OpenViDial: A Large-Scale, Open-Domain Dialogue Dataset with Visual Contexts

Yuxian Meng, Shuhe Wang, Qinghong Han
Xiaofei Sun, Fei Wu, Rongbin Ouyang, Rui Yan and Jiwei Li

Zhejiang University, Computer Center of Peking University
Gaoling School of Artificial Intelligence, Renmin University of China
Shannon.AI

\{yuxian_meng, qinghong_han, xiaofei_sun, jiwei_li\}@shannonai.com
wangshuhe@stu.pku.edu.cn, ouyang@pku.edu.cn, wufei@zju.edu.cn, ruiyan@ruc.edu.cn

Abstract

When humans converse, what a speaker will say next significantly depends on what he sees. Unfortunately, existing dialogue models generate dialogue utterances only based on preceding textual contexts, and visual contexts are rarely considered. This is due to a lack of a large-scale multi-module dialogue dataset with utterances paired with visual contexts.

In this paper, we release OpenViDial, a large-scale multi-module dialogue dataset. The dialogue turns and visual contexts are extracted from movies and TV series, where each dialogue turn is paired with the corresponding visual context in which it takes place. OpenViDial contains a total number of 1.1 million dialogue turns, and thus 1.1 million visual contexts stored in images.

1 Introduction

Giving machines the ability to converse like humans in the open domain is a key point towards passing the Turing test (Turing, 2009), and developing open-domain dialogue agents is of growing interest (Li et al., 2017; Ghazvininejad et al., 2017; Zhou et al., 2017; Gao et al., 2018; Asghar et al., 2018; Zhou et al., 2020). Existing approaches towards developing open-domain dialogue agents are mostly data-driven, for which a large-scale dataset is first collected. The dataset usually consists of millions of turns of dialogue utterances from real human conversations. A neural model is then trained on the dataset, learning to predict the upcoming dialogue turn conditioned on the previous textual contexts. (Li et al., 2016b,a; Zhang et al., 2018; Huang et al., 2020)

One important aspect that existing open-domain dialogue models miss is the consideration of multi-modal features in dialogue, especially visual features. When humans converse, what a speaker should say next significantly depends on what he sees. The granularity of visual features could be as large as the location that a conversation takes place in (e.g., a cafeteria or a theater), or as small as his dialogue partner’s facial expressions. For example, in Figure 1, we present two short conversations where visual contexts are crucial. In both examples, if the model has no access to visual information, it is hard to correctly generate dialogue utterances “see the picture” and “moving to the attic” in response to the preceding contexts. Unfortunately, existing dialogue models generate dialogue utterances only based on preceding textual contexts and no visual contexts are considered. This is because of the lack of a large-scale multi-modal dialogue dataset with utterances paired with visual context.

In this paper, we collect and release OpenViDial, a large-scale open-domain dialogue dataset with visual contexts. The dialogue turns and visual contexts are extracted from movies and TV series, where each dialogue turn is paired with the corresponding visual context in which it takes place. OpenViDial contains a total number of 1.1 mil-
lion dialogue turns, and thus 1.1 million of visual contexts stored in images.

2 Related Work

2.1 Existing Dialog Datasets

Open Domain Dialog Datasets Over the past few years, various open-domain dialog datasets have been developed. The OpenSubtitle dataset (Tiedemann, 2009, 2012; Lison and Tiedemann, 2016) consists of large-scale movie conversations extracted from the OpenSubtitle website. It includes a total number of 1,782 bitexts with 3.35G sentence fragments. The Twitter Triple Corpus (Sordoni et al., 2015) consists of 4,232 Twitter conversation triples evaluated from 33K candidate triples by human raters, with 2,118 triples as tuning set and 2,114 as test set. The Cornell Movie-Dials Corpus (Danescu-Niculescu-Mizil and Lee, 2011) contains a collection of fictional conversations extracted from raw movie scripts. Other plain-text dialog datasets include the Ubuntu Dialog Corpus (Lowe et al., 2015), PersonaChat (Zhang et al., 2018), EmpatheticDialogues (Rashkin et al., 2018), etc. The datasets described above only consist of texts in the form of dialogues, with no visual information included.

