Interpretable User Retention Modeling in Recommendation

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ABSTRACT

Recommendation usually focuses on immediate accuracy metrics like CTR as training objectives. User retention rate, which reflects the percentage of today's users that will return to the recommender system in the next few days, should be paid more attention to in real-world systems. User retention is the most intuitive and accurate reflection of user long-term satisfaction. However, most existing recommender systems are not focused on user retention-related objectives, since their complexity and uncertainty make it extremely hard to discover why a user will or will not return to a system and which behaviors affect user retention. In this work, we conduct a series of preliminary explorations on discovering and making full use of the reasons for user retention in recommendation. Specifically, we make a first attempt to design a rationale contrastive multi-instance learning framework to explore the rationale and improve the interpretability of user retention. Extensive offline and online evaluations with detailed analyses of a real-world recommender system verify the effectiveness of our user retention modeling. We further reveal the real-world interpretable factors of user retention from both user surveys and explicit negative feedback quantitative analyses to facilitate future model designs. The source codes are released at https://github.com/dinry/IURO.

CCS CONCEPTS

• **Recommender Systems**; • **User Retention**; • **Interpretability**;

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KEYWORDS

recommender systems, interpretable user retention modeling, contrastive learning

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1 INTRODUCTION

With the information explosion, recommender systems are playing a central role in various scenarios [28, 33, 37, 40]. Most recommendation models are mainly trained by immediate user positive feedback (e.g., click), for they are relatively high-quality and abundant [10, 12, 13, 16, 17, 20, 21, 35, 41]. More importantly, they are modeled easily[38, 39]. However, simply optimizing click-related metrics has been increasingly criticized to be insufficient to measure user long-term and real satisfaction [2, 3, 6, 7, 9, 24, 27]. **User retention**, the percentage of users that return the systems in subsequent periods, can better indicate users' long-term satisfaction. The increase in user retention not only indicates the improvement of recommendation accuracy but also implies the expansion of users. Recently, very few pioneers have explored *user retention-oriented optimizations* based on sequential decision-making formalization[1, 29, 36]. The *accuracy of user retention modeling* has been considered while there is still large room for further improvement.

As the other side of the coin, *the interpretability of user retention modeling* denotes why users return to recommender systems and which behaviors affect user retention ultimately. It plays a crucial role in promoting the construction of the ecosystem of recommendations. With interpretability, recommender systems could be better guided to provide higher-quality personalized services to improve users' long-term engagement. However, several existing user retention-oriented optimizations in recommendations all focus too much on improving explicit accuracy, failing to explore the implicit reasons that affect user retention. This is because the interpretable user retention modeling in recommendation presents several intractable challenges practically: (1) ***Offline training and online serving of user retention-oriented optimization are significantly different and there are no explicit retention signals to model the reasonability of user retention.*** The online serving should rank different items for a user according to the user-item retention scores. In contrast, the only supervised signal of user retention prediction in offline training is whether a user will return in the next few days (based on all user information), where no explicit retention signals are available for a specific user-item pair. The huge gaps between offline and online optimization goals and inputs of user retention constitute the major challenge. (2) ***The reasons for user retention are far more complicated and difficult to model than other behaviors.*** Unlike clicks, user retention has more randomness that can be affected by many factors, even including unpredictable external factors that cannot be captured by systems (e.g., bad mood or busy work). Thankfully, the main factor (i.e., users' impressed and clicked items given by the system) are controllable, while it is extremely difficult and uncertain to identify which behaviors and factors affect user retention ultimately due to their weak causality. (3) ***The supervised information of user retention is much sparser than clicks.*** Users can have hundreds of clicks but only one retention behavior (return or not) per day, posing huge challenges for user retention modeling.

