Improving the Diversity of Unsupervised Paraphrasing with Embedding Outputs

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Abstract

We present a novel technique for zero-shot paraphrase generation. The key contribution is an end-to-end multilingual paraphrasing model that is trained using translated parallel corpora to generate paraphrases into "meaning spaces" – replacing the final softmax layer with word embeddings. This architectural modification, plus a training procedure that incorporates an autoencoding objective, enables effective parameter sharing across languages for more fluent monolingual rewriting, and facilitates fluency and diversity in generation. Our continuous-output paraphrase generation models outperform zero-shot paraphrasing baselines, when evaluated on two languages using a battery of computational metrics as well as in human assessment.[1]

1 Introduction

Paraphrasing aims to rewrite text while preserving its meaning and achieving a different surface realization. It is an eminently practical task, useful in educational applications (Inui et al., 2003; Petersen and Ostendorf, 2007; Pavlick and Callison-Burch, 2016; Xu et al., 2016), information retrieval (Duboue and Chu-Carroll, 2006; Harabagiu and Hickl, 2006; Fader et al., 2014), in dialogue systems (Yan et al., 2016), as well as for data augmentation in a plethora of other tasks (Berant and Liang, 2014; Romano et al., 2006; Fadaee et al., 2017; Jin et al., 2018; Hou et al., 2018).

Generating diverse and coherent paraphrases is a difficult task. Unlike in machine translation, where naturally occurring parallel data in the form of translated news, books and talks are available in abundance on the web, naturally occurring paraphrase corpora are scarce. Most common approaches to paraphrasing are based on translation, in the form of bilingual pivoting (Mallinson et al., 2017a,b) or back-translation (Wieting and Gimpel, 2018; Hu et al., 2019a,b). This stems from the hypothesis that if two sentences in a language (e.g. English) have the same translation in another, (e.g. French) they must be paraphrases of each other. While these pipeline approaches bypass the problem of missing data, they propagate errors. Further, all neural paraphrasing models (e.g., Prakash et al., 2016; Gupta et al., 2018; Wang et al., 2019) predict discrete tokens through a final softmax layer. We hypothesize that softmax-based architectures restrict the diversity of outputs, biasing the models to copy words and phrases from the input, which has an effect opposite to the intended one in paraphrasing.

In this work, we introduce PARAVMF – a simple and effective method of training paraphrasing models by generating into embedding spaces (§2). Since parallel paraphrasing data is not available even in otherwise high-resource languages like French, we focus on an unsupervised approach. Using bilingual parallel corpora, we adapt multilingual machine translation (Johnson et al., 2017) to monolingual translation. We propose to train this model with translation and autoencoding objectives. The latter helps simplify the training setup by using only one language pair, whereas prior work required multiple language pairs and more data to stabilize training (Tiedemann and Scherrer, 2019; Buck et al., 2018; Guo et al., 2019; Thompson and Post, 2020). To encourage diversity, we propose to replace the final softmax layer in the decoder with a layer that learns to predict word vectors (Kumar and Tsvetkov, 2019). We show that predicting into word meaning representations increases diversity in paraphrasing by generating semantically similar words and phrases which are often neighbors in the embedding space.

We evaluate our proposed model on paraphras-

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[1]The code is available at https://github.com/monisha-jega/paraphrasing_embedding_outputs

ing English and French sentences (§3). In several setups, standard automatic metrics and human judgment experiments show that our zero-shot paraphrasing model with embedding outputs generates more diverse and fluent paraphrases, compared to state-of-the-art methods (§4).

2 The PARAvMF Model

Let the language to paraphrase in be L_1. Our goal is to learn a mapping $f(\mathbf{x};\theta)$ parameterized by θ. f takes a text $\mathbf{x} = (x_1, x_2, \cdots, x_m)$ containing m words as input, which can be a sentence or a segment in L_1. It then generates $\mathbf{y} = (y_1, y_2, \ldots, y_n)$ of length n in the same language such that $\mathbf{x}$ and $\mathbf{y}$ are paraphrases. That is, $\mathbf{y}$ represents the same meaning as $\mathbf{x}$ using different phrasing. We assume that no direct supervision data is available, but there exists a bilingual parallel corpus between L_1 and another language L_2. We are also given pre-trained embeddings (Bojanowski et al., 2017) for words in both L_1 and L_2. The dimension of both the embedding spaces is d.

