What Can This Robot Do? Learning Capability Models from Appearance and Experiments

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Abstract

As autonomous robots become increasingly multifunctional and adaptive, it becomes difficult to determine the extent of their capabilities, i.e. the tasks they can perform and their strengths and limitations at these tasks. A robot's appearance can provide cues to its physical as well as cognitive capabilities. We present an algorithm that builds on these cues and learns models of a robot's ability to perform different tasks through active experimentation. These models not only capture the robot's inherent abilities but also incorporate the effect of relevant extrinsic factors on a robot's performance. Our algorithm would find use as a tool for humans in determining "What can this robot do?".

We applied our algorithm in modelling a NAO and a Pepper robot at two different tasks. We first illustrate the advantages of our active experimentation approach over building models through passive observations. Next, we show the utility of such models in identifying scenarios a robot is well suited for in performing a task. Finally, we demonstrate the use of such models in a collaborative human-robot task.

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First, I would like to thank my advisor, Manuela Veloso. When I started off as a Masters student, I had little knowledge about the areas of interest of the CORAL group. Manuela gave me an opportunity to be a part of the group with the only expectation that I work hard. Throughout my time at CMU I have tried to live up to this expectation. Manuela's ideas greatly shaped this thesis. She provided me with the freedom to determine the best possible approach to tackle the problems I addressed in this work all the while ensuring that I did not digress.

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Chapter 1

Introduction

Suppose we get a multipurpose robot but are not familiar with all of its functionalities. How do we identify the different tasks that it can perform? Appearance and specifications of a robot can convey information about its physical as well as cognitive capabilities. Seeing a legged robot equipped with a camera and a microphone could make one wonder if it can climb stairs, recognize faces, detect hand gestures or interpret voice commands. How do we identify which of these appearance-deduced tasks it can actually perform?

Although physical appearances can provide rich cues about a robot's capabilities they are not sufficient to identify the scenarios in which it can function well. The robots Roomba and Braava appear similar and are both used for cleaning floors. But the Roomba can clean carpets and not wet floors, which is exactly the opposite of what Braava can do. For a human working collaboratively with a robot, knowing the robot's strengths and shortcomings is especially useful. A robot's spec sheet provides information about various sensors and actuators it is equipped with. But inevitably how well a robot performs a task depends on the way it is programmed and, for a naive user, this is difficult to determine simply based on appearance and specifications.

Experimenting with a robot can help identify the tasks it can perform and the scenarios it is well suited for. But experimentation is tedious and intelligent robots are capable of learning new skills and adapting to new scenarios over time. This motivates the need for an algorithm which could be used to intelligently experiment

with robots, identify their skills and quantify their applicability in different scenarios. Humans can use such an algorithm in identifying the range of functionalities of a robot and, its strengths and limitations at the same.

In this thesis, we tackle the problem of inferring capabilities of a new unknown robot through systematic experimentation. We present an approach to identify from a robot's appearance the tasks it can potentially perform. Furthermore, we provide an algorithm for building models of a robot's ability to carry out these tasks through experimentation. We call these models as Capability Models. The outcomes of experiments with a robot can be non-deterministic. Moreover, apart from a robot's inherent capabilities, certain extrinsic factors may affect its performance at a task. Assuming some of these factors are controllable, our algorithm systematically tests the robot at different settings of controllable factors. Capability Models quantify the robot's ability to carry out a task as a function of these factors while incorporating the non-determinism in the experiments. However, knowing the set of extrinsic factors relevant to a particular robot and a task a priori is not feasible. Assuming we have a list of possibilities, our algorithm identifies factors that are pertinent to a robot's ability to perform a task. Lastly, we introduce a metric to quantify a robots ability to carry out a task in different scenarios.

1.1 Outline

The thesis is outlined as follows.

Chapter 2 illustrates the pertinent related work.

In Chapter 3, we introduce Capability Models. We present our algorithm for building a Capability Model for a task. Moreover, we introduce a metric to quantify the robot's performance in different scenarios. This metric allows us to identify situations in which a robot can reliably carry out the task.

Chapter 4 discusses our method to incorporate a robot's appearance in identifying tasks it can potentially perform. Additionally, we present results of a survey we conducted for identifying relevant factors to include in a Capability Model for a task.

Chapter 5 describes our experiments with a Pepper and a NAO robot. We show that active experimentation learns better models than those learned by passively observing a robot. Furthermore, we use Capability Models to identify favorable

scenarios for a robot to carry out the task. We demonstrate that familiarity with a robot's strengths and shortcomings is helpful for a human working in collaboration with the robot.

Chapter 2

Related Work

Earlier works on learning from experimentation either address domains that are inherently deterministic [14, 19] or assume that the experiments they conduct are deterministic [8]. Owing to noisy actuation and sensing, outcomes of experiments with robotic systems are nondeterministic and, hence the problem of deducing a robot's capabilities through experimentation is challenging.

Affordance [11] is a relation between a certain effect, a class of objects and certain robot action. Learning affordances is similar to learning the physical capabilities of a robot. For example, learning to identify traversable terrains for a mobile robot from images and laser data [18] or building a probabilistic model to capture the effect of motor commands on a particular object [3]. These models capture a mapping from raw sensor data and commands to effects. It is difficult for a human to use such models in identifying scenarios a robot is well suited for. Some works [15, 16] characterize objects with visual features (Size, Shape, Color etc.) and learn Bayesian Networks that capture the effects (Object displacement, Contact type etc.) of a robot's actions (Tap, Grasp, Push). However, these works emphasize on building models that can be used for immitaion [16] or predicting actions that generate the observed effects [15]. They provide no concrete method to quantify a robot's capability. Furthermore, all of these works [3, 15, 16, 18] use passive methods to learn and do not explicitly consider their existing models to reason about what to explore next.

Learning forward models [12] for robots is another relevant line of work. Such models predict the effects of a robot's action in different scenarios. Active approaches

for learning forward models exist. A common strategy is to use the prediction error from the foward model to guide exploration in the sensorimotor space [1, 5, 21]. Some works attempt to jointly learn policies for different tasks and use forward models to deicde which tasks to attempt [2, 6]. However, forward models only predict the immediate effects of an action from the raw state i.e. predict the next state given the current state and action. Moreover, the emphasis in these works is on learning a policy. They provide no approach to identify from the forward model, the likelihood of successful task execution in different scenarios. Some works [10, 17] learn abstract states and actions and build predictive models of the environment over these higher level states and actions. However, these approaches learn from scratch and do not use the learned models in guiding exploration. They are quite data intensive and unrealistic for modelling physical systems.

Chapter 3

Capability Models

3.1 Definition

Suppose we decide to build a model of an anthropomorphic robot at the task of kicking a ball. Relevant extrinsic factors for this task could be, the size of the ball and turf on which the robot is playing. Among these factors, the size of the ball is likely to be controllable. An experiment for this task would constitute commanding the robot to kick a ball in certain direction from a particular position and observing the outcome. A robot's perception and actuation are noisy and, therefore the outcome is not deterministic. To capture this non-determinism, we use a Bayesian Network.

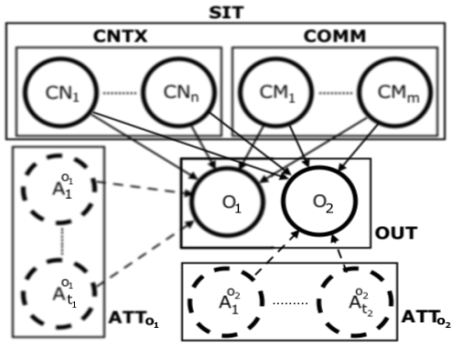
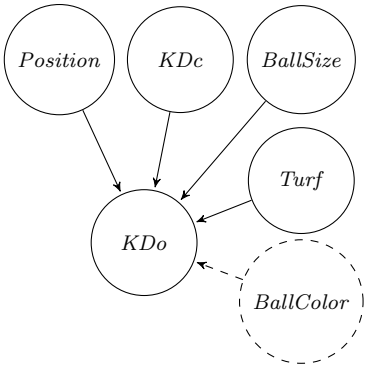


Figure 3.1: Capability Model

We introduce Capability Model (Fig. 3.1), a Bayesian Network which consists of the following types of nodes:



(a)

SIT = {*KDc*, *Position*, *Turf*, *BallSize*},
CNTX = {*Turf*, *BallSize*},
COMM = {*Position*, *KDc*},
OUT = {*KDo*}, ATT_{KDo} = {*BallColor*}

(b)

Position ∈ {*LeftSide*, *Middle*, *RightSide*},
Turf ∈ {*Grass*, *Synthetic*, *Sand*},
BallSize ∈ {*Small*, *Large*},
BallColor ∈ {*Yellow*, *Orange*},
KDc ∈ {*Left*, *Mid*, *Right*},
KDo ∈ {*Left*, *Mid*, *Right*, *None*}

(c)

Figure 3.2: Capability Model for the *BallKick* task. (a) depicts the Bayesian Network, (b) shows the type of each variable in the model and, (c) describes the values each variable can take.

- SIT = CNTX ∪ COMM, is the set of variables that describe the situation in which the robot is performing the task.
  - CNTX is the set of extrinsic factors (context) for the task.
  - COMM is the set of commands given to the robot.
- OUT is the set of variables denoting the outcomes of the task.
- ATT_{O} is the set of attributes for variable O ∈ OUT. These variables are not explicitly accounted in the model. Section 3.2.2 addresses their need and utility.

We capture the robot's ability to perform a task in the conditional probability tables associated with this Bayesian Network.

Fig. 3.2 presents a Capability Model for the *BallKick* task discussed before using the notation we just introduced. *Position* represents the location of the ball with respect to the robot before it kicks. *BallSize* is the size of the ball and *Turf* is the type of turf in the experiment. *KDc* and *KDo* denote the commanded and observed kick direction respectively. *KDo* is *None* if the robot attempts but fails to kick the ball or does not attempt to kick. The former may be because of its inability to kick in certain positions. The latter may mean it does not detect the ball or does not know

how to perform a kick. The set OUT is singleton here. In general this may not be the case. How far a robot kicks a ball could be another outcome for the *BallKick* task.

3.2 Building Capability Models

To build a Capability Model, we need to identify the right set of extrinsic factors (CNTX) and learn the conditional probabilities that quantify a robot's ability. We assume we have a set CNTX when we start experimenting with a robot. Some factors in this set may be redundant while there may be a few missing. First, we present a method to learn conditional probability tables of a Capability Model keeping the set CNTX fixed. Later, we describe our approach for updating this set as we learn the probability tables. We assume all variables in a model are discrete and have a Multinomial distribution. Extrinsic factors may be continuous and, we explain later how we accommodate them in our models. First, we introduce some notation.

- A Bayesian Network is a tuple $(\mathbf{G}, \boldsymbol{\theta})$
  - $\mathbf{G} \equiv (\mathbf{V}, \mathbf{E})$ is a graph, $\mathbf{V}$ is the set of nodes and $\mathbf{E}$ is the set of edges
  - $\mathbf{V} = \text{SIT} \cup \text{OUT}$ are random variables with Multinomial distribution
  - $\mathbf{E}$ capture the conditional dependencies amongst the nodes $\mathbf{V}$
  - $\boldsymbol{\theta}$ parameterize the conditional probability distributions
- *Domain*(X) where $\text{X} \in \mathbf{V}$, is the set of all possible values of variable X
- Instantiation of a set $\mathbb{X} \subseteq \mathbf{V}$, is a mapping from variables $\text{X} \in \mathbb{X}$ to values in *Domain*(X)
- *Domain*($\mathbb{X}$) where $\mathbb{X} \subseteq \mathbf{V}$, is the set of all possible instantiations of the set $\mathbb{X}$
- $P(\mathbb{X})$ where $\mathbb{X} \subseteq \mathbf{V}$, denotes the joint probability distribution of variables in $\mathbb{X}$
- $P(\mathbb{X}|\mathbb{Y} = y)$ where $\mathbb{X}$, $\mathbb{Y} \subseteq \mathbf{V}$, denotes the joint probability distribution of variables in $\mathbb{X}$ given the instantiation y of the set $\mathbb{Y}$
- $P_{\boldsymbol{\theta}}$ denote the probabilities parametrized by $\boldsymbol{\theta}$
- $D_{KL}(P_1||P_2) = \sum_i P_1(i) \log \frac{P_1(i)}{P_2(i)}$ is the KL-Divergence from distribution P_2 to P_1
- Q $\subset$ SIT is the set of controllable variables. All command variables are

controllable, i.e. COMM $\subset$ Q

- Variables in SIT $\setminus$ Q either have a fixed value or are assigned some value by the environment in each experiment
- Instantiations of CNTX, COMM, OUT and Q are called *Context*, *Command*, *Outcome* and *Query*[1]respectively. *Situation* = *Context* $\cup$ *Command*

3.2.1 Active Learning for Bayesian Networks

We adopt a Bayesian approach to learn parameters $\boldsymbol{\theta}$ assuming the structure of the Bayesian Network is fixed. We use the algorithm presented in [20] to build a distribution over $\boldsymbol{\theta}$. Here we give an overview of the approach.

