Combating Echo Chambers In Online Social Network By Increasing Content Diversity In Recommendation

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Abstract. In today's digital landscape, social networks crucially shape perceptions and preferences but often facilitate echo chambers, limiting diverse thought and increasing polarization. This research addresses echo chambers on social networks, specifically Facebook, by developing diverse recommender systems using the MovieLens 100k dataset. We implement collaborative filtering, content-based filtering, and hybrid approaches to increase content diversity and reduce echo chamber effects. Our analysis confirms the presence of echo chambers and evaluates various recommendation algorithms' effectiveness in mitigating these effects. We propose enhancements for recommendation algorithms, including incorporating serendipity and novelty, diversifying data sources, and integrating user feedback to promote diverse viewpoints. Our experiment shows that the clustering distance-based method performs best for both movie and social network datasets with diversity values of 0.84 and 0.56 respectively. This study enriches the literature on online echo chambers and suggests strategies for more inclusive recommendation systems to encourage open dialogue and understanding.

Keywords: social network · echo chamber · content diversity · recommendation.

1 Introduction

In recent years, the echo chamber phenomenon has gained significant attention due to its detrimental effects on societal cohesion, democratic discourse, and the spread of misinformation [1, 2]. Traditional approaches to mitigating echo chambers have often focused on user education and platform-level interventions, yet these strategies have shown limited effectiveness in addressing the root causes of the issue [3]. Recognizing the pivotal role of algorithmic recommendation systems [4] in shaping user experiences and content consumption patterns, there is a growing consensus on the potential of recommender systems to serve as a catalyst for promoting content diversity and mitigating echo chambers. By integrating principles of diversity and inclusivity into the recommendation process, recommender systems can play a pivotal role in exposing users to a wider array of perspectives, ideologies, and information sources [5]. However, achieving this goal requires a nuanced understanding of user preferences, information needs, and the intricate interplay between algorithmic recommendations and user behavior.

This paper explores the intersection of recommender systems and echo chambers, focusing on their impact in social networks like Facebook. Using the MovieLens 100k dataset, we develop various recommender systems, including collaborative filtering, content-based filtering, and hybrid methods, to enhance content diversity and mitigate echo chambers. Our findings confirm the presence of echo chambers and evaluate the effectiveness of different algorithms in addressing them. We investigate enhancements such as integrating serendipity and novelty, diversifying data sources, and incorporating user feedback to promote diverse viewpoints. Notably, our Clustering Distance-based Method significantly improves content diversity, achieving scores of 0.84 for movies and 0.56 for social network datasets.

Through a combination of empirical studies, theoretical analyses, and practical recommendations, this research aims to provide platform designers, policymakers, and stakeholders with the tools and insights necessary to combat echo chambers and foster a more diverse and robust digital ecosystem.

The main contributions of this paper are summarized as follows:

- **Demonstrate Echo Chamber Formation:** We experiment to demonstrate how recommender systems substantially reduce content diversity and contribute to echo chamber formation over time in social networks.
- **Introduce two innovative methods to enhance content diversity**: We introduce the Clustering Distance-based Method and the Diversity-Based Re-ranking Method, designed to create more open and inclusive social media environments through enhancing diversity in recommendation.
- **Performance metrics:** We present three performance metrics: Diversity, Novelty, and Intra-list Similarity. Our findings show that the Clustering Distance-based Method outperforms other techniques in both movie and social network datasets, with noted diversity values.

2 Background

In this section, we describe some related background on recommender systems and echo chambers.

2.1 Recommendation Systems

Collaborative Based Filtering. Collaborative filtering, a key part of recommendation systems, uses collective user behavior for personalized suggestions [6].

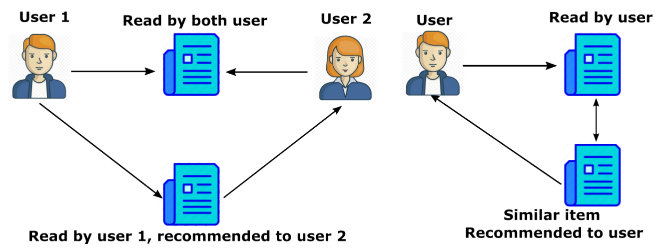

Fig. 1. Collaborative and Content-Based Filtering

It assumes users with similar past preferences will have similar future ones. User-based filtering matches a user's preferences with others', suggesting items liked by similar users. Item-based filtering suggests items similar to those highly rated by the user. These techniques don't need explicit attributes but rely on user interactions. However, they face issues with new users or items and sparsity in large datasets. Despite this, collaborative filtering is a powerful method for personalized recommendations in many domains.

