KddRES: A Multi-level Knowledge-driven Dialogue Dataset for Restaurant Towards Customized Dialogue System

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Abstract

Compared with CrossWOZ (Chinese) and MultiWOZ (English) dataset which have coarse-grained information, there is no dataset which handle fine-grained and hierarchical level information properly. In this paper, we publish a first Cantonese knowledge-driven Dialogue Dataset for RESTaurant (KddRES) in Hong Kong, which grounds the information in multi-turn conversations to one specific restaurant. Our corpus contains 0.8k conversations which derive from 10 restaurants with various styles in different regions. In addition to that, we designed fine-grained slots and intents to better capture semantic information. The benchmark experiments and data statistic analysis show the diversity and rich annotations of our dataset. We believe the publish of KddRES can be a necessary supplement of current dialogue datasets and more suitable and valuable for small and middle enterprises (SMEs) of society, such as build a customized dialogue system for each restaurant. The corpus and benchmark models are publicly available.

1 Introduction

Task-oriented dialogue system is a system or chatbot which can help human to complete one predefined task (e.g. finding a restaurant or an attraction), which can be grouped into three classes, pipeline, end-to-end and between the above two types which some systems use joint models that combine some (but not all) of the four dialog components (Takanobu et al., 2020). Human-computer conversation becomes very important due to its promising alluring and potential commercial values (Chen et al., 2017). However, there still is less application for small and middle enterprises (SMEs) than big companies because of the lack of large-scale high-quality dialogue data. Many corpus (Zhu et al., 2020; Budzianowski et al., 2018; Zhou et al., 2020; Eric et al., 2019; Zang et al., 2020) before were collected to build a decathlon instead of specialist, which consist of multi-domain, cross-domain and try to handle various sub-tasks in one dialogue which is rare in real scenario, and some datasets (Wen et al., 2016a; Henderson et al., 2014) which focus on one domain ignores the fine-grained slots information and the complexity of real scenario.

The first Chinese large-scale cross-domain task-oriented dataset (CrossWOZ), which contains 6k dialogue sessions and 102k utterances for 5 domains, including hotel, restaurant, attraction, metro and taxi (Zhu et al., 2020). This dataset focuses on hotel, restaurant and attraction, trying to handle cross-domain tasks like finding a hotel near-by the specific attraction and so on. Although it can provide invaluable suggestions and guidelines for tourists, it ignores fine-grained slots and values in a specific domain, which is a common problem for current corpus. For example, the restaurant domain in CrossWOZ ignores the price of dishes, location, operation time and so on. By contrast, (Budzianowski et al., 2018) released a multi-domain English dialogue dataset spanning 7 distinct domains, it contains 10k dialogue sessions with annotation of system-side dialogue states and dialogue acts. But the follow-up work (Eric et al., 2019; Zang et al., 2020) indicates the presence of substantial noise in the dialogue state annotations and dialogue utterances and then fixed some annotation errors. All datasets put more attention on building a task-oriented dialogue system, which can handle composite tasks from different domains.

To handle the aforementioned problems, we propose the first Cantonese knowledge-driven dialogue dataset for restaurant (KddRES). The elaborate experiments and data analysis shows that our data has a more complicated data format and captures more information which more likely happened in a real
scenario not only by the complexity of Cantonese but also the fine-grained slots information. Figure 1 shows a few turns of a dialogue in KddRES. Our contributions can be grouped into three folds.

- We published one knowledge-driven dialogue dataset for restaurant (KddRES), as far as we know, this is the first Cantonese dialogue dataset for task-oriented dialogue system.

- We also provide natural language understanding baselines and the result shows the current pre-trained language model still cannot get satisfactory performance in our dataset.

- Exhaustive data analysis and experiments show our dataset is more diverse and complicated because of various and reasonable data formats existing in real scenarios, which indicate the potential capability to develop a customized dialogue system for a specific restaurant.

