Generalizable Autonomy in Robot Manipulation

Animesh Garg
Generalizable Autonomy in Robot Manipulation

Vacuuming  Sweeping/Mopping  Cooking  Laundry
Generalizable Autonomy in Robot Manipulation

Diversity: New Scenes, Tools,…

Complexity: Long-term Settings
Generalizable Autonomy in Robot Manipulation

Vision: Build Intelligent Robotic Companions towards Human Enrichment and Augmentation
Generalizable Autonomy in Robot Manipulation

1956 Dartmouth AI Project
Generalizable Autonomy in Robot Manipulation

Aspirational Robotic Assistant

Dartmouth AI Meeting

UNIMATE
1st Industrial robot

1956 ‘61 1968
Generalizable Autonomy in Robot Manipulation

ATLAS CAN WALK IN TOUGH CONDITIONS,

Dartmouth AI Meeting

UNIMATE
1st Industrial robot

1956 ‘61 1968

2013

Boston Dynamics
Generalizable Autonomy in Robot Manipulation

Dartmouth AI Meeting

UNIMATE
1st Industrial Robot
1961

Personal Robot Assistant

2013

Atlas Robot
Humanoid
2018

Generalizable Autonomy in Robot Manipulation

Sony AI x Cooking
Generalizable Autonomy in Robot Manipulation

Dartmouth AI Meeting

UNIMATE
1st Industrial robot

Unstructured/Unknown New Environment

1956 '61 1968

2013 2018 2019
Generalizable Autonomy in Robot Manipulation

Then

1956 '61 1968

Dartmouth AI Meeting
UNIMATE 1st Industrial robot
Personal Robot Assistant

Now

2013 2018 2019

Structured Environments
Staged Repeated Tasks
Atlas Robot Humanoid

How to Generalize to Unstructured Scenarios?
Generalizable Autonomy in Robot Manipulation

How to Generalize to Unstructured Scenarios?

Manufacturing/Retail  Personal/Service  Healthcare/Medicine
Generalizable Autonomy in Robot Manipulation

Vision: Build Intelligent Robotic Companions

Approach: Learning with Structured Inductive Bias and Priors

Demonstration

Instructional Input
(Teleoperation, Video, Language)

Task Imitation

Learn to do the task in
Same Environment

Generalization

New Task Variations
in Novel Environments
Layers of Imitation

Movement Skills

- Control
- Planning
- Perception

Skill Sequencing

Semantic Purpose

Task Specification

Cheng et al. Sci.Rob. 2019
Generalizable Autonomy in Robot Manipulation

Control
Visuo-Motor Skills

Planning
Compositional Planning

Perception
Task Structure

Data for Robotics

Robotics Perception Control Planning
Generalizable Autonomy in Robot Manipulation

Visuo-Motor Skills

Compositional Planning

Task Structure

Data for Robotics
Visuo-Motor Skills

**Challenge:** Algorithmic frameworks to learn a diversity of skills

**Approach:** Close the Visuo-Motor Loop with Learning based Control

- Vacuuming
- Sweeping/Mopping
- Cooking
- Cleaning
Visuo-Motor Skills: **Generalization**

**Cleaning**

Skills: **Surface Wiping**

- Hard Stains – Push Harder?
- Different Surfaces – Be Gentle?
Visuo-Motor Skills: Current Paradigm

Model Based Task (Operational) Space Control

Actual State: Image, Force, Joint Enc.
Desired State: $x_d$
Robot Model Parameters: $M, J$
Action: $\tau$

Robot Model

$$\dot{x}_{ref} = K_p(x_d - x) + K_p(\dot{x}_d - \dot{x}) + \ddot{x}_d$$

$$M(q, \dot{q}) + C(q, \dot{q}) + G(q) + \varepsilon(q, \dot{q}) = \tau$$

$$\tau = J^T (JM^{-1}J^T)^{-1}(\ddot{x}_{ref} - \dot{j}\dot{q} + JM^{-1}F)$$

- Leverages Robot Model
- Compliant Control

- Needs Environment (Task) Model
- Task Dependent State
- Explicit State Estimation

[Khatib.1987], [Bruyninckx et al., '96], [Schaal '03], [Rodriguez et al. 2012], [Vijaykumar et al. '11], [Ijspreet et al. '13] [Li, Billard, et al. '14], [Lee, Abbeel et al. '15]
Deep Reinforcement Learning

Agent

Training Environment

Testing Environment

State: Image
Policy $\pi$
Action: Torque $\tau$

Reward

- Sample Inefficient
- Learn robot model (implicitly)

+ Model Free: No Environment Model
+ State is Image

- If Training $\not\approx$ Testing: Policy Fails!

