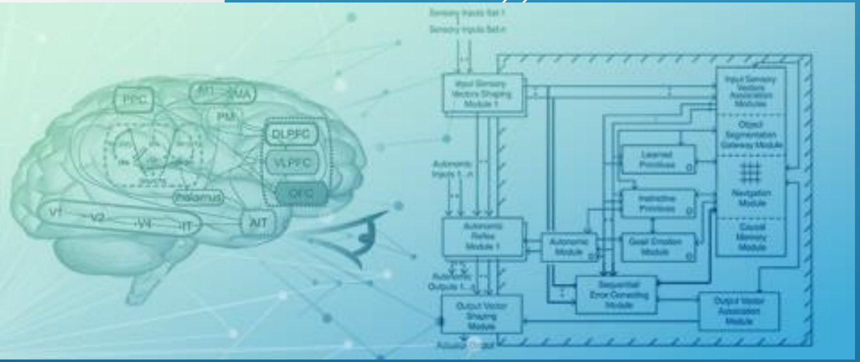
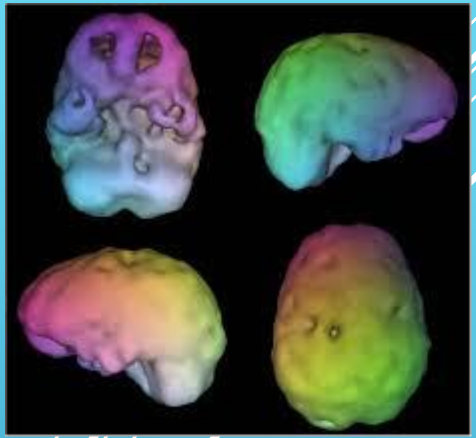
FROM PLAY-DOH TO:
-HOW THE HUMAN BRAIN EVOLVED
-HOW THE HUMAN BRAIN WORKS
-BUILDING AN AGI BASED ON THE BRAIN

Howard Schneider

ISAN MEETING MAY 16/24



PLAY-DOH WHILE WAITING FOR MONTHLY SPECT SCAN READINGS AT MOUNT SINAI

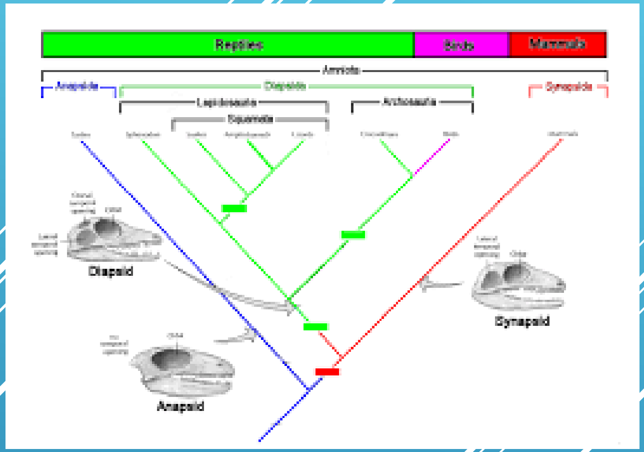


What I wanted to make....

What I actually created.....

PLAY-DOH AXIOMS

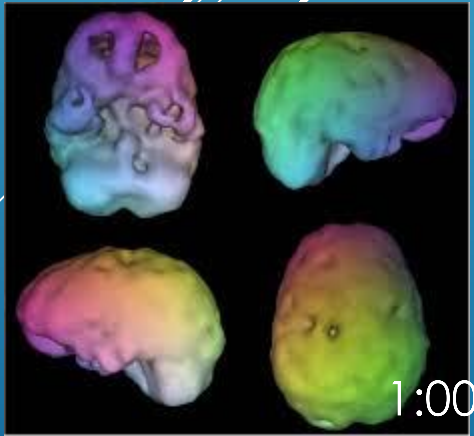
Cambrian explosion – full 'thinking' and moving animals at 540Myrs – HAVE SOME NAVIGATION SYSTEMS



Carboniferous – amniotes 310 Myrs – soon divergence into synapsids (eventually become mammals) and diapsids (dinosaurs, modern reptiles, birds) – HAVE NAVIGATION SYSTEMS

Triassic – mammals 225 Myrs – CORTEX NYD
Primates – Paleocene 58 Myrs – NO COMPOSITIONALITY, NO CAUSALITY, NO PSYCHOSIS but good pre-causal

Chimpanzee-Human Last Common Ancestor – 5 Myrs (end of gene flow date) – CAUSALITY, COMPOSITIONAL LANGUAGE, PSYCHOSIS (BUT OTHER PSYCHIATRIC ILLNESSES THE SAME)



Brief Note:

-DOES NOT PROVE OR DISPROVE ANYTHING ABOUT THEOLOGY (WHY WE ARE HERE)

- Divine creation?
- Evolution from the beginning?
- Super-advanced civilization alien high school experiment or simulation?

    ….

    ….

→Regardless, need mechanisms

We will be talking about "AI" later, so a small primer:

AI Primer

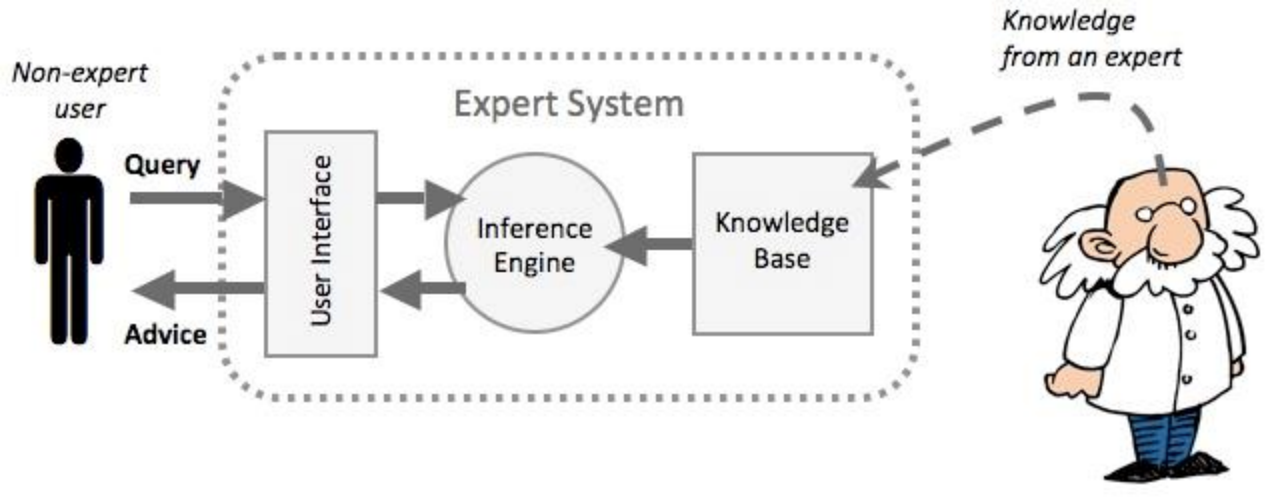
AI = "Artificial Intelligence"
-- before 2012:

If… then…

If… then…

If… then…

If… then…

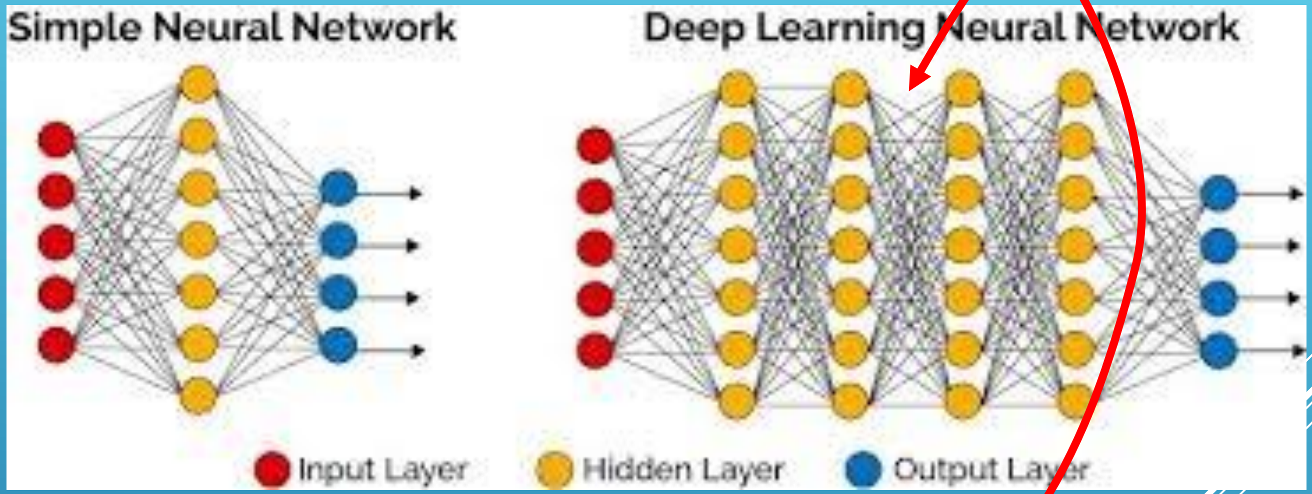


2:00

AI Primer

AI = "Artificial Intelligence"
-- after 2012:

"Neural Networks"
"Deep Learning"



-Pattern recognition

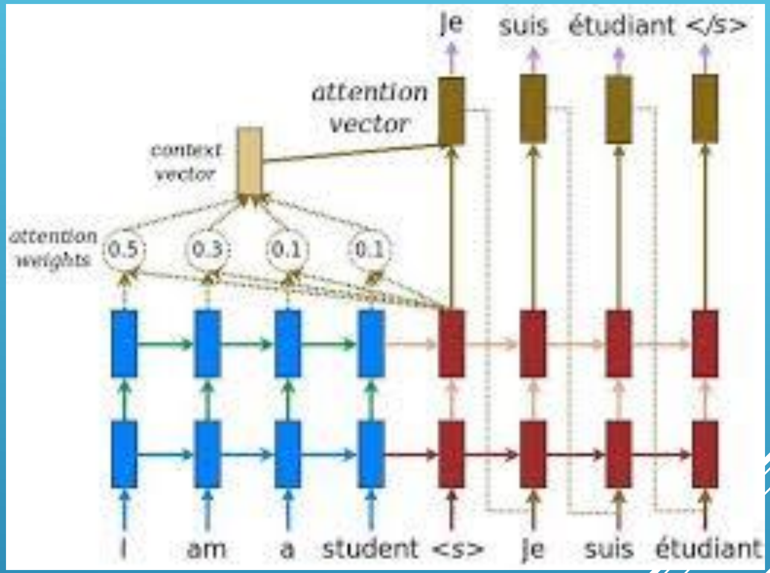
-Quasi-automatic feedback to allow automatic machine learning

AI Primer

AI = "Artificial Intelligence" -- after 2017:

"Transformers"
"Generative AI"

-Predict the next word
e.g., ChatGPT



3:00

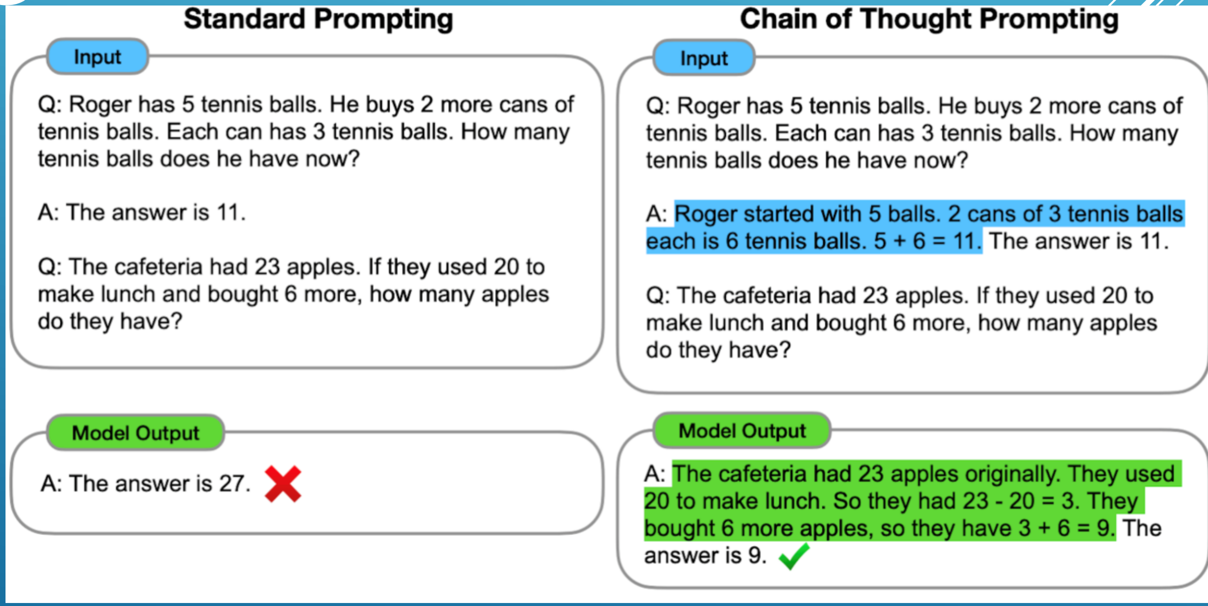
AI Primer

AI = "Artificial Intelligence" -- after 2023:

"Generative AI" + "Logic"

e.g., "Chain/Tree/etc of Thought", etc.

e.g., GPT4



AI Primer

essentially this is “narrow AI”

AI = Artificial Intelligence = some tasks that would normally take human-like intelligence

HLAI > AI

broader concept; HLAI subset of AGI

HLAI = Human-Level AI <= AGI = Artificial General Intelligence = AI can perform any intellectual task a human can

Superintelligence > AGI

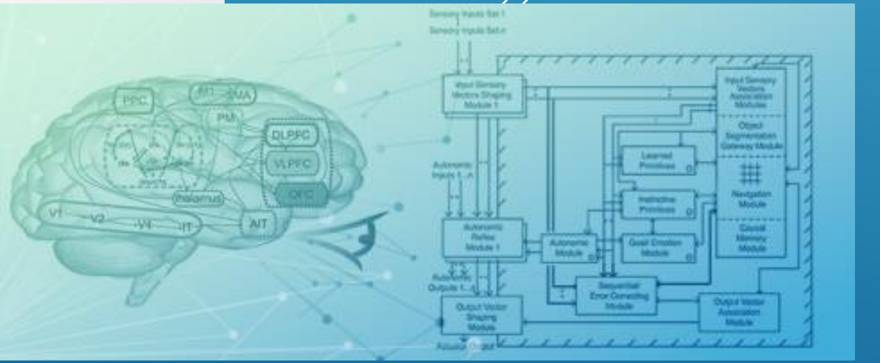
Superintelligence = AI that can outperform the best human brains in every field

4:00

FROM PLAY-DOH TO:
-HOW THE HUMAN BRAIN EVOLVED
-HOW THE HUMAN BRAIN WORKS
-BUILDING AN AGI BASED ON THE BRAIN
(IN ~15 MINUTES)J

Howard Schneider

ISAN MEETING MAY 16/24



POSTULATION:

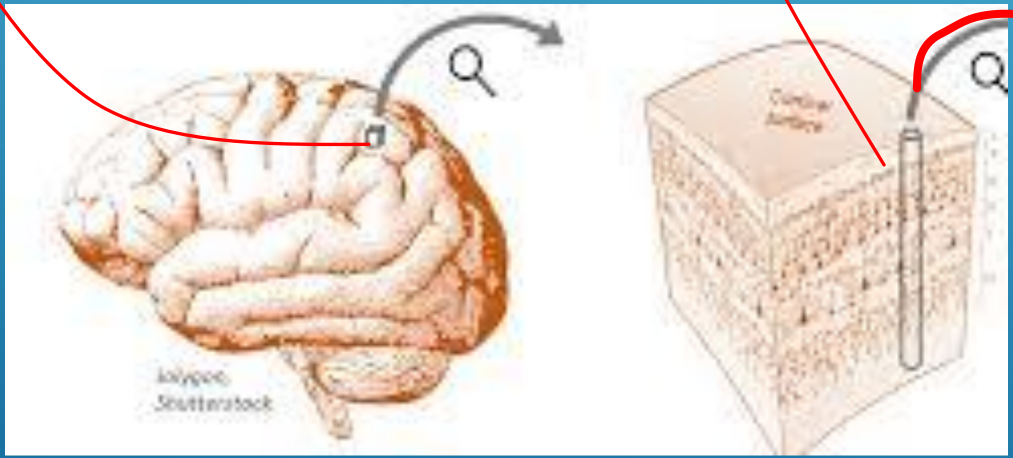
Amniotic ancestor of mammals – navigation circuits duplicated many times to eventually form the neocortex

THEREFORE IMPLIES:

Millions of neocortical minicolumns are essentially millions of "navigation maps"

~2 million (macro)columns

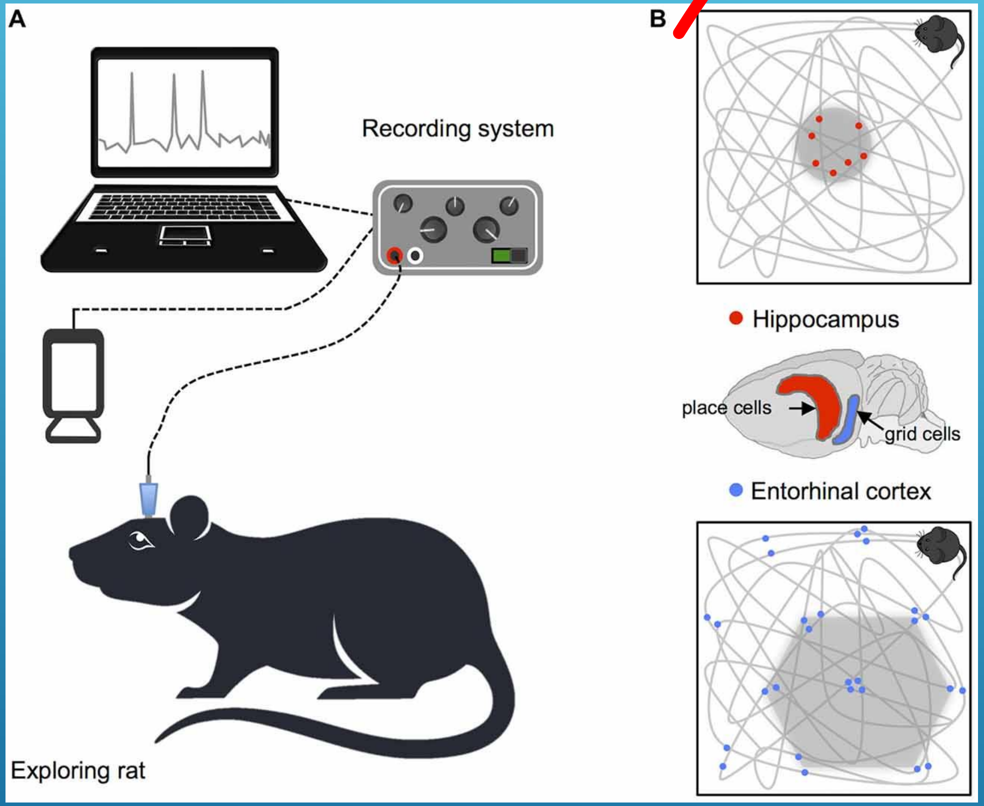
~200M (@~80-90 neurons)

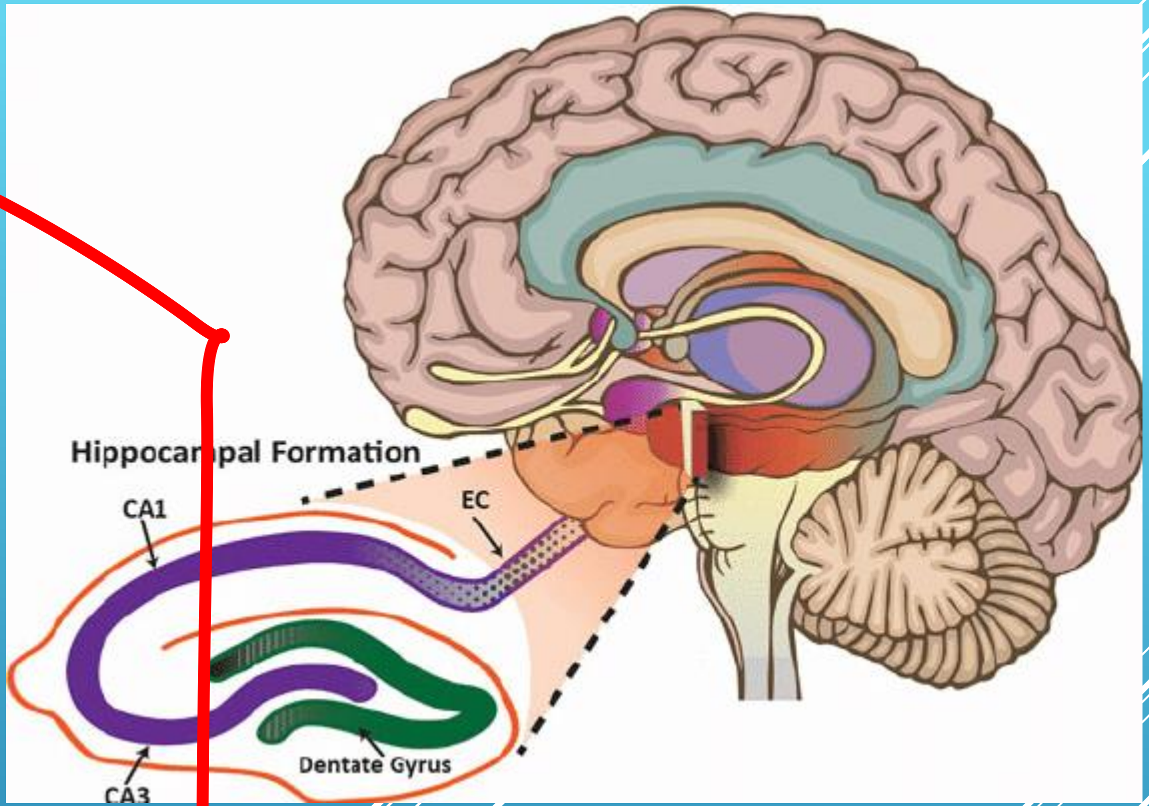


16 billion neurons in neocortex; 69 billion in cerebellum; 1 billion other structures = ~ 86 billion neurons in human brain (chimpanzee neocortex 6B (~75M minicol), brain 28B; dog neocortex 0.5B (~7M minicol), brain 2.2B; mouse neocortex 14M (~1M minicols), brain 71M)

L1- molecular layer (horiz dend, axons);
L2 – external granular layer (small pyramidal) (cortical region inputs);
L3 – external pyramidal layer (transmit btwn cortical areas);
L4 – internal granular layer (small stellate) (sensory inputs);
L5 – internal pyramidal layer (large pyramidal) (transmit to subcortical, outputs);
L6 – multiform layer (assoc with feedback connections)

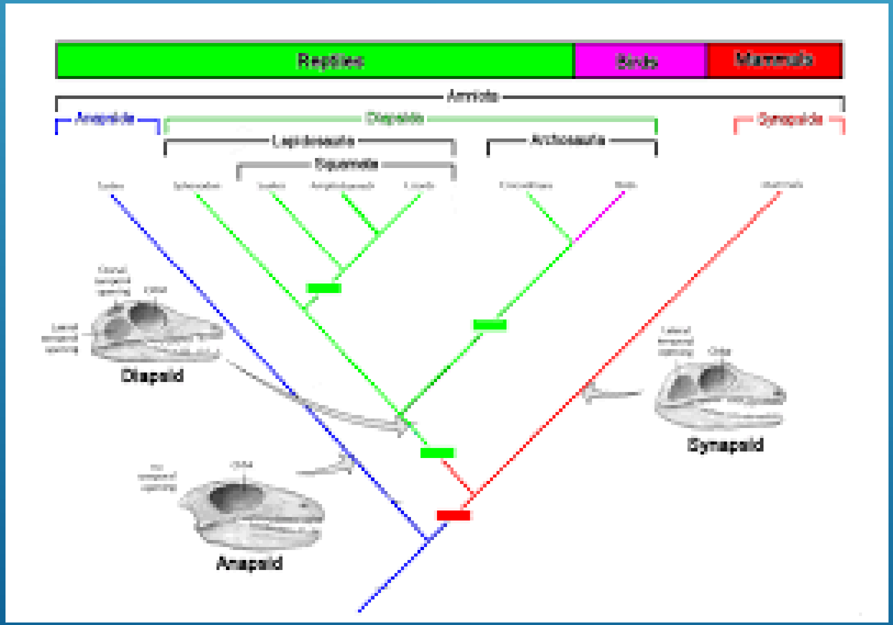
5:00

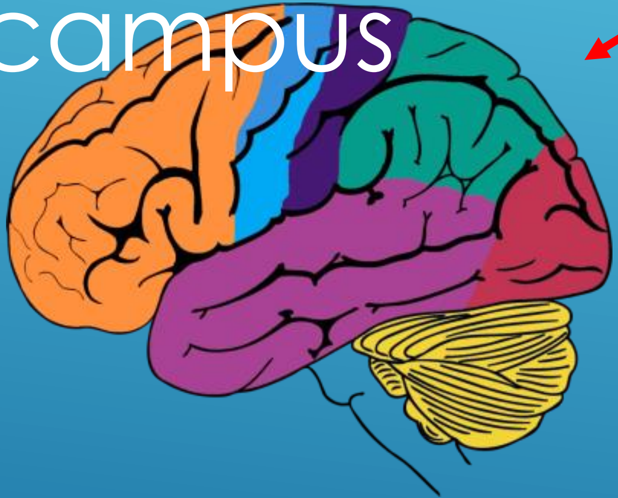




Spatial Navigation Maps

- From postulation: Hundreds of millions of years of mutations/adaptations → Will not be identical to hippocampus





Duplication of navigation circuits

6:00

```
self.total_labels = TOTAL_ASSOCIATION_LABELS #default 4
self.gb = np.empty((self.total_maps, 6, 6, 6, self.total_seg
# self.gb = np.empty((1000,6,6,6,16,4), dtype=object) (at ti
# gb[n,x,y,z,s,a]
# 1000 maps each 6×6×6 cube with up to 9 mapped objects -- a
```

Navigation Map

Python version

Play-doh to Python transition….

$\mathbf{NM}_{\mathbf{mapno}} \in R^{mxnxo}$, $\mathbf{IPM}_{\mathbf{mapno}} \in R^{mxnxo}$, $\mathbf{LPM}_{\mathbf{mapno}} \in R^{mxnxo}$ (23)

$\boldsymbol{\Theta}$**_NM** := total NM's $\in$ N, $\boldsymbol{\Theta}$**_IPM** := total IPM's $\in$ N, $\boldsymbol{\Theta}$**_LPM** := total LPM

$all\_LNMs_t := [all\_maps_{1,t}, all\_maps_{2,t}, all\_maps_{3,t}, \ldots, all\_maps_{n\_\sigma,t}]$ (25)

$all\_NMs_t := [NM_{1,t}, NM_{2,t}, NM_{3,t}, \ldots, NM_{\Theta\_NM,t}]$ (26)

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$all\_LPMs_t := [LPM_{1,t}, LPM_{2,t}, LPM_{3,t}, \ldots, LPM_{\Theta\_LPM,t}]$ (28)

$all\_navmaps_t := [all\_LNMs_t, all\_NMs_t, all\_IPMs_t, all\_LPMs_t]$ (29)

modcode := module identification code $\in$ N (30)

mapcode := [*modcode*, *mapno*] (31)

$\chi := [mapcode, x, y, z]$ (32)

feature $\in$ R, **action** $\in$ R (33)

$\boldsymbol{\Phi}$**_feature** := last **feature** contained by a cube, $\boldsymbol{\Phi}$**_action** := last **action** contain

$\boldsymbol{\Phi}\_\chi$:= last χ (i.e., address to link to) contained by a cube (34)

$cubefeatures_{\chi,t} := [\mathbf{feature}_{1,t}, \mathbf{feature}_{2,t}, \mathbf{feature}_{3,t}, \ldots, \mathbf{feature}_{\Phi\_feature,t}]$ (35)

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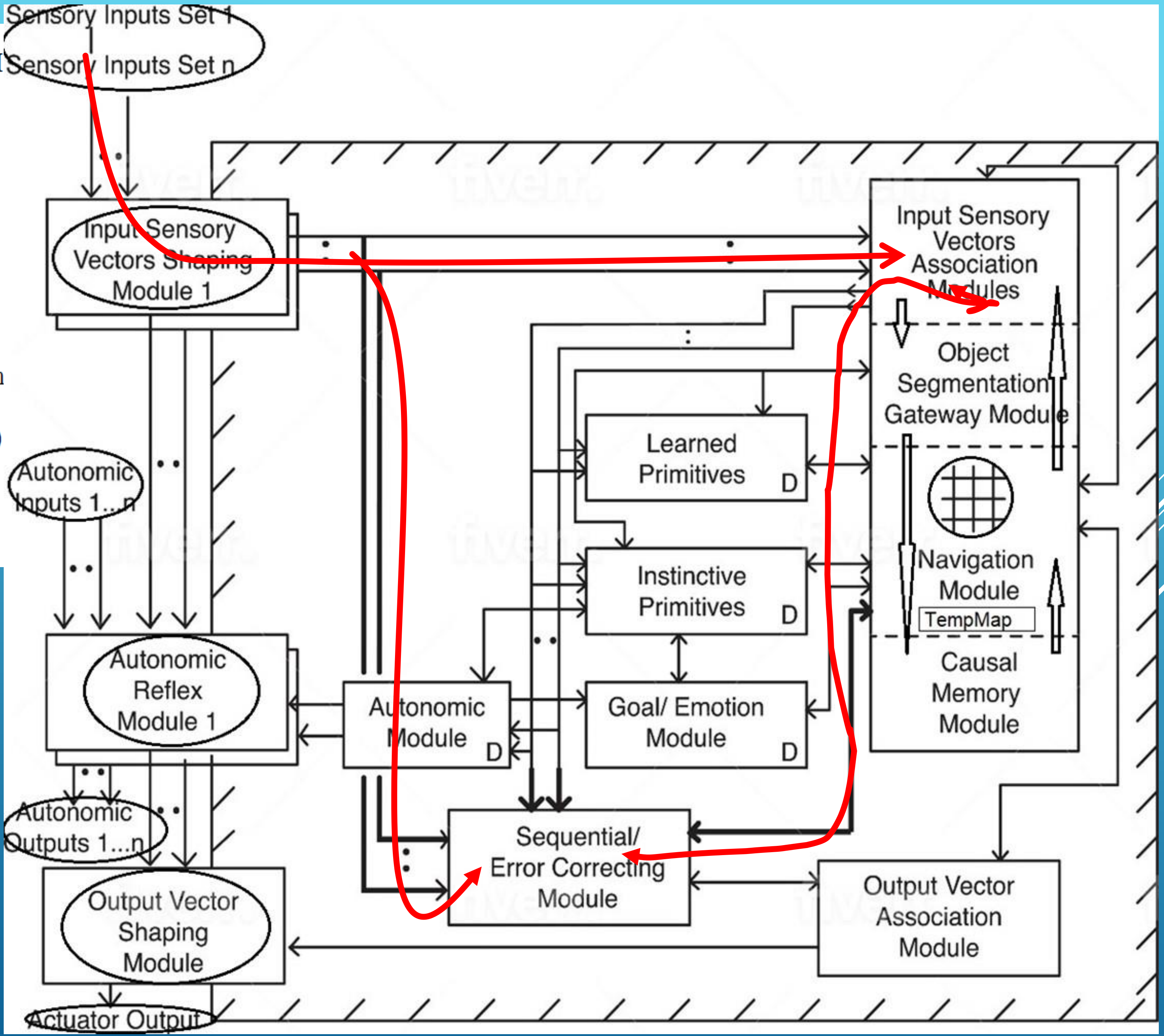
$linkaddresses_{\chi,t} := [\chi_{1,t}, \chi_{2,t}, \chi_{3,t}, \ldots, \chi_{\Phi\_\chi,t}]$ (37)

