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Dialogue-AMR: Abstract Meaning Representation for Dialogue

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Abstract

This paper describes a schema that enriches Abstract Meaning Representation (AMR) in order to provide a semantic representation for facilitating Natural Language Understanding (NLU) in dialogue systems. AMR offers a valuable level of abstraction of the propositional content of an utterance; however, it does not capture the illocutionary force or speaker's intended contribution in the broader dialogue context (e.g., make a request or ask a question), nor does it capture tense or aspect. We explore dialogue in the domain of human-robot interaction, where a conversational robot is engaged in search and navigation tasks with a human partner. To address the limitations of standard AMR, we develop an inventory of speech acts suitable for our domain, and present "Dialogue-AMR", an enhanced AMR that represents not only the content of an utterance, but the illocutionary force behind it, as well as tense and aspect. To showcase the coverage of the schema, we use both manual and automatic methods to construct the "DialAMR" corpus—a corpus of human-robot dialogue annotated with standard AMR and our enriched Dialogue-AMR schema. Our automated methods can be used to incorporate AMR into a larger NLU pipeline supporting human-robot dialogue.

Keywords: Dialogue, Abstract Meaning Representation, Illocutionary Force

1. Introduction

This paper describes a schema that enriches Abstract Meaning Representation (AMR) (Banarescu et al., 2013) to support Natural Language Understanding (NLU) in human-robot dialogue systems. AMR is a formalism for sentence semantics that abstracts away many syntactic idiosyncrasies and represents sentences with rooted directed acyclic graphs (Figure 1a shows the PENMAN notation of the graph). Although AMR provides a suitable level of abstraction for representing the content of sentences in our domain, it lacks a level of representation for speaker intent, which would capture the pragmatic effect of an utterance in dialogue.

Pragmatic information is critical in dialogue with a conversational agent. For example, a request for information and a request for action serve distinct dialogue functions. Similarly, a promise regarding a future action and an assertion about a past action update the conversational context in very different ways. In our problem space, which involves a robot completing search and navigation tasks, the robot communicates about actions it can take in the environment such as moving, searching, and reporting back. While the robot is insensitive to many lexical differences, such as those between the movement terms *go*, *move*, and *drive*, it needs to understand specific instructions such as how far to go and when, as well as communicate and discuss the status of a given task. Additionally, it needs to understand if the illocutionary force of communications are commands, suggestions, or clarifications.

To address these needs, we introduce a detailed and robust schema for representing illocutionary force in AMR called "Dialogue-AMR" (Figure 1b). This expands and refines previous work which proposed basic modifications for how to annotate speech acts and tense and aspect information within AMR (Bonial et al., 2019a). The contributions of the present research are: i) a set of speech acts finalized and situated in a taxonomy (Section 3.1); ii) the refinement of the Dialogue-AMR annotation schema to provide coverage of novel language (Sections 3.2 and 3.3); and iii) the creation of the "DialAMR" corpus, a collection of human-robot dialogues to which the new Dialogue-AMR schema has been applied (Section 4).[1] DialAMR has additionally been annotated with standard AMR, thus constituting one of the first corpora of dialogue annotated with AMR (see related work in Section 5) and allowing for comparison of both AMR schemas on the same data. Although some of the domain-specific extensions are tailored to our human-robot search and navigation application, the addi-

```
(a) (d / drive-01 :mode imperative
       :ARG0 (y / you)
       :destination (d2 / door))
(b) (c / command-SA
       :ARG0 (c2 / commander)
       :ARG2 (r / robot)
       :ARG1 (g / go-02 :completable +
          :ARG0 r
          :ARG3 (h / here)
          :ARG4 (d/ door)
          :time (a2 / after
               :op1 (n / now))))
```

Figure 1: The utterance *Drive to the door* represented in (a) standard AMR form, (b) Dialogue-AMR form.

[1]DialAMR consists of 1122 utterances with standard AMR and Dialogue-AMR; it is presently available by requests emailed to the first author and a web release is planned for Summer 2020.

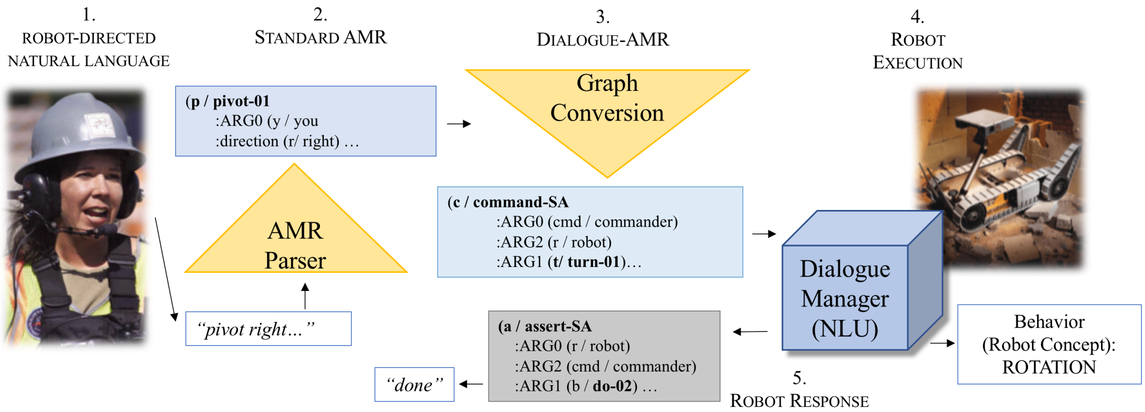

Figure 2: Planned NLU Pipeline—Verbal instructions are parsed into standard AMR using automated parsers, converted into Dialogue-AMR via graph-to-graph transformation, then, if executable, mapped to a robot behavior. The robot responds with questions or feedback.

tion of illocutionary force to AMR is useful for many applications of human-agent conversation. Furthermore, the general paradigm of extending AMR is useful for applications which need to gloss over some linguistic distinctions while retaining others.

