# Multi-granularity Fatigue in Recommendation


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## ABSTRACT

Personalized recommendation aims to provide appropriate items according to user preferences mainly from their behaviors. Excessive homogeneous user behaviors on similar items will lead to fatigue, which may decrease user activeness and degrade user experience. However, existing models seldom consider user fatigue in recommender systems. In this work, we propose a novel multi-granularity fatigue, modeling user fatigue from coarse to fine. Specifically, we focus on the recommendation feed scenario, where the underexplored global session fatigue and coarse-grained taxonomy fatigue have large impacts. We conduct extensive analyses to demonstrate the characteristics and influence of different types of fatigues in real-world recommender systems. In experiments, we verify the effectiveness of multi-granularity fatigue in both offline and online evaluations. Currently, the fatigue-enhanced model has also been deployed on a widely-used recommendation system of WeChat.



## CCS CONCEPTS

• **Information systems** → **Recommender systems**.

## KEYWORDS

recommendation; user fatigue; multi-granularity fatigue

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## 1 INTRODUCTION

Personalized recommendation focuses on providing items to users according to their interests mainly from users' historical behaviors [21, 29]. Lots of works have explored learning the positive feedback from user behaviors [7, 19], while most of them ignore the implicit, negative yet essential factor, i.e., fatigue, of users in practice. **Fatigue** is a ubiquitous phenomenon that indicates that users will *gradually get tired and bored with repeatedly impressed factors* in a session. In practice, users interact with recommendation systems via their behaviors (e.g., click, read, refresh, browse). These behaviors will lead to certain time and operation costs, which inevitably bring in fatigue that decreases user activeness. In general, larger fatigue has more negative impacts on recommendation. Hence, it is essential to precisely model fatigue for a better recommendation.

There are very few works that have explored the influence of fatigue. Moreover, most pioneer works mainly concentrate on the fatigue of repeatedly impressed *items* in display ad/news systems [12]. In Fig. 1, we propose a novel notion **multi-granularity fatigue**, which reflects user fatigue on three levels in recommendation:

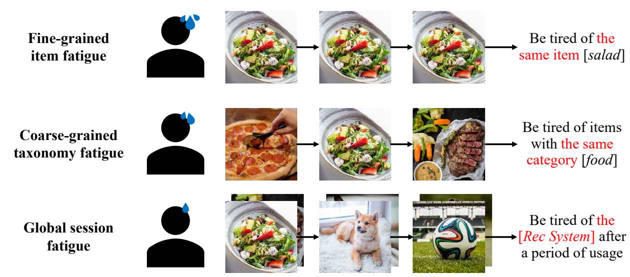


**Figure 1: Multi-granularity fatigue in recommendation.**

(1) **Fine-grained item fatigue.** This fatigue reflects a straightforward phenomenon that users will lose interest in repeatedly impressed items [12]. The number of the target item clicked before is a classical item fatigue feature. The item fatigue widely functions in display ad/news recommender systems, where the number of overall item candidates is relatively small and items are likely to be repeatedly recommended. However, item fatigue may not function well in other scenarios such as article feeds, since most impressed items are de-duplicated in these scenarios as a hard constraint.

(2) **Coarse-grained taxonomy fatigue.** The taxonomy fatigue, viewed as a generalized item fatigue, focuses on the duplications of item taxonomies (e.g., category). Users have intrinsic preferences on specific taxonomies (e.g., food), and repeatedly reading items having the same taxonomy does imply strong interests. However, too many homogeneous items in a session also harm the performance, since the information gain will gradually decrease and users will get tired

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of similar contents eventually. Generally, the coarser the taxonomy, the lower the effect of its taxonomy fatigue on users.

(3) **Global session fatigue.** We first propose a novel global session fatigue to measure the user fatigue on the whole recommender system. Users will click different items under different global fatigue. For example, a user may be willing to spend time on in-depth articles at the beginning of a session, while tend to read more easy contents at the end due to the global session fatigue. Considering such global fatigue helps to improve user experience in practice.

