

CAUSAL COGNITIVE ARCHITECTURE 3 (CCA3): A SOLUTION TO THE BINDING PROBLEM

Howard Schneider

Sheppard Clinic North, Ontario, Canada

Cognitive Systems Research, in press
Supplementary Video File

GITHUB Username: "CausalCog"
<https://github.com/CausalCog>

VIDEO #4



- CCA3 Overview ✓
- Binding Problem Overview ✓
- Software Overview ✓
- Operations Overview ←←
- Operations Causal
- Software in More Detail
- More videos, code on
GitHub “CausalCog”
(If interest, continued updating on GitHub)



START EVALUATION CYCLES

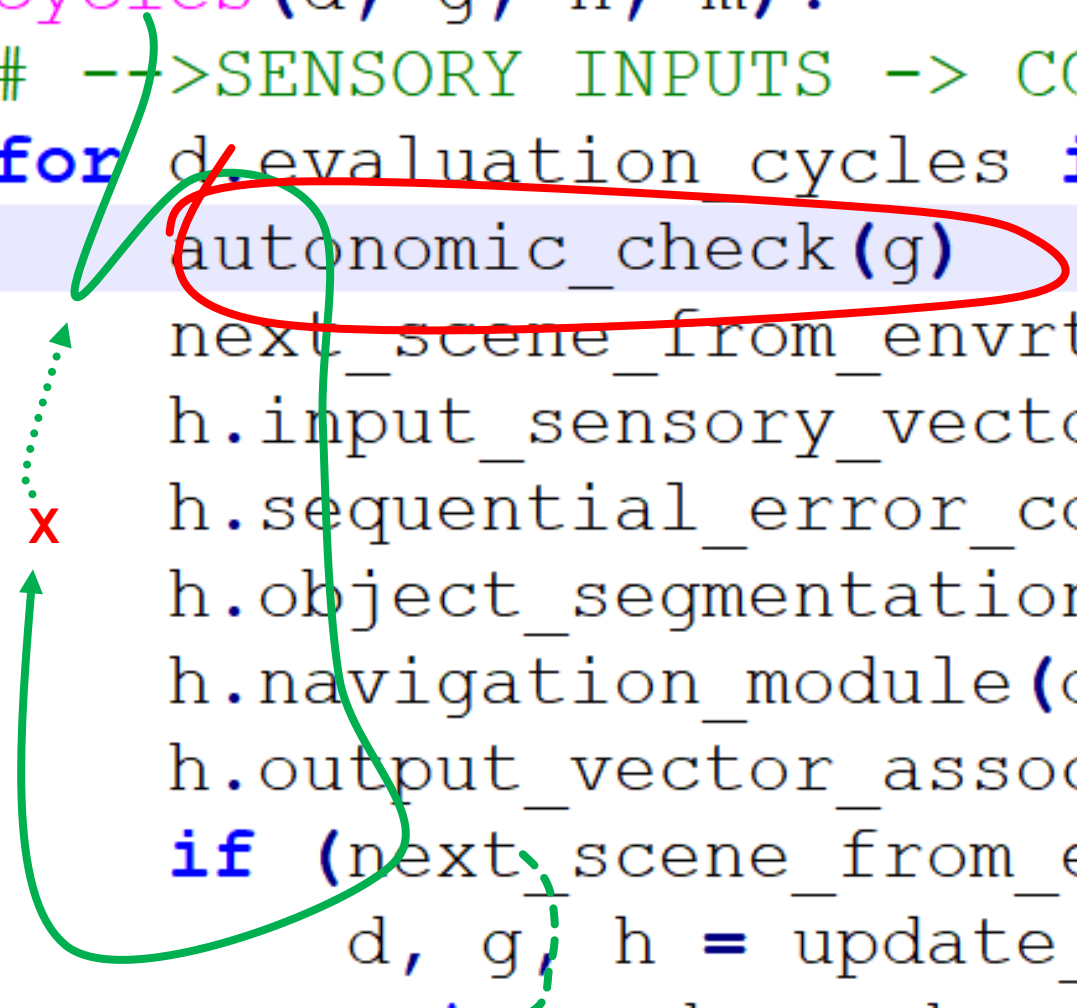
(nb. Each 'evaluation cycle' is one loop through the CCA3 architecture. Sometimes a new scene will occur after an 'evaluation cycle', sometime. Recall that the 'cycle' is a cycle of processing through the architecture being presented to the CCA3 architecture. A number of processing cycles for a particular sensory scene. 'cycle' is internal processing, 'scene' is stimuli being presented (or simulated) to the CCA3.)

The equations in the CCA3 Binding paper cover only one "cycle". In the next "cycle" the equations largely repeat, although not re-init



main_mech.cycles()

```
def cycles(d, g, h, m):  
    # -->SENSORY INPUTS --> CCA3 --> MOTOR  
    for d_evaluation cycles in range(sys.  
        autonomic_check(g)  
        next_scene_from_envrt = (h.envrt_  
        h.input_sensory_vectors_associati  
        h.sequential_error_correcting_mod  
        h.object_segmentation_module(g)  
        h.navigation_module(d, g)  
        h.output_vector_association_module  
        if (next_scene_from_envrt < 0 or  
            d, g, h = update_expected_val  
        return d, g, h, m
```



AUTONOMIC MODULE SIMULATION

Press ENTER to continue...

