Graph-Based Audience Expansion Model for Marketing Campaigns

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ABSTRACT

Audience Expansion, a technique for identifying new audiences with similar behaviors to the original target or seed users. The major challenges include a heterogeneous user base, intricate marketing campaigns, constraints imposed by sparsity, and limited seed users, which lead to overfitting. In this context, we propose a novel solution named AudienceLinkNet, specifically designed to address the challenges associated with audience expansion in the context of Rakuten's diverse services and its clients. Our approach formulates the audience expansion problem as a graph problem and explores the combination of a Pre-trained Knowledge Graph Embedding Model and a Graph Convolutional Networks (GCNs). It emphasizes the structural retention properties of GCNs, enabling the model to overcome challenges related to cross-service data usage, sparsity and limited seed data. AudienceLinkNet simplifies the targeting process for small and large marketing campaigns and better utilizes demographics and behavioral attributes for targeting. Extensive experiments on our advertising platform, Rakuten AIris Target Prospecting, demonstrate the effectiveness of our audience expansion model. Additionally, we present the limitations of AudienceLinkNet.

CCS CONCEPTS

• **Information systems → Information retrieval**;

KEYWORDS

Audience Expansion, Recommendation, Graph Learning

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1 INTRODUCTION

The dynamic landscape of online advertising is continually shaped by the precision of audience targeting. Audience expansion is the task of finding users who are similar to a given set of seed users and likely to achieve the business goal of the target campaign. Tech companies e.g., Facebook, Google [12], LinkedIn [15] provide several marketing campaign platforms. Marketers often grapple with the intricacies of interactive audience expansion, aiming to pinpoint users based on specific traits or features, mostly demographic features. Only focusing buying behaviors or demographics characteristics often limit us from reaching latent users who might have high chances to convert [25, 26]. So, one robust method is required which can capture explicit and implicit traits of users. Another big challenge for Rakuten to meet the expectations of marketing campaigns or clients. Some campaigns only require expansion up to couple of thousands of users while other campaigns may require expansion up to a few million. So based on business needs the list of target users has to be optimized.

Each target prospecting task is unique and can cover a wide range of topics. Rakuten offers over 70 services, including e-commerce, telecom, and travel. We have noticed that many users are active in one Rakuten service but inactive in others, and vice versa. We believe that an audience expansion model should not only focus on users' preferences but also consider other hidden factors such as affordability and lifestyle. Integrating across services can address these issues. We also observe that users' preferences change dynamically and vary with seasons or surroundings. They may suddenly change their interests in different products. We need an effective way to understand the complex latent characteristics of our users and their connections across different Rakuten services. In response to these challenges, AudienceLinkNet utilizes a knowledge graph built from various service data within the Rakuten Ecosystem. AudienceLinkNet tackles the complexities of audience expansion by merging pre-trained knowledge graph embeddings with graph convolution networks. This fusion preserves the properties from the pre-trained knowledge graph embeddings while achieving superior model performance.

We argue that homophily (Homophily in graphs is typically defined based on similarity between connected node pairs) holds in graphs that emerge in audience expansion tasks, and AudienceLinkNet uses three different kinds of aggregation techniques (please refer to Sect. 3.3.1) of node features which enhances our pre-trained model with smoothing [41]. AudienceLinkNet takes slightly different strategy compare to traditional KG-GNN models [37, 38] by leveraging KG triples or knowledge queries, represented as sum of entity and relation embeddings for aggregation, rather than only aggregating neighbor entity embeddings. This departure from traditional neighbor entity embeddings mitigates oversmoothing or irrelevant smoothing, thereby enhancing the precision of audience expansion.

The main contributions of our work are organized as follows: (a) We propose an audience expansion model that is suitable for cross-service scenarios; (b) AudienceLinkNet provides a new perspective of combining a pre-trained KG embeddings and graph convolutional network, which help us to learn users' implicit and explicit interactions and behaviours with various services and products. Comprehensive experiments are conducted to demonstrate our approach's effectiveness.

2 RELATED WORK

In this section, we introduce the related work from various aspects. Some work uses similarity-based methods [18] or clustering [3, 11, 39, 40, 46], meta-task learning [4, 14, 42, 47] , matrix factorization [12, 16, 45] , classification-based methods [1] and rule-based methods [6, 34] . Knowledge graphs embedding models [2, 10, 20–23, 27, 29–32, 35, 43]and GNNs [7, 9, 13, 17, 33, 36, 37, 44] based models also can be used in recommender systems to address lookalike modeling. There has also been some work that extracts rules/feature vectors for scoring. Similarity-based methods expand a given seed-list via calculating the similarity of all pairs between seed users and candidate users [5, 18, 19]. Rule-based methods match similar users with specific demographic features or interests or personas that are targeted by marketers. However, one major difference with ours is that we utilize cross-service data leveraging graphs.

