Talk-to-Resolve: Combining scene understanding and spatial dialogue to resolve granular task ambiguity for a collocated robot

Pradip Pramanick, Chayan Sarkar, Snehasis Banerjee, and Brojeshwar Bhowmick
Robotics and Autonomous Systems, TCS Research, India

Abstract
The utility of collocating robots largely depends on the easy and intuitive interaction mechanism with the human. If a robot accepts task instruction in natural language, first, it has to understand the user’s intention by decoding the instruction. However, while executing the task, the robot may face unforeseeable circumstances due to the variations in the observed scene and therefore requires further user intervention. In this article, we present a system called Talk-to-Resolve (TTR) that enables a robot to initiate a coherent dialogue exchange with the instructor by observing the scene visually to resolve the impasse. Through dialogue, it either finds a cue to move forward in the original plan, an acceptable alternative of the original plan, or affirmation to abort the task altogether. To realize the possible stalemate, we utilize the dense captions of the observed scene and the given instruction jointly to compute the robot’s next action. We evaluate our system based on a data set of initial instruction and situational scene pairs. Our system can identify the stalemate and resolve them with appropriate dialogue exchange with 82% accuracy. Additionally, a user study reveals that the questions from our systems are more natural (4.02 on average on a scale of 1 to 5) as compared to a state-of-the-art (3.08 on average).

Keywords:

1. Introduction
The idea behind the collocated robot is to employ them in various activities where they can lend a helping hand and make our living/workspace
simpler and coherent. Though the number of robots in our daily surroundings is increasing day by day, their usability remains restricted due to a lack of an intuitive interaction interface, especially for non-expert users. As natural language interaction increases the acceptability and usability of a robot, a large number of research efforts have focused on enabling natural human-robot interaction [1].

Figure 1 depicts a real-life scenario in a home environment where a fellow human being asks a robot to bring the red container from the dining table. Assuming that the robot knows the environment, it first moves to the location of the dining table. However, there is no guarantee that the mentioned object is the only object available at the location. So, first, the robot has to identify the exact and/or alternate entities in the scene to decide further course of action accordingly. In Figure 1, the robot can find only a blue container at the location whereas the user has asked for a red one. Thus, given a task instruction in natural language and a scene from a robot’s ego-view, the robot either generates an execution plan if doable in the current scenario or engages in a dialogue if there is any ambiguity in understanding what action is to be performed. As there can be different types of ambiguities that cannot be predicted, the first challenge is how to detect the nature of the problem the robot is facing. The subsequent question is how to convey the veracity of the problem to fellow human beings and seek guidance or directive.

In this work, we present Talk-to-Resolve (TTR), a multimodal natural interaction interface for robots for task ambiguity resolving. We utilize a state-of-the-art dense-caption generation system [2] as the primary level of
scene understanding. However, existing caption generation systems do not consider any instruction as a precursor to the scene analysis. As a result, captions are generated about every possible object that is available in the scene. Often multiple captions are generated about the same object, where each caption may provide a different description of the object. We perform caption merging and filtering operations to narrow down our search for detecting the desired object or location mentioned in the instruction. This step includes all the possible alternatives of the specified entities if there are multiple occurrences of the same object. After caption filtering and merging, we determine the level of ambiguity in the scene concerning the initial instruction. We have judiciously defined dialogue templates for each ambiguous state and generate a dialogue based on the predicted ambiguous state.

To the best of our knowledge, this is the first work that generates contextual and informative questions during task execution to resolve both ambiguity and visual uncertainty by performing scene analysis. The main contributions of this work are three-fold.

- Given a natural language description about an object and a scene understanding, we develop a novel method to identify the relevant object(s) while suppressing the redundant information efficiently.

- We meticulously design a set of dialogue states and develop a dialogue system that resolves all possible types of ambiguity in scene understanding.

- Our dialogue system asks questions in a natural way that ensures that the user can understand the type of confusion the system is facing.
2. Related work

Executing natural language instruction given to a robot is a well-studied problem, particularly for object fetching and navigational instruction. However, the existing works in the literature mostly focus on instruction understanding for plan generation [3, 4] and assume that a generated plan can be executed without failure or further human intervention. Natural language instructions are prone to ambiguity and incompleteness that are often tackled using dialogue [5] and knowledge-based reasoning [6]. However, these systems only focus on the linguistic information provided by the human and do not take the uncertainty of the robot’s perception into account when attempting to execute a plan. For example, in our earlier works, we have handled the natural language task instruction parsing to generate a high-level execution plan for the robot [3, 7]. These systems are supported by a dialogue engine that can raise a suitable query for the human user if the robot could not understand the task [8]. However, the robot would fail if the referenced object in the task cannot be identified uniquely (due to ambiguity) while executing the task.

