
Hierarchical task and motion **Planning in the Know**

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Real robot meets real world: uncertainty



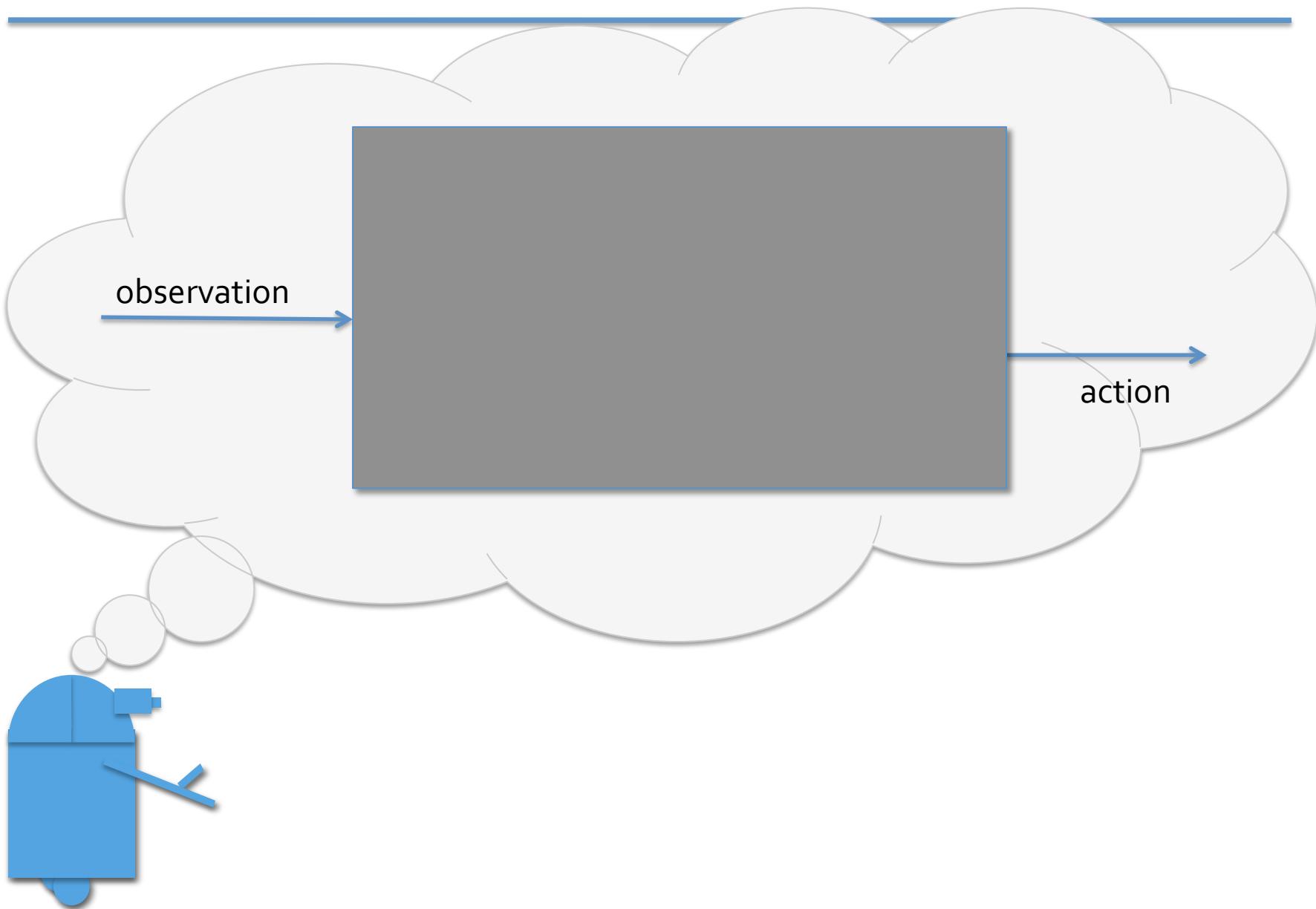
Current-state uncertainty

- What is inside the tupperware?
- Is the dishwasher clean?
- What is the exact pose of the pot?
- What's the friction of a wet dish?