Content Based Filtering. Content-based filtering, a vital part of recommendation systems, relies on item characteristics for personalized suggestions. Unlike collaborative filtering, it focuses on item features rather than user interactions [7]. By analyzing attributes like text or metadata, it finds items similar to those the user has liked before. Particularly useful when explicit item attributes are available, like in music or movie domains, it effectively addresses the cold-start problem for new users. However, it may suffer from overspecialization and limited diversity in recommendations. Still, content-based filtering is valuable for delivering personalized suggestions across various applications.

2.2 Echo Chambers

Echo chambers are environments where individuals encounter primarily information and viewpoints that reinforce their existing beliefs [8]. In these spaces, people often engage with content that aligns with their views, resulting in confirmation bias and limited exposure to diverse perspectives.

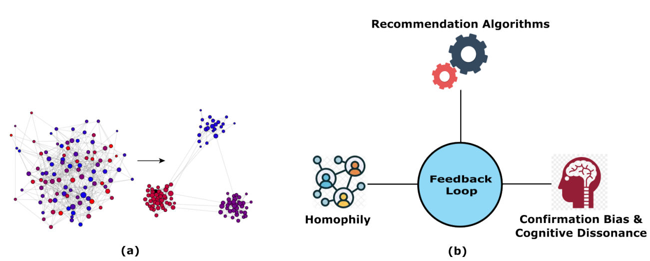

Fig. 2. Echo Chamber (a) Formation, (b) Mechanisms

Attributes of Echo Chambers. Echo chambers in online social networks persist due to several key factors: Confirmation Bias, Limited Exposure, Isolation, Reinforcement, Polarization, and Resistance to Contradictory Information [9]. Participants seek information that confirms their beliefs, resulting in Confirmation Bias, and are exposed mainly to similar viewpoints, leading to Isolation. This narrow exposure reinforces shared attitudes and contributes to Reinforcement. Echo chambers exacerbate societal polarization by amplifying differences and reducing common ground, with participants often resisting contradictory information, fostering closed-mindedness. Figure 2(a) illustrates echo chamber formation.

Mechanisms of Echo Chambers. This section examines the key mechanisms of echo chambers, as shown in Figure 2(b). These include recommendation algorithms, confirmation bias and cognitive dissonance, and homophily [10]. Recommendation algorithms reinforce users' beliefs by filtering out diverse perspectives. Confirmation bias drives individuals to consume content that supports their worldview, while cognitive dissonance strengthens existing beliefs and limits open-mindedness. Homophily leads individuals to like-minded networks, reinforcing their beliefs and increasing societal fragmentation.

Echo Chamber Prevention. Preventing echo chambers in online social networks requires a multifaceted approach. Algorithmic strategies include using diversification algorithms and serendipity-enhancing features to present varied content. Additionally, promoting media literacy, fostering diverse online communities, and implementing transparency regulations are effective methods [1]. A combination of these algorithmic, educational, community, and regulatory measures can help reduce echo chambers and encourage inclusive discourse.

3 Related Works

3.1 Recommendation Systems

Early research in recommendation systems focused on collaborative filtering, with content-based methods emerging as a complement. Hybrid approaches and deep learning have since enhanced model sophistication. Research also explored novel evaluation metrics, benchmark datasets, and interdisciplinary collaborations. Liu et al. introduced the New Heuristic Similarity Model (NHSM) to measure similarity using user ratings and global preferences [11]. Zhu et al. used cosine similarity to calculate user similarity based on weighted item ratings [12]. Liu et al. developed a personalized tag recommendation system for Flickr, matching new photos with geo-specific tags [13].

Xu et al. [14] explored user preferences on microblogs by utilizing information from their connected users. They focused on filtering out unnecessary connections to accurately predict the preferences of specific users, rather than using traditional methods that seek out relevant users.

3.2 Echo Chambers

In the domain of social networks, echo chambers are self-reinforcing information bubbles where individuals are exposed mainly to content aligning with their beliefs [15]. This can lead to polarization and the amplification of biased narratives. Studies have explored factors such as algorithmic recommendation systems and user engagement patterns contributing to echo chambers [2]. Various metrics and methodologies have been proposed to quantify echo chamber effects. Mitigation efforts include algorithmic interventions, design changes, and user education strategies promoting information diversity and critical thinking. Despite ongoing efforts, echo chambers remain a complex challenge, requiring interdisciplinary collaboration for solutions [3].

