The Psychology of Conflictive Uncertainty

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Abstract. In the literature on multi-view learning techniques, "view disagreement" is listed as among the major challenges for multi-view representation learning. View disagreement is distinct from nonshared features in alternative views, because it gives rise to a type of uncertainty that humans find especially aversive, i.e., "conflictive uncertainty". This chapter presents an overview of the psychological effects of conflictive uncertainty, and then provides some guidance for resolving and communicating about conflictive uncertainty that may avoid its problematic impacts on decision making and source credibility. Implications are discussed for developing explainable multi-view methods in the face of view disagreement.

Keywords: View disagreement, Conflictive uncertainty, Nonshared information, Ambiguity, Trust, Credibility

1 Introduction

Data from multiple sources may generate conflicting (disagreeing) views, estimates, or predictions, thereby requiring methods for resolving such disagreements. Recent reviews of multi-view learning techniques [1,2] list " view disagreement" as one of the challenges facing multi-view representation learning. However, these surveys do not treat this problem as distinct from nonshared information across views, and instead discusses techniques as though alternative views always provide "complementary" information that can be safely resolved via techniques for data fusion and modeling associations among variables, or "nonshared" information that may be discarded in the process of resolving divergent views. Such approaches may suffice when disagreement is a matter of degree (e.g., drug X is 60% effective according to one study but 40% effective according to another) but not when two or more alternatives cannot simultaneously be true (e.g., drug X is effective according to one study but ineffective and harmful according to another).

The position taken in this chapter is that view disagreement is distinct from nonshared features in alternative views, because it gives rise to a type of uncertainty that humans find especially aversive. In this chapter uncertainty arising from disagreeing or conflicting information will be called "conflictive uncertainty", or CU. While developing normatively adequate methods for resolving CU is undoubtedly important, it also is important to ensure that these methods are explainable and well-suited to the decision-makers who will use them. For instance, in a meta-analysis of factors influencing trust in human-robot interaction, Hancock et al. [3] recommend “transparency” in system designs and algorithms that are accessible and clear to human users, and currently explainable artificial intelligence is a fast-growing area of research and development.

A key influence on decision-makers' attitudes towards alternative methods of resolving CU is their attitude toward CU itself. Understanding how decision makers think about and respond to uncertainty arising from conflicting information may provide guidance for designing and implementing such methods. It turns out that people treat CU differently from other kinds of uncertainty. Psychological research on this topic over two decades has consistently found that people view CU as more aversive than uncertainty arising from ambiguity, vagueness, or probability. CU also has been shown to have potentially deleterious consequences for decision making. Lastly, there are communications dilemmas for sources that provide inputs potentially leading to CU because communications resulting in CU can decrease trust in those sources.

These findings have implications for best design-practices in resolving CU and communicating about it to non-specialists. This chapter presents an overview of the relevant literature on the psychological effects of CU, and then provides some guidance for resolving and communicating about CU that may avoid or reduce effects that are problematic for decision making and source credibility.

2 Conflictive uncertainty

Conflictive uncertainty refers to uncertainty arising from disagreement about states of reality that the cognizer believes cannot be true simultaneously. If one source tells us that today is Tuesday and another tells us that today is Thursday, then we will regard these statements as conflicting if we believe that Tuesday and Thursday cannot occur simultaneously. If we do not know what day it is, then the two statements will arouse CU for us. Thus, CU occurs when two or more hypothetical states that cannot simultaneously be true are stated as true by separate sources and/or the same source on separate occasions, and the recipient of these statements does not know which (if either) to believe.

Conflict is related to ambiguity and vagueness, and the distinction between them is somewhat blurry. An early definition of ambiguity defined it as a condition in which a referent has several distinct possible interpretations, but these may be able to be true simultaneously [4]. Smithson [5] gives an example of ambiguity in the statement "this food is hot", potentially referring to the food having high temperature, or being spicy, or sexy, or fashionable, or having been stolen. All of these states could hold about the food at the same time, so the statement is ambiguous but not conflictive. Thus, conflicting states seem to be a special case of ambiguous states.

Some formal perspectives allow this kind of distinction, but not all of them do. For instance, Shafer's belief function framework distinguishes between conflictive and non-conflictive forms of uncertainty [6]. In that framework, conflict occurs when nonzero weights of evidence are assigned to two or more disjoint subsets of a universal set. However, there also are generalized probability frameworks that deal in sets of probabilities, where the distinction between ambiguity and conflict appears unnecessary or irrelevant (an accessible survey of such frameworks is provided in [7].

The connection between conflict and ambiguity regarding psychological states of mind was first suggested in Einhorn and Hogarth's pioneering study when they claimed that conflict can be experienced as ambiguity [8]. However, it was not clear at the time whether the uncertainty aroused by conflicting information would be equivalent to that evoked by ambiguity. More recently, a popularization of this type of uncertainty [9] refers to it as "noise" without distinguishing it from ambiguity or other kinds of uncertainty. Nevertheless, we shall see that people treat the distinction between them as real. There are clues about this possibility in the psychological literature as far back as Festinger's [10] discussion about people's aversion to inconsistency, and attribution theory's inclusion of consensus among the three major determinants of causal attribution [11].

Whether alternative states are *perceived* as conflicting crucially depends on beliefs about when or whether different states can hold at the same time and attributions regarding why they differ. A vaccine cannot be effective and ineffective at the same time for the same person, but it can be effective for one person and ineffective for another. If the vaccine is effective for 50% of the persons tested in clinical trial A and also for 50% tested in trial B then this usually would not be regarded as conflicting information, but if it was 100% effective in trial A and 0% ineffective in trial B then this would be regarded as conflictive.

