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Intent Mining for the Good, Bad & Ugly Use of Social Web: Concepts, Methods, and Challenges

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Abstract. The social web has empowered us to easily share information, express opinions, and engage in discussions on events around the world. While users of social media platforms often offer help and emotional support to others (the good), they also spam (the bad) and harass others as well as even manipulate others via fake news (the ugly). In order to both leverage the positive effects and mitigate the negative effects of using social media, intent mining provides a computational approach to proactively analyze social media data. This chapter introduces an intent taxonomy of social media usage with examples and describes methods and future challenges to mine the intentional uses of social media.

Keywords: Intent Mining, Help Intent, Harassing Intent, Malicious Intent, Fake News, Disinformation, Social Bots, Vitriol.

1 Introduction

The rapid adoption of social media has made the activity on online social networks (OSNs) an integral part of our daily lives. As per Pew Research Center survey[1], nearly seven in every ten people in the U.S. use some type of OSNs (as of January 2018). The trend for the adoption of OSNs is not limited to the U.S. alone but worldwide, as evident from more than 2 billion monthly active users on Facebook across the world. The large scale of such digital connectivity comes with a medium to share information rapidly and interact with others virtually anywhere and anytime. Thus, OSNs facilitate an opportune playground for the users with varied intent (the purpose for an action), from helping others during disasters [37] to harassing and hate speech conversations [31] as well as manipulation with fake news [45] and bots [16]. The good, bad, and ugly uses of OSNs have a profound impact on the evolution of our society. In fact, the gush[2] of fury and vitriol on the OSN companies in recent times for their inability to control the spread of disinformation [28] [43] [5] motivates the need to better understand the diverse uses of OSNs during real-world events.

[1] http://www.pewinternet.org/fact-sheet/social-media/
[2] https://journalistsresource.org/studies/society/internet/fake-news-conspiracy-theories-journalism-research

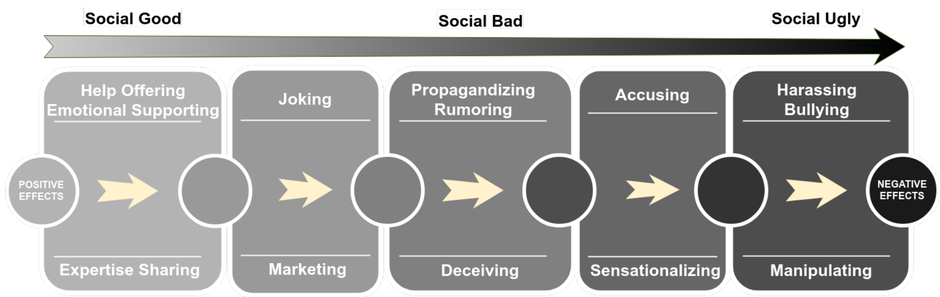

Fig. 1. A spectrum to demonstrate the variety of user intents existing on social media for the diverse uses from the social good to ugly.

We have seen many examples of the diverse usage of OSNs in the last decade, such as for coordination and self-organization during different types of social activism. For instance, #BlackLivesMatter [11] and #OccupyWallStreet [10] for justice and inequality, #Metoo [54] and #ILookLikeAnEngineer [26] for eradicating workplace harassment and stereotypes, etc. Likewise, OSNs have provided a valuable information exchange platform to support and rebuild communities after catastrophic natural disasters such as #HurricaneSandy [37] and #HaitiEarthquake [30] as well as enable community healing after man-made disasters such as mass shootings [19] and terror attacks [21]. Unfortunately, OSNs have also facilitated the amplification of malicious agenda such as to harass and bully others especially youth [34, 8], to spread disinformation for alternative narratives as well as to manipulate public opinions via fake news during elections [2, 45].

One approach to understanding the nature and motives of information sharing on OSNs is to analyze the potential intent types (c.f. Figure 1) associated with the OSN user interactions. Recognizing user intent helps collect evidences for interpreting and predicting potential actions and consequences – analogous to the problem of plan recognition in Artificial Intelligence [47]. We can model intent based on the content of the message shared, activity logs of the user sharing the message, and the link structure in OSNs that support the information flow of the message. Given the volume, variety, and velocity of information flowing on OSNs, computational approaches of intent mining provide a promising direction to help study the varied types of intent at large-scale.

