Papers

[1] A metric for Filter Bubble measurement in recommender algorithms considering the news domain

Provide the HL metric for filter bubbles, exploring the effect of diversification. Only some diversification algorithm are effective
https://www.sciencedirect.com/science/article/abs/pii/S1568494620307092

Related work:

- **exploring the filter bubble: The effect of using recommender systems on content diversity (Nguyen et al)**
  Analyze filter bubbles impact on the movie domain (static)
  https://dl.acm.org/doi/pdf/10.1145/2566486.2568012

- **HowAlgorithmic Confounding in Recommendation Systems Increases Homogeneity and Decreases Utility (Chaney et al.)**
  Use of Jaccard index to verify filter bubbles existence, generation of data to simulate user behavior
  https://arxiv.org/pdf/1710.11214

- **Exposure diversity as a design principle for recommender systems (Helberg et al)**
  Diversity as a design system to prevent filter bubbles
  https://pure.uva.nl/ws/files/17932244/Exposure_diversity_as_a_design_principle.pdf

- **Understanding and Controlling the Filter Bubble through Interactive Visualization: A User Study (Nagulendra et al)**
  interactive visualization to increase user perceptions of bubbles
  https://julita.usask.ca/Texte/ht84nagulendra.pdf

- **Same, Same, but Different Algorithmic Diversification of Viewpoints in News(Tintarev et al)**
  Treat filter bubbles with a system that diversifies the viewpoint of the same news.
  https://pure.tudelft.nl/ws/portalfiles/portal/52000140/Same_Same_but_Different.pdf

[2] Degenerate feedback loops in recommender systems (Jiang et al)

Examines the role of user dynamics and algorithms, disentangling the echo chamber effect from the filter bubble effect. Proposes solutions to slow down system degeneracy, based on the assumption that user interest may degenerate or remain stable depending on their internal dynamics, while the recommender system can only slow down or accelerate this process.
https://arxiv.org/pdf/1902.10730

Related works:

- **exploring the filter bubble: The effect of using recommender systems on content diversity (Nguyen et al)**
  Analyzing MovieLens dataset, found that user interest naturally degenerate over time

https://dl.acm.org/doi/pdf/10.1145/2566486.2568012

- **Filter Bubbles, Echo Chambers, and Online News Consumption (Flaxman et al)**
  Online services are associated with increased political polarization but also increased exposure to the less preferred side of political opinion
  https://sethrf.com/files/bubbles.pdf

- **Tweeting from left to right: Is online political communication more than an echo chamber? (Barbera et al)**
  Present evidence of echo chamber related to political issues on twitter, but counterevidence on online news consumptions,
  https://connorjerzak.com/wp-content/uploads/2016/08/Psychological-Science-2015-Barbera%CC%81-1531-42.pdf

- **Exposure to ideologically diverse news and opinion on Facebook (Bakshy et al.)**
  Measured the effect of user choices separately from that of the recommendation algorithm, and found that individual choices play a larger role than the algorithm in creating echo chamber on Facebook
  https://www.science.org/doi/epdf/10.1126/science.aaa1160

- **Bandit algorithm (Lattimore et al)**
  Description of the UCB recommender algorithm (chapter 8)
  https://tor-lattimore.com/downloads/book/book.pdf

- **Diversity on recommender systems: A survey (Kunaver et al)**
  Way to favor diversity in the set of items proposed by a recommendation algorithm
  https://papers-gamma.link/static/memory/pdfs/153-Kunaver_Diversity_in_Recommender_Systems_2017.pdf

[3] Echo Chambers, Filter Bubbles, and Polarisation: a Literature Review (Argueda et al)

Explain the concept of filter bubble, echo chamber and polarization, present studies that show echo chambers are small and less prevalent than commonly assumed, analyzed the effect of supply distribution and demand, blaming user for bubbles
https://reutersinstitute.politics.ox.ac.uk/sites/default/files/2022-01/Echo_Chambers_Filter_Bubbles_and_Polarisation_A_Literature_Review.pdf

Related works:

- **The filter bubble: what the internet is hiding from you (Pariesier)**
  Original definition of the filter bubble
  https://hci.stanford.edu/courses/cs047n/readings/The_Filter_Bubble.pdf

