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UNCERTAINTY QUANTIFICATION OF SEISMIC STRUCTURAL SYSTEMS: THE ROLE OF GENERALIZED INFORMATION THEORY

R. Corotis [(1)]

[(1)] *Professor, Dept of Civil, Environmental & Architectural Engineering, University of Colorado, Boulder, USA, corotis@colorado.edu*

Abstract

Uncertainty is inherent in the assessment and prediction of the seismic performance of structures and community infrastructure when evaluating risk, hazard mitigation and community vulnerability/resilience. Increasingly, community risk-informed infrastructure decisions need to reflect multiple issues of society, including social, political, economic and cross-disciplinary factors. This breadth introduces challenges regarding information/partial knowledge and disparate characteristics of uncertainty from different sources. Traditionally, probabilistic methods have been employed to systematically treat the uncertainty for structural reliability theory. Although these methods or probabilistic methods can address partial information in the face of uncertainty, they are not the most appropriate or powerful approaches for comprehensive incorporation of broader contexts of uncertainty reflecting expert judgement, imprecision, and possibility and evidence theories. Certainly, subjective probabilities can capture expert judgments, but the combination of conflicting opinions remain a challenge. Limitations in probability theory have often led to a failure to fully understand the implications of the broader aspects of uncertainty in human decision-making incorporating judgement and unpredictability.

Methods under the umbrella of *Generalized Information Theory* (GIT) provide a natural framework for linguistic and imprecise data, as is typical from field evaluations both before and after an earthquake. One particular technique, fuzzy classification, has been explored recently to examine general tendencies of damage to concrete buildings from seismic events. This current paper provides some additional background and analysis of that study, and utilizing actual data based on individual building observations, seeks to uncover the existence of building damage patterns among structural, geotechnical and hazard parameters. Additional methods of generalized uncertainty, such as monotone measures, are discussed in the context of augmenting traditional probability approaches to better predict the behavior of buildings during earthquakes.

Keywords: building performance; field evaluation; fuzzy classification; risk assessment; seismic performance

1. Introduction

There are many situations involving uncertainty for which probability theory may not be the most natural framework in which to quantitatively incorporate that uncertainty. One of those is structural vulnerability to seismic hazards, in which multiple experts use subjective judgment to estimate the potential damage to individual structures. Two aspects of this situation are not conveniently handled with probability: (1) conflicting expert opinion, and (2) a significant degree of ignorance. This paper is principally concerned with one aspect of generalized uncertainty theory: the replacement of crisp sets with fuzzy classification for earthquake building damage states. It also introduces some further discussion of other aspects of generalized uncertainty.

In the case of multiple opinions, one can of course combine these in a Bayesian fashion, which is based on the concepts of subjective probability or degree of belief. But such an approach can lead to averaged results that do not convey the nature and degree of conflict if it is strong. The Delphi method is a useful unbiased technique to facilitate reaching a consensus from multiple opinions, but it relies on several cycles in which the experts are willing to move toward a common convergence.

The issue of ignorance is also of interest. Consider the case where there is a certain degree of evidence (or belief) that an event A belongs to a certain collection of points (A, and or subsets of A). This can be designated the belief in A, or $Bel(A)$. Suppose we also have a degree of belief that the event does not belong to A or any of its subsets; this is denoted $Bel(\bar{A})$. This last term reflects the belief that the event is not encompassed by A, and can be used to define the plausibility of A; $Pl(A) = 1 - Bel(\bar{A})$. The plausibility of A, then, is the lack of belief in the event not being contained within A. There are clearly cases when the degree of evidence supporting A, $Bel(A)$, and the degree of evidence supporting "not A", $Bel(\bar{A})$, do not sum to unity. That weakness, when it exists, is termed the ignorance. Only in the case of no ignorance do the belief measures become probabilities [1]

Beliefs and plausibilities form the basis of evidence theory. As discussed by Ross [1], there may be circumstances for which we have quantifiable information on the occurrence of an event, A, but do not have evidence for the occurrence of $\bar{A}$ (that is, the non-occurrence of A). In such a case evidence theory becomes essential, since it is free from the axiom of probability theory that requires $P(\bar{A}) = 1 - P(A)$.

