

Unsupervised Paraphrase Generation via Dynamic Blocking

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Abstract

We propose Dynamic Blocking, a decoding algorithm which enables large-scale pretrained autoregressive models (such as BART, T5, GPT-2 and XLNet) to generate high-quality paraphrases in an unsupervised setting. In order to obtain an alternative surface form, whenever the language model emits a token that is present in the source sequence, we prevent the model from generating the subsequent source token for the next time step. We show that our approach achieves state-of-the-art results on benchmark datasets when compared to previous unsupervised approaches, and is even comparable with strong supervised, in-domain models. We also propose a new automatic metric based on self-BLEU and BERT-score which not only discourages the model from copying the input through, but also evaluates text similarity based on distributed representations, hence avoiding reliance on exact keyword matching. In addition, we demonstrate that our model generalizes across languages without any additional training.

1 Introduction

Paraphrase generation restates text input in a different surface form while preserving its semantic meaning. It has diverse applications on downstream NLP tasks including text summarization (Cao et al., 2016), semantic parsing (Berant and Liang, 2014), as well as diversifying text generation for user-facing systems such as a chatbot. A paraphraser can be used to generate adversarial examples to evaluate model robustness. The generated examples can also be leveraged to train neural networks so that they become more robust to adversarial attacks (Iyyer et al., 2018). For QA systems, paraphrasing questions can not only augment QA models with more training data, but also makes it more likely to match with key words in

a knowledge base (Fader et al., 2014; Yin et al., 2015).

However, it is expensive to annotate paraphrases, resulting in only a few human-labeled datasets. The existing ones are either small-scale like MRPC (Dolan and Brockett, 2005) or of closed domain like QQP¹ which consists entirely of questions. Consequently, previous work also explored automatically annotated datasets such as ParaNMT (Wieting and Gimpel, 2017), Twitter (Lan et al., 2017), or re-purposed noisy datasets such as MSCOCO (Lin et al., 2014) and WikiAnswers (Fader et al., 2013). The scarcity of high-quality paraphrase data motivates us to consider transfer learning approach, which leverages large-scale pretrained autoregressive language models like BART (Lewis et al., 2019).

The effectiveness of BERT-score (Zhang et al., 2019) in paraphrase identification hints that pretrained language models are already equipped with extensive knowledge in text similarity. This knowledge may be attributed to the fact that text spans that share similar context stay semantically close to each other, word embedding (Mikolov et al., 2013) being a typical example. In other words, tapping the language models for paraphrasing capability naturally leverages the strong correlation between context and semantic similarity. In fact, previous work have explored leveraging such implicit knowledge in GPT-2 (Radford et al., 2019) in both a supervised (Witteveen and Andrews, 2019) and a weakly supervised settings (Hegde and Patil, 2020).² In this work, we also make use of pretrained autoregressive models for paraphrasing, but in an unsupervised setting.

¹<https://www.kaggle.com/c/quora-question-pairs>

²Hegde and Patil (2020) adopt a weakly supervised approach though it is claimed to be unsupervised. We will discuss the distinction in Section 6.

However, for the purpose of paraphrasing, decoder-only models only output a continuation of the input, while Sequence-to-Sequence (Seq2Seq) models like BART tend to copy the input through because because the probabilities of the input tokens during generation are all peaked. This makes it hard for popular decoding algorithms, be they greedy decoding, beam search or top- k/p sampling (Holtzman et al., 2019). In this work we propose dynamic blocking, a decoding algorithm that effortlessly transforms pretrained autoregressive language models into natural paraphrasers. In order to obtain a surface form different from the input, whenever we emit a token that is present in the source sequence, this algorithm prevents the model from generating its immediate successor for the next generation step. This algorithm is based on the intuition that during inference, although the top candidate at each generation step corresponds to a peaked probability, the rest of the distribution (when re-normalized) still contains rich linguistic knowledge suitable for paraphrasing. This is in similar spirit with using soft targets for model distillation (Hinton et al., 2015).