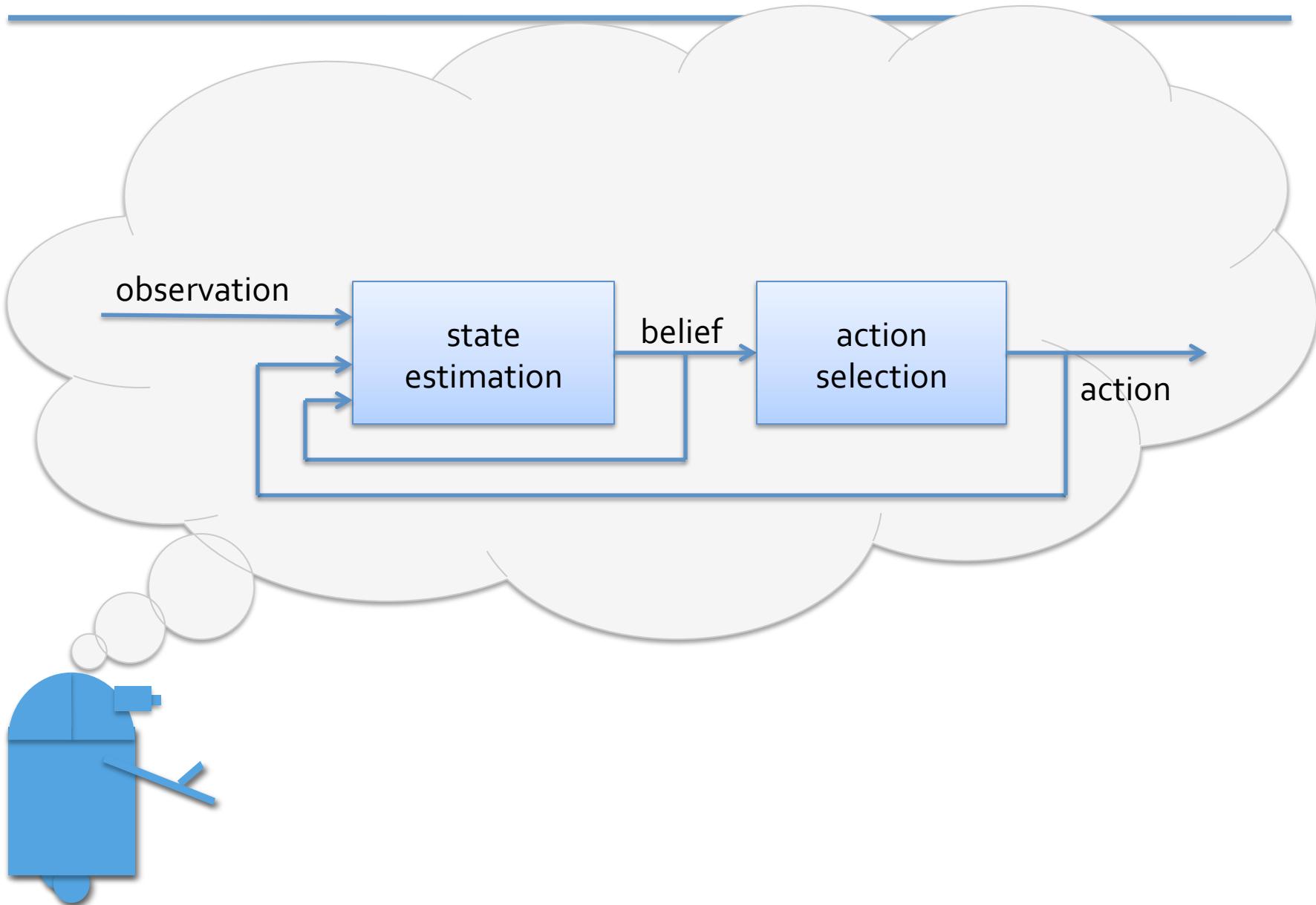
Predictive uncertainty

- What will happen when the robot lifts the cookie sheet?
- What is the error in the motor control?
- When will the inhabitants come home?

Observations to actions



Observations to actions



Perception as action

Perception is never free

- Select perception actions as needed for task
- Information requirements for tasks must be explicitly stated

Actions generate information

Our approach

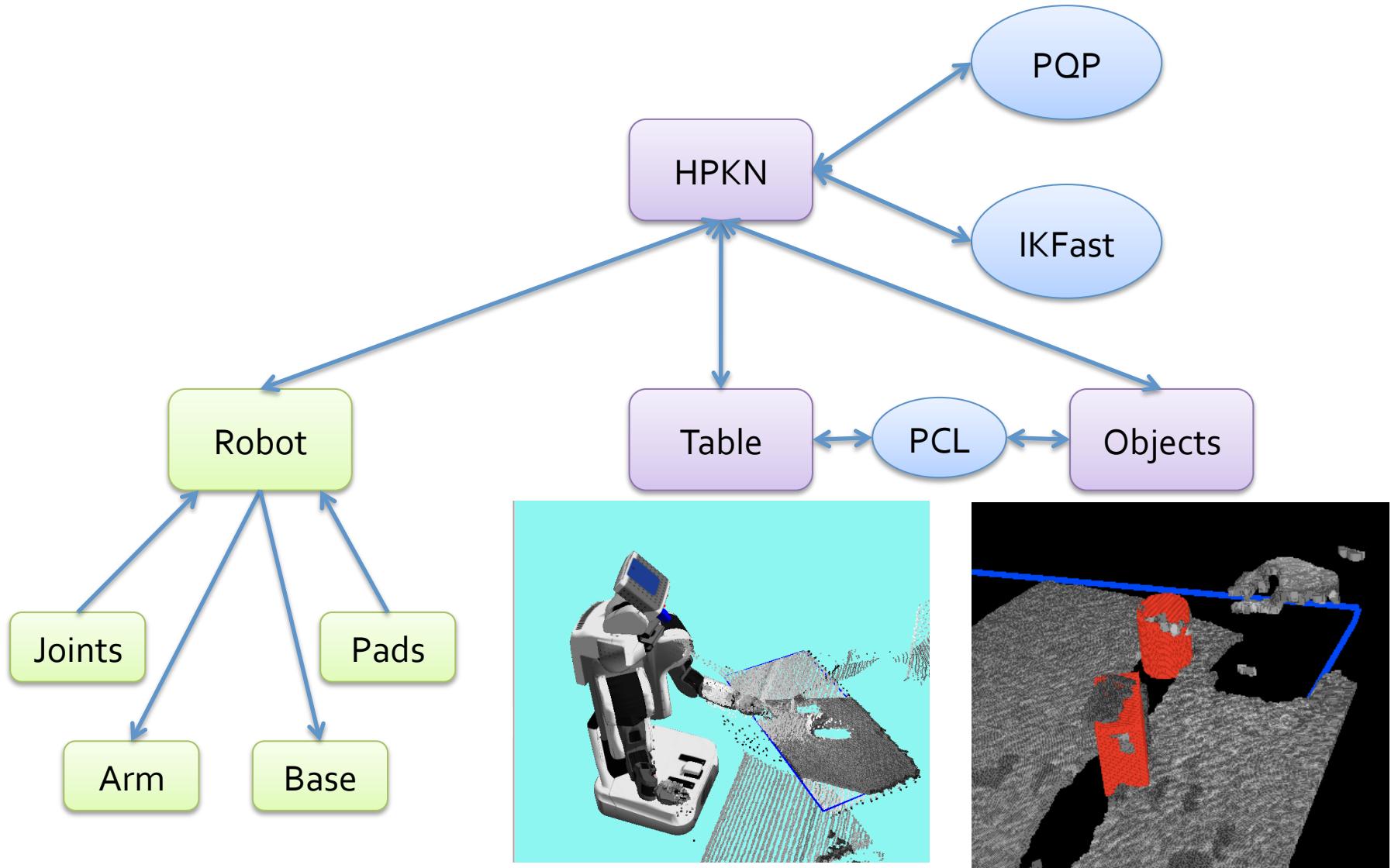
- Plan explicitly in belief space
- Use symbolic / geometric planning operators to characterize preimages of **belief goals** in belief space