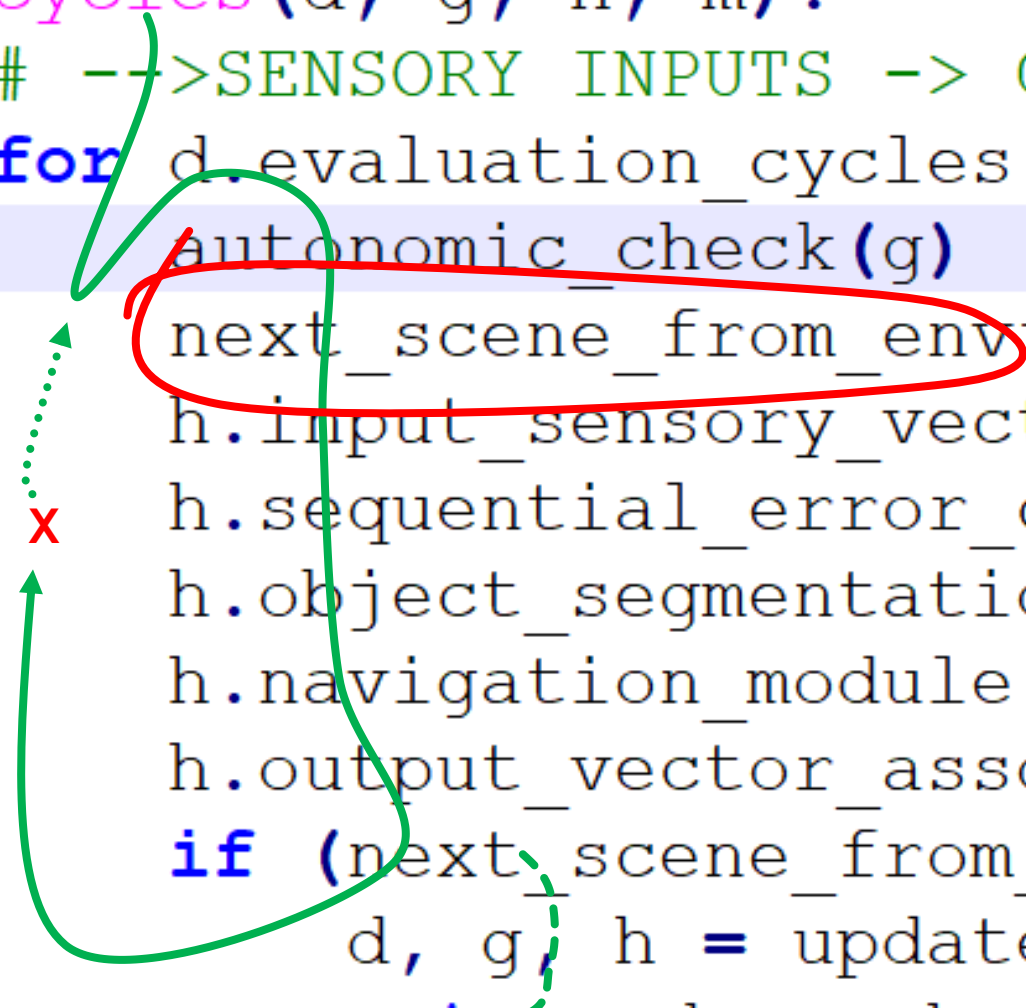
Simplified simulation of sleep/wake cycle and energy management.
CCA3 in wake state. Energy usage state is normal.
Autonomic system was not modeled in the equations of the CCA3 Binding
Core CCA3 autonomic check is passed -- no set of immediate actions r
No attention needed for any CCA3 peripheral autonomic actions.