Likewise, agreed-upon ambiguity or vagueness from multiple sources is not perceived as conflicting information. If experts C and D both claim that a vaccine may be effective for either 30% or 60% of a population then laypeople would be unlikely to perceive conflict there because the experts are in agreement. However, they would perceive conflict if C says the vaccine is 30% effective while D says it is 60% effective. The primary feature distinguishing conflict from ambiguity is disagreement among sources or inconsistency by a source over time, and we shall see that it is this distinction that seems to be most important psychologically.

3 Conflictive uncertainty aversion

The first type of non-probabilistic uncertainty found to influence decision makers was ambiguity of a particular kind [12]. The Ellsberg-type demonstration that ambiguity is psychologically reactive involves asking people to choose between betting on drawing, say, a red ball from a "risky" urn that has 50 red and 50 white balls therein, versus betting on drawing a red ball from an "ambiguous" urn with 100 red and white balls of unknown composition. A uniform (or even a symmetric) prior over the probability of drawing a red ball from the ambiguous urn should result in a rational agent being indifferent between the unambiguous 50-50 urn and the ambiguous urn. However, numerous experiments of this kind have shown that most people prefer the unambiguous risky urn (see the review in [13]). This phenomenon often is referred to as "ambiguity aversion".

Reactions to uncertainty arising from ambiguity have been much more widely studied than reactions to CU, partly because the latter was not systematically investigated until the late 1990's. Some of the findings in the ambiguity literature apply to CU, although others do not, and their comparison is instructive. We therefore will briefly survey the main findings regarding responses to ambiguity and discussions about whether or when such responses are irrational.

There has indeed been considerable debate over whether or when ambiguity aversion is irrational. Briefly, most of the arguments for its irrationality focus on just the first moment of the distributions of outcomes for repeated gambles under ambiguity versus risk, i.e., their respective expected values. In the classic Ellsberg setup the expected values of both urns are identical, so by this line of reasoning concern over ambiguity is irrelevant. Some arguments against irrationality draw attention to the second distribution moment, observing that draws from an urn whose composition randomly (and symmetrically) varies around 50-50 will be greater than draws from a constant 50-50 urn, and if an agent assigns less utility to greater variance then they are not irrational in preferring the 50-50 risky urn. It is not difficult to imagine scenarios where concern about variability in outcomes would make sense [14]. For instance, humans would be well-advised to strongly prefer dwelling in a room whose temperature is constantly, say, 22 degrees Celsius over a room whose average temperature also is 22 degrees but assigns its daily temperature via random draws from a Gaussian distribution with a mean of 22 and a standard deviation of 40.

There also is a long-running debate over whether rational agents must have precise credences (subjective probabilities), or whether they may still be rational if they have imprecise (ambiguous) credences. The default model for a Bayesian decision making agent assumes that the agent has precise probabilities [15], but there has been increasing allowance for rational agent models in which the agent deals in sets of probability functions [16, 17]. Some scholars in this debate even have argued that rationality actually requires credences to be indeterminate and therefore imprecise [18].

Returning now to ambiguity aversion, [12] speculated and subsequent research has confirmed that it is neither universal nor ubiquitous. It holds generally for prospects of gains with moderate to high likelihoods, but even there many people appear to be indifferent to ambiguity versus risk. Moreover, experimental evidence on ambiguity attitudes where the prospective outcome is a loss indicates ambiguity aversion mainly for low likelihood losses, but ambiguity seeking for moderate to high likelihood losses [19, 20]. Likewise, ambiguity seeking often is found for low likelihood gains, especially when the stakes are high [13]. Using an elaborate experimental design, [21] report widespread ambiguity-neutrality under all conditions deviating from a gain prospect with moderate likelihood, and some evidence of ambiguity-seeking under low-likelihood prospects.

To what extent do CU reactions parallel reactions to ambiguity? And are they at similar levels, i.e., if people are given a choice between informationally equivalent agreeing- ambiguous sources versus disagreeing-unambiguous sources, do they exhibit a preference? Two early, independent, investigations produced evidence that people prefer agreeing-ambiguous information over disagreeing-unambiguous information. These investigations were the first to suggest that people distinguish between uncertainty arising from ambiguity and uncertainty arising from conflicting information.

Viscusi [22] employed an experimental setup in which respondents considered the choice of moving to one of two locations, each posing a cancer risk from air pollution. One area had full information regarding the risk, whereas the risk information for the other area came from two sources. Viscusi set up these conditions so that a Bayesian learner would be indifferent between the two areas' risks, with the expected utility functions equating an imprecisely assessed probability to one for which there is expert consensus. The results showed a consistent preference for the full-information area. Viscusi also reports that participants in the experiment devoted "excessive" attention to worst-case scenarios. He concludes that disagreeing risk information from experts results in greater risk overestimation by laypersons than risk information on which experts agree.

Smithson [5] experimentally investigated ambiguity vs conflict preferences in several hypothetical scenarios. His first experiment adapted a scenario from [8], offering participants a choice between two situations as jury members in a trial for armed robbery with testimony from two eyewitnesses: One witness saying that the getaway vehicle was green but the other saying it was blue, vs both witnesses saying that the vehicle was either green or blue. His second scenario involved precise but conflicting computer forecasts of the path of a cyclone versus agreeing but ambiguous forecasts, both of which were informationally equivalent about the cyclone's possible paths. Smithson reports strong preferences for ambiguity over conflict in both scenarios, thereby also demonstrating that this effect holds for nonhuman as well as human information sources. A second round of experiments shows this preference holding to a similar degree regardless of whether the decisions had consequences for the decision maker, another person, or the environment. Smithson [5] called this preference for ambiguity over conflict "conflict aversion".

