FPAdaMetric: False-positive-aware Adaptive Metric Learning for Session-based Recommendation

Jongwon Jeong, [1] Jeong Choi, [2*] Hyunsouk Cho, [3*†] Sehee Chung [1]

[1] Knowledge AI Lab, NCSOFT. Corp., Republic of Korea
[2] NAVER, Republic of Korea
[3] Ajou University, Republic of Korea
jwjeong@ncsoft.com, kunimi00@naver.com, hyunsouk@ajou.ac.kr, seheechung@ncsoft.com

Abstract

Modern recommendation systems are mostly based on implicit feedback data which can be quite noisy because of false positives caused by many reasons, such as misclick or quick curiosity. Numerous collaborative filtering-based recommendation models have leveraged post-click user behavior (*e.g.*, skip) to identify false positives. False positives can be effectively involved in the model supervision as negative-like signals. Yet, they had not been considered in the previous session-based recommendation systems (SBRs). False positives provide just as deleterious effects on the session-based user preferences as in CF-based recommendations. To resolve false positives in SBRs, we first introduce **FP-Metric** model by reformulating the objective of the session-based recommendation with false-positive constraints into metric learning regularization. In addition, we propose **FP-AdaMetric** by improving those metric-learning regularization terms using the adaptive module for applying false-positive impact differently in the sequential pattern. We verify that **FP-AdaMetric** can improve several session-based recommendation models' performances in terms of Hit Rate (HR), MRR, and NDCG on datasets from several domains including music, movie, and game. Furthermore, we show that the adaptive module plays a much more crucial role in **FP-AdaMetric** model than in other baselines.

Introduction

Collaborative Filtering based Recommendation Systems have received great attention due to their outstanding performance in numerous personalized services (Zhang et al. 2019). Although explicit feedback data such as user ratings can give direct supervision regarding user preferences, they are often expensive and lack in sizes in real world scenarios (Rendle et al. 2012). Alternatively, implicit feedback data have been widely adopted as the main resource for training recommendation models (Hu, Koren, and Volinsky 2008; Yi et al. 2014; He et al. 2017; Guo et al. 2017). They are solely based on user behavior logs and thus much easier to collect (Koren, Bell, and Volinsky 2009; Rendle et al. 2012).

Especially, music or video streaming service users tend to find it difficult to decide whether they would prefer the item recommended by services. Unless they click and play the contents recommended by streaming services, they are not able to realize their preference. They get to show preferences by playing or skipping in the early section. This behavior is even stronger when in subscription-based services because users have full access of items at zero additional cost. For example, 50% of positive signals are false positives (such as skipping or a backward button click within 10 seconds) in music streaming services, meaning that half of click logs are triggered out of simple curiosity (Wen, Yang, and Estrin 2019). Therefore, several works on collaborate filtering dealt with how to consider false-positive clicks better by dwell-time (Yi et al. 2014), skip (Wen, Yang, and Estrin 2019) or other ways (Wu et al. 2020; Wang et al. 2021b).

Meanwhile, the sequential patterns in user feedbacks have become a major factor of the recommendation problem, and have been extensively studied in the field of session-based recommendation system (SBRs) (Fang et al. 2020; Wang et al. 2021a). Since gradual changes take place in user preferences over time, SBRs splits each user's entire log sequence into a number of session-level segments to conjugate both local and global preferences. Although the SBRs models have been successful in capturing user preferences, the noisiness or the underlying false-positive signals of the implicit feedback data are mostly neglected. We argue that they

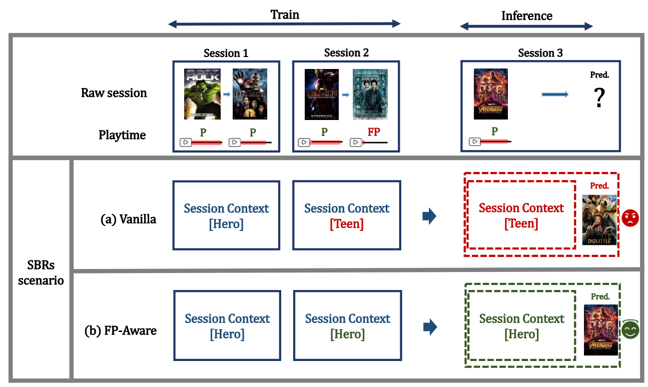


Figure 1: Example about **Importance of False-Positive(FP)** on SBRs in Movie service. False-positives depend on playtime of items, and the user does not like "Teen" movie.

*this work is done when he was at NCSoft.
†Corresponding author

could be just as harmful in SBRs tasks as in non-sequential cases (Yi et al. 2014; Wen, Yang, and Estrin 2019; Wu et al. 2020; Wang et al. 2021b). A few works have taken false-positives into account in certain sequential recommendation tasks (Zhao et al. 2018b,a; Xie et al. 2020; Wang and Cao 2021; Bian et al. 2021), however, to the best of our knowledge, no work has been done for the SBRs problem. As shown in Figure 1, false-positive signals could play crucial roles especially in SBRs scenarios. Figure 1.(a) shows not considering FPs scenario. Session context hurts by "Teen" movie as in session #2 so that recommended item can be "Teen" movie. However, Figure 1.(b) shows the scenario that is considering FPs. FP-aware method can help to not recommend FPs so that recommended item can be "Hero", which the user prefers.

To directly resolve the false-positive signals in the SBRs problem, we first define the general objective function with constraints where the false-positive item embedding should necessarily be far away from the current sequence embedding. This constraint can be applied due to our assumption 1 of false-positives in SBRs. Then, we show that this optimization is equivalent to learning an embedding function that maps data into our desired metric space by using a triplet loss objective (Kaya and Bilge 2019). We call this **FP-Metric**. In addition, we propose **FP-AdaMetric**, a novel architecture which better represents false-positive items during training by learning an additory function that adapts the input and positive embeddings for applying degree of false-positive differently. We show that this adaptive module improves the triplet loss-based metric learning procedure.

We evaluate our proposed method in the data-sets from different multimedia streaming services, *i.e.*, LastFM, Spotify, Amazon Movies, and FUSER[1]. Then, we quantitatively verify our proposed method can improve the session-based recommendation performance in terms of Hit Ratio, MRR and NDCG. In all four data-sets, **FP-AdaMetric** outperforms the baselines. In addition, by investigating the visualization of the learned embedding space, we show that our proposed method better discriminate false-positive embedding from the session embedding than other baselines.

