Radical Platonism and Radical Empiricism

A discussion of Michael Levin's work as it pertains to his new research on morphospace and “radical platonism” including the use of probabilistic knowledge graphs and other formal methods to test these novel hypotheses.

Most specifically, how can we formalize the language of form itself?

Outline

Levin Lab Research Program
Key philosophical questions
Morphospace-etymology and evolution
Morpho-empiricism 101
Levin Lab Morphospace
Bayesian + Knowledge Graphs
Knowledge Graphs in Science
Levin in PKGs
Beauty and form, a side topic?
Next steps

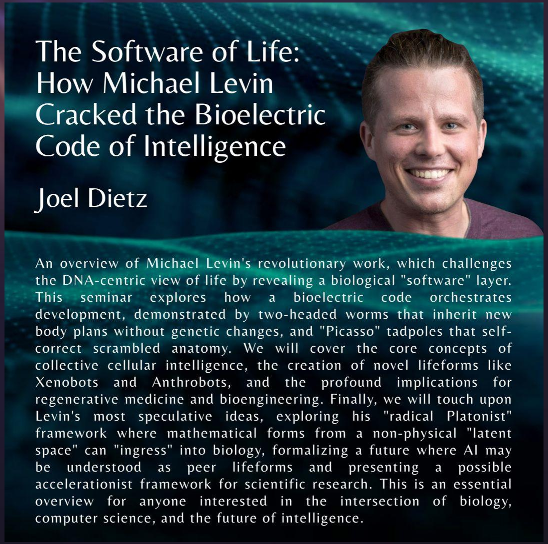
Disclaimer : firehose

Research Program:

- Build new interfaces to observe new ingressing forms - our synthetic morphology work provides tools/vehicles/periscopes for exploration of the space.
- Infer a rigorous mapping between properties of the pointers and the patterns they facilitate
- Quantify the "free lunch" aspects - how much information/influence/evolvability is injected into the physical world? Free compute?
- Are the contents of this space under positive pressure?
- Is the space sparse? Are some attractors "better" than others?
- Are the contents of this space purely passive (eternal, unchanging) or can we define a kind of "chemistry" of how these things interact and live in their own space?
- Are mathematical objects really "low agency"? Can we extend standard behaviorist tests to their native space?
- Why? Where did the Platonic Space and its structure/contents 'come from'? Could it have been otherwise?

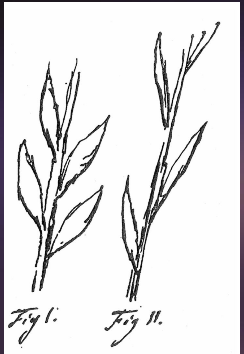
Methodology

What do we actually know?
How can we extend this knowledge?
If we find an edge case that shows “ingress” or phenomena not covered in our formal system, how can we evolve the system without introducing “fuzzy logic”? (i.e. classic problem of platonisms)
How can we teach this knowledge to others and allow them to do the same?



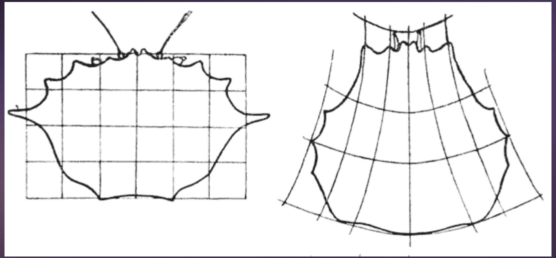
Morphospace

History

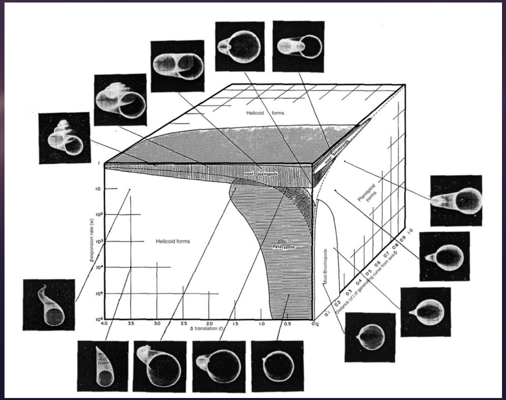


Goethe, 1786 , “ Urpflanze”

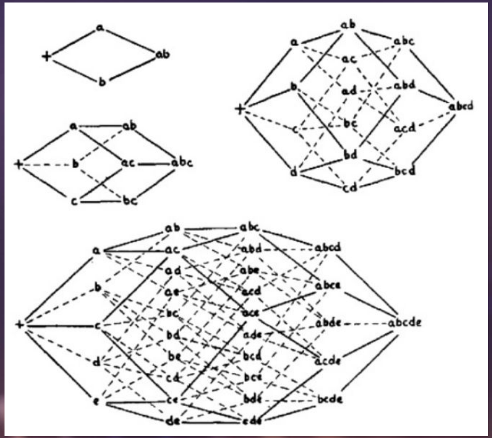
Ulrich E Stegmann, Annals of Botany, Volume 127, Issue 4, 1 April 2021, Pages 411–412



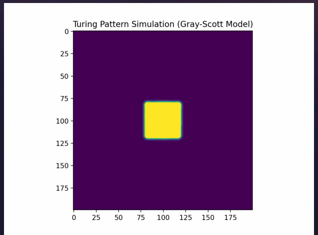
D’Arcy Thompson, Growth and Form, 1917



Raup DM (1966) Geometric analysis of shell coiling: General problems. Journal of Paleontology 40: 1178–1190.



Wright S (1932) The roles of mutation, inbreeding, crossbreeding, and selection in evolution. Proceedings of the Sixth International Congress of Genetics 1: 356–366



Alan Turing, The Chemical Basis of Morphogenesis, 1952

Raup (1962)

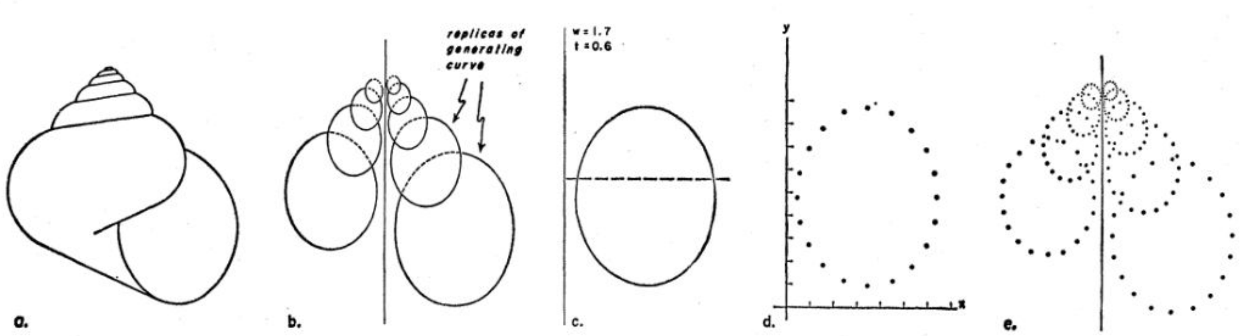


Fig. 1. Stages in the reconstruction of snail form from the four basic parameters.

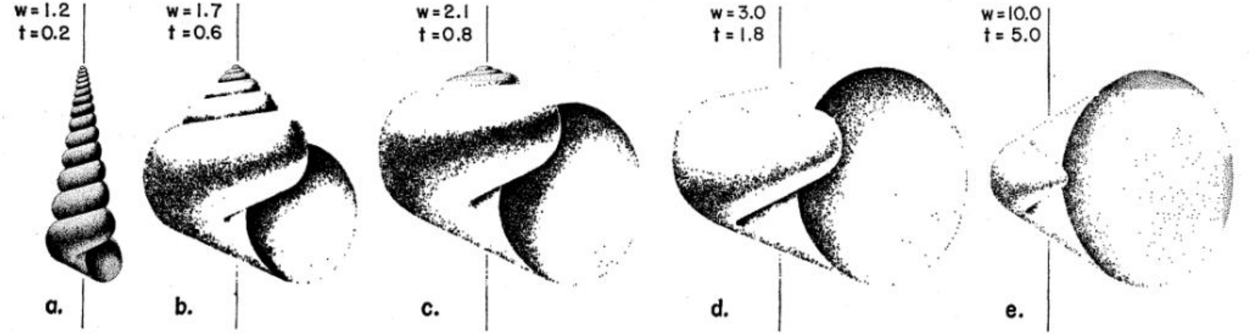
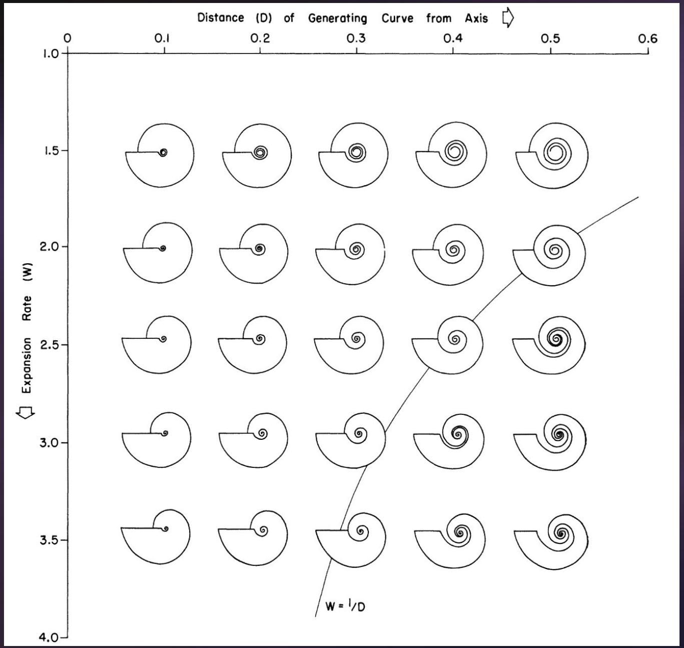
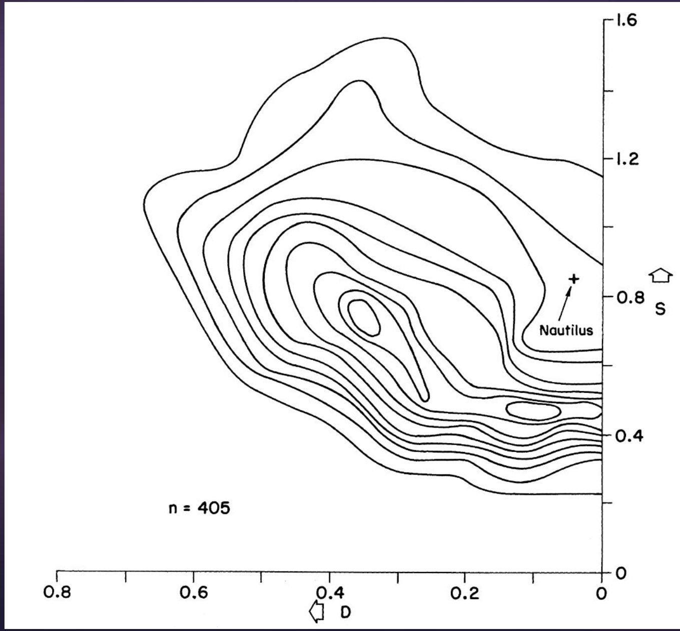


Fig. 2. Hypothetical snail forms drawn from cross sections made by the computer method.

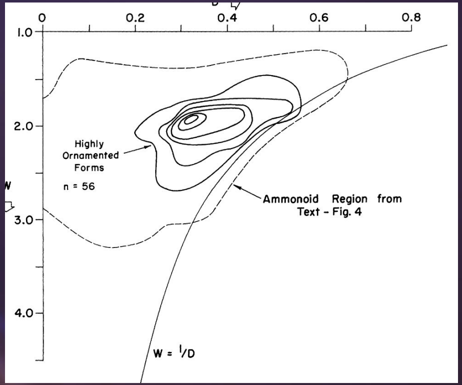
Raup (1967+)



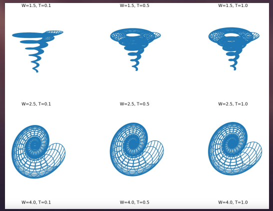
Distance (D) of Generating Curve from Axis
0
0.1
0.2
0.3
0.4
0.5
0.6
1.0
1.5
2.0
2.5
3.0
3.5
4.0
Expansion Rate (W)
W = 1/D



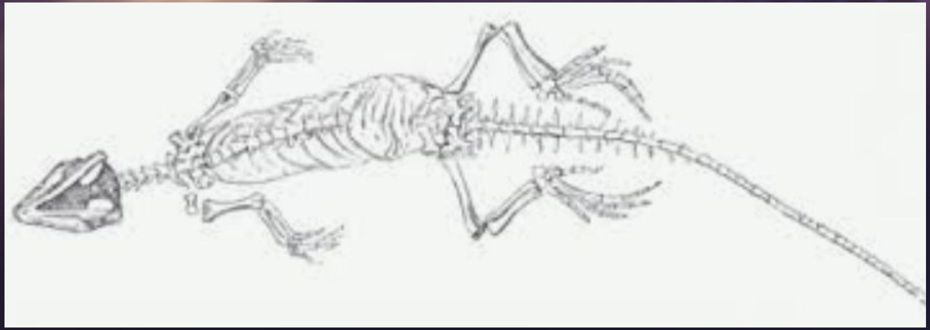
1.6
1.2
0.8
0.4
0
S
Nautilus
n = 405
0.8
0.6
0.4
0.2
0
D

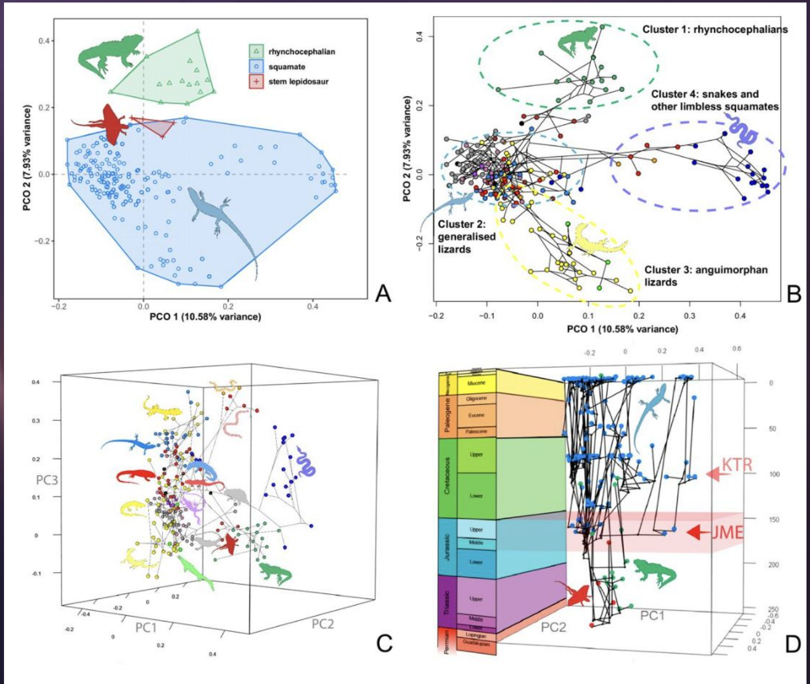


0
0.2
0.4
0.6
0.8
1.0
2.0
3.0
4.0
Highly Ornamented Forms
n = 56
Ammonoid Region from Text - Fig. 4
W = 1/D