Visual Dialog Datasets The task of Visual Dialog is first introduced by Das et al. (2017a), where a model is required to answer a series of questions grounded in an image, given a dialog history and the image itself as contexts. Further, Das et al. (2017a) released the VisDial v0.9 and v1.0 datasets as benchmarks. The v1.0 dataset contains 120K images from MS COCO and each image is associated with 10 rounds of question-answer conversations, making up 1.2M examples in total. The Guess-What?! dataset (de Vries et al., 2017) focuses on high-level image understanding and is more goal-oriented: models need to locate an unknown object in an informative image scene by answering a sequence of “yes or no” questions. The CLEVER-Dialog (Kottur et al., 2019) and MNIST-Dialog (Seo et al., 2017) datasets are developed for diagnostic purposes. They are crafted to test the reasoning capability of visual dialog models based on the image and prior dialog turns. More recently, the Audio Visual Scene-Aware Dialog (AVSD) dataset (Hori et al., 2018; Alamri et al., 2019) was introduced. It contains more than 11,000 conversations paired with videos of human-centered activities, serving as a benchmark for the scene-aware video dialog task. The datasets described above mainly focus on answering questions regarding an image or video, and thus are more concerned about question answering rather than dialogue generation.

2.2 Dialogue Generation Models

Open Domain Dialog Generation Building open-domain dialog systems that can converse with humans has a long history in natural language processing (Weizenbaum, 1966; COLBY, 1975; Wallace, 2009). Recent advances of neural networks have spurred great interests in developing neural-based data-driven dialog models (Vinyals and Le, 2015; Li et al., 2015; Dodge et al., 2016; Serban et al., 2016; Zhao et al., 2017; Xie et al., 2017; Lee et al., 2019; Ghandeharioun et al., 2019; Li, 2020; Han et al., 2020; Zhang et al., 2019; Roller et al., 2020). Built on top of sequence-to-sequence frameworks (Sutskever et al., 2014; Vaswani et al., 2017), neural-based dialog models are able to generate coherent (Li et al., 2016b, 2017; Tian et al., 2017; Bosselut et al., 2018; Adiwardana et al., 2020), diverse (Xu et al., 2018; Baheti et al., 2018; Tao et al., 2018), personalized (Li et al., 2016a; Luan et al., 2017; Zheng et al., 2019a,b; Madotto et al., 2019), informative (Shao et al., 2017; Lewis et al., 2017; Ghazvininejad et al., 2017; Young et al., 2017; Zhao et al., 2019) and knowledge-fused (Hua et al., 2020; Zhao et al., 2020; He et al., 2020) responses, as well as bias toward different specific attributes or topics (Xing et al., 2016; Zhou et al., 2017; Wang et al., 2017; Niu and Bansal, 2018; See et al., 2019).

Visual Dialog Generation Since natural utterances and visual images are in different modalities, attention mechanisms to model the interplay between conversational utterances and visual contents are widely used (Lu et al., 2017; Kottur et al., 2018; Jiang et al., 2019; Yang et al., 2019; Guo et al., 2019; Niu et al., 2019; Kang et al., 2019; Park et al., 2020; Jiang et al., 2020b). Seo et al. (2017) employed memories to store (attention, key) pairs that can be used to retrieve the most relevant attention maps for the current question in text. Schwartz et al. (2019) designed the factor graph attention model to connect an arbitrary number of modalities with attention flows. Gan et al. (2019) proposed ReDAN, a recurrent dual attention network enhanced by a multi-step reasoning mechanism. Techniques

2http://mscoco.org/
such as reinforcement learning (Das et al., 2017b; Wu et al., 2018), variational auto-encoders (Masiceti et al., 2018) and graph networks (Zheng et al., 2019c; Jiang et al., 2020a) have also been applied to deal with the visual dialog task. Empowered by large-scale pretraining techniques, pretraining based models have made promising progress (Lu et al., 2019; Tan and Bansal, 2019; Su et al., 2019; Alberti et al., 2019; Li et al., 2019a,b; Chen et al., 2019; Wang et al., 2020; Li et al., 2020), significantly boosting the performances in terms of different metrics.

