Natural-Language Multi-Agent Simulations of Argumentative Opinion Dynamics

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Abstract

This paper develops a natural-language agent-based model of argumentation (ABMA). Its artificial deliberative agents (ADAs) are constructed with the help of so-called neural language models recently developed in AI and computational linguistics. ADAs are equipped with a minimalist belief system and may generate and submit novel contributions to a conversation. The natural-language ABMA allows us to simulate collective deliberation in English, i.e. with arguments, reasons, and claims themselves—rather than with their mathematical representations (as in formal models). This paper uses the natural-language ABMA to test the robustness of formal reason-balancing models of argumentation [Mäs and Flache 2013, Singer et al. 2019]: First of all, as long as ADAs remain passive, confirmation bias and homophily updating trigger polarization, which is consistent with results from formal models. However, once ADAs start to actively generate new contributions, the evolution of a conservation is dominated by properties of the agents as authors. This suggests that the creation of new arguments, reasons, and claims critically affects a conversation and is of pivotal importance for understanding the dynamics of collective deliberation. The paper closes by pointing out further fruitful applications of the model and challenges for future research.

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1 Introduction

During the last decade, a variety of computational models of argumentative opinion dynamics have been developed and studied [e.g. Betz, 2012, Mäs and Flache, 2013, Olsson, 2013, Borg et al., 2017, Singer et al., 2019, Banisch and Olbrich, 2021]. These agent-based models of argumentation (ABMAs) have been put to different scientific purposes: to study polarization, consensus formation, or the veritistic value of argumentation; to understand the effects of different argumentation strategies, ascriptions of trustworthiness, or social networks; to provide empirically adequate, or epistemically ideal descriptions of joint deliberation. Moreover, ABMAs differ radically in terms of how they represent argumentation, ranging from complex dialectical networks of internally structured arguments, to abstract argumentation graphs, to flat pro/con lists, to deflationary accounts that equate arguments with evidence. However, all these models are formal in the sense that they are built with and process mathematical representations of natural language arguments, reasons, claims, etc.—rather than these natural language entities themselves.

This paper presents a computational model of argumentation that is decidedly not formal in the following sense: It is not built from abstract representations of arguments, but from the very natural language arguments and claims (which are merely represented in formal models) themselves. Our natural-language ABMA directly processes and runs on English sentences. A key component of our natural-language ABMA is what we call the artificial deliberative agent (ADA), which we construct with the help of game-changing NLP technology recently developed in AI and computational linguistics [Vaswani et al., 2017, Devlin et al., 2019, Radford et al., 2019, Brown et al., 2020]. Our design and study of ADAs bears similarities to research on dialogue systems [Zhang et al., 2020, Bao et al., 2020] and chatbots [Adiwardana et al., 2020] powered with neural language models; however, unlike these neural dialogue systems, ADAs are equipped with additional cognitive architecture, in particular a minimalist belief system. As illustrated in Figure 1, ADAs have a limited (and changing) perspective of a conversation, which determines their opinion vis-à-vis the central claims of the debate. In addition, ADAs may contribute to a conversation by generating novel posts conditional on their current perspective.

Now, what is the motivation for developing ADAs and natural-language models of argumentative opinion dynamics in the first place?

A first motive for studying natural-language ABMAs is to de-idealize formal models and to test their results’ structural robustness. If, for example, groups with over-confident agents typically bi-polarize in formal models but not in their natural-language counterparts, the original result is not robust and ought to be treated with care.
A second motive is to "reclaim new territory" by computationally investigating novel phenomena that have not been (and possibly cannot be) represented by formal models. Metaphorical language [Hesse 1988], slurs [Rappaport 2019], framing effects [Grüne-Yanoff, 2016], or the invention of entirely new arguments [Walton and Gordon, 2019] is difficult to represent in formal models, but relatively easy in natural-language ones.

A third motive is to create computational models with implicit, natural semantics. Formal models of deliberation cannot escape assumptions about the "semantics" and "logic" of argument, specifically the evaluation of complex argumentation. These assumptions concern, for instance, whether individual reasons accrue by addition, whether the strength of a collection of reasons is merely determined by its weakest link, whether undefended arguments are universally untenable, whether every argument can be represented by a deductive inference, or whether our non-deductive reasoning practice is governed by probabilistic degrees of beliefs. In other words, formal models of argumentative opinion dynamics inevitably rest on highly contested normative theories. With natural-language ABMAs, however, there is no need to take an explicit stance regarding these theoretical issues, because the neural language model, which underlies the ADA, comes with an implicit semantics of argument and takes care of argument evaluation itself. That’s why natural-language ABMAs may turn out to be neutral ground and a common point of reference for formal models from rivaling theoretical paradigms.

