Graph Neural Networks for Recommendation: Reproducibility, Graph Topology, and Node Representation

TUTORIALS

LoG CONFERENCE

Part 0. Introduction and Background

20 minutes

POLITECNICO DI BARI

SISINF LAB

ABOUT US



Tommaso DI NOIA
Professor of Computer Science

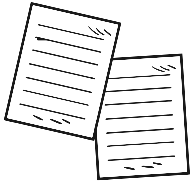
tommaso.dinoia@poliba.it
@TommasoDiNoia

Daniele MALITESTA
Ph.D. Candidate

daniele.malitesta@poliba.it
@dmalitesta

Claudio POMO
Research Fellow

claudio.pomo@poliba.it
@scne



USEFUL RESOURCES

All useful materials for this tutorial (slides, papers, codes) are accessible at our website:

https://sisinflab.github.io/tutorial-gnns-recsys-log2023/

Scan me!

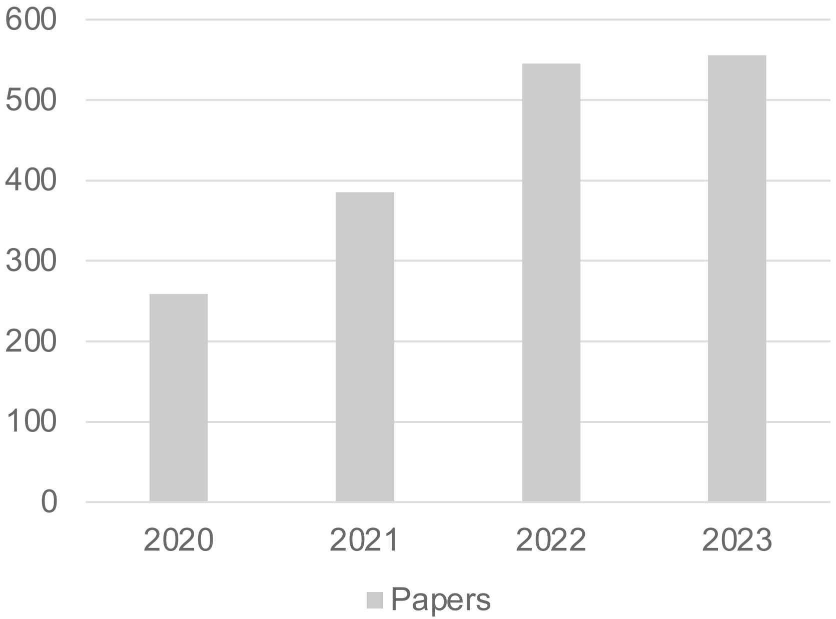
TABLE OF CONTENTS

01

INTRODUCTION & MOTIVATIONS

Why a tutorial on GNNs-based recommendation?

A RISING INTEREST



As searched on DBLP through the keywords "**graph**" and "**recommend**".

RecSys acm.org

aaai

SIGIR
Special Interest Group on Information Retrieval

wsdm

THE WEB CONFERENCE

KDD

CIKM

IJCAI
International Joint Conferences on Artificial Intelligence Organization

PREVIOUS RELATED TUTORIALS

Reference	Venue	Website	Slides	Video
Wang et al. [25]	WSDM 2020	[link]	[link]	✗
El-Kishky et al. [13]	KDD 2022	[link]	[link]	✗
Gao et al. [15]	WSDM 2022	[link]	[link]	[link]
Purificato et al. [20]	UMAP 2023	[link]	[link]	✗
Purificato et al. [19]	CIKM 2023	[link]	[link]	✗

*The table with clickable links is accessible at our website!

They provide a **general overview** of GNNs-based recommendation, or address **different topics** from our tutorial

- Highly-related topics to LoG.
- Different from previous tutorials.
- Covers three topics widely debated in GRL.

LoG CONFERENCE

TOPICS

01

REPRODUCIBILITY

02

GRAPH TOPOLOGY

03

NODE REPRESENTATION

TOPICS

01

REPRODUCIBILITY

How can we reproduce SOTA graph-based recommendation approaches?