To solve the above challenges, we conduct a series of preliminary explorations on the rationale[5, 30, 31] and interpretability of user retention in recommendations. We propose a novel ***interpretable user retention-oriented optimization (IURO)*** framework, which directly discovers and utilizes the interpretable factors of user retention in the recommendation from four efforts: (1) First, we propose an offline user retention prediction task to directly bring in retention-related supervised signals. Precisely, we design a ***contrastive multi-instance learning (CMIL)*** module, attempting to dig out the rationale of retention and explore which behaviors induce users to return. CMIL first generates user-item retention scores for each behavior via a UI scorer and then combines all retention scores via instance-level attention. It smartly bridges the gaps between offline training (jointly considering all UI scores of a user) and online serving (using the UI scorer for one user-item pair). (2) Inspired by the "Aha Moment" (i.e., a surprising, rare, and pleasure-oriented experience that is verified to have large impacts on user growth) assumption [26], we assume that only several high-quality "***aha items***" in historical behaviors are the dominating reasons of user retention. Hence, we introduce a contrastive learning (CL) task to broaden the gaps between high- and low-attention items, increasing the sharpness of "aha items". (3) To further bring more interpretability in finding high-impact aha items, we build a ***rationale multi-instance learning (RMIL)*** module to adjust the output of CMIL via a Jensen-Shannon divergence between CMIL's and RMIL's distributions. The next-few-day clicks are used as high-potential causal keys to dig out high-impact historical behaviors during model training as an essential supplement to rational understanding. (4) In addition, we try to explicitly reveal the reasons for user retention in users' own words via some user surveys and negative-feedback quantitative analyses to discover the real rationales for users to stay. These analyses could not only be utilized to support the design of our interpretable user retention modeling but also provide valuable insights for future efforts in user retention-oriented optimizations.

The major contributions of our work include: (1) We conduct a series of preliminary explorations on the rationale and interpretability of user retention in recommendation and propose a novel interpretable user retention modeling framework to capture and utilize these factors, attempting to make them affect the design of ecosystems of recommendation in reverse. (2) We propose an offline user retention prediction task to directly bring in retention-related supervised signals, and design a novel interpretable user retention-oriented optimization framework with joint rationale and contrastive multi-instance learning to capture aha items that are beneficial for user retention prediction and understanding. (3) We conduct extensive offline and online experiments and analyses and achieve significant improvements in real-world industrial scenarios. (4) We carefully conduct some user surveys and negative-feedback quantitative analyses on a widely-used article recommender system, making an attempt to explicitly disclose the real rationale and interpretability of user retention. These analyses can provide precious insights into user retention to facilitate future retention research.

2 RELATED WORKS

Recommender systems are becoming an integral part of our daily life and have gained immense success over the years[38, 39], mainly focusing on users' immediate responses. However, over-focusing on immediate metrics can lead to undesirable recommendations, such as clickbait contents which hurt long-term engagement[25]. The drawback of over-optimizing the immediate metrics has been recognized, so researchers begin to explore the optimization of users' long-term satisfaction. On the one hand, some works explore to improve user's long-term engagement through modeling users' dwell time and bounce rate[4, 19, 32, 42]. For example, Kapoor et al.[19, 22] predict users' return times on free web services based on the Cox's proportional hazard regression model from survival analysis. In their following works[18], they utilize a sequential decision-making model to model the time interval, indirectly improving user retention. In addition, Zhang et al.[34] designed a counterfactual estimate to model users' relayed feedback. On the other hand, very few pioneers have explored user retention-oriented optimizations [1, 14, 36]. For example, Dror[11] and Kushal[8] predict user retention by exploring user-level retention factors (e.g., the number of impressions, the number of clicks, user's age and gender), failing to optimize online user retention directly by reranking high-impact items. Recently, Kesen Zhao et al.[36] propose optimizing user retention with Decision Transformer (DT), which avoids the offline difficulty by translating the reinforcement learning as an autoregressive problem. However, this work only evaluates user retention in an offline manner on two benchmark datasets. In addition, Cai et al.[1] proposed that user retention is long-term feedback after multiple interactions between users and the system, and it is hard to decompose retention rewards to each item or a list of items. So they formulate the problem as an infinite-horizon request-based Markov Decision Process and minimize the accumulated time interval of multiple sessions by utilizing reinforcement learning. All the works assume the user's long-term engagement tasks as sequential tasks and adopt sequential models (such as survival analysis, bandit framework, Markov chains, and reinforcement learning) to model some potential long-term metrics, such as users' dwell time and time interval, which however may fail to optimize user retention accurately in online serving since the sequential decision-making tasks pay more attention to the effect of sequential behaviors on user retention neglecting the impact of high-quality immediate items of online serving on user retention. They also fail to answer "Which behaviors drive retention directly?". What's worse, they only focus on the explicit accuracy of user retention-oriented optimization[1, 4, 36]. We argue that the intrinsic reasonability of user retention modeling is more essential than accuracy which can facilitate the construction of ecosystems in recommendation. So We make a first attempt to explore the interpretability of user retention and answer "Which behaviors drive retention directly?" by utilizing selective rationalization[31] (It can explain the prediction of complex networks by finding a small subset of the input which yields the same outcome as the original data, consisting of two components, rationale generator, and predictor). These interpretable factors can better guide recommender systems to provide higher-quality personalized online services and attract more users.

