Priors, informative cues and ambiguity aversion

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Abstract

Ambiguity aversion, or the preference for options with known rather than unknown probabilities, is a robust phenomenon within the decision making literature (e.g., Camerer & Weber, 1992). There are some suggestions that this aversion is due to people inferring differences in the prior distribution for the ambiguous option (Güney & Newell, 2015). In this study we investigated the relationship between prior distributions and experienced information cues on people's decision making and their judgments about the underlying distribution in the ambiguous item. We used three different prior cues; POSITIVE (suggesting a positive underlying distributional cue), NEUTRAL (no distributional cue) and NEGATIVE (suggesting a negative underlying distributional cue) and five different information cues, varying both the bias of the information and the degree of ambiguity. While we found that both prior and information manipulations had the expected impact for participants' judgements of underlying distributions, they only impacted the decisions participants made some of the time. We discuss the implications of this.

Keywords: ambiguity; uncertainty; priors; information

Introduction

When dealing with real data, the practicing statistician should explicitly consider the process that causes missing data far more often than he does.

– Donald Rubin (1976, p. 592)

A classic finding in the human decision making literature is that people are *ambiguity averse*: when presented with a choice between options that ostensibly offer the same expected reward, one of which is specified in more precise terms than the other, people typically prefer to select the less ambiguous option (Ellsberg, 1961; Camerer & Weber, 1992). For example, people will typically prefer to bet on the flip of a fair coin – where the probability of heads is known to be 50% – rather than bet on the outcome of a weighted coin, where the bias θ on the coin is unknown. However, following Laplace's "principle of insufficient reason", a Bayesian reasoner should specify a symmetric prior $P(\theta)$ over the coin bias, leading to the conclusion that in the absence of any other information, the two bets are equivalent for all practical purposes. Human decision makers rarely show this indifference, with the majority of people preferring to avoid the ambiguity inherent in the second example (Liu & Colman, 2009).

Why does this occur? One possibility is that people tend to be pessimistic about their prospects when ambiguity is present. On the surface, the ambiguity in the biased coin scenario seems innocuous, but it need not be so. If a professional stage magician were offering you the bet – or a social psychologist for that matter – you might have reason to be suspicious. Perhaps they know something about the situation that you do not. Ambiguous scenarios maximize the potential for malfeasance, and a cautious decision maker might be wise to avoid them. This tension can be seen in the "tennis match" scenarios discussed by Gardenfors and Sahlin (1982): if you and I both know that players A and B are matched in skill and have played each other many times, you have far fewer opportunities to take advantage of me by virtue of superior knowledge than if the two contestants have never played each other. When competing against others, missing data matters and ambiguity aversion seems reasonable, because the things you do not know can be used against you.

There is some evidence to support the idea that people evaluate ambiguous options pessimistically. Keren and Gerritsen (1999) asked people to predict which of two decision-makers – one who chose a precise option, the other an ambiguous option – were most likely to succeed in their bets. Participants rated the decision-maker who chose the precise option as more likely to win. Viewed in Bayesian terms, this makes sense if the prior $P(\theta)$ that people use to evaluate an ambiguous option is pessimistic, and to assume that the omitted information is biased against them. Interestingly, in experimental scenarios that allow people to verify that the "ambiguous" option is constrained by a simple stochastic process that is not biased against them (i.e., ambiguity is reduced to "mere" second order probability), people do not display ambiguity aversion to the same extent (Güney & Newell, 2015).

In this paper we extend this idea, introducing a manipulation that aims to shape the PRIOR that people use to evaluate the ambiguous option by providing a causal story for why some information is missing. At the same time, we manipulate the amount of information available to people as well as the apparent favorability of the gambles (the INFORMATION CUE). There is some evidence that these two factors may interact (Garcia-Retamero, Müller, Catena, & Maldonado, 2009). For instance, Tversky and Kahneman (1980) suggest that observed base rates are only taken into account when they appear to be causal (i.e. directly related to the outcome), Garcia-Retamero et al. (2009) find that people also display a confirmation bias, attending to informational cues only to the degree that they support the initial base rate. Here we manipulate each of these factors more systematically.