Rest of the chapter provides an extensive overview of concepts, methods, and challenges in mining intent. In particular, section 2 describes related concepts for a taxonomy of intent types, section 3 provides an overview of different methods to process content, user, and network structure data for modeling intent, where the data may exist in different modalities – text, images, and videos. Finally, section 4 describes the challenges in mining intent for future research directions to lead the society towards the good use of OSNs.

2 Concepts

This section describes first the concept of intent from multidisciplinary perspective, followed by describing the taxonomy of intent types for the diverse uses of OSNs, on a spectrum of positive to negative effects as shown in Figure 1.

2.1 Intent: multidisciplinary perspective

Intent in the simplest form can be defined as a purpose for an action. In a more in-depth form, one can understand the broader view of intent from the concept of ‘intentional stance’ proposed by the well-known philosopher and cognitive scientist Daniel Dennett [13]. Intentional stance is the highest abstract level of strategies for predicting and thereby, explaining and understanding the behavior of an entity (e.g., OSN user). Likewise, in Artificial Intelligence research community, the intent recognition problem has been studied for understanding the behavior of agents in the context of goal and plan recognition [47]. The power to recognize the plans and goals of other agents enables effective reasoning about the actions of the agents. In our context of the different uses of OSNs, a user can express desires and beliefs for certain intentionality in either message content or through his interactions and activities on OSNs. Therefore, a variety of factors can affect an individual’s expression of intentionality through different information modalities. For example, “I wanna give #blood today to help the victims #sandy” shows the intent to donate blood for the desire to help and for the belief of resource scarcity to treat victims in the aftermath of hurricane Sandy [37]. Intent can be expressed both explicitly and implicitly in a given content. Table 1 shows examples of messages with different intent types.

2.2 Intent Taxonomy

Given the diverse uses of OSNs and the endless possibilities of actions, the variety of intent behind the actions would be vast. Therefore, an approach to better understand the diverse uses and organize the associated intent for actions, we can consider a spectrum representation for the OSN uses with positive to negative effects. We also create a taxonomy of intent types as shown in the Figure 1. On the left side of the spectrum, social good uses of OSNs lead to the positive, enlightening effects of inspiration, cooperation, and trust in our society and strengthen the value of social networking in our lives. On the other hand, as we move towards the right end, social bad and ugly uses start to lead the negative effects of creating distrust, radicalization, and fear in our society. The social bad and ugly uses discredit and ruin the social networking values in our lives.

The proposed spectrum of Figure 1 is flexible to extend the OSN uses as well as the intent taxonomy with different interpretations in the future. We broadly define five types of intent: (a.) intent for the social good use, (b.) intent for the social bad use, (c.) intent for the social ugly use, (d.) intent for the mixed social good and bad uses, and (e.) intent for the mixed social bad and ugly uses.

Table 1. Modified examples (for anonymity) of OSN messages from past events, with intent expressed in the textual content. Intent can also be expressed using other information modalities (image, audio, or video); Figure 2 shows an image example.

Social Media Message	**Intent** [Implication]
M1. *I want to send some clothes for hurricane relief #sandy*	Offering Help [community rebuilding and trust for collective action]
M2. *I support what u said about shooting here in Florida, Ill stand with u at any time. I am a retired teacher*	Emotional Supporting [community healing for psychological support]
M3. *You can find the @user student Developer Pack here: URL*	Expertise Sharing [improving learning from experiences of peers and mentors]
M4. *it's better to start 3rd-world war instead of letting Russia & assad commit #HolocaustAleppo*	Propagandizing [group-specific beliefs leading to echo chambers]
M5. *hi @user, we sincerely apologize for your inconvenience, in order to regain access to your account, please visit: URL*	Deceiving [financial frauds and stealth of personal information]
M6. *One of the suspects (according to BPD) is Sunil Tripathi. The missing Brown student NEWS reported on in March URL*	Rumoring [creating uncertainty in situational awareness for poor decision support]
M7. *youre a despicable whore*	Harassing [affecting mental health and physical well-being]
M8. *We are a people whose true lives begin after their death. #hijrah #jihad #shahadah*	Manipulating [shifting public attitude towards radicalized outfits]
M9. *DONT EVEN ASK EM WHO DEY WIT JUS BLOW EM FACES*	Bullying [threatening and creating fear and insecurity in the society]
M10. *theres a new drink called Sandy, it is a watered down Manhatten*	Joking [creating junk for some sections of the community]
M11. *No luck needed to #SAVE up to 60% off! Visit URL details of #vacation package*	Marketing [spamming in the information ecosystem]
M12. *white women have lied about rape against black men for generations*	Accusing [giving an alternative, supporting narrative to stereotypical groups]
M13. *Theres no New Clinton, never has been. Shes same rape defending, racist, homophobic liar shes been for 70 yrs*	Sensationalizing [diverting from key issues and politicizing environment]

The proposed intent types are described in the following with real examples of OSN messages in Table 1.