The Smithson and Viscusi papers stimulated two streams of research: Further tests and extensions of the conflict aversion hypothesis and possible explanations for it, and investigations into the consequences of communicating CU for the credibility and trustworthiness of its sources. The latter stemmed from [5] reporting a strong tendency for subjects to see ambiguous but agreeing experts as more knowledgeable than precise but disagreeing ones. The remainder of this section surveys the first line of research, and the second line of research is reviewed in the next section.

The conflict aversion hypothesis has been verified in numerous studies, including several in realistic settings. Cabantous [23] obtained data from professional actuaries (from the French Institute of Actuaries), demonstrating that they assigned higher premiums for insurance against risks with ambiguous loss probabilities than precise probabilities, and still higher premiums if the indeterminacy in the probabilities stemmed from disagreeing estimates. Cabantous, et al. [24] followed this initial study with data from American insurers, finding that they also would charge higher premiums under ambiguity than under precisely estimate risk. While they also charged more under conflict than ambiguity for flood and hurricane hazards, this did not hold for fire hazards. Cabantous, et al. report that under ambiguity insurers were more likely to attribute the uncertainty to the difficulty of the risk assessment problem, whereas they tended to attribute conflicting estimates to incompetence or unreliability in the assessors.

Han et al. [25] investigated the impact of conflict aversion on uptake of medical tests. They presented people with one of two vignettes describing a hypothetical new screening test for colon cancer: A "missing information" vignette in which they were told that the new test was potentially better than existing tests but only a few small studies had so far been conducted; and a CU vignette in which they were told that studies of the screening test produced differing results and experts disagreed about recommending it. They report that respondents in the CU vignette were less willing to undergo the test than those in the missing-information vignette.

Smithson [5] investigated framing effects on conflict aversion along lines suggested by prospect theory [26]. Prospect theory asserts that people are risk-averse under prospects of gain and risk-seeking under prospects of loss, and it has received substantial empirical support. Smithson reports a reduced degree of conflict aversion under prospect of loss, including a modest tendency to prefer conflict over ambiguity when there is a high likelihood of a negative outcome, but otherwise finds that conflict aversion prevails [5].

Smithson's findings echoed prospect theory's predictions to some extent. In an unpublished experiment, [27] presented participants with hypothetical medical scenarios in which the prospective gain was curing victims of an illness and the loss was the victims remaining ill. Participants were randomly assigned to choosing between one of the three possible pairs (risky vs ambiguous, risky vs conflicting, and ambiguous vs conflicting) of estimates of the probability of either the gain or the loss. The results exhibited both ambiguity and conflict aversion, along with a framing effect that was similar for all pairs, namely a tendency to weaken the preference for precisely specified risk under a prospect of loss.

Lohre, et al. [28] identified another framing effect, involving the use of directional terms (e.g., "over 50%" vs "under 50%") for imprecise probabilities. They find that disagreement is perceived as greater when sources use opposite directional terms than when they use terms in the same direction. For instance, an estimate that P(E) is "over 40%" is perceived as disagreeing more with an estimate that P(not E) is "under 30%" than with a logically identical estimate that P(E) is "over 70%". However, it is not clear whether this effect arises from confusion about comparing the probability of an event with the probability of its complement. Smithson, et al. [29] identify a tendency for laypeople to be less consistent and to have less of a consensus in their numerical translations of verbal probability expressions when these expressions are negative (e.g., "unlikely") than when they are positive (e.g., "likely").

Conflict aversion occurs for indeterminate outcomes as well as probabilities of outcomes. Smithson et al. [30] report two studies where judges encounter ambiguity or CU in the sampled outcomes. Examples of an ambiguous outcome are an inconclusive blood test, or an inconclusive expert assessment of the provenance of an artwork. They find that ambiguity aversion is not less than when people are given a range of probabilities of the outcomes without reference to ambiguous outcomes. They also find that conflict also does not decrease when the uncertainty is in the outcomes rather than in the probabilities.

What are possible explanations for conflict aversion? Again, we may borrow some ideas from the more extensive literature on ambiguity attitudes. The most popular explanations already have been described. The first of these is sensitivity to variability in outcomes and/or outcome probabilities. Rode, et al. [14] present evidence from the literature on foraging and their own experiments that people avoid alternatives with high outcome variability even when probabilities are not explicitly stated, except when their level of need is greater than the expected value of the outcome.

A related explanation that can be applied to CU is that it violates expectations that sources will agree, or at least that any differences between them will be within a tolerated range. Kahneman, et al. [9] observe that there is substantially more disagreement among professional and expert judgments that is either expected or tolerated in fields ranging from jurisprudence to medical diagnosis to actuarial assessments. In one of their surveys they asked executives and underwriters from an insurance company about the amount of variation they would expect between two underwriters' assignments of a premium to the same case, the most popular estimate was 10% of the premium. When they put this to a test, they found that the median difference was 55%.

Although there is, to my awareness, no systematic empirical evidence for this in the general sense, it seems plausible that when expectations for agreement among judges are violated, people will find this violation more aversive when the judgments involve evaluations and/or consequential decisions than when they are only estimates or predictions. For example, mounting evidence of considerable differences among American judges in the sentences they would deliver for identical crime cases resulted in attempts to standardize sentencing by the Federal government during the 1980's. The tone of the 1983 Senate Report [31] in its leadup to recommendations conveys a level of outrage:

> "... every day Federal judges mete out an unjustifiably wide range of sentences to offenders with similar histories, convicted of similar crimes, committed under similar circumstances. One offender may receive a sentence of probation, while another-convicted of the very same crime and possessing a comparable criminal history-may be sentenced to a lengthy term of imprisonment." (pg. 38)

The recommendations thereafter highlight a reason for why inconsistencies in consequential evaluations may be especially aversive: Violations of fairness or justice. The Senate Report makes this concern explicit in their criteria for sentencing law reformation: "... it should assure that sentences are fair both to the offender and to society, and that such fairness is reflected both in the individual case and in the pattern of sentences in all Federal criminal cases." (pg. 39).