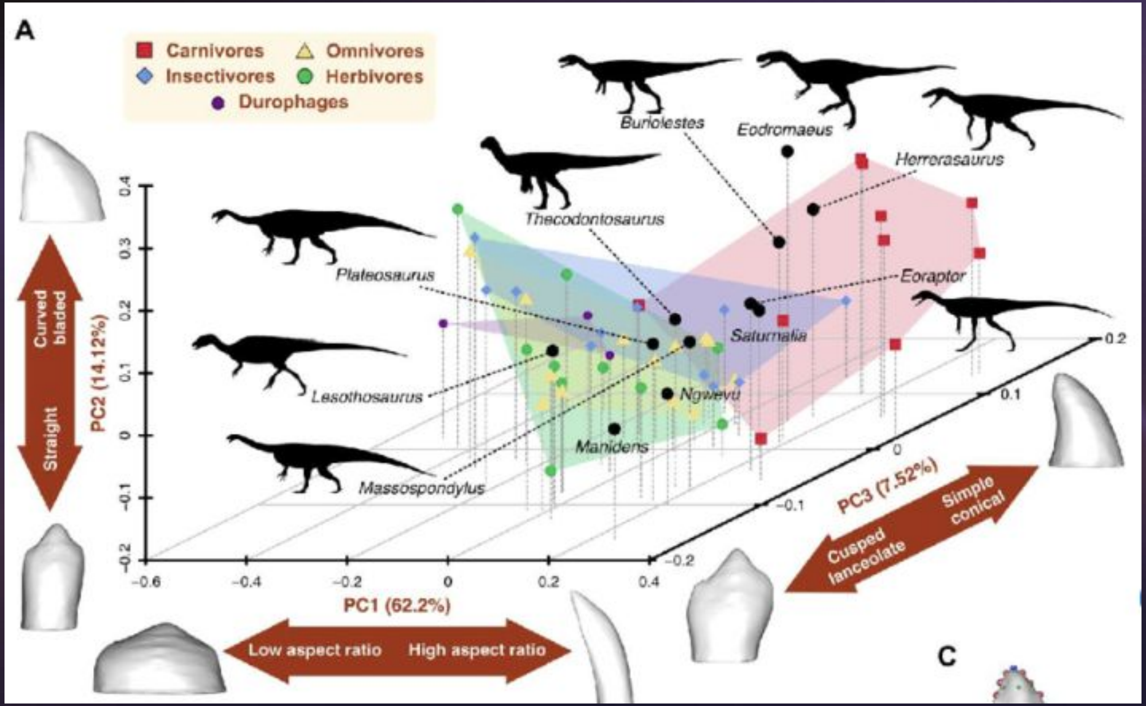
Squamata morphospace

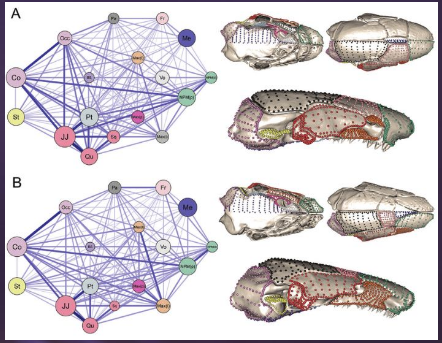


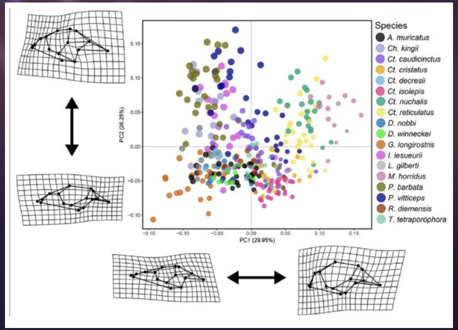


Arnau BoletThomas L StubbsJorge A Herrera-FloresMichael J Benton (2022) The Jurassic rise of squamates as supported by lepidosaur disparity and evolutionary rates eLife 11:e66511. https://doi.org/10.7554/eLife.66511

Dental and cranial morphospace



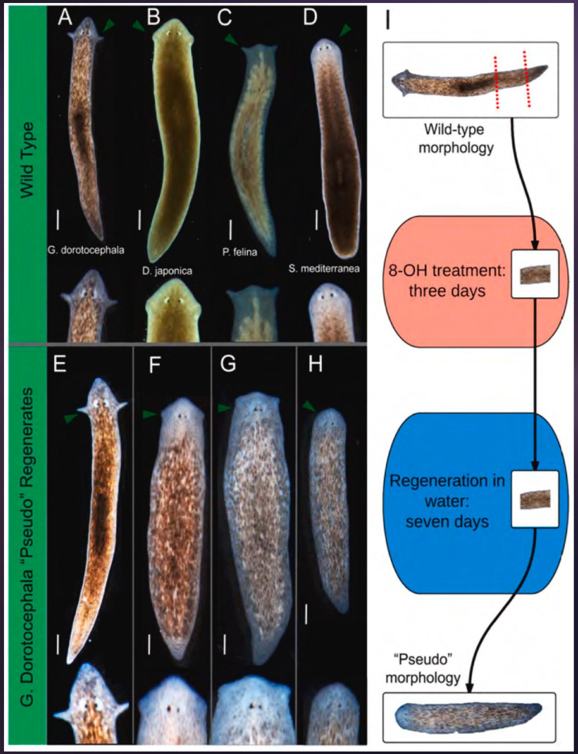


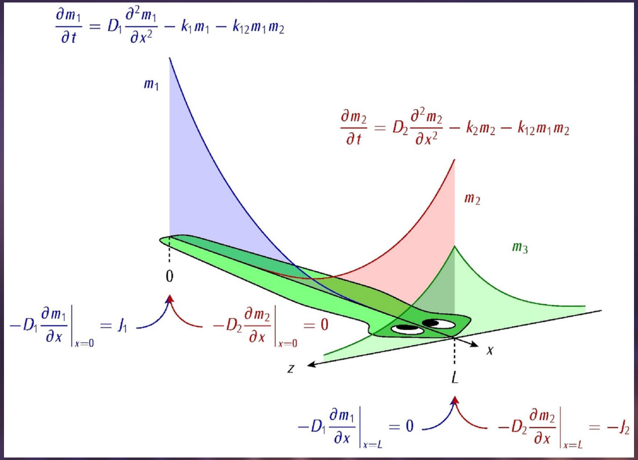


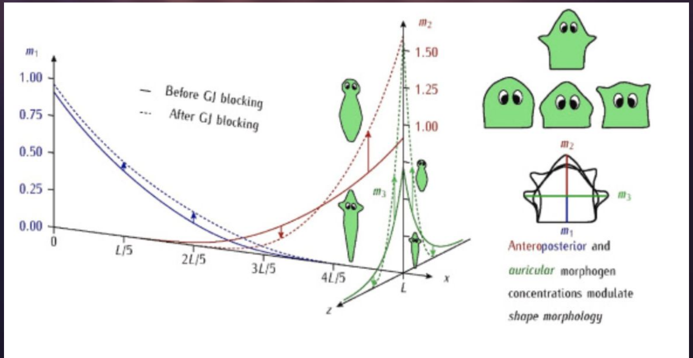
Ballell, Antonio & Benton, Michael & Rayfield, Emily. (2022). Dental form and function in the early feeding diversification of dinosaurs. Science Advances. 8. 10.1126/sciadv.abq5201.

Marshall, Ashleigh & Bardua, Carla & Gower, David & Wilkinson, Mark & Sherratt, Emma & Goswami, Anjali. (2019). High-density three-dimensional morphometric analyses support conserved static (intraspecific) modularity in caecilian (Amphibia: Gymnophiona) crania. Biological Journal of the Linnean Society. 126. 721-742. 10.1093/biolinnean/blz001.

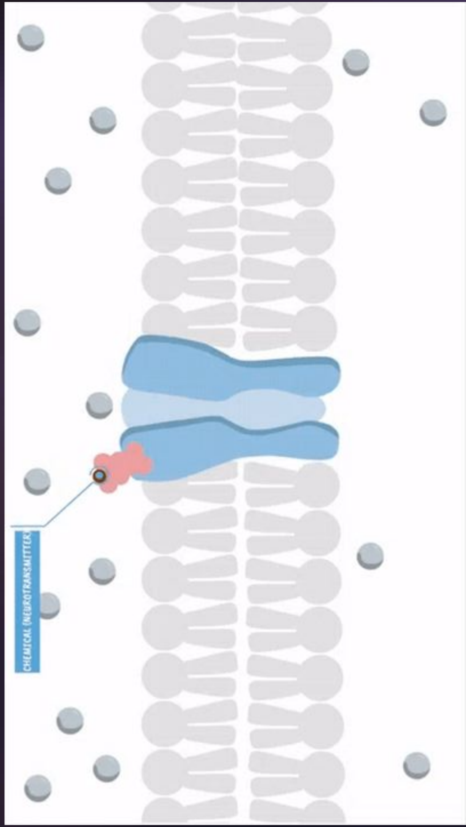
Levin morphospace

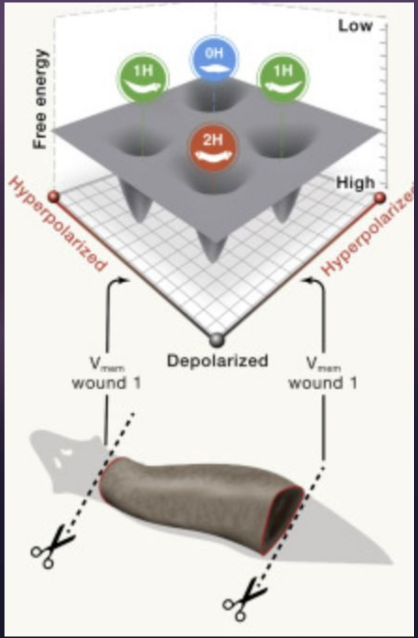






Basal cognition and Biomedical implications

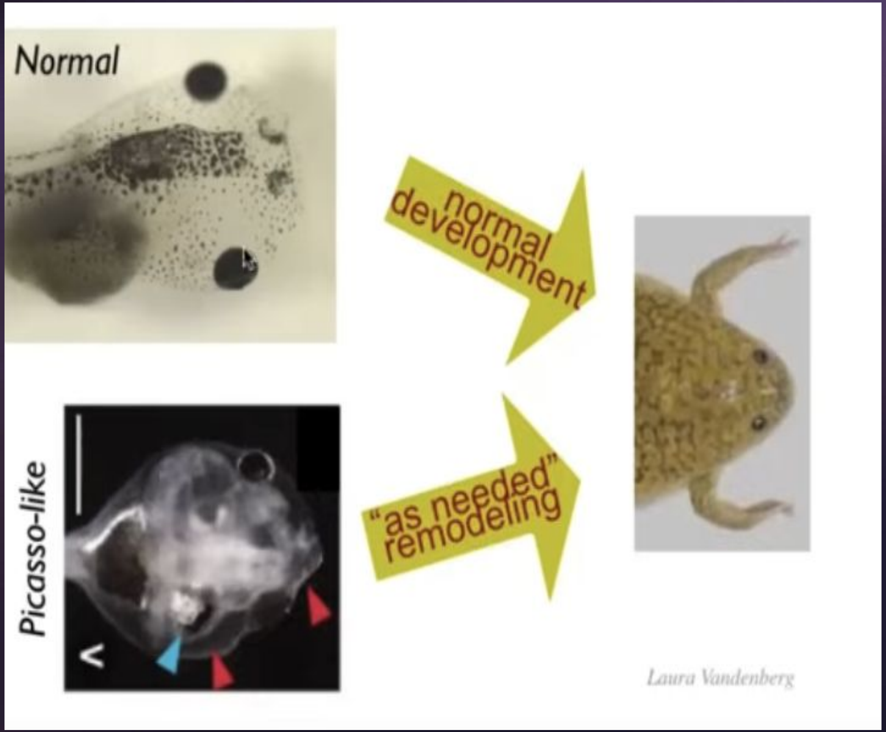


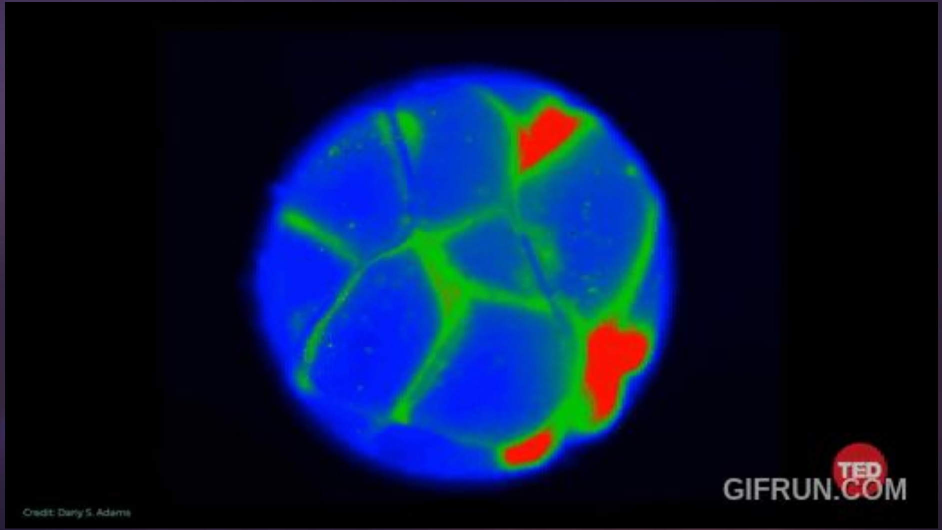


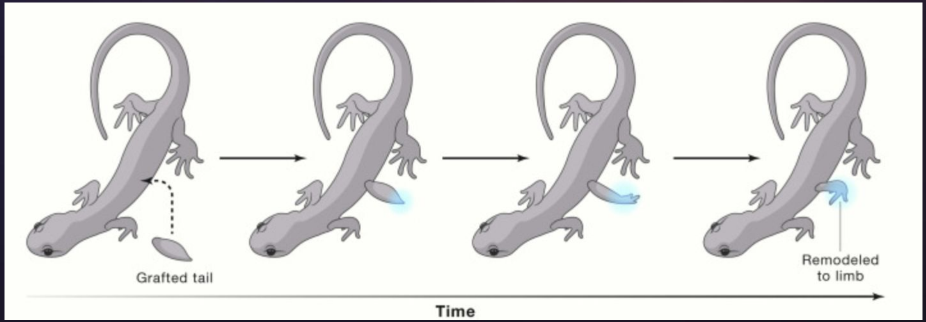
"Ion-channel-targeting drugs are the 3rd best-selling group of prescribed drugs, and only a few of the estimated 400 annotated ion-channel genes predicted in the human genome have yet been targeted"

Levin M. Bioelectric signaling: Reprogrammable circuits underlying embryogenesis, regeneration, and cancer. Cell. 2021 Apr 15;184(8):1971-1989. doi: 10.1016/j.cell.2021.02.034. Epub 2021 Apr 6. PMID: 33826908.

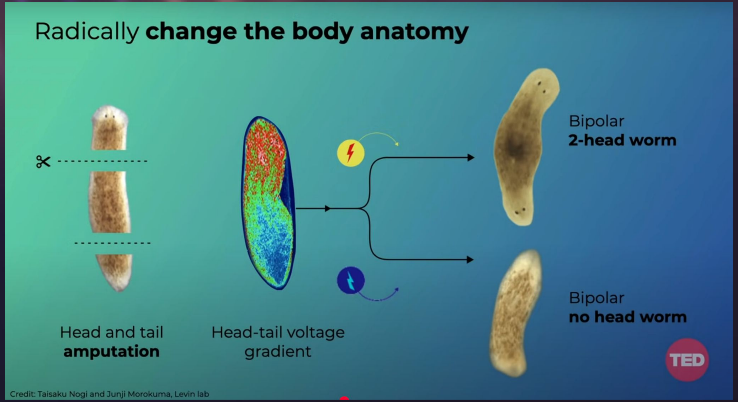
Morphogenesis and the Picasso tadpole (2012)



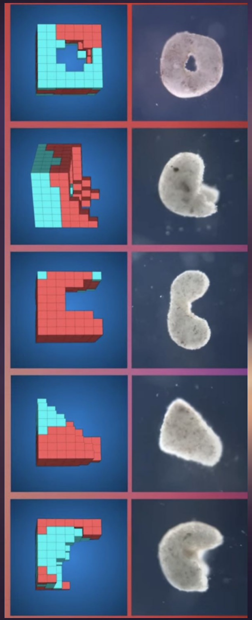


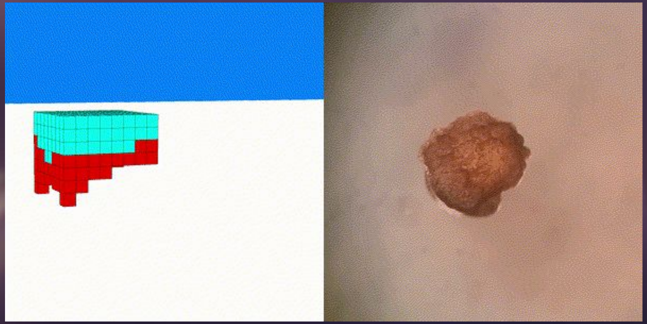


Anatomical Homeostasis & Bioelectric Memory (2018)



