Event Memory in Soar

Steven Jones

Computer Science and Engineering, University of Michigan, Ann Arbor

scijones@umich.edu

May 9, 2019

Overview

1. Theoretical Alignment
   - "Aren't event memory elements just operators?"
2. Improving Functionality of Architecture
   - Example Improvement
   - Further Improvements

Timescales of Cognition

"By event we mean a segment of time at a given location that is conceived by an observer to have a beginning and an end. In particular we focus on the events that make up everyday life on the timescale of **a few seconds to tens of minutes** *things like opening an envelope, pouring coffee into a cup, changing the diaper of a baby or calling a friend on the phone."*[1]

[1] Kurby, C. A., & Zacks, J. M. (2008). Segmentation in the perception and memory of events. Trends in cognitive sciences, 12(2), 72-79.

Timescales of Cognition

Scale (s)	Time Units	System	Theory
10^7	months		Social
10^6	weeks		Social
10^5	days		Social
10^4	hours	Task	Rational
10^3	10 min	Task	Rational
10^2	minutes	Task	Rational
10^1	10 s	Unit task	Cognitive
10^0	1 s	Operations	Cognitive
10^{-1}	100 ms	Deliberate act	Cognitive
10^{-2}	10 ms	Neural circuit	Biological
10^{-3}	1 ms	Neuron	Biological
10^{-4}	100 µs	Organelle	Biological

Newell, A. (1994). Unified theories of cognition. Harvard University Press.

Computation that humans perform to enable Event Memory[1]

[1] Heavily paraphrased from Franklin, N., Norman, K. A., Ranganath, C., Zacks, J. M., & Gershman, S. J. (2019). Structured event memory: a neuro-symbolic model of event cognition. BioRxiv, 541607.

Computation that humans perform to enable Event Memory[1]

- Segmentation (rapid/short-timescale)
  - Humans identify event boundaries from continuous sensor stream.

[1] Heavily paraphrased from Franklin, N., Norman, K. A., Ranganath, C., Zacks, J. M., & Gershman, S. J. (2019). Structured event memory: a neuro-symbolic model of event cognition. BioRxiv, 541607.

Computation that humans perform to enable Event Memory[1]

- Segmentation (rapid/short-timescale)
  - Humans identify event boundaries from continuous sensor stream.
- Learning (over a lifetime)
  - Humans acquire knowledge about internal structure of event schemas.

[1] Heavily paraphrased from Franklin, N., Norman, K. A., Ranganath, C., Zacks, J. M., & Gershman, S. J. (2019). Structured event memory: a neuro-symbolic model of event cognition. BioRxiv, 541607.

Computation that humans perform to enable Event Memory[1]

- Segmentation (rapid/short-timescale)
  - Humans identify event boundaries from continuous sensor stream.
- Learning (over a lifetime)
  - Humans acquire knowledge about internal structure of event schemas.
- Inference (rapid to tens of minutes)
  - Humans use event models for virtual sensing by pattern completion.

[1] Heavily paraphrased from Franklin, N., Norman, K. A., Ranganath, C., Zacks, J. M., & Gershman, S. J. (2019). Structured event memory: a neuro-symbolic model of event cognition. BioRxiv, 541607.

Computation that humans perform to enable Event Memory[1]

- Segmentation (rapid/short-timescale)
  - Humans identify event boundaries from continuous sensor stream.
- Learning (over a lifetime)
  - Humans acquire knowledge about internal structure of event schemas.
- Inference (rapid to tens of minutes)
  - Humans use event models for virtual sensing by pattern completion.
- Prediction (rapid to tens of minutes)
  - Humans use event models to predict world state.

[1] Heavily paraphrased from Franklin, N., Norman, K. A., Ranganath, C., Zacks, J. M., & Gershman, S. J. (2019). Structured event memory: a neuro-symbolic model of event cognition. BioRxiv, 541607.

