Nipping in the Bud: Detection, Diffusion and Mitigation of Hate Speech on Social Media

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Since the proliferation of social media usage, hate speech has become a major crisis. Hateful content can spread quickly and create an environment of distress and hostility. Further, what can be considered hateful is contextual and varies with time. While online hate speech reduces the ability of already marginalised groups to participate in discussion freely, offline hate speech leads to hate crimes and violence against individuals and communities. The multifaceted nature of hate speech and its real-world impact have already piqued the interest of the data mining and machine learning communities. Despite our best efforts, hate speech remains an evasive issue for researchers and practitioners alike. This article presents methodological challenges that hinder building automated hate mitigation systems. These challenges inspired our work in the broader area of combating hateful content on the web. We discuss a series of our proposed solutions to limit the spread of hate speech on social media.

1. INTRODUCTION

Digital platforms are now becoming the de-facto mode of communication. Owing to diverse cultural, political, and social norms being followed by the users worldwide, it is extremely challenging to set up a universally accepted cyber norms\textsuperscript{1}. Compounding this complexity with the issue of online anonymity [Suler 2004], the cases of predatory and malicious behaviour have increased with Internet penetration. Users may (un)intentionally spread harm to other users via spam, fake reviews, offensive, abusive posts, hate speech and so on. This article mainly focuses on hate speech on social media platforms.

United Nations Strategy and Plan of Action defined hate speech as "any kind of communication in speech, writing or behaviour, that attacks or uses pejorative or discriminatory language with reference to a person or a group on the basis of who they are, in other words, based on their religion, ethnicity, nationality, race, colour, descent, gender or other identity factor."\textsuperscript{2} Across interactions, what can be considered hateful varies with geography, time, and social norms. However, the underlying intent to cause harm and bring down an already vulnerable group/person by attacking a personal attribute can be considered a standard point for defining hate speech. It leads to a lack of trust in digital systems and reduces the democratic nature of the Internet for everyone to interact freely [Stevens et al.

\textsuperscript{1}https://bit.ly/3mwbzQq
\textsuperscript{2}https://bit.ly/32psoWv
Fig. 1. A framework for analysing and mitigating hate speech consists of the following: (a) Input signals made of ‘endogenous signals’ (obtained from textual, multi-modal and topological attributes within the platform) and ‘exogenous signals’ obtained from real-world events. (b) The input signals are curated to develop models for detecting hateful content and its spread; once detected, we can have a method to counter/mitigate hateful content. Since online platforms also involve large-scale interactions of users and topics, we require a framework for visualising the same. Once trained, these models can be deployed with feedback incorporating debasing and life-long learning frameworks. (c) Users, content moderators, organisations, and other stakeholders are at the receiving end of the framework. Their feedback and interactions directly impact the deployed systems.

2. EXISTING CHALLENGES

The area of hate speech poses multiple challenges [MacAvaney et al. 2019] for researchers, practitioners and lawmakers alike. These challenges make it difficult to implement policies at scale. This section briefly discusses some of these issues that inspire our body of work.

(1) **C1: What is considered as hateful?** Different social media platforms have different guidelines to manage what communication is deemed acceptable on the platform. Due to the lack of a sacrosanct definition of hate speech, researchers and practitioners often use hate speech as an umbrella term to capture anti-social behaviours like toxicity, offence, abuse, provocation, etc. It makes determining the malicious intent of an online user challenging. A blanket ban on users for a single post is, therefore, not a viable
(2) **C2: Context and subjectivity of language:** Human language is constantly evolving, reflecting the zeitgeist of that era. Most existing hate speech detection models fail to capture this evolution depending on a manually curated hate lexicon. On the other hand, offenders constantly find new ways to evade detection [Gröndahl et al. 2018]. Apart from the outdated hate-lexicons lies the problem of context (information about the individual’s propensity for hate and the current worldview). Determining isolated incidents of hate speech is difficult even for a human with world knowledge.

(3) **C3: Multifaceted nature of communication on the Internet:** Online communication exists in varying forms of text, emoji, images, videos or a combination of them. These different modalities provide varying cues about the message. In this article, we talk specifically about memes as a source of harmful content [Kiela et al. 2020; Oriol et al. 2019]. Memes are inherently complex multi-modal graphics, accommodating multiple subtle references in a single image. It is difficult for machines to capture these real-life contexts holistically.