Method

Participants

79 University of Adelaide first-year psychology students and 364 Amazon Mechanical Turk (AMT) Workers participated on their own computer or laptop. Of the initial participants, 73 were randomly allocated to a control condition with no ambiguity, just to make sure the instructions were clear. As expected, they showed no preference between options. They are thus are excluded from all subsequent analyses, leaving 370 in the full dataset. Of these, 167 were female, 201 were male, and 2 marked ‘other’ for gender; ages ranged from 17 to 73 (mean: 32.2). Student participants were given course credit, while AMT workers were paid $1 for the five minute task. Initial analysis indicated no qualitative difference in performance between the two subject pools, so all have been combined for all analyses.

Materials & procedure

Regardless of condition, people were told they were taking part in a study about making choices. According to the cover story, they were part of a promotion being held by a fictitious chocolate factory, which produced boxes containing eight chocolates. As a part of the promotion, the researcher would select one chocolate randomly from the box. If it was blue, the participant would be awarded 100 points, but if it was red, they would not be awarded anything. The job of each participant was to choose which of two boxes they would like the researcher to choose a chocolate from.

Importantly, as shown in Figure 1, participants always had to choose between one box in which the distribution of chocolates was fully known, and another in which it was fully or partially ambiguous. The side with the ambiguous box was randomized. All participants were told the same cover story explaining the ambiguity: the machine that wrapped the chocolates had malfunctioned and randomly re-wrapped some chocolates with a white wrapper. This did not impact the wrapping underneath, so if a white wrapper was selected people would be given points based on whether the wrapper underneath was blue or red.

This particular cover story was chosen for two main reasons. With the first part we could manipulate the underlying prior distribution for the ambiguous tokens (either expecting more red, more blue or a neutral condition). With the second part we introduced a reason for ambiguity that was, to the best of our powers, neutral and separate to the underlying distribution of red or blue wrappers in a given box.

The study manipulated two main factors. The first was the PRIOR expectation participants had about how many chocolates of each kind might be found in each box, which we accomplished through a cover story that relied on their social reasoning. The second was the amount of INFORMATION provided about the more ambiguous box. The experiment was fully between-subjects, with each participant randomly allocated to one of the 15 conditions (3 PRIOR x 5 INFORMATION level). Each participant was thus asked to make one choice and one estimate of the number of chocolates in the study.

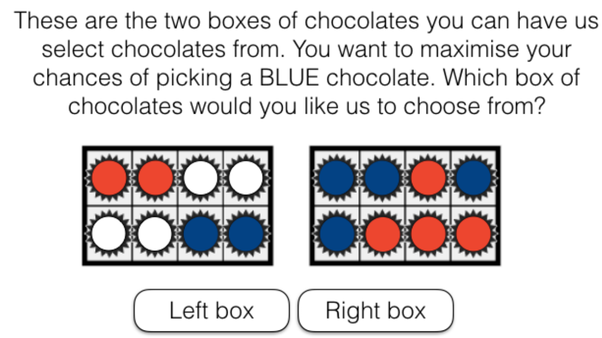


Figure 1: **The basic scenario.** Participants were asked to select a box from which the experimenter would randomly select one chocolate: blue ones were worth 100 points and red ones were worth nothing. In all conditions, people had to choose from one box in which the distribution of red (which looks medium grey in greyscale) and blue (dark grey) items was fully apparent; the other box was fully or partially ambiguous, represented by chocolates in white wrappers that could be either red or blue underneath.

Manipulating the prior expectations

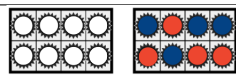
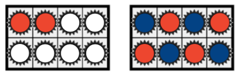
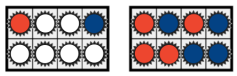
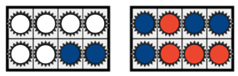
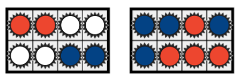
One of our main questions was how people form prior expectations of what an ambiguous situation might indicate, and how those would affect their degree of ambiguity aversion. The manipulation of prior assumptions therefore depended on a social cover story about a worker at the factory with different kinds of motivations. In the POSITIVE condition, the worker was trying to help people win points by putting more blue chocolates in the boxes; in the NEGATIVE condition they were trying to make them more likely to lose by putting more red ones in; and in the NEUTRAL condition they were rearranging chocolates with no bias one way or another. We were careful to note in all cases that the employee didn’t affect all of the chocolates, so that there would be doubt about the exact nature of the distribution the ambiguous candies reflected. The exact instructions are:

- POSITIVE: “One of our employees wants to increase the odds that people will get prize money so he randomly puts more blue chocolates in some of the boxes, though he didn’t get to all of them.”
- NEUTRAL: “One of our employees enjoys rearranging the order of the chocolates in the boxes, though he doesn’t change which ones go where and he didn’t get to all of them.”
- NEGATIVE: “One of our employees who thinks the company is losing money on this promotion randomly puts more red chocolates in some of the boxes, though he didn’t get to all of them.”