Noisy perception of robot and object poses

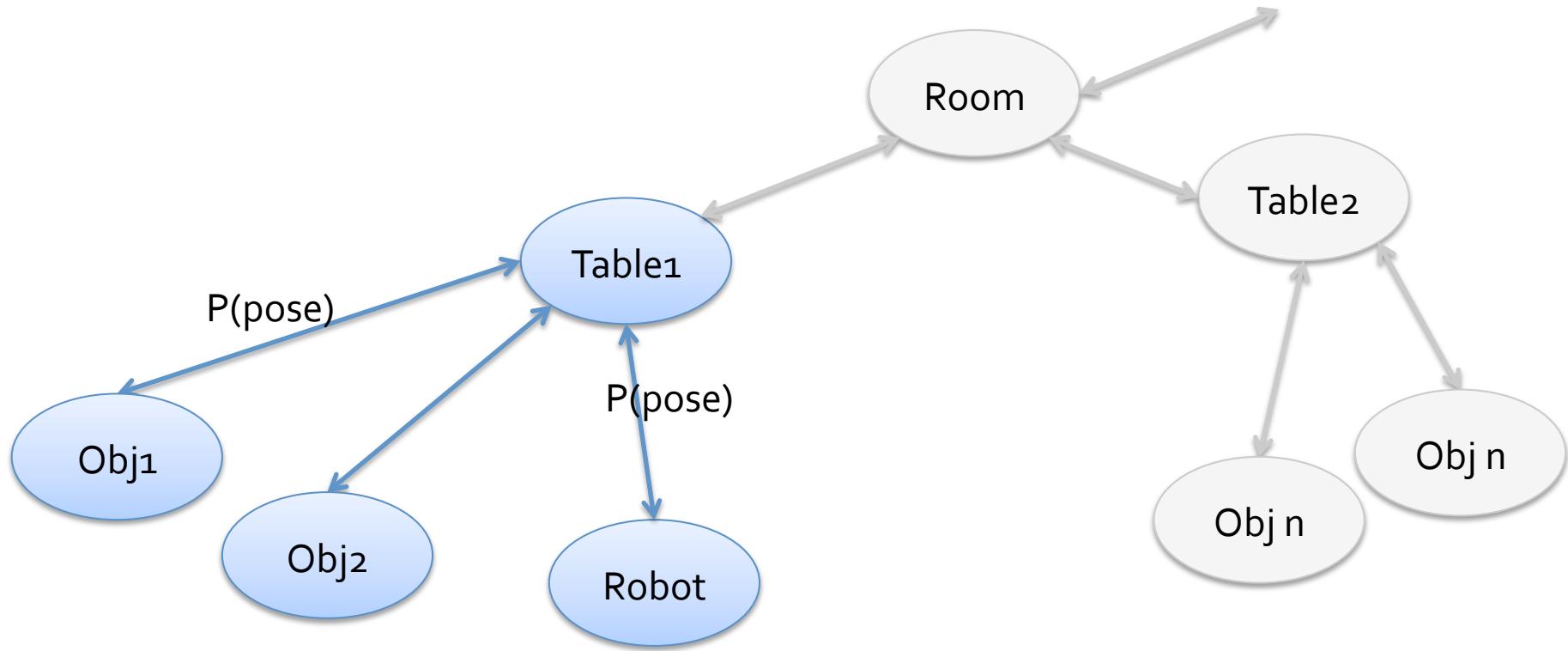


4x + Long, tedious gaps elided

HPKN / MandM Software Architecture



State estimator: relative pose distribution tree



- Pose estimates updated based on observations
- Accuracy is number of observations
- Robot pose estimate reset on move
- Object pose estimate reset on place

Planning operator: Pick

Pick(0):

exists: ObjLoc $\in \{\text{modeCurrLoc}\} \cup \text{generateParking}(0)$
exists: P $\in \text{generatePickPaths}(\text{ObjLoc})$

pre: ClearX(sweptVol(P), 0)
Holding(None)

KVObjLoc(0, ObjLoc)
KVRobotLoc(basePose(P))

result: Holding(0)
prim: PickPrim(0, ObjLoc)

Planning operator: LookObj

LookObj(0, N):

exists: ObjLoc = modeCurrLoc(0)

exists: P ∈ generateLookPaths(ObjLoc)

pre: ClearX(sweptVol(P), 0)

KVRobotLoc(basePose(P))

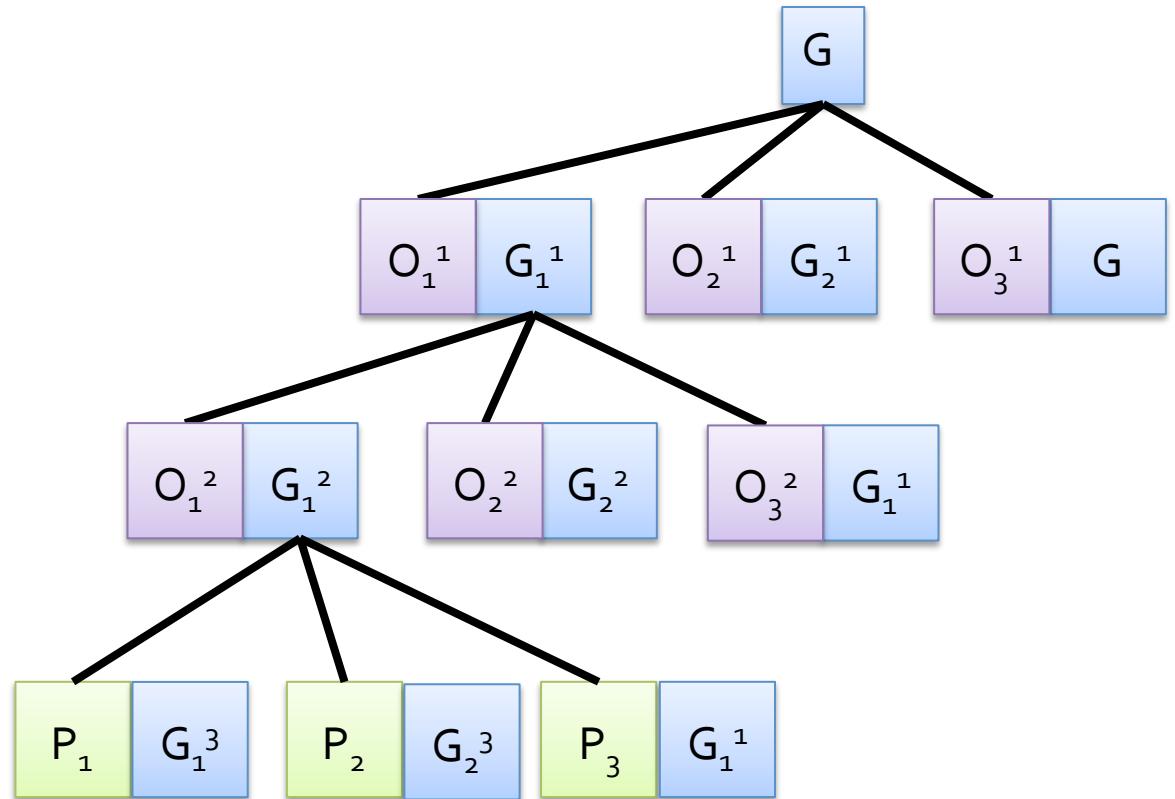
KObjLoc(0, N-1)

result: KObjLoc(0, N)

