
UNSUPERVISED PARAPHRASE GENERATION USING PRE-TRAINED LANGUAGE MODELS

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ABSTRACT

Large scale Pre-trained Language Models have proven to be very powerful approach in various Natural language tasks. OpenAI’s GPT-2 [1] is notable for its capability to generate fluent, well formulated, grammatically consistent text and for phrase completions. In this paper we leverage this generation capability of GPT-2 to generate paraphrases without any supervision from labelled data. We examine how the results compare with other supervised and unsupervised approaches and the effect of using paraphrases for data augmentation on downstream tasks such as classification. Our experiments show that paraphrases generated with our model are of good quality, are diverse and improves the downstream task performance when used for data augmentation.

1 Introduction

Paraphrasing is well known problem in NLP which has wide gamut of applications including data augmentation, data curation, intent mapping, semantic understanding. Paraphrasing can be used to generate synthetic data to augment existing scarce datasets for training, and to enhance performance of downstream tasks such as classification. It can also be used to extend existing datasets to more variations, so that it becomes more generalizeable, because of the linguistic variability added by paraphrasing.

The supervised approach towards paraphrasing suffers from lack of domain specific parallel data. The unsupervised approaches towards paraphrasing is heavily reliant on machine translation which still requires bilingual parallel data corpus. Also, performance of machine-translation based back-translation depends on performance constituting machine translation systems. Both supervised approach and machine translation-based paraphrasing suffers when there is a severe domain shift during inference [2].

GPT-2 [1] is exceptional at language generation. It predicts the next token in the sequence given all the tokens before it, i.e it optimizes for $P(X_i | X_{<i})$. The pre-trained version of GPT-2 generates bland text without any goal. By making the model to generate Target T by conditioning on the Source S, the language generation capability of GPT-2 can be utilized for generating meaningful text.

In this paper, we propose a novel unsupervised paraphrasing technique using GPT-2. As this is a unsupervised approach, the model can be trained on the domain specific independent sentences at hand and generate paraphrases without suffering from domain shift. We formulate the unsupervised paraphrasing task as sentence reconstruction task from corrupted input. From a sentence, we omit all the stop words to form a corrupted sentence, lets call it Source S, and the original sentence is used as Target T. We use GPT-2 to generate the Target sentence given Source. i.e $P(T|S)$

2 Related Work

The task of textual paraphrasing has been of high interest in NLP research and has been tackled using variety of approaches. Some earlier approaches towards paraphrasing like [3], [4] and [5] were mostly based on linguistic

structures. In last few years, there has been a lot of work on framing generation of paraphrases as a Seq2seq task [6][7][8]. Paraphrasing has also been explored as a means to improve Question answering in [9] and [10] by making the training more robust by incorporating reformulations.

Deep generative models and discrete latent structures for paraphrasing [11] have also been explored, and [12] proposed a combined the approaches of VAE and Seq2Seq model, by conditioning both encoder and decoder on the source sentence. Else ways, [13] and [14] involve reinforcement learning.[15] suggests using multiple generators to generate more diverse and robust variations, whereas [16] investigates generating paraphrases that conform to a certain target syntactic form.

Unsupervised paraphrasing is picking up a lot of pace in paraphrasing related research work. Approaches such as [17] and [18] employ variational autoencoders for sampling paraphrases from learned latent space. [19] use Vector-Quantized AutoEncoders [20] based model, claiming ability to generate more diverse while semantically closer sentences from input. [21] formulate paraphrasing as a stochastic searching problem and involve unsupervised searching algorithm, simulated annealing to generate paraphrases. Difference between these unsupervised approaches, and our approach is that, we aim to explore the power of large-scale pre-trained language model, which due to the sheer size and breadth of corpus they are trained on, perform extremely well on downstream tasks. As these models are primarily trained in a way to effectively learn to predict next word by understanding context, we explore it's effectiveness in paraphrasing problem setup. The only other work to this end involving use of pre-trained large language model for paraphrasing is in [22]. Our work, although being similar to architecture proposed in [22], the approach taken is completely different, as they fine-tune GPT-2 on labelled paraphrasing dataset, by contrast, we aim to do it completely unsupervised, by making the model learn more on reconstruction task rather than learn from labelled paraphrasing data. The evaluation in [22] is also significantly different, we run exhaustive quantitative evaluation and compare with reported standard metric numbers from other methods, including supervised and unsupervised methods, on same datasets, to better demonstrate its effectiveness, along with evaluation of paraphrasing quality, diversity and correctness.

