Abstract

Large datasets are essential for many NLP tasks. Current publicly available open-domain dialogue datasets offer a trade-off between size and quality (e.g., DailyDialog (Li et al., 2017b) vs. Opensubtitles1 (Tiedemann, 2012)). We aim to close this gap by building a high-quality dataset consisting of 14.8M utterances in English. We extract and process dialogues from publicly available online books. We present a detailed description of our pipeline and heuristics and an error analysis of extracted dialogues. Better response quality can be achieved in zero-shot and finetuning settings by training on our data than on the larger but much noisier Opensubtitles dataset. Researchers can easily build their versions of the dataset by adjusting various trade-off parameters. The code can be extended to further languages with limited effort2.

1 Introduction

Current open-domain dialogue datasets offer trade-offs between quality and size. High-quality datasets are usually too small to contain the plethora of topics and knowledge chatbots should possess. Large datasets often lack good turn-segmentation and suffer from other errors, making trained models ineffective. In Section 2 we analyze the styles and trade-offs of publicly available dialogue corpora. The lack of large, high-quality dataset motivates our work. We build a dataset of 14.8M utterances in English using publicly available books from Project Gutenberg3. Heuristics and their influence on data quality are discussed in Section 3. We offer a detailed error analysis both at the utterance and dialogue level. With our MIT licensed code, researchers can easily build different dataset versions by adjusting parameters affecting the size-quality trade-off and other aspects of the dialogues.

In Section 4 we evaluate our dataset in a generative setting using the Transformer (Vaswani et al., 2017). We compare models trained on Gutenberg and Opensubtitles (Tiedemann, 2012) by evaluating zero-shot and finetuning performance on two smaller datasets. Extension to other languages is ongoing, and we welcome contributions from the research community. Our modular code requires a limited amount of language-specific effort for each new language. We discuss potential improvements and further work in Section 5.

2 Background

Open-domain dialogue datasets vary in size, quality, and source, among other properties (Table 1). Generally, smaller datasets are constructed using controlled crowdsourcing environments, making them high-quality (e.g. PersonaChat (Zhang et al., 2018)). Crowdsourcing platforms like Amazon Mechanical Turk4 are employed to hire instructed workers to carry out free-form conversations. Considering labour expenses crowdsourcing is not scalable, thus dialogues are automatically extracted from various text sources to build larger datasets (e.g. Opensubtitles and Reddit (Henderson et al., 2019)). Opensubtitles contains movie subtitles in multiple languages and Reddit is a discussion forum with millions of daily comments on various topics. Automatic extraction offers less quality control, and the data source heavily influences conversation characteristics. In Reddit data, everyday chit-chat is less common and comments are tied to the post. Two-party dialogues are rare as threads

This is a preprint expected to change in the next months.
1http://www.opensubtitles.org/
2https://github.com/ricsinaruto/gutenberg-dialog (Contains all data downloading links.)
3https://www.gutenberg.org/
4https://www.mturk.com/
| Dataset                          | Size   | Source            | Quality          |
|---------------------------------|--------|-------------------|------------------|
| DailyDialog (Li et al., 2017b)  | 90k    | textbooks         | auto-extracted   |
| Wizard-of-Wikipedia (Dinan et al., 2019) | 100k | crowdsourcing     | human-written    |
| Document-grounded (Zhou et al., 2018) | 100k | crowdsourcing     | human-written    |
| Persona-Chat (Zhang et al., 2018) | 150k  | crowdsourcing     | human-written    |
| Self-dialogue (Fainberg et al., 2018) | 150k | crowdsourcing     | human-written    |
| Cornell Movie Corpus (Danescu-Niculescu-Mizil and Lee, 2011) | 300k | movie scripts     | auto-extracted   |
| Self-feeding chatbot (Hancock et al., 2019) | 500k | human-bot dialogs | human-written (half) |
| Twitter corpus $^5$            | 5M     | twitter posts/replies | auto-extracted   |
| Opensubtitles (Henderson et al., 2019) | 320M | movie subtitles   | auto-extracted   |
| Reddit (Henderson et al., 2019) | 730M   | reddit threads    | auto-extracted   |

