TOGETHER IS *WAY* BETTER WITH GRAPH NEURAL NETWORKS

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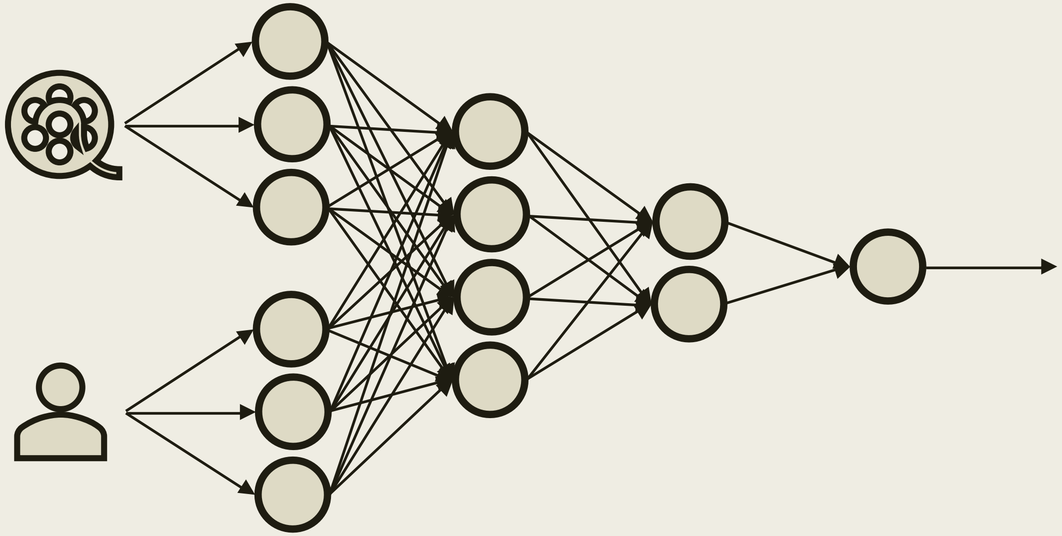
Objective

- Introduction of **Graph Neural Networks** (GNNs) in existing deep recommender systems architectures
- Research questions:
  - *How GNNs perform in contrast with Knowledge Graph Embeddings (KGE) models for learning collaborative features ?*
  - *How GNNs can be integrated in both collaborative and content-based hybrid deep recommender systems ?*

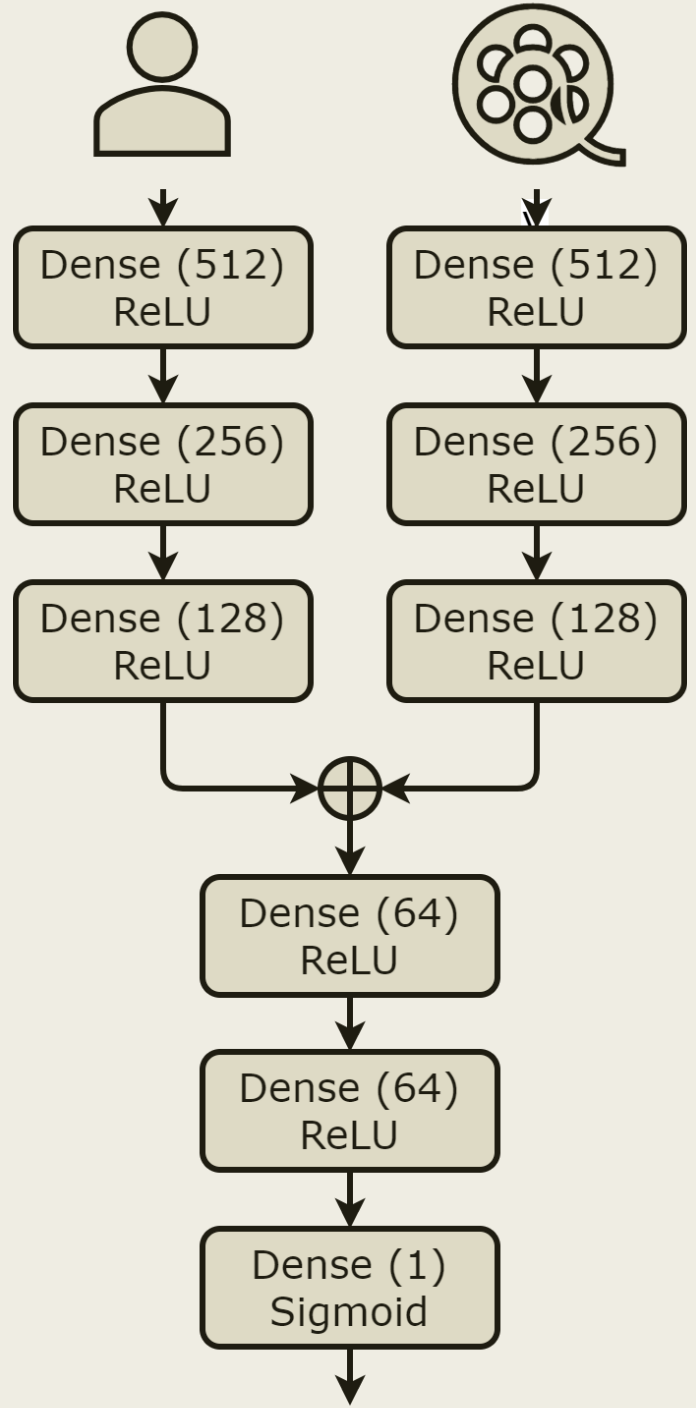
Previous Works
Deep Amar

- **Hybrid** architectures for recommendations based on Neural Networks
- Take user ***u*** and item ***i*** and return a relevance score ***s(u,i)***
- Usage of Knowledge Graph Embeddings and Word Embeddings

