Using graph models with relational information in recommender systems has shown promising results. Yet, most methods are transductive, i.e., they are based on dimensionality reduction architectures. Hence, they require heavy retraining every time new items or users are added. Conversely, inductive methods promise to solve these issues. Nonetheless, all inductive methods rely only on interactions, making recommendations for users with few interactions sub-optimal and even impossible for new items. Therefore, we focus on inductive methods able to also exploit knowledge graphs (KGs). In this work, we propose SimpleRec, a strong baseline that uses a graph neural network and a KG to provide better recommendations than related inductive methods for new users and items. We show that it is unnecessary to create complex model architectures for user representations, but it is enough to allow users to be represented by the few ratings they provide and the indirect connections among them without any user metadata. As a result, we re-evaluate state-of-the-art methods, identify better evaluation protocols, highlight unwarranted conclusions from previous proposals, and showcase a novel, stronger baseline for this task.

1 INTRODUCTION

Many Recommender Systems (RSs) identify user preference patterns assuming that users with similar past behavior have similar preferences, e.g., users that watch the same movies are likely to do so also in the future; this approach is commonly referred to as Collaborate Filtering (CF) [2, 6, 7, 18, 26]. Usually, this translates to embedding users and items into a low-dimensional space, where the representation of a user is similar to the representations of the items that are more likely to be relevant to them. Yet, many existing methods only work in a transductive setting, where it is assumed that all users and items have been seen during training [4, 34]. In contrast, in an inductive setting, users and items exist that are not in the training set. The method should be able to provide predictions on these users and items when information about them is acquired. This is typical in real-world online recommendation scenarios where users and items are continuously added. An inductive method therefore does not require retraining each time a new user, item, or rating is added to the system like transductive methods do; instead, it can immediately reason about the newly added information and update its predictions.

However, current inductive methods [24, 29, 32–35] only use interaction data, such as ratings, making them unable to handle situations where this type of data is sparse, e.g., long-tail users and items. Instead, including Knowledge Graph (KG) information would allow to handle long-tail users and items. Hence, we propose SimpleRec, a new simple-yet-powerful architecture that uses KG information to handle long-tail users and items when information about them is acquired. This is typical in real-world online recommendation scenarios where users and items are continuously added. An inductive method therefore does not require retraining each time a new user, item, or rating is added to the system like transductive methods do; instead, it can immediately reason about the newly added information and update its predictions.

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Table 1: Related methods, whether they use User Metadata, whether they handle Relational information (i.e., KG), the Task they support among (C) Node Classification, (R) Ranking, and (P) Rating Prediction, and whether the method constructs a Subgraph from user-item pairs.

| Model      | Inductive User | Inductive Item | User Metadata | Relational Task | KG | Subgraph |
|------------|----------------|----------------|---------------|-----------------|----|----------|
| NCAT [26]  | ✗              | ✗              | ✗             | ✗               | ✔  | ✗        |
| KGAT [25]  | ✗              | ✗              | ✗             | ✗               | ✔  | ✗        |
| KPRN [27]  | ✗              | ✗              | ✗             | ✗               | ✔  | ✗        |
| MeLU [12]  | ✗              | ✗              | ✗             | ✗               | ✔  | ✗        |
| LGCN [6]   | ✗              | ✗              | ✗             | ✗               | ✔  | ✗        |
| GraphSAGE [4] | ✗              | ✗              | ✗             | ✗               | ✔  | ✗        |
| PinSAGE [32] | ✗              | ✗              | ✗             | ✗               | ✔  | ✗        |
| IGMC [35]  | ✗              | ✗              | ✗             | ✗               | ✔  | ✗        |
| IDCF [29]  | ✗              | ✗              | ✗             | ✗               | ✔  | ✗        |
| PGD [24]   | ✗              | ✗              | ✗             | ✗               | ✔  | ✗        |
| ICP [34]   | ✗              | ✗              | ✗             | ✗               | ✔  | ✗        |
| GIMC [33]  | ✗              | ✗              | ✗             | ✗               | ✔  | ✗        |
| SimpleRec  | ✗              | ✗              | ✗             | ✗               | ✔  | ✗        |

The evaluation suite and re-implemented state-of-the-art methods at https://anonymous.4open.science/r/SimpleRec-DB4F. Finally, we present our evaluation methodology, overcoming existing issues, as well as the promising performances of our new proposed baseline.