A frequent dilemma in designing meaning representations for limited-domain dialogue systems is whether to preserve a general purpose representation that is adequate for capturing most language expressions, or whether to focus on only the small subset that the system will be able to deal with. The former can make the representations more complex, language interpretation more ambiguous, and system-specific inference more difficult. The latter approach addresses these problems but may lose the ability to transfer to even a very similar domain and may require more in-domain data than is available for a new project. In order to try to maintain the advantages of each approach, we are leveraging DialAMR to develop an NLU pipeline (Figure 2) which contains both a general purpose representation language (Standard AMR) as well as Dialogue-AMR, which is more amenable to inferences that a robot needs to make when engaged in a collaborative navigation task. This pipeline converts automatically generated standard AMR graphs of the input language (Section 4.2.1) into Dialogue-AMR graphs augmented with tense, aspect, and speech act information (Section 4.2.2).

2. Background

We begin with an overview of the human-robot navigation setting and the dialogue data we annotate with Dialogue-AMR (the SCOUT corpus). We then describe the strengths and shortcomings of standard AMR for this domain as motivation for developing Dialogue-AMR.

2.1. Human-Robot Dialogue

The Situated Corpus of Understanding Transactions (SCOUT) is a collection of dialogues from the robot navigation domain (Marge et al., 2016; Marge et al., 2017). SCOUT was created to explore the natural diversity of communication strategies in situated human-robot dialogue. As such, data collection efforts leveraged "Wizard-of-Oz" experiment design (Riek, 2012) in which participants directed what they believed to be an autonomous robot to complete search and navigation tasks. Behind the scenes, two "wizard" experimenters controlled the robot's dialogue processing and robot navigation capabilities. This design permitted participants to instruct the robot without imposing artificial restrictions on the language used.

Dialogues in SCOUT were collected using the following experimental setup. A participant acts as a Commander and issues verbal instructions to a remotely-located robot in an unexplored environment. The participant can see a dynamically-updating 2D map of the robot's location and can request static images; they do not have a video feed of what the robot sees. Participant instructions are interpreted by a dialogue manager wizard (DM) who listens to the speech and, acting as the robot, replies to the participant through text messages with clarification requests and feedback. For example, participant instructions referring to an ambiguous object (e.g., *Enter the doorway on the right* when there are two doorways on the robot's right) require a clarification request, whereas unambiguous instructions are acknowledged with a status update like *Executing*. Instructions deemed completable are passed to a robot navigator wizard (RN) for execution, who then teleoperates the robot to fulfill the participant's instructions. As needed, the RN provides feedback or status updates to the DM, such as when instructions are completed or if there are problems fulfilling them, and then the DM passes these messages back to the participant. An example interaction is given in Table 1. The dialogues are divided into two conversational floors, each involving only two interlocutors: the left conversational floor consists of dialogue between the participant and the DM, and the right consists of dialogue between the DM and the RN. The participant and RN never speak directly to or hear each other; instead, the DM acts as an intermediary passing communication between the participant and the RN.

In total, the current SCOUT contains over 80 hours of human-robot dialogue from 83 participants. All speech data (collected from the participant and RN) are transcribed and time-aligned with text messages produced by the DM. SCOUT also includes annotations of *dialogue structure*

	Left Conversational Floor		Right Conversational Floor	
#	**Participant**	**DM → Participant**	**DM → RN**	**RN**
1	proceed to the doorway ahead			
2		I see more than one doorway.		
3		Which doorway?		
4	the doorway closest to you			
5		processing		
6			move into Kitchen	
7		moving...		
8				done
9		done		

Table 1: Navigation instruction initiated by the participant (#1), its clarification (#2-4), subsequent translation to a simplified form (Dialogue Manager (DM) to Robot Navigator (RN), #6), and acknowledgement of instructions (#5, 7, 9) and execution by the RN (#8).

(Traum et al., 2018) that allow for the characterization of distinct information states (Traum and Larsson, 2003). However, this dialogue structure annotation schema does not provide a markup of the semantic content in participant instructions.

2.2. AMR

AMR is a formalism for sentence semantics that abstracts away from some syntactic idiosyncrasies (Banarescu et al., 2013). Each sentence is represented by a rooted directed acyclic graph (DAG) in which variables (or graph nodes) are introduced for entities, events, properties, and states. Leaves are labeled with concepts (e.g., `(r / robot)`). Relational concepts in AMR use a lexicon (shared with PropBank (Palmer et al., 2005) comprised of numbered senses of a relation, each of which lists a set of numbered participant roles (`Arg0-5`). For ease of creation and manipulation, annotators work with notation from the PENMAN project (Penman Natural Language Group, 1989), which is the notation used in this paper (e.g., Figure 1a). AMR has been used to support NLU, generation, and summarization (Liu et al., 2015; Pourdamghani et al., 2016), as well as machine translation (Langkilde and Knight, 1998), question answering (Mitra and Baral, 2016), information extraction (Pan et al., 2015), and biomedical text mining (Garg et al., 2016; Rao et al., 2017; Wang et al., 2017).

