Robot Intelligence

Leslie Pack Kaelbling
MIT CSAIL
A dream of robots

Commercial reality

Research frontier

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Robots and AI were once very close

SRI Shakey

MIT Copy Demo

Robotics drove advances in artificial intelligence: planning, learning, reasoning, vision, natural language....

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Should we give it another try?
The best of times

Good robot hardware
• range sensors, cameras, actuators, ...

Fast computers

Good fundamental algorithms for
• robot motion planning, visual object recognition, ...

Technical advances in
• probabilistic inference, machine learning, knowledge representation

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The worst of times

Super-human robot fallacy:
  • Focus on optimality limits our vision

Fragmented research community
  • Subfields with individual standards, vocabulary, benchmarks
  • Pieces won’t fit together

Many other attractive and important applications
  • Web applications, data mining, finance, …
The age of wisdom

How to build the ‘central’ computational mechanisms for

• closed-loop control of a system with
• sensors and actuators that has
• long-term goal-directed interactions with
• a complex
• imperfectly predictable external environment

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Three technical levers

Compact description of functions and sets in large spaces
  - continuity, geometry
  - factoring, logical languages

Explicit representation of uncertainty
  - knowing what you don’t know

Approximation
  - independence, optimism, …
Interaction with an external environment

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What to learn? What to build in?

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Prior + Experience = Learned competence

How ‘big’ is the prior? Where does it come from?

Engineers must do for robots what evolution did for us
  • Build in architectural constraints and fundamental truths (e.g. physical laws)

Agents must learn niche-specific competences (and things the engineers can’t articulate)
  • sensory-motor loops
  • world model at several levels of abstraction
  • strategies for managing internal computation

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Internal architecture

observation → state estimation → belief → action selection → action

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Internal architecture

- Observation
  - State estimation
  - World model
    - Belief
    - Action selection
      - Action
Internal architecture

- Model learning
- World model
- State estimation
- Belief
- Action selection

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This talk: getting leverage

Sample points in the technical space

• **state estimation** method
  • combining logic, probability, and approximation

• **3 action selection** examples
  • combining logic or geometry, probability, and approximation

• **model learning** method
  • combining logic, probability, and approximation

Important areas neglected:

• perception, actuation, language and human interaction, multi-agent systems, ...
The epoch of belief and of incredulity

State estimation: Explicitly represent state of knowledge about external environment using probability

Joint work with Luke Zettlemoyer and Hanna Pasula

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State estimation

**Problem:** given history of past observations and actions, what do we know about the current state of the world?

**Lazy:** store history of observations, do inference when necessary

**Eager:** maintain an explicit representation of the current distribution over the state of the world (“filtering”)
Filtering: Bayesian belief state update

Update after executing an action and receiving an observation

\[
\Pr(s_{t+1} \mid a_t, o_{t+1}) \propto \Pr(o_{t+1} \mid s_{t+1}) \sum_{s_t} \Pr(s_{t+1} \mid s_t, a_t) \Pr(s_t)
\]

- posterior belief
- observation model
- transition model
- prior belief
Representing the belief state

Gaussian

Histogram

Set of particles

Bayesian network

Dieter Fox

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A big (toy) world

- dimensions are unknown (possibly infinite)
- walls between some locations
- locations have appearance
- R moves (with error) through the world
- R observes (with error) the color at his location

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A day in the life

R is booted up,
• sees a red square
• tries to move right
• sees a green square

What does R know about the world?

Combine logic and probability to get compact representations of beliefs in complex domains

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First-Order particle filtering

**Hypothesis:** set of states that are indistinguishable based on the history of observations and actions

\[
Pr(s \mid o_{0:t}, a_{1:t}) \propto Pr(o_{0:t} \mid s, a_{1:t}) Pr(s)
\]