To sum up, our contributions are as follows:

- We highlight the importance of false-positive signals in the session-based recommendation systems. We revisit the false-positive constraints in the optimization problem by transforming metric-learning regularization.
- To better represent false-positives, we propose an adaptive embedding modules in our metric-learning architecture.

Related Works

Neural Session-based Recommendation

Session-based recommendation, which is related to the sequential, or session-aware recommendation, learns patterns through item consumption in certain durations, which we call the sessions (Fang et al. 2020; Wang et al. 2021a). GRU4REC and their variants (Hidasi et al. 2015; Hidasi and Karatzoglou 2018) introduce GRU (Chung et al. 2014) to learn sequential patterns of sessions. Recently, NARM (Li et al. 2017) introduces the attention method in GRU4REC to aggregate global and local user preferences. STAMP (Liu et al. 2018) uses attention and memory networks to capture better long-term preferences. With the improvement of GNN, SRGNN (Wu et al. 2019) and TAGNN (Yu et al. 2020) try to model the sessions as the graphs to improve performance. SASREC (Kang and McAuley 2018) and BERT4REC (Sun et al. 2019) apply Transformers (Vaswani et al. 2017) to catch long-term preferences. They are more related to sequential recommendation, not SBRs.

Though conventional recommendations, such as collaborate filtering (Hu, Koren, and Volinsky 2008), address the gap between user preference and implicit feedback (Fox et al. 2005; Yi et al. 2014; He et al. 2017; Guo et al. 2017; Wen, Yang, and Estrin 2019; Wang et al. 2021b), most previous SBRs models consider implicit click signals only as positive signals. From the other domains for using sequential patterns, DEERS (Zhao et al. 2018b,a) tries to generate the reinforcement learning problem for implicit feedback recommendation. DFM (Xie et al. 2020) and DUMN (Bian et al. 2021) want to solve Click Through Rate (CTR) problem through explicit and implicit sequences. HAEM (Wang and Cao 2021) introduce next basket prediction (NBP) learning by intra and inter coupling the basket of clicked and uncliked items. As far as we know, our work is the first trial to directly apply false-positives (*e.g.*, skip) into the SBRs, especially in the next-item prediction problem.

Deep Metric Learning in Recommendation

Deep metric learning is a method to learn appropriate representations by positive and negative samples (Hoffer and Ailon 2015). In the recommendation system, metric learning is widely studied in the collaborate filtering (CF) with implicit feedback (Zhang et al. 2019). One of the most pronounced works, CMF (Hsieh et al. 2017) first introduces metric-learning approaches to learn user and item relations by Mahalanobis distance in the collaborate filtering. To improve geometric flexibility over Mahalanobis distance, LRML (Tay, Anh Tuan, and Hui 2018) introduces latent relational vectors to learn user and item embedding. To catch better item user relationships, NGCF (Wang et al. 2019) applies Graph Neural Network (GNN) to learn better user and item embedding. Several works (Wang et al. 2018; Tran et al. 2019) tries to improve sampling strategies of negative items for training efficiency.

However, a few studies were done in the session-based or sequential recommendation domain. SML (Twardowski, Zawistowski, and Zaborowski 2021) first applies metric-learning loss in the session-based recommendation to transform original loss, such as BPR and TOP1, which are used in previous works (Hidasi et al. 2015; Hidasi and Karatzoglou 2018). The most related work, XDM (Lv et al. 2020), tries to consider unclick behaviors (implicit negative) in the sequential recommendation by asymmetric metric learning and confidence fusion layer for unclick sequences as input in original model. We consider false-positive items in the session-based recommendation. We give theoretical in-

[1]This is the community-based music game service.

sight into the metric-learning regularization and introduce the adaptive module to improve our regularization.

Preliminaries

Problem definition: Next item prediction in the Session

Let $U = \{u_1, ...u_{|U|}\}$ be the user set and $I = \{i_1, ...i_{|I|}\}$ be the item set where $|U|$ and $|I|$ is the number of users and items respectively. For the Session-based Recommendation Problem (SBRp), we can also define the click sequence, which user's item consumption at certain standard period (session). i.e., $S_k^u = \{x_l\}_{l=1}^{|S_k^u|}$ for $x_l \in I$ be the k^{th} sort session sequence for user u. Since all the users in the dataset contain several sessions, we define those sequences for the certain user u as follows: $S^u = \{S_k^u\}_{k=1}^{|S^u|}$.

Simple Objective We can now define the SBRs of this work by the problem of next-item prediction in the session tasks. The objective of the SBRp is to find the most possible next items which is similar to true next-item distribution in the sessions. Following the recent works (Li et al. 2017; Wu et al. 2019; Song et al. 2019; Kang and McAuley 2018; Sun et al. 2019), we mathematically define the SBRp objective by negative log liklihood (NLL) loss (a.k.a Cross Entropy loss) as in (1).

$$\min_{\theta} \mathop{\mathbb{E}}_{u} \left[\mathop{\mathbb{E}}_{S^u} \left[\sum_{k=2}^{|S^u|} -log \left(p_\theta^u(x = x_k | x_1, \ldots, x_{k-1}) \right) \right] \right] \quad (1)$$

where $p_\theta^u \left(\cdot | x_1, \ldots x_{k-1} \right)$ be the target probability parameterized by θ with given $x_1, \ldots, x_{k-1}$ item sequences in S^u.

Considered False-positives Objective For the certain user click sequence S_k^u, we can divide the true-positive (*e.g.*, complete click) and false-positive (*e.g.*, skip) sequence into two set by predefined criteria as follows: $S_k^u = S_k^{u,p} \cap S_k^{u,fp}$. We also define the sequence set of the user $S^u = S^{u,p} \cap S^{u,fp}$, where $S^{u,p} = \{S_k^{u,p}\}_{k=1}^{|S^{u,p}|}$ and $S^{u,fp} = \{S_k^{u,fp}\}_{k=1}^{|S^{u,fp}|}$.

Since the goal of SBRp is to recommend possible positive items to users, the considered false-positives objective is as follows.

$$\min_{\theta} \mathop{\mathbb{E}}_{u} \left[\mathop{\mathbb{E}}_{S^{u,p}} \left[\sum_{k=2}^{|S^{u,p}|} -log(p_\theta^u(x = x_k | x_1, \ldots x_{k-1}) \right] \right] \quad (2)$$

General Session-based Recommendation model

We summarize the session-based recommendation model by general formula in this sub-section, where trainable parameter is θ. The session-based recommendation model can be divided into 1) embedding layer with θ_e, 2) sequential layer with θ_{seq}, and 3) recommendation layer (Jang et al. 2020; Lv et al. 2020). The trainable parameter consists of like this: $\theta = \{\theta_e, \theta_{seq}, \theta_{concat}(\text{optional})\}$, where $\theta_e = \left\{\theta_e^i, \theta_e^u\right\}$

Embedding Layer The items and users (if exists) are originally given by a unique ids as integer in general. The embedding layer transforms the ids into d dimensional embedding vector e, *i.e.*, $f_{\theta_e} : \mathbb{R} \to \mathbb{R}^d$. In this work, we use the lookup embedding matrix as f_{θ_e}, which is commonly used in Natural Language Processing (NLP) domain. we define the item and user (if exists) embedding matrix as $f_{\theta_e^i}$ and $f_{\theta_e^u}$ respectively.

