

# Theory Choice, Theory Change, and Inductive Truth-Conduciveness

Konstantin Genin

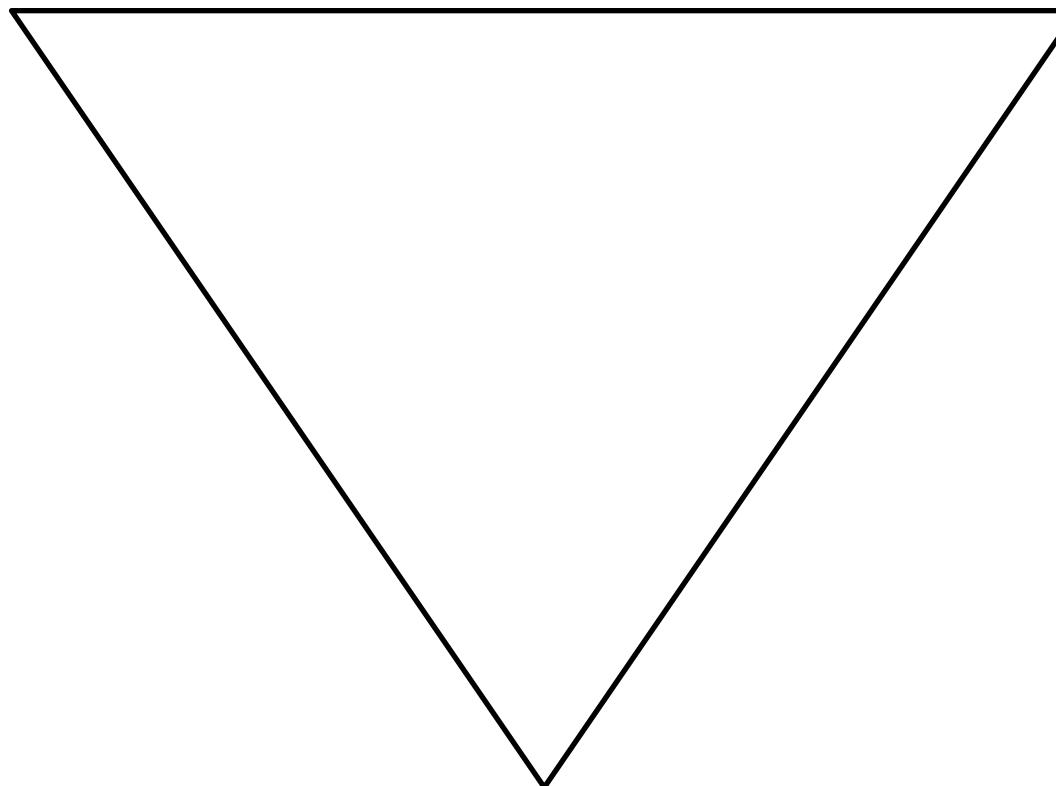
Kevin T. Kelly

Bristol, 2015

# This talk is about ....

norms  
of choice

norms  
of change

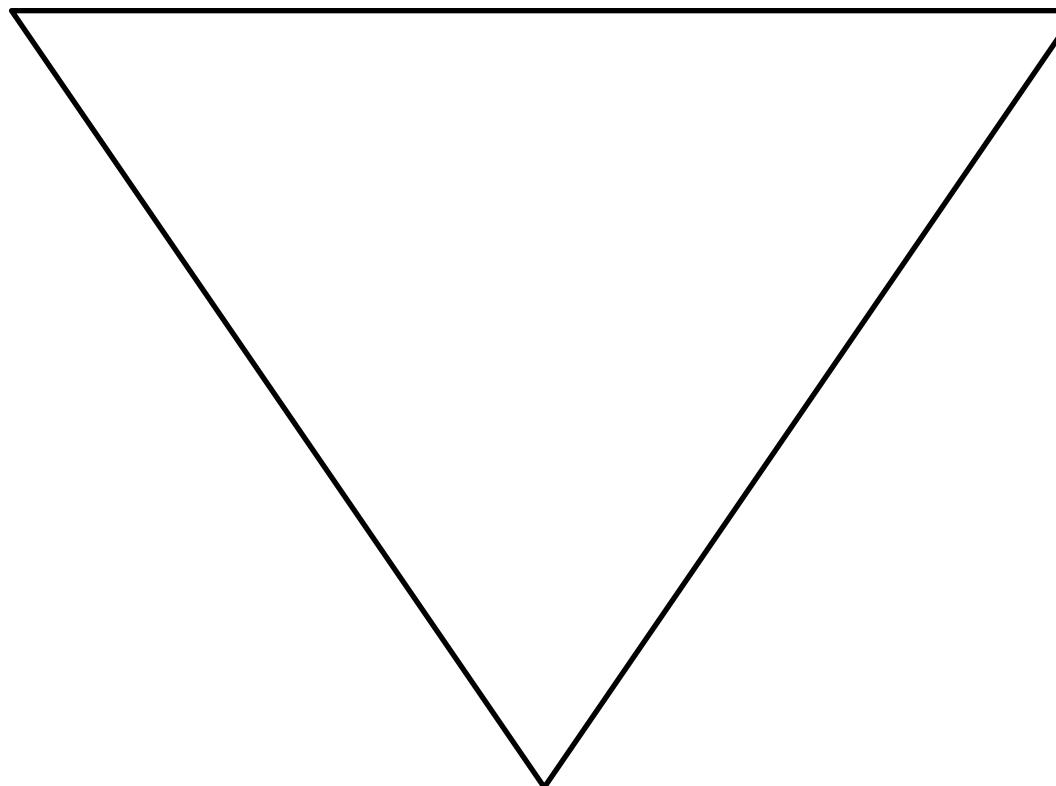


reliability

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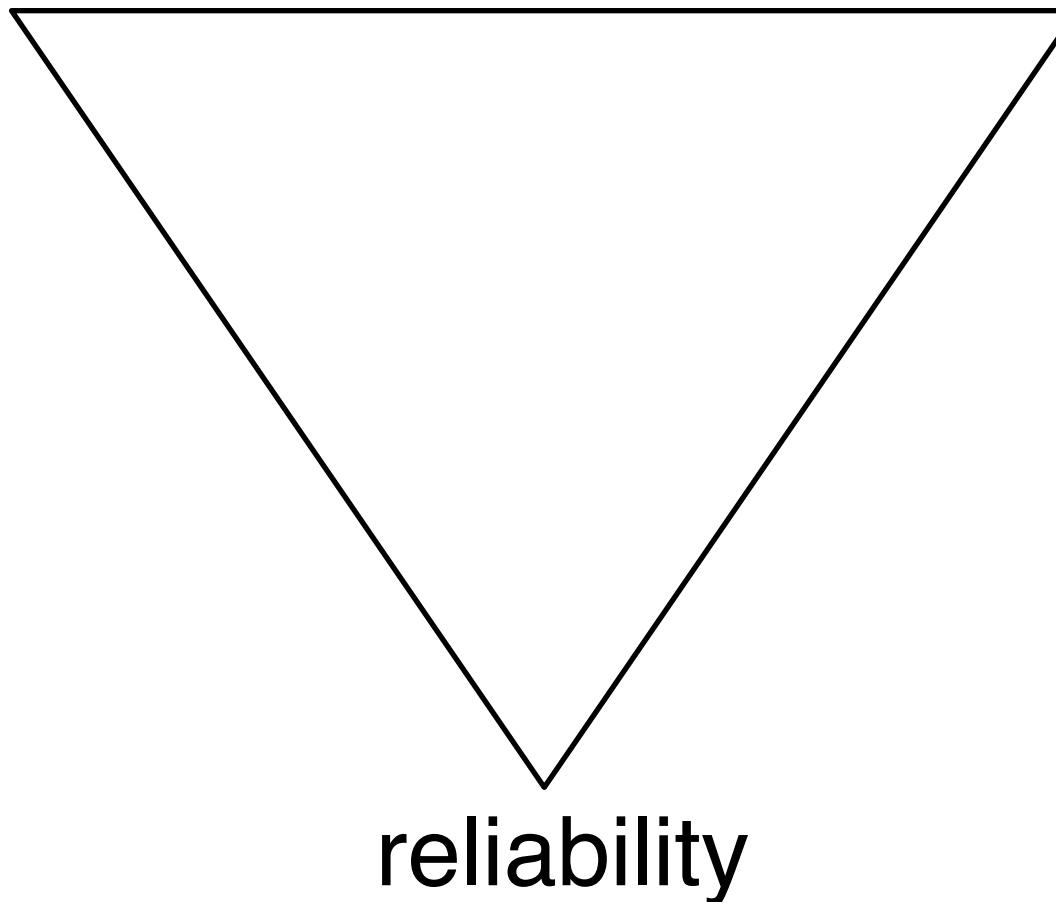


**reliability**

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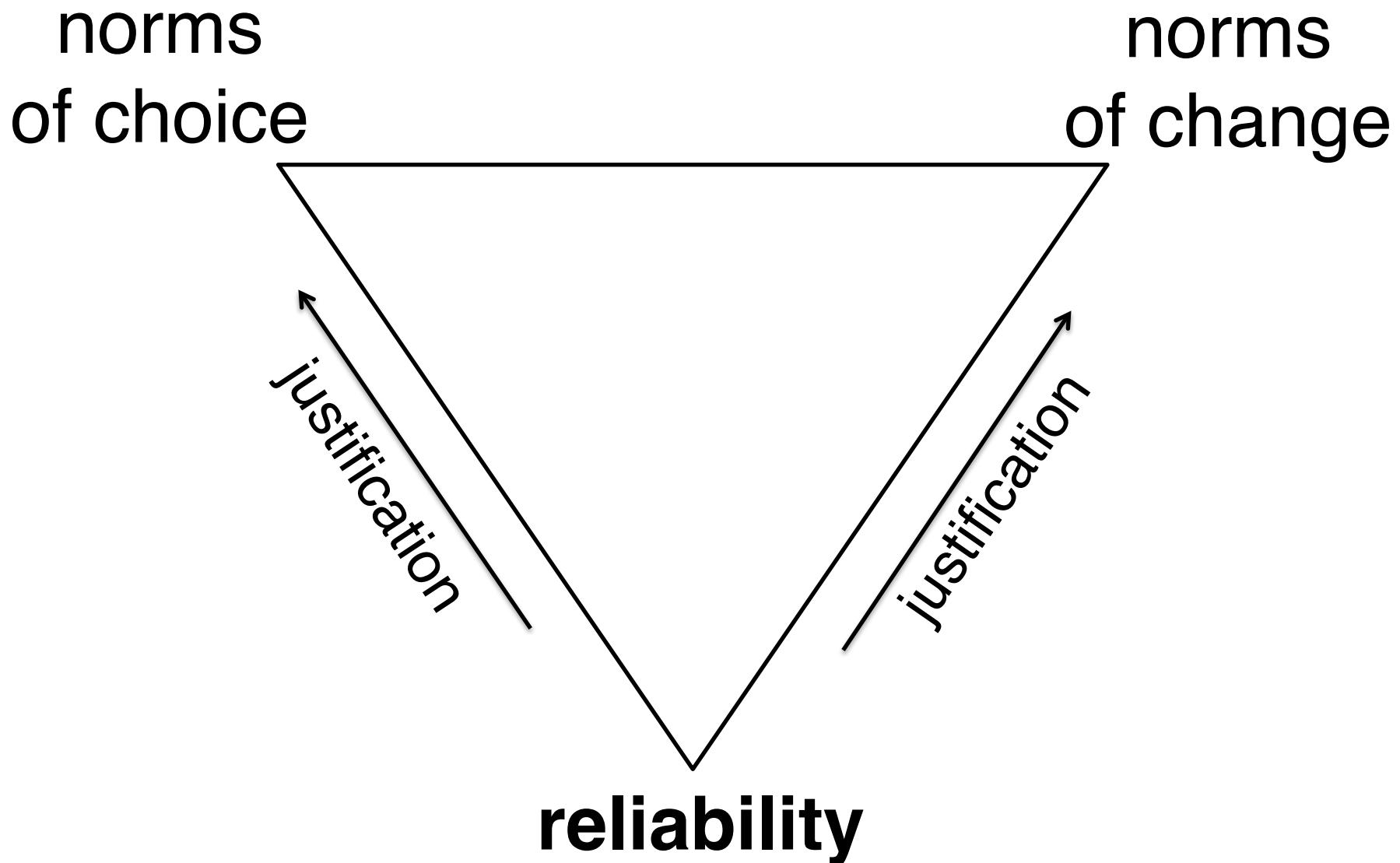
**norms  
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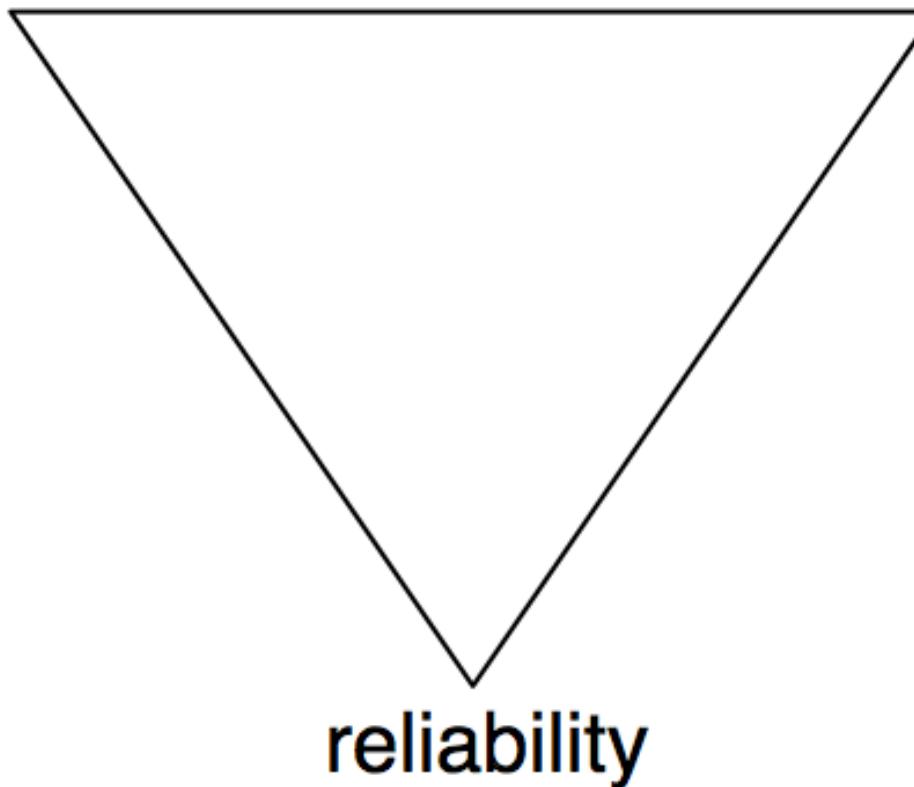
**reliability**

# This talk is about ....



**norms  
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Synchronic norms of theory choice restrict the theories one can choose in light of given, empirical information.

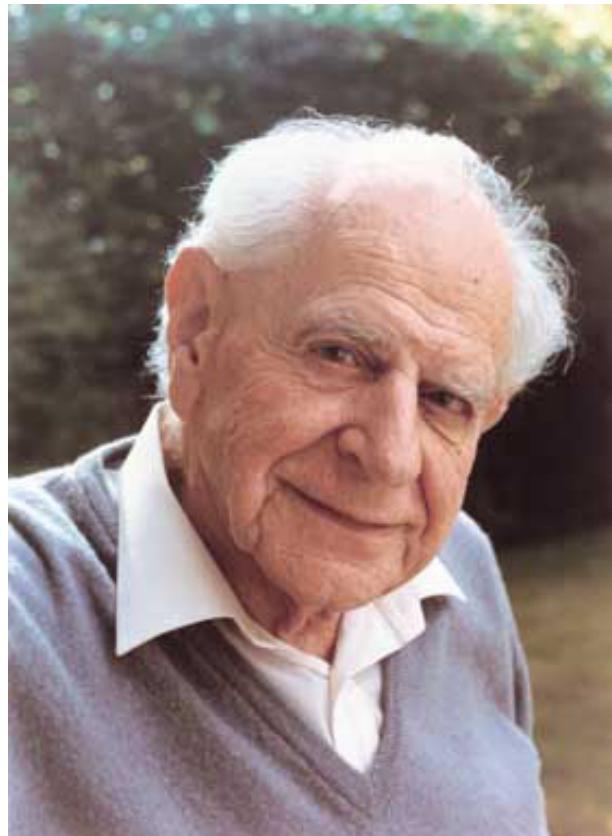
# Norm of Choice: Ockham's Razor

- **Ockham:** “Pluralitas non est ponenda sine neccesitate.”
- **Science:** “All else equal, prefer simpler theories.”
- **Complexity:**
  - Free parameters
  - Multiple mechanisms
  - Coincidences
  - Ad hoc hypotheses



# Norm of Choice: Popper's Dictum

- **Popper:** “All else equal, prefer more falsifiable theories.”



# Reconstruction vs. Reliability

## Rational Reconstruction

- Is the simpler theory more **plausible**?
- Can prior probabilities **encode** that preference?

# Reconstruction vs. Reliability

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# Reconstruction vs. Reliability

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- Is the simpler theory more **plausible**?
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## Reliability

- Does favoring the simpler theory **lead one to the truth** better than alternative strategies?

# Reconstruction vs. Justification

## Rational Reconstruction

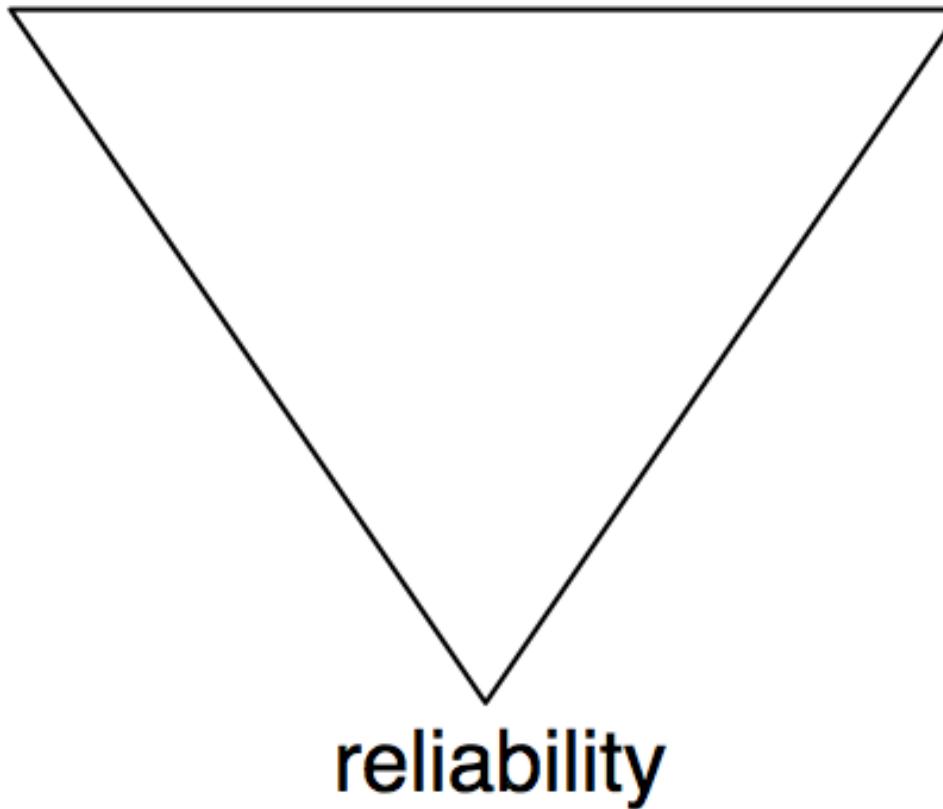
- Is the simpler theory more **plausible**?
- Can prior probabilities **encode** that preference?
- Of course!

## Reliability

- Does favoring the simpler theory **lead one to the truth** better than alternative strategies?
- How **could** you show that, without assuming that the world is simple?

**norms  
of choice**

**norms  
of change**



Diachronic norms of theory change govern how one should change one's *current* beliefs, in light of *new* information.

# Norm of Minimal Change

**Alchourrón, Gärdenfors, Makinson:**

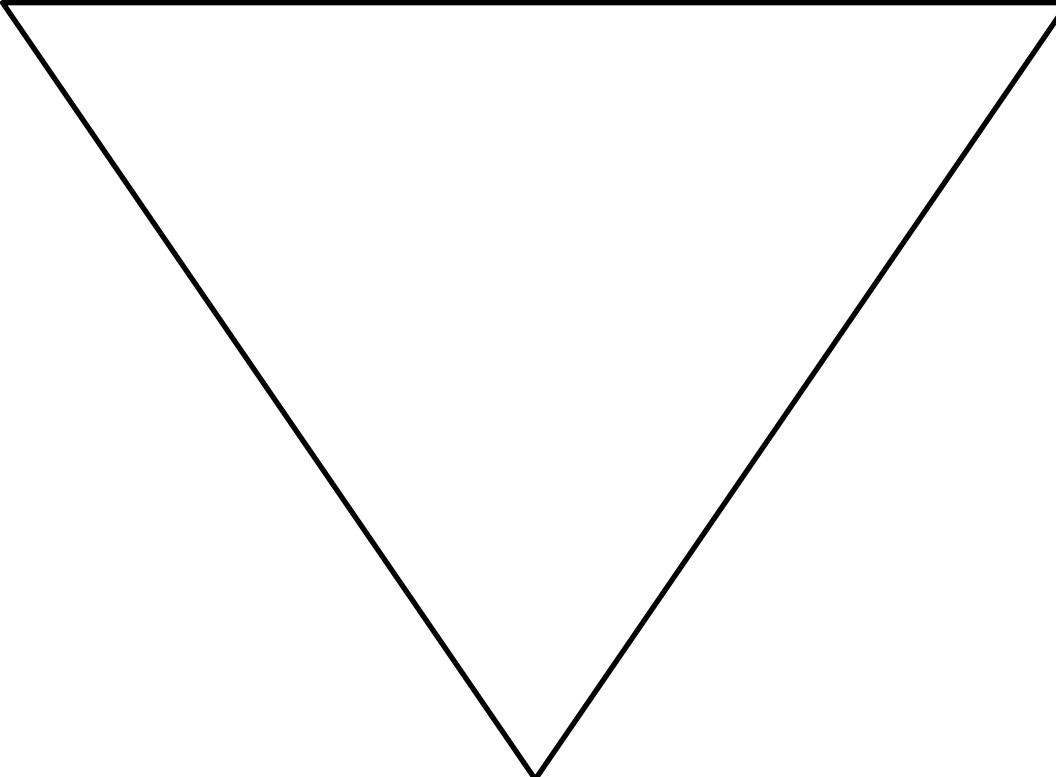
To *rationally* accommodate new evidence, one ought to (1) add only those new beliefs, and (2) remove only those old beliefs, that are *absolutely compelled* by incorporation of new information.



**norms  
of choice**

?

**norms  
of change**



**reliability**

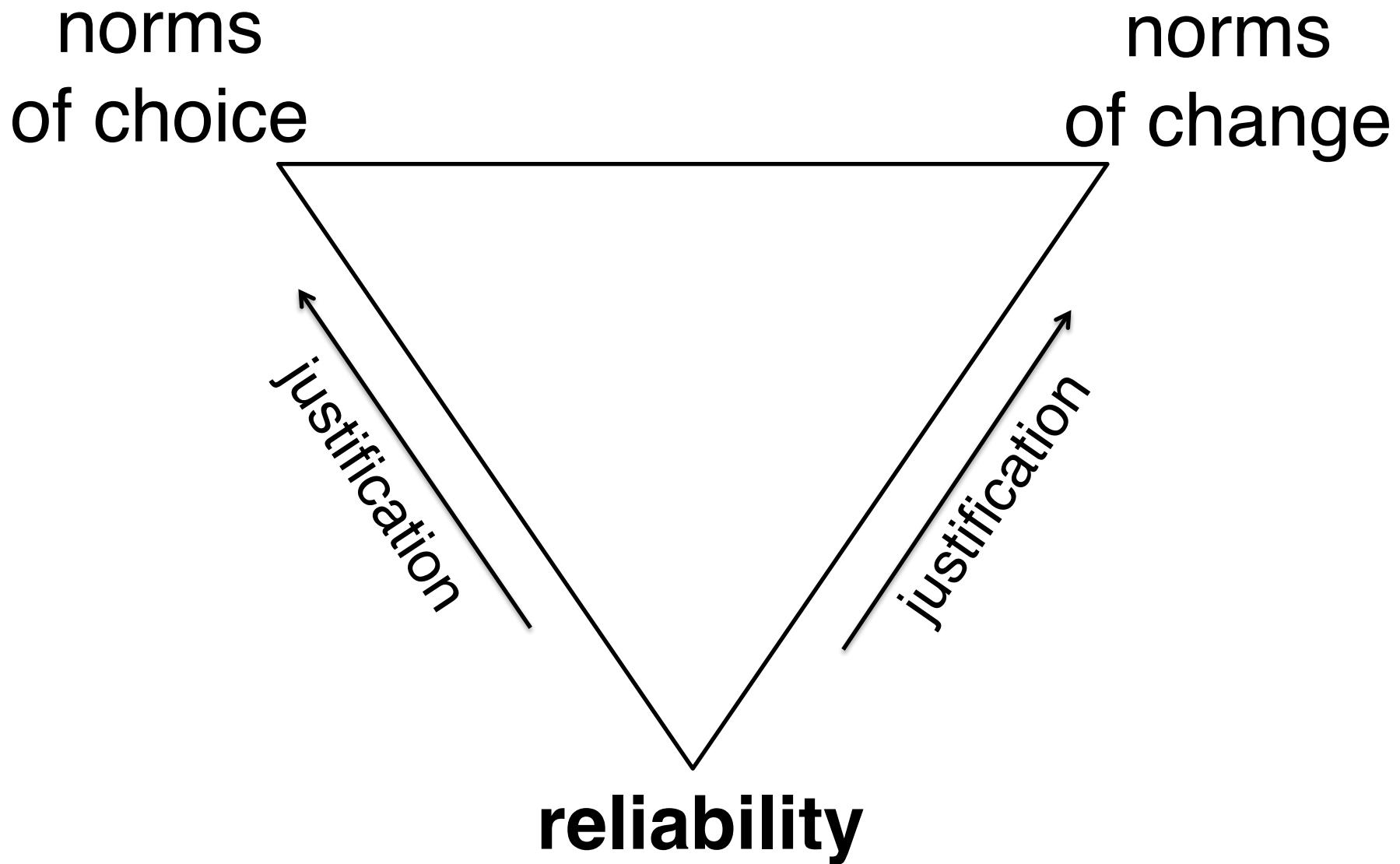
How are the norms of change related to the norms of choice?

# **norms of choice**

?

# **norms of change**

It is a strange coincidence that the philosophy of science has focussed on the monadic (nonrelational) features of theory choice, while philosophical logic has emphasized the dyadic (relational) features of theory change. I believe that it is time for researchers in both fields to overcome this separation and work together on a more comprehensive picture (Rott, 2000, p. 15).



***Epistemic justification*** consists in showing that the norms are, in some sense, ***reliable***, or ***truth-conducive***.

Traditionally, truth-conduciveness has been **too strictly** conceived:

Traditionally, truth-conduciveness has been **too strictly** conceived:

“. . . justifying an epistemic principle requires answering an epistemic question: why are parsimonious theories more likely to be true?” (Baker, 2013)

When your standards are too high, you are led either to  
[metaphysics](#),

“Nature is pleased with simplicity, and affects not the pomp of superfluous causes” (Newton et al., 1833).

... or despair.

“[N]o one has shown that any of these rules is more likely to pick out true theories than false ones. It follows that none of these rules is epistemic in character” (Laudan, 2004).

# Truth Conduciveness: Too Strong

- Theoretical virtues do not *indicate* the truth the way litmus paper indicates pH.
- Inductive inferences made in accordance with the rationality principles are still subject to *arbitrarily high chance of error*.

# Truth Conduciveness: Too Strong

We can make progress if we don't demand the impossible:

“The fact that the truth of the predictions reached by induction cannot be guaranteed does not preclude a justification in a weaker sense” (Carnap, 1945).

# Truth Conduciveness: Too Weak

- Truth-indicativeness is too strong a standard. But mere convergence to the truth in the limit is too weak to mandate any behavior in the short run.

“Reichenbach is right ... that any procedure, which does not [converge in the limit] is inferior to his rule of induction. However, his rule ... is far from being the only one possessing that characteristic. The same holds for an infinite number of other rules of induction. ... Therefore **we need a more general and stronger method for examining and comparing any two given rules of induction ...**” (Carnap, 1945)

# Truth Conduciveness: Just Right

Truth-  
Indicative

---

?

Converges  
In the limit

Is there something in between?

# Reasoning

## Deductive Reasoning

- Non-ampliative
- Infallible
- Monotonic



# Reasoning

## Deductive Reasoning

- Non-ampliative
- Infallible
- Monotonic



## Inductive Reasoning

- Ampliative
- Fallible
- Non-monotonic



# Reliability

## Deductive Reliability

- Converge to the truth  
*directly*
- Information *determines* the right answer



# Reliability

## Deductive Reliability

- Converge to the truth **directly**
- Information **determines** the right answer



## Inductive Reliability

- Converge to the truth **indirectly**
- **Anything goes** in the short run.



# Reliability

## Deductive Reliability

- Converge to the truth **directly**
- Information **determines** the right answer



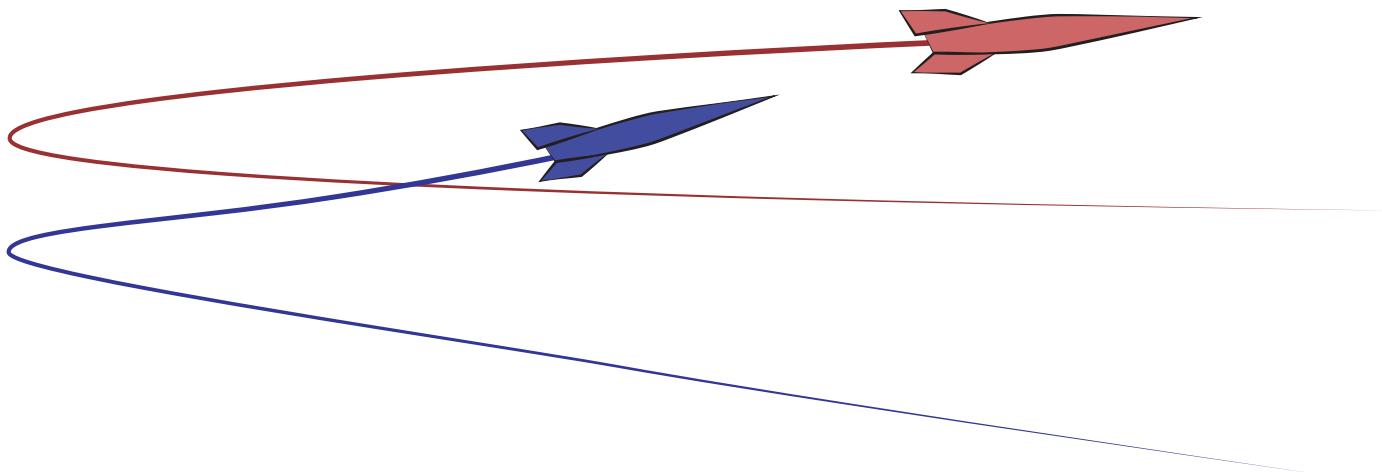
## Optimal Inductive Reliability

- Converge to the truth as **directly as possible**.
- Implies **strong** short-run norms. E.g....



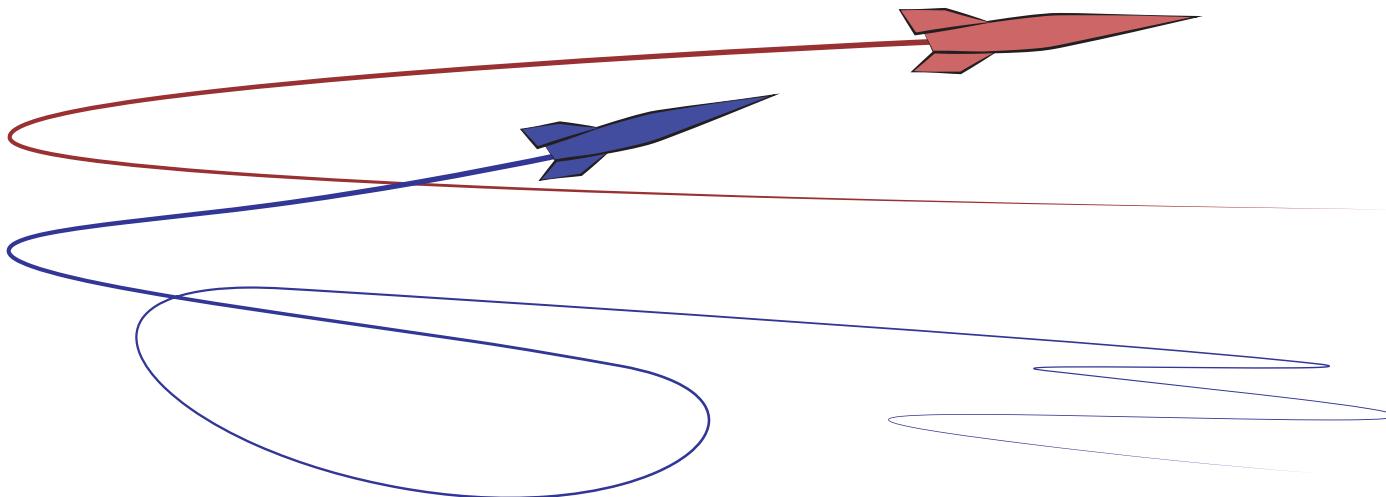
# Reliability

Pursuit of truth ought to be as direct as possible.

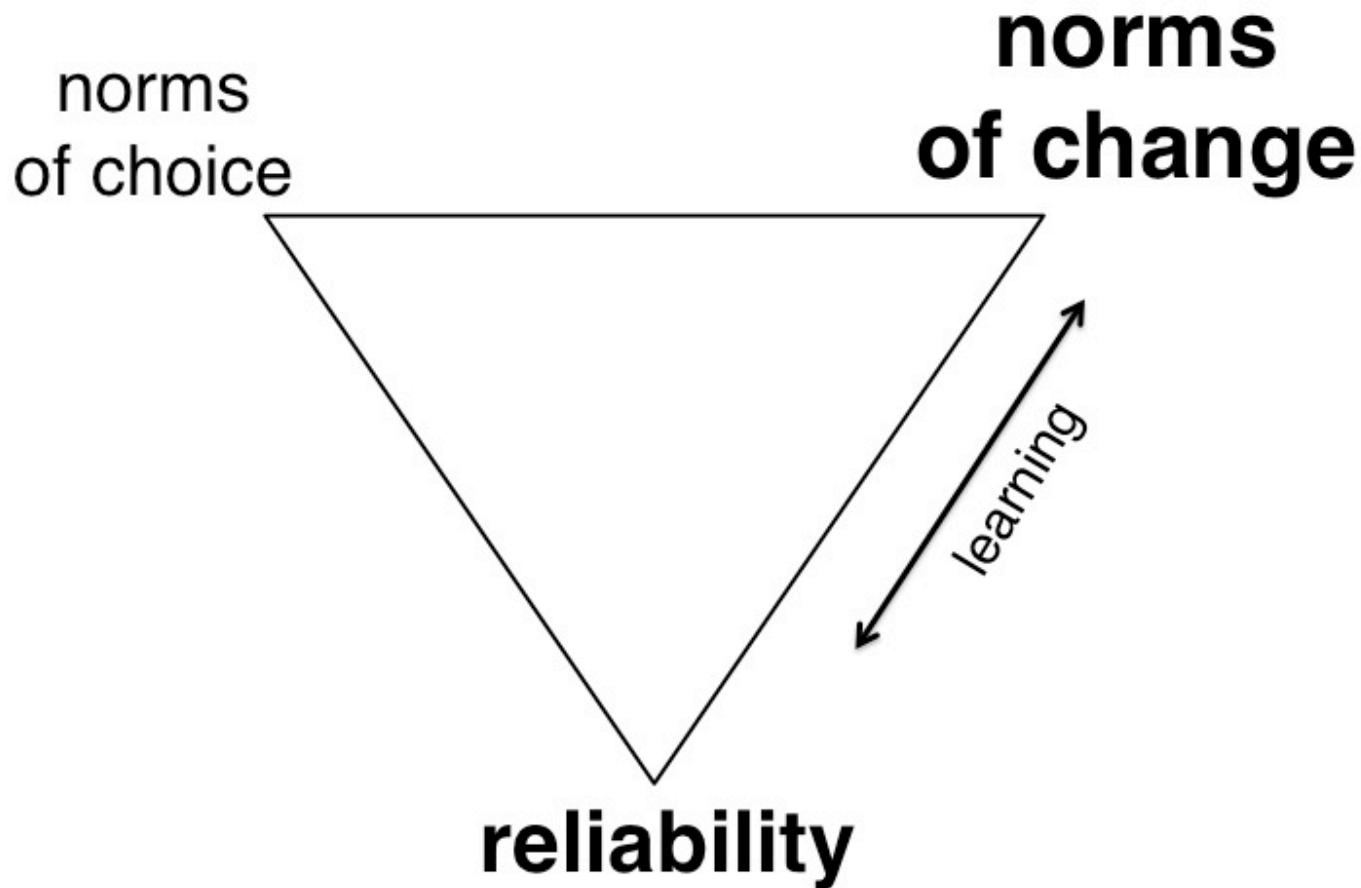


# Reliability

Needless cycles and reversals ought to be avoided.