$cubevalues_{\chi,t} := [cubefeatures_{\chi,t}, cubeactions_{\chi,t}, linkaddresses_{\chi,t}]$ (38)

$cubevalues_{\chi,t} = all\_navmaps_{\chi,t}$ (39)



Linear Equations

(via Python)

Cognitive Architecture

(via Python, Linear Equations)

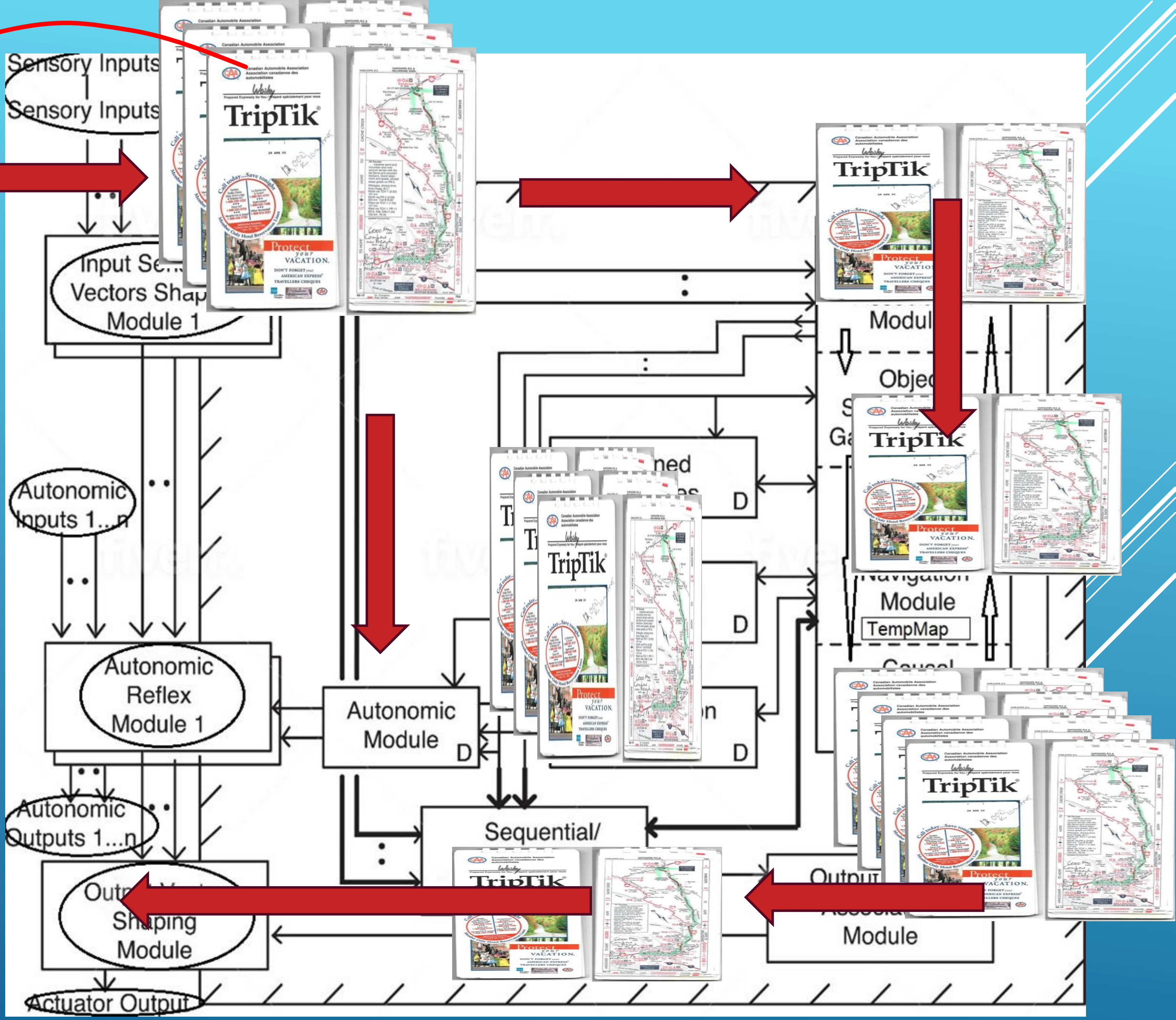
Very different type of circuit from typical neuroscience or typical AI (pre-2012) or typical AI (post-2012)

NavMaps

Synapses

Bytes, Symbols

Deep Learning ANN Circuits



7:00

LET'S DEVELOP A BRAIN…

Cambrian explosion – full 'thinking' and movi
540Myrs – HAVE SOME NAVIGATION SYSTEMS

Carboniferous – amniotes 310 Myrs – soon di
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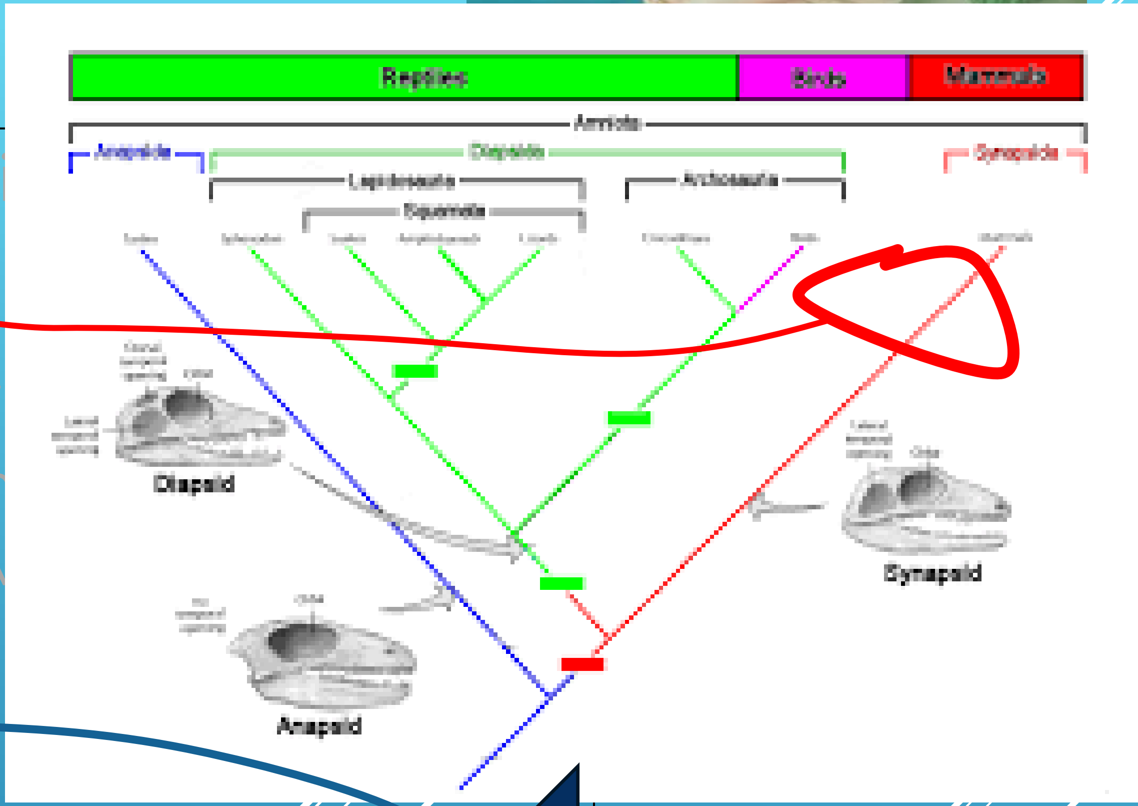
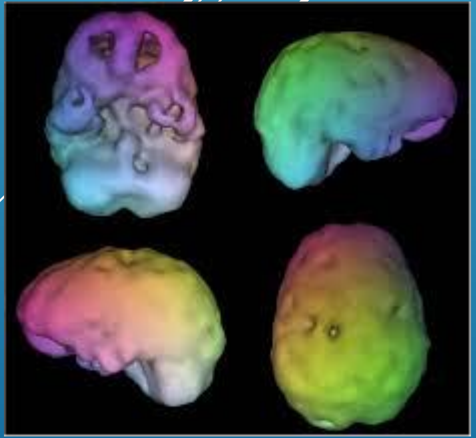


Triassic – mammals 225 Myrs – CORTEX NYD
Primates – Paleocene 58 Myrs – NO COMPOSITIONALITY, NO CAUSALITY, NO PSYCHOSIS but good pre-causal



Chimpanzee-Human Last Common Ancestor – 5 Myrs (end of gene flow date) – CAUSALITY, COMPOSITIONAL LANGUAGE, PSYCHOSIS (BUT OTHER PSYCHIATRIC ILLNESSES THE SAME)

PRIMATE ←→NON-PRIMATE MAMMALIAN BRAIN

-Prefrontal Cortex more development

-More developed hippocampus

-Larger brain, more neocortex (gyrations)

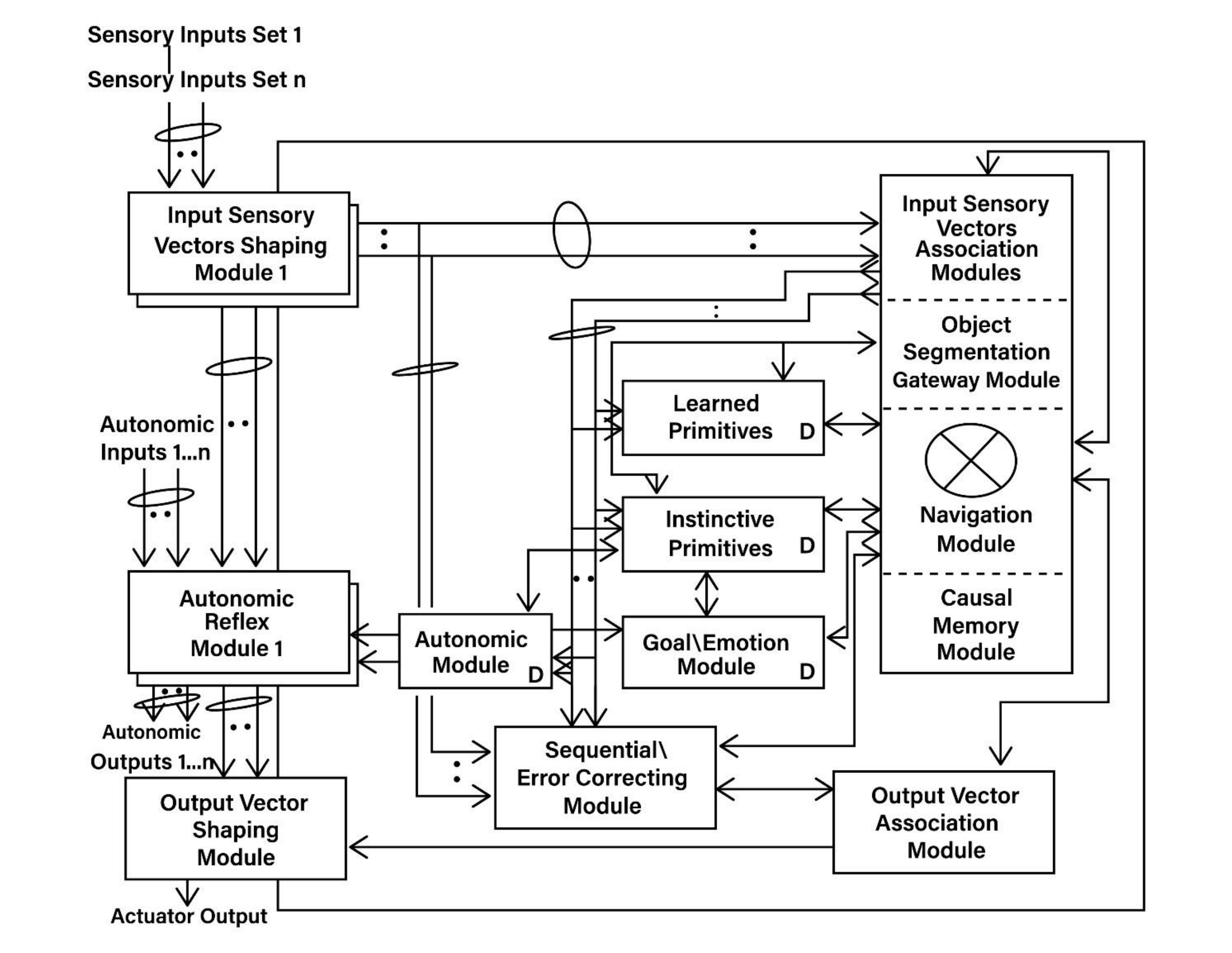
-More development of visual processing

BUT:

- NO FULL CAUSAL REASONING
- NO ANALOGICAL REASONING
- NO COMPOSITIONALITY OR COMPOSITIONAL LANGUAGE
- NO PSYCHOSIS

cognitive architecture

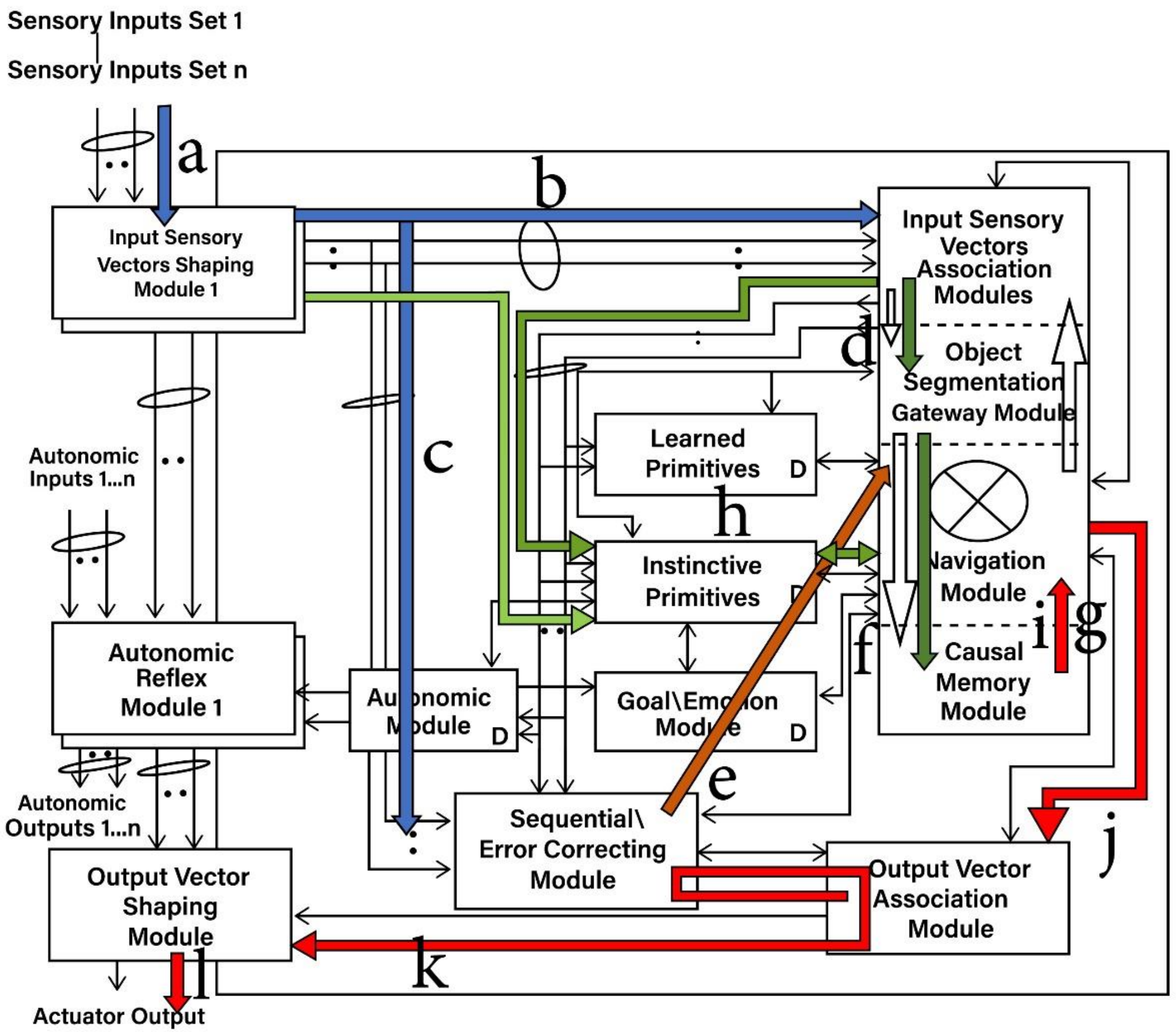
“Causal Cognitive Architecture” (Schneider)

