USC Institute for Creative Technologies

University of Southern California

# Σ The Sigma Cognitive Architecture/System


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& the Sigma Group


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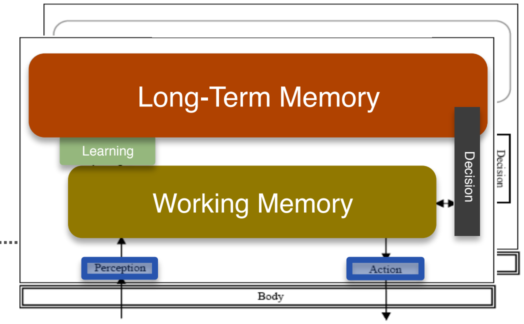
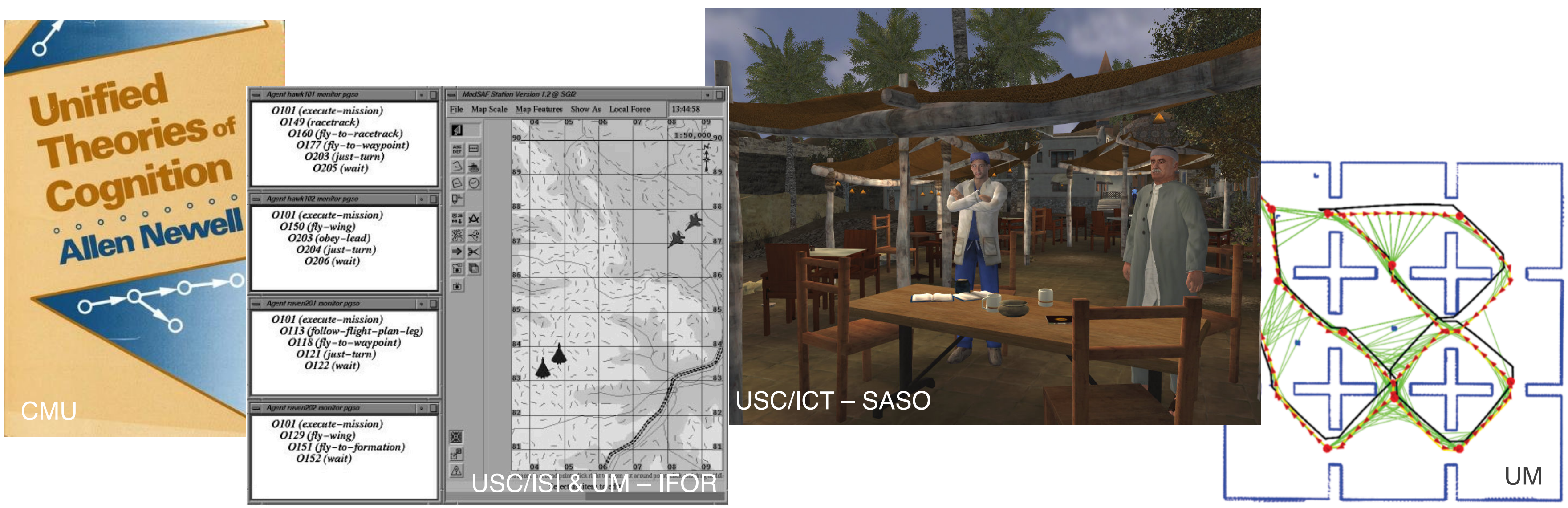
# Cognitive Architecture




- Model of the fixed structure of a/the mind
  - Memory, reasoning, learning, interaction, ...
  - Integration across these capabilities
- Supports knowledge and skills above the architecture



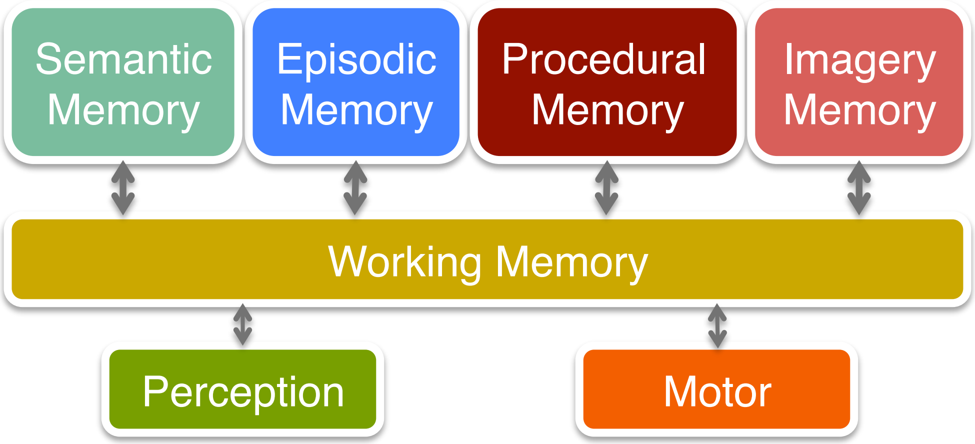

**Examples are from Soar**

# Overall Desiderata for the Sigma (Σ) Architecture

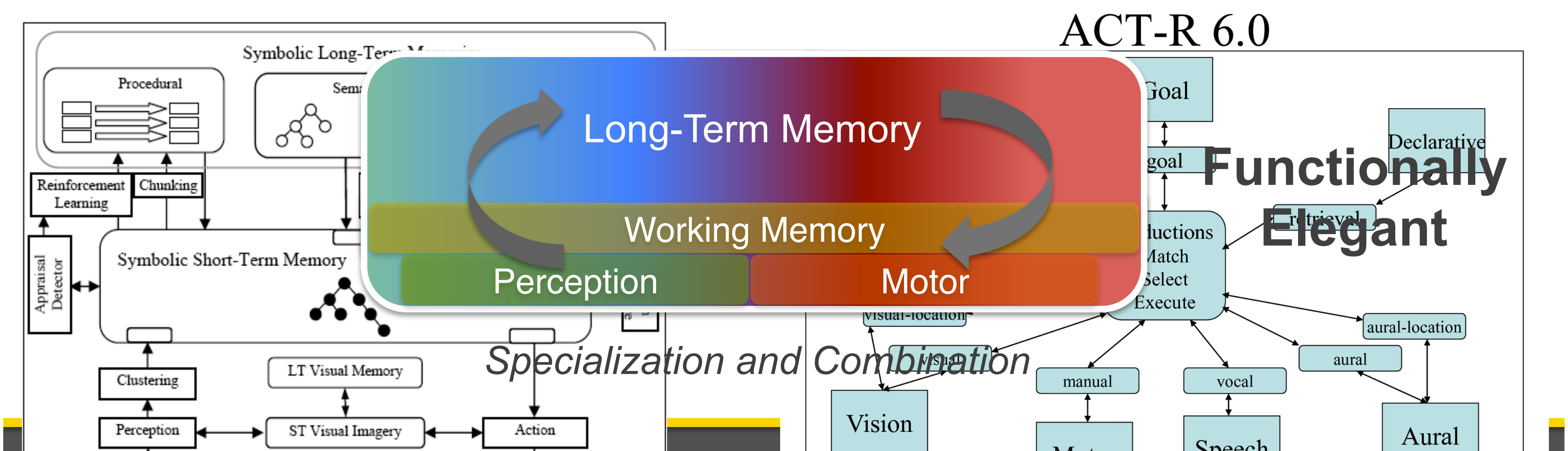
- A new breed of cognitive architecture that is
  - *Grand unified*
    - Cognitive + key non-cognitive (perceptuomotor, affective, attentive, …)
  - *Generically cognitive*
    - Spanning both natural and artificial cognition
  - *Functionally elegant*
    - Broadly capable yet simple and theoretically elegant
      - "cognitive Newton's laws"
  - *Sufficiently efficient*
    - Fast enough for anticipated applications
- For virtual humans & intelligent agents/robots that can
  - Think – Broadly, deeply and robustly *cognitive*
  - Behave – *Interactive* with their physical and social worlds
  - Learn – *Adaptive* given their interactions and experience

*Hybrid*: Discrete + Continuous
*Mixed*: Symbolic + Probabilistic

# Modular versus Functionally Elegant




**Modular**




**Functionally Elegant**

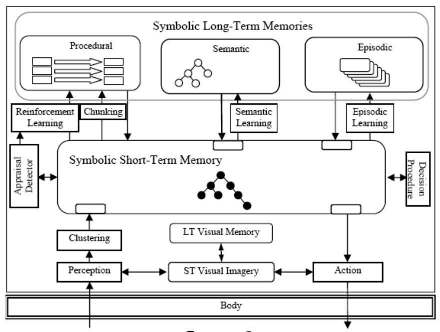
*Specialization and Combination*

**Goal: Advancing *elegance, depth* and *breadth***

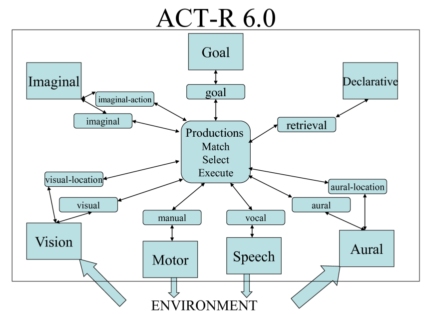
# Approach: Graphical Architecture Hypothesis

Key to success is *blending what has been learned from over three decades of independent work* in **cognitive architectures** and **graphical models**

**Cognitive Architectures**



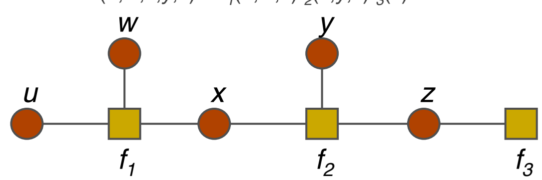

**Soar 9**




**+**

**Graphical Models**

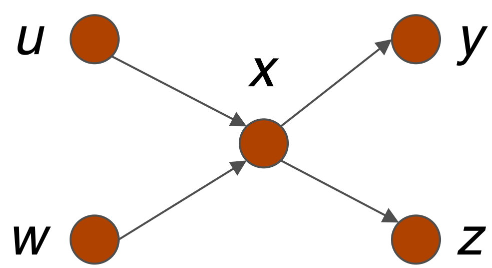
$f(u,w,x,y,z) = f_1(u,w,x)f_2(x,y,z)f_3(z)$



# Graphical Models

- Efficient computation over multivariate functions by leveraging forms of independence to decompose them into products of simpler subfunctions
  - Bayesian/Markov networks, Markov/conditional random fields, factor graphs