3 METHODOLOGY

3.1 Problem Statement and Preliminary

In an audience expansion setting, a list of m seed users $S_u = (u_1, u_2, \ldots, u_m)$ is given to the model and the task is to find n similar users to the seed list S_u where $n \gg m$.

We utilize a knowledge graph built from data sourced across user and item interactions within the Rakuten Ecosystem. We divide AudienceLinkNet into two stages: the pre-training stage and the audience expansion stage. For notations, we denote a triplet by (u, r, v). We use bold lowercase letters to represent embeddings and bold uppercase letters for matrices.

3.2 Pre-trained Knowledge Graph Embedding (PKGE) Model

In the pre-training stage, we aim to learn a model $f_{\text{pre}}(\cdot; \theta_{\text{pre}})$ parameterized with θ_{pre}. This model is designed to generate embeddings of entities $e \in E$ in the knowledge graph G, formulated as $h_e = f_{\text{pre}}(G; \theta_{\text{pre}})$. The knowledge graph provides rich information and a solid knowledge base for solving the audience expansion problem. The KG can easily demonstrate how our users are linked up and engaging with various Rakuten services. Different user-item (or service) interactions, e.g., buy, click, favorite, exhibit user's interest and buying behavior [8, 28]. The task of audience expansion is to learn to find similar users who are interacting similarly on our platforms. To capture the dynamic intentions of users, we design a link prediction task considering different user-item interactions. We use a margin-based loss function for this task, which is defined as:

$$\mathcal{L}_{\text{pre}} = \sum_{(u,r,v) \in \mathcal{E}} \sum_{(u',r,v') \in \mathcal{E}^{-1}} \left[\gamma + f(u,r,v) - f(u',r,v')\right]_+, \quad (1)$$

where (u, r, v) is positive triples, which actually exist in the KG, (u', r, v') is broken triples, γ is the margin, $f(u, r, v)$ is the score function, and $[\cdot]_+ = max(0, \cdot)$.

Here, the score function is defined as $f(u, r, v) = \|\boldsymbol{e}_u + \boldsymbol{e}_r - \boldsymbol{e}_v\|_{1,2}$, where $\boldsymbol{e}_u$, $\boldsymbol{e}_r$ and $\boldsymbol{e}_v$, are the embeddings of head entities, relations and tail entities, respectively. From the other perspective, sum of a head and relation embeddings reaches a near point to the related tail embeddings, therefore it can be regarded as a query to visit tail entities related to the head entity with the relation. In this paper, we term it *knowledge query*. Audience expansion model, which is described in the next section, aggregates the knowledge queries for aligning neighbor node embeddings in the vector space.

3.3 Audience Expansion Model

Upon completion of Pre-trained Knowledge Graph Embedding (PKGE) training, the resultant embeddings are passed through a Graph Convolution Network, which applies a smoothing process. This stage is the most important one for our proposed AudienceLinkNet method, which adheres to the Message Passing (MP) framework, comprising two primary steps: aggregation and update.

Regarding aggregation, AudienceLinkNet aggregates *knowledge queries* instead of neighboring node features. A knowledge query (for definition refer to Sect. 3.2) from a source node u to a destination node v with a relation r, aggregated during the update of the destination node features, is defined as: $Q(u, r, v) = \boldsymbol{e}_u + \boldsymbol{e}_r$. where $\boldsymbol{e}_u$ and $\boldsymbol{e}_r$ represent embeddings of the source node and the relation, respectively, and the triple (u, r, v) exists within the Knowledge Graph (KG). One of the primary benefits of aggregating knowledge queries is the alignment of node embeddings within the vector space. In the update phase, AudienceLinkNet combines the aggregated knowledge queries with the target node embedding using linear transformation.

3.3.1 Aggregator. Here, we propose mean and attention-based aggregators. We redefine the notation of knowledge queries for multiple layers of AudienceLinkNet as:

Table 1: Datasets statistics (A~E represent the top 5 brands from Rakuten).

