Addressing the Elephant in the Room: Opinionated Virtual Characters

Sasha Azad, Chris Martens
Principles of Expressive Machines (POEM) Lab, North Carolina State University
{sasha.azad, crmarten} @ncsu.edu

Abstract

A number of recent models for empirically-grounded social simulation have emerged recently from games and interactive narrative research, generally exploring models of trust, emotion, and social graph changes that occur in the process of inter-character interactions. However, these models so far failed to provide realistic models of opinion change and predisposition to new knowledge. Equipped with such a notion, these emergent social simulations can express both real and fictionalized depictions of modern phenomena like adverse media influence, the spread of "fake news," and the polarization of ideological sects. We present a preliminary computational investigation into modeling opinion change in virtual characters with this goal in mind.

Introduction

Humans are rational and emotional beings. Their social systems are complex and contextual. Understanding and simulating humans with virtual characters requires reasoning not just about observable social network graphs or social interactions, but also about geography, economics, and increasingly, online participation and discourse. However, these simulated models typically do not account for some of the most important features of social networks, namely that of the *social dynamics of opinion change*.

In this paper, we describe a simulation we have designed for a society of virtual characters that can discuss and exchange their views amongst one another. We define a character's view on the topic as a combination of their internal, personal attitude on a topic of discussion and their externally expressed opinion. We allow for conversationalists to influence each others' opinions based on existing literature from the social science regarding group conformity and acceptance, as well as by the strength of the overall public opinion. We describe a conversational model that allows virtual characters to subscribe to information sources based on the source biases and opinions, share new information with one another, and form and exchange their opinions on the various issues at hand.

For virtual characters to be socially adept and add to the experience of the player, they must have a sizable expressive range of conversational repertoire. We advance an abstract knowledge base for the characters that groups various objects of discussion under overarching topics, tracks the sources from which they originate with their inherent bias or ratings, and allow the non-player characters (NPCs) to form opinions based on individual preferences or cultural norms. Our system can track the spread of influence (adverse or otherwise) and change in the views of the participant NPCs.

Finally, we demonstrate our system with a case study that showcases a series of conversations where virtual characters discuss current political news from the U.S., exchange their views on individual news articles or issues of interest, and reevaluate their political ideologies and affiliations over time. For instance, an NPC growing up in a more liberal society may eschew conservative ideals, and have a low opinion of the same. Our simulated NPCs are aware of the difference in their internal attitude on a topic of discourse as well as the public opinion shared by other NPCs during their interactions. These differences can lead to the NPCs changing their attitudes over time or expressing opinions different from their attitudes to conform to the society they reside in over time.

We posit that the holding of these opinions on the various topics could lead to the virtual character having access to choices and interactions that would otherwise need to be authored in the character's preferences or goals. For instance, an NPC growing up in a country with strict gun control, or that holds an unfavorable opinion of gun ownership may choose never to buy a gun.

We imagine that in the future our opinion model could be used to evaluate how a virtual society would integrate and accept new additions with new members learning of the views and opinions of the society while bringing with them new ideas and concepts from their own culture. Similarly, opinion modeling for virtual characters could be used to study the spread of debatable ethical or moral influence and media bias. Characters could choose to accede to peer pressure (from the media or society) and change their behaviors in order to feel a mix of both private acceptance (that they are acting based on their views) and public conformity (to gain acceptance by the group). We believe the behaviors resulting from virtual characters modeled by this system would be more believable and improve a player's interactive experience.

Related Work

Prior work discusses how designing for richer social behaviors and interactions amongst virtual characters improve the believability of the character and the player's interactive experience with the system (Afonso and Prada 2008; Swartout et al. 2006). Vinciarelli et al. describe the social signals as "accounting for our attitudes towards other participants in the current social context." (Vinciarelli et al. 2008). Researchers have approached NPC social networking through simulation of interactions between a collection of NPCs that are reactive, appear intelligent, and motivated (Riedl and Stern 2006; Mateas and Stern 2003; Ryan, Mateas, and Wardrip-Fruin 2016; Samuel et al. 2016). These systems model worlds with a society of NPCs that have individual goals, beliefs, and desires upon which they act.

