Incremental Acquisition of Verb Hypothesis Space towards Physical World Interaction

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Abstract

As a new generation of cognitive robots start to enter our lives, it is important to enable robots to follow human commands and to learn new actions from human language instructions. To address this issue, this paper presents an approach that explicitly represents verb semantics through hypothesis spaces of fluents and automatically acquires these hypothesis spaces by interacting with humans. The learned hypothesis spaces can be used to automatically plan for lower-level primitive actions towards physical world interaction. Our empirical results have shown that the representation of a hypothesis space of fluents, combined with the learned hypothesis selection algorithm, outperforms a previous baseline. In addition, our approach applies incremental learning, which can contribute to life-long learning from humans in the future.

1 Introduction

As a new generation of cognitive robots start to enter our lives, it is important to enable robots to follow human commands (Tellex et al., 2014; Thomason et al., 2015) and to learn new actions from human language instructions (Cantrell et al., 2012; Mohan et al., 2013). To achieve such a capability, one of the fundamental challenges is to link higher-level concepts expressed by human language to lower-level primitive actions the robot is familiar with. While grounding language to perception (Gorniak and Roy, 2007; Chen and Mooney, 2011; Kim and Mooney, 2012; Artzi and Zettlemoyer, 2013; Tellex et al., 2014; Liu et al., 2014; Liu and Chai, 2015) has received much attention in recent years, less work has addressed grounding language to robotic action. Actions are often expressed by verbs or verb phrases. Most semantic representations for verbs are based on argument frames (e.g., thematic roles which capture participants of an action). For example, suppose a human directs a robot to “fill the cup with milk”. The robot will need to first create a semantic representation for the verb “fill” where “the cup” and “milk” are grounded to the respective objects in the environment (Yang et al., 2016). Suppose the robot is successful in this first step, it still may not be able to execute the action “fill” as it does not know how this higher-level action corresponds to its lower-level primitive actions.

In robotic systems, operations usually consist of multiple segments of lower-level primitive actions (e.g., move to, open gripper, and close gripper) which are executed both sequentially and concurrently. Task scheduling provides the order or schedule for executions of different segments of actions and action planning provides the plan for executing each individual segment. Primitive actions are often predefined in terms of how they change the state of the physical world. Given a goal, task scheduling and action planning will derive a sequence of primitive actions that can change the initial environment to the goal state. The goal state of the physical world becomes a driving force for robot actions. Thus, beyond semantic frames, modeling verb semantics through their effects on the state of the world may provide a link to connect higher-level language and lower-level primitive actions.

Motivated by this perspective, we have developed an approach where each verb is explicitly represented by a hypothesis space of fluents (i.e., desired goal states) of the physical world, which is incrementally acquired and updated through interacting with humans. More specifically, given a human command, if there is no knowledge about the
corresponding verb (i.e., no existing hypothesis space for that verb), the robot will initiate a learning process by asking human partners to demonstrate the sequence of actions that is necessary to accomplish this command. Based on this demonstration, a hypothesis space of fluents for that verb frame will be automatically acquired. If there is an existing hypothesis space for the verb, the robot will select the best hypothesis that is most relevant to the current situation and plan for the sequence of lower-level actions. Based on the outcome of the actions (e.g., whether it has successfully executed the command), the corresponding hypothesis space will be updated. Through this fashion, a hypothesis space for each encountered verb frame is incrementally acquired and updated through continuous interactions with human partners. In this paper, to focus our effort on representations and learning algorithms, we adopted an existing benchmark dataset (Misra et al., 2015) to simulate the incremental learning process and interaction with humans.

Compared to previous works (She et al., 2014b; Misra et al., 2015), our approach has three unique characteristics. First, rather than a single goal state associated with a verb, our approach captures a space of hypotheses which can potentially account for a wider range of novel situations when the verb is applied. Second, given a new situation, our approach can automatically identify the best hypothesis that fits the current situation and plan for lower-level actions accordingly. Third, through incremental learning and acquisition, our approach has a potential to contribute to life-long learning from humans. This paper provides details on the hypothesis space representation, the induction and inference algorithms, as well as experiments and evaluation results.

2 Related Work

Our work here is motivated by previous linguistic studies on verbs, action modeling in AI, and recent advances in grounding language to actions.