Autonomic not
modelled in
equations

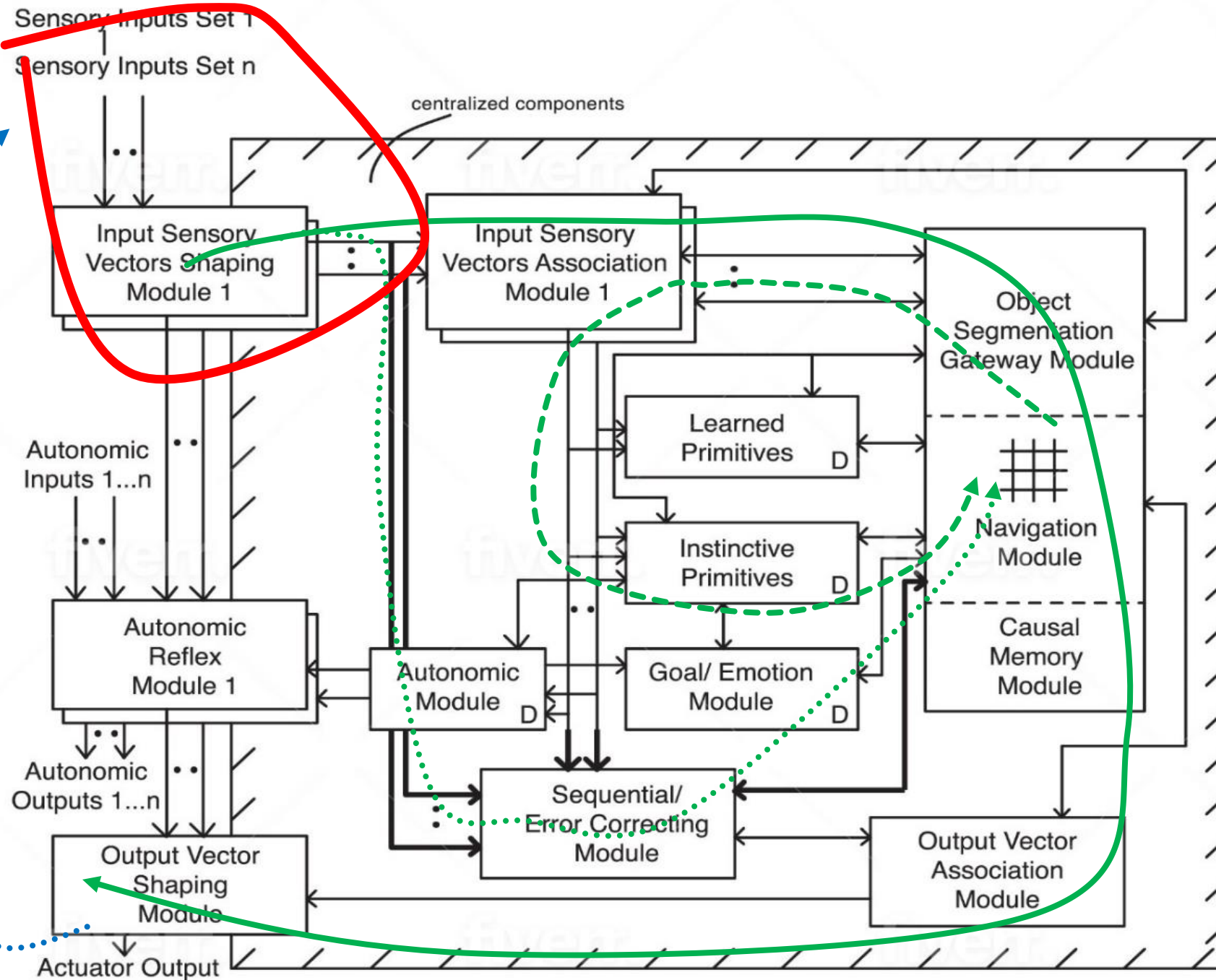


main_mech.cycles()

```
def cycles(d, g, h, m):  
    # -->SENSORY INPUTS --> CCA3 --> MOTOR  
    for d.evaluation_cycles in range(sys.  
        autonomic_check(g)  
        next_scene_from_envrt = (h.envrt_  
        h.input_sensory_vectors_associati  
        h.sequential_error_correcting_mod  
        h.object_segmentation_module(g)  
        h.navigation_module(d, g)  
        h.output_vector_association_module  
        if (next_scene_from_envrt < 0 or  
            d, g, h = update_expected_val  
        ←--return d, g, h, m
```



next sensory input



INPUT VECTORS

SHAPING

MODULES

SIMULATION OF `envrt_interaction_and_input_sensory_vectors_shaping_modules`

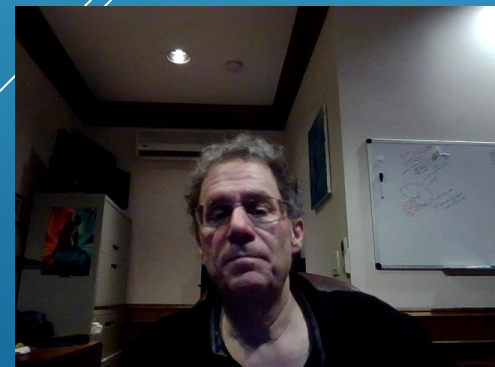


An approximate image of visual input sensory scene will be shown now
(....then please exit from it to return back to this program)

Press ENTER to continue to image....

This image represents visual stimuli being presented to the CCA3
i.e., equations 3 and 4. The image taken from paper for sake of
description. In reality, less detailed image being presented, and
CNN recognition bypassed with manual recognition encoded in the Nump
sensory simulation variable and system.





EQUATIONS 3 - 13....

Sensory systems defined: visual_far, visual_close, auditory, olfactory

Eq #13 $s'(t)$ output here, albeit as labelled groups in program vector `self.current_sensory_scene`

Effectively we now have transformed the input sensory data from the sensory electronics into a form which is compatible with the remainder of the architecture of the CCA3.

As noted above, the robot is simulated thus it does not have cameras, etc, thus inputs are from an environment Numpy variable `[ext]` where labels manually generated rather than a CNN

(3) – (13) occur here
 $s'(t)$ created (12/13)