In practice, a robot may encounter unexpected situations during the execution of a plan, despite understanding the meaning of the instruction. To tackle this, a visual understanding of the environment, concerning the linguistic input, shows a promising direction. Recent works in vision and language navigation [9] and object manipulation [10] can handle complex instructions using multi-modal information, but they still suffer from ambiguity and cascading errors due to misprediction. Although several works have specifically focused on the visual grounding of natural object descriptions [11, 12, 13], they do not tackle ambiguity and incompleteness using dialogue. Moreover, the predominant approach of end-to-end training for visual grounding is difficult to use in a dialogue system, because the generation of a question pertaining to the instruction, requires a finer-grained understanding of the scene. Although visual question-answering systems can perform fine-grained scene analysis [14, 15], they are limited to answering questions, as opposed to generating a specific question to execute an instruction in a given scenario. Also, existing visual question generation models cannot be directly integrated into a robotic system, because they only generate natural questions about a given scene [16, 17], irrespective of any given instruction. Moreover, such visual dialogue systems use the feedback from multiple questions to arrive at the conclusive question, which is undesirable in a human-robot dialogue for task
Method | Ambiguity detection in grounding | Granular ambiguity states | Query on ambiguity
--- | --- | --- | ---
FETCH-POMDP [18] | implicit | binary ambiguity | non-informative, fixed query
Interactive Picking [19] | explicit | binary ambiguity | non-informative, fixed query
INGRESS [20] | explicit | binary ambiguity | informative, but fixed query
INVIGORATE [21] | explicit | binary ambiguity | informative, but fixed query
TTR (our system) | explicit | multi-level ambiguity | informative, contextual query

Table 1: Comparison of TTR with respect to the state-of-the-art systems for ambiguity handling.

execution, where the scope of asking multiple questions is limited.

On the other hand, existing dialogue systems for robotic instruction understanding, mostly focus on eliciting missing information [5, 8] and interactive task semantics learning [22], but do not tackle visual ambiguity and inconsistency. The most relevant works only focus on grounding and use dialogue in a very limited scope. Table 1 lists the closest works with respect to the problem that is tackled in this article. Whitney et al. [18] proposed a POMDP based object fetching task where pointing gestures are used to tackle ambiguities arising from open-ended instructions. They implicitly handle only binary type ambiguity, i.e., is there one object (non-ambiguous) or more object (ambiguous) and raise the same query if it is ambiguous. Hatori et al. proposed a system for interactive picking that uses dialogue to resolve ambiguity in a picking task. However, the dialogue system tackles only binary ambiguity and it generates generic and open-ended questions such as “which one?”, which often leads to further ambiguities. Shridhar et al. proposed a similar system called INGRESS [20] where a referential expression generation technique is used to generate questions where binary answers are possible. However, their system only considers two dialogue states, i.e., the instruction is either ambiguous or completely understood (binary ambiguity). Recently, Zhang et al. proposed an improved system called INVIGORATE [21] that combines multiple neural network systems using a
POMDP model to tackle the uncertainty of each system jointly. However, their system is limited to binary ambiguity only; hence it restricts the usability of the system in a generic setup. In particular, the system would either lead to many rounds of question-answering with the human being or fail to resolve the ambiguity beyond the restrictive setup. In contrast, our system can resolve multiple variants of ambiguity. Also, it asks specific questions by conveying the robot’s understanding of the scene that are easier to answer correctly (informative, contextual query).

To the best of our knowledge, none of the existing works specifically focus on generating questions to complete a task by performing scene analysis, where the questions are asked to resolve both ambiguity and visual uncertainty at a granular level. Moreover, our system is more accurate in predicting the dialogue states and generating more natural questions.

3. System Overview

In this section, we provide a high-level overview of “Talk-to-Resolve (TTR)”. It consists of four major components, as shown in Figure 2.

1. A task instruction understanding component that parses a given instruction to predict the task type and arguments.
2. A task (re)planning component that generates the task execution plan by translating the parsed instruction to an abstract action sequence that the robot actuates to satisfy the task goal. It also re-plans after resolving visual ambiguity (if any) with the feedback through the dialogue.
3. A component for visual uncertainty analysis that locates the exact referred object(s) mentioned in the task instruction. In case there is visual uncertainty, it triggers the dialogue system to resolve the ambiguity by engaging with the human. If the referred object(s) can be visually pinpointed, the task execution continues; otherwise the task is aborted (after dialogue exchange with the human).
4. A dialogue system to resolve visual uncertainty by asking a question that suitably elucidates the ambiguity that the robot is facing.

In this article, we focus on the visual uncertainty analysis and dialogue to resolve the uncertainty, where we incrementally ground the entities of the abstract plan. We attempt to visually ground only those entities that are required by the current action. During visual grounding, TTR analyses the
Table 2: Description of task types that are used to train and test our system. Italicized words are argument types associated with the task. The system is scalable and easily extendable for our types of tasks.

| Task type   | Description                                                                 |
|-------------|-----------------------------------------------------------------------------|
| Bringing    | Bring an *object* to a *beneficiary* from a *source*.                      |
| Change state| Manipulate a *device* to a desired *state*.                                |
| Check state | Assert the given *state* of an *object*.                                  |
| Motion      | Move to a given *goal*.                                                    |
| Placing     | Place an *object* on a *goal*.                                             |
| Searching   | Look for an *object* in an *area*.                                          |
| Taking      | Pick up an *object* from a *source*.                                       |

current ego-view of the robot to decide if such a grounding is possible. In the cases of grounding failure and ambiguity, it invokes the dialogue component, which uses visual uncertainty analysis to formulate questions for the human co-worker. As TTR generates specific questions that can be answered by either a binary yes/no or choosing an answer from a set of suggestions, the answer is direct and unambiguous. In the case of an indirect answer, it is treated as a rephrased description of the same argument and processed in the same pipeline.

4. Talk-to-Resolve (TTR) in Details

In this section, we describe our approach in detail and explain the integration of individual modules.

