Evaluation of Herd Behavior Caused by Population-scale Concept Drift in Collaborative Filtering

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ABSTRACT

Concept drift in stream data has been well studied in machine learning applications. In the field of recommender systems, this issue is also widely observed, as known as temporal dynamics in user behavior. Furthermore, in the context of COVID-19 pandemic related contingencies, people shift their behavior patterns extremely and tend to imitate others' opinions. The changes in user behavior may not be always rational. Thus, irrational behavior may impair the knowledge learned by the algorithm. It can cause herd effects and aggravate the popularity bias in recommender systems due to the irrational behavior of users. However, related research usually pays attention to the concept drift of individuals and overlooks the synergistic effect among users in the same social group. We conduct a study on user behavior to detect the collaborative concept drifts among users. Also, we empirically study the increase of experience of individuals can weaken herding effects. Our results suggest the CF models are highly impacted by the herd behavior and our findings could provide useful implications for the design of future recommender algorithms.

CCS CONCEPTS

• **Information systems** → *Evaluation of retrieval results.*

KEYWORDS

concept drift, herd behavior, collaborative filtering

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1 INTRODUCTION

Collaborative Filtering (CF) – a prevalent Recommender System (RS) technique – offers recommendations based on homophily [29]: like-minded users share similar tastes. Typical CF models assume that users show consistent preferences over time. This assumption introduces a bias that when user behavior patterns drift, RSs cannot detect the drift and adjust prediction functions. This concern is referred to as *concept drift* [10, 22].

The decision behaviors of individuals in RSs can be motivated by two factors: 1) an inner need state: Maslow [28] proposes a hierarchy of such needs and states that different needs yield different behaviors; 2) external assimilation from peers: the theory of social identity [45] suggests that people tend to learn from peers in their same social group. We believe that the inner need state of a user evolves gradually. Behavior driven by interactions with peers, however, can spread, sometimes rapidly, which can lead to a herding effect via information cascades. The strength of the herding effect can cause user to deviate from their inner needs. For example, in the early days of the COVID-19 pandemic, the rush to hoard toilet paper was an example of an external assimilation from peers [49].

Modeling macro-trends of population dynamics and identifying potential herd like behaviors are required in order for RSs to be able to detect and adapt to such behaviors. Since the behavior is collective, it cannot be deduced by analyzing users in isolation [20]. We propose a community-aware framework for evaluating the evolution of herd behaviors in RSs. We contend that the interactions between users in RSs can be integrated into a social network, in which vertices are users and edges are social ties between them. The ties between two users can be obtained through their explicit social connections (e.g., friendship in social media [7]), or inferred from their similar interests on items (e.g., purchasing in e-commerce systems [18]). We detect potential communities in the network based on a modularity-optimizing mechanism, which clusters users with similar interests. From this, we can deploy empirical analysis on the evolution of the detected communities.

The contributions of this research can be summarized as follows:

- We identify herd behavior caused by population-scale concept drifts in CF in a non-stationary environment.
- We develop an evaluation framework based on modularity-optimizing community detection algorithms to understand and evaluate the herding effects.

- With extensive experiments on real-world datasets, we verify the effectiveness of the proposed evaluation method and demonstrate the roles of two factors of herding effect: self-information and peer effects.

2 RELATED WORK

2.1 Concept Drift in Learning Algorithms

Modeling the dynamic nature of data, literally known as *concept drift* [39, 47], is a critical problem in machine learning. Gama et al. [10] sums up 4 patterns of drift from the *time*-dimension: sudden drift, gradual drift, incremental drift and reoccurring drift. For example, a sudden drift in consumer behavior may happen in response to the outbreak of COVID-19 pandemic while they may hesitate to (gradually) return to "normal" after the pandemic economic restrictions have been lifted. Minku et al. [30] categorize concept drift into 14 from other dimensions, e.g., severity, predictability, frequency and recurrence. The detection strategies of concept drift can base on online learning error, e.g., Drift Detection Method (DDM) [9].

