Checks and Strategies for Enabling Code-Switched Machine Translation

Thamme Gowda and Mozhdeh Gheini and Jonathan May
Information Sciences Institute and Computer Science Department
University of Southern California
{tg,gheini,jonmay}@isi.edu

Abstract

Code-switching is a common phenomenon among multilingual speakers, where alternation between two or more languages occurs within the context of a single conversation. While multilingual humans can seamlessly switch back and forth between languages, multilingual neural machine translation (NMT) models are not robust to such sudden changes in input. This work explores multilingual NMT models' ability to handle code-switched text. First, we propose checks to measure switching capability. Second, we investigate simple and effective data augmentation methods that can enhance an NMT model’s ability to support code-switching. Finally, by using a glass-box analysis of attention modules, we demonstrate the effectiveness of these methods in improving robustness.

1 Introduction

Neural machine translation (NMT) (Sutskever et al., 2014; Bahdanau et al., 2015; Vaswani et al., 2017) has made significant progress, from supporting only a pair of languages per model to simultaneously supporting hundreds of languages (Johnson et al., 2017; Zhang et al., 2020; Tiedemann, 2020; Gowda et al., 2021b). Multilingual NMT models have been deployed in production systems and are actively used to translate across languages in day-to-day settings (Wu et al., 2016; Caswell, 2020; Mohan and Skotdal, 2021). A great many metrics for evaluation of machine translation have been proposed (Doddington, 2002; Banerjee and Lavie, 2005; Snover et al., 2006; Popović, 2015; Gowda et al., 2021a); simply citing a more comprehensive list would exceed space limitations, however, except context-aware MT, nearly all approaches consider translation in the context of a single sentence. Even approaches that generalize to support translation of multiple languages (Zhang et al., 2020; Tiedemann, 2020; Gowda et al., 2021b) continue to use the single-sentence, single-language paradigm. In reality, however, multilingual environments often involve language alternation or code-switching (CS), where seamless alternation between two or more languages occurs (Myers-Scotton and Ury, 1977).

CS can be broadly classified into two types (Myers-Scotton, 1989): (i) intra-sentential CS, where switching occurs within sentence or clause boundary, and (ii) inter-sentential CS, where switching occurs at sentence or clause boundaries. An example for each type is given in Table 1. CS has been studied extensively in linguistics communities (Nilep, 2006); however, the efforts in the MT community are scant (Gupta et al., 2021).

| Intra | Ce moment when you start penser en deux langues at the same temps. (The moment when you start to think in two languages at the same time.) |
|-------|---------------------------------------------------------------------------------------------------------------------------------|
| Inter | Comme on fait son lit, you must lie on it. (As you make your bed, you must lie on it.)                                            |

Table 1: Intra- and inter-sentential code-switching examples between French and English.

In this work, we show that, as commonly built, multilingual NMT models are not robust to multi-sentence translation, especially when CS is involved. The contributions of this work are outlined as follows: Firstly, a few simple but effective checks for improving the test coverage in multilingual NMT evaluation are described (Section 2). Secondly, we explore training data augmentation techniques such as concatenation and noise addition in the context of multilingual NMT (Section 3). Third, using a many-to-one multilingual translation task setup (Section 4), we investigate the relationship between training data augmentation methods and their impact on multilingual test cases. Fourth,
we conduct a glass-box analysis of cross-attention in the Transformer architecture and show visually as well as quantitatively that the models trained with concatenated training sentences learn a more sharply focused attention mechanism than others. Finally, we examine how our data augmentation strategies generalize to multi-sentence translation for a variable number of sentences, and determine that two-sentence concatenation in training is sufficient to model many-sentence concatenation in inference (Section 5.2).

2 Multilingual Translation Evaluation: Additional Checks

Notation: For simplicity, consider a many-to-one model that translates sentences from $K$ source languages, $\{L_k | k = 1, 2, ... K\}$, to a target language, $T$. Let $x_i^{(L_k)}$ be a sentence in the source language $L_k$, and let its translation in the target language be $y_i^{(T)}$; where unambiguous we omit the superscripts.

