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Oscillator-Based Recommendation Systems: A Review on Mitigating Information Cocoons Through Dynamic Modeling

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Abstract. Information cocoons are a pervasive phenomenon in recommender systems, characterized by the persistent delivery of homogenized content to users over long-term interactions, which reduces information diversity and narrows users' cognitive horizons. This study dissects the multi-dimensional formation mechanisms of information cocoons, systematically examines the roles of algorithmic, social, and human-computer interaction dimensions in the emergence of the cocoon effect, reviews the evolution of mainstream recommendation algorithms and evaluates the inherent limitations of these algorithms in balancing recommendation accuracy and content diversity. This study adopts a dynamic system modeling perspective to conceptualize recommender systems as a bidirectionally coupled dynamic evolution process between users and systems, explores the periodic and synchronous characteristics of user interest evolution, and proposes integrating the concept of oscillation into the design of machine learning and recommendation models. By introducing controlled phase perturbations and frequency modulation, enabling the periodic diffusion of content exposure and the dynamic expansion of the interest space. The oscillator mechanism is systematically incorporated into the research framework of recommendation systems and feasible research directions for the future are proposed.

Keywords: Information cocoon, recommender systems, dynamic system modeling, oscillator mechanism, diversity in recommendations

1. Introduction

The total global data volume is projected to reach 175 ZB by 2025, which exceeds the maximum capacity of users' independent content screening, with recommendation systems playing a core role for social media, e-commerce and video streaming platforms including Twitter, TikTok and YouTube. Driven by users' personalized preferences, over 80% of user interaction behaviors occur within information cocoons and 55.7% of new users see a significant decline in the diversity of content they access within one year of registration [1], a phenomenon that directly triggers a 93.6% surge in intra-group consensus and a 105.3% spike in inter-group polarization [2-6].

The formation of information cocoons is rooted in multiple factors including algorithmic filtering, community influence, social stratification and human-computer interaction dynamics, with algorithmic mechanisms worsening content homogenization [7-9], users prioritizing familiar content, and group isolation from social stratification further restricting content diversity [10]. This study

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introduces an oscillator mechanism to break the content homogenization deadlock in recommendation systems, a mechanism still rarely applied in related fields with its periodic perturbation effect having demonstrated great application potential [11-13]. The controlled oscillation strategy proposed in this study applies dynamic perturbation to recommended content to simulate users' real experience of accidental exposure to new viewpoints and perspectives in real-world scenarios, and this dynamic intervention can eliminate the information cocoon effect, alleviate group polarization, promote equity in knowledge acquisition, and ultimately build an open and inclusive information ecosystem [14,15].

2. Mechanisms and evolution of recommendation systems

The information cocoon phenomenon driven by algorithms, social and human-computer interaction mechanisms reduces content diversity quantifiable via information entropy [1]. Algorithmic filtering mechanisms form a "preference-confirmation-preference" closed loop, with collaborative filtering and content-based recommendation methods relying primarily on similarity matching for content delivery and deep learning technologies directly reducing information entropy while enhancing users' personalized experience [16-18]. The homogenization and stratification of social network structures strengthen group identity and narrow users' access to diversified content; the information entropy of content accessible to resource-constrained users falls by 20% to 30% [10,19-21]. The human-computer interaction process forms a "user selection-algorithm reinforcement-reselection" closed loop, driving a 20% to 40% decline in the information entropy of user-accessible content within a few months [1,22,23].

Recommendation systems have evolved from early statistical models to current deep learning-driven frameworks, bringing improved distribution efficiency and intensified "filter bubble" effects [7,24,25]. Collaborative filtering technology adapts to large-scale dataset processing scenarios with inherent limitations of cold start and content homogenization; content-based recommendation methods effectively resolve cold start issues with latent risks of fostering information cocoons. Hybrid recommendation systems compensate for the shortcomings of single recommendation technologies through multi-method integration; deep learning technologies achieve extremely high recommendation accuracy with high computing resource requirements and insufficient interpretability. Sequence modeling technology accurately captures users' dynamically changing interest preferences; diversity enhancement strategies including determinantal point process (DPP) and re-ranking algorithms improve the fairness of recommendation systems with difficulty in balancing recommendation accuracy and content diversity. Future recommendation systems need to integrate efficient data fusion and optimization strategies to achieve comprehensive improvement of system diversity, fairness and scalability in diversified application scenarios [25].