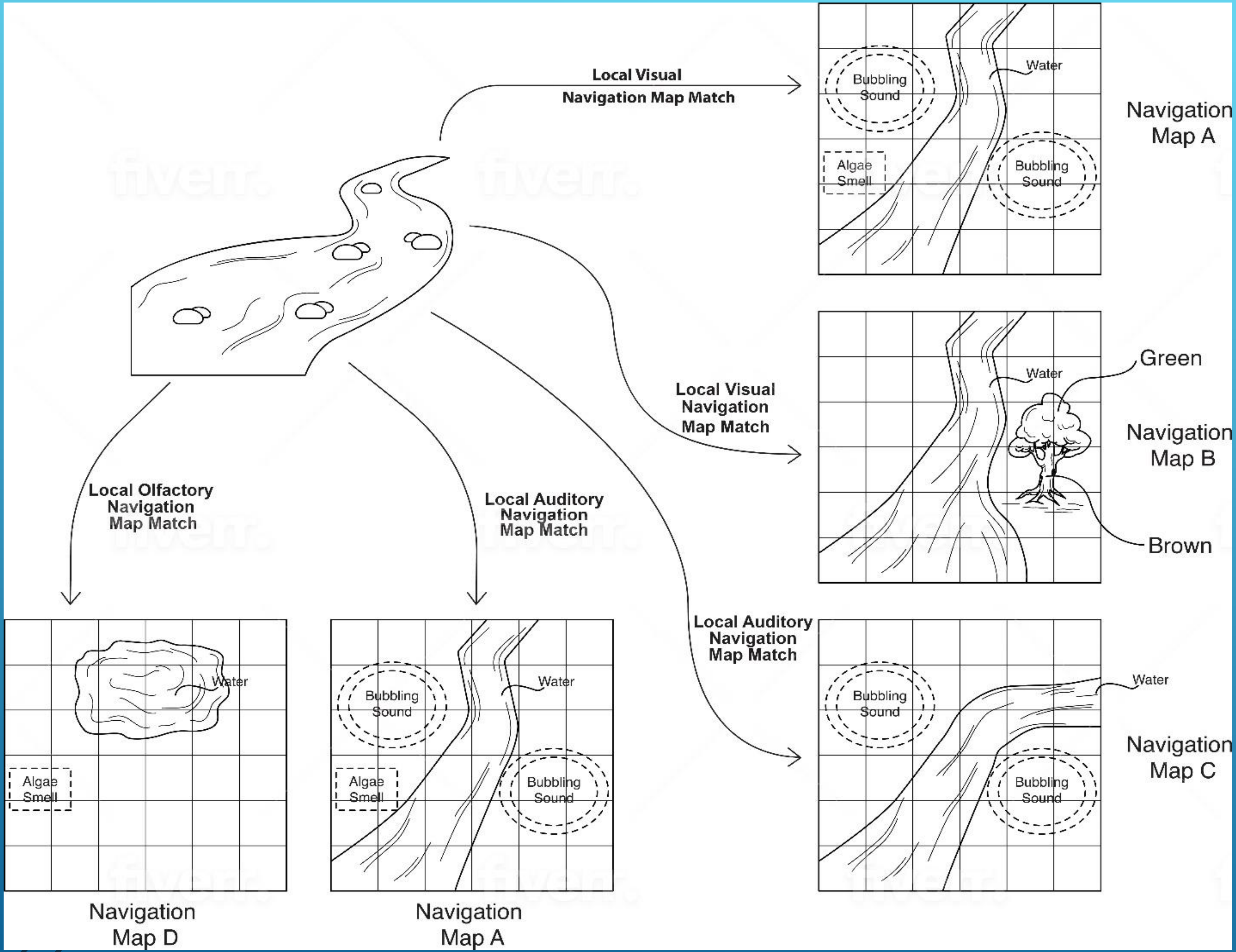


8:00

→processing is very different from:
- normal symbolic (pre-2012) AI
-deep learning (post-2012 AI)
-gen AI (e.g., ChatGPT)
-typical neural circuits see in neurology

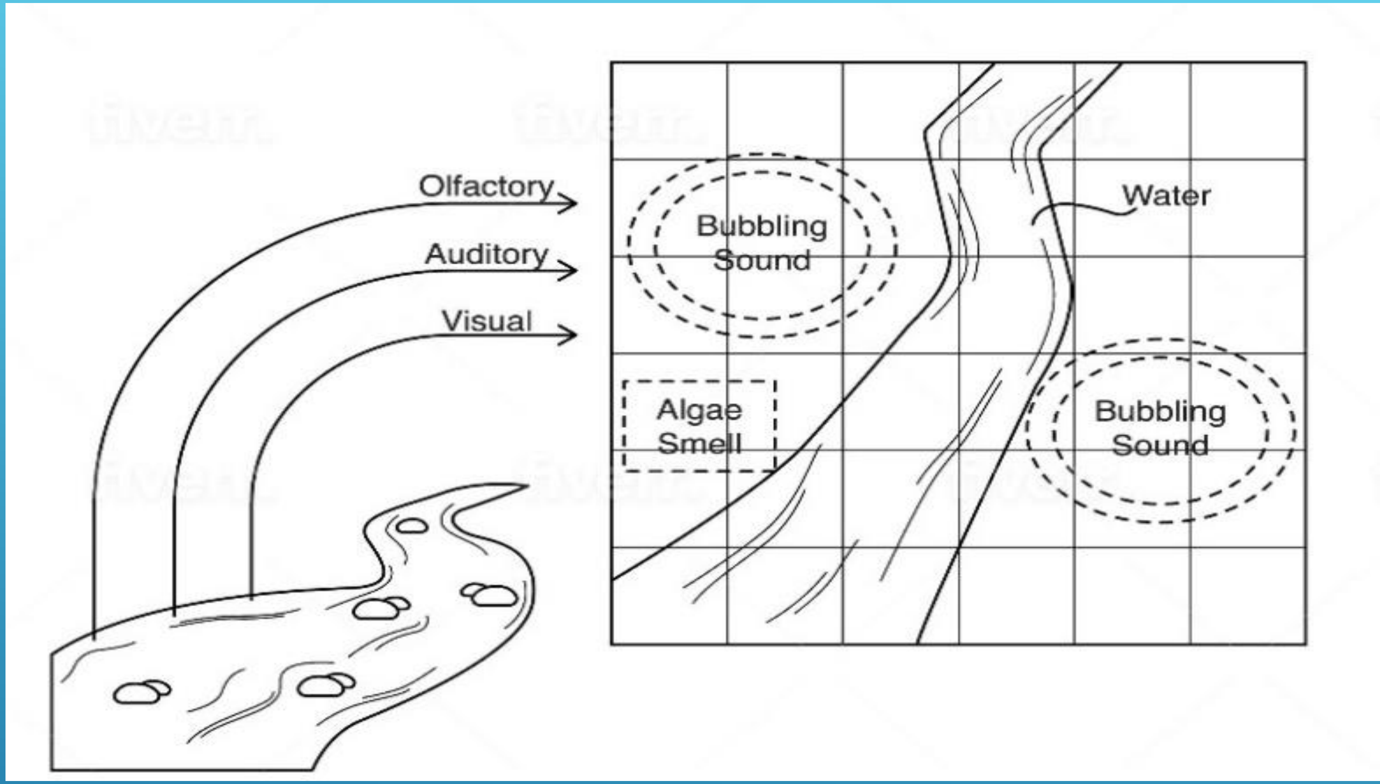
→modifed predictive coding – propagation of error signals (easiest to have emerged over the eons)





Spatial binding of navigation maps

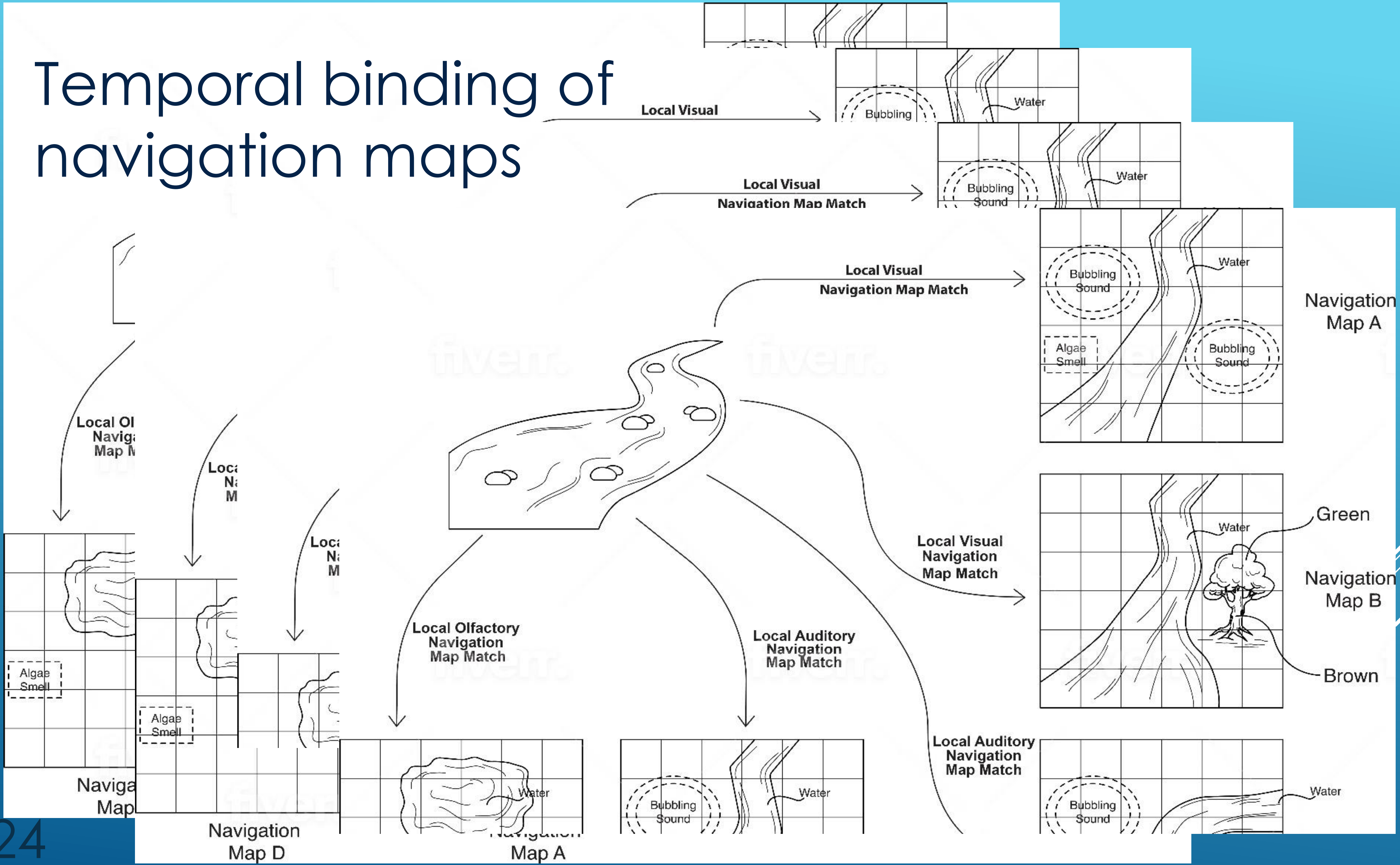
Not normal "perception" but match to pre-existing model of the world

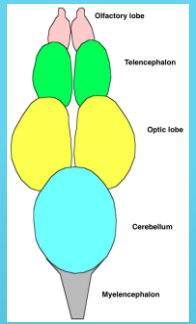


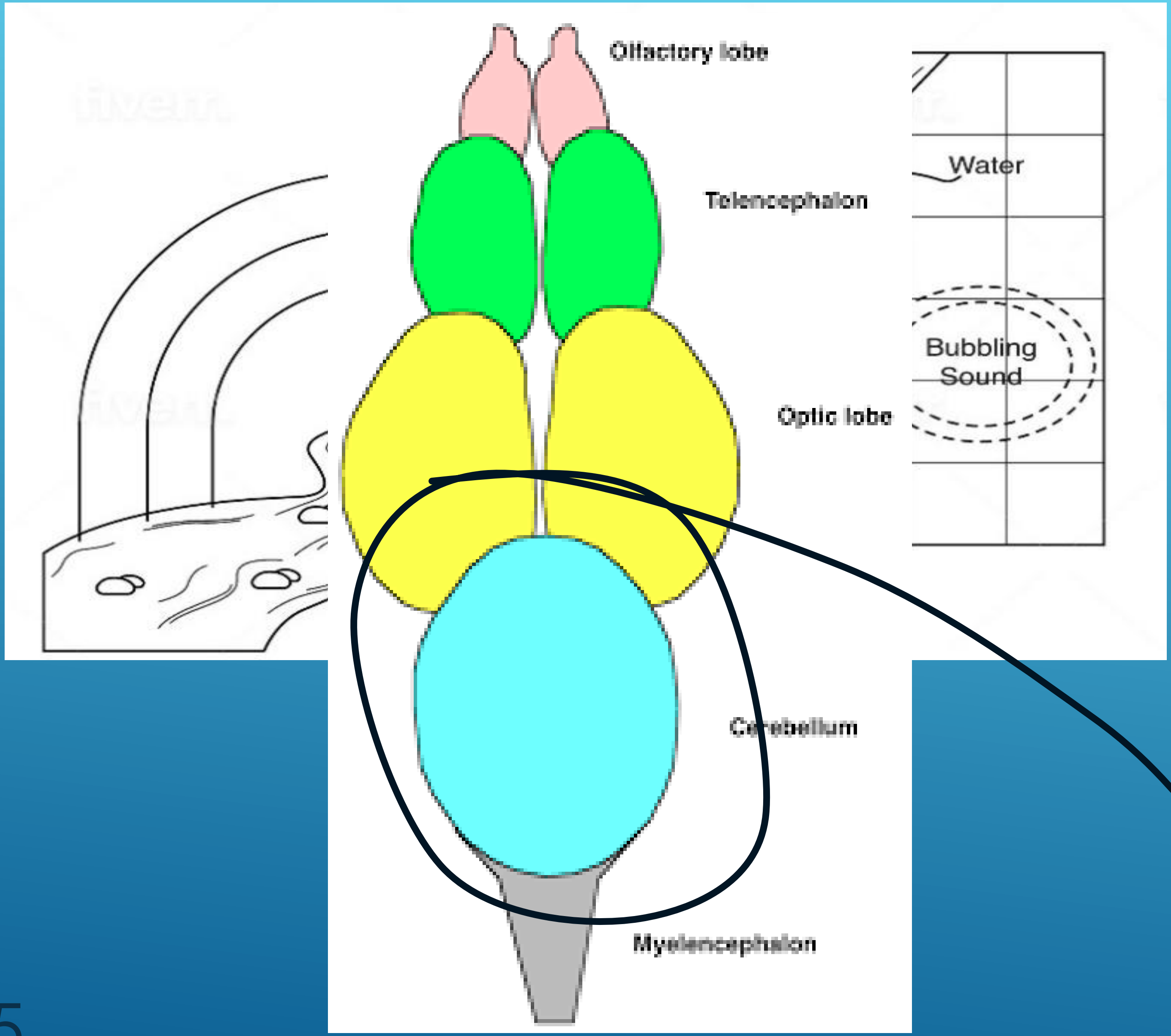
Spatial binding of navigation maps

(update the matched model)