2.2 Concept Drift in Recommender Systems

Recommender systems (RSs) are representative learning applications that matches user preferences to products. It has also observed temporal changes in user preferences. Modeling such concept drift has introduced new challenges [22]. From the standpoint of *users*, the typical scenarios of concept drift are that consumers change their interest gradually in products (e.g., movies, groceries) or develop seasonal shopping patterns like Christmas shopping and anniversary purchasing; while from the perspective of *items*, changes in the "shelves" can also drive people's attention. Koren [22] argues that the aforementioned drift adaption methodologies may fail in RSs because recklessly neglecting past user transactions may lose the signal to understand certain user's long-term preference or to model their neighborhood networks. Therefore, a more sensitive and accurate methodology is required. Rendle et al. [37] combine the MF and Markov chains (MC) models to build a personalized transition graph for next-basket prediction. They establish a transition tensor consisting of stochastic matrices describing the MC model of each user. It can learn the sequential evolution in user behavior by the extended BPR [36]. Then the drift and the latest taste of users can be captured. He and McAuley [13] model users' dynamic preferences in visual factors of fashion products for a One-Class Collaborative Filtering (OCCF) setting. Kang and McAuley [19] balance the long-term vs. short-term preference and sparse data vs. dense data by incorporating the MCs and recurrent neural networks (RNNs) in a self-attentive sequential model. Recent research (e.g., [26] dives into temporal drift topics following the similar trajectories (i.e., modeling users' dynamic portraits in *compatible* long-/short- term preferences) based on the Self-Attention mechanism.

2.3 Herd Behavior

Herd Behavior describes how individual in a group can act collectively without centralized direction. Human beings have different levels of needs [28] which will motivate their corresponding behaviors. For example, one may seek food and water while being dominated by physiological needs. It theorizes the links between implicit self-identity and explicit behaviors of individuals. However, as a member of society, one's decision may not always derive from their own need as their cognition is often affected by others around. The theory of *social identity* [1, 45] suggests that individuals tend to recognize themselves as belonging to a social group, wherein they share similar values and preferences with other members. Besides, an organization can change the beliefs and behaviors of those members who feel strong emotional ties to the group. As a result, people usually *discount own information* and *imitate each other* [41]. Furthermore, Lee et al. [24] differentiate the herding effect of crowd and friend networks and Sunder et al. [44] discriminate the positive effect of contingencies governing herding behaviors.

2.4 Community Detection

The user profiles in RS can be embedded in a social context as users share their preferences by interacting with the system, e.g., purchasing, rating. Subsequent users can learn and reference these behaviors to make decisions. Therefore, the data in RS can be converted into a social network in which the users with similar interests can be clustered into a small community. A big and centralized community indicate the potential herd exists. Many researchers attempt to develop the community detection algorithms which aim to divide large networks of users into highly cohesive communities. Girvan and Newman [11] propose the detection algorithm that identifies edges between vertices by computing the edge betweenness score. However, it requires to scan the entire graph and lead to NP-hard complexity. The more efficient modularity optimization algorithms are developed hereafter (e.g., [2, 6, 31]). Besides, Palla et al. [34] focus on the overlapping communities in which vertices can be assigned into multiple communities. Fani et al. [7] identify and extract communities by multi-modal feature learning embeddings.

3 METHODOLOGY

3.1 Preliminaries

3.1.1 Building network. Given a dataset with records of tuples of finite user set, item set and their associated ratings over a time horizon T, i.e., $\{< u, i, r_{uit} > | u \in \mathcal{U}, i \in \mathcal{I}, r \in \mathcal{R}\}_{t \in T}$, we build a graph $G =< V, E >$ with a set V of vertices and a set E of edges, in which the vertices represent users: $\mathcal{U} \mapsto V$ and the number of vertices is $n = |V|$. The edge between two vertices $e_{xy} \in E$ is a social tie between two users u_x and u_y and the weight is established by their preference similarities on items. A threshold θ can be set to discard those edges with low similarity: $w_{xy} = sim(u_x, u_y)$ when $sim(u_x, u_y) > \theta$, otherwise 0, where w_{xy} is the weight of e_{xy} and $sim(\cdot)$ is a modular similarity measurement between users, e.g., Mean Squared Difference (MSD) [48], cosine [42], Pearson correlation coefficient (PCC) [42] and Jaccard similarity [33].

