TOOLNET: Using Commonsense Generalization for Predicting Tool Use for Robot Plan Synthesis

Rajas Bansal*, Shreshth Tuli*, Rohan Paul and Mausam
Department of Computer Science and Engineering, Indian Institute of Technology Delhi
* Contributed equally

Abstract—A robot working in a physical environment (like home or factory) needs to learn to use various available tools for accomplishing different tasks, for instance, a mop for cleaning and a tray for carrying objects. The number of possible tools is large and it may not be feasible to demonstrate usage of each individual tool during training. Can a robot learn commonsense knowledge and adapt to novel settings where some known tools are missing, but alternative unseen tools are present? We present a neural model that predicts the best tool from the available objects for achieving a given declarative goal. This model is trained by user demonstrations, which we crowd-source through humans instructing a robot in a physics simulator. This dataset maintains user plans involving multi-step object interactions along with symbolic state changes. Our neural model, TOOLNET, combines a graph neural network to encode the current environment state, and goal-conditioned spatial attention to predict the appropriate tool. We find that providing metric and semantic properties of objects, and pre-trained object embeddings derived from a commonsense knowledge repository such as ConceptNet, significantly improves the model’s ability to generalize to unseen tools. The model makes accurate and generalizable tool predictions. When compared to a graph neural network baseline, it achieves 14-27% accuracy improvement for predicting known tools from new world scenes, and 44-67% improvement in generalization for novel objects not encountered during training.

I. INTRODUCTION

Advances in autonomy are enabling robots to enter human-centric domains such as homes and factories where we envision them performing general purpose tasks such as transport, assembly, and clearing. In such domains, we expect an intelligent robot to make effective use of available tools. For example, a robot asked to remove many fruits from a table can use a tray to efficiently perform the task. Similarly, it should be able to use a ramp to navigate to an an elevated platform or a stick for fetching an object beyond physical reach. In essence, the ability to use appropriate tools can guide the robot towards feasible and efficient plans.

Learning the relevance of objects as tools for an intended goal is challenging for several reasons. First, the usefulness of a tool varies with context. For example, placing milk in the cupboard may require the robot to elevate itself vertically using a ramp if the milk is placed at a height unreachable by the robot, but if the milk is kept on a table, a simple tray might suffice. Second, realistic work-spaces are typically large with an expansive space of possible tools and interactions. Acquiring data for all feasible tool objects or exploring the space of tool interactions is challenging for a learning algorithm. Ideally, an intelligent agent must be able to generalize its knowledge and adapt to objects unseen at training time. For example, knowing that trays are useful for transport tasks, a robot should be able to reason that a box could be a useful candidate for a new transport task based on shared context and similar attributes.

Humans possess innate commonsense knowledge about contextual use of tools for an intended goal (Allen et al. [1]). We hypothesize that humans possess commonsense knowledge about which objects could serve as tools for an intended goal. For example, a human actor when asked to move objects is likely to use trays, boxes, or even improvise with a new object with a flat surface. This work aims at enabling such commonsense generalization in a robotic agent. We leverage human demonstrated robot plans as a data source that elucidates commonsense knowledge about contextual and goal-directed tool use. The ability to predict useful tools for a task can guide a robot to quickly generate feasible plans.

Our technical approach is as follows. We first crowd-source a dataset of human-instructed plans where a human teacher

Fig. 1: Overview. Our goal is to predict the commonsense use of objects as tools to enable a robot to perform a task. We crowd-source a data set of humans instructing a robot to perform a tasks such as transporting, fetching, clearing etc. while making use of objects such as trays, ramps, sticks as tools. A graph neural architecture predicts contextual tool use incorporating goal-conditioned attention, fusion of metric-symbolic embeddings and use of knowledge base embeddings. The learner generalizes to novel object instances (predicting use of a “box” from prior demonstrations of using “trays”), enabling task completion in novel contexts.
guides a simulated mobile manipulator to perform assembly, transport and fetch tasks using visible objects as tools. The process results in a corpus of ≈ 1,500 human demonstrated robot plans involving multi-step tool interactions. This corpus is used to supervise a (1-step) neural imitation learner that predicts tool applicability given the knowledge of the world state and the intended goal.

We introduce a graph neural architecture, TOOLNET, that encodes both the metric and relational attributes of the world state as well as available taxonomic resources such as ConceptNet (Speer et al. [2]). The TOOLNET model predicts tool use by learning an attention over entities that can potentially serve as tools. Implicitly, the model acquires knowledge about primitive spatial characteristics (typically an output of a mapping system) and semantic attributes (typically contained in taxonomic resources) enabling generalization to novel contexts with previously unseen objects. The predictions of the learned model can be utilized by an underlying symbolic planner while exploring feasible plans to the intended goal.

Experimental evaluations in simulated home and factory-like environments with a mobile manipulator reveal both accurate prediction of goal-relevant tools as well as generalization to scenarios with unseen objects. This work contributes a step in the direction of acquiring commonsense knowledge relayed through human instruction for the purposes of attaining semantic goals. The data set and implementation is available at https://github.com/reail-iitd/commonsense-task-planning.

