

Cognition-Enabled Robot Control for the Realization of Home Chore Task Intelligence

Michael Beetz

Intelligent Autonomous Systems
Technische Universität München

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Robot Skill Learning and Cognition
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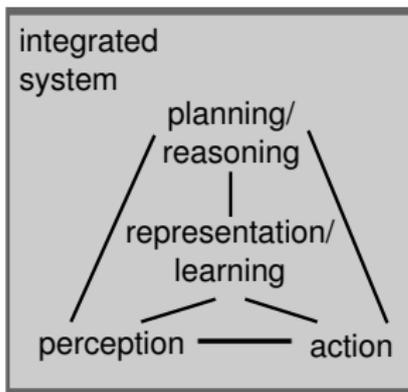




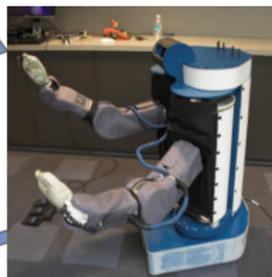
Everyday Robot Manipulation

Where we want to go

Nils Nilsson's challenge: a robot that can do what is reasonable to expect from it given its sensors and actuators



validate



inform/
challenge

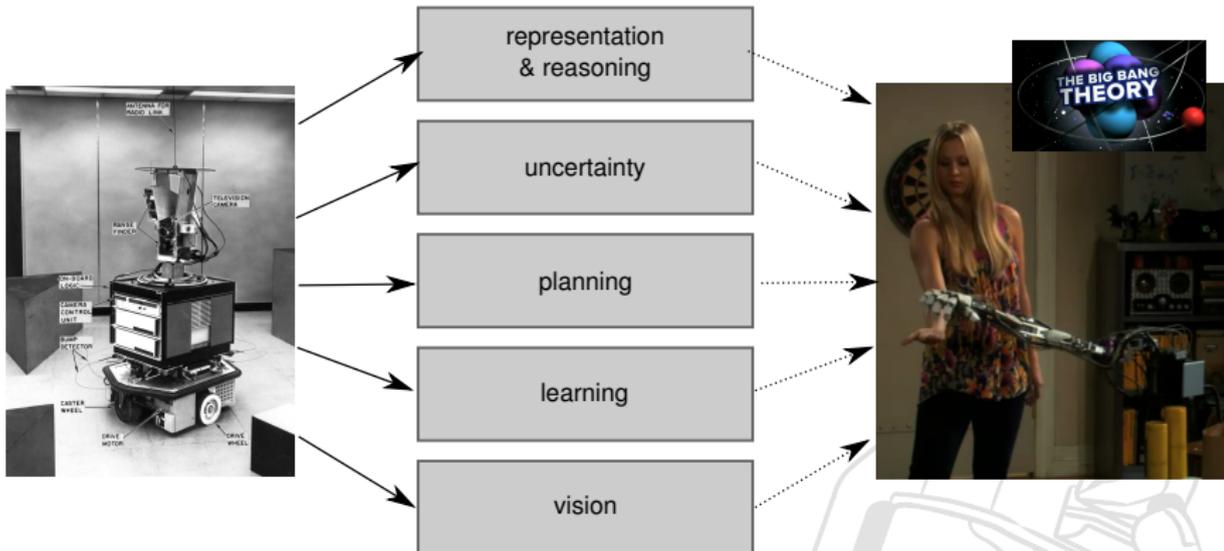
[Eric Berger, Stanford Univ]

Robotic roadmaps and white papers: robot (co-)workers, autonomous robot assistants, robot companions



Everyday Robot Manipulation

Where We are :-)





What we can be proud of . . .

Integrated Systems

Autonomous Driving



[Google]

Watson



[IBM]

Siri Agent



[Siri/Apple]



Everyday manipulation is really hard

Picking up an object

decide on

- ▶ where to stand?
- ▶ which hand(s) to use?
- ▶ how to reach?
- ▶ which grasp?
- ▶ where to grasp?
- ▶ how much force?
- ▶ how much lift force?
- ▶ how to lift?
- ▶ how to hold?





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based on context:

- ▶ object, object states,
environment, task, ...





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Challenge

- ▶ doing the **appropriate** thing
- ▶ to the **appropriate** object
- ▶ in the **appropriate** way

Cognition-enabled Control

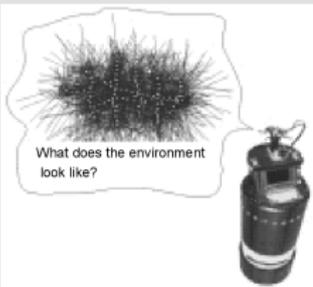




Cognition-enabled Control — the Very Idea

Example: Map Acquisition and Map-based Navigation

Model Acquisition



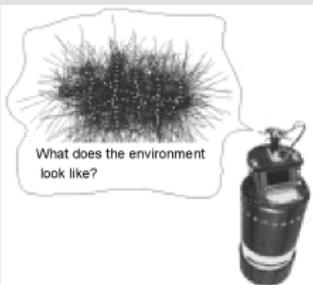
courtesy: Wolfram Burgard



Cognition-enabled Control — the Very Idea

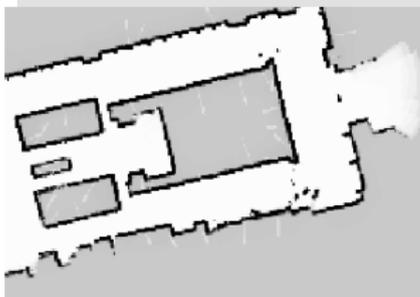
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Model Acquisition



courtesy: Wolfram Burgard

Model Use





Cognition-enabled Control — the Very Idea

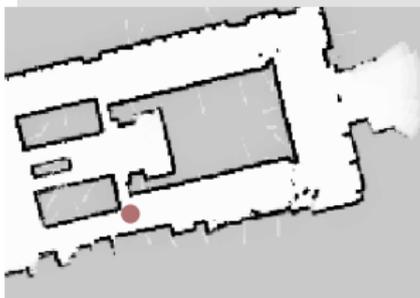
Example: Map Acquisition and Map-based Navigation

Model Acquisition



courtesy: Wolfram Burgard

Model Use



Where am I?



Cognition-enabled Control — the Very Idea

Example: Map Acquisition and Map-based Navigation

Model Acquisition



courtesy: Wolfram Burgard

Model Use



Where am I?

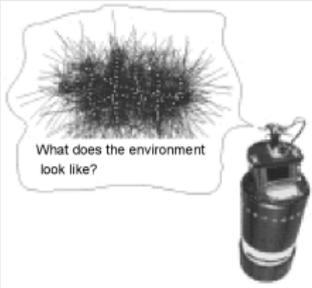
Where is L?



Cognition-enabled Control — the Very Idea

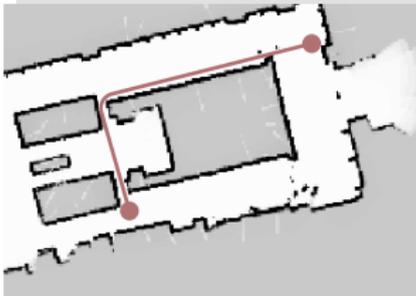
Example: Map Acquisition and Map-based Navigation

Model Acquisition



courtesy: Wolfram Burgard

Model Use



Where am I?

Where is L?

How do I get there?



Why Cognition-enabled Control?

General Navigation Routine

routine navigate $\langle tsk \rangle$

in parallel do continually estimate your position

whenever you are lost **do** relocalize

main process

if reachable(dest($\langle tsk \rangle$))

then nav-plan \leftarrow compute-nav-plan(curr-pos, dest($\langle tsk \rangle$))

execute nav-plan



Why Cognition-enabled Control?