4.1. Task instruction understanding

We assume that a given instruction contains a task, having an unambiguous goal. The task is decomposed into a sequence of robot executable actions by task planning. To generate such a plan from the instruction, we utilize Conditional Random Field (CRF) models introduced in our previous work [3, 7]. The CRF models are trained to recognize a set of generic tasks with the corresponding arguments from text input, as shown in Table 2. The task types and arguments are defined according to the theory of semantic frames [23]. Given the predicted task type and the complete set of arguments for the task, we attempt to ground the arguments to the entities in the environment. As an example, for the following instruction, we consider
grounding the argument values for object and source to a unique red-colored cup that is visible and a unique location called the kitchen, respectively.

[Take] taking [a red cup] object [from the kitchen] source.

Considering a robot in an office environment, these task types are chosen. However, the system design is scalable and easily extendable for other task types. This just requires the CRF models to be trained with datasets (annotated textual instructions) for those data types. Since the primary objective of this article is to resolve various ambiguity levels to ground the referred object, it is not dependant on the task type. Hence, the core contribution of this article remains applicable to the extended system as well.

4.2. Plan generation

Given the task type and arguments mentioned in the instruction, we generate a high-level task plan to execute the task. We encode the instruction in a PDDL planning problem \[24\] by using templates of initial and goal conditions for the predicted task and use a forward-search planner to generate the plan \[3\]. An example of a task plan is given below.

1. MOVE TO source
2. LOCALIZE object source
3. PICK UP object source

We utilize the abstract task plan to enable the incremental grounding process. Before executing an action in the plan, such as MOVE TO, we attempt to ground its argument(s), e.g., source in the action. The source location ‘kitchen’, being a static geo-fencing area, the navigation goal can be determined from the robot’s knowledge. Therefore, the execution of subsequent actions, where the object (a red cup) must be grounded visually, can be deferred until the robot reaches the source location. We assume that an initial occupancy map of the environment is known and the geo-fencing areas are annotated with names. For the entities that are not present in the knowledge base (such as movable objects), we resort to visual grounding.

4.3. Visual uncertainty analysis

The visual uncertainty analysis module aims to localize an argument to the bounding box of a unique entity in the scene. It also decides if this localization is uncertain and infers the nature of the uncertainty. To perform this localization, we first predict the entities present in the scene along with
their bounding boxes and generate a description for each of them. To generate the descriptions in natural language, we utilize a dense image captioning network, DenseCap [2]. Given an image, it generates multiple region proposals, encodes the region features using a CNN, and uses a recurrent network (LSTM) to generate descriptions of the proposed regions. As the region proposal network in DenseCap is not constrained to any particular object type, the generated descriptions are not restricted to the objects mentioned in the instruction. Therefore, to find the most likely candidate object(s) in the scene, we rank the generated captions according to their semantic similarity with the argument phrase.

However, a direct semantic mapping is often not possible, as the perception of the same object can differ for the robot and a human due to poor lighting, viewing angle, clutter, and partial occlusion. Also, there can be multiple objects of the same type and due to mismatch in the vocabulary of natural language and that of the LSTM language model of DenseCap, the same object can be referred to by different words. For example, in Figure 1 there are three bottles, one containing wine and the others containing water. An instruction to simply fetch a bottle in this scenario is ambiguous. Also, an instruction like “bring me a coffee mug” does not have any lexical match with the description “a red plastic cup”, although it is likely to be the intended object. In the same scene, the cup’s material is also wrongly predicted to be plastic. Although, utilizing pre-trained word embeddings to compute the cosine distance between a pair of words [25] yields a semantic similarity metric that addresses some of these issues, defining such a similarity function to compare a caption and an argument is still non-trivial.

- Both the argument and the caption contain a variable number of tokens, so the pairwise similarity between the tokens [25] cannot be calculated directly.
- Although vector-composition based models [26, 27] encode a variable-length phrase, they do not yield an optimal relevancy ranking. This is because such models aim to capture a generic summary of the word embeddings, failing to exploit important local features. For example, if the instruction is about finding a red lamp, a caption ‘a lamp on the table’ is relevant but ‘a red table’ is not.
- The generated captions are complete sentences. Whereas the argument is often an incomplete phrase, which leads to a large length mismatch.
This limits the applicability of n-gram alignment techniques such as METEOR [28] used in [20].

Therefore, we introduce a new semantic similarity metric, where we encode the words into pre-trained GloVe embeddings [25] and compute a convex combination of the embeddings to generate a vector of fixed dimension. In contrast to existing vector composition models that assign weights to individual word vectors [29, 26], we classify the words into a set of semantic classes and only assign weights to the semantic classes. This results in a much simpler learning problem, as we only optimize weights for \( k \) semantic classes, as opposed to learning a composite, \( d \) dimensional embedding (\( k << d \)), through supervision [29]. In the following, we define the similarity metric and describe how it is applied to determine a dialogue state for question generation.