Previous linguistic studies (Hovav and Levin, 2008; Hovav and Levin, 2010) propose action verbs can be divided into two types: manner verbs that “specify as part of their meaning a manner of carrying out an action” (e.g., *nibble, rub, laugh, run, swim*), and result verbs that “specify the coming about of a result state” (e.g., *clean, cover, empty, fill, chop, cut, open, enter*). Recent work has shown that explicitly modeling resulting change of state for action verbs can improve grounded language understanding (Gao et al., 2016). Motivated by these studies, this paper focuses on result verbs and uses hypothesis spaces to explicitly represent the result states associated with these verbs.

In AI literature on action modeling, action schemas are defined with preconditions and effects. Thus, representing verb semantics for action verbs using resulting states can be connected to the agent’s underlying planning modules. Different from earlier works in the planning community that learn action models from example plans (Wang, 1995; Yang et al., 2007) and from interactions (Gil, 1994), our goal here is to explore the representation of verb semantics and its acquisition through language and action.

There has been some work in the robotics community to translate natural language to robotic operations (Kress-Gazit et al., 2007; Jia et al., 2014; Sung et al., 2014; Spangenberg and Henrich, 2015), but not for the purpose of learning new actions. To support action learning, previously we have developed a system where the robot can acquire the meaning of a new verb (e.g., *stack*) by following human’s step-by-step language instructions (She et al., 2014a; She et al., 2014b). By performing the actions at each step, the robot is able to acquire the desired goal state associated with the new verb. Our empirical results have shown that representing acquired verbs by resulting states allow the robot to plan for primitive actions in novel situations. Moreover, recent work (Misra et al., 2014; Misra et al., 2015) has presented an algorithm for grounding higher-level commands such as “microwave the cup” to lower-level robot operations, where each verb lexicon is represented as the desired resulting states. Their empirical evaluations once again have shown the advantage of representing verbs as desired states in robotic systems. Different from these previous works, we represent verb semantics through a hypothesis space of fluents (rather than a single hypothesis). In addition, we present an incremental learning approach for inducing the hypothesis space and selecting the best hypothesis.

3 An Incremental Learning Framework

An overview of our incremental learning framework is shown in Figure 1. Given a language
Figure 1: An incremental process of verb acquisition (i.e. learning) and application (i.e. inference).

command $\mathcal{L}_i$ (e.g. “fill the cup with water.”) and an environment $\mathcal{E}_i$ (e.g. a simulated environment shown in Figure 1), the goal is to identify a sequence of lower-level robotic actions to perform the command. Similar to previous works (Pasula et al., 2007; Mouro et al., 2012), the environment $\mathcal{E}_i$ is represented by a conjunction of grounded state fluents, where each fluent describes either the property of an object or relations (e.g. spatial) between objects. The language command $L_i$ is first translated to an intermediate representation of grounded verb frame $v_i$ through semantic parsing and referential grounding (e.g. for “fill the cup”, the argument the cup is grounded to Cup1 in the scene). The system knowledge of each verb frame (e.g., $\text{fill}(x)$) is represented by a Hypothesis Space $\mathcal{H}$, where each hypothesis (i.e. a node) is a description of possible fluents - or, in other words, resulting states - that are attributed to executing the verb command. Given a verb frame $v_i$ and an environment $\mathcal{E}_i$, a Hypothesis Selector will choose an optimal hypothesis from space $\mathcal{H}$ to describe the expected resulting state of executing $v_i$ in $\mathcal{E}_i$. Given this goal state and the current environment, a symbolic planner such as the STRIPS planner (Fikes and Nilsson, 1971) is used to generate an action sequence for the agent to execute. If the action sequence correctly performs the command (e.g. as evaluated by a human partner), the hypothesis selector will be updated with the success of its prediction. On the other hand, if the action has never been encountered (i.e., the system has no knowledge about this verb and thus the corresponding space is empty) or the predicted action sequence is incorrect, the human partner will provide an action sequence $\tilde{A}_i$ that can correctly perform command $v_i$ in the current environment. Using $\tilde{A}_i$ as the ground truth information, the system will not only update the hypothesis selector, but will also update the existing space of $v_i$. The updated hypothesis space is treated as system knowledge of $v_i$, which will be used in future interaction. Through this procedure, a hypothesis space for each verb frame $v_i$ is continually and incrementally updated through human-robot interaction.

