Effective and Efficient Memory for Generally Intelligent Agents

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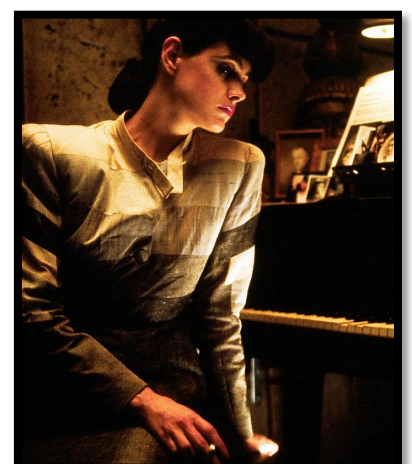
My Long-Term Research Goal

General Intelligence

Agents that persist for long periods of time, exhibiting robust and adaptive behavior in a variety of tasks and situations.



Inspiration from Humans: Memory

Class of mechanism to cope with dynamic, partially-observable environment

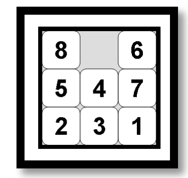
- **Encodes** experience
- **Stores** internally
- Supports **retrieval**

Without memory, agents are reactive, stuck in the *here* and *now*

Prior Work: Benefits of Memory

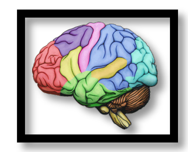
More capable in problem solving

- Individually (e.g. Nuxoll & Laird, 2012)
- Collaboratively (e.g. Deutsch et al., 2008)



Better modeling of human cognition

- Language learning (e.g. Ball et al., 2010)
- Memory blending (e.g. Brom et al., 2010)



More believable

- Virtual characters (e.g. Gomes et al., 2011)
- Long-term companions (e.g. Lim et al., 2011)

Computational Challenge of Memory

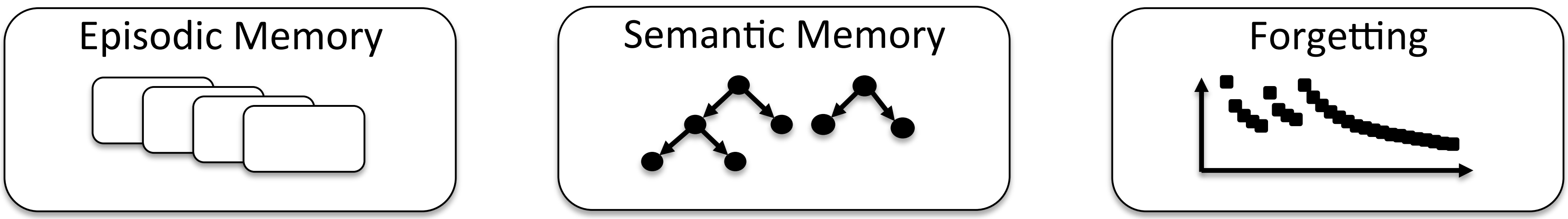
How to maintain <u>effective</u> and <u>efficient</u> access to large amounts of knowledge as it accumulates over long periods of time.

Limitations of current approaches…

- task-specific,
  (e.g. Macedo & Cardoso, 2004)
- restricted representation, and/or
  (e.g. Tecuci & Porter, 2007; 2009)
- do not scale to large amounts of experience
  (e.g. Kuppuswamy et al., 2006; Douglass et al., 2009)

This Work

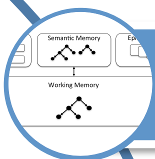
Effective and Efficient Memory



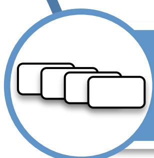
<u>Desiderata</u>

- **Generality**: effective across a variety of tasks
- **Reactivity**: decisions < 50 milliseconds
- **Scalability**: support large amounts of knowledge

Outline

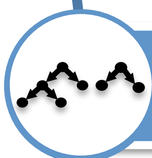


Architectural Integration



Episodic Memory

[ICCBR ‘09], [BRIMS ‘11], [AAMAS ’12], [AAAI ’12a], [AAAI ’12b]

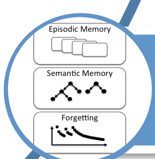


Semantic Memory

[ICCM ’10], [BRIMS ’11], [AAAI ’11], [AAAI ’12b], [ICCM ’12a]

Forgetting

[ICCM ’12a], [ICCM ’12b]



Summary & Discussion

Cognitive Architecture

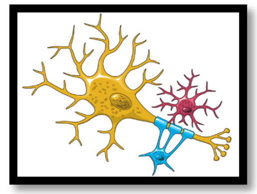
Specification of those aspects of cognition that remain constant across the lifetime of an agent

- Memory systems of agent's beliefs, goals, experience
- Knowledge representation
- Functional processes that lead to behavior
- Learning mechanisms

Goal. Develop and understand intelligence across a diverse set of tasks and domains

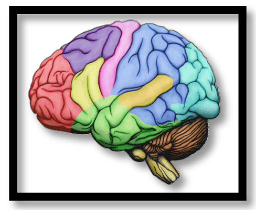
Research Focus

Biological Plausibility



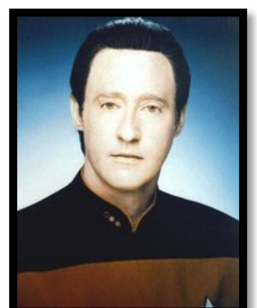
Leabra

Psychological Plausibility



ACT-R
CLARION
EPIC

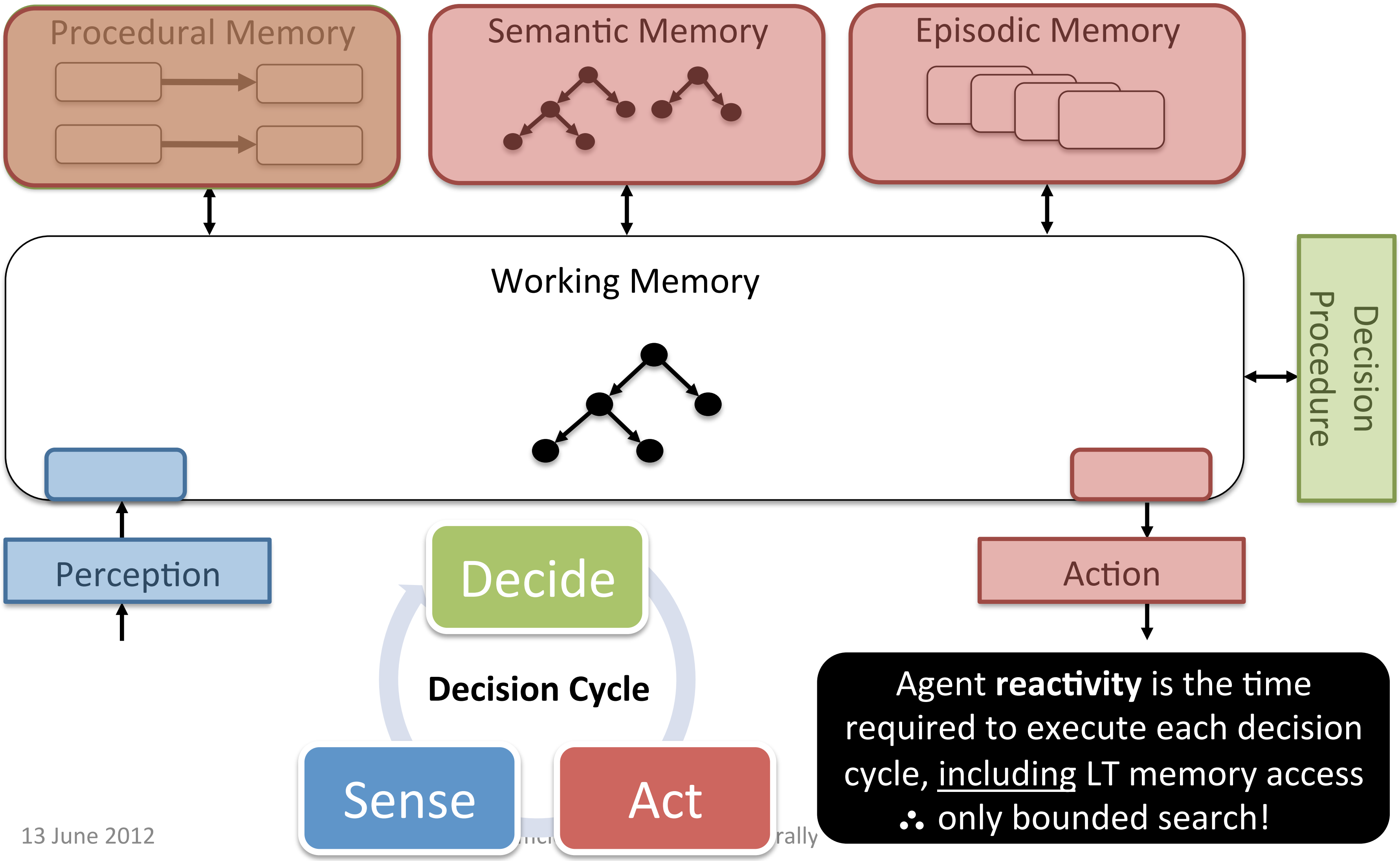
Agent Functionality



Companions
ICARUS
LIDA
Graphical
Soar

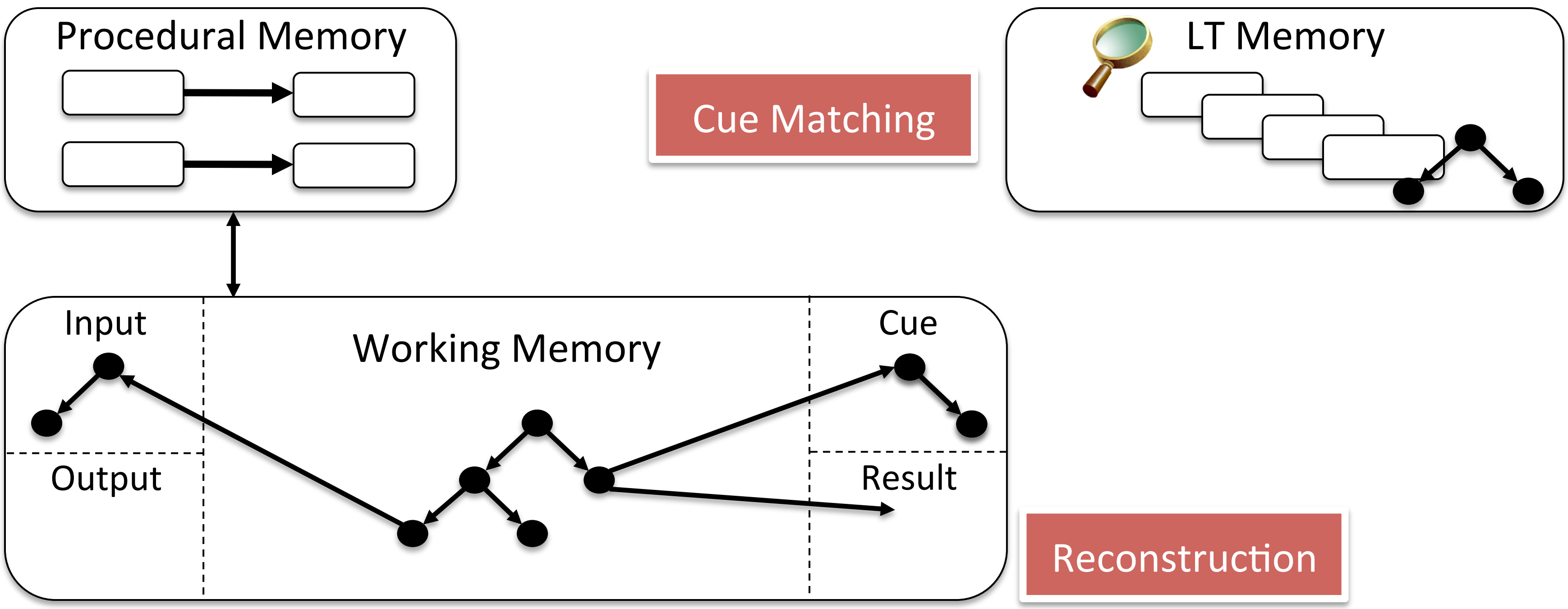
Soar (Laird, 2012)

