

NACS 645 – Quantitative Perspectives

–
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DEPARTMENT OF
PSYCHOLOGY



PROGRAM IN
NEUROSCIENCE &
COGNITIVE SCIENCE

Evolution of practices in hypothesis-testing (2015-2025; non-exhaustive)

Statistics:

- t-test, ANOVA
- z-test, kolmogorov-smirnov, etc.
- Effect sizes
- Linear models, link functions
- Simulating power, sim. increasing {n, x}
- SEM, MLM (partial pooling)
- emmeans
- Comp. modelling: DDM, RL, Bayesian
- Distributions in the Bayes. domain, Bayes factor
- Bayesian estimation: MCMC, VBA

fMRI:

- GLM then t-test, ANOVA
- Increasing covariants
- 2nd-level analysis
- Model-based fMRI

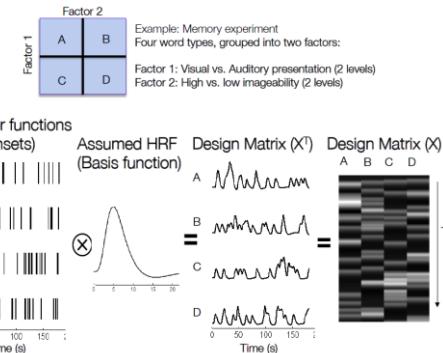
A standard GLM can be written:

$$Y = X\beta + \epsilon \quad \epsilon \sim N(\mathbf{0}, V)$$

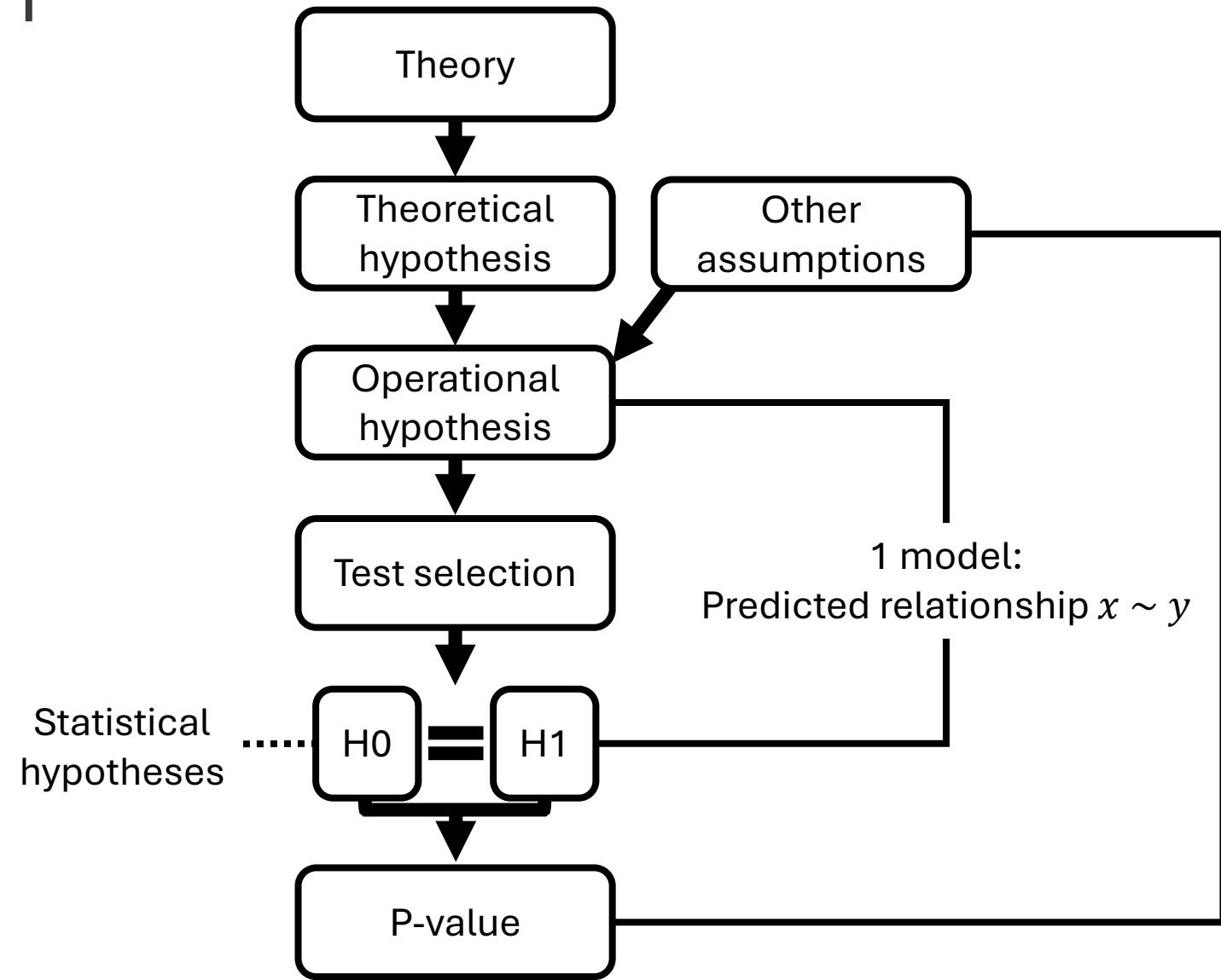
where

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix} = \begin{bmatrix} 1 & X_{11} & \cdots & X_{1p} \\ 1 & X_{21} & \cdots & X_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & X_{n1} & \cdots & X_{np} \end{bmatrix} \times \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_p \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_n \end{bmatrix}$$

V is the covariance matrix whose format depends on the noise model.



NHST & Reverse inference



Reverse inference: the engagement of a particular Y is inferred from finding the activation of a particular X.

Avoid the problem of reverse inference with

- > Hierarchical, model-based fMRI (verify the presence of cognitive processes first)?

- > Bayesian hypothesis testing?

- > Activation maps as priors?

Point-Null Fallacy: exactly zero-difference is virtually never true

- > Biology/social domain introduces small effects through complex causal relationships

- > Many underlying assumptions (Duhem-Quine thesis) (e.g., preprocessing)

Operational level

- 1. Relationship $x \sim y$
- 2. We predict y varies with x
- 3. $y \sim x_1$ and $y \sim x_2$ generate 2 different data point **distributions**

NHST

- 2 statistical hypotheses: H_0 (no difference) and H_1 (difference - **can be anything**)
- Distributions from our 2 samples come from the same population distribution (cond. 1 & 2 follow H_0)

$p < 1 - \alpha$ (i.e., $p < .05$):

- *Significant difference* = the risk to be wrong at (effect-value) is low enough.
We can reject the Null Hypothesis because it is likely to be false.
- We reject H_0 ; we don't accept H_1 (**H_1 can be anything**).
We learn: it is very likely that our non-control condition doesn't follow H_0 .

Statistical level
(test-level)

$p > 1 - \alpha$:

- *No significant difference* = the risk at (effect-value) to be wrong is too high.
We failed to reject H_0 because it is very not likely to be false
- We can't conclude about conditions 1 & 2 except:
We failed to reject a non-difference between cond. 1 & 2. **We learn nothing** regarding H_0 nor H_1 .

What evidence does NHST provide?

- What we can learn is restricted to our conclusions regarding H_0 for 1 model via 1 NHST test
 - We know nothing about how probable our results are

[Null hypothesis significance testing: a review of an old and continuing controversy.](#)

RS Nickerson - [Psychological methods, 2000 - psycnet.apa.org](#)

Null hypothesis significance testing (NHST) is arguably the most widely used approach to hypothesis evaluation among behavioral and social scientists. It is also very controversial. A ...

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NACS 645 – The need for paradigms

