Technology-facilitated Societal Consensus

Timotheus Kampik

Department of Computing Science
Umeå University
Umeå, Sweden
tkampik@cs.umu.se

Amro Najjar

Department of Computing Science
Umeå University
Umeå, Sweden
AI-Robolab/ICR
Computer Science and Communications
University of Luxembourg
Esch-sur-Alzette, Luxembourg
najjar@cs.umu.se

ABSTRACT

The spread of radical opinions, facilitated by homophilic Internet communities (*echo chambers*), has become a threat to the stability of societies around the globe. The concept of choice architecture—the design of choice information for consumers with the goal of facilitating societally beneficial decisions—provides a promising (although not uncontroversial) general concept to address this problem. The choice architecture approach is reflected in recent proposals advocating for recommender systems that consider the societal impact of their recommendations and not only strive to optimize revenue streams. However, the precise nature of the goal state such systems should work towards remains an open question. In this paper, we suggest that this goal state can be defined by considering target opinion spread in a society on different topics of interest as a multivariate normal distribution; i.e., while there is a diversity of opinions, most people have similar opinions on most topics. We explain why this approach is promising, and list a set of cross-disciplinary research challenges that need to be solved to advance the idea.

KEYWORDS

Choice architecture, Recommender systems, Persuasion

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1 INTRODUCTION

The technology-facilitated erosion of societal consensus has been a topic of intense discussion in and beyond the academic community since the publication of Sunstein's *Republic.com* [45] and gained further attention after the events around the 2016 United States presidential election, the rise of far-right parties in Europe [1, 17], and the vote for the *Brexit* [9]. Socio-economic problems (in particular, increasing income inequality [38]) are likely facilitating these

developments. In the wake of these events, activists call for the development of (social) technology that prioritizes the wellbeing of individual users and society as a whole over monetary rewards for application designers, investors, or other potentially manipulative stakeholders [36]. In this paper, we suggest that the strength of opinions on a set of relevant topics can be modeled as a multivariate distribution and that the shape of the distribution can be used as an indicator of the health of societal opinion discourse. We propose that an interdisciplinary, data-driven approach can be used to develop information systems that employ this indicator to facilitate social consensus and rational discourse.

2 BACKGROUND

To motivate our work and ground it in the state-of-the-art, we provide an overview of emerging research on technology-facilitated social tensions, as well as of recent developments around the concept of user-centered technology.

2.1 Technology-facilitated Social Tensions

Both in popular and scientific literature, the effect of technology-facilitated social influence phenomena on society is a topic of intense interest and debate. Below, we describe and critically examine the most prominent phenomena:

Filter bubbles. According to Eli Pariser, who coined the term in popular literature, filter bubbles emerge when (social) Internet applications extrapolate data on a user's preferences, social contacts, and interests to select what content to show to this user [35]. Hence, filter bubbles create a unique universe of information for each user. It is not clear to what extent filter bubbles are *de facto* a prevalent Internet phenomenon; while empirical studies exist, they are typically limited in scope and find no [16, 30] to some [3] evidence.

Echo chambers. The term *echo chamber* refers to “a bounded, enclosed media space that has the potential to both magnify the messages delivered within it and insulate them from rebuttal” [18]. When users are in an echo chamber, their beliefs are likely to be reinforced and their positions radicalized because new information they receive is typically aligned with their pre-existing beliefs. Empirical evidence for the existence of echo chambers exists (e.g. [2]), although the strength of the phenomenon is questioned by some researchers [34].

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Information cascades. Information cascades occur when it appears optimal for an individual, having observed the actions of those acting ahead of them, to follow the others' behavior without regarding their own information [5]. Consequently, the social equilibrium may suffer a radical shift; masses of individuals converge to one action, or one ideological position, on the basis of little information. Several approaches have been proposed to model information cascades. These approaches are either grounded in opinion dynamics (e.g. [15, 20]) or game theory (e.g. [24, 31]). In the first family of models (e.g. [15, 20, 48]), the aim of agents in the network is to spread their information, whereas in the second type (e.g. [24, 31]) agents seek to maximize the payoff of their utility function. Recent studies provide evidence for information cascades on social media (e.g., Twitter) [39] and person-to-person recommender systems for online retail [25].