Memory Integration

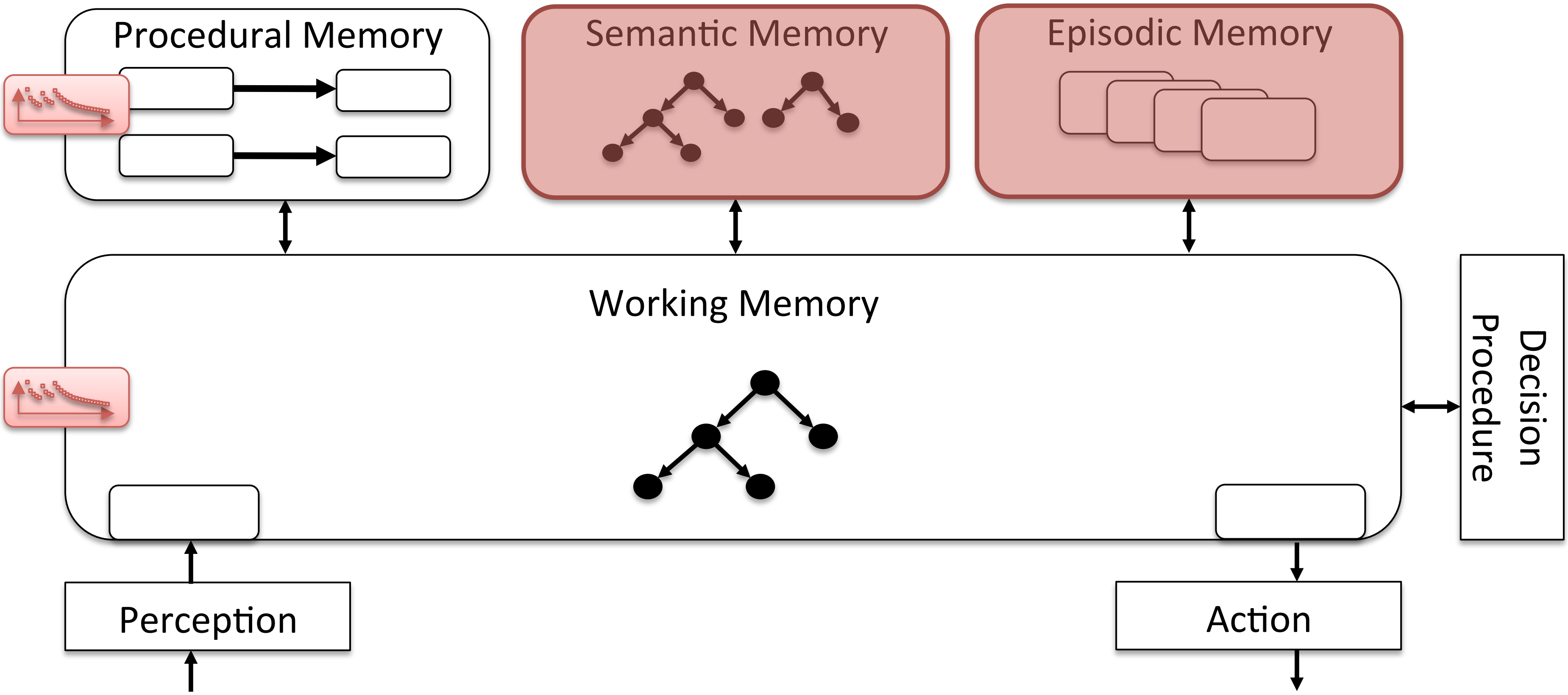


Soar

LT Memory Access



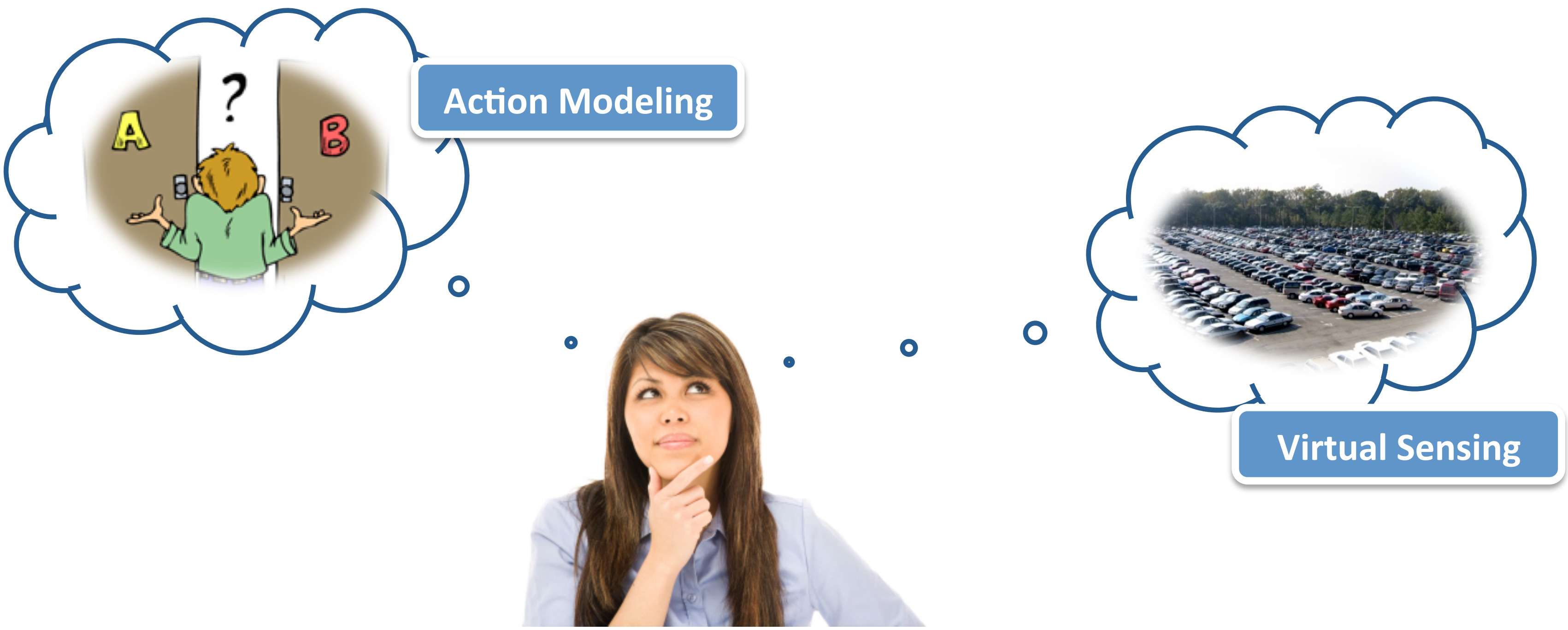
This Work



Open Source, Cross Platform, Documented in Soar v9.3.2 [soar.googlecode.com]

Episodic Memory

Long-term, contextualized store of specific events (Tulving, 1983)



Episodic Memory
Problem Formulation

Representation

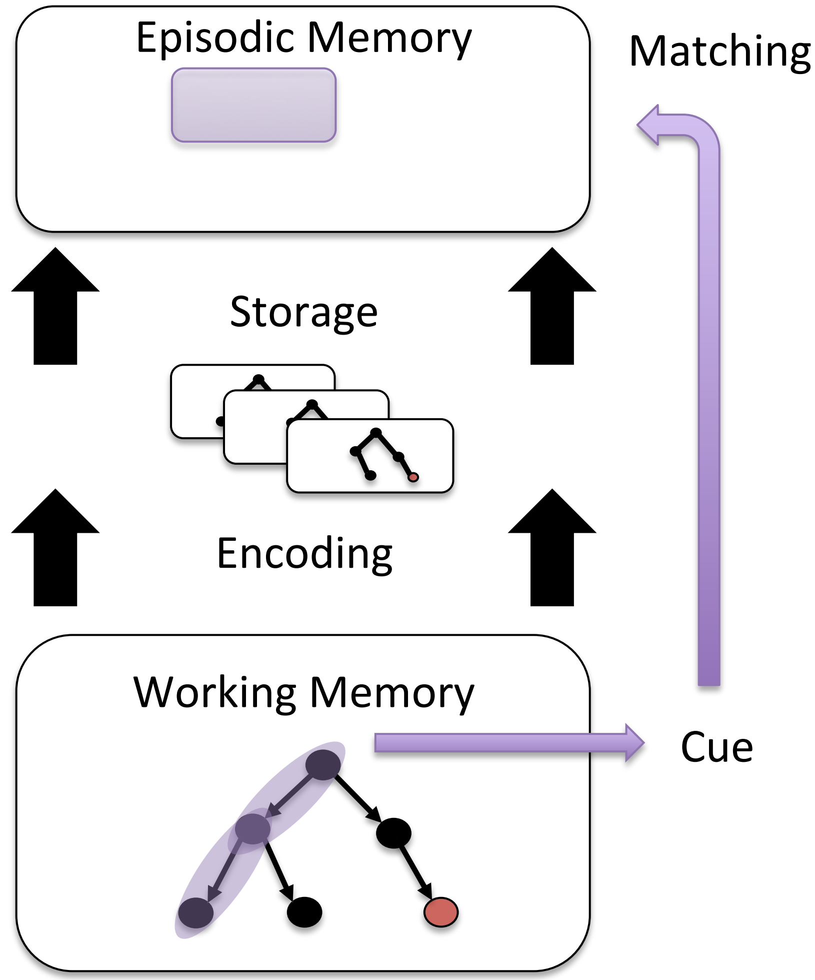
- Episode: connected di-graph
- Store: temporal sequence

Encoding/Storage

- Automatic
- No dynamics

Retrieval

- Cue: acyclic graph
- Semantics: desired features in context
- Find the most recent episode that shares the most leaf nodes in common with the cue



Episodic Memory
Computational Challenges

Arbitrary, dynamic state

Scaling potential, agent…

- state (1000s nodes/edges)
- life (10^6-10^9 episodes ~ days)

Cue-matching optimality

- Constrained subgraph isomorphism (NP-complete)
- Search: O(# episodes)

Analysis & Algorithms
[ICCBR ‘09], [AAMAS ‘12]

Properties

- Temporal Contiguity

  |state changes| << |state|
- Structural Regularity

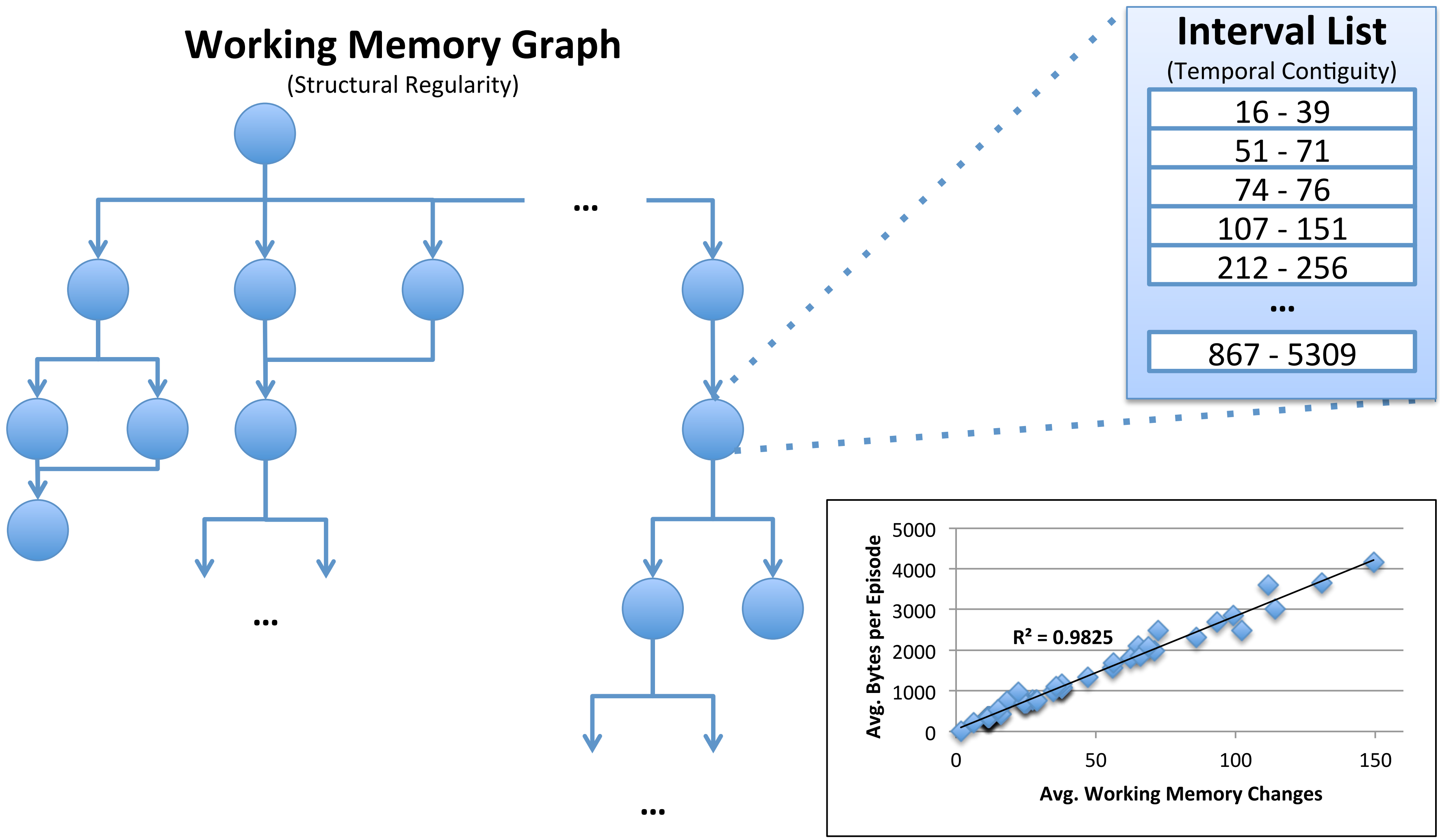
  |distinct structures| << |all experienced structures|

Algorithms

- **Storage**: dynamic graph index*
- **Cue Matching**: 2-phase search*
- **Reconstruction**: relational interval tree

  (Kriegel et al. 2000)

Dynamic Graph Index



2-Phase Cue Matching

1. **Surface**
   a) Identify cue-feature changes via ordered interval-walking algorithm
      - Priority queue of b+-tree pointers

   b) Incrementally score features independently
      - Discrimination network (DNF Graph)

2. **Structure**
   a) Graph match + standard heuristics (e.g. MCV)

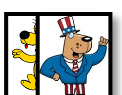
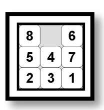
Empirical Evaluation
[AAAI '12a]

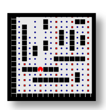
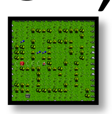
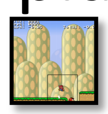
<u>Performance Characterization</u>

- Temporal Selectivity + Co-Occurrence
  O(Search Distance)
- Structural Selectivity
  O(Episode Hyper-edges)

<u>Empirical Evaluation</u>

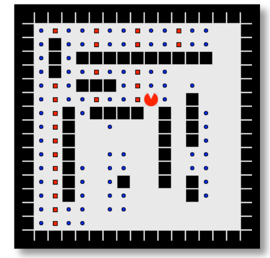
- 49 domains: WSD, planning, robotics, games

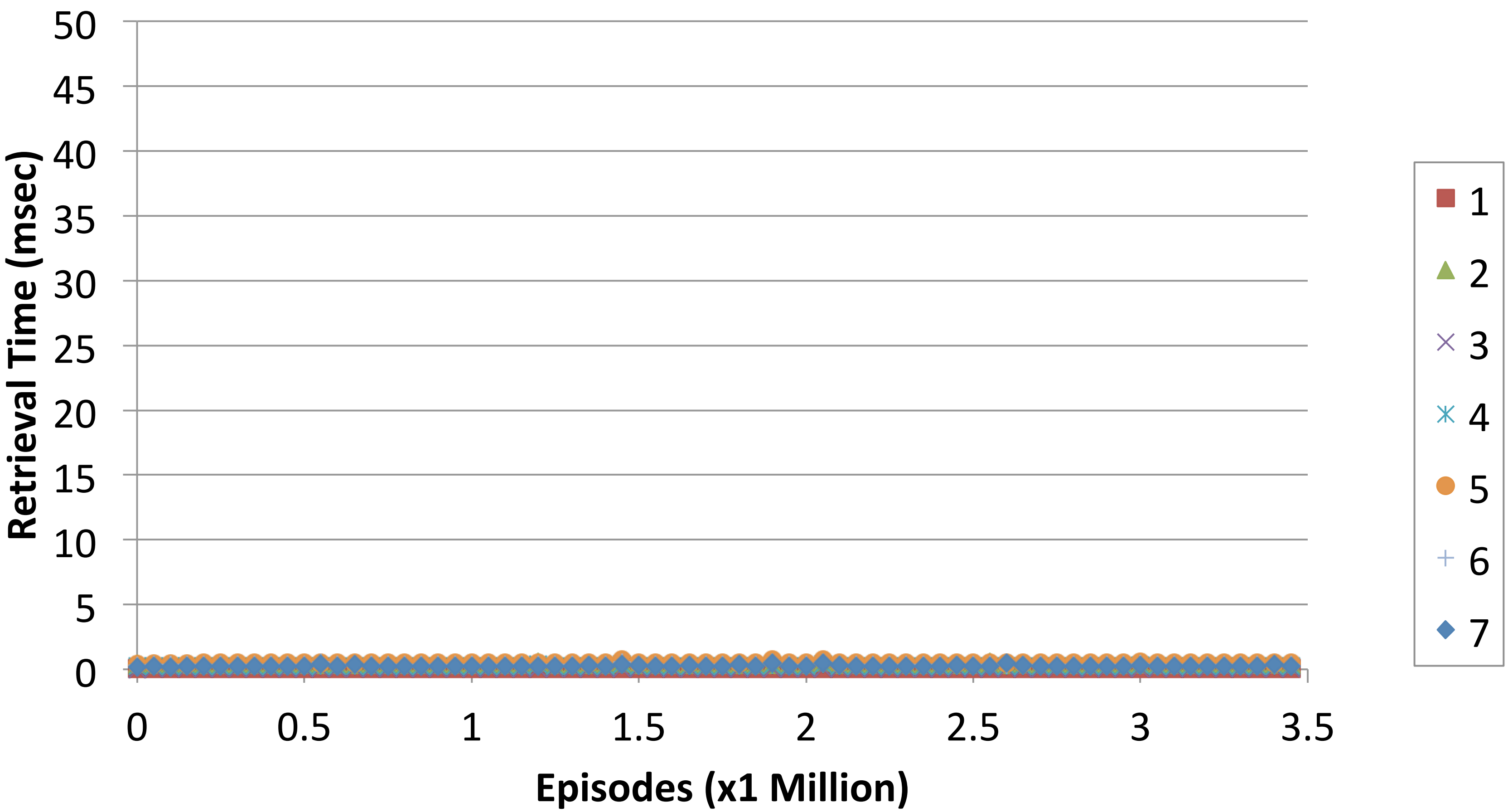
 

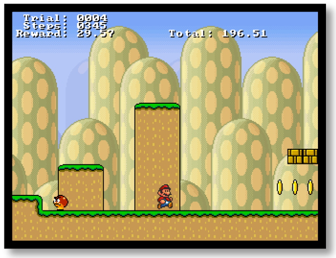
- 10^5-10^8 episodes ~ days of real time, >100 cues

