

Bayes' Rule, Bayesian Thinking, and the Extrapolation of Destructive Testing Data



By Lonnie Haughton, MCP, CDT

This article uses photographs and results from an actual investigation to supplement a theoretical examination of how Bayes' Rule could be used to extrapolate sampling data.

Consider a large four-story residential complex (*Photo 1*) in a city near San Francisco. The apartments are served by 187 wood-framed decks with stucco-clad guard walls. The 2½-in. concrete walking surface atop these decks is installed over a fluid-applied waterproofing membrane, which is drained by sheet metal scupper boxes. Let's assume

that we have been tasked with evaluating the waterproofing performance of these decks.

INVESTIGATION

As seen in *Photo 2*, we readily observe “concrete stalactites”¹ forming at about 20% of the exterior hoods attached to these scupper boxes. Our knowledge and experience lead us to opine that these stalactites

result from slow seepage of ponded water under the deck concrete.

To evaluate this assessment, we remove stucco directly below one of the scuppers, exposing dramatic evidence (see *Photo 3*) of water drainage from under the scupper box. These conditions also are consistent with seepage—likely via flashing or waterproofing defects—of ponded water under the concrete.



Photo 1 – The apartment complex has 187 wood-framed decks.

We then destructively sample this concrete adjacent to one of the deck scuppers, revealing a pond of water (*Photo 4*) atop the waterproofing membrane and the typical “filter fabric and drainage mat” that separates and protects this membrane from the concrete. As seen in *Photo 5*, we find that the ponding results from a failure to provide positive slope for drainage.

Our destructive testing at another deck reveals similar conditions: Concrete removal releases trapped

Photo 3 – Seepage from under the scupper box, likely from a hidden pool of trapped water.



Photo 2 – “Concrete stalactites” are evidence of slow seepage of ponded water.



water (Photo 6) that cannot fully drain due to negative slope in front of the scupper (Photo 7), which is exacerbated by concrete debris within the scupper’s throat (Photo 8).

Further, our sampling of the soffits below several other decks (which do not exhibit visible evidence of hidden damage) reveals water-damaged decking (Photo 9) that also is consistent with slow seepage—via flashing/waterproofing defects—of trapped water under the concrete.



Photo 5 – Waterproofing is negatively sloped away from the scupper.



Photo 4 – Water ponds under the deck’s concrete covering.



Photo 6 – Concrete removal releases a flood of trapped water.



Photo 7 – Water ponds due to negative slope and other construction deficiencies.

The deficiencies and damage revealed during our concrete removal work at Decks 1 through 4, and during our soffit removal below the three other decks, are fully consistent with our initial assessment (of hidden pools of water under the concrete) made after we observed the stalactites.

Let's assume that the combined data, supplemented by expertise and past experience, support a preliminary finding that the great majority of the decks at this apartment complex likely will have generally similar negative drainage conditions at their scuppers, potentially creating problematic pooling and resulting damage.

Support for this inductive hypothesis includes our experience that a general consistency of construction is the common result of the "portable production line" processes that are typical for large-scale residential projects driven by tight financial pressures. "Large-volume builders organize house construction as a portable production line. By keeping subcontractors busy without having to travel between jobs, builders can obtain their services for less and offer their houses at competitive prices."²

For the purposes of this article, let's assume that you agree that "general consistency of construction" means generally similar installation/construction practices (whether good, fair, or poor) will be found at a minimum of 80% of large-scale residential projects at a minimum of 90% of their locations. For brevity, let's call this the "80/90 Rule."³



Photo 8 – Concrete debris within the scupper's throat impedes positive drainage.



Photo 9 – Soffit removal below another deck reveals evidence of water seepage from above.

At this point in our investigation, is it possible to integrate our combined sampling data with our 80/90 Rule to create a mathematical approach for the additional testing necessary to extrapolate the results of our testing to all of the decks?