In this work, we aim to analyze the impact of multi-granularity fatigue on recommendation, so as to use it to improve the online performance. Most existing efforts focus on item fatigue in those systems where items are usually repeatedly impressed and clicked by users [12]. In contrast, we conduct explorations on the general *recommendation feed* scenario, paying more attention to the *coarse-grained taxonomy fatigue* and the *global session fatigue*. We first conduct comprehensive analyses on the existence, characteristics, and impacts of different types of fatigues. Next, based on these findings, we design a straightforward yet effective framework to jointly consider the multi-granularity fatigue in recommendation. The significant offline and online improvements verify the effectiveness. Our contributions of this work are concluded as follows:

- We are the first to systematically propose, analyze, and utilize the multi-granularity fatigue in recommendation feed.
- We creatively propose the coarse-grained taxonomy fatigue and the global session fatigue in recommendation feed, which considers more generalized user fatigue in practice.
- Extensive analyses and evaluations are conducted for deeper understandings on user fatigue. The fatigue-enhanced model has been deployed on WeChat Top Stories.

## 2 METHODOLOGY AND ANALYSES

### 2.1 Motivation of Fatigue Modeling

The central objective of recommendation is user preference learning. Many researchers have devoted themselves to learning what users may like from positive factors such as historical clicks. However, we argue that understanding what users dislike from negative factors (e.g., fatigue) is also essential for improving user experience.

The **fatigue** of user is an informative but under-explored negative factor, which reflects the negative impacts of repeatedly impressed factors in a session. We suggest that these repeated factors should include items, taxonomies, and even the overall recommender system from fine to coarse. The essence of user fatigue comes from the mismatching between the information gain brought by the repeated factors and the users' costs. Through model analyses, we discover that users' activeness and preferences will drift with the float of multi-granularity fatigues. Hence, it will be beneficial if we could successfully capture fatigue features. In this work, we conduct analyses and deployment on a widely-used article feed, where item fatigue is roughly considered as a hard constraint by item de-duplication. The following explorations mainly focus on the global session fatigue and the coarse-grained taxonomy fatigue.

### 2.2 Global Session Fatigue

We first discuss the novel notion of global session fatigue, which aims to measure user's fatigue on the whole recommender system. Precisely, we investigate four user behaviors that may cause the global session fatigue, including click, read, impression, and refresh.

*2.2.1 Global Fatigue on Click and Read.* Both clicks and dwell time reflect high time costs users have already spent in a session, which have direct connections to the global session fatigue. In Fig. 2, we display the overall CTR trends with different clicked item numbers and dwell time in a session. We find that: (1) generally, more clicked items and more dwell time often result in lower CTR, which verifies the existence of global fatigue. (2) CTR first slightly increases at the beginning of a session (e.g., from 1 to 3 clicks). It implies that users begin to enter a focused reading state after a few "warm-up" clicks and reads. Next, CTR drops dramatically as more items are clicked/read, which indicates the global session fatigue starts to take control. Note that we only analyze on user instances having enough long sessions, since the fatigue mainly functions when users have clicked several items. Ensuring the consistency of analyzed users could also avoid user group bias (dominated by light users having low CTR, lowing CTR in short sessions). Inspired by this, we define two novel effective features for global session fatigue, namely the numbers of clicked items (**session click**) and the dwell time of clicked items (**session dwell time**) in the current session.

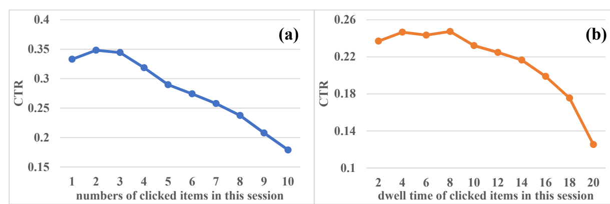


**Figure 2: CTR trends with different (a) clicked item numbers and (b) dwell time users spend on clicked items in a session.**

*2.2.2 Global Fatigue on Impression and Refresh. Click* and *dwell time* are high-cost feedbacks that are highly related to global fatigue. We suggest that other user behaviors with lower costs may also generate global fatigue, such as *impression* and *refresh*. An impression behavior indicates an item is exposed (but not necessarily clicked) to a user in the feed. Refresh happens when a user wants to receive new recommendation results. In some feeds, refresh is usually triggered by sliding down at the end of the last recommended list (e.g., each refresh will get 11 recommended items in our system).

