The AAAI 2017 Spring Symposium on
Computational Context: Why It's Important, What It Means, and Can It Be Computed?
Technical Report SS-17-03

Responsible Recommendations for Irrational People

Ciara Sibley
Naval Research Laboratory, 4555 Overlook Avenue SW, Washington, DC
Ciara.Sibley@nrl.navy.mil

Abstract

Recommender systems are omnipresent in online interactions, tailoring content to users by filtering data and identifying contextually relevant information. These personalized services are valuable in shaping the decisions and opinions of individuals, but it is unclear how these technologies may be impacting society. This paper presents a gap in this research and suggests that simulation can be a useful tool for understanding the societal consequences of recommender systems.

Introduction

Since the advent of the internet, people have had access to an unprecedented amount of information and commerce. This has fundamentally changed the way individuals purchase items, consume information (e.g., the news), communicate, forge relationships and learn, to name a few. Brick and mortar stores are beginning to seem antiquated as shopping malls shut down while technology giants like Amazon, Google, Facebook and Netflix dominate the stock market.

The limitless amount of information and choices available on the internet necessitated the development of tools for users to sift through the vast expanse of noise. Search engines and recommender systems addressed this problem by helping identify relevant websites and suggesting content, based upon users' contextual requirements. Amazon and Google profited immensely for their superiority in getting users what they want, but it is unclear how these technologies may be impacting society.

Technology has become seamlessly integrated into our daily lives. In 2015, 72% of Americans owned a smartphone (Poushter, 2016), many of whom appear to treat them as an extension of their body and cognition. Of people under 50, the preference is to obtain news online (Mitchell, Gottfried, Barthel, & Shearer, 2016). People continue to debate whether print media is dead or just dying, but it is clear that the instant gratification provided online is the new norm. While relishing in convenience, however, it is easy to overlook how much trust and control individuals cede to algorithms that ultimately shape opinions, beliefs and decisions.

What are Recommender Systems?

Some of the first recommender systems emerged in the 1990s. Since then, three approaches for predicting ratings have been widely recognized and utilized: content-based, collaborative filtering and hybrid methods (Adomavicius & Tuzhilin, 2005; Goldberg, Nichols, Oki, & Terry, 1992). User preference profiles are first constructed by gathering users' explicit and implicit evaluations of items, e.g., actual product ratings or navigation behaviors, respectively (Pu, Chen, & Hu, 2012; Resnick & Varian, 1997).

Content-based systems decompose items into features and assess similarity among items; they predict that a user will have similar opinions about similar items. Collaborative filtering systems predict a user's rating for a new item based on other users' ratings. User-based collaborative filtering recommends items that like-minded users (those who share similar rating patterns) rated highly, while item-based collaborative filtering suggests items that are similar to the other well-liked items. Hybrid systems essentially use content-based methods in concert with collaborative filtering.

Performance of recommender systems are typically evaluated by comparing predicted ratings with actual ratings, as well as considering subjective user satisfaction with recommendations, when available. Many researchers have suggested that performance can be improved by developing better user models which incorporate contextual information.

Thinking Irrationally

Social psychology explores how people are influenced by their social context and in particular how people's thoughts, feelings and behaviors are shaped by others. A large focus of this domain addresses how individuals process and make sense of conflicting influences (Aronson, Wilson, & Akert, 2007). Cognitive dissonance theory (Festinger, 1962) describes the way in which individuals change their behaviors, rationalize actions, and/or distort reality to reduce dissonance which threatens one's self-image. For example, Jones and Kohler (1958) showed how people recalled plausible arguments in support of their position on a controversial topic as well as implausible arguments opposing their position, yet failed to remember plausible arguments against or implausible arguments for their side.

Groupthink (Janis, 1972, 1982) is another psychological phenomenon whereby all facts are not equally considered and divergent thinking is generally discouraged, due to the dominant desire to maintain group cohesiveness and solidarity. This is most likely to occur when a group is highly cohesive, isolated from contrary opinions, and ruled by a leader who makes his or her viewpoint known. This kind of concurrence-seeking behavior has also been shown at the individual level, known as confirmation bias (Nickerson, 1998). Here, people tend to seek out and interpret data points as evidence endorsing a previously held supposition and discredit or discount evidence which challenges their beliefs.