BAYES' RULE AND CONDITIONAL PROBABILITIES

While we already believe it likely that negative drainage conditions exist at the scuppers at most (perhaps all) of the decks, we have decided that supplemental sampling of the concrete at decks that do not exhibit concrete stalactites at their scuppers is needed to validate this hypothesis.⁴

Let's also assume that our additional testing and review processes must (perhaps for legal purposes) be carried out in conformance with fundamental principles of statistical sampling. From which branch of statistical analysis—"frequentist" or "Bayesian"—should our sampling design be developed? (Did you even know there were alternate branches of statistics?) "Most engineers are surprised to learn that statistics is not monolithic, nor statisticians of one stripe."⁵

The frequentist approach to statistical analysis often is first encountered in Statistics 101. The frequentist instructor might inform us that stating a particular event or hypothesis has X% probability of occurring is equivalent to saying that if we were to infinitely repeat our random evaluation process, then the average frequency of these infinite outcomes would be X out of every 100 repetitions.

The frequentist process requires rigorous random sampling and a good understanding of "confidence limits," "confidence intervals," "margins of error," and "normal distributions" (bell curves). Even then, the results of such frequentist calculations can be described incorrectly.⁶

Further, the frequentist instructor would insist that our random sampling protocols for this particular project could not be based upon our prior experience and knowledge, including the 80/90 Rule, no matter how valid (and valuable) we believe this information to be.⁷

In contrast, the Bayesian⁸ approach to probability and statistics specifically enables us, via Bayes' Rule (or Bayes' Formula), to mathematically evaluate and update our beliefs and knowledge upon receiving new information. This new data does nothing to change the actual likelihood of our hypoth-

esis, which of course remains set to occur with the same outcome; instead, Bayes' Rule simply defines how well (or not) the new information improves our prior degree of certainty:

"Bayes' Rule, by itself, is a skimpy theorem relating conditional probabilities, one possible way to deal with uncertainty in a complex world. It asserts that given an initial belief about a phenomenon and objective new data about it, we can obtain a new and improved belief that updates our initial one. As such, it both introduces subjective opinion into a mathematical statement and lays bare a blueprint for rational learning by linking causality and inference."⁹

The logic and potential power of frequentist statistics derive from large sets of randomly selected samples that permit extrapolation to even larger populations in accordance with formalized calculations, confidence limits, and intervals. However, extensive practical experience informs many of us that the various ranges of time, access, logistical, budgetary, aesthetic, and/or legal constraints commonly encountered by forensic investigators at large-scale residential projects generally preclude unfettered random sampling in accordance with frequentist protocols.¹⁰

In contrast, the provisional beliefs and "conditional probabilities"¹¹ that might be considered bias (and therefore a weakness) in frequentist sampling comprise the inductive core of Bayesian thinking: "On its face, Bayes' Rule is a simple, one-line theorem: By updating our initial belief about something with objective new information, we get a new and improved belief."¹²

Here is a simple example of informal Bayesian thinking: You prefer to drive fast during your daily commute, but you cannot afford any more speeding tickets. Today, however, you already are late for work. You know from years of daily commuting experience that whenever the local state trooper is out patrolling (sporadically, one or two days per week), he hides behind a particular overpass about 80% of the time and at scattered other locations the remaining 20%. After weighing these conditional probabilities (How likely is it that the trooper is on duty today? If so, where might he be hiding?), you decide to obey traffic laws while traveling past the overpass, but to otherwise

risk getting a ticket.

While your internal calculations for this example likely were not arithmetical, the mathematically inclined could input these conditional probabilities into an algebraic form of Bayes' Rule to calculate the best odds for when (and when not) to risk speeding.

In his acclaimed book, *The Signal and the Noise*,¹³ statistician/pollster Nate Silver reports this:

"If the philosophical underpinnings of Bayes' theorem are surprisingly rich, its mathematics are stunningly simple. In its most basic form, it is just an algebraic equation with three known variables and one unknown one. But this simple formula can lead to vast predictive insights. ...Bayes' theorem is concerned with conditional probability. That is, it tells us the probability that a theory or hypothesis is true if some event has happened."

