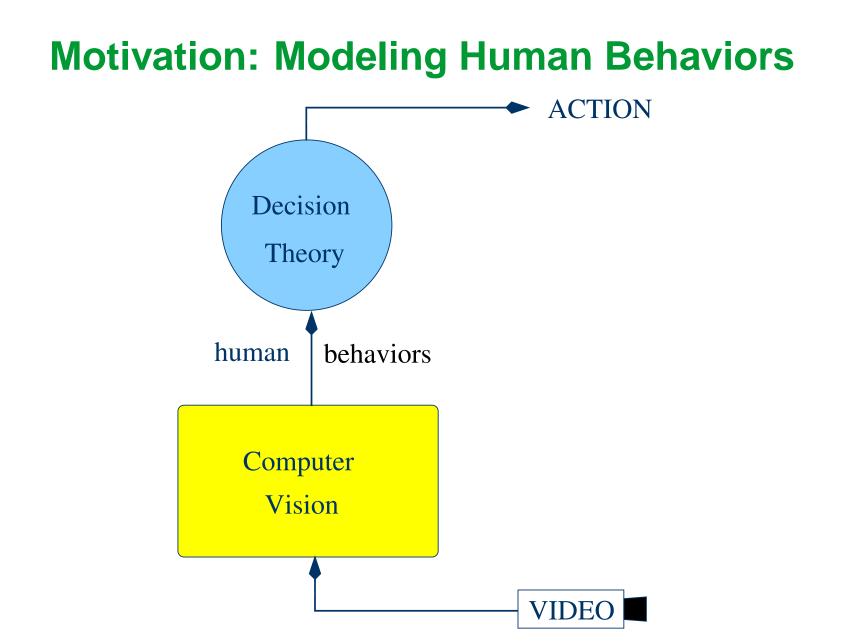
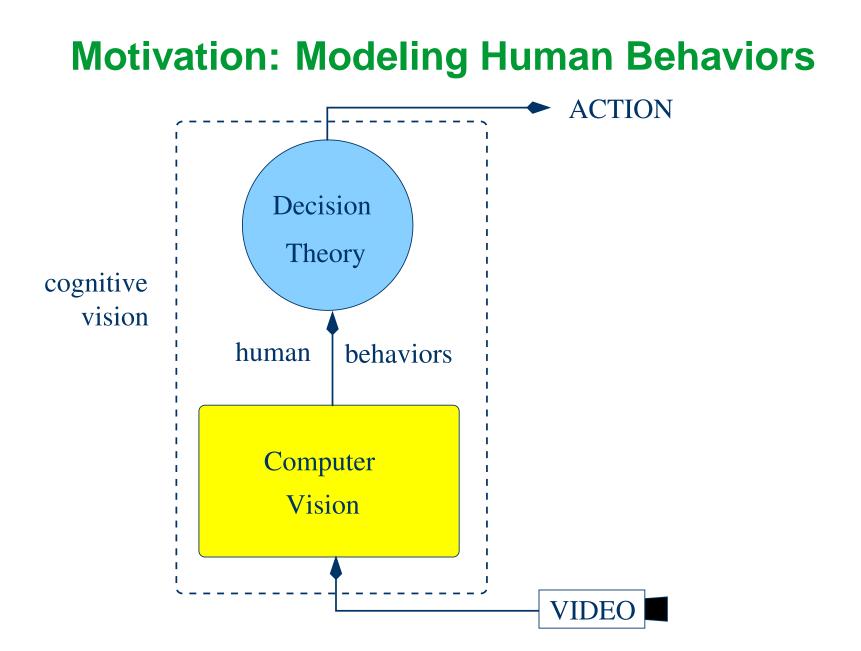
Learning Models of Human Behavior using a Value Directed Approach