### 3 Constructing OpenViDial

In this section, we describe the details for OpenViDial construction. The main idea of dataset generation is to pair conversation scripts with images in movies or TV series, and use these images as visual contexts for dialogue learning.

We collect a raw dataset containing English movies and TV series with a total length of roughly 8,000 hours. Each second of videos can be further divided into 20∼40 frames, where each frame is an image.

#### 3.1 Subtitle Extraction based on OCR

Because of the fact that only a small proportion of movies readily come with subtitle files, and that for most movies, subtitles are embedded in images, we need to build models to extract conversation scripts from images. To build a conversation dataset with millions of turns of image-text pairs, it is prohibitively expensive and time-intensive to employ human labors to separate each image frame with embedded scripts. We thus rely on the technique of optical character recognition (OCR) for automatic extraction of conversation subtitles from movie images. We tailor the OCR model to the task of subtitle extraction, and achieves an almost perfect accuracy.

Existing open-sourced OCR models are not fit for our purpose since they are not tailored to subtitle extraction in the context of movies and TV series. We thus need to train our own OCR model.

#### Training Data Generation

We first synthesize the OCR training dataset, where we embed texts into images to form training examples. To achieve this goal, we first need to collect text-free images from raw videos, which will be later added. This is done by running an existing open-sourced OCR model on video images, and pick images with no text character identified by the model. Since at this stage, our goal of identifying whether an image contains text character is a relatively easy task, a super accurate OCR model is not necessary and the open-sourced OCR model suffices to fulfill our need. With text-free images in hand, we pair them with texts. Texts are randomly selected from the CommonCrawl English corpus, then added to the images. Texts in images are generated using different fonts and sizes. We generated a dataset containing about 10M images paired with texts.

#### Model Training

Standard OCR training involves two stages, the detection of the bounding box of texts, and the recognition of characters. For detection, we use the PSE model as the backbone (Wang et al., 2019), which is built upon the FPN model (He et al., 2016) with ResNet pre-trained on ImageNet dataset. For recognition, we use the Convolutional Recurrent Neural Network (CRNN) model (Shi et al., 2016) as the backbone. We omit the details since the discussion on training OCR models is beyond the scope of this paper. We use a held-out dataset for evaluation, and the trained OCR model gets an accuracy higher than 99.98% at character level and 98.4% at the image/sentence level.

#### Post Processing

The trained OCR model is applied to videos and TV series for script extraction. Since each second of the video consists of 20∼40 frames, most of which are nearly identical, we pick 3 frames for each second and discard the rest. We also construct an English vocabulary with top 200,000 words by frequency using a part of the CommonCrawl dataset, and remove images with unknown word from the vocabulary. This further

---

3. An alternative is to extract scripts from audios. We find extracting scripts using OCR from images obtains a much higher accuracy than speech recognition from audios. We thus adopt the former strategy.

4. https://github.com/JaidedAI/EasyOCR

5. This task can be made even easier by sacrificing recall (images without characters) for precision, by making sure that all selected images do not contain characters.

6. https://www.myfonts.com/WhatTheFont/
helps us remove the influence from incorrect characters by the OCR model. In addition, the following scenarios need to be handled: (1) there are cases where a consecutive number of images are paired with the same texts. We only preserve the middle image and abandon the rest; (2) There are cases where a full dialogue turn is truncated into multiple consecutive images, with each image containing only part of the text in that dialogue turn. We train a simple discriminative model to identify whether a word in a context is the end of a sentence. Using this model, we merge texts from multiple images into a single turn and pair the text with the middle image.

### 3.2 Statistics for OpenViDial

We collect a final dataset of 1.1M turns, where each turn consists of a sequence of words and an image. The size of the image is either 1280×720 or 1920×1080 based on different video resources. We employ the BPE tokenizer (Sennrich et al., 2016) for text processing. The detailed statistics for OpenViDial are shown in Table 1. We split the dataset into 1M/50K/50K for training, dev and test.