3 METHODOLOGY

3.1 Model Overview

In this work, we propose a novel interpretable user retention-oriented optimization framework to directly discover and utilize the rationale and interpretability of user retention in recommendation. We propose an offline user retention prediction task to directly bring in retention-related supervised signals, and design a rationale contrastive multi-instance learning framework to make an attempt to discover precious but rare "aha items" that induced users to return to the system, exploring the rationale and interpretability of user retention. Fig. 1(a) shows the overall architecture of our proposed interpretable user retention-oriented optimization, IURO. In offline training, IURO should predict whether a user will return in the next several days given his/her cumulative features and behaviors. Contrastive multi-instance learning (CMIL) models user retention interpretably via instance-level attention. It first generates UI retention scores for every interacted item of a user via a UI scorer, then aggregates all UI retention scores via attention, finding the most impacting historical behavior that leads to retention. Contrastive learning is introduced to broaden the gaps between high- and low- attention items to discover rare but high-impact aha items. Besides, rationale multi-instance learning (RMIL) further uses future behaviors as high-potential causal keys to dig out rational retention factors. By aligning the distributions between CMIL's and RMIL's attention, the model could generate more interpretable high-quality aha items of our proposed IURO. In online serving, the UI retention scores generated by UI scorer in CMIL are combined with classical CTR scores for the online prediction, smartly bridging the gap between offline and online retention modeling.

3.2 Contrastive Multi-instance Learning

To explicitly find which behaviors affect user retention and bridge the gaps between offline training and online serving, we build the CMIL framework with an instance-level attention[23], as shown in Fig. 1(b). Given users' static features (i.e., user attributes, user long-term behaviors), CMIL first generates UI retention scores for short-term behaviors via **UI scorer module** in offline training. Here, we leverage a 3-layer feedforward network ($FFN_3(\cdot)$, ReLu as the activation function) to model UI scorer module and generate UI retention score for user and item, $s_{ui} = FFN_3(concat(\boldsymbol{u_p}, \boldsymbol{u_l}, \boldsymbol{v_i}))$, where $\boldsymbol{u_p}$ is user's attributes feature, $\boldsymbol{u_l}$ is user's long-term behaviors feature, and $\boldsymbol{v_i}$ is item i's feature (users' short-term behaviors feature in offline training and candidate items feature in online serving). Then CMIL combines all UI retention scores via the instance-level attention to predict whether the user will return in the next three days.

$$y_{MIL_u} = \sum_{i \in seq_u} \text{softmax}(\frac{concat(\boldsymbol{u_p}, \boldsymbol{u_l})\boldsymbol{v_i}}{\sqrt{d}}) s_{ui}, \tag{1}$$

