Utterance Pair Scoring for Noisy Dialogue Data Filtering

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Abstract

Filtering noisy training data is one of the key approaches to improving the quality of neural network-based language generation. The dialogue research community especially suffers from a lack of less-noisy and sufficiently large data. In this work, we propose a scoring function that is specifically designed to identify low-quality utterance–response pairs to filter noisy training data. Our scoring function models the naturalness of the interconnection within dialogue pairs and their content-relatedness, which is based on previous findings in dialogue response generation and linguistics. We then demonstrate the effectiveness of our scoring function by confirming (i) the correlation between automatic scoring by the proposed function and human evaluation, and (ii) the performance of a dialogue response generator trained with filtered data. Furthermore, we experimentally confirm that our scoring function potentially works as a language-independent method.

1 Introduction

Sentence generation technology has been rapidly developing with recent advancements in deep neural network (DNN) techniques and a surge in training data availability. In the dialogue response generation field, some million-scale data have become available in recent decades, for instance, movie scripts or posts of social networking services (SNSs) (Henderson et al., 2019). These training data can be expected to improve the performance of DNN models owing to their quantity; however, these data are generally not of high quality. For example, OpenSubtitles (Lison and Tiedemann, 2016; Lison et al., 2018), the most widely used large-scale dialogue corpus, is constructed by collecting consecutive two lines of movie subtitles, under the simplified assumption that one line of a movie subtitle is one utterance. Inevitably, this corpus will include low-quality utterance–response pairs that are clearly unacceptable as dialogue\textsuperscript{1} (Vinyals and Le, 2015; Li et al., 2016; Baheti et al., 2018).

To confirm how much low-quality data the corpus actually contains, we manually assessed the acceptability of utterance–response pairs in the corpus as a preliminary experiment.\textsuperscript{2} Native speakers were asked to score how acceptable they consider each utterance’s response. Figure 1 shows the result on the English OpenSubtitles corpus. We found that at least 25\% of the pairs were unacceptable. Some samples of the actual unacceptable or acceptable pairs as dialogue, by humans are listed in Table 1.

In the field of machine translation (MT), it has been confirmed that the performance of machine translators can be improved by automatically removing low-quality data from noisy training corpora (Koehn et al., 2018; Junczys-Dowmunt, 2018). Here, the purpose of this work is to improve the performance of the dialogue system by filtering out

\textsuperscript{1}For example, unrelated utterances that cross scenes will be also included in the corpus as dialogue pairs.

\textsuperscript{2}See Appendix A for detailed experimental settings.
such low-quality dialogue pairs in the noisy training data, which is very different in nature from the parallel corpus for MT.

In this work, we propose a data-agnostic automatic scoring function for filtering out noisy utterance–response pairs. Our scoring function is designed to reflect the two aspects that have been considered to contribute to the quality of dialogue pairs: (i) the naturalness of the connection and (ii) the content relatedness. Specifically, the naturalness of the connection of an utterance–response pair is computed by the extent to which it contains well co-occurring phrase pairs. The content relatedness between an utterance and its response is computed by the similarity between their sentence embeddings.

The contributions of this paper are three-fold.

• We propose a novel unsupervised scoring function to detect noisy utterance–response pairs. Our method is designed to be data-independent and theoretically applicable to any dialogue data.

• We experimentally demonstrate that our scoring function performs well to determine low-quality utterance–response pairs.

• Furthermore, we confirm that our method is consistently effective for other corpora with different languages and data sizes.

2 Idea: How to Judge the Quality of dialogue pairs?

Our goal is to automatically detect and filter out low-quality dialogue pairs from noisy dialogue corpora. In other words, how can we compute the quality of each text pair as a dialogue? In this work, we focus on two aspects: (i) the naturalness of the interconnection of the two sentences as a conversational sequence, and (ii) their content relatedness.

2.1 Criteria for Manual Evaluation

To determine which characteristics of two sentences are judged as a dialogue, we first surveyed previous studies in the dialogue response generation community. Specifically, we focused on the criteria for manually evaluating sentences, because manual evaluation implicitly assumes that humans are able to effectively judge the quality of a dialogue on the basis of certain criteria. As a result of the survey, we found that most criteria can be summarized into the following two major aspects.

The first is naturalness of the interconnection as a conversational sequence. For instance, Shang et al. (2015) asked evaluators whether a response is considered an appropriate and natural response to the post and Xing et al. (2017) asked whether the response can be used as a reply. In addition, Pei and Li (2018) asked whether the answer is natural for the question. Many other studies also have evaluated the aspect of the interconnection of utterances and responses using keywords, such as semantically appropriate for (Akama et al., 2017) or coherent with (Shen et al., 2017) the previous utterance or whether there is coherence (Lowe et al., 2017).

The second is content relatedness. For instance, Galley et al. (2015) asked human evaluators to evaluate responses in terms of their relevance to utterances and, similarly, other researchers also consider the relevance between an utterance and its response (Xu et al., 2018; Pei and Li, 2018; Lowe et al., 2017). Li et al. (2016) instructed evaluators to prefer responses that were more specific to utterances when choosing the better responses. In addition, Ritter et al. (2011) insisted that an appropriate response should be on the same topic as the utterances.

In fact, in the field of sociolinguistics, these two aspects are considered the important features of conversation (Sacks, 1989; Sidnell, 2010).