02

GRAPH TOPOLOGY

03

NODE REPRESENTATION

TOPICS

01

REPRODUCIBILITY

How can we reproduce SOTA graph-based recommendation approaches?

02

GRAPH TOPOLOGY

Do topological properties of the datasets influence the performance of graph-based recsys?

03

NODE REPRESENTATION

TOPICS

01
REPRODUCIBILITY
How can we reproduce SOTA graph-based recommendation approaches?

02
GRAPH TOPOLOGY
Do topological properties of the datasets influence the performance of graph-based recsys?

03
NODE REPRESENTATION
What are the most popular strategies to represent nodes in graph-based recsys?

TUTORIAL SCHEDULE

Total duration: 180 minutes

Introduction and background: 20 minutes

- Introduction and motivations of the tutorial: 5 minutes
- Basics concepts of recommender systems & GNNs-based recommendation: 15 minutes

Reproducibility: 60 minutes

- [Hands-on #1] Implementation and reproducibility of GNNs-based recsys in Elliot with PyG and reproducibility issues: 35 minutes
- Performance comparison of GNNs-based approaches to traditional recommendation systems: 10 minutes

Break and Q&A: 15 minutes

Graph topology: 30 minutes

- Concepts and formulations of graph topological properties of the user-item graph: 15 minutes
- Impact of topological graph properties on the performance of GNNs-based recsys: 15 minutes

Node representation: 45 minutes

- Design choices to train node embeddings from scratch: 20 minutes
- [Hands-on #2] Leveraging item's multimodal side-information for node embeddings: 25 minutes

Closing remarks and Q&A: 10 minutes

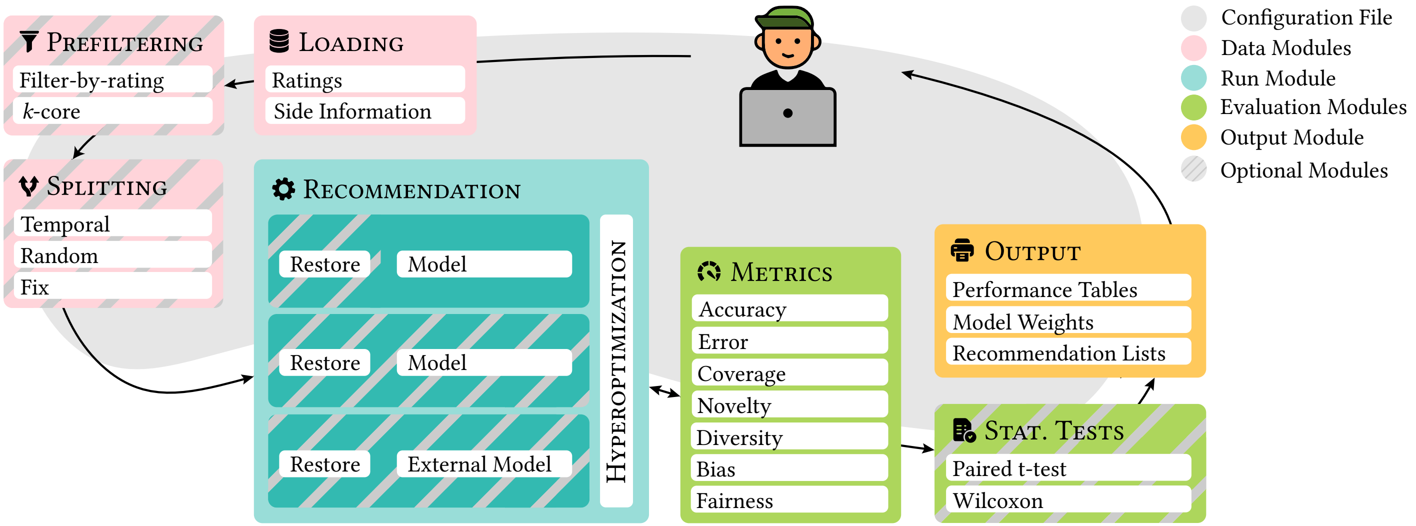
02

RECOMMENDER SYSTEMS

"**Recommender Systems** are software **tools** and **techniques** providing **suggestions** for **items to** be of use of **a user**. The suggestions provided are aimed at **supporting** their users in various **decision-making** processes, such as items to **buy**, what music to **listen** , or what news to **read**."

