사용자의 추가 정보 벡터를 학습 가능한 온라인 글 추천 모델 개선 방안 연구

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APGT: Improving Personal and Global Temporal preferences news recommendation system by adding Additional user information.*

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요 약

The study proposes a new session-based online article recommender system APGT, which improves upon the current model by adjusting the model structure. It efficiently learns additional information about users. The recommendation performance of APGT was evaluated and optimized using online web magazine read data, and Netflix data to show improved scalability for various types of data.

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1. Introduction

In the era of online media, relevant article recommendations have gained significant importance. Previous studies have explored recommender systems that consider both article and user characteristics [1, 2, 3]. A notable approach is the news recommendation model called Personal Global temporal preference (PGT), which incorporates the dynamic nature of news articles and user interests [3]. However, effectively incorporating additional user information remains a challenge. In this study, we propose modifications to the PGT structure that leverage unique dataset characteristics as additional information to enhance recommendation performance. By incorporating user preferences, such as the web magazine author following list, the model efficiently learns from additional user information by concatenating a new vector. Our contributions are summarized as follows.

- We created a new model APGT that uses additional information about user.
- We maximized performance of APGT through recommender system performance evaluation and parameter optimization.
- By evaluating the performance of APGT models on Kakao Brunch [4], Netflix [5] dataset, we have improved the scalability of the model for various types of data.

2. Background

2.1 PGT architecture

Existing PGT model consists of a layer that extracts global temporal preference and a layer that extracts personal preference. Finally, recommended articles are derived through a similarity test between the candidate items and final news recommendation vector. This model worked well with Adressa [5] dataset by considering personal preference and Top-K popular or fresh articles at that time together. The overall structure of the PGT model is shown in Figure 1.

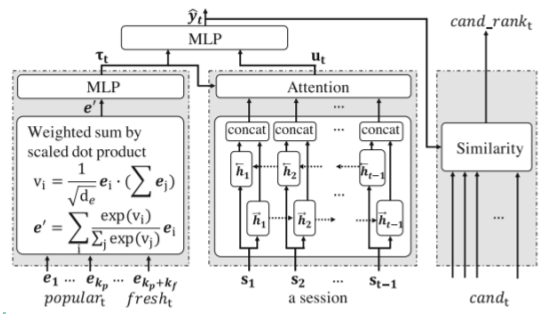

Figure 1. Architecture of PGT [1]

2.2 Kakao Brunch Dataset

Brunch dataset consists of read, metadata, user data. We preprocessed the period of read data to use full user data.

Periods	# Users	# Articles	# History
2018.10.01~2019.02.21	296,520	643,105	20,624,144

Table 1. Description of Brunch dataset

The Adressa and Brunch datasets are all session-based, with many views concentrated in top items. Users viewed an average of 70 articles at least once, with up to 83,688 articles viewed. In user data, there is a list of authors followed by each user. 97.67 percent of all users subscribe more than one author, and they subscribe to an average of 8.42 authors. We collected author keywords and observed authors writing on similar topics continuously.

2.3 Netflix Dataset

A total of 161,918 users' watched history were recorded in the Netflix dataset, and an average of 4.14 movies per user, at least once, and up to 737 movies were watched.

Periods	# Users	# Movie Title	# Total rows
2017.01.01~2019.06.30	161,918	7,925	672,000

Table 2. Description of Netflix dataset

In data, we could get each user's movie genre preference. For one user's genre preference, we collected a list of all genres assigned to each movie that the user have seen. On average, users are fond of 5.32 genres, at least one, and up to 23 genres.

Like Brunch, Netflix is a session-based dataset, with many watched records concentrated on top movie articles. We collected "all genre preference information" by extracting all the unique genre information for the movies each user watched.

3. Proposed methods

When creating APGT, we considered the unique dataset feature related to the user. For instance, utilizing keywords from authors followed by users enables more precise understanding of user preferences. Subscribing to an author indicates the user's interest in their article topics and intention to continue reading their work. Hence, we concluded that using followed authors' keywords as a representation of user interests would be a valid approach. Similarly, the genre information of movies watched by users on Netflix can be considered as additional user preference data. To incorporate this, we generate a user-keyword vector using Doc2Vec to represent additional user preferences. This vector is then concatenated with the existing session based PGT model and passed through an MLP layer or attention layer.

3.1. APGT-MLP

APGT-MLP is a model in which user-keyword information extracted from data is connected to an input value of the final Multi-Layer Perceptron (MLP) layer. The output of the final MLP layer becomes the prediction vector of the article. The structure is shown in Figure 2.

3.2. APGT-Attn

AGPT-Attn is a model that links user-keyword information to the input of the attention mechanism of personal preference and then puts it in the final MLP layer. The APGT-Attn model is designed to reflect personal preferences well by reflecting the user's keyword information in the process of extracting individual preferences. The structure is shown in Figure 3.

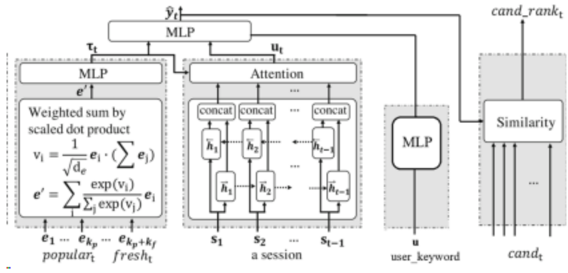

Figure 2. Architecture of APGT-MLP

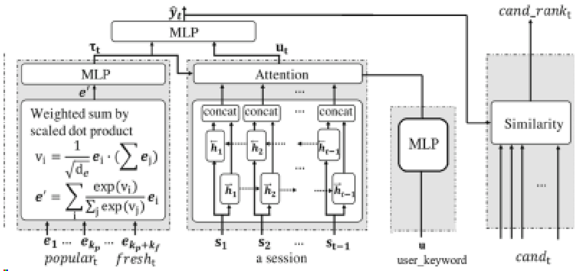

Figure 3. Architecture of APGT-Attn

4. Evaluation

In this section, we conducted three experiments to show the APGT model's performance and find the best parameter settings.