3 Methodology

3.1 Paraphrase Generation using GPT-2

Paraphrasing is a technique of generating a Target sentence T for a the reference sentence P where the newly generated Target Sentence T is semantically similar to reference sentence P.

GPT-2 [1] is a auto-regressive model which has achieved state-of-the art result in many of the benchmark tasks. It has up-to 1.5 Billion parameters and was trained simply to predict the next word in 40GB of Internet text. We utilize Huggingface Transformers Library [23] to finetune the GPT-2 model on a sentence reconstruction task to generate paraphrases.

3.2 Data Preparation

We take unsupervised approach towards Paraphrase generation and hence no parallel corpora for paraphrasing has been utilized, instead we create a dummy dataset for sentence re-construction task. We corrupt the input sentence by removing all the stop words, further we randomly shuffle and replace the remaining words 20% of the time. We call the corrupted sentence as source sequence S and the original uncorrupted sequence as target T. Goal is to reconstruct the sentence T from the keywords/corrupted sentence S, $P(T|S)$.

A : Set of stop words ; T : Sentence

S : $T - A$;

R : Paraphrase/Reconstructed Sentence;

Our stop word set has total of 252 words. After removing the stop words from sentences to form Source S, we encourage model to generate diverse paraphrases by shuffling the words 20% of the time. 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.

3.3 Model Fine-tuning for Paraphrase Generation

We utilize pre-trained GPT-2 checkpoint from Huggingface Library and we further finetune the model on Sentence Reconstruction task. We concatenate the Source and Target sequence separated by a special symbol to form the input

Table 1: Paraphrasing Examples : Output from our model

Type	Sentence
In	how do you send a private message to someone you're following on quora?
Corrupted	send private message following quora ?
Out	how do i send a private message through quora?
Out	how do i send a private message to a few of my friends on quora?
In	do you believe donald trump can make america great again?
Corrupted	believe donald trump america great ?
Out	do you believe donald trump is doing everything that he can to make america great again?
In	if we see something in our dreams and it happens to come out true after few days, what does that mean?
Corrupted	dreams happens come out true after days, mean?
Out	if dreams happens to come out true in a few days, what does it mean?
In	what do i gift my boyfriend for his birthday?
Corrupted	gift boyfriend birthday?
Out	what gift can i get my boyfriend for his birthday?
Out	what gifts should i give my boyfriend on his birthday?

sequence X . Let $X = x_0, x_1, x_2 \dots x_m, [sep], x_{m+1}, \dots x_n$. We denote the Source sequence as $S = x_0, x_1, \dots x_m$ and Target sequence as $T = x_{m+1}, x_{m+2}, \dots x_n$. Special character $[SEP]$ is added to distinguish between source tokens and target tokens and it serves as a prompt during inference.

3.4 Candidate Paraphrase Generation and Scoring

To generate more than one paraphrase for a given input sentence, we use top-k sampling [24]. We generate 10 paraphrases for every input sentence, lets call the paraphrased sentence as R . We eliminate the ones that are same as original sentence T or is different by only few characters. To make sure that the paraphrases are semantically similar to the input sentence T , we use Sentence Transformers Library [25] to embed the Sentence T and Paraphrase R and compute cosine similarity between them. We form a valid candidate set by retaining only those paraphrases that has threshold above 0.75 and hence making sure the meaning is preserved. From now on, candidate set refers to valid candidate set. Few examples of paraphrases can be seen in the table 1.