Starting with a prior $p(\boldsymbol{\theta})$, we build a posterior $p'(\boldsymbol{\theta})$ by actively experimenting with the subject. In each experiment, we pick a *Query* and request the robot to perform the task. A standard Bayesian update on the prior p, for the parameters of the conditional distributions identified by the *Situation* ($P(\mathrm{O}|\mathit{Situation})\forall \mathrm{O} \in \mathrm{OUT}$) based on the *Outcome*, yields the posterior p'. The posterior becomes the prior for the next experiment.

To generate a *Query* from the current estimate of the distribution p, we need a metric to evaluate how good an estimate the distribution p is. We can then quantify the improvement in p brought about by different *Query*s and pick the one which leads to the biggest improvement. Let $\boldsymbol{\theta}^\star$ be the true parameters of the model and $\boldsymbol{\theta}'$ be a point estimate. $\sum_{\mathrm{O}\in\mathrm{OUT}} D_{KL}\big(P_{\boldsymbol{\theta}^\star}(\mathrm{O})||P_{\boldsymbol{\theta}'}(\mathrm{O})\big)$ denotes the error in point estimate $\boldsymbol{\theta}'$. $\boldsymbol{\theta}^\star$ is not known, but we do have p which is our belief over values of $\boldsymbol{\theta}^\star$ given the prior and observations. Error in point estimate $\boldsymbol{\theta}'$ with respect to p can be quantified as in Eq. (3.1).

$$\mathrm{Error}_p(\boldsymbol{\theta}') = \sum_{\mathrm{O}\in\mathrm{OUT}} \int_{\boldsymbol{\theta}} D_{KL}(P_{\boldsymbol{\theta}}(\mathrm{O})||P_{\boldsymbol{\theta}'}(\mathrm{O}))p(\boldsymbol{\theta})d\boldsymbol{\theta} \tag{3.1}$$

$$\mathrm{ModelError}(p) = \min_{\boldsymbol{\theta}'} \mathrm{Error}_p(\boldsymbol{\theta}') \tag{3.2}$$

We use ModelError(p), defined in Eq. (3.2), as the measure of quality for the estimate

[1] *Query* $\in$ *Domain*(Q), *Context* $\in$ *Domain*(CNTX), *Command* $\in$ *Domain*(COMM) and *Outcome* $\in$ *Domain*(OUT).

Algorithm 1 BestQuery($p(\boldsymbol{\theta})$, Q)

$\delta_{\min} \leftarrow \infty$
for $Query \in Domain(\mathrm{Q})$ **do**
  if $\mathrm{EPE}(p(\boldsymbol{\theta}), Query) < \delta_{\min}$ **then**
    $\delta_{\min} \leftarrow \mathrm{EPE}(p(\boldsymbol{\theta}), Query)$
    $Query_{best} \leftarrow Query$
return $Query_{best}$

$p(\boldsymbol{\theta})$. Lower the ModelError, better the estimate. We would want to see observations that reduce the ModelError associated with p. But we can only control the *Query*. For a particular *Query*, we take an expectation over possible observations to evaluate the Expected Posterior Error (EPE). In every experiment the algorithm picks the *Query* with the lowest EPE.

$$\mathrm{EPE}(p(\boldsymbol{\theta}), Query) = E_{\Theta \sim p(\boldsymbol{\theta})}\big(E_{Outcome \sim P_\Theta(\mathrm{OUT}|\mathrm{Q}=Query)}\big(\mathrm{ModelError}(p')\big)\big) \tag{3.3}$$

In Eq. (3.3), p' represents the posterior obtained after updating prior p with sample drawn from $P_\Theta(\mathrm{OUT}|\mathrm{Q} = Query)$. Algorithm 1 outlines the method. For further details, please refer [20]. We use $\boldsymbol{\theta}_T$ as defined in Eq. (3.4) to parameterize the conditional probabilities of the Capability Model for task T. We compute $\boldsymbol{\theta}_T$ using the learned distribution $p(\boldsymbol{\theta})$.

$$\boldsymbol{\theta}_T = \int_{\boldsymbol{\theta}} \boldsymbol{\theta} p(\boldsymbol{\theta}) d\boldsymbol{\theta} \tag{3.4}$$

3.2.2 Model Refinement

Every robot may have a different set of extrinsic factors relevant for a task. Consider the *BallKick* task (Section 3.1), if the robot only detects balls of a certain color, a variable *BallColor* should be included in the model. The initial guess of the model could be wrong and, the set CNTX may have certain relevant factors missing and might include some redundant ones. In Section 3.1 we defined $\mathrm{ATT_O}$ to be attributes of the variable $\mathrm{O} \in \mathrm{OUT}$ not explicitly accounted in the model. We assume that the missing variables, if any, belong to this set. Including all of them makes the

model unnecessarily large and difficult to learn. We need a metric to quantify the dependence of variables in the set OUT on those in CNTX and $\text{ATT}_\text{O} \forall \text{O} \in \text{OUT}$ to identify the relevant ones.

A variable is relevant if an the task outcome depends on it, more formally if the distribution of some $\text{O} \in \text{OUT}$ conditioned on the variable is drastically different for different values of the variable in at least one of the observed *Situation*s. We define a metric, Coefficient of Mutual Information $\text{R}(\text{O};\text{X}|Situation)$ (Eq. (3.5)), to quantify the variation in distributions of O conditioned over different values of variable X in a particular *Situation*. In Eq. (3.5) and Eq. (3.6), $H(P)$ returns the entropy of distribution P. $\text{I}(\text{O};\text{X}|Situation)$ (Eq. (3.6)) denotes the Mutual Information between O and X given the *Situation* and $\text{R}(\text{O};\text{X}|Situation)$ is a normalized form of Mutual Information. $\text{R}(\text{O};\text{X}|Situation) \in [0, 1]$.

$$\text{R}(\text{O};\text{X}|Situation) = \frac{\text{I}(\text{O};\text{X}|Situation)}{\min(H(P(\text{O}|Situation)), H(P(\text{X})))} \tag{3.5}$$

$$\begin{aligned}\text{I}(\text{O};\text{X}|Situation) = \; & H(P(\text{O}|Situation)) - \\ & \sum_x H(P(\text{O}|\text{X} = x, Situation))P(\text{X} = x|Situation)\end{aligned} \tag{3.6}$$

We use the same metric, the Coefficient of Mutual Information, to decide which variables in the model to discard and for determining the attributes to include. However, the methodology for computing the probability distributions required to evaluate this metric is slightly different in the two scenarios. We describe here in detail how we compute and use the Coefficient of Mutual Information. Algorithm 2 summarizes the approach.

Which attributes to include?

In every experiment, we randomy pick values for attributes that are controllable. If $\text{R}(\text{O};\text{A}^\text{O}_\text{j}|Situation)$ is greater than a threshold R_ThIn in at least one of the observed *Situation*s then, we incorporate $\text{A}^\text{O}_\text{j}$ as a dependency to variable O (Algorithm 2, Lines 8 - 17). While evaluating the Coefficient of Mutual Information, we need to ensure that $P(\text{O}|\text{A}^\text{O}_\text{j}, Situation)$ is well defined. Therefore, we only consider values of $\text{A}^\text{O}_\text{j}$ in $Domain_{valid}(\text{A}^\text{O}_\text{j}|Situation)$, which is the set of values of $\text{A}^\text{O}_\text{j}$ that have been observed sufficiently in a particular *Situation* (Line 12-13). We compute $P(\text{A}^\text{O}_\text{j}|Situation)$ from

observations in the past experiments.

Which variables to exclude?

To determine if a variable $\mathrm{CN}_i \in \mathrm{CNTX}$ should be excluded from the model, we consider a Capability Model without this variable. If $\mathrm{R}(\mathrm{O}; \mathrm{CN}_i | \mathit{Situation})$ is less than the threshold $\mathrm{R}_{\mathrm{ThEx}}$ in every *Situation* corresponding to this reduced model, we remove CN_i from the dependencies of variable O (Algorithm 2, Lines 18 - 28). If CN_i is removed from the dependencies of every $\mathrm{O} \in \mathrm{OUT}$, we exclude it from the model. All variables in SIT (CNTX $\cup$ COMM) are independent, hence $P(\mathrm{CN}_i | \mathit{Situation}) = P(\mathrm{CN}_i)$ (Algorithm 2, Lines 21-23). In our experiments, values for controllable variables Q are chosen and never sampled. Therefore, if $\mathrm{CN}_i \in \mathrm{Q}$, we assign the same probability to every $c \in \mathit{Domain}(\mathrm{CN}_i)$. If $\mathrm{CN}_i \notin \mathrm{Q}$, we compute the probabilities using observations from the past experiments. We use $\boldsymbol{\theta}_T$, as defined in Eq. (3.4), to compute $P(\mathrm{O}|\mathrm{CN}_i, \mathit{Situation})$ (Algorithm 2, Line 21). As we start with a prior over the values of $\boldsymbol{\theta}$, $P_{\boldsymbol{\theta}_T}(\mathrm{O}|\mathrm{CN}_i, \mathit{Situation})$ is always well defined.

3.2.3 Incorporating Continuous Variables

We assumed all variables in our model to be discrete. This assumption is quite limiting, especially when we are modelling physical systems. How far can a robot perceive? How heavy a load can it lift? How far can a robotic arm reach? These factors may affect a robot's ability to perform different tasks. Capability Model of a robot should have the capacity to incorporate such factors. Discretizing continuous variables and treating them similar to the discrete ones, can be a possible approach. However, arbitrary discretization can lead to an unnecessarily complicated model or an oversimplified one. We assume every continuous variable can be discretized into ranges, such that a robot's performance (distribution of the outcome) is invariant for values in a range. However, the number of such ranges and the bounds for each range are unknown. Consider a robot equipped with a camera, an arm, and a gripper. Suppose it can detect and pick up objects of a particular shape. Such a robot would have certain limitations on the size and weight of the objects it can pick up. We assume that the robot's ability to pick up is invariant for sizes and weights that lie within these limits. However, knowing these limits for a particular robot a priori, is

Algorithm 2 Refine(CNTX, COMM, OUT, $\mathbf{E}$, $p(\boldsymbol{\theta})$, ATT, Q, Observations, $\mathrm{R}_{\mathrm{ThEx}}$, $\mathrm{R}_{\mathrm{ThIn}}$)

