Abstract

We present Contextual Query Rewrite (CQR) a dataset for multi-domain task-oriented spoken dialogue systems that is an extension of the Stanford dialog corpus (Eric et al., 2017a). While previous approaches have addressed the issue of diverse schemas by learning candidate transformations (Naik et al., 2018), we instead model the reference resolution task as a user query reformulation task, where the dialog state is serialized into a natural language query that can be executed by the downstream spoken language understanding system. In this paper, we describe our methodology for creating the query reformulation extension to the dialog corpus, and present an initial set of experiments to establish a baseline for the CQR task. We have released the corpus to the public\footnote{https://github.com/alexa/alexa-dataset-contextual-query-rewrite} to support further research in this area.

1 Introduction

Spoken language understanding (SLU) for dialogue systems is designed to correctly interpret a user utterance, a unit of communication given a specific context (Grice, 1968). For successful interpretation, the system may classify user intent (the action that the user would like the system to perform) and resolve slot values (particular attributes associated with intents). Task-oriented dialogues currently most often consist of a one-shot utterance said by the user for the digital assistant to perform a task (e.g., ‘What is the weather like?’). In some cases, however, a dialogue may involve multiple turns, each turn a sequence of user and system utterances. Reasoning over multi-turn dialogues, in which user and agent add information incrementally to specify the user’s intent, is a challenge which only increases in difficulty when the agent needs to resolve referring expressions across turns, either explicit references (example - pronominal and nominal anaphora) or implicit ones (example - zero anaphora).

In this paper, we approach the referring expression resolution task in multi-turn discourse as a query reformulation task - the utterance containing the referring expression is rewritten to contain all relevant slot values from the context, a process we call contextual query rewrite (CQR). In order to be feasible, query reformulation must be able to leverage multi-turn context, be intuitive, and learnable, principles we apply in the creation of our corpus extended via crowd-sourcing and then used to train an end-to-end dialogue system without a need for explicit state trackers. Our main contributions are:

1. We introduce a new task - contextual query rewrite - for resolving referring expressions without explicit need to track the state.
2. We release a publicly available corpus consisting of gold standard and crowd-sourced rewrites as an extension to an existing task-oriented dialogue corpus.

2 Problem

2.1 Motivation

We motivate contextual query rewriting (CQR) with an example shown in Table 1. Typically,
we would expect a digital assistant to understand the second user utterance (U2) as referring to traffic near the coffee shop, rather than defaulting to the user’s current location, although here this is not explicitly stated. Our correct interpretation of this utterance is possible via an implicit reference to the location using zero anaphora (e.g., “What’s the address (of the coffee shop?)”), recognized as the predominant anaphora type observed cross-linguistically (Givón, 2017). The user could also refer to the same coffee shop using a nominal anaphoric reference (“that coffee shop”), or a locative form (“there”), or as a pronominal form (e.g., “it”).

More generally, the task of referring expression resolution can be solved as a carryover task, where the relevant slots from the context are carried over to the current turn (Naik et al., 2018). For our working example described in Table 1, the result of the carryover task shows up as additional slots associated with the utterance, as show in in Figure 1a. A challenge is dealing with domain-specific schemas requiring accurate transformations even for emergent slots where there is very little data available to train these mappings correctly. Another solution is to make the natural language understanding system contextually aware (Gupta et al., 2018). However, updating the domain-specific NLU sub-systems is more complex, as it requires re-training the production sub-systems, often a time-consuming and laborious task. Moreover, this approach does not work for systems that model the meaning using frameworks other than intents and slots.

In this paper, we propose query reformulation, where we take an otherwise ambiguous utterance such as “how’s the traffic” in Table 1 and add the relevant slot values from the context, here the name of the place (“coffeeeworks”), to make a reformulated query: “how’s the traffic to coffeeeworks?”, as shown in Figure 1b. We call this approach to resolving referring expressions contextual query rewrite (CQR). The main advantage of this approach is that it does not require updating the domain specific NLUs, and takes advantage of the fact that these systems are optimized for single slot performance. Resolving referring expressions is now equivalent to generating a single shot natural language query, thereby making this process invariant to the meaning representation and domain specific schema changes.

2.2 CQR Task Formulation

We can now formally define the CQR task. We define a sequence of $D$ dialogue turns $\{u_{t-D+1}, \ldots, u_{t-2}, u_{t-1}\}$; the current user utterance $u_t$, where $u \in \mathcal{W}$ is a sequence of tokens $\{w_i\}_{i=1}^N$. Associated with the $D$ dialogue turns and the current turn is a set of slot values $v = \{v_1, v_2, \ldots, v_N\}$. The CQR task is to learn a mapping $\mathcal{F}(u_t \cup D) \rightarrow u'_t$ where the reformulated user turn $u'_t$ contains tokens copied either from the vocabulary $\mathcal{W}$ or from a subset of relevant slot values from $v$. The challenge is to learn a reformulated user utterance that has implicitly selected the subset of slots that are relevant at turn $t$, while retaining the semantics associated with turn $t$.