General Navigation Routine

```
routine navigate  $\langle tsk \rangle$   
  in parallel do continually estimate your position  
  whenever you are lost do relocalize  
  main process  
    if reachable(dest( $\langle tsk \rangle$ ))  
    then nav-plan  $\leftarrow$  compute-nav-plan(curr-pos, dest( $\langle tsk \rangle$ ))  
    execute nav-plan
```

Cognitive mechanisms enable us to control the robot

- ▶ reliably
- ▶ flexibly
- ▶ efficiently

in concise control programs



Cognition-enabled Robot Control

A Working Definition

- = information processing, perception, and action control infrastructure for **decision making** and **action parameterization** that
- ▶ enables an **agent *agt***
 - ▶ to perform a set of **tasks *tsk***
 - ▶ better wrt **performance measure *p***
(typically generality, flexibility, reliability, performance, ...)
 - ▶ based on
 - ▶ **experience and learning**
 - ▶ **knowledge/models and reasoning**
 - ▶ **forward models and planning/prediction**about the **consequences of actions**

Cognition-enabled Robotics in the Housework Domain





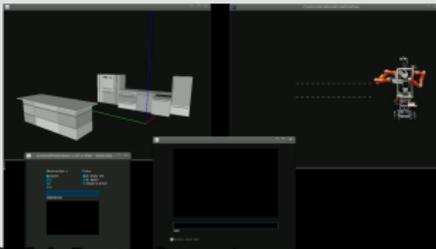
Robotic Roommates Making Pancakes

Our Vision: Robotic workers, co-workers, assistants that can

- ▶ perform **human-scale** tasks and jobs;
- ▶ execute **naturalistic** task & action specifications and instructions ;
- ▶ perform **everyday manipulation**;
- ▶ **extend** their repertoire of services by acquiring new skills using information resources intended for human use.

in realistic domestic and factory settings

Plan Generation



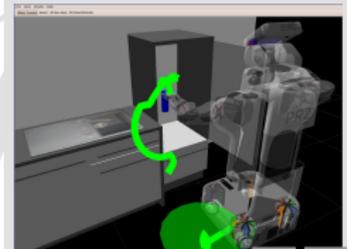
LCCC & Rosetta Symposium

Everyday Manipulation

Plan Execution



Plan Explanation



Michael Beetz





Making “Weisswürste” and Going Shopping

Shopping & cleaning up

1. shopping with basket



2. clean up according to organizational principles



Making “Weisswürste”

1. putting “Weisswürste” into pot



2. fishing “Weisswürste”



3. cutting bread

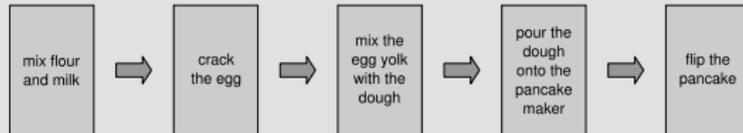




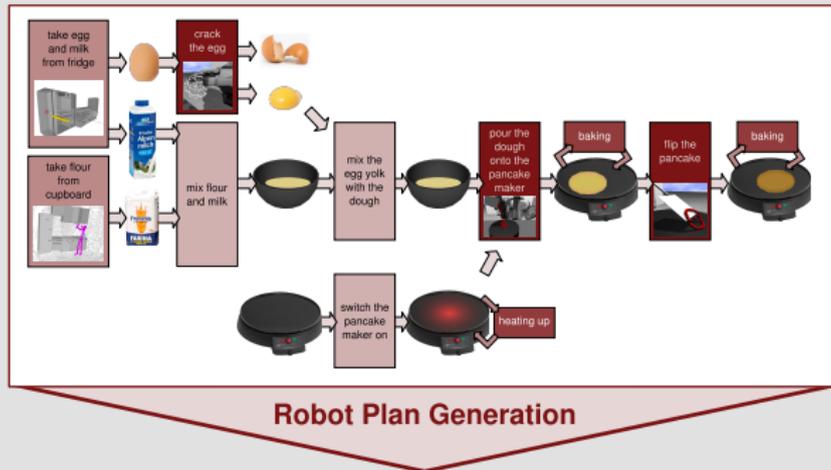
Robots Doing Housework (1)

What are the problems?

From:



To:





Robots Doing Housework (2)

What are the problems?

Naturalistic Action Description

push the spatula under the pancake

Effective Action Specification

hold the handle of the spatula and push the blade of the spatula under the pancake such that

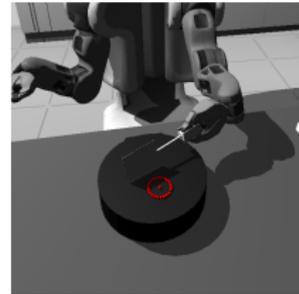
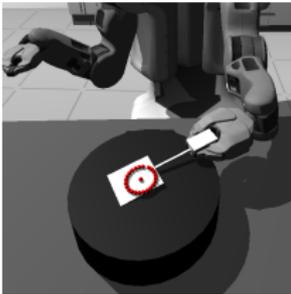
- you can lift the pancake safely,
- don't damage the pancake, and
- don't push the pancake off the oven



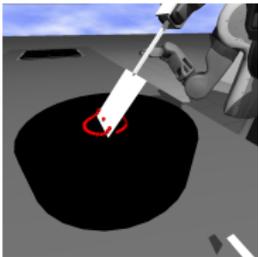
Robots Doing Housework (3)

What are the problems?

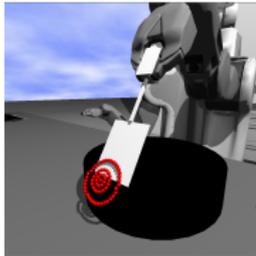
- ▶ **Parameters:** angle of spatula
- ▶ **Outcomes:** turned, not turned



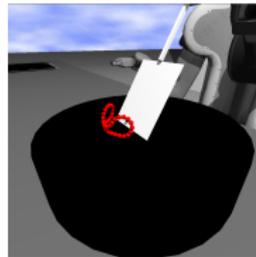
- ▶ **Common failures:**



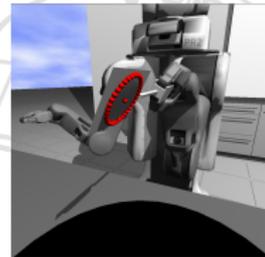
break



push off



fold



stick on

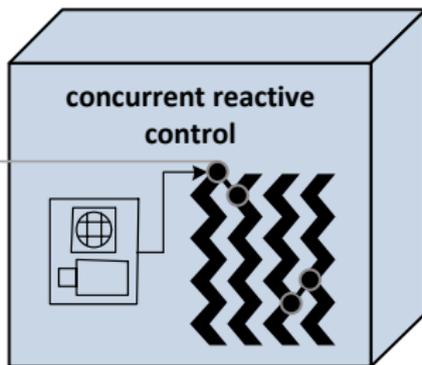
Principles





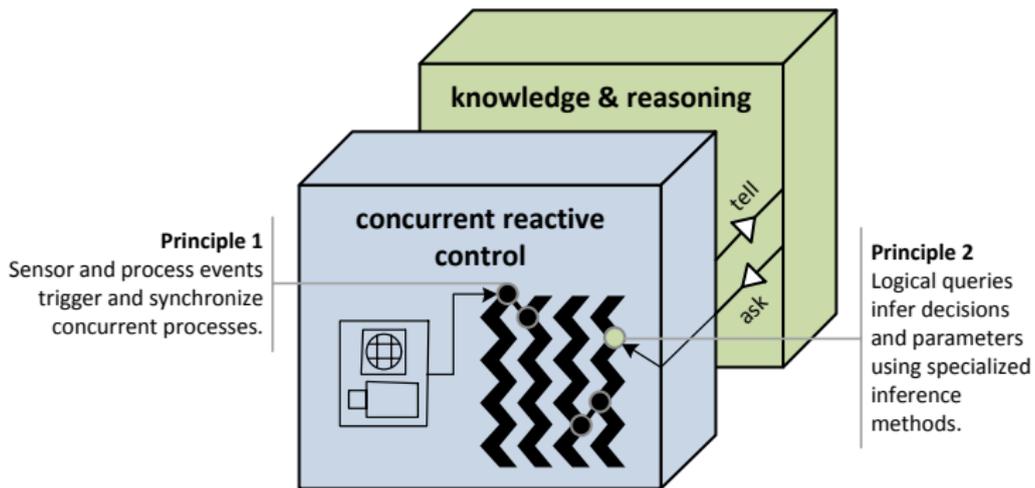
Cognition-enabled Control: Three Principles

Principle 1
Sensor and process events
trigger and synchronize
concurrent processes.