ATTIn$\leftarrow$ {}
CNTXEx$\leftarrow$ {}
SIT $\leftarrow$ CNTX $\cup$ COMM
$\boldsymbol{\theta}_T \leftarrow \int_{\boldsymbol{\theta}} \boldsymbol{\theta} p(\boldsymbol{\theta}) d\boldsymbol{\theta}$
for O $\in$ OUT **do**
    ATTIn[O] $\leftarrow$ []
    CNTXEx[O] $\leftarrow$ []
    for $\mathrm{A}_\mathrm{j}^\mathrm{O} \in$ ATT[O] **do** ▷ ATT[O] $\equiv \mathrm{ATT}_\mathrm{O}$
        for S $\in$ *Domain*(SIT) **do**
            from Observations
                compute $Domain_{valid}(\mathrm{A}_\mathrm{j}^\mathrm{O}|\mathrm{S})$, $P(\mathrm{A}_\mathrm{j}^\mathrm{O}|\mathrm{S})$ and $P(\mathrm{O}|\mathrm{A}_\mathrm{j}^\mathrm{O}, \mathrm{S})$
            $P(\mathrm{O}|\mathrm{S}) \leftarrow \sum_{a \in Domain_{valid}(\mathrm{A}_\mathrm{j}^\mathrm{O}|\mathrm{S})} P(o|\mathrm{A}_\mathrm{j}^\mathrm{O} = a, \mathrm{S}) P(\mathrm{A}_\mathrm{j}^\mathrm{O} = a|\mathrm{S})$
            $\mathrm{I}(\mathrm{O}; \mathrm{A}_\mathrm{j}^\mathrm{O}|\mathrm{S}) \leftarrow H(P(\mathrm{O}|\mathrm{S})) - \sum_{a \in Domain_{valid}(\mathrm{A}_\mathrm{j}^\mathrm{O}|\mathrm{S})} H(P(\mathrm{O}|\mathrm{A}_\mathrm{j}^\mathrm{O} = a, \mathrm{S})) P(\mathrm{A}_\mathrm{j}^\mathrm{O} = a|\mathrm{S})$
            $\mathrm{R}(\mathrm{O}; \mathrm{A}_\mathrm{j}^\mathrm{O}|\mathrm{S}) \leftarrow \frac{\mathrm{I}(\mathrm{O}; \mathrm{A}_\mathrm{j}^\mathrm{O}|\mathrm{S})}{\min\left(H(P(\mathrm{O}|\mathrm{S})), H(P(\mathrm{A}_\mathrm{j}^\mathrm{O}|\mathrm{S}))\right)}$
            if $\mathrm{R}(\mathrm{O}; \mathrm{A}_\mathrm{j}^\mathrm{O}|\mathrm{S}) > \mathrm{R}_{\mathrm{ThIn}}$ **then**
                ATTIn[O].append($\mathrm{A}_\mathrm{j}^\mathrm{O}$)
                break
    for $\mathrm{CN}_i \in$ CNTX **such that** $(\mathrm{CN}_i, \mathrm{O}) \in \mathbf{E}$ **do**
        count $\leftarrow 0$
        for S $\in$ *Domain*(SIT $\setminus$ CN_i) **do**
            $P(\mathrm{O}|\mathrm{S}) \leftarrow \sum_{c \in Domain(\mathrm{CN}_i)} P_{\boldsymbol{\theta}_T}(\mathrm{O}|\mathrm{CN}_i = c, \mathrm{S}) P(\mathrm{CN}_i = c)$
            $\mathrm{I}(\mathrm{O}; \mathrm{CN}_i) \leftarrow H(P(\mathrm{O}|\mathrm{S})) - \sum_{c \in Domain(\mathrm{CN}_i)} H(P_{\boldsymbol{\theta}_T}(\mathrm{O}|\mathrm{CN}_i = c, \mathrm{S})) P(\mathrm{CN}_i = c)$
            $\mathrm{R}(\mathrm{O}; \mathrm{CN}_i|\mathrm{S}) \leftarrow \frac{\mathrm{I}(\mathrm{O}; \mathrm{CN}_i|\mathrm{S})}{\min\left(H(P(\mathrm{O}|\mathrm{S})), H(P(\mathrm{CN}_i))\right)}$
            if $\mathrm{R}(\mathrm{O}; \mathrm{CN}_i|\mathrm{S}) > \mathrm{R}_{\mathrm{ThEx}}$ **then**
                break
            count $\leftarrow$ *count* $+ 1$
        if *count* $== |Domain(\mathrm{SIT} \setminus \mathrm{CN}_i)|$ **then**
            CNTXEx[O].append(CN_i)

ATT, CNTX, Q, $\mathbf{E}$, $p(\boldsymbol{\theta})$, Observations $\leftarrow$ **UpdateDependence**(ATTIn, CNTXEx, ATT, CNTX, Q, $\mathbf{E}$, $p(\boldsymbol{\theta})$, Observations)

return ATT, CNTX, Q, $\mathbf{E}$, $p(\boldsymbol{\theta})$, Observations

very difficult. We present a method to incorporate continuous variables in Capability Models by finding the appropriate discretization through experiments.

We assume continuous variables in a Capability Model, if any, belong to the set SIT. All the attribute variables $\mathrm{ATT_O} \forall \mathrm{O} \in \mathrm{OUT}$ are discrete. For a continuous variable X in the model, $\mathit{Domain}(\mathrm{X})$ is an interval $(\mathrm{X_{min}}, \mathrm{X_{max}})$ where $\mathrm{X_{min}}$ and $\mathrm{X_{max}}$ are finite and are known a priori. An increasing sequence of cutpoints[2] $\mathrm{U^X} = (u_1^{\mathrm{X}}, \cdots, u_n^{\mathrm{X}})$, demarcates the ranges of X. Discretization of X is a function $\mathrm{D_{U^X}} : \mathit{Domain}(\mathrm{X}) \rightarrow \mathbb{Z}$ (Eq. (3.7)), which maps values of X to an integer label corresponding to the appropriate range. For accommodating X in a Capability Model, we treat it as a discrete variable that can take values in the image of $\mathrm{D_{U^X}}$. We further assume the robot's performance (distribution of outcome) can be captured using an optimal discretization $\mathrm{D_{U^{\star X}}}$ as in Eq. (3.8), where P_i are Multinomial distributions. Our objective is to find sequence $\mathrm{U^{\star X}}$ for every continuous variable X, while learning the conditional probabilities.

$$\mathrm{D_{U^X}}(x) = \begin{cases} 0 & \text{if } \mathrm{X_{min}} < x \leq u_1^{\mathrm{X}} \\ \vdots & \vdots \\ i & \text{if } u_i^{\mathrm{X}} < x \leq u_{i+1}^{\mathrm{X}} \\ \vdots & \vdots \\ n & \text{if } u_n^{\mathrm{X}} < x < \mathrm{X_{max}} \end{cases} \tag{3.7}$$

$$P(\mathrm{OUT}|\mathrm{X}) = \begin{cases} P_0 & \text{if } \mathrm{D_{U^{\star X}}}(\mathrm{X}) = 0 \\ \vdots & \vdots \\ P_i & \text{if } \mathrm{D_{U^{\star X}}}(\mathrm{X}) = i \quad \text{where } P_i \neq P_{i+1} \\ \vdots & \vdots \\ P_m & \text{if } \mathrm{D_{U^{\star X}}}(\mathrm{X}) = m \end{cases} \tag{3.8}$$

We start with a single range for every continuous variable X in the model, i.e. $\mathrm{U^X}$ is empty and $\mathrm{D_{U^X}}(x) = 0 \, \forall x \in \mathit{Domain}(\mathrm{X})$. In each experiment, Algorithm 1 (Section 3.2.1) returns a *Query*, then we sample values for continuous variables from the respective ranges chosen in the *Query*. For each X, we maintain a list of observations $\mathrm{L^X} = [\cdots, (x_j, \mathit{Outcome}_j, \mathit{Situation}_j), \cdots]$, where $x_j \in \mathit{Domain}(\mathrm{X})$ and, $\mathit{Outcome}_j$ and $\mathit{Situation}_j$ are as defined in Section 3.2. $\mathrm{L^X}$ is a sorted list in

[2] We call $u_i^{\mathrm{X}} \in \mathit{Domain}(\mathrm{X})$ as cutpoints because they cut $\mathit{Domain}(\mathrm{X})$ into several ranges.

increasing order of x_j. Once we have sufficient observations in L^{X}, we use these x_js in determining the appropriate cutpoints to include in U^{X}. We adopt a greedy approach to incrementally build U^{X}. We consider points mid-way[3] between x_j and x_{j+1} as candidate cutpoints to add to U^{X}. We add a candidate to U^{X} to generate the sequence $\underline{\mathrm{U}}^{\mathrm{X}}$. CutValue$(\underline{\mathrm{U}}^{\mathrm{X}}, \mathrm{U}^{\mathrm{X}})$, as defined in Eq. (3.9), determines how good a candidate cutpoint is. In Eq. (3.10), $Domain(\mathrm{SIT}|\mathrm{U}^{\mathrm{X}})$ is the set of all possible *Situations* when variable $\mathrm{X} \in \mathrm{SIT}$ is discretized using the sequence U^{X}. If the highest CutValue is greater than a threshold $\mathrm{CutValue}_{\mathrm{Th}}$, we add the cutpoint corresponding to this value to U^{X} (Algorithm 3, Lines 11-25).

$$\mathrm{CutValue}(\underline{\mathrm{U}}^{\mathrm{X}}, \mathrm{U}^{\mathrm{X}}) = \sum_{\mathrm{O} \in \mathrm{OUT}} \Big(\mathrm{I}(\mathrm{O}; \mathrm{SIT}|\underline{\mathrm{U}}^{\mathrm{X}}) - \mathrm{I}(\mathrm{O}; \mathrm{SIT}|\mathrm{U}^{\mathrm{X}}) \Big) \tag{3.9}$$

$$\mathrm{I}(\mathrm{O}; \mathrm{SIT}|\mathrm{U}^{\mathrm{X}}) = H(P(\mathrm{O})) - \sum_{Situation \in Domain(\mathrm{SIT}|\mathrm{U}^{\mathrm{X}})} H(P(\mathrm{O}|Situation, \mathrm{U}^{\mathrm{X}}))P(Situation|\mathrm{U}^{\mathrm{X}}) \tag{3.10}$$

The principle of Minimum Description Length is often used for determining suitable discretizations in classification problems [4] and while learning Bayesian Networks [7]. These approaches use the information gain, similar to the CutValue defined in Eq. (3.9), to compute discretizations that generate the most compact representation for the observed data. Our objective was to identify a discretization that induces conditional distributions as described in Eq. (3.8). Appendix 7.1 discusses how CutValue is a suitable metric for identifying such a discretization.

Algorithm 4 combines the active experimentation approach (Algorithm 1), the model refinement method (Algorithm 2) and the discretization routine (Algorithm 3) to learn a Capability Model. It takes as input an initial guess of the model (CNTX, COMM, OUT, ATT, the set of edges $\mathbf{E}$ and prior $p(\boldsymbol{\theta})$) and returns a learned model. *Attributes* (Algorithm 4, Line 9) is an instantiation of $\cup_{\mathrm{O} \in \mathrm{OUT}} \mathrm{ATT}_{\mathrm{O}}$. CONT is the set of continuous variables and *Continous* (Algorithm 4, Line 10) is an instantiation for this set.

[3] Any point in the interval (x_j, x_{j+1}) is an equally valid candidate. We choose to use the midpoint.

