Edit Distance Based Curriculum Learning for Paraphrase Generation

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Abstract

Curriculum learning has improved the quality of neural machine translation, where only source-side features are considered in the metrics to determine the difficulty of translation. In this study, we apply curriculum learning to paraphrase generation for the first time. Different from machine translation, paraphrase generation allows a certain level of discrepancy in semantics between source and target, which results in diverse transformations from lexical substitution to reordering of clauses. Hence, the difficulty of transformations requires considering *both* source and target contexts. We propose an edit distance between a paraphrased sentence pair as a difficulty metric in curriculum learning. Experiments on formality transfer using GYAFC showed that our curriculum learning with edit distance improves the quality of paraphrase generation. Additionally, the proposed method improves the quality of difficult samples, which was not possible for previous methods.

1 Introduction

Paraphrase generation is a task that transforms expressions of an input sentence while retaining its meaning. While there are various subtasks in paraphrase generation, formality transfer (Rao and Tetreault, 2018; Niu et al., 2018; Kajiwara, 2019; Wang et al., 2019; Kajiwara et al., 2020; Zhang et al., 2020; Wang et al., 2020; Chawla and Yang, 2020) has been extensively studied. As paraphrase generation can be regarded as a machine translation task (Finch et al., 2004; Specia, 2010) within the same language, the same models (Bahdanau et al., 2015; Vaswani et al., 2017) have been applied to a monolingual parallel corpus.

Recent studies (Platanios et al., 2019; Liu et al., 2020) have shown that curriculum learning (Bengio et al., 2009) achieves faster convergence and improved translation quality on neural machine translation. Curriculum learning designs a training process starting from easy training samples and gradually proceeds to difficult training samples. In these previous studies, curriculum learning that uses source-side features, *i.e.*, sentence length and word rarity, as a metric to determine the difficulty has improved the quality of translation.

In this study, we adopt curriculum learning to the paraphrase generation task. Paraphrasing allows a certain level of semantic divergence between source and target sentences. For example, some paraphrases only require just a small number of transformations as shown in Table 1, while some others require drastic transformations as Table 2 shows. For the former, transformation is easy because the target sentence can be generated by copying almost all the input sentence's words. For the latter, transformation is difficult because the input sentence requires replacement and reordering of clauses besides lexical and phrasal paraphrasing. Because of this feature in paraphrase generation, *difficulty* in transformations requires to consider both source and target contexts.

To address this problem, we propose to use an edit distance between a paraphrased sentence pair as a difficulty metric that approximates necessary amounts of transformations. We evaluate our method on a formality transfer task using Grammarly's Yahoo Answers Formality Corpus (GYAFC) (Rao and Tetreault, 2018). The result of paraphrase generation from informal English to formal English confirmed the effectiveness of curriculum learning based on the edit distance. The detailed analysis revealed that the proposed method contributes to performance improvement in difficult samples regardless of the difficulty metrics, while sentence length and word rarity based methods degraded the performance.

Proceedings of the Joint Conference of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing: Student Research Workshop, pages 229–234

Source Sentence	Target Sentence
Yeah I think it would be funny.	I think it would be funny.
I have one brother and three sisters.	I have one brother and three sisters.
Do you mean which is least horrible?	Do you mean which is **the** least horrible?
Their first two albums were **pretty** good.	Their first two albums were **very** good.

Table 1: Examples with simple transformations (bold fonts indicate words that should be rewritten)

Source Sentence	Target Sentence
whats the **name** of **the** song	**What is** the **title** of **this** song**.**
not sure thank you for the two points	**Unsure, appreciate the pair of** points**.**
no where there is no such thing	**That does not exist.**
they **just got a little agressive ;)**	**Suddenly** they **became angrier.**

Table 2: Examples with drastic transformations (bold fonts indicate words that should be rewritten)

2 Preliminary: Curriculum Learning for Neural Machine Translation

Initial curriculum learning methods for neural machine translation considered only the difficulty of the training sample (Kocmi and Bojar, 2017; Zhang et al., 2018). These methods achieved faster convergence; however, they could not improve machine translation quality after convergence. Following these studies, Platanios et al. (2019) and Liu et al. (2020) proposed a method that considers both the difficulty of the training samples and the model competence, which achieved both of faster convergence and improvement in the translation quality.

This study bases on the model proposed by Platanios et al. (2019), who introduced the model competence in machine translation. Their method defines $\bar{d}_i \in [0, 1]$ that is the difficulty score of the i-th training sample, and $c(t) \in [0, 1]$ that is the model competence at the training step t. The method trains the model using only easier training samples than the model competency at each training step. In other words, the number of training samples increases as the training proceeds. Their method improved the translation quality while reduced the training time.

