CrossDial: An Entertaining Dialogue Dataset of Chinese Crosstalk

Baizhou Huang\textsuperscript{1,2}, Shikang Du\textsuperscript{3} and Xiaojun Wan\textsuperscript{1,2}
\textsuperscript{1}Wangxuan Institute of Computer Technology, Peking University
\textsuperscript{2}The MOE Key Laboratory of Computational Linguistics, Peking University
\textsuperscript{3}Ecole Polytechnique
\{hbz19, wanxiaojun\}@pku.edu.cn
shikang.du@polytechnique.edu

Abstract

Crosstalk is a traditional Chinese theatrical performance art. It is commonly performed by two performers in the form of a dialogue. With the typical features of dialogues, crosstalks are also designed to be hilarious for the purpose of amusing the audience. In this study, we introduce CrossDial, the first open-source dataset containing most classic Chinese crosstalks crawled from the Web. Moreover, we define two new tasks, provide two benchmarks, and investigate the ability of current dialogue generation models in the field of crosstalk generation. The experiment results and case studies demonstrate that crosstalk generation is challenging for straightforward methods and remains an interesting topic for future works.

1 Introduction

Crosstalk, also known by its Chinese name 相声/\textit{xiangsheng}, is a traditional Chinese theatrical performance art. It is commonly performed by two performers. One performer is the leading role (逗哏/\textit{dougen} in Chinese) and the other is the supporting role (捧哏/\textit{penggen} in Chinese).

The form of crosstalks is just like chat or gossip with two persons responding to each other alternately. But there are several conventional performance patterns in crosstalks that are different from daily dialogues. First, the crosstalk is a complete story with one main topic to entertain the audience. The two performers should discuss strictly around the main topic instead of changing topics casually like gossip. Second, the language patterns of the two performers are different in crosstalks. The leading role is the one who dominates the dialogue and drives the plot forward. Mostly, the leading role tells stories and jokes during the performance. On the other hand, the supporting role gives short comments to support or question the leading role’s opinion. In some cases, the supporting role may point out the humorous point in the leading role’s utterance to explain to the audience, or even add fuel to the fire to make it funnier. Third, the crosstalk language is rich in comedy acting skills, such as puns, and is usually delivered in a rapid, bantering style. For the purpose of bringing laughter to the audience, the language of crosstalk features humorous dialogues (Link, 1979; Moser, 1990; McDougall et al., 1984). We provide two excerpts in Figure 1.

In the study, we are concerned with generating Chinese crosstalks automatically. Currently, the traditional art is suffering from the lack of scripts which is hard to write even for humans. It is of high artistic value to design a model that can automatically generate crosstalks. Apart from this, the ability to generate entertaining dialogue re-
responses is also very useful in many commercial products (e.g. chat-bots) by making them more appealing. Though daily dialogue generation has been widely explored and achieved great success in previous studies (Li et al., 2016b, 2017; Wen et al., 2017), it remains unknown whether entertaining dialogues can be automatically generated or not. The special language style and the two-role pattern of crosstalks make it a challenging but interesting task to be explored.

To support research on automatic crosstalk generation, we build CrossDial, the first open-source crosstalk dataset that covers most classic Chinese crosstalks. It is a large-scale dialogue dataset consisting of 1257 crosstalk scripts and 140432 data samples crawled from the Internet.

To investigate the automatic generation of such entertaining dialogues over the proposed dataset, we design two different tasks. The first is a generation task, i.e. Crosstalk Response Generation. That is, given several continuous utterances as context, the model is required to generate the next utterance as response. Considering the one-to-many problems in current generation metrics and the difficulty in automatic humor evaluation, we then additionally introduce a more basic retrieval task, i.e. Crosstalk Response Selection. That is, given several continuous utterances as context, the model is required to find the best response from the supported choices.

We implemented several typical neural models as baselines and evaluate them on the newly defined tasks. The results of automated metrics show the difficulty of our proposed tasks. The human evaluation and case studies further demonstrate the challenges of generating crosstalks.

