Challenges and Considerations with Code-Mixed NLP for Multilingual Societies

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Abstract

Multilingualism refers to the high degree of proficiency in two or more languages in the written and oral communication modes. It often results in language mixing, a.k.a. code-mixing, when a multilingual speaker switches between multiple languages in a single utterance of a text or speech. This paper discusses the current state of the NLP research, limitations, and foreseeable pitfalls in addressing five real-world applications for social good—crisis management, healthcare, political campaigning, fake news, and hate speech—for multilingual societies. We also propose futuristic datasets, models, and tools that can significantly advance the current research in multilingual NLP applications for societal good. As a representative example, we consider English-Hindi code-mixing but draw similar inferences for other language pairs.

1 Introduction

The term “multilingualism” refers both to an individual’s ability to use several languages and the coexistence of different language communities in one geographical area. Contrary to the general belief, most of the world’s population is bilingual or multilingual. Monolingualism is characteristic only of a minority of the world’s population (Valdés, 2007). Multilingualism sometimes uses elements of multiple languages when conversing with each other, resulting in a code-mixed conversation. Code-mixing (aka code-switching), as formally defined by Bokamba (1989), is the mixing of words, phrases, and sentences from two distinct grammatical (sub)systems within the same speech event. With the wide-reaching popularity of social media platforms, code-mixing has emerged as one of the significant linguistic phenomena among multilingual communities (Das and Gambück, 2015). Throughout this paper, we only consider code-mixing as intra-sentential wherein language switching occurs inside the sentence.

In this paper, we present five real-world applications for social good—crisis management, healthcare, political campaigning, fake news, and hate speech—and discuss the current ability of the NLP tools in handling code-mixed data. We critically analyze the progress in NLP in processing code-mixed data and present immediate research directions and potential pitfalls. In contrast to existing survey literature on code-mixing, we primarily focus on the NLP applications for societal good and evaluate NLP venues’ contribution towards such applications from a code-mixing perspective.

As a representative example, in this paper, we primarily focus on Hinglish, a portmanteau of Hindi and English. Highlish is highly prevalent in the Indian sub-continent. Baldauf (2004) projected in 2004 that the world’s Hinglish speakers (>350 million) might soon outnumber native English speakers. Hinglish presents significant linguistic challenges. In contrast to other code-mixed pairs such as Spanglish (a portmanteau of Spanish and English), which carries a relative similarity in Spanish and English syntactic structure, Hinglish is constructed over two syntactically divergent languages (Berk-Seligson, 1986).
2 Applications for societal good

This paper focuses on five popular applications for social good and discusses these applications from a multilingual community perspective, wherein the data generated comprises code-mixed text, largely available over the internet. Next, we describe each application in detail.

2.1 Crisis Management

Crisis encompasses both man-made and natural events. Man-made crisis events include military war, explosions, acts of terrorism, extreme pollution levels, hazardous material spills, fires, transportation accidents, structure failures, and mining accidents. In contrast, natural crisis events include catastrophic events with atmospheric, geological, and hydrological origins (e.g., droughts, earthquakes, floods, hurricanes, landslides) (Prasad and Francescutti, 2017). Interestingly, the current COVID-19 crisis can be attributed to both man-made and natural crises.

As expected, these crisis events affect a large population, resulting in a large volume of multimodal data such as text messages, videos, and images. The generated text data includes real-time casualty and loss statistics, donation announcements, volunteering calls, relief camp locations, along with negative aspects such as misinformation, disinformation, and rumors during a health emergency. Thus, the primary role of NLP systems in crisis data management is not only to enable a large proportion of the affected population to consume the factually correct data but also to reduce the effect of incorrect/false information before it reaches the affected population (hereafter, crisis data misinformation (CDM)). Another important NLP goal is disaster response, wherein the system identifies information related to emotional support to the affected population, donations and volunteering and caution and advice from government bodies and social organizations, government announcements related to infrastructure (hereafter, crisis data response (CDR)). The third major goal is to summarize the large temporal data volume in real-time and present it in a meaningful fashion for easier consumption (hereafter, crisis data summarization (CDS)).