Computation that humans perform to enable Event Memory[1]

- Segmentation (rapid/short-timescale)
  - Humans identify event boundaries from continuous sensor stream.
- Learning (over a lifetime)
  - Humans acquire knowledge about internal structure of event schemas.
- Inference (rapid to tens of minutes)
  - Humans use event models for virtual sensing by pattern completion.
- Prediction (rapid to tens of minutes)
  - Humans use event models to predict world state.
- Memory (tens of seconds and beyond)
  - Humans reconstruct the past with event structure.

[1] Heavily paraphrased from Franklin, N., Norman, K. A., Ranganath, C., Zacks, J. M., & Gershman, S. J. (2019). Structured event memory: a neuro-symbolic model of event cognition. BioRxiv, 541607.

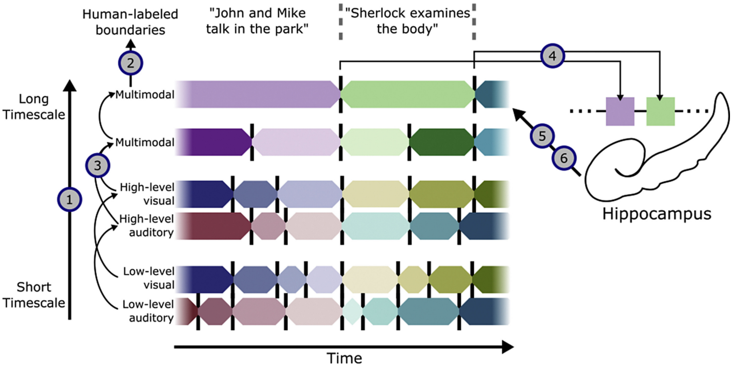
Computation that humans perform to enable Event Memory[1]

- Segmentation (rapid/short-timescale)
  - Humans identify event boundaries from continuous sensor stream.
- Learning (over a lifetime)
  - Humans acquire knowledge about internal structure of event schemas.
- Inference (rapid to tens of minutes)
  - Humans use event models for virtual sensing by pattern completion.
- Prediction (rapid to tens of minutes)
  - Humans use event models to predict world state.
- Memory (tens of seconds and beyond)
  - Humans reconstruct the past with event structure.

These computations do not each map to architectural mechanisms.

[1] Heavily paraphrased from Franklin, N., Norman, K. A., Ranganath, C., Zacks, J. M., & Gershman, S. J. (2019). Structured event memory: a neuro-symbolic model of event cognition. BioRxiv, 541607.

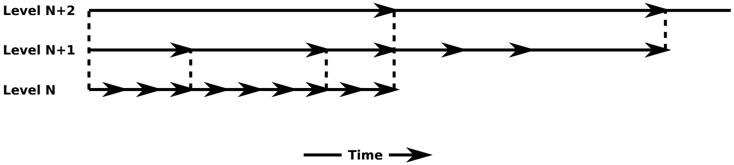
Hierarchical Event Segmentation



Theory of Event Segmentation and Memory

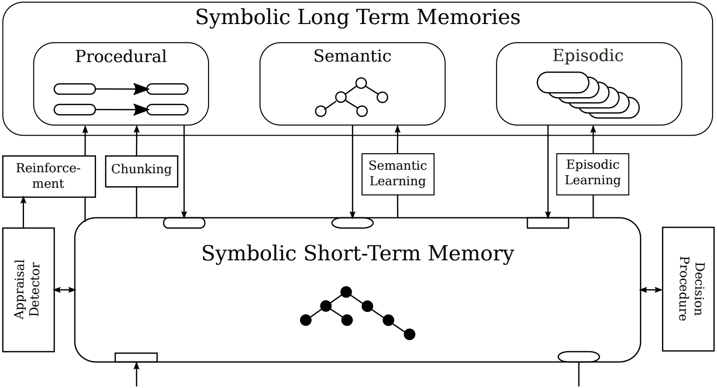
See Baldassano, C., Chen, J., Zadbood, A., Pillow, J. W., Hasson, U., & Norman, K. A. (2017). Discovering event structure in continuous narrative perception and memory. Neuron, 95(3), 709-721. figure 1.

