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25 Error

Abstract: This entry traces some of the transformations of error in the management of suspect populations, the policing of crime, and the taming of the uncertainties and complexities of governing populations digitally. It shows that what counts as error has changed from statistics to machine learning. Moreover, error is enacted differently depending on cultural, social, and political articulations of normality and abnormality.

Keywords: error, governmentality, statistics, machine learning, suspect populations

What is error?

Error has an ambiguous meaning. On the one hand, to err means "to ramble, roam, stray, wander" (Oxford English Dictionary, 2023). On the other, to err is to "go astray" (Oxford English Dictionary, 2023) from the correct path, to deviate. While the first meaning is now obsolete, this ambiguity of error as wandering or deviation has preoccupied philosophers and historians since the entry of error in the 18th-century *Encyclopaedia of Diderot and d'Alembert* (Bringman, 2013 [1755]). Given the multitude of forms errors could take, the *Encyclopaedia* entry proposed to find the cause and origin of error. The search for the cause of errors has continued to trouble philosophers and scientists alike.

For the historian of science Lorraine Daston (2005: 5), "epistemology since the seventeenth century has consisted largely in an elaborate nosology of errors: what their species and varieties are, and how they may best be avoided or cured." The classification, evaluation, and avoidance of errors do not only characterize scientific knowledge. The knowledge required for the government of individuals and populations has been shaped by vigilance against error and a corrective ethos. Drawing lines between the normal and the abnormal, the criminal and the law-abiding, the citizen and the non-citizen is fraught with possibilities of and anxieties about error.

Philosopher of science Giora Hon points to the heterogeneity of error as "a multifarious epistemological phenomenon of great breadth and depth" (Hon, 2008). Given this breadth and depth, error is impossible to define, contain, and eliminate. Therefore,

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as governing actors have attempted to tame error, we need to ask: 'how is error?' rather than 'what is error?'. 'How is error?' is an inquiry into what kinds of errors surface more frequently than others and how they can be ranked so that some require more intense attention and vigilance than others. 'How is error?' allows us to map what counts as error in the government of populations, how errors are contested, and how they are transformed through the use of various technologies, including digital technologies.

This entry traces some of the transformations of error in the management of suspect populations, the policing of crime, and the taming of the uncertainties and complexities of governing populations digitally. It shows how errors have always been produced as technical and political.

Governing suspect populations: from statistics to machine learning

From medical errors to errors of justice and from grammatical errors to biometric errors (see Biometric Failure by Magnet and Din), errors are ubiquitous in social and political life. However, some errors carry more severe consequences than others. If errors can never be entirely eliminated, then they need to be hierarchized, categorized, and minimized so that they don't have too detrimental or destructive effects on knowledge production and social life. The categorization and minimization of error played out differently in the historical entwinement of statistics and the government of populations: from the 'error curve' of measurement to error as a failure of scientific methods (Roberts, 2011: 65).

As statistics was deployed to manage populations and draw distinctions between risky and non-risky individuals (Foucault, 2007), error was the rationale that enabled distinctions between normality and abnormality. The awareness that measurement could always contain errors had led astronomers to discover that errors followed an 'error curve.' In the 19th century, the Belgian mathematician Adolphe Quetelet developed his social physics based on the astronomers' theory of error. The 'average man' as the mean of the normal curve distribution was the equivalent of the mean of measurement error. Subsequently, the mean was assumed to be a correct measurement and, therefore, truthful knowledge. The truth of the average had political effects for the untruth of deviation. As historian of statistics Theodore Porter (1985: 65) has aptly put it: "Quetelet's idealization of the mean as the standard of beauty and goodness implied that all variation—everything exceptional—was to be regarded as flawed, the product of error."

