MultiWOZ-DF - A Dataflow implementation of the MultiWOZ dataset

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Abstract
In this paper we introduce MultiWOZ-DF, a dataflow implementation of the well known MultiWOZ dataset. The implementation demonstrates how to both convert and execute MultiWOZ dialogues as dataflow dialogues. Our goal is to encourage the research community to further investigate the dataflow dialogue paradigm.

Keywords: Dialogue systems, dataflow

1. Introduction
Semantic Machines (SM) have introduced the use of the dataflow (DF) paradigm to dialogue modelling, using computational graphs to hierarchically represent user requests, data, and the dialogue history (Semantic Machines et al., 2020).

Although the main focus of that paper was the SM-CalFlow dataset (to date, the only dataset with “native” DF annotations), they also reported some results of an experiment using a transformed version of the commonly used MultiWOZ dataset (Budzianowski et al., 2018) into a DF format.

In this paper, we expand the experiments using DF for the MultiWOZ dataset, exploring some additional experimental set-ups. The code and instructions to reproduce the experiments reported here have been released.

The contributions of this paper are:
1. A DF implementation capable of executing MultiWOZ dialogues;
2. Several versions of conversion of MultiWOZ into a DF format are presented;
3. Experimental results on state match and translation accuracy.

2. The MultiWOZ dataset
The MultiWOZ dataset (Budzianowski et al., 2018) consists of 10K annotated dialogues in 7 domains (hotels, restaurants, trains, attractions, hospitals, police, taxi). The collection of the dataset was done using a Wizard-Of-Oz set-up, where both the user and the system (agent) are played by human participants. The user is presented with a set of goals they need to achieve (e.g. book a hotel, restaurant, etc.) as well as a set of constraints for the goals (e.g. the hotel should be in a specific area, in a specific price category etc). The user has no direct access to the data, and thus needs to communicate with the agent to achieve the pre-specified goals. The agent accesses the data (e.g. hotel information) through a database interface, and their job is to convert the user’s requests into database queries, informing the user when the requests succeeds or fails, supplying the information found by the database search, and prompting the user for additional information in case the request is incomplete, or when the request can not be satisfied.

Two types of annotations are present in MultiWOZ:

• Dialogue state - the database query that the agent ran at each turn is saved, and is used as a proxy for the dialogue state - i.e. considered as a representation of the agent’s belief regarding the user’s wishes at that time point. This represents an accumulation of all the turns until that point, and may depend on the agent’s subjective interpretation of the user requests;

• Dialogue acts - a separate annotation pass was done (by a separate group of annotators), marking what information was actually communicated in each turn (separately for user and agent).

The MultiWOZ dataset has been used by many researchers, and is one of the most commonly used dataset for comparison and benchmarking in dialogue system research.

2.1. Annotation issues
Both the annotation format, as well as the actual annotations have gone through several iterations of improvements, underlying the inherent difficulties in trying to achieve complete and objective annotation of natural dialogues. In this work, we use the MultiWOZ-2.2 version (Zang et al., 2020), which is considered the cleanest version of the dataset.

Despite this, there are still many issues with this annotation, stemming from the assumption that the agent’s database query is an exact and objective description of the dialogue state.

In some cases, the values entered into the database query are clearly wrong (the agent may have mistyped,
The prominent features of this paradigm are: user's calendar appointments on an external database), through API's to external services (e.g. updating the message), and optionally producing some side effects executed, which results in manipulating the dialogue state/history. In addition, the DF expressions can be executable expressions. The computational graphs (also referred to as DF graphs, where each computational graph typically represents one user turn; • It has a refer operation to search over the current and previous computational graphs (as well as external resources) which allows easy look-up and re-use of graph nodes which occurred previously in the dialogue; • It has a revise operation which allows modification and reuse of previous computations • It has an exception mechanism which allows convenient interaction with the user (e.g. asking for missing information, and resuming the computation once the information is supplied).

These features correspond to essential phenomena in natural conversations (referring to previous turns, modifying previous requests, reacting to wrong information, etc.), which allows the system to effectively handle these kinds of user requests.