Temporal binding of navigation maps







Temporal → spatial binding of navigation maps

(update the matched model)

Massive cerebellum in the fish brain

9:00

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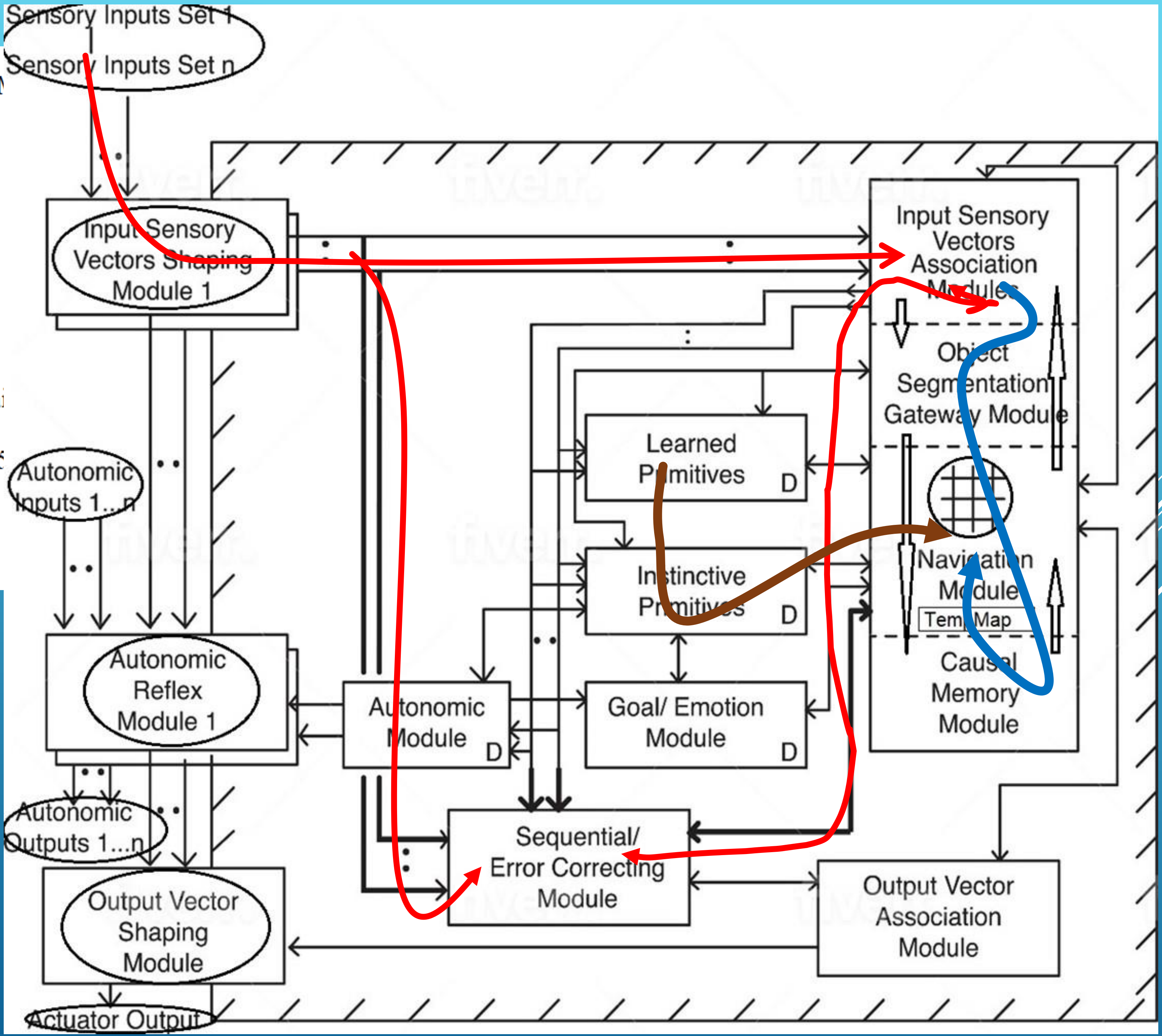

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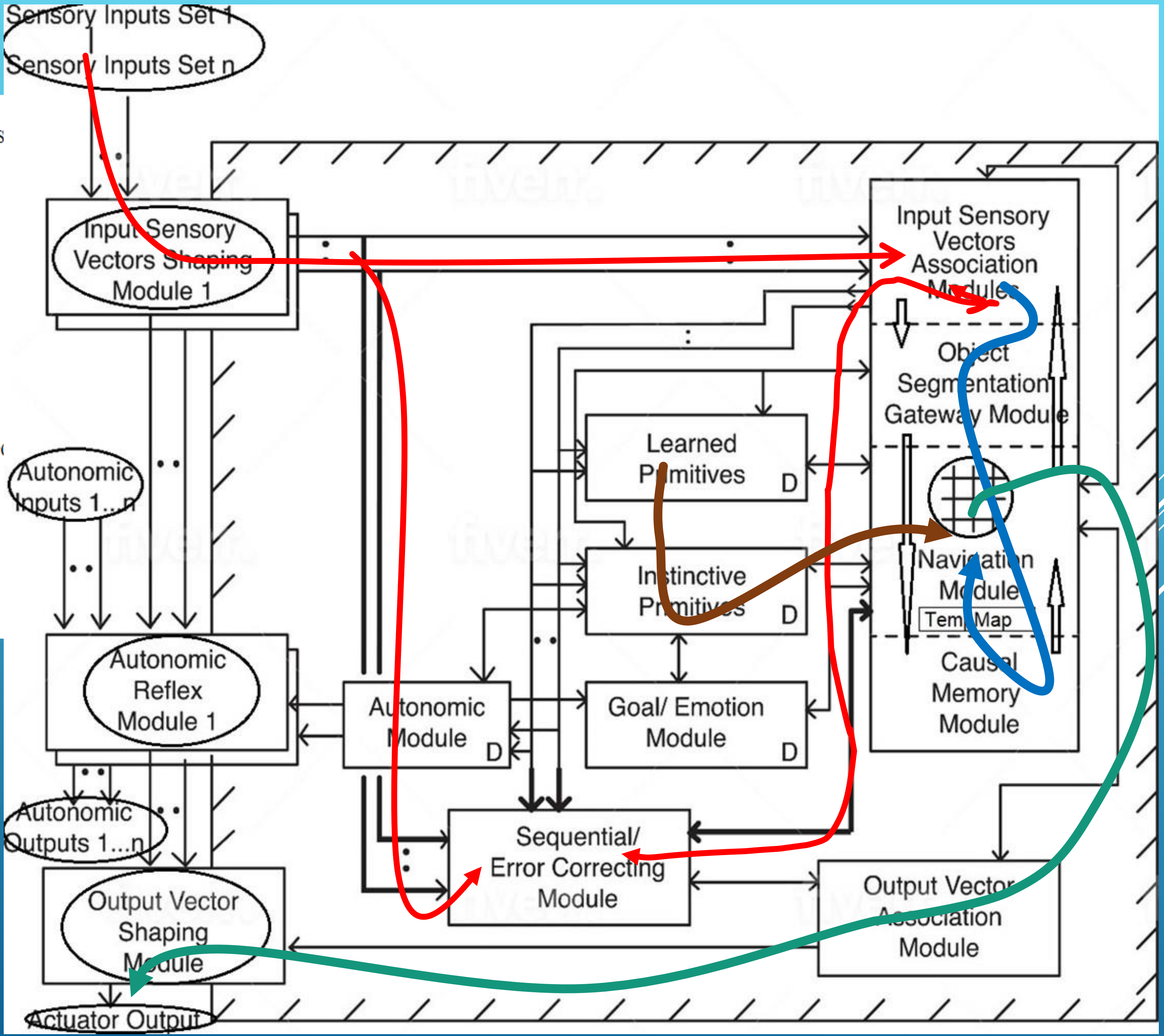
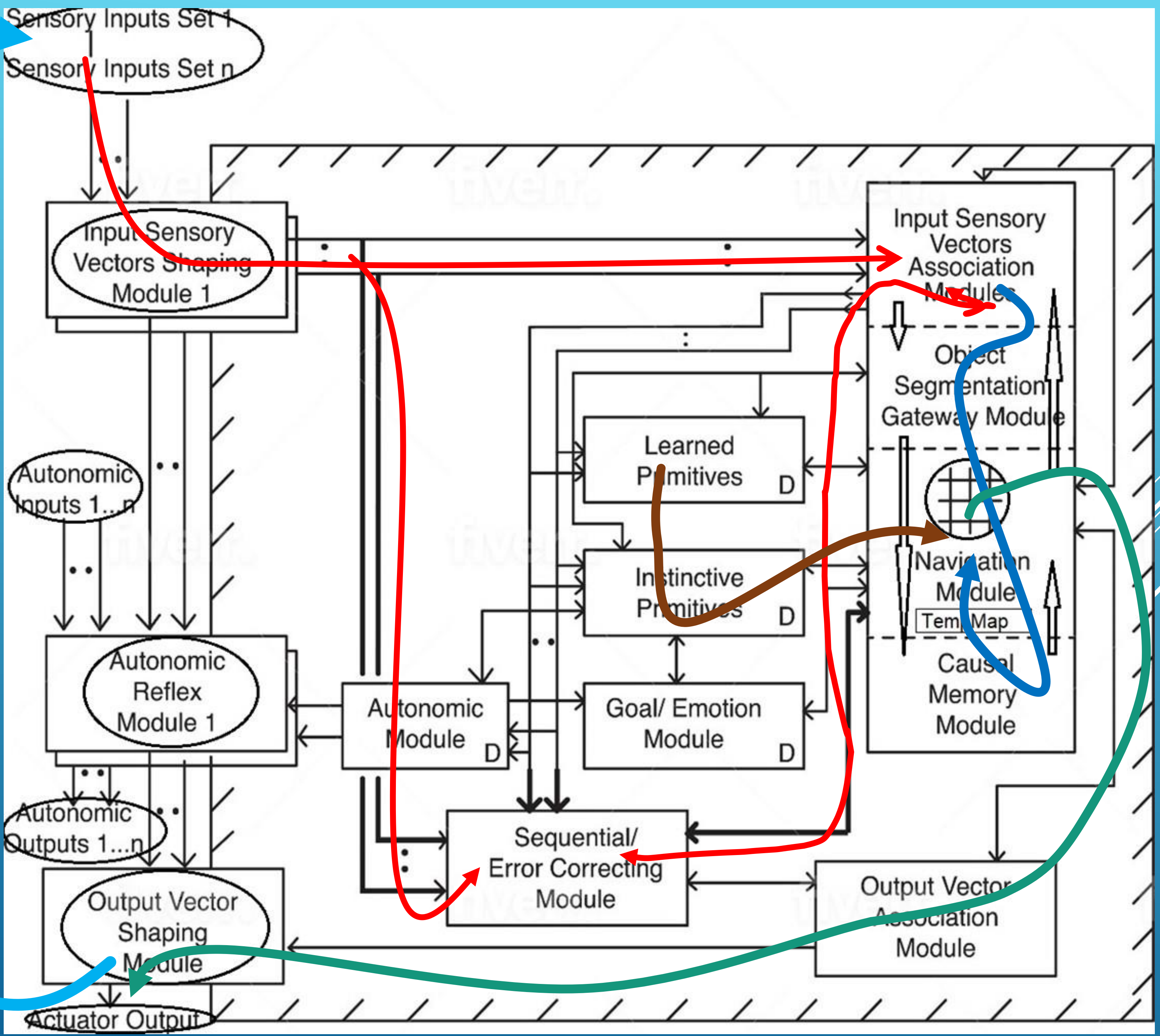


“cognitive cycle”