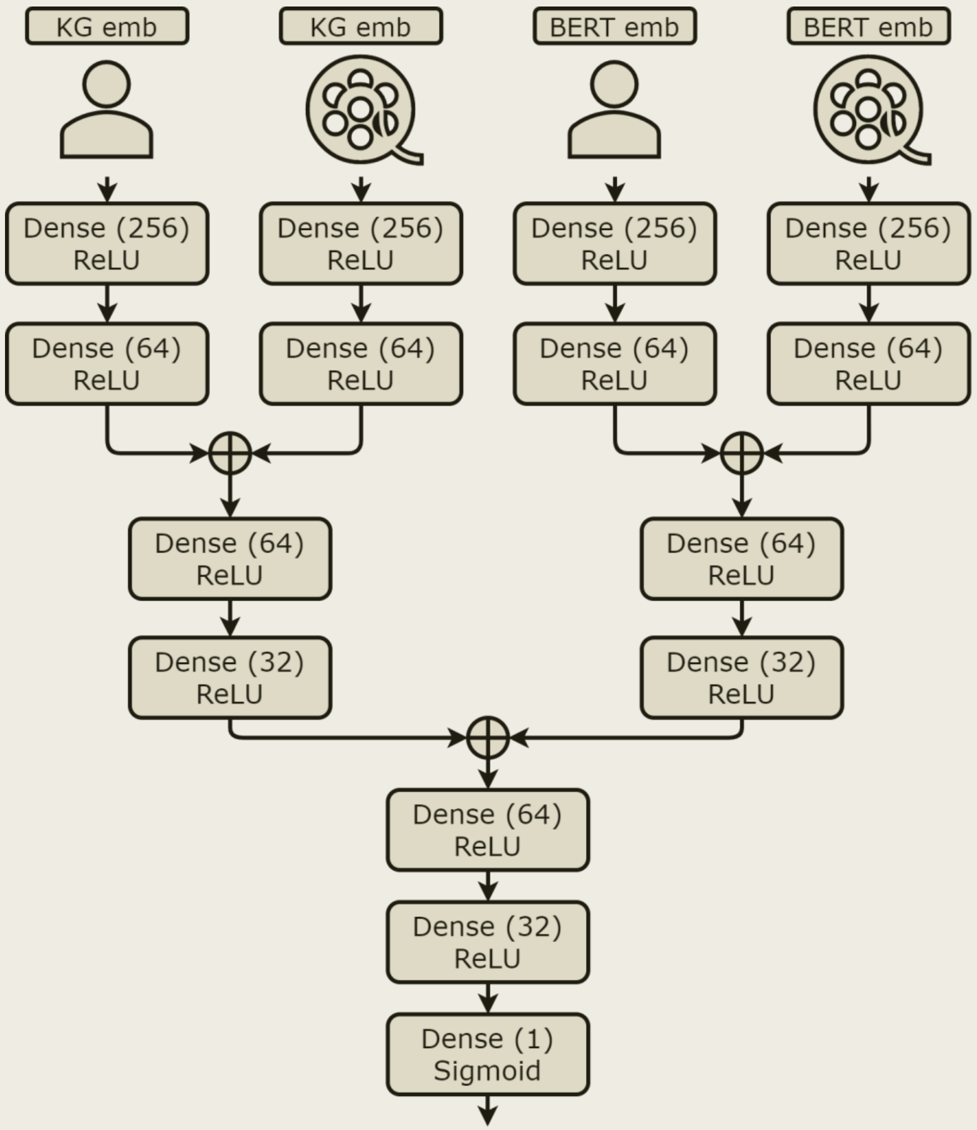


Previous Works
Deep Amar Revisited - BASIC

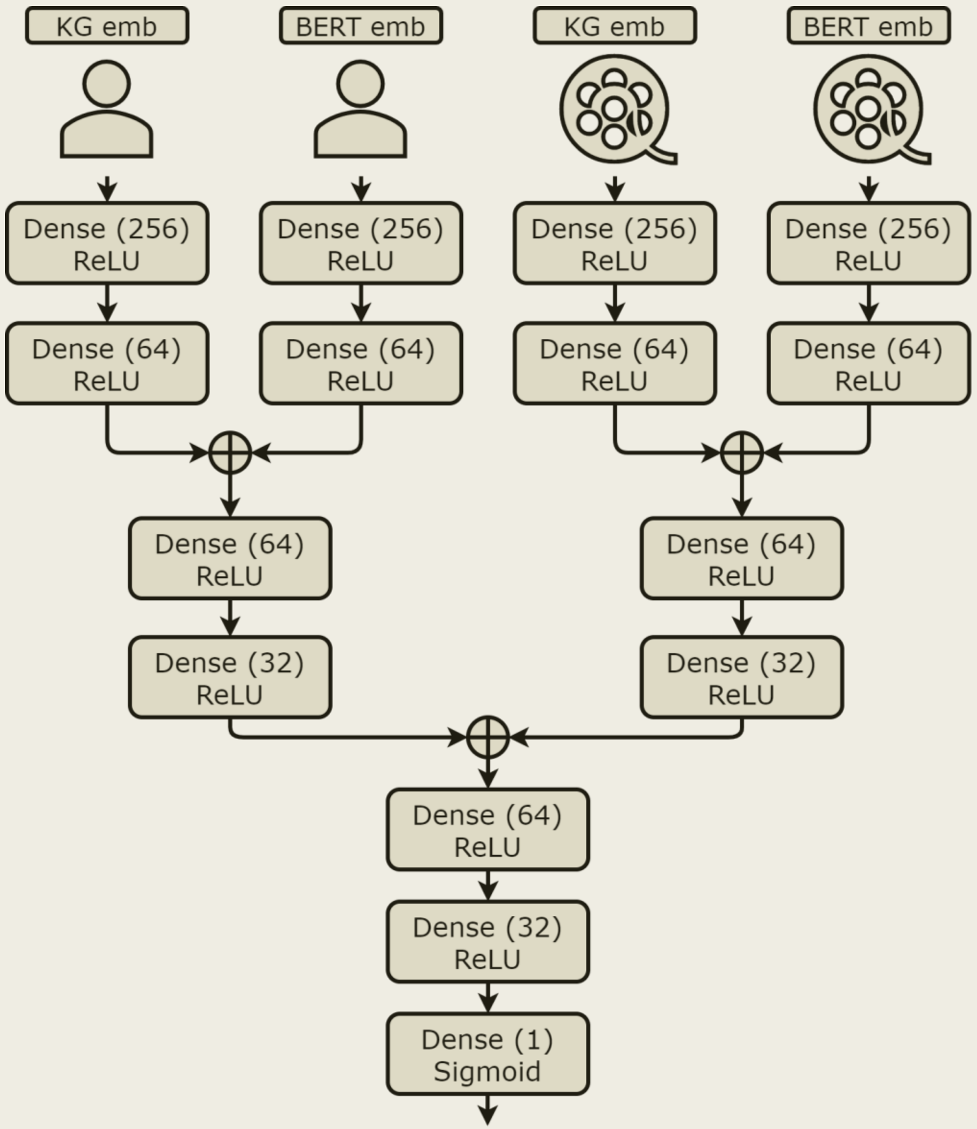
- User and Movie features as inputs
  - *KG embeddings (e.g. TransH)*
  - *Word embeddings (e.g. BERT)*