[Ricci et al.]

RECOMMENDATION PIPELINE

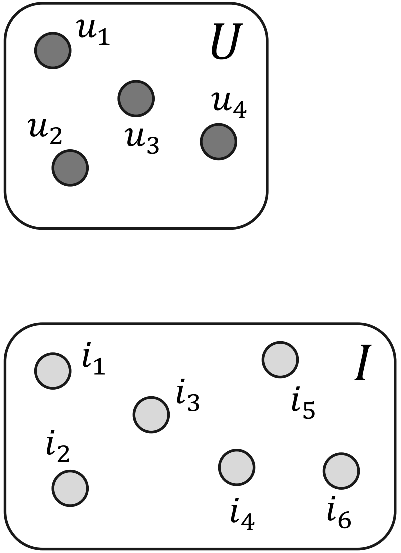


Overview of our framework **Elliot [Anelli et al.]** for **reproducible** recommender systems **evaluation**.

RECOMMENDATION DATASET

users

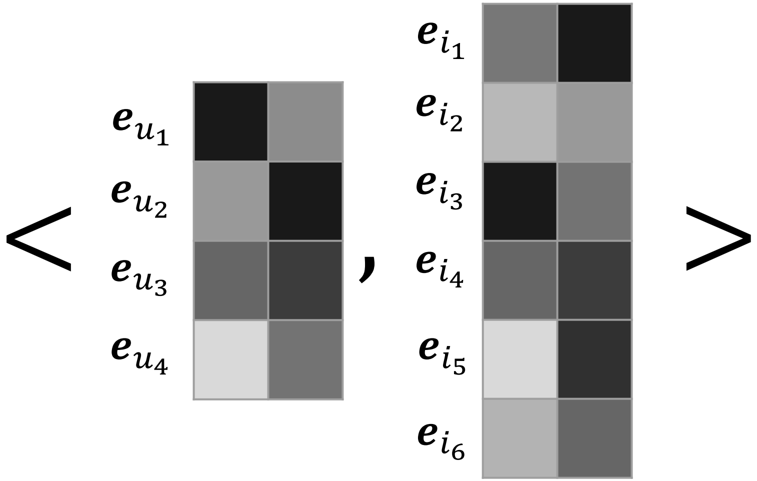
items



	i_1	i_2	i_3	i_4	i_5	i_6
u_1	1	0	1	1	1	0
u_2	0	0	0	0	1	0
u_3	1	1	1	0	0	0
u_4	0	0	1	1	0	1

