Abstract

To date, efforts in the code-switching literature have focused for the most part on language identification, POS, NER, and syntactic parsing. In this paper, we address machine translation for code-switched social media data. We create a community shared task. We provide two modalities for participation: supervised and unsupervised. For the supervised setting, participants are challenged to translate English into Hindi-English (Eng-Hinglish) in a single direction. For the unsupervised setting, we provide the following language pairs: English and Spanish-English (Eng-Spanglish), and English and Modern Standard Arabic-Egyptian Arabic (Eng-MSAEA) in both directions. We share insights and challenges in curating the “into” code-switching language evaluation data. Further, we provide baselines for all language pairs in the shared task. The leaderboard for the shared task comprises 12 individual system submissions corresponding to 5 different teams. The best performance achieved is 12.67% BLEU score for English to Hinglish and 25.72% BLEU score for MSAEA to English.

1 Introduction

Linguistic code-switching refers to the linguistic phenomenon of alternating between two or more languages or varieties of language both across sentences and within sentences (aka intra sentential code-switching, which is the type we focus on in this work) (Joshi, 1982). The wide use of social media platforms (e.g., Twitter, Facebook, Reddit, etc.) where users communicate with each other more spontaneously, rendering significantly more written code-switched data. Accordingly, this raises an increasing demand for more tools and resources to process code-switched data. However, current NLP technology is lagging in the development of resources and methodologies that can effectively process such phenomena. This is true for even

| Example 1) Eng - Hinglish |
|---------------------------|
| **English:** I don’t totally trust them either. I never let reviews stop me from watching a film. |
| **Hinglish:** Main poori tarah se un par bharosa nahin karta. Mainne kabhi bhi apney aap ko reviews key based per movie dekhney se nahin roka. |

| Example 2) Spanglish - Eng |
|---------------------------|
| **Spanglish:** I’m expecting dos camionetas llenas de rosas This weekend. |
| **English:** I’m expecting two trucks full of roses This weekend. |

Figure 1: Examples from the dataset. The irregular grammar and non-standard syntactic rules make it difficult to translate from one language to the other.

the large multilingual pre-trained models such as mBART (Liu et al., 2020) and mT5 (Xue et al., 2021). At the same time, the growing adoption of smart devices and automated assistants that rely on speech interfaces makes it even more pressing for the NLP field to deal with code-switched language data.

In this work, we present the new task of machine translation (MT) from and to Code Switched language. We create a community task, defining and curating datasets and evaluation metrics. We leverage already existing standard code-switching datasets that were created in the community as used in the previous workshops on Computational Approaches to Linguistic Code-Switching (CALCS). We created a series of shared tasks focusing primarily on enabling technology for code-switching, including language identification (LID) (Solorio et al., 2014), part of speech (POS) tagging (Molina et al., 2016), and named entity recognition (NER) (Aguilar et al., 2018). In our task, we leverage previously created data sets and extend them for the task of machine translation (MT) under code-switching settings in multiple language combinations and directions. General challenges to the
processing of code-switched language persist in this setting but notably, the following challenges are especially significant to the MT problem space: 1) irregular grammar and spelling of utterances; 2) non-standard syntactic rules; and 3) ambiguous words (e.g., ‘car’ in French and English), etc. For example, in Figure 1, the irregular grammar and non-standard syntactic rules make it difficult to translate from one language to the other. With this in mind, we host a new community task for machine translation on code-switched data. The goal is to provide code-switched MT datasets and to continue to motivate new research and energize the NLP community to take on the challenges posed by code-switched data.

For the community task, we provide two modes for participation: supervised and unsupervised. For the supervised setting, we ask participants to translate English into Hindi-English (Eng-Hinglish) in a single direction. For the unsupervised setting, we provide the following language pairs: English and Spanish-English (Eng-Spanglish), and English and Modern Standard Arabic-Egyptian Arabic (Eng-MSAEA) in both directions. We received 12 individual public system submissions from 5 different teams. The best performance achieved is 12.67% BLEU score for English to Hinglish and 25.72% BLEU score for MSAEA to English. Our contributions are multi-fold:

1. We introduce the novel task of translating into code-switched language;
2. We create new standard datasets for evaluating MT for code-switched data: English→Hinglish, English-Modern Standard Arabic-Egyptian Arabic, and English-Spanglish;
3. We provide baseline systems for MT for several pairs of languages: English-Hinglish, English-Spanglish;
4. We present and discuss some of the challenges of generating evaluation data for code-switched language.