The contributions of this paper are summarized as follows:

1) We propose the first open-source Chinese crosstalk dataset which contains most classic Chinese crosstalks. The dataset will be released.
2) We design two different tasks and provide two benchmarks respectively for mainstream methods.
3) Both automatic evaluation and human evaluation are performed to evaluate the ability of typical models for automatic crosstalk generation.

2 Related Work

2.1 Dialogue Dataset

With the explosive growth of social networks, a large number of dialogue corpora have been collected from multiple data sources (Danescu-Niculescu-Mizil and Lee, 2011; Tiedemann, 2012; Lowe et al., 2015; Wu et al., 2017). For example, Cornell Movie-Dialogue Corpus (Danescu-Niculescu-Mizil and Lee, 2011) and OpenSubtitles (Tiedemann, 2012) collected dialogues from scripts of movies and TV series. The Ubuntu Dialogue Corpus (Lowe et al., 2015) and Douban (Wu et al., 2017) collected unstructured dialogues from large-scale comments on social media. PersonaChat (Zhang et al., 2018) collected dialogues where each participant plays the part of a specific persona. The area of dialogue generation has witnessed great developments based on these resource-based studies.

2.2 Dialogue Generation Architectures

As we mentioned above, Chinese crosstalk is a special form of dialogue. It is trivial to generate crosstalks similarly to dialogue generation. Previous works in this field relied on rule-based methods, from learning generation rules from a set of authored labels (Oh and Rudnicky, 2000) to building statistical models based on templates and heuristic rules (Levin et al., 2000). After that, information retrieval (IR) based methods (Ji et al., 2014) and the statistical machine translation (SMT) based methods (Ritter et al., 2011) dominated this field gradually.

More recently, the neural network was introduced in this field in the form of end-to-end learning methods (Serban et al., 2015; Li et al., 2016b, 2017). Among numerous neural models, transformer (Vaswani et al., 2017) has proven to be one of the best backbone models and has been applied to various tasks. On the basis of that, several pre-trained language models (Devlin et al., 2019; Radford and Narasimhan, 2018) were proposed and the pretrain-finetune paradigm has achieved great success. Therefore, we chose transformer-based pretrained language models as baseline models.

2.3 Computational Humor

Computational humor is also related to this study. Humor detection and humor generation are two main topics in this field. Humor detection is commonly formalized as a classification task. Plenty
of methods have been applied to solve this problem (Yang et al., 2015; Chen and Soo, 2018; Weller and Seppi, 2019). Humor generation is much more challenging than humor detection. Previous studies mainly focused on one specific type of humor, such as puns (Yu et al., 2018; He et al., 2019; Yu et al., 2020). The crosstalk is a comprehensive performing art consisting of many forms of humor, such as homophone, hyperbole, sarcasm and so on. Although we only conducted experiments over straightforward methods, we believed it would be beneficial to introduce semantic structure of humor into the models. Particularly, Du et al. (2017) preliminarily discussed the automatic generation of crosstalks. But it mainly focused on SMT based methods and the dataset is not released to the community. In this study, we provided benchmarks for most neural network-based methods, especially pretrained language models. Moreover, we carefully collected and cleaned the crosstalks scripts from the Internet, constructed the first open-source crosstalk dataset with both response generation and response selection tasks.

3 Task Definition

We formulate the problem of crosstalk generation as the next utterance prediction task as in daily dialogue generation. In particular, we define two sub-tasks namely Crosstalk Response Generation (CRG) and Crosstalk Response Selection (CRS). Given continuous utterances as context $c = \{u_1, u_2, ..., u_{n-1}\}$, the agent is required to generate the next utterance as response $r = u_n$ in the CRG task or distinguish the positive response $x^{pos} = u_n$ from the other three distractors $\{x_0^{neg}, x_1^{neg}, x_2^{neg}\}$ in the CRS task.

In the CRG task, the generated response is expected to be grammatical and coherent to the context, as in the general dialogue generation task. It should also be compatible with the specific pattern of the role that the agent plays. Moreover, the level of amusement and humor should be taken into consideration.

