beta\mathbf{E}^{(0)} + (1-\beta)\tilde{\mathbf{A}}\mathbf{E}^{(k)}$$

$$\begin{aligned}
\mathbf{E}^{(K)} &= \beta\mathbf{E}^{(0)} + (1-\beta)\tilde{\mathbf{A}}\mathbf{E}^{(K-1)}, \\
&= \beta\mathbf{E}^{(0)} + \beta(1-\beta)\tilde{\mathbf{A}}\mathbf{E}^{(0)} + (1-\beta)^2\tilde{\mathbf{A}}^2\mathbf{E}^{(K-2)} \\
&= \beta\mathbf{E}^{(0)} + \beta(1-\beta)\tilde{\mathbf{A}}\mathbf{E}^{(0)} + \beta(1-\beta)^2\tilde{\mathbf{A}}^2\mathbf{E}^{(0)} + \ldots + (1-\beta)^K\tilde{\mathbf{A}}^K\mathbf{E}^{(0)}
\end{aligned}$$

- LightGCN shares the strength of APPNP in combination over-smoothing

LightGCN

☐ Model Training

- Trainable parameter : only the embeddings of the 0-th layer
- *Bayesian Personalized Ranking (BPR)* loss 를 사용

$$L_{BPR} = -\sum_{u=1}^{M} \sum_{i \in \mathcal{N}_u} \sum_{j \notin \mathcal{N}_u} \ln \sigma(\hat{y}_{ui} - \hat{y}_{uj}) + \lambda ||\mathbf{E}^{(0)}||^2$$

  - ☐ A pairwise loss
  - ☐ Observed/unobserved user-item interaction 사이의 상대적 우선순위 고려
  - ☐ 유자의 선호를 더 반영하는 observed interaction 에 unobserved interaction 보다 높은 점수 부여

Experiments

- LightGCN closely follows the setting of the NGCF work

Table 3: Performance comparison between NGCF and LightGCN at different layers.

Dataset		Gowalla		Yelp2018		Amazon-Book	
Layer #	Method	recall	ndcg	recall	ndcg	recall	ndcg
1 Layer	NGCF	0.1556	0.1315	0.0543	0.0442	0.0313	0.0241
	LightGCN	0.1755(+12.79%)	0.1492(+13.46%)	0.0631(+16.20%)	0.0515(+16.51%)	0.0384(+22.68%)	0.0298(+23.65%)
2 Layers	NGCF	0.1547	0.1307	0.0566	0.0465	0.0330	0.0254
	LightGCN	0.1777(+14.84%)	0.1524(+16.60%)	0.0622(+9.89%)	0.0504(+8.38%)	0.0411(+24.54%)	0.0315(+24.02%)
3 Layers	NGCF	0.1569	0.1327	0.0579	0.0477	0.0337	0.0261
	LightGCN	0.1823(+16.19%)	0.1555(+17.18%)	0.0639(+10.38%)	0.0525(+10.06%)	0.0410(+21.66%)	0.0318(+21.84%)
4 Layers	NGCF	0.1570	0.1327	0.0566	0.0461	0.0344	0.0263
	LightGCN	0.1830(+16.56%)	0.1550(+16.80%)	0.0649(+14.58%)	0.0530(+15.02%)	0.0406(+17.92%)	0.0313(+18.92%)

*The scores of NGCF on Gowalla and Amazon-Book are directly copied from Table 3 of the NGCF paper (https://arxiv.org/abs/1905.08108)

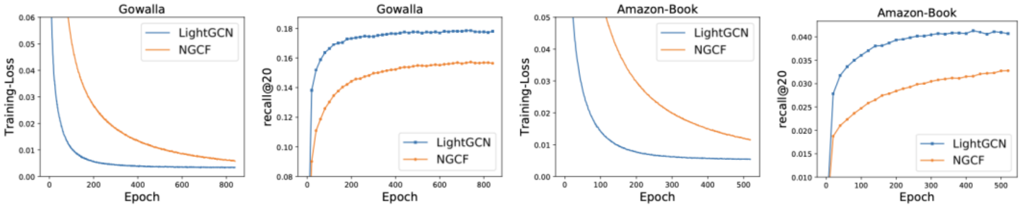


Figure 3: Training curves of LightGCN and NGCF, which are evaluated by training loss and testing recall per 20 epochs on Gowalla and Amazon-Book (results on Yelp2018 show exactly the same trend which are omitted for space).