2.2 Observation

Next, we observe how the two aforementioned aspects appear in actual dialogue pairs scored by humans, on the basis of our preliminary experiment results in Section 1. Regarding the naturalness as a conversational sequence, in the pairs with high scores, the response side contains the phrases corresponding to the phrases in the utterance side, in terms of dialogue (shown in blue in Table 1). We could certainly confirm that typical phrase pairs often appeared in highly rated dialogue pairs; for example, the pair (ask for, isn’t it) represents a request and consent. Other typical pairs include (why, because) and (what do you want, I want), such as the concept of cohesive devices in linguistics. We found that it is sufficient when some corresponding phrases are present, and it is not necessary that all phrases included in the utterance and response are in correspondence.
| Utterance | Response | Human |
|----------|----------|-------|
| 1: It’ll be like you never left. | painted a white line on the street way over there. | 1.4 |
| 2: You’re gonna get us assimilated. | Switch to a garlic shampoo. | 1.8 |
| 3: I probably asked for too much money. | Money’s always a problem. Isn’t it? | 4.2 |
| 4: All automobile companies make family cars. | Wouldn’t it more exciting to be the first to produce a sports car? | 4.6 |
| 5: You’ve been borderline stalking Angela as long as we’ve been friends. | We’ve been friends since we were five. | 4.6 |

Table 1: Samples of pairs scored by humans in our preliminary experiments (English). Phrases considered to be interconnected are highlighted in blue. The estimated sentence topic is written under each sentence.

Regarding the content-relatedness, in a high-score pair, both the utterance and the response mentioned the same topic. There were many words that suggested common situations and themes.

In summary, to judge the quality as a dialogue for two sentences, it is necessary to compute the following criteria: (i) whether some phrase pairs correspond to each other, and (ii) whether the topic that the sentence refers to is common. Then both criteria can overlap with each other.

3 Proposed Method

Based on the observations and ideas explained in the previous section, we propose an unsupervised scoring measure for utterance–response pairs that takes into account both the naturalness of the interconnection and the content-relatedness.

3.1 Task

Formally, let $D$ be a noisy corpus that consists of a set of utterance–response pairs, that is,

$$D = \{(x_i, y_i)\}_{i=1}^n,$$

where $x_i$ is the $i$-th utterance, $y_i$ is the $i$-th response, and $n$ is the number of utterance–response pairs in $D$. Then, the task we tackle in this paper is to establish a function $S$ that scores the degree of acceptability of each pair $(x, y) \in D$.

3.2 Naturalness of Dialogue Interconnection

As described in Section 2.2, the key phrase overlap is a good clue for estimating the degree of naturalness. We take the following two-step procedure to compute the degree of naturalness, which we refer to as $S_1$.

First, we obtain a set of key phrases $\mathcal{P}$, which consists of phrase pairs $\{(f_i, e_i)\}_i$. We define that $f_i$ and $e_i$ are always obtained from $x$ and $y$, respectively. Let $\phi(x, y)$ be a function that returns a set of all possible phrase $(n$-gram) pairs obtained from the sentence pair $(x, y)$. We can define a finite set of all possible phrase pairs obtained from the entire dialogue data $D$ as $\mathcal{P}_D = \bigcup_{(x,y) \in D} \phi(x, y)$. Then, $\mathcal{P}$ is essentially a subset of $\mathcal{P}_D$, i.e., $\mathcal{P} \subseteq \mathcal{P}_D$.

To obtain a set of meaningful key phrase pairs $\mathcal{P}$, we take advantage of a technique of the phrase table extraction method developed in SMT research, e.g., Moses (Koehn et al., 2007). We further extend the phrase extraction algorithm that fits to the key phrase extraction since only some phrase pairs can contribute to the naturalness of sentence pair $(x, y)$. We set the null alignment ratio (i.e., probability of no alignment) to 0.5 in the experiments.3

Then, we propose to measure the strength of the interconnection, $S_1(x, y)$, as follows:

$$S_1(x, y) := \sum_{(f,e) \in \phi(x,y) \cap \mathcal{P}} \text{nPMI}(f,e) \times \frac{|f|}{|x|} \times \frac{|e|}{|y|},$$

where $|s|$ denotes the number of words in the phrase or sentence $s$. Intuitive explanation of the behavior of the above equation is as follows:

- If a phrase pair $(f,e)$ has a high co-occurrence, the association strength of $(x, y)$ including $(f,e)$ might also be high. We compute the strength of interconnection of a phrase pair by the normalized pointwise mutual information (nPMI) (Bouma, 2009).

3See Section 2.2 for more details of phrase pair extraction and alignment procedures.
We conducted experiments using two languages.

- If a phrase $f$ or $e$ occupies almost the entire sentence $x$ or $y$, $(f, e)$ is a strong indicator of the association of $(x, y)$.

3.3 Content Relatedness

To compute the similarity between the topics mentioned in the given utterance $x$ and response $y$, we exploit the similarity between sentence vectors $v(x)$ and $v(y)$:

$$S_R(x, y) := \cos(v(x), v(y)).$$

We believe that a sentence vector that encodes all the words contained in it is appropriate for the computation of the topic represented by the whole sentence. In this paper, specifically, a sentence vector $v(s)$ for each sentence $s$ is created by combining pre-trained word embeddings in the methods by Arora et al. (2017), i.e. the SIF weighting and the common component removal.

3.4 Summary

Eventually, combining the above two functions, we propose the following function:

$$S_{I+R}(x, y) := \alpha S_I(x, y) + \beta S_R(x, y),$$

where $\alpha, \beta \in \mathbb{R}_{\geq 0}$ are hyperparameters that weighs two viewpoints. For our experiments in the next section, we fix:

$$\alpha = 1 / \left( \frac{1}{n} \sum_{(x,y) \in D} S_I(x, y) \right)$$

$$\beta = 1 / \left( \frac{1}{n} \sum_{(x,y) \in D} S_R(x, y) \right)$$

to balance the two perspectives.

4 Experiments: Data Scoring

This section describes our experiments that validate the effectiveness of the proposed scoring.

4.1 Dataset

We conducted experiments using two languages with different linguistic properties and data sizes, i.e., English (Section 4, 5) and Japanese (Section 6). In this work, we create a noisy dialogue corpus from OpenSubtitles (Lison et al., 2018), where raw English data contains 441M lines and raw Japanese data contains 3M lines, roughly.