Use logic sentences to describe hypotheses

Only represent likely hypotheses

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R wakes up

• One hypothesis

True

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R sees a red square

\[ \exists x. \text{at}(R, x) \land \text{red}(x) \]

\[ \exists x. \text{at}(R, x) \land \text{green}(x) \]

\[ P(\text{see red} \mid \text{at red square}) = 0.8 \]
R tries to move right

\[ \exists x, y. at(R, y) \land red(x) \land rightOf(y, x) \]

\[ \exists x, y. at(R, y) \land green(x) \land rightOf(y, x) \]

\[ \exists x, y. at(R, x) \land red(x) \land rightOf(y, x) \]

\[ \exists x, y. at(R, x) \land green(x) \land rightOf(y, x) \]

\[ \exists x. at(R, x) \land red(x) \land \neg \exists y. rightOf(y, x) \]

\[ \exists x. at(R, x) \land green(x) \land \neg \exists y. rightOf(y, x) \]

Prob wall to right: 0.3
Prob fail to move (if no wall): 0.1
Prob fail to move (if wall): 1.0

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R tries to move right: sample

\[ \exists x, y. \text{at}(R, y) \land \text{red}(x) \land \text{rightOf}(y, x) \]

\[ \exists x, y. \text{at}(R, y) \land \text{green}(x) \land \text{rightOf}(y, x) \]

\[ \exists x, y. \text{at}(R, x) \land \text{red}(x) \land \text{rightOf}(y, x) \]

\[ \exists x. \text{at}(R, x) \land \text{red}(x) \land \neg \exists y. \text{rightOf}(y, x) \]

Prob wall to right: 0.3
Prob fail to move (if no wall): 0.1
Prob fail to move (if wall): 1.0

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R sees a green square

\[
\exists x. \text{at}(R, x) \land \text{red}(x) \land \text{rightOf}(y, x) \land \text{red}(y)
\]

\[
\exists x, y. \text{at}(R, x) \land \text{red}(x) \land \text{rightOf}(y, x)
\]

\[
\exists x. \text{at}(R, x) \land \text{red}(x) \land \neg \exists y. \text{rightOf}(y, x)
\]

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R sees a green square: sample

\( \exists x. \text{at}(R, y) \land \text{red}(x) \land \text{rightOf}(y, x) \land \text{red}(y) \)

\( \exists x. \text{at}(R, x) \land \text{red}(x) \land \neg \exists y. \text{rightOf}(y, x) \)

\( \exists x. \text{at}(R, y) \land \text{red}(x) \land \text{rightOf}(y, x) \land \text{green}(y) \)

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Technical Story

Rao-Blackwellization:

\[
\mathbb{E}_{Pr(x_1, x_2)} f(x_1, x_2) = \mathbb{E}_{Pr(x_2)} \mathbb{E}_{Pr(x_1 | x_2)} f(x_1, x_2)
\]

\[
\approx \frac{1}{n} \sum_{\text{samples from } Pr(x_2)} \mathbb{E}_{Pr(x_1 | x_2)} f(x_1, x_2)
\]

For us:

- \(x_2\): logical partition
- \(x_1\): state within the partition
- \(f(x_1, x_2)\): Am I in room 6?

Many other possible \(f\)

created dynamically depending on observations

depends only on prior

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Demand-driven complexity

Logical particle filter:
- complexity of **logical form** driven by observations
- concentrates on **most probable** part of the space

Be lazier!
- focus on small set of objects and properties relevant to current goal
- dynamically change focus
- use observation history to initialize new filters
Action selection

Plan in belief space:

- every action gains information and changes the world
- changes are reflected in new belief via estimation
- goal is to believe that the environment is in a desired state
The spring of hope and the winter of despair

In domains that lack terrible outcomes:
  • plan assuming actions will result in most likely transition and observation
  • replan if expectation is violated at runtime

Great success of FF-Replan at ICAPS probabilistic planning competition

Same principle as feedback control using an idealized model
Optimistic (re)planning in belief space

- **control with state-dependent observation noise:** continuous state, action, observation spaces
- **robot grasping with tactile sensing:** continuous state, action, observation spaces
- **household robot with local observation:** mixed continuous and relational spaces
The season of light, the season of darkness

- robot in $x, y$ space
- good position sensing in light regions; poor in dark

Joint work with Rob Platt, Russ Tedrake and Tomás Lozano-Pérez
Control in belief space: underactuated