II. RELATED WORK

**Learning tool manipulation skills.** Learning control policies for manipulating tools has received recent attention in robotics. Finn et al. [3] and Park et al. [4] learn tool manipulation policies from human demonstrations. Xie et al. [5] and Wu et al. [6] learn physics models and effects enabling goal-directed compositional use. Liu et al. [7] address the problem of learning primitive physical decomposition of tool like object through its physical and geometric attributes enabling their human-like use. Wu et al. [8] learn physical properties of objects from unlabeled videos. Toussaint et al. [9] learn to compose physics tool interactions using a logic-based symbolic planner. Nair et al. [10] and Lynch et al. [11] learn to interact with objects in a self-supervised setup. Efforts such as Holladay et al. [12], and Antunes et al. [13] plan tool interactions modeling contact and force interactions. Our paper considers the complementary problem of predicting which objects may serve as tools for a given task while delegating the issue of tool manipulation to the aforementioned works.

**Learning symbolic action sequences.** Alternative efforts have focused on enabling robots to perform high-level tasks. Puig et al. [14] build a data base of symbolic programs constituting high-level tasks in a home by using human subject instructing a virtual agent in a simulation environment. Liao et al. [15] use the corpus to learn translations of domain independent task sketches to executable programs in the agent’s physical context. Shridhar et al. [16] take a similar approach by collecting natural language corpora describing high-level tasks and learn to associate instructions to spatial attention over the scene. Our approach draws inspiration from the above mentioned works in that we learn to predict tools that can be considered as sub-goals to guide planning for a high-level task. However, our problem differs in two ways. First, we explicitly model the physical constraints arising from a mobile manipulator interacting in the work-space. Second, instead of learning actions predicated on specific object instances, we address generalization to new object instances using primitive spatial and semantic characteristics.

**Commonsense knowledge in instruction following.** Acquisition of common sense knowledge has been explored for the task of robot instruction following. Nyga et al. [17] present a symbolic knowledge base for procedural knowledge of tasks that is utilized for interpreting under specified task instructions. Efforts such as Kho et al. [18] propose a similar data base encoding common sense knowledge about object affordances (objects and their common locations). Misra et al. [19] use the learned model for interpreting instructions in the kitchen domain. Chen et al. [20] present an instruction grounding model that leverages common sense taxonomic and affordance knowledge learned from linguistic co-associations. Bisk et al. [21] consider the problem of learning physical common sense associated with objects and interactions required to achieve tasks from language only data sets. They study this problem in the context of question-answering to enable synthesis of textual responses that capture such physical knowledge. This paper focuses on a learning common sense tool use in the context of following instructions that require multiple object interactions to attain the intended goal.

**Synthetic Interaction Datasets.** Virtual environments have been used to collect human demonstrations for high-level tasks. Puig et al. [14] introduce a knowledge base of actions required to perform activities in a virtual home environment. Shridhar et al. [16] provide a vision-language dataset translating symbolic actions for a high-level activity to attention masks in ego-centric images. Nyga and Beetz [22] curated data sets that provide a sequence How-To instructions for tasks such as preparing recipes. Others such as Jain et al. [23], Scalisie et al. [24] and Mandlekar et al. [25] present simulation environments and data sets for tasks such as learning spatial affordances, situated interaction or learning low-level motor skills. The present data sets possess two limitations that make them less usable for the learning task addressed in this work. First, the data sets are collected using human actors or avatars but do not explicitly model a robot in their environment. Second, a majority of the data sets aim at visual navigation and limited physical interaction with objects. They are less amenable to interactions (e.g., containment, pushing and attachment etc.) inherent in tool use.

III. PROBLEM SETUP

A. Robot and World Model

We consider a mobile manipulator operating in a work space populated with a set of objects. The robot is situated in a home or factory like environment where the robot can
The task of moving all fruits must be on the kitchen

We assume that the robot’s actions can be realized by the

We encode the geometric

Semantic Relations

On top, Inside, Connected to, Near

Metric Properties

Position, Orientation, Size

Home Objects

floor\textsuperscript{1}, wall, fridge\textsuperscript{1,2,3,4}, cupboard\textsuperscript{2,4,5}, tables\textsuperscript{4}, couch\textsuperscript{4,5}, big-tray\textsuperscript{4}, tray\textsuperscript{4}, book\textsuperscript{4}, paper, cubes, light switch\textsuperscript{4}, bottle, box\textsuperscript{4,5}, fruits, chair\textsuperscript{10}, stick, dumpster\textsuperscript{2}, milk carton, shelf\textsuperscript{1}, glue\textsuperscript{6}, tape\textsuperscript{6}, stool\textsuperscript{12} mop\textsuperscript{7}, sponge\textsuperscript{8}, vacuum\textsuperscript{8}, dirt\textsuperscript{7}, door\textsuperscript{7}