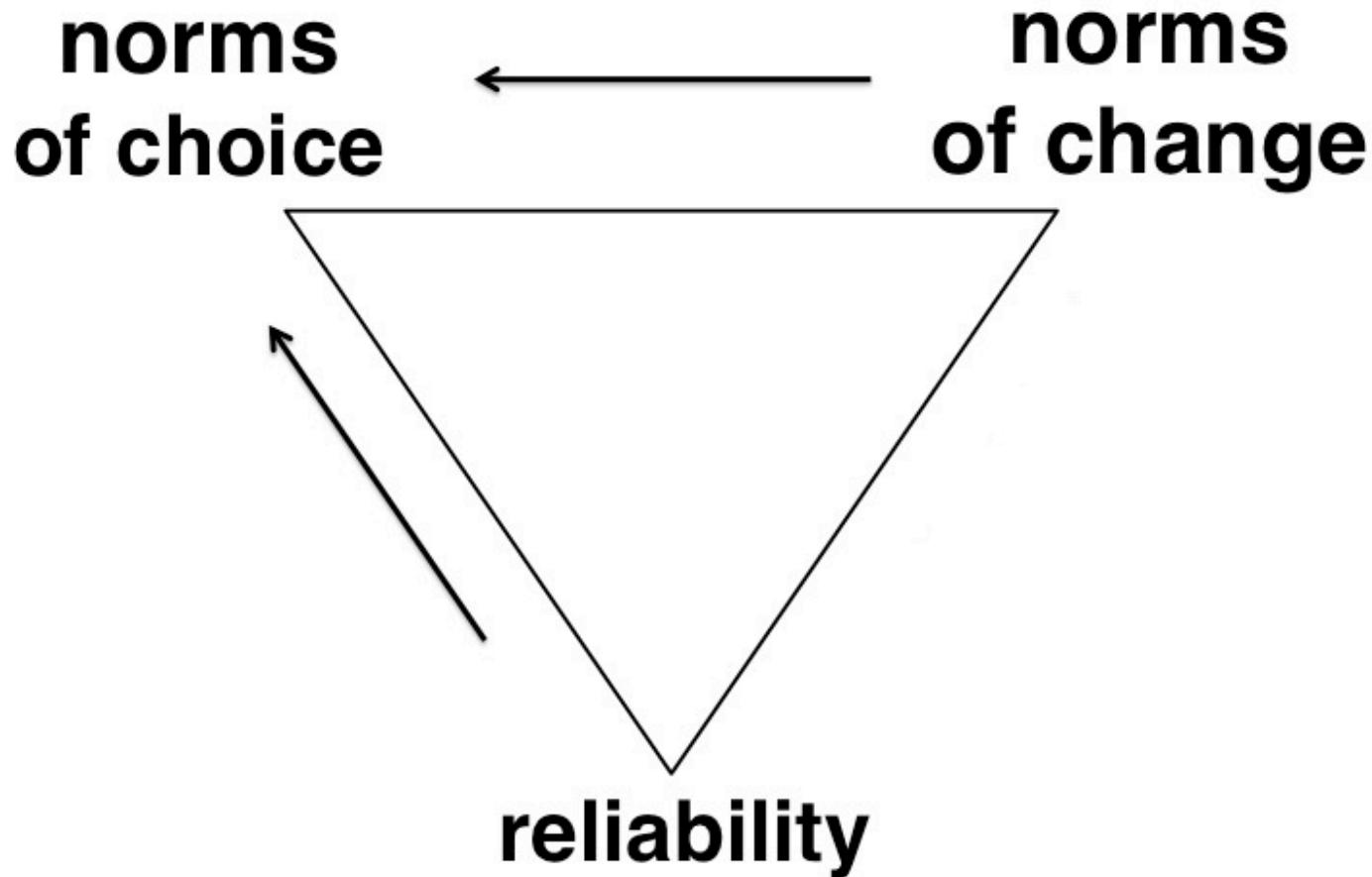


# Main Thesis



Once limiting convergence is imposed, cycle-avoidance is **equivalent** to a norm of change.

# Main Thesis

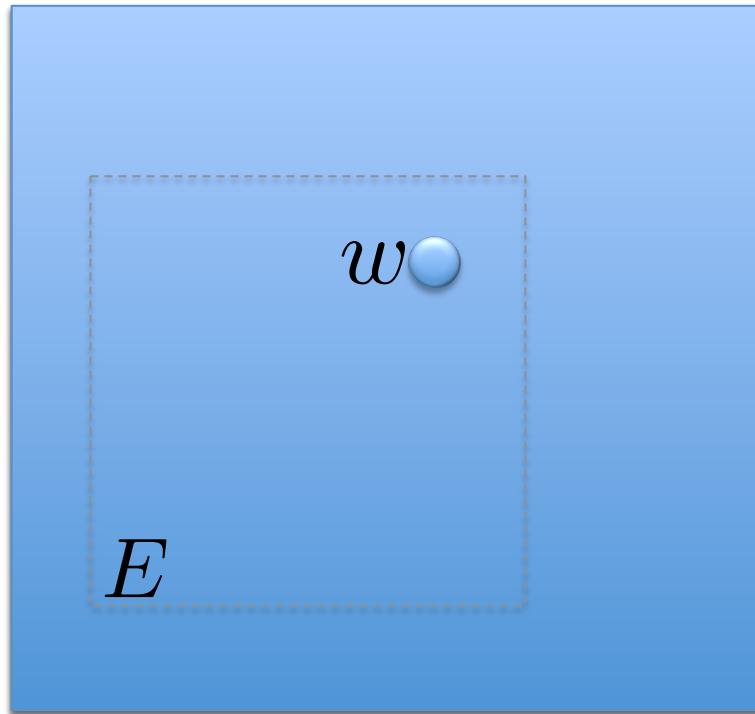


Both necessitate a preference for **simpler**, and  
**more falsifiable** theories.

# **1. EMPIRICAL PROBLEMS**

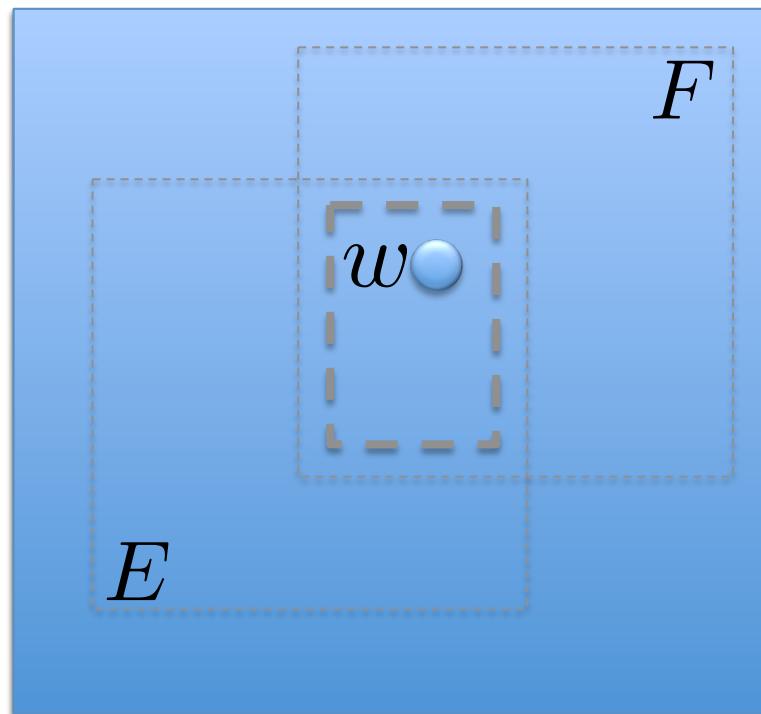
# Information Spaces

- $W$  is a set of possible worlds.
- A proposition is a set of possible worlds.
- $\mathcal{I}$  is a countable set of propositional information states.



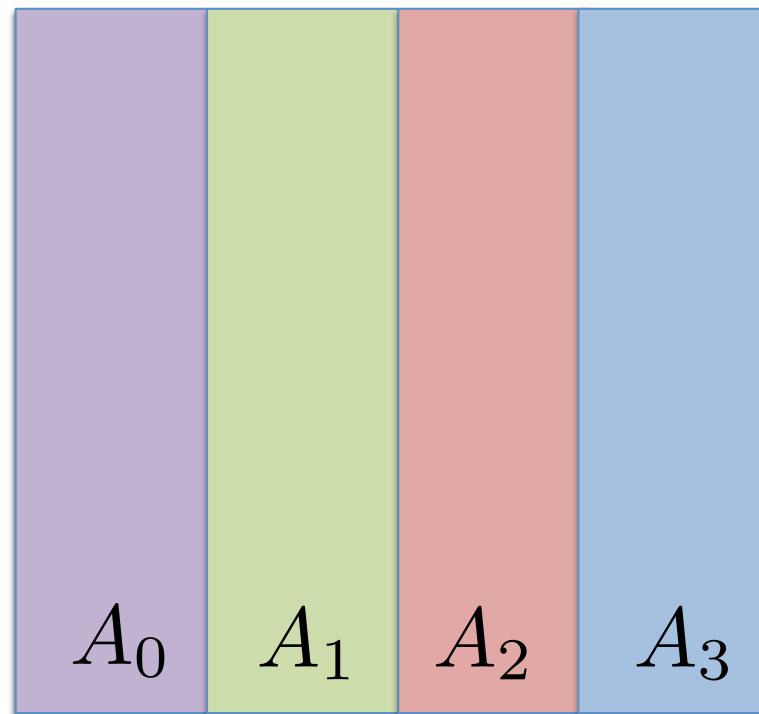
# Axioms on Information

1. **Existence:** Each world makes some information state true.
2. **Cumulativity:** Each finite conjunction of information states true in  $w$  is entailed by an information state true in  $w$ .



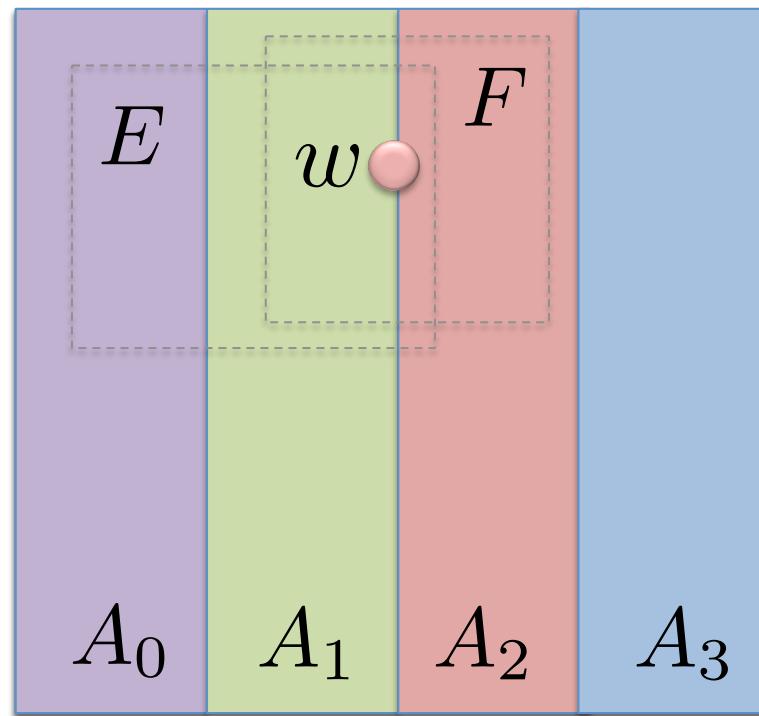
# Questions

- A **question** partitions  $W$  into countably many possible answers (Hamblin 1958).
- **Relevant responses** are disjunctions of answers.



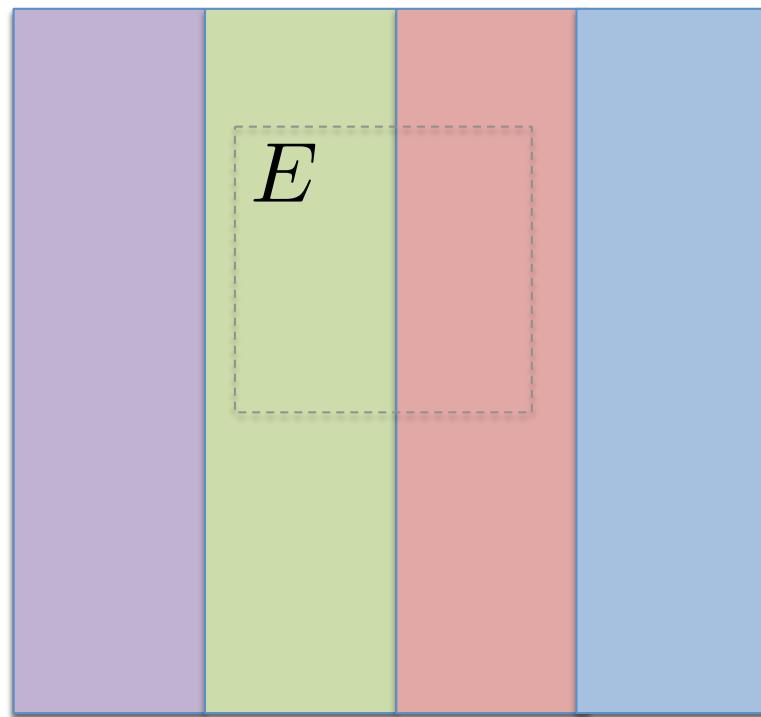
# Empirical Problem

$$\mathfrak{P} = (W, \mathcal{I}, \mathcal{Q}).$$



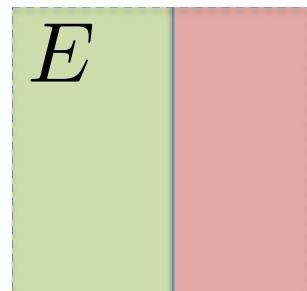
# Problem Restriction

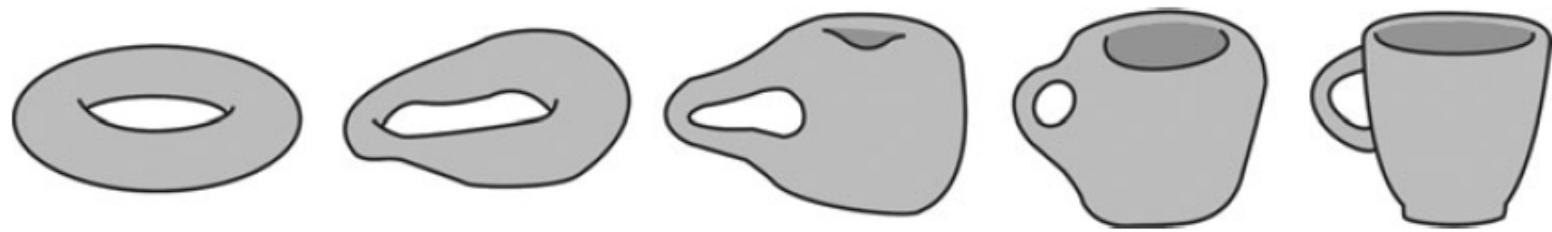
$\mathfrak{P}$



# Problem Restriction

$\mathfrak{P}|_E$

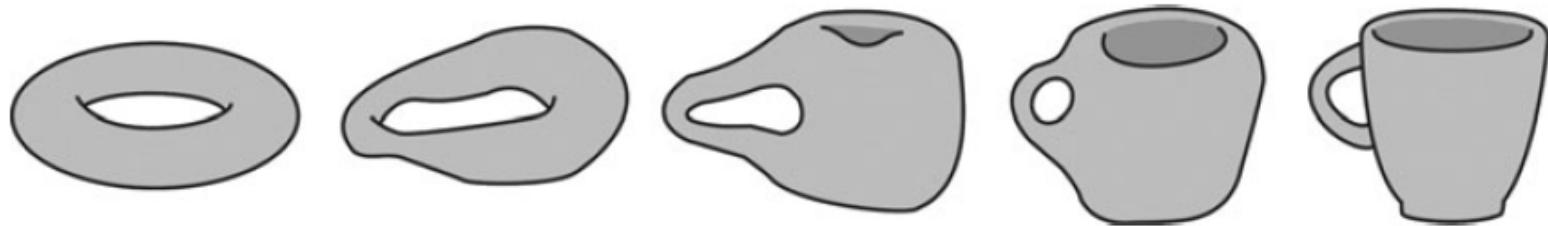




## 2. INFORMATION TOPOLOGY

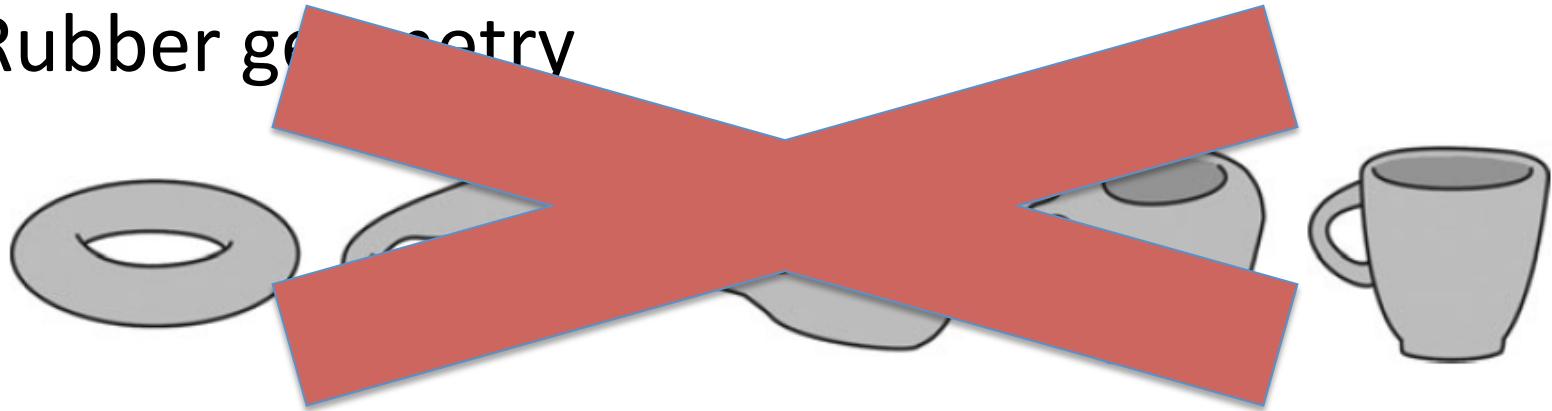
# Topology

Rubber geometry



# Topology

Rubber geometry

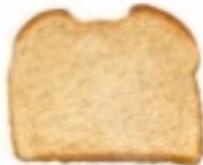


Logic of **verification** (Kelly 1996, Vickers 1996).

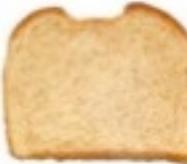
# Topology and Underdetermination

The bread, which I formerly ate, nourished me ... but does it follow, that other bread must also nourish me at another time, and that like sensible qualities must always be attended with like secret powers? The consequence seems nowise necessary (Enquiry Concerning Human Understanding).

# Hume, Topologized.



# Hume, Topologized.



# Hume, Topologized.



# Hume, Topologized.



# Interior of $A$

$\text{Int } A$  = it will be verified that  $A$ .



$$\text{Int } \{ \text{skull} \} = \{ \text{skull} \}$$

$$\text{Int } \{ \text{bread} \} = \emptyset$$

# Open = Verifiable

$A$  is **open** iff  $A$  entails that  $A$  will be verified  
iff  $A$  entails  $\text{Int } A$ .



$$\text{Int } \{ \text{skull} \} = \{ \text{skull} \}$$

$$\text{Int } \{ \text{bread} \} = \emptyset$$

# Closure of $A$

- $\text{Cl } A = A$  will never be refuted  
= not- $A$  will never be verified  
= not Int not  $A$ .



$$\text{Cl } \{\text{skull}\} = \{\text{bread}, \text{skull}\}$$

$$\text{Cl } \{\text{bread}\} = \{\text{bread}\}$$

# Closed = Refutable

$A$  is closed iff  $\text{not-}A$  entails that  $A$  will be refuted  
iff that  $A$  will never be refuted entails  $A$   
iff  $\text{Cl } A$  entails  $A$ .



$$\text{Cl } \{\text{骷髅}\} = \{\text{面包}, \text{骷髅}\}$$

$$\text{Cl } \{\text{面包}\} = \{\text{面包}\}$$

# Frontier of $A$

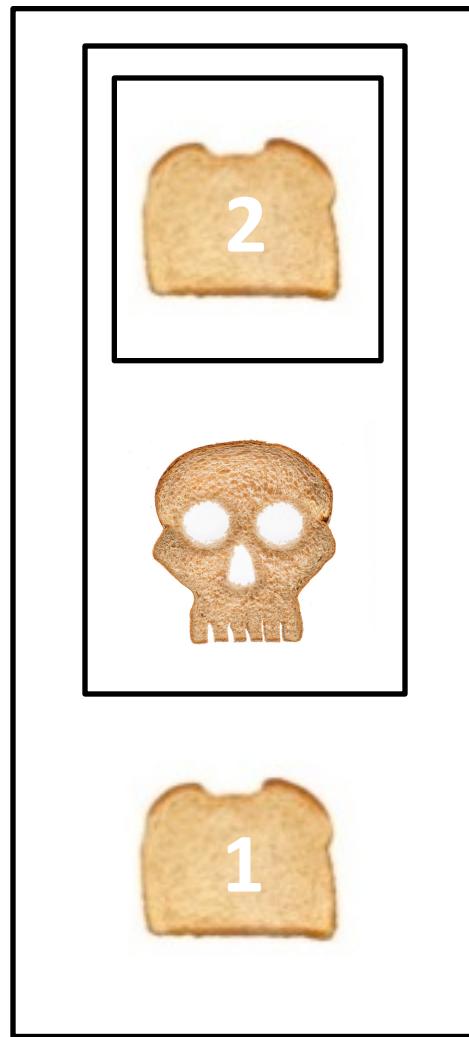
$\text{Frntr } A = A$  is false, but will never be refuted  
=  $\text{Cl } A$ , but not  $A$ .



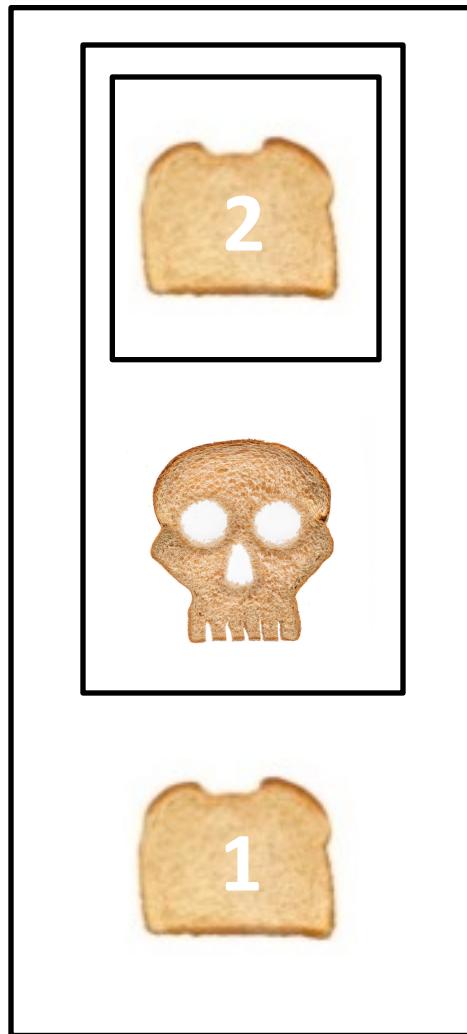
$\text{Frntr } \{\text{skull}\} = \{\text{bread}\}$

$\text{Frntr } \{\text{bread}\} = \emptyset$

# Hume's Problem, Enhanced.

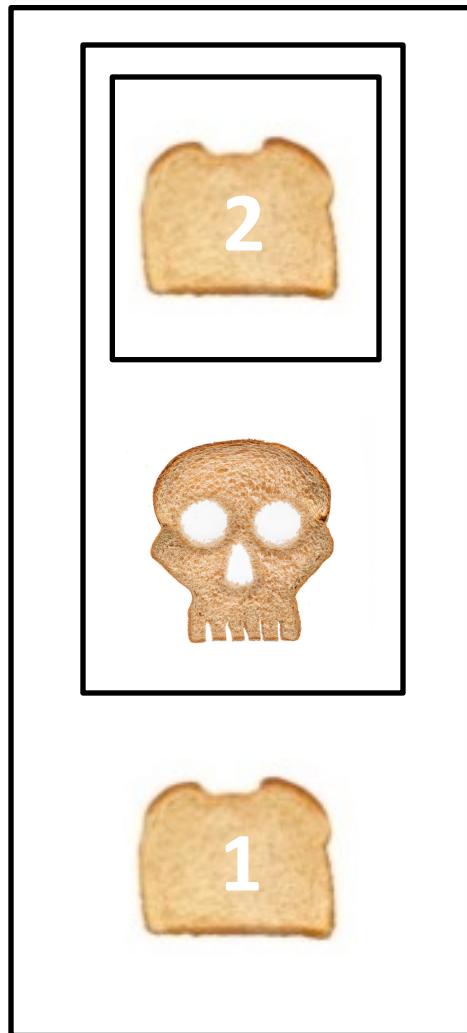


# Hume's Problem, Enhanced.



Frntr { } = { }

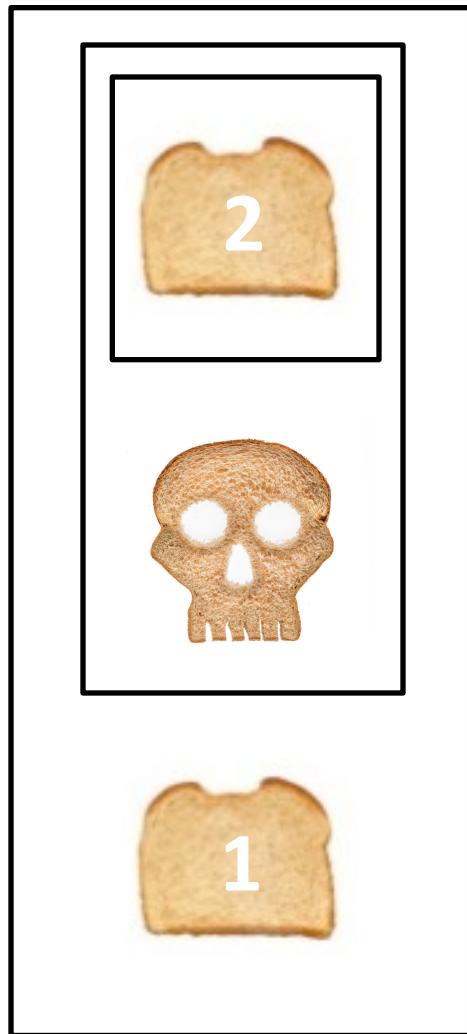
# Hume's Problem, Enhanced.



Frntr { } = { }

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# Hume's Problem, Enhanced.



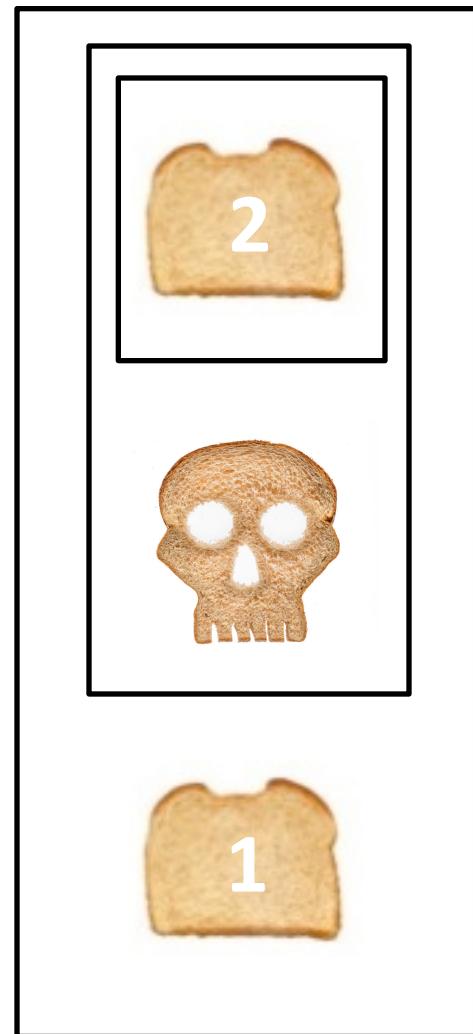
Frntr { } = { }

Frntr { } = { }

Frntr { } =

# Locally Closed

$A$  is locally closed iff  $\text{Frntr } A$  is closed.



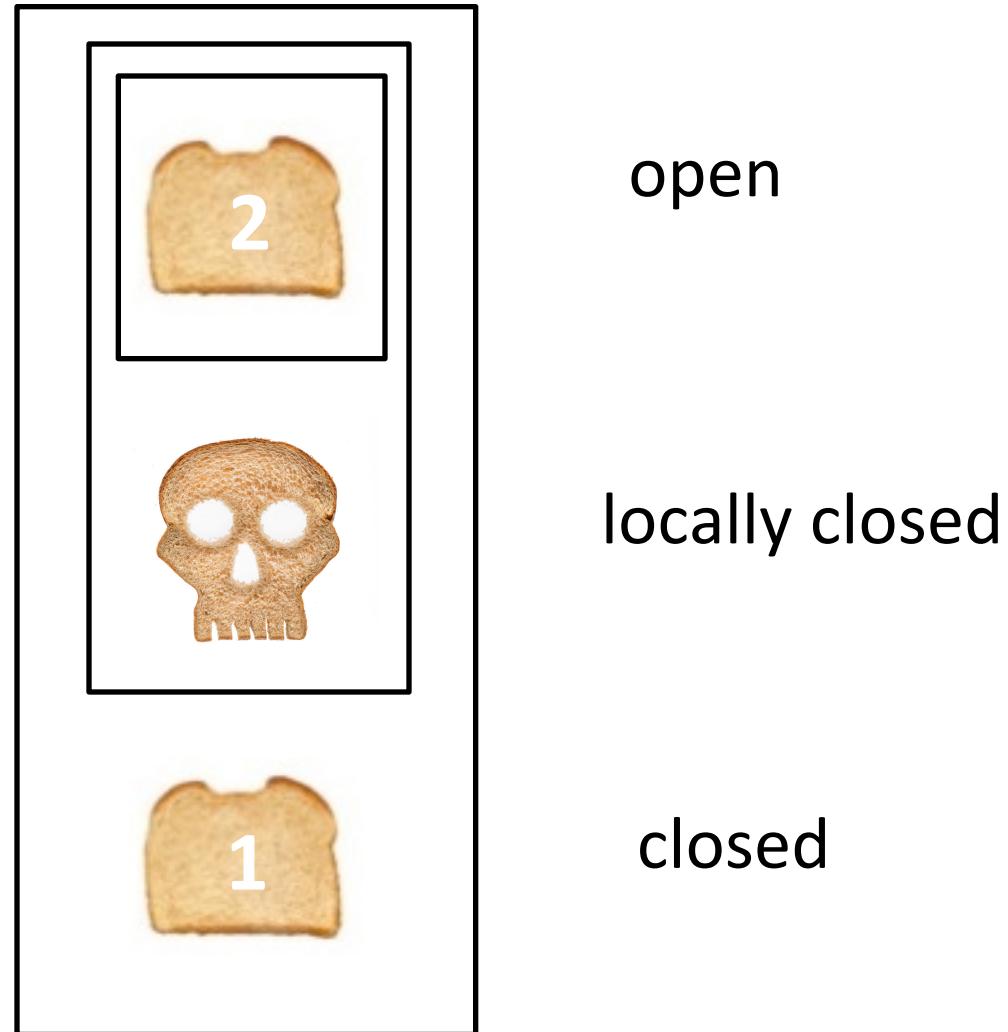
open

locally closed

closed

# Locally Closed

$A$  is **locally closed** iff  $A$  entails that  $A$  will become refutable (closed).

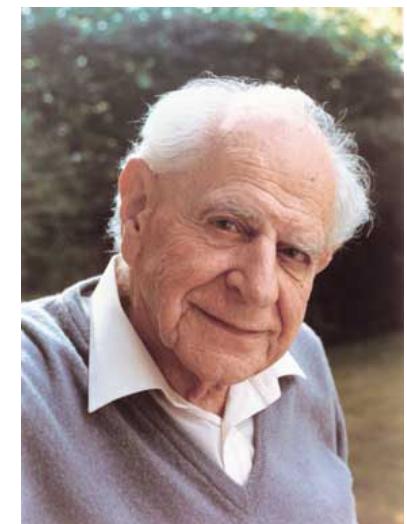
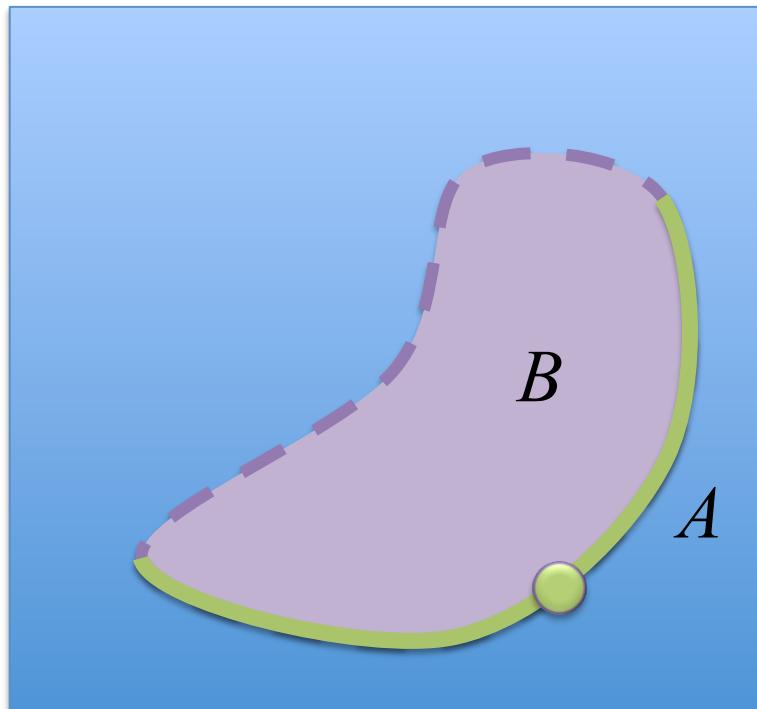


### **3. EMPIRICAL SIMPLICITY**

# Simpler = More Falsifiable

$A \preceq B$  iff  $A \subseteq \text{cl}B$

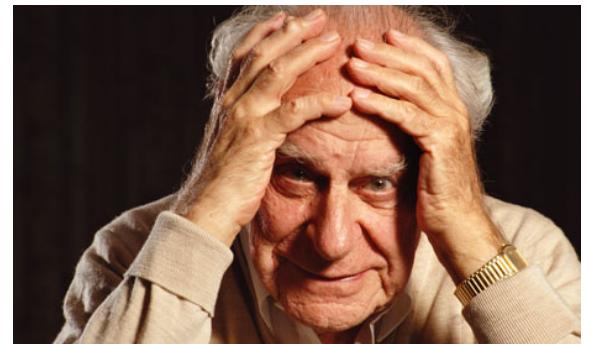
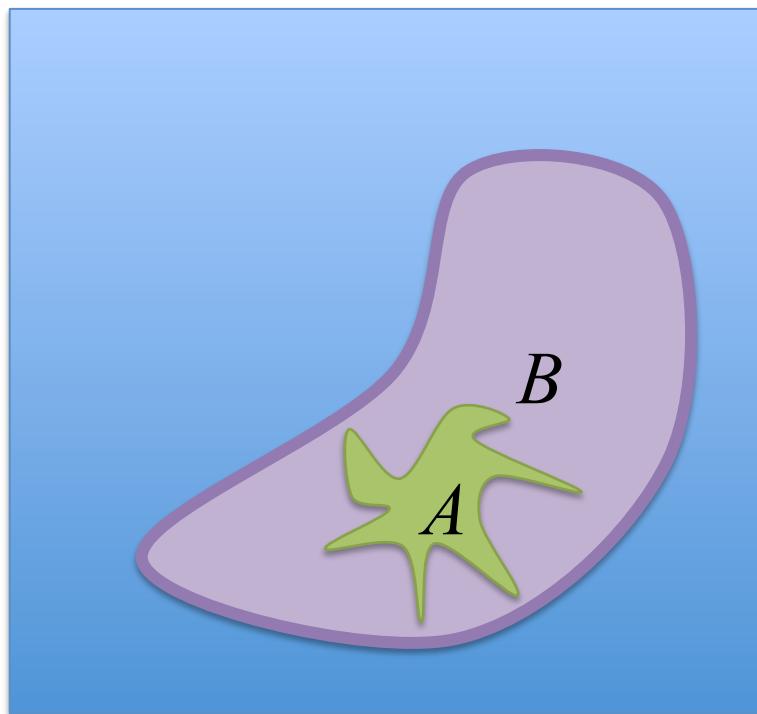
iff all information compatible with  $A$  is compatible with  $B$   
iff all information refuting  $B$  also refutes  $A$ .



