Three Applications of Means-Ends Epistemology

Oliver Schulte

Department of Philosophy and School of Computing Science

Simon Fraser University

Vancouver, Canada

oschulte@cs.sfu.ca `

Outline

- The Means-Ends Approach to Inductive Inference
- Induction in Particle Physics
  - Will a particle reaction be observed?
  - Find conservation laws explaining which reactions are observed.
- A Goodmanian Riddle of Induction
- Explaining Observed Correlations with Causal Models

Philosophical Roots of Means-Ends Epistemology (Learning Theory)

Peirce

Reichenbach

Putnam

Glymour, Kelly

Peirce:

• In inquiry, some things are settled, some are in doubt.

•Inquiry settles on true opinion in the limit.

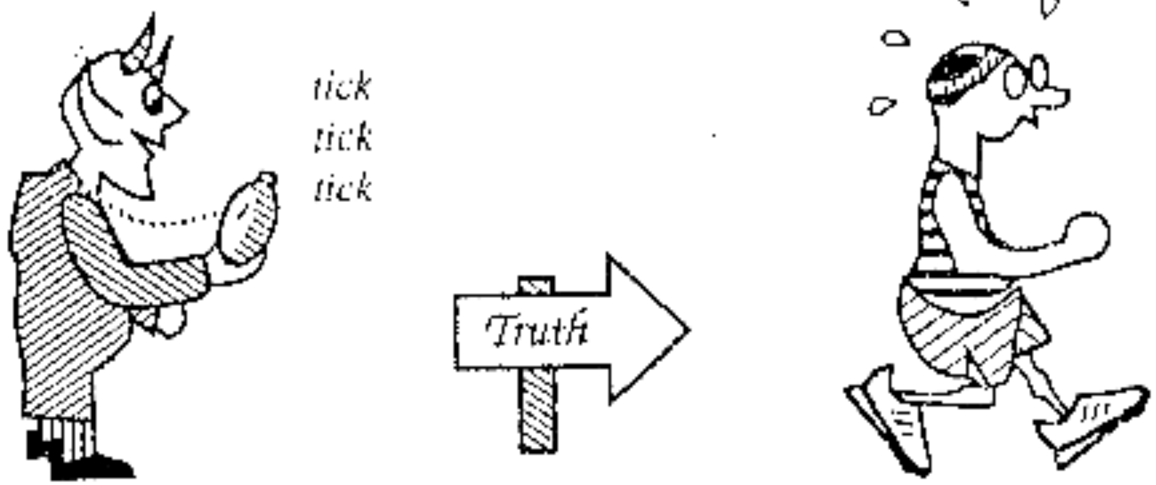
Reichenbach, "Vindication of Induction": guaranteed convergence to the right opinion.

Convergence to the Correct Theory in the Limit of Inquiry

Inductive Axiology

- Consider epistemic goals **in addition to** long-run convergence (Putnam 1965)
- Analyze relationship between different goals, e.g.:
- Fast Convergence
- Stable Convergence - avoid theory changes (Plato, Putnam 1965, "epistemic conservatism" Sklar 1975, Kuhn)
- Mistake Bounds - avoid false predictions

