ABSTRACT

Code-Switching (CS) is referred to the phenomenon of alternately using words and phrases from different languages. While today’s neural end-to-end (E2E) models deliver state-of-the-art performances on the task of automatic speech recognition (ASR) it is commonly known that these systems are very data-intensive. However, there is only a few transcribed and aligned CS speech available. To overcome this problem and train multilingual systems which can transcribe CS speech, we propose a simple yet effective data augmentation in which audio and corresponding labels of different source languages are concatenated. By using this training data, our E2E model improves on transcribing CS speech and improves performance over the multilingual model, as well. The results show that this augmentation technique can even improve the model’s performance on inter-sentential language switches not seen during training by 5.03% WER.

Index Terms— speech recognition, code-switching, multilingual speech recognition, zero-shot code-switching

1. INTRODUCTION

Due to increasing globalization, a growing number of people use multiple languages while speaking. This often results in Code-Switching (CS), which is referred to as the change between languages while speaking. An example of German-English CS would be the phrase ‘Das war sehr strange’ (‘That was very strange’).

From a linguistic perspective, CS can be divided into multiple categories [1]:

- Inter-sentential CS: The switch between languages happens at sentence boundaries. Usually, the speaker is aware of the language shift.

- Intra-sentential CS: Here the second language is included in the middle of the sentence. This switch mainly occurs unaware of the speaker. Additionally, the word borrowed from the second language can happen to be adapted to the grammar of the matrix language as well.

- Extra-sentential CS: In this case, a tag element from a second language is included, for example at the end of a sentence. This word is more excluded from the main language.

Such examples, despite occurring frequently, pose a great challenge for all neural-network-based end-to-end ASR models. As of today, there are only a few CS data available for a very limited number of languages. Some example corpora available are [2] for CS between French and Algerian speech, [3] containing utterances switching between Mandarin and English, and [4] having gathered data with CS between English and Cantonese.

As an exemplary case, in this work, we focus on developing a multilingual ASR system capable of transcribing CS utterances between German and English. Considering the increased amount of Arabic-speaking people in Germany another common language that is mixed with German is Arabic and thus we included it as a third language. These languages are specifically interesting to analyze as German and English are from the same Indo-European language family while Arabic is part of the Afro-Asiatic language family. In our scenario, training would require not just transcribed monolingual, but also Code-Switching data between Arabic, German and English. As training data is not available in our scenario, we conduct multiple experiments using a straightforward CS data augmentation technique. We train an LSTM-based S2S model and show the ability to transcribe CS data, while simultaneously improving on monolingual data. Specifically, we present the following contributions:

First, we present a simple yet effective data augmentation technique designed for CS models in data-scarce scenarios. In particular, we take the utterances of our monolingual training data and append the features of audio signals after each other. The target labels are also concatenated accordingly, without the need for any additional information, such as the language tags for instance. Second, we perform an extensive evaluation of our model on intra- & inter-sentential CS test sets, as well as monolingual ones. During training, we use CS augmented data explained in [5]. Our evaluation is conducted on artificial as well as real data. We are also interested in the effects of this approach on only three languages in which one of which
is from a different language family using a completely different writing system. Our experiments yield interesting results section [5], including 1) enabling the model to reliably transcribe CS, 2) improving the performance of the multilingual model on monolingual test sets and 3) the capability of transcribing CS utterances for language pairs not switched during training.

2. RELATED WORK

As transcribing Code-Switching utterances inherently needs an ASR model which is multilingual to some degree, we want to refer to some of the early work in this research area such as [6], [7], [8], [9], [10] and [11].

As there are only a few CS data available there has not been too much research for language pairs without such data. Our work is based on the [12] with the difference that they add language tags to the labels when combining them and they have constraints of sampling and combining different utterances depending on the proportion of each language in the training data. They also restrict the number of times utterances can be used when generating CS data. An example target sequence would then look like this:

"[DE] ALSO VORWÄRTS [EN] WHERE ARE YOU"

In [12], it is also proposed to use curriculum learning. First, the authors train the multilingual models on data without code-switching. In the second step, training is continued with the above-mentioned code-switching data. Another work that focuses on CS where there are very few paired speech and text data available was presented in [13]. The authors of this paper used ASR models with a separate TDNN-LSTM [14] as an acoustic model, as well as a separate language model. Thus they were able to utilize CS speech-only data for enhancing the acoustic model and used CS text-only data they artificially created, using different approaches, for enhancing their language model.

Most of the work on Code-Switching, however, focuses on language pairs with some available CS data. In [15] the authors aim at solving the problem of code-switching using a multi-task learning (MTL) approach. The authors investigate training a model predicting a sequence of labels as well as predicting a language identifier at different levels. They also report that first training with monolingual data and fine-tuning it with CS speech improves their performance. In [16] the writers analyzed the effect of fine-tuning toward CS data on monolingual ASR. They show that fine-tuning a model on CS and monolingual data yields a better overall Word Error Rate (WER) than when only using Code-Switching data. In [17] the authors propose to train two separate models. One CTC model for speech recognition and another one for frame-level language prediction. During decoding, if the current frame has a very high probability for the blank symbol the blank label is emitted, otherwise the output probabilities of English tokens are multiplied by the probability of this frame being English and the Chinese labels are multiplied by the probability of this frame being Chinese speech. While improving the CS WER they report a decrease in monolingual speech recognition performance.

3. MODEL

For our experiments, we used a Sequence-to-sequence encoder-decoder-based model, as described in [18]. The model consists of an encoder and a decoder network. The encoder is made up of two two-dimensional CNN [19], [20] layers with 32 filters. The window size is three over both the time and the frequency dimensions. The stride with which the window is moved is defined as two for both dimensions. The outputs are then inputted into six bidirectional Long short-term memory (LSTM) [5] layers. The decoder is made up of two unidirectional LSTM layers. Afterward, the output of the decoder and encoder LSTMs are fed to the Multi-Head Attention (MHA) network. Next, the output is forwarded through a linear layer followed by a residual connection. This is then put into a linear layer, which projects the input to the label dimension. An abstract description of the neural network would look like this:

$$
	ext{enc} = \text{Bi-LSTM} (\text{CNN} (\text{logMel Spectrum}))
$$
$$
\text{tgt} = \text{LSTM} (\text{Embedding} (\text{out tokens}))
$$
$$
\text{dec} = (\text{MHA} (\text{enc}, \text{enc}, \text{tgt} + \text{tgt emb}) + \text{tgt emb})
$$
$$
\text{output} = \text{log softmax}(\text{dec})
$$

As input, we use 40-dimensional log-Mel features calculated on frames of 25 ms with a stride of 15 ms. In contrast to previous other works, we use one Byte pair encoding (BPE) [21] calculated on all three languages. This means we have in total 4000 labels for all languages. When calculating the BPE we made sure to use the same amount of text data for the three languages. The resulting BPE contains 2553 English, German, and 1444 Arabic tokens. The other three tokens are the unknown, start of sequence, and end of sequence tokens. The labels for the monolingual experiments were calculated on monolingual text data. We used the same number of parameters for all our experiments. 1024 dimensional LSTMs are trained using Adam optimizer [22] with a maximum learning rate of 0.002 and 8000 warm-up steps. An early abortion was applied if there were no improvements over five epochs with a model pool size of five. For tests, the epoch with the lowest validation perplexity during training was chosen.

4. DATA

As already mentioned in Section 1 we used three languages in this work, namely Arabic, German and English. The English training data is made up of How2 [23] and TED-LIUM (TED) [24] data sets. For the German training data we used Common
For our tests, we have monolingual test sets for each language. The Alj.2h data was dialect-free Arabic data extracted as explained in [29]. In order to evaluate the CS performance, we generated a test set (artificial) by applying the data augmentation technique, using CV, Alj.2h, and WSJ test sets, as described in Section 5. However, as we wanted to test our models on real CS data we used several different test sets as well. For intra-sentential CS with German as the matrix and English as the embedded language. We use our in-house Lect. test set where English words have been manually annotated. We combined this data with a small set of read speeches, collected by us. This is depicted as Deng. in Table 2. Important to note is that the overwhelming amount of this set are German words and only 4.5% are English. We also tested our models on the German-English intra-sentential CS test set derived from the Spoken Wikipedia Corpus (SWC) provided by [30], depicted as SWC-CS. Detailed information about our test sets can be taken from Table 2. Both of these intra-sentential sets have German as the matrix language with English words embedded. tst-inter is an inter-sentential CS set we derived from MuST-C (tst-COMMON) [31] data. At sentence boundaries, the sentence was continued in either English or German in a CS manner. These sentences were then read by two persons. We also collected a German-English CS test set (D-E-CS) and a German-Arabic test set (D-A-CS) which contain switches at dependent and independent clauses and as such contain longer intra-sentential CS data, as well as inter-sentential Data. This data was generated by using our Lect. test set and tst-common and translating clauses into inter-sentential Data. This data was generated by using our in-house Lect. test set where English words have been manually annotated. We combined this data with a small set of read speeches, collected by us. This is depicted as Deng. in Table 2. Important to note is that the overwhelming amount of this set are German words and only 4.5% are English. We also tested our models on the German-English intra-sentential CS test set derived from the Spoken Wikipedia Corpus (SWC) provided by [30], depicted as SWC-CS. Detailed information about our test sets can be taken from Table 2. Both of these intra-sentential sets have German as the matrix language with English words embedded. tst-inter is an inter-sentential CS set we derived from MuST-C (tst-COMMON) [31] data. At sentence boundaries, the sentence was continued in either English or German in a CS manner. These sentences were then read by two persons. We also collected a German-English CS test set (D-E-CS) and a German-Arabic test set (D-A-CS) which contain switches at dependent and independent clauses and as such contain longer intra-sentential CS data, as well as inter-sentential Data. This data was generated by using our Lect. test set and tst-common and translating clauses into the respective language. Afterward, the utterances were read by 4 and 2 speakers for the D-E-CS and D-A-CS respectively, using TEQST tool [31]. In D-E-CS 57.3% of the clauses are German and 42.7% are English. In D-A-CS 50% of the clauses are German and 50% are Arabic. While the speakers reading in the D-E-CS set were of German origin, the speakers reading D-A-CS originated from Arabic countries. Speakers reading utterances containing English were L1 in German and L2/B1 in English. Speakers recording text with Arabic as a language pair were L1 in Arabic and L3/B1 in German.

5. APPROACH

As there are only very little data available and for most languages, there is no CS data at all, we propose a simplified data augmentation of the proposed method in [12]. As it turned out to be an important factor in training the model, we also enable to set a specified relative amount of CS utterances in the training set. We concatenate the log-Mel features of different languages after each other. For the target labels, we also concatenate the respective labels after each other. During data augmentation, we only have three restrictions. First, we limit the amount of CS data set to a specific percentage. Meaning if we for example have a total of 100.000 utterances and we limit the CS part to 50%, the new data set will contain 50.000 utterances of monolingual and 50.000 utterances of CS speech. In order to assure that all data is present in the new training set we first add each utterance that was not used in the data augmentation. If the proportional amount of monolingual utterances are not reached we randomly sample utterances and add them to the data, as well. When we analyzed our monolingual training data we saw that most utterances are less than 10 seconds long. Due to that our second restriction is that, the length of the CS data is restricted as well. 25% of the CS data was made to be five seconds, another 25% up to 10 seconds another 25% 15 seconds long. Utterances of 20 and 25 seconds each made up 12.5% of the newly generated CS data. The last restriction is that speech of one language can only be followed by an utterance of another language, as it could not be considered CS otherwise. For each of the above-mentioned time ranges, we generate CS data the following way. First, a language is chosen randomly with an equally distributed probability. Afterward, an utterance is randomly picked out of all the sequences in that language. These steps

| Language  | Corpus  | Speech [h] | Utterances |
|-----------|---------|------------|------------|
| English (EN) | How2 | 345 | 210k |
|           | TED   | 439 | 259k |
| German (DE) | CV    | 314 | 196k |
|           | Europarl | 46 | 20k |
|           | Lect. | 504 | 353k |
|           | MINI-Data | 1 | 498 |
| Arabic (AR) | Alj. | 1127 | 375k |
|           | MINI-Data | 39 | 9k |

Table 1. Data used during training.

| Language  | Corpus  | Speech [h] | Utterances |
|-----------|---------|------------|------------|
| English   | TED    | 3 | 1k |
| German    | CV     | 25 | 15k |
|           | Lect.  | 5.2 | 5k |
| Arabic    | Alj.   | 10 | 5k |
|           | Alj.2h | 2 | 1k |
| Intra-sent. | SWC-CS | 34.1 | 12437 |
|           | Deng.  | 0.95 | 293 |
| Inter-sent. | artificial | 1.9 | 1687 |
|           | tst-inter | 0.85 | 284 |
| Mix-sent.  | D-E-CS | 1.42 | 562 |
|           | D-A-CS | 1.09 | 398 |

Table 2. Data used for testing.

[30] Eurovat [26], a data set of recorded lectures and interviews (Lect.) and Mini-international Neuropsychiatric Interview (MINI)-Data. As Arabic training data, we used MGB2 (Alj.) data from [27] and MINI data [28]. An overview of our training data is given in Table 1.

Voice (CV) [25]. Europarl [26], a data set of recorded lectures and interviews (Lect.) and Mini-international Neuropsychiatric Interview (MINI)-Data. As Arabic training data, we used MGB2 (Alj.) data from [27] and MINI data [28].
are repeated until the CS duration of the sequence is up to two
seconds shorter than the current time range.

6. EXPERIMENTS

6.1. Baselines

As for baselines, we trained four different models. One monolinguall model for each of the languages Arabic (Mono-Ar), German (Mono-De), and English (Mono-En). And the fourth baseline is a multilingual model (Mult.), which we trained using the concatenated data set of the three languages. In Table 3 the WER performances of our baseline models are reported on monolingual test sets. While the multilingual model is able to transcribe all languages, a drop in performance can be seen in all tests when compared with the monolingual counterpart.

The performance of our baseline models on multilingual CS data is provided in Table 4. For Mono-Ar and Mono-En, it can be seen that the performance on CS data is quite bad. On our intra-sentential tests, the monolingual German model has the best results, this is due to German being the matrix language and as mentioned in English words are only embedded sporadically in these utterances. Looking at tst-inter and the D-E-CS, it is visible that Mono-De and Mono-En perform very badly as well.

Mono-De has a slightly lower WER probably due to the fact that there are more German clauses in the test set than English ones. Another reason is, that it was able to decode some of the English words as well, which hints that there are some English words in our training data. The strong baseline performance of the Mono-De model on Denglish data hints, that nowadays it is so common to embed English words in German speech that our German data set contains such appearances, although they are not marked as such.

While the multilingual model decreased the performance by relative 7.69% WER on the intra-sentential CS, it was able to outperform the Mono-De model by relative 52.58% WER on tst-inter and relative 43.67% WER on D-E-CS.

Interestingly on D-A-CS we can see similar scores for Mono-DE and Mult.. Looking at the transcriptions we see that the multilingual model only transcribes parts of the utterance in one of the two languages. Similar to Mono-DE which only transcribes German parts of the utterance. Compared to the improvements in D-E-CS this shows that sharing the language scripts can have major benefits for multilingual models.

6.2. Data augmented Code-Switching

In our first experiment, we tried to train a multilingual model with the data augmentation described in Section 5. Directly training the model with 50% artificially created CS data leads to quite unstable gradients. We trained the model multiple times. While the performances were not that different the number of epochs used for training was very different 109 and 198 for Mult.-noc1 and Mult.-noc2 Table 5 respectively. We reason the unstable gradients to be present due to the difficult data, as well as the nature of the task. While the Arabic language is Phonetically and script wise very different from German or English, the quality of the used audio can also improve the difficulty of the task.

As mentioned in we apply a curriculum learning and first train on monolingual that which can act as a regularization. For the second stage of the curriculum, we took the multilingual model from Section 6.1 and used the epoch with the lowest perplexity as a pre-trained model this model is denoted as Mult.cur50. This model was trained in only 39 Epochs compared to 109 Epochs without curriculum learning which shows a significantly faster convergence. We also applied the second curriculum step with only 20% CS augmented data to see the effect it has on the training (Mult.-cur20). As we have more updates with a higher learning rate in the two-stage approach we also trained the initial multilingual model a second time without CS data (Mult.-noCS).

The results of monolingual tests are shown in Table 5. As Multiling.-cur20 has a slightly better performance compared to Mult.-cur50, we will focus on the model which was trained with 20% CS augmented data. We can see that training the CS models with the two-step approach yield the best performances and even outperform the monolingual models in table 5. The only exception is the German CV data, however, while the Mult.-noCS model has a relative decrease of 17.93% WER, training with CS mitigates the drop in performance to only a 9.64% decrease compared to Mono-DE.

In Table 6 the CS results after the second-curriculum are depicted. On our own small intra-sentential Denglish set we see that training without curriculum hurts the performance, compared to the Mult.-noCS model which was trained without data augmentation. The other data-augmented models are

| model  | EN     | AR     | DE     |
|--------|--------|--------|--------|
| Mono-De | 11,82  | 17,78  |        |
| Mono-Ar |    9,74 | 16,00  |        |
| Mono-En |     7,58 |        |        |
| Mult.  | 17,15  | 21,27  |        |

Table 3. Results of baseline models on monolingual test sets. Results are reported in WER%.

| model  | intra-sent. | inter-sent. | mix-EN | mix-CS | inter-sent. |
|--------|-------------|-------------|--------|--------|-------------|
| Deng   |             |             |        |        |             |
| SWC-CS |             |             |        |        |             |
| inter-sent. |             |             |        |        |             |
| mix-EN |             |             |        |        |             |
| mix-CS |             |             |        |        |             |
| inter-sent. |             |             |        |        |             |
| D-E-CS |             |             |        |        |             |
| D-A-CS |             |             |        |        |             |

Table 4. Results of baseline models on multilingual CS test sets. Results are reported in WER%.
The results of multilingual models on monolingual test sets. Results are reported in WER%.

| model         | EN     | AR     | DE     |
|---------------|--------|--------|--------|
|               | Ted    | Alj.2h | Alj.   |
| Mult.         | 9.25   | 10.48  | 16.64  |
| Mult.-noCS    | 7.76   | 10.22  | 15.44  |
| Mult.-noc1    | 7.77   | 9.84   | 15.82  |
| Mult.-noc2    | 8.67   | 10.70  | 16.82  |
| Mult.-cur50   | 7.12   | 9.32   | 15.11  |
| Mult.-cur20   | 7.14   | 9.30   | 15.33  |

Table 5

| table | DE-EN | DE-AR | DE-AR-EN |
|-------|-------|-------|----------|
|       | intra-sent. | inter-sent. | mix-CS | mix-CS | intra-sent. | artificial |
| model | Deng. | SWC-CS | tst-inter | D-E-CS | D-A-CS |         |
|       |       |       |          |       |       |         |
| Mult. | 20.45 | 31.19 | 23.02    | 28.63 | 60.74 | 39.88    |
| Mult.-noCS | 16.38 | 28.64 | 20.91    | 25.98 | 53.90 | 44.32    |
| Mult.-noc1 | 18.28 | 28.98 | 20.12    | 25.47 | 55.57 | 9.25     |
| Mult.-noc2 | 19.30 | 31.24 | 19.82    | 26.79 | 54.97 | 10.73    |
| Mult.-cur50 | 16.23 | 27.99 | 18.81    | 23.63 | 45.67 | 5.66     |
| Mult.-cur20 | 16.40 | 27.90 | 18.66    | 23.76 | 45.40 | 8.71     |

Table 6

The results of multilingual models on CS test sets. Results are reported in WER%.

able to keep roughly the same WER. On the bigger German-English intra-sentential SWC-CS test set we can observe a relative improvement of 2.27% and 2.58% WER for the Mult.-cur20 and Mult.-cur50 models over the baseline multilingual model (Mult.-noCS). More importantly, however, compared to training without CS data, utilizing a CS augmentation of 20% yields relative improvements of 10.76% WER on the tst-inter data and a relative improvement of 8.55% WER on the D-E-CS test set, as well as a relative improvement of 25.26% on D-A-CS. Similar to previous work we also evaluated on artificially created CS data with switches between all languages (DE-AR-EN). The Mult.-cur20 yields a relative improvement of 80.35% WER compared to the multilingual model without CS, which is extremely high when compared to our tests on real data. This is why we ignore this test case in our ablation studies, as we believe that testing on artificial data yields inflating improvements, which do not hold on our data although it is only read speech.

The results depicted in Table 5 and Table 6 show that using CS augmented data does not just improve models on CS data but also improves the model’s performance over the monolingual model on the respective monolingual test sets, as well.

6.3. Ablation studies

After seeing the results in Section 6.2, we further wanted to analyze the effect of utilizing this kind of artificially created CS data during training. Specifically, in a scenario with many more languages, the question will arise if we need to ensure generating CS data with transitions between all possible languages, and do we need to ensure that bidirectional transitions from one language to all others need to be present to enable CS during inference?

For that reason, we conducted several further experiments. All experiments apply the same curriculum learning regime and use the multilingual model described in Section 6.1 as a starting point. The results are depicted in Table 7 and Table 8. The ending of model names depicts which transition was not present during training, for example, "nodear" means there was no transition from German to Arabic. "nodex" means that German utterances were not used in the data augmentation. In contrast, "odex" depicts the case in which all the transitions were from and to German, and there was no switch between English and Arabic.

The results of monolingual tests Table 7 give interesting insights into using artificially created CS data for multilingual models. We can see that all models which saw CS data during training outperform the baseline multilingual model (Mult.-noCS). We can appreciate that usually depending on which language or language transition was kept out of the training the performance on the respective test seems to degrade slightly compared to the Mult.-cur model. The reason is that these restrictions make the other languages proportionally more present in the training data. This is also supported by the WER improvements on the other languages which were not restricted. An example would be the performance of Mult.-nodeen on the TED performance and the Alj.2h set. Compared to Mult.-cur20 the WER on Ted decreased from 7.14% WER to 7.21%, while the performance on Alj.2h improved from 9.30% WER to 9.12%.

Looking at Table 8 we can see similar behaviour to Table 7 when it comes to intra-sent. sets. In the second last row x-noarx the model trained with only German and English switches is depicted. Compared to x-cur20 this results in more German and English utterances being seen during training and thus slightly improves over the model by 3.48% relative WER. This is due to the intra-sent. test set only containing examples with German as the matrix language and English words embedded.

When looking at inter-sent. and mix-CS examples for DE-EN language pairs, we can see that the model trained without German switches decreases performance compared to x-cur20 from 18.66% WER to 20.38%. However, it still performs slightly better than the baseline multilingual model with 20.91% WER. Models which never saw switches from German to English (x-nodeen) also lose a bit of performance compared to x-cs20, however, looking at the transcriptions we can see that the model is still able to transcribe switches from German to English, which shows that the model is able to generalize the possibility of switching between languages and not just learns one specific switch. The answer to one of the questions of this ablation study is very well answered on the D-A-CS test data. Here the worst performing model
which has seen any kind of CS with Arabic is the x-oex model which only saw switches containing English. The performance of this still model improves over the baseline multilingual model relative by 9.33% WER although the model never saw switches between Arabic and German. This shows that when training models to transcribe CS especially in the inter-sentential case there is no need to provide switches between all language pairs.

Intra-sentential CS is a very interesting phenomenon, in which words from the embedded language, in our case English, can happen to be adapted according to the grammar of the matrix language. This being the case we also report the accuracy of correctly transcribed English words in percent.

| model         | EN | AR | DE |
|---------------|----|----|----|
| Mult.-noCS    | 7.76 | 10.22 | 15.44 | 13.94 | 17.84 |
| Mult.-cur20   | 7.14 | 9.30 | 15.33 | 12.96 | 17.32 |
| Mult.-nodeen  | 7.21 | 9.12 | 13.08 | 13.08 | 17.68 |
| Mult.-nodear  | 7.19 | 9.23 | 15.15 | 12.84 | 17.36 |
| Mult.-nodelx  | 7.23 | 9.26 | 15.17 | 13.39 | 17.80 |
| Mult.-odelx   | 7.20 | 9.43 | **14.90** | 12.88 | 17.20 |
| Mult.-noen.de | 7.28 | 9.13 | 15.12 | 13.11 | 17.42 |
| Mult.-noen.ar | 7.22 | 9.14 | 15.06 | 12.86 | 16.99 |
| Mult.-noen.x  | 7.32 | 9.36 | 15.06 | 12.86 | 17.46 |
| Mult.-oex     | 7.28 | 9.42 | 15.34 | 12.91 | 17.42 |
| Mult.-noarde  | 7.29 | 9.14 | 15.00 | 12.98 | 17.58 |
| Mult.-noaren  | 7.20 | 9.44 | 15.52 | 12.89 | 17.31 |
| Mult.-noar    | 7.17 | 9.57 | 15.18 | **12.68** | **16.92** |
| Mult.-oar     | 7.19 | 9.01 | 15.06 | 12.97 | 17.00 |

Table 7. Results of multilingual models on monolingual test sets. Models were trained using 20% data augmentation with varying restrictions. Results are reported in WER%.

7. CONCLUSION

In this work, we described a simple yet effective way of artificially generating CS data to improve on the inter-sentential CS task. We showed that our collected read-speech test data is more reliable for performance evaluation than using artificially generated test data. We also saw that this approach can be treated as a data augmentation technique that improves the monolingual performance of multilingual models, without any changes in the model architecture. More importantly, we enable a language-agnostic multilingual model to automatically transcribe CS speech without providing any real CS data. Our experiments reveal that a model trained on CS data between language $x \leftrightarrow y$ and $y \leftrightarrow z$ is able to transcribe CS utterances with $x \leftrightarrow z$ as the two languages. In such a scenario our model (x-oex) improves over the baseline multilingual model by 5.03% WER.

8. ACKNOWLEDGEMENT

The project on which this report is based was funded by the Federal Ministry of Education and Research (BMBF) of Germany under the numbers 01EF1803B (RELATER) and 01IS18040A (OML).
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