Fake news. Fake news can be defined as fabricated information that mimics media content in form but not in organizational processes or intent [23]. Fake news are spread by outlets lacking the *editorial norms* that were established in the first half of the 20th century to ensure accuracy and credibility of information. Despite being a technology-agnostic concept, the spread and influence of fake news witnessed a significant increase with the advent of online social networks, which have become one of the main sources of information for large parts of the population [43]. The impact of fake news conveyed on social network platforms is aggravated by two factors: (i) social: aside from reaching the user as integrated and openly available content provided through social network platforms, fake news can benefit from the network of the users' relatives and friends (i.e., a piece of fake news shared by close friends can have a stronger impact on the receiver). Furthermore, the emergence of homogeneous social networks accentuated the problems of homophilia, which increases polarization and reduces tolerance for alternative views. (ii) technical: the use of social bots [13], whose number is estimated to be in the order of tens of millions on Facebook and Twitter [47], can facilitate the spread of fake news on these social networks and allow fake news and propaganda publishers to automatize and scale their fake news production and distribution [42]. The activity of social bots intensifies during critical political campaigns, e.g., during the presidential elections in the USA [37] and France [12], and during the 2017 German federal elections [32].

One can conclude that—although the impact strength of some of the aforementioned phenomena is disputable—evidence exists for a) increased erosion of the political center in societies across the globe and b) a link between this erosion and the aforementioned social media phenomena.

2.2 Behavioral Economics and User-centered Technology

The field of behavioral economics emerged in the second half of the 20th century and revolutionized economic research and decision making by acknowledging that human agents in markets are typically not acting rationally [19]. Thaler *et al.* have built

upon behavioral economics to devise the concept of *choice architecture* [4], which describes the preparation of information in a way that helps agents of limited rationality make good decisions. In addition, Thaler *et al.* have devised the related maxim of *libertarian paternalism* [46], which advocates a benevolent, limitedly paternalistic state that allows its citizens to make decisions freely (*libertarian*) but arranges choice information in a way that facilitates decision-making in the interest of society (*paternalistic*). Recently, the initial works on choice architecture and libertarian paternalism have been criticized for primarily approaching the issue from a utopian perspective and not thoroughly addressing manipulative aspects of choice architecture [34]. Indeed, data analytics firm Cambridge Analytica, who played a major role in a social media data privacy scandal, has reportedly employed choice architecture concepts for purely manipulative purposes [50].

The issues outlined by the critics of choice architecture are reflected in socio-technical problems with personalized information technology. Such technology typically makes use of recommender systems, which suggest content or items for users based on the preferences of their friends (*collaborative filtering*), on their demographic data (e.g. age), or on previous user behavior for personalization purposes [6]. The potentially damaging social effects of recommender systems are well described in academic literature. Vulnerability against manipulation is one of the key concerns. Manipulation occurs when some users provide dishonest preferences to skew the recommendation (also called *shilling*) [21]. Further research suggests that even simple attack techniques can significantly distort the recommendations provided by common recommender algorithms [22, 29]. Recent research establishes the need to explore how recommender systems can be designed and configured to achieve positive social outcomes and to “put [...] the user in control” [21]. The aforementioned developments are well-known by industry practitioners. In particular, the *Center for Humane Technology*, founded by a number of early employees of Silicon Valley tech giants, spearheads the so-called *time well spent*-movement of industry practitioners who argue that consumer information technology is too often designed to maximize the time the user spends with an application or device and want to shift the focus back to optimizing utility for the user [36].