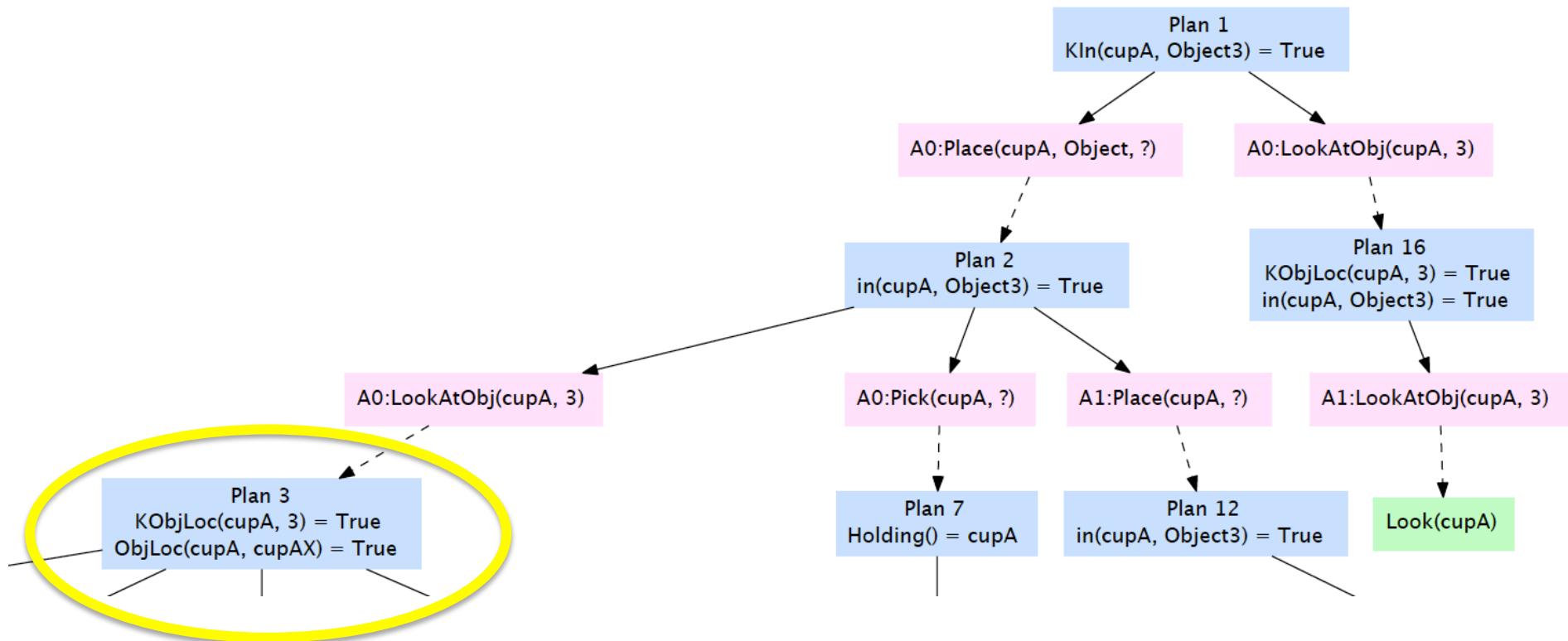
prim: LookPrim(ObjLoc)

Hierarchical planning in the now

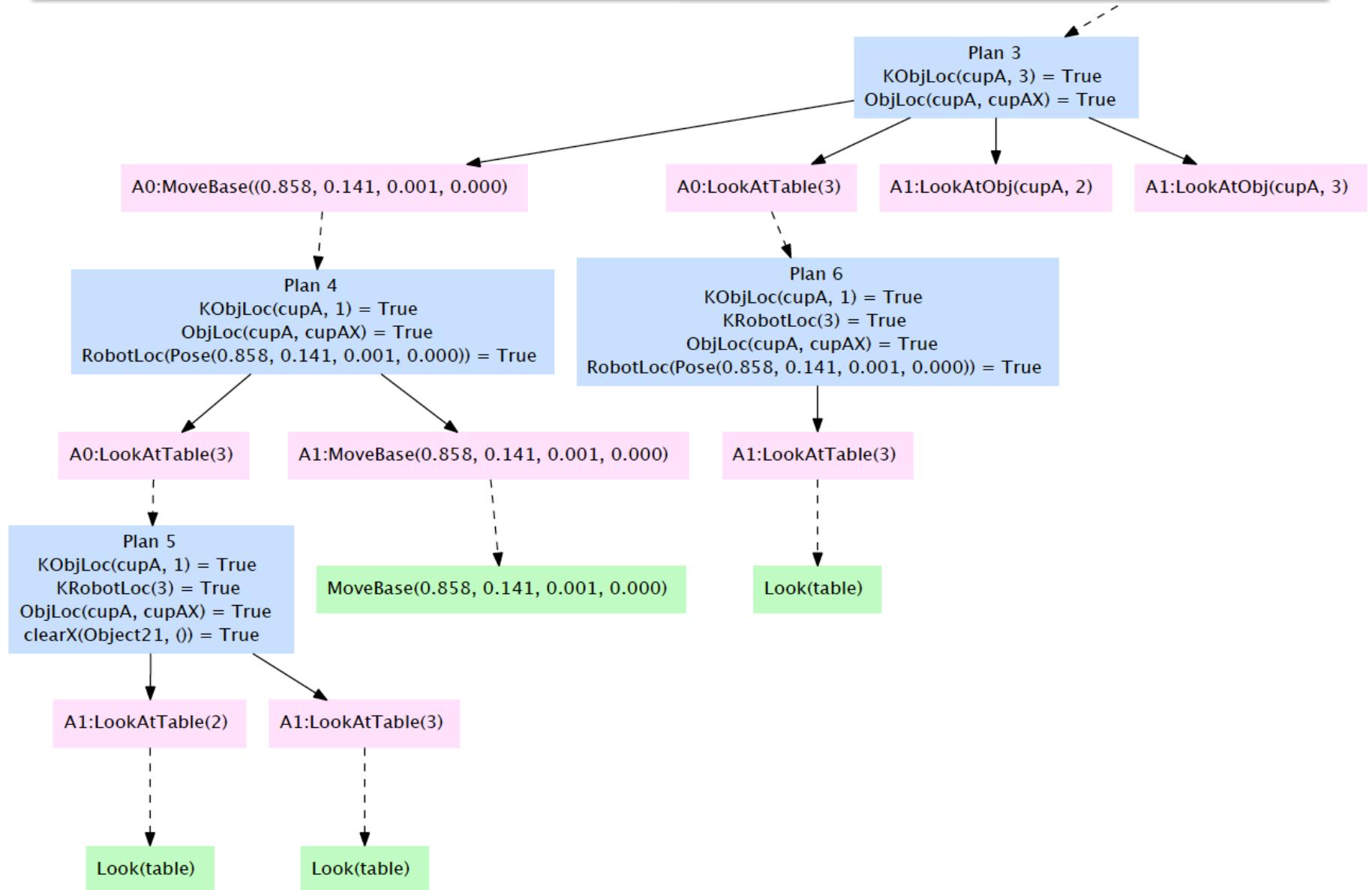
- maintain left expansion of plan tree
- each level uses a higher-fidelity model
- keep track of pre-image for each operation
- recursively plan to achieve those preconditions
- execute primitives