AMR provides an appropriate level of abstraction for NLU in our human-robot dialogue application. As the goal of AMR research is to capture core facets of meaning unrelated to surface structure, the same underlying concept realized alternatively as a noun (*a left turn*), verb (*turn to the left*), or light verb construction (*make a left turn*) are all represented by identical AMRs. This is well-suited to our setup: the robot has a limited number of executable behaviors it can perform, and any user utterance needs to be mapped to a simple yet structured representation that the robot can understand. In turn, the robot only needs to communicate back to the user regarding those same concepts. Thus, the AMR formalism smooths away many syntactic and lexical features that are unimportant to the robot. Existing AMR parsers can be utilized to obtain an initial interpretation of a user utterance, making the interpretation process easier than parsing natural language text directly into a robot-oriented representation.

Standard AMR nevertheless omits certain semantic information essential to our domain. Specifically, AMR omits both tense and aspect information, assuming that some of this information may be gleaned from morphosyntactic information already well-represented in syntactic treebanks. The formalism also lacks illocutionary force, considering it distinct from core contentful meaning. We therefore add these properties to the robot's semantic representation (Section 3).

3. Development of Dialogue-AMR

To develop augmentation of AMR that addresses the requirements in human-robot dialogue, we iteratively refine an inventory of speech acts (Section 3.1) and introduce tense and aspect representations not included in standard AMR (Section 3.2). These additional elements of meaning are brought together in our annotation schema for Dialogue-AMR (Section 3.3), in which the propositional content is also normalized by replacing a variety of lexical items in the input language (e.g., *turn, pivot, rotate*) with an assigned relation (e.g., `turn-01`) that maps to a single robot concept (e.g., ROTATION) corresponding to one of its executable behaviors.

3.1. Speech Act Inventory

We embrace much of the higher-level categorization and labeling of speech acts outlined by Searle (1969), including the basic categories of Assertions (termed "representatives" by Searle), Commissives, Directives, and Expressives. Additionally, based on Bunt et al. (2012), we introduce an early distinction in classifying our speech acts between Information Transfer Functions and Action-Discussion Functions (see Figure 3).

In terms of dialogue function, this division allows us to monitor the status of distinct dialogue contexts. For Information Transfer Types, we can monitor the quantity and quality of general-purpose information exchanged in the dialogue that is relevant to the larger task at hand. For example, *Robot, do you speak any foreign languages?* may not directly impact a current task, but it introduces information into the dialogue that may be useful at a later point. For

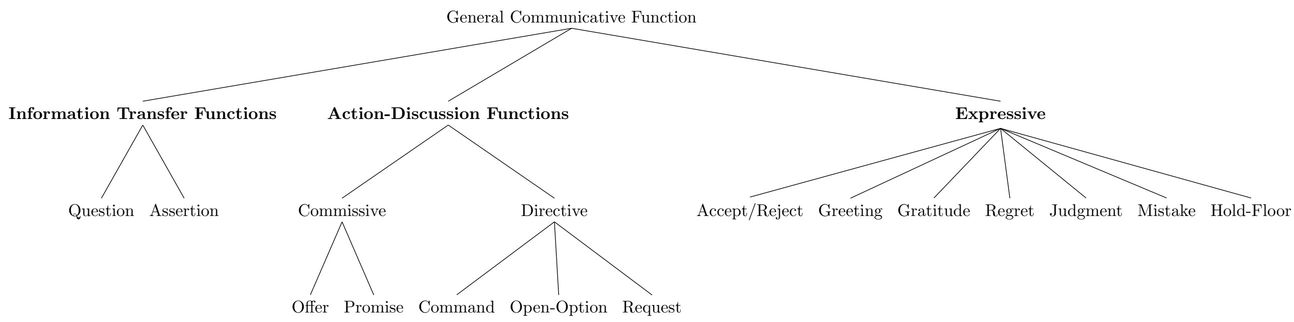

Figure 3: Dialogue-AMR Speech Act Taxonomy

Action-Discussion types, we can assess the status of individual tasks as the dialogue progresses. For example, (*Moving to the wall*) and (*I moved to the wall*) convey two points on a timeline related to current task completion. For Expressive types, we can model the changing relationship between interlocutors—for example, how utterances of gratitude, acceptance or rejection, and admission of mistakes impact the level of trust between the two interlocutors.

Beyond these higher-level categories, we iteratively refined the speech act categories needed for our domain based upon rounds of surveying and annotating our data. These iterations began with the annotation of "dialogue moves" over participant instructions only (Marge et al., 2017) and evolved with varying numbers and types of speech acts (Bonial et al., 2019a) to the inventory set forth here.

In delineating and defining our speech acts, we focus on the effects of an utterance relating to belief and obligation (Traum, 1999; Poesio and Traum, 1998). These are not mutually exclusive, and utterances can and do often convey both the commitment to a belief and evoke an obligation in either the speaker or the hearer. We focus on these pragmatic effects as they are critical for agents navigating dialogue—in planning, agents can choose to pursue either goals or obligations and must reason about these notions so that the choice can be explained. Mutual beliefs about the feasibility of actions and the intention of particular agents to perform parts of that action are captured in the notion of *committed*, which is a social commitment to a state of affairs, rather than an individual commitment (Traum, 1999). Definitions of our speech acts are given in Table 4 in the Appendix.