2. Damage States

The development and discussion in this paper are based on a case study from the 1994 Northridge, California earthquake. The results were reported by Elwood and Corotis [2], but space limitations prevented a discussion of the philosophy behind many interesting aspects of assigning data to quantitative measurable sets based on linguistic descriptors.

2.1 ATC Database

As described in Elwood and Corotis [2], data were obtained from an Applied Technology Council report, ATC-38, describing the damage to structures in the Los Angeles, California area from the 1994 Northridge earthquake [3]. This set of reported observations will be referred to as the ATC database. While damage is generally associated with a quantitative measure, damage assessment is actually a consequence of evaluator judgment, is based on observable portions of the building, and reflects estimates of the underlying structural characteristics. Therefore, while the damage itself is observable, the act of ascribing it to a damage state represents a fuzzy assignment. Different documents have sought differing levels of granularity in these damage states. The ATC-38 document reporting the Northridge damage used the four states shown in the following table. It should be noted that these states represent an overall assessment of the building, which may have very different degrees of damage in different parts or for different elements.

Table 1. ATC-38 Overall damage states used in the ATC database

Code	Description
N	No damage visible, either structural or nonstructural
I	Insignificant damage, requiring only cosmetic repairs (no structural)
M	Moderate, displaying repairable structural damage, capable of being done in place without substantial demolition
H	Heavy damage, requiring extensive repair with major demolition or replacement

The evaluators assessed "overall" building damage in terms of the linguistic descriptors above. They assigned ATC-13 damage classes as listed below to four building element categories separately: structural, nonstructural, equipment and contents. We combined the structural and nonstructural ATC-13 assignments, as will be discussed later, and then used all element categories to assign overall building damage in terms of building replacement cost, as prescribed in Applied Technology Council guide ATC-13 [4]. For this classification, cost is based on the structural system, nonstructural elements, equipment and contents. These ATC-13 states are finer than the first method adopted in ATC-38, but also involve a greater degree of judgment.

Table 2. ATC-13 Damage states used in the ATC database

Damage State	Repair as % of Replacement Cost
1 – None	0%
2 – Slight	0% - 1%
3 – Light	1% - 10%
4 – Moderate	10% - 30%
5 – Heavy	30% - 60%
6 – Major	60% - 100%
7 – Destroyed	100%

While the ATC-13 damage states are useful in assessing overall impact to individual buildings, there is significant uncertainty in these assignments, especially since the four building element categories had to be combined. Clearly the two different approaches listed above are intended to provide similar information regarding the amount of damage to a structure. The damage states described in ATC-13 were chosen as the basis for the fuzzy pattern recognition in Elwood and Corotis [2] since they were consistent with the damage estimates reported in a second database described in the next section.

The ATC-13 damage states have a relatively finer granularity for damages in the range of 0% to 10%, where much of the damages were reported for the Northridge earthquake. In fact, however, it is difficult for the inspectors to distinguish among these states. Also, in a practical sense, such distinction might not be of major importance. Additional uncertainty relates to the question of exactly what physical losses are recorded by the inspectors.

It is interesting to note the similarity of linguistic terms used with ATC-38 approach and those from the ATC-13 document in the ATC database. In the former they are intended to relate to the types of repairs required, while in the latter they are related to cost of repair. Since the surveys for the ATC database assigned both sets of damage statistics, the following table provides some insight into the consistency as reported in actual surveys.

The ATC databased consists of 530 building records. For the fuzzy pattern recognition reported in Elwood and Corotis [2], it was decided only to use buildings identified as concrete structures. This provided a set of 93 records from which to attempt a preliminary classification reflecting characteristics such as number of stories, code at time of construction, soil stiffness and peak ground acceleration. The following table shows the degree of consistency for 89 of the 93 concrete records between the ATC-13 and ATC-38 recordings (note that four records did not contain damage information). It can be seen that for the lower damage states, there is relatively good agreement (if the ATC-38 state of Insignificant was construed by the surveyors as sometimes corresponding to the ATC-13 state Slight and sometimes None), but that the disparity increases with the higher damage states. For instance, the ATC-13 Damage State of Light was classified as both Insignificant and Moderate in ATC-38, and in one case the ATC-13 classification Moderate was considered Insignificant in ATC-38. It is recalled that the ATC-13 Damage States were created by combining the structural and nonstructural damage (separately from the equipment and contents), whereas the ATC-38 approach does not distinguish.