	A	B	C	D	E	Tencent
# Seeds	76304	96072	1654	72670	37300	421961
# Training	306114	387615	6652	283671	149601	1812791
# Validation	42277	53005	840	38456	20122	226598
# Testing	44995	50108	4387	36779	37145	226600

$$Q^{l-1}_{(u,r,v)} = \boldsymbol{h}^{l-1}_u + \boldsymbol{h}^{l-1}_r, \tag{2}$$

where l indicates the l-th layer, $Q^l_{(u,r,v)}$ is the l-th query from source u to destination v with relation r, and $\boldsymbol{h}^l_u$ and $\boldsymbol{h}^l_r$ represent the l-th embeddings of the source and relation, respectively. Initial embeddings of all nodes and relations obtained from PKGE are utilized, i.e., $\boldsymbol{h}^0 u = \boldsymbol{e}_u$, $\boldsymbol{h}^0 r = \boldsymbol{e}_r$. For subsequent layers, node and relation embeddings outputted from the previous layer serve as inputs. Two types of aggregators are formulated as follows.

Mean aggregator. This aggregator simply computes the average of neighboring knowledge queries:

$$\boldsymbol{m}^l_Q = \text{MEAN}\left(\left\{Q^{l-1}_{(u,r,v)}, u \in \mathcal{N}(v), r \in \mathcal{R}(u,v)\right\}\right), \tag{3}$$

where $\boldsymbol{m}^l_Q$ is the l-th message of knowledge queries, $\mathcal{N}(v)$ is the set of neighbor nodes of node v, $\mathcal{R}(u,v)$ is the set of relations between u and v.

Attention aggregator. Unlike the mean aggregator, the attention aggregator considers the importance of each knowledge query and aggregates them with different weights. Two types of attention aggregators are provided:

$$\boldsymbol{m}^l_Q = \sum_{u \in \mathcal{N}(v)} \alpha_{(u,r,v)} Q^{l-1}_{(u,r,v)}, \tag{4}$$

$$\alpha_{(u,r,v)} = \frac{e_{(u,r,v)}}{\sum_{k \in \mathcal{N}(v)} e_{(k,r,v)}}, \tag{5}$$

$$(Attention1) \quad e_{(u,r,v)} = \left(Q^{l-1}_{(u,r,v)}\right)^T \boldsymbol{h}^{l-1}_v, \tag{6}$$

$$(Attention2) \quad e_{(u,r,v)} = \text{LeakyReLU}\left(\boldsymbol{a}^T \left(Q^{l-1}_{(u,r,v)} \parallel \boldsymbol{h}^{l-1}_v\right)\right), \tag{7}$$

where $\alpha_{(u,r,v)}$ is the normalized attention coefficient, $\boldsymbol{a} \in \mathbb{R}^{2H}$ is the trainable parameter, H is the dimension of the embeddings, and $\parallel$ denotes concatenation. The first method (Eq. (6)) employs the inner product between the knowledge query and the destination node to calculate attention coefficients, akin to the attention mechanism of Knowledge Graph Convolutional Networks [37]. Knowledge queries closer to the destination node in the vector space are aggregated with higher weights. The second method (Eq.(7)) introduces trainable parameters that enable automatic adjustment of how knowledge queries are aggregated based on the loss function.

3.3.2 Update. Following the aggregation of knowledge queries, new embeddings of all nodes and relations are obtained by combining the destination node embedding with the aggregated knowledge queries. The following update rule is employed:

$$\boldsymbol{h}^l_v = W^l(\boldsymbol{h}^{l-1}_v + \boldsymbol{m}^l_Q) + \boldsymbol{b}^l, \boldsymbol{r}^l = W^l \boldsymbol{r}^{l-1} + \boldsymbol{b}^l \tag{8}$$

where $\boldsymbol{h}^l_v$ and $\boldsymbol{r}^l$ represent the updated embeddings of the target nodes v and all relations, serving as inputs for the next layer. W^l and $\boldsymbol{b}^l$ represent the l-th trainable weight parameters. This update rule involves the addition of the destination node embedding and the aggregated knowledge queries, followed by mapping to a new vector space via linear transformation. The transformation is also applied to relation embeddings, facilitating translation between entities and relations in the new vector space. Consequently, non-linear functions are not employed in this formulation.

3.3.3 Training. As our goal here is to obtain user embeddings from the AudienceLinkNet. Therefore, we employ the following unsupervised loss function for training AudienceLinkNet.

$$\mathcal{L}_{\text{final}} = \sum_{(\mathcal{U},\mathcal{I}) \in \mathcal{P}} \sum_{(\mathcal{U},\mathcal{I}') \in \mathcal{P}^{-1}} [\gamma + f(\boldsymbol{h}_{\mathcal{U}}, \boldsymbol{h}_{\mathcal{I}}) - f(\boldsymbol{h}_{\mathcal{U}}, \boldsymbol{h}_{\mathcal{I}'})]_+ \tag{9}$$

where $(\mathcal{U},\mathcal{I}) \in \mathcal{P}$ is the positive pairs of various interactions between users and items, $(\mathcal{U},\mathcal{I}') \in \mathcal{P}^{-1}$ is the negative one, We obtain the user embeddings as output of AudienceLnkNet and use these embeddings with a similarity threshold T to filter the closest users of each seed users and generate the new list as target prospecting for each marketing campaigns.