Algorithm 3 Discretize(U, CONT, CNTX, COMM, OUT, $p(\boldsymbol{\theta})$, Observations, $\text{CutValue}_{\text{Th}}$)

SIT $\leftarrow$ CNTX $\cup$ COMM
for X $\in$ CONT **do** ▷ CONT is the set of continuous variables.
  $\text{U}^{\text{X}} \leftarrow \text{U}[\text{X}]$ ▷ $\text{U} \leftarrow \cup_{\text{X}\in\text{CONT}}\{\text{X} : \text{U}^{\text{X}}\}$
  $\boldsymbol{\theta}_T \leftarrow \int_{\boldsymbol{\theta}} \boldsymbol{\theta} p(\boldsymbol{\theta}) d\boldsymbol{\theta}$
  $\text{CutValue}_{\max} \leftarrow -\infty$
  for O $\in$ OUT **do**
    $\text{I}(\text{O};\text{SIT}|\text{U}^{\text{X}}) \leftarrow H(P_{\boldsymbol{\theta}_T}(\text{O})) - \sum_{\text{S}\in \mathit{Domain}(\text{SIT}|\text{U}^{\text{X}})} H(P_{\boldsymbol{\theta}_T}(\text{O}|\text{S},\text{U}^{\text{X}}))P_{\boldsymbol{\theta}_T}(\text{S}|\text{U}^{\text{X}})$
  from Observations
    compute L^{X}
  for $j \in \{0,\cdots,\mathit{length}(\text{L}^{\text{X}})-2\}$ **do**
    $u \leftarrow (\text{L}^{\text{X}}[j][0] + \text{L}^{\text{X}}[j+1][0])/2$ ▷ $\text{L}^{\text{X}}[j] = (x_j, \mathit{Outcome}_j, \mathit{Situation}_j)$
    $\underline{\text{U}}^{\text{X}} \leftarrow$ **AddToSequence**(U^{X}, u)
    from L^{X} and $\underline{\text{U}}^{\text{X}}$
      compute $P(\text{O}|\text{S},\underline{\text{U}}^{\text{X}})\ \forall \text{O}\in\text{OUT}, \forall \text{S}\in \mathit{Domain}(\text{SIT}|\underline{\text{U}}^{\text{X}})$
      compute $P(\text{S}|\underline{\text{U}}^{\text{X}}),\ \forall \text{S}\in \mathit{Domain}(\text{SIT}|\underline{\text{U}}^{\text{X}})$
    for O $\in$ OUT **do**
      $\text{I}(\text{O};\text{SIT}|\underline{\text{U}}^{\text{X}}) \leftarrow H(P_{\boldsymbol{\theta}_T}(\text{O})) - \sum_{\text{S}\in \mathit{Domain}(\text{SIT}|\underline{\text{U}}^{\text{X}})} H(P(\text{O}|\text{S},\underline{\text{U}}^{\text{X}}))P(\text{S}|\underline{\text{U}}^{\text{X}})$
    $\text{CutValue}(\underline{\text{U}}^{\text{X}},\text{U}^{\text{X}}) \leftarrow \sum_{\text{O}\in\text{OUT}} \big(\text{I}(\text{O};\text{SIT}|\underline{\text{U}}^{\text{X}}) - \text{I}(\text{O};\text{SIT}|\text{U}^{\text{X}})\big)$
    if $\text{CutValue}(\underline{\text{U}}^{\text{X}},\text{U}^{\text{X}}) > \text{CutValue}_{\max}$ **then**
      $\text{CutValue}_{\max} \leftarrow \text{CutValue}(\underline{\text{U}}^{\text{X}},\text{U}^{\text{X}})$
      $u_{\max} \leftarrow u$

  if $\text{CutValue}_{\max} > \text{CutValue}_{\text{Th}}$ **then**
    $\text{U}^{\text{X}} \leftarrow$ **AddToSequence**$(\text{U}^{\text{X}}, u_{\max})$
    $\text{U}, p(\boldsymbol{\theta}), \text{Observations} \leftarrow$ **UpdateDiscretization**$(\text{U}^{\text{X}}, \text{U}, p(\boldsymbol{\theta}), \text{Observations})$

return $\text{U}, p(\boldsymbol{\theta}), \text{Observations}$

Algorithm 4 LearnModel (CNTX, COMM, OUT, $\mathbf{E}$, $p(\boldsymbol{\theta})$, ATT, Q, CONT, maxIter, $\mathrm{R}_{\mathrm{ThIn}}$, $\mathrm{R}_{\mathrm{ThEx}}$, $\mathrm{CutValue}_{\mathrm{Th}}$)

Observations $\leftarrow$ [ ]
U $\leftarrow$ { }
for X $\in$ CONT **do** ▷ CONT is the set of continuous variables.
    U[X] $\leftarrow$ () ▷ U $\leftarrow \cup_{\mathrm{X}\in\mathrm{CONT}}\{\mathrm{X} : \mathrm{U}^{\mathrm{X}}\}$
$i \leftarrow 0$
while $i <$ maxIter **do**
    $i \leftarrow i + 1$
    Query $\leftarrow$ **BestQuery**($p(\boldsymbol{\theta})$, Q)
    Attributes $\leftarrow$ **SampleAttributes**(ATT) ▷ ATT $\leftarrow \cup_{o\in\mathrm{OUT}}\{o : \mathrm{ATT}_o\}$
    Continuous $\leftarrow$ **SampleContinuous**(CONT, U, *Query*)
    Outcome, *Situation* $\leftarrow$ **Experiment**(*Query*, *Continous*, *Attributes*)
    $p(\boldsymbol{\theta}) \leftarrow$ **UpdateDistribution**($p(\boldsymbol{\theta})$, *Situation*, *Outcome*)
    Observations.append((*Continuous*, *Outcome*, *Situation*, *Attributes*))

    ATT, CNTX, Q, $\mathbf{E}$, $p(\boldsymbol{\theta})$, Observations $\leftarrow$ **Refine**(CNTX, COMM, OUT, $\mathbf{E}$, $p(\boldsymbol{\theta})$, ATT, Q, Observations, $\mathrm{R}_{\mathrm{ThEx}}$, $\mathrm{R}_{\mathrm{ThIn}}$)

    U, $p(\boldsymbol{\theta})$, Observations $\leftarrow$ **Discretize**(U, CONT, CNTX, COMM, OUT, $p(\boldsymbol{\theta})$, Observations, $\mathrm{CutValue}_{\mathrm{Th}}$)

$\mathbf{V} \leftarrow \mathrm{CNTX} \cup \mathrm{COMM} \cup \mathrm{OUT}$
$\mathbf{G} \leftarrow (\mathbf{V}, \mathbf{E})$
return $(\mathbf{G}, \mathrm{U}, p(\boldsymbol{\theta}))$

3.3 Quantifying Capabilities

To determine how well a robot performs a task in different scenarios, we need a reference that indicates the expected performance and, a metric that quantifies how the robot fares against this standard. We assume the reference for task T is a distribution of the outcome variables conditioned on the commands i.e. $P^{T}_{\text{ref}}(\text{OUT}|\text{COMM})$. Eq. (3.11) shows a possible reference for the *BallKick* task (Section 3.1).

$$P^{BallKick}_{\text{ref}}(KDo|KDc, Position) = \begin{cases} 1 & \text{if } KDo = KDc \\ 0 & \text{otherwise} \end{cases} \tag{3.11}$$

This reference implies that a robot is expected to always kick in the commanded direction. $Score(Context)$, defined in Eq. (3.13), denotes how well a robot fares at a task T in certain *Context*. Lower values indicate poor performance. We use the *Score* to identify favourable *Context*s for the robot to perform a task.

$$Mismatch(Context) \overset{Command}{=} \frac{\sum D_{KL}\big(P^{T}_{\text{ref}}(\text{OUT}|Command)||P_{\boldsymbol{\theta}_T}(\text{OUT}|Situation)\big)}{|Domain(\text{COMM})|}^{4,5} \tag{3.12}$$

$$Score(Context) = \frac{1}{1 + Mismatch(Context)} \tag{3.13}$$

[4] $Situation = Context \cup Command$ (Section 3.2). Thus *Mismatch* is a function of the *Context*. $|Domain(\text{COMM})|$ is the number of possible *Command*s.

[5] $P_{\boldsymbol{\theta}_T}$ is the distribution parameterized by $\boldsymbol{\theta}_T$. For a task T, $\boldsymbol{\theta}_T$ is defined in Eq. (3.4)

Chapter 4

Role Of Appearance

We set out to develop an algorithm that can be used by humans as a tool for determining a robot's capabilities, i.e., the tasks the robot can perform and its strengths and limitations at these tasks. In Chapter 3, we introduced an algorithm for building a model of a robot's ability to carry out a particular task. However, our algorithm requires a guess of the model to initiate the learning process. How do we generate this guess? Moreover, for a new unknown robot, how do we identify the different tasks that it can perform?

We address these issues in this chapter.

4.1 Which tasks to test?

Robots are usually designed based on the functions they are required to perform. Therefore, a robot's appearance can provide rich cues about its capabilities. Asking a human for suggestions can be a possible approach to identify candidate tasks to test. However, for a naive user this may be quite difficult. Moreover, humans some times have unrealistic expectations from a robot [13]. Instead of relying on human input, we assume we have a database of reference robots whose capabilities are known. These may be robots that we have tested in the past. Furthermore, we assume that visually similar robots have similar capabilities. For a new robot, known capabilities of the visually closest reference robot can provide candidate tasks to test. We identified four visually distinct robots (Fig. 4.1) with known capabilities (Table 4.1) as reference

(a) Pepper (b) Parrot AR (c) FANUC R-2000*i*B (d) NAO

Figure 4.1: Reference Robots

robots.

Robot	Capabilities
Pepper	PickUp
Parrot AR	Fly
FANUC R-2000*i*B	PickUp, Catch, Throw
NAO	BallKick, PickUp

Table 4.1: List of tasks that each robot in Fig. 4.1 can perform. BallKick is defined in Section 3.1. The PickUp task entails picking up different objects off a table. The Catch task involves catching an object thrown towards a robot. The Throw task involves throwing different objects in a specified direction and Fly involves performing flying maneuvers at different speeds and wind conditions.

For identifying the visually closest reference robot, we learned an image-similarity model (Fig. 4.2) which returns a similarity score for a pair of robot images. The model consists of two components, a neural network which extracts features from a pair of input images and a Support Vector Machine (SVM) which computes the similarity score using these features. We created a database of 150 robot images of 4 different categories (Drones, Humanoids, Service Robots and Manipulator Arms) for training this model, Fig. 4.3. We train the neural network and the SVM separately.

We first describe our approach to train the neural network and then illustrate the training method for the SVM.

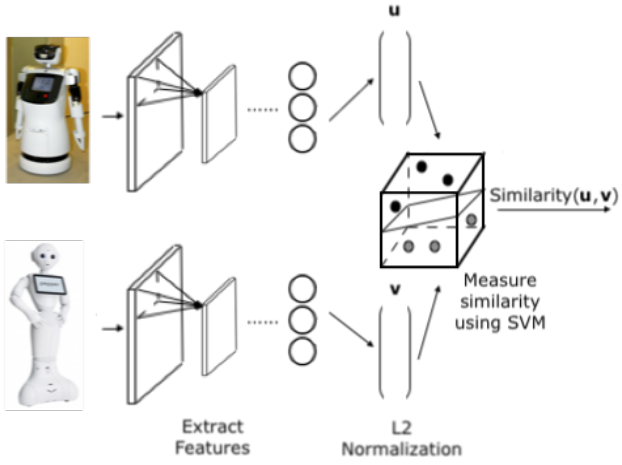


Figure 4.2: Overview of the image-similarity model.

- **Training the Neural Network**
  We use the same neural network architecture as ResNet-18 [9] and initialize the weights with the ResNet-18 pre-trained weights. For finetuning, we train the neural network to classify images from our dataset into the appropriate category. We use the normalized output of the penultimate layer of our network as features for an input image. Fig. 4.4 depicts the process. We train the SVM over the space of these features.

- **Training the SVM**
  We train the SVM to classify pairs of images as positive or negative. A pair of images is labeled positive if both the images belong to the same category (Drone, Humanoid, Service Robot or Manipulator Arm), negative otherwise. We paired images of reference robots with other robots in our dataset to generate data for training the SVM. We pose the training problem as presented in Eq. (4.1), where $\boldsymbol{u}_i$ and $\boldsymbol{v}_i$ are the features of images, and $y_i \in \{-1, 1\}$ is the label for the pair. The formulation is similar to learning a linear SVM for vectors $\boldsymbol{x}_i = (\boldsymbol{u}_i - \boldsymbol{v}_i) \odot (\boldsymbol{u}_i - \boldsymbol{v}_i)$[1] with labels y_i. The weights $\boldsymbol{w}$ and bias b in Eq. (4.1)

[1] $\boldsymbol{a} \odot \boldsymbol{b}$ denotes elementwise product of $\boldsymbol{a}$ and $\boldsymbol{b}$. Resultant vector has same dimension as $\boldsymbol{a}$ and $\boldsymbol{b}$.

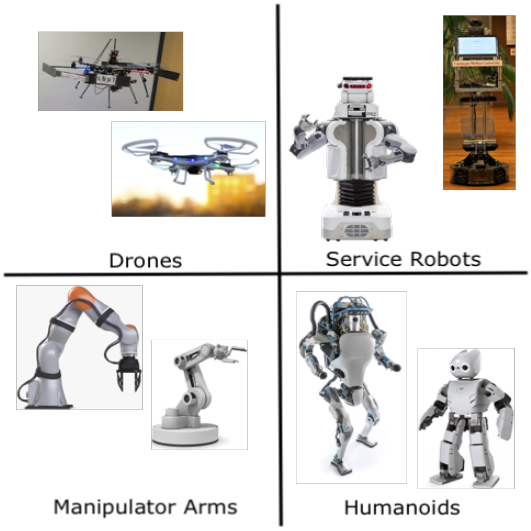


Figure 4.3: Dataset of robot images. It consists of 4 categories of robots namely Drones, Humanoids, Service Robots and Manipulator Arms.

can be computed using any standard technique to learn an SVM.