Table 3. Comparison of ATC-13 and ATC-38 Classifications

ATC-13 Damage State	**ATC-38 Overall Damage State**			
	None	Insignificant	Moderate	Heavy
1 – None	12	6	0	0
2 – Slight	1	36	4	0
3 – Light	0	9	16	0
4 – Moderate	0	1	1	2
5 – Heavy	0	0	1	0
6/7 – Major/Destroyed	0	0	0	0

It is clear that the differences among linguistic descriptions of damage levels can lead to ambiguity in building damage estimates, and that estimates based on qualitative descriptions of damage repair can differ significantly from estimates based on costs of repair.

2.2 OES Database

A separate database, also reported in Elwood and Corotis [2], was obtained and used in conjunction with a description from the State of California Geographic Information System Group of the Governor’s Office of Emergency Services (OES) and reported by the consulting firm EQE International [5,6]. Information for the OES database was supplemented by information posted by the University of California [7]. This information will be referred to as the OES database. This was a very large database of buildings throughout the Los Angeles area, with damage reported two ways: as a percentage of building cost, and in terms of color tags. A red tag indicated that the building could not be occupied a yellow tag indicated that the building was not safe to be immediately occupied, and a green tag indicated that it could be occupied while repairs were being done. In some cases, inspectors also provided approximate damage estimates in terms of dollar value loss or percentage of damage. The tag assignment provides valuable information for recovery plans, reflecting safety concerns, attempting to assess life-safety incorporating the possibility of aftershocks [8]. Because of these multiple objectives, there is the potential for a great deal of uncertainty between actual building damage states and the tag color. For instance, buildings might be declared unsafe because they are located on unstable ground or adjacent to structures that may pose a safety hazard, although this could be due to adjacent buildings rather than damage to the particular structure. For the ATC data set, only a handful of records included tag assignment information. Because of these reasons, including the fact that there are only three tag colors, it was decided that there is the potential for a great deal of uncertainty in attempting to relate these tag data to the ATC approach. Therefore, the percentage of building cost damage approach was selected from this second database, and these could be readily related to the ATC-13 damage states reported for the ATC database.

For the OES database, the reported building damage factor estimates combine structural and nonstructural damage, but only to the principal building on a lot (the report specifically excludes fences, automobiles, etc.), and not to additional insurance losses such as damaged contents, theft, living expenses and business interruption. To make the two databases comparable, it was necessary to combine the estimates for structural and nonstructural damage in the ATC database in order to obtain a total damage figure comparable to the OES database. This was done from historical data relating the cost of structural to nonstructural damage as a function of building construction type [9]. Replacement costs were then computed for structural items, acceleration-sensitive nonstructural items, and drift-sensitive nonstructural items. The results are presented in Table 4.

Table 4. Construction replacement costs (in $ per square foot) by structure type (SFD: single-family dwelling; MFD: multi-family dwellings; B/B/Other: brick/block/other concrete) [10, 11] as reported by EQE [5, Table 4-6, p. 4-18].

Construction Items	**SFD Wood**[1] (per sf)	**MFD Wood** (per sf)	**Steel Frame** (per sf)	**Concrete Frame** (per sf)	**B/B/Other Concrete** (per sf)
Structural Costs	$15	$11	$14	$14	$8
Acceleration-sensitive nonstructural	$17	$35	$35	$35	$37
Drift-sensitive nonstructural	$32	$34	$24	$24	$6
Total	$64	$80	$73	$73	$51
% Structural (approximate)	23%	14%	19%	19%	16%
% Nonstructural (total approximate)	77%	86%	81%	81%	84%

[1] ATC-38 assumed 40%/60% for a typical California wood frame building (ATC 2001, p. 52).

To compare the damage information from the OES database with that of the ATC database, the information in Table 4 was used with the ATC database information [4] and the assigned damage factors for the structural and nonstructural damage separately. These ratings were converted to estimated cost of damage for each, and then combined for total damage. This was done for each building, with analysis limited to concrete buildings, as noted earlier.