We propose the following checks to be used for multilingual NMT:

C-TL: Consecutive sentences in the source and target languages. This check tests if the translator can translate in the presence of inter-sentential CS, and preserve phrases that are already in the target language. For completeness, we can test both source-to-target and target-to-source CS, as follows:

$$x_i^{(L_k)} + x_{i+1}^{(L_k)} \rightarrow y_i + y_{i+1} \quad (1)$$

$$y_i + x_{i+1}^{(L_k)} \rightarrow y_i + y_{i+1} \quad (2)$$

In practice, we use a space character to join sentences, indicated by the concatenation operator ‘+’. This check requires the held-out set sentence order to preserve the coherency of the original document.

C-XL: This check tests if a multilingual translator can function in light of a topic switch among its supported source languages. For any two languages $L_k$ and $L_m$ and random positions $i$ and $j$ in their original corpus, we obtain a test segment by concatenating them as:

$$x_i^{(L_k)} + x_j^{(L_m)} \rightarrow y_i + y_j \quad (4)$$

This method makes the fewest assumptions about the nature of held-out datasets, i.e., unlike previous methods, neither multi-parallelism nor coherency in sentence order is necessary.

C-SL: Concatenate consecutive sentences in the same language. While this check is not a test on CS, this helps in testing if the model is invariant to a missed segmentation, as it is not always trivial to determine sentence segmentation in continuous language. This check is possible if held-out set sentence order preserves the coherency of the original document. Formally,

$$x_i^{(L_k)} + x_{i+1}^{(L_k)} \rightarrow y_i + y_{i+1} \quad (5)$$

3 Achieving Robustness via Data Augmentation Methods

In the previous section, we described several ways of improving test coverage for multilingual translation models. In this section, we explore training data augmentation techniques to improve robustness to code-switching settings.

3.1 Concatenation

Concatenation of training sentences has been proven to be a useful data augmentation technique; Nguyen et al. (2021) investigate key factors behind the usefulness of training segment concatenations in bilingual settings. Their experiments reveal that concatenating random sentences performs as well as consecutive sentence concatenation, which suggests that discourse coherence is unlikely the driving factor behind the gains. They attribute the gains to three factors: context diversity, length diversity, and position shifting.

In this work, we investigate training data concatenation under multilingual settings, hypothesizing that concatenation helps achieve the robustness checks that are described in Section 2. Our training concatenation approaches are similar to our check sets, with the notable exception that we do not consider consecutive sentence training specifically, both because of Nguyen et al. (2021)’s finding and because training data gathering techniques...
can often restrict the availability of consecutive data (Bañón et al., 2020). We investigate the following sub-settings for concatenations:

**CatSL:** Concatenate a pair of source sentences in the same language, using space whenever appropriate (e.g., languages with space separated tokens).

\[ x_i^{(L_k)} + x_j^{(L_k)} \rightarrow y_i + y_j \]  

**CatXL:** Concatenate a pair of source sentences, without constraint on language.

\[ x_i^{(L_k)} + x_j^{(L_m)} \rightarrow y_i + y_j \]  

**CatRepeat:** The same sentence is repeated and then concatenated. Although this seems uninteresting, it serves a key role in ruling out gains possibly due to data repetition and modification of sentence lengths.

\[ x_i^{(L_k)} + x_i^{(L_k)} \rightarrow y_i + y_i \]  

### 3.2 Adding Noise

We hypothesize that introducing noise during training might help achieve robustness and investigate two approaches that rely on noise addition:

**DenoiseTgt:** Form the source side of a target segment by adding noise to it. Formally, \( noise(y; r) \rightarrow y \), where hyperparameter \( r \) controls the noise ratio. Denoising is an important technique in unsupervised NMT (Artetxe et al., 2018; Lample et al., 2018).

**NoisySrc:** Add noise to the source side of a translation pair. Formally, \( noise(x; r) \rightarrow y \). This resembles back-translation (Sennrich et al., 2016a) where augmented data is formed by pairing noisy source sentences with clean target sentences.

The function \( noise(\ldots; r) \) is implemented as follows: (i) \( r\% \) of random tokens are dropped, (ii) \( r\% \) of random tokens are replaced with random types uniformly sampled from vocabulary, and (iii) \( r\% \) of random tokens’ positions are displaced within a sequence. We use \( r = 10\% \) in this work.