2 Related Work

Task-oriented dialogue system attracts more attention since the application of virtual assistant Apple’s Siri\(^1\), Microsoft’s Cortana\(^2\) and XiaoIce\(^3\), Google Assistant\(^4\), and Amazon’s Alexa\(^5\)\(^6\). All virtual assistants come from big companies but small and middle enterprises (SMEs) also want to build their own dialogue system to help the customers. Due to a lack of corresponding datasets and tremendous investment, task-oriented dialogue system still cannot be a usual and normal marketing tool for SMEs.

To facilitate the development of conversational models, most of the existing corpus focus on multi-domain or cross-domain, mainly focus on hotel, restaurant and so on. Stanford dialog dataset\(^7\)\(^8\) contains 3031 dialogues which span schedule, weather and navigation. Another well-known dataset is derived from a series of competitions on the task of Microsoft dialogue challenge.\(^9\)\(^10\) released human-annotated conversational data in three domains(movie-ticket booking, restaurant reservation, and taxi booking). Until the appearance of the largest multi-domains

\(^1\)https://www.apple.com/ios/siri/
\(^2\)https://www.microsoft.com/en-us/cortana/
\(^3\)https://www.msXiaoIce.com/
\(^4\)https://assistant.google.com/
\(^5\)https://developer.amazon.com/alexa/

Figure 1: A few turns of a dialogue in KddRES.
Lots of researchers also publish some Chinese dialogue datasets recently. JDDC Corpus (Chen et al., 2019a) is a large-scale real scenario Chinese E-commerce conversation corpus with more than 1 million multi-turn dialogues. CrossWOZ (Zhu et al., 2020) is the first Chinese cross-domain Wizard-of-Oz task-oriented dataset which encourages natural transition across domains in context. All aforementioned datasets which focus on multi-domains try to build a decathlon dialogue system, but ignore more fine-grained slots information and user requirements in one domain. For example, people may want to inquire about the price of a dish, the location of the restaurant and the operation time when they finally decide to book a table but most of the current datasets ignore the requirement.

As for specific restaurant domain, DSTC2 (Henderson et al., 2014) is a human-to-machine restaurant booking dataset which used for dialogue states tracking, bAbI (Bordes et al., 2016) tasks data is more commonly used in end-to-end dialogue system because of lack of annotation information. (Wen et al., 2016b) introduced CamRest676 which has a set of coarse dialogue acts for each user turn.

Compared with previous datasets in restaurant, our dataset has rich annotations and can be used for both task-oriented dialogue system and end-to-end system. To best of our knowledge, this is the first Cantonese knowledge-driven dialogue dataset for restaurant in Hong Kong, we hope the publication of this dataset can be the catalyst of appearance of customized dialogue system for SMEs.

3 Data Collection

The dialogue database simulates the real scenario where users in Hong Kong seek restaurant information and make a booking at one specific restaurant, which is the biggest difference of our corpus. User and System, two roles in a dialogue session, exchange values of different slots with each other, and make annotations of actions and states for each dialogue explicitly. The data collection process is outlined as follows:

- Database Construction: We first choose 10 representative restaurants with different styles in Hong Kong from Web to build the database. The corresponding slots are extracted from their information. And some new slots are added to better imitate the real scenario like waiting time and table size.

- Goal Generation: The goal generator was designed based on the restaurant information database. A dialogue goal, usually as a user goal, contains two types of slots: informable slots and requestable slots. The former indicates the user’s preference and information that user need to inform the system, but the later one requires the user to ask the system for the information. For example, an inform slot, such as time=“18:00”, means the user wants to have a dinner at 18:00 which he needs to inform the system, and a request slot, like price=“?” , request the user to ask this information. To make it easier for workers to understand the goal, we elaborated templates to form natural language task descriptions.

- Dialogue Collection: A website was developed to collect dialogue data, which randomly assigns two roles to workers: user and system, to simulate real-life restaurant consultation dialogues. In the dialogue, users request information from systems or inform something to them according to the task description, and the system responds accordingly.