[4] HowAlgorithmic Confounding in Recommendation Systems Increases Homogeneity and Decreases Utility (Chaney et al.)
Use of Jaccard index to verify filter bubbles existence, generation of data to simulate user behavior, confounding analysis
https://arxiv.org/pdf/1710.11214

related work:

- **Recommendations as treatments: debias learning and evaluation (Schnabel et al)**
  Users introduce bias (explicitly through vote or implicitly through actions). Propensity weighting technique to remove user selection bias for explicit rating.
  https://proceedings.mlr.press/v48/schnabel16.pdf

- **Modeling user exposure in recommendation (Liang et al)**
  use language of causal analysis to describe a model of user exposure to items
  https://www.cs.toronto.edu/~lcharlin/papers/expo-mf.pdf

- **Counterfactual reasoning and learning systems: the example of computational advertising (Bottou et al)**
  formal causal inference technique can assist in the design of deployed learning systems to avoid confounding
  https://jmlr.org/papers/volume14/bottou13a/bottou13a.pdf

- **Reducing offline evaluation bias in recommendation system (De Myttenaere et al)**
  weighting techniques for address the problem of bias in confounded data (consume data taken from recommended systems)
  https://apiacoa.org/publications/2014/demyttenaeregolden2014reducing-offline.pdf

[5] Causal Inference in Recommender Systems: A Survey and Future Directions (Chen et al)
Provide a survey of causal inference use in recommender systems. Among these, some method against filter bubbles
https://arxiv.org/pdf/2208.12397

Related work

- **A metric for Filter Bubble measurement in recommender algorithms considering the news domain (Gabriel Machado Lunardi et al.)**
  Analyze the formation of filter bubbles using popular collaborative filtering (CF) methods: people tend to gravitate towards a comfort zone, seeking opinions they are interested in or agree with… over time, filter bubbles narrow individuals' perspectives and can lead to the radicalization of their ideas.
  https://pdf.sciencedirectassets.com/272229/1-s2.0-S1568494620X0010X/1-s2.0-S1568494620307092/main.pdf

- **Click can be cheating: counterfactual recommendation for mitigating clickbait issue (Wang et a.)**
  Wang et al. proposed a causal inference framework to alleviate filter bubbles with the help of user control, along with a backdoor adjustment to further reduce their effects.
  https://hexiangnan.github.io/papers/sigir21-clickbait.pdf

- **Adversarial counterfactual learning and evaluation for recommender system (Xu et al)**
  It also proposes a dynamic causal collaborative filtering (DCCF) model that leverages backdoor adjustment to estimate post-intervention user preferences and employs counterfactual reasoning to alleviate the echo chamber effect.
  https://proceedings.neurips.cc/paper/2020/file/9cd013fe250ebffc853b386569ab18c0-Paper.pdf

[6] Exploring the filter bubble: The effect of using recommender systems on content diversity (Nguyen et al)

This study analyzes filter bubbles in recommender systems using MovieLens data, comparing content diversity across users who follow and ignore recommendations. It measures content diversity via Euclidean distance between movie tag relevance scores and evaluates changes over time with t-tests.
https://dl.acm.org/doi/pdf/10.1145/2566486.2568012

Related works:

- **The Filter Bubble: What the Internet Is Hiding from You (Parisier et a)**
  Demonstrates how systems can trap humans in unchanging environments, the filter bubbles, reducing creativity and learning ability.
  https://hci.stanford.edu/courses/cs047n/readings/The_Filter_Bubble.pdf

- **Expert Political Judgment: How Good Is It? How Can We Know? (Tetlock et al)**
  Found that ordinary people made more accurate predictions than experts, whose views of the world are often "fixed."
  https://emilkirkegaard.dk/en/wp-content/uploads/Philip_E._Tetlock_Expert_Political_Judgment_HowBookos.org_.pdf

- **Republic.com 2.0 (Sunstein et al.)**
  Argues that through personalized experiences, users share fewer and fewer common experiences, until it becomes hard to understand each other.
  https://edisciplinas.usp.br/pluginfile.php/4088104/mod_resource/content/1/Republic.com%202.0%20-%20Cass%20Sunstein.pdf