Newell's Hierarchical Systems



Expansion of time with levels

See Newell, A. (1994). Unified theories of cognition. Harvard University Press. figure 3-2.



Symbolic Long Term Memories
Procedural
Semantic
Episodic
Reinforce-
ment
Chunking
Semantic
Learning
Episodic
Learning
Symbolic Short-Term Memory
Appraisal
Detector
Decision
Procedure

Segmentation?

Segmentation: When the situation no longer matches the current working model, retrieve and ground a schema or *make a new one.*

Segmentation?

Segmentation: When the situation no longer matches the current working model, retrieve and ground a schema or *make a new one.*
Translation: When the operator no longer matches the current working memory, propose and apply another operator or *impasse.*

Types of Event Models

"Perceived"

"Deliberate" (**not** operators)

Types of Event Models

"Perceived"

- represents current event

"Deliberate" (**not** operators)

Types of Event Models

"Perceived"

- represents current event
- within working memory

"Deliberate" (**not** operators)

Types of Event Models

"Perceived"

- represents current event
- within working memory
- retrieval based on current context

"Deliberate" (**not** operators)

Types of Event Models

"Perceived"

- represents current event
- within working memory
- retrieval based on current context
- predicts near-future state

"Deliberate" (**not** operators)

Types of Event Models

"Perceived"

- represents current event
- within working memory
- retrieval based on current context
- predicts near-future state

"Deliberate" (**not** operators)

- could ground to any time

Types of Event Models

"Perceived"

- represents current event
- within working memory
- retrieval based on current context
- predicts near-future state

"Deliberate" (**not** operators)

- could ground to any time
- instance retrieved to working memory

Types of Event Models

"Perceived"

- represents current event
- within working memory
- retrieval based on current context
- predicts near-future state

"Deliberate" (**not** operators)

- could ground to any time
- instance retrieved to working memory
- must be deliberately aligned to current state for comparison

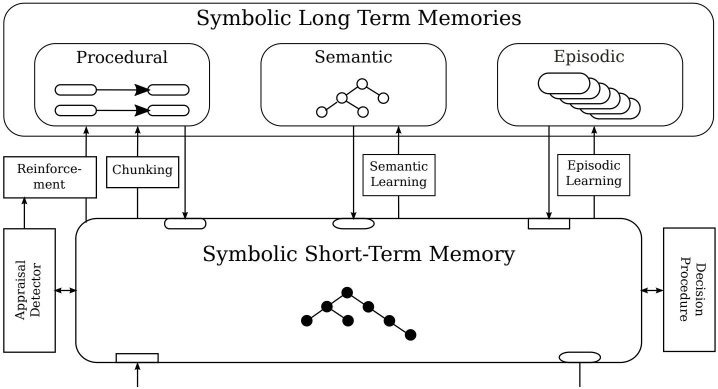
Types of Event Models

"Perceived"

- represents current event
- within working memory
- retrieval based on current context
- predicts near-future state

"Deliberate" (**not** operators)

- could ground to any time
- instance retrieved to working memory
- must be deliberately aligned to current state for comparison
- could just contain history


Symbolic Long Term Memories
Procedural
Semantic
Episodic
Reinforce-ment
Chunking
Semantic Learning
Episodic Learning
Appraisal Detector
Symbolic Short-Term Memory
Decision Procedure

Improving Functionality of Architecture

1. Theoretical Alignment
   - "Aren't event memory elements just operators?"

2. Improving Functionality of Architecture
   - Example Improvement
   - Further Improvements

Event Memory research describes humans, but what is it good for?

Event Memory research describes humans, but what is it good for?

Potential mechanisms

Event Memory research describes humans, but what is it good for?

Potential mechanisms

High level *specification* of functionality/ capability

Event Memory research describes humans, but what is it good for?

Potential mechanisms

High level *specification* of functionality/capability

and the links between the two.

