

# Efficient Activation-based Working Memory Forgetting

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# Architecturally Why Forget Working Memory Elements?

## **Bounding Memory Retrievals**

- Procedural (Forgy, 1982)
- Episodic (Derbinsky & Laird, 2009)

## **Attention-biased Behavior**

- Episodic (Nuxoll & Laird, 2007)
- Appraisals (Marinier & Laird, 2004)

## **Reduced Programmer Burden**

- Topographic locality (Laird, Derbinsky, & Voigt 2011)

# Challenges

## Model Efficacy

Ongoing

Reflect intentional focus (Nuxoll, Laird & James 2004; Chong 2003)

## Implementation Efficiency

This Talk

Scale to large memory stores and dynamic agents

## General Agent Development

John Laird

Support agent robustness to dynamic knowledge availability

# Working Memory Activation in Soar

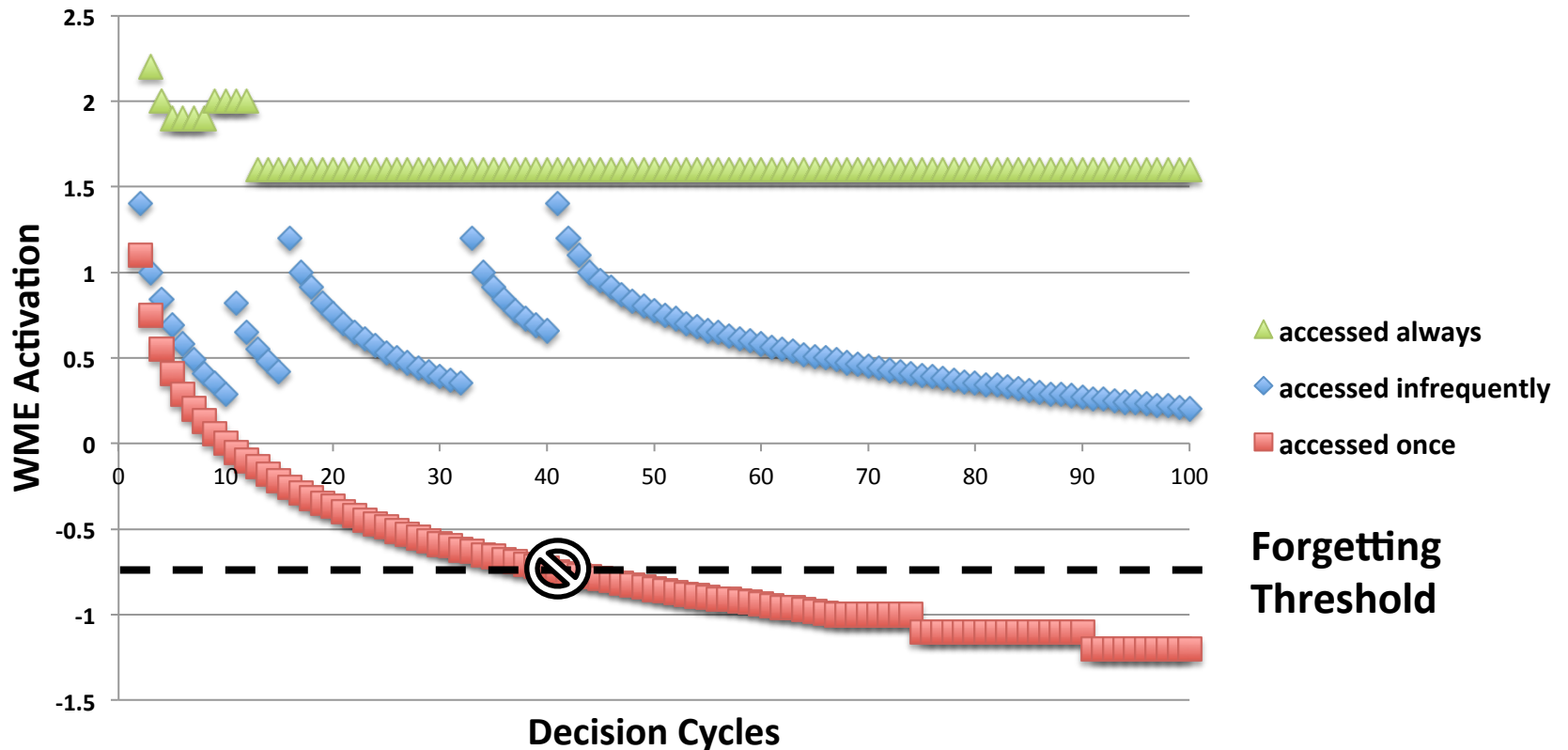
## Base-level Activation

- Activating events: create new WME, test WME (Nuxoll, Laird & James 2004)
- Bounded history window (Petrov 2006)