(a) *Intent for the Social Good Use*
People have good intentions and attitudes who believe in the social welfare and who would come forward to help others in the times of needs. OSNs facilitate a medium for such users to not only assist during disasters to provide emotional support and donations, but also in general, offer help with the expertise to educate, inform, and caution-advice others. Illustrative intents in this category are:
   - **Help Offering:** to express assistance to people in need of a resource or service. For example, message M1 in Table 1 shows a user offering clothing donations for disaster relief during Hurricane Sandy [37]. Likewise, users also offer to help with resources often, like blood donation. [39]
   - **Emotional Supporting:** to express care and sympathy for someone affected by an event. For example, message M2 in Table 1 shows support for the affected community of a mass shooting event. OSNs have played such roles in supporting a community for psychological well-being and caring of the affected people from depression and trauma [19].
   - **Expertise Sharing:** to suggest or give advice to an information seeker based on expertise. For example, message M3 in Table 1 shows the answer to a user with a query to seek resources. OSNs provide hashtag and reply based affordances for conversation chains, to allow expertise and knowledge sharing.

(b) *Intent for the Social Bad Use*
OSN users are not just humans but also social bots, who often participate for different motives in the conversations on social media. Both these types of users have contributed to create propaganda and spread the spamming content extensively in the recent years. Illustrative intents in this category are:
   - **Propagandizing:** to create certain perception or belief towards an agenda of an organization or a group. For example, message M4 in Table 1 shows a strong justification for the government policies and attempts to convince the audience to believe in them. [27]
   - **Deceiving:** to spread spam or malicious content for a financial fraud or the purposeful misleading. For example, message M5 in Table 1 shows a clickbait and a potential scam for attracting readers to malicious sites related to buying some products and then stealing personal and financial information. [25]
   - **Rumoring:** to share unverified information aligned with emotions of someone that creates uncertainty. For example, message M6 in Table 1 shows a rumor indicating an emotionally charged message during Boston bombing and drawing everyone's attention to a misguided fact. [46]

(c) *Intent for the Social Ugly Use*
Unfortunately, OSNs have become an avenue for conspiracy theories in recent years, where fake user accounts incite social tensions and radicalize others. Further, OSNs provides a medium to easily connect and converse with anyone that is abused (especially among youth) to engage in the online harassment and bullying, with the strong mental health implications. Illustrative intents in this category are:
   - **Harassing:** to cause emotional distress to someone by insults, misogyny or hateful messages and trolling for publicly shaming someone. For example, message M7 in Table 1 shows a sender harassing a receiver, which can lead to both mental and physical harm to the receiver. [14]
   - **Manipulating:** to purposefully divert a discourse to radicalize as well as politically or socially divide people. For example, message M8 in Table 1 shows how a potential member of a terror group can influence others and boost their recruitment drives. [17]
   - **Bullying:** to threaten or intimidate for creating a fear among a recipient. For example, message M9 in Table 1 shows a message of a gang member involved in illegal activities who threatens the rival gang, creating a fear in the social environment of the local region. [3]

(d) *Intent for the Mixed Social Good and Bad Uses*
OSN users come from all sections of our society and their participation motives can range from personal to commercial usage. In this case, not all members of the society would benefit from all the activities of such users (e.g., a repetitive irrelevant advertisement) and therefore, the OSN use can be considered as mixed. Illustrative intents in this category are:
   - **Joking:** to ridicule for fun or make a mockery of some event, object or person. For example, message M10 in Table 1 shows a user making fun of hurricane Sandy that may be amusing to some but contributes to the information overload on others, such as emergency services who would be working hard to monitor OSN streams for situational awareness. [37]
   - **Marketing:** to promote and advertise a product or service for selling. For example, message M11 in Table 1 shows a brand user creating a marketing pitch to attract more buyers that may be useful to some users who are looking to buy a travel package but a spam for those who are not traveling. [12]

