What can mathematical modelling contribute to a sociology of quantification?

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Abstract

Sociology of quantification has spent relatively less energies investigating mathematical modelling than it has on other forms of quantification such as statistics, metrics, or algorithms based on artificial intelligence. Here we investigate whether concepts and approaches from mathematical modelling can provide sociology of quantification with nuanced tools to ensure the methodological soundness, normative adequacy and fairness of numbers. We suggest that methodological adequacy can be upheld by techniques in the field of sensitivity analysis, while normative adequacy and fairness is targeted by the different dimensions of sensitivity auditing. The analysis offers material for a possibly useful interdisciplinary exchange.

Keywords: Ethics of quantification, sensitivity analysis, sensitivity auditing, uncertainty, post-normal science.

Introduction

Historians, sociologists and politologists have studied how numbers are produced, used, trusted or feared in relation to different aspects of life, such as empowering systems of governance or control, promoting consumption or consensus, variously facilitating or complexifying human experience. Important contributions to this debate have also come from scholars of law and economics, merging into the societal discussion about risks from new numerical technologies and practices. This new attention to numbers – a true sociology of quantification, is an expanding field touching on many families where numbers are produced, from data science, to algorithms, quantified self and indicators of various level of aggregation (Box 1).

Some aspects surprisingly less visited by these works are the science reproducibility crisis (Smaldino and McElreath 2016; Saltelli and Funtowicz 2017), and the important role played by statistics, rightly or wrongly accused of having permitted misuse or abuse of statistical tests at the core of the reproducibility storm (Leek and Peng 2015; Leek et al. 2017; Stark and Saltelli 2018). This omission is all the more surprising as statisticians, mired in the crisis, have been vigorously debating what to do in what have been termed ‘Statistics Wars’ (Wasserstein and Lazar 2016; Mayo 2018; Amrhein, Greenland, and McShane 2019). Mathematical modelling has been kept out of this debate, partially because it is not a discipline (Saltelli 2019), and several communities of scientists go about modelling without universally agreed norms of adequacy and quality control (Padilla et al. 2018; Eker et al. 2018). However, many modellers agree on the need for a structured approach to quantify uncertainty in model predictions and discern the sensitivity of a model to its input variables (Saltelli, Jakeman, et al. 2021).

===Box 1 Studies of quantification

According to recent reviews (Popp Berman and Hirschman 2018; Mennicken and Espeland 2019), the field of sociology of quantification is burgeoning with work coming from different fields of scholarship, including sociology of quantification proper (Mennicken and Salais 2022), where two important French schools of sociology of numbers – the so-called Foucauldian studies of quantification and the school of Economics of Convention (Desrosières 1998; Mennicken and Salais 2022) – have led to the present movements of statactivists under the slogan "another number is possible" (Bruno, Didier, and Prévieux 2014a). Concern about negative features of quantification has been expressed from data scientists, considering the full spectrum of quantifications from models to algorithms to indicators (O'Neil 2016), to jurists (Supiot 2017) fearing the end of a society ruled by just laws, to economists scared by the advent of surveillance capitalism (Zuboff 2019). The known seduction of numbers (Merry 2016), their performativity (Espeland and Sauder 2016) and their increased penetration in all aspects of life (Couldry and Mejias 2019) are creating movements of resistance (Bruno, Didier, and Prévieux 2014a; Cardiff University 2020; Algorithmic Justice League 2020) and mediatic echo (Kantayya 2020; Orlowski 2020). Anticipated by sociologists of quantification (Espeland and Stevens 2008), the idea of an "ethics of quantification" to be monitored by societal actors is receiving attention (Saltelli, Andreoni, et al. 2021; Saltelli and Di Fiore 2020).

===Box 1 ends here

In this paper we discuss the extent to which two frameworks from mathematical modelling, sensitivity analysis (SA) and sensitivity auditing (SAUD), may be useful to other families of quantification. While SA complements an uncertainty analysis by identifying the inputs/structures that convey the most uncertainty to the model output (Saltelli et al. 2008), SAUD extends the examination to the entire model generation and application process and looks at possible stakes, biases, interests and worldviews of the developers, seeking for blind spots and overlooked narratives (Saltelli et al. 2013). Both approaches have the potential to 'tame' the opacity of algorithms – such as that of exploring different sets of choices in their making (Amoore 2020) – and of apportioning the uncertainty and ambiguity of a quantification to its underlying assumptions.