Cognitive Capabilities

	Past	Present	Future	nonspecific
Egocentric	Episodic Memory	Perception & Action	Episodic Future Thinking	Personal Semantics
Allocentric	(thinking about historical events)	Virtual Sensing	Semantic Future Thinking	Semantic Memory

Cognitive Capabilities

	Past	Present	Future	nonspecific
Egocentric	Episodic Memory	Perception & Action	Episodic Future Thinking	Personal Semantics

Cognitive Capabilities

Underline = Can use knowledge, **Bold** = Can learn knowledge reactively

	Past	Present	Future	nonspecific
Egocentric	Episodic Memory	Perception & Action	Episodic Future Thinking	Personal Semantics

Cognitive Capabilities

Underline = Can use knowledge, **Bold** = Can learn knowledge reactively

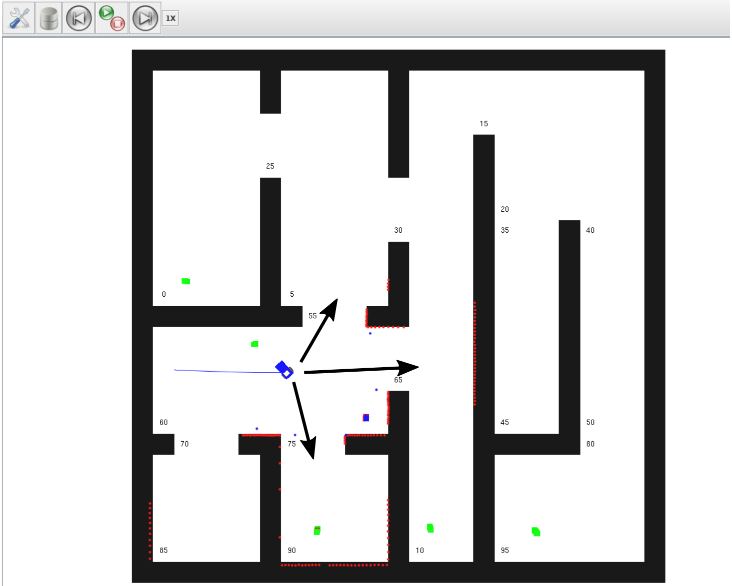
	Past	Present	Future	nonspecific
Egocentric	**Episodic Memory**	**Perception & Action**	**Episodic Future Thinking**	**Personal Semantics**

Cognitive Capabilities

Underline = Can use knowledge, **Bold** = Can learn knowledge reactively

Egocentric	Past	Present	Future	nonspecific
Humans	**Episodic Memory**	**Perception & Action**	**Episodic Future Thinking**	**Personal Semantics**
Soar	**Episodic Memory**	**Proposal, Application, & Elaboration**	Look-ahead Planning	Action Models

Look-ahead planning in Soar



What's missing in Soar?

learning look-ahead planning knowledge

What's missing in Soar?

learning look-ahead planning knowledge (learning new action models)

What's missing in Soar?

learning look-ahead planning knowledge (learning new action models)
(learning an apply rule which predicts an outcome)

What's missing in Soar?

learning look-ahead planning knowledge (learning new action models)
(learning an apply rule which predicts an outcome)

- online, when needed

What's missing in Soar?

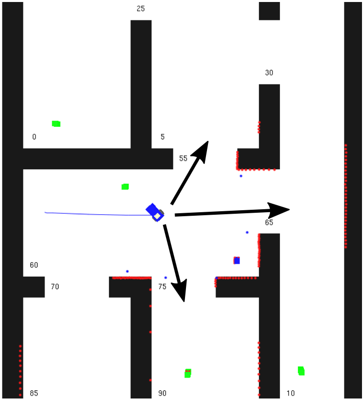
learning look-ahead planning knowledge (learning new action models)
(learning an apply rule which predicts an outcome)

- online, when needed
- in a task-general manner

How can Soar learn **apply rules** which predict outcomes?

How can Soar learn **apply rules** which predict outcomes?