These discussions and calculations show the difficulty of separating structural and nonstructural damage from reported surveys. Costs for each are dependent on several factors, including building design, owner requirements, geographical location and issues such as seismic upgrade requirements [11]. These costs are also dependent on occupancy type as well as construction material. It is interesting to note that in about half of the ATC database and almost all of the OES database the reported nonstructural damage state was higher than the structural damage state. These reports reinforce the importance of reliable estimates for the amount of nonstructural damage. One source [12] suggests that for stiff structures the amount of structural and nonstructural damage tend to be similar, concluding that drift levels in these structures result in both types of damage. This seems to imply that more flexible structures can experience larger drifts that cause nonstructural damage while avoiding structural damage.

2.3 Linguistic Descriptors of Additional Variables

In addition to damage levels, other variables of interest related to the seismic performance of buildings can introduce challenges. In fuzzy classification, linguistic descriptors are associated with membership functions.

Each of these will be examined in the next subsections. These sections illustrate the type of adjustments to raw data that are sometimes necessary in order to perform linguistic-based analysis of fuzzy-based pattern recognition or clustering [2]. The symbol v_{ij} is used for the variable in each case (the subscripts are not utilized in this paper, but are kept since they relate to analyses in the original paper [2]).

2.3.1 Building Height

Building height descriptions are adapted from the FEMA 154 Data Collection Form for High Seismicity [13]. These are *Low*, *Mid* and *High*. These are considered too coarse for pattern recognition, so intermediate descriptors were introduced and defined as shown in Table 5.

Table 5.Linguistic description assignments for building height.

Building Height Description	Prototype Value Range (Number of Stories)
Low-Rise (L)	$1 \leq v_{ij} < 3$
Low/Mid-Rise (L/M)	$3 \leq v_{ij} < 5$
Mid-Rise (M)	$5 \leq v_{ij} < 7$
Mid/High Rise (M/H)	$7 \leq v_{ij} < 8$
High-Rise (H)	$8 \leq v_{ij}$

2.3.2 Building Age

Building age descriptions are generally adopted from FEMA 154 [13]. Linguistic description assignments for building age are listed in Table 6.

Table 6. Linguistic description assignments for building age.

Building Age Description	Prototype Value Range (Year Built)
Pre-Code	$v_{ij} < 1941$
Moderate Code	$1941 \leq v_{ij} \leq 1975$
Post-Benchmark	$1975 < v_{ij}$

2.3.3 Soil Type

Descriptions for soil type are adopted from FEMA 154, with intermediate soil type descriptions added at the boundaries of classes [13]. Letter designations for the additional intermediate soil types were developed based on the following convention: *X/Y*, where *X* is the FEMA 154 reported class, and *Y* is the nearest bordering class. Linguistic description assignments for soil type are listed in Table 7.

Table 7. Linguistic description assignments for soil type.

Soil Type Description	Prototype Value Range (Vs, feet/sec)
Hard Rock (Type A)	$v_{ij} > 5{,}000$
Rock (Type B)	$2{,}500 < v_{ij} \leq 5{,}000$
Soft Rock (Type C/B)	$2{,}300 < v_{ij} \leq 2{,}500$
Very Dense Soil (Type C)	$1{,}400 < v_{ij} \leq 2{,}300$
Dense Soil (Type C/D)	$1{,}200 < v_{ij} \leq 1{,}400$
Very Stiff Soil (Type D)	$900 < v_{ij} \leq 1{,}200$
Stiff Soil (Type D/E)	$600 \leq v_{ij} \leq 900$
Soft Soil (Type E)	$v_{ij} < 600$

2.3.4 Earthquake Intensity

Descriptions of earthquake intensities are adapted from Wald et al [14]. They report that these labels are not consistent with observed intensities, but rather, consistent with intensities that are, on average, levels of perceived shaking that have been calibrated to earthquake recordings based on a number of past earthquakes. Wald et al. [14] state that the word descriptions were generally derived from Modified Mercalli Intensity descriptions but that for Modified Mercalli Intensities VII and higher, the descriptions are exaggerated. This is apparently due to evidence that peoples' perceptions of shaking at these levels are generally indistinguishable.

Linguistic description assignments for earthquake intensity are listed in Table 8. One intermediate description has been added to the *Very Strong* range of horizontal peak ground accelerations. A similar naming convention described for intermediate ranges of soil types is used to label this range of earthquake intensities.

Table 8. Linguistic description assignments for horizontal peak ground acceleration.