4 EXPERIMENTS

4.1 Datasets

Rakuten datasets: These are marketing campaign datasets of the top 5 brands (by revenue generation) sold in Rakuten. We use anonymous user data for modeling and code names have been used here for products. Brand A and Brand E are very popular brands for health-related products e.g., vitamins, mineral, stress relievers etc. Brand B and D sell beauty products and toiletries. Brand C is a famous beverage brand.

Tencent dataset: It is a public dataset[1] which was proposed for Tencent Ads competitions in 2018. This dataset contains hundred of different seed sets (total 421,961 seed users). In this dataset, each user has 14 features including user demography and insterests. Each advertisment task in this dataset has 6 categorical features: ad category, advertiser ID, campaign ID, product ID, product type, creative size. Similar to our knowledge graph format, we aggregate user to product and capture the connections with product to other categorical features and applied AudienceLinkNet for comparison.

The details of the datasets are shown in Table 1. Please note that user data and brand/company data are anonymized, and actual identification is unknown to the models. For Rakuten top clients we run the campaigns in monthly/bi-monthly basis.

4.1.1 Baselines.

Baseline Target Prospecting (TP): The current baseline model for AIris TP is based on XGBoost model. This model uses four different features for Rakuten datasets:*(i) Demographic Features*: Demographic features such as age, gender, region. *(ii) Points Summary*: Rakuten users can gain points while buying different products/services. *(iii) Point Features*: Transaction of points such as acquired/used points from online/offline shops/ merchants. *(iv) Genre level Purchase History*: Like other E-commerce companies,

[1] https://pan.baidu.com/s/1tzBTQqA0Q9qexFr32hFrzg (password: ujmf)

Table 2: Model Performance on Rakuten and public datasets.

	A			B			C			D			E			Tencent		
Models	Prec.	Recall	Pr-auc	Prec.	Recall	Pr-auc	Prec.	Recall	Pr-auc	Prec.	Recall	Pr-auc	Prec.	Recall	Pr-auc	Prec.	Recall	Pr-auc
Baseline TP	0.527	0.722	0.693	0.491	0.754	0.678	0.406	0.750	0.593	0.598	0.772	0.749	0.572	0.773	0.732	0.301	0.461	0.689
PKGE	0.537	0.729	0.706	0.498	0.761	0.699	0.418	0.763	0.604	0.611	0.778	**0.786**	0.585	0.775	0.737	0.321	0.495	0.701
LRLM	0.519	0.688	0.671	0.457	0.722	0.640	0.399	0.690	0.551	0.549	0.674	0.699	0.533	0.664	0.670	0.272	0.428	0.691
MetaHeac	0.541	0.734	**0.716**	0.499	0.772	0.702	0.420	0.774	0.619	0.610	0.801	0.775	0.582	0.774	0.740	**0.334**	0.511	0.721
AudienceLinkNet(mean)	0.544	**0.768**	0.712	**0.516**	**0.819**	0.703	**0.420**	0.799	0.607	0.622	**0.825**	0.784	**0.598**	**0.831**	**0.749**	**0.334**	**0.519**	**0.734**
AudienceLinkNet(attn1)	**0.550**	0.754	0.708	0.511	0.796	**0.705**	0.417	**0.801**	0.606	**0.629**	0.812	0.781	0.589	0.812	0.741	0.330	0.512	0.708
AudienceLinkNet(attn2)	0.545	0.742	0.710	0.508	0.764	0.702	0.418	0.776	**0.612**	0.622	0.798	**0.786**	0.582	0.799	0.740	0.331	0.509	0.710

Rakuten Group maintains "genre" hierarchy. In this feature we capture shopping trends in popular genres. For the Tencent dataset all features are directly fed to a XGBoost model.

Logistic Regression-based Lookalike Model (LRLM): In this model [24], for a given user u_i who has a feature vector v_i, a logistic regression model gets trained and model the probability of being lookalike users to seed users.

Pre-trained Knowledge Graph Embedding (PKGE): We utilize the user embeddings from the PKGE (please refer to Sect. 3.2) model for retrieving the potential audiences.