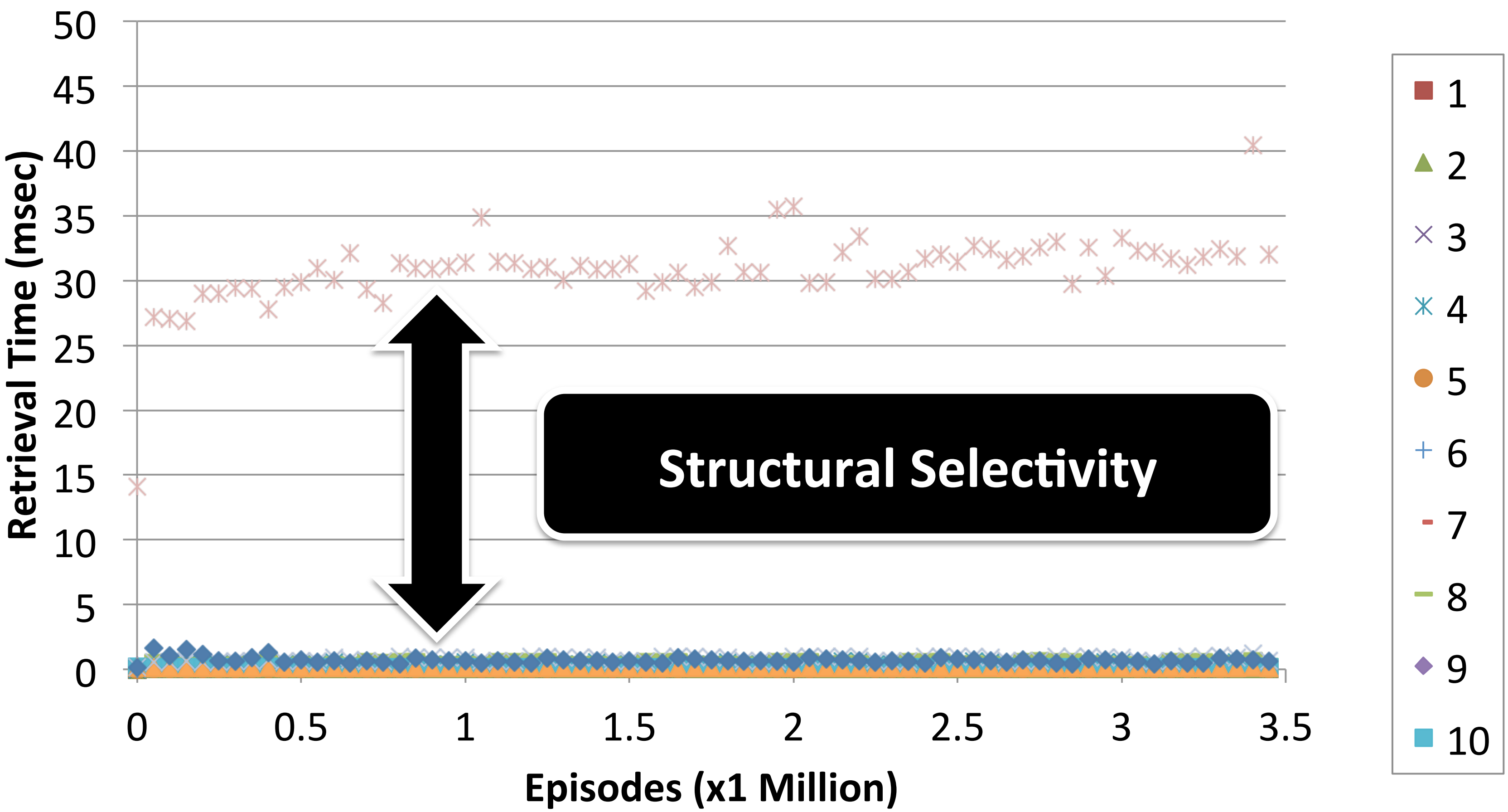
Data: Eaters



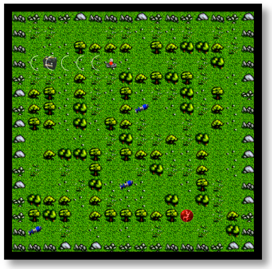

Retrieval Time (msec)
50
45
40
35
30
25
20
15
10
5
0
0
0.5
1
1.5
2
2.5
3
3.5
Episodes (x1 Million)
1
2
3
4
5
6
7

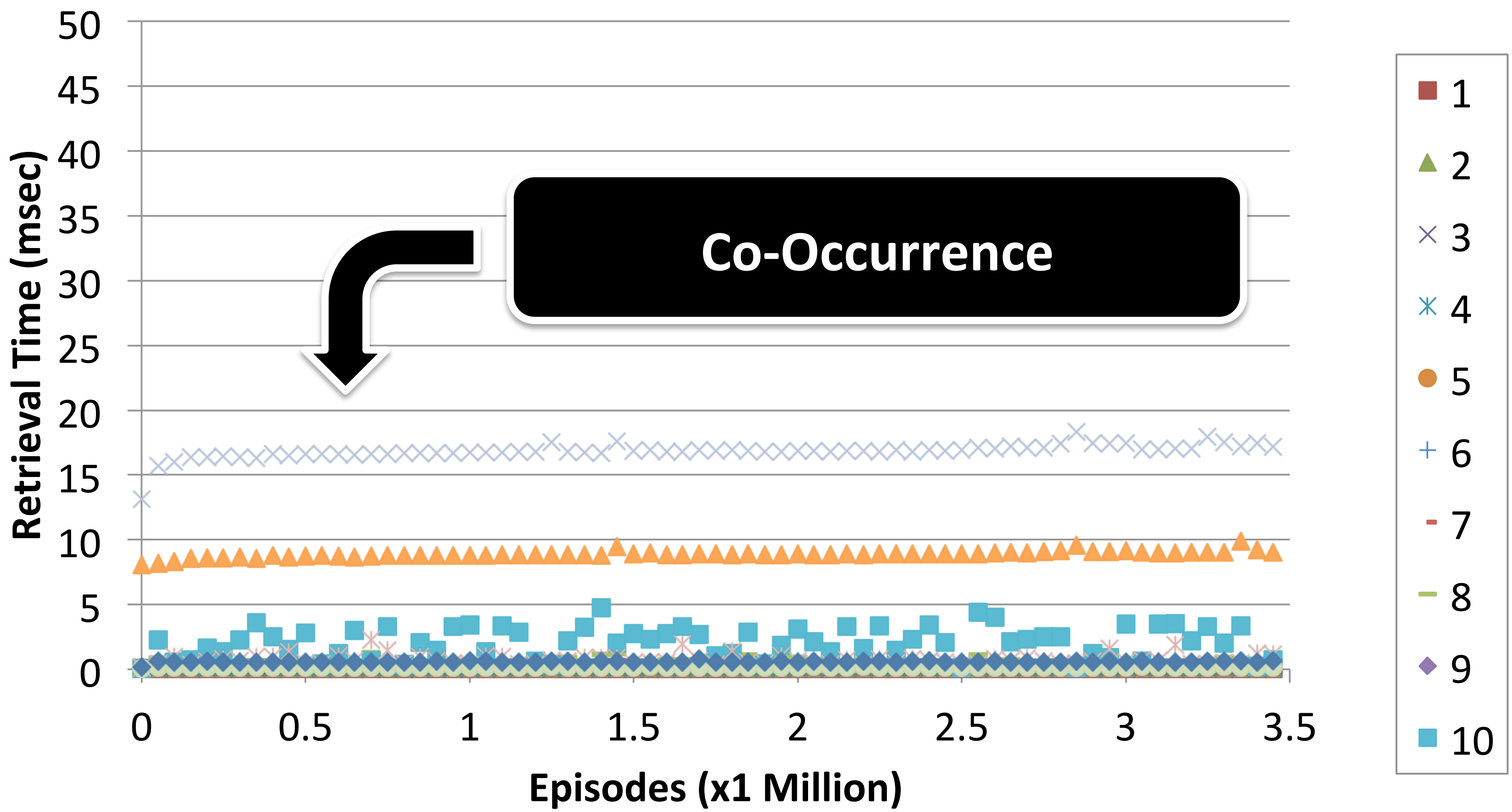
Data: Infinite Mario



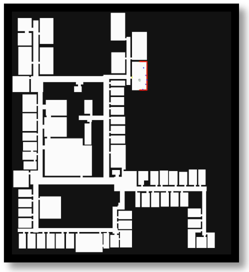


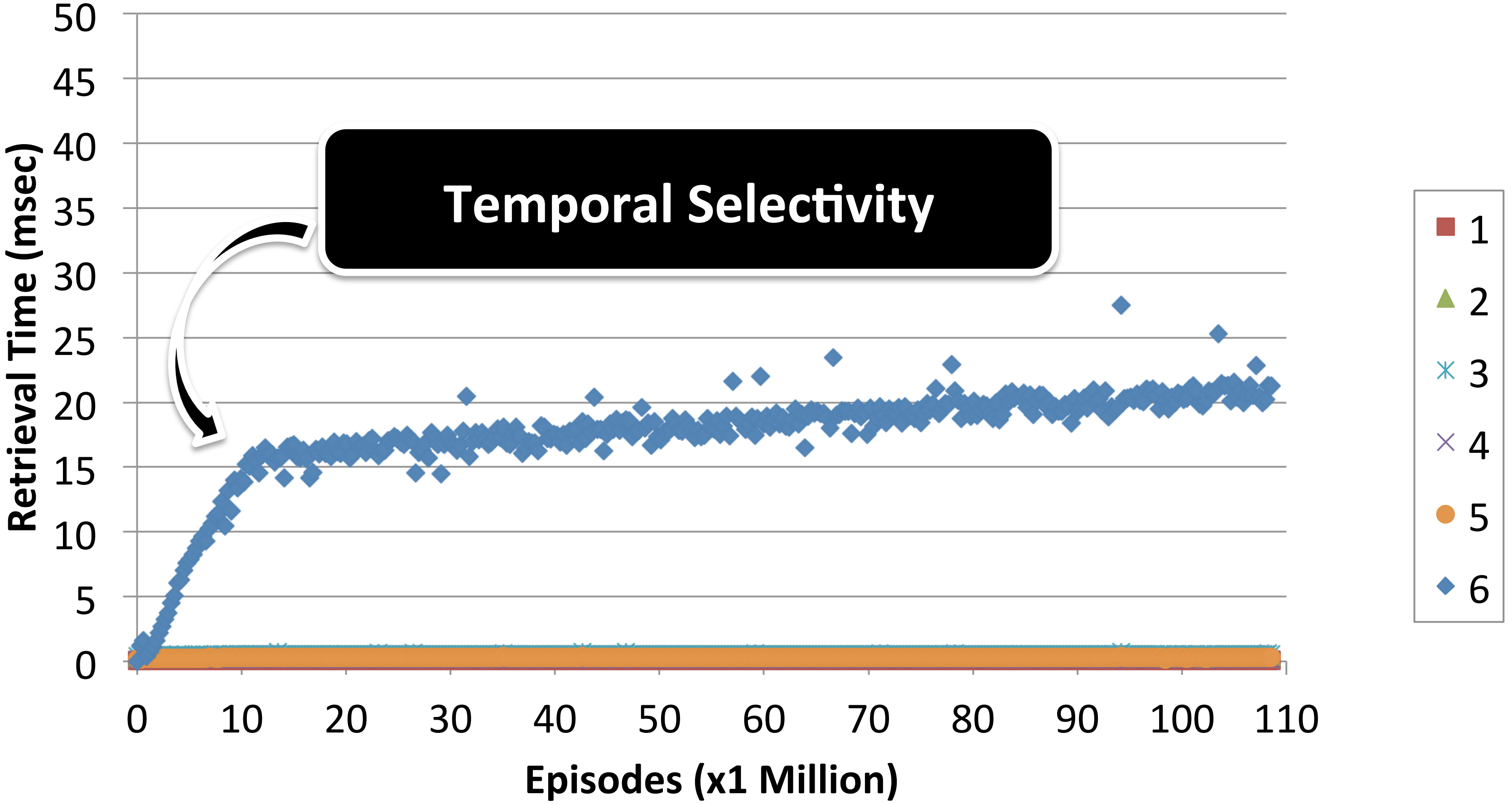
Data: TankSoar





Data: Mobile Robotics



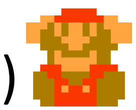


Evaluation Results

Generality

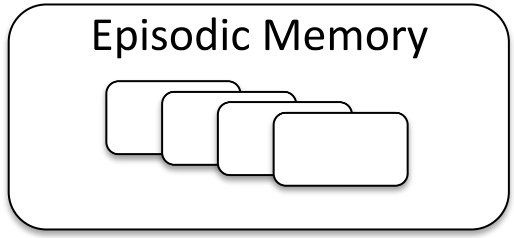
- Demonstrated 7 cognitive capabilities
  - Virtual sensing, action modeling, long-term goal management, …

Reactivity

- <50 msec. storage time for all tasks (ex. temporal discontiguity) 
- <50 msec. cue matching for many cues

Scalability

- No growth in cue matching for many cues (days!)
  - Validated predictive performance models
- 0.18 - 4 kb/episode (days – months)



- Algorithms that are reactive and scalable for many tasks and cues
- Performance characterization w.r.t. general properties of environments, tasks, and agents
- Demonstrated useful capabilities in a variety of problem domains

Semantic Memory

Long-term store of general facts and relations about the world, independent of the context in which they were originally learned

<u>Agent Benefits</u>

- Access to large KBs
- Retrieval bias as a reasoning heuristic

SUMO (upper ontology)
- 4.5K classes, 250K facts

WordNet (lexicon)
- 212K senses, 820K assertions

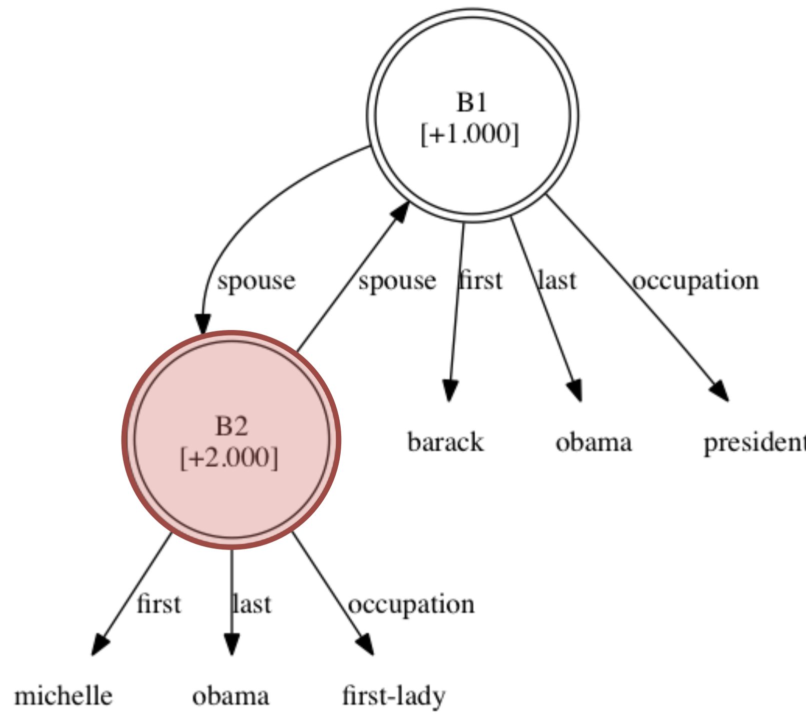
Cyc ("common sense")
- 500K concepts, 5M facts

