Abstract

High-quality datasets for task-oriented dialog are crucial for the development of virtual assistants. Yet three of the most relevant largescale dialog datasets suffer from one common flaw: the dialog state update can be tracked, to a great extent, by a model that only considers the current user utterance, ignoring the dialog history. In this work, we outline a taxonomy of conversational and contextual effects, which we use to examine MULTIWOZ, SGD and SMCALFLOW, among the most recent and widely used task-oriented dialog datasets. We analyze the datasets in a model-independent fashion and corroborate these findings experimentally using a strong text-to-text baseline (T5). We find that less than 4% of MULTIWOZ’s turns and 10% of SGD’s turns are conversational, while SMCALFLOW is not conversational at all in its current release: its dialog state tracking task can be reduced to single-exchange semantic parsing. We conclude by outlining desiderata for truly conversational dialog datasets.

1 Introduction

Virtual assistants such as Alexa, Cortana, Google Assistant and Siri help users carry out all sorts of tasks, ranging from checking the weather and setting alarms to online shopping. While the development of these agents is a soaring area of research, known as task-oriented dialog, their usage lacks in naturalness, interactivity and in the possibility of accomplishing complex goals requiring rich multi-turn conversation and strong tracking abilities.

Indeed, in a task-oriented dialog, agents are not only required to carry out tasks specified using single natural language utterances, but they should also be able to interactively combine specifications given over multiple turns (conversationality), handling various dialog phenomena such as long and short range references, revisions and error-recovery, while robust to linguistic variations. Beyond the present dialog’s history, agents might need to take into account information from an earlier conversation, or even external information that is not explicitly mentioned in the conversation, but should be derived from context (contextuality) with varying degrees of ambiguity.

At the crux of these challenges lies the Dialog State Tracking (DST) task. It consists of estimating the dialog state (also known as “belief state”) at a given turn of the dialog. The DST task raises important questions related to the dialog state’s representation and the modeling of a conversation’s history and context. To research and answer these questions, however, we need richly conversational and contextual task-oriented datasets that exhibit these challenges. New dialog datasets covering more domains, containing longer dialogs and utterances as well as with richer dialog state representations have been released recently. But do these metrics translate to more conversational and contextual dialogs?

We focus on the two most-cited task-oriented dialog datasets to date (MULTIWOZ and SGD), as well as on SMCALFLOW for its novel approach of representing dialog state as a graph. While varying in terms of data collection methodology, dataset scale and dialog state representation, our findings show that all three datasets lack in conversationality and contextuality. The contribution of this paper are therefore:

• We outline a taxonomy of contextuality / conversationality for dialog datasets (Section 3).
• We analyze three of the most recent large, multi-domain, task-oriented dialog datasets, (MULTIWOZ, SGD and SMCALFLOW) (Section 2) in light of this taxonomy in a model-independent fashion (Section 4).
• We corroborate the model-independent analysis’ findings experimentally using T5 (Raffel et al., 2019) (Section 5).
• We show that under 4% of MULTIWOZ’s
turns are conversational. SGD is more conversational (ca. 10%), but this is due to annotation policy rather than dialog richness. SM-CALFLOW is non-conversational in its current setup and dataset release, and is akin to a single-exchange non-conversational semantic parsing dataset than to a dialog dataset.

2 Related Work & Datasets

MULTIWOZ Collected through a Wizard-of-Oz process (Kelley, 1984), MULTIWOZ (Budzianowski et al., 2018) was a breakthrough dataset for task-oriented dialog research. At about an order of magnitude larger than the task-oriented dialog datasets available thus far and featuring 7 task domains as well as over 7k multi-domain dialogs (Table 1), MULTIWOZ became a standard benchmark for various dialog tasks including DST.

SGD (Schema Guided Dataset) (Rastogi et al., 2020) features a much larger number of domains than MULTIWOZ and several different services (or schemas) for a given domain by using a dialog simulator to generate templates of dialogs including dialog state and asking crowdworkers to formulate these structures into natural language. It is the most cited task-oriented dialog dataset after MULTIWOZ to date.

