To Paraphrase or Not To Paraphrase: User-Controllable Selective Paraphrase Generation

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Abstract

In this article, we propose a paraphrase generation technique to keep the key phrases in source sentences during paraphrasing. We also develop a model called TAGPA with such technique, which has multiple pre-configured or trainable key phrase detector and a paraphrase generator. The paraphrase generator aims to keep the key phrases and increase the diversity of the paraphrased sentences. The key phrases can be entities provided by our user, like company names, people’s names, domain-specific terminologies, etc., or can be learned from a given dataset.

1 Introduction

Notions of semantic similarity and paraphrase are highly context dependent. Consider “I’m looking for cheap hotels in New York.” vs. “What are cheap lodging options in Beijing?”: from the perspective of intent classification, both express similar intents, but from the perspective of paraphrasing in a community QA application, a user looking for the answer to one question would not find the other response helpful. This is because the location “New York” anchors the information need, and any changes to it would be unacceptable to the user.

It is not always the case the named entities are “immutable” in this respect: consider a user looking for vacation destinations in the South of France. From the perspective of an advertiser, there might be good reason to tempt the user with alternative locations such as the Italian Riviera; the user may even welcome these suggestions. Furthermore, it is not always the case that these immutable anchors are named entities: For example, some metrics assign high similarity to antonyms, and so “cheap hotels” and “expensive hotels” might be considered semantically close, but obviously not from the perspective of an end user looking for inexpensive lodging.

Although whether or not certain words can be changed without affecting the meaning of a sentence is highly dependent on context, the user for a paraphrase generation system usually would know. Consider the application of paraphrase generation in a community QA application, where a developer wishes to automatically generate question variants to increase the chances of a semantic match: A naïve system will indeed generate “What are cheap lodging options in Beijing?” as a paraphrase to “I’m looking for cheap hotels in New York.”

What if we are able to provide the user with a way to explicitly tag portions of the input so that a paraphrase generator knows what parts of the input to repeat verbatim? For example, a simple annotation scheme like “What are cheap lodging options in ⟨tag⟩ Beijing ⟨/tag⟩?”, where words between ⟨tag⟩ and ⟨/tag⟩ should not be paraphrased. The contribution of our work is to provide exactly such a mechanism.

2 Model Structure

Our Model, TAGPA, contains two parts: the Tagger and the Paraphrase Generator.

The Tagger aims to identify key phrases that should be kept during paraphrase generation and tag them with special tokens. As mentioned above, the key phrases here can be foreign language phrases, company names, domain-specific terminologies, etc. Obviously, if a user knows exactly what are the key phrases, our tagger can simply look up those phrases in a user-provided dictionary. When the user don’t have such dictionary, we also provide them with several alternatives mentioned below.

The Paraphrase Generator, as the name suggests, generate paraphrases. It also needs to keep the tagged contents as it is during paraphrase generation. Moreover, to generate diverse paraphrases,
the generator also needs to change the non-tagged parts of the source sentence as much as possible, while keeping the semantic meaning.

2.1 Taggers

2.1.1 Oracle Tagger

The Oracle Tagger is an upper bound of our model, which tags the key phrases in our source sentences that also appear in all the ground-truth reference sentences. To be more specific, Oracle Tagger goes over all reference sentences, keep track of consecutive word sequences that appears in both source sentence and all the references, and prune the language-specific common phrases that are too common to be key phrases (e.g. “a”, “the”, “there be”, “what is”, “how about” in English). Then, we tag the key phrases in our source sentences and regard those tagged sentences as our input.

Since the Oracle Tagger sees all the test references, it simulates the circumstance when our user knows exactly what should be kept during the paraphrase. Though we assume in the above sections a good user should provide us a dictionary that contains all the key phrases to be tagged, not all users are oracles. To serve them better, we also provide our users with two alternatives:

2.1.2 NER Tagger

As the name suggests, the NER Tagger identifies key phrases to tag with an Name Entity Recognizer. The user can choose between BERT-BASE-Cased (Devlin et al., 2018) finetuned on the CoNLL-2003 shared task: Language-independent named entity recognition or ID-CNN (Strubell et al., 2017). Our below experiments uses ID-CNN for better performance.