- Increasing the # of layers can improve the performance of LightGCN
- LightGCN obtains lower training loss, but transfers to better testing accuracy

Experiments

- Performance comparison with other SOTA

Dataset	Gowalla		Yelp2018		Amazon-Book	
Method	**recall**	**ndcg**	**recall**	**ndcg**	**recall**	**ndcg**
NGCF	0.1570	0.1327	0.0579	0.0477	0.0344	0.0263
Mult-VAE	0.1641	0.1335	0.0584	0.0450	0.0407	0.0315
GRMF	0.1477	0.1205	0.0571	0.0462	0.0354	0.0270
GRMF-norm	0.1557	0.1261	0.0561	0.0454	0.0352	0.0269
LightGCN	**0.1830**	**0.1554**	**0.0649**	**0.0530**	**0.0411**	**0.0315**

- LightGCN consistently outperforms other methods on all data sets
- Hight effectiveness with simple yet reasonable designs

Experiments

- Comparison of LightGCN and LightGCN-single

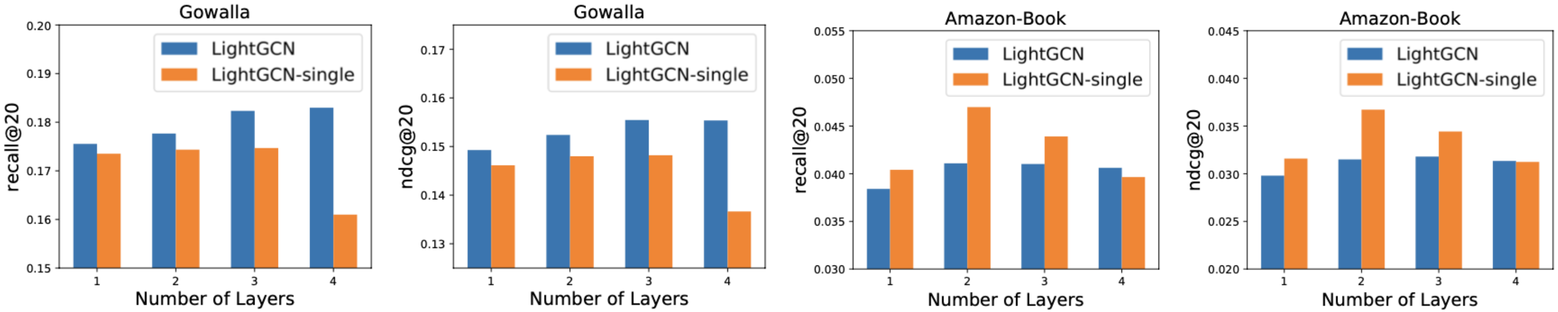


Figure 4: Results of LightGCN and the variant that does not use layer combination (i.e., LightGCN-single) at different layers on Gowalla and Amazon-Book (results on Yelp2018 shows the same trend with Amazon-Book which are omitted for space).

- For Gowalla, LightGCN's performance is not degraded with increasing layers
- But not on Amazon-Book and Yelp2018
  - LightGCN-single : setting α_k = 1 and 2 respectively
  - Simply setting as 1/(K+1) unifromly

Conclusion

- **Problem**
  - Unnecessarily complicated design of GCNs for collaborative filtering
- **Solution**
  - LightGCN – beign simple
    - consists of two essential components
      - Light graph convolution
        - Discarding feature transformation and nonlinear activation
      - layer combination
        - Recovering the effect of self-connection and helpful to control over-smoothing

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