3. Dynamic modeling algorithm

Dynamic modeling algorithms play a vital role in recommender systems. By capturing the temporal evolution of user preferences and recommendation interactions, such algorithms can analyze the emerging feedback loops, that is, the multidimensional mechanisms driving the formation of information cocoons and their interactions over time. This serves as a robust mathematical foundation for diagnosing the causal drivers of filter bubble formation and designing intervention strategies to restore information diversity [26,27].

The framework of dynamic modeling algorithms involves the following steps: First, preferences $(p(0))$ and recommendations $(r(0))$ are initialized from historical data (e.g., clicks), and $(r(t))$ is generated using Neural Collaborative Filtering (NCF) [22]. Second, preferences are updated through differential equations that incorporate confirmation bias:

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$$\frac{dp(t)}{dt} = \alpha(r(t) - p(t)) + \beta \cdot sim(p(t), p(t-1)) \cdot p(t-1),$$

where ($\beta \in [0,0.5]$)denotes the bias weight, and (sim) represents the cosine similarity [1]. Finally, by performing 50,000 iterations using distributed computing (e.g., Spark), the entropy ($H(t) = -\sum p_i(t) \log p_i(t)$) was evaluated, confirming that it decreased to 3.21 in the absence of intervention [1]. Compared with the static model (which showed a 30% reduction in categories) and the HMM (which lacked long-term convergence), dynamic modeling demonstrated higher accuracy and scalability on large-scale datasets, although at the cost of increased computational demands (50,000 iterations on a single machine required 10 hours).

Dynamic modeling faces computational challenges from nonlinear simulations and limited data coverage (e.g., 80% tag coverage on Amazon). Scalability for millions of users requires Spark or GPU acceleration [1]. Future research should enhance model design, integrate multimodal data, and develop interventions to increase information entropy and recommendation diversity [27].

4. Oscillator mechanism

The oscillator mechanism, derived from dynamical systems and control engineering, counters steady-state convergence through periodic perturbations, enhancing dynamic diversity [11,27,28]. In complex adaptive systems, such interventions can prevent local optimal retention and pattern solidification [12,14,15]. The recommendation system can be modeled as a dynamic system with multi-agent interaction, and its feedback loop updates user preferences and recommendation outputs. Therefore, the application of oscillator mechanisms to recommender systems is theoretically consistent and feasible:

(1) Dynamical isomorphism: The equations governing preference evolution in recommender systems mirror the evolution of state variables in classical dynamical systems, and both can be modeled using differential equations or discrete mappings;

(2) Analogy of perturbation effects: In control theory, moderate periodic perturbations enhance the exploration of the state space; similarly, in recommender systems, analogous "information perturbations" can increase the entropy and diversity of the candidate set [13];

(3) Feedback stability: Oscillator mechanisms offer controllable perturbation amplitudes and frequencies, allowing the system to maintain accuracy while preventing excessive divergence, which aligns with the optimization goal of balancing "exploration and exploitation" in recommendation tasks [10]. Formally, oscillator interventions can be modeled from two perspectives:

1. Phase-coupled models, which are suited for analyzing critical points of group synchronization or desynchronization;

2. Vector or damped oscillator models, which are used to describe the continuous evolution of preference vectors or probability distributions over time.

A typical representation of the former is:

$$\dot{\theta}_i = \omega_i + \sum_j K_{ij}(t) \sin(\theta_j - \theta_i) + F_i(t) + \eta_i(t),$$

Here, θ_i denotes the "phase preference" of users or items, K_{ij} represents the coupling strength, and $F_i(t)$ indicates the controllable external drive. Such models facilitate the derivation of synchronization degree and critical coupling strength, which characterize the transition between synchronization and echo chamber states.

For the preference vector$p(t) \in R^d$that is more suitable for engineering implementation, a damped vector dynamics framework is adopted:

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$$\ddot{p}_i + \gamma \dot{p}_i + \Omega p_i = \sum_j K_{ij}(t)\, g(p_j, p_i) + F_i(t) + \eta_i(t),$$

Here, $g(\cdot,\cdot)$ may serve as a similarity-based coupling function, $F_i(t)$ represents an exogenous periodic or quasi-periodic perturbation term, and η_i denotes noise. This vector-based formulation is compatible with embedding-based recommender systems and can be used to simulate the evolution of user preferences under continuous-time dynamics or their discrete approximations—similar to recent approaches that apply ODEs or GNNs to continuous-time sequence recommendation.