- Dialogue Annotation: Annotations are divided into dialogue actions and states. There are different types of dialogue actions: general, request, inform, info-confirm and so on. States are user states and system states, which record the change process of semantic forms on the user and system side. Workers are required to make annotations for their own messages before sending them. Finally, each dialogue contains a structured goal, task description and a message history (includes user state/system state, action, and message text). After that, four experts are hired to double-check the dialogue action, state and other elements to ensure the quality of the dialogue database.

3.1 Database Construction

10 different styles Hong Kong restaurants are selected from Facebook\textsuperscript{6} and OpenRice\textsuperscript{7} to build the database. The corresponding slots are extracted from this information. However, this information

\textsuperscript{6}https://www.facebook.com/
\textsuperscript{7}https://www.openrice.com/en/hongkong
can only cover a few scenarios in real life, in order to better imitate the real scenario, some new slots are added. For example, reservation number, current waiting number, current waiting time, and table size are added as new slots to simulate the scene of the customer’s reservation. When a user wants to make a reservation, he needs to provide the number of people, date and time of his meal plan to the chatbot, and get a reservation number from the chatbot. Table 1 shows the comparison of slots between the restaurant realm of CrossWOZ (Zhu et al., 2020) and our dataset KddRES. Compared with CrossWOZ (Zhu et al., 2020), KddRES has more slots and can cover more scenarios. Besides, CrossWOZ (Zhu et al., 2020) consists of many domains and focuses more on multi-domain or cross-domain which ignores the fine-grained slots’ information in one domain. KddRES improves this by introducing the secondary slots.

| Common                                  |
|-----------------------------------------|
| name, rating, cost, recommend dishes    |
| address, phone, open time               |
| Crosswoz(restaurant)                   |
| nearby attract, nearby rest, nearby hotels |
| KddRES                                  |
| characteristic, dishes, subway, bus    |
| table size, number of comments         |
| current waiting number                 |
| current waiting time, take out         |
| querying for number support, parking, parking, discount |

Table 1: All slots in Crosswoz(restaurant) and KddRES (translated into English). Slots in bold means this slot of KddRES can be divided into secondary slots shown in Table 2

A secondary slot refers to a slot that containing more detailed information. For example, when a user wants to know about a restaurant’s dishes, task-oriented dialogue system can not only tell the name of the dishes, but also the price of the dishes. User can also specifically ask about the price of a certain dish. Dishes and Dishes-price are the secondary slots in this scenario. Table 2 shows the slots with this feature in KddRES.

3.2 Goal Generation

To generate a reasonable dialogue goal, we firstly classify all slots into four groups 1) basic information 2) location(subway and bus) 3) dishes and discount 4) additional information. There are different types of slots in these groups. And then we will generate the sub-goal with different probability $P$ for each group like 0.6 for group 1 but 0.4 for group 4. Also, we require the goal to meet some constraints. For example, the dialogue goal must have one slot in each of the first three groups and one in the last group. We encourage the user to change the goal during the session if there is no-offer or user wants to know more details and the changed goal is also stored.

3.3 Dialogue Collection

A website was developed specifically which allows two persons to mimic different roles for dialogue collection. It allows two workers to talk synchronously and exchange their own message. To ensure workers are trained well, operating instructions and video demonstrations are provided in the website. After workers fill on the necessary personal information, like their name, they can freely choose the role: user or system and start a conversation.