(4) **C4: Lack of standardised large-scale datasets for hate speech:** A random crawling of online content from social media platforms is always skewed towards non-hate [Davidson et al. 2017; Founta et al. 2018]. Due to the content-sharing policies of social media platforms, researchers cannot directly share text and usually release a set of post ids for reproducibility. By the time these ids are crawled again, the platform moderators have taken down explicit hate speech, and the respective user accounts may be suspended. Additionally, due to changes in the context of hate speech, text once annotated as hate may need to be rechecked and reannotated, leading to a lack of standardised ground-truth for hate speech [Kovács et al. 2021].

(5) **C5: Multilingual nature of hate speech:** All the challenges discussed above compound for the non-English system. Natural language processing models consume text as data and determine usage patterns of words and phrases. It is hard to develop statistically sound systems for low-resource and code-mixed content without training on large-scale data [Ranasinghe and Zampieri 2021]. Take, for example, the case of collecting and annotating datasets under code-mixed settings. It is hard to train systems to detect which word is being spoken in which language. Consider, for example, a word spelt out as “main”, which means “primary” in English, and in “I, myself” in Hindi. Depending on the language of the current word, the meaning conveyed by a code-mixed sentence can change.

3. **RESEARCH QUESTIONS AND PROPOSED SOLUTIONS**

3.1 **RQ1 –** Following the challenges C2 and C4, can we predict the spread of hate on Twitter?

**Background.** For the experiments discussed in this section, we use textual and topological content extracted from the Twitter platform. A tweet is the smallest unit of communication in Twitter. A user can include text, images, URLs, hashtags in the tweet. Once posted, other users who follow the said users can observe the new tweet on their timeline. Upon exposure, a user can retweet, with or without appending anything to it or comment to start a thread. Each tweet is associated with a unique tweet id, each user with its unique user id.
Using a combination of a tweet and user ids, we can use the Twitter APIs to crawl tweets and followers of a user holding a public account.

3.1.1 RQ1.1 – Predicting retweeting activity of hateful users. Conversations on any online platform reflect events happening in the real-world (exogenous signals) and vice-versa. Capturing these signals can help us better understand which users are likely to participate in which conversation. In our work [Masud et al. 2021], we explore the theme of topic-dependent models for analysing and predicting the spread of hate. We crawled a large-scale dataset of tweets, retweets, user activity history, and follower networks, comprising more than 41 million unique users. We also crawled 300k news articles. It was observed that hateful tweets spread quickly during the initial hours of their posting, i.e., users who engage in malicious content intend to propagate their hurtful messages as far and wide as quickly possible. These observations are in line with hateful behaviour on other platforms like Gab [Mathew et al. 2019]. Additionally, it was observed that users’ propensity to engage in seeming hateful hashtags varies across different socio-political topics. Based on these observations, we proposed a model which, given a tweet and its hate markers (ratio of hateful tweets and hateful retweets on the user’s timeline), along with a set of topical and exogenous signals (news title in this case), predicts which followers of the said user are likely to retweet hateful posts. The motive behind using exogenous signals is to incorporate the influence of external events on a user’s posting behaviour [Dutta et al. 2020]. Interestingly, we observed that existing information diffusion models that do not consider capturing any historical context of a user or incorporate exogenous signals perform comparably on non-hateful cascades but fail to capture diffusion patterns of hateful users. It happens because the dataset is skewed towards non-hateful cascades. In the absence of latent signals, only topological features are not enough to determine the spread of hate.

3.1.2 RQ1.2 – Predicting hatefulness of Twitter reply threads. In another set of work [Dahiya et al. 2021], we define the problem of forecasting hateful replies – the aim is to anticipate the hate intensity of incoming replies, given the source tweet and a few of its initial replies. The hate intensity score constitutes a prediction probability of a hate speech classifier and the mapping of words from hate-lexicon, which had a score manually curated for each hate word. Over a dataset of 1.5k Twitter threads, we observed that the hatefulness of the source tweet does not correlate with the hatefulness of the replies eventually received. Hate detection models on individual tweets could not predict the inflexion going from benign to hateful. By modelling the thread as a series of discrete-time hate intensities over a moving window, we proposed a “blind state deep model” that predicts the hate intensity for the next window of the reply thread. Here blind means one does not need to specify the underlying function, and the deep state captures the non-linearity. Our experimental results found that the proposed model is more robust than baselines when controlled for the underlying hate speech classifier model, the length of the reply thread and the type of source tweet considered (fake, controversial, regular, etc.). This robustness is expected from a model deployed for environments as dynamic and volatile as the social media platforms.