Acrobot

State space:
\[ x = \begin{pmatrix} \theta \\ \dot{\theta} \end{pmatrix} \]

Planning objective:
\[ x_g = \begin{pmatrix} \pi \\ 0 \end{pmatrix} \]

Underactuated dynamics:
\[ \ddot{\theta} = f(\theta, \dot{\theta}, u) \]

Gaussian belief:
\[ b = \begin{pmatrix} m \\ \Sigma \end{pmatrix} \]
\[ b_g = \begin{pmatrix} x_g \\ 0 \end{pmatrix} \]

???
Belief space dynamics

Dynamics specify next belief state, as a function of previous belief state and action

• state update: generalized Kalman filter

\[(\mu_{t+1}, \Sigma_{t+1}) = GKF(o_t, a_t, \mu_t, \Sigma_t)\]

• substitute expected observation in for actual one

\[\begin{align*}
(\mu_{t+1}, \Sigma_{t+1}) &= F(a_t, \mu_t, \Sigma_t) + N \\
&= GKF(\tilde{o}(\mu_t), a_t, \mu_t, \Sigma_t) + N
\end{align*}\]

• continuous Gaussian non-linear dynamics: apply tools from control theory

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Light-dark plan
Replanning

Replan when new belief state deviates too far from planned trajectory
Replanning: light-dark problem
Replanning: light-dark problem
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Optimistic (re)planning in belief space

- control with state-dependent observation noise: continuous state, action, observation spaces

- robot grasping with tactile sensing: continuous state, action, observation spaces

- household robot with local observation: mixed continuous and relational spaces
Goal: pick up object of known shape with specific grasp

Visual localization and detection works moderately well...

Joint work with Kaijen Hsiao and Tomás Lozano-Pérez
Hypothesis space

Robot pose:
• 11 DOF
• model as fully observable

Object pose:
• 3 DOF
• model as partially observable

State estimate: probability distribution over object pose
Macro actions

Execute a trajectory:
  • stop moving arm if any contact is felt
  • close each finger until it makes contact

Fixed set of parameterized trajectories, always executed with respect to most likely state
Observations

• Arm trajectory according to proprioception
Observations

- Arm trajectory according to proprioception
- 6-axis force-torque sensors on fingertips

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Observations

- Arm trajectory according to proprioception
- 6-axis force-torque sensors on fingertips
- Binary contact sensors

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**Observation model:** $\Pr(o \mid s, a)$

<table>
<thead>
<tr>
<th>Actual $o$</th>
<th>Contact</th>
<th>no contact</th>
</tr>
</thead>
</table>
| **Contact** | Gaussian density on dist to closest $a'$ that would not have caused interpenetration
  X
Gaussian density on dist between contact positions and normals | Gaussian density on dist to closest $a'$ that would have caused contact
  $X$
Gaussian density on dist between contact positions and normals |
| **no contact** | Gaussian density on dist to closest $a'$ that would not have caused contact | Max value of Gaussian density used for nominal contact case |

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Transition model: $\Pr(s_{t+1} \mid s_t, a_t)$

- **No contact**: no change

- **Contact**: probability of being bumped depends on observation

- **Reorientation**: similar to contact with large rotational variances

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Initial belief state
Tried to move down — finger hit corner
Updated belief

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Another grasp attempt
Goals in belief space

- Specify set of desirable ranges in $X, Y, \Theta$
- Satisfied if probability that the pose is in that set is high
What if Y coordinate of grasp matters?
Action selection

How to select among the actions?