3.1.2 Detecting community. A community in a large network is a cluster of users (vertices) with similar preferences that $C \subseteq G$. We use C_x to indicate the community to which user u_x is attached. For any community, we have the *intra-cluster density* to measure the relative density of internal edges w.r.t the number of all possible internal edges of the specified community [8], i.e., $\sigma_{int}(C) = \frac{2m_C^{int}}{n_C(n_C-1)}$,

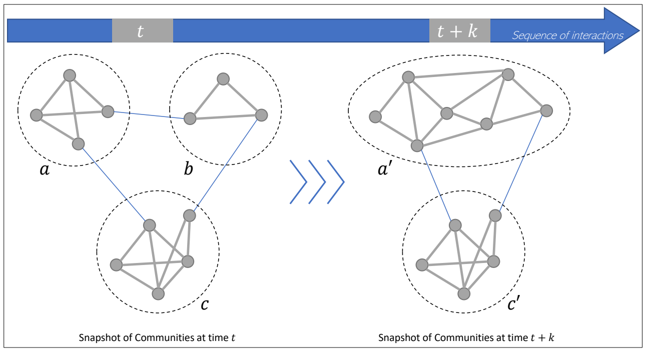


Figure 1: Illustration of Evolution of Communities
Communities a and b are merged into one community a' at time $t+k$, indicating that involved users act similarly and herds may form.

where m_C^{int} is the number of internal edges and n_C is the number of vertices in community C. Besides, we have the *inter-cluster density* to measure the ratio of existing exserted edges of community C in comparison with its all possible inter-cluster edges [8], i.e., $\sigma_{out}(C) = \frac{m_C^{out}}{n_C(n-n_C)}$, where m_C^{out} is the number of existing exserted edges of community C.

The basic rationale behind community detection method is to isolate each community from others where vertices are densely interconnected inside while loose connected from distinct communities. The optimal partitioning strategy will maximizes the discrepancy of σ_{int} and σ_{out} across all detected communities. This strategy can be integrated into the modularity Q as objective function to optimize the quality of the partitioning of communities [2]:

$$Q = \frac{1}{2\omega}\sum_{xy}\left[w_{xy} - \frac{\omega_x \omega_y}{2\omega}\right]\delta(C_x, C_y), \tag{1}$$

where ω is the sum of all edge weights in community: $\omega = \frac{1}{2}\sum_{xy} w_{xy}$; ω_x is the unilateral sum of weights of edges connected to vertex u_x: $\omega_x = \sum_y w_{xy}$; $\delta(C_x, C_y) = 1$ if $C_x = C_y$ and 0 otherwise that indicates if u_x and u_y are attached to the same community.

Initially, each vertex is considered a built community. By reassigning vertices to the new community and disconnecting from the original one, we can assess whether the new community partition is better based on the change in modularity Q. The final modularity of detected communities will be the quality of the partitioning.

3.2 Evolution of Communities

Herd behavior can be motivated by peer effects when individuals lack their own prior experience [3]. How to adopt the opinions of peers depends on whether the social ties between them are strong or weak. The social ties can be explicit friendship in social network [7]. Similarly, in RSs, users implicitly build social ties through interactions with the similar items [18], regardless of their physical distance and real-world acquaintanceship. Therefore, the data for training RSs can be naturally convert into a social network.

In the proposed evaluation method, we treat user historical interactions associated with timestamps in RSs as temporal sequences. By dividing the entire sequence into small chunks in chronological order (e.g., weekly or monthly), the snapshots of network are collected. We build the snapshot networks by converting the user set

Figure 2: Synthetic datasets for Pandemic-like events

$\mathcal{U}$ into vertices V in different chunks. Then, like-minded users are connected based on their similarities with the threshold θ, which can be determined via cross validation (e.g., we set it to 0.9 in the experiments).

Given the established networks, we cluster users with similar interests into communities (i.e., subgraphes of a large social network) based on the detection algorithm. Users may shift their preferences over time. When population-scale concept drifts occur in data, users may move synergistically and affect each other. Instead of analyzing individual behavior in isolation, we focus on the group behavior in the social network of RSs. We measure the evolution of population-scale concept drifts in disguise by assessing the changes in the communities that are detected. As shown in Fig. 1, users in community a at time t can be reassigned into community a' at time $t+k$ because act similarly to original users in community b.