Sir Karl Popper

# The “Tack-on” Objection

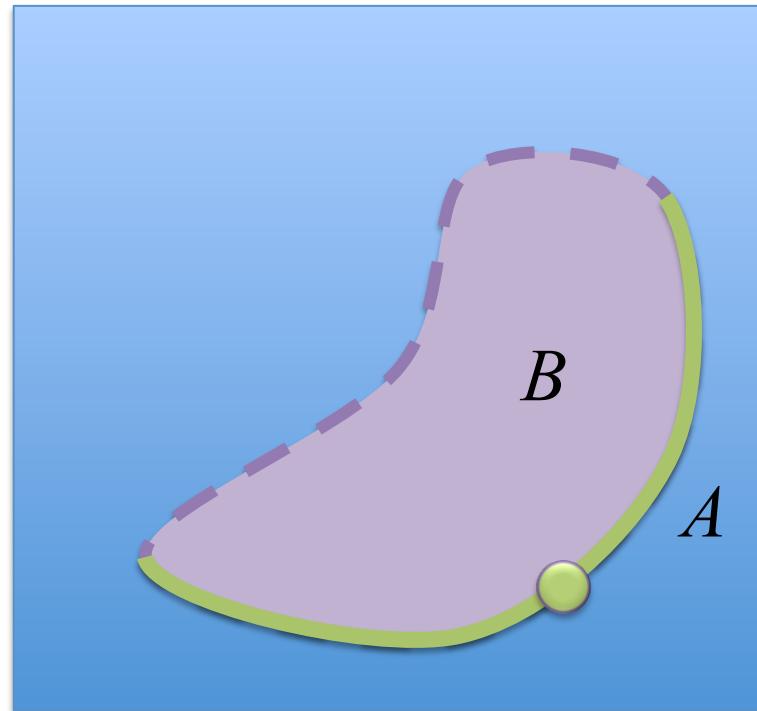
- Adding complex principles to a theory doesn't make it simpler (Glymour 1980).



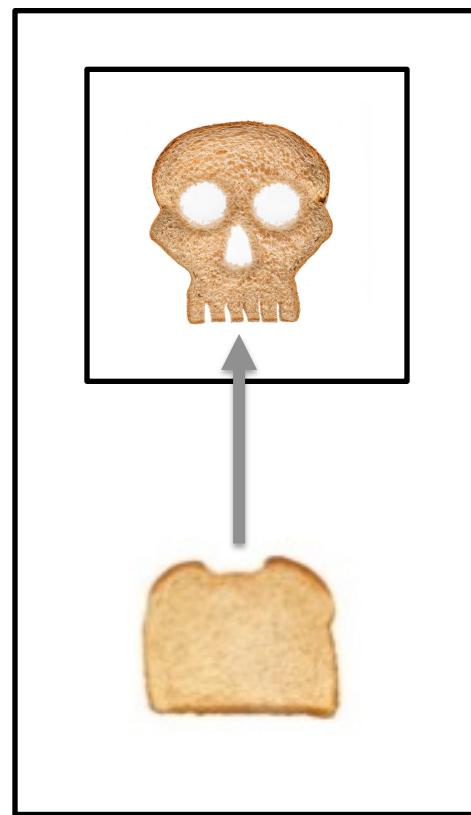
# Improved Definition

$A \prec B$  iff  $A \subseteq \text{Frntr}B$ .

iff  $A$  entails that  $B$  is false  
but will never be refuted.



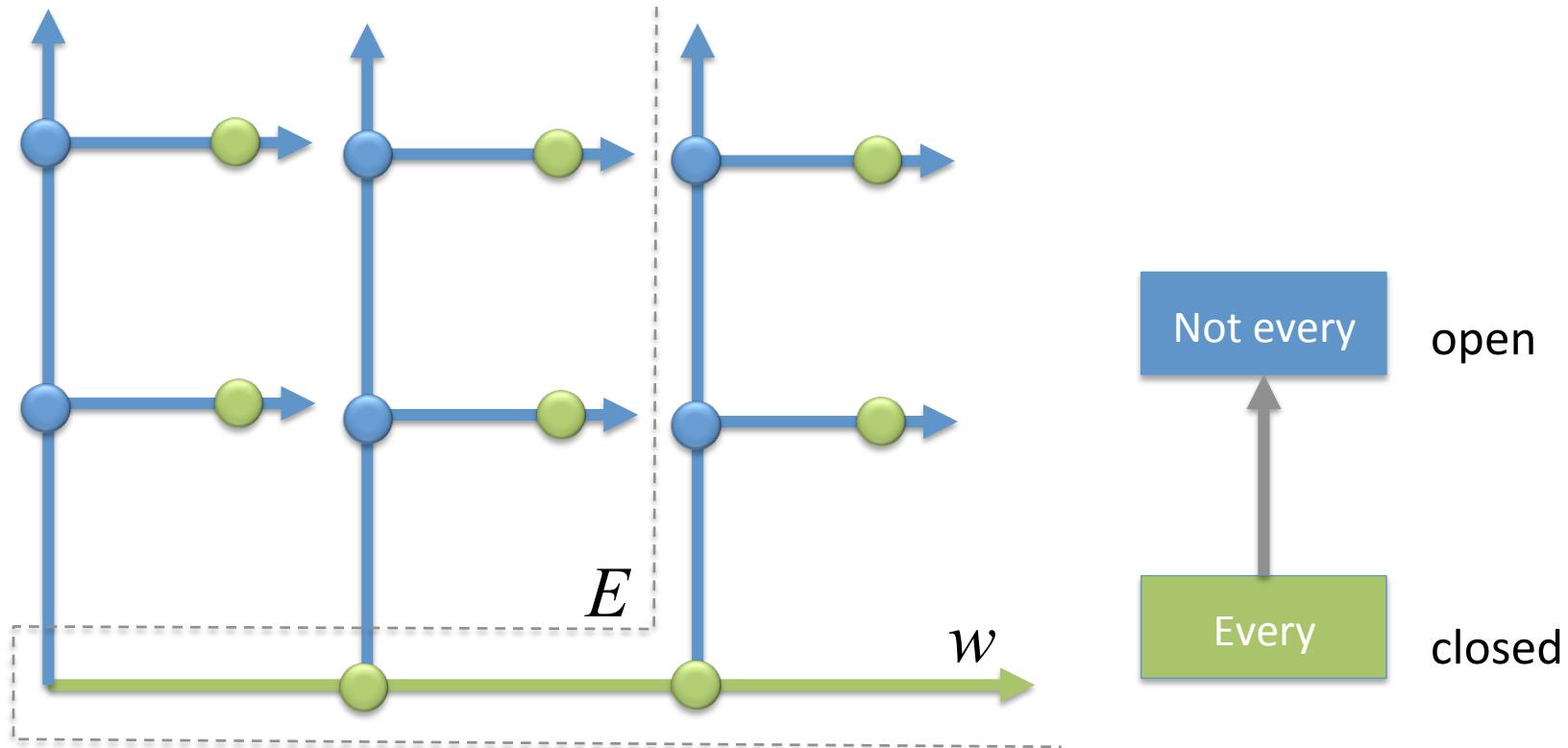
# Example: Hume's Problem



# Example: Discrete Outcomes

$Q$  = Will every outcome be green?

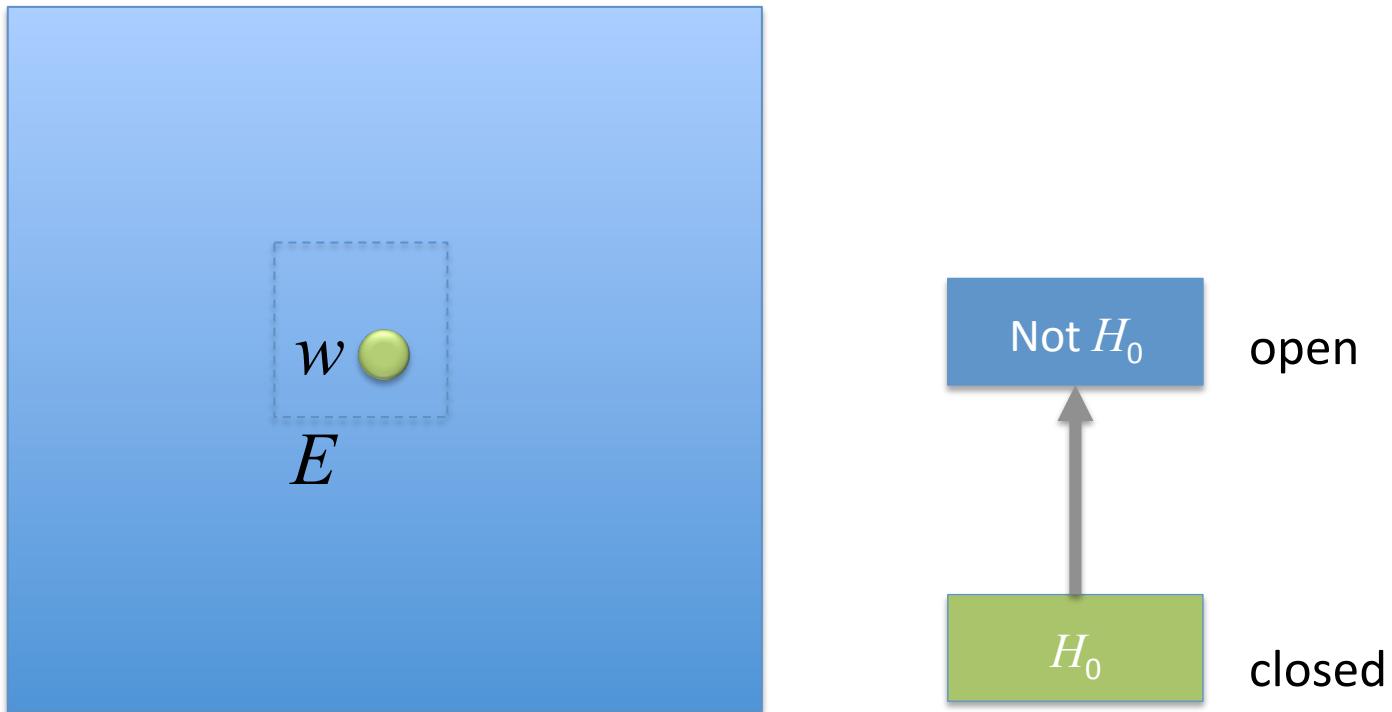
$\mathcal{I}$  = observation histories.



# Example: Real Parameter

$\mathcal{Q}$  = Is the sharp null hypothesis true?

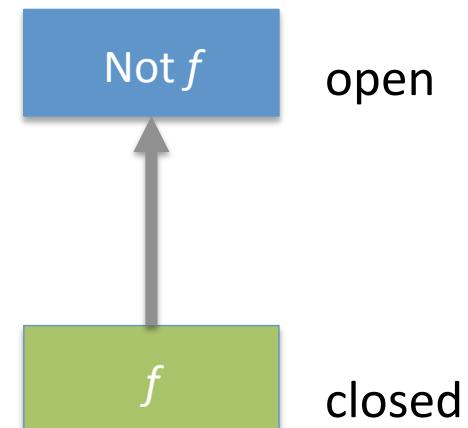
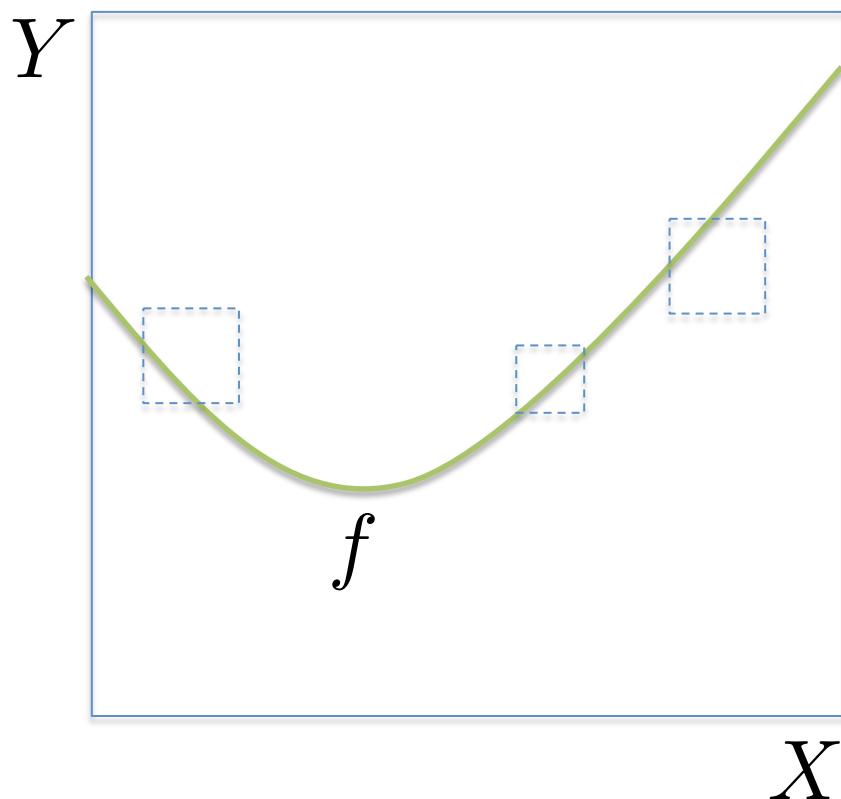
$\mathcal{I}$  = open rectangular estimates.



# Example: Continuous Laws

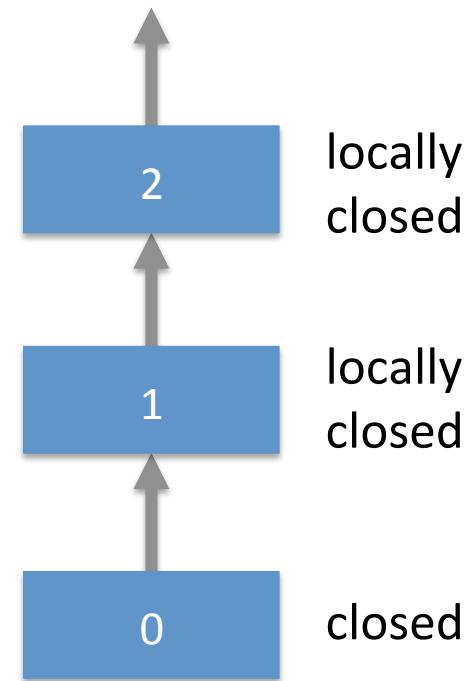
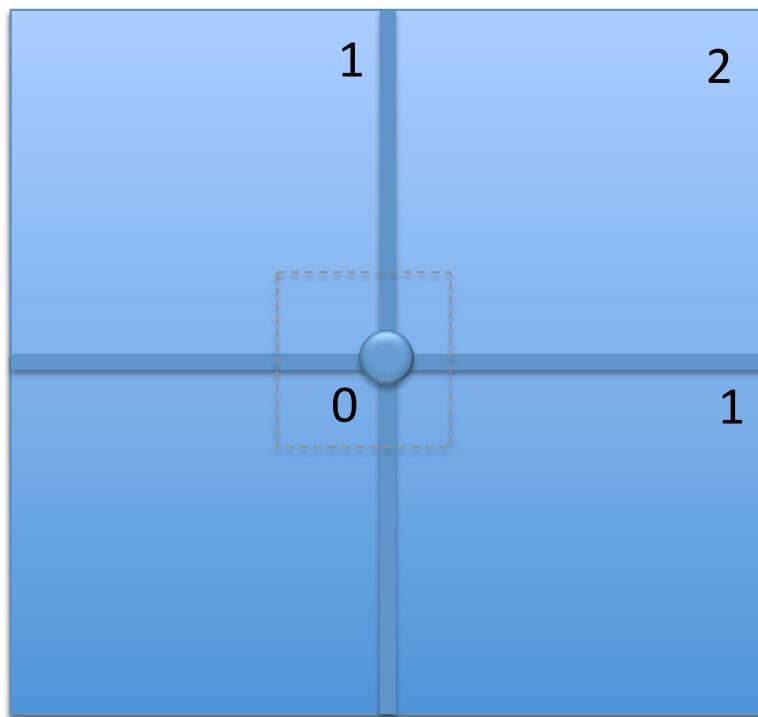
$\mathcal{Q}$  = Does  $Y = f(X)$  ?.

$\mathcal{I}$  = finitely many inexact measurements.



# Example: Parametric Models

$Q$  = How many parameters are free?



# Example: Quantitative Laws

$\mathcal{Q}$  = What is the true polynomial degree?

$\mathcal{I}$  = finitely many inexact measurements.

$$Y = \sum_{i=0}^N a_i X^i.$$

degree



$$Y = a_0.$$

$$Y = a_0 + a_1 X.$$

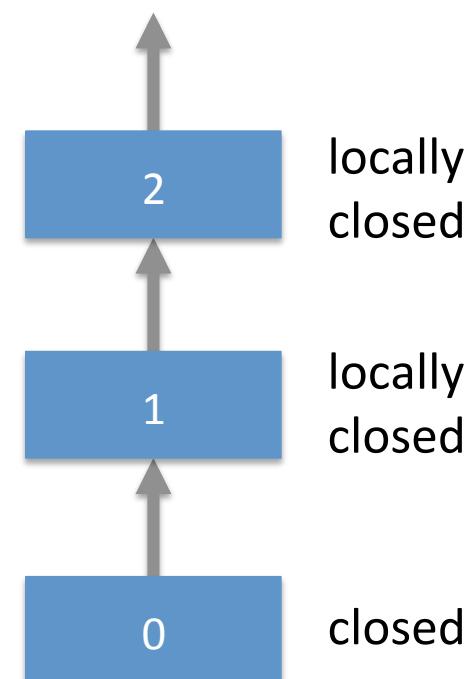
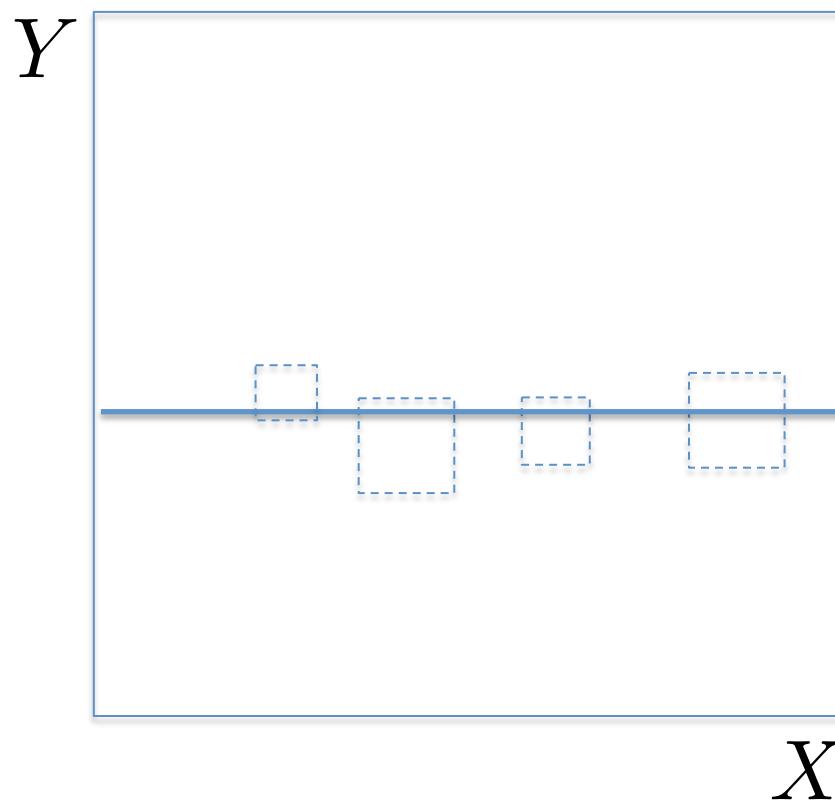
$$Y = a_0 + a_1 X + a_2 X^2.$$

⋮

# Example: Quantitative Laws

$Q$  = What is the true polynomial degree?

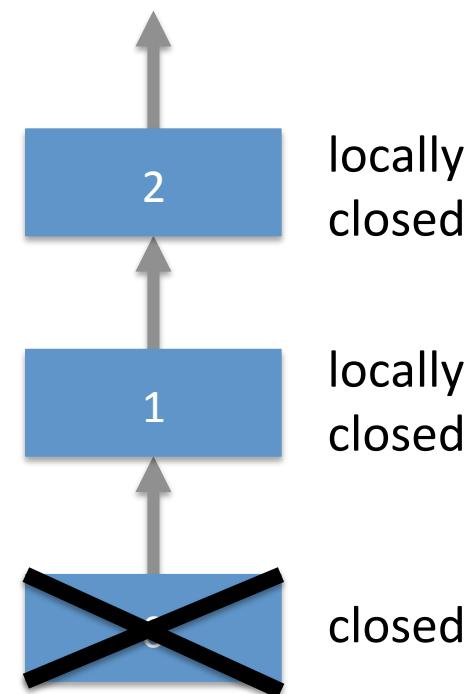
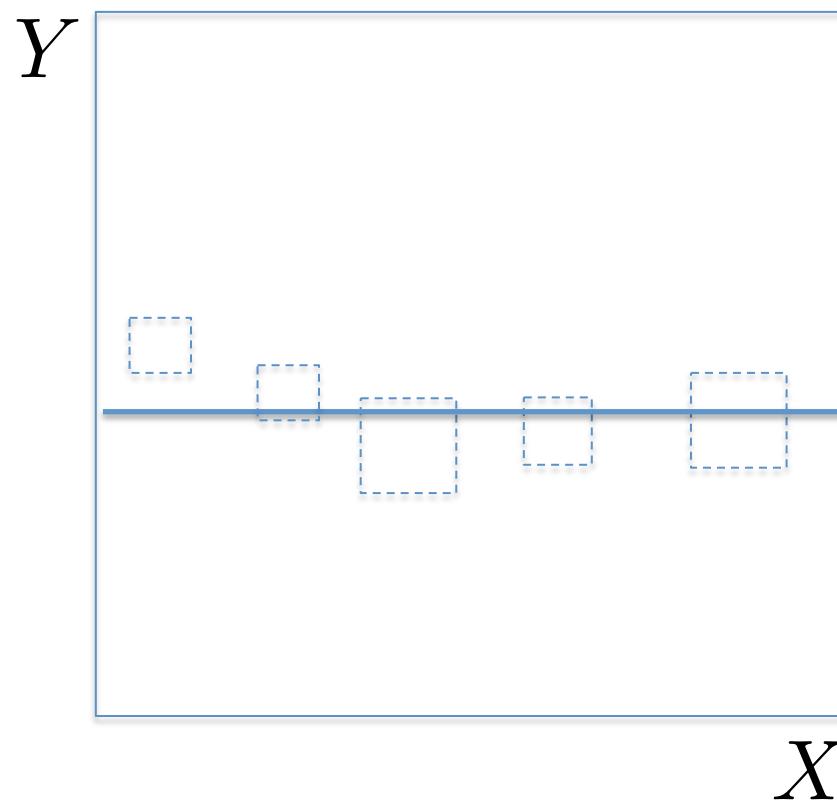
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# Example: Quantitative Laws

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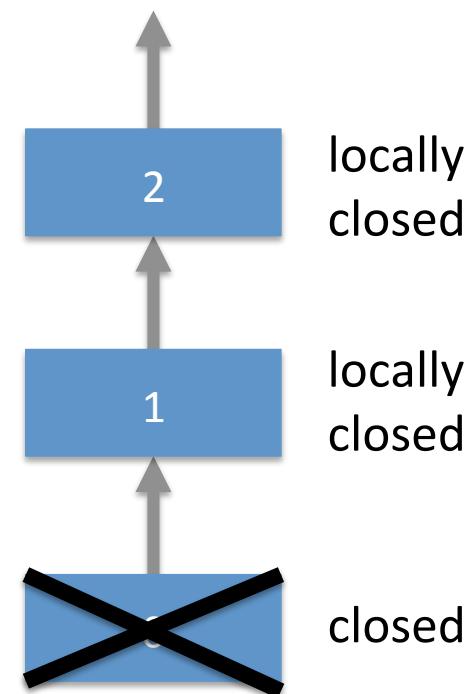
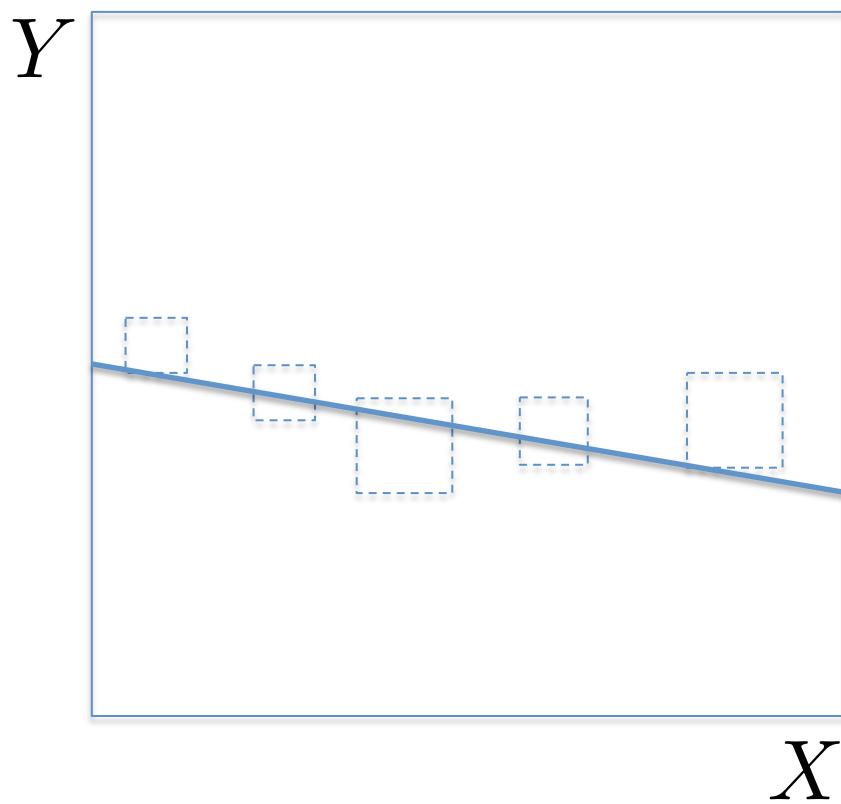
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# Example: Quantitative Laws

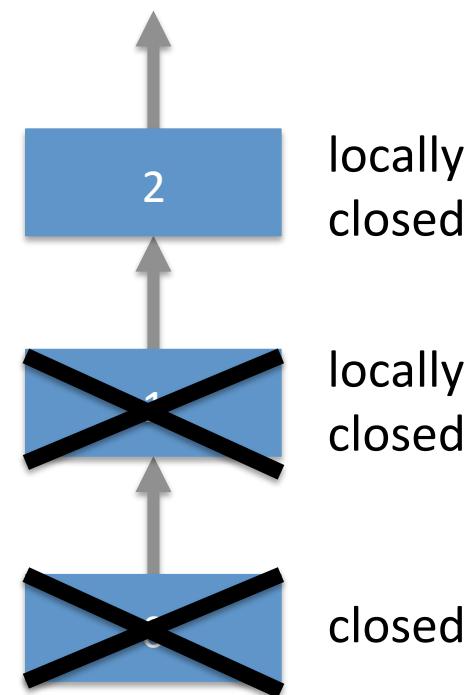
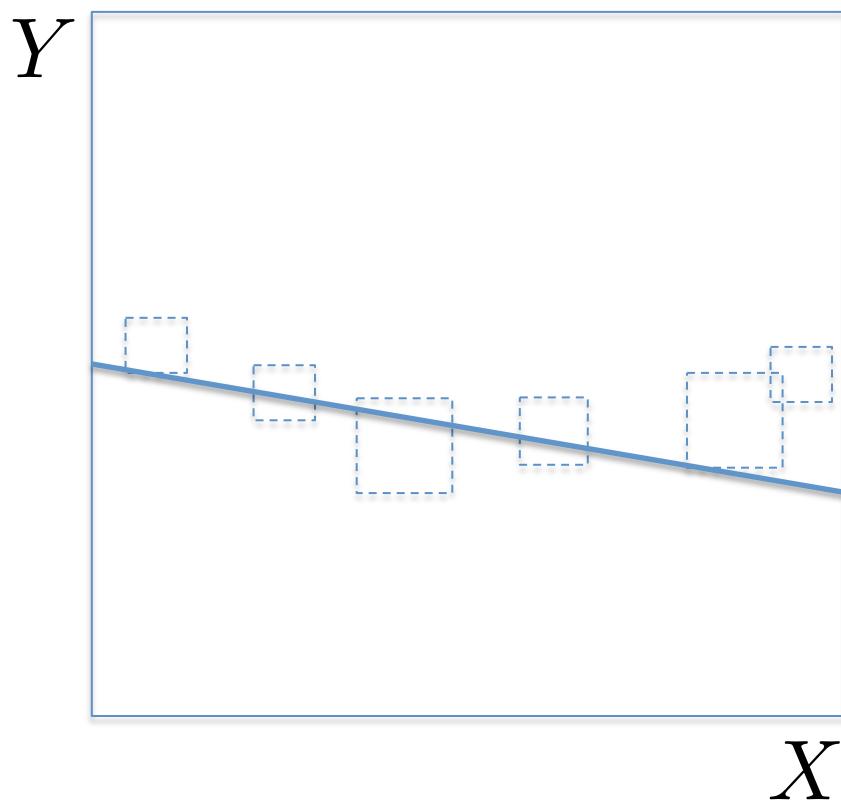
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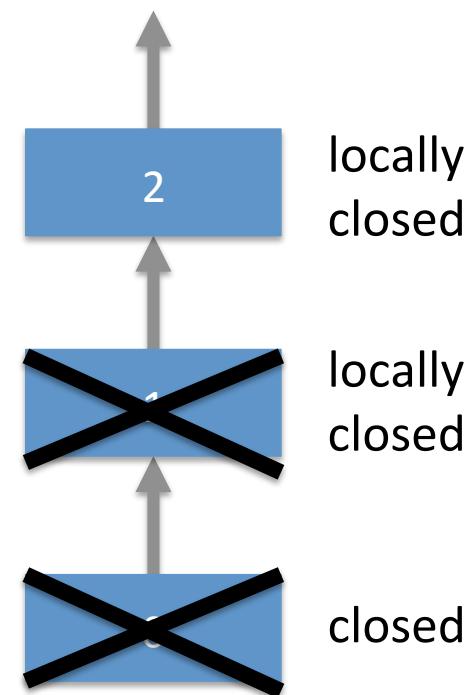
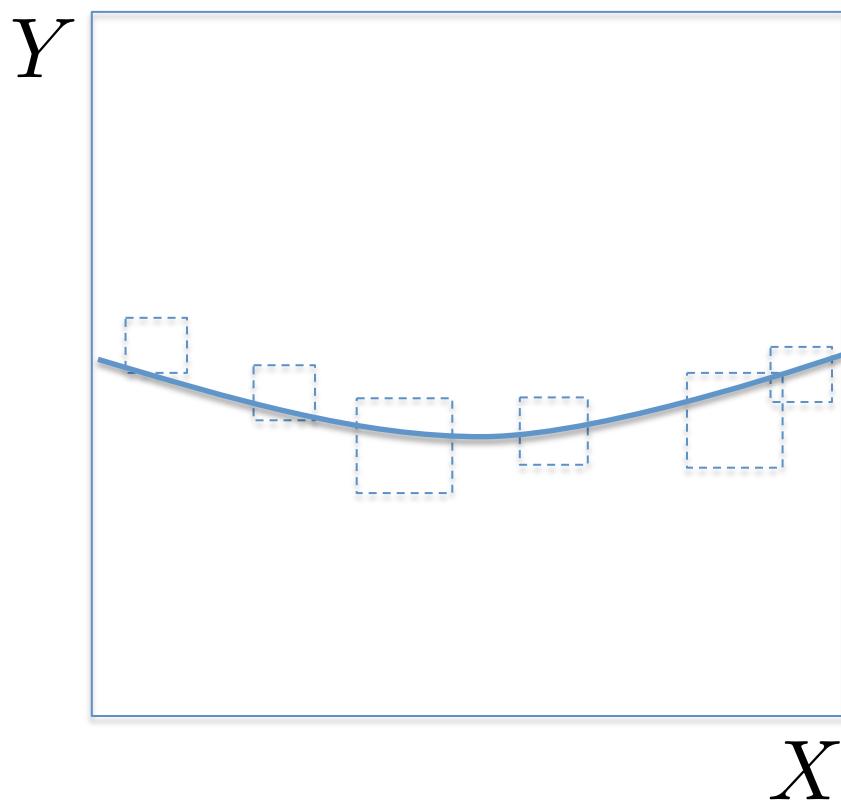
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# Example: Competing Paradigms

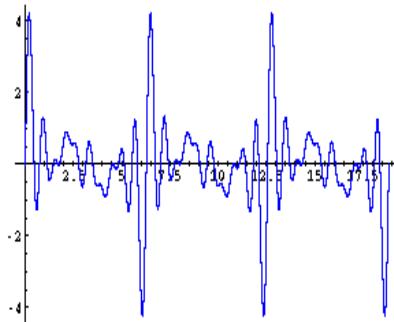
Polynomial paradigm

$$Y = \sum_{i=0}^N a_i X^i.$$



Trigonometric polynomial paradigm

$$Y = \sum_{i=0}^N a_i \sin(iX) + b_i \cos(iX).$$



# Example: Competing Paradigms

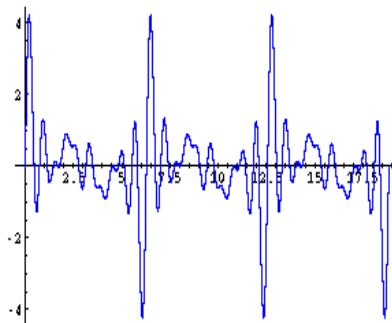
Polynomial paradigm

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degree

Trigonometric polynomial paradigm

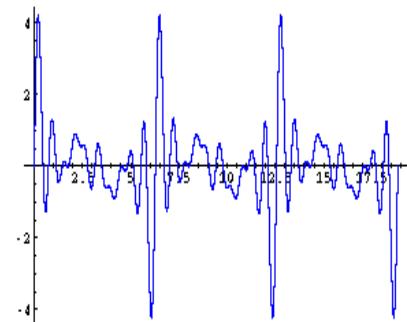
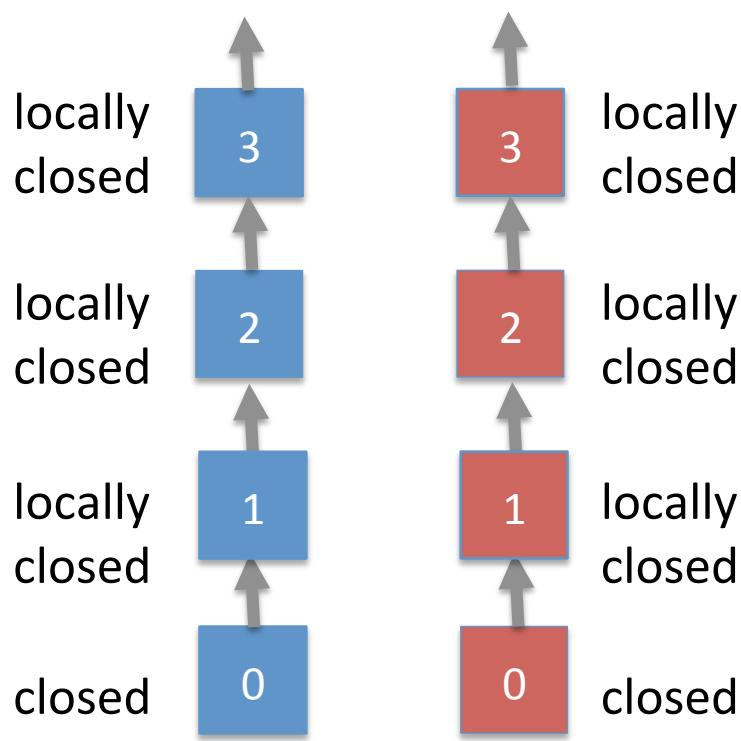
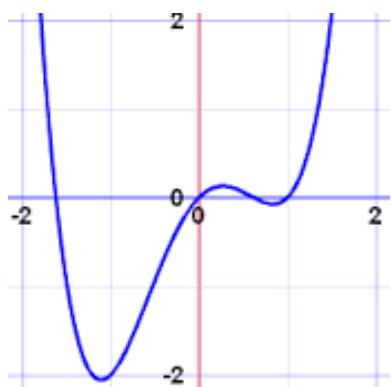
$$Y = \sum_{i=0}^N a_i \sin(iX) + b_i \cos(iX).$$



# Example: Competing Paradigms

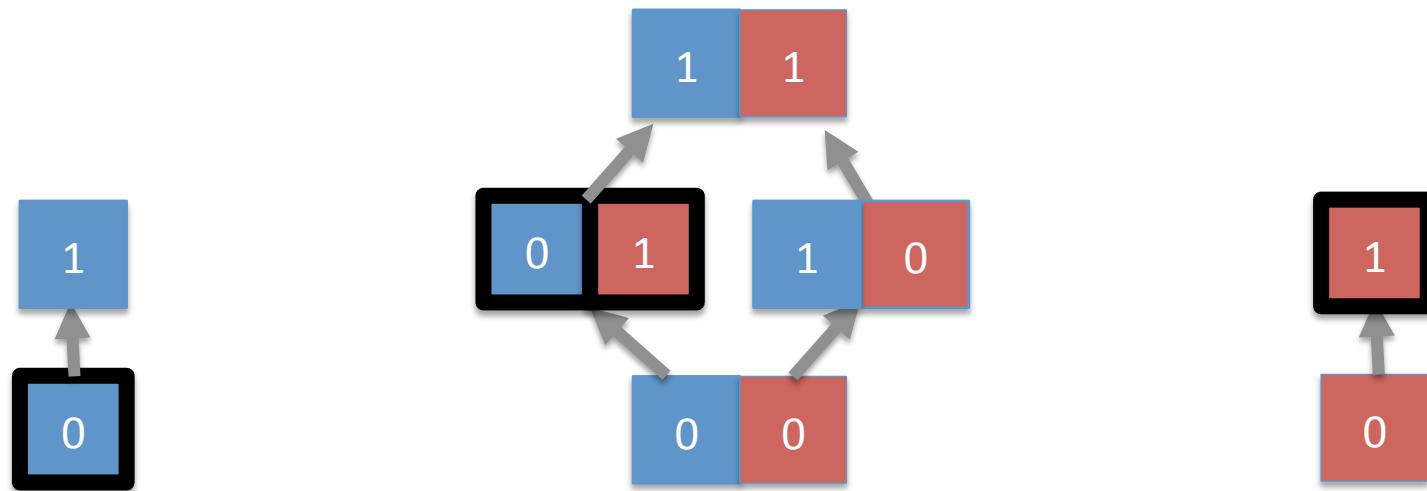
$\mathcal{Q}$  = which degree and which paradigm is true?