A fourth motive is to close the gap between computational simulations on the one side and the vast amount of linguistic data about real conversations on the other side. As natural-language ABMAs do not process mathematical representations of text, but text itself, it is much more straightforward to apply and test these models on text corpora (we’ll come back to this in the concluding section).

A fifth and final motive for studying natural-language ABMAs is to explore the capabilities of neural language models. It seems there is currently no clear scientific consensus on what to make of these AI systems. On the one hand, performance metrics for NLP benchmark tasks (translation, text summarization, natural language inference, reading comprehension, etc.) went literally off the chart with the advent of neural language models. On the other hand, some performance gains have been shown to be spurious, as they were just triggered by statistical cues in the data; what’s more, the suspicion that large neural language models have simply memorized sufficiently many tasks from the Internet looms large. In this context, the ability of neural language models (mediated via ADAs) to engage in and carry on a self-sustaining, sensible conversation about a topic, while allowing ADAs to reasonably adjust their opinions in its course, may provide further evidence for the cognitive potential, if not capacities of neural language models.

The paper is organized as follows. Section 2 presents, step-by-step, the outline of our natural-language ABMA, including key features of ADAs, i.e.: the way an agent’s opinion is elicited given her perspective, the way an agent chooses peers in a conversation, the way an agent updates her perspective, and the way an agent generates a new contribution. Note that the guiding design principle in setting up the natural-language ABMA is to rebuild formal reason-balancing models of argumentation [Mäs and Flache, 2013; Singer et al., 2019] – which stand in the tradition of Axelrod’s model of cultural dissemination [Axelrod, 1997] – as faithfully as possible and to deviate from these models only where the natural language processing technology requires us to do so.

As further detailed in Section 3, we run various simulation experiments with the model to test the effects of (i) different updating strategies and (ii) active contributions to a debate. A closer look at an illustrative simulation run (Subsection 4.1) suggests that our model gives rise to meaningful natural language conversations and that, in particular, ADAs respond to changes in their perspective in a sensible way (as regards both opinion revision and active generation of further posts). Our main findings are reported in Subsection 4.2. First of all, the natural-language ABMA with passive agents qualitatively reproduces the results of formal reason-balancing models regarding the effects of updating strategies on group polarization and divergence. This establishes the robustness of the originally observed effects. Secondly, active generation of novel posts heavily influences the collective opinion dynamics—to the extent that properties of the agents qua authors totally dominate the evolution of the conversation. So, the natural-language ABMA identifies a mechanism which is not covered in formal models, but which is potentially of pivotal importance for understanding the dynamics of collective deliberation.

We close by arguing that there are further fruitful applications of the model, which can be naturally extended to account for phenomena such as multi-dimensional opinion spaces, topic mixing, topic
changes, digression, framing effects, social networks, or background beliefs (Section 5). Although
we report results of a preliminary sensitivity analysis in Subsection 4.3 (suggesting our findings are
robust), a systematic exploration of the entire parameter space as well as of alternative initial and
boundary conditions appears to be a prime desideratum of future research.

2 Model

2.1 Basic Design and Terminology

A conversation evolves around a topic, where a topic is defined by a pair of central claims that
characterize the opposing poles of the conversation. For example, the claims {"All drugs should be
legal.", "Decriminalize drugs!"} on the one side and {"No drugs should be legal.", "Drugs should be
illegal."} on the opposite side may define the topic "legalization of drugs."

A post is a small (<70 words) natural language message that can be submitted to a conversation. The
conversation’s timeline contains all posts that actually have been contributed to the debate (POSTS),
including their submission date and author. Let $\text{POSTS}_t$, $\text{POSTS}_{\leq t}$ refer to all posts submitted at,
respectively at or before, step $t$.

Agents participate, actively or passively, in a conversation ($\text{AGENTS} = \{a_1, \ldots, a_n\}$). Every agent
$a_i$ adopts a specific perspective on the conversation, i.e., she selects and retains a limited number
of posts which have been contributed to the conversation. Formally, $\text{PERSP}_i^t = \langle p_1, p_2, \ldots, p_k \rangle$
with $p_j \in \text{POSTS}_{\leq t}$ for $j = 1 \ldots k$.

An agent’s perspective fully determines her opinion at a given point in time, $\text{OPIN}_i^t \in [0, 1]$ (see also
Subsection 2.3).

Every agent $a_i$ has a (possibly dynamically evolving) peer group, formally: $\text{PEERS}_i^t \subseteq \text{AGENTS}$ (see
also Subsection 2.4). As agents update their perspective (see Subsection 2.5), they exchange their
points of view with peers only.