- **Being Digital (Negroponte et al.)**
  Suggests that users can use recommender systems in a way that helps them learn and explore new things. Regarding the Daily US agent that explores and summarizes topics outside the user's interest, it states that such systems are the unequivocal future for computing.
  https://web.stanford.edu/class/sts175/NewFiles/Negroponte.%20Being%20Digital.pdf

- **Eli Pariser Is Wrong (Linde et al.)**
  Argues that Amazon's recommender system doesn't narrow user choice. Instead of limiting options, it increases serendipity by helping users discover items they were not previously aware of.
  https://glinden.blogspot.com/2011/05/eli-pariser-is-wrong.html

- **The krakatoa chronicle - an interactive, personalized newspaper on the web (Kamba et al.)**
  Discuss systems in which users can balance the amount of personalized items, allowing for a more flexible and controlled user experience.
  https://www.researchgate.net/publication/27521595_The_Krakatoa_Chronicle_-_An_Interactive_Personalized_NewsPaper_on_the_Web

- **Blockbuster Culture's Next Rise or Fall: The Impact of Recommender Systems on Sales Diversity" (Fleder et al.)**
  Shows that users are directed toward common experiences because recommender systems cannot recommend items with less data. While an item may be new for a given user, overall, all users are treated similarly.
  https://repository.upenn.edu/server/api/core/bitstreams/451e93a5-8a8b-4760-80ce-0af70502ae63/content

- ***Will the global village fracture into tribes: recommender systems and their effects on consumers (Hosengar et al.)***
  Argues that users consume the same items, but because iTunes' recommender system helps users widen their interests, it increases the chance of consuming those same items.
  https://www.researchgate.net/publication/228233814_Will_the_Global_Village_Fracture_Into_Tribes_Recommender_Systems_and_Their_Effects_on_Consumer_Fragmentation

- **The Tag Genome: encoding community knowledge to support novel interaction" (Vig et al.)**
  Built the tag-genome for MovieLens, which is not used for recommendations but to assist users in their exploration of movies.
  https://files.grouplens.org/papers/tag_genome.pdf

- **Improving Recommendation lists through topic diversification (Ziegler et al.)**
  developed a measure of diversity as the average pairwise diversity scores of the items and found that increasing diversity can improve user satisfaction.
  https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=bc5646cde88b948e91c655f34d91e0e1fff22f63

[7] HowDoes Empowering Users with Greater System Control Affect News Filter Bubbles (Liu et al)

Experiment if a RS that summarize the information the system has collected about user

preferences may help user to understand if they are in a filter bubble
https://ojs.aaai.org/index.php/ICWSM/article/view/31364/33524

[8] Exposure to ideologically diverse news and opinion on Facebook (Bakshy et al.)
Compared with algorithm, individuals choice play a stronger role in limiting crosscutting content
https://isps.yale.edu/sites/default/files/files/Exposure%20to%20Ideologically%20Diverse%20News%20and%20Opinion%20on%20Facebook.pdf

[1] Degenerate feedback loops in recommender systems (Jiang et al)

Recommender systems are trained on user choices and can influence user preferences, which are then turned into feedback, creating a feedback loop—a self-reinforcing pattern of narrowing exposure and shifts in user interests.

A lot of research (Kunaver and Porl) attempts to increase density in the set of recommended items. However, the current understanding of echo chambers and filter bubbles is limited, and experimental analyses often report conflicting results.

In this paper, we adopt the following definitions:

- **Echo chamber**: The effect of a user being positively or negatively reinforced through repeated exposure to certain items or categories of items. This is a generalization of Sunstein's definition, which states that overexposure to similar political opinions reinforces existing beliefs. Our definition differs from the one provided by Argueda et al.
- **Filter bubble**: As described by Pariser, this refers to the fact that recommender systems select limited content to serve users online. Thus, the filter bubble is a property of the algorithm, while user interests refer to the individual's behavior.

Model

We define a finite or countably infinite set of items M
A recommender system is denoted as $r(\theta)=\{a1,\dots,al \in M\}$
User interest is expressed as $ut(a\in M):M\to R$.

Given a recommendation $a(t)=\{a1(t),\dots,al(t)\}$, the user provides feedback based on their current interests, $c(t)=\{u1(t),\dots,ul(t)\}$, where higher values represent greater interest, and lower values represent lesser interest.