3https://hatebase.org/
3.2 RQ2 – Following challenges C3, can harmful memes be a precursor for conveying hate?

**Background.** With the proliferation of memes, they are now being used to convey harmful sentiments. Owing to their subtle messaging, they easily bypass automatic content flagging. Offensive memes that target individuals or organisations based on personal attributes like race, colour, and gender are deemed hateful. On the other hand, harmful memes are a rather border category. These memes can be offensive [Suryawanshi et al. 2020], hateful, abusive or even bullying⁴ in nature. Additionally, harm can be intended in multiple ways like – loss of credibility of the target entity or disturbing mental peace and self-confidence of the target entities. In the next set of works, we propose some benchmark datasets and models to detect the harmfulness of online memes as well as their targeted entities.

3.2.1 **RQ2.1 – Harmful meme benchmark dataset.** To narrow down the scope of harmful memes, we begin by selecting the topic of COVID-19. The variety of content covered by this topic and its social relevance in the current times make it an apt choice for our work [Pramanick et al. 2021]. From Google Image Search and public pages of Instagram and Reddit, we curated a dataset of 3.5k memes. This dataset is named as HarMeme. In the first step of the annotation, we labelled the memes as ‘very harmful’, ‘partially harmful’ or ‘harmless’. In the second step, we additionally annotated the harmed target entity as either an ‘individual’ (e.g., Barack Obama), ‘organisation’ (e.g., WHO), ‘community’ (e.g., Asian-American), or ‘society’ at large. On this dataset, we evaluated various baselines under uni-modal and multi-modal settings. Even our best performing method, a multi-modal architecture with an accuracy of 81.36%, failed to reach the human benchmark of 90.68%. This benchmark was annotated by a group of expert annotators (separate from those who participated in crowd annotation). For our second problem of detecting the target of harm, we again found that the best performing multi-modal framework falls short of the human benchmark (75.5% vs 86.01% accuracy). These differences in accuracy highlight the non-trivial nature of the harmful meme detection task.

3.2.2 **RQ2.2 – Detecting harmful memes under multi-modal setting.** In a subsequent work [Pramanick et al. 2021], we extended the above HarMeme dataset to include US Politics as a topic as well. Following the same annotation process, we ended up with two harmful meme datasets, called Harm-C and Harm-P, covering the Covid-19 and US-politics, respectively. We then proposed a multi-modal framework that encodes image and text features along with image attributes (background, foreground, image attributes) obtained from the Google Vision API. These features are fused via inter and cross-modal attention mechanisms and trained under a multi-task setting. Compared to the best performing multi-modal baseline, our proposed model improved ≈ 1.5% accuracy in both tasks. However, the gap between the human benchmark (as described in Section 3.2.1) and the proposed method is still significant. It begs the question of adding more signals to capture context. Additionally, we performed ablation of domain transfer where we trained on one set of harm memes and tested on others. The proposed model incorporating pretrained encoding from CLIP [Radford et al. 2021] showed improved transferability compared to baselines.

⁴https://wng.org/sift/memes-innocent-fun-or-internet-bullying-1617408938
Research Question | Proposed Solution | Dataset Curated
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RQ1.1 Can we predict hateful retweets? | Exogenous attention modeling. | Tweets, retweets, user history, & follower networks (413M unique users), 300K news articles. Manually annotated 17k tweets for hate/non-hate.
RQ1.2 Can we predict hatefulness of reply threads? | Blind state deep model. | Tweet reply threads consisting of 1.5k threads with average length 200 per thread.
RQ2.1 Can we curate a meme dataset for type and target of harm? | Benchmark existing uni and multi-modal frameworks for harmful memes. | ≈ 7.5k memes annotated for harmful or not, as well as target of harm. Human benchmarks against the annotated dataset are also provided.
RQ2.2 Can we bring the performance of harmful meme detection models closer to human benchmarks? | Inter and Intra-modal attention in a multi-task multi-modal framework. | Combined from five existing datasets of offensive trait predictions in Hinglish.
RQ3 Can offensive traits lead to hate? | Pseudo-labelled multi-task framework to predict the offensive traits. | Combined from five existing datasets of offensive trait predictions in Hinglish.

