Quantifying User Agency vs. Algorithmic Influence in Movie Recommender Systems

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Contents

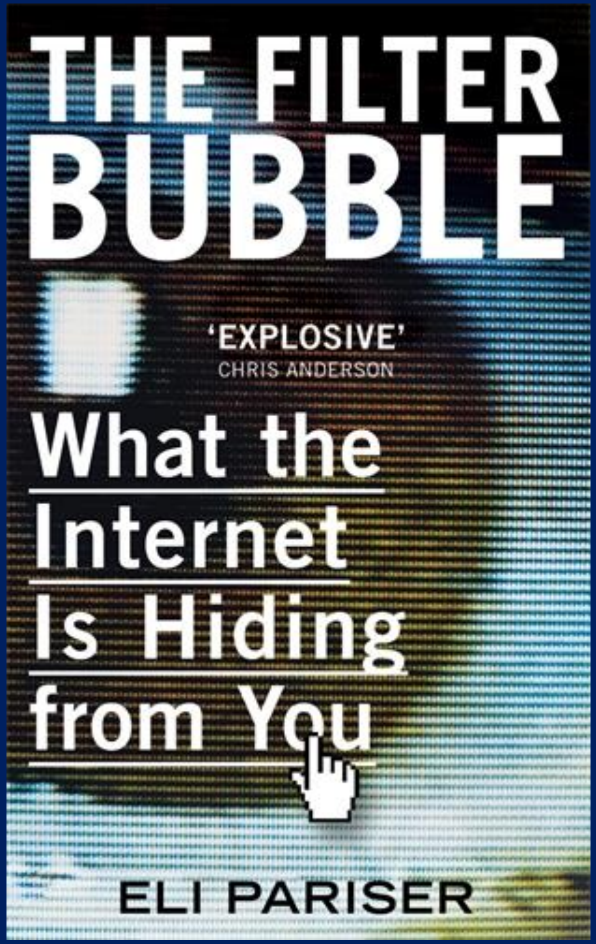
Motivation

- **FILTER BUBBLE**:A filter bubble occurs when a recommender system's personalized content suggestions create an echo chamber that progressively narrows a user's exposure to diverse information.

- Economic Impact:
  - Big-budget franchises dominate as algorithms favor "safe" recommendations
  - Marketing costs increase to break through established viewing patterns

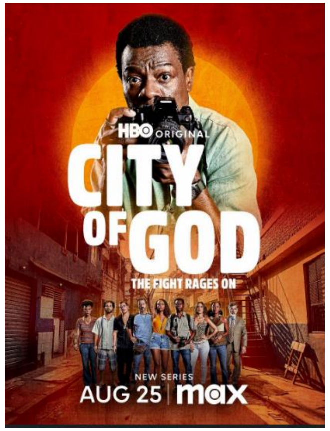
- Ethical Impact:
  - Cultural perspectives become limited as algorithms favor familiar content
  - Independent/foreign films struggle for visibility

Does the algorithm or the user cause the formation of the filter bubble



Filter Bubble

Filter Bubble



No Bubble

Heterogeneity Score

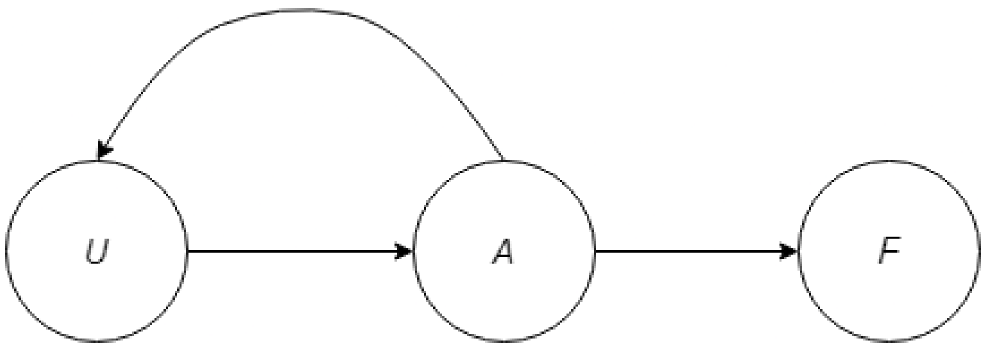
- Tag-genome score:
  - A quantitative measure of content similarity between movies based on their shared metadata tags. This score evaluates the overlap in descriptive keywords that characterize each film's themes, style, and content.