Statistics afforded criminology "its intellectual orientation and recognition by the scientific community" (Beirne 1987: 1145). Statistical analysis of deviation from the 'average' enabled distinctions between "the recalcitrant minority with incorrigible criminal tendencies" (Beirne 1987: 1161) and those whose minimal deviances could be governed through the “inevitable progress of civilization” (Beirne 1987: 1161). The focus on the ‘dangerous classes’ in the social physics of deviance was entwined with anxieties about mobility or what historian Simon Cole (2002: 9) has described as the “increasing formal criminalization of mobility.” For example, fraud and swindling were seen to be “crimes of mobility.” Given 19th-century anxieties about mobility and the “dangerous classes,” measuring the body and related statistical calculations promised to identify individuals who otherwise might have escaped the gaze of policing. Here, the measurement promised to identify a person with minimal error. As Cole has explained, “the identification techniques of the time focused on rendering identities stable, on the processes of capturing and fixing identity, for which the freeze-frame served as such an appropriate metaphor” (Cole, 2002: 22). Alongside photographs, French policeman Alphonse Bertillon introduced statistics in the measurement of criminal individuals for the purpose of identification. Limiting deviation in measurement was supposed to yield a true measurement, which could then be compared with other individuals’ measurements (Bertillon, 1885).

However, statistical measurement, as undertaken by Bertillon, seemed to have offered only limited accuracy and certainty. Eugenicist and initiator of the statistics of variation Francis Galton castigated Bertillon’s method of bodily measurements for its errors (Galton, 1892). Error was here a matter of scientific methods rather than measurement. Statistical variables had to be independent, Galton argued, but the variables Bertillon used were not. The measurements of the human body were co-dependent and could only lead to erroneous conclusions. Bertillon’s measurements were plagued both by “theoretical error,” namely treating measurements that were “undoubtedly correlated” as independent, and practical error of measurement through “the absence of a sufficiently detailed account of the practical difficulties experienced in its employment” (Galton 1892: 158). Taking measurements of the human body required craft, instruments, and experience. Instead of Bertillon’s anthropometry, Galton proposed fingerprinting as an almost error-free method. Fingerprints, he contended, “may therefore be treated without the fear of any sensible error” (Galton, 1892: 167).

This controversy was not decisive in how biometrics and anthropometry were subsequently used for the purposes of identification and policing. Another historian of statistics has argued that the popularity of fingerprints was not due so much to infallibility but “to the striking visual appearance of fingerprints in the courts,” a few “dramatically successful cases,” and the inattention to non-unique or changeable fingerprints (Stigler, 1995: 860). Nevertheless, the effects fingerprints had in courts depended on the imagination of accuracy and certainty that they appeared to offer to questions of identification.

Since Galton’s time, biometrics have expanded to identify criminals and their victims, migrants and citizens, and even to detect spies. In the late 20th century, the polygraph or the use of DNA in courts became such public controversies about errors (on the exceptional status of DNA evidence in courts, see Lynch, 2013). In October 1983, the *New Scientist* reported on the introduction of the polygraph at the Government Communications Headquarters (GCHQ), the UK’s signals intelligence agency, whose existence had only been recently recognized by the government. According to the union at GCHQ, “polygraph screening tests wrongly clear one in four of guilty subjects and wrongly accuse 50 per cent of the totally innocent subjects” (New Scientist, 1983). The introduction of the polygraph led to a decade of labour strikes, also in the wake of the prohibition of unions at GCHQ announced by the Thatcher government in 1984 (Aldrich, 2010, chapter 21).

These controversies over the errors of statistics and biometric measurements draw attention to error not just as a scientific and technical concept but also as a social and cultural one. More recently, the literature on biometrics has situated errors in a social and cultural context. Surveillance studies scholar Shoshana Magnet (2011) has argued that the understanding of biometric error needs to be expanded beyond what the biometric industry renders as technical varieties of error: “failure to enroll” and “failure to capture” rates to “false accept” and “false reject” rates. These are what she has called “technological crashes” (Magnet 2011: 13). However, and more significantly, “biometrics fail to work on particular communities in ways connected to race, class, gender, sexuality, and disability” (Magnet 2011: 7). Magnet has mapped the wide range of biometric errors in processes of identification and verification, “from high rates of unbiometrifiability to the misapplication of statistical technique in the codification of bodily identities and the misunderstanding of cultural trends, even with respect to hairstyle and clothing” (Magnet, 2011: 153).