For the purposes of our construction defects analysis at the decks, the four variables of Bayes' Rule can be summarized



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| | | |
|----------------------------|-------------------------|---|
| 1) x = | Prior Probability | Initial odds (our degree of belief) that our hypothesis is true |
| 2) y = | Conditional Probability | Odds of newly-acquired information (which appears to support our hypothesis) appearing conditional upon our hypothesis being correct: True Positive |
| 3) z = | Conditional Probability | Odds of newly-acquired information (which appears to support our hypothesis) appearing conditional upon our hypothesis being false: False Positive |
| 4) $xy / ((xy + z(1-x)) =$ | (Bayes' Formula) = | Updated estimate or odds (our degree of belief) that our hypothesis is true: Posterior Probability |

Figure 1 – The four variables of Bayes' Rule.

algebraically, as shown in Figure 1.¹⁴

“... Bayes' theorem is not any kind of magic formula—in the simple form that we have used here, it consists of nothing more than addition, subtraction, multiplication, and division. We have to provide it with information, particularly our estimates of the prior probabilities, for it to yield useful results.”¹⁵

A BAYESIAN APPROACH TO OUR DECK EVALUATION PROCESS

As discussed, Bayes' formula requires us to quantify our prior beliefs and also the conditional information derived during our destructive investigation. For our evaluation of the decks that do not exhibit concrete stalactites, let's assume these percentages:

Prior Probability. Our conservatively estimated minimum odds that our consistency hypothesis (negative drainage conditions exist at generally all of the decks) is correct = 50%.¹⁶

Conditional Probability. If our consistency hypothesis is correct, then the 80/90 Rule (that you have agreed to accept for the purposes of this article) informs us that the minimum odds of these generally deficient drainage conditions being found at the decks that do not exhibit concrete stalactites = 90%.¹⁷

Conditional Probability. However, if our consistency hypothesis is not correct (perhaps the overall work instead is inconsistently “good”), then the negative evidence that we already have observed represents “false positives.” If so, we estimate that the minimum percentage of such false positives existing at the decks that do not exhibit concrete stalactites = 30%.¹⁸

Figure 2, then, demonstrates how our algebraic equation processes the ongoing conditional interplay between “true positives” and “false positives” (or, when applicable, “true negatives” and “false negatives”) at the randomly sampled decks.

- The first testing of our consistency hypothesis is to remove concrete at Deck 5—where we again find the

same negative drainage conditions. As demonstrated in Step 1, this new data enables us, via Bayes' Rule, to update our prior probability of 50% to a posterior probability of 75%.

- Subsequent concrete removal at randomly sampled Decks 6 and 7 reveals generally identical defects. As shown in Steps 2 and 3, the repeated iterations of Bayes' Rule (with our latest posterior probability becoming our newest prior probability each time) enable us to become 96% confident that our consistency hypothesis is correct.¹⁹

SUMMARY DISCUSSION

During the past few decades, universities and research institutions across North America have developed numerous fields

and applications of advanced Bayesian statistics as equally broad, deep, and complex as advanced frequentist statistics. “Scientific and technical interest in Bayes' Rule has exploded.”²⁰

In contrast, our proposed use of Bayes' Formula is neither complex nor advanced. Indeed, all this simple algebraic equation requires from us is the ability to quantify the conditional probabilities that already comprise the foundation of our qualitative processes.²¹

Even though the Bayesian terminology is unfamiliar, skilled construction professionals already are integrating (informally) the latest data derived from evaluating a conditional probability into their most current prior probability in order to produce an updated posterior probability.²²

Clearly, such cognitive evaluations of building envelope performance correspond with Bayesian thinking. In contrast, these qualitative processes are inconsistent with the rigidly predetermined randomness of frequentist statistics.²³