Jesse Hoey Computer Science Department University of Toronto

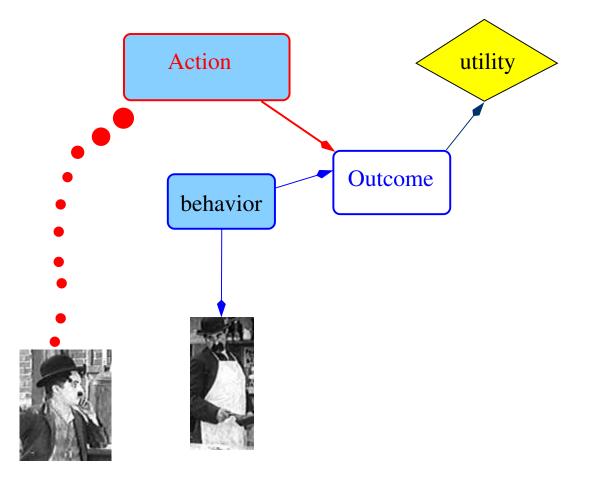
http://www.cs.toronto.edu/~jhoey/

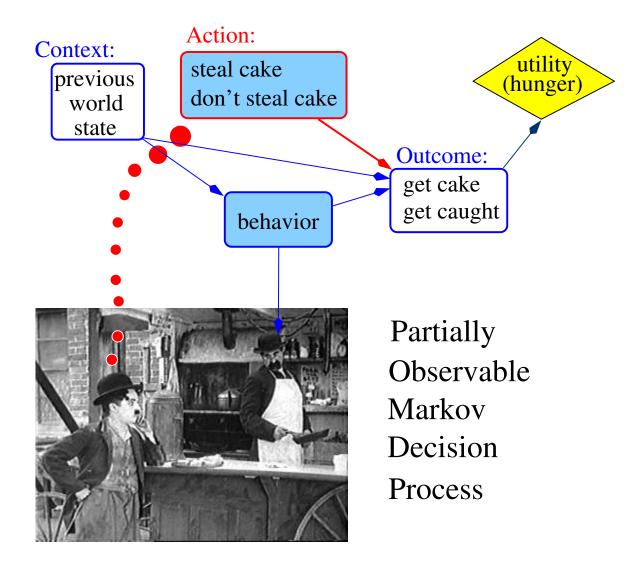
IRIS Learning Workshop - June 9, 2004











Overview

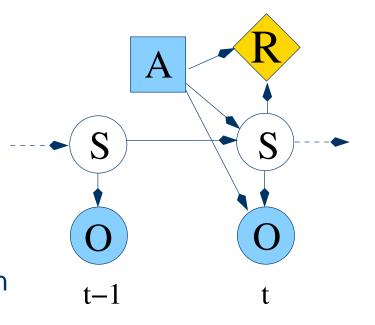
- → POMDPs for Display Understanding in Context
- → Computer Vision: Modeling video sequences
 - spatial abstraction
 - temporal abstraction
- → Learning POMDPs
- → Solving POMDPs
- → Value-Directed Learning
- → Experiments
 - Robot Control
 - Card Matching Game
- → Conclusions, Current & Future Work

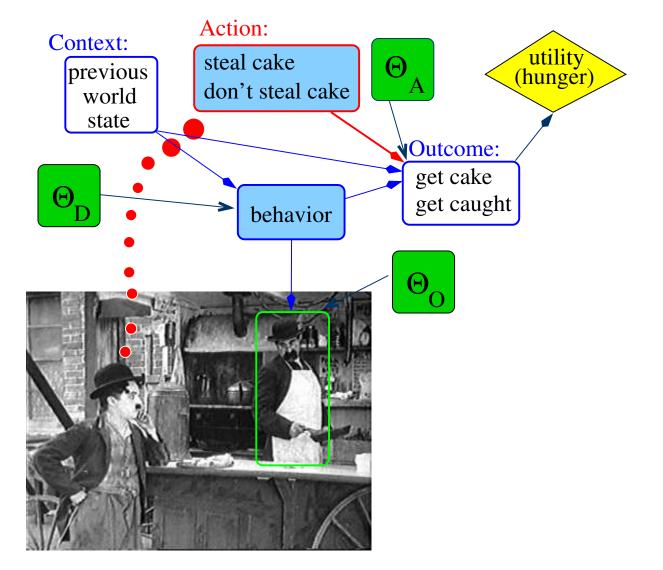
Partially Observable Markov Decision Processes (POMDPs)

A POMDP is a probabilistic temporal model of agent interacting with its environment :

