Paper Review

Simplifying and Powering Graph Convolution Network for Recommendation

(LightGCN)

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

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HTET ARKAR

School of Computer Science and Engineering

Chung-Ang University

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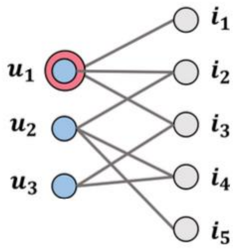
NGCF – Problem

- High-hop neighbors로 sub-graph 구조의 사용을 심화한 모델 (GCN으로부터 발전된 모델)
- **Ablation Study 결과 두가지를 발견**
  - Feature transformation과 nonlinear activation이 성능에 오히려 악영향을 끼치고 있음
  - 제거 후 상당한 성능 향상으로 이어짐
- Collaborative filtering에서는 user-item 사이의 one-hot ID로만 설명됨
  - Sematic 한 정보가 없어서 성능을 저하함



User-Item Interaction Graph

Solution

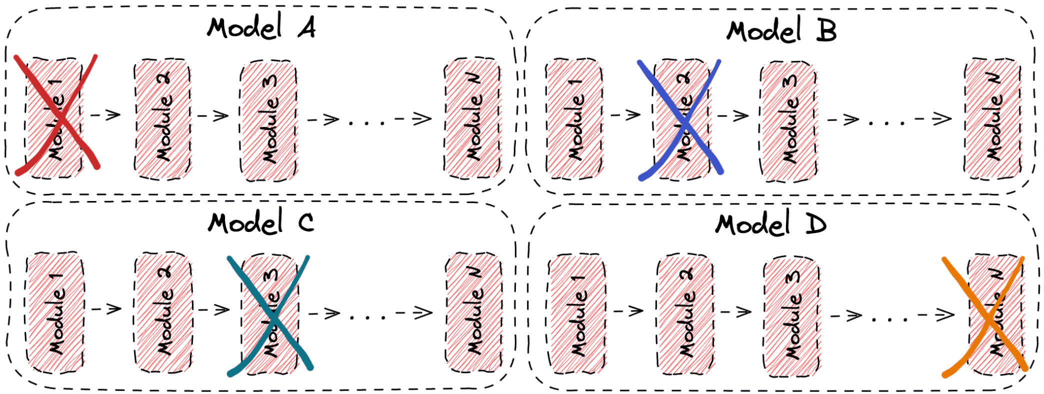
GCN을 단순화하여 추천에 더 간결하고 적합하게 하는 모델

GCN 에 가장 필수적인 neighborhood aggregation만을 사용

LightGCN

Ablation Study

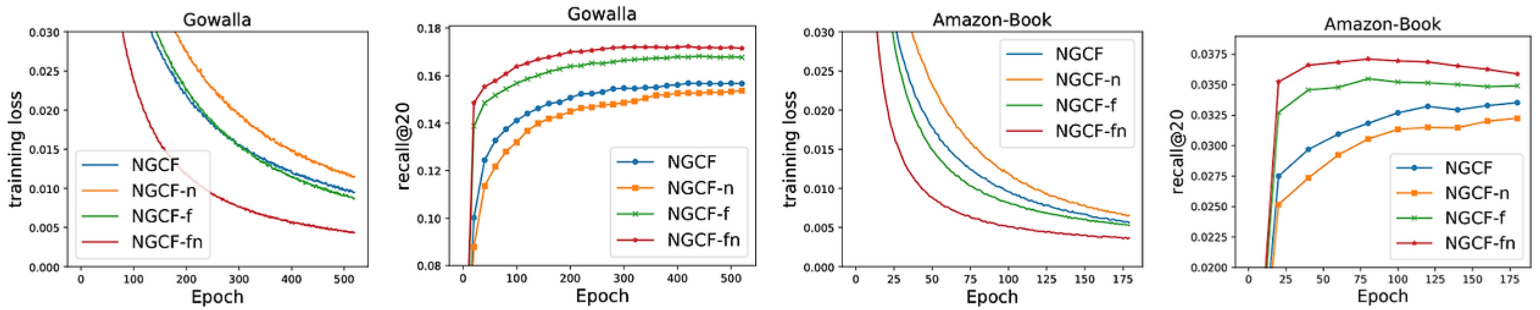
"Machine learning system의 building blocks을 제거해서 전체 성능에 미치는 효과에 대한 insight를 얻기 위한 과학적 실험"