2 Related Work

Code-switching is a phenomenon where multilingual speakers communicate by switching back and forth between the languages they speak or write when communicating with other multilingual speakers (Joshi, 1982). It tends to be more common in informal settings such as social media platforms where interactions are more casual. Previous work has studied code-switching for many languages from different perspectives. Toribio (2001) presents new methodologies for gathering code-switched data, examining permissible and unacceptable language alternations. Goyal et al. (2003) introduces a bilingual syntactic parser that operates on input strings from Hindi and English and develops grammars for Hindi and English. Lately, researchers mainly focus on exploring this phenomenon at the core level of NLP pipelines, including language identification (Solorio and Liu, 2008; Aguilar and Solorio, 2020), language modeling (Garg et al., 2018; Gonen and Goldberg, 2019), and Named Entity Recognition (Winata et al., 2019; Aguilar et al., 2018), etc.

Recent advances in large pre-trained models (Devlin et al., 2019; Lewis et al., 2020) have led to significant performance gains in many multilingual tasks. Without further pre-training and extra neural network components, these large pre-trained models (e.g., mBART (Liu et al., 2020) and mT5 (Xue et al., 2021)) can be easily adapted to code-switching tasks. However, the pre-training tasks of these models are performed on monolingual text without language alternation. Applying these techniques to the task of code-switching machine translation may not result in a good performance due to the challenges mentioned in Section 1.

Machine translation on code-switched data has been recently receiving increasing attention in the NLP community. For this task, there are two main focused efforts: 1) data resources, and 2) efficient methods. For data resources, Srivastava and Singh (2020) presents a parallel corpus for Hindi-English (Hinglish) and English and proposes a translation pipeline built on top of Google Translate. Tarunesh et al. (2021) adapts a neural machine translation model to automatically generate code-switching Hindi-English data. However, due to the lack of resources, this phenomenon remains challenging, especially for social media genres where annotated data is limited. In this work, in addition to the Hinglish-English dataset, we further propose standardized datasets for translating from monolingual data to code-switched data. Critically, we are proposing standard datasets for evaluating to and from code-switched data. For efficient methods, Singh and Solorio (2017) employs the n-best-
list generation approach to address the spelling variation in the text and also enrich the resource for translation. Yang et al. (2020) proposes a simple yet effective pre-training approach to align the cross-lingual information between the source and target language. Xu and Yvon (2021) designs a new method to simultaneously disentangle and translate the two mixed languages. In this paper, we compare different systems from the participating teams in terms of methodology (e.g., model architecture and training strategy) and performance. We further provide in-depth analysis. In the spirit of reproducibility, we make our data and experiments publicly available to support future research in this area.

3 Task Description

The goal of the community task is to motivate new research and energize the community to take on challenges posed by code-switched data. Most research to date has focused on translation from code-switched language to monolingual language, albeit without establishing standard data sets for the task. In our work, we establish standard datasets in three different language pairs. Moreover, we introduce the novel task of translating into code-switched language. Generating plausible code-switched language is a challenge for systems in general and it is still an untapped novel territory in NLP. As mentioned earlier, code-switching is pervasive among multilingual speakers as well as among even monolingual speakers given the global nature of communication. Catering to such users requires systems that are able to produce more natural language consistent and coherent with their manner of speaking, e.g., in conversational AI. We contend that such natural language interactions with code-switching understanding and generation will be the next frontier in human language technology interaction. Hence an initial challenge is to create standardized evaluation datasets that reflect the code-switched phenomenon. Machine translation serves both ends exemplifying understanding and generation. With this in mind, we hosted a new shared community task on machine translation for code-switched language. The shared task mainly focuses on translating a source sentence into a target language while one of the directions contains an alternation between two languages. Given a monolingual/code-switched sentence, the goal is to translate it into a code-switched/monolingual sentence, respectively. In this shared task, we provide the following two settings for participation:

**Supervised settings** We primarily focus on translating from monolingual text to code-switched text. This setting only has one language pair with a single direction, i.e., English → Hinglish. We provide parallel training data and participants are required to build systems for translating an English sentence to a Hinglish sentence.

**Unsupervised settings** This setting comprises two language pairs: English to/from Spanish-English (Eng-Spanglish), and English to/from Modern Standard Arabic-Egyptian Arabic (Eng-MSAEA). We focus on machine translation in two directions, either from monolingual text to code-switched text or from code-switched text to monolingual text. To this end, we provide raw data with no reference translations (no parallel data). Participants are required to provide translations for both directions for either or both language pairs.