(e) *Intent for the Mixed Social Bad and Ugly Uses*
Users on OSN platforms may hold specific beliefs and may be associated with specific ideological identities such as political, religious, and social activist groups. Thus, their propaganda activities on OSNs can be motivated to meet the purpose of those belief and ideologies, however giving rise to echo chambers, which are the drivers of conspiracies. Illustrative intents in this category are:
   - **Accusing:** to accuse someone and doubt publicly for creating an alternative reality. For example, message M12 in Table 1 shows a user trying

to develop a narrative by accusing a female rape victim publicly and thus, trying to undermine the key social issue of rape myths. [4, 36]

– **Sensationalizing:** to provoke the audience to divert to an issue for frightening and politicizing the environment. For example, message M13 in Table 1 shows how a social issue can be mixed with a political context and divert the focus in a conversation away from the social issue (i.e., against rape.) [40]

Fig. 2. Fake image shared during hurricane sandy 2012 [3]

3 Methods

This section presents different types of methods to mine intent types described in the previous section.

Early research in online intent mining was focused on search engines, question-answering and product review forums, ad recommendation systems as well as spam detectors in information networks. For search systems, the key challenge was to understand information seeking intent of users in the queries on search engines using logs and give the relevant results to the users. Although, user query intent covers only a few categories of the broad variety of intents possible for uses of OSNs. In particular, query intent can be navigational, informational or transactional information to meet a user's information requirement [23], but the intent types in a social environment relate to communication and engagement with others in a conversation for different purposes, such as offering help or manipulating others. For question-answering and product forums, the possible intent types are centered around information seeking and knowledge sharing. For the ad recommendation systems, the commercial intent of buying and selling are

[3] `https://mashable.com/2012/10/29/fake-hurricane-sandy-photos/\#Wc2mpf4QXgqV`

priorities. For spam detection in networks, researchers focus on modeling patterns of malicious behavior but there are other types of intent possible for OSNs. Additionally, researchers have investigated intent across different modalities of information than the textual content, such as fake images [20] for rumors (see fig. 2). Literature shows intent modeling in OSNs based on content of a message, user profile activities over time, and the network of user interactions as well as structural links of friendship and trust. We describe the methods under three major categories of content-based, user-based, and network-based approaches.

3.1 Content-based Intent Mining

This type of methods solve the problem of inferring intent from a given instance of a message content shared on an OSN. Inferring intent from content is challenging due to possibilities of multiple natural language interpretations in a given text message. Therefore, to make the intent mining problem computationally tractable, prior research primarily exploited the text classification problem format [38]. Although it is different from the well-studied text analytics tasks of topic classification (focused on the subject matter) as well as opinionated text classification of sentiment or emotion (focused on the current state of affairs). For instance, in a message "people in #yeg feeling helpless about #yycflood and wanting to help, go donate blood", the task of topic classification focuses on the medical resource 'blood', the task of sentiment and emotion classification is focused on the negative feeling expressed for being helpless. In contrast, intent classification concerns the author's intended future action, i.e. 'wanting to help/donate'. Therefore, the choice of feature representation is different across the tasks (e.g., adjectives are considered important for capturing sentiment and emotion and likewise, verbs are important for indicating intent or action.) Given the complexity to understand intent from natural language, researchers have explored various classifier designs using both rule-based systems and machine learning techniques.

Rule-based approaches are appropriate for small-scale data while for the large-scale data with intent labels, machine learning approaches can be leveraged. We summarize few approaches from the literature for brevity. Among rule-based classification approaches, Ramanand et al. [41] created rules for transactional (buying-selling) wishes in the product review text (e.g., '$<$*modal verb* $><$*auxiliary verb* $>\{$*window of size 3*$\}$ $<$*positive opinion word*$>$') and Purohit et al. [39] created rules for help seeking and offering behavior during disasters (e.g., '*(Pronoun except you = yes)* $\wedge$ *(need/want = yes)* $\wedge$ *(Adjective = yes/no)* $\wedge$ *(Thing = yes)*' for seeking help about a 'Thing' such as food). Among machine learning approaches, we can develop a classifier for detecting credible information messages to undermine potential rumor intent, such as Castillo et al. [7] proposed a classification method using the diverse features from message content, posting and re-tweeting behavior of users, and from citations to external sources. The key challenge of classification methods is to design good features that can efficiently capture the intent representation. Hollerit et al. [22] created a binary classifier for buying-selling posts on Twitter by exploring n-grams and POS tags based features and Carlos & Yalamanchi [6] proposed a supervised learning classifier for commercial intent based on features grounded in speech act theory. Purohit et al. [37] [38] proposed pattern-aided supervised classification approaches to identify the intent of help-seeking or offering during disasters, by combining the features from a bag-of-tokens model with patterns extracted from a variety of declarative and psycholinguistic knowledge sources. Likewise, Nazer et al. [33] proposed a system for identifying help-seeking request intent during disasters by combining content-based and context-based features such as the device type of a message source, location, etc. While creating an exhaustive set of user-defined features from the user-generated content of social media can be challenging, researchers also explored deriving some valuable data-driven features for better generalization. Wang et al. [50] proposed a semi-supervised learning approach using the link prediction task in a graph of the tweet and intent-specific keyword nodes, in order to categorize intent tweets into different categories of general interests such as food & drink, travel, and goods & services. Given the possible lack of sufficient labeled data in an application domain, one can also use the transfer learning paradigm. Among such approaches, Chen et al. [9] built a combined classifier based on two classifiers trained on different source and target domains, in order to identify cross-domain intentional posts of commercial value (buying/selling) in discussion forums. Likewise, Ding et al. [15] proposed a convolutional neural network based method for identifying user consumption intent for product recommendations, by transferring the mid-level sentence representation learned from one domain to another by adding an adaptation layer. Pedrood & Purohit [35] proposed sparse coding-based feature representation for efficient transfer learning to detect intent of help-seeking or offering in the future disaster event by exploiting data of historic disaster events.