2.2 Healthcare

The Healthcare domain has witnessed tremendous advancements in the last two decades. Many healthcare systems allow patients to access their electronic health record (EHR) notes online through patient portals. Applications such as personalized healthcare chatbots are increasingly be-
coming popular (Futurist, 2020). Online medical portals such as Prato¹ and Plushcare² are helping patients to connect and find doctors. Online healthcare blogs present well-rounded, perceptive, and informative news sources and opinions from healthcare experts.

Understanding healthcare information from the above sources requires NLP at its core. The major goal of NLP is to understand the medical jargon and construct a mapping between non-standard terminologies used in different geographies. This understanding helps in constructing association between medical processes (hereafter, healthcare knowledge graph construction (HKG)). The second major goal is in developing personalized healthcare chat agents (hereafter, healthcare chatbots (HCB)). The third major goal is to debunk the misinformation associated with the health and medical terms (hereafter, healthcare misinformation (HMI)).

### 2.3 Political campaigning

Social platforms play a critical role in the new political campaigning paradigm. Politicians exchange views on the latest partisan developments and invite the public and citizens to comment, share ideas, and adhere to their political program (Phillips and Young, 2009). Previous research shows that the successful social media campaign positively correlates with the election outcomes (Baxter and Marcella, 2012; Barclay et al., 2015; Kanungo, 2015; Heredia et al., 2018). Similarly, in the recent U.S. elections, a study (Wharton Business Daily, 2020) shows that within the first month of using Twitter, politicians were able to raise between 1% and 3% of what they would have raised in a traditional two-year campaign. Some of the positive aspects of social media-based political campaigns are wider reach, no traditional media filter, two-way discussions, and negligible funding requirements. Some of the negative aspects include malicious propaganda against rival parties and exaggerated achievements.

NLP systems can be deployed to understand the ongoing political campaigns and to make people aware of the factually correct information and re-flag the misinformation (hereafter, political data misinformation (PDM)). Another important goal is to measure the public perception about the ongoing political campaigns and present it to the political parties and the general mass. These opinions help a political party to plan its programs and visions and a voter to see both sides of campaigns (hereafter, political opinion extraction (POE)).

### 2.4 Fake news

Fake news is a critical yet challenging problem in NLP. The rapid rise of social networking platforms has yielded a vast increase in information accessibility and accelerated the spread of fake news (Oshikawa et al., 2020). We witness fake news spreaders on diverse platforms ranging from political discussions, movie recommendations, e-retail product reviews. In the last decade, we witness a surge in fake news on sensitive and critical topics like pandemic (Kar et al., 2020), disasters (Kwanda and Lin, 2020), and war (Salem et al., 2019). In the ongoing pandemic scenario, where major business, education, and political activities have been confined to online settings, the volume of fake news has grown substantially (Sujeet K Sharma and Chandwani, 2020).

As the menace of fake news encompasses multiple domains, the primary goal of the NLP system is to detect such fake messages, posts, or reviews (hereafter, fake news detection (FND)). FND is highly challenging in a real-time setting, where incoming messages are flagged according to the likelihood of being fake. The second major goal is the course correction, i.e., to summarize and present facts against the fake news (hereafter, fake news explanation (FNE)).

### 2.5 Hate speech

Hate speech is commonly defined as any communication that disparages a person or a group based on some characteristic such as race, color, ethnicity, gender, sexual orientation, nationality, or religion (Nockleby, 2000). Due to the massive rise of user-generated web content, the amount of hate speech is also steadily increasing (Schmidt and Wiegand, 2017). Government organisations (Singh, 2020; Bayer and Bárd, 2020) have framed strict laws to deal with offensive messages sent through social media and online messaging applications. The major challenge in hate speech detection lies in the diversity of characteristics. An NLP system, depending on the characteristics of hate speech, should be able to...
process and detect such hateful content effectively (hereafter, hate speech detection (HSD)).

To summarize, in this section, we elaborate on five applications of NLP for societal good. For each application, we propose multiple sub-tasks. Table 1 presents representative Hinglish examples for each application described in this section. Since we focus on the applications from a code-mixed data perspective, the next section describes the current NLP research status addressing the above issues in code-mixed data.

## 3 The current state of the research

We study two different perspectives to understand the current state of the computational linguistic research for the societal good applications in multilingual societies. First, we analyze the five major ACL and non-ACL conferences to understand the NLP community’s global trend. Next, we present an analysis of the currently available resources and some top-performing systems for each of the five societal good applications.