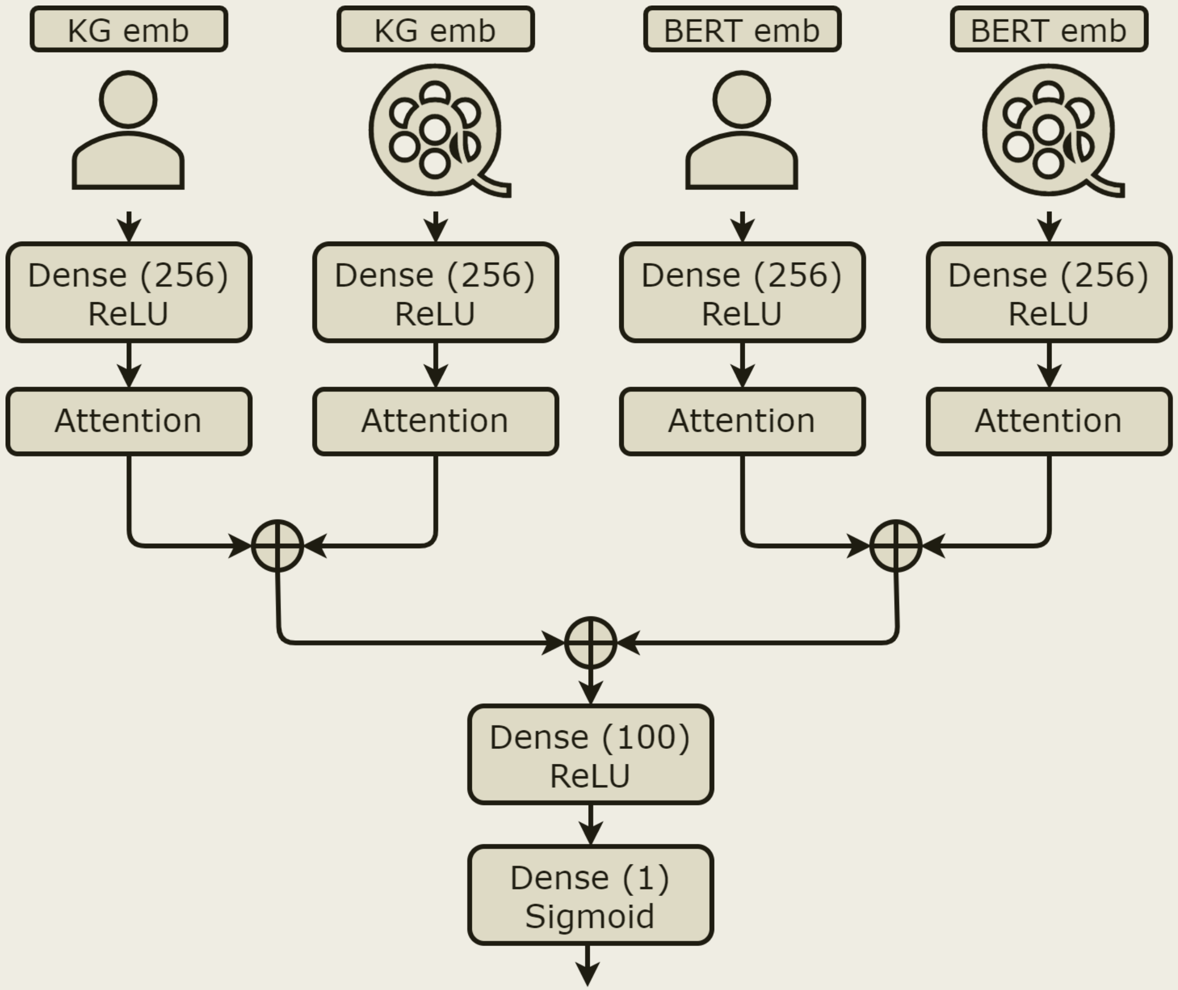
PREVIOUS WORKS
DEEP AMAR REVISITED
MIXED
FEATURE BASED

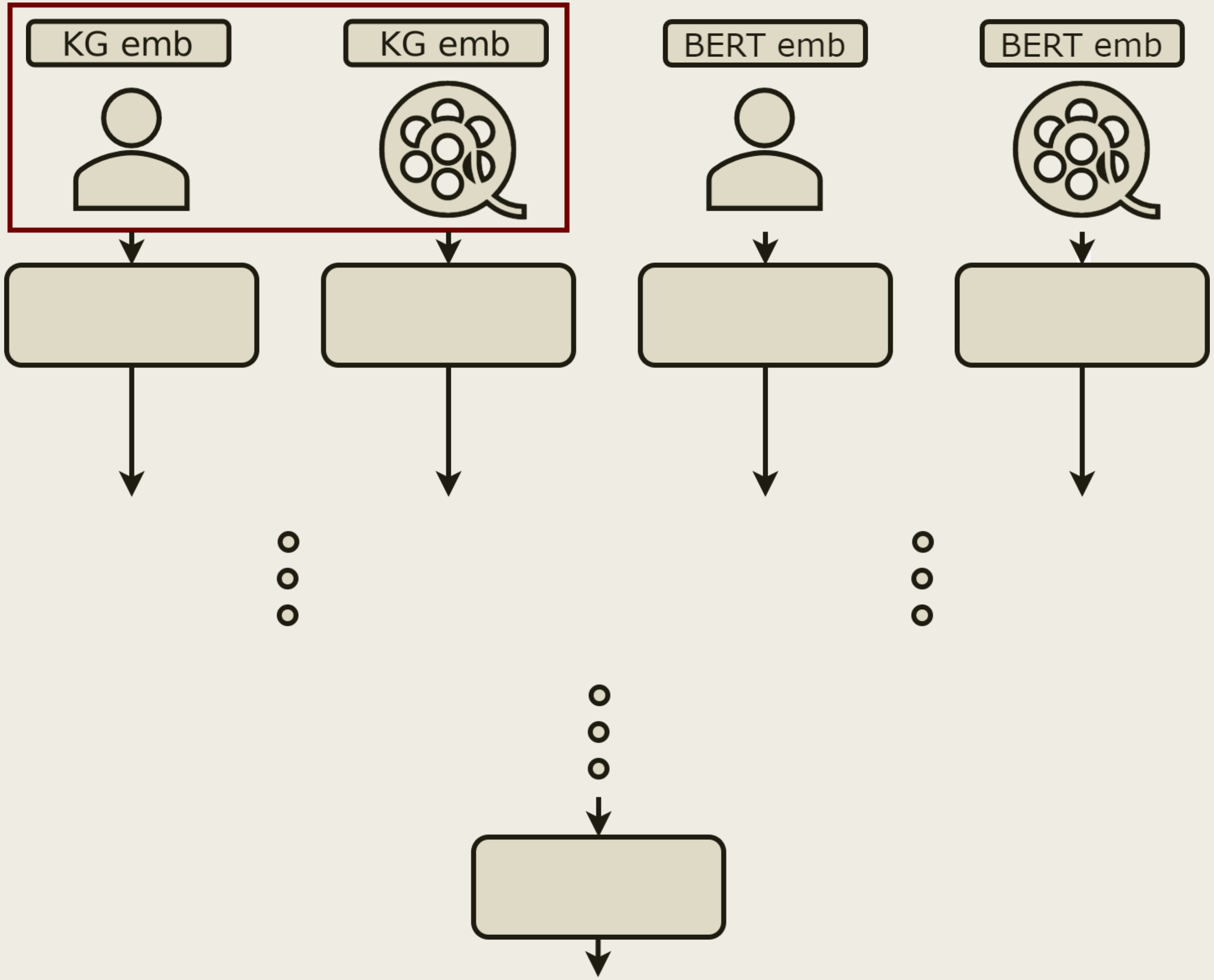


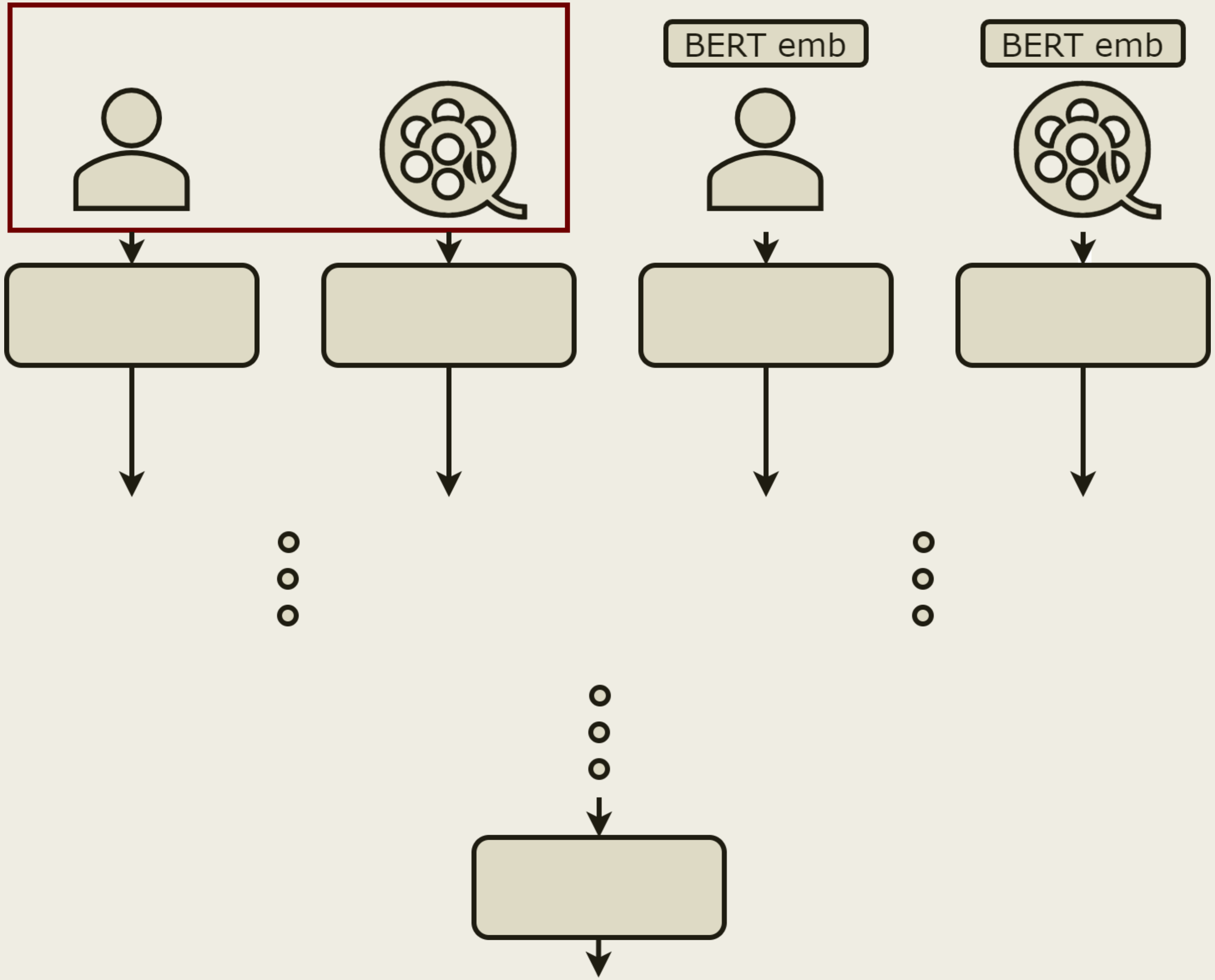
PREVIOUS WORKS
DEEP AMAR
REVISITED
MIXED
ENTITY BASED

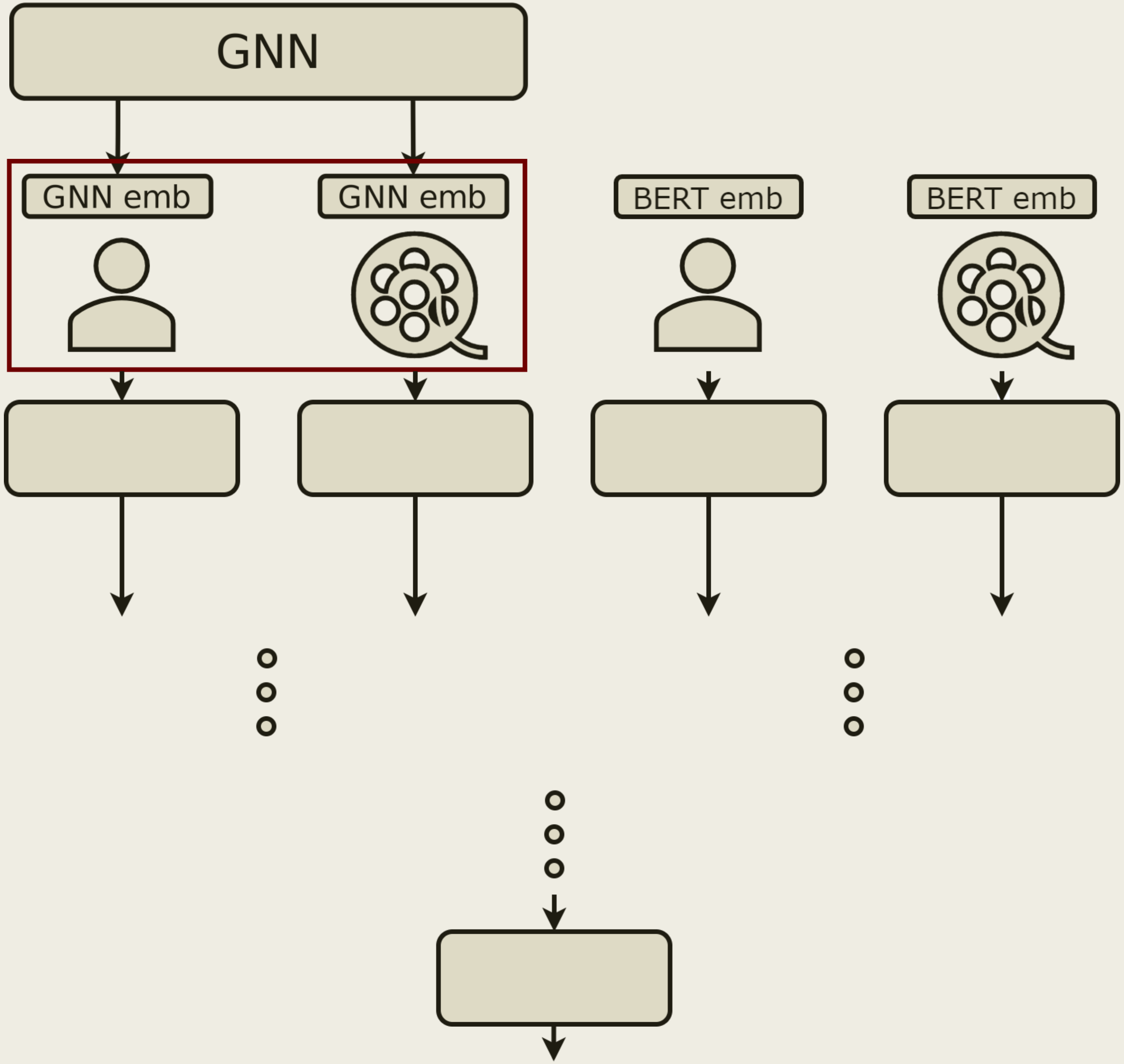


PREVIOUS WORKS
DEEP AMAR
REVISITED
EXTENDED




KG emb
KG emb
BERT emb
BERT emb

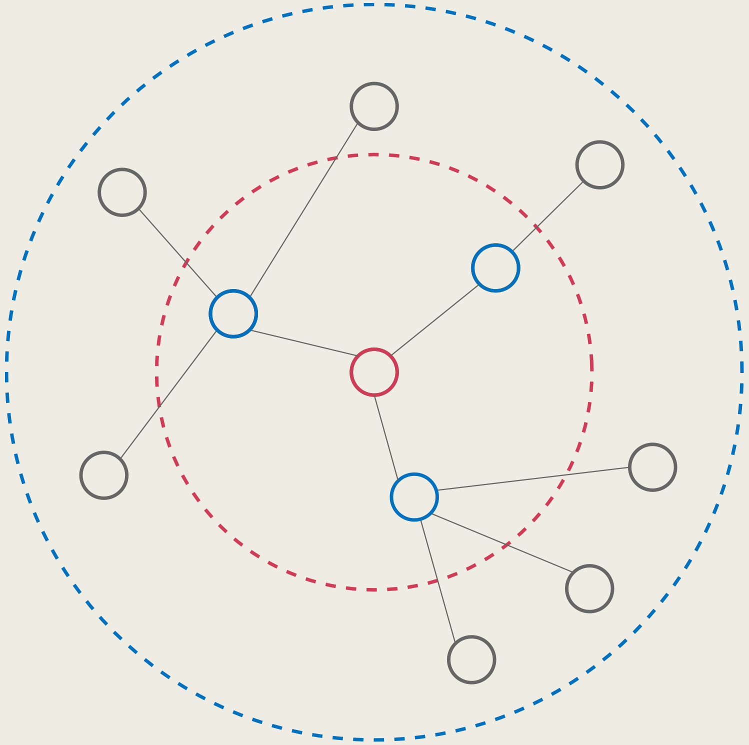

BERT emb
BERT emb


GNN
GNN emb
GNN emb
BERT emb
BERT emb

Graph Neural Networks

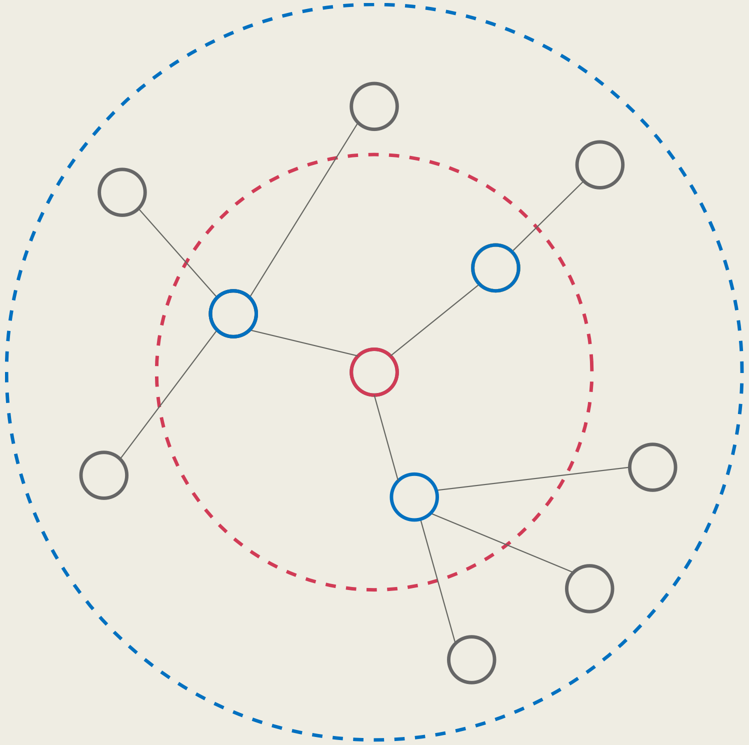
- Neural Network which directly operates on **graph data**
- Neighborhood aggregation as most important operation
- Able to catch higher order interactions
  - *Stacking multiple layers*

$$\mathrm{H}^{(l+1)} = F\left(\mathrm{H}^{l}, \mathrm{X}\right)$$



