Intra-session Context-aware Feed Recommendation in Live **Systems**

Luo Ji DAMO Academy, Alibaba Group Hangzhou, China jiluo.lj@alibaba-inc.com

Mingyang Yin DAMO Academy, Alibaba Group Hangzhou, China hengyang.ymy@alibaba-inc.com

ABSTRACT

Feed recommendation allows users to constantly browse items until feel uninterested and leave the session, which differs from traditional recommendation scenarios. Within a session, user's decision to continue browsing or not substantially affects occurrences of later clicks. However, such type of exposure bias is generally ignored or not explicitly modeled in most feed recommendation studies. In this paper, we model this effect as part of intra-session context, and propose a novel intra-session Context-aware Feed Recommendation (INSCAFER) framework to maximize the total views and total clicks simultaneously. User click and browsing decisions are jointly learned by a multi-task setting, and the intra-session context is encoded by the session-wise exposed item sequence. We deploy our model online with all key business benchmarks improved. Our method sheds some lights on feed recommendation studies which aim to optimize session-level click and view metrics.

CCS CONCEPTS

• Information systems → Multimedia information systems; Learning to rank; Recommender systems; · Computing method**ologies** \rightarrow *Multi-task learning*.

KEYWORDS

Feed Recommendation, User Behavior Modeling, Sequential Model, Intra-Session Context, Sequence Generation, Multi-Task Learning

ACM Reference Format:

Luo Ji, Gao Liu, Mingyang Yin, and Hongxia Yang. 2022. Intra-session Context-aware Feed Recommendation in Live Systems. In Proceedings of the 31st ACM International Conference on Information and Knowledge Management (CIKM '22), October 17-21, 2022, Atlanta, GA, USA. ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3511808.3557618

CIKM '22, October 17-21, 2022, Atlanta, GA, USA

© 2022 Association for Computing Machinery.

ACM ISBN 978-1-4503-9236-5/22/10...\$15.00

https://doi.org/10.1145/3511808.3557618

Gao Liu DAMO Academy, Alibaba Group Hangzhou, China liugao.lg@alibaba-inc.com

Hongxia Yang* DAMO Academy, Alibaba Group Hangzhou, China yang.yhx@alibaba-inc.com

INTRODUCTION 1

In recent years, feed recommendation (FR) has gained increasing popularity by providing never-ending and content-blended feeds in a waterfall form of item exhibitions. Generally, ranking in FR shares similar methodology with traditional learning-to-rank (LTR) methods, including traditional pointwise methods, as well as pairwise and listwise [2, 3] methods which consider surrounding effect around items. In the original configuration of modeling, it is assumed that user observes item candidates with equal probabilities. This assumption has been questioned by some eve-tracking studies and works have been done to reimburse the positional, exposure or selection bias [5]. Recently there are also increasing efforts to make the model more consistent with the actual live environments, including session-based recommendation [8, 13], sequential recommendation [17] and context-aware recommendation [4]. Within the scope of these works, both inter- and intra- context impacts are thoroughly studied and components such as RNN, GNN, transformer are widely adopted to capture the context-aware user preferences.

However, these studies seldom consider the interactive scenario of user browsing decisions, even for algorithms designed especially for FR [9, 18]. In a typical waterfall form of feeds, people first see the top item in default, then decide if click it or browse the next item. Obviously, this browsing decision is different from the click decision, and the next item could not be observed without that browsing operation ¹. As a result, the likelihood of a user's later click is affected by previous browsing behavior, which results in substantial exposure bias. Furthermore, this time dependency on different item positions suggests that global views or clicks might be better business metrics than click-through rate (CTR), to highlight the user stickiness. Given such an objective, optimizing the instant CTR could reach localized optima which is deviated from the global optimum (for example, putting the most favorable item on the top might not always be a statistically best idea, since user would probably click it then leave the session immediately.). Unfortunately, most FR models by so far neither do not have explicit modeling of the browsing behaviors, nor try to solve the global metrics. While some optimization-based method such as reinforcement learning (RL) could be theoretically suitable to solve such type of problems, they are usually subject to computational complexity or exploration

^{*}Corresponding author

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

¹In our definition, a user click itself is not considered as the end of session, but it is the end if the user never returned from the clicked page.