[Agrawal et al., '16], [Levine et al., '16], [Peng et al., '17], [Gu et al., '16], [Chebotar et al., '17], [Yahya et al., '16], [James et al., '17], [Popov et al., '17]
Visuo-Motor Skills: Our Approach

RL with Variable Impedance Task-Space
Visuo-Motor Skills: Our Approach

RL with Variable Impedance Task-Space

Model-Free RL Agent $\pi$

Action $a$

Controller $f$

Environment

Action $\tau = f(\pi(o_t))$

Reference Generator (learned)

Robot Model (Deterministic)

IROS 2019
Visuo-Motor Skills: Our Approach

RL with Variable Impedance Task-Space

\[ \tau = f(\pi(o_t)) \]

- Model-Free RL Agent
- Controller \( f \)
- Interpolation
- Sensory Obs. \( o_t \)
- Environment
- Action \( a \) (20 Hz)
- Torque \( \tau \) (500 Hz)

\[ \pi(o_t) = a: [x_d, \dot{x}_d, K_p, K_v] \]

\[ \tau = f(x_d, \dot{x}_d, K_p, K_v) \]

+ Model Free: No Environment Model
+ State is Image
+ Leverages Robot Model
+ Compliant Control
+ Sample Efficient
+ Transferable

IROS 2019
Visuo-Motor Skills: Action Representation

Surface Wiping

Input: Image (48x48)

Reward: $\lambda_1 \sum (\text{dirt}_\text{on}_\text{table}) + \lambda_2 (\text{distance}_\text{to}_\text{table}) - \lambda_3 \mathbb{I} (F \geq 40N)$

- Minimize the number of Dirty Tiles
- Maintain Contact with the Table
- Don’t push with more than Robot Payload

Trained Policy Rollout (Ours)

Policy Output

Performance Gap after 1M steps

Evaluation During Training (PPO)

EE Var Imp (Ours)

EE Fixed Imp. (Med.)

EE Fixed Imp. (High)

Joint Var. Imp.

Joint Velocity

Joint Imp.

EE Imp (low)

Joint Torque

IROS 2019
Visuo-Motor Skills: Action Representation

\[ \tau = f_{Sim}(\pi(o_t)) \]

Training on Panda

\[ \tau = f_{Real}(\pi(o_t)) \]

Evaluation on Real Robot without Fine-Tuning

Success 80% (10 Trials)
Generalizable Autonomy in Robot Manipulation

Visuo-Motor Skills

Compositional Planning

Task Structure

Data for Robotics
Skills: Imitation from Heuristics

Promise of Deep RL closed loop-control with images ...

... albeit, with a lot of training

[Kalashnikov et al (2018), Levine et al. (2016), Pinto et al. (2016), Kalashnikov et al. (2018), Yu et al. (2016), Haarnoja et al. (2018), Lee et al. (2019), Vecerik et al. (2017)]
Skills: **Heuristics often beat RL**

RL struggles with structured, multi-step skills

Even simple heuristics beat RL

IROS 2019, Mahmood et al. 2018
Skills: Exploration without Guidance

Random Exploration is slow ...even when first steps are obvious

Can Human Intuition Guide Exploration?

Gu et al. 2017
Skills: Imitation from Heuristics

- Teachers
- Intuition
- Implement Useful Skills
  ...but not full solution

- Teachers
- Black-box controllers
  solving parts of the task
Skills: *Imitation from Heuristics*

**Goals:**
A) *faster* agent training  
B) *optimal* test-time agent performance
Skills: Imitation from Heuristics

Naive action choice might not work well!
Off-Policy RL: DDPG Review

\[ \nabla_{\theta^\mu} J(\theta) \approx \nabla_{\alpha} Q(s, a) \nabla_{\theta^\mu} \mu(s|\theta^\mu) \]

\[ y_i = r_i + \gamma Q'(s_{i+1}, \mu'(s_{i+1}|\theta^\mu')|\theta^{Q'}) \]

Lillicrap et al. 2015
AC-Teach: Actor-Critic with Teachers

Agent Policy
Actor \( \pi_{\theta} \)

Teacher 1

Teacher 2

Teacher N

Environment

Off-Policy Data Added to Buffer \( \pi_{\theta} \)

Action Selection \( \pi_{b} \)