4 Dataset

We create a posts dataset comprising user posts, and user reactions (like, love, care, laugh, wow, sad, angry, comment, share). We label the dataset with post categories which include sports, politics, education, lifestyle, advertisement, etc. 93 categories in total. Then we calculate the user engagement score based on the interactions the user does with a given post. According to Equation 1, the engagement score is calculated as the sum of the product of each reaction r and its corresponding weight w_r.

$$Score_{engagement} = \sum_{r \in R} r \times w_r \tag{1}$$

Where R = {0, 1} and it means a user can react any single reaction from the reaction list. $S_{reaction} = \{like, love, care, lough, wow, sad, angry, comment, share\}$ is the reaction list. And $S_{weight} = \{1, 2, 3, 4, 5, 6, 7, 8, 9\}$ which is the weight of each reaction which is multiplied by 0 or 1. We use this engagement score analogous to movie ratings. The engagement score value ranges from 0 to 7 without considering the comment, or share. Users can react to a post and comment, or share a post. In that case, the value can be calculated using Equation 1.

The MovieLens 100k dataset [16] is pivotal in recommender system research. It contains 100,000 anonymized movie ratings ranging from 1 to 5, user demographics, and movie metadata, offering a detailed view of user preferences. Widely used for benchmarking and advancing recommendation algorithms, it is a key resource in personalized recommendation technology.

5 Methodology

5.1 Baseline Recommendation Systems and Echo Chambers Formation

This study addresses echo chambers and content diversity in online social networks. Using a 15K dataset (including Facebook posts, reactions, comments,

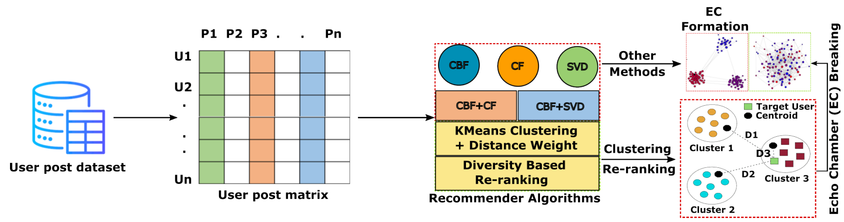

Fig. 3. Breaking Echo Chambers

and usernames) and the MovieLens 100k dataset, we evaluate recommender algorithms: Collaborative Filtering (CF), Content-Based Filtering (CBF), Singular Value Decomposition (SVD), and hybrid approaches. CF focuses on user-item interactions, CBF on item attributes, and hybrid methods combine these for broader recommendations. Our aim is to explore how these approaches can enhance content diversity and promote a more inclusive online environment.

Reactions	Impact	Weight(w_r)
angry	strong negative	1
sad	negative	2
like	low positive	3
care	mid positive	4
lough	positive	5
wow	strong positive	6
love	stronger positive	7

Table 1. Ratings Matrix for Post Data

Collaborative Filtering Method In our experimentation with collaborative filtering, we focus on the user-based approach for both our dataset and the MovieLens 100k dataset. This method recommends items by identifying similar users based on their past behavior. Recommendations are then made based on items liked by these similar users but not yet experienced by the target user. We construct a user-item matrix representing user-item interactions and employ similarity metrics i.e. cosine similarity between users' rating patterns. In our experiment, we try to generate recommendations for top N items.

Top N Recommendation In the collaborative filtering experiment we implement mean post rating to generate recommendations of top N posts. Let $S(u)$ be the set of top k most similar users to user u in dataset D. We calculate the similarity between users using a similarity metric, such as cosine similarity. For each post m: Let $R_m(u)$ be the mean rating of post m by users in set $S(u)$. Compute $R_m(u)$ as follows:

$$R_m(u) = \frac{1}{|S(u)|} \sum_{v \in S(u)} D_{v,m} \quad (2)$$

Equation 2 represents the calculation of the mean post rating $R_m(u)$ for user u. where $D_{v,m}$ is the rating of user v for post m. Then we sort the mean ratings $R_m(u)$ in descending order based on the computed mean post ratings. Let $T(u)$ be the top n posts from the sorted list based on mean post ratings $R_m(u)$. Finally, the top n recommended posts for user u are given by $T(u)$.