We show that our approach achieves state-of-the-art results on the Quora Question Pair (QQP) dataset when compared to previous models. On the ParaNMT dataset, our model is even comparable with strong supervised, in-domain models, hence closing the gap with supervised approaches. We also propose a new automatic metric, which is the harmonic mean of BERT-score (Zhang et al., 2019) and self-BLEU that correlates better with human evaluation. Through qualitative analysis, we demonstrate that Dynamic Blocking produces high-quality paraphrases that are both coherent and syntactically diverse. We also show with concrete examples that our approach can generate paraphrases in German without any additional training.

2 Model

In this section, we introduce Dynamic Blocking using BART as the underlying language model, and later explain how it can be generalized to other auto-regressive models by performing task adaptation (Section 2.3) followed by self-supervised training (Section 2.4). The pre-training objective of BART is to reconstruct the original document from its corrupted version by an autoregressive decoder. This endows the model with capabilities of

both attending to the source sequence and paying attention to the context to generate coherent output.

2.1 Dynamic Blocking

As mentioned in Section 1, BART with greedy decoding or top- k/p sampling always copies through the source sequence. In order to force the model to generate in a different surface form, we propose Dynamic Blocking (Figure 1) as the decoding algorithm. As illustrated in Algorithm 1, we represent the source sequence S as a list of tokens $S = (S_0, S_1, \dots, S_M)$ and the generated sequence as $G = (G_0, G_1, \dots, G_N)$. Suppose that during generation, the model generates G_j that is identical to some S_i (it is not necessary that $i = j$). Then during generation of G_{j+1} , the algorithm forbids the model to generate S_{i+1} . Such blocking forces the generated sequence to deviate from the original one by imposing $G_{j+1} \neq S_{i+1}$. Note that the blocking of S_{i+1} only lasts for one step.³ After G_{j+1} is generated, we will perform a different blocking iff $G_{j+1} \in S$.

Algorithm 1: Dynamic Blocking

```

input : A source sequence  $S$  consisting of a list of
tokens  $S = (S_1, S_2, \dots, S_M)$ , and a BOS
token to start the decoding process
1 Initialize  $j \leftarrow 0$ 
2 Generate  $G_j$ 
3 while  $G_j \neq \text{EOS}$  do
4   if  $G_j = S_i \in S$  then
5     |  $P(G_{j+1} = S_{i+1} | S, (G_0, \dots, G_j)) \leftarrow 0$ 
6   end
7   Generate  $G_{j+1}$ 
8    $j \leftarrow j + 1$ 
9 end
output:  $G = (G_0, G_1, \dots, G_N)$ 
```

The reason to block for only one time step is to allow pure syntactic variation of the original sequence, meaning that all tokens are kept but their order is permuted. To demonstrate this, let us consider a decoding algorithm that completely prevents the model from generating a source token at all time steps – an algorithm we named *Static Blocking*. Suppose that we intend to paraphrase “*I like apples and oranges.*” as “*I like oranges and apples.*”. This is a valid paraphrase, but if we completely block the word “*apples*” at all time steps, it will be impossible to arrive at

³Of course we could block for more steps to incur more syntactic variance, but we found through early experiments that blocking for one step already generates decent enough paraphrases.