Factory Objects

floor\textsuperscript{1}, wall, ramp, worktable\textsuperscript{7}, tray\textsuperscript{4}, box\textsuperscript{4}, crates\textsuperscript{1}, stick, long-shelf\textsuperscript{4}, lift\textsuperscript{1}, cupboard\textsuperscript{23}, drill\textsuperscript{4}, hammer\textsuperscript{44}, ladder\textsuperscript{9}, trolley\textsuperscript{2}, brick, blow dryer\textsuperscript{48}, spraypaint\textsuperscript{1}, welder\textsuperscript{4}, generator\textsuperscript{4}, gasoline, coal, toolbox\textsuperscript{2}, wood cutter\textsuperscript{4}, 3D printer\textsuperscript{4} screw\textsuperscript{9}, nail\textsuperscript{9}, screwdriver\textsuperscript{49}, wood, platform\textsuperscript{4}, oil\textsuperscript{2}, water\textsuperscript{7}, board, mop\textsuperscript{5}, paper, glue\textsuperscript{6}, tape\textsuperscript{6}, assembly station, spare parts, stool\textsuperscript{15}

TABLE I: Domain Representation. Robot symbolic actions, semantic attributes, relations to describe the world state and objects populating the scene in Home and Factory Domains. Legend: 1: surface, 2: can open/close, 3: container, 4: can operate, 5: can climb, 6: can apply, 7: can be cleaned, 8: cleaning agent, 9: can 3D print. Bold objects can be used as tools.

The robot possesses a set of behaviours or symbolic actions such as Moving towards an object, Grasping, Releasing/Dropping or Pushing an object or Operating an entity to imply actions that induce discrete state changes such as opening the door before exiting, turning on a switch etc. We assume that the robot’s actions can be realized by the presence of an underlying controller. We encode the geometric requirements for actions as symbolic pre-conditions. Examples include releasing an object from the gripper before grasping another, opening the door before trying to exit the room.

B. Semantic Goals and Interactions

The robot’s goal is to perform tasks such as transporting or delivering objects to appropriate destinations, making an assembly, clearing or packing items or performing abstract tasks such as illuminating or cleaning the room. We assume that the robot is instructed by providing declarative goals. For example, the task of moving all fruits must be on the kitchen  

Table can be modeled as a set intended constraints between the objects of interaction. Finally, the robot must synthesize a plan of executable actions to satisfy the goal constraints. The presence of a rich space of interactions gives rise to plans with multiple interactions between objects. For example, “packing items into a basket and carrying the basket to the goal region”, “using a stick to fetch and drop an object beyond reach into a box”, “using a ramp/stool to elevate itself to fetch an object”.

C. Predicting Generalized Tool Use

We assume that the robot is primed with a set of primitive symbolic actions but lacks knowledge about how object characteristics can facilitate their use as in acquiring high-level goals. Hence, the robot cannot predict the use of tray-like objects in transportation tasks, or the use of a stick to fetch an object at a distance. Indeed, it is such commonsense association between semantic goals and use of objects as tools that we seek to learn. Thus, as a step towards finding a satisficing plan to the goal, this work investigates the intermediate problem of learning to predicting the best tool to use to achieve the given goal.

Formally, let $O$ denote the set of objects present in the work-space. Let $S$ denote the world state consisting of metric locations of the objects (including the robot) as well as the set of expressed semantic relationships between entities. Next, we denote the goal provided to the robot as $\Lambda_g$ composed of linguistic description of the semantic constraints that must be satisfied by the agent (for example, “place books on the cupboard”). Let $\tau$ denote the set of tool objects that the robot can use in its plan $\tau$ denoted in bold in Table I. Our goal is to predict a tool useful for the goal in the context of the current world state. To achieve this, our model learns to output a likelihood $p(t \in \tau \mid S, \Lambda_g)$ Online, the robot may encounter unseen objects in its environment. Hence, we consider the open world setup where the robot must generalize its knowledge to reason over novel object instances, that may be unseen in training.

D. Learning from Human Teaching

We assume the presence of human teachers who can guide the robot to perform a range of tasks in the environment. Human guidance is in the form of a sequence of symbolic actions for the robot to execute in order to complete the desired task. We assume that the human teachers are cooperative and instruct the robot to utilize tools in order to efficiently find a feasible plan to the stated goal. The data set of human instructed robot plans elucidates our common sense knowledge about contextual tool use. Note that plan variations can occur between human teachers where different objects may be utilized as tools in pursuit of similar goals. We use the demonstration data set of plans to supervise a (1-step) imitation learner with a range of tool use occurrences in varied instances.

\textsuperscript{iii}Except by discovering via explicit simulation which may be infeasible or intractable in large planning domains.