CIKM '22, October 17-21, 2022, Atlanta, GA, USA

cost thus industrial application is limited. In this work, we try to build a supervised framework in which user sequential behaviors are explicitly modeled as a series of Markov events of clicks and scrolls, and total views and clicks are ranking objectives. This is to the best of our knowledge the first time to eliminate the session exposure bias of FR by such a methodology.

In this paper, we propose a novel INtra-Session Context-Aware FEed Recommendation (INSCAFER) framework which considers the aforementioned mechanism on mobile-based applications. On the mobile devices, browsing items are achieved by user operations of scrolling the screen down. To model user scroll and click behaviors, we define the intra-session context as the user browsing experience within the current session. We model the browsing and clicking events within a session as a Markov Chain, with the intrasession context as a latent variable, and click and scroll decisions conditioned on it. We solve the problem by maximizing the negative likelihood loss of the session events sequence, which is converted into a multi-task classification training with historical click and scroll as ground truth labels. The entire framework is similar to Generative Pre-Train (GPT) [11], including a pre-training stage and a sequence generation stage. During pre-training stage, an intrasession context encoder is co-trained with a long-term interest net and a Multi-gate Mixture-of-Experts (MMOE) [10] module. The pre-trained encoder is then deployed on the server, and a recommendation sequence generation task is conducted with intra-session context dynamically calculated during servicing stage. The major contributions of this paper are as follows:

- We explicitly consider the user scroll decisions and subsequent time-dependency of intra-session behaviors, which is more close to the real FR scenario.
- The model loss and architecture are designed from a theoretical starting point, with the objective of the expected total views and clicks.
- We design a clear and fast framework similar to GPT to train and launch the model in a large-scale industrial system.

2 METHOD

2.1 Markov Modeling of Session Events

The basic idea of our work is motivated from the concept of session events shown in Figure 1, which characterizes typical FR scenario from traditional recommendation. User views the first item by default when entering into the session. Upon the *t*th item is *seen*, user makes two independent decisions: *click* indicating whether click the current item, and *scroll* indicating whether scrolling the screen down to browse the next item. The session stops when a 'not scroll any more' decision is made. At a specific position, the probability of click and scroll can be expressed by multiplication of two conditional probabilities

$$P(scroll, click|seen)P(seen|user, item, position)$$
 (1)

where 'item' is the item profile, and 'user' denotes the user perception affected by both the user long-term interest as well as the short-term experience within the current session. From this manner of definition, *user* should be a latent variable recurrently affected by previous events. As a result, expressions of Eq. 1 at different positions are not independent and identically distributed (i.i.d.)

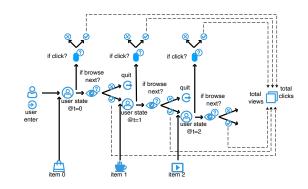


Figure 1: The logical flow of user events in a typical feed session. At each position t, user decides if click the current item and/or browse the next item, or quit the session. The sessionlevel recommending objective is to maximize the total views and clicks.

(*e.g.*, a false *click* will stops the session such that later *seen* is always false), which violates the basic assumption of pointwise LTR. Instead, Figure 1 indicates an unidirectional time-dependency of timely event sequence, *i.e.*, the former decisions will impact the later decisions, but reversely not. Similar conception can be found from the 'user cascade model' in [6] and also in DIEN [19]. On the contrary, bidirectional time-dependent methods such as [14] might be more suitable for Top-K recommendation instead of FR.

