Filter Bubbles and Content Diversity? An Agent-Based Modeling Approach

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Abstract. Personalisation algorithms play an important role in catering the information that is relevant to us. The best results are achieved by the algorithms when they monitor the user activity. Most of the algorithms adapt to the users' personal preferences by filtering out the information that is irrelevant to the user. However, one of the criticisms of this process is that it is leading to informational bubbles called the filter bubbles which is a personal space of content familiar to the user, which would reinforce their confirmational biases or create informational blind spots. This phenomena however is highly debated. In this light, we propose an agent based model study, which tries to verify the implications claimed by the filter bubble theorists and also create an hypothetical environment that does not have a filter bubble and test difference in the information dispersion and opinion formation in both the environments.

Keywords: Filter bubbles · Agent based modeling · Personalisation algorithms

1 Introduction

The Internet has a lot of information among which some would be relevant, some would be good, and some would be irrelevant to users. Sifting through all the information to find the one relevant to our interests, has become an essential need of users. This is addressed by Internet application providers. These providers rely on personalization algorithms or recommender algorithms to achieve this goal [6]. Social media websites, search engines, and other online applications work towards the goal of providing their users with the content that is interesting to them, for which they constantly monitor their users' activity. These recommender algorithms running in the background, filter out the information that seems irrelevant to the users' activity [6]. The performance of these algorithms to a large extent depends on users' activity or behavior. The other factors include the interaction of the algorithms with other algorithms, scalability of the algorithm, prediction accuracy, types of recommended items, etc [19].

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At the same time, there seems to be something off with personalization. Users do not find their digital personal assistants to be right all the time. Most of the time users, seem to be losing their friends to the algorithmic abyss of social media's news feed. Many times the content users come across online seems to repeat the same topics [13].

1.1 Recommendation Algorithms and Filter Bubble

There is a general paradox that lies at the heart of personalization. Personalization is used as an aide to modify our interaction experience online concerning our interests. Simultaneously, our interactions online shape us, influence us and guide our everyday choices and actions. These incomprehensible algorithms sometimes make independent decisions on our behalf. Due to filtering, the number of visible choices is reduced thereby restricting our agency [13].

Eli Pariser coined the term "filter bubble" in 2011 in his book "Filter bubble – What the Internet is hiding from us". [13] Pariser describes the filter bubble as a personalized information bubble that everyone is in. This bubble is the personal space that is not shared with others consisting mostly of the ideas and information that is interesting to us. It contains the different versions of the expected content that is presented to us by the different internet entities. However, being surrounded by the information that is only familiar to us and that is tailored to our tastes would deprive us of all the possible information that has been filtered out by the algorithms classifying them as unwanted. This would reinforce the confirmation bias that many of us already possess unconsciously [13]. Confirmation bias is the tendency to search for or interpret the information (either real or imagined) to confirm our previous ideas or views [19]. There is a general paradox that lies at the heart of personalisation. Personalisation is used as an aide to modify our interaction experience online with respect to our personal interests. Simultaneously, our interactions online shapes us, influence us and guide our everday choices and actions. These incomprehensible algorithms sometimes make indepedent decisions on our behalf. Due to filteration, the number of visible choices is reduced thereby restricting our personal agency [13].

Our information bubble also exists offline. However, it becomes more apparent online as the user reactions can be magnified on a virtual context [13]. In this paper, we try to broaden the understanding of the filter bubble effect by developing agent based models to study whether the filter bubble affects the opinion formation in the society and how different would the opinion formation be affected if there was no filter bubble.

2 Related Work

The place where the filter bubble would be an advantage is the e-commerce applications, where narrowing the search results to match the preferences of the user is very critical. This increases the chances of matching potential products to its buyers [13]. However, the disadvantages of the filter bubble become evident when it is connected with the process of fostering one's creativity. As being surrounded by familiar point of view would not provoke one's anxiety or instigate the curiosity that encourages to discover different view points [13,20].

This has given rise to the common criticism of recommendation algorithms in the recent years, that the algorithms may be responsible for causing filter bubbles as they filter the content choices over time effectively leading to polarised preferences [18]. However, this claim is in dispute, as Flaxman et al. found evidence that the recommendation algorithms both increase and decrease various aspects of filtering that leads to polarisation [8]. This has encouraged the research towards understanding the different design aspects of the recommendation system. In the literature, we find two common response to the filter bubble problem: algorithm centered and user centered [18].