Semantic Memory
Problem Formulation

Representation
- Directed graph

Encoding/Storage
- Incremental
- Deliberate

Retrieval
- Cue: set of features/relations
- Semantics: subset query
- Single result, ranked by bias value [#]



Example cue:
`last(obama),spouse(X)`

Semantic Memory
Computational Challenges

Dynamic…

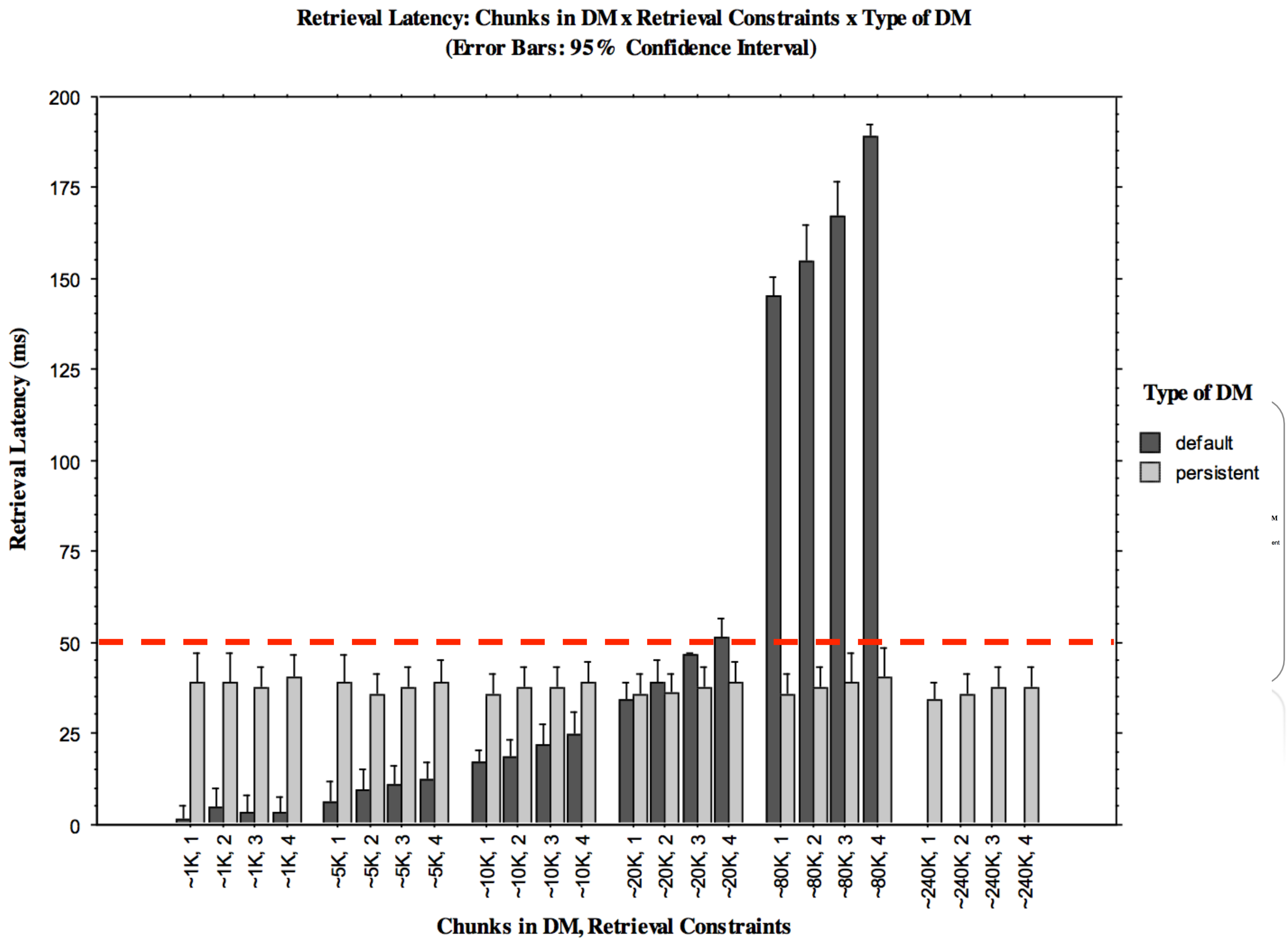
- number of nodes/edges
- symbol vocabulary

Scaling potential

- Nodes ~ millions
- Edges ~ 10 per node

Cue-matching optimality

- Feature satisfaction, ranking w.r.t. bias value
- *O*(|cue| x |objects|)


Retrieval Latency: Chunks in DM x Retrieval Constraints x Type of DM
(Error Bars: 95% Confidence Interval)
Retrieval Latency (ms)
200
175
150
125
100
75
50
25
0
Type of DM
default
persistent
~1K, 1
~1K, 2
~1K, 3
~1K, 4
~5K, 1
~5K, 2
~5K, 3
~5K, 4
~10K, 1
~10K, 2
~10K, 3
~10K, 4
~20K, 1
~20K, 2
~20K, 3
~20K, 4
~80K, 1
~80K, 2
~80K, 3
~80K, 4
~240K, 1
~240K, 2
~240K, 3
~240K, 4
Chunks in DM, Retrieval Constraints

Analysis & Algorithms
[ICCM '10], [AAAI '11]

<u>Properties</u>

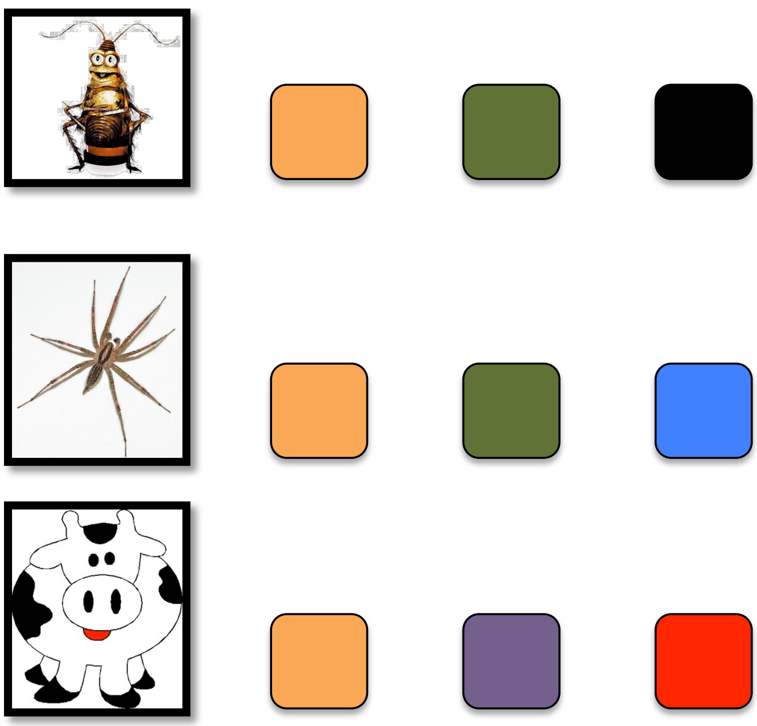
- Object Cardinality
  Few objects with large # of features/relations

<u>Algorithms</u>

- **Storage**: incremental inverted index (b+ trees)
  (Zobel and Moffat, 2006)
- **Cue Matching**:
  - Statistical query optimization (Chaudhuri, 1998)
  - Hybrid ranking via *locally efficient* bias functions*

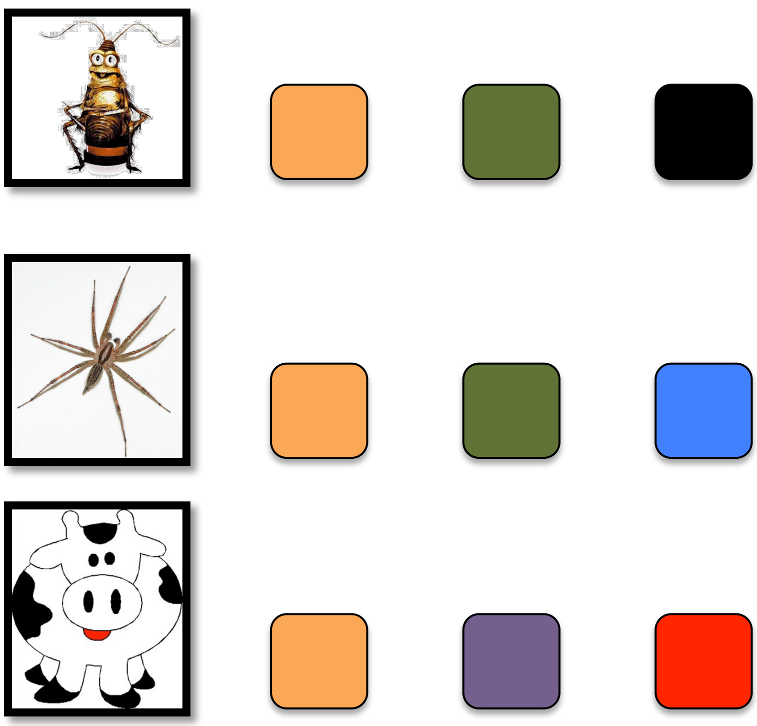
Example Semantic Knowledge

Semantic Objects: Features

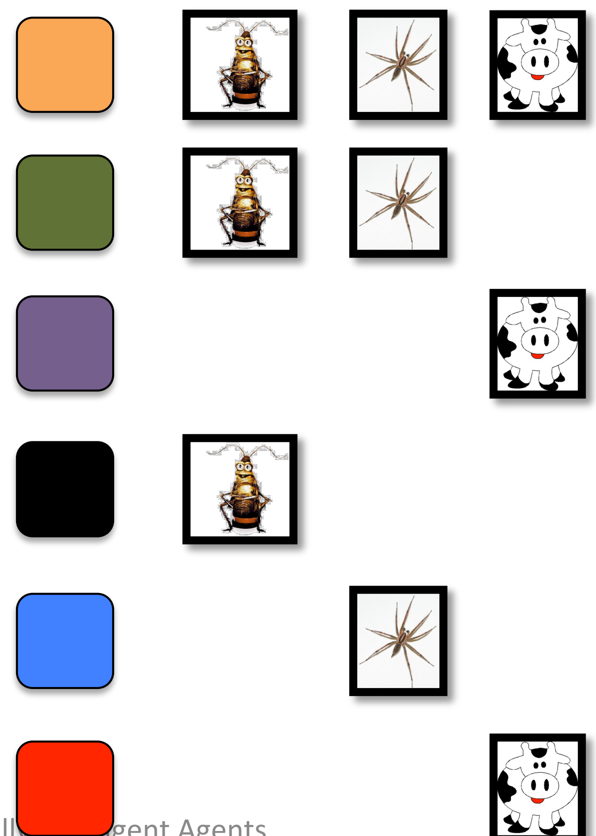


Inverted Indexing

Semantic Objects: Features



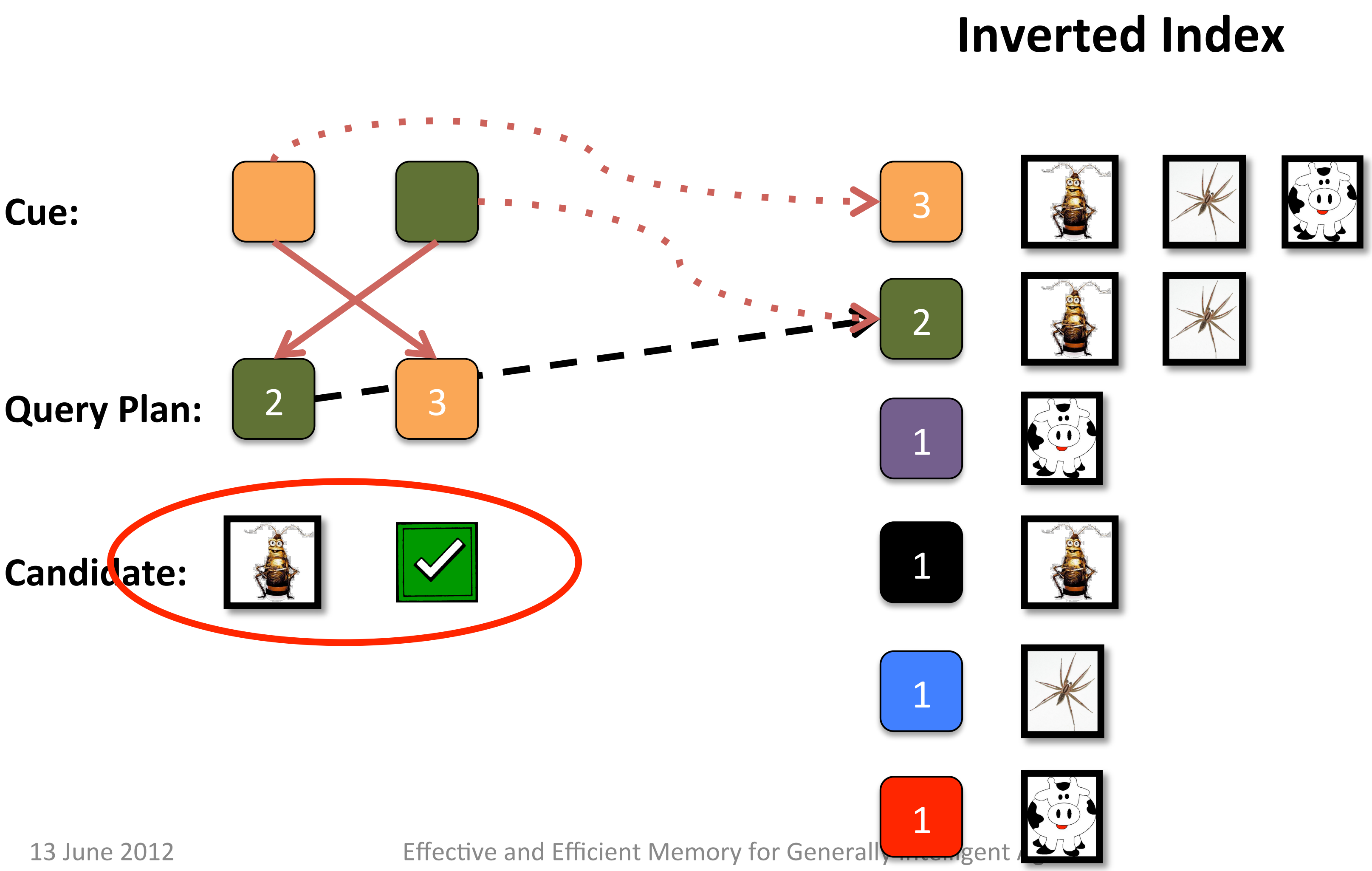
Inverted Index



Feature Statistics

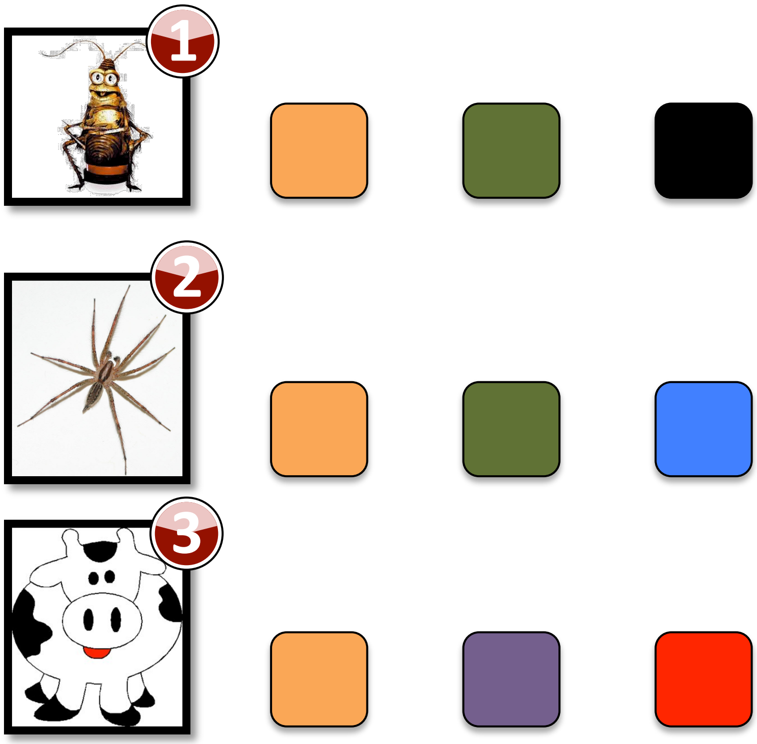
Semantic Objects: Features **Inverted Index**