2.2 The Main Loop

The following pseudo-code describes the main loop of the simulation of a single conversation.

\begin{algorithm}
\caption{Main Loop of the Simulation}
\begin{algorithmic}
\For{$t$ in $[1 \ldots t_{\text{max}}]$}
  \For{$i$ in $\text{AGENTS}$}
    \State determine the peers of agent $i$ ($\rightarrow \text{PEERS}_i^t$);
    \State update the perspective of agent $i$ ($\rightarrow \text{PERSP}_i^t$);
    \If{agent $i$ is contributing at $t$}
      \State generate and submit a new post;
    \EndIf
    \State elicit the opinion of agent $i$ ($\rightarrow \text{OPIN}_i^t$);
  \EndFor
\EndFor
\end{algorithmic}
\end{algorithm}

2.3 Opinion Elicitation

The opinion of agent $a_i$ at step $t$ is a function of $a_i$’s perspective at step $t$. We define a universal
elicitation function $\mathbf{O}$ to determine an agent’s opinion:

$$\text{OPIN}_i^t = \mathbf{O}(\text{PERSP}_i^t)$$

$$\mathbf{O} : \wp(S) \rightarrow [0, 1]$$

where $\text{PERSP}_i^t$ is a sequence of posts.
Function $O$ is implemented with the help of neural language modeling technology (see Appendix). First, we transform the posts in the perspective into a single word sequence (basically by concatenating and templating, as described in the Appendix), which yields a natural language query $Q_{\text{elic}}(\text{PERSP}_i)$. We elicit the opinion of the agent regarding the conversation’s central claims by assessing, roughly speaking, the probability that the agent generates a pro-claim rather than a con-claim given her perspective. More specifically, we calculate the so-called conditional perplexity [cf. Manning and Schütze 1999, 78] of the pro claim / con claim given the query previously constructed (see also Appendix):

$$PPL_{\text{GPT2}}(\cdot, Q_{\text{elic}}(\text{PERSP}_i)).$$

Note that perplexity corresponds to inverse probability, so the higher a sequence’s perplexity, the lower its overall likelihood, as assessed by the language model.

Now, let $PPL_i^j(\text{pro})$ and $PPL_i^j(\text{con})$ denote the mean conditional perplexity averaged over all pro claims, resp. con claims, conditional on the agents perspective $\text{PERSP}_i^j$. The opinion of agent $a_i$ at step $t$ is then given by

$$O(\text{PERSP}_i^t) = \frac{PPL_i^t(\text{con})}{PPL_i^t(\text{pro}) + PPL_i^t(\text{con})}$$

Function $O$ measures the extent to which an agent leans towards the pro rather than the con side in a conversation, as defined by its central claims (recall: low perplexity $\sim$ high probability). It is a polarity measure of an agent’s opinion, and we alternatively refer to the opinion thus elicited as an agent’s "polarity."

The mean perplexities ($PPL_i^t(\text{pro})$, $PPL_i^t(\text{con})$), however, reveal more than an agent’s tendency towards the pro side or the con side in a conversation. If, e.g., both $PPL_i^t(\text{pro})$ and $PPL_i^t(\text{con})$ are very large, the agent’s perspective is off-topic with respect to the central claims. We define an agent’s pertinence as

$$P(\text{PERSP}_i^t) = 0.5(PPL_i^t(\text{pro}) + PPL_i^t(\text{con}))$$

Measure $P$ allows us to track whether agents change the topic in the course of a conversation.

### 2.4 Peer Selection

We explore two peer selection procedures: a simple baseline, and a bounded confidence mechanism inspired by the work of Hegselmann and Krause [2002].

**Universal (baseline).** Every agent is a peer of every other agent at any point in time. Formally, $\text{PEERS}_i^t = \text{AGENTS}$ for all $i, t$.

**Bounded confidence.** An agent $a_j$ is a peer of another agent $a_i$ at some point in time if and only if their absolute difference in opinion is smaller than a given parameter $\varepsilon$. Formally, $\text{PEERS}_i^t = \{a_j \in \text{AGENTS} : |\text{OPIN}_j^{t-1} - \text{OPIN}_i^{t-1}| < \varepsilon\}$
2.5 Perspective Updating

Agents update their perspectives in two steps (contraction, expansion), while posts that an agent has contributed in the previous time step are always added to her perspective:

Algorithm 2: Perspective Updating, Overview

```python
def perspective_updating(i, t):
    # retrieve the old perspective, PERSP_NEW = PERSP_{i,t-1};
    randomly drop k posts from PERSP_NEW according to how long each post has been included in the perspective;
    if agent i has been contributing at t-1 then
        add the post generated by agent i at t-1 to PERSP_NEW;
        k = k - 1
    end
    add k further posts to PERSP_NEW according to perspective_expansion_method;
    set new perspective, PERSP_i^t = PERSP_NEW;
```

The contracted perspective, PERSP_NEW, of agent a_i at step t is expanded with posts from the perspectives of all peers, avoiding duplicates, i.e., the agent selects – according to her specific updating method – k eligible posts, with \( POSTS_{el} = \bigcup_{j \in PEERS_{i,t-1}} PERSP_j^{t-1} \setminus PERSP_{i,t-1} \subseteq POSTS_{el} \).