Fast Convergence to the Truth

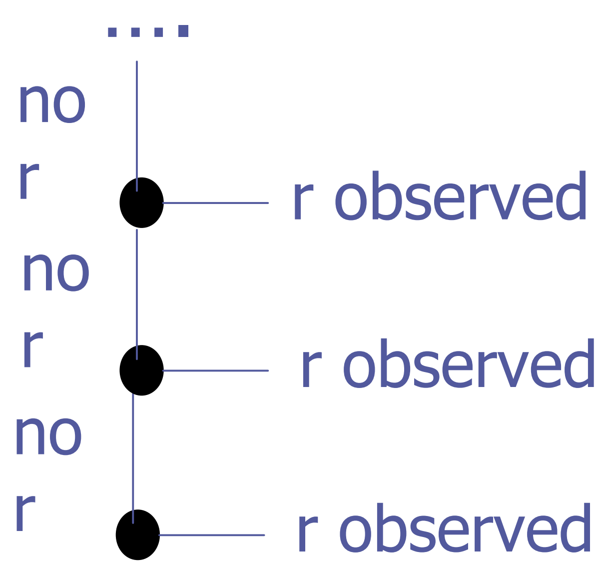


Reliable Stable Convergence: An Example

Is a certain reaction possible?, e.g.
$r = n + n \rightarrow p + p + e^- + e^-$

Rules

- Inquirer makes conjecture (“yes”, “no”, ?)
- Demon shows experimental outcomes (“observed” or not).
- Inquirer pays for abandoning “yes” or “no”.



Mean-Ends Analysis for “Is this reaction possible?”

Proposition All inference rules that converge to the right answer with at most one mind change conjecture ? or “reaction is forbidden” until the reaction is observed.

Induction in Particle Physics

Particle Review 2005:
$2v \rightarrow 2p + 2e^-$
observed

I see!
$2v \rightarrow 2p + 2e^-$
is impossible.

Particle Review 2004:
no
$2v \rightarrow 2p + 2e^-$

Particle Review 2003:
no
$2v \rightarrow 2p + 2e^-$

Particle Review 2002:
no
$2v \rightarrow 2p + 2e^-$

I must find a conservation law that explains this.

Additive Conservation Laws

	Particle	Charge	Baryon#	Tau#	Electron#	Muon#
1	Σ^-	-1	1	0	0	0
2	$\overline{\Sigma}^+$	1	-1	0	0	0
3	Σ^0	0	1	0	0	0
4	$\overline{\Sigma}^0$	0	-1	0	0	0
5	n	0	1	0	0	0
6	$\overline{n}$	0	-1	0	0	0
7	p	1	1	0	0	0
8	$\overline{p}$	-1	-1	0	0	0
9	K^0	0	0	0	0	0
10	$\overline{K}^0$	0	0	0	0	0
11	K^+	1	0	0	0	0
12	K^-	-1	0	0	0	0
13	π^+	1	0	0	0	0
14	π^-	-1	0	0	0	0
15	π^0	0	0	0	0	0
16	γ	0	0	0	0	0
17	τ^-	-1	0	1	0	0
18	τ^+	1	0	-1	0	0
19	ν_τ	0	0	1	0	0
20	$\overline{\nu}_\tau$	0	0	-1	0	0
21	μ^-	-1	0	0	0	1
22	μ^+	1	0	0	0	-1
23	ν_μ	0	0	0	0	1
24	$\overline{\nu}_\mu$	0	0	0	0	-1
25	e^-	-1	0	0	1	0
26	e^+	1	0	0	-1	0
27	ν_e	0	0	0	1	0
28	$\overline{\nu}_e$	0	0	0	-1	0

Table 1: Some Common Particles and Quantum Number Assignments

Assuming the empirical adequacy of Conservation Principles entails unobserved reactions

Hypothetical Scenario

observed reactions

$$\Sigma^- \rightarrow \pi^- + n$$
$$\pi^- \rightarrow \mu^- + \nu_\mu$$
$$\mu^- \rightarrow e^- + \nu_\mu + \bar{\nu}_e$$
$$n \rightarrow e^- + \bar{\nu}_e + p$$
$$p + p \rightarrow p + p + \pi$$

not yet observed reactions

$$n \rightarrow e^- + \bar{\nu}_e$$

$$p + p \rightarrow p + p + \pi + \pi$$

entailed

The Strict Inference Method

- Strict Method: suppose that reaction r has not been observed so far.
  - If there is no possible conservation principle that rules out r, conjecture that r is possible.
  - If some possible conservation principle rules out r, conjecture that r is forbidden, and introduce a conservation principle to explain why.

• Nobel Laureate Cooper (1970): “In the analysis of events among these new particles, where the forces are unknown and the dynamical analysis, if they were known, is almost impossibly difficult, one has tried by observing *what does not happen* to find selection rules, quantum numbers, and thus the symmetries of the interactions that are relevant.”