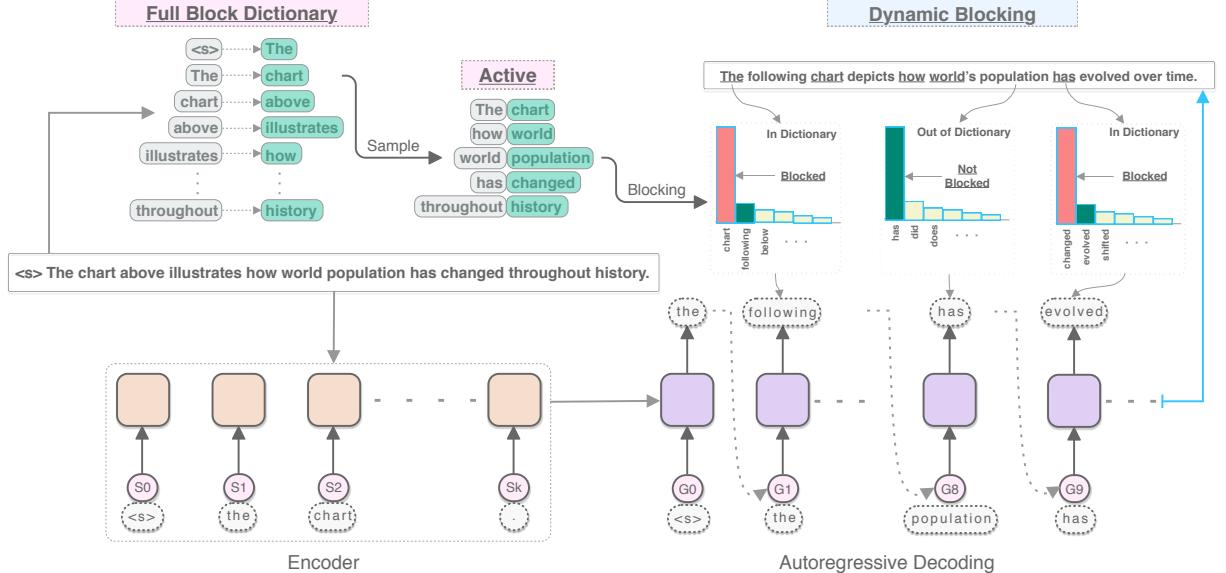


Figure 1: Illustration of the Dynamic Blocking algorithm on a real model output. The algorithm first constructs a block dictionary based on the input, which maps each token to its immediate successor to be blocked, and then samples from this dictionary to form an active block sub-dictionary to be used for the current sequence. Multiple such sub-dictionaries can be obtained from one input sequence. During generation, the blocking takes place whenever any item in the active dictionary is triggered.

this paraphrase. However, with Dynamic Blocking the model will still be able to generate the word “*apples*” later on even though this word has briefly been blocked after “*and*” is generated. As shown in Figure 1, Dynamic Blocking builds a block dictionary which maps each token in the source sequence to its immediate successor. We then sample from this dictionary with a probability p for each entry. This hyperparameter controls how different we want the paraphrase to be from the source input. For two extreme cases: when $p = 0.0$, the model does not block any tokens and most likely copies through the source sequence; when $p = 1.0$, the model always blocks the immediate next token, leading to a drastically different surface form. In this work, we take the middle ground and set $p = 0.5$ so that for each blocking action, there will be half of the candidates taking that path.

To achieve the diversity needed for text generation, quite a few previous works (Goyal and Durrett, 2020; Hegde and Patil, 2020) employ top- k/p sampling. However, this usually results in incoherent sentences containing repeated tokens. To avoid this downside, we count on sampling multiple different block dictionaries to ensure *diversity* among candidates, while leveraging beam search to ensure *coherence*. For each sampled block dictionary, we use beam search to generate four can-

didates and keep the top-ranked two. Though beam search alone could not generate decent paraphrases, it significantly improves the generation quality with the help of Dynamic Blocking.

2.2 Re-ranking of candidates

Similar to (Li et al., 2019), we consider both semantic similarity and surface-form dissimilarity to the source input for re-ranking the generated candidates. For semantic similarity we use BERT-score, which computes cosine similarity for each token in the candidate sentence with each token in the reference sentence using contextual embeddings.⁴

In order to ensure that key information (often conveyed through relatively rare words) is retained in the paraphrase, we also apply IDF-reweighing on each of the tokens when computing BERT-score, which is an internal feature of this metric. We use BookCorpus dataset (Zhu et al., 2015) to obtain the IDF weights.