Research has been conducted on social rules and practices that virtual agents in the system must conform to as designed by authors and designers (Mateas and Stern 2003). In Versu (Evans and Short 2014), we see the virtual characters that interact with one another using the notion of common "social practices" and templates. Characters undertake interactions based on their desires and goals, with social practices authored to be agnostic about which characters are assigned to the roles undertaken. Similarly with social systems such as CiF, in Prom Week, McCoy et al. constructs a social physics architecture model to decide how NPCs behave in a variety of different social scenarios rich with the potential for drama (McCoy et al. 2011a; 2011b). Our system aims to add to the richness and diversity of the virtual character's roles, the interactions they undertake with the player and one another, and the character archetypes generated. Our approach varies from these social-physics scenarios. Virtual characters consider themselves belonging to a new group based on their recognition of their internal attitudes at a given moment corresponding with the opinions of the society around them. These groups could now form their own social rules over time as interactions that go against the group's values would be looked upon unfavorably by its members. We believe this would reduce the authoring burden of the social rules or templates (Evans and Short 2014; McCoy et al. 2011b), allowing for interesting emergent gameplay.

Other research explores the simulation of conversations and influence amongst NPCs. They view how societal norms and popular opinions could affect the behavior of generated NPCs in a multi-agent system. In Social Role Awareness (Prendinger and Ishizuka 2001), agents choose conversational responses based on their perception of their roles within the social context. A secretary addressing her manager could be more polite and responsive than one addressing an aspirant visiting the office. PyschSim (Pynadath and Marsella 2005) models influence amongst group members by examining how participants in a conversation view their relationships with one another and their beliefs and motivations about the world. Other work has virtual characters sharing their knowledge or gossiping about the world with one another with their bias (Evans and Short 2014). The most significant differences between our approach and the works previously mentioned are that our agents can reevaluate their biases or changes over time by subscribing to new opinion pools from their peers or other sources of information. We hope our model allows for a more natural conversation flow, with agents advancing and modifying their opinions over time. We hope our system will add to the believability and behaviors generated by these works by providing further motivation for character relationships and interactions.

Background

Group Formation

Group formation has been studied in depth by social scientists, historians, and psychologists to understand how humans respond to group (or societal) archetypes and opinions. When modeling group conversations, the physical or virtual space where conversationalists congregate can be used to contextualize the interaction, allowing us to incorporate the history, physical affordances, or cultural significance of the geographic location or the topic in question. Merely reading the news enables one to gain a perspective of humans forming groups to support various issues. These could be geographic groups, with articles describing how the *Scottish* voted to "overwhelmingly remain" in the Brexit vote; or political ideology groups, with reports on *Democrats* discussing immigration resolutions; groups based on shared interests, with news on *Whovians* that approve or condone representation of women in Doctor Who (Jowett 2014); or by grouping an occupation, with articles describing how *Tech executives* are contrite about election meddling. Latour discusses how individuals relating to one group or another is an ongoing process made up of uncertain, fragile, controversial and ever-shifting ties (Latour 2005).

Self Perception Agents for Opinion Dynamics

We review the problem of simulating agents capable of conversing and sharing opinions with one another. We model the change in the opinions of the agents based on the model proposed by Wang, Huang, and Sun in their 2014 paper (Wang, Huang, and Sun 2014). Individual agents can influence each other's views and construct their self-opinions over the course of multiple interactions with one another.

Agents are modeled as individual nodes in a social network graph. Agents may exchange opinions with other agents if an edge links the nodes in the graph. Wang, Huang, and Sun defines how agents every agent's feelings on a topic is informed by an inner **"attitude"** towards the topic that cannot be perceived by other agents, an outward expressed **"opinion"** and the level of **"uncertainty"** they feel about their opinion. Agents may adjust their internal attitudes or express modified opinions from their attitudes, on hearing the opinion of other agents (Wang, Huang, and Sun 2014).