Algorithm 1: Top N Post Recommendation Algorithm

```
Input: u (User ID), D (User-Post Dataset), k (Number of Neighbors),
       N (Number of Posts to Recommend)
Output: R (Top N recommended posts)
Require:
Find top k most similar users to user u in dataset D;
S ← Top k most similar users to user u;
for each post m in dataset D do
    R_m ← (1/|S|) Σ_{s∈S} Rating_{s,m};
Sort posts R_m in descending order based on mean rating;
R ← Top N posts from sorted list;
return R;
```

Content-Based Filtering Method For content-based filtering experimentation with our 15k user post dataset, we extract post metadata features like categories, length, and platform to characterize items. User profiles are constructed based on previously reacted posts, represented using TF-IDF or word embeddings. Recommendations are generated by computing the similarity between user profiles and item features, with the most similar items recommended. We compute diversity performance metrics diversity, novelty, and intra-list similarity to measure the performance.

Matrix Factorization In our experiments, we use Singular Value Decomposition (SVD), a popular matrix factorization method in recommendation systems [17]. SVD decomposes the user-item matrix into three lower-dimensional matrices, capturing latent features of user preferences and item attributes to generate personalized recommendations. We applied SVD to both the MovieLens dataset and our 15K user post dataset, uncovering patterns and generating accurate top-N recommendations. Additionally, we evaluate the diversity increase using various metrics for different values of N.

Hybrid Recommendation Approach We experiment with two hybrid approaches. One is a combination of Collaborative filtering and content-based filtering and another is collaborative filtering and SVD. In both cases, we first generate recommendations using collaborative filtering and also generate by the other 2 methods. Then we combine the results from from both algorithms and get the top N items. For the hybrid case, we also compute the diversity performance.

5.2 Breaking Echo Chambers

In this section, we examine the mechanisms fueling echo chambers and propose strategies to dismantle them. By addressing algorithmic recommendation systems, and social network structures, we aim to foster a more diverse and inclusive digital environment.

Clustering Distance-based Method Clustering is a key unsupervised learning technique that groups data points based on their similarities. KMeans is a popular and simple clustering method [18]. It assigns data points to the nearest centroid and updates the centroids based on the mean of points in each cluster, repeating this process until convergence. For recommendations, we cluster users and then calculate the distance between a target user's centroid and other centroids. Items are selected from clusters in proportion to the reciprocal of these distances.

Centroid Calculation. Calculating cluster centroids involves determining the central point or representative of each cluster formed based on user preferences as shown in Equation 3.

$$C = \left(\frac{1}{n} \sum_{i=1}^{n} x_{i1}, \frac{1}{n} \sum_{i=1}^{n} x_{i2}, \ldots, \frac{1}{n} \sum_{i=1}^{n} x_{im} \right) \tag{3}$$

This equation represents the centroid C of a cluster, where n is the number of data points, m is the dimensionality of the data, x_{ij} is the j-th component of the i-th data point, and the sums compute the mean of each component across all data points.

Algorithm 2: Recommend Items from Clusters

Input : Clusters, TargetUserCluster, top_n
Output: SelectedItemsFromClusters

Calculate centroids of each cluster;

Calculate distance between cluster centroids and TargetUserCluster centroid:

$d_i = distance(C_i, TargetUserCluster)$ for $i = 1, 2, \ldots, k$;

Sort clusters based on distances (closest first): $C_1, C_2, \ldots, C_k$;

Select portions of the top N items from each cluster based on distance order;

foreach *cluster* C_i **do**
  Assign portion of items based on distance rank: $N_i = f(d_i)$;
end

$$N = \sum_{i=1}^{n} \frac{1}{d_i} \times C_i \tag{4}$$

Using Equation 4 we multiply the top_n item number with the inverse of the distance of the cluster from the target user cluster.

Diversity Based Re-ranking Method Diversity-based reranking in recommendation systems enhances user experience by promoting a variety of recommended items. Traditional approaches prioritize accuracy over diversity, leading to repetitive recommendations. The diversity-based reranking algorithm quantifies item diversity using similarity metrics and calculates a diversity score for each recommended item [19]. Items with higher diversity scores are prioritized in the reranked list, ensuring a diverse range of options for users and enhancing user satisfaction.