DF is an object-oriented approach to dialogue design, encouraging modularization and re-use, and may offer practical advantages in terms of scaling and ease of implementing actual dialogue systems. One interesting aspect of this design is that state (dialogue history), data and computations are all represented using the same format (well structured graphs), which could be useful for new machine learning graph based models (e.g. methods using graph attention), as it allows the model easy access to the state/data.

4. MultiWOZ and DF

Despite the fact that MultiWOZ's annotation is essentially flat intent/entity frames, as opposed to the hierarchical (deep) annotations of SMCalFlow, (Semantic Machines et al., 2020) showed that a DF approach may still be advantageous for MultiWOZ. In an experiment, the MultiWOZ annotations were converted into DF expressions, which were then fed into the same pipeline used for training and evaluating the SMCalFlow seq2seq model. The results showed a small improvement in the joint goal (average dialogue-state exact match) and dialogue (average dialogue-level exact match) metrics, compared to the TRADE (Wu et al., 2019) baseline. Unfortunately, SM did not release the code for real execution of the DF expressions, which hinders examination and further experimentation with this approach. In this work, we release an executable version of the DF implementation of MultiWOZ (based on OpenDF), which should allow researchers to reproduce the MultiWOZ-DF experiments, as well as to extend the work presented here.

4.1. Converting MultiWOZ

When converting MultiWOZ to the DF format, SM converted a dialogue state to a call to a find function, which gets as parameters the type of service (domain), as well as the values for specified slots. Within a dialogue, any turn that initiates a new type of booking is
re-annotated as a call to \textit{find}. Turns that merely modify some of the slots are re-annotated as \textit{revise()} calls. \textit{refer()} calls are used to substitute slot values which do not appear verbatim in the user request (provided the refer is correctly resolved).

While the code for converting the MultiWOZ annotations to the DF format were released by SM, we use a different conversion scheme. The differences are described below.

4.1.1. DF format
SM's DF expressions use the S-Expression format (a LISP-like format), while our annotations use a Python-like format (which is the standard in OpenDF).

4.1.2. MultiWOZ version
SM used MultiWOZ version 2.1. As mentioned above we use the cleaner version 2.2.

4.1.3. Conversion source
SM's conversion used the annotated dialogue state as the base of conversion. As mentioned above, the dialogue state annotation is derived from the database query, which is manually written by the human agent to describe the user's wishes at that time (the agent generates one query after getting the user's request). SM's conversion used the "state delta" (simply put, the difference between two successive queries) to decide which slots and values should be included in the DF expression for the current user turn. Note that the state delta does not explicitly state which slots/values came from the user, and which from the agent.

Our conversion, on the other hand, is based on the dialogue act annotations. In this conversion, the DF expressions include only the slots mentioned in the user's dialogue acts (which has separate annotation for user and agent turns).

In most cases, the two conversions produce essentially similar results (although in different formats). However, when information from the agent is incorporated into the dialogue state, the conversions produce different results. As a concrete example, look at the following dialogue:

1. User: "I want a restaurant in the center of town"
2. Agent: "How about Restaurant X?"
3. User: "good. I want to book a table on Monday"
4. Agent: "...

Looking at the conversion for the second user turn (turn #3), the converted DF expression contains the following slots:

- Using the state delta based conversion: 
  \texttt{(day=Monday, name=Restaurant X)}

- Using the dialogue acts based conversion: 
  \texttt{(day=Monday)}

Practically, this means that for dialogue state based DF expressions, the translation of the user’s text request to a DF expression has to also look at the agent’s text in order to extract relevant agent’s slots/values from it (in this example - the restaurant name).

For dialogue act based DF expressions, the translation needs only to extract the user’s slots/values. The information from the agent (described by the dialogue acts of the agent) is incorporated into the graphs not through DF expressions, but rather consumed directly by the execution logic.

This makes the DF expression closer to the user request’s surface form, and reduces the load on the seq2seq model.

In a practical dialogue system set-up, this assumption is reasonable, since at run time the human agent is replaced by a programmed agent, which gives us direct access to its internal state and decisions (see section 5 for more detail).

4.1.4. Conversion scope
SM’s conversion is focused on achieving a dialogue state which matches the manual MultiWOZ state annotation.