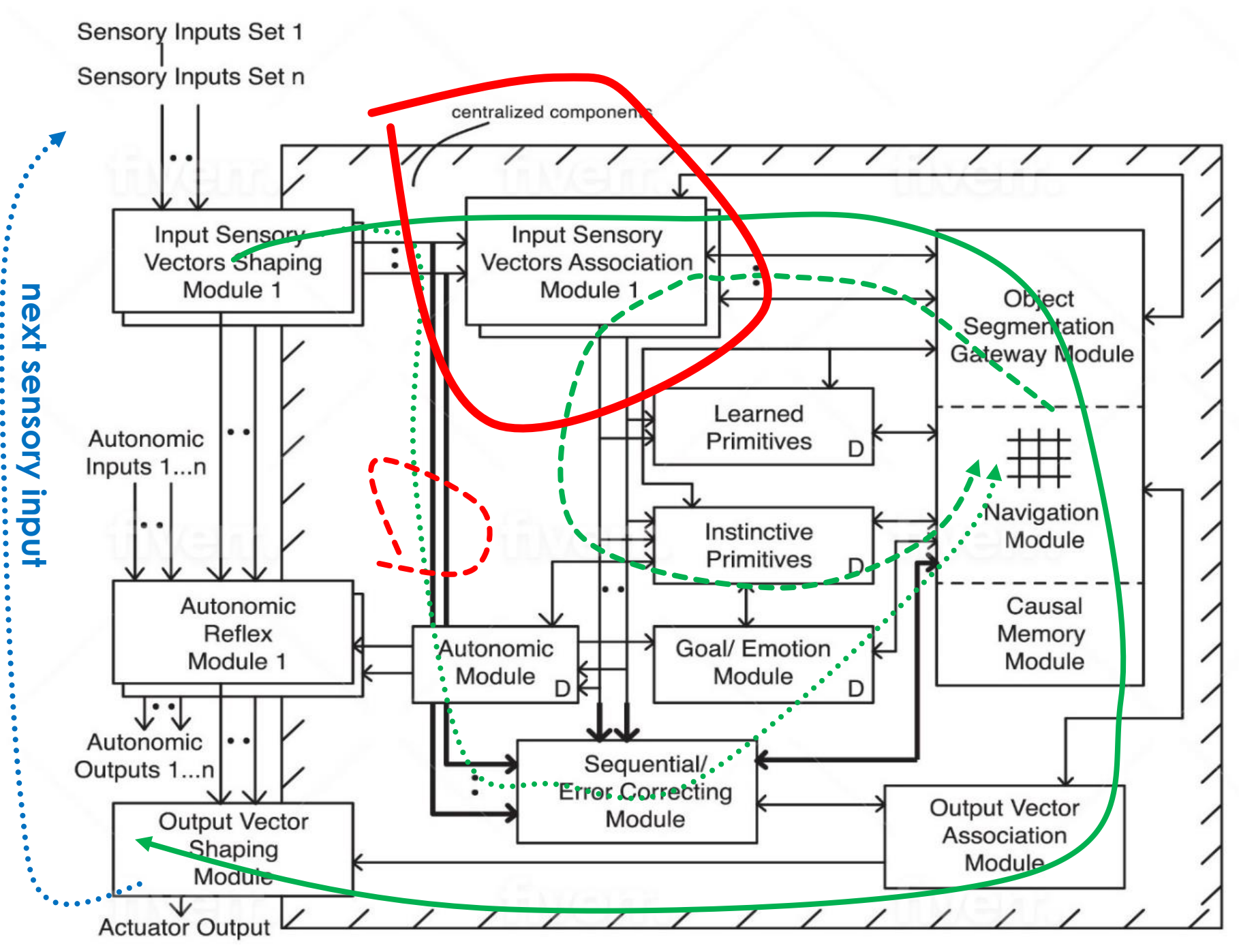


main_mech.cycles()

```
def cycles(d, g, h, m):  
    # -->SENSORY INPUTS --> CCA3 --> MOTOR  
    for d.evaluation_cycles in range(sys.  
        autonomic_check(g)  
        next_scene_from_envrt = (h.envrt_  
        h.input_sensory_vectors_associati  
        h.sequential_error_correcting_mod  
        h.object_segmentation_module(g)  
        h.navigation_module(d, g)  
        h.output_vector_association_module  
        if (next_scene_from_envrt < 0 or  
            d, g, h = update_expected_val  
        return d, g, h, m
```

A diagram illustrating a loop in the code. A green arrow starts from the 'return' statement, goes up to a red 'x' on the left, then loops back to the 'for' loop. A red oval highlights the 'next_scene_from_envrt' assignment and the 'if' condition. A dashed green arrow points from the 'return' statement to the 'if' condition.





INPUT SENSORY

VECTORS

ASSOCIATION

MODULES

SIMULATION OF input_sensory_vectors_association_modules



Ok....since we are using a simulated sensory scene (as noted above), we wa
the real world, i.e., noisy, less than perfect recognition of sensory input
in this step, which actually completes equation 12 $s'(t)$ and corresponding
....then, we set up the Local Navigation Maps, i.e., equations 14 - 18.
....then, we simulate equation 19 Input_Sensory_Vectors_Associations
_Module_sensory_system_sigma.match_best_local_navigation_map(S', t)

$$\mathbf{LNM}_{(\sigma, \text{mapno})} \in \mathbb{R}^{m \times n \times o} \quad (16)$$

$$\mathbf{all_maps}_{\sigma, t} = [\mathbf{LNM}_{(\sigma, 1, t)}, \mathbf{LNM}_{(\sigma, 2, t)}, \mathbf{LNM}_{(\sigma, 3, t)}, \dots, \mathbf{LNM}_{(\sigma, \theta, t)}] \quad (17)$$

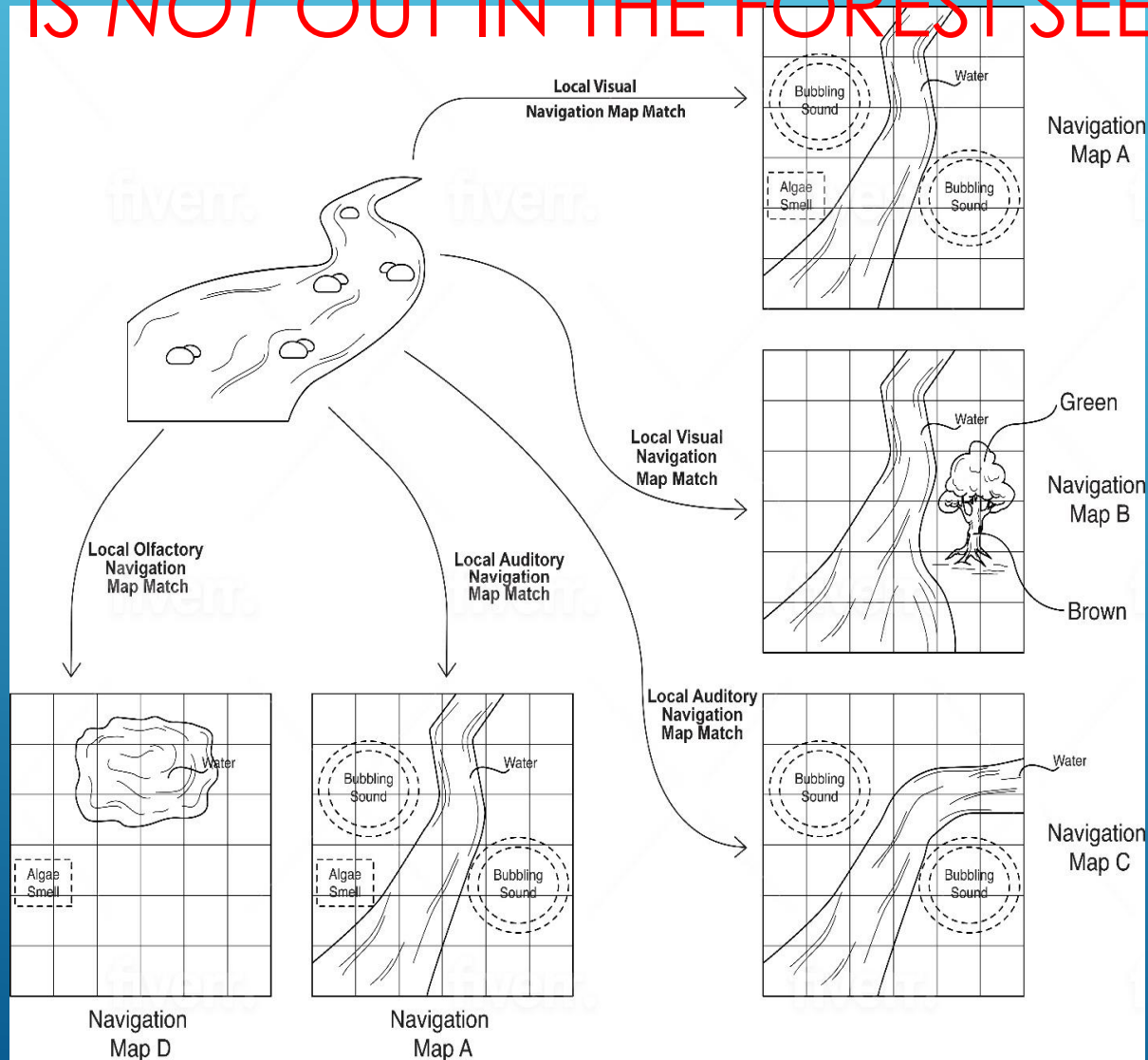
$$\Upsilon := \mathbf{mapno} \text{ of best matching map in set of navigation maps } \in \mathbf{mapno} \quad (18)$$