This kind of perspective expansion is governed by one of the following methods:

**Random (baseline).** Randomly choose and add k eligible posts \((\subseteq POSTS_{el})\) to the perspective.

**Confirmation bias (lazy).** First, randomly draw k posts from \( POSTS_{el} \); if all chosen posts confirm the agent’s opinion (given the contracted perspective \( PERSP_{i,t-1} \)), then add the k posts; else, draw another k posts from \( POSTS_{el} \) and add the k best-confirming ones from the entire sample (of size 2k) to the perspective.

**Homophily (ACTB).** Choose a peer \( a_j \in PEERS_{i,t-1} \) in function of the similarity between the agent’s and the peer’s opinion; randomly choose k posts from the perspective of peer \( a_j, PERSP_{j,t-1} \).

Note that homophily (ACTB), which mimics the ACTB model by [Mäs and Flache 2013], evaluates the eligible posts \textit{ad hominem}, namely, based on the opinion of the corresponding peer only, while a post’s semantic content is ignored. In contrast, confirmation bias (lazy), which implements ‘coherence-minded’ updating from the model by [Singer et al. 2019], only assesses the eligible posts’ argumentative role, irrespective of who actually holds the post. Moreover, we have implemented a “lazy” version of confirmation bias, as described above, for computational reasons: a confirmation-wise assessment of \( all \) eligible posts is practically not feasible.

A full and more precise description of the perspective expansion methods is given in the Appendix.

2.6 Text Generation

Causal language models like GPT-2 are essentially probabilistic next-word prediction machines. Given an input sequence of words \( x_1...x_k \), the language model predicts—for all words \( w_i \) in the vocabulary—the probability that \( w_i \) is the next word in the sequence, \( Pr(x_{k+1} = w_i|x_1...x_k) \). It is obvious that such conditional probabilistic predictions can be used to generate a text word-by-word, and there exist various ways for doing so. This kind of text generation with statistical language models is commonly referred to as \textit{decoding}, and it represents a research field in NLP in its own [c.f. Holtzman et al. 2019, Welleck et al. 2020]. Pre-studies have suggested to use randomized beam search (with nucleus sampling) as decoding algorithm (see also Appendix). The key parameters we use to control decoding are

- **temperature**, which rescales the predicted probabilities over the vocabulary (increasing low and decreasing high probabilities if temperature is greater than 1);
- **top_p**, which restricts the set of eligible words by truncating the rank-ordered vocabulary (let the vocabulary be sorted by decreasing probability, and let \( r \) be the greatest rank such
that the probability that the next word will be \( w_1 \) or \( w_r \) is still below \( \text{top}_p \), then only \( w_1 \) \ldots \( w_r \) are eligible for being inserted).

In the experiments, we explore the following two decoding profiles:

| profile  | temperature | top_p |
|----------|-------------|-------|
| narrow   | 1.0         | 0.5   |
| creative | 1.4         | 0.95  |

Metaphorically speaking, the narrow profile emulates a conservative, narrow-minded author who’s sticking with the most-obvious, common, usual, and most likely options when writing a text. The creative profile, in contrast, characterizes an author who is much more willing to take surprising turns, to use unlikely phrases and unexpected sentences, who is easily carried away, prone to digress, and much harder to predict.

Pre-studies show that conversations are extremely noisy if each agent generates and submits a post at every time step; in the following, the probability that an agent is contributing a novel post at a given time step is set to 0.2.

3 Experiments

3.1 Initialisation

To run simulations with our natural-language ABMA, the initial perspectives of the agents \((\text{PERSP}_i^0, i = 1 \ldots n)\) have to contain meaningful posts that fall within the conversation’s topic. Additionally, it seems desirable that the initial perspectives give rise, group-wise, to a sufficiently broad initial opinion spectrum.

To meet these requirements, we define topics that correspond to specific online debates on the debating platform [kialo.com](https://kialo.com) from where we crawl and post-process potential posts. Post-processing involves filtering (maximum length equals 70 words) and conclusion explication. As we crawl posts from a nested pro-con hierarchy, the argumentative relation of each post to the central pro / con claims (root) can be inferred, which allows us to add, to each post, an appropriate pro / con claim as concluding statement. For example, the post “If drugs being illegal prevented addiction, there would be no drug addicted person. Thus, there is no prevention by just keeping drugs illegal.” is expanded by “So, legalization of drugs is a pretty good idea.” In order to increase diversity of posts, we expand only half of all the posts retrieved by such a conclusion statement.

The experiments described below are run on the topic of the legalization of drugs, initial perspectives are sampled from 660 posts, of which 442 justify or defend the pro claim (legalization).

3.2 Scenarios

We organize our experiments along two main dimensions, namely (i) peer & perspective updating, and (ii) agent type.