SMCALFLOW (Andreas et al., 2020) provides a richer representation of the dialog state than the semantic frames (a structured intent-slot-value list) employed in MULTIWOZ and SGD: it is a dataflow graph, equivalently expressed as a program in Lispress (a programming language proposed by the datasets’ authors) which fulfills the user’s request. The graph representation can potentially create opportunities to capture richer and more complex dependencies throughout the dialog, and in turn provide more extensive context modeling explorations. Its dialog states also feature explicit functions for references and revisions.

Context Modeling for Dialog The research into dialog history modeling is much more extensive for open-domain dialog than task-oriented dialog (Tian et al., 2017). In the former, dialog history representation has been explored by, e.g., representing the entire dialog history as a linear sequence of tokens (Sordoni et al., 2015), using a fixed-size window to represent only the recent dialog history (Li et al., 2016), designing hierarchical representations (Serban et al., 2016; Xing et al., 2018; Shen et al., 2019; Zhang et al., 2019), leveraging structured attention (Qiu et al., 2020; Su et al., 2019) as well as summarizing (Xu et al., 2021) or re-writing (Xu et al., 2020) dialog history to handle long dialogs.

The literature around dialog history modeling for task-oriented dialog on the other hand is sparser: many DST models are supplied only with the last exchange utterances, i.e., the last agent and the current user utterance (Rastogi et al., 2020; Andreas et al., 2020), some even with just the current user utterance (Platanios et al., 2021). Cross-domain transfer (Wu et al., 2019), slot-correlations (Ye et al., 2021b), pre-training (Zhao et al., 2021) are topics that have been explored for DST modeling. In this paper, we focus however on the datasets and investigate their conversationality/contextuality.

3 A Taxonomy of Dialog: Conversationality & Contextuality

We define a dialog as a succession of written natural language utterances in which a user (i.e., a human with one or multiple intended goals) and an agent (i.e., an automated system tasked with fulfilling these goals) take turns contributing to the dialog. Each participation is therefore called a turn, and we define a pair made up of an agent turn and its consecutive user turn as one exchange.

Conversationality We define a given turn in a dialog as conversational in the DST task if the dialog history (i.e., the turns prior to the current exchange) is required for correctly tracking the current turn’s dialog state. In other words, in a truly conversational dialog, utterances cannot be parsed in isolation, because their meaning is highly dependent on what was said in previous turns. We
quantify this property using the conversational distance $\delta_c$, which measures the number of turns a system has to look back into the dialog history to accurately predict a given turn’s dialog state update. Slots whose values are found in the current user turn (i.e., the turn immediately preceding the dialog state, such as the [train-arriveby] slot in Figure 1) are defined as non-conversational, as they have a conversational distance $\delta_c = 0$. We also consider slots whose values are found in the last agent turn (i.e., at a conversational distance of $\delta_c = 1$) as non-conversational. Indeed, they too belong to the current exchange; as such, their value is only represented in the previous agent utterance, but not yet recorded in the dialog state at this stage of the conversation. By contrast, slots such as [train-day] in Figure 1 with $\delta_c = 4$ are regarded as conversational. Finally, a turn has a $\delta_c$ equal to the maximum $\delta_c$ of all slot-values in its dialog state update. A robust DST system should support such conversational effects for both short and long ranges, as well as revisions and ambiguities in references. In the extreme case, DST could even depend on information provided in past conversations, as is the case for Multi-Session Chat open-domain dialog dataset (Xu et al., 2021).

**Contextuality** We define a given turn in a dialog as contextual in the DST task if the dialog state at a given turn is dependent not only on the dialog history, but also on elements beyond the conversation itself, that are not explicitly mentioned in the conversation. These elements could be:

1. **Situational**: the slot value in the dialog state depends on the circumstances of the dialog, e.g., its date or location, that are not explicitly mentioned. For example, in the utterance: [USER: “Hey, I feel like listening to some tunes right now. Can you find me something from two years ago?”], the dialog state tracker must recognize that the current year is 2022 in order to track the state [year = “2020”].

2. **Knowledge about the user**: the dialog state depends on some knowledge about the user (e.g., dietary restrictions or movie preferences).