Table 2 shows the comparison between different datasets. Comparing against OpenSubtitles (Lison and Tiedemann, 2016), OpenViDial has fewer sentences but contains multi-modal features. Additionally, the OpenSubtitles dataset is an extremely noisy dataset, where consecutive lines may not appear in the same conversation or scene, and may not even be spoken by the same character. Comparing with other datasets with visual features, i.e., VisDial, Guess-What?! and AVSD, OpenViDial focuses more on dialogue learning rather than question answering.

### 4 Conclusion

In this paper, we release OpenViDial, a large-scale open-domain dialogue dataset with visual contexts. In OpenViDial, each dialogue turn is paired with the corresponding visual context in which it takes place. Our work marks an important step towards large-scale multi-modal dialogue learning.

### References

Daniel Adiwardana, Minh-Thang Luong, David R So, Jamie Hall, Noah Fiedel, Romal Thoppilan, Zi Yang, Apoorv Kulshreshtha, Gaurav Nemade, Yifeng Lu, et al. 2020. Towards a human-like open-domain chatbot. arXiv preprint arXiv:2001.09977.

Huda Alamri, Vincent Cartillier, Abhishek Das, Jue Wang, Anoop Cherian, Irfan Essa, Dhruv Batra, Tim K Marks, Chiori Hori, Peter Anderson, et al. 2019. Audio visual scene-aware dialog. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 7558–7567.

Chris Alberti, Jeffrey Ling, Michael Collins, and David Reitter. 2019. Fusion of detected objects in text for visual question answering. arXiv preprint arXiv:1908.05054.

Nabiba Asghar, Pascal Poupart, Jesse Hoey, Xin Jiang, and Lili Mou. 2018. Affective neural response generation. In European Conference on Information Retrieval, pages 154–166. Springer.

Ashutosh Baheti, Alan Ritter, Jiwei Li, and Bill Dolan. 2018. Generating more interesting responses in neural conversation models with distributional constraints. arXiv preprint arXiv:1809.01215.

Antoine Bosselut, Asli Celikyilmaz, Xiaodong He, Jianfeng Gao, Po-Sen Huang, and Yejin Choi. 2018. Discourse-aware neural rewards for coherent text generation. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 173–184, New Orleans, Louisiana. Association for Computational Linguistics.

Yen-Chun Chen, Linjie Li, Licheng Yu, Ahmed El Kholy, Faisal Ahmed, Zhe Gan, Yu Cheng, and Jingjing Liu. 2019. Uniter: Learning universal image-text representations. arXiv preprint arXiv:1909.11740.

KENNETH MARK COLBY. 1975. Chapter 4 - language-recognition processes for understanding dialogues in teletyped psychiatric interviews. In KENNETH MARK COLBY, editor, Artificial Paranoia, pages 37 – 49. Pergamon.

Cristian Danescu-Niculescu-Mizil and Lillian Lee.
Abhishek Das, Satwik Kottur, Khushi Gupta, Avi Singh, Deshraj Yadav, José M. F. Moura, Devi Parikh, and Dhruv Batra. 2017a. Visual dialog.

Abhishek Das, Satwik Kottur, José MF Moura, Stefan Lee, and Dhruv Batra. 2017b. Learning cooperative visual dialog agents with deep reinforcement learning. In Proceedings of the IEEE international conference on computer vision, pages 2951–2960.

Jianfeng Gao, Michel Galley, and Lihong Li. 2018. Neural approaches to conversational ai. In The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval, pages 1371–1374.

Zhe Gan, Yu Cheng, Ahmed El Kholy, Linjie Li, Jingjing Liu, and Jianfeng Gao. 2019. Multi-step reasoning via recurrent dual attention for visual dialog. arXiv preprint arXiv:1902.00579.

Jesse Dodge, Andreea Gane, Xiang Zhang, Antoine Bordes, Sumit Chopra, Alexander Miller, Arthur Szlam, and Jason Weston. 2016. Evaluating prerequisite qualities for learning end-to-end dialog systems.

Zhe Gan, Yu Cheng, Ahmed El Kholy, Linjie Li, Jingjing Liu, and Jianfeng Gao. 2019. Multi-step reasoning via recurrent dual attention for visual dialog. arXiv preprint arXiv:1902.00579.

