Leveraging model-learning for extreme generalization

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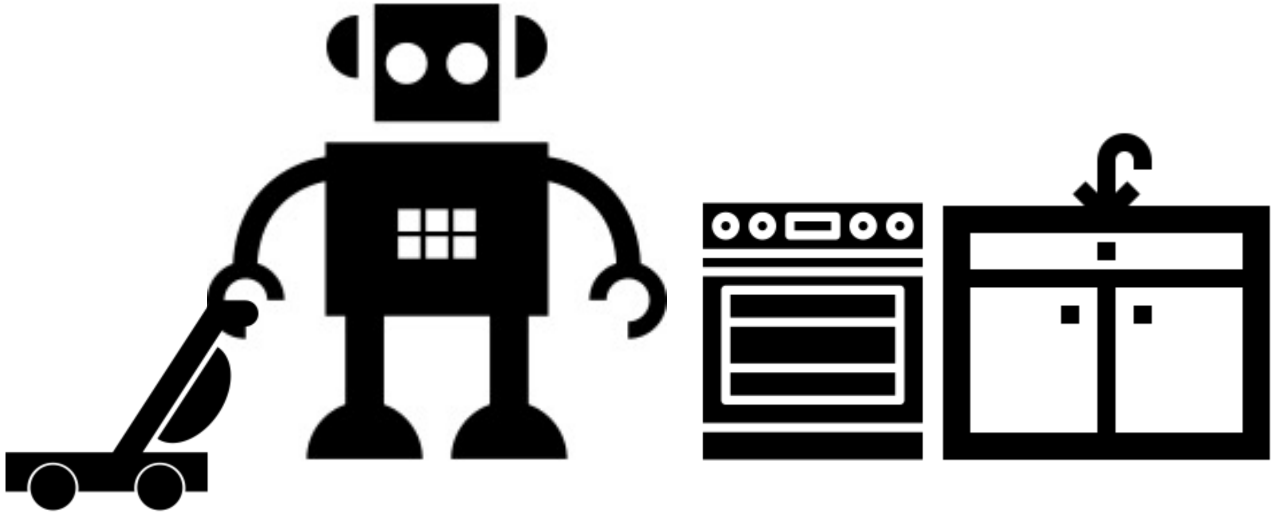
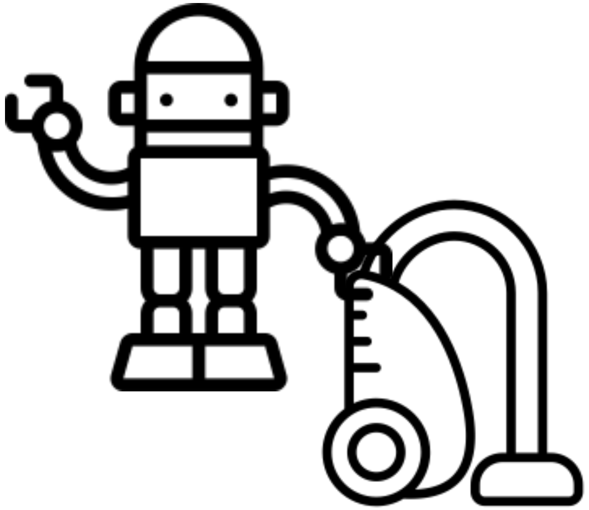
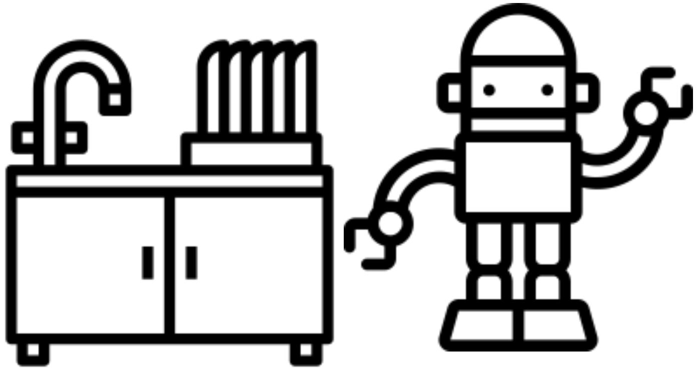
Research goal:
understand the computational mechanisms necessary to make
a general-purpose intelligent robot

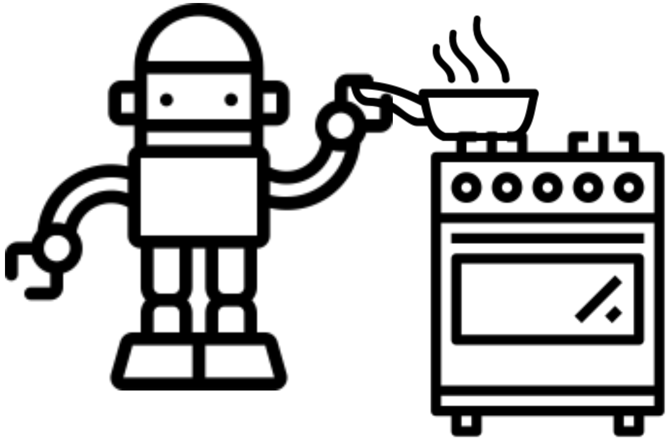


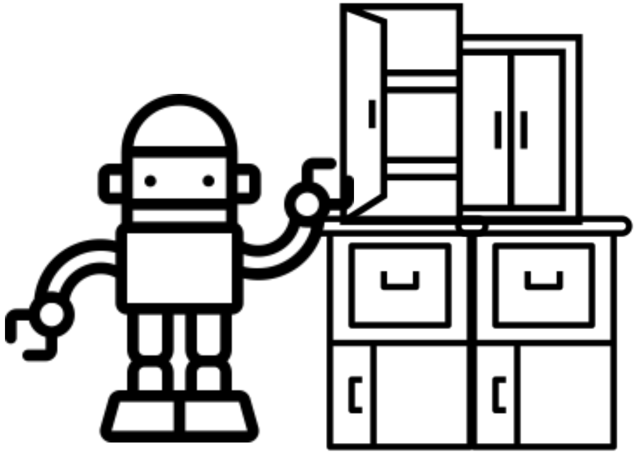
Domain variability: Make tea in any kitchen

Task variability: Do any household job





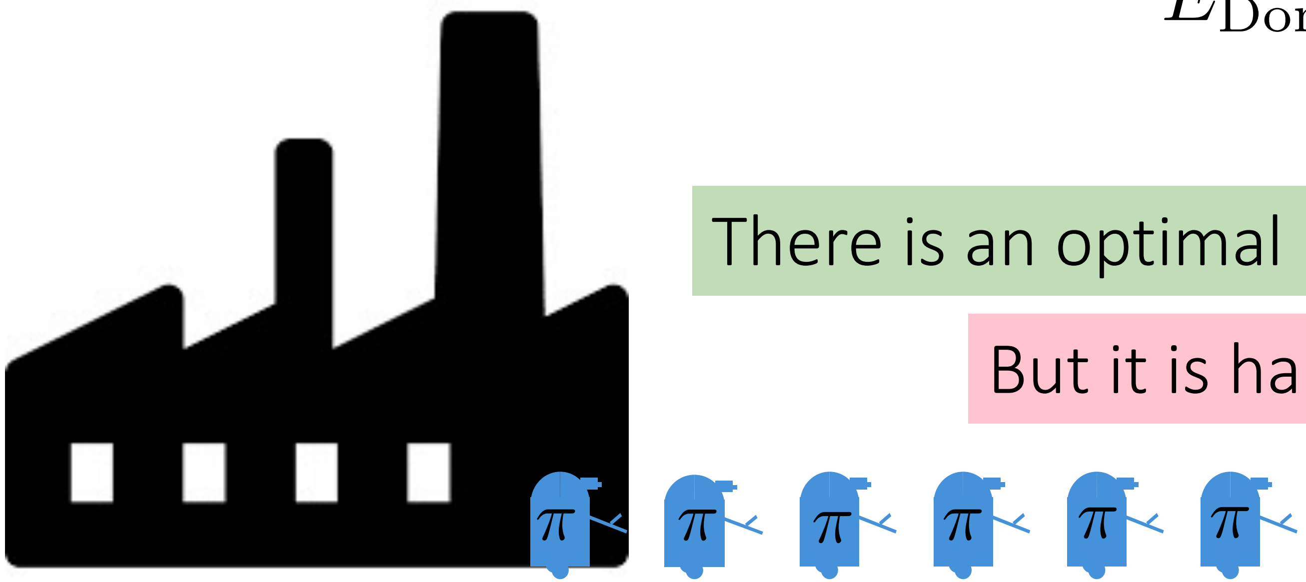




Robot **factory** generates robots that work in the **wild**

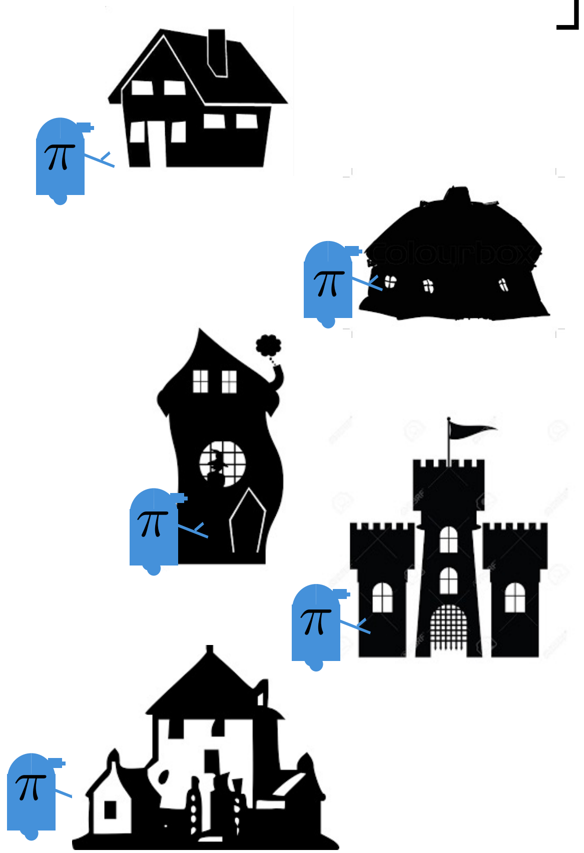
Find a mapping $\pi : (o, a)^* \rightarrow a$ that optimizes

$$E_{\text{Dom}}\left[\sum_{t=0}^{T_{\text{dom}}} R_{\text{dom}}(s_t, a_t) \mid \pi, W_{\text{dom}}\right]$$



There is an optimal policy :-)

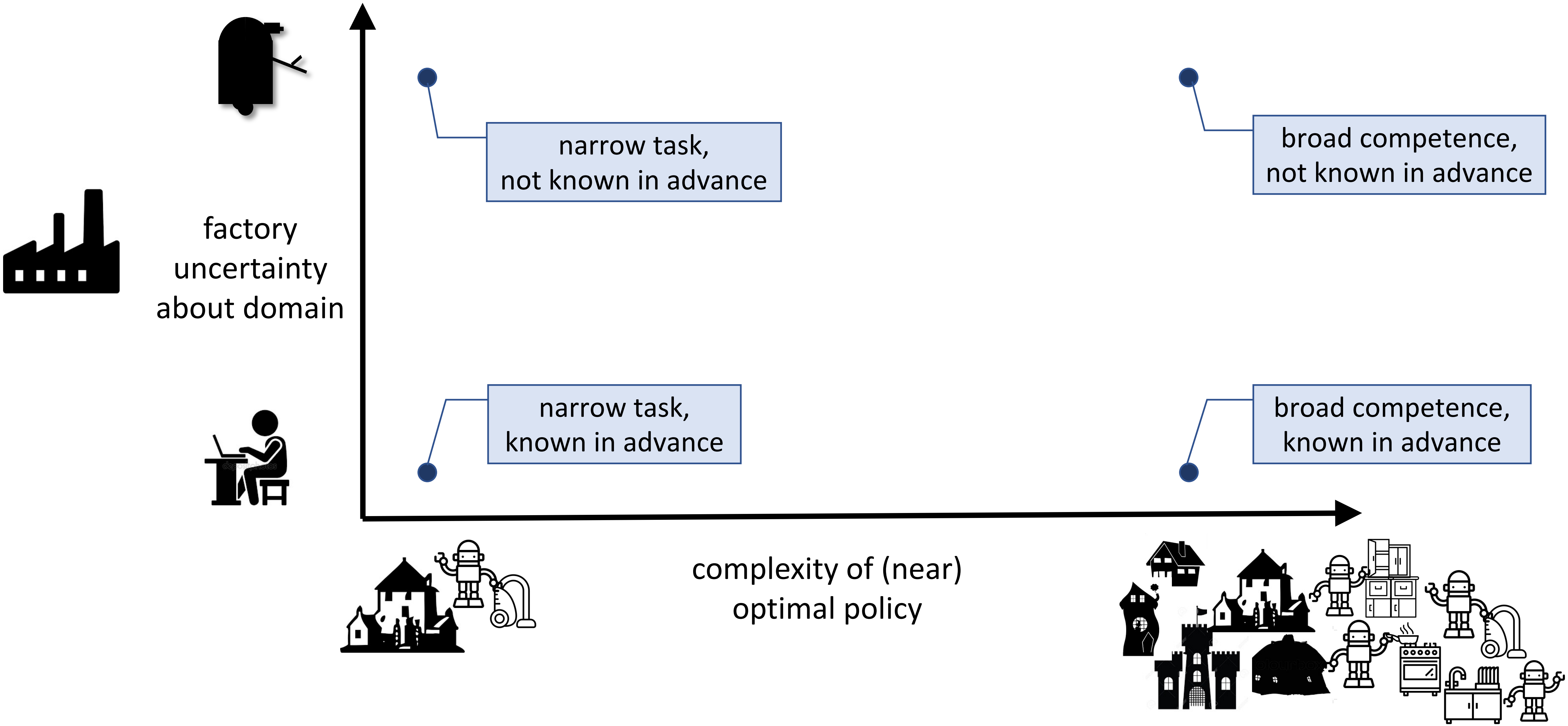
But it is hard to find :-(



Domain specifies

- World (start state dist, transition dynamics)
- Horizon T (could average or discount)
- Reward function (need not be additive, dense, shaped)

The space of distributions over domains $P(\mathrm{Dom})$



How to construct a good policy for a given $P(\mathrm{Dom})$?

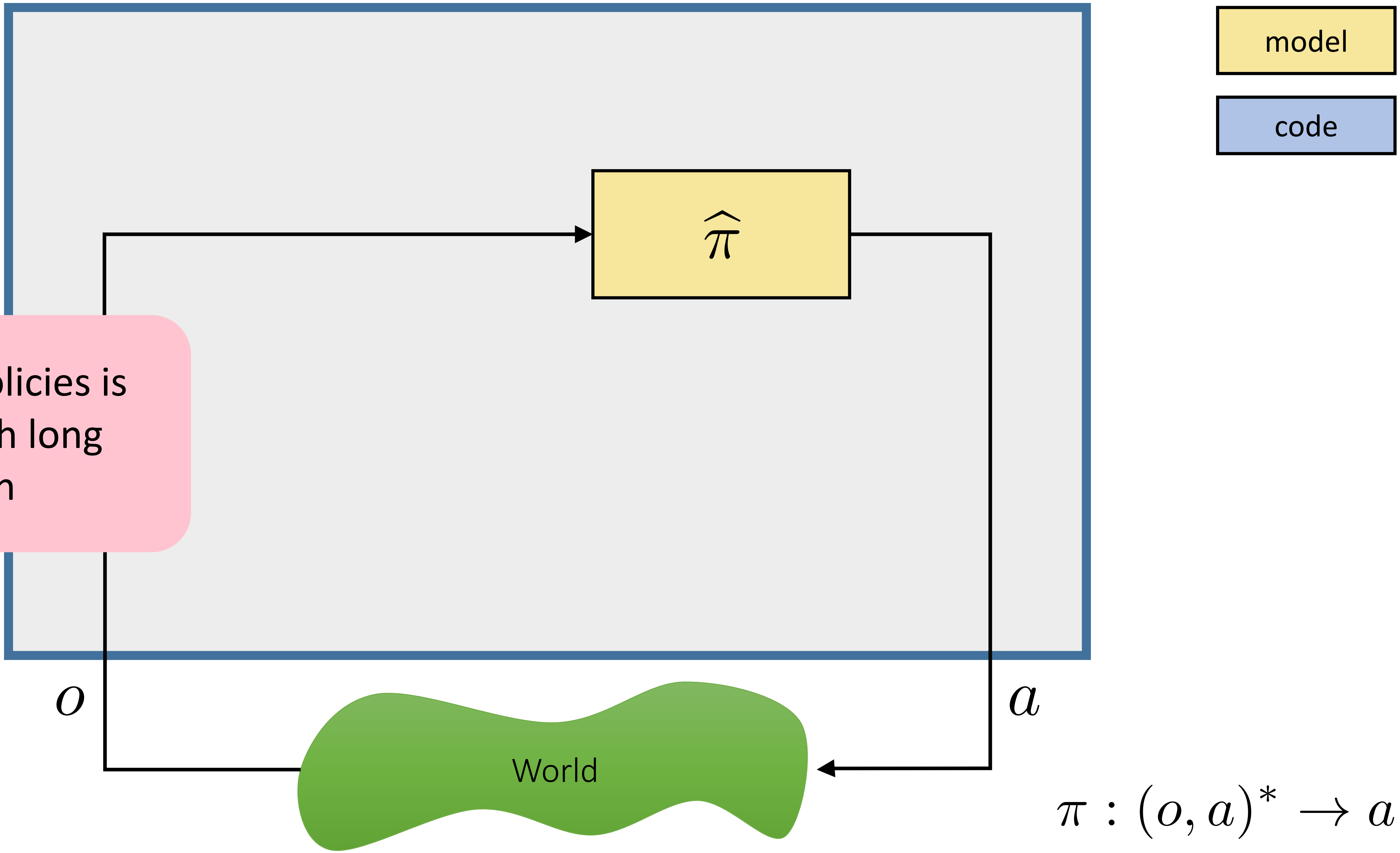
Pick a **model class** and **methodology for acquiring the models** that **perform well** while **minimizing total construction cost:**

- Human
  - model specification
  - simulator (physical or software) construction
  - reward shaping
  - data labeling, gathering, …
- Machine
  - optimization
  - learning
  - parameter tuning

Pick model class where

- humans have most insight
- optimization is easiest
- learning will generalize best

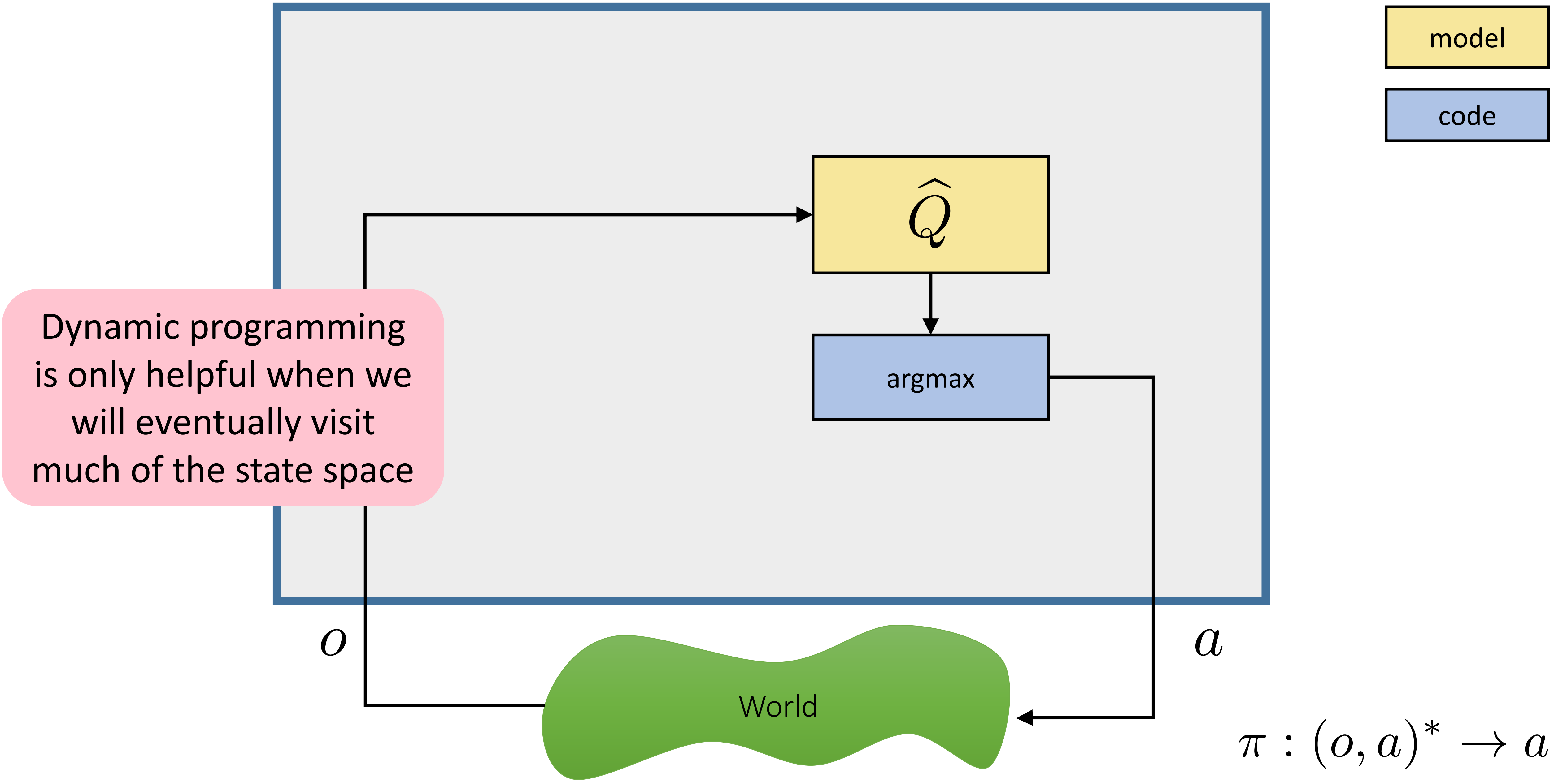
Ways to represent a policy: a policy!