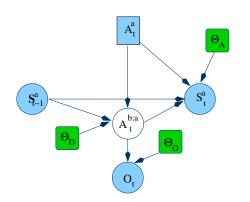
a tuple $\langle S, A, T, R, O, B \rangle$

S: finite set of unobservable states A: finite set of agent actions $T: S \times A \rightarrow S$ transition function $R: S \times A \rightarrow \mathcal{R}$ reward function O: set of observations $B: S \times A \rightarrow O$ observation function

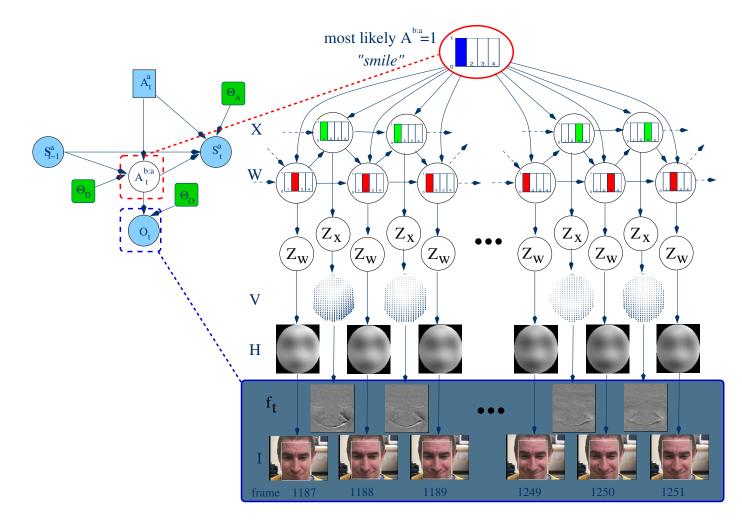




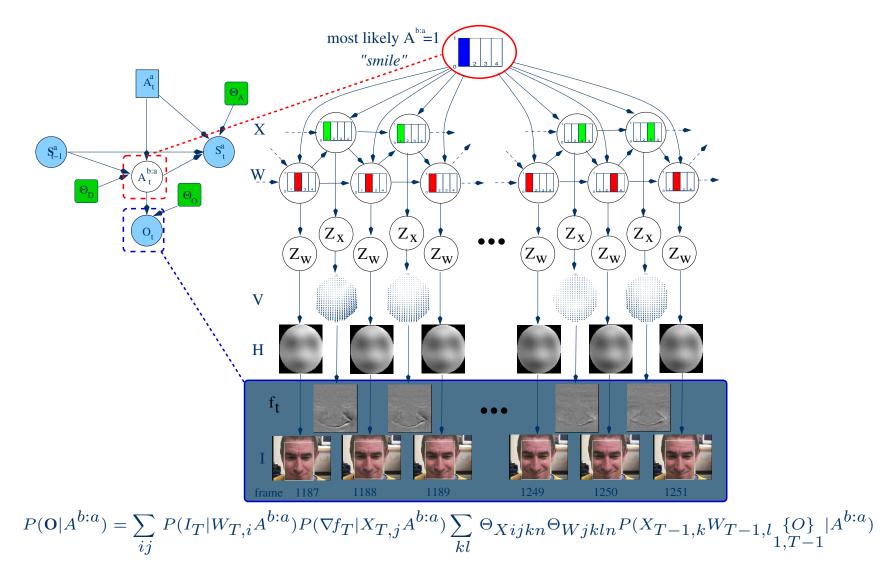
Output Model

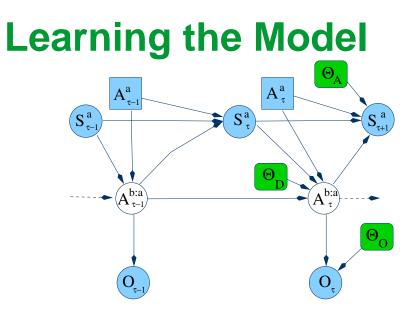


Output Model



Output Model





Find parameters, $\Theta^* = \underset{\Theta}{\arg \max} P(\mathbf{O}, \mathbf{S^a}, \mathbf{A^a}\Theta)$