3. **External knowledge**: the slot value in the dialog state depends on some world knowledge and requires, e.g., a query from an external database. In the dialog in Figure 1, for example, the dialog state tracker must deduce [train_destination = “cambridge”] by understanding that “there” refers to “University Arms Hotel”, then querying some external database to get the train stop corresponding to this location. Note that the value “cambridge” is never mentioned explicitly in the dialog.

**Dialog state value normalization** In addition to conversationality and contextuality, a robust DST system must be robust to linguistic variations, meaning it should recognize semantically equivalent expressions and convert them into a normalized form. Examples of such normalization include: (i) Typos (e.g., “18:15” → [time =
In terms of **conversational**ity, over 85% of MultiWOZ’s turns and over 80% of SGD’s turns have either (i) an empty dialog state update (i.e., nothing to predict) or (ii) a dialog state update that can be predicted by considering only the current user turn (i.e., $c_\ell = 0$). If we further include the last agent turn (i.e., $c_\ell = 1$), over 96% of MultiWOZ’s turns and over 90% of SGD’s turns can be predicted correctly without using the latest dialog state and/or its corresponding information, and are therefore **non-conversational**. This leaves only under 4% (MultiWOZ) and 10% (SGD) of turns with a conversational distance above $c_\delta \geq 2$, which require looking at a conversational window beyond the most recent exchange for their dialog state to be tracked correctly. MultiWOZ is therefore much less conversational than SGD.

However, even for SGD, information beyond the latest exchange is irrelevant to the dialog state update most of the time. This lack of conversationality can be attributed, at least in part, to the dataset’s design: in the data collection procedure, crowd-workers are asked to paraphrase dialog structures, as generated by a dialog simulator, into natural language by writing out the current slot values verbatim, and without resorting, for example, to shorthand references (such as “that”, “the first one”). One might have thought that this strategy would entirely eliminate the reference issue, and render the dataset non-conversational, but that is not the case. To understand why, let us look at the distribution of conversational distances in MultiWOZ and SGD’s conversational slices.

Figure 3 shows the distribution of turns’ conversational distances in the conversational slices for the two datasets. The maximum $c_\delta$ in MultiWOZ is of 17, while SGD reaches further, with $c_\delta$ of more than 24. The majority of MultiWOZ’s references are approximately evenly distributed at distances between 3 and 5, whereas SGD features a peak at $c_\delta = 3$. This is due to a frequent dialog structure in SGD that explains its conversationality and can be summarized as follows: (i) at $c_\delta = 3$, the agent asks for a confirmation before booking (this utterance contains information relevant to the dialog state, but the dialog state is not updated); (ii) at $c_\delta = 2$, the user asks a clarification question; (iii) at $c_\delta = 1$ the agent answers, (iv) then the dialog state is updated at $c_\delta = 0$, upon user confirmation, with values that were stated by the agent at $c_\delta = 3$. This patterns follows from a dataset

**MultiWOZ & SGD** With the taxonomy of conversational and contextual effects at hand (Section 3), we analyze each turn of the MultiWOZ version 2.4 (Ye et al., 2021a) (dev. and test sets) and SGD (test set) dialogs semi-automatically. The results are summarized in Table 2.

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1Refer to Table 5 in the Appendix for a more detailed list and additional examples.

2Our analysis on a sample of training data shows similar characteristics in training sets.

3The pseudocode can be found in Figure 4 of the Appendix. We plan to open-source the associated scripts.

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Table 2: Model independent analysis: % of turns in the MultiWOZ and SGD datasets that feature effects from the taxonomy defined in Section 3. The percentages of normalization effects add up to >100% since there are turns that feature multiple different normalization effects.