2 COLLABORATIVE KNOWLEDGE GRAPHS

A KG is a heterogeneous graph \( G : (\mathcal{V}, \mathcal{E}) \) representing entities as vertices (also nodes) \( \mathcal{V} \) and the semantic relations connecting them as labeled edges \( \mathcal{E} : \mathcal{V} \times \mathcal{R} \times \mathcal{V} \), given the relation types \( \mathcal{R} \). In Figure 1, nodes represent recommendable items \( (I \subset \mathcal{V}) \), i.e., movies, and their connected entities \( (N \subset \mathcal{V}) \), e.g., actors, directors, and a taxonomy of genres, s.t. \( N \cap I = \emptyset \). Edges represent how nodes are connected, e.g., the entity “Inception” is connected to the genre “Heist” through the relation “has genre”. Furthermore, we adopt the concept of a Collaborative Knowledge Graph (CKG) [25], i.e., a knowledge graph augmented with users’ \( (U \subset \mathcal{V}) \) and user interactions, e.g., (Max, likes, Don Jon). We note that linking nodes in a KG also gives access to additional information that can be attached to nodes, e.g., encyclopedic texts about entities or product descriptions for items. Conversely, we explicitly avoid to assume any additional personal information about users, e.g., age or gender, as this information is usually not available and its storage constitutes more often a liability because of privacy concerns [22].

In practice, we model our task as a top-k recommendation problem. We aim at learning a model that ranks items according to a user’s preferences estimated as \( \hat{y}_{ui} \); i.e., \( \hat{y}_{ui} > \hat{y}_{uj} \), if user \( u \) prefers item \( i \) over \( j \). Furthermore, in line with previous literature [12, 29, 35], we define two types of users: warm-start users \( U_w \) where some interactions are known at training time and cold-start users \( U_c \), for which no interaction is known at training time, but some become known at inference time. Thus, we only assume that entities in the KG itself remain unchanged, and we evaluate methods able to provide recommendation for the cold-start users.

3 RELATED WORK

Most existing recommendation methods are not able to represent nodes that were not present during training and are also limited in handling sparse datasets. First, most models are transductive, i.e., they embed each node in the graph within the same low-dimensionality space [25, 27]. Second, most of them utilize only bipartite graphs of user interactions with items [6, 26, 32]. Instead, inductive learning models generate predictions for unseen nodes by directly reasoning over the features that describe them. Here, we provide an overview of inductive methods, detailing their limitations as compared to our proposal (as summarized in Table 1).

GraphSAGE [4] was the first inductive Graph Neural Network (GNN) able to efficiently generate embeddings for unseen nodes by leveraging node features, e.g., textual attributes. It was later modified for the recommendation task in PinSAGE [32], also using MapReduce to scale the computation. Unfortunately, PinSAGE was designed for item-item recommendations, i.e., assuming we have boards of items and want to add a new item to a board. The method therefore does not explicitly handle user-item ratings but assumes that items closer in an embedding space will be rated similarly.

Other methods have been proposed for inductive matrix completion [8, 30], most recently IGMC [35] and GIMC [33], which extract subgraphs around each user-item pair to obtain the necessary representations, passing such sub-graphs through multiple layers of a GNN. These approaches are designed for the single rating-prediction task and not for the ranking task. Generating these sub-graphs is prohibitively space- and time-consuming. Thus, they cannot efficiently produce user-item ratings, since a sub-graph is generated for all user-item pairs\(^2\). Furthermore, these methods do not use KG information; thus, they cannot provide predictions for new items with no interactions. Therefore, instead of constructing subgraphs, we employ subsampling of neighboring nodes to obtain a scalable prediction mechanism [4, 32] and we use KGs to gain information also about items with few user interactions.

Some methods, e.g., PDG [24] and MeLU [12], exploit instead user metadata, e.g., gender and age information. Yet, this information is rarely available, making it impossible to use these methods in almost all cases\(^3\). Moreover, MeLU [12] retrains the model for each user, which is not scalable. Hence, in our method, we assume no user metadata, learning instead how to aggregate information.