Fig. 3 and Fig. 4 show the CTR and dwell time trends with impression and refresh behaviors. We have: (1) in general, the CTR and dwell time per click will decrease when more refresh behaviors are conducted and more items are impressed to users, which indicates that too many historical impressions and refresh behaviors (though having lower costs) also lead to global session fatigue. (2) Comparing Fig. 3 with Fig. 4, we find that instead of smoothly monotonic decreasing, the CTR and dwell time trends on impressions go up and down periodically. The results will suddenly rise right after each refresh, and then gradually fall inside each recommended list until the next refresh. It is because that the refresh behavior often implies high activeness of users in receiving more recommendations, which acts as short-term adrenaline against user fatigue. Inspired by this, we also consider the numbers of historical refresh and impression behaviors in the current session to model global fatigue. We name these two features as **session impression** and **session refresh**.

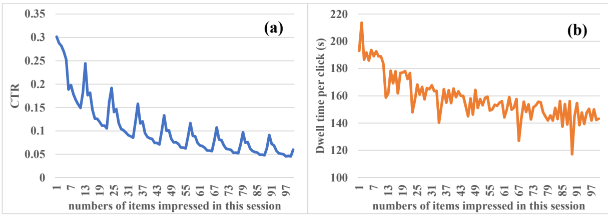


**Figure 3: The (a) CTR and (b) dwell time per click trends with impressed item numbers (i.e., item positions) in a session.**

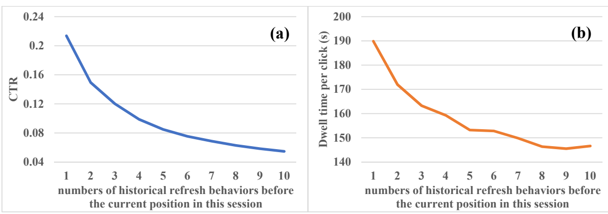


**Figure 4: The (a) CTR and (b) dwell time per click trends with different historical refresh behavior numbers in a session.**

## 2.3 Coarse-grained Taxonomy Fatigue

We further analyze the coarse-grained taxonomy fatigue focusing on duplication at the taxonomy level. The taxonomy could be any type of item attribute, including item producer, category, and tag. Specifically, for a target item with a category $c$, we count the number of historical clicked items having the same category $c$ in the session, regarding the number as a coarse-grained taxonomy fatigue feature.

In Fig. 5, we find that: (1) CTR is lower with more same-category clicks, which confirms the existence of taxonomy fatigue. We analyze three instance groups with 3/5/7 overall same-category click lengths and find the conclusion is consistent, which confirms the universality of taxonomy fatigue with different activeness. (2) We also draw another CTR trend (orange) on other categories as a control group. If a same-category item is counted in position 2 of the blue trend, its adjacent items with other categories are also counted in position 2 to form the orange trend, alleviating position bias. We observe that the same-category CTR decreases more rapidly than other-category CTR (especially at the end). Although the same-category clicks usually imply very strong interests of users, too many same-category clicks will eventually bring in taxonomy fatigue. Hence, we propose three taxonomy fatigue features, recording the numbers of clicked items having the same taxonomies (i.e., item producer, category, tag) of the current item in the session.