The updated recommendation model is: $\theta(t+1)=f(\theta(t),a(t),c(t))$ and the new user interest (assumed to change freely) is: $u(t+1)=g(u(t),a(t),c(t))$.
User interests are considered **weakly degenerate** if $u(a,t)$ takes values arbitrarily different from the initial interest $u(a,0)$, such that:

$\lim\to\infty\|u(t)-u(0)\| >M, \forall M$ almost surely

If, once drifted from $u(a,0)$, $u(a,t)$ remains so, we have **strong degeneracy**.
For simplicity, $// u(t)-u(0) //$ is replaced by $\sup|u(a,t)-u(a,0)|$

Echo Chamber

Setting $l=1$ and $a(t)=a$ for all t, we eliminate the recommender system's influence to study user interest dynamics independently. Assuming the drift $|u(t+1)-u(t)||$ is a nonlinear stochastic function:

$u(t+1)=u(t)+f(u(t),\varepsilon(t))$

The degeneracy of user interests depends on the structure of f. The weak degeneracy and strong degeneracy theorem presented in this paper prove that user interests degenerate under mild conditions on f. Degeneracy can be avoided if each item is shown only a finite number of times.

Filter Bubble

Since real-world user interest dynamics are unknown, the paper assumes a scenario where user interests degenerate and seeks to design a recommender system to stop or slow this degeneration.

Model accuracy: Assuming an oracle model perfectly predicting user interests, $\theta(t)=u(t)$, the surface assumption is that serving the top l items according to $u(t)=\theta(t)$, a subset of items leading to positive degenerative dynamics will take the top position. The idea is that, serving items according to u(t), they are going to receive positive feedback, leading to a self reinforcement loop.
We need to reduce the accuracy, for example adding random noisy to $\theta(t)$

Amount of exploration: Random exploration may slow degeneration but could also help discover positively degenerative items, reinforcing the surface assumption. The optimal strategy is to limit the number of times a degenerative item is served. Since detecting such items is difficult, degeneration can be prevented by serving each item only a finite number of times.

Growing candidate pool: At each step, a new set of items becomes available. Adding new items at least linearly often is necessary to avoid degeneration; otherwise, eventually, an item will be served infinitely often (pigeonhole principle). With a linear rate of new items, the system can operate indefinitely while serving each item a finite number of times.

Simulation and conclusion

1. Growing candidate pool: m(t) increases at each step.
2. At each time step, the algorithm selects the top l items from m(t) based on $\theta(t)$
3. User interest increases with clicks and decreases otherwise.
4. The system updates the model using different algorithms:
    - **Random model**: The set is a simple random sample (SRS).
    - **Oracle**: $\theta(t)=u(t)$.
    - **Optimal oracle**: $\theta t=\delta(ut)$ -> select the fastest degenerating items.
    - **Upper Confidence Bound (UCB) multi-armed bandit algorithm** (Lattimore et al.).
    - **Thompson sampling** multi-armed bandit algorithm.

The results indicate the following degeneracy speeds, measured as $/\!/ u(t)-u(0) /\!/$:

Optimal oracle > oracle > TB > UCB > random model

Degeneracy speed decreases for Thompson Sampling, UCB, and the random model as pool size increases. UCB forces exploration of unobserved items, and a larger pool requires more exploration time. With sublinear pool growth, UCB and the random model stop degenerating.

In contrast, optimal and regular oracles can potentially pick a more degenerative item from a larger pool.

The best strategy to reduce degeneracy involves continuous exploration and a growing candidate pool. Further analysis may explore item and user dependencies.

[2] A metric for Filter Bubble measurement in recommender algorithms considering the news domain (Lunardi et al)

BACKGROUND

Recommender systems suggest items based on interaction history:

- **Implicit**: Obtains information through interaction.
- **Explicit**: Obtains information through feedback.

There are three main approaches:

1. **Content-based filtering**
2. **Collaborative filtering**: The most popular approach, typical in social network environments.
3. **Hybrid**

Collaborative filtering suggests items preferred by similar users in the past. It uses a user-item matrix that contains the ratings of each user for each item to make predictions for the empty cells. This can be:

- **Neighborhood or memory-based**:
  - **User-based**: Estimates item relevance using similar users' ratings for the same item.
  - **Item-based**: Uses similarity in item ratings.
- **Model-based**: Learns a user behavior model with machine learning from ratings and usage, and uses it for predictions.