3 Related work

Dialogue corpora: There are various dialogue corpora, and collection methodologies. (Weston et al., 2015) have the objective of improving algorithms for text understanding by modularizing each reasoning task; two of their tasks involve coreference; however, these appear to involve the resolution of pronominal forms exclusively, forms which in on our data represent only a small fraction of all anaphoric references. (Bordes et al., 2017) released a corpus of 18,000 synthetic dialogues for a single domain (restaurant reservations), however, these do not reflect real user behavior. Human efforts may also be directed in a Wizard-of-Oz schema using the interactions of crowd-sourced workers to develop corpora. For example, (Wen et al., 2017) create a corpus of approximate six hundred eighty dialogues for a single domain (restaurants), and like them we also set out to avoid handcrafting and labeled datasets by representing slot-value pairs explicitly. (Eric et al., 2017a) use the same approach to create $3k$ dialogues for three domains (weather, navigation, and calendar scheduling), a corpus particularly rich with anaphoric references.

State tracking Dialogue state tracking (DST) is considered to be a higher-level module as it has to combine information from previous user utterances and system responses with the current utterance to infer full meaning. Many deep-learning
Table 1: Multi-turn dialogue with implicit reference in (U2) to the slot (poi=coffeeworks). The turn U2 is handled by the Traffic domain NLU, with its own domain schema - the slot (poi=coffeeworks) needs to be transformed to the slot (location=coffeeworks). Contextual query rewriting (CQR) would resolve the implicit referring expression by reformulating the query as shown for U2 in a schema agnostic way.

| speaker | domain | utterance | Resolved referenced slots(key=value) | Reformulated query |
|---------|--------|-----------|--------------------------------------|--------------------|
| U1      | POI    | any coffee shops nearby | poi.type=coffee shop, distance=nearby |                    |
| V1      | POI    | found a coffeeworks 2 miles away | poi=coffeeworks, distance=2 miles |                    |
| U2      | Traffic| how’s the traffic | location=coffeeworks | how’s the traffic to coffeeworks |

(a) Resolving referring expressions by determining the slots in the context that are relevant at the current turn.

(b) Resolving referring expressions by reformulating the query.

Figure 1: Contextual Query Rewrite Architecture - Referring expression resolution happens before running the language understanding component, compared to the traditional approach where the reference resolution usually takes place after language understanding.

Text Generation

Seq2Seq models with attention (Sutskever et al., 2014; Bahdanau et al., 2014) have seen rapid adoption in automatic summarization (See et al., 2017; Rush et al., 2015). (Madotto et al., 2018; Eric et al., 2017b) propose end-to-end generative approaches where a copy mechanism is used to copy entities from a knowledge base when generating the response. Closest to this work, is the copy mechanism based user query reformulation for search-based systems (Dehghani et al., 2017). Exploring black-box methods like query re-writing allow us to benefit from the progress made in these fields and apply them to state tracking and reference resolution tasks in dialogue.

4 Contextual Query Rewrite Dataset

4.1 Query reformulation methodology

To build a corpus of query reformulations, we begin first with the principles that guided our decision-making process.

1. Multi-turn: We expect human-computer interaction will soon more often involve multi-
ple turns (where each turn consists of a single user and agent utterance pair); anaphoric references are likely to occur more in multi-turn discourse; and, cross-linguistically, anaphor is a standard linguistic strategy for referring to the same entity and increase discourse cohesiveness (Hobbs, 1979) signaling what new versus known information is; within-sentence anaphoric references fall outside the scope of the present research framework;

2. **Intuitive**: Deciding which slot values are relevant given a particular dialogue history should be intuitive, assessed as the agreement among individuals;

3. **Interpretable**: Evaluating the output of a model should be straightforward, i.e., given the guidelines for query reformulation (below), an analyst will be able to assess quickly performance;

4. **Learnable**: An end-to-end dialogue system should be able to resolve anaphoric references to increase user satisfaction; the extent to which a model learns to identify which slot values are relevant can be examined, explored in Section 5.