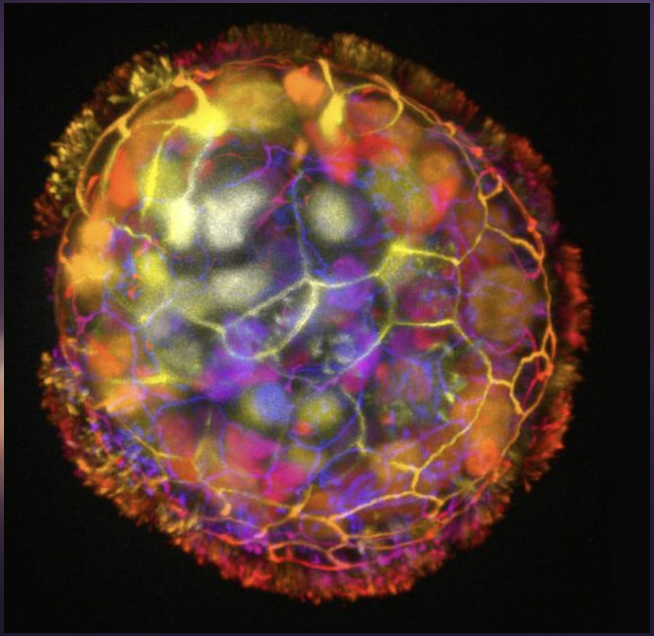
Xenobots (2020)

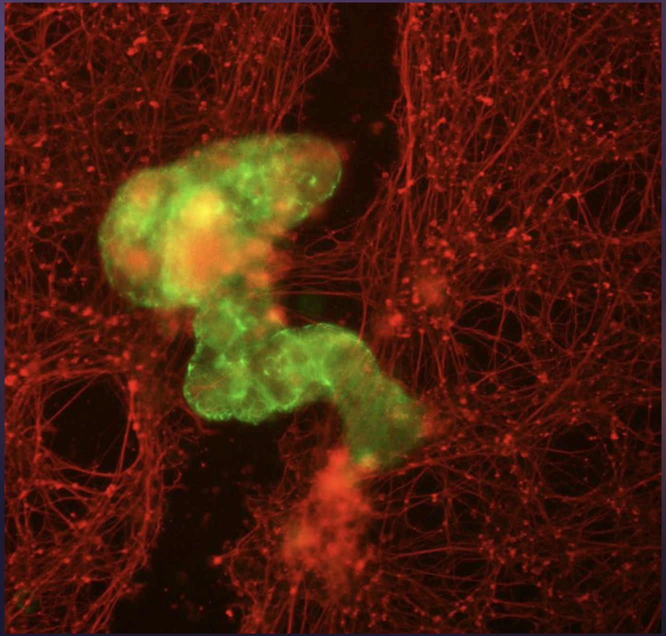




https://xenobots.github.io/
https://github.com/skriegman/reconfigurable_organisms

Anthrobots

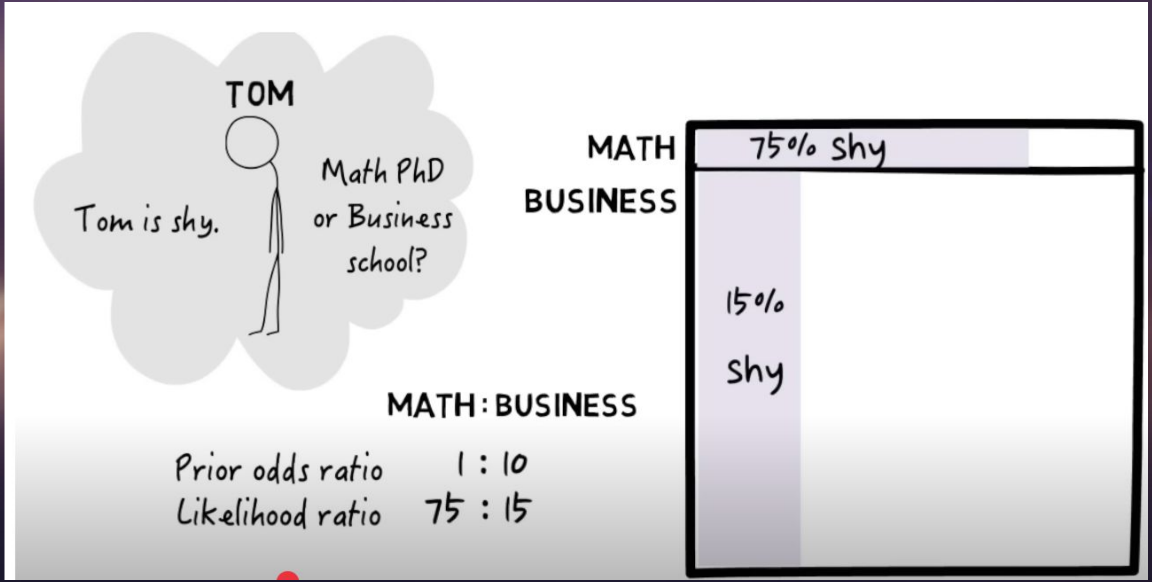




Gizem Gumuskaya, Tufts University

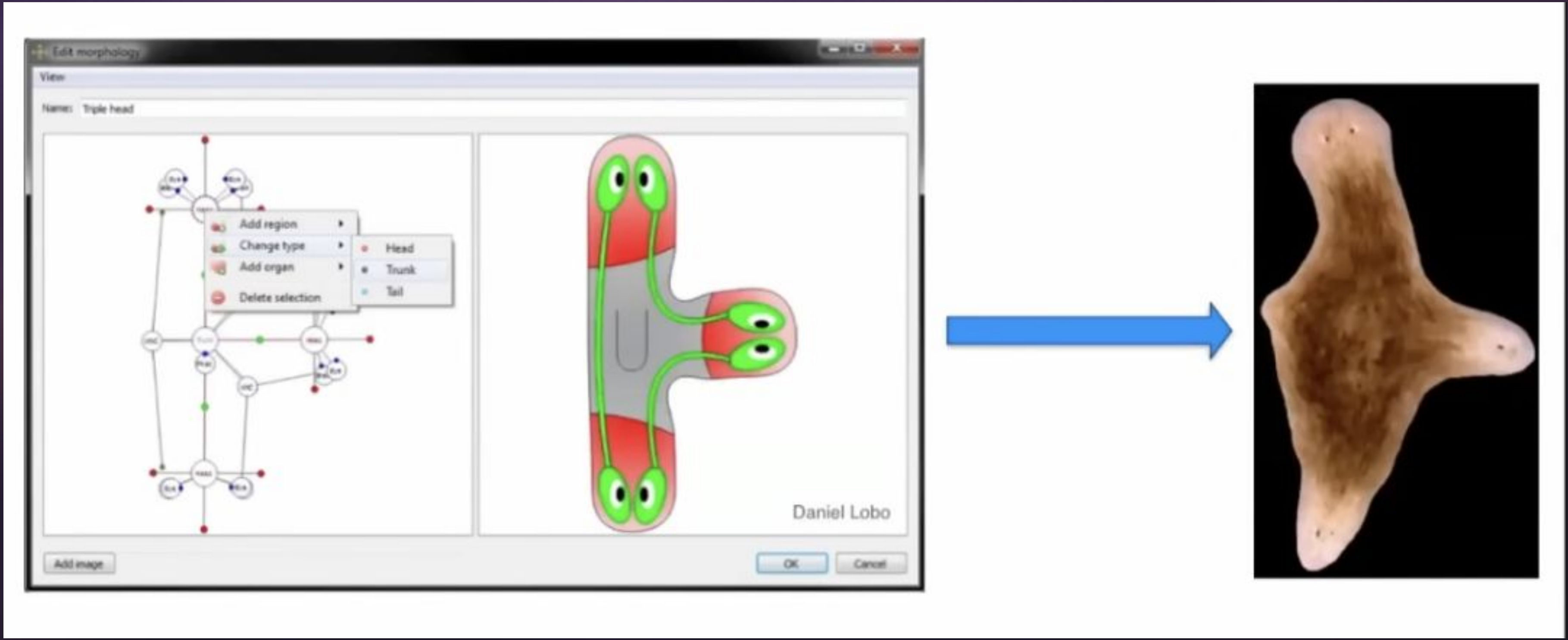
Bayesian Thinking 101

Hypothesis -> Simulation -> Test data against empiricism -> restart loop

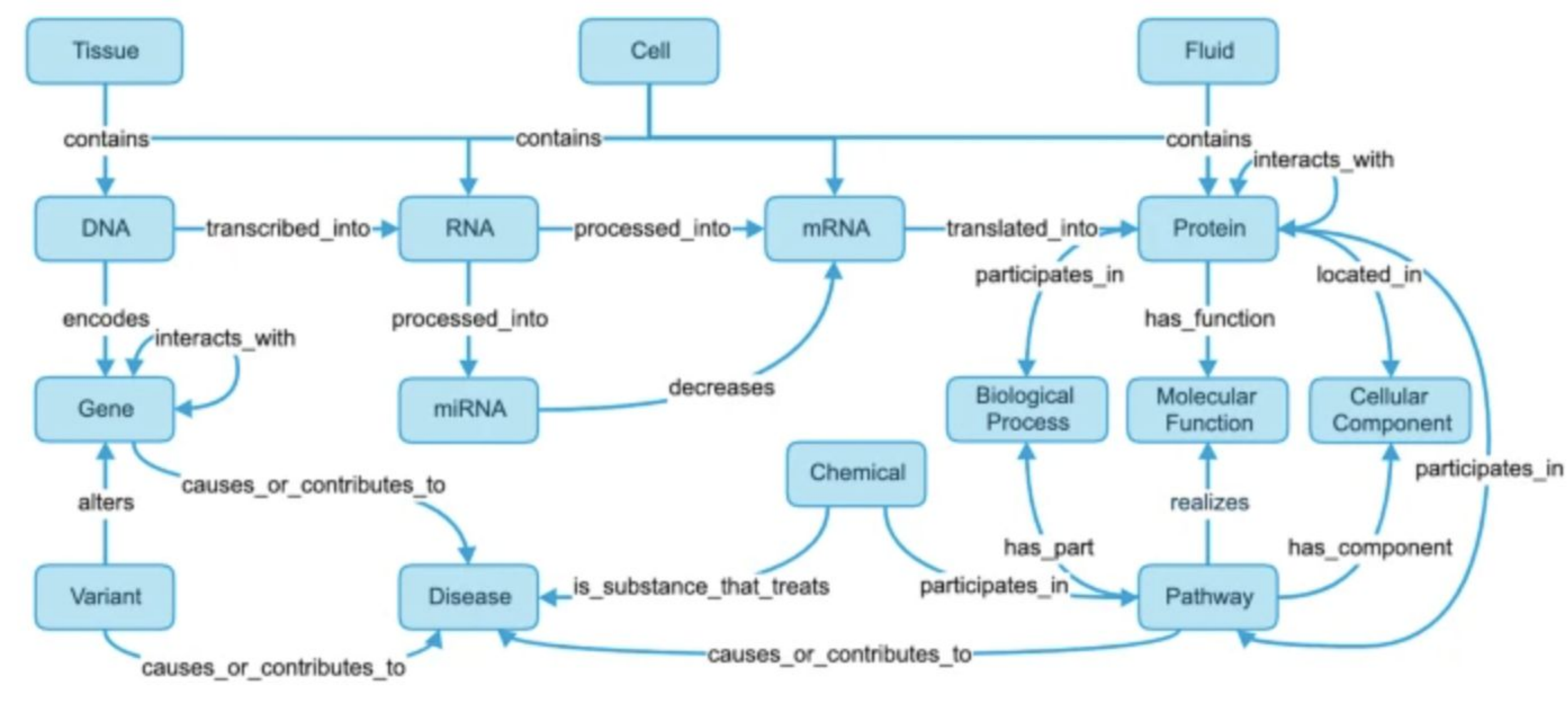


Galef, J. (2016, September 29). A visual guide to Bayesian thinking [Video]. YouTube. https://www.youtube.com/watch?v=BrK7X_XlGB8

Anatomical Compiler

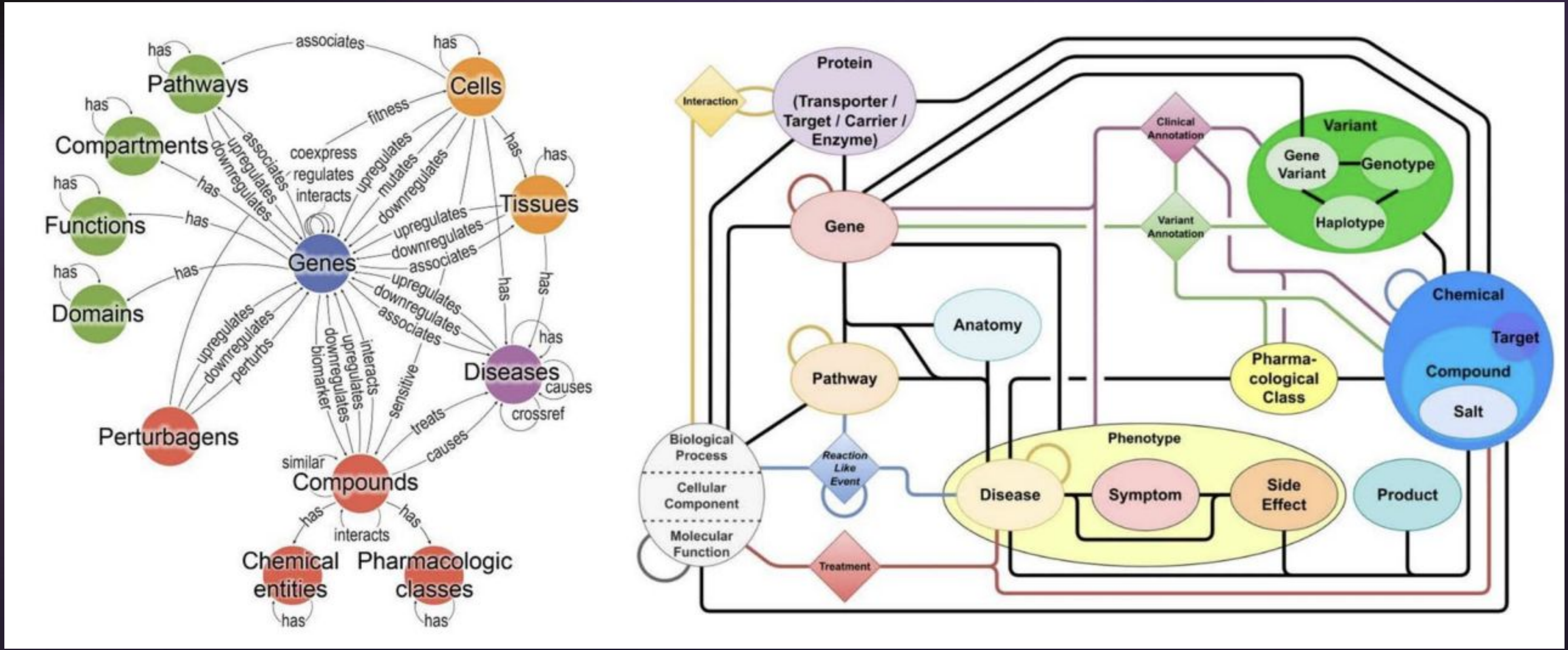


Knowledge graphs in science



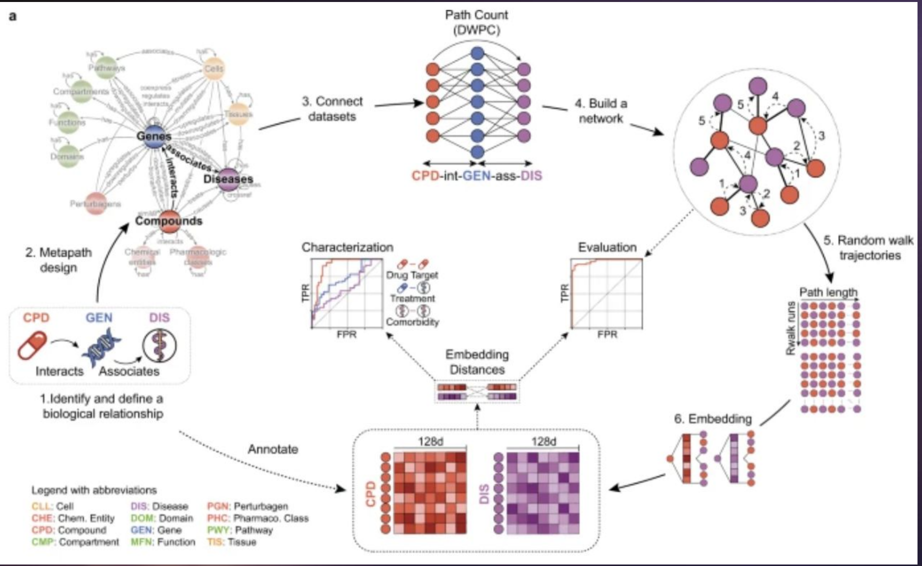
Callahan, T. J., I. J. Tripodi, A. L. Stefanski, L. Cappelletti, S. B. Taneja, J. M. Wyrwa, E. Casiraghi, et al. 2024. "An Open Source Knowledge Graph Ecosystem for the Life Sciences." Scientific Data 11 (1): 363. https://doi.org/10.1038/s41597-024-03171-w.