Given an image of a new robot, we use the neural network to generate features. We then use the trained SVM weights ($\boldsymbol{w}$ and b) to measure visual similarity (Eq. (4.2)) with the reference robots. The reference robot that returns the highest similarity score (Eq. (4.2)) is visually closest to the new robot.

$$\begin{aligned} &\min_{\boldsymbol{w},b,\xi_i}(|\boldsymbol{w}|^2 + \mathrm{C}\textstyle\sum_i \xi_i) \\ \text{s.t.} \quad &\Big(\textstyle\sum_j \boldsymbol{w}(j)\big(\boldsymbol{u}_i(j) - \boldsymbol{v}_i(j)\big)^2 + b\Big) y_i \geq 1 - \xi_i \end{aligned} \tag{4.1}$$

$$\text{Similarity}(\boldsymbol{u}, \boldsymbol{v}) = \Big(\sum_j \boldsymbol{w}(j)\big(\boldsymbol{u}(j) - \boldsymbol{v}(j)\big)^2 + b\Big) \tag{4.2}$$

We tested our image-similarity model on the images in the dataset not used for training. If the visually closest reference robot has the same category as the robot in the test image, we call it a correct match. The trained image-similarity model achieved an accuracy of 86% on the test set. Fig. 4.5 shows examples of correct (enclosed in green) and incorrect (enclosed in red) matches.

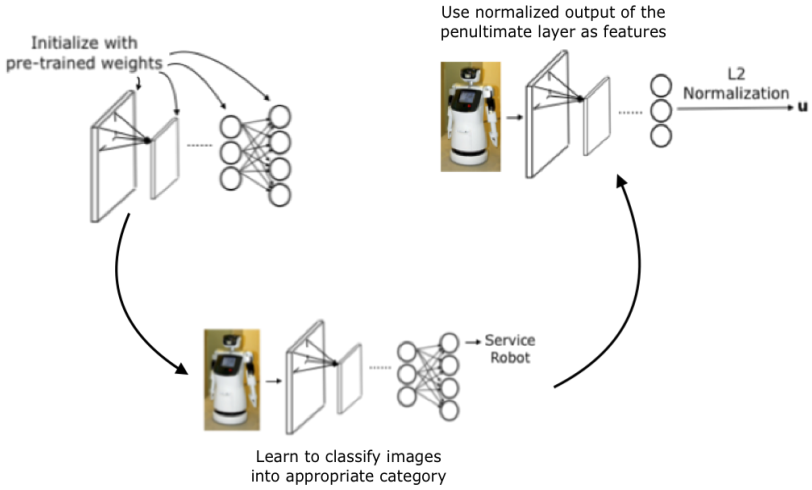


Figure 4.4: Approach to train the Neural Network and extract features from images.

4.2 Initialize Capability Models

In Chapter 3, we defined a Capability Model to be a Bayesian Network. The outcomes of a task (OUT), the commands for a task (COMM) and the extrinsic factors that affect (CNTX) or may affect ($\text{ATT}_\text{O} \forall \text{O} \in \text{OUT}$) a robot's ability, constituted the nodes of this Bayesian Network. The outcomes and commands are part of a task's definition. However, we need a set of extrinsic factors for initializing a model. Our earlier approach of using visually similar reference robots to draw inferences would not work because even for the same robot the relevant extrinsic factors may be different if the robot is programmed differently. Consider the *BallKick* task introduced in Section 3.1. A robot's ability would be affected by the size of the ball if it detected a ball based on size and shape. If the same robot instead used color and shape, the size of the ball would not make a difference.

We assume a human suggests extrinsic factors for initializing the model. A person's suggestions could be based on their prior knowledge about the robot and the task or from a few preliminary experiments with the robot. We conducted a survey to assess if people can identify the appropriate factors from a few experiments. In this survey, we showed participants videos of the NAO and Pepper robots (Fig. 4.6) performing the *BallKick* (Section 3.1) and the *PickUp* tasks respectively.

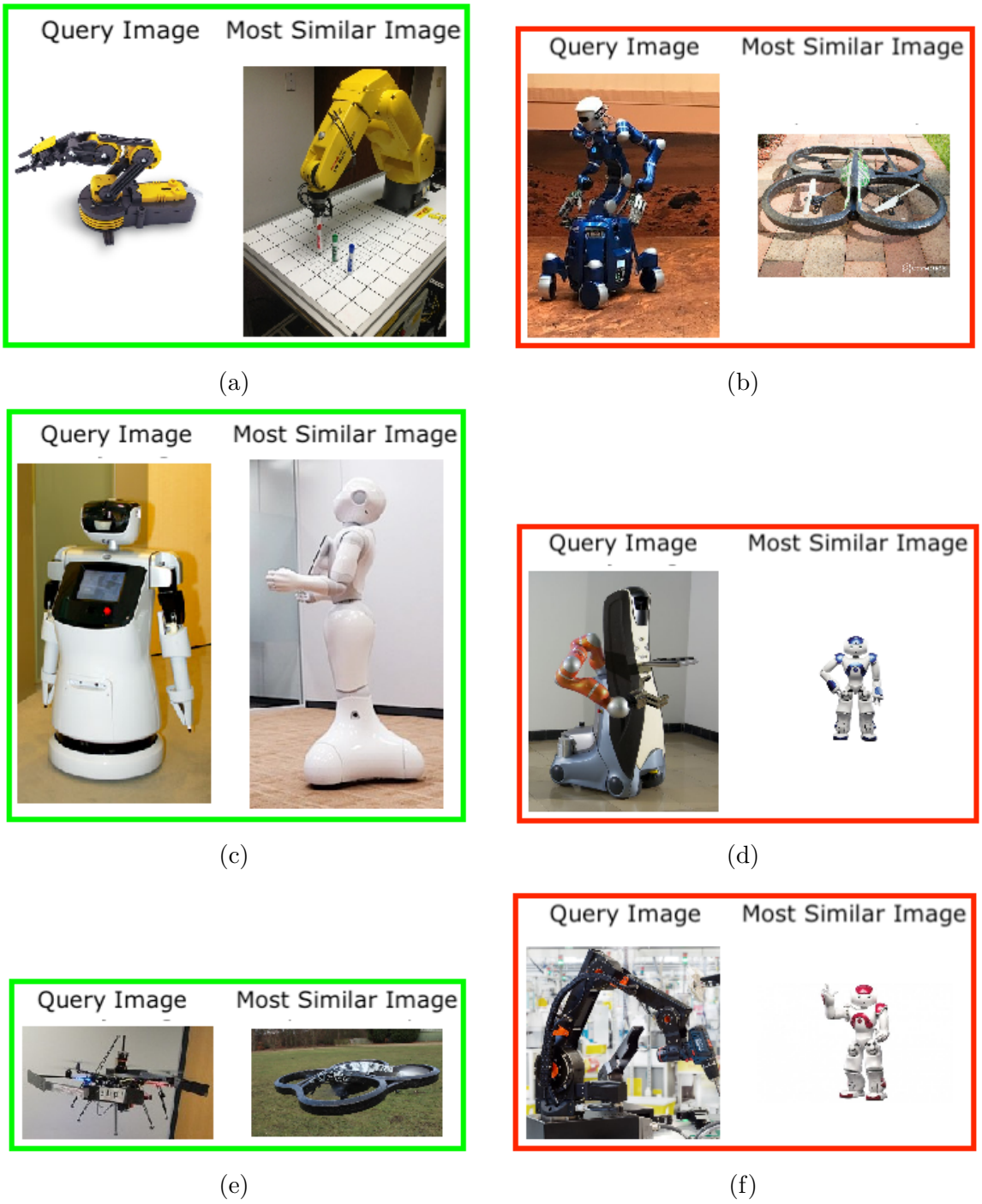
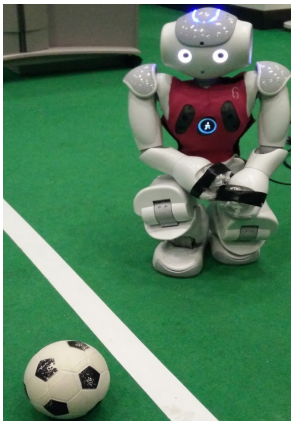


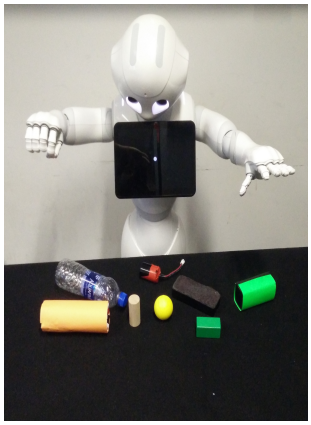
Figure 4.5: Examples of matches found by the trained image-similarity model. Green boxes indicate a correct match where as the red ones indicate an incorrect match.

As part of the *PickUp* task, the Pepper picked up different objects off a table. The different objects can be seen in Fig. 4.6b. The participants were then asked to answer a few yes/no questions (Tables 4.3 and 4.2). Fig. 4.7 shows a summary of their responses.

The videos in the survey depicted 2-3 instances of the robot executing a task. Thy were not informative about how the robot fares at the task in all the different scenarios. The participant's responses to the questions were partly based on their intuition. These intuitions are correct in some cases. The NAO robots have difficulty in walking over softer terrains and, a lot of participants indicated that the NAO robot would not be able to kick reliably on different Turfs (Fig. 4.7a). Sometimes these intuitions are wrong, and thus the model refinement (Section 3.2.2) part of our algorithm is necessary. In the video for the *PickUp* task the robot only used its right arm. As can be seen in Fig. 4.7b, a lot of participants answered that the robot would not be able to reliably pick up objects with either of its arms, when in fact it can. Moreover, many participants perceived that the Pepper robot could lift an object that weighed less than a pound. In reality, the robot has difficulty even lifting objects that weigh half a pound.



(a) NAO



(b) Pepper

Figure 4.6: Robots for experiments

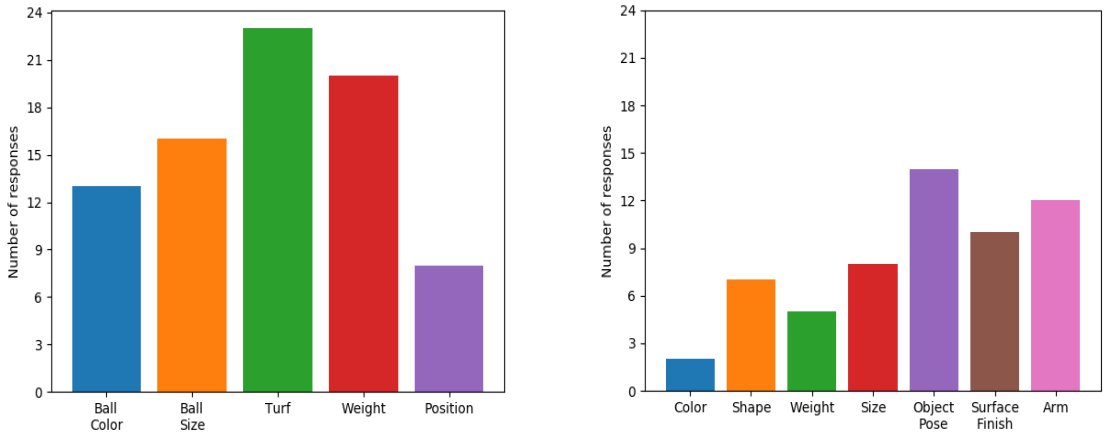
Factors	Question
Color	Would the robot be able to kick a ball of any color?
Size	Would the robot be able to kick a ball of any size, ranging from a ping-pong ball to a football?
Turf	Would the robot be able to kick reliably on any turf, sand, grass or synthetic?
Weight	Would the robot be able to kick balls of different weights, ranging from a ping-pong ball to a football?
Position	Would the robot be able to kick a ball from different positions (of the ball with respect to the robot)?

