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The role of models in measurement outside the laboratory

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ABSTRACT

For measurement outside the laboratory, uncertainty evaluations have to be model-based. Therefore models should not only represent the measurand but also its environment. For measurement in social science these models will be too complex, therefore instead of white-box models, grey-box (modular-designed) models are preferred. They are much simpler. Uncertainty evaluations of measurements outside the laboratory are more of the kind of Type B evaluations. In social science, due to the lack of authoritative scientific institutions, Type B evaluations will be of a different character. In case of measurements based on grey-box models they are the so-called structure-oriented behaviour tests.

1. Introduction: Builder of Metrological Bridges

> The gap between the abstract philosopher's approach and that of the pragmatic instrument designer is gradually bridged (Finkelstein [1]).

Ludwik Finkelstein had a life-long interest in the epistemological and logical foundations of measurement. As far as I know, his very first article on this issue, 'Principles of Measurement', published in 1963, presented "a survey of some of the philosophy of measurement from the point of view of instrument and control engineering" [2, p. 181]. This article has some remarkable elements which characterizes Finkelstein as a scholar and so also his later contributions on the foundations of measurement.

Firstly, Finkelstein wished "the field to which modern methods of instrumentation, computation and control are applied" to be "widened to encompass biology, psychology and economics as well as physical measurements of a less conventional type" [2, p. 181]. Secondly, he very soon saw that the classical view of measurement based on measurements in physics had proven to be "unduly limited when dealing with scientific investigation outside that field" [2, p. 182]. Therefore the classical theory of measurement had to be extended. An important first step in that direction was, according to Finkelstein, taken by the works of the psychologist Stanley Smith Stevens in the late 1940s.

Stevens' work led to the Representational Theory of Measurement (RTM), which Finkelstein introduced to instrument and control engineering in his 1975 article 'Fundamental concepts of measurement: definition and scales' [3]. It is interesting to see that on one hand Finkelstein already in an early stage of the development of RTM saw its value for instrument and control engineering, but on the other hand also saw its limitations. RTM does not account for errors and uncertainty in measurement. Therefore, Finkelstein suggested, RTM has to be extended to encompass the issues of errors and uncertainty, issues that became later the focus of the *Guide to the Expression of Uncertainty Measurement* (GUM) [4].

This article is dedicated to Finkelstein's aspirations to bridge philosophy and measurement science. In line of these aspirations, it aims to extent RTM to encompass measurements outside the laboratory. The term 'laboratory' is used here to indicate that for measurement purposes control of background conditions and intervention of the measurand are possible. Therefore, the term 'outside the laboratory' is used to capture measurements for which

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there are no possibilities of control and intervention, in other words, when measurements are based on 'passive observations'.[1] An important and large field of measurement outside the laboratory is econometrics. The ideas discussed in this article are arrived at by studying this field.

To extent RTM to encompass measurements outside the laboratory, this article takes the same starting point as Finkelstein took in his later work: the representations to which RTM refers are mathematical models, therefore RTM is sometimes called the Model Theory of Measurement. RTM emphasizes the central role mathematical models have in measurement. For measurements outside the laboratory, measurement results are the outcomes of models representing the measurand. The extension of RTM to fields where no control and interventions on the measurand are possible means, however, that not only the measurand should be modelled but also its environment [5]. Modelling environments, that is background conditions, implies accounting for errors and uncertainties. It will be shown that this has implications for the GUM approach [4], which is mainly focused on laboratory measurements.

2. Expressions of uncertainty

GUM [4] distinguishes between two types of evaluations of uncertainties. Type A evaluation is an evaluation of a component of measurement uncertainty by a statistical analysis of measurement results obtained under defined measurement conditions. Type B evaluation is an evaluation of measurement uncertainty determined by means other than a Type A evaluation of measurement uncertainty. These defined measurement conditions range from repeatability to reproducibility:

1. Repeatability: same measurement procedures, same operators, same measuring system, same operating conditions and same location, and replicate measurements on the same or similar objects over a short period of time.
2. Intermediate precision: same measurement procedure, same location, and replicate measurements on the same or similar objects over an extended period of time, but may include other conditions involving changes.
3. Reproducibility: different locations, operators, measuring systems, and replicate measurements on the same or similar objects.

Going from conditions of repeatability (1) to conditions of reproducibility (3) can be seen as going from laboratory conditions to conditions applicable outside the laboratory. A shift from inside-laboratory conditions to outside-laboratory conditions implies a shift from Type A evaluations to Type B evaluations. These latter evaluations are based on information:

- Associated with authoritative published quantity values.
- Associated with the quantity value of a certified reference material.
- Obtained from a calibration certificate.
- About drift.
- Obtained from the accuracy class of a verified measuring instrument.
- Obtained from limits deduced through personal experience.

The problem with this last list is that when one would like to use it for a social science as economics, one would soon discover that these authoritative sources of information do not exist, or at least do not have the same level of authority: There is no central authority for published quantity values, but instead various institutions competing for authority. There are no certifications for reference materials and calibration in social science, because that would presume a central authority providing them.

Does a shift from measurements inside a laboratory to measurements outside a laboratory, and the resulting shift from Type A evaluations to Type B evaluations, therefore imply an increase of subjectivity, e.g. increasing role of evaluations based on personal experience? Not necessarily, the use of models for measurement and the evaluation of its uncertainties can also increase objectivity. It only means that we have to reconsider what else could be implied by 'scientific judgment'.

> Knowledge about an input quantity X_i is inferred from repeated indication values (*Type A evaluation of uncertainty*) [...], or scientific judgement or other information concerning the possible values of the quantity (*Type B evaluation of uncertainty*) [6, p. 5].

This paper suggests that a scientific judgment should be model-based, particularly in case of measurements outside the laboratory.

3. The problem of passive observations

To discuss this problem of scientific judgement for outside-laboratory measurement in social science, consider the following problem. In most cases, a measurand Y is not measured directly, but is inferred from N other quantities $X_1, X_2, \ldots, X_N$ through a functional equation [4, p. 8]:

$$Y = f(X_1, X_2, \ldots, X_N) \tag{1}$$

These quantities X_i can only provide information about Y if they influence the magnitude of Y. Therefore Eq. (1) is rewritten in such a way to express the relation between these quantities X_i and the measurand Y in terms of influences:

$$\Delta Y = \partial f/\partial X_1 \cdot \Delta X_1 + \ldots + \partial f/\partial X_N \cdot \Delta X_N \tag{2}$$

The derivatives, $\partial f/\partial X_i$, often called sensitivity coefficients, describe how the output estimate Y varies with changes in the values of the input estimates $X_1, X_2, \ldots, X_N$ [4, p. 19].

[1] 'Passive observations' are data obtained without control and intervention. They can be both of a qualitative as quantitative nature.