Jan-Philipp Fränken
Room S35, 7 George Square
University of Edinburgh
Edinburgh EH8 9JZ, UK
Email: jp.franken@ed.ac.uk

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Dear Professor Squazzoni,

We appreciate the time taken by you and the reviewers in assessing our manuscript and we are grateful for the valuable feedback. In response to these comments, we have made the following changes:

- As suggested by both reviewers, we made a number of changes to the manuscript in order improve the clarity of our presentation and make our assumptions and reasoning more transparent. We specifically focused on reworking the structure of section 3 (Agent-based Model) and included additional illustrations to simplify our model descriptions.
- We also provide point by point responses and descriptions of our revisions below, interlaced in red among the original review.

This revision has helped us to improve the paper substantially, and we are very grateful for having been given the opportunity to do so. We hope that the revised version of the manuscript is considered fit for publication in JASSS.

Thank you for your time and consideration.

Kind regards,

Jan-Philipp Fränken and Toby Pilditch

Reviewer 1's comments:

Section 3 (Agent-based Model)

This paper show through simulations that partner self-selection and information sharing among agents is sufficient to produce echo chambers in sparse networks. I found this paper interesting, though a bit difficult to read due to some writing choices. Most importantly the description of the model is not clear. JASSS has a readership specialized in simulation models (ABMs in particular). The model part is particularly important because with ABM "the model is the theory". Let me go through some things that are not clear (although I suggest a complete rewriting of this section).

- The JASSS readership definitely doesn't need to be told what an ABM is or why they are important (3.1).
- Response 1: We have now excluded section 3.1
- 3.2 leaves unanswered the question of which are the individuals with which our agents are forming "forming social ties based on proximity". What is the process that leads to this network formation? How many connections are generated? Do the agents move or stay still in this environment? What is the two-dimensional space even represents? Why this choice instead of building a network directly?
- Response 2: We reworked this paragraph and included an illustration (Fig. 2) showing our network setup prior to the start of the simulations:

  "We built an idealised social network with $N = 1000$ agents. At the start of each run of the model (i.e. a single model simulation), agents were randomly assigned to x-y coordinates in a two-dimensional environment. An agent's location did not change during subsequent interaction. Following spatial allocation, each agent formed n (static) social ties with their nearest network neighbors. Ties represent the social network connections between users and allowed for the communication of beliefs between agents. Ties persisted during a model simulation irrespective of changes in agents' beliefs. Distance to other agents was measured by Euclidean distance, a proxy for relational proximity in social networks (Duggins, 2017; Pilditch, 2017)."

- in 3.3 you state that "Our agent-based model (ABM) captured agents' social environment (social ties with peers) and the temporal dynamics of belief change (updating beliefs through interaction), which both form necessary requirements for the observation of echo chambers.". These two dimensions are also reported as your key result. It is unclear to me if the role of these 2 dimensions is your hypothesis or an assumption you make.
- Response 3: We have removed the above descriptions and focused on highlighting the importance of a single interaction and perceived source credibility for the formation of echo chambers. We have dedicated a separate section in the background for both single interactions without preferential rewiring (Sections 2.1-2.4) and source credibility (sections 2.5-2.13) to more clearly motivate our work. Subsequent model setups and results have been carefully connected to these two sections to improve the clarity of our presentation.

- Additionally, reviewer 1 had several specific comments that have been addressed in our updated manuscript version:
  - Eq. In 3.8 and 3.9 requires some explanations and justifications. Why are they like that? Are they taken verbatim from Hahn 2009 and Harris 2016 or they have been modified?
  - Response 4: These were taken from Hahn and Harris verbatim. We have now specifically mentioned this:

    "In line with the initial introduction of the BSCM model (Hahn, Harris, & Corner, 2009; Harris, Hahn, Madsen, & Hsu, 2016), we define the likelihood of a source's communication rep assuming that the hypothesis is true h and under consideration of the target's perceived expertise $P(e)$ and trustworthiness $P(t)$ of the communicating source as..."
  - - 3.12; what is the bold e variable? is it different from those used in the eq. 2 and 3?
  - Response 5: This variable has now been removed. The bold **e** variable has now become τ and represents the expertise strength / level of expertise of a communicating source (see also Table 1). It can take values of 0, 0.2, and 0.4.
  - - 3.13: priors are taken from a gaussian. Why is it? In many opinion dynamics models the priors are taken from a uniform distribution (see for example Weisbuch et al 2002 on Complexity and the follow-up literature). The difference should be discussed. Which are the consequences of this choice?
  - Response 6: We have specifically addressed this choice which was motivated by previous work using BSCM for Micro Targeted Campaining (Madsen & Pilditch, 2018). We also sanity-checked different priors and values for σ^2:

    "Following previous work (Madsen, Bailey, & Pilditch, 2018; Madsen & Pilditch, 2018), agents in our network sampled a prior belief $P(h)$ from univariate Gaussians with a neutral mean $\mu = 0.5$. We tested different values of σ^2. To ensure that our simulation results were not a consequence of a Gaussian prior, we also explored settings in which beliefs were sampled from a uniform distribution, which is a common choice in the related complexity literature (Hegselmann & Krause, 2002; Lorenz, 2007). None of these variations significantly influenced our model results, and in the remainder of this paper we focus on a setting in which agents sampled $P(h)$ from $\mathcal{N}(\mu = 0.5, \sigma^2 = 0.2)$".
  - - 3.14: why do you dichotomize the belief? and what are the effects?
  - Response 7: This was partially an arbitrary choice to simplify the problem. However, it was motivated by the dichotomous nature of several topics / beliefs affected by echo chambers, such as Brexit, two-party politics, True/False, or yes/no votes. In the manuscript, we have addressed this as follows:

    "...where $\mathcal{H}$ corresponds to the set of hypotheses $\{h, \neg h\}$. Selecting a binary set $\mathcal{H}$ was an intended simplification allowing us to account for the dichotomous nature of several prominent topics affected by echo-chamber formation (e.g., Brexit with two-party politics)."
  - - How large are your simulations? Did you robust-check the population size?
  - Response 8: This is a very important point, and we have now been more specific on both the population size $N = 1000$ and the number of times we repeated each of our possible 900 parameter combinations. Specifically, we ran each specific parameter combination 50

times, each in an independent simulation with a random initialization of agent-positions and prior beliefs. The reported values in our results correspond to the mean of each of these 50 simulations for each parameter combination to ensure stable estimates of each combination. Additionally, we sanity-checked different values for N. Here, it is important to point out that N alone has no impact on our simulations, but that N interacts with the P(Declaration) probability and connectivity density of our network. If connectivity density and P(Declaration) are low, it will reduce the chance of cascading effects as agents will only possess a small number of social ties, which, when coupled with low P(Declaration), can lead to the network fracturing. In this case, increasing N will increase chances of cascades, as increasing N (while keeping connectivity density constant) means that each agent has more social ties (and thus fracturing is less likely). We chose $N = 1000$ in the present work for computational convenience as increasing population size dramatically increases the run time of simulations. Furthermore, our findings do not depend on N if P(Declaration) and connectivity density are adjusted accordingly. Rather, they depend on the ratio between these three variables and we believe that our present model is sufficient for providing insights into the relationship between network size, density, and P(Declaration). In our manuscript, we have dedicated an additional sentence to this issue:

"...To further test the robustness of our simulations, we varied the size N of networks in separate simulations ($N = [100, 500, 1000, 2000]$)..."

- - 3.16: you study the effect of density in the attempt to simulate the time it takes for info to permeate the network. Together with the fact that you assume a random placement of agents, this means that you have a Bernoulli (is it?) random network. Regardless of connectivity, these networks are very fast to travel (the average shortest path scales with the log of the number of nodes). How does this reflect on results? Have you attempted a simulation of other kinds of networks?
- Response 9: We are very grateful for this important comment. We also tested a scale-free network in which agents form ties according to a power law. Like previous work (Madsen et al., 2018), our findings were not dependent on this specific choice which is why our key results focus on the random network setup reported in the present paper. We have directed the interested reader to our source code which allows to intuitively play with different network setups to observe resulting cascading effects:

  ..."Additionally, following (Madsen et al., 2018), we contrasted our random network setup with a scale free network (Amaral, Scala, Barthelemy, & Stanley, 2000) which is commonly used for the study of social networks (Duggins, 2017; van der Maas, Dalege, & Waldorp, 2020). Overall, varying network setup and size showed that the results for the present setup were only directly dependent on the network size if P(Declaration) was so small that the network fractured (i.e. no cascade occurred, see Results), and similar to (Madsen et al., 2018), switching from a random to a scale free network did not result in a substantial aggravation / reduction of echo chambers formation. Our model interface allows for intuitive changes to all mentioned robustness checks (and more), and if of interest to the reader, these can be explored by downloading our code (see Model documentation, for details)."

- [...] In synthesis: I would suggest rewriting a more clear Model section in the paper, including also some of the details now reported in the methods. I believe that in a journal like JASSS (more specialistic than - say PNAS, Nature communications or SciRep) the readership is fully able and requires a focus on the model specifics immediately, rather than in a final section.

- Response 10: We are very grateful for all the detailed comments on section 3, and we have reworked the whole section. We also removed the appendix and included relevant details in section 3 which is now called "Agent-based model."