2.3 Task-adaptation

Although BART and its variations (e.g., mBART) can directly work with Dynamic Blocking to gen-

⁴ Witteveen and Andrews (2019) uses Universal Sentence Encoder (Cer et al., 2018), while Hegde and Patil (2020) employs Sentence-BERT (Reimers and Gurevych, 2019), both serving a similar purpose.

erate paraphrases, the other pretrained autoregressive language models such as T5 (Raffel et al., 2019), GPT-2 (Radford et al., 2019) and XLNet (Yang et al., 2019) still require task adaptation. Following Gururangan et al. (2020), we apply task-adaptive training on the target dataset treating its training set as a concatenation of non-parallel sentences. For each sentence, we take its corrupted version as the source input and the original sequence as the target. Unlike previous work (Devlin et al., 2018; Lewis et al., 2019), we do not corrupt the input with masks, but rather directly remove the corrupted tokens. This is to avoid pretrain-finetune discrepancy in denoising autoencoding models (Yang et al., 2019) because the inputs to the paraphraser do not contain any masks.

2.4 Self-supervision

To help the model internalize the regularizations imposed by Dynamic Blocking and re-ranking strategies, we also perform self-supervision so that during inference the model is less reliant on them and hence generate more diverse candidates with Dynamic Blocking. Hence our main model follows the pipeline of *domain adaptation followed by self-supervision*. To provide further insight into what benefits each of the finetuning steps bring, we report results from two ablation studies: *domain adaptation only*, and for BART-like models *self-supervision only*. Note that if we generate the pseudo training examples with a task-adapted model, we will start with the pretrained language model rather than with the task-adapted one to avoid catastrophic forgetting (Chronopoulou et al., 2019; Chen et al., 2020).

3 Experimental Setup

3.1 Details of Dynamic Blocking

Block variation and inflections In our early experiments, we observed that when blocking a word (e.g. “give”), the model usually tries to generate its capitalized (“Give”) or upper (“GIVE”) version, or its inflections (“gives”, “gave”, “giving”, “given”). In both cases, from we human’s perspective these are usually not good paraphrases – intuitively we would prefer a different word. Hence we use the *pattern* library⁵ to enumerate all inflections of a word to block. This is available for most languages that involve inflections. Also, similar

⁵<https://github.com/clips/pattern>

to whole-word masking introduced in later versions of BERT,⁶ we only block the beginning of the word rather than any subword.

Block closed-class words We also leverage linguistic knowledge to help boost the quality of the paraphrases by avoiding blocking closed-class words, or functional words.⁷ The closed classes in English include pronouns, determiners, conjunctions, and prepositions. In contrast, open-class words include nouns, lexical verbs, adjectives, and adverbs. There are two justifications for blocking these words. First, because they are closed-class, there are less synonyms available; second, blocking such words is error-prone. For example, changing determiners (e.g. from “you” to “I”) may lead to grammar errors, and modifying conjunctions (e.g. from “and” to “or”) may lead to change in logical relationships.

3.2 Automatic evaluation

Dataset We evaluate on the Quora Question Pair (QQP) and the ParaNMT dataset.⁸ QQP contains 140K paraphrase pairs and 640K nonparallel sentences. The sizes of dev and test sets are 3K and 20K, respectively. The ParaNMT dataset (Wieting and Gimpel, 2017) was constructed by back-translating sentences in Czech in the CzEng (Bojar et al., 2016) dataset. For evaluation we directly obtain the test set of SOW-REAP from the authors of Goyal and Durrett (2020). For task-adaptive training we sample 500K nonparallel sentences from ParaNMT-5M, while for self-supervised training we sampling 20K from the same corpus. Note that we filter out any sentences coming from SOW-REAP’s test set to avoid training on test examples.