$\mathcal{I}$  = finitely many inexact measurements.



# Tack-on Redux

- There **is** something wrong with tacking a **complex** answer onto a **simple** one.
- It is that the tack-on conjunction is more complex than some **simpler** conjunction (if the joint question is **natural**).



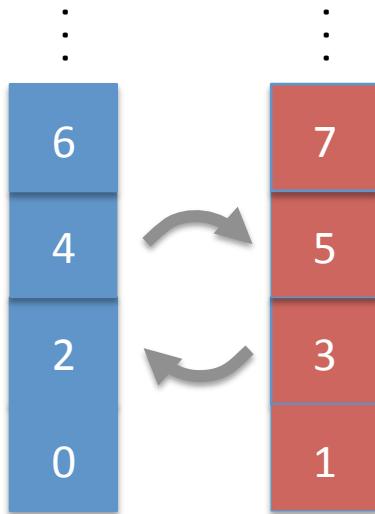
## **4. NATURAL QUESTIONS**

# The Question Question

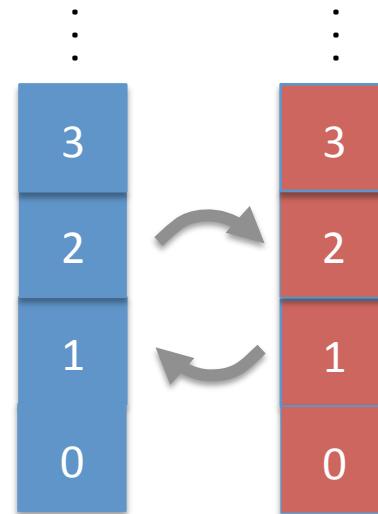
Questions guide inquiry.

What makes some more **natural** than others?

# Intransitive Simplicity



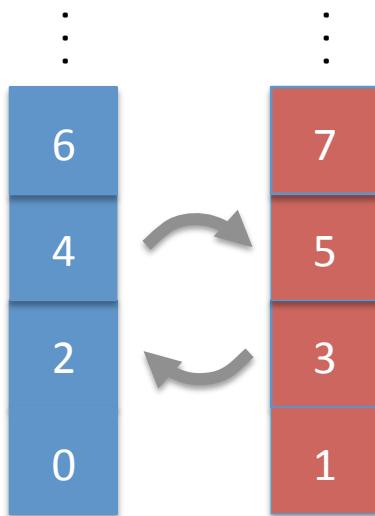
Even/ Odd



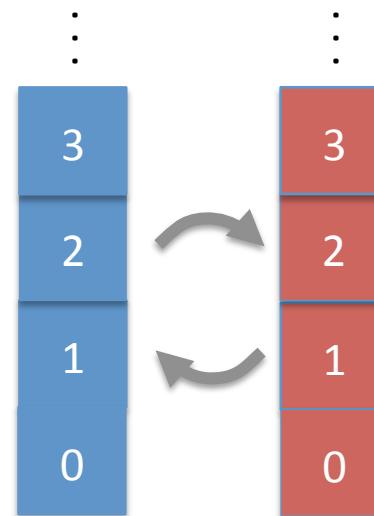
Poly/ Trig poly

# Remedy

**Proposition.** The simplicity relation is transitive if every answer is **locally closed**.



Even/ Odd



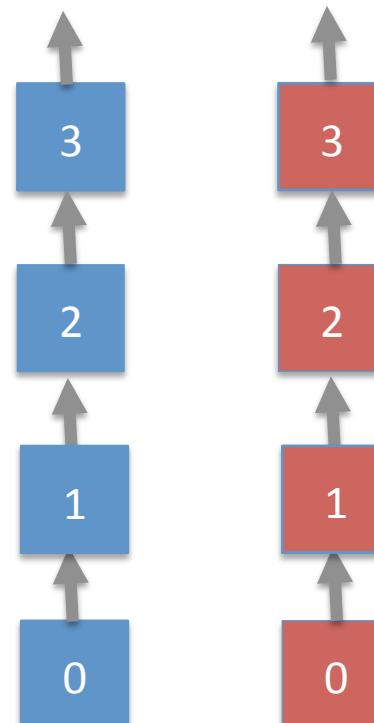
Poly/ Trig poly

# Remedy

**Proposition.** The simplicity relation is transitive if every answer is locally closed.



Even/ Odd



Poly/ Trig poly

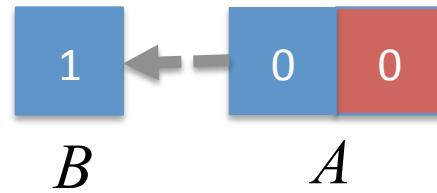
# Concealed Simplicity



Poly/Trig-poly

# Homogeneity

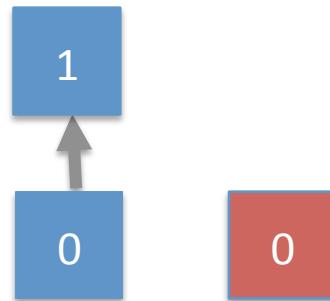
If any **part** of answer  $A$  is **simpler** than relevant response  $B$ , then **all** of  $A$  is **simpler** than  $B$ .



violation

# Homogeneity

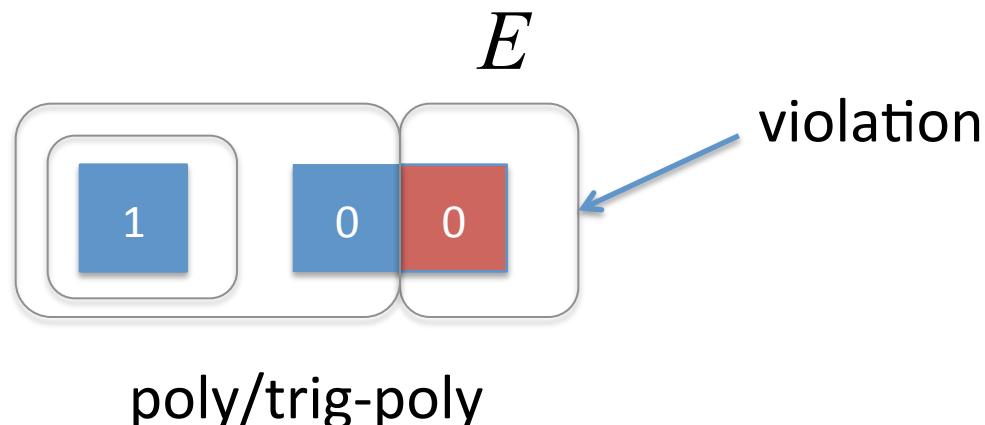
If any **part** of answer  $A$  is **simpler** than relevant response  $B$ , then **all** of  $A$  is **simpler** than  $B$ .



fixed

# Homogeneity

**Proposition.** Homogeneity is equivalent to:  
the disjunction of the set of all answers  
compatible with information  $E$  is verifiable.



# Natural Questions

A question is **natural** in a problem iff

1. Each answer is **locally closed**;
2. Each answer is **homogeneous**.

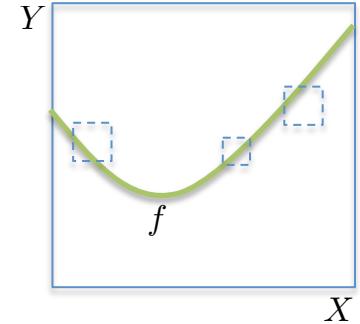
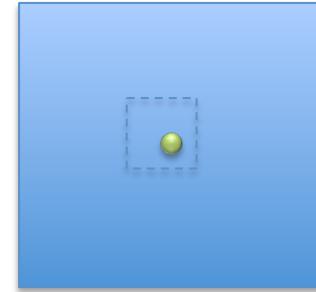
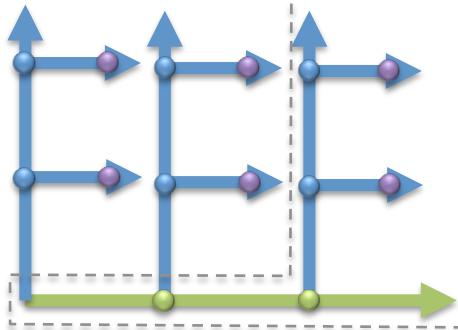
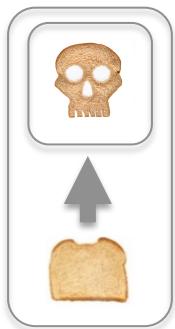
# Natural Questions

A question is **natural** in a problem iff

1. Each answer is locally closed;
2. Each answer is homogeneous.

In algebraic geometry, **natural questions** are thought of geometrically as **stratifications** of the underlying topology.

# Epistemic Equivalence



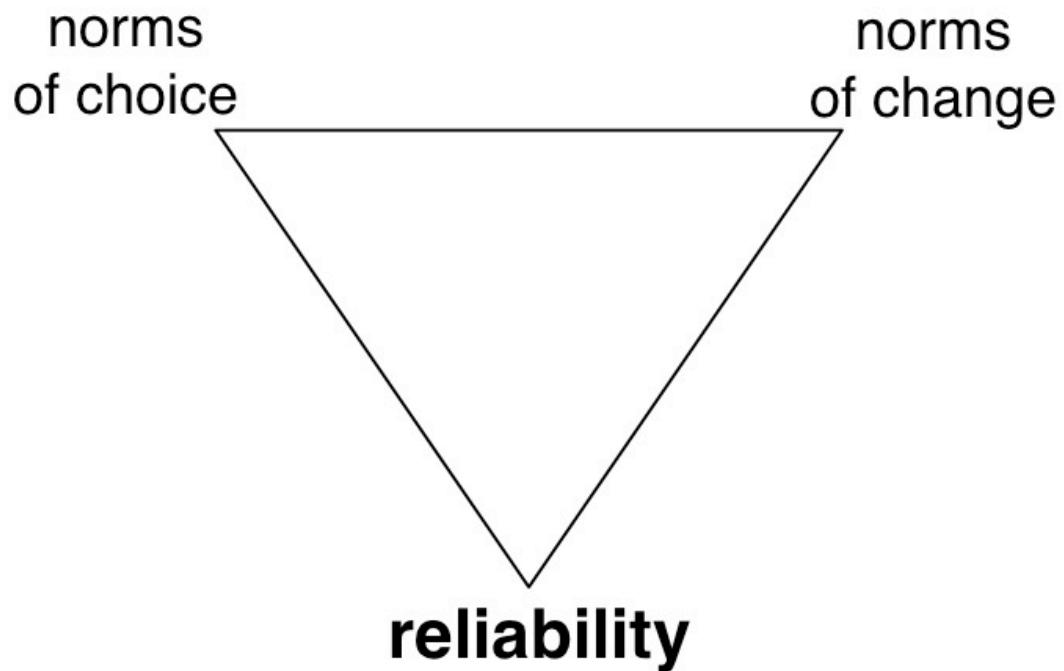
different problems



natural  
problems

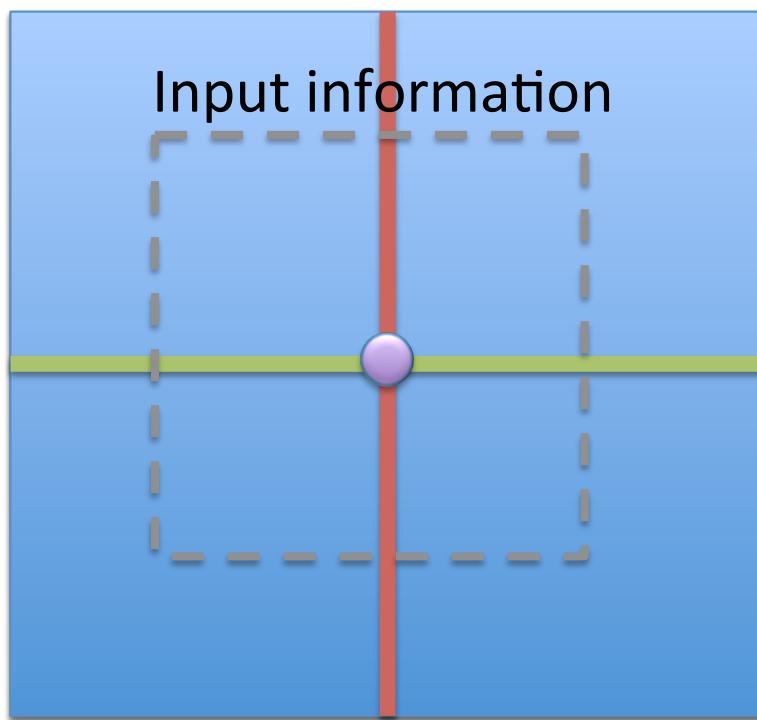


same simplicity structure  
same **epistemological** structure

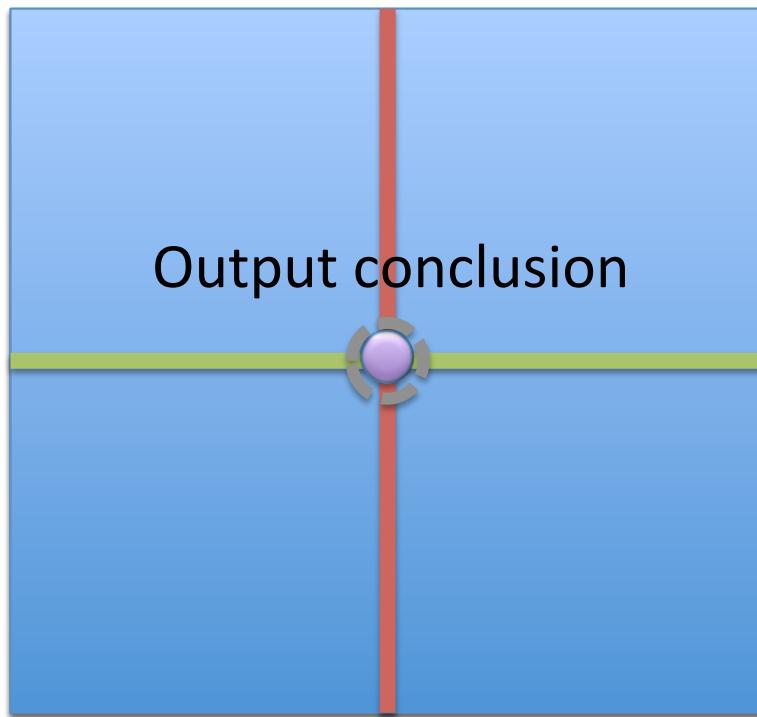


## 5. METHODS AND CONVERGENCE

# Inductive Inference

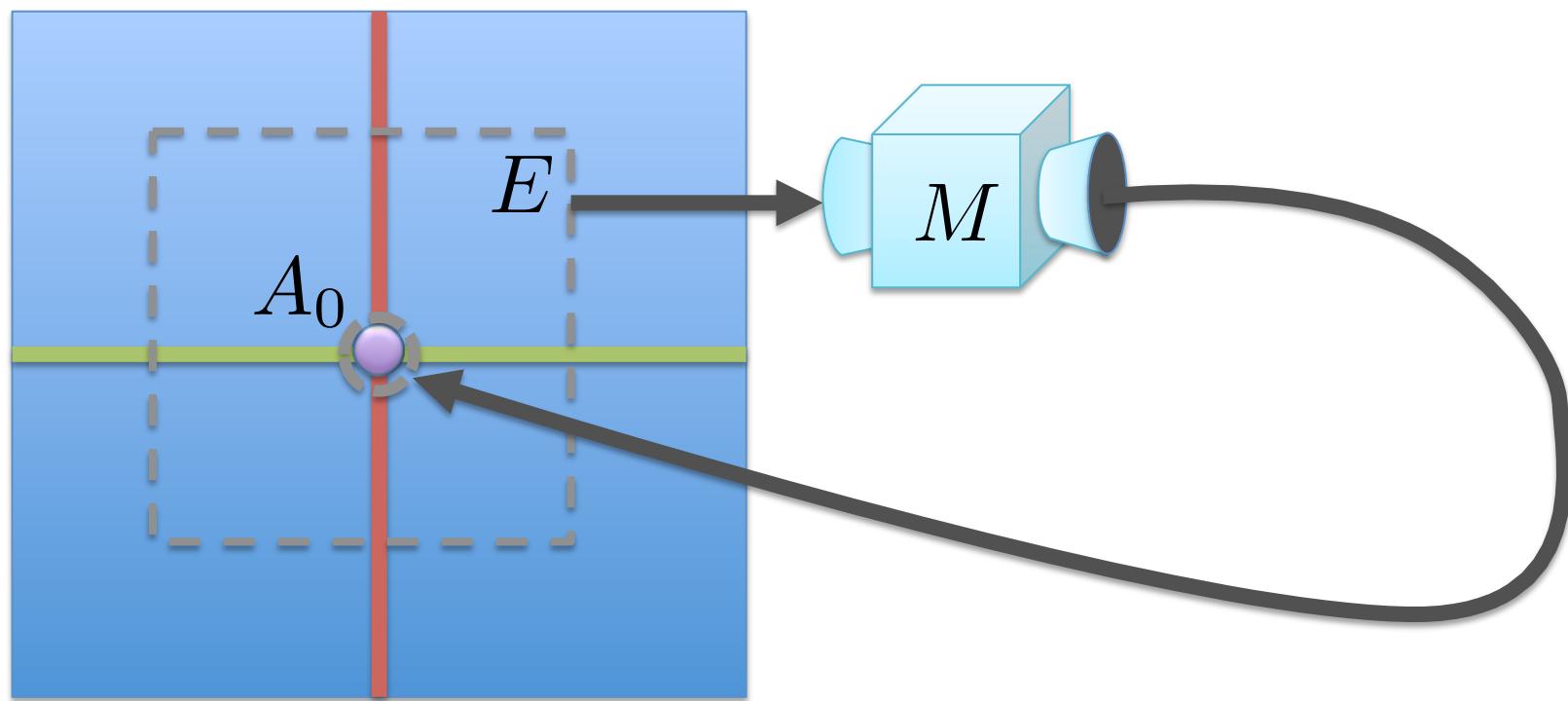


# Inductive Inference



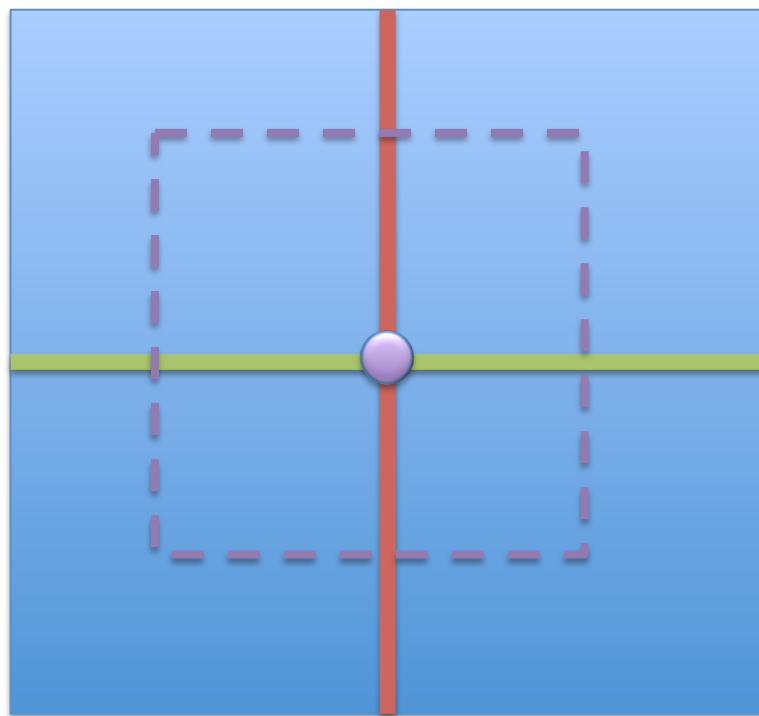
# Inductive Methods

Information in, relevant response out.



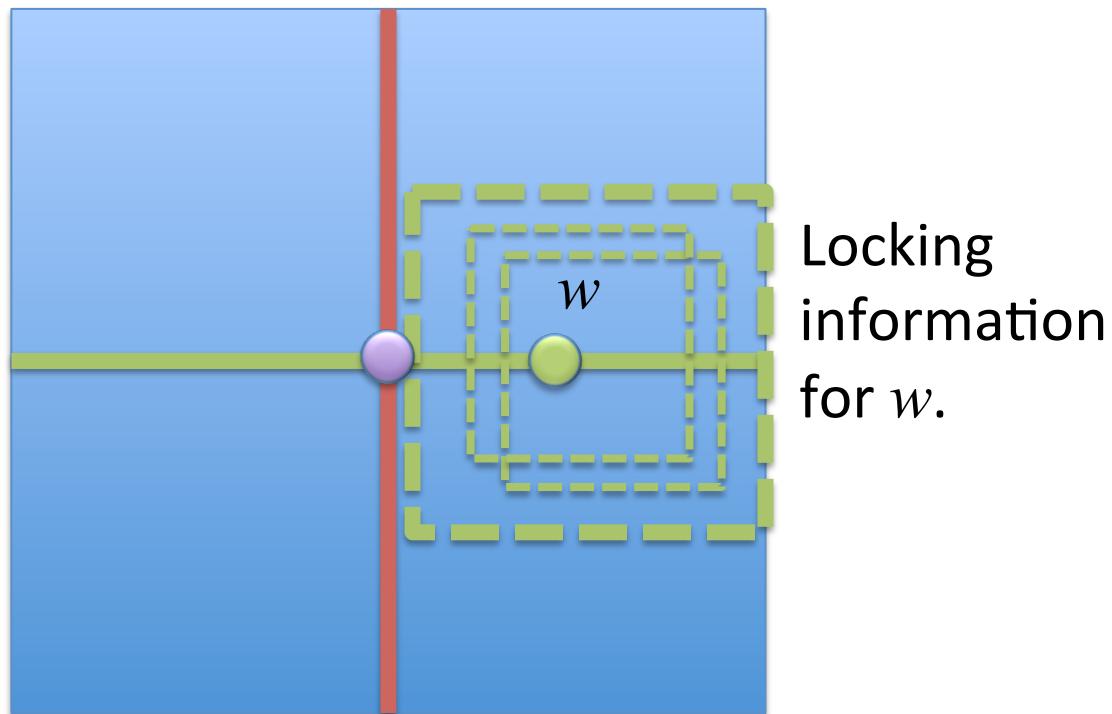
# Inductive Methods

Cleaner diagram.



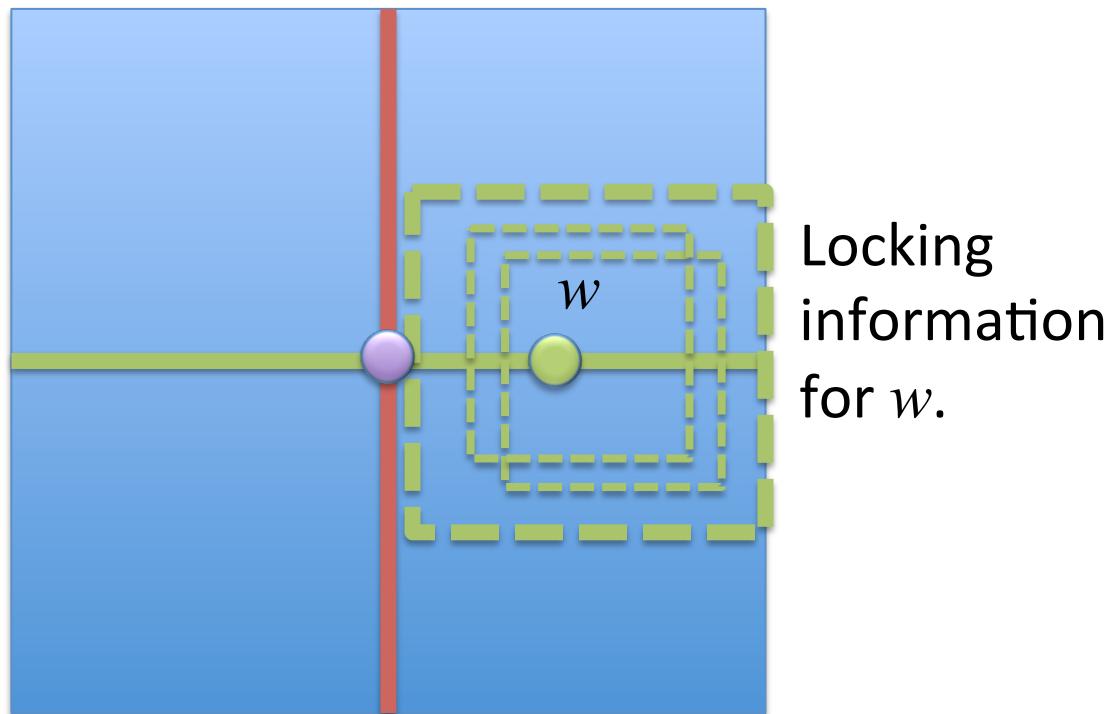
# Solution in the Limit

$M$  solves a problem in the limit iff each world  $w$  presents information such that  $M$  produces the true answer in  $w$  on any further information true in  $w$ .



# Solution in the Limit

$M$  solves a problem in the limit iff each world  $w$  presents information such that  $M$  produces the true answer in  $w$  on any further information true in  $w$ .

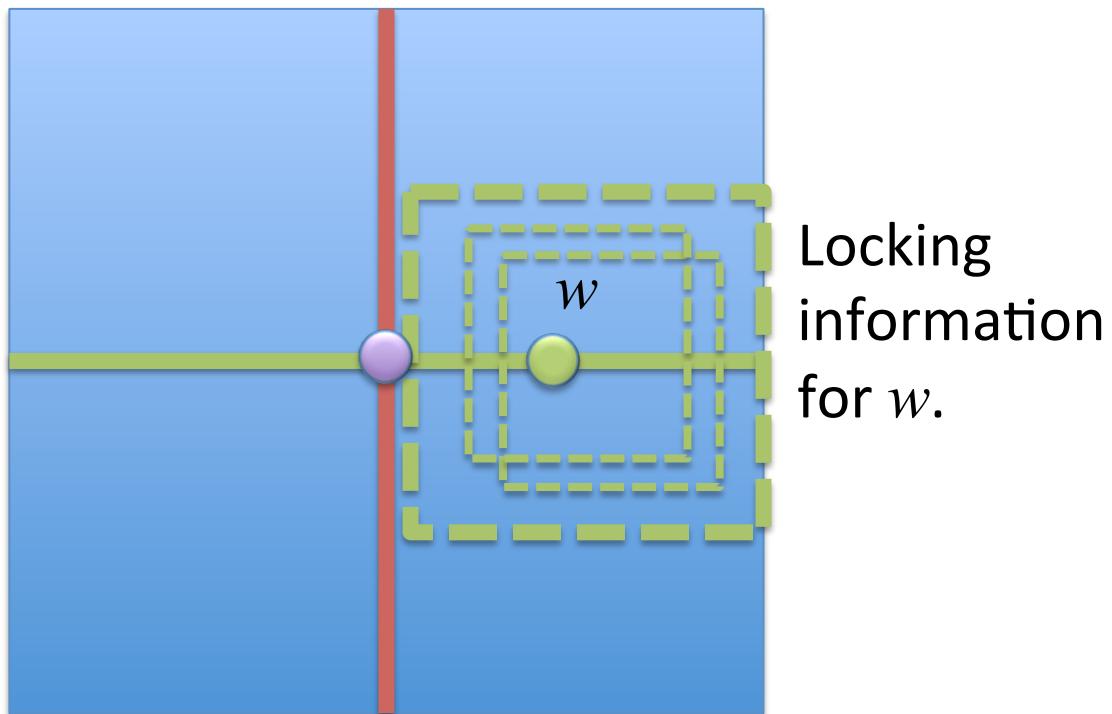


# Solution in the Limit

$M$  solves  $(W, \mathcal{I}, \mathcal{Q})$  in the limit

iff  $M$  stabilizes to the true answer in each world

iff  $(\forall w \in W)(\exists E \in \mathcal{I}_w)(\forall F \in \mathcal{I}_w)(F \subseteq E \Rightarrow M(F) = \mathcal{Q}_w)$ .



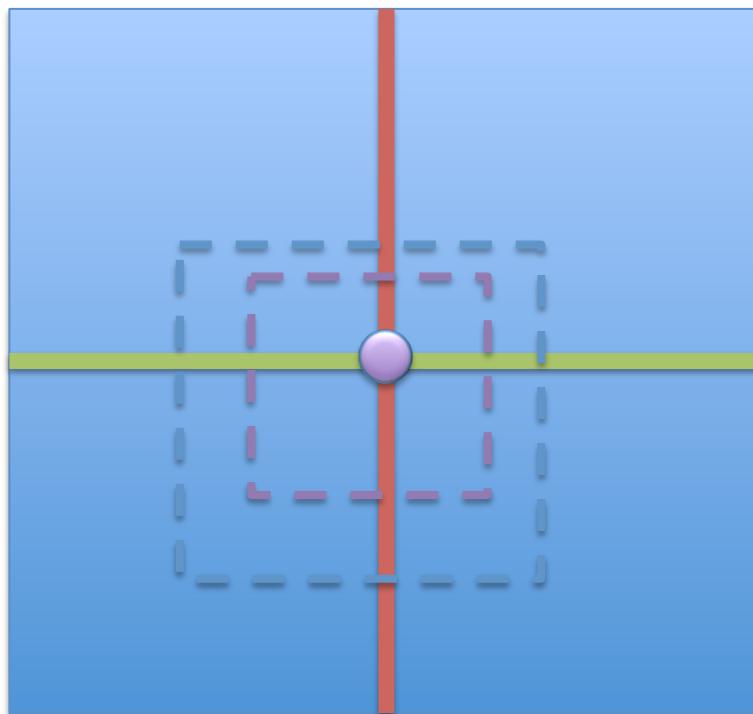
# Solvability and Topology

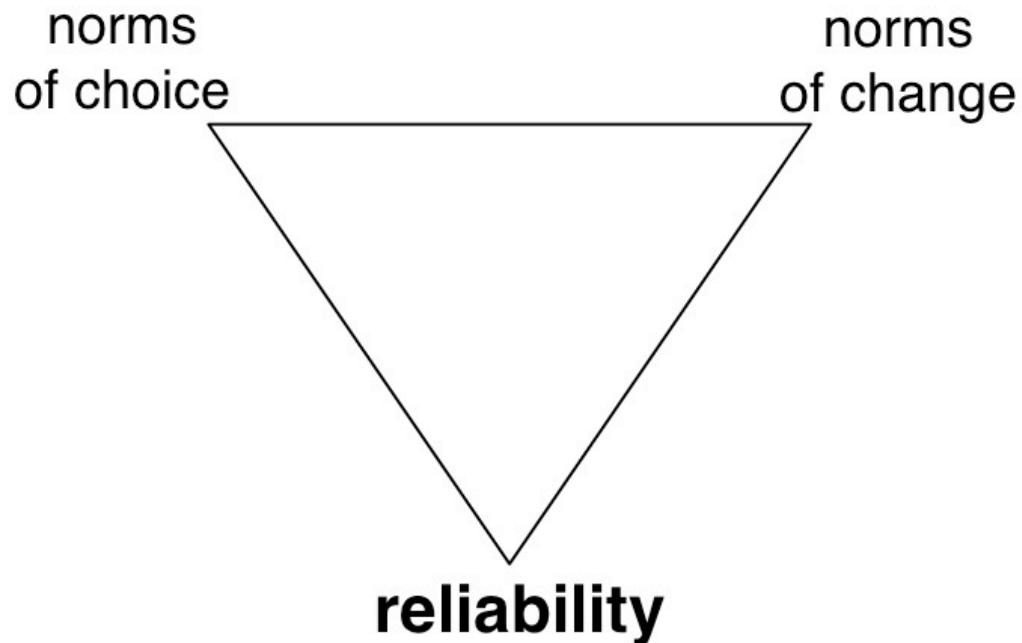
**Proposition** (Yamamoto and DeBrecht 2010, Kelly 2004, Baltag, Gerasimczuk and Smets 2015):

A problem is solvable in the the limit iff each answer is a countable disjunction of locally closed propositions.

# Solution in the Limit

- Solution in the limit implies **no constraint** on what to say in response to a given information state.
- Convergence can always begin **later**.





## 7. STRAIGHTEST CONVERGENCE

# Two Departures from Straightness



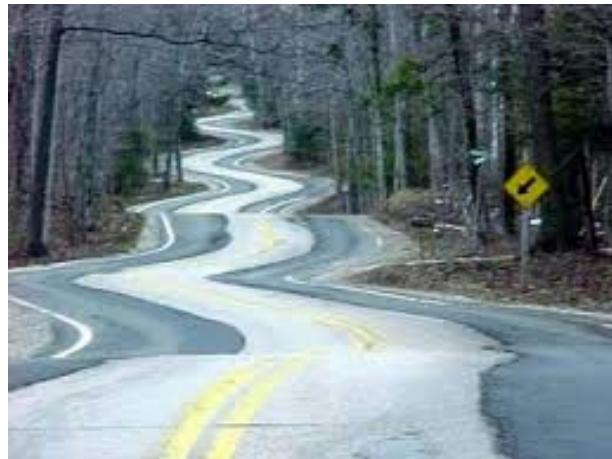
Course-reversals



Cycles

# Doxastic Reversal Sequence

- A finite sequence of relevant responses in which each entry **contradicts** its predecessor.



# Doxastic Cycle Sequences

- A reversal sequence whose terminal entry entails its first entry.



# Cycle Free Solutions

- Solution  $M$  is cycle free iff:

There exists no nested sequence of information states

$$e = (E_i)_{i=1}^n$$

such that

$$M(e) = (M(E_i))_{i=1}^n$$

is a cycle sequence.