| Normalization       | MultiWOZ TEST | MultiWOZ DEV | SGD TEST | SGD DEV |
|---------------------|---------------|--------------|---------|---------|
| **Conversational**  |               |              |         |         |
| nothing to predict  | 32.63         | 31.15        | 45.66   |         |
| $+\delta_\ell = 0$  | 85.75         | 85.83        | 80.91   |         |
| $+\delta_\ell = 1$  | 96.48         | 96.26        | 90.42   |         |
| $\delta_\ell \geq 2$| 3.52          | 3.64         | 9.58    |         |
| **Contextuality**   |               |              |         |         |
| non-contextual      | 99.96         | 99.96        | 100     |         |
| situational         | 0.01          | 0.03         | 0       |         |
| knowledge about the user | 0.03  | 0.01 | 0 | |
| **Normalization**   |               |              |         |         |
| verbatim            | 87.30         | 87.40        | 93.92   |         |
| typos               | 2.14          | 2.52         | 0       |         |
| semantic understanding | 5.12     | 4.95         | 6.49    |         |
| computation         | 0.08          | 0.05         | 0.11    |         |
| other               | 5.86          | 5.64         | 3.72    |         |

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(198:15’’), (ii) **Entity Recognition** (e.g., “thirty bucks” $\rightarrow$ [price = “$30”]) (iii) **Semantic Understanding** (e.g., “on a budget” $\rightarrow$ [price_range = “inexpensive”]), and (iv) **Computation** (“from tuesday through thursday” $\rightarrow$ [book_stay = “2”])

These effects can also occur in combination with one another.

Some of these linguistic variations could be handled using components developed independently, e.g. auto-corrects or entity linkers, and incorporated into dialog systems. Still, the challenge of how to recognize these values as semantically equivalent and how to normalize them accurately must be addressed by robust agents and must therefore be represented in research datasets.

4 Model-independent Analysis

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We plan to open-source the associated scripts.
design decision, where the dialog state is updated only following an INFORM, SELECT, AFFIRM or NEGATE intent by the user. In contrast, in MULTIWoz, if a slot value is mentioned by the agent, and is not confirmed nor rejected by the user, the dialog state is nevertheless updated immediately.4 Hence the conversationality of a dataset results not only from the richness of its dialogs and natural language utterances, but to a large extent from the annotation policy chosen.

In terms of value normalization (Table 2), an overwhelming majority of slot values can be found verbatim in the dataset (87.30% for MULTIWoz, 93.92% for SGD), limiting the possibility of evaluating DST systems’ robustness to linguistic variations. The semantic understanding slice, which is at the core of semantic parsing (be it conversational or non-conversational), is of 5.12% and 6.49% respectively. Arguably the most challenging of these effects, namely turns requiring computation, are negligible (ca. 0.1%). For MULTIWoz, the proportion of non-verbatim turns (12.70%) is much larger than the proportion of conversational turns (3.52%), indicating that value normalization effects are more predominant than conversational and contextual effects in this benchmark. This suggests that MULTIWoz measures a model’s robustness to lexical variation more than it measure a model’s conversational capacities.

SMCAlFlow Contrary to MULTIWoz and SGD, the dialog state of SMCAlFlow does not take the form of a semantic frame (a structured intent-slot-value list). Instead, an exchange between user and agent is conceptualized as follows: (i) the user formulates an utterance in natural language, (ii) the system predicts a Lispress program which, when executed, will fulfill the user’s request and is formally a dataflow graph representing a shared belief of the state of the dialog, (iii) the program is evaluated, and the results are added as nodes extending the dataflow graph, and (iv) the agent’s natural-language response is generated.

The graph/program formalism provides opportunities to capture complex tasks, including modeling of compositionality across domains, intents and/or arguments as well as conversational phenomena such as reference and revisions with non-trivial dependencies. Indeed, the dialogs are quite conversational: the percentage of turns featuring a reference is 29.19% (Lispress program with call to function refer()) and the percentage of turns featuring a revision (Lispress program with revise()) is 8.77%. However, the API of these functions do not contain the resolved referents but only an optional constraint on the type, property or role of the referred-to object. The DST task, as conceptualized in SMCAlFlow, does not entail reference or revision resolution. Rather these must be obtained through a separately-trained saliency model. This formalism is unobjectionable in and of itself, but

4See dialog PMUL3897, turn 8, in MULTIWoz, for example, where the user asks for more information before booking.

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**Figure 3:** Distribution of the conversational distances $\delta_c$ of turns from MULTIWoz and SGD’s test set. For scale, we represent only the turns with $\delta_c \geq 2$.