We first applied several data filtering methods, which were typically used in the literature. Then, we obtained 79,445,453 and 1,893,477 utterance–response pairs for English and Japanese training data, respectively. We used them as base corpora for all the experiments explained below unless otherwise specified.

Hereinafter, we report the experimental results for the English dataset at first.

4.2 Scoring

We first compute the naturalness of the interconnection, $S_I$. We obtain a phrase table which provides phrases and their alignments with some statistics using fastAlign (Dyer et al., 2013), which is an IBM Model-based alignment tool, and Moses (Koehn et al., 2007) to learn the correspondence between utterances and responses. We then removed phrase pairs from the table that have a low co-occurrence frequency or are completely composed of the same phrases. Afterwards, the phrase table contained 68,891 phrase pairs. We computed $S_I$ for all utterance–response pairs in the noisy training data by Equation (4) using the phrase in the table.

Next, we compute the content relatedness as $S_R$. We used pre-trained fastText (Bojanowski et al., 2017; Mikolov et al., 2018; Grave et al., 2018) for the word embeddings and created a sentence vector with SIF weighting and the common component removal (Arora et al., 2017). The method of Arora et al. (2017)”s has already been confirmed to be effective in computing the relatedness (i.e. topic similarity) between two sentences (Marelli et al., 2014b,a; Conneau et al., 2017; Subramanian et al., 2018). In addition, their effectiveness has also been confirmed in previous dialogue research (Baheti et al., 2018). We learned the common components using the 30K sentences which randomly extracted from the training data in order to reducing learning costs appropriately, and then removed the first common component for all sentence vectors. We computed $S_R$ for all utterance–response pairs in the noisy training data by Equation (3).

Finally, we provided the score to utterance–response pairs by Equation (4). Samples of the actual scored pairs by our method are shown in Table 2. The distribution of our $S_I$, $S_R$, and $S_{I+R}$ are shown in Appendix C.

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See Appendix B for details on our data preparation procedure.
4.3 Human Evaluation

To verify our scoring ability for detecting noisy pairs, we measured the correlation between human intuition using crowdsourcing.

For comparison, we also applied two previous methods to score all the pairs in the dataset. The first one is the dual conditional cross-entropy filtering method (Junczys-Dowmunt, 2018) for MT task using an encoder-decoder model. The method achieved the highest performance on noisy parallel corpus filtering task at WMT2018. To adapt the method of filtering in the dialogue, we prepared the pre-trained dialogue models which trained on the same data, non-filtered training data in this work, but in inverse directions. The second one is the entropy-based filtering method which removes generic utterances from the training data for promoting a less-boring response generation (Csáky et al., 2019).

We used Amazon Mechanical Turk (MTurk) as our crowdsourcing platform choice for English data evaluation. We randomly extracted 200 pairs from the dataset and requested five workers to evaluate each pair. We filtered out unqualified workers by using attention checks. We asked the human workers, who are native speakers of English, to answer with a five-point Likert scale (5: Strongly agree to 1: Strongly disagree) (Likert, 1932) the following question: Is the sequence of the two utterances acceptable as a dialogue?. We used the average of the scores from the five workers as the human judgment score for the pair.

| Utterance | Response | \( S_I \) | \( S_R \) | \( S_{I+R} \) | Human |
|-----------|----------|----------|----------|----------|-------|
| 1: Hi, gorgeous boy. | With only days to go, the primate team has each part of the move expertly planned. | 0.00 | 0.00 | **0.00** | 2.0 |
| 2: What is the anarchy facing the jail of the sick passion? | Gosh, it’s really cold! | 0.32 | 0.00 | **0.32** | 1.4 |
| 3: Pushers won’t let the junkie go free. | Across 110th Street. | 0.00 | 0.42 | **0.42** | 2.4 |
| 4: It started when I was 17. | They’d make a cash drop, | 0.63 | 0.00 | **0.63** | 2.0 |
| 5: A big nail should be put in your head | Who are they | 0.74 | 0.00 | **0.74** | 1.2 |
| 6: He told me so. | Oh, he did, huh? | 2.21 | 0.00 | **2.21** | 4.8 |
| 7: Wasn’t the outpost constructed to withstand the conditions? | It was, but this is no ordinary storm. | 0.69 | 2.12 | **2.88** | 5.0 |
| 8: There’s a laundry. | Have your clothes dry-cleaned, okay? | 0.81 | 2.89 | **3.70** | 4.4 |
| 9: Then if I win, what are you going to do? | When you win? | 1.04 | 7.01 | **8.05** | 4.2 |
| 10: But what do you want me to do? | We want you to kick her off the team. | 10.20 | 1.53 | **11.72** | 5.0 |

Table 2: Samples of utterance–response pairs scored with our method and human judgements (English). The scores of \( S_I \) and \( S_R \) were normalized by \( \alpha, \beta \).

| Scoring method | Spearman’s \( r \) | p-value |
|----------------|-------------------|---------|
| Csáky et al. (2019) SRC | -0.1173 | 9.8 \( \times \) 10^{-2} |
| Csáky et al. (2019) TRG | 0.0462 | 5.2 \( \times \) 10^{-1} |
| Junczys-Dowmunt (2018) | 0.2973 | 1.9 \( \times \) 10^{-5} |
| Ours \( S_{I+R} \) | **0.3751** | 4.4 \( \times \) 10^{-8} |
| Ours \( S_I \) | 0.2044 | 3.7 \( \times \) 10^{-3} |
| Ours \( S_R \) | 0.3007 | 1.5 \( \times \) 10^{-5} |

Table 3: Correlation with human judgments (English).

4.4 Results and Analysis

Samples of actual pairs scored high or low by our method are shown in Table 2. This shows the contribution of each element of the scoring function, \( S_I \) and \( S_R \), to a final score, \( S_{I+R} \), which is consistent with human judgments.