# Reversal Sequence Comparison

- Reversal sequence  $s$  reverses as much as reversal sequence  $s'$  (of the same length) iff each entry in  $s$  entails the corresponding entry in  $s'$ .

$$\left( \begin{array}{c|c} \text{purple} & \text{red} \\ \hline \end{array}, \quad \text{green} \right) < \left( \text{purple}, \quad \text{green} \right)$$

# Forcible Reversal Sequences

- Reversal sequence  $s$  is **forcible** iff every solution to  $\mathfrak{P}$  performs a reversal sequence  $s' > s$ .

$$\left( \begin{array}{c|c} \text{purple} & \text{red} \\ \hline \end{array}, \quad \text{green} \right) < \left( \text{purple}, \quad \text{green} \right)$$

# Forcible Sequences

In natural problems,  $(A_i)_{i=1}^n$  is forcible iff

$$A_1 \prec A_2 \prec \cdots \prec A_{n-1} \prec A_n.$$

# Forcible Sequences

In general,  $(A_i)_{i=1}^n$  is forcible iff

$$A_1 \cap \text{Frntr}(A_2 \cap \text{Frntr}(\cdots \cap \text{Frntr}(A_{n-1} \cap \text{Frntr}(A_n)))) \neq \emptyset$$

# Method Comparison

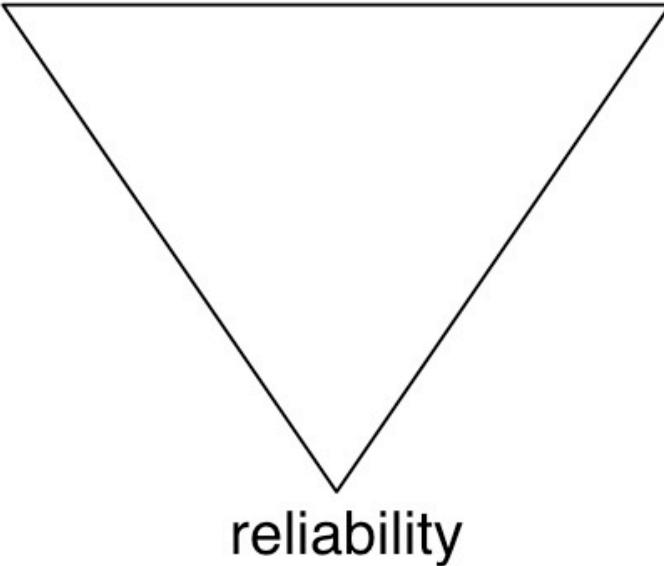
- Solution  $M'$  reverses as much as solution  $M$  iff:  
For each reversal sequence generated by solution  $M$ ,  
method  $M'$  generates a reversal sequence at least as bad  
in some world.

# Optimal Truth Conduciveness

- Solution  $M$  is reversal-optimal iff every reversal it performs is forcible.

norms  
of choice

**norms  
of change**



reliability

## 6. MINIMAL CHANGE

# Conditionalization

A method  $M$  satisfies conditionalization iff for all information states  $E, F$ :

$$M(E) \cap Q(E \cap F) \subseteq M(E \cap F).$$

In slogan form:

**“no induction without refutation.”**

# Rational Monotony

A method  $M$  is rationally monotone iff

$$M(E \cap F) \subseteq M(E) \cap Q(E \cap F),$$

for all information states  $E, F$  such that

$$M(E) \cap Q(E \cap F) \neq \emptyset.$$

In slogan form:

**“no retraction without refutation.”**

# Reversal Monotony

A method  $M$  is reversal monotone iff

$$M(E \cap F) \cap M(E) \neq \emptyset,$$

for all information states  $E, F$  such that

$$M(E) \cap Q(E \cap F) \neq \emptyset.$$

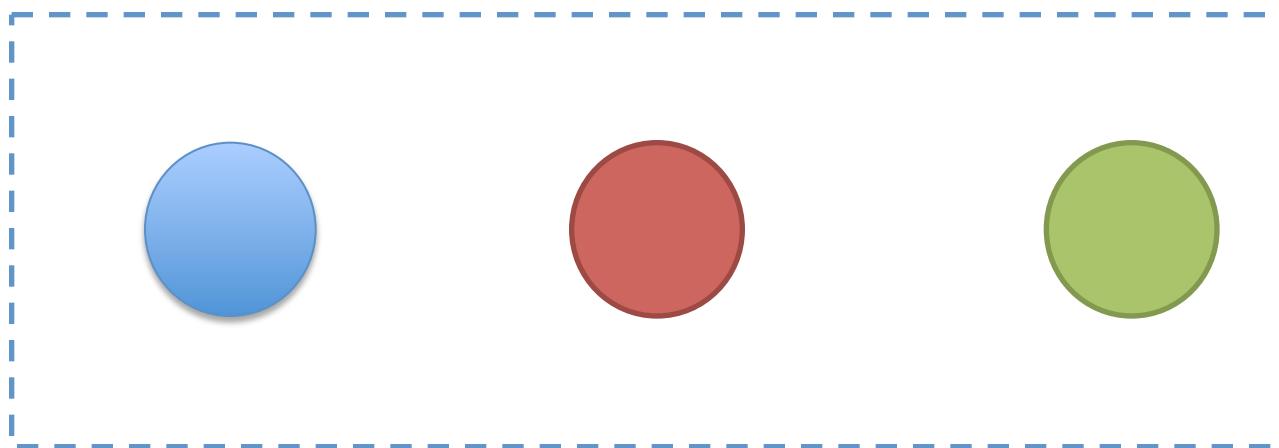
In slogan form:

**“no reversal without refutation.”**

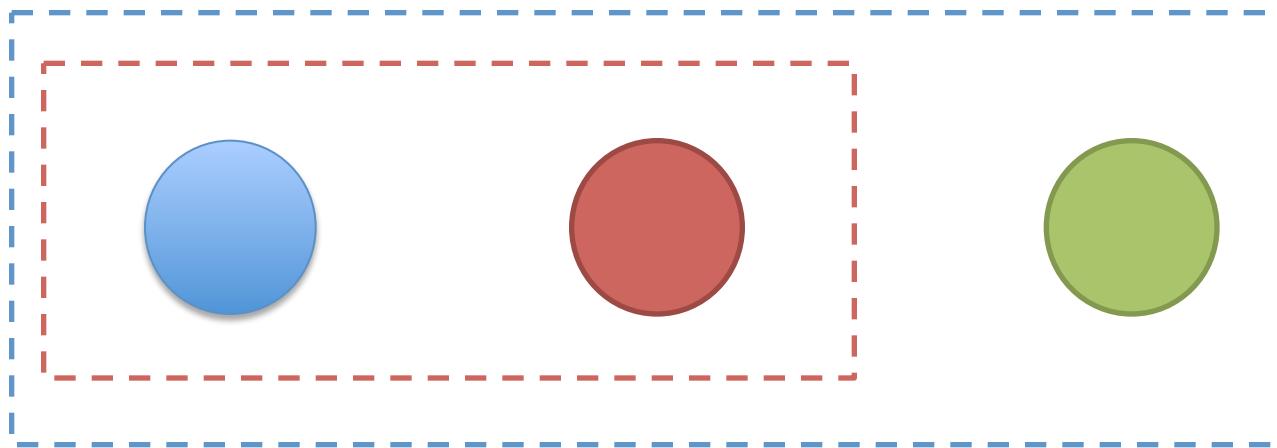
# Theorem

If  $M$  is a consistent solution to  $\mathfrak{P}$ , then  $M$  cycle-free iff  $M$  is reversal monotone.

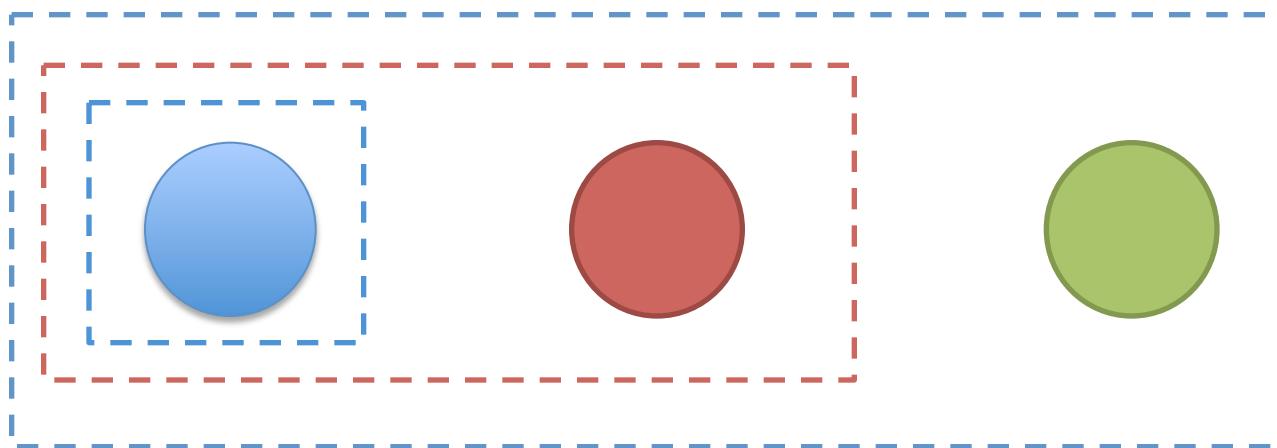
# The Proof Idea



# The Proof Idea



# The Proof Idea



# Theorem

If  $M$  is a consistent solution to  $\mathfrak{P}$ , then  $M$  is cycle-free iff  $M$  is reversal monotone.

conditionalizer



rationally monotone



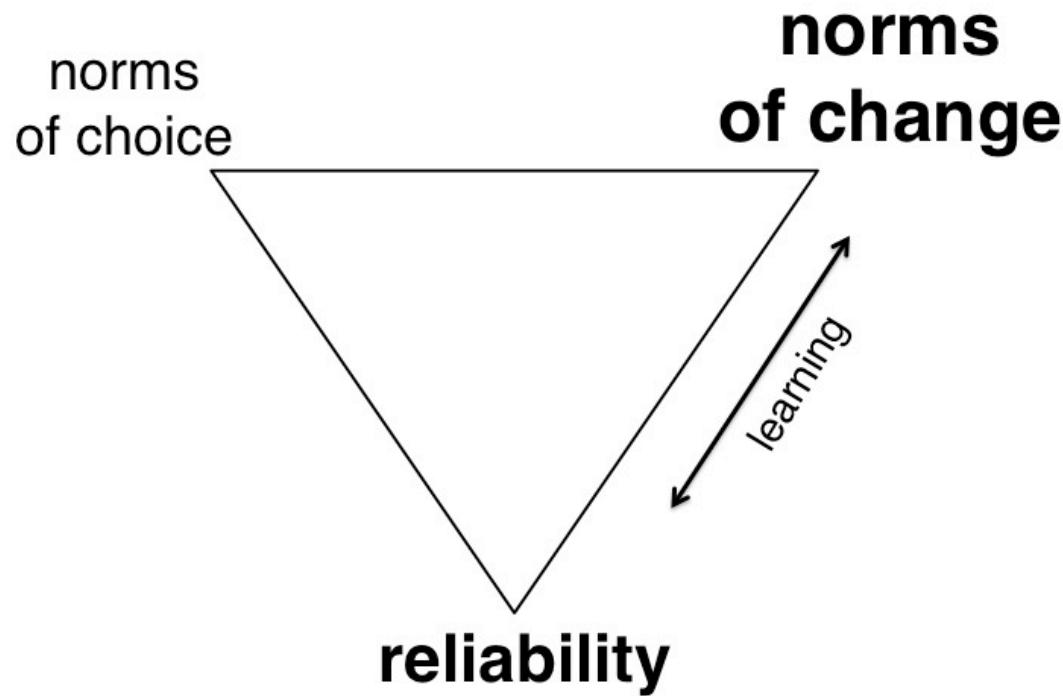
reversal monotone

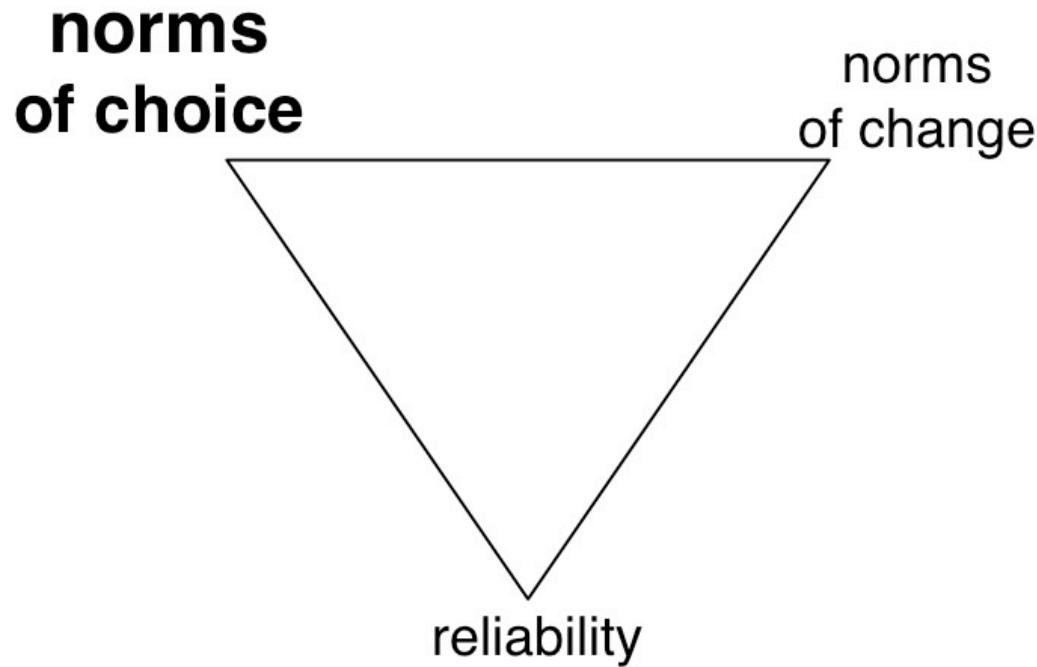


cycle-free

# Theorem

If  $M$  is a consistent solution to  $\mathfrak{P}$ , then  $M$  is cycle-free iff  $M$  is reversal monotone.





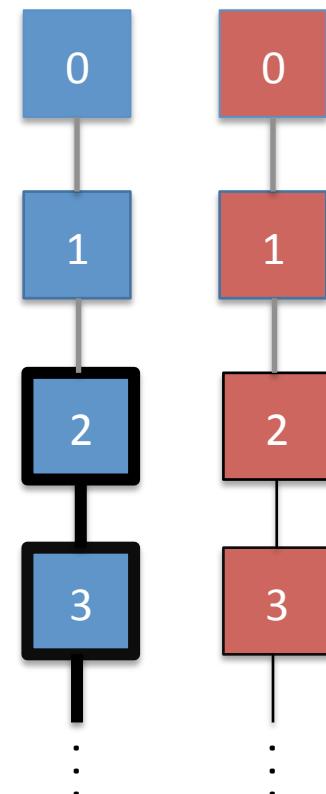
## 7. OCKHAM'S RAZOR

# Simplest Relevant Responses Given $E$

$B$  is a **simplest relevant response given  $E$**  iff any relevant response simpler than  $B$  is incompatible with  $E$ .

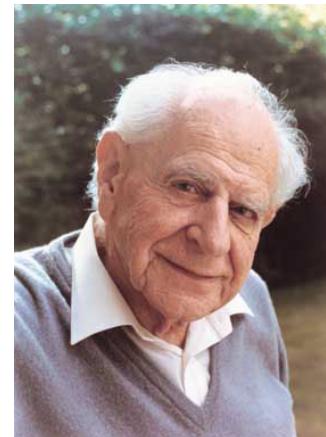
# Ockham's Razor

- Output a **simplest** relevant response given  $E$ .
  - Allows for suspension of judgment.
  - Rules out “even” in co-finite even/odd problem.
  - Makes sense for infinite descending chains.



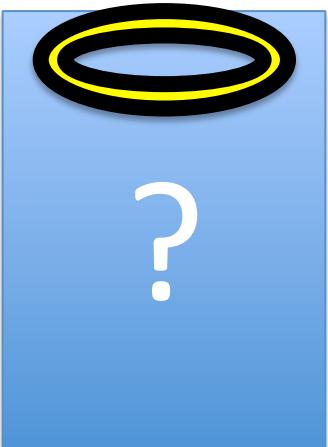
# *Popper's Razor*

- Output a relevant response that is **refutable** (**closed**) in the problem restricted to  $E$ .



# Error Razor

- “Err on the side of simplicity”.
- In arbitrary world  $w$ , never produce a relevant response  $B$  such that the true answer  $A_w$  is strictly simpler than  $B$ .

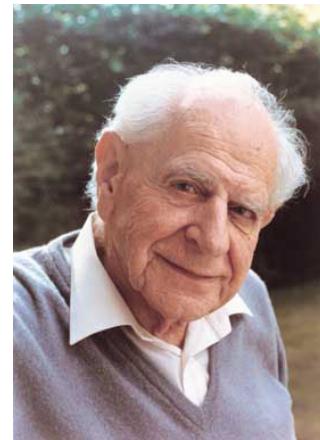


# Theorem

For natural problems, Ockham's Razor = Popper's Razor.

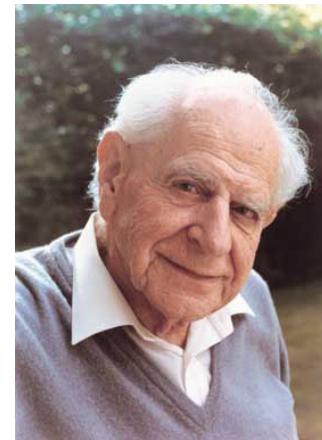
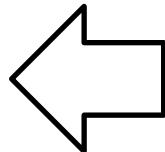


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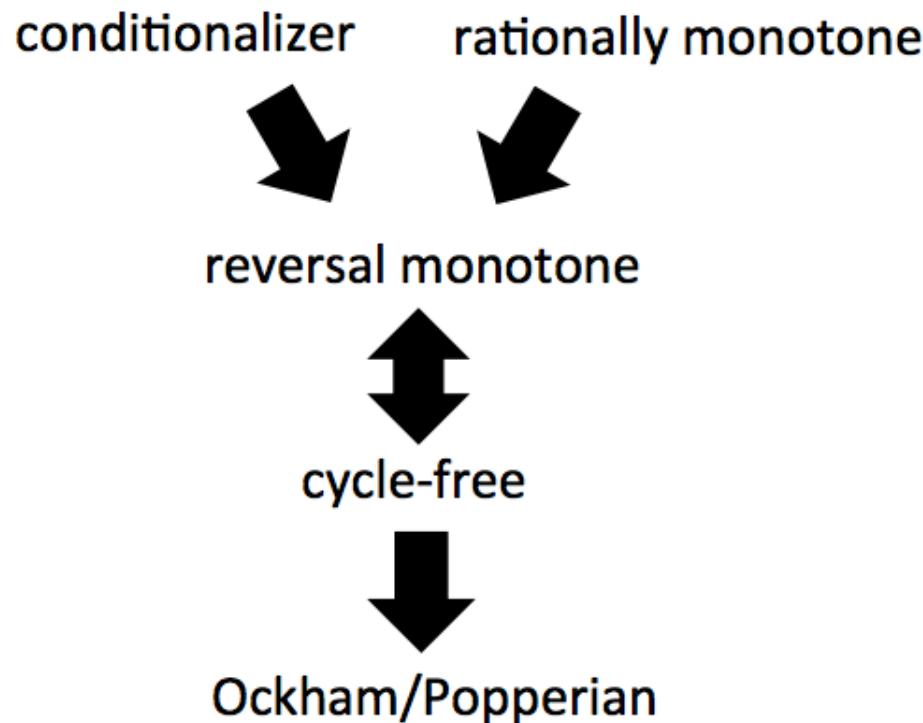
# Theorem

In general, Popper's razor is stronger.



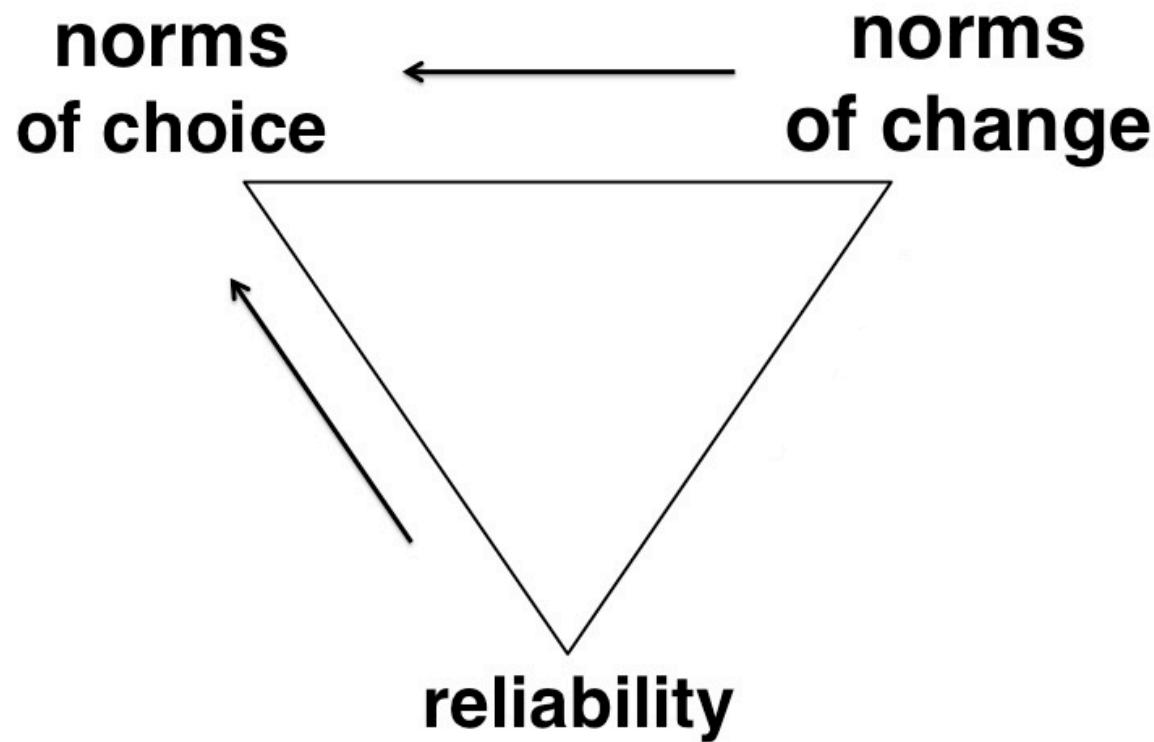
# Theorem

If  $M$  is a cycle-free solution, then  $M$  is Popperian.

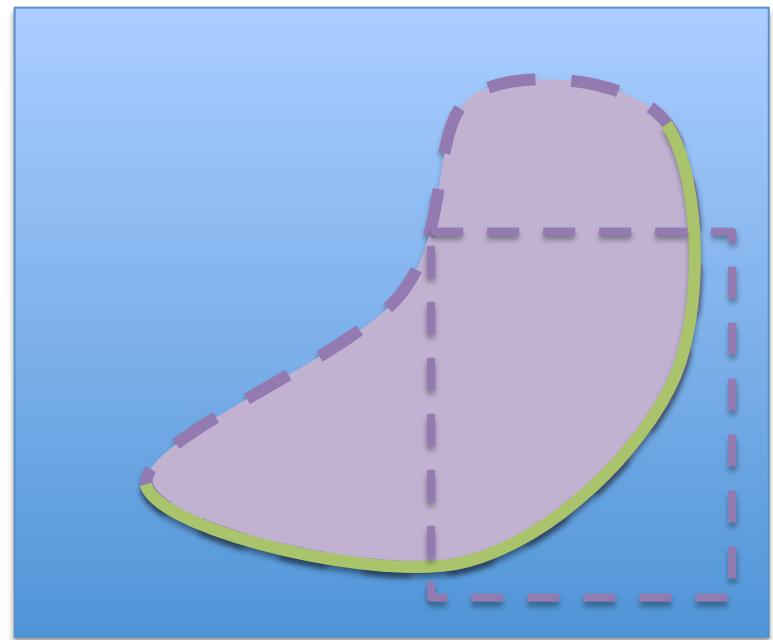


# Theorem

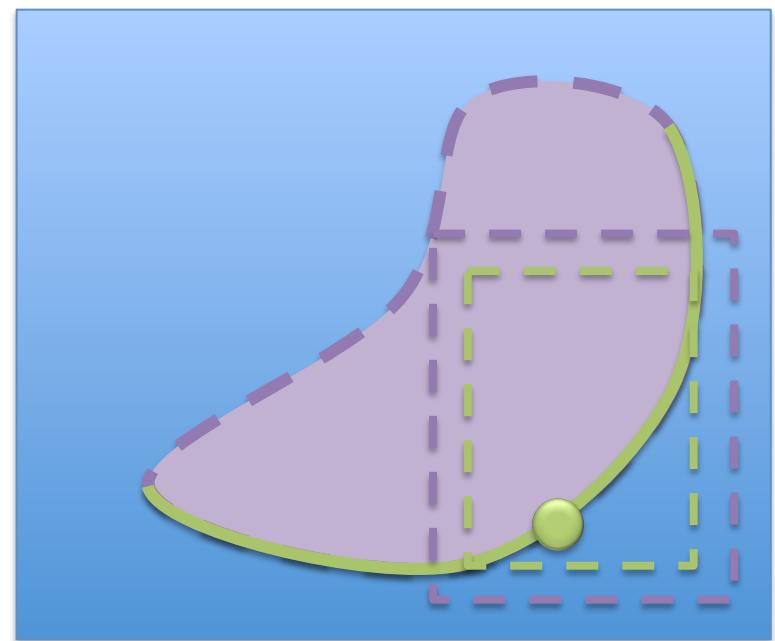
If  $M$  is a cycle-free solution, then  $M$  is Popperian.



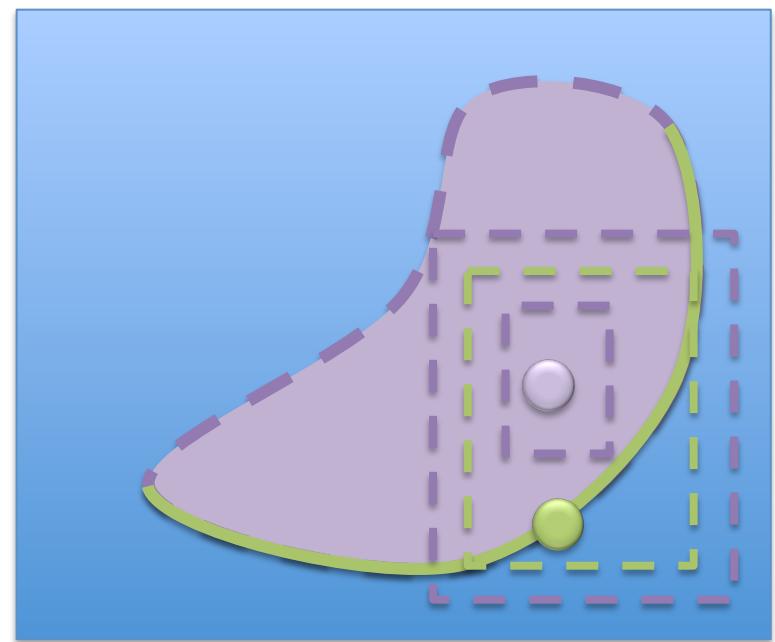
# The Proof Idea



# The Proof Idea



# The Proof Idea



# Theorem

Every natural problem has a cycle-free solution  
(and every such solution is Ockham).

# Equivalence

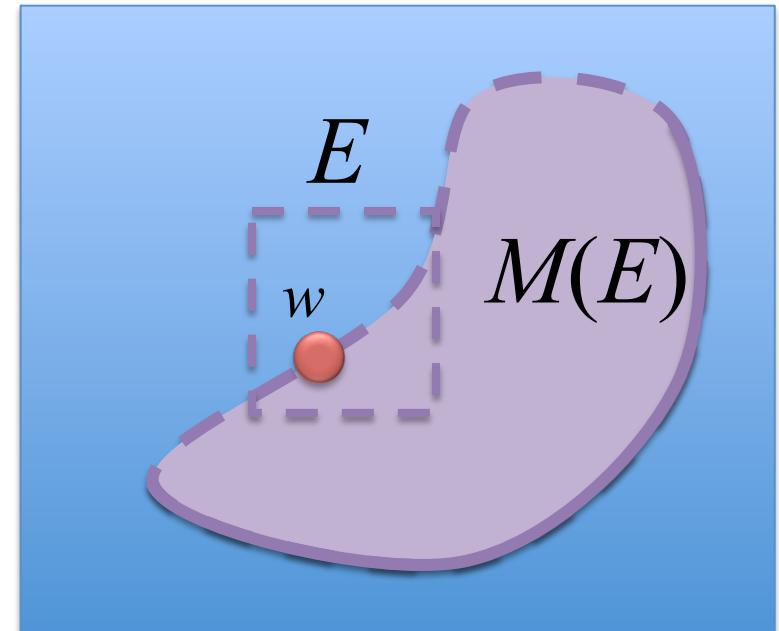
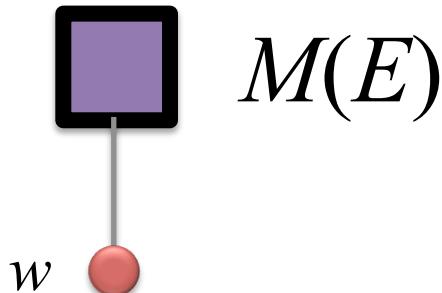
**Lemma 1:** Error razor implies Popper's razor.

Suppose that  $M$  violates Popper's razor on  $E$ .

So  $M(E)$  isn't closed given  $E$ .

Let  $w$  be a missing boundary point.

So  $\{w\}$  is simpler than  $M(E)$ .



# Equivalence

**Lemma 1:** Error razor implies Popper's razor.

Suppose that  $M$  violates Popper's razor on  $E$ .

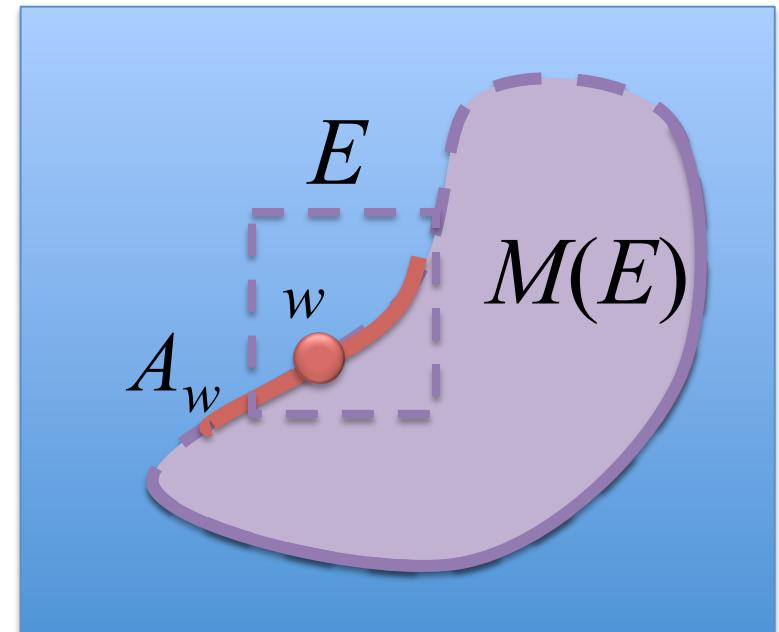
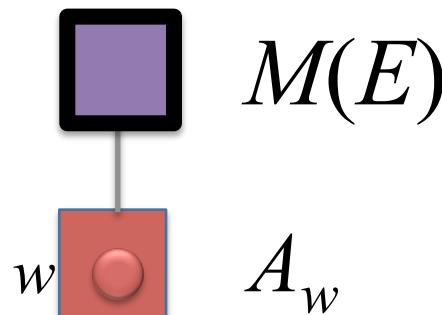
So  $M(E)$  isn't closed given  $E$ .

Let  $w$  be a missing boundary point.

So  $\{w\}$  is simpler than  $M(E)$ .

Apply homogeneity.

So  $A_w$  is simpler than  $M(E)$ .

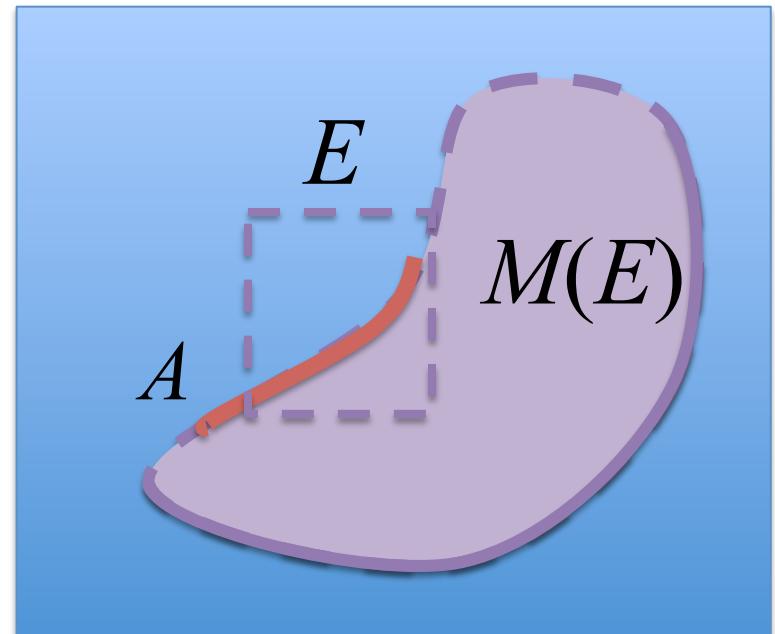
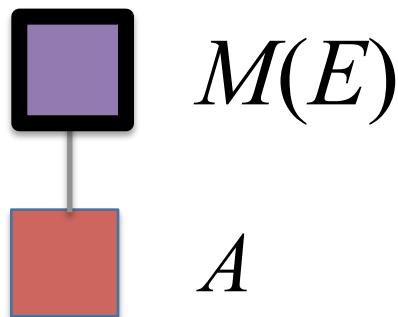


# Equivalence

**Lemma 2:** Popper's razor implies Ockham's razor.

Suppose that  $M$  violates Ockham's razor on  $E$ .

So some  $A$  compatible with  $E$  is simpler than  $M(E)$ .



# Equivalence

**Lemma 2:** Popper's razor implies Ockham's razor.

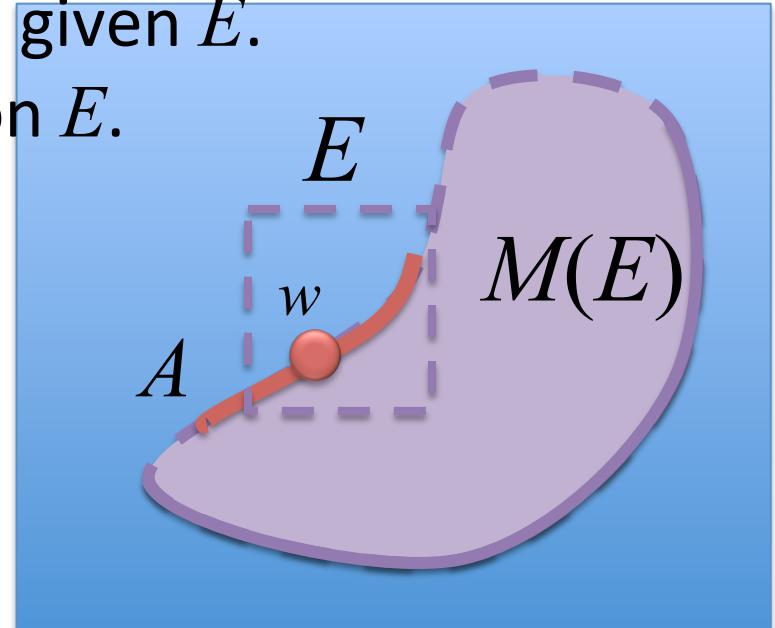
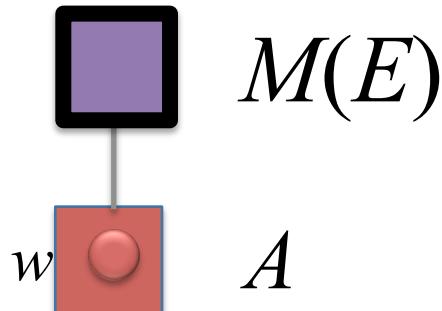
Suppose that  $M$  violates Ockham's razor on  $E$ .

So some  $A$  compatible with  $E$  is simpler than  $M(E)$ .

Choose  $w$  to witness compatibility.

$w$  witnesses that  $A$  is not closed given  $E$ .

So  $M$  violates Popper's razor on  $E$ .