$p(u,w,x,y,z) = p(u)p(w)p(x|u,w)p(y|x)p(z|x)$

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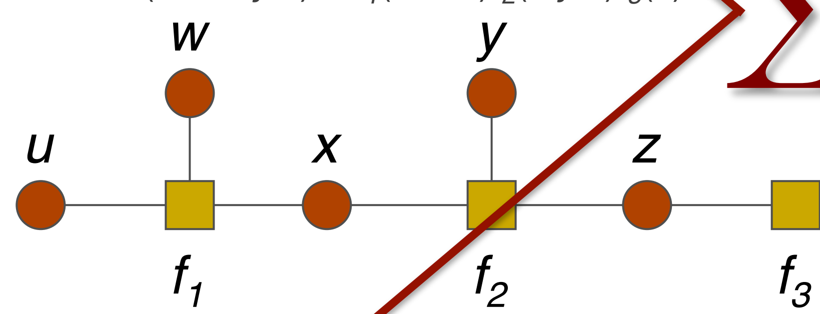


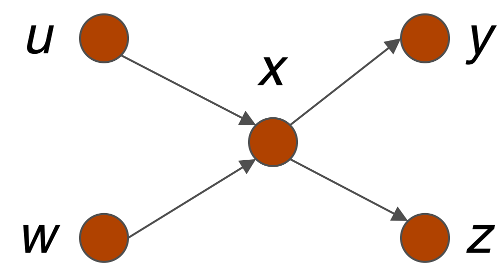

$\Sigma$

- Solve typically via some form of message passing or sampling
- State of the art performance across *symbols*, *probabilities* and *signals* from uniform representation and reasoning algorithm
  - (Loopy) belief propagation, forward-backward algorithm, Kalman filters, Viterbi algorithm, FFT, turbo decoding, arc-consistency, production match, …
- Can support mixed and hybrid processing
- Several neural network models map directly onto them

# Bayesian Network vs. Factor Graph

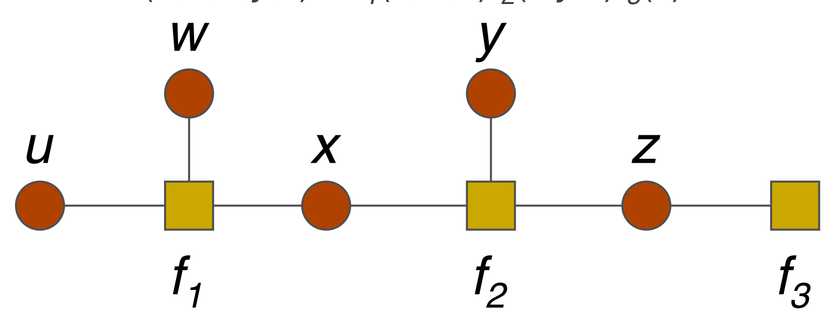
- Bayesian network
  - Directed graph
  - Only variable nodes
  - A distribution at each node *n*
    - $p(n \mid parents_n)$
  - Decompose probabilities

$p(u,w,x,y,z) = p(u)p(w)p(x|u,w)p(y|x)p(z|x)$




- Factor graph
  - Undirected graph
  - Variable and factor nodes
  - A function at each factor node *n*
    - $f_n(vs_n)$
  - Decompose arbitrary functions

$f(u,w,x,y,z) = f_1(u,w,x)f_2(x,y,z)f_3(z)$



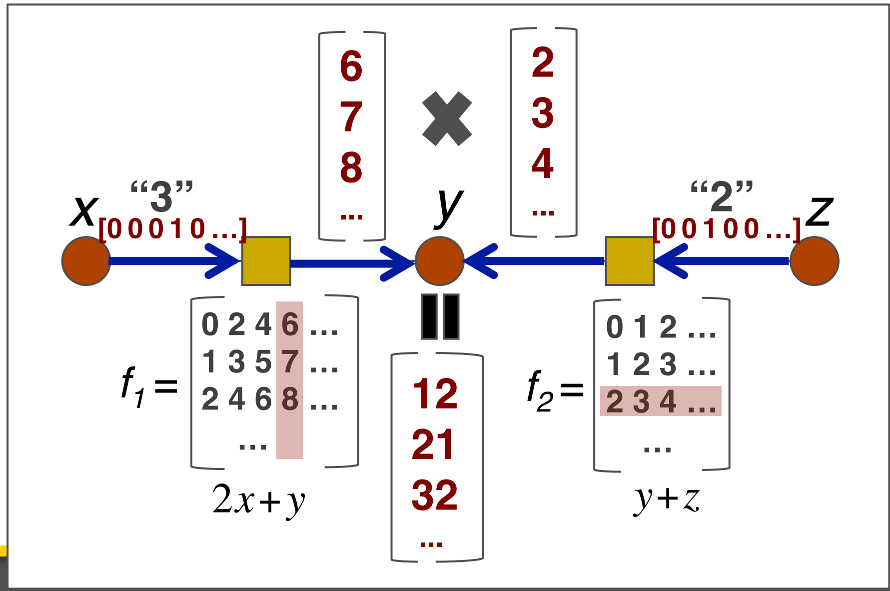
# Summary Product Algorithm

- Compute variable marginals (*sum-product*/*integral-product*) or mode of entire graph (*max-product*)
- Pass messages on links and process at nodes
  - Messages are distributions over link variables (starting w/ *evidence*)
  - At variable nodes messages are combined via *pointwise product*
  - At factor nodes do products, and summarize out unneeded variables:

$$m(y) = \int_x m(x) \times f_1(x,y)$$

$$f(x,y,z) = y^2 + yz + 2yx + 2xz$$
$$= (2x+y)(y+z) = f_1(x,y) f_2(y,z)$$

In Sigma, both functions and messages are piecewise linear



# Piecewise Linear Functions

- Unified representation for *continuous*, *discrete* and *symbolic* data
- At base have multidimensional continuous functions
  - One dimension per variable, with multiple dimensions providing *relations*
  - Approximated as *piecewise linear* over *arrays/tensors of regions*
- *Discretize domain* for discrete distributions (& symbols)
- *Booleanize range* (and add symbol table) for symbols

  Color($O_1$, Brown) & Alive($O_1$, T)
- Dimensions/variables are *typed*

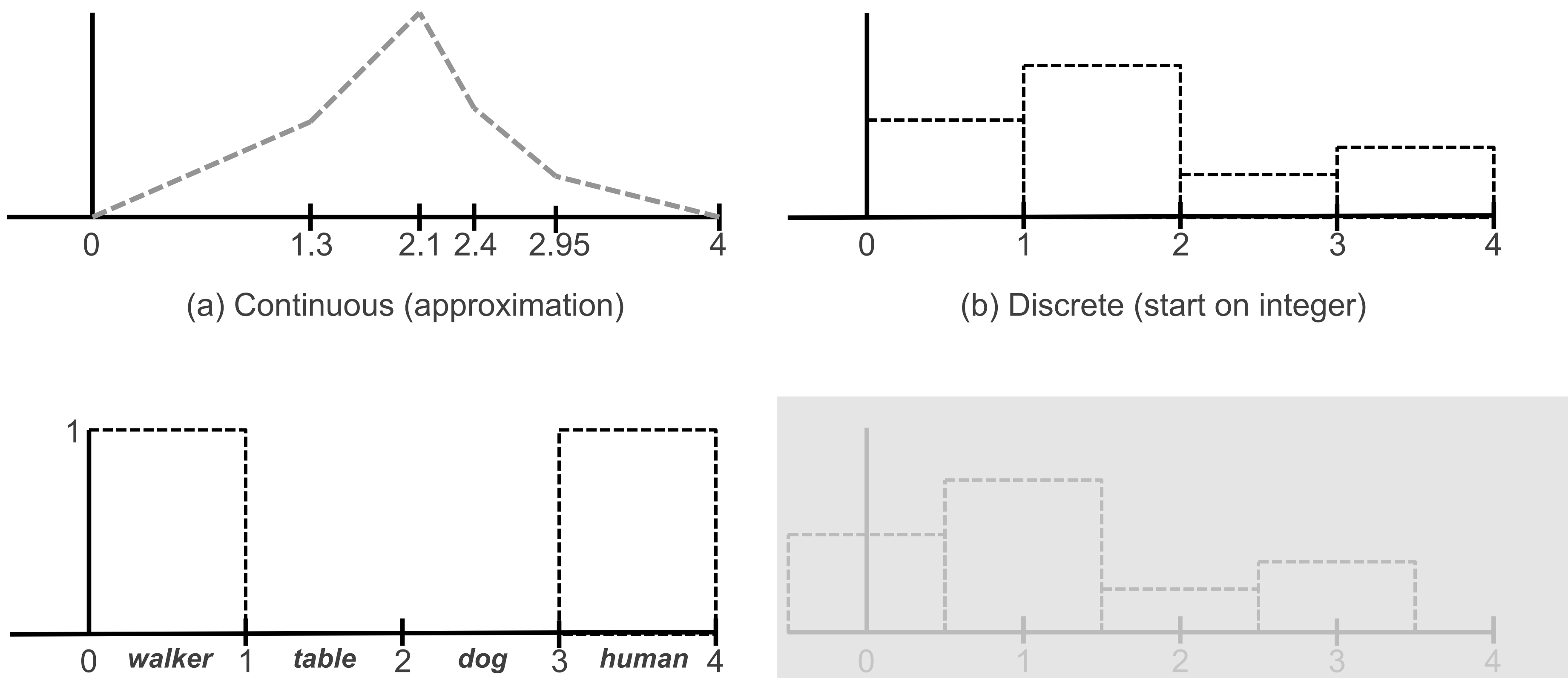
| $O_1$ | Brown | Silver | White |
|---|---|---|---|
| T | 1 | 0 | |
| F | 0 | | |

| P(*legs* \| *concept*) | Walker | Table | … |
|---|---|---|---|
| 1 | 0 | 0 | … |
| 2 | 0 | 0 | … |
| 3 | 0 | .1 | … |
| 4 | 1 | .9 | … |

| P(*weight* \| *concept*) | Walker | Table | … |
|---|---|---|---|
| [1,10> | .01*w* | .001*w* | … |
| [10,20> | .2-.01*w* | " | … |
| [20,50> | 0 | .025-.00025*w* | … |
| [50,100> | " | " | … |

**Analogous to implementing digital circuits by restricting an inherently continuous underlying substrate**

# Piecewise Linear Functions




(a) Continuous (approximation)

