An Exploratory Study of Information Cocoon on Short-form Video Platform

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ABSTRACT

In recent years, short-form video platforms have emerged rapidly and attracted a large and wide variety of users, with the help of advanced recommendation algorithms. Despite the great success, the algorithms have caused some negative effects, such as information cocoon, algorithm unfairness, *etc.* In this work, we focus on the *information cocoon* that measures overwhelmingly homogeneity of users' video consumption. Specifically, we conduct an exploratory study of this phenomenon on a top short-form video platform, with one-year behavioral records of new users. First, we evaluate the evolution of users' information cocoons and find the limitation of the diversity of video content that users consume. In addition, we further explore user cocoons via the correlation analysis from three aspects, including user demographics, video content, and user-recommender interactions driven by algorithms and user preferences. Correspondingly, we observe that video content plays a more significant role in affecting user cocoons than demographics does. In terms of user-recommender interactions, more accurate personalization does not contribute to more severe information cocoons necessarily, while users with narrow preferences are more likely to be trapped. In summary, our study illuminates the current concern of information cocoons that may hurt user experience on short-form video platforms, and offers potential directions for mitigation implied by the correlation analysis.

CCS CONCEPTS

• **Information systems** → **Data mining**; **Personalization**;

KEYWORDS

Information Cocoon; Short-form Video; Recommender System

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1 INTRODUCTION

Nowadays, short-form video platforms have rapidly crowded out a large share of the market of online services, as well as users' fragmented entertainment time. At the same time, more and more concerns of information cocoons emerge from both ordinary users and recommender designers [24–26]. That is to say, users are consuming homogeneous video content and isolated from other diverse content that they may be interested in. Consequently, users' usage experience is suboptimal and even their opinions about certain events are unconsciously confined [18]. Besides, we argue that it is hard for platforms to further improve long-term user activity (#active days, spent time, *etc.*) without increasing the diversity of recommended video content.

While similar concepts of the filter bubble and echo chamber have been proposed and studied on various online platforms, there are some differences compared with our concentrated information cocoons. Specifically, the filter bubble emphasizes the **algorithmic effect** of confining users to more and more narrow contents or viewpoints [16]. The echo chamber stresses homogeneous communication with **social communities** with which users share similar opinions like political leanings [23]. In contrast, we utilize the term of *information cocoon* [22] to focus on the phenomenon that users are trapped in homogeneous contents, regardless of possible factors leading to it. In addition, there are still no relevant studies on short-form video platforms.

To fill the gap of related researches, we conduct an exploratory study of information cocoons on a top short-form video platform. Specifically, we first evaluate long-term evolution of new users' information cocoons over one year. Moreover, we further explore how and why cocoons are reinforced or mitigated from three perspectives of user demographics, video content, and user-recommender interactions. The detailed analysis demonstrates that there is no disparity in video consumption in terms of homogeneity among users with different demographics. Nevertheless, users are indeed more likely to be trapped in cocoons with more consumption of certain video content like 'Games'. In addition, we observe that users encountering over-personalization recommendations don't necessarily tend to be trapped in severe information cocoons, but users with homogeneous preferences do. Besides, some users' diverse preferences are not completely captured by recommender systems.

Taken together, this work is the first, to the best of our knowledge, to provide a large-scale and long-term study of information cocoons on short-form video platforms. Furthermore, we shed light on critical factors that recommender designers should concentrate on when attempting to mitigate information cocoons.

2 RELATED WORK

2.1 Filter Bubble and Echo Chamber

In recent years, the filter bubble and echo chamber are popular concepts concerning over-homogeneous online consumption of news, music, products, and so on. Many researches evaluate them in the way of quantification [1, 3, 6, 7, 9, 14] or simulation [2, 4, 20]. As stated in the introduction, studies of the filter bubble concentrate on the effects of recommender systems. For example, Nguyen et al. [14] quantify the filter bubble with the diversity of user ratings and observe a slightly more narrowing set of items from recommender exposure over time. As for the echo chamber, most works study user opinions on social media platforms. Cinelli et al. [6] compare the segregation of homophilic opinions clusters about several controversial topics across four dominant platforms, and observe significantly different tendencies.