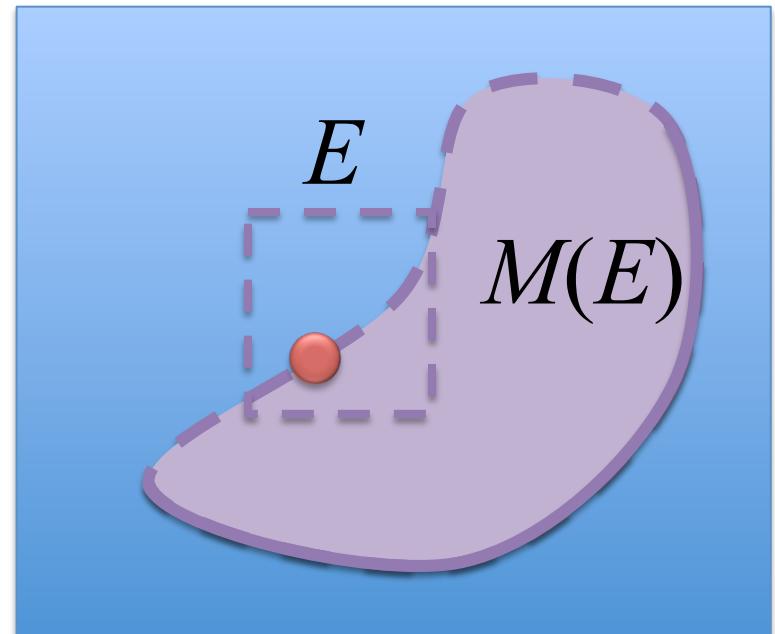
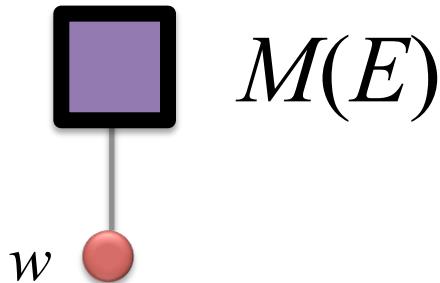


# Equivalence

**Lemma 3:** Ockham's razor implies Error razor.

Suppose that  $M$  violates the error razor in  $w$ .

So  $w$  presents  $E$  such that  $A_w$  is simpler than  $M(E)$ .



# Equivalence

**Lemma 3:** Ockham's razor implies Error razor.

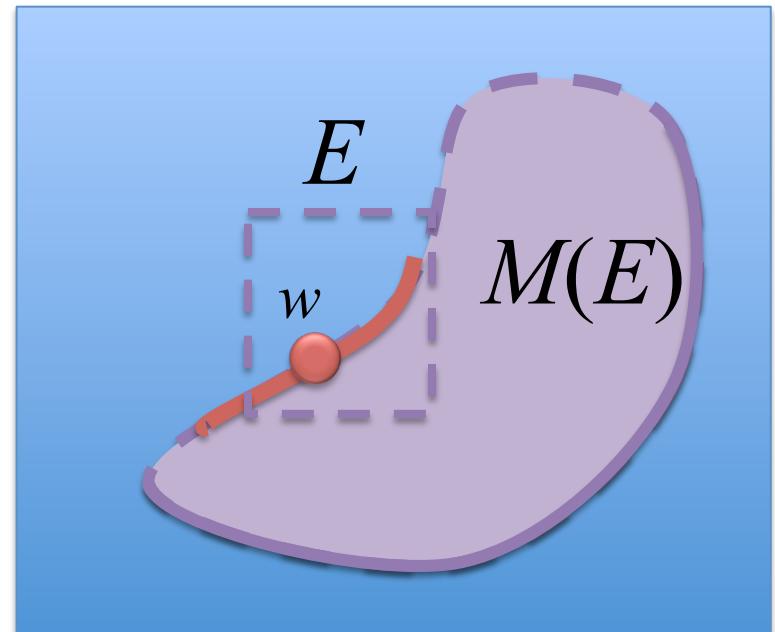
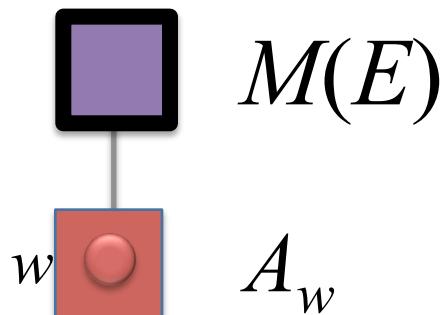
Suppose that  $M$  violates the error razor in  $w$ .

So  $w$  presents  $E$  such that  $A_w$  is simpler than  $M(E)$ .

Apply homogeneity.

So  $A_w$  is simpler than  $M(E)$ .

That is an Ockham violation.

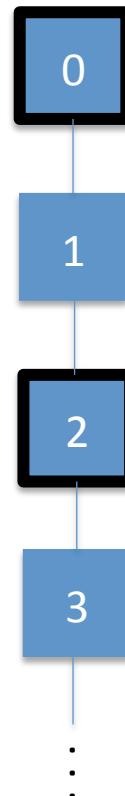


# *Patience*

- Never rule out a simplest relevant response given  $E$ .
  - Says that **Ockham's razor** is the **only** reason for inductive leaps beyond experience.
  - Logically independent of Ockham's razor.



Patient but  
not Ockham



# *Patience*

- Never rule out a simplest relevant response given  $E$ .
  - Says that **Ockham's razor** is the **only** reason for inductive leaps beyond experience.
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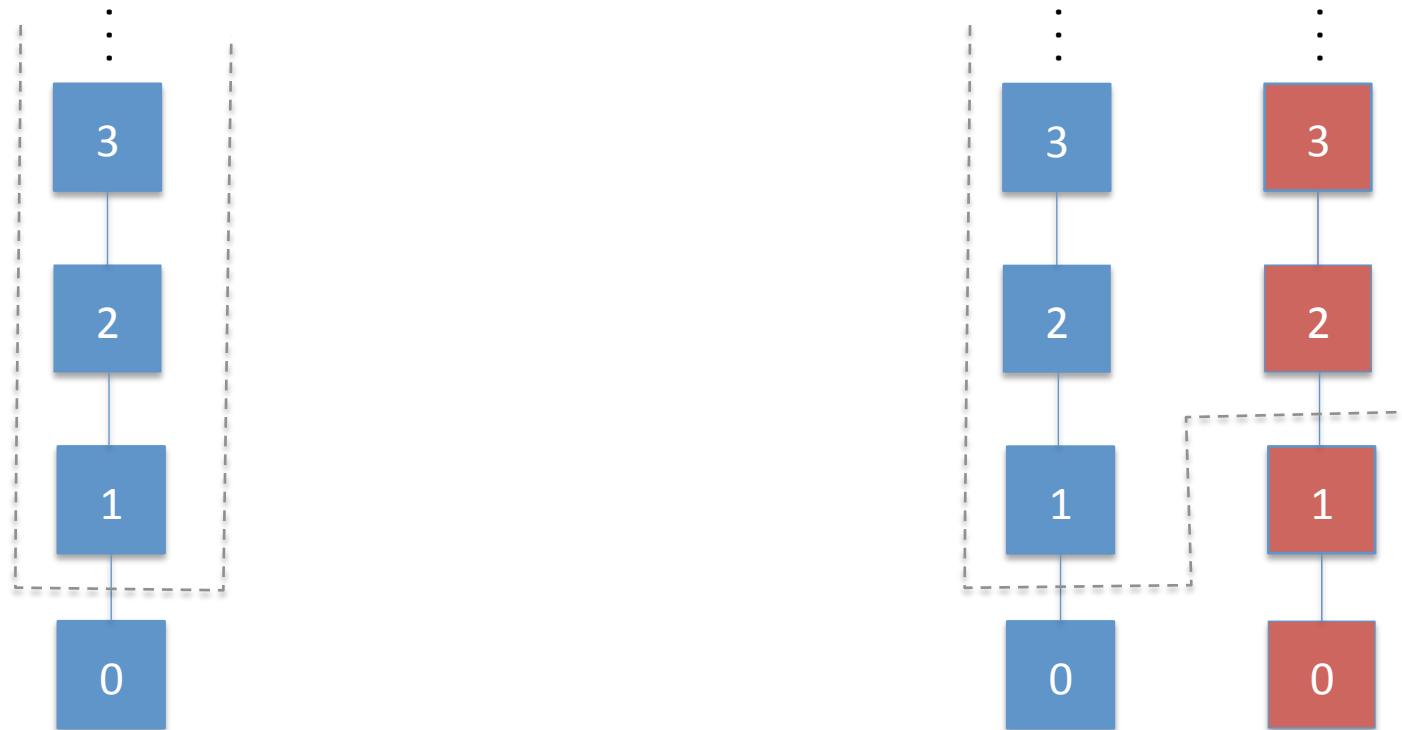


Ockham but  
not patient



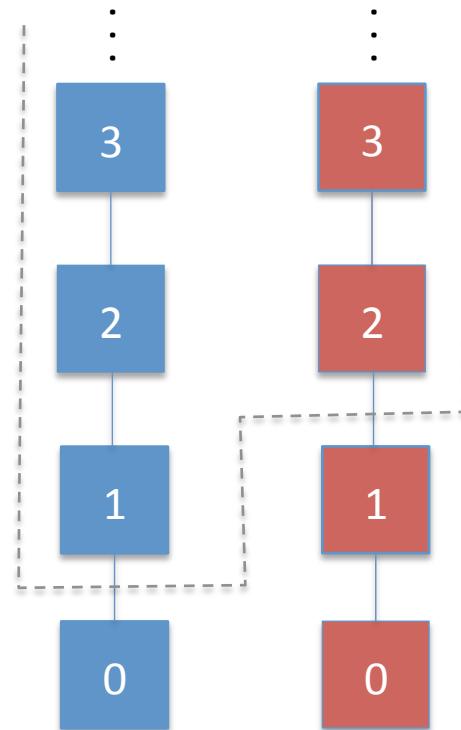
# Normal Science vs. Revolutionary Science

- A problem is **normal** iff the disjunction of every upward-closed set of answers in the simplicity order is verifiable.
- Else it is **revolutionary**.



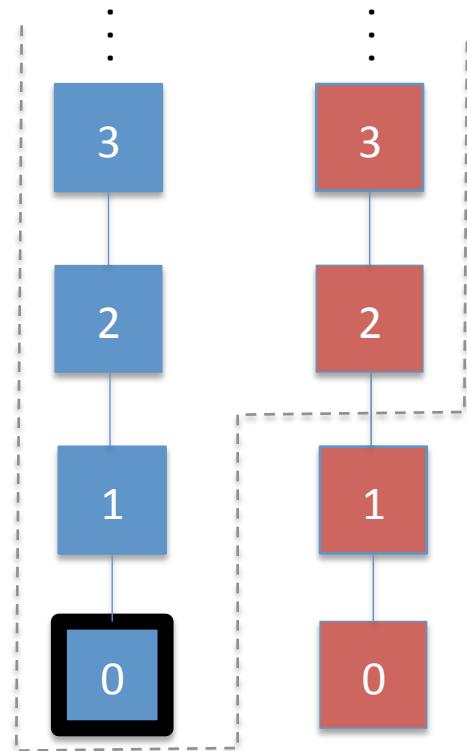
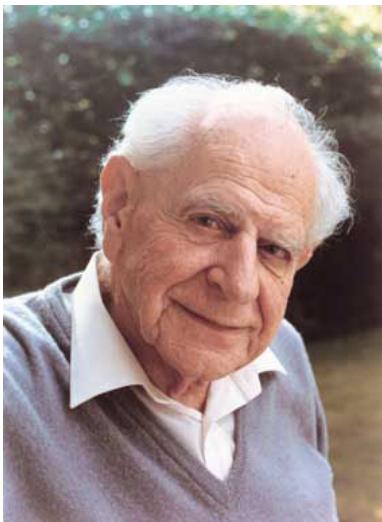
# Patient Learnability

- **Proposition.** A natural problem has reversal-optimal solution iff it is normal.
- **Idea:** Just suspend judgment until some answer is uniquely simplest.



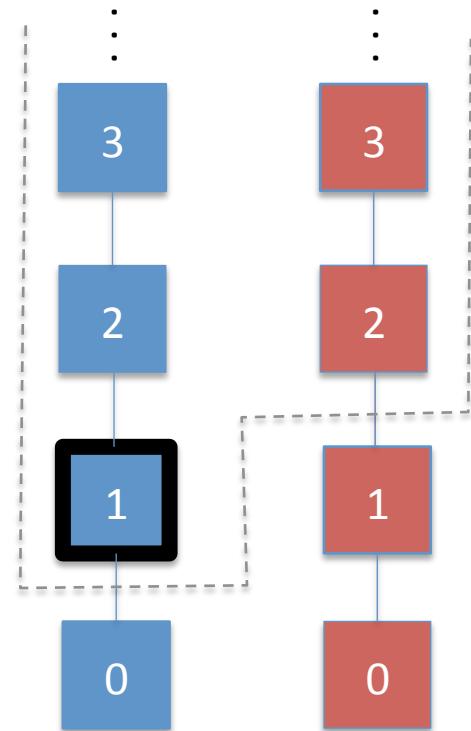
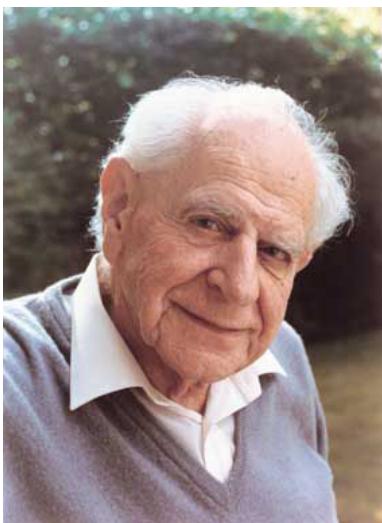
# Revolutionary Ockham Solutions

“Popper”:  
choose the  
paradigm  
with **fewer**  
free  
parameters.



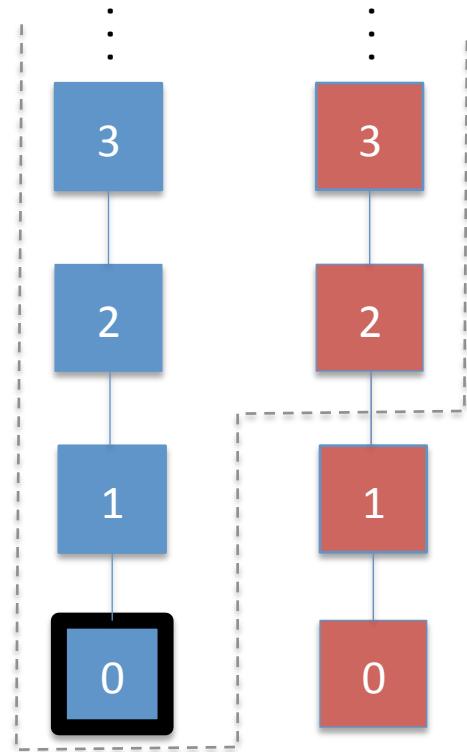
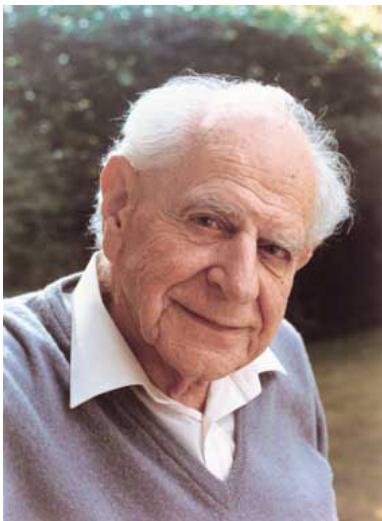
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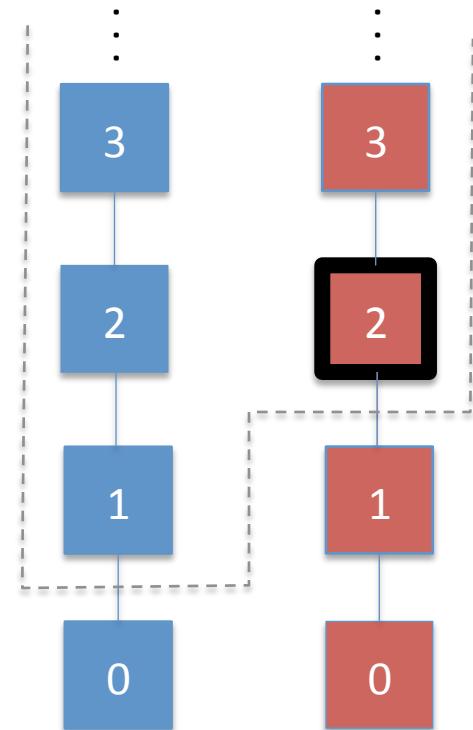
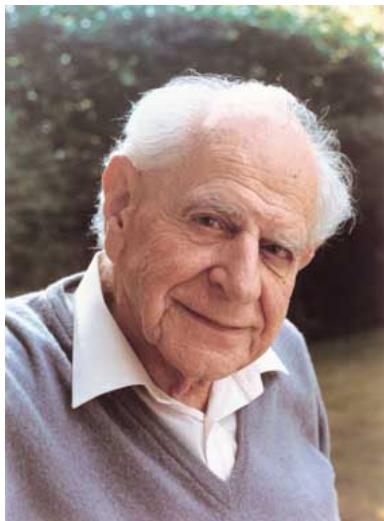


Lakatos:  
choose the  
paradigm that  
was **adjusted**  
least recently.



# Revolutionary Ockham Solutions

“Popper”:  
choose the  
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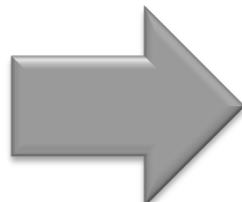


# Contextual Justification

- If patience is truth-conducive in **your** problem, its feasibility in some **other** problem is irrelevant.

# Theorem

In **normal** problems, a solution is **reversal optimal** iff it is **patient**.



# Summary and Discussion

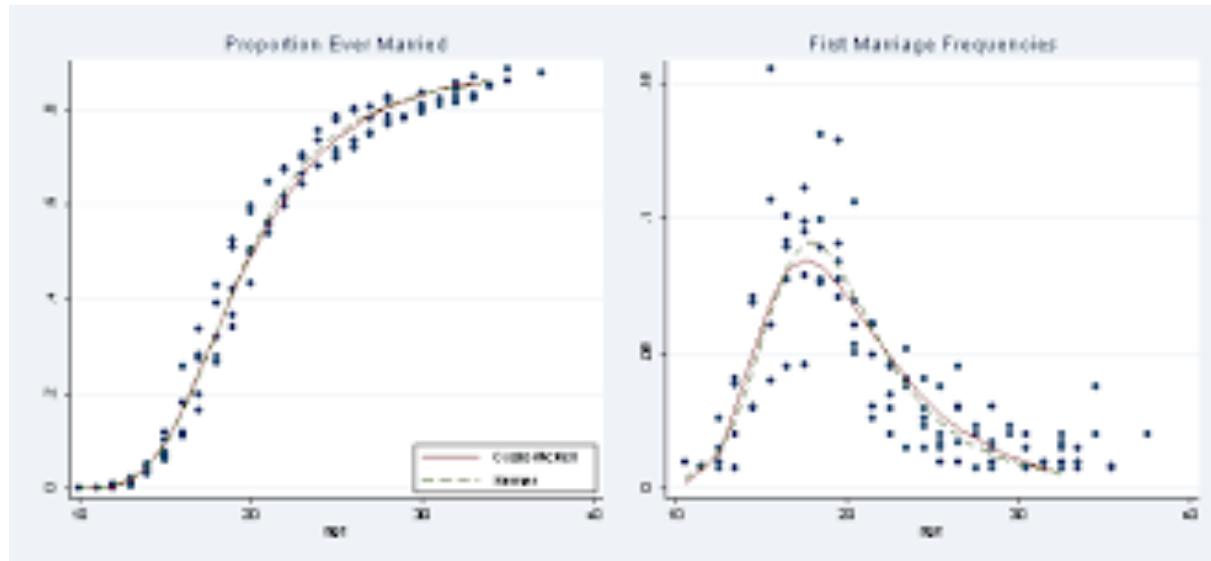
- Simplicity is a **topological** feature of **problems**.
- Ockham's razor is **necessary** for **cycle-optimal** convergence to the true answer.
- Patience is **necessary** for **reversal-optimal** convergence to the true answer.
- Optimally straight convergence is **weak**, but its implications for scientific method are **strong**.



## 9. OCKHAM'S STATISTICAL RAZOR

# Noisy Data

- How do the preceding results extend to stochastic theories?
- Every theory is stochastic due to measurement error.



# *Stats Wars*

## Bayesianism

- (+) Induction
- (-) Unreliable

## Frequentism

- (-) No induction
- (+) Reliable

Come to the coherence side, Luke, and together we will believe a complete theory of the universe!



Darth Bayeser

Luke Estimator

Never! Without reliability, I'll just use theories for prediction without believing them!

# *Stats Wars*

## Bayesianism

- (+) Induction
- (-) Unreliable

## Frequentism

- (-) No induction
- (+) Reliable

Luke, predicting the results of novel policies requires inductive causal knowledge.



Darth Bayeser

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# *Stats Wars*

## Bayesianism

- (+) Induction
- (-) Unreliable

## Frequentism

- (-) No induction
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Luke, predicting the results of novel policies requires inductive causal knowledge.



Darth Bayeser

Luke Estimator

# *Stats Peace*

## Frequentist theory of **inductive inference**

- (+) Induction
- (+) Optimal inductive reliability
- (+) Bayesian methods are an option



Darth Bayeser

Luke Estimator

# Short Story (after 15 years)

Everything carries over very nicely, if you do it just right.  
A glance at how it is done follows.



# “In Chance” Translation

## Topology

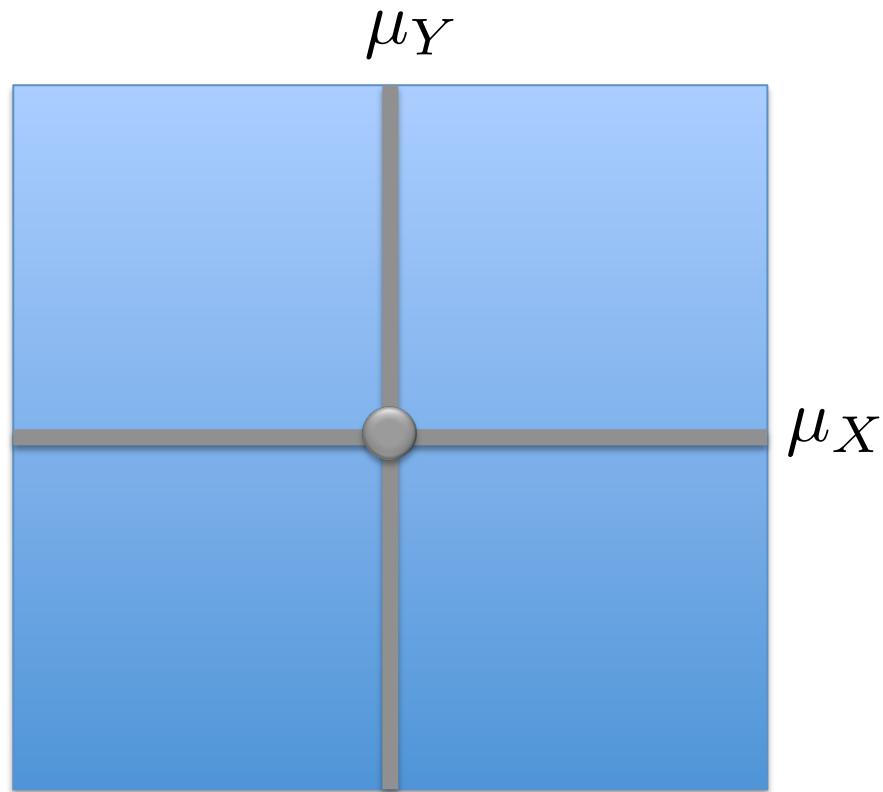
- $W$
- Input information
- Method
- Topology on  $W$
- Simplicity
- Convergence
- Reversals
- Ockham’s razor
- Patience

## Statistics

- A set of probability measures
- Random (iid) sample  $\mathbf{X}_N$
- A measurable function  $M_N$  of  $\mathbf{X}_N$
- $f(p) = p(\mathbf{X}_N \in S)$  is continuous
- Simplicity
- Convergence in chance
- Reversals in chance
- Error razor in chance
- Error patience in chance

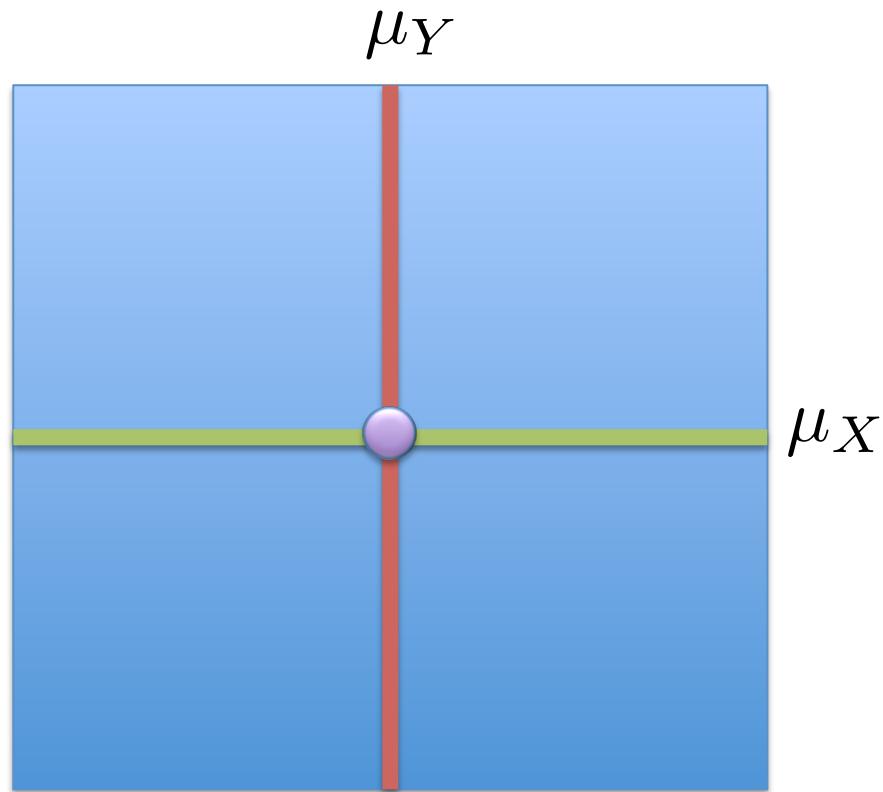
# Example

- **Worlds:** bivariate independent normal distributions.



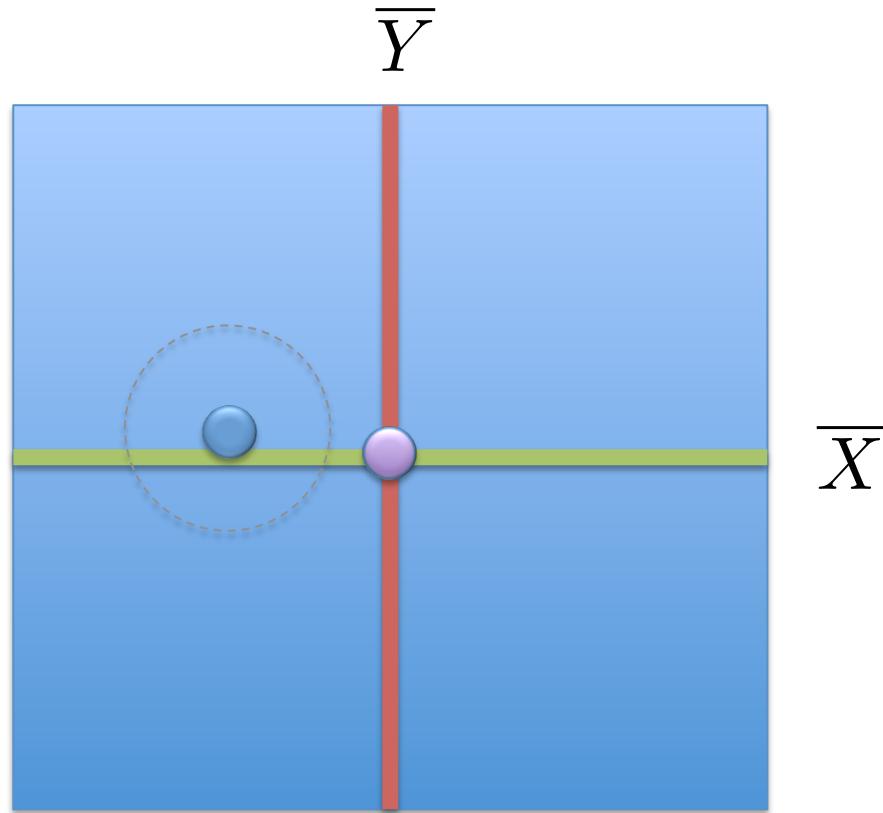
# Example

- **Worlds:** bivariate independent normal distributions.
- **Question:** which mean components are non-zero?



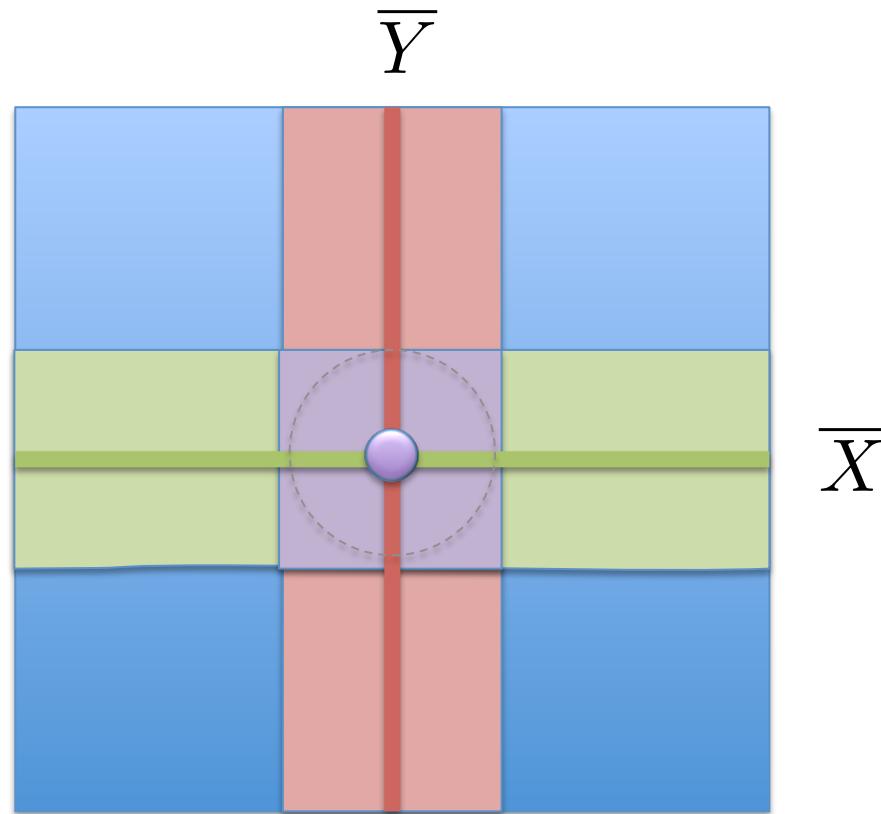
# Example

- **Worlds:** bivariate independent normal distributions.
- **Question:** which mean components are non-zero?
- **Input:** sample mean vector at sample size  $N$ .



# Example

- Method: maps possible samples to answers.



# Information Topology on $W$

The **information topology** on  $W$  is the weakest topology for which the function

$$f(p) = p(\mathbf{X}_N \in S)$$

is continuous from  $W$  to  $R$ , for arbitrary  $N$  and Borel event  $S$  in  $\mathbb{R}^N$ .

Thus  $g(p) = p(M_N = B)$  is continuous.

# Reversals in Chance

Sampling distribution:	$p$
Method:	$M$
Reversal sequence:	$(A_0, A_1, A_2)$
Ascending sample sizes:	$(N_0, N_1, N_2)$
Output chances:	$p_j^i := p_{N_j}(M = A_i).$
Pre-reversal odds:	$a_i := p_i^{i+1}/p_i^i.$
Post-reversal odds:	$b_i := p_{i+1}^{i+1}/p_{i+1}^i.$
Odds differences:	$d_i := b_i \dot{-} a_i.$

# Reversals in Chance

Reversal sequence:  $(A_0, A_1, A_2)$

Ascending sample sizes:  $(N_0, N_1, N_2)$

“How much of the drop in chance of producing  $A_i$  can be accounted for by the rise in chance of producing  $A_{i+1}$ ? ”



$$p_j^i := p_{N_j}(M = A_i).$$

$$d_i := (p_i^i - p_{i+1}^i) \div (p_{i+1}^{i+1} - p_i^{i+1}).$$

Drop for  $A_i$

Rise for  $A_{i+1}$

# Reversals in Chance

Reversal sequence:  $(A_0, A_1, A_2)$

Ascending sample sizes:  $(N_0, N_1, N_2)$

“How much of the drop in chance of producing  $A_i$  can be accounted for by the rise in chance of producing  $A_{i+1}$ ? ”



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# Reversals in Chance

Reversal sequence:  $(A_0, A_1, A_2)$

Ascending sample sizes:  $(N_0, N_1, N_2)$

“How much of the drop in chance of producing  $A_i$  can be accounted for by the rise in chance of producing  $A_{i+1}$ ? ”



$$p_j^i := p_{N_j}(M = A_i).$$

$$d_i := (p_i^i - p_{i+1}^i) \div (p_{i+1}^{i+1} - p_i^{i+1}).$$

# Reversals in Chance Compared

$$(A_0, \underbrace{A_1, A_2})_{d_0, d_1}$$

reverses as  
badly as

$$(A'_0, \underbrace{A'_1, A'_2})_{d'_0, d'_1}$$

iff  $A_i \subseteq A'_i$ , for  $i \leq 2$ ;  
 $d_i \geq d'_i$ , for  $i < 2$ .

# Comparison with $\alpha$ Tolerance

$$(A_0, \underbrace{A_1, A_2}_{d_1})$$

reverses as  
 $\alpha$ -badly as

$$(A'_0, \underbrace{A'_1, A'_2}_{d'_1})$$

iff  $A_i \subseteq A'_i$ , for  $i \leq 2$ ;  
 $d_i \geq d'_i + \alpha$ , for  $i < 2$ .

# Method Comparison

- Solution  $M'$  reverses as  $\alpha$ -badly as solution  $M$  iff:

For each reversal sequence generated by solution  $M$  at some  $p$  and sample sizes,  
method  $M'$  generates a reversal sequence at some  $p'$  and sample sizes that reverses as  $\alpha$ -badly.
- Similarly for cycles.
- Strict partial order, for  $\alpha > 0$ .



# Optimal Truth Conduciveness

- Solution  $M$  is  $\alpha$  reversal-optimal iff:  
Each solution in chance reverses as  $\alpha$ -badly as  $M$ .
- Similarly for  $\alpha$  cycle-optimality.

# Error Razor

- “Err on the side of simplicity”.
- In arbitrary world  $w$ , never produce a relevant response  $B$  such that the true answer  $A_w$  is strictly simpler than  $B$ .

# Equivalence

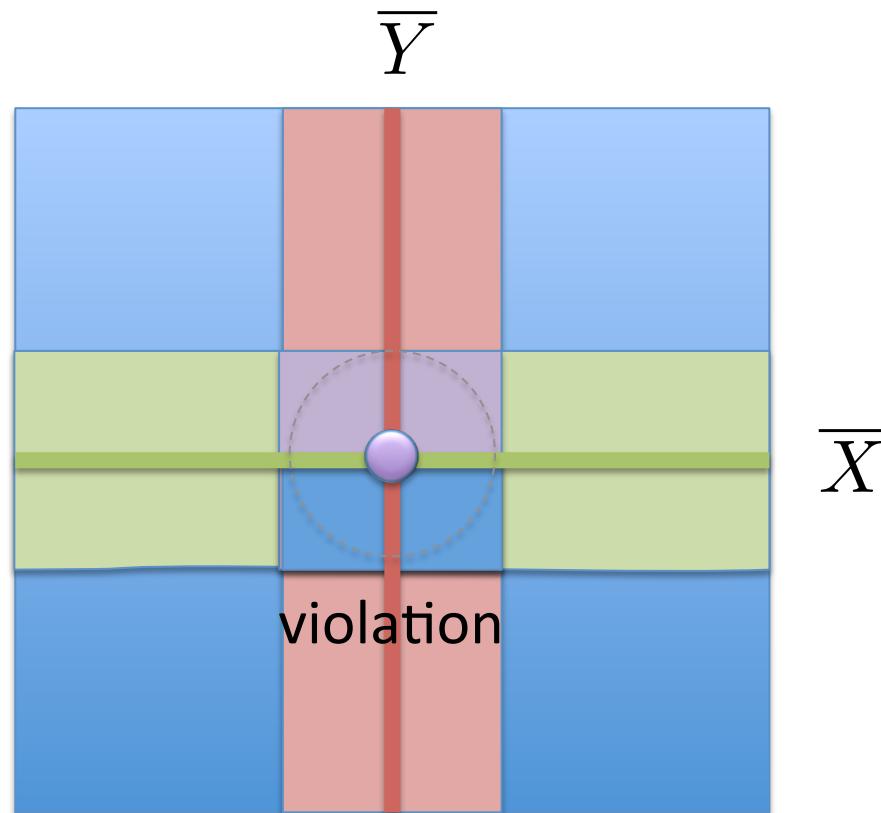
**Proposition.** In natural problems:

Ockham's razor = Popper's razor = error razor.