Table 3 shows the correlation between human judgments and the automatically computed scores by each method. Our method showed the highest correlation with human judgments among the methods compared. As an ablation study, we also examined the results of using the scores of two aspects individually (denoted as \( S_I \) and \( S_R \)) to a final score, \( S_{I+R} \), which is consistent with human judgments. This result supports our assumption that the quality of dialogue could be judged by considering these two aspects comprehensively.

Figure 2 shows the distribution of automatically computed scores corresponding to human judgments and allows a more detailed discussion about the tendency of each scoring method. We found that our method, as shown in (d), tends to estimate the quality of dialogue pairs as lower instead
of higher. This finding suggests that our method has a high accuracy of detecting the unacceptable pairs especially in terms of recall. This tendency is unique to our method compared with others; therefore, we conclude that the proposed scoring function is concluded as an effective and suitable for noisy paired-data filtering on dialogue.

5 Case Study: Noisy Paired-Data Filtering for Response Generation

To verify the effectiveness of our method, we applied it to the OpenSubtitles dataset and evaluated performance on the dialogue response generation task. We found that our method successfully improved the quality of the dataset which subsequently lead to an increase in performance. As a further analysis, we used several automatic measures and a human evaluation to compare the non-filtered data, the data after filtering using previous methods, and after filtering with our method.

5.1 Training Settings

We obtained the filtered data by removing approximately 10% or 50% pairs with lower scores from training data and used them for model training.

For the response generation model, we trained a Transformer (Vaswani et al., 2017) based encoder-decoder model using the fairseq toolkit (Ott et al., 2019) with the byte pair encoding (BPE) technique (Sennrich et al., 2016b). Transformer has demonstrated high performance in many NLP tasks and is recently becoming one of the most familiar models in also response generation (Dinan et al., 2019). We trained the models on the default configuration of the ‘--arch transformer_wmt_en_de_big’ option with setting maximum training steps to 100K. We set the vocabulary size of BPE to 16K.

5.2 Results and Analysis

Automatic evaluation. We first compare the datasets using the following automatic metrics: the average response length in tokens (len), the type-token ratio for \{1, 2\}-grams (distinct-\{1, 2\}), and two reference-based token overlap metrics which are most commonly used, BLEU-1 and ROUGE, following previous work (Sordoni et al., 2015; Li et al., 2016; Xing et al., 2017; Baheti et al., 2018). We especially focus on the scores on the response length and distinctiveness metrics, which point to the diversity of the generated responses. Table 4 shows the results of the automatic evaluation for generated responses. Applying our filtering method resulted in data with a higher score on distinct-\{1, 2\} while maintaining a moderate length. This points towards our filtered data being more diverse than both non-filtered data and data filtered by other methods.\(^5\)

\(^5\)We provide more extensive automatic evaluation results in Appendix D.
| Training data | # of pairs | len | distinct1 | distinct2 | BLEU-1 | ROUGE |
|--------------|-----------|-----|-----------|-----------|--------|-------|
| non-filtered | 79,445,453 | 8.44 | 127/0.030 | 238/0.064 | 8.8 | 7.71 |
| Filtered out 10%: | | | | |
| Csáky et al. (2019) SRC | 70,000,000 | 8.59 | 122/0.028 | 222/0.058 | 9.3 | 8.17 |
| Csáky et al. (2019) TRG | 70,000,000 | 16.73 | 194/0.023 | 507/0.064 | 6.0 | 7.25 |
| Junczys-Dowmunt (2018) | 70,000,000 | 8.91 | 126/0.028 | 222/0.058 | 8.9 | 7.68 |
| Ours \(S_I+R\) | 70,000,000 | 8.43 | 183/0.043 | 403/0.108 | 9.2 | 7.92 |
| Ours \(S_I\) | 70,000,000 | 8.60 | 130/0.030 | 231/0.061 | 9.1 | 7.95 |
| Ours \(S_R\) | 70,000,000 | 8.42 | 155/0.037 | 306/0.083 | 9.2 | 7.89 |
| Filtered out 50%: | | | | |
| Csáky et al. (2019) SRC | 40,000,000 | 7.97 | 165/0.041 | 329/0.094 | 9.1 | 7.76 |
| Csáky et al. (2019) TRG | 40,000,000 | 18.25 | 213/0.023 | 591/0.069 | 5.4 | 6.86 |
| Junczys-Dowmunt (2018) | 40,000,000 | 8.63 | 206/0.048 | 478/0.125 | 9.4 | 8.32 |
| Ours \(S_I+R\) | 40,000,000 | 7.13 | 345/0.097 | 853/0.278 | 9.4 | 7.50 |
| Ours \(S_I\) | 40,000,000 | 7.31 | 201/0.055 | 466/0.148 | 9.2 | 7.56 |
| Ours \(S_R\) | 40,000,000 | 7.91 | 270/0.068 | 662/0.192 | 9.4 | 7.65 |

Table 4: Automatic evaluation results for generated responses (English). BLEU-1 and ROUGE (×100) are computed without symbols. The bold denotes the best result in the same data size in each metric.

**Human evaluation.** We asked native speakers to evaluate the quality of responses generated by models trained on variously filtered datasets for 100 utterance inputs by scoring the plausibility of each generated response given its utterance. Due to the high cost of human evaluation, we conducted the human evaluation for only the best case determined by automatic evaluation, which is the case of 50% filtered out. We compared the quality of the responses generated by training on the non-filtered dataset and dataset filtered by the previous scoring methods (Csáky et al. (2019) SRC, Csáky et al. (2019) TRG, and Junczys-Dowmunt (2018)), proposed scoring method \((S_I+R)\), its components \((S_I)\) and \((S_R)\). Table 5 shows the results of the human evaluations and Table 6 shows samples of the responses to the given utterances generated by the models. Our filtering method achieved the highest score on the human evaluations, which further supports the effectiveness of our method for improving response generation.