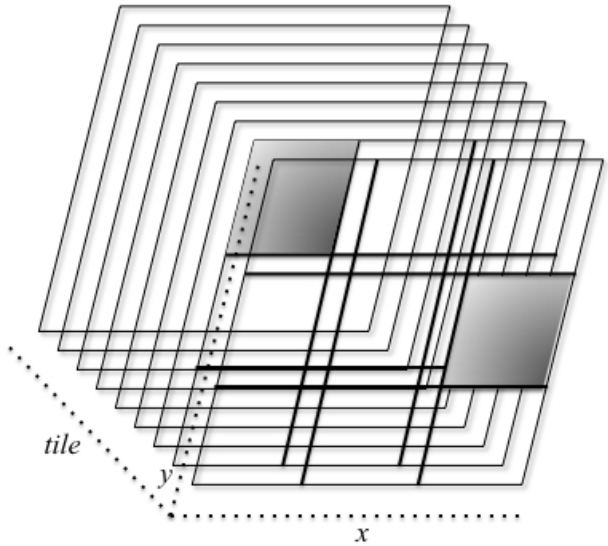
(b) Discrete (start on integer)

(d) Symbolic

(c) Discrete (center on integer)

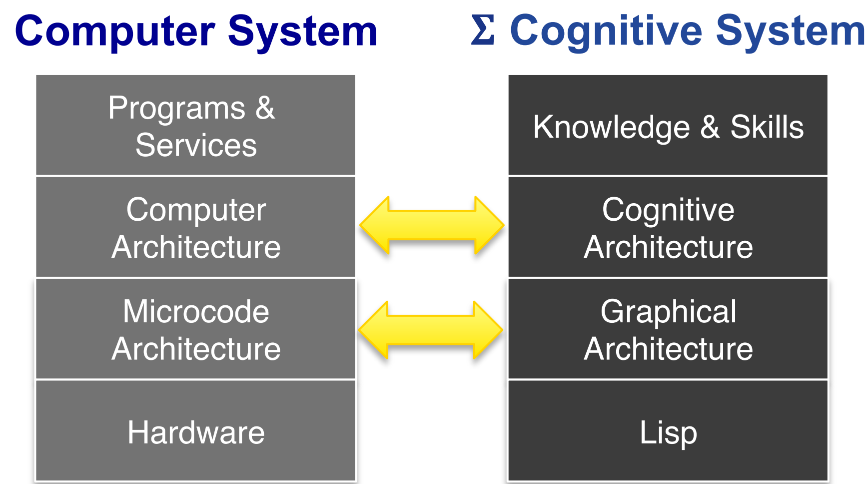
# The Eight Puzzle


- Classic sliding tile puzzle
- Represented symbolically in standard AI systems
  - **LeftOf**(*cell*$_{11}$, *cell*$_{21}$), **At**(*tile*$_1$, *cell*$_{11}$), etc.
- Instead represent as a hybrid 3D function
  - Continuous spatial *x* & *y* dimensions
    - `dimension[0-3)`
  - Discrete *tile* dimension (an *xy* plane)
    - `tile[0:9)`
  - Region of plane with tile has value 1
    - All other regions have value 0

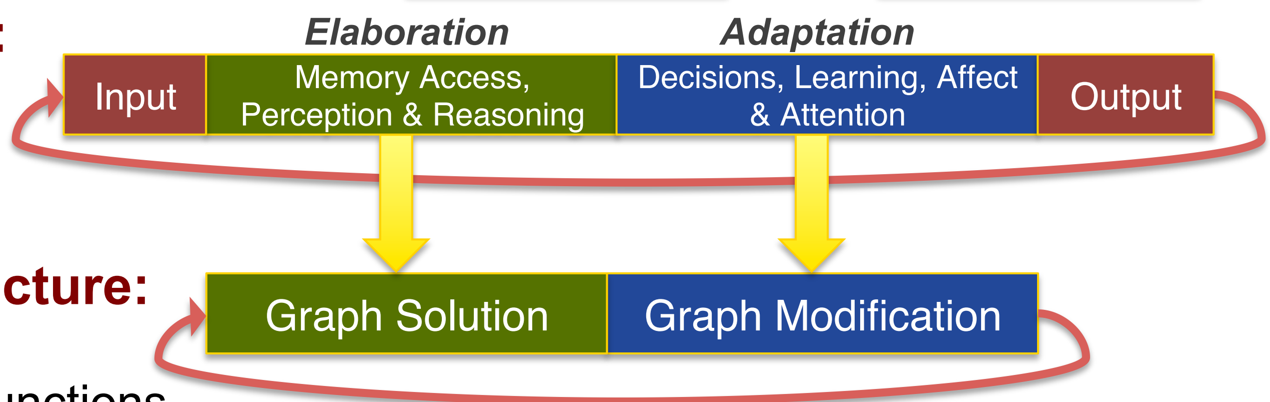


# The Structure of Sigma

Σ




**Cognitive Architecture:**
- Predicates
- Conditionals
- Nested tri-level control

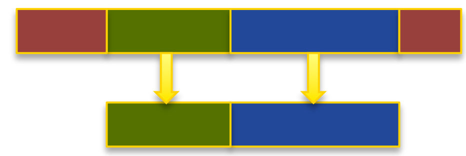



**Graphical Architecture:**
- Graphical models
- Piecewise linear functions
- Gradient-descent learning

# (Soar-like) Nested Tri-Level Control

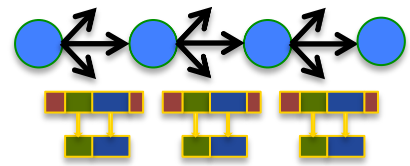
- **A (parallel) *reactive* layer**
  - Single graph/cognitive cycle

*Which acts as the inner loop for*

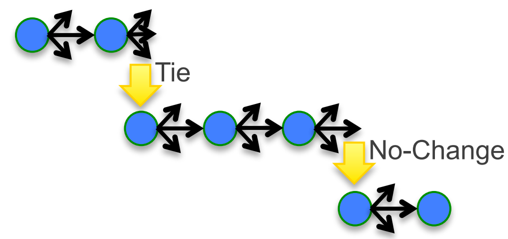


- **A (serial/iterative) *deliberative* layer**
  - Repeated operator selection & application

*Which acts as the inner loop for*



- **A (recursive) *reflective* layer**
  - Impasse-driven meta-level processing




- Maps onto bi-/tri-level models in
  - Cognitive Psychology (automatic vs. controlled, System 1 vs. 2, …)
  - Robotics (3T, …)
  - Emotion modeling

# Fundamental Questions about Sigma

- Can full range of capabilities be provided in this manner?
- Can it all be sufficiently efficient for real time behavior?
- What are the functional gains?
- Can the human mind (and brain) be modeled?

Winner of **Kurzweil Award** at AGI 2011 & 2012

# Overall Progress on Sigma

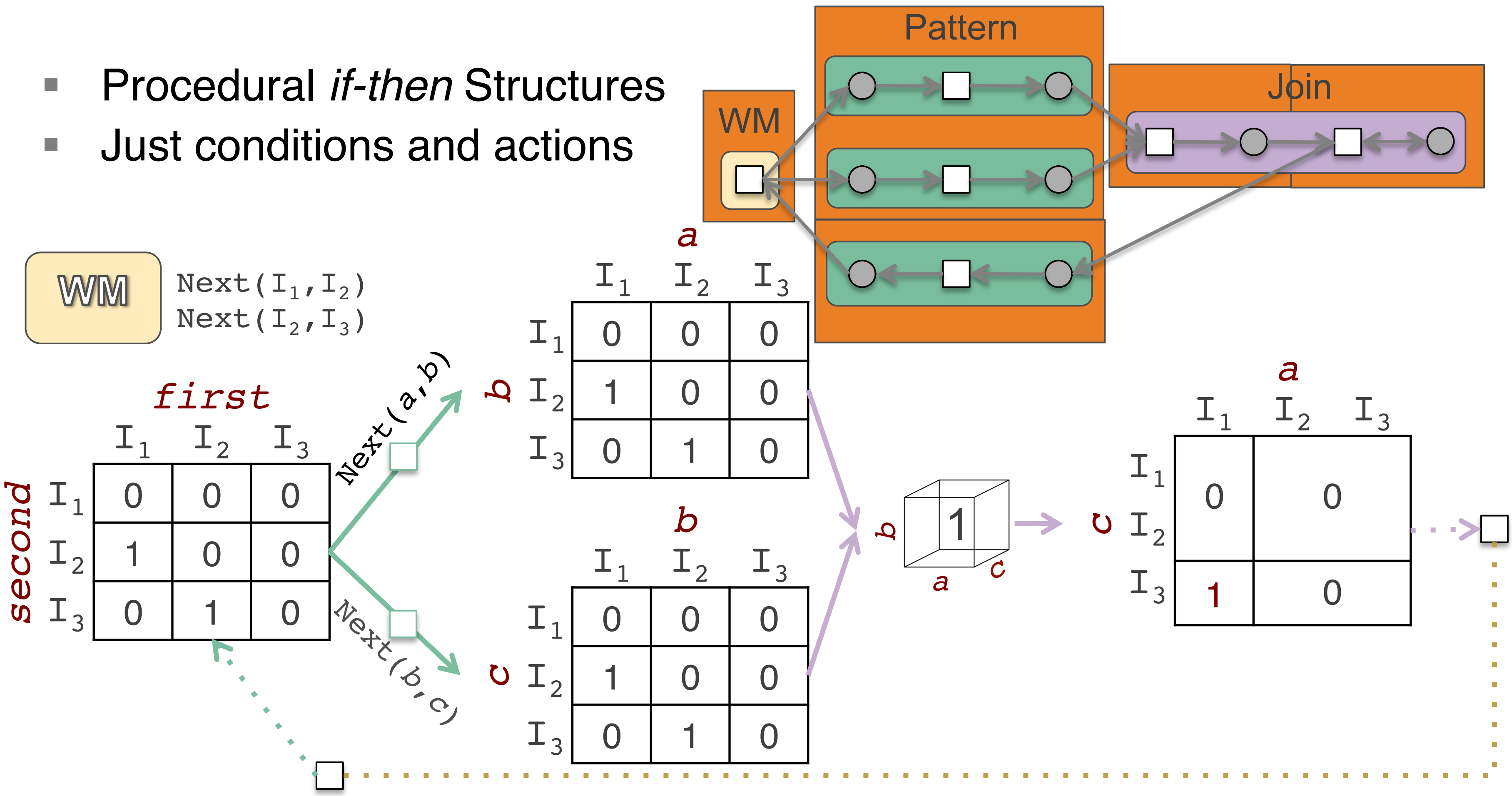
- Memory [ICCM 10]
  - Procedural (rule)
  - Declarative (semantic/episodic) [CogSci 14]
  - Constraint
  - Distributed vectors [AGI 14a]
  - Perceptual [BICA 14a, AGI 15]
  - Neural network
- Problem solving
  - Preference based decisions [AGI 11]
  - Impasse-driven reflection [AGI 13]
  - Decision-theoretic (POMDP) [BICA 11b]
  - Theory of Mind [AGI 13, AGI 14b]
- Learning [ICCM 13]
  - Concept (supervised/unsupervised)
  - Episodic [CogSci 14]
  - Reinforcement [AGI 12a, AGI 14b]
  - Action/transition models [AGI 12a]
  - Models of other agents [AGI 14b]
  - Perceptual (including maps in SLAM)
- Efficiency [ICCM 12, BICA 14b]
- Mental imagery [BICA 11a, AGI 12b]
  - 1-3D continuous imagery buffer
  - Object transformation
  - Feature & relationship detection
- Perception
  - Object recognition (CRFs) [BICA 11b]
  - Spoken word recognition (HMMs) [BICA 14a]
  - Localization [BICA 11b]
- Natural language
  - Word sense disambiguation [ICCM 13]
  - Part of speech tagging [ICCM 13]
  - Sentence identification [WS 15]
  - Dialogue [WS 15]
- Affect [AGI 15]
  - Appraisal (expectedness, desirability)
  - Attention (perceptual, cognitive)
- Integration
  - CRF+Localization+POMDP [BICA 11b]
  - Rules+SLAM+RL+ToM+VH [IVA 15, WS 15]
  - SentenceID+Dialogue [WS 15]