Learning an action model from an impasse




```
: ==>S: S1
:    O: O3167 (deliver-to-john)
:    ==>S: S360 (operator no-change)
:       O: O3168 (go-to-adjacent-room)
:       ==>S: S361 (operator tie)
:          O: O3169 (evaluate-operator)
:          ==>S: S366 (operator no-change)
```

Learning an action model from an impasse

Default rules for Soar support look-ahead planning by using action models.

Learning an action model from an impasse

Default rules for Soar support look-ahead planning by using action models.
What if an agent has no action model?

Learning an action model from an impasse

Default rules for Soar support look-ahead planning by using action models.
What if an agent has no action model?

- It will not know how the “apply” (simulate) an action when planning.

Learning an action model from an impasse

Default rules for Soar support look-ahead planning by using action models. What if an agent has no action model?

- It will not know how the "apply" (simulate) an action when planning.
- This (now) results in an operator no-change impasse within planning.

Where does the action model knowledge come from?

From previous Soar work:

[2] Nuxoll, A. M., & Laird, J. E. (2007, July). Extending cognitive architecture with episodic memory. In AAAI (pp. 1560-1564).

[3] Richmond, L. L., & Zacks, J. M. (2017). Constructing experience: Event models from perception to action. Trends in cognitive sciences, 21(12), 962-980.

Where does the action model knowledge come from?

From previous Soar work:

> *"Action Modeling: An agent can retrieve an episode of a similar situation where it has performed an action. It can then compare that episode to what came next to determine how the action affects the world."*[2]

[2] Nuxoll, A. M., & Laird, J. E. (2007, July). Extending cognitive architecture with episodic memory. In AAAI (pp. 1560-1564).

[3] Richmond, L. L., & Zacks, J. M. (2017). Constructing experience: Event models from perception to action. Trends in cognitive sciences, 21(12), 962-980.

Where does the action model knowledge come from?

From previous Soar work:

> *"Action Modeling: An agent can retrieve an episode of a similar situation where it has performed an action. It can then compare that episode to what came next to determine how the action affects the world."*[2]

(very loose paraphrase of event memory work):

> *The working event models described by event segmentation are used to guide action adaptively.*[3]

---

[2] Nuxoll, A. M., & Laird, J. E. (2007, July). Extending cognitive architecture with episodic memory. In AAAI (pp. 1560-1564).

[3] Richmond, L. L., & Zacks, J. M. (2017). Constructing experience: Event models from perception to action. Trends in cognitive sciences, 21(12), 962-980.

Where does the action model knowledge come from?

From previous Soar work:

> *"Action Modeling: An agent can retrieve an episode of a similar situation where it has performed an action. It can then compare that episode to what came next to determine how the action affects the world."*[2]

(very loose paraphrase of event memory work):

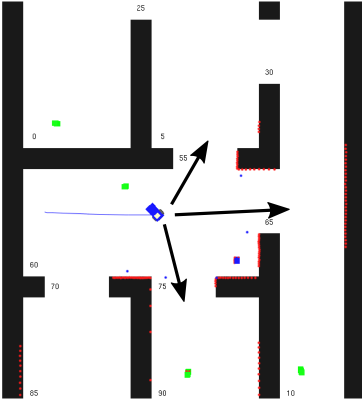
> *The working event models described by event segmentation are used to guide action adaptively.*[3]

Episodic Memory "events"

[2] Nuxoll, A. M., & Laird, J. E. (2007, July). Extending cognitive architecture with episodic memory. In AAAI (pp. 1560-1564).

[3] Richmond, L. L., & Zacks, J. M. (2017). Constructing experience: Event models from perception to action. Trends in cognitive sciences, 21(12), 962-980.

go-to-adjacent-room needs to be in EpMem




```
: ==>S: S1
:    O: O3167 (deliver-to-john)
:    ==>S: S360 (operator no-change)
:       O: O3168 (go-to-adjacent-room)
:       ==>S: S361 (operator tie)
:          O: O3169 (evaluate-operator)
:          ==>S: S366 (operator no-change)
```

Potentially necessary change: Hierarchical EpMem

Substates in Episodic Memory!