Here we introduce some abbreviated notations of events, in which the latent variable *h* denotes *user*, *x* represents the item embedding, *c* denotes probability of *click* and *s* denotes probability of *scroll*. *T* is the total length of session and a specific position is $t \in [0, T]$. The bold version of variable denotes a sequence of events in a timely order, *e.x.* $c := \{c_0, c_1, \dots, c_T\}$. Given an ordered exhibition of items x, the joint probability of feed session events is

$$P(\mathbf{c}, \mathbf{s}, \mathbf{h} | \mathbf{x}) = \prod_{t=0}^{T} P(c_t | h_t, x_t) P(s_t | h_t, x_t) P(h_{t+1} | h_t, x_t, s_{t-1})$$
(2)

considering the Markov dependency. The objective is then to maximize the expectation of total views and clicks of all sessions

$$\max V = \mathbb{E} \sum_{t=0}^{T} (c_t + s_t)$$
(3)

Intra-session Context-aware Feed Recommendation in Live Systems

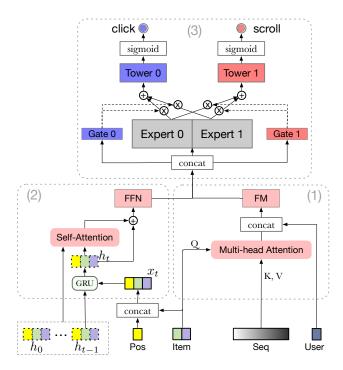


Figure 2: Network structure for logits calculation at each ranking position, including three components: (1) The Interest net, (2) The context encoder, and (3) The MMOE module. More configuration details can be referred to Subsection 3.1.

2.2Model

Similar with traditional LTR, optimizing the objective in Eq. (3) can be derived from maximizing the likelihood of Eq. (2), by parameterizing the conditional probabilities by trainable θ

$$\begin{split} \min_{\mathbf{h},\theta} L(\mathbf{h};\theta) &= -\log P_{\theta}(\mathbf{c},\mathbf{s}|\mathbf{h},\mathbf{x}) = -\log \frac{P_{\theta}(\mathbf{c},\mathbf{s},\mathbf{h}|\mathbf{x})}{P_{\theta}(\mathbf{h}|\mathbf{x})} \\ &= -\log \prod_{t=0}^{T} P_{\theta}(c_{t}|h_{t},x_{t})P_{\theta}(s_{t}|h_{t},x_{t}) \\ &= -\sum_{t=0}^{T} \log P_{\theta}(c_{t}|h_{t},x_{t}) + \log P_{\theta}(s_{t}|h_{t},x_{t}) \end{split}$$
(4)

which indicates that the session-wise learning can be decomposed into consecutive position-wise multitask learning, jointly with estimation of the recurrent contextual state h. At each position, learning is multitask with BCEs of two classifications, *click* and *scroll*. Although derivation of Eq. (4) seems trivial, there is no previous work which explicitly model the scroll behavior aside with click as multitask problem, to the best of our knowledge.

Eq. (4) implies our model structure, as shown in Figure 2, with three modules: 1) the Interest net with a multi-head attention block followed by a Factorization Machines (FM) [12] layer which studies the user long-term interest; 2) the intra-session context encoder which models user short-term interest shift, mutual-item influence and the positional impact encoded by GRU, followed by a selfattention [15] block; and 3) an MMOE [10] module with click and

CIKM '22, October 17-21, 2022, Atlanta, GA, USA

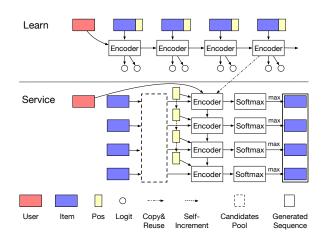


Figure 3: Framework of INSCAFER. Learn: Sequential context encoding. Service: Greedy sequence generation.

scroll subtasks. We name our approach as intra-session contextaware feed recommendation (INSCAFER).

Learning and service framework 2.3

INSCAFER has a similar learning paradigm with the famous Generative Pre-Train (GPT) framework [11], which is decoupled into two stages: the offline pre-training and online sequence generation, as shown in Figure 3. During the offline training stage, the context encoder is first initialized with the user embedding, then recurrently updated with each exposed item embedding concatenated with the position lookup embedding as input; while the MMOE logits of click (logit^c) and scroll (logit^s) are supervised by their labels². During the service stage, a greedy sequence generation task is executed with the pre-trained context encoder retrieved and inferenced. The position embedding is self-incremented and looked up during this stage. With K items left, the next item is decided by maximizing the following softmax:

$$\arg\max_{k} \frac{\exp\left(\operatorname{logit}_{k}^{c} + \operatorname{logit}_{k}^{s}\right)}{\sum_{k'}^{K} \exp\left(\operatorname{logit}_{k'}^{c} + \operatorname{logit}_{k'}^{s}\right)}$$
(5)

. . .