Pros: No need to know item attributes (only uses user interactions).
Cons: Cold start problem (few or no ratings), sparsity of the rating matrix (making predictions difficult).

Filter bubble: The algorithm exposes users exclusively to content of their interest, disregarding other information needs and creating intellectual isolation.

- The algorithm plays an important role, but users also contribute: They tend to consume content that aligns with their views, avoiding ideas that challenge them (comfort zone, homophily).
- Filter bubbles are invisible, and people often do not realize they are seeing content different from what others see, believing their opinions to be correct.
- One solution is promoting diversity (Helberger et al.), but users must be aware of filter bubbles.

Echo chamber: In a filter bubble, a user's opinion is reinforced by the news they see.

Diversity: Key quality features for a recommendation system include:

- **Diversity**: Addressing various tastes.
  - **Individual or intra-list diversity**: Diversity within a user's recommendation list.
  - **Aggregate or inter-list diversity**: Diversity across all users.
- **Novelty**: The non-obviousness of items.
- **Serendipity**: Items that are new and positively surprising.

Approaches for diversification:

1. **Enhancing the recommendation algorithm** to generate diverse recommendation lists.
2. **Post-filtering** to create a diversified final list from a recommended list (independent of the recommendation algorithm).
3. **Maximal Marginal Relevance (MMR)**: Maximizes an objective function that weights recommendation rating and item similarity:
   $MMR(i) = \alpha * rating(i) + (1 - \alpha) * avg\_j(1 - similarity(i, j))$
4. **Topic diversification (TD)**: Merges the original list with a highly diversified recommendation list (generated from the former).

EXPERIMENT
The paper analyzed the role of common recommendation algorithms in generating filter bubbles, aiming to show that content diversity can reduce the filter bubble effect. It introduces a metric for filter bubbles (Homogeneity Level, HL) and provides a dataset with user ratings for true and fake news recommendations. The experiment was conducted in a dummy social network (Bozdag et al. mention the difficulty of validating social network results regarding filter bubbles since users don't provide access to their data).

METRICS
The filter bubble is defined as the homogeneity of the recommendation set (R). Since there are no established metrics, the authors introduce the Homogeneity Level (HL), based on Chaney et al.'s work:
$HL = \{ \Sigma\_n[(n_i \cup n_{\square}) / (n_i \cap n_{\square})] \} / \{ (p^2 - p) / 2 \}$
Range: Zero (less homogeneous) to One (more homogeneous).

- *P* is the number of items in set R, and *n* is the feature vector for a given item.
- The accuracy of recommended items is measured using the Root Mean Square Error (RMSE), the square root of the empirical mean between predicted and actual ratings.

RESULTS
The hypothesis that diversity reduces filter bubbles was partially supported, but not as expected. Statistical significance tests did not confirm that all diversification approaches decreased homogeneity. Possible reasons include:

- As accuracy increases, the diversification factor remains static.

- Some different items may have topic overlap, while items on the same topic may carry different content.
- Automatic feature extraction.
- The HL metric is novel, and some features may be more relevant than others.
- Users may still prefer to stay in their comfort zones.
- Small data size.

FUTURE WORK

- Develop methods to dynamically detect filter bubble formation and adjust diversification to prevent it.
- Use alternative measures of bubble effects (beyond topics).
- Explore other diversification algorithms.
- Examine the system's long-term use and the potential for stronger bubbles.

[3] Echo Chambers, Filter Bubbles, and Polarisation: a Literature Review (Argueda et al)

There isn't always a clear consensus on the exact definitions of *filter bubble*, *echo chamber*, and *polarization*.

Limitations of this type of study:

- There is no single-source ground truth that captures all media use.
- Surveys depend on the accuracy of respondents.
- There is no standard for what constitutes news or opinion, or what is impartial or partisan reporting.

Echo Chamber:

An echo chamber is a situation where people are confined, either due to media supply or their own choices. It refers to a bounded and enclosed media space that can amplify or weaken the messages delivered within. Analyzing echo chambers requires examining different platforms.