Errors are inescapable given the assumptions of a ‘normal body’ inscribed in biometric technologies. What counts as ‘normal’ is a techno-scientific average and a socio-cultural normal imbued with assumptions about abnormality. In the case of India’s gigantic Aadhaar programme, which assigns a unique number to residents based on biometric data, the “unbiometrifiability of bodies” has been part of “heated debates about the feasibility of aadhaar” (Jacobsen and Rao, 2018: 29). For example, those whose fingerprints are uncapturable or damaged become ‘errors.’ The production of biometric errors in the Aadhaar system has far-reaching consequences, as anthropologists Elida K. Jacobsen and Ursula Rao have noted: “The discrimination of those not given an aadhaar number is amplified in a context of interoperability, whereby denial at one access point can lead to chains of exclusion” (Jacobsen and Rao, 2018: 34).

More recently, these concerns about error have been magnified through the use of machine learning algorithms to process biometric data (see Algorithm by Leese). While scholars and activists have drawn attention to errors in training data and bias towards gendered and racialized categories of population, the roll-out of machine learning-powered biometric technologies such as facial recognition has continued apace (Aradau and Blanke, 2021). The National Institute of Standards and Technology (NIST) in the USA explains that “Face recognition accuracy has improved markedly due to the development of new recognition algorithms and approaches” (NIST, 2023). However, error is far from eliminated, as NIST acknowledges the persistence of “increased error rates in applications where photography of faces is difficult or when stringent thresholds must be applied to recognition outcomes to reduce false positives” (NIST, 2023).

With machine learning, error entails a process of optimization or "adjusting machine learning models to achieve the best possible performance within a particular use case" (Aradau and Blanke, 2021: 8). The aim is not to eliminate or even necessarily minimize error but to optimize it. The optimization of error is a political decision about what a specific biometric technology does in the world. As digital culture scholar Nanna Bonde Thylstrup (2021: 197) has formulated the problem of big data errors, error is "a fundamental, and fundamentally political, part of knowledge production." She has drawn attention to computer science vocabularies that integrate error into a continuum of terms such as glitch, anomaly, fault, flaw, etc. (Thylstrup, 2021: 193).

These multiplicities, optimizations, and ambiguities of error mean that problematizing error cannot be done in the name of scientific accuracy, precision, validity, or truth. As the history of biometric technologies from the age of statistics to that of machine learning shows, biometric technologies cannot be perfect, both because they are probabilistic and because they are social, cultural, and geopolitical. Critical engagements with error can open new spaces of contestation and problematization of what counts as suspect populations, risky behaviors, and predictions of criminality (see Prediction by Ķīlis, Gundhus and Galis). To do so, critical engagements with error need to problematize the politics of producing and identifying errors, what counts as acceptable or unacceptable error and how distinctions between error, glitch, bias, or failure are drawn (Aradau and Blanke, 2021; Thylstrup, 2021; Ananny, 2022).

Conclusion: how is error?

Error has shaped not only questions about the accuracy of knowledge production but also about how and with which technologies populations are made governable. Starting from the normal curve, which saw the distribution of measurement or behavior as undesirable if deviant from 'averages,' error was imbricated with social, cultural, and political concerns. As error has been mobilized in scientific and public controversies about when and how biometric technologies are used to govern suspect populations, it is crucial to attend to its forms and transformations. What counts as error has changed from statistics to machine learning. Moreover, what counts as error is enacted differently depending on cultural, social, and political articulations of normality and abnormality. For instance, facial recognition has recently attracted intense attention as its errors are deeply entwined with racialized and gendered classifications of populations (see Facial Recognition by Fussey). Yet, from statistics to machine learning, errors have also changed, as the anxieties of identifying and correcting errors have been supplemented by the ambiguities of optimizing errors.

If errors are inscribed into the digital technologies deployed to govern populations, then social scientists need to address their multiple articulations by asking: 'How is error?' Errors reproduce historical patterns of inequality so that racialized individuals and groups come to be read as 'errors.' Errors enable decisions on the thresholds of probability that make some biometrically recognizable and others not. Errors can infuse scientific and academic controversies over the invention and use of some technologies rather than others. Errors also etch economic rationalities of cost and efficiency into what can be problematized, addressed, or redressed and what will remain unspoken and unaccounted. Mapping the variations and mobilizations of error avoids ceding its political terrain to technical competencies only.

Suggested reading

Ananny, M. (2022). Seeing like an algorithmic error: What are algorithmic mistakes, why do they matter, how might they be public problem? *Yale Journal of Law & Technology*, 24, 342 – 364.