Related works therefore either: (i) create subgraphs, which do not scale in the ranking task; (ii) use personal user data, which is almost never available; or (iii) predict a single user rating, which under-performs in the ranking task, even compared to non-personalized methods [2]. Hence, (Table 1) only GraphSAGE [4], PinSAGE [32] and IDCF [29] are feasible methods to recommend for users that have not been seen during training, but they do not exploit KGs. Thus, we are the first to propose a scalable inductive method for user-personalized recommendation that learns to extract knowledge from a KG while not requiring any user metadata.

4 INDUCTIVE RELATIONAL GNN FOR RECOMMENDATION

We now present our architecture Simple and strong inductive baseline for Recommendation (SimpleRec), which is able to generate node vector representations for recommendation in an inductive manner for both users and items using a CKG without any user metadata. The model consists of three components: (i) an embedding layer,
where we compress node feature information to create node embeddings (see Figure 2 A); (ii) a gated propagation layer, which chooses which information to propagate from the embeddings of neighboring nodes in a KG (see Figure 2 C); and (iii) a prediction layer, which uses the output of all propagation layers to create a user and an item embedding, producing a ranking score (see Figure 2 D).

**Embedding.** As for other methods exploiting KGs [4, 32], we assume most items and connected entities have textual information and employ node embedding techniques and node degrees as initial features. We use a pre-trained version of Sentence-BERT [17] to process the textual description of each entity and produce sentence embeddings. Nonetheless, when the non-recommendable entities \( N \) are missing textual information, we can still learn their embeddings using Knowledge Graph Embedding (KGE) methods, since these entities are static (i.e., the KG excluding user and items, is not bound to change often). Specifically, we use ComplEx [21], trained with all triples in the KG, where we limit the output embeddings to be only on connected entities \( N \), while items \( I \) are always represented using textual descriptions. Thus, we do not need retraining if new users or items are added. Yet, the initial features are too large (\( d \geq 756 \)) for the subsequent layers leading to out of memory errors and very slow training times. The dimensionality therefore has to be reduced before being passed to the GNN layers. Hence, we introduce an AutoEncoder (AE) layer to reduce dimensionality [10]. The loss of the AE is defined as:

\[
L_{AE} = \text{MSE}\left(\hat{X}, \text{AE}_e(X)\right)
\]

where \( \text{AE}_e: \mathbb{R}^{|N| \times d} \rightarrow \mathbb{R}^{|N| \times d'} \), with \( d' \ll d \), is the encoding function mapping the initial feature vector for each node to a set of lower dimensionality vectors. We define an AE for each embedding type, i.e., one for textual embeddings and one for KGE, converting the embeddings into a shared embedding space. The output of the encoder is used as the input for the GNNs (see Figure 2 B).

**Propagation.** We apply multiple layers of GNNs [4, 32]. Yet, existing inductive GNN are not designed to use relational information. We therefore define relational gates as:

\[
e_{Nh}^{(l+1)} = \frac{1}{|\mathcal{F}_h|} \sum_{(h,r,t) \in \mathcal{F}_h} g^{(l+1)}(h,r,t)e_t^{(l)}
\]

where \( \mathcal{F}_h \) defines the ego-network of node \( h \in V \), \( g \) is the gating function, and \( e_t^{(l)} \in \mathbb{R}^{d(l)} \) is the embedding of node \( t \in V \). During the first graph convolution \( d^{(0)} = d' \), i.e., the output dimensionality of the AE. In contrast to other gated networks (e.g., MGAT [20] and GGCN [14]), our model’s gates are relation-specific, allowing it to propagate different information from different parts of an entity’s embedding based on the relation to it [8]. Hence, our gate is \( g^{(l+1)}(h,r,t) = \sigma(W_r^{(l+1)}e_h^{(l)}||e_t^{(l)}) \), with the sigmoid activation function \( \sigma \), the concatenation operator \( || \), and \( W_r^{(l+1)} \in \mathbb{R}^{d(l) \times 2d(l)} \).