2.1 Algorithm Based Approach

A conventional algorithm-based approach for the filter bubble is to develop more diversity aware recommendation algorithms [18]. The research mainly focuses on improving the diversity, novelty and relevance of the algorithms. The methods proposed are topic diversification approach [26], user centered clustering [1]. Many of the approaches proposed, although increased the diversity, affected the accuracy of the recommendation. The challenge in the research thus is to propose a method that improves the diversity of the recommendations without hampering the recommendation accuracy [18]. Smyth and Bridge found diversity based on the hamming distance on whether or not the items had been rated helped retrieve a target item most efficiently [16].

2.2 User-Based Approach

In the user based approach, the focus is more on developing diversity aware interfaces, where users receive the justification for the recommended item. Although developing such interfaces helped in tackling the filter bubble phenomena, it does not solve it completely [17]. The work of [11] showed that visualisation interfaces were used to increase the users understanding of the filter bubble phenomena. Still, it did not make an impact in trying to reduce it. It was however found that increasing the trust of the users by developing the interfaces that aid in the understanding of the recommendation system helped the users in giving better feedback that was in turn used in increasing the recommendation quality [9,17].

2.3 The Filter Bubble Debate

The topic of the filter bubble has divided the scientific community into two groups. There is an ongoing debate about the phenomena, as one community believes that reduced diversity in the information caused by the recommendation algorithms, to an extent where the challenging or the controversial content disappears virtually from the viewing systems of the users is constructing these bubbles [27]. The other community, however, is concerned about the lack of scientific evidence for this phenomena. They claim that the amount of scientific evidence that filter bubble is leading to polarisation is not enough as the algorithm users can navigate through the information to identify the relevant information, thereby being the gatekeepers of the information they consume. In other words, this would give rise to highly individualised gates for the information that fit each users interests [10].

2.4 Impact of the Filter Bubble

Both the approaches mentioned above have a common goal of trying to reduce the effect of filter bubble either by improving the algorithms or by developing better interfaces. It is equally important to study the extent of the impact of the filter bubble. Nguyen et al., examine the longitudinal implications of recommender system on users and measure the filter bubble effect in terms of content diversity at the individual level [12]. Though this was a long term study, it had two exciting results, the users who used recommender systems found that the recommendations narrowed over time. But, the users who consumed the items recommended had reduced narrowing effects [12]. We try to address similar questions as Nguyen et al. [12], with the focus of opinion formation as the impact factor by using Agent-based modeling, as agent-based models fit perfectly for studying the emergent phenomena like filter bubbles.

3 Method

It is challenging to model human behavior. When building an agent-based model the challenge is to make the trade-off between how simple and traceable the model should be and how realistic and psychologically plausible should the behavior of the agents be modeled. We cannot find much guidance in this respect theoretically as the existing theories on human behaviour are mostly contradictory [7]. In this paper, we develop two simple agent-based models. The agents are characterized by attributes derived from theoretical approaches. The agents are modeled to be boundedly rational. They exhibit this behavior in the different cognitive levels of information processing and the different levels at which the consumed information could be effective. The focus on developing models lies in the implication of information distribution in filter bubble phenomena. But, the model can be expanded to include empirical studies as well as to study the different environmental factors like the social networks and influence of other agent's opinion.

3.1 Bounded Rationality - Decision Making of Agents

In many agent-based models, agents use multicriteria evaluation problems, for example in an agent-based simulation of planting crops, agents make the decision of choosing the land area in the simulation environment [4]. The main challenge in modeling these agents that represent a real scenario of human decision-makers is to figure out how each agent solves the multicriteria problem of choosing locations in the simulated landscape as a function of varying spatial parameters with respect to the production activity. When evolutionary programming is used to solve this problem, the agent's decision making is represented as a form of bounded rationality [7].

Perfect rationality was one of the common theories of social sciences. However, a number of new alternate theories are being popular now, one of which is bounded rationality. While statistical regression models are used to express perfect rationality. Bounded rationality is best implemented with evolutionary programming. Bounded rationality was introduced by Simon, as the "rational choice that takes into account the cognitive limitations of the decision-maker - limitations of knowledge and computational capacity" [15]. We implement the bounded rationality in our model by introducing two attributes to the agent - cognitive threshold and effective threshold. The threshold values being generated randomly to represent the real scenario.

3.2 The Agent-Based Model

As mentioned above, we develop two agent-based models in this paper - one to model the filter bubble environment, the other to model the environment with no filtering. We use the LightGraphs package [14] and the Barabasi Albert model for network simulation [24]. The language used to write the simulation model is Julia [3]. The focus is to study the opinion formation in the network. We compare the two models to address the following questions: Does the filter bubble cause a significant impact on opinion formation? How is the opinion formation pattern different from the network with no filter bubble? How easy or difficult is it to get out of the filter bubble effect?