4 Experiment

4.1 Dataset

For training and evaluation purpose, we use Quora Question Pair (QQP) dataset¹. QQP dataset has 400k labelled examples out of which 140k examples are actual paraphrases, and 300k unlabeled sentence pairs. Each entry in QQP dataset has (*question1*, *question2*, *is_duplicate*) fields where *question1* and *question2* are sentences and *is_duplicate* indicates whether or not they are paraphrases. Out of 140k actual paraphrase sentence pairs, we take random 30k sentence pairs for our test set as done in [21] and [18] for the sake of easier comparison. We take all the unique *question1* from remaining 370k labelled and 300k unlabeled sample giving total of 523010 unique sentences. We take 463010 sentences for training and 60000 sentences for validating the sentence reconstruction task.

To demonstrate the performance enhancement of using paraphrasing for data augmentation, we use Stanford Sentiment Treebank (SST-2) dataset [26] as done in [19] which has 6920 train examples and 1821 test examples.

4.2 Training

We initialize our model with GPT-2 medium checkpoint which has 345M parameters. The sentences are corrupted by removing the stop words. The model is finetuned on sentence reconstruction task the same way GPT-2 was trained in [1]. validation set's perplexity is used to do early stopping. The model is fine-tuned on one Nvidia V100 DGX machine for 2-5 epochs which takes 28 mins per epoch.

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

Table 2: Paraphrasing Results - Compared with Supervised models

Model	↑METEOR	↓self-BLEU4
D-PAGE	28.54	85.41
PG-BS	28.88	61.89
qian-etal-2019[15]	29.28	40.55
Ours(best candidate)	50.48	N/A
Ours(taking top 3 candidates)	49.45	30.27
Our Model Human Evaluation: (Average Accuracy) =		75.5%

Table 3: Paraphrasing Results - Compared with unsupervised and supervised models

Model		↑ROUGE-1	↑ROUGE-2
Supervised	ResidualLSTM	59.22	32.40
	VAE-SVG-eq	59.98	33.30
	Pointer-generator	61.96	36.07
	Transformer	60.25	33.45
	Transformer+copy	63.34	37.31
	DNPG	63.73	37.75
Unsupervised	VAE	44.55	22.64
	CGMH	48.73	26.12
	UPSA	56.51	30.69
	Ours(best candidate)	60.33	34.59
	Ours(top 3 candidates)	59.43	33.61

4.3 Evaluation Metric

We use different evaluation metrics to measure quality, correctness, diversity and usefulness of the generated paraphrases.

- **Quality** : We use ROUGE-L [27] and METEOR [28] for measuring the quality of generated paraphrase. while BLEU-n calculates n gram overlap, ROUGE-L measures longest matching sequence, and it does not require consecutive matches but in-sequence matches that reflect sentence level word order. METEOR compares the texts using not just word matching, but stemming and synonym matching, which is more desirable to gauge in paraphrasing quality.
- **Diversity** : To measure the diversity of candidate paraphrases, we use self-BLEU from [29]. Given set of paraphrase candidates for an input sentence, every candidate is picked once and others are used as references to compute BLEU score. And the average of all the BLEU scores computed for this candidate set is self-BLEU. A lower self-BLEU score indicates better diversity.
- **Usefulness** : Using paraphrases for data augmentation for a downstream task can answer questions such as how good/diverse are paraphrases and do they provide any signal that was not provided by the original sentence and hence improving the downstream task’s performance. We report % increment in performance of the downstream task.
- **Correctness** : Though we filter the paraphrase candidates using high threshold on cosine similarity, it doesn’t promise 100% correctness. To measure what percent of the generated paraphrases are semantically similar to input sentence, we make human evaluation of the model output.

4.4 Results

4.4.1 Quality and Diversity

We compute METEOR between generated paraphrase R and *question2* from QQP test set for all 30k examples. We conduct multiple experiments with respect to final paraphrase selection from candidate paraphrases. In one of the experiments, we only take the best one out of all the candidates, where as in the second one we compute values for each candidate against *question2* and take the average of them. We have further calculate the self-BLEU among the paraphrase candidates. All these values can be seen in Table 2.