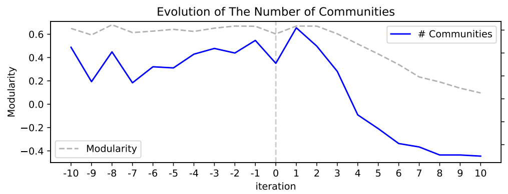
From the global view of the network, the potential herds forms when the number of detected communities rapidly reduced. Besides, communities will become more cohesive and inter-cluster connections will become looser. Therefore, the density and distribution of communities in RSs can be effective metrics to measure the degree of herding effects that the potential herd is easily formed in a tightly interconnected community. Also, we can measure the drift in user preferences by monitoring the properties of communities in which he/she is located at different time. For example, the user may be more inclined to follow other people's decisions when he/she appears in a larger community, whereas he/she is more assertive about his/her own preferences. Furthermore, we train the baseline CF models on the previous snapshot and empirically evaluate the performance of CF models and the quality of recommendations on current one. The adaptability of CF models can be measured by the correlation between their snapshot performance and properties of communities.

4 EXPERIMENTS

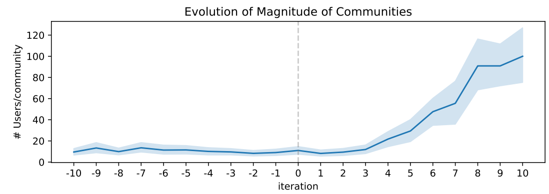
4.1 Experiment Settings

Datasets. We investigate the proposed evaluation method on both synthetic and real common-used RS datasets. Specifically, we investigate the positive effect of high-intensity contingencies (e.g, COVID-19 pandemic or related events) on a set of synthetic datasets, then deploy the proposed evaluation method to common-used RS datasets to measure the influence of crowd on user behavior in relatively mild events.

Baselines. 16 baselines from various categories of CF models are evaluated, including:



(a)



(b)

Figure 3: Evolution of the number of communities (a) and the magnitude of communities (b)

- *Conventional CF*: User-*k*NN [42], Item-*k*NN [38], SlopeOne [25], SVD [23], SVD++ [21], BPR [35];
- *Network based CF*: RSTE [27], SocialMF [17], NeuMF [15], CFGAN[5], LightGCN [14];
- *Temporal Aware CF*: RNN4Rec [16], Caser [46];
- *Non-personalized*: MostPopular, ItemMean, Random.

Metrics. We deploy *n*DCG@*k* [40] metric to measure the accuracy of recommendations and Mean Intra User Distance(MIUD) [4] to measure the *intra-user* diversity of recommendations.

4.2 Evaluation on Pandemic-like Events

As shown in Fig. 2, we deploy a set of synthetic datasets to simulate the non-stationary environment brought by pandemic-like events. Each dataset contains 1000 users and 1000 items. We define the magnitude of the event across 21 different iterations. Specifically, iterations -10 to -1 are interaction data in the normal days where users rate items freely according to their own needs. Since iteration 0, the extreme contingency begins to occur and infect test and training datasets to varying degrees (at a rate of 10% ratings per iteration). The timing of occurrence of the outlier event divides the horizon into two event stages (i.e., `pre-event` and `during-event`). At `during-event` stage, people suddenly shift their private needs and preferences in response, e.g, panic buying phenomenon [43, 49]. Then, we investigate the following hypotheses.

Hypothesis 1. *The pandemic-like events can positively aggravate herding effects in CF.*

Fig. 3a demonstrates the drift of the number of detected communities in the pandemic-like event data. The gray dash line indicates the quality of detected communities has been stable. At the `pre-event` stage (i.e., iterations -10 to -1), the number of communities oscillates between 90 and 100. At iteration 1, the early stage of the contingency, the number of communities jumps to 122 among 1000 users. Then these communities rapidly vanish and merge in subsequent iterations, until only 10 remained in the final iteration, i.e., there are an average of 100 members in each community. Fig. 3b further shows the change in the number of members in each community. These results suggest that as extreme events progress, users with previously diverse interests exhibit similar patterns of preference. As a result, we infer that users become more predictable as the variation in recognizable user types becomes smaller and user portraits become monolithic.