# Ockham's $\alpha$ -Razor

Violate the **error razor** with at most chance  $\alpha$ .

If  $A_p$  is properly simpler than  $B$ , then  $p(M_N = B) < \alpha$ .



# *Error patience*

- In arbitrary world  $w$ , never output a relevant response that rules out all answers as simple as  $A_w$ .



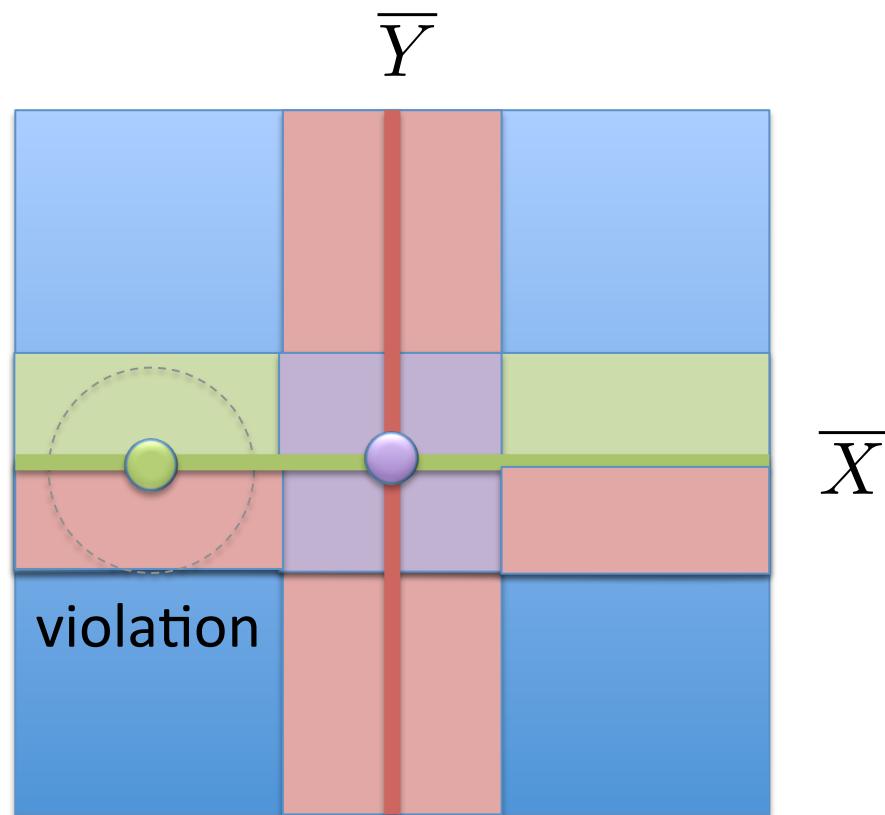
# Equivalence

- **Proposition:** Error patience is equivalent to patience.

# $\alpha$ -Patience

Violate error patience with at most chance  $\alpha$ .

If  $B$  rules out every answer as simple as  $A_p$ , then  $p(M_N = B) < \alpha$ .



# Theorem

- **Proposition:** Every  $\alpha$ -cycle optimal solution in chance to a statistical problem satisfies Ockham's  $\alpha$ - razor.

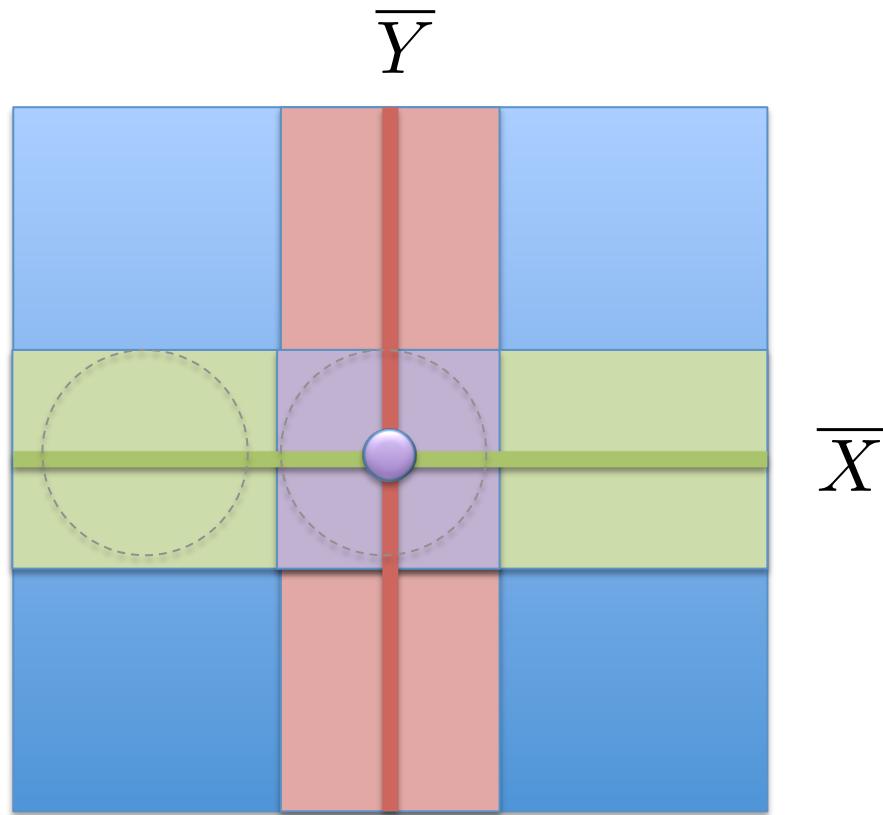


# Theorem

- **Proposition:** Every  $\alpha$ -reversal optimal solution in chance to a statistical problem satisfies  $\alpha$ -patience.

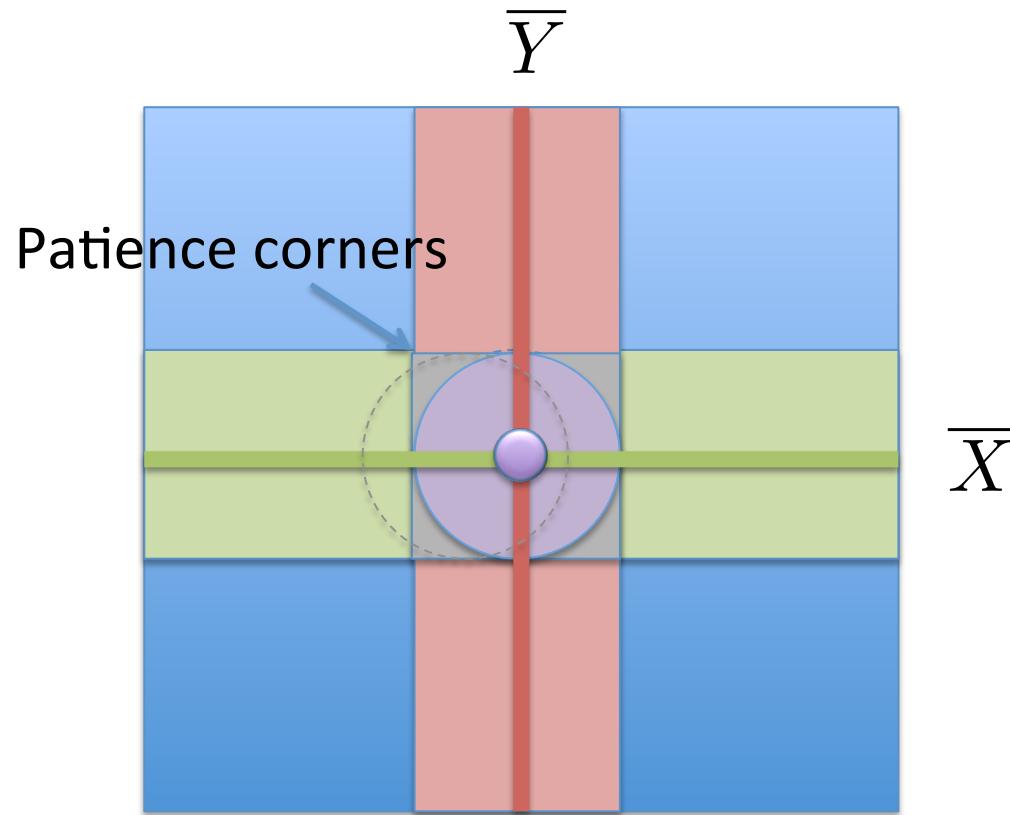


# $\alpha$ -Patient, $\alpha$ -Ockham Solution



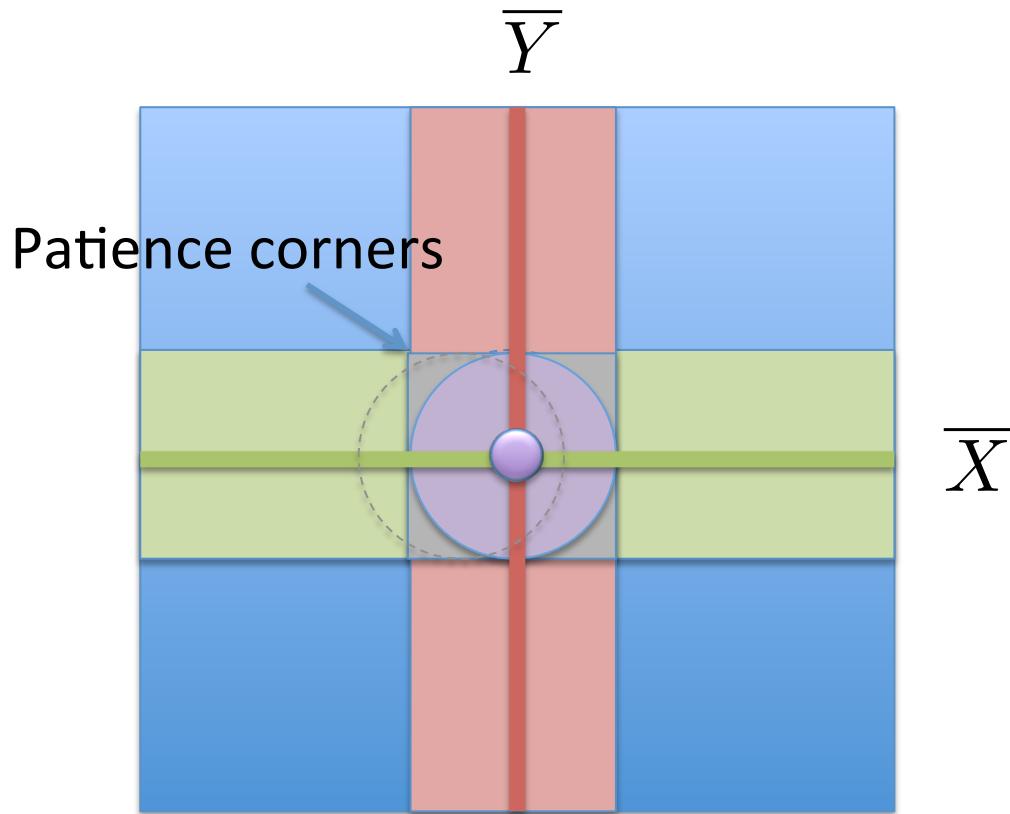
# $\alpha$ -Patient, $\alpha$ -Ockham Solution

- Power-optimized version



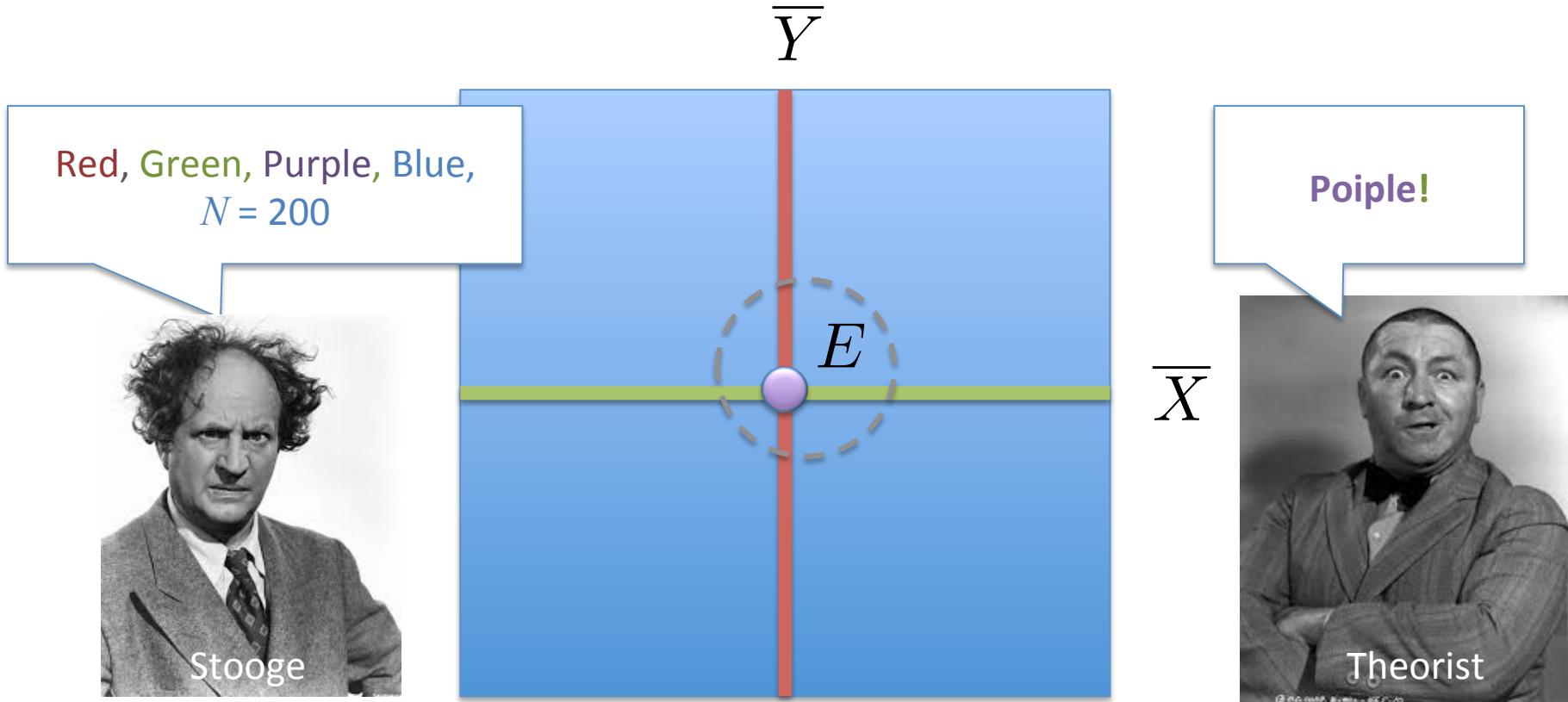
# Fishing with Tests

“Power” = get the unavoidable reversals over with as soon as possible for given  $\alpha$ .



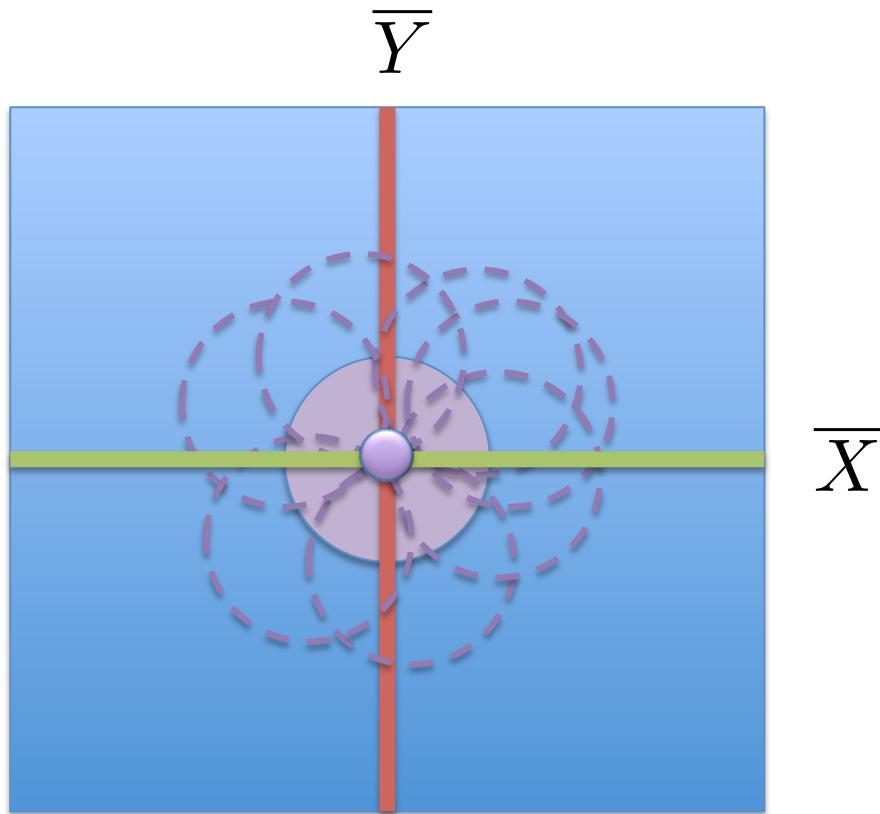
# Confidence Intervals as Information

- Statistician's **stooge** constructs a confidence ball  $E$  and reports to the **theorist** the sample size  $N$  and which **answers** are **logically compatible** with  $E$ .
- **Theorist** applies the **logical** versions of Ockham's razor and patience.



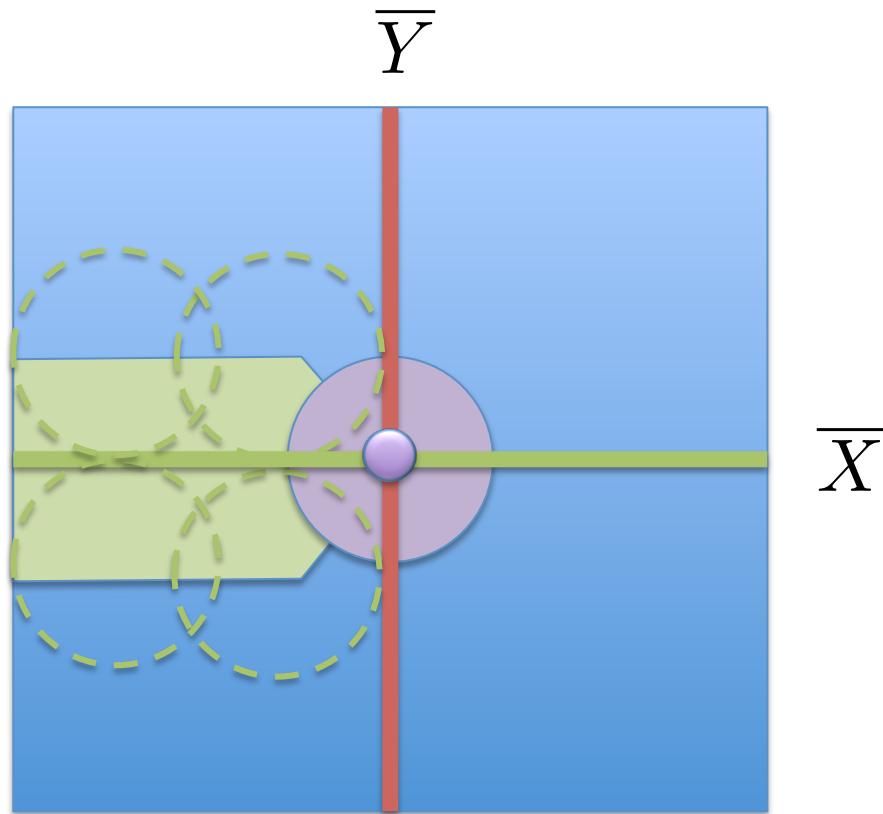
# Confidence Intervals as Information

- Statistician's *stooge* constructs a confidence ball  $E$  and reports to the *theorist* which *answers* are *logically compatible* with  $E$ .
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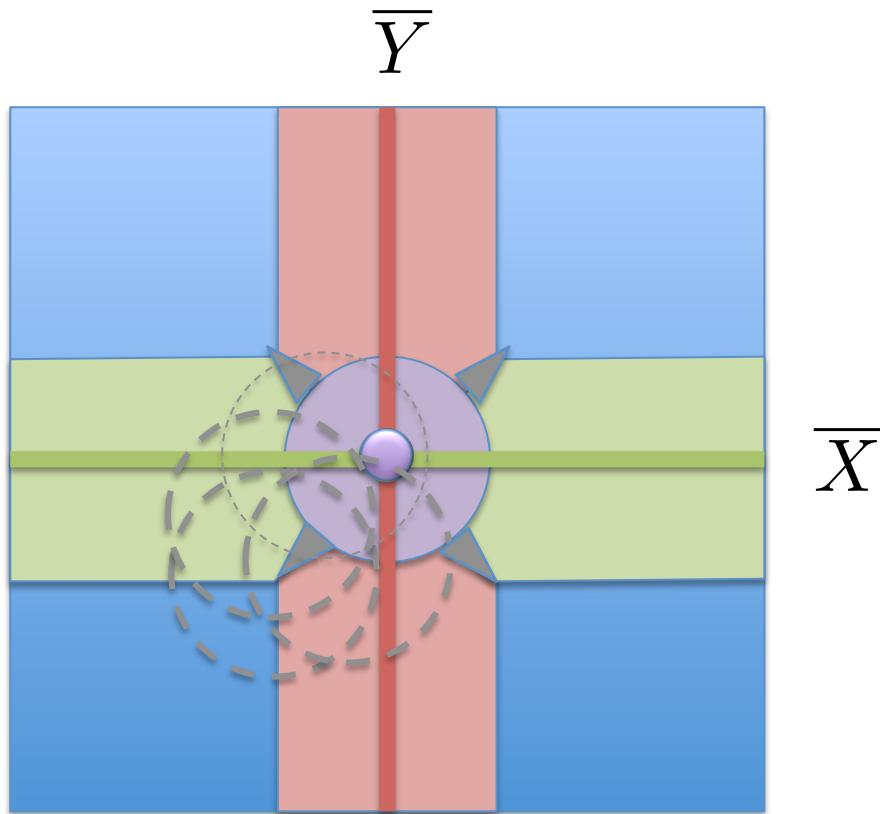
# Confidence Intervals as Information

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# Confidence Intervals as Information

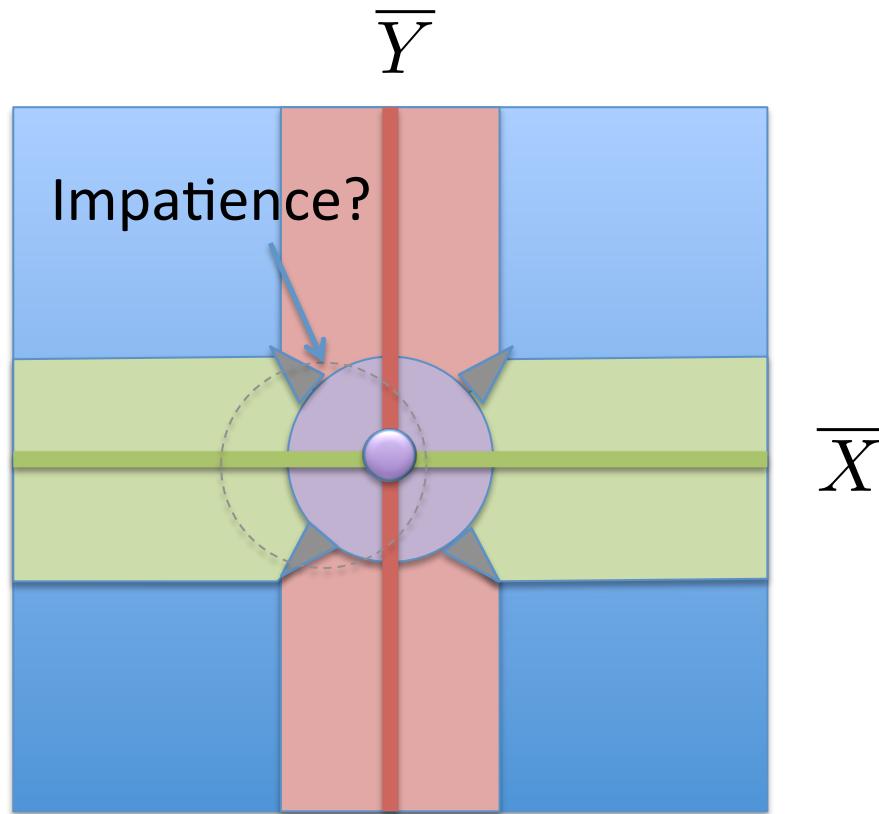
- Statistician's **stooge** constructs a confidence ball  $E$  and reports to the **theorist** which **answers** are **logically compatible** with  $E$ .
- Apply the **logical** versions of Ockham's razor and patience.



# Confidence Intervals as Information

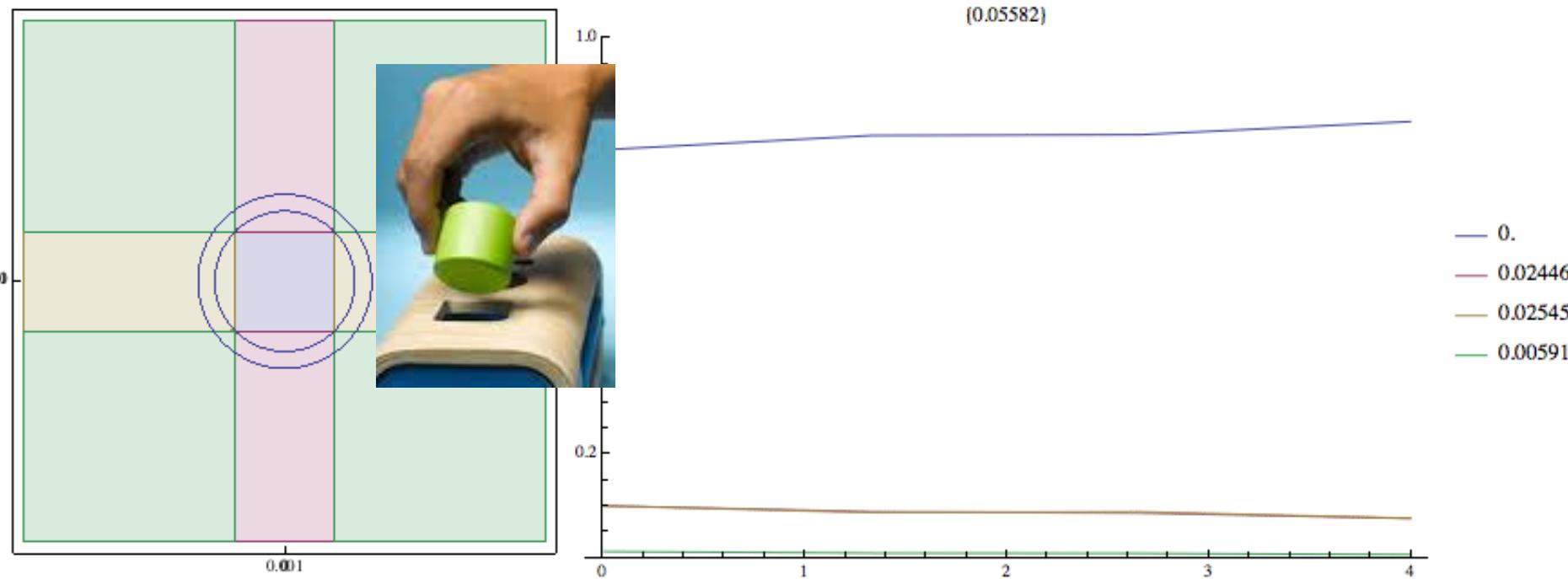
Reversal sub-optimal due to impatience?

Fishing with tests may be better.



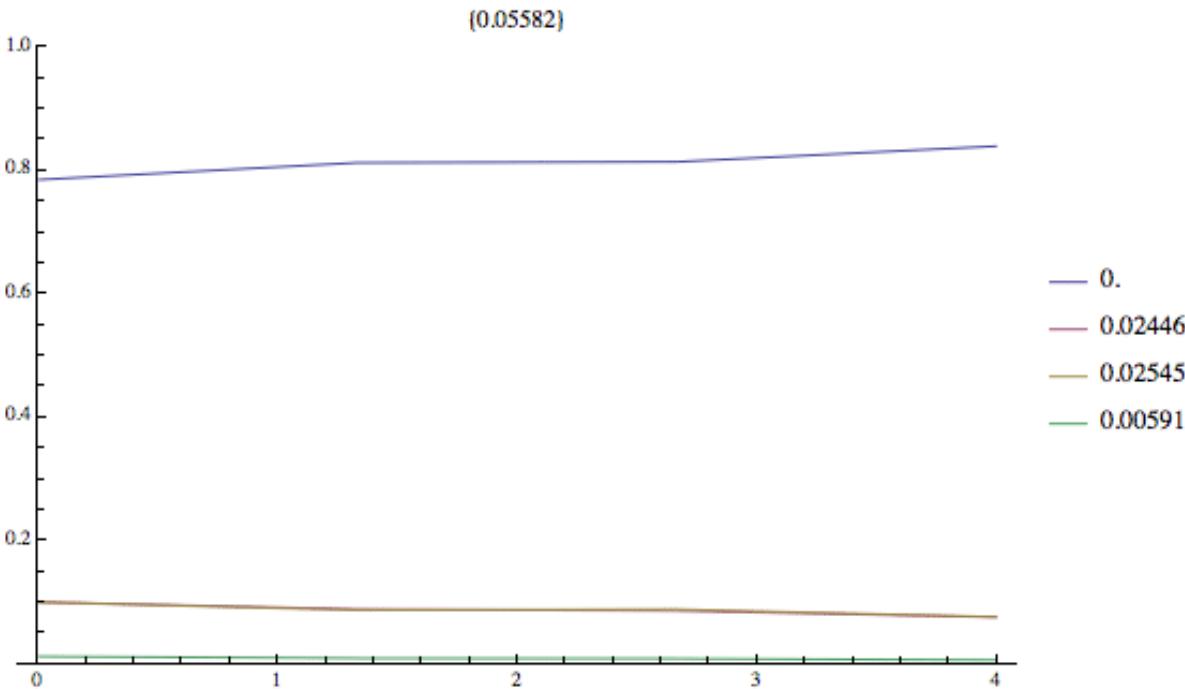
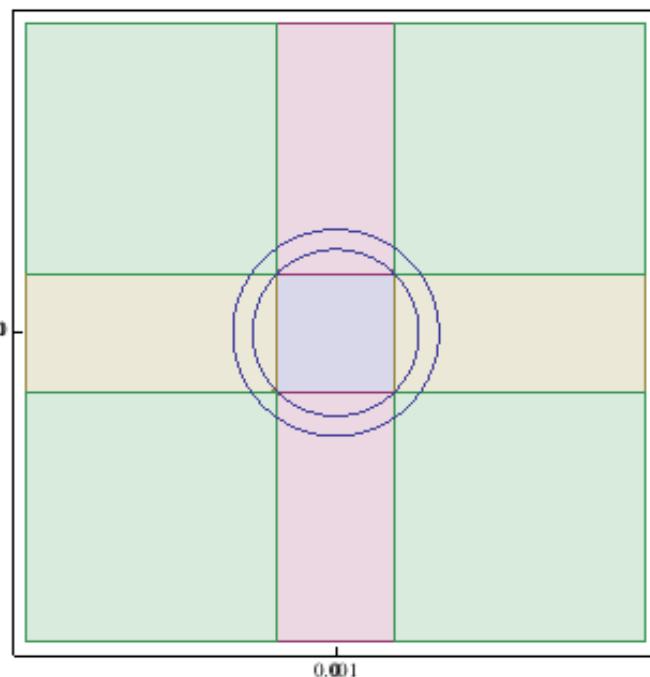
# Simulations

- Method: Minimize BIC score.
- 20% Ockham violation near 0,0.
- 10% impatience near 0,0.
- Blue zone is optimized against small errors in simplicity.