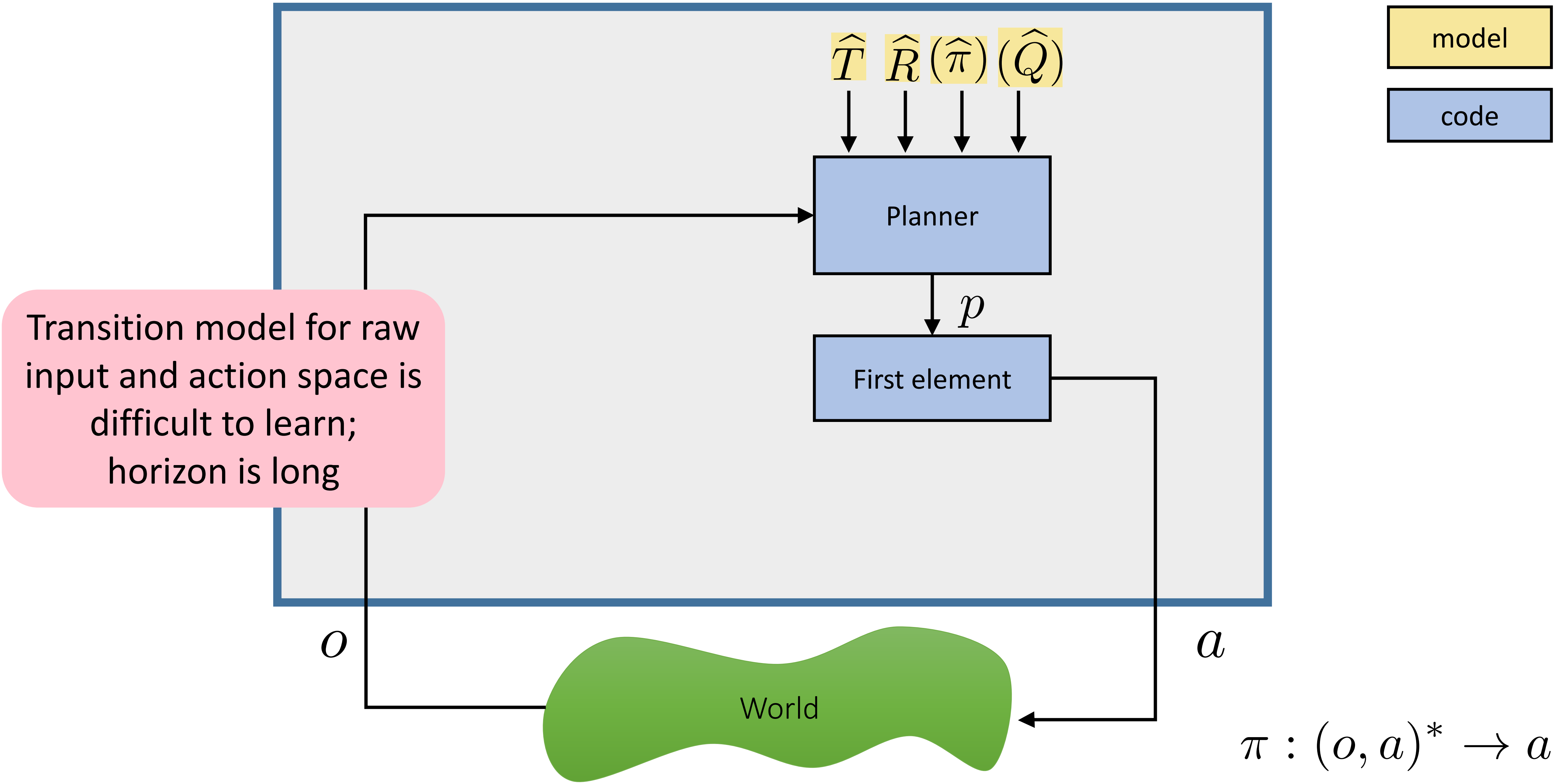
Search for policies is difficult with long horizon

$$\pi : (o, a)^* \to a$$

Ways to represent a policy: Q values

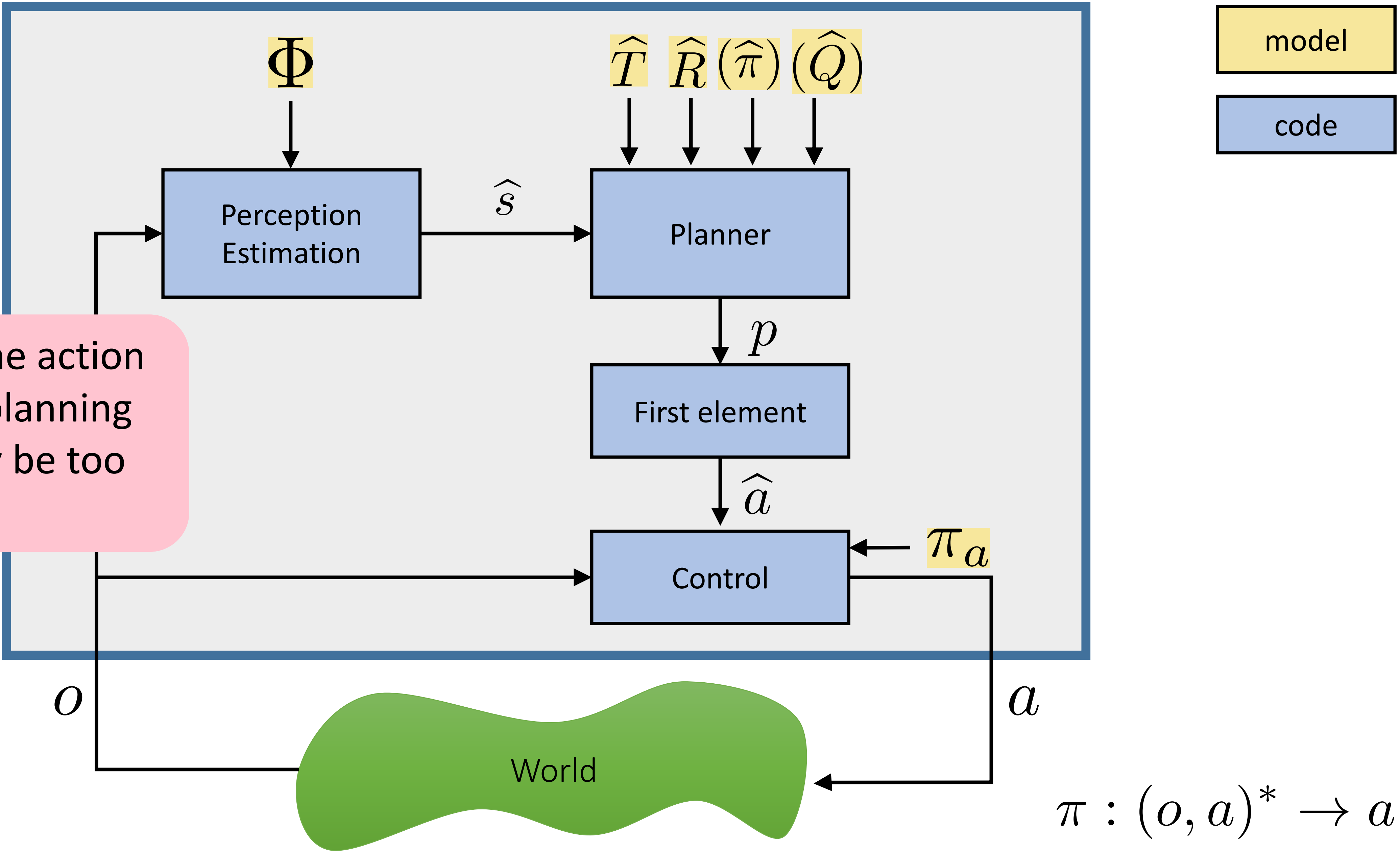


Ways to represent a policy: plan online, with search control



$$\pi : (o, a)^* \to a$$

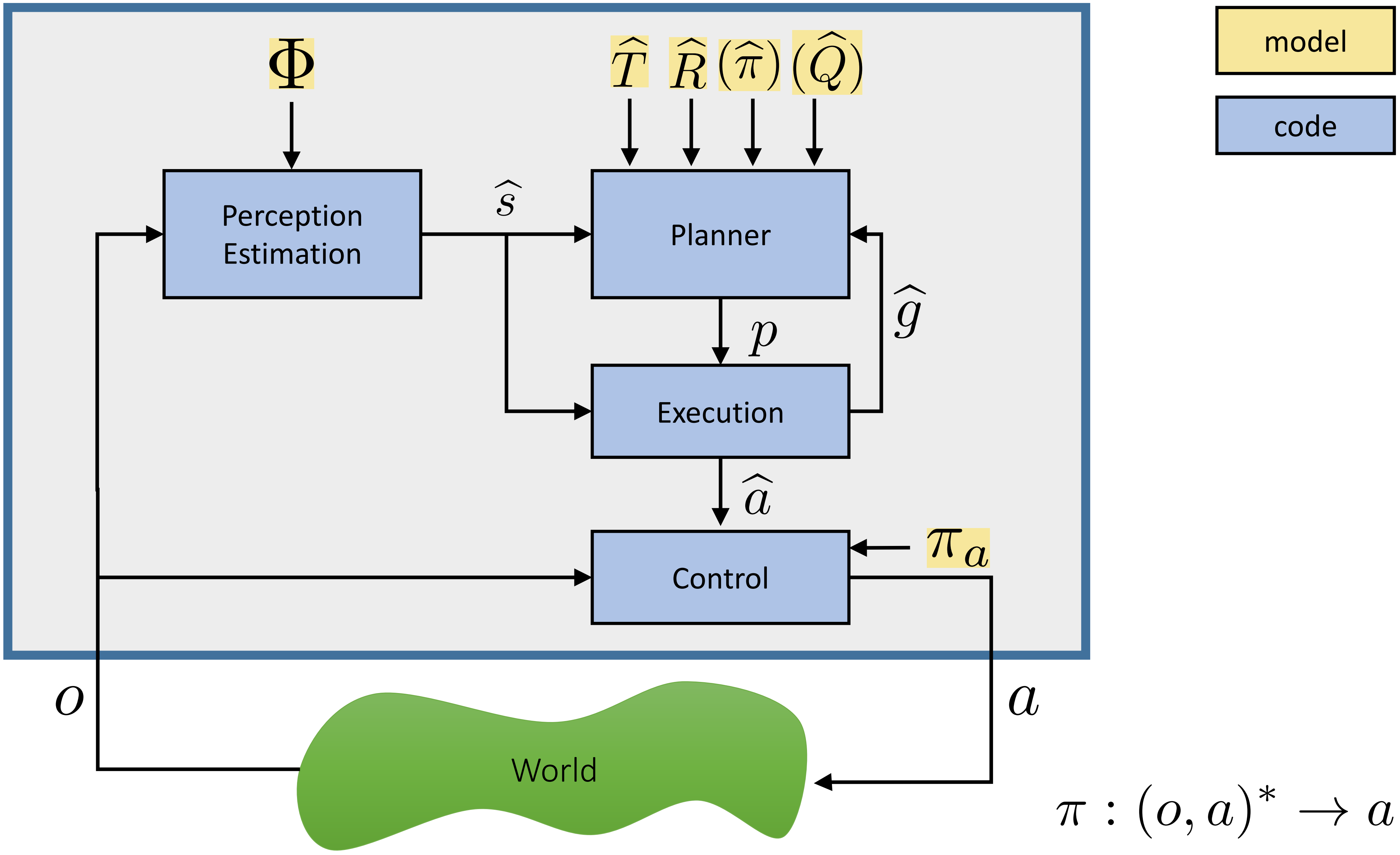
Ways to represent a policy: plan at higher level of abstraction



Even with some action abstraction, planning horizons may be too long

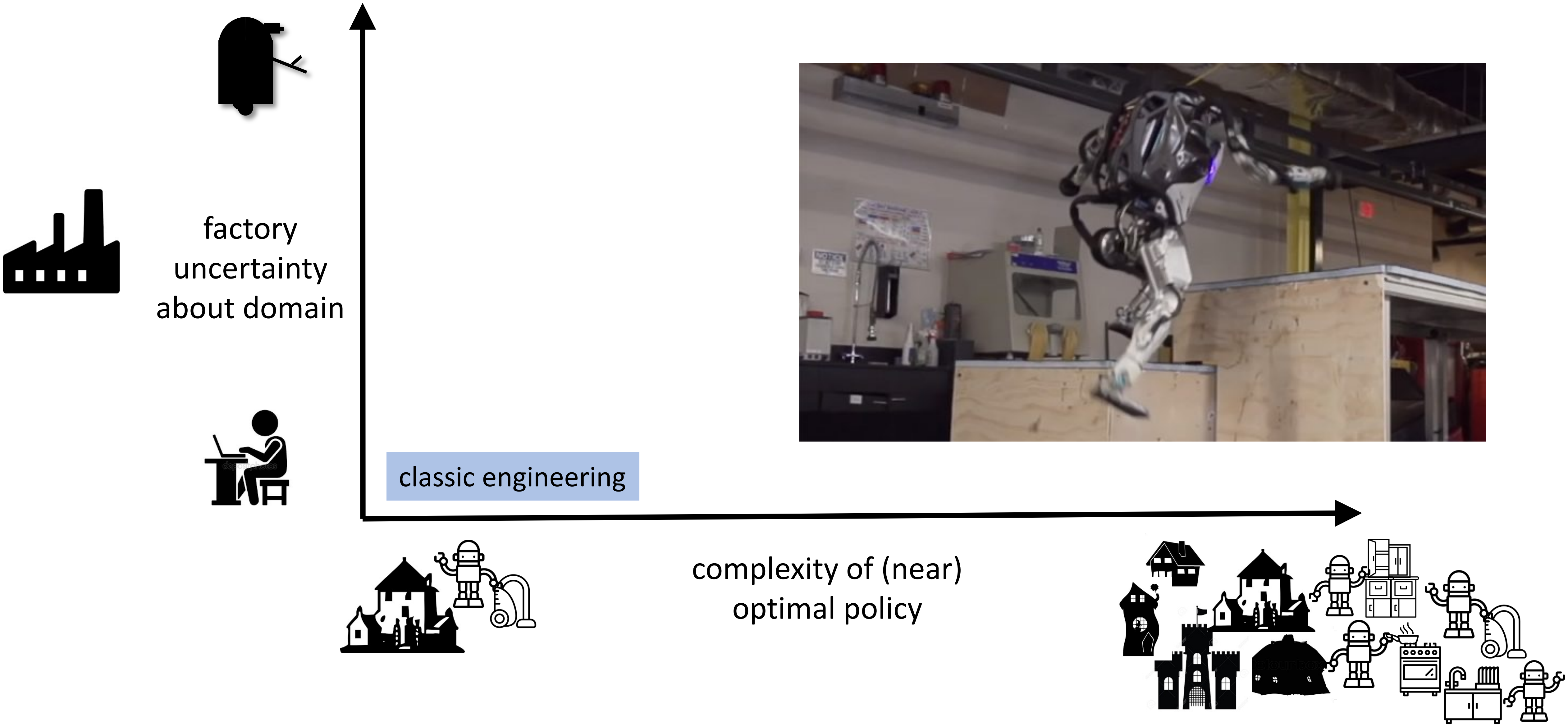
$$\pi : (o, a)^* \to a$$

Ways to represent a policy: add hierarchical plan / execution

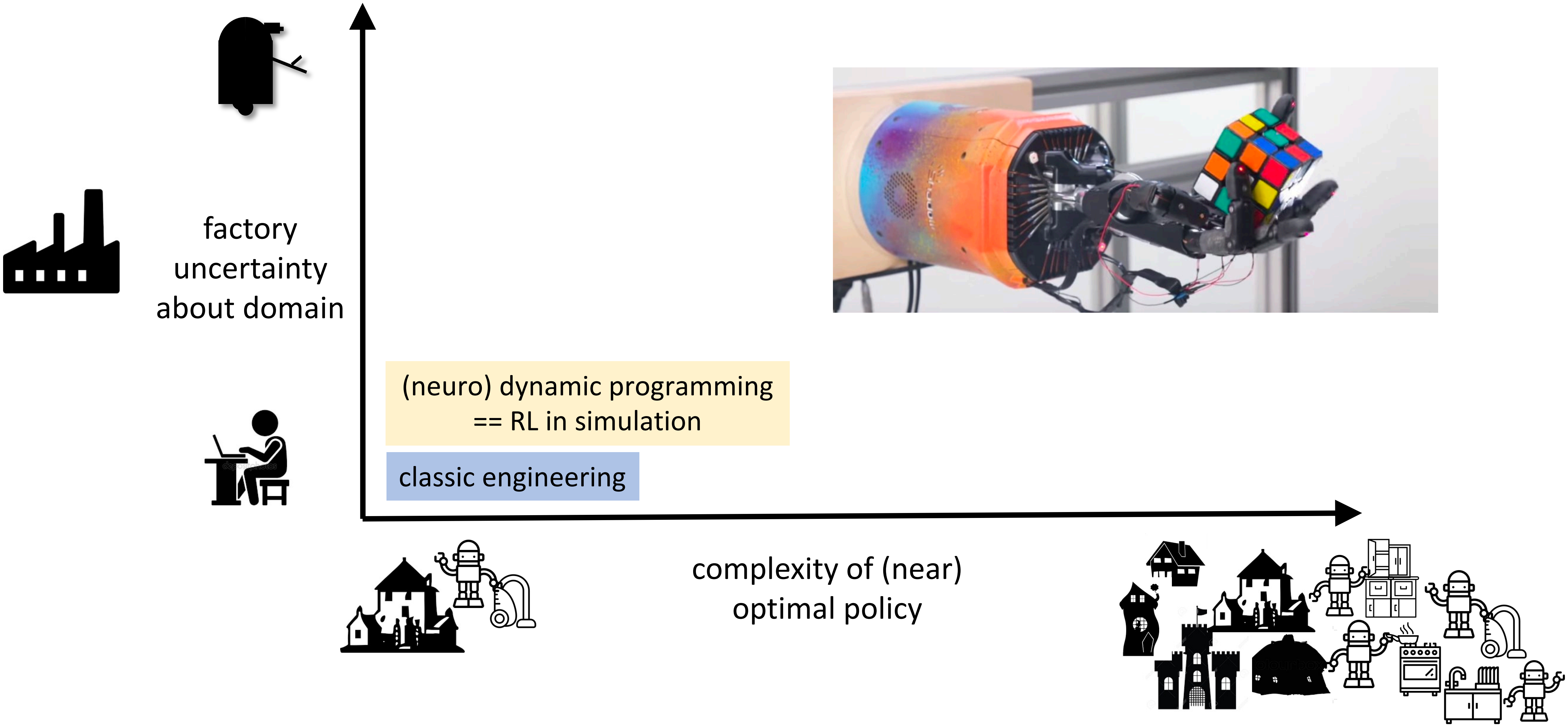


$$\pi : (o, a)^* \to a$$

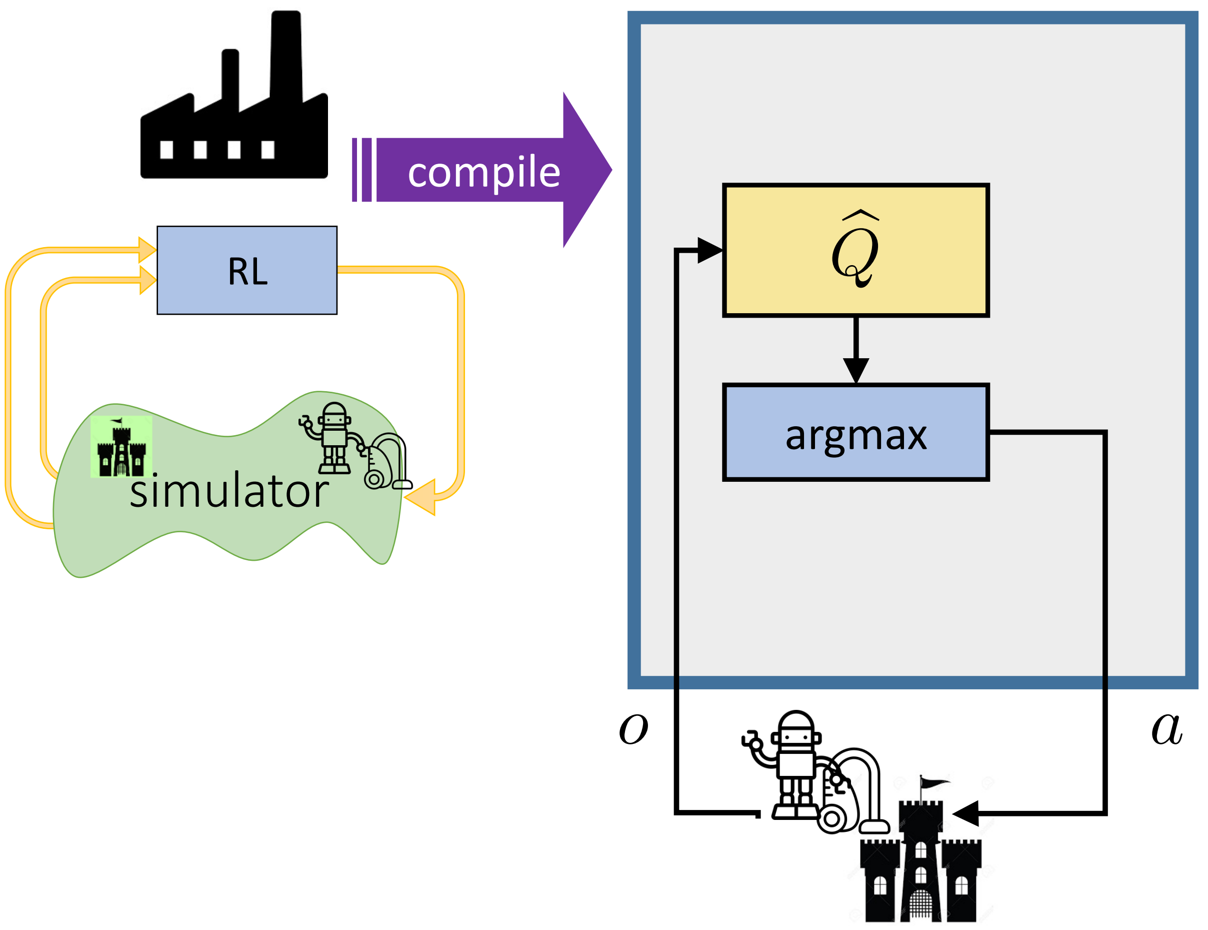
Different ways to obtain a policy



Different ways to obtain a policy

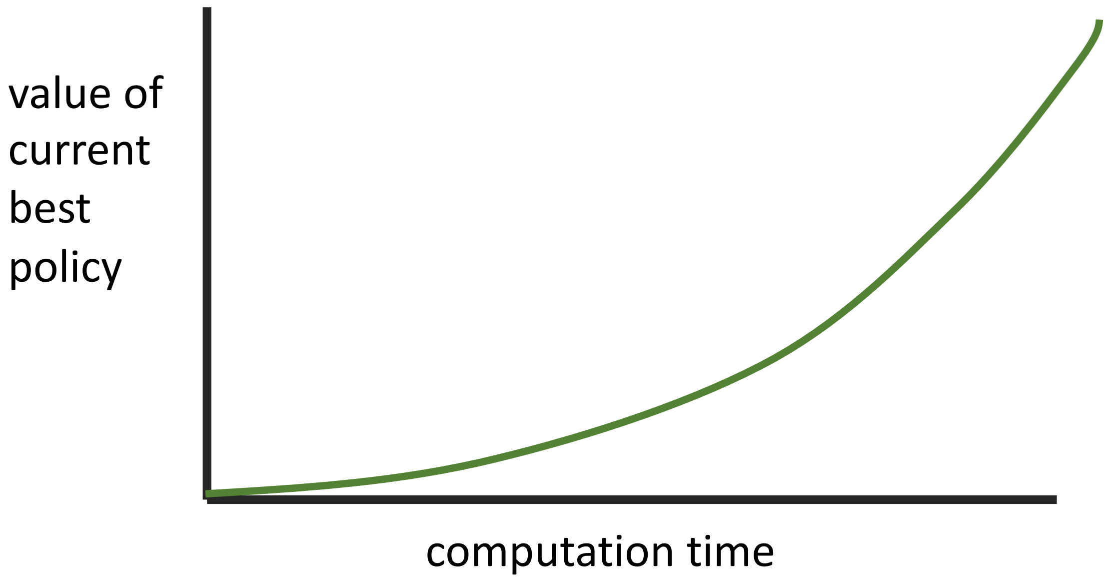


RL in the factory



Evaluation

- Reward during learning doesn't matter
- Number of interactions with simulator doesn't matter
- Measure quality of best policy found versus computation time