Hypothesis 2. *The accuracy based performance of CF is positively related to the herding effects.*

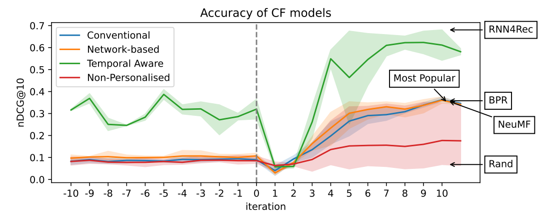


Figure 4: Accuracy of recommendations of CF models

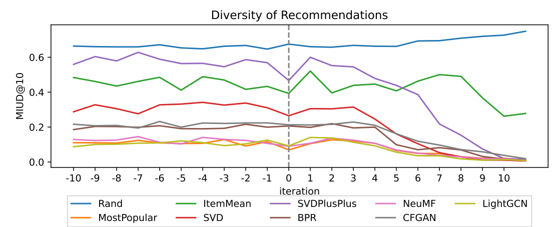


Figure 5: Diversity of recommendations of CF models

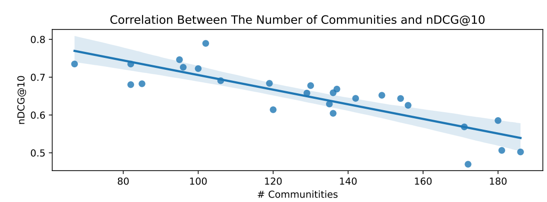


Figure 6: nDCG@10 vs the # communities (MovieLens 1M)

Fig. 4 shows the *n*DCG@10 of different CF models on the set of synthetic data. The overall trend in performance is negatively correlated with the curve of the number of communities. As such, intuitively, the fewer and more focused communities of interest formed between users, the better the performance of the model. The herd behavior has seemingly "improved" CF models.

Hypothesis 3. *The diversity of recommendations of CF is negatively related to the herding effects.*

However, in terms of the diversity of recommendations, as shown in Fig. 5, most CF models suggest more homogeneous recommendations as the impact of the event on users deepens. The contingency exacerbates the long-tail problem and results in intense herding for popular items.

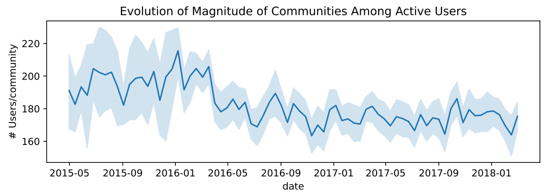


Figure 7: Evolution of magnitude of communities (Amazon)

4.3 Evaluation on General Events

We evaluate the proposed model for general events on real benchmark datasets with the same experiment settings, including MovieLens 1M [12] and Amazon Reviews [32], both of which contain milder events than pandemic-like events. Based on the evaluation method, we train the CF model upon snapshot at time t and evaluate it on snapshot at $t+1$. Fig. 6 shows the high correlation between nDCG@10 (from SVD++) and the number communities over time, which shows the same trend as pandemic-like environment. The pandemic-like contingencies exacerbate the peer effects by reducing individuals' confidence in their established knowledge and experience. Oppositely, we hypothesize:

HYPOTHESIS 4. *In the stationary and mild non-stationary environment, the herding effects between peers will be alleviated as personal experience grows.*

To verify the above hypothesis, we assume that the experience of users in RS will grow as their rating activities increase. We screen out the active users who rated more than 100 items across 3 years in the Amazon Electronics dataset [32]. We monitor the communities in which these active users are located during different time periods, and measure the evolution of magnitude of these communities. As shown in Fig. 7, most users are assigned into relatively large communities when they were just getting into the system. It suggests that people are inclined to follow others if they have little experience with new-touch platforms. The scale of communities of these active users oscillates down over time, indicating that users explore more diverse products as their experience increases. Thus the peer effects are alleviated.

5 CONCLUSION

We propose a community detection based evaluation approach to evaluate the potential herds in RSs under the extreme outlier event and mild environment. We empirically studied the evolution of communities among users and evaluate how CF models performs in different situations. Our results suggest that the number of communities highly correlates with the performance of CF models. And the herd effect will weaken when users gain more experience and knowledge.

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