EXPERIMENT 3

We apply our approach on a world-leading E-Payment platform which also provides a comprehensive recommendation application, including goods, restaurants and online services. We first perform substantial offline evaluations, including the classification metrics of click and scroll, to prove the superiority of INSCAFER. Ablation study is also conducted to verify the necessary of different components. Data ³ and codes ⁴ have been made public.

3.1 Configurations

Figure 4 shows the distribution of view occurrences and CTR according to the top 8 positions. One can see both of them decay quickly as position becomes larger ⁵, resulting in tremendous exposure bias

²More precisely, this stage is similar with the 'supervised fine-tuning task' of GPT. ³https://tianchi.aliyun.com/dataset/dataDetail?dataId=109858&lang=en-us

⁴https://github.com/AaronJi/RecINSCAFER

⁵Note CTR at the first position is lower than the second and the third ones. The reason is that it is by design user will observe the first item by default. Only active and

CIKM '22, October 17-21, 2022, Atlanta, GA, USA

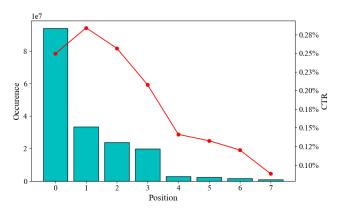


Figure 4: View occurrences and CTR curves w.r.t. positions. Data is slightly rescaled due to confidential requirement.

for long sessions. Significant deviation would be introduced with an i.i.d. assumption.

System has about 200 million users and a billion number of views per day. Upon each query at most 15 items are selected and sorted for exhibition. Embedding dimension is set to 16. Two heads are encoded in the multi-head attention layer and the cosine form of similarity is used. The shape of GRU latent state is the same with item embedding. There are 8 experts, 4 tasks and 64 as the expert shape in the MMOE module. The tower nets in MMOE are MLP with [128, 32] hidden units and sigmoid as the last activation. The ADAM optimizer is used with learning rate of 0.0001. Training costs more than 180k steps and loss converges after about 60k steps.

3.2 Offline Evaluation

Classification metric such as Area Under the ROC Curve (AUC) is evaluated for both *click* and *scroll* tasks. Experiments are repeated 10 times to report the averaged metric. Considering that our main purpose is to validate the effectiveness of loss in Eq. (4), we choose offline baselines which are close to our online model, as well as some combinations of them and modules of *INSCAFER*:

- DIN: the Deep Interest Network [20], as a standardized solution of industrial pointwise CTR model..
- *DIN-ListNet*: A listwise version of Vanilla with loss replace by a listwise loss defined in [3].
- *MMOE*: An MMOE model with *click* and *scroll* as subtasks, sharing the same bottom structure with *INSCAFER* [10].
- *GRU4rec*: A session-based method with a latent state calculated by GRU [7].
- *GRU4rec-MMOE*: The *GRU4rec* method combined with the MMOE structure to include *scroll* consideration.
- *Ptr-net*: The pointer network method [16] which applies the seq2seq idea combined with attention blocks, and has similar sequence generation mechanism with us. We train it in the supervised mode of *click* like work in [1].

