Where is the context? – A critique of recent dialogue datasets

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Abstract

Recent dialogue datasets like MultiWOZ 2.1 and Taskmaster-1 constitute some of the most challenging tasks for present-day dialogue models and, therefore, are widely used for system evaluation. We identify several issues with the above-mentioned datasets, such as history independence, strong knowledge base dependence, and ambiguous system responses. Finally, we outline key desiderata for future datasets that we believe would be more suitable for the construction of conversational artificial intelligence.

1 Introduction

The recent dialogue datasets MultiWOZ [Budzianowski et al., Eric et al.] and Taskmaster-1 [Byrne et al.] facilitate the construction of task-oriented machine learning dialogue systems, as exhaustively reviewed by [Gao et al.], where a user wants to know or do something, while the system has to understand the user’s utterance and reply appropriately. Learning to model these datasets is presently among the most challenging tasks for state-of-the-art dialogue systems, as they cover multiple task domains and contain dialogues in which users change their goal during the conversation. Nevertheless, both MultiWOZ and Taskmaster-1 suffer from a number of issues, which we discuss in the present paper.

The issues we discuss concern the task of predicting the next action of the system, given the dialogue history. Here, we define a system action as a combination of task domain (restaurant, hotel, etc.), dialogue act type (inform, recommend, etc.), and slots filled by the system, following Zhang et al..

As a first issue we find that, when comparing multiple dialogues, different actions follow from the same dialogue history and thus a system trained on these dialogues cannot learn deterministic behaviour. Such ambiguous actions can only be handled by systems that are designed to model a distribution of system actions, such as in the recent work of [Zhang et al.], who also acknowledged this issue as a “one-to-many” property of human dialogue in general. Presently, however, most supervised systems only predict a single best response [Mehri et al., Chen et al., Madotto et al.]

As a second issue, we observe that dialogue models do not seem to benefit from knowing the dialogue history beyond the last user input and its preceding system action, which indicates an unnatural simplicity of the dialogues.

Throughout this article we follow [Mrki et al., Wen et al.] and decouple the training data from the knowledge base, as the system’s choice of action should primarily depend on the number of items (hotels, pizza toppings, etc.) that satisfy the user’s criteria, not their specific names.

In this article, we do not seek to improve on the performance of state of the art models on the datasets we consider, nor do we compare our models to them. Instead, we use different models as a tool to identify problems within these datasets.

We first discuss the MultiWOZ dataset in §2, and then briefly the Taskmaster-1 dataset in §3, before we conclude with §4 where we summarize our findings and outline ways to circumvent the identified problems. The program code used in this paper is available under https://github.com/RasaHQ/multiwoz-paper.

2 MultiWOZ

The MultiWOZ dataset [Budzianowski et al.], contains over 10k task-oriented conversations on hotels, restaurants, taxi and train bookings, attractions, hospitals, and police stations in the city of Cambridge. Many of the dialogues cross several
of these domains and, on average, span about 14
turns per dialogue. Most MultiWOZ dialogues
come with annotations for the system’s action and
gold belief state (the user’s goal and slot values),
which sets it apart from other multi-domain dia-
logue datasets such as MetaLWOz [Schulz et al.]

The MultiWOZ dialogues are collected with a
Wizard-of-Oz setup [Kelley], where the system’s
role is taken by a human, ensuring that the sys-
tem’s output utterances are formulated naturally.
In the MultiWOZ setup the wizard chooses a re-

response, which is distinct from the paraphrasing ap-

proach of [Rastogi et al.], where the dialogue acts
are fixed by a schema, and crowd workers par-
phrase the dialogue acts.

All dialogues were collected via Amazon Me-
chanical Turk [Crowston]. Turkers in the user’s
role were asked to want to achieve a certain goal,

e.g. find a hotel in the city center with free WiFi
and then book it (goals were revealed to the turker
over time), and turkers in the system’s role (wiz-
dards) were asked to respond appropriately and
check for the availability of requested hotel rooms,
etc., via a specially designed user interface. The
conversations were then annotated with action la-

gels and gold belief states of the wizards. Here
we consider the revised version, MultiWOZ 2.1,
in which many labeling errors have been corrected
manually [Eric et al.]. Throughout this Section,
we split MultiWOZ into a training and a test set
at a 80/20 ratio.

2.1 Ambiguous system actions

In this Section we demonstrate that, when compar-
ing multiple dialogues, we find that different ac-
tions follow from the same dialogue history and

thus a system trained on these cannot learn deter-

ministic behaviour. To this end, we train a “memo-

rization model” that simply memorizes sequences
of events in the training data. The events are sys-
tem actions on the one hand, and the user’s dia-

logue acts, represented as tuples of user intents
[Budzianowski et al.] as well as slots that the user

wants to fill, on the other hand. The number of
events that are taken into account for prediction is
limited by max_history, which we set to 10.
If the memorization model cannot achieve an F1
score of 1.0 on the training set, then the system’s
actions are ambiguous.