A second explanation for conflict aversion is that CU invokes pessimistic probability estimates, as initially hypothesized by [8]. Smithson, et al. [30] find that ambiguity and conflict aversion are partly (but not entirely) explained by more pessimistic outcome forecasts by participants in their experiments. This holds regardless of whether the conflictive uncertainty is presented in the form of indeterminate probabilities or indeterminate outcomes. They further report that pessimism may be due to uncertainty about how the chance of a desirable outcome in an ambiguous or conflictive setting compares with an equivalent alternative with precise probabilities.

Third, attributions regarding the causes of ambiguity also have been studied as possible influences on ambiguity attitudes. Stuart et al. [32] report experimental evidence that when ambiguity (or even possibly CU, which they do not distinguish from ambiguity) is believed to be due to something that the decision maker can control or that they are optimistic about, then the decision maker will exhibit ambiguity-seeking. Du et al. [33] proposed and tested a hypothesis that investors prefer ambiguous (vague) earnings forecasts over precise forecasts for an investment when their prior belief is that little is known about the performance of the investment.

The most common CU-specific explanation for conflict aversion is attributions of incompetence or other detrimental inferences about the sources and/or information, resulting in a decline in their credibility or trustworthiness [5, 24, 34], and thereby a discounting of their judgments or predictions. Another is that CU can require decision makers to "take sides" (e.g., choosing one estimate and discarding all others), especially if a compromise or middle-ground resolution is not available [5]. It seems plausible that most of the influences on CU attitudes that are not shared by ambiguity attitudes will involve social factors regarding perceptions of the sources and the perceiver's relationships with the sources.

Summing up, conflictive uncertainty appears to be more aversive to many people than either risk (in the sense of probabilities) or ambiguity. Is conflict aversion irrational, or does it lead to irrational behavior? There has been relatively little discussion about this, with several authors taking the position that it results in irrational decision-making, although others seem more agnostic on the topic.

People tend to be more pessimistic under CU than under ambiguity or risk, and they put greater weight on pessimistic forecasts. This tendency can be irrational, but under some conditions it can be prudent. Several researchers observe that CU can result in irrationally “alarmist” responses, such as placing disproportionate weight on high-risk estimates when given multiple disagreeing risk estimates [5, 22, 35]. Baillon et al. [35] demonstrated that this effect does not occur under ambiguous uncertainty. These sets of findings underscore a tendency for people to be more risk-averse under CU than under other kinds of uncertainty, whether greater risk-aversion is rational or not. Nevertheless, it is not difficult to find justifications for conflict aversion, particularly when the sources are experts. Laypeople are not unreasonable in expecting experts to agree on matters within their domain of expertise. As Viscusi and Chesson [36] point out, agreement among experts suggests that we should have more confidence in their assessments than if they disagree.

Various computational models have been proposed and tested to account for ambiguity attitudes, but most of these specialize in ambiguity about probability estimates. Several models attempt to jointly model ambiguity and CU attitudes in more general settings, and these are briefly surveyed here. Smithson [37] proposed two types of models, variance and distance based. The simplest versions of these assume that there are two judges (or sources), each providing ambiguous quantitative estimates in the form of intervals, where p can be any quantity (i.e., not limited to probabilities), and k = {1,2} and indexes the judges. Following [14], Smithson defined ambiguity for each judge as the variance of their interval limits:

$$A_k = \sum_{j=1}^{2} \left(p_{kj} - \overline{p}_{k.} \right)^2 \Big/ 2, \tag{1}$$

where $\overline{p}_{k.}$ denotes the arithmetic mean taken over j, so that the total ambiguity is the sum of the A_k. One measure of conflict, then, is the between-judges variance,

$$C_1 = \sum_{k=1}^{2} \left(\overline{p}_{k.} - \overline{p}_{..} \right)^2 \Big/ 2 . \tag{2}$$

However, another measure is the variance among the order-statistics of the same rank (recalling that $p_{k1} \leq p_{k2}$,):

$$C_2 = \sum_{k=1}^{2} \sum_{j=1}^{2} \left(p_{kj} - \overline{p}_{.j} \right)^2 \Big/ 4 . \tag{3}$$

The first model predicts that a pair of interval estimates with the same midpoints will not be perceived as conflictive, regardless of differences in the interval widths, whereas the second model predicts that they will be conflictive. Smithson's experimental evidence indicated that the conflict measure in equation (3) predicts conflict attitudes better than the one in equation (2), suggesting that people are sensitive to disagreements about the uncertainty of an estimate.

Smithson's [37] distance-based models evaluate ambiguity and conflict in terms of distances between order statistics. An index of ambiguity using Euclidean distance is

$$A_k = \sum_{j_1=1}^{2} \sum_{j_2=1}^{2} \left(p_{kj_1} - p_{kj_2} \right)^2 \Big/ 4 \quad . \tag{4}$$

As before, conflict can be evaluated in two ways. First is the absolute value of the sum of the differences over ranks:

$$C_1 = \sum_{k_1=1}^{2} \sum_{k_2=k_1+1}^{2} \left| \sum_{j=1}^{2} \left(p_{k_1 j} - p_{k_2 j} \right) \right| \tag{5}$$

Second is the sum of the absolute differences between pairs of order-statistics of the same rank:

$$C_2 = \sum_{k_1=1}^{2} \sum_{k_2=k_1+1}^{2} \sum_{j=1}^{2} \left| p_{k_1 j} - p_{k_2 j} \right| \tag{6}$$

Similarly to the two variance-based conflict indexes, C_1 predicts that a pair of interval estimates with identical midpoints will not be perceived as conflictive, whereas C_2 predicts that they will be, and again C_2 performed better on empirical data.