Bayesian Critic \( Q_{\phi} \)

Estimate quality of the advice

AC-Teach: CoRL 2019
Experiments

Task:

Teachers:

- grab hook
- position hook
- pull
- push

AC-Teach: CoRL 2019
AC-Teach is able to leverage a single teacher well
AC-Teach speeds up training given multiple teachers
AC-Teach has agent learn behaviors not in teacher set
Visuo-Motor Skills

Action Representations and Weak-Supervision provide structure to enable learning efficiency and generalization.
Generalizable Autonomy in Robot Manipulation

Visuo-Motor Skills

Compositional Planning

Task Structure

Data for Robotics

Object Arrangement

Grasp Move Release

Pick Place Stack

RSS 2018, IJRR 2019
Sequential Skills

Skills: Surface Wiping

Skills: Tool Use

Primitive Skills
- Grasping
- Pushing
- Picking
- Wiping
- Open door

Sequential Skills
- Hammering (with unknown objects)
- Cutting (with new knife)
- Sweeping (with new broom)
Sequential Skills: Manipulation with Tools

**Task-Oriented Grasping**

**Initial State** Task-Agnostic Grasping

- **Unknown Object**

- **Optimizes for Grasp Success Only**

- **Suboptimal for Task!**

**Tool-Use**

- **Hammering**

- **Sweeping**

---

1 Pinto et al. ‘16, Levine et al. ‘16, Mahler et al. ‘18, Kalashnikov et al. ‘18
Visuo-Motor Skills: Task-Oriented Grasping

**Input =**
- Depth Image $o$
- Task $T$

**Output =**
- Grasp Parameters $g = (g_x, g_y, g_z, g_\phi)$
- Policy $a = \pi(o, g)$

**Score Function**

$$g^*, \pi^* = \arg\max_{g,\pi} Q_T^{\pi}(o, g)$$

$$Q_T^{\pi}(o, g) = P_{\pi}(S_T = 1 | S_G, \pi) P(S_G = 1 | o, g)$$

$$Q_T^{\pi}(o, g) = Q_T^{\pi}(\text{Task Success}) Q_T^{\pi}(\text{Grasp Success})$$

**Task Success**

**Grasp Success**
Visuo-Motor Skills: Task-Oriented Grasping

CNN Model

Input: Depth Image (64x64)

grasping model

Task-Oriented Grasping Model

Manipulation

Output

\[ Q_G(o, g) \]

\[ \mathcal{L}(S_G, Q_G(o, g; \theta_1)) \]

\[ Q^{\pi}_{T|G}(o, g) \]

\[ \mathbb{I}(S_G = 1) \mathcal{L}(S_T, Q^{\pi}_{T|G}(o, g; \theta_2)) \]

\[ \pi(a | o, g; \theta_3) \]

\[ \nabla_{\theta_3} \log \pi(a | o, g; \theta_3) \]

Loss Function

Training

18K diverse training objects

large-scale data collection (1.5m Episodes)

RSS 2018, IJRR 2019
Visuo-Motor Skills: Task-Oriented Grasping

Testing

Sample grasp candidates

task-oriented grasping model

grasp ranking

robust task-oriented grasp

manipulation policy

hammering task

RSS 2018, IJRR 2019
Sequential Skills: Task-Oriented Grasping

Trained Policy Rollout (Ours)
Unseen Test Objects

RSS 2018, IJRR 2019
Sequential Skills: Task-Oriented Grasping

Trained Policy Rollout (Ours)
Unseen Test Objects

Hammering

Success Rate

- Antipodal Baseline
- Task-Agnostic
- Our Model

RSS 2018, IJRR 2019
Sequential Skills: Task-Oriented Grasping

Trained Policy Rollout (Ours)
Unseen Test Objects

Success Rate

- Hammering
  - Antipodal Baseline
  - Task-Agnostic
  - Our Model
  - Joint Optimization

- Sweeping
  - Antipodal Baseline
  - Task-Agnostic
  - Our Model
  - Two-Stage Optimization

RSS 2018, IJRR 2019
Sequential Skills

Skills: Surface Wiping

Skills: Tool Use

Primitive Skills
- Grasping
- Pushing
- Picking
- Wiping
- Open door

Sequential Skills
- Hammering (with unknown objects)
- Cutting (with new knife)
- Sweeping (with new broom)
Sequential Skills: Multi-Step Reasoning