2.1.3 Auto Tagger

The Auto Tagger is a trained tagger, in order to automatically identify key phrases from source sentences. The concept of Auto Tagger combines both Oracle Tagger and NER Tagger. A one-line description of its functionality would be: Auto Tagger tries to replicate the performance of Oracle Tagger with a token classifier. To be more specific, our training data contains sets of sentences with the same semantic meaning (e.g. MSCOCO), thus we can find out key phrases just as how we do it in Oracle Tagger. Then, we label the key phrases in our source sentences, forming into a NER-style token classification task. Finally, we use BERT-BASE-Cased (Devlin et al., 2018) with a linear layer to serve as a token classifier. The trained classifier is our Auto Tagger, and should be able to tag the key phrases in new sentences.

In our experiments, we found that we can have a good enough Auto Tagger only if we have a relatively large number of semantic clusters (sentences with the same semantic meaning) to learn from.

2.2 Paraphrase Generator

For paraphrase generation, we use the mBART-large (Liu et al., 2020) to encode the source sentence and decode such source sentence given one of the reference sentences. Since the authors of mBART published their pretrained weights, we only need to finetune it with paraphrase generation task, as shown in the architecture of the Paraphrase Generator. When testing, only the source sentence will be given, and the outputs are autoregressive.

During the finetuning time, our paraphrase generator learns to keep the key phrases between ⟨tag⟩ and ⟨/tag⟩ tokens, since the content inside the enclosed tags are not changed from a source to its reference sentence. It also learns to generate paraphrases since the reference sentence is a paraphrase of source sentence.

In addition to the original mBART architecture, we add another loss term to encourage diversity in generated paraphrases. During finetuning, we also maximized the entropy between our paraphrase distribution and the source sentence. The entropy term is also controlled by hyperparameter weight, indicates how ‘diverse’ we want our paraphrases to be compared to the source sentence. By default, such weight is set to 0.3.

2.2.1 Why mBART?

Firstly, it is Cheap and Extendable, since mBART released their pre-trained weights. Our tagging technique aims to achieve a good paraphrase generation performance with a low-cost finetuning task that utilizes already published pretrained models. As compare to other Pointer Generator Network approaches like (Ravuru et al., 2019), our approach is cheaper and more flexible given pre-trained weights. Furthermore, easy modifications can be made based on our source code to make TAGPA work with other (future) pretrained encoder-decoder architectures. Secondly, mBART was pretrained on 25 languages, makes TAGPA multilingual. We will discuss this with more detail in section Other Languages.
3 Experiments

We use four English datasets to test our tagging tricks, two of which (MSCOCO (Lin et al., 2014) and QQP (Iyer et al., 2017)) are already widely used in our paraphrase generation community and the other two of which (Parabank-Eval (Hu et al., 2019) and ComQA (Abujabal et al., 2018)) are newly introduced. Among those datasets, MSCOCO, Parabank-Eval and ComQA have semantic clusters (the sentences are grouped by similar semantic meanings, thus all the sentences in one cluster are paraphrases of each other) and QQP has only paraphrase sentence pairs. So for MSCOCO, Parabank-Eval and ComQA, we pick one sentence from the cluster as the paraphrase source sentence and the rest as the ground-truth references. For QQP, we pick one sentence as the source and the other one as the reference. More specifically, MSCOCO contains 118k “semantic clusters” and each cluster contains 5 sentences. Parabank-Eval contains 400 semantic clusters with non-constant number of long sentences. ComQA contains 1809 semantic clusters with non-constant numbers of sentences in the form of questions. QQP contains 70k sentence pairs in the form of questions. We divide all datasets with 80% in the training set and 20% in the testing set.

3.1 Overall Results

In above tables, we demonstrate the overall performance of all the models. B-1, B-2, B-3 and B-4 stand for BLEU-1, BLEU-2, BLEU-3 and BLEU-4 (Papineni et al., 2002) scores with (1.0, 0, 0, 0), (0.5, 0.5, 0, 0), (0.33, 0.33, 0.34, 0) and (0.25, 0.25, 0.25, 0.25) weights on 1-gram, 2-gram, 3-gram and 4-gram respectively. R-1, R-2, R-3, R-4, R-L and R-W stand for ROUGE-1, ROUGE-2, ROUGE-3, ROUGE-4, ROUGE-L and ROUGE-w metrics proposed by (Lin, 2004). For MSCOCO and QQP dataset, The first eight rows are directly copied from the paper (Fu et al., 2019). The Seq2Seq and Residual Seq2seq-Attn are both from (Prakash et al., 2016), represents seq2seq LSTM with residual connections and attention mechanism, respectively. $\beta$-VAE is from (Higgins et al., 2016). BOW-Hard, LBOW-Top k, LBOW-Gumbel and Cheating BOW are all from (Fu et al., 2019), where BOW-Hard is the lower bound of the latent bag-of-words algorithm and Cheating BOW is the cheating upper bound.