### 3.1 Are we organizing enough workshops for the societal good?

Workshops are major sources to promote the research in a dedicated area of study. In this paper, we analyze five major NLP conferences (ACL, EMNLP, NAACL,$^3$ COLING, and LREC$^4$) organized in the past five years (2016–2020). Over the years, almost all the top preferred conferences in the NLP community are organizing workshops to promote and include community members’ diverse research interests (see Table 2). Specifically, in the healthcare domain, we see a significant number of workshops in ACL, EMNLP, and LREC. For other societal good applications, the number of organized workshops is considerably low. Also, except the workshop on computational approaches to linguistic code-switching (CALCS), none of these workshops primarily focus on code-mixed text.

### 3.2 What is accomplished so far? Is it really “state-of-the-art’’?

Here, we explore some major works in the five societal good applications for multilingual societies. We provide an empirical study to highlight various strengths and limitations of these notable works.

| Application          | ACL | EMNLP | NAACL | COLING | LREC | Total |
|----------------------|-----|-------|-------|--------|------|-------|
| Crisis Management    | 1   | 1     | 0     | 0      | 0    | 3     |
| Healthcare           | 9   | 8     | 2     | 2      | 3    | 25    |
| Political Campaigning| 0   | 0     | 1     | 0      | 0    | 1     |
| Fake News            | 0   | 3     | 0     | 0      | 0    | 3     |
| Hate Speech          | 0   | 2     | 3     | 2      | 2    | 11    |

Table 2: Distribution of the societal good workshops organized during the five-year interval (2016–2020) in the five major NLP conferences. Total represent total number of workshops in the five-year interval.

Since we consider the majority of the popular and recent works in this discussion, it will help capture the community’s diverse research interests. It will also pave the way for developing effective systems in the future.

### 3.2.1 Crisis management

In Section 2.1, we discuss several NLP tasks in crisis and disaster management. To the best of our knowledge, we do not find any work primarily focusing on code-mixed data. However, we find several works that process noisy social-media text for generating insights and responses. We list these works below:

- **CDM**: We witness a large volume of work on addressing the crisis data misinformation. Particularly, majority of the recent works focus on curating misinformation social-media posts during COVID-19 pandemic (Shahi and Nandini, 2020; Li et al., 2020; Kar et al., 2020; Patwa et al., 2020b; Qazi et al., 2020). Although all these works report multilingual data curation, we do not find any proposed misinformation identification model that leverages these datasets to train misinformation detection models. Additionally, we find several other monolingual datasets discussing events like Ukrainian conflict (Khaldarova and Pantti, 2016), Syrian War (Salem et al., 2019) and Palu earthquake (Kwanda and Lin, 2020). The majority of the crisis datasets are monolingual and present limited opportunities to develop tools to identify multilingual misinformation content. This limitation fosters the code-mixed misinformation spreader to spread the false information in a time of crisis easily.

- **CDR**: We witness very few works addressing crisis data response. For example, Imran et al. (2013) extracted valuable information nuggets relevant to disaster response from microblogs. They curated a small dataset of 1,233 English sentences. However, we do not find any work

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$^3$NAACL happened in the year 2016, 2018, and 2019.

$^4$LREC happened in the year 2016, 2018, and 2020.
that curates the above extremely time-sensitive information available in the code-mixed language.

- **CDS**: We witness few recent works on summarizing crisis-related data available as microblogs (Rudra et al., 2015, 2016, 2018a). All these works address the problem in two phases. In the first phase, they extract the relevant situational information from among the large volume of tweets. In the second phase, they summarize the extracted information. Note that the proposed methods only work for the English Language. Off-the-shelf usage of these works for the code-mixed languages might not give the desired results.

### 3.2.2 Healthcare

In Section 2.2, we discussed the importance and the necessities to address the various healthcare-related challenges. We layout three major sub-fields (HKG, HCB, and HMI) where computational linguistic could play a major role. We could not find any dedicated study pertaining to the code-mixed languages to the best of our knowledge. Here, we present some well-known works in other languages and draw insights from them that present future research directions in the code-mixing domain.