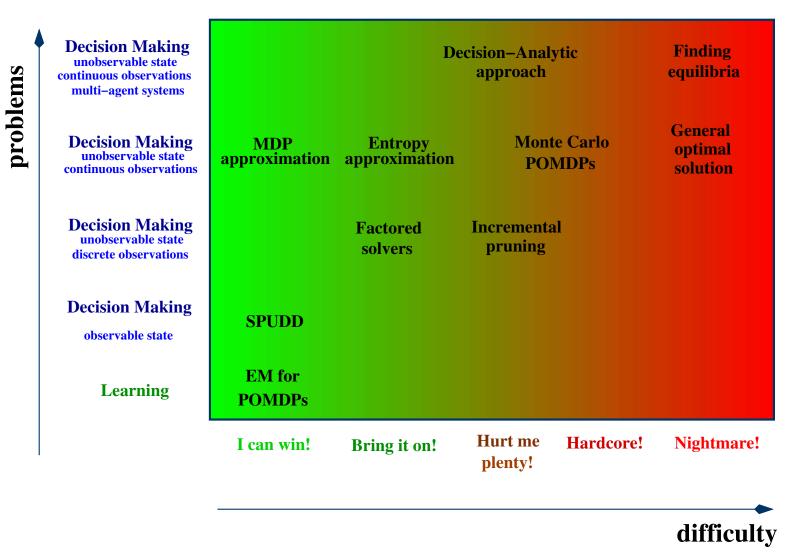
Use expectation-maximization(EM)algorithm:

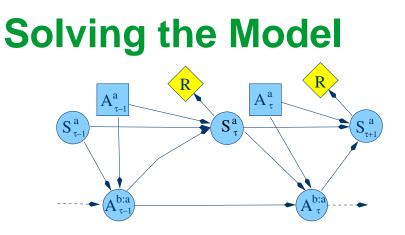
$$\Theta^* = \underset{\Theta}{\operatorname{arg\,max}} \left[\sum_{\mathbf{A}^{\mathbf{b}:\mathbf{a}}} P(\mathbf{A}^{\mathbf{b}:\mathbf{a}} | \mathbf{OS}^{\mathbf{a}} \mathbf{A}^{\mathbf{a}}, \theta') \log P(\mathbf{A}^{\mathbf{b}:\mathbf{a}} \mathbf{OS}^{\mathbf{a}} \mathbf{A}^{\mathbf{a}} | \Theta) + \log P(\Theta) \right]$$

finds local maximum of a posteriori probability

IRIS Learning Workshop - June 9, 2004

Solution Techniques





MDP Approximation: Assume $A^{b:a}$ is observable

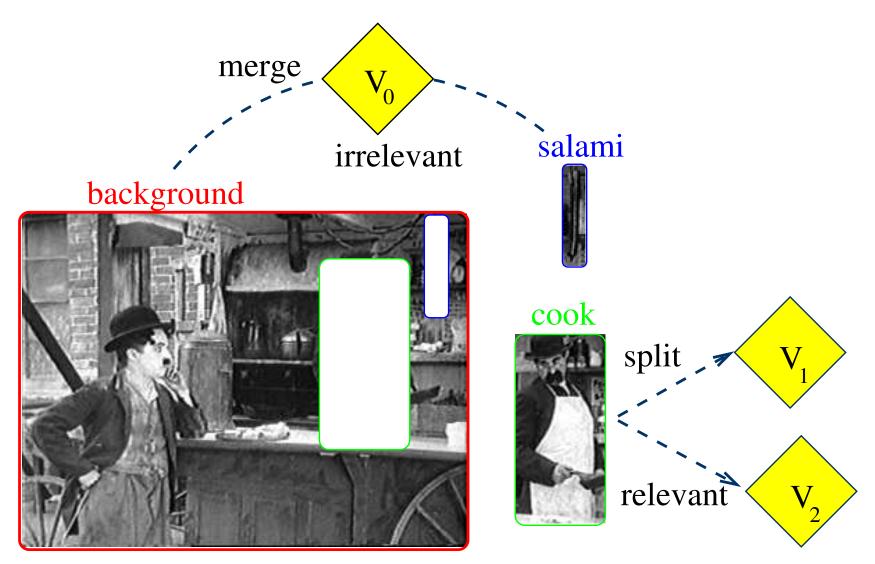
Dynamic Programming: Value Iteration

$$V^{n+1}(s) = R(s) + \max_{a \in \mathcal{A}} \left\{ \sum_{t \in \mathcal{S}} Pr(t|a, s) \cdot V^n(t) \right\}, \qquad V^0 = R$$