CRG is a one-to-many problem. In other words, there are many responses appropriate for one given context. Most of the current generation metrics (e.g. BLEU) are based on the comparison between the reference and the generated response. Therefore they cannot reflect the true level of the agent’s generation ability. As a complement, we introduce the CRS task to evaluate the agent’s capability more objectively.

4 CrossDial Dataset

4.1 Overview

The objective of this work is to introduce the task of crosstalk generation and facilitate the study of both the CRG and CRS tasks. For this, we propose a large-scale Chinese crosstalk dataset CrossDial, a web-crawled dataset that covers most classic Chinese crosstalks. The dataset contains two types of utterances, i.e., dougen and penggen, corresponding to the leading role and the supporting role. Each sample for the CRG task consists of two fields: context and positive response, and each sample for the CRS task involves with three additional negative responses (distractors) constructed by us.

The dataset creation consists of three stages:

1) Data Collection: we crawled a set of 1257 crosstalk scripts from the Internet which contains most Chinese crosstalks.

2) Sample Creation: we split all crosstalk scripts into context-response pairs as data samples for the CRG task. To be compatible with the two-role patterns in crosstalk, we divided the dataset into two subsets.

3) Distractor Generation: we designed delicate distractors for the CRS task. To avoid false negatives of distractors, we recruited eight annotators to review all the distractors and filtered invalid ones.

After all, we created a dataset consisting of 140432 data samples in the form of context-response pair. Basic statistics of CrossDial are shown in Table 1. In the following, we will describe all stages in more detail.

4.2 Data Collection

We crawled a total of 1,551 excerpts of classic crosstalks scripts from the Internet. Due to reproductions among websites, one crosstalk script might be collected from different sources. Therefore, we only kept one script and dropped the other copies. In detail, two scripts were considered the same if they have an overlap of more than 15 seven-word-longer utterances. We also noticed several similar crosstalks because of a large number of script adaptations. We kept them as the status quo since they were indeed different scripts. We also

---

1http://www.xiangsheng.org, http://www.tquyi.com, et al.

2The thresholds were set based on manual inspection of the data.
took several heuristic methods for data cleaning. Finally, a total of 1257 crosstalks were collected after this process.

4.3 Sample Creation

We extracted continuous utterances from collected crosstalk scripts as context-response pairs. Specifically, for each utterance in crosstalk scripts noted as positive response, we extracted the sequence of no more than twenty utterances prior to it as context.

With the above extraction process, the response utterance in one sample may appear in the contexts of others. To avoid information leakage from the test set to the training set, we split train, validation, and test sets at the granularity of scripts instead of context-response pairs. To be exact, we randomly sampled 75 scripts for the test set, 175 scripts for the validation set, and 1007 scripts for the training set.

Considering the different speech patterns between the leading role and the supporting role, it is interesting to divide the dataset into two subsets: dougen and penggen. Each subset included only the context-response pairs where the response belonged to the corresponding role.

For the fast-paced performance before an audience, many utterances in crosstalks are designed to be short and meaningless, especially for the supporting role’s lines. This is called generic response (Li et al., 2016a) in NLG, which may impede the diversity of dialogue systems. So we created a set of common and meaningless words. We removed data samples of which over half words of the response were in the set. We also limited the text lengths of responses to \([2, 128)\) to avoid too long responses.

4.4 Distractor Generation

We generated distractors for the CRS task. It is both time-consuming and expensive to crowd-source human-written distractors for such a large dataset. Mostly, distractors are sampled randomly in previous work (Zhang et al., 2018; Lowe et al., 2015; Wu et al., 2017). We argue that randomly sampled distractors are so simple that models may leverage shortcuts to achieve better performance. For example, random distractors commonly have fewer n-gram overlaps with context than golden response. Instead, we aim to generate high-quality distractors that are 1) similar to the golden response in order to avoid the model from using shortcuts, and 2) consistent with the semantics of context to confound the model.