### 4 Setup

#### 4.1 Dataset

We use publicly available datasets from The Workshop on Asian Translation 2021 (WAT21)’s Multilingual IndicMT (Nakazawa et al., 2021)\(^2\) shared task. This task involves translation between English(EN) and 10 Indic Languages, namely: Bengali(BN), Gujarati(GU), Hindi(HI), Kannada(KN), Malayalam(ML), Marathi(MR), Oriya(OR), Punjabi(PA), Tamil(TA) and Telugu(TE). The development and held-out test sets are multi-parallel and contain 1,000 and 2,390 sentences, respectively. The training set contains a small portion of data from the same domain as the held-out sets, as well as additional datasets from other domains. All the training data statistics are given in Table 2. We focus on the Indic-English (many-to-one) translation direction in this work.

Following the definitions in Section 2, we create C-SL, C-TL, C-XL, and R-XL versions of development and test sets; statistics are given in Table 3. An example demonstrating the nuances in all these four methods is shown in Table 4. Following the definitions in Section 3, we create CatSL, CatXL, CatRepeat, DenoiseTgt, and NoisySrc augmented training segments. For each of these training corpus augmentation methods, we restrict the total

| Language   | In-domain | All-data |
|------------|-----------|----------|
| Bengali (BN)| 23.3k/0.4M/0.4M | 1.3M/19.5M/21.3M |
| Gujarati (GU)| 41.6k/0.7M/0.8M | 0.5M/07.2M/09.5M |
| Hindi (HI)| 50.3k/1.1M/1.0M | 3.1M/54.7M/51.8M |
| Kannada (KN)| 28.9k/0.4M/0.6M | 0.4M/04.6M/08.7M |
| Malayalam(ML)| 26.9k/0.3M/0.5M | 1.1M/11.6M/19.0M |
| Marathi (MR)| 29.0k/0.4M/0.5M | 0.6M/09.2M/13.1M |
| Oriya (OR)| 32.0k/0.5M/0.6M | 0.3M/04.4M/05.1M |
| Punjabi (PA)| 28.3k/0.6M/0.5M | 0.5M/10.1M/10.9M |
| Tamil (TA)| 32.6k/0.4M/0.6M | 1.4M/16.0M/27.0M |
| Telugu (TE)| 33.4k/0.5M/0.6M | 0.5M/05.7M/09.1M |
| All | 326k/5.3M/6.1M | 9.6M/143M/175M |

Table 2: Training dataset statistics: segments / source / target tokens, before tokenization.

| Name | Dev | Test |
|------|-----|------|
| Orig | 10k/140.5k/163.2k | 23.9k/331.1k/385.1k |
| C-TL | 10k/303.7k/326.4k | 23.9k/716.1k/770.1k |
| C-XL | 10k/283.9k/326.4k | 23.9k/670.7k/770.1k |
| R-XL | 10k/216.0k/251.2k | 23.9k/514.5k/600.5k |
| C-SL | 10k/281.0k/326.4k | 23.9k/662.1k/770.1k |

Table 3: Development and test set statistics: segments / source / target tokens, before subword tokenization.

The row named ‘Orig’ is the union of all ten individual languages’ datasets, and the rest are created as per definitions in Section 2. Dev-Orig set is used for validation and early stopping in all our multilingual models.

http://lotus.kuee.kyoto-u.ac.jp/WAT/indic-multilingual/
We use a Transformer base model (Vaswani et al., 2017) which has 512 hidden dimensions, 6 encoder and decoder layers, 8 attention heads, and intermediate feedforward layers of 2048 dimensions. We use a Pytorch based NMT toolkit. Tuning the vocabulary size and batch size are important to achieve competitive performance. We use byte-pair-encoding (BPE) (Sennrich et al., 2016b), with vocabulary size adjusted as per the recommendations from Gowda and May (2020). Since the source side has many languages and the target side has only a single language, we use a larger source vocabulary than that of the target. The source side vocabulary contains BPE types from all 11 languages (i.e., ten source languages and English), whereas to improve the efficiency in the decoder’s softmax layer, the target vocabulary is restricted to contain English only. Our in-domain limited-data setup learns BPE vocabularies of 30.4k and 4.8k types for source and target languages. Similarly, the all-data setup learns 230.4k and 63.4k types.

The median sequence lengths in training after subword segmentation but before sentence concatenation are 15 on the Indic side and 17 on the English side. We model sequence lengths up to 512 time steps during training. We use the same learning rate schedule as Vaswani et al. (2017). We train our models until a maximum of 200k optimizer steps, and use early stopping with a patience of 10 validations. Validations are performed after every 1000 optimizer steps. All our models are trained using one Nvidia A40 GPU per setting. The smaller in-domain setup takes less than 24 hours per run, whereas the larger all-data setup takes at most 48 hours per run (or less when early stopping criteria are reached). We run each experiment two times and report the average. During inference, we average the last 5 checkpoints and use a beam decoder of size 4 and length penalty of $\alpha = 0.6$ (Vaswani et al., 2017; Wu et al., 2016).