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Scientific revolutions

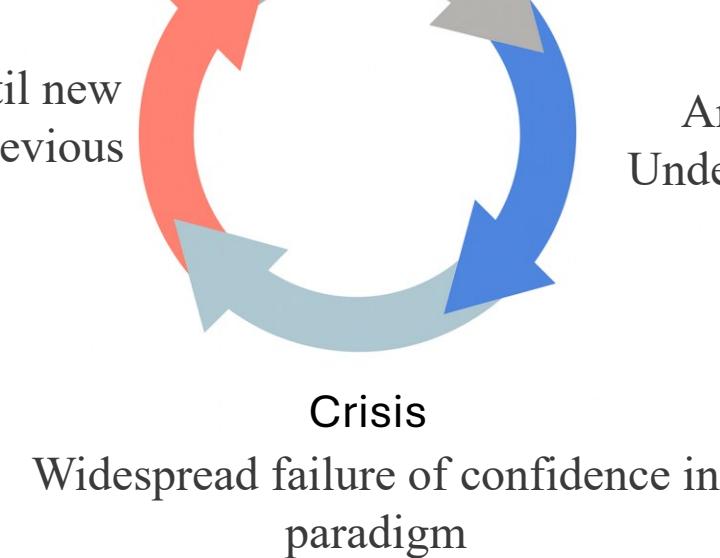
A paradigm can be defined as the generally accepted concepts and practices of a field.

Pre-paradigm
Lack of consensus on procedures, theories, presuppositions, etc.

Normal Science
Puzzles are solved within the context of the dominant paradigm

A paradigm shift is different from incremental developments

Paradigm Shift
Competition among ideas until new paradigm that accounts for previous puzzles & anomalies