Means-Ends Justification for Maximally Strict Inferences

Theorem. Suppose we have *n* known particles. The strict inference method is the **only** inference rule that

1. is guaranteed to eventually arrive at an empirically adequate set of conservation principles, and
2. changes its predictions at most *n* times.

The Naturalist's Question: Comparison with Practice

Finding: The standard laws Electric Charge, Baryon#, Muon#, Electron#, Tau# form a maximally strict set for the current reaction data.

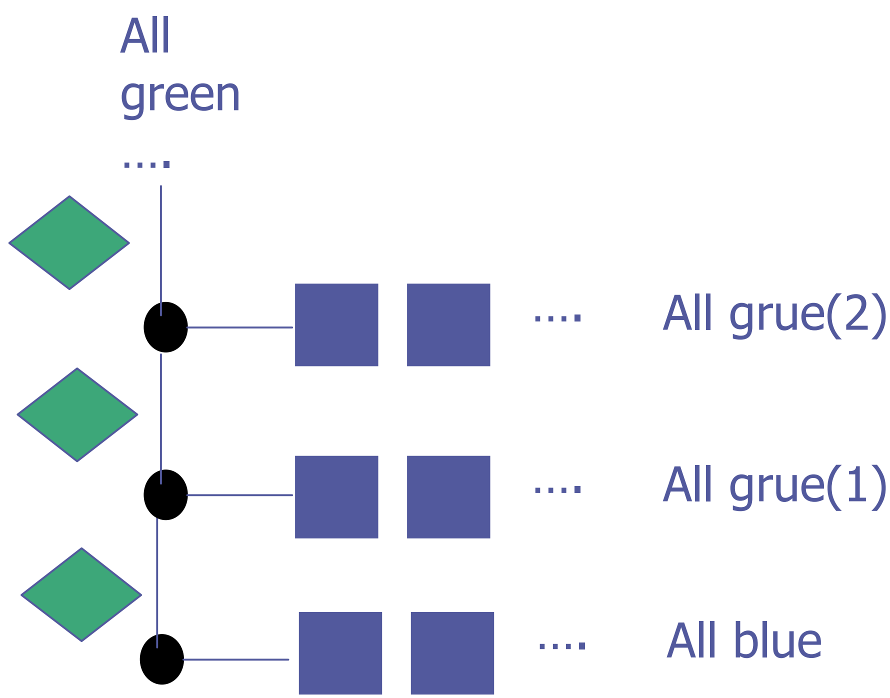
Physicists have acted as if they are following the methodology described so far. [Program]

Green and Grue

Goodman (1983). "Grue applies to all things examined before t just in case they are green but to other things just in case they are blue."

Rules

- Inquirer projects generalization (e.g. "all green")
- Demon chooses color of next emerald.
- Inquirer pays for mistaken predictions.



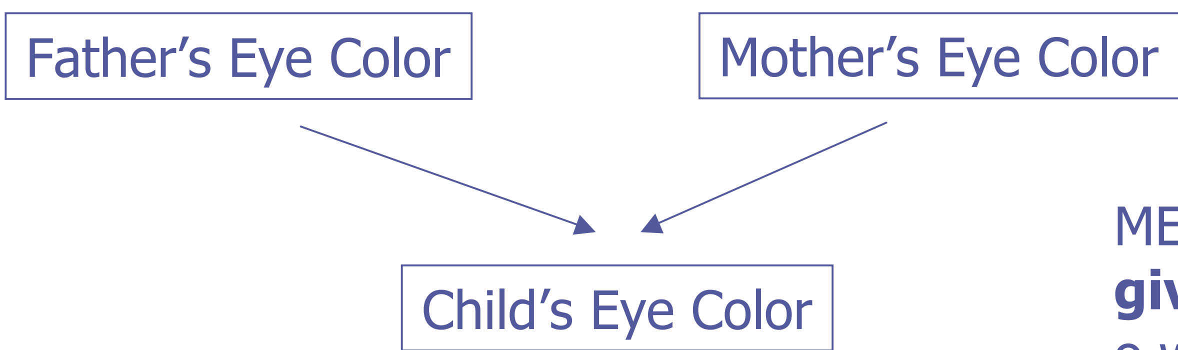
Means-Ends Justification for The Natural Projection Rule

Theorem. Given the possible observation sequences shown before, the natural projection rule (project "all green") is the **only** projection rule that

1. is guaranteed to eventually arrive at an empirically adequate generalization about emerald colors, and
2. makes at most 1 false prediction.