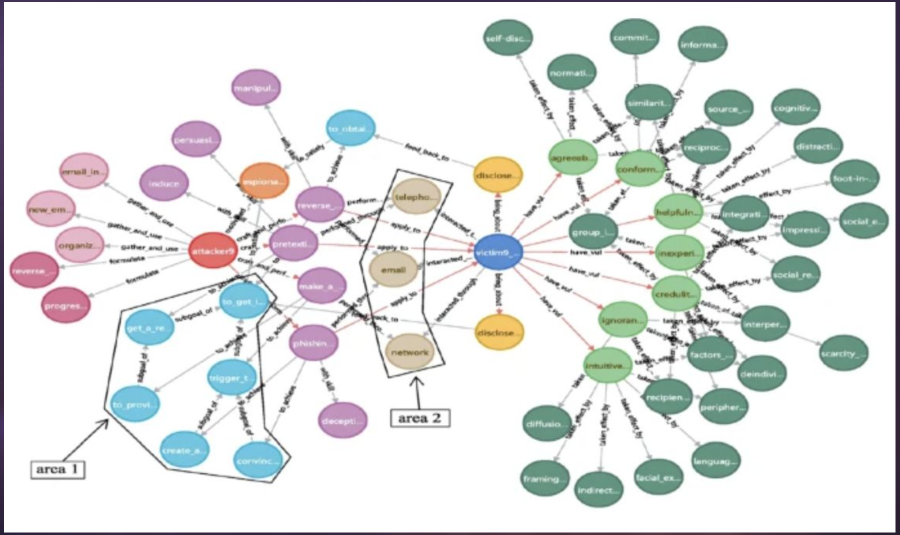
Knowledge graphs in science



Pablo Perdomo-Quinteiro, Alberto Belmonte-Hernández, Knowledge Graphs for drug repurposing: a review of databases and methods, Briefings in Bioinformatics, Volume 25, Issue 6, November 2024, bbae461, https://doi.org/10.1093/bib/bbae461

Knowledge graphs and machine learning

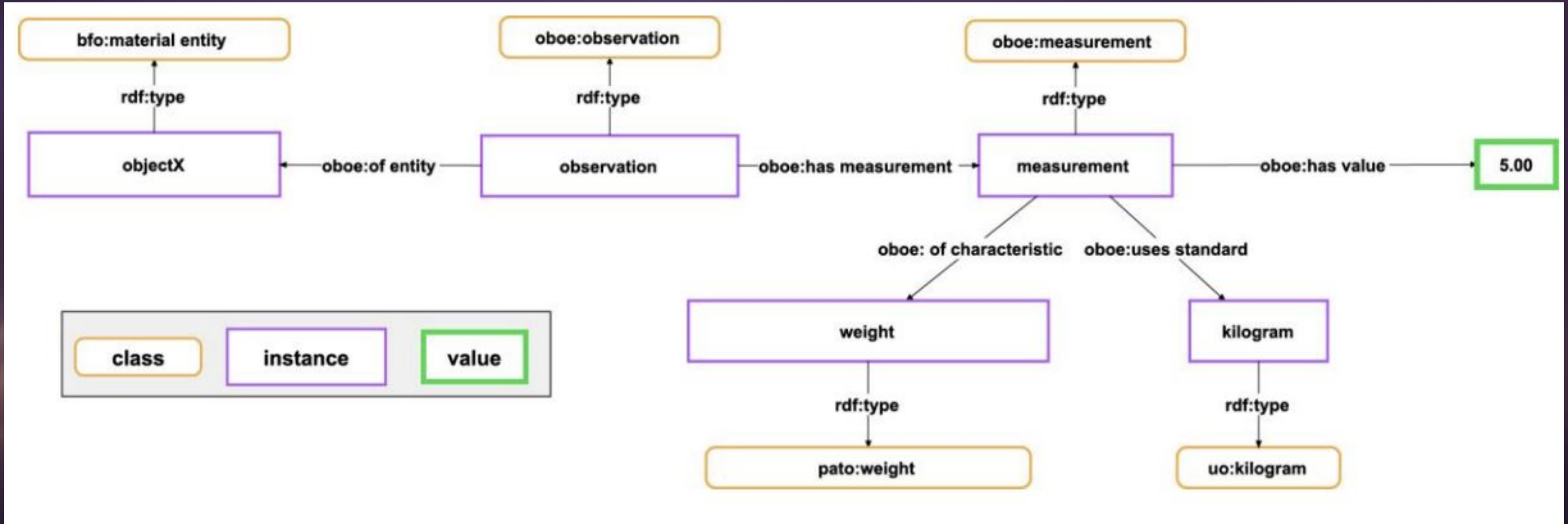




Fernández-Torras, A., Duran-Frigola, M., Bertoni, M. *et al.* Integrating and formatting biomedical data as pre-calculated knowledge graph embeddings in the Bioteque. *Nat Commun* 13, 5304 (2022). https://doi.org/10.1038/s41467-022-33026-0

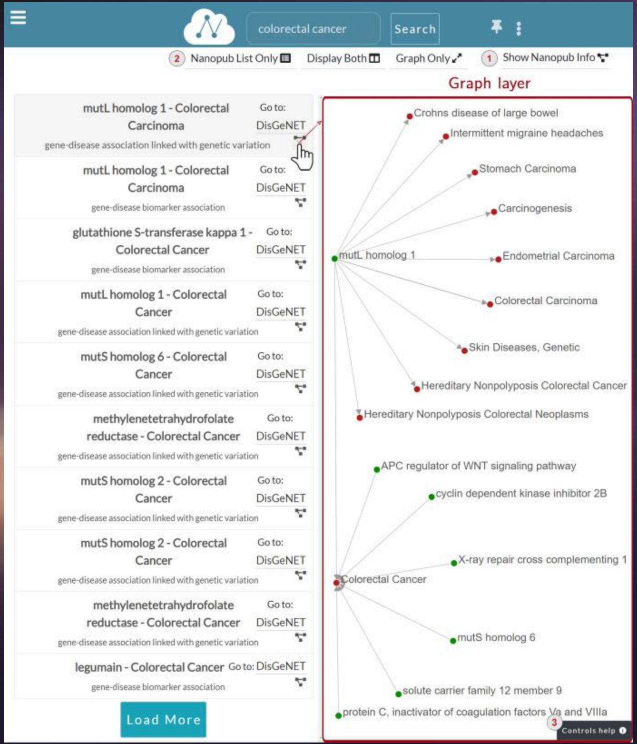
Sikos, L.F. Cybersecurity knowledge graphs. Knowl Inf Syst 65, 3511–3531 (2023). https://doi.org/10.1007/s10115-023-01860-3

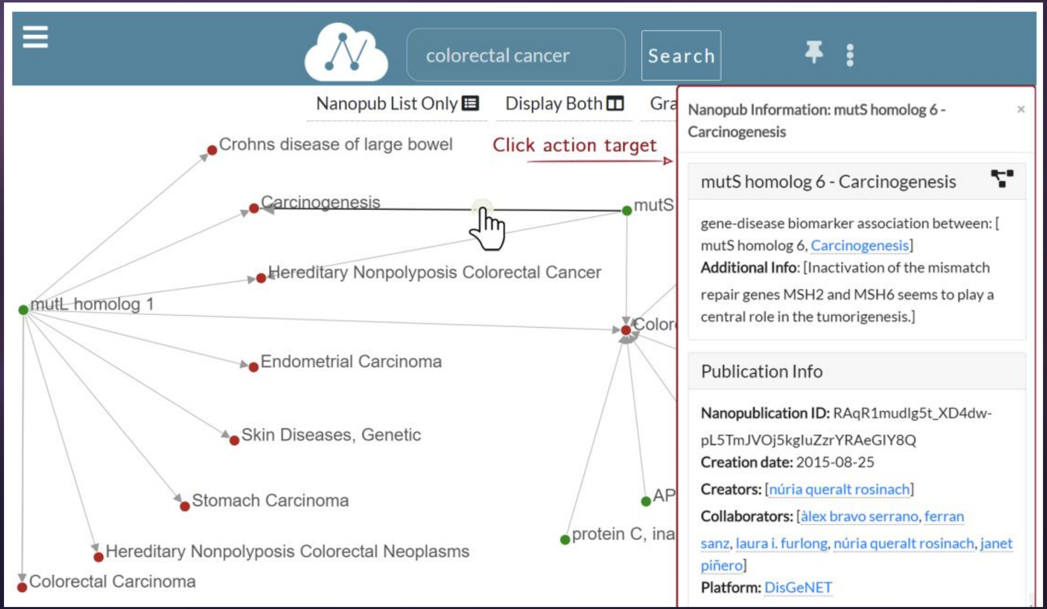
Knowledge graph ontology



Vogt, Lars, Tobias Kuhn, and Robert Hoehndorf. 2023. “Semantic Units: Organizing Knowledge Graphs into Semantically Meaningful Units of Representation.” arXiv, January 3, 2023. https://doi.org/10.48550/arXiv.2301.01227.

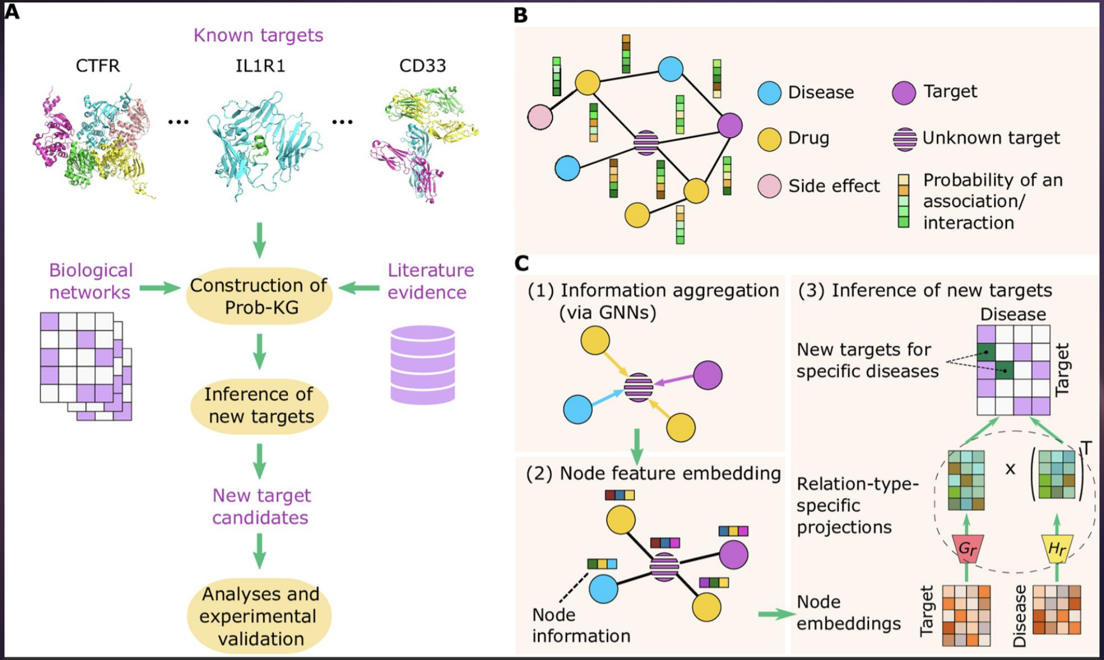
Knowledge graph and nanopublications



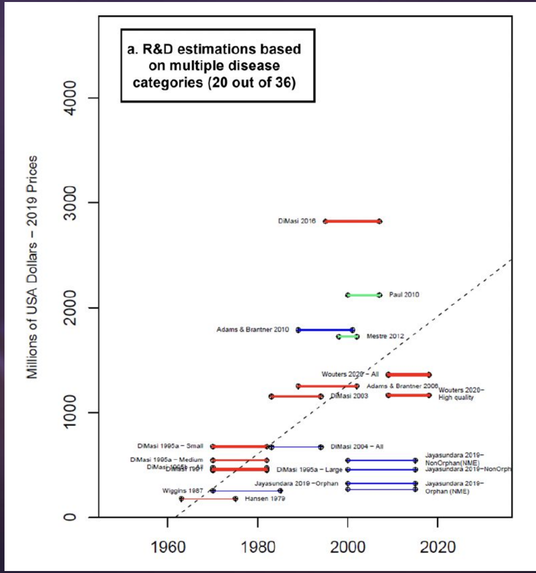


Giachelle F, Dosso D, Silvello G. Search, access, and explore life science nanopublications on the Web. PeerJ Comput Sci. 2021 Feb 4;7:e335. doi: 10.7717/peerj-cs.335. PMID: 33816986; PMCID: PMC7959622.

Probabilistic knowledge graphs in drug discovery



Liu C, Xiao K, Yu C, Lei Y, Lyu K, Tian T, et al. (2024) A probabilistic knowledge graph for target identification. PLoS Comput Biol 20(4): e1011945. https://doi.org/10.1371/journal.pcbi.1011945



Schlander, M., Hernandez-Villafuerte, K., Cheng, CY. et al. How Much Does It Cost to Research and Develop a New Drug? A Systematic Review and Assessment. PharmacoEconomics 39, 1243–1269 (2021). https://doi.org/10.1007/s40273-021-01065-y

Overview

Weight of Evidence (WoE). For a hypothesis H and evidence E,

$$\mathrm{WoE}(E \to H) = \log \frac{P(E \mid H)}{P(E \mid \neg H)}.$$

WoE adds in log-odds space. If $E_1, \ldots, E_k$ are evidence items and $p_0 = P(H)$,

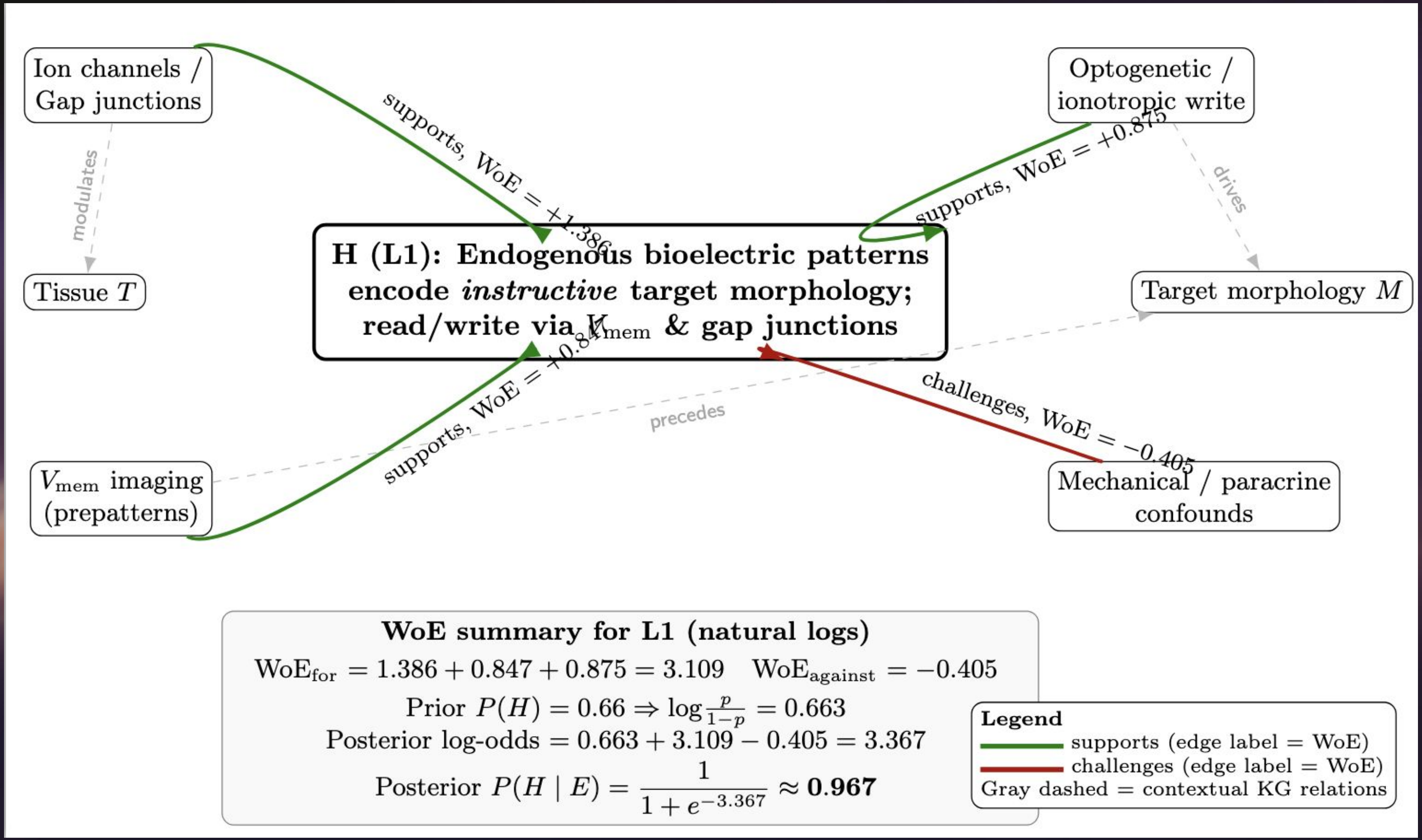
$$\operatorname{logit} P(H \mid E_{1:k}) \approx \operatorname{logit} p_0 + \sum_{i=1}^{k} \mathrm{WoE}(E_i \to H), \qquad P(H \mid E_{1:k}) = \frac{1}{1 + \exp\big(-\operatorname{logit} P(H \mid E_{1:k})\big)}.$$

