An Adaptive Logic for Inductive Prediction

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The adaptive logics developed in [**?**] and [**?**] concern the logics of inductive generalization—from a set of data and (possibly falsified) background hypotheses and theories inductive generalizations are derived. The present paper concerns an adaptive logic **IP** for inductive prediction. **IP** does not agree with the usual standard and differs from other adaptive logics in several interesting respects.

Consider the very simple data set $\Gamma = \{Pa \wedge Qa, Pb \wedge Qb, Pc \wedge Qc, Pd \wedge {\sim}Qd, Pe\}$ and let one be interested in whether Qe is inductively derivable from it. Obviously $(\forall x)(Px \supset Qx)$ is not inductively derivable from the data. Nevertheless, it seems reasonable to predict Qe in this case. Moreover, if one were able to obtain further observational data on the Q-hood of other Ps, these would clearly be relevant for this prediction.

IP will be based on Classical Logic (**CL**). To be more precise, **IP** defines a consequence set that is an extension of the **CL**-consequence set of the premises. It is instructive to compare **IP** with other members of the family of (adaptive) inductive logics.

In the logic of induction $\mathbf{IL}^{\mathbf{r}}$ from [**?**], for example, the classical consequence set is extended with a set of generalizations that is *compatible* with the data (as well as with any set of generalizations that is itself compatible with the data). $\mathbf{IL}^{\mathbf{r}}$ handles this problem in a simple way: each generalization G is linked with a specific abnormality A and whether G is derivable depends merely on the derivability of minimal disjunctions of abnormalities that contain A. The usual adaptive strategies, such as the Reliability strategy and the Minimal Abnormality strategy, may be applied here.

The inductive predictions derivable by **IP** require a new and very different strategy. The *general idea* is that one choose between (for example) the predictions Qe and ${\sim}Qe$ depending on which of them *implies less abnormalities than the other.* This idea has some far-reaching consequences. First, one has to *count* abnormalities. Next, one has to *balance* the two predictions against one another. Furthermore, new data may change the balance. Finally, new data may not only change the number of abnormalities implied by either prediction, but may also change the types of abnormalities that are generated.

In our lecture we will spell out the **IP**-semantics and define its dynamic proof theory for an (important) fragment of the language. A peculiarity of the semantics is that the abnormalities refer to the model and not to the formulas it verifies. A peculiarity of the dynamic proof theory is that formulas are not marked (at a stage) in view of the question whether definite (disjunctions of) abnormalities have been derived (at that stage), but in view of a numerical comparison between abnormalities that have been shown (at the stage) to be implied by the respective predictions.

Incidentally, it will be shown that an approach in terms of the non-standard quantifier "most" does not lead to adequate inductive predictions.

References

[1] Diderik Batens. On a logic of induction. To appear.

[2] Diderik Batens and Lieven Haesaert. On classical adaptive logics of induction. *Logique et Analyse*, in print.