SA and SAUD can check the quality of numbers on two different dimensions, respectively the technical for SA and the normative for SAUD, echoing in their tasks the double requirement – technical and normative – for quantification put forward by Amartya Sen (1990) in his 'Informational Basis for a Judgment of Justice' [see also discussion in Salais (2022)]. The idea that the quality of numbers needs technical rigour and normative transparency is not new, and was at the root of early attempts to advance the use of pedigrees for numbers used in policy decisions – mostly risk and cost-benefit analysis, intended as a reasoned assessments of the quality of a quantification and of the potential bias of its producers, see e.g. NUSAP (Funtowicz and Ravetz 1990). Both SA and SAUD are inspired by post-normal science, an approach to science for policy that finds use in the presence of uncertainties, conflicted values and interests, and urgent decisions (Box 2; Saltelli et al. 2008, pp. 4-5).

===Box 2 Post-normal science

Post-normal science (PNS) is an approach for the treatment of problems at the science-policy interface (Funtowicz and Ravetz, 1993). PNS applies when problems are characterized by uncertainty, urgency, high stakes and conflicting values. PNS presents tools to engage with a science that does not pretend neutrality and that aspires to achieve quality rather than universal truth. Many natural scientists increasingly refer to PNS in the treatment of so-called wicked problems (Rittel and Webber 1973), i.e., problems where the same definition of the issue is contested.

Quantification and mathematical modelling in particular are central to the reflection of PNS, as well as of its antecedent works by the same authors (Ravetz 1971; Funtowicz and Ravetz 1990). PNS targets critically issues of spurious precision, reduction of complexity and transformation of political problems into technical ones via risk or cost-benefit analyses (Funtowicz and Ravetz 1994). A central concept of PNS is that of a humble science that operates within an *extended peer community*, intended as including experts as well as lay citizens, investigative journalists and whistle blowers, and whoever has stakes and interest in the issue being addressed.

===Box 2 ends here

The wisdom of SA and SAUD can be translated into a set of norms or precepts to feed into an epistemology of quantification – i.e., a theory of knowledge to use when numbers are involved. Since we tend to perceive numbers as more neutral and factual than they can be, how should we adjust our perception and expectation when a quantification is offered to us? Models and other instances of quantification may come in the form of black boxes or present themselves with considerable interpretative obscurities; we can use here the expression of 'hermeneutics of quantification', i.e. looking at these objects as to ancient texts whose wisdom has to be deciphered.

In the next section we offer some definition of uncertainty quantification, SA and SAUD; we then discuss how SA and SAUD can be extended to various instances of quantification using as a starting point a recent work for responsible modelling (Saltelli, Bammer, et al. 2020). We illustrate how some relevant dimensions of modelling, such as the impossible candour of SA, or the concept of modelling of the modelling process, may find their way into sociology of quantification studies. We conclude by examining some policy implications derived from our approach.

Uncertainty quantification, sensitivity analysis (SA) and sensitivity auditing (SAUD)

Mathematical modelling is not a discipline such as statistics (Saltelli 2019), so its quality assessment methodologies tend to be scattered among several disciplines (Padilla et al. 2018). Additionally, there are myriads of diverse models and contexts of application. Different taxonomies of models are available as well as several discipline-specific guidelines for model quality.[i] One of the most relevant acid tests for the quality of models is uncertainty analysis, which quantifies how variable the model-based inference is when the inputs feeding into the model (e.g., parameters, boundary conditions, model structures) are uncertain. This is usually followed by SA in order to appraise the relative importance that these uncertain input factors have in conveying uncertainty to the model output. Global SA in particular (Saltelli et al. 2008) aims to ensure that the entire space of the input uncertainties is properly explored. The specification 'global' is needed here as many SA exercises seen in the literature are 'local', i.e. they explore model behaviour only around specific points or axes in the input space and hence do not appraise interactions between inputs (Ferretti, Saltelli, and Tarantola 2016). Local methods can be proven to grossly underestimate the uncertainty in the output (Saltelli et al. 2019) as – for instance – extremal output values can be generated by moving simultaneously more than one uncertain input. This behaviour is not captured by a local analysis of sensitivity.