**Overall.** The results of the automatic evaluation and human evaluation indicate that our method leads to the generation of responses with diversity and plausibility to humans, albeit short. This case study confirmed the existence of a noise issue in the dialogue response generation field, and that our scoring function, when used for filtering, provides a dataset that leads to improved model performance.

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6. **Multilingual Availability**

In this section, we demonstrates that our scoring function, \(S_{I+R}\), is not an English-specific method but potentially works as a language-independent method. To prove this, we selected Japanese dialogue data as another case study. This is because the linguistic phenomenon between Japanese and English is very different from each other, which is an appropriate property for our evaluation. Moreover, we can obtain a fair amount of noisy Japanese dialogue data as well as English. Following the experimental settings explained in the previous section, we investigate that our scoring function is correlated with human subjectivity (Section 6.1) and is effective for training data filtering to generate dialogue responses (Section 6.2).

### 6.1 Data Scoring

**Scoring.** For \(S_I\), we used Moses and FastAlign to obtain a set of key phrase pair, \(P\), where we obtained \(|P| = 68,891\) for this experiment. For \(S_R\), we calculated the sentence vector from the...
1. After a week undercover,
   A: I don’t know what you’re talking about.
   B: I don’t know what you’re talking about.
   C: I don’t know what you’re talking about, but I don’t know what you’re talking about.
   D: I don’t know what I’d do without you.
   Ours: I was in the middle of a murder investigation.

2. Well, I thought we’d wait for Mr. Oliver.
   A: I don’t think so.
   B: I’ll be right back.
   C: I’m sorry, but I have to get back to work.
   D: No, I don’t think so.
   Ours: Oh, I’m sorry.

3. Are you heading home?
   A: No, I don’t think so.
   B: No, I don’t think so.
   C: No, no, no, no, no, no, no, no, no, no.
   D: No, I don’t think so.
   Ours: No, I’m not.

4. Because we want to keep him safe.
   A: I don’t know what you’re talking about.
   B: I don’t know what you’re talking about.
   C: I don’t care if he’s dead or alive or dead.
   D: I don’t know what you’re talking about.
   Ours: We need to get him out of here.

5. Quite soon, now, you’ll be able to travel.
   A: I don’t think so.
   B: I’ll be back in a minute.
   C: I’ll be back in a few days, then I’ll be back.
   D: I don’t want to see you again.
   Ours: No, I’m not going anywhere.

6. It sucks, doesn’t it?
   A: I don’t know what you’re talking about.
   B: I don’t know what you’re talking about.
   C: I don’t know what you’re talking about, but I don’t know what you’re talking about.
   D: I don’t know what you’re talking about.
   Ours: No, it doesn’t.

7. Which is where exactly?
   A: I don’t know.
   B: I don’t know.
   C: I don’t know what you’re talking about, but I don’t know where you are.
   D: I don’t know.
   Ours: I don’t know.

Table 6: Samples of input utterances (bold) and responses generated by models trained on (A) non-filtered data, filtered by (B) Csáky et al. (2019)’s SRC method, (C) Csáky et al. (2019)’s TRG method, (D) Junczys-Dowmunt (2018)’s method, and ours $S_{I+R}$ (English; filtered out 50%).

Table 7: Correlation with human judgments (Japanese).

| Scoring method | Spearmans $r$ | p-value |
|----------------|--------------|---------|
| Csáky et al. (2019) SRC | −0.0553 | $4.4 \times 10^{-1}$ |
| Csáky et al. (2019) TRG | −0.0366 | $6.1 \times 10^{-1}$ |
| Junczys-Dowmunt (2018) | 0.1074 | $1.3 \times 10^{-1}$ |
| Ours $S_{I+R}$ | **0.2491** | **3.8 \times 10^{-4}** |
| Ours $S_I$ | 0.1395 | $4.9 \times 10^{-2}$ |
| Ours $S_R$ | 0.1504 | $3.3 \times 10^{-2}$ |

Human evaluation. We used Yahoo! crowdsourcing as our crowdsourcing platform choice for Japanese data evaluation. The task setting and protocol for human evaluation are the same as those for English described in Section 4.3, regardless of which the crowdsourcing platform is used.

Results and Analysis. Table 7 shows the correlation between human judgment and score calculated by each method. According to Table 7, $S_{I+R}$ showed the highest correlation with human intuition among all verified methods, including the ablation study of our method, $S_I$ and $S_R$. This result suggests that the combination of two perspectives, that is, “naturalness of the interconnection” and “content-relatedness”, is effective in expressing the human intuition.

Figure 3 shows the distribution of automatically computed scores corresponding to human judgments. We confirmed that our method works similarly to both English and Japanese. Moreover, the results revealed that our method always provided underestimation, which should be suitable for data filtering since we significantly reduce the risk of selecting noisy data as clean data.

6.2 Data Filtering for Response Generation

Training Settings. We prepared the filtered data and trained the models in the same way as described in Section 5.1.

Results and Analysis. Table 9 shows the human evaluation results and Table 8 shows the automatic evaluation results for generated responses. Due to the evaluation cost, we conducted the human...
evaluation for only the best case determined by automatic evaluation, which is the case of 10% filtered out. Training data with 10% filtered out by the proposed method improved the automatic evaluation metrics distinct-1,2 and the human evaluation compared with the non-filtered data. Furthermore, our filtering method outperformed the others when 10% of the data were filtered out. It is indicated that the training data filtered by our method promote the diversity of the generated responses while maintaining the appropriateness of the responses. Therefore, our method is effective in improving the performance of the response generation model in Japanese, as well as in English.

Incidentally, when 50% of the data were filtered out, the results of the evaluation became worse overall. It is probably because the quantity of data remaining after filtering was not sufficiently large to train the models.