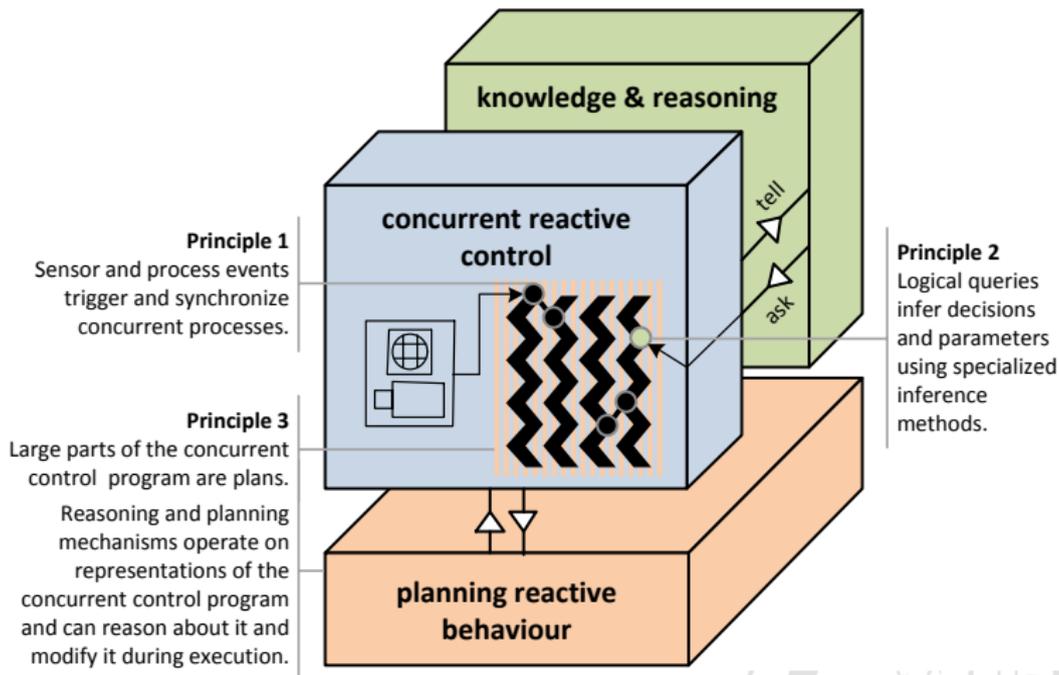


Cognition-enabled Control: Three Principles





Cognition-enabled Control: Three Principles

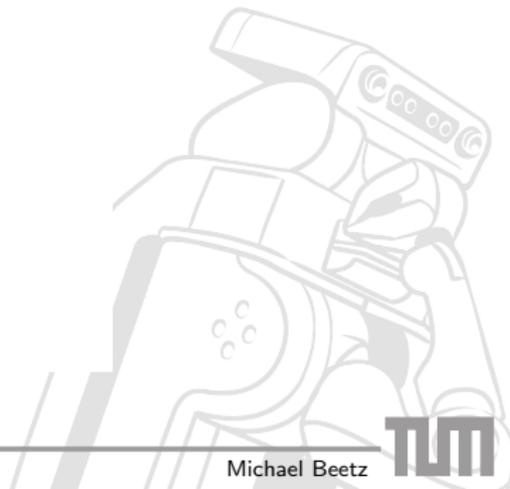
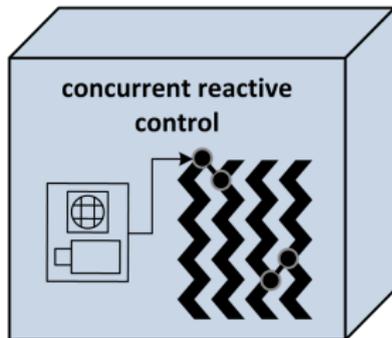




Concurrent Percept-guided Control

Principle 1

Cognition-Enabled Perception-Guided Control Programs





Concurrent, Percept-guided Control

Robot control programs specify how the robot is to respond to percepts and events (failures, etc) to accomplish its goals.

AI Approach	Cognition-enabled Control
plans are (partially ordered) sets of plan steps	plans are concurrent, reactive control programs
actions have preconditions	actions are “universal”
robots have to reason about all the plans	... only about plans they generate ensure plans are easy
provably correct plans (optimal, most robust)	improve expected performance
single query property	exploit everyday property

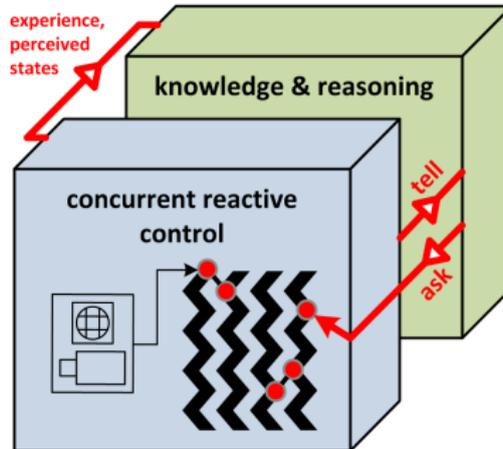
↪ **Cognition-enabled control can efficiently reason about plans that generate high-performance behavior**



Inference by Plan Statements

Principle 2

Cognition-Enabled Perception-Guided Control Programs

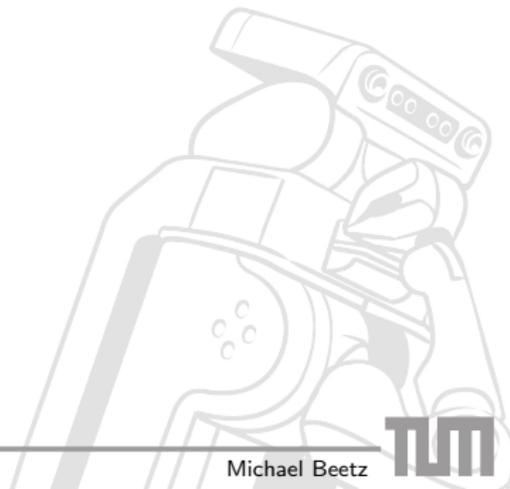




The Need for Specialized Reasoning Methods

Example Programs

- ▶ **clean up:**
for each object on the table do
put object **where it belongs**
- ▶ **set the table:**
for each **object that is needed** do
put object **where it belongs**
- ▶ **push the spatula under the pancake:**





The Need for Specialized Reasoning Methods

Example Programs

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for each **object that is needed** do
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- ▶ **push the spatula under the pancake:**

Specialized Reasoning

Inference tasks are

- ▶ too complex,
- ▶ too varied,
- ▶ too strongly affected by
 - ▶ uncertainty,
 - ▶ real-time constraints,
 - ▶ real-world conditions

to be addressed by
general-purpose reasoning



PROLOG as a Uniform Framework

The pose **?pose** for putting down an object based on the current and an expected future location of the robot where it will pick it up later.

- ▶ reachable from both of these locations
- ▶ stable on the kitchen counter
- ▶ visible from the robot's expected future location.

```

objectPose(W, Cup, ?pose),
  on(?pose, CounterTop),
  currentRobotPos(?currPos),
  expectedRobotPos(?expectedPos),
  stable(W, Cup),
  reachableFrom(W, ?currPos, Cup),
  reachableFrom(W, ?expectedPos, Cup),
  visible(W, ?expectedPos, Cup)
  