<u>Political partisan news echo chamber</u>: Some people get news and information only from sources that are clearly aligned with one side of the political spectrum.

Filter Bubble:

A *filter bubble* (a term coined by activist and entrepreneur Eli Pariser) captures the concern that increasing personalization in the ranking of search engine results, social media feeds, and recommendation systems creates a unique universe of information for each person. This personalization can erode the possibility of shared perspectives and hide content we are less inclined to see.

An echo chamber is a form of bubble, but the term does not assume why people are inside it. They may have actively chosen it, or it could be the result of an algorithm. A filter bubble, specifically, is an echo chamber produced by ranking algorithms—a passive form of personalization that does not involve any active choice on our part (potentially due to how news or information is distributed online).

Analysts worry that echo chambers and filter bubbles may fuel polarization, diminish mutual understanding, and create situations where people have so little common ground that they seem to inhabit different realities.

Empirical Research Findings:

Some researchers reveal that echo chambers are small and less prevalent than commonly assumed. Most people have a diverse media diet, and only a minority rely exclusively on partisan sources.

- **Fletcher et al.**: In the UK, 2% of people are in left-leaning echo chambers, and 5% in right-leaning echo chambers. Similar results were found in Austria, Denmark, Germany, Norway, and Spain. The US is an outlier, with over 10% of respondents relying solely on partisan news sources.
- **Dahlgren et al.**: In Sweden, there is more cross-cutting exposure than isolated echo chambers. They found, “Citizens who frequently use online news from one side of the ideological spectrum also tend to frequently use news from the other side.”
- **Masip et al.**: In Spain, there is little evidence of widespread news echo chambers. Most people access “non-like-minded media” at least sometimes.
- **Gentzkow and Shapiro**: In the US, “internet news consumers with homogeneous news diets are rare.”
- **Gatter**: The idea that large numbers of people are trapped in purely ideological news echo chambers, cut off from other perspectives, is exaggerated and incorrect.
- **Yang et al.**: There is little evidence of ideological selective exposure and evidence of increasing co-exposure to various news sources over time. The note that “many more internet users consume no online news at all”.

Considerations for Supply, Distribution, and Demand:

- **Supply**: The availability of news has increased in recent years, and it is difficult to argue that supply alone leads to the formation of echo chambers.
- **Distribution**: Distribution mechanisms may create filter bubbles by reducing the diversity of information people encounter. However, empirical studies often find the opposite: distribution algorithms are associated with more diverse news consumption. Furthermore, there is no strong evidence supporting the filter bubble hypothesis that algorithmic ranking leads to echo chambers.
  The effect of algorithms is not the same for all people. It's true that passive personalization, based on past behavior, may lead algorithms to recommend more news to those who are already highly engaged. However, this can also be beneficial for people who do not seek out news on their own.
- **Demand**: Self-selection is a possible mechanism, where people opt into echo chambers because they prefer news that aligns with and reinforces their pre-existing views or because they avoid information that challenges their beliefs.

[4] HowAlgorithmic Confounding in Recommendation Systems Increases Homogeneity and Decreases Utility (Chaney et al.)

The feedback loop effect of recommender systems, which leads to filter bubbles and echo chambers, can be seen as a form of algorithmic confounding. Since this influence affects user perception of the world, societal polarization, exposure to diverse opinions, and decision-making processes, we have an ethical responsibility to develop fair and transparent recommender systems that prioritize not only accuracy but also diversity.

Additionally, some companies produce content based on consumer data. Recommender systems can influence not only which items are prioritized but also the items that are available for users to choose from.

The impact of feedback loops is characterized by three main claims:

1. It causes homogenization of user behavior at both the population and individual levels.
2. Users experience a loss in utility due to homogenization effects, which can lead them to make suboptimal choices.
3. It amplifies the influence of the algorithm on the distribution of certain items.

Background

Users introduce both explicit (e.g., votes) and implicit (e.g., actions) selection biases. The quantity of interest is the probability of selecting an item, and the goal is to predict, not correct, this selection bias.

Recommender systems introduce confounding factors, making it difficult to determine whether user interactions reflect true user preferences or the effects of the recommendations. This complexity makes it hard to analyze user preferences without accounting for confounding influences.