Table 4 also lists the relation integrated into the Dialogue-AMR to represent the speech act. Unlike the numbered relations of standard AMR, we propose a new set of speech act relations all ending with `-SA`. Although we explored adopting existing AMR relations that best fit with each speech act (e.g., `Question-01, Command-02`) (Bonial et al., 2019a), we opted to introduce new relations so that the Dialogue-AMR is clear in what portion represents propositional content and what portion represents the illocutionary force.[2] Additionally, we found that existing AMR relations were inconsistent in the argument structure representing the speaker, addressee, and content of the speech act. For example, while `Command-02` represents the addressee or impelled agent as `Arg1` and the impelled action as `Arg2`, `Assert-02` represents the addressee as `Arg2` and the content of the assertion as `Arg1`. Our roles in our speech acts maintain the following consistent argument structure (as seen in Figure 1b):

```
Arg0:  Speaker
Arg1:  Content
Arg2:  Addressee
```

The roles of `Arg0` and `Arg2` correspond consistently to Speaker and Addressee, respectively; the semantics of the `Arg1` shifts depending upon the particular speech act. For example, the `Arg1-content` of `Command-SA` is an action, whereas the `Arg1-content` of `Regret-SA` is the stimulus of the mental state, or the thing regretted.

3.2. Tense and Aspect in Dialogue-AMR

There are patterned interactions between tense and aspect and illocutionary force that are critical for conveying the robot's current status in our domain. These include the distinctions between a promise to carry out an instruction in the future, a declarative statement that the instruction is being carried out currently, and an acknowledgment that it has been carried out in the past. Standard AMR lacks information that specifies *when* an action occurs relative to speech time and whether or not this action is completed (if a past event) or able to be completed (if a future event). For example, standard AMR represents the common feedback utterances (*I will move forward 10 feet*), (*I am moving...*), and (*I moved...*) with one identical graph (see Figure 4).

```
(m / move-01
      :ARG0 (i / i)
      :direction (f / forward)
      :extent (d / distance-quantity
            :quant 10
            :unit (f2 / foot)))
```

Figure 4: Because standard AMR lacks tense and aspect representation, the phrases *I will move / I am moving / I moved... forward 10 feet* are represented identically.

We integrate tense and aspect information into Dialogue-AMR by adopting the annotation schema of Donatelli et al. (2018), who propose a four-way division of temporal annotation and four multi-valued categories for aspectual

[2]The corpus release includes a mapping allowing for conversion of SA relations into existing AMR numbered relations.

annotation that fits seamlessly into existing AMR annotation practice. We reduced the authors' proposed temporal categories to three[3], in order to capture temporal relations before, during, and after the speech time. In addition to the aspectual categories proposed by Donatelli et al. (2018), we added the category `:completable +/-` to signal whether or not a hypothetical event has an end-goal that is executable for the robot (see Donatelli et al. (2019) for a sketch of this aspectual category). Our annotation categories for tense and aspect can be seen in Figure 5.[4]

TEMPORAL ANNOTATION	ASPECTUAL ANNOTATION

`:time`
1. `(b / before :op1 (n / now))`
2. `(n / now)`
3. `(a / after :op1 (n / now))`
	`:stable +/-`
	`:ongoing +/-`
	`:complete +/-`
	`:habitual +/-`
	`:completable +/-`

Figure 5: Three categories for temporal annotation and five categories for aspectual annotation are used to augment existing AMR for collaborative dialogue.

Notably, this annotation schema is able to capture the distinctions missing in Figure 4. Updated AMRs for utterances that communicate information about a MOVEMENT event relative to the future, present, and past are shown in Figure 6. Using the schema presented in Figure 5, our Dialogue-AMRs allow for locating an event in time and expressing information related to the boundedness of the event, i.e., whether or not the event is a future event with a clear beginning and endpoint, a present event in progress towards an end goal, or a past event that has been completed from start to finish.

3.3. Full Annotation Schema in Dialogue-AMR

Our meaning representation is intended to bridge the gap from totally unconstrained natural language input to the appropriate action specification in the robot's limited repertoire, including clarification actions. In order to understand an input utterance such that it is actionable, the robot must recognize both the illocutionary force and the propositional content of the utterance. We integrate both these levels of meaning into a single Dialogue-AMR representation. The Dialogue-AMRs can be thought of as templates or skeletal AMRs in which the top anchor node is a specific relation corresponding to an illocutionary force (e.g., `assert-SA`) and its arguments hold the propositional content of the utterance, where the latter consists of a relation (e.g., `turn-01`, `go-02`) corresponding to an action specification from the robot's concept repertoire (e.g., ROTATION, MOVEMENT). The relation's arguments are filled in given the specifics of the utterance (see Figure 7).

In our planned pipeline (Figure 2), we leverage both automatically generated standard AMR as well as the Dialogue-

[3]Eliminating the `up-to` temporal relationship.