## Application

- Parameterized episodic retrieval bias

# Activation-based Forgetting Illustrated



**Problem.** Efficiently detect when element activation falls below threshold (and thus should be removed from working memory)

# Characteristics Pertinent to Evaluating an Activation-based Forgetting Mechanism

- Number of elements in working memory (**N**)
  - Large memory: **↑N**
- Number of WME activation events/cycle (**E**)
  - Dynamic agent: **↑E**
- WME lifetime (**L**)
  - Frequently accessed elements: **↑L**
  - High element turnover: **↓L**

# Naïve Approach

## Algorithm

- At each decision
  - For each WME
    - If ( Activation < Threshold )
      - » Forget

## Efficiency Evaluation

- Per Decision:  $O(N)$
- Per WME:  $O(L)$

# Efficient Approach: Decay Prediction

Algorithm ~ (Nuxoll, Laird & James 2004)

- On new activation event
  - *Predict\** time of future decay
  - Add to *cycle-indexed priority queue\**
- Each cycle
  - Remove decayed elements at front of priority queue

## Efficiency Evaluation

- Per Decision:  $O(\# \text{ decayed WMEs} + \mathbf{E}^*[\text{Prediction Cost}])$



# Efficient Decay Prediction

1. Cheaply approximate decay on each access
  - Underestimate time of decay by treating each memory access independently:  $O(1)$
2. Exact determination
  - Binary parameter search:  $O(\log_2 L)$
  - Not needed if WME is removed by #1 estimate
  - Otherwise, reduced by the degree to which #1 is accurate

# Novel Base-level Decay Approximation

## Given

constants

- Decay threshold ( $\theta$ )
- Decay parameter value ( $d$ )

and a set of memory accesses...

- Time since access ( $s$ )
- Number of accesses ( $n$ )

solve for...

- Time till memory decay ( $t$ )

## Algorithm

For each memory access...

$$\ln(n \cdot [t + s]^{-d}) = \theta$$

$$\ln(n) - d \cdot \ln(t + s) = \theta$$

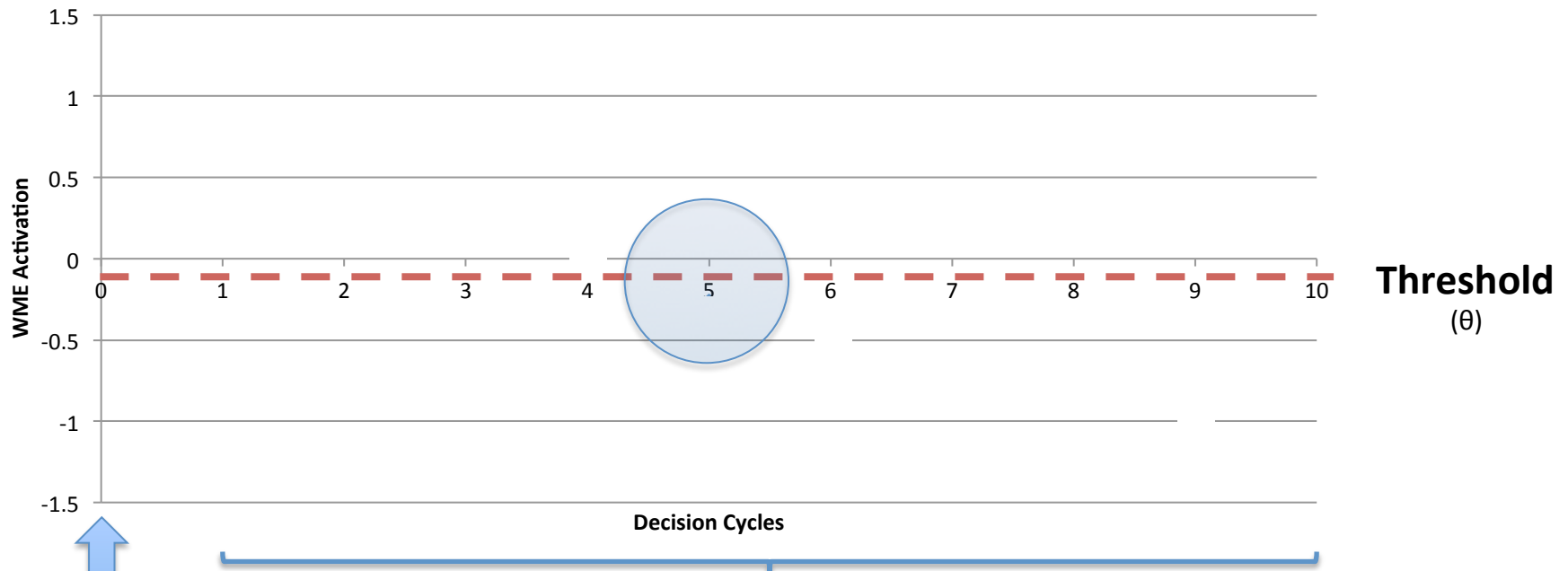
$$\ln(t + s) = \frac{\theta - \ln(n)}{-d}$$