Description for Perceived Shaking	**Prototype Value Range (Peak Acceleration, g)**	**Instrumental Intensity**
Not felt (N)	$0 \le v_{ij} < 0.0017$	I
Weak (W)	$0.0017 \le v_{ij} < 0.014$	II-III
Light (L)	$0.014 \le v_{ij} < .039$	IV
Moderate (M)	$0.039 \le v_{ij} < .092$	V
Strong (ST)	$0.092 \le v_{ij} < .18$	VI
Very strong/Strong (VS/S)	$0.18 \le v_{ij} < 0.26$	VII
Very strong (VS)	$0.26 \le v_{ij} < 0.34$	VII
Severe (SE)	$0.34 \le v_{ij} < 0.65$	VIII
Violent (V)	$0.65 \le v_{ij} < 1.24$	IX
Extreme (E)	$1.24 \le v_{ij}$	X+

3. Effectiveness of Fuzzy Pattern Recognition

Results of the clustering approach are reported in Elwood and Corotis [15] and of the fuzzy pattern recognition in Elwood and Corotis [2]. The reader is referred to those papers for more details on those results. Those publications, however, did not contain an analysis of the effectiveness of this approach using pattern recognition (which it could be argued is more abstract than traditional probability-based approaches, such as regression analysis).

Table 9. Confusion matrix for the ATC data.

Damage Class Reported		**Classifier Label (Assigned Pattern Label)**					
		1 (None)	**1 or 2[1] (N/S)**	**2 (Slight)**	**3 (Light)**	**4 (Moderate)**	**5 (Heavy)**
Reported Label (True Label)	1 (None)	7	0	5	1	0	0
	1 or 2 (N/S)	0	9	0	0	0	0
	2 (Slight)	1	0	31	3	0	0
	3 (Light)	2	1	6	14	0	0
	4 (Moderate)	1	2	0	1	0	0
	5 (Heavy)	0	0	0	0	0	1

[1] Classifications were counted correct if the data sample is classified as either ATC-13 *None* (1) or ATC-13 *Slight* (2).

Table 9 gives the Damage Class that was predicted by the fuzzy pattern recognition (the columns) in comparison to the Damage Class assigned by the evaluator (the rows) for the ATC-38 information used in the ATC database for concrete structures.

The training error for these data is 27% (23 errors in 85 cases), which is rather high, and as the *confusion matrix* in Table 9 indicates, in 13 of those cases the classifier label differed from the field label by more than one class. About half of these errors of more than one category are associated with buildings where the surveyed results were listed as None.

The pattern recognition results in Table 9 are based on a fuzzy pattern that indicated that seven clusters of data were reasonable. This is a tradeoff of accuracy and simplicity, and the use of more clusters would have given more "uniqueness" of features for each cluster and potentially less overlap. A larger number of clusters, however, runs the risk of creating false indications of delineation (cause and effect) when the data have an inherent degree of vagueness, as is the case here.

The algorithm was also run with the seven clusters for concrete structures on the OES data, which had not been used in developing the clusters. In this case there were 51 data points, and the classifier label was only correct within one class in about half the cases, Interestingly, however, the errors were generally in the classifier assigning None as damage to cases that were recorded as having anywhere from Slight to Major damage. Without those incorrect assignments to None, the classifier was correct (within one class) in 26 out of 30 cases.

There could be several reasons for the disparity in training with the ATC training data and the OES data. The results should not be heavily dependent on the differing frequency of occurrences in the different classes between the two sets since the classification is based on degree of compatibility, as opposed to frequency of observed characteristics. Such differences in frequency, however, do lead to sensitivity of results. Differences in training of the personnel between the two databases is a strong possibility.

4. Believability Basis for Damage Class Assignment

Consider the use of FEMA 154 [13] and ATC 20 [8], in which the seismic damage states are discretized as follows:

None (N)
Slight (S)
Light (L)
Moderate (M)
Heavy (H)

One of the challenges with these states (as with all the damage state approaches discussed earlier in this paper) is that they really represent fuzzy sets, without a clear or crisp delineation among them. Therefore, methods of fuzzy classification should be employed to assign individual structures [2]. Another issue as discussed earlier, applying to both crisp and fuzzy sets, is that the axioms of probability can be overly restrictive in relation to the use of expert judgment in assigning the "likelihood" of occurrence or beliefs of these states, taken both individually and in combinations. Given building and seismic hazard characteristics, an individual expert might have an estimate for the likelihood of each of the five states above. But it is conceivable that he or she would feel somewhat uncomfortable with specific probabilities, recognizing the possibility that damage within a structure might be associated with more than one state. Similarly the expert might feel more comfortable if some states were combined.