Table 1: Comparison of open-domain dialogue datasets. Size is the rough number of utterances, Source describes where the data comes from, and Quality distinguishes between dataset collection techniques.

are almost always multi-speaker. Twitter conversations have similar problems and they are constrained by a specific character limit. Extracting conversations from Twitter and Reddit is straightforward as speaker segmentation is included and the thread chain can be used as dialogue history.

Books have seen little use as dialogue source. In DailyDialog (Li et al., 2017b), 90,000 high-quality utterances are extracted from English textbooks (extraction steps are not detailed). The quality of these dialogues and the lack of a larger book-based dataset motivates our work. Dialogues extracted from books, like movie subtitles, lack context, but their usefulness is evidenced by the Cornell Corpus and DailyDialog. As argued by Danescu-Niculescu-Mizil and Lee (2011) and Fainberg et al. (2018) artificial dialogues in movies and books generally resemble natural conversations. Unfortunately, the Cornell Corpus (Danescu-Niculescu-Mizil and Lee, 2011) is relatively small, and Opensubtitles lacks dialogue and turn segmentation, resulting in a lot of non-dialogue text and other errors. Subtitle lines are equated to turns and dialogue history consists of the previous $n$ lines. Because of these characteristics almost zero processing and heuristics are used (e.g. Henderson et al. (2019) remove short and long utterances). In addition, the types and amount of errors has not been explicitly analyzed for these datasets. For our dataset we build a multi-step extraction pipeline, and analyze the performance of heuristics and error types in the final corpus.

The size of our corpus facilitates effective training of large Transformer-based models (Radford et al., 2019; Yang et al., 2019). Recently, pre-training and finetuning large language models on specific tasks (including dialogue modelling) has gained popularity (Wolf et al., 2018; Devlin et al., 2019). We show Gutenberg’s effectiveness for pre-training in Section 4, comparing it to Opensubtitles pre-training (Csaky and Recski, 2017; Li et al., 2016b; Krause et al., 2017; Xing and Fernández, 2018).

3 Dataset

3.1 Project Gutenberg

Most of Project Gutenberg’s 60,000 online books are in English (47,300 books; 3 billion words), followed by a long tail of various languages. French, Finnish, and German, the most common foreign languages, contain 3000, 2000, 1750 books, and 194M, 74M, 82M words, respectively. Dutch, Spanish, Italian, Portuguese, and Chinese are all above 10M words. We used the Gutenberg python package$^6$ to download books and query their license, language, and author metadata.

3.2 Pipeline

This section describes heuristics and methods used to extract dialogues from books and remove noise.

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$^5$https://github.com/Marsan-Ma-zz/chat_corpus

$^6$https://github.com/ageitgey/Gutenberg
Conversations in text are typically delimited by some special characters, such as quotation marks in English or em-dashes in Hungarian. The main challenges are identifying changes between speakers within a dialogue and separating sets of utterances that do not belong to the same dialogue, i.e. they have separate locations, time, or speakers. We develop simple heuristics that can extract relatively high-quality dialogues at scale. Tunable parameters of our system offer various trade-offs between data quality and size. Using our open-source system researchers can build custom versions of the Gutenberg Dialog Dataset that best suit their applications.

**Pre-filtering** After downloading and separating by language, copyrighted books are removed. We filter books containing different or older language: if the KL divergence between a book’s word distribution and the total (all books) distribution is above a threshold (2) it is removed. The method is less accurate for short books with less than 20 000 words, thus these are not filtered. In the English dataset, 2090 books were removed (4.42%). By analyzing 100 filtered and 100 non-filtered books randomly, the precision and recall are 0.92 and 0.91, respectively.