The selection of SA and SAUD as a contribution from mathematical modelling to other fields appears motivated by these methods' capacity to probe deep uncertainty (Steinmann et al. 2020), by their visibility in policy-related science (Saltelli, Bammer, et al. 2020), and by their closeness to PNS (Box 3).

=== Box 3, Uncertainty quantification, SA and SAUD (Fig. 1).

Uncertainty analysis: the study of the uncertainty in model output – see also uncertainty cascade (Christie et al. 2011).

SA: the study of the relative importance of different input factors on the model output (Saltelli et al. 2008).

SAUD: "Sensitivity auditing is a wider consideration of the effect of all types of uncertainty, including structural assumptions embedded in the model, and subjective decisions taken in the framing of the problem" (European Commission 2021).

=== Box 3 ends here

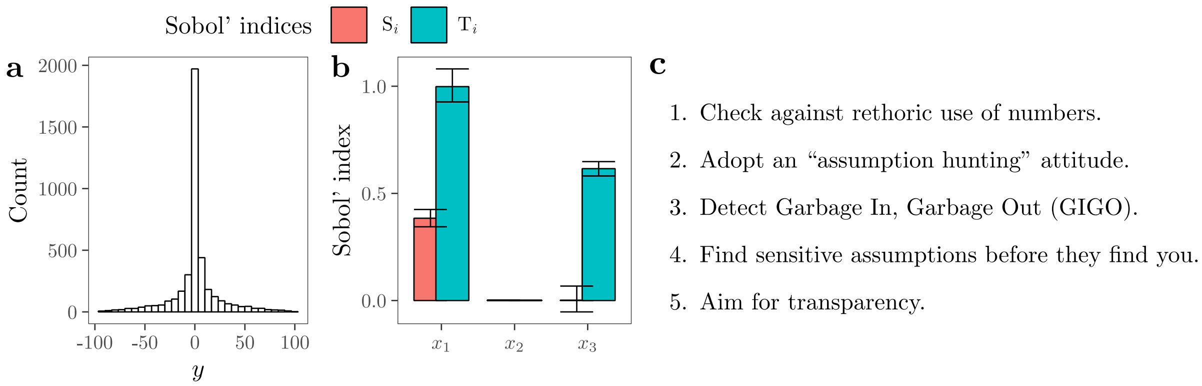

Fig. 1. Graphical representation of uncertainty analysis, SA and SAUD. We illustrate the first two approaches using as a toy model the Ishigami and Homma (1990) function, which has three uncertain input factors. a) Distribution of the model output y once uncertainties are propagated through the model. b) SA of the model output y. S_i reflects the first-order effect of the parameter x_i, i.e., the proportion of variance conveyed to y by x_i. T_i denotes the total-order effect of x_i, i.e., the first-order effect of x_i plus the effect derived from its interactions with all the other uncertain parameters. Note how the parameter x_3 impacts the model output y only through interactions and that x_2 does not convey any uncertainty at all. C) The five main suggestions of SAUD after Saltelli et al. (2013).

Bridging mathematical modelling with sociology of quantification

In this section we explore what can SA and SAUD bring to improve the transparency, adequacy and fairness of numbers in quantitative-oriented disciplines, and hence become material for a sociology of quantification. Our discussion draws from the guidelines recently put forward by a work on responsible modelling that merged concepts and approaches from modelling, economy, philosophy and sociology of quantification (Saltelli, Bammer, et al. 2020).

1. Mind the assumptions: assess uncertainty and sensitivity

"Sensitivity analysis could help" is the title of a famous article by econometrician Edward E. Leamer (1985), who recommended SA to stress-test econometric studies by changing their modelling assumptions. This, for Leamer, would ensure that the proposed inference is robust. Another econometrician, Peter Kennedy (2008), made this into one of the commandments of applied econometrics, observing that SA amounts to a sort of 'confession' from the analyst, adding that this confession would ultimately help to anticipate criticism. Note that both Leamer and Kennedy were writing well before the non-reproducibility of large part of economic research became exposed (Ioannidis, Stanley, and Doucouliagos 2017). In a more recent work, Leamer (2010) commented that the reluctance of modellers to adopt SA is that, in its candour, SA can reveal the fragility of the evidence – “their honesty seems destructive”, adding that “a fanatical commitment to fanciful formal models is often needed to create the appearance of progress.”