\textsuperscript{iv}Note that only movable objects in the scene are considered as potential tools. Hence, $\tau \subseteq O$. 

\begin{table}[h]
\centering
\begin{tabular}{|c|c|}
\hline
\textbf{Robot Actions} & Push, Climb up/down, Open/Close, Switch on/off, Drop, Pick, Move to, Operate device, Clean, Release material on surface, Push until force \\
\hline
\textbf{Object Attributes} & Grabb\textsuperscript{ed}/Free, Outside/Inside, On/Off, Open/Close, Sticky/Not Sticky, Dirty/Clean, Welded/Not Welded, Drilled/Not Drilled, Driven/Not Driven, Cut/Not Cut, Painted/Not Painted \\
\hline
\textbf{Semantic Relations} & On top, Inside, Connected to, Near \\
\hline
\textbf{Metric Properties} & Position, Orientation, Size \\
\hline
\textbf{Home Objects} & floor\textsuperscript{1}, wall, fridge\textsuperscript{1,2,3,4}, cupboard\textsuperscript{2,4,5}, tables\textsuperscript{4}, couch\textsuperscript{4,5}, big-tray\textsuperscript{4}, tray\textsuperscript{4}, book\textsuperscript{4}, paper, cubes, light switch\textsuperscript{4}, bottle, box\textsuperscript{4,5}, fruits, chair\textsuperscript{10}, stick, dumpster\textsuperscript{2}, milk carton, shelf\textsuperscript{1}, glue\textsuperscript{6}, tape\textsuperscript{6}, stool\textsuperscript{12} mop\textsuperscript{7}, sponge\textsuperscript{8}, vacuum\textsuperscript{8}, dirt\textsuperscript{7}, door\textsuperscript{7} \\
\hline
\textbf{Factory Objects} & floor\textsuperscript{1}, wall, ramp, worktable\textsuperscript{7}, tray\textsuperscript{4}, box\textsuperscript{4}, crates\textsuperscript{1}, stick, long-shelf\textsuperscript{4}, lift\textsuperscript{1}, cupboard\textsuperscript{23}, drill\textsuperscript{4}, hammer\textsuperscript{44}, ladder\textsuperscript{9}, trolley\textsuperscript{2}, brick, blow dryer\textsuperscript{48}, spraypaint\textsuperscript{1}, welder\textsuperscript{4}, generator\textsuperscript{4}, gasoline, coal, toolbox\textsuperscript{2}, wood cutter\textsuperscript{4}, 3D printer\textsuperscript{4} screw\textsuperscript{9}, nail\textsuperscript{9}, screwdriver\textsuperscript{49}, wood, platform\textsuperscript{4}, oil\textsuperscript{2}, water\textsuperscript{7}, board, mop\textsuperscript{5}, paper, glue\textsuperscript{6}, tape\textsuperscript{6}, assembly station, spare parts, stool\textsuperscript{15} \\
\hline
\end{tabular}
\caption{Domain Representation. Robot symbolic actions, semantic attributes, relations to describe the world state and objects populating the scene in Home and Factory Domains. Legend: 1: surface, 2: can open/close, 3: container, 4: can operate, 5: can climb, 6: can apply, 7: can be cleaned, 8: cleaning agent, 9: can 3D print. Bold objects can be used as tools.}
\end{table}
world context and a diverse set of goals in the environment. Online, the learned model predicts the relevance likelihood of tools given novel contexts and goals which can be utilized by the robot to find a feasible plan.

IV. DATASET CREATION FROM HUMAN DEMONSTRATIONS

Our goal is to learn common sense knowledge about tool usage from human teachers instructing the robot to attain declarative goals. We proceed by creating a physics simulation environment to model a mobile manipulator capable of executing symbolic actions for a diverse range of tasks. We then use the environment to collect a data set of human demonstrations that instruct the robot to perform tasks in the environment.

A. Virtual Environment and User Interaction

A simulation environment (based on Bullet physics engine by Coumans and Bai [26]) was used to encode a home-like and a factory-like domain. A virtual mobile manipulator could pursue the following categories of semantic goals: (a) transporting objects from one region to another (including space on top of or inside other objects), (b) fetching objects where the robot must reach, grasp and return with, and (c) inducing state changes such as illuminating the room or removing dirt on the floor. The robot’s interactions were implemented with a low-level motion planner with a set of encoded discrete conditions such as moving close to an object before manipulating etc. arising due to physical constraints of the robot. The set of abstract interactions such as attachment, operating a tool or specifics of grasping were encoded symbolically as the establishment or release of constraints. The effects of actions such as pushing, moving and contact with a stick-like object were simulated and propagated to the next time step. Two domains of home and factory were implemented with objects as states in Table I. The objects in the domains were derived from real-world home and factory scenes and diverse object types that span Facebook Replica Dataset (Straub et al. [27]) and YCB object dataset (Calli et al. [28]). For each domain, 8 different goals were given to human instructors as stated in Table II. A lexical parser was built to convert goal specification to constraints on the state of the simulator. Moreover, 10 different scenes for each domain were created by randomly positioning different objects based on likely semantic placements. For instance, fruits could be placed OnTop of table or Inside the fridge.