4.3.1. Semantic similarity calculation

The DenseCap model outputs a set of bounding boxes \( B_{1:n} \) and captions \( C_{1:n} \) for a given scene. We define the semantic similarity function \( f(A, c_i) \), to compare the argument phrase \( A \) with a given caption \( c_i \), and thus find an optimal relevancy ranking. Firstly, given a sequence of tokens, we predict a semantic class \( s \in SC \) for each token. In our context, \( SC \) consists of the classes - object, attribute, spatial_landmark and a others class to account for any other class of word. We model this semantic class prediction as a sequence labeling problem and train a CRF model to perform the labeling. Given a token sequence \( t_{1:n} \), we perform inference on the CRF to find the most probable sequence of semantic class labels \( s_{1:n} \),

\[
s_{1:n} = \arg \max_{s_i \in SC} P(s_i|t_{1:n}, s_{i-1}).
\]

We extract several grammatical features in the feature functions of the CRF. The features include the lemma, POS tag, and dependency tag of the token and its direct neighbors of the dependency parse tree, including a transition feature \( s_{i-1} \). To estimate a composite weighted embedding of a sequence of tokens \( t_{1:n} \), we interpolate the token embeddings with the corresponding class weight. Therefore, given \( n \) token embeddings of an argument phrase or a caption as \( d \) dimensional vectors, we find the convex combination as,

\[
V^d = \sum_{i=1}^{n} \lambda_i E(t_i)^d,
\]
where $\lambda_i$ and $E(t_i)$ are the interpolation weight and the embedding of the token $t_i$, respectively. Given the encoded argument as $V^d_A$, and an encoded caption as $V^d_{c_i}$, we find their pairwise similarity as,

$$f(A, c_i) = V^d_A \cdot V^d_{c_i} \frac{\|V^d_A\| \|V^d_{c_i}\|}{\|V^d_{c_i}\|}.$$ 

4.3.2. Redundancy suppression

Given the set of bounding boxes and the corresponding captions, ranked according to the caption’s similarity with the argument, we analyze the bounding boxes for possible redundancy. The caption generation model predicts the most probable sequence of words, given an image region as a proposal. However, such region proposals often overlap with each other, which results in redundant caption generation. Although a greedy non-maximum suppression (NMS) can be applied to prune region proposals with high overlap [2], i.e., Intersection over Union (IoU), setting the IoU threshold is generally difficult [30]. The difficulty increases when the robot must detect objects of varying size, distributed in varying distances; where larger and closer objects may lead to multiple captions. Thus naive NMS often fails to suppress captions that are about the same object, having a slightly different sequence of words. We consider two distinct types of redundancy in the generated captions and tackle them with different strategies.

- Object redundancy - when multiple bounding boxes are proposed for the same object that results in captions, where either no attribute is associated with the object, or the attributes are the same across the captions.

- Caption redundancy - when multiple captions are generated for the same object, whose attribute sets are disjoint.

Resolving object redundancy is important for avoiding false detection of ambiguity. Whereas, in the case of actual ambiguity, multiple instances of the same object must be considered separately. In the case of caption redundancy, although redundant captions are suppressed, the distinct attributes are merged to capture a distinct description of the object. We apply a greedy heuristic to keep the most relevant captions by jointly applying a semantic similarity and an IoU cutoff. Given the ranked captions, $c_{1:n}$, we consider $c_1$ to be the most probable candidate, i.e.,

$$c_1 = \arg\max f(A, c_i)$$
Firstly, we prune irrelevant captions by applying a semantic similarity cutoff $\alpha$. Thus, we estimate the set of relevant captions,

$$C_R = \{c_i : f(A, c_i) > \alpha, 1 < i \leq n\}.$$  

Then we find the set of candidate captions by pruning the remaining captions $c_i \in C_R$ that satisfy the following,

$$\text{IoU}(c_i, c_1) > \beta, f(c_i, c_1) > \alpha,$$

where $\alpha$ and $\beta$ are the semantic similarity and IoU cutoffs, respectively. While pruning a relevant caption, i.e., $c_i \in C_R$, we suppress caption redundancy by utilizing the previously predicated semantic class labels. Let $t_o$ denote the token corresponding to an object class label in $c_1$. Then if $t_o$ is present in a caption to be pruned, we merge the tokens in $c_i$ having the attribute label, with the set of attribute tokens in $c_1$. While merging such a caption $c_i$ with $c_1$, we also change the bounding box of $c_1$ as $b'_1 = b_1 \cup b_i$. We find the optimal values of $\alpha$ and $\beta$ through a grid search in the range $(0, 1)$ minimizing error in dialogue state identification, using a validation dataset.

4.3.3. Dialogue state identification

We analyze the final set of candidate captions to decide if a question should be asked. We define a set of dialogue states so that the specific problem faced by the robot is mapped to one of the states, and an appropriate question for that state can be formed. Unlike the existing work that decides only binary ambiguity, i.e., there is ambiguity only if there is more than one object, we define multi-level ambiguity states. Firstly, ambiguity can arise even if there is only one object – the physical or spatial properties mentioned in the instruction do not match with the object on the ground. Secondly, ambiguity can arise if there are multiple instances of the objects along with the object properties that may or may not match with the description (if any) in the instruction. Sometimes, even if there are multiple instances of the referred object, which is usually termed as ambiguity in most of the existing works, it may not be ambiguous if only one instance matches with the object description in the instruction. Our system handles all such scenarios, which leads to a multi-level ambiguity resolution. As a result, the query generated by the system is more informative and contextual, which helps the human to realize the exact nature of the impasse that the system is facing. Based on
Table 3: Description of dialogue states identified by comparing visual information with the argument.