Graph Neural Networks

- Graph Convolutional Networks (GCNs)
- GraphSage (SAmple and aggreGatE)
- Graph Attention Networks (GATs)
- Gated Graph Neural Networks
  (for sequential recommendation)
- … and several others!

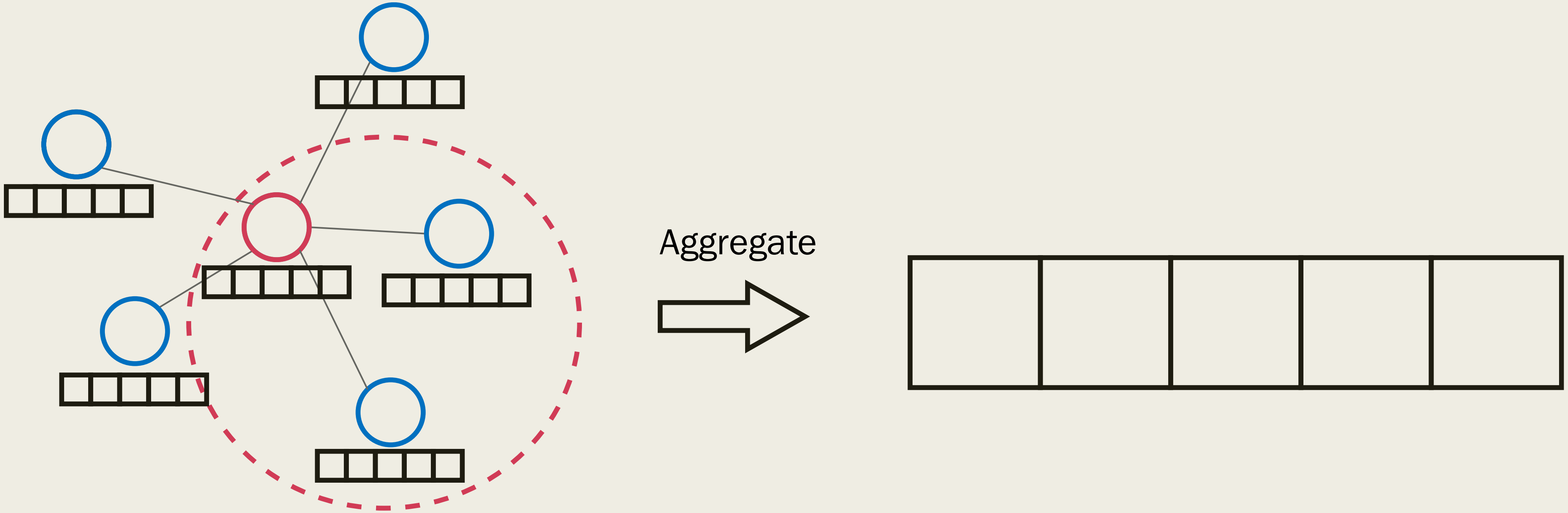


Graph Convolutional Networks (GCNs)

- Preprocess the **adjacency matrix** to be a symmetrically normalized Laplacian matrix
- Neighbors' features are weighted equally
- A non-linear transformation using a weight matrix is then applied
- LightGCN: the same as for GCN, but without the non-linear transformation
  → less parameters and more efficient

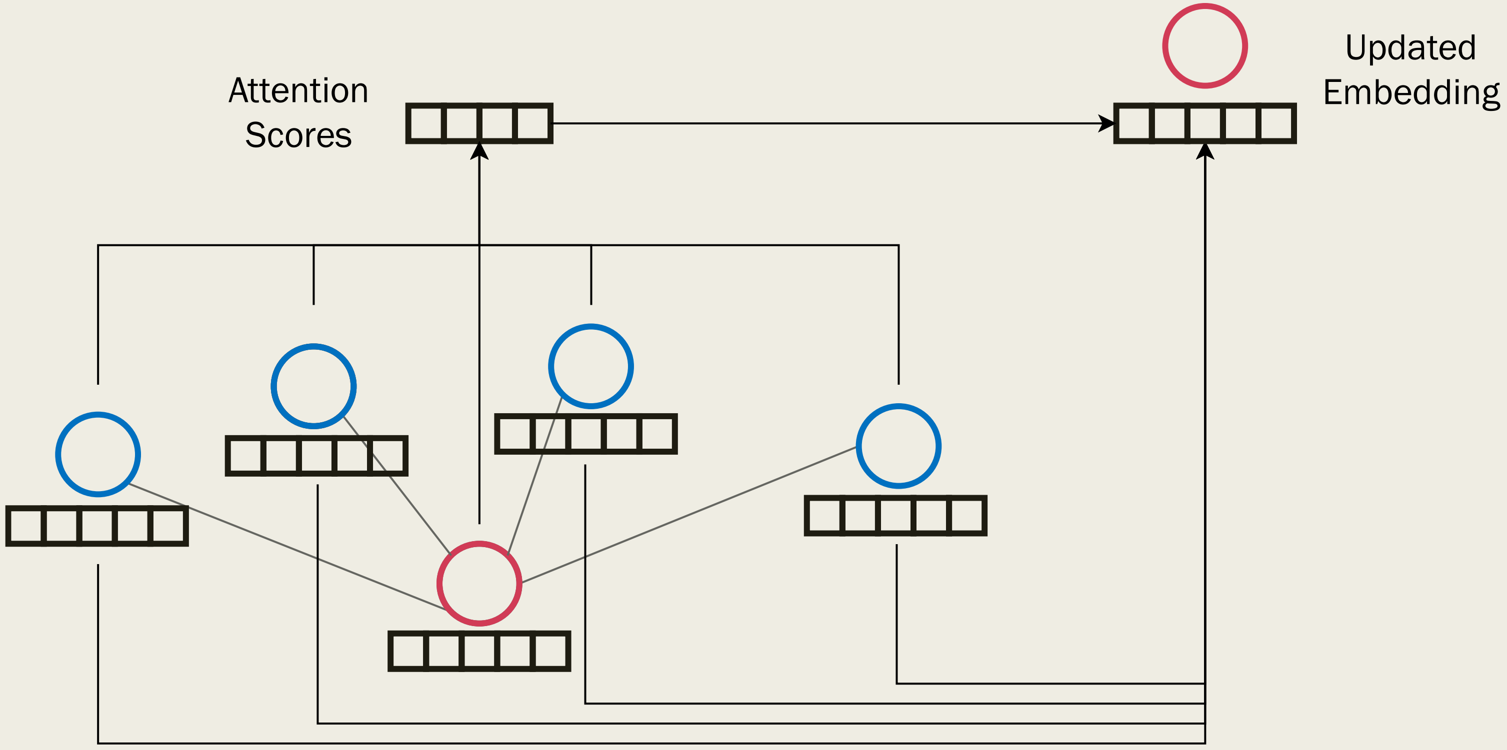
Graph SAGE (SAmple and aggreGatE)

- Sample neighbors
- Aggregates (mean, sum, pooling)
- Multiply with Weight Matrix
- Activation Function