The input and output spaces of the memoriza-
tion model are the user input and the possible sys-
tem actions, similarly to the POMDP-based meth-
ods [Young et al., 2013] and in contrast with end-
to-end models. We call dialogue models that op-
erate on these simplified input and output spaces
“modular models”, following [Wen et al.].

While the system actions are already part of
the MultiWOZ annotation, the user intents are not.
Thus, we follow Vlasov et al. and define two in-
tents, inform and bye. A user input has the
intent inform, unless it is the last intent of the
dialogue and the user did not provide any slots. In
this case we assume (based on reading a sample of
dialogues) it is a farewell and thus assign the intent
bye.

We infer the slots provided by the user from
changes in the system’s belief state after a user in-

put. For example, a user intent/slot tuple for the
phrase “I’d like to stay at a 4-star hotel” is thus
inform("hotel_stars": "specific").

Note, that we do not store the actual number of
stars in the example above, but the generic tags
specific or do-not-care, since the partic-
ular star rating of the hotel should not matter for
next-action prediction.

In addition, we slightly augment the action la-

tels of the MultiWOZ dataset. Specifically, we

infer the domain (hotel, restaurant, etc.) of the sys-
tem’s Booking-Book action from the last men-
tioned domain and add this information to the la-
bel, resulting, e.g., in Hotel-Booking-Book.
A typical dialogue, as seen by a modular model,
may now look like the first example presented in
Appendix A.1.

At this point, the memorization model achieves
an F1 score of 0.84 on the training set, indicating
that system actions are ambiguous (see Table 1).
Throughout the remaining section we simplify the
training data further, until all dialogues are consist-
tent.

The first problem leading to a consistency is
that the availability of venues is not annotated,
even though this knowledge is required to cor-

rectly choose the next action. We add these an-
notations in the form of special “status” slots for
each venue type, which take the values unique,
NA, or available, respectively for the three sit-
uations. In addition, the status slots take the value
booked after the system has booked a particular
venue. At this point, the representation of a typi-
cal MultiWOZ dialogue could look like the second
example given in Appendix A.1. Adding status
|          | Memorization | Modular LSTM | Modular TED | End-to-end TED |
|----------|--------------|--------------|-------------|----------------|
| Initial  | Training     | Testing      | Training    | Testing        |
|          | 10           | 0.84         | 0.51        | 0.50           | 0.22           |
|          | 2            | 0.51         | 0.47        | 0.47           | 0.22           |
| Simplified| 10           | 1.00         | 0.95        | 0.95           | 0.69           |
|          | 2            | 0.95         | 0.92        | 0.94           | 0.69           |

Table 1: F1 scores of the modular memorization, LSTM and TED models, as well as of the end-to-end TED model. For the results in the first row, "initial", we use the inferred intents without any simplifications or, in the end-to-end case, the plain text utterances. For the results in rows 3 and 4, "simplified", we simplify the dialogue data, as explained in §2.1. The second column indicates the setting for max history. Appendix A.3 contains a more detailed table that also shows accuracy scores.

slots improves the memorization model’s F1 score to 0.87.

By examining the mistakes made by the model, we find that this low F1 score stems from the fact that multiple system actions are “correct”. For example, when the wizard has a few dining options available, she may

- recommend one of the options,
- recommend one of the options and ask if there is anything else she can do,
- list all options,
- ask for more information from the user.

All of these actions are “correct” in the sense that they seem natural to the user, and which action is chosen depends on the mood and character of the person who takes the role of the system. Nevertheless, these actions are assigned distinct action types (Recommend, Reqmore, Select, Request), once again leading to ambiguous behaviour. To remedy this issue, we recombine action labels as follows: The action types Inform, Recommend, Select, and Request merge to the single type Reply, and the action types Goodbye, Welcome, and Greet merge to the single type Welcome.

Merging the action types in this way still does not remove all the unobservable information: The system actions are still ambiguous, as the memorization model’s scores are only 0.90. Once more, we examine the mistakes that are made by the model and find that the action General-Reqmore is unpredictable. Specifically, whether or not the system (wizard) asks if the user requires anything else is a random choice. Therefore, we remove all General-Reqmore actions from the dataset, unless it is the only action that the system takes in between user inputs. This, again, increases the F1-score.

However, for the memorization model to reach an F1-score of 1.0, we have to get rid of all ambiguities in the dataset. By identifying branch points in the tree of all dialogue histories and recursively removing ambiguous branches, we identify the largest subset of parsed MultiWOZ dialogues that is unambiguous. This subset contains 1691 of the 8534 MultiWOZ dialogues (MultiWOZ 2.1 contains 10438 dialogues, but 1904 of those are not completely annotated and can therefore not be parsed).