# MEMORY AND DECISIONS

```
CONDITIONAL Transitive
   Conditions: Next(a,b)
               Next(b,c)
   Actions: Next(a,c)
```

# Procedural Memory (Rules)

- Procedural *if-then* Structures
- Just conditions and actions

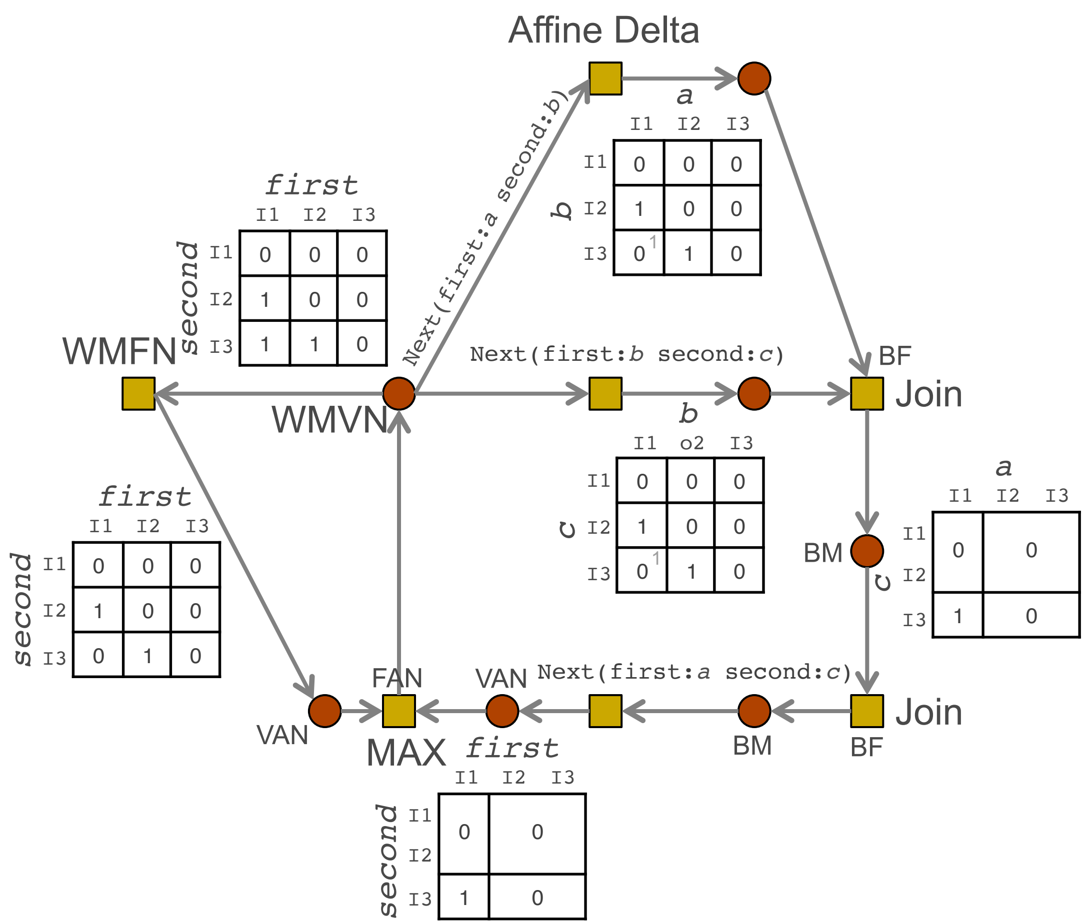


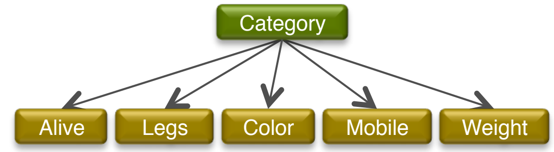

```
(type 'ID :constants '(I1 I2 I3))
(predicate 'Next '((first ID) (second ID)) :world 'closed)
```

# Procedural Memory (Rules)

## In More Detail

```
CONDITIONAL Transitive
   Conditions: Next(a,b)
               Next(b,c)
   Actions: Next(a,c)
```



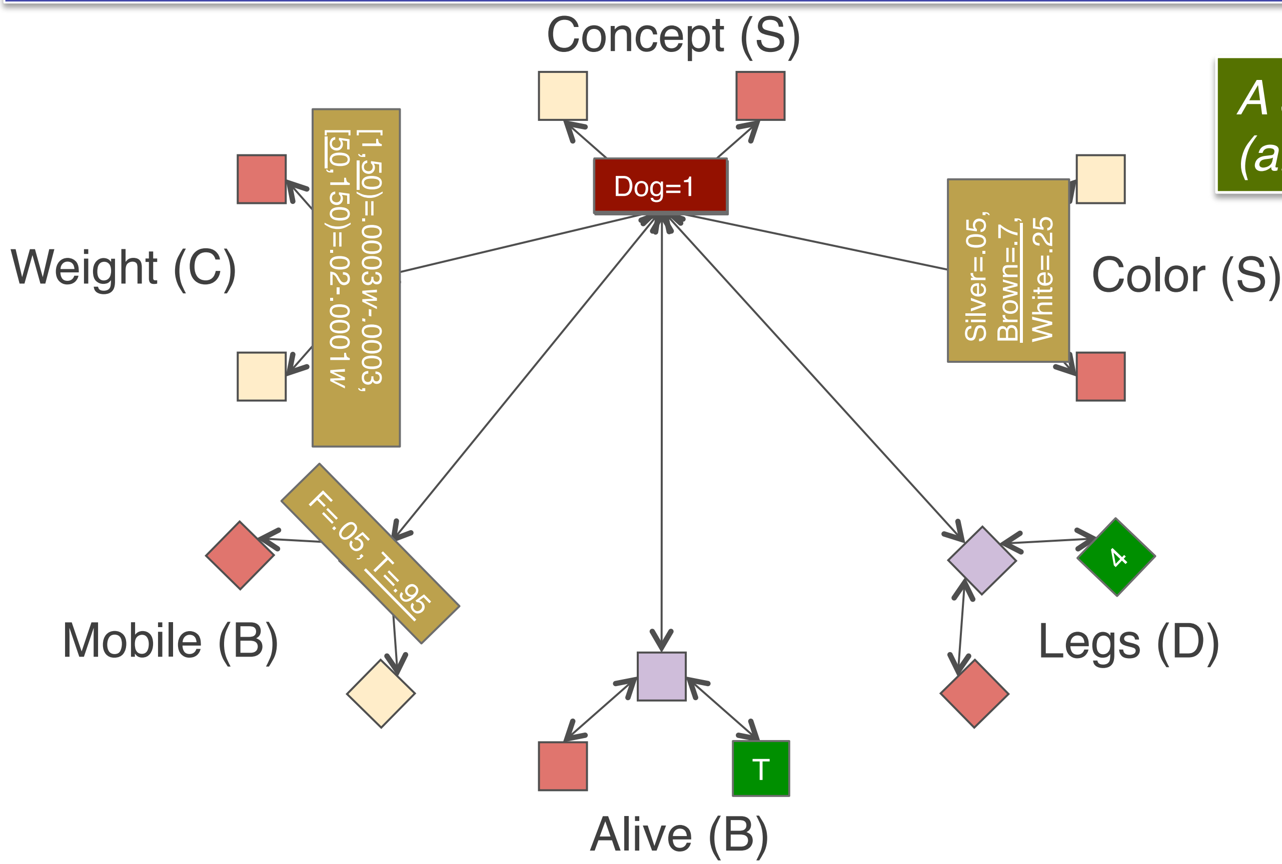


Naïve Bayes classifier

# Semantic Memory (Classifier)

**Given** cues, **retrieve/predict** object category and missing attributes

E.g., **Given** *Alive*=T & *Legs*=4 **Retrieve** *Category*=Dog, *Color*=Brown, *Mobile*=T, *Weight*=50