$$\mathbf{LNM}_{(\sigma, \Upsilon, t)} = \text{Input_Sensory_Vectors_Associations_} \\ \text{Module}_{\sigma}.\text{match_best_local_navigation_map}(S'_{\sigma, t}) \quad (19)$$

"then a miracle occurs" – summarize some
algorithmic portions with dot notation



****THIS IS EXAMPLE ONLY OF MATCHING NAVMAPS****
CCA3 IN CURRENT EXAMPLE IS WORKING AS A PATIENT-AIDE
IT IS NOT OUT IN THE FOREST SEEING RIVERS



OK.... at this point we have updated the matched Local Navigation Maps LNM's with the actual sensory input S' -- equations 20a, 20b, 21, 22

differences $(S'_{\sigma,t}, \text{LNM}(\sigma, \gamma, t)) \mid \leq h$, $\Rightarrow \text{LNM}'(\sigma, \gamma, t) = \text{LNM}(\sigma, \gamma, t) \oplus S'_{\sigma,t}$ (21)

differences $(S'_{\sigma,t}, \text{LNM}(\sigma, \gamma, t)) \mid > h$, $\Rightarrow \text{LNM}'(\sigma, \gamma, t) = \text{LNM}(\sigma, \text{new_map}, t) \oplus S'_{\sigma,t}$

Given the contrived nature of the simulated sensory stimuli above, and given that we already have entered noise at one step for more realism, we are not matching against every LNM, as we will later for the multi-sensory navigation maps or creating newer maps if differences exceed 'h', but more simply matching and inserting the new info. In more realistic sensory stimuli version we will match the LNM's as we do the NM's. For now, this treatment is appropriate.

h = number of differences allowed copied onto existing map $\in \mathbb{R}$ (20a)

new_map := **mapno** of new local navigation map added to $\sigma \in \text{mapno}$ (20b)

$\mid \text{differences}(S'_{\sigma,t}, \text{LNM}_{(\sigma, \gamma, t)}) \mid \leq h$, $\Rightarrow \text{LNM}'_{(\sigma, \gamma, t)} = \text{LNM}_{(\sigma, \gamma, t)} \cup S'_{\sigma,t}$ (21)

$\mid \text{differences}(S'_{\sigma,t}, \text{LNM}_{(\sigma, \gamma, t)}) \mid > h$, $\Rightarrow \text{LNM}'_{(\sigma, \gamma, t)} = \text{LNM}_{(\sigma, \text{new_map}, t)} \cup S'_{\sigma,t}$ (22)




```

self.visual_inputs_motion_modules    []
self.tactile_inputs_assocn_module    []
self.visual_inputs_assocn_module     ['left_hand>walker', 'right_hand>walker']
self.auditory_inputs_assocn_module    []
self.olfactory_inputs_assocn_module   []
self.visual_inputs_zoom_out_assocn_module ['patient,walker, patient>walke
self.visual_inputs_zoom_out_motion_modules []
self.radar_inputs_assocn_module      []

```

These set of LNM's represent $lnm(t)$ Equation 23

$$lnm_t = [LNM'_{(1, \gamma, t)}, LNM'_{(2, \gamma, t)}, LNM'_{(3, \gamma, t)}, \dots, LNM'_{(n_{\sigma}, \gamma, t)}] \quad (23)$$

$$NM_{mapno} \in R^{mxnxo}, IPM_{mapno} \in R^{mxnxo}, LPM_{mapno} \in R^{mxnxo} \quad (24)$$

$$all_navmaps_t := [all_LNM_s_t, all_NM_s_t, all_IPM_s_t, all_LPM_s_t] \quad (30)$$



Thus at this point we arrive at equations 42 and 43 where we consider grounded features. As the equations specify, we take a pragmatic approach to the grounding problem -- every cube in a navigation map that is not an ungrounded feature (i.e., most fundamental feature going back to a sensor) or else a link to a cube somewhere else. Features are grounded in sensory features or can be grounded in abstract higher level concepts have been developed and it would be tedious to trace their origins, especially if these concepts have been developed at several levels.



Symbol Grounding Problem

- Harnad 1990
 - symbolic model of mind – symbol strings, rules can manipulate
 - how can capture thoughts or beliefs?
 - e.g., learn Chinese from Chinese-Chinese dictionary
-
- Barsalou 2020
 - how can abstract symbols of a “cognition module” understand the world?