Introduction

- peer-to-peer transmission of information is considered by the authors to be important in driving the creation of echo chambers. However, in the introduction, it is not clear what the authors mean with the peer-to-peer transmission of information and, as opposed to what other type of transmission. From 1.4 this is not clear.

- Response 11: We have now included an example to clarify this:

  "This is motivated by an important element of social networks: users can share information directly in a peer-to-peer manner. For example, consider a single person that shares a tweet with their friends. Subsequently, each of their friends retweets the initial tweet. Assuming that each users has 100 friends that share no social ties with another user's friends, the 'second-generation' of friends that has access to the initial tweet already has a size of 10000. If this process is repeated for only a few generations of friends, a single initial piece of information can permeate rapidly through a social network without requiring repeated interactions between individual users. Considering people's ability to rapidly spread information on social media, we thus see a single-interaction model of echo chamber formation as an important contribution expanding previous models focusing on repeated interaction and network pruning over time (see also (Lorenz, 2007; Sikder, Smith, Vivo, & Livan, 2020))."

- Section 1.3: When saying "and it has been suggested that the majority of social media users do not necessarily self-select into echo chambers", it would be worth saying that the but social network algorithm however does the selection for them.

- Response 12: We addressed this via including:

  "However, the formation of social ties is influenced by social network algorithms, e.g., via selective user recommendations (Chen & Syu, 2020), which can limit a user's exposure to other people with different beliefs or preferences."

Background

- The literature review is well done, but might be more complete on the subject (central to the narrative of the paper) of the co-evolution between network and behavior. This is a topic that has emerged in several fields. For example, it has been shown that cooperation is sustainable when individuals control their social ties. A few examples...

- Response 13: We are grateful for the suggested references and have included an additional sentence pointing to the importance of rewiring of ties for the evolution of cooperative behaviours:

  " In addition to contributing to the formation of echo chambers, it is important to point out that selective rewiring can also foster cooperative behaviours. For example, it has been shown that cooperative behaviours are more likely to evolve (Righi & Takács, 2014; Yamagishi, Hayashi, & Jin, 1984) and survive (Santos, Pacheco, & Lenaerts, 2006) in networks where individuals can self-select and prune their social ties."

Results

- Figure 2: graphs are to empty I strongly suggest to find a more effective way of presenting them (eg. Log scales, rescaling the x-axis so not to have half of the graphs with no variations. Figure 2: graphs: what are the dashed lines? If they are the axes they are not needed. Are the results derived from individual simulations? If yes these are not sufficient. Results should be reproduced many times for each parameter set and the outcomes should be statistically assessed.

- Response 14: We have now rescaled the x-axis for the global belief proportions (Figure 4) and included an additional Figure 3 to show these distributions via histograms across all parameter combinations. We also included statistical comparisons between our 'social' agent population in which credibility is computed according to Equations 4-5 (i.e. based on the support a source's communication finds in the receiver's network) and the 'asocial' control group which samples credibility randomly:

  ..." As expected, we can see that the average global belief proportions of social agents approximated 50/50. Running a Wilcoxon rank sum comparison revealed that global belief proportions in the social agent population did not differ significantly from our asocial control group ($W = 3636508$, $p = 0.882$)."

  and

- "...When combining clustering effects across all parameter combinations, the social population showed significantly larger proportions of clustering (mean = 51.51, SD = 5.46) than the asocial control population (mean = 49.76, SD = 1.96; $W = 5836752$, $p < 0.001$)."

Comments on Model and Graphs

- At the stage, no. The model section should be made much more clear

- Response 15: We have reworked the entire model section and hope that this concern has now been resolved.

- Not really. Graphs can be increased significantly.
- Response 16: We have included two additional graphs (Figure 2 and Figure 3) and also split the initial Figure 2 into two figures with a re-scaled x axis for global belief proportions (now Figure 4).

Reviewer 2's comments:

- 1. First, the introduction to the paper and the subsequent background and motivation feel somewhat disconnected. In particular, my impression is that the actual contributions of the paper do not entirely live up to the sweeping claims in the introduction. From the introduction, one gets the impression that showing that homophily and peer-to-peer social influence are sufficient to create echo is the paper's main "discovery". Further on in the paper, however, it seems that similar claims have already been made by earlier papers (eg., by Sasahara et al), and the contribution of this paper is to further specify such claims (e.g., a single interaction is enough). While I do not dispute the usefulness of the paper's actual contributions, I would recommend to make the introduction to the paper more consistent with these contributions, and not over-sell them.

- Response 17: We have reworked our introduction and background section to better point towards our key contributions: (1) single-interaction and information sharing between peers without preferential rewiring and (2) influence of source credibility.