- **HKG**: Healthcare knowledge graphs (Lindberg et al., 1993; Oliveira et al., 2017) are extremely useful in converting enormous healthcare data in the machine-understandable format. HKG is also useful in informing healthcare practitioners of the latest research results (Sadeghi and Lehmann, 2019). It has proven useful in multiple instances such as diagnosis prediction (Choi et al., 2017; Ma et al., 2018) and analytics (Aasman and Mirhaji, 2018). Code-mixed data available on various social media platforms (e.g., Twitter and Facebook) and healthcare discussion forums (e.g., India medical hub5 and patient6) can be used to expand existing monolingual HKGs.

- **HCB**: Healthcare chatbots are the future for query resolution (Amato et al., 2017; Bates, 2019), consultation (Kowatsch et al., 2017), medical history analysis (Divya et al., 2018), and treatment (Cameron et al., 2018; Bibault et al., 2019; Chaix et al., 2019). The majority of the HCBs are designed for formal communication, making it difficult for the multilingual speakers to have a human-like conversation with these chatbots as they lack the human emotions (Palanica et al., 2019).

- **HMI**: Misinformation in the healthcare domain can result in a serious negative impact on the well-being of the people (Tasnim et al., 2020). Recently, a wave of misinformation related to the COVID-19 pandemic has propagated and studied (Brennen et al., 2020; Pennycook et al., 2020; Kouzys et al., 2020). Several domain-specific misinformation detection systems (Cui et al., 2020; Hou et al., 2019; Bal et al., 2020; Cui and Lee, 2020) have been proposed to check the healthcare-related misinformation. The majority of these works focus on the monolingual data available on various social media platforms. However, due to the popularity of code-mixing conversations in multilingual communities, the risk of misinformation spread increases manifold. Most healthcare-related information is generated in monolingual language at the source (hospitals, healthcare centers, and diagnostic labs).

### 3.2.3 Political campaigning

The recent thrust on social media and online news platforms has contributed significantly to the change of medium for political campaigning. These platforms greatly facilitate reaching the masses quickly, but it adds several challenges such as misinformation and hate speech. Here, we explore two sub-fields (PDM and POE) where computational linguistic could help improve the situation. Since we cannot find any study for the code-mixed languages, we will explore monolingual and multilingual works.

- **PDM**: Misinformation during election campaigning misleads people with manipulated facts and rumors (Badawy et al., 2018; Cantarella et al., 2020). Multiple works identify the spread of political misinformation on various platform such as WhatsApp (Garimella and Eckles, 2020; Machado et al., 2019; Resende et al., 2019), Facebook (Guess et al., 2019; Mena, 2020), and Twitter (Shin et al., 2017; Grinberg et al., 2019; Neudert et al., 2017). In order to address political misinformation, various fact-checking platforms have been introduced (Hassan et al., 2015; Myslinski, 2015; Rashkin et al., 2017;
Fake news is one of the biggest challenges on social media platforms. Over the years, it has been an active area of research for the computational linguistic community. Unfortunately, we could not find any work for the fake news propagation in the code-mixed languages. Here, we explore some prominent works in other languages for the two major subareas (FND and FNE).

- **FND**: Detecting fake news and the fake news spreaders is the primary step in checking the propagation of fake news (Shu et al., 2017; Meel and Vishwakarma, 2019). Over the years, various benchmark datasets have been proposed (Wang, 2017b; Golbeck et al., 2018; Nakamura et al., 2020) to detect fake news on various platforms. Recently, FND for low-resource (Hossain et al., 2020; Amjad et al., 2020) and multilingual (Schwarz et al., 2020; Shahi and Nandini, 2020) languages have gained interest from the computational linguistic community.

- **FNE**: Black-box models for the fake news detection adds to the complexity of identifying and filtering the fake news (Reis et al., 2019). The reasoning, interpretability, and the explanation (Shu et al., 2019) of the fake news detection models are extremely important for websites with extensive outreach (e.g., social media and news websites). Real-time prediction and the visualization of the fake news and its interpretation (Yang et al., 2019) could be extremely useful in several cases for multilingual societies.