A human instructor could interact with the robot agent by selecting a goal and specifying a sequence of symbolic action to execute. The specified plan was then simulated showing the robot interacting with objects and changing the world state. The human subjects are encouraged to instruct the robot such that the task is completed as quickly as possible, making use of available tools in the environment. Figure 2 illustrates the user interface used for data collection in simulation.

B. Dataset Characteristics

The dataset was collected from human instructors by presenting different goal, scene pairs. For each domain, every goal was combined with each scene to give 8 × 10 = 80 such pairs. For each pair, 8 to 12 plans were collected based on the level of complexity and possible plan diversity. From 12 instructors, a complete set of 708 plans for home and 784 plans for factory domain were collected. The original set of human demonstrated robot plans provides a limited set of environment contexts in which the plan are feasible. We augment the original set of demonstrations by exploring successful plans in perturbed environment contexts. Two plan

Fig. 3: Diversity of tool usage in human demonstrated plans. The distribution of tool usage count of top 10 tools with associated goals in the dataset. Human instructed plans show diversity in the use of tools for the robot to attain the intended goals.
augmentation strategies were used. Firstly, the plans that were successful for a goal in a world scene were tested on other scenes and were added to the dataset if on execution they lead to the goal state in the simulated environment. Secondly, we created more plans by randomly removing up to 5 objects that are neither in the goal description nor interacted with in the plan. After augmentation, the training datasets consist of 3540 and 3920 plans for home and factory, respectively.

Our dataset contains activities with several examples. Table II analyzes the plan diversity and shows the variation of actions, total plan simulation time, number of interacted objects and tasks with goals in each domain. The number of objects interacted with and number of tools used varies greatly as goals change. Plans corresponding to simpler goals like “switching off light” are much shorter in terms of plan length and execution time compared to goals such as “assemble”. Plans corresponding to more complex goals of objects interacted with and number of tools used varies greatly as goals change. Plans corresponding to simpler goals like “assemble” are much shorter in terms of plan length and execution time compared to goals like “assemble”.

V. LEARNING TO PREDICT TOOL USE

We assume an object-centric environment representation and model the robot’s world state as a graph expressing object attributes and relations. Given the current world state \( S \) (as a graph) and the goal description \( \Lambda_g \), our neural model estimates the likelihood \( p(t \mid S, \Lambda_g) \) over candidate tool objects \( t \in \tau \) in the environment. We build on the ResActGraph model by Liao et al. [15] as the baseline and extend the model to our problem setup. Figure 4 presents the final TOOLNET model.

A. Graph-structured World Representation (GGCN)

We encode the robot’s world state \( S \) in the form of an object-centric graph. The graph \( G = (V, R) \) consists of object instances as the vertex set \( V \subseteq \Omega \) and semantic relations as the edge set \( R \subseteq \Omega \times \Omega \). Each node \( v \in V \) indicates the object instance of the scene and has a pre-trained FastText embedding \( e_v \) (Joulin et al. [29]), its semantic states \( l_v \), and metric properties including position \( pos_v \) and size \( size_v \). Note that \( V \) includes a node for the agent. The edge \( r \in R \) encodes semantic relations between two objects \( v_1 \) and \( v_2 \) as \( r(v_1, v_2) \in R \). Each node also has a bit, \( g \), which is set to 1 if the object is mentioned in the goal and 0 otherwise.

The node features along with relations are used to obtain vector embeddings for each object using Gated Graph Convolution Networks (GGCNs) (Liao et al. [15]) as described below. The initial embedding of each node is a concatenation of all features mentioned above, i.e. \( [e_v; l_v; pos_v; size_v; g_v] \). The hidden state of a node, \( h_v^0 \), is initialized as a lower dimensional projection of the initial embedding for the object:

\[
    h_v^0 = \tanh(W_{init}[e_v; l_v; pos_v; size_v; g_v]),
\]

where \( W_{init} \) are learnable weights. At each propagation step \( s \), each node embedding is created using the hidden states of its neighbours \( v' \in N(v) \) at propagation step \( s-1 \), so applying graph convolutions:

\[
    x_v^s = \sum_{j \in R} \sum_{v' \in N(v)} W_{pj} h_{v'}^{s-1}.
\]

After aggregating this information, the gating stage of the GGCN is realized using a Gated Recurrent Unit (GRU) described as follows:

\[
    z_v^s = \sigma(W_z[x_v^s; h_v^{s-1}] + b_z),
\]

\[
    r_v^s = \sigma(W_r[x_v^s; h_v^{s-1}] + b_r),
\]

\[
    \hat{h}_v^s = \tanh(W_h[x_v^s; r_v^s \odot h_v^{s-1}] + b_h),
\]

\[
    h_v^s = (1 - z_v^s) \odot h_v^{s-1} + z_v^s \odot \hat{h}_v^s.
\]

We use \( k = 2 \) propagation steps of gated graph convolutions in our model. This results in a hidden state vector \( h_v^k \) for each node \( v \) in the graph which aggregates all information about the corresponding object. The embedded node vectors are added together to get the scene representation, i.e.