3.2 User Profile-based Intent Mining

This type of methods solve the problem of inferring the intent of a user by exploiting the patterns of activities or messages of the user in his historic profile data. It is similar to the idea of personalized recommender systems, which exploit all the historical data of a user to create his interest profile. The primary focus of these types of methods for OSNs is to model malicious user behavior such as spamming behavior to identify spammer networks or specific orientation towards some beliefs. We explain a few approaches for brevity. The majority of such methods for learning and modeling the user behavior from historic data rely on machine learning techniques given the possibility to leverage large-scale historic data.

Intent mining literature has different methods from supervised to unsupervised learning for modeling user behavior, by leveraging features of all modalities such as text and images as well as temporal patterns of user activities. For instance, Jin et al. [25] created a detection system for users with malicious intent (spamming) by using both image and textual content features from the historic user profiles as well as the social network features. Lee et al. [29] created a supervised classifier to identify malicious content polluters using a diverse set of features from historic profile data including demographics, social network structure, the content of messages as well as temporal behavior patterns in the activity. Among unsupervised learning approaches, Mukherjee et al. [32] proposed a method to exploit observed behavioral footprints of fake reviewers using a Bayesian framework. Furthermore, Ferrara et al. [16] reviews different methods for social bot detection using both feature-based as well as graph-based and crowdsourcing-based approaches.

Beyond the bot users, human users are also involved in the social bad and ugly uses of OSNs, such as with the intents of bullying and threatening others. Squicciarini et al. [44] proposed an approach to study both the detection of cyberbullies and the identification of the pairwise interactions between OSN users, who contributed in spreading the bullying intent. Salawu et al. [42] provides an extensive survey of the state of the art cyberbullying detection approaches. Likewise, Balasuriya et al. [3] studied the problem of detecting gang member profiles on Twitter that often share messages with the threatening intent, by proposing a method of supervised classification with diverse features of tweet text, profile information, usage pattern of emoji symbols as well as additional information from the descriptions and comments on the external links of YouTube videos. On the other side of the OSN use spectrum, we can also model the user behavior in general for understanding the intent of non-malicious kind. For instance, Tomlinson et al. [48] proposed a method to detect a user's long-term intent and analyzing differences across cultures in expressing intent. Authors captured the latent cultural dimensions via the Singular Vector Decomposition technique. Such methods can be valuable for large-scale studies to assist multidisciplinary research at the intersection of social, humanities, and computing sciences.

3.3 Network-based Intent Mining

Methods in this category focus on inferring the intent of a user by exploiting a given network structure of social relationships of the user in an OSN. The patterns of network structure can inform the membership to spam communities as well as information propagation cascades with the distinctive signatures of fake or rumor spreading intent. The network-based approaches have an advantage of being language independent of the content, although they have to deal with a challenge of acquiring the network structure for any data modeling. Social network analysis methods are valuable for extracting the structural patterns. We summarize some of these approaches next.