Lastly, it is noteworthy that while the value of a slot can be changed from one exchange to the next (e.g. [area = “center”] at turn $T$ − 2 and [area = “north”] at turn $T$), it is only very rarely dropped or changed to “dontcare”. In fact, this happens in $2.08\%$ of turns for MULTIWoz and $0.27\%$ of turns for SGD. In other words, constraints expressed in the dialog state are sometimes changed, but a constraint is almost never relaxed, which is why a DST system trained on these datasets cannot learn when to remove slot-values from the dialog state, only when to add.

In terms of contextuality. Table 2 showcases that the overwhelming majority of both datasets turns (99.96% for MULTIWoz, 100% for SGD) are non-contextual, in that the dialog state of these datasets can be estimated by and large only by looking at the dialogs themselves, without taking circumstances, knowledge about the user or world knowledge into account. In that respect, they fall short of conversing in the way humans do: assuming knowledge about the world, themselves, and the circumstances of the conversation.
because the evaluated programs (step (iii) described above) are missing from the public release, the data that would be needed to train such a saliency model is not available to the research community. In a nutshell, the DST task simply requires to predict the correct \texttt{refer}() or \texttt{revise}() call, without resolving it, and the task therefore renders to non-conversational semantic parsing.

Similarly, while SMCalFlow has the potential to provide rich contextuality, particularly in user context with calendar entries and contacts, the unavailability of this knowledge base in its public release renders the data non-contextual for researchers at large.

## 5 T5 Experiments

| Input representation          | Linearization |
|-------------------------------|---------------|
| current user turn             | $U_T$         |
| + last agent turn             | $A_{T-1}$     |
| + previous dialog state       | $S_{T-2}$     |
| full dialog history           | $U_0, A_1, \ldots, A_{T-1}$ |

Table 3: Linearizations of the dialog for a given user turn $T$ and different input representations exhibiting more or less conversational context. In the table, $U_T$, $A_T$ and $S_T$ stand respectively for user utterance, agent utterance and linearized state at turn $T$.

In this section, we run experiments with a strong text-to-text baseline, T5 (Raffel et al., 2019), to investigate how and to what extent the findings from the model-independent analysis (Section 4) are reflected in T5 models.

### 5.1 Method

Traditionally, in DST for task-oriented dialog, intent prediction has been framed as a classification task and slot-value prediction as a span labelling task (Rastogi et al., 2020; Chen et al., 2020). However, recent works have explored DST in the seq2seq setting (Wen et al., 2018; Gao et al., 2019; Feng et al., 2021). We follow this formalization as it is flexible enough to generalize to multi-intent and multi-domain utterances, as well as to dialog state representations more complex than intent-slot-value triplets, such as Lispress programs.

The results obtained from the T5 model are shown in Table 4. Non-oracle JGA results are given for multiWOZ and SMCalFlow, except we use the same tags as the dataset authors (“\_User”, \_Agent and \_State”) for a fair comparison.

### Evaluation metrics

For MultiWOZ and SGD, we report Joint Goal Accuracy (JGA), using the TRADE (Wu et al., 2019) evaluation script\(^7\) and the DSTC8 evaluation script\(^8\), respectively. We report both oracle (i.e., the predicted state update is added to the gold previous state) and non-oracle (i.e., the predicted dialog state update at turn $T$ is added to the predicted state at turn $T - 1$) results. For SMCalFlow, we use the evaluation script published by the datasets’ authors\(^9\) and report exact-match accuracy. SMCalFlow’s test split has not been made public, which is why we train on the training split and evaluate on the validation split.

### 5.2 Results

The results obtained from the T5 model are shown in Table 4. Non-oracle JGA results are given for

\(^7\)https://github.com/jasonwu0731/trade-dst
\(^8\)https://github.com/google-research/google-research/tree/master/schema_guided_dst
\(^9\)https://github.com/microsoft/task_oriented_dialogue_as_dataflow_synthesis

\(^1\)Refer to Table 6 in the Appendix for additional details on the experimental setup.
MULTIWOZ and SGD to allow for comparison (merely for the sake of reference) with previous state-of-the-art results on these datasets. While non-oracle JGA is more true to the actual performance of a DST system, it has the disadvantage of introducing numerous accumulation errors which make it difficult to isolate the reason for a model’s failing. Since our objective is not to evaluate the performance of a given DST system against previous approaches, but rather to evaluate the conversationality of widely-used DST benchmarks, we use oracle JGA for the purposes of our work. It allows us to zero in on the turn a system didn’t track right, preserving just the original error and eliminating propagation effects.