Additionally, in both settings, participants are allowed to use any external resources. We employ the BLEU score metric for evaluation as proposed by Post (2018). Participants can submit their predictions for test data to the Linguistic Code-switching Evaluation (LinCE) platform (Aguilar et al., 2020). The leaderboard in the LinCE platform averages the BLEU scores across multiple language pairs and directions to determine the position. Participants can submit their results while comparing with others in real-time.

4 Datasets

4.1 Eng-Hinglish

**Data Curation** The CMU Document Grounded Conversations Dataset (Zhou et al., 2018) contains a set of conversations between users, with each conversation being grounded in a Wikipedia article about a particular movie. A subset of this dataset is translated into Hinglish (code-switched Hindi-English) and is available as the CMU Hinglish Document Grounded Conversations Dataset (Gupta et al., 2019). The English sentences from the former dataset and their corresponding Hinglish translations make up the parallel corpus used for our task, however, we plan on extending the datasets to include code-switched data source to code-switched data target in the near future.
### Table 1: Distribution Statistics for the data sets for each language pair.

|                  | Supervised |                     | Unsupervised |                     |
|------------------|------------|---------------------|--------------|---------------------|
|                  | Eng→Hinglish | Eng→Spanglish | Spanglish→Eng | Eng→MSAEA | MSAEA→Eng          |
|                  | Train  | Dev  | Test | Raw  | Text | Raw  | Test | Raw  | Test | Raw  | Test |
| Sentences        | 8,060  | 960  | 942  | 15,000 | 5,000 | 15,000 | 6,500 | 15,000 | 5,000 | 12,000 | 6,500 |
| Tokens           | 93,025 | 11,465 | 11,849 | 166,649 | 212,793 | 228,484 | 189,465 | 166,649 | 104,429 | 219,796 | 303,998 |
| Eng tokens       | 33,886 | 4,273  | 4,333 | 116,617 | 97,646  | 43,869  | 100,000 | 116,617 | 38,967  | -      | 181,890 |
| Non-Eng tokens   | 58,381 | 7,130  | 7,420 | -      | -      | 98,412  | 41,839  | -      | 36,676  | -      | 149,087 |
| Other tokens     | 758    | 62    | 96   | 50,032 | 52,560  | 86,203  | 47,626  | 50,032 | 28,831  | 70,709 | 41,328  |

The dataset has multiple translations for some of the English sentences. These sentences are pre-processed to remove newline and tab characters. These parallel sentences could be used for machine translation in either of the 2 directions (English → Hinglish or Hinglish → English). We chose the former as it involves the generation of code-switched text and represents a more challenging task overall. It is worth noting that this setup renders a single Hinglish translation per English sentence.

**Data distribution:** The data statistics are shown in Table 1. We use the same train/dev/test splits as originally created by Zhou et al. (2018).

### 4.2 Eng-Spanglish

**Data Curation** For the Eng-Spanglish language pair, we leverage the English-Spanish language identification corpus introduced in the first CALCS shared task Solorio et al. (2014) and the second CALCS shared task Molina et al. (2016). We randomly sample a subset from this dataset where we add translations for both directions, namely the task for this language pair comprises two directions: Eng → Spanglish and Spanglish → Eng. As the original data was collected from Twitter, we normalized some social media special tokens, e.g., replace username mentions with `<username>`.

**Data distribution** The data statistics for both directions Eng → Spanglish and Spanglish → Eng are shown in Table 1. We also provide raw data from the code-switched Spanglish data from previous collections. Those statistics are also shown in Table 1. The idea for providing the raw data is to provide the participants with a sense of the data genres and domains and the code-switching style of the data used in the task. As shown in Table 1, it is worth noting that there are no Spanish tokens in the raw data for Eng → Spanish. Likewise, the ratios of English tokens for Spanglish → Eng in raw and test data are 19.2% and 19.5%. The skewed distribution poses a great challenge considering that the model may not see enough words in the target language. However, we think that the skewness can be reasonably handled with the provided data. Moreover, the raw and test sets draw a very similar data distribution, which can also help adapt the learning from training to testing.