Non-Biased Retrieval Algorithm

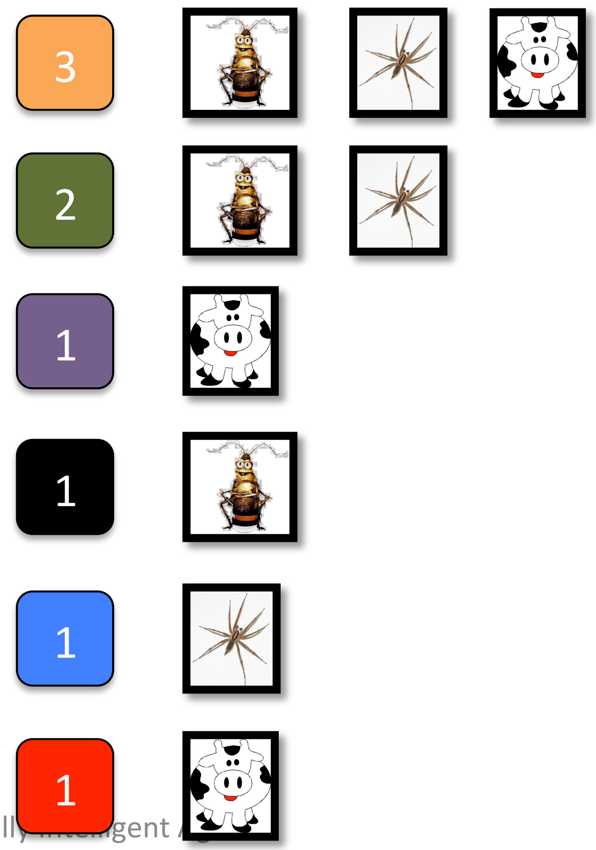


Introducing Bias

Semantic Objects: Features

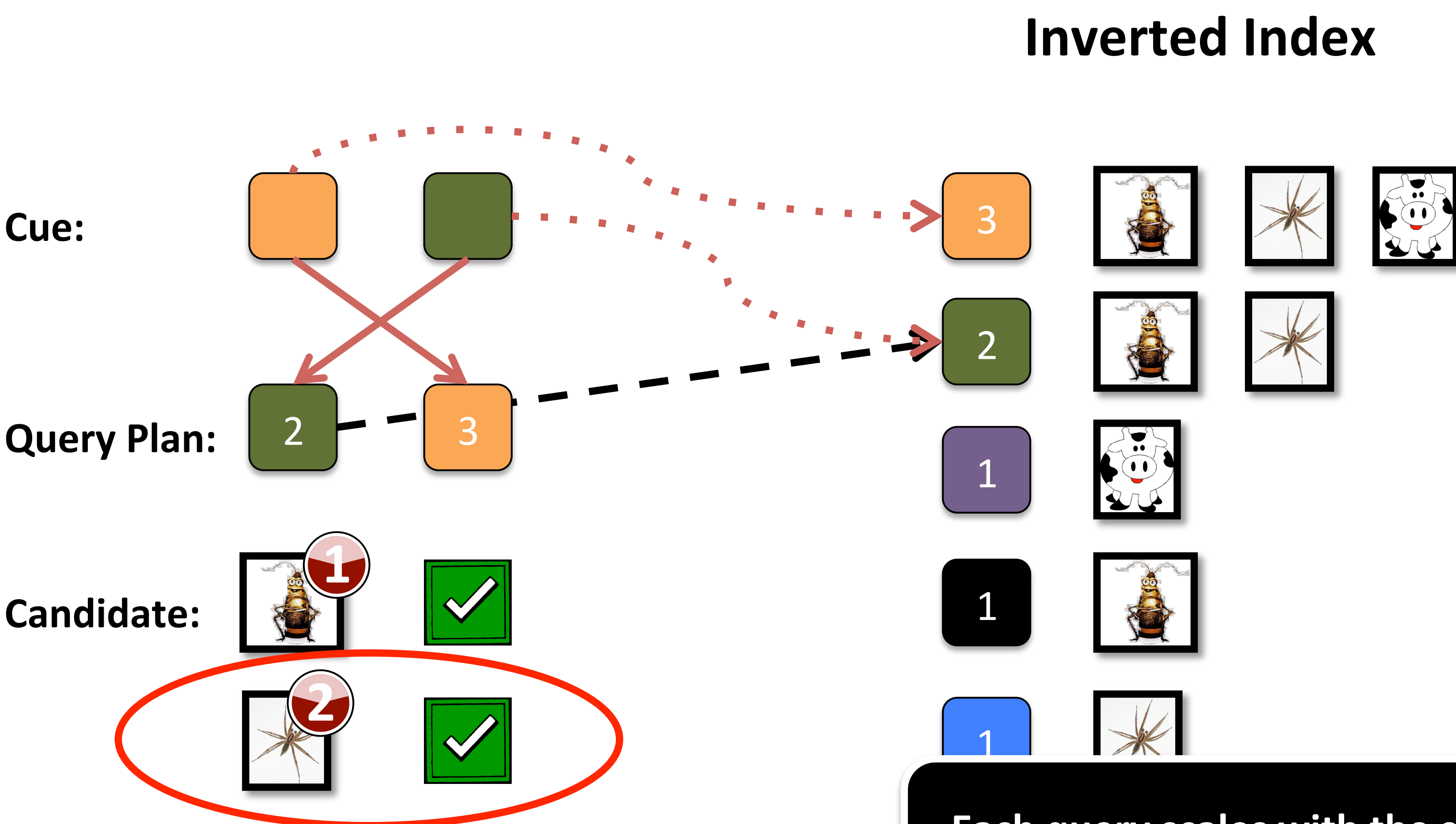


Inverted Index



Biased Retrieval Algorithm #1

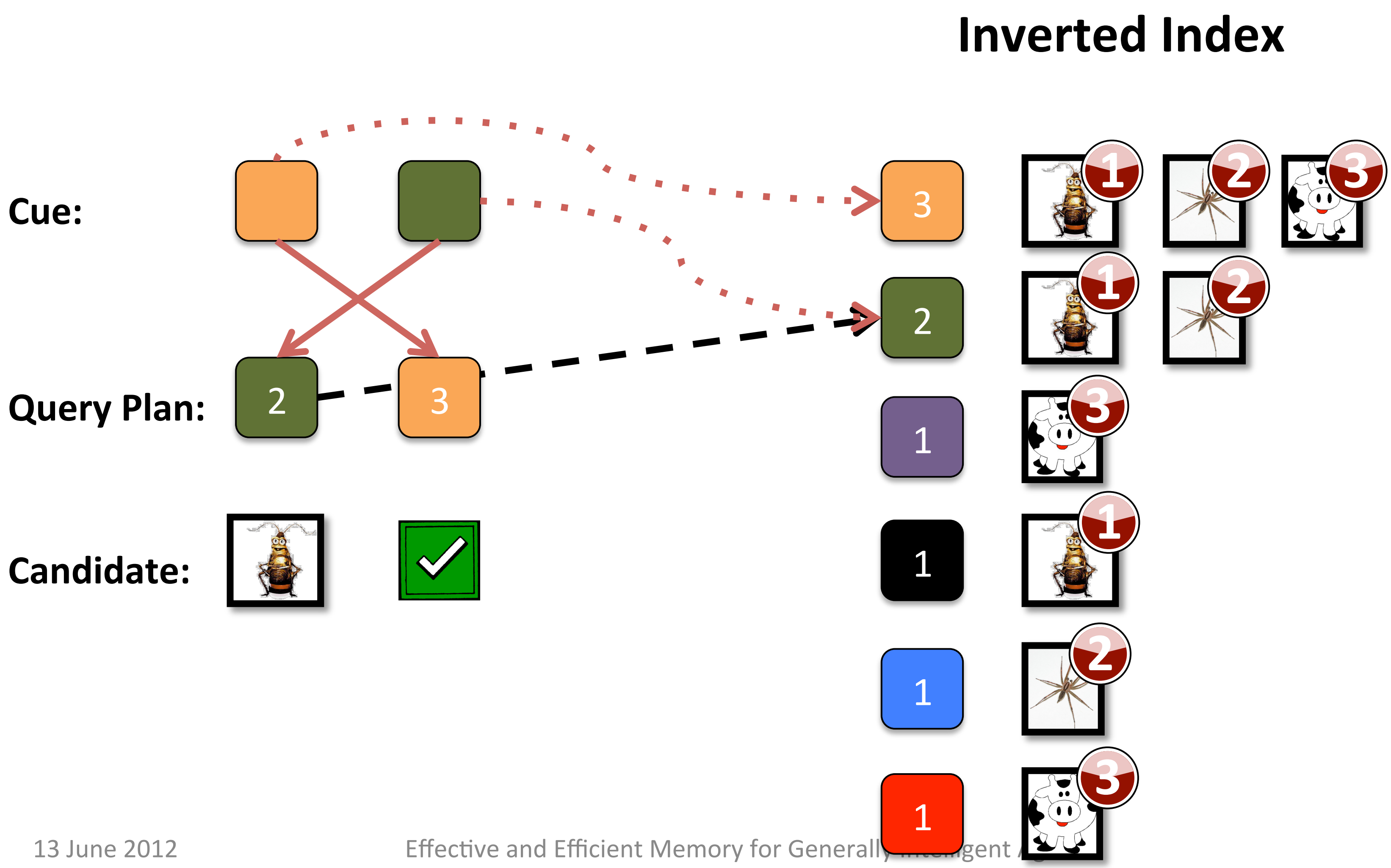
Sort on Query



Each query scales with the size of the candidate list!

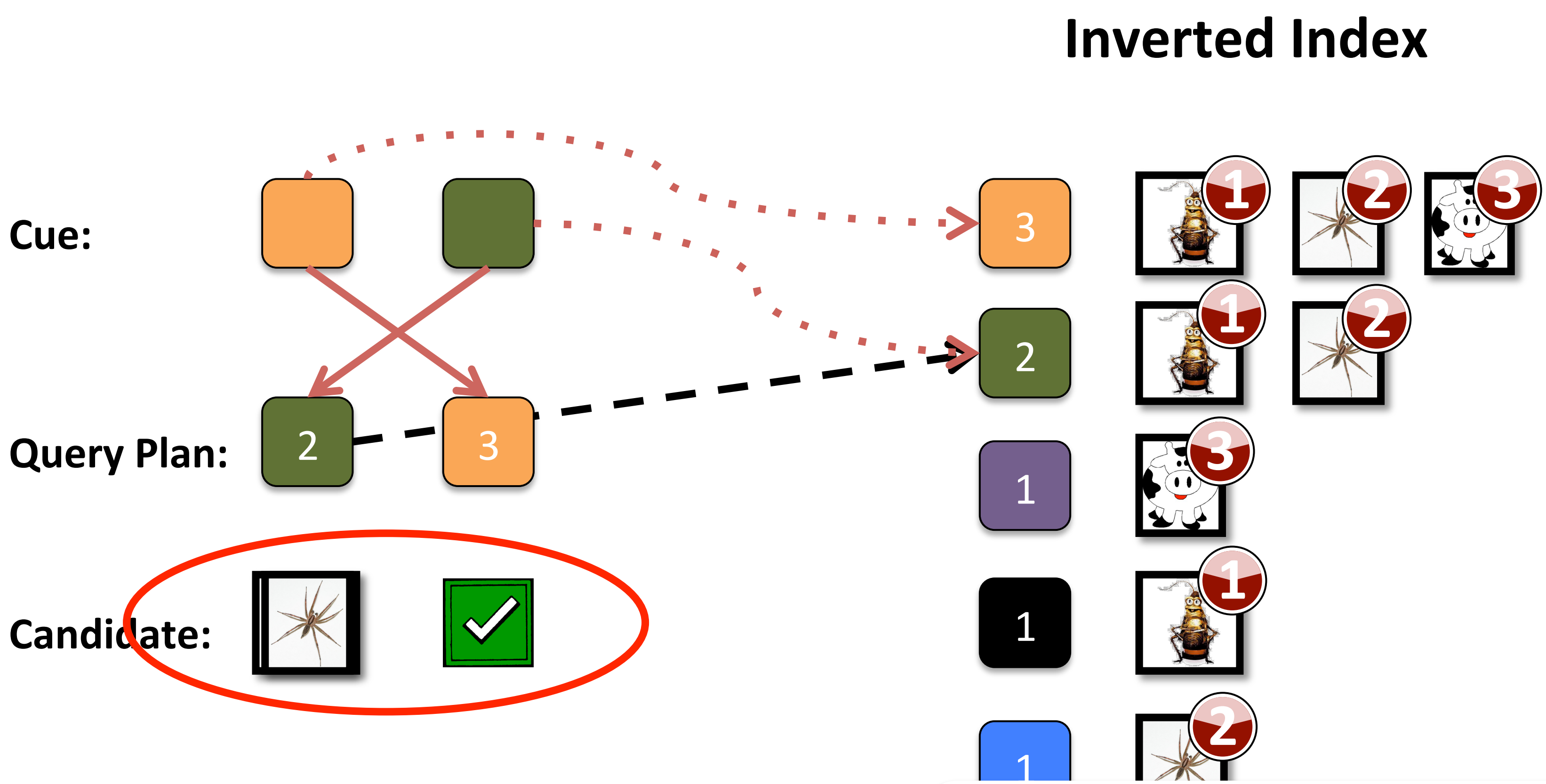
Biased Retrieval Algorithm #2

Static Sort



Biased Retrieval Algorithm #2

Static Sort



Each bias-value update scales with feature cardinality!