$$t = e^{\frac{\theta - \ln(n)}{-d}} - s$$

$$\text{Decay estimate} = \sum t$$

# Activation-based Forgetting

## *Example*



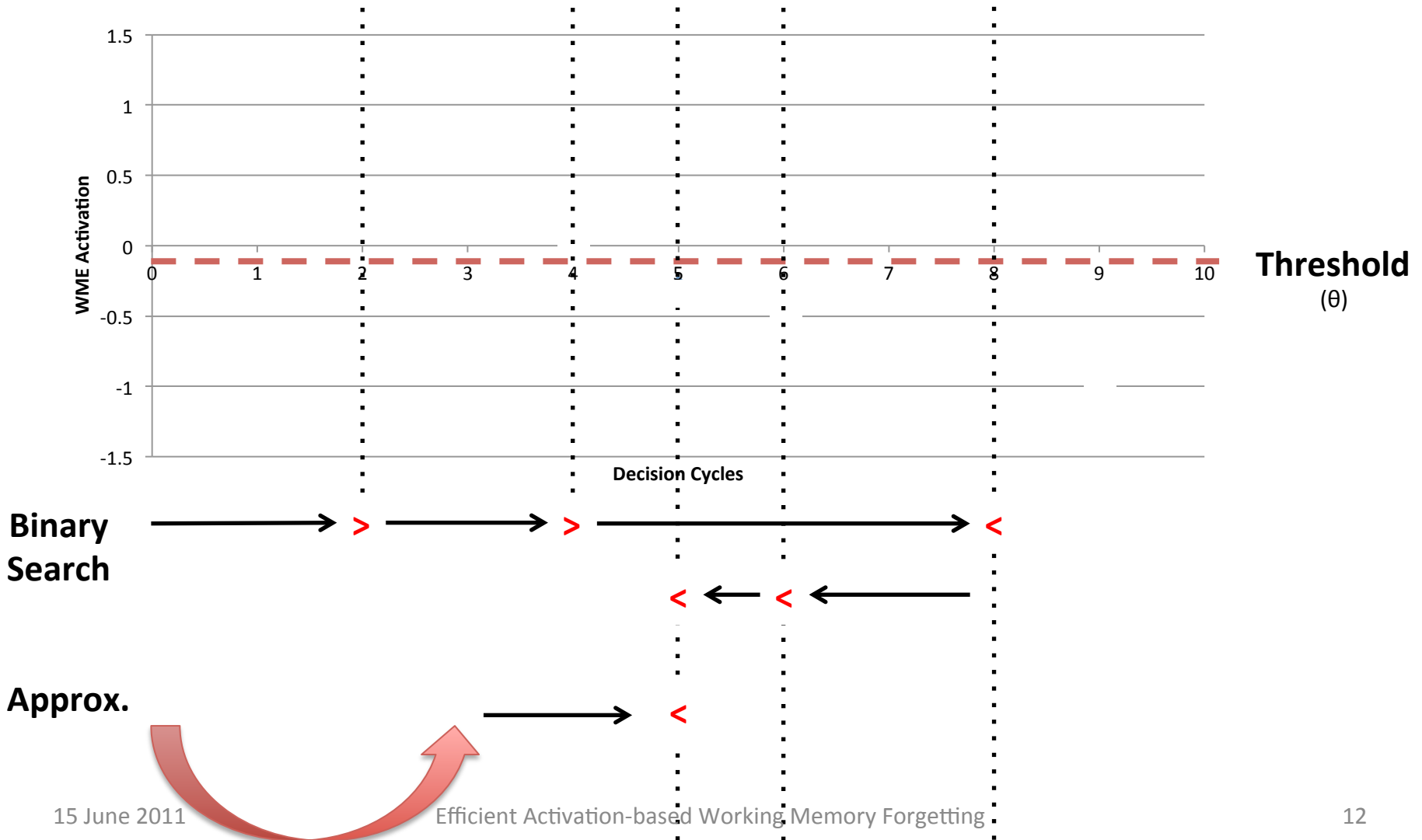
How far in the future will the memory decay?