7 Related work

Any study that improves the quality or quantity of training data, especially for sequence-to-sequence models, is related to our present study. In this section, we specifically review studies on machine translation, which has been especially investigated and actively researched.

Effectiveness of data approach. The current trend of NMT focuses on studying methodolo-
gies of acquiring (or augmenting) rich, high-quality paralleled translation data, such as using back-translation techniques (Sennrich et al., 2016a), more than improving the model architecture itself. Motivated by these works, in this paper, we discussed how to improve data in the dialogue domain. Since the dialogue response generation task is modeled with the same frameworks as NMT, such as sequence-to-sequence models (Sutskever et al., 2014) or Transformers (Vaswani et al., 2017), by considering the user utterance as the input sentence and the system response as the output sentence (Vinyals and Le, 2015; Shao et al., 2017), we expect that high-quality and rich utterance–response pairs will improve the performance in the dialogue response generation task in the same way as in the machine translation task.

Difficulties in dialogue data. Presently, in dialogue response generation, the methodology for acquiring high-quality and rich utterance–response pairs has hardly been discussed. There are at least two difficulties in data acquisition for the response generation task by simply diverting MT technology. The first is high-quality data availability. For example, in the NMT field, millions of high-quality parallel translation pairs are freely available as training data for WMT (Koehn et al., 2018). Thus, one can train a strong NMT model and generate relatively

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8http://www.statmt.org/wmt19/
Table 8: Automatic evaluation results for generated responses (Japanese). BLEU-1 and ROUGE ($\times 100$) are computed without symbols. The bold denotes the best result in the same data size in each metric.

| Training data | # of pairs | len | distinct1 | distinct2 | BLEU-1 | ROUGE |
|---------------|------------|-----|-----------|-----------|--------|-------|
| non-filtered  | 1,893,477  | 5.91| 268/0.091 | 509/0.207 | 13.4   | 10.98 |
| Filtered out 10%: |
| Cs´aky et al. (2019) SRC | 1,700,000 | 5.75| 295/0.102 | 550/0.231 | 13.2   | 10.79 |
| Cs´aky et al. (2019) TRG | 1,700,000 | 7.06| 336/0.095 | 662/0.219 | 11.6   | 9.91  |
| Junczys-Dowmunt (2018) | 1,700,000 | 5.31| 284/0.107 | 516/0.240 | 12.6   | 9.84  |
| Ours $S_I$+R | 1,700,000 | 5.68| 319/0.112 | 582/0.249 | 13.9   | 11.22 |
| Ours $S_I$ | 1,700,000 | 5.51| 264/0.096 | 492/0.218 | 13.7   | 10.74 |
| Ours $S_R$ | 1,700,000 | 5.73| 296/0.103 | 555/0.234 | 12.5   | 9.85  |
| Filtered out 50%: |
| Cs´aky et al. (2019) SRC | 1,000,000 | 5.93| 355/0.120 | 651/0.264 | 11.4   | 9.84  |
| Cs´aky et al. (2019) TRG | 1,000,000 | 6.94| 405/0.117 | 811/0.273 | 12.2   | 10.77 |
| Junczys-Dowmunt (2018) | 1,000,000 | 5.99| 421/0.140 | 802/0.321 | 11.2   | 9.25  |
| Ours $S_I$+R | 1,000,000 | 5.53| 405/0.146 | 741/0.327 | 12.4   | 9.20  |
| Ours $S_I$ | 1,000,000 | 5.48| 318/0.116 | 599/0.267 | 11.9   | 9.14  |
| Ours $S_R$ | 1,000,000 | 5.76| 404/0.140 | 747/0.314 | 12.7   | 10.34 |
| reference    |           | 7.29| 750/0.206 | 1446/0.460 | -     | -     |

Table 9: Results of human evaluation for generated responses (Japanese). The size of the filtered data used to train models is 1,700,000 (filtered out 10%).

| Training data | Human (0.1) (1.2) (2.3) (3.4) (4.5) |
|---------------|-----------------------------------|
| non-filtered  | 3.35 | 0.00 | 0.55 | 0.38 | 0.23 |
| Cs´aky et al. (2019) | 3.47 | 0.00 | 0.29 | 0.30 | 0.33 |
| Cs´aky et al. (2019) | 3.37 | 0.00 | 0.25 | 0.45 | 0.21 |
| Junczys-Dowmunt (2018) | 3.46 | 0.00 | 0.26 | 0.38 | 0.30 |
| Ours $S_I$+R | 3.61 | 0.00 | 0.24 | 0.44 | 0.29 |
| Ours $S_I$ | 3.44 | 0.00 | 0.26 | 0.43 | 0.25 |
| Ours $S_R$ | 3.56 | 0.00 | 0.27 | 0.42 | 0.28 |

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A Preliminary Experiment Settings

Dataset. For our preliminary experiment, we use OpenSubtitles (Lison et al., 2018) in English, one of the largest corpora of movie scripts that is freely available and has been used in many data-driven dialogue response generations. We automatically obtained dialogue paired-data from the corpus which does not contain speaker annotations on the dialogue turns following the previous method. Specifically, we extracted the consecutive two lines as an utterance–response pair based on the violent assumption that regarding each line as corresponding to a full speaker turn. We excluded the pairs which violated the condition that the lengths of utterance and response is out of 3-25 words, from the dataset and obtained the dialogue dataset. For tokenization, we used mecab\textsuperscript{10} for Japanese and SpaCy\textsuperscript{11} for English and counted the sentence length.

Evaluation settings. We used Amazon Mechanical Turk (MTurk) to evaluate the data manually. In our experiments, randomly sampled 100 utterance–response pairs were evaluated by native speakers of English. We filtered out unmotivated workers by integrating attention checks. We requested five workers to evaluate each pair and asked them to answer using a five-point Likert scale (5 :Strongly agree to 1 :Strongly disagree) (Likert, 1932) the following question: Is the sequence of the two utterances acceptable as a dialogue?