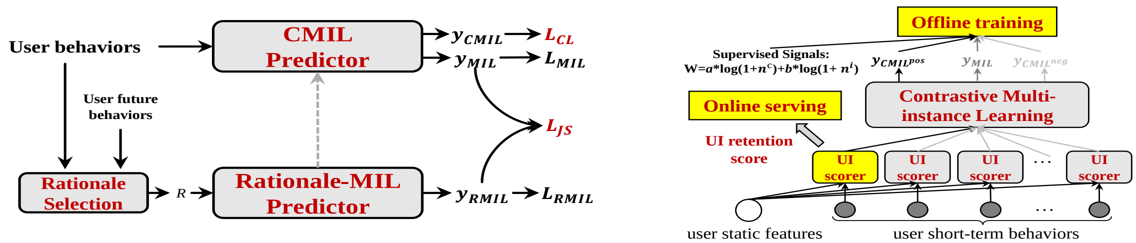
where seq_u is the short-term behavior sequence of the user u ($u \in U$, U is the user set.), and d is the dimension of features. To reduce the randomness and noise of user retention, next-three-days cumulative features (clicked- and impressed- items numbers) are introduced as supervised signals to quantify user retention accurately, increasing the confidence of user retention, $W_u = a\log(1 + n_u^c) + b\log(1 + n_u^i)$, where n_u^c and n_u^i are user u's next-three-days clicked- and impressed- items number, respectively. a and b are the hyper-parameters. Thus, the objective loss of MIL is $L_{MIL} = \sum_{u \in U} W_u * MSE(y_u, y_{MIL_u})$, where y_u is user's real retention. Although MIL can fit the offline user retention task well, UI retention scores generated by UI scorer may be inaccurate due to the severe bias between offline training and online serving on user retention. We believe that historical behaviors that fascinate users and induce user retention are rare but precious, so we introduce contrastive learning to broaden the gaps between high- and low- attention items to discover these rare but precious aha items, exploring the reasonability and interpretability of UI scorer, as follows:

$$L_{CL} = \sum_{u \in U} max(0, |y_{MIL_u} - y_{CMIL_u^{pos}}| - |y_{MIL_u} - y_{CMIL_u^{neg}}| + m). \tag{2}$$

where y_{MIL_u} is the user's retention score aggregated by multi-instance attention, $y_{CMIL_u^{pos}}$ and $y_{CMIL_u^{neg}}$ are the user's retention score predicted by multi-instance attention via masking the lower-attention items and higher-attention items, respectively. m is a hyper-parameter of margin loss.

3.3 Rationale Multi-instance Learning

While CMIL can fit the offline training well and discover rare but precious aha items, we argue that the optimization direction and confidence of UI scorer may be improper and not convincing due to lack of efficient guidance and supervision induced by the biases between offline training and online serving (The intersection of aha items selected by different initializations is only nearly 35%, indicating that the randomness of parameters has a strong influence on UI retention scores.). A non-robust UI scorer not only fails to optimize retention but also hurts other metrics like CTR. Future perspective is always a guide for current behaviors which can lead



(a) Framework of our proposed IURO.

(b) Framework of contrastive multi-instance learning.

Figure 1: Model overview of IURO. We attempt to explicit the intrinsic rationale of user retention via CMIL and RMIL.

us to excavate rare but important historical behavior for retention. Thus, we build a rationale multi-instance learning module (RMIL) with the same structure as MIL where the next-few-day clicked items of positive users are introduced as high-potential external-causal keys to infer high-impact rational historical behaviors for user retention (i.e., top 5 historical behaviors ranked by the dot product between the mean of future click behaviors feature and short-term historical behaviors feature.). Then RMIL predicts user retention based on these rational behaviors (We have verified the confidence of rational behaviors on user retention: the intersection of aha items selected by different initializations is nearly 70%, indicating the robustness of IURO). CMIL (offline training) supervised by RMIL (external knowledge) via a Jensen-Shannon divergence between RMIL's and CMIL's distribution can optimize user retention distribution rationally and generate robust-accurate UI retention scores with more interpretability. The Jensen-Shannon loss is formulated as: $L_{JS} = \mathbb{E}_{u \in U}[JS(y_{MIL_u} || y_{RMIL_u})]$. The objective loss of RMIL L_{RMIL}, is equal to L_{MIL}, and the overall objective is $L = \lambda_1 L_{MIL} + \lambda_2 L_{CL} + \lambda_3 L_{RMIL} + \lambda_4 L_{JS}$, where λ_1, λ_2, λ_3, and λ_4 are the hyper-parameters.

4 EXPERIMENTS

4.1 Direct Interpretability Analyses From User Explicit Feedback

We conduct a direct interpretability analysis from user explicit feedback (e.g., user surveys and explicit negative feedback analyses) to reveal the real interpretable factors and rationales of user retention in our article recommendation feed. These analyses could be utilized to guide the design of interpretable user retention modeling. What's more, they can also provide valuable insights for future research in other user retention-oriented optimizations.