| State                              | Description                                                                 |
|------------------------------------|-----------------------------------------------------------------------------|
| No question (NQ)                   | All the information is available.                                            |
| Ambiguous attribute (AA)           | Multiple matching objects, but no attribute mentioned in instruction.        |
| Implicitly matching attribute (IMA) | Unique object with attribute, but no attribute mentioned in instruction.    |
| Attribute mismatch (AM)            | Unique object, but its attribute is different from the instruction.          |
| Attribute not found (ANF)          | Unique object without attribute, but attribute is mentioned in instruction. |
| Ambiguous object and attribute (AOA)| Multiple matching objects that have either none or the same attributes.      |
| Not found (NF)                     | The object can’t be found, possibly an error in object detection.            |

Figure 3: Deriving the multi-level ambiguity states (listed in Table 3) considering all possible ambiguous scenarios.
our analysis of various situations and instruction, we define seven dialogue
states, as described in Table 3 that are sufficient to capture all possible object
ambiguities. The analysis is depicted in Figure 3 considering the possible
scenarios that may arise on the ground.

To identify a dialogue state we again utilize the CRF model we introduced
for semantic class prediction. We extract the semantic entities from the arg-
ument and compare it with extracted entities in the candidate captions,
utilizing the semantic classes that are predicted in the visual uncertainty
analysis stage (Section 4.3). Specifically, we check if the same object token
is mentioned in the candidate captions. If there is a unique candidate with
a matching object, we check the attribute tokens of both the argument and
the candidate. In the case of an argument mismatch, the AM state is iden-
tified, and ANF is identified when the argument is missing in the candidate.
Also, we take the strategy to confirm the object’s attribute if not explicitly
mentioned in the argument, i.e the IMA state. Otherwise, in the case of a
unique and exact match, we refrain from asking questions (NQ).

In the case of multiple candidates, we check if any attribute is mentioned
in the argument. If so, we check if multiple candidates with matching objects
have either the same or no attribute and thereby identify the AOA state.
Otherwise, we ask for clarity on the attribute for disambiguation, therefore
identifying the AA state. Finally, if no candidates are found, or there is no
matching object in the set of candidates, we decide on the NF state.

4.4. Question generation

After visual analysis of the scene, followed by dialogue state identification,
TTR generates a question if the dialogue state is the one where an argument
can’t be uniquely grounded, or such a grounding is uncertain. The question
is crafted to convey the robot’s partial understanding of the scene and also
pinpoint the ambiguity/uncertainty. To generate such questions, we use a
set of templates, where each template contains multiple slots, that are filled
using the semantic entities and filler words, from both the instruction and the
candidate captions. We designed the question templates in a pragmatically
appropriate manner and present the user with choices whenever applicable.
Moreover, we left out any task-specific terms in the templates so that they
are generalized across multiple task types. The templates used in TTR are
shown in Table 4.

The question generator uses the predicted semantic classes of the ar-
ument and the candidate captions to replace the occurrence of the corre-
Table 4: Mapping of question templates with dialogue states, where the underlined and the boldface slots are filled from the candidate captions and the argument, respectively.

| State | Template |
|-------|----------|
| AA    | I see a attribute-1 object and a attribute-2 object. Which one did you mean? |
| ANF   | I see a object, but not sure if it’s attribute. Should I continue? |
| IMA   | I see a attribute object. Should I continue? |
| AM    | I see a object, but its attribute. Should I continue? |
| AOA   | I see #num attribute objects. Which one did you mean? |
| NF    | I can’t find any attribute object. What should I do? |

sponding slots. Although we define one template per dialogue state for our experiment, it is possible to use multiple templates for the same state, making the questions seem non-repetitive. This can be done by re-phrasing the template, utilizing the same set of slots.

5. Evaluation

We evaluate our system using a curated dataset of indoor scenes, task instruction, and appropriate dialogue state triplets. We have introduced a CRF model for semantic class prediction as a crucial component of our system. Therefore, we also evaluate the model using a separate dataset of annotated semantic class labels.

5.1. Datasets

To train the CRF for semantic class prediction, we have collected a total of 242 object descriptions from the Visual Genome dataset [31] that is used to train DenseCap [2]. We have sampled descriptions of image regions around everyday objects from 40 different indoor images. We have tokenized and annotated each token of a description as a sequence of semantic class labels, using a text annotation tool [32]. This results in the annotation of 4.48 (SD=1.19) classes per description, on average. We have trained the CRF with 80% of the data, and have evaluated using the remaining 20%.

To evaluate our dialogue state identification method, we have collected a total of 88 indoor scenes from an indoor scene recognition dataset [33]. For each image, we have written multiple instructions conveying different task types and referring to different objects in the image. Also for every
Table 5: Semantic class labeling result (F1-score) of our CRF model, compared to a grammar based baseline.

| Semantic class         | Grammar baseline | CRF ours |
|------------------------|------------------|---------|
| Object                 | 0.76             | 0.91    |
| Attribute              | 0.67             | 0.96    |
| Spatial landmark       | 0.83             | 0.91    |
| Other                  | 0.74             | 0.97    |
| Avg.                   | 0.72             | 0.95    |

object type in an image, we have written instructions by referring to the same object type with a varying granularity of attributes and intentionally mistaken attributes. This results in a balanced dataset of different ambiguity and mismatch scenarios. We annotated the most appropriate dialogue state for a given image-instruction pair. Two of the authors have written the instructions and annotated the states. Another author reviewed and corrected the annotations for the entire dataset. The final dataset contains 358 image-instruction pairs. There are 7 different task types and 7 different dialogue states in the dataset as shown in Table 2 and Table 3, respectively. We select a random split of 10% of the data as a validation set for tuning the semantic class weights $\lambda_i$, the semantic similarity, and IoU cutoffs and use the remaining 322 image-instruction pairs as the test set.