We have now arrived at a dialogue dataset that is deterministic, i.e. the F1 score of the memorization model is 1.0, as can be seen in Table 1. Note, that this resulting simplified dataset is not in any way more realistic than the original. The fact that it significantly differs from the original should only illustrate the severity of the issue of ambiguous system responses.

2.2 History independence

To establish the history independence of the MultiWOZ dialogues, in addition to the memorization model, we also train two other modular models: a long-short term memory (LSTM) model loosely following [Williams et al.] and the recently introduced Transformer Embedding Dialogue (TED) model [Vlasov et al.].

For completeness, we also train the TED model in end-to-end (retrieval) mode, where it takes the history of plain text utterances as input, and picks an appropriate response from the list of all responses. To compute the scores of this end-to-end model, we associate the picked response with its action label(s). While we could have used stricter evaluation metrics, such as human evaluation or the BLEU score [Papineni et al.], this allows us to compare results directly to those of the modular approach. Again, our models are a means of investigating properties of the dataset and are not in-
tended to improve upon the state of the art.

We observe that the end-to-end model performs consistently worse than the modular TED and LSTM models (see Table 1), which is not surprising since it has to solve the harder problem of mapping plain text utterances to plain text utterances, while the amount of training data is the same.

The history independence becomes apparent when we reduce the length of dialogue history that the three models take into account. Specifically, reducing max_history, as defined in §2.1, from 10 to 2 barely changes the scores of either model, no matter if the dataset has been simplified (as described in §2.1) or not (see Table 1). Thus, none of the policies benefit from knowing the dialogue history beyond the last user input and its preceding system action.

Note, that Vlasov et al. have shown that the TED model attends to relevant pieces of a significantly longer dialogue history to predict the next system action. Thus, our result is indeed an issue of the dataset, not of the models used.

The apparent history independence is also plausible when we consider the excerpt from conversation MUL0104, displayed in Appendix A.2. Given the first two events (system and user utterance), anyone could predict the content of the subsequent system output. No further information would be required. In particular, the remaining history of the conversation is irrelevant. We observe the same situation repeatedly throughout the MultiWOZ dataset. Furthermore, we also note that some of the best-performing models on MultiWOZ and similar datasets either neglect the dialogue history [Rastogi et al., Chao and Lane], or use a form of LSTM to encode it, which is naturally biased towards the most recent parts of the history [Mehri et al.].

3 Taskmaster-1

We repeat our analysis with Taskmaster-1, which by itself consists of two datasets: one which is collected via a Wizard-of-Oz setup, similar to MultiWOZ, and another for which each dialogue is written by a single human. In this paper we only consider the latter, for which each dialogue concerns one of the following domains: Uber/Lyft ride bookings, movie ticket and restaurant reservations, coffee or pizza orders, and car repairs. The Taskmaster-1 dialogues come with detailed annotations for utterance segments, including clues about the general intent and domain of the utterance in which they appear.

To remove the knowledge base dependence, we delexicalize annotated segments [Mrki et al.] and tag utterances with (i) the dialogue domain, (ii) the domain as classified by a simple regex, and (iii) the annotated segments that occur in the utterance. We then run the same end-to-end retrieval setup as we do with MultiWOZ. Once more, we find that the resulting scores are almost history independent (see Table 3 in Appendix A.3), which can also be concluded from reading the dialogues. From analyzing prediction mistakes and reading the dialogues it is evident that the system responses are ambiguous in the same sense as in the MultiWOZ dataset.

4 Conclusions

We have analysed two recent dialogue datasets: MultiWOZ 2.1 and Taskmaster-1. Both datasets are purely human-generated and therefore contain natural utterances on both the user and system sides. In addition, both datasets contain useful annotations. We show, however, that

1. both MultiWOZ and Taskmaster-1 are not suitable to train supervised dialogue systems on next-action prediction, unless they predict the probability distribution of system actions instead of a single best action, and
2. dialogues in these datasets are nearly history independent.

The ambiguities in the action selection that make it impossible to train unique-response systems stem from the fact that the dialogues are highly dependent on the knowledge base, as well as on unobservable information such as the personality and mood of the wizard. Furthermore, we hypothesize that the history independence stems from the greater problem that turkers are asked to pretend to want to achieve a goal. Thus, they are not actually interested in the information they obtain, but are motivated only to complete each dialogue as soon as possible.

We suspect that instead of prescribing what the user ought to want, it would be better to describe a scenario to the user and let him/her explore the available options through interaction with the system. To remedy the ambiguities, an automatic system response should be enforced during data col-
lection if the same dialogue state has been encountered before.