MetaHeac: It is a state-of-the-art audience expansion model for advertising and has been deployed in WeChat [47].

Model settings. The models run on a single GPU 'NVIDIA Tesla V100'. We use grid search to find the best hyperparameters for the models. We choose the embeddings dimensionality d among {50, 100, 150, 200, 250}, the learning rate among {0.001, 0.01, 0.1}, and the margin γ among {1, 5, 10}. We implement our method and baselines with Pytorch 1.8.2 in Python 3.6 environment.

4.2 Empirical Results

We evaluated the performance of the models using Precision, Recall, and PR-AUC. Table 2 displays the performance of our proposed AudienceLinkNet models alongside the baselines. Results in bold font represent the best obtained outcomes. The aim of this study is to assess the models behind the Rakuten AIris TP.

From Table 2, we have the following findings: (1) AudienceLinkNet (mean) and AudienceLinkNet (attn1) achieved the best performances compared to other methods when using both the Rakuten datasets and Tencent datasets. MetaHeac also achieved competitive results in some cases, such as for Brand D. AudienceLinkNet (mean) showed 4.06% and 7.18% average improvement in precision and recall metrics, respectively, on Rakuten datasets; (2) We observed that AudienceLinkNet (mean and attn1) exhibits more stable performance than others. This indicates that the mean aggregator's performance is the best, while attn2 aggregator's performance is unstable, possibly due to the imbalance in knowledge queries per node. The attention mechanism of AudienceLinkNet is automatically designed by the loss function of the pre-training model, making it difficult to construct an attention mechanism suitable for this particular problem; (3) MetaHeac [47] developed by WeChat achieved competitive results on Rakuten and public datasets; (4) Although AudienceLinkNet is customized for Rakuten AIris TP, it also demonstrates competitive performance on the public dataset.

4.3 Ablation Study and Limitations

Our model has two main parts: Pre-training and Audience Expansion Model (which uses a graph convolution technique). To understand how different components and combinations work, we created two variations. Figure 1 illustrates the recall over the Rakuten datasets. In all cases without the pre-trained model, PKGE, the performance decreases. In cases where the number of seed users is fewer, the performance without PKGE is the worst, so the recall value of Brand C without PKGE decreases sharply. It appears that the model has the potential to acquire a deeper understanding of both implicit and explicit interactions between users and items through pre-training.

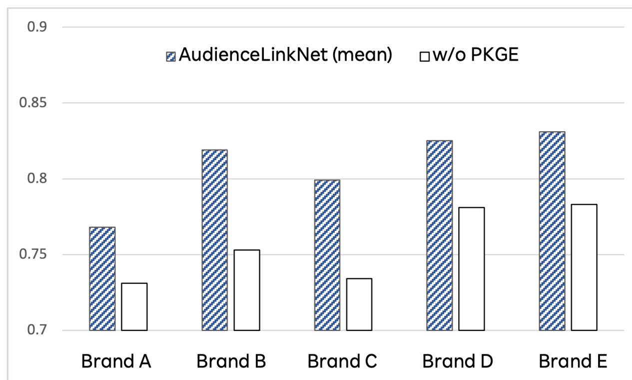

Figure 1: Impact of PKGE (y-axis represents Recall).

The size of the seed lists plays a crucial role in any audience expansion model. While AudienceLinkNet can operate with a small number of seed users by linking user interactions across various services, it still faces challenges when the number of seed users is below 500 for any marketing campaigns. Another noteworthy observation is that if the proportion of new or cold users in the seed lists exceeds 30%, it adversely affects the performance of AudienceLinkNet. Therefore, we still have room for improvement in our model, particularly for cold users and when dealing with limited seed users.

5 CONCLUSION

This study focuses on leveraging cross-service graph data to address the audience expansion challenge within Rakuten's advertising platform for audience expansion. We assess the efficacy of our approach across Rakuten's top five brands and the Tencent public dataset. AudienceLinkNet demonstrates promising effectiveness for successful user targeting.

MAIN PRESENTER

Dr. Md Mostafizur Rahman is a Lead Research Scientist in Rakuten Institute of Technology (RIT) – the research division of Rakuten Group, Inc. He has been with Rakuten since 2020, developing machine learning algorithms to enhance customer experience across Rakuten's various platforms and his recent focus is productionizing the graph based machine learning solutions developed by RIT. Previously, he was a Senior Engineer and Development Team Lead in Samsung Electronics Ltd. He was a Visiting Researcher at the University of Queensland, Australia and worked as a Knowledge Graph Researcher in National Institute of Informatics, Japan.

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