Aradau, C., & Blanke, T. (2021). Algorithmic surveillance and the political life of error. *Journal of the History of Knowledge* 2(1).

Daston, L. (2005). Scientific error and the ethos of belief. *Social Research*, 72(1), 1 – 28.

Thylstrup, N. B. (2021). Error. In N. B. Thylstrup, D. Agostinho, A. Ring, C. D'Ignazio, & K. Veel (eds.), *Uncertain Archives: Critical Keywords for Big Data* (pp. 191 – 199). Cambridge, MA: MIT Press.

References

Aldrich, R. J. (2010). *GCHQ: The Uncensored Story of Britain's Most Secret Intelligence Agency.* London: Harper Press.

Ananny, M. (2022). Seeing like an algorithmic error: What are algorithmic mistakes, why do they matter, how might they be public problem? *Yale Journal of Law & Technology*, 24, 342 – 364.

Aradau, C., & Blanke, T. (2021). Algorithmic surveillance and the political life of error. *Journal of the History of Knowledge*, 2(1). https://journalhistoryknowledge.org/article/view/11370.

Beirne, P. (1987). Adolphe Quetelet and the origins of positivist criminology. *American Journal of Sociology*, 92(5), 1140 – 1169. https://doi.org/10.1086/228630..

Bertillon, A. (1885). *Identification anthropométrique. Instructions signalétiques.* Ministère de l'Intérieur, Paris: Melun.

Bringman, G. (2013 [1755]). Error. *The Encyclopedia of Diderot & d'Alembert Collaborative Translation Project.* Michigan Publishing. Accessed 3 April. http://hdl.handle.net/2027/spo.did2222.0002.683.

Cole, S. A. (2002). *Suspect Identities. A History of Fingerprinting and Criminal Identification.* Cambridge, MA: Harvard University Press.

Daston, L. (2005). Scientific error and the ethos of belief. *Social Research*, 72(1), 1 – 28.

Foucault, M. (2007). *Security, Territory, Population. Lectures at the Collège de France, 1977 – 78.* Basingstoke: Palgrave.

Galton, F. (1892). *Finger Prints.* London: Macmillan and Co.

Hon, G. (2008). Error: The long neglect, the one-sided view, and a typology. In G. Hon, J. Schickore, & F. Steinle (eds.), *Going Amiss in Experimental Research* (pp. 11 – 26). Dordrecht: Springer.

Jacobsen, E. K., & Rao, U. (2018). The truth of the error. In M. Maguire, U. Rao, & N. Zurawski (eds.), *Bodies as Evidence. Security, Knowledge, and Power* (pp. 24 – 42). Durham, NC: Duke University Press.

Lynch, M. (2013). Science, truth, and forensic cultures: The exceptional legal status of DNA evidence. *Studies in History and Philosophy of Science Part C: Studies in History and Philosophy of Biological and Biomedical Sciences*, 44(1), 60 – 70. https://doi.org/https://doi.org/10.1016/j.shpsc.2012.09.008.

Magnet, S. A. (2011). *When Biometrics Fail: Gender, Race, and the Technology of Identity.* Durham, NC: Duke University Press.

New Scientist. (1983). Why spies like lie detectors. 20 October 1983, 161.

NIST. (2023). *Face Analysis Technology Evaluation (FATE) Quality.* Accessed 29 September. https://pages.nist.gov/frvt/html/frvt_quality.html.

Oxford English Dictionary. (2023). err, v. Oxford: Oxford University Press.

Porter, T. M. (1985). The mathematics of society: Variation and error in Quetelet's Statistics. *The British Journal for the History of Science*, 18(1), 51 – 69.

Roberts, J. (2011). *The Necessity of Errors.* London: Verso.

Stigler, S. M. (1995). Galton and identification by fingerprints. *Genetics*, 140(3), 857 – 860.

Thylstrup, N. B. (2021). Error. In N. B. Thylstrup, D. Agostinho, A. Ring, C. D'Ignazio, & K. Veel (eds.), *Uncertain Archives: Critical Keywords for Big Data* (pp. 191 – 199). Cambridge, MA: MIT Press.