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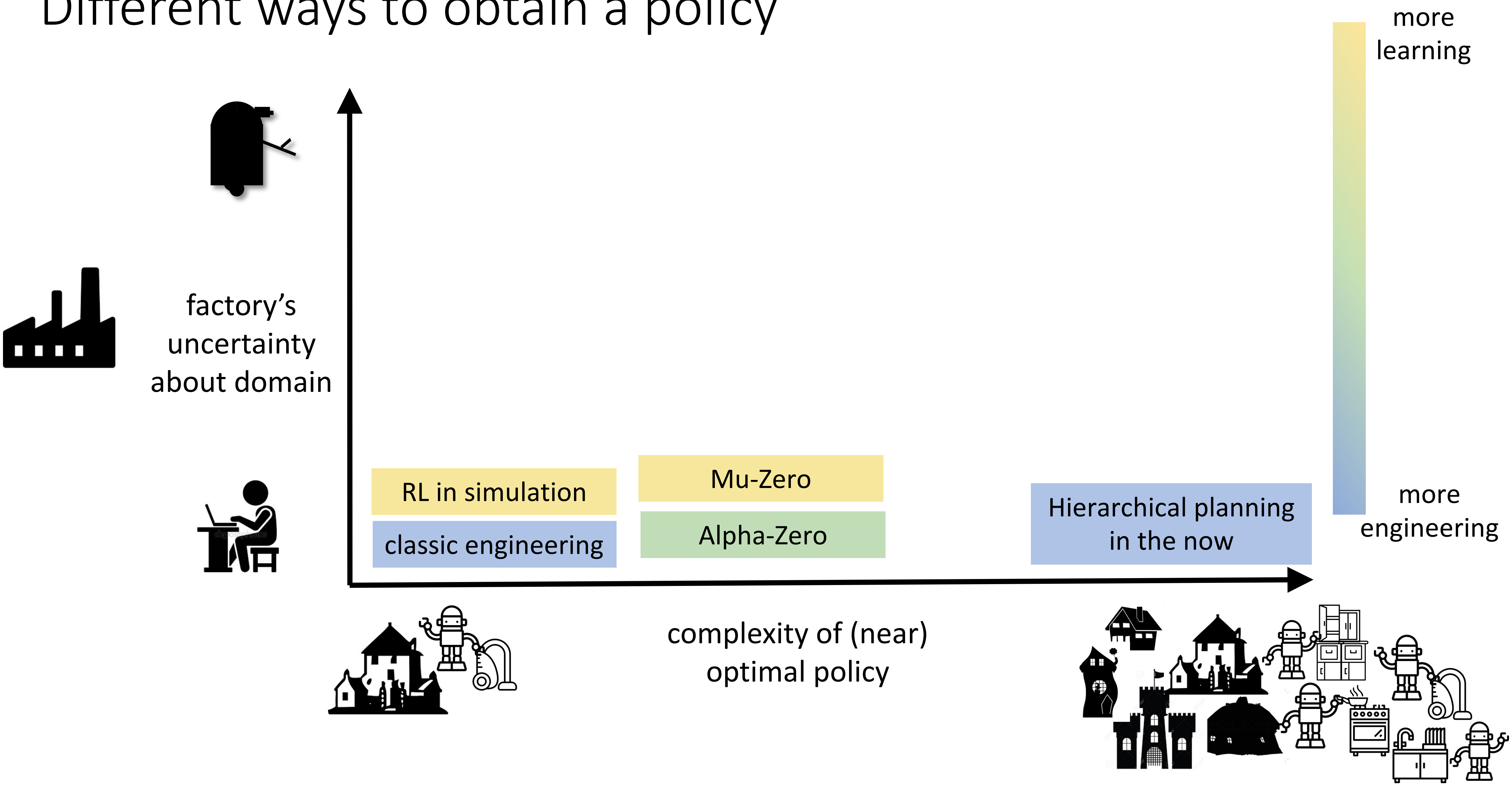
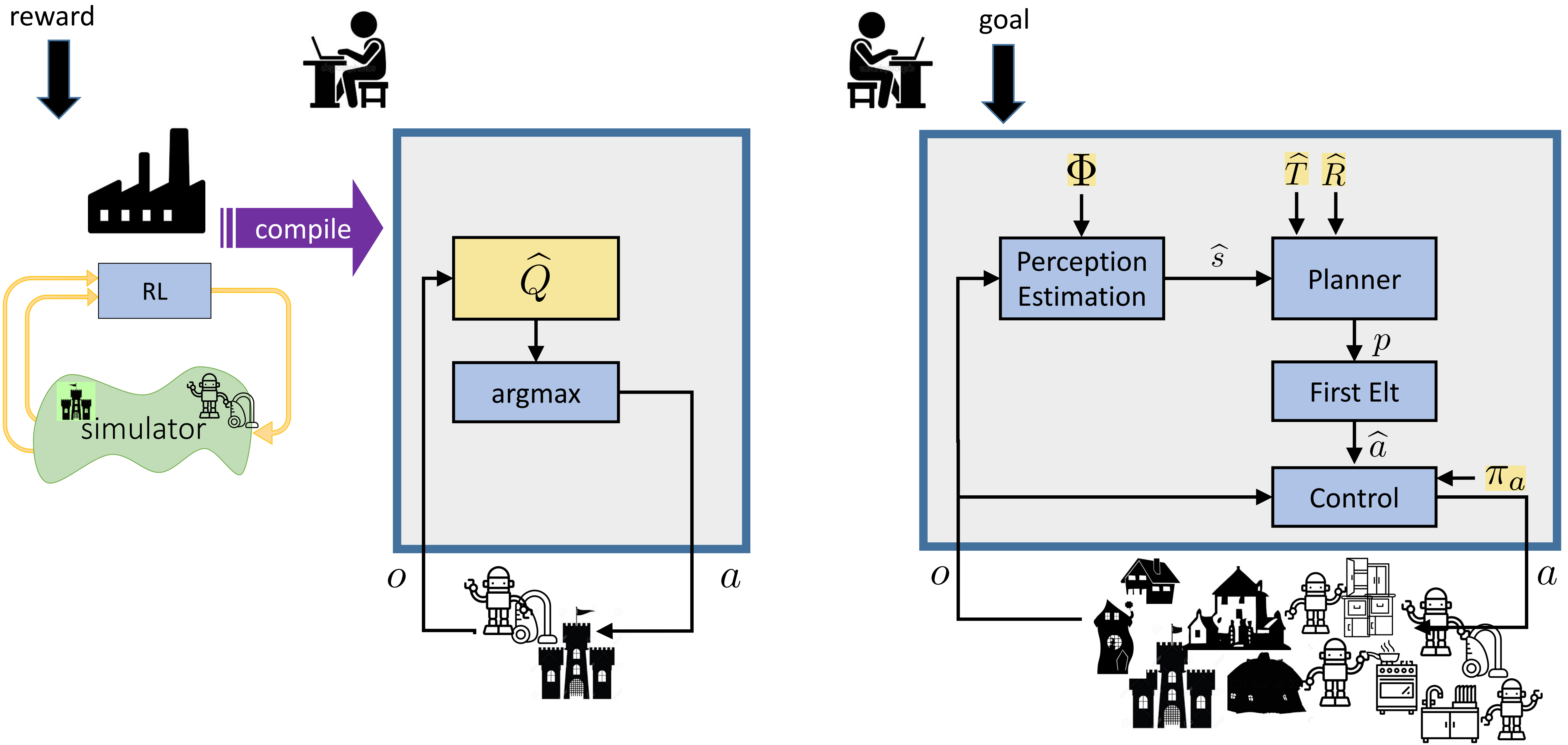
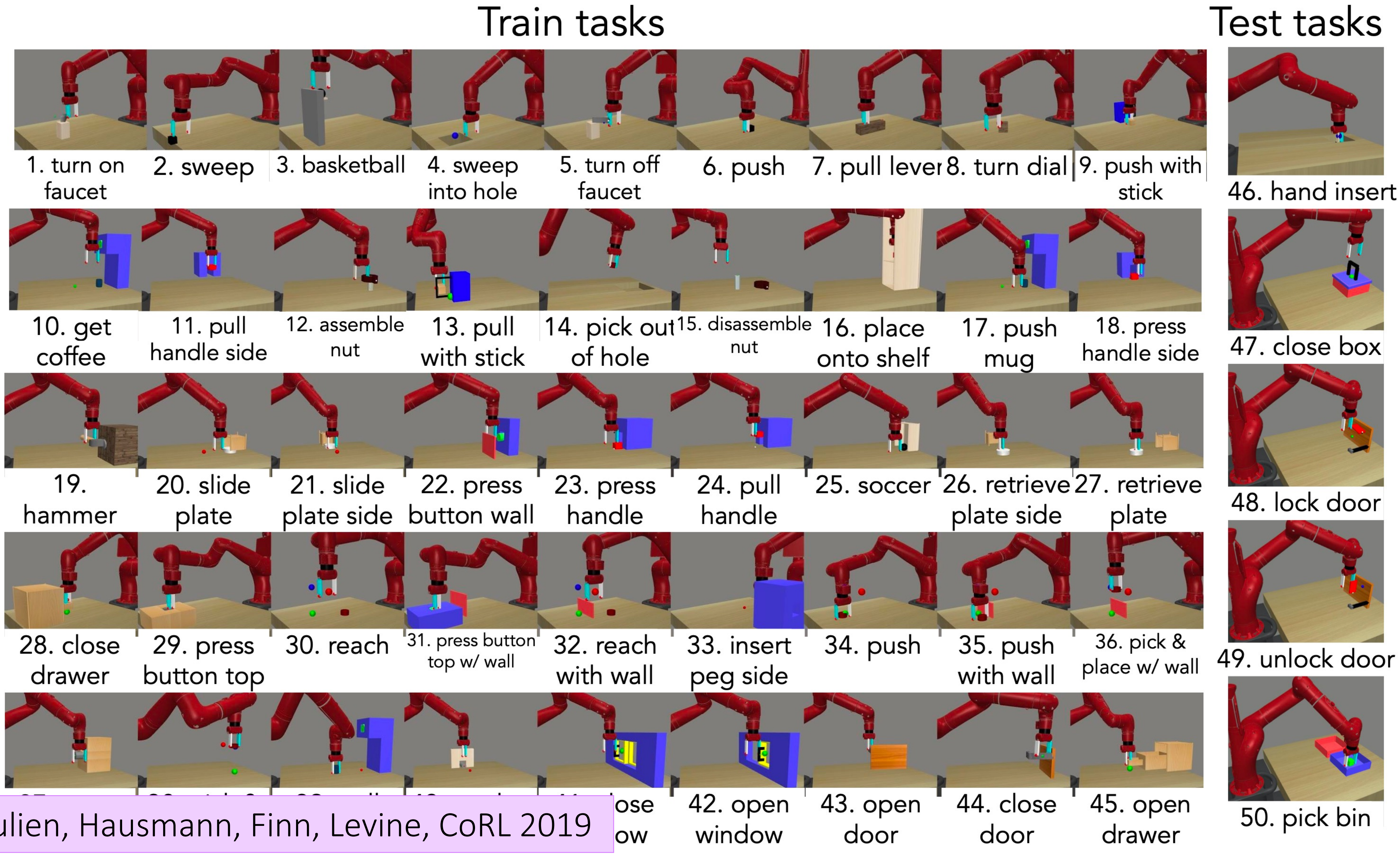


RL in the factory vs planning in the wild: engineering effort



MetaWorld: suite of RL problems designed for meta-learning



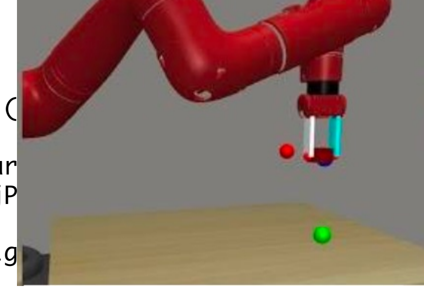
Yu, Quillen, He, Julien, Hausmann, Finn, Levine, CoRL 2019

Reward function for pick and place task

```
  def compute_reward(self, actions, obs, mode = 'general'):
       if isinstance(obs, dict):
           obs = obs['state_observation']
       objPos = obs[3:6]

       rightFinger, leftFinger =
self.get_site_pos('rightEndEffector'),

self.get_site_pos('leftEndEffector')
       fingerCOM  =  (rightFinger + leftFinger)/2

       heightTarget = self.heightTarget
       placingGoal = self._state_goal

       reachDist = np.linalg.norm(objPos - fingerCOM)
       placingDist = np.linalg.norm(objPos[:2] -
placingGoal[:-1])

       def reachReward():
           reachRew = -reachDist# + min(actions[-1], -1)/50
           reachDistxy = np.linalg.norm(objPos[:-1] -
fingerCOM[:-1])
           zRew = np.linalg.norm(fingerCOM[-1] -
self.init_fingerCOM[-1])
           if reachDistxy < 0.06: #0.02
               reachRew = -reachDist
           else:
               reachRew =  -reachDistxy - zRew
           #incentive to close fingers when reachDist is
small
           if reachDist < 0.05:
               reachRew = -reachDist + max(actions[-
1],0)/50
           return reachRew , reachDist

       def pickCompletionCriteria():
           tolerance = 0.01
           if objPos[2] >= (heightTarget- tolerance):
               return True
           else:
               return False

       if pickCompletionCriteria():
           self.pickCompleted = True
```

```
  def objDropped():
           return (objPos[2] <
(self.objHeight + 0.005)) and (placingDist
>0.02) and (reachDist > 0.02)
           # Object on the ground, far away
from the goal, and from the gripper
           #Can tweak the margin limits

       def objGrasped(thresh = 0):
           sensorData = self.data.sensordata
           return (sensorData[0]>thresh) and
(sensorData[1]> thresh)

       def placeCompletionCriteria():
           if abs(objPos[0] - placingGoal[0])
< 0.05 and \
               abs(objPos[1] -
placingGoal[1]) < 0.05 and \
               objPos[2] < self.objHeight +
0.05:
              return True
           else:
              return False
       if placeCompletionCriteria():
           self.placeCompleted = True

       def orig_pickReward():
           # hScale = 50
           hScale = 100
           if self.placeCompleted or
(self.pickCompleted and not(objDropped())):
               return hScale*heightTarget
           # elif (reachDist < 0.1) and
(objPos[2]> (self.objHeight + 0.005)) :
           elif (reachDist < 0.1) and
(objPos[2]> (self.objHeight + 0.005)) :
               return hScale*
min(heightTarget, objPos[2])
           else:
               return 0

       Dist]
```

```
def general_pickReward():
           hScale = 50
           if self.placeCompleted or (
objGrasped()):
               return hScale*heightTar
           elif objGrasped() and (objP
0.005)):
               return hScale* min(heig
           else:
               return 0

       def placeReward():
           # c1 = 1000 ; c2 = 0.01 ; c3 = 0.001
           c1 = 1000 ; c2 = 0.01 ; c3 = 0.001
           placeRew = 1000*(self.maxPlacingDist - placingDist)
+ c1*(np.exp(-(placingDist**2)/c2) + np.exp(-
(placingDist**2)/c3))
           placeRew = max(placeRew,0)
           if mode == 'general':
               cond = self.pickCompleted and objGrasped()
           else:
               cond = self.pickCompleted and (reachDist < 0.1)
and not(objDropped())
           if self.placeCompleted:
               return [-200*actions[-1] + placeRew,
placingDist]
           elif cond:
               if abs(objPos[0] - placingGoal[0]) < 0.05 and \
                   abs(objPos[1] - placingGoal[1]) < 0.05:
                   return [-200*actions[-1] + placeRew,
placingDist]
               else:
                   return [placeRew, placingDist]
           else:
               return [0 , placingDist

       reachRew, reachDist = reachReward()
       if mode == 'general':
           pickRew = general_pickReward()
       else:
           pickRew = orig_pickReward()
       placeRew , placingDist = placeReward()
       # assert ((placeRew >=0) and (pickRew>=0))
       if self.placeCompleted:
           reachRew = 0
           reachDist = 0
       reward = reachRew + pickRew + placeRew
       return [reward, reachRew, reachDist, pickRew, placeRew,
placing
```



Reward function for pick and place task

hand close to obj	obj grasped	pick ever completed	hand close to goal	place ever completed	reward
0	0	*	*	0	-distXY(hand, obj) – distZ(hand,obj)
1	0	0	*	0	-dist(hand, obj) + c1 * closeCmd
1	1	0	*	0	-dist(hand,obj) + c1 * closeCmd + c2 * min(obj.z, targetHt)
1	1	1	*	0	-dist(hand,obj) + c1 * closeCmd + c2 * targetHt + placeRew
1	1	1	0	0	-dist(hand,obj) + c1 * closeCmd + c2 * targetHt + placeRew + c3 * openCmd
*	*	*	*	1	c2 * targetHt + placeRew + c3 * openCmd

place ever completed: |objx – goalx| < c4 and |objy-goaly|< c5 and |objz – goalz| < c6
pick ever completed: objz > targetHt + c7
obj grasp: test on current finger sensors
hand close to obj, hand close to goal: constant x,y,z thresholds
placeDist = |objxy – goalxy|
placeRew = max(0, c8*(c9- placingDist) + c10*(exp(-(placingDist**2)/c11) +exp(-(placingDist**2)/c12)))

Reward function for pick and place task

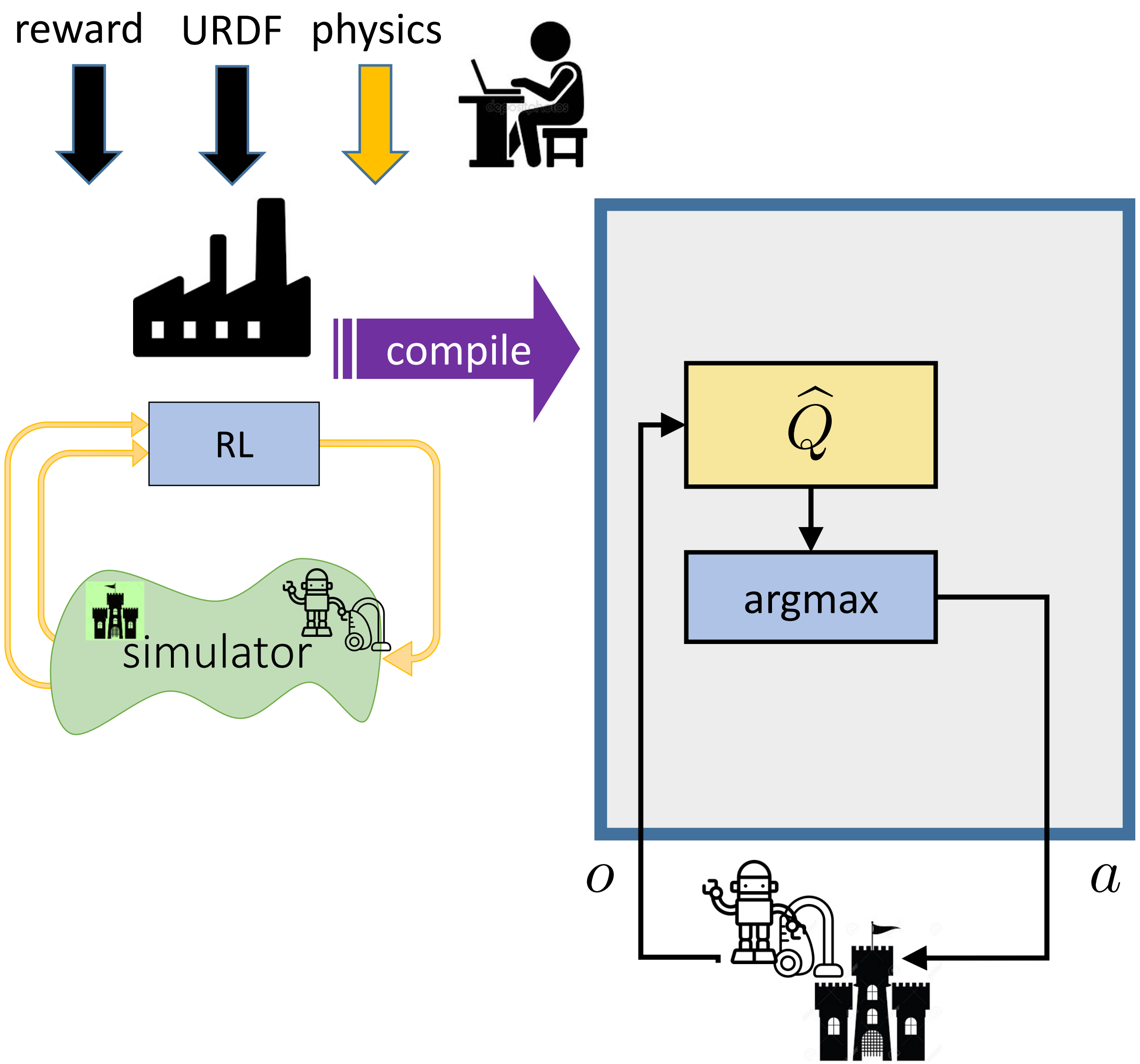
hand close to obj	obj grasped	pick ever completed	hand close to goal	place ever completed	reward
0	0	*	*	0	move toward object
1	0	0	*	0	move toward object + close fingers
1	1	0	*	0	move toward object + close fingers + raise
1	1	1	*	0	move toward object + close fingers + move toward goal
1	1	1	0	0	move toward object + close fingers + move toward goal + open fingers
*	*	*	*	1	move toward goal + open fingers