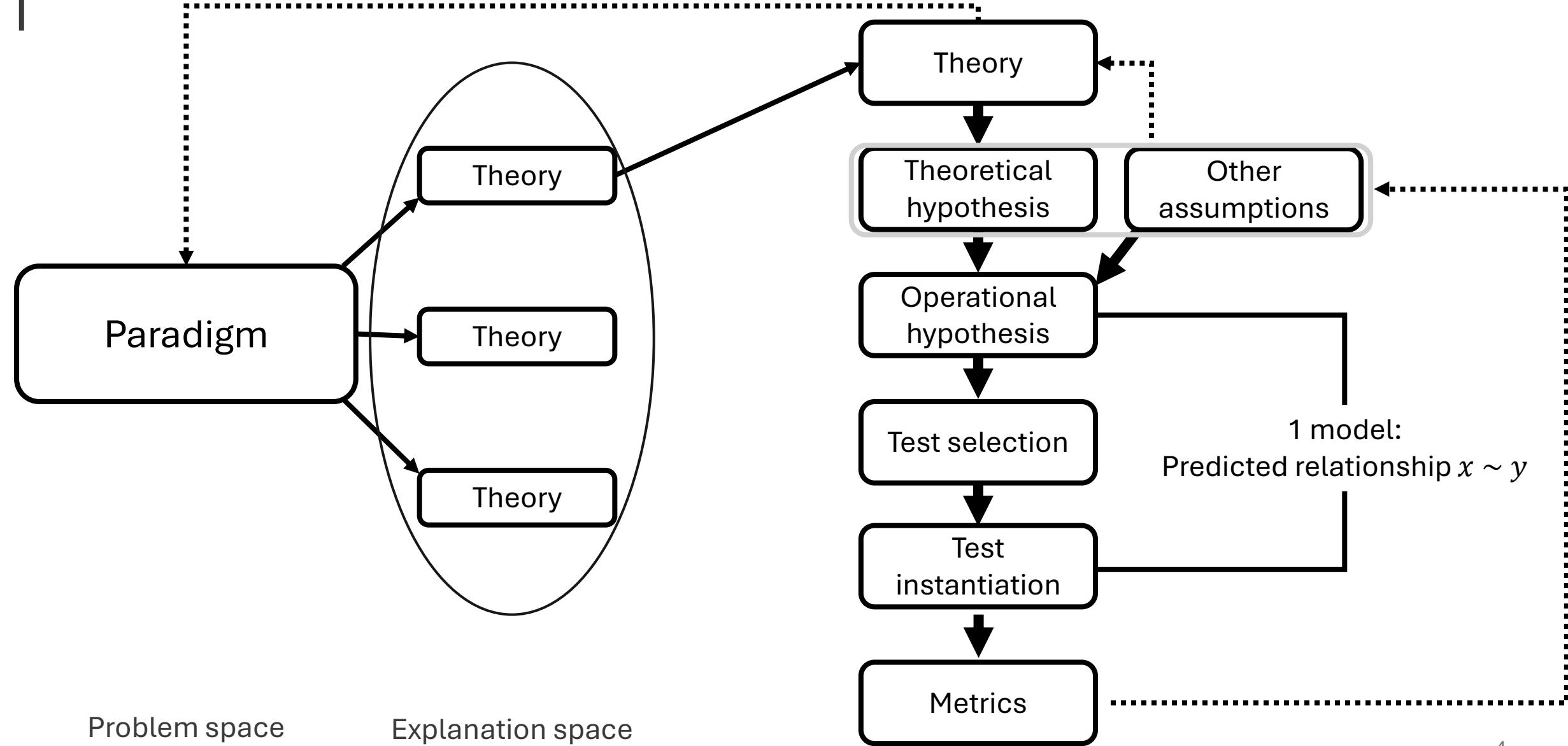
Paradigms

More specifically, a paradigm is the shared set of symbolic generalizations, models, values, and exemplars that organize how a scientific community defines, investigates, and evaluates problems.

- Behavior:
 - **Behaviorism** (*black box*),
 - **Cognitivism** (information-processing),
 - **Symbolism** (*steps*),
 - **Connectionism** (distributed networks),
 - **Embodied and enactive cognition**
- Explanation:
 - **Reductionism** (*reduced to physical*),
 - **Emergentism** (*emerges from physical*),
 - **Pluralism?** (*multiple explanatory levels*)
- Brain:
 - **Localizationism**,
 - **Functionalism**,
 - **Computational neuroscience**,
 - **Dynamic systems / Networks?**
- Any domain-level, area-level, function-level, process-level, ...
- **Methodology** (*not Kuhnian*):
 - **Neurophysiology** (*electrophy, single-unit*),
 - **Neuroimaging** (*PET, fMRI, EEG, MEG*),
 - **Interventional** (*tDCS, TMS, optogenetics*)