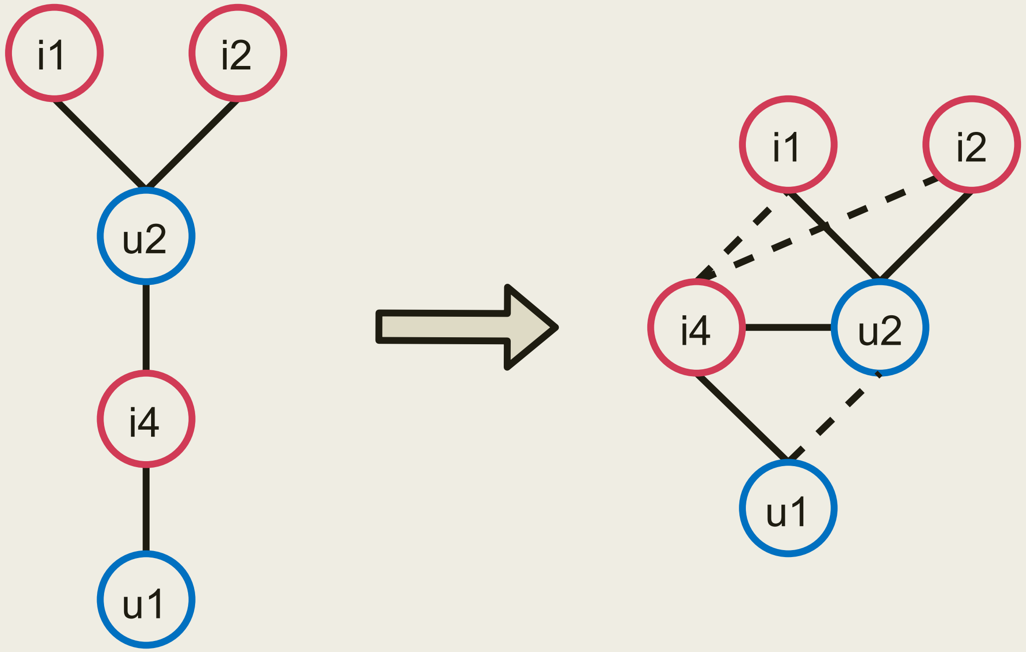
Graph Attention Network (GAT)

- The neighbors' features are weighted differently, by using an attention mechanism
- The **aggregated features** are then passed through a non-linear transformation



Deoscillated Graph Collaborative Filtering (DGCF)

- Try to avoid the «Oscillation problem»
  - *Cross-hop matrix*
  - *Laplacian normalization*
    - High-Pass Filter
- BPRLoss
  - *Maximizes distance between positives and negatives item relevance scores*
- Locality-Adaptive Weights
  - *Weights each node*



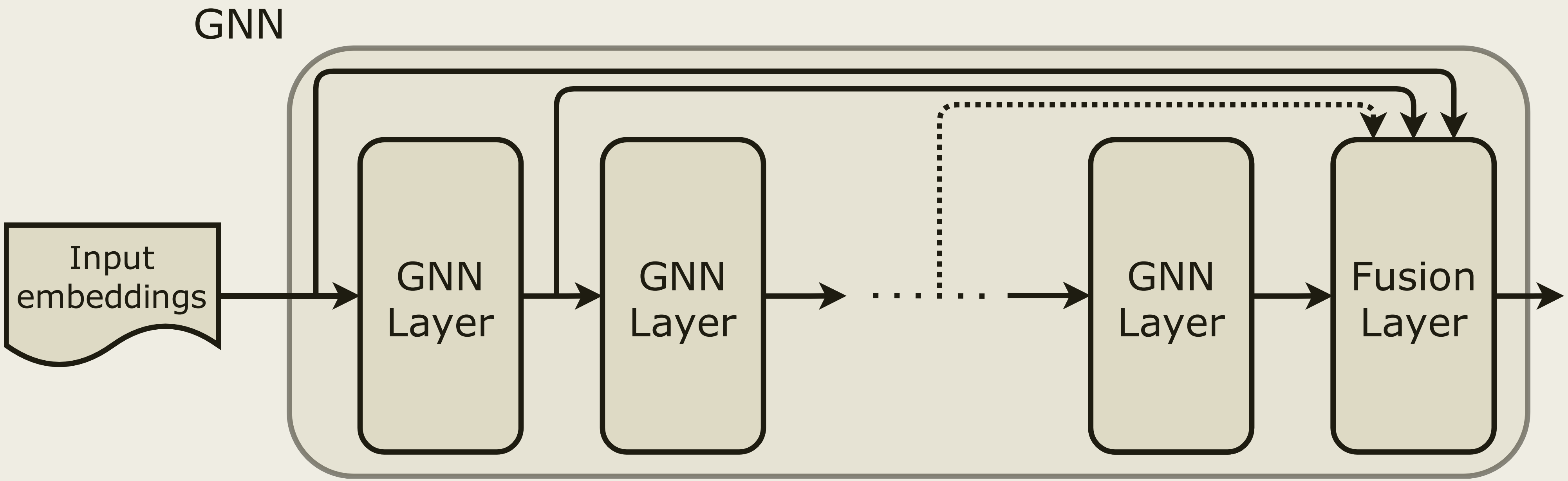
Adding cross-hop connections example

The Oversmoothing Problem

- With a relatively high number of GNN layers, nodes have approximately the same higher order neighbors in common
- The learned embeddings of nodes will be very similar, hence not permitting to effectively differentiate the nodes
- A simple solution is to limit the number of GNN layers

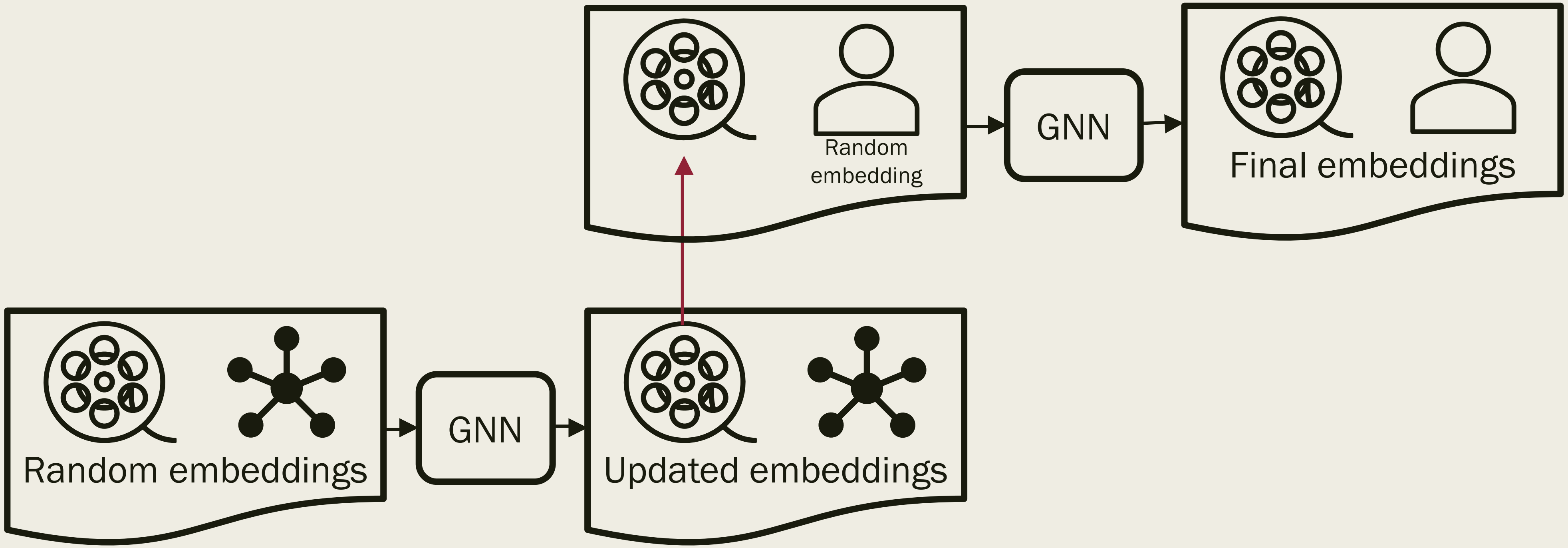
General GNN architecture

- Input embeddings: given or random
- Fusion layer: concatenation / mean / sum / etc...