[4]The `:habitual` aspectual category is absent from the current annotated data. However, we maintain it as a possible category in anticipation of future work and the potential to refer to habitual robot actions.

```
1. (m / move-01 :completable +
      :ARG0 (i / i)
      :direction (f / forward)
      :extent (d / distance-quantity
            :quant 10
            :unit (f2 / foot))
      :time (a / after
            :op1 (n / now)))

2. (m / move-01 :ongoing + :complete -
      :ARG0 (i / i)
      :direction (f / forward)
      :extent (d / distance-quantity
            :quant 10
            :unit (f2 / foot))
      :time (n / now))

3. (m / move-01 :ongoing - :complete +
      :ARG0 (i / i)
      :direction (f / forward)
      :extent (d / distance-quantity
            :quant 10
            :unit (f2 / foot))
      :time (b / before
            :op1 (n / now)))
```

Figure 6: Updated AMRs for (1) *I will move...*, (2) *I am moving...*, and (3) *I moved....* New temporal and aspectual information is bold-faced.

```
(a) (m / move-01 :mode imperative
        :ARG0 (y / you)
        :ARG1 y
        :ARG2 (w / wall))
(b) (c / command-SA
        :ARG0-speaker
        :ARG2-addressee
        :ARG1 (g / go-02 :completable +
            :ARG0-goer
            :ARG1-extent
            :ARG3-start point
            :ARG4-end point
            :path
            :direction
            :time (a / after
                :op1 (n / now))))
(c) (c / command-SA
        :ARG0 (c2 / commander)
        :ARG2 (r / robot)
        :ARG1 (g / go-02 :completable +
           :ARG0 r
           :ARG3 (h / here)
           :ARG4 (w / wall)
           :time (a2 / after
                :op1 (n / now))))
```

Figure 7: The utterance *Move to the wall* represented in (a) standard AMR form, (b) Dialogue-AMR template form, and (c) as a filled-in Dialogue-AMR.

AMR to tame the variation found in natural language and map this to the robot's constrained set of behaviors. While the standard AMR abstracts away from some idiosyncratic syntactic variation, it largely maintains the lexical items from the input language. The Dialogue-AMR, in contrast, maps several lexical items to one robot concept corresponding to an action specification. This concept is realized in the Dialogue-AMR using a particular AMR roleset that is part of what we term the robot's lexicon. Table 2 illustrates an example of the translation from input language to the robot concept of ROTATION.

Input	AMR	Dialogue-AMR
Turn left 90 degrees.	`turn-01`	
Make a left turn.		
Rotate left.	`rotate-01`	`turn-01`
90 degrees left.	`:angle-quantity...`	
Pivot 90 left.	`pivot-01`	

Table 2: Unconstrained input language is compared with its somewhat generalized form in standard AMR, and its consistent representation with a single relation in Dialogue-AMR, corresponding to a concept within the robot's repertoire of behaviors.

Although we had originally hypothesized that we could use a fixed set of templates to cover all allowable combinations between particular speech acts and particular actions (Bonial et al., 2019a), we have since found that our schema is more flexible and robust to expanding our domain if we eschew a set of fixed templates in favor of a limited set of speech acts, which combine with an easily expandable robot lexicon. This facilitates coverage of all possible combinations of speech act and robot concepts, as opposed to limiting ourselves to templates corresponding only to what we have seen thus far. Nonetheless, there are clear patterns as to how illocutionary force clusters with propositional content in our data, as well as some general constraints on allowable combinations.

On the Information Transfer side of our taxonomy (Figure 3), both Questions and Assertions readily combine with robot concepts such as abilities (e.g., *I can't manipulate objects*), the surrounding environment (*What is the current temperature?*), equipment (*I don't have arms, just wheels!*), the robot's history and familiarity with certain things (*Have we been here before?*), as well as the overarching task presented to the human-robot team (e.g., searching for shoes or shovels, determining if the space has been occupied). Assertions also readily combine with concepts corresponding to the robot's action repertoire, as the robot will assert what it has done (*I moved forward three feet*). On the Action-Discussion side of our taxonomy, Commissives and Directives are more limited to content corresponding to search and navigation actions (*Robot, move forward three feet*). Expressives are unique in that they do not require additional propositional content; thus, while it's plausible for some type of `Arg1-content` to be expressed (e.g., *Thanks **for teaming up with me today***), the expressive speech acts generally stand alone as formulaic expressions (e.g., *Thanks!*, *Okay*, *Good*, *Woops!*, *Sorry!*). Although not exhaustive as to what could be seen in the language of our domain, a table detailing which robot concepts readily combine with which speech acts is given in the Appendix in Table 5.

4. Annotated Corpus of AMRs

Our corpus, DialAMR, consists of 1122 utterances from SCOUT, annotated both as standard AMR and Dialogue-AMR. Other existing AMR corpora that have been released are largely from text, including Wall Street Journal and Xinhua news sources, as well as web discussion forum data.[5] There is a small amount (about 200 instances) of broadcast news conversation corpora but none centered around natural dialogue. Thus, this is one of the first efforts to use AMR to annotate dialogue (see Section 5 for further discussion). Although we begin with the SCOUT data for annotation, we aim to expand the DialAMR corpus with other dialogue data. In the sections to follow, we describe the development of the corpus, including data selection and the use of existing parsers and a novel graph-to-graph system to provide an initial automatic pass of standard and Dialogue-AMR followed by manual corrections.