Different from these studies, we focus on short-form video platforms and investigate users' information cocoons from more comprehensive perspective

2.2 Diversity in Recommender Systems

As a beyond-accuracy evaluation of recommender systems, diversity has attracted more and more attention to designing recommendation algorithms. According to the process of distributing items [8], related works can be classified in the stage of ranking [5, 25], re-ranking [17, 26] and displaying [11, 24] items. Zheng et al. [25] enhance graph convolutional networks with the diversity-oriented neighbor and negative sampling for better diversification. Ziegler et al. [26] apply a novel topic diversification algorithm on recommendation lists to improve user satisfaction. Hu et al. [11] show the critical role of the organization interface for recommendation diversity that users can perceive.

Instead of designing specific algorithms, we provide potential directions for diversification recommendations and cocoons elimination based on a data-driven exploration.

3 DATASET AND RESULTS

As an emerging short-video platform, Kuaishou[1] has more than 320 million daily active users by the end of 2021[2]. On such a platform, a huge number of interaction behaviors between users and videos are generated, which are supported by deep-learning based (recurrent neural networks [19], graph neural networks [13], *etc*) collaborative filtering [10] recommender systems. In this work, we leverage rich and continuous data on Kuaishou to investigate information cocoons.

Table 1: Dataset statistics.

#users	#active users/day	#videos/day	#records/day
569,975	77,290	1,748,782	11,930,333

3.1 Dataset and Method

Dataset. Considering the long-term evolution of users' information cocoons, we focus on interaction behaviors of **new users** for **one year**. Specifically, the records of users who registered on January 1st, 2021 are collected until December 31st, 2021. Besides, we restrict interaction contexts in 'Finding Page' and 'Featured Page', which are the most commonly used scenarios. Overall statistics of the dataset are shown in Table 1, including basic numbers of daily information on average. Each interaction record consists of various behaviors (watching progress[3], like, comment, *etc.*) of a user on a video. We also collect user demographics like gender, age, *etc*, and Kuaishou also tags the videos with 820 hierarchical categories (manually or based on machine-learning algorithms) of three levels in total, including 36 *level-1*, 301 *level-2* and 483 *level-3* categories. For example, a video about pandas will be tagged as 'Animals' (level-1), 'Wild animals' (level-2), and 'Panda' (level-3).

Measure information cocoons. As stated in the introduction, we concentrate on the facts about whether information cocoons exist on Kuaishou or not. In other words, the homogeneity of video content that users interact with under various behaviors is an essential measurement. Therefore, we utilize the diversity metrics to quantify users' information cocoon based on video categories. Suppose that a user interacts with n_i videos with level-1 category i and m_j videos with the most fine-grained category j under a certain behavior, and denote the probability distribution of categories as $p_i = n_i / \sum_i n_i$, the metrics under this behavior are formulated as follows,

- **Coverage** [12]. $\sum_j \mathbb{1}[m_j > 0]$, where $\mathbb{1}[\cdot] = 1$ if the condition is true, otherwise it is 0. This metric evaluates the number of categories that all the interacted videos cover.
- **Entropy** [12]. $-\sum_i p_i \log p_i$. It takes the difference among categories into consideration to measure the unevenness of categories distribution.

3.2 Evolution of Information Cocoons

We first evaluate how users' information cocoons evolve over time, in terms of the diversity of video content exposed by the recommender and watched[4] by users. Specifically, we segment one year into some time windows and calculate the aforementioned diversity metrics for each user in each active window when he/she uses Kuaishou. Furthermore, diversity metrics in a user group with a close number of active time windows are averaged. Figure 1 shows

[1]https://www.kuaishou.com/en

[2]https://ir.kuaishou.com/news-releases/news-release-details/kuaishou-technology-announces-fourth-quarter-and-full-year-2021

[3]We define this as the ratio of watching time to video duration in seconds.

[4]We only consider user-video interactions where the watching progress is no less than 50%, and selecting other thresholds gives similar results.