Based on the above model, the oscillator mechanism can be embedded into the recommendation pipeline as follows: first, the initial preference vector $p(t)$ and cultural/class embeddings $c(t)$ are learned from users' historical behavior, and the baseline recommender $f$generates the initial scores or candidate items $r(t) = f(p(t), c(t), X)$. Secondly, to mitigate the homogenization effect, a periodic perturbation is applied to the candidate scoring, formulated as:

$$r'(t) = normalize\,(r(t) + Asin\,(\Omega t)\,\xi(t)),\ \mathbf{r}'(t)\ ,$$

Let $\xi(t)$ be a zero-mean random vector (e.g., standard normal), *normalize* denote the clipping or normalization applied to the score vector. The parameter A, Ω controls the intensity and frequency of the perturbation. In implementation, this term should be explicitly normalized and clipped to ensure the validity of the candidate distribution and to prevent numerical instability.

To simulate the amplifying effect of confirmation **bias** or **self-selection** on preference evolution, preference updates incorporate a constrained weighting term, which takes the following discretized form:

$$p_{t+1} = (1 - \alpha)\, p_t + \alpha\, r'_t + \beta \cdot s_t \cdot proj\,(p_t)\ ,$$

Here, $s_t = clip\,(cos\,(p_t, p_{t-1}), 0, 1)$ constrains the cosine similarity within the range [0,1], and $proj(\cdot)$represents the necessary normalization or projection (e.g., projection onto the probability simplex or L_2/L_1- normalization) to ensure both numerical and semantic stability.To incorporate cross-group diversity (cross-stratum optimization), the final candidate score is computed using a linear mixture:

$$r''_t = (1 - \lambda)\, r'_t + \lambda\, q_t \quad , \quad q_t = \text{normalize}\,(\text{score}\,(c(t), X)\ ,$$

Here, $(\text{score}(c(t), X)$ denotes the score of items that are complementary to (or weakly correlated with) the current user, calculated based on cultural or stratum embeddings. $\lambda \in [0,1]$ controls the strength of cross-stratum candidate injection; in practical systems, λcan be interpreted as the proportion of cross-stratum candidates inserted during each recommendation cycle. Compared to simple vector augmentation, this mixing strategy is better suited for implementing insertion-based diversification in top-N lists and allows for the application of soft constraints to safeguard user experience (e.g., inserting no more than 1–2 cross-stratum items per 10 candidates).

The evaluation must consider both short-term utilities (e.g., Precision@K, NDCG) and long-term dynamic indicators. Static diversification methods (like DPP) and dynamic recommendation methods should be used as benchmarks to figure out the long-term benefits and short-term trade-offs of oscillator intervention. DPP increases diversity by simulating statistical exclusion, but it is very hard to compute. Dynamic graphs and the ODE framework can show how preferences change over time [27].

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5. Conclusion and outlook

In this paper we discuss how algorithmic filtering (selection bias), social influence and manmachine interface contribute in forming information cocoons. We argue for applying dynamical modelling with an oscillatory device to enhance recommender engines so it becomes less problematic. Selection bias is caused through limiting user's information exposure through prioritizing similarity.Community influence and stratification caused by social homophily and resources inequality strengthen the intra-group agreement and widen inter-group differences. Feedback loops in human-computer interaction can accelerate the convergence of user preferences. Dynamic modeling can quantitatively analyze this process and locate the key preference convergence nodes [19].

This oscillator mechanism ensures the accuracy of recommendations by introducing information diversity and content distribution fluctuations, and achieves a balance between accuracy and exploration through temporal dynamics. Possible directions for future research include:

1. Fine-tuning the parameters of the adaptive oscillator. The model will be able to adaptively change the amplitude and frequency according to users' behaviors;
2. Extend the model into different domains (e.g., news domain, video domain and e-learning domain) for exploring the generalization ability;
3. Formulate an overall optimization problem incorporating the considerations of content diversity, user satisfaction, company profits as well as social ethics;

In summary, our oscillator-based dynamic recommendation method can provide a new idea for mitigating information cocoons. As the improvement of explainable and domain transfer ability, which will have an important impact on future work for designing recommendations systems that build up a more diverse and fair information ecology.

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