Now

Given: decay rate ( $d$ ), access history ( $t_1, t_2, t_3, \dots$ )

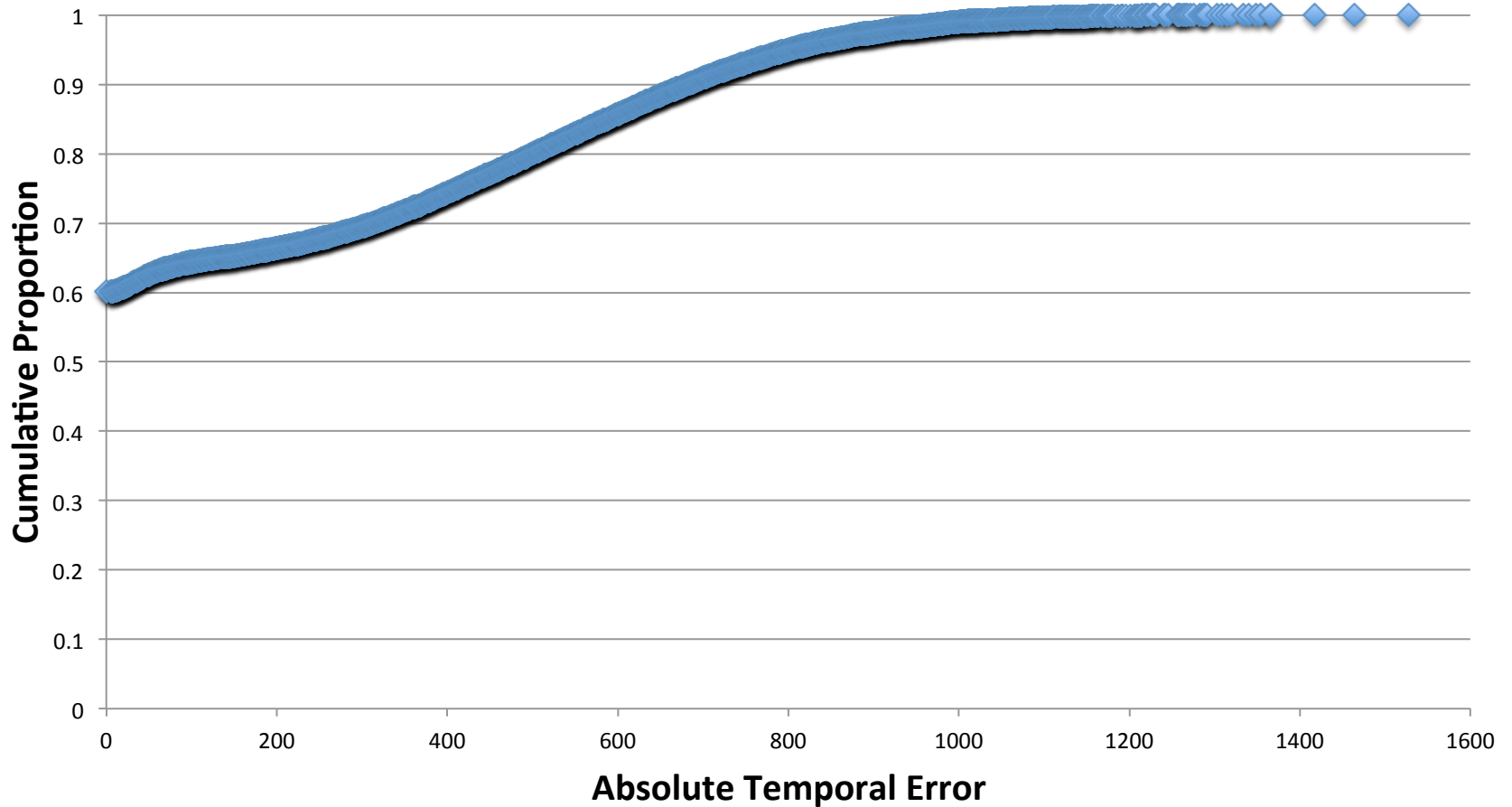
# Activation-based Forgetting

## Example