### 5 Results and Analysis

We train multilingual many-to-one models for both in-domain and all data. Table 5 presents our results from a limited quantity in-domain dataset. The baseline model (#I1) has strong performance on individual sentences, but degrades on held-out sets involving missed sentence segmentation and code-switching. Experiments with concatenated data, namely CatXL (#I3) and CatSL (#I4), while they appear to make no improvements on regular held-out sets, make a significant improvement in BLEU scores on C-SL, C-XL, and R-XL. Furthermore, both CatSL and CatXL show a similar trend. While they also make a small gain on the C-TL setting. DenoiseTgt method is clearly an outperformer on C-TL. The model that includes both concatenation and denoising (#I7) achieves consistent gains across all the robustness check columns. In contrast, the CatRepeat (#I2) and NoisySrc (#I5) methods do not show any gains.

Our results from the all-data setup are provided in Table 6. While none of the augmentation methods appear to surpass baseline BLEU on the regular held-out sets (i.e., Orig column), their improve-
Table 5: Indic-English BLEU scores for models trained on in-domain training data only. *Abbreviations:* Orig: average across ten languages’ original held-out set, C-: consecutive sentences, R-: random sentences, TL: target-language (i.e, English), SL: same-language, XL: cross-language.

| ID     | All-data | Dev   | Test  |
|--------|----------|-------|-------|
| #A1 Baseline (B) | 35.0 | 43.1 | 30.0 | 29.5 | 32.4 | 42.2 | 27.8 | 27.3 | 26.1 |
| #A2 B+CatRepeat | 34.5 | 43.7 | 30.3 | 29.9 | 32.0 | 42.9 | 28.0 | 27.6 | 26.3 |
| #A3 B+CatXL | 34.1 | 53.3 | 31.9 | 33.7 | 34.4 | 31.6 | 52.4 | 29.7 | 31.0 | 31.2 |
| #A4 B+CatSL | 33.6 | 54.0 | 32.5 | 32.2 | 34.3 | 31.3 | 53.3 | 30.4 | 29.9 | 31.1 |
| #A5 B+NoisySrc | 34.9 | 42.1 | 29.8 | 29.2 | 27.8 | 32.3 | 41.7 | 27.6 | 27.1 | 25.8 |
| #A6 B+DenoiseTgt | 33.3 | 60.0 | 28.9 | 28.4 | 27.3 | 31.3 | 59.4 | 27.1 | 26.5 | 25.4 |
| #A7 B+CatXL+DenoiseTgt | 33.3 | 65.8 | 31.1 | 33.0 | 35.6 | 31.0 | 64.7 | 28.9 | 30.4 | 30.3 |

Table 6: Indic-English BLEU scores for models trained on all data. (Abbreviations are same as Table 5.)

| ID     | All-data | Dev   | Test  |
|--------|----------|-------|-------|
| #A1 Baseline (B) | 14.3 | 10.4 | 10.3 | 10.1 | 14.3 | 10.6 | 10.5 | 10.3 |
| #A2 B+CatRepeat | 12.3 | 8.9 | 8.9 | 8.6 | 12.5 | 9.0 | 9.0 | 8.7 |
| #A3 B+CatXL | 5.8 | 7.2 | 4.3 | 4.3 | 5.8 | 7.2 | 4.4 | 4.3 |
| #A4 B+CatSL | 5.3 | 6.2 | 6.1 | 5.2 | 5.4 | 6.2 | 6.2 | 5.2 |
| #A5 B+NoisySrc | 17.4 | 16.1 | 16.1 | 15.8 | 17.5 | 16.2 | 16.2 | 15.9 |
| #A6 B+DenoiseTgt | 7.9 | 8.3 | 8.4 | 8.0 | 8.1 | 8.5 | 8.5 | 8.1 |
| #A7 B+CatXL+DenoiseTgt | 4.3 | 6.8 | 3.9 | 4.1 | 4.4 | 7.0 | 4.0 | 4.1 |

Table 7: Cross-attention bleed rate (lower is better). All numbers are scaled from [0, 1] to [0, 100] for easier interpretation, and the best settings per test are indicated with bold font. Models trained on concatenated sentences have lower attention bleed rate. Denoising is better than baseline, but not as much as concatenation. The lowest bleed rate is achieved by using both concatenation and denoising methods. (Abbreviations are same as Table 5.)