Our conversion also tries to approximate the behaviour of a more complete dialogue system (the converted expressions should actually execute the dialogues in a way which is acceptable to users).

In a case when the state delta (used by SM) is empty (e.g. when the user asks for some information, like the price of a train), they produce an empty expression. While this behaviour still results in a correct (unchanged) state, it is not a desirable behaviour for a real dialogue system.

In our conversion, such cases are converted into domain relevant \texttt{get-info} expressions (which will then produce an answer with the requested information), when the dialogue act indicates information requests by the user. In addition, our implementation takes care of prompting the user for input and keeping the conversation "alive", rather than passively waiting for the user's next input.

5. Agent oracle
Developing a dialogue system, like any other software development, is a process of iterative improvements: the system is tested on real data, problems are identified, solutions are implemented, followed by more tests, etc.

Due to the context dependent nature of dialogues, a different response from a new version of the system in one turn may cause the rest of the dialogue to follow a different path. This is not a problem if the system interacts with live users, but during the development phase, repeatedly collecting large sets of human-machine interactions for successive iterations of the system is not practical.

Instead, the collection of user interactions is done once, using either a fixed implementation for the system (agent) part, or a WOZ set-up where another human plays the agent.
Therefore, developers face a problem: how to use a fixed dialogue to test a changing system? More specifically, the problem is how to use the fixed part of the human user (since the agent part can be re-generated). The problem is more severe when the dialogue system introduces some non-deterministic behaviour. For example, when several pieces of information are missing, a fully deterministic system may ask for the information pieces one by one in a fixed order, while a non-fully-deterministic system may ask for the information in random order, either one piece at a time or several together (and use different wordings), or even proactively suggest or recommend some values. The WOZ set-up, where the agent is played by a human, exacerbates the problem further.

5.1. Agent oracle

In our implementation we handle this problem by allowing an agent oracle to influence the system behaviour. Conceptually, the human agent is considered as a non-deterministic system. In the implementation of the agent, we separate the non-deterministic part (the decision what actions to take) from the deterministic part (the execution of the decision). Using this separation, we can run the system in different modes during training (where the given agent annotations act as an oracle influencing the decision) and inference (where a rule based decision can be made).

The system can be switched between one of three ‘agent oracle’ modes:

1. **Oracle off**: no oracle is present - the agent behaviour and output are generated by executing the programmed logic of the dialogue, this is the typical mode used when running the final system on unseen dialogues;

2. **Full Oracle**: an agent’s (human) behaviour and response is available - output the agent’s response as is. This is equivalent to the approach taken by (Semantic Machines et al., 2020);

3. **Partial Oracle**: an agent’s behaviour and response are available - use the agent’s behaviour (specifically, the agent’s dialogue acts) to guide the programmed logic, and generate the output programmatically.

The partial oracle mode may also be used to standardize the dialogues (by replacing the human agent’s language by the response programmatically generated by the programmed logic), and thus make the seq2seq translation model’s work easier. We plan to explore this further in the future.

Using the oracle makes it possible to have “live” interactions with the dialogue system - the dialogues are actually executed by the system, generating DF graphs corresponding to the actual dialogue path. In other words, this means the annotation of MultiWOZ can be extended by complete execution graphs, which could be used for learning and evaluating various models. Although the oracle’s policy (action selected given a specific state) may not always match the policy of the implemented system, the graphs are (hopefully) similar enough to allow the learning of useful inference models.

6. Conversion alternatives

We have experimented with two annotation schemes for the DF expressions representing MultiWOZ turns.

6.1. Full expressions

This style of DF expressions is closer to the original SM annotations, making direct use of the “raw” revise() function, which requires the explicit inclusion of “formal” parameters (such as empty type constraints).

6.2. Simplified expressions

Similar to the work in (Meron, 2022), we also implemented a simplified version of the annotation, where the expressions use a modified version of the revise() function, resulting in shorter, more natural looking expressions, which are closer to the surface natural language request. The simplified expressions were originally introduced to both improve understandability (less relevant in this context) and help the natural language to DF expression translation model.