Table I. Summary of research questions, methods and curated datasets discussed in this article.

3.3 RQ3 – Following challenges C1 and C4, can we use cues from anti-social behaviour to predict hatefulness?

Our recent work [Sengupta et al. 2021] explored the detection of various offensive traits under a code-mixed Hinglish (Hindi+English) setting. We combined our dataset from existing Hinglish datasets on aggression [Kumar et al. 2018], hate [Bohra et al. 2018], humour [Khandelwal et al. 2018], sarcasm [Swami et al. 2018a] and stance [Swami et al. 2018b]. Since a single data source consisting of all the above categories does not exist, we developed pseudo-labels for each task and at each data point. Our ablation studies showed that using pseudo-labels under a multi-task setting improved the performance across all predictive classes. We further looked at microscopic (word-level) as macroscopic (task/category-level) causality that can help explain the model’s prediction. To perform word-level dependency on a label, we generated a causal importance score [Vig et al. 2020] for each word in a sentence. It captures the change in the confidence level of prediction in a sentence’s presence vs absence of that word. We observed that the mean of the importance score lies around zero for all categories, with low variance for the overtly aggressive and hate classes. On the other hand, we observed a higher variance in importance score for sarcasm, humour, and covert aggression. It follows from puns and wordplay that contextually impacts the polarity of words. Further, we employed the Chi-square test between all pairs of offensive traits to determine how the knowledge of a prior trait impacts the prediction for the trait under consideration. We observed that an overtly aggressive text has 25% higher chances of being hateful than other classes, and knowing that it is not aggressive lowers its chance of being hateful by 50%. Therefore, prior knowledge about the aggressiveness of a text can impact posterior probabilities of the text being hateful.

4. FUTURE WORK

We summarize the entire discussion in Table I. Off-the-shelf hate speech classifiers were employed in diffusion and intensity prediction models. However, existing hate speech classifiers have been reported to be biased against the very communities they hope to help [Sap SIGWEB Newsletter Autumn 2007
et al. 2019]. Therefore, incorporating debased models and proposing such techniques for code-mixed settings can be a direction for future work. Further, other forms of unintended bias like political bias have been studied very scantily and require additional investigations [Wich et al. 2020]. Apart from the problem of bias is the issue of static hate-lexicons. We need robust and explainable systems that evolve. Many regional languages on social media go unnoticed until some socio-political unrest surges in the region, e.g., Facebook’s inability to timely moderator content in Myanmar\(^5\). Like the multilingual transformer models, research in hate speech calls for developing transfer learning systems [Ranasinghe and Zampieri 2021] that can contextually capture target entities and hateful phrases across domains. Other multi-media contents like gifs and short clips are also worth exploring for analysing harmful content. The gap in human benchmarks and our best performing multi-modal frameworks shows that detecting harmful memes requires additional context beyond visual and textual features [Pramanick et al. 2021]. Knowledge graphs [Maheshappa et al. 2021], and diffusion patterns are potential signals to incorporate in future studies. As both knowledge graphs and diffusion cascades are hard to analyse and comprehend, various tools have been proposed in visualising these systems at scale [Sahnan et al. 2021; Ilievski et al. 2020].

Meanwhile, studies have shown that the best counter to hate speech is not banning content but producing more content that sensitises the users about hate speech [Hangartner et al. 2021]. In this regard, reactive and proactive counter-speech strategies need to be worked out [Chaudhary et al. 2021]. While we have primarily spoken about tackling hate speech from a computer science perspective, a topic as historically rich and sensitive as hate speech requires multi-disciplinary efforts. Theories from sociology and physiology might help researchers and practitioners better understand the emergence and spread of hate from a socio-cultural perspective. Additionally, by involving stakeholders like representatives from minority communities, journalists, content moderators, we will be able to deploy solutions that are human-centric and not data-centric.

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\(^5\)https://www.reuters.com/investigates/special-report/myanmar-facebook-hate/
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