Learning Causal Models from Correlations

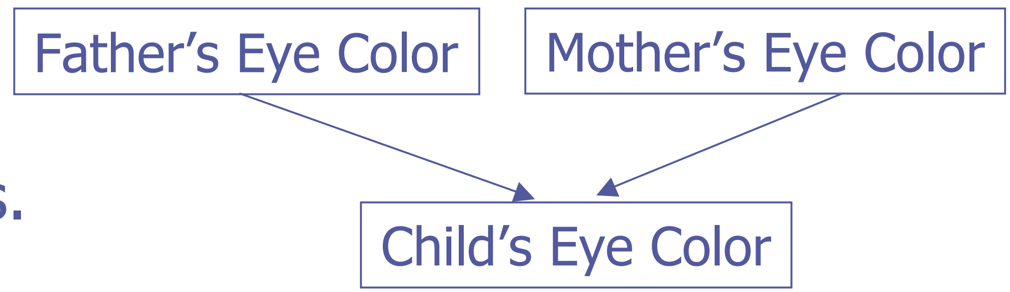
- Hume: causes are inferred from "constant conjunctions".
- Reichenbachian principle: every correlation has a causal explanation, e.g. by common cause.
- Need to consider **conditional correlations**.



ME correlates with FE **given** CE = green, o.w. independent.

Causal Graphs and Conditional Correlations

- A 3-variable graph (A,B,C) entails the following correlations.
  - A correlates with B if there is a link A—B (either direction), or a path A→C→B or A←C←B or A←C→B.
  - A correlates with B given C if there is a link A—B or a path A→C←B.



- FE corr CE
- ME corr CE
- FE corr ME given CE

Causal Learning from Correlations

Children may show spots on their stomachs. A doctor wonders whether there is a causal connection with measles or an allergic reaction.

Rules

- Inquirer proposes causal graph or ?.
- Demon chooses next correlation(s) or "nothing new".
- Inquirer pays for abandoning a causal model.

The Mind-Change Optimal Causal Learner

- Consider the following causal learner: Given a list of observed correlations, if there is a graph G consistent with the observations such that all other consistent graphs have more edges than G, output G. Otherwise output ?.
- Explain the observed correlations with the fewest direct causal links.
- **Theorem** Let *n* variables (nodes) be given. The causal learner above succeeds with $\binom{n}{2}$ mind changes.

Notes on Causal Learning Result

- The edge-minimizer is the fastest causal learner that minimizes mind changes no matter what correlations are observed.
- A variant: conjecture the **set** of graphs that are consistent with the observed correlations and have a minimum number of edges.
- There is no fast program for computing minimum-edge graphs (Schulte,Greiner, Luo 2007).

Extensions and Directions

- Characterize *deep structure* of inductive problem (point-set topology).
- Relate to other aims (speed, simplicity).
- Relate to “categorical imperatives”, e.g. Bayesian conditioning, minimal belief change postulates.
- Address computational questions → algorithmic learning theory.

Summary

- Means-Ends Analysis: Convergence to the truth, stable and fast convergence, correct predictions.
- For specific problems, a set of inductive goals → methods that achieve these goals.
- 3 Illustrations/Applications:
  - Conservation laws in particle physics: conjecture maximally strict law sets.
  - Goodmanian Riddle: conjecture "all emeralds are green".
  - Learning Causal Models: Conjecture the model that explains the observed correlations with a minimum number of direct causal links (edges).
- These are instantiations of a single generic mind change optimal inference rule.

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