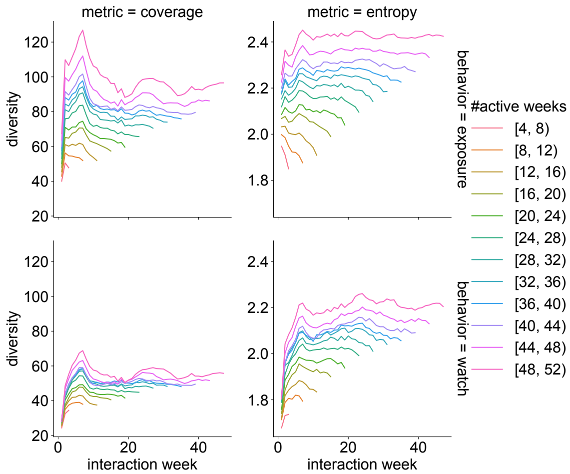
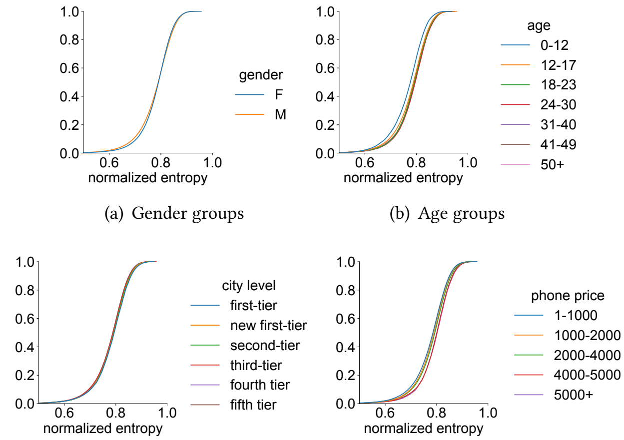


Figure 1: Overall diversity evolution of videos that users are exposed (top row) and watch (bottom row).



(a) Gender groups

(b) Age groups

(c) City-level groups

(d) Phone-price groups

Figure 2: Empirical cumulative distribution function of watching diversity across user groups with different demographics.

the overall evolution of diversity under different metrics and user behaviors in the time window of the week[5], and results are similar for the window of the day.

- New users are trapped in their cocoons with homogeneous video content, although they attempt to explore diverse ones. Specifically, diversity metrics go up in the first two months, which indicates that new users have needs of accessing to various content with relatively high diversity. However, metrics go down (or remain stable for the entropy of extremely active users) after that, especially for coverage, and this demonstrates the limitation of content diversity and the formation of information cocoons.
- Users tend to further narrow down the cocoons provided by recommendations. This is proved by lower diversity of videos watched by users compared with that of exposed by the recommender, which owns to individual selection preferences.

3.3 Demographic Effect

Note that the analysis of the relationship between entropy and other factors will be confounded by the activity, since users with more interactions consume more diverse video content on the whole [1]. Inspired by [15], we define normalized entropy as dividing the entropy by theoretical maximum: $(-\sum_i p_i \log p_i)/\log(\sum_i \mathbb{1}[p_i > 0])$, to balance the confounding effect. As such, lower normalized entropy means a more pronounced tendency for user consumption of specific categories of videos.

We first investigate the relationship between users' self-reported demographics and their information cocoons, measured by the content diversity of their watching videos. Specifically, the normalized entropy throughout the whole year for each user is calculated, and users are divided into groups based on the gender, age, level of the resident city, and phone price. Figure 2 shows the empirical cumulative distribution function (eCDF) of diversity for each demographic group. We summarize the comparisons as, 1) the gender, city level, and phone price have no trivial impacts on user cocoons, and 2) users of different ages have a slight disparity in video consumption in terms of homogeneity. In particular, children tend to be caught in cocoons more likely compared to other older users.

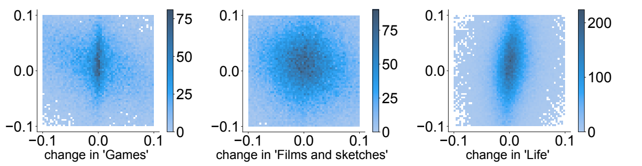
Furthermore, we conduct a regression analysis, where independent variables are the four user demographics, and the dependent variable is the normalized entropy. The regression gives $R^2 = 0.011$ and demonstrates that demographic effects on user cocoons are trivial.

3.4 Video Content in Cocoons

From the perspective of videos, we investigate what kind of contents are more likely to promote the formation of user cocoons. We compare the difference between watching videos in the first two weeks and that in the last two weeks for each user with no less than four weeks of retention on the platform. Specifically, the changes of normalized entropy and each video category's watching proportion in all the videos are calculated, and Figure 3 shows three typical cases of relationships between them. The diversity change is negatively correlated (The spearman coefficient is -0.174, Two-sided $p < 0.01$), unrelated (The spearman coefficient is -0.055, Two-sided $p < 0.01$), and positively correlated (The spearman coefficient is -0.204, Two-sided $p < 0.01$) with the change of consumption on 'Games', 'Films and sketches', and 'Life' videos, respectively. We conclude that excessive consumption on some types of video content indeed is more likely to contribute to homogeneous (diverse) experiences, such as 'Games' ('Life') videos.