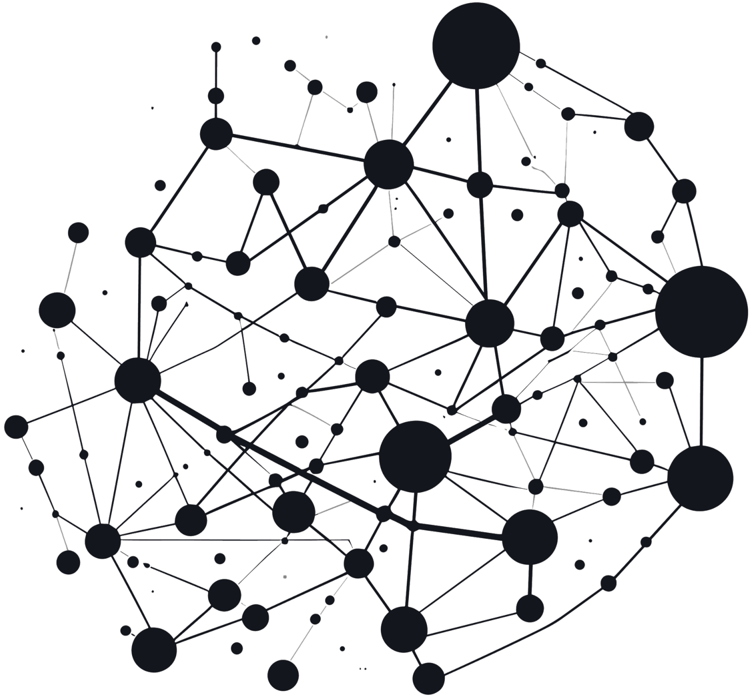
user-item
interaction matrix

FACTORIZATION-BASED MODELS



$\approx$

	i_1	i_2	i_3	i_4	i_5	i_6
u_1	1	0	1	1	1	0
u_2	0	0	0	0	1	0
u_3	1	1	1	0	0	0
u_4	0	0	1	1	0	1



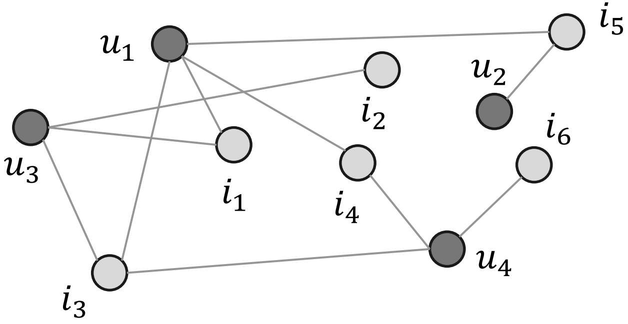
03

GNNs & RECOMMENDATION

A NON-EXHAUSTIVE TIMELINE

- **2017-2018**: Pioneer approaches proposing GCN-based aggregation methods **[van den Berg et al., Ying et al.]**
- **2019**: Explore inter-dependencies between nodes and their neighbours **[Wang et al. (2019a)]**, use graph attention networks to recognize meaningful user-item interactions at higher-grained level **[Wang et al. (2019b)]**
- **2020**: Lighten the graph convolutional layer **[Chen et al., He et al.]**, use graph attention networks to recognize meaningful user-item interactions at higher-grained level **[Wang et al. (2020b), Tao et al.]**
- **2021-2022**: Self-supervised and contrastive learning **[Wu et al., Yu et al.]**
- **2021-2022**: Simplify the message-passing formulation **[Mao et al., Peng et al., Shen et al.]**
- **2021-2022**: Explore other latent spaces **[Shen et al., Sun et al., Zhang et al.]**
- **2022**: Exploit hypergraphs **[Wei et al., Xia et al.]**
- **2022**: Use graph attention networks to recognize meaningful user-item interactions at finer-grained **[Zhang et al.]** level

USER-ITEM GRAPH



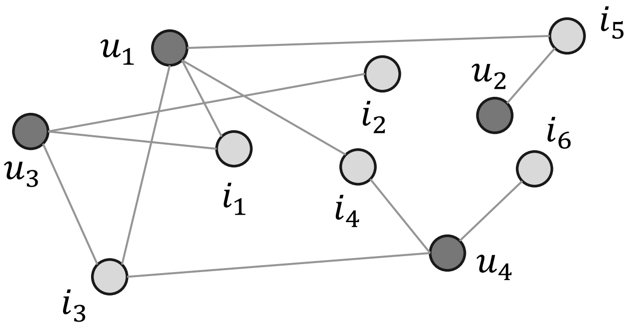
	i_1	i_2	i_3	i_4	i_5	i_6
u_1	1	0	1	1	1	0
u_2	0	0	0	0	1	0
u_3	1	1	1	0	0	0
u_4	0	0	1	1	0	1

user - item
interaction matrix

	u_1	u_2	u_3	u_4	i_1	i_2	i_3	i_4	i_5	i_6
u_1	0	0	0	0	1	0	1	1	1	0
u_2	0	0	0	0	0	0	0	0	1	0
u_3	0	0	0	0	1	1	1	0	0	0
u_4	0	0	0	0	0	0	1	1	0	1
i_1	1	0	1	0	0	0	0	0	0	0
i_2	0	0	1	0	0	0	0	0	0	0
i_3	1	0	1	1	0	0	0	0	0	0
i_4	1	0	0	1	0	0	0	0	0	0
i_5	1	1	0	0	0	0	0	0	0	0
i_6	0	0	0	1	0	0	0	0	0	0

adjacency matrix

USER-ITEM GRAPH



	i_1	i_2	i_3	i_4	i_5	i_6
u_1	1	0	1	1	1	0
u_2	0	0	0	0	1	0
u_3	1	1	1	0	0	0
u_4	0	0	1	1	0	1

