Paraphrase Generation as Zero-Shot Multilingual Translation: Disentangling Semantic Similarity from Lexical and Syntactic Diversity

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Abstract

Recent work has shown that a multilingual neural machine translation (NMT) model can be used to judge how well a sentence paraphrases another sentence in the same language; however, attempting to generate paraphrases from the model using beam search produces trivial copies or near copies. We introduce a simple paraphrase generation algorithm which discourages the production of n-grams that are present in the input. Our approach enables paraphrase generation in many languages from a single multilingual NMT model. Furthermore, the trade-off between semantic similarity and lexical/syntactic diversity between the input and output can be controlled at generation time. We conduct human evaluation to compare our method to a paraphraser trained on a large English synthetic paraphrase database and find that our model produces paraphrases that better preserve semantic meaning and grammatically, for the same level of lexical/syntactic diversity. Additional smaller human assessments demonstrate our approach also works in non-English languages.

1 Introduction

Paraphrasing has been a longstanding interest in the NLP community (McKeown, 1983) and has been used for data augmentation in natural language understanding, question answering, and machine translation (MT), and task oriented dialog (Niu and Bansal, 2018, 2019; Hu et al., 2019a; Khayrallah et al., 2020) and automatic evaluation of MT (Banerjee and Lavie, 2005; Zhou et al., 2006; Denkowski and Lavie, 2010; Thompson and Post, 2020).

A good paraphrase of a sentence is one that is semantically similar to that sentence while being syntactically and/or lexically different from it (Baghat and Hovy, 2013). A common approach to paraphrasing is training a paraphrase model on synthetic paraphrases generated via back-translation of parallel bitext. In this case, the trade-off between semantic similarity and lexical/syntactic diversity is implicitly set by the back-translation method

Recently, Thompson and Post (2020) demonstrated that a multilingual NMT model can be used as a paraphraser to score paraphrastic pairs; they treat paraphrasing as a zero-shot translation task (e.g., “translation” from English to English) and obtain state-of-the-art MT metric performance by force-decoding and scoring MT system outputs conditioned on their respective human translations. However, they find that generating from their model via beam search produces copies or near copies of the input, since a multilingual NMT model does not exhibit a bias to produce output which is lexically/syntactically different from the input.

We introduce a simple method to enable paraphrase generation from a multilingual NMT model. Our method discourages the model from producing n-grams that match n-grams in the input sentence, resulting in non-trivial paraphrases. When considered together with the multilingual training regime presented in Thompson and Post (2020), this approach offers several potential advantages over training a paraphrase model on a dataset of synthetic paraphrases (which jointly optimizes semantic similarity and lexical/syntactic diversity):

- The trade-off between semantic similarity and lexical/syntactic diversity can be controlled at generation time instead of training time.
- The approach works in many languages, with a single model.

\footnote{For example, lexical/syntactic diversity can be increased by adding constraints in decoding}
Training can be done entirely on naturally occurring bitext, eliminating the need to produce synthetic paraphrases and minimizing the possibility of introducing artifacts or errors during back-translation.

Our approach addresses an inherent shortcoming in creating synthetic paraphrases from bitext in which ambiguities in one language can create errorful synthetic paraphrases in the other (see section 6).

We conduct human evaluations to compare our proposed method to a strong English baseline paraphraser trained on the ParaBank2 dataset (Hu et al., 2019c), which consists of 50M synthetic examples generated by back-translating Czech–English bitext. We find that our method outperforms this baseline—in terms of semantic similarity and grammaticality—when our system is adjusted to match the lexical/syntactic diversity of the baseline. We also present small scale evaluations that suggest the method is effective in other languages.

2 Related Work

Paraphrase Generation Machine translation techniques can be used to train paraphrase models (Quirk et al., 2004). Another method to generate a paraphrase is to translate a text to a different language and then back again (Mallinson et al., 2017). Multiple translations, in multiple languages, can also be used to encode the meaning of a sentence (Aziz and Specia, 2013), at the expense of complication, to lessen the effect of inherent ambiguities in the pivot language(s). Several works have focused on training on paraphrase data, including synthetic data created by starting with bitext and translating one side into the other to create synthetic paraphrases (Prakash et al., 2016; Wieting and Gimpel, 2018; Hu et al., 2019c). Ideas such as adversarial training (Iyyer et al., 2018), reinforcement learning (Li et al., 2018), and variational autoencoders (Gupta et al., 2018; Chen et al., 2019b) have also been explored in the context of paraphrase generation.

Diversity in Generation Creating paraphrases which differ from their input in non-trivial ways is a challenging problem. Hu et al. (2019c) use constrained decoding (Hokamp and Liu, 2017) in conjunction with a set of constraints (e.g., avoiding certain words which are present in the input) when creating synthetic paraphrases via back-translating (Sennrich et al., 2016). Kajiwara (2019) also uses hard constraints, but at decoding time. Our work is similar but uses “soft” constraints (i.e., down-weighting tokens which complete n-grams in the input, but not disallowing them all together). Another approach is to control generation with syntactic examples (Iyyer et al., 2018; Chen et al., 2019a) or codes (Shu et al., 2019).

Multilingual NMT Multilingual NMT (Dong et al., 2015) has been shown to enable zero-shot translation—that is, translation between languages pairs not included in training (e.g., translating from Spanish→Arabic at test time when the model was trained on Spanish→English and English→Arabic, but not Spanish→Arabic) (Johnson et al., 2017; Gu et al., 2018; Pham et al., 2019). Zhou et al. (2019) also explored incorporating paraphrase data into training to improve multilingual NMT performance.

Tiedemann and Scherrer (2019) explored the idea of using paraphrase recognition to test the semantic abstraction of a fairly small multilingual NMT system trained on Bibles and also demonstrate the model’s ability to paraphrase in English. However, they do not perform a human evaluation of paraphrase quality, and Thompson and Post (2020) found that simply generating via beam search from a large multilingual NMT model trained on a large general domain corpus results in trivial copies most of the time. We build upon Tiedemann and Scherrer (2019) by using a larger, general domain model, introducing a novel generation algorithm to produces output with syntactic/lexical diversity, and performing human evaluations.

Paraphrastic similarity Similarity between intermediate representations produced by a multilingual NMT encoders have been used to measure semantic similarity and/or paraphrastic similarity (Schwenk and Douze, 2017; Wieting et al., 2019; Raganato et al., 2019). Similarly, Thompson and Post (2020) use a paraphraser for scoring MT system outputs conditioned on their associated human reference translations. They use a multilingual NMT model as a paraphraser in part because they find it does not exhibit a lexical/syntactic bias away from the input sentence, as a typical generative paraphraser does, which is advantageous in their application. We build on this work by adding the lexical/syntactic bias away from the input back in at
Algorithm 1: Before paraphrasing a sentence, buildPenalties() is called to construct a mapping of word prefixes to subwords that require penalties. Then, penalize() is called to modify the model prediction targetLogProbs at every decoder timestep.

```python
def buildPenalties(source):
    penalties = defaultdict(list)
    for n in [1, 2, 3, 4]:
        for ngram of size n in subwords2words(source):
            prefix, word = ngram[0:-1], ngram[-1]
            for subword in targetVocab:
                if word.lower().startsWith(subword.lower()):
                    penalties[prefix].append(subword)
    return penalties

def penalize(history, penalties, targetLogProbs):
    for n in [1, 2, 3, 4]:
        prefix = subwords2words(history)[-(n-1):]
        for subword in penalties[prefix]:
            targetLogProbs[id(subword)] -= alpha * (n ** beta)
```

generation time, enabling the use of a multilingual NMT model as a generative paraphraser.

3 Method

Let $x$ and $y$ be sentences, let $M(x)$ represent the meaning of $x$, and let $X(x, y)$ measure the lexical and/or syntactic similarity between the two sentences. Formally, we can state the problem of paraphrasing as finding $\hat{y}$:

$$\hat{y} = \arg\max_y p(y | M(x)) - \alpha X(x, y)$$  \hspace{1cm} (1)

where $\alpha$ is the user-defined trade-off between semantic similarity and lexical/syntactic diversity.

3.1 Semantic Model

Following Thompson and Post (2020), we use a multilingual NMT model to approximate the intralingual probability $p(y | M(x))$.

3.2 Lexical/Syntactic Diversity

We propose a simple n-gram overlap measure that penalizes the production of n-grams in the input sequence to approximate $X(x, y)$, which we incorporate into beam search during generation.

The proposed algorithm begins by constructing a set of all (word) n-grams, $1 \leq n \leq 4$, from the input. At each decoding step, the algorithm checks whether any of the target vocabulary sub-words begin the last word of an input n-gram. All such subwords are penalized by subtracting $\alpha n^\beta$ from the output probabilities of the NMT model (in log space) before selecting candidates to extend the beam, where $n$ is the n-gram length, $\alpha$ is the user-specified trade-off between semantic similarity and lexical/syntactic diversity, and $\beta$ is another hyperparameter. We experiment with penalizing 1-, 2-, 3-, and 4-grams equally but find it produces disfluent output, as the algorithm tended to avoid all words in the input. The exponential weight allows us to penalize the decoder for producing larger overlapping n-grams more harshly than small ones. All experiments in this work use $\beta = 4$, as this produced output in English which appeared fluent to the authors. Finally, the NMT model’s vocabulary contains case variants, and we do not want to add variation by trivially changing the case of words, so we penalize all case variants of next tokens (e.g., “his” and “His”). Pseudocode for our approach is provided in Algorithm 1.

3.3 Diversity Control

The $\alpha$ parameter in Equation 1 provides the user with a knob to control how strongly the output is “pushed” away from the input, in lexical/syntactic diversity.

\footnote{We apply the penalty at the start of the generation of the last word of an input n-gram so that the decoder is not encouraged to produce an unnatural completion to an already-begun word.}
space, during generation. In contrast to positive and negative hard lexical lexical constraints (Post and Vilar, 2018; Hu et al., 2019c) our method requires no user-defined constraints, making it simpler and perhaps more language agnostic.  

4 Experimental Setup

4.1 Primary Model

We use the multilingual NMT model released with Prism (Thompson and Post, 2020), which uses a Transformer (Vaswani et al., 2017) architecture with approximately 750M parameters. The model was trained in fairseq (Ott et al., 2019). The authors take several steps to encourage the encoder and decoder to be language agnostic, including specifying the target language as the first token in the target, so that the encoder does not know the target language, and training on several datasets that include a large number of different language pairs. The model was trained on several open source datasets including Wikimatrix (Schwenk et al., 2019), Global Voices, EuroParl (Koehn, 2005) SETimes, and United Nations. After filtering, this resulted in approximately 100M translation pairs and is trained in 39 languages. The model uses a shared, multilingual vocabulary of 64k SentencePiece tokens (Kudo and Richardson, 2018).

4.2 Baseline Model

As a baseline, we train an English-only paraphraser in fairseq on the Parabank2 dataset (Hu et al., 2019c) with approximately 253M parameters and a SentencePiece vocabulary of 16k tokens. We train a Transformer with an 8-layer encoder, 8-layer decoder, 1024 dimensional embeddings, embedding sizes of 1024, feed-forward size of 4096, and 16 attention heads. Dropout is set to 0.3, label smoothing to 0.1, and learning rate to 0.0005. Other parameters match the fairseq defaults.

4.3 Evaluation

We conducted a manual evaluation in English using Mechanical Turk workers and conduct smaller scale manual evaluations in German and Spanish, with the help of colleagues who are native speakers. We perform human evaluations following (Hu et al., 2019b), described in more detail below.

4.3.1 English Evaluation

Paraphrase evaluation is complicated by the fact that paraphrases are typically evaluated in at least two dimensions: semantic similarity and lexical/syntactic diversity. For the model trained on ParaBank2, the trade-off between semantic similarity and lexical/syntactic diversity is fixed and built into the model. To make a fair comparison, we adjust our overlap penalty (\(\alpha\)) such that the output of our method matches the diversity\(^6\) of the baseline.

We evaluate in English using Mechanical Turk workers who were selected from a curated list of previously vetted workers. Annotators were presented with a reference sentence and four paraphrases: three paraphrases from our proposed method (at three different operating points), and one from ParaBank2, presented in random order. For each paraphrase, the annotators were asked to (1) rate the paraphrase as (i) grammatical, (ii) having one or two small grammatical errors, or (iii) ungrammatical, and (2) rate the semantic similarity of the paraphrase using an analog slider bar from 1–100. We randomly select 200 sentences from the English side of the WMT19 German–English test set (Barrault et al., 2019) and obtain ratings from three annotators, for each sentence at each paraphrase system/setting combination. Annotators were paid $0.50 per HIT.

For our proposed method, we choose three operating points: \(\alpha = 0.0005\), \(\alpha = 0.003\), and \(\alpha = 0.006\) (Figure 1). The middle point of \(\alpha = 0.003\) was chosen so as to produce output with the same lexical/semantic diversity as the paraphraser trained on ParaBank2. We decode with a beam size of 5, using the fairseq defaults.

4.3.2 German & Spanish Evaluation

We also collected human judgments in German and Spanish. We followed the evaluation procedure described for the English paraphraser except that annotations were done by colleagues who were native speakers in these languages. For Spanish,\(^5\)

\(^3\)One concern with hard constraints is that there are certain words or phrases such as proper nouns (e.g., Algeria or Gates Foundation) that should not be disallowed, as doing so is likely to dramatically change the meaning of the sentence. Thus heuristics are required to determine which words/phrases should be constrained.

\(^4\)http://casmacat.eu/corpus/global-voices.html

\(^5\)http://nlp.ffzg.hr/resources/corpora/setimes/

\(^6\)Following Hu et al. (2019c), we use uncased BLEU (Papineni et al., 2002), computed between input and output, to estimate the lexical/syntactic diversity between the input and output.
we used the target side of the WMT 2013 English–Spanish test set (Bojar et al., 2013). For German, we used the target side of the WMT 2019 English–German test set. We obtained 50 judgments per set of 3 paraphrases by one German annotator, and 150 judgments per set of 3 paraphrases by three Spanish annotators, both on a random sample of sentences.

As before, multiple paraphrases from our proposed method at different operating points (i.e., different values of $\alpha$) were shown to the annotator.

5 Results

Figure 2: Human judgments of English paraphrases for semantic similarity (rated 1-100) and the percentage of sentences produced which were rated as grammatical, both as a function of lexical/syntactic diversity (measured via un-cased BLEU between input and output). We evaluated our generation method at three operating points ($\alpha=0.0005$, $\alpha=0.003$, and $\alpha=0.006$). $\alpha$ increases from right to left in both plots. $\alpha=0.003$ was chosen to match such that the proposed method had the same diversity as the model trained on Paracrawl2. At that operating point, humans rated output of our method to be more semantically similar to the reference (87.5 vs. 81.0), and grammatical slightly more often (95.0% vs. 94.5%).

5.1 English Results

Human evaluation results in English are shown in Figure 2. We find that $\alpha$ controls the trade-off between semantic similarity and lexical/syntactic diversity, as expected. We also see that grammaticality also tracks inversely with $\alpha$—this is to be expected, as the model is being forced to produce output which it finds less likely.

We find that at the operating point $\alpha = 0.003$, selected such that our method has the same lexical/syntactic diversity as the model trained on Paracrawl2, the paraphrases from our method were judged to be both more semantically similar to the input and grammatical (slightly) more often.

5.2 German & Spanish Results

The human evaluation results in German and Spanish, along with English for reference, are shown in Figure 3. Note that we have no way to normalize between annotators in different languages, thus the results should not be used to draw conclusions about the relative performance of the paraphraser of these languages. However, we find the trends are similar across all three languages, and that semantic similarity and grammaticality judgements for Spanish and German are both reasonably high.

6 Discussion

We hypothesize that our method outperforms the baseline by addressing a fundamental shortcoming
in creating synthetic paraphrase data from bitext: namely that inherent ambiguities present in one language (but not the other) can cause erroneous synthetic paraphrases in the other language (Aziz and Specia, 2013).

For the sake of discussion we will use gender as our ambiguity. Suppose we created synthetic English paraphrases from Turkish–English data, and our bitext contained the following (valid) sentence pair: (“O mağazaya gitti.”, “She went to the store.”) Turkish is a gender-neutral language, so when we back-translate the Turkish side it is equally valid to translate the sentence to “He went to the store.” Pairing the original English translation with the back-translation results in the synthetic paraphrase example (“She went to the store.”, “He went to the store.”). Since English is gendered, this results in an invalid synthetic paraphrase.

In contrast, consider what happens if “She went to the store.” is paraphrased by our method. First, the sentence is converted to an intermediate representation by the encoder. If the encoder were from an English→Turkish system, it is plausible that the encoder would discard gender information, as it is not needed in the target language. However, our encoder comes from a multilingual system which can produce output in many different languages. Thus, as long as the model has seen a sufficient number of training examples between English and at least one other gendered language, we can reasonably expect that the intermediate representation will preserve gender. Thus, when this representation is passed to the decoder and English is requested as the target language, the model should put low probability on any output for which the subject is male.

7 Conclusions

We present a method to control the lexical and semantic diversity of paraphrases generated from a multilingual NMT model, enabling paraphrase generation in many languages. Our approach gives a user fine-grained control over the trade-off between semantic similarity and lexical/syntactic diversity at generation time. Our work outperforms an English baseline trained on a large synthetic paraphrase dataset (Hu et al., 2019b). This improvement in performance may be because our method addresses the issue that ambiguities in the pivot language use to create synthetic paraphrase data can cause errors in synthetic data. Small experiments indicate the method is also performing well in German and Spanish. Finally, multilingual NMT is an active research area and we are optimistic that this approach will pave the way for even stronger paraphrase generation in the future, as multilingual NMT methods continue to improve.

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7Czech is, of course, gendered, so we would not expect the ParaBank2 dataset (which was created from Czech–English bitext) to have gender errors. But the logic presented here should generalize to many other ambiguities.
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