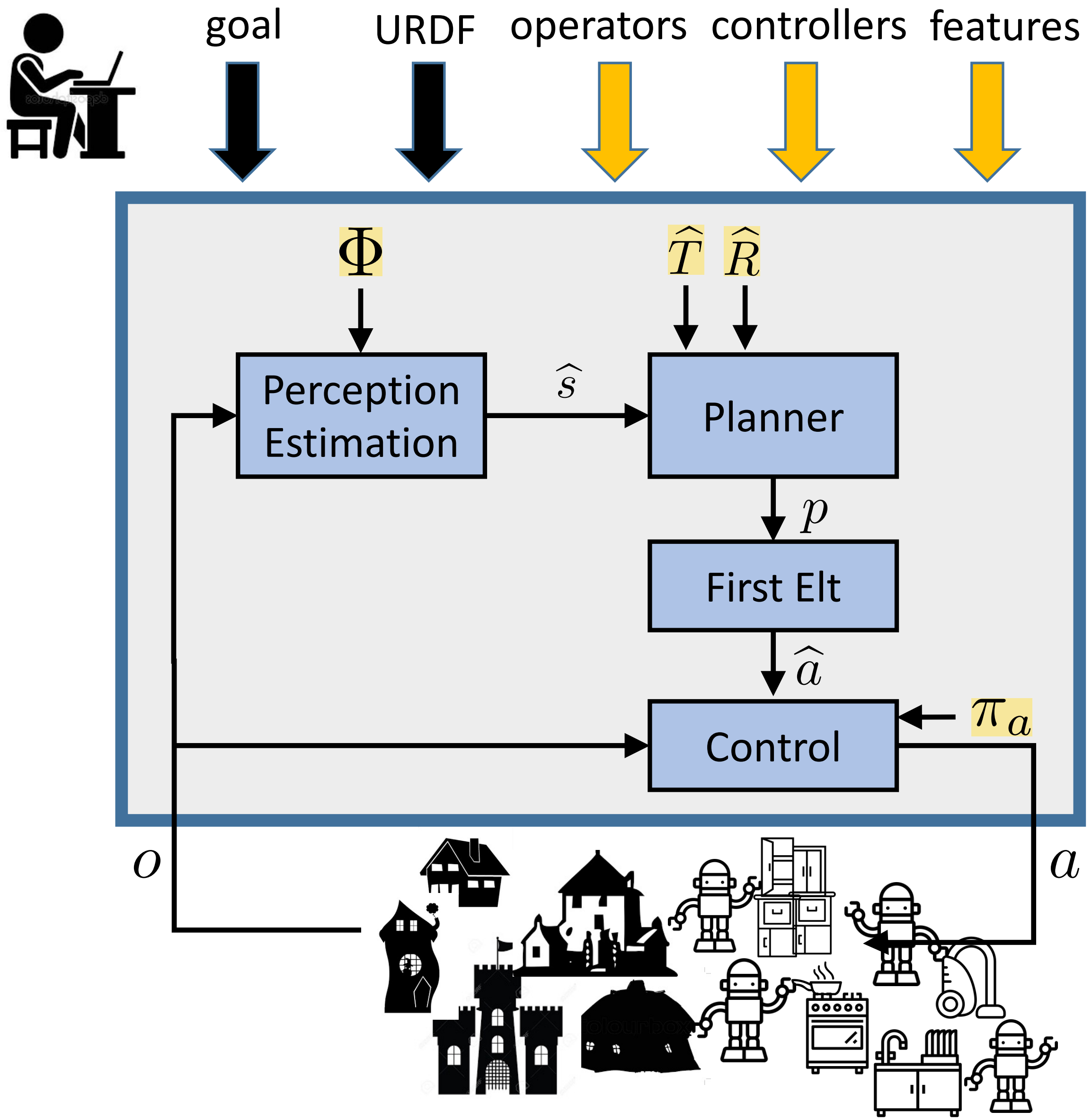
place ever completed: |objx – goalx| < c4 and |objy-goaly|< c5 and |objz – goalz| < c6
pick ever completed: objz > targetHt + c7
obj grasp: test on current finger sensors
hand close to obj, hand close to goal: constant x,y,z thresholds
placeDist = |objxy – goalxy|
placeRew = max(0, c8*(c9- placingDist) + c10*(exp(-(placingDist**2)/c11) +exp(-(placingDist**2)/c12)))

Goal for HPN planner

```
goal = Goal([Pose(target_obj, (0.2, -0.1, 0.5, 3.14)])
```

RL in the factory vs planning in the wild: engineering effort





Models for robot manipulation planning

Raw simulator

- Action space: incremental joint torques or displacements
- Horizon: several 1000
- Heuristic: learned goal-conditioned v
- Exploration needed to learn heuristic

What makes an abstraction useful?

- Makes computational problem much easier
- Doesn’t make solution quality too much worse
- Not too hard to implement / maintain
- Solves most problems you care about

Proposed abstract model

- Action space is
  - **lifted**: independent of particular objects
  - **compositional**: can address huge space of states and goals
- Horizon: hierarchical ~8 mode-level, ~20 motion-level, ~2 controller-level
- Heuristic: domain independent (can be improved by learning)
- Exploration: not needed

Multi-modal motion planning: a useful abstraction for many problems!

Assume:

- robot and objects (for now) are kinematic
- state represented in terms of poses (and c

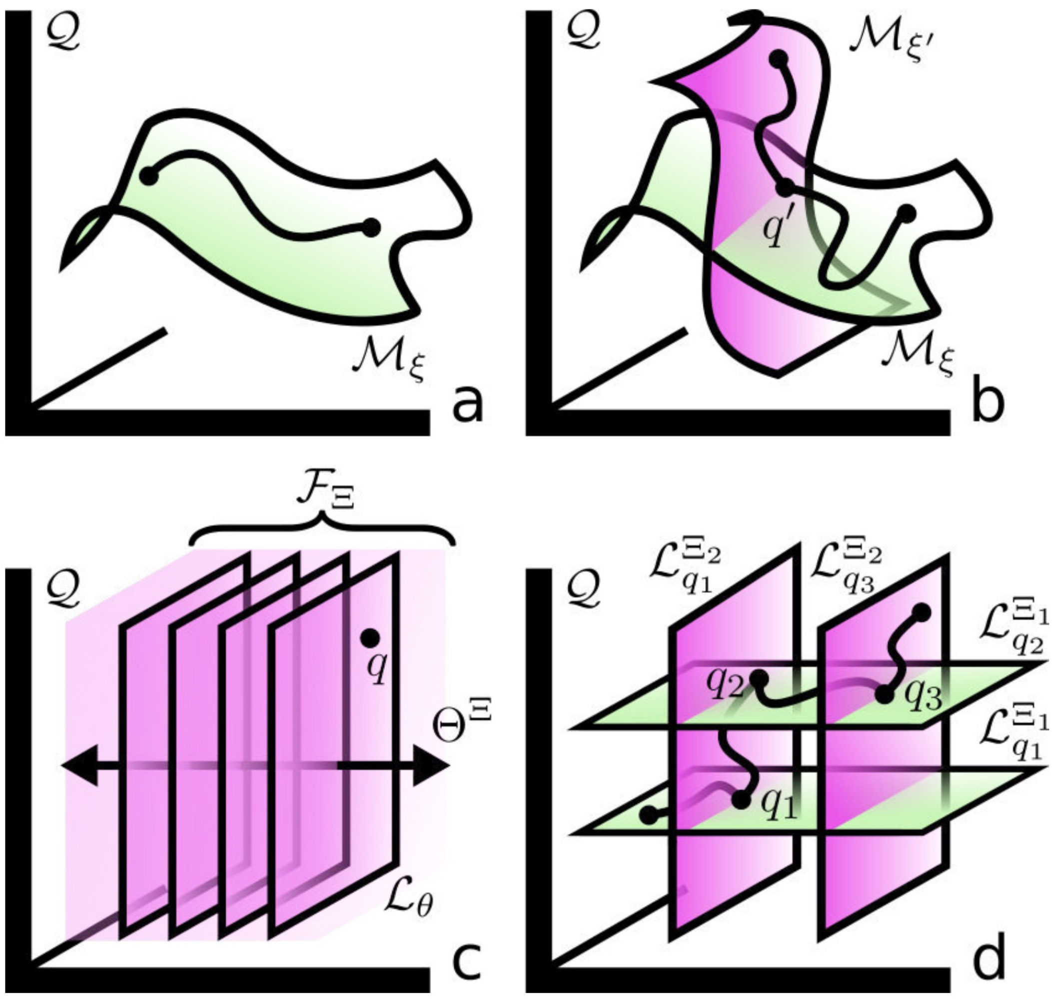
Mode: smooth **dynamics of a small set of state**

- robot moving in free space
- robot moving while holding A in grasp G a
- …

Mode family: set of modes with same changing

Mode family specified by:

- changeable params
- controller for entering, moving through, a
- testable description of set of world configu and into which it can be exited



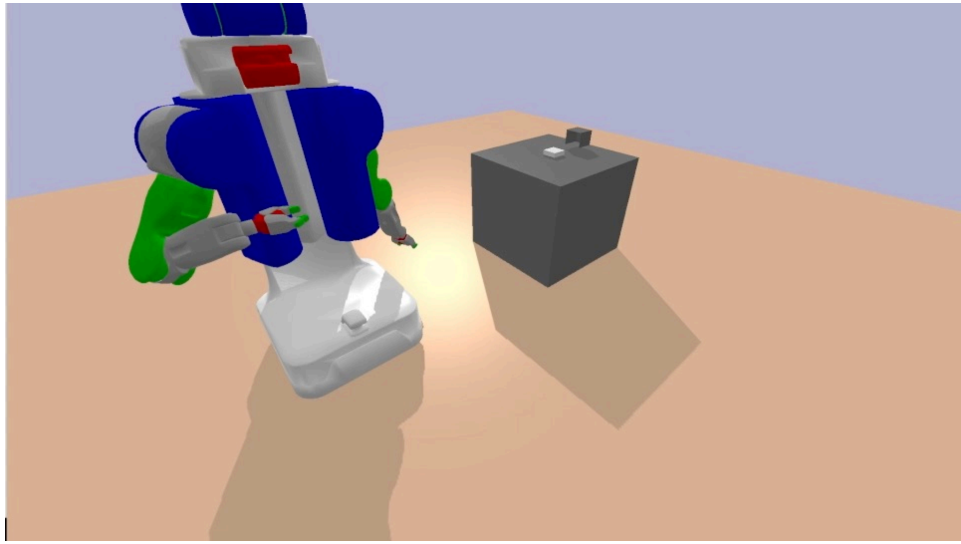
Kingston, Wells, Moll, Kavraki ICRA 2020

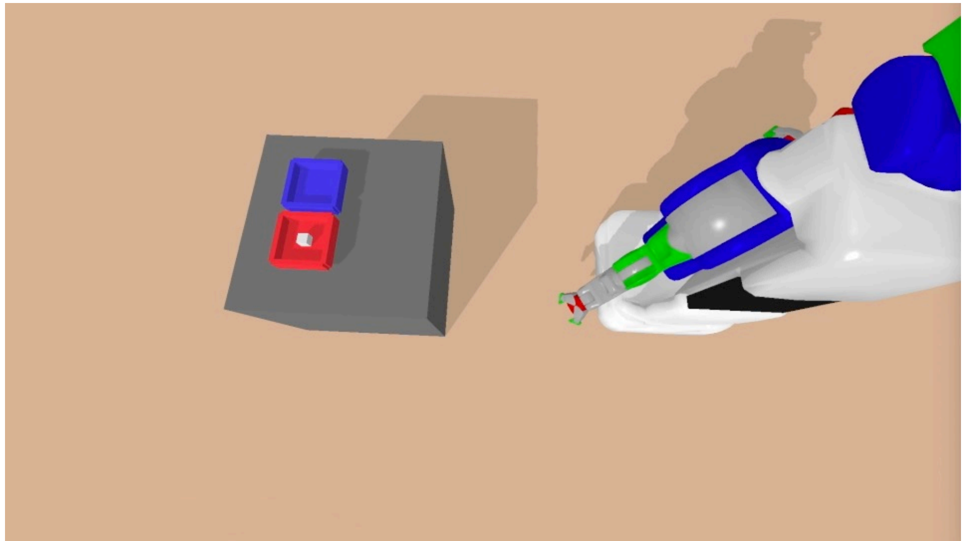
Multi-modal motion planning:
a useful abstraction for many problems!

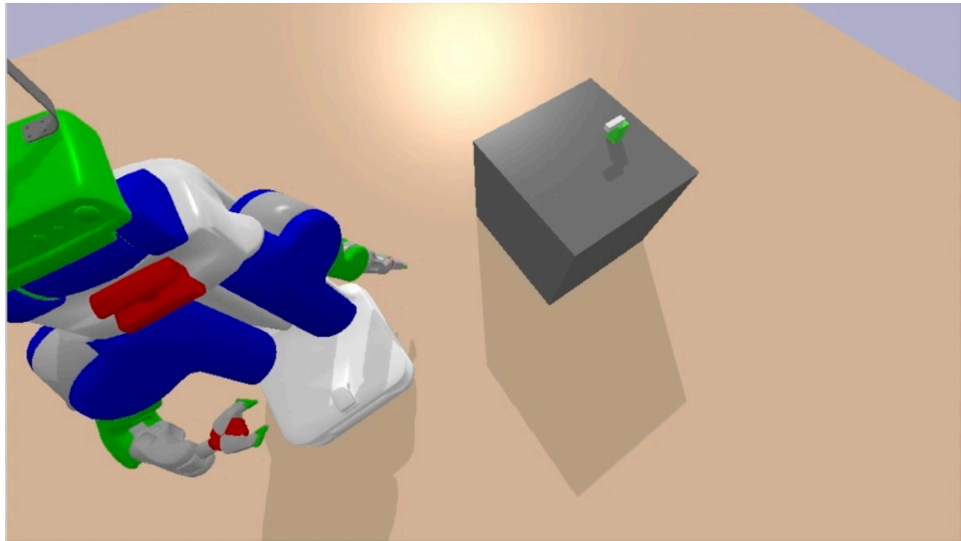
We model meta-world as a **lifted** MMMP with mode families:

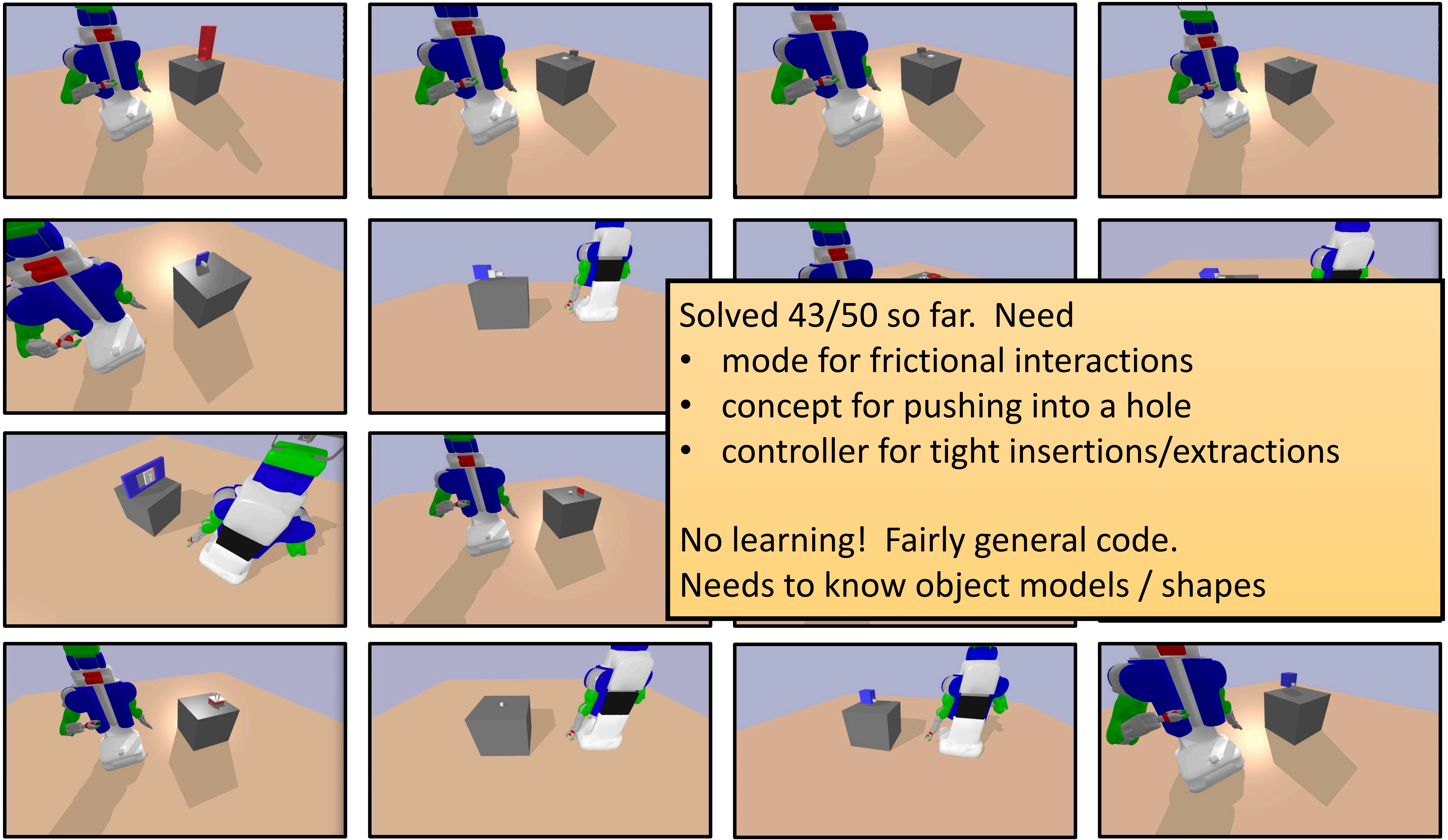
- free-space motion
- pick; move-holding; place
- touch; push; disengage
- grasp; operate; ungrasp

Easy to add new ones!









Solved 43/50 so far. Need

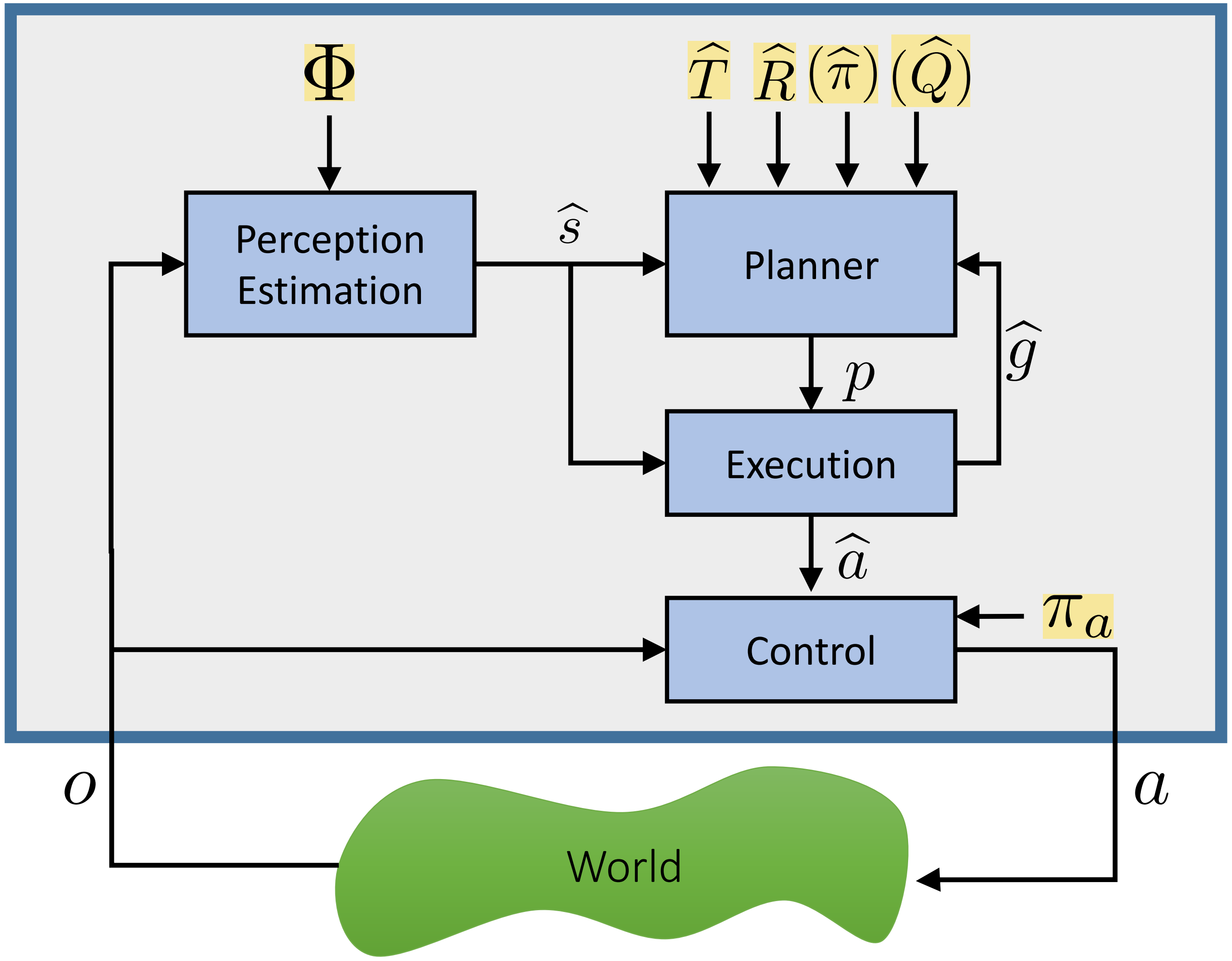
- mode for frictional interactions
- concept for pushing into a hole
- controller for tight insertions/extractions

No learning! Fairly general code.
Needs to know object models / shapes

Built-in mechanisms: planner, hierarchical execution

Modules and models:

- control
  - basic pick and place controllers
- perception
  - object segmenters and
  - simple shape matching
- planning
  - operator models for basic controllers