Table 4.2: Survey questions for the *BallKick* task. Fig. 4.7a depicts the number of participants that responded with 'No'.

Factors	Question
Color	Would the robot be able to pick up objects of any color?
Shape	Would the robot be able to pick up objects of any shape, cylindrical, cubical, spherical or prism?
Weight	Would the robot be able to pick up any object with weight less than a pound?
Size	Would the robot be able to pick up objects of different sizes[2]?
Pose	Would the robot be able to pick up objects placed in different orientations (Horizontal/Vertical)?
SurfaceFinish	Would the robot be able to pick up objects with a smooth surface finish?
Arm	Would the robot reliably pick up objects with either of its arms?

Table 4.3: Survey questions for the *PickUp* task. Fig. 4.7b depicts the number of participants that responded with 'No'.

[2]Not greater than the size of the robot's palm.



(a) (b)

Figure 4.7: (a) and (b) show the number of participants that voted for a factor affecting a robot's performance at the *BallKick* and *PickUp* tasks respectively.

Chapter 5

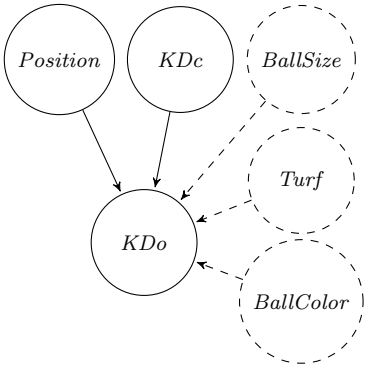
Experiments

We present results of applying our algorithm in building Capability Models of a NAO robot (Fig. 4.6a) performing the task of kicking a ball and a Pepper robot (Fig. 4.6b) picking up different types of objects and clearing them off a table.

5.1 Active vs Passive

We demonstrate the advantages of the active experimentation algorithm through experiments with the NAO robot. In every experiment the robot was commanded to kick a ball from a particular position in certain direction. We built a model of the robot's ability to kick a ball in the commanded direction through experiments. However, without knowing the ground truth we cannot say how good the learned model is. Therefore, we created our own ground truth, i.e. we programmed the robot to behave according to a predefined model with parameters $\boldsymbol{\theta}_{predefined}$. We use $D_{KL}(P_{\boldsymbol{\theta}_{predefined}}(\text{OUT})||P_{\boldsymbol{\theta}_{BallKick}}(\text{OUT}))$ to determine how close the learned and predefined models are. $\boldsymbol{\theta}_{BallKick}$ is as defined in Eq. (3.4) for the *BallKick* task. Fig. 5.1 shows the initial guess of the Capability Model.

Passively observing a robot, where you do not control the scenarios in which you witness it perform a task, is equivalent to randomly picking *Situation*s to test. We learned a model using our approach and another one by randomly picking *Situation*s. Fig. 5.2a depicts the Bayesian Network for the predefined model. We experimented with a single ball on a synthetic turf and thus variables *Turf*, *BallColor* and *BallSize*



(a)

SIT = {*KDc*, *Position*},
CNTX = {*Turf*, *BallSize*},
COMM = {*Position*, *KDc*},
OUT = {*KDo*},
ATT_{KDo} = {*BallSize*, *Turf*, *BallColor*}

(b)

Position ∈ {*LeftSide*, *Middle*, *RightSide*},
Turf ∈ {*Grass*, *Synthetic*, *Sand*},
BallSize ∈ {*Small*, *Large*},
BallColor ∈ {*Yellow*, *Orange*},
KDc ∈ {*Left*, *Mid*, *Right*},
KDo ∈ {*Left*, *Mid*, *Right*, *None*}

(c)

Figure 5.1: Initial guess of the Capability Model for the *BallKick* task. (a) depicts the Bayesian Network, (b) shows the type of each variable in the model and, (c) describes the values each variable can take.

were excluded from the predefined model. A point to note, the experiments were noisy. In every experiment we picked a *Situation* to test, sampled a direction from $P_{\boldsymbol{\theta}_{predefined}}(KDo|Situation)$ and commanded the robot to kick in this direction. However, owing to noisy perception and actuation, sometimes the robot kicked in directions it wasn't commanded to. Despite noisy experiments the active approach converged faster, Fig. 5.3a.

5.2 Model Refinement

Here we present results of the model refinement approach applied in conjunction with the active experimentation algorithm. As before, the robot was programmed to behave according to a predefined model. Moreover, we initialized the Capability Model such that the CNTX set included some redundant factors and had a few relevant ones missing.

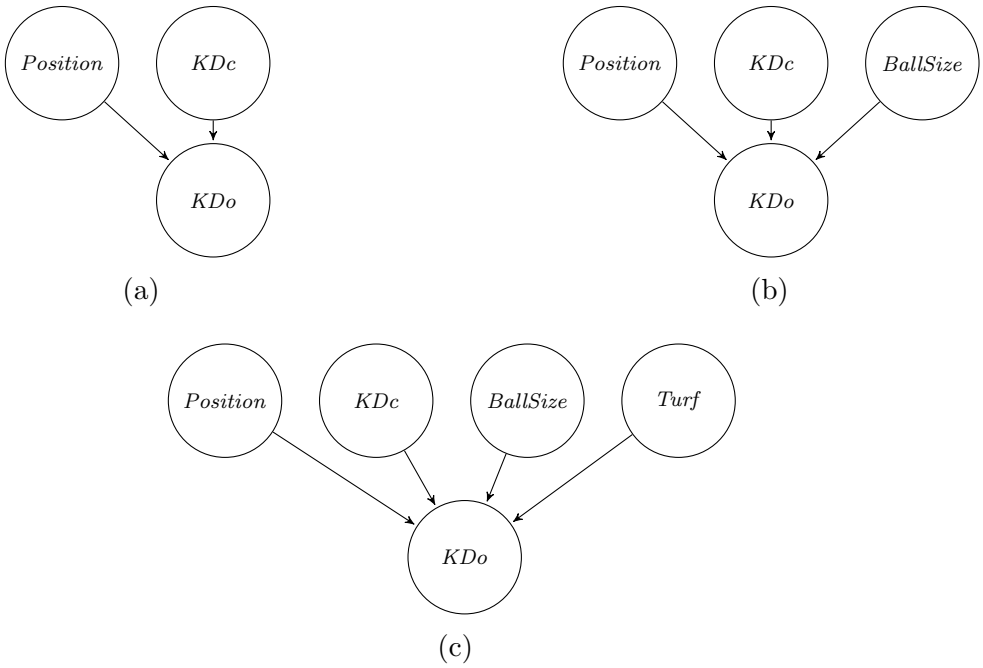


Figure 5.2: (a), (b) and (c) depict the Bayesian Networks for the predefined models. Nodes are as defined in Fig. 5.1c

5.2.1 BallKick Task

We programmed the NAO robot to detect balls of any color but only of a specific size. *KDo* would be *None* if the robot were asked to kick a ball of different size. On detecting a ball, the robot behaved according to the predefined model described earlier. Fig. 5.2b depicts the Bayesian Network for the predefined model for this set of experiments. Fig. 5.1 shows the initial guess of the Capability Model. The blue curve in Fig. 5.3b illustrates the learning trend for this model. The algorithm correctly identified the missing variable to be *BallSize*. Once identified it resets the conditional probabilities (hence the jump in the trend) and restarts the learning process with the updated model. To demonstrate that including relevant attributes yields a model better representative of the robot's abilities we learned another model which included *BallSize* from the start. The green curve in Fig. 5.3b depicts that this model converged to a lower KL Divergence. Moreover, post refinement the trends for both models are almost same.

We tested in simulation, how our approach fares as the number of missing attributes increase. In these experiments, the robot could only detect balls of a certain size and,

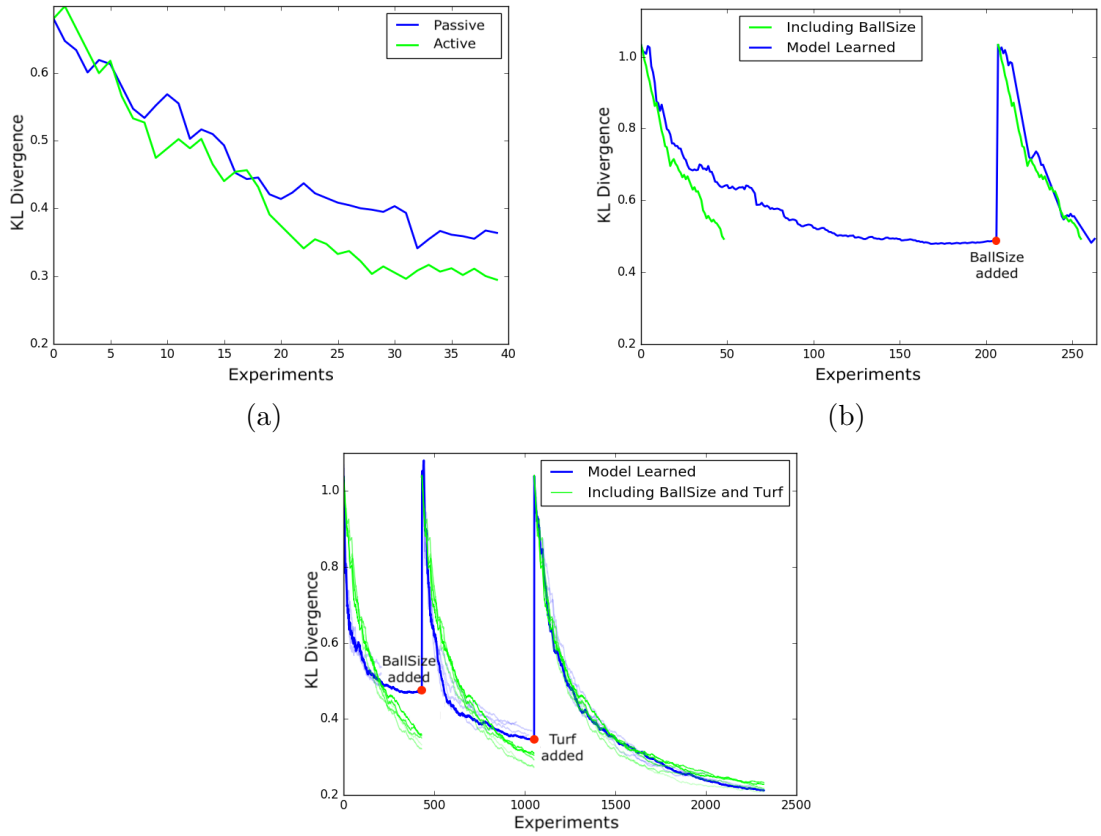
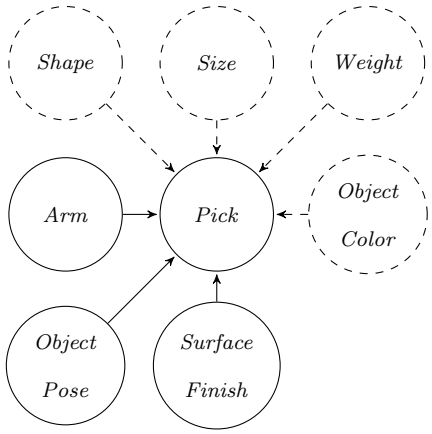


Figure 5.3: (a), (b) and (c) depict the trend in $D_{KL}(P_{\boldsymbol{\theta}_{predefined}}(KDo)||P_{\boldsymbol{\theta}_{BallKick}}(KDo))$. (a) compares the trends when learned actively vs passively. In (b) and (c), blue curves depict trend for the learned models as the algorithm identifies relevant factors to include, red points mark the instances when a new variable is added and green curves depict the trend if the model were initialized with the right variables.

it's ability to kick differed on different turfs, i.e., *BallSize* and *Turf* were the missing relevant variables. Fig. 5.2c depicts the Bayesian Network for the predefined model. To simulate noisy experiments we sampled *KDo* uniform randomly 10% of the time. We performed multiple runs and, the results in Fig. 5.3c demonstrate that including all the relevant variables gives a better model. More the number of missing variables, more the number of experiments needed to identify them all. Moreover, it becomes progressively harder. As a variable gets included in the model, possible *Situation*s increase. We only consider the distributions of O conditioned over values of A_j^O that have been observed more than a certain number of times in a *Situation* while

evaluating $R(O; A_j^O | Situation)$ (Eq. (3.5)). The active learning algorithm avoids repeating *Situation*s and, thus it becomes incrementally harder to identify relevant variables.



(a)

SIT = {*ObjectPose*, *SurfaceFinish*, *Arm*}
CNTX = {*ObjectPose*, *SurfaceFinish*},
COMM = {*Arm*}
OUT = {*Pick*},
ATT_{Pick} = {*Shape*, *Size*, *Weight*}

(b)

Arm ∈ {*Left*, *Right*},
Shape ∈ {*Sphere*, *Cuboid*, *Cylinder*, *Pyramid*},
Size ∈ {*Small*, *Large*},
ObjectPose ∈ {*Horizontal*, *Vertical*},
ObjectColor ∈ {*Red*, *Green*, *Blue*},
SurfaceFinish ∈ {*Smooth*, *Rough*},
Weight ∈ {*Light*, *Heavy*},
Pick ∈ {*Success*, *Failure*},

(c)

Figure 5.4: Initial guess of the Capability Model for the *Pickup* task. (a) depicts the Bayesian Network, (b) shows the type of each variable in the model and, (c) describes the values each variable can take.

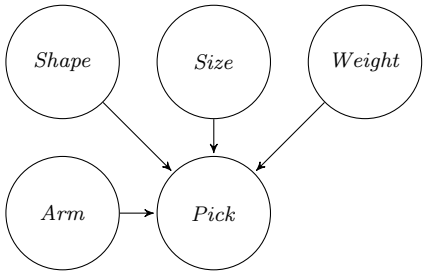


Figure 5.5: Bayesian Network of the predefined model for the *PickUp* task. Nodes are as defined in Fig 5.4c.

5.2.2 PickUp Task

We conducted additional experiments in simulation at the *PickUp* task. In each experiment, the robot was commanded to pick up an object with one of its arms. Objects could have one of four different shapes, namely spherical, cuboidal, cylindrical and pyramidal. We experimented with two sets of weights and two sizes for each shape. The robot could reliably pick up spherical and cuboidal objects of the smaller size and lighter weight. Fig. 5.4 depicts the initial guess of the Capability Model and Fig. 5.5 presents the Bayesian Network corresponding to the predefined model.

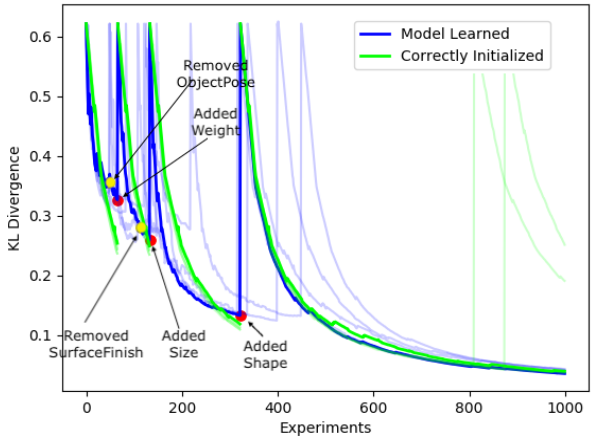
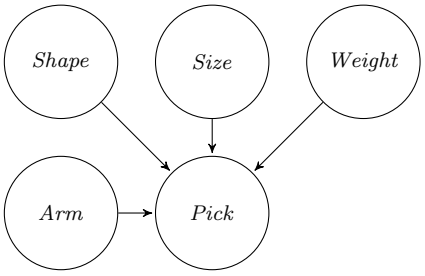


Figure 5.6: Trend in $D_{KL}\big(P_{\boldsymbol{\theta}_{predefined}}(Pick)||P_{\boldsymbol{\theta}_{PickUp}}(Pick)\big)$. The blue curves depict the trend for the learned models as the algorithm identifies relevant factors to include and the redundant ones to discard, red points mark the instances when a new variable is added, yellow points mark the instances when a variable is removed and the green curves depict the trend if the model were initialized with the right set of variables.

The algorithm correctly identified the relevant missing variables (*Weight*, *Shape* and *Size*) and discarded the redundant ones (*ObjectPose* and *SurfaceFinish*). The green curves depict the learning trends when the model was initialized with the right set of variables. Sometimes the algorithm spuriously incorporated redundant variables and thus we see spikes in some of the green curves. We conducted 60 runs and about 93% of the time the algorithm converged to the right model.

5.3 Putting It All Together

We tested in simulation how the model refinement approach, the discretization routine and the active learning algorithm perform together. We performed experiments at the *PickUp* task. The robot was skilled at picking up objects of spherical and cuboidal shapes. It could lift objects of the smaller size and those that weighed less than half a pound. Fig. 5.7 represents the true Capability Model for this simulated robot.



(a)

SIT = {*Size*, *Shape*, *Weight*, *Arm*}
CNTX = {*Size*, *Shape*, *Weight*},
COMM = {*Arm*}
OUT = {*Pick*}, ATT = {}

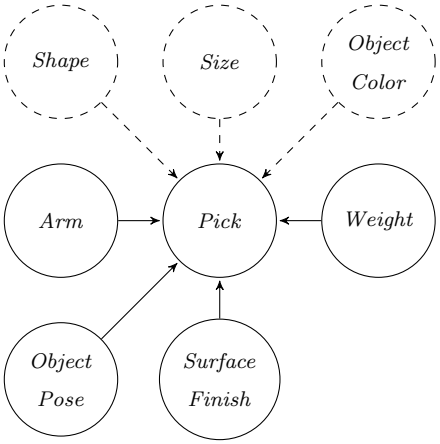
(b)

Arm ϵ {*Left*, *Right*},
Shape $\in$ {*Sphere*, *Cuboid*, *Cylinder*, *Pyramid*},
Size $\in$ {*Small*, *Large*},
Weight $\in$ {*Light*:[0,0.5], *Heavy*:[0.5,1]},
Pick $\in$ {*Success*, *Failure*},

(c)

Figure 5.7: Capability Model of the simulated robot for the *PickUp* task. (a) depicts the Bayesian Network, (b) shows the type of each variable in the model and, (c) describes the values each variable can take.

We performed multiple runs of our algorithm with two different initial model guesses. Fig. 5.9a and 5.9b illustrate the results. Curves in blue show the learning trends when initialized with the model shown in Fig. 5.8. The curves in green depict the learning trends when the initial guess of the model includes the right set of variables with the appropriate discretization. Almost 80% of the time the algorithm correctly identifies all the relevant variables to include, the redundant variables to discard and the appropriate discretization for the variables in the model. However, 20% of the times, the algorithm either misses to discard a redundant variable, or is unable to identify a missing relevant variable, or fails to find the right discretization.



(a)

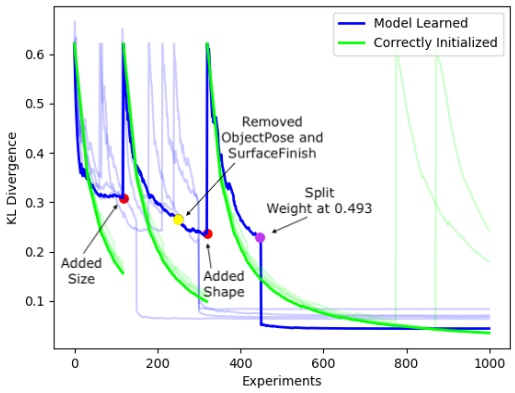
SIT = {*ObjectPose*, *SurfaceFinish*, *Weight*, *Arm*}
CNTX = {*ObjectPose*, *SurfaceFinish*, *Weight*},
COMM = {*Arm*}
OUT = {*Pick*}, ATT = {*Size*, *Shape*, *ObjectColor*}

(b)

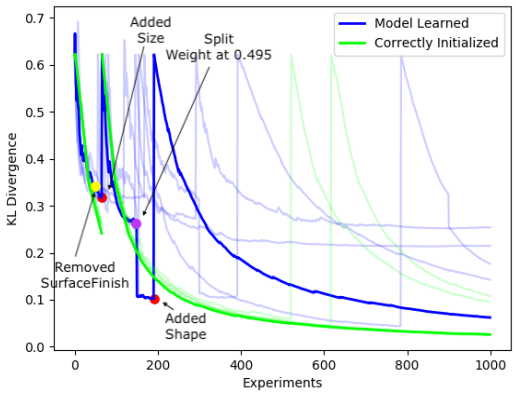
Arm ∈ {*Left*,*Right*},
Shape ∈ {*Sphere*, *Cuboid*, *Cylinder*, *Pyramid*},
Size ∈ {*Small*, *Large*},
ObjectPose ∈ {*Horizontal*, *Vertical*},
ObjectColor ∈ {*Red*, *Green*, *Blue*},
SurfaceFinish ∈ {*Smooth*, *Rough*},
Weight ∈ {W:[0,1]},
Pick ∈ {*Success*, *Failure*},

(c)

Figure 5.8: Initial guess of the Capability Model for the *PickUp* task. (a) depicts the Bayesian Network, (b) shows the type of each variable in the model and, (c) describes the values each variable can take.



(a) Learning trends for runs that converged to the correct model

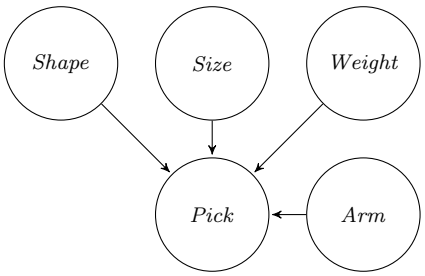


(b) Learning trends for runs that converged to an incorrect model

Figure 5.9: (a) and (b) depict the trend in $D_{KL}(P_{\boldsymbol{\theta}_{predefined}}(KDo)||P_{\boldsymbol{\theta}_{PickUp}}(KDo))$. The curves in blue depict the trends for the learner's model as it identifies the relevant factors, red points mark instances when a new variable is added, yellow points mark instances when a variable is removed from the model and purple points mark instances when a cutpoint is chosen for a continuous variable. The curves in green depict the trend if the model were initialized with the right variables.

5.4 Quantifying Capabilities

We programmed a Pepper robot (Fig. 4.6b) to detect and pickup objects of three shapes viz. spherical, cuboidal and cylindrical. We experimented with two sets of weights and two sizes for each shape (in total 12 types of objects). Fig. 5.10 depicts the Capability Model of Pepper at the *PickUp* task. A *Context* (*Size*, *Shape* and *Weight*) denotes an object type. In every experiment Pepper was asked to pick up a particular type of object with one of its arms.



(a)

SIT = {*Shape*, *Size*, *Weight*, *Arm*}
CNTX = {*Shape*, *Size*, *Weight*},
COMM = {*Arm*}
OUT = {*Pick*}, $\text{ATT}_{Pick} = \{\}$

(b)

Arm ∈ {*Left*, *Right*},
Shape ∈ {*Sphere*, *Cuboid*, *Cylinder*},
Size ∈ {*Small*, *Large*},
Weight ∈ {*Light*, *Heavy*},
Pick ∈ {*Success*, *Failure*},

(c)

Figure 5.10: Capability Model for the *Pickup* task. (a) depicts the Bayesian Network, (b) shows the type of each variable in the model and, (c) describes the values each variable can take.

We performed 2 trials with 70 experiments each to learn the conditional probability tables associated with the Capability Model. We computed *Score*, as defined in Eq. (3.13), for each object type using the reference P_{ref}^{PickUp} defined in Eq. (5.1). We identified object types with score higher than a threshold at the end of both trials, as favourable for Pepper to pickup.

$$P_{\text{ref}}^{PickUp}(Pick|Arm) = \begin{cases} 1 & \text{if } Pick = Success \\ 0 & \text{otherwise} \end{cases} \tag{5.1}$$

Having knowledge of the scenarios a robot is well suited for could help in a collaborative task. To demonstrate this, we employed the robot along with a human to clear a cluttered table. In every experiment, the human cleared all but 4 objects off the table and, the robot had to clear the rest. The robot was allowed 3 tries per object (12 in total). We performed such experiments in two settings. In the first setting, the human randomly selected objects for the robot to pick up and in the second, the human only selected objects of favourable types. We conducted 5 experiments in each setting. Table 5.1 summarizes the results.