\[
    h_{scene} = \sum_{v \in V} h_v^k.
\]

The goal is embedded through a bag-of-words (BoW) using FastText embeddings \( \hat{e}_g \) which is the embedding of the word \( w \) of the goal text representing the goal \( \Lambda_g \). Thus the goal embedding \( \hat{e}_g \) is:

\[
    \hat{e}_g = \frac{1}{|\Lambda_g|} \sum_{w \in \Lambda_g} f_w.
\]

We augment the tool set \( \tau \) with no-tool category, to give \( \hat{\tau} \), to account for the case where a tool is not required to achieve the goal. In the baseline model, the scene and the goal encoding are used to predict a distribution over \( \hat{\tau} \). Hence,

\[
    p_{\hat{\tau}} = \sigma(W[h_{scene}; \hat{e}_g]).
\]

B. Fusion of Metric and Semantic Attributes (+Metric)

When we have two semantically different feature sets, symbolic and metric, passing them through separate networks allows our model to exploit them independently. Thus, unlike the baseline GGCN model, we handle the semantic attributes using graph convolutions (GGCN) and metric attributes using Fully Connected Network (FCN). We then combine the two representations to form the scene embedding (the late fusion as shown in the figure). This late fusion allows the downstream prediction to give more emphasis to the separated feature, which may be lost in early fusion (Lu et al. [30]). Late fusion of the metric properties along with the hidden states of objects obtained through the GCN ensures that information like object position and size are available when predicting tool likelihoods.

The metric properties are thus encoded separately using a Parameterized ReLU (PReLU) layer \( m_v^0 = PReLU(W_{metric}[e_v; pos_v; size_v]) \). At \( k^{th} \) layer,

\[
    m_v^k = PReLU(W_{metric}[m_v^{k-1}]).
\]
Now, the hidden state used to embed the scene is \[
h_{\text{scene}} = \sum_{v \in V} \alpha_v[h^k_v; m^k_v] \text{ where,} \]
\[
e^o_g = \frac{1}{|A^o_g|} \sum_{w \in A^o_g} f_w, \text{ and } \alpha_v = \text{softmax}(W[h^k_v; m^k_v; e^o_g]). \tag{8}
\]

C. Goal-Conditioned Attention (+Attn)

Our current encoding of the environment is independent of the goal that needs to be completed by the tool. As common work spaces have large number of objects, we estimate a local context using goal specifications. We create a goal-conditioned attention module in figure 4. Thus we define
\[
h_{\text{scene}} = \sum_{v \in V} \alpha_v[h^k_v; m^k_v] \text{ where,} \]
\[
e^o_g = \frac{1}{|A^o_g|} \sum_{w \in A^o_g} f_w, \text{ and } \alpha_v = \text{softmax}(W[h^k_v; m^k_v; e^o_g]). \tag{9}
\]

D. Factored Likelihood over Tool Instances (+L)

The model discussed till now does not possess the ability to generalize to objects not seen during training time. In order to allow the model to generalize to unseen tools, instead of prediction over the pre-defined tool set \(\hat{\tau}\), we allow the model to predict a likelihood score of a tool \(t\) (which may not be present in any of the scenes in the training set) to be used as a tool using its FastText embedding \((e_t)\). This recurrence is shown in the factored tool likelihood module in Figure 4. For the \(\text{no-tool}\) case, an embedding consisting of all zeros is used. Likelihood of each tool is computed for each \(t\) using,
\[
p_t = \sigma(W[e_t; h_{\text{scene}}; e^o_g]) \forall t \in \hat{\tau}. \tag{10}
\]

E. Incorporating Tool Relevance/Non-relevance (+NT)

We observe that not using any tool (\(\text{no-tool}\)) to complete a goal is possible for a large set of scene-goal pairs and it is difficult for the model to learn in this skewed class distribution. Thus we factor the problem into two parts: (a) predicting if a tool will be used (the tool relevance module in the figure), and (b) predicting which tool will be used, given a tool needs to be used (the factored tool likelihood module in the figure). Thus (b) predicts over the set \(\tau\), which gives
\[
p_\tau = || \sigma(W[e_t; h_{\text{scene}}; e^o_g]). \tag{11}
\]
Prediction of (a) is done using,
\[
p_{\text{no-tool}} = \sigma(W[h_{\text{scene}}; e^o_g]). \tag{12}
\]

F. Incorporating Learned Knowledge base Embeddings (+C)

Pretrained ConceptNet Numberbatch embeddings (Speer et al. [32]) are used as a source of relational knowledge about objects like relative sizes, relations like similar to and capable of. It is built using an ensemble that combines data from ConceptNet, word2vec, GloVe, and OpenSubtitles 2016, using a variation on retrofitting with ConceptNet knowledge graph containing semantic information. Retrofitting ensures objects of similar "type" to have closer vector representations. ConceptNet Numberbatch provides a richer semantic space for generalization compared to FastText embeddings. It allows our model to incorporate a rich space of semantic properties and relations to extrapolate to other tools and tool types from tool use observed in human demonstrated plans.