$$d_{(m_i,m_j)} = \sqrt{\sum_{k=1}^{m}[rel(t_k,m_i) - rel(t_k,m_j)]^2}$$

Jumanji	
tag	**relevance**
adventure	0.97375
action	0.60900
adapted from:book	0.49975
adaptation	0.44250
action packed	0.40425
alter ego	0.32450

Experiment 1

Determine the Causal Effect of: *User Choice (U) & Recommendation Algorithm (A) on* ***Filter Bubble Formation***



U: User choice

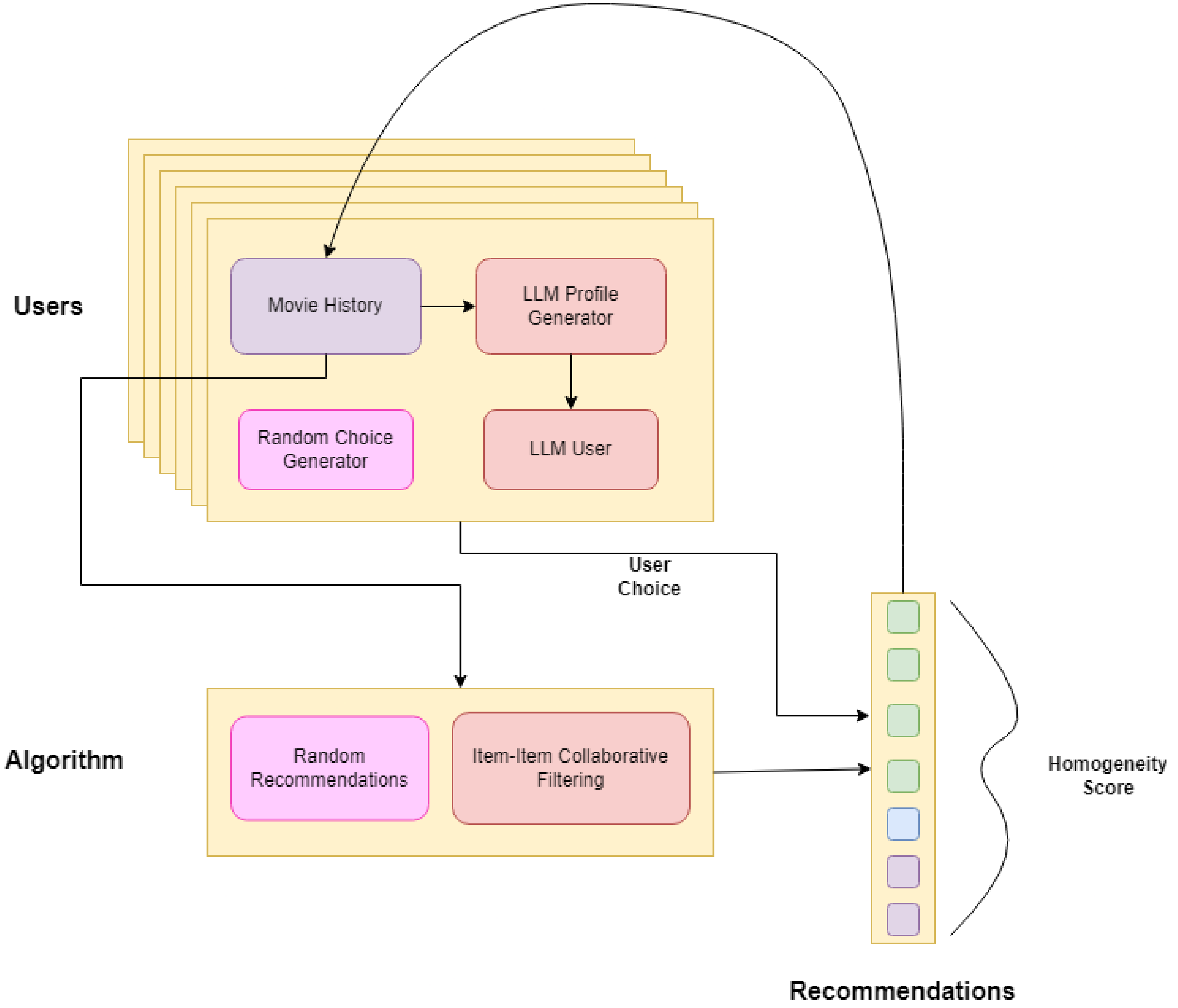
A: Recommendation Algorithm

F: Formation of Filter Bubble

Experiment 1 (MovieLens Data)

Users: 5 users, 10 recommendations each, over 10-time steps

- **User Types**:
  - **Random Behavior**: Interacts randomly.
  - **Preference-Based**: Simulated using an LLM, generates profiles and ratings based on movie history.
- **Recommender Systems**:
  - Collaborative Filtering
  - Random Recommendations
- **Configurations**:
  - Random-LLM
  - Collab-Random
  - Collab-LLM
- To Compare recommender performance across user behaviors.