Platanios et al. (2019) defined the difficulty $d(s_i)$ based on sentence length and word rarity. Here, an input sentence s_i consists of a word string $\{w_1, ..., w_{N_i}\}$. Considering translation of a long sentence is more difficult than a shorter one, the sentence length is adopted as one of the metrics:

$$d_{\text{length}}(s_i) \triangleq N_i. \tag{1}$$

Besides, they considered words that infrequently appear in a training corpus are also difficult to translate because these words have fewer learning opportunities. Therefore, Platanios et al. (2019) also adopted word rarity:

$$d_{\text{rarity}}(s_i) \triangleq -\sum_{j=1}^{N_i} \log \hat{p}(w_j), \tag{2}$$

where $\hat{p}(w_j)$ is the unigram probability of word w_j in the training corpus. The final difficulty score $\bar{d}_i$ is computed using the cumulative distribution functions of $d(s_i)$ values.

Platanios et al. (2019) defined the model competence $c(t)$ at the training step t:

$$c(t) \triangleq \min(1, \sqrt{t\frac{1 - c_0^2}{T} + c_0^2}), \tag{3}$$

where c_0 is the initial competence and T is the number of training steps estimated as necessary for convergence. They assumed that the competence is small at the beginning of training and increases monotonically as the training proceeds, which reaches the maximum value 1 when $t = T$.

3 Proposed Method

We approximate the difficulty of transformation in paraphrase generation as edit distance between a paraphrased sentence pair:

$$d_{\text{distance}}(s_i, t_i) \triangleq \text{LevenshteinDistance}(s_i, t_i), \tag{4}$$

where $\text{LevenshteinDistance}(\cdot, \cdot)$ computes the Levenshtein distance between the source sentence and the target sentence t_i. The edit distance between sentences with simple transformations like Table 1 is small, and the edit distance between sentences with drastic rewriting like Table 2 is large. Hence, our curriculum learning starts training with paraphrases with a small number of transformations and gradually learns more dynamic transformations.

Algorithm 1 Edit-distance based curriculum learning

Input: Dataset $D = \{(s_i, t_i)\}_{i=1}^{M}$, consisting of M samples, neural machine translation model θ.

Output: Trained neural machine translation model θ.

List of difficulty values $L \leftarrow \emptyset$
for $i = 1, ..., M$ **do**:
    $L \leftarrow L \cup \{d_{\text{distance}}(s_i, t_i)\}$.
end for
Compute a cumulative distribution function from difficulty values in L
for $i = 1, ..., M$ **do**:
    Compute the difficulty score $\bar{d}_i$
end for
for $t = 1, ..., T$ **do**: ▷ Curriculum learning
    Compute the model competence $c(t)$.
    Sample a data batch B_t uniformly from all $s_i \in D$, such that $\bar{d}_i \leq c(t)$.
    Train neural machine translation model θ using B_t as input.
end for

We apply the edit-distance based difficulty metric to the competence-based curriculum learning (Platanios et al., 2019) framework. The entire algorithm is shown in Algorithm 1.

4 Experiment

We evaluate the performance of edit-distance based curriculum learning on a style transfer task: paraphrase generation from informal English to formal English using GYAFC[1] (Rao and Tetreault, 2018).

4.1 Corpus and Evaluation Metric

GYAFC provides parallel sentences from two domains, Entertainment & Music (E&M) and Family & Relationships (F&R). Following Niu et al. (2018), we expand the training set by combining sentences of each domain and add the label `2formal` or `2informal` at the beginning of an input sentence. Statistics of GYAFC corpus are shown in Table 3.

As preprocessing, we used Moses toolkit[2] (Koehn et al., 2007) for tokenization and normalize-punctuation. We also used byte-pair encoding[3] (Sennrich et al., 2016) to limit the number of token types to $16,000$.

	Train	Train*	Dev	Test
E&M	$52,595$	$209,124$	$2,877$	$1,416$
F&R	$51,967$	$209,124$	$2,788$	$1,332$

Table 3: Statistics of GYAFC (Train* indicates the training set after expansion.)

On GYAFC, Rao and Tetreault (2018) reported that a correlation exists between manual annotation and BLEU (Papineni et al., 2002) scores for the task of informal to formal English transfer. Hence, we used BLEU as an evaluation metric.

4.2 Setup

As a paraphrase generation model, we implemented transformer (Vaswani et al., 2017) model using Joey NMT[4] (Kreutzer et al., 2019). Our transformer model has four-layers with a hidden size of 512 and a four attention heads for both the encoder and decoder. We used word embeddings of 512 dimensions tying the source, target, and the output layer's weight matrix. We also added dropout to the embeddings and hidden layers with a probability of 0.2. We trained using the Adam optimizer (Kingma and Ba, 2015) with the learning rate of 0.0002. The batch size was $4,096$ tokens. We saved the model every 800 updates applying early stopping with patience of five.