G. Training Loss

The loss used to train all models is Binary Cross-Entropy with each \(v \in \hat{\tau}\) acting as a class. The class label, \(y^i\) is assigned 1 if it is used in a given demonstration, \(i\) and 0 otherwise. Thus, the loss function is defined as
\[
L = - \sum_i \sum_j y^i_j \log(p(y^i_j)) + (1 - y^i_j) \log(1 - p(y^i_j)). \tag{13}
\]

We use categorical weights based on plan execution time to encourage shorter plans. However, the knowledge of the time taken for different plans has not been injected into the model.
In order to make this notion explicit to the model we use loss weighting (+W) such that,
\[
L = - \sum_i \alpha_i \sum_j y_j^i \log(p(y_j^i)) + (1 - y_j^i) \log(1 - p(y_j^i)),
\]
where, \(\alpha_i\) is a high for optimal plans (shortest among human demonstrations) and low otherwise.

VI. RESULTS

Our experiments answer the following questions. (1) What is the performance of our complete ToolNet architecture compared to baseline models for the task of tool prediction? (2) How robust is ToolNet when tested in a variety of generalization scenarios such as unseen tools and other objects? (3) What is the incremental contribution of each model improvement in ToolNet, and where does it help?

A. Evaluation Setup

We test ToolNet’s tool prediction capabilities in two settings. In the first setting, we use the dataset as described in Section IV and split it according to the scene instance. We use augmented data corresponding to 9 scenes as the training set and split data for the remaining scene instance equally to form validation and testing sets. We use accuracy as our performance measure. Here, a tool prediction is deemed correct if the predicted tool is used in at least one of the various annotated plans for the (goal, scene) pair and incorrect otherwise.

To test model’s generalization abilities, we generate novel (goal, scene) pairs by sampling unseen object locations and object replacement based on contexts specified in Table III. It describes five types of generalization test-cases. In Type I, we change an object’s position to test whether, of the multiple possible choices, the model predicts the tool that is closer to the goal object. For example, we replace the positions of tray and box for the goal "place fruits in the cupboard" to check if the model predicts the tool closer to the fruits. In Type II, we remove the tool predicted by the model for all plans in the training set. This verifies whether the model predicts a reasonable alternative if the most likely tool is absent from the scene. In Type III, we replace a tool with an alternate tool that is unseen at training time. For example, box is replaced with bucket and stool with ladder. We extract these object/tool replacements from the ConceptNet graph. Type IV scenes replace a tool with random objects unrelated to the task (stool to headphone) or with tools used for a different task. The goal is to evaluate the model’s ability to predict an alternative tool relevant for the task or estimate the absence of a relevant tool. Finally, we also replace goal objects to check if the model predicts alternate tools or not based on new object’s metric/semantic properties like size/position. For example, to transport an apple, a tray might work. However, to transport larger object like pillow, a box would be needed. We make these changes on the existing annotated data points and call it the GenTest data-set, which consists of 1, 406 scenes.

Since predicting tool is a new problem, no existing algorithms exist for it. We compare against the basic GGCN model of Section V-A as our baseline model, since its encoder incorporates technical ideas from recent imitation learning works (Shridhar et al. [16], Liao et al. [15]) on action prediction.

B. Results

Table IV shows the final accuracies on the test-set (Test) and generalization test-set (GenTest) with individual accuracies for each test-type. The results of the complete ToolNet architecture are in the last row of the table. On the regular test set, ToolNet outperforms the GGCN baseline by 14 and 27 accuracy points on Home and Factory domains, respectively. Each model component improves the accuracy numbers, with the exception of factored likelihood – it makes the model more complex to aid prediction of an unseen tool as the output. In all earlier models, each tool is an independent class; that restriction solves an easier problem obtaining better performance on the regular test set.

A similar pattern is found in the generalization test set, where each model component brings tremendous value. The improvement in accuracy is dramatic in Factory domain: a 67 point accuracy improvement is seen on top of the GGCN baseline. Analyzing a component’s effectiveness across different generalization types, we obtain further insights on models’ workings. The late fusion of metric properties of each object (+Metric) allows such information to be emphasized in model. This gets significant improvements in almost all test cases. For instance, it allows the model to predict box (instead of tray) when transporting a pillow by using pillow’s size information (a metric property). Major improvements are observed in Type I as those scenarios require reasoning about object nearness based on their locations (another metric property).