Automatic metrics To evaluate the quality of paraphrasing, we follow Li et al. (2019) to report iBLEU (Sun and Zhou, 2012) and ROUGE (Lin, 2004) on QQP, and report BLEU (Papineni et al., 2002) and ROUGE (Lin, 2004) on ParaNMT. Note that for ParaNMT BLEU is calculated by

⁶<https://github.com/google-research/bert>

⁷<https://mailman.uib.no/public/corpora/attachments/2011124/6c58cb02/attachment.txt>

⁸We do not evaluate on WikiAnswers like previous work did because Abujabal et al. (2018) found that the paraphrasing clustering in this dataset has a low accuracy when trying to build upon it to create the ComQA dataset (https://huggingface.co/datasets/com_qa). We observed the same during early experiments.

first selecting the candidate that achieves the best sentence-level score with the ground truth, and then compute the corpus-level BLEU of all these candidates. We use *py-rouge*⁹ to compute ROUGE score and the *Datasets* library from *HuggingFace*¹⁰ to compute BLEU score.

3.3 Human evaluation

Reproducing previous model To compare with previous work, for QQP we reproduce the model from [Hegde and Patil \(2020\)](#), which we refer to as CorruptLM. This model is similar to our task-adaptive finetuning approach (Section 2.3). A key difference is that they corrupt the input by removing all stop words rather than a fixed percentage of any tokens. Because the original paper did not provide the source of the stop words, we extracted the first 252 words from The Corpus of Contemporary American English ([Davies, 2010](#)) just to match the number. Instead of GPT-2 as used by their work, we use BART which shows stronger results on diverse downstream tasks. The rest of the settings remain the same. Note that to encourage the model to have new words in the reconstructed sentence that were not in the original sentence, 20% of the words are randomly replaced with a synonym using syn-net ([Miller, 1998](#)) (also applied during inference). In other words, the supervision signal mostly comes from annotations by syn-net, while the model learns to copy the synonyms through. Thus we treat CorruptLM as a weakly supervised model.

For ParaNMT we use the SOW-REAP model released by [Goyal and Durrett \(2020\)](#)¹¹ to successfully reproduce their results reported in their paper, which is also presented in Table 3.

Evaluation setup For each experiment we compare our final model head-to-head with one of the three models: CorruptLM, the final model without Dynamic Blocking during inference, and the ground-truth. When comparing with a previous model, we ask the annotators to identify which paraphrase they like better. We intentionally do not ask them to separately evaluate semantic similarity and diversity because the latter is easy to check with self-BLEU. What is hard to evaluate with automatic metrics is the overall quality of the

⁹<https://pypi.org/project/py-rouge/>

¹⁰<https://huggingface.co/metrics/sacrebleu>

¹¹<https://github.com/tagoyal/sow-reap-paraphrasing/>

	Model	Quora			
		iBLEU	BLEU	Rouge-1	Rouge-2
Supervised	ResidualLSTM	12.67	17.57	59.22	32.40
	VAE-SVG-eq	15.17	20.04	59.98	33.30
	Pointer-generator	16.79	22.65	61.96	36.07
	Transformer	16.25	21.73	60.25	33.45
	+ Copy	17.98	24.77	63.34	37.31
	DNPG	18.01	25.03	63.73	37.75
Supervised (Wiki)	Pointer-generator	5.04	6.96	41.89	12.77
	Transformer + Copy	6.17	8.15	44.89	14.79
	Shallow fusion	6.04	7.95	44.87	14.79
	Multi-task learning	4.90	6.37	37.64	11.83
	+ Copy	7.22	9.83	47.08	19.03
	DNPG	10.39	16.98	56.01	28.61
Weakly Supervised	CorruptLM	12.51	17.36	49.20	26.26
Unsupervised	VAE	8.16	13.96	44.55	22.64
	CGMH	9.94	15.73	48.73	26.12
	UPSA	12.02	18.18	56.51	30.69
	PUP	14.91	19.68	59.77	30.47
No model	Dynamic Blocking	20.93	26.76	67.49	42.33
	Copy-input	24.79	30.98	65.60	42.09

Table 1: Automatic metrics results on the QQP dataset. Models we (re)produced and SOTA results in each category are boldfaced. “Wiki” in “Supervised (Wiki)” stands for models trained on WikiAnswers and evaluated on QQP.

paraphrases. For each experiment we randomly sample 100 examples from QQP’s test set.