To evaluate the effectiveness of the edit distance[5] on curriculum learning (denoted as CL-ED), we compared to curriculum learning with sentence length (denoted as CL-SL) and word rarity (denoted as CL-WR). To compute the model competency with Equation (3), we need to set two hyperparameters of c_0 and T. We set c_0 to 0.01 and T to the number of training steps necessary for the transformer model with ordinary training reaches the 95% of the maximum BLEU score on the development set.

4.3 Results

The experimental results are shown in Table 4, where 'Baseline' is the transformer model trained without curriculum learning. In the E&M domain,

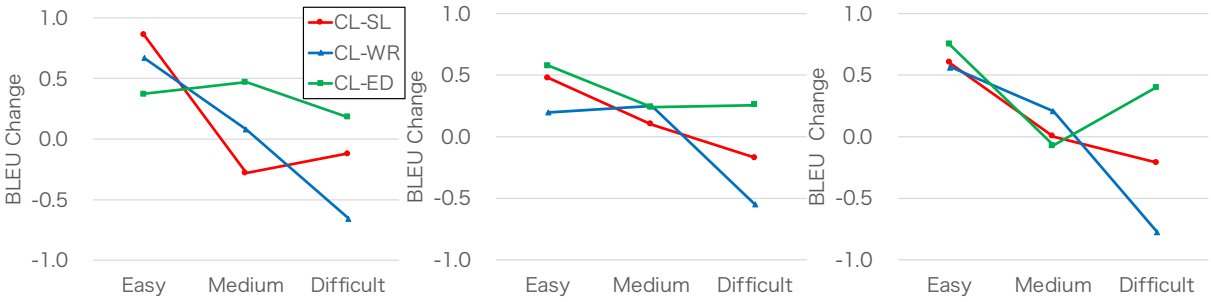
[1] https://github.com/raosudha89/GYAFC-corpus
[2] https://github.com/moses-smt/mosesdecoder
[3] https://github.com/rsennrich/subword-nmt
[4] https://github.com/joeynmt/joeynmt
[5] https://github.com/roy-ht/editdistance

	E&M	F&R
Source	49.19	50.94
Baseline	69.81	75.02
CL-SL	69.83	74.90
CL-WR	70.05	74.62
CL-ED	**70.34**	**75.41**

Table 4: BLEU scores on the GYAFC test set

Source	dead on arrival... there relationship is dead on arrival
Reference	Their relationship is dead on arrival.
Baseline	Dead on arrival, there relationship is dead on arrival.
CL-SL	Dead on arrival is dead on arrival.
CL-WR	Dead on arrival is dead on arrival.
CL-ED	The relationship is dead on arrival.

Table 5: Examples of generated sentences by each model



(a) Sentence length (b) Word rarity (c) Edit distance

Figure 1: Changes in BLEU scores compared to Baseline for each difficulty metric

CL-ED and CL-WR improved BLEU score of Baseline. In the F&R domain, only CL-ED outperformed Baseline. These results indicate that existing curriculum learning based on sentence length and word rarity is not effective in paraphrase generation. In contrast, curriculum learning with the edit distance was effective on both domains.

4.4 Discussion

We investigated which type of sentences that the curriculum learning improved their paraphrase quality. We divided all the test sets into three classes: Easy, Medium, and Difficult, of the same size (916 sentences each) using difficulty metrics of sentence length, word rarity, and edit distance, respectively. We then computed a BLEU score of each class and calculated improvements over Baseline.

Figure 1 shows the BLEU score differences of CL-SL, CL-WR, and CL-ED, compared to Baseline, respectively. Overall, the performance improvement on the Easy class is significant across the methods, which is intuitive as such sentences are easy to learn and used for training throughout curriculum learning. CL-SL and CL-WR degraded the BLEU scores on Medium class, and even deteriorated the baseline transformer on the Difficult class. In contrast, CL-ED improved the BLEU scores of Baseline even on the Difficult class, regardless of the metric of difficulty.

Table 5 shows output examples. The Baseline output almost the same sentence as the input without necessary transformations. While CL-SL and CL-WR output a sentence that does not make sense, CL-ED, which is our method, successfully paraphrases the source sentence.

5 Summary and Future Work

In this study, we applied the edit distance to curriculum learning for paraphrase generation. Experiment results on an informal to formal style transfer task confirmed the effectiveness of our method, particularly for paraphrasing difficult sentences.

Curriculum learning can be applied to any task when reasonable metrics for task difficulty are available. Transfer learning using a pre-trained model (Devlin et al., 2019; Lewis et al., 2020) has significantly improved the performance of various natural language processing tasks. In transfer learning, fine-tuning samples similar to the ones in the pre-training corpus should be easier to learn. We plan to apply our edit-distance based curriculum learning to transfer learning.

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