Table 4: Data Augmentation for Classification

Model	Metric	SST-2	
		Acc.	F1
NB-SVM (trigram)	Roy and Grangier(2019)[19]: Baseline	81.93	83.15
	Roy and Grangier(2019)[19] Enhanced	82.12	83.23
	% increment	0.23%	0.1%
NB-SVM (trigram)	Ours Baseline	77.14	77.56
	Ours Enhanced	79.39	79.71
	Ours % increment	2.92%	2.77%
TFIDF+RF	Ours Baseline	0.62	0.62
	Ours Enhanced	0.68	0.67
	Ours % increment	9.68%	8.06%

We compare our results with both supervised and un-supervised methods. The selective supervised methods we compare our method to in table 2, are D-PAGE [30] and Pointer generator with Beam-search (PG-BS) [31] and [15]. Values seen in the table 2 are reported as per [15] for all these methods. The unsupervised methods that we compare our results with are VAE [17], CGMH [18] and UPSA [21]. The values for these papers seen in table 3 are taken from [21].

While we don't have access to exact test set used in [21], we follow the exact guideline from [21], [18] and [15] where they mention taking random 30k sample out of 140k paraphrases from QQP dataset.

4.4.2 Usefulness

To demonstrate the usefulness of paraphrases on a downstream task, we trained NB-SVM and Random Forest Classifier on SST-2 and TREC dataset. We have reported the percentage change in accuracy before and after using paraphrases for data augmentation. Table 4 shows that the improvement in performance is significant when compared to [19]. Our baseline results doesn't match with [19] but absolute numbers shouldn't matter as we keep all the settings same before and after data augmentation for measuring the % increment except for the training data.

4.4.3 Human Evaluation for Correctness: Higher/[Lower] BLEU does "not" mean better/[worse] Paraphrase

BLEU score measures how similar is the candidate text is to the reference texts by looking at the overlapping n-grams. If an example x_i has lower BLEU when compared against the paraphrase given in evaluation set, it doesn't mean that x_i is not the correct paraphrase, but it means that x_i has different set of tokens than the reference sentence from evaluation set. While self-BLEU captures diversity, we use human evaluation to measure correctness.

We form two human evaluation sets containing 100 examples each from QQP dataset having model generated paraphrase sentence R and ground truth paraphrase sentence(*question2*), we asked 2 humans who are fluent in English to label whether or not R and *question2* are paraphrases. Each of the annotators were asked to label it as 0 or 1, where Label=0 means not a paraphrase and Label=1 means they are paraphrases. We compute average accuracy and saw that 75.5% of the time, model generated paraphrase was correct.

4.4.4 Takeaway

Table 2 shows that our model has significantly higher METEOR score than supervised models, highlighting the higher quality of paraphrases. Low self-BLEU among candidates generated by our model indicate that the candidate sentences are more diverse than the candidate paraphrases generated by other supervised methods. table 3 compares quality of paraphrase generated by our model with more model performances on Quora dataset with ROUGE metric, and our model does better in comparison to all unsupervised methods here as well, with being very much closely comparable to the supervised methods. Human evaluation of the paraphrases by our model shows them to be correct 75.5% of the time. We further show that the generated paraphrases are not redundant but useful by showing improvement in performance on two tasks using two models when paraphrases are used for data augmentation on a downstream task. Finally, in table 4 we report that augmenting the training set of SST-2 dataset with generated paraphrases from our model, sees much higher gain as compared to experiments reported in [19].

5 Conclusion and Future Work

In this paper, we have introduced an unsupervised paraphrasing model that generates good quality, diverse and helpful paraphrases. We demonstrate the usefulness of paraphrases by using them to augment the training data of downstream tasks. Since the model doesn't need labelled data, it can be trained as sentence reconstruction task on independent sentences pertaining to any domain without suffering from domain shift problem faced by most of the supervised models.

The sentence corruption technique has a lot of scope for further exploration and improvement, and as future work, we'd like to explore more complex and sophisticated way of corrupting the input sentence, and it's effect on the robustness in terms of reconstruction and generated paraphrases. We have seen that number of epochs for training the model is a trade-off between correctness and diversity, and we'd like to investigate more on that too in subsequent experiments.

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