Manipulating the distribution of observations

Because our primary question was how ambiguity aversion relates to the combination of prior beliefs about the distribution as well as the information they did have, we also manipulated the information provided about the ambiguous box.

Table 1: The five INFORMATION conditions, which varied the degree of ambiguity and the distribution implied by the visible pieces in the ambiguous box. The other box always contained half red and half blue pieces, all visible. In the actual experiment the side that the ambiguous box appeared on was randomized.

Condition	Stimuli
100%	
Negative 75%	
Neutral 75%	
Positive 75%	
50%	

There were two components to this. The first is the total amount of ambiguity: what percentage of the wrappers in the "ambiguous" box were ambiguous, i.e., white? The second is, when the ambiguity wasn't total, what the revealed wrappers suggested about the true distribution.

This resulted in five experimental conditions, as shown in Table 1. Ambiguity ranged from 100% (in which all of the wrappers were white) to 50% in which half were white. To manipulate information content, we split the 75% condition into three versions. In the 75% NEGATIVE the two non-white wrappers were red, in the 75% POSITIVE they were both blue, and in the 75% NEUTRAL one was red and one was blue. These conditions are interesting because they are mostly ambiguous but provide a small amount of information about the true underlying distribution, and thus are ideal for teasing apart the roles of the amount of ambiguity and the nature of the observed information on the other. In order to test the success of this manipulation, after making their choice we asked each participant how many of the hidden chocolates they thought were red, how many were blue, and how many might have been another color.

Results & Discussion

The effect of prior knowledge

Our first question was whether manipulating the prior assumptions affected people's levels of ambiguity aversion. To analyze this, we evaluated whether the proportion of people choosing the ambiguous option differed between PRIOR conditions, collapsing across the amount of ambiguity but excluding the cases where there were additional cues (i.e. the 75% negative and positive conditions). There was a significant effect, which can be seen by considering the overall difference between the colored bars in Figure 2 ($\chi^2(2) = 25.98, p < 0.001$).[1] Indeed, those in the POSITIVE condition were much more likely to choose the ambiguous box. In that condition the aversion to ambiguity was eliminated ($\chi^2(1) = 14.75, p < 0.001$, Holm correction for multiple tests used) since people actually preferred the ambiguous box: an eminently sensible choice if they thought it was more likely to contain more blue chocolates. People in both the NEUTRAL ($\chi^2(1) = 4.55, p < 0.05$, Holm corrected) and NEGATIVE ($\chi^2(1) = 7.58, p < 0.05$, Holm corrected) conditions did show the standard ambiguity aversion, preferring to avoid the ambiguous box.

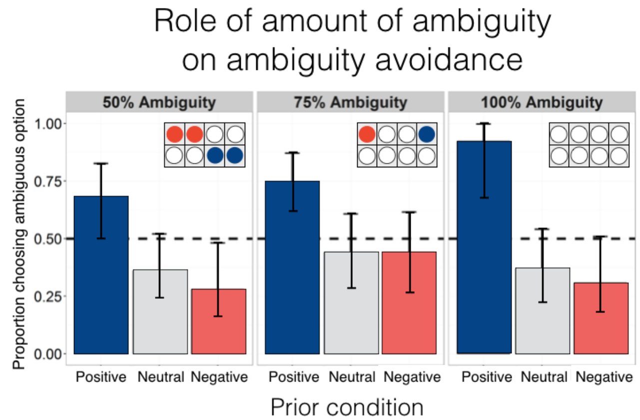


Figure 2: **Proportion of participants choosing the ambiguous option as a function of degree of ambiguity.** The x axis reflects the prior manipulation affecting people's expectations about what the ambiguous box held, with people in the POSITIVE condition expecting that it held more good (blue) chocolates and the NEGATIVE condition expecting it held more red. Each of the three panels depicts different degrees of ambiguity with example stimuli shown in the insets. It is clear that people in the POSITIVE condition tended to choose the ambiguous box, with a stronger preference as the degree of ambiguity grew. Those in both the NEUTRAL and NEGATIVE conditions showed the classic ambiguity aversion affect. Interestingly, it did not seem to change with the degree of ambiguity.