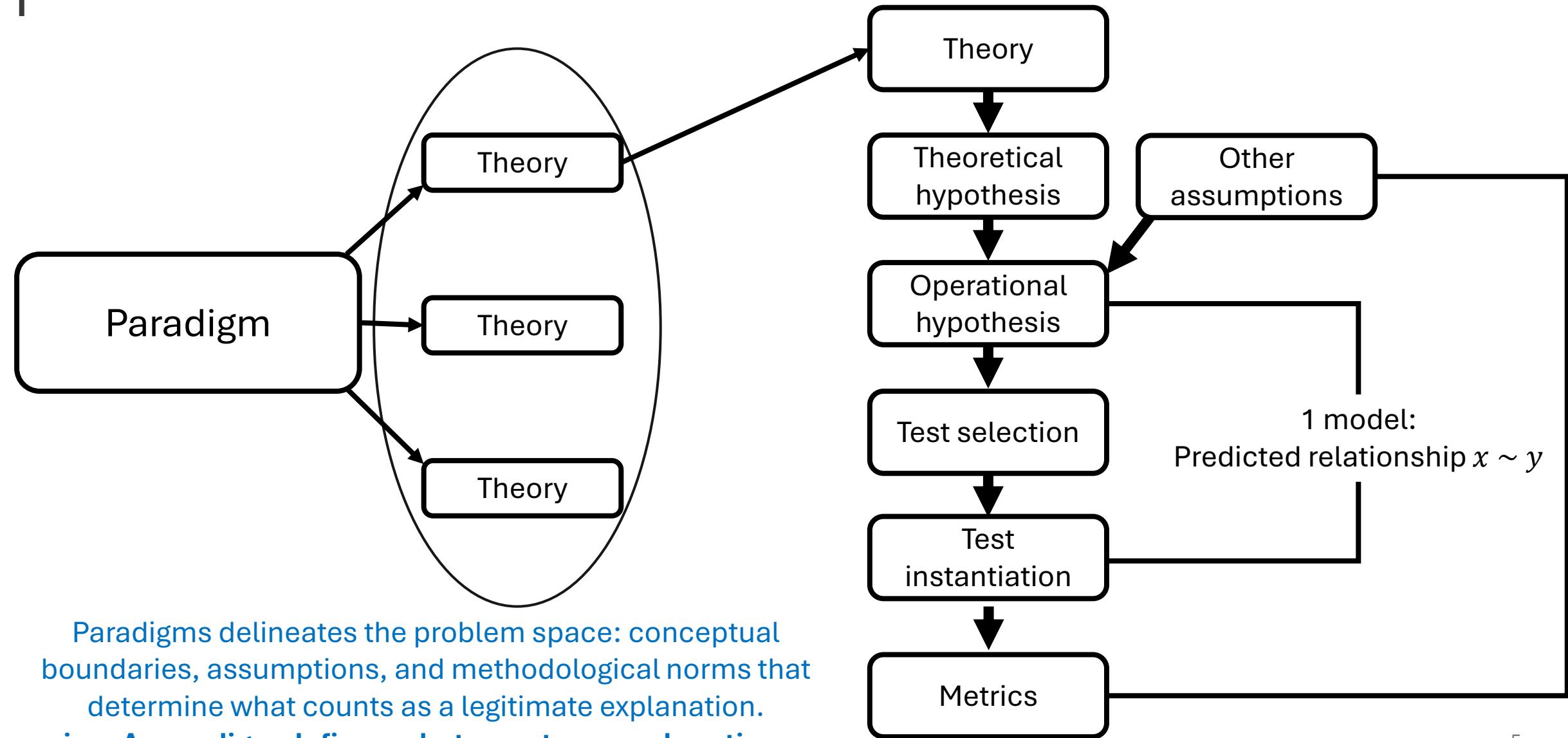
Hypothesis testing

Paradigm: shared set of symbolic generalizations, models, values, and exemplars



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One cannot escape paradigms

All hypotheses have underlying assumptions.

All assumptions are grounded in a body of work (~axioms) that cohere within a given paradigm.

Accepting some assumptions automatically (& logically) rules out competing assumptions.

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What are theories for

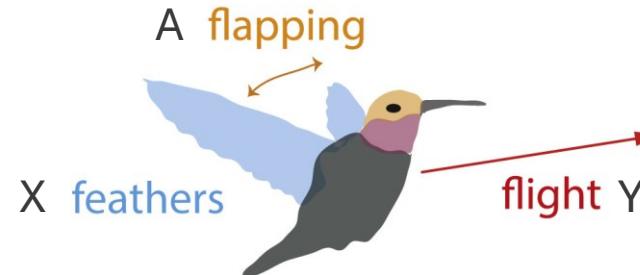
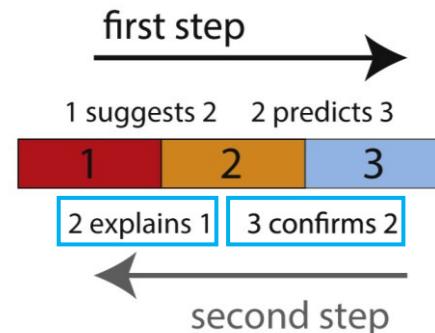
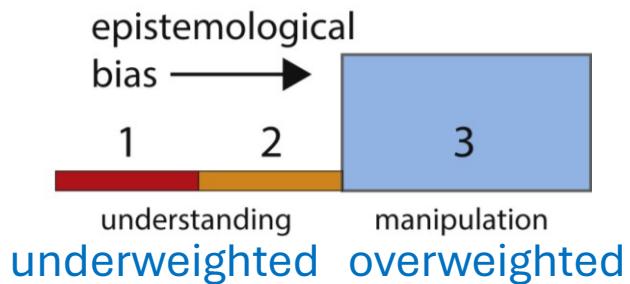
A Marr's levels of analysis

LEVELS

Computation 1 why (problem)

Algorithm 2 what (rules)

Implementation 3 how (physical)

**B****C**

1. **Describe:** We observe X, Y; X is *involved* in Y
2. **Explain:** Y occurs because the system is solving a problem by algorithm A implemented via X
3. **Predict:** Given state S and model M ($Y \sim X$), the system will produce \hat{Y}

Marr:
A model only counts as explanatory if it captures a sufficient range of the processes it claims to represent.