### 4.3 Eng-MSAEA

**Data Curation** For the Eng-MSAEA language pair, we combine the datasets introduced in the CALCS-2016 (Molina et al., 2016) and CALCS-2018 (Aguilar et al., 2018) as the new corpora for the current machine translation shared task. The data was collected from the Twitter platform and Blog commentaries. The tweets that have been deleted or belong to the user whose accounts have been suspended were removed and eliminated. We also perform normalization on each tweet to reduce the impact of social media special tokens. Similar to the Eng-Spanglish setting, we provide only test data and raw data.

**Data distribution** We have two directions for Eng-MSAEA language pair: Eng → MSAEA and MSAEA → Eng. The data statistics for each direction are listed in Table 1. From Table 1, we can see that there are no tokens from the target language in the raw data.
4.4 General Translation Guidelines
The following are some of the overall guidelines used for curating translations: The translators are required to follow the standard grammar rules and typos should be corrected in the translation. The translated text should also be normalized. Slang, special forms, and expressions are to be translated to literal equivalents or to a more formal/standard form. The typos should be eliminated in translation, e.g., “Happo Birthday” should be translated to “Feliz Cumpleaños”. Additionally, speech effects should not be reflected in translation, e.g., “Happy Birthdayyy” should be translated to “Feliz Cumpleaños”. Social media special tokens, including username mentions, URLs, hashtags, and emojis, should not be translated even if they are transferable/translatable. Moreover, measurement units should not be converted or localized, e.g., “2LB” should not be translated to “1kg”. When translating from Spanglish into English, the translators were instructed to reword the English fragments when the translation warrants it. For translation from code-switched text to monolingual text, we requested one gold reference. For the case where the target translation is in the code-switched language, we requested three gold references. It is worth noting that we did not prescribe how and when the translations should include a code-switch. We only emphasized that we expect the resulting language to be a plausible code-switching of the two languages. We also provided ample examples per language pair. We expect there to be significant variation among the translations, as different translators would choose to code-switch at different points. We hope that this elicited data set could be eventually compared to naturally occurring code-switched data to investigate where and how they vary.

4.5 Dataset Evaluation
To measure the quality of the datasets we created, and understand the inherent characteristics of code-switched corpora, we evaluate our datasets following the statistics proposed by Guzmán et al. (2017) and Gambäck and Das (2014), including:

- **Code-Mixing Index (CMI):** The fraction of total words that belong to languages other than the most dominant language in the text;
- **Multilingual Index (M-Index):** A word-count-based measure that quantifies the inequality of the distribution of language tags in a corpus of at least two languages;

- **Integration Index (I-Index):** A proportion of how many switch points exist relative to the number of language-dependent tokens in the corpus;
- **Language Entropy (LE):** The number of bits of information are needed to describe the distribution of language tags;
- **Span Entropy (SE):** The number of bits of information are needed to describe the distribution of language spans;
- **Burstiness:** A measure of quantifying whether switching occurs in bursts or has a more periodic characteristic.

The code-switching evaluation statistics of our datasets are shown in Table 2.

5 Methods
We received submissions from five different teams. Four teams submitted system responses for Eng-Hinglish, making this language pair the most popular in this shared task. On the other hand, we had no external submissions for Spanglish-Eng. Below we provide a brief description of the two baselines as well as participant systems:

- **baseline1** We use mBART (Liu et al., 2020) as the baseline model trained for 5 epochs with a batch size of 8 and a learning rate of 5e-5. For the supervised setting, we simply fine-tune it on the parallel data. For the unsupervised setting, we directly generate translations without fine-tuning.

- **Echo (baseline)** This baseline simply passes inputs as outputs and the goal is to measure how much the overlap in input/output can contribute to the final performance. It is inspired by preliminary observations that there is a high token overlap between the source and target sentences. Also, many tokens common in social media (e.g., username mentions, URLs, and emoticons) have no clear translations and annotators left them unchanged.

- **UBC_HImt** (Jawahar et al., 2021). They propose a dependency-free method for generating code-switched data from bilingual distributed
representations and adopt a curriculum learning approach where they first fine-tune a language model on synthetic data then on gold code-switched data.

- **IITP-MT** (Appicharla et al., 2021). They propose an approach to create a code-switching parallel corpus from a clean parallel corpus in an unsupervised manner. Then they train a neural machine translation model on the gold corpus along with the generated synthetic code-switching parallel corpus.

- **UBC_ARmt** (Nagoudi et al., 2021). They collect external parallel data from online resources and fine-tune a sequence-to-sequence transformer-based model on external data then on gold code-switched data.

