Explicit Representation of the Translation Space: Automatic Paraphrasing for Machine Translation Evaluation

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Abstract

Following previous work on automatic paraphrasing, we assess the feasibility of improving BLEU (Papineni et al., 2002) using state-of-the-art neural paraphrasing techniques to generate additional references. We explore the extent to which diverse paraphrases can adequately cover the space of valid translations and compare to an alternative approach of generating paraphrases constrained by MT outputs. We compare both approaches to human-produced references in terms of diversity and improvement in BLEU’s correlation with human judgments of MT quality. Our experiments on the WMT19 metrics tasks for all into-English language directions show that somewhat surprisingly, the addition of diverse paraphrases, even those produced by humans, leads to only small, inconsistent changes, suggesting that BLEU’s ability to correctly exploit multiple references is limited.

1 Introduction

There is rarely a single correct way to translate a sentence; in fact, work attempting to efficiently encode the entire translation space of a sentence suggests there may be billions of valid translations (Dreyer and Marcu, 2012). Despite this, in machine translation (MT), system outputs are usually evaluated against only a single reference. This especially affects MT’s dominant metric, BLEU (Papineni et al., 2002), since it is a surface metric that operates on explicit n-gram overlap (cf. Fig. 1). However, BLEU’s entire raison d’être was to permit multiple references, in concession to the importance of meaningfully representing the space of valid translations.\(^1\) Unfortunately, multiple references are rarely available due to the high cost and effort required to produce them.

\(^1\) Cf. Sec. 2 and (Papineni et al., 2002) for details.

Ref: This did not bother anybody.

MT\(_1\): This didn’t bother anybody.
MT\(_2\): Nobody was bothered by this.
MT\(_3\): Nobody was troubled by it.

Figure 1: Three adequate MT outputs with little overlap with a reference.

A natural way to inexpensively create extra references is to automatically paraphrase them. Doing so has the potential to cover more of the translation space, with the caveat that this could produce imperfect references. Automatic paraphrasing of references has been tried before (Zhou et al., 2006; Kauchak and Barzilay, 2006), but only recently have paraphrase systems become good enough to generate fluent, high-quality sentential paraphrases based on Transformer architectures for neural MT (NMT). Moreover, it is currently unclear (i) how much diversity can be achieved through automatic paraphrasing, (ii) whether this diversity leads to a better coverage of the translation space (iii) whether or not paraphrases can improve BLEU, and (iv) how this compares to the use of human-produced paraphrased references.

We explore these questions in the context of attempting to improve BLEU’s correlation with human MT quality judgements. We compare two different approaches. The first is to generate maximally diverse references in a bid to cover as much of the translation space as possible. The second uses features of system outputs themselves to influence the paraphraser to generate references that are more likely to cover the part of the translation space relevant to the outputs being evaluated.

We test all methods on all into-English language directions of the WMT 2019 metrics shared task (Ma et al., 2019), and compare both the diversity and usefulness of the automatically produced references against human-produced ones. We do
this both at the standard, corpus level, but also at the segment level. Our experiments show that paraphrasing does offer small gains to correlations with human judgements. However, contrary to common wisdom, adding paraphrases does not result in significant and systematic improvements to BLEU, and our analyses suggest this may be true even for paraphrases produced by humans aiming for maximal diversity, suggesting that the adequacy of paraphrases has less of an impact than expected on the resulting correlations.

2 BLEU

BLEU (Papineni et al., 2002) is the most used automatic evaluation metric in MT. It is a document-level metric that works by accumulating over all sentences counts between the overlap between sequences of tokens (n-grams) in a machine translated text and human-produced reference translation. A modified form of n-gram precision, it is calculated by averaging n-gram precisions \(p_n\) and multiplying by a brevity penalty (BP) used to penalise overly short translations:

\[
\text{BLEU} = \text{BP} \cdot \exp \left( \sum_{n=1}^{N} w_n \log p_n \right) \tag{1}
\]

\[
\text{BP} = \begin{cases} 1 & \text{if } c > r \\ e^{1-r/c} & \text{if } c \leq r \end{cases} \tag{2}
\]

\[
p_n = \sum_{h \in H} \frac{\sum_{ngram \in h} \#(ngram)}{\sum_{ngram' \in H} \#(ngram')} \text{clip}(ngram) \tag{3}
\]

with \(c\) and \(r\) the lengths of the hypothesis and reference sets respectively, \(H\) is the set of hypothesis translations, \#(ngram) the number of times ngram appears in the hypothesis, and \#clip(ngram) is the same but clipped to the maximum number of times it appears in any one reference.

The metric is more reliable when calculated over a large test set, and so BLEU scores are traditionally calculated on the corpus-level. The sentence-level variant requires a smoothing strategy to counteract the effect of 0 n-gram precision, which are more probable with shorter texts.

BLEU has received fervent criticism (Callison-Burch et al., 2006) mainly due to its lack of flexibility to surface form variation. Take for instance the three MT outputs in Example (1), all valid but different from the reference. The number of matching tokens (indicated in bold) vary for each output, MT\(_3\) having no tokens in common with the reference, despite being a valid translation.

This problem is reduced when multiple references are used, as Equation 3 takes into account n-grams that appear in any of the multiple references; there is therefore an increased chance of valid MT outputs containing n-grams that overlap with those in a reference (Finch et al., 2004).

3 Related Work

3.1 Paraphrasing for MT evaluation

Using paraphrasing to overcome the limitations of BLEU-style metrics has a long history in MT evaluation. Some early approaches relied on external resources such as Wordnet to provide support for synonym-matching (Banerjee and Lavie, 2005; Kauchak and Barzilay, 2006; Denkowski and Lavie, 2014). However more automatic methods of identifying paraphrases have also been developed. An early example of this is ParaEval (Zhou et al., 2006), which uses automatically constructed paraphrase sets extracted from SMT phrase tables to provide local paraphrase-support. More recently, Apidianaki et al. (2018) exploit contextual word embeddings to build automatic HyTER networks. They achieved mixed results however, particularly when evaluating high performing (neural) MT models.

The use of MT systems to produce paraphrases has also been explored previously. Albrecht and Hwa (2008) create pseudo-references by using out-of-the-box MT systems. They see improved correlations with human judgments, helped by the systems being of good quality relative to those evaluated, providing on average more help than harm. This method was revived and improved recently by Yoshimura et al. (2019), who filter the pseudo-references for quality. An alternative strategy is to use MT-style systems as paraphrasers, applied to the references. Madnani et al. (2007) show that additional (paraphrased) references, even noisy ones, reduce the number of human references needed to tune an SMT system, without significantly affecting MT quality. However their aim for coverage over quality means that the outputs are unlikely to be good enough for use in a final evaluation metric.

Despite the attention afforded to the task, success has been limited by the fact that until recently, there were no good sentence-level paraphrasers. Earlier attempts (e.g. Naples et al., 2016) using earlier MT paradigms were not able to produce fluent output, and publicly available
paraphrase datasets have only been made available in the past few years (Wieting and Gimpel, 2018; Hu et al., 2019a). Moreover, the majority of the work has focused on synonym substitution rather than more radical changes in sentence structure, which inevitably limits the coverage achieved. Recently, Federmann et al. (2019) undertook an evaluation of paraphrase generation, showing that neural techniques outperformed humans when measuring adequacy (as well as cost).

3.2 Structurally diverse outputs

Diverse generation is important to ensure a wide coverage of possible translations. Diversity, both lexical and structural, has long been a major concern of text generation tasks (Colin and Gardent, 2018; Iyyer et al., 2018). State-of-the-art (MT-style) neural text generation models used for paraphrasing (Prakash et al., 2016; Mallinson et al., 2017) typically suffer from limited diversity in the beam. Sampling from the model distribution or from noisy outputs have been proposed to tackle this (Edunov et al., 2018) but can be to the detriment of output quality.

An effective strategy to encourage structural diversity in particular is to add syntactic information to the generated text, which can be varied. The constraints can be manually specified, for example by adding a parse structure (Colin and Gardent, 2018; Iyyer et al., 2018) or by specifying more abstract constraints such as rewriting embeddings (Xu et al., 2018). A similar but more flexible approach was adopted more recently by Shu et al. (2019), who augment target training sentences with cluster pseudo-tokens representing the structural signature of the output sentence. At decoding time, the top cluster codes are selected automatically using beam search and for each one, a different hypothesis is selected. We adopt Shu et al.’s approach here, due to the automatic nature of constraint selection and the flexibility afforded by constraint definition, allowing us to test different types of diversity by varying the type of sentence clustering method.

4 Generating paraphrased references

We look at two different automatic approaches to generating paraphrased references, both using English–English NMT architectures (cf. Sec. 5.4). The aim of the first (Sec. 4.1) is to increase coverage of the space of possible translations by producing paraphrases that are lexically and syntactically diverse from the existing human-produced reference. This is often difficult (and costly) to achieve manually. So can automatic paraphrasing generate more diversity and, importantly, the diversity needed to cover valid MT outputs? Our second set of approaches (Sec. 4.2) produces output-guided reference paraphrases using weak signals from the system outputs. These approaches, while less realistic, aid in the study of the problem of whether additional references can improve BLEU’s performance as a metric. In our experiments, we compare these two methods to manually produced paraphrases of references, which we produce for a subset of one of the test sets (Sec. 6.1).

4.1 Creating diverse paraphrases

To encourage diverse paraphrases, we use Shu et al.’s (2019) method for diverse MT, which consists in clustering sentences according to their ‘type’ and training a model to produce outputs corresponding to each ‘type’. Applied to our paraphrasing scenario, the methodology is as follows:

1. Cluster target sentences by some property (e.g. semantic representation, syntax);
2. Assign a code to each cluster and prefix each target sentence in the training data with its code (a pseudotoken), as shown in Ex. (1);
(1) ⟨cl_14⟩ They knew it was dangerous . ⟨cl_101⟩ They had chickens, too . ⟨cl_247⟩ That ’s the problem .
3. Train an NMT-style paraphrase model using this augmented data;
4. At test time, apply the paraphraser to each reference in the test set; beam search is run for each of the $n$ most probable sentence codes to produce $n$ paraphrases per reference.

To produce clusters that are as representative of the type of diversity sought as possible, we test two categories of clustering method as in (Shu et al., 2019): semantic methods using the sentential semantic embeddings LASER (Artetxe and Schwenk, 2019) and syntactic methods using TreeLSTM encoders (Tai et al., 2015).

**Semantic method** We use pretrained sentential LASER embeddings (Artetxe and Schwenk, 2019) to encode each sentence. The resulting vectors are of dimension 1024, and clustered using $k$-means.
Syntactic methods We follow Shu et al. (2019) in deriving syntactic codes from constituency parse trees. The parses are encoded into hidden vectors using a TreeLSTM-based recursive autoencoder, which we use in two ways: (i) we cluster them using $k$-means (TREELSTM$_p$), and (ii) we introduce a bottleneck layer (cf. the improved semantic hashing network (Kaiser and Bengio, 2018)), between the encoder and decoder to discretise the vectors end-to-end to directly produce a code (TREELSTM$_s$). As in (Shu et al., 2019), the TREELSTM$_s$ model also encodes the source sentence (i.e. has some semantic input) to improve the clustering quality.

4.2 Output-guided constrained paraphrases

In the previous section, we described methods designed to produce a diverse set of translations, in the hope of creating better coverage of the translation space for each sentence. A more direct approach that may increase our ability to generate relevant paraphrases is to condition the paraphrase generation on the system outputs themselves in order to target the areas of the translation space relevant to the MT outputs. We test this approach in two ways: (i) by generating a single paraphrased reference for each MT output, conditioned on that output, and (ii) by using constrained decoding to produce paraphrases containing unrewarded $n$-grams found in top-scoring system outputs.

Using sentence representations To create an additional reference that is more like the MT output being evaluated, we generate a representation of the output, which is used by the paraphraser to guide its output’s structure. We reuse the sentence encoding methods described in Sec. 4.1 and train a paraphraser using sentence clusters on the source side of the data in order to have manual control over which cluster is used.

Constrained decoding with top-scoring $n$-grams A second approach is to make use of unrewarded $n$-grams in the system outputs. An unrewarded $n$-gram is an $n$-gram in a system output that is not present in the reference(s). We identify these $n$-grams with the following procedure: For each sentence in a test set, we find all $n$-grams that are (a) not in the reference but (b) are present in at least 75% of the system outputs, (c) limiting the voting to systems that were ranked in the top-half of all systems in the human system-level evaluation (Barrault et al., 2019). We then filter the matched $n$-grams for each sentence, removing all that are sub-sequences of longer $n$-grams.

For each reference sentence, we now have a set of $n$-grams that have passed the above filter. We then use our model to generate one paraphrase for each $n$-gram constraint using the constrained decoding approach described in Post and Vilar (2018). The resulting set of paraphrased references (which varies in number for each input sentence) can then be used with BLEU.

Finally, in order to test the generalization ability of this approach, we randomly split the submitted systems into two groups. The first set is used to compute the $n$-grams and therefore to build the system-directed references. The second set is then used to evaluate segment-level correlation. We repeat this ten times and report the average correlation across the splits.

5 Experiments

Our goal is to assess the feasibility of covering the translation space with diverse paraphrases of references and to compare it to a more explicit approach where we target specific areas of the translation space. We therefore perform experiments (i) evaluating the degree of diversity of our diverse paraphrasing methods (Sec. 6.3) and (ii) comparing the usefulness of all paraphrasing methods in improving the correlation of BLEU with human MT quality assessments (Sec. 5.1).

5.1 Metric evaluation

For each set of additional references, we produce a multi-reference BLEU metric, which is used to score all into-English system outputs from WMT19. The scores are then evaluated by calculating their correlation with direct assessment (DA) scores produced by the WMT manual evaluation. As per the WMT 2019 task (Ma et al., 2019), system-level scores are evaluated using Pearson’s correlation. Statistical significance of improvements (against the BLEU baseline) are calculated using the Williams significance test (Williams, 1959), as recommended by Graham and Baldwin (2014). Segment-level judgments are transformed into relative rankings and correlations are calculated using Kendall’s $\tau$ and significance levels using bootstrap resampling.
5.2 Baseline and contrastive systems

The true baselines we compare to are corpus BLEU and sentence BLEU (with exponential smoothing), which use the single original human reference available, both calculated using sacreBLEU (Post, 2018). We also present results from several contrastive paraphrasing systems: (i) BEAM, in which the additional references correspond to the n-best paraphrases in the beam and (ii) SAMPLED, sampling from the top 80% of the probability mass at each time step (Edunov et al., 2018). For the sentence encoding methods, we include a third baseline, RANDOM, where randomly selected cluster codes are used at training and test time.

5.3 Paraphrase training data

Our paraphrase data is from Parabank 2 (Hu et al., 2019b), containing nearly 100M sentences, having paired a smaller input dataset with up to five paraphrases each. We use only the first paraphrase, for a training set size of $\approx 20$M sentences. We preprocess by removing sentences longer than 100 (raw, untokenised) words on either side of the data and duplicate sentence pairs. We then use Sentence-Piece (Kudo and Richardson, 2018) to build a unigram model (Kudo, 2018) of size 16k. Because our data is large, we sample 5M sentences at a time and turn on input shuffling during training. The data splits were created by randomly shuffling all the data and reserving 3k pairs each for dev and test (cf. Tab. 1 for dataset sizes).

| #sentences | #words       |
|------------|--------------|
| train      | 19,225,150   |
|            | 529,249,190  |
| dev        | 3,000        |
|            | 80,675       |
| test       | 3,000        |
|            | 81,367       |

Table 1: Paraphrase data statistics.

For syntactic sentence encoding methods (TREE LSTM$_p$ and TREE LSTM$_s$), we parse the data with the Berkeley Parser (Petrov et al., 2006). The parser applies its own tokenization to raw input sentence (-tokenize) and prioritizes accuracy over speed (-accurate). We experiment using trees pruned to different depths (cf. Tab. 2 for the number of distinct trees), opting for a depth of 4 in our experiments.

5.4 Models

All paraphrase models are Transformer base models (Vaswani et al., 2017): 6 layers, 8 heads, word embedding dimension of 512, feedforward dimension of 2048. We set dropout to 0.1 and tie all embeddings to the output layer with a shared vocabulary size of 33,152. We use the same vocabulary (including the 256 unique cluster codes) for all models. We adopt Adam optimisation with a scheduled learning rate (initial $3 \times 10^{-4}$) and mini-batch size of 64. We train each model on 4 GTX Titan X GPUs with a gradient update delay of 2, and select the final model based on validation BLEU. All models are trained using the Marian NMT toolkit (Junczys-Dowmunt et al., 2018), except for the sampling-based approaches and the constraint approach, for which we use the Sockeye toolkit, since Marian does not support these features (Hieber et al., 2018).

For baseline models, we produce n additional references by selecting the n-best candidate paraphrases from the beam, using a beam size of 20, which is the maximum number of additional references we test. For models using cluster codes, paraphrases are produced by selecting the n-best cluster codes at the first decoding step and then decoding each of these hypotheses using separate beam searches (with a beam size of 6).

We set k to 256 for k-means clustering. We train TREE LSTM sentence encoders using Adagrad with a learning rate of 0.025, weight decay of $10^{-4}$ and batch size of 400 for a maximum of 20 iterations. We set the model size to 256 and limit the maximum number of child nodes to 10. For TREE LSTM$_s$ we set the bottleneck layer’s number of bits to 8 (i.e. $2^8 = 256$ codes). All other settings follow (Shu et al., 2019).

6 Evaluating Paraphrase Quality

It is crucial to ascertain whether our automatically produced paraphrases are of sufficient quality. To this end, we manually paraphrase a subset of reference translations to serve as a baseline for quality evaluation, and then we evaluate paraphrase qual-

| depth | no leaves | type/token | with leaves |
|-------|-----------|-------------|-------------|
| 1     | 16        | 0%          | 16          |
| 2     | 207,794   | 1.0%        | 207,794     |
| 3     | 2,158,114 | 11.2%       | 2,629,907   |
| 4     | 6,089,874 | 31.6%       | 10,631,249  |
| 5     | 8,865,720 | 46.1%       | 14,102,645  |
| $\infty$ | 13,054,272 | 68.1%      | 17,362,448  |

Table 2: Number of distinct pruned trees in different depths with and without leaves in the parsed data.
ity along two dimensions: adequacy (i.e. faithfulness to the original meaning) and diversity.

6.1 Human paraphrases

We produce five paraphrases for each of the first 500 references of the WMT19 de–en test set. Annotators had access to the original references and to all existing manual paraphrases. They were instructed to produce paraphrases that were maximally different (lexically and syntactically) from both the reference and the other paraphrases, without altering the original meaning. The annotators were two English native speakers, each producing two or three paraphrases alternately for each reference over a total period of ~50 hours. These paraphrases will be made publicly available.

6.2 Adequacy

Adequacy is determined by manually evaluating paraphrases for the first hundred sentences of the WMT19 de–en test set. We compare a subset of the automatic approaches (beam, sampled, laser, TreeLSTMp) and the human-produced ones.

Five annotators (two native English speakers and three fluent) rated the adequacy of the paraphrases using direct assessment (Graham et al., 2013), indicating on a slider bar how much of the official reference’s meaning is preserved by a given system’s paraphrased reference. We collected 25 judgements per sentence, with paraphrases sampled from the top 5 paraphrases for each system and presented blindly to the annotators. System-level scores are produced by averaging across all annotations for each system, and score are normalized for each annotator.

| Method    | adequacy | normalized |
|-----------|----------|------------|
| BEAM      | 91.7     | 0.133      |
| SAMPLED   | 85.0     | -0.357     |
| LASER     | 90.1     | 0.007      |
| TreeLSTMp | 88.0     | -0.146     |
| Human     | 95.2     | 0.380      |

Table 3: Direct assessment scores for the first hundred sentences of the WMT19 German–English test set

Whilst the task is inherently subjective, the results (Tab. 3) show a clear preference for the human paraphrases, providing a reference point for interpreting the scores. The automatic paraphrase systems are not that far behind, and the scores are further corroborated in that the lowest score was attributed to the sampled output, which we expect to be less faithful to the reference meaning.

6.3 Diversity

We evaluate the diversity of paraphrased references using two diversity scores (DS):

$$DS = \frac{1}{|Y|(|Y| - 1)} \sum_{y \in Y} \sum_{y' \in Y, y' \neq y} 1 - \Delta_y(y, y')$$

where $Y$ is the set of paraphrases of a sentence produced by a given system, and $\Delta_y$ calculates the diversity of paraphrases $y$ and $y'$. We use two different functions: $\Delta_{bow}$ (for lexical diversity) and $\Delta_{tree}$ (for syntactic diversity). Both give scores between 0 (identical) and 1 (maximally diverse), $\Delta_{bow}$ is the lexical overlap between the sets of words in two paraphrases. $\Delta_{bow}(y, y')$ corresponds to the number of unique words in common between $y$ and $y'$, divided by their mean length.

$\Delta_{tree}$ uses $\Delta_{tree}$, the average tree kernel similarity score between paraphrases. We compute tree kernels using the “subset tree” (SST) comparison tree kernel similarity function presented in (Moschitti, 2006, §2.2), with a decay value\(^3\) of $\lambda = 0.5$, and excluding leaves ($\sigma = 0$).

| $n$ | Method     | $\Delta_{bow}$ | $\Delta_{tree}$ |
|-----|------------|----------------|-----------------|
| 2   | BEAM       | 0.19           | 0.25            |
|     | RANDOM     | 0.10           | 0.01            |
|     | SAMPLED    | 0.37           | 0.51            |
|     | LASER      | 0.20           | 0.27            |
|     | TreeLSTM\(_s\) | 0.23          | 0.35            |
|     | TreeLSTM\(_p\) | 0.25          | 0.42            |
| 5   | BEAM       | 0.22           | 0.30            |
|     | RANDOM     | 0.10           | 0.01            |
|     | SAMPLED    | 0.41           | 0.56            |
|     | LASER      | 0.24           | 0.33            |
|     | TreeLSTM\(_s\) | 0.25          | 0.40            |
|     | TreeLSTM\(_p\) | 0.28          | 0.47            |
|     | Human\(*\) | 0.50           | 0.68            |
| 20  | BEAM       | 0.27           | 0.37            |
|     | RANDOM     | 0.10           | 0.01            |
|     | SAMPLED    | 0.51           | 0.65            |
|     | LASER      | 0.31           | 0.45            |
|     | TreeLSTM\(_s\) | 0.29          | 0.47            |
|     | TreeLSTM\(_p\) | 0.32          | 0.53            |
|     | MT submissions | 0.37          | 0.51            |

Table 4: Diversity scores of paraphrased references averaged over all into-English WMT19 test sets, where $n$ is the number of paraphrases generated. The final row indicates diversity among MT outputs. *Human results are just for the 500-sentence subset.

\(^3\)We tried 0.1, 0.5 and 0.9 with no difference in the result.
The results (Tab. 4), reveal that all methods lead to more diversity than standard beam search. Shu et al.’s method succeeds in encoding relevant information, supported by the fact that random codes (encoding no information), leads to mostly identical paraphrases, differing only in the sentence code selected (removed in post-processing), resulting in almost zero diversity.

Diversity increases for all methods as paraphrases are added. Both types of diversity are cluster-dependent; of the ‘diverse’ paraphrasing methods, the TREE LSTM$_p$ variant produces the most diverse references structurally (DS$_{tree}$) and has high lexical diversity too (DS$_{BOW}$), despite codes being produced from entirely syntactic representations. This suggests that structural diversity leads to varied lexical choices. The most lexically and structurally diverse model overall is actually the sampled baseline, but which is likely to be due to the noise added with the method.

Compared to the MT submissions, most methods achieve less diversity across all metrics. This is not a sign of insufficient diversity per se, as MT outputs’ lexical variety is also likely to be due to poor translations. The very similar DS$_{tree}$ scores notably between TREE LSTM$_p$ and the MT outputs suggests that our paraphrases are sufficiently syntactically diverse, and the adequacy scores shown previously suggest that this is true diversity rather than poor paraphrases.

### 7 Results

**System-level** Tab. 5 reports system-level correlation for various paraphrasing systems with different numbers of synthetic paraphrases.\(^4\) The results are mixed and highly dependent on the language pair, with gains seen when adding paraphrases for most of them (de-en, kk-en, lt-en, ru-en, zh-en), although we see some deterioration in the correlation for others (gu-en, fi-en). Although adding more paraphrases (cf. the comparison between diversity +1 and +5 approaches) does increase the correlation slightly, differences are often not significant. Importantly, there is no clear pattern as to which ‘diverse’ method leads to the greatest gains, despite there being tangible differences in the adequacy and diversity of the paraphrases produces (cf. Sec. 6). The best method across the board appears to be the SAMPLED approach, which is surprising, as although it is the most diverse automatic method, it is the least adequate, adding more noise to the paraphrases. The constraints-based approaches do sometimes achieve better scores than the diverse approaches, often outperforming or rivalling SAMPLED (for zh-en, ru-en, kk-en, gu-en, fi-en), although there is little pattern in terms of which number of n-gram helps best.

**Segment-level** Segment-level results are shown in Tab. 6, this time comparing against sentence-level BLEU. We again see small improvements over this baseline, although this is inconsistent across languages pairs and not significant. Again, there is little difference in the gains of the diverse methods, even with respect to using random cluster codes, which gave the least diversity. This suggests that the type of diversity being achieved

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\(^4\)The table only reports up to 5 paraphrases; adding 10 or 20 did not improve any of the correlations further.
**Table 5: (WMT19 system-level) Pearson correlations of different versions of reference-augmented BLEU computed against WMT19 system-level human rankings. Results that are significantly better than the sacreBLEU baseline are indicated as follows: \( p \leq 0.05 \) (*), \( p \leq 0.01 \) (**), \( p \leq 0.001 \) (***)}. Results that are equal to or better than the best WMT19 systems are marked in bold.

| Approach          | Method   | de-en (16) | li-en (12) | gu-en (11) | kk-en (11) | lt-en (11) | ru-en (14) | zh-en (14) | Ave. |
|-------------------|----------|------------|------------|------------|------------|------------|------------|------------|------|
| Baseline          | sentenceBLEU | 0.890      | 0.985      | 0.799      | 0.943      | 0.969      | 0.862      | 0.888      | 0.905 |
| Paraphrase        | BEAM     | 0.926*     | 0.984      | 0.793      | 0.961*     | 0.986*     | 0.921*     | 0.900      | 0.925 |
| baselines (+5)    | RANDOM   | 0.916*     | 0.986      | 0.805      | 0.957*     | 0.983**    | 0.908*     | 0.898      | 0.922 |
|                   | SAMPLED  | 0.937*     | 0.984      | 0.798      | 0.966      | 0.989**    | 0.929*     | 0.902      | 0.929 |
| Diversity (+1)    | LASER    | 0.919*     | 0.987      | 0.799      | 0.957*     | 0.981*     | 0.909*     | 0.904      | 0.922 |
|                   | TREE LSTM | 0.917*     | 0.985      | 0.798      | 0.960*     | 0.983**    | 0.910*     | 0.897      | 0.921 |
|                   | TREE LSTMp | 0.921*    | 0.985      | 0.800      | 0.958      | 0.982**    | 0.910*     | 0.901      | 0.922 |
| Diversity (+5)    | LASER    | 0.934*     | 0.985      | 0.795      | 0.963*     | 0.987*     | 0.918*     | 0.896      | 0.925 |
|                   | TREE LSTM | 0.929*     | 0.983      | 0.789      | 0.964*     | 0.986*     | 0.919*     | 0.896      | 0.924 |
|                   | TREE LSTMp | 0.933*    | 0.982      | 0.796      | 0.964      | 0.987*     | 0.918*     | 0.898      | 0.925 |
| Output-specific (+1) | LASER    | 0.913      | 0.983      | 0.794      | 0.960*     | 0.978*     | 0.903*     | 0.891      | 0.917 |
|                   | TREE LSTM | 0.921*     | 0.984      | 0.794      | 0.959*     | 0.979*     | 0.908*     | 0.895      | 0.920 |
|                   | TREE LSTMp | 0.921*    | 0.983      | 0.792      | 0.961*     | 0.980*     | 0.903*     | 0.894      | 0.919 |

| Constraints       |        |            |            |            |            |            |            |            |      |
| 2-grams           |        | 0.884      | 0.981      | 0.876      | 0.969      | 0.986      | 0.919      | 0.903      | 0.931 |
| 3-grams           |        | 0.879      | 0.989      | 0.805      | 0.967      | 0.987      | 0.863      | 0.904      | 0.913 |
| 4-grams           |        | 0.869      | 0.988      | 0.792      | 0.973      | 0.983      | 0.930      | 0.921      | 0.922 |

|                  | WMT-19 best | 0.950**    | 0.995      | 0.993****   | 0.998****   | 0.989*     | 0.979**    | 0.988***   | 0.985 |
|                  | (YIS1-3SRL) | (METEOR)   | (YIS1-0)   | (WMDO)      | (ESIM)      | (YIS1-1)   | (ESIM)     |            |      |

**Table 6: (WMT19 segment-level) Kendall’s \( \tau \) correlations of BLEU with different paraphrase sets (size indicated in brackets) against segment-level human judgements. Results significantly better than sentenceBLEU are indicated as follows: \( p \leq 0.05 \) (*), \( p \leq 0.01 \) (**), \( p \leq 0.001 \) (***)}.**
Table 7: Correlations on the 500-sentence subset.

| Method       | Correlation System | Correlation Segment |
|--------------|--------------------|---------------------|
| Baseline     | (sentence)BLEU     | 0.895               |
| Baselines (+5) | BEAM               | 0.934*              |
|              | RANDOM             | 0.926**             |
|              | SAMPLED            | 0.939*              |
| Diversity (+5) | LASER              | 0.935*              |
|              | TREELSTMa          | 0.941**             |
|              | TREELSTMp          | 0.939*              |
| Constraints  | 2-gram             | 0.885               |
|              | 3-gram             | 0.879               |
|              | 4-gram             | 0.868               |
| Human        |                    | 0.934**             |

is not successfully improving the metric as might be expected. The SAMPLED approach achieves amongst the greatest gains, as with system-level scores amongst the paraphrase approaches.

For the constraint-based approach, the impact of additional references depends inevitably on the language pair, since paraphrases are constrained using previous system outputs. Apart from kk-en, which is an anomaly, the constraint-based approaches appear to achieve slightly higher results than the diverse approaches, although again there is no pattern suggesting with number of n-gram should be used.

Human subset We report correlations for the 500-sentence WMT19 de-en subset with human results in Tab. 7. Although a small subset, a few observations can be made. Firstly we see a lot of variance, both across and within methods. Most importantly, the manual paraphrases do not achieve higher results than the other methods, including the baselines. The method with the highest correlation on this subset is again SAMPLED, which reinforces the previous observations that adequacy is not necessarily a defining factor; even if the paraphrases are of good quality (i.e. produced by humans), these paraphrases will not necessarily help BLEU’s performance. As with the main results tables, here the constraints-based approach tends to help slightly more with segment-level correlations, suggesting that it could be slightly more beneficial to target areas of the translation space for sentenceBLEU than to produce as diverse reference as possible.

8 Discussion

What effect do more references have? Adding more references adds more diversity, but does not always improve correlation results significantly. The relationships between the number of additional references and metric correlation shown in Fig. 3 (system-level) and Fig. 4 (segment-level) show that increasing the number of references does improve the correlation, but for most test sets, it is the initial paraphrase that has the most impact, whereas the subsequent ones lead to lesser gains or even deteriorations in correlation.

Does diversity help? Despite the increase in diversity seen in Sec. 6 by the diverse paraphrasing methods, they did not provide systematic improvements to either BLEU or sentenceBLEU with respect to other baseline paraphrasing methods. To better understand what effect adding additional references has on BLEU scores, we take a look at how the sentence-level comparisons between different system outputs vary when using difference metrics. With respect to the sentenceBLEU base-
line, we calculate the percentage of comparisons for which the decision is improved (the baseline scored the worse translation higher than the better one and the new metric reversed this) and for which the decision is degraded (the opposite reversal). Results of this comparison, shown in Fig. 5 show that although all the systems are improving a fair number of comparisons (up to 9.6% for some metrics), they are also degrading almost as many. So, while paraphrasing adds references that represent the space of valid translations, references are being added that match with the space of invalid ones too. Interestingly, the same pattern can be seen when human paraphrases are used, 6.46% of comparisons being degraded vs. 8.3% improved, suggesting that even when gold standard paraphrases are produced, the way in which the references are used by BLEU still rewards invalid translations.

Figure 5: % of improvements and degradation (with respect to the sentence-BLEU baseline) for metrics with 5 additional references for WMT19.

What is the effect on individual \( n \)-grams? System-level correlations (Tab. 5) for ru-en and de-en improved the most with the addition of paraphrases. To understand what may be being improved, we study what new \( n \)-grams are being matched by the additional paraphrased references. We collect, for each sentence, the set of \( n \)-grams from all system outputs, and count those that were not in the original reference but were in the five additional paraphrases of the beam-based system. These counts were accumulated across all sentences in the test set. We also looked at the most frequent \( n \)-grams not found at all, even with the help of the paraphrases (i.e. the unrewarded \( n \)-grams from §4.2).

5Better’ and ‘worse’ systems are determined by the official DA human assessments of MT quality.

6We applied sacreBLEU’s default v1.3a tokenization prior to counting.

Table 8 contains the most common 1- and 4-grams, along with their frequencies. For 1-grams, we unsurprisingly see many common words that might be present (or not) in any sentence; it is hard to draw conclusions from them in general. For 4-grams, however, we see some interesting patterns. Present in both lists are acronym variants such as U. S. and p. m.; their presence on both sides indicates success in sometimes grabbing this variant as well as failure to do so consistently. We also see phrasal variants such as , according to and , ” he said. These last points corroborate a point made by Freitag et al. (2020, §7.2) that references can often miss these.

It also suggests a more focused method for generating paraphrases: identifying a high-precision set of phrases and their common variants, and ensuring that all of them are attested in the set of references, via constrained decoding or some other means (in the spirit of Meteor’s (Denkowski and Lavie, 2011) paraphrase-based matching). We note however, that our paraphrasing methods do tend to contain complementary information from Meteor, also improving correlations slightly in a similar fashion (cf. App. A for full results using Meteor).
| N  | newly matched ngrams | missing ngrams |
|----|----------------------|----------------|
| 1  | a (494) of (370) in (364) The (315) the (273) is (204) for (196) has (196) on (193) was (179) have (171) that (166) be (155) at (145) been (140) with (138) and (134) | to (921) in (921) on (870) is (802) of (798) a (786) for (568) The (556) with (509) it (508) has (505) are (482) by (480) was (478) have (449) - (443) at (437) as (426) which (386) |
| 4  | U. S. (63) the U. S (39) as well as (19) p. m. (15) for the first time (13) in accordance with the (12) the United States (11) in the United States (10) a member of the (10) of the United States (9) The U. S (9) m. on (9) in order to (9) the United States and (8) of course (8) U. S. Navy (8) m. (8) the Chinese Academy of (8) Chinese Academy of Engineering (8) the renaming of the (7) | U. S. (136) according to the (99) " he said (77) the U. S (55) of the United States (48) of the Ministry of (39) the end of the (38) " said the (37) same time (36) such as (36) as well as (35) (Xinhua) – (34) and so on (33) he said (32) the head of the (32) the head of (31) as well as (30) on the basis of (30) and so on (29) |

Table 8: Most frequently newly matched and missing n-grams across the German– and Russian–English WMT19 test sets for the beam paraphraser (five paraphrases).

Can we trade paraphrases for test set size? Given the expense of producing test sets, we wondered whether paraphrases are more helpful with small test set sizes. Can we trade (cheap) paraphrases for (expensive) additional references? We simulate smaller test sets by randomly sampling from the full test set. On each subset, we compute the metric score for all systems and then correlation with the official human ranking. Each data point is the average of ten randomly-sampled subsets. Figure 6 plots German and Gujarati system-level correlations for various systems as a function of the test set size. We plot both baseline corpus-level BLEU (with just the reference) against the simplest paraphraser with both one and five paraphrases. For German–English, paraphrases reach significantly higher correlations, although all methods level off at samples of around size 600. For Gujarati–English, the pattern is the same, but with less relative improvement from the paraphrased systems.

9 Conclusion

We examined the effect of supplementing the WMT19 human-produced (English) reference translations with automatically generated paraphrased references in a bid to improve BLEU, a task that had not been possible prior to the advent of fluent NMT-based paraphrasers. Up until now, it has not been clear whether BLEU’s middling performance in the WMT metrics task was due to it being used “incorrectly,” with a single reference. We were also interested in whether diversity of paraphrasing mattered. To our surprise, our attempts have shown only marginal and inconsistent gains over the baseline single-reference BLEU on the WMT19 metrics data. Measuring with intrinsic diversity metrics suggests that we are getting more diverse outputs, but this does not translate into the improvements in BLEU we could have expected, as invalid translations also get rewarded. This also appears to be the case even when using our human-produced paraphrases, engineered to be diverse with respect to each other and the original reference, or output-directed and constrained paraphrases, chosen with the systems themselves in mind.

In summary, our results suggest that the problems with BLEU run deeper than its conventional reliance on a single reference. BLEU’s performance as a metric is ultimately upper-bounded by its reliance on an explicitly-represented translation space. We conclude that there could be a real limit to the modelling capacity of BLEU in particular and perhaps surface-level metrics more generally, due to additional references contributing to covering both valid and invalid translations.

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A Results with the Meteor metric

Although we focus on ways of improving BLEU using paraphrases in this article, as BLEU is the dominant metric, it is also interesting to look at how adding paraphrases could help similar metrics. We apply the same method to improving the Meteor metric (version 1.5) (Denkowski and Lavie, 2014), a metric which already integrates synonym support.

Results are shown in Tab. 9 for system-level correlations and Tab. 10 for segment-level correlations. We observe that the true baselines are improved in both cases, much like the results for BLEU, showing that the information added by the paraphrases is complementary to the synonym support offered by Meteor.
| Approach          | Method  | de-en (16) | fi-en (12) | gu-en (11) | kk-en (11) | lt-en (11) | ru-en (14) | zh-en (15) |
|-------------------|---------|------------|------------|------------|------------|------------|------------|------------|
| Baseline          | Meteor  | 0.909      | 0.993      | 0.883      | 0.969      | 0.972      | 0.825      | 0.941      |
| Paraphrase baselines | BEAM    | 0.927*     | 0.994      | 0.887      | 0.976      | 0.983**    | 0.862      | 0.949*     |
|                   | RANDOM  | 0.920*     | 0.994      | 0.889      | 0.974      | 0.981**    | 0.853      | 0.945      |
| (+5) Diversity    | LASER   | 0.924*     | 0.995      | 0.886      | 0.975*     | 0.979*     | 0.851      | 0.948**    |
| (+1) Diversity    | TREE-LSTM_s | 0.922* | 0.995      | 0.885      | 0.975*     | 0.982***   | 0.853      | 0.946*     |
|                   | TREE-LSTM_p | 0.923* | 0.994      | 0.889      | 0.974      | 0.979**    | 0.850      | 0.947*     |
| Output-specific   | LASER   | 0.932*     | 0.995      | 0.890      | 0.978*     | 0.983**    | 0.860      | 0.950*     |
| (+1) Diversity    | TREE-LSTM_s | 0.928* | 0.995      | 0.890      | 0.977      | 0.984***   | 0.866      | 0.948*     |
|                   | TREE-LSTM_p | 0.930* | 0.995      | 0.894      | 0.977      | 0.983***   | 0.864      | 0.950*     |
| WMT-19 best       |         | **0.950**  | **0.995**  | **0.993**  | **0.998**  | **0.989**  | **0.979**  | **0.988**  |

Table 9: ParMeteor (system-level) correlations for WMT19

| Approach          | Method  | de-en (85,365) | fi-en (38,307) | gu-en (31,139) | kk-en (27,094) | lt-en (21,862) | ru-en (46,172) | zh-en (31,070) |
|-------------------|---------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|
| Baseline          | sentenceMeteor | 0.061          | 0.243          | 0.197          | 0.356          | 0.275          | 0.145          | 0.351          |
| Paraphrase baselines | BEAM    | 0.08           | 0.26           | 0.22           | 0.38           | 0.29           | 0.15           | 0.36           |
|                   | RANDOM  | 0.072          | 0.254          | 0.219          | 0.364          | 0.281          | 0.156          | 0.356          |
| (+3) Diversity    | LASER   | 0.079          | 0.258          | 0.209          | 0.370          | 0.283          | 0.150          | 0.359          |
| (+1) Diversity    | TREE-LSTM_s | 0.077          | 0.252          | 0.211          | 0.369          | 0.285          | 0.148          | 0.356          |
|                   | TREE-LSTM_p | 0.074          | 0.255          | 0.210          | 0.374          | 0.284          | 0.149          | 0.357          |
| Output-specific   | LASER   | 0.070          | 0.253          | 0.215          | 0.359          | 0.282          | 0.152          | 0.357          |
| (+1) Diversity    | TREE-LSTM_s | 0.073          | 0.251          | 0.211          | 0.376          | 0.287          | 0.148          | 0.357          |
|                   | TREE-LSTM_p | 0.073          | 0.261          | 0.213          | 0.377          | 0.289          | 0.149          | 0.360          |
| WMT-19 best       |         | **0.20***      | **0.35***      | **0.31***      | **0.41***      | **0.38***      | **0.22***      | **0.43***      |

Table 10: ParMeteor (sentence-level) correlations for WMT19