Algorithm 3: Diversity-based Reranking Algorithm

Input: User ID u, N top recommendations
Output: Re-ranked items

`rerank`(u, N);

Retrieve items rated by user u;

Calculate diversity scores for recommended items based on their similarity to rated items by user u;

Sort recommended items in descending order of diversity scores;

return *N top reranked items*;

$$ds[m\_id] = \frac{\sum_{i=1}^{N} sim[item\_1, item\_2]}{count} \tag{5}$$

Content Diversity. We measure the similarity between two items following Equation 6. If the item is post each post m_i is represented in post-category space as a vector of length N, and there are M posts in total. The relevance of a particular post-category t_k to a given post m_i is represented as $rel(t_k, m_i)$, and we denote the post-category relevance matrix as $R \in R^{N \times M}$, where $R_{k,i} = rel(t_k, m_i)$.

We compute the Euclidean distance (L2 distance) d between two posts m_i and m_j in post-category space as:

$$d(m_i, m_j) = \sqrt{\sum_{k=1}^{N} (R_{k,i} - R_{k,j})^2} \tag{6}$$

Smaller distances represent posts that are more similar to one another based on their content, as expressed by their relevant post-categories. For a set of posts m, we define the diversity $D(m)$ as the average Euclidean distance of all unique pairwise combinations of those posts. That is:

$$D(m) = \frac{1}{|m|(|m|-1)} \sum_{i=1}^{|m|} \sum_{j=i+1}^{|m|} d(m_i, m_j) \tag{7}$$

Where $|m|$ is the number of posts in m.

6 Evaluation Metrics

Diversity This function assesses diversity by calculating the coverage metric [20]. Coverage measures the ratio of unique items in the recommendation list to the total number of unique items in the dataset. It indicates the extent to which the recommendation list spans a wide range of items, providing users with diverse choices.

Novelty This function evaluates novelty by computing the novelty metric. Novelty assesses the proportion of unique items in the recommendation list compared to the total number of unique items in the dataset [21]. It measures the freshness and uniqueness of recommendations, ensuring users are exposed to new and less commonly recommended items.

Intra-list Similarity This function determines intra-list similarity by calculating the intra-list similarity metric. Intra-list similarity quantifies the similarity between items within the recommendation list [22]. It evaluates how similar the recommended items are to each other, aiming to provide a balanced mix of diverse but relevant recommendations to users.

7 Experiment

In this section, we describe how to implement collaborative filtering, content-based filtering, SVD, and their hybrid approaches. Finally, we describe our methods which are clustering-based and re-ranking-based recommendation generation.

7.1 Collaborative Filtering Method

We implement a Collaborative Filtering Model for item recommendation using user similarities in both datasets. This model applies cosine similarity to measure how users' item preferences align. The fit method computes the user similarity matrix, adjusting diagonal values to prevent recommending items a user has already rated. The recommend method retrieves a user's item ratings, calculates similarities with other users, and identifies the closest matches. It then filters out items the user has already reacted to and generates recommendations based on these similarities, returning the top suggestions.

7.2 Content-Based Filtering Method

We implement a content-based recommendation system using the Nearest Neighbors (NN) algorithm from scikit-learn. The model is configured to find the 100 nearest neighbors based on cosine similarity and trained on user item features. For item recommendations, we use a function that takes an item index, its features, and the trained NN model. This function identifies similar items, returns a data frame with recommended items and their distances, and excludes the input item from the recommendations. This approach provides personalized recommendations based on item features.

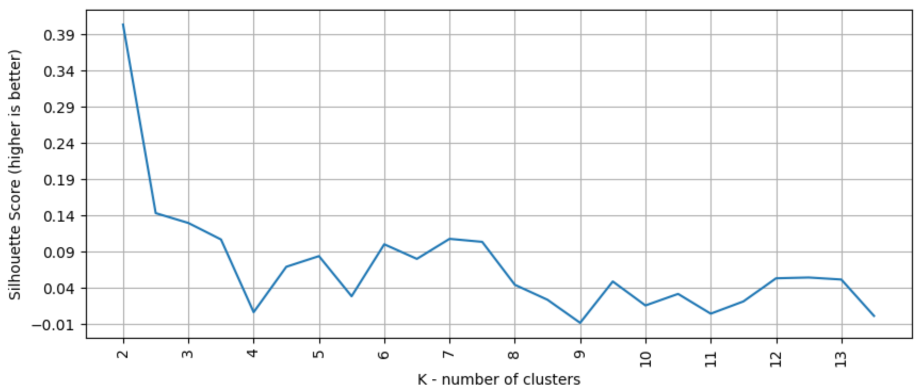

Fig. 4. Finding Optimal Value of K Using Silhouette Score

7.3 Clustering Distance-Based Method

In this section, we describe how we find the optimal value of k which is the cluster number, and how we implement the distance-based item selection from clusters.