Model1: Filter Bubble. For the purpose of simplification, we make the following assumptions: the interaction of agents is only limited to sharing the topics or the messages. If an agent notices the message and then shares it, that signifies an opinion change. For implementing the message filtering, we have created messages initialized with a cognitive and affective value, the affective value being the message weight. If the message is shared by the agent the weight of message is increased by 10% and if the message is ignored by the agent then the weight of the message is decreased by 10% and if the message is seen by the agent then the weight of the message is kept same. Every agent has a bubble threshold, limit to interact with the message. A message is consumed by the agent only if the cognitive value of the message is higher than the bubble threshold. We use Mersennetwister to generate the random numbers that are allotted to the threshold values and to keep the values between 0 and 1.

Model2: No Filter Bubble. We keep the same assumptions mentioned in the filter bubble model here. For implementing the no filtering of messages we try three scenarios: first, we ran simulations initializing the bubble threshold to 0. Like in the filter bubble model, the weight of the message increased by 10% when the message was shared, decreased by 10% when the message was ignored and remained the same when the message was read. In the second case, we ran simulations with a bubble threshold value, but the weights of the messages did not change when the message was shared or ignored. In the third case, we ran simulations with the bubble threshold value set to 0 and no change in the weights of the messages.

All data is available at the open science foundation repository under https://osf.io/xvna6/.

4 Results

We ran each simulation with the agents ranging from 1000, 2500 and 5000 in 10 batches and 15 steps. We ran the simulations for two main cases: one where only one message was posted by the source agent and second where four different messages were posted. The simulations were run for both the filter bubble and no filter bubble. For the no filter bubble, three subcases were tested. The first case was with bubble threshold initialized to 0, the second case was with topic weights not being modified dynamically, the last case was with both bubble threshold set to 0 and topic weights not modified.

4.1 Simulation Run

The initial setup of the simulation experiment was initialized to have 1 message topic. An agent can be in one of the following states: read, sharing, shared, ignored and new. The simulation was run as explained in the steps below: 1. One agent is selected as a “source agent” at random. This agent spreads the messages and its state is new. 2. All other agents become the “target agents” that receive the messages with the state read, the agents that do not receive the message will have the state ignored. 3. The target may or may not choose to share the received message. 4. If the target agent decides to share the message, its state is sharing and the agents that have shared a message in the previous step would be in the state shared. The simulation is run until there is no more source agent or when all the agents have received the message. The next round of simulations was run for 4 message topics, the topics were differentiated based on their associated values and weights.

4.2 Analysis of the Results

In Fig. 1 we see the graphs depicting the number of agents sharing the message and number of agents that did not receive the message in the filter bubble environment. From the plots, we can infer that all the agents have received a message by the end of the simulation as the number of agents in the ignored state is 0. An agent goes to the ignored state only when it does not receive a message.

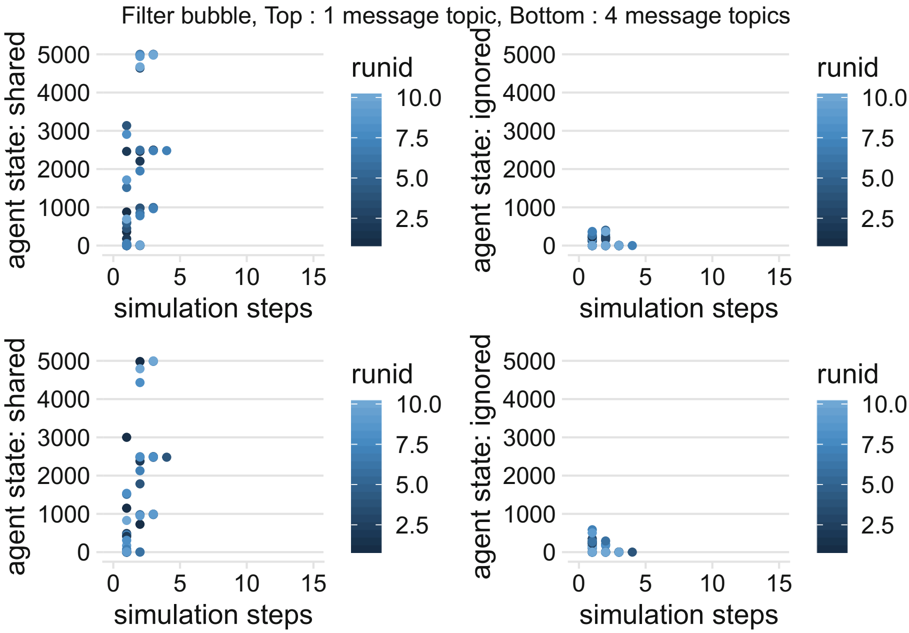

Fig. 1. Plots showing the number of agents that have shared the message and the number of agents that did not receive any message in filter bubble environment. row 1: No. of message types = 1, row 2: 4 message types

The Fig. 2 shows the graphs depicting the number of agents sharing the message and number agents that did not receive the message in a no filter bubble environment for the first case, where bubble threshold is initialised to 0. From the plots we can infer that, when there is no bias from the agents then they would receive all the messages, even when the filtering mechanism is present in the system.