While uncertainty can be artificially compressed to defend the relevance of an assessment, it can as well be inflated, for example to diminish the relevance of studies conducted by regulators. In the ‘regulation game’[ii] (Owen and Braeutigam 1978) uncertainty can be played both ways (Oreskes 2018; Saltelli 2018) with techniques of increasing sophistication when science and its quantification become functional to processes of regulatory capture (Saltelli et al. 2022).

At the same time, the resistance of some modellers to come to terms with the full uncertainty of their work has motivations such as that of ‘navigating the political’ (van Beek et al. 2022), i.e., defending the role of modelling work in policy relevant settings, for which epistemic authority needs to be preserved (Robertson 2021). This may result in the production of impossibly precise numbers that feed into the policy process. Recent example are the social cost of carbon, obtained by mathematical simulation of the economy three centuries into the future (Coy 2021; Rennert et al. 2021), and the unreasonable reliance on an average reproduction rate R for COVID-19 in the course of the pandemic (Miller 2022). A lucid conclusion reached by philosopher Jerome R. Ravetz is that

> *We have perhaps reached a complex epistemic state, where on the one hand ‘everybody knows’ that some numbers are pseudo-precise and that numbers can be gamed, while the game works only because most people don’t know about it* (Ravetz 2022).

Sociologist Theodor Porter noted situations where numbers become paradoxically serious – taking centre stage in the public discourse – in spite of their fragility. He describes the numbers of financial econometrics, one of the causes of the subprime mortgage crisis (Wilmott and Orrell 2017), as ‘Funny Numbers’ (Porter 2012), referring to the almost comical contrast between the scene where these numbers present themselves with uncontested authority and the behind-the-scene fights for the positioning of the same numbers.

The construction of a mathematical model often extends in time, with several choices and assumptions being done during its construction. To achieve a better domestication between models and society an essential step is to retrace the steps of the analysis so influential assumptions, e.g., those that have a bearing on the model output, are identified and discussed. This modelling of the modelling process can easily be extended to other forms of quantification to reveal the volatility of aggregate or composite indicators (Michaela Saisana, D’Hombres, and Saltelli 2011; M. Saisana, Saltelli, and Tarantola 2005), while the same approach is suggested by ethicists to open the box of algorithms (Amoore 2020). The neutrality or ‘facticity’ of system of indicators can be challenged when different aggregations can be compared with one another (Kuc-Czarnecka, Lo Piano, and Saltelli 2020). For instance, an uncertainty analysis of the technology achievement index (TAI), which ranks the technological capacity of countries, revealed that Singapore participates in creating and using technology more than the Netherlands, thus contradicting the original TAI (M. Saisana, Saltelli, and Tarantola 2005).

When faced with ambiguities in model formulation the initial instinct of a mathematically trained mind is to fix it, to get the right unambiguous formulation of the problem. Typically in statistics, a very delicate discipline where ambiguity is always behind the corner, this is exemplified by Peter Hand’s (1994) effort at deconstructing and then rectifying poorly posed statistical questions. While this is partly viable for statistics, the messiness of real-life problems where mathematical modelling is applied often prevents such a clear-cut reformulation of context and purpose, also because the ambiguity of the problem definition, disliked by mathematical minds, creates in practice the space for negotiation among parties with different cultures, stakes or worldviews. This is the idea behind the concept of ‘clumsy solutions’:

> *… solutions are clumsy when those implementing them converge on or accept a common course of action for different reasons or on the basis of unshared epistemological or ethical principles* (Rayner 2012).