Procedure

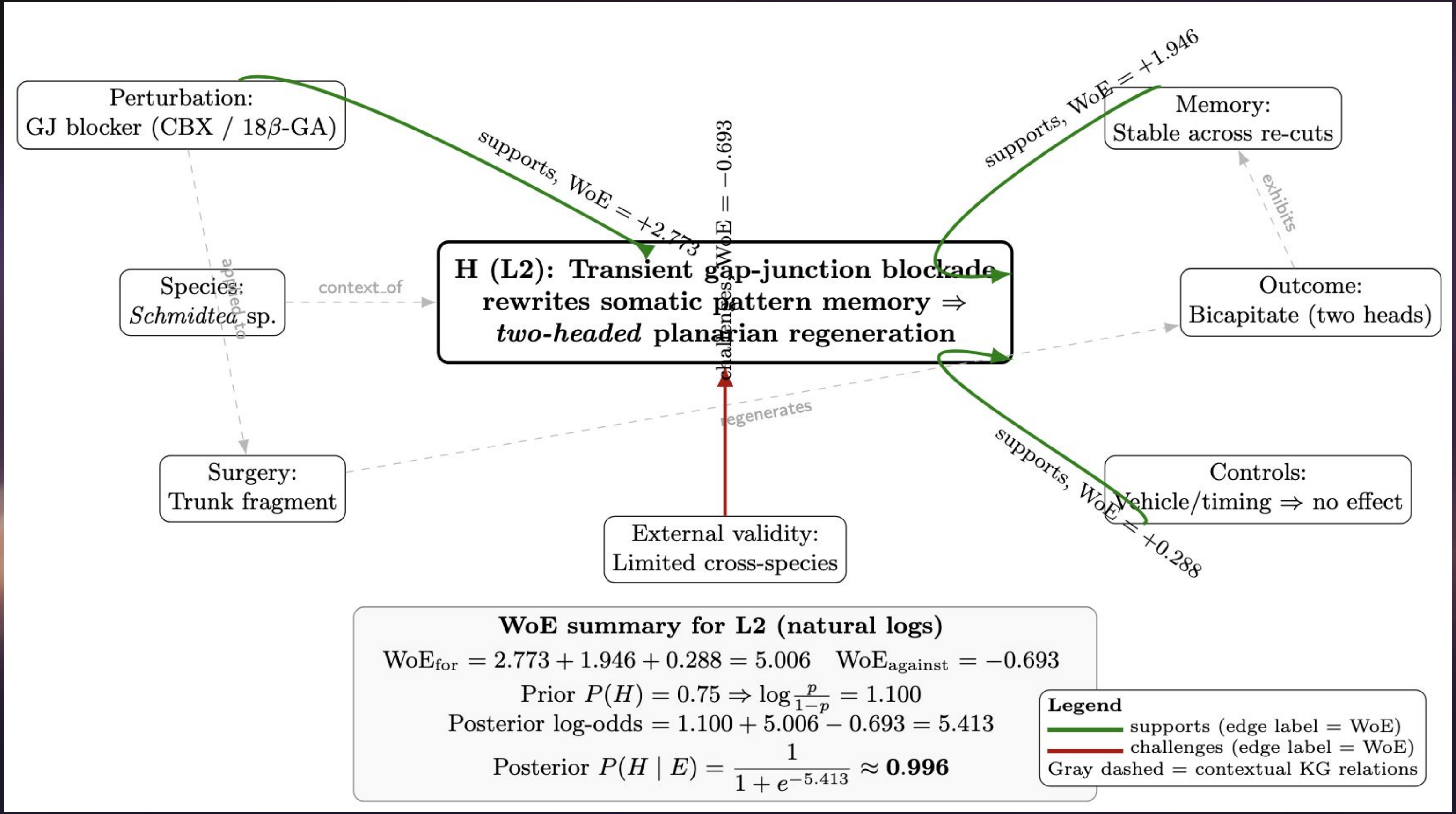
1. Define a KG hypothesis H (e.g., truth of a triple (u, r, v) or a predicted outcome).
2. Choose graph-derived evidence units E_i (motifs, metapaths, rules, provenance, calibrated model scores).
3. Estimate $\hat{P}(E_i \mid H)$, $\hat{P}(E_i \mid \neg H)$ on labeled data (with smoothing); compute WoE_i.
4. Combine additively or via a regularized logistic model to handle dependence and calibrate.
5. Store `posterior_prob`, `woe_total`, `woe_breakdown`, and provenance in the KG.

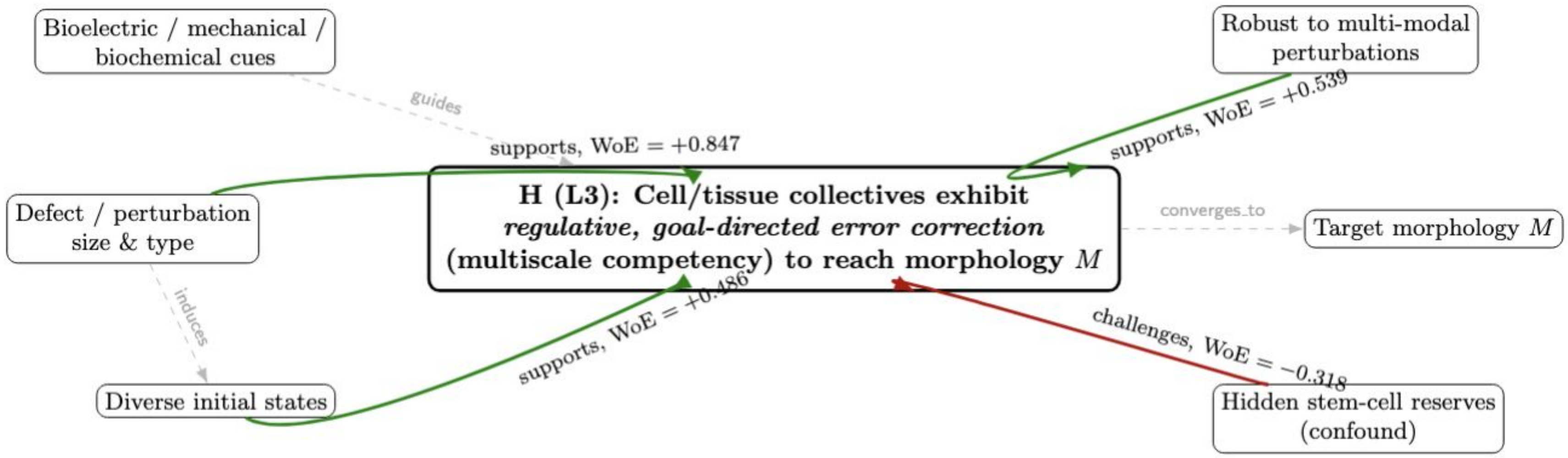
Table 1: Summary (All Hypotheses)

Hypothesis	Prior $P(H)$	WoE for	WoE against	Posterior $P(H \mid E$
L1 Bioelectric "code" is instructive/read-write	0.660	3.109	-0.405	0.967
L2 Somatic pattern memory & bistability (planaria)	0.750	5.006	-0.693	0.996
L3 Multiscale competency (regulative error correction)	0.600	1.872	-0.318	0.876
L4 Pre-neural bioelectric computation → GRNs/anatomy	0.670	2.660	-0.251	0.958
L5 Cancer as bioelectric network disorder (normalization helps)	0.550	1.476	-0.424	0.778
L6 Morphological attractors; brief inputs switch basins	0.580	1.800	-0.154	0.877
L7 Bioelectric gradients in LR/AP patterning (timing critical)	0.700	2.747	-0.223	0.967
L8 "Cognitive glue": GJ coupling scales competencies	0.580	1.214	-0.223	0.788
L9 Reconfigurable body plans (Xenobots): design → function	0.550	2.244	-0.182	0.906



Ion channels / Gap junctions
modulates
Tissue T
supports, WoE = +1.386
Optogenetic / ionotropic write
supports, WoE = +0.875
drives
Target morphology M
H (L1): Endogenous bioelectric patterns encode *instructive* target morphology; read/write via V_{mem} & gap junctions
supports, WoE = +0.847
precedes
challenges, WoE = −0.405
V_{mem} imaging (prepatterns)
Mechanical / paracrine confounds
WoE summary for L1 (natural logs)
$\text{WoE}_{\text{for}} = 1.386 + 0.847 + 0.875 = 3.109 \quad \text{WoE}_{\text{against}} = -0.405$
Prior $P(H) = 0.66 \Rightarrow \log \frac{p}{1-p} = 0.663$
Posterior log-odds $= 0.663 + 3.109 - 0.405 = 3.367$
Posterior $P(H \mid E) = \dfrac{1}{1 + e^{-3.367}} \approx \mathbf{0.967}$
Legend
supports (edge label = WoE)
challenges (edge label = WoE)
Gray dashed = contextual KG relations


Perturbation:
GJ blocker (CBX / 18β-GA)
supports, WoE = +2.773
challenges, WoE = −0.693
supports, WoE = +1.946
Memory:
Stable across re-cuts
exhibits
Species:
Schmidtea sp.
applied_to
context_of
H (L2): Transient gap-junction blockade rewrites somatic pattern memory ⇒ two-headed planarian regeneration
Outcome:
Bicapitate (two heads)
regenerates
Surgery:
Trunk fragment
supports, WoE = +0.288
Controls:
Vehicle/timing ⇒ no effect
External validity:
Limited cross-species
WoE summary for L2 (natural logs)
WoE_for = 2.773 + 1.946 + 0.288 = 5.006 WoE_against = −0.693
Prior P(H) = 0.75 ⇒ log p/(1−p) = 1.100
Posterior log-odds = 1.100 + 5.006 − 0.693 = 5.413
Posterior P(H | E) = 1/(1 + e^−5.413) ≈ 0.996
Legend
supports (edge label = WoE)
challenges (edge label = WoE)
Gray dashed = contextual KG relations



WoE summary for L3 (natural logs)

$\mathrm{WoE}_{\mathrm{for}} = 0.847 + 0.486 + 0.539 = 1.872 \quad \mathrm{WoE}_{\mathrm{against}} = -0.318$

Prior $P(H) = 0.60 \Rightarrow \log \frac{p}{1-p} = \ln(1.5) \approx 0.405$

Posterior log-odds $= 0.405 + 1.872 - 0.318 = 1.959$

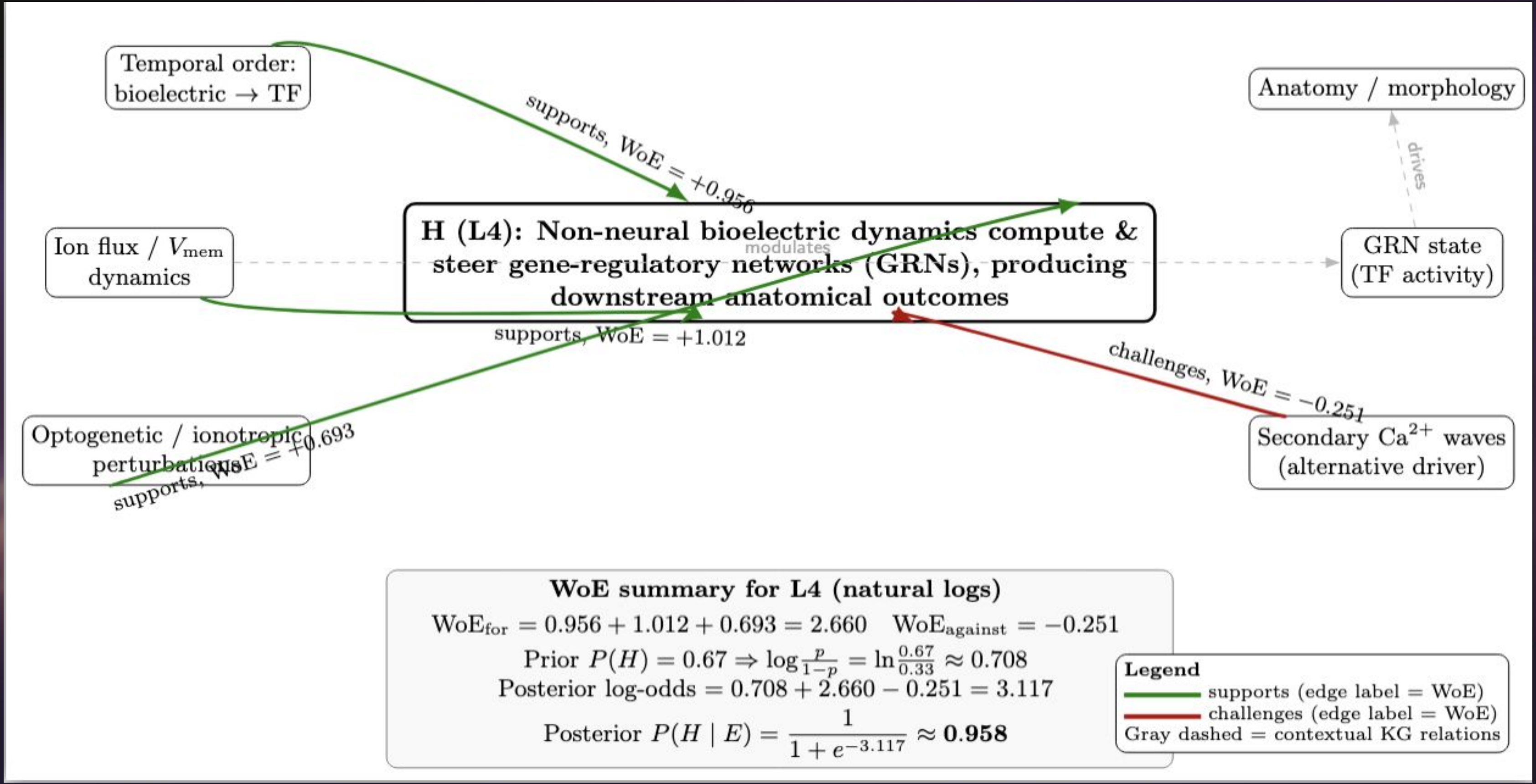
Posterior $P(H \mid E) = \dfrac{1}{1 + e^{-1.959}} \approx \mathbf{0.876}$