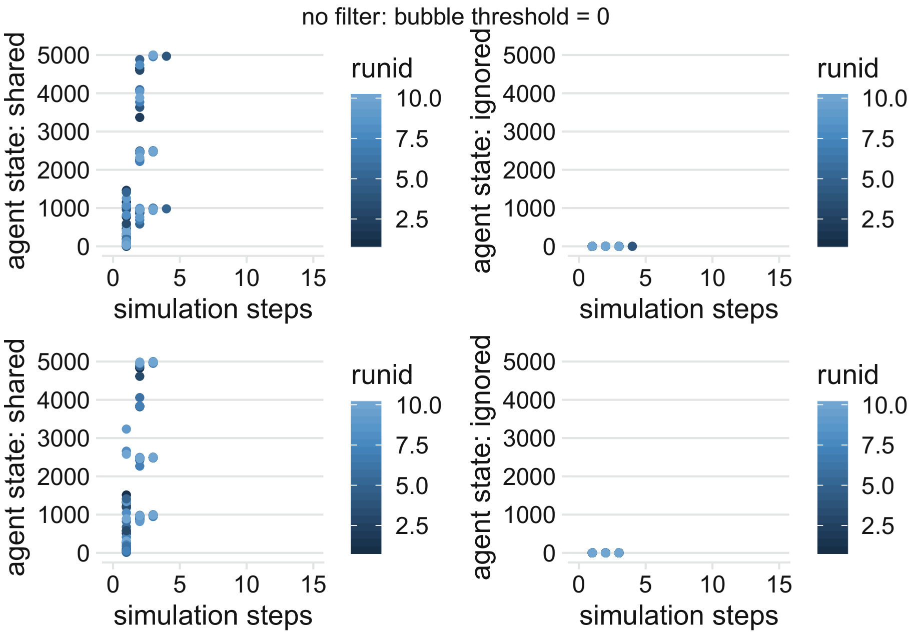

Fig. 2. Plots showing the number of agents shared the message and number of agents that did not receive the message in no filtering environment. Bubble Threshold = 0, row 1: No. of message types = 1, row 2: 4 message types

The Fig. 3 shows the graphs depicting the number of agents sharing the message and number agents that did not receive the message in a nofilter bubble environment for the second case, where the topics weights were not changed dynamically. From the plots it can be inferred that even when the filtering of the information is turned off, all the agents do not receive the messages. Even by the end of the simulation, the number of agents in the ignored state is not 0.

The Fig. 4, shows the graphs depicting the number of agents sharing the message and number agents that did not receive the message in a no filter bubble environment for the third case, where both the bubble threshold was initialised to 0 and the topic weights were not changed dynamically. From the plots it can be inferred that all the messages are received by the agents, as 0 agents stay in the ignored state from the first simulation run. This could be called an ideal case scenario, where there is no kind of filtering of information and no initial biases among the agents.