Due to space restrictions, we refer readers to the Wang, Huang, and Sun (2014) paper, and the Asch (1955) paper for the details on their experiment. We recognize that the threshold values and model evaluated in the Wang, Huang, and Sun paper may not exactly conform to an exhaustive list of objects of discussion or topics of discourse. However,

Topics	Objects of Discussion	Source	Rating
Political Issues e.g. Immigration, Gun Control	Individual news articles	Online or Print Media	Political Bias or Affiliation
Political Issues e.g. Immigration, Gun Control	Political candidates	Articles, Interviews, Candidate Rally	Approval Rating
Research Topics e.g. AI, Games	Conference Papers	Journals, Conference Proceedings	Journal or Conference Rankings
Film Genres e.g. Horror, Sci-Fi	Movies	Movie Studios	Rotten Tomatoes ratings

Table 1: Examples showing how discussions can be simulated on various datasets using the proposed knowledge model

their proposed agent model combines normative social influences with a continuous dynamics model in a novel approach. Our objective is to extend these current theories of dynamic opinion modeling research to the narrative intelligence community with the goal to simulate virtual societies capable of exploring complex issues of politics, religion, or even simply movie ratings.

Towards this goal, our contribution builds on that of Wang, Huang, and Sun's in the following ways:

- Prior work fails to model the complex and ever-changing social relationships between conversationalists. The authors assume a grid-based society where the same neighboring agents surround an individual throughout their simulation. Our method proposes a more utilitarian definition of social relationships where NPCs with differing or similar opinions could change relationships over time, allowing their old social connections to dissolve over time.
- Instead of a single object of discussion, we allow characters to discuss a variety of information clustered by topics. This allows for relationships where characters that agree over a few views but disagree over others to change their affinity for one another over time.
- We allow for the simulation to add new concepts and topics over time. We believe this could lead to virtual characters to extend their knowledge base while retaining their individual views on existing knowledge.

Goals

We list our goals for the project as follows:

- Account for bias in characters where agents may have a predisposition to adopt a specific view from prior experience.
- Account for bias in the information. Information and sources producing information may have an inherently biased perspective.
- Ability for characters with similar opinions to form relationships, and allow ad-hoc groups developing during social interactions to discuss their opinions on various topics.
- Be able to use the same discussion model for a variety of different data sources to simulate opinion modeling on discussions.

Our Model of Knowledge

The model we use to define in-game knowledge is described as follows. For a single discussion, the participants in the discussion choose an *Object of Discussion* to converse on, obtained from a *Source*. The Source and the Object of Discussion are associated with a *Rating*. Multiple objects of discussion can be clustered to form a *Topic*.

A major contribution of our paper is that this model of the knowledge base can be used for a large variety of datasets while affording the same discussion and opinion modeling. For instance, simulating debates among NPCs about *current news articles* clustered by *political issues* and ranked by their *bias*. Similarly, we could use our model to discuss the merits of various *journal articles* clustered together by *research topics* and ranked by *journal rankings* or have audience members discuss their *movie preferences* clustered by *movie genres* and ranked by their *Rotten Tomatoes rankings*. Some datasets considered during the design phase have been highlighted in Table 1.

Rating of the Information

We define the rating as the value of the information learned by the NPC in the system. This rating could represent either (1) the personal judgment or favor associated with the presentation of the information, or (2) a measure of the impartiality of the unit of information. The rating is the merit or value of the information that is debated by the NPCs in our system. For instance, this could represent the ratings for a movie, reviews for a paper, or a bias rating for a media source.

Topics

We describe **topics** as a clustering of information regarding a specific subject, or field of information. A specific information unit can be a part of multiple topics at the same time. For instance, a discussion of procedural content generation could belong to the topics of both artificial intelligence or game design. A virtual character may periodically reevaluate his rating of a topic by considering the rating of all the objects of discussion within a topic.

Object of Discussion

This single unit of information forms the basis of our discussion model. While interacting with one another, virtual characters search through their knowledge base and conversational repertoire, choosing a single object of discussion to debate. An NPC that adds a new object of discussion to his knowledge base will note the original authorial rating intended to be affiliated with the information, and associate with it their own opinions on the topic. These views could be based on prior discussions of the information with conversationalists that introduce the character to the information, as well as on the character's current view of the topic to which the information belongs.