4.1. DialAMR Data Selection

DialAMR was created using different sampling strategies to obtain coverage and diversity of the SCOUT dialogues. First, a set of 137 randomly sampled utterances from commander participants were selected in order to measure AMR coverage for this dialogue domain (we refer to this as the *Random-Commander* subset; see Table 3). These utterances were manually annotated using standard AMR annotation guidelines[6] by one senior and two recently trained AMR annotators. Inter-annotator agreement (IAA) among the initial independent annotations obtained adequate scores of .82, .82, and .91 using the Smatch metric (Cai and Knight, 2013).[7] Next, we manually selected 474 utterances consisting of short, sequential excerpts (including all interlocutors from both conversational floors) representative of the variety of common exchange types in the corpus (called the *Representative-Excerpts* subset). These utterances were distinct from the Random-Commander subset, and were independently double-annotated (IAA 87.8%) and adjudicated by two authors of this paper trained in AMR annotation. The Random-Commander and Representative-Excerpts subsets constitute a relatively representative subset of the SCOUT corpus, to which standard AMR was manually applied.

To establish a gold standard set of Dialogue-AMRs and to explore the adequacy of our annotation schema, the same two authors manually transformed and adjudicated the first 290 utterances (IAA 86.6%) from the Representative-Excerpts subset. This process revealed illocutionary forces hypothesized for this domain, but unattested in the sample. To address these potential gaps in coverage, we manually selected 207 additional instances from the corpus believed to be questions, requests, or expressives based upon the dialogue structure annotations accompanying those instances (called the *Q-Request-Express* subset). This sub-

[5] `https://catalog.ldc.upenn.edu/LDC2017T10`

[6] `https://github.com/amrisi/amr-guidelines/blob/master/amr.md`

[7] According to AMR development group communication, 2014, IAA Smatch scores on AMRs are generally between .7 and .8, depending on the complexity of the data.

Subsets	# Utterances	Manual Standard AMR	Manual Dialogue-AMR
Random-Commander	137	137	0
Representative-Excerpts	474	474	290
Q-Request-Express	207	207	50
Continuous-Trial	304	0	0
Total	**1122**	**818**	**340**

Table 3: Summary of DialAMR corpus with number of utterances in each subset, as well as the number of entirely manual annotations completed for both standard and Dialogue-AMR; the remainder of the corpus is manually corrected after an initial automatic pass.

set was manually single-annotated and adjudicated for standard AMR and Dialogue-AMR.

Finally, in order to evaluate the coverage of our schema and its potential for representing ongoing dialogue, we randomly selected for annotation one continuous 20-minute experimental trial, which contains 304 utterances (called the *Continuous-Trial* subset).

4.2. Automatic AMR Annotation

Manual annotation of standard AMR on one utterance from the SCOUT corpus takes approximately five minutes. Manually augmenting this representation into Dialogue-AMR can range from 1-15 minutes depending upon the complexity and novelty of the utterance. To quickly annotate our DialAMR corpus and allow for future expansion of the corpus into additional domains, we employed automated systems to generate both standard AMR and Dialogue-AMR after which manual correction was applied. Table 3 summarizes the number of entirely manual, from-scratch annotations were completed for this corpus; the remainder were automatically generated and then manually corrected. We leveraged publicly available and state-of-the-art AMR parsers to produce the standard AMR (Section 4.2.1), and developed a novel graph-to-graph system to transform standard AMR into Dialogue-AMR (Section 4.2.2). In addition to speeding up the annotation, these automated systems are critical components of our planned extended dialogue system (Figure 2).

4.2.1. Standard AMR Parsing

While a variety of relatively robust parsers can be leveraged to automatically convert the transcribed dialogue into AMR, these parsers are trained on the AMR release data, which, as mentioned previously, does not include natural dialogue, nor does it include much instruction-giving or commands. Nonetheless, we applied parsers to the SCOUT corpus to determine which could achieve the best performance with the least manually annotated in-domain training data. These experiments are ongoing, and full results will be reported in a future paper. Here, we limit our description to what is relevant for the automatic annotation pass used to efficiently create the DialAMR corpus.

First, we tested two long-standing parsers, JAMR (Flanigan et al., 2014) and CAMR (Wang et al., 2015), on the Random-Commander set of gold-standard, manually annotated standard AMRs. Performance was far below reported f-scores on LDC AMR test data (Bonial et al., 2019b). Particularly problematic areas included missing `mode :imperative` markers on all imperative utterances, failure to include implicit subjects (e.g., the `Arg0-mover` in utterances such as *Moving...*), and failure to correctly represent the *photographing* semantics of the common light verb construction *take a photo/picture* (instead representing this as a *taking* event in the sense of grasping/moving). Next, we evaluated more recent state-of-the-art parsers by Lyu and Titov (2018), Lindemann et al. (2019), and Zhang et al. (2019). After retraining the parsers on the approximately 800 manually-annotated utterances, we opted to use both the Zhang et al. and Lindemann et al. parsers to obtain the standard AMR for manual corrections, as each correctly captured several of the extremely frequent aspects of the corpus, including the `mode :imperative` marker.