“By its very nature, enclosure condition assessment technique is often at odds with random sampling and

| BAYESIAN ANALYSIS - STEP 1 | | |
|----------------------------|---|---|
| 1) x = | Prior Probability | Initial estimated odds that our consistency hypothesis is true = 50% |
| 2) y = | Conditional Probability | Odds of the new information from Deck 5 appearing conditional upon our consistency hypothesis being correct: True Positive = 90% |
| 3) z = | Conditional Probability | Odds of the new information from Deck 5 appearing conditional upon our consistency hypothesis actually being false: False Positive = 30% |
| 4) $xy / ((xy + z(1-x)) =$ | Bayes' Formula = Posterior Probability | $\frac{\{(0.50 * 0.90)\}}{\{((0.50 * 0.90) + ((0.30 * (1 - 0.50)))\}} = 0.75$ Updated level of certainty that our hypothesis is true = 75% |
| BAYESIAN ANALYSIS - STEP 2 | | |
| 1) x = | Prior Probability | Updated odds that our hypothesis is true = 75% |
| 2) y = | Conditional Probability | That the new information from Deck 6 would appear conditional upon our consistency hypothesis being correct: True Positive = 90% |
| 3) z = | Conditional Probability | That the newly-acquired information from Deck 6 would appear conditional upon our consistency hypothesis actually being false: False Positive = 30% |
| 4) $xy / ((xy + z(1-x)) =$ | Bayes' Formula = Posterior Probability | $\frac{\{(0.75 * 0.90)\}}{\{((0.75 * 0.90) + ((0.30 * (1 - 0.75)))\}} = 0.90$ Updated level of certainty our hypothesis is true = 90% |
| BAYESIAN ANALYSIS - STEP 3 | | |
| 1) x = | Prior Probability | Updated odds that our consistency hypothesis is true = 90% |
| 2) y = | Conditional Probability | That the new information from Deck 7 would appear conditional upon our consistency hypothesis being correct: True Positive = 90% |
| 3) z = | Conditional Probability | That the newly-acquired information from Deck 7 would appear conditional upon our consistency hypothesis actually being false: False Positive = 30% |
| 4) $xy / ((xy + z(1-x)) =$ | Bayes' Formula = Posterior Probability | $\frac{\{(0.90 * 0.90)\}}{\{((0.90 * 0.90) + ((0.30 * (1 - 0.90)))\}} = 0.9643$ Updated level of certainty that our hypothesis is true = 96% |

Figure 2 – Bayesian assessment of data from destructive sampling of the concrete at Decks 5, 6, and 7.

statistical methodologies. ...In its basic form, qualitative analysis hinges on the ability to use information-rich sampling, based on prior knowledge, to build a further analysis of the assessment.”²⁴

We are not suggesting that formalized Bayesian calculations should be a required component of an investigator’s extrapolative processes. Still, efforts to better understand the mechanics of Bayes’ equation certainly can broaden our expertise and might help persuade nonprofessionals (insurance adjusters, for example) of the merits of our forensic analyses.

Additionally, requiring all consultants in a construction dispute to quantify their conditional probabilities could lead to mutual understandings of the opinions and fundamental mindsets of these various reviewers. Some professionals may opine that probabilities of “consistency” and “inconsistency” are construction variables that never can be quantified. Others may believe that hidden work and construction practices always should be assumed to be consistently good unless frequentist sampling proves them otherwise. Others may simply assert that inconsistently poor construction has become the industry norm for large-scale residential construction.

Still, for those who are able to quantify their conditional probabilities (no matter how far their specific values differ from those of other consultants), simple Bayesian algebra provides a mechanism and path for all parties to achieve consensus. “A primary motivation for believing Bayesian thinking important is that it facilitates a common-sense interpretation of statistical conclusions.”²⁵

In the theoretical decks investigation presented in this article, the foundation of our Bayesian analysis is our 80/90 Rule: Generally similar installation/construction practices (whether good, fair, or poor) will be found at a minimum of 80% of large-scale residential projects at a minimum of 90% of their locations.²⁶

It is instructive to recalculate the above concrete sampling examples (Steps 1, 2, and 3) with differing values for the “true positives” and “false positives” to explore the interplay between these conditional probabilities.