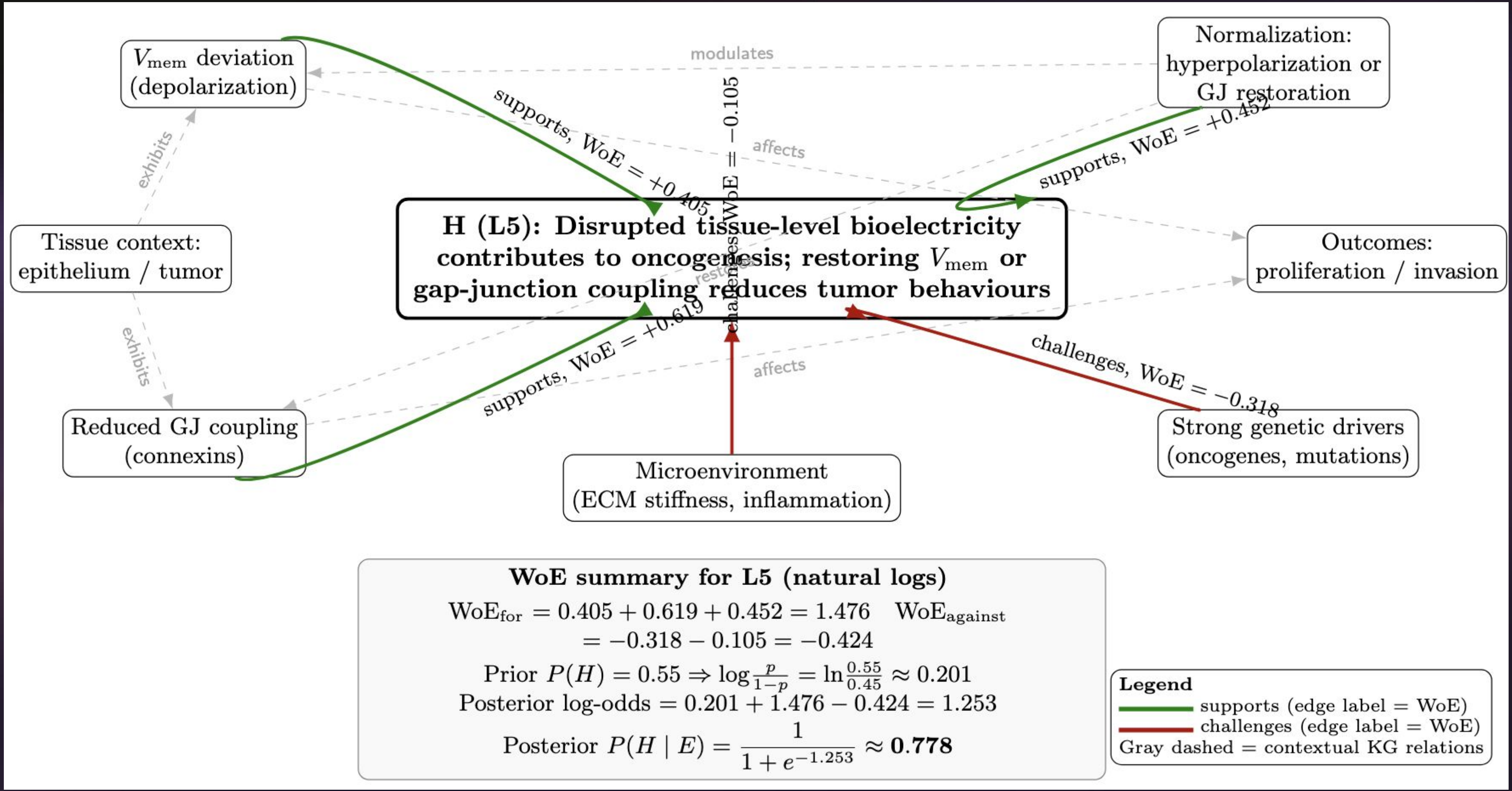
Legend

supports (edge label = WoE)

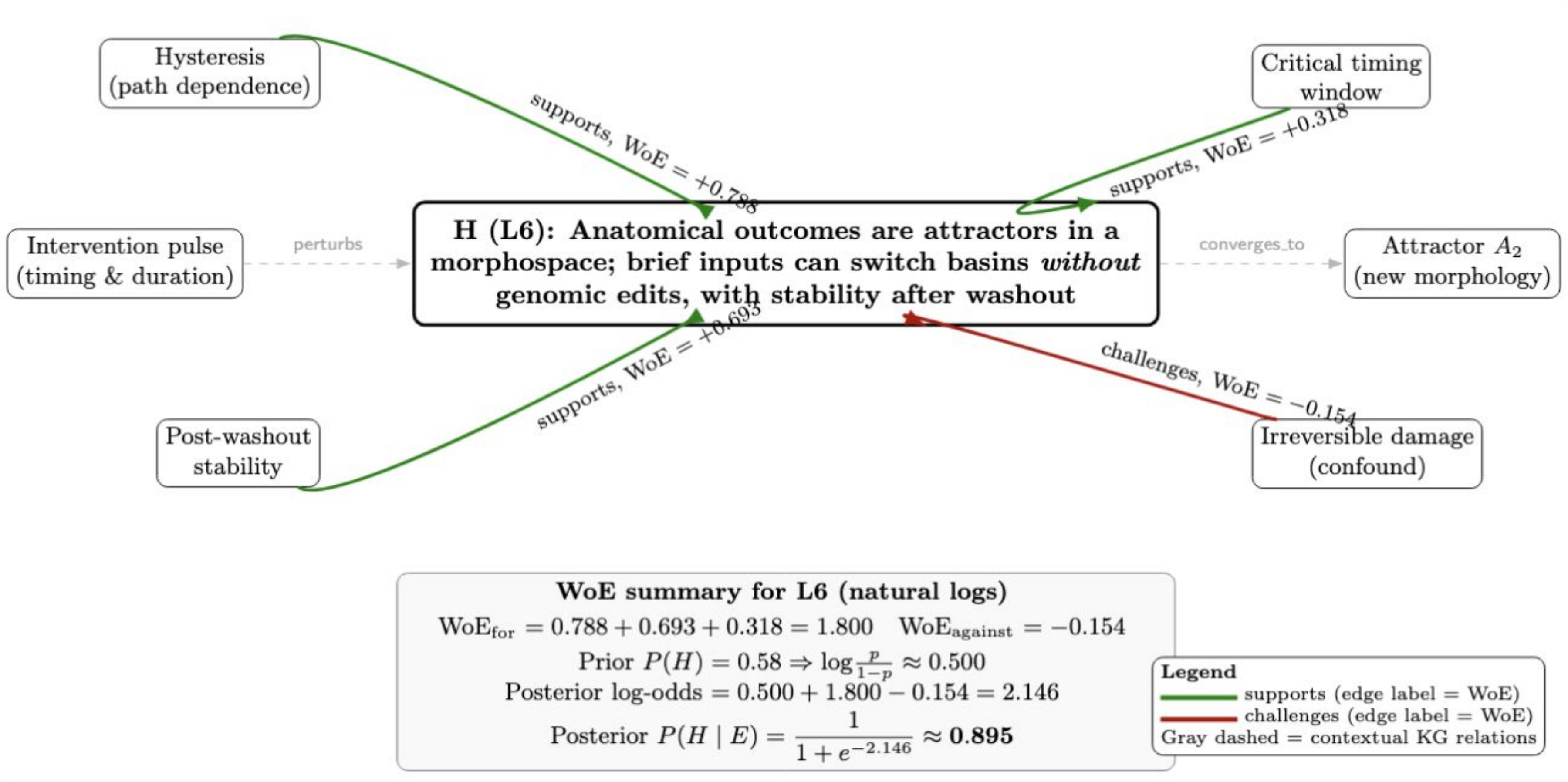
challenges (edge label = WoE)

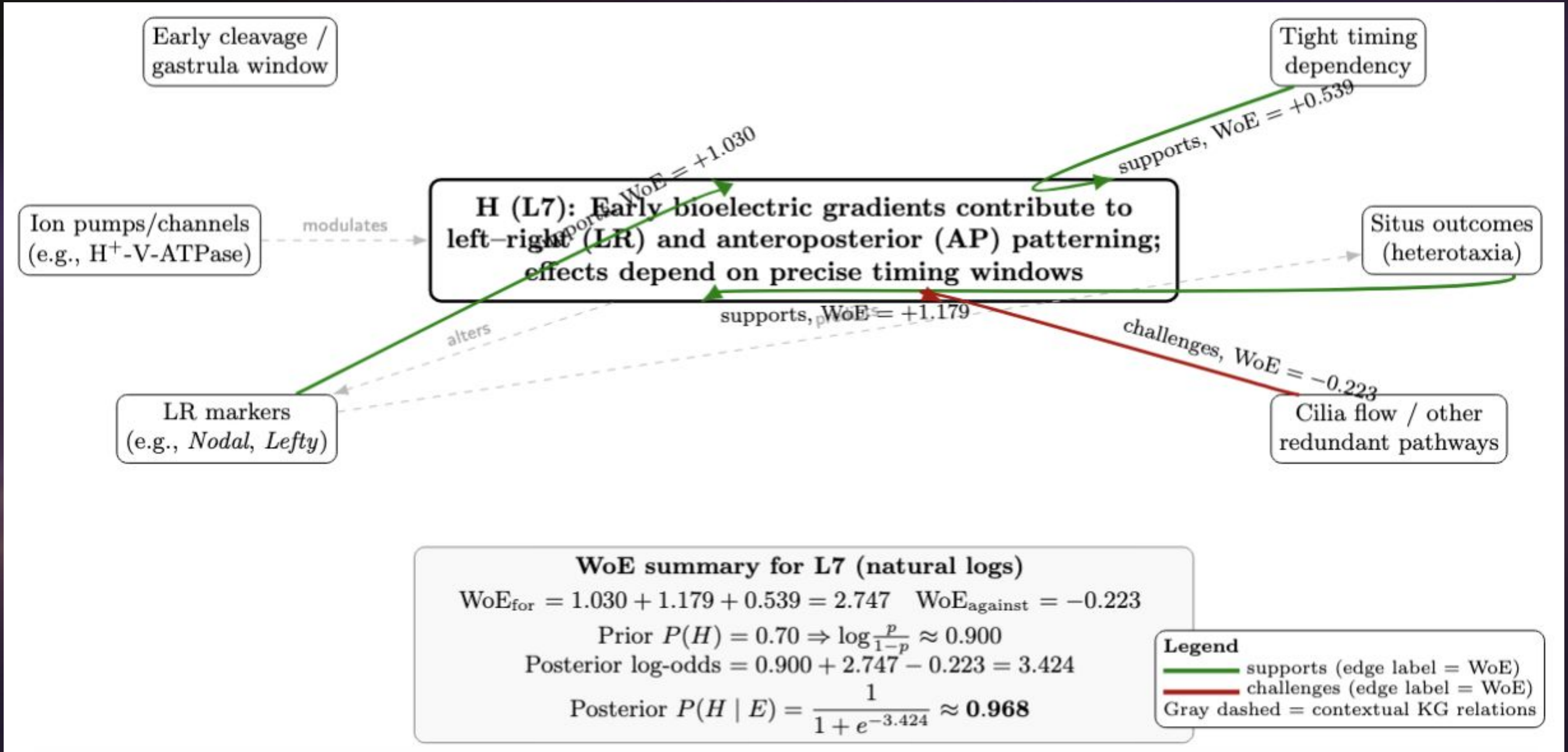
Gray dashed = contextual KG relations

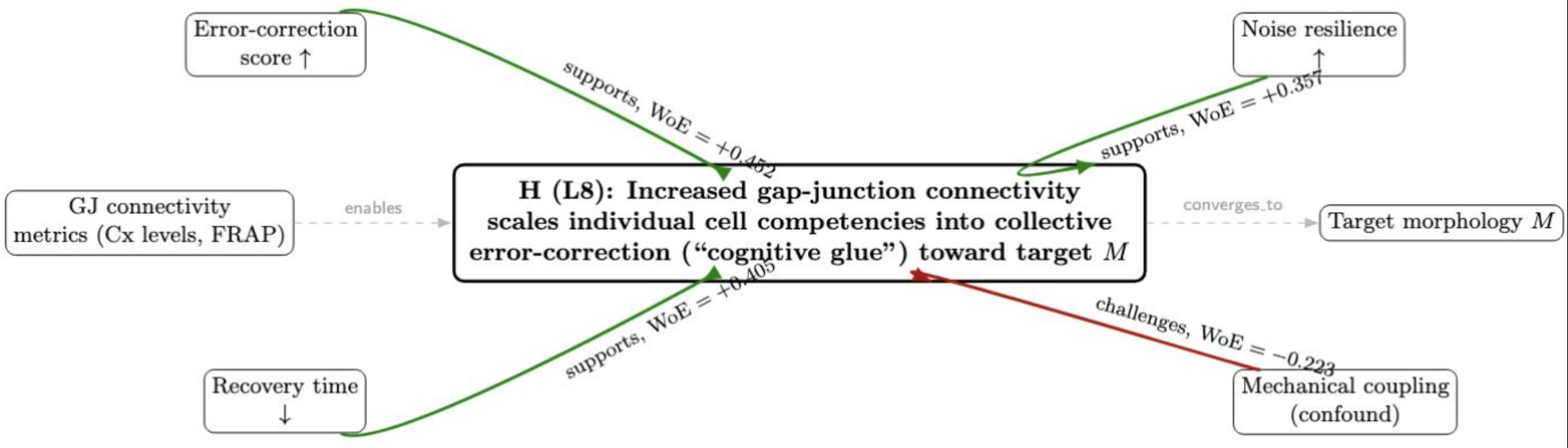

Temporal order: bioelectric → TF
supports, WoE = +0.956
Anatomy / morphology
drives
Ion flux / V_{mem} dynamics
H (L4): Non-neural bioelectric dynamics compute & steer gene-regulatory networks (GRNs), producing downstream anatomical outcomes
modulates
GRN state (TF activity)
supports, WoE = +1.012
challenges, WoE = −0.251
Optogenetic / ionotropic perturbations
supports, WoE = +0.693
Secondary Ca^{2+} waves (alternative driver)
WoE summary for L4 (natural logs)
$WoE_{for} = 0.956 + 1.012 + 0.693 = 2.660 \quad WoE_{against} = -0.251$
Prior $P(H) = 0.67 \Rightarrow \log \frac{p}{1-p} = \ln \frac{0.67}{0.33} \approx 0.708$
Posterior log-odds $= 0.708 + 2.660 - 0.251 = 3.117$
Posterior $P(H \mid E) = \frac{1}{1 + e^{-3.117}} \approx \mathbf{0.958}$
Legend
supports (edge label = WoE)
challenges (edge label = WoE)
Gray dashed = contextual KG relations



Vmem deviation (depolarization)
Normalization: hyperpolarization or GJ restoration
modulates
supports, WoE = +0.405
challenges, WoE = −0.105
affects
supports, WoE = +0.452
exhibits
Tissue context: epithelium / tumor
H (L5): Disrupted tissue-level bioelectricity contributes to oncogenesis; restoring Vmem or gap-junction coupling reduces tumor behaviours
restores
Outcomes: proliferation / invasion
supports, WoE = +0.619
challenges, WoE = −0.318
affects
exhibits
Reduced GJ coupling (connexins)
Microenvironment (ECM stiffness, inflammation)
Strong genetic drivers (oncogenes, mutations)
WoE summary for L5 (natural logs)
WoEfor = 0.405 + 0.619 + 0.452 = 1.476 WoEagainst = −0.318 − 0.105 = −0.424
Prior P(H) = 0.55 ⇒ log p/(1−p) = ln 0.55/0.45 ≈ 0.201
Posterior log-odds = 0.201 + 1.476 − 0.424 = 1.253
Posterior P(H | E) = 1/(1 + e^−1.253) ≈ 0.778
Legend
supports (edge label = WoE)
challenges (edge label = WoE)
Gray dashed = contextual KG relations


Hysteresis (path dependence)
supports, WoE = +0.788
Critical timing window
supports, WoE = +0.318
Intervention pulse (timing & duration)
perturbs
H (L6): Anatomical outcomes are attractors in a morphospace; brief inputs can switch basins *without* genomic edits, with stability after washout
converges_to
Attractor A_2 (new morphology)
supports, WoE = +0.693
challenges, WoE = −0.154
Post-washout stability
Irreversible damage (confound)
WoE summary for L6 (natural logs)
$\mathrm{WoE}_{\mathrm{for}} = 0.788 + 0.693 + 0.318 = 1.800 \quad \mathrm{WoE}_{\mathrm{against}} = -0.154$
Prior $P(H) = 0.58 \Rightarrow \log\frac{p}{1-p} \approx 0.500$
Posterior log-odds $= 0.500 + 1.800 - 0.154 = 2.146$
Posterior $P(H \mid E) = \frac{1}{1+e^{-2.146}} \approx \mathbf{0.895}$
Legend
supports (edge label = WoE)
challenges (edge label = WoE)
Gray dashed = contextual KG relations


Early cleavage / gastrula window
Tight timing dependency
Ion pumps/channels (e.g., H+-V-ATPase)
modulates
H (L7): Early bioelectric gradients contribute to left–right (LR) and anteroposterior (AP) patterning; effects depend on precise timing windows
supports, WoE = +1.030
supports, WoE = +0.539
Situs outcomes (heterotaxia)
supports, WoE = +1.179
alters
challenges, WoE = −0.223
LR markers (e.g., Nodal, Lefty)
Cilia flow / other redundant pathways
WoE summary for L7 (natural logs)
WoE_for = 1.030 + 1.179 + 0.539 = 2.747   WoE_against = −0.223
Prior P(H) = 0.70 ⇒ log p/(1−p) ≈ 0.900
Posterior log-odds = 0.900 + 2.747 − 0.223 = 3.424
Posterior P(H | E) = 1/(1 + e^−3.424) ≈ 0.968
Legend
supports (edge label = WoE)
challenges (edge label = WoE)
Gray dashed = contextual KG relations



WoE summary for L8 (natural logs)

$\text{WoE}_{\text{for}} = 0.452 + 0.405 + 0.357 = 1.214 \quad \text{WoE}_{\text{against}} = -0.223$