- Until probability of failure given belief is < $\epsilon$
- Select WRT by searching forward from belief
- Execute WRT, and get observations $o$
- Update belief

WRTs include:
- target grasp
- information-gain trajectories
- re-orientation
Forward search

- Compute k-step risk using backward induction
- Prune and cluster to decrease observation branching
- Depth 2 sufficed in our problems
- Risk at leaves is likelihood of failure of target grasp
Objects and desired grasps
Dark blue box: most likely state
Light blue boxes: belief state variance (1 std)
Brita results: 10 / 10 successful grasps

Grasping a Brita Pitcher
50x
Low deviation
Powerdrill: 10 / 10 successful grasps

25× speed

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Optimistic (re)planning in belief space

- control with state-dependent observation noise: continuous state, action, observation spaces
- robot grasping with tactile sensing: continuous state, action, observation spaces
- household robot with local observation: mixed continuous and relational spaces
Classes of robotics problems in which:

• Problems are huge:
  • long horizon
  • many continuous dimensions
  • combinatoric discrete aspects
• No terrible outcomes
• Geometry is not intricate
• Partial observability: local but fairly reliable

Joint work with Tomás Lozano-Pérez
Symbols to Angles

Initial state known in geometric detail

Goal set is abstract, symbolic

\[ tidy(house) \land charged(robot) \]

Operator descriptions:
- STRIPS-like, with continuous values
- procedures suggest values for existential vars
- geometric reasoning

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Wash a block and put it away
Clean(a) and In(a, storage): Regression structure

7 primitive steps; 3000 search nodes

Wash[a]
Place[a, washer]
Pick[a, washer]
Pick[a, aStart]
Place[a, storage]
clearX[sweptVol(path(a, washer, storage)), [a]]
remove[d, sweptVol(path(a, washer, storage))]
Place[d, parking]
Pick[d, dStart]

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Hierarchy crucial for large problems

Subtrees represent **serialized subtasks**

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Subgoal is an abstract operator:

What does it mean to sequence two subgoals?

Depends on who gets to choose the outcome:

Wolfe, Marthi, Russell

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Planning in the now

• maintain left expansion of plan tree
• execute primitives
• plan as necessary
Satanic semantics

We have to handle any outcome the devil picks

Okay if: Preconditions of op2 can be achieved from any state resulting from op1

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Wash a block and put it away

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• solves 10 planning problems
• sizes 3, 3, 6, 5, 2, 7, 6, 8, 13, 129
• takes 9 primitive steps
• Flat: 1 problem, 3000 nodes, 7 primitive steps
Planning in the Know

Plan in the **now in belief space**:
- Make a single plan that will succeed with high probability
- Replan on unexpected observations

Plan at the **knowledge level**
- Traditional to plan in the powerset of the state space
- We have infinite state space
- Use explicit logical representation of knowledge and lack of knowledge

Plan at **level of abstraction** supported by current belief state

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Going on a tiger hunt

move(Room):
  res: robotLoc = Room
listen:
  pre: robotLoc = hall
  result: KV(tigerLoc)
shoot:
  pre: robotLoc = tigerLoc
  result: deadTiger

P(tigerLoc = leftRoom) = 0.8
Going on a tiger hunt: regression search tree

move(Room):
  res: robotLoc = Room
listen:
  pre: robotLoc = hall
  result: KV(tigerLoc)
shoot:
  pre: robotLoc = tigerLoc
  result: deadTiger

\[ P(\text{tigerLoc} = \text{leftRoom}) = 0.8 \]
Monitor execution and replan

Plan 2
TigerDead() = True

- A0:Listen()
- A0:MoveTo(leftRoom)
- A0:Shoot()
- Replan
- A0:MoveTo(rightRoom)
- A0:Shoot()

ListenPrim
MoveTo(rightRoom)
ShootPrim

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Cleaning house

Goal: vacuum four of the rooms in the house

- have to put away junk items before vacuuming
- location of junk is unknown
- location of vacuum is unknown
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Plan hierarchy can pose small filtering problems

\[ B(S_0) \]

\[ B(\text{loc}(\text{Joe}), \text{loc}(\text{friend}(\text{Joe}))) \mid O_{0:t} \]

\[ B(\text{loc}(\text{Joe}), \text{hidingPlaces}(\text{Room1}), \text{locked}(\text{Closet})) \mid O_{0:t} \]

\[ B(\text{loc}(\text{key}(\text{Closet}))) \mid O_{0:t} \]

\[ \exists r. B(\text{in}(\text{Joe}, r)) \]

\[ B(\text{in}(\text{Joe}, \text{Room1})) \lor B(\neg \text{in}(\text{Joe}, \text{Room1})) \]

\[ \exists r. r \neq \text{Room1} \land B(\text{in}(\text{Joe}, r)) \]

\[ \text{holding}(\text{key}(\text{Closet})) \]

\[ \text{open}(\text{Closet}) \]

\[ \text{explored}(\text{Closet}) \]

\[ \text{withinReach}(\text{Robot}, \text{key}(\text{Closet})) \]

\[ \text{primGrasp}(\text{key}(\text{Closet})) \]