By adopting the strategy of modelling of the modelling process one can replace the identification of the right formulation with the exploration of many different formulations. In statistics this has been discussed as the problem of the garden of the forking paths (Gelman and Loken 2013); taking inspiration from a short story of Argentinian novelist Jorge Luis Borges, the garden of the forking paths is a metaphor for the statistician or modeller having to take decision (left or right) in navigating the garden of building a solution to a problem, thus leaving several alternative and potentially legitimate paths unexplored. The solution suggested by sensitivity auditing is to take both left and right at each bifurcation, like the Chinese writer in the short story of Borges – to stay with the metaphor – and to propagate the uncertainties accordingly.

Consider the impossible candour of SA and SAUD and the modelling of the modelling process.

2. Mind the hubris: complexity can be the enemy of relevance

Larger models are in general the result of the modellers’ ambition to achieve a better description of their systems and reduce the uncertainty through the addition of model detail. There is also a political economy in mathematical modelling whereby larger models command more epistemic authority and better inhibit external scrutiny from non-experts. Such trend towards model complexification leads to overambition and hubris (Quade 1980; Puy et al. 2022; Puy and Saltelli 2022) , two features that also apply to other instances of quantification. For example, composite indicators displaying an impressive number of input variables, meant to convey an impression of complexity and completeness, often depend upon a much smaller subset (Olczyk, Kuc-Czarnecka, and Saltelli 2022), suggesting a possibly rhetorical use of numericized evidence.

In modelling, where there are available data against which to compare the model predictions, information criterion such as (Akaike's (2011) or Schwarz's (1978) can be used to balance model complexity with parsimony. Lacking a validation data set, uncertainty quantification and sensitivity analysis can be used to gauge the uncertainty in the inference and its sources (Puy et al. 2022). For each family of quantification agreed rules should be established to gauge complexity.

Consider if the degree of complexity of a quantification can be gauged against agreed criteria.

3. Mind the framing: match purpose and context

Models embed the normative values and worldviews of their designers, and no model can serve all purposes and contexts. They need transparency and participation to realize their potential. Transparency in the frames puts quantification in a context of social discovery (Dewey 1938; Boulanger 2014), allowing different frames to be contested and compared as suggested by the French statactivists (Bruno, Didier, and Prévieux 2014b; Bruno, Didier, and Vitale 2014).

The agenda of this movement is to ‘fight against’ as well as ‘fight with’ numbers. Its repertoire of tactics against perceived statistical abuse include:

- Self-defence or ‘statistical judo’ – i.e., gaming the metrics, a strategic use of the Goodhart law;
- Exposing the faults of existing measures, e.g., by denouncing the middle-class bias of the existing French consumer price index (PPI);

- Developing new measures, e.g., in relation to the above, a new PPI in defence of the purchasing power of the poor;
- Identifying areas of exclusion and neglect of existing official statistics.

Democracy suffers when numbers are used to create cognitive ambiguity and to ensure quantitative proofs and justifications that hamper the articulation of alternative legitimate claims (Salais 2022). Cognitive ambiguity in modelling goes under the name of displacement, a term that describes the situation where the attention is focused on the output of a model rather than on the real world purportedly described by the model (Rayner 2012). Displacement of this nature can be operated via quantification by a plurality of actors, from corporate or political interests to regulators, from issue advocates to the scientists themselves (Saltelli et al. 2022). In the Chesapeake Bay Program watershed treated by Rayner (2012) the loading of nutrients in the basin is read from the model rather than from the basin. There is a political economy, in modelling as well as in other forms of quantification, whereby practitioners tune their quantification for political impact (van Beek et al. 2022).

Sociologist of quantification Robert Salais (2022) distinguished *statistics* from *governance driven quantification*. The former, starting toward the end of the XIX century and lasting well into the XX, was meant to 'build things that hold together' (Desrosières 1998) via a categorization and classification that allowed the creation of social conventions and concepts that could be used to tackle political actions. With *governance driven quantification*, statistical objects are meant instead to ground – and at the same time foster –, policies with preselected objectives. For Salais, this operates a reversal of the statistical pyramid, i.e., starting from the desired political objective to produce the desired system of measurement; a move from evidence-based policy to policy-based evidence whose ultimate objective is to demonstrate that the selected policies are successful.