5.2. Performance of semantic class prediction

We compare our CRF model with a grammar based baseline, where we convert a dependency parse tree of the text to semantic class labels. Following the parse tag definitions in [34], we label a token as the Object class if it is the root of the parse tree. Subsequently, we label the tokens having adverbial modifier (‘amod’ [34]) dependency as Attribute and having the indirect object dependency (‘iobj’ [34]) as Spatial_landmark, while any other tag is labeled as Other class. The semantic class prediction results are shown in Table 5. The results suggest that the CRF surpasses the grammar-baseline and has decent accuracy for using in the semantic similarity function and caption comparison.

5.3. Performance of dialogue state identification

We compare our approach with two baseline systems, where we analyze different semantic similarity metrics for caption relevancy ranking and mea-
Table 6: Dialogue state identification results (F1 score) of TTR and baselines. Boldface numbers are highest.

| State | METEOR baseline | DAN baseline | SWI ours | TTR ours |
|-------|-----------------|--------------|----------|----------|
| AA    | 0.79            | 0.49         | 0.73     | 0.76     |
| IMA   | 0.64            | 0.74         | 0.82     | 0.85     |
| AM    | 0.60            | 0.62         | 0.73     | 0.73     |
| ANF   | 0.42            | 0.56         | 0.75     | 0.75     |
| AOA   | 0.58            | 0.58         | 0.60     | 0.65     |
| NF    | 0.84            | 0.88         | 0.94     | 0.94     |
| NQ    | 0.57            | 0.58         | 0.56     | 0.68     |
| Avg.  | 0.71            | 0.72         | 0.80     | 0.82     |

sure the effect of redundancy suppression. The following describes the system variants used in the experiment.

- **METEOR** - We use the METEOR metric [28] as the semantic similarity function to prune irrelevant captions, but do not suppress redundancy.

- **Deep Averaging Network (DAN)** - We use a state-of-the-art deep averaging network [27] to encode the caption and the argument, followed by a cosine similarity computation. No redundancy suppression is applied to the ranked captions.

- **Semantic Weight Interpolation (SWI)** - Our proposed weighted vector composition model is used for semantic similarity, without redundancy suppression.

- **TTR** - Our full model, where both the object and caption redundancy suppression are applied, along with our proposed vector composition model for semantic similarity.

We optimize the cutoff thresholds for all the baseline systems using the same validation set and use the same task and argument labeling models. Also, we augment the proposed CRF model for semantic class labeling in all the baselines to enable dialogue state prediction. By comparing with the test data annotation, we report the dialogue state identification results in Table 6.
The baseline system that uses METEOR, closely resembling the work of Shridhar and Hsu [20], can only achieve an overall F1 score of 0.71. We observe that it is somewhat accurate in predicting the AA dialogue state, where the n-gram alignment in METEOR gives a better ranking to captions with a matching object type, whose attribute set is empty. However, it fails to tackle slight dissimilarities in the attributes, resulting in poor performance on the IMA, AM, and ANF states. For the prediction of these states, it is necessary to consider captions as relevant, even if the captions with a matching object have no attribute or have a different set of attributes. We see the opposite effect when using DAN, where the word vectors corresponding to the object are not explicitly given a high weight during composition, leading to low-ranking of captions describing the objects without any attribute, thereby failing to predict AA accurately. However, the continuous-space word representation of DAN slightly improves the accuracy for other states, improving the overall accuracy to 0.72.

Our proposed method of weighted vector interpolation (SWI) outperforms METEOR and DAN by large margins. We achieved a 0.8 score, even without redundancy suppression, particularly improving for IMA, AM, and ANF states. Finally, our full model achieved the best score of 0.82, also achieving the best scores in individual states, except for AA. Suppressing redundancy prominently helps the AOA state identification, where determining ambiguity is crucial; also improving the false-positive rates of NF and NQ.

5.4. User study

We have conducted a small scale user study, specifically to evaluate the actual questions generated by TTR. We compare our natural language question generation with Ingress, proposed by Shridar and Hsu [20]. To the best of our knowledge, their work is most similar to ours, as they also focus on asking questions for visual disambiguation of objects in a human-robot dialogue scenario. Moreover, they also use DenseCap [2] for generating linguistic descriptions of objects, for a direct comparison with the given instruction.

In this study, a participant is shown multiple image-instruction pairs to evaluate. The participant assesses a given scene and then rates the generated questions in response to the instruction. The participants are asked to rate two questions per image, one generated by TTR and another by INGRESS. The participant rates both the questions on a semantic differential scale with numeric points 1-5. We have asked the participants to give their ratings about how correct and natural they perceived the questions to be for the
Figure 4: From user experience study, average score (5==Best) at 95% confidence intervals for correctness and naturalness across different dialogue states and all states combined.
scenario. In the first scale, a 5 rating denotes a completely correct question and 1 denotes completely incorrect question. Whereas for the second scale, a 5 rating denotes a human-like natural question and 1 denotes a completely unnatural question. A total of 17 participants (9 male, 8 female) from our organization have volunteered for the study. The participants are from the age group 23-38, and all of them are fluent English speakers having at least a bachelor’s degree. Four of them have been familiar with the broad research area of robotics, but none of them have any expertise in human-robot interaction and dialogue systems. Each participant repeats the rating process for 14 random image-instruction pairs from our dataset. During the study, we did not reveal which question is generated by which system.