Evidence theory was discussed in the Introduction to this paper. One other non-probabilistic concept that is important to introduce is that of possibility theory. As with evidence theory, possibility theory deals with incomplete information, and requires a pair of descriptors (these were beliefs and plausibilities in the case of evidence theory, and are termed possibilities and necessities in the case of possibility theory). Possibility theory forms the basis of imprecise probabilities (usually associated with upper and lower bounds of probability), and can be a useful tool in transforming belief functions into possibilities and necessities, and thence to more commonly recognized probability measures.

Given building and seismic hazard characteristics, an individual expert might have an estimate for the likelihood of each of the five states above. It may be that the judgement of an expert in assigning “likelihoods” to these states is much closer to the concepts of believability in evidence theory than to the strict rules of probability. In particular, expert opinion is often solicited in terms of basic evidence assignments, which assign evidence to sets and subsets of outcomes. In the case of damage assessment in particular, it is likely that an expert would feel somewhat uncomfortable having to assign specific probabilities associated with damage level, recognizing the possibility that damage within a structure might be associated with more than one state. Similarly, if some states were combined, the expert might be able to assign a higher believability. One solution to address this uneasiness is to work with the power set of all possible states.

Consider the state of damage, D, to be defined in terms of the five single and distinct individual damage terms defined above, and their combinations. The power set (or technically, the first-order power set of D) is defined by the following 32 elements (there are 2^N power sets for any set of order N):

No elements:	{Ø}
Single elements:	{N}, {S}, {L}, {M}, {H}
Double elements:	{N,S}, {N,L}, {N,M}, {N,H}, {S,L},{S,M}, {S,H}, {L,M}, {L,H}, {M,H}
Triple elements:	{N,S,L}, {N,S,M}, {N,S,H}, {N,L,M}, {N,L,H}, {N,M,H}, {S,L,M}, {S,L,H}, {S,M,H}, {L,M,H}
Quadruple elements:	{N,S,L,M}, {N,S,L,H}, {N,S,M,H}, {N,L,M,H}, {S,L,M,H}
Quintuple element:	{N,S,L,M,H}

At first glance, it may seem unreasonable to ask an expert to assign values to so many options. But the alternative is to decrease the accuracy and value of the assignments by forcing responses into either a single category, or likelihoods of the single elements. The challenge is to develop a scheme or system for evaluator experts that is consistent with the way they are likely to express their feelings of likelihood in terms of basic evidence.

An advantage of evidence theory is that the beliefs of multiple inspectors can be combined into a total assessment. Because beliefs are monotone measures, and they can be converted something termed basic evidence assignments, or Mobius measures [1, 16]. The measures can be combined from multiple experts [16, page 539], and then converted back into consensus beliefs.

5. Conclusions

Traditional quantitative techniques to deal with uncertainty have served the earthquake engineering community very well. These include both frequentist and subjective fundamentals of probabilistic theory, and particularly the use of Bayesian network concepts for updating of information and targeted cause and effect analysis. As the community has attempted to incorporate broader issues of concern, such as social, political and economic well-being, it has faced the challenge of integrating qualitative measures, as well as differing types of quantitative measures that have very dissimilar types of uncertainty. The relatively new field of Generalized Information Theory attempts to develop measures that are freed from some of the axioms of probability theory. Several of these measures are founded on natural approaches to expressing uncertainty. An extended explanation of the various measures used in a recently published fuzzy classification study for building damage states following the 1994 Northridge, California earthquake is provided. These demonstrate the degree of subjective judgement that might be necessary in combining various input measures for an analysis, even when they are of the traditional seismic analysis nature, and do not include sociological aspects. An outline of how concepts of believability might be used in damage class assignments in place of strict probabilities is then presented.

The broader impacts of these approaches provide exciting new opportunities in the incorporation of field data and in communicating to a seismic risk-informed community. Disparate sources of quantitative and linguistic uncertainty could be incorporated under a design philosophy umbrella capable of handling vagueness, ambiguity, expert opinions and confidence.

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