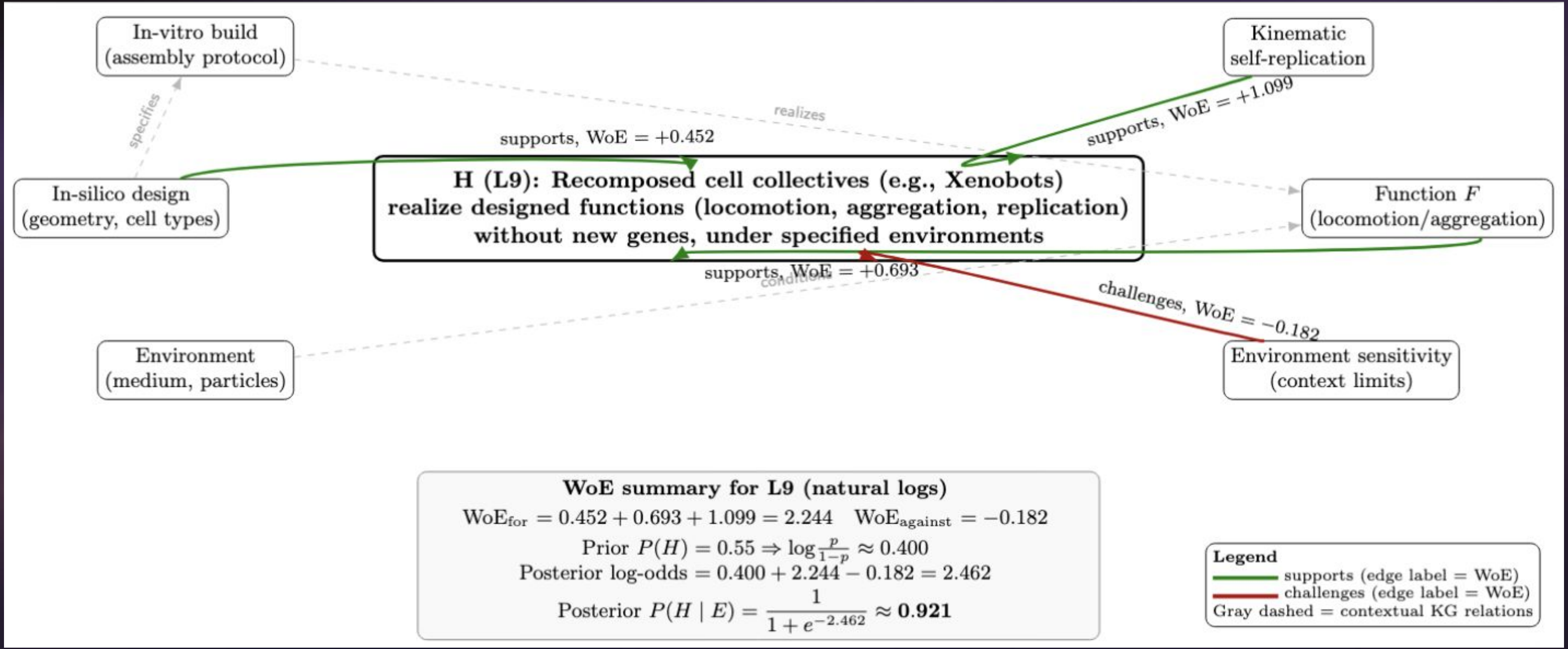
$\text{Prior } P(H) = 0.58 \Rightarrow \log\frac{p}{1-p} \approx 0.500$

$\text{Posterior log-odds} = 0.500 + 1.214 - 0.223 = 1.491$

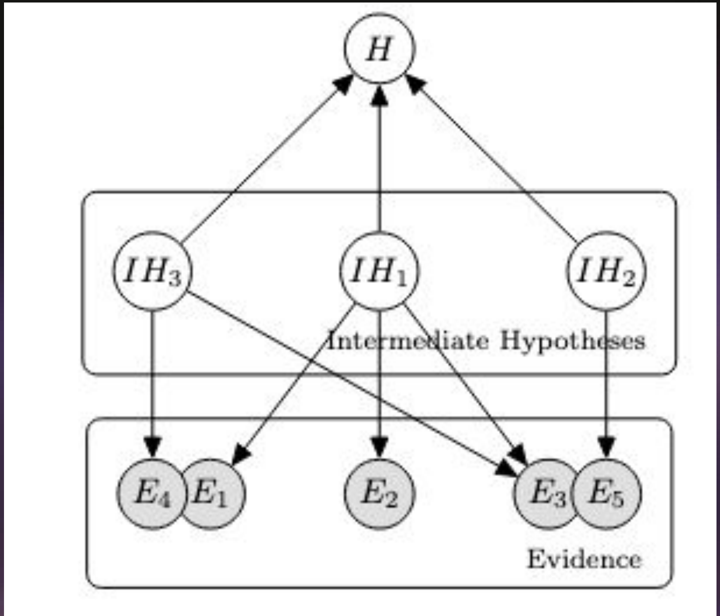
$$\text{Posterior } P(H \mid E) = \frac{1}{1+e^{-1.491}} \approx \mathbf{0.816}$$

Legend
- supports (edge label = WoE)
- challenges (edge label = WoE)

Gray dashed = contextual KG relations


In-vitro build
(assembly protocol)
specifies
realizes
Kinematic
self-replication
supports, WoE = +1.099
supports, WoE = +0.452
In-silico design
(geometry, cell types)
H (L9): Recomposed cell collectives (e.g., Xenobots)
realize designed functions (locomotion, aggregation, replication)
without new genes, under specified environments
Function F
(locomotion/aggregation)
supports, WoE = +0.693
conditions
challenges, WoE = −0.182
Environment
(medium, particles)
Environment sensitivity
(context limits)
WoE summary for L9 (natural logs)
WoE_for = 0.452 + 0.693 + 1.099 = 2.244   WoE_against = −0.182
Prior P(H) = 0.55 ⇒ log p/(1−p) ≈ 0.400
Posterior log-odds = 0.400 + 2.244 − 0.182 = 2.462
Posterior P(H | E) = 1/(1 + e^−2.462) ≈ 0.921
Legend
supports (edge label = WoE)
challenges (edge label = WoE)
Gray dashed = contextual KG relations

Radical Platonism



Node Definitions:

H: Radical Platonism is True

IH_1: Non-Local Information Storage is True

IH_2: Multiscale Competency is True

IH_3: Access to Latent Space of Forms is True

E_1: Bioelectric Pre-patterns Observed

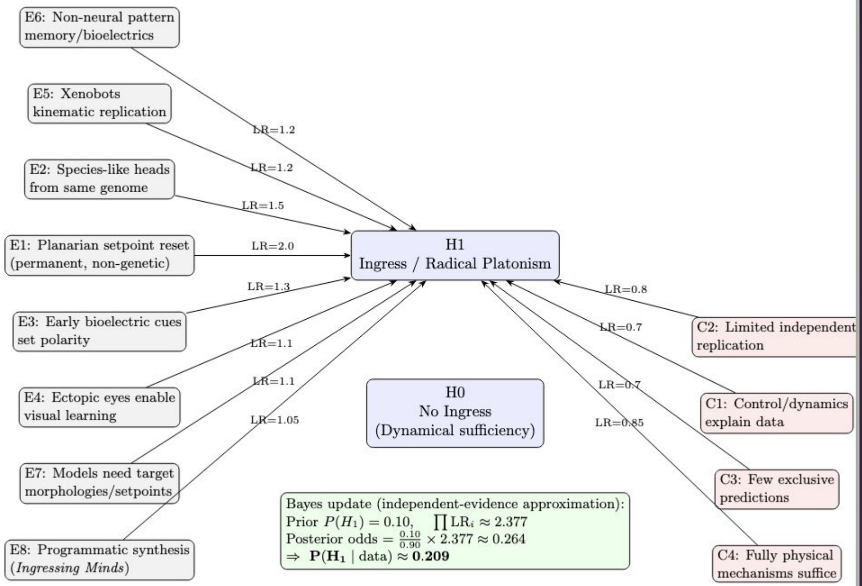
E_2: Planarian Memory Persistence Observed

E_3: Planarian Morphology Rewrite Observed

E_4: Xenobot Novel Behaviors Observed

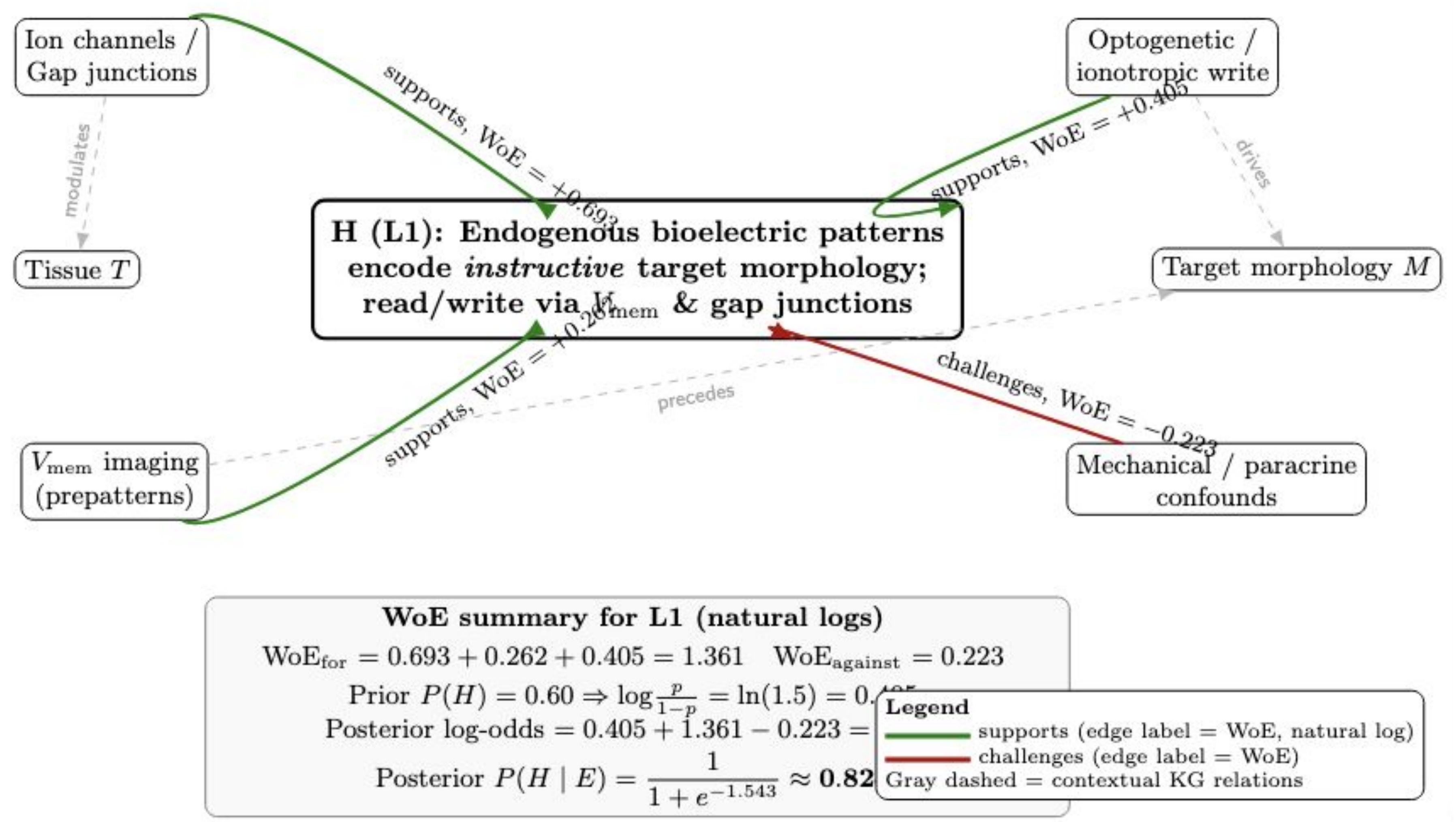
E_5: Ectopic Eye Function Observed

Probabilistic Knowledge Graph: Ingress / Radical Platonism

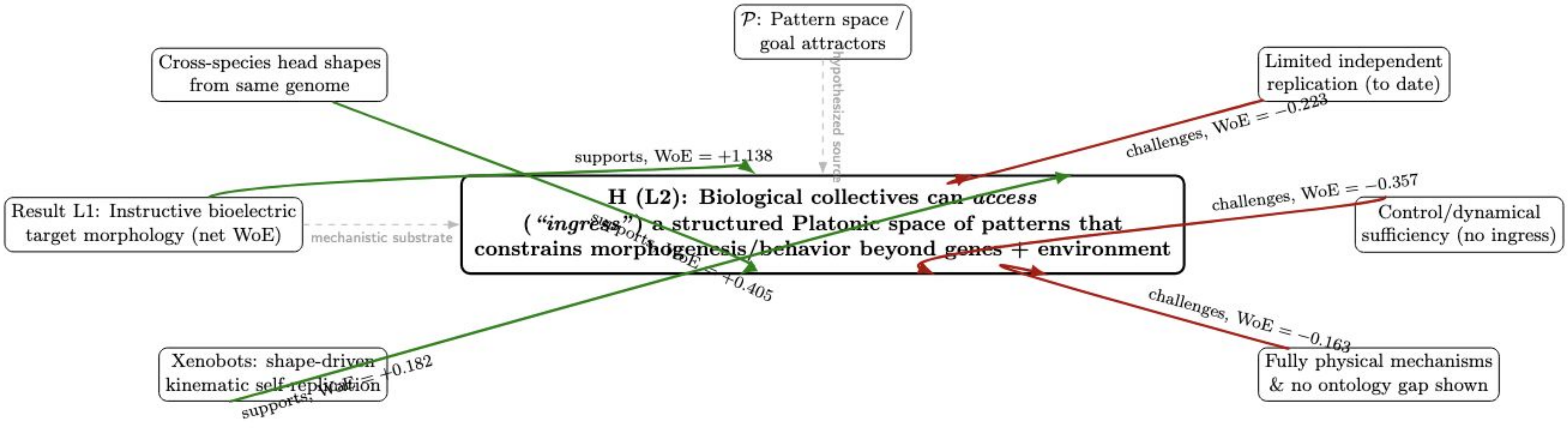


Weights of evidence (Good's decibans) and bits

Item	LR	$\log_{10}$ LR	decibans	bits ($\log_2$ LR)
E1	2.000	0.301	3.010	1.000
E2	1.500	0.176	1.761	0.585
E3	1.300	0.114	1.139	0.379
E4	1.100	0.041	0.414	0.138
E5	1.200	0.079	0.792	0.263
E6	1.200	0.079	0.792	0.263
E7	1.100	0.041	0.414	0.138
E8	1.050	0.021	0.212	0.070
C1	0.700	−0.155	−1.549	−0.515
C2	0.800	−0.097	−0.969	−0.322
C3	0.700	−0.155	−1.549	−0.515
C4	0.850	−0.071	−0.706	−0.234
Total	2.377	0.376	3.761	1.249



Ion channels / Gap junctions
modulates
Tissue T
supports, WoE = +0.693
H (L1): Endogenous bioelectric patterns encode *instructive* target morphology; read/write via V_{mem} & gap junctions
Optogenetic / ionotropic write
supports, WoE = +0.405
drives
Target morphology M
supports, WoE = +0.262
precedes
challenges, WoE = −0.223
V_{mem} imaging (prepatterns)
Mechanical / paracrine confounds
WoE summary for L1 (natural logs)
$\mathrm{WoE}_{\mathrm{for}} = 0.693 + 0.262 + 0.405 = 1.361 \quad \mathrm{WoE}_{\mathrm{against}} = 0.223$
Prior $P(H) = 0.60 \Rightarrow \log \frac{p}{1-p} = \ln(1.5) = 0.$
Posterior log-odds $= 0.405 + 1.361 - 0.223 =$
Posterior $P(H \mid E) = \frac{1}{1 + e^{-1.543}} \approx$ **0.82**
Legend
supports (edge label = WoE, natural log)
challenges (edge label = WoE)
Gray dashed = contextual KG relations



WoE summary for L2 (natural logs)

$\mathrm{WoE}_{\mathrm{for}} = 1.138 + 0.405 + 0.182 = 1.725 \quad \mathrm{WoE}_{\mathrm{against}} = 0.357 + 0.223 + 0.163 = 0.743$

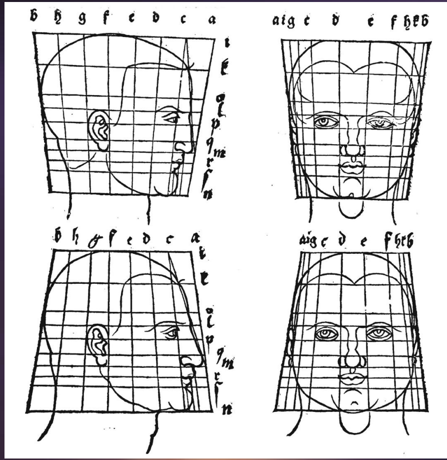
Prior $P(H) = 0.10 \Rightarrow \log\frac{p}{1-p} = \ln(0.1/0.9) = -2.197$

Posterior log-odds $= -2.197 + 1.725 - 0.743 = -1.215$

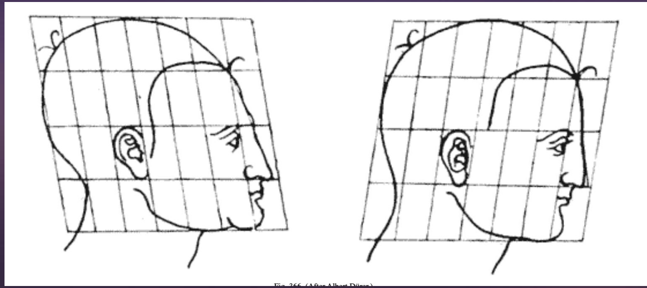
$$\text{Posterior } P(H \mid E) = \frac{1}{1 + e^{1.215}} \approx \mathbf{0.229}$$

Legend
supports (edge label = WoE, natural log)
challenges (edge label = WoE)
Gray dashed = contextual KG relations

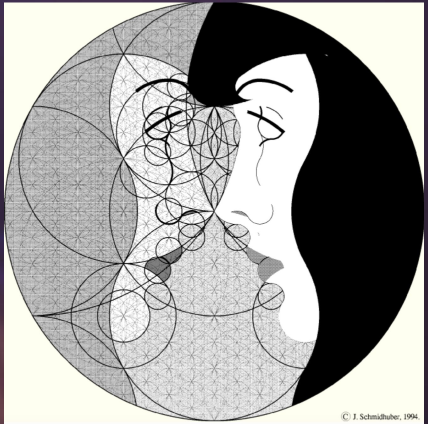
Beauty, a side topic?