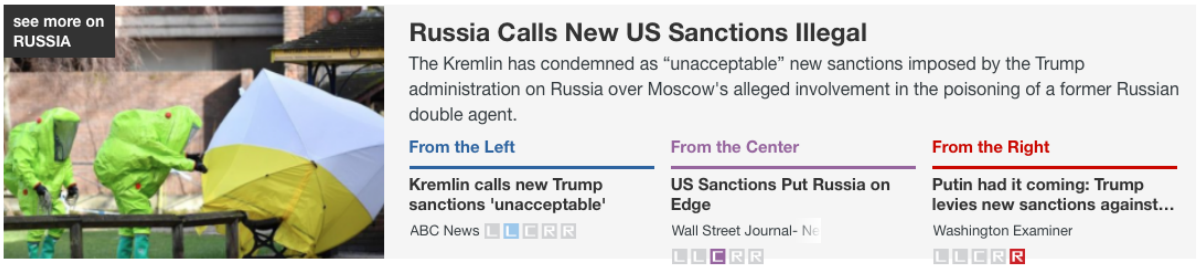

Figure 1: Case Study: Example of a topic of discourse, Russia, and some news articles associated with it, each labeled with their own media bias (AllSides 2018)

Sources

may create information covering a wide variety of objects of discussions and topics. Sources may also have associated with them a rating, representing the expected rating of the information they produce. NPCs may use this rating to choose to subscribe or unsubscribe to these over time based on their current inclinations. For instance, an NPC studying in the computer science domain may subscribe to AAAI for periodic information on the research in their field.

Modeling a Character's Views

Every participant in the discussion has their own *Bias* and *View* on the information and can express their opinions on the object of discussion at hand. These elements and our dataset have been described in further detail below. The attributes of an agent's view are modeled based on those by Wang, Huang, and Sun.

- **Bias**: We define an agent's bias to be the agent's predisposition to adopt a particular view on a topic in a discussion. This bias is informed by either (1) the agent's views inherited from their parents or (2) a mean of their views on all objects of discussion under the said topic or (3) the initial bias they learn from the conversationalists when the topic was added to their knowledge base during a discussion.
- **Attitude** (att): the agent's private views on a specific issue. Attitude is a real number in the range $[-1, 1]$, and represents an evaluation of the object of discussion.
- **Opinion** (op): an agent's outwardly expressed or shared views on a specific issue. Like attitude, opinion is a real number in the range $[-1, 1]$ and reveals the agent's opinion on the object of discussion to the other dialogists. There may be a discrepancy in the attitudes and opinions of the character since a character may not represent their attitudes accurately to participants. A human example of the situation where this is apparent can be seen in examples of an employee in conversation with his managers who choose not to express his disagreement to avoid being punished.
- **Uncertainty** (unc): a measure of an agent's confidence in their view. The higher the uncertainty, the more likely the agent is to change his mind or accept other perspectives. As an example, an NPC may express opinions about the legality of abortion in their town. However, the agent may have lower confidence in their attitude if (1) information in their existing knowledge base inadequately back them, (2) if contradictory opinions are presented to the agent with high certainty, or (3) if the agent is surrounded by a society a majority of whom disagrees with him. unc is a real number in the range $[0, 1]$.
- **Public Compliance Threshold** (pub_thr): When the strength of the public opinion exceeds this value, the agent will choose to comply with the public opinion to feel accepted within the community. pub_thr has a default value of 0.6.
- **Private Acceptance Threshold** (pri_thr): When the strength of the public opinion is below this value, the agent will choose to stand by their views. The pri_thr is a real number in the range $[0, 1]$. Professors or experts on a particular topic in our simulation would have higher values to indicate their expertise.

Social Interactions and Discussions

During initial generation, the NPC population is assigned random cultural biases on topics in the knowledge base. From this stage on, children inherit as bias the mean of their parent's biases (i.e., representing "nature") while tending to agree more with one parent or the other about individual issues. However, the children may change these opinions over time (i.e., representing "nurture") over the course of several social interactions between the agents.

Discussion Method

We begin by clustering the expressed opinions of all participants of the conversation using the Jenks optimization method (Jenks 1967) and choose the grouping with the lowest square error. The number of opinion groups formed indicates whether a public consensus on the matter has developed and the presence of normative social influence (or peer pressure). The fewer the groups that form, the more likely it is that an agent who maintains their views contrary to public opinion will feel rejected.

Public Opinion Formed If the agent has high uncertainty (i.e., $agent.unc > 0.8$), they are more likely to accept the views of their fellow dialogists. We assign these agents the attitude and opinion equal to the mean of the largest group in the consensus.