Confirmation: A is likely because X is present

Reverse inference: Y is present because X is present

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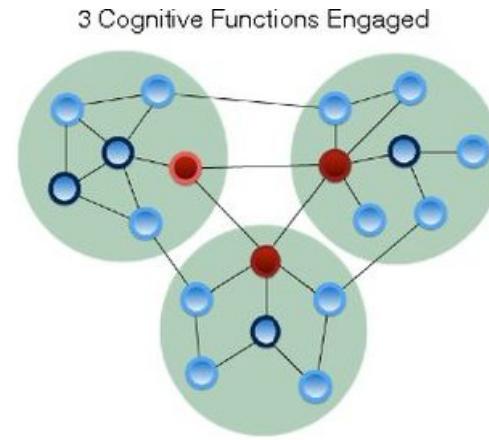
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- **Bickle, 2016. *Frontiers in Systems Neuroscience***
Neuroscience advances through “tool-driven revolutions”: moments when a new technique transforms experimental practice and thereby shifts what counts as legitimate explanation.
- **Parker, 2018. *Biology & Philosophy***
Paradigm shifts in neuroscience are primarily conceptual. Tools were necessary for empirical progress but insufficient to drive Kuhnian revolutions.

The need for qualitative leaps

Paradigms impose constraints on problem formalization and grammar

Fodor's (1983) modularity

1. Domain specificity
2. Mandatory operation
3. Limited central accessibility
4. Fast processing
5. Informational encapsulation
6. 'Shallow' outputs
7. Fixed neural architecture
8. Breakdown patterns
9. Ontogenetic pace

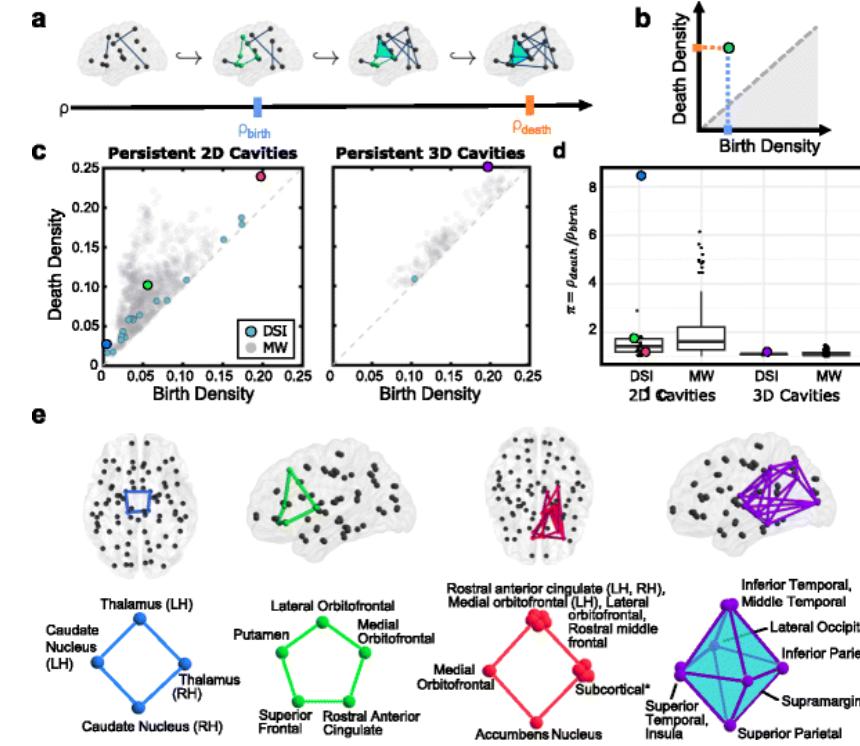


Bertolero, Yeo & D'Esposito,
2015. PNAS.
Model of *modular functional
architecture*

Old paradigm
Structural

Qualitative leap
Connectionist

New paradigm?
Topological



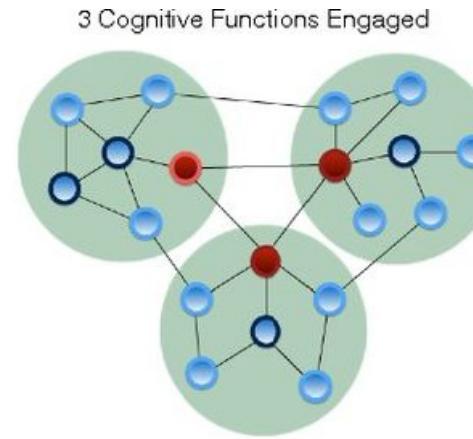
Sizemore et al., 2017. *Journal of
Computational Neuroscience*
Dynamics of cliques and cavities