Sequential Layer The sequential layer $f_{\theta_{itemseq}}(e_{x_1}, \cdots, e_{x_{k-1}}) : \mathbb{R}^{d \times k} \to \mathbb{R}^d$ maps the sequence of item embedding to the sequence vectors, where e_i is the item embedding, d is the dimension of embedding vectors. The sequential layer can be all kinds of deep-learning model which architecture is for sequential patterns, such as RNN (Chung et al. 2014; Hidasi et al. 2015), GNN (Wu et al. 2019; Qiu et al. 2020) Transformer (Kang and McAuley 2018; Sun et al. 2019) and so on. If the users exist (Qiu et al. 2020), the concatenation layer $f_{\theta_{concat}} : \mathbb{R}^{d \times 2} \to \mathbb{R}^d$ aggregates the output of sequential layer with the user embedding. The summary of the final output e_{seq}, which stands for sequential embedding, is represented as follows:

$$e_{seq} = \begin{cases} f_{\theta_{concat}}(f_{\theta_{seq}}(e_{x_1}, \cdots, e_{x_{k-1}}), e_u), & \text{if } u \text{ exists} \\ f_{\theta_{seq}}(e_{x_1}, \cdots, e_{x_{k-1}}), & \text{if } u \text{ not exists} \end{cases} \quad (3)$$

Recommendation Layer The purpose of recommendation layer is to calculate the score of items r_i which is the most relevant next items given sequential embedding e_{seq} as in (4). Although there are several ways to choose similarity measure D_{sim}, we choose dot product to calculate score of items due to high performance and low complexity result (Rendle et al. 2020). The equation of recommendation score can be represented as follows:

$$r_i = D_{sim}(e_{seq}, e_i) = {e_{seq}}^T \cdot e_i \quad (4)$$

Where e_i be the embedding for item i.

The final output of logits is r_i. For training this model by the equation (1) or (2), we define the probability $p_\theta^u(\cdot | x_1, \ldots, x_{k-1})$ as in equation (5), *i.e.*, Softmax Layer.

$$p_\theta^u(i | x_1, \ldots x_{k-1}) = \frac{\exp(r_i)}{\sum_{x \in |I|} \exp(r_x)} \quad (5)$$

Methodology

Motivation: Direct usage of false-positives

Previous works (Li et al. 2017; Wu et al. 2019) passively consider false-positive feedback, *i.e.*, only neglecting false-positives. However, various session-based services that pay low cost to explore new content require methods to use false-positives actively to improve the quality of recommendations. To address this challenge, we introduce the false-positive-feedback constraint by using the common assumption 1 about false-positives.

Assumption 1 (False-positive Characteristics)**.** *1) Sequence does not affect False-positives. 2) False-positive items does not get higher score than other items in general.*

The assumption 1-1) means that the false-positives are consistent whatever their consumption sequence is. Since false-positives mean that the users do not like those items, false-positive property does not change dynamically with respect to any sequences. It is common in many content service, so that the false-positives can apply anywhere in the sequence. Also, the assumption 1-2) shows that false-positives reveal additional preference information. Users do not want to show false-positives rather than others. We need the constraint that false-positives are not similar to session embedding in terms of given similarity measure. Applying these two assumptions, we now introduce appropriate constraint as shown in definition 1:

Definition 1 (False-positive Constraint SBRp)**.** *For the User set U and Item set I, there exists the positive sequence set $S^{u,pos} = \{S_k^{u,pos}\}_{k=1}^{|S^{u,pos}|}$ and false-positive set $S^{u,fp} = \{S_k^{u,fp}\}_{k=1}^{|S^{u,fp}|}$. From the assumption 1, we can consider false-positive item sets: $FP^u = \{x_i | x_i \in S^{u,fp}\} \subset I$. Under these, the objective of SBRp can be shown as below:*

$$\min_{\theta} \mathbb{E}_{u}\left[\mathbb{E}_{S^{u,pos}}\left[\sum_{k=2}^{|S^{u,pos}|} -log(p_\theta^u(x_k|x_1, \ldots x_{k-1})\right]\right] \quad (6)$$

$$s.t. \ \mathbb{E}_{u}\left[\mathbb{E}_{FP^u, S^{u,pos}}\left[\sum_{k=2}^{|S^{u,pos}|} D_{sim}\big(f_{\theta_e^i}(fp), e_{seq}\big)\right]\right] \leq \epsilon \quad (7)$$

Where ϵ is given and D_{sim} be the similarity measure (high is better), *e.g.*, dot product.

Theoretical Analysis

We now analyze the problem setting in definition 1. First, we need to show that additional constraint does not hurt the optimal value in the problem in (2).

Proposition 1 (Optimality Equivalence)**.** *Let be $fp \in FP^u$, $fp \notin S^{u,pos}$, and θ^* be the optimal parameter of (2). Then, there exists ϵ such that θ^* also be the optimal value the problem definition 1.*

Proof. Proof by contradiction. Detailed in Appendix. □

From Prop.1, we now conclude that the problem defined in 1 is used for SBRp as well. Also, the constraint restricts the search space of θ so that the finding optimality could be better for real usage. After this Proposition, we need to change the appropriate form of definition 1 in practice. Prop. 2 gives the evidence about that.

Proposition 2 (Metric-learning View)**.** *If there exists optimal Lagrange multiplier $\lambda > 0$, the problem which is defined in definition 1 is identical to objective as in the equation 8.*

$$\min_{\theta} \mathbb{E}_{u}\left[\mathbb{E}_{S^{u,pos}}\left[\sum_{k=2}^{|S^{u,pos}|} -log(p_\theta^u(x_k|x_1, \ldots x_{k-1})\right]\right] \quad (8)$$

$$+ \lambda \left[\mathbb{E}_{u}\left[\mathbb{E}_{FP^u, S^{u,pos}}\left[\sum_{k=2}^{|S^{u,pos}|} L_{met}(x_k, fp, seq; \theta)\right]\right]\right] \quad (9)$$

where $L_{met}(x_k, fp, seq; \theta) = \max\left(-D_{sim}(pos, seq) + D_{sim}(fp, seq) + m, 0\right)$, and $D_{sim}(pos, seq) = D_{sim}\big(f_{\theta_e^i}(x_k), e_{seq}\big)$ and $D_{sim}(fp, seq) = D_{sim}\big(\mathbb{E}_{fp\sim p(FP^u)}\left[f_{\theta_e^i}(fp)\right], e_{seq}\big)$.