Optimal Number of Clusters The silhouette score [23] measures how similar an object is to its own cluster (cohesion) compared to other clusters (separation). It ranges from -1 to 1, where a high silhouette score indicates that the object is well-matched to its own cluster and poorly matched to neighboring clusters. Therefore, a higher silhouette score suggests better-defined clusters. We run the KMeans for the range of [2, 182]. In Figure 4 we show k values up to 13.

7.4 Diversity Based Re-ranking Method

This reranking method aims to enhance recommendation diversity by considering the pairwise similarity between recommended items. Here's a breakdown of how it works:

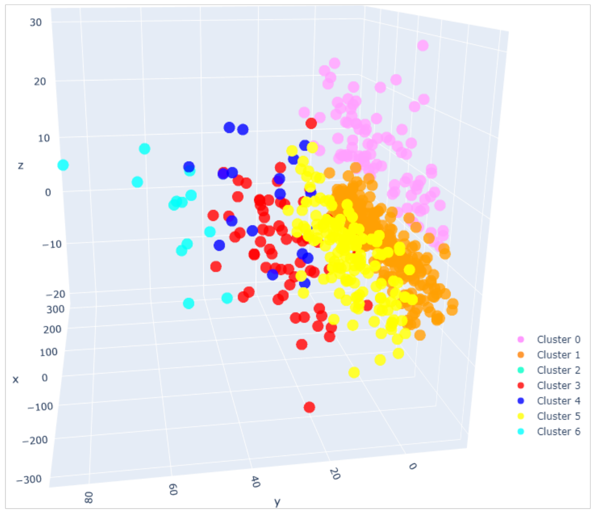

Fig. 5. 3D Visualization of 7 Clusters.

Precomputation of Item-Item Similarity Matrix. First, the item-item cosine similarity matrix is precomputed using the cosine similarity metric. This matrix quantifies the similarity between items based on their genre information.

Calculation of Diversity Scores. For each unrated movie, the method computes a diversity score. This score is obtained by averaging the cosine similarities between the unrated movie and each movie already rated by the user. The higher the average similarity, the higher the diversity score, indicating that the unrated movie is more similar to the movies the user has already rated.

Reranking Based on Diversity Scores. Finally, the method reranks the recommended movies based on their diversity scores. Movies with higher diversity scores are prioritized in the reranking process, ensuring that the final list of recommendations includes diverse options that complement the user's preferences.

8 Results

In this section, we describe the experimental result.

8.1 Choosing Optimal K

Our analysis shows that the clustering algorithm achieved the highest silhouette score with k=7. The silhouette score, ranging from -1 to 1, measures how well objects fit within their cluster compared to other clusters. A higher score indicates well-defined clusters with clear separation. The optimal k=7 suggests effective clustering with distinct, internally consistent groups. Figure 5 displays a 3D view of these 7 clusters, highlighting the strong clustering structure and revealing key patterns in the dataset.