Potentially necessary change: Hierarchical EpMem

Substates in Episodic Memory!

Only a rudimentary version has been tried, but it mostly worked.

Lacking even more Functionality in comparison with Event Memory specification

<u>Underline</u> = Can use knowledge *efficiently*, **Bold** = Can learn knowledge reactively *without prior expert knowledge*

Egocentric	Past	Present	Future	nonspecific
Humans	**<u>Episodic Memory</u>**	**<u>Perception & Action</u>**	**<u>Episodic Future Thinking</u>**	**<u>Personal Semantics</u>**
Soar	**Episodic Memory**	<u>Proposal, Application, & Elaboration</u>	<u>Look-ahead Planning</u>	<u>Action Models</u>

Additional potential changes under investigation

- surprise-based episode retrieval (implemented a naive version)
- surprise-based episode iteration (implemented a naive version)
- structure-based episode iteration (implemented)
- default rules for state no-change (other than "wait") to learn from EpMem (in progress)
- ...?

Nuggets and Coal

Nuggets

Coal

ACT-R: Khemlani, S. S., Harrison, A. M., & Trafton, J. G. (2015). Episodes, events, and models. Frontiers in human neuroscience, 9, 590.

Icarus: Mnager, D., Choi, D., Roberts, M., & Aha, D. W. (2018). Learning Planning Operators from Episodic Traces. In 2018 AAAI Spring Symposium Series.

Nuggets and Coal

Nuggets

Coal

- ACT-R and Icarus made passes at this before us.

ACT-R: Khemlani, S. S., Harrison, A. M., & Trafton, J. G. (2015). Episodes, events, and models. Frontiers in human neuroscience, 9, 590.

Icarus: Mnager, D., Choi, D., Roberts, M., & Aha, D. W. (2018). Learning Planning Operators from Episodic Traces. In 2018 AAAI Spring Symposium Series.

Nuggets and Coal

Nuggets

Coal

- ACT-R and Icarus made passes at this before us.
- Development featuring changes to default rules, new agent design, and changes to architecture all at once.

ACT-R: Khemlani, S. S., Harrison, A. M., & Trafton, J. G. (2015). Episodes, events, and models. Frontiers in human neuroscience, 9, 590.

Icarus: Mnager, D., Choi, D., Roberts, M., & Aha, D. W. (2018). Learning Planning Operators from Episodic Traces. In 2018 AAAI Spring Symposium Series.

Nuggets and Coal

Coal

- ACT-R and Icarus made passes at this before us.
- Development featuring changes to default rules, new agent design, and changes to architecture all at once.

Nuggets

- ACT-R and Icarus made passes at this before us.

ACT-R: Khemlani, S. S., Harrison, A. M., & Trafton, J. G. (2015). Episodes, events, and models. Frontiers in human neuroscience, 9, 590.

Icarus: Mnager, D., Choi, D., Roberts, M., & Aha, D. W. (2018). Learning Planning Operators from Episodic Traces. In 2018 AAAI Spring Symposium Series.

Nuggets and Coal

Coal

- ACT-R and Icarus made passes at this before us.
- Development featuring changes to default rules, new agent design, and changes to architecture all at once.

Nuggets

- ACT-R and Icarus made passes at this before us.
- new epmem functionality in development

ACT-R: Khemlani, S. S., Harrison, A. M., & Trafton, J. G. (2015). Episodes, events, and models. Frontiers in human neuroscience, 9, 590.

Icarus: Mnager, D., Choi, D., Roberts, M., & Aha, D. W. (2018). Learning Planning Operators from Episodic Traces. In 2018 AAAI Spring Symposium Series.

Nuggets and Coal

Coal

- ACT-R and Icarus made passes at this before us.
- Development featuring changes to default rules, new agent design, and changes to architecture all at once.