- **CMMTOne** (Dowlagar and Mamidi, 2021). They present a gated convolutional sequence to sequence encoder and decoder models for machine translation on code-switched data. The sliding window inside the convolutional model renders it able to handle contextual words and extract rich representations.

- **LTRC-PreCog** (Gautam et al., 2021). They propose to use mBART, a pre-trained multilingual sequence-to-sequence model and fully utilize the pre-training of the model by transliterating the roman Hindi words in the code-mixed sentences to Devanagri script.

In Table 3, we listed the main components and strategies used by the participating systems. Most systems are based on transformer architectures, including multilingual transformers such as mT5 and mBART. It is worth noting that all teams applied deep neural networks techniques. Among the five participating teams, three of them (IITP-MT, UBC_ARmt, CMMTOne) trained the model from scratch while two of them (UBC_HImt, LTRC-PreCog) fine-tuned the models with pre-trained knowledge on monolingual data. To tackle the challenge of low-resource data, two teams (IITP-MT, LTRC-PreCog) transliterated Hindi to Devanagari during training to fully utilize monolingual resources available in the native Devanagari script, and then back-transliterated Devanagari to Hindi to improve performance. Additionally, four teams (UBC_HImt, IITP-MT, UBC_ARmt, LTRC-PreCog) leveraged external resources (e.g., parallel datasets and text processing libraries). Moreover, two teams (UBC_HImt, IITP-MT) applied data augmentation techniques to generate synthetic data to increase the size of the training data.

### 6 Evaluation and Results

#### 6.1 Evaluation Metric

The evaluation of the shared task was conducted through a dedicated platform, where participants can obtain immediate feedback of their submissions after uploading translations for the test data. The platform then scores the submissions and publishes the results in a public leaderboard for each language pair direction.

We use BLEU Papineni et al. (2002) to rank participating systems. BLEU is a score for comparing a candidate translation of the text to one or more reference translations.

#### 6.2 Results

As listed in Table 4, 5 teams participated in this shared task. 4 teams submitted systems for Eng→Hinglish language directions, and one team submitted systems for the MSAEA→Eng language direction.

**Baselines** For the supervised task (i.e., Eng→Hinglish), baseline1 achieves a BLEU score of 11.00%. It outperformed the Echo baseline by 4.16%, indicating that the multilingual
model has acquired some useful knowledge about code-switching during pretraining. This is aligned with findings in literature about the usefulness of pretraining transformer models with in domain data (Doddapaneni et al., 2021). For the unsupervised tasks, we simply use the model to make predictions based on the pre-trained knowledge it has learned on monolingual data. Surprisingly, on all four unsupervised tasks, the results from baseline1 are lower than the ones from Echo, suggesting that the pre-trained knowledge from the monolingual data cannot be effectively adapted to the code-switched data.

**Participating systems** Table 4 shows the BLEU score results for all the teams/systems. For Eng→Hinglish, two teams (UBC_HImt, LTRC-PreCog) outperform the baseline. The best performance achieved was from UBC_HImt with a BLEU score of 12.67%, outperforming the baseline by 1.67%. For the task of MSAEA→Eng, the only one submission received was from UBC_ARmt with a BLEU Score of 25.72%, outperforming the baseline by 23.92%.

### 7 Analysis

Although most of the scores reported by the participants outperformed the baselines for both Eng→Hinglish and MSAEA→Eng, we notice that the BLEU metric takes overlapped tokens into consideration, which may potentially result in a higher score. Additionally, the overall results are arguably lower compared to results achieved by the state-of-the-art systems on monolingual data for these language pairs, i.e. in the absence of code-switching. We conduct error analysis to understand and expose the bottleneck of machine translation on code-switched data.

#### 7.1 Evaluation Metrics

In Table 4, it is worth noting that the Echo system, with inputs as outputs, could outperform the transformer-based baseline1 system in four out of five language translation directions. We suspect the high scores from the Echo system are because of the high overlap between the training and testing data. Therefore, to minimize such impact, we normalize the text by removing the overlapping tokens from the data, including username mentions, emoji expressions, and URLs. The results of BLEU and normalized BLEU scores on each system for the task of Eng→Hinglish are shown in Table 6 where we note significant drops in performance ranging from 0.43% to 6.13 BLEU score. After normalizing the text, the Echo system can only reach 0.71 BLEU points, which is far lower than the performance of baseline1. Although the performances of participating systems also decrease drastically, some can still outperform the baseline1.
Table 5: Poor translation Examples for the task of Eng→Hinglish. Errors in translations from participating systems are highlighted in bold in brackets (e.g., [shailee]). Reference translations are provided for comparison.