### 3.2.5 Hate speech

In contrast to the above societal good applications, hate speech detection in the code-mixed languages has been an active area of exploration (Santosh and Aravind, 2019; Chopra et al., 2020; Kamble and Joshi, 2018). Here, we discuss two very popular datasets (for the code-mixed languages) by Bohra et al. (2018) (hereafter, HD1) and Mandl et al. (2019) (hereafter, HD2) to detect hate speech on social media platforms. HD1 presents a dataset of 4,575 Hinglish tweets annotated with either of the binary labels: *hate speech or normal speech*. HD2 is a fine-grained hate-speech detection dataset in Hinglish. Labels in HD2 can be used to identify hate speech, offensive language, and the profanity in the 5,983 tweets. Even though these works address the data scarcity issue for the code-mixed languages, the quality and the quantity of the examples in the dataset remains debatable. The size of HD1 and HD2 datasets is significantly small as compared to HD datasets in other monolingual languages (Davidson et al., 2017; Mathew et al., 2020).

### 4 Limitations

As discussed in Section 3.2, the majority of the research for good societal applications for multilingual societies has enormous opportunities. This section discusses some major limitations that text NLP researchers and practitioners encounter very often in code-mixing. Srivastava and Singh (2020b) highlights six major limitations with the machine translation systems on the code-mixed text. The majority of these limitations stand true in dealing with societal good applications as well. Here, we present a comprehensive list of challenges and limitations that need to be carefully addressed to build robust and efficient systems and an encouraging environment in the multilingual research community.

- **Limited text processing tools**: The limited availability of the text processing tools build especially for the code-mixed language makes it extremely challenging to create large scale robust and efficient systems. Efficient tools with functionalities like POS tagging, named entity recognition, language identification, transliteration, key phrase extraction, and topic modeling are yet to be developed at a large scale. The scarcity of high-quality datasets for these tasks
makes it a vicious cycle to build multilingual societies’ solutions.

- **Identifying and filtering code-mixed data:**
  One of the major challenges with the code-mixed data is the coexistence with other languages. We rarely find any platform where people communicate solely in code-mixed languages. The non-availability of automatic filtering tools makes it extremely challenging to create a large-scale code-mixed corpus. In most cases, people employ humans in the loop to identify and filter the code-mixed data (Kumar et al., 2018; Vyas et al., 2014; Chandu et al., 2019), but this approach is highly time and cost extensive.

- **Human bias:** Inherent human bias is one of the most significant and dangerous challenges for most NLP systems. Code-mixed languages also suffer from such biases very often. In addition to the bias present in the data generated on the various platforms (Twitter, Facebook, WhatsApp, Reddit, and Quora), we observe a very high bias in the dataset annotation by the human annotators (Geva et al., 2019; Srivastava and Singh, 2020a). On manual inspection, we observe a significantly high ambiguity in the sentiment classification datasets for the Hinglish language (see Example I in Figure 2). The primary reason for this ambiguous behavior can be attributed to the underlying bias of the human annotators.

- **Annotator’s proficiency:** The lack of grammatical standardization (see Example II & IV in Figure 2) for the code-mixed languages presents the challenge of spelling variation, dialect, and readability. This standardization scarcity makes it challenging to employ human annotators for an annotation task. Also, evaluating an annotator’s proficiency in a particular code-mixed language is a challenge. The natural language generation tasks such as machine translation, text generation, data to text generation, and summarization suffer heavily due to this constraint.

- **Evaluation metrics:** The evaluation metrics developed for the monolingual languages does not seem to capture the linguistic diversity of the code-mixed languages. The majority of the widely used NLG related metrics such as Bilingual Evaluation Understudy (BLEU) (Papineni et al., 2002), Word Error Rate (WER) (Levenshtein, 1966), and Translation Error Rate (TER) (Snover et al., 2006), gives a false impression of the system performance (see Example III in Figure 2). We need metrics that can account for the various attributes of the code-mixed languages, such as spelling variations, informal writing style, and contextual information.

- **Reproducibility:** Reproducibility is a major issue for the majority of the NLP research (Wieling et al., 2018). Code-mixing, which is a relatively understudied area of research, suffers significantly due to the non-reproducible research. Be it off the self-usage or baseline comparison, the non-reproducible research is a significant bottleneck for the code-mixing research. Also, the lack of publicly available datasets limits the scope of future opportunities.

- **Benchmark:** Recently, we witness several efforts (Aguilar et al., 2020; Khanuja et al., 2020) to benchmark various datasets and tasks in code-mixed language. The majority of these benchmarks leverage very small-scale datasets, which make generalizability and large-scale applicability nearly impossible. Most critical NLP tasks, such as question-answering, machine translation, and summarization, are still unaddressed due to either lack of research or the unavailability of publicly available datasets and systems.