Several aspects of these results are interesting. First, people in the NEUTRAL condition were just as ambiguity-averse as those in the NEGATIVE condition ($\chi^2(1) = 0.18, p = .67$). Second, the degree of ambiguity aversion in both the NEUTRAL and NEGATIVE conditions also did not appear to change based on the amount of ambiguity: people were just as averse to selecting chocolates out of a box with four hidden chocolates ones as with eight hidden, despite the fact that the former situation contains more information about the true distribution of chocolates (NEUTRAL: $\chi^2(2) = 0.43, p = .81$), NEGATIVE: $\chi^2(2) = 1.63, p = .44$). This is especially interesting in light of the fact that in the POSITIVE condition, people *did* seem to be sensitive to the amount of ambiguity: as it increased, they were more likely to choose the ambiguous box (Bayes Factor "more likely" vs "all different" = 6.92, "more likely" vs "all the same" = 2.64).[2]

[1] For this analysis we collapsed across the neutral ambiguity conditions, but excluded the conditions that gave distribution cues. Including these two conditions made no difference to the outcome.

[2] We used Bayes Factors for this analysis because of the ease with

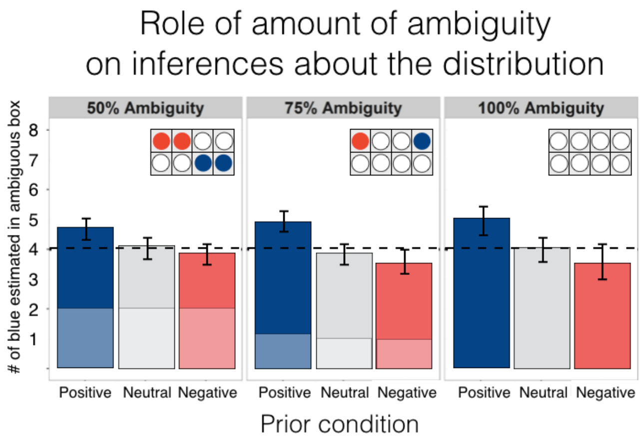


Figure 3: **Estimated number of blue chocolates in the ambiguous box as a function of degree of ambiguity.** The y axis shows the number of chocolates that people estimated were in the ambiguous box. Only the people in the POSITIVE condition assumed that the ambiguous box contained more than 50% blue chocolates, those in the NEUTRAL condition assumed that about half were blue, and those in the NEGATIVE condition thought half or fewer were blue. For reference, the lightly shaded boxes at the bottom of the bars indicate how many of the estimated chocolates were directly visible in that condition.

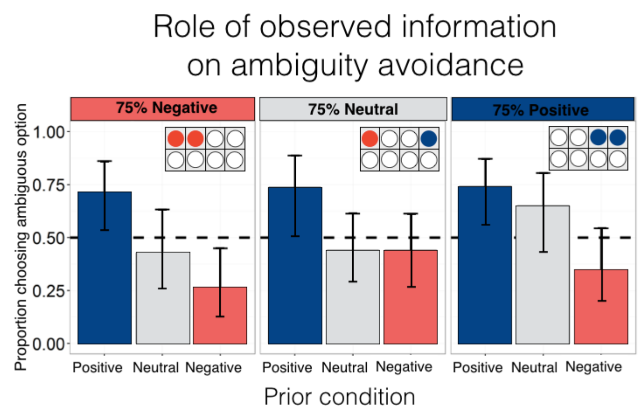


Figure 4: **Proportion of participants choosing the ambiguous option as a function of observed information.** Each of the three panels show boxes with 75% ambiguity (i.e., two known chocolates and six unknown) but differ in the distributional makeup of the known chocolates, as shown in the inset diagrams: in the 75% NEGATIVE condition both chocolates were red, in the 75% NEUTRAL condition there was one of each, and in the 75% POSITIVE condition both were blue. It is clear that informational content did not affect ambiguity aversion except in the 75% NEUTRAL condition, suggesting that only then were people's priors weak enough to be overcome by data.

Why might people be doing this? One possibility is that people in the POSITIVE condition believed that it contained more blue chocolates, while those in the NEUTRAL and NEGATIVE conditions believed it to be mostly red, thus inducing ambiguity aversion. To test this possibility, we analyzed participants' estimates of the number of blue chocolates in the ambiguous box. As Figure 3 shows, those in the POSITIVE condition inferred that more than half of the chocolates were blue ($\bar{X} = 4.72, t(56) = 5.45, p < 0.001$), those in the NEUTRAL condition did not have strong opinions either way ($\bar{X} = 3.99, t(87) = -0.13, p = .90$), and those in the NEGATIVE condition felt that half or less were blue ($\bar{X} = 3.68, t(75) = -2.76, p < 0.01$).