5.1 Attention Bleed

Figures 1 and 2 visualize cross-attention from our baseline model without augmentation as well as models trained with augmentation. Generally, the NMT decoder is run autoregressively; however, to facilitate the analysis described in this section, we force-decode reference translations and extract cross-attention tensors from all models. The cross-attention visualization between a pair of concatenated sentences, say \((x_{i1} + x_{i2} \rightarrow y_{i1} + y_{i2})\), shows that models trained on augmented datasets appear to have less cross-attention mass across sentences, i.e. in the attention grid regions representing \(x_{i2} \leftarrow y_{i1}\), and \(x_{i1} \leftarrow y_{i2}\). We call attention mass in such regions attention bleed. This observation confirms some of the findings suggested by Nguyen et al. (2021). We quantify attention bleed as follows: consider a Transformer NMT model with \(L\) layers, each having \(H\) attention heads and a held-out dataset of \(\{(x_i, y_i) | i = 1, 2, \ldots, N\}\) segments. Further more, let each segment \((x_i, y_i)\) be a concatenation of two sentences i.e. \((x_{i1} + x_{i2}, y_{i1} + y_{i2})\), with known sentence boundaries. Let \(|x_i|\) and \(|y_i|\) be the sequence lengths after BPE segmentation.

\[^4\text{Also known as encoder-decoder attention.}\]
He said the aim is to complete this task by 2022. The Prime Minister said that the Government is working on several schemes with clear objectives and timelines.

We have set a target to complete this task by 2022. The Prime Minister said that the Government is working on a number of schemes with clear targets and timelines.

Reference:

Table 8: Example translations from the models trained on all-data setup. See Table 6 for quantitative scores of these models, and Figures 1 and 2 for a visualization of cross-attention.

and \( |x_{i+1}| \) and \( |y_{i+1}| \) be the indices of the end of the first sentence (i.e., the sentence boundary) on the source and target sides, respectively. The average attention bleed across all the segments, layers, and heads is defined as:

\[
\bar{B} = \frac{1}{N \times L \times H} \sum_{i=1}^{N} \sum_{l=1}^{L} \sum_{h=1}^{H} b_{i,l,h} \tag{9}
\]

where \( b_{i,l,h} \) is the attention bleed rate in an attention head \( h \in [1, H] \), in layer \( l \in [1, L] \), for a single record at \( i \in [1, N] \). To compute \( b_{i,l,h} \), consider that an attention grid \( A_{i,l,h}^{(i,l,h)} \) is of size \( |y_{i}| \times |x_{i}| \). Then

\[
b_{i,l,h} = \frac{1}{|y_{i}|} \left[ \sum_{t=1}^{|y_{i}|} \sum_{s=|x_{i}|+1}^{|x_{i}|} A_{t,s}^{(i,l,h)} \right] \tag{10}
\]

where \( A_{t,s}^{(i,l,h)} \) is the percent of attention paid to source position \( s \) by target position \( t \) at decoder layer \( l \) and head \( h \) in record \( i \). Intuitively, a lower value of \( \bar{B} \) is better, as it indicates that the model has learned to pay attention to appropriate regions. As shown in Table 7, the models trained on augmented sentences achieve lower attention bleed.

5.2 Sentence Concatenation Generalization

In the previous sections, only two-segment concatenation has been explored; here, we investi-
datasets having up to four sentences. As shown in Table 9, the model trained with just two segment concatenation achieves a similar BLEU as model trained with up to four concatenations.

### 6 Related Work

**Robustness and Code-Switching:** MT robustness has been investigated before within the scope of bilingual translation settings. Some of those efforts include robustness against input perturbations (Cheng et al., 2018), naturally occurring noise (Vaibhav et al., 2019), and domain shift (Müller et al., 2020). However, as we have shown in this work, multilingual translation models can introduce new aspects of robustness to be desired and evaluated. The robustness checklist proposed by Ribeiro et al. (2020) for NLP modeling in general does not cover translation tasks, whereas our work focuses entirely on the multilingual translation task. Clinchant et al. (2019) and Niu et al. (2020) create synthetic test sets to increase test coverage, however, unlike our work, their synthetic tests do not simulate CS. Belinkov and Bisk (2018) investigate the effect of noise on character based NMT and find that excess noise is detrimental to performance as models are brittle. Yang et al. (2020) artificially create CS text via unsupervised lexicon induction for pretraining NMT in bilingual settings, and Song et al. (2019) make CS training data to achieve lexically constrained translation, however, neither of these investigate model’s ability to translate CS text at evaluation time.