We use a standard transformer-based encoder-decoder model (Vaswani et al., 2017) as the underlying architecture for f. As visualized in the system diagram presented in the Appendix, f is jointly trained to perform three tasks with a shared encoder and decoder: (1) translation from L_1 to L_2, (2) translation from L_2 to L_1 and (3) reconstructing the input text in L_1 (autoencoding).[2]

Towards our primary goal of meaning preservation, the translation objectives help the encoder map the inputs in both the languages to a common semantic space, whereas the decoder learns to generate language-specific outputs. On the other hand, with the autoencoding objective, we expose the model to examples where the input and output are in the same language, biasing the model to adhere to the start token supplied to it and decode monolingually. Using this training algorithm, we find in our experiments (§4), that the resulting paraphrases albeit meaning-preserving still lack in diversity. We identify two reasons for this issue. First, the model overfits to the autoencoding objective and just learns to copy the input sentences. We address this issue by using only a small random sample of the total training sentences for training with this objective.[3]

Second, we find that cross-entropy loss used to train the model results in peaky distributions at each decoding step where the target words get most of the probability mass. This distribution being another signal of overfitting also reduces diversity (Meister et al., 2020). We find in our preliminary experiments, that prior work to address this issue by augmenting diversity inducing objectives to the training loss (Vijayakumar et al., 2018) often comes at a cost of reducing meaning preservation. In this work, we propose using a different training loss which naturally promotes output diversity. We follow Kumar and Tsvetkov (2019), and instead of treating each word w in the vocabulary as a discrete unit, we represent it using a unit-normalized pre-trained vector $\mathbf{e}$ learned using monolingual corpora (Bojanowski et al., 2017). At each decoding step, instead of predicting a probability distribution over the vocabulary using a softmax layer, we predict a d-dimensional continuous-valued vector $\hat{\mathbf{e}}$. We train our proposed model by minimizing von Mises-Fisher (vMF) loss—a probabilitistic variant of cosine distance—between the predicted vector and the pre-trained vector. At each step of decoding, the output word is generated by finding the closest neighbor (using cosine similarity) of the predicted output vector $\hat{\mathbf{e}}$ in the pre-trained embedding table. Since this loss does not directly optimize for a specific token but for a vector subspace which contains many similar meaning words, we observe that it has a higher tendency to generate diverse outputs than softmax-based models, both at the lexical and syntactic level as we show in our experiments.

Overall, the contribution of this work is twofold: (1) a translation and autoencoding based training objective to enable paraphrasing while preserving meaning without any parallel paraphrasing data, and (2) optimizing for vector subspaces instead of token probabilities to induce diversity of outputs.

3 Experiments

Datasets We evaluate paraphrasing in two languages: English and French. IWSLT'16 En↔Fr corpus (Cettolo et al., 2016) with ∼220K sentence pairs is used for training with translation objective, and 4450 sentences, randomly sampled ∼1% of the training data in L_1 (either En or Fr), for au-

[2] To bias the model against always decoding in the other language, unlike in Johnson et al. (2017); Tiedemann and Scherrer (2019), we provide a language-specific start token in the encoder input, in addition to the decoder input.

[3] We empirically determine this sample size to be ∼1% of the total number of training examples.

toencoding. We use the L_1 side of the IWSLT'16 dev set for early stopping with the autoencoding objective. We use IWSLT'16 test set for automatic evaluation consisting of 2331 samples in En and Fr each. For human evaluation we subsample 200 sentences from this set. We tokenize and true-case all the data using Moses preprocessing scripts (Koehn et al., 2007). We conduct additional experiments with a larger En–Fr corpus constructed using a 2M sentence-pair subset of the combination of the WMT'10 Gigaword (Tiedemann, 2012) and the OpenSubtitles corpora (Lison and Tiedemann, 2016).

Implementation We modify the standard seq2seq transformer model in OpenNMT (Klein et al., 2017) to generate word embeddings (Kumar and Tsvetkov, 2019), and train it with the vMF loss with respect to target vectors. We initialize and fix the input embeddings of the encoder and decoder with off-the-shelf (sub-word based) fasttext embeddings (Bojanowski et al., 2017) for both En and Fr and align the embeddings to encourage cross-lingual sharing (Artetxe et al., 2018). With a vocabulary size of 50K for each language, the combined vocabulary size of the encoder and the decoder is 100K. Both encoder and decoder consist of 6 layers with 4 attention heads. The model is optimized using Adam (Kingma and Ba, 2015), with batch size 4K, and 0.3 dropout. The hidden dimension size is 1024, the dimension of the embedding layers is 512. We add a linear layer to transform 300-dimensional pre-trained embeddings to 512-dimensional input vectors to the model. After decoding, we postprocess the generated output to replace words from L_2 by a look-up in the dictionary induced from the aligned embedding spaces.

Baselines Although unsupervised methods of paraphrasing with only monolingual data have been explored in recent works (Gupta et al., 2018; Yang et al., 2019; Roy and Grangier, 2019; Patro et al., 2018; Park et al., 2019) they have not been shown to outperform translation based baselines (West et al., 2020). Hence we compare our proposed approach with translation-based baselines only. First, we compare with bilingual pivoting baselines (Mallinson et al., 2017a,b) which pipeline two separate translation models, $L_1 \rightarrow L_2$, and $L_2 \rightarrow L_1$. We use two bilingual pivoting baselines, one based on continuous-output model (**BP-vMF**; the output vectors of the first model are first converted to discrete tokens before being fed to the next) and another based on softmax-based model (**BP-CE**).

To evaluate the impact of embedding outputs, we also compare our proposed model **ParavMF** to softmax-based baseline **ParaCE**, leaving other model components unchanged. **ParaCE** is a modified bilingual version of the multilingual method proposed in Guo et al. (2019), the current state-of-the-art in zero-shot paraphrasing.

Evaluation setup There are many ways to paraphrase a sentence, but no manually crafted multi-reference paraphrase datasets exist, that could be used as test sets (and there are no datasets in languages other than English). We thus evaluate the generated paraphrases on semantic similarity and lexical diversity compared to the *input text*. Following prior work, we use the n-gram based metric **METEOR** (Banerjee and Lavie, 2005). Despite accounting for synonyms, it is not well-suited to evaluate paraphrases, since it typically assigns lower scores to novel phrasings, due to incomplete synonym dictionaries. We thus also include **BERTScore** (Zhang et al., 2020), computing cosine similarity between the contextual embeddings of two sentences. Naturally, just copying the inputs can also lead to high scores in these metrics. To evaluate lexical diversity, we follow Hu et al. (2019b) and include **IoU** – Intersection over Union (also called Jaccard Index) and Word Error Rate (**WER**). To measure structural diversity we use (constituency) Parse Tree Edit distance (**PTED**).[4] Note that model outputs that do not preserve meaning in paraphrasing (and generate totally different sentences) will also obtain high diversity scores, but these are not indicative of quality paraphrasing but will falsely contribute to high diversity scores if averaged across the entire test set. We thus measure the diversity only on subsets of the test set for which the strongest baseline (ParaCE) and our model generate meaning-preserving paraphrases measured using BERTScore thresholds. We report the diversity scores for three such thresholds: 0.95, 0.9, 0.85, selected empirically such that the sample size is sufficiently large.

4 Results

Automatic evaluation We observe in table 1 that ParavMF outperforms all baselines in meaning-

[4]Before computing the PTED, we prune the tree to a max height of 3, and discard all the terminal nodes. We employ Stanford CoreNLP (Manning et al., 2014) for parsing and APTED algorithm for edit distance (Pawlik and Augsten, 2015).

Model	English		French	
	BS↑	MET.↑	BS↑	MET.↑
BP-CE	75.0	75.0	69.4	67.5
BP-vMF	72.1	72.2	65.5	64.2
ParaCE	83.5	87.4	82.3	81.6
ParavMF	**88.6**	**91.6**	**87.2**	**86.4**

Table 1: Meaning-preservation in generated paraphrases. BS: BertScore, MET: METEOR

preservation. Both pivoting based baselines perform poorly on average. This is a consequence of error propagation exacerbated in BP-vMF[5]. As a result, a very small fraction of generated sentences show meaning preservation (as measured by achieving a BERTScore greater than 0.85). Hence, we only compare the diversity in the two best meaning-preserving models, **ParaCE** and **ParaVMF**. As shown in table 2, across all thresholds the latter model achieves higher lexical and syntactic diversity in the outputs. Ablation results in the Appendix show that both the autoencoding objective and the final embedding layer contribute to the improved quality of paraphrases. An additional benefit of our proposed model is that by replacing the softmax layer with word embeddings, ParavMF is trained 3x faster than the ParaCE baseline.

We further conduct a **manual evaluation** which quantifies the rate at which annotators find paraphrases fluent, consistent with input meaning, and novel in phrasing. In an A/B testing setup, we compare our proposed approach with the strongest baseline ParaCE.[6] 200 sentences sampled from the IWSLT English test were scored by two annotators independently, which yielded the inter-annotator agreement of 0.37 (fair agreement). Out of the sentences on which both annotators agree (142 out of 200), we find that ParavMF model outperforms the ParaCE model in 73% of votes. We show more details and some examples of ParavMF and ParaCE system outputs in the Appendix.

Finally, we also evaluate that our results hold on a **larger dataset in different domain**. We retrain ParavMF and ParaCE on $2M$ En–Fr corpus described in §3. [7] The results of automatic evaluation are presented in the Appendix. We conduct human evaluation on a sample of 200 sentences from this test set following the same A/B testing procedure as described above, with each sample rated by three annotators, resulting in a pairwise-average kappa agreement index of 0.21.[8] 42.9% ParavMF outputs were selected as better paraphrases, compared to 24.5% outputs from ParaCE, supporting our main results on the IWSLT dataset.

5 Related Work

Bilingual pivoting is a common technique used with bilingual data (Barzilay and McKeown, 2001; Ganitkevitch et al., 2013; Pavlick et al., 2015; Mallinson et al., 2017a). ParaNMT (Wieting and Gimpel, 2018) is a large psuedo-parallel paraphrase corpus constructed through back-translation (Wieting et al., 2017). Iyyer et al. (2018) augment it with syntactic constraints for controlled paraphrasing; ParaBank (Hu et al., 2019a) improves upon ParaNMT via lexical constraining of decoding; and ParaBank 2 (Hu et al., 2019b) improves the diversity of paraphrases in ParaBank through a clustering-based approach. Note that these works are focused on English. Here, we propose a language-independent approach relying only on abundant bilingual data. Our approach is most similar to Guo et al. (2019) who use bilingual and multilingual translation for zero-shot paraphrasing. They, however, observe that bilingual models are insufficient for paraphrasing and are often unable to produce the output in the correct language. We incorporate an autoencoding objective which simplifies and stabilizes training, and embedding-based outputs improving the diversity in paraphrasing.

6 Conclusion

We present ParavMF, an end-to-end model for generating paraphrases, trained solely with bilingual data, without any paraphrase supervision. We propose to generate paraphrases into meaning

[5]This is expected as vMF has been shown to slightly underperform CE for translation in prior work (Kumar and Tsvetkov, 2019). Our training procedure with an autoencoding objective alleviates this issue in ParavMF.

[6]Each judge is presented with a set of questions, each consisting of an input sentence and paraphrases generated by the two models as options, and is asked to choose the sentence that is fluent, meaning-preserving and offers a novel phrasing of the input. They are asked to choose neither if both sentences are dis-fluent and/or not able to preserve content. The options are shuffled.

[7]We use 4K English sentences subsampled (∼0.1% of the training data) from the same corpus for autoencoding. To further discourage copying, we use denoised autoencoding (Lample et al., 2018).

[8]We discarded around 53 samples with no clear majority among the annotator ratings and report the results on the remaining samples, further ignoring cases where the paraphrases from both the models were rated to be of similar quality.