These results suggest three things. First, they indicate that ambiguity aversion can be overcome if there is reason to believe that the ambiguous item is more appealing than the unambiguous item (in this case, that it contains more than 50% of blue chocolates). Second, they suggest that ambiguity aversion is not solely caused by the prior: people showed the ambiguity aversion in the NEUTRAL condition while simultaneously estimating that the ambiguous box contained the same number of blue chocolates as the unambiguous one (i.e., four). Moreover, among those who received the POSITIVE cover story, preference for the ambiguous box was higher in the 100% case than the 50% case despite the fact that the estimated number of blue chocolates was nearly identical ($t(27.84) = -1.063, p = .31$).

Overall, these results suggest that people's prior assumptions play a strong but not dispositive role in ambiguity aversion: when people are given a reason to believe that an ambiguous choice is better they are entirely willing to choose it. Moreover, people are sensitive to a cover story about how the observations were generated, and are willing to adjust their decision making on the basis of their beliefs about this generative process. Nevertheless, it is noteworthy that prior beliefs are not the entire story: people are ambiguity averse even when they believe the ambiguous option is statistically identical to the unambiguous one.

The effect of distributional information

As the previous section illustrates, people's prior beliefs about an ambiguous situation are sensitive to the causal explanation for why the missing information is missing. We now consider the question of how sensitive people are to the distribution of observed evidence. To that end we consider the three 75%-ambiguous conditions, all of which are matched on ambiguity, but present people with evidence that is positive (two blue chocolates are observed), negative (two reds), or neutral (one blue and one red).

The results, shown in Figure 4, reveal that people were largely insensitive to the distribution of observed chocolates, at least for the POSITIVE and NEGATIVE cover stories. People given the POSITIVE cover story tended to prefer the ambiguous box regardless of what the two visible chocolates looked like, ($\chi^2(2) = 0.06, p = .97$) while those given the NEGATIVE cover story avoided it regardless ($\chi^2(2) = 1.87, p = .39$). In these two conditions, people's prior beliefs about the source of the ambiguity (i.e., the cover story) overwhelmed any effect that the observed chocolates might have had. Only in the NEUTRAL condition – where no clear reason for the ambiguity was provided – did people change their behavior consistently, picking the ambiguous box more often when the

which it allowed us to test an ordinal hypothesis for binomial data.

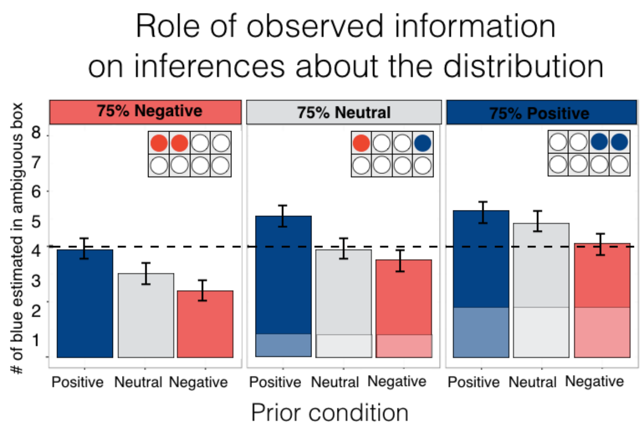


Figure 5: **Proportion of participants choosing the ambiguous option as a function of observed information.** The *y* axis shows the number of chocolates that people estimated were in the ambiguous box. People were sensitive to both the prior (cover story) and data (visible chocolates). Priors played a role, with people (regardless of the pattern of visible chocolates) estimating the most blue chocolates when they were given the POSITIVE cover story and the least when given the NEGATIVE cover story. The data played a role too, with people (regardless of cover story) inferring the fewest blue chocolates when two red ones were visible, and the most when two blue ones were.

two visible chocolates were blue (BF "increasing" vs "all the same" = 2.54, BF "increasing" vs "all different" = 2.02). While it seems plausible that people would be willing to adjust their behavior in the POSITIVE and NEGATIVE conditions if the quantity of observations were larger (e.g., a box with 99 blue chocolates observed and 1 unknown is much better than one with 50 blue chocolates and 50 red, regardless of how maliciously the 1 ambiguous chocