Learning Lexical Entries for Robotic Commands using Crowdsourcing

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Abstract

Robotic commands in natural language usually contain various spatial descriptions that are semantically similar but syntactically different. Mapping such syntactic variants into semantic concepts that can be understood by robots is challenging due to the high flexibility of natural language expressions. To tackle this problem, we collect robotic commands for navigation and manipulation tasks using crowdsourcing. We further define a robot language and use a generative machine translation model to translate robotic commands from natural language to robot language. The main purpose of this paper is to simulate the interaction process between human and robots using crowdsourcing platforms, and investigate the possibility of translating natural language to robot language with paraphrases.

Introduction

Natural language provides an efficient way for untrained human to instruct a robot to perform collaborative tasks, e.g., navigation and manipulation. However, learning to interpret the meaning of natural language commands is a challenging task [Dukes 2014, Perera and Allen 2013, Chen and Mooney 2011], especially when the robot has little or no prior knowledge of the phrasal expressions in natural language. Due to high flexibility of natural language, it is non-trivial for a robot to cover all the phrasal expressions in natural language when its interpretation module is initially built.

Popular crowdsourcing platforms such as Amazon Mechanical Turk, provide a fast and cheap way to collect interactive data from participants in a wide range of different communities. Hence, simulating the human machine interaction process for information extraction on crowdsourcing platforms has attracted lots of research interests [Nguyen, Wallace, and Lease 2015, Hladká, Han, and Luksová 2014, Goldberg, Wang, and Kraska 2013]. To encourage the diversity of robotic commands, we simulate the interactive process between a robot and various untrained users on Amazon Mechanical Turk, and collect robotic commands during the process. We further apply a phrase-based machine translation model to mapping natural language command to a robotic language that can be understood by a robot.

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Phrase-based Machine Translation Model

To tackle the problem of translating natural language commands to language that can be understood by robots, we first define a robot language that consists of predefined key concepts in the robotic task domains. For example, in the navigation task domain, we define the following key concepts.

- Action:= navigate
- Object:= traffic barrel | building | car
- Relation:= left | right | front | back

Each robot language command can be deterministically constructed by a combination of key concepts in the task domains. See Figure 1 for an illustration. We then adapt a phrase-based machine translation model to translate robotic commands from natural language to the robot language. For the phrase-based machine translation model, the key component is the extracted phrase table that stores several lexical entries. For a particular input (source-language) sentence $s = s_1 \cdots s_n$, each lexical entry is defined as a tuple $(b, e, r)$, specifying that the span $s_b \cdots s_e$ in the source-language sentence can be translated as the target-language string $r$. For each lexical entry $p = (b, e, r)$, we estimate a score $g(p)$ in $\mathbb{R}$ that measures the likelihood of translating the span to the target language string by relative frequency under the translation model. For a given lexicon entry $p, b(p), e(p), r(p)$ denote its three components respectively. A derivation $y$ of a source-language sentence is defined as a finite sequence of phrases, $p_1, p_2, \cdots p_L$. For any derivation $y, r(y)$ refers to the translation sentence constructed by concatenating the strings $r(p_1), r(p_2), \cdots r(p_L)$. For a source-language sentence $s$, we denote $\mathcal{Y}(s)$ as a set of possible derivations of $s$.

Based on the above notations, we aim to extract lexical entries from parallel textual corpus collected on crowdsourcing platforms, and seek the optimal derivation $y^*$ using beam search for the maximum derivation score $f(y^*)$ among all possible derivations $\mathcal{Y}(s)$ under a phrase-based translation model.

In Equation [1] the score $f(y)$ of a derivation $y$ consists of three parts: (1) $h(r(y))$ is the log-probability of the target string $r(y)$ under a smoothed trigram language model; (2) $g(p_k)$ is the score of $p_k$ under a translation model; (3) $e(p_k) + 1 - b(p_{k+1})$ is the distortion penalty for reordering
word alignments between source and target languages.

\[ f(y) = w_h h(r(y)) + w_g \sum_{k=1}^{L} g(p_k) + w_d \sum_{k=1}^{L-1} e(p_k) + 1 - b(p_{k+1}) \]  

(1)

where \( w_h \), \( w_g \) and \( w_d \) are the weights of the scores given by the language model, the translation model and the distortion penalty respectively. Hence the optimal derivation of a source-language sentence \( s \) can be obtained by \( \arg \max_{y \in \mathcal{Y}(s)} f(y) \).