Regarding peer & perspective updating, we explore four parameter combinations:

- **random**: baseline update rules for peers (universal) and perspective (random);
- **bounded confidence**: bounded confidence peer selection and random perspective updating;
- **confirmation bias**: universal peers and lazy confirmation bias (for perspective updating);
- **homophily**: universal peers and homophily (for perspective updating).

Regarding agent type, we distinguish passive, and two types of active (i.e., generating) agents:

- **listening**: agents are not generating, they only forget, share and adopt posts that have been initially provided;
• generating narrow: agents can generate posts, text generation is controlled by the narrow decoding profile;
• generating creative: agents can generate posts, text generation is controlled by the creative decoding profile.

So, all in all, the simulations are grouped in $4 \times 3$ scenarios. For each scenario, we run an ensemble of 150 individual simulations. (An online demo will be made available for inspecting the ensemble results.)

4 Results

4.1 An Illustrative Case

In this subsection, we present an illustrative simulation run and follow a single ADA during a brief episode of the conversation. The case study is not intended to be representative. Its purpose is two-fold: (i) to illustrate what exactly is going on in the simulations, and (ii) to demonstrate that the model is not just producing non-sense, by showing that we can interpret the ADA’s opinion trajectory as an episode of reasonable belief revision.

Figure 2 plots the opinion trajectories (polarity) of 20 agents over the entire simulation run. Agents select peers in accordance with the bounded confidence mechanism ($\varepsilon = 0.04$). After the initialisation phase (steps 0–4), the collective opinion spectrum ranges from 0.4 to 0.8. Opinion diversity stays high for the next 20 steps, when the collective profile starts to collapse and more and more agents settle on an opinion around 0.55. From step 65 onwards, a noisy equilibrium state has seemingly been reached.

Figure 2 highlights the opinion trajectory of agent $a_8$. One of its outstanding features is that agent $a_8$ holds an initial perspective that induces a strong opinion pro legalization ($\text{OPIN}^8_0 = 0.8$). In steps 12–20, however, agent $a_8$ completely reverses her opinion. We will now try to make sense of this drastic opinion reversal in terms of changes in the agent’s perspective. We limit our discussion to steps 17–19, during which the opinion falls from 0.64 to 0.54 and further to 0.49 (see also Figure 2b).

In the following display of the agent’s perspectives (starting with step 17), posts are highlighted according to whether they have been generated by the agent, are newly added to the perspective at this step, have been generated by the agent at the previous step and are hence newly added, or will be removed from the perspective at the next step.

At step 17, the agent’s perspective contains a majority of posts plainly pro legalization (17-1, 17-3, 17-5, 17-6, 17-7, 17-8) and no clear reasons against legalization (and that’s how it should be, reckoning that the agent comes from the extreme pro side and has – thanks to bounded confidence – exchanged posts only with like-minded, pro-legalization peers):
When you legalize drugs, it’s absurd to lock people up for using drugs that they choose to make themselves. If they wanted to get high, they’d do it somewhere else. [18-7] If someone wants to go to the supermarket and pick up a few cakes, why shouldn’t they? Why shouldn’t they be allowed to do so? [18-8] People should be able to ingest anything they want without getting in any trouble for it.

The newly added post 17-8 represents a reason pro legalization, which might explain the slight increase of polarity compared to to step 16. Marked for removal in step 18 are: 17-1, an explicit pro reason, and 17-4, a rather nuanced statement which advocates a differentiated policy. Here is how these posts are replaced (cf. 18-7 and 18-8):

![Image](https://www.addictioncenter.com/rehab-questions/cost-of-drug-and-alcohol-treatment/)

The perspective in step 19 newly embraces two posts against legalization, adopted from peers. Post 19-7, in particular, is an explicit con reason, post 19-8 draws attention towards overdosing and hence towards the negative effects of drug use. So, four posts in the perspective now speak against...
(a) clustering coverage  (b) number of clusters

(c) bipolarization ratio  (d) full consensus ratio

Figure 3: Clustering metrics: clustering coverage, number of clusters, frequency of bipolarization (in percent), frequency of full consensus (in percent).

legalization – compared to 6 pro reasons and no con reason in step 17. Plus, the four con reasons are also the most recent posts (recall that order matters when prompting a language model) and, in a sense, "overwrite" the three previously stated pro claims (19-2 to 19-4). In sum, this explains the sharp opinion change from step 17 to step 19.

4.2 Global Consensus and Polarization Effects

In this subsection, we characterize and compare the simulated opinion dynamics across our 12 experiments (see Subsection 3.2), and provide results averaged over the corresponding simulation ensembles.

Based on a cluster analysis (see Appendix for details), we measure the degree of polarization (in terms of clustering coverage and number of clusters), the frequency of bipolarization, and the frequency of full consensus in the simulated conversations. Moreover, we report opinion variance and min-max spread as divergence measures, plus average squared opinion difference – \((\text{OPIN}_t - \text{OPIN}_{t-1})^2\) – as volatility measure. Conversations are evaluated at \(t = 150\).