The final part combines an entity’s current embedding \( e_h^{(l)} \) with the aggregated ego-network embedding \( e_{Nh}^{(l+1)} \), defined as \( e_h^{(l+1)} = f(e_h^{(l)}, e_{Nh}^{(l+1)}) \), where \( f \) is an aggregator function. Among recent aggregators [4, 9, 25], we identified the best performance with \( f(e_h^{(l)}, e_{Nh}^{(l+1)}) = e_{Nh}^{(l+1)} \) [6]. We refer to Appendix A for the formal definition of the aggregators.

**Prediction.** As in previous approaches [9, 20, 25], we concatenate the output after each layer for a user and an item as: \( e_u^{(l)} = e_u^{(l)} || \ldots || e_u^{(l)} \) and \( e_i^{(l)} = e_i^{(l)} || \ldots || e_i^{(l)} \) efficiently obtaining the final prediction via dot-product as \( \hat{y}_{ui} = e_u^{(l)}e_i^{(l)}^\top \), which usually outperforms learned, non-linear, similarities [19].

**Optimization.** The final loss function is a combination of autoencoder loss in Equation 1 and the Bayesian Personalized Ranking (BPR) loss [6, 18, 20, 25], s.t. we learn to encode an embedding suitable for ranking while maintaining the information of the original features, computed as: \( L = L_{BPR} + \lambda L_{AE} + \gamma \| \Theta \|_2^2 \), where \( \lambda \) and \( \gamma \) are tuned during hyperparameter optimization and \( \Theta \) are the learnable parameters. We study the effects of the AE loss in Appendix B.

**Scalability.** Our embedding approach, calculating the aggregation (\( e_h^{(l+1)} \)), and the prediction (\( \hat{y} \)) are all bounded by the number of nodes.

See Appendix B for the gating mechanism related improvements.
in the graph, while the calculation of the ego-network \( (e^{(I+1)}) \) is bounded by the number of edges. As these steps are applied sequentially and \(|V| \ll |E|\), we know that the complexity of our method is bounded by the ego-network aggregation complexity, more specifically, the linear transformation of the gate calculation. When naïvely applying the gates over all edges, the complexity is \( O(|E|d) \), where \( d \) is the largest dimension utilized during graph convolutions. Yet, as \( W_r e_1 + W_e e_2 \) we only need to compute the transformation for each unique \((h, r)\) and \((r, t)\) pair instead of each unique \((h, r, t)\) triple. Therefore, we can apply a MapReduce computation [32] to have at most \( 2(|V||R|) \) calculations, leading to the complexity \( O(|V||R||d|) \ll O(|E|d) \).

As our prediction is a dot product after graph convolutions, our method can predict in \( O(e^{(I+1)}|I|) \) for a single user as the vector dot product complexity is \( O(e^{(1)}|I|) \), which we do \(|I| \) number of times. This is less than PinSAGE, which requires the dot product between all items and the user’s rated items, s.t. \( (|I|^2) \) = \( O(|I|^2) \) for a worst-case where a user has rated half the entities and we want to rank the other half. Our prediction is less computationally complex, as the reduced dimension, even when taking the number of layers into account as \( d \times L \ll |I| \), is far less than the number of items.

## 5 EXPERIMENTS

Inductive approaches are designed to provide recommendations in a cold-start setting, where ratings for new users are only known at inference time. Yet, as we will show, these baselines do not perform in this setting due to poor selection of learning metrics, evaluation methodologies, or other complexities. In the following, we aim at answering the questions: RQ1 Are existing inductive approaches really competitive when compared to SimpleRec? RQ2 Why do other architectures under-perform? and, RQ3 What negative item sampling strategy is the most appropriate for the evaluation?