Further, the mathematically adventurous may wish to consider how Bayes’ formula processes a new sample that does

not exhibit negative drainage: Does this contrary result simply represent a “false negative” (remember, even our 80/90 consistency rule accepts inconsistent construction at up to 10% of its areas), or might it instead be a “true negative” that evidences a fatal flaw in our hypothesis?

In either case, successive iterations of the equation produce updated posterior probabilities that incrementally increase our knowledge, leading inexorably toward strong Bayesian certainty that our consistency rule is (or is not) valid.²⁷

In contrast, frequentist sampling often is an all-or-nothing affair. For example, let’s assume that a consultant engineer has determined that to prove (or disprove) our consistency hypothesis, a minimum of 73 of the 150 decks that do not exhibit concrete stalactites at their scuppers must be sampled in strict accordance with frequentist statistical protocols.²⁸ Further, the projected unit cost for the evaluation process at each deck is \$4,000.²⁹

Now, let’s assume that after spending \$144,000 to sample 36 of these 73 decks, the funding is terminated and the client requests a summary report of statistically valid findings. After 50% completion of the frequentist sampling protocol, what have you learned that proves (or disproves) the consistency hypothesis?

The correct answer would seem to be “nothing.” Even if your destructive testing to date had found negative drainage conditions at 33 of the 36 decks, the incomplete sampling still cannot be considered “representative,” because the predetermined frequentist protocol required you to sample all 73 of the decks. In real-world situations similar to this, some frequentists will find a way to opine, after the fact, that the incomplete sampling actually had been sufficient to produce “statistically significant” results.

Clearly, any such analysis where a prior probability (the rigid, predetermined frequentist sampling protocol) is then modified by a conditional probability (data gained from incomplete sampling) to produce an updated posterior probability (a post-sampling alternative assessment of what constitutes a “significant” finding) is representative of Bayesian reasoning, even if presented in a frequentist guise.

This example also is a good illustration of the commonly inefficient and impractical nature of frequentist sampling proposals for most construction investigations. It is telling that such recommendations often



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come from consultants representing parties with a vested interest in derailing the evaluation process. (Even more telling are the actions of those consultants who practice informal Bayesian analysis during their own investigations, but will argue for frequentist sampling when hired to criticize other consultants' investigations.)

In the end, the merits of any construction analysis—whether qualitative, Bayesian, or frequentist—depend upon the competence and integrity of the investigator.³⁰ Therefore, while it is our experience that frequentist sampling protocols are unrealistic due to the time, access, logistical, budgetary, aesthetic, and/or legal constraints commonly encountered at large-scale residential projects, any such proposal still warrants consideration.

Similarly, even the staunchest advocates of frequentist sampling may be willing to accept the potential merits of our consistency rule for evaluating “production line” construction of large-scale projects. If so, then Bayes' formula warrants their consideration.³¹

It is reasonable to speculate that in coming years, formal (mathematical) applications of Bayes' Rule will blossom in the fields of construction forensics and associated litigation. A particularly fertile ground for initially exploring Bayes' Rule might be evaluation of very large (>1000 squares) low-slope roof covering systems, which certainly must be considered prone to a general consistency of construction related to the portable production line nature of such work. 

*A plethora of resources are available to introduce Bayes' Formula to reviewers with prior mathematical training. For example, see “An Intuitive Explanation of Bayes' Theorem” at yudkowsky.net/rational/bayes. For the nonmathematical, an excellent introduction to real-world applications of Bayes' Rule is Nate Silver's book, *The Signal and the Noise*.³²*