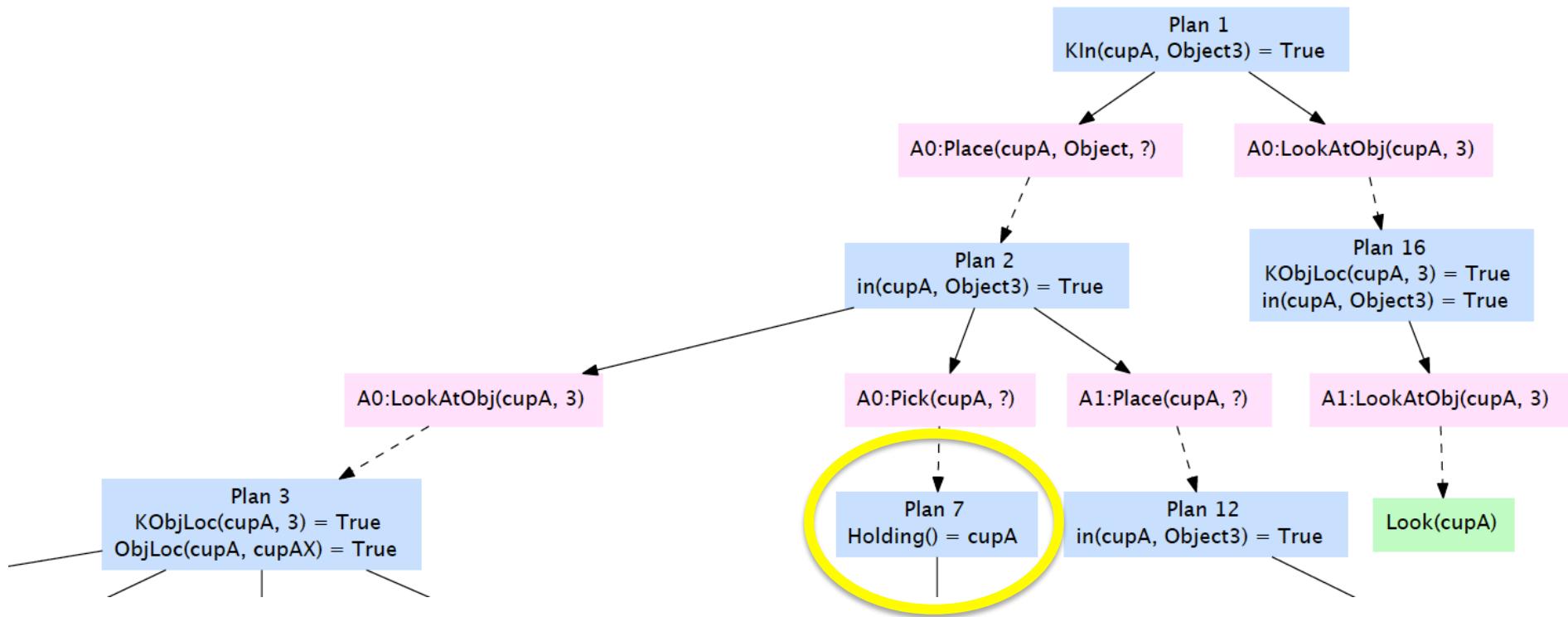
Simple pick and place: KIn(cupA, target)