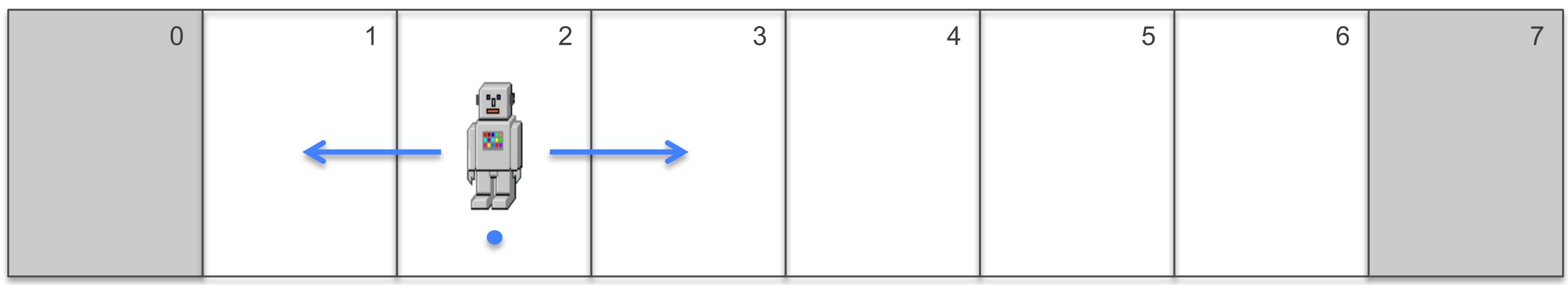

*A subset of factor nodes (and no variable nodes)*

Function
Perception
Join

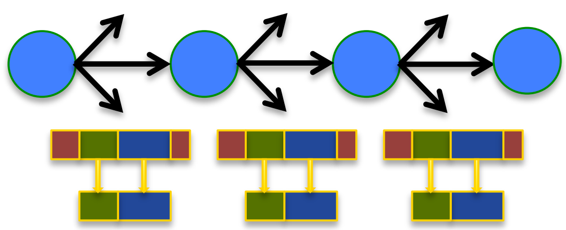
B: Boolean
S: Symbolic
D: Discrete
C: Continuous

# Random Walk on 1D Grid

```
CONDITIONAL RW-1D
   Actions: Selected(left)
            Selected(right)
            Selected(none)
```




- 1D Grid of discrete cells
- Agent can move one cell to left or right, or stay where is



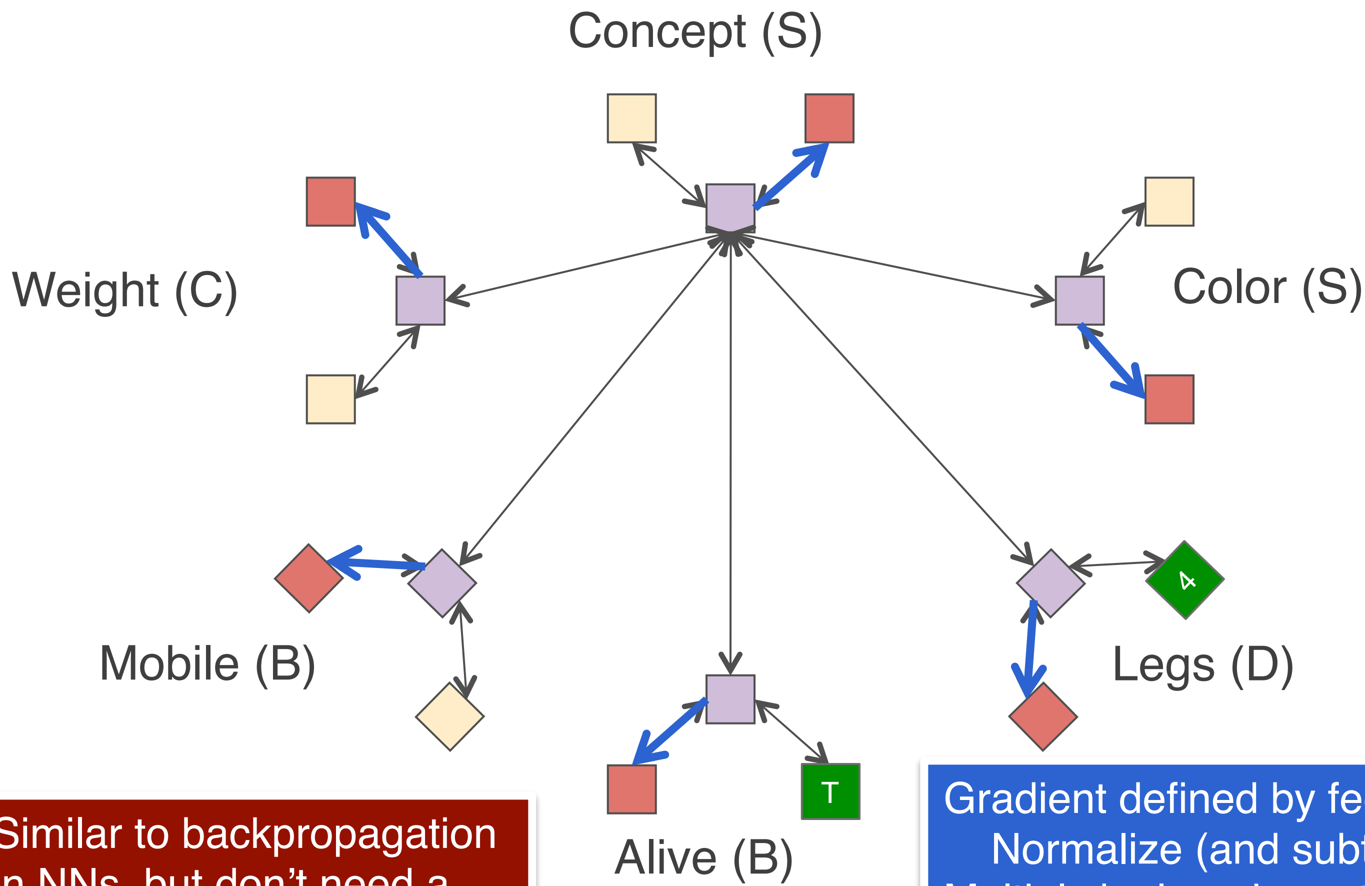
# Replicating a Virtual Human "Mind"

- Immersive Naval Officer Training System (INOTS)
  - Targets leadership and basic counseling for junior Navy leaders
  - Trained over 5000 sailors since 2012


- INOTS "mind" based on two tools
  - Statistical query-answering tool (NPCEditor)
  - Transition diagram for dialogue management
- Both aspects reimplemented and integrated together in Sigma
  - Query answering via semantic memory (*reactive*)
  - Dialogue management by sequences of operators (*deliberative*)

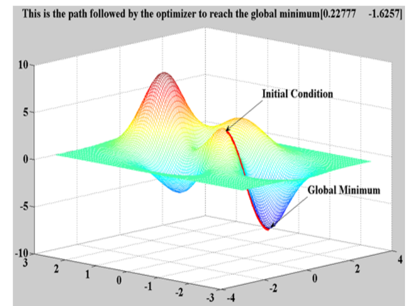
# LEARNING

# Parameter Learning via Gradient Descent




Gradient descent

Local, incremental search for optimal weights




Similar to backpropagation in NNs, but don't need a separate backprop phase

Gradient defined by feedback to function node
- Normalize (and subtract out average)

Multiply by learning rate

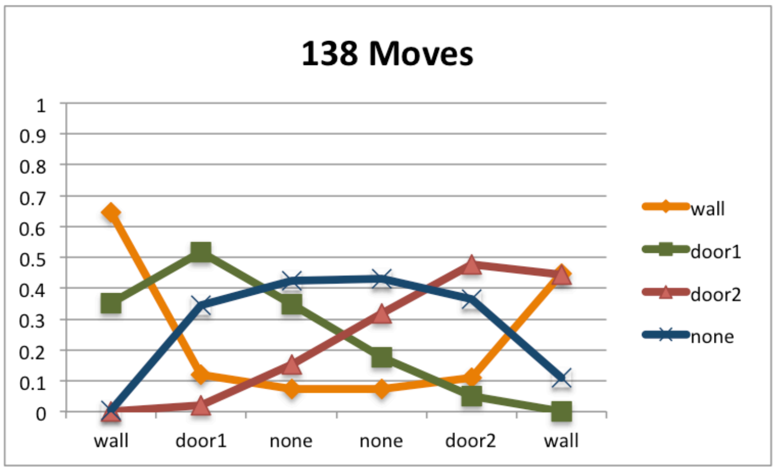
Add to function, smooth and normalize

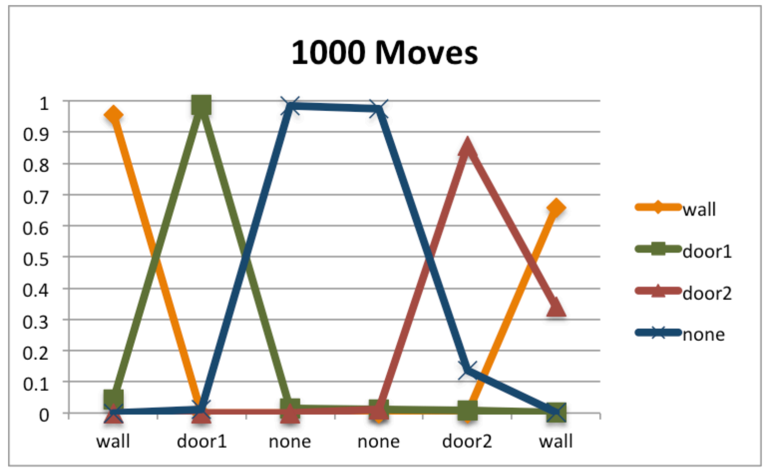
# Learning Maps

- Map: **P**(Objects | Locations)

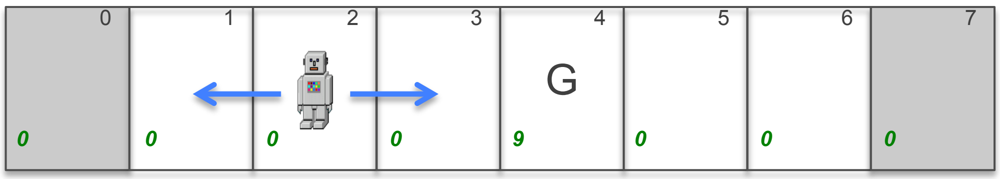
```
CONDITIONAL Object-Location-Map
    Conditions: Object(value:o)
    Condacts:   Location(x:x)
    Function(x,o): .25
```

| wall | door1 | | | door2 | wall |
|---|---|---|---|---|---|



# Reinforcement Learning




Learn values of actions for states by backwards propagation of rewards received during exploration:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha[r_t + \gamma Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t)]$$

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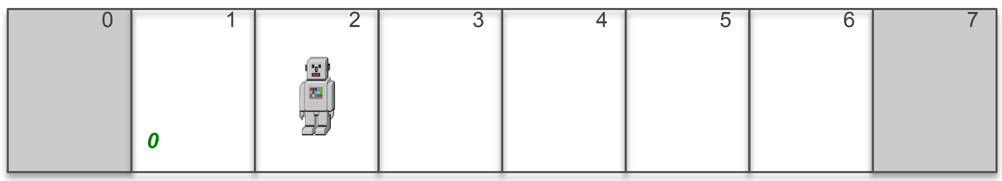