REFERENCES

1. <http://en.wikipedia.org/wiki/Stalactite>: “The way stalactites form on concrete is due to different chemistry than those that form naturally in limestone caves and is the result of the presence of calcium oxide in concrete. This calcium oxide reacts with any rainwater that penetrates the concrete and forms a solution of calcium hydroxide. ...Over time, this calcium hydroxide solution reaches the edge of the concrete and, if the concrete is suspended in the air—for example, in a ceiling or a beam—then this will drip down from the edge. When this happens, the solution comes into contact with air and another chemical reaction takes place. The solution reacts with carbon dioxide in the air and precipitates calcium carbonate. ...When this solution drops down, it leaves behind particles of calcium carbonate; and, over time, these form into a stalactite. They are normally a few centimeters long and with a diameter of approximately 5 mm (0.20 inches).”
2. E. Allen and R. Thallon. *Fundamentals of Residential Construction, 3rd Ed.*, John Wiley & Sons, NJ, 2011: “Large-volume production of new houses is achieved by working on large tracts of repetitive units, and contractors achieve success in this arena by managing labor and materials on the building site as they would a housing production line in a factory.”
3. The 80/90 Rule specifically addresses projects that have been constructed in a single phase under the direction of one general contractor using the same primary subcontractors throughout. However, it is not uncommon for this basic “rule” to remain valid for multiphase projects using the same general contractor, but differing subcontractors, in successive phases.
4. For the purposes of this article, assume that you agree with our assessment that the concrete stalactites constitute conclusive evidence of negative drainage at 20% of the deck scuppers.
5. Charles Annis, PE: <http://www.statisticalengineering.com>.
6. W.M. Bolstad. *Introduction to Bayesian Statistics, 2nd Ed.*, John Wiley & Sons, NJ, 2007: “Clients will interpret a frequentist confidence interval as a probability interval. The statistician knows that this interpretation is not correct but also knows that the confidence interpretation relating the probability to all possible data sets that could have occurred, but didn't, is of no particular use to the scientist.”
7. *Ibid.*: “The ‘objectivity’ of frequentist statistics has been obtained by disregarding any prior knowledge about the process being measured. Yet in science, there usually is some prior knowledge about the process being measured. Throwing this prior information away is wasteful of information (which often translates to money). Bayesian statistics uses both sources of information: the prior information we have about the process and the information about the process contained in the data. They are combined using Bayes' theorem.”
8. The term “Bayesian” refers to the 18th-century mathematician and theologian Thomas Bayes, one of the first to define and calculate conditional probabilities. However, it was the great French mathematician Pierre-Simon Laplace who (circa 1774) independently discovered and developed what is now called Bayes' Rule: “Laplace stated the principle not with an equation, but in words: The probability of a cause (given an event) is proportional to the probability of the event (given its cause).” (http://lesswrong.com/lw/774/a_history_of_bayes_theorem.)
9. Michele Bottone: <http://www.significancemagazine.org>.
10. D.A. Hodgin. “Expert Witness 101: Balancing Professional Ethics With Client Desires,” *Forensic Engineering 2012: Gateway to a Safer Tomorrow*, American Society of Civil Engineers, 2013: “Statistical relevance, while providing a high level of confidence to the testifying expert, is typically unrealistic and cost-prohibitive.”
11. Conditional probabilities are those probabilities whose value depends on the value of another probability; for example, the odds of eventually dying a rich man increase greatly if one marries a wealthy woman.
12. S.B. McGrayne. *The Theory That Would Not Die: How Bayes' Rule Cracked the Enigma Code, Hunted Down Russian Submarines, and Emerged Triumphant From Two Centuries of Controversy*; Yale University Press, CT, 2011.
13. N. Silver. *The Signal and the Noise: Why So Many Predictions Fail—but Some Don't*, Penguin Press, NY, 2012.