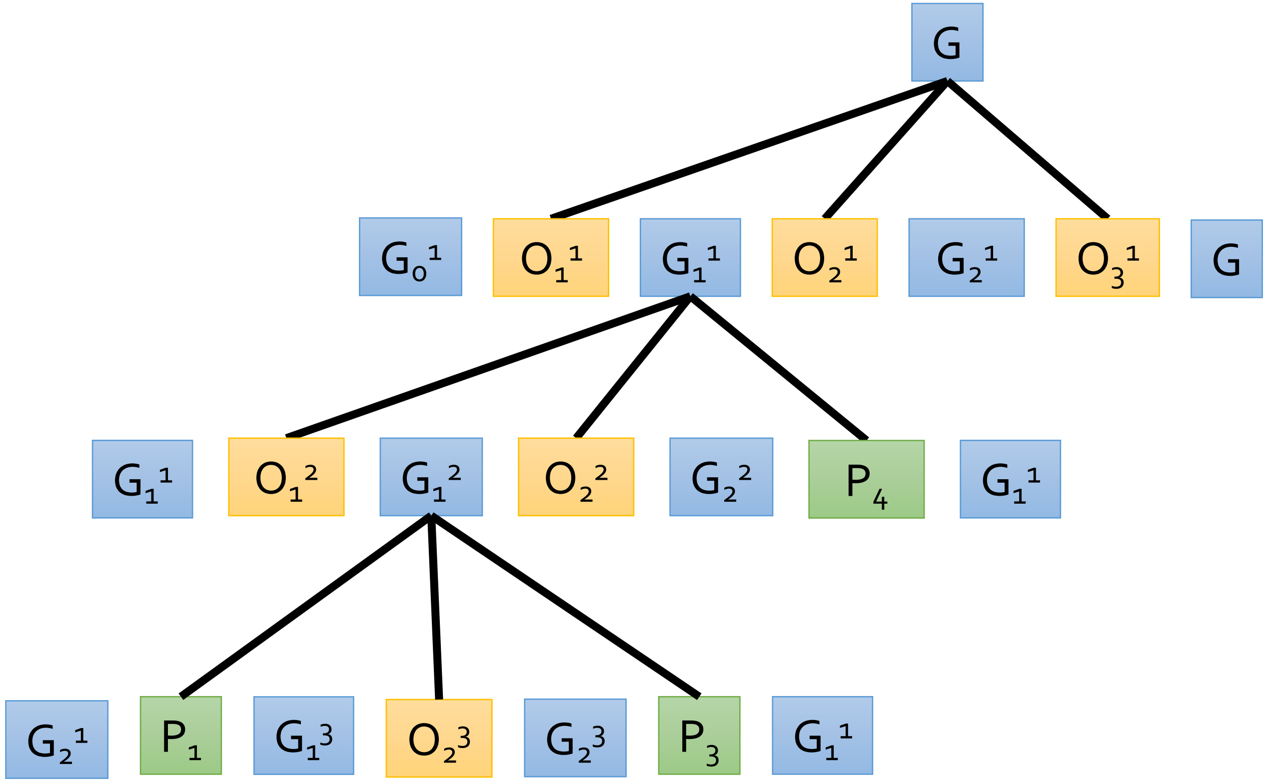


Hierarchical planning in the now

many short plans

optimistic execution

flexible reconsideration and replanning

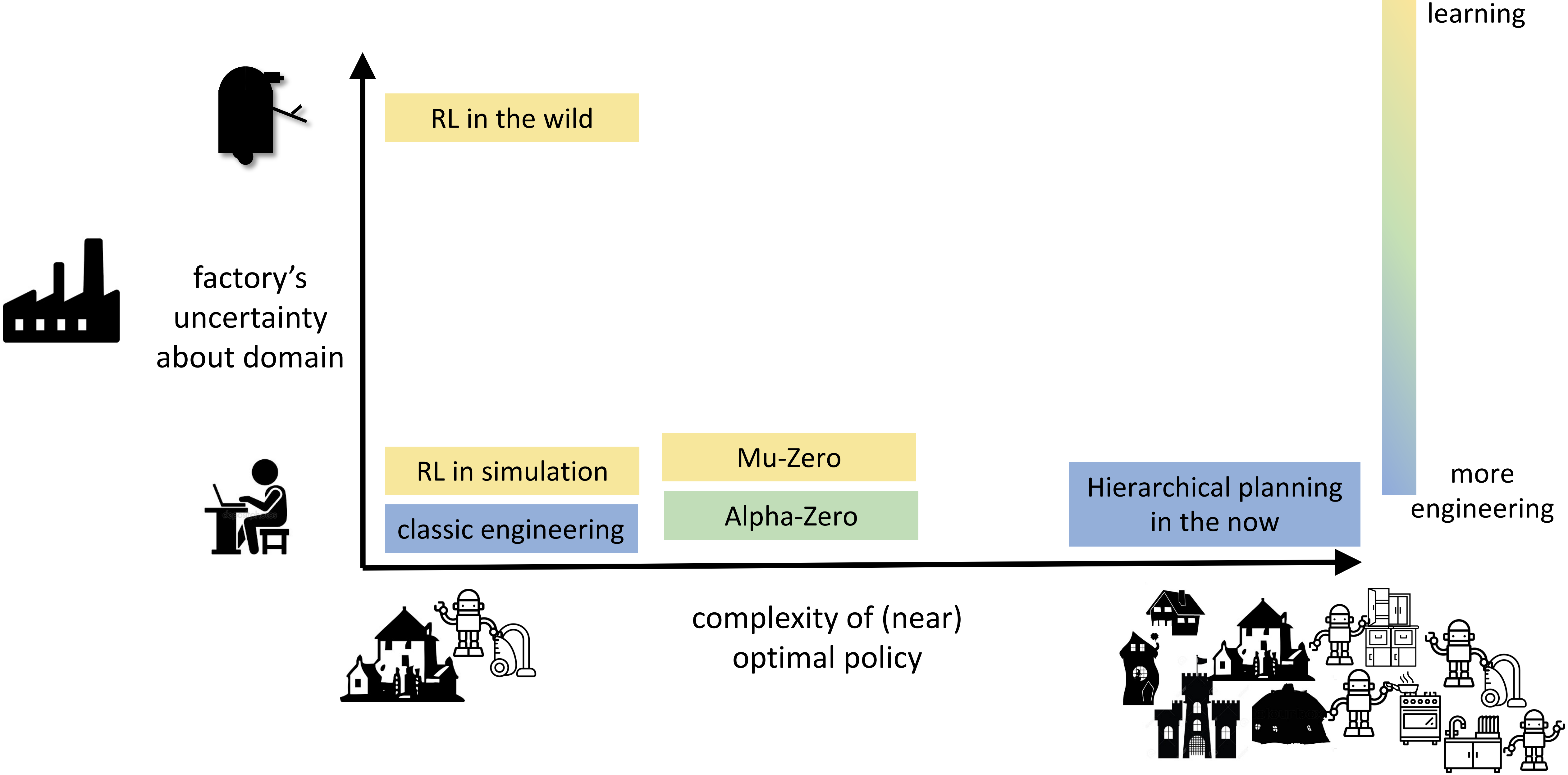


LPK and Lozano-Perez, IJRR 2013

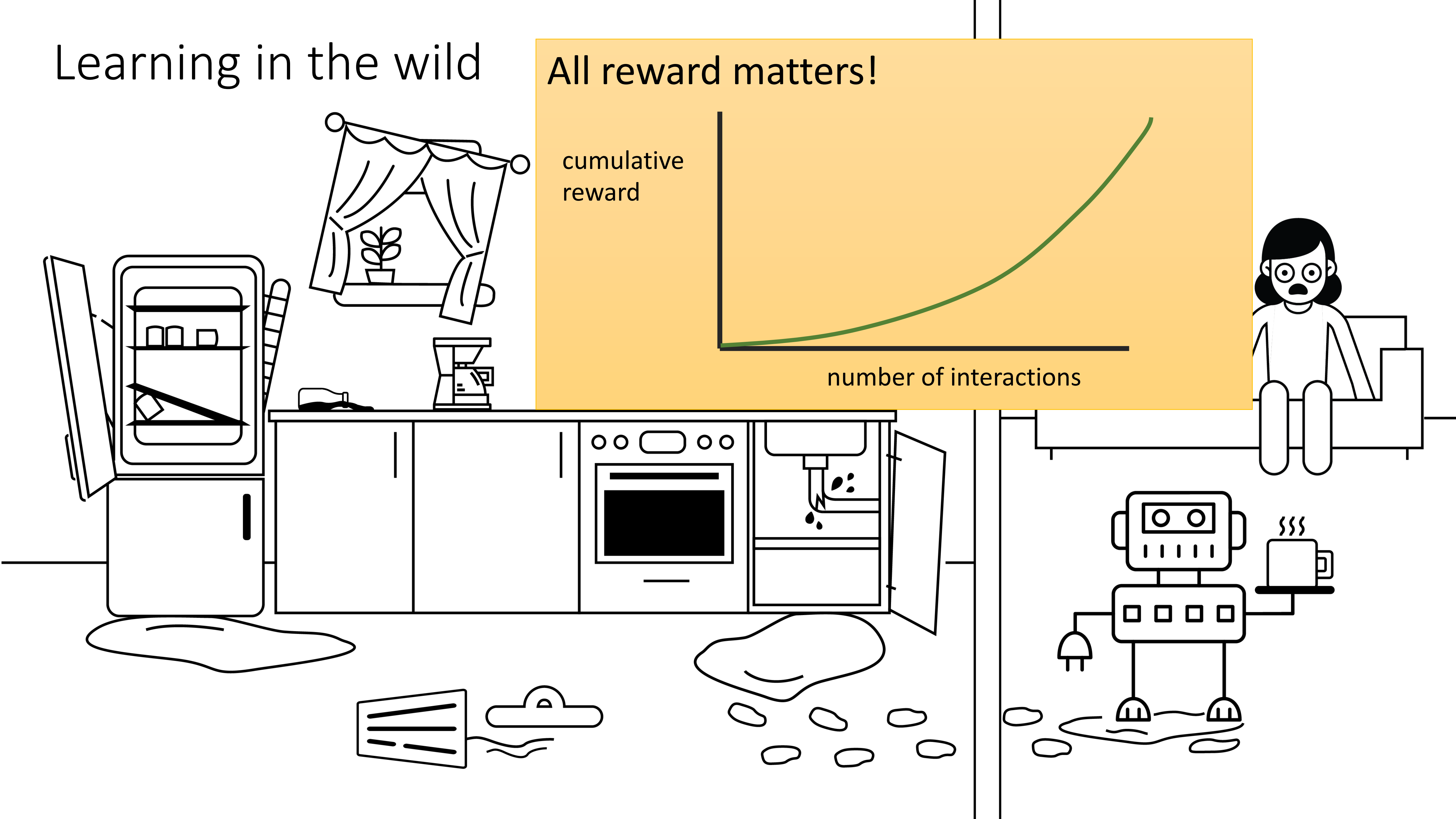
Hierarchical planning in the now

Only learning was done by lpk and tlp, not the robot!

Domain uncertainty requires learning in the wild



Learning in the wild



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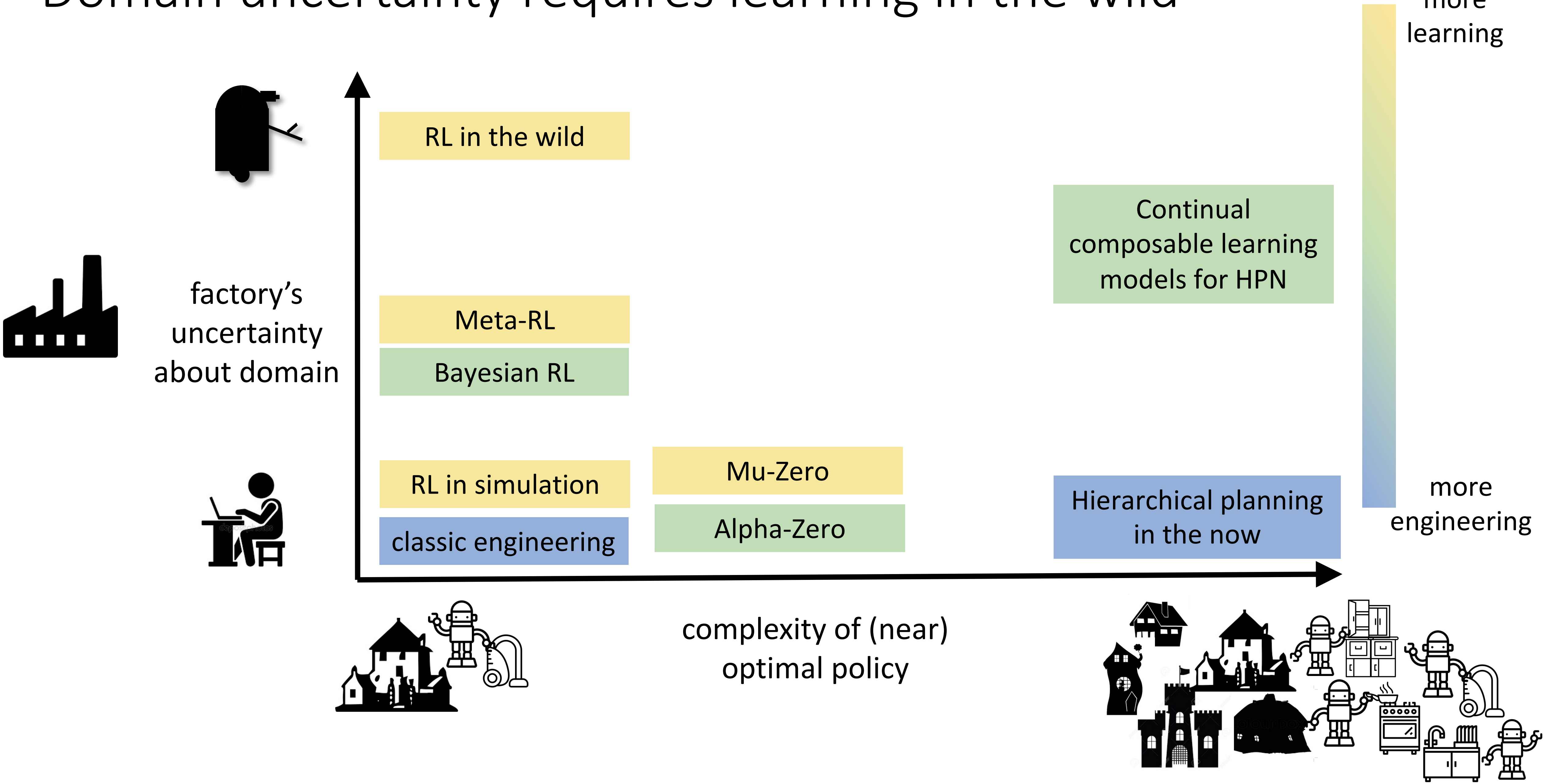
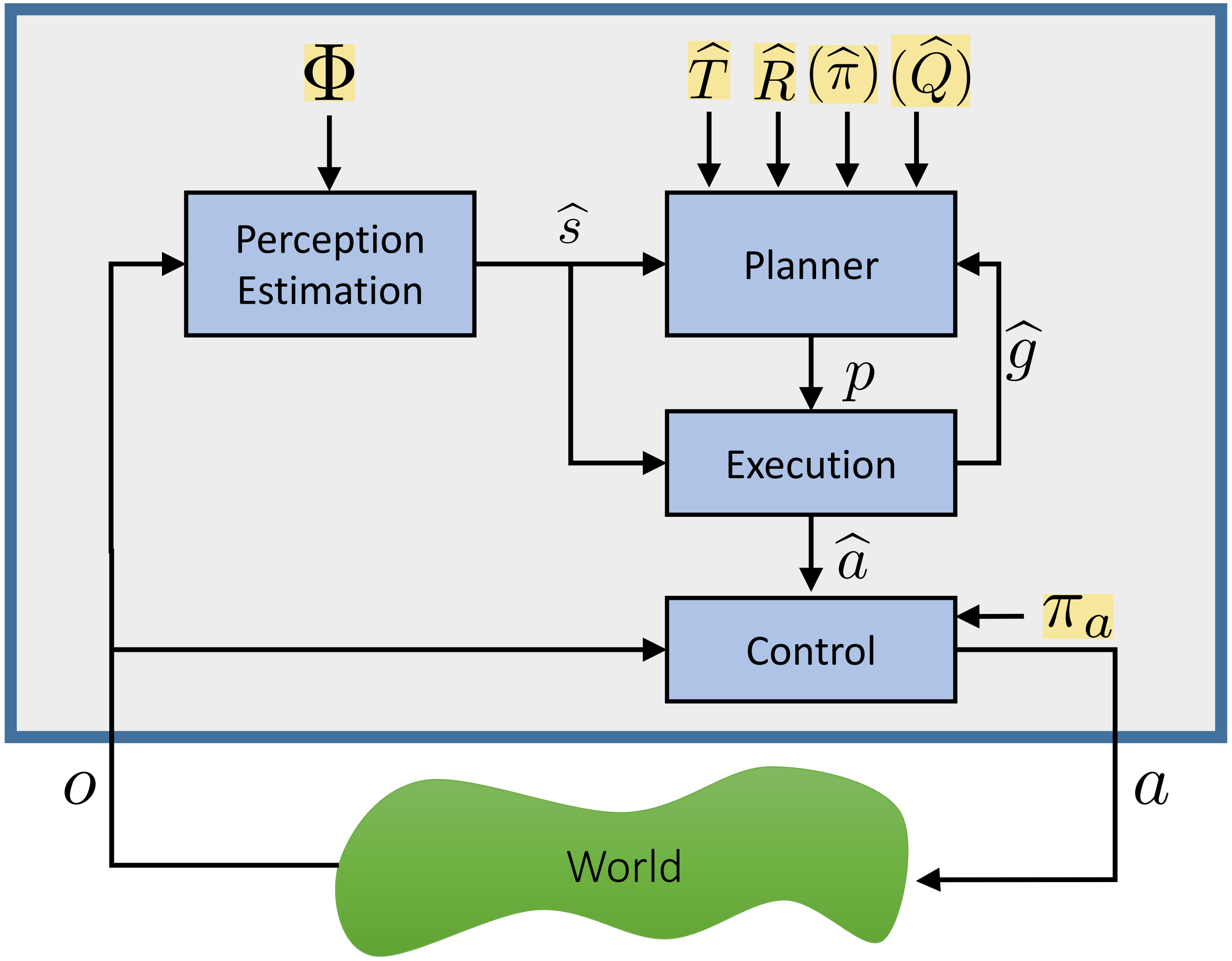


Now, what can we learn?

Modules and models:

- control
  - sensorimotor controllers
- perception
  - object segmenters and
  - feature detectors
- execution
  - abstract **partial** polices
- planner
  - operator models for controllers and policies



Now, what can we learn?

Modules and models:

- control
    - sensorimotor controllers
- perception
    - object segmenters and
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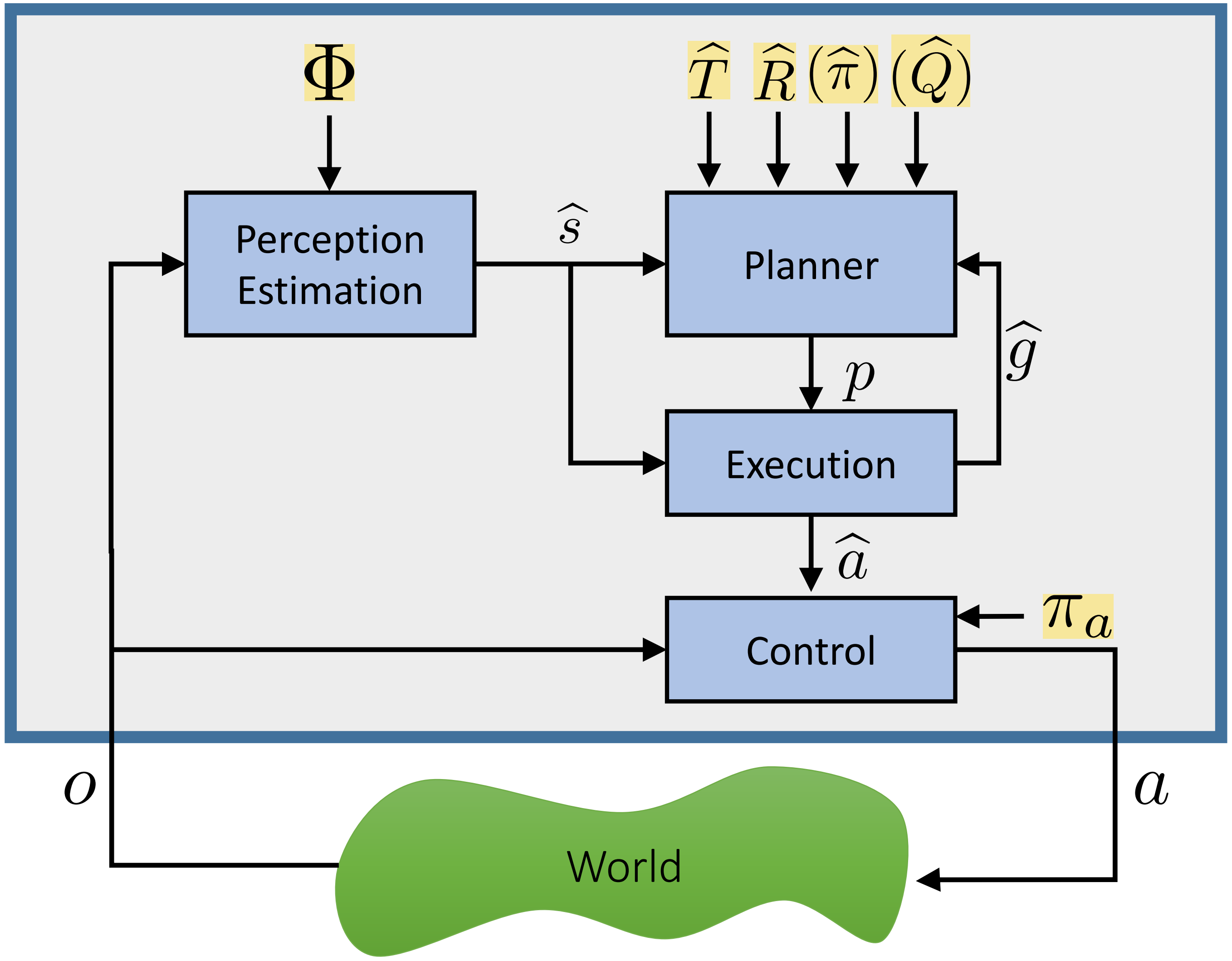
- execution
    - abstract **partial** polices
- planner
    - **operator models for new controllers and policies**