**Extracting** Extracting high-quality dialogues from books is comprised of three main steps. 1. Conversational and non-conversational (narrative) text is separated. 2. Dialogic text is split into separate dialogues. 3. Dialogues are segmented into separate turns (utterances). In most books conversational text is highlighted; e.g. placed between single/double quotation marks in English, or started by an em-dash in Hungarian. Naturally, these delimiters have other uses as well, but such cases are rare (about 5% of utterances; Section 3.3). Figure 1 shows a sample dialogue highlighting exemplifying our heuristics.

Before dialogue extraction books with less than 150 delimiters per 10 000 words are removed. We assume that such books do not contain dialogues, and we empirically set this ratio by increasing it until the assumption starts failing. Since many books do not contain dialogues, almost half were removed (20 500) in the English pipeline. Sampling 100 filtered and non-filtered books, the precision and recall are 0.92 and 0.81, respectively. In a sample of the final dataset, less than 5% of utterances were non-conversational (Section 3.3).

If the number of characters in the non-conversational text between two dialogue segments highlighted by delimiters is high (above 150) they will not be considered part of the same dialogue. This heuristic, the dialogue gap, will always offer a false positive/negative trade-off since text length variability between dialogues is high. We tuned this trade-off by reasoning that shorter dialogues are less problematic than incoherent dialogues (3.5 times less false negatives as shown in Section 3.3). We observe a linear relationship between the dialogue gap and average dialogue length. In most books, utterances are in separate paragraphs, which provides our turn segmentation. This assumption fails in roughly 4% of utterance pairs as shown in Section 3.3.

"Read what I have written," she gasped. "It may be utterly unintelligible."

For answer, Morton folded the sheet and placed it in an envelope.

"Address this, if you please," he said.

She obeyed his request, limply forcing herself to make the effort; and, as the pen once more fell from her fingers, she glanced up at him with a haggard piteousness in her eyes.

"Will you not read what I have written?" she asked again.

"I see no reason why I should," he answered. "I have no wish to intrude. You are simply doing your duty towards your daughter; such a proceeding is not open to criticism."

Figure 1: A dialogue example. Utterances are in separate paragraphs, sometimes broken up by non-conversational text.

**Post-filtering** During dialogue extraction utterances with more than 100 words are removed to ensure that remaining utterances are truly conversational and to facilitate neural model training (Dai et al., 2019). As all other parameters in the pipeline, this is adjustable to the needs of the person or task. We remove dialogues with more than 20% rare words (not in the top 100 000), removing noise and facilitating neural model training. Finally, dialogues are split randomly into train (90%), validation (5%), and test (5%) data. Dialogues from the same book are in exactly one split.

Languages differ only in the dialogue extraction step. The modular pipeline can be easily extended to new languages by specifying conversational delimiters and a minimal implementation of dialogue and turn segmentation, generally adaptable from...
| Method          | Parameter           | Filtered          | What                                      |
|----------------|---------------------|-------------------|-------------------------------------------|
| Pre-filter     | 2 (KL-div)          | 2090 books (4.42%)| Old books and noise                       |
| Delimiter filter | 150 delimiters / 10 000 words | 20 500 books (43.3%) | Books with no dialogues                     |
| Long utterances | 100 words           | 610 000 utterances (3.95%) | Non-conversational utterances             |
| Post-filter    | 20% rare words      | 20 478 dialogues (0.8%) | Dialogues containing many rare words       |

Table 2: The various filtering steps for the English dataset.

English. In some languages delimitation is less clear, inducing noise (e.g. a French utterance: “– Eh bien! la mère, qu’est-ce que vous la vendez donc? demanda Buteau la paysanne.”). Delimiters and parameters for other languages were not analyzed as profoundly as for English, leaving room for improvements in future work. We aim to show that good dialogue datasets can be constructed with minimal effort, as a first step towards a high-quality multi-language dataset ensemble.