| # | Sentence | Gold Standard/Reference Translation | System Prediction |
|---|----------|--------------------------------------|-------------------|
| 1 | Yes you definitely should haan tumhe definitely dekhna chahiye | haan, [jurur aapako] |  |
| 2 | It’s about a mute cleaner and she works at a secret government lab | ye ek mute cleaner ke baare mein hai jo secret government lab mein work karti hai | yah ek mute cleaner ke baare mein hai aur [wo] secret government lab par kaam karta hai |
| 3 | I wasn’t sure about those two to start out with, they just didn’t seem like they’d be good together | mujhe un donon ke baare mein nishchit nahin tha ki ve shuruaat kar sakate hain, unhen aisa nahin lagata tha ki ve ek saath achchhe honge | mujhe un dono ke baare mein [start out mein sure nahi tha], unhe aisa [lagta hai wo acche sath mein rehne nahin lagte hain] |
| 4 | I mean not rated well | mujhe lagta hai ki ise thik se rate nahi kiya gaya | meray mathalab [yah nahem tha ki] |
| 5 | The shape of water is a great movie | The shape of water ek bahut achchi movie hai | [shailee] ke ek mahaan philm hai |

Table 6: The BLEU and the normalized BLEU scores on the task of Eng→Hinglish. The largest number for each column is in bold.

| System   | BLEU | BLEU_norm | Drop |
|----------|------|-----------|------|
| **Baselines** | | | |
| Baseline1 | 11.00 | 6.05 | 4.95 |
| Echo | 6.84 | 0.71 | 6.13 |
| **Participating Systems** | | | |
| UBC_HImt | 12.67 | 7.58 | 5.09 |
| IITP-MT | 10.09 | 6.33 | 3.76 |
| CMMTOne | 2.58 | 2.15 | 0.43 |
| LTRC-PreCog | 12.22 | 6.70 | 5.52 |

7.2 Error Analysis

Although most of the scores reported by the participants outperform the baseline, there are many mistakes made by the models. Thus, we manually inspect the predictions from participating systems. Table 5 shows some cases where the participating systems produce low quality translations for the task of Eng→Hinglish.

Based on our findings, there are two main errors among the predictions: grammar errors and semantic errors. For the grammar errors, we find that many predicted sentences have incorrect word/phrase orders. Although linguistic theories of code-switching argue that code-switching does not violate syntactic constraints of the languages involved (Poplack, 1980, 2013), it may still impact models ability to correctly capture grammatical structures from the involved languages. Moreover, we observe that some translations may have extra punctuation or incorrect pronouns. Gender translation errors are also common in MT systems for monolingual data (Stanovsky et al., 2019; Saunders and Byrne, 2020). For the semantic errors, it is worth noting that many sentences can only be translated partially. Understanding the semantics of code-switching is difficult as the model has to learn the word representations and dependencies for all involved languages. This may result in incomplete or irrelevant translations.

8 Conclusion

This paper summarizes the insights gained from creating a task on MT for code-switched language. Given a monolingual/code-switched sentence, the goal is to translate it into a code-switched/monolingual sentence. We introduced a machine translation dataset focused on code-switched social media text for three language pairs: English-Hinglish, English-Spanglish, and English-Modern Standard Arabic-Egyptian Arabic with one or two directions for each pair. We received 12 submissions from 5 teams, 4 of them submitted to English→Hinglish and 1 of them submitted to Modern Standard Arabic-Egyptian Arabic→English. While the participating systems are different, we observed that there is a strong trend favoring the use of transformer-based models (e.g, mBART) as a key ingredient in the proposed architectures. The best performances achieved were 12.67% BLEU score for English→Hinglish and 25.72% BLEU score for Modern Standard Arabic-Egyptian Arabic→English. Compared to monolingual formal text, the reported BLEU scores are significantly lower, which highlights the difficulty of both, the linguistic properties in code-switched data, and the noise attributed to the social media genre. More investigations need to be carried out to disentangle the effects of each factor. However, this shared task demonstrates that performing machine translation on code-switched data
is a new horizon of interest in the NLP community and more work needs to be done to bring performance on par to monolingual systems. It is also likely that advances in MT for code-switched data will lead to groundbreaking contributions to the general field of MT.