Result. As a result of our preliminary experiment, we discover that, out of all scores given for pairs, 25\% was that the response is unacceptable (scored as 1 or 2) and almost half was that the response is acceptable (scored as 4 or 5). The inter-annotator agreement (Krippendorff’s alpha) was 0.3275.

\textsuperscript{10}https://taku910.github.io/mecab/
\textsuperscript{11}https://spacy.io/
B Dialogue Corpus Construction for Our Experiments

In our experiments, we used the OpenSubtitles as an example of the noisy million-scales dialogue corpus. In addition to the previous method for the extraction of pair data (described in Appendix B), we cleaned the data with some heuristic preprocessings. Some processing was inspired by the technique of noisy-parallel corpus filtering on MT fields. The additional preprocessings that we conducted are as follows:

- Using languid\textsuperscript{12} which is the tool detects the language for given sentences, we removed the pairs judged as not desired language.
- Removed the pairs being parrot back.
- The dialogue pair must be unique (all other similar pairs were removed).

Eventually, we obtained 79,621,506 pairs for English and 1,917,721 pairs for Japanese, as our dialogue dataset. For our experiments, the data was divided into training, validation, and test sets.

|                  | # works | # lines (sentences) | # pairs | # our pairs |
|------------------|---------|---------------------|---------|-------------|
| **English Data** |         |                     |         |             |
| Corpus:          | 446,612 | 441,452,475         | 230,597,913 | 79,621,506  |
| train:           | 442,433 | 441,065,310         | 230,392,431 | 79,445,453  |
| valid:           | 200     | 195,297             | 104,007  | 90,317      |
| test:            | 200     | 191,868             | 101,475  | 85,736      |

| **Japanese Data** | # works | # lines (sentences) | # pairs | # our pairs |
|-------------------|---------|---------------------|---------|-------------|
| Corpus:           | 3,546   | 3,170,155           | 2,266,127 | 1,917,721   |
| train:            | 3,506   | 3,135,812           | 2,240,847 | 1,893,477   |
| valid:            | 20      | 15,489              | 11,939   | 11,486      |
| test:             | 20      | 18,854              | 13,341   | 12,758      |

Table 10: The statistics of the corpora and our dataset. “# pairs” indicates the number of pairs obtaining by the previous method which described in Appendix B.

\textsuperscript{12}\url{https://github.com/saffsd/langid.py}
C The distributions of scores related to our method

![Distribution of scores related to our method on English corpus.](image)

Figure 4: Distribution of scores related to our method on English corpus.

D The evaluation results for generated responses by automatic metrics

| English       | # of pairs | len  | dist1  | dist2  | B1  | B1 bp | B1bp* | B1 bp | B1 bp | MET  | ROU  | CID  | EA   | VE   | GM   |
|---------------|------------|------|--------|--------|-----|-------|-------|-------|-------|------|------|------|------|------|------|
| non-filtered  | 79,445,453 | 8.44 | 127|0.030  | 238|0.064 | 16.5 | 0.93  | 15.4 | 8.8  | 9.6  | 4.83 | 7.71 | 11.03| 0.667| 0.463| 0.686|
| Csáky et al. (2019) SRC | 70,000,000 | 8.59 | 122|0.028  | 222|0.058 | 16.7 | 0.95  | 15.8 | 9.3  | 9.1  | 5.38 | 8.17 | 12.48| 0.680| 0.466| 0.691|
| Csáky et al. (2019) TRG | 70,000,000 | 16.73| 194|0.023  | 507|0.064 | 10.8 | 1.00  | 10.8 | 6.0  | 6.0  | 5.63 | 7.25 | 4.11 | 0.699| 0.440| 0.683|
| Junczys-Dowmunt (2018) | 70,000,000 | 8.91 | 126|0.028  | 225|0.057 | 16.2 | 0.99  | 16.0 | 8.9  | 8.9  | 5.12 | 7.68 | 8.55 | 0.673| 0.466| 0.688|
| Ours SI+R   | 70,000,000 | 8.43 | 183|0.043  | 403|0.108 | 16.4 | 0.93  | 15.3 | 9.2  | 9.5  | 4.95 | 7.92 | 10.26| 0.674| 0.462| 0.687|
| Ours SI     | 70,000,000 | 8.60 | 130|0.030  | 231|0.061 | 16.3 | 0.95  | 15.5 | 9.1  | 9.9  | 5.11 | 7.95 | 10.53| 0.682| 0.467| 0.688|
| Ours SI     | 70,000,000 | 8.42 | 155|0.037  | 306|0.083 | 16.8 | 0.93  | 15.6 | 9.2  | 9.5  | 4.93 | 7.89 | 8.76 | 0.664| 0.464| 0.687|
| Csáky et al. (2019) SRC | 40,000,000 | 7.97 | 165|0.041  | 329|0.094 | 16.7 | 0.88  | 14.6 | 9.1  | 9.0  | 4.99 | 7.76 | 11.36| 0.673| 0.463| 0.688|
| Csáky et al. (2019) TRG | 40,000,000 | 18.25| 213|0.023  | 591|0.069 | 10.1 | 1.00  | 10.1 | 5.4  | 5.4  | 5.15 | 6.86 | 3.33 | 0.701| 0.453| 0.682|
| Junczys-Dowmunt (2018) | 40,000,000 | 8.63 | 206|0.048  | 478|0.125 | 17.0 | 0.95  | 16.2 | 9.4  | 9.8  | 5.16 | 8.32 | 10.25| 0.668| 0.463| 0.688|
| Ours SI+R   | 40,000,000 | 7.13 | 345|0.097  | 853|0.278 | 18.3 | 0.76  | 14.0 | 9.4  | 7.5  | 4.21 | 7.50 | 10.69| 0.655| 0.452| 0.682|
| Ours SI     | 40,000,000 | 7.31 | 201|0.055  | 466|0.148 | 15.9 | 0.79  | 12.5 | 9.2  | 8.0  | 4.38 | 7.56 | 13.54| 0.674| 0.463| 0.685|
| Ours S      | 40,000,000 | 7.91 | 270|0.068  | 662|0.192 | 17.5 | 0.87  | 15.2 | 9.4  | 8.6  | 4.59 | 7.65 | 10.07| 0.667| 0.458| 0.685|
| reference   | 9.04 | 130|0.288  | 324|0.807 |