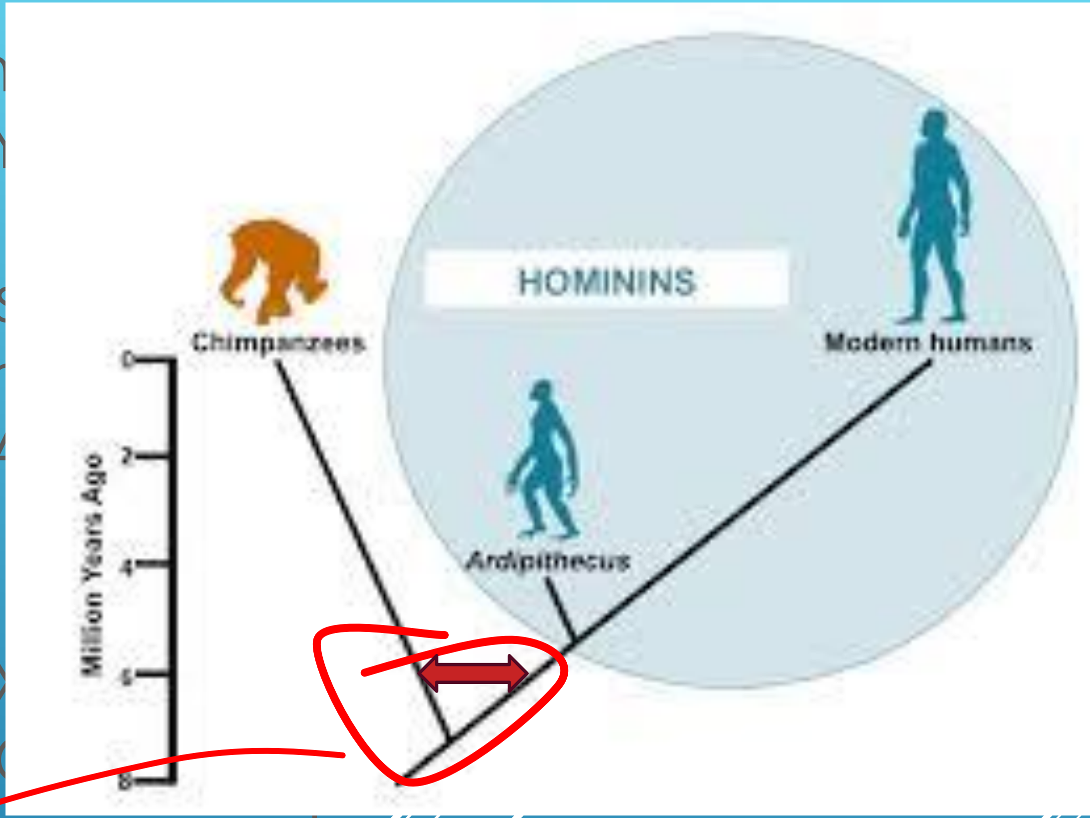
10:00

LET'S DEVELOP A BRAIN…

Cambrian explosion – full 'thinking' an
540Myrs – HAVE SOME NAVIGATION SY

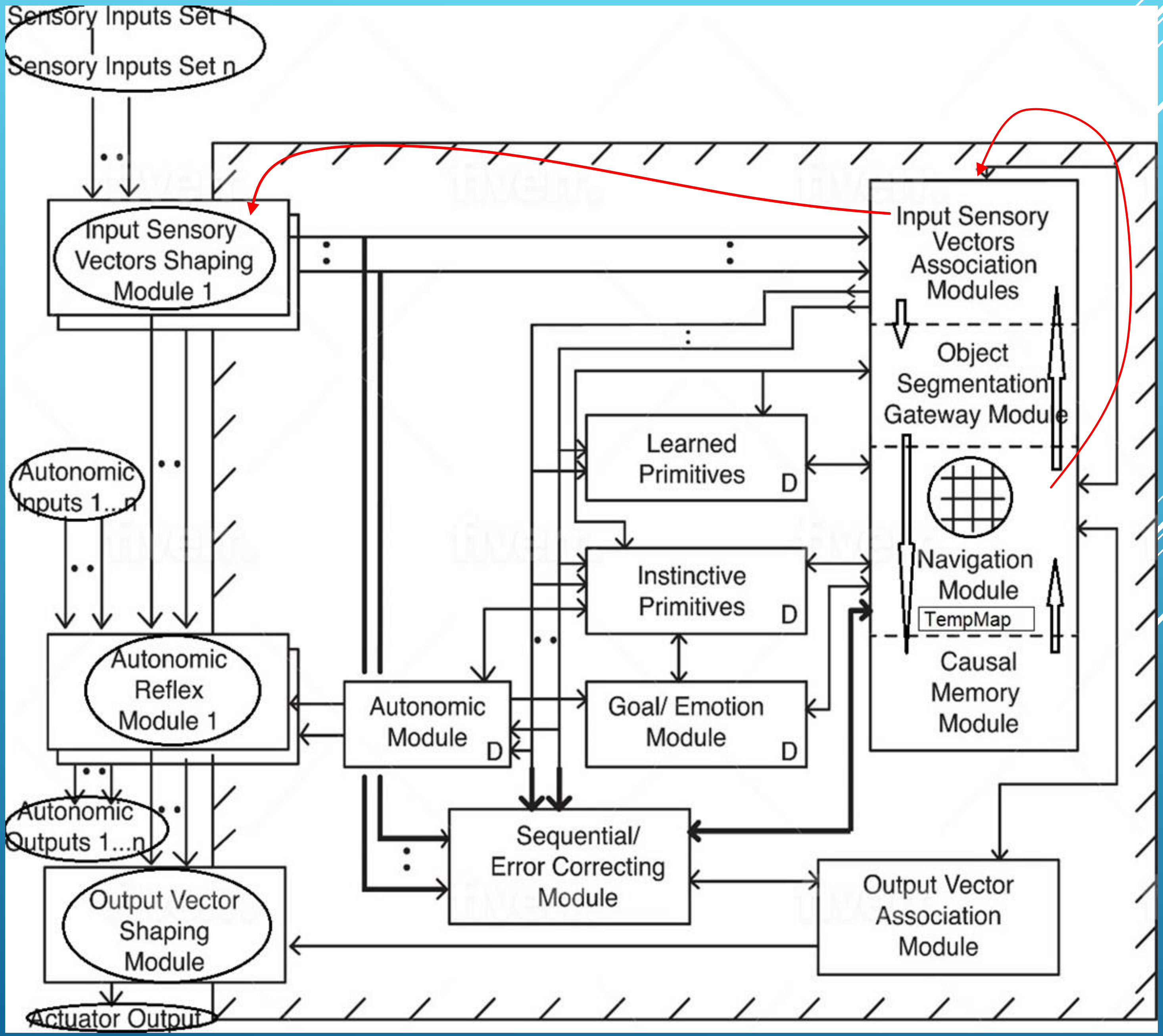
Carboniferous – amniotes 310 Myrs – s
synapsids (eventually become mamm
(dinosaurs, modern reptiles, birds) – HA
SYSTEMS

Triassic – mammals 225 Myrs – CORTEX
Primates – Paleocene 58 Myrs – NO C
CAUSALITY, NO PSYCHOSIS but good pre-causal



Chimpanzee-Human Last Common Ancestor – 5 Myrs (end of gene flow date) – CAUSALITY, COMPOSITIONAL LANGUAGE, PSYCHOSIS (BUT OTHER PSYCHIATRIC ILLNESSES THE SAME)

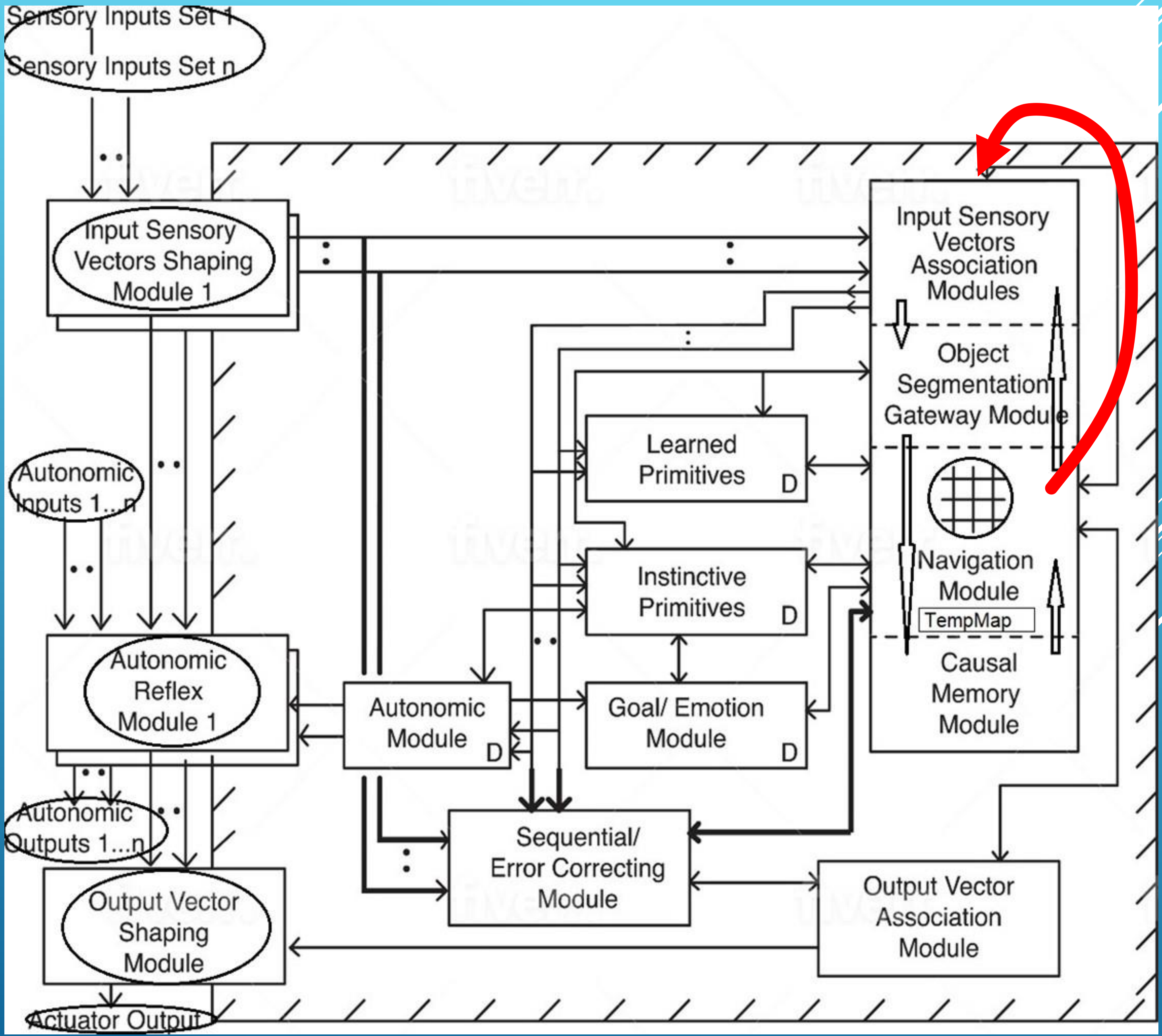
Ubiquitous feedback pathways (mammalian brain) BECAUSE modified predictive coding



Increase in feedback pathway

→full causal abilities

(chimpanzees – no)

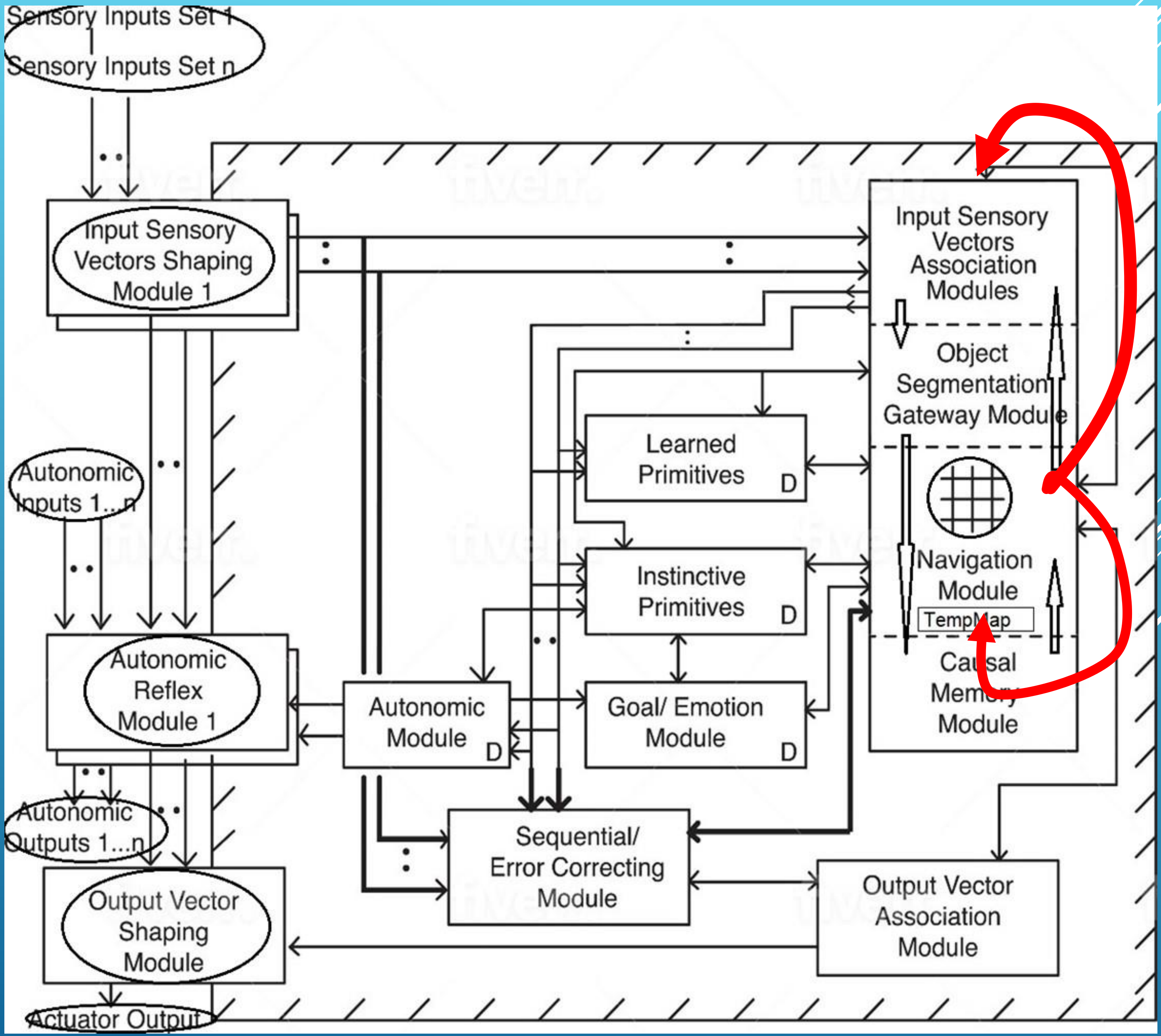


FULL CAUSAL REASONING EMERGES!! (SYSTEM 2 VS SYSTEM 1)

- ($action_t \neq$ “move*” and $\mathbf{WPR}_t \neq$ [“discard*”]) or $\mathbf{WPR}_t =$ [“feedback*”],
- $\Rightarrow$ `Nav_ModA.feedback_to_assocn_mod(`$\mathbf{WNM'}_t$`)` (88)
- $\Rightarrow \forall_\sigma : \mathbf{LNM}_{(\sigma,\Upsilon,t)} =$ `Input_Sens_Vectors_Assoc_Module`$_{\boldsymbol{\sigma}}$`.extract_`σ`(`$\mathbf{WNM'}_{t\text{-}1}$`)` (89)

Another small mutation →full analogical reasoning

(chimpanzees – no)

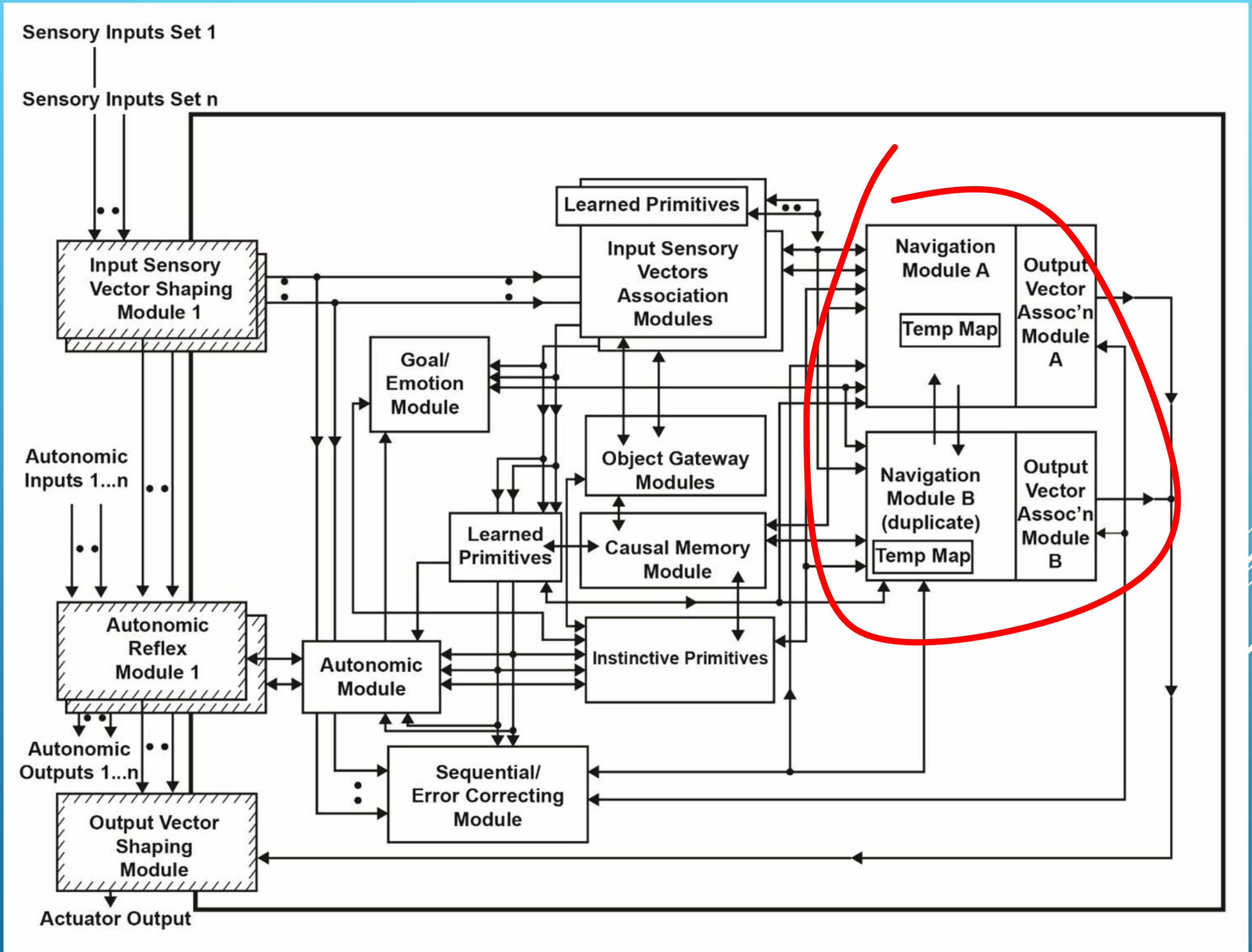


11:00

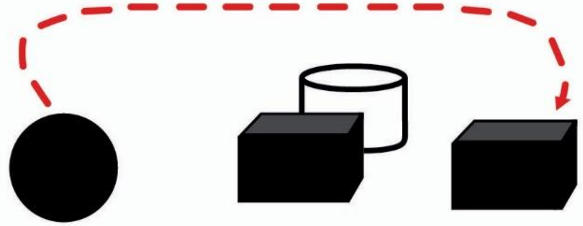
Full Analogical Reasoning Emerges!!