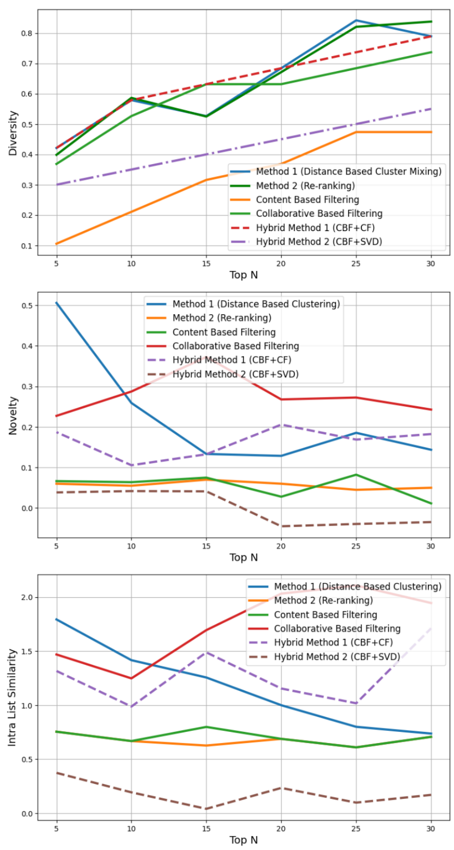

Fig. 6. Performance Measures of Movie Data

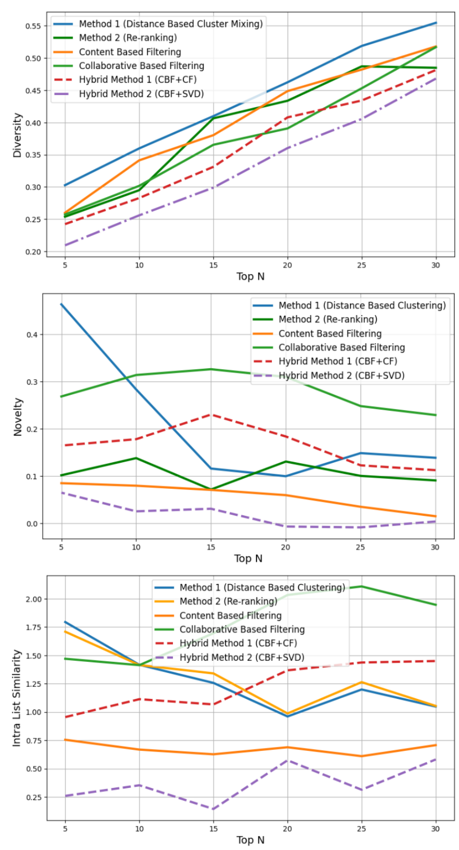

Fig. 7. Performance Measures of Social Network Data

8.2 Performance of Different Models on Movie Rating Dataset

Diversity. Method 1 (distance-based clustering) achieves the highest diversity with a value of 0.84 at N=25 (see Figure 6). Hybrid Method 1 (CBF+CF) also performs well, integrating content-based and collaborative filtering aspects. Content-Based Filtering (CBF) generally offers lower diversity by recommending similar items.

Novelty. Content-Based Filtering shows the highest novelty, recommending more novel items. Hybrid Method 2 (CBF+SVD) has lower novelty, indicating limited enhancement in recommendation novelty.

Intra-List Similarity (ILS). CBF exhibits the highest ILS, meaning its recommendations are more similar. CF has lower ILS values, indicating higher diversity. Hybrid methods like CBF+CF and CBF+SVD offer intermediate ILS values, balancing similarity and diversity.

8.3 Performance of Different Models on Social Network Dataset

Diversity. Method 1 (Distance-Based Cluster Mixing) achieves the highest diversity, with a value of 0.56 at N=25 (see Figure 7). This method effectively enhances recommendation diversity by mixing clusters. Hybrid Method 2 (CBF+SVD) shows lower diversity, indicating that combining content-based filtering with SVD does not improve diversity significantly.

Novelty. Collaborative filtering exhibits decreasing novelty with fewer recommendations, showing a bias toward popular items. Content-based filtering maintains consistent novelty by focusing on item characteristics, while hybrid methods offer moderate novelty by balancing popularity and novelty.

Intra-List Similarity (ILS). Collaborative Filtering has the highest ILS, indicating similar recommendations within lists. Content-Based Filtering has lower ILS, suggesting more diverse recommendations. Hybrid methods like CBF+CF and CBF+SVD provide intermediate ILS, combining collaborative and content-based approaches for a balanced recommendation quality.

Overall, in terms of diversity Clustering and distance-based method performs best. In other metrics, another model performs better for both datasets.

9 Conclusion

Recommendation systems serve to enrich user experiences by anticipating and proposing content tailored to their preferences. However, an unintended consequence of these systems is the potential reduction in content diversity accessible to users. In this study, we conducted a quantitative analysis to examine this phenomenon within collaborative filtering systems. By simulating user interactions with the MovieLens dataset and observing changes in content diversity over time, we made several key observations: 1. The diversity of content recommended by collaborative filtering models declines significantly with repeated interactions. We experiment with our two methods of cluster distance based method and reranking based on diversity score. Our finding shows that our first method is able to increase diversity in recommendation and eventually break the echo chambers formation.

10 Acknowledgment

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