4 State Hypothesis Space

To bridge human language and robotic actions, previous works have studied representing the semantics of a verb with a single resulting state (She et al., 2014b; Misra et al., 2015). One problem of this representation is that when the verb is applied in a new situation, if any part of the resulting state cannot be satisfied, the symbolic planner will not be able to generate a plan for lower-level actions to execute this verb command. The planner is also not able to determine whether the failed part of state representation is even necessary. In fact, this effect is similar to the over-fitting problem. For example, given a sequence of actions of performing $\text{fill}(x)$, the induced hypothesis could be “$\text{Has}(x, \text{Water}) \land \text{Grasping}(x) \land \text{In}(x, o_1) \land \neg(\text{On}(x, o_2))$”, where $x$ is a graspable object (e.g. a cup or bowl), $o_1$ is any type of sink, and $o_2$ is any table. However, during inference, when applied to a new situation that does not have any type of sink or table, this hypothesis will not
be applicable. Nevertheless, the first two terms 
$Has(x, Water) \land Grasping(x)$ may already be
sufficient to generate a plan for completing the verb
command.

To handle this over-fitting problem, we propose a
hierarchical hypothesis space to represent verb
semantics, as shown in Figure 2. The space is or-
organized based on a specific-to-general hierarchi-
structure. Formally, a hypothesis space $H$ for
a verb frame is defined as: $\langle N, E \rangle$, where each
$n_i \in N$ is a hypothesis node and each $e_{ij} \in E$
is a directed edge pointing from parent $n_i$ to child
$n_j$, meaning node $n_j$ is more general than $n_i$ and
has one less constraint.

In Figure 2, the bottom hypothesis ($n_1$) is
$Has(x, Water) \land Grasping(x) \land In(x, o1) \land
\neg (On(x,o2))$. A hypothesis $n_i$ represents a conjunc-
tion of parameterized state fluents $l_k$:

$$n_i := \land k, \text{ and } l_k := [\neg \text{pred}_k(x_{k_1}, x_{k_2})]$$

A fluent $l_k$ is composed of a predicate (e.g. object
status: $Has$, or spatial relation: $On$) and a set of
argument variables. It can be positive or negative.
Take the bottom node in Figure 2 as an example, it
contains four fluents including one negative term
(i.e. $\neg (On(x,o2))$) and three positive terms. Dur-
ing inference, the parameters will be grounded to
the environment to check whether this hypothesis
is applicable.

5 Hypothesis Space Induction

Given an initial environment $E_i$, a language com-
mand which contains the verb frame $v_i$, and a cor-
responding action sequence $\overline{A}_i$, $\{E_i, v_i, \overline{A}_i\}$ forms
a training instance for hypothesis space induction.
First, based on different heuristics, a base hypo-
thesis is generated by comparing the state difference
between the final and the initial environment. Sec-
ond, a hypothesis space $H$ is induced on top of this

**Base Hypothesis** in a bottom-up fashion. And dur-
ing induction some nodes are pruned. Third, if the
system has existing knowledge for the same verb
frame (i.e. an existing hypothesis space $H_i$ for
the same verb frame), this newly induced space will
be merged with previous knowledge. Next we ex-
plain each step in detail.

5.1 Base Hypothesis Induction

One key concept in the space induction is the Base
Hypothesis (e.g. the bottom node in Figure 2),
which provides a foundation for building a space.
As shown in Figure 3, given a verb frame $v_i$ and
a working environment $E_i$, the action sequence
$\overline{A}_i$ given by a human will change the initial
environment $E_i$ to a final environment $E'_i$. The state
changes are highlighted in Figure 3. Suppose a
state change can be described by $n$ fluents. Then
the first question is which of these $n$ fluents should
be included in the base hypothesis. To gain some
understanding on what would be a good represen-
tation, we applied different heuristics of choosing
fluents to form a base hypothesis as shown in Fig-
ure 3:

- $H_{1\text{argonly}}$: only includes the changed states
  associated with the argument objects speci-
  fied in the frame (e.g., in Figure 3, Kettle1
  is the only argument).
- $H_{2\text{manip}}$: includes the changed states of all
  the objects that have been manipulated in the
  action sequence taught by the human.
- $H_{3\text{argrelated}}$: includes the changed states of
  all the objects related to the argument objects
  in the final environment. An object $o$
is considered as “related to” an argument ob-
ject if there is a state fluent that includes both
and an argument object in one predicate.
(e.g. stove is related to the argument object
Kettle1 through $On(Kettle1, Stove)$).
Input: A Base Hypothesis $h$
Initialization: Set initial space $H : (N, E)$ with $N : [h]$ and $E : [\]$.
Set a set of temporary hypotheses $T : [h]$

while $T$ is not empty do
  Pop an element $t$ from $T$
  Generate children $[t^{(0)}, ..., t^{(k)}]$ from $t$ by removing each single fluent
  foreach $i = 0 \rightarrow k$ do
    if $t^{(i)}$ is consistent with $t$ then
      Append $t^{(i)}$ to $T$;
      Add $t^{(i)}$ to $N$ if not already in;
      Add link $t \rightarrow t^{(i)}$ to $E$ if not already in;
    else
      Prune $t^{(i)}$ and any node that can be generalized from $t^{(i)}$
  end
end

Output: Hypothesis space $H$

Algorithm 1: A single hypothesis space induction algorithm. $H$ is a space initialized with a base hypothesis and an empty set of links. $T$ is a temporary container of candidate hypotheses.

- $H_{all}$: includes all the fluents whose values are changed from $E_i$ to $E'_i$ (e.g. all the four highlighted state fluents in $E'_i$).

5.2 Single Space Induction

First we define the consistency between two hypotheses:

Definition. Hypotheses $h_1$ and $h_2$ are consistent, if and only if the action sequence $A_1$ generated from a symbolic planner based on goal state $h_1$ is exactly the same as the action sequence $A_2$ generated based on goal state $h_2$.

Given a base hypothesis, the space induction process is a while-loop generalizing hypotheses in a bottom-up fashion, which stops when no hypotheses can be further generalized. As shown in Algorithm 1, a hypothesis node $t$ can firstly be generalized to a set of immediate children $[t^{(0)}, ..., t^{(k)}]$ by removing a single fluent from $t$.

For example, the base hypothesis $n_1$ in Figure 2 is composed of 4 fluents, such that 4 immediate children nodes can potentially be generated. If a child node $t^{(i)}$ is consistent with its parent $t$ (i.e. determined based on the consistency defined previously), node $t^{(i)}$ and a link $t \rightarrow t^{(i)}$ are added to the space $H$. The node $t^{(i)}$ is also added to a temporary hypothesis container waiting to be further generalized. On the other hand, some children hypotheses can be inconsistent with their parents. For example, the gray node $(n_2)$ in Figure 2 is a child node that is inconsistent with its parent $(n_1)$. As $n_2$ does not explicitly specify $Has(x, Water)$ as part of its goal state, the symbolic planner generates less steps to achieve goal state $n_2$ than goal state $n_1$. This implies that the semantics of achieving $n_2$ may be different than those for achieving $n_1$. Such hypotheses that are inconsistent with their parents are pruned. In addition, if $t^{(i)}$ is inconsistent with its parent $t$, any children of $t^{(i)}$ are also inconsistent with $t$ (e.g. children of $n_2$ in Figure 2 are also gray nodes, meaning they are inconsistent with the base hypothesis). Through pruning, the size of entire space can be greatly reduced.

In the resulting hypothesis space, every single hypothesis is consistent with the base hypothesis. By only keeping consistent hypotheses via pruning, we can remove fluents that are not representative of the main goal associated with the verb.

5.3 Space Merging

If the robot has existing knowledge (i.e. hypothesis space $H_t$) for a verb frame, the induced hypothesis space $H$ from a new instance of the same verb will be merged with the existing space $H_t$. Currently, a new space $H_{t+1}$ is generated where the nodes of $H_{t+1}$ are the union of $H$ and $H_t$, and links in $H_{t+1}$ are generated by checking the parent-child relationship between nodes. In future work, more space merging operations will be explored, and human feedback will be incorporated into the induction process.