For the rest of the lines, we show the result of baselines and our TAGPA model with different components. For the baselines, source to ref directly evaluates the metrics of our paraphrase generation source to the ground-truth references, provides an upper-bound regarding how much of
### Table 1: Results on the English datasets.

| Models                          | MSCOCO dataset | QQP dataset | ComQA dataset | Parabank-Eval dataset |
|--------------------------------|----------------|-------------|---------------|-----------------------|
|                                | B-1 | B-2 | B-3 | B-4 | R-1 | R-2 | R-3 | R-4 | R-L | R-W | B-1 | B-2 | B-3 | B-4 | R-1 | R-2 | R-3 | R-4 | R-L | R-W | B-1 | B-2 | B-3 | B-4 | R-1 | R-2 | R-3 | R-4 | R-L | R-W | B-1 | B-2 | B-3 | B-4 | R-1 | R-2 | R-3 | R-4 | R-L | R-W | B-1 | B-2 | B-3 | B-4 | R-1 | R-2 | R-3 | R-4 | R-L | R-W |
|--------------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Seq2seq                        | 69.61 | 47.14 | 31.64 | 21.65 | 40.11 | 14.31 | &nbsp; | &nbsp; | 36.28 | &nbsp; | &nbsp; | 56.42 | 40.41 | 31.25 | 24.97 | 57.27 | 33.04 | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; | &nbsp; 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our key phrases can be kept (since our source sentences to generate paraphrase from must contain all the key information). No tag means we do not tag any key phrase, should be viewed as a lower bound of our model. To be more specific, scores of no tag evaluates the quality of generated paraphrases versus ground-truth references. The scores of vs. S evaluates the similarity of generated paraphrases versus the source sentence of such paraphrases, serve as a negative score, since we want our paraphrase to be as diverse as possible, the higher our BLEU scores are versus source means the less diverse our model is.

TAGPA + Oracle Tagger is an upper bound of our model, where the Oracle Tagger tags the key phrases in our source sentences that also appear in all the ground-truth reference sentences, as described above in Oracle Tagger. TAGPA + Auto Tagger uses the Auto Tagger described in Auto Tagger and TAGPA + NER Tagger uses NER Tagger.

All of no tagged, NER tagged and auto tagged experiments share the same set of hyperparameters (including training epochs) to form into a fair comparison.

### 3.2 MSCOCO

The MSCOCO dataset was originally developed for image captioning. Each image is associated with 5 different captions. These captions are generally close to each other since they all describe the same image. However, the captions always change the semantic they use in describing things, e.g. “an open market full of people and piles of vegetables.” and “large piles of carrots and potatoes at a crowded outdoor market.” are of the same picture. So, the captions are not exactly semantic clusters, though they have some degree of similarity. For this dataset, our main goal is to find out whether our tagger can keep the tagged phrases and the key information, which is partially represented with ROUGE scores.

For our Auto Tagger, the token classification cross entropy loss is 0.0115 during the test time, and 99.7% of the tagged phrases are kept as it is during paraphrasing. Our ROUGE scores for mBART + Auto Tagger is higher than all our baselines and reaches state-of-the-art performance. Moreover, the mBART + NER Tagger also has a pretty good performance in terms of ROUGE scores, which means that it also captures the key information from the source sentence. The negative diversity (vs. S) is relatively low, which means our model generates diversified paraphrases.