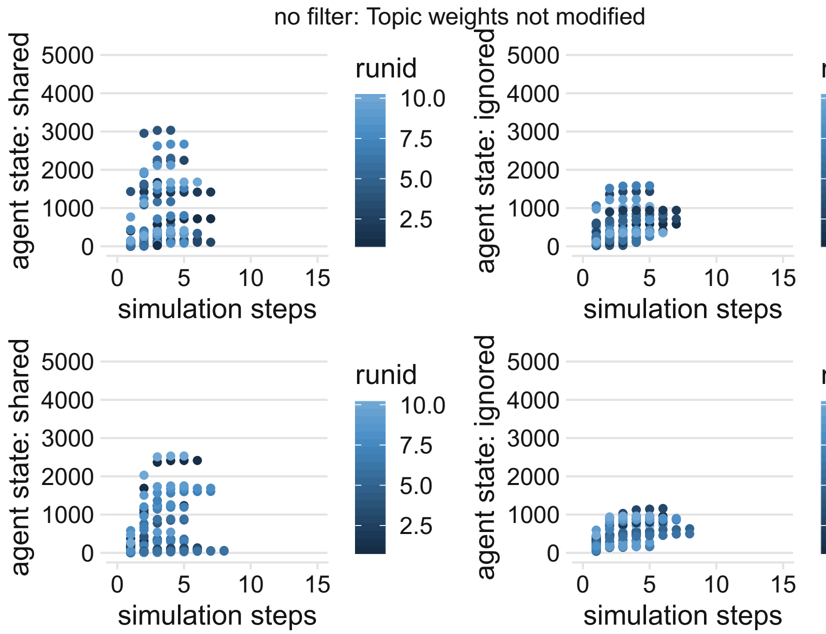

Fig. 3. Plots showing the number of agents shared the message and number of agents that did not receive the message in no filtering environment. Topic weights not modified, row 1: No. of message types = 1, row 2: 4 message types

5 Discussion

In this paper, we have attempted to simulate two environments (filter bubble and no filter bubble) and differentiate their impact on the consumption of information - impact on the diversity of the information. We see that the only way to achieve minimum filtering leading to maximum diversity in the information is when there is no threshold on the agents consuming the information and no bias formed after the consumption of the information which is the ideal case or when the agents have no bias. However, we see that the messages are filtered when there is a bubble threshold or weights associated with the message. It is interesting to note that, by the end of the simulation, all the agents in the filter bubble environment receive messages, implying that no agent remains in the ignored state. Whereas, in the no filter bubble environment where the topic weights are not modified dynamically, the agents remain in the ignored state at the simulation end. This is interesting as the bubble threshold indicating the agent's personal bias is taken into consideration and the topic weight modification representing the filtering of information is stopped making all the information reach every agent.

We have kept the model primitive, focusing only on the message (information) filtering aspect of the phenomena. It would be interesting to see the outcome when other variables like the influence of bias of the agent on one another, the

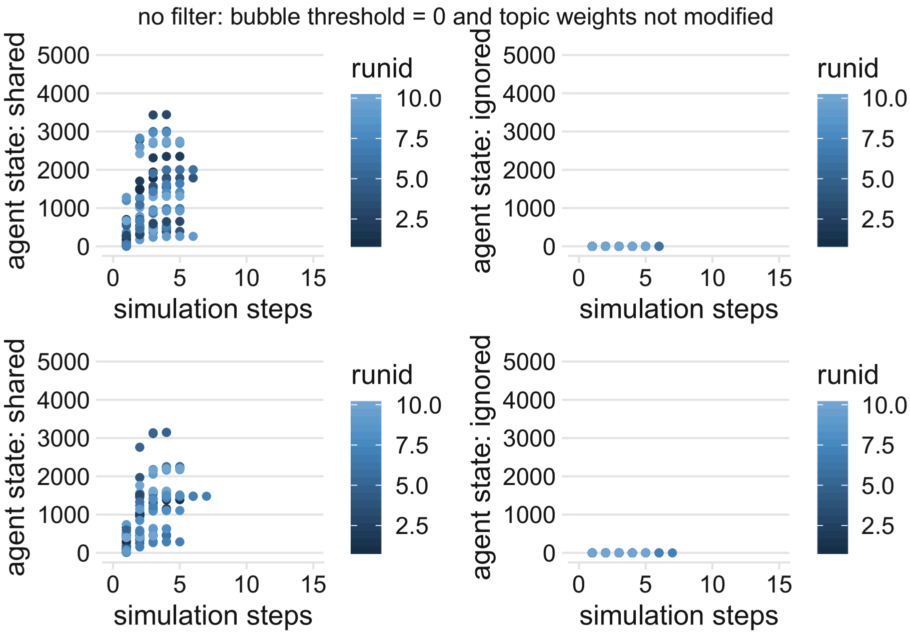

Fig. 4. Plots showing the number of agents shared the message and number of agents that did not receive the message in no filtering environment. Bubble threshold = 0 and topic weights not modified. Row 1: No. of message types = 1, row 2: 4 message types

different algorithmic filtering, topic interests of the agents are considered. We would like to improve the model by introducing the variables mentioned in the future.

Though the scientific evidence for filter bubbles is not enough. It does not mean that there is no reason to be concerned about the underlying problems. The more important matter that lies here is the concern about the algorithms that run in the background and the impact of the new data-driven forms of communication on the diversity of the content consumed in the media. The increasing importance in the role of social media in the exchange of information. Finally, when we consider the filter bubble, it is equally important to see the diversity of the information within the bubble - inclusion effect as it is to see the exclusion effect - the amount information that was filtered out because of algorithmic filtering, user interests, and other reasons.

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