Proof. Base on KKT conditions (Boyd, Boyd, and Vandenberghe 2004) in convex optimization. Detailed in Appendix. □

As a result, we can introduce metric-learning regularization terms in the original problem (equation (6)), which stands for **FP-Metric**. Metric-learning (Hoffer and Ailon 2015; Kaya and Bilge 2019) is well-known approach to learn appropriate representation via false-positive and positive samples in computer vision (Karpusha, Yun, and Fehervari 2020; Venkataramanan et al. 2021) and audio (Chung et al. 2020; Xu et al. 2020) domains. Also, the metric-learning gets the great attention nowadays due to high-performance in self-supervised and unsupervised approaches (Jaiswal et al. 2021). Although other works in metric-learning focused on using themselves, we use it to regularization about the original loss due to focus on the false-positive items. We leave the proof about other types of metric-learning loss, such as N-pairs (Sohn 2016) or contrastive loss (Chen et al. 2020) for the future works.

Proposed Method: FP-AdaMetric

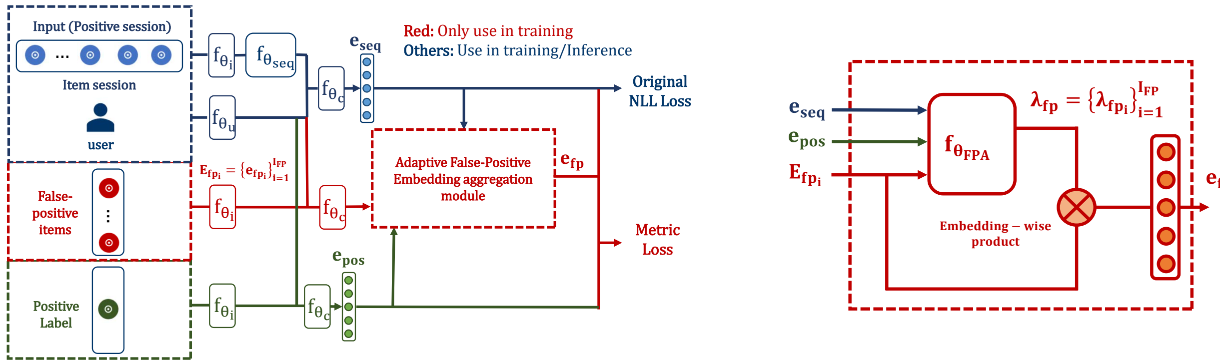
From the finding in the Proposition 2, we now propose the metric-learning regularization method to apply the false-positive items in the session-based recommendation actively as shown in equation 8. It can be effective as shown in the experiment part.

Although this regularization is mathematically and experimentally effective, there are still limitations. All of false-positives do not give the same impact to the users. For example, the certain users hate the scary movie. The terrifying amount of the movie makes the users' false-positives differently. This property is summarized as in the remark 1.

Remark 1 (Degree of Dislike)**.** *false-positives are not the same for the certain user. The degree of dislike property for each false-positive items may be different.*

The equation 8 does not contain this property. Therefore, we propose the adaptive ways to apply false-positive differently by adaptive module in the false-positive part metric-learning loss in the remark 2. The summary of our proposed method is shown in Figure 2. The proposed method which use metric-learning regularization with adaptive module stands for **FP-AdaMetric**.

Remark 2 (FP-AdaMetric)**.** *Let us define the adaptive module for all false-positives as follows: $f_{\theta_{FPA}}(e_u, e_{fp}, e_{seq}) : \mathbb{R}^{d\times 3} \rightarrow \mathbb{R}$, where $e_{fp} = f_{\theta_e^i}(fp)$. Base on this, we propose FP-AdaMetric which apply adaptive false-positives in*



(a) OverallFramework

(b) Adaptive False-Positive module details

Figure 2: Proposed framework for applying false-positive items in session-based recommendation. (a) Overall framework for FP-AdaMetric, (b) Adaptive FP embedding aggregation module details.

the false-positive parts of embedding.

$$\min_{\theta} \mathbb{E}_{u} \left[\mathbb{E}_{S^{u,pos}} \left[\sum_{k=2}^{|S^{u,pos}|} -log(p_{\theta}^{u}(x_k|x_1, \ldots x_{k-1}) \right] \right] \quad (10)$$

$$+ \lambda \left[\mathbb{E}_{u} \left[\mathbb{E}_{FP^u, S^{u,pos}} \left[\sum_{k=2}^{|S^{u,pos}|} L_{adamet}(x_k, fp, seq; \theta) \right] \right] \right] \quad (11)$$

where $L_{adamet}(x_k, fp, seq; \theta) = \max(-D_{sim}(pos, seq) + D_{sim}(fp, seq) + m, 0)$ *which is metric-learning loss structure. Also,* $D_{sim}(pos, seq) = D_{sim}(f_{\theta_e^i}(x_k), e_{seq})$ *and* $D_{sim}(fp, seq) = D_{sim}(\mathbb{E}_{fp \sim p(FP^u)}[f_{\theta_{FPA}}(e_u, e_{fp}, e_{seq}) \times e_{fp}], e_{seq})$.

Experiment Setting

Datasets

We evaluate 4 real data-set: LastFM, Spotify, AmazonMovie and FUSER. The detailed statistics for the final data are summarized in table 1. We split those data-set into 80% of train, 10% of validation, and 10% of test sets. The additional information about data-sets is in the appendix.