Positive user retention factors from user survey. We conduct some user surveys to gain a comprehensive understanding of which factors users care about and why they return to the recommender systems under user approval. Our surveys results show that: (1) *Personalized interests, News, and Variety Shows are the most favorite topics in our system.* In addition, users with different attributes tend to have different preferences. (2) Most users claim that they will return to the recommender system if recommended items are *positive, nutritious, and interesting*. Especially, *relaxing and stress-relieving* items are the most attractive for user retention, and about 69% of participants claim that they will return to the system if items are relaxing and stress-relieving. (3) Lots of participants do not like negative content, such as gory horror, advertising, and negative news. Recommending such contents should be more careful with better personalization ability. (4) Furthermore, page layout also has a strong impact on user retention. For example, some young people said that if the page design is stuffy or not hierarchical, they will reduce the retention of this system, since they think it may be designed for older people.

Negative user retention factors from quantitative analyses on user explicit feedback. We collect negative-feedback information from users on items through an interactive interface deployed on our industrial recommender system to explore and quantify the impact of negative factors on user retention. Table 1 demonstrates the relative average user retention rates of different negative feedback reasons compared to all negative-feedback users' retention rates for 7 consecutive days (about 1 million cases per day, user information is well protected via data masking). We can find that: (1) Users claiming "Not interested in items" have the lowest retention among all reasons, indicating that interest mismatching is the most frustrating and unproductive reason. Such signals should be highly valued and responded to in time. (2) "Low-quality content" and "Advertising promotion" are also representative negative factors for user retention. Recommender systems should avoid these low-quality factors, such as bloodiness, violence, fraud, and advertisements, to improve users' long-term engagement. (3) "Poor diversity" and "Exaggerating titles" also harm user retention compared to the average rate. (4) It is surprising that users having "Repeated recommendation" and "Don't like the author/content" are the negative reasons for the lowest impacts. We guess that such negative feedback does not mean that the user is disappointed with the system and will not return. In contrast, they may imply that these users are heavy users of our systems and hope our system can solve these problems.

4.2 Offline Evaluation

Datasets. We explore user retention on two real-world datasets, ZhihuRec[15], and an industry dataset. ZhihuRec 1M has 7,963 users, 81,214 items, and 1,271,751 behaviors across 10 days. We split the behaviors of the first seven days as the training set, and the last three days as the test set in ZhihuRec 1M. The industry dataset, captured from a widely-used article recommender system, contains about 1 million users and 500,000 items with 97 million behaviors over 18 days. All data are processed via data masking to protect user privacy. The last three days are used as the test set.

Table 1: Relative average user retention rates of different negative feedback reasons.

Explicit reasons of negative feedback	Next-day Retention	Next-three-day Retention
Not interested in items	35.38%	36.45%
Low-quality content (bloodiness, violence, fraud)	90.29%	91.78%
Advertising promotion	91.89%	93.06%
Poor diversity	97.33%	98.36%
Exaggerating titles	98.98%	99.05%
Don't like the author/content	102.29%	102.03%
Repeated recommendation	113.51%	108.07%

Experimental settings. In offline training, we regard the user retention prediction task as a regression task and evaluate whether the user will return in the next three days using AUC. which is essential to online recommendation. Precisely, we formulate users' short-term behaviors as the latest three days' behaviors which we think will have impacts on user retention. empirically.

Offline results and ablation study. To guarantee the effectiveness of user retention optimization and explore a series of baselines as follows: Base MLP: We input users' static features and all behaviors into a 3-MLP retention prediction model (*infeasible in online serving without UI scorer serving for user-item pairs*). IURO(AVG): We hypothesize that the impact of each item on user retention is the same. IURO(MIL): We introduce instance-level attention based on IURO(AVG). IURO(MIL+MSS): We consider future cumulative features as supervised signals on the basis of IURO(MIL). IURO(CMIL+MSS): We introduce contrastive learning on the basis of IURO(MIL+MSS). IURO(RCMIL+MSS): We introduce a rationale mechanism on the basis of IURO(CMIL+MSS). All baselines share the same settings and features.