4 Results

4.1 Automatic evaluation

QQP The automatic evaluation results are presented in Table 1, which shows that our unsupervised model achieves state-of-the-art results on iBLEU, BLEU and ROUGE scores even when compared with supervised, in-domain models. This is the model with task adaptation followed by self-supervision while not applying Dynamic Blocking during inference. Part of the performance gain of our model comes from the strength of the pretrained language model. An interesting observation on previous results is that domain-adapted supervised models perform worse than in-domain unsupervised models. This shows that the performance gain for the unsupervised models mainly come from learning QQP’s data distribution. Our approach also benefits from such training due to the task adaptation phase (Section 2.3).

All these results look exciting until we move to the last row. Other than scores from previous work, we additionally report copy-input results, which achieves the top performance on iBLEU and BLEU while obtaining the second best ROUGE scores, indicating that these metrics fail to punish against copying through the input. This is consistent with observations from [Mao and Lee \(2019\)](#) who find that parroting usually achieves state-of-the-art results.

Recall that we arrive at our final model through

Model		Quora			
Training	Inference	iBLEU	BLEU	Rouge-1	Rouge-2
-	Dynamic Blocking	11.89	16.51	55.08	28.33
Task-adaptation	Dynamic Blocking	10.66	15.35	63.03	32.25
Self-supervision	-	15.24	20.29	55.18	31.54
Both	Dynamic Blocking	10.59	15.14	63.38	31.21
Both	-	20.93	26.76	67.49	42.33

Table 2: Ablation studies on the two unsupervised fine-tuning steps: task-adaptation and self-supervision. Top results are boldfaced.

two steps: task-adaptation and self-supervision. In Table 2 we provide ablations studies for each step. One interesting observation from the table is that task-adaptation significantly improves ROUGE, while self-supervised training boosts BLEU scores. The former is understandable because ROUGE is a recall-based metric, and our task-adaptation training encourages the model to add words to the corrupted sequences without deletion. However, we could not yet think of a reason to explain why self-supervised training enhances BLEU performance. Another trend to pay attention to is that when we perform task-adaptation followed by self-supervision, the resulting performance is almost identical to task-adaptation alone, showing that Dynamic Blocking, which brings diversity to the output, is the main factor which influences the BLEU scores.

ParaNMT On the ParaNMT dataset we not only report our final model performance, but also report domain adapted results including both CorruptLM and Dynamic Blocking task-adapted to QQP and evaluated on ParaNMT. From the table we can see that although CorruptLM achieves decent performance on QQP, the model is not robust when evaluated cross-domain. In contrast, our model performs much better on this aspect, achieving results very close to our in-domain final model (last row). This also shows that learning ParaNMT’s data distribution is much less effective than learning QQP’s to boost automatic performance. We hypothesize that for ParaNMT, supervised models gain its performance mainly from sequence-level distillation (Kim and Rush, 2016), where the distillation data comes from the underlying round-trip translation models. Our model, when not trained on any parallel data, will have low automatic metric scores as expected. However, we still note that our unsupervised performance is close to that of SCPN, a strong supervised model.