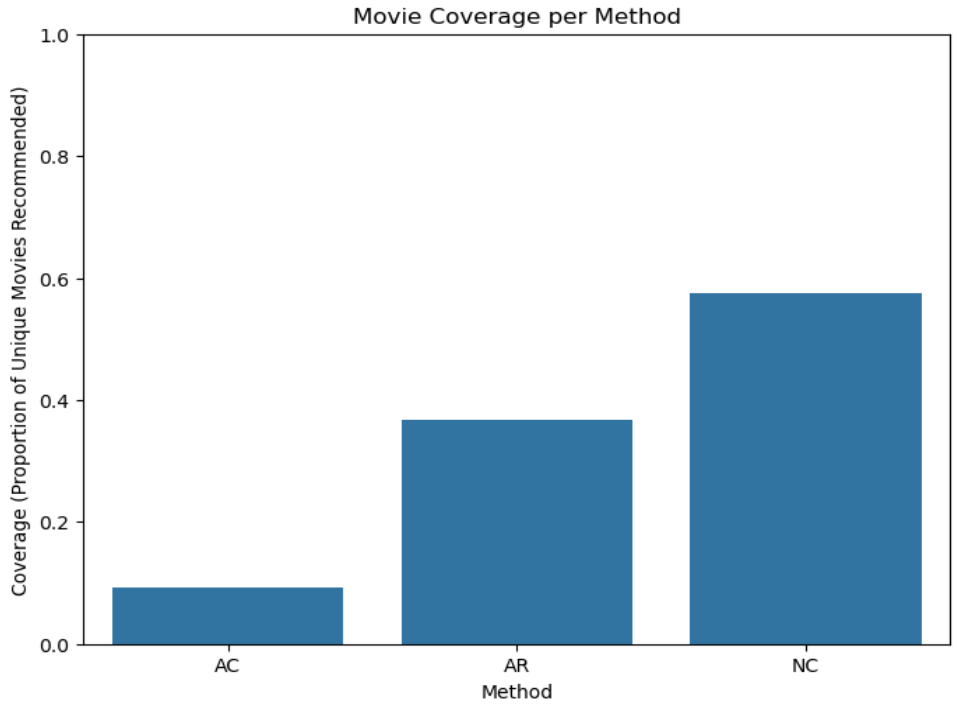
System Diagram

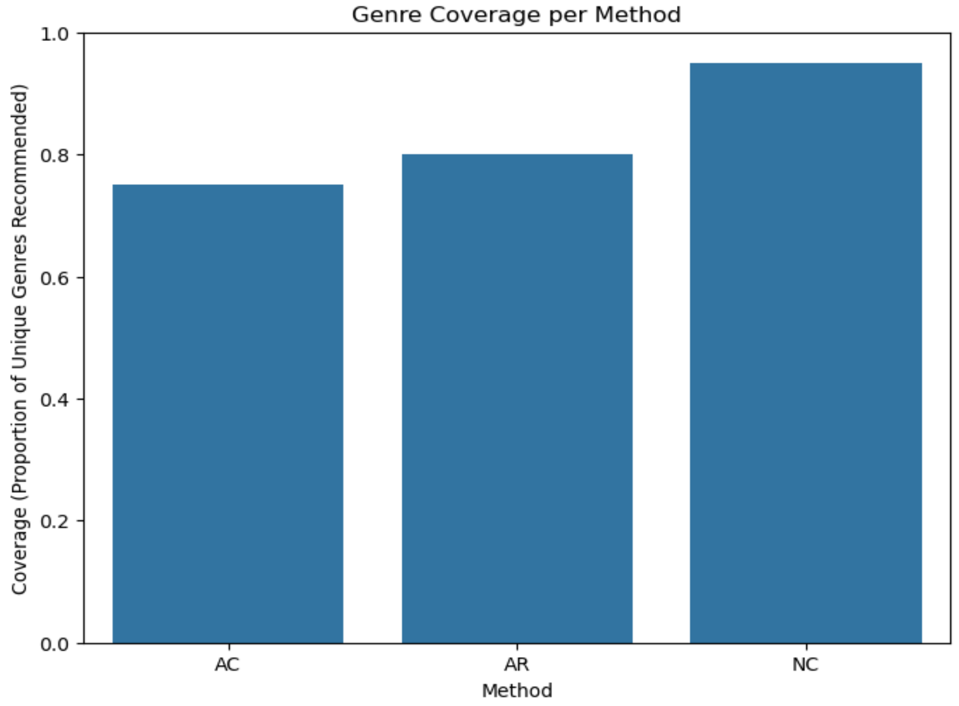
- Process Per time step
- Data Collected:
  - User Choices
  - Recommendations
  - Homogeneity scores