Statistics	LastFM	Spotify	AmazonMovie	FUSER
Num. Users	0.5 K	None	None	8 K
Consumption cost	Low	Low	High	High
Num. Items	18 K	136 K	35 K	18 K
Num. Sess	84 K	125 K	8 K	59 K
False-positive (FP) decision	skip	skip	low score	skip
FP ratio (%)	10	50	30	20

Table 1: Data statistics used in the experiment

Baseline and Metric

Model We choose most popular SBRs models as baselines: **NARM** (Li et al. 2017), **SRGNN** (Wu et al. 2019), **STAMP** (Liu et al. 2018), and so on. **NARM** introduces attention layer to learn global and local preference of user preference in the sessions. **SRGNN** proposes Graph Neural Network (GNN) to capture more complex item consumption in the sessions. **STAMP** utilizes the short-term attention and memory priority to capture users' general interests and current interests better. Our results contain **NARM** and **SRGNN** since the paper's limitation. Other models' results (*e.g.* **STAMP**) are in the appendix. Due to the low performance of the traditional non-deep learning methods (Jang et al. 2020; Qiu et al. 2020) - Sequence Popularity (S-POP) or First-order Markov Chain (FOMC)- are excluded in the baseline.

Method To show that **FP-AdaMetric** is effective for applying false-positives, we choose two simple baseline method as follows:

- **Vanilla**: False-positive items are not removed as in the equation (1). All click signals regards as implicit positive signals.
- **FP-Simple**: False-positive items are simply removed like in the equation (2). False-positives are selected by skip (for LastFM, Spotify and FUSER) or scores below than 2 (for AmazonMovie).

Evaluation Metric We choose HR@K (Hit Ratio), MRR@K (Mean Reciprocal Rank) and NDCG@K (Normalized Discounted Cumulative Gain) for evaluating the session-based recommendation models. Those metrics were widely used in the many previous works (Jang et al. 2020; Lv et al. 2020). Also, We select $K \in \{5, 10, 20, 50, 100\}$ due to clarify robust improvement in various cases.

All implementations of the experiments can be shown in https://github.com/nc-ai/knowledge [2].

Experiment Result

Our experiment is designed to verify the following research questions:

[2]It will be opened at published version due to company's policy

Dataset	Base Model	Method	HR@K (%)					MRR@K (%)					NDCG@K (%)				
			5	10	20	50	100	5	10	20	50	100	5	10	20	50	100
LastFM	NARM	Vanilla	33.63	37.69	42.05	48.02	53.03	28.90	29.44	29.74	29.94	30.01	30.08	31.39	32.49	33.68	34.49
		FP-Simple	33.65	37.69	42.06	48.07	53.04	28.95	29.48	29.78	29.97	30.04	30.12	31.41	32.51	33.70	34.51
		FP-AdaMetric	**33.71**	**37.86**	**42.27**	**48.24**	**53.17**	**28.95**	**29.50**	**29.80**	**29.99**	**30.06**	**30.13**	**31.47**	**32.58**	**33.77**	**34.56**
	SRGNN	Vanilla	34.28	38.21	42.48	48.37	53.30	29.53	30.06	30.35	30.54	30.61	30.72	31.98	33.06	34.23	35.03
		FP-Simple	34.25	38.17	42.49	48.44	53.35	29.52	30.03	30.33	30.52	30.59	30.70	31.95	33.03	34.21	35.01
		FP-AdaMetric	**34.31**	**38.25**	**42.56**	**48.49**	**53.38**	**29.57**	**30.09**	**30.39**	**30.57**	**30.64**	**30.75**	**32.02**	**33.10**	**34.27**	**35.07**
Spotify	NARM	Vanilla	22.95	29.93	36.37	43.11	47.58	14.77	15.70	16.16	16.38	16.44	16.80	19.06	20.69	22.04	22.77
		FP-Simple	81.25	82.09	82.88	83.80	84.45	79.43	79.54	79.60	79.63	79.64	79.89	80.16	80.36	80.55	80.65
		FP-AdaMetric	**81.43**	**82.22**	**82.99**	**83.90**	**84.54**	**79.87**	**79.97**	**80.03**	**80.06**	**80.06**	**80.26**	**80.52**	**80.71**	**80.89**	**81.00**
	SRGNN	Vanilla	58.51	63.81	67.88	72.14	74.78	34.42	35.14	35.42	35.56	35.60	40.57	42.30	43.33	44.19	44.62
		FP-Simple	81.36	82.25	83.14	84.14	84.83	79.15	79.27	79.33	79.36	79.37	79.71	80.00	80.22	80.45	80.54
		FP-AdaMetric	**81.58**	**82.49**	**83.37**	**84.41**	**85.11**	**79.34**	**79.46**	**79.53**	**79.56**	**79.57**	**79.91**	**80.21**	**80.43**	**80.64**	**80.75**
Amazon Movie	NARM	Vanilla	5.92	7.42	9.39	13.08	16.91	4.37	4.57	4.70	4.82	4.87	4.76	5.24	5.73	6.46	7.08
		FP-Simple	8.25	9.33	10.90	14.61	20.16	7.23	7.37	7.47	7.55	7.60	7.49	7.82	8.18	8.74	9.23
		FP-AdaMetric	**8.35**	**9.38**	**10.87**	**14.85**	**20.51**	**7.38**	**7.51**	**7.61**	**7.69**	**7.73**	**7.62**	**7.94**	**8.29**	**8.83**	**9.32**
	SRGNN	Vanilla	6.08	7.35	9.06	12.36	15.89	4.88	5.05	5.16	5.27	5.32	5.18	5.58	6.02	6.67	7.24
		FP-Simple	**8.29**	**9.25**	10.66	14.26	19.79	**7.37**	**7.49**	**7.58**	**7.66**	**7.70**	**7.60**	**7.89**	**8.23**	**8.75**	9.22
		FP-AdaMetric	8.27	9.24	**10.68**	**14.44**	**20.24**	7.34	7.47	7.56	7.64	7.69	7.57	7.88	**8.23**	**8.75**	**9.23**
FUSER	NARM	Vanilla	2.38	4.16	7.14	14.19	22.04	1.17	1.40	1.61	1.82	1.93	1.47	2.04	2.79	4.18	5.44
		FP-Simple	2.91	5.31	9.22	17.35	26.05	1.40	1.71	1.97	2.22	2.35	1.77	2.54	3.51	5.12	6.52
		FP-AdaMetric	**3.08**	**5.48**	**9.45**	**17.81**	**26.75**	**1.48**	**1.80**	**2.07**	**2.33**	**2.45**	**1.87**	**2.64**	**3.63**	**5.28**	**6.72**
	SRGNN	Vanilla	1.91	3.43	5.97	12.05	19.67	0.89	1.09	1.26	1.45	1.55	1.14	1.63	2.27	3.46	4.68
		FP-Simple	2.44	4.36	7.62	14.90	23.48	1.18	1.43	1.65	1.88	2.00	1.49	2.10	2.92	4.35	5.74
		FP-AdaMetric	**2.54**	**4.54**	**7.90**	**15.49**	**24.19**	**1.23**	**1.49**	**1.71**	**1.95**	**2.07**	**1.54**	**2.18**	**3.03**	**4.51**	**5.92**

Table 2: Overall performance comparison on various data-sets in terms of Hit Ratio, MRR, and NDCG@K where K$\in \{5, 10, 20, 50, 100\}$. The best value and second-best value are highlighted as **bold** and underline respectively.