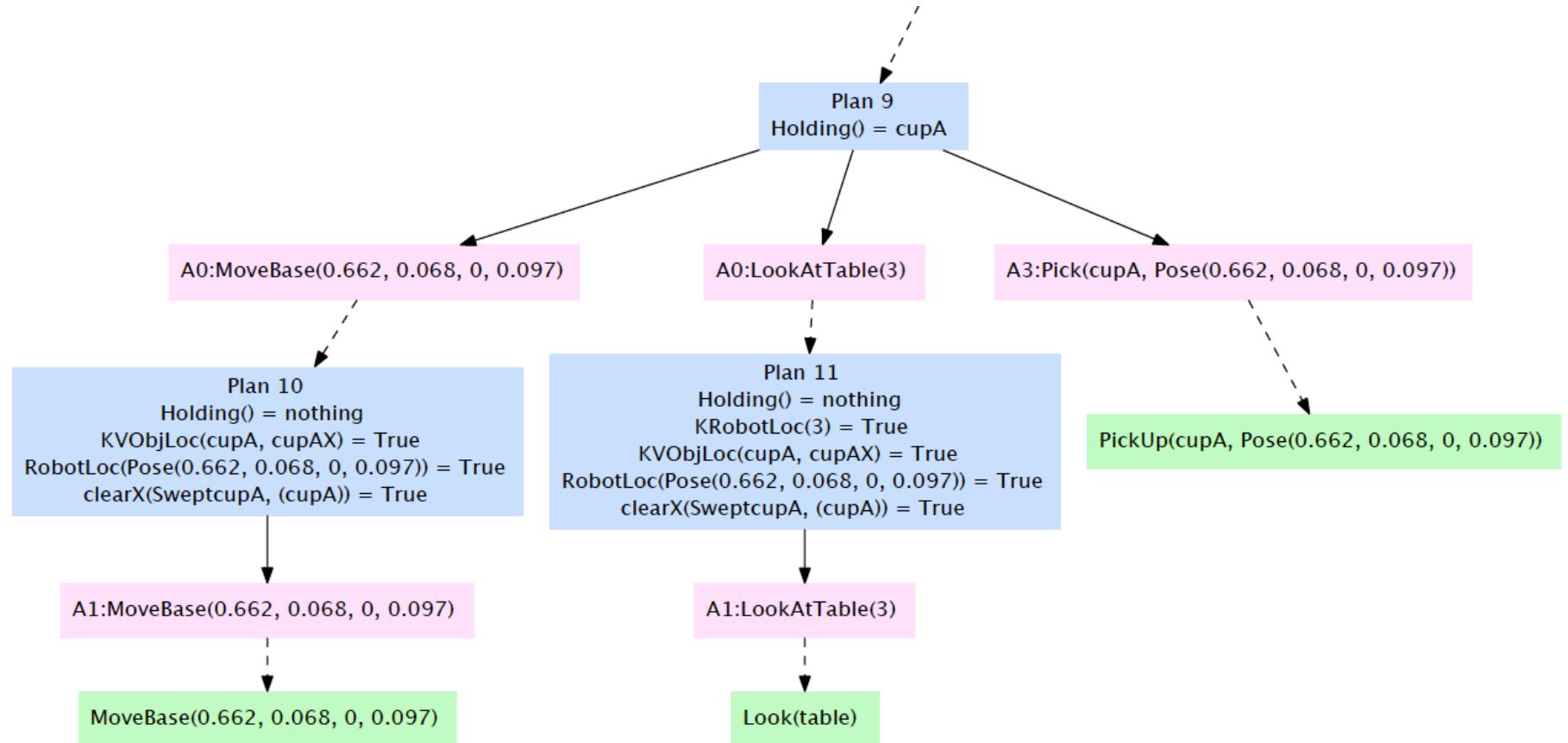
Finding cupA



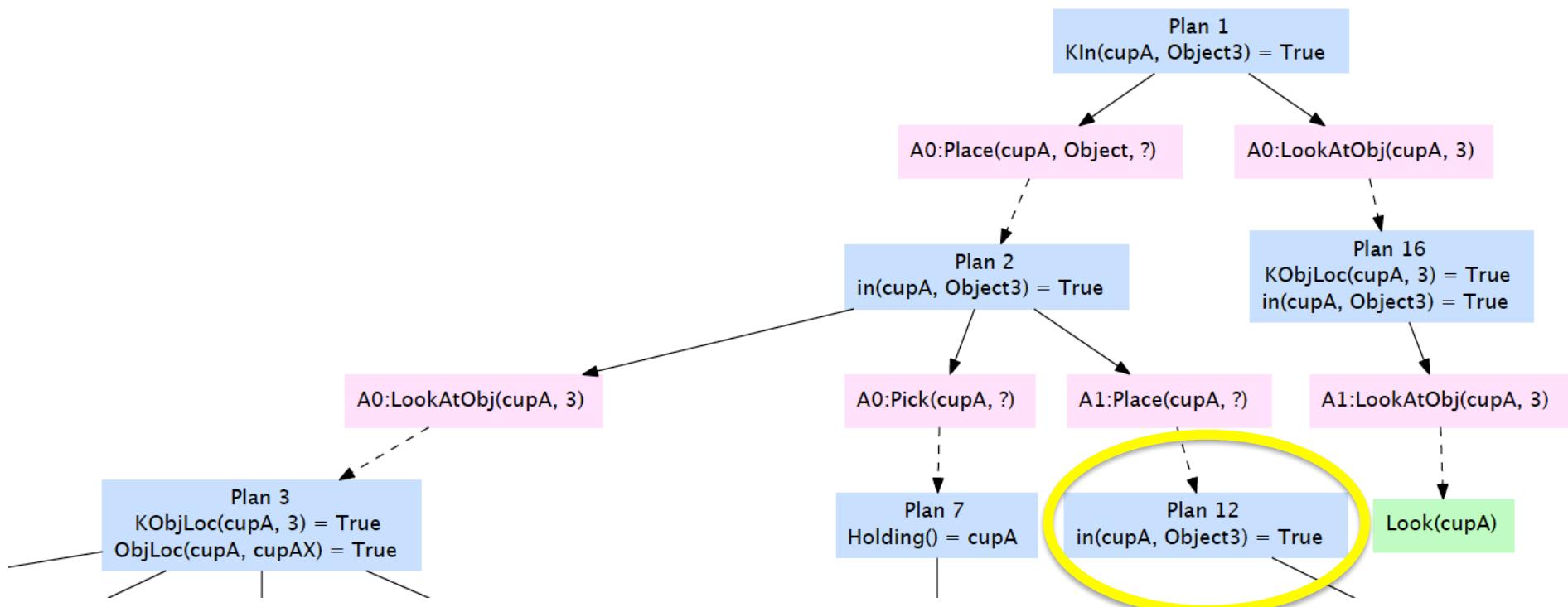
Simple pick and place



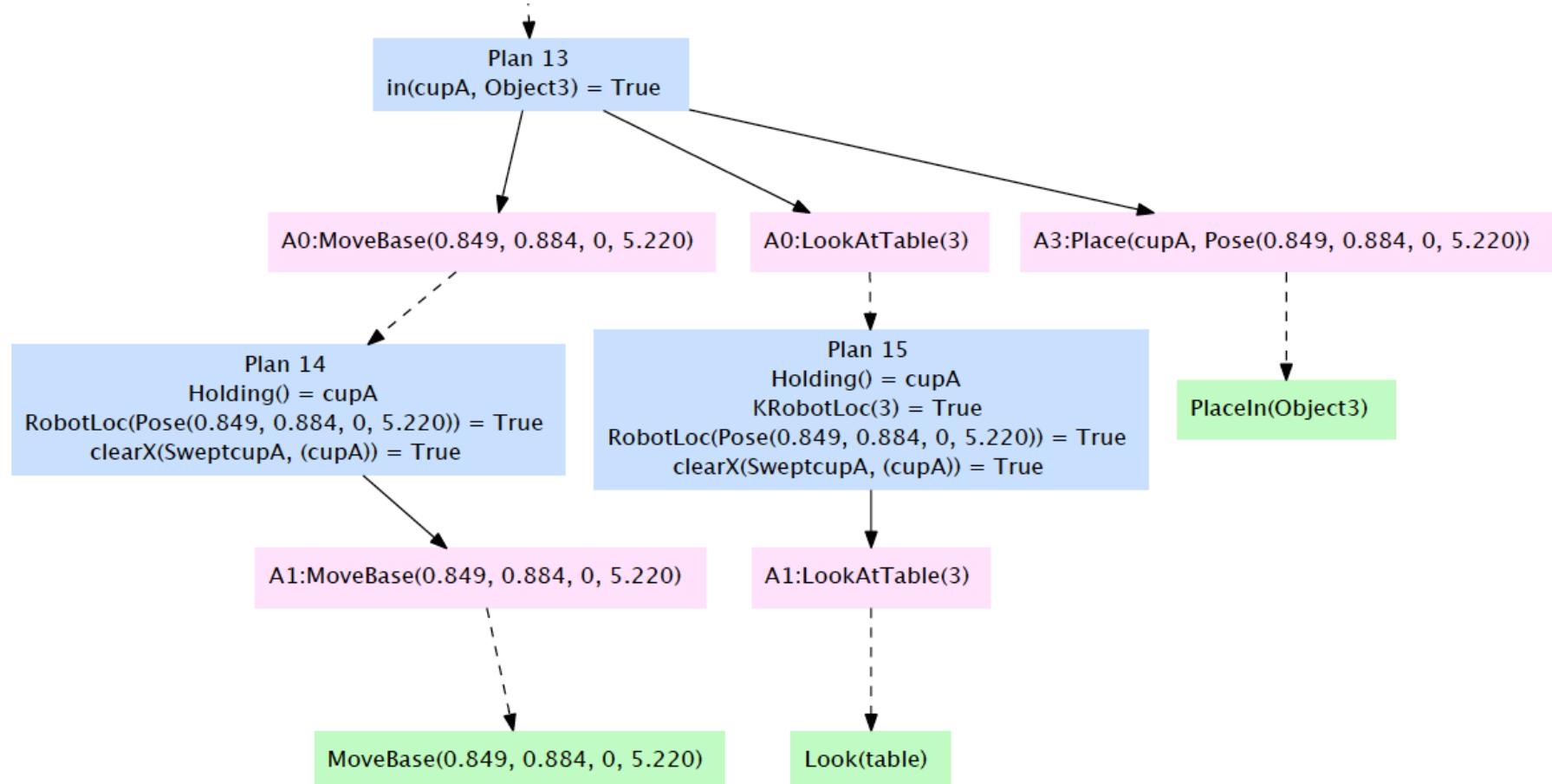
Picking cup A



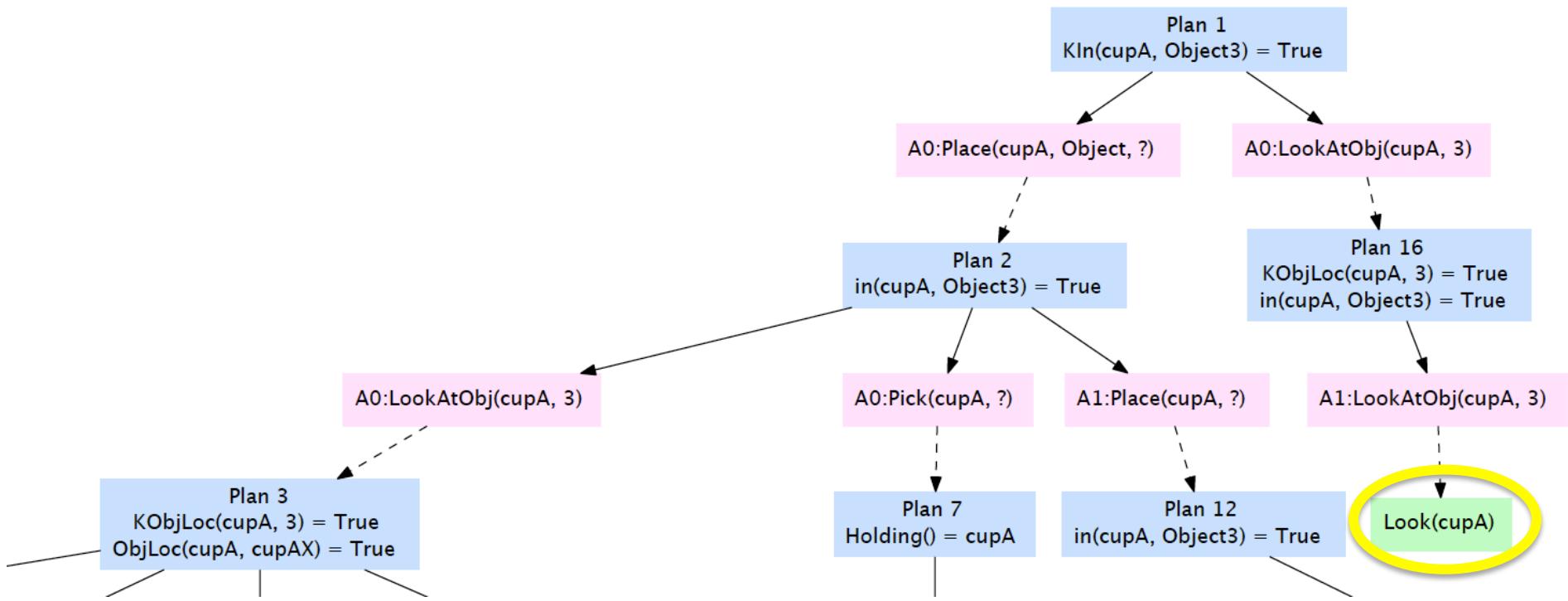
Simple pick and place



Placing cup A



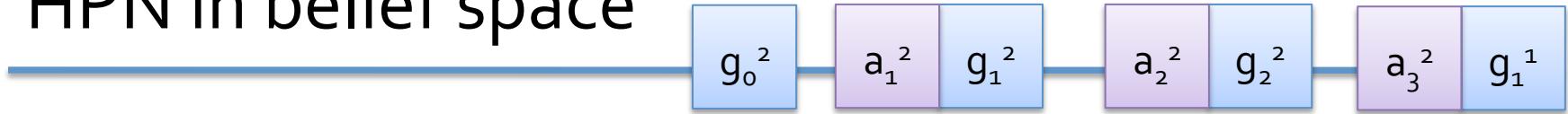
Verifying cup A is in the right location



Handling stochastic actions

- In belief space, next state depends on observation
- Observations are stochastic
- Make plan assuming most likely observations
- Monitor plan during execution
- Replan if conditions are violated

HPN in belief space



BHPN(*belief, goal, abs, world*):

$p = \text{PLAN}(\text{belief}, \text{goal}, \text{abs})$

for (a_i, g_i) **in** p

while $\text{belief} \in g_{i-1}$ **and not** $\text{belief} \in g_i$

if ISPRIM(a_i)