n-stage to go Policy: actions that maximize expected value

$$\pi^{n}(s) = \arg \max_{a \in \mathcal{A}} \left\{ \sum_{t \in \mathcal{S}} \Pr(t|a, s) \cdot V^{n}(t) \right\}$$

Value Directed Structure Learning



Value Directed Structure Learning

State merging:

repeat

1.learn the POMDP model

2.compute value functions for behaviors

- 3.compute distance between value functions
- 4.if policies agree,

merge behaviors closest in value

until number of behaviors stops changing

State splitting

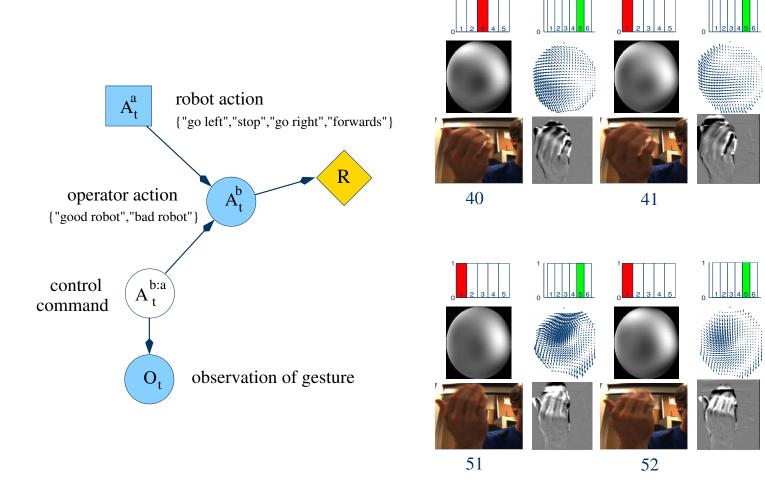
repeat

- 1.learn the POMDP model
- 2.examine states for predicitve power entropy?
- 3.Split behaviors which predict

different outcomes

until number of behaviors stops changing

Experiments: Robot Control Gestures



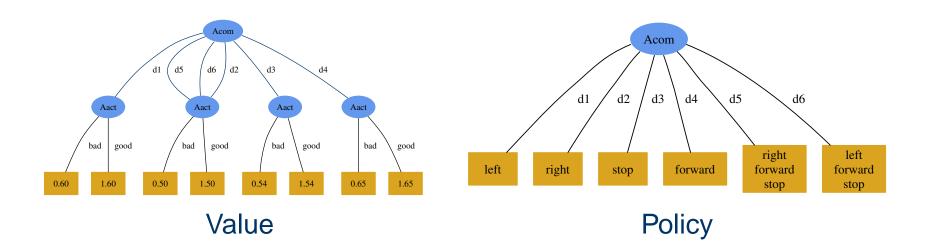
IRIS Learning Workshop - June 9, 2004

53

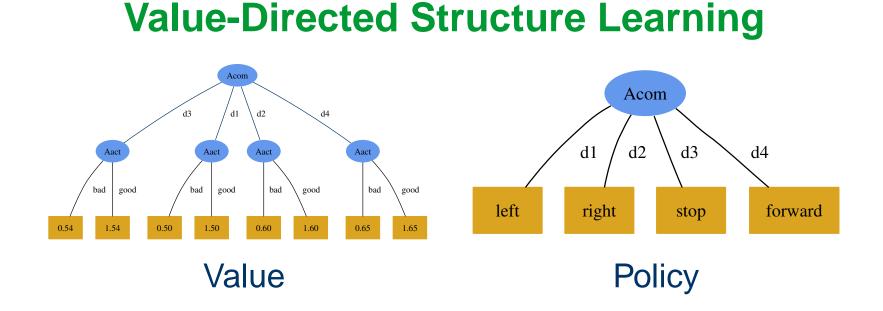
42

Value-Directed Structure Learning

Part of Value function & policy for robot control:



- Some states of *Acom* are redundant
- detect & merge using state aggregation in the policy and value function
- re-compute policy

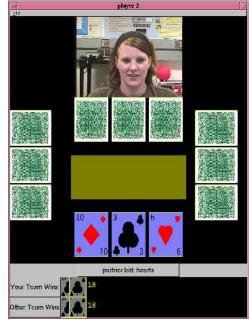


- Leave-four-out cross validation (12 times)
- Take actions and accumulate rewards
- Success rate: 47/48 = 98% or 11/12 correct policies
- Merges to 4 states all 12 times.

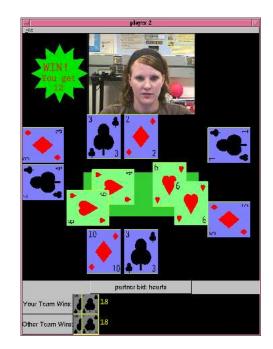
Experiments: Card Matching Game

Cooperative two player game

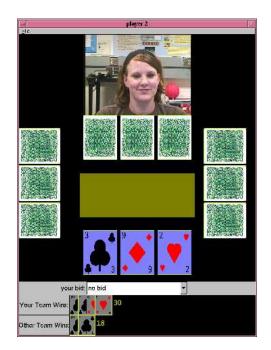
Goal: match cards



stage 1



stage 2



stage 3

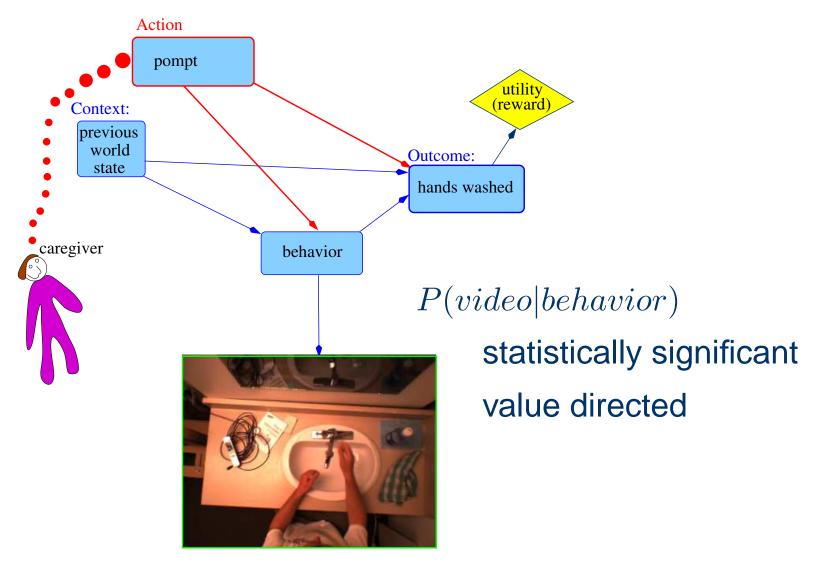
Card Matching Results

3 behaviors identified: nodding, shaking, null Predicts:

- 6/7 human actions in test data
- 19/20 human actions in training data.

Errors: lack of POMDP data, temporal segmentation problems

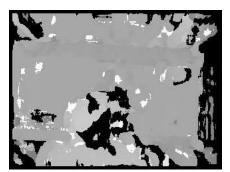
Handwashing Behavior Understanding



Difficult Cases



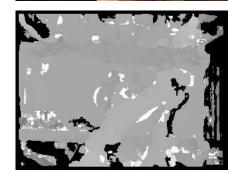




self-occlusion















object occlusion

IRIS Learning Workshop - June 9, 2004

Conclusions

- Computer Vision + Probabilistic Models + Decision Theory
- Learning *purposeful* human behavior models from *unlabeled* data.
- System is general and portable no reliance on expert knowledge
- Applications: HCI, surveillance, assisted living, driver support
- Future work
 - Spatial segmentation and representation + tracking
 - Multimodal observations
 - Temporal segmentation
 - POMDP solutions
 - Value-directed learning (Hoey & Little, CVPR 2004)