Meta-Abduction

Inference to the Best Prediction

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Project Information

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Introduction

There are three main inferences used in science:

- deduction
- induction
- abduction, we consider only: inference to the best explanation IBE

Deduction is justified due to its guaranteed truth preservation.

Induction can be vindicated.

How about IBE? We will differentiate two forms:

- Inference to the best explanation
- Inference to the best prediction

We argue: Both forms can be epistemically justified.

To show the latter is harder and presupposes the vindication of induction.

Contents

Induction and its Meta-Inductive Justification

Prediction Games

Let's consider a series of events $e_1, e_2, \dots$ with outcomes in $[0,1]$.

Now, consider prediction methods for the event outcomes:
$pred_1, \dots, pred_n$ of the form $pred_i(e_t) \in [0,1]$

A simple prediction method for binary events would be, e.g., a binarized likelihood method: $pred(e_t) = 1$ if $\frac{E_1 + \dots + E_{t-1}}{t-1} \geq 0.5$ otherwise $pred(e_t) = 0$

	e_1	e_2	e_3	e_4	e_5	e_6	e_7	...
E_i	0	0	1	1	1	1	0	
$pred_1$	1	0	0	0	1	1	1	

Now, assume that past predictions and event outcomes (E's) are available.

Then we can evaluate prediction methods according to their success.

Problem: There is no guarantee for success of induction.

Reichenbach's Approach: Induction as Best Alternative

1. "If we cannot realize the sufficient conditions of success, we shall at least realize the necessary conditions." (p.348)
2. "Let us introduce the term "predictable" for a world which is sufficiently ordered to enable us to construct a series with a limit." (p.350)
3. "The principle of induction [i.e. the straight rule which transfers the observed frequency to the limit] has the quality of leading to the limit, if [the world is predictable]." (p.353)
4. "Other methods [might also] indicate to us the value of the limit." (p.353)
5. "The inductive principle will do the same;" (p.355)
6. [Hence, asymptotical convergence with the inductive principle is a necessary condition.]

(Reichenbach 1938)

Problem: Assumption that the frequency of E_i is limited.

An Expansion: Meta-Induction

1. Nothing in Reichenbach's argument excludes that God-guided clairvoyants may be predictively much more successful than the object-inductivist.
2. He was well aware of this problem, and he remarked that if successful future-teller existed, then the inductivist would recognize this by applying induction to the success of prediction methods.
3. But he did neither show nor even attempt to show that by this meta-inductivistic observation the inductivist could have equally high predictive success as the future-teller.
4. Skilful application of results from machine learning serve this aim.

(cf. Schurz 2008, p.281)

The Meta-Inductive Recipe

How to cook up $pred_{MI}$:

- We measure the past success of a method by inverting the loss.

E_i	0	0	0
$pred_1$	1	0	1
$pred_2$	0	0	1

$\Rightarrow$

success
0.33
0.66

- We measure the attractivity of a method for the *MI*-method ($pred_{MI}$) by cutting off worse than *MI*-performing methods.

$pred_{MI}$	0.66
$pred_1$	0.33
$pred_2$	0.66

$\Rightarrow$

attractivity
0.0
0.66

- We calculate weights out of the attractivities.

	attractivity
$pred_1$	0.0
$pred_2$	0.66

$\Rightarrow$

weight
0.0
1.0

- We define $pred_{MI}$ by attractivity-based weighting of predictions $pred_i$.

Formal Details

$$success(pred_i, t) = \frac{\sum_{k=1}^{t} 1 - loss(pred_i(e_k), E_k)}{t}$$

$$attractivity(pred_i, t+1) = \begin{cases} success(pred_i, t), & \text{if } success(pred_i, t) \geq \\ & success(pred_{MI}, t) \\ 0, & \text{otherwise} \end{cases}$$

$$weight(pred_i, t+1) = \frac{attractivity(pred_i, t+1)}{\sum_{k=1}^{n} attractivity(pred_k, t+1)}$$

$$pred_{MI}(e_{t+1}) = \sum_{k=1}^{n} weight(pred_k, t+1) \cdot pred_k(e_{t+1})$$

Application to the Problem of Induction

Main result of the meta-inductive research programme: long-run optimality; In the long run $pred_{MI}$'s performs at least as good as any other method, if loss is convex:

$$lim_{t \longrightarrow \infty} success(pred_{MI}, t) - success(pred_i, t) \geq 0, \quad \text{for all } 1 \leq i \leq n$$

By this success-based induction is justified (*per comparationem*).