Table 11: Evaluation results of generated responses in English data. BLEU-1(B1) with symbols(*) and brief penalty(bp), ROUGE(ROU) × 100, METEOR(MET) × 100, CIDEr(CID) × 100. Embedding-based Metrics: Embedding Average Cosine Similarity(EA), Vector Extrema Cosine Similarity(VE), Greedy Matching(GM).
E The Experiments with Other Language: Japanese

E.1 The distributions of scores related to our method

![Graphs showing distributions of scores related to our method](image)

Figure 5: Distribution of scores related to our method on Japanese corpus.

E.2 The Automatic Evaluation Results for Generated Responses

| Japanese          | # of pairs | len* | dist1* | dist2* | B1*  | bp*  | B1bp* | B1   | B1bp | MET  | ROU  | CID  | EA  | VE  | GM  |
|-------------------|------------|------|--------|--------|------|------|-------|------|------|------|------|------|-----|-----|-----|
| non-filtered      | 1,893,477  | 5.91 | 268/0.091 | 509/0.207 | 14.0 | 0.79 | 11.1  | 13.4 | 0.79 | 10.6 | 5.44 | 10.98 | 16.27 | 0.723 | 0.438 | 0.585 |
| Csáky et al. (2019) SRC | 1,700,000  | 5.75 | 295/0.102 | 550/0.231 | 13.9 | 0.77 | 10.6  | 13.2 | 0.76 | 10.0 | 5.09 | 10.79 | 15.03 | 0.711 | 0.430 | 0.575 |
| Csáky et al. (2019) TRG | 1,700,000  | 7.06 | 336/0.095 | 662/0.219 | 12.0 | 0.97 | 11.6  | 11.6 | 0.96 | 11.1 | 5.75 | 9.91  | 11.23 | 0.730 | 0.434 | 0.581 |
| Junczys-Dowmunt (2018) | 1,700,000  | 5.31 | 284/0.107 | 516/0.240 | 13.3 | 0.69 | 9.2   | 12.6 | 0.68 | 8.5  | 4.87  | 9.84  | 14.89 | 0.711 | 0.441 | 0.574 |
| Ours SI+R        | 1,700,000  | 5.68 | 319/0.112 | 582/0.249 | 14.4 | 0.75 | 10.8  | 13.9 | 0.75 | 10.5 | 5.42  | 11.22 | 17.22 | 0.725 | 0.441 | 0.585 |
| Ours SI          | 1,700,000  | 5.51 | 264/0.096 | 492/0.218 | 14.4 | 0.72 | 10.4  | 13.7 | 0.72 | 9.8  | 5.28  | 10.74 | 15.43 | 0.724 | 0.447 | 0.586 |
| Ours SR          | 1,700,000  | 5.73 | 296/0.103 | 555/0.234 | 13.2 | 0.76 | 10.1  | 12.5 | 0.76 | 9.5  | 5.20  | 9.85  | 12.82 | 0.719 | 0.441 | 0.579 |
| Csáky et al. (2019) SRC | 1,000,000  | 5.93 | 355/0.120 | 651/0.264 | 11.8 | 0.80 | 9.4   | 11.4 | 0.80 | 9.1  | 5.02  | 9.84  | 13.71 | 0.719 | 0.438 | 0.574 |
| Csáky et al. (2019) TRG | 1,000,000  | 6.94 | 405/0.117 | 811/0.273 | 12.8 | 0.95 | 12.2  | 12.2 | 0.95 | 11.5 | 5.39  | 10.77 | 13.77 | 0.719 | 0.420 | 0.574 |
| Junczys-Dowmunt (2018) | 1,000,000  | 5.99 | 421/0.140 | 802/0.321 | 11.7 | 0.81 | 9.4   | 11.2 | 0.79 | 8.9  | 5.02  | 9.25  | 16.41 | 0.706 | 0.421 | 0.561 |
| Ours SI+R        | 1,000,000  | 5.53 | 405/0.146 | 741/0.327 | 12.9 | 0.73 | 9.4   | 12.4 | 0.72 | 9.0  | 4.95  | 9.20  | 13.58 | 0.707 | 0.428 | 0.565 |
| Ours SI          | 1,000,000  | 5.48 | 318/0.116 | 599/0.267 | 12.7 | 0.72 | 9.1   | 11.9 | 0.71 | 8.5  | 4.94  | 9.14  | 16.25 | 0.714 | 0.429 | 0.570 |
| Ours SR          | 1,000,000  | 5.76 | 404/0.140 | 747/0.314 | 13.3 | 0.77 | 10.2  | 12.7 | 0.76 | 9.6  | 5.48  | 10.34 | 18.84 | 0.711 | 0.436 | 0.569 |
| reference        | 7.29       | 750/0.206 | 1446/0.460 |        |      |      |      |      |      |      |      |      |      |      |      |

Table 12: Evaluation results of generated responses in Japanese data. BLEU-1(B1) with symbols(*) and brief penalty(bp), ROUGE(ROU)×100, METEOR(MET)×100, CIDEr(CID)×100. Embedding-based Metrics: Embedding Average Cosine Similarity(EA), Vector Extrema Cosine Similarity(VE), Greedy Matching(GM).