```

procedural attachment

physics simulation

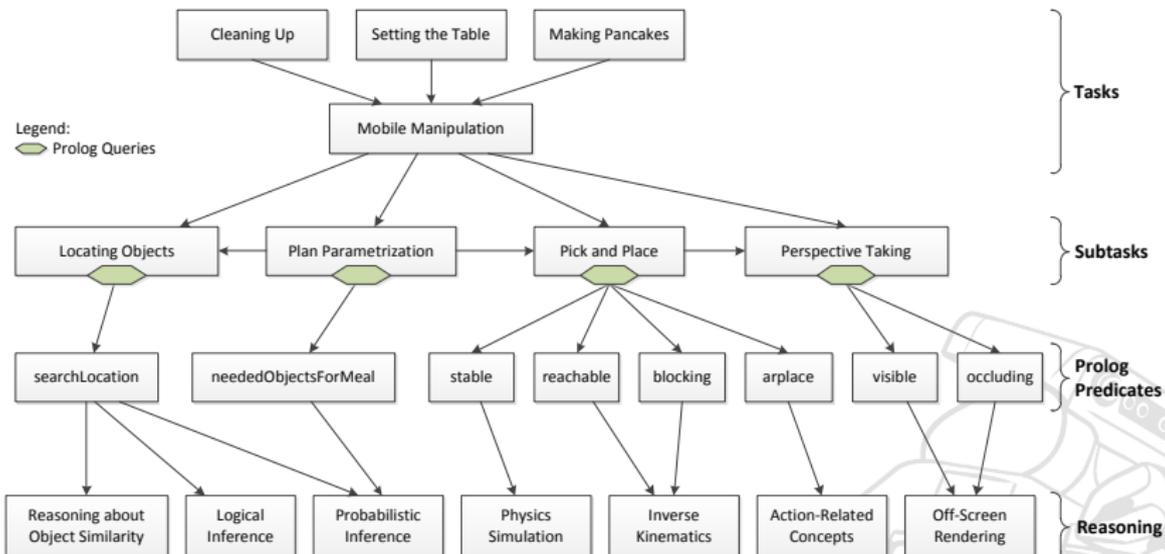
inverse kinematics

inverse kinematics

opengl



PROLOG as a Uniform Framework





Using the Program as a Knowledge Base

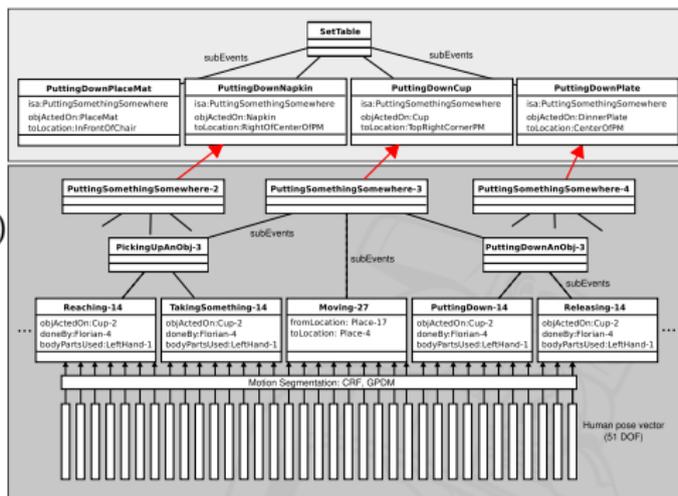
Inference Method 1

Example:

subtask(Super,Sub)

1. **subtask**(Super, Sub):-
var(Super), **var**(Sub),
!, fail.
2. **subtask**(Super, Sub):-
var(Super), **nonvar**(Sub),
Super ← procCall Sub→Super(Sub,tasktree)
3. **subtask**(Super, Sub):-
nonvar(Super), **var**(Sub),
Sub ← procCall SubTask(Super,tasktree)
4. **subtask**(Super, Sub):-
nonvar(Super), **nonvar**(Sub),
Sub = procCall SubTask(Super,tasktree)

Action task tree





Parameterizing Actions with their Effects

Inference Method 2

Put the pancake mix away

(perform (an action

(type put-away)

(object ?obj = (the object

(type pancake-mix)))

(destination ?loc = (a location

(on counter)

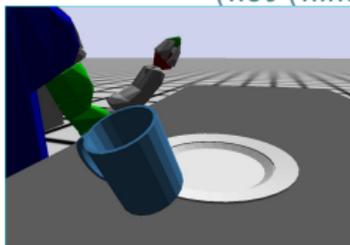
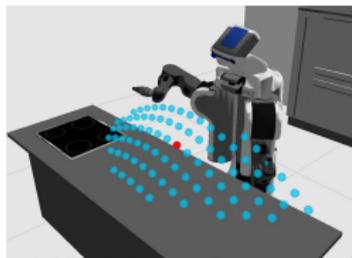
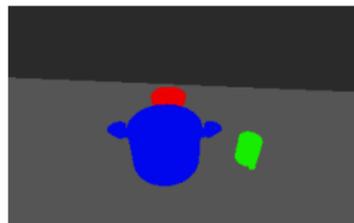
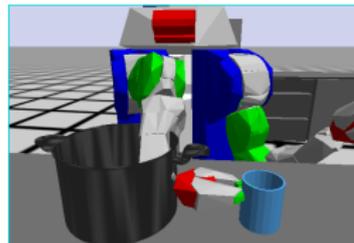
(stable ?obj)

(reachable t)

(visible-for James)

(not (hindering (the activity

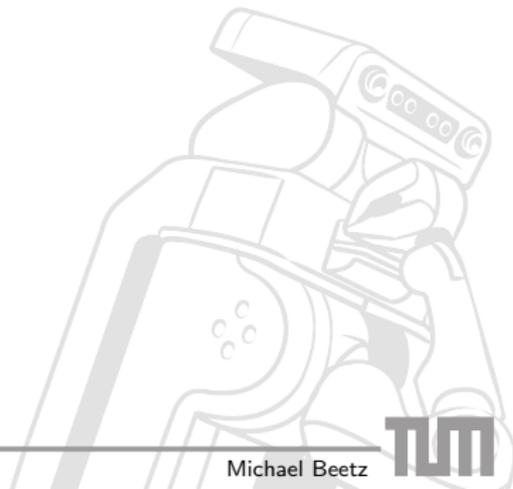
(type pancake-making))))))))))





Effect-based Action Parameterization

$\text{setof } ?\text{Pose On}(\text{Counter}, ?\text{Pose}) \text{ ?Poses} \wedge \text{member}(?P, ?\text{Poses})$
 $\wedge \text{Pose}(\text{Cup}, ?P) \wedge \text{stable}(\text{Cup})$



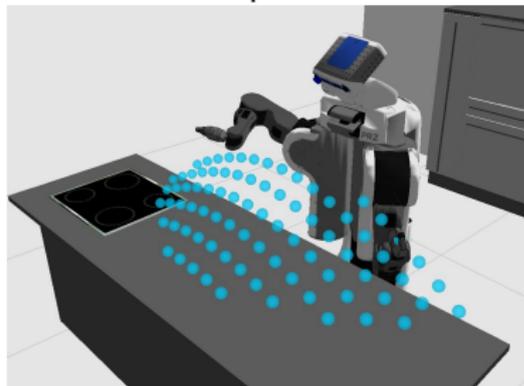


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1. $\text{setof } ?\text{Pose On}(\text{Counter}, ?\text{Pose}) ?\text{Poses}$
2. $\text{member}(?\text{P}, ?\text{Poses})$
3. $\text{Pose}(\text{Cup}, ?\text{P})$
4. $\text{stable}(\text{Cup})$

Create distribution for sampling
poses



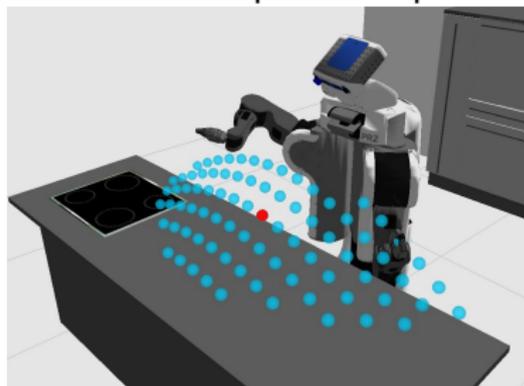


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2. $\text{member}(?\text{P}, ?\text{Poses})$
3. $\text{Pose}(\text{Cup}, ?\text{P})$
4. $\text{stable}(\text{Cup})$

Draw a pose sample



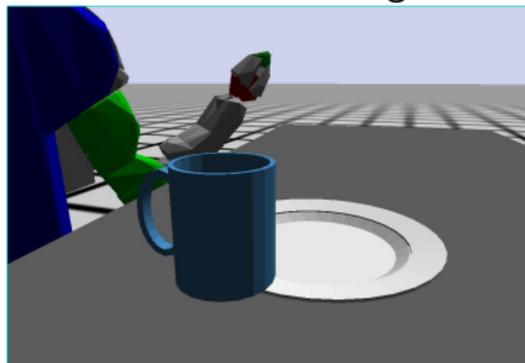


Effect-based Action Parameterization

setof ?Pose On(Counter, ?Pose) ?Poses \wedge member(?P, ?Poses)
 \wedge Pose(Cup, ?P) \wedge stable(Cup)

1. setof ?Pose On(Counter, ?Pose) ?Poses
2. member(?P, ?Poses)
3. Pose(Cup, ?P)
4. stable(Cup)