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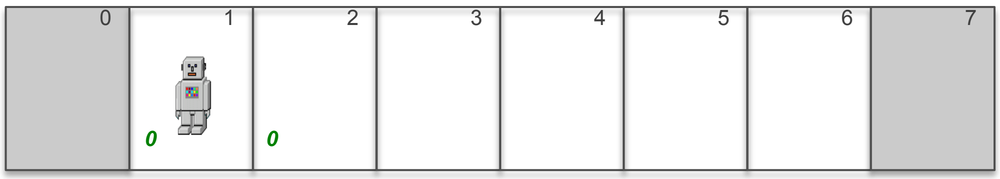


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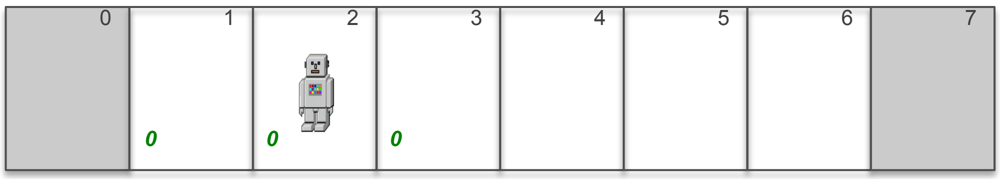


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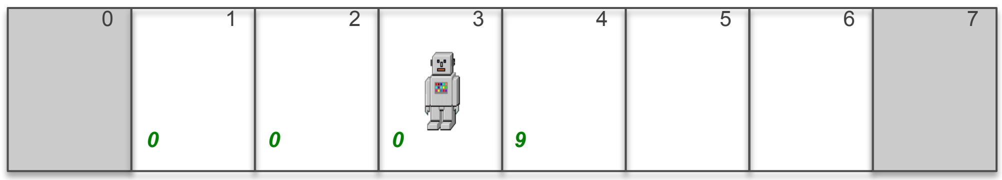


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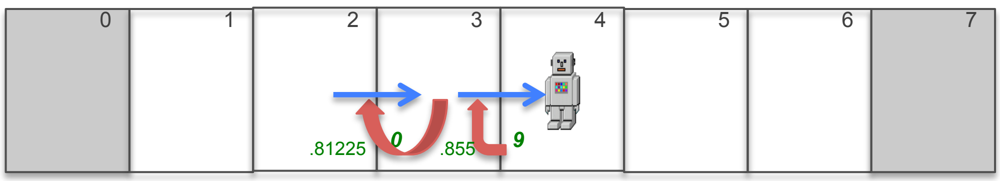


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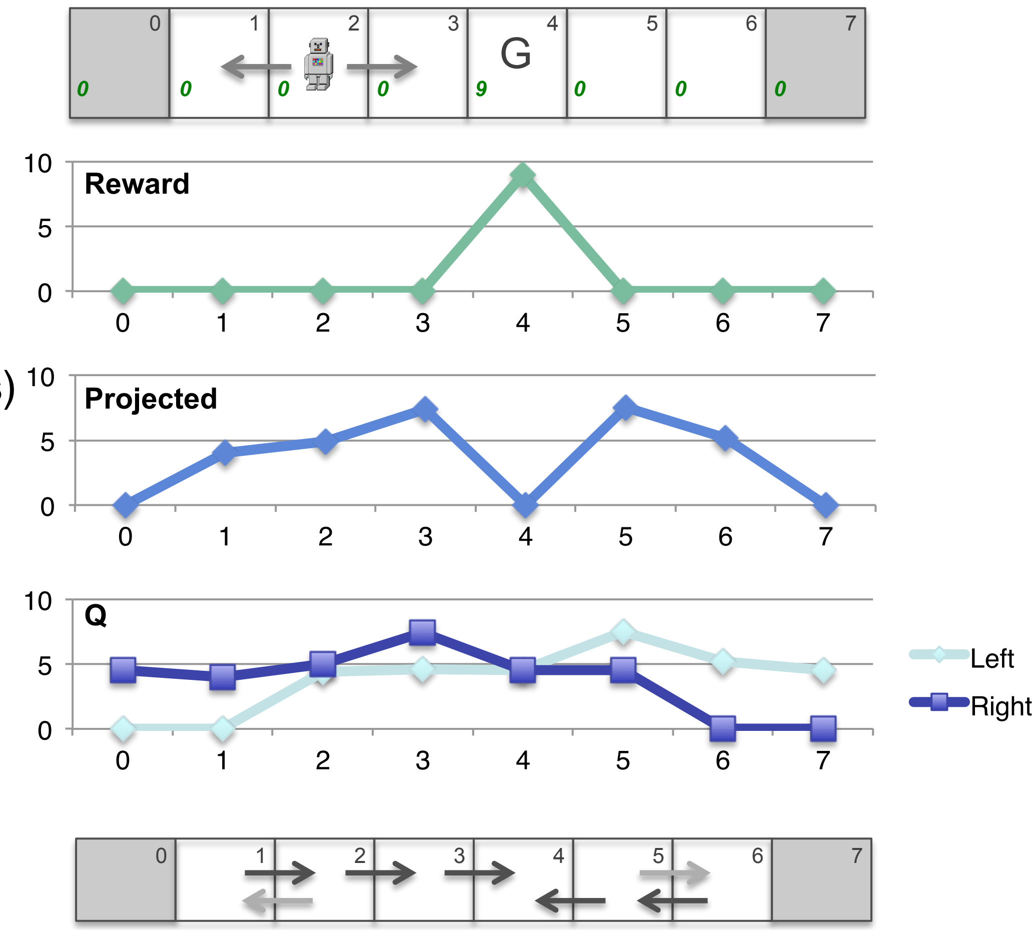
$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha[r_t + \gamma Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t)]$$

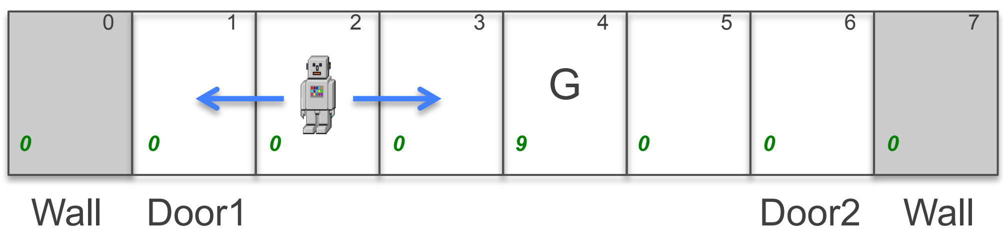
# Deconstructing RL in Sigma

- Knowledge:
  - Initial uniform predictors for:
    - Current reward (*R*)
    - Projected future reward (*P*)
    - Action preferences (*Q*)
  - Regression (backup) knowledge
  - Action models (predict next states)
- Supervised learning of:
  - Current reward (*R)*
  - Projected future reward (*P)*
  - Action preferences (*Q*)
- Add *Diachronic cycles* to also learn action models




Graphs are of expected values, but learning is actually of full distributions

# Integration




- Determine location in corridor
- Map corridor
- Learn to go to goal location in corridor
- Learn to model action effects

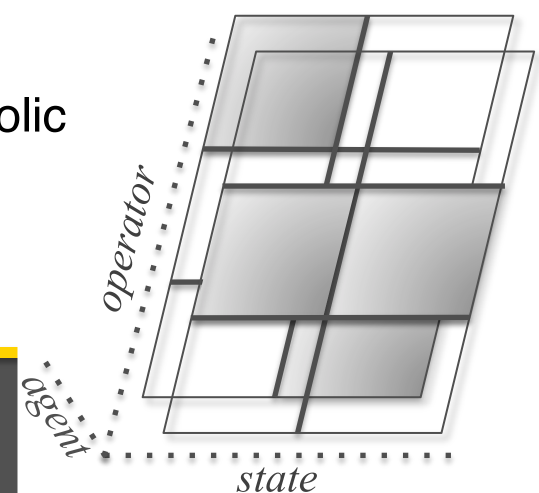
SLAM

RL

# THEORY OF MIND
# (& MULTIAGENT SYSTEMS)

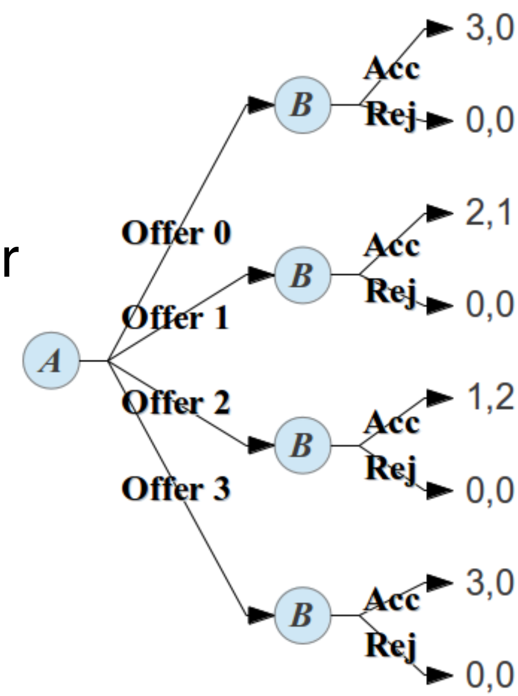
# Theory of Mind (ToM) in Sigma

- ToM models the minds of others, to enable for example:
  - Understanding multiagent situations
  - Participating in social interactions
- ToM approach based on *PsychSim* (Marsella & Pynadath)
  - Decision theoretic problem solving based on POMDPs
  - Recursive agent modeling
- Multiagent Sigma: Add agent argument to predicates
  - E.g., Selected(*agent*, *operator*, *state*)
  - A discrete dimension, but may be numeric or symbolic



# Sequential Games

- Players (*A*, *B*) alternate moves
  - E.g., *Ultimatum*, *centipede* and *negotiation*
- Ultimatum game
  - *A* starts with a fixed amount of money (3)
  - *A* decides how much (in 0-3) to offer *B*
  - *B* decides whether or not to accept the offer
    - If *B* accepts, each gets the resulting amount
    - If *B* rejects, both get 0
  - Each has a utility function over money
    - E.g., <.1, .4, .7, 1>



# Solving Sequential Games in Sigma

- Decision-theoretic approach with *softmax combination*
  - Use expected value at each level of search
  - Action **P**s assumed exponential in their utilities (à la Boltzmann)
- There may be many *Nash equilibria*
- Instead seek stricter concept of *subgame perfection*
  - Overall strategy is an equilibrium strategy over any subgame
- **Key result:** Games solvable in two modes:
  - Reactive/automatic/system-1
  - Reflective/controlled/system-2