Settings	Number of objects cleared	Number of tries
Objects of any type	1.8 ± 0.98	8.8 ± 1.7
Objects of favourable types	3.4 ± 0.49	6.6 ± 1.2

Table 5.1: Results of the clear-the-table task ($\mu \pm \sigma$) after 5 experiments per setting.

Performance at the task is better in terms of number of tries as well as number of objects cleared, when the robot is employed in a favourable scenario.

5.5 Summary

The contributions of this thesis can be summarized as follows

- We presented Capability Model, a framework to capture a robot's ability to perform a task. This framework incorporates uncertainity inherent to physical systems (robots) as well as the effect of extrinsic factors on a robot's capability.
- We developed an algorithm to build Capability Models from active experimentation. Our algorithm identifies relevant extrinsic factors from a list of possibilities. Moreover, it quantifies the robot's ability to accomplish the task in different settings of these factors.
- We introduced a metric to identify favourable scenarios for deploying a robot to carry out a particular task.
- We illustrated a method for drawing inferences from a robot's appearance about the different tasks it can potentially perform. Our algorithm for building Capability Model for a task requires a list of possibly relevant extrinsic factors. We proposed requesting a human to provide this list. We discussed results of a

survey we conducted to evaluate how accurately people identify extrinsic factors that affect a robot's capability at a task.

A video describing our work can be found here.

Chapter 6

Conclusions and Future Work

As robots become increasingly multifunctional, it becomes difficult to ascertain what tasks they can perform and how good they are at those tasks. To the best of our knowledge, inferring capabilities from appearance and active experimentation is a novel problem. We proposed a method to build models of a robot's capabilities and presented experiments with a NAO and a Pepper robot performing two different tasks. We demonstrated the utility of such models in working collaboratively with a robot.

Some interesting future directions are as follows,

- Robots are capable of learning new skills and adapting to new scenarios over time. However, there are certain limitations a robot can never learn to overcome. For example, a robot can learn new ways to grasp enabling it to pick up a wider range of objects but, it can never lift anything that weighs beyond its physical limitations. How do we incorporate this knowledge into our learning routine or learn to identify factors that are intrinsically limiting?
- A robot's spec sheet presents information about the sensors and actuators used to build the robot. This information can be useful in determining the tasks a robot can perform and its physical limitations (Field of view, sensing range, actuation limits, etc.). How do we utilize this information in building models?
- We assumed that experimenting with a robot in any *Situation* has the same cost. Depending on the task, this may be quite far from reality. How do we learn models in such scenarios?

Chapter 7

Appendix

7.1 CutValue Maximization

Consider a simple network as shown in Fig. 7.1. Without loss of generality assume $Domain(\mathrm{X}) = (0,1)$. Furthermore, $\mathrm{U}^{\star \mathrm{X}} = (u_1^{\star \mathrm{X}}, \cdots, u_m^{\star \mathrm{X}})$ and, $P(\mathrm{O}|\mathrm{X}) = P_i$ if $\mathrm{D}_{\mathrm{U}^{\star \mathrm{X}}}(\mathrm{X}) = i$ such that $P_i \neq P_{i+1}$. We show that cutpoints in $\mathrm{U}^{\star \mathrm{X}}$ are local maximas of CutValue (Section 3.2.3, Eq. (3.9)). Therefore, the sequnce U^{X} built by greedily picking cutpoints based on their CutValue is infact $\mathrm{U}^{\star \mathrm{X}}$.

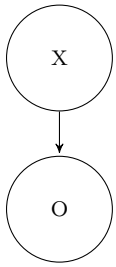


Figure 7.1: Example Bayesian Network. X is continuous and O is discrete.

Assume $\mathrm{U}^{\mathrm{X}} = ()$. Consider a cutpoint $u \in (u_j^{\star \mathrm{X}}, u_{j+1}^{\star \mathrm{X}})$ and the subsequent sequence $\underline{\mathrm{U}}^{\mathrm{X}}$ obtained after adding u to U^{X}.

$$\begin{aligned}\text{CutValue}(\underline{\text{U}}^{\text{X}}, \text{U}^{\text{X}}) &= \text{I}(\text{O};\text{X}|\underline{\text{U}}^{\text{X}}) - \text{I}(\text{O};\text{X}|\text{U}^{\text{X}}) \quad (7.1)\\ &= \int_{\text{X}} H(P(\text{O}|\text{X},\text{U}^{\text{X}}))P(\text{X}|\text{U}^{\text{X}}) - \int_{X} H(P(\text{O}|\text{X},\underline{\text{U}}^{\text{X}}))P(\text{X}|\underline{\text{U}}^{\text{X}})\\ &= \int_{\text{X}} H(P(\text{O}|\text{X},\text{U}^{\text{X}}))P(\text{X}|\text{U}^{\text{X}}) - F(u) \quad (7.2)\end{aligned}$$

$F(u) = \int_{\text{X}} H(P(\text{O}|\text{X},\underline{\text{U}}^{\text{X}}))P(\text{X}|\underline{\text{U}}^{\text{X}})$ is the only term that depends on $\underline{\text{U}}^{\text{X}} = (u)$,

$$\begin{aligned}F(u) &= H(P(\text{O}|\text{X} \le u))P(\text{X} \le u) + H(P(\text{O}|\text{X} > u))P(\text{X} > u)\\ &= H(P(\text{O}|\text{X} \le u))u + H(P(\text{O}|\text{X} > u))(1-u) \quad (7.3)\end{aligned}$$

From our assumption about the distribution of O, we can simplify $H(P(\text{O}|\text{X} \le u))$ and $H(P(\text{O}|\text{X} > u))$ as follows

$$P(\text{O}|\text{X} \le u) = \sum_{i=0}^{j-1} P_i \frac{(u_{i+1}^{\star\text{X}} - u_i^{\star\text{X}})}{u} + P_j \frac{(u - u_j^{\star\text{X}})}{u} \text{ (where } u_0^{\star\text{X}} = 0) \quad (7.4)$$

$$P(\text{O}|\text{X} > u) = P_j \frac{(u_{j+1}^{\star\text{X}} - u)}{1-u} + \sum_{i=j+1}^{m} P_i \frac{(u_{i+1}^{\star\text{X}} - u_i^{\star\text{X}})}{1-u} \text{ (where } u_{m+1}^{\star\text{X}} = 1) \quad (7.5)$$

Therefore,

$$\begin{aligned}F(u) =& uH\Big(\frac{\sum_{i=0}^{j-1}(u_{i+1}^{\star\text{X}} - u_i^{\star\text{X}})P_i + (u - u_j^{\star\text{X}})P_j}{u}\Big) + \quad (7.6)\\ & (1-u)H\Big(\frac{(u_{j+1}^{\star\text{X}} - u)P_j + \sum_{i=j+1}^{m}(u_{i+1}^{\star\text{X}} - u_i^{\star\text{X}})P_i}{1-u}\Big)\end{aligned}$$

In the interval $(u_j^{\star\text{X}}, u_{j+1}^{\star\text{X}})$, $F(u)$ is concave with the lowest value at either $u_j^{\star\text{X}}$ or $u_{j+1}^{\star\text{X}}$. We can show this by considering the following

$$\frac{dF(u)}{du} = -\sum_{o \in Domain(\mathrm{O})} P_j(o)\Big[\log\Big(\frac{\sum_{i=0}^{j-1}(u_{i+1}^{\star \mathrm{X}} - u_i^{\star \mathrm{X}})P_i(o) + (u - u_j^{\star \mathrm{X}})P_j(o)}{u}\Big) + \log\Big(\frac{1-u}{(u_{j+1}^{\star \mathrm{X}} - u)P_j(o) + \sum_{i=j+1}^{m}(u_{i+1}^{\star \mathrm{X}} - u_i^{\star \mathrm{X}})P_i(o)}\Big)\Big] \quad (7.7)$$

$\frac{dF(u)}{du}$ keeps decreasing as u goes from $u_j^{\star \mathrm{X}}$ to $u_{j+1}^{\star \mathrm{X}}$. Thus $F(u)$ is minimum (and the CutValue($\underline{\mathrm{U}}^{\mathrm{X}}, \mathrm{U}^{\mathrm{X}}$) maximum) at $u = u_j^{\star \mathrm{X}}$ or $u = u_{j+1}^{\star \mathrm{X}}$. Here, we considered U^{X} to be empty however, the approach is exactly the same for a non-empty U^{X}.

Fig. 7.2 shows the CutValue for different possible cutpoints for two different U^{X}. In this example, $\mathrm{U}^{\star \mathrm{X}} = (0.3, 0.6, 0.9)$. As can be seen, $u = 0.3$ has the highest CutValue when U^{X} is empty. When $u = 0.3$ is incorporated, we still see local maximas at the true cutpoints. This example demonstrates that greedily picking cutpoints yields the true sequnce.

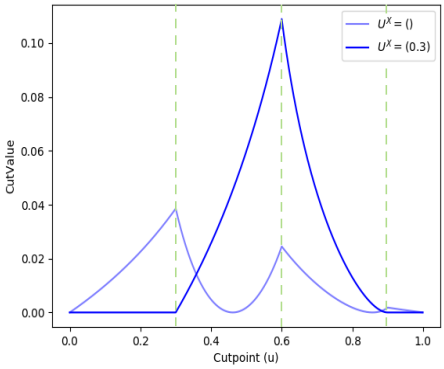


Figure 7.2: Trend in CutValue($\underline{\mathrm{U}}^{\mathrm{X}}$, U^{X}) for two different U^{X}. The dotted lines indicate $u_i^{\star \mathrm{X}}$, $\mathrm{U}^{\star \mathrm{X}} = (0.3, 0.6, 0.9)$

When the set OUT is not singleton, the analysis is similar

$$\begin{aligned}\text{CutValue}(\underline{\text{U}}^{\text{X}}, \text{U}^{\text{X}}) &= \sum_{\text{O}\in\text{OUT}} \text{I}(\text{O};\text{X}|\underline{\text{U}}^{\text{X}}) - \text{I}(\text{O};\text{X}|\text{U}^{\text{X}}) \\ &= \sum_{\text{O}\in\text{OUT}} \Big(\int_{\text{X}} H(P(\text{O}|\text{X},\text{U}^{\text{X}}))P(\text{X}|\text{U}^{\text{X}}) - \\ &\qquad \int_{X} H(P(\text{O}|\text{X},\underline{\text{U}}^{\text{X}}))P(\text{X}|\underline{\text{U}}^{\text{X}}) \Big) \end{aligned} \tag{7.8}$$

As $\text{O} \in \text{OUT}$ are independent given X, $P(\text{OUT}|\text{X}) = \Pi_{\text{O}\in\text{OUT}} P(\text{O}|\text{X})$. Therefore, $H(P(\text{OUT}|\text{X},\text{U}^{\text{X}})) = \sum_{\text{O}\in\text{OUT}} H(P(\text{O}|\text{X},\text{U}^{\text{X}}))$.

$$\begin{aligned}\text{CutValue}(\underline{\text{U}}^{\text{X}}, \text{U}^{\text{X}}) &= \int_{\text{X}} H(P(\text{OUT}|\text{X},\text{U}^{\text{X}}))P(\text{X}|\text{U}^{\text{X}}) - \int_{X} H(P(\text{OUT}|\text{X},\underline{\text{U}}^{\text{X}}))P(\text{X}|\underline{\text{U}}^{\text{X}}) \\ &= \int_{\text{X}} H(P(\text{OUT}|\text{X},\text{U}^{\text{X}}))P(\text{OUT}|\text{U}^{\text{X}}) - F(u) \end{aligned} \tag{7.9}$$

When the set OUT has additional dependencies, the analysis is not that simple.

Chapter 8

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