The results in Table 4 experimentally confirm the conclusions drawn from the model-independent analysis: namely that these datasets can be solved, to a large extent, by showing the model only the current user utterance: we obtain over 63% accuracy in SGD and over 70% in MULTIWOZ and SM-CalFlow by feeding the model only with the current user utterance and no further context or dialog history at all. Moreover, the percentage point improvements brought by each wider conversational window are in line with the model-independent analysis: for MULTIWOZ, results are consistently around 10% below the proportion found to be solvable at this $\delta_c$ for each conversational window. For SGD, results are consistently around 20% below the proportion found to be solvable at this $\delta_c$. The lower accuracy on SGD is unsurprising since SGD is a harder benchmark than MULTIWOZ due to its more extensive ontologies, numerous services and existence of multiple services per domain.

MULTIWOZ Overall, the T5 model for MULTIWOZ does benefit from being trained on dialog history beyond just the last user turn. However, most of the percentage point improvement comes from adding the last agent utterance (+$8.52 \text{ pp}$), while including the previous dialog state or the full dialog history bring much more modest improvements of +$3.42$ or +$4.21 \text{ pp}$. This is consistent with the findings from the model independent analysis, which showed that many more turns require slot values to be retrieved from $\delta_c = 1$ (10.73%) than from $\delta_c \geq 2$ (3.52%).

From the +$8.52 \text{ pp}$ improvement brought by adding the last agent utterance, the majority (74%) of turns are indeed turns of $\delta_c = 1$, where one of the slot values, names or domains is stated by the agent. The remainder is mostly cases involving the [hotel-type], [leaveat] or [arriveby] slots: “hotel” is both a domain and a candidate value of the [hotel-type] slot, leading to confusions; [leaveat] or [arriveby] slots should only be updated updated when they refer to a requested time, not a concrete timetable reading, which is sometimes unclear from the current user utterance alone. The improvements brought from including the previous dialog state or the full dialog history are due to information at $\delta_c \geq 2$ to a slightly lesser extent: $48\%$ and $68\%$, respectively. The leftover errors are most often a missing [name] slot of an attraction, restaurant or hotel.

SGD For SGD, providing the model with the last agent utterance similarly improves JGA by +$6.69 \text{ pp}$, and providing the previous dialog state in addition improves by +$3.17 \text{ pp}$. However, training a model with the full dialog history improves over the last-exchange baseline by a much larger +$8.18 \text{ pp}$. This can be explained by the fact that SGD’s conversational slice is a lot larger than MULTIWOZ’s (9.58% vs. 3.52%, see Table 2) and by the fact that in SGD’s conversational slice, most slots are found at $\delta_c = 3$ (see Figure 3), the values of which can only be retrieved by the full dialog

| Input representation | MULTIWOZ | SGD | SM-CalFlow |
|-----------------------|----------|-----|------------|
| current user turn     | 77.19    | 63.20 | 71.53     |
| + last agent turn     | 85.71    | 69.89 | 78.50     |
| + previous d. state   | 89.13    | 73.06 | 79.13     |
| full dialog history   | 89.92    | 78.07 | 79.10     |
| JGA                   |          |      |            |
| current user turn     | 43.00    | 22.96 |           |
| + last agent turn     | 59.43    | 28.66 |           |
| + previous d. state   | 66.16    | 35.25 |           |
| full dialog history   | 68.91    | 43.65 |           |

Table 4: Dialog State Tracking (DST) results in a seq2seq setup with T5 in % with different input representations (see Table 3). We report Joint Goal Accuracy (JGA, oracle and non-oracle), on MULTIWOZ’s and SGD’s test set, and exact-match accuracy (Ex. M.) on SM-CalFlow’s validation set (unseen during training). Each score corresponds to a single run. For reference, state-of-the-art results on MULTIWOZ (Ye et al., 2021b,a), SGD (Ruan et al., 2020) and SM-CalFlow (Platanios et al., 2021) are shown.