- **RQ1 (Performance)**: Could **FP-AdaMetric** improve the performance of SBRs with considering false-positives?
- **RQ2 (Domain Difference)**: Is there a difference between domains for false-positives?
- **RQ3 (Ablation Study)**: What is the impact of the each module?
- **RQ4 (Embedding Analysis)**: Do users have similar preferences close to each other in the embedding space?

Overall Performance

We summarize overall results about 4 kinds of data-sets in Table 2. By comparing **Vanilla** with **FP-Simple** which simply considers false-positive items, the performance for HR, MRR, and NDCG can be increased about 22%, 101%, and 65% on average. In addition, FP-Simple increases the metric for the ranking of true-positive items (*i.e.*, MRR and NDCG) than HR. The results show that false-positive items in the session contaminate the true preference of items in sessions so that the truly preferred item ranking can be decreased. Also, it means that considering false positives is essential for the session-based recommendation which we claim for. Especially, the result shows better performance improvement of **FP-Simple** compared to Vanilla on a dataset with a high false-positive ratio, such as Spotify and Amazon Movie. Next, we verify our proposed methods. The results show that **FP-AdaMetric** consistently outperforms all metrics in all domains we considered. Our proposed method is effective in improving several baseline models in the problem defined in the definition 1, thus answering **RQ1**.

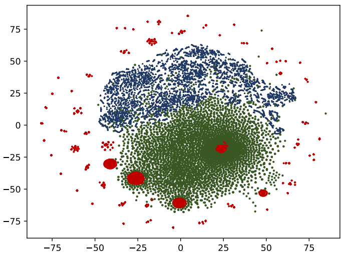
We compare the performance increasing property between **FP-Simple** and **FP-AdaMetric** in various domains: LastFM, Spotify, AmazonMovie, and FUSER. The improvement in Amazon Movie and FUSER is larger than LastFM and Spotify in general. As shown in Table 1, users in Movie or Game domains are more concentrated on the content consumption. Unlike them, users in the music streaming domains such as LastFM and Spotify passively consumes the contents. Thus, considering false-positives through our proposed method is much more significant compared to **FP-Simple** in actively item consumption domains, such as Movie and Game. This analysis answers **RQ2** which explains relation between domain difference and proposed method.

Dataset	Method	Metric@100		
		HR	MRR	NDCG
Spotify	FP-AdaMetric	84.54	**80.06**	**81.00**
	w/o Adaptive	**84.84**	79.95	80.97
	w/o Metric	84.45	79.64	80.65
	Vanilla	47.58	16.44	22.77
Amazon Movie	FP-AdaMetric	**20.51**	**7.73**	**9.32**
	w/o Adaptive	20.21	7.69	9.27
	w/o Metric	20.16	7.60	9.23
	Vanilla	16.91	4.87	7.08

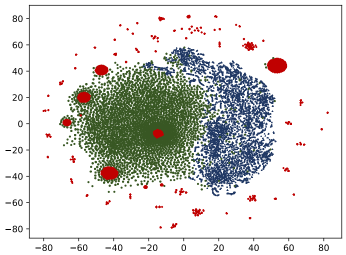
Table 3: Ablation study comparing FP-Metric and FP-Simple in baseline NARM model.

Ablation Study

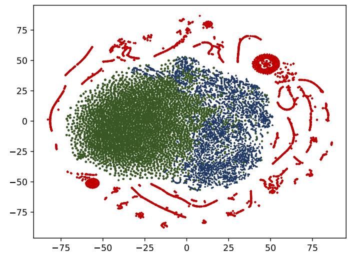
We show the effectiveness of each module in FP-AdaMetric in this section. FP-AdaMetric consists of 1) metric learning and 2) the adaptive module. To see each modules' effectiveness, we compare **FP-AdaMetric** with **FP-Metric** which contains no adaptive module and **FP-Simple**. **FP-Metric** and **FP-Simple** represent as "w/o Adaptive" and "w/o Metric" respectively in Table 3 due to easy understanding. We show the NARM's performance in terms of HR, MRR, and NDCG@100 on Amazon Movie and Spo-



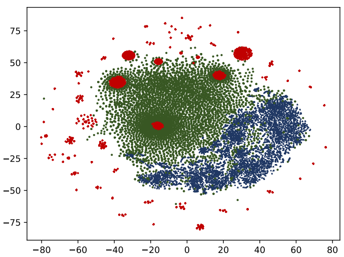
(a) **NARM + Vanilla**



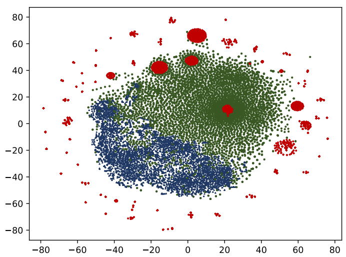
(b) **NARM + FP-Simple**



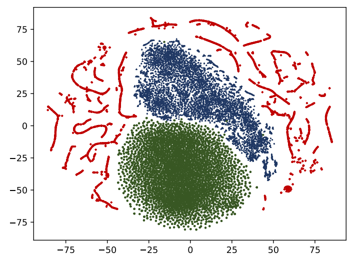
(c) **NARM + FP-AdaMetric**



(d) **SRGNN + Vanilla**



(e) **SRGNN + FP-Simple**



(f) **SRGNN + FP-AdaMetric**

Figure 3: Embedding Space Comparsion between **Vanilla**, **FP-Simple** and **FP-AdaMetric** (Proposed method) on NARM and SRGNN in Amazon Movie Test Data-set via PCA initilization + T-SNE. (Blue: session-embedding, Green: True-positive embedding, Red: False-positive embedding)

tify. Table 3 shows that each part of our proposed method, **FP-AdaMetric**, affects the performance differently. It can resolve **RQ3** as follows. The metric-learning parts consistently increase all metric's performance, especially the Hit Ratio (HR). Since the constraint in the definition 1 makes false-positive embedding far away from the sequential embedding, not attract positives, the constraint forces that the probability of false-positive existence in the top-k ranking can be decreased, which means HR can be better. In addition, inserting the adaptive module (**FP-AdaMetric**) improves MRR and NDCG than HR. It means the adaptive module helps to force the true-positive item's ranking much higher. We leave the future work showing this relationship.