We summarize these results in Table 1, with evaluation of the click-through rate abbreviated as ctr and scroll rate abbreviated as

Luo Ji, Gao Liu, Mingyang Yin, & Hongxia Yang

Model	AUC-ctr	AUC-scr
DIN	0.7771 ± 0.0042	0.5673 ± 0.0032
DIN-ListNet	0.7362 ± 0.0053	0.5186 ± 0.0061
MMOE	0.7682 ± 0.0045	0.7983 ± 0.0048
GRU4rec	0.7812 ± 0.0037	0.5362 ± 0.0049
GRU4rec-MMOE	0.7673 ± 0.0044	0.7885 ± 0.0035
Ptr-net	0.7790 ± 0.0065	0.5642 ± 0.0052
INSCAFER (w/o gru)	0.7701 ± 0.0043	0.8313 ± 0.0040
INSCAFER (w/o atten)	0.7792 ± 0.0032	0.8429 ± 0.0052
INSCAFER (w/o pos)	0.7722 ± 0.0034	0.7918 ± 0.0044
INSCAFER	$\textbf{0.7836} \pm 0.0035$	$\textbf{0.8562} \pm 0.0056$

scr. One can found that our INSCAFER has the best AUC for ctr and scr, and the third best MRR of scr. As comparisons, DIN and Ptr-net have reasonable ctr performances, but can not predict scr well, verifying that *scroll* has a different distribution with *click*. Simply switching its loss to the listwise form as in DIN-ListNet, can not solve the problem either. GRU4rec with the context consideration has an improved ctr performance but scr is still bad. On the other hand, MMOE can have good scr prediction because of its multitask setting but at the cost of ctr performance degradation. Combining GRU4rec with MMOE has similar balanced ctr and scr performances.

In Table 1, we also perform some ablation tests, by each time excluding the GRU unit, the self-attention block, or the position embedding. Not surprisingly, INSCAFER still has the best performance, suggesting these key components are all crucial.

3.3 Live Experiments

The live experiment starts on September 3th, 2021 and lasts for about a week, in which its baseline is DIN ensembled with a conversion rate (CVR) model as well as a model optimizing user views, corresponding to comprehensive business considerations. Due to limited online resource and business performance requirements, we only launch INSCAFER and DIN to compare with the baseline. Gains of some important business metrics of INSCAFER and DIN are shown in Table 2. Not surprisingly, DIN can improve CTR performance further but at the cost of other metrics. In the contrary, our method have increased almost all key indicators, especially for views per user (1.16%), scrolls per user (1.56%), and total conversions (1.56%). This solid live result indicates our model formulation has a better depiction of FR scenario and provides a more reasonable solution for global metric optimization.

Table 2: Gains of Live Metrics to Online Baseline

Model	DIN	INSCAFER
CTR	+0.20%	+0.13%
total views	+0.01%	+0.24%
views per user	-0.14%	+1.16%
scrolls per user	-0.54%	+1.56%
views per session	-0.06%	+0.38%
users to scroll	-0.06%	+0.42%
total conversions	-0.06%	+1.56%

interested user will scroll down the screen and see the next items. Our model is able to capture such effects by explicit modeling.

Intra-session Context-aware Feed Recommendation in Live Systems

4 CONCLUSION

In this paper, we propose a novel INSCAFER method which solves the feed recommendation problem by considering the intra-session context. In feed recommendation, user's previous operations, especial decisions to browsing the next item or not, affect distribution of later operations, resulting in substantial exposure bias. We start our model formation from maximizing the likelihood of the joint probability of session events, with explicit consideration of the timely dependency of user intra-session behaviors. Such intra-session context is studied during training and considered in servicing by a GPT-like framework. Both offline and live experiments have verified our method's superiority over several popular baselines.