A Dürer, Four Books on Human Proportion, 1528



D’Arcy Thompson, Growth and Form, 1917



J. Schmidhuber. Facial beauty and fractal geometry. Note IDSIA-28-98, IDSIA, June 1998

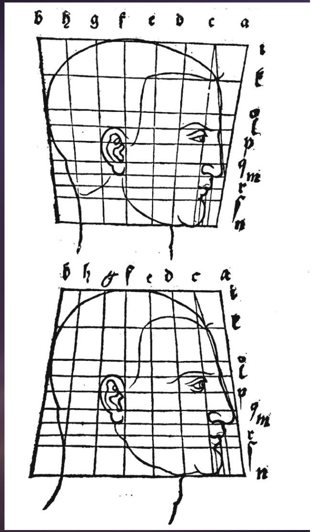
J. Schmidhuber. **Simple Algorithmic Principles of Discovery, Subjective Beauty, Selective Attention, Curiosity & Creativity**. In V. Corruble, M. Takeda, E. Suzuki, eds., Proc. 10th Intl. Conf. on Discovery Science (DS 2007) p. 26-38, LNAI 4755, Springer, 2007. Also in M. Hutter, R. A. Servedio, E. Takimoto, eds., Proc. 18th Intl. Conf. on Algorithmic Learning Theory (ALT 2007) p. 32, LNAI 4754, Springer, 2007. (Joint invited lecture for DS 2007 and ALT 2007, Sendai, Japan, 2007.) Preprint: arxiv:0709.0674.

In the morphology of living things the use of **mathematical methods** and symbols has made **slow progress** ; and there are various reasons for this failure to employ a method whose advantages are so obvious in the investigation of other physical forms. To begin with, there would seem to be a psychological reason lying in the fact that the student of living things is by nature and training an observer of concrete objects and phenomena, and the habit of mind which he possesses and cultivates is alien to that of the theoretical mathematician. But this is by no means the only reason; for in the kindred subject of mineralogy, for instance, crystals were still treated in the days of Linnaeus as wholly within the province of the naturalist, and were described by him after the simple methods in use for animals and plants: but as soon as Haüy showed the application of mathematics to the description and classification of crystals, his methods were immediately adopted and a new science came into being.

A large part of the neglect and suspicion of mathematical methods in organic morphology is due (as we have partly seen in our opening chapter) to an ingrained and **deep-seated belief** that even when we seem to discern a regular mathematical figure in an organism, the sphere, the hexagon, or the spiral which we so recognise merely resembles, but is never entirely explained by, its mathematical analogue; in short, that **the details in which the figure differs from its mathematical prototype are more important and more interesting than the features in which it agrees** , and even that the **peculiar aesthetic pleasure** with which we regard a living thing is somehow bound up with the departure from mathematical regularity which it manifests as a peculiar attribute of life. This view seems to me to involve a misapprehension. There is no such essential difference between these phenomena of organic form and those which are manifested in portions of inanimate matter[642]. No chain hangs in a perfect catenary and no raindrop is a perfect sphere: and this for the simple reason that forces and resistances other than the main one are inevitably at work. The same is true of organic form, but it is for the mathematician to unravel the conflicting forces which are at work together. And this process of investigation may lead us on step by step to new phenomena, as it has done in physics, where sometimes a knowledge of form leads us to the interpretation of forces, and at other times a knowledge of the forces at work guides us towards a better insight into form. I would illustrate this by the case of the earth itself. After the fundamental advance had been made which taught us that the world was round, Newton showed that the forces at work upon it must lead to its being imperfectly spherical, and in the course of time its oblate spheroidal shape was actually verified. But now, in turn, it has been shown that its form is still more complicated, and the next step will be to seek for the forces that have deformed the oblate spheroid.
{722}

D'Arcy Wentworth Thompson

Fractals and beauty?



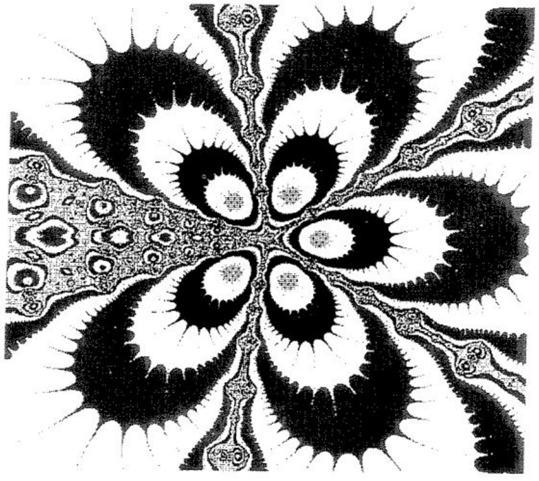


Fig. 12. Halley plot, x: $-5.0 \rightarrow 5.0$, y: $-5.0 \rightarrow 5.0$, $z = z^{5.5} - 1$.

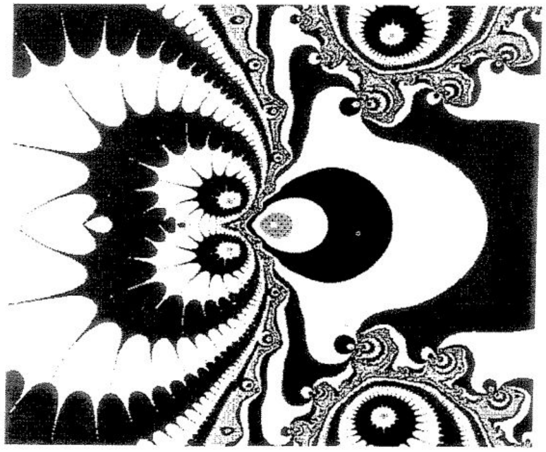
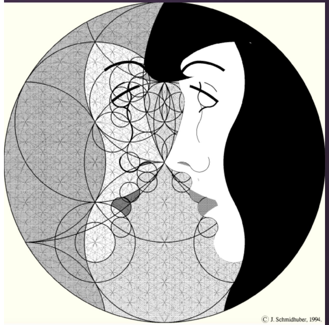


Fig. 14. Newton plot, x: $-5.0 \rightarrow 5.0$, y: $-5.0 \rightarrow 5.0$, $z = z^{2.3} + \sin(z)$.

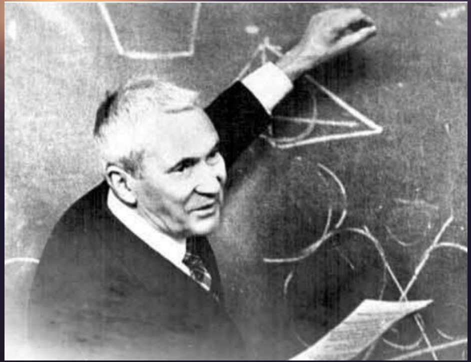


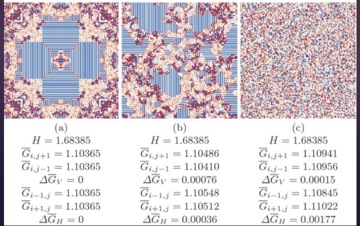
Michael Levin, “Discontinuous and Alternate Q-System Fractals,” Computers & Graphics 18, no. 6 (1994): 873–884, https://doi.org/10.1016/0097-8493(94)00107-3 .

What’s our baseline?

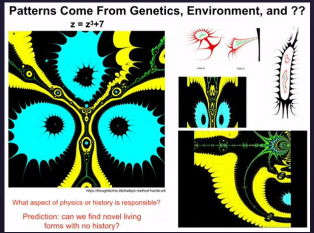
Shut up and engineer? “ Our lab mission is not to produce philosophy that is undecidable and will hang out among the long list of ideas that have been kicked around for centuries with no resolution in sight. … Engineering in the broad sense is a critical method for deciding between competing worldviews and frameworks: the best ones are the ones that enable the most fruitful relationships with the world and its diverse levels of agency”

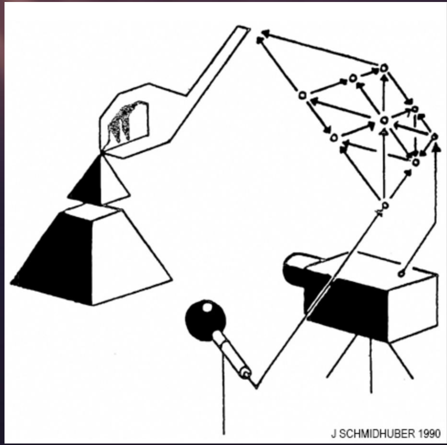
What is “fruitful” ?



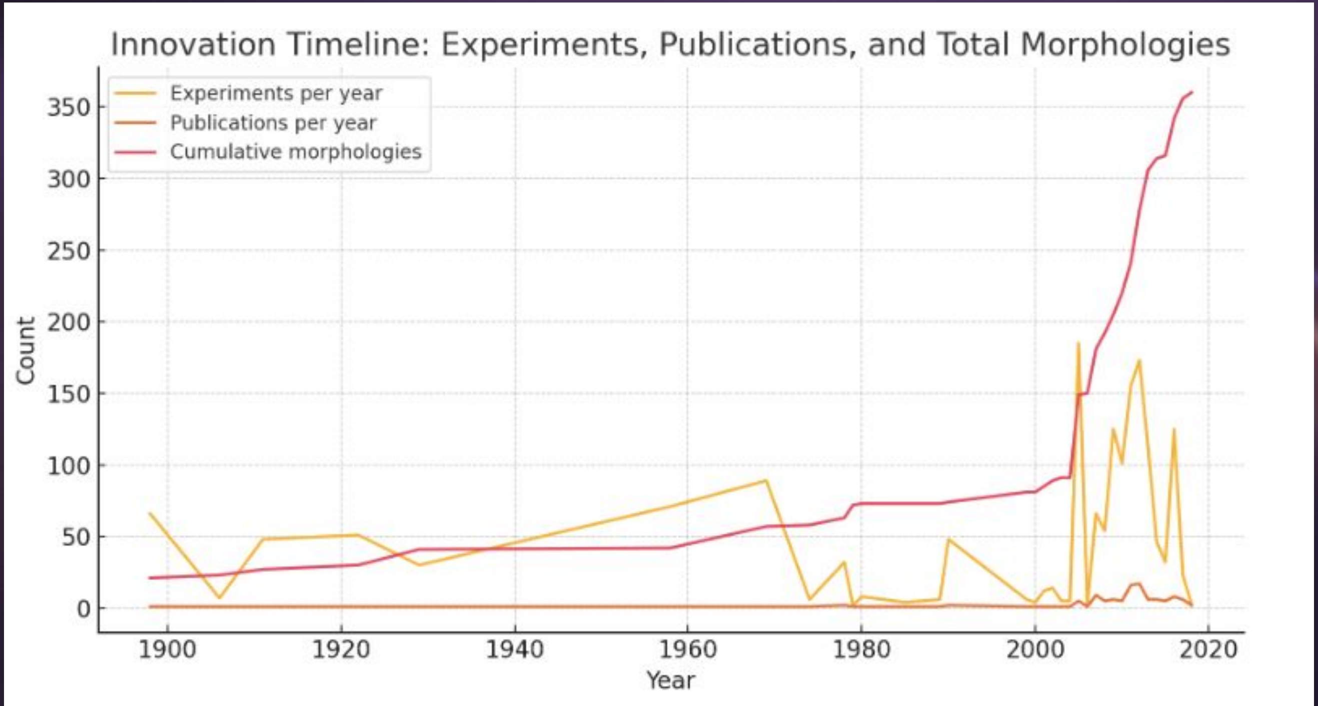


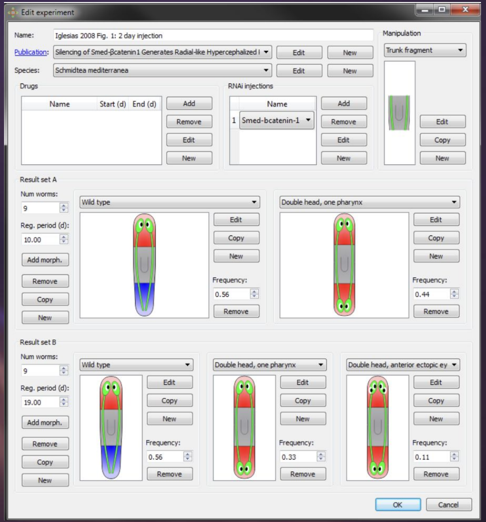
Javaheri Javid, M.A. (2022). Aesthetic Evaluation of Experimental Stimuli Using Spatial Complexity and Kolmogorov Complexity. In: Martins, T., Rodríguez-Fernández, N., Rebelo, S.M. (eds) Artificial Intelligence in Music, Sound, Art and Design. EvoMUSART 2022. Lecture Notes in Computer Science, vol 13221. Springer, Cham. https://doi.org/10.1007/978-3-031-03789-4_8





Planform morphospace





- `thompson-1917.py` : A simple demonstration of D'Arcy Thompson's theory of transformations, showing how one shape can be deformed into another.
- `turing-morpho.py` : A simulation of the Gray-Scott reaction-diffusion model, which generates classic Turing patterns like spots and stripes.
- `raup.py` : Implements Raup's classic model of shell coiling, generating a variety of 3D shell forms.
- `Cervera-Levin-Mafe.py` : A reaction-diffusion demo inspired by Cervera–Levin–Mafe (2021), exploring morphogen antagonism and its effect on pattern formation.
- `morpho-range.py` : Generates a grid of abstract shapes by sweeping through a morphospace of reaction-diffusion parameters.
- `planarian-morphogen.py` : Simulates the generation of a planarian body shape, including eyes and pharynx, from underlying morphogen gradients. Can produce an animated GIF of the process.
- `levin-pkg.py` : An incomplete script intended to build an interactive knowledge graph of Michael Levin's work.

https://github.com/fractastical/infinitemorphospace

Next steps

1. **Developing a predictive morphospace language that cracks the bioelectric Code:** (i.e. mapping specific bioelectric patterns to specific downstream gene expression cascades and morphological outcomes) ← Raup 2.0
2. **Elucidating the Mechanism of Non-Neural Memory**
3. **Education** and **knowledge maps** of what we know including LLM input

Many thanks

SEMF

- Carlos Zapata Carratalá
- Álvaro Moreno-Vallori
- Alex Sospedra
- Fotis Tsiroukis
- Mariana Valdetaro

Sandy Pentland, MIT Media Lab
Derek Lomas, TU Delft
Jürgen Schmidhuber
Eric Bonabeau, UC Berkeley ...
Carl Hayden Smith, University of East London
Tobias Kuhn, VU University Amsterdam
Allison Duettmann, Foresight Institute
Jim Rutt, CIMC/Santa Fe Institute
Trent McConaghy, Ocean AI
David Kammeyer, Mentality.ai