Place the mug



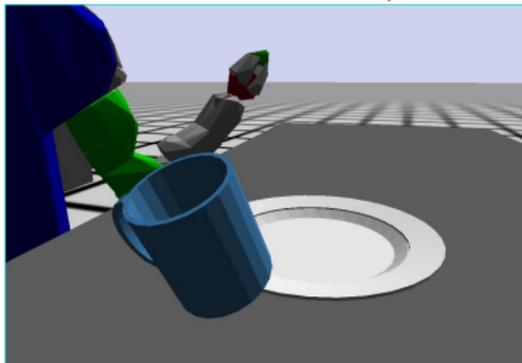


Effect-based Action Parameterization

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1. setof ?Pose On(Counter, ?Pose) ?Poses
2. member(?P, ?Poses)
3. Pose(Cup, ?P)
4. stable(Cup)

Simulate for 50ms, **fail!**



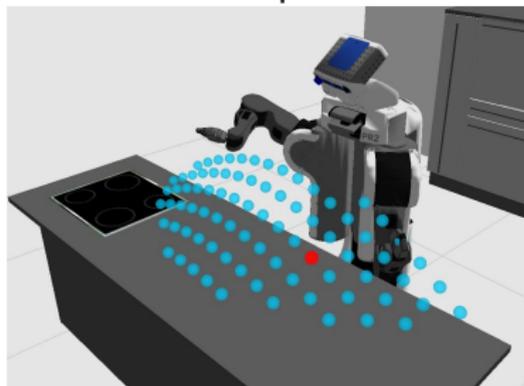


Effect-based Action Parameterization

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1. $\text{setof } ?\text{Pose On}(\text{Counter}, ?\text{Pose}) ?\text{Poses}$
2. $\text{member}(?\text{P}, ?\text{Poses})$
3. $\text{Pose}(\text{Cup}, ?\text{P})$
4. $\text{stable}(\text{Cup})$

Backtrack, draw another pose sample



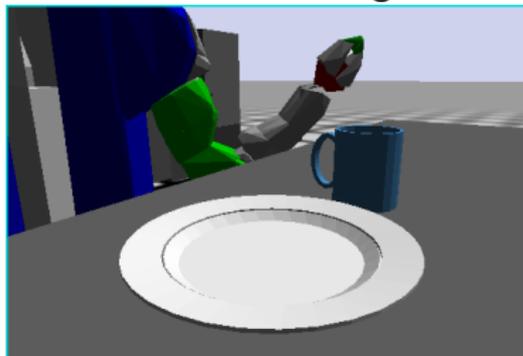


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4. stable(Cup)

Place the mug



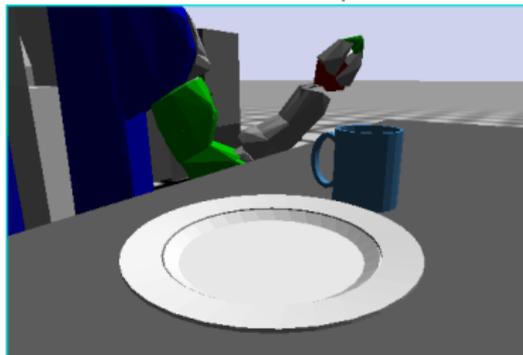


Effect-based Action Parameterization

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2. member(?P, ?Poses)
3. Pose(Cup, ?P)
4. stable(Cup)

Simulate for 50ms, **succeed!**





Action-related Concepts

Inference Method 3

instead of prespecifying decisions

```
(at-location < OBJ.POS.x - 60, OBJ.POS.y - 10 >
  (pick-up OBJ))
```

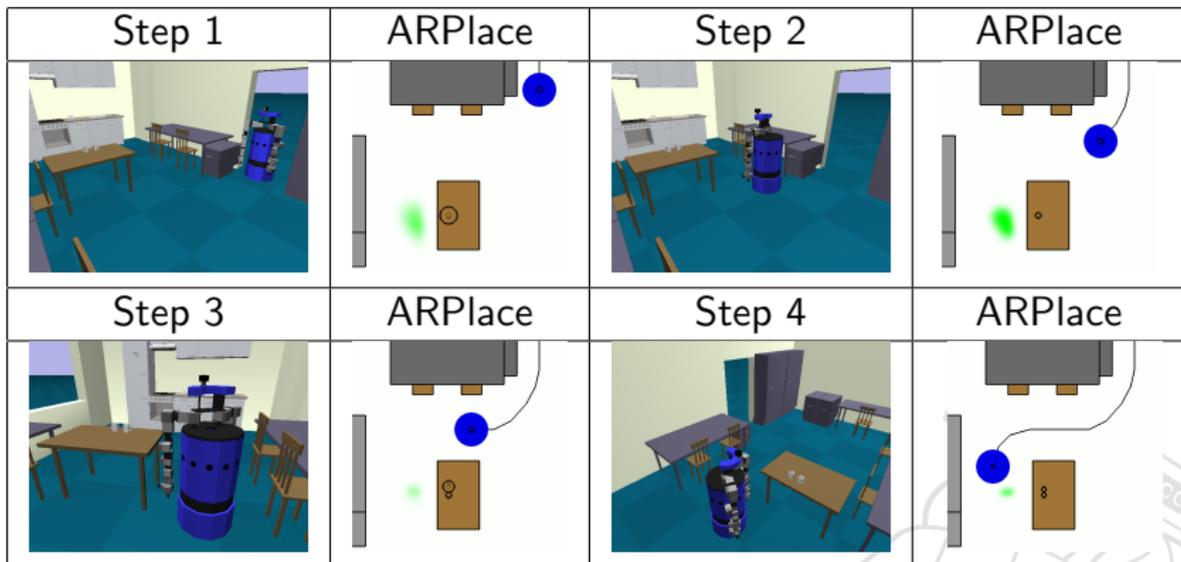
let the robot infer the decision

```
(at-location (the ARPlace
  (task (a task (task-action pick-up)
    (objectActedOn (a cup on table))))))
  (with parameters
    ((reaching-trajectory ... ) (grasp-type ... ))
    (grasp-type ... ))
    (pick-up all cups))
```



Inferring Control Decisions

Lazy, evidence-based decision making



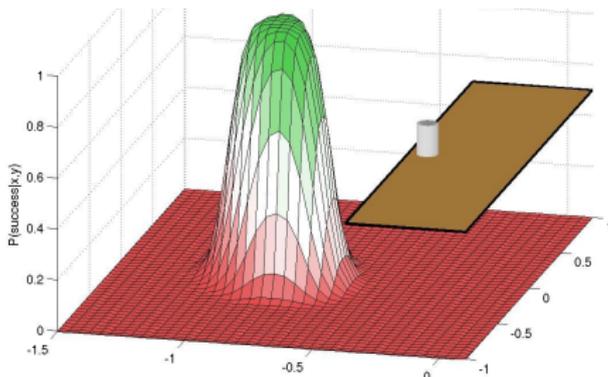
“A **decision** is a commitment to a plan or an action parameterization based on evidence and the expected costs and benefits associated with the outcome.”

adapted from Resulaj et al, *Changes of mind in decision-making*



Learning Action-related Places

- ▶ Representation:
 - ▶ Discretized space of potential manipulation places
 - ▶ Mapping to expected utilities

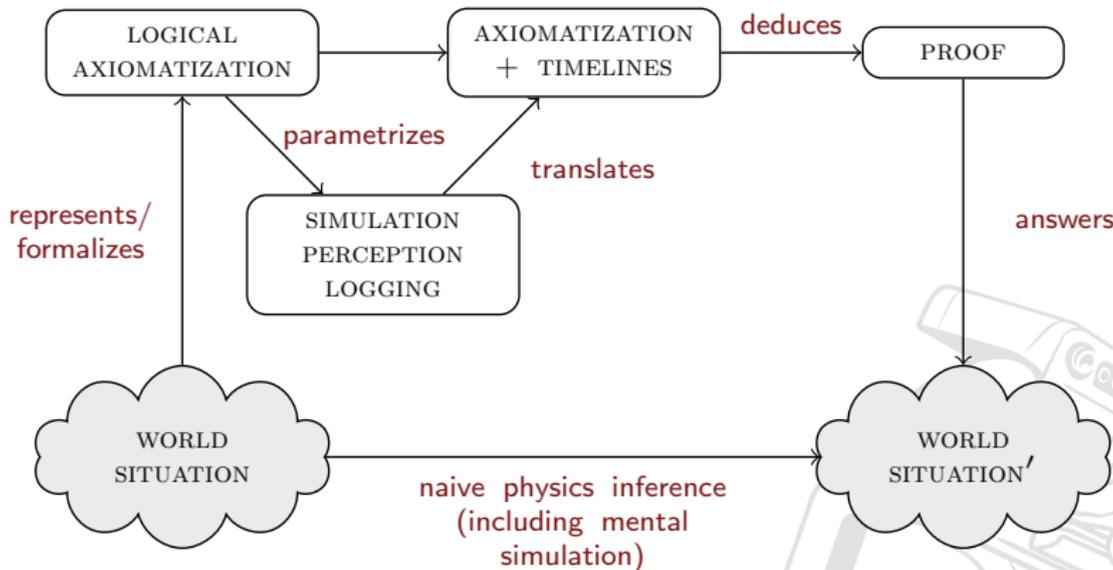


- ▶ Advantages:
 - ▶ are learned from and are grounded in observed experience
 - ▶ take state estimation uncertainties into account
 - ▶ enable least-commitment planning
 - ▶ maximize expected utility



Simulation-based Temporal Projection

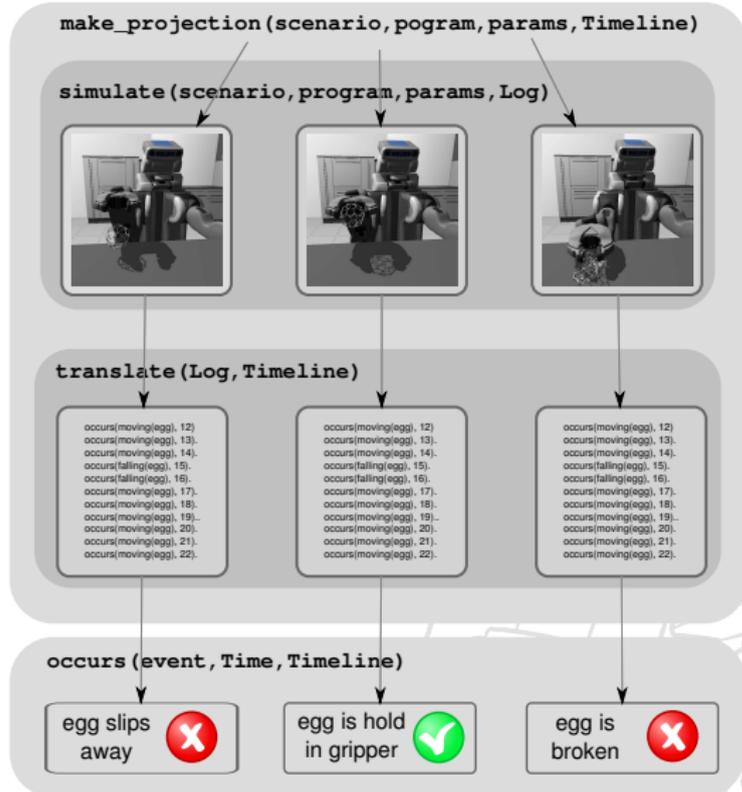
Inference Method 4





Temporal Projection Process

- **make_projection:**
sample parameters
 - ▶ **simulate:**
setup simulator
run simulation
 - ▶ **translate:**
ground predicates
in logged
simulations
- **evaluate:**
events/fluents
specialized predicates

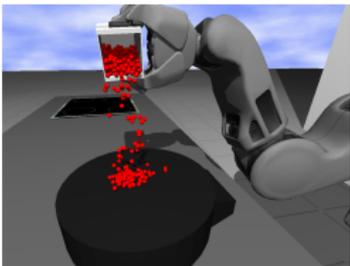




Example: Making a Pancake

Pouring

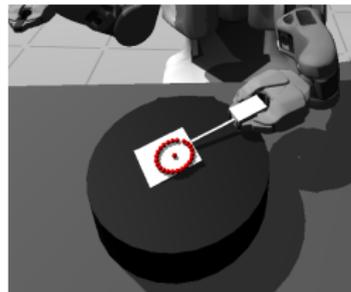
- ▶ **Parameters:** position, time, angle
- ▶ **Outcomes:** number of particles on pan (spilled on table)



- ▶ Specialized predicates on particle sets: **round/centered**

Flipping

- ▶ **Parameters:** angle of spatula
- ▶ **Outcomes:** turned, not turned



Common failures:

- ▶ break, push off, fold, stick on

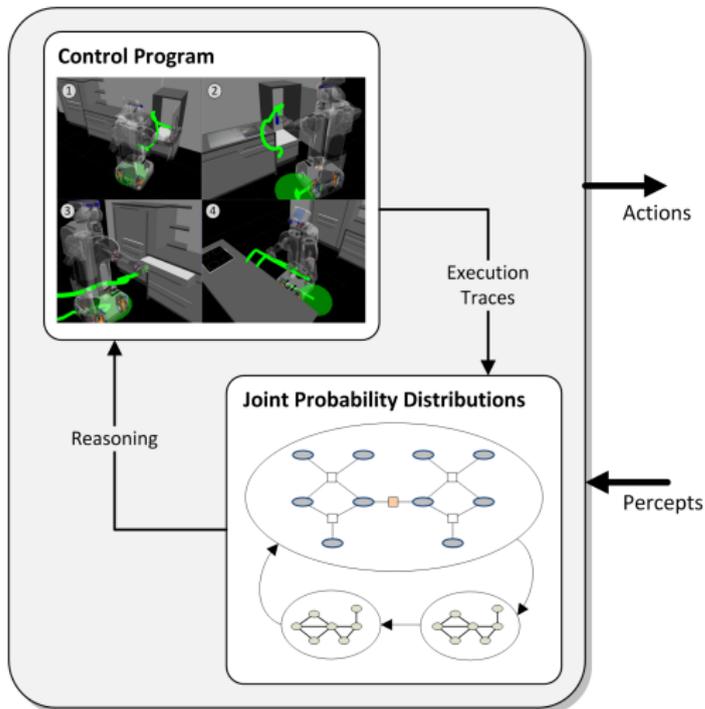
↪ **Parameters that lead to desired outcomes are inferred**





Bayesian Cognitive Robotics

Inference Method 5

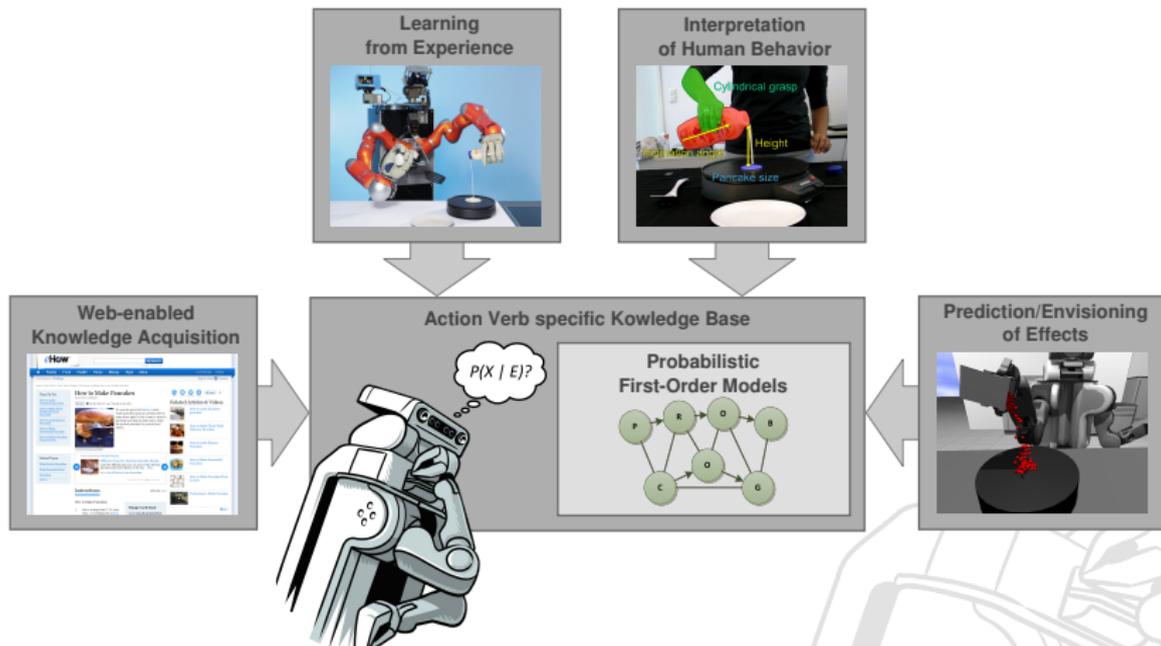


- ▶ generate probabilistic model structures from semantic plans
- ▶ models of continuous & discrete behaviour
- ▶ learn model parameters from execution traces
- ▶ complex situational dependencies (relational descriptions)