- (($action_t$ ≠" move*" or **WPR**$_t$ = ["analogical*"]) and **WPR**$_t$ ≠ ["discard*"] and **WPR**$_t$ ≠ ["feedback*"]),
- ⇒`Nav_ModA.feedback_to_assocn_mod(`**WNM'**$_t$`)` (90)
- ⇒ **WNM'**$_t$ = `Causal_Mem_Mod.match_best_map(`**WNM'**$_t$`)` (91)
- ⇒ **TempMap**$_t$ = `Nav_ModA.use_linkaddress1_map(`**WNM'**$_t$`)` (92)
- ⇒ **WNM'**$_\mathbf{t}$ = `Nav_ModA.subtract(`**WNM'**$_t$, **TempMap**`)` (93)
-
- (($action_{t-1}$ ≠ "move*" or **WPR**$_{t-1}$ = ["analogical*"]) and **WPR**$_{t-1}$ ≠ ["discard*"] and **WPR**$_{t-1}$ ≠ ["feedback*"]),
- ⇒ **WNM'**$_t$ = `Nav_ModA.retrieve_and_add_vector_assocn()` (94)
  - $P_1\mathbf{x}$ **&** $P_2\mathbf{x}$ **& …** $P_n\mathbf{x}$ (100)
  - $P_1\mathbf{y}$ **&** $P_2\mathbf{y}$ **& …** $P_n\mathbf{y}$ (101)
  - **Ny** (102)
  - ∴ **Nx** □ (103)

- Duplication of the Navigation Modules → Compositional Language Emerges
- (chimpanzee no)



A



B

air	air	air	air	air	air
air	air	air	air	air	air
air	air	air	air	air	air
air	air	air	air	air	air
air	air	cylinder, white, link {0023,0,0,0}	air	air	air
sphere, black, link {0024,0,0,0}	air	block, black, link {0022,3,3,0}	air	black, block, link {0021,0,0,0}	air

C

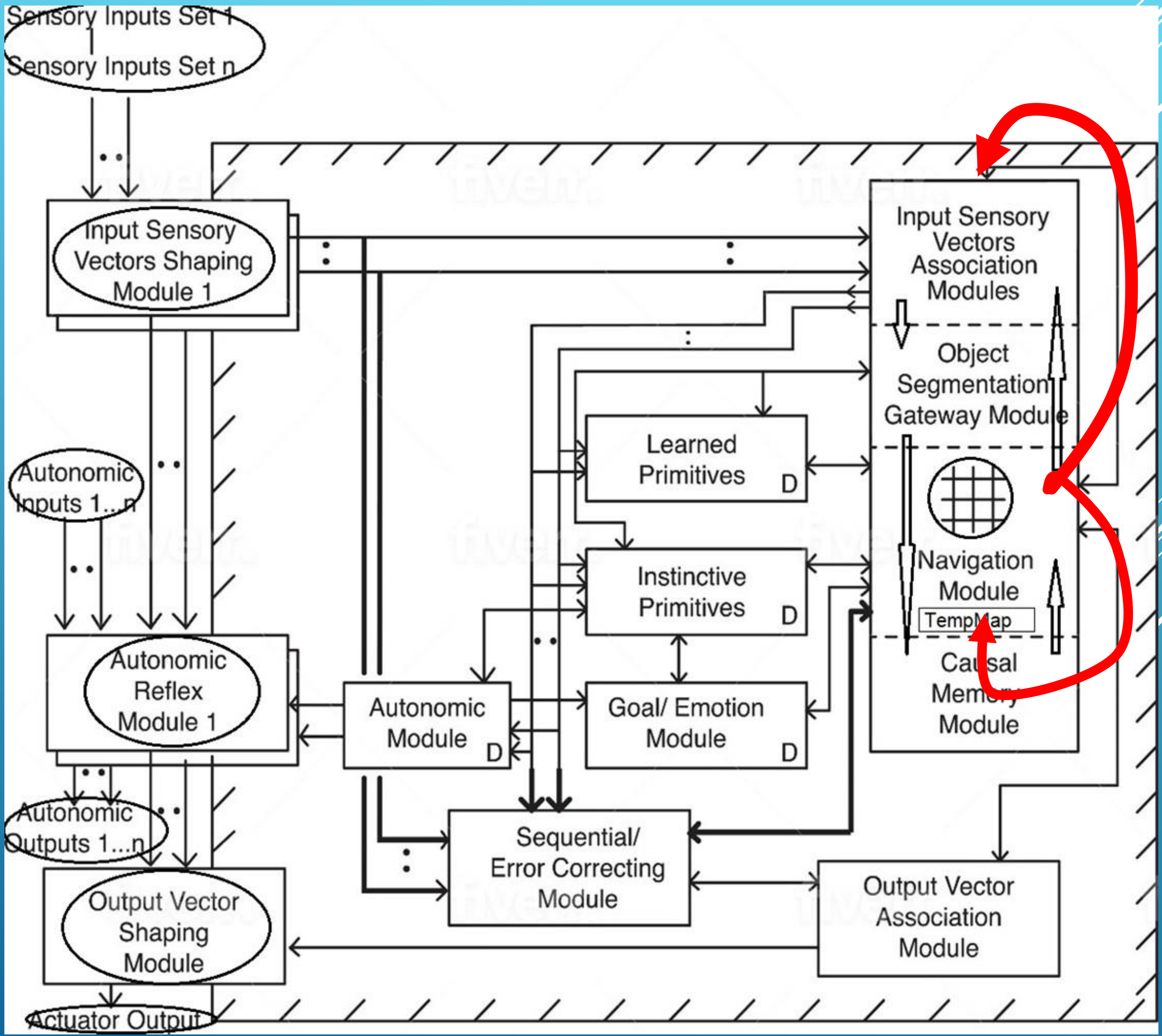
“not”, link {+}	“near”, link {+}	“a”, link {+}	“cylinder”, link {+}		
“of”, link {+}	“the”, link {+}	“black”, link {+}	“block”, link {+}	“which”, link {+}	“is”, link {+}
“place”, link {+}	“the”, link {+}	“black”, link {+}	“sphere”, link {+}	“on”, , link {+}	“top”, link {+}

NEAR-FULL COMPOSITIONAL LANGUAGE EMERGES!!

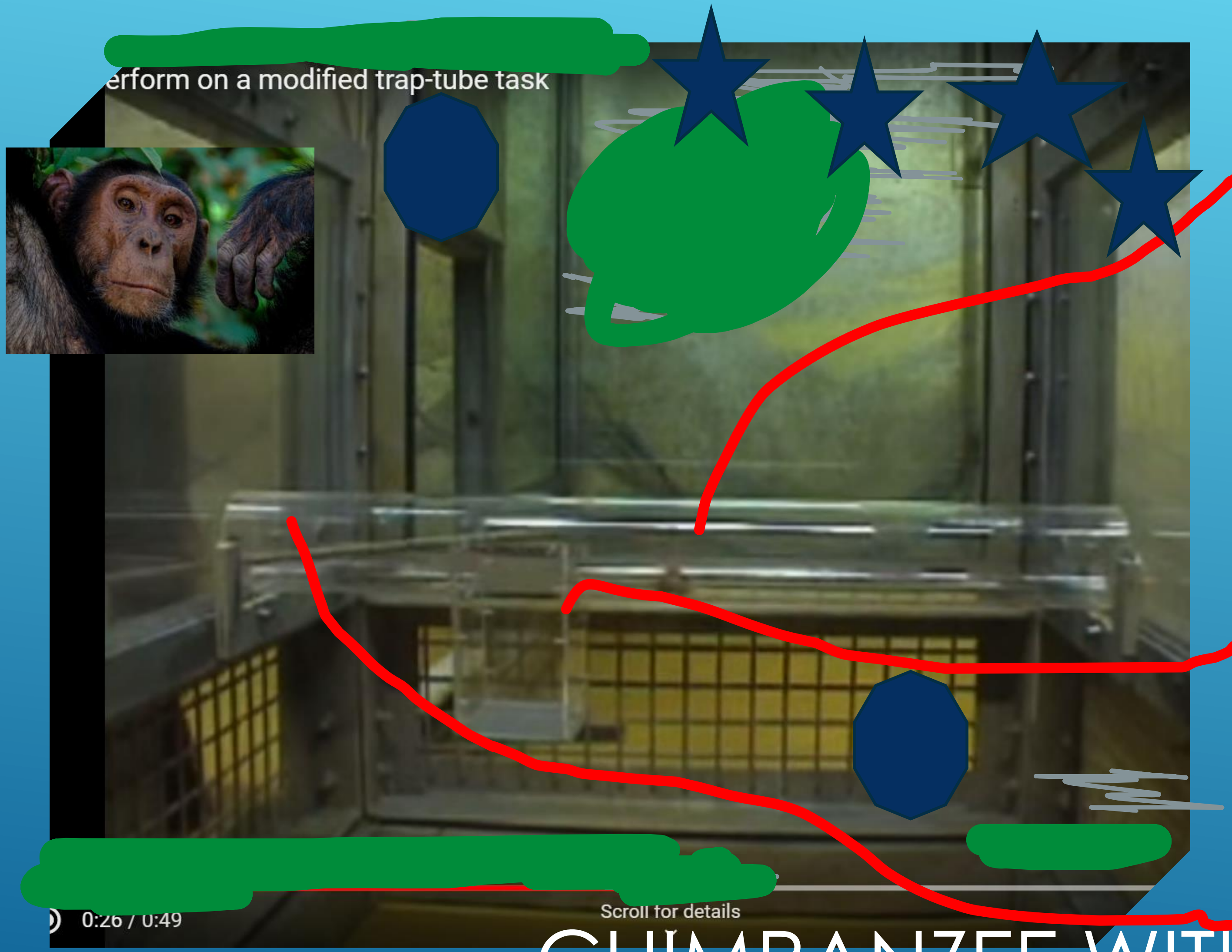
- (*instruction_sentence*),
- ⇒**WNMB'**$_t$ = `Nav_ModB.parse_sentence.copy()` (109)
- ⇒ `Nav_ModB.parse_sentence.parse(`**WNMB'**$_t$`),` (110)
- ⇒ `Nav_ModB.parse_sentence.parse.match()` (111)
- ⇒ ***near_trigger*,**
- ⇒`Nav_ModB.physics_near_object()` (112)
- ⇒ ***end_of_communication*,**
- <*place*>,
- ⇒ `Nav_ModA.place_object()` (113)
- ⇒ `Nav_ModA.move()` (114)

→psychosis

(chimpanzees – no)



12:00



FOOD IN PLEXIGLASS TUBE

GRAVITY TRAP

CHIMPANZEE WITH STICK

youtube image modified by author plus unsplash license chimpanzee face

WHY PREVALENCE OF PSYCHOSIS IN HUMANS?

17% some other psychosis or psychosis-like (van Os et al 2001)
(albeit, 1% schizophrenia)

FROM PLAY-DOH TO:
-HOW THE HUMAN BRAIN EVOLVED √
-HOW THE HUMAN BRAIN WORKS √
-BUILDING AN AGI BASED ON THE BRAIN

Howard Schneider

ISAN MEETING MAY 16/24

FROM PLAY-DOH TO:
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Howard Schneider

ISAN MEETING MAY 16/24

frontiers | Frontiers in Computational Neuroscience

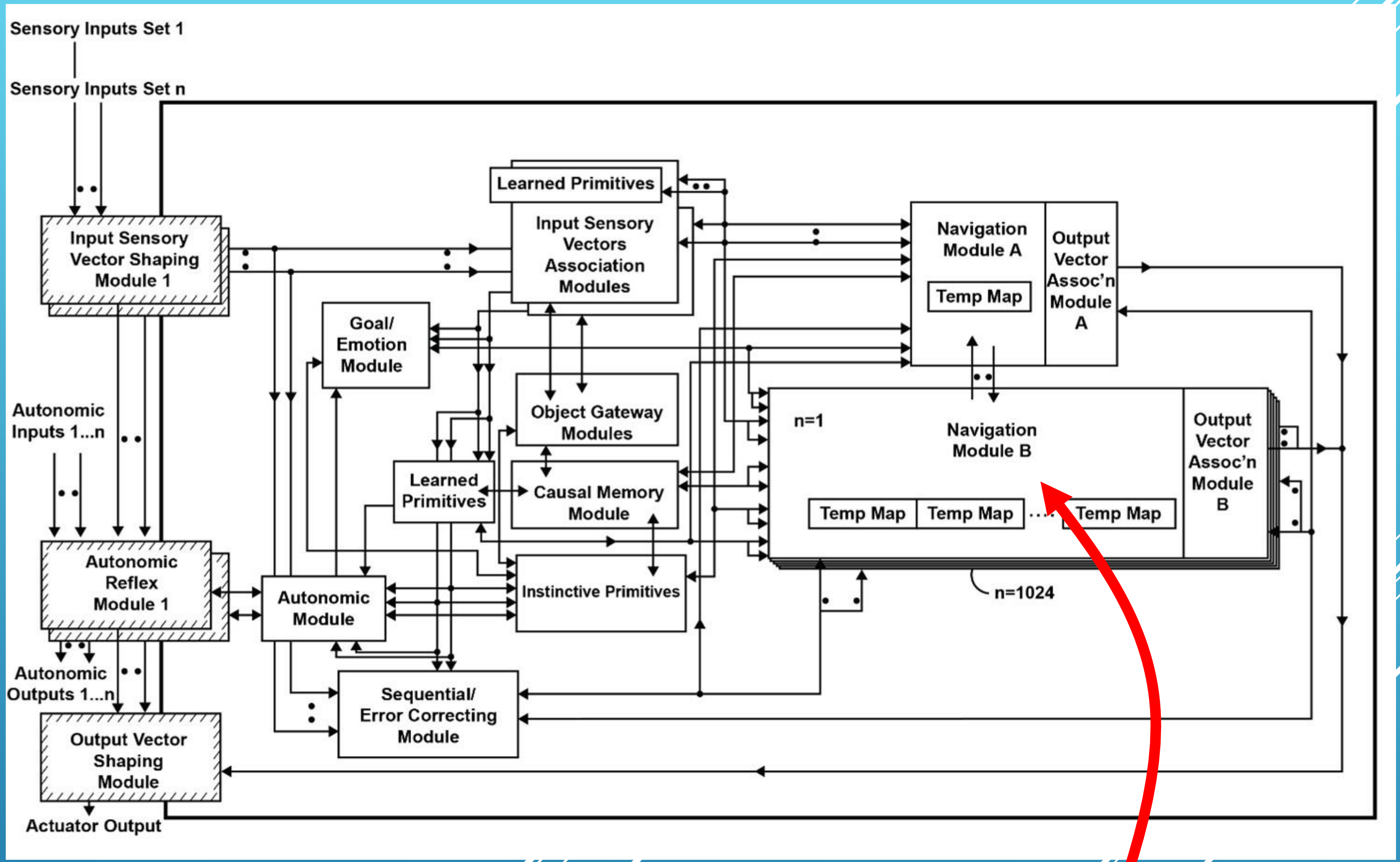
TYPE Hypothesis and Theory
PUBLISHED 07 May 2024
DOI 10.3389/fncom.2024.1367712