In total, the four filtering steps removed about 12.5% of utterances (detailed in Table 2). 14 773 741 utterances were extracted (in 2 526 877 dialogues), with an average utterance and dialogue length of 22.17 and 5.85, respectively. The standard deviation of dialogue length in English is 6.09, and there are 87 500 dialogues with at least 20 utterances. The average dialogue length can be linearly adjusted with the dialogue gap parameter as mentioned before.

### 3.3 Error Analysis

**Utterance-level** To assess single-turn quality in the English dataset we analyzed 100 random utterance pairs with book context. We found 2 major error types, remaining errors occurring in only 1% of cases. The extracted text is not conversational in 5% of pairs, a consequence of the delimiter threshold and other sources of noise. Utterances of a single speaker were falsely treated as multiple turns in 4% of cases, most often because of our “paragraph breaks signal dialogue turns” assumption (e.g. Figure 5).

This fresh and clear morning, with a south wind blowing and a blue sky overhead, made even the back yard of Quiney’s premises look cheerful, though the surroundings were mostly empty barrels and boxes. And he was singing, too, as he went on with his task; sometimes–

"Play on, minstrl, play on, minstrl, My lady is mine only girl;"

Figure 2: Non-dialogue text detected as an utterance.

Carry pins, is it? said Tom. Ye can carry yer head level, me boy. So at it ye go, an’ ye’ll bate Rory fer me, so ye will.

Well then, cried Barney, I will, if you give me first choice, and I’ll take Tom here.

Hooray! yelled Tom, I’m wid ye. So it was agreed, and in a few minutes the sides were chosen, little Ben Fallows falling to Rory as last choice.

We’ll give ye Ben, said Tom, whose nerve was coming back to him. We don’t want to hog on ye too much.

Never you mind, Ben, said Rory, as the little Englishman strutted to his place among Rory’s men. You’ll earn your supper to-day with the best of them.

Figure 3: First three and last two utterances are not part of the same conversation, but they were merged because of the dialogue gap threshold.

Richard curbed an impatient rejoinder, and said quietly, “William Durgin had an accomplice.”

Mr. Taggett flushed, as if Richard had read his secret thought. Durgin’s flight, if he really had fled, had suggested a fresh possibility to Mr. Taggett. What if Durgin were merely the pliant instrument of the cleverer man who was now using him as a shield? This reflection was precisely in Mr. Taggett’s line. In absconding Durgin had not only secured his own personal safety, but had exonerated his accomplice. It was a desperate step to take, but it was a skillful one.

“He had an accomplice?” repeated Mr. Taggett, after a moment. “Who was it?”

Figure 4: A single conversation cut up because of the long paragraph between the two utterances.

**Dialogue-level** Errors in whole dialogues exhibit a much greater variety. Based on a manual analysis of just 50 dialogues in the English dataset we identified 7 error categories (Figure 6). 32% of dialogues contained 0 errors, 42% contained 1 error type, 22% contained 2 types, remaining dialogues containing 3.

Utterances from the same conversation ended up in different dialogues frequently (34% of cases) because of the dialogue gap threshold (e.g. Figure 4). The inverse, a dialogue containing utterances from

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Figure 2: Non-dialogue text detected as an utterance.
In his progress he passed the door of the dormitory of his victim; he paused a moment, and listened attentively. Then in a voice of deep anguish he said,

She can sleep—she can sleep—no ghostly vision scares slumber from her eyes while

He shuddered, and passed a step or two on, then pausing again, he said,

Oh, if she, the young and innocent—the loved of Heaven—if she would but bid me a good night, I think I could sleep—I asked her once, and she would not—no, she would not give me so much peace; she would not say good night to me!

Figure 5: Two consecutive turns uttered by the same speaker.

Figure 6: Ratio of dialogues affected by the various errors.

multiple conversations, occurred in 10% of cases (e.g. Figure 3). While it is challenging to set this parameter, we think this is a good trade-off. Shorter dialogues equate to less data, which is less problematic, than dialogues containing utterances from multiple conversations, which are incoherent, thus affecting data quality. In Section 5 we discuss better ways to segment conversational text.