**Datasets.** To evaluate existing methods, we adopt two real-world datasets: (i) MovieLens-20m (ML-20m) [5], a dataset with ratings on movies and (ii) Amazon-Book (2014) (AB) [15], a dataset with reviews on books. Neither dataset has an associated KG. We therefore use the MindReader KG [1] for the ML-20m dataset, and for the AB dataset the KG constructed to evaluate KGAT [25]. In both cases, we keep only items mapped to the KG. We highlight how some methods compare performances over different versions of the AB dataset, e.g., the 2018 used in IDCF [29] is different from the version used in other works [3, 6, 25, 26]. Since users and items have an average of 39.9 and 22.9 ratings, respectively, on the 2018 dataset, while the users have an average of 12.0 ratings and items
ability to provide high-quality recommendations in the top of a ranked list. Yet, when subsampling negative items, the methods’ relative performance can change, meaning that the best performing method might not provide any or few relevant recommendations when challenged with the complete list of possible items. E.g., we see GraphSAGE outperforms IDCF on I-NDCG in both ML-S+1250 and AB-S+15%, though clearly performing worse in the appropriate NDCG@20. On a different Amazon dataset, the Amazon-Beauty dataset, not reported here for space constraints, when utilizing the faulty I-NDCG, we also found TopPop (not included in the IDCF evaluation) outperforming all methods results (including IDCF) reported in IDCF [29]. However, when using NDCG@20 we see up towards 3x times better performance when utilizing our method, compared to TopPop.

6 CONCLUSION AND FUTURE WORK

In this work, we propose a simple and strong baseline for inductive recommendation. Our goal was to demonstrate the feasibility and advantages of this kind of architecture when compared to other inductive architectures. In particular, we devise a scalable GNN architecture to perform inductive learning for recommendation, able to utilize high-order connectivities in CKGs. We show that our method can outperform related work and showcase methodological limitations in the evaluation methods used. Overall, we conclude that more attention is needed towards this kind of architecture, especially given their ability to: (1) scale to large graphs and large numbers of users using MapReduce, and (2) maintain good prediction while being simple; i.e., performing no complex sampling methods or non-standard learning steps. Finally, we raise attention to the need for more sound evaluation protocols and for more transparency on the dataset adopted.

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B ABLATION STUDIES

We study the effect of different components and parameters in the cold-start setting. In particular, we investigate the effect of a gating mechanism, the autoencoder and using only a bipartite graph. In both Table 5 and Table 6, bold is the best performing method and "*" signifies statistical significant improvement over the next best performing model. Furthermore we define Cov as

\[
\text{Cov@k} = \frac{\sum_{u \in U} \text{Recommendations} @ k(u)}{|U|}
\]

where Recommendations @ k(u) is the set of the top-k items recommended given to a user u. The naïve TopPop would always have a score of \( \frac{k}{|U|} \) while a random model would recommend all items given enough users, leading to a coverage score of 1. Intuitively, the metric therefore defines the diversity in a methods recommendations without taking the quality of the recommendations into account. We note that it is impossible to calculate statistical significance for coverage as all users have k unique items and therefore does not change between methods.

B.1 Gating mechanism and KG structure

Gates. The results of the method with different gating mechanisms can be seen in Table 6. In the table, ‘w/o relation’ is the gating mechanism without relation type, i.e., a single type shared for all edges, and ‘w/o gates’ is the method without the gating mechanism.

- Overall, the gating mechanism improves performance, as we can adaptively select information from neighboring nodes seeing it outperform the two other models in all metrics.
- Disregarding relation types leads to worse performance on all datasets and completely removing the gates leads to dramatically lower performance.
- The models performance without gates is worse than PinSAGE, though still better than IDCF. Only using the users interactions without a gating mechanism, is therefore still better than the reconstruction using in IDCF.
- Even without relation types, we see large and statistical significant increase in performance. Allowing the model to select information based on itself and its neighbors are therefore very relevant for the models performance.

Effect of the KG. We create a version of the method where it only uses the collaborative graph instead of the CKG, named Bipartite in Table 6.

- We observe that the bipartite model performs very well on the ML-20m dataset, and less so on the AB dataset. The AB dataset is less dense making edges added by the KG more important when clustering users according to their preferences.
- Even with its almost equivalent performance w.r.t. NDCG, the bipartite model lacks diversity. Furthermore, on all datasets, the SimpleRec will outperform the bipartite model on at least one metric with statistical significance. On the AB we see a large difference in the coverage of the model compared to the bipartite model. This is also visible on the ML-20m datasets, though less prevalent.
- Combining the Cov and NDCG metric, we see that using KG information leads to more diverse recommendations without

A AGGREGATORS

In the following we formally define the different aggregators used in the literature that we initially explored in our architecture.