\text{Input representation} | \text{ORACLE JGA} | \text{EX. M.} |
|-----------------------------|------------------|--------------|
| current user turn           | 73.62            | 73.75        |
| + last agent turn           | 89.13            | 89.13        |
| + previous d. state         | 73.06            | 73.06        |
| full dialog history         | 82.00            | 82.00        |
history model, not by the previous-state model.

Similarly to MultiWOZ, not all improvements brought by wider conversational windows are due to conversationality. In fact, 48%, 57% and 61% of the improved-upon turns in the last agent, previous dialog state and full history, respectively, are due to the surfacing of information of corresponding $\delta_c$. The most prominent other source of errors is slot name confusion, whereby a slot value is predicted correctly, but there is a confusion between two schemas, e.g. $[\text{city} = \text{“danville”}]$ vs. $[\text{location} = \text{“danville”}]$.

**SMCalFlow** Similarly to SGD, the “current user turn” baseline has a very high accuracy (71.53%). While this baseline is significantly improved upon by showing the model the last agent utterance (78.50%, i.e. +6.97 pp), adding the previous dialog state (79.13%, i.e. +0.63 pp) or the full dialog history (79.10%, i.e. +0.60 pp) bring only marginal improvements. The T5 experiments therefore confirm the finding from the model-independent analysis, namely that since reference and revision mechanisms must simply be predicted by an API call at DST time and not actually resolved, the DST task as formalized in this dataset is inherently non-conversational and can be reduced to a semantic parsing task.

This lack of conversationality is implicitly given away in the dataset paper (Andreas et al., 2020): there, the authors explore contexts of conversational distance $\delta_c = 0, 1$ and 2, then use a context window of 1 because it gives them the best results. In their follow-up paper (Platanios et al., 2021) however, the authors completely ignore dialog history and train using the last user turn exclusively, and in doing so, they obtain a better per-turn exact match accuracy of 80.4%. In both cases, they do not use any contextual information. The fact that they obtain such a high accuracy without any conversational modeling improvements, by only showing the model the latest user turn implies that the dataset is not conversational nor contextual.

Furthermore, error analysis reveals the presence of a questionable type of error: our model predicts the program entirely correctly for certain turns, which are nevertheless evaluated to an accuracy of 0 by the authors’ evaluation script. These turns are marked in the dataset as refer _are_in correct, and because of that, they are scored with an accuracy as 0, no matter the accuracy of the predicted program. Hence, that the program prediction task cannot be solved entirely on this dataset using the setting proposed by its authors.

6 Conclusion

In this work, we outlined a taxonomy of conversational, contextual and linguistic normalization effects that a robust dialog state tracking system should support. We evaluated three recent large-scale task-oriented dialog datasets (MultiWOZ, SGD, SMCalFlow) against this taxonomy in a model-independent fashion and found that both MultiWOZ and SGD exhibit a low rate of conversational turns (under 4% and 10%, respectively). The majority of SGD’s conversational turns have a conversational distance $\delta_c = 3$. We showed this is due to SGD’s annotation policy rather than to the inherent richness of its dialogs. Though SMCalFlow prominently features conversational effects such as references (29.19%) and revisions (8.77%), its conversational effects are abstracted away from the DST task and the dataset’s public release does not feature all the elements needed (i.e. evaluated programs or an execution module for Lispress) for the wider community to investigate the modeling of said references and revisions. SMCalFlow’s DST task is therefore non-conversational in its current setup and release, and can be reduced to a single-exchange non-conversational semantic parsing task. Finally, we corroborated these findings experimentally with a strong text-to-text baseline.

We limited the scope of this work to three datasets, but for completeness, more datasets (in particular non-english, multi-modal and spoken datasets) should be studied. Moreover, we focused on the DST task while a complete study of dialog would have to examine the conversationality and contextuality of the response generation task as well, for instance.

