The Inductive Roots of Abduction: A Task Analysis

Chris Thornton
Cognitive and Computing Sciences
University of Sussex
Brighton
BN1 9QN
UK

Email: Chris.Thornton@cogs.susx.ac.uk
WWW: http://www.cogs.susx.ac.uk
Tel: (44)1273 678856

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Abstract

The paper uses a task analysis of induction to justify the idea that induction and abduction are extreme points on a single dimension of learning processes.

Topic areas: frameworks of integration of abduction and induction, abduction in inductive Machine Learning

1 Introduction

The distinction between induction and abduction can sometimes seem unclear. In the call-for-papers for this workshop[1] the two processes are described thus.

> Abduction is used to generate a reason, an explanation, for the truth of the observation in terms of hypotheses which are typically specific to the situation and individual objects at hand ... On the other hand, induction is used when we want to synthesize the information conveyed by the observations into a hypothesis that can account for all the observations together in a common way.

[1] ECAI-96 workshop on the relationship between induction and abduction.

In the present case this is not productive since both possible values of x_3 have the same unconditional probability. This is just the chance value of 0.5, i.e.,

$$P(x_i = v) = \frac{1}{|V|}$$

where V is the set of all possible values of x_i.

Second, we can look at the probability of seeing a particular value conditional on explicit instantiations of the other values, i.e.,

$$P(x_i = v_a | x_j = v_b ...)$$

where v_a and v_b are possible values and '...' denotes the optional inclusion of other instantiations. This is more rewarding since it turns out that

$$P(x_3 = f | x_4 = a) = 0.8$$

In other words, we see x_3 =f in 4 of the 5 cases where we see x_4 =a.[2]

Third and finally we can look at the probability of seeing a particular value conditional on there being an *implicit* property (i.e., a relationship) among the instantiations of other variables:

$$P(x_i = v | g(X) = v_g)$$

Here X is the entire datum and v_g is the value of an imaginary function g, which evaluates the relationship. This is more rewarding still since it turns out that

$$P(x_3 = h | duplicates(X)) = 1$$

where the duplicates function is a predicate which tests whether there are duplicated values in the datum. In other words, it turns out that we always see x_3 =h when there are duplicates among the other values.

These three formulae represent the *only* ways in which a particular guess might be empirically justified.[3] In fact, there are really only two formulae to consider since we can always regard an unconditional probability as a conditional probability with an empty condition. Thus the task analysis shows that there are really just two sources inductive justification: one based on *explicitly* observed probabilities and the other based on *implicitly* observed probabilities.[4]

[2] Of course this is not the only significant conditional probability.

[3] If this seems counter-intuitive note that the third formula acts as a kind of catch-all since it covers *any* computational, mathematical or functional justification for an inductive guess.

[4] The assumption is made that the concept of 'implicit property' is well defined. Without this assumption, any mapping over the data might be viewed as measuring an 'implicit property' and thus every guess would have a justification.

If we want to make an inductive guess regarding the missing value of disposition to focus attention on certain types of relationship. We can regard this as a form of knowledge or a set of hypotheses about the data. The process of relational learning can then be viewed as the task of assimilating observations to a specific set of hypotheses, i.e., as a form of abduction. The process of statistical learning, on the other hand, involves exploitation of observed statistical associations and is thus more easily viewed as a form of induction. The task analysis, then, suggests that, to a first approximation, abduction can be equated with relational learning while induction can be equated with statistical learning.

However, there is an alternative way of utilising the analysis which leads to a more interesting viewpoint. Relational learners are always potentially 'recursive'. The identification of any set of relational effects involves the application of evaluations (functions) to the original data. This effectively creates new values and thus new data. These new data can themselves be processed for statistical and relational effects in a recursive manner. A full-blown relational learner thus operates recursively and necessarily generates *structured hypotheses* about the original data. Statistical learning carried out at higher levels within such structures has the effect of assimilating raw data within (or 'to') the relevant structured hypothesis. This is a process which appears to be strongly abductive in character.

The general implication of the analysis, then, is that abduction is what happens when we move beyond exploitation of statistical associations into the realms of knowledge-based discovery. It suggests that the distinction between induction and abduction is not black-and-white but rather a question of degree. Inductive processes can be more or less abductive and vice versa. The more relational the learning is, and the deeper the generated recursion, the more 'abductive' is the underlying learning (or reasoning) process. If there is little use of relational bias and no recursion then the process is 'minimally abductive'. In extreme cases, we maywe

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