The need for qualitative leaps

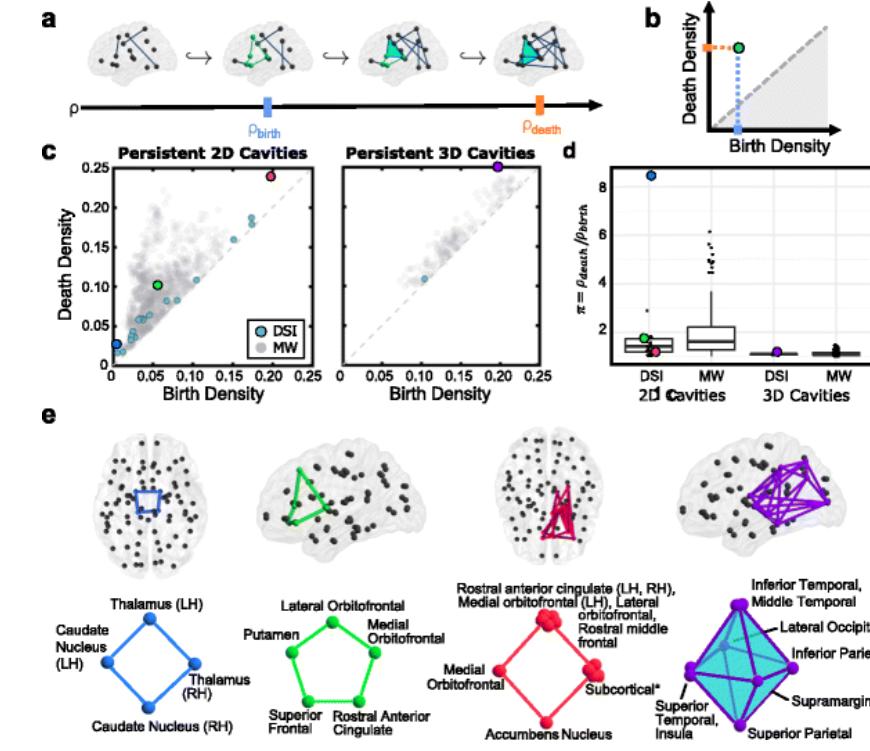
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What counts as explanation?

If the current paradigm is topological, does a structural account counts as explanation?

Implementing Occam's razor Or Flatland fallacy?

Gigerenzer & Brighton, 2009. TICS

Jolly & Chang, 2019. Topics in Cognitive Science

Parsimony can lure us toward simplistic accounts of high-dimensional problems (flatland fallacy).

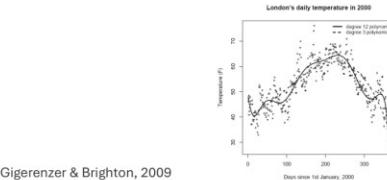
- If parsimonious is preferred between many explanations (Occam's Razor, higher truthlikeness) &
- If psychological phenomenon are high-dimensional,
- How can we form an ethos for evaluating the plausibility of hypotheses that account for psychological phenomenon?
 - Are parsimonious hypotheses/models better?

When small sample sizes and high-dimensional signals, lower dimensional models with greater bias error make more accurate out-of-sample predictions.

When biases lead to better inferences (vs. complex models)

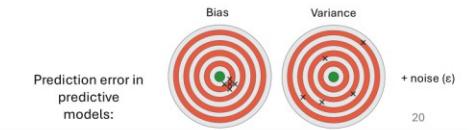
When information is scarce, degraded, uncertain, complex, noisy
When the environment is sufficiently predictable

- Predictive superiority
- Robustness to uncertainty
Ignoring information can make predictions less sensitive to noise and small samples
- Cognitive efficiency
Reduces cost while maintaining sufficient performance (Martignon et al., 2008)



Gigerenzer & Brighton, 2009

- By simplifying, heuristics introduce a bias:
 - This bias reduces the instability of predictions (variance)
 - Improves robustness and generalizability to similar situations, especially under uncertainty
- By complicifying, models reduce bias but become more sensitive to noise :
 - This increases the variance of predictions
 - Reduces ability to generalize to new situations



- We benefit from parsimony and bias (low-dim hypotheses) when predicting complex psychological phenomenon from small, degraded, uncertain, noisy datasets.
- We benefit from complexity and total evidence (high-dim hypotheses) when predicting complex psychological phenomenon from large datasets.