BERTScore threshold	Model	# (out of 2K)	English IoU↓	English WER↑	English PTED↑	# (out of 2K)	French IoU↓	French WER↑	French PTED↑
0.85	ParaCE	710	94.3	4	**0.5**	710	94.3	3.9	**0.55**
	ParavMF		**92.4**	**4.1**	0.42		**92.7**	**4.1**	0.42
0.9	ParaCE	539	96.2	2.6	**0.34**	580	96.1	2.6	**0.34**
	ParavMF		**94.5**	**2.9**	0.29		**94.5**	**2.9**	0.29
0.95	ParaCE	300	98.8	0.8	0.15	380	98.7	0.8	0.15
	ParavMF		**97.7**	**1.2**	**0.16**		**97.7**	**1.2**	**0.16**

Table 2: Diversity of meaning-preserving paraphrases compared to the test set. ParavMF outperforms a strong baseline ParaCE for both English and French, across all metrics for thresholds 0.85 and 0.9, and in IoU and WER for threshold of 0.95.

spaces as opposed to discrete tokens. This leads to significant improvements in quality and diversity of paraphrasing over strong baselines.

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Model	Semantic Similarity	
	BERTScore	**METEOR**
PARANMT	61.6	62.1
BP (vMF)	44.6	57.4
BP (CE)	45.0	60.4
PARACE	65.9	81.7
PARAVMF	**68.9**	**83.9**

Table 3: Evaluation of paraphrase generation on the PARANMT test set.

Tianyi Zhang, Varsha Kishore, Felix Wu, Kilian Q. Weinberger, and Yoav Artzi. 2020. BERTScore: Evaluating text generation with bert. In *International Conference on Learning Representations*.

A System diagram

The PARAVMF system is represented diagrammatically in Figure 1.

B Example outputs

Sample outputs of the PARAVMF and PARACE models are shown in table 5.

C Training on a Larger Translation Dataset

To measure the impact of the size of parallel translation data used for training, we conduct an experiment with a larger French-English corpus constructed using a $2M$ sentence-pair subset of the combination of the WMT'10 Gigaword (Tiedemann, 2012) and the OpenSubtitles corpora (Lison and Tiedemann, 2016). The semantic similarity scores and the diversity results are presented in table 4. The results of human evaluation are presented in the main paper.

D Evaluation on PARANMT-50M Test Set

We evaluate the PARAVMF model (trained on English-French two-way translation data and English autoencoding data from the IWSLT'16 dataset) on test data sampled from PARANMT-50M (Wieting and Gimpel, 2018), to demonstrate its paraphrasing ability on out-of-domain input, in addition to enabling direct comparison with back-translated data, as shown in table 3. However, it is to be noted that the comparison is not a fair one, since PARAVMF is trained on just 220K data samples, wherease PARANMT is back-translated using a translation model that was trained on a bilingual dataset with a size of around $70M$.

E Ablation

We proposed three changes in a multilingual MT setup to use bilingual data for paraphrasing, (1) predicting continuous outputs and training with vMF loss, (2) language-specific start tokens in the encoder, and (3) an autoencoding objective. In the results section of the main paper, by comparing our method to PARACE, we already established the importance of using vMF compared to cross-entropy. As shown in table 7, ablating either of the other remaining two components leads to considerable performance drop. This is because the ablated models generate outputs in L_2 since they are never exposed to monolingual examples during training. Additional, in our preliminary experiments, we also observe that increasing the size of autoencoding data too much beyond $\sim 1\%$ of the size of parallel translation data leads to a performance drop because the model just starts to learn to copy the input as-is rather than rephrasing.

Model	ENGLISH	
	BERTScore↑	**METEOR↑**
PARACE	62.2	73.6
PARAVMF	**71.6**	**79.6**