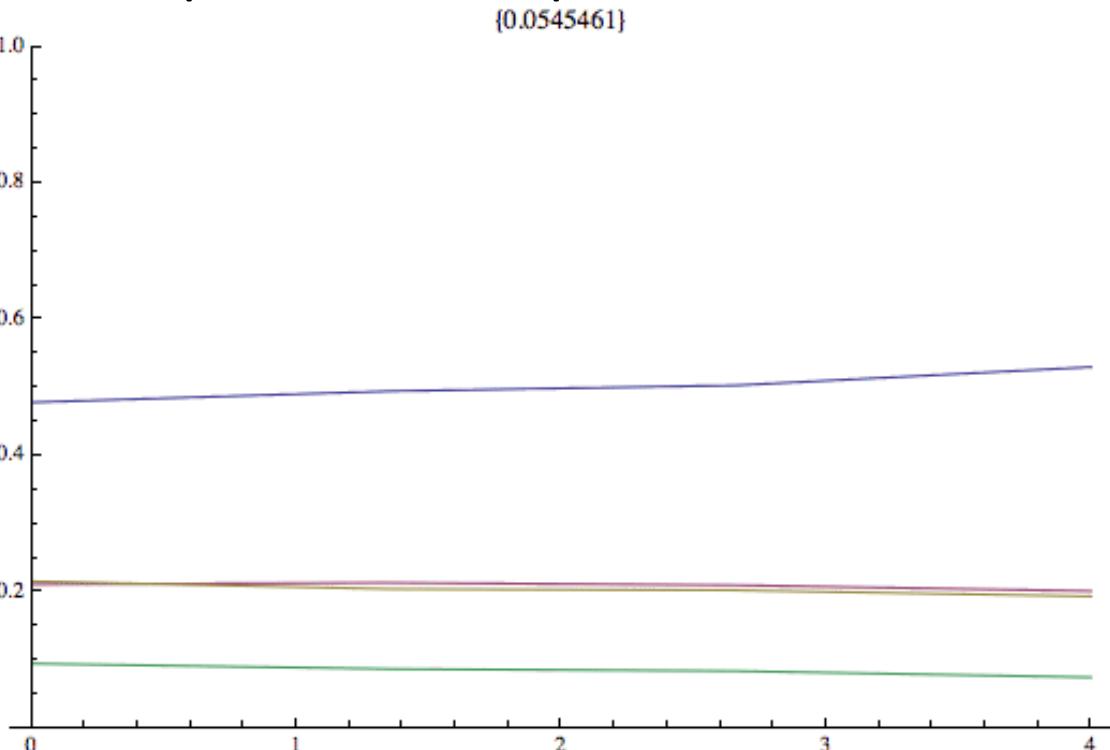
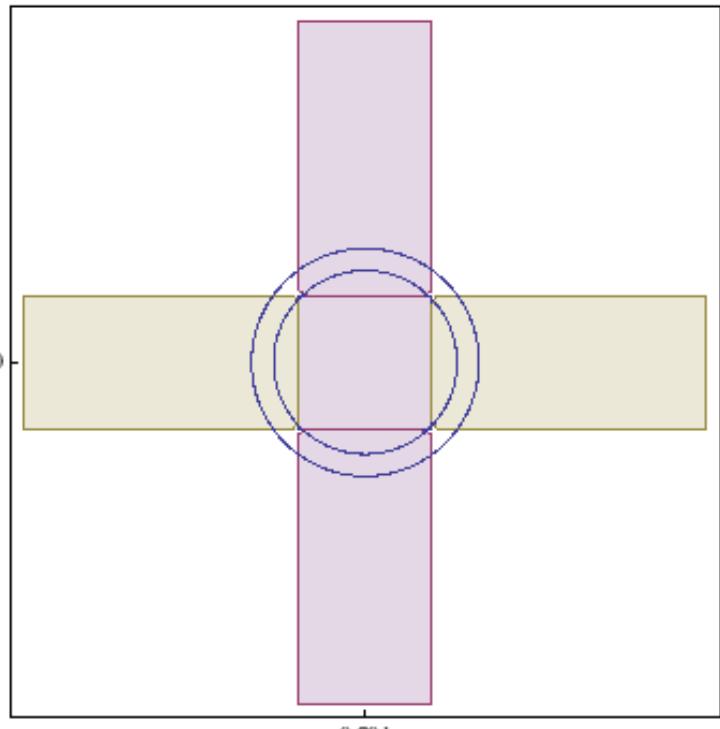
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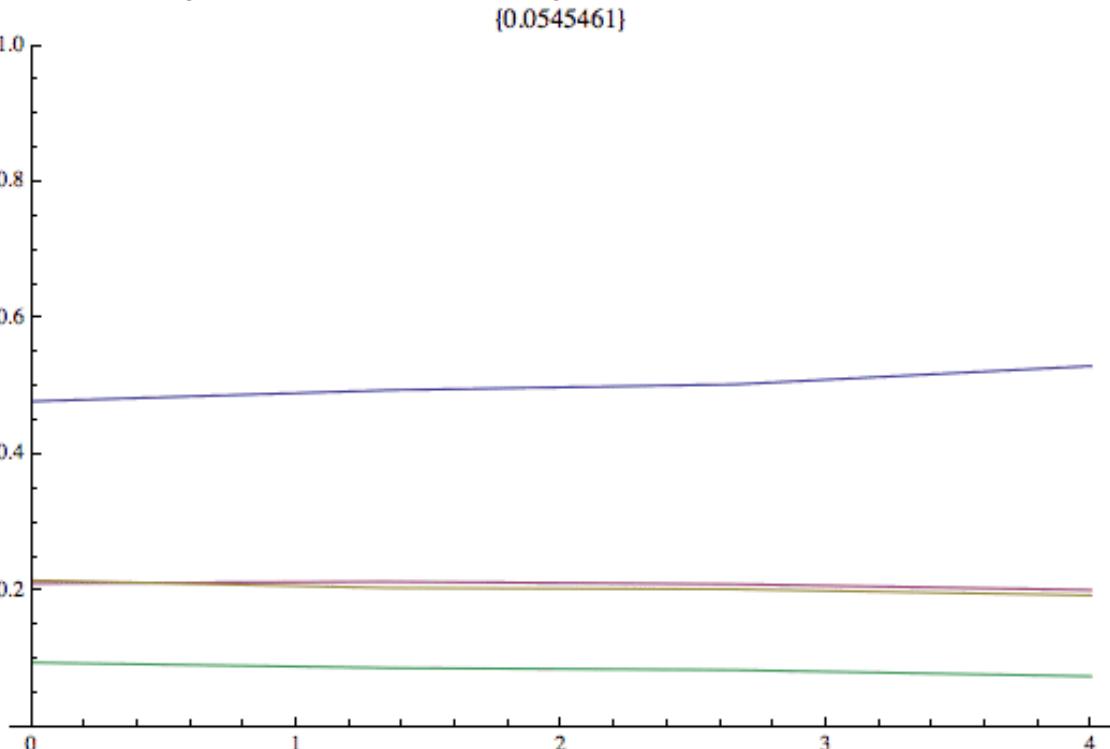
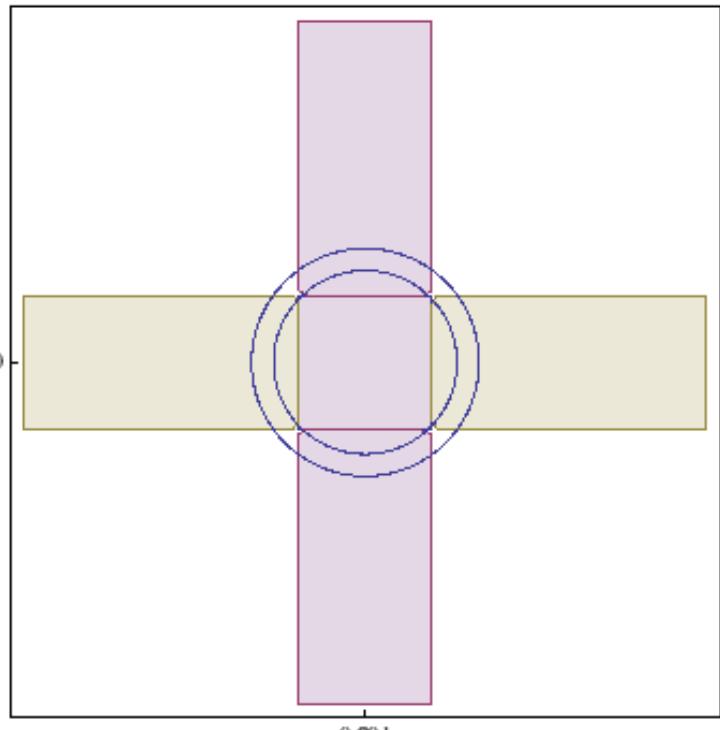
# Bayes

- Method: Maximize Bayesian credence,
- Even priors on models, Gaussian priors on parameters.
- 20% Ockham violation, 20% impatience, bad power.



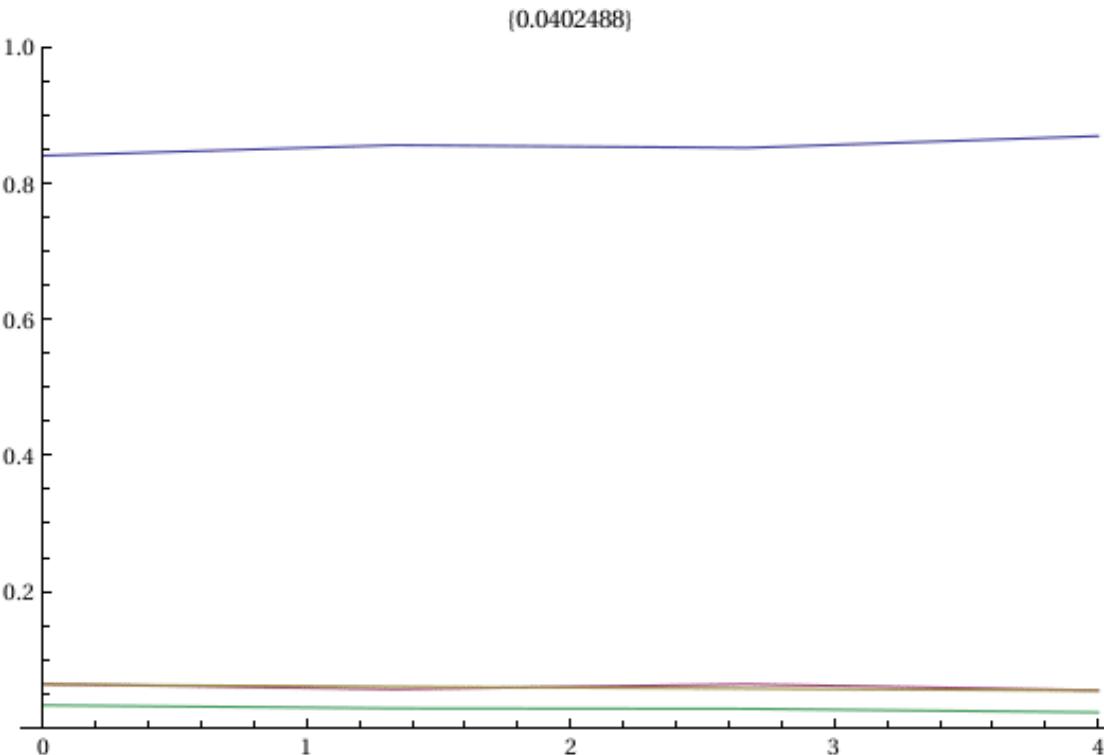
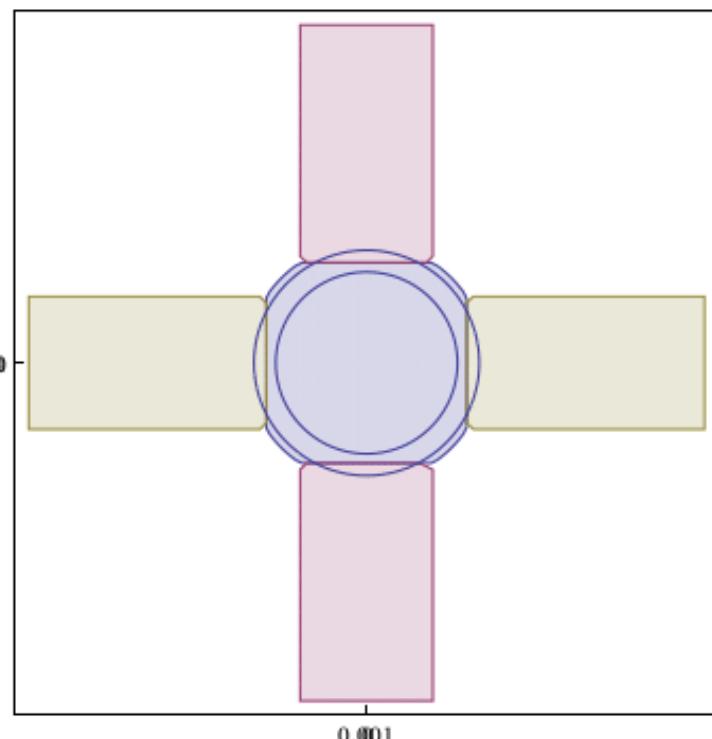
# Bayes

- Method: Maximize Bayesian credence,
- Even priors on models, Gaussian priors on parameters.
- 20% Ockham violation, 20% impatience, bad power.



# Bayes

- Method: Maximize Bayesian credence,
- Prior bias toward simplicity, Gaussian priors on parameters.
- 7% Ockham violation, 7% impatience, bad power.

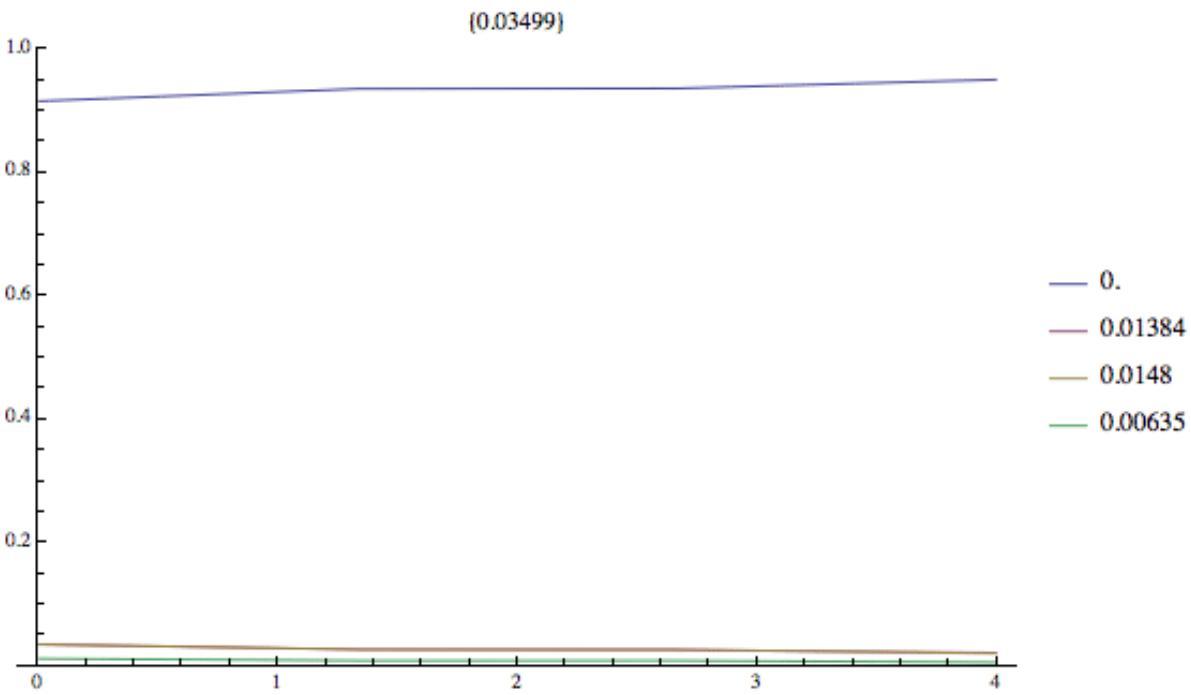
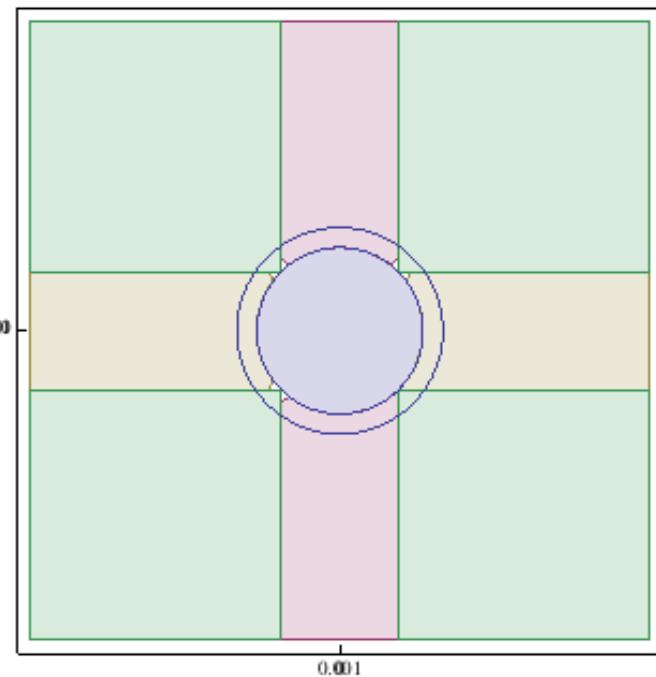


# *Plausible Advice*

- Boost the prior on simple models to **eliminate  $\alpha$  cycles** in chance.
- Then **optimize power** to get reversals over a.s.a.p.

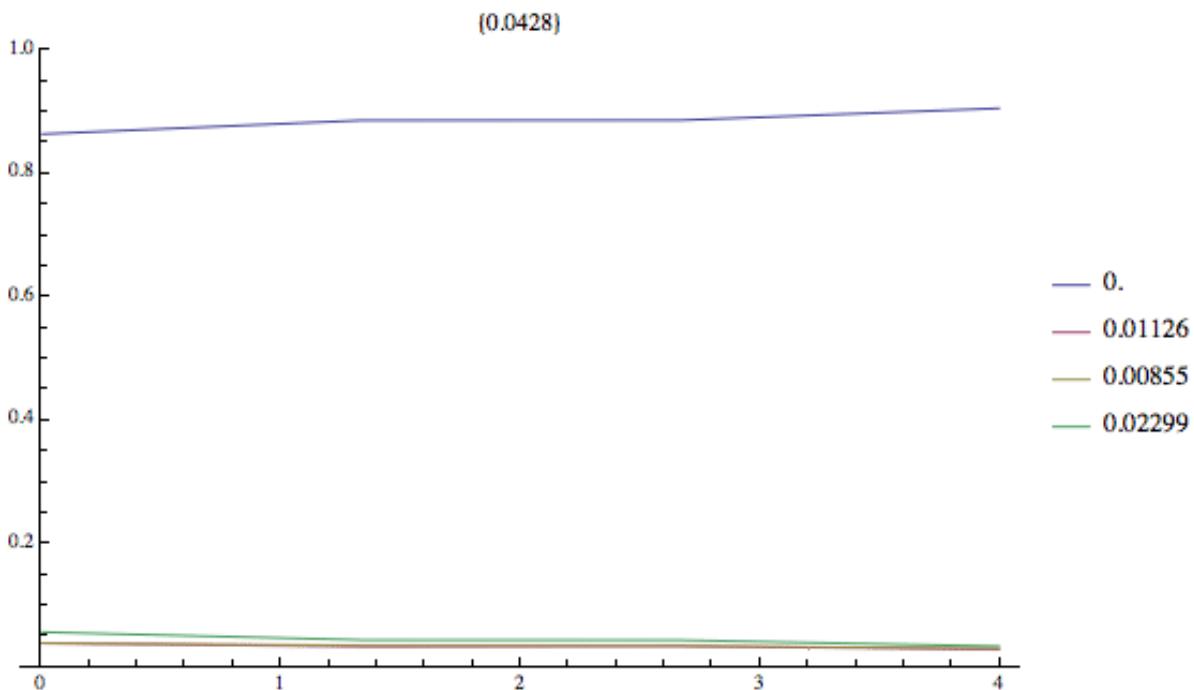
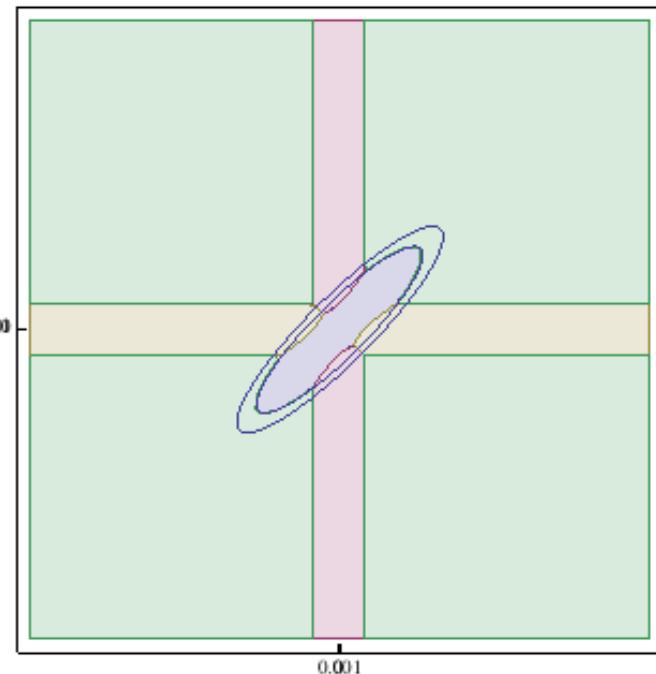
# Simulations

- Method: Nested BIC.



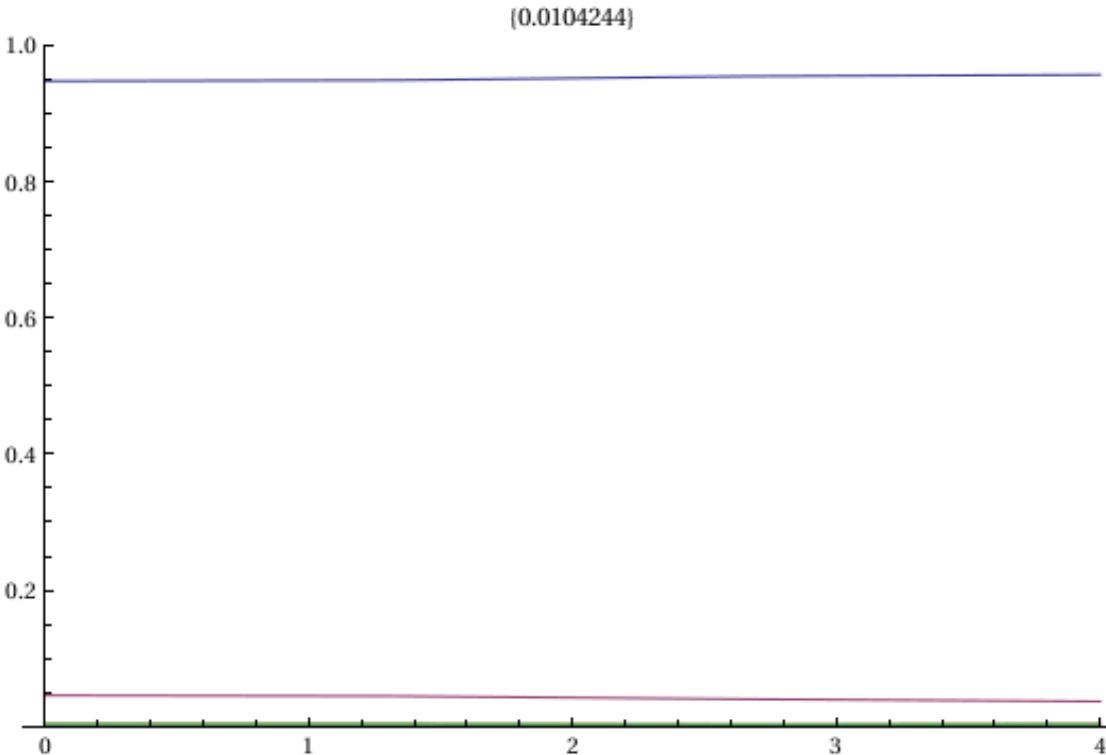
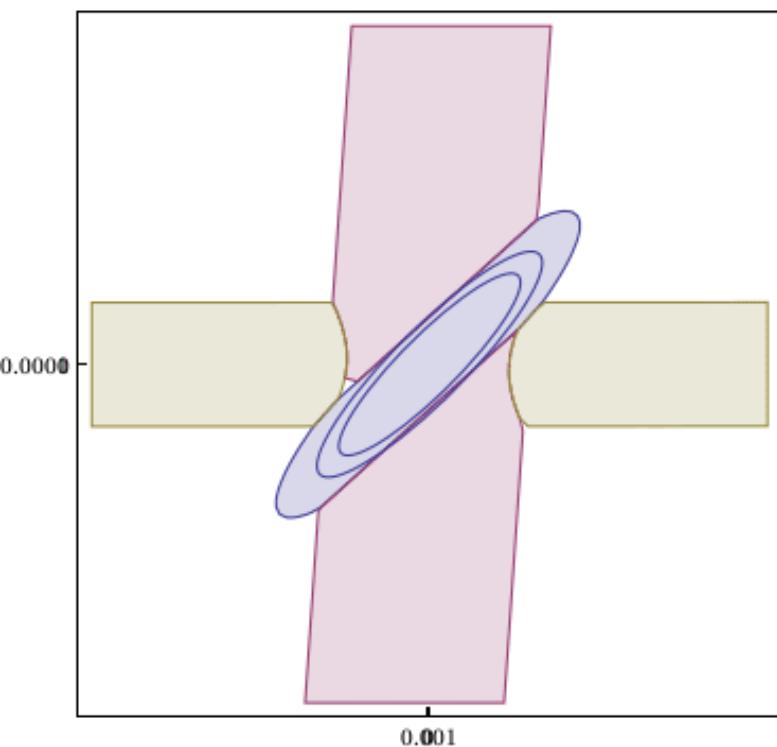
# Simulations

- Method: Minimize BIC.



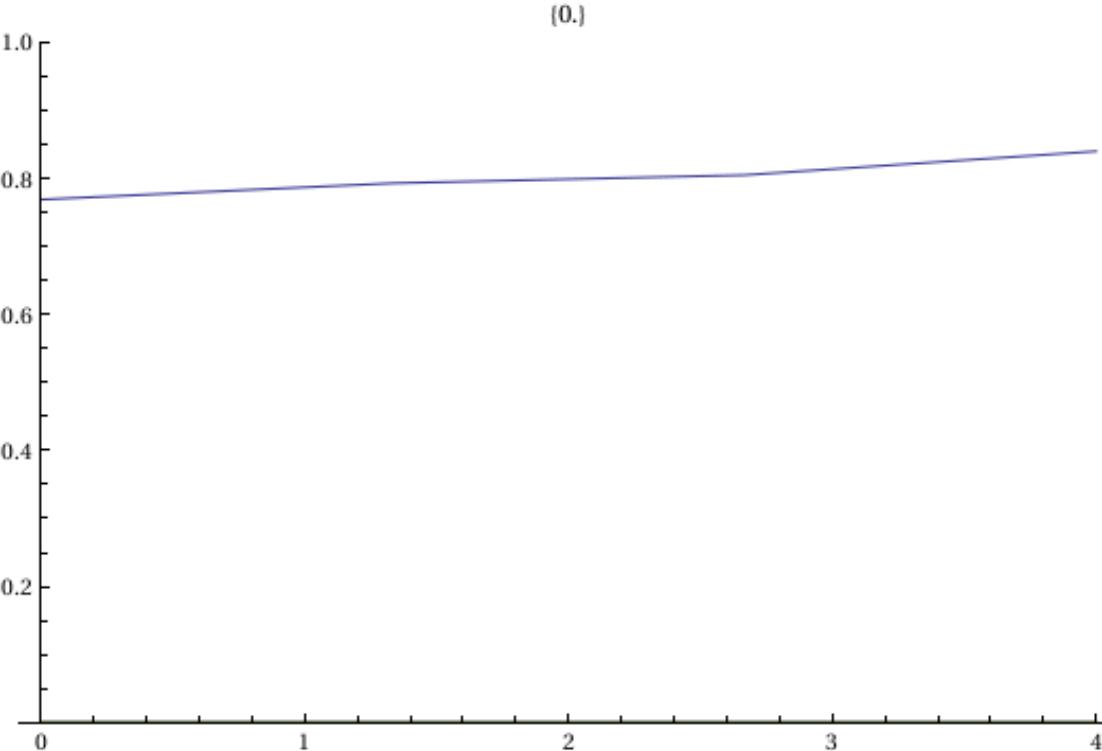
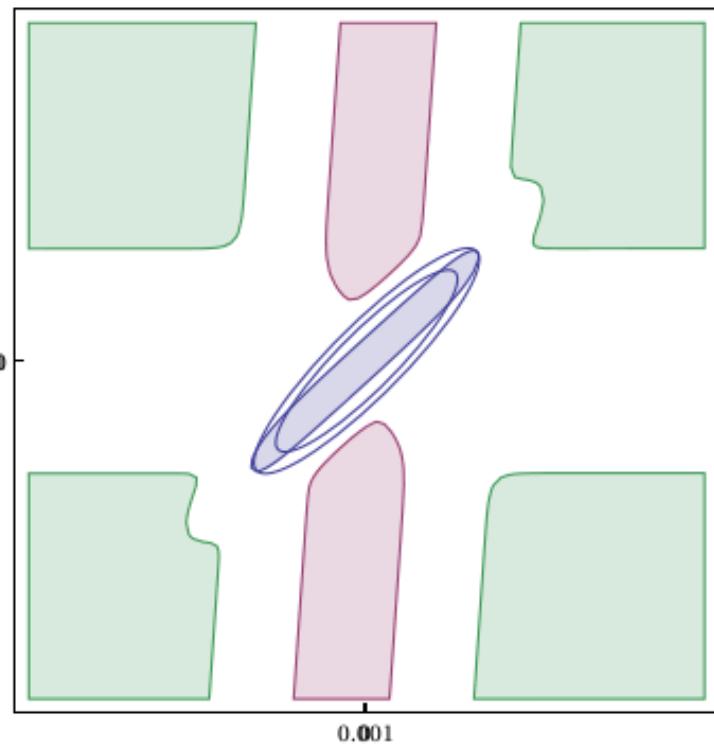
# Bayes with Correlation

- Method: Maximize Bayesian credence,
- Prior bias toward simplicity, Gaussian priors on parameters.
- 40% impatience, bad power.



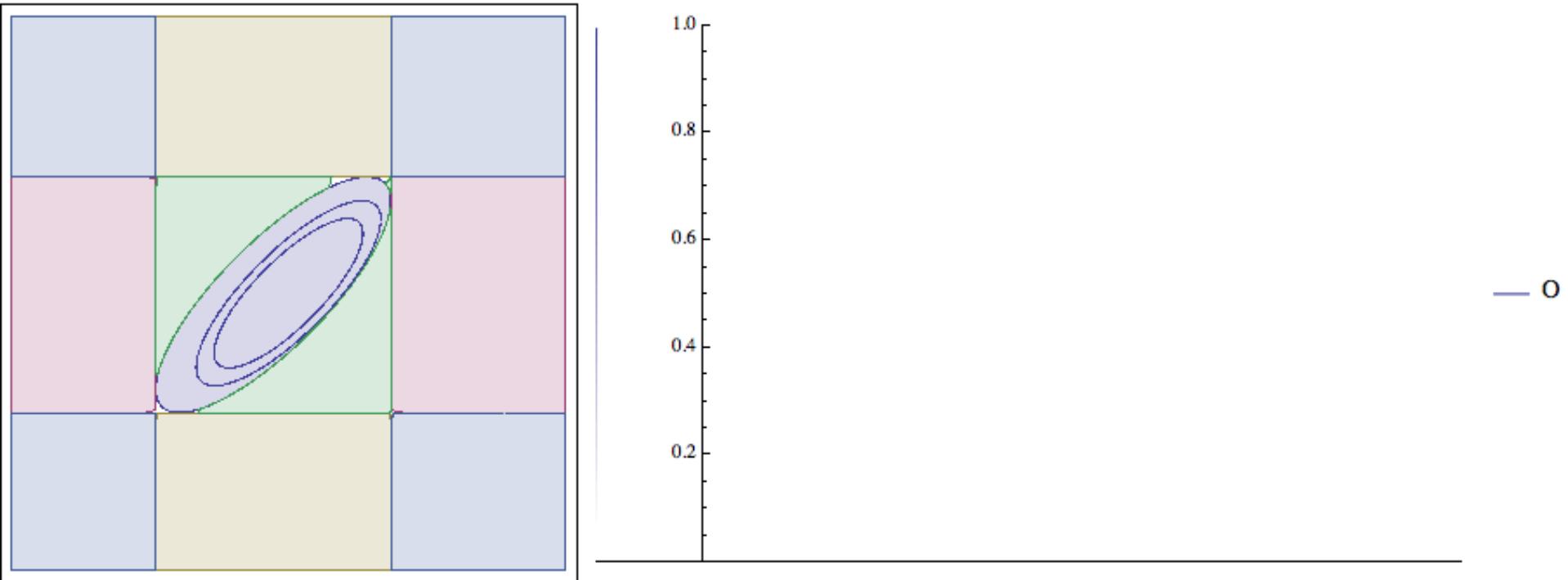
# The Power of Modesty

- Method: 95% threshold for Bayes Posterior
- Waiting for “confirming data” brings reversals in chance down to around 5%.



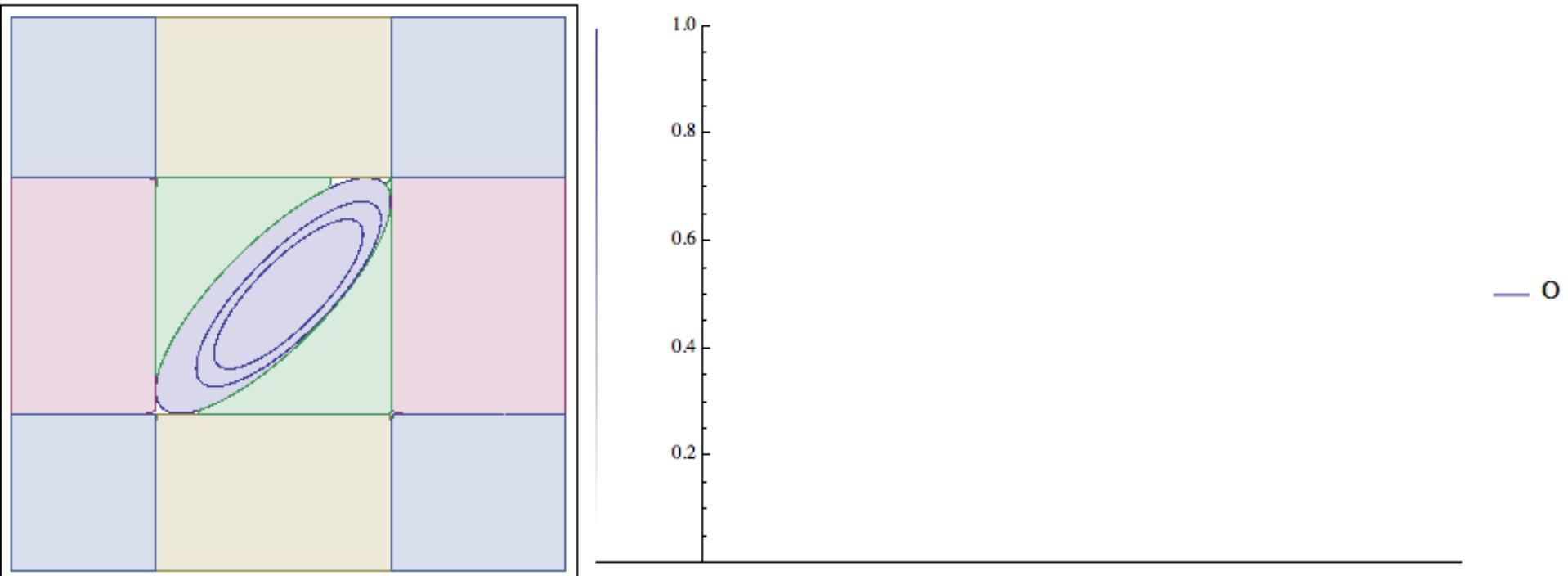
# Ockham's Frequentist Razor

- Choose powerful nested tests at significance  $\alpha$ .
- Disjoin the **simplest** models whose tests do not reject.



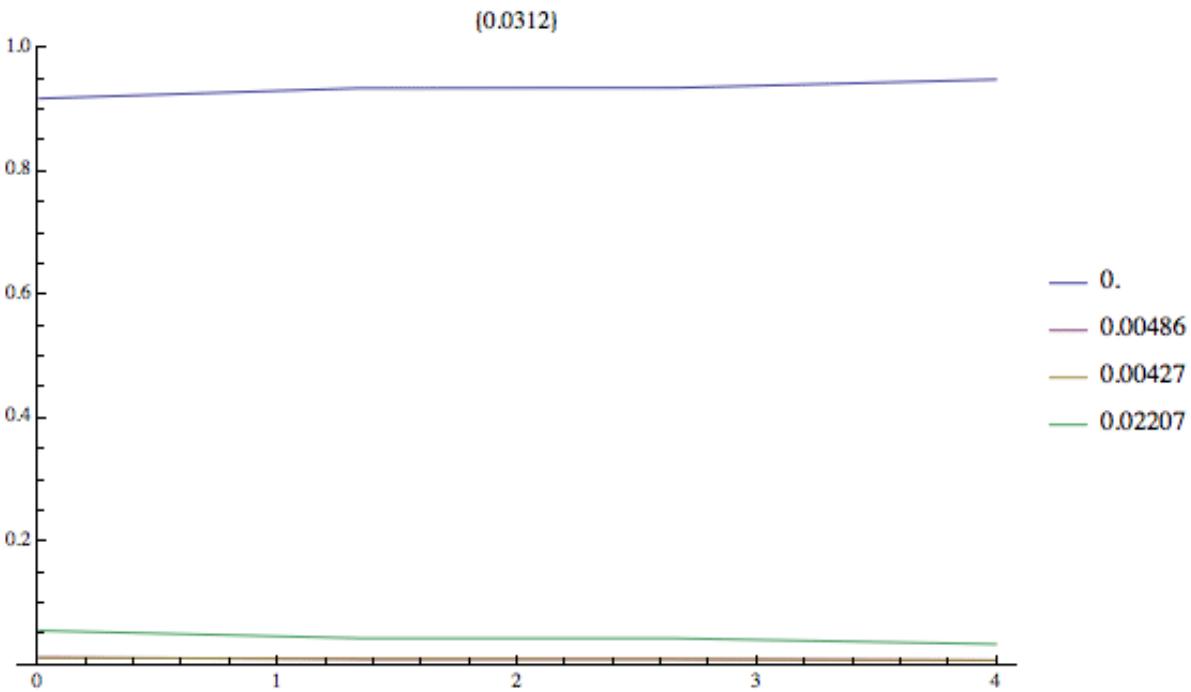
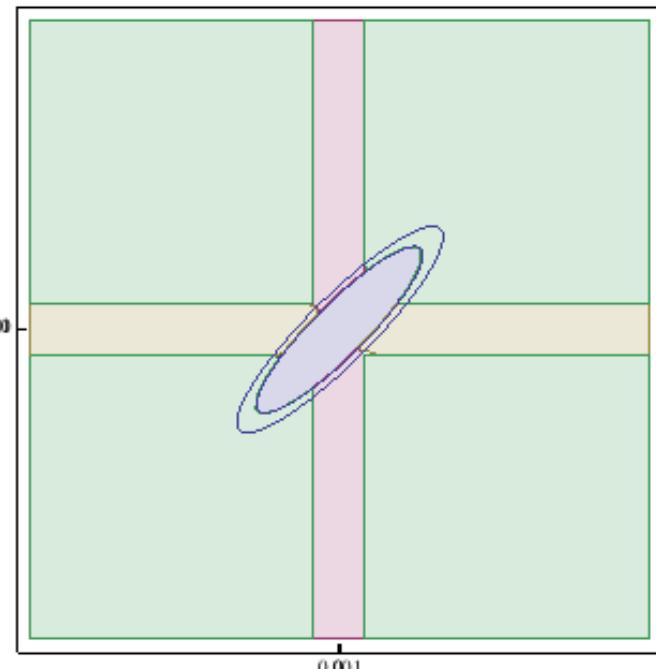
# Significance and Power Reinterpreted

- “Significance” = tolerance on cycles and reversals in chance.
- “Power” = if you are destined to drop a model, get it over with a.s.a.p.



# Simulations

- Method: Nested BIC



# *Thanks for your patience!*