Gajdos and Vergnaud [38] also defined a model of decision making under ambiguity and conflict based on the maxmin framework. It was originally limited to dealing with probability estimates, and more importantly, was intended as a model of a rational agent taking account of both ambiguity and conflict aversion. Smithson [37] generalizes the two-state, two-judge special case of their model to judgments of magnitudes and tested it empirically along with the models described above. In the variance and distance models above, two weight parameters, α and θ, are used to estimate both attitude and sensitivity toward the ambiguity and conflict indexes. In the [38] model, these modify the order statistics of each judge. The θ parameter shrinks the width of the $[p_{k1},\ p_{k2}]$ interval by $1-\theta$, so that the lower and upper bounds become

$$\begin{aligned} \pi_{k1} &= p_{k1}(1+\theta)/2 + p_{k2}(1-\theta)/2, \\ \pi_{k2} &= p_{k1}(1-\theta)/2 + p_{k2}(1+\theta)/2. \end{aligned} \tag{7}$$

Gajdos and Vergnaud do not define an ambiguity measure but Smithson constructs one by summing the differences $\pi_{k2} - \pi_{k1}$. Likewise, their model treats α as contracting the pairs of interval endpoints p_{kj} and p_{mj} around their mean at the rate $1-\alpha$. The order statistics are modified as follows:

$$\begin{aligned} \gamma_{kj} &= p_{kj}(1+\alpha)/2 + p_{mj}(1-\alpha)/2, \\ \gamma_{mj} &= p_{mj}(1+\alpha)/2 + p_{kj}(1-\alpha)/2. \end{aligned} \tag{8}$$

A conflict measure can be constructed by summing the absolute values of the $\gamma_{kj} - \gamma_{mj}$ differences, which yields an index similar to the one in equation (6).

Smithson [37] tested these models by presenting participants with choices between two pairs of interval estimates, with four sets of these as shown in Figure 1. The second kind of variance and distance models and the [38] model outperformed the first kind of variance and distance models, and the relative effects of the ambiguity and conflict indexes on the preference-rates exhibited by experimental participants suggested that Conflict aversion and ambiguity aversion operate relatively independently of one another.

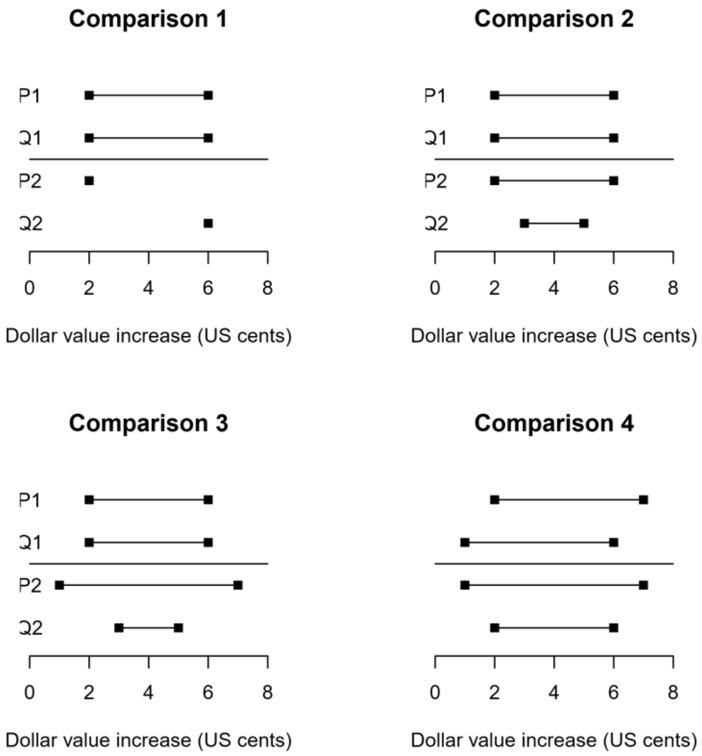

Figure 1. Four Comparisons of Ambiguous-Conflicting Estimates

The best-performing models correctly accounted for the tendency to prefer pairs of estimates with identical interval widths over those whose widths differed (Comparisons 2 and 3). However, none of the models succeeded in accounting for people's tendency to prefer the top pair of intervals with mismatching midpoints over the bottom pair with identical midpoints in Comparison 4. This finding indicates that people may sometimes be more sensitive to mismatching uncertainties than to mismatching estimates.

4 Consequences of conflictive uncertainty for risk communication

As mentioned earlier, the second line of research inspired by [22] and [5] has focused on the consequences of communicating CU for its recipients' appraisals of the information and its sources. Smithson reported tendencies for people to downrate the knowledgeability of disagreeing sources [5]. If generally true, then experts' communications resulting in CU (or having it attributed to them) could suffer losses of credibility and trust from the public.

Science communicators are not unaware of this possibility, and some of them realize that they face a "Chicken-game" dilemma when considering how to frame statements of their views on issues where there is scientific controversy. Forthright statements from them and those on the other side of a controversy run the risk of yielding discreditation of all sources involved in the debate. On the other hand, softening one's position by appearing to agree on some points with an opponent runs the risk of exploitation by the opponent. Indeed, [39] identified evidence that at the height of controversy over anthropogenic climate change, scientists over-emphasized scientific uncertainty, and that even when refuting contrarian claims they often do so in a manner that reinforced those same claims.