3.3.1 User Side

There are three components on the user side: task description, slot-value box, and dialog box. The task description is the natural language description of the dialogue goal. It tells the user what information needs to request and gives some constraints, such as the date and time of booking a table. The slot-value box is a table that every row combines a checkbox, slot, and value. The user selects a checkbox to mark dialogue action and fills in the value to update the user state. The user synchronizes the dialogue with the system in the dialog box. In each conversation, the user needs to write a message

| Primary slots | Secondary slots |
|---------------|----------------|
| dishes        | dishes-name     |
|               | dishes-price    |
| open time     | open time-date  |
|               | open time-time  |
| table size    | table size-name |
|               | table size-size |
| current waiting number | current waiting number-table name |
|               | current waiting number-number |
| current waiting time | current waiting time-table name |
|               | current waiting time-time |
| take out      | take out-support |
|               | take out-time   |
| parking       | parking-support |
|               | parking-price   |

Table 2: All secondary slots and their primary slots in KddRES (translated into English)
based on the system reply. 2) make annotations in the slot-value box before sending a message, and submit them. 3) terminates the dialogue if the dialogue goal is completed.

3.3.2 System Side

Compared with the user side, the system side has no task description, and the slot-value box adds a column of restaurant information. In each round, the system needs to 1) make appropriate responses in natural language based on previous user conversations and restaurant information. 2) make annotations in the slot-value box before sending a message. If there is no offer to the user’s inquiry, the system will try to make a recommendation.

3.4 Dialogue Annotation

The whole processing of dialogue annotation is divided into two stages. At the first stage, the two roles in a dialogue session already explicitly choose the slot and fill the value during dialogue collection. Secondly, we used some rules to fine-tune the result from the first stage. Compared with CrossWOZ(Zhu et al., 2020), we introduce one new intent names info-confirm, this intent is designed for some special scenario like the user wants to know whether or not the restaurant has this dish.

4 Data Statistics

A dialogue is considered an incomplete dialogue when the goals in a dialogue are not all achieved. After removing these incomplete dialogues, we collect 832 dialogues in total, the dataset is divided randomly into training set, validation set, and test set with a number of 600, 116 and 116. Table 3 shows the statistical indicators of the dataset.

| Statistical Indicators | Train | Valid | Test  |
|-------------------------|-------|-------|-------|
| Dialogues               | 600   | 116   | 116   |
| Turns                   | 5795  | 1118  | 1109  |
| Tokens                  | 97121 | 17758 | 18232 |
| Vocab                   | 931   | 728   | 705   |
| Avg.goals per dialogue  | 7.9   | 7.8   | 7.2   |
| Avg.turns per dialogue  | 9.7   | 9.6   | 9.6   |
| Avg.tokens per turn     | 16.8  | 15.9  | 16.4  |
| Avg.dialogue acts per turn | 1.3  | 1.2   | 1.2   |
| POSS                    | 66.8% | 66.7% | 74.7% |

Table 3: Data statistics, POSS is the proportion of dialogues that contain the secondary slots

Dialogues and Turns refer to the total number of completed dialogues and utterances. Tokens refers to the number of all chars and vocabs refers to the number of vocabularies that have appeared in the dataset. The average goals and turns in a dialogue, tokens and dialogue actions in a turn are also calculated. We also calculate the proportion of dialogues that contain the secondary slots(POSS). POSS can reflect the ratio of detailed scenarios in the dataset. The POSS of KddRES in the training set, test set and validation set all exceed 60%, which indicates that KddRES has a more detailed simulation of the real scenarios. The results indicate the diversity, delicacy and the ability of simulating real scenarios of our data.

Table 4 compares KddRES with other influential restaurant datasets. Because CrossWOZ(Zhu et al., 2020) and MultiWOZ(restaurant)(Zang et al., 2020) pay more attention on the dialogues in multi-domain goal, the size of them is very large. Even so, the Avg.turns of Single-domain type dialogues in Crosswoz is only 6.8, less than kddRES. Meanwhile, the information in one specific domain is not detailed enough which limits the application. The average turns of KddRES is higher than CamRest676(Wen et al., 2016a) and DSTC2(Henderson et al., 2014). The average turns reflects the depth and breadth of a dataset. On this index, KddRES has reached a good level, indicating that KddRES has depth and breadth. In addition, Slots can reflect the richness of the scenario and context in a dataset. The number of slots in KddRES is much higher than the others, which indicates that KddRES contains rich contexts. The result of Table 4 indicates that our data reaches a good level both in quantity and quality. Also, these rich fine-grained slots bring many new challenges to NLU research in the following aspects:

- Relation extraction: The introduction of fine-grained slots make some slots separate into multi levels. For example, “dishes” is divided into two secondary slots: dish-name and dish-price. Figure2 shows the hierarchy of these slots. The values in these secondary slots are one-to-one corresponding. During the building of a dialogue system, especially the natural language understanding part. whether this kind of relation can be correctly extracted is important. For example, in the fifth turn of Figure 1, HK$31 corresponds to the price of Tofu Cheese Cake, and HK$25 corresponds to the price of rose mocha. It is not difficult for a human to understand this from the reply of
| Type          | Multi-domain | Single-domain |
|--------------|--------------|---------------|
| Dataset      | CrossWOZ    | DSTC2         |
|              | MultiWOZ    | CamRest676   |
|              | DSTC2 CamRest676 | KddRES     |
| Language     | CN EN       | EN EN CN(Cantonese) |
| Dialogues    | 6012 10438  | 3235 676     |
| Turns        | 101626 132610 | 25488 1500 8022 |
| Avg.turns    | 16.9 13.7   | 7.9 2.2 9.6 |
| Slots        | 72 25       | 8 3 20       |

Table 4: Comparison of KddRES and other influential restaurant datasets, the Avg.turns are for each dialogue system, but it’s still difficult to make the system have the ability to extract this relation too. Besides, evaluating the ability of a dialogue system and building RL-based policy require establishing a non-human user simulator. In order to make the user simulator stable and reliable, how to solve this issue is also very meaningful.

Exhaustive data statistics analysis shows our dataset have a more complicated data format and more suitable for customized dialogue system, which requires the model to capable to reason and retrieve correct answers. For example, most people will ask how long they need to wait to have a table. The model needs to find a suitable table size according to the number of persons to eat, and then find the waiting time.

5 Experiment

Traditional task-oriented dialogue system is assembled from four components (Natural Language Understanding, Dialogue State Tracking, Dialog Policy and Natural Language Generation), but can not assure the best performance when assembling four best model in corresponding sub-task (Takanobu et al., 2020), Natural Language Understanding is the first part of a pipeline dialogue system, which takes an utterance as input and output its corresponding dialogue act. (Takanobu et al., 2020) shows that a combination of model-based NLU and other rule-based components can get the best performance for task-oriented dialogue system, which indicates the importance of this task. NLU task can be usually divided into two sub-tasks, one is the intent classification, the other one is the slot filling. Intent classification is usually regarded as a classification problem to detect the user’s intention. In contrast, Slot filling is usually regarded as a sequential labeling problem, the words in an utterance are assigned with semantic labels.
5.1 Models

**BiLSTM** (Graves et al., 2013) model can better capture the long-distance dependence because LSTM can learn what to remember and what to forget through the training process. However, there is a problem when using LSTM to encode sentences: the information from back to front cannot be encoded. BiLSTM (Graves et al., 2013) is composed of forward LSTM and backward LSTM, which can better capture the bidirectional semantic dependency.

**BiLSTM-CRF** (Huang et al., 2015) can efficiently use past input features via a BiLSTM (Graves et al., 2013) layer and sentence level tag information via a CRF (Lafferty et al., 2001) layer. CRF (Lafferty et al., 2001) layer can add some constraints to the final predicted tags to ensure that the predicted tags are legal. With these constraints, the probability of illegal sequences in tag sequence prediction will be greatly reduced.

**BERTNLU** (Chen et al., 2019b) Pre-trained models like BERT (Devlin et al., 2018) have been proved to reach the state-of-art performance on lots of downstream tasks including natural language understanding (Zhu et al., 2020). BERTNLU uses BERT (Devlin et al., 2018) to joint training and complete the intent classification task and slot filling task.

**BERT-CRF** Almost the same as BERTNLU (Chen et al., 2019b) except an extra CRF layer to help improve the performance of the slot filling task.