4.2.2. Graph-to-Graph Transformation for Dialogue-AMR

In order to automatically generate Dialogue-AMRs with the tense, aspect, and illocutionary force information critical to the navigation domain, we developed a graph-to-graph transformation system that converts standard AMRs into our Dialogue-AMRs through a mixed-methods approach that leverages both rule-based and classifier-based systems (Abrams et al., 2020). Both the standard AMR and original natural language utterance are required as input to the graph-to-graph transformer. From the utterance, the speech act and tense are determined by employing classifiers. From the standard AMR, the relations (e.g., `go-02`, `turn-01`) corresponding to robot concepts are determined by matching the standard AMR root relation against a dictionary of keywords associated with a particular robot concept (see Table 2). Next, the aspectual information is extracted based upon speech act and tense patterns (e.g., present-tense assertions are `complete - ongoing +`). Finally, a rule-based slot filling approach extracts portions of the standard AMR to fill the appropriate slots in the Dialogue-AMR template. While most slots are preserved with the same labels, some transformations change argument and coreferent labels (e.g., `:ARG0 (y / you)` → `:ARG0 robot`).

The Dialogue-AMRs generated by the graph-to-graph system were manually inspected and corrected to establish the gold standard for inclusion in the DialAMR corpus. We incrementally refined the graph-to-graph transformation during the process of manual correction and error analysis.

5. Related Work

In order to engage in dialogue, an interlocutor must interpret the meaning of a speaker's utterance on at least two levels, as first suggested by Austin (1962): (i) its propositional content and (ii) its illocutionary force. While semantic representations have traditionally sought to represent propositional content, speech act theory has sought to delineate and explicate the relationship between an utterance and its effects on the mental and interactional states of the conversational participants. Speech acts have been used as part of the meaning representation of task-oriented dialogue systems since the 1970s (Bruce, 1975; Cohen and Perrault, 1979; Allen and Perrault, 1980). For a summary of some of the earlier work in this area, see Traum (1999).

Although the refinement and extension of Austin's (1962) hypothesized speech acts by Searle (1969) remains a canonical work on this topic, there have since been a number of widely used speech act taxonomies that differ from or augment this work, including an ISO standard (Bunt et al., 2012). Nevertheless, these taxonomies often have to be fine-tuned to the domain of interest to be fully useful. While we adopt many of the categories of Searle's taxonomy for our own speech act inventory, we integrate distinctions from the ISO standard and, following Traum (1999) and Poesio and Traum (1998), define our speech acts according to the effects of an utterance relating to the beliefs and obligations of the interlocutors (see Section 3.1).

Our work forms part of a larger, growing interest in representing various levels of interpretation in existing meaning representation frameworks, and in AMR in particular. Bastianelli et al. (2014) present their Human Robot Interaction Corpus (HuRIC) following the format of AMR. This corpus is comprised of paired audio interactions and transcriptions. Though all text is annotated in the format of AMR, AMR is significantly altered by incorporating detailed spatial relations, frame semantics (Fillmore, 1985), and morphosyntactic information. Shen (2018) further presents a small corpus of manually annotated AMRs for spoken language to help the parsing task. The study presents similar findings to our own: while AMR offers a clean framework for the concepts and relations used in spoken language, the mapping between AMR and computer-interpretable commands is not trivial, especially in the case that very little of training data is provided. Both of these corpora point to the need for more annotation of AMR for dialogue and training on parsers, to which our paper contributes.

Such work is paralleled by a more sustained recognition of and interest in the multifunctionality of utterances in dialogue across the dialogue literature (e.g. Allwood, 1992; Bunt, 2005, 2006). O'Gorman et al. (2018) present a Multi-Sentence AMR corpus (MS-AMR) designed to capture coreference, implicit roles, and bridging relations. Though not strictly speech acts, the interconnected approach to meaning that this corpus annotates is directly relevant for deducing illocutionary force in a dialogue context. Kim et al. (2019) similarly describe an annotation schema designed to capture discourse inferences via underlying semantic scope relations. Hajicova (2019) outlines an argument for modeling information and discourse relations explicitly in meaning representations. Though none of these proposals looks at illocutionary force directly, the recognition that meaning representations for dialogue need to be expanded to capture levels of interpretation beyond the propositional content is growing in NLP.

6. Conclusions and Future Work

This paper presents an inventory of speech acts suitable for human-robot navigation dialogue, and a Dialogue-AMR schema that captures not only the content of an utterance but the illocutionary force behind it. These Dialogue-AMR, as well as standard AMR, have been applied to human-robot dialogue data to create the DialAMR corpus, one of the first efforts to apply AMR to dialogue data. We continue to improve the automated parsing techniques to obtain AMRs by exploring the use of active learning to target the most informative data for manual annotation. Given the relative paucity of AMR dialogue data, we are also exploring improving parsing results with domain adaptation methods (McClosky et al., 2010; Ziser and Reichart, 2016) as well as back-translation (He et al., 2016). We are working to improve the robustness of the graph-to-graph system by leveraging lexical resources, such as WordNet (Miller, 1998) and VerbNet (Schuler, 2005), to extend the vocabulary associated with robot concepts in the graph-to-graph system. We hypothesize that the illocutionary force addition to AMR is extensible and valuable to a variety of dialogue domains; thus, we are evaluating the coverage of our Dialogue-AMR schema and graph-to-graph system on other human-agent and human-human navigation corpora.