An Action Verb specific Knowledge Base

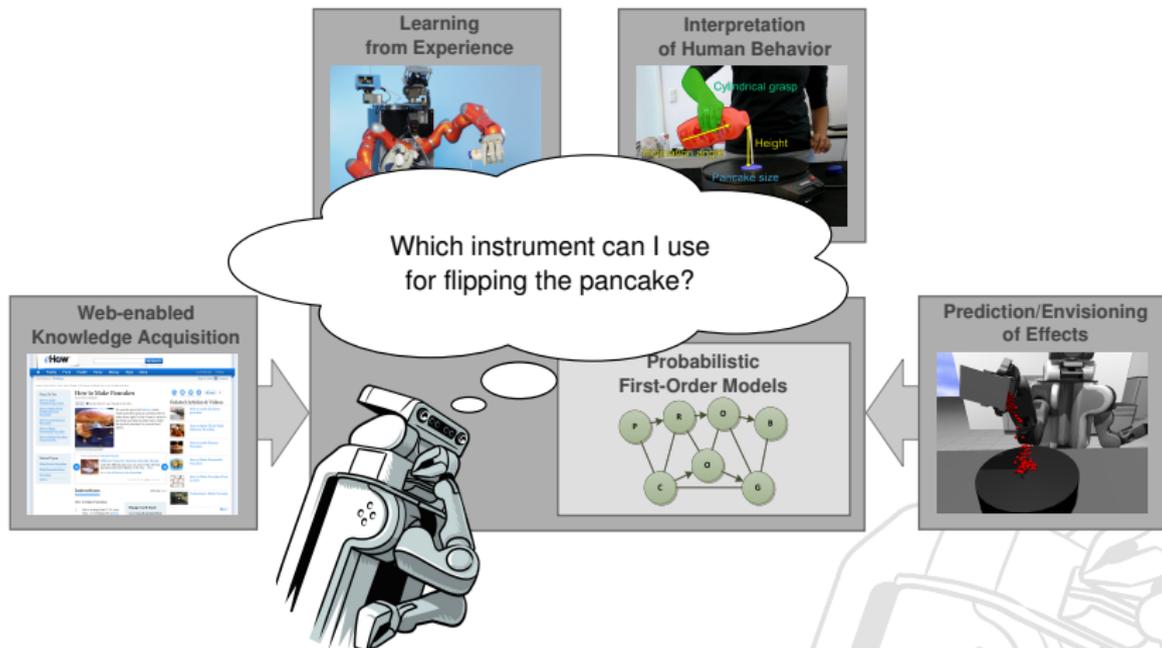
Sources of Knowledge and Cognitive Capabilities





Example

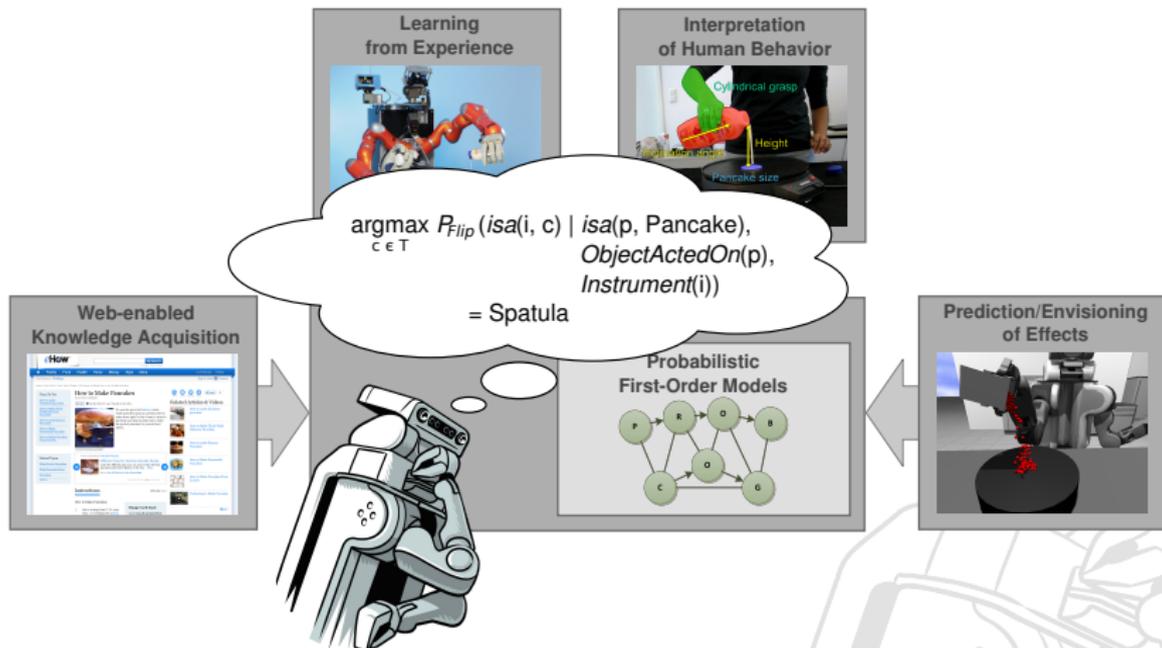
“Flip the pancake!”





Example

"Flip the pancake!"





Reasoning Patterns

► Prediction

$$P(\text{successful}(\text{Robot}, \text{Grasp}, \text{Obj}, \text{Sit}) \mid \\ \text{graspType}(\text{Grasp}, \text{SidewaysRight}) \wedge \text{objectType}(\text{Obj}, \text{Cup}) \wedge \\ \text{relOrientation}(\text{Robot}, \text{Cup}, 0.05, \text{Sit}) \wedge \text{relPos}(\text{Robot}, \text{Obj}, 5.8, -3.2, \text{Sit}) \wedge \\ \text{obstructs}(\text{Clutter1}, \text{Obj}, \text{Sit}) \wedge \text{relPos}(\text{Clutter1}, \text{Obj}, 3.45, 5.23, \text{Sit}) \wedge \\ \text{size}(\text{Clutter1}, 4.2, 3.5, \text{Sit}))$$

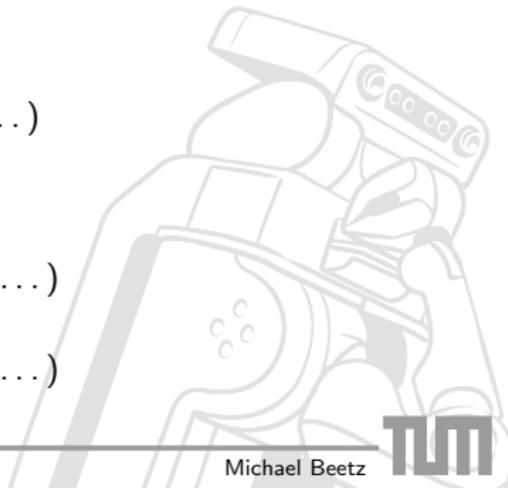
$$P(\text{successful}(\text{Robot}, \text{Grasp2}, \text{Obj2}, \text{Sit2}) \mid \\ \text{successful}(\text{Robot}, \text{Grasp1}, \text{Obj1}, \text{Sit1}) \wedge \text{precedes}(\text{Sit1}, \text{Sit2}))$$

► Evaluating Alternatives

$$P(\text{graspType}(\text{Grasp}, \text{?type}) \mid \\ \text{successful}(\text{Robot}, \text{Grasp}, \text{Obj}, \text{Sit}) \wedge \dots)$$

► Diagnosis

$$P(\text{localizationQuality}(\text{Robot}, \text{Bad}, \text{Sit}) \mid \\ \neg \text{successful}(\text{Robot}, \text{Grasp}, \text{Obj}, \text{Sit}) \wedge \dots)$$