4.1. Environments

Two GP102 [TITAN Xp] GPUs were employed on the server. The Bruch, Netflix dataset were vectorized using Doc2Vec from the Gensim library. We created a dictionary mapping article IDs(movieIDs) to concatenated vectors of titles and subtitles(titles). Adam optimization algorithm was utilized to optimize parameters, with an initial learning rate of 0.025 for two Doc2Vec processes, progressively decreasing by 0.001 every 10 epochs. We fixed total epochs to 20, 40 for Brunch, Netflix dataset, respectively. The model's performance was evaluated using three metrics HR@5, which measures the proportion of relevant items in the top-5 recommended article list; Area Under ROC curve (AUC), which indicates good performance through rapid increases; and Mean Reciprocal Rank (MRR), which calculates the average reciprocal rank of relevant items, indicating how well the first relevant item is ranked.

4.2. Experiments

We created user read sessions based on a window size. Since the timestamp format follows the pattern 'yyyymmddhh', we can consider the window size of 100 as representing one day.

Effects of additional information and optimal structure

To examine the impact of additional user information on performance, we conducted an ablation study. We fixed the window and embedding size of the article at 100 and 250, respectively, and kept the number of popular/recent articles at

5/3, consistent with the PGT. We compared the three metrics presented in Table 3. Since users select only one item from the recommended list, we chose the optimal model based on the presence of relevant items (HR) in the recommended list, rather than their ranking (MRR). Our results showed that the optimal model was APGT-MLP with an embedding size of 250 for user-keyword information. This implies that concatenating additional information with a larger embedding size is more effective for performance than considering the additional information at the same position as the user's history vector.

		PGT	APGT-MLP		APGT-Attn	
	emb_size	-	250	100	250	100
Brunch	HR@5	0.912	**0.915**	0.913	0.913	0.912
	AUC@20	0.940	**0.942**	0.941	0.942	0.942
	MRR@20	0.894	0.895	0.895	**0.896**	0.896
Netflix	HR@5	0.943	0.986	**1**	0.909	0.69
	AUC@20	0.953	0.954	**0.961**	0.946	0.888
	MRR@20	0.772	0.765	**0.776**	0.729	0.598

Table 3. Comparing HR, AUC, and MRR Across Different Embedding Sizes In PGT and Two APGT Models

Optimal numbers of popular and fresh articles

Using the APGT-mlp model with an embedding size of 250 for the additional information vector, which had good overall performance in experiment 1, we explored optimal model with varying numbers of trendy and recency articles. The result is shown in Table 4, and the optimal performance was achieved when using a combination of 5/5 trendy/recent articles as input in each dataset.

#t	**#r**	**Brunch**			**Netflix**		
		HR@5	AUC @20	MRR @20	HR@5	AUC @20	MRR @20
3	**3**	0.912	0.940	0.889	**1**	0.979	0.868
3	**5**	0.913	0.940	0.890	0.672	0.889	0.600
3	**10**	0.912	0.942	0.896	0.680	0.883	0.596
5	**3**	**0.915**	0.942	0.895	0.986	0.954	0.765
5	**5**	**0.915**	**0.944**	**0.898**	**1**	**0.995**	**0.954**
5	**10**	0.911	0.941	0.896	0.909	0.946	0.729
10	**3**	0.912	0.942	0.896	0.907	0.934	0.715
10	**5**	0.914	0.942	0.897	0.846	0.919	0.680
10	**10**	0.913	0.943	0.897	**1**	**0.995**	**0.954**

Table 4. Comparison of Model Performance Across Trendy and Recent Articles

Effects of session window size

We aimed to show the impact of the window size for the user-keyword vector. The result is shown in Table 5, and best performance was achieved when using a window size of 100. This demonstrates that users' interests are changing rapidly, and it can be inferred that a session length of one day is more appropriate than two days.

	Brunch			**Netflix**		
window	HR@5	AUC@20	MRR@20	HR@5	AUC@20	MRR@20
100	**0.915**	**0.944**	**0.898**	**1**	**0.995**	**0.954**
200	0.912	0.941	0.894	1	0.980	0.923

Table 5. Performance Analysis of APGT_MLP with Varying Window Sizes

5. Conclusions and future work

We propose APGT, a new session-based online article recommender system that leverages user's additional information from the Brunch dataset (including a following list and keywords) and the Netflix dataset (including genre information). The model incorporates this information by generating a user-keyword vector using Doc2Vec, which is then concatenated with the existing PGT model. We introduce two variants, APGT-MLP and APGT-Attn, and evaluate their performance on the Brunch, Netflix dataset. The optimal model is APGT-MLP with an embedding size of 250 for user-keyword information, 5/5 trendy/recent articles, and a one-day session length. By enhancing the model structure from PGT to APGT, we better capture user's interests and achieve improved performance. We also demonstrate the scalability and stability of the model across various datasets. This approach holds promise for other domains where temporal relevance is crucial. For future work, we aim to explore further architectural modifications to enable faster and more accurate learning in specific experimental settings.

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