From Table 2 we can observe that: (1) IURO(MIL) outperforms Base MLP and IURO(AVG) indicating that the impacts of different behaviors on user retention are different and instance-level attention can better discover higher-impact items compared with others to guide user retention-oriented optimization. (2) The cumulative feature as multiple supervised signals can be used to improve retention indicating that they can quantify retention more accurately. (3) The performance of IURO(CMIL+MSS) is superior to IURO(MIL+MSS)'s indicating that IURO(CMIL+MSS) can further sharpen the surprising aha items to explore the inherent reasonability of user retention. (4) The performance of IURO(RCMIL+MSS) is similar to IURO(CMIL+MSS)'s showing that IURO(CMIL+MSS) supervised by RMIL also can predict the offline user retention task well, meanwhile making UI scorer more robust and interpretable.

4.3 Online Evaluation

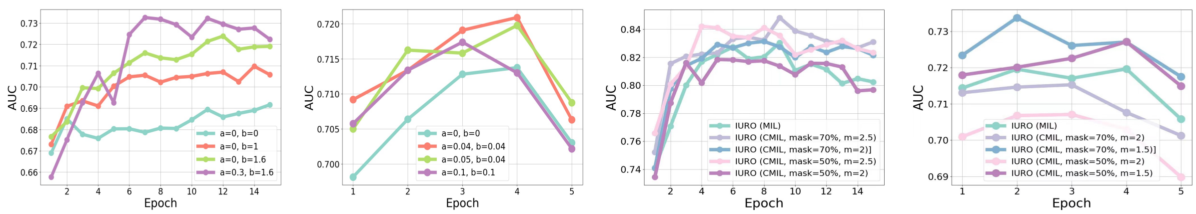
Online settings and results. We conduct an online A/B test with over 3 million users to verify the performance of IURO in real-world industrial scenarios. The only difference is the usage of our UI retention scorer. Control Group (Con. Group) is dominated by the base model deployed initially (current model deployed in real-world industrial scenarios), and Experiment Group (Exp. Group) reranks the candidate items combining UI retention scores generated by UI scorer (s_{ui}) and Click-Through Rate scores generated by the base model (ctr_{ui}), $r_{ui} = \lambda ctr_{ui} + (1-\lambda)s_{ui}$, where λ is a hyper-parameter tuned by online systems. We mainly focus on next-day retention and next-three-day retention in online serving since these two metrics are the central retention-related goals in our industrial system. Table 3 demonstrates the relative improvement of Exp. Group (IURO) in user retention compared with Con. Group's, and we can find that: Exp. Group achieves consistent improvements on two metrics compared with Con. Group, verifying the interpretability of user retention is dug out reasonably and revealing the effectiveness of IURO on retention by emphasizing high-impact items in online scenarios.

IURO does not harm other click/duration metrics. We conduct comprehensive online analyses to better understand the overall performance of IURO. Here, we define the *hit item* as an item that is (a) recommended by IURO and (b) impressed to a user in Exp. Group, and the user is noted as *hit user* of IURO. The average CTR per item is 0.082 for Exp. Group, 0.083 for Con. Group, and 0.129 for hit items. In addition, the average duration per item is 18.86 for Exp. Group, 18.55 for Con. Group, and 98.73 for hit items. From this item-level performance, we can find that: (1) the average CTR/duration per item is comparable in the Con. Group and Exp. Group, indicating that our IURO improves user retention without damaging other metrics like CTR and duration. (2) The average CTR/duration of hit items is much higher than Con. Group's, implying that hit items are all high-quality recommendations generally.

Interpretable findings in online analyses. We also conduct extensive analyses to explore the possible interpretability of IURO. We find that: (1) Hit users, the categories of whose clicked items on the next day intersect with the categories of whose clicked hit items on the first day, account for 64.66% of total hit users. It indicates that *users are more likely to click items similar to hit items in the future, and these hit items have a positive effect on user retention.* (2) The average percentage of the same categories of hit items still being clicked by hit users on the next day is 61.72%. By contrast, the average percentage of non-hit items is 48.78%. It demonstrates that *hit items recommended by IURO are more similar to future clicks, implying that IURO could recommend more attractive items for users.* (3) Clicked items whose categories are still clicked by this user on the next day make up 61.09% of all clicked items in Exp. Group, and 60.62% in Con. Group. It indicates that historical and future behaviors have connections. *The future clicks could be viewed as an approximate rationale key in finding high-impact items, verifying our assumption in RMIL.* Moreover, the performance of Exp. Group is superior to Con. Group, showing that items recommended by Exp. Group are more in line with user interests. (4) Our IURO could recommend high-impact items with novel categories that users have not viewed in the last few days (i.e., exploring new interests for users), and approximately 34.08% of these users even start to follow these surprising categories in their future clicks (far more than the base model). *It implies the capability of IURO in escaping from the filter bubbles and discovering users' new interests.*

Table 2: Results of offline user retention prediction (AUC).