6 Hypothesis Selection

Hypothesis selection is applied when the agent intends to execute a command. Given a verb frame extracted from the language command, the agent will first select the best hypothesis (describing the goal state) from the existing knowledge base, and then apply a symbolic planner to generate an action sequence to achieve the goal. In our framework, the model of selecting the best hypothesis is incrementally learned throughout continuous interaction with humans. More specifically, given a correct action sequence (whether performed by the robot or provided by the human), a regression model is trained to capture the fitness of a hypothesis given a particular situation.

Inference: Given a verb frame $v_i$ and a working environment $E_i$, the goal of inference is to estimate how well each hypothesis $h_k$ from a space $H_t$ describes the expected result of performing $v_i$.
in $\mathcal{E}_i$. The best fit hypothesis will be used as the goal state to generate the action sequence. Specifically, the “goodness” of describing command $v_i$ with hypothesis $h_k$ in environment $\mathcal{E}_i$ is formulated as follows:

$$f(h_k | v_i; \mathcal{E}_i; \mathcal{H}_t) = W^T \cdot \Phi(h_k, v_i, \mathcal{E}_i, \mathcal{H}_t)$$ (1)

where $\Phi(h_k, v_i, \mathcal{E}_i, \mathcal{H}_t)$ is a feature vector capturing multiple aspects of relations between $h_k$, $v_i$, $\mathcal{E}_i$ and $\mathcal{H}_t$ as shown in Table 1; and $W$ captures the weight associated with each feature. Example global features include whether the candidate goal $h_k$ is in the top level of entire space $\mathcal{H}_t$ and whether $h_k$ has the highest frequency. Example local features include if most of the fluents in $h_k$ are already satisfied in current scene $\mathcal{E}_i$ (as this $h_k$ is unlikely to be a desired goal state). The features also include whether the same verb frame $v_i$ has been performed in a similar scene during previous interactions, as the corresponding hypotheses induced during that experience are more likely to be relevant and are thus preferred.

**Parameter Estimation:** Given an action sequence $\mathcal{A}_i$ that illustrates how to correctly perform command $v_i$ in environment $\mathcal{E}_i$ during interaction, the model weights will be incrementally updated with\(^1\):

$$W_{t+1} = W_t - \eta(\alpha \frac{\partial R(W_t)}{\partial W_t} + \frac{\partial L(J_{ki}, f_{ki})}{\partial W_t})$$

where $f_{ki} := f(h_k|v_i; \mathcal{E}_i; \mathcal{H}_t)$ is defined in Equation 1. $J_{ki}$ is the dependent variable the model should approximate, where $J_{ki} := J(s_i, h_k)$ is the Jaccard Index (details in Section 7) between hypothesis $h_k$ and a set of changed states $s_i$ (i.e. the changed states of executing the illustration action sequence $\mathcal{A}_i$ in current environment). $L(J_{ki}, f_{ki})$ is a squared loss function. $\alpha R(W_t)$ is the penalty term, and $\eta$ is the constant learning rate.

### 7 Experiment Setup

**Dataset Description.** To evaluate our approach, we applied the dataset made available by (Misra et al., 2015). To support incremental learning, each utterance from every original paragraph is extracted so that each command/utterance only contains one verb and its arguments. The corresponding initial environment and an action sequence taught by a human for each command are also extracted. An example is shown in Figure 3, where $\mathcal{E}_i$ is a language command, $\mathcal{E}_i$ is the initial working environment, and $\mathcal{A}_i$ is a sequence of primitive actions to complete the command given by the human. In the original data, some sentences are not aligned with any actions, and thus cannot be used for either the learning or the evaluation. Removing these unaligned sentences resulted in a total of 991 data instances, including 165 different verb frames.

Among the 991 data instances, 793 were used for incremental learning (i.e., space induction and hypothesis selector learning). Specifically, given a command, if the robot correctly predicts an action sequence\(^2\), this correct prediction is used to update the hypothesis selector. Otherwise, the agent will require a correct action sequence from the human, which is used for hypothesis space induction as well as updating the hypothesis selector.

