Lexical Normalization for Code-switched Data and its Effect on POS-tagging

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Abstract

Social media provides an unfiltered stream of user-generated input, leading to creative language use and many interesting linguistic phenomena, which were previously not available so abundantly. However, this language is harder to process automatically. One particularly challenging phenomenon is the use of multiple languages within one utterance, also called Code-Switching (CS). Whereas monolingual social media data already provides many problems for natural language processing, CS adds another challenging dimension.

One solution that is commonly used to improve processing of social media data is to translate input texts to standard language first. This normalization has shown to improve performance of many natural language processing tasks. In this paper, we focus on normalization in the context of code-switching. We introduce a variety of models to perform normalization on CS data, and analyse the impact of word-level language identification on normalization. We show that the performance of the proposed normalization models is generally high, but language labels are only slightly informative. We also carry out POS tagging as extrinsic evaluation and show that automatic normalization of the input leads to 3.2% absolute performance increase, whereas gold normalization leads to an increase of 6.8%.

1 Introduction

Social media provides an invaluable source of information for natural language processing (NLP) systems. However, its informative and spontaneous nature leads to many problems for most existing NLP models, as phenomena like non-standard words, spelling errors and abbreviations are very common. One particularly challenging and interesting phenomenon is the use of multiple languages within the same utterance, which is also called code-switching (CS) (Gumperz, 1982; Myers-Scotton, 1995).

Because most NLP models are designed to process canonical and monolingual data, their performance drops enormously when having to process CS social media data. One solution to performance drops for the social media domain is lexical normalization; the translation of social media text to its canonical equivalent (Han and Baldwin, 2011). Previous work has shown that by standardizing the data, we can improve the applicability of NLP systems (Derczynski et al., 2013; Bhat et al., 2018). An example social media post which contains Indonesian-English code-switching annotated for normalization is shown in Figure 1. This example shows that normalization is harder for CS data, because it can be unclear which language to normalize to (for example the word ak, which should be normalized to aku ‘I’ in Indonesian, could have been normalized to ok in English as well).

Recently, there has been an increasing interest in the automatic processing of CS data, however, there has not been much work on the task of lexical normalization for CS data. To the best of our knowledge,

![Figure 1: A code-switched sentence annotated with lexical normalization for Indonesian-English.](image-url)
only Adouane et al. (2019) focuses entirely on lexical normalization for CS data in their work. Other work commonly uses simple rule-based normalization strategies to tackle a downstream task for CS data: chunking (Sharma et al., 2016), parsing (Bhat et al., 2017; Bhat et al., 2018), or machine translation (Barik et al., 2019).

The contributions of this paper are:

- We provide a code-switched dataset annotated for lexical normalization for a novel language pair; namely Turkish-German (Tr-De). We also align existing annotation layers – language IDs (LID) and part-of-speech (POS) tags – to normalization annotations.
- We evaluate three types of sequence taggers for word-level language identification.
- We introduce a variety of models to perform normalization for CS data, and reach performance in a similar range as monolingual models.
- We show that we can improve the POS tagging of code-switched social media data by normalizing the input data before tagging.

2 Related Work

Traditionally, approaches to normalization of social media data can be broadly divided into two types. The first stream of work uses techniques borrowed from machine translation (Aw et al., 2006; Pennell and Liu, 2011; Ljubešić et al., 2016), which could be constrained to lexical normalization (on the word-level), but also go beyond the word level. Another stream of work is based on a classic spelling correction framework (noisy-channel models) (Han, 2014). They apply three steps, detecting which words need to be replaced, generating candidates, and ranking these candidates. Later, it became evident that a two-step approach is sufficient (Jin, 2015; van der Goot, 2019), and the detection step was skipped by considering the original word a normalization candidate.

The current state-of-the-art model for most languages is MoNoise (van der Goot, 2019), which is a model based on this two-step approach. A variety of modules are used for the generation of candidates. For the ranking, MoNoise complements features from the generation step with additional features, which are all combined in a random forest classifier that predicts the probability that a candidate is a ‘correct’ candidate. MoNoise is described in more detail in Section 3.2.

More recently, sequence-to-sequence models (Lourentzou et al., 2019) and contextual embeddings (Muller et al., 2019) have been proposed to be used for the lexical normalization task. These approaches reach performances close to MoNoise (van der Goot, 2019) for the English data, and are faster to run. However, especially in low-resource settings MoNoise has an advantage because of its strong dependence on external data, which is the main reason we choose to use MoNoise as a baseline and starting point in this work.

Like most NLP tasks, most research on normalization has been done on English datasets (Han and Baldwin, 2011; Baldwin et al., 2015). However, there has been some efforts on other languages, where usually only one language is considered, we refer to Sharf and Rahman (2017) and van der Goot (2019) for an overview of available resources.

Early work on normalizing CS data focused on Hindi-English, as part of pipelines to achieve downstream tasks (Sharma et al., 2016; Bhat et al., 2017; Bhat et al., 2018). As Hindi is Romanized in datasets and additional Hindi resources are in the Devanagari script, they include back-transliteration into the normalization step, thus defining the task beyond the scope of this paper. Nevertheless all systems report a positive impact of normalization on their final task.

Barik et al. (2019) experiment on normalization for Indonesian-English. They use a rule based approach supplemented by clusters derived from word embeddings, and show that normalization can be used to improve machine translation.

Adouane et al. (2019) work on Algerian Arabic data mixed with Modern Standard Arabic, French, Berber, and English. They employ sequence-to-sequence models, by alternating encoder and decoder architectures. They show that their edit distance-based token-level aligner helps improve normalization.
Because some of our proposed models depend on language labels, we require a language identification system. There is a wide variety of approaches used for this task, where early systems mostly used CRFs (Sequiera et al., 2015; Molina et al., 2016). More recently also neural networks have been employed for this task and have shown superior performance (Zhang et al., 2018). We opt for three different architectures to observe the effect of language identification on normalization.

We adapted one of the data sets we employ so that it has POS tags. This gives us the opportunity to apply POS tagging as extrinsic evaluation. Besides research on Hindi-English that combines normalization and transliteration, most work focuses on either using normalization to improve tagging performance on monolingual social media data (Derczynski et al., 2013; van der Goot et al., 2017), or on POS tagging of CS data without normalization (AlGhamdi et al., 2016; Soto and Hirschberg, 2018). In this work, we combine these angles.

3 Models

In this section we describe the models used for word-level language identification (3.1), lexical normalization (3.2) and POS tagging (3.3).

3.1 Word-level language identification

We treat language identification as a sequence labeling task where the label of each word is simply a language ID. We evaluate three sequence labeling libraries: MarMoT (Mueller et al., 2013), a higher-order conditional random fields tagger, Bilty (Plank et al., 2016), a BiLSTM tagger, also incorporating character level information, and we will use a BERT-based (Devlin et al., 2019) tagger named MaChAmp (van der Goot et al., 2020b). For Bilty, we project polyglot embeddings (Al-Rfou et al., 2013) of each language of the language pairs to the same space using MUSE (Conneau et al., 2017), whereas for MaChAmp, we use multilingual BERT. We use the default settings for all toolkits.

3.2 Normalization

Below we first introduce the standard MoNoise model, and then all the proposed extensions which are focused on code-switched data. A schematic overview of all models is shown in Figure 2.

Monolingual (Figure 2a)

We use the MoNoise model (van der Goot, 2019) as a baseline and starting point. MoNoise consists of two parts, a candidate generation step and a candidate ranking step. For the generation of candidates, a spelling correction system (Aspell), word embeddings and a dictionary based on the training data are used. Features from these modules are then supplemented with n-gram probabilities based on Wikipedia and Twitter data and other features indicating whether a word is present in the Aspell dictionary, whether it contains an alphabetical character, whether its characters are in the same order as the original word, the length of a candidate compared to the original word, and whether it starts with a capital. For the novel models we propose, we will split up the features based on whether they require language-specific resources (spelling correction, word embeddings and n-grams features; yellow and red in Figure 2), or whether they are language agnostic (all other features; blue in Figure 2). For the ranking of the candidates a random forest classifier (Breiman, 2001) is used, which predicts the probability whether a candidate is correct. Because of its dependence on external data, this model only requires little training data, which is perfect for our setup (see also data statistics in Table 2).

We use the version of MoNoise including capitalization handling (van der Goot et al., 2020a), because capitalization correction is annotated in both datasets. We use Wikipedia dumps from 01-01-2020 and random tweets collected throughout 2012 and 2018 from the Twitter API, filtered by the fastText language classifier (Joulin et al., 2017) for all languages to generate n-grams and word embeddings. Statistics on this raw data is provided in Appendix A.
Figure 2: Overview of the different proposed variations of MoNoise. Dashed lines mean that only one of the two paths is taken, decided by the language identification. For model (a), there can be two versions, one with features from Lang. 1 (shown here) and one based on Lang. 2.

Fragments (Figure 2b)
Instead of adapting the model itself, we can also split the data into monolingual fragments and train two separate models. During test-time we then also split the input into fragments, and run the monolingual models on the fragments. We create monolingual fragments by splitting the data at every code-switching point. We convert words that do not belong to either language, such as punctuation, to the language of the previous word. This setup has the advantage that the normalization model itself does not need any adaptation, and it can thus be used with any normalization model. The disadvantages are that it is dependent on a language label, two separate classifiers have to be trained and the context is interrupted.

Multilingual (Figure 2c)
Instead of using two separate random forest classifiers, we can exploit both feature sets simultaneously in one classifier. This means that for every language-specific feature, we now have two features. In this setup, the model is not explicitly informed about the language of its input words; however, some of the features (especially n-gram probabilities) will have a very high correlation with this information. This model has the advantage that only one classifier has to be trained, and no language labels are necessary. It has the disadvantage that it uses more features for the classifier compared to the Monolingual and Fragments models, which arguably makes the classification harder.

Language-aware (Figure 2d)
Some of the language-specific features of the Multilingual model will be rather superfluous for words in the other language. For example, it will search for Turkish words in German word embeddings, and also use n-gram counts based on the German Wikipedia. To avoid this, we can use only one copy of each language-specific feature, and generate them based on the language label (the same language labels as in the Fragments model are used). More concretely, this means that for a German word, we will generate uni-gram probabilities based on German data, whereas for Turkish we will use Turkish data; these are then modeled as one feature in the model. On top of this, we also add a feature which indicates which language a word belongs to. There might be some mismatches in importance’s of features because different data sources and languages are used. Because the language label is known, and a random forest classifier can model feature interactions intrinsically (Breiman, 2001) this should not be a problem. This model has the advantage that the number of features stays almost the same as in the Multilingual model, but a disadvantage is that it requires language labels.

3.3 POS tagging
For POS tagging, we examine the same three sequence modeling systems as used for language identification (Section 3.1); MarMoT, Bilty and MaChAmp. The taggers are applied to the original data, and
for each normalization setting we apply the normalization on the input data before running the tagger to evaluate the effectiveness of normalization.

4 Data

In this section we first describe the design decisions of the novel Turkish-German dataset, then we compare some basic statistics together with the existing Indonesian-English dataset (Barik et al., 2019).

4.1 Turkish-German code-switched normalization corpus

We use the Turkish-German Twitter corpus from Çetinoğlu (2016) in our experiments. It consists of 17K tokens as 1,029 tweets. The raw tweets of the corpus has undergone three main steps of alternations after the collection: tokenization, normalization, segmentation.\(^3\) In addition, usernames and URLs are anonymised as @username and [url] respectively, and CS boundaries are marked in Mixed tokens. Each alternation layer is exemplified on a sentence from the corpus in Figure 3.

The Seg+CS layer is annotated with language IDs and POS tags (Çetinoğlu and Çöltekin, 2016). The language ID (LID) tag set consists of TR (Turkish), DE (German), Lang3 (third language), Mixed (intra-word CS), NE (named entity), Ambig (both Turkish and German and cannot be disambiguated in given context), Other (punctuation, numbers, URLs, emoticons, symbols). Additionally, named entities are tagged with their language label TR, DE, or Lang3. The POS annotation adopts the Universal Dependencies (UD) (Nivre et al., 2016) tag set.

Preprocessing for normalization The original version of the corpus has Raw and Seg+CS layers, but not the intermediate ones. As our work focuses only on normalization, we removed the segmentation and CS boundaries on the Seg+CS layer and obtained Norm. We also anonymized and tokenized the raw tweets to achieve the Tok+Anon layer. For tokenization, we use a slightly modified version of twokenize.py\(^4\) (O’Connor et al., 2010). After this stage, we aligned Tok+Anon and Norm on the token level automatically using Giza++ (Och and Ney, 2003). We parsed the resulting alignment files to align actual tokens and corrected them manually. There are 15,715 1:1, 520 1:n, and 147 n:1 alignments.

LID and POS alignment The original LID and POS tags are on the Seg+CS layer; since we base most of our experiments on the Tok+Anon layer, we need to map the annotations. This is done in two steps following the Seg+CS ⇒ Norm ⇒ Tok+Anon order. Due to segmentation merges in the first step, and 1:n and n:1 token alignments in the second step, there are non-trivial LID and POS alignments. Table 1 demonstrates a segmented word in the first column. The first part Semesterda ‘in semester’ is Mixed with German Semester and Turkish locative case marker da, and the copular -yım ‘I am’ is TR. Their POS tags are NOUN and VERB respectively. When segmentation is undone in the second column (Norm), their LID and POS are merged too. If two tokens have the same LID, the merged token takes the same LID. If they are different, the resulting token is Mixed. POS tag rules can get more complicated, therefore we used a heuristic that favors the second token in most cases.\(^5\) The combination of NOUN and

\(^3\)Morphosyntactic split of words into subwords, cf. (Çetinoğlu and Çöltekin, 2016) for details.

\(^4\)github.com/brendano/tweetmotif

\(^5\)Turkish is agglutinative. Segmentation often happens by splitting derivational suffixes that bear the final POS tag.
Table 1: Mapping LID and POS tags from Seg+CS to Norm to Tok+Anon for the mixed word *Semesterdayım* ‘I am in semester’.

| Tokens       | Seg+CS      | Norm         | Tok+Anon     |
|--------------|-------------|--------------|--------------|
| Semesterdayım-yım | Semesterdayım | semesterdayım |             |

| LID        | Mixed TR ⇒ Mixed ⇒ Mixed |
|------------|--------------------------|
| POS        | NOUN VERB VERB VERB      |

Table 2: Descriptive normalization and code-switching statistics on the training split of the datasets. CMI is the code-mixing index (Das and Gambäck, 2014), averaged over all training sentences.

|        | #words | %changed | %split | %merge | %lang1 | %lang2 | %un. | CMI |
|--------|--------|----------|--------|--------|--------|--------|------|-----|
| Tr-De  | 13,217 | 25.97    | 3.01   | 1.04   | 54.45  | 21.65  | 23.90| 22.44|
| Id-En  | 18,758 | 26.76    | 1.33   | 0.17   | 48.86  | 24.86  | 26.28| 28.20|

VERB results in a VERB when tokens they are assigned to are merged. The alignment between Norm and Tok+Anon is 1:1 in this case, thus LID and POS are directly carried over.

The Id-En data uses only three labels: IN, EN, UN (Unspecified), whereas the Tr-De includes 12 labels (Section 4.1). To simplify the models and improve comparability, we map the language labels of the Tr-De dataset to TR, DE and UN. Mixed tokens are mapped to DE as they are German words with Turkish inflection. The UN label is assigned to Lang3, Ambig and Other tokens.

4.2 Dataset statistics

On top of the data described in the previous section, we use the Id-En data from (Barik et al., 2019). We choose to not use the Hindi-English data from (Bhat et al., 2018) because they annotated back-transliteration and normalization jointly, while we only focus on normalization.

Statistics of the training splits of the datasets are shown in Table 2. The datasets are relatively small, but a high ratio of words is normalized, including a high percentage of splits and merges. The percentage of in-vocabulary words is especially low in the Tr-De data, which is mainly due to the morphological richness of Turkish. The code-mixing index (Das and Gambäck, 2014) indicates the (average of the) amount of words not written in the majority language for each sentence. The code-mixing index for both datasets is relatively high, indicating a large amount of code-switching in the data.

5 Evaluation

In this section we evaluate each of the three sub-tasks, where for the latter two we also examine the effect of exploiting the prediction of the previous tasks. Unless mentioned otherwise, we report the results of 10-fold cross-validation on the first 80% of the data and leave the remainder for testing purposes.

5.1 Language identification

Results for the language identification task are reported in Table 3. Unsurprisingly, the performances are in line with the chronological order of the introduction of the systems, and their computational complexity.\(^6\) It should be noted that for MaChAmp we used pre-trained embeddings which were trained on the largest amount of external data. The hardest class is ‘Unspecified’; even though this class contains quite some easy cases (punctuation), there are also many harder cases, where a word belongs to any language other than Lang1 and Lang2, or when the annotator is uncertain. From the single label results, we can see that Bilty is more balanced compared to MarMoT, and that MaChAmp consistently outperforms the other two models. Barik et al. (2019) use a conditional random fields classifier with a variety of features for this task, and report 90.11 accuracy for the Id-En dataset in a 5-fold cross-validation setting.

\(^6\)Confirming results of Aguilar et al. (2020), which was published right before submitting this paper.
Table 3: Word level accuracies for language identification (10-fold).

| Lang1 (Id/Tr) | Indonesian-English | Lang2 (En/De) | Total |
|---------------|--------------------|---------------|-------|
|               | MarMoT | Bilty | MaChAmp | MarMoT | Bilty | MaChAmp |
| Lang1 (Id/Tr) | 96.79 | 97.29 | 97.53 | 96.90 | 96.91 | 97.54 |
| Lang2 (En/De) | 92.11 | 93.57 | 94.81 | 86.65 | 90.88 | 93.71 |
| Unspecified   | 85.68 | 87.75 | 91.11 | 88.86 | 91.29 | 92.75 |
| Total         | 92.71 | 93.86 | 95.17 | 92.76 | 94.26 | 95.57 |

Table 4: Results on the normalization task. Reported scores are accuracy on the word level (10-fold).

| Model                                      | Id-En | Tr-De |
|--------------------------------------------|-------|-------|
| LAI                                        | 73.24 | 74.03 |
| MFR                                        | 88.35 | 78.57 |
| Monolingual-lang1 (Tr/Id)                 | 94.76 | 79.81 |
| Monolingual-lang2 (De/En)                 | 94.31 | 80.58 |
| Fragments                                  | 94.73 | 81.29 |
| Multilingual                               | 94.84 | 81.74 |
| Language-aware                             | 94.79 | 81.85 |

(b) Effect of different language predictions on normalization models (accuracy).

Table 5: Normalization.

5.2 Normalization

For lexical normalization, a wide variety of evaluation metrics is used in the literature, ranging from accuracy (Han and Baldwin, 2011), F1 score (Baldwin et al., 2015) and precision over out-of-vocabulary words (Alegria et al., 2013), to CER and BLUE score (Ljubešić et al., 2016). Because the word order is fixed in our task, and to ease interpretation of the results, we opt to use simple accuracy on the word level, where we consider all words (also the words which are not normalized).

To interpret the scores, we include three baselines: 1) leave-as-is (LAI), which always outputs the original word, i.e. its accuracy is similar to the percentage of words that are not normalized 2) most-frequent-replacement (MFR), which uses the most frequent replacement from the training data for each word. 3) monolingual MoNoise, which can be trained on either of the languages (two models).

Results for the different models are compared in Table 4a. For the Id-En dataset, the differences for the models are rather small and the most frequent baseline already performs well. Even the monolingual models perform remarkably well, and only small gains are observable when using the multilingual adaptations. For the Tr-De dataset the scores are generally lower, indicating that this dataset (and perhaps language-pair) is harder. This is probably also an effect of the low number of in-vocabulary words (Table 2). Especially on the Tr-De results, we can observe that the code-switched adaptations lead to substantially higher scores; especially the language aware model performs well. This is probably because it combines the language information without leading to having too many features. The multilingual model score remarkably close without having access to the language labels. In general, the performances are in a similar range as for monolingual datasets (van der Goot, 2019).\(^7\)

Besides the results reported in the table, we also examined precision and recall. Precision is generally much higher (10-100%), especially for Tr-De, which is in line with previous observations (van der Goot, 2019). This means that the model is conservative, and only replaces cases for which it is rather certain, which arguably is the desirable behaviour. Furthermore, we checked the performance while ignoring

\(^7\)van der Goot (2019) use error reduction rate as main evaluation metric, for which the multilingual model would score 80.72 (Id-En) and 30.42 (Tr-De). The reported scores on monolingual datasets are 77.09 for English and 28.94 for Turkish.
Table 5: Accuracies for POS tagging, using a variety of normalization strategies.

|                | LAI  | Multilingual | Language-aware | Gold |
|----------------|------|--------------|----------------|------|
| MarMoT–POS     | 60.47| 63.96        | 63.93          | 67.52|
| Bilty–POS      | 63.77| 66.41        | 66.68          | 70.37|
| MaChAmp–POS    | 64.18| 66.71        | 66.57          | 69.63|

capitalization mistakes, this showed similar trends as the results reported in Table 4a, but consistently approximately five percentage points higher for Tr-De, whereas for Id-En the baselines mostly gained from this and the other scores improved only slightly (0.5 % point). The larger difference for Tr-De can be explained by the fact that capitalization in German is a harder task (as nouns are also capitalized).

By manually looking at the mistakes made by the best system (Language-aware), we found that there are not many frequent mistakes. Furthermore, all merge replacements (n:1) and many splittings (1:n, see also Section 4.1) are not found. Other common mistakes include capitalization, special characters (m↦→mi), and truly ambiguous cases (your→{you’re, your}). Finally, we looked at the differences of performances across language labels, and saw that the worst performance is consistently scored on respectively Indonesian and Turkish. This was to be expected, as for these languages the model has less external data (Section 3.2) and while the model was originally not evaluated for Indonesian, Turkish had the lowest performance in van der Goot (2019).

Effect of the quality of language predictions To evaluate the effect of the language predictions, we run both the Fragments and the Language-aware model with all language predictions from Section 5.1 as well as the gold language labels. The results (Table 4b) show that for the Id-En language pair, the differences between the different predictions are minimal, and only a minor gain can be achieved from using gold labels. For the Tr-De data, the performance differences are similar compared to the scores on the language identification task (Table 3); so further improvements on the language labeling will most likely propagate.

5.3 POS tagging as extrinsic evaluation

For POS tagging, we trained the taggers on the concatenation of the Turkish-IMST and German-GSD datasets of Universal Dependencies 2.5 (Zeman et al., 2019), and evaluated on the full training split of the CS data. Even though we have POS tags available for the gold normalization (Section 4.1), we do not have gold tags for predicted normalization, and to keep the comparison fair we evaluate using the original POS tags. When a word is split or merged, we use the alignment and check whether the correct tag is present. In other words: we select one tag based on an oracle selection.

Comparing the different models, we see that MarMoT underperforms on all settings. On the raw data, MaChAmp outperforms the BiLSTM by a rather large margin (Table 5), however, this advantage vanishes when using the normalized data and on the gold data Bilty even outperforms MaChAmp by a margin. A manual inspection revealed that this is mainly due to misclassification of emoticons (as PUNCT), which do not occur in the training data. We also experimented with a 10-fold setting (i.e. in-domain training, see Appendix B), where MaChAmp instead outperformed Bilty. In this setup, performance was generally higher, and the gains when using normalization were smaller.

5.4 Test data

On the test data we only run the best settings with a focus on comparing normalization strategies. This means that we use MaChAmp for language identification, compare not using normalization (LAI base-

\footnote{We also attempted to compare our results to Barik et al. (2019), but their evaluation metric is non-deterministic, as they use accuracy over unique OOV words (which can be normalized differently dependent on context, we confirmed this with the authors). However, our average estimated result would have been 69.83 for that metric, whereas they scored 68.50.}

\footnote{It should be noted that this makes splitting beneficial, and this metric can easily be tricked by splitting every token so it should be used with caution. However, our proposed normalization models have a low rate of splitting (114 versus 398 in gold) and merging is not handled at all.}
Table 6: Accuracies of normalization (Id-En, Tr-De) and POS tagging (Tr-De) on test data, comparing the baselines to the best two normalization models.

| Dataset | Task  | LAI   | Multilingual | Language-aware | Gold   |
|---------|-------|-------|--------------|----------------|--------|
| Id-En   | norm. | 74.03 | 94.27        | 94.32          | 100.00 |
| Tr-De   | norm. | 67.02 | 78.28        | 77.83          | 100.00 |
| Tr-De   | pos   | 59.60 | 62.86        | 62.72          | 66.47  |

6 Discussion and Conclusion

Code-switching provides many challenges for natural language processing systems. In this work we attempt to overcome some of these challenges by identifying the word level language labels and normalizing the data. We showed that normalization can be beneficial for POS tagging, both for in-domain and cross-domain settings, normalized input data consistently outperforms unnormalized data across various normalization models and POS taggers. Gold normalization experiments show that there is still room for improvement for normalization models to help POS tagging.

To evaluate for all these tasks, we use an Indonesian-English dataset (Barik et al., 2019) as well as a German-Turkish dataset, for which we provide novel layers adapted for normalization, and LID and POS annotation mappings for these new layers.

For the language identification, we examine three different sequence prediction models. Somewhat unsurprisingly, a BERT tagger outperforms a BiLSTM tagger, which in turn outperformed a CRF tagger.

For the normalization, we introduced three different models to process code-switched data. The first method splits the data into monolingual fragments before normalizing it, and thus uses monolingual normalization models. The second model did not use any explicit language labels, and just modeled all language specific features twice. The third model instead only generated features for the language of the current token. In general, the best performance was achieved by the last model (except for the Tr-De test data), because it combines a small feature-space while also modeling language-specific features. However, the multilingual model performs only slightly worse, while having the attractive property that it does not require language labels. In general all models outperform the baselines as well as the monolingual models (trained on the same data).

An interesting property of the proposed normalization models is that they are trained on data which is code-switched within the sentence level (intrasentential), but this is not a hard requirement. These models could potentially also be trained by mixing two monolingual normalization datasets (resulting in a dataset with only intersentential code-switching), and then be used on intrasentential CS data. This approach enables a much wider use case; with the seven languages used in (van der Goot, 2019) this would enable training of a code-switched model for 21 language pairs (however, for evaluation, a CS normalization annotated dataset is necessary). We expect the model to perform rather well; it is not heavily dependent on context, and perhaps synthetic intrasentential code-switched data can be generated to improve the performance even further.

The Tr-De dataset is available on www.github.com/ozlemcek/TrDeNormData and the source code for the experiments can be found on www.bitbucket.org/robvanderg/codeswitchmonoise.
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### Table 7: Size of raw data (in million words) from both data sources.

| Source | Indonesian | English | Turkish | German |
|--------|------------|---------|---------|--------|
| Wikipedia | 75         | 2,162   | 55      | 776    |
| Twitter   | 510        | 5,018   | 203     | 89     |

### Table 8: Accuracies for POS tagging, using a variety of normalization strategies.

|         | LAI   | Multilingual | Language-aware | Gold  |
|---------|-------|--------------|----------------|-------|
| Bilty   | 83.35 | 83.82        | 84.27          | 87.03 |
| MaChAmp | 86.29 | 86.46        | 86.79          | 89.07 |

### A Statistics on raw data collections

The sizes of the collected raw datasets are shown in Table 7. Duplicate sentences were removed.

### B Results of in-domain pos-tagging

Results of the in-domain POS tagging experiments are shown in Table 8. Compared to the out-of-domain training, the results are much higher, and gains are modest.