We proposed two similarity-based methods to retrieve distractors from the dataset that satisfy the above two requirements. We used the cosine distance of sentence embeddings to measure the similarity between two utterances. Pretrained language models have achieved state-of-the-art performance in the field of sentence embeddings (Reimers and Gurevych, 2019; Gao et al., 2021; Kim et al., 2021; Giorgi et al., 2021). Given this fact, we borrowed the off-the-shelf tool, sentence transformers\(^3\) to generate sentence embeddings for all utterances.

**Response-Similar Distractor** For every data sample, we searched the corpus for similar responses as distractors with the golden response as the query. If the similarity score of the two responses is high, we consider the extracted one as a high-quality distractor.

**Context-Consistent Distractor** For every data sample, we searched the corpus for similar contexts with the context of the current sample as the query and took the corresponding response as the distractor. We regard the chosen distractor to be consistent with the current context since it is the golden response to the searched context, and the two contexts resemble each other in semantics. An example of the generated distractors is shown in Table 2.

Extremely confusing and disorienting though the generated distractors are, it is worth considering that they can be appropriate responses. As seen in Table 2, the CCD can also be used as response

\(^3\)https://github.com/UKPLab/sentence-transformers and used two pretrained models sbert-base-chinese-nli and distiluse-base-multilingual-cased-v1.
We implemented several typical models, experimented on our proposed CrossDial dataset, and provided performance benchmarks for both CRG and CRS tasks. In the following, we first introduce the automated metrics used for evaluation. Then we report the results of commonly used models. At last, we show the human evaluation and case studies of the generated responses.

5.1 Automated Metrics

We adopt perplexity, BLEU-4, ROUGE-2, ROUGE-L, Distinct-1, and Distinct-2 as automated metrics for the CRG task. BLEU (Papineni et al., 2002) and ROUGE (Lin, 2004) are the most commonly used metrics for natural language generating tasks. They are both based on the n-gram overlaps between a generated response and a reference response. Distinct-1 and Distinct-2 (Li et al., 2016a) are also n-gram-based metrics and are used to measure the diversity of the agent’s generated responses. We adopt accuracy for the CRS task since it is essentially a selection problem.

5.2 Baseline Methods

We leveraged the open-source community huggingface\(^5\) to build two classes of models: generative models and retrieval models. For the CRG task, we only experimented with generative models. Whereas for the CRS task, both classes were evaluated. Retrieval models take the concatenation of the context and one candidate response as input, and score it. Generative models take the context as input, and score each candidate with its generation probability. Both classes select the highest-scored candidate as the response.

In particular, we consider the following generative baselines:

- **Trans**: Transformer (Vaswani et al., 2017) is a SEQ2SEQ model which has been widely used in natural language processing. We adopted a Transformer-base model in the experiment.

- **BART**: BART (Lewis et al., 2020) is a Transformer pretrained as a denoising autoencoder. We adopted BART-base\(^6\) in the experiment.

- **GPT**(Radford and Narasimhan, 2018): GPT is also a pretrained language model. But unlike BART, it only has a Transformer decoder as backbone. We adopted GPT-2\(^7\).

---

\(^{4}\lambda\) was tuning according to manual inspection of samples. Finally, we set \(\lambda = 0.8\).

\(^{5}\)https://huggingface.co/

\(^{6}\)https://huggingface.co/uer/bart-base-chinese-cluecorpusmall

\(^{7}\)https://huggingface.co/uer/gpt2-chinese-cluecorpusmall

| Context | 您还喜欢看小说？
Do you also like fictions? |
|---------|-------------------------------|
| Response | 不是看而是研究，尤其是对我国古典小说像《列国》、《水浒》、《红楼梦》、《西游》我都爱看，特别是对《三国演义》我敢说有独特的见解。
Do research instead of just reading. I’m quite a fan of Chinese classical fictions such as lieguo, shuihu, honglou, xiyou. Especially for sanguo, I have unique insights about it. |
| RSD | 你说的三国，水浒古典名著那你研究研究，这个有点意思。
It’s worth studying if you’re talking about classical fictions such as sanguo and shuihu. These are quite interesting. |
| CCD | 唉，我喜欢看的那都是古典文学呀。
Oh, all I’d like to read is classical literature. |

Table 2: An example of generated distractors. RSD is short for response similar distractor and CCD is short for context consistent distractor.

to the context. To avoid the false negatives of distractors, we set a threshold \(\lambda\) \(^4\) to filter all retrieved outputs that had too high cosine similarity.