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A Appendices
A.1 Example of a parsed conversation
The modular policies (memorization, LSTM, and modular TED) operate on training data as presented in the following example.

- inform("hotel_area": "specific")
Here, lines starting with a ‘*’ indicate a user turn and provide the user intent (inform or bye) as well as the slots the user wishes to inform the system about. The lines starting with a ‘-’ indicate a system action. If status slots are provided, the example becomes

- inform("hotel_area": "specific")
  - Hotel-Select
- inform("hotel_name": "specific")
  - Hotel-Booking-Book{
    "hotel_status": "booked",
    "hotel_reference": "AHG32K"
  }
  - Hotel-Inform
- bye
  - General-Goodbye

where slot{...} denotes a slot being set by a knowledge base.

A.2 Example excerpt

This is an excerpt of conversation MUL0104 from MultiWOZ 2.1:

- There are two options - the University Arms Hotel in the centre and the Huntingdon Marriott Hotel in the west. Do you have a preference?
  
    - The University Arms Hotel. Can you book that for 5 nights please?

- What day would you like to stay and how many people will be staying?

A.3 Detailed scores
### Table 2: Training and test scores on MultiWOZ 2.1 for the modular TED and LSTM models, as well as the TED-based end-to-end model and the memorization model. The scores are presented for each model as the dataset is made increasingly consistent through various techniques described in §2.1 and denoted in the `Note` column. \( N \) represents the number of dialogues used for training.

| Model          | \( \text{max\_history} \) | \( N \) | Note                                      | Training F1 accuracy | Testing F1 accuracy |
|----------------|---------------------------|-------|-------------------------------------------|----------------------|---------------------|
| TED            | 10                        | all   | use inferred intents                      | 0.84                 | 0.83                |
|                | 10                        | all   | + add status slots                        | 0.87                 | 0.87                |
|                | 10                        | all   | + merge action labels                     | 0.90                 | 0.90                |
|                | 10                        | all   | + remove reqmore                          | 0.91                 | 0.91                |
|                | 10                        | 1691  | + remove ambiguous dialogues              | 1.00                 | 1.00                |

| TED            | 10                        | all   | use inferred intents                      | 0.50                 | 0.67                |
|                | 2                         | all   |                                            | 0.47                 | 0.67                |
|                | 10                        | all   | + add status slots                        | 0.65                 | 0.74                |
|                | 10                        | all   | + merge action labels                     | 0.84                 | 0.87                |
|                | 10                        | all   | + remove reqmore                          | 0.87                 | 0.89                |
|                | 10                        | 1691  |                                            | 0.94                 | 0.96                |
|                | 10                        | 1691  | + remove ambiguous dialogues              | 0.95                 | 0.96                |
|                | 2                         | 1691  |                                            | 0.94                 | 0.94                |

| LSTM           | 10                        | all   | use inferred intents                      | 0.51                 | 0.67                |
|                | 2                         | all   |                                            | 0.47                 | 0.66                |
|                | 10                        | all   | + add status slots                        | 0.65                 | 0.75                |
|                | 10                        | all   | + merge action labels                     | 0.85                 | 0.88                |
|                | 10                        | all   | + remove reqmore                          | 0.90                 | 0.94                |
|                | 10                        | 1691  |                                            | 0.93                 | 0.96                |
|                | 10                        | 1691  | + remove ambiguous dialogues              | 0.95                 | 0.97                |
|                | 2                         | 1691  |                                            | 0.95                 | 0.97                |

| End-to-end TED | 10                        | all   | use plain-text utterances                 | 0.22                 | 0.61                |
|                | 2                         | all   |                                            | 0.22                 | 0.62                |
|                | 10                        | all   | + add status slots                        | 0.28                 | 0.64                |
|                | 10                        | all   | + merge action labels                     | 0.61                 | 0.81                |
|                | 10                        | all   | + remove reqmore                          | 0.73                 | 0.87                |
|                | 2                         | all   |                                            | 0.68                 | 0.84                |
|                | 10                        | 1691  |                                            | 0.68                 | 0.82                |
|                | 10                        | 1691  | + remove ambiguous dialogues              | 0.69                 | 0.84                |
|                | 2                         | 1691  |                                            | 0.69                 | 0.84                |

### Table 3: Training and test scores of the end-to-end TED model on 3000 training and 750 test dialogues from the Taskmaster-1 self-dialogues dataset. Results change little when \( \text{max\_history} \) is reduced from 10 to 2.

| \( \text{max\_history} \) | Training F1 accuracy | Testing F1 accuracy |
|---------------------------|----------------------|---------------------|
| 10                        | 0.14                 | 0.13                |
| 2                         | 0.12                 | 0.10                |