Skills: Multi-Step Reasoning

Generalization
Can we learn multi-step reasoning in robotics under physical and semantic constraints
Model-based learning

choose action sequence
\[ a_t, \ldots, a_{t+H} \]

dynamics
\[ s' \sim f(\cdot \mid s, a) \]

[Deisenroth et al, RSS ’07], [Guo et al, NeurIPS ’14], [Watter et al, NeurIPS ’15], [Finn et al, ICRA ’17], ……
Model-based learning

[Deisenroth et al. RSS’07]  [Agrawal et al. ICRA’16]

[Janer et al. ICRA’19]

[Deisenroth et al. RSS’07]  [Agrawal et al. ICRA’16]  

[Ebert et al. CoRL’17]  [Janer et al. ICRA’19]
CAVIN: Hierarchical planning in learned latent spaces

Leverage Hierarchical Abstraction in Action Space
Without Hierarchical Supervision

CAVIN Planner

effect code $c$

motion code $z$
CAVIN: Hierarchical planning in learned latent spaces

CAVIN Planner

effect code $c$

motion code $z$

subgoals
CAVIN: Hierarchical planning in learned latent spaces
CAVIN: Hierarchical planning in learned latent spaces

choose $c \sim p(c)$

meta-dynamics
CAVIN: Hierarchical planning in learned latent spaces

choose
\( c \sim p(c) \)

meta-dynamics
Hierarchical planning in learned latent spaces

![Diagram of a robot arm and a grid environment with a path]

- Choose $c \sim p(c)$
- Choose $z \sim p(z)$

**Meta-dynamics**

**Action generator**
CAVIN: Hierarchical planning in learned latent spaces

\[
\begin{align*}
\text{choose } & \quad c \sim p(c) \\
\text{choose } & \quad z \sim p(z) \\
\text{meta-dynamics} & \\
\text{action generator} & \\
\text{dynamics} & \\
\end{align*}
\]
Learning with cascaded variational inference

task-agnostic interaction

\[ h (s'' | s, c) \]

\[ q_h (c | s, s'') \]

\[ q_g (z | s, c, a) \]

\[ g (a | s, c, z) \]

\[ \mu_c \]

\[ \Sigma_c \]

\[ \mu_z \]

\[ \Sigma_z \]
kinect2 sensor

visual observation

preprocess

$S_t$

CAVIN Planner

action

$[x, y, \Delta x, \Delta y]$
Tasks

- **clearing**: Clear all objects within the area of blue tiles.
- **insertion**: Move the target to the goal without traversing red tiles.
- **crossing**: Move the target to the goal across grey tiles.
Quantitative Evaluation

Hierarchical Latent space dyn.
Better performance with sparse reward signal

Averaged over 3 Tasks with 1000 test instances each

MPC (Guo et al. ‘14, Agrawal et al. ‘16, Finn et al. 17); CVAE-MPC (Ichter et al. 18), SeCTAR (Co-Reyes et al ‘18)
Move 2 obstacles

5x
5x  Squeeze through
Compositional Planning

Self-Supervision and Structured Latent Variable Models lead to good representations that generalize
Visuo-Motor Skills

Compositional Planning

Generalizable Autonomy in Robot Manipulation

Object Arrangement

Task Structure

Data for Robotics
Complex Task Structure

Visuo-Motor Skills

- Grasping
- Picking
- Wiping
- Pushing
- Open door
- Hammering
- Cutting
- Sweeping

Complex Task Structure

Do Laundry
- Put Soap
- Open
- Pick
- Push
- Put in Washer

Object Arrangement
- Pick
- Grasp
- Move
- Release
- Stack
Compositional Planning: Current Paradigm

Reinforcement Learning
- Sample Inefficient
- Multi-step Structured Tasks
- Needs non-trivial Reward Shaping

Imitation Learning
- Task Segmentation is non-trivial
- Multi-modality of Search Space
- Fixed Permutation of Primitives

Meta Imitation Learning
- New Task Structures
- Few-Shot performance
- Input State as Video

RL: [Schaal 1997], [Chebotar et al., '17], [Yahya et al., '16], [James et al., '17], [Popov et al., '17], [Zhu et al. 18], [Hausman et al. 18]
Imitation: [Calinon et al 2008], [Argall et al 2009], [Kober, Peters, et al. 09], [Pastor et al, 09], [Schulman et al. 2013], [Kroemer et al, 15], [Garg et al 2017]
Compositional Planning: Challenge