Apart from automatic filtering rules, we randomly drew two percent of generated distractors for quality evaluation. We found that only 5.28% of distractors were false negative. It proved that it was feasible to use generated distractors as negative responses.

In particular, for the test set, we recruited eight expert annotators to review all distractors. To simulate the process in which a model generates response conditioning on the context, we provided annotators with six rounds of prior utterances as context. Annotators were asked to select all appropriate responses from a supported choice set that is composed of generated distractors. We also added the golden response to the choice set to ensure the quality of annotation results. After annotation, we dropped invalid distractors, and randomly sampled three negative responses out of the rest for each sample.

5 Experiment

We implemented several typical models, experimented on our proposed CrossDial dataset, and provided performance benchmarks for both CRG and CRS tasks. In the following, we first introduce the automated metrics used for evaluation. Then we report the results of commonly used models. At last, we show the human evaluation and case studies of the generated responses.

---

\(^{4}\lambda\) was tuning according to manual inspection of samples. Finally, we set \(\lambda = 0.8\).
| Method | perplexity | BLEU-4 | ROUGE-2 | ROUGE-L | Distinct-1 | Distinct-2 |
|--------|------------|--------|---------|---------|------------|------------|
| Trans  | 14.63  | 3.64  | 1.59   | 15.17  | 1.37       | 6.14       |
| BART   | 7.76   | 5.55  | 6.41   | 19.61  | 7.37       | 37.95      |
| GPT    | 8.09   | 3.49  | 4.18   | 19.80  | 4.74       | 22.79      |
| T5     | 8.80   | 5.75  | 6.71   | 21.75  | 5.47       | 32.54      |

Table 3: Comparison of generative models on the CRG task

| Method | perplexity | BLEU-4 | ROUGE-2 | ROUGE-L | Distinct-1 | Distinct-2 |
|--------|------------|--------|---------|---------|------------|------------|
| Trans  | 15.30  | 2.21  | 2.06   | 15.43  | 1.37       | 9.39       |
| BART   | 9.41   | 2.98  | 4.19   | 18.00  | 3.69       | 29.16      |
| GPT    | 8.75   | 2.24  | 2.35   | 16.25  | 3.00       | 22.30      |
| T5     | 9.71   | 3.32  | 5.10   | 19.79  | 2.73       | 24.24      |

We performed six hyper-parameters search trials for each model. Hyper-parameters and final checkpoints of baselines were both tuned with perplexity (for generative models) or accuracy (for retrieval models) on the validation set.

5.3 Result and Analysis

| Subset | penggen | dougen |
|--------|---------|--------|
| Trans  | 14.47   | 16.01  |
| BART   | 38.61   | 33.16  |
| GPT    | 42.11   | 38.59  |
| T5     | 36.53   | 35.29  |

Table 4: Accuracy of various models on the CRS task. SIM and CLS are trivial methods for analysis.

We trained and tested the baselines on the penggen and dougen subsets separately. The main results are reported in Table 3 and Table 4.

Pretrained or not? We observe that pretrained language models outperform models without pretraining on both tasks, and the results proved the effectiveness of pretraining. However, the BLEU and ROUGE scores for the CRG task are still very low, showing the great challenge of response gen-

---

8 https://huggingface.co/uer/t5-base-chinese-cluecorpussmall
9 https://huggingface.co/hfl/chinese-bert-wwm-ext
10 https://huggingface.co/hfl/chinese-roberta-wwm-ext
11 https://huggingface.co/nghuyong/ernie-1.0
Penggen vs. Dougen

Dougen is the one who drives the dialogue forward, while penggen often acts as a go-between with short sentences. Intuitively, the language patterns of dougen are more complex to learn. The results on the CRG task show that the same model performs worse in the dougen subset than in the penggen subset, which is consistent with this intuition. However, experiments on the CRS task show the opposite result that retrieval models perform worse on the penggen subset. We attribute the phenomenon to the different difficulties of distractors of the two subsets. Since the supporting role has a relatively fixed form of response, it is more likely to retrieve high-quality distractors for the penggen subset, which makes it harder than the dougen subset.