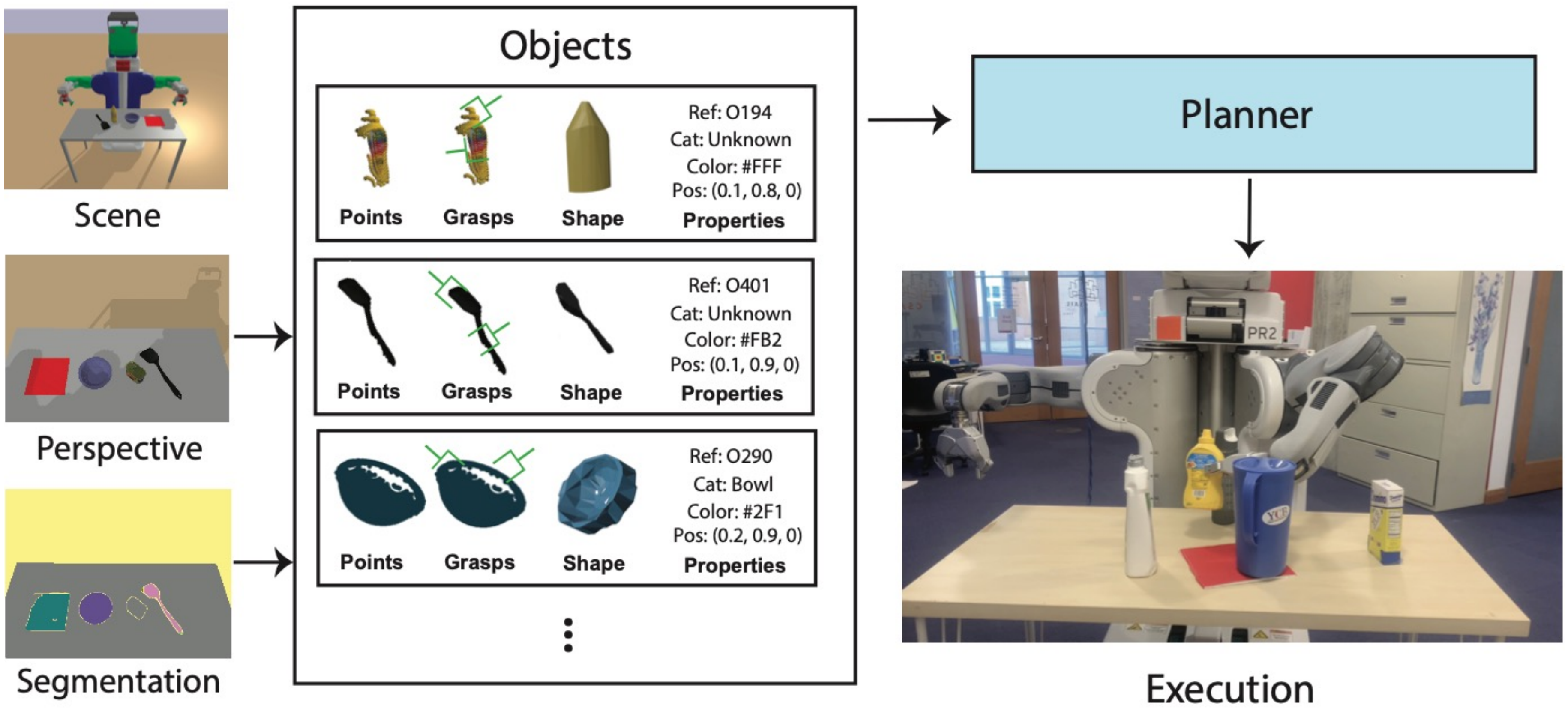


Curtis, Fang, Garrett, LPK, Lozano-Perez

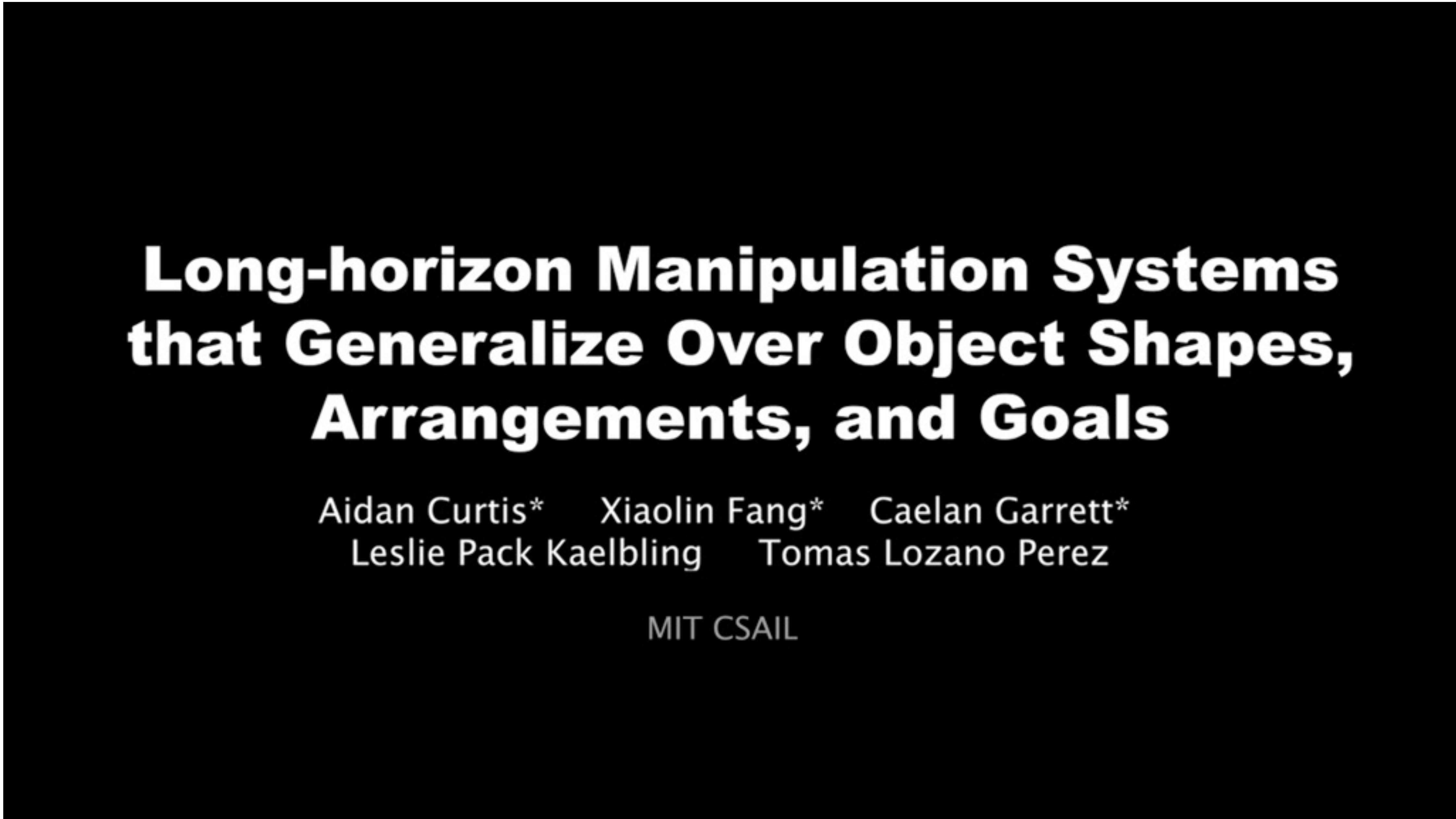
M0M: Manipulation with 0 Models

We
- believe in objects (for now restricted to be rigid)
- know the robot kinematics, and an abstract multi-modal model for pick/place/push

Use **pre-trained** perception modules
- **UOIS-Net** for class agnostic (!) segmentation [Xie et al, 2020]
- **GPD** to predict grasps [Gualtieri et al, 2016]
- **MSN** for point-cloud shape completion [Liu et al, 2020]
- **MaskRCNN** for some category detections [He et al, 2017]



Look M0M, no additional learning!



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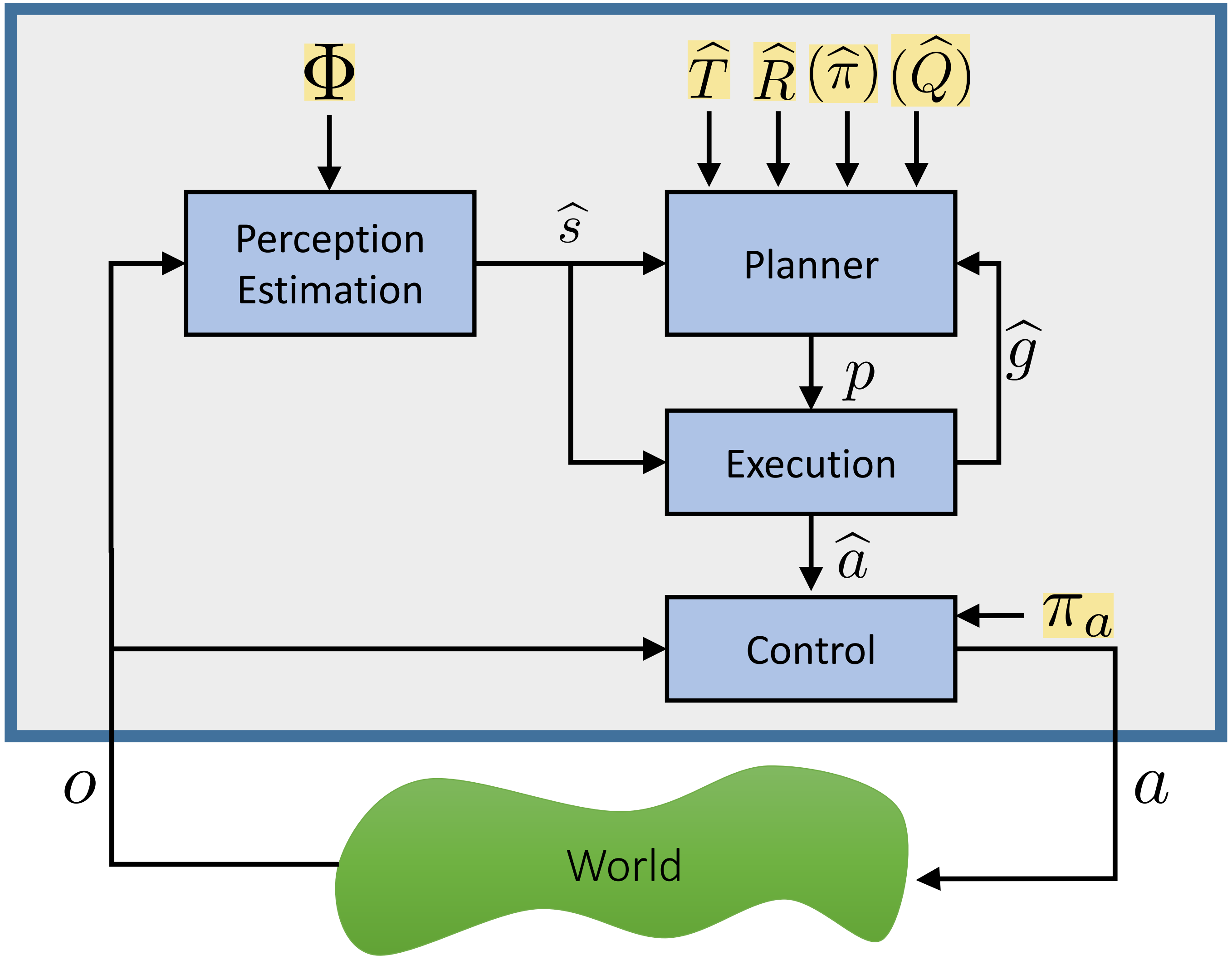


How can a **competent** robot acquire a new ability?

- Learn new primitive skill
  - Examples: Cutting, pushing, stirring, pouring, throwing
  - Closed-loop low-level policy intended to achieve some objective, possibly parameterized

Most robot learning: assume given

- Add that skill to existing skill set to accomplish new goals!
  - For flexibility, use a general-purpose planner
  - Learn description of skill's preconditions and effects
  - Representation should generalize over objects, locations, etc.

Our focus

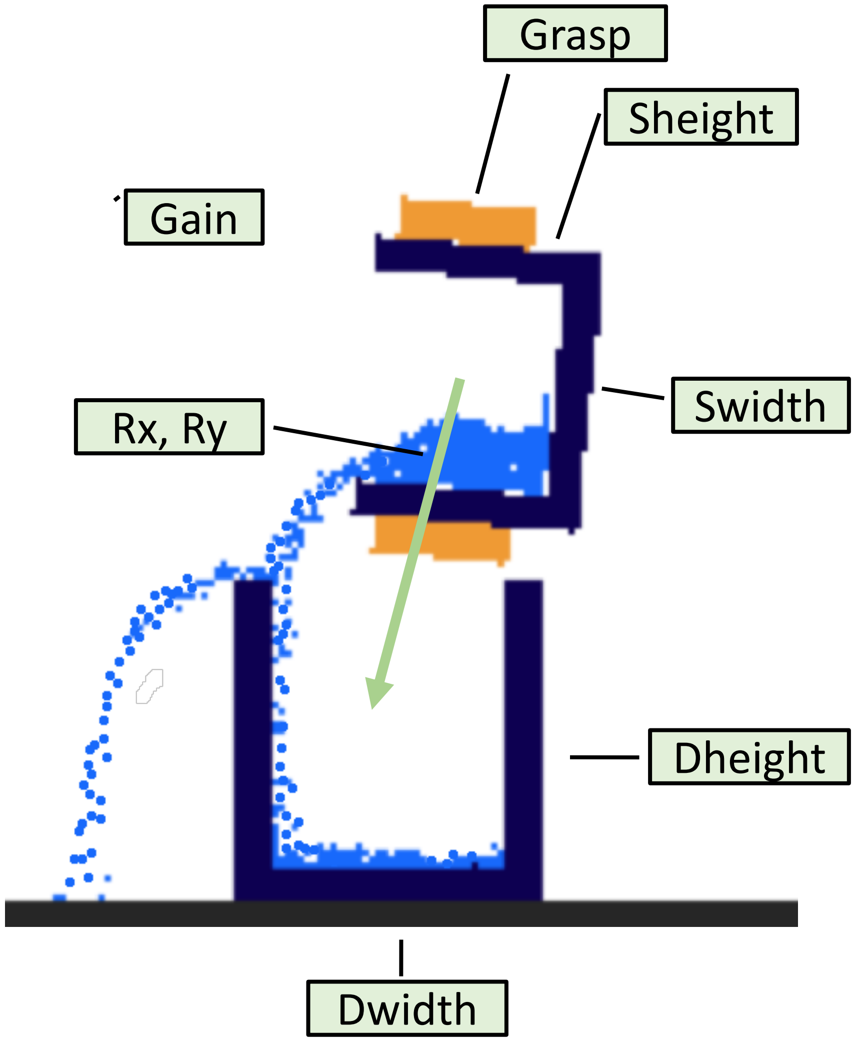
Operator description: when will **skill** achieve **result**?
Generalized idea of mode switch

Result: Contains(Dest, Liquid)

Skill: Pour(**Gain**)

Preconditions:

- Contains(Source, Liquid)
- Holding(Source, **Grasp**)
- Shape(Source) = (**Swidth, Sheight**)
- Shape(Dest) = (**Dwidth, Dheight**)
- RelPose(Source, Dest) = (**Rx, Ry**)
- **Constraint(Sw, Sh, Dw, Dh, Rx, Ry, Grasp, Gain)**

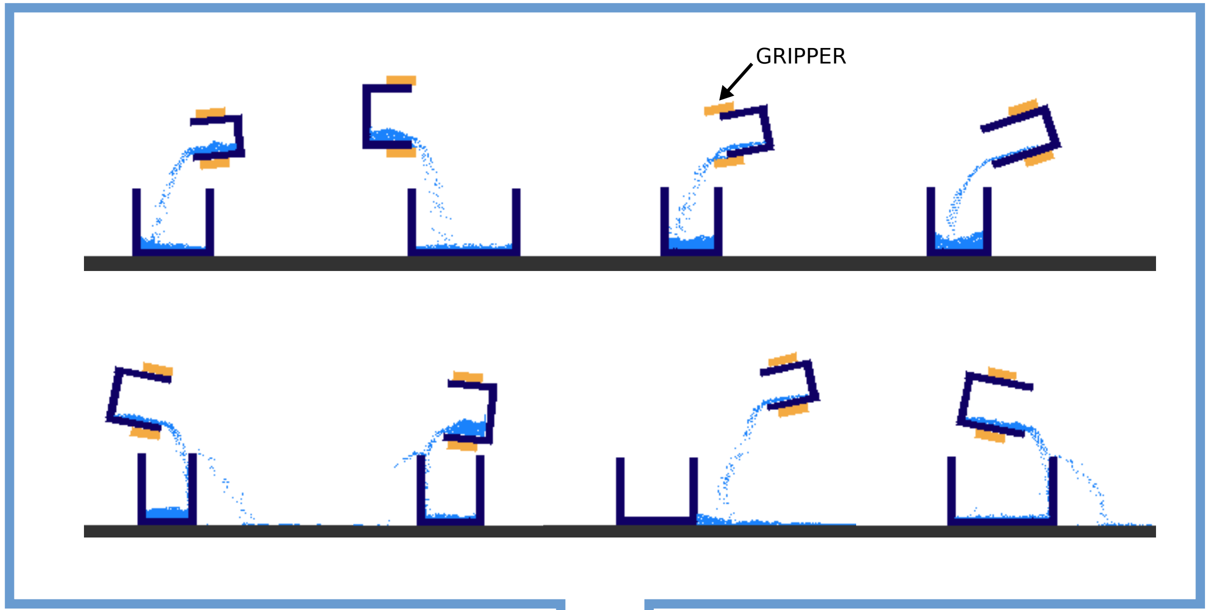


Wang, Garrett, LPK, Lozano-Perez, IROS 2018

Learning the operator constraint: supervised training

$$\text{constraint}(\theta) \equiv g(\theta) > 0$$

labeled training data



Sw, Sh, Dw, Dh, Rx, Ry, Grasp, Gain

θ

Gaussian Process Regression

score

$g(\theta)$

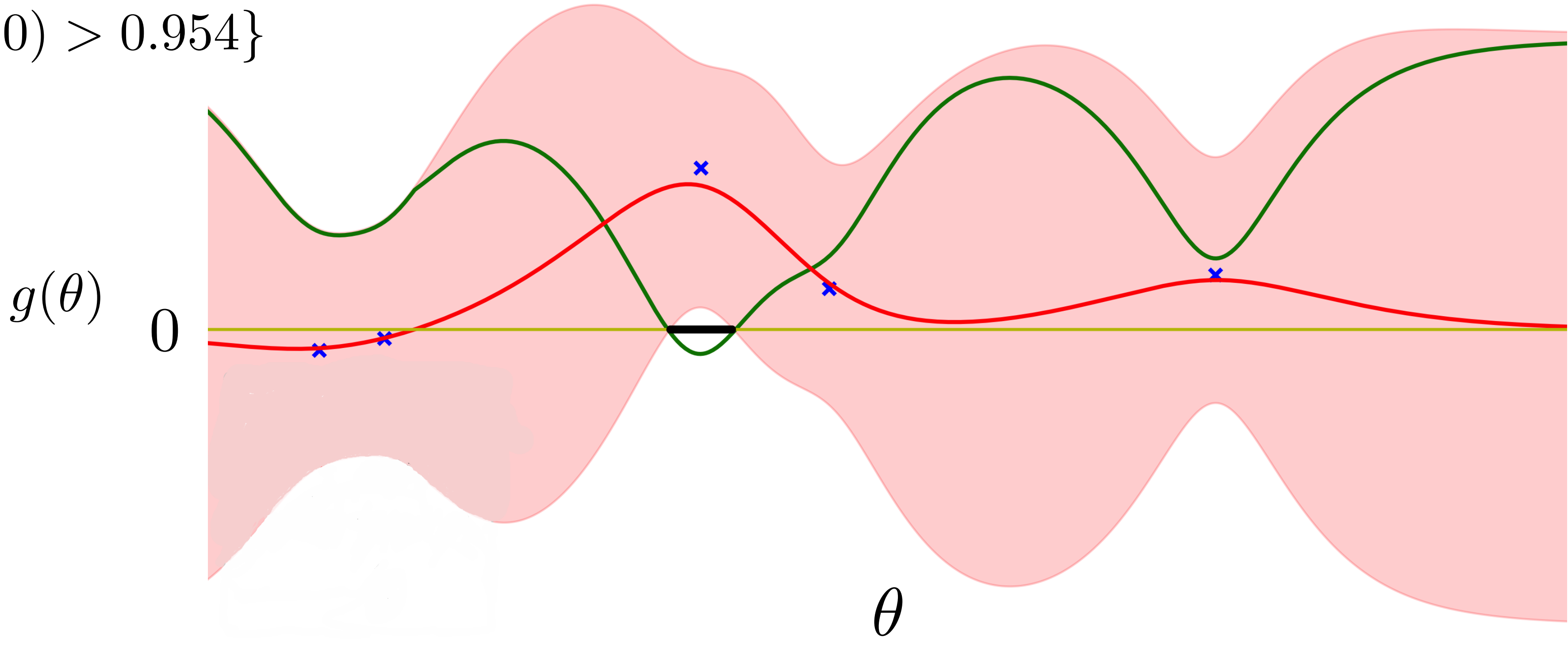
Gaussian process regression

Represent distribution over functions!

$$\text{constraint}(\theta) \equiv g(\theta) > 0$$

- ✕ : observations $(\theta_i, g(\theta_i))$
- — : mean $\mu(\theta)$
- ■ : stdev $\mu(\theta) \pm 2\sigma(\theta)$
- — : high probability super level set

$$\{\theta \mid P(g(\theta) > 0) > 0.954\}$$



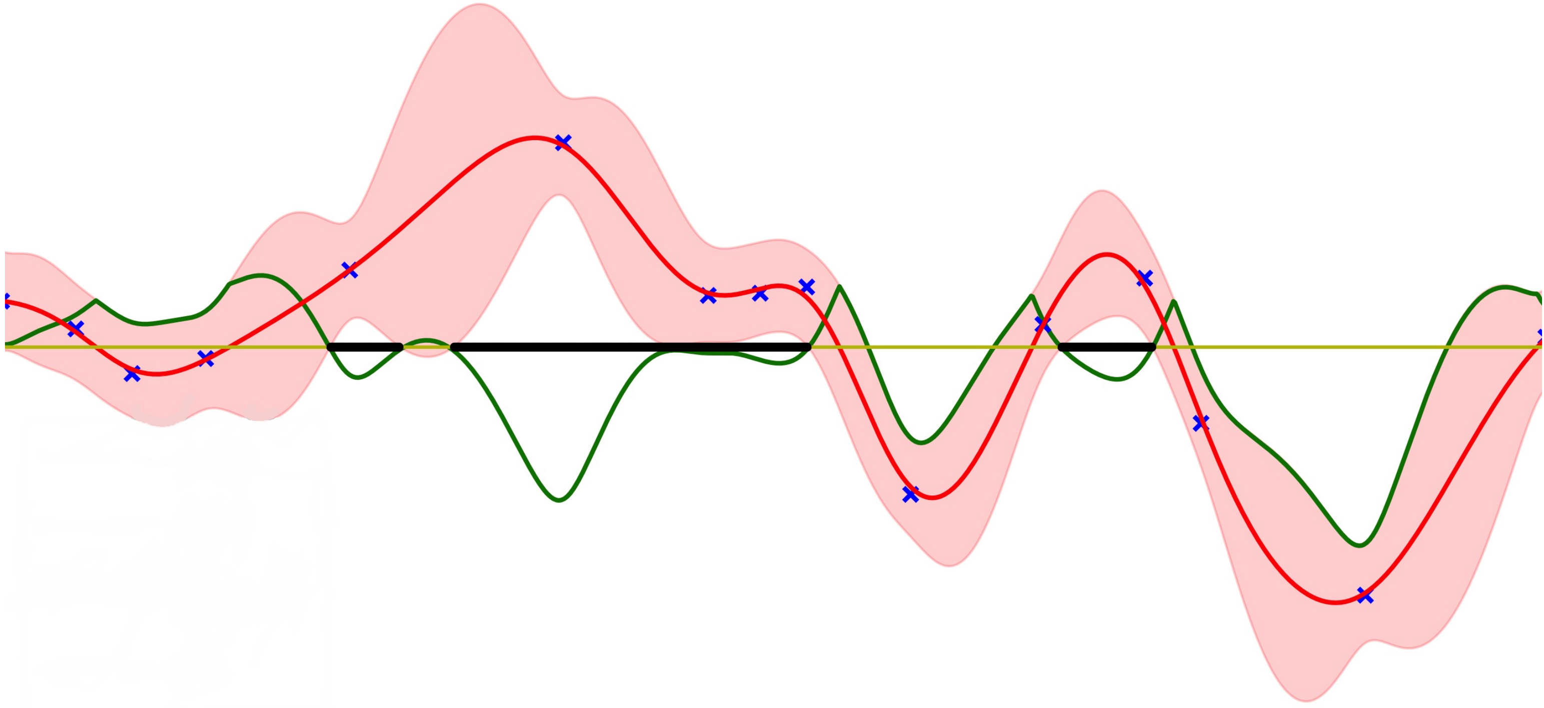
Active learning: robot experience is expensive!