Quantification thus plays an important role in the context of technocratic approaches to governance (van Zwanenberg 2020). Some see it as a relevant actor in the promotion of inequality and the undermining of democracy, with a combination of (i) the already mentioned 'justificationism', where to objective of a number is to justify a policy, (ii) the pretence of objectivity, whereby the purported neutrality of numbers is used as a shield of facticity against possible ideological resistance (Porter 1995; Saltelli, Benini, et al. 2020), as well as (iii) a tendency to reductionism, whereby complex sociological realities are reduced to simple metrics and the attendant uncertainty is suppressed (Scoones and Stirling 2020).

For Salais (2022) democracy mutates into a-democracy when the citizens are de facto deprived of agency – they can formally participate, but not influence the outcome of a decisional process. This is where quantification plays an important role by imposing on possible contesters the obligation to articulate alternative claims via an alternative edifice of facts[iii].

The solution to this use of quantification is for Salais the construction of an "Informational Basis of Judgment in Justice" (IBJJ), as proposed by Amartya Sen (1990). For Sen an informational basis should satisfy criteria of fairness, admitting the existence of multiple 'factual territories'. Adopting Sen's capability approach, fairness is intended as the freedom for different persons to lead different lives. It is not sufficient for two people to have the same amount of primary goods in order to have the same set of capabilities, and they may differ in their occasion and capacity to transform goods into desired outcomes. For Sen and Salais, technical quality (correctness) for a system of measurement is insufficient if it is not complemented by fairness that can only be achieved if the involved parties have been permitted to negotiate and compromise on what should be measured and how.

This resonates with John Dewey's (1938) process of 'social discovery' as well with the concept of extended peer community advocated by PNS (Box 2)[iv].

In line with what proposed by the French movement of statactivists (Bruno, Didier, and Prévieux 2014a; Samuel 2022), the unknown known need to be extracted/discovered by direct engagement with the affected citizens, the "quantified people […] who know without knowing that they know."

Consider the use of SA and SAUD for the inspection of both technical and normative adequacy.

4. Mind the consequences: quantification may backfire

Models for policy-making that retreat to being "theoretical" or "building blocks" when their unrealistic assumptions are criticized are known as "chameleon models"(Pfleiderer 2020). This shape-shifting may lead to undesired outcomes, as that of the 'funny' numbers of financial econometrics just mentioned (Porter 2012). More examples of modelling causing harms are described in a series of important model-centred works (Sarewitz, Pielke, and Byerly 2000; Pilkey and Pilkey-Jarvis 2009; Anderson and Leigh Anderson 2007) as well as in (Saltelli, Bammer, et al. 2020). SA and SAUD can contribute to sociology of quantification by deconstructing indicators fraught with important social impact. For example, SA can show how higher education rankings are both fragile (Michaela Saisana, D'Hombres, and Saltelli 2011) and conceptually inconsistent in the way variables are aggregated (Paruolo, Saisana, and Saltelli 2013), a sort of model-activism, or 'modactivism' on par with statactivism (Bruno, Didier, and Prévieux 2014a). This work can support initiatives such as the recent fight against the Word Bank Doing Business Index, closed in 2021[v]. In general, quantitative and qualitative tools developed from SA and SAUD can be used to contrast reductionist or technocratic tendencies on international bureaucracies (van Zwanenberg 2020), or to broaden the policy definition of an issue. To make an example, many definitions of cohesion – and ways of constructing its indicators – are possible among EU countries, leading to diverging policy implications (Kuc-Czarnecka, Lo Piano, and Saltelli 2020).

The issue of perverse effects of algorithms is one of the most visited in the literature of sociology of and ethics of quantification, as noted above. An interesting line of work suggested by Louise Amoore (2020) concerns the fact that making algorithms 'good' or 'transparent' is beyond the point. Algorithms create new norms of good or bad, define what is normal and acceptable. Thus Amoore argues that rather than asking from algorithms an impossible transparency, one should engage with their opacity instead. In order to "oppose the violence in the algorithmic foreclosure of alternative futures", she advocates distributed forms of the writings of algorithms. If we understand this author well, this would amount to participatory forms of modelling of the modelling process. This is a program where the tools suggested here could help.