Results & Analysis

Objective:
Evaluate the balance between user agency and algorithmic influence

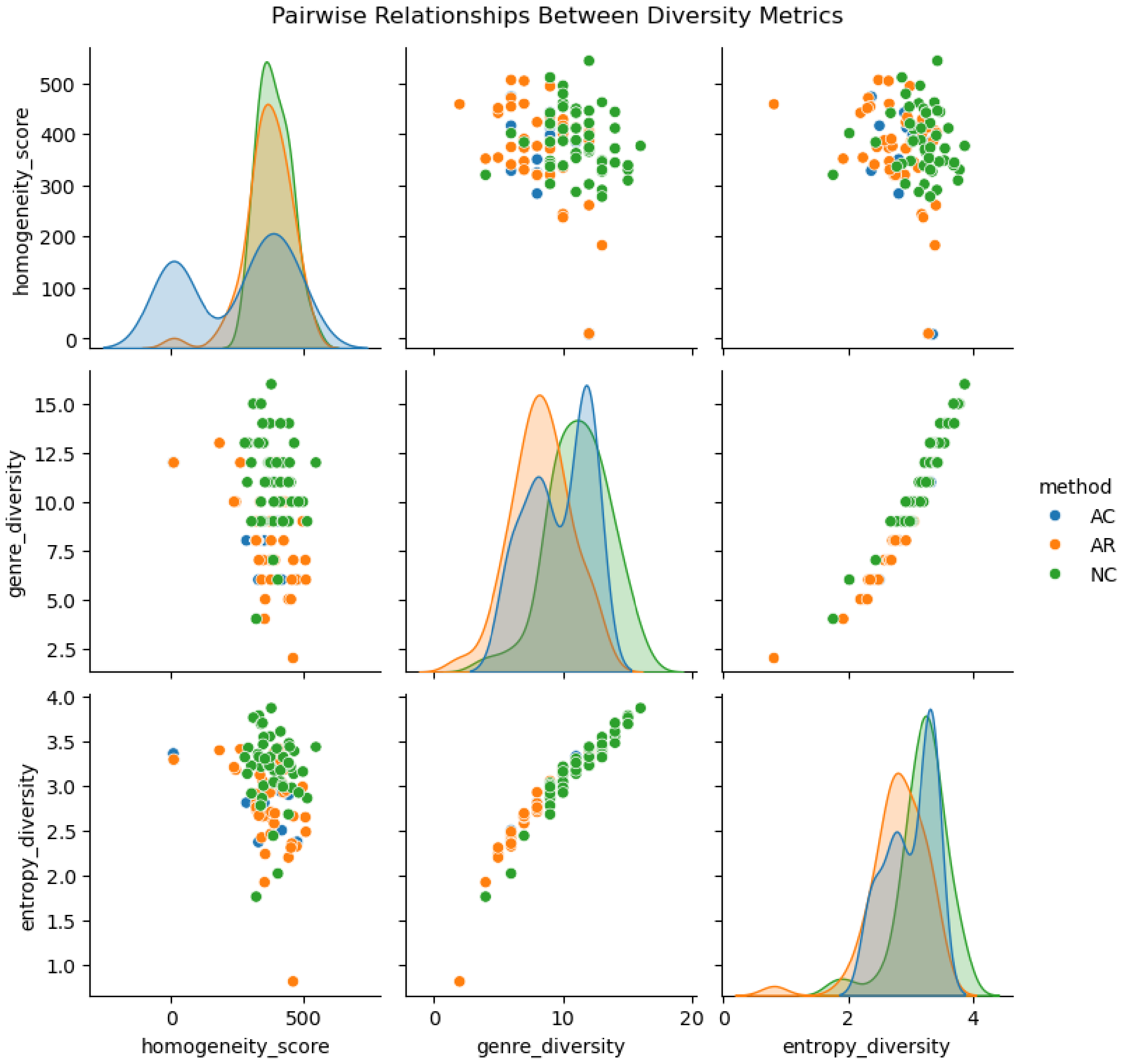
Key Metrics Analyzed:
- Homogeneity score: Measures content similarity.
- Genre Diversity: Count of unique genres in the recommendations made.
- Entropy Diversity: Randomness in genre distribution.





Results & Analysis

- **Homogeneity Score:**
  - **AC:** Bimodal distribution indicates both diverse but clustered recommendations.
  - **AR:** Moderate clustering and diversity, balancing relevance with exploration.
  - **NC:** Most clustered (high homogeneity), despite broad exploration.
- **Genre and Entropy Diversity:**
  - **AC:** Limited diversity, constrained by algorithmic optimization for relevance.
  - **AR:** Higher diversity than AC, boosted by randomness.
  - **NC:** Highest diversity, reflecting unrestricted exploration but lacking relevance.



Results & Analysis

- **Homogeneity Score:**
  - A Backdoor analysis showed that switching from non-algorithm to algorithm reduced homogeneity score by 82 points.
  - A Refutation and Placebo Treatment analysis did not significantly alter the results showing that the causal model holds well.
- **Genre and Entropy Diversity:**
  - **Tukey HSD Analysis** for entropy showed that having an algorithm has a similar effect on entropy compared to not having an algorithm.
  - The same analysis for Genre Diversity did not return any significat results.

```
## Realized estimand
b: homogeneity_score~algorithm_type
Target units: ate

## Estimate
Mean value: -82.20051859302458
p-value: [0.00064653]
```

```
Refutation Results:
Refute: Add a random common cause
Estimated effect:-82.20051859302458
New effect:-82.4219458252751
p value:0.86
```

```
Placebo Treatment Refutation Results:
Refute: Use a Placebo Treatment
Estimated effect:-82.20051859302458
New effect:0.8012913766855564
p value:0.98
```

```
Tukey HSD for Entropy Diversity:
Multiple Comparison of Means - Tukey HSD, FWER=0.05
====================================================
group1 group2 meandiff p-adj   lower  upper  reject
----------------------------------------------------
    AC     AR  -0.1911 0.0535 -0.3846 0.0023  False
    AC     NC   0.1973 0.0444  0.0039 0.3907   True
    AR     NC   0.3885    0.0  0.1951 0.5819   True
----------------------------------------------------
```