The hypothesis spaces and regression based selectors acquired at each run were evaluated on the other 20% (198) testing instances. Specifically, for each testing instance, the induced space and the hypothesis selector were applied to identify a desired goal state. Then a symbolic planner\(^3\) was applied to predict an action sequence $\mathcal{A}^{(p)}$ based on this predicted goal state. We then compared $\mathcal{A}^{(p)}$ with the ground truth action sequence $\mathcal{A}^{(g)}$ using the following two metrics.

- **IED (Instruction Edit Distance)** measures

\(^1\)The SGD regressor in the scikit-learn (Pedregosa et al., 2011) is used to perform the linear regression with L2 regularization.

\(^2\)Currently, a prediction is considered correct if the predicted result ($c^{(p)}$) is similar to a human labeled action sequence ($c^{(g)}$) (i.e., $SJI(c^{(g)}, c^{(p)}) > 0.5$).

\(^3\)The symbolic planner implemented by (Rintanen, 2012) was utilized to generate action sequences.

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Table 1: Current features used for incremental learning of the regression model. The first two are binary features and the rest are real-valued features.

| Features on candidate hypothesis $h_k$ and the space $\mathcal{H}_t$ | 1. If $h_k$ belongs to the top level of $\mathcal{H}_t$. |
|---|---|
| 2. If $h_k$ has the highest frequency in $\mathcal{H}_t$. |

| Features on $h_k$ and current situation $\mathcal{E}_i$ | 3. Portion of fluents in $h_k$ that are already satisfied by $\mathcal{E}_i$. |
|---|---|
| 4. Portion of non-argument objects in $h_k$. Examples of non-argument objects are $o_1$ and $o_2$ in Figure 2. |

| Features on relations between a testing verb frame $v_i$ and previous interaction experience | 5. Whether the same verb frame $v_i$ has been executed previously with the same argument objects. |
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| 6. Similarities between noun phrase descriptions used in current command and commands from interaction history. |

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  - 5. Whether the same verb frame $v_i$ has been executed previously with the same argument objects.
  - 6. Similarities between noun phrase descriptions used in current command and commands from interaction history.
similarity between the ground truth action sequence $\vec{A}^{(g)}$ and the predicted sequence $\vec{A}^{(p)}$. Specifically, the edit distance $d$ between two action sequences $\vec{A}^{(g)}$ and $\vec{A}^{(p)}$ is first calculated. Then $d$ is rescaled as $IED = 1 - \frac{d}{\max(\vec{A}^{(g)}, \vec{A}^{(p)})}$, such that $IED$ ranges from 0 to 1 and a larger $IED$ means the two sequences are more similar.

- **SJI (State Jaccard Index).** Because different action sequences could lead to the same goal state, we also use Jaccard Index to check the overlap between the changed states. Specifically, executing the ground truth action sequence $\vec{A}^{(g)}$ in the initial scene $E_i$ results in a final environment $E'_i$. Suppose the changed states between $E_i$ and $E'_i$ is $c^{(g)}$. For the predicted action sequence, we can calculate another set of changed states $c^{(p)}$. The Jaccard Index between $c^{(g)}$ and $c^{(p)}$ is evaluated, which also ranges from 0 to 1 and a larger $SJI$ means the predicted state changes are more similar to the ground truth.

**Configurations.** We also compared the results of using the regression based selector to select a hypothesis (i.e., RegressionBased) with the following different strategies for selecting the hypothesis:

- **Misra2015:** The state of the art system reported in (Misra et al., 2015) on the command/utterance level evaluation.

- **MemoryBased:** Given the induced space, only the base hypotheses $h_{k_1}$ from each learning instances are used. Because these $h_{k_1}$s don’t have any relaxation, they represent purely learning from memorization.

- **MostGeneral:** In this case, only those hypotheses from the top level of the hypothesis space are used, which contain the least number of fluents. These nodes are the most relaxed hypotheses in the space.

- **MostFrequent:** In this setting, the hypotheses that are most frequently observed in the learning instances are used.