Figure 3 shows how clustering metrics vary across the \(4 \times 3\) scenarios. Consider, firstly, passive agents who are only sharing but not generating novel posts (column \textit{listening}). With the baseline update mechanism (row \textit{random}), 6\% of the agents fall within an opinion cluster (Figure 3a), and there exists, on average, one cluster in one out of three conversations (Figure 3b). Clustering is much more pronounced for the alternative update mechanisms, with \textit{homophily} in particular attaining more than 70\% coverage and 1.65 clusters per conversation. Let us say that a conversation is in a state of bipolarization (full consensus) if and only if clustering coverage is greater than 0.9 and there exist two clusters (exists a single cluster). We observe, accordingly, no instances of bipolarization or consensus in the baseline scenario, very few instances for \textit{bounded confidence} and \textit{confirmation bias}, and a significant frequency of bipolarization and full consensus for \textit{homophily} (Figure 3c,d).

This global picture changes entirely as we turn, secondly, to active agents that are generating posts in line with one of the two decoding profiles (cf. Subsection 2.6). Regarding creative authors (column \textit{gen_creat}) and irrespective of the particular update mechanism, clustering coverage is between 0.3 and 0.6, there exist approximately 1.5–2 clusters, we observe bipolarization in up to 5\% and full consensus in less than 2\% of all conversations. So we find, compared to passive agents, much stronger clustering in the baseline scenario but significantly less clustering in the \textit{homophily} scenario. Regarding narrow-minded authors (column \textit{gen_narro}), however, clustering coverage is greater than 0.9, there exists roughly a single cluster per conversation, bipolarization is frequent, and more than 70\% of the debates reach full consensus.
Figure 4 describes the extent to which opinions diverge in the 12 simulation experiments. Concerning passive agents, disagreement is most pronounced (both in terms of opinion variance and max–min spread) with bounded confidence updating, closely followed by the baseline scenario. Conversations with active agents, in contrast, give rise to much lower levels of disagreement, while narrow-minded authoring is even more agreement-conducive than creative generation, reducing divergence by an entire order of magnitude compared to passive agents.

As Figure 5a shows, there exist huge differences in terms of per-agent opinion volatility, which is most pronounced for passive agents that randomly adopt novel posts. Structured updating procedures (bounded confidence, confirmation bias, and homophily) have, ceteris paribus, a stabilizing effect and significantly reduce volatility. Creative generation has mixed effects on volatility (depending on the update procedure), while narrow-minded agents possess maximally stable opinions. Finally, Figure 5b reports mean pertinence values for the different scenarios. Recall that pertinence measures the relevance of a perspective for a given pair of central pro/con claims while (cf. Subsection 2.3): the lower the pertinence value, the more relevant the perspective. Accordingly, agents retain the most relevant perspectives in the baseline scenario. As soon as agents start to generate their own posts, pertinence value increases. However, the conversations stay, on average, faithful to the initial topic (that wouldn’t be the case for perplexities above 20, though). Mean pertinence value is, somewhat surprisingly, even slightly lower for creative than for narrow-minded agents.

4.3 Sensitivity Analysis

By varying the number of agents per conversation, the maximum number of posts an agent can hold in her perspective, as well as update-specific parameters (epsilon interval, homophily strength) in the simulation experiments, we obtain a preliminary understanding of the model’s sensitivity. Yet, these experiments fall short of a systematic exploration of the entire parameter space, which has not been carried out due to its computational costs, and is certainly a desideratum for future research.

In general, the model seems to yield qualitatively similar results when varying key parameters. In particular, structured updating (bounded confidence, confirmation bias, and homophily) with passive agents gives rise to polarization, and once agents get active and start to generate posts, the collective opinion evolution is dominated by decoding parameters – in the latter case, changes in community or perspective size have quantitatively very little effect.

Regarding homophily and confirmation bias updating with passive agents, increasing the number of agents per conversation results in more full consensus and less bipolarization. With more agents covering the ground, it seems to be more difficult for subgroups to isolate from other agents and to
build a shared, sufficiently distinct perspective. Moreover, increasing the perspective size decreases the frequency of both full consensus and bipolarization, and weakens clustering in general. With more posts in a perspective it takes – certeris paribus – longer for an agent to entirely change her perspective; characteristic collective opinion profiles hence build up more slowly and we observe, at a fixed time step, lower polarization and consensus. Plus, it’s clear from a look at the time-series that the conversations with homophily and confirmation bias have not reached a (possibly noisy) equilibrium state at \( t = 150 \), yet. It’s therefore a desideratum for future research to run the simulations for much longer time spans.