Try pouring in situations that will give us the **most useful** information

- sample to maximize **acquisition function**

$$\phi(\theta) = 2\sigma(\theta) - |\mu(\theta)|$$

- high values when
  - mean is close to 0
    (near a boundary)
  - stdev is high
    (uncertain about the value)
- —: $\phi(\theta)$

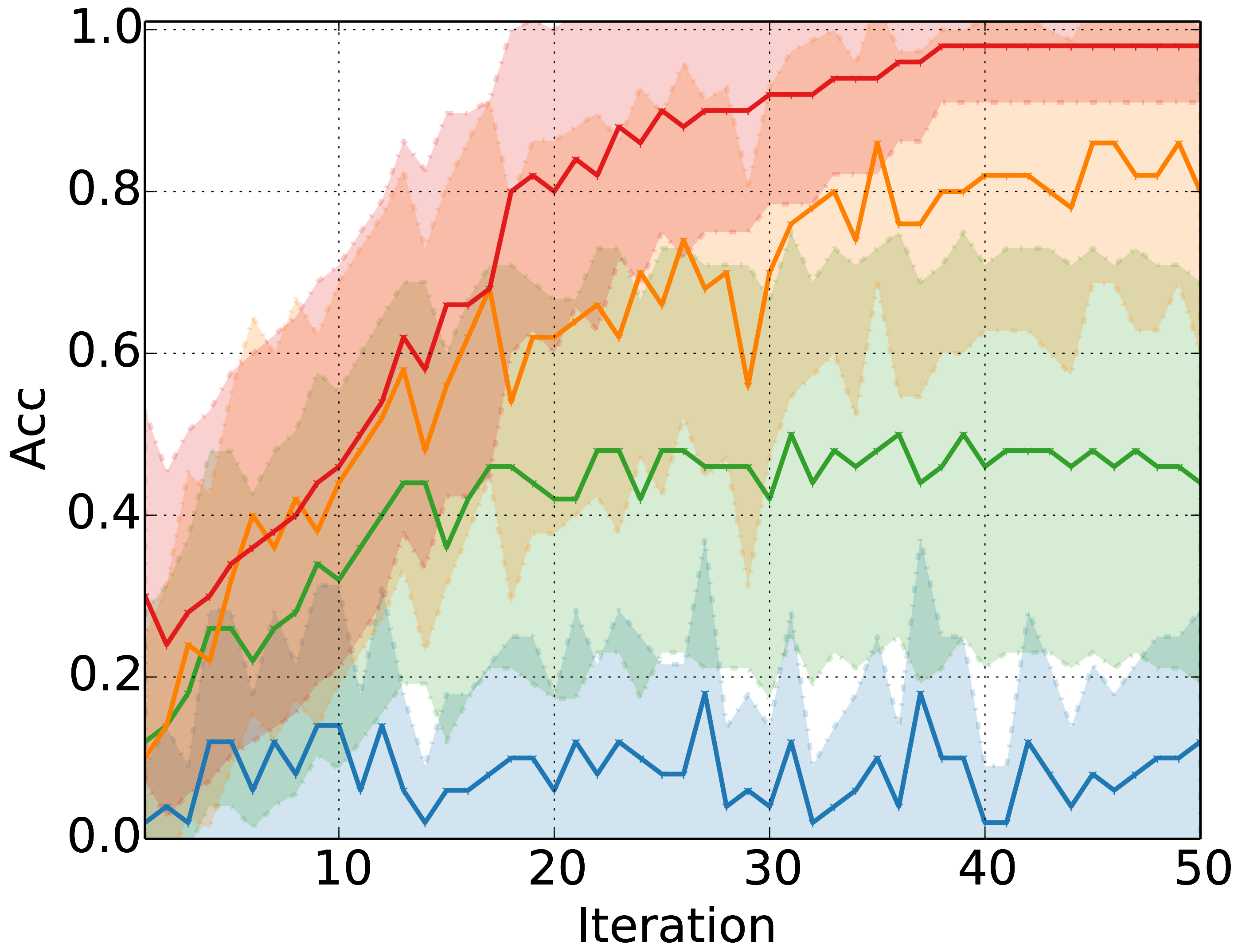


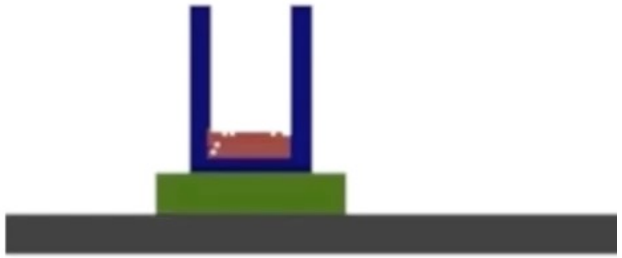
Straddle algorithm, Bryan et al, NIPS 2016

GP learning is data efficient and better for sampling!

Percent successful **pouring** actions as a function of the **number of training examples**

- : randomly chosen
- : neural network classifier
- : neural network regression
- : GP active learning

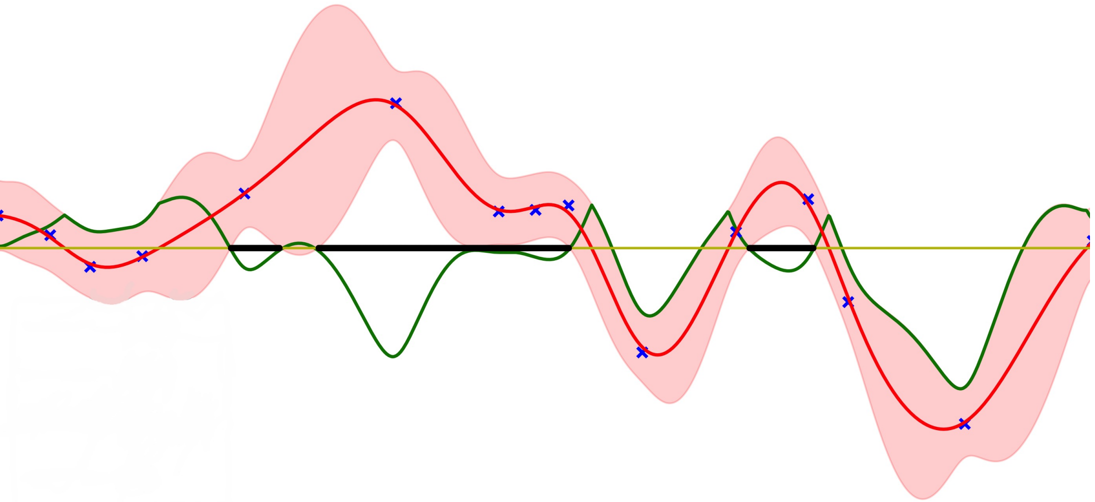


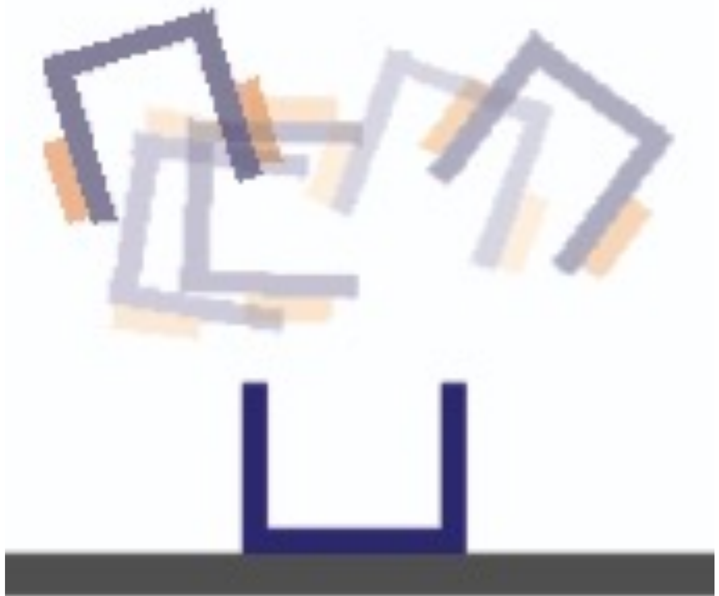


Sampling for planning: quality and diversity

Given values for some parameters, sample values of the others so that:

- action is likely to be successful
  - start with most likely to succeed: $\arg\max_{\theta} \frac{\mu(\theta)}{\sigma(\theta)}$
  - continue with guided rejection sampling in super level set
- action differs from previous attempts $D(S) = \log\det(\Xi^S + I)$





Training on real robot is expensive!

Note that we do grasp and motion planning during data acquisition!

Integrated results on real robot

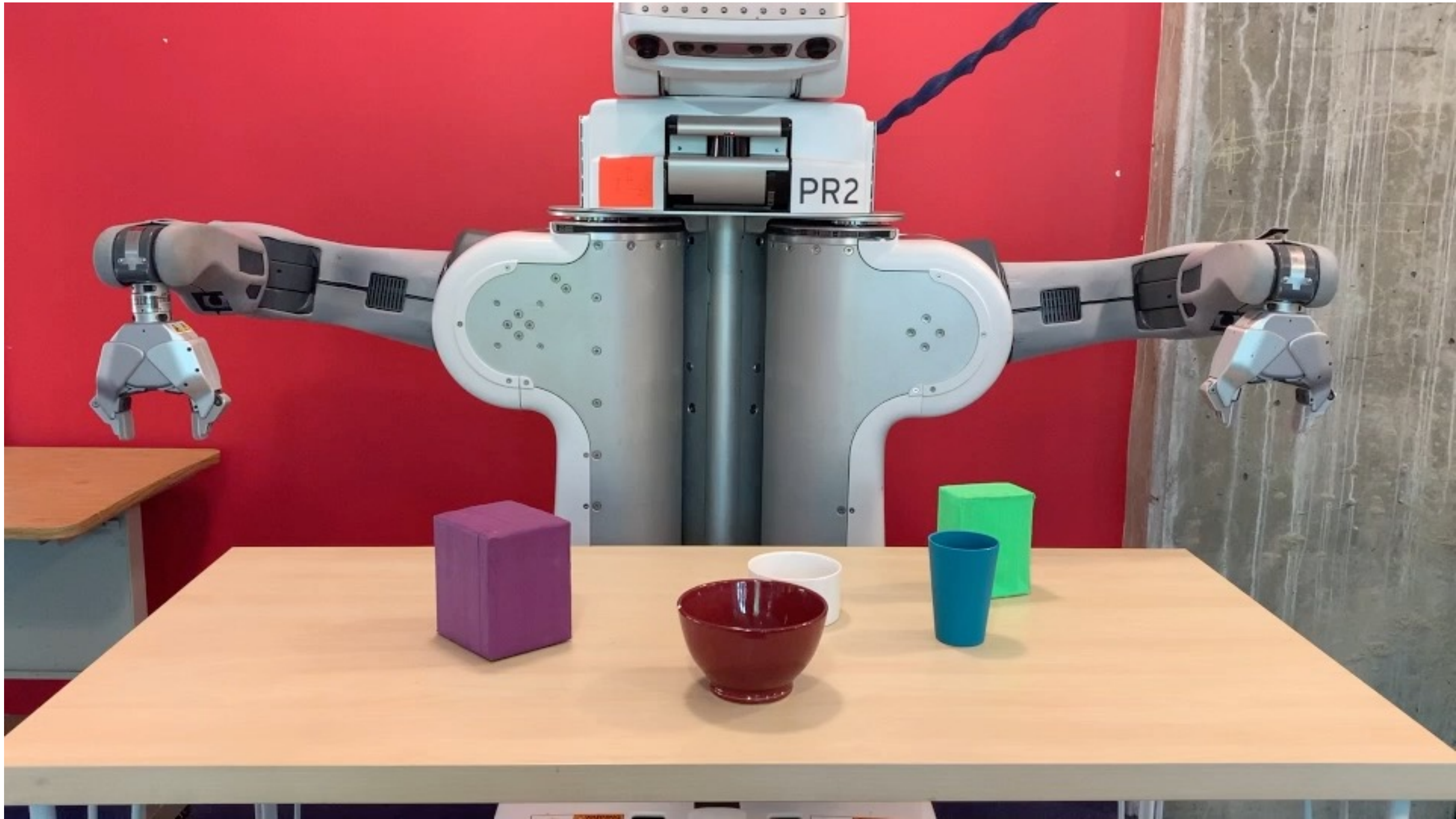
Substantial variability in

- starting arrangement
- goal

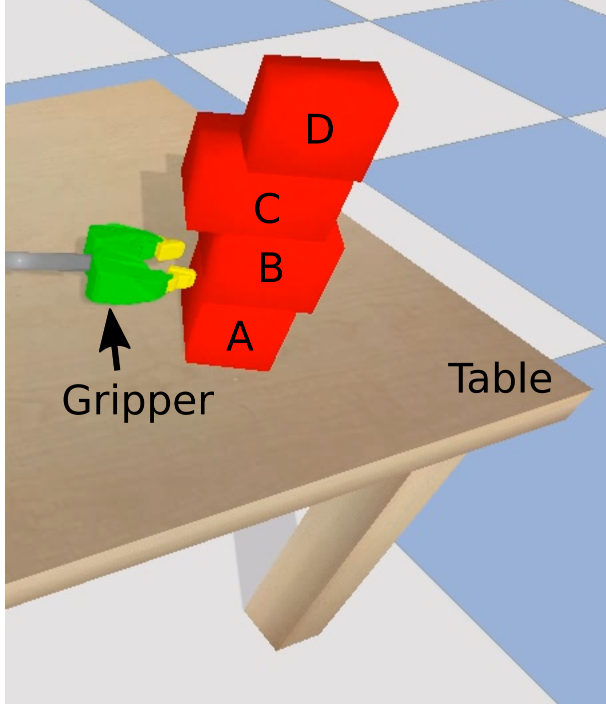
Given pick/place operators

Learned pour and push

PDDLStream planner

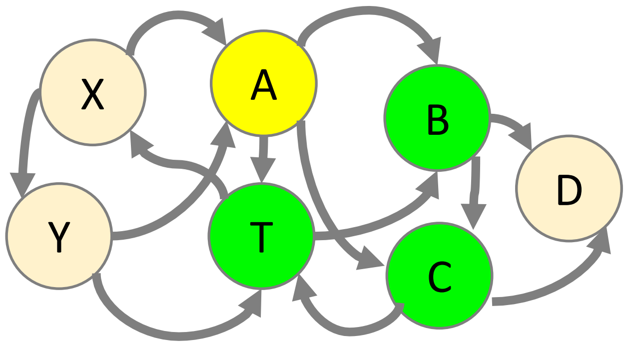


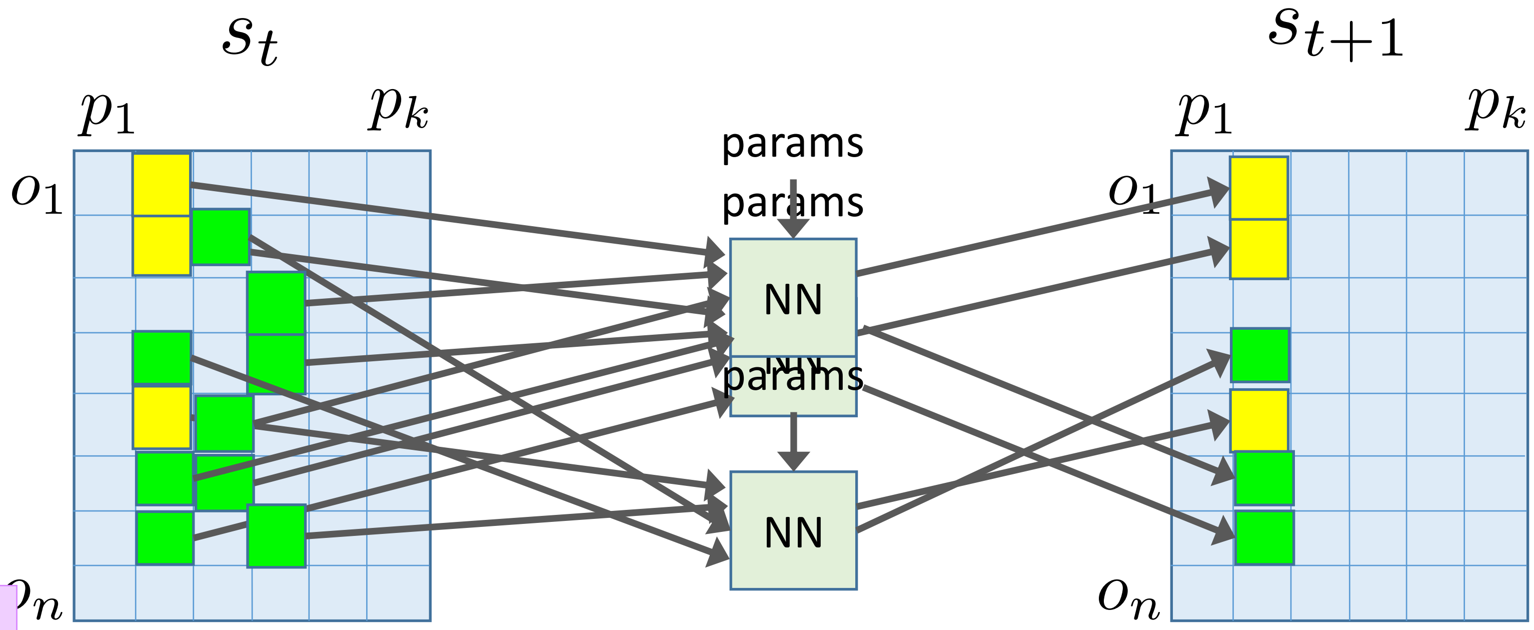
Deictic rule: "lifted" neural network



Like a graph neural-network, in that

- finite size neural network "kernel"
- can be applied to inputs and outputs of different dimension
- generalizes over object identity



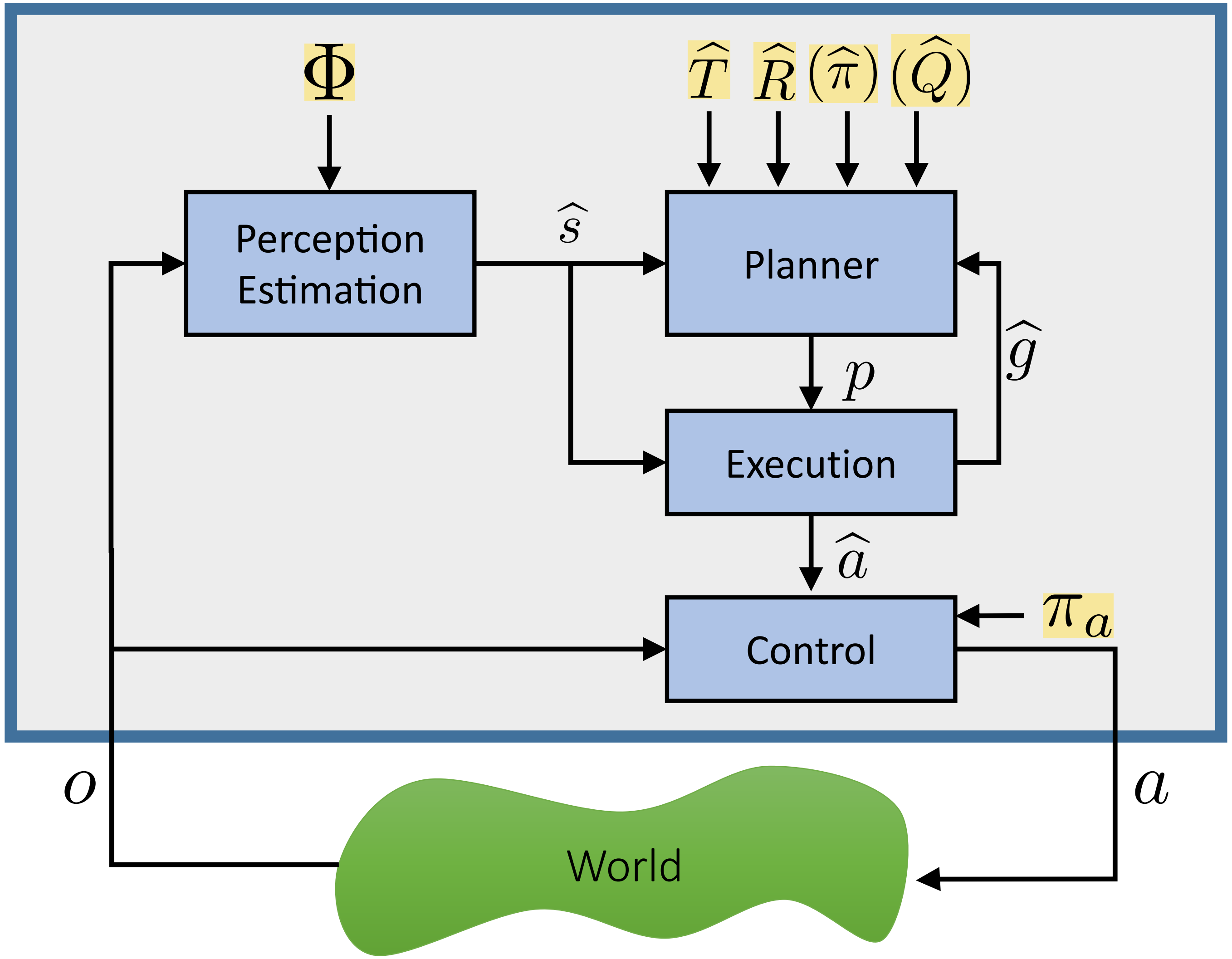


Xia, Wang, Allen, Silver, K, ICLR19

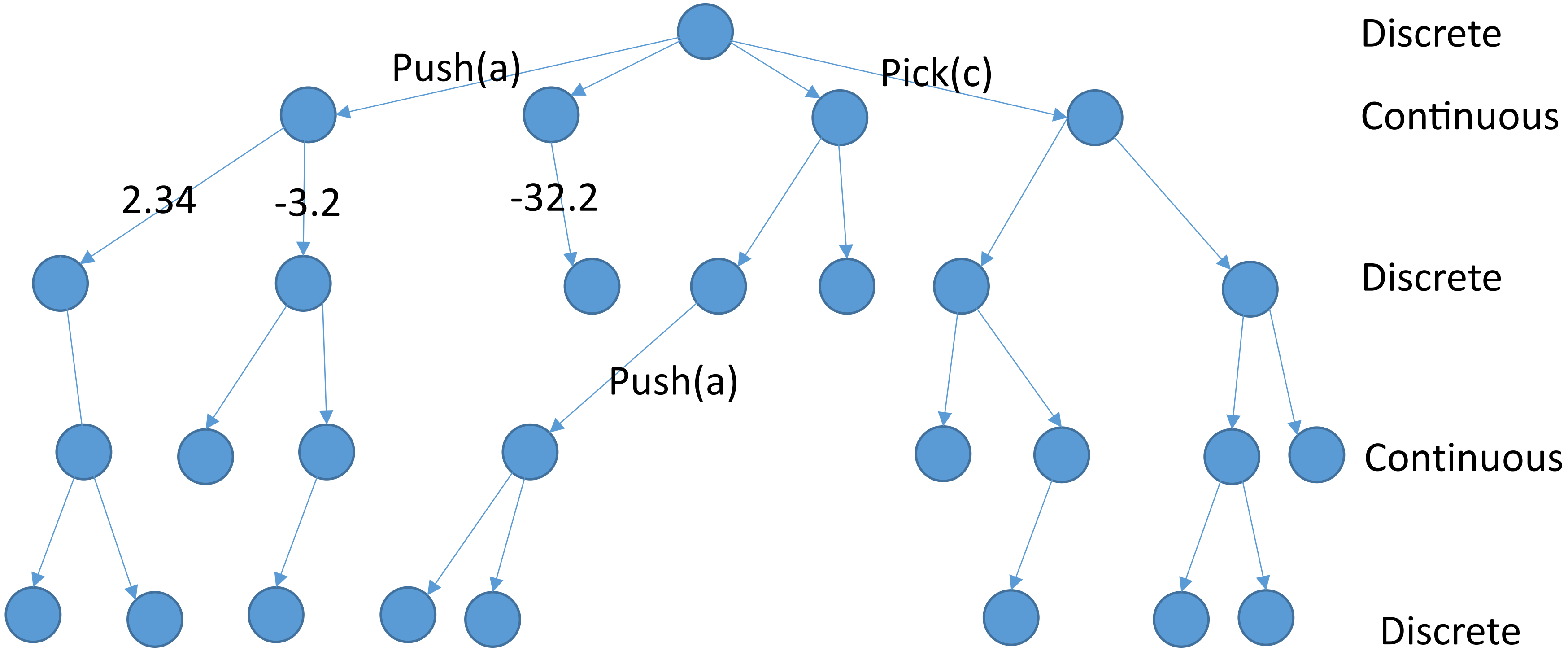
Now, what can we learn?