  *Both modes well documented in humans for general processing*

  *Combination not found previously in ToM models*

# Reactive/Automatic Approach

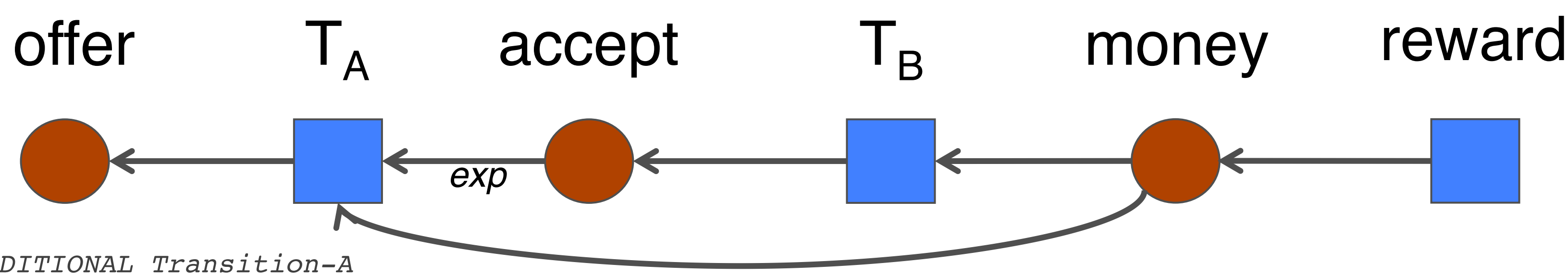
- A trellis (factor) graph in LTM with one stage per move
- Focus on backwards messages from reward(s)

```
CONDITIONAL Transition-B
  Conditions: Money(agent:B quantity:moneyb)
  Condacts: Accept(offer:offer acceptance:choice)
  Function(choice,offer,moneyb): 1<T,0,0>, 1<T,1,1>, 1<T,2,2>,
                                 1<T,3,3>, 1<F,*,0>
```

$$V_B(\mathit{offer},\mathit{choice}) = \mathrm{Reward}_B(\mathrm{Money}_B(\mathit{offer},\mathit{choice}))$$

$$V_A(\mathit{offer}) = \sum_{\mathit{choice}} \mathrm{Reward}_A(\mathrm{Money}_A(\mathit{offer},\mathit{choice})) * e^{K * V_B(\mathit{offer},\mathit{choice})}$$

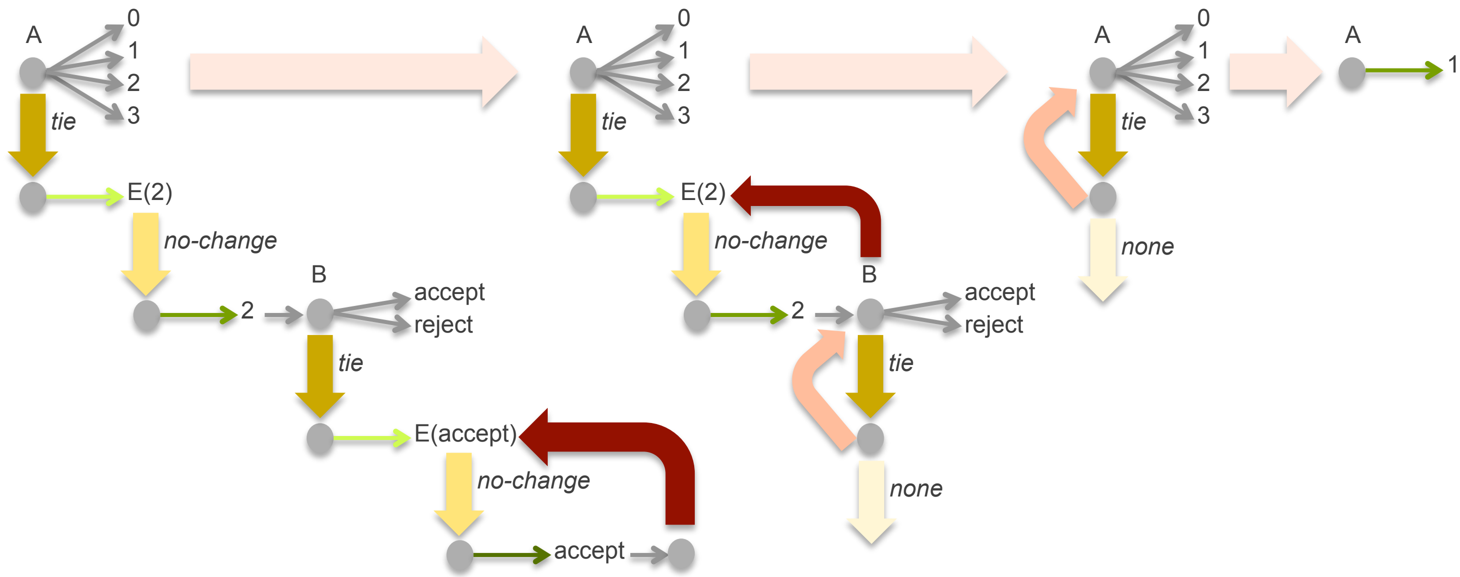
```
CONDITIONAL Reward
  Condacts: Money(agent:agent quantity:money)
  Function(agent,money): .1<*,0>, .4<*,1>,
                         .7<*,2>, 1<*,3>
```




```
CONDITIONAL Transition-A
  Conditions: Money(agent:A quantity:moneya)
              Accept-E(offer:offer acceptance:choice)
  Condacts: Offer(agent:A quantity:offer)
  Function(choice,offer,moneya): 1<T,0,3>, 1<T,1,2>, 1<T,2,1>,
                                 1<T,3,0>, 1<F,*,0>
```

# Reflective/Controlled Approach

- Decision-theoretic problem-space search across metalevels
  - Very Soar-like, but with softmax combination
    - Depends on *summary product* and Sigma's *mixed* aspect
  - Corresponds to PsychSim's online reasoning



# Comments on the Ultimatum Game

- Reactive version (5 conditionals)
  - A's normalized distribution over offers: <.315, .399, .229, .057>
  - 1 decision (94 messages) and **.02 s** (on a MacBook Air)
- Reflective version (19 conditionals)
  - A's normalized distribution over offers: <.314, .400, .229, .057>
  - 72 decisions (868 messages/decision) and **126.69 s**

Distributions Comparable

Speed Ratio >6000

- Same result, with distinct computational properties
  - Reactive is fast and occurs in parallel with other memory processing, but is not (easily) penetrable by new bits of other knowledge
  - Reflective is slow, sequential, but can (easily) integrate new knowledge
  - Distinction also maps onto *expert vs. novice* behavior in general

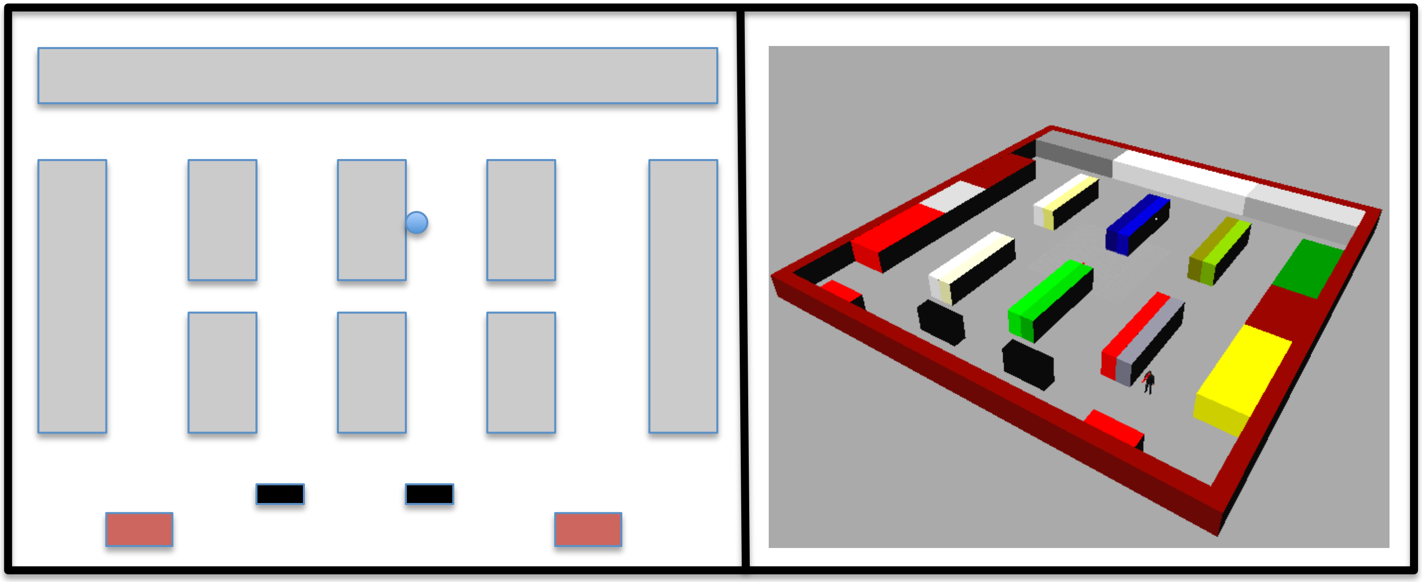
*Raises possibility of a generalization of Soar's chunking mechanism*

  - Compile/learn reactive trellises from reflective problem solving
  - Finer grained, mixed(/hybrid) learning mechanism