Task Domain

I. Learn **Multiple Tasks** in the Same Domain
II. Generalize to New Tasks with a **Single Demo**

Instructional Demos

Training Tasks

Test Task
Compositional Planning

Models input demonstration as a **flat sequence**

Models input demonstration as a **Compositional Hierarchy**

One Shot Imitation Learning from Videos

[Duan et al. 17; Finn et al. 2017; Wang et al. 2017; Yu et al. 2018]

Our Method
[ICRA’18], [CVPR’19], [IROS’19]
Block Stacking (...):
while (done):
    pick_and_place (RED, BLUE):
        pick (RED):
            move_to (RED)
            Grasp (RED)
        <end> Pop
        place (BLUE):
            move_to (BLUE)
            Release (RED)
        <end> Pop
    <end> Pop
    <end> Pop

Task 1
Sub-task 1
Move Red-block on top of Blue
Compositional Planning: Task Programming

Block Stacking (...): Program 1

Block Stacking (...): Program 2
while (done):
  pick_and_place (RED, BLUE):
    pick (RED):
      move_to (RED)
      Grasp (RED)
      <end> Pop
    place(BLUE):
      move_to (BLUE)
      Release (RED)
      <end> Pop
    <end> Pop

Training Task Structures

[ICRA’18, CVPR ’19]
Neural Task Programming (NTP)

Demo
Kinematics or Video

Current State

Current Program
pick_place(blue, green)

Hierarchical Program Trace

Demo Conditional Policy

Training supervision

End-to-End LSTM Model

Loss: Compare with Ground Truth Program

Hierarchical Policy Learning as Program Induction

[ICRA'18, CVPR '19]
Pick and Place
Block Stacking
Pick
Move_to (Blue)
Grasp (Blue)
Move_to (Red)
Release( )
Neural Task Programming

Autonomous Execution

Demo

[ICRA '18]
Recovery from Intermediate Failures

Output is not an Open Loop State Machine

Closed Loop Feedback Policy
Neural Task Programming Results

Test Task Structures with State Input

- Flat Policy
- NTP (Ours)

Better Generalization than Flat Policy + Works with Vision

Pose Est. + Plan
E2E Plan

[ICRA'18, CVPR '19]
Compositional Planning: Task Programming

Demo
Kinematics or Video

Current State

Current Program
pick_place(blue, green)

Black-Box Model

End-to-End LSTM Model

meta-learning model

Demo Conditional Policy

Compositional Model Prior

Next Program
pick (blue)

Program Induction
Inductive Bias on Input-Output

ICRA’18, CVPR ’19
Compositional Planning: Task Graphs

Demo Kinematics or Video

Hierarchical Policy Learning as Graph Induction

[ICRA’18, CVPR ‘19]
Neural Task Graphs (NTG)

Demo Kinematics or Video

Task Graph Generator → Neural Task Graph

Parsed Sequence

Hierarchical Policy Learning as Graph Induction

Task Graph Executor

meta-learning model

Demo Conditional Policy

Current Observation

[ICRA’18, CVPR ’19]
Hierarchical Policy Learning as **Graph Induction**
Neural Task Graphs (NTG): Representation

Task Graph

- Nodes: States
- Edges: Action

Conjugate Task Graph

- Nodes: Actions
- Edges: States (Preconditions)

Valid States

{ ... }

[ICRA'18, CVPR '19]
Neural Task Graphs (NTG): Execution

Observation

Node Localizer

Edge Classifier

Selected Node

Place (Green)

Selected Edge

Pick (Green)

Pick (Orange)

Pick (Red)

Place (Red)

Pick (Red)

Selected Next Action
Neural Task Graphs (NTG)

Hierarchical Policy Learning as Graph Induction

Demo Kinematics or Video

Training supervision

Demo Conditional Policy

Current Observation

Hierarchical Policy Learning as Graph Induction

[ICRA'18, CVPR '19]
Neural Task Graph Results

Test Task Structures with State Input

- Flat Policy
- NTP (Ours)
- NTG (Ours)

Performance Accuracy

# of Training Tasks

91% 90%

Test Task Structures with Vision Input

- NTP (Detector)
- NTP (Ours)
- NTG (Ours)

Performance Accuracy

# of Training Tasks

90% 62% 35%

Weaker Supervision and Better Generalization
Compositional Planning: NTP and NTG

Object Sorting (NTP)

Table Clean Up (NTP)

Sequential Search and Prediction AI2 Thor with NTG

[ICRA'18, CVPR '19]
Compositional priors with modular structure enable generalizable learning in hierarchical domains.
Data for Robotics