Jianfeng Gao, Michel Galley, and Lihong Li. 2018. Neural approaches to conversational ai. In The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval, pages 1371–1374.

Asma Ghandeharioun, Judy Hanwen Shen, Natasha Jaques, Craig Ferguson, Noah Jones, Agata Lapedriza, and Rosalind Picard. 2019. Approximating interactive human evaluation with self-play for open-domain dialog systems. In Advances in Neural Information Processing Systems, pages 13658–13669.

Marjan Ghazvininejad, Chris Brockett, Ming-Wei Chang, Bill Dolan, Jianfeng Gao, Wen-tau Yih, and Michel Galley. 2017. A knowledge-grounded neural conversation model. arXiv preprint arXiv:1702.01932.

Dan Guo, Hui Wang, and Meng Wang. 2019. Dual visual attention network for visual dialog. In IJCAI, pages 4989–4995.

Qinghong Han, Yuxian Meng, Fei Wu, and Jiwei Li. 2020. Non-autoregressive neural dialogue generation.

Kaining He, Xiangyu Zhang, Shaqing Ren, and Jian Sun. 2016. Identity mappings in deep residual networks. In European conference on computer vision, pages 630–645. Springer.

Wanwei He, Min Yang, Rui Yan, Chengming Li, Ying Shen, and Ruifeng Xu. 2020. Amalgamating knowledge from two teachers for task-oriented dialogue system with adversarial training. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 3498–3507. Online. Association for Computational Linguistics.

Chiori Hori, Huda Alamri, Jue Wang, Gordon Wichern, Takaaki Hori, Anoop Cherian, Tim K. Marks, Vincent Cartillier, Raphael Gontijo Lopes, Abhishek Das, Irfan Essa, Dhruv Batra, and Devi Parikh. 2018. End-to-end audio visual scene-aware dialog using multimodal attention-based video features.

Kai Hu, Zhiyuan Feng, Chongyang Tao, Rui Yan, and Lu Zhang. 2020. Learning to detect relevant contexts and knowledge for response selection in retrieval-based dialogue systems. In Proceedings of the 29th ACM International Conference on Information Knowledge Management, CIKM ’20, page 525–534, New York, NY, USA. Association for Computing Machinery.

Minlie Huang, Xiaoyan Zhu, and Jianfeng Gao. 2020. Challenges in building intelligent open-domain dialogue systems. ACM Transactions on Information Systems (TOIS), 38(3):1–32.

Xiaoze Jiang, Siyi Du, Zengchang Qin, Yajing Sun, and Jing Yu. 2020a. Kbgn: Knowledge-bridge graph network for adaptive vision-text reasoning in visual dialogue. In Proceedings of the 28th ACM International Conference on Multimedia, pages 1265–1273.

Xiaoze Jiang, Jing Yu, Zengchang Qin, Yingying Zhuang, Xingxing Zhang, Yue Hu, and Qi Wu. 2019. Dualvdl: An adaptive dual encoding model for deep visual understanding in visual dialogue.

Xiaoze Jiang, Jing Yu, Yajing Sun, Zengchang Qin, Zihao Zhu, Yue Hu, and Qi Wu. 2020b. Dam: Deliberation, abandon and memory networks for generating detailed and non-repetitive responses in visual dialogue.

Gi-Cheon Kang, Jaeseo Lim, and Byoung-Tak Zhang. 2019. Dual attention networks for visual reference resolution in visual dialog. arXiv preprint arXiv:1902.09368.

Satwik Kottur, José MF Moura, Devi Parikh, Dhruv Batra, and Marcus Rohrbach. 2018. Visual coreference resolution in visual dialog using neural module networks. In Proceedings of the European Conference on Computer Vision (ECCV), pages 153–169.

Satwik Kottur, José M. F. Moura, Devi Parikh, Dhruv Batra, and Marcus Rohrbach. 2019. Clevr-dialog: A diagnostic dataset for multi-round reasoning in visual dialog.