We also note one special aspect of Table 3 to make it easier to interpret. Unlike on QQP, the per-

	Model	Oracle Quality (10 sentences)			
		BLEU	Rouge-1	Rouge-2	Rouge-L
Supervised	copy-input	18.4	54.4	27.2	49.2
	SCPN	21.3	53.2	30.3	51.0
	Transformer seq2seq	32.8	63.1	41.4	63.3
	+ diverse-decoding	24.8	56.8	33.2	56.4
	SOW-REAP (LSTM)	27.0	57.9	34.8	57.5
	SOW-REAP	30.9	62.3	40.2	61.7
Weakly Supervised	CorruptLM (QQP)	6.9	31.9	11.5	31.7
Unsupervised	DBlock (QQP)	19.4	58.5	31.3	52.4
	DBlock	20.9	58.3	31.5	52.4

Table 3: Automatic metrics results on the Para-NMT dataset. “DBlock” stands for Dynamic Blocking task-adapted and self-supervised on the QQP dataset rather than in-domain ParaNMT data.

formance of copy-input on ParaNMT is the lowest among all models. However, this is not a completely fair comparison because all the other results are based on 10 candidates where only the ones with the highest sentence-level score are retained for the final score computation. In contrast, copy-input only has one candidate. Thus readers are encouraged to view this table with a grain of salt.

4.2 Human evaluation

Table 4 presents human evaluation results on our final model against another three models.¹² From the table we can see that though CorruptLM and our model both leverages pretrained BART, our model still outperforms CorruptLM by a large margin. This indicates the effectiveness of our task-adaptation and self-supervised training when holding the BART factor as a constant. When comparing with the same model but without Dynamic Blocking during inference on the test set, we observe a strikingly different trend from the automatic evaluation results. Recall in Table 2, we found that applying Dynamic Blocking during inference actually hurts automatic metric performance, which shows that BLEU and ROUGE can be misleading at times. The last row shows that our unsupervised model outputs is overall not as strong as those produced by humans. However, considering that human annotators think our model outputs are equal to or better than ground-truth 52% of the time, we could still interpret our model’s performance as competitive.

¹²We did not compare with UPSA or PUP for human evaluation because their codes are not released. UPSA provided a Github link in the paper, but unfortunately it is no longer valid.

Model	v.s. Model	Win	Tie	Loss
	CorruptLM	55	34	11
DBlock	w/o DBlock inference	55	16	29
	Ground-truth	20	32	48

Table 4: Human evaluation results. We compare Dynamic Blocking (first column) with each of the models in the second column. “w/o DBlock inference” stands for final model without Dynamic Blocking during inference. Each experiment is performed over 100 samples from the QQP test set; hence each row adds up to 100.

5 Analysis

5.1 Curse of BLEU on paraphrase evaluation

In Section 4, we see that models achieving higher BLEU scores nevertheless receive lower human evaluation scores. The reason that BLEU does not correlate well with human perception is that there are two opposing forces. The first force comes from keeping the important information, such as named entities, which should be matched verbatim; on the other hand, the second force comes from using different wording to express the same underlying semantics – the better the model is at this, the worse the BLEU. For a model good at both, the gain in BLEU for matching key entities and the loss for using different words cancel each other, hence preventing BLEU from faithfully evaluating the paraphrasing quality. On the other hand, BERT-score still encourages the first force while not punished much by the second, positioning itself as a better metric. However, parroting the input will still fool BERT-score alone. Hence we also include self-BLEU to encourage diversity just like in iBLEU.

5.2 Generalization to other languages

We found with surprise that although BART was not explicitly trained on German corpus, nor was its vocabulary created specifically for German, the model is already equipped with the capability to paraphrase. In Table 5, we present such an example as well as their English translations by the Google Translator. We can see that all sentences in German (left column) have different surface forms, while all translations in English (right column) share similar meanings. To our best knowledge, this is the first unsupervised model that can paraphrase in a language other than English.

6 Related Work

Paraphrase generation has been a long-standing problem that has several applications on downstream NLP tasks including text summarization (Cao et al., 2016), semantic parsing (Berrant and Liang, 2014), and question answering (Yu et al., 2018). Early works on paraphrase generation mostly rely on rule-based or statistical machine translation systems (McKeown, 1980; Meteer and Shaked, 1988; Bannard and Callison-Burch, 2005).