Generative vs. Retrieval

Both generative models and retrieval models are able to handle the CRS task. The results indicate that retrieval models perform much better than generative models. It is obvious since the training objective of retrieval models is consistent with the CRS task. But still some generative models perform quite poor, especially Trans. The reason may be that the training of generative models is based on token-level loss while the CRS task requires a good measure of sentence-level probability to select the true response.

Shortcut Analysis

Models might use unseen patterns as shortcuts in the CRS task. We proceeded with two trivial methods, SIM and CLS, to empirically negate the phenomenon in the proposed dataset. SIM is an untrained method that utilizes RoBERTa to acquire sentence embeddings for the context and all candidates, and scores the candidates with the cosine similarity. CLS is a trained selector that takes only the candidates without context as input. We adopted the Transformer-base encoder as its backbone model. The poor performance of both methods showed that the phenomenon is not notable in the proposed dataset.

5.4 Human Evaluation

We employed two human annotators to assess 100 samples for the CRG task. Each generated response is assessed from three aspects. Readability measures the fluency of generated responses, including the grammar and phrase correctness; Relevance reflects the semantic relevance between context and response. It measures the logical and sentimental consistency of the dialogue as well; Entertainment reflects the level of humor of the response. For a better evaluation, we recruited two expert annotators from Tianjin, the origin of crosstalks, and familiar with the performing art of crosstalks.

Each annotator was presented with one context and five responses (including 1 golden response and 4 responses generated by different models), and asked to assign an integer score to each generated response with respect to each aspect. The scores are rated on a scale from 0(not at all) to 3(perfect without flaws).

Results are shown in Table 5. Most models can gain comparable performance with golden responses in readability. However, it can clearly be seen that generated responses are quite poor in entertainment. It indicates a huge difference between the typical models’ outputs and the real crosstalks since entertainment is the most important feature of crosstalks. We can also observe that pretrained models outperform models without pretraining in all aspects by a large margin. It again proves the usefulness of pretraining.

5.5 Case Study

We make case studies to better understand the performance of models for the CRG task. Some sampled cases are shown in Table 6. We find that generated responses lack diversity, especially for models trained on penggen. Many generic replies appear frequently, such as “这都不像话!(Nonsense)!” or “可不! (Sure enough!)” . At the same time,
models are unable to start a new topic, no matter whether they are trained on **dougen** or **penggen**. However, we also notice that models have learned some simple language patterns in crosstalk performance such as rhetorical patterns.

Following the initial goal to automatically generate crosstalks, we paired the best model\(^\text{12}\) trained on **penggen** with the best one trained on **dougen**. Given the beginning of a human-written script, the two models were asked to play their corresponding roles, and generate responses alternately. All of the fifty generated crosstalks got stuck in repetitions of similar utterances after three rounds. The reason could be the lack of diversity and the similar patterns of generating responses. As a pipeline, this process also suffers from the accumulation of errors in every step.

### 6 Conclusions and Future Work

In this paper, we proposed the first open-source Chinese crosstalk dataset **CrossDial** for both the CRG task and the CRS task, and investigated the possibility of automatic generation of entertaining dialogues in Chinese crosstalks. Through experiments, we found that special language patterns of Chinese crosstalks were difficult for current neural models. We provided two performance benchmarks and hoped that they would push forward the automatic generation of the traditional Chinese art.

In future work, we will try to exploit other dialogue data in similar domains to further improve the performance. We will also try to generate the whole crosstalk from scratch, which may be very beneficial for the crosstalk industry. Last but not least, we will explore automated metrics for a better evaluation of generated crosstalks from the perspective of humor.

### 7 Limitations

The crosstalk scripts in our dataset are from multiple sources. For audio-based transcriptions, error might be introduced. We have made efforts to clean the data yet still observed misspellings and incorrect punctuation in our final dataset.