The guidelines for the task of query reformulation are summarized here:

1. Identify the utterance which most closely matches the user’s intent or request; we call this the basic utterance;

2. Reformulate the basis utterance to be a one-shot utterance, making the user’s intent unambiguous by including all relevant slot values from the previous context; determining what is ‘relevant’, however, is dependent on how much we assume a model may automatically be able to infer given a specific utterance;

3. When a place is not referred to directly by poi_type (e.g., “I want some pizza”), the poi_type is assumed to be inferable, e.g., as “pizza restaurant”.

4. Some cases are not subject to reformulation, e.g., confirmation of the agent’s decision (e.g., Agent: “Would you like directions?”, User: “Yes please”), or when giving thanks or otherwise signaling the end of the dialogue;

5. Slot values from the context replace an anaphoric reference (whether nominal, pronominal, or zero) in the basis utterance;

6. Only certain types of anaphora need to be attended to, specifically references to slot values from the given domain; we ignore non-slot values (e.g., “We want coffee” does not need to be resolved to “you and I”), as well as anaphoric references to propositions or events (e.g., “That sounds good”);

7. When multiple values for a specific slot are available from context or in the current utterance, only use the most specific slots values, e.g., “Take me via the fastest route”, specifying route conditions precludes the need to specify traffic information further, e.g., “avoid all heavy traffic”;

8. For utterances with multiple anaphora (e.g., “Give me the address and let’s go there”), resolve both references: e.g., “Give me the address of the coffee shop Coupa and let’s go to the coffee shop Coupa’); this is not strictly enforced;

9. Intent may need to be carried over in addition to slots, e.g., “How about another coffee shop?” is reformulated as “Give me directions to another coffee shop...”; this is rare;

**4.2 Corpus selection and first modifications**

With the principles above (multi-turn dialogue with cross-sentential anaphora), we selected a publicly available corpus (Eric et al., 2017a), a corpus composed of approximately three thousand dialogues over three domains (weather, scheduling, and navigation). For additional statistics regarding the original corpus, we refer the reader to (Eric et al., 2017a). Applying the guidelines above to the first task of query reformulation, we arrived at a modified corpus to begin our study and later experiments, noticing primarily the anaphora types described in Section 1. In the released corpus, we include flags for each anaphora type.

Figure 2 shows the final distribution of anaphora types in the modified corpus, with total counts for anaphora types shown in Table 2. As an initial estimate of how much more information the

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3We also include flags for other interesting linguistic forms, incl. **either** (as in, “Let’s go to either...”) and **besides**, to exclude an option (e.g., “Let’s go to another coffee shop besides...”)
Table 2: Distribution of anaphora (zero, pronominal, locative, nominal) in modified corpus.

|       | #reformulations | #zero | #pronominal | #locative | #nominal |
|-------|-----------------|-------|-------------|-----------|----------|
| dev   | 206             | 143   | 31          | 34        | 21       |
| test  | 214             | 155   | 21          | 43        | 20       |
| train | 1867            | 1138  | 393         | 162       | 143      |
| Total | 2287            | 1436  | 445         | 239       | 184      |

Table 3: Average number of tokens in each utterance before and after reformulation with the average number of slots in the reformulations.

Table 4: Crowd-sourced data collection effort.

Table 5: Example rewrites with basis utterance, gold rewrites as well as 5 crowd-sourced rewrites.

We also assessed each crowd-sourced rewrite quantitatively by determining F1 and BLEU (Papineni et al., 2002) score between the gold reformulation and each rewrite. To do this, we delexicalize slot values, using labels from the original corpus; we provide an example in Table 6 that results in F1 of 1.0 (all slot values are the same, meaning semantic similarity is high) with a BLEU score of 0.30 (low n-gram similarity indicative of syntactic/lexical variations).
For the entire extended corpus of rewrites, we arrived at the similarity metrics presented in Table 7. In addition to F1 and BLEU scores, we also counted how many slots each gold reformulation has on average compared to rewrites, where we see, for example, that the gold reformulations have on average almost one more slot value per utterance than rewrites; this is indicative of how unnatural it may be to compose utterances that specify an entity so unambiguously (e.g., “Take me to the gas station Chevron two miles away.”)

| BLEU     | 0.419 |
|----------|-------|
| F1       | 0.890 |
| Mean # slots in each gold | 4.03 |
| Mean # slots in each rewrite | 3.20 |
| Difference # slots (gold vs rewrites) | 0.823 |

Table 7: Similarity measures for gold reformulations vs crowd-sourced rewrites.

We also compared the five rewrites as a group to their corresponding gold reformulation: first, we grouped the rewrites for each dialogue (2042 total); next, we determined mean F1, BLEU, and difference in number of slots for each group pairwise compared to the gold reformulation; then, each group’s F1 and BLEU scores were binned as shown in Figure 3, where mean F1 scores are indicative of high in-group semantic similarity; and low BLEU scores indicative of syntactic and lexical variation within each group.