Supervised Approaches Neural sequence-to-sequence models have also been leveraged to address this task (Prakash et al., 2016; Gupta et al., 2017; Li et al., 2017; See et al., 2017; Vaswani et al., 2017; Gupta et al., 2018). There have been several prior work (Iyyer et al., 2018; Chen et al., 2019; Li et al., 2019) that leverages syntactic structures to produce more diverse paraphrases. Most recently, Goyal and Durrett (2020) proposes to reorder the source sentence through syntactic structures to guide the neural paraphrasing model, while Qian et al. (2019) employs distinct generators to produce diverse paraphrases. Retrieval-augmented generation methods have also been investigated (Kazemnejad et al., 2020; Lewis et al., 2020) for paraphrase generation task. However, most of these approaches require parallel paraphrase data, which is usually scarce MRPC (Dolan and Brockett, 2005) or domain-specific QQP.¹³

Unsupervised Approaches Unsupervised paraphrasing, on the other hand, is a rather less explored and a more challenging problem in NLP. Round-trip translation between two languages (i.e., back-translation) using strong neural machine translation (NMT) models has become a widely used unsupervised approach to paraphrase generation (Yu et al., 2018). Bowman et al. (2016) trains a VAE with the objective of maximizing the lower bounds for the reconstruction log-likelihood of the input sentence without requiring any parallel paraphrase corpus. Sampling from the trained VAE’s decoder leads to sentences that can practically be considered as paraphrases as the decoder aims to reconstruct the input sentence by its training objective. Liu et al. (2019) casts the paraphrase generation as an optimization problem, where it searches the sentence space to find the

¹³<https://www.kaggle.com/c/quora-question-pairs>

	German	Translation from German
Input	Warum finden keine Brandschutzbelehrungen statt ?	Why are there no fire instructions?
Candidates	Warum lieen keine Geschutzbelehrungen statt? Warum finden keine Geschutzbelehrungen statt? Warum lieen keine Brandschutzbelehrungen statt? Warum finden keine Geschutzbelehrungen statt? Warum finden wir keine Geschutzbelehrungen statt? Warum finden wir keine Brandschutzbelehrungen statt? Warum finden vor keine Brandschutzbelehrungen ein? Warum finden keine Brandschutzbelehrungen statt?	Why were there no protection instructions? Why are there no protection instructions? Why weren't there any fire safety instructions? Why are there no protection instructions? Why are there no protection instructions? Why are we not giving fire safety instructions? Why are there no fire safety instructions? Why are there no fire protection instructions?

Table 5: Paraphrasing with German input using the unsupervised BART. Translations on the right are given by the Google Translator, except that the first one is the ground-truth translation. Note that the candidates are ranked by multi-lingual BERT rather than RoBERTa-based when paraphrasing in English.

optimal point with respect to an objective function that takes semantic similarity, expression diversity, and language fluency into account. Siddique et al. (2020) optimizes a similar objective by leveraging deep reinforcement learning.

Transfer learning There have been few works leveraging pretrained language models (LM) to generate paraphrases, either in a supervised (Witteveen and Andrews, 2019) or a weakly supervised (Hegde and Patil, 2020) setting. Both works employ GPT-2 as their backbone generation model either with parallel or weakly annotated data. To our best knowledge, we are the first to propose an unsupervised model that can generate paraphrases with an LM.

7 Conclusion

In this work we design a decoding algorithm named Dynamic Blocking that is able to generate paraphrases with a pretrained autoregressive language model in an supervised setting. We demonstrate with automatic metric and human evaluations that our model achieves the state-of-the-art results on benchmark datasets. We also show with analysis that the model is able to generalize across different languages without training. An interesting direction is context-aware paraphrase generation, where the output conditions not only on the text to be paraphrased, but also on the context around it. We leave this as future work.

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