CCA3 Pragmatic Grounding Solution:

- every cube in a navmap must contain a grounded feature or a link somewhere
- links can be to actual low-level sensory features or to higher concepts

$$\textit{grounded_feature} := \forall_{\textit{feature}} : \textit{feature} \in \textit{all_LNMs}_{\chi} \quad (42)$$

$$\forall_{\chi,t} : \textit{all_navmaps}_{\chi,t} = \textit{grounded_feature}$$

$$\text{OR } \textit{link}(\textit{all_navmaps}_{\chi,t}) \neq []$$

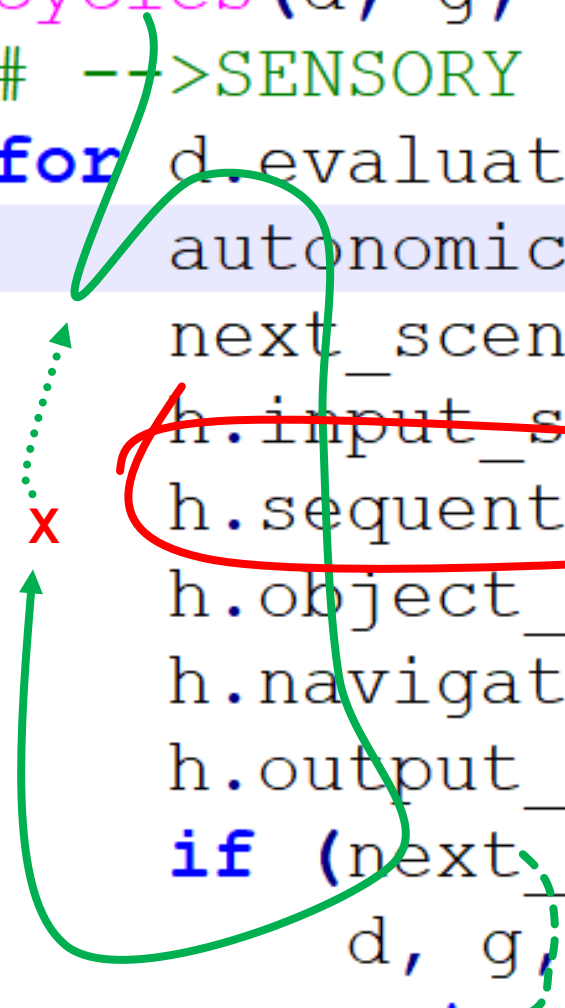
$$\text{OR } \textit{all_navmaps}_{\chi,t} = [] \quad (43)$$

for all values of address χ , cube contains a grounded feature or a link somewhere

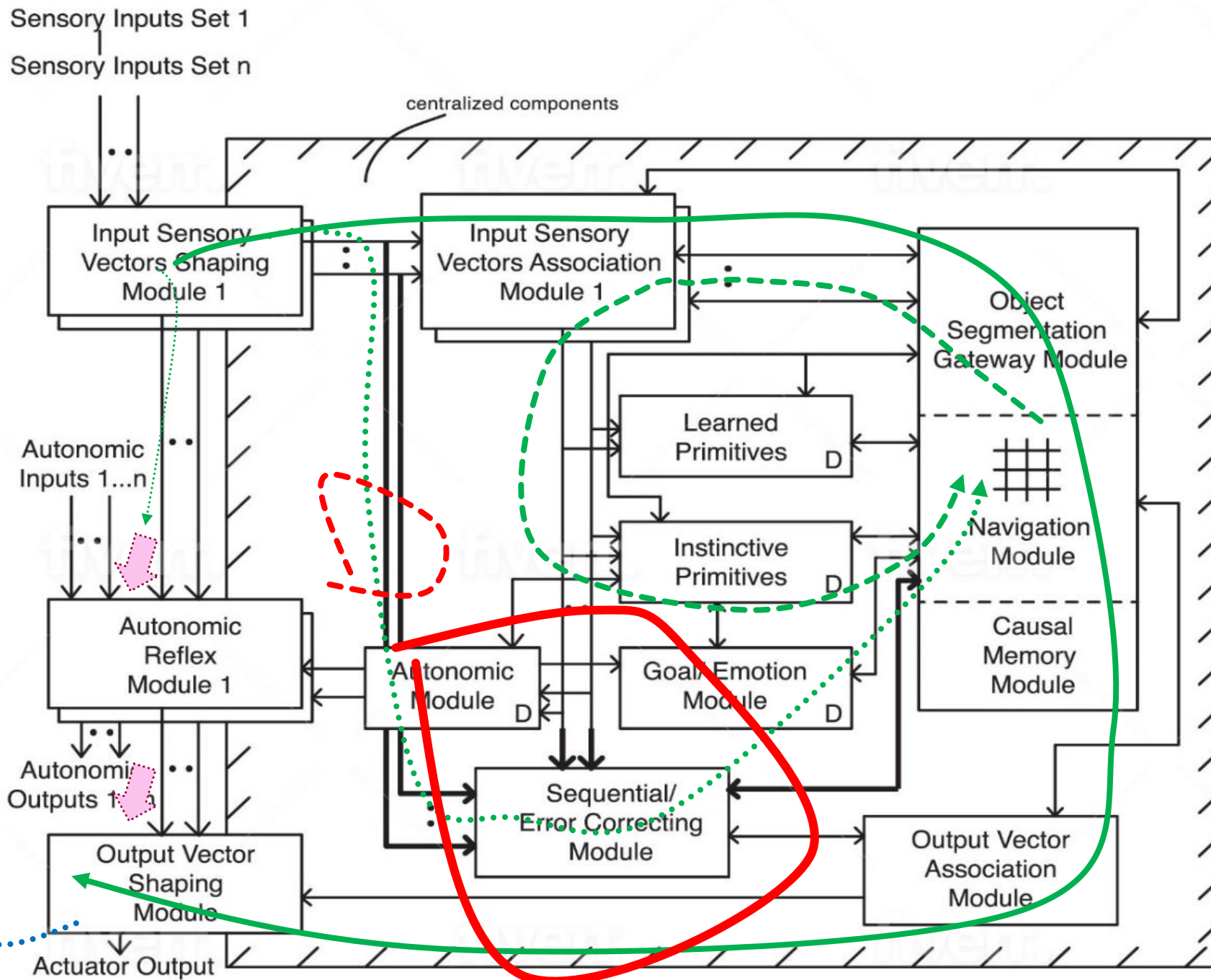


main_mech.cycles()

```
def cycles(d, g, h, m):  
    # -->SENSORY INPUTS --> CCA3 --> MOTOR  
    for d.evaluation_cycles in range(sys.  
        autonomic_check(g)  
        next_scene_from_envrt = (h.envrt_  
        h.input_sensory_vectors_associati  
        h.sequential_error_correcting_mod  
        h.object_segmentation_module(g)  
        h.navigation_module(d, g)  
        h.output_vector_association_module  
        if (next_scene_from_envrt < 0 or  
            d, g, h = update_expected_val  
        --return d, g, h, m
```