While the approaches of various recommender systems differ, their overall objective remains the same – to proactively make a suggestion that will be perceived favorably by a user. If user preferences are guiding suggestions and people tend to favor homophily and confirmatory information, then could these technologies be inadvertently fractioning societies into like-minded groups (i.e., echo chambers)?

Political scientists have documented the growing polarization of the American electorate across party lines (Iyengar & Westwood, 2015), as accusations abound of media bias. Haidt and Abrams (2015) state that "liberals and conservatives dress differently, decorate their rooms differently, read different books, take different vacations and drink different alcoholic beverages". Could recommender systems be culpable for polarizing groups of people or will people always find reasons to support what they want to believe?

The Case for Simulation

Simulations provide a powerful medium to explore social phenomena and understand nonlinear systems, which is typically not possible to do using purely analytical methods (Gilbert and Troitzch, 2005). Agent-based models (ABMs) in particular are valuable for exploring social systems and human behavior. Within ABMs individual agents behave autonomously, according to a set of rules, and directly interact with and influence other agents and their environment. Furthermore, behavioral rules are typically goal-oriented and can adapt over time and to the environment.

People rarely have complete information about the environment or decision space in which they are operating. ABMs provide the ability to instantiate agents with imperfect information about their world, instead of assuming rational behavior in a perfect world (Crooks and Heppenstall, 2012). Furthermore, simulations enable exploration of different hypotheses and how individual actions impact system level behavior. There appears to be a gap in research investigating or modeling the impact recommender systems have on societies; this area is ripe for new understanding.

Should recommender systems always provide users content to which they already generally conform and subscribe? How are these systems impacting society? Could a new line of algorithms expose individuals to a diversity of ideas and products? Could these systems achieve high user satisfaction? Future work will explore an iterative process of ABM development and human-in-the-loop experimentation to investigate whether "responsible recommender systems" could possibly mitigate affective partisan polarization, or if people will simply discount contrary information and even possibly become more entrenched in their opinions.

References

Adomavicius, G., & Tuzhilin, A. (2005). Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions. *IEEE Transactions on Knowledge and Data Engineering, 17*(6), 734-749.

Aronson, E., Wilson, T. D., & Akert, R. M. (2007). *Social psychology*. Upper Saddle River, NJ [etc.]: Pearson Prentice Hall, Pearson Education International.

Crooks, A. T., & Heppenstall, A. J. (2012). Introduction to agent-based modelling *Agent-based models of geographical systems* (pp. 85-105): Springer.

Duarte, J. L., Crawford, J. T., Stern, C., Haidt, J., Jussim, L., & Tetlock, P. E. (2015). Political diversity will improve social psychological science. *Behavioral and Brain Sciences, 38*.

Festinger, L. (1962). *A theory of cognitive dissonance* (Vol. 2): Stanford university press.

Goldberg, D., Nichols, D., Oki, B. M., & Terry, D. (1992). Using collaborative filtering to weave an information tapestry. *Commun. ACM, 35*(12), 61-70.

Haidt, J., & Abrams, S. (2015). The top 10 reasons American politics are so broken. *The Washington Post*.

Iyengar, S., & Westwood, S. J. (2015). Fear and Loathing across Party Lines: New Evidence on Group Polarization. *American Journal of Political Science, 59*(3), 690-707.

Janis, I. L. (1972). Victims of groupthink: a psychological study of foreign-policy decisions and fiascoes.

Janis, I. L. (1982). *Groupthink: Psychological studies of policy decisions and fiascoes* (Vol. 349): Houghton Mifflin Boston.

Jones, E. E., & Kohler, R. (1958). The effects of plausibility on the learning of controversial statements. *The Journal of Abnormal and Social Psychology, 57*(3), 315.

Mitchell, A., Gottfried, J., Barthel, M., & Shearer, E. (2016). The Modern News Consumer: News attitudes and practices in the digital era. *Pew Research Center.*

Nickerson, R. S. (1998). Confirmation bias: A ubiquitous phenomenon in many guises. *Review of General Psychology, 2*(2), 175-220.

Poushter, J. (2016). Smartphone Ownership and Internet Usage Continues to Climb in Emerging Economies. *Pew Research Center: Global Attitudes & Trends*.

Pu, P., Chen, L., & Hu, R. (2012). Evaluating recommender systems from the user's perspective: survey of the state of the art. *User Modeling and User-Adapted Interaction, 22*(4), 317-355.

Resnick, P., & Varian, H. R. (1997). Recommender systems. *Commun. ACM, 40*(3), 56-58.