**Augmentation Through Concatenation:** Concatenation has been used before as a simple-to-incorporate augmentation method. Concatenation can be limited to consecutive sentences as a means to provide extended context for translation (Tiedemann and Scherrer, 2017; Agrawal et al., 2018), or additionally include putting random sentences together, which has been shown to result in gains under low resource settings (Nguyen et al., 2021; Kondo et al., 2021). While in a multilingual setting such as ours, data scarcity is less of a concern as a result of combining multiple corpora, concatenation is still helpful to prepare the model for scenarios where code-switching is plausible. Besides data augmentation, concatenation has also been used

| Dev   | Test  |
|-------|-------|
| C-SL  | C-4SL |
| C-SL  | C-4SL |

Table 9: Indic-English BLEU on held out sets containing up to 4 consecutive sentence concatenations in same language (C-4SL). The two sentences dataset (C-SL) is also given for comparison. The model trained on two concatenated sentences achieves comparable results on C-4SL, indicating that no further gains are obtained from increasing concatenation in training.

Figure 2: Cross-attention visualization (... continuation from Figure 1) The model trained on both concatenated and denoising sentences has least attention mass across sentences.
to train multi-source NMT models. Multi-source models (Och and Ney, 2001) translate multiple semantically-equivalent source sentences into a single target sentence. Dabre et al. (2017) show that by concatenating the source sentences (equivalent sentences from different languages), they are able to train a single-encoder NMT model that is competitive with models that use separate encoders for different source languages. Backtranslation (Sennrich et al., 2016a) is another useful method for data augmentation, however it is more expensive when the source side has many languages, and does not focus on code-switching.

Attention Weights: Attention mechanism (Bahdanau et al., 2015) enables the NMT decoder to choose which part of the input to focus on during its stepped generation. The attention distributions learned while training a machine translation model, as an indicator of the context on which the decoder is focusing, have been used to obtain word alignments (Garg et al., 2019; Zenkel et al., 2019, 2020; Chen et al., 2020). In this work, by visualizing attention weights, we depict how augmenting the training data guides attention to more neatly focus on the sentence of interest while decoding its corresponding target sentence. We are also able to quantify this by the introduction of the attention bleed metric.

7 Conclusion

We have described simple but effective checks for improving test coverage in multilingual NMT (Section 2), and have explored training data augmentation methods such as sentence concatenation and noise addition (Section 3). Using a many-to-one multilingual setup, we have investigated the relationship between these augmentation methods and their impact on robustness in multilingual translation. While the methods are useful in limited training data settings, their impact may not be visible on single-sentence test sets in a high resource setting. However, our proposed evaluation checks reveals the robustness improvement in both the low resource as well as high resource settings. We have conducted a glass-box analysis of cross-attention in Transformer NMT showing both visually and quantitatively that the models trained with augmentations, specifically, sentence concatenation and target sentence denoising, learn a more sharply focused attention mechanism (Section 5.1). Finally, we have determined that two-sentence concatenation in training corpora generalizes sufficiently to many-sentence concatenation inference (Section 5.2).

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Limitations

1. This work is focused on translating CS input, and does not attempt to generate CS text during translation. We consider the general problem of many-to-many translation with CS text on both input and output as a promising future direction.

2. As mentioned in Section 2, some of the multilingual evaluation checks require the datasets to have multi-parallelism, and coherency in the sentence order. When neither multi-parallelism nor coherency in the held-out set sentence order is available, we recommend R-XL.

3. While the proposed checks serve as starting points for testing CS, we do not claim that they are exhaustive of all manner of CS. The proposed checks specifically simulate intersentential CS; intra-sentential CS checks are left for future work.

4. We have investigated robustness under Indic-English translation tasks where all languages use space characters as word-breakers; we have not investigated other languages such as Chinese, Thai, etc. We use the term Indic language to collectively reference 10 Indian languages only, similar to MultiIndicMT shared task. While the remaining Indian languages and their dialects are not covered, we believe that the approaches discussed in this work generalize to other languages in the same family.
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