An interesting application of global sensitivity analysis is in determining possible incursion of algorithms into "protected attributes" such as gender and race even if these attributes are not explicitly present in a machine learning algorithms (O'Neil 2016). Sensitivity analysis of the characteristics of the algorithm (features) can ensure that the algorithm is 'fair' in this respect (Bénesse et al. 2021).

Identify structured strategies to both discuss, negotiate, and or possibly deconstruct measurements, especially in relation to their unintended or malicious effects.

Example: use SA to ascertain that an algorithm does not make implicit use of protected attributes.

5. Mind the unknowns: acknowledge ignorance

Often, and especially in the use of evidence-based policy, a political problem is transformed via quantification into a technical problem (Ravetz 1971) which entails the artificial suppression of uncertainty via quantitative concepts and methods, such as 'cost–benefit', 'expected utility', 'decision theory', 'life-cycle assessment', 'ecosystem services', all under the heading of 'evidence-based policy' (Stirling 2019; Scoones and Stirling 2020). The way modellers can contrast this is by showing that uncertainties are larger than stipulated – as discussed in the hubris section above, and by opening the box of quantification to approaches such as modelling of the modelling process. Failure to acknowledge ignorance may limit the space of the policy options and offer politicians a way to abdicate responsibility and accountability.

Modellers can contribute to a sociology of quantification also offering tools to partition the uncertainty in the inference between data-driven and model-driven, or by contrasting prediction uncertainty with policy option uncertainty: if two policy options differ in their outcome by an interval smaller than that governed by data and model uncertainty, then the two options are undistinguishable. For instance, it may be unable to advocate for incineration or disposal of urban waste when the uncertainty brought about by the system of indicators adopted 'hides' the difference between the two policy options (Saltelli, Tarantola, and Campolongo 2000).

SA and SAUD can also be considered as part of the 'reverse engineering' operated by data activists in their 'hackatons' to bring the normative bias of algorithms to the surface (O'Neil 2016), as just discussed in relation to protected attributes.

One can imagine that models can be read as metaphors of the real, and that a future historian will look at the pervasive mathematical modelling of the present age as another may look at an ancient religious text whose obscurity needs an exercise of hermeneutics to tease out a meaning long lost. The idea to look at mathematical modelling with the lenses of hermeneutics is not new (Coyne and Snodgrass 1992; Tudor 1991) and has been mentioned by practitioners of sensitivity analysis (Saltelli, Jakeman, et al. 2021). The concept draws attention to the need of careful consideration of how models come to life, away from the metaphor of models as truth-machines.

When it comes to methods of quantification, facts and value can become hard to separate. This calls for an integrated, qualitative and quantitative assessment of system uncertainties and normative omission or invisibilities. A plain quantitative error propagation analysis (uncertainty quantification) is a valid starting point. It can be used via negativa, i.e. to demonstrate that there is simply not enough evidence to offer a measure, or that the measure is totally driven by untestable hypotheses rather than by available evidence.

Avoid "quantifying at all costs" and discern when the data available/the scientific goal does not sit well with quantification.

Conclusions

Due to the large use of mathematical models during the pandemic, problematic aspects of mathematical modelling have come to the fore. Models were praised for spurring action (Landler and Castle 2020) as well as vilified as 'Wild-ass models' (Pielke 2020), 'Public troubles' (Rhodes and Lancaster 2020) or promoters of ill-conceived policies (Caduff 2020). More recently professional politicians such as Bob Seely – a British MP – could go through an extremely well-documented reconstruction of the failures of the Imperial College epidemic model (Sharp 2022), again to the effect that policies based on these models were not necessarily best or good. Clearly something was (and is) wrong in the way mathematical models were called to play a role in society, not because model-based policies were necessary wrong as suggested in the quotes just mentioned, but – apparently – because it was so difficult to form a judgment about the matter.

Results from models and other instances of quantification will reflect the interests, disciplinary orientations and biases of their promoters and this has become especially apparent with the covid-19 pandemic. Put crudely, one cannot but take note of the "dramatic extent to which the people who did best during the pandemic resemble those who built the model", as containment measures were evidently more bearable or advantageous for modellers working on their laptop at home than they were for people working at meat processing plants (Winsberg 2022).