Recommender systems have a natural connection to the explore/exploit trade-off, which involves balancing the recommendation of items with a high probability of being consumed against items with a low probability to learn more about user preferences. This requires developing an appropriate reward function, potentially enhanced with a Markov Decision Process.

Assumptions

1) User utility for item consumption is defined as: $V=P+Q$, where P is known and Q is unknown to the user (if Q were known, a recommendation algorithm would not be needed). We can approximate V as static over time.

2) Total utility is modeled as a Beta distribution (ranging from 0 to 1) of user preferences p and item attributes a.

3) Both p and a are fixed but unknown to both the user and the recommender system and are drawn from a Dirichlet distribution.

4) The known utility is a noisy approximation of the true utility V.

5) At every step, user u interacts with exactly one item i(t), with a high probability of selecting items presented earlier in a ranked list.

6) Each user interacts with item i at most once, reflecting the notion of decreasing utility with repeated interactions with the same item.

7) New and recommended items are interleaved; when no recommender system is used (early startup), the system suggests the newest items.

Simulation
Each recommender system provides a score sss representing how much user u will enjoy item i at time t, given user preferences θ and item attributes β:

$S(u,i,t)=\theta(u,t)\beta(i,t)$

The research employs a simulation process using generated social networks. The findings indicate that, even if systems do not change user preferences, they influence user behavior, leading to increased homogeneity.

The recommender systems analyzed, in order of increasing homogenization effects, are:

- Popularity-based systems
- Matrix factorization filters
- Social filters
- Content filters
- Ideal recommender systems using true utility
- Random recommendation systems

Jaccard Index and Gini Coefficient
Homogenization effects are not inherently negative, as they may indicate that the algorithm has learned meaningful patterns. Some level of homogeneity is expected for optimal utility. The issue arises when homogeneity does not lead to increased utility.
RSmust maximize utility while avoiding excessive homogenization, balancing the explore/exploit paradigm and mitigating "tyranny of the majority" and "echo chamber" effects.

The degree of homogeneity between two users is measured using the **Jaccard Index**, where D represents the items consumed:

$J_{u,v} = |D_u \cap D_v| / |D_u \cup D_v|$

By comparing this to the Jaccard Index of the same users exposed to ideal recommendations, we can measure relative homogeneity.
In the simulation, all recommender systems (except the random one) increased user behavior homogenization more than necessary. Furthermore, lower utility levels were observed for users with higher homogeneity with their neighbors.

The **Gini coefficient**, used to measure inequality in item consumption distribution, further demonstrated the shift caused by recommender systems (0 indicates equal consumption rates, while 1 indicates maximal inequality).

Accounting for Confounding
When a recommender system is evaluated using confounded data (generated by a similar system), the results are biased in favor of algorithms similar to the one that generated the data. For example, evaluating a RS on the MovieLens dataset will likely favor collaborative filtering systems.

Some systems use social network data to improve recommendations, but it remains unclear whether these models capture true user preferences or merely reflect platform-specific features.

Research by Schnabel et al, de Myttenaere et al and Bottou et al. has shown that propensity weighting and other causal inference techniques can improve utility, reduce homogenization and help account for confounding

[5] Causal Inference in Recommender Systems: A Survey and Future Directions (Chen et al)

Causal inference has many applications in recommender systems. First of all, causal recommendations are more reliable than those based solely on correlation. Recommender systems can be split into two categories:

- **Collaborative Filtering (CF):** Focuses on user historical behavior and is based on the assumption that users with similar historical behaviors will tend to have similar future behaviors. The most representative method is the matrix factorization model (MF). A common problem is non-exposure (i.e., unobserved user-item interactions).
- **Click-through Rate (CTR):** Leverages attributes and features of users, items, and context to enhance recommendations. An example is the factorization machine (FM).

Causal inference in recommender systems can address the following issues:

- **Data bias** due to observational data, which can be resolved by treating the bias as a confounder or using backdoor adjustment.
- **Missing data or noise**, as counterfactual reasoning can be used to construct a counterfactual world to generate uncollected data.
- **Explainability and fairness**, as causal inference can facilitate the development of an interpretable and controllable model.
- **Filter bubble problems**, which can be mitigated with counterfactual learning and backdoor adjustment.