## 2.4 Multi-granularity Fatigue Encoding

The proposed multi-granularity fatigues can be easily used as feature fields in most recommendation models (e.g., [8], [18]). Moreover, we also conduct a fatigue-aware enhanced version of a classical sequential model DIN [29]. Specifically, we concatenate the

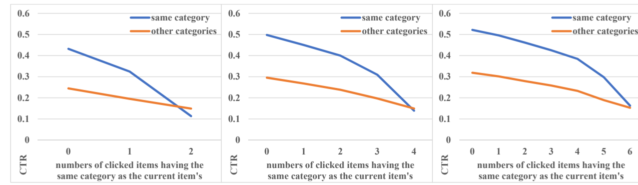


**Figure 5: The CTR trends with different numbers of clicked items having the same/other category. We show CTR trends of users having 3/5/7 total same-category clicked items from left to right separately to avoid the user group bias.**

multi-granularity fatigue features $\boldsymbol{f}_{k,j}$ (containing the above 4 global and 3 taxonomy fatigue features) of the k-th user $u_k$ on the j-th target item $d_j$ to $\boldsymbol{d}_j$ as the query in the attention as:

$$\boldsymbol{u}_{k,j} = \sum_{i=1}^{n} w_i \boldsymbol{b}_{k,i} = \sum_{i=1}^{n} \mathrm{ATT}(\boldsymbol{d}_j || \boldsymbol{f}_{k,j}, \boldsymbol{b}_{k,i}). \quad (1)$$

$\boldsymbol{u}_{k,j}$ is the fatigue-enhanced user representation. $\boldsymbol{b}_{k,i}$ is the i-th behavior embedding of $u_k$ viewed as the value, while $\boldsymbol{d}_j || \boldsymbol{f}_{k,j}$ is the query and $||$ is concatenation. $\mathrm{ATT}(\cdot)$ is the same attention in [29].

# 3 EXPERIMENTS

## 3.1 Deployment and Experimental Settings

We deploy our multi-granularity fatigue on a widely-used article recommendation feed in WeChat Top Stories. The offline dataset contains nearly 18.5$M$ users and 5.2$M$ items with 179$M$/180$M$ train/test instances. We add the fatigue features as both additional feature fields in the feature interaction module and in the DIN-based sequential modeling module as Sec. 2.4. We have 7 fatigue features in total 48 feature fields. The field dimension is 16 following online. All data are preprocessed via data masking for users' privacy.

## 3.2 Offline Evaluation

To verify the effectiveness and universality of our multi-granularity fatigue, we deploy the fatigue features on three classical base models: (1) DeepFM [8], which conducts neural FM and DNN in parallel. (2) AutoInt [18], which adopts self-attention for feature interaction. And (3) DFN [22], which jointly considers Wide, FM, and DNN components after a sequential modeling. The deployed online base model is similar to DFN with its deep feedback interaction module replaced by DIN (note as DFN*). All baselines share the same settings and features (except the fatigue features). We use the classical AUC and RelaImpr for evaluation as [8, 18, 22].

From Table 1 we can observe that: All fatigue-enhanced models have significant improvements over their original base models, with the significance level $p < 0.01$. Considering the huge number of test instances (180$M$), the improvements are impressive (compared with the ±0.0002 deviation of models' multiple runs). It verifies the effectiveness and universality of our multi-granularity fatigue on various base models. The improvements may derive from the more accurate modeling ability on users' preference drifting with different global session and coarse-grained taxonomy fatigues.

| Model | AUC | RelaImpr |
|---|---|---|
| DeepFM | 0.7739 | 0.00% |
| DeepFM (+fatigue features) | **0.7779** | **1.46%** |
| AutoInt | 0.7761 | 0.00% |
| AutoInt (+fatigue features) | **0.7795** | **1.23%** |
| DFN* | 0.7793 | 0.00% |
| DFN* (+fatigue features & encoder) | **0.7835** | **1.50%** |

**Table 1: Offline evaluation on different base models. All improvements are significant ($p < 0.01$ with paired t-tests).**

## 3.3 Online Evaluation

We further conduct an online A/B test to verify the effectiveness of multi-granularity fatigue in real-world scenarios. The only difference is the usage of our fatigue features. We mainly focus on four online metrics: (a) CTR, (b) average click numbers per user (ACN), (c) dwell time (DT), and (d) average refresh number per user (ARN). We conduct the A/B test for 7 days, affecting nearly 5 million users.

| Model | CTR | ACN | DT | ARN |
|---|---|---|---|---|
| +fatigue features & encoder | +1.23% | +1.73% | +1.34% | +0.59% |

**Table 2: Online A/B tests on a real-world recommendation feed. The improvements are significant with $p < 0.05$.**

From Table 2 we can find that: (1) our fatigue-enhanced model achieves significant improvements on all online metrics, which indicates the effectiveness of fatigue in online scenarios. (2) The improvements of ACN, DT, and ARN imply that users are willing to click, read, and browse more items in our system. Considering user fatigue could successfully improve user activeness.