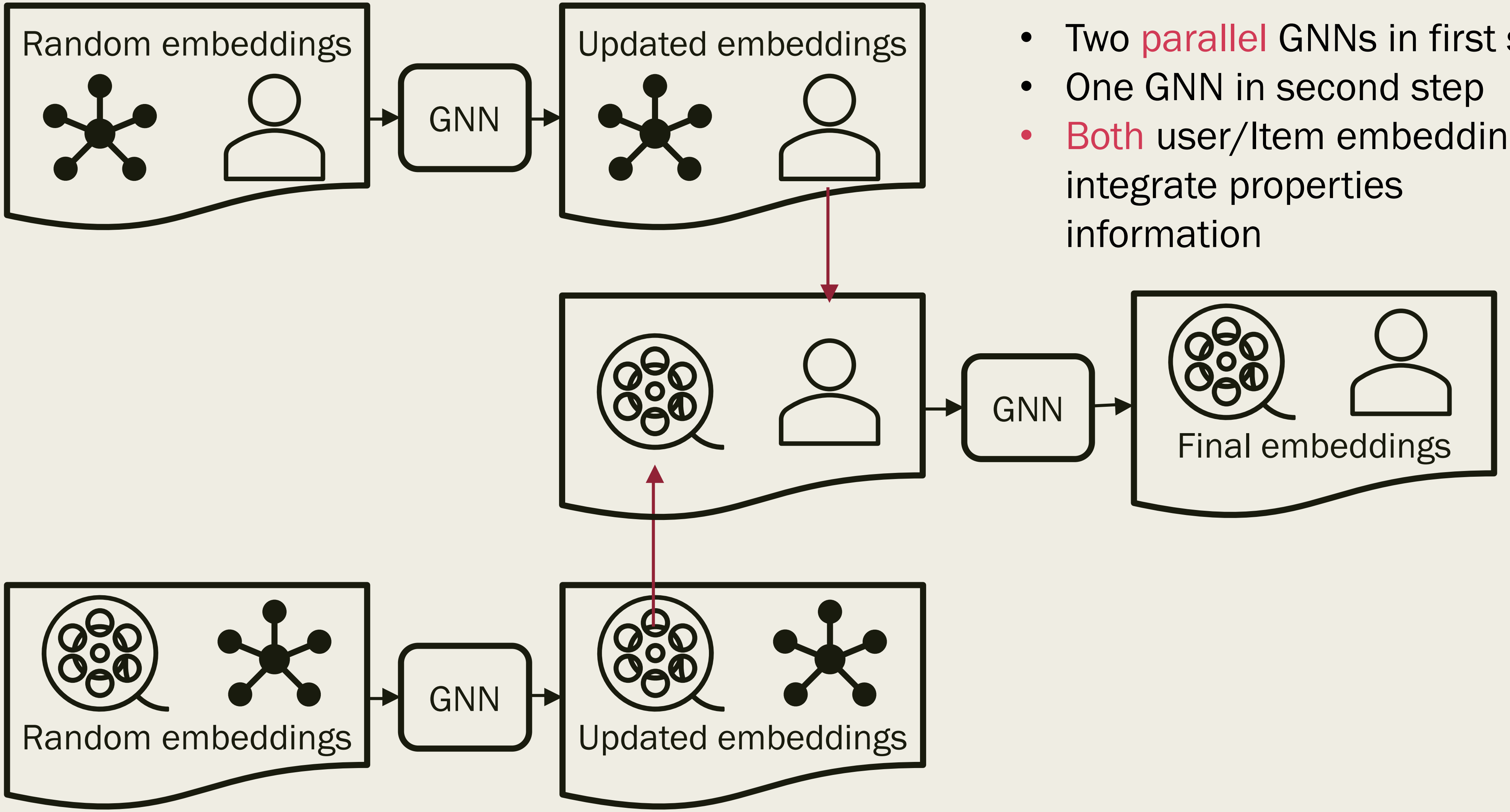


Two-Step GNN

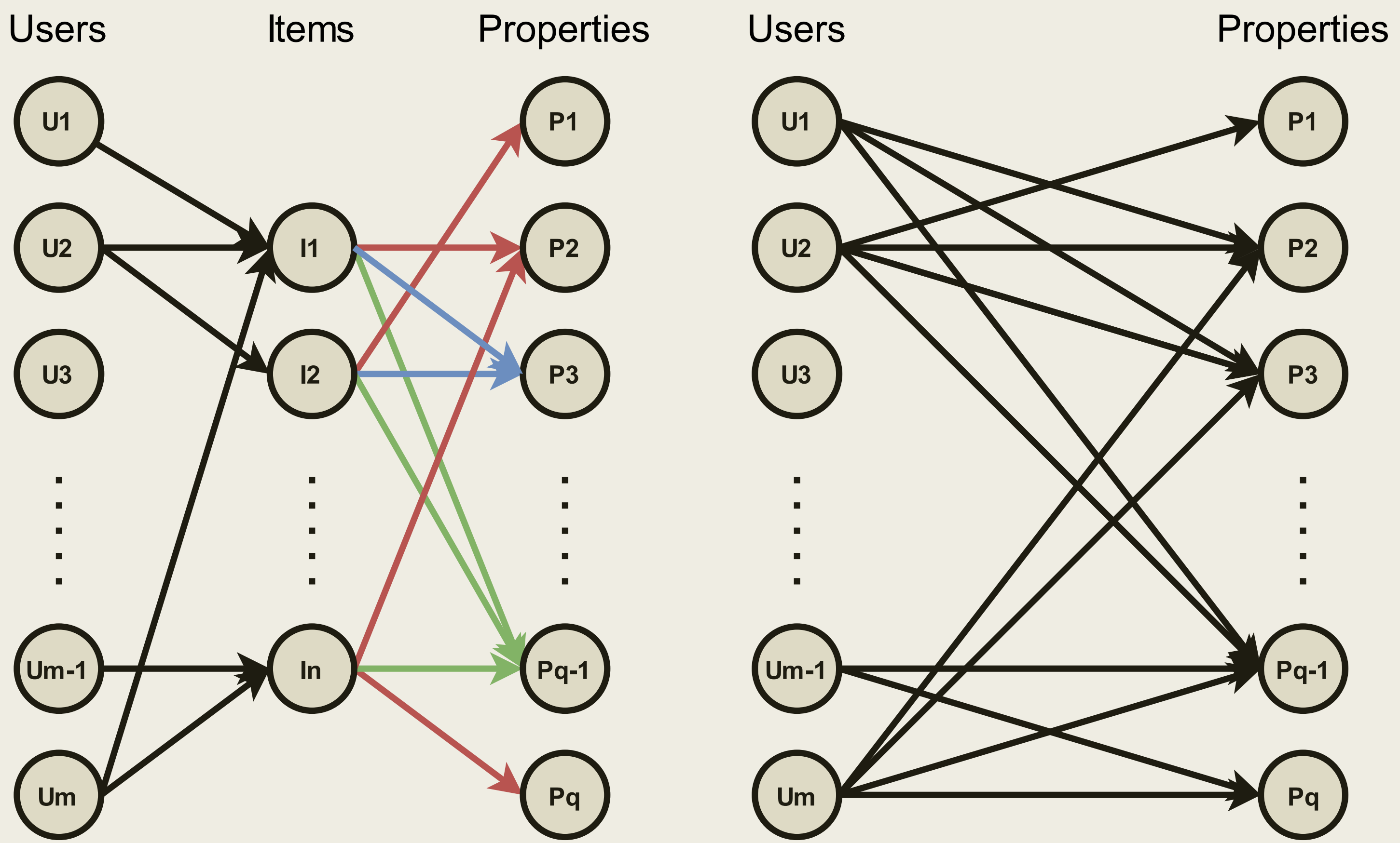
- Two sequential GNNs
- Item embeddings integrate properties information



Two-Way GNN

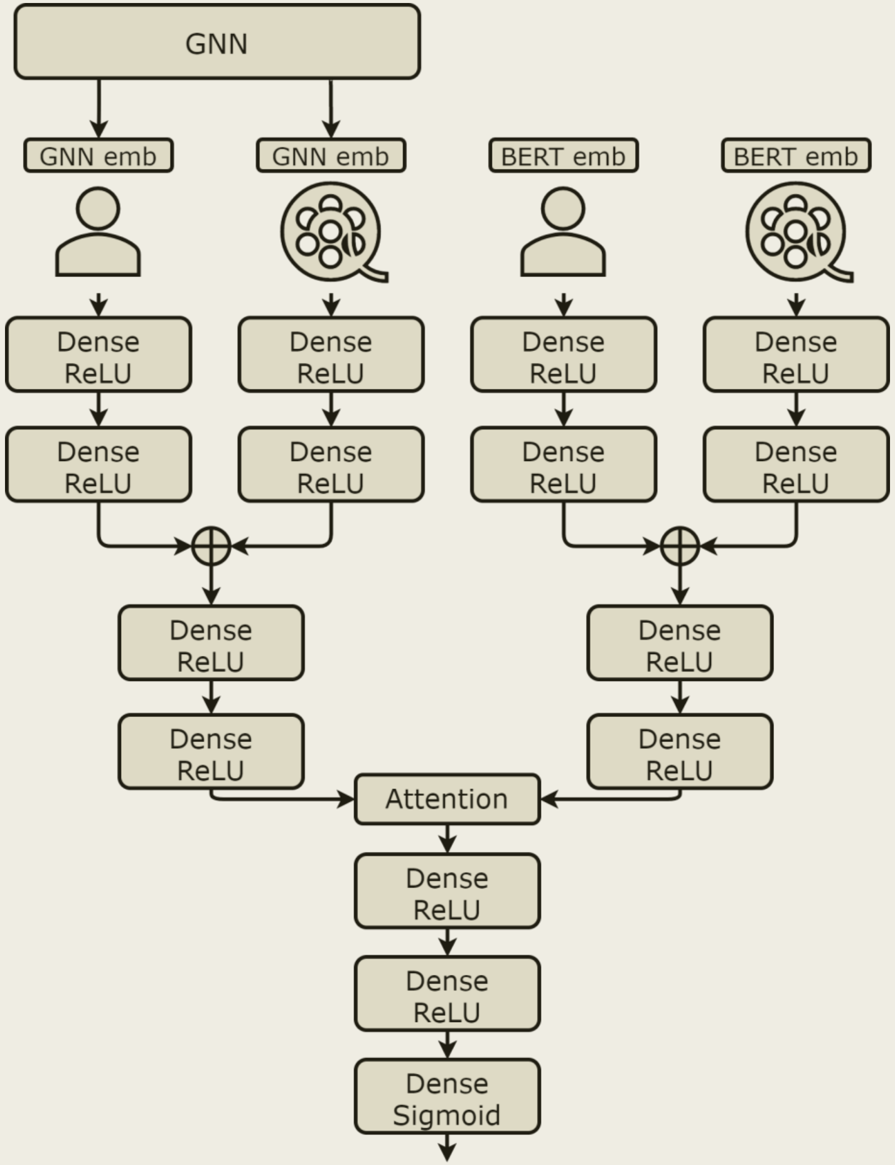


- Two parallel GNNs in first step
- One GNN in second step
- Both user/Item embeddings integrate properties information