6.3. Expression scope

As mentioned previously, our focus was to make a functional DF dialogue system which can demonstrate how this paradigm works, while using a well known domain. While the goal of SM’s experiment was to maximize the match with the annotated state match, our implementation tried to include some additional aspects. For example, when the user asks for information, and the answer does not change the state (e.g. after a restaurant was chosen, the user asks: “Is it expensive?”) the SM conversion would produce an empty expression. In our conversion, we actually want the system to respond to the answer with a question, so this will be converted to “get_restaurent_info(pricerange)”.

On top of the full and simplified expression alternatives, a flag - omit_get_info - can be used to omit these get_info expressions from the conversion.

7. Metrics

In this section we describe the metrics used in our experiments. Figure[1] gives an overview of the way these metrics are used.

7.1. Translation match

This metric compares the translation of the users’ natural language requests to DF expressions. In SM’s paper, the exact match metric is used.
Figure 1: Overview of comparisons and metrics used in our experiments. Blue arrows indicate exact match, green arrows indicate lenient match.

### 7.2. State match
This metric compares the dialogue state annotations of MultiWOZ 2.2, at each dialogue turn, to a dialogue state collected from the execution graphs for the same turn.

The collection of the state from the graph is done in the following way:

- For complete tasks, we take the complete information - e.g., if a specific hotel was agreed on, all of that hotel’s information (which were retrieved from the database and used to instantiate a full hotel sub graph) are added to the collected state.
- For incomplete tasks, we take the currently existing fields for the corresponding constraint - e.g., if the user requested a hotel in a price range, but a specific hotel was not selected yet, the collected state will only include the price range field.

Our DF conversion is based on the dialogue act annotations of MultiWOZ 2.2. During dialogue execution, we perform a comparison of MultiWOZ’s manual dialogue state annotation with the dialogue state collected from the execution graph (as described above). This means that we execute the dialogue acts, but compare the result to the dialogue state, which is bound to cause mismatch when the two separate manual annotations do not agree.

In our current version, for the test set, about 45% of the dialogues have one or more state mismatch, and almost 15% of turns have a state mismatch. Taking a small set of dialogues with state mismatch (randomly selected 25 mismatching dialogues from the development set), we carried out a manual analysis of the cause of the mismatch. The result showed that all of these cases are the result of human annotation errors. Note that when comparing the manually annotated state (MS) to the graph state (GS), a more lenient state matching is used than when comparing MS to MS. This is due to practical reasons.

The GS has a set of fields, and for each one (assuming it exists) there can be only one value, while for each MS field there can be a list of values. During comparison we check the following: 1. The set of GS fields is a superset of the set MS fields. 2. For MS field, at least one of the values is in the corresponding GS field.

The motivation for this were the many cases where the state is ambiguous (and the annotation is arbitrary) - the agent made a suggestion, but it’s not clear if the suggestion should be considered as accepted by the user (MultiWOZ, unlike SMCalFlow, does not include explicit annotation for accept/reject suggestions). Further work is needed to address this issue in more detail.

### 8. Experiments
The implemented MultiWOZ-DF was in the following experiments (as shown in figure 1):

#### 8.1. Translation accuracy
The users’ natural language requests were translated to DF expressions using the same seq2seq translation pipeline used by [Semantic Machines et al., 2020]. The translation accuracy results are shown in table 1. The table confirms that simplified annotations are simpler for the seq2seq translation model to learn, despite the fact that they have identical semantics. It also confirms that omitting the added get_info expressions further increases translation accuracy.

| Conversion            | Turn level exact match |
|-----------------------|------------------------|
| Original              | 71.8%                  |
| Simplified            | 73.5%                  |
| Original omit         | 76.5%                  |
| Simplified omit       | 78.3%                  |

#### 8.2. State match
Table 2 shows the match result between the manual dialogue state annotation and the execution results of the different conversion alternatives.

| Conversion            | Dialogue | Turn   |
|-----------------------|----------|--------|
| Original, Converted   | 55.8%    | 87.2%  |
| Simplified, Converted | 56.1%    | 87.8%  |
| Original, Translated  | 40.9%    | 77.9%  |
| Simplified, Translated| 42.7%    | 82.1%  |

Table 1: Turn exact match, on test set. (not averaged over several runs)

Table 2: State match, full-dialogue level as well as turn level, on the test set.
Table 3: Graph state match, comparing converted vs. translated execution graphs, full-dialogue level as well as turn level, on the test set.

|                | Dialogue | Turn |
|----------------|----------|------|
| Original       | 47.9%    | 72.2%|
| Simplified     | 54.3%    | 76.0%|

exact match (as opposed to the more lenient comparison in table 2).