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Learning a model

Joint work with Hanna Pasula and Luke Zettlemoyer

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Blocks with physics
Representing a world model

Probabilistic state transition dynamics:

\[ \Pr(s_t \mid s_{t-1}, a) \]

Representation should:

• allow effective generalization
• be useful for planning
• be efficiently learnable
Probabilistic dynamic rules

Combine logic and probability to model effects of actions in complex, uncertain domains

\[ \begin{align*}
\text{pickup}(X): & \{ Y: \text{on}(X,Y) \} \\
\text{clear}(X), \text{inhand-nil}, \text{size}(X) > 2, \text{size}(X) < 7 \rightarrow \\
0.803 & : \neg \text{on}(X,Y) \\
0.093 & : \text{no change}
\end{align*} \]
Is $X$ on $Y$?

Useful symbolic vocabulary should be learned.

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Neoclassical learning

Given experience, \( \{s_t, a_t, s_{t+1}\} \)

Find rule set that optimizes

\[
\text{score}(R) = \sum_t \log \Pr(s_{t+1} \mid s_t, a_t, R) - \alpha |R|
\]

Start with one default rule: “stuff happens”

- **Symbolic**: add, delete rule; change rule conditions

- **Greedy**: choose set of outcomes

- **Convex optimization**: find maximum likelihood probabilities

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New concepts allow predictive theory to be expressed more compactly and learned from less data

\[ p1(X) :\neg \exists Y. \text{on}(X,Y) \quad X \text{ is in the hand} \]

\[ p2() :\neg \exists Z. p1(Z) \quad \text{nothing is in the hand} \]

\[ p3(X) :\neg \exists Y. \text{on}(Y,X) \quad X \text{ is clear} \]

\[ p4(X,Y) :\text{on}(X,Y) \quad X \text{ is above } Y \]

\[ p5(X,Y) : p3(X) \land p4(X,Y) \quad X \text{ is on the top of the stack containing } Y \]

\[ f6(X) :\#Y. p4(X,Y) \quad \text{the height of } X \]
pickup(X): {Y: on(X,Y)}
clear(X), inhand-nil, size(X)>2, size(X)<7 \rightarrow 
0.803 : \neg on(X,Y) 
0.093 : no change

Rules learned from data

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Rules learned from data

pickup(X):
clear(X), inhand-nil, ¬size(X)<7 →
0.906 : no change

it’s impossible to pick up very big blocks

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Rules learned from data

pickup(X): \{T: table(T)\}, \{Y: on(X,Y), on(Y,T)\}
clear(X), inhand-nil, size(X)<2 \rightarrow
0.105 : ¬on(X,Y)
0.582 : ¬on(Y,T)
0.312 : no change

if a tiny block is on another block that is on the table, and we try to pick up the tiny block, we’ll often pick up the other block as well, or fail
Planning with learned rules

![Graph showing human performance with respect to the number of training examples. The graph indicates a constant total reward of 16 across various numbers of training examples.](image-url)
Planning with learned rules

![Graph showing total reward versus number of training examples]

- **Total Reward**
- **Number of Training Examples**

**Legend:**
- no concepts
- human performance
Planning with learned rules

![Graph showing Total Reward vs Number of Training Examples]

- **learned concepts**
- **no noise outcome**
- **no concepts**
- **human performance**
compact representation
explicit uncertainty modeling
approximation

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What should we be doing?

Thinking hard about representation in open, uncertain domains
  • What do you know about your house?

Everything else: planning, learning, reasoning, ...

Talking to each other
  • vision, natural language, robotics, logic, probability, learning, ...
Thanks!

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