- Somewhat relatedly, while the paper talks on many instances about the role of social network structure, the role of (non-trivial) structure actually seems limited. My impression is that the authors look only at regular networks, and only vary density as a robustness check. That is fine in itself, but does not do really do justice to the rich literature on the role of network structure (e.g., small world effects, etc) in information diffusion. I would suggest that the authors either drop the use of the "network structure", or make clear early on what do mean by its use (and what not).

- Response 18: We have dropped the repeated use of network structure, and hope that our reworked and dedicated Background sections (one for each contribution) help in clarifying our key contributions.

- While the paper starts off with a clear and justified empirical motivation, the extend to which empirical knowledge on social networks, belief formation, and echo chambers motivates or informs the modeling exercise disappears from sight after the introduction. I would invite the authors to make more explicit which specific empirical puzzles motivate their study, which assumptions are based on empirical observations (and which are not), and how their findings relate to empirical research.

- Response 19: In line with previous related work (Hegselmann & Krause, 2002; Lorenz, 2007; Madsen et al., 2018; Madsen & Pilditch, 2018; Sasahara et al., 2019), our aim was to provide a proof-of-principle account of potentially sufficient causes of echo chambers in social networks. As such, the present paper does not include empirical data. Throughout the paper, however, we have clarified where assumptions and parameters have directly been informed by empirical observation from other work. For example, we now motivate the use of our credibility model by a more elaborate introduction of the BSCM model and previous empirical work using BSCM (e.g., including the reference (Madsen, 2016) which used BSCM with empirical data from the 2016 US election). We also included a new reference showing that people account for expertise and trustworthiness when combining their own beliefs with communications from others:

"Both expertise and trustworthiness received independent support in recent work showing that people account for these properties when updating their prior beliefs based on belief communications from someone else (Hawthorne-Madell & Goodman, 2019)."

We have also included an additional paragraph in the discussion pointing to limitations of our approach and future work that might consider empirical findings showing how people deal with dependencies in social networks and integrate their own observations with those of others:

"An important avenue for further work might be a closer examination of the belief updating process of the present agent populations. Specifically, agents in the present populations updated beliefs sequentially based on the declarations of previous generations (see also (Bikhchandani, Hirshleifer, & Welch, 1992; Pilditch, 2017)). Recent empirical studies demonstrated that people are sensitive to such statistical dependencies in social learning. For example, (Whalen, Griffiths, & Buchsbaum, 2018) showed that when beliefs of others were formed sequentially, people updated their prior beliefs less. Considering such findings, an important step for follow-up simulations involves testing the robustness of echo chambers between varying levels of belief dependencies in a network. An additional extension might focus on the declaration functions used prior to communicating beliefs. In the present work, agents used a deterministic decision rule. Potential alternatives that might be contrasted in future work include probability matching (Shanks, Tunney, & McCarthy, 2002) or the communication of full probability densities (Fränken, Theodoropolous, Moore, & Bramley, 2020)."

Overall, we hope that these changes show that while our work is a proof-of-principle account, the use of BSCM was empirically motivated. In addition, we hope to show that our work allows for simple incorporation of additional empirical findings, such as changing the belief declaration function or communications of beliefs. Here, we point to findings from (Fränken et al., 2020; Whalen et al., 2018) which might be relevant for extensions.

- On a number of important substantive aspects, the paper provides unclear or insufficient explanation. Most crucially, I find the explanation of the simulation's main manipulation of "social " and "asocial" populations confusing. The main narrative of the paper is about how actors select links, but in 6.2-6.5 ecom and tcom seem to already depend on the network structure. Also, the different roles of ecom and tcom are hardly explained, and the same holds for the network formation process. While it is possible to reconstruct some of the details (such as the number of links per agent seems to be constant) from the pseudo-code in the appendix, since the paper's main claim rests on this manipulation, I think it is crucial to explain it in detail in the main text, along with a discussion of the substantive assumptions that underlie its implementation. For example, what is the empirical justification of the assumption that actors select their friends based on credibility? On a related note, equations 4 and 5 are also confusing in themselves: while they are explained as denoting credibility estimates that a communication target assigns to a communicating source, ecom and tcom are not indexed for two actors as one would then expect, and only one undefined index i appears in the equations.
- Response 20: As mentioned in our specific responses to reviewer 1, we have reworked the entire section (Agent-based model, section 3) and hope that these concerns have now been addressed. We also provided more explicit definitions of our 'social' agents and 'asocial' control group and included all relevant details in the main text.

- In equation 1, h' is not introduced or explained (and the same holds for the "'" variables in eqs 2 and 3).
- Response 21: We have amended all Equations and included set definitions (e.g., $\mathcal{H}$) to resolve the above concerns.
- The paper repeatedly refers to a non-existent "Methods" section, which gives the impression that the paper was initially prepared for a different journal and then somewhat half-heartedly adapted for JASSS.
- Response 22: We have removed our Appendix (Methods) component and included relevant details in the main text

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