Books often contain dialogues between more than two speakers, our second most frequent error. However, such conversations are still coherent and provide useful data for model training. In contrast, the same speaker uttering at least two consecutive turns can break coherence in 14% of cases. Tackling these issues would have to involve speaker identification and increase the complexity of our pipeline (see Section 5). As in the utterance-level analysis, there were some dialogues (8%) in which non-conversational text got mixed in (e.g. Figure 2). The remaining errors, delimiter missing and different speakers in same paragraph occurred in only 1 dialogue out of 50.

4 Experiments

4.1 Evaluation Metrics

Most automatic evaluation methods correlate poorly with human judgment (Liu et al., 2016), and recently proposed metrics that correlate better (Li et al., 2017a; Lowe et al., 2017; Tao et al., 2018) are harder to measure than perplexity or BLEU (Papineni et al., 2002). Human evaluation also has its shortcomings, like high variance, cost, and replication difficulty (Zhang et al., 2018; Tao et al., 2018). The best approach is not apparent, as some researchers use only automatic metrics (Xing and Fernández, 2018; Kandasamy et al., 2017; Xu et al., 2018b), others resort to human evaluations (Krause et al., 2017; Fang et al., 2018), and some use both (Shen et al., 2018; Xu et al., 2018a; Baheti et al., 2018).

We conduct an extensive automatic evaluation using the DIALOG-EVAL repository which implements 17 metrics used frequently in the literature (Csáky et al., 2019). Metrics in the result tables are noted in the following order. Response length (\(|U|\)), i.e. number of words in response. Per-word and per-utterance unigram (\(H^u\)) and bigram (\(H^b\)) entropy measuring the non-genericness of responses (Serban et al., 2017). Unigram and bigram-level KL divergence (\(D^{u}_{kl}, D^{b}_{kl}\)) between model and ground truth response sets (Csáky et al., 2019). Embedding metrics average (AVG), extrema (EXT), and greedy (GRE) measuring similarity between response and target embeddings (Liu et al., 2016). Coherence (COH), computing the cosine similarity between pairs of input and response (Xu et al., 2018b). Distinct-1 and distinct-2 (d1, d2) measuring the ratio of unique unigrams/bigrams in all responses (Li et al., 2016a). The 4 BLEU metrics (b1, b2, b3, b4), measuring overlaps between respective n-grams (n=1,2,3,4) of response and target (Shen et al., 2018; Xu et al., 2018b).

4.2 Trainings

In all experiments, a Transformer is trained on utterance pairs using the TENSOR2TENSOR repository. We used the Adam optimizer (Kingma and Ba, 2014) and hyperparameters can be seen in Table 6. The vocabulary is set to the top 100 000 words for Gutenberg and Opensubtitles trainings. On these
datasets, models were trained for 21 epochs, because of time and hardware constraints, but the validation loss was still decreasing. Training took about 80 hours on a single RTX 2080 Ti, with batch size set to the memory limit. We evaluate Gutenberg and Opensubtitles pre-trained models in zero-shot and finetuning scenarios on DailyDialog and PersonaChat. After pre-training for 21 epochs on the same amount of data, models are finetuned until the validation loss minimum on target data.

We remove overlapping utterance pairs between the official train and test sets from the DailyDialog training set. We observed that inflated results reported on DailyDialog (Csáky et al., 2019) are partly due to this overlap. Gutenberg pre-training performs better than Opensubtitles on DailyDialog across nearly all metrics in both zero-shot (ZS) and finetuned (FT) scenarios (Table 3). On some metrics (e.g. KL-div and embedding metrics) Gutenberg pre-training outperforms even the model trained only on DailyDialog. There are only three metrics in which the baseline DailyDialog training is significantly better than the finetuned model, pointing to the effectiveness of pre-training on Gutenberg.