# INTERACTIVE, ADAPTIVE VIRTUAL HUMANS

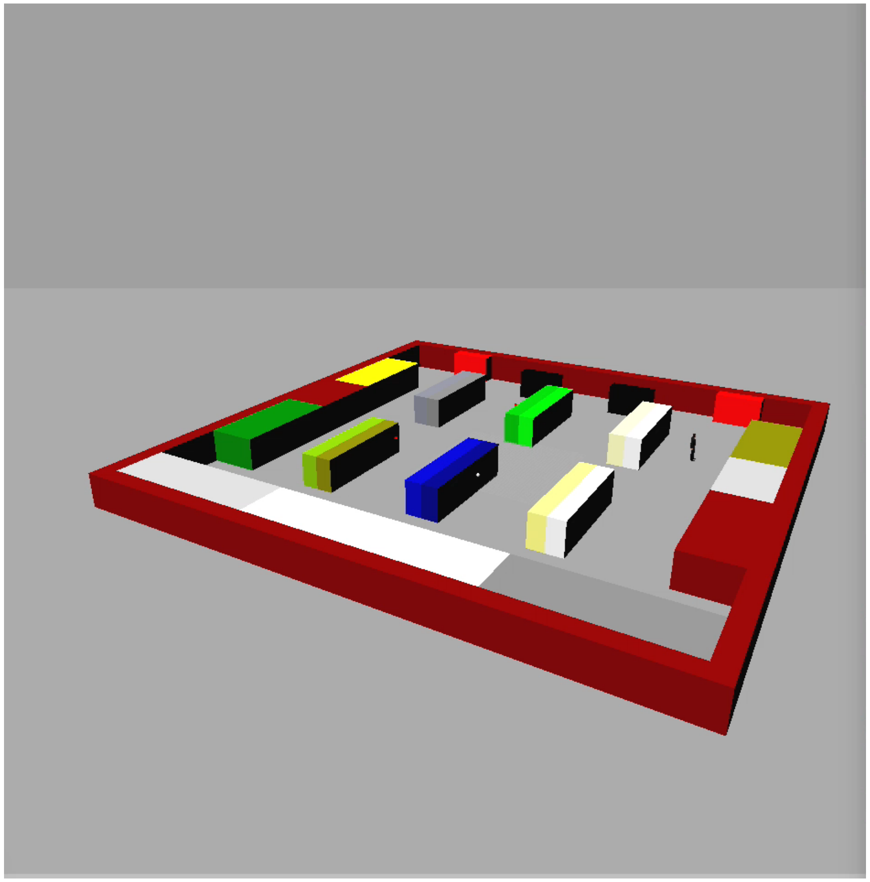
# Interactive, Adaptive Virtual Humans

- Control behavior of SmartBody VH(s) in a retail store scenario
  - A civilian instance of a *physical security system*

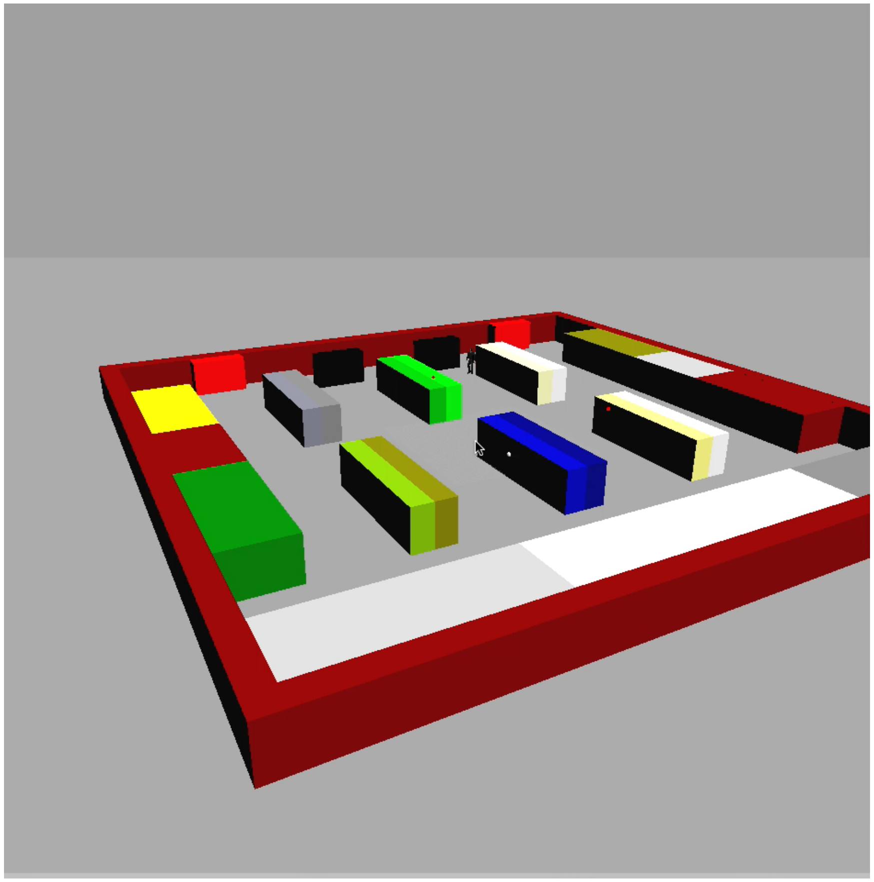


  - Rule-based, probabilistic and social reasoning (ToM)
  - Simultaneous localization and mapping (SLAM)
  - Multiagent reinforcement learning (RL)
  - [Appraisal+attention-based control]

# Simultaneous Localization and Mapping (SLAM)

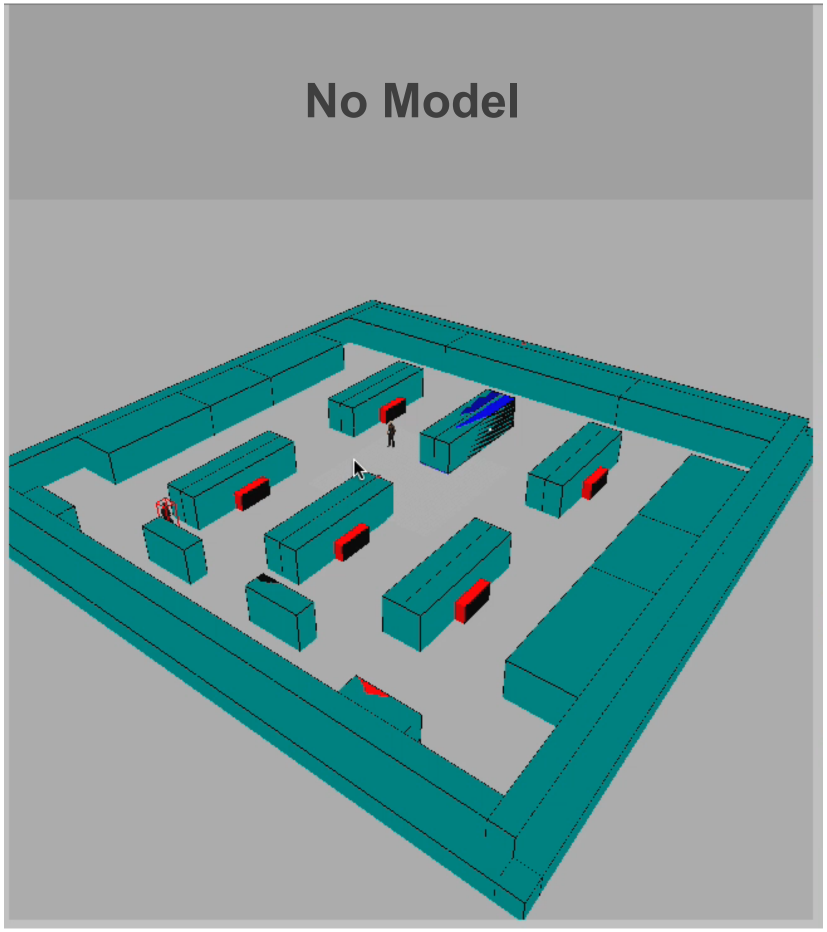


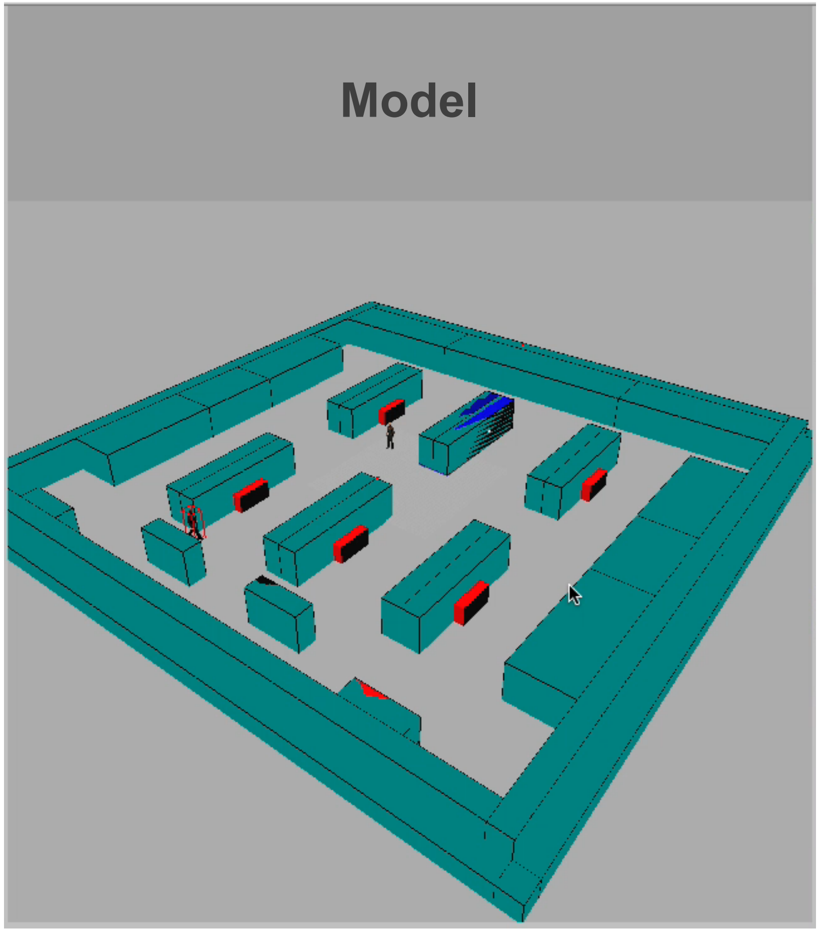
No Map



Map

# Multiagent Reinforcement Learning (RL)



# SUMMARY

## Current and Near Future Topics

- Scaling up memory, reasoning and learning
- Continuous speech understanding, and its integration with language and cognition
- Theory of Mind
- Emotion/affect and its relationship to the architecture
- Distributed vectors/semantics (i.e., word embeddings)
- (Deep) neural networks
- A generalized skill acquisition mechanism (chunking)
- A new level below the graphical architectural
- Exploiting parallelism and GPUs for efficiency
- Interactive, adaptive, intelligent, emotional virtual humans

## Wrapping Up

- Replicating capabilities from existing architectures in a functionally elegant manner
- Extending uniformly to capabilities only possible with existing architectures via interfaces to external modules
- Continuously working on efficiency

- Sigma website is http://cogarch.ict.usc.edu
  - Most papers on Sigma can be found there
  - New papers on which I'm an author usually appear online sooner at http://cs.usc.edu/~rosenblo/pubs.html
- Public release, with online tutorial, available in May