In particular, epsilon and homophily exponent control bounded confidence, respectively homophily updating. The model reacts to changes in these parameters as expected: As we increase the epsilon interval, we obtain (with bounded confidence updating / passive agents) more clustering and more agreement. Increasing the homophily exponent results (with homophily updating / passive agents) in stronger clustering (more consensus, more bipolarization) and greater disagreement.

5 Discussion and Future Work

Structural robustness of formal models. As regards passive agents, our natural-language ABMA reproduces qualitative results obtained with formal reason-balancing models: homophily and confirmation bias updating lead to bipolarization, in line with the findings of Mäs and Flache [2013] resp. Singer et al. [2019]. Bounded confidence updating increases polarization and disagreement, consistent with Hegselmann and Krause [2002]. Due to requirements imposed by language modeling technology, the natural-language ABMA is structurally similar to, albeit not identical with the corresponding formal models (e.g., confirmation bias implements, for computational reasons, local rather than global search). In addition, the context sensitive, holistic processing of reasons in the natural-language ABMA departs from the strictly monotonic and additive reason aggregation mechanism built into the formal models. All these structural dissimilarities, however, further strengthen the robustness of the findings concerning passive agents.

Limitations of formal models. We have observed that once agents start to generate and submit their own posts, the evolution of the collective opinion profile is dominated by decoding parameters (i.e., properties of the agents as authors). With active agents, we obtain entirely different results for polarization, consensus and divergence than in the experiments with passive agents. In formal reason balancing models, however, agents cannot generate new reasons (or rephrase, summarize, mix, and merge previous ones). So, the natural-language ABMA identifies a potentially pivotal mechanism that’s currently ignored by formal models, whose explanatory and predictive scope seems, accordingly, to be limited to conversations and collective deliberations with a fixed set of reasons to share.

Sensitivity analysis. A systematic sensitivity analysis of the natural language model seems urgent and should go beyond an exploration of the entire parameter space and longer simulation runs. First, some implementation details are worth varying (e.g., the generation of prompts used to query the language model, the post-processing of generated posts, the functional form of the confirmation measure, local search). Second, the initial conditions should be altered, too; in particular, conversations should be simulated on (and be initialized with) different topics.

Empirical applications. There are multiple routes for empirically applying and testing natural-language ABMAs, which are closed for purely formal models and which might be explored in future work – as the following suggestions are supposed to illustrate. On the one hand, one can derive and empirically check macro predictions of the model: (a) One may test whether groups of conservative authors are more likely to reach full consensus than groups of creative authors. (b) One might try to explain statistical properties of an observed opinion distribution in a debate by initializing the model with posts from that debate and running an entire (perturbed-physics style) ensemble of simulations. (c) Or one might check whether the macro patterns of semantic similarity [Reimers and Gurevych 2019] within a simulated conversation correspond to those in empirical discourse. On the other hand, one can test the micro dynamics built into the natural language model: (a) One might verify whether deliberating persons respond to reasons and aggregate reasons in the way the ADA does. (b) Alternatively, one might try to infer – by means of the natural-language ABMA – (unobserved,
evolving) agent perspectives from (observed) agent contributions so as to account for the agents’ (observed) final verdicts on a topic.

**Model extensions.** The natural-language ABMA is extremely flexible, as its agents (ADAs) understand and speak English. This allows us to address further linguistic phenomena (slurs, thick concepts) and cognitive phenomena (fallacious reasoning, framing effects) with relative ease, e.g., by systematically changing the prompts used to query the agents, by intervening in a simulated conversation and inserting targeted posts at given step, or by controlling for these phenomena during the initialisation. Likewise, taking opinion pertinence (in addition to opinion polarity) into account in the updating process, eliciting multi-dimensional opinions (with additional pairs of pro-con claims), and mixing multiple topics in one and the same conversation are further straight-forward and easy-to-implement extensions of the model. Obviously, it’s also possible to define a neighborhood relation and simulate conversations on social networks. A further set of model extensions regards the heterogeneity of agents: As the model presented in this paper contains (except for their initial condition) identical agents, a first way to increase diversity is to allow for agent-specific (updating and decoding) parameters. Furthermore, we can model background beliefs by fixing immutable posts in an agent’s perspective. Finally, there’s no reason (besides a computational, practical one) to use one and the same language model to power ADAs; in principle, each agent might be simulated by a specific instance of a language model (with particular properties due to its size, pre-training and fine-tuning) – plus, these language models might actually be trained and hence evolve in the course of a simulated conversation. The practical effect of this last modification is that agents would display different initial (empty perspective) positions and that an agent might have different opinions at two points in time although she holds one and the same perspective.