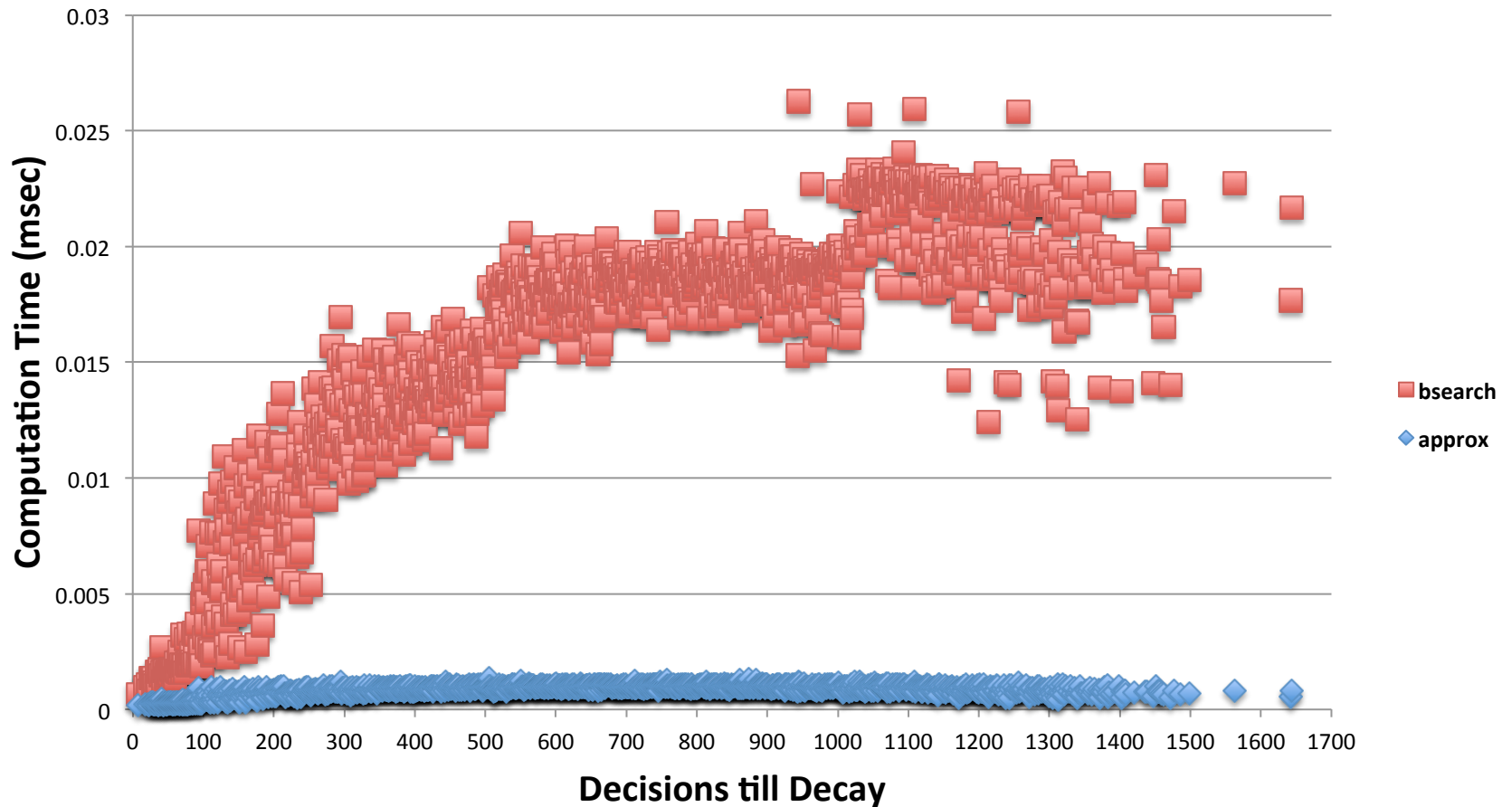
# Approximation Quality

*50k random histories*



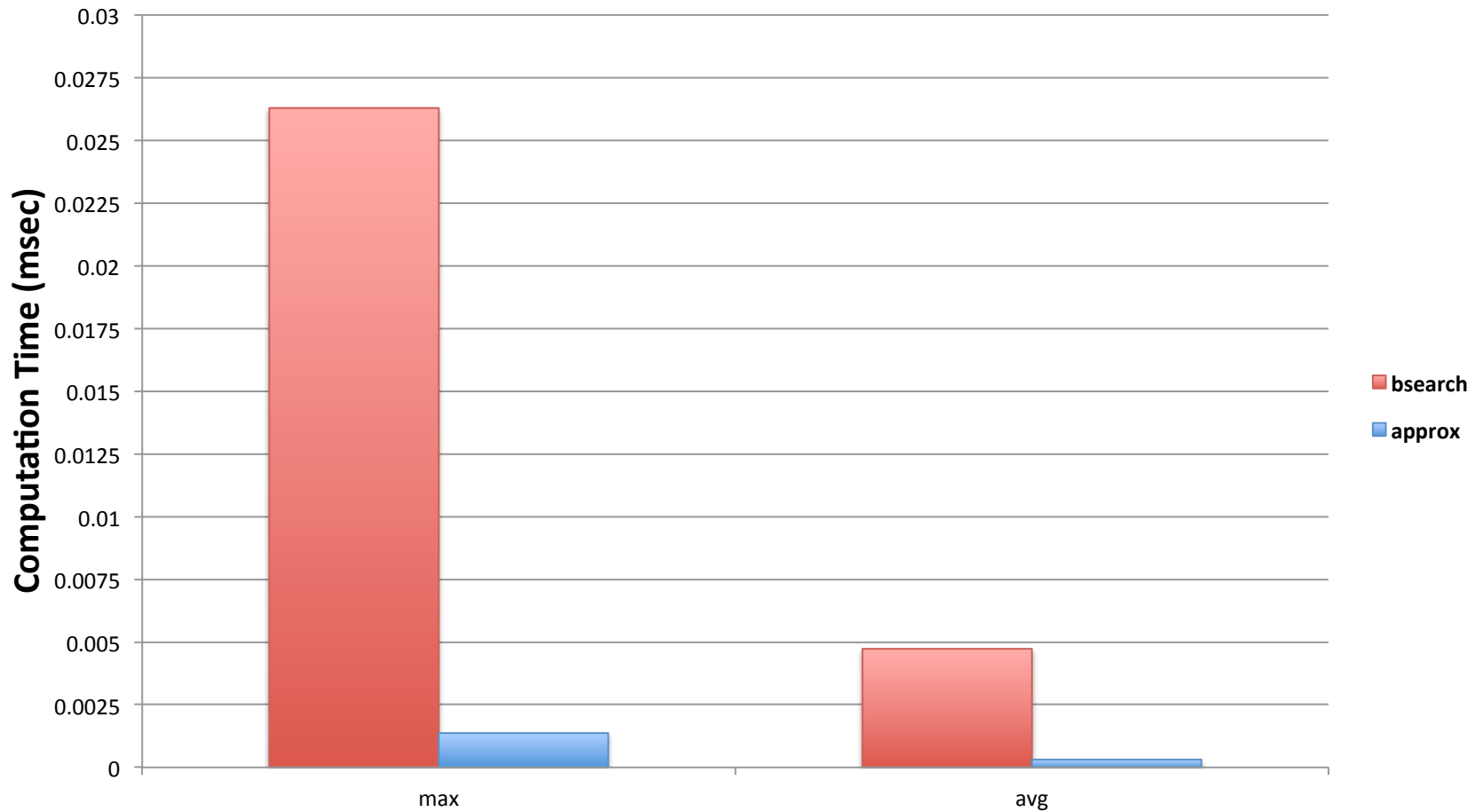
# Prediction Computation Comparison

*Complexity (50k random histories)*