The question of whether scientific experts should or should not communicate uncertainty about theories or research to the public has been the subject of considerable research. Nonetheless, in a review of 48 articles on the effects on science communication generally, Gustafson and Rice [40] observe that the literature on science communication is divided on whether communicating scientific uncertainty generally will have positive or negative effects (e.g., on trust or credibility accorded to scientists or to science generally). As a result, advice from this literature for science communicators is confusing at best.

Gustafson and Rice [40] examine what they identify as four kinds of uncertainty: Deficient, technical scientific, and consensus (the latter is CU). Deficient uncertainty refers to gaps in knowledge, technical uncertainty mainly to imprecision in estimates or measurement, scientific uncertainty to the notion that all scientific knowledge is tentative, and consensus uncertainty to disagreement or controversy. Are the consequences of CU different from other kinds of uncertainty for risk communication?

We already have reviewed evidence that people prefer agreeing but ambiguous or vague sources over precise but disagreeing sources, even though their collective estimates or accounts are informationally identical. Evidence that people also regard disagreeing sources as less credible or trustworthy often has been borne out in studies of the effects of disagreements among scientists on public attitudes toward scientists and, indeed, science. For instance, [41] observed that in the context of the Swedish acrylamide scare, public disagreements between epidemiologists and toxicologists over the link between acrylamide and cancer led to public distrust in scientists. Similarly, Regan et al. [42] Investigated the effects of third-party communication on trust in risk messages. New information emphasizing the benefits of red meat and contradicting a previous risk message led to judgments that the original risk message was less credible. Evaluation of the new message was not affected by any apparent conflict with the original risk message. Instead, the trustworthiness of the third-party communicating the new message influenced its credibility. In an experimental study, Gustafson and Rice [43] tested the effects of their four uncertainty types in three scientific topics, and found that CU was the only kind that had consistent significant effects on beliefs, risk perceptions, or behavioral intentions, and all of these effects were negative.

To some extent, the impact of CU created through disagreement among scientists may depend on contextual factors, such as the topic. For example, Jensen and Hurley [44] observe that uncertainty about the health effects of dioxin (a possible carcinogen) increased the credibility and trustworthiness of scientists, whereas they report a deleterious effect for conflicting claims about risks regarding wolf reintroduction in the USA. Moreover, Gustafson and Rice's [43] negative findings about CU pertained mainly to just one of their three topics, climate change, but not to either GMO food labeling or machinery risks. Likewise, [45] report no detrimental effects from CU on perceived trustworthiness of experts' messages about genetically modified food risks, although they did find that consensus reduced the perceived risks themselves. Unfortunately, the current understanding regarding when and why people find CU aversive and its sources untrustworthy is in an inconclusive and confused state, with no convincing overview or synthesis yet.

Nevertheless, the [40] survey of the literature identified CU as the only type of uncertainty that had consistently negative effects on public perceptions of scientists and/or science. Communications of technical uncertainty showed no negative effects, and often enhanced public trust and esteem in scientists instead. Deficient and scientific uncertainties exhibited a mix of effects, some of which were moderated by the beliefs and prior knowledge of those receiving the communication. However, the negative impact of CU has been shown in some instances to spread discreditation beyond its immediate sources. For instance, Nagler’s [46] survey revealed that people reporting greater exposure to CU regarding the effects of consumption of various kinds of food were more likely to discount nutrition research altogether.

Taking all this into account, CU is arguably the most corrosive kind of uncertainty whose psychological effects have been investigated systematically. Public exposure to CU has increased in recent times. For the past several decades, the public in a variety of countries has increasingly been exposed to divergent risk messages in various salient domains, such as financial investment, health risks, terrorism, and climate change [47]. A RAND report highlights increasing disagreements about facts and analytical interpretations of data, a blurring of the line between opinion and fact, an increasing influence of opinion over fact, and a declining trust in formerly respected sources of fact [48].

These trends can be partly attributed to the so-called "democratization" of journalism, but even traditional journalism prior to the advent of the internet tended to aggrandize disagreements. Normal journalistic coverage of disagreements or controversies tends to give equal exposure to all sides, regardless of their expertise or evidentiary basis, thereby often amplifying laypeople's concerns and uncertainties. Viscusi [22] observes that "the media and advocacy groups often highlight the worst case scenarios, which will tend to intensify the kinds of biases observed here." Stocking [49] has a somewhat more balanced account, pointing out that journalists often are under competing pressures to simplify science, which often entails omitting caveats and other expressions of uncertainty, but also to exercise impartiality and thoroughness in presenting alternative viewpoints on issues where conclusions have yet to be reached.

Moreover, the detrimental effects of CU on trust have been exploited, in at least some cases deliberately, by politically-motivated agents in public policy debates and negotiations on issues such as the link between tobacco smoking and lung cancer [50] and, more recently, climate change [51]. Even scientists in such debates have been found to revise their positions in ways they would be unlikely to take in the absence of outspoken contrarian opposition [39]. As mentioned earlier, they face a dilemma between decreased public trust in their expertise by sticking with "hard-line" risk messages versus conceding points to their opponents.

5 Dealing with and communicating about conflictive uncertainty

The evidence from psychological research on conflictive uncertainty generally lends support to the following propositions:

1. People distinguish between CU and other kinds of uncertainty such as ambiguity and probability.
2. They usually find CU more aversive than other kinds of uncertainty and may be willing to trade CU for an alternative kind of uncertainty.
3. Communications from sources or inconsistent communications from a single source resulting in CU tend to erode the credibility and trustworthiness of those sources.