Nuggets

- ACT-R and Icarus made passes at this before us.
- new epmem functionality in development
- Increased theory alignment between common model of cognition and brain.

ACT-R: Khemlani, S. S., Harrison, A. M., & Trafton, J. G. (2015). Episodes, events, and models. Frontiers in human neuroscience, 9, 590.

Icarus: Mnager, D., Choi, D., Roberts, M., & Aha, D. W. (2018). Learning Planning Operators from Episodic Traces. In 2018 AAAI Spring Symposium Series.

Nuggets and Coal

Coal

- ACT-R and Icarus made passes at this before us.
- Development featuring changes to default rules, new agent design, and changes to architecture all at once.

Nuggets

- ACT-R and Icarus made passes at this before us.
- new epmem functionality in development
- Increased theory alignment between common model of cognition and brain.
- Impasse-driven case-based reasoning already provides much of the Event Memory functionality.

ACT-R: Khemlani, S. S., Harrison, A. M., & Trafton, J. G. (2015). Episodes, events, and models. Frontiers in human neuroscience, 9, 590.

Icarus: Mnager, D., Choi, D., Roberts, M., & Aha, D. W. (2018). Learning Planning Operators from Episodic Traces. In 2018 AAAI Spring Symposium Series.

Do we have a way to account for event memory computation?

Do we have a way to account for event memory computation?

- Segmentation
  - new surprisal mechanism in EpMem, typical operator rule-matching

Do we have a way to account for event memory computation?

- Segmentation
  - new surprisal mechanism in EpMem, typical operator rule-matching
- Learning
  - learning action models when needed, retrieval by surprise metadata and further deliberate reasoning.

Do we have a way to account for event memory computation?

- Segmentation
  - new surprisal mechanism in EpMem, typical operator rule-matching
- Learning
  - learning action models when needed, retrieval by surprise metadata and further deliberate reasoning.
- Inference
  - operators matching to current state, episodic memory deliberate grounding to current state and pattern-matching in retrieval.

Do we have a way to account for event memory computation?

- Segmentation
  - new surprisal mechanism in EpMem, typical operator rule-matching
- Learning
  - learning action models when needed, retrieval by surprise metadata and further deliberate reasoning.
- Inference
  - operators matching to current state, episodic memory deliberate grounding to current state and pattern-matching in retrieval.
- Prediction
  - lookahead planning with operators.

Do we have a way to account for event memory computation?

- Segmentation
  - new surprisal mechanism in EpMem, typical operator rule-matching
- Learning
  - learning action models when needed, retrieval by surprise metadata and further deliberate reasoning.
- Inference
  - operators matching to current state, episodic memory deliberate grounding to current state and pattern-matching in retrieval.
- Prediction
  - lookahead planning with operators.
- Memory
  - new methods for iterating through EpMem, storing substates in EpMem.

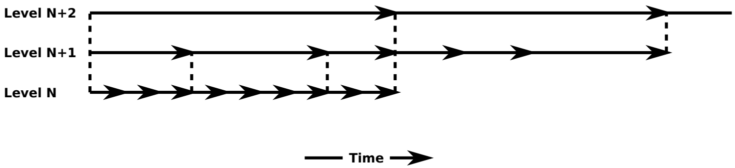
Cognitive capabilities improved by with Event Memory

(making capabilities more automatic and/or efficient)

- Sensing:
  - Detecting Novelty (surprise)
  - Detecting Repetition (not ... surprise)
- Reasoning:
  - Action Modeling (analysis of historical instances of action execution *during planning* and analysis of more than just top-state.)
- Learning:
  - Retroactive Learning (deferring analysis of surprising things when under time pressure)
  - Explaining Behavior (efficient replay of behavior)

Nuxoll, A. M., & Laird, J. E. (2007, July). Extending cognitive architecture with episodic memory. In AAAI (pp. 1560-1564).

Newells Event Segmentation



Expansion of time with levels

See Newell, A. (1994). Unified theories of cognition. Harvard University Press. figure 3-2.