To sum up, for avoiding possible information cocoons, recommender systems should pay more attention to the content rather than user population with specific demographics when distributing videos.

[5]Note that there is the difference of the number of active windows in the same group of users, and we only display the diversity of early windows in the group. For example, the first four weeks are displayed for the user group [4, 8).



(a) Games (b) Films and sketches (c) Life

Figure 3: Relationship between the change of diversity and videos consumption in specific categories. Color shade represents the number of users.

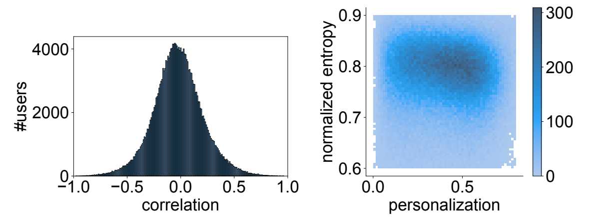
3.5 User-Recommender Interactions

As the most important components in the recommender design, we also investigate whether the change of information cocoons is dependent on recommender personalization or user preferences.

The recommender personalization is defined as the ratio of the number of watching videos to exposed videos, *i.e.*, how accurately the recommender system estimates user preferences. From the individual level, we calculate the spearman rank correlation coefficient between daily personalization and normalized entropy of watching videos for each user. From the population level, we evaluate the correlation for all the users in the time scale of the whole year. Figure 4 shows the relationship in both levels, including the distribution of spearman coefficients and the joint distribution. As we can see, there is no obvious skewness in the distribution of daily correlation for each user, which is concentrated around zero. In terms of the correlation across different users, there are still no pronouncedly positive or negative trends between personalization and diversity. Besides, the spearman coefficient is just -0.052 (Two-sided $p < 0.01$). To sum up, more accurate personalization does not happen along with more severe information cocoons necessarily.

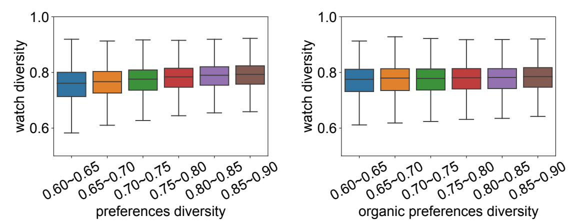
We leverage what kind of 'authors' that users 'follow' to define preferences, because 'follow' is a typical behavior representing users' inherent interests in specific video content explicitly. Similar to video categories, author categories are defined as the most common categories in all the published videos. In this way, we can obtain the diversity of the following authors for each user throughout the whole year, *i.e.*, preference diversity. Moreover, we also investigate users' 'organic' preferences [1], which are represented by categories of authors that users follow in other contexts **without the recommender**[6], such as searching, sharing from friends, *etc.* Figure 4 shows the diversity relationship between user preferences and watched videos, including both complete preferences in all the contexts and organic preferences. Obviously, users' preference diversity is positively correlated with watching diversity (The spearman coefficient is 0.167, Two-sided $p < 0.01$), but it's almost unrelated for organic preferences (The spearman coefficient is 0.004, Two-sided $p < 0.22$). From the comparison, we conclude that, 1) users with a more broad range of preferences tend to have more moderate information cocoons, and 2) users' requirements for watching diverse videos are not completely captured by the recommender.

[6]In contrast, the dataset introduced in Subsection 3.1 only includes the contexts driven by the recommender.



(a) Individual level (b) Population level

Figure 4: Relationship between recommender personalization and diversity of watched videos.



(a) Complete preferences (b) Organic preferences

Figure 5: Relationship between user preferences and diversity of watched videos.

In summary, the general perception of personalization causing information cocoons is not always accurate, and that the diversity of user preferences matters a lot in user cocoons to some extent.

4 CONCLUSION AND FUTURE WORK

In this work, we study information cocoons of new users with a large-scale and long-term dataset collected on a top short-form video paltform. First, we observe that users' requirements for diversity are limited. Furthermore, we identify the factors leading to severe information cocoons with correlation analysis, *i.e.*, certain video content and users' preferences diversity. These provide potential directions for mitigating information cocoons in recommender designs. Specifically, video content that easily attract user attention should be distributed moderately on the platform. Additionally, except for accurate personalizations, recommender systems should also capture user preferences as completely as possible, especially for preferences diversity. Some limitations of our current study include that, 1) the correlation analysis can not give causal conclusions, and 2) information cocoons can be measured in other macroscopic and systematic methods, such as community structure of video-video networks [21]. We will conduct further studies in the future work.

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