Datasets	Base MLP	IURO (AVG)	IURO (MIL)	IURO (MIL+MSS)	IURO (CMIL+MSS)	IURO (RCMIL+MSS)
ZhihuRec	0.7180	0.5838	0.8269	0.8312	0.8437	**0.8445**
Industry	0.6827	0.6732	0.7209	0.7255	0.7291	**0.7301**



(a) Impacts of SS on ZhihuRec. (b) Impacts of SS on Industry. (c) Results of CMIL on ZhihuRec. (d) Results of CMIL on Industry.

Figure 2: Exploration on interpretable user retention-oriented optimization.

Table 3: Online A/B test on a widely-used industrial article recommendation feed.

Model	Next-day Retention	Next-three-day Retention
IURO(RCMLI+MSS)	+0.76%	+0.65%

4.4 Model Analyses

Future cumulative features as additional supervised signals for user retention. We explore the impacts of cumulative features (number of future click and impression behaviors) in the next three days on user retention via W_u mentioned in section 3.2. Fig. 2(a) and Fig. 2(b) reflect that these factors as supervised signals are beneficial for better quantifying user retention since the performance of IURO without future click and impression behaviors ($a = 0, b = 0$) is inferior to others' with supervised signals, and $a = 0.3, b = 1.6$ in ZhihuRec and $a = 0.04, b = 0.04$ in Industry are best.

Different contrastive multi-instance learning strategies. The performance of contrastive learning on user retention is shown in Fig. 2(c) and Fig. 2(d), where mask=70% means that we use items with top 30% attention values as positive items and items with bottom 30% attention values as negative items in CL. We find that IURO(CMIL) is superior to IURO(MIL), especially when mask=70% and $m = 2$. Our CL aims to broaden the retention score gap between high/low attention items. The improvements verify that our assumption of sharpening aha items is superior and CL is effective.

Categorical analyses for user retention. We cluster users into 10 groups and then visualize the click-behaviors category distribution on the industry dataset. Fig. 3 shows the results of a certain user group, including items with high UI scores (top 20%), low UI scores (bottom 20%), and all items. We find that items of *Marriage*, *Chicken Soul*, and *Wine* have higher retention scores, and items from *Trivia* have lower retention scores for this user group. Different user groups share some general interests as well as community-specific preferences. In addition, we also analyze the category distribution of high- and low- attention behaviors, and have some interpretable findings: (1) The category distribution of low attention is very similar to that of all items, while high attention's is different. (2) Items of *Social Life* and *Marriage* have higher impacts on deciding whether users will return. (3) Items of *Trivia* and *Superstar* may have lower impacts on user retention. *Such insights could be used to build the top-level designs of retention modeling.*

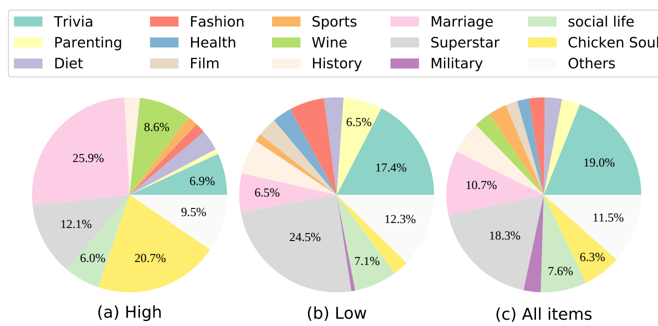


Figure 3: Category distribution of a user group's historical click behaviors with different UI retention scores.

5 CONCLUSION

In this paper, we conduct some preliminary explorations on the reasons for user retention and make an attempt to design a rationale framework to optimize user retention by introducing interpretable factors. In addition, we further reveal the real-world interpretable factors for user retention from both user surveys and explicit negative feedback analyses to facilitate future user retention modeling.

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