To advance the state-of-the-art in task-oriented dialog research, dataset design and collection procedures may increase focus on (i) references that are ambiguous (e.g., that could refer to multiple different entities previously mentioned in the conversation) and with a variety of reference ranges; (ii) slot values / program arguments and functions to be predicted that are not present verbatim in the current utterance, but require normalization or derivation from the dialog’s context: its situation, user knowledge or world knowledge.
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Appendix

for (slot, value) in turn’s dialog state update do
  while value is not found in dialog do
    if value in turn(i) then
      δc ← i
      context ← verbatim
    else if denormalized value in turn(i) then
      δc ← i
      context ← normalization
    else if value in turn(i) with context then
      δc ← i
      context ← context type
    else
      i ← i − 1  // rewind by 1 turn
    end if
  end while
end for

Figure 4: Pseudo-code used for the model-independent dataset analysis. The procedure is applied to each dialog in a dataset’s test set and each user turn of a dialog (there is no dialog state tracking for agent turns) to measure the turn’s conversationality and contextuality. Slot values that can be found programmatically by generating denormalized variations and regex matching are tagged automatically, the others are inspected manually in order to identify annotation errors and contextual effects.
| Normalized value | Span in utterance |
|------------------|------------------|
| time = "18:15"   | "18:15"          |
| area = "centre"  | "located in the centre" |

**Entity Alternative**

| [area = "center"] | "centre" |
| [attraction = "theater"] | "theatre" |

**Numbers**

| [price = "$30"] | "thirty bucks" |
| [people = "3"] | "three" |

**Date & Time**

| [time = "4:30 pm"] | "half past 4 in the evening" |
| [book_stay = "7"] | "a week" |

**Shortcuts**

| [location = "San Francisco"] | "San Fran", "SF", "SFO" |
| [start_day = "saturday"] | "sat" |

**Semantic Understanding**

| [smoking_allowed = "True"] | "smoker-friendly", "allowed to smoke" |
| [has_seating_outdoors = "True"] | "in the patio", "Al Fresco" |
| [price_range = "inexpensive"] | "low-cost", "budget", "low priced" |

**Computation**

| [year = "2017"] | "two years ago" |
| [book_people = "3"] | "yes, and my 2 companions" |
| [book_stay = "2"] | "from Tuesday through Thursday" |

Table 5: Examples of value normalizations in the dialog state tracking task. The right column features spans from user or agent utterances, while the left column shows their corresponding normalized slot and value as represented in the dialog state. All examples in this table are taken from the MUTIWOZ or SGD datasets.

| Dataset | Input representation | Fine-tuning steps | input seq. length | output seq. length | training time [hours] | CO2 emissions (estimate in kg) |
|---------|----------------------|-------------------|-------------------|-------------------|------------------------|-------------------------------|
| MULTIWOZ | current user turn | 5k | 256 | 128 | 0.690 | 2.09 |
|          | + last agent turn | 5k | 256 | 128 | 0.712 | 2.16 |
|          | + prev. dialog state | 5k | 256 | 128 | 0.708 | 2.14 |
|          | full dialog history | 5k | 1024 | 128 | 1.216 | 3.68 |
| SGD     | current user turn | 20k | 256 | 128 | 1.093 | 3.31 |
|          | + last agent turn | 20k | 256 | 128 | 1.112 | 3.37 |
|          | + prev. dialog state | 20k | 256 | 128 | 1.149 | 3.48 |
|          | full dialog history | 20k | 1024 | 128 | 1.328 | 4.02 |
| SMCALFLOW | current user turn | 5k | 2048 | 2048 | 3.180 | 9.63 |
|          | + last agent turn | 5k | 2048 | 2048 | 3.893 | 11.79 |
|          | + prev. dialog state | 5k | 2048 | 2048 | 3.707 | 11.22 |
|          | full dialog history | 5k | 2048 | 2048 | 3.661 | 11.08 |

Table 6: Hyperparameters used for training the Dialog State Tracking (DST) with T5, corresponding to results in Table 4. We trained on Google Cloud TPU v3 with 32 cores and followed the high estimate procedure in (Patterson et al., 2021) to estimate the resulting carbon emissions.