**Lessons for AI.** This paper has adopted recent technology from AI and NLP to advance computational models of argumentative opinion dynamics in the fields of formal and social epistemology and computational social science. Now, this might in turn have repercussions for AI: The fact that we’ve been able to simulate self-sustainable rational argumentative opinion dynamics suggests that the language model we’re using to power agents possesses minimal argumentative capabilities and is, in particular, able to process and respond to reasons in a sensible way. Otherwise, the successful simulation of collective deliberation would be a miracle. Plus, our experiments can be interpreted – inside out – as a single agent’s attempt to think through a topic by consecutively adopting alternative perspectives (and hence mimicking a deliberation); which suggests that language models are capable of sensible self-talk, consistent with Shwartz et al. [2020] and Betz et al. [2021]. Finally, such argumentative multi-agent systems might be a fruitful design pattern to address tasks in AI and NLP that are difficult to solve with standard systems built around a single agent / a single language model.

**Appendix**

**Language Model**

In opinion elicitation and text generation, we rely on the pretrained autoregressive language model GPT-2 [Radford et al., 2019] as implemented in the Transformer Python package by Wolf et al. [2019].

**Prompt Generation**

Let $\text{PERSP}_i^t = \langle p_1 \ldots p_k \rangle$ be the perspective of agent $a_i$ at $t$. To elicit the opinion of agent $a_i$ at $t+1$, we prompt the language model with the following query:

```
Let’s discuss legalization of drugs!
p_1
\ldots
p_k
I more or less agree with what my peers are saying here. And therefore, all in all,
```

When generating a new post at $t+1$, the model is prompted with
Let’s discuss legalization of drugs!

I more or less agree with what my peers are saying here. Regarding the legalization of drugs, I’d just add the following thought:

**Perplexity**

Let \( \mathbf{v} = \langle v_1 \ldots v_k \rangle \) and \( \mathbf{w} = \langle w_1 \ldots w_l \rangle \) be two sequences of words. A causal language model (LM) predicts next-word probabilities. Let \( p_i \) be the probability that the next word is \( w_i \) given the previous sequence \( v_1, \ldots, v_k, w_1, \ldots, w_{i-1} \), i.e.

\[
p_i := \text{Prob}_{LM}(w_i|v_1 \ldots w_{i-1}).
\]

The conditional perplexity of sequence \( \mathbf{w} \) given sequence \( \mathbf{v} \) is defined as the inverse geometric mean of the predicted conditional probabilities for words in \( \mathbf{w} \),

\[
PPL(\mathbf{w}|\mathbf{v}) = \sqrt[k]{\prod_i \frac{1}{p_i}}.
\]

**Parameters**

Global parameters of the simulation runs are:

| Parameter                       | Value |
|---------------------------------|-------|
| number of agents                | 20    |
| perspective size                | 8     |
| maximum steps                   | 150   |
| relevance deprecation           | .9    |
| memory loss (passive)           | 1     |
| memory loss (active)            | 2     |
| confirmation bias exponent      | 50    |
| homophily bias exponent         | 50    |
| epsilon                         | 0.04  |

Parameters that control specifically decoding are:

| Parameter           | Value |
|---------------------|-------|
| number of beams     | 5     |
| repetition penalty  | 1.2   |
| sampling            | True  |

**Perspective Updating Methods**

With **homophily** updating, agent \( a_i \) chooses a peer \( a_j \in \text{PEERS}^i \) (we drop time indices for convenience) from whom new posts are adopted in function of the similarity in opinion,

\[
sim(i, j) = 1 - |\text{OPIN}^i - \text{OPIN}^j|.
\]

The weight agent \( a_i \) assigns to peer \( a_j \) in randomly choosing her communication partner is further determined by the homophily exponent, hpe:

\[
\text{weight}(i, j) = \text{sim}(i, j)^{\text{hpe}}.
\]
With **confirmation bias** updating, agent $a_i$ evaluates eligible posts in terms of their argumentative function. This is modeled by one-sided relevance confirmation, which measures the degree to which a post $p$ confirms the opinion which corresponds to a given perspective $\text{PERSP}$ for an agent $a_i$ at step $t$:

$$\text{conf}(p) = \begin{cases} 
|\text{O}(\text{PERSP} + p) - \text{OPIN}_{0}^i| & \text{if } \text{O}(\text{PERSP} + p) > \text{OPIN}_{0}^i \leftrightarrow (\text{OPIN}_{t-1}^i > \text{OPIN}_{0}^i) \\
0 & \text{otherwise} 
\end{cases}$$

**Cluster Analysis**

We carry out the cluster analysis with the help of density based clustering [Ester et al., 1996] as implemented in the Python package SciKit learn (setting eps=0.03 and min_samples=3). As the opinion trajectories are – depending on the experiment – very noisy, a clustering algorithm risks to detects merely coincidental clusters that have emerged by chance if it is applied to single data points. In order to identify stable clusters, we therefore apply the clustering algorithm to short opinion trajectories; more specifically, we cluster opinion triples $(\text{OPIN}_{t-2}^i, \text{OPIN}_{t-1}^i, \text{OPIN}_{t}^i)$.

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