next sensory input



SEQUENTIAL

ERROR

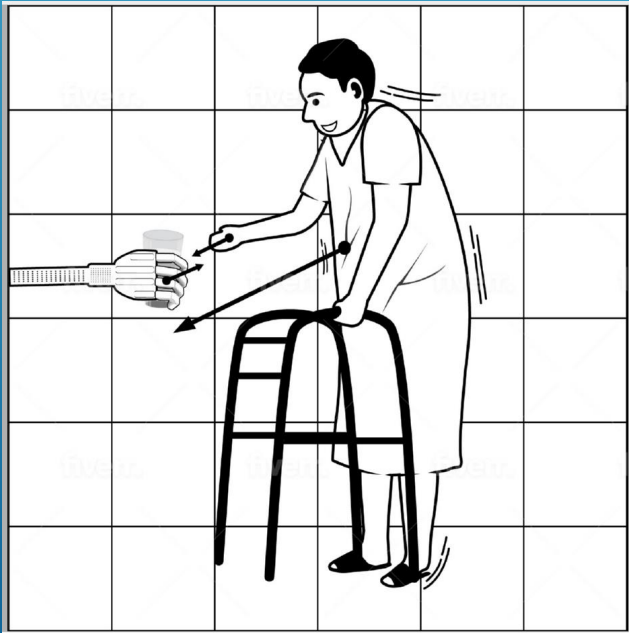
CORRECTING

MODULE

SIMULATION OF sequential_error_correcting_module



```
self.visual_inputs_motion_modules ** ['motion right_hand']
self.tactile_inputs_assocn_module []
self.visual_inputs_assocn_module ['left_hand>walker']
self.auditory_inputs_assocn_module []
self.olfactory_inputs_assocn_module []
self.visual_inputs_zoom_out_assocn_module ['patient,walker, patient>walker, robot]
self.visual_inputs_zoom_out_motion_modules ** ['motion body']
self.radar_inputs_assocn_module []
```



(49,50a, 50b) $VNM''(t)$ the visual navigation map is updated with the visual and auditory motion information extracted by this module. Then in (51) processed sound patterns, i.e., speech and other such sounds, are extracted from the `auditory_series(t)` to yield $AVNM(t)$ although in this simulation we are using such information at present in a very limited way. In `self.visual_inputs_zoom_out_motion_modules` and `self.visual_inputs_motion_modules` we have effectively extracted the object visual motion as per (52, 53, 54) to yield `visseg_motion(t)` which updates the Visual Segmented Navigation Map to yield $VSNM'(t)$ (equation 55)

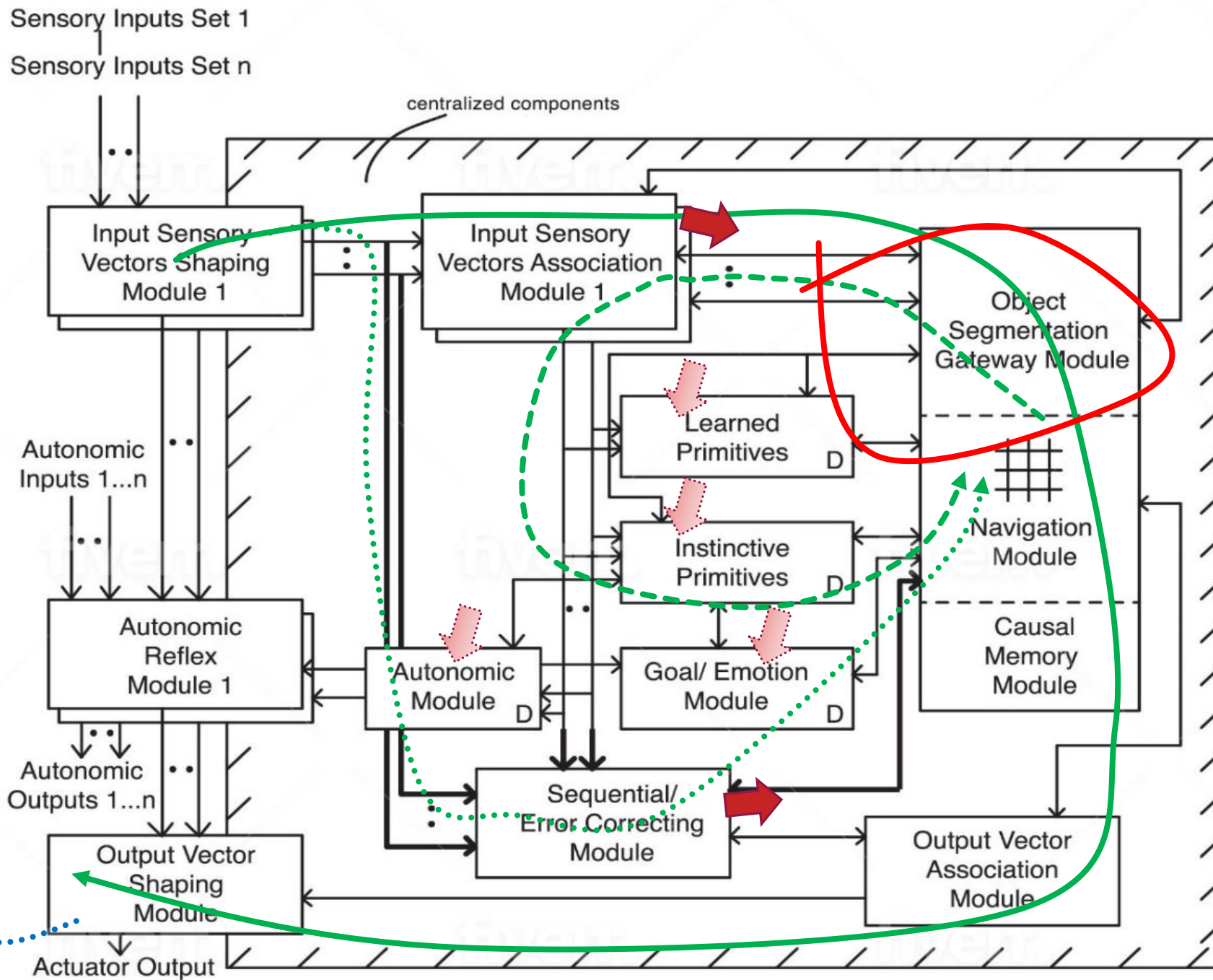
$VNM''(t)$ Vector Navigation Map updated with *visual_motion(t)* and *auditory_motion(t)*