Figure 4a shows the average correctness ratings for the dialogue states. The questions generated by TTR are perceived to be more accurate for the image-instruction pairs that belong to the ANF, AOA, and IMA states. This result is most likely due to the absence of the fine-grained dialogue states in INGRESS. INGRESS uses generic questions to tackle different scenarios in a similar way, which possibly impacts the correctness perceived by the participants. Also, the questions generated by TTR are perceived to be more natural across all the dialogue states, as shown in Figure 4b. We show the overall rating comparison in Figure 4c, where the average correctness rating for TTR is 3.46 (SD=1.52) and for Ingress is 3.0 (SD=1.63). Also, the the average naturalness rating for TTR is 4.02 (SD=1.32) and for Ingress is 3.08 (SD=1.56). A paired two-tailed t-test reveals the results are statistically significant for both perceived correctness and naturalness. For correctness ratings, the t value is 4.79, \(p < 0.00001\). For naturalness ratings, the t value is 9.27, \(p < 0.00001\).

6. Conclusions

In this article, we describe our Talk-to-Resolve (TTR) system that helps a robot in resolving visual ambiguity and inconsistent perception, while executing an instruction. By taking natural language instruction as input, our system analyzes the scene perceived by the robot to convey the exact problem, which helps a human user to correctly signal a confirmation or modification of the task. To achieve this, we propose a semantic similarity function to find relevant object description(s) of the scene and a semantic class labeling model to compare the object descriptions with the instruction. Thus, we identify the appropriate dialogue state so that the exact problem
faced by the robot can be expressed as a question. Our experiments suggest that we benefit from our proposed approach for dialogue state identification in comparison to several baseline systems. We further improve the robustness of our proposed method by suppressing redundant object descriptions. In a user study, we also find that human users perceive the questions from our system to be more accurate and natural, in comparison to the state-of-the-art. Thus, TTR provides a significant leap forward in achieving an easy-to-use collocated robotic system in any indoor space.

References

[1] R. Liu, X. Zhang, A review of methodologies for natural-language-facilitated human–robot cooperation, International Journal of Advanced Robotic Systems 16 (3) (2019) 1729881419851402.

[2] J. Johnson, A. Karpathy, L. Fei-Fei, Densecap: Fully convolutional localization networks for dense captioning, in: Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 4565–4574.

[3] P. Pramanick, C. Sarkar, P. Balamuralidhar, A. Kattepur, I. Bhattacharya, A. Pal, Enabling human-like task identification from natural conversation, in: 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), IEEE, 2019, pp. 6196–6203.

[4] D. Lu, Y. Zhou, F. Wu, Z. Zhang, X. Chen, Integrating answer set programming with semantic dictionaries for robot task planning, in: Proceedings of the 26th International Joint Conference on Artificial Intelligence, IJCAI’17, AAAI Press, 2017, p. 4361–4367.

[5] J. Thomason, A. Padmakumar, J. Sinapov, N. Walker, Y. Jiang, H. Yedidsion, J. Hart, P. Stone, R. J. Mooney, Improving grounded natural language understanding through human-robot dialog, in: 2019 International Conference on Robotics and Automation (ICRA), IEEE, 2019, pp. 6934–6941.

[6] H. Chen, H. Tan, A. Kuntz, M. Bansal, R. Alterovitz, Enabling robots to understand incomplete natural language instructions using commonsense reasoning, in: 2020 IEEE International Conference on Robotics and Automation (ICRA), IEEE, 2020, pp. 1963–1969.
[7] P. Pramanick, H. B. Barua, C. Sarkar, Decomplex: Task planning from complex natural instructions by a collocating robot, in: 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2020, pp. 6894–6901. doi:10.1109/IROS45743.2020.9341289.

[8] P. Pramanick, C. Sarkar, I. Bhattacharya, Your instruction may be crisp, but not clear to me!, in: 2019 28th IEEE International Conference on Robot and Human Interactive Communication (RO-MAN), IEEE, 2019, pp. 1–8.

[9] P. Anderson, Q. Wu, D. Teney, J. Bruce, M. Johnson, N. Sunderhauf, I. Reid, S. Gould, A. van den Hengel, Vision-and-language navigation: Interpreting visually-grounded navigation instructions in real environments, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2018.

[10] D. Misra, A. Bennett, V. Blukis, E. Niklasson, M. Shatkhin, Y. Artzi, Mapping instructions to actions in 3d environments with visual goal prediction, in: Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, 2018, pp. 2667–2678.

[11] V. Cohen, B. Burchfiel, T. Nguyen, N. Gopalan, S. Tellex, G. Konidaris, Grounding language attributes to objects using bayesian eigenobjects, in: 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), IEEE, 2019, pp. 1187–1194.

[12] A. Magassouba, K. Sugiiura, A. T. Quoc, H. Kawai, Understanding natural language instructions for fetching daily objects using gan-based multimodal target–source classification, IEEE Robotics and Automation Letters 4 (4) (2019) 3884–3891.