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References

Gustavo Aguilar, Fahad AlGhamdi, Victor Soto, Mona Diab, Julia Hirschberg, and Thamar Solorio. 2018. Named entity recognition on code-switched data: Overview of the CALCS 2018 shared task. In Proceedings of the Third Workshop on Computational Approaches to Linguistic Code-Switching, pages 138–147, Melbourne, Australia. Association for Computational Linguistics.

Gustavo Aguilar, Sudipta Kar, and Thamar Solorio. 2020. LinCE: A centralized benchmark for linguistic code-switching evaluation. In Proceedings of the 12th Language Resources and Evaluation Conference, pages 1803–1813, Marseille, France. European Language Resources Association.

Gustavo Aguilar and Thamar Solorio. 2020. From English to code-switching: Transfer learning with strong morphological clues. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 8033–8044, Online. Association for Computational Linguistics.

Ramakrishna Appicharla, Kamal Kumar Gupta, Asif Ekbal, and Pushpak Bhattacharyya. 2021. IITP-MT at CALCS2021: English to Hinglish neural machine translation using unsupervised synthetic code-mixed parallel corpus. In Proceedings of the Fifth Workshop on Computational Approaches to Linguistic Code-Switching, pages 31–35, Online. Association for Computational Linguistics.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Sumanth Doddapaneni, Gowtham Ramesh, Anoop Kunchukuttan, Pratyush Kumar, and Mitesh M Khapra. 2021. A primer on pretrained multilingual language models. arXiv preprint arXiv:2107.00676.

Suman Dowlagar and Radhika Mamidi. 2021. Gated convolutional sequence to sequence based learning for English-hinglish code-switched machine translation. In Proceedings of the Fifth Workshop on Computational Approaches to Linguistic Code-Switching, pages 26–30, Online. Association for Computational Linguistics.

Björn Gambäck and Amitava Das. 2014. On measuring the complexity of code-mixing. In Proceedings of the 11th International Conference on Natural Language Processing, Goa, India, pages 1–7.

Saurabh Garg, Tanmay Parekh, and Preethi Jyothi. 2018. Code-switched language models using dual RNNs and same-source pretraining. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 3078–3083, Brussels, Belgium. Association for Computational Linguistics.

Devansh Gautam, Prashant Kodali, Kshitij Gupta, Anmol Goel, Manish Shrivastava, and Ponnurangam Kumaraguru. 2021. CoMeT: Towards code-mixed translation using parallel monolingual sentences. In Proceedings of the Fifth Workshop on Computational Approaches to Linguistic Code-Switching, pages 47–55, Online. Association for Computational Linguistics.

Hila Gonen and Yoav Goldberg. 2019. Language modeling for code-switching: Evaluation, integration of monolingual data, and discriminative training. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 4175–4185, Hong Kong, China. Association for Computational Linguistics.

P Goyal, Manav R Mital, A Mukerjee, Achla M Raina, D Sharma, P Shukla, and K Vikram. 2003. A bilingual parser for hindi, english and code-switching structures. In 10th Conference of The European Chapter, page 15.

Shaleen Kumar Gupta, Sahitya Poturi, Aishwarya Reganti, Harsh Lara, and Alan W. Black. 2019. Cmu hinglish grounded conversations dataset.

Gualberto A Guzmán, Joseph Ricard, Jacqueline Sergios, Barbara E Bullock, and Almeida Jacqueline Toribio. 2017. Metrics for modeling code-switching across corpora. In INTERSPEECH, pages 67–71.

Ganesh Jawahar, El Moatez Billah Nagoudi, Muhammad Abdul-Mageed, and Laks Lakshmanan, V.S. 2021. Exploring text-to-text transformers for English to Hinglish machine translation with synthetic code-mixing. In Proceedings of the Fifth Workshop on Computational Approaches to Linguistic Code-Switching, pages 36–46, Online. Association for Computational Linguistics.
Aravind K. Joshi. 1982. Processing of sentences with intra-sentential code-switching. In Coling 1982: Proceedings of the Ninth International Conference on Computational Linguistics.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020. BART: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7871–7880. Online. Association for Computational Linguistics.

Yinhan Liu, Jiatao Gu, Naman Goyal, Xian Li, Sergey Edunov, Marjan Ghazvininejad, Mike Lewis, and Luke Zettlemoyer. 2020. Multilingual denoising pre-training for neural machine translation. Transactions of the Association for Computational Linguistics, 8:726–742.