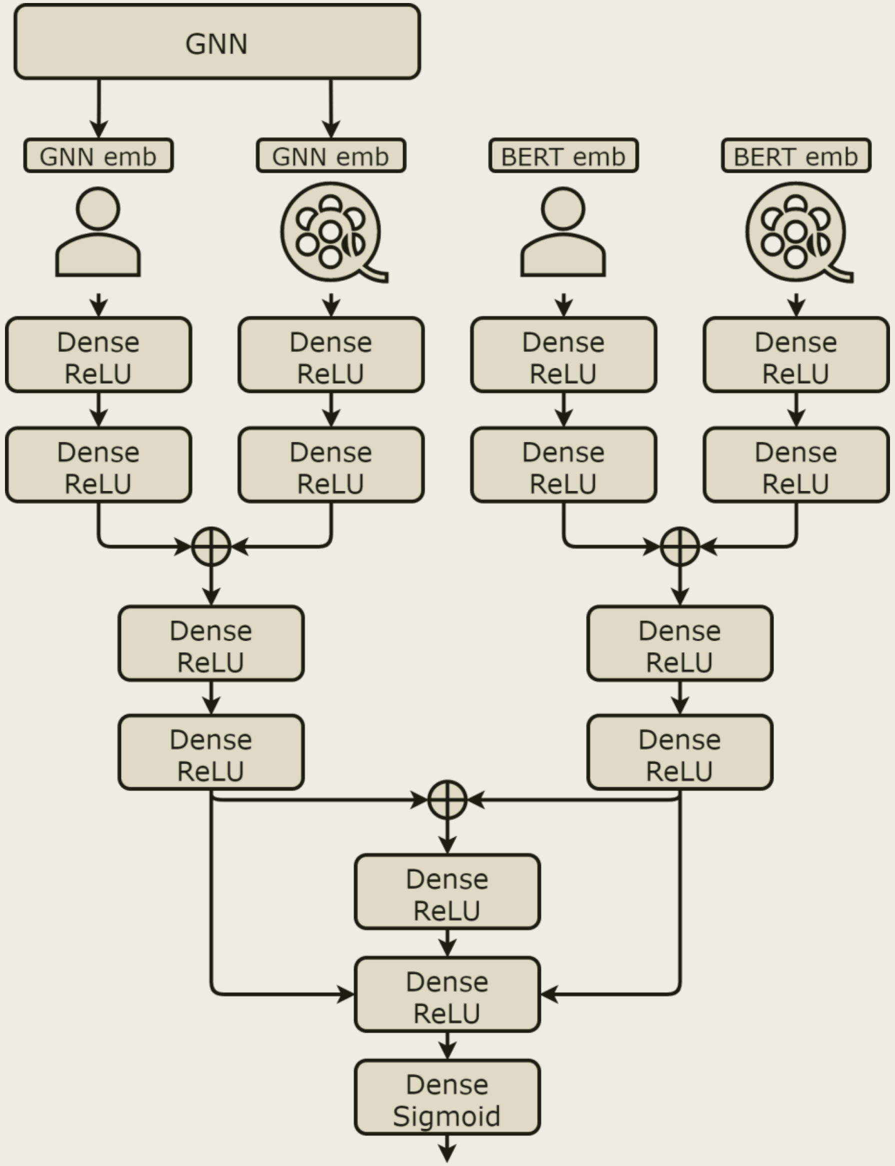
User-Properties Graph

- Dereification of items
- Outdegree of Resulting graph is the product of User-Items and Item-Properties
  - *Adjacency matrix is less sparse*



Hybrid Architecture Tweaks

- Attention layer instead of concatenation



Hybrid Architecture Tweaks

- Residual connection of embeddings before concatenation

Experiments

The Dataset

- Movielens-1M with user-item **positive** and **negative** ratings
- Two item-properties relations settings:
  - **RS1** {*subject, director, starring, writer, language, editing, narrator*}
  - **RS2** {*subject, director, starring, writer, language, editing, cinematography, musicComposer, country, producer, basedOn*}
- The item-properties adjacency matrix is **way sparser** than the user-item one

Experiments

Grid Search

- **Basic** architecture with GNNs

BasicRS	Reduce
GCN	Concatenate
GraphSage	Average
GAT	Concatenate
LightGCN	Concatenate
DGCF	Average

X

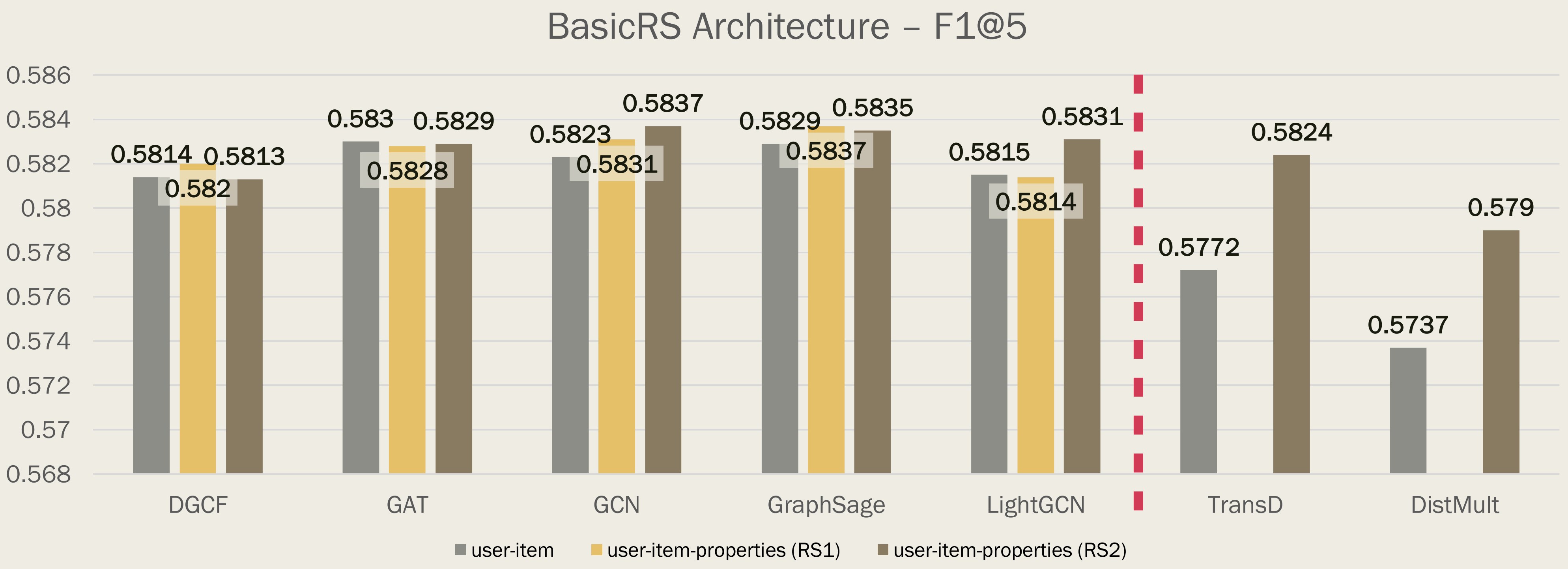
Dense Units	Channels	# Layers
(24, 24)	8	2
(32, 32)	8	3
(48, 48)	16	2
(64, 64)	16	3
(96, 48)	32	2
(128, 64)	32	3

X

L_2 Reg.
10^{-5}
10^{-4}
10^{-3}

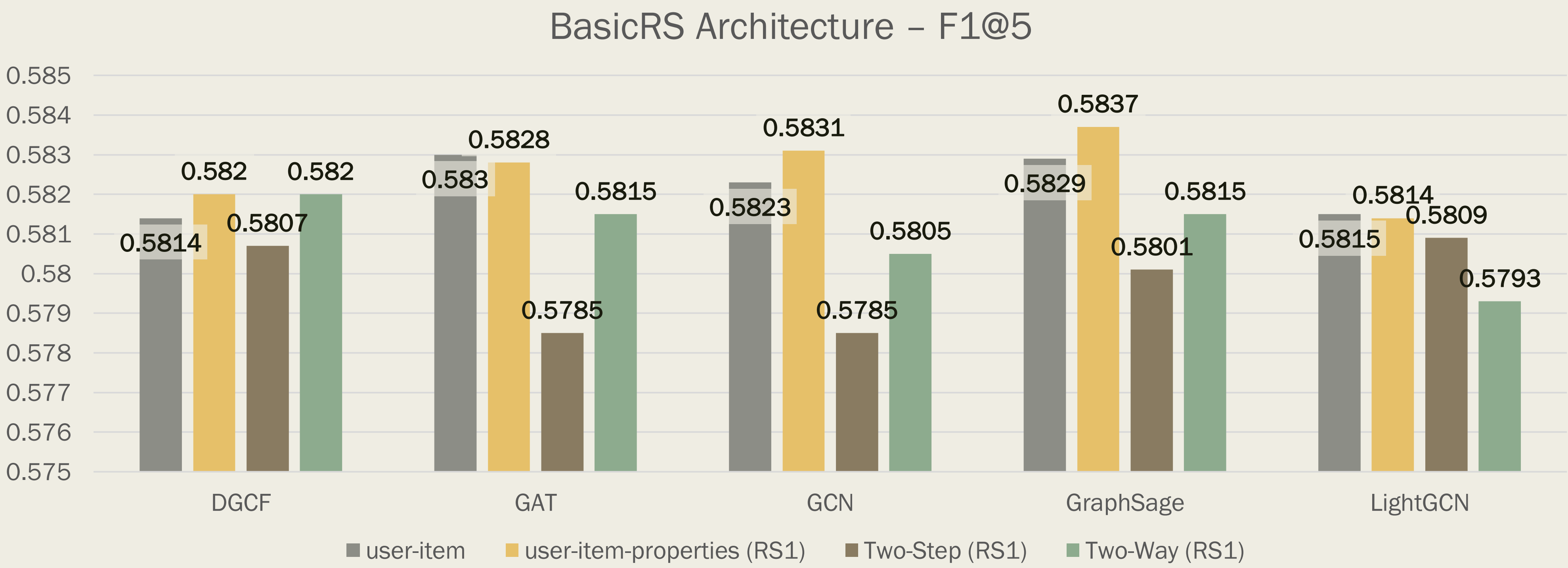
Experiments

Results - GNN / KGE comparison



Experiments

Results – UI GNN / UIP GNN / Two-Step / Two-Way comparison



Experiments

Grid Search

- **Feature-based Hybrid** architecture with GNNs

HybridCBRS	Reduce
GCN	Concatenate
GraphSage	Average
GAT	Concatenate
LightGCN	Concatenate
DGCF	Average