### 8 Results

#### 8.1 Overall performance

The results of the overall performance across different configurations are shown in Figure 4. For both of the IED and SJI (i.e. Figure 4(a) and Figure 4(b)), the hypothesis spaces with the regression model based hypothesis selector always achieve the best performance across different configurations, and outperforms the previous approach (Misra et al., 2015). For different base hypothesis induction strategies, the $H_{4all}$ considering all the changed states achieves the best performance across all configurations. This is because $H_{4all}$ keeps all of the state change information compared with other heuristics. The performance of $H_{2manip}$ is similar to $H_{4all}$. The reason is that, when all the manipulated objects are considered, the resulted set of changed states will cover most of the fluents in $H_{4all}$. On the other dimension,
(a) Use regression based selector to select hypothesis, and compare each base hypothesis induction heuristics. (b) Induce the base hypothesis with $H_{4\text{all}}$, and compare different hypothesis selection strategies.

Figure 5: Incremental learning results. The spaces and regression models acquired at different incremental learning cycles are evaluated on testing set. The averaged Jaccard Index is reported.

the regression based hypothesis selector achieves the best performance and the MemoryBased strategy has the lowest performance. Results for MostGeneral and MostFrequent are between the regression based selector and MemoryBased.

8.2 Incremental Learning Results
Figure 5 presents the incremental learning results on the testing set. To better present the results, we show the performance based on each learning cycle of 40 instances. The averaged Jaccard Index (SJI) is reported. Specifically, Figure 5(a) shows the results of configurations comparing different base hypothesis induction heuristics using regression model based hypothesis selection. After using 200 out of 840 (23.8%) learning instances, all the four curves achieve more than 80% of the overall performance. For example, for the heuristic $H_{4\text{all}}$, the final average Jaccard Index is 0.418. When 200 instances are used, the score is 0.340 (0.340/0.418≈81%). The same number holds for the other heuristics. After 200 instances, $H_{4\text{all}}$ and $H_{2\text{manip}}$ consistently achieve better performance than $H_{1\text{argonly}}$ and $H_{3\text{argrelated}}$. This result indicates that while change of states mostly affect the arguments of the verbs, other state changes in the environment cannot be ignored. Modeling them actually leads to better performance. Using $H_{4\text{all}}$ for base hypothesis induction, Figure 5(b) shows the results of comparing different hypothesis selection strategies. The regression model based selector always outperforms other selection strategies.

8.3 Results on Frequently Used Verb Frames
Beside overall evaluation, we have also taken a closer look at individual verb frames. Most of the verb frames in the data have a very low frequency, which cannot produce statistically significant results. So we only selected verb frames with frequency larger than 40 in this evaluation. For each verb frame, 60% data are used for incremental learning and 40% are for testing. For each frame, a regression based selector is trained separately. The resulting SJI curves are shown in Figure 6.

As shown in Figure 6, all the four curves become steady after 8 learning instances are used. However, while some verb frames have final SJIs of more than 0.55 (i.e. $\text{take}(x)$ and $\text{turn}(x)$), others have relatively lower results (e.g. results for $\text{put}(x,y)$ are lower than 0.4). After examining the learning instances for $\text{put}(x,y)$, we found these data are more noisy than the training data for other frames. One source of errors is the incorrect object grounding results. For example, a problematic
training instance is “put the pillow on the couch”, where the object grounding module cannot correctly ground the “couch” to the target object. As a result, the changed states of the second argument (i.e. the “couch”) are incorrectly identified, which leads to incorrect prediction of desired states during inference. Another common error source is from automated parsing of utterances. The action frames generated from the parsing results could be incorrect in the first place, which would contribute to a hypothesis space for a wrong frame. These different types of errors are difficult to be recognized by the system itself. This points to the future direction of involving humans in a dialogue to learn a more reliable hypothesis space for verb semantics.

9 Conclusion

This paper presents an incremental learning approach that represents and acquires semantics of action verbs based on state changes of the environment. Specifically, we propose a hierarchical hypothesis space, where each node in the space describes a possible effect on the world from the verb. Given a language command, the induced hypothesis space, together with a learned hypothesis selector, can be applied by the agent to plan for lower-level actions. Our empirical results have demonstrated a significant improvement in performance compared to a previous leading approach. More importantly, as our approach is based on incremental learning, it can be potentially integrated in a dialogue system to support life-long learning from humans. Our future work will extend the current approach with dialogue modeling to learn more reliable hypothesis spaces of resulting states for verb semantics.

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