### Experiment

We present the process of collecting experimental data on Amazon Mechanical Turk, a popular crowdsourcing platform, and extract parallel lexical entries using Moses (Koehn et al. 2007), a machine translation tool.

#### Stimulation and Data Collection

By showing an image that depicts the behaviour of a robot, a turker is first asked to give a command in English (denoted as \( s \)) that clearly indicates the spatial information between objects in the environment for a robot. Next, the turker is shown some robotic concepts in several drop-down lists, and asked to select the correct robotic concepts that can be used to construct a robotic command (denoted as \( r \)) for the same image. Finally we simulate the scenario where the robot can actively ask for a paraphrase sentence (denoted as \( t \)) of the robotic command \( r \) in order to help it understand \( s \). Totally we collect 88 tuples of \((s, t, r)\) for navigation task and 120 tuples of \((s, t, r)\) tuples for manipulation task.

### Phrasal Lexicon Extraction and Translation

To investigate the possibility of using paraphrase sentences to enhance the phrase-based machine translation, we first use Moses to extract parallel phrases between \( s \) and \( r \). Then we use Moses to extract parallel phrases between \( t \) and \( r \). Table 1 shows the total number of extracted lexical entries when we translate from \( s \) to \( r \) and from \( t \) to \( r \). Comparing the second column with the third one in Table 1, we observe that more lexical entries are extracted from parallel sentences between \( t \) and \( r \) than those between \( s \) and \( r \). This convinces our idea that turkers usually paraphrase natural language commands that are more semantically closed to the robot language commands after the robotic concepts are shown to them. Table 2 shows some lexical entries extracted from natural language commands \( t \) paired with robot language commands \( r \). We observe that the extracted lexical entries capture the similarity between source-language phrases and target-language phrases, thus enabling many-to-one mapping from syntactic variants in natural language to unique robotic concepts.

#### Table 1: Number of extracted lexical entries

| Task         | \# phrase from \((s, r)\) | \# phrase from \((t, r)\) |
|--------------|--------------------------|--------------------------|
| Navigation   | 160                      | 748                      |
| Manipulation | 128                      | 298                      |

By optimizing the objective function in Equation 1, we generate the translated robot language sentence using the

### Conclusion

In this paper, we simulate the human robot communication on Amazon Mechanical Turk and collect robotic commands for navigation and manipulation tasks using crowdsourcing. We further investigate the possibility of bridging the gap between natural language command and robot language command using paraphrasing. We will conduct our future work in several challenging aspects. First, lexical entries extracted from different but similar robotic tasks can be shared across tasks. Second, machine teaching by paraphrasing can be integrated with active learning techniques. Robots can perform reasoning over the confusing phrases and actively ask their human partners for paraphrasing.

### Table 2: Examples of extracted lexical entries

| Natural Language | Robot Language |
|------------------|---------------|
| go straight until you reach a car | navigate to the car |
| find the car which stands before | behind the building |
| move forward to located at the right hand side of | to the car |
| is not completely correct because the natural language command contains the detail steps for the navigation task. Mapping detail descriptions to highly abstract robot concepts requires more sophisticated semantic reasoning over the natural language. We leave it as our future work. |

### Table 3: Examples of phrase-based translation

| Natural Language | Translated Robot Language |
|------------------|--------------------------|
| go to the traffic barrel that is located on the right hand side of the building | navigate (Action) to the traffic barrel (Object) that is on the right (Relation) of the building (Object) |
| go straight forward until you reach the building. go to the car behind the building. | navigate (Action) to the building (Object) that is navigate (Action) to the car (Object) that is behind (Relation) the building (Object) |
Acknowledgments
This work was conducted in part through collaborative participation in the Robotics Consortium sponsored by the U.S. Army Research Laboratory under the Collaborative Technology Alliance Program, Cooperative Agreement W911NF-10-2-0016, and in part by ONR under MURI grant “Reasoning in Reduced Information Spaces” (no. N00014-09-1-1052). The views and conclusions contained in this document are those of the authors and should not be interpreted as representing the official policies, either expressed or implied, of the Army Research Laboratory of the U.S. Government. The U.S. Government is authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notation herein.

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