### Table III: Generalization test set

<table>
<thead>
<tr>
<th>Type Number</th>
<th>Generalization context</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>Change goal object location</td>
<td>Replace tray positions, Place milk carton on table instead of on top of fridge</td>
</tr>
<tr>
<td>II</td>
<td>Remove maximum likelihood tool</td>
<td>Remove tray, mop, glue, box, wood</td>
</tr>
<tr>
<td>III</td>
<td>Tool to alternate tool replacement</td>
<td>Box → crate, basket, stool → seat, step-ladder; toolbox → box, bucket</td>
</tr>
<tr>
<td>IV</td>
<td>Tool to non alternate object replacement</td>
<td>Stool → headphone; Lift → headphone</td>
</tr>
<tr>
<td>V</td>
<td>Goal object to another goal object replacement</td>
<td>Apple → Orange, Guava, Pillow</td>
</tr>
</tbody>
</table>

### Table IV: Evaluation

<table>
<thead>
<tr>
<th>Model</th>
<th>Test</th>
<th>GenTest-Type</th>
<th>GenTest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Home</td>
<td>Factory</td>
<td>I</td>
<td>II</td>
</tr>
<tr>
<td>GGCN Baseline</td>
<td>61.53</td>
<td>80.36</td>
<td>63.15</td>
</tr>
<tr>
<td>+Attn</td>
<td>83.07</td>
<td>91.06</td>
<td>66.67</td>
</tr>
<tr>
<td>+L</td>
<td>83.07</td>
<td>91.06</td>
<td>66.67</td>
</tr>
<tr>
<td>+W</td>
<td>88.88</td>
<td>100</td>
<td>73.45</td>
</tr>
<tr>
<td>+W (ToolNet)</td>
<td>88.88</td>
<td>100</td>
<td>73.45</td>
</tr>
</tbody>
</table>
The Attn component also makes across the board improvements with maximum impact to types II and V. The impact to Type V is natural, since goal objects get replaced in those examples. Explicitly biasing the model to use the features of those objects (through conditioned attention) increases their importance, and likely reduces overfitting. An example for Type II is when generator is specified in the goal, and wood (the fuel for generator, and the most likely tool) is made absent from the scene. The model could err in giving attention to the wood-cutter tool, which is often correlated with wood. However, conditioned attention gives low attention to wood-cutter and predicts gasoline, instead.

The factored likelihood (+L) predictably helps the most in Type III scenarios, since without this component, the model cannot predict any unseen tool. A decent performance of earlier models on Type III is attributed to alternative possible correct answers (any alternative seen tool or no-tool) due to multiple annotations per scenario. The NT component, which splits the problem into two predictions (whether to use the tool and which one), helps in Type II cases, where the most likely tool is removed. In such cases a no-tool prediction is often correct, which is correctly predicted by the NT predictor focusing on whether to use the tool. The ConceptNet embeddings (+C) likely contain commonsense knowledge about unseen tools and objects, for example, whether a new tool is flat or not (which should help in ascertaining whether it can be used for transport or not). Using these embeddings makes huge improvement in Type III cases where entirely new objects are to be predicted as tools. Finally, giving higher weight to optimal plans (+W) allows the model to differentiate tools by plan execution time and not human usage frequency. This helps in improved metric generalization, predicting nearby tools in test-type I. Overall, the complete architecture provides the maximum generalization accuracy among all models.

Additionally, we performed preliminary experiments to assess the utility of the learned model in aiding plan synthesis. We used an symbolic planner that encoded the world state and robot action representation described previously. The planner used uninformed search to explore the space of robot interactions in the environment during plan search. The estimated tool likelihoods prioritized the exploration of candidate object interactions while expanding the search tree. Table V illustrates cases where the model predicts the use of novel tools: a “box” object for transport task and a “nails” to attach a board to the wall. An underlying symbolic planner prioritizes model predictions over other possible tool object interactions during search for a feasible plan. Preliminary evaluation revealed a reduction in the effective branching factor from $37.29 \pm 1.99$ to $4.24 \pm 0.13$ in the Home domain and $56.89 \pm 4.01$ to $9.10 \pm 3.21$ in the Factory domain using the predictions of the learned model compared to an uninformed plan search. However, extensive evaluation remains part of future work.

### VII. Conclusions

We addressed the problem of learning common sense knowledge of contextual tool use for a robot operating in environments with potentially new objects not encountered before. We crowd source a data set of robot plans where a humans instructs a simulated robot to perform tasks involving interaction with objects as tools in home and factory-like environments. The demonstrated plans are used to train TOOLNET, a neural learner that predicts the contextual use of tools enabling the robot to synthesize a plan for the intended goal. The model builds on gated graph convolution networks and incorporates goal-conditioned attention, fusion of semantic and metric representations and use of existing knowledge sources such as ConceptNet. The imitation learner demonstrates accurate generalization to environments with novel object instances using the learned knowledge of shared spatial and semantic characteristics.

Future work will investigate use of the learned model with a symbolic planner, handling partially observable environments and extensions for imitating multi-step tool interactions.

### Table V: Utility of model predictions

Preliminary experiments indicate the the utility of model predictions in synthesizing a feasible symbolic plans for a simulated mobile manipulator in home and factory domains. The learned model predicts the utility of tool objects a-priori unseen in training. The model prediction likelihoods are used to inform exploration of robot interactions (including tool use) during plan search. Figure illustrates the robot using novel tools to complete the task (images in temporal order with execution time indicated above).

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