Our Hybrid Approach

Empirically supported cardinality threshold, θ

If (cardinality > θ): Sort on Query [#1]

- Candidate enumeration scales with # of objects with large cardinality (which *should* be rare)

If (cardinality $\leq \theta$): Static Sort [#2]

- Bias updates must be **locally efficient**
  - Objects affected: $O(1)$
  - Computation: $O(1)$

Empirical Evaluation
[ICCM '10], [AAAI '11]

Performance Characterization

- Selectivity + Co-occurrence

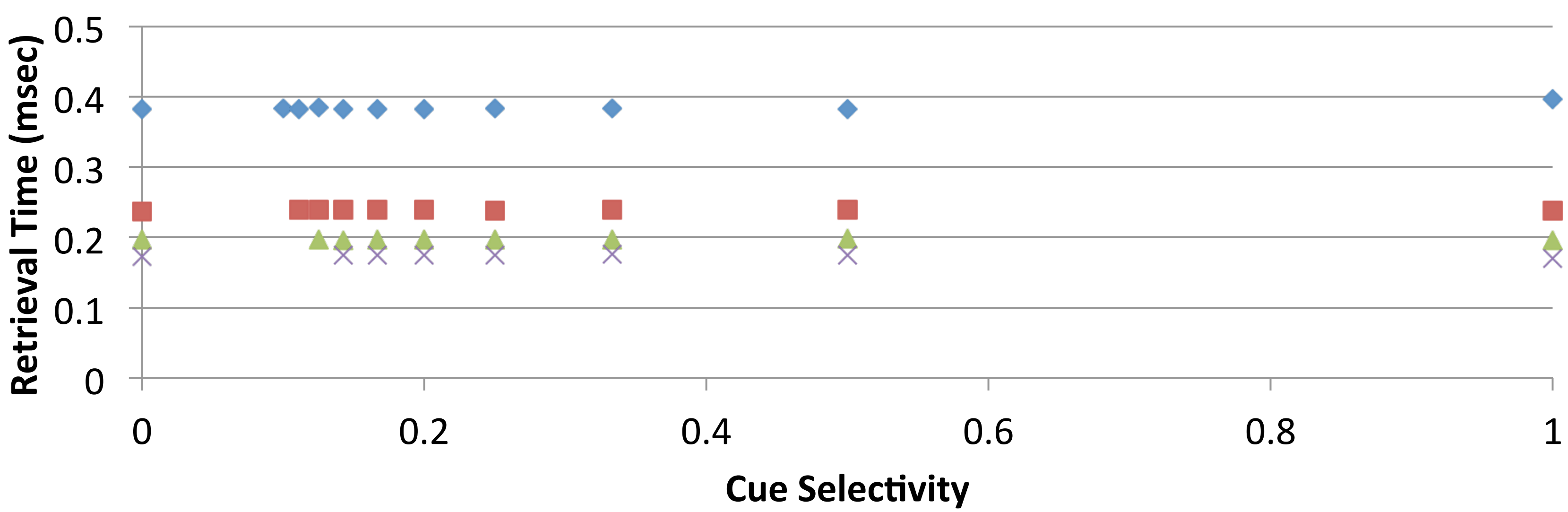
  O(Failed Candidates)

Empirical Evaluation

- Synthetic: efficiency/scaling of cue matching
- WSD: efficiency/usefulness of biased retrievals

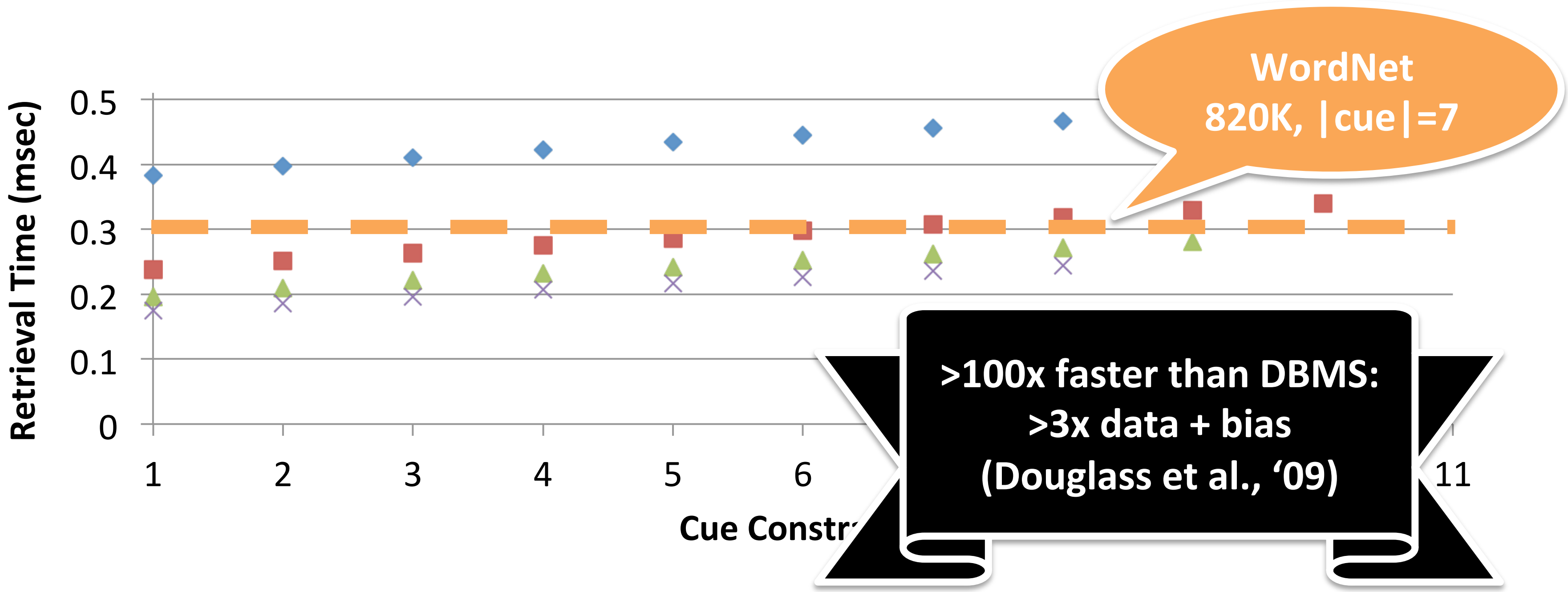
Synthetic Evaluation

- Scaling parameter: k
- Nodes = k!, Edges = [k+1]!



Synthetic Evaluation

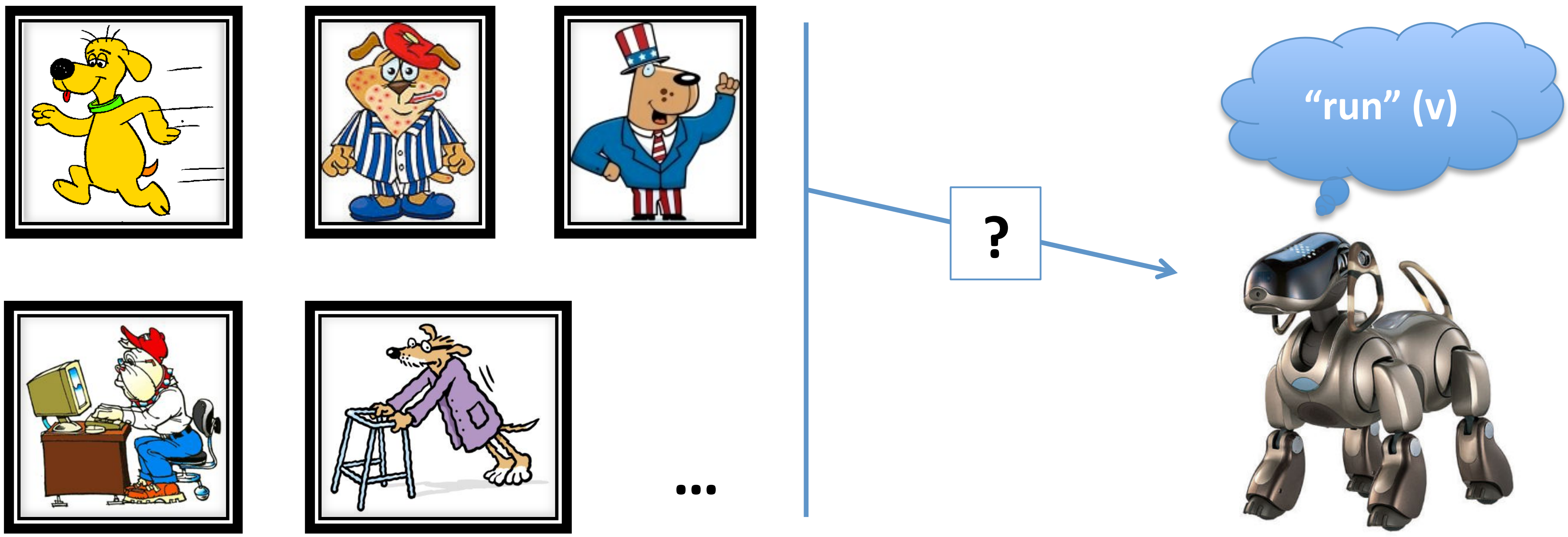
- Scaling parameter: k
- Nodes = k!, Edges = [k+1]!



WSD Evaluation

Motivation

Memory **Agent**



Problem. Ambiguous Cues
Hypothesis. Retrieval History is Useful
Application. Word Sense Disambiguation

WSD Evaluation

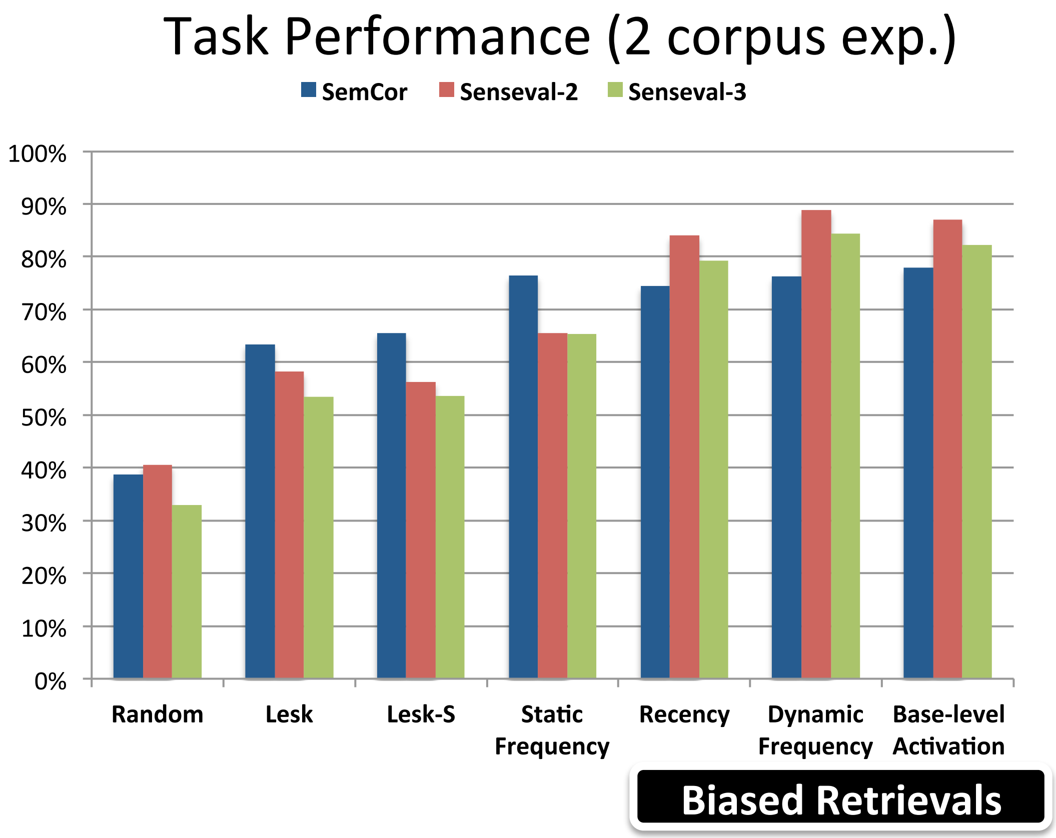
Historical Memory Retrieval Bias

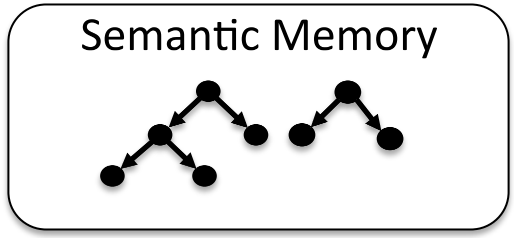
Experimental Setup

- Input: "word", POS
- Given: WordNet v3
- Correct sense(s) after each attempt

Efficiency & Scaling

- R/DF: *O*(1), ≤ 0.87 msec.
- Base-Level Activation:
  - Naïve: *O*(# obj's), ≤ 13.25 msec.
  - *Locally Efficient* Approximation: *O*(1), ≤ 1.34 msec.





- Algorithms that are reactive and scalable for real tasks and KBs
- Performance characterization w.r.t. general properties of environments, tasks, and agents
- Bias functions that are efficient, scalable, and useful for heuristic reasoning

Forgetting

Problem. Extended tasks that involve learning large amounts of knowledge can lead to performance degradation in existing systems (e.g. Kennedy & Trafton, 2007).

Approach. Selectively retain learned knowledge.

Challenge. Balance…

- maintenance of high task performance
- reduction of computational resources

across a variety of tasks.

Approach

Hypothesis. Rational to forget a memory if…

1. not useful (via *base-level activation*) &
2. likely can *reconstruct* if necessary

Evaluation. 2 complex tasks, 2 memories

Mobile Robot Navigation

Working Memory

- bounds decision time
- completes task
  - 1 hour

Multi-Player Dice

Procedural Memory

- 50% memory reduction
- competitive play
  - days

Task Independent

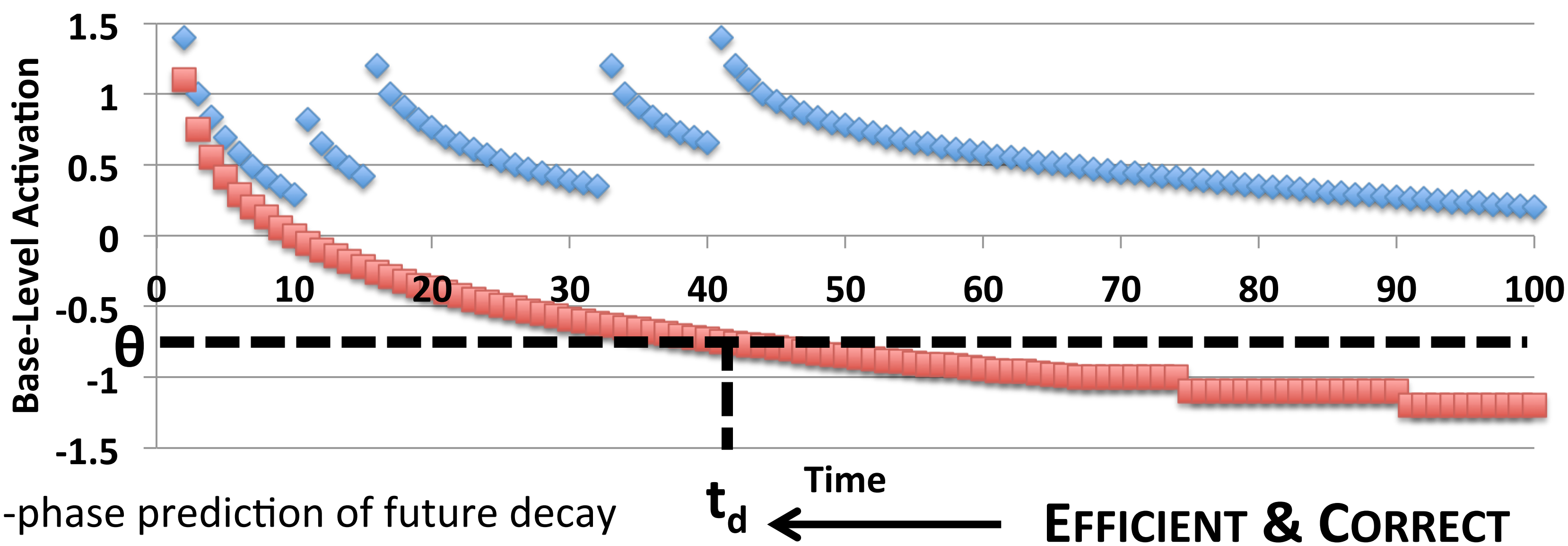
Base-Level Decay

(Anderson et al., 2004)