- **GCN aggregator** [9] summing the two vectors and applying a nonlinear transformation:

\[
f_{\text{GCN}} = \text{LeakyReLU}(W(e_h + e_N))
\]

- **GraphSAGE aggregator** [4] concatenating the two vectors before applying a nonlinear transformation:

\[
f_{\text{GS}} = \text{LeakyReLU}(W(e_h||e_N))
\]

- **LightGCN aggregator** [6] removing all transformations and simply propagating the ego-network vector:

\[
f_{\text{LightGCN}} = e_N
\]

6
B.2 Autoencoder

We study the impact of the AE loss, finding it to have minimal effect or decreasing performance (see Table 5). When comparing the best performing model where $\lambda \neq 0$ with the model where $\lambda = 0$, we often see no statistical significant increase or decrease.

- We initially hypothesized that the encoded features trained without the AE loss would overfit and that the model would have a difficult time extracting relevant information through multiple GNN layers. The AE loss would therefore help with extracting information while allowing the recommendation loss to tailor the encoded embedding to the recommendation setting. Yet, the results do not indicate that the AE loss improves the performance for our model.
- On the ML-20m and AB datasets, we see a statistic significant decrease in performance between $\lambda = 0$ and $\lambda = 2$. A high AE loss therefore does not give better recommendation capabilities.
- Lower values of $\lambda$ either decreases performance or maintains it without statistical significant increases. We therefore leave it as future work to find out if it is possible to utilize the AE loss in a meaningful way for similar methods.

Table 5: Effect of autoencoder loss measured at 20.

| $\lambda$ | MovieLens Subsampled + 1250 users | MovieLens Subsampled + 90% | Amazon Book Subsampled + 15% |
|-----------|---------------------------------|--------------------------|-----------------------------|
|           | NDCG Recall Precision Cov       | NDCG Recall Precision Cov | NDCG Recall Precision Cov   |
| 0.00      | 0.18123 0.18123 0.08292 0.19831 | 0.18367 0.24374 0.08335 0.44127 | 0.06842 0.14469 0.01171 0.20390 |
| 0.01      | 0.18013 0.23694 0.08232 0.20402 | 0.18260 0.24241 0.08320 0.43915 | 0.06745 0.14217 0.01141 0.17612 |
| 0.10      | 0.17642 0.23271 0.08152 0.17989 | 0.17947 0.23806 0.08138 0.37545 | 0.06812 0.14230 0.01166 0.24278 |
| 0.50      | 0.17708 0.23583 0.08076 0.17016 | 0.17818 0.23729 0.08139 0.33672 | 0.06861 0.14270 0.01170 0.22322 |
| 1.00      | 0.16832 0.22822 0.07860 0.15302 | 0.17339 0.23201 0.07925 0.29397 | 0.06251 0.13347 0.01089 0.18574 |
| 2.00      | 0.17089 0.22536 0.07736 0.14857 | 0.17295 0.23021 0.07838 0.27429 | 0.05939 0.12721 0.01034 0.13888 |

Table 6: Effect of the gating mechanism and KG measured at 20.

| Mechanism | MovieLens Subsampled + 1250 users | MovieLens Subsampled + 90% | Amazon Book Subsampled + 15% |
|-----------|---------------------------------|--------------------------|-----------------------------|
|           | NDCG Recall Precision Cov       | NDCG Recall Precision Cov | NDCG Recall Precision Cov   |
| Bipartite | 0.18331 0.24071 0.08264 0.17778 | 0.18379 0.24341 0.08309 0.42455 | 0.06386 0.13484 0.01108 0.18751 |
| W/o relations | 0.17720 0.24193 0.08288 0.18243 | 0.17799 0.23688 0.08140 0.34519 | 0.06451 0.13595 0.01110 0.18465 |
| W/o gates | 0.12482 0.17000 0.05848 0.08148 | 0.09416 0.13479 0.04331 0.05122 | 0.03663 0.0634 0.00927 0.07673 |
| SimpleRec | 0.18085 0.24618 0.08460 0.18540 | 0.18411 0.24482 0.08365 0.42646 | 0.06472 0.14055 0.01144 0.21460 |