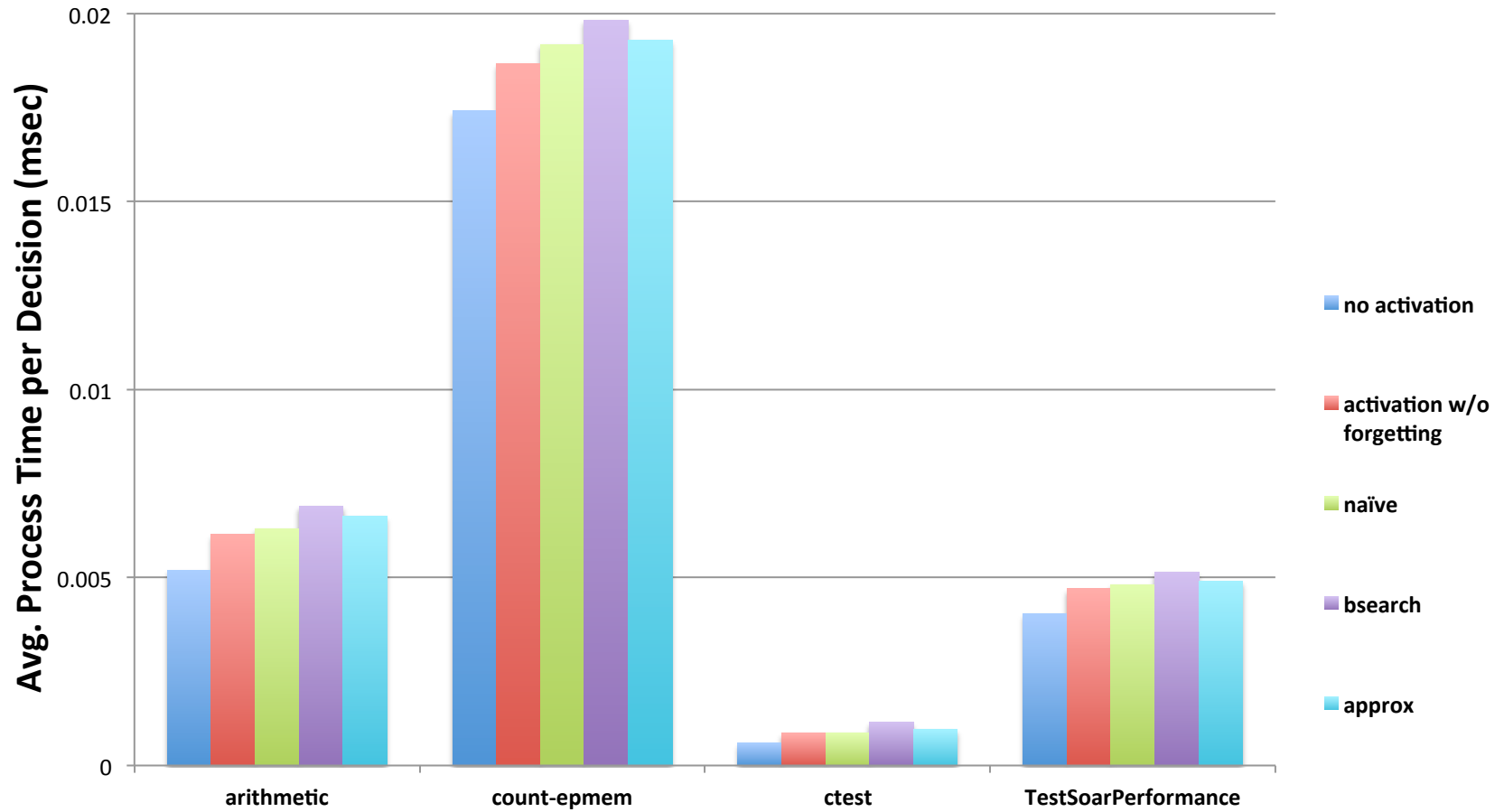
# Prediction Computation Comparison

## *Aggregate Prediction Time (50k random histories)*



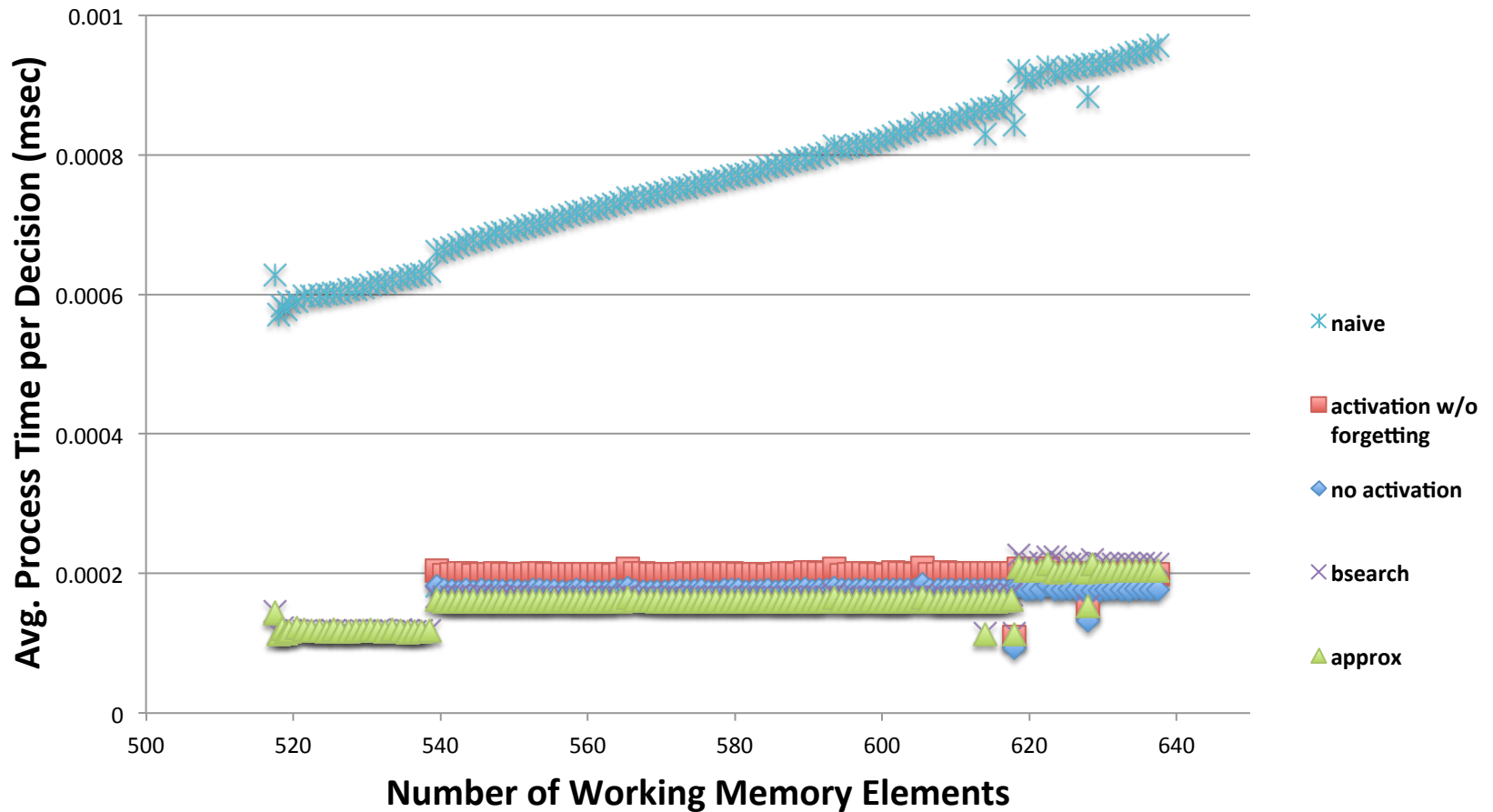
# Preliminary Agent Results: Counting

*small memory, frequent changes*





# Preliminary Agent Results: Caching *Monotonically Growing Memory*



# Evaluation

## **Nuggets**

- Preliminary empirical evidence of efficient activation-based forgetting of WMEs
- Implemented in Soar 9.3.1

## **Coal**

- Limited agent evaluation