Hence, given the past success of inductive methods as, e.g., the so-called *straight rule*, a success-based choice of these methods is also justified.

Provisos: garbage in $\Rightarrow$ garbage out, $pred_{MI}$ is "parasitical", optimality of $pred_{MI}$ holds only for the long run and only for real-valued predictions, the number of object-methods has to be finite, etc.

General Schema

1. Meta-induction selects according to past success rates. (by definition)
2. It is an optimal selection strategy. (analytical result)
3. Induction was most successful in past. (empirical fact)
4. Hence, an optimal strategy selects induction also for future predictions. (from 1–3)

Inference to the Best Explanation and its Justification

Inference to the Best Explanation: IBE

Inference to the Best Explanation (cf., e.g., Lipton 2004):

Given $H_1, \ldots, H_n$ separately explain E, then choose best H_i.

Two conditions for *best explanation*:

- Maximise the data's plausibility in the light of the inferred laws: $Pr(explanandum\ E \mid H\ explanans)$
- Maximise simplicity = minimise complexity: $c(H\ explanans)$

The complexity of a model H, i.e. $c(H)$, is typically identified with its degree.

The Epistemic Justification of IBE

As framed here, IBE has two main ingredients: Pr and c.

Pr is an epistemic notion, but is also c?

It can be shown that minimising c is in some sense truth-apt.

This is done, e.g., in the curve-fitting literature with information measures. Take as proxy the *Akaike information criterion* (cf. Forster and Sober 1994):

$$AIC(E, H) \propto \log(Pr(E|H)) - c(H) \tag{AIC}$$

Then IBE can be specified to:

$$\begin{aligned} &H_i \text{ can be inferred from } E \text{ by abduction iff} \\ &\qquad \text{for all } j \in \{1, \ldots, N\},\ j \neq i: \\ &\qquad AIC(E, H_i) \ > \ AIC(E, H_j) \end{aligned} \tag{AIC-IBE}$$

Rationale: E contains errors $\Rightarrow \downarrow c \Rightarrow \downarrow$chances of overfitting

The Optimality of IBE

IBexplanation is by definition optimal.

This was the reason why IBE is justified.

Furthermore, since all ingredients (Pr, c) are truth-apt, it is epistemically justified.

So much for the inference to the best explanation.

But how about an inference to the best prediction?

Inference to the Best Prediction and its Justification

The Problem

We have outlined that meta-induction provides a justification for induction.

Note that meta-induction might be considered as some form of inference to the best prediction.
(E.g., induction was best and meta-induction infers its predictions.)

However, *best* is characterised only via the *loss*, e.g. in the sense of the absolute difference between prediction and outcome.

We are after *best* predictions in terms of Pr, c.

So, the problem consists in transforming the meta-inductive justification to one for IBE w.r.t. predictions.

The Problem

Assume that $loss(E, H)$ is the squared distance: $(E - H)^2$.

Then, given some common assumptions, it holds (cf. Sober 2008, p.84):

$$loss(E, H) = 1 - Pr(E|H)$$

So, meta-induction can be considered as optimising with respect to the Pr-ingredient of IBE only.

However, given the possibility of error in the data E, we are also interested in the c-ingredient of IBE.

Meta-Abduction

We can rationalise the importance of c by assuming that possibly:

$$E_k \neq \text{true event value at round } k$$

... recall, E_k entered the MI-recipe via $loss(pred_i(e_k), E_k)$.

Then we can shift the task from predicting E_k to predicting the best balance between Pr and c w.r.t. E_k.

We do so by normalising AIC:

$$NAIC(E, pred_i) = \frac{AIC(E, pred_i) - (\log(\epsilon) - r)}{-\log(\epsilon)}$$

r ... highest polynomial we are going to consider

ϵ ... all values and predictions will be $> \epsilon > 0$

$\Rightarrow$ Meta-induction applied to $NAIC$ = Meta-abduction.

Justification of IB*prediction* via meta-abduction's optimality.

Summary

- We differentiated two forms of IBE:
  - Inference to the best explanation
  - Inference to the best prediction

- Both forms have as main ingredients Pr and c.

- IB*explanation* is justified by definition (optimality) and the truth-aptness of its ingredients.

- IB*prediction* can be justified by reframing the meta-inductive vindication of induction to a form of meta-abduction.

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