Sungjin Lee, Qi Zhu, Ryuichi Takeanobu, Xiang Li, Yaoqin Zhang, Zheng Zhang, Jinchao Li, Baolin Peng, Xiujun Li, Minlie Huang, et al. 2019. Convlab: Multidomain end-to-end dialog system platform. arXiv preprint arXiv:1904.08637.

Mike Lewis, Denis Yarats, Yann Dauphin, Devi Parikh, and Dhruv Batra. 2017. Deal or no deal? end-to-end learning of negotiation dialogues. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 2443–2453. Copenhagen, Denmark. Association for Computational Linguistics.

Gen Li, Nan Duan, Yuejian Fang, Ming Gong, Daxin Jiang, and Ming Zhou. 2019a. Unicoder-vl: A universal encoder for vision and language by cross-modal pre-training.

Jiwei Li. 2020. Teaching machines to converse. arXiv preprint arXiv:2001.11701.
Jiwei Li, Michel Galley, Chris Brockett, Jianfeng Gao, and Bill Dolan. 2015. A diversity-promoting objective function for neural conversation models. *arXiv preprint arXiv:1510.03055.*

Jiwei Li, Michel Galley, Chris Brockett, Georgios P Spithourakis, Jianfeng Gao, and Bill Dolan. 2016a. A persona-based neural conversation model. *arXiv preprint arXiv:1603.06155.*

Jiwei Li, Will Monroe, Alan Ritter, Michel Galley, Jianfeng Gao, and Dan Jurafsky. 2016b. Deep reinforcement learning for dialogue generation. *arXiv preprint arXiv:1606.01541.*

Jiwei Li, Will Monroe, Tianlin Shi, Sébastien Jean, Alan Ritter, and Dan Jurafsky. 2017. Adversarial learning for neural dialogue generation. *arXiv preprint arXiv:1701.06547.*

Liunian Harold Li, Mark Yatskar, Da Yin, Cho-Jui Hsieh, and Kai-Wei Chang. 2019b. Visualbert: A simple and performant baseline for vision and language. *arXiv preprint arXiv:1908.03557.*

Xujiun Li, Xi Yin, Chunyuan Li, Pengchuan Zhang, Xiaowei Hu, Lei Zhang, Lijuan Wang, Houdong Hu, Li Dong, Furu Wei, et al. 2020. Oscar: Object-semantics aligned pre-training for vision-language tasks. In *European Conference on Computer Vision*, pages 121–137. Springer.

P. Lison and J. Tiedemann. 2016. Opensubtitles2016: Extracting large parallel corpora from movie and tv subtitles. In *LREC*.

Ryan Lowe, Nissan Pow, Iulian Serban, and Joelle Pineau. 2015. The ubuntu dialogue corpus: A large dataset for research in unstructured multi-turn dialogue systems. *arXiv preprint arXiv:1506.08909.*

Jiasen Lu, Dhruv Batra, Devi Parikh, and Stefan Lee. 2019. Vilbert: Pretraining task-agnostic visiolinguistic representations for vision-and-language tasks. In *Advances in Neural Information Processing Systems*, pages 13–23.

Jiasen Lu, Anitha Kannan, Jianwei Yang, Devi Parikh, and Dhruv Batra. 2017. Best of both worlds: Transfering knowledge from discriminative learning to a generative visual dialog model.

Yi Luan, Chris Brockett, Bill Dolan, Jianfeng Gao, and Michel Galley. 2017. Multi-task learning for speaker-role adaptation in neural conversation models. *arXiv preprint arXiv:1710.07388.*

Andrea Madotto, Zhaoliang Lin, Chien-Sheng Wu, and Pascale Fung. 2019. Personalizing dialogue agents via meta-learning. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 5454–5459.

Daniela Massiceti, N Siddharth, Puneet K Dokania, and Philip HS Torr. 2018. Flipdial: A generative model for two-way visual dialogue. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 6097–6105.

Tong Niu and Mohit Bansal. 2018. Polite dialogue generation without parallel data.

Yulei Niu, Hanwang Zhang, Manli Zhang, Jianhong Zhang, Zhiwu Lu, and Ji-Rong Wen. 2019. Recursive visual attention in visual dialog. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 6679–6688.