Visuo-Motor Skills
- Grasping
- Pushing
- Picking
- Wiping
- Open door

Sequential Tasks
- Grasp
- Move
- Release
- Object Arrangement

Complex Task Structure
- Pick
- Stack
- Place

Procedural Execution from Videos

Dataset Size
- 10^6
- 10^5
- 10^3

Reinforcement Self-Supervision
Structured Supervision
Weakly Supervised

How to get Larger Sets of Structured Supervision?
Data for Robotics: Imitation + RL

Rajeswaran et al. (2018)
25 demonstrations
~ 10 Minutes

Finn et al. (2017)
30 demonstrations
~ 10 Minutes

Vecerik et al. (2017)
100 demonstrations
~ 30 Minutes
Large-scale supervision in robotics is difficult

Expert needs to demonstrate, not label
Data for Robotics: RoboTurk

+ Scales easily with commodity hardware
+ Natural 6-DoF Free Space Control

[CoRL ’18, IROS 2019]
RoboTurk: Scaling Imitation with Cloud
RoboTurk: Imitation for everyone, everywhere
RoboTurk Pilot Datasets

Simulated Data
- 137.5 hours of demonstrations
- 22 hours of total platform usage
- 3 dexterous manipulation tasks
- 3224 total attempted demos
- 15 novice, remote users

Real Robot Data
- 111 hours of robot demos
- 1 week of data collection
- 3 dexterous manipulation tasks
- 2144 total demonstrations
- 54 non-expert users

[CoRL '18, IROS 2019]
Data for Robotics: RoboTurk

![Bar Chart]

- **JIGSAWS** (1.66 hours) by Gao et al. (2014)
- **Deep Imitation** (2.35 hours) by Zhang et al. (2018)
- **DAML** (4.08 hours) by Yu, Finn et al. (2018)
- **MIME** (13.7 hours) by Sharma et al. (2018)

[CoRL ’18, IROS 2019]
Data for Robotics: RoboTurk

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Dataset Size (Hours)</th>
</tr>
</thead>
<tbody>
<tr>
<td>JIGSAWS</td>
<td>1.66</td>
</tr>
<tr>
<td>Deep Imitation</td>
<td>2.35</td>
</tr>
<tr>
<td>DAML</td>
<td>4.08</td>
</tr>
<tr>
<td>MIME</td>
<td>10x</td>
</tr>
<tr>
<td>RoboTurk-Sim</td>
<td>137.5</td>
</tr>
<tr>
<td>RoboTurk-Real</td>
<td>111.25</td>
</tr>
</tbody>
</table>

- Gao et al. 2014
- Zhang et al. 2018
- Yu, Finn et al. 2018
- Sharma et al. 2018
- Ours (CoRL 2018)
- Ours (IROS 2019)
Data for Robotics: RoboTurk

Imitation + RL

Task Performance vs. Number of Demonstrations

Task Performance

Number of Demonstrations

Pure RL (Sparse Reward)

Distributed PPO with curriculum: 32 workers, 24/48 hours

Nut Assembly

Bin Picking

[CoRL '18, IROS 2019]
Structured supervision for Robotics through scalable crowdsourcing can empower robot learning in complex tasks.
Generalizable Autonomy in Robot Manipulation

- Control: Visuo-Motor Skills
- Planning: Compositional Planning
- Perception: Task Structure
- Data for Robotics

Compositional Planning

Visuo-Motor Skills

Task Structure

Data for Robotics

Generalizable Autonomy in Robot Manipulation
Opportunity: Personal Robotics

Instructional Youtube Video
How to make Meatball Pasta?

Where / How should Rosie start?
What is the recipe?
How to execute the plan?
How to plan?
Reasoning for Physical Interaction
Understanding Purpose

Ideal Tool During Training

Task-Based Tool Adaptation During Execution
Grounding: So many ways to “make eggs”
Generalizable Autonomy in Robot Manipulation

- Perception for Physical Interaction
- Reasoning through Learned Dynamics
- Transfer Learning with Formal Guarantees
- Continual Skill Adaptation & Accumulation

Higher-Order Semantics

What makes an object a hammer?

State Change: Breaking Eggs

Success

Failure
Generalizable Autonomy in Robot Manipulation

Learning with Structured Inductive Bias and Priors

- Efficiency and Generalization
- Combine: Domain Expertise + Data-Driven Methods
Generalizable Autonomy in Robot Manipulation

garg@cs.toronto.edu
@Animesh_Garg