Visualization result

To qualitatively analyze learned embedding space, three different types (sequence, true-positive item, and false-positives item) of the embedding are plotted by T-SNE (Van Der Maaten 2014) with PCA initialization (Abdi and Williams 2010), which the simple and high quality visualization method widely used for embedding analysis (Kobak and Linderman 2021). Figure 3 shows the learned embedding space about three method explained in table 2: **Vanilla** **FP-Simple** and **FP-AdaMetric** (proposed) on Amazon Movie data-set. Although the embeddings are not separated in **Vanilla** and **FP-Simple** method, we verify that **FP-AdaMetric** push out the false-positive items (green) from true-positive and sequence embedding. True-positive and sequence embedding exist in the same space, and are not mixed with false-positives. Therefore, we conclude that the **FP-AdaMetric** can push the false-positives far away from sequential embedding. The probability of recommending false-positives is lower than the probability in **Vanilla** or **FP-Simple** case. This result answers **RQ4** that similar preference exists close to each other in our proposed algorithm.

Conclusion

In this paper, we study the false-positive implicit data impact on the session-based recommendation problem, especially the next-item prediction problem. We introduce the constraint optimization equation for SBRs and show that this equation can transform into metric-learning regularization loss. Using the fact that the degree of dislike property for false positives may be different, we propose the adaptive modules for false positives to improve our regularization effect. Diverse experiments show our proposed regularization including **FP-Metric** and **FP-AdaMetric** is effective in terms of several performance metrics, and **FP-AdaMetric** is much more crucial at certain domains, such as Movie and Game.

We suggest potential future research directions as follows. To begin with, automatically finding false positives is required for better usage of false positives, like in Wang et al. (2021b). Moreover, we can extend our theoretical analysis in other metric-learning losses, such as N-pairs (Sohn 2016) or contrastive loss (Chen et al. 2020). Also, we further analyze other kinds of data-sets, such as news and e-commerce, for future works.

Acknowledgments

We appreciate Hoyeop Lee, Sungwon Jang, and anonymous reviewers for the great discussion about our work.

References

Abdi, H.; and Williams, L. J. 2010. Principal component analysis. *Wiley interdisciplinary reviews: computational statistics*, 2(4): 433–459.

Bian, Z.; Zhou, S.; Fu, H.; Yang, Q.; Sun, Z.; Tang, J.; Liu, G.; Liu, K.; and Li, X. 2021. Denoising User-aware Memory Network for Recommendation. *arXiv preprint arXiv:2107.05474*.

Boyd, S.; Boyd, S. P.; and Vandenberghe, L. 2004. *Convex optimization*. Cambridge university press.

Chen, T.; Kornblith, S.; Norouzi, M.; and Hinton, G. 2020. A simple framework for contrastive learning of visual representations. In *International conference on machine learning*, 1597–1607. PMLR.

Chung, J.; Gulcehre, C.; Cho, K.; and Bengio, Y. 2014. Empirical evaluation of gated recurrent neural networks on sequence modeling. *arXiv preprint arXiv:1412.3555*.

Chung, J. S.; Huh, J.; Mun, S.; Lee, M.; Heo, H. S.; Choe, S.; Ham, C.; Jung, S.; Lee, B.-J.; and Han, I. 2020. In defence of metric learning for speaker recognition. *arXiv preprint arXiv:2003.11982*.

Fang, H.; Zhang, D.; Shu, Y.; and Guo, G. 2020. Deep learning for sequential recommendation: Algorithms, influential factors, and evaluations. *ACM Transactions on Information Systems (TOIS)*, 39(1): 1–42.

Fox, S.; Karnawat, K.; Mydland, M.; Dumais, S.; and White, T. 2005. Evaluating implicit measures to improve web search. *ACM Transactions on Information Systems (TOIS)*, 23(2): 147–168.

Guo, H.; Tang, R.; Ye, Y.; Li, Z.; and He, X. 2017. DeepFM: a factorization-machine based neural network for CTR prediction. *arXiv preprint arXiv:1703.04247*.

He, X.; Liao, L.; Zhang, H.; Nie, L.; Hu, X.; and Chua, T.-S. 2017. Neural collaborative filtering. In *Proceedings of the 26th international conference on world wide web*, 173–182.

Hidasi, B.; and Karatzoglou, A. 2018. Recurrent neural networks with top-k gains for session-based recommendations. In *Proceedings of the 27th ACM international conference on information and knowledge management*, 843–852.

Hidasi, B.; Karatzoglou, A.; Baltrunas, L.; and Tikk, D. 2015. Session-based recommendations with recurrent neural networks. *arXiv preprint arXiv:1511.06939*.

Hoffer, E.; and Ailon, N. 2015. Deep metric learning using triplet network. In *International workshop on similarity-based pattern recognition*, 84–92. Springer.

Hsieh, C.-K.; Yang, L.; Cui, Y.; Lin, T.-Y.; Belongie, S.; and Estrin, D. 2017. Collaborative metric learning. In *Proceedings of the 26th international conference on world wide web*, 193–201.

Hu, Y.; Koren, Y.; and Volinsky, C. 2008. Collaborative filtering for implicit feedback datasets. In *2008 Eighth IEEE International Conference on Data Mining*, 263–272. Ieee.

Jaiswal, A.; Babu, A. R.; Zadeh, M. Z.; Banerjee, D.; and Makedon, F. 2021. A survey on contrastive self-supervised learning. *Technologies*, 9(1): 2.

Jang, S.; Lee, H.; Cho, H.; and Chung, S. 2020. CITIES: Contextual Inference of Tail-item Embeddings for Sequential Recommendation. In *2020 IEEE International Conference on Data Mining (ICDM)*, 202–211. IEEE.

Kang, W.-C.; and McAuley, J. 2018. Self-attentive sequential recommendation. In *2018 IEEE International Conference on Data Mining (ICDM)*, 197–206. IEEE.

Karpusha, M.; Yun, S.; and Fehervari, I. 2020. Calibrated neighborhood aware confidence measure for deep metric learning. *arXiv preprint arXiv:2006.04935*.

Kaya, M.; and Bilge, H. Ş. 2019. Deep metric learning: A survey. *Symmetry*, 11(9): 1066.

Kobak, D.; and Linderman, G. C. 2021. Initialization is critical for preserving global data structure in both t-SNE and UMAP. *Nature biotechnology*, 39(2): 156–157.

Koren, Y.; Bell, R.; and Volinsky, C. 2009. Matrix factorization techniques for recommender systems. *Computer*, 42(8): 30–37.