X

Dense Units	Channels	# Layers
(24, 24)	8	2
(32, 32)	8	3
(48, 48)	16	2
(64, 64)	16	3
(96, 96)	32	2
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X

L_2 Reg.
10^{-5}
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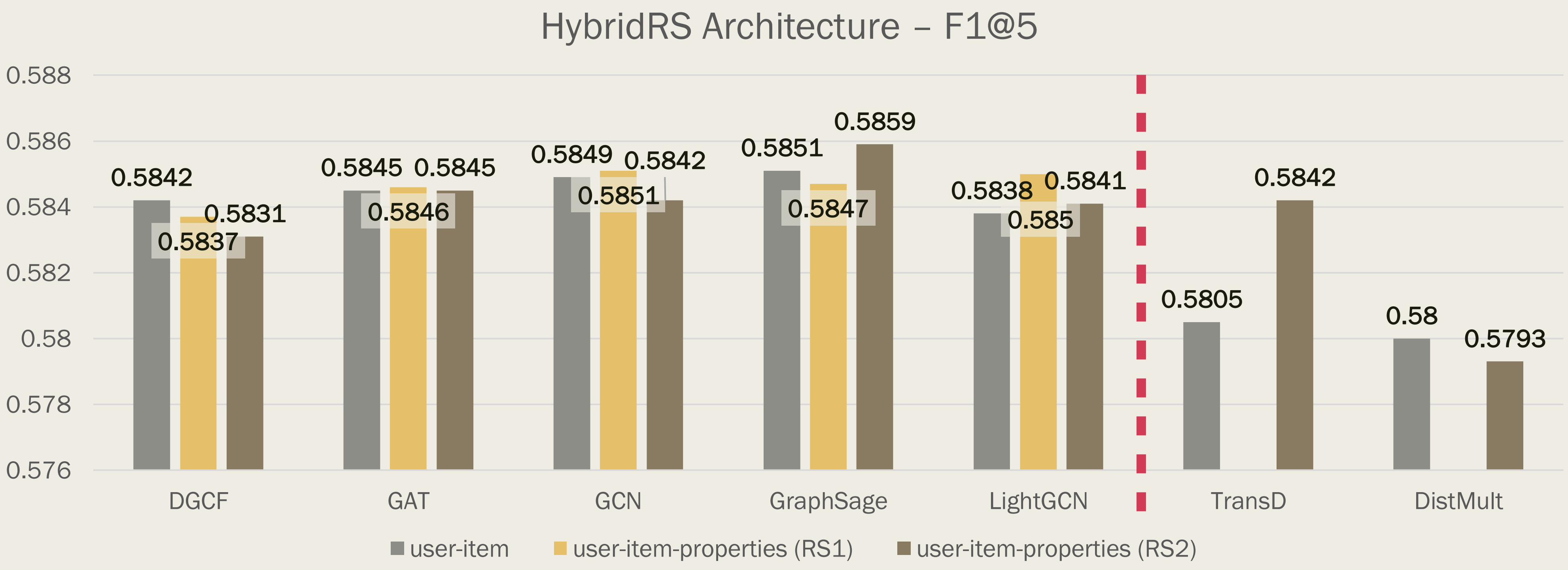
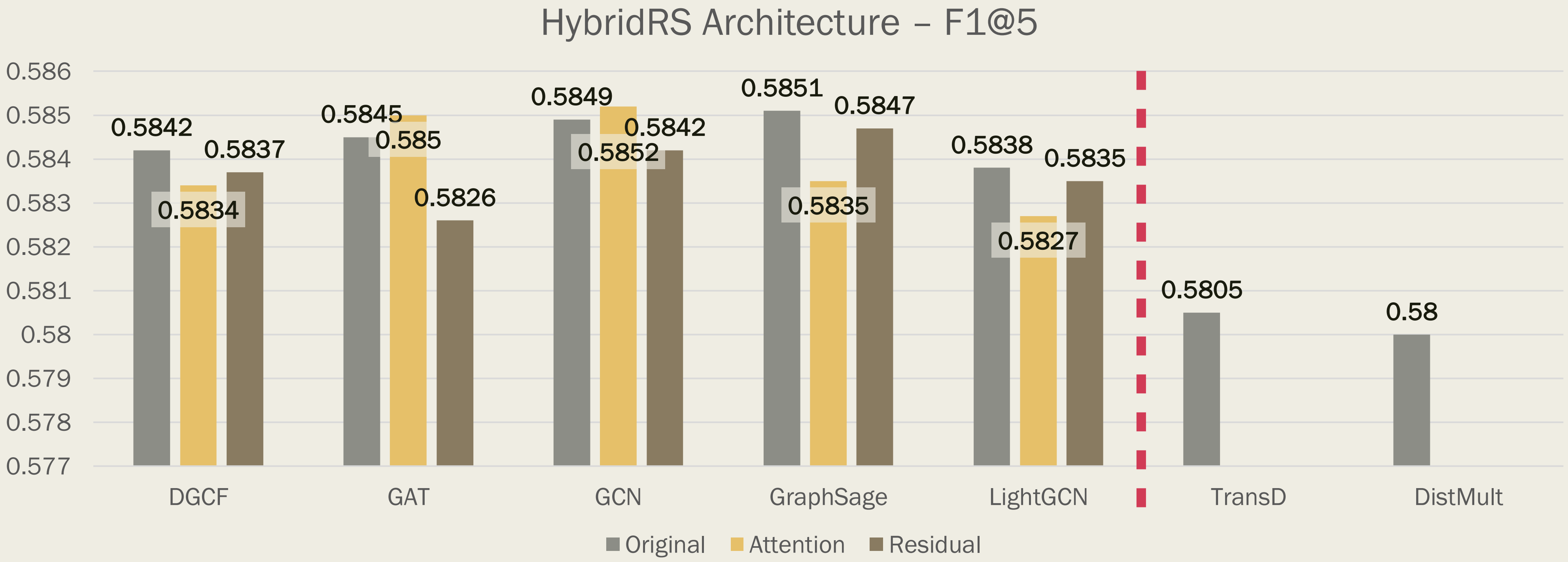
Experiments

Results - GNN / KGE comparison



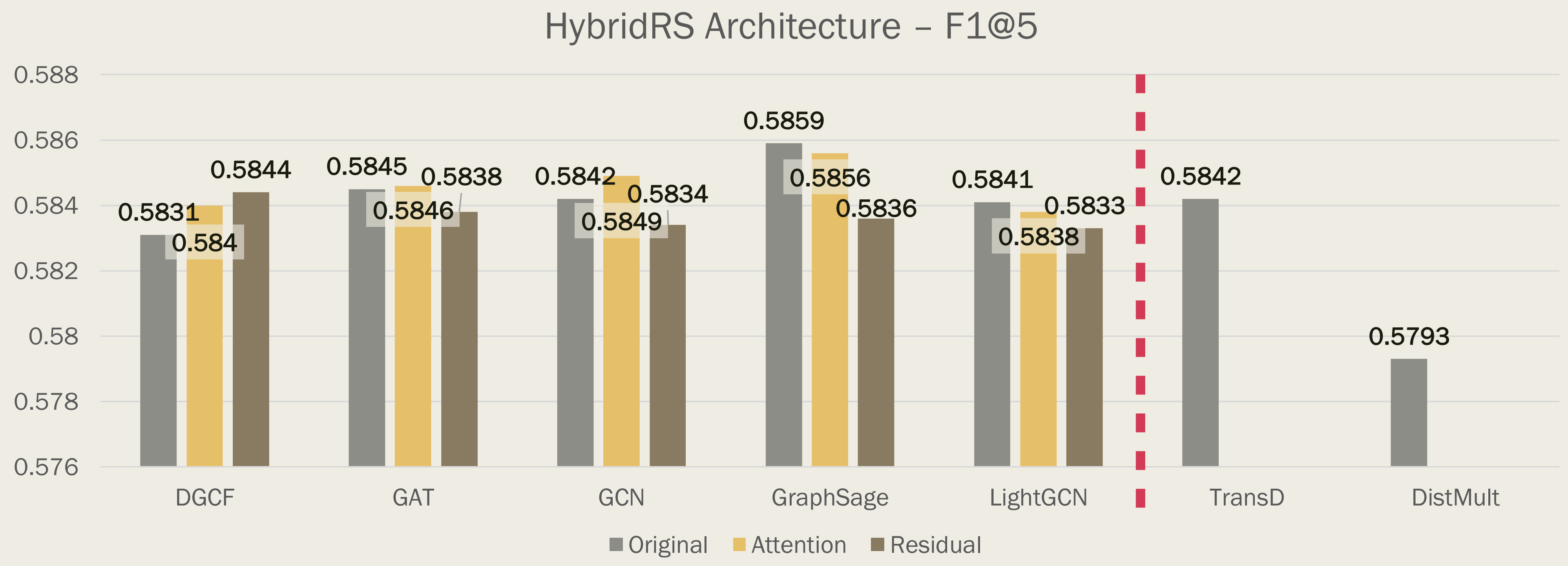
Experiments

Results – User-Item - Original / Tweaks comparison



Experiments

Results – User-Item-Properties (RS2) - Original / Tweaks comparison



Conclusion

- Graph Neural Networks are good for **graph data** applied to recommendation tasks
- The learned embeddings are more **expressive**, with way less parameters
- It is possible to learn models in an end-to-end fashion

Future Works

- Evaluate such models on more datasets with a richer set of properties
- Introduce a transformer-based model to learn items' content embeddings **jointly** with the rest of the model