**ERNIE** (Sun et al., 2019) is a pre-trained model like BERT (Devlin et al., 2018) but it also adds word segmentation information. Compared with BERT (Devlin et al., 2018), ERNIE (Sun et al., 2019) learns the semantic relationships in the real world by modeling prior semantic knowledge such as entity concepts in massive data directly, which enhanced the semantic representation ability of the model. To use ERNIE (Sun et al., 2019) in NLU, we use the concat of token embedding, segment embedding and position embedding as the input of ERNIE (Sun et al., 2019) and use the output to joint train the intent classification task and slot filling task.

5.2 Implement Details

BertAdam optimizer is used with the learning rate of $3 \times 10^{-5}$ and epsilon of $10^{-8}$. The batch size is chosen as 20, and the hidden size is 768. ReLU (Agarap, 2018) is selected as the activation function. Before the output of pre-trained language model go to the next hidden layer, it will go through a dropout layer with a rate of $10^{-1}$ firstly. The model is trained for $4 \times 10^4$ steps.

5.3 Result

The number of results of intention classification and slot filling for one utterance is usually much less than all possible results. In this task We pay more attention to whether the identified intent and slot (positive examples) are accurate. meanwhile, Accuracy can not reflect the performance of a classifier when the distribution of positive and negative samples is unbalanced. Therefore, we choose F1, the harmonic average of precision and recall as the evaluation index of these models. Table 5 shows the result of these models on F1.

| Model         | In(F1) | Sl(F1) | Overall(F1) |
|---------------|--------|--------|-------------|
| BiLSTM        | 90.69  | 91.95  | 91.37       |
| BiLSTM+CRF    | 91.89  | 91.65  | 91.76       |
| BERT          | 92.46  | 94.02  | 93.39       |
| BERT+CRF      | 92.03  | 94.34  | 93.42       |

Table 5: Experiment result

Just like BERT’s (Devlin et al., 2018) good capability in other NLP tasks, BERT (Devlin et al., 2018) also has a good result here. The F1 scores of Intent, Slot and Overall are all better than BiLSTM (Graves et al., 2013) and BiLSTM+CRF (Huang et al., 2015). However, we notice that ERNIE (Sun et al., 2019) has not achieved significant results. We think the main reason is that the pre-trained corpus of ERNIE (Sun et al., 2019) only includes Simplified Chinese text, does not include Cantonese (Traditional Chinese) text. At the same time, these indicators show that KddRES has diversity and delicacy, which provides more challenges for the future research of task-oriented dialogue system.

6 Conclusion and Future Works

In this paper, we publicly release one multi-Level Knowledge-driven Dialogue Dataset for restaurant in real scenario with detailed data analysis and rerun competitive natural language understanding baselines on this dataset. All corpus and code will be available on the KddRES github. We hope the publication of this dataset can facilitate the development of customized dialogue system for SMEs.
We left other components of task-oriented dialogue system like dialogue state tracking, policy learning to future work, and also we will expend our data to more domains.

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References

Abien Fred Agarap. 2018. Deep learning using rectified linear units (relu).

Antoine Bordes, Y-Lan Boureau, and Jason Weston. 2016. Learning end-to-end goal-oriented dialog.

Paweł Budzianowski, Tsung-Hsien Wen, Bo-Hsiang Tseng, Ihigo Casanueva, Stefan Ultes, Osman Ramadán, and Milica Gašić. 2018. Multiwoz – a large-scale multi-domain wizard-of-oz dataset for task-oriented dialogue modelling.

Hongshen Chen, Xiaorui Liu, Dawei Yin, and Jiliang Tang. 2017. A survey on dialogue systems. ACM SIGKDD Explorations Newsletter, 19(2):25–35.

Meng Chen, Ruixue Liu, Lei Shen, Shaozu Yuan, Jingyan Zhou, Youzheng Wu, Xiaodong He, and Bowen Zhou. 2019a. The jddc corpus: A large-scale multi-turn chinese dialogue dataset for e-commerce customer service.