$AVNM(t)$ Audio Vector Navigation Map from `auditory_series(t)`

$VSNM'(t)$ Visual Segmented Navigation Map is sent from Object Segmentation Mod at $t-3, t-2, t-1, t$ visual input sensory data \rightarrow `visseg_motion(t)` vector which is bound to $VSNM(t)$ creating **$VSNM'(t)$**

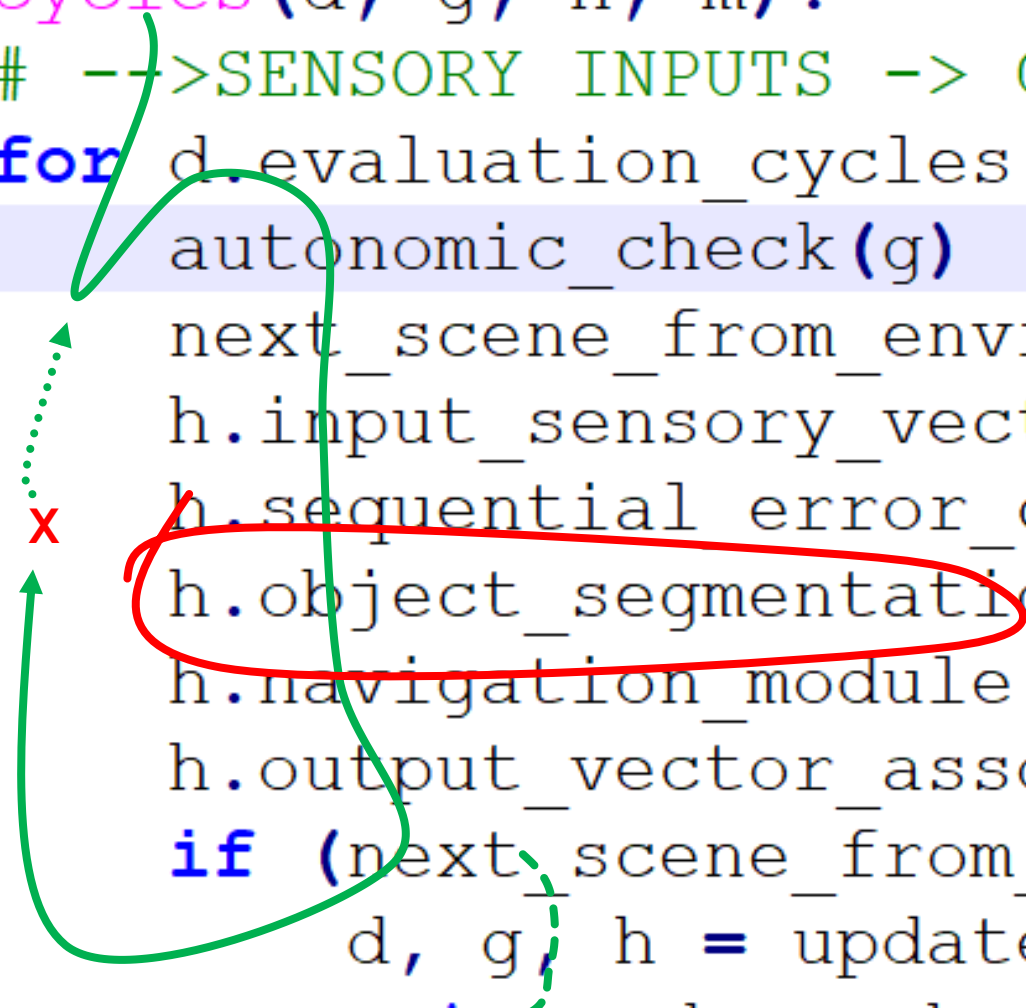


next sensory input



main_mech.cycles()

```
def cycles(d, g, h, m):  
    # -->SENSORY INPUTS --> CCA3 --> MOTOR  
    for d.evaluation_cycles in range(sys.  
        autonomic_check(g)  
        next_scene_from_envrt = (h.envrt_  
        h.input_sensory_vectors_associati  
        h.sequential_error_correcting_mod  
        h.object_segmentation_module(g)  
        h.navigation_module(d, g)  
        h.output_vector_association_module  
        if (next_scene_from_envrt < 0 or  
            d, g, h = update_expected_val  
        --return d, g, h, m
```



OBJECT

SEGMENTATION

MODULE

The object_segmentation_module calls the following methods:

```
self.visual_zoom_out_into_navmap(g)
self.auditory_into_navmap(g)
self.olfactory_into_navmap(g)
self.visual_into_navmap(g)
best_navmap = self.match_to_best_causal_memory_navmap(g)
self.current_navmap_zoom_in_largest_mismatch(best_navmap)
self.update_navmap(g, best_navmap)
```

We will link the equations from the CCA3--A Solution to the Binding to the software operations as we proceed through these methods.





....continued in VIDEO 5

balloon from powerpoint stock image