If the agent has low uncertainty (i.e., $agent.unc \leq 0.8$), we find the largest clustered opinion group with views closest to that of the agent. We then calculate the public opinion strength for the selected group and decide if an agent's attitudes or opinions are affected. The public opinion strength (op_str) is calculated as described by Wang, Huang, and Sun by normalizing and finding the mean of the sum of the following factors:

- The size (f_a) of the group. The larger the group, the stronger the public opinion.

$$f_a = \begin{cases} 0, \text{if } x_a \leq 1 \\ x_a/10, \text{if } 1 < x_a \leq 10 \\ 1, \text{if } x_a > 10 \end{cases}$$

- The homogeneity (f_b) in the opinion of the group defining if the group come to a consensus

$$f_b = 1/(1 + e^{24x_b - 6})$$

- The discrepancies (f_c) in the agent's opinion and attitude.

$$f_c = 1/(1 + e^{-12x_c + 6})$$

Next, the agent measures their own uncertainty with the strength of the public opinion by calculating two threshold values, $th_1 = 1 - agent.unc$ and $th_2 = \max(0.6, th_1)$.

- Low Opinion Strength ($op\_str < th_1$): If the opinion strength is too weak, the conversationalist does not change their mind, recognizing the discrepancy between their internal attitudes and ideas and those of the group.
- Moderate Opinion Strength ($th_1 \leq op\_str < th_2$):
  - Members with a low uncertainty find the opinion strength of their group strong enough to modify their opinions to the mean of the group. Agents then find their internal attitudes, and their expressed behaviors are inconsistent, and so change their attitudes to match. In this case, agents believe that the change in their views are a natural and expected evolution, and do not realize they are bending to public opinion.
  - Agents with large uncertainty realize that they are conceding the discussion, and bending to public opinion. They change their external opinions and internal attitudes to match.
- High Opinion Strength ($op\_str \geq th_2$): The agent realizes the strength of the opinion. In this case, the agent may choose to conform to the public opinion with their outwardly expressed views and change their opinion to the mean of the group. However, they *do not* change their inner attitudes, and in the absence of external pressure will revert to their attitudes.

No Public Opinion Formed If public opinion has not formed yet, then after clustering the agent finds the cluster of opinions with the opinions most similar to that of the NPC. The NPC modifies their opinion to the mean of the cluster and their internal attitudes on the information being discussed.

Case Study: Political Ideologies

In this divisive age, it is difficult (yet unavoidable) to discuss current political events with family or friends. APIs for major media sources are available with access to news articles on various topics. As a case study, our simulation uses a corpus of news articles (AllSides 2018), grouped by their political issues. Characters are initially assigned political affiliations and biases. The rating system, in this case study, is based on that of the U.S political-ideological system. For the simulation, in the beginning, characters are subscribed to sources that confirm their political bias. For instance, a Centrist NPC may subscribe to the *Associated Press* as a news source.

News Source	AllSides Media Bias Ranking
New York Daily News	Left
New York Times	Lean Left
Associated Press	Center
Boston Herald	Lean Right
Fox News Editorial	Right

Table 2: Examples of the AllSides Media Bias Rankings obtained for NPC subscriptions to media sources

- **Rating**: We use media bias as our rating and associate with each bias a value as follows: *Left*(-1.0), *Lean Left*(-0.5), *Center*(0.0), *Lean Right*(0.5), *Right*(1.0). The bias ratings in our dataset are obtained from AllSides using a combination of blind bias surveys, editorial reviews, third-party research, independent research, and community votes to calculate media bias of the information (AllSides 2018) as can be seen in Table. 2.
- **Topics**: We use U.S. Political Issues such as Civil Rights, Immigration, Healthcare, Free Speech, Gun Control, and Abortion (AllSides 2018) each with an equal number of articles representing every bias.
- **Objects of Discussions**: Individual news articles are our objects of information. A character will note the original authorial bias of the information and associate with it their views based on their current attitude towards to the topic, their overall political affiliations, and their discussions on the article with other conversationalists.
- **Sources**: Sources are media sources that publish articles on a wide variety of issues. NPCs may subscribe or unsubscribe to these over time based on their current political inclinations. **Overall Political Affiliation**: is a weighted average of the agent's attitudes of all topics in the agent's knowledge base (ranked by an agent's priorities). For instance, a simple measure how Liberal or Conservative a person is could be expressed as a weighted average of their attitudes on the topics of gun control, abortion, homosexuality, tax reform, and so on.