The integration of speech acts into AMR paves the way for implementation of a full dialogue system and execution of robot movement in the collaborative human-robot navigation domain. We are exploring the usage of these AMRs for NLU, dialogue management, natural language generation, and robot concept specification. The Dialogue-AMR relations classify speaker intention, while the argument roles allow for flexible representation of previously unseen values (e.g., *Turn left 100 degrees* compared to a more typical number of degrees, such as 90) and compositional construction of referring expressions. Furthermore, the `completable` annotation attached to goal-oriented Dialogue-AMRs allow a dialogue management system to determine if all the arguments required for execution of the instruction are present, and, if not, the system can follow up with a clarification (Xu and Rudnicky, 2000). This structured approach is expected to be less brittle than the statistical similarity and retrieval model implemented in Lukin et al.'s (2018) NLU component in this human-robot dialogue domain, which has difficulty generalizing to novel, unseen commands.

We expect promising results from integrating Dialogue-AMR into our human-robot dialogue architecture. Furthermore, our annotation schema and corpus will contribute to a growing set of resources supporting meaning representation that goes beyond propositional content to model speaker intention in the conversational context.

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Appendix: Speech Acts & Robot Concepts

Speech Acts	Dialogue-AMR Relations	Commitments & Obligations
Question	Question-SA	Speaker (S) committed to desire to know answer; Addressee (A) obliged to respond to question
Assertion	Assert-SA	S committed to a state of affairs
Offer	Offer-SA	S committed to feasibility of plan of action; A obliged to consider action and respond
Promise	Promise-SA	S committed to feasibility of plan of action and obliged to do action
Command	Command-SA	S committed to desire for A to do something and feasibility of action; A obliged to do action
Open-Option	Open-Option-SA	S committed to feasibility of action(s)
Request	Request-SA	S committed to desire for A to do something and feasibility of action; A is obliged to consider action and respond[8]
Accept/Reject	Accept-SA	S committed to a state of general acceptance or rejection[9]
Greeting	Greet-SA	S committed to recognizing presence of A and willingness to interact
Gratitude	Thank-SA	S committed to state of gratitude
Regret	Regret-SA	S committed to state of regret
Judgment	Judge-SA	S committed to evaluative stance
Mistake	Mistake-SA	S committed to acknowledging error
Hold Floor	Hold-Floor-SA	S committed to holding conversational floor for continued speech

Table 4: Dialogue-AMR Speech Act Lexicon

[8] Response might be by doing the action, rejecting it, accepting it, or discussing desirability.

[9] We leave the Expressive types (Request and subsequent rows) unspecified as to the resulting obligations and some further commitments, since some derive as much from context and committed mental state as well as the act itself, and some are culture-specific. For example, an acceptance of a Request generally commits the accepter to act, and an acceptance of an Offer generally commits the offerer to act.

Robot Concepts	Dialogue-AMR Relations	Compatible Speech Acts	Examples
ABILITY	Able-01	Question, Assertion	*Are you able to move that orange cone in front of you?; I'm not able to manipulate objects.*
SCENE	See-01	Question, Assertion	*Do you see foreign writing?; I see two yellow helmets to my left.*
ENVIRONMENT	Sense-01	Question, Assertion	*What is the current temperature?; My LIDAR map is showing no space behind the TV.*
READINESS	Ready-02	Question, Assertion	*Are you ready?; I'm ready.*
FAMILIARITY	Familiarize-01	Assertion, Open-Option	*I think you are more familiar with shoes than I am; If you describe an object, you can help me learn what it is.*
EQUIPMENT	Equip-01	Question, Assertion	*What kind of sensors do you have?; I have no arms, only wheels!*
MEMORY	Remember-01	Question, Assertion	*How did we get here from last time?; Yes (we've been here before).*
PROCESSING	Process-01	Assertion	*Processing...; Hmm...*
TASK	Task-01	Assertion, Command	*We're looking for doorways; End task.*
SEND-IMAGE	Send-image-XX (domain-specific)	Assertion, Offer, Command, Open-Option, Promise	*Image sent; Would you like me to take a picture? Take a picture; I can send a picture; I will send a picture.*
MOVEMENT	Go-02	Assertion, Offer, Command, Open-Option, Promise	*I moved forward one foot I will move forward one foot, ok? Back up three feet; You can tell me to move a certain distance or to move to an object; I will move forward one foot.*
ROTATION	Turn-01	Assertion, Command, Open-Option, Promise	*Turning... Turn to face West; You can tell me to turn a number of degrees or to face something; I will turn 90 degrees.*
REPEAT	Repeat-01	Offer, Command, Request	*Would you like me to repeat the last action?; Do the following four times... Can you repeat that?*
CANCEL	Cancel-01	Command	*Cancel command; Stop; Nevermind*
DO	Do-02	Question, Assertion	*Did I successfully do what you asked? Executing; Done*
CLARIFY	Clarify-10	Assertion, Request	*Brown, not round; How much is a little bit?*
STOP (motion)	Stop-01	Command	*Stop there; Stop!*
HELP	Help-01	Command, Request, Open-Option	*Help! I need your help to find shoes; You can ask for help at any time.*
LOCATE	Locate-02	Assertion, Command	*(I've located) 3; Find doorways; ...and locate shoes*
CALIBRATE	Calibrate-01	Assertion, Command	*Calibrating...; Calibration complete Calibrate*
INSTRUCT	Instruct-01	Request	*What should we do next?; Then what?*
WAIT	Wait-01	Command, Request	*Wait! Please wait.*
PERMISSION	Permit-01	Request	*Robot, can I call you Fido?*
UNDERSTANDING	Understand-01	Question, Assertion	*Did I misunderstand?; Ok, I think I got it.*

Table 5: Robot concepts with associated Dialogue-AMR relations, attested speech act types, and examples.