3 AN OPINION DISTRIBUTION HEALTH MEASURE THAT INFORMS RECOMMENDER SYSTEM BEHAVIOR

To address the problem we introduced above, we propose a model that provides a simplified perspective on the state of societal consensus (the opinion distribution among members of society/*citizens*) on a particular topic of interest as a univariate distribution. Such a topic of interest would typically be a potential or existing policy, for example the legal recognition of same-sex marriages; the opinion strength is a quantification of an individual's support or disapproval. Figure 1 shows three example consensus states on a topic:

- *Social tensions* (parabolic distribution): society is divided on the topic. Citizens tend to have an extreme opinion, which is equally likely to be on either side of the scale;

Figure 1: Distributions that indicate social tensions (red), healthy discourse (blue, dashed), and opinion dictate/stagnation (black, dotted); the vertical axis indicates opinion density, the horizontal axis opinion strength for or against a given policy.

- *Dictatorship/Stagnation* (low-variance Gaussian): although almost all citizens have approximately the same opinion, variance is not tolerated and societal evolution on the topic stalls. This can either be the case if people avoid expressing diverging opinions in fear of retaliation¹, or if societal consensus on a given topic has been reached.
- *Healthy discourse* (high-variance Gaussian): citizens tend to have similar opinions on the topics. However, there is still a diversity of opinions that allows for societal progress.

It can be expected that interdependencies between opinions on different topics exist. For example, when an event causes an individual to change their opinion on reproductive rights, it could be that the same event also affects this individual's opinion on parental benefits. Hence, it appears reasonable to model the opinion distribution of *all* (n) relevant opinions as an n -dimensional multivariate distribution. The model reflects Nietzsche's concept of moral values as "formations in the mountain of humanity" [33, p. 63] (although it takes it to new dimensions). Figure 2 presents a simplified bivariate example.

We suggest that social media and other content-serving applications can facilitate societal consensus as follows:

- (1) **Determine the opinion distribution** by mining topics of societal relevance and assessing opinion strength;
- (2) **Assess the health of the opinion distribution** based on the collected opinion strength information.
- (3) **Derive actions** from the health assessment that adjust the behavior of the recommender systems to provide recommendations that are likely to move the opinion strength distribution to a "healthy" shape.

The overall architecture can be viewed as a socio-technical multi-agent system (see, e.g. Wooldridge [49]): end-users, different applications (which need to align their behavior to prevent a tug of

¹In this case, the *stable* opinion might be extreme in comparison to other societies.

Figure 2: Simplified (bivariate) example of a multivariate target distribution: radical fringes in light red; strong, moderate center in dark blue; the vertical axis indicates opinion density, the horizontal axes indicate opinion strength, e.g. for or against reproductive rights and parental benefits, respectively.

war of opinion influencing), and a regulating body (which imposes rules the applications need to follow) can be seen as agents (see: Figure 3). The proposed approach aligns well with open research problems as identified by scientists from different disciplines. It can be considered a "system enhancer" and "information organizer" as proposed by Sen *et al.* [41], as well as an application of "smart nudges" as proposed by the psychologists and economists Smith *et al.* [44].

4 SOCIO-TECHNICAL CHALLENGES AND INTERDISCIPLINARY SOLUTIONS

In this section, we explain the three-step process introduced above (*determine opinion distribution, assess opinion distribution health, and derive actions*). Along the way, we highlight related socio-technical challenges and potential interdisciplinary solutions.

4.1 Determining the Opinion Distribution

To determine a multivariate distribution of opinion strengths on all topics of societal importance, one first needs to decide which topics are relevant (topic identification) and then assess the strengths of all available existing opinions on all given topics (sentiment analysis). For topic identification and sentiment analysis, well established tools and methods are available (see, for example: [27]). However, open research challenges exist, as the opinion strength distribution needs to be determined across a complex landscape of diverse information systems, and the positions of potentially "silent" individuals needs to be estimated. Moreover, the health indicator should consider interdependencies between opinions on different topics. For this, methods like word vector-based sentiment analysis [28] can be adjusted and applied. To mine accurate opinions and to provide effective recommendations, an approach similar to the

Figure 3: Socio-technical landscape as a multi-agent system system.

holistic recommendation concept as proposed by Cena *et al.* [7] can be employed.