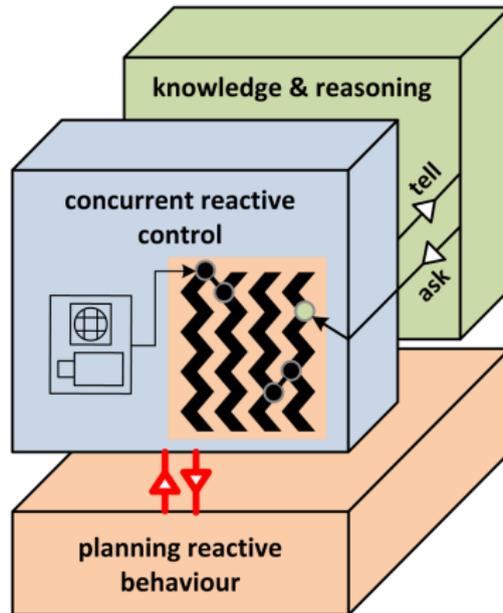
$$P(\text{perceptionAccuracy}(\text{Robot}, \text{Bad}, \text{Sit}) \mid \\ \neg \text{successful}(\text{Robot}, \text{Grasp}, \text{Obj}, \text{Sit}) \wedge \dots)$$




Plan-based Robot Control

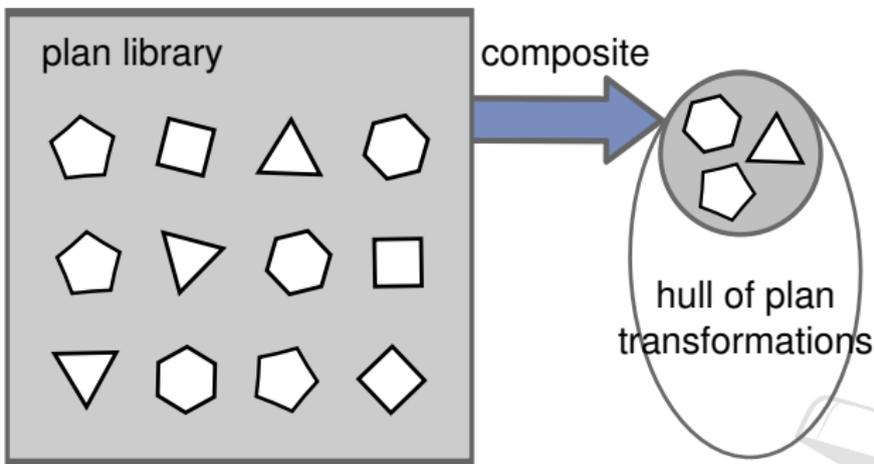
Principle IV

Cognition-Enabled Perception-Guided **Action Plans**





Operational Definition of the Plan Language



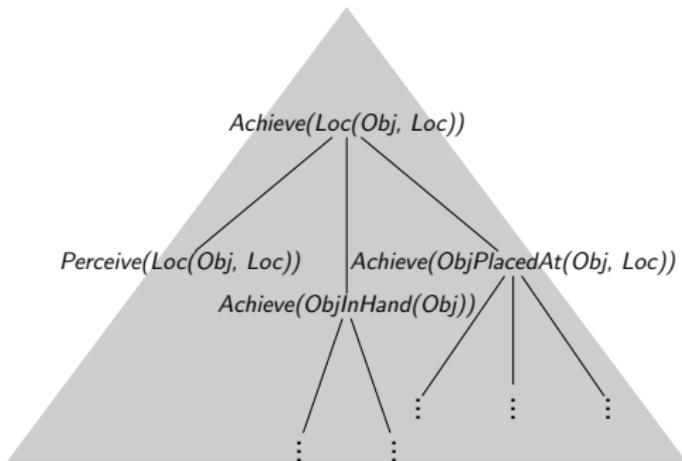
All plans have property p if

- ▶ the plan schematas in the plan library satisfy p
- ▶ plan composition preserves p
- ▶ plan transformation preserves p



Transparent Plan Property

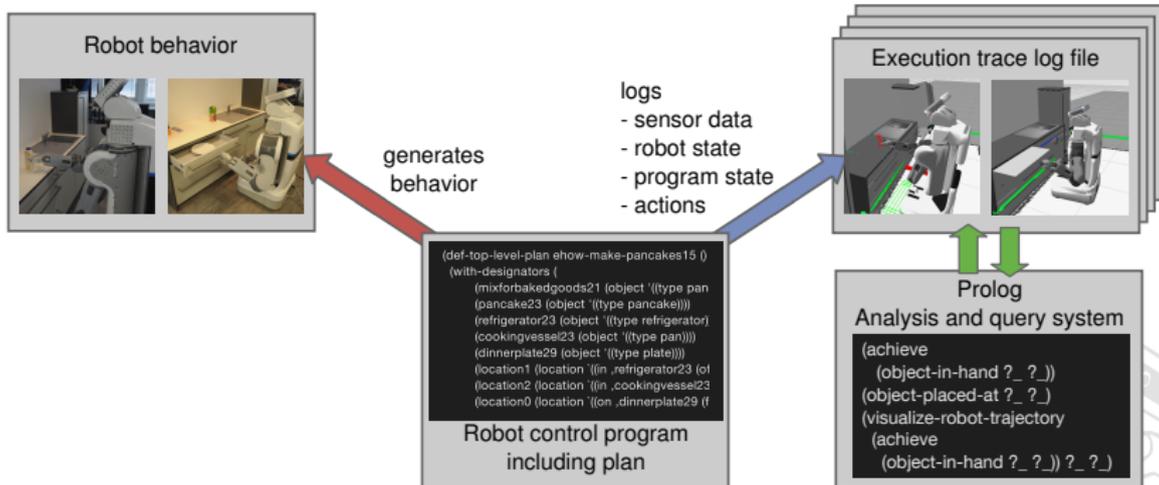
Declarative Goal Hierarchies



- ▶ the plan is structured into code pieces that have the names $\text{achieve}(g)$, $\text{perceive}(p)$, $\text{maintain}(g)$, ...
- ▶ if a plan segment is named $\text{achieve}(g)$ **if and only if** it is intended to achieve g



Reasoning about Execution Traces





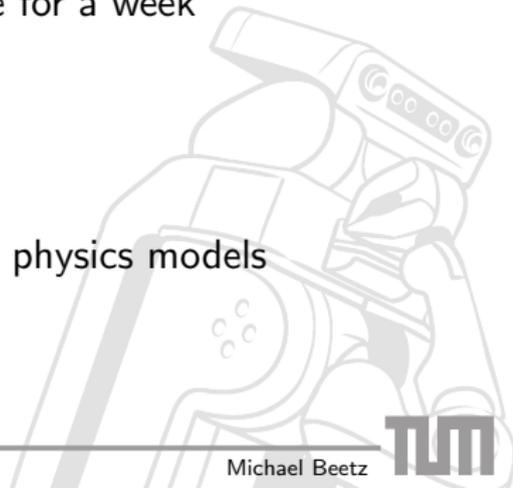
Conclusions

- ▶ **Perception-guided control programs** define how a robot is to respond to sensory inputs and failures in order to accomplish its goals.
- ▶ They become **cognitive** by reasoning about control decisions in order to achieve superior...
 - ▶ robustness
 - ▶ flexibility
 - ▶ efficiency
- ▶ By turning control programs into **semantically interpretable action plans**, a robot can...
 - ▶ explicitly represent its goals and monitor success during temporal projections
 - ▶ reason about plan execution and explain its behaviour to humans
 - ▶ learn models based on data gathered during plan execution



Selected Next Steps

- ▶ movement as first-class objects (symbolic: constraints and objective functions, subsymbolic: iTASC, Stack of Tasks)
- ▶ imitation learning through physics-based interactive games
- ▶ learning action-based knowledge bases (from the web, from experience)
- ▶ performing generalized pick and place for a week
- ▶ Bayesian Cognitive Robotics
- ▶ web-enabled Robots
- ▶ robot crowd sourcing
- ▶ imitation learning with deep task and physics models





Thank you for your attention



Thanks to:



TUM ROS Package Repository:

<http://www.ros.org/wiki/tum-ros-pkg>

Contact:

<http://ias.cs.tum.edu/>