Social Interactions and Discussions

We simulate a town where characters can interact with one another. Our preliminary experiment allows for two types of organizations, Schools, and Businesses, to facilitate group discussion.

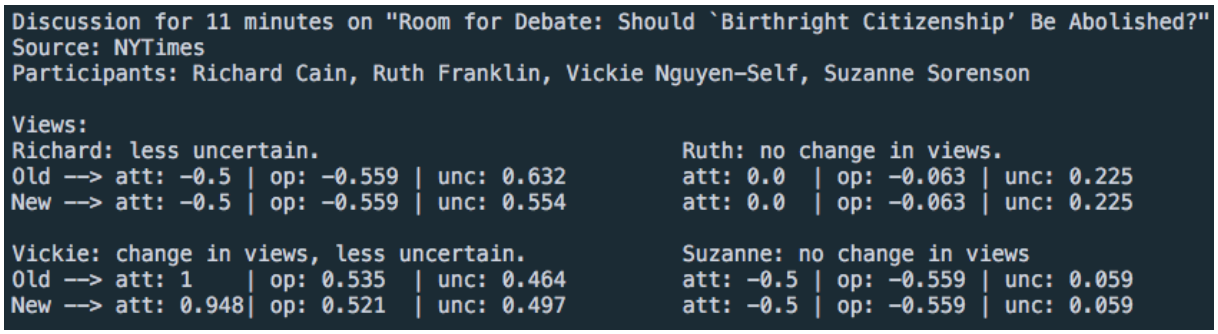

Figure 2: Sample discussion outcome involving four virtual characters on a news article from NYTimes.

Schools Schools choose a subset of topics from the world to teach their students. Professors are modeled to have a low uncertainty value regarding their views. This in combination with the fact that they are regarded as authority figures in the simulation implies that a student is more likely to adopt their views. In Fig. one can see the knowledge base of a recent graduate after he reevaluates his views on Immigration.

Businesses NPCs may apply to work at open positions in various local businesses. The application to these positions is based on the knowledge as well as the opinions an NPC acquires over time. For instance, an NPC may be required to have specific views on the topic of abortion as a qualification to work at a local hospital that matches those of their colleagues.

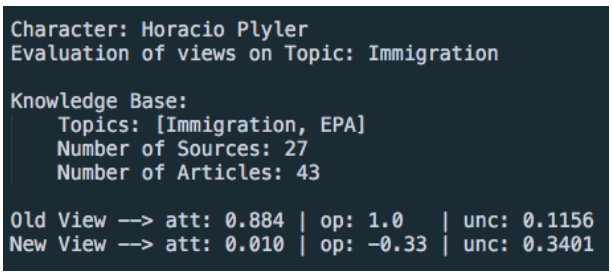

Figure 3: The political news and opinions knowledge base for a character that graduated from school

Sample Discussion Outcomes : We decode in prose a typical outcome for a discussion from our simulation as shown in Fig. 2. NPCs discuss an article titled *"Room for Debate: Should 'Birthright Citizenship' Be Abolished"* at work with colleagues. The article falls under the topic of *Immigration* and is published by the source *NY Times* with an original authorial bias calculated by AllSides as *Leaning Left*. The duration of the discussion is *11 minutes*, representing the number of times the algorithm is run, and the views of the participants are updated.

Ruth and Suzanne learn about the article for the first time. They choose to accept the outcome of the discussion as their opinion after applying any pre-existing bias on the topic of Immigration. Richard, whose political views Leaned Left ($att = -0.5$) before the discussion, is more convinced about his views after reading the article. As such his uncertainty on the subject reduces, but his views stay the same. Vickie, whose political views were aligned Right ($att = 1.0$) before the discussion changes her views slightly over the course of discussion ($att = 0.948$) and finds herself a little more uncertain about her view on the article.

However, since the internal attitudes of all four participants on the article and the topic of Immigration (not shown in Fig. 2) remain the same, their overall Political Affiliations do not change... yet.