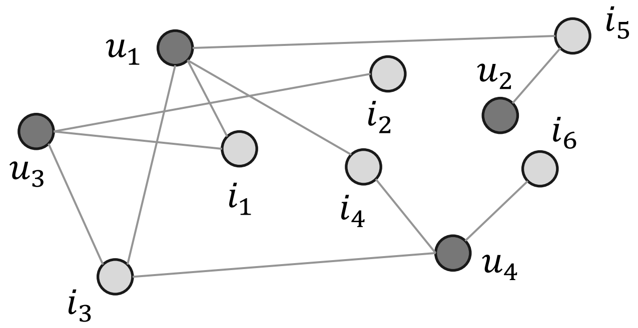
user-item
interaction matrix

BIPARTITE

	u_1	u_2	u_3	u_4	i_1	i_2	i_3	i_4	i_5	i_6
u_1	0	0	0	0	1	0	1	1	1	0
u_2	0	0	0	0	0	0	0	0	1	0
u_3	0	0	0	0	1	1	1	0	0	0
u_4	0	0	0	0	0	0	1	1	0	1
i_1	1	0	1	0	0	0	0	0	0	0
i_2	0	0	1	0	0	0	0	0	0	0
i_3	1	0	1	1	0	0	0	0	0	0
i_4	1	0	0	1	0	0	0	0	0	0
i_5	1	1	0	0	0	0	0	0	0	0
i_6	0	0	0	1	0	0	0	0	0	0

adjacency matrix

USER-ITEM GRAPH



	i_1	i_2	i_3	i_4	i_5	i_6
u_1	1	0	1	1	1	0
u_2	0	0	0	0	1	0
u_3	1	1	1	0	0	0
u_4	0	0	1	1	0	1

user-item
interaction matrix

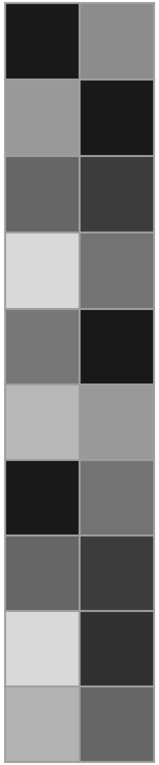
UNDIRECTED

	u_1	u_2	u_3	u_4	i_1	i_2	i_3	i_4	i_5	i_6
u_1	0	0	0	0	1	0	1	1	1	0
u_2	0	0	0	0	0	0	0	0	1	0
u_3	0	0	0	0	1	1	1	0	0	0
u_4	0	0	0	0	0	0	1	1	0	1
i_1	1	0	1	0	0	0	0	0	0	0
i_2	0	0	1	0	0	0	0	0	0	0
i_3	1	0	1	1	0	0	0	0	0	0
i_4	1	0	0	1	0	0	0	0	0	0
i_5	1	1	0	0	0	0	0	0	0	0
i_6	0	0	0	1	0	0	0	0	0	0

adjacency matrix

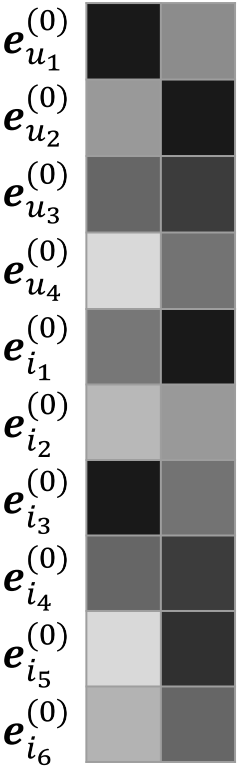
MESSAGE-PASSING (LAYER 1)