Winsberg and Harvard (2022) note that performativity (producing change in the observed phenomenon) is not advisable for mathematical models, as this would generate a conflict of interest and dubious incentives. Even the well-meaning modeller would be tempted to paint bleak futures in order to prevent them from happening. But is this what society needs from models?

A critical question remains of how we can keep the advantages of encoded mathematics without becoming their victims, or simply subordinates subjects devoid of agency. A related question is how we can do that without being entrapped into the straight jacket of the so-called deficit model, whereby increasing the scientific literacy – and in this case model-literacy – of citizens would solve our problems. Citizens are not the only subjects whose literacy needs to improve.

Mathematical models – as statistical measures and indicators - can be an important process of social discovery, but as discussed here they can be used as well to make this discovery – and a possible resulting agency – more arduous[vi]. Models have thus far remained elusive to tackle for a sociology of quantification: we have statactivists (Bruno, Didier, and Prévieux 2014a; Samuel 2022), data activists (Cardiff University 2020) and vast movement of sensitization around the use of algorithms in public matters, e.g. about algorithmic justice (Algorithmic Justice League 2020). Where are the activists for mathematical modelling?

Following Dewey, the making of democracy is predicated on the existence of publics sharing commonly understood facts. Once the wall of numericized facts is built from above, citizens are cut out from meaningful and deliberative participation. Opposing such a trend needs bridges to be built across all sectors of society – as advocated by statactivists, by Shoshana Zuboff (2019) at the end of her volume on the dangers of 'surveillance capitalism', by Alain Supiot when defending a state governed by just laws (2017), and by many others. If the 'Informational basis of judgment in justice' is where the battle needs to be fought, meaning by this a focus on both the quality of numericized evidence and on its fairness, then an extended peer community involving both modellers and those interested in their use needs to be established. The process may not be entirely peaceful.

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[i] Some pointer to literature is available in the supplementary material of (Saltelli, Bammer, et al. 2020).
[ii] “The Regulation Game: Strategic Use of the Administrative Process” is the title of a work by Owen and Braeutigam (1978) that instructs industrial and commercial actors as to how to benefit from administrative and regulatory processes, and argues that regulation can be gamed at the advantage of incumbents, shielding them from competition. The book also instructs lobbyists with remarkable candour as to how they should enrol scientists to defend industrial agenda. This should be done “with a modicum of finesse”, as the expert must now become aware that “they have lost their objectivity and freedom of action” p.7.
[iii] As an example, Salais compares the concept and indicators of employments as historically determined from the stage of the invention of the concept of employment using statistics to the present stage, where the concept of unemployment as a social and statistical category is emptied and is replaced by the maximizing of a target of rate of employment. This is achieved by declassifying short periods of unwork (relabelled as

transitions) with the result of increased precariousness. In a reductionist move, precariousness is not recognized as a valuable category of social policy (Salais 2022), p. 388).

[iv] "*As the members of the community possess the ultimate practical knowledge of the concrete reality of situations, they themselves only can provide access to what remains inaccessible even to the smartest researcher or observer, the data coming from their experience of the situation.* […] *access to such data is not only a question of inquiry in the classical social sciences conception; it has to do with an "extraction" from the people of intimate practical knowledge that they know without knowing that they know it; which means that they should deliberate with researchers all along in the process of inquiry".* (Salais 2022), pp. 404-405.

[v] The index is being reconsidered at the moment of writing the present work as Business Enabling Environment (BEE, Cobham 2022), an indication of the high stakes associate with this measure.

[vi] When pragmatist philosopher John Dewey discussed the concept of social discovery in the 30's he noted that there are 'publics' affected by transaction taking place somewhere else. "[…] machine age has so enormously expanded, multiplied, intensified and complicated the scope of the indirect consequences […] that the resultant public cannot identify and distinguish itself" (Dewey 1938). Dewey's warning takes on a new urgency now that the machine age has expanded to artificial intelligence and new media, colonizing hitherto virgin aspects of human existence (Zuboff 2019; Couldry and Mejias 2019; Lanier 2006). Models are part of this picture, potentially helpful or harmful, as a particularly effective instruments for the displacement of attention (Rayner 2012).