9. Further Work

This work explored the application of the DF paradigm to MultiWOZ. MultiWOZ has an intent-and-entities type of annotation, which is a flat (non-hierarchical) annotation. DF expressions are inherently hierarchical, capable to easily accommodate richer annotations, as exemplified in SMCalFlow.

Still, even for flat annotations datasets, DF may offer benefits. On one hand, it could lead to improvement in learning related aspects of the system (e.g. reducing the need for learning capacity through the use of the refer() and revise() functions). On the other hand, DF has a potential to simplify the practical aspects of dialogue system design, with its different approach to dialogue flow design (e.g. as compared to systems based on a state-machine dialogue management).

10. Conclusion

In this work we presented MultiWOZ-DF, a dataflow implementation of the widely used MultiWOZ dataset. We also showed several alternative strategies for converting the MultiWOZ dataset to a dataflow dataset, and the effect this can have on translation and execution accuracy.

The code to reproduce this work has been publicly released at https://github.com/telepathylabsai/OpenDF.

Previous experiments on a dataflow version of MultiWOZ were reported in (Semantic Machines et al., 2020), but since that system is not publicly available, follow-up work has been limited.

While direct quantitative comparison of that work’s result to our is difficult due to different design decisions taken, our main goal was to allow researchers to get hands-on experience with a functioning dataflow dialogue system using a familiar dataset, and to encourage further work in this direction.

11. Bibliographical References

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A. Examples of Dataflow expressions

Table 4 shows some examples of user requests translated to different alternatives of DF expressions: the SM version, our original version (non-simplified), and our simplified version.

B. Example dialogue

Figure 2 shows the execution of a short dialogue, and table 5 shows the user requests, their translation to DF expressions (for the simplified version), and the agent responses for the same dialogue. For the agent response, the table shows both the original agent text ("full oracle"), and the response generated programmatically by the implemented DF nodes.
I am looking for a particular restaurant called city stop restaurant.

Yes, I would. Please reserve a table for 4 at 17:30 on Thursday.

OK, city stop restaurant, serves european food, in the north, expensive price range, is a restaurant, and is located at Cambridge City Football Club Milton Road Chesterton.

In the north, The price is expensive
| Turn | source   | text                                                                 |
|------|----------|----------------------------------------------------------------------|
| 1    | user     | I am looking for a particular restaurant called city stop restaurant. |
| 1    | DF-expression | revise_restaurant(name=city stop restaurant)                          |
| 1    | full oracle | It is an expensive european restaurant in the north part of town.   |
|      |           | Would you like to make a booking?                                   |
| 1    | partial oracle | OK, city stop restaurant, serves european food, in the north, expensive price range, ... |
|      |           | On which day would you like to book the restaurant?                 |
| 2    | user     | Yes, I would. Please reserve a table for 4 at 17:30 on Thursday.    |
|      |           | I would like the reference number as well, please.                 |
| 2    | DF-expression | revise_restaurant(bookday=thursday, bookpeople=4, booktime=17:30)  |
| 2    | full oracle | Alright, I’ve booked a table for 4 at 17:30 on Thursday. Your reference number is VLG5U01Z. |
| 2    | partial oracle | I have made the reservation as requested. The confirmation code is VLG5U01Z. |
|      |           | Is there anything else I can do for you?                           |
| 3    | user     | Thanks, that’s all I need. Have a nice day.                        |
| 3    | DF-expression | General_bye()                                                      |
| 3    | full oracle | You too, enjoy your meal!                                          |
| 3    | partial oracle | Thank you! Goodbye!                                                |

Table 5: User requests, DF expressions, and agent responses (full oracle and partial oracle) for the turns of the short dialogue SNG0551.