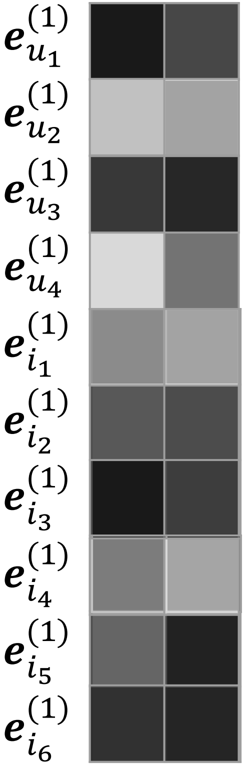
$$G_{NN}^{(1)}\left(\begin{array}{|c|c|c|c|c|c|c|c|c|c|} \hline 0 & 0 & 0 & 0 & 1 & 0 & 1 & 1 & 1 & 0 \\ \hline 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ \hline 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 \\ \hline 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline 1 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline \end{array} \;, \; \begin{matrix} \boldsymbol{e}_{u_1}^{(0)} \\ \boldsymbol{e}_{u_2}^{(0)} \\ \boldsymbol{e}_{u_3}^{(0)} \\ \boldsymbol{e}_{u_4}^{(0)} \\ \boldsymbol{e}_{i_1}^{(0)} \\ \boldsymbol{e}_{i_2}^{(0)} \\ \boldsymbol{e}_{i_3}^{(0)} \\ \boldsymbol{e}_{i_4}^{(0)} \\ \boldsymbol{e}_{i_5}^{(0)} \\ \boldsymbol{e}_{i_6}^{(0)} \end{matrix} \right)$$



MESSAGE-PASSING (LAYER 1)

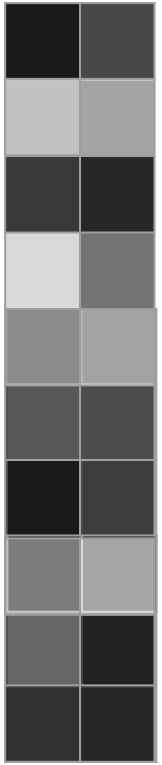
$$G_{NN}^{(1)}\left(\begin{array}{|c|c|c|c|c|c|c|c|c|c|} 0 & 0 & 0 & 0 & 1 & 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \end{array}, \;\; \cdot \right) = \;\; \cdot$$





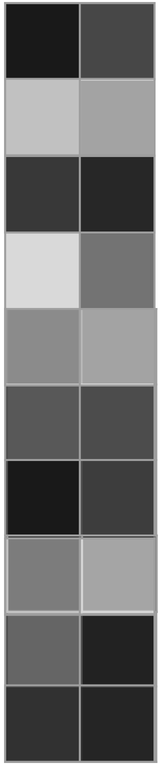
MESSAGE-PASSING (LAYER 2)

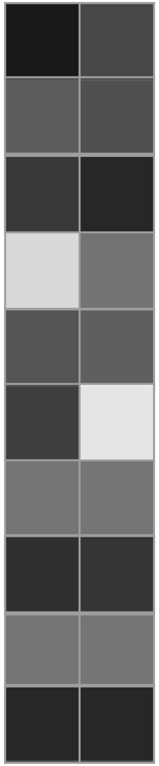
$$G_{NN}^{(2)}\left(\begin{array}{|c|c|c|c|c|c|c|c|c|c|}
\hline
0 & 0 & 0 & 0 & 1 & 0 & 1 & 1 & 1 & 0 \\ \hline
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ \hline
0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 \\ \hline
0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 \\ \hline
1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline
1 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline
1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline
1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline
\end{array}\ ,\ \begin{array}{c}
\boldsymbol{e}_{u_1}^{(1)} \\
\boldsymbol{e}_{u_2}^{(1)} \\
\boldsymbol{e}_{u_3}^{(1)} \\
\boldsymbol{e}_{u_4}^{(1)} \\
\boldsymbol{e}_{i_1}^{(1)} \\
\boldsymbol{e}_{i_2}^{(1)} \\
\boldsymbol{e}_{i_3}^{(1)} \\
\boldsymbol{e}_{i_4}^{(1)} \\
\boldsymbol{e}_{i_5}^{(1)} \\
\boldsymbol{e}_{i_6}^{(1)}
\end{array}\right)$$