$obs = \text{world.EXECUTE}(a_i)$

$\text{belief.UPDATE}(a_i, obs)$

State estimation

else

$\text{BHPN}(\text{belief}, g_i, \text{NEXTLEVEL}(\text{abs}, a_i), \text{world})$

if not $\text{belief} \in g_i$ **return**

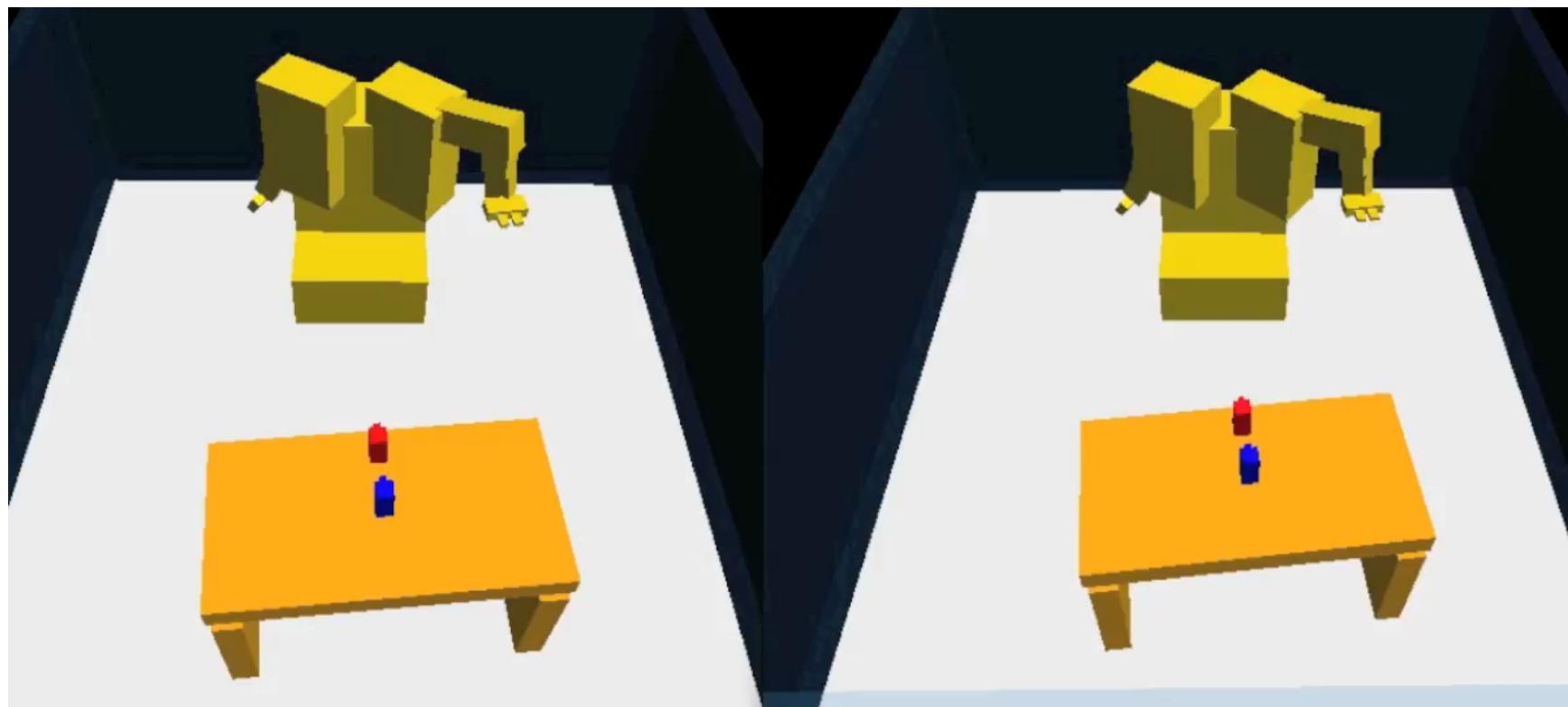
Preconditions failed

Preconditions hold

Result does not hold

Example with errors: 5 cm perception stdev

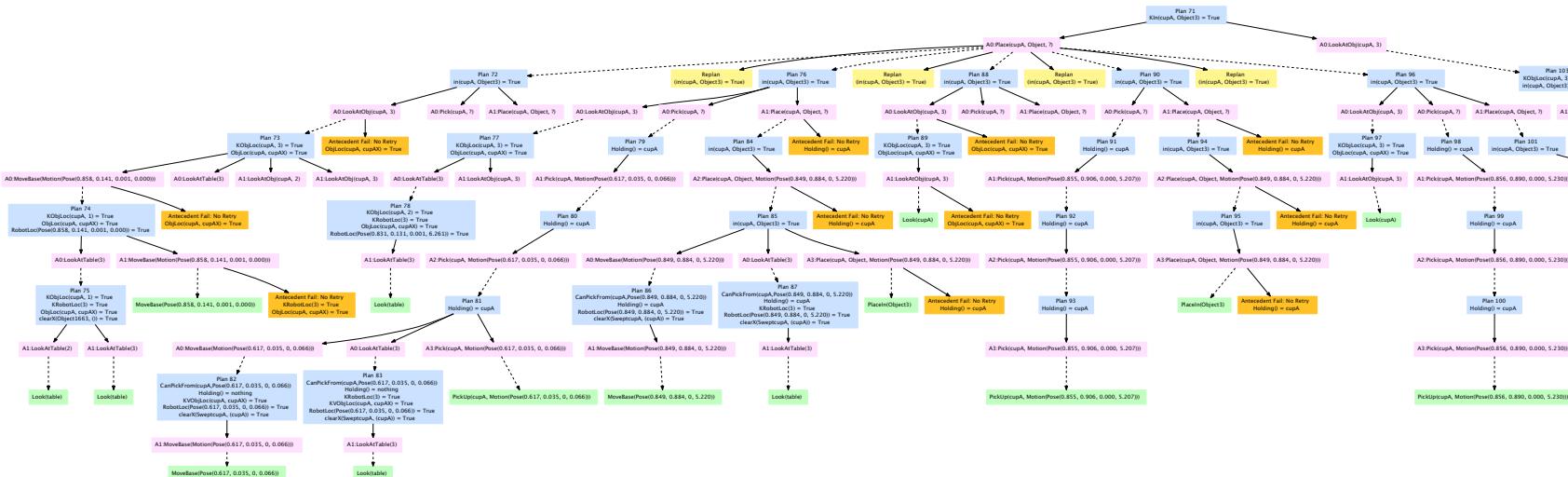
“Real” world



Max likelihood belief

Example with errors

Orange: precondition failure
 Yellow: replan



Characterizing certainty

Characterize concentration of distribution with PNM: amount of probability mass within delta of the mode of the dist'n

For Gaussian:

$$PNM(X, \delta) = \Phi(\mu + \delta) - \Phi(\mu - \delta) = \operatorname{erf}\left(\frac{\delta}{\sqrt{2}\sigma}\right)$$

Regression condition:

$$\theta_t = PNMregress(\theta_{t+1}, \delta, \sigma_o^2) = \operatorname{erf}\left(\sqrt{\operatorname{erf}^{-1}(\theta_{t+1})^2 - \frac{\delta^2}{2\sigma_o^2}}\right)$$

Application to tactile sensing

Integrating tactile observations for pose estimation