Moreover, both mBART + Auto Tagger and mBART + NER Tagger outperforms mBART + No Tagger by a large margin in both key information protection and paraphrase diversification, which means our tagging technique greatly helps in reaching both goals. We can also see that with similar BLEU scores, our Auto Tagger even out-plays the Oracle Tagger in ROUGE scores. It shows that the Auto Tagger tags more information it thinks that should be tagged, to make sure the paraphrases are still semantically equivalent (even though the references are not always sharing the same meaning). Also notice that our model on MSCOCO dataset has relatively poor BLEU scores. We claim that it is the expected behaviour: as the above example shows, captions in the MSCOCO dataset are often not semantically equivalent. Since our model tries to keep the key phrases and increased the generation diversity, the similarity of our generated paraphrases to other “far away” references is not so high.

### 3.3 QQP

The Quora Question Pair dataset is originally developed for duplicated question detection. Duplicated questions are labeled by human annotators and guaranteed to be paraphrases. For this dataset, we don’t have an Auto Tagger or Oracle Tagger, since there are no semantic clusters. We can see that our mBART + NER Tagger reaches a highest ROUGE score, and again our paraphrases are punished if they are too close to the source sentence. Compares to MSCOCO, we have a relatively close BLEU score comparing with LBOW (Fu et al., 2019) even with such punishment. To be more specific, The BLEU-1 score of our mBART + NER Tagger is 50.63 compare to LBOW-Topk’s 55.79, the BLEU-4 score of our mBART + NER Tagger is 25.85 compare to LBOW-Topk’s 26.17. It shows that the larger grams we use, the closer the BLEU score goes. Even though maximized entropy forces our Paraphrase Generator to change the wording, the semantic meaning is kept in a larger scale during paraphrasing.

### 3.4 ComQA

The ComQA dataset was collected from WikiAnswers, which was originally for Question Answer-
ing. We collect questions with the same answer, thus those questions should share similar semantic meanings. We tried to train an Auto Tagger on ComQA, but since there are only 1.4k clusters in the training set, the cross entropy loss of our BERT-BASE-Cased token classifier is 1.65, which means it can only generate garbage tags. However, the NER Tagger still has a good performance and gets relatively close to Oracle Tagger.

3.5 Parabank-Eval
The Parabank-Eval dataset contains human judgments collected when evaluating ParaBank. We only pick grammatical sentences with high human evaluation scores to keep the dataset integrity. Though it only contains 400 clusters, each cluster contains on average 14 sentences, and some sentences are very long. Again the cross entropy loss of our BERT-BASE-Cased token classifier is a poor number 1.35, but our NER Tagger reaches a good performance compare to the upper-bound Oracle Tagger. As a baseline, our mBART + No Tagger generates noisy paraphrases with the same set of hyperparameters, which shows that tagging is important here to have good paraphrases.

3.6 Other Languages
Since both our Auto Tagger (BERT) and paraphrase generator (mBART) has pre-trained weights for multiple languages, given different training dataset we can generate paraphrases in different languages. We trained and tested TAGPA on our internal Chinese dataset, which outperforms all other models we’ve previously tried. Even though we are not able to release our Chinese paraphrase dataset, we could share the code we use to train and generate Chinese Paraphrases.

4 Conclusions and Future Work
Our proposed tagging approach can keep the substrings that our users want to keep, and can also keep out-of-vocabulary substrings during paraphrasing. When the key phrases are well protected, our additional diversity loss encourages the paraphrases to be stated in different ways and still share the same semantic meaning subject to our users’ need. Our model TAGPA reaches state-of-the-art in multiple datasets, and can also deal with multiple different languages. The finetuning process of our model given the pretrained weights is cheap, and can be easily upgraded to other pretrained encoder-decoder models. Moreover, we proposed two new datasets to perform paraphrase generation on, and provided them with relatively strong baselines. Furthermore, we believe that the proposed tagging technique can help us to keep the key phrases not only in paraphrase generation, but also in a variety of other domains. Internally, we tried the tagging technique to aid our intent detection tasks, where slots of key phrases should be kept. Also, during machine translation, there might be some part of the sentence we don’t want to translate, again like company names and abbreviations, and like “What is the meaning of the word 'puppy' in French?” should be translated to “Quelle est la signification du mot ‘puppy’ en français?”, where ‘puppy’ should be kept as it is. We could even force the model to change the parts we tagged, when we want to provide our users with more options. As pointed above, the tagging technique has many possibilities, and is easy to adopt since it only needs the users to finetune on a dataset, without any direct change to encoder-decoder architectures.

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