## 3.4 Ablation Study

We also conduct an ablation study in Table 3 to show the effectiveness of all components in our model. We find that: (1) both the global session fatigue and the coarse-grained taxonomy fatigue are essential in recommendation. (2) The fatigue-enhanced DIN can further improve the results via our fatigue-aware attention.

| Model | AUC | RelaImpr |
|---|---|---|
| DFN* (+fatigue features & encoder) | **0.7835** | **1.50%** |
| w/o all fatigue information | 0.7793 | 0.00% |
| w/o global session fatigue | 0.7809 | 0.57% |
| w/o coarse-grained taxonomy fatigue | 0.7814 | 0.75% |
| w/o fatigue encoder | 0.7828 | 1.25% |

**Table 3: Ablation tests on different fatigues and the encoder. All improvements are significant with $p < 0.01$.**

## 3.5 Online Analyses

We also conduct comprehensive online analyses to better understand the impacts of multi-granularity fatigue on our system. From Fig. 6 we can find that: (1) our fatigue-enhanced model does achieve consistent CTR and dwell time improvements (2% – 6% relative improvements) with different numbers of refresh. The fatigue modeling does benefit the recommendation. (2) We also compare the non-overlapping item rates of each refresh between the base and fatigue-enhanced models. An item is viewed as overlapped if it has been recommended as a candidate in the previous refresh of this session. With the help of fatigue, the non-overlapping rates increase average 3.8% in the first 10 refreshes and even 8.0% in the second 10 refreshes, which indicates our (taxonomy) fatigue features can truly generate more diverse items with more refresh behaviors.

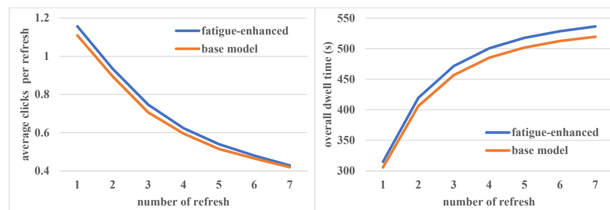


**Figure 6: Online average click and overall dwell time trends.**

## 4 RELATED WORKS

User fatigue has been successfully verified on various tasks [14, 17], while only several works explore using user fatigue in recommendation. Ma et al. [12] observes that a user will quickly lose interest in repeatedly recommended items. The authors mainly focus on the item fatigue in Bing Now news recommendation (where an item is likely to be repeatedly impressed and clicked many times), which cannot be used in our recommendation feed (where items are directly de-duplicated). [1] conducts a soft frequency capping, adding ads' historical frequencies as features. [2] considers marketing and content fatigue in generating recommendation sequences. Other works also explore the impression discounting [11, 15, 16]. Differing from them, our fatigue model is designed for recommendation feed with more types of fatigue. Hence, we mainly focus on the novel global session fatigue and the taxonomy fatigue in this work.

Recently, various neural models are proposed to model feature interactions and user behaviors [8, 18, 22, 26, 29], some of which are used as our base model. Some sequential recommendation models highlight the similarities between the target item and historical behaviors in user modeling [7, 27, 29]. Considering multi-interest [3, 5], disentangled modeling [4, 13], multi-behavior [10, 20], diversity [6, 9, 23, 24, 28], and information gain [25] maybe also be promising to avoid homogenization and handle taxonomy fatigue. Different from these models, we explicitly analyze and model different types of user fatigue based on different behaviors and granularities.

## 5 CONCLUSION AND FUTURE WORK

In this work, we systematically highlight, analyze, and utilize the multi-granularity fatigue in recommendation. The proposed multi-granularity fatigue has shown its power via extensive analyses and offline/online evaluations. In the future, we will explore better and customized fatigue modeling models for better user experiences.

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