Understanding the psychology behind reactions to CU can contribute to the effectiveness of methods for resolving conflicting information and communicating about resolutions and/or decisions under conflictive uncertainty in the following ways:

- Knowing the aspects of CU that amplify its aversiveness can aid the choice and/or development of methods for dealing with CU to diminish or eliminate those aspects.
- Knowing how people prefer to deal with CU can provide the means for tailoring CU resolution methods to match those preferences where possible.
- Understanding the reasons behind the erosion of trust in CU sources can guide communicators about CU and its resolution in finding ways to prevent or minimize that erosion.

Conflict aversion seems to stem from (and to be exacerbated by) the following contingencies:

1. Violation of expectations of agreement (e.g., among experts),
2. Perceptions that no compromise or middle-ground position is available to resolve the disagreements,
3. Perceptions that no additional information is available that might resolve the disagreements,

4. Perceptions that the conflicting information involves evaluations or consequential decisions, and

5. Personal relevance, especially if any of the conflicting information also disagrees with one's own prior beliefs.

The first three of these aspects are amenable to being mitigated by the ways in which CU situations are framed.

The sense of violated expectations of agreement may be reduced or prevented by framing situations so that people know in advance to expect disagreements. If they perceive differing views and debates as normal and to be expected, then CU may not be as aversive. For instance, [52] present evidence that people respond more positively to uncertainty about research if they see science as a matter of engaging in debates with constant revisions and improvements than if they see science as mainly about arriving at absolute truths.

It may be beneficial to revise expectations regarding CU among the sources of the conflicting judgements or estimates producing CU. Observing that the extent of actual variability in judgements by experts often flies in the face of beliefs about the consensus levels among the experts themselves, [9] recommend conducting what they call "noise audits". These amount to experiments with appropriate designs and controls to assess the variability among experts in their assessments of the same cases or problems. Properly conducted, noise audits can provide experts with realistic perspectives on the extent to which disagreements are likely to occur in their domain, which in turn pave the way to communicating those perspectives to their clients or to the public. If [9] are correct in their assertions that many communities of professionals and experts under-estimate the extent to which their professional judgments are likely to disagree with one another, then the revelations of a noise audit may also motivate these communities to seek ways to reduce unnecessary or avoidable disagreement, thereby reducing the incidence of unwanted CU.

What approaches to resolving CU do ordinary people take? People's preferences for ways of eliminating or reducing CU have yet to be fully systematically studied. However, there is some data on how people go about resolving CU in everyday life. Smithson [27] elicited descriptions of everyday episodes of CU from a sample of 308 adults from the UK and asked how they went about resolving the conflicting information. The most popular responses were seeking more information (21.6%), finding a compromise and/or decide that the alternative positions could be true simultaneously (19.0%), or choosing one of the alternatives and discounting the others (14.0%). This third alternative seemed to be chosen only when participants regarded one source as more credible than the others.

The kinds of disagreement likely to pose the greatest difficulties for people are those presented as mutually exclusive states (i.e., "zero-sum") with no prospect of a compromise or middle-ground position. On the other hand, various kinds of "averaging" have intuitive appeal to people, both in terms of understandability and also fairness. Where possible, framing conflicting positions as having the potential for middle-ground or compromise resolutions is likely to make CU less aversive and such resolutions more acceptable and believable.

In some settings, it may not be feasible to resolve disagreeing judgments by arriving at a precise or single resolution. Instead, it may be necessary to retain a range or set of judgments. Nevertheless, given the evidence that people prefer ambiguity to CU, employing deliberate ambiguity or vagueness to absorb disagreement can aid the construction of a workable consensus in the face of CU. When people believe that full resolution is impossible, they may find an ambiguous resolution more plausible than a precise one. Joslyn and LeCerc [53], for instance, report that quantitative displays of uncertainty in the form of interval estimates result in greater trust in risk messages about climate change than pointwise estimates. The precise estimates may be violating public expectations about the uncertainty involved in such estimates.

Additionally, a focus on processes and procedural fairness instead of solely on outcomes can reduce conflict aversion. If people trust the processes by which assessments have been arrived at, and if they believe that reasoned discussion will continue as part of the resolution process then they are more likely to accept the eventual outcome. Where possible, the methods by which CU is resolved should be explicit and explicable to laypeople. For example, the arithmetic average of two alternative probability estimates is far more likely to be comprehended by laypeople than the [16] linear-vacuous model or even a geometric average. Recalling the words of the U.S. Senate Report [31] recommendations on sentence law reform, a resolution of CU should provide people with reasons for choosing it rather than relevant alternative resolutions.

Turning now to the issue about CU that involves evaluations or consequential decisions, this kind of situation exacerbates CU aversiveness because it raises or intensifies moral considerations regarding both the judgments and the judges. This effect is not unique to CU. Generally, for example, uncertainties regarding reversible or steerable decisions are less detrimental to trust and assurance than uncertainties about irrevocable decisions [54, 55].

The most common moral consideration regarding resolutions of uncertainty of any kind is fairness, and fairness in algorithmic decision making currently is a widely discussed issue. The topic initially arose when deliberately built-in biases in algorithms for assigning prices to consumer goods were detected [56], but attention rapidly shifted to unintentional biases built into automata such as algorithms for assessing recidivism risk, allocating health care, and selecting candidates for recruitment [57]. Inadvertent bias or discrimination can arise in multiple ways, including the nature of the training data, the variables selected for risk assessment, and the criteria for optimization. Worse still, "fairness" turns out to have multiple definitions and criteria (e.g., achieving identical "at risk" assignments across subpopulations but also attaining identical false-positive and false-negative rates across the same subpopulations), and some of these cannot be achieved simultaneously [58].