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

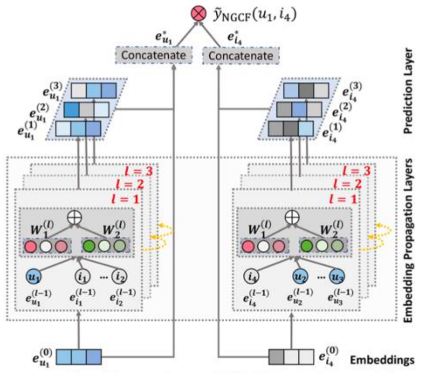
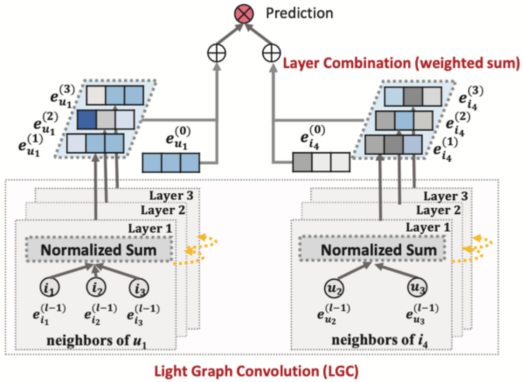


Figure 2: An illustration of NGCF model architecture



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-smoothing 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 : $\mathbf{R} \in \mathrm{R}^{M \times N}$
- Adjacency matrix : $A = \begin{bmatrix} \mathbf{0} & \mathbf{R} \\ \mathbf{R}^T & \mathbf{0} \end{bmatrix}$
- $E^{(0)} \in \mathrm{R}^{(M+N) \times T}$ (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 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 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)

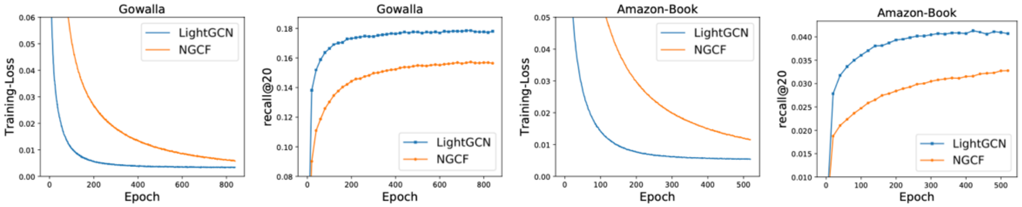


Figure 3: Training curves of LightGCN and NGCF, which are evaluated by training loss and testing recall per 20 epochs on Gowalla and Amazon-Book (results on Yelp2018 show exactly the same trend which are omitted for space).

- 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

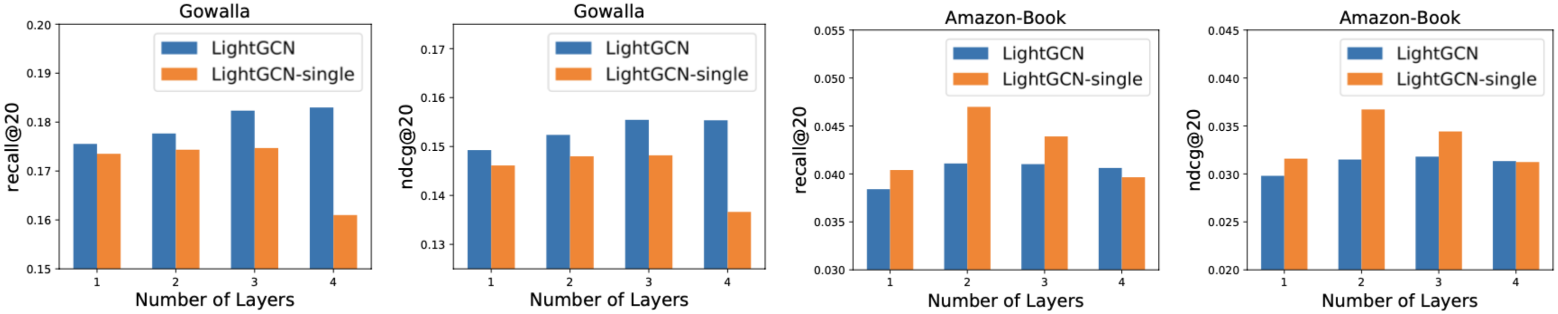


Figure 4: Results of LightGCN and the variant that does not use layer combination (i.e., LightGCN-single) at different layers on Gowalla and Amazon-Book (results on Yelp2018 shows the same trend with Amazon-Book which are omitted for space).

- Layer combination의 효과로 over-smoothing 문제를 잘 해결한다고 판단 할 수 있음
  - LightGCN-single : Layers의 수가 증가할수록 모델의 성능이 떨어짐 (over-smoothing이 발생)
  - LightGCN : Layers의 수가 증가할수록 일관성 있게 성능이 좋아짐

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

HTET ARKAR (hak3601@cau.ac.kr)