Giovanni Molina, Fahad AlGhamdi, Mahmoud Ghoneim, Abdelati Hawwari, Nicolas Rey-Villamizar, Mona Diab, and Thamar Solorio. 2016. Overview for the second shared task on language identification in code-switched data. In Proceedings of the Second Workshop on Computational Approaches to Code Switching, pages 40–49, Austin, Texas. Association for Computational Linguistics.

El Moatez Billah Nagoudi, AbdelRahim Elmadany, and Muhammad Abdul-Mageed. 2021. Investigating code-mixed Modern Standard Arabic-Egyptian to English machine translation. In Proceedings of the Fifth Workshop on Computational Approaches to Linguistic Code-Switching, pages 56–64, Online. Association for Computational Linguistics.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics, pages 311–318, Philadelphia, Pennsylvania, USA. Association for Computational Linguistics.

Shana Poplack. 1980. Sometimes i’ll start a sentence in spanish y termino en espanol: toward a topology of code-switching1.

Shana Poplack. 2013. “sometimes i’ll start a sentence in spanish y termino en espanol”: Toward a topology of code-switching. Linguistics, 51(s1):11–14.

Matt Post. 2018. A call for clarity in reporting BLEU scores. In Proceedings of the Third Conference on Machine Translation: Research Papers, pages 186–191, Brussels, Belgium. Association for Computational Linguistics.

Danielle Saunders and Bill Byrne. 2020. Reducing gender bias in neural machine translation as a domain adaptation problem. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7724–7736. Online. Association for Computational Linguistics.

Thoudam Doren Singh and Thamar Solorio. 2017. Towards translating mixed-code comments from social media. In International Conference on Computational Linguistics and Intelligent Text Processing, pages 457–468. Springer.

Thamar Solorio, Elizabeth Blair, Suraj Maharjan, Steven Bethard, Mona Diab, Mahmoud Ghoneim, Abdelati Hawwari, Fahad AlGhamdi, Julia Hirschberg, Alison Chang, and Pascale Fung. 2014. Overview for the first shared task on language identification in code-switched data. In Proceedings of the First Workshop on Computational Approaches to Code Switching, pages 62–72, Doha, Qatar. Association for Computational Linguistics.

Thamar Solorio and Yang Liu. 2008. Learning to predict code-switching points. In Proceedings of the 2008 Conference on Empirical Methods in Natural Language Processing, pages 973–981, Honolulu, Hawaii. Association for Computational Linguistics.

Vivek Srivastava and Mayank Singh. 2020. PHINC: A parallel Hinglish social media code-mixed corpus for machine translation. In Proceedings of the Sixth Workshop on Noisy User-generated Text (W-NUT 2020), pages 41–49, Online. Association for Computational Linguistics.

Gabriel Stanovsky, Noah A. Smith, and Luke Zettlemoyer. 2019. Evaluating gender bias in machine translation. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 1679–1684, Florence, Italy. Association for Computational Linguistics.

Ishan Tarunesh, Syamantak Kumar, and Preethi Jyothi. 2021. From machine translation to code-switching: Generating high-quality code-switched text. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 3154–3169, Online. Association for Computational Linguistics.

Almeida Jacqueline Toribio. 2001. Accessing bilingual code-switching competence. International Journal of Bilingualism, 5:403–436.

Genta Indra Winata, Zhaojiang Lin, and Pascale Fung. 2019. Learning multilingual meta-embeddings for code-switching named entity recognition. In Proceedings of the 4th Workshop on Representation Learning for NLP (RepL4NLP-2019), pages 181–186, Florence, Italy. Association for Computational Linguistics.

Jiatao Xu and François Yvon. 2021. Can you traducir this? machine translation for code-switched input. In Proceedings of the Fifth Workshop on Computational Approaches to Linguistic Code-Switching,
Linting Xue, Noah Constant, Adam Roberts, Mihir Kale, Rami Al-Rfou, Aditya Siddhant, Aditya Barua, and Colin Raffel. 2021. mT5: A massively multilingual pre-trained text-to-text transformer. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 483–498, Online. Association for Computational Linguistics.

Zhen Yang, Bojie Hu, Ambyera Han, Shen Huang, and Qi Ju. 2020. CSP: code-switching pre-training for neural machine translation. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 2624–2636, Online. Association for Computational Linguistics.

Kangyan Zhou, Shrimai Prabhumoye, and Alan W Black. 2018. A dataset for document grounded conversations. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 708–713, Brussels, Belgium. Association for Computational Linguistics.