Fairness is very likely to be a concern with CU and its resolution, and algorithmically implemented resolutions will need to be transparent to users about how fairness is dealt with. Turning to a simple hypothetical example, suppose we have two equally credible sources estimating the probability of event E, and source 1 produces an estimate $p_1(\mathrm{E}) = 0.1$ whereas source 2 produces $p_2(\mathrm{E}) = 0.6$. The familiar "best" resolution of this disparity is their arithmetic mean, $p(\mathrm{E}) = 0.35$. An algorithm using this resolution also will be perceived as being "fair" by many laypeople because it gives equal weight in averaging to the two equally credible sources.

But now suppose that the algorithm is using the linear-vacuous model for lower-upper probabilities [16], which takes the interval width, $p_2(\mathrm{E}) - p_1(\mathrm{E}) = w = 0.5$, to be the probability that both sources actually are ignorant of $p(\mathrm{E})$ and that the real state of knowledge about this probability is the "vacuous" interval [0,1]. The linear-vacuous model then has

$$\begin{aligned} p_1(\mathrm{E}) &= (1-w)\,p(\mathrm{E}) \\ p_2(\mathrm{E}) &= (1-w)\,p(\mathrm{E}) + w \end{aligned} \tag{9}$$

and its resolution therefore is $p(\mathrm{E}) = p_1(\mathrm{E})/(1-w) = 0.2$. This resolution will not only be unfamiliar to laypeople, but it also may seem "unfair" because, from their perspective of averaging, it appears to give greater weight to source 1 than to source 2. Moreover, the linear-vacuous resolution will seem pessimistic if event E is desirable or optimistic if E is undesirable.

Turning now to remaining considerations about how best to communicate CU and how to persuade clients or the public to accept and trust a method for resolving it, communicating uncertainty can be thought of as a way of framing science communication [59. 60]. We already have seen several ways in which the aversiveness of CU can be reduced by framing it: As expected and normal, amenable to resolution via a middle-ground or compromise positions, resolvable in a way that is transparent, sensible, understandable, and fair; and both its genesis and resolution framed as products of reasoned, regulated, and fair discussion or debate. Communications about CU and its resolutions will be better received when they employ these frames wherever possible.

Finally, one concept that communicators should keep in mind is that recipients of their messages are likely to engage in what psychologists call "motivated reasoning" as they try to make sense of those messages and also to deal with their own reactions to them. Motivated reasoning [61] refers to the selective use of cognitive strategies and attention to evidence as determined by motivational factors. For instance, Chang [62] suggests that because CU induces discomfort, motivation to reduce that discomfort drives reasoning about the credibility of the sources and evidence involved. A readymade way of reducing this discomfort is to discount the evidence and/or sources as untrustworthy, and Chang's studies show that this is a commonplace response.

On the one hand, findings such as Chang's can be regarded as good news because they indicate that the public is not entirely gullible. On the other hand, discreditation of expert sources and/or carefully martialed evidence often is not a desirable outcome. An effective counter-measure against reasoning dominated by a motive to reduce discomfort from CU is for communications about CU and its resolution to catalyze other motives. Kunda's [61] review highlights research showing that when people are more strongly motivated to find the most accurate view or estimate, they are more likely to engage in deeper and more impartial reasoning. Impartiality in reasoning also is increased when people are motivated to be fair or just in their assessments or decisions. Finally, if the recipient is having to make decisions under CU, it is helpful if framing can remove concerns about blameworthiness and enhance motivation to produce the best outcomes for those affected by the decisions.

6 Conclusion and suggestions for multi-view modeling practices

We conclude with three recommendations for further developments in multi-view learning. First of all, more attention should be devoted to the problem of view disagreement, and to the question of whether it requires techniques that differ from those employed in its absence. The extent of this problem needs greater acknowledgement than has appeared throughout much of the multi-view literature and it should be treated as separate from nonshared or ambiguous information. While problems of missing and ambiguous data commonly feature in this literature, outright disagreement seldom is squarely faced and oftentimes simply goes unmentioned. Moreover, in some approaches it is essentially swept under the carpet. Consider, for example, one of the assumptions underpinning the so-called "information bottleneck" method of unsupervised learning, namely that each view has the same task-relevant information and therefore a "robust" representation can be generated by "abandoning the information not shared by views, i.e., removing the view-specific nuisances." [2]. This assumption equates disagreement with nonshared information and thence irrelevance (nuisance).

Second, more attention also needs to be devoted to developing explainable multi-view methods, especially in the face of view disagreement and the potential for CU. The importance of explainability is crucial, as [63] demonstrated that users distrust even a high-performing automated system unless they are provided with reasons for why performance errors have occurred. A recent survey concludes with this observation about the state of the art for explainable multi-view learning models: "Although existing deep MVL models have shown superior advantages in various applications, they fail to provide an explanation for the decision of different models." [2]. The currently fashionable deep-learning models pose an even greater difficulty regarding explainability than older techniques based on multivariate statistical approaches such as canonical correlation.

Finally, in both the design and implementation of multi-view techniques, greater use should be made of knowledge about human attitudes toward and responses to automation under uncertainty. This recommendation is a corollary of an admonition voiced by several researchers investigating issues of machine learning trustworthiness, e.g.: "... the fundamental tensions between adversarial robustness and model accuracy, privacy and transparency, and fairness and privacy invite more rigorous and socially grounded reasonings about trustworthy ML." [64]. The main goal in writing this chapter has been to pave the way toward this third recommendation, i.e., incorporating knowledge available from psychology about the nature of CU and human responses to it into the development and implementation of multi-view learning algorithms.

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