Sungjin Park, Tae sun Whang, Yeo choon Yoon, and Hueiseok Lim. 2020. Multi-view attention networks for visual dialog. *arXiv preprint arXiv:2004.14025.*

Hannah Rashkin, Eric Michael Smith, Margaret Li, and Y-Lan Boureau. 2018. Towards empathetic open-domain conversation models: A new benchmark and dataset. *arXiv preprint arXiv:1811.00207.*

Stephen Roller, Emily Dinan, Naman Goyal, Da Ju, Mary Williamson, Yinhan Liu, Jing Xu, Myle Ott, Kurt Shuster, Eric M Smith, et al. 2020. Recipes for building an open-domain chatbot. *arXiv preprint arXiv:2004.13637.*

Idan Schwartz, Seunghak Yu, Tamir Hazan, and Alexander G Schwing. 2019. Factor graph attention. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 2039–2048.

Abigail See, Stephen Roller, Douwe Kiela, and Jason Weston. 2019. What makes a good conversation? how controllable attributes affect human judgments. *arXiv preprint arXiv:1902.08654.*

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. Neural machine translation of rare words with subword units. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1715–1725, Berlin, Germany. Association for Computational Linguistics.

Paul Hongsuck Seo, Andreas Lehrmann, Bohyung Han, and Leonid Sigal. 2017. Visual reference resolution using attention memory for visual dialog. In *Advances in neural information processing systems*, pages 3719–3729.

Jiwei Li, Michel Galley, Chris Brockett, Georgios P Spithourakis, Jianfeng Gao, and Bill Dolan. 2016. Using attention memory for visual dialog. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 6097–6105.
Yun Nie, Jianfeng Gao, and Bill Dolan. 2015. A neural network approach to context-sensitive generation of conversational responses. *arXiv preprint arXiv:1506.06714*.

Weijie Su, Xizhou Zhu, Yue Cao, Bin Li, Lewei Lu, Furu Wei, and Jifeng Dai. 2019. VLS: Pre-training of generic visual-linguistic representations. *arXiv preprint arXiv:1908.08530*.

Ilya Sutskever, Oriol Vinyals, and Quoc V Le. 2014. Sequence to sequence learning with neural networks. In *Advances in neural information processing systems*, pages 3104–3112.

Hao Tan and Mohit Bansal. 2019. LxMERT: Learning cross-modality encoder representations from transformers. *arXiv preprint arXiv:1908.07490*.

Chongyang Tao, Shen Gao, Mingyue Wang, Wei Wu, Dongyan Zhao, and Rui Yan. 2018. Get the point of my utterance! learning towards effective responses with multi-head attention mechanism. In *Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence, IJCAI-18*, pages 4418–4424. International Joint Conferences on Artificial Intelligence Organization.

Zhiliang Tian, Rui Yan, Lili Mou, Yiping Song, Yangsong Feng, and Dongyan Zhao. 2017. How to make context more useful? an empirical study on context-aware neural conversational models. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 231–236, Vancouver, Canada. Association for Computational Linguistics.

J. Tiedemann. 2009. News from opus — a collection of multilingual parallel corpora with tools and interfaces. J. 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).

Alan M Turing. 2009. Computing machinery and intelligence. In *Parsing the turing test*, pages 23–65. Springer.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Advances in neural information processing systems*, pages 5998–6008.

Oriol Vinyals and Quoc Le. 2015. A neural conversational model. *arXiv preprint arXiv:1506.05869*.

Harm de Vries, Florian Strub, Sarath Chandar, Olivier Pietquin, Hugo Larochelle, and Aaron Courville. 2017. Guesswhat?! visual object discovery through multimodal dialogue.

Richard S. Wallace. 2009. *The Anatomy of A.L.I.C.E.*, pages 181–210. Springer Netherlands, Dordrecht.

Di Wang, Nebojsa Jojic, Chris Brockett, and Eric Neyberg. 2017. Steering output style and topic in neural response generation. *arXiv preprint arXiv:1709.03010*.

Wenhai Wang, Enze Xie, Xiang Li, Wenbo Hou, Tong Lu, Gang Yu, and Shuai Shao. 2019. Shape robust text detection with progressive scale expansion network. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 9336–9345.

