Noise, Deviation, Anomaly, & Mistake: On Targets and Quadrants of Variability

A summary of a preprint

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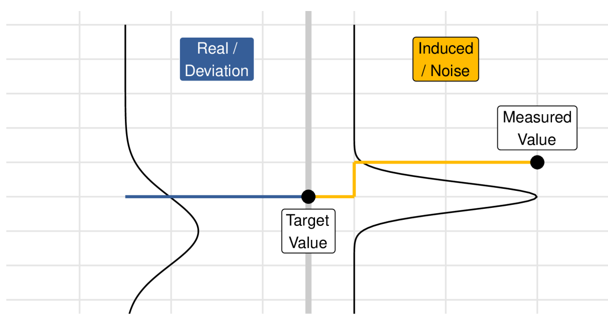
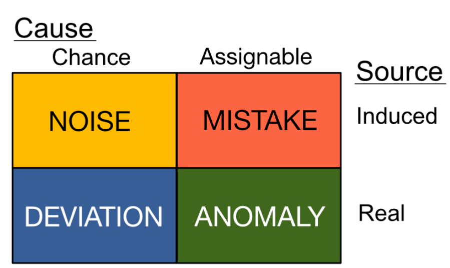
Variability is ubiquitous in science and engineering: Repeated measurements of “the same” quantity rarely produce the same value. However, the treatment of variability is often facile and sometimes dangerous. A recent investigation of industry-standard aircraft design reveals probabilistic errors that admit significantly higher failure rates than legally acceptable [1]. The *facts* of the error are easy to describe (use of a point estimate rather than interval), but the *nature* of the error is not succinct to describe in current statistical parlance. Clearly, developments in the language and terminology of variability are needed, in part to facilitate collaboration between scientists, engineers, and statisticians.

The concepts of *cause* and *source* of variability can help scientists and engineers communicate with statisticians and improve statistical modeling. The concept of *chance and assignable causes* was formulated by Shewhart [2, Ch.2] to help find and eliminate sources of variability in manufacturing. Chance cause is random and not easily explained, while assignable cause is traceable and controllable. Wild and Pfannkuch [3] introduced the notion of *real and induced sources* of variability; I have clarified this notion by distinguishing between a *target value* and *measured value* (Fig. 1a). Real variability affects a target value, while induced variability corrupts a measured value. Considering cause and source as two axes yields the *cause-source variability quadrants*, shown in Figure 1b. These quadrants can be given lucid names: noise, deviation, anomaly, and mistake. The next page makes direct comparisons between the quadrants.



(a) Real variability produces a target value, which is corrupted by induced variability during measurement. When chance (random) in cause, these variations are deviation and noise.



(b) Considering axes of chance/assignable cause against real/induced source yields the cause-source quadrants.

Figure 2 illustrates quadrant examples in a manufacturing setting with the target value as the realized material strength:

(Noise) Electrical corruption of measurement
(Deviation) Presence of cracks in part affecting strength
(Anomaly) Departures from ASTM manufacturing standard
(Mistake) Improper fixture during measurement

Present aircraft design ignores the possibility of real-chance variability (deviation) in certain material properties: The cause-source quadrants clarify the nature of the error mentioned above. In terms of the cause-source quadrants, the present criteria confuse a source of deviation for a source of noise. Teaching the cause-source quadrants to scientists and engineers will help prevent such dangerous errors in the future.

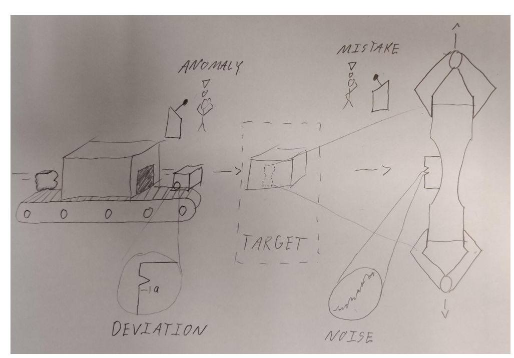


Figure 2: Cause-source quadrant examples in manufacturing and characterization of strong components.

Each variability quadrant should be treated differently in experimental design and analysis, as the next page details.

Noise vs Deviation

Similarities Both noise and deviation are inherently random.

Differences Deviations affect the quantity we aim to measure; they are part of the "signal." Noise corrupts the quantity we aim to measure; it is not part of the "signal."

Design of Experiments If deviations are present, prepare and measure multiple samples. If noise is present, perform multiple measurements on each sample. If both deviation and noise are present, use a nested design.

Analysis Noise is appropriately modeled as a zero-mean random variable; the uncertainty arising from noise can be reduced by repeated measurements. Deviations are appropriately modeled as a (non-zero-mean) random variable; repeated measurements will better estimate distribution parameters, but deviation cannot be reduced without interfering with the physical system.

Noise vs Mistake

Similarities Both noise and mistakes are induced; they corrupt a measurement.

Differences Noise is inherently random and *unassignable*; there is no simple explanation for noise variability. A mistake is assignable; there exists some explanation for a mistake.

Design of Experiments If noise is present, perform multiple measurements on each sample. To detect and understand mistakes, experimental metadata must be recorded: Mistakes are frequently due to departures from the proper experimental protocol.

Analysis Noise is appropriately modeled as a zero-mean random variable. To eliminate a mistake, review the experimental (meta)data and search for an assignable cause.

Deviation v Anomaly

Similarities Both deviations and anomalies are real; they affect the quantity we aim to measure.

Differences Deviations are inherently random and *unassignable*; there is no simple explanation for deviation variability. An anomaly is assignable; there exists some explanation for an anomaly.

Design of Experiments If deviations are present, prepare and measure multiple samples. To detect and understand anomalies, experimental metadata must be recorded.

Analysis Deviations are appropriately modeled as a (non-zero-mean) random variable. To learn from an anomaly, review the experimental (meta)data and search for an assignable cause.

Anomaly v Mistake

Similarities Both anomalies and mistakes are due to assignable causes.

Differences Anomalies are real; they affect the quantity we aim to measure. Mistakes are induced; they corrupt the quantity we aim to measure.

Design of Experiments Assignable causes are often *found* by reviewing data, but *explained* by reviewing metadata: Documenting the conditions of data collection is necessary.

Analysis Mistakes arise due to errors in our measurement model, often due to a departure from the experimental protocol. An anomaly arises due to a misunderstanding in our model for the target value; sometimes this corresponds to a scientific discovery (finding previously unknown physics).

[1] Zachary del Rosario, Richard W Fenrich, and Gianluca Iaccarino. When are allowables conservative? *AIAA Journal*, 59(5):1760–1772, 2021.

[2] Walter Andrew Shewhart. *Economic control of quality of manufactured product*. Macmillan And Co Ltd, London, 1931.

[3] Chris J Wild and Maxine Pfannkuch. Statistical thinking in empirical enquiry. *International statistical review*, 67(3):223–248, 1999.