The malicious users whether social bots or spammers or even radicalized group users often form community structures in the network, for sharing content and giving others a deceiving perception of general users. For instance, Ghosh et al. [18] investigated Twitter network for link farming – an approach to acquire a large number of follower links – by studying nearly 40 thousand spammer accounts suspended by Twitter. Their analysis showed that the link farming is very common, where a majority of the links are acquired from a small fraction of Twitter users that are themselves seeking links. Likewise, a study conducted by Al-khateeb et al. [1] discovered cyber propaganda campaigns against NATOs Trident Juncture Exercise 2015 using social network analysis. There are also approaches for combining both features of network structure and content or user interaction patterns. Yu et al. [53] proposed a subgroup detection method to identify deceptive groups from their conversations, by combining linguistic signals in the content of interactions and signed network analysis for dynamic clustering. Among the approaches to model information propagation for identifying the intent of users, Starbird [45] studied the network generated from the common URL domains in the potentially malicious user messages on Twiter, which contained alternative narratives about mass shooting events and discovered the patterns of different domains and how they connect to each other. A model proposed by Wu & Liu [52] for the propagation of messages in OSNs infers embeddings of users with network structures as well as represents and classifies propagation pathways of a malicious intent message. Jiang et al. [24] provide an extensive survey of the approaches for malicious intent behavior detection across the categories of traditional spam, fake reviews, social spam, and link farming.

On the other side of the spectrum in Figure 1 for positively using OSNs also, researchers have designed network-based approaches to glean intent of social good to help others. Welser et al. [51] identified key roles of Wikipedia editors such as substantive experts and vandal fighters by extracting patterns from edit histories as well as egocentric networks of users. Likewise, Tyshchuk et al. [49] presented a methodology that combined natural language processing and social network analysis to construct a network of actionable messages, for discovering communities and extracting leaders with a social good intent to help.

In summary, the approaches described above provides an overview of how one can study a variety of intent types in OSN uses by leveraging the message content, user profile history, and the social network structure.

4 Challenges and Future Research Directions

The use of OSNs in the future is going to be dependent on how OSN providers address the concerns of intent related to the social bad and ugly uses, which have given the perception that social networks are broken[4]. It is an open question – how we can create OSN platform affordances that would help manage both accountability of user activities and verification for trusted user networks, while discouraging the actors with social bad intents[5]. Similarly, it will be very important to boost the OSN uses with social good intents, such that we can still

[4] `https://www.technologyreview.com/s/610152/social-networks-are-broken-this-man-wants-to-fix-them`
[5] `https://datasociety.net/output/dead-reckoning/`

preserve some level of trust for OSN uses in the society. We describe some of these challenges in the following that future researchers can build on:

- **Profiling anonymous identities.** The cases for bullying and harassing intents often include harassers with anonymous profiles. The impact of such virtual anonymity leads to a lack of accountability and trust, due to the abuse of the medium of information sharing on OSNs. The anonymous users can spread information with malicious agenda but still remain unaccountable for the consequential effects. We need to address the challenge of understanding content and interaction patterns of such anonymous profiles for designing efficient user profiling methods.
- **Transforming social bots.** It is not clear how many users of OSNs are actually human users versus social bots, some of those present a threat to the information ecosystem of our society. While existing methods of bot detection provide some capability at scale to detect the bots, it is not clear beyond suspending them if we could alternatively transform the behavior of these bots. For example, teaching the intent behavior of social good as opposed to social bad (e.g., as observed in 2016, for the Microsoft chatbot[6]) could present an interesting opportunity to the human-in-the-loop Artificial Intelligence research.
- **Fixing erroneous spreading of malicious intent.** Sometimes the OSN users rapidly spread unverified, fake information due to emotional provocation such as after looking at an image of a disaster-affected site, although without a malicious goal. In this case, even if the user would like to change his course of action, the current OSN affordances only allow deletion of content for that individual user but the effect on the network is not handled effectively. Future research can also investigate this challenge of how to fix the issue of controlling message propagation.
- **Hybrid information filtering.** OSNs have been criticized lately to control what information a user can see, based on their content filtering and ranking algorithms. It leads to the formation of echo chambers with negative consequences. There is a need for fairness and diversity in representation of information shown to a user such that the resulting content covers the varied intents of a story. It should further de-prioritize strongly subjective content and also, provide an opportunity to the user to change the prioritization.

To conclude, this chapter presented a detailed overview of different uses of OSNs on the spectrum of social good to social ugly and also introduced an intent taxonomy. It further described intent mining methods and future challenges, which can help discover the varied types of intent behind the uses of OSNs.

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[6] `http://www.bbc.com/news/technology-35890188`

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