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How Neighborhood Exploration influences Novelty and Diversity in Graph Collaborative Filtering

Vito Walter Anelli, Yashar Deldjoo, Tommaso Di Noia, Eugenio Di Sciascio, Antonio Ferrara, Daniele Malitesta, Claudio Pomo

Politecnico di Bari

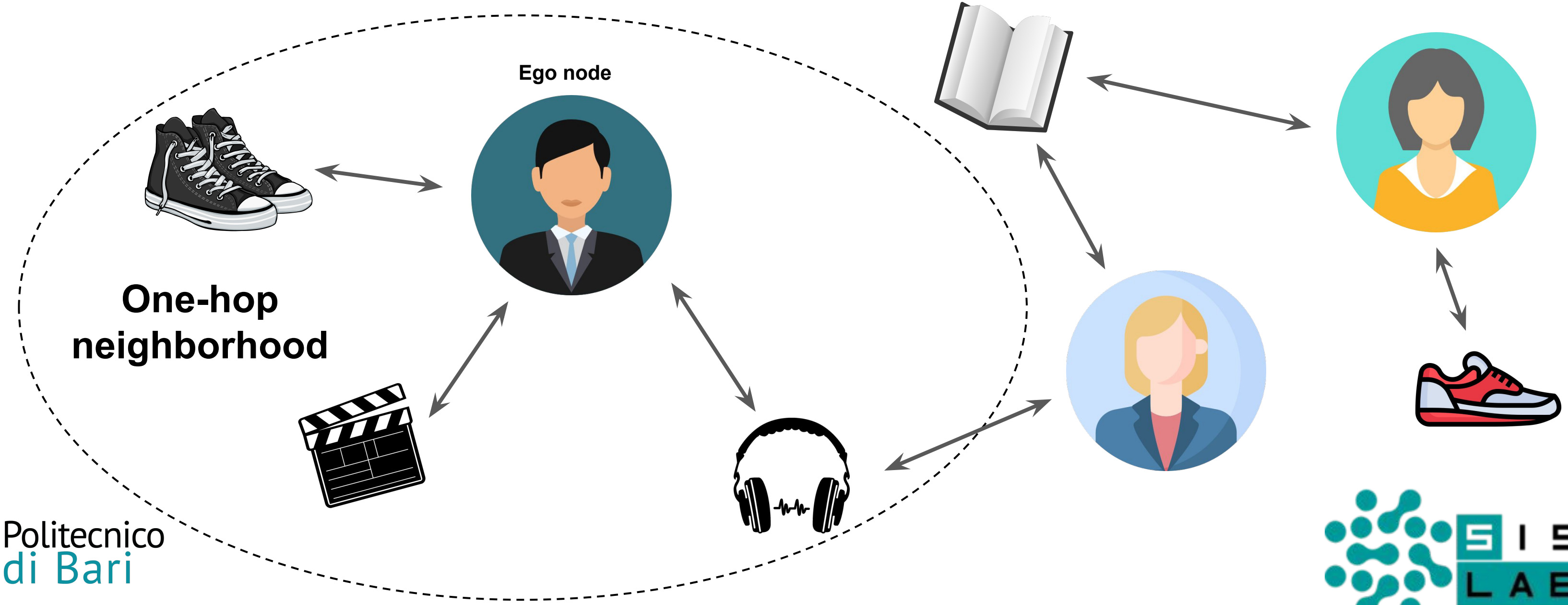
Bari, Italy

email: firstname.lastname@poliba.it

Introduction and Contributions

Graph collaborative filtering

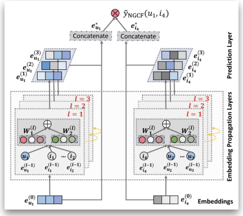
In collaborative filtering (CF), graph convolutional networks (GCNs) have gained momentum thanks to their ability to **aggregate neighbor** nodes **information** into ego nodes at multiple hops (i.e., **message-passing**), thus effectively **distilling** the **collaborative signal**.

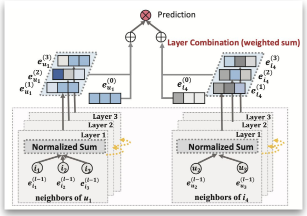


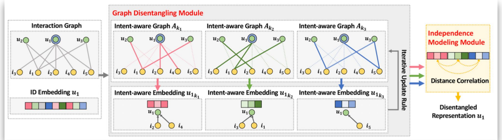
Neighborhood exploration strategies

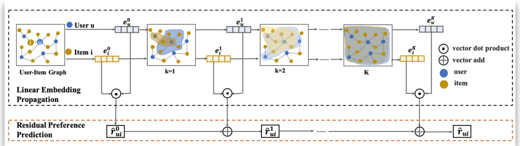
Explicit message-passing

It is always possible to derive a **formulation** where user and **item** node representations are **explicitly updated** through their multi-hop neighbors.









Implicit message-passing

We **introduce** the concept of **implicit** message-passing, where message aggregation is **replaced** and improved through ad-hoc **mathematical proxies**.

$$s_u = r_u \left(\tilde{R}^T \tilde{R} + \alpha D_I^{-\frac{1}{2}} \bar{U} \bar{U}^T D_I^{\frac{1}{2}} \right)$$

$$\mathcal{L}_I = - \sum_{(u,i) \in N^+} \sum_{j \in S(i)} \omega_{i,j} \log(\sigma(e_u^\top e_j))$$

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Multi-objective recommendation and graph CF

Graph CF has shown **remarkable results** on the sole recommendation **accuracy**. However, designing RSs trying to **optimize multiple objectives** at once is the new goal in the recent literature, as a way to embrace both **users' and business' interests**.

So far, in graph CF:

- **limited attention** put on the **accuracy-diversity** trade-off
- **no** in-depth **analysis** of the **neighborhood exploration** influence

Our contributions:

❖ assessment of the **accuracy-novelty-diversity** recommendation **trade-off** of **explicit** and **implicit** message-passing models from the state-of-the-art (**six** baselines)
❖ simple **mathematical reformulation** of **explicit** message-passing, where **same-** and **different-**type node explorations are highlighted, and **extend** the trade-off study **analysis** on this **new dimension**

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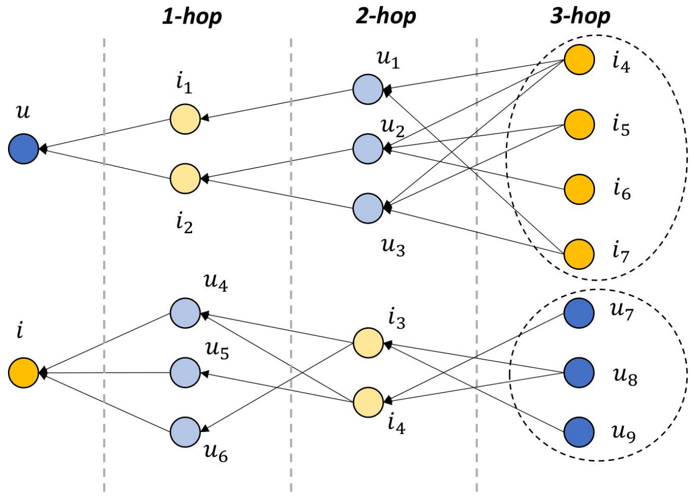
Explicit message-passing reformulation

Useful notation

- $\mathbf{e}_u^{(0)}, \ \mathbf{e}_i^{(0)}$ are the user/item node embeddings
- $\omega(\cdot)$ is the message aggregation function
- $\mathcal{N}(\cdot)$ is the neighborhood of the ego node



Message-passing reformulation (1/2)

After one hop (Eq.1):

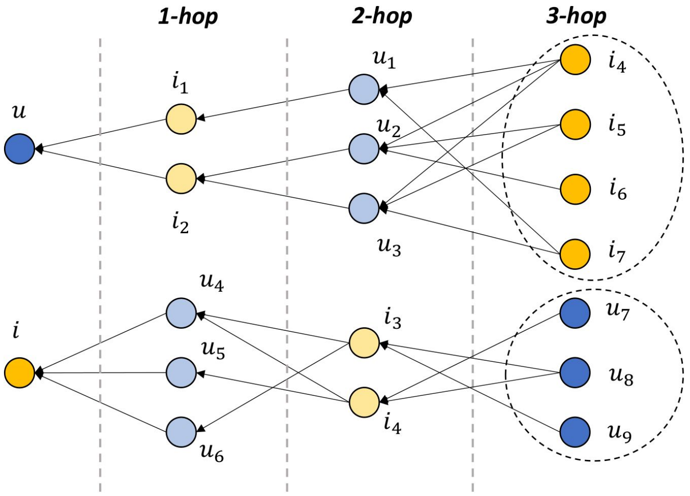
$$\mathbf{e}_u^{(1)} = \omega\left(\left\{\mathbf{e}_{i'}^{(0)}, \forall i' \in \mathcal{N}(u)\right\}\right), \quad \mathbf{e}_i^{(1)} = \omega\left(\left\{\mathbf{e}_{u'}^{(0)}, \forall u' \in \mathcal{N}(i)\right\}\right)$$

After two hops (Eq.2):

$$\mathbf{e}_u^{(2)} = \omega\left(\left\{\mathbf{e}_{i'}^{(1)}, \forall i' \in \mathcal{N}(u)\right\}\right), \quad \mathbf{e}_i^{(2)} = \omega\left(\left\{\mathbf{e}_{u'}^{(1)}, \forall u' \in \mathcal{N}(i)\right\}\right)$$

After three hops (Eq.3):

$$\mathbf{e}_u^{(3)} = \omega\left(\left\{\mathbf{e}_{i'}^{(2)}, \forall i' \in \mathcal{N}(u)\right\}\right), \quad \mathbf{e}_i^{(3)} = \omega\left(\left\{\mathbf{e}_{u'}^{(2)}, \forall u' \in \mathcal{N}(i)\right\}\right)$$

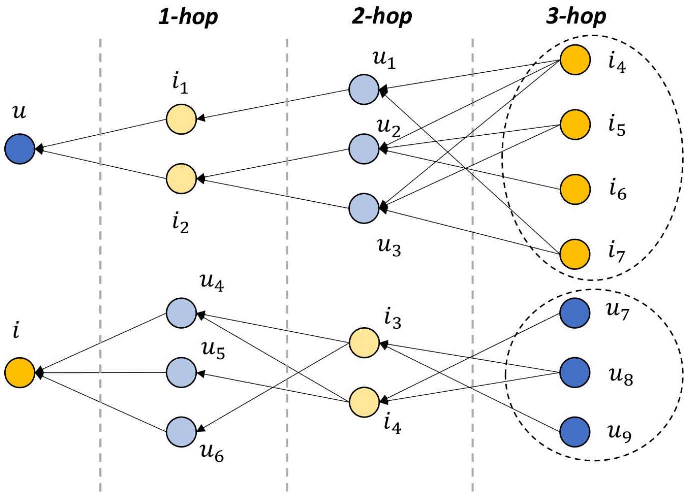


Message-passing reformulation (2/2)

We rewrite Eq.2 and Eq.3 through Eq.1 and Eq.2:

$$\mathbf{e}_u^{(2)} = \omega\Bigg(\bigg\{\omega\Big(\Big\{\mathbf{e}_{u''}^{(0)}, \underbrace{\forall u'' \in \mathcal{N}(i') \setminus \{u\}}_{\text{2-hop}}\Big\}\Big), \underbrace{\forall i' \in \mathcal{N}(u)}_{\text{1-hop}}\bigg\}\Bigg)$$

$$\mathbf{e}_u^{(3)} = \omega\Bigg(\bigg\{\omega\Big(\Big\{\omega\Big(\Big\{\mathbf{e}_{i'''}^{(0)}, \underbrace{\forall i''' \in \mathcal{N}(u'') \setminus \{i''\}}_{\text{3-hop}}\Big\}\Big), \underbrace{\forall u'' \in \mathcal{N}(i') \setminus \{u''\}}_{\text{2-hop}}\Big\}\Big), \underbrace{\forall i' \in \mathcal{N}(u)}_{\text{1-hop}}\bigg\}\Bigg)$$



OBSERVATION: Message-passing works on **same-** and **different-**type node explorations, where the **former** occur for **even** number of hops, the **latter** occur for **odd** number of hops.

Experimental settings

Datasets

Dataset	# Users	# Items	# Interactions	Sparsity
*Movielens-1M**	5,915	2,753	570,622	0.9650
*Amazon Digital Music**	8,328	6,275	99,400	0.9981
*Epinions**	14,341	13,145	269,170	0.9986

* Datasets have been pre-processed through score binarization (scores > 3 are considered as positive interactions) and filtered with the *p*-core strategy.

Graph baselines

Explicit message-passing

- Neural graph collaborative filtering (NGCF) [Wang et al., SIGIR 2019]
- Light graph convolutional network (LightGCN) [He et al., SIGIR 2020]
- Disentangled graph collaborative filtering (DGCF) [Wang et al., SIGIR 2020]
- Linear residual graph convolutional collaborative filtering (LR-GCCF) [Chen et al., AAAI 2020]

Implicit message-passing

- Ultra simplification of graph convolutional networks (UltraGCN) [Mao et al., CIKM 2021]
- Graph filter based collaborative filtering (GFCF) [Shen et al., CIKM 2021]

Evaluation Metrics

Accuracy

- *Recall@K*
- *nDCG@K*

Novelty

- *EPC@K* (expected number of recommended unknown items which are also relevant)
- *EFD@K* (expected number of recommended known items which are also relevant)

Diversity (how unequally a recommender shows different items to users)

- *Gini@K*
- *SE@K*

Results and Discussion

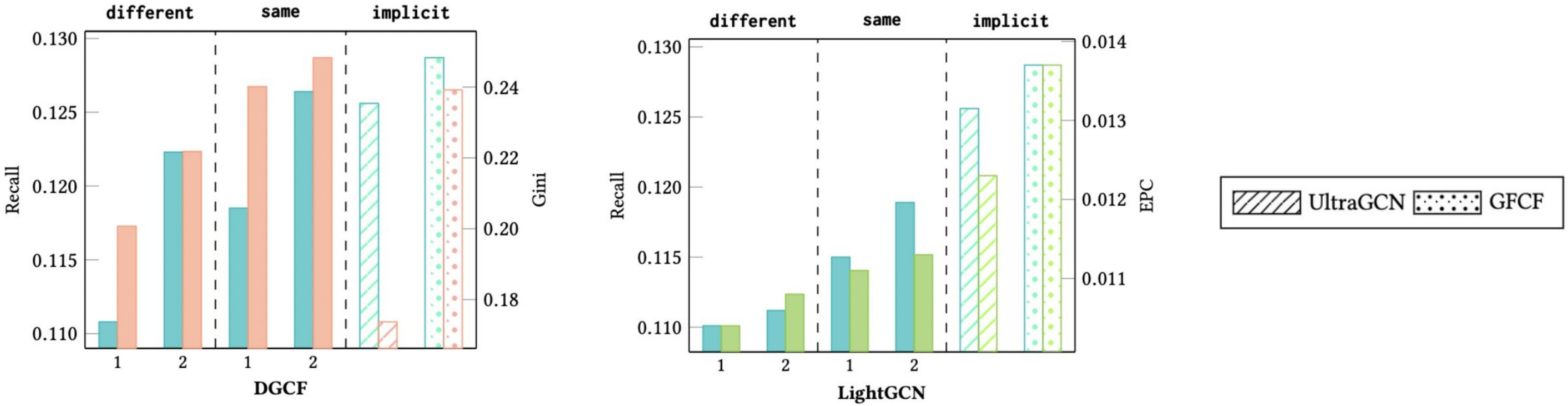
(Amazon Digital Music)

RQ1: Overall recommendation performance

Models	Accuracy		Novelty		Diversity	
	Recall	*nDCG*	*EPC*	*EFD*	*Gini*	*SE*
Explicit message-passing						
NGCF	0.1127	0.0606	0.0109	0.1270	**0.4130**	**11.6953**
LightGCN	0.1189	0.0628	0.0113	0.1310	0.3148	11.2940
DGCF	<u>0.1264</u>	0.0674	<u>0.0123</u>	<u>0.1400</u>	0.2483	10.8904
LR-GCCF	0.1246	0.0664	0.0119	0.1388	<u>0.4037</u>	<u>11.6542</u>
Implicit message-passing						
UltraGCN	0.1256	<u>0.0675</u>	<u>0.0123</u>	0.1382	0.1737	10.0458
GFCF	**0.1287**	**0.0744**	**0.0137**	**0.1544**	0.2392	10.4923

Observation 1: While the **accuracy/novelty** trade-off does **not depend** on the explicit/implicit **message-passing**, the **accuracy/diversity** trade-off is preserved only when **explicitly propagating messages**, at the expense of (**limited**) recommendation **accuracy drops**.

RQ2: A finer trade-off evaluation



Observation 2: To confirm observation 1, **explicit message propagation** (even at 1 hop) can reach a **better accuracy/diversity** trade-off than **implicit** propagation; then, **same-**type node explorations may lead to **improved** accuracy/novelty and accuracy/diversity trade-offs

Conclusion and Future Work

Conclusion

- Accuracy-novelty-diversity trade-off in graph collaborative filtering for different neighborhood exploration strategies and depths
- Accuracy-diversity trade-off better reached when explicitly propagating messages
- User-user and item-item interactions may be leveraged to reach the trade-off

Future work

- Study other graph collaborative filtering approaches optimizing diversity
- Better investigate the same-type node exploration

Thank you! How to reach us out…

Our official GitHub repository:

GitHub

http://github.com/sisinflab/Novelty-Diversity-Graph

Contacts:

vitowalter.anelli@poliba.it

yashar.deldjoo@poliba.it

tommaso.dinoia@poliba.it

eugenio.disciascio@poliba.it

antonio.ferrara@poliba.it

daniele.malitesta@poliba.it (PRESENTER)

claudio.pomo@poliba.it

RecSys acm.org

Politecnico di Bari

SISINF LAB