Table 3: Metrics computed on the test set of DailyDialog. Pre-trained models on Gutenberg (GUT) and Opensubtitles (OPEN) are compared. TRF is a Transformer trained only on DailyDialog, evaluated at the validation loss minimum. RT refers to randomly selected responses from the DailyDialog training set, and GT to the ground truth response set. Significantly better results (95% confidence interval) are highlighted separately for the zero-shot (ZS) and finetuned (FT) scenarios. The TRF row is only highlighted if significantly better than every pre-trained setting.

| | $|U|$ | $H_w^u$ | $H_w^h$ | $H_v^u$ | $H_v^h$ | $D_{gl}^u$ | $D_{gl}^h$ | AVG | EXT | GRE | COH | d1 | d2 | b1 | b2 | b3 | b4 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **ZS** | **GUT** | 7.5 | 6.93 | 11.7 | 53 | 73 | .90 | 1.71 | .638 | .463 | .638 | .863 | .0258 | .111 | .098 | .095 | .091 | .083 |
| | **OPEN** | 4.8 | 6.65 | 10.6 | 32 | 41 | 2.05 | 3.55 | .606 | .466 | .610 | .604 | .0009 | .002 | .075 | .068 | .063 | .056 |
| **FT** | **GUT** | 8.7 | **7.09** | 11.8 | 63 | 90 | **.51** | **1.02** | **.674** | **.479** | **.659** | **.701** | **.0292** | **.147** | **.140** | .132 | .126 | .115 |
| | **OPEN** | **8.8** | 6.68 | 10.2 | 59 | 80 | 2.93 | 4.15 | .645 | .466 | .625 | .643 | .0020 | .005 | .106 | .117 | .118 | .110 |
| **DD** | **TRF** | **9.9** | 7.12 | 11.5 | 72 | **95** | .89 | 1.60 | .663 | .461 | .642 | .666 | .0132 | .063 | .127 | .128 | .127 | .117 |
| | **RT** | 13.6 | 8.38 | 14.1 | 117 | 179 | .04 | .16 | .667 | .390 | .604 | .666 | .0671 | .411 | .086 | .117 | .127 | .122 |
| | **GT** | 13.8 | 8.37 | 13.7 | 118 | 153 | 0 | 0 | 1 | 1 | 1 | 1 | .717 | .0635 | .408 | 1 | 1 | 1 | 1 |

Table 4: Metrics computed on the test set of PersonaChat. Pre-trained models on Gutenberg (GUT) and Opensubtitles (OPEN) are compared. TRF is a Transformer trained only on PersonaChat, evaluated at the validation loss minimum. RT refers to randomly selected responses from the PersonaChat training set, and GT to the ground truth response set. Significantly better results (95% confidence interval) are highlighted separately for the zero-shot (ZS) and finetuned (FT) scenarios. The TRF row is only highlighted if significantly better than every pre-trained setting.

| | $|U|$ | $H_w^u$ | $H_w^h$ | $H_v^u$ | $H_v^h$ | $D_{gl}^u$ | $D_{gl}^h$ | AVG | EXT | GRE | COH | d1 | d2 | b1 | b2 | b3 | b4 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **ZS** | **GUT** | 8.3 | **6.99** | 11.9 | 58.8 | 83 | **.98** | **2.21** | **.620** | **.478** | **.617** | **.680** | **.0159** | **.078** | **.478** | **.617** | **.680** | **.0159** | **.078** |
| | **OPEN** | 6.6 | 6.70 | 11.5 | 45.2 | 67 | 2.02 | 2.84 | .607 | **.497** | **.617** | .611 | .0005 | .001 | .094 | .098 | .095 | .088 |
| **FT** | **GUT** | 11.0 | **6.49** | 10.4 | 72.4 | 105 | 1.26 | 2.13 | **.653** | **.500** | **.651** | **.713** | **.0104** | **.048** | .165 | .164 | .155 |
| | **OPEN** | 10.6 | 6.37 | 10.1 | 68.3 | 98 | 2.58 | 2.66 | .580 | .482 | .624 | .585 | .0011 | .002 | .148 | .151 | .154 | .146 |
| **PC** | **TRF** | 11.1 | 6.89 | 11.0 | **76.6** | **111** | 1.28 | 2.21 | **.658** | **.488** | **.642** | .695 | .0047 | .018 | .164 | .163 | .165 | .156 |
| | **RT** | 11.6 | 8.50 | 14.0 | 98.5 | 201 | .03 | .14 | .672 | .422 | .589 | .671 | .0489 | .349 | .127 | .136 | .131 |
| | **GT** | 11.5 | 8.46 | 13.4 | 97.9 | 126 | 0 | 0 | 1 | 1 | 1 | 1 | .717 | .0416 | .336 | 1 | 1 | 1 | 1 |