Due to the cost constraints, we only recruited one annotator for each sample and annotated 100 data samples. We may perform a more thorough human evaluation for future works.

### 8 Ethical Consideration

We propose a novel dataset in this study. In terms of intellectual properties, all crosstalk scripts in our

---

\(^{12}\) According to the automated metrics, we used the T5 model in the experiment.
We compensated them for approximately ¥60 per hour. We first conducted in-house annotation to determine the speed. Typically, one hundred data samples took about one hour, and we compensated the workers for ¥0.6 per sample.

We manually reviewed the dataset and performed several rule-based methods to remove offensive language. Despite our efforts to minimize bias, there still can be some utterances that may trigger offenses.

References

Peng-Yu Chen and Von-Wun Soo. 2018. Humor recognition using deep learning. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers), pages 113–117, New Orleans, Louisiana. Association for Computational Linguistics.

Yiming Cui, Wanxiang Che, Ting Liu, Bing Qin, and Ziqing Yang. 2021. Pre-training with whole word masking for chinese bert. IEEE/ACM Transactions on Audio, Speech, and Language Processing, 29:3504–3514.

Cristian Danescu-Niculescu-Mizil and Lillian Lee. 2011. Chameleons in imagined conversations: A new approach to understanding coordination of linguistic style in dialog. In Proceedings of the 2nd Workshop on Cognitive Modeling and Computational Linguistics, pages 76–87, Portland, Oregon, USA. Association for Computational Linguistics.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Shikang Du, Xiaojun Wan, and Yajie Ye. 2017. Towards automatic generation of entertaining dialogues in chinese crosstalks.

Tianyu Gao, Xingcheng Yao, and Danqi Chen. 2021. SimCSE: Simple contrastive learning of sentence embeddings. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 6894–6910, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

John Giorgi, Osvald Nitski, Bo Wang, and Gary Bader. 2021. DeCLUTR: Deep contrastive learning for unsupervised textual representations. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 879–895, Online. Association for Computational Linguistics.

He He, Nanyun Peng, and Percy Liang. 2019. Pun generation with surprise. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 1734–1744, Minneapolis, Minnesota. Association for Computational Linguistics.

Zongcheng Ji, Zhengdong Lu, and Hang Li. 2014. An information retrieval approach to short text conversation.

Taeuk Kim, Kang Min Yoo, and Sang-goo Lee. 2021. Self-guided contrastive learning for BERT sentence representations. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 2528–2540, Online. Association for Computational Linguistics.

E. Levin, R. Pieraccini, and W. Eckert. 2000. A stochastic model of human-machine interaction for learning dialog strategies. IEEE Transactions on Speech and Audio Processing, 8(1):11–23.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020. BART: Denoising sequence-to-sequence pretraining for natural language generation, translation, and comprehension. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7871–7880, Online. Association for Computational Linguistics.

Jiwei Li, Michel Galley, Chris Brockett, Jianfeng Gao, and Bill Dolan. 2016a. A diversity-promoting objective function for neural conversation models. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 110–119, San Diego, California. Association for Computational Linguistics.

Jiwei Li, Will Monroe, Alan Ritter, Dan Jurafsky, Michel Galley, and Jianfeng Gao. 2016b. Deep reinforcement learning for dialogue generation. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pages 1192–1202, Austin, Texas. Association for Computational Linguistics.

Jiwei Li, Will Monroe, Tianlin Shi, Sébastien Jean, Alan Ritter, and Dan Jurafsky. 2017. Adversarial learning for neural dialogue generation. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 2157–2169,
Copenhagen, Denmark. Association for Computational Linguistics.

Chin-Yew Lin. 2004. **ROUGE: A package for automatic evaluation of summaries.** In *Text Summarization Branches Out*, pages 74–81, Barcelona, Spain. Association for Computational Linguistics.

E.P. Link. 1979. *The Genie and the Lamp: Revolutionary Xiangsheng*.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach.