The emergence of enhanced intelligence in a brain-inspired cognitive architecture

I am claiming elements of superintelligence

Howard Schneider*

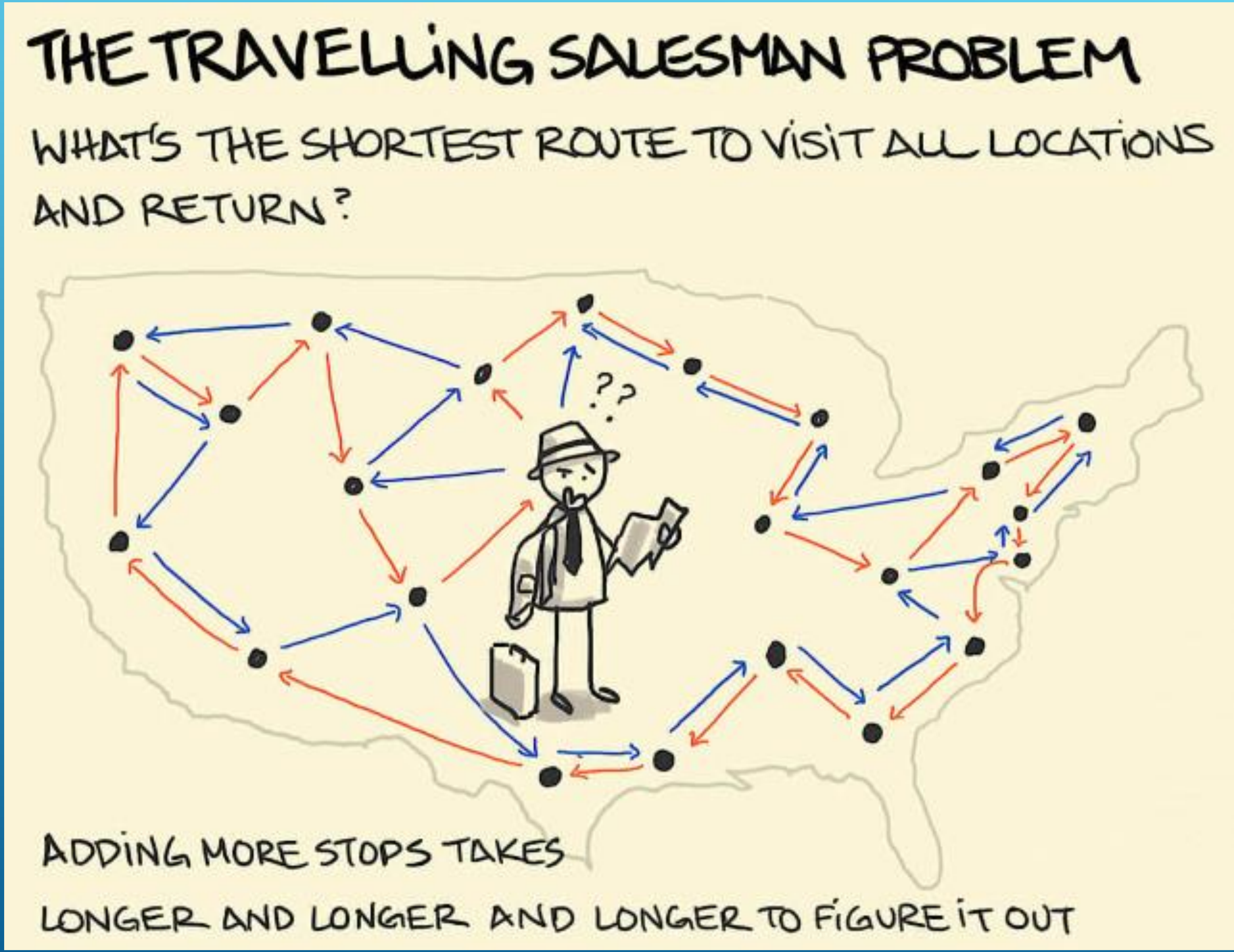
Another route to AGI (CCA7) (super-human)



Duplication of Navigation Module B

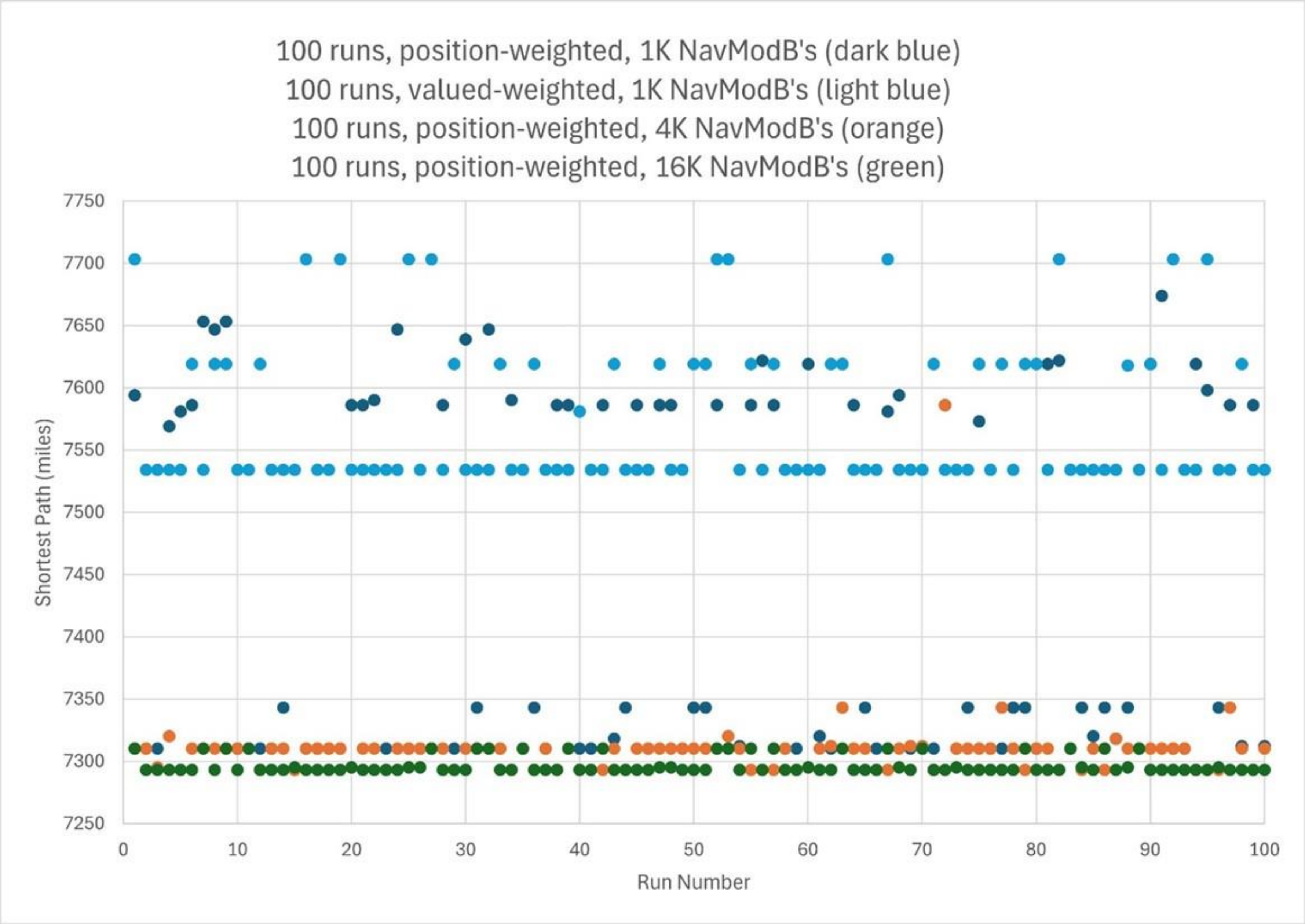
13:00

Traveling Salesperson Problem



Traveling Salesperson Problem

City#0: [0, 2451, 713, 1018, 1631, 1374, 2408, 213, 2571, 875, 1420, 2145, 1972],
City#1: [2451, 0, 1745, 1524, 831, 1240, 959, 2596, 403, 1589, 1374, 357, 579],
City#2: [713, 1745, 0, 355, 920, 803, 1737, 851, 1858, 262, 940, 1453, 1260],
City#3: [1018, 1524, 355, 0, 700, 862, 1395, 1123, 1584, 466, 1056, 1280, 987],
City#4: [1631, 831, 920, 700, 0, 663, 1021, 1769, 949, 796, 879, 586, 371],
City#5: [1374, 1240, 803, 862, 663, 0, 1681, 1551, 1765, 547, 225, 887, 999],
City#6: [2408, 959, 1737, 1395, 1021, 1681, 0, 2493, 678, 1724, 1891, 1114, 701],
City#7: [213, 2596, 851, 1123, 1769, 1551, 2493, 0, 2699, 1038, 1605, 2300, 2099],
City#8: [2571, 403, 1858, 1584, 949, 1765, 678, 2699, 0, 1744, 1645, 653, 600],
City#9: [875, 1589, 262, 466, 796, 547, 1724, 1038, 1744, 0, 679, 1272, 1162],
City#10:[1420, 1374, 940, 1056, 879, 225, 1891, 1605, 1645, 679, 0, 1017, 1200],
City#11:[2145, 357, 1453, 1280, 586, 887, 1114, 2300, 653, 1272, 1017, 0, 504],
City#12:[1972, 579, 1260, 987, 371, 999, 701, 2099, 600, 1162, 1200, 504, 0]



100 runs, position-weighted, 1K NavModB's (dark blue)
100 runs, valued-weighted, 1K NavModB's (light blue)
100 runs, position-weighted, 4K NavModB's (orange)
100 runs, position-weighted, 16K NavModB's (green)
Shortest Path (miles)
7750
7700
7650
7600
7550
7500
7450
7400
7350
7300
7250
0
10
20
30
40
50
60
70
80
90
100
Run Number

Simulated Animal/Tech Group Selected	Traveling Salesperson Problem			Compositionality Problem		
	n (trials)	ave distance	p (vs superhuman)	n (trials)	successful trials	p (vs superhuman)
Fish-like brain/AI	20	20,000.0 (n/c)	p<0.001	20	0%	p<0.001
Reptilian-like brain/AI	20	20,000.0 (n/c)	p<0.001	20	0%	p<0.001
Mammalian-like (non-primate) brain/AI	20	20,000.0 (n/c)	p<0.001	20	0%	p<0.001
Human-like brain/HLAI	20	8131.0	p<0.001	20	100%	p<0.001
Superhuman-like brain/AGI	20	7430.2	--	20	100%	--
Alien AGI (ChatGPT 3.5)	20	10221.3	p<0.001	20	3%	p<0.001
Alien AGI (ChatGPT4)	20	7899.6	p<0.001	20	55%	p<0.001

Table 3. Results of attempts to solve the traveling salesperson problem and the compositionality problem (described in the text) by the different selections of the simulation. A distance of "20,000.0 (n/c)" means the agent was unable to complete the traveling salesperson problem.

14:00

“Navigation Map” Model of the brain seems to work….

FROM PLAY-DOH TO:

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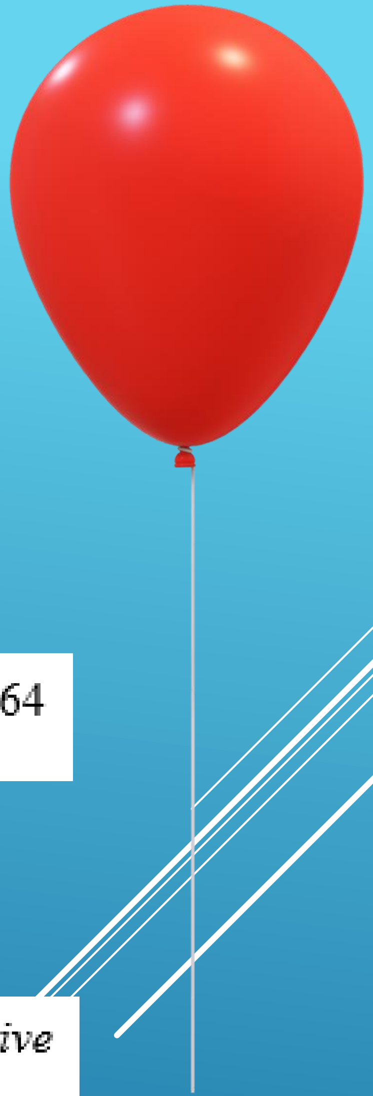
MORE DETAILS



Cognitive Architecture with Navigation Maps and Emergence of Causal Reasoning

Schneider, H. (2021). Causal Cognitive Architecture 1: Integration of connectionist elements into a navigation-based framework. *Cognitive Systems Research* **66**:67-81 doi: 10.1016/j.cogsys.2020.10.021

Schneider, H. (2022b). Navigation Map-Based Artificial Intelligence. *AI*, **3**(2) 434-464 doi:10.3390/ai3020026

Spatial and temporal binding onto Navigation Maps

Schneider, H. (2022a). Causal cognitive architecture 3: A Solution to the binding problem. *Cognitive Systems Research* **72**:88-115 doi: 10.1016/j.cogsys.2021.10.004

MORE DETAILS

Grounding
Lifetime Learning
Emergence of Analogical Reasoning

Schneider, H. (2023). An Inductive Analogical Solution to the Grounding Problem. *Cognitive Systems Research*, 77:74-216 doi: 10.1016/j.cogsys.2022.10.005

Emergence of Compositionality and Compositional Language

Schneider, H. (2024). The emergence of compositionality in a brain-inspired cognitive architecture. *Cognitive Systems Research*, **86**, 101215. https://doi.org/10.1016/j.cogsys.2024.101215

MORE DETAILS

Emergence of Psychotic Disorder in Humans
(earlier architecture but very similar)

Schneider, H. (2020). The Meaningful-Based Cognitive Architecture Model of Schizophrenia. *Cognitive Systems Research* **59** 73-90 doi: 10.1016/j.cogsys.2019.09.01

Emergence of AGI and Superintelligence from the Model

Schneider, H., & Bołtuć, P. (2023, May). Alien Versus Natural-Like Artificial General Intelligences. In *International Conference on Artificial General Intelligence* (pp. 233-243). Cham: Springer Nature Switzerland.

Schneider, H. (2024).The Emergence of an Enhanced Intelligence in a Brain-Inspired Cognitive Architecture, *Frontiers in Computational Neuroscience*, 18: 1367712. https://www.frontiersin.org/articles/10.3389/fncom.2024.1367712/abstract