- **Official status:** Since the code-mixed languages do not possess an official status, it becomes challenging to enforce standardization. The majority of the recent efforts in NLP for the multilingual communities (Kakwani et al., 2020; Hu et al., 2020; Xue et al., 2020) do not include the code-mixed languages even though the number of speakers for such languages is very high.
Table 3: Various possible code-mixed data source(s) for the societal good applications. Already existing datasets in various languages could be used to generate the synthetic data for each of these tasks. Here ‘En’ represents English and ‘Es’ represents Spanish language.

| Possible code-mixed data source(s) | Already existing datasets (Language) |
|-----------------------------------|--------------------------------------|
| CDM: Shibli and Sundim (2020), Li et al. (2020), Li et al. (2020), Kar et al. (2020), Patwa et al. (2020b), Montesi (2020) | English |
| CDR: crisislink.qcri.org | English (En) |
| CDS: crisislink.qcri.org | English (Es) |
| HKG: patient.info, emednews, in, indiansmashalili, healthvissin.m | English (En), Kannada (Ka) |
| HCB: nh.gov.in, nhsrcindia.org, nathealthindia.org, uma.india.org | English (En) |
| HMI: newschecker.in, politifact.com, factcrescendo.com, vishvasnews.com, factly.in, maldita.es | English (En) |
| PDM: newschecker.in, politifact.com | English (En) |
| POE: guidelines.nyu.edu/politicalevents/public-opinion-data, ucd-idhguides.com/data-statistics/publicopinion | English (En) |
| FND: factsandcontroveris.com, truthloader.com, factchecker.in | English (En) |
| HSD: haispechdata.com, NEWS comments (Conversation, 2016, commonitor, 2016) | English (En) |

5 The Futuristic NLP for Applications of Social Good

This section proposes futuristic datasets, models, and tools that can significantly advance the current state of the research in multilingual NLP applications for societal good.

5.1 Datasets

As noted in the previous sections, natural code-mixed datasets are rare and small in size, with a major focus on selected applications. Here, we present some primary data sources for all the five societal good applications. We summarize our findings in Table 3. There are several good quality datasets already available in various other languages for these tasks (see Table 3, third column). We could effectively utilize these monolingual datasets to create the code-mixed datasets using various code-mixed text generation systems (Gupta et al., 2020; Pratapa et al., 2018). Since most of these systems use parallel sentences to generate code-mixed text, we can create parallel data from state-of-the-art translation systems by first translating the original monolingual source data and then use these systems to generate the code-mixed text. We can also use this technique to convert the monolingual data from the possible code-mixed data sources (mentioned in Table 3, second column) to get the code-mixed data. This approach can significantly address the data scarcity problem in the code-mixed languages.

5.2 Models

The recent NLP advancements contribute to popular contextual representations constructed using (semi-)unsupervised language models (Vaswani et al., 2017). As these language models are trained on large monolingual datasets, they do not perform well in code-mixing tasks (Khanuja et al., 2020). We, therefore, propose the construction of pre-trained models from the large-scale code-mixed text. The proposed datasets (see Section 5.1) can be used for this pretraining and further task-specific fine-tuning.

5.3 Tools

In the future, we envisage several NLP tools deployed in the field that can efficiently curate and process code-mixed data. For example, significant

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7Due to the ease of accessibility of the code-mixed text on the social media platforms (WhatsApp, Facebook, and Twitter), majority of the works considers these platforms. Here, we present the platforms which could also be a good alternative to curate the code-mixed datasets.
information is available to debunk a fake tweet by just looking into the replies. In most cases, the replies are comparatively more informal and contain facts in code-mixed language. The facts can be extracted and encoded into completely data-driven automatic fake news detectors for code-mixed text. This also helps in reducing political and ethical bias towards the source of fake news (van der Linden et al., 2020). Several media websites that curate and track hate speech are currently shutdown under political pressure. Thus, an automatic curation and tracking tool for hate speech in a multilingual community—where the text is mostly informal and contains large volumes of code-mixing—can benefit society.

6 Conclusion

This paper discusses five applications for social good and presents the current state of the research in each application area. We critically analyze the code-mixing research in each application area and show an extensive opportunity for future research for dataset curation, modeling, and tool development. We aim to develop and extend our expertise in handling the large volume of code-mixed data in the future.
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