5 Experiments and Analysis

5.1 Establishing the baseline

Spoken language understanding consists usually of two tasks, domain classification/intent determination (e.g., Weather, Navigation, etc.) and slot-filling which identifies the spans of text in the utterance assigned to a slot value-attribute pair given the domain. In the dialogue corpus used here, the three domains and their corresponding slot values are: Weather (location, date, weather attribute); Navigation (point of interest type, point of interest, address, traffic information, distance); and Calendar scheduling (date, time, location, party, agenda). As a baseline, we first compare the original dialogues and the gold reformulations on the domain classification and slot-filling tasks.

To assess this, we use a joint classifier for both
tasks, an attention-based RNN for domain classification & slot filling (Liu and Lane, 2016; Mesnil et al., 2015). We evaluate performance on two different inputs from the proposed dataset:

**Original** The input is the original dialogue (concatenated user plus system utterances) and the output is the relevant slot values and domain at the user turn.

**Gold CQR** The input is the gold reformulation for the above user turn and the output is the relevant slot values and domain i.e we treat the dialogue as a single shot utterance.

For pre-processing, we encode the data using BIO tags. We perform the classification task on the two datasets and then compare the accuracy of the semantic labeler on the slots that both setups share (i.e., ignoring how the classifier does on the newly added slots in the gold reformulations).

| Input Type  | Domain Classification Accuracy | Slot F1 |
|-------------|-------------------------------|---------|
| Original    | 0.98                          | 0.89    |
| Gold CQR    | 0.98                          | 0.91    |

Table 8: Comparing original dialogue vs gold reformulations (Gold CQR) on two tasks domain classification and slot-filling. Domain classification accuracy between the original dataset and the reformulated query is similar. Slot-filling accuracy for reformulated query is higher than that for the original dataset.

Results in Table 8 indicate that while for domain classification there is no significant gain when comparing gold reformulations against the original dataset, for slot-filling task, increased prediction accuracy is evident for the gold reformulations. This suggests that query reformulation could lead to potentially better language understanding performance downstream as it is relatively easier to train and optimize NLU systems for single-shot utterances compared to multi-turn utterances.

### 5.2 Query Rewriting Experiments

In a second set of experiments, we would like to test the query rewriting more directly. As described in Section 2.2, we view this as summarizing a dialogue into a single utterance unambiguously specifying user intent. For the experiment, we delexicalize slot values using the canonical entity type from the original corpus (e.g., poi_type = place of interest type), giving an example in Table 9.

| (input) USER i need directions to a poi_type | SYSTEM i have a poi_type that is distance | USER give me the address |
| (output) give me the address of poi_type | |

Table 9: Input/output for CQR model

We train two separate models drawing from different distributions: one of only gold reformulation data and the other including crowd-sourced reformulations. To quantify task complexity, we note that over the entire corpus, 67% of slots are carried over from dialogue to reformulation, an indication of the non-triviality of the task. For reproducibility, we use the open source neural sequence modeling system OpenNMT (Klein et al., 2017). The only hyper-parameter changed from initial settings is to remove copy_loss_by_seqlength, which improves overall accuracy. Error rates for the training and dev sets are presented in the Figure 4 with observed accuracy metrics presented in Table 10. The dev set error for the Mturk extensions is higher indicating that there is lexical diversity in the reformulations, which is also seen in the BLEU scores in Table 10. The entity F1 scores is higher, as the model has seen many more variations around the carryover entities.

| train/dev/test | F1 | Bleu |
|----------------|----|------|
| Gold           | 2100/230/230 | 0.838 | 0.711 |
| Gold + Mturk   | 10045/1279/1279 | **0.897** | 0.397 |

Table 10: Accuracy metrics for contextual query rewrite task

### 6 Conclusion

We show that anaphora is quite common in a single, human-created corpus (Eric et al., 2017a) of multi-turn dialogues used to train task-oriented, spoken dialogue systems. We introduce contextual query rewrite (CQR), where the referring expressions resolution task is defined as query reformulations given the dialogue history. We show a principled approach to creating a corpus of query reformulations, and how this can be extended via crowd-sourcing. Two experiments demonstrate that query reformulations can be used to train high
accuracy models for the task of generating fully unambiguous single-shot utterances as well as for more standard tasks of domain classification and slot filling, indicating that this approach may be suitable for anaphora resolution at larger scales.

In future work, we intend to extend query reformulation for multiple languages, as well as to assess if anaphora resolution using query reformulation is also possible for longer dialogues. As a step towards improving dialogue systems in general and encouraging work on anaphora resolution specifically, we make our corpus publicly available.

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