Understanding the Results

AC (Algorithm + ChatGPT):

- **Highest susceptibility to filter bubbles**.
- Indicates that users who follow recommendations willingly are more prone to forming filter bubbles.

AR (Algorithm + Random):

- Introducing **randomness** from the user's side reduced susceptibility to filter bubbles.
- Highlights the benefit of non-deterministic user behavior.

NC (No Algorithm + ChatGPT):

- **No algorithmic optimization** resulted in users either:
  - Staying within their pre-existing bubbles.
  - Falling prey to inherent **data biases**.
- Demonstrates the trade-offs of removing recommender systems entirely.

Homogeneity score

- For the nature of collaborative filtering algorithm, we may end up with "diversity" in a single racommendation, but with all user being recommended the same films.

- **Global homogeneity score**

$$global\ homogenity = \frac{|recommendation\ \cap topK|}{|recommendation|}$$

TOP-K MOVIES

RECOMMENDATION

Homogeneity score: 3/5

Experiment 2

Objective: Estimate the ATE of the recommendation system on the formation of filter bubbles.

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Current Limitation: We have:

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but we still need:

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But we can't disable the algorithm!

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But we can't disable the algorithm!

Objective: For each record in the MovieLens dataset, compute the recommendation for the user and check if the rated film is inside.
We can divide users that follow recommendations and users who do not.

	follow	total	heterogeneity	homogeneity	last_recommendation
userId					
514	28	397	7.413260	0.066667	[Braveheart (1995), Shawshank Redemption, The ...
258	4	25	7.175944	0.466667	[Inception (2010), Forrest Gump (1994), Lord o...
519	2	26	7.518331	0.466667	[Fight Club (1999), Matrix, The (1999), Pulp F...
272	1	31	7.068569	0.533333	[Inception (2010), Fight Club (1999), Raiders ...
153	11	179	7.229156	0.333333	[Shawshank Redemption, The (1994), Silence of ...
25	14	26	7.549077	0.266667	[Fight Club (1999), Shawshank Redemption, The ...

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Some ideas:

- **Users are "recommendation followers"** if at least 20% of the movies they watch are recommended.
- **A recommendation is homogeneous** if heterogeneity score is less than 7
- **A recommendation is homogeneous** if homogeneity score is greater than 0.5.

The homogeneity score is more suitable, given the nature of the user-user collaborative filtering algorithm.

$$P(User = follower) = P(F) \approx 30\%$$

$$P(User = follower\ , global\ homogenity) = \mathrm{P(H, F)} \approx 6\%$$

$$P(User \neq follower\ , global\ homogenity) = \mathrm{P(H, {\sim}F)} \approx 10\%$$

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Now we can estimate the ATE of recommendation on filter bubble formation:

$$ATE = P(H|F) - P(H|{\sim}F) = \frac{P(H, F)}{P(F)} - \frac{P(H, \sim F)}{1 - P(F)} \approx 10\%$$

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- What about **examining the sequence of visualizations**? This allow to analyze more the user role.
- There are **many different scenarios** with varying algorithms, amounts of training, and simulations, all of which need to be analyzed.

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- The **metric** or the **threshold may need to be redefined**.
- Homogeneity is good, but ... **what about different clusters of users**, each with its own specific films? We need a local top-k for each cluster
- What about **examining the sequence of visualizations**? This allow to analyze more the user role.
- There are **many different scenarios** with varying algorithms, amounts of training, and simulations, all of which need to be analyzed.
- Indeed ... Many **paper** came out with different result.

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