REFERENCES

- Irwan Bello, Sayali Kulkarni, Sagar Jain, and Craig Boutilier. 2019. Seq2Slate: Re-ranking and Slate Optimization with RNNs. In Proceedings of the Workshop on Negative Dependence in Machine Learning at the 36th International Conference on Machine Learning (ICML '19).
- [2] Christopher J.C. Burges. 2010. From RankNet to LambdaRank to LambdaMART: An Overview. Technical Report MSR-TR-2010-82. https://www.microsoft.com/en-us/research/publication/from-ranknet-tolambdarank-to-lambdamart-an-overview/
- [3] Zhe Cao, Tao Qin, Tie-Yan Liu, Ming-Feng Tsai, and Hang Li. 2007. Learning to Rank: From Pairwise Approach to Listwise Approach. In Proceedings of the 24th International Conference on Machine Learning (ICML '07).
- [4] Daqing Chang, Jintao Liu, Ziru Xu, Hang Li, Han Zhu, and Zhu Xiaoqiang. 2019. Context-aware Tree-based Deep Model for Recommender Systems. In 3rd Workshop on Deep Learning Practice for High-Dimensional Sparse Data with KDD 2021 (DLP-KDD '21).
- [5] Jiawei Chen, Hande Dong, Xiang Wang, Fuli Feng, Meng Wang, and Xiangnan He. 2021. Bias and Debias in Recommender System: A Survey and Future Directions. arXiv:2010.03240 [cs.IR]
- [6] Georges Dupret and Benjamin Piwowarski. 2008. A user browsing model to predict search engine click data from past observations.. In Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR '08).
- [7] B. Hidasi, A. Karatzoglou, L. Baltrunas, and D. Tikk. 2016. Session-based Recommendation with Recurrent Neural Networks. In Proceedings of the 4th. International Conference on Learning Representation (ICLR '16).

- [8] Chao Huang, Jiahui Chen, Lianghao Xia, Yong Xu, Peng Dai, Yaqing Chen, Liefeng Bo, Jiashu Zhao, and Jimmy Xiangji Huang. 2021. Graph-Enhanced Multi-Task Learning of Multi-Level Transition Dynamics for Session-based Recommendation. In Proceedings of the thirty-fifth AAAI Conference on Artificial Intelligence (AAAI '21).
- [9] Yanhua Huang, Weikun Wang, Lei Zhang, and Ruiwen Xu. 2021. Sliding Spectrum Decomposition for Diversified Recommendation. In *The 27th ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD '21).*
- [10] Jiaqi Ma, Zhe Zhao, Xinyang Yi, Jilin Chen, Lichan Hong, and Ed H. Chi. 2018. Modeling Task Relationships in Multi-task Learning with Multi-gate Mixture-of-Experts. In The 24th ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD '18).
- [11] Alec Radford and Karthik Narasimhan. 2018. Improving Language Understanding by Generative Pre-Training.
- [12] Steffen Rendle. 2010. Factorization Machines. In 2010 IEEE International Conference on Data Mining (ICDM '10).
- [13] Heng-Shiou Sheu and Sheng Li. 2020. Context-aware Graph Embedding for Session-based News Recommendation. In Fourteenth ACM Conference on Recommender Systems (RecSys '20).
- [14] Fei Sun, Jun Liu, Jian Wu, Changhua Pei, Xiao Lin, Wenwu Ou, and Peng Jiang. 2019. BERT4Rec: Sequential Recommendation with Bidirectional Encoder Representations from Transformer. In Proceedings of the 2019 ACM on Conference on Information and Knowledge Management (CIKM '19).
- [15] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention Is All You Need. In Proceedings of the 30th International Conference on Neural Information Processing Systems (NIPS '17).
- [16] Qriol Vinyals, Meire Fortuno, and Navdeep Jaitly. 2015. Pointer Network. In Proceedings of the 28th International Conference on Neural Information Processing Systems (NIPS '15).
- [17] Shoujin Wang, Liang Hu, Yan Wang, Cao Longbing, Quan Z. Sheng, and Mehmet Orgun. 2019. Sequential Recommender Systems: Challenges, Progress and Prospects. In Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligenc (IJCAI '19).
- [18] Chuhan Wu, Fangzhao Wu, Tao Qi, and Yongfeng Huang. 2021. FeedRec: News Feed Recommendation with Various User Feedbacks. In *The 27th ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD '21).*
- [19] Huangbin Zhang, Chong Zhao, Yu Zhang, Wang Danlei, and Haichao Yang. 2021. Deep Latent Emotion Network for Multi-Task Learning. ArXiv abs/2104.08716 (2021).
- [20] Guorui Zhou, Chengru Song, Xiaoqiang Zhu, Ying Fan, Han Zhu, Xiao Ma, Yanghui Yan, Junqi Jin, Han Li, and Kun Gai. 2018. Deep Interest Network for Click-Through Rate Prediction. In *The 24th ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD '18).*