Modules and models:

- control
  - sensorimotor controllers
- perception
  - object segmenters and
  - feature detectors
- execution
  - abstract **partial** polices
- planner
  - operator models for controllers and policies
  - search control Q



One class of task and motion planning methods: sample-based forward search



Branching factor: huge!

Discrete layer

- operation, objects

Continuous layer

- values in R^d

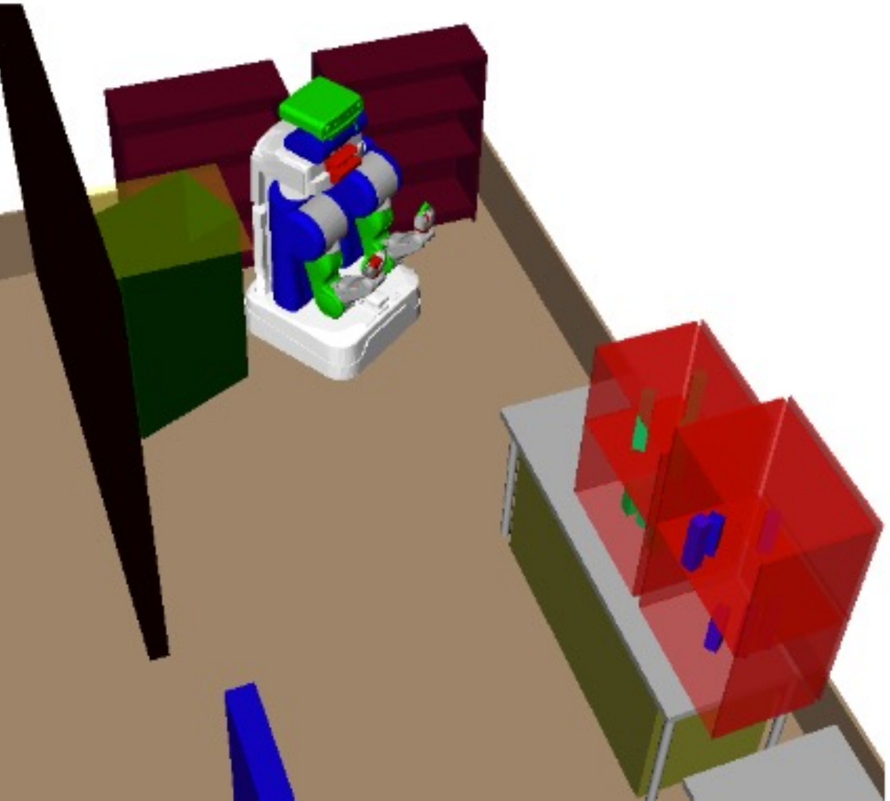
Node expansion: expensive!

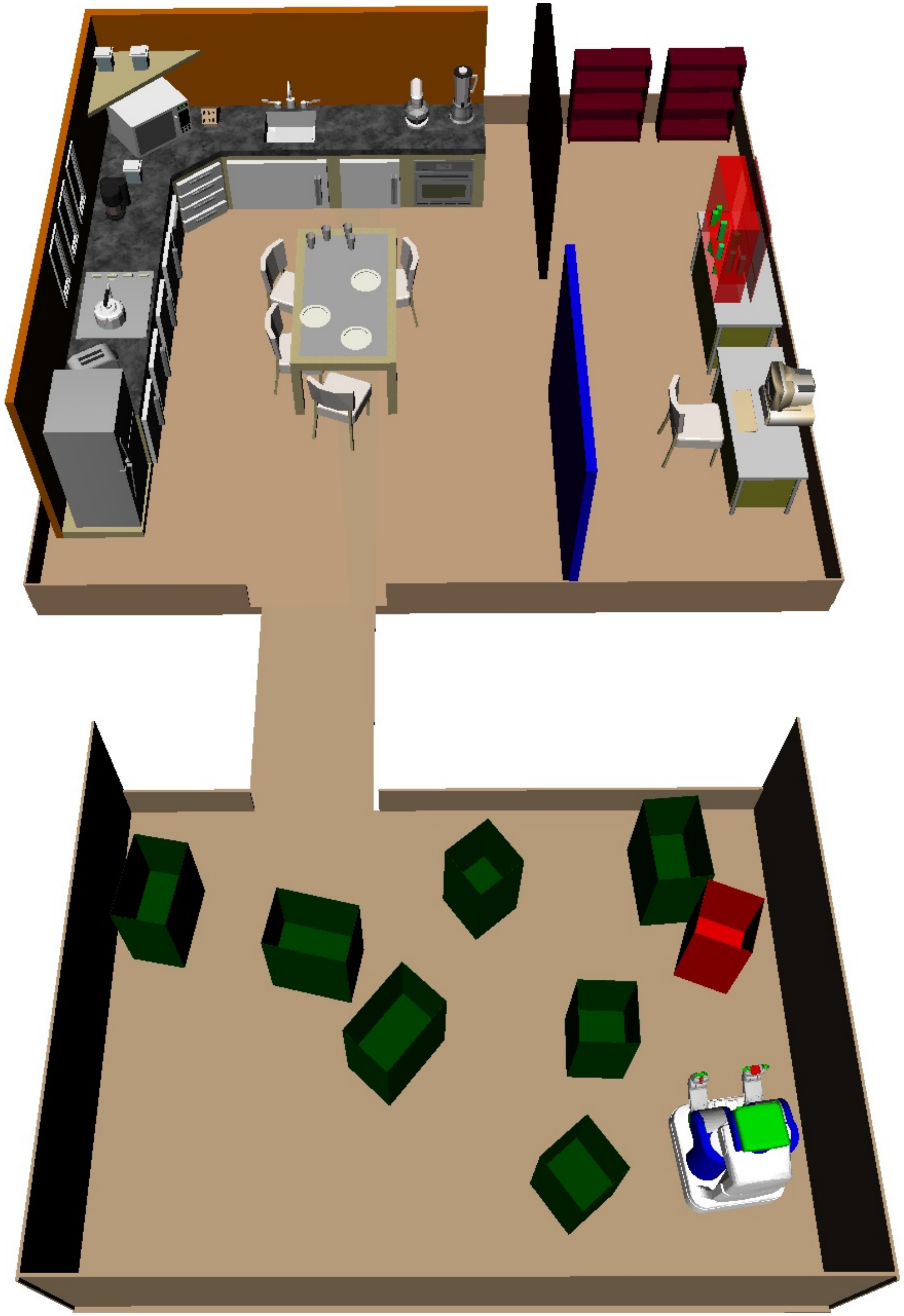
- inverse kinematics
- robot motion planning

Kim and Shimanuki, CORL 2019

Learning search control

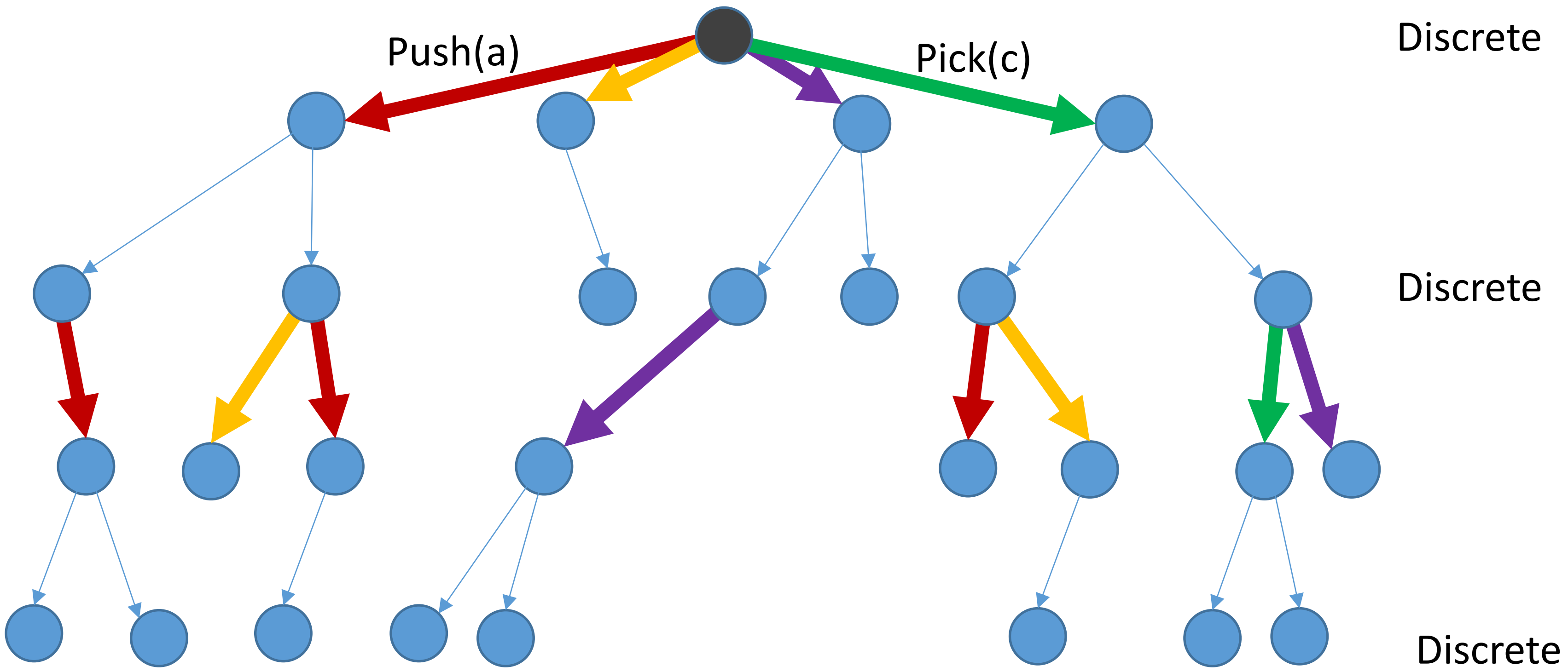
- Learning value function and policy worked great for AlphaZero!
- In our problem:
  - how to represent a state is much less clear
  - we need very **aggressive generalization**





Learn to predict value of abstract action choices

$$Q(s, a_{\text{discrete}}) = \sup_{a_{\text{continuous}}} Q(s, (a_{\text{discrete}}, a_{\text{continuous}}))$$

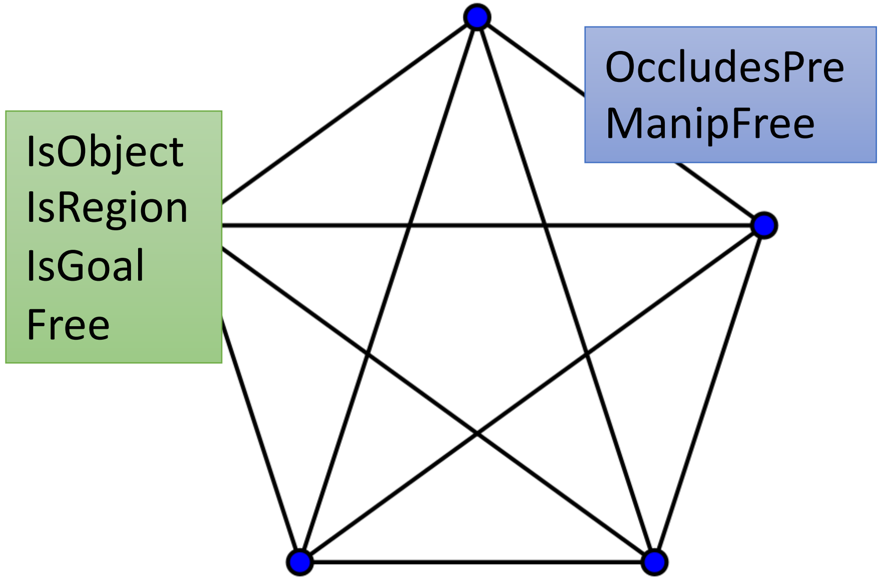


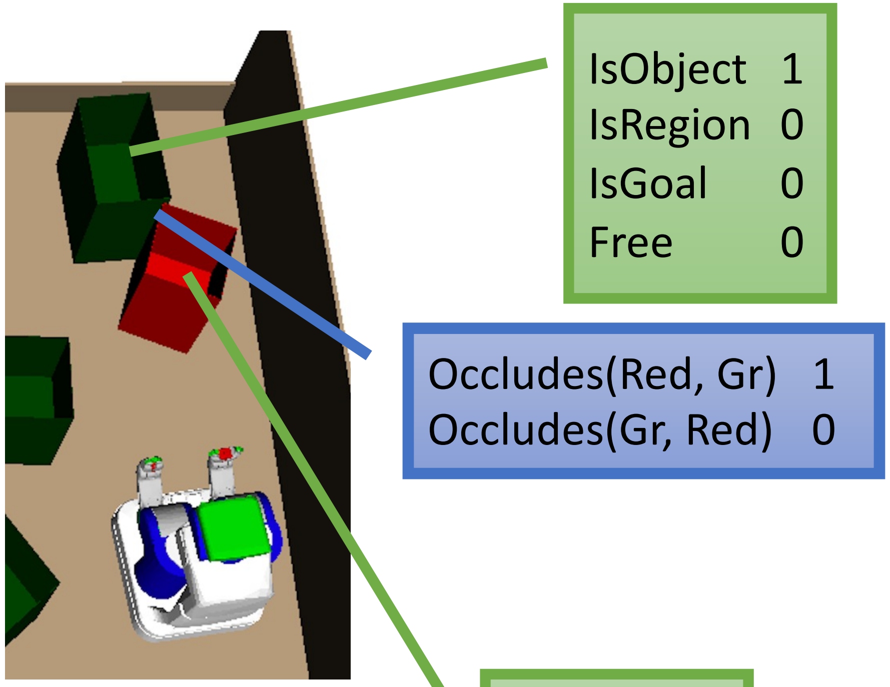
Reduce effective branching

Agenda contains (s,a) pairs

Abstract action values generalize well

Graph NN representation generalizes over scenes and goals





Graph neural network with fixed-size parameterization

- W1: map node and arc input to initial node state
- W2: map neighboring node states and arc inputs to message
- W3: map aggregate node states to predicted output

Use several rounds of message-passing to infer relational Q value

Training based on solving simple planning problems

Training data tuples: (s, g, op, q)

- squared loss for (s, g, op) in training data
- enforce margin Q(s, g, op') < Q(s, g, op) – 1 for op' not in training data

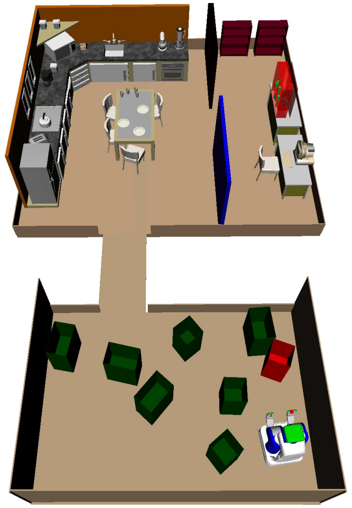
Square error on predicted Q value

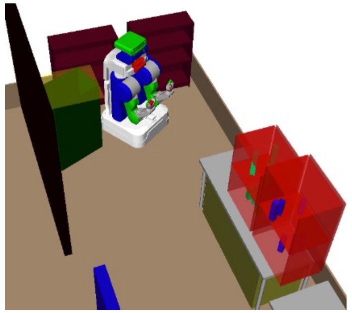
predicted Q value should be < Q value of action in training set

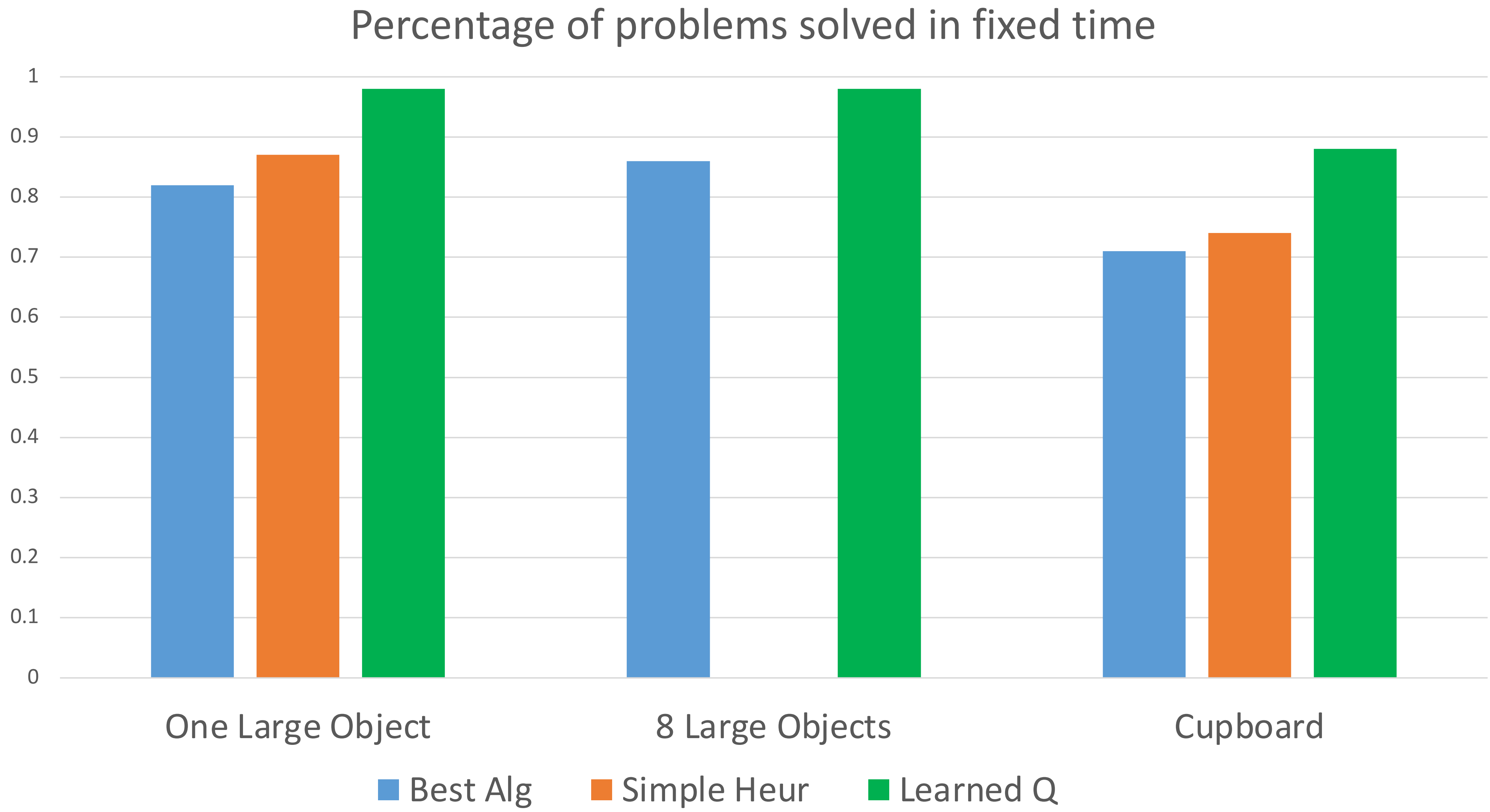
$$\mathcal{L}_{LM}(\theta) = \sum_{(s,\mathcal{G}\delta,q)\in\mathcal{D}_{\mathsf{o}}} (\widehat{Q}_{\mathsf{o}}(\alpha(s,\mathcal{G}),\delta;\theta) - q)^2 + \lambda \max(0, 1 - M_Q(\alpha(s,\mathcal{G}),\delta;\theta))$$

$$M_Q(\alpha(s,\mathcal{G}),\delta;\theta) = \widehat{Q}_{\mathsf{o}}(\alpha(s,\mathcal{G}),\delta;\theta) - \max_{\delta'\in\Delta\setminus\{\delta\}} \widehat{Q}_{\mathsf{o}}(\alpha(s,\mathcal{G}),\delta';\theta) \ .$$

Early results: trained only moving one large object







IJCAI 1997

IJCAI 2019

Conclusions

really enormously

- There has been major progress in algorithms for supervised and reinforcement learning
- This does not directly yield solutions for building generally intelligent autonomous agents
- Human insight is needed to complement the strengths of these algorithms

in the form of algorithmic and structural biases

Thanks to lots of people!

- Tomas Lozano-Perez
- Caelan Garrett
- Aidan Curtis
- Xiaolin Fang
- Beomjoon Kim
- Luke Shimanuki
- Zi Wang

Out-takes to watch during questions