Yue Wang, Shaqiq Joty, Michael R Lyu, Irwin King, Caiming Xiong, and Steven CH Hoi. 2020. Vl-bert: A unified vision and dialog transformer with bert. *arXiv preprint arXiv:2004.13278*.

Joseph Weizenbaum. 1966. Eliza—a computer program for the study of natural language communication between man and machine. *Communications of the ACM*, 9(1):36–45.

Qi Wu, Peng Wang, Chunhua Shen, Ian Reid, and Anton Van Den Hengel. 2018. Are you talking to me? reasoned visual dialog generation through adversarial learning. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 6106–6115.

Zhang Xie, Sida I Wang, Jiwei Li, Daniel Lévy, Aiming Nie, Dan Jurafsky, and Andrew Y Ng. 2017. Data noising as smoothing in neural network language models. *arXiv preprint arXiv:1703.02573*.

Chen Xing, Wei Wu, Yu Wu, Jie Liu, Yalou Huang, Ming Zhou, and Wei-Ying Ma. 2016. Topic aware neural response generation. *arXiv preprint arXiv:1606.08340*.

Jingjing Xu, Xuancheng Ren, Junyang Lin, and Xu Sun. 2018. Dp-gan: diversity-promoting generative adversarial network for generating informative and diversified text. *arXiv preprint arXiv:1802.01345*.

Tianhao Yang, Zheng-Jun Zha, and Hanwang Zhang. 2019. Making history matter: History-advantage sequence training for visual dialog.

Tom Young, Erik Cambria, Iti Chaturvedi, Minlie Huang, Hao Zhou, and Subham Biswas. 2017. Augmenting end-to-end dialog systems with commonsense knowledge. *arXiv preprint arXiv:1709.05453*.

Saizheng Zhang, Emily Dinan, Jack Urbanek, Arthur Szlam, Douwe Kiela, and Jason Weston. 2018. Person-alizing dialogue agents: I have a dog, do you have pets too? *arXiv preprint arXiv:1801.07243*.

Yizhe Zhang, Siqi Sun, Michel Galley, Yen-Chun Chen, Chris Brockett, Xiang Gao, Jianfeng Gao, Jingjing Liu, and Bill Dolan. 2019. Dialogpt: Large-scale generative pre-training for conversational response generation. *arXiv preprint arXiv:1911.00536*.

Tiancheng Zhao, Kaige Xie, and Maxine Eskenazi. 2019. Rethinking action spaces for reinforcement learning in end-to-end dialog agents with latent variable models. *arXiv preprint arXiv:1902.08858*. 
Tiancheng Zhao, Ran Zhao, and Maxine Eskenazi. 2017. Learning discourse-level diversity for neural dialog models using conditional variational autoencoders. *arXiv preprint arXiv:1703.10960*.

Xueliang Zhao, Wei Wu, Can Xu, Chongyang Tao, Dongyan Zhao, and Rui Yan. 2020. Knowledge-grounded dialogue generation with pre-trained language models. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 3377–3390, Online. Association for Computational Linguistics.

Yinhe Zheng, Guanyi Chen, Minlie Huang, Song Liu, and Xuan Zhu. 2019a. Personalized dialogue generation with diversified traits. *arXiv preprint arXiv:1901.09672*.

Yinhe Zheng, Rongsheng Zhang, Xiaoli Mao, and Minlie Huang. 2019b. A pre-training based personalized dialogue generation model with persona-sparse data.

Zilong Zheng, Wenguan Wang, Siyuan Qi, and Song-Chun Zhu. 2019c. Reasoning visual dialogs with structural and partial observations. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 6669–6678.

Hao Zhou, Minlie Huang, Tianyang Zhang, Xiaoyan Zhu, and Bing Liu. 2017. Emotional chatting machine: Emotional conversation generation with internal and external memory. *arXiv preprint arXiv:1704.01074*.

Li Zhou, Jianfeng Gao, Di Li, and Heung-Yeung Shum. 2020. The design and implementation of xiaoice, an empathetic social chatbot. *Computational Linguistics*, 46(1):53–93.