4.2 Assessing the Health of the Opinion Distribution

When the opinion strength distribution has been determined, its *health*—i.e., the state of societal consensus—needs to be assessed in the best possible way. For this, a simple indicator, similar to the Gini coefficient for measuring income inequality [14] could be devised². In addition to considering the properties of a *static* snapshot of the opinion strength distribution at a specific point in time (for example: the variance), one should consider the rate of opinion change; i.e., a too fast rate of change could imply instability, whereas a lack of change over time could imply a stalemate in the competition of opinions.

A related challenge is the reinforcement of rational and trustworthy opinions. Treating all opinions equally, no matter how abstruse or well-reasoned they are, can hinder an enlightened evolution of opinions. Hence, we propose that content that facilitates rational and trustworthy opinions should be preferred over content of dubious quality. In the spirit of Leibniz, who stated that if “controversies were to arise, there would be no more need of disputation; [it would suffice to say:] let us calculate” [40, p. 170], formal argumentation (in particular: *argument mining* [26]) can be applied to assess the rationality of opinions.

4.3 Deriving Actions (Recommender System Behavior)

Based on the health assessment of the opinion strength distribution, the behavior of the applications’ recommender systems need to be adjusted, with the goal to move from the *current opinion strength distribution* to a *target distribution*; i.e., the recommender systems should present content to users that is likely to prevent opinion

radicalization or expected to facilitate opinion diversification (depending on a given user’s opinion and the current opinion strength distribution). To assess the impact of changes in recommender system behavior, social multi-agent system simulations [8] can be employed. Alternatively, one can use control-theoretical approaches as applied by other self-adaptive software like cloud computing environments [11] to implement self-adapting recommender systems. To optimize the impact of individual recommendations, techniques that consider the open-mindedness of a user when deciding on how “diverse” (i.e., how divergent from the user’s current opinion) a recommendation should be—as suggested by Eskandarian *et al.* [10]—can be employed.

5 SOCIO-ETHICAL CONCERNS

Considering the social nature of the problem at hand, the proposed approach comes with a set of socio-ethical implications. Like any application of choice architecture (c.f. [34]), our approach raises the question to what extent it is facilitating societal welfare and to what extent it is manipulating users in the interests of the system designers. An important concern is the implementation of governance and abuse prevention mechanisms that ensure the actions the system determines are in fact benefiting society as a whole and not a limited number of influential stakeholders. While the proposed concept is meant to be applied to prevent the erosion of societal consensus and to mitigate societal tensions *without* stifling discourse, a conceptually similar approach can be employed by authoritarian governments to ensure that opinions do not diverge from the regime’s doctrine. A technical solution to prevent this form of misuse appears to be out of reach. Instead, the ethical nature of the application is dependent on the organization that governs it. As outlined by Sunstein [45], incentives for implementing societally beneficial types of choice architecture can either be provided through regulation or consumer choice. In light of the complexity of the socio-technical system in focus, we regard regulation as the more realistic option. Critics of choice architecture might argue that the solution to the problem is not the implementation of recommender systems that try to improve societal consensus, but the abolishment of recommender systems in general. However, such an approach would ignore the positive impact recommender systems can have on user experience (if applied in the interest of the user), as well as the potential of recommender systems to dissolve tensions caused by unrelated phenomena.

The proposed architecture is merely a partial solution to the problem in focus; it is unlikely that the problems at hand can be solved with a technocratic approach alone. Society’s ability to engage in an enlightened, democratic discourse that informs public policy is a necessary condition for the approach to work. The proposed concept has the potential to make a society with a healthy discourse culture and working democratic institutions more resilient, but can hardly move a strongly divided or authoritarian society to a state of enlightened societal discourse.

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²A discussion of the strengths and weaknesses of the Gini coefficient is beyond the scope of this paper.

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