Table 5: Metrics computed on the test set of Gutenberg. TRF is the trained Transformer, RT refers to randomly selected responses from the training set, and GT is the ground truth response set.

| | $|U|$ | $H_w^u$ | $H_w^h$ | $H_v^u$ | $H_v^h$ | $D_{gl}^u$ | $D_{gl}^h$ | AVG | EXT | GRE | COH | d1 | d2 | b1 | b2 | b3 | b4 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **TRF** | 9.4 | 7.30 | 12.4 | 69 | 103 | 1.03 | 2.16 | .654 | .447 | .621 | .713 | .00216 | .020 | .0651 | .0650 | .063 | .0582 |
| **RT** | 21.9 | 9.16 | 16.2 | 201 | 343 | .03 | .08 | .694 | .377 | .591 | .695 | .00654 | .136 | .0578 | .0877 | .100 | .0992 |
| **GT** | 21.8 | 9.18 | 16.1 | 201 | 329 | 0 | 0 | 1 | 1 | .730 | .00547 | .132 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
Gutenberg pre-training achieves better results than Opensubtitles in all metrics after finetuning on PersonaChat (Table 4). In the zero-shot scenario, Opensubtitles achieves better BLEU scores, however, both scores are much lower than randomly selected responses, questioning the validity of this comparison. Gutenberg pre-training outperforms the baseline PersonaChat training on some metrics after finetuning, further testament to Gutenberg’s usefulness. Considering the domain mismatch between the older Gutenberg books and the modern chit-chat style datasets this is especially impressive.

Table 5 presents the Gutenberg training’s results on its own test set. In some metrics, it performs worse than random responses from the training set. This is expected for entropy and distinct metrics, but we think that BLEU scores would be higher after further training. Overfitted models have been shown to perform better on these metrics (Csáky and Recski, 2017; Csáky et al., 2019), thus many more epochs could be required for optimal performance. This lack of stopping criteria also makes fair comparison challenging.

## 5 Conclusion

We presented the Gutenberg Dialogue Dataset consisting of 14.8M utterances in English. We described heuristics used in our dialogue extraction pipeline and conducted a detailed error analysis to uncover the causes of errors and assess data quality. In a pre-training comparison between Gutenberg and Opensubtitles we found that Gutenberg performs better on downstream datasets in both zero-shot and finetuning scenarios.

This is a preprint. Extension to other languages and currently ongoing experiments using GPT-2 (Radford et al., 2019) will be added in the next months. For future work, we wish to improve heuristics and dataset quality. A classifier could be trained to decide whether two consecutive utterances are part of the same dialogue (looking at non-conversational context as well). Positive and negative examples could be generated with a very low/high dialogue gap, or by manual annotation. Speaker related errors could be diminished using speaker identification. We wish to extend and improve the quality of the dataset in other languages as well. This involves delimitation analysis, implementation of heuristics, and error analysis. We welcome contributions from the community, as our open-source modular pipeline minimizes the required effort for new languages.

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