Future Work

In the future, we hope to be able to simulate cultural or regional opinion preferences by associating opinions with locations at the beginning of the population generation. For instance, NPCs originating in Japan may have a bias for highly restrictive gun control laws. Additionally, some articles or knowledge may be regional, prompting stronger opinions among members directly associated with an issue or allowing for the modeling of an exchange of cultural knowledge. We believe that NPCs with an ability to share and exchange opinions could lead to the generation of a virtual society that has more diversity in beliefs and preferences. A greater awareness regarding the variety of opinions that exist could be extrapolated in the future causing them to revisit the certainty of their opinions on other topics of discourse; thus allowing for more realistic machine enculturation.

We aim to enable the creation of virtual communities sharing opinions that form to discuss their views. These groups could then inform classes of actions available to their members. For instance, a group of students could petition to reduce the school's carbon footprint. We hypothesize the spread of opinions and influences will enable us to study how more believable information dissemination could occur in simulated populations and narratives.

Acknowledgement

We thank Chung-Che Hsiao from NC State University for his insight towards the research of this paper. We would also like to express our gratitude to Scott J. McDonald and the AllSides team for providing us with API endpoints and bias rated media articles to use in our Political News Case Study.

References

Afonso, N., and Prada, R. 2008. Agents that relate: Improving the social believability of non-player characters in role-playing games. In *International Conference on Entertainment Computing*, 34–45. Springer.

AllSides. 2018. Balanced news via media bias ratings for an unbiased perspective.

Asch, S. E. 1955. Opinions and social pressure. *Readings about the social animal* 193:17–26.

Evans, R., and Short, E. 2014. Versua simulationist storytelling system. *IEEE Transactions on Computational Intelligence and AI in Games* 6(2):113–130.

Jenks, G. F. 1967. The data model concept in statistical mapping. *International yearbook of cartography* 7:186–190.

Jowett, L. 2014. The girls who waited? female companions and gender in doctor who. *Critical Studies in Television* 9(1):77–94.

Latour, B. 2005. *Reassembling the social: An introduction to actor-network-theory*. Oxford university press.

Mateas, M., and Stern, A. 2003. Façade: An experiment in building a fully-realized interactive drama. In *Game developers conference*, volume 2.

McCoy, J.; Treanor, M.; Samuel, B.; Mateas, M.; and Wardrip-Fruin, N. 2011a. Prom week: social physics as gameplay. In *Proceedings of the 6th International Conference on Foundations of Digital Games*, 319–321. ACM.

McCoy, J.; Treanor, M.; Samuel, B.; Wardrip-Fruin, N.; and Mateas, M. 2011b. Comme il faut: A system for authoring playable social models. In *AIIDE*.

Prendinger, H., and Ishizuka, M. 2001. Social role awareness in animated agents. In *Proceedings of the fifth international conference on Autonomous agents*, 270–277. ACM.

Pynadath, D. V., and Marsella, S. C. 2005. Psychsim: Modeling theory of mind with decision-theoretic agents. In *IJCAI*, volume 5, 1181–1186.

Riedl, M. O., and Stern, A. 2006. Believable agents and intelligent scenario direction for social and cultural leadership training. In *Proceedings of the 15th Conference on Behavior Representation in Modeling and Simulation*.

Ryan, J.; Mateas, M.; and Wardrip-Fruin, N. 2016. A simple method for evolving large character social networks. *Proc. Social Believability in Games*.

Samuel, B.; Ryan, J.; Summerville, A. J.; Mateas, M.; and Wardrip-Fruin, N. 2016. Bad news: An experiment in computationally assisted performance. In *International Conference on Interactive Digital Storytelling*, 108–120. Springer.

Swartout, W.; Hill, R.; Gratch, J.; Johnson, W. L.; Kyriakakis, C.; LaBore, C.; Lindheim, R.; Marsella, S.; Miraglia, D.; and Moore, B. 2006. Toward the holodeck: Integrating graphics, sound, character and story. Technical report, University Of Southern California Marina Del Rey CA Inst For Creative Technologies.

Vinciarelli, A.; Pantic, M.; Bourlard, H.; and Pentland, A. 2008. Social signals, their function, and automatic analysis: a survey. In *Proceedings of the 10th international conference on Multimodal interfaces*, 61–68. ACM.

Wang, S.-W.; Huang, C.-Y.; and Sun, C.-T. 2014. Modeling self-perception agents in an opinion dynamics propagation society. *Simulation* 90(3):238–248.