Li, J.; Ren, P.; Chen, Z.; Ren, Z.; Lian, T.; and Ma, J. 2017. Neural attentive session-based recommendation. In *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management*, 1419–1428.

Liu, Q.; Zeng, Y.; Mokhosi, R.; and Zhang, H. 2018. STAMP: short-term attention/memory priority model for session-based recommendation. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, 1831–1839.

Lv, F.; Li, M.; Guo, T.; Yu, C.; Sun, F.; Jin, T.; Wen, H.; Lin, G.; Yang, K.; and Ng, W. 2020. XDM: Improving Sequential Deep Matching with Unclicked User Behaviors for Recommender System. *arXiv preprint arXiv:2010.12837*.

Qiu, R.; Yin, H.; Huang, Z.; and Chen, T. 2020. Gag: Global attributed graph neural network for streaming session-based recommendation. In *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*, 669–678.

Rendle, S.; Freudenthaler, C.; Gantner, Z.; and Schmidt-Thieme, L. 2012. BPR: Bayesian personalized ranking from implicit feedback. *arXiv preprint arXiv:1205.2618*.

Rendle, S.; Krichene, W.; Zhang, L.; and Anderson, J. 2020. Neural collaborative filtering vs. matrix factorization revisited. In *Fourteenth ACM Conference on Recommender Systems*, 240–248.

Sohn, K. 2016. Improved deep metric learning with multi-class n-pair loss objective. In *Advances in neural information processing systems*, 1857–1865.

Song, W.; Xiao, Z.; Wang, Y.; Charlin, L.; Zhang, M.; and Tang, J. 2019. Session-based social recommendation via dynamic graph attention networks. In *Proceedings of the Twelfth ACM international conference on web search and data mining*, 555–563.

Sun, F.; Liu, J.; Wu, J.; Pei, C.; Lin, X.; Ou, W.; and Jiang, P. 2019. BERT4Rec: Sequential recommendation with bidirectional encoder representations from transformer. In *Proceedings of the 28th ACM international conference on information and knowledge management*, 1441–1450.

Tay, Y.; Anh Tuan, L.; and Hui, S. C. 2018. Latent relational metric learning via memory-based attention for collaborative ranking. In *Proceedings of the 2018 World Wide Web Conference*, 729–739.

Tran, V.-A.; Hennequin, R.; Royo-Letelier, J.; and Moussallam, M. 2019. Improving collaborative metric learning with efficient negative sampling. In *Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval*, 1201–1204.

Twardowski, B.; Zawistowski, P.; and Zaborowski, S. 2021. Metric Learning for Session-based Recommendations. *arXiv preprint arXiv:2101.02655*.

Van Der Maaten, L. 2014. Accelerating t-SNE using tree-based algorithms. *The Journal of Machine Learning Research*, 15(1): 3221–3245.

Vaswani, A.; Shazeer, N.; Parmar, N.; Uszkoreit, J.; Jones, L.; Gomez, A. N.; Kaiser, Ł.; and Polosukhin, I. 2017. Attention is all you need. In *Advances in neural information processing systems*, 5998–6008.

Venkataramanan, S.; Psomas, B.; Avrithis, Y.; Kijak, E.; Amsaleg, L.; and Karantzalos, K. 2021. It Takes Two to Tango: Mixup for Deep Metric Learning. *arXiv preprint arXiv:2106.04990*.

Wang, Q.; Yin, H.; Hu, Z.; Lian, D.; Wang, H.; and Huang, Z. 2018. Neural memory streaming recommender networks with adversarial training. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, 2467–2475.

Wang, S.; Cao, L.; Wang, Y.; Sheng, Q. Z.; Orgun, M. A.; and Lian, D. 2021a. A survey on session-based recommender systems. *ACM Computing Surveys (CSUR)*, 54(7): 1–38.

Wang, W.; and Cao, L. 2021. Interactive sequential basket recommendation by learning basket couplings and positive/negative feedback. *ACM Transactions on Information Systems (TOIS)*, 39(3): 1–26.

Wang, W.; Feng, F.; He, X.; Nie, L.; and Chua, T.-S. 2021b. Denoising implicit feedback for recommendation. In *Proceedings of the 14th ACM International Conference on Web Search and Data Mining*, 373–381.

Wang, X.; He, X.; Wang, M.; Feng, F.; and Chua, T.-S. 2019. Neural graph collaborative filtering. In *Proceedings of the 42nd international ACM SIGIR conference on Research and development in Information Retrieval*, 165–174.

Wen, H.; Yang, L.; and Estrin, D. 2019. Leveraging post-click feedback for content recommendations. In *Proceedings of the 13th ACM Conference on Recommender Systems*, 278–286.

Wu, C.; Wu, F.; Qi, T.; and Huang, Y. 2020. User Modeling with Click Preference and Reading Satisfaction for News Recommendation. In *IJCAI*, 3023–3029.

Wu, S.; Tang, Y.; Zhu, Y.; Wang, L.; Xie, X.; and Tan, T. 2019. Session-based recommendation with graph neural networks. In *Proceedings of the AAAI Conference on Artificial Intelligence*, 346–353.

Xie, R.; Ling, C.; Wang, Y.; Wang, R.; Xia, F.; and Lin, L. 2020. Deep Feedback Network for Recommendation. In *IJCAI*, 2519–2525.

Xu, J.; Wang, X.; Feng, B.; and Liu, W. 2020. Deep multi-metric learning for text-independent speaker verification. *Neurocomputing*, 410: 394–400.

Yi, X.; Hong, L.; Zhong, E.; Liu, N. N.; and Rajan, S. 2014. Beyond clicks: dwell time for personalization. In *Proceedings of the 8th ACM Conference on Recommender systems*, 113–120.

Yu, F.; Zhu, Y.; Liu, Q.; Wu, S.; Wang, L.; and Tan, T. 2020. TAGNN: Target attentive graph neural networks for session-based recommendation. In *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*, 1921–1924.

Zhang, S.; Yao, L.; Sun, A.; and Tay, Y. 2019. Deep learning based recommender system: A survey and new perspectives. *ACM Computing Surveys (CSUR)*, 52(1): 1–38.

Zhao, X.; Xia, L.; Zhang, L.; Ding, Z.; Yin, D.; and Tang, J. 2018a. Deep reinforcement learning for page-wise recommendations. In *Proceedings of the 12th ACM Conference on Recommender Systems*, 95–103.

Zhao, X.; Zhang, L.; Ding, Z.; Xia, L.; Tang, J.; and Yin, D. 2018b. Recommendations with negative feedback via pairwise deep reinforcement learning. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, 1040–1048.