14. In probability theory, Bayes' Rule commonly is expressed as: $P(A|B) = P(B|A) P(A) / P(B)$. This algebraic formulation, $[(xy / ((xy + z(1-x)))]$ is copied from Nate Silver's book (*The Signal and the Noise*) and, for the purposes of this article, has been verified by multiple authorities, including a preeminent professor of Bayesian statistics.
15. Silver.
16. Even though we think it likely that generally consistent construction can be expected at 90% or more of the decks, for credibility purposes, we choose to begin our Bayesian calculations with much lower odds (50%). Potential critics of this assessment are free to assign lower (or higher) values to this prior probability.
17. Remember that you have agreed temporarily—solely for reviewing purposes—to accept the validity of the 80/90 Rule. While this “rule” finds broad acceptance by our peers, one purpose of this article is to introduce this general consistency concept to a broader audience.
18. While basic algebra shows us that setting an even higher value for this conditional probability (false positives) would lead to extra rounds of sampling, it should be noted that consultants representing original contractors opine strongly that the overall percentage of negative drainage at the decks that do not exhibit concrete stalactites actually is much lower. Our estimation of this value simply reflects professional expertise and experience.
19. In short, Bayes' Rule has enabled us to become 96% confident that at least 90% of the decks have negative drainage and related deficiencies.
20. McGrayne.
21. W.M. Bolstad. *Introduction to Bayesian Statistics, 2nd Ed.*, John Wiley & Sons, NJ, 2007: “Bayesian statistics has a single tool, Bayes' theorem, which is used in all situations.”
22. C.L. Searls and T.N. Stubblefield. “Investigation of Large-Scale Building Envelope Leakage.” *Forensic Engineering* (Volume 166). Institution of Civil Engineers. London, United Kingdom, 2013: “The building envelope investigation is not based on conventional hypothesis testing and quantitative random sampling, but rather on scientifically valid principles of qualitative analysis (ASTM, 2012; Haughton and Murphy, 2007). The building is known to leak, and the purpose of the investigation is to determine why it leaks, the extent of leakage and possible repairs. This is done through a process of observation, testing, and analysis using the engineer's experience. Investigation is a problem-solving process that is often not linear.”
23. L.L. Haughton and C.R. Murphy. “Qualitative Sampling of the Building Envelope for Water Leakage,” *Journal of ASTM International*, Vol. 4, No. 9, paper ID JAI100815, 2007: “...There are relatively few building envelope investigations for which statistical random sampling, in and of itself, is a legitimate or practical methodology for achieving a comprehensive understanding of the sources and mechanisms of water leakage; and therefore, the use of quantitative (i.e., statistical) survey protocols to evaluate the validity of purposeful qualitative sampling of the building envelope is not appropriate.”
24. *Building Enclosure Rehabilitation Guide: Multiunit Residential Wood-Framed Buildings*, Oregon Housing and Community Services, Salem, OR, 2011: “From this perspective, it is favorable to utilize information-rich sampling, rather than random, blind sampling. This methodology is well established in the field of qualitative analysis. In their paper, ‘Qualitative Sampling of the Building Envelope for Water Leakage,’ Lonnie L. Haughton and Colin R. Murphy provide a useful lay discussion of qualitative analysis and its direct benefit with use in the building assessment industry.”
25. A. Gelman, J.B. Carlin, H.S. Stern, and D.B. Rubin. *Bayesian Data Analysis*, Chapman & Hall / CRC Press LLC, Boca Raton, FL, 2000.
26. Note again that our 80/90 Rule specifically addresses projects that have been constructed in a single phase under the direction of one general contractor using the same primary subcontractors throughout.
27. C. Howson and P. Urbach. *Scientific Reasoning: The Bayesian Approach*, 1989: “There is a subjective element in the Bayesian approach which offends many, but this element, we submit, is wholly realistic; perfectly sane scientists with access to the same information often do evaluate theories differently, although, as the Bayesian predicts, they normally approach a common view as the evidence accumulates.”
28. Assume a 95% “confidence interval” and a 5% “margin of error” with a predicted 90% “response distribution.”
29. I.e., the budget for labor, materials, coordination, observation, documentation, analysis, review and reporting is \$4,000 per deck.
30. Haughton and Murphy. “...For their findings to be considered substantive, building envelope professionals must avoid any degree of biased advocacy that hides, distorts, or selectively interprets the collected data.”
31. K.W. Harrison. “If You've Ever Used Engineering Judgment, You Just Might Be a Bayesian.” *Journal of Environmental Engineering*, March 2005.
32. Silver.

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