(a) Semantic similarity between the test set and generated paraphrases

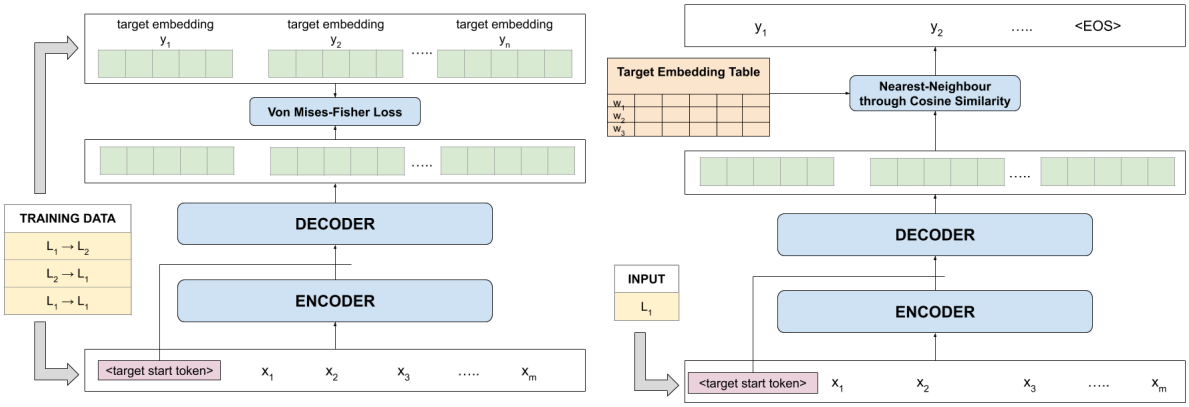
BERTScore threshold	**Model**	# (out of 2K)	ENGLISH **IoU↓**	**WER↑**	**PTED↑**
0.85	PARACE	559	85.5	11.9	**1.43**
	PARAVMF		**82.5**	**12.4**	1.42
0.9	PARACE	327	91.2	7.0	**0.81**
	PARAVMF		**87.9**	**8.3**	0.64
0.95	PARACE	196	95.9	3.3	0.28
	PARAVMF		**93.9**	**3.9**	**0.29**

(b) Diversity of meaning-preserving paraphrases compared to the test set

Table 4: Evaluation of paraphrase generation with PARAVMF trained on $2M$ English-French sentence pairs. It outperforms a strong cross-entropy based baseline (PARACE) on semantic similarity and majority of diversity metrics.

Input	It 's expensive , it takes a long time , and it 's very complicated .
PARACE	It 's expensive takes a time , and it 's very complicated .
PARAVMF	It 's costly , It takes a long time , and it 's very difficult .
Input	These are things to talk about and think about now , with your family and your loved ones .
PARACE	These are things to talk about and think about now , with your family and your loved ones .
PARAVMF	These are things to speak of and think of now , with your family and the ones you love.
Input	So what opened my eyes ?
PARACE	So what opened my eyes ?
PARAVMF	So what is it that opened my eyes up ?
Input	And this work has been wonderful . It 's been great .
PARACE	And this work has been wonderful . It 's been great .
PARAVMF	This work has been wonderful and great .
Input	I wasn 't doing anything that was out of the ordinary at all .
PARACE	I wasn 't doing anything that was out of the regular regular at all .
PARAVMF	I was doing nothing that was not ordinary .
Input	It will make tons of people watch , because people want this experience .
PARACE	It will make tons of people watch , because people want this .
PARAVMF	Tonnes of people will look because they want this experience .

Table 5: Comparison of selected sample outputs for the IWSLT Test Set between PARAVMF model and the baselines. PARAVMF not only exhibits content preservation, but also demonstrates fluency as well as lexical and syntactic diversity.



(a) Training Procedure

(b) Testing Procedure

Figure 1: The PARAvMF Model: The decoder generates continuous-valued vectors at each step. It is trained by minimizing von Mises-Fisher loss between the output vectors and the pre-trained embeddings of the target words. Start tokens signalling the target language are supplied to both the encoder and the decoder. The training data consists of translation samples, $L_1 \leftrightarrow L_2$ and autoencoding samples, $L_1 \rightarrow L_1$. During testing, the word in the target vocabulary whose embedding is closest to the generated output in terms of cosine similarity is output.

Model	Votes (%)
PARACE	39 (27.3%)
PARAvMF	**104** (**72.7%**)

Table 6: PARAvMF outperforms the baseline in manual A/B testing (English).

Model	BLEU	BS	MET.
PARAvMF	64.0	88.6	91.6
- encoder start token	0.86	46.0	12.0
- autoencoding	0.85	46.0	12.1

Table 7: Performance of PARAvMF without the proposed enhancements - removing either leads to a drastic performance drop