Predict future usage via history

Used to model human retrieval bias, errors, and forgetting via failure

$$\ln\left(\sum_{j=1}^{n} t_j^{-d}\right)$$



2-phase prediction of future decay

- Novel approximation
- Binary parameter search

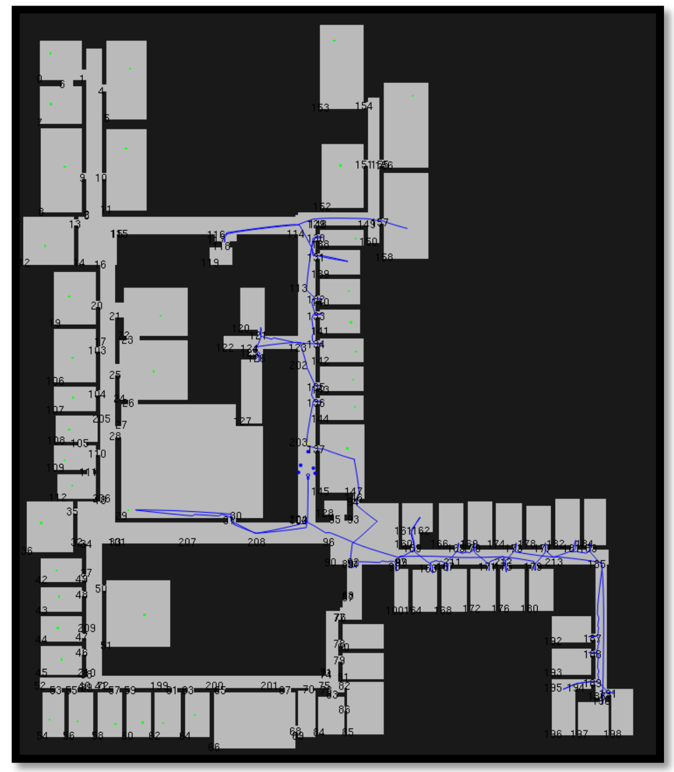
EFFICIENT & CORRECT

~~O(# memories)~~

Task #1: Mobile Robotics

Simulated Exploration & Patrol

- 3rd floor, BBB Building, UM
  - 110 rooms
  - 100 doorways
- Builds map in memory from experience



Problem: Decision Time

Issue. Large working memory

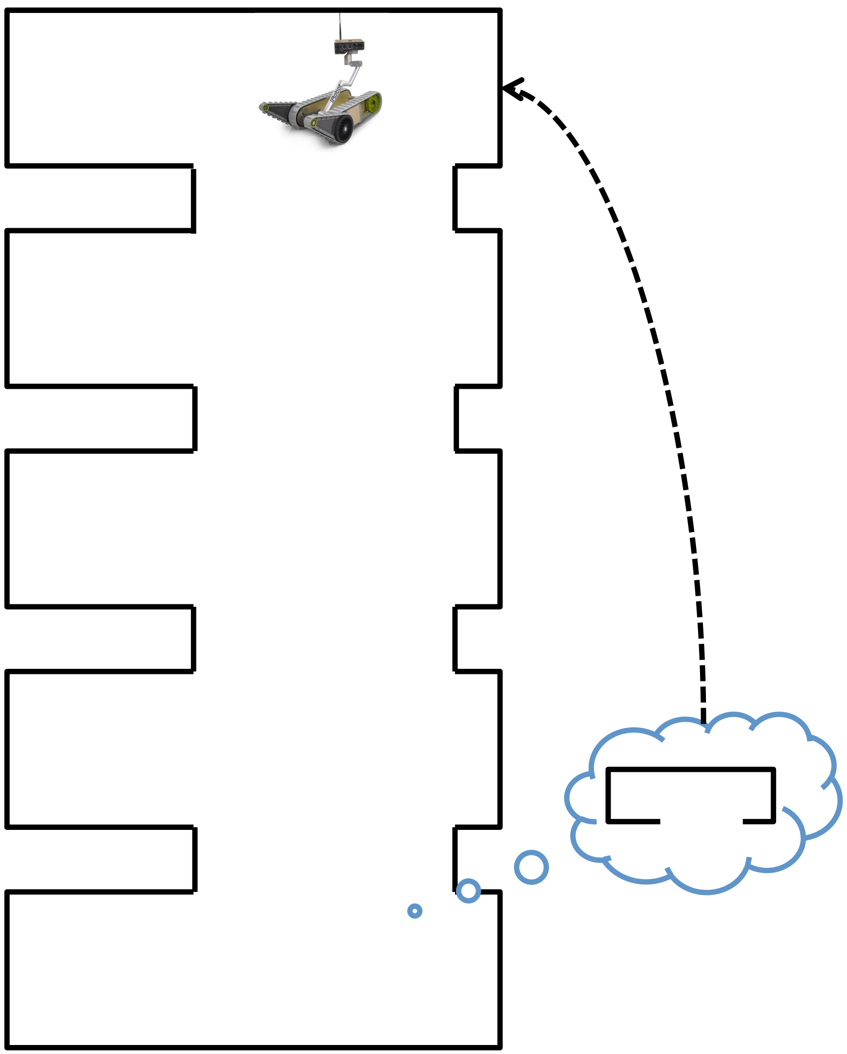
– Minor: rule matching (Forgy, 1982)
– Major: episodic reconstruction
  • |episode|~|working memory|

Forgetting Policy. Memory hierarchy

1. Forget unused short-term features of long-term objects
2. Retrieve from SMem as necessary

Task Independent

Map Knowledge



Room Features

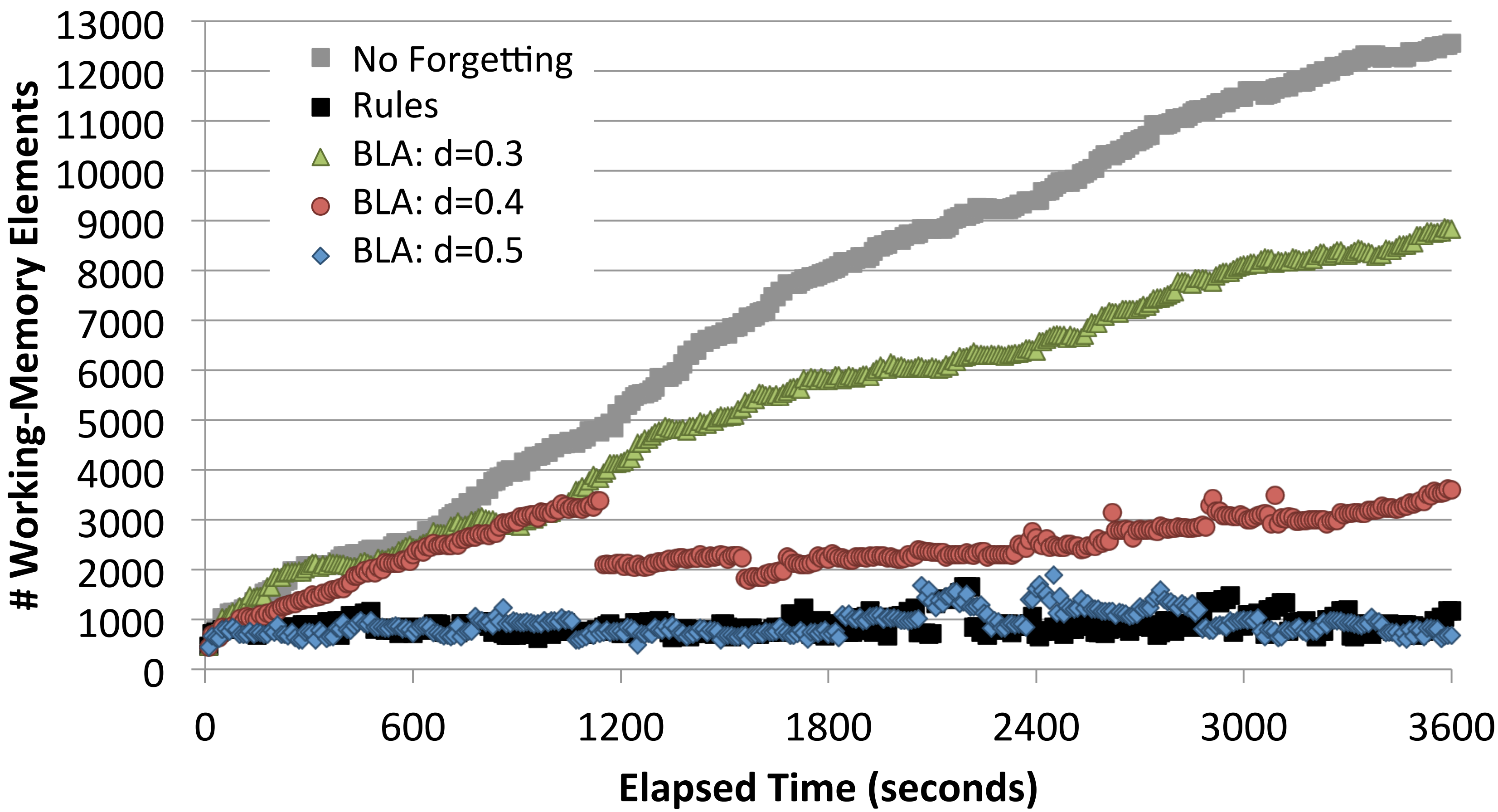
- Position, size
- Walls, doorways
- Objects
- Waypoints

Usage

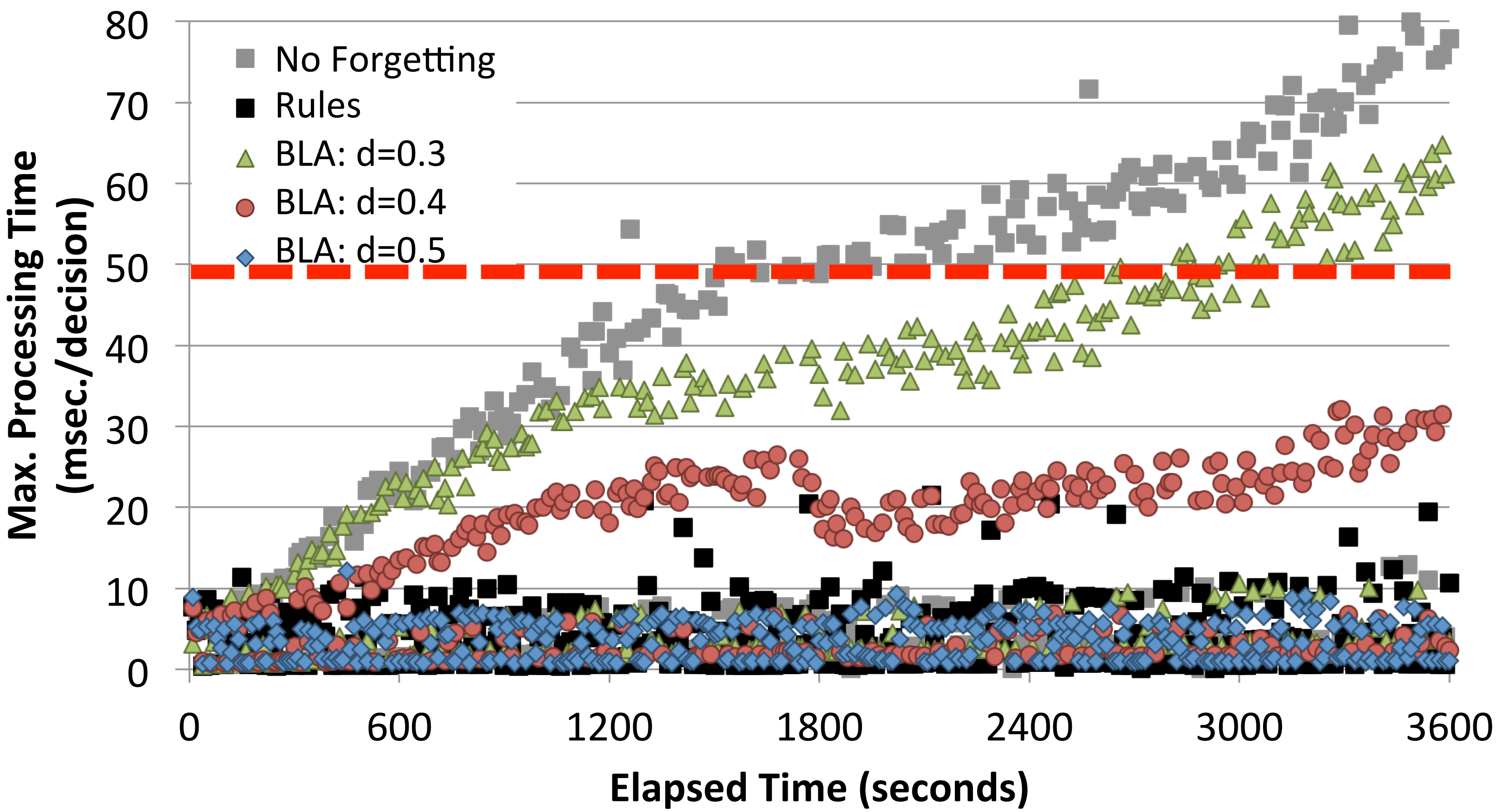
- Exploration (-->SMem)
- Planning/navigation (<--SMem)

  Reconstruction

Results: Working-Memory Size



Results: Decision Time

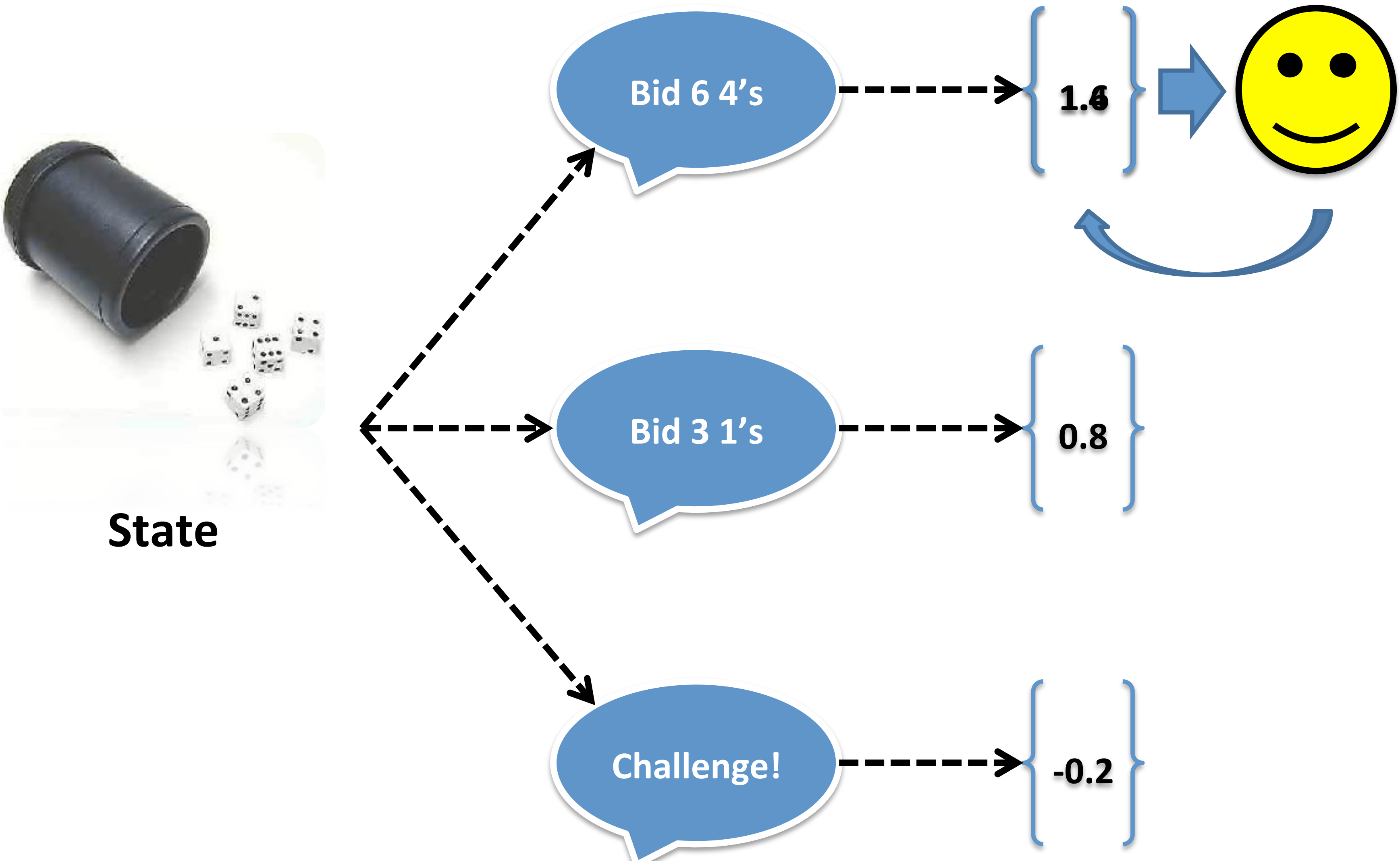


Task #2: Liar's Dice

- Complex rules, hidden state, stochasticity
  - Rampant uncertainty

- Agent learns via reinforcement learning (RL)
  - Large state space (10^6-10^9 for 2-4 players)