Qian Chen, Zhu Zhuo, and Wen Wang. 2019b. Bert for joint intent classification and slot filling.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding.

Mihail Eric, Rahul Goel, Shachi Paul, Adarsh Kumar, Abhishek Sethi, Peter Ku, Anuj Kumar Goyal, Sanchit Agarwal, Shuyang Gao, and Dilek Hakkani-Tür. 2019. Multiwoz 2.1: A consolidated multi-domain dialogue dataset with state corrections and state tracking baselines.

Mihail Eric and Christopher D. Manning. 2017. Key-value retrieval networks for task-oriented dialogue.

Alex Graves, Abdel rahman Mohamed, and Geoffrey Hinton. 2013. Speech recognition with deep recurrent neural networks.

Matthew Henderson, Blaise Thomson, and Jason D. Williams. 2014. The second dialog state tracking challenge. In Proceedings of the 15th Annual Meeting of the Special Interest Group on Discourse and Dialogue (SIGDIAL), pages 263–272, Philadelphia, PA, U.S.A. Association for Computational Linguistics.

Zhiheng Huang, Wei Xu, and Kai Yu. 2015. Bidirectional lstm-crf models for sequence tagging.

John D. Lafferty, Andrew McCallum, and Fernando C. N. Pereira. 2001. Conditional random fields: Probabilistic models for segmenting and labeling sequence data. In Proceedings of the Eighteenth International Conference on Machine Learning. ICML ’01, page 282–289, San Francisco, CA, USA. Morgan Kaufmann Publishers Inc.

Xiujuan Li, Yu Wang, Siqi Sun, Sarah Panda, Jingjing Liu, and Jianfeng Gao. 2018. Microsoft dialogue challenge: Building end-to-end task-completion dialogue systems.

Heung-Yeung Shum, Xiaodong He, and Di Li. 2018. From eliza to xiaoice: Challenges and opportunities with social chatbots.

Yu Sun, Shuohuan 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. arXiv e-prints, page arXiv:1904.09223.

Ryuichi Takanobu, Qi Zhu, Jinchao Li, Baolin Peng, Jianfeng Gao, and Minlie Huang. 2020. Is your goal-oriented dialog model performing really well? empirical analysis of system-wise evaluation.

Tsung-Hsien Wen, Milica Gašić, Nikola Mrkšić, Lina M. Rojas-Barahona, Pei-Hao Su, Stefan Ultes, David Vandyke, and Steve Young. 2016a. Conditional generation and snapshot learning in neural dialogue systems. arXiv preprint: 1606.03352.

Tsung-Hsien Wen, David Vandyke, Nikola Mrksic, Milica Gasic, Lina M. Rojas-Barahona, Pei-Hao Su, Stefan Ultes, and Steve Young. 2016b. A network-based end-to-end trainable task-oriented dialogue system.

Xiaoxue Zang, Abhinav Rastogi, Srinivas Sunkara, Raghav Gupta, Jianguo Zhang, and Jindong Chen. 2020. MultiWOZ 2.2 : A dialogue dataset with additional annotation corrections and state tracking baselines. In Proceedings of the 2nd Workshop on Natural Language Processing for Conversational AI, pages 109–117, Online. Association for Computational Linguistics.

Hao Zhou, Chujie Zheng, Kai Li Huang, Minlie Huang, and Xiaoyan Zhu. 2020. Kdconv: A chinese multi-domain dialogue dataset towards multi-turn knowledge-driven conversation.

Li Zhou, Jianfeng Gao, Di Li, and Heung-Yeung Shum. 2018. The design and implementation of xiaoice, an empathetic social chatbot.

Qi Zhu, Kai Li Huang, Zheng Zhang, Xiaoyan Zhu, and Minlie Huang. 2020. Crosswoz: A large-scale chinese cross-domain task-oriented dialogue dataset.