Ryan Lowe, Nissan Pow, Julian Serban, and Joelle Pineau. 2015. The Ubuntu dialogue corpus: A large dataset for research in unstructured multi-turn dialogue systems. In *Proceedings of the 16th Annual Meeting of the Special Interest Group on Discourse and Dialogue*, pages 285–294, Prague, Czech Republic. Association for Computational Linguistics.

P.B.S. McDougall, B.S. McDougall, P. Clark, S.S.R. Council, and J.C.C. Studies. 1984. *Popular Chinese Literature and Performing Arts in the People’s Republic of China, 1949-1979*. Comparative Studies of Health Systems and Medical Care. University of California Press.

David Moser. 1990. Reflexivity in the humor of xiangsheng. *CHINOPERL*, 15:45–68.

Alice H. Oh and Alexander I. Rudnicky. 2000. Stochastic language generation for spoken dialogue systems. In *ANLP-NAACL 2000 Workshop: Conversational Systems*.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics*, pages 311–318, Philadelphia, Pennsylvania, USA. Association for Computational Linguistics.

Alec Radford and Karthik Narasimhan. 2018. Improving language understanding by generative pretraining.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of Machine Learning Research*, 21(140):1–67.

Nils Reimers and Iryna Gurevych. 2019. Sentence-BERT: Sentence embeddings using Siamese BERT-networks. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 3982–3992, Hong Kong, China. Association for Computational Linguistics.

Alan Ritter, Colin Cherry, and William B. Dolan. 2011. Data-driven response generation in social media. In *Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing*, pages 583–593, Edinburgh, Scotland, UK. Association for Computational Linguistics.

Iulian V. Serban, Alessandro Sordoni, Yoshua Bengio, Aaron Courville, and Joelle Pineau. 2015. Building end-to-end dialogue systems using generative hierarchical neural network models.

Yu Sun, Shuhuang Wang, Yukun Li, Shikun Feng, Xuyi Chen, Han Zhang, Xin Tian, Danxiang Zhu, Hao Tian, and Hua Wu. 2019. Ernie: Enhanced representation through knowledge integration.

Jörg Tiedemann. 2012. Parallel data, tools and interfaces in OPUS. In *Proceedings of the Eighth International Conference on Language Resources and Evaluation (LREC’12)*, pages 2214–2218, Istanbul, Turkey. European Language Resources Association (ELRA).

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Ł ukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Advances in Neural Information Processing Systems*, volume 30. Curran Associates, Inc.

Orion Weller and Kevin Seppi. 2019. Humor detection: A transformer gets the last laugh. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 3621–3625, Hong Kong, China. Association for Computational Linguistics.

Tsung-Hsien Wen, David Vandyke, Nikola Mrkšić, Milica Gašić, Lina M. Rojas-Barahona, Pei-Hao Su, Stefan Ultes, and Steve Young. 2017. A network-based end-to-end trainable task-oriented dialogue system. In *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 1, Long Papers*, pages 438–449, Valencia, Spain. Association for Computational Linguistics.

Yi Wu, Wei Wu, Chen Xing, Ming Zhou, and Zhoujun Li. 2017. Sequential matching network: A new architecture for multi-turn response selection in retrieval-based chatbots. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 496–505, Vancouver, Canada. Association for Computational Linguistics.

Diyi Yang, Alon Lavie, Chris Dyer, and Eduard Hovy. 2015. Humor recognition and humor anchor extraction. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 2367–2376, Lisbon, Portugal. Association for Computational Linguistics.
Zhiwei Yu, Jiwei Tan, and Xiaojun Wan. 2018. A neural approach to pun generation. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1650–1660, Melbourne, Australia. Association for Computational Linguistics.

Zhiwei Yu, Hongyu Zang, and Xiaojun Wan. 2020. Homophonic pun generation with lexically constrained rewriting. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 2870–2876, Online. Association for Computational Linguistics.

Saizheng Zhang, Emily Dinan, Jack Urbanek, Arthur Szlam, Douwe Kiela, and Jason Weston. 2018. Personalizing dialogue agents: I have a dog, do you have pets too? In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 2204–2213, Melbourne, Australia. Association for Computational Linguistics.