[13] A. Sadhu, K. Chen, R. Nevatia, Zero-shot grounding of objects from natural language queries, in: Proceedings of the IEEE International Conference on Computer Vision, 2019, pp. 4694–4703.

[14] J. Johnson, B. Hariharan, L. van der Maaten, L. Fei-Fei, C. Lawrence Zitnick, R. Girshick, Clevr: A diagnostic dataset for compositional language and elementary visual reasoning, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 2901–2910.
[15] D. Teney, P. Anderson, X. He, A. Van Den Hengel, Tips and tricks for visual question answering: Learnings from the 2017 challenge, in: Proceedings of the IEEE conference on computer vision and pattern recognition, 2018, pp. 4223–4232.

[16] C. Patil, M. Patwardhan, Visual question generation: The state of the art, ACM Computing Surveys (CSUR) 53 (3) (2020) 1–22.

[17] J. Zhang, Q. Wu, C. Shen, J. Zhang, J. Lu, A. Van Den Hengel, Goal-oriented visual question generation via intermediate rewards, in: Proceedings of the European Conference on Computer Vision (ECCV), 2018, pp. 186–201.

[18] D. Whitney, E. Rosen, J. MacGlashan, L. L. Wong, S. Tellex, Reducing errors in object-fetching interactions through social feedback, in: 2017 IEEE International Conference on Robotics and Automation (ICRA), IEEE, 2017, pp. 1006–1013.

[19] J. Hatori, Y. Kikuchi, S. Kobayashi, K. Takahashi, Y. Tsuboi, Y. Unno, W. Ko, J. Tan, Interactively picking real-world objects with unconstrained spoken language instructions, in: 2018 IEEE International Conference on Robotics and Automation (ICRA), 2018, pp. 3774–3781.

[20] M. Shridhar, D. Hsu, Interactive visual grounding of referring expressions for human-robot interaction, in: Proceedings of Robotics: Science and Systems, Pittsburgh, Pennsylvania, 2018.

[21] H. Zhang, Y. Lu, C. Yu, D. Hsu, X. La, N. Zheng, Invigorate: Interactive visual grounding and grasping in clutter, arXiv preprint arXiv:2108.11092 (2021).

[22] L. She, J. Chai, Interactive learning of grounded verb semantics towards human-robot communication, in: Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), 2017, pp. 1634–1644.

[23] C. F. Baker, C. J. Fillmore, J. B. Lowe, The berkeley framenet project, in: Proceedings of the 17th international conference on Computational linguistics-Volume 1, Association for Computational Linguistics, 1998, pp. 86–90.
[24] M. Ghallab, A. Howe, C. Knoblock, D. McDermott, A. Ram, M. Veloso, D. Weld, D. Wilkins, Pddl-the planning domain definition language, AIPS-98 planning committee 3 (1998) 14.

[25] J. Pennington, R. Socher, C. D. Manning, Glove: Global vectors for word representation, in: Empirical Methods in Natural Language Processing (EMNLP), 2014, pp. 1532–1543.

[26] S. Arora, Y. Liang, T. Ma, A simple but tough-to-beat baseline for sentence embeddings, in: 5th International Conference on Learning Representations, ICLR 2017, 2019.

[27] D. Cer, Y. Yang, S.-y. Kong, N. Hua, N. Limtiaco, R. S. John, N. Constant, M. Guajardo-Cespedes, S. Yuan, C. Tar, et al., Universal sentence encoder, arXiv preprint arXiv:1803.11175 (2018).

[28] S. Banerjee, A. Lavie, Meteor: An automatic metric for mt evaluation with improved correlation with human judgments, in: Proceedings of the acl workshop on intrinsic and extrinsic evaluation measures for machine translation and/or summarization, 2005, pp. 65–72.

[29] M. Iyyer, V. Manjunatha, J. Boyd-Graber, H. Daumé III, Deep unordered composition rivals syntactic methods for text classification, in: Proceedings of the 53rd annual meeting of the association for computational linguistics and the 7th international joint conference on natural language processing (volume 1: Long papers), 2015, pp. 1681–1691.

[30] N. Bodla, B. Singh, R. Chellappa, L. S. Davis, Soft-nms–improving object detection with one line of code, in: Proceedings of the IEEE international conference on computer vision, 2017, pp. 5561–5569.

[31] R. Krishna, Y. Zhu, O. Groth, J. Johnson, K. Hata, J. Kravitz, S. Chen, Y. Kalantidis, L.-J. Li, D. A. Shamma, et al., Visual genome: Connecting language and vision using crowdsourced dense image annotations, International journal of computer vision 123 (1) (2017) 32–73.

[32] J. Yang, Y. Zhang, L. Li, X. Li, YEDDA: A lightweight collaborative text span annotation tool, in: Proceedings of ACL 2018, System Demonstrations, Association for Computational Linguistics, 2018, pp. 31–36.
[33] A. Quattoni, A. Torralba, Recognizing indoor scenes, in: 2009 IEEE Conference on Computer Vision and Pattern Recognition, IEEE, 2009, pp. 413–420.

[34] J. Nivre, M.-C. De Marneffe, F. Ginter, Y. Goldberg, J. Hajic, C. D. Manning, R. McDonald, S. Petrov, S. Pyysalo, N. Silveira, et al., Universal dependencies v1: A multilingual treebank collection, in: Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC’16), 2016, pp. 1659–1666.