Reasoning --> Action Knowledge



Problem: Memory Consumption

Issue. RL value-function representation: (s,a)->#

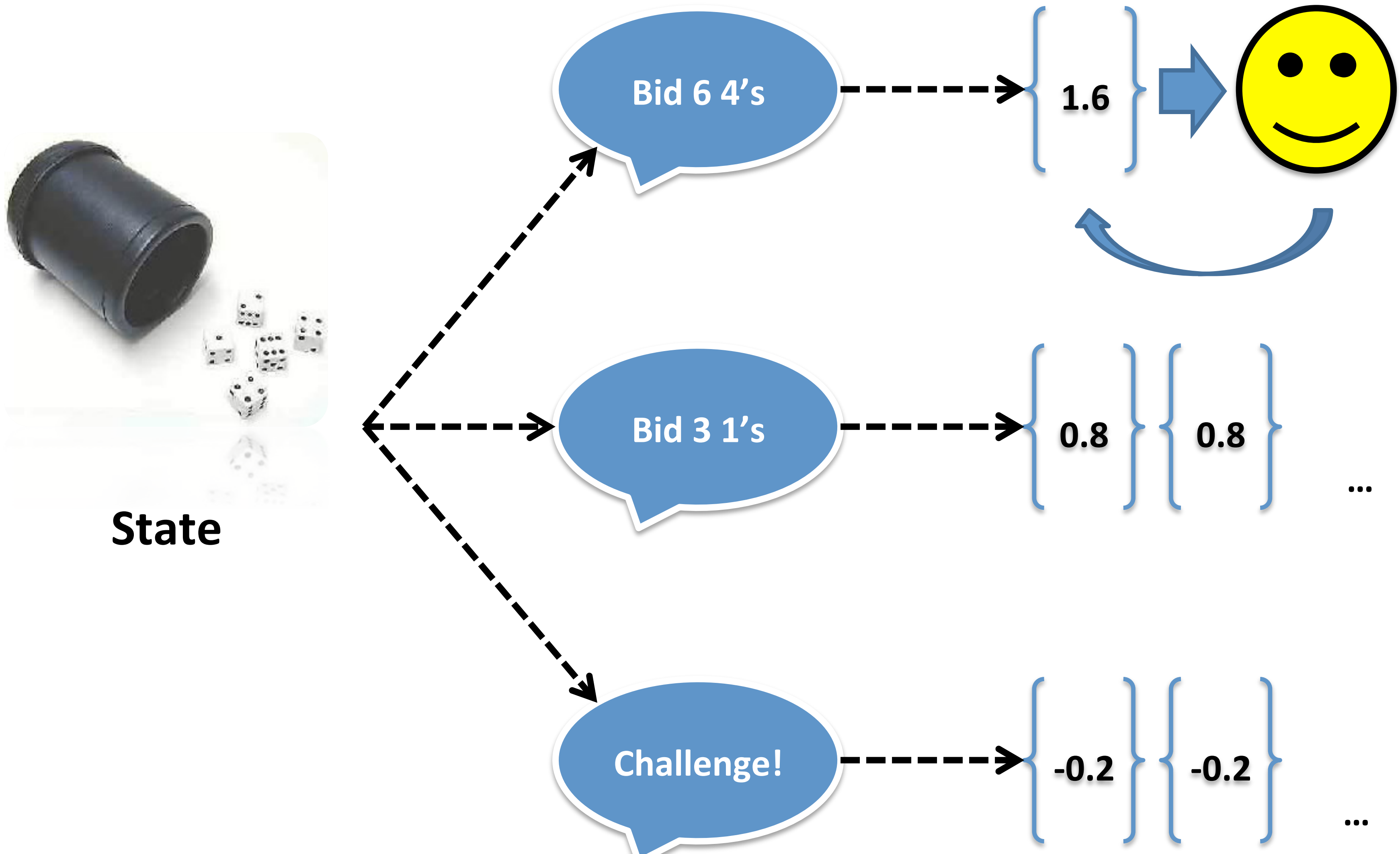
- Soar: procedural knowledge (*RL* rules)
- Many possible actions per turn;
  at most feedback for a single action

Forgetting Policy. Keep what you can't reconstruct

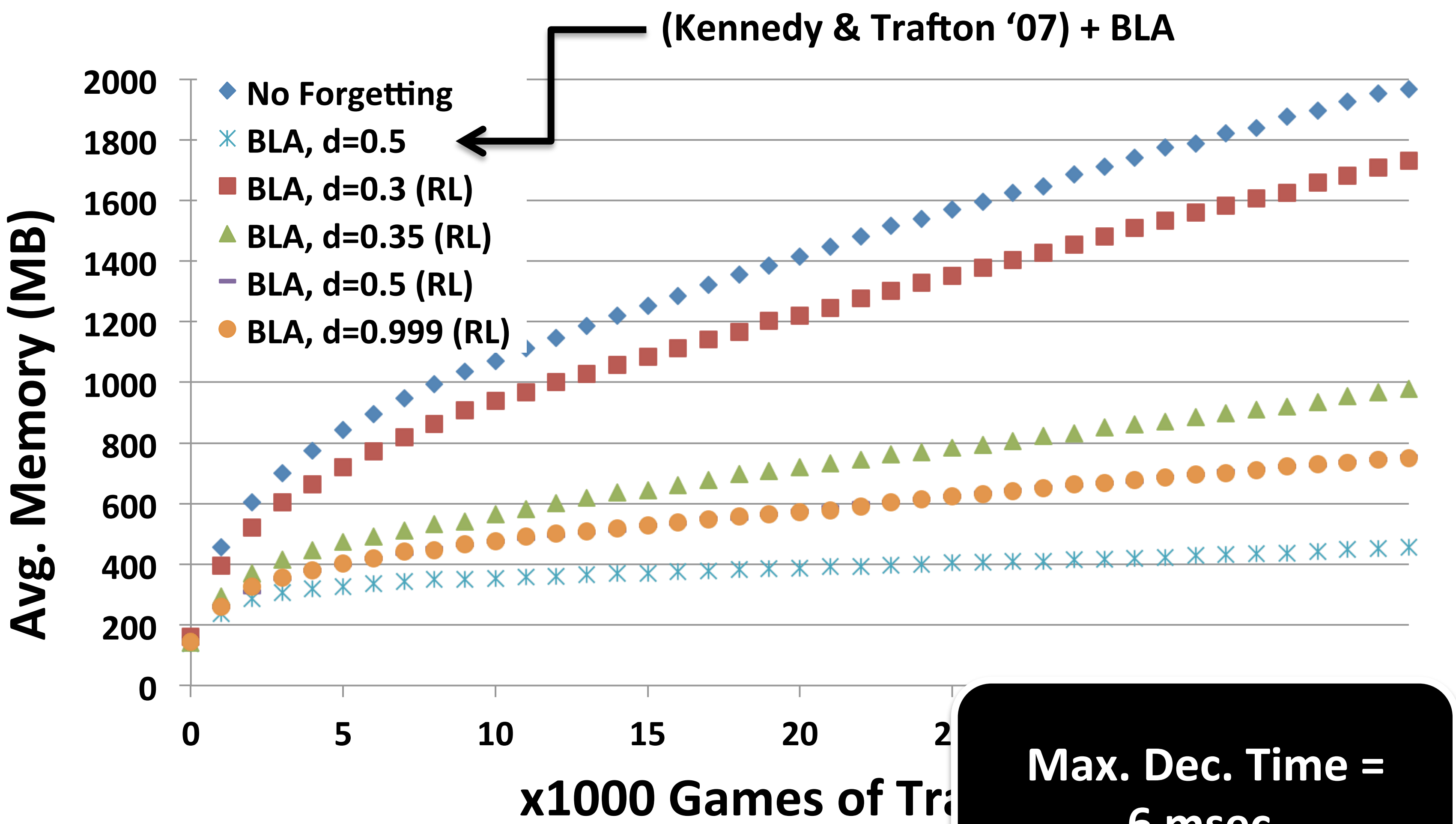
1. Forget unused RL rules that have not been rewarded
2. Learn rules via reasoning as necessary ("chunking")

Task Independent

Forgetting Action Knowledge

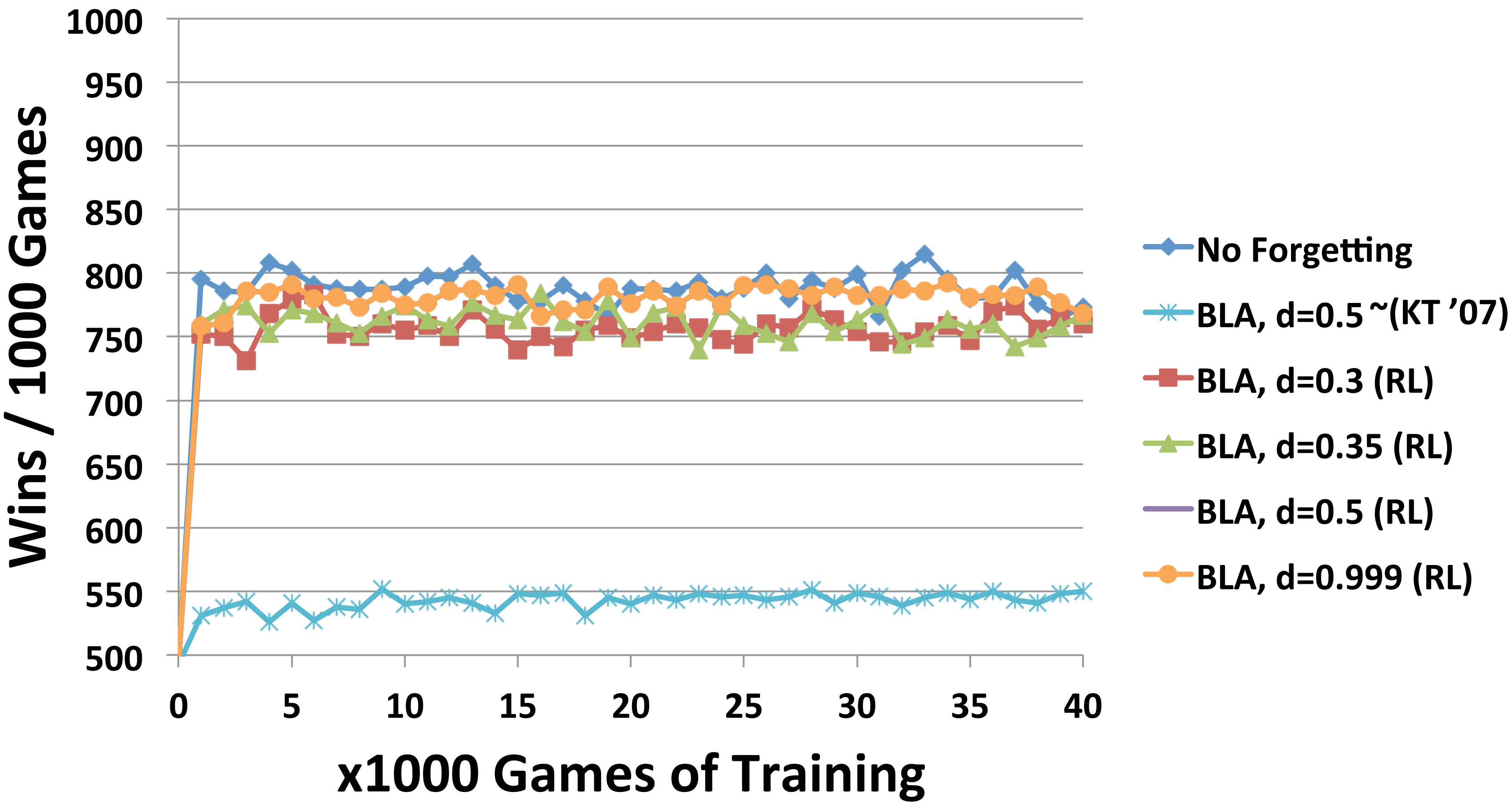


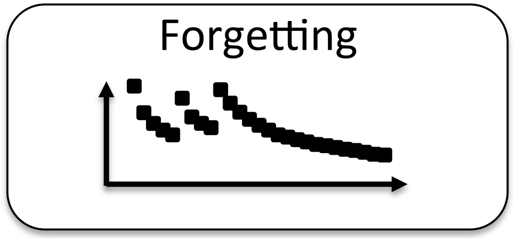
Results: Memory Usage



Max. Dec. Time =
6 msec.

Results: Competence





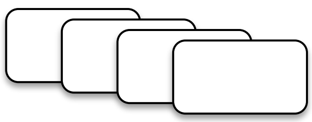
- Explored common forgetting hypothesis in two memories, two complex tasks

- Developed <u>efficient</u> and <u>correct</u> method of forgetting via base-level activation model

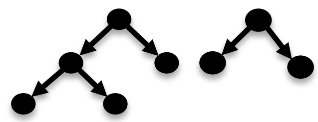
- Improves <u>reactivity</u> and <u>scaling</u> for long lifetimes and large amounts of knowledge, with <u>high task performance</u>

Summary

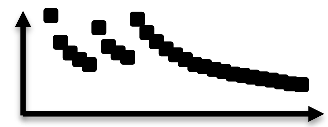
Episodic Memory

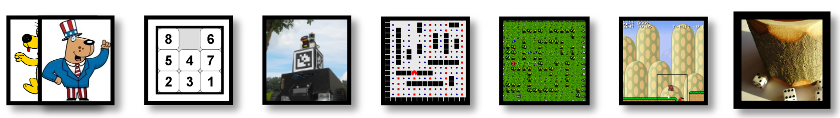


Semantic Memory



Forgetting



- **Analysis**. Properties of Environment, Task, Agent
  - Algorithms: Efficient, Scalable, Task-Independent
- **Integration**. Soar v9.3.2
- **Evaluation**. 

  - Demonstration of Agent Benefits

Work @ UH

Making Memories in the Robot House

- Effective uses
  - Increase robot autonomy
  - Improve user trust
- Learning opportunities
  - User schedule, activities, preferences, …
- Scaling challenges
  - Real-time learning
  - Long-term HRI (months-years!)

Thank You :)

Questions?