Counterfactual Learning:

Wang et al. proposed a causal inference framework to alleviate filter bubbles with the help of user control. This control allows users to seek content outside of their bubble at different granularities. Additionally, they propose a counterfactual learning method to generate new user embeddings.

Backdoor Adjustment:

Wang et al. used the imbalanced item distribution as a confounder between user embeddings and prediction scores. Specifically, the authors applied backdoor adjustment to block the effect of the imbalanced item category distribution in the training data, partially alleviating filter bubbles.

Xu et al. used a causal graph with loops to represent the dynamic recommendation process that leads to filter bubbles. They also proposed a dynamic causal collaborative filtering (DCCF) model that leverages backdoor adjustment to estimate post-intervention user preferences and employs counterfactual reasoning to alleviate the echo chamber effect. The model is validated through experiments on real-world datasets.

[6] Exploring the filter bubble: The effect of using recommender systems on content diversity (Nguyen et al)

Recommender systems lower user decision effort and improve decision quality, but they may also cause the global village to fracture into tribes, leading to balkanization or filter bubbles, a narrowing of exposure that reduces creativity, learning, and connection. Studying filter bubbles requires:

1. Access to longitudinal user data.
2. The ability to distinguish between users who act on system recommendations and those who don't.

Three important questions to consider are:

1. Do received recommendations narrow over time?
2. Does consumed content narrow over time?
3. Do recommendations provide a positive experience?

MovieLens Data Set

The MovieLens dataset contains longitudinal user rating data with timestamps. The "Top Picks for You" page provides 15 recommendations per user. This dataset uses collaborative filtering (CF), a popular recommender system known for its performance and scalability. Additionally, it includes a tag genome for each movie, rating tags based on how well they describe the film.

Process

1. **Discretize user history** into blocks of 10 films (the median number of ratings for a three-month period). Discretizing by time or login sessions wouldn't make sense due to users' varying usage frequencies.
2. **Discard the first 15 films** for each user, as initial recommendations are generally broad.

3. **Discard the first three months of data** to allow the algorithm to learn about the user and the user to become familiar with MovieLens, filtering out the initial surge of ratings for films watched before joining.
4. **Define recommendation consumption**: a user is considered to have watched a recommended film if it's viewed between three hours and three months after the recommendation.
5. **Group users**:
    - **Following group**: users who took at least one recommendation in 50% of their blocks.
    - **Ignoring group**: the remaining users.

Measuring Content Diversity

Given a set of M movies and a set T of tags, each tag has a relevance score rel(t,m) from 1 to 5. Content similarity between two films I and j is calculated using Euclidean distance on tag relevance scores:

D(mi,mj) = sqrt(k=1:m [rel(tk,mi)-rel(tk,mj)]^2)

A lower distance indicates higher similarity. This metric is effective because two films may share similar ratings or metadata (actors, directors) but differ significantly in content.

The content diversity metric for a group of movies is the average pairwise distance in users' lists, as developed by Ziegler et al. Another approach uses the maximum pairwise distance.

Evaluation

For each block:

- **Within-group comparison**: The shift in the means of the content diversity distribution from the beginning to the end of the rating history indicates the RS's effect on content diversity.
- **Between-group comparison**: The difference in means of the content diversity distribution between the following and ignoring groups shows the variation in experience.

The statistical significance of differences is evaluated with a t-test.

Results

1. **Content diversity of recommendations** narrows over time in a statistically significant way for both groups (the ignoring group's lack of ratings on recommended films impacts the algorithm).
2. Initially (after three months), there's no difference in consumed content diversity between the two groups. However, over time, content diversity reduces for both groups, with the following group consuming more diverse content.
3. Both groups experience a drop in ratings, but the following group consumes more enjoyable movies in a statistically significant way.

Thus, for users following recommendations, the risk of a filter bubble appears reduced. The tendency for users to narrow their consumption (once we've watched the most popular diverse films, we tend to turn to lesser-known movies that are closer to our comfort zone) may be mitigated by recommendations, which introduce variety.

Approaches to Discourage Narrowing: Display statistics of recorded information and forcibly introduce diversity in recommended lists to improve user satisfaction, as suggested by Ziegler et al.

Limitations

This study is limited to analyzing the "Top Picks for You" page, and it cannot confirm if users genuinely follow MovieLens recommendations.