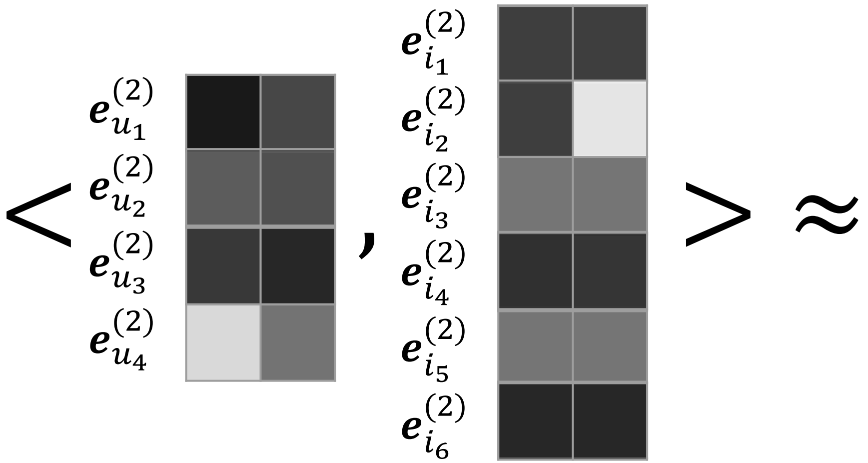
MESSAGE-PASSING (LAYER 2)

$$G_{NN}^{(2)}\left(\begin{bmatrix} 0&0&0&0&1&0&1&1&1&0\\ 0&0&0&0&0&0&0&0&1&0\\ 0&0&0&0&1&1&1&0&0&0\\ 0&0&0&0&0&0&1&1&0&1\\ 1&0&1&0&0&0&0&0&0&0\\ 0&0&1&0&0&0&0&0&0&0\\ 1&0&1&1&0&0&0&0&0&0\\ 1&0&0&1&0&0&0&0&0&0\\ 1&1&0&0&0&0&0&0&0&0\\ 0&0&0&1&0&0&0&0&0&0 \end{bmatrix},\ \begin{matrix} \boldsymbol{e}_{u_1}^{(1)}\\ \boldsymbol{e}_{u_2}^{(1)}\\ \boldsymbol{e}_{u_3}^{(1)}\\ \boldsymbol{e}_{u_4}^{(1)}\\ \boldsymbol{e}_{i_1}^{(1)}\\ \boldsymbol{e}_{i_2}^{(1)}\\ \boldsymbol{e}_{i_3}^{(1)}\\ \boldsymbol{e}_{i_4}^{(1)}\\ \boldsymbol{e}_{i_5}^{(1)}\\ \boldsymbol{e}_{i_6}^{(1)} \end{matrix}\right) = \begin{matrix} \boldsymbol{e}_{u_1}^{(2)}\\ \boldsymbol{e}_{u_2}^{(2)}\\ \boldsymbol{e}_{u_3}^{(2)}\\ \boldsymbol{e}_{u_4}^{(2)}\\ \boldsymbol{e}_{i_1}^{(2)}\\ \boldsymbol{e}_{i_2}^{(2)}\\ \boldsymbol{e}_{i_3}^{(2)}\\ \boldsymbol{e}_{i_4}^{(2)}\\ \boldsymbol{e}_{i_5}^{(2)}\\ \boldsymbol{e}_{i_6}^{(2)} \end{matrix}$$





FACTORIZATION & MESSAGE-PASSING



	i_1	i_2	i_3	i_4	i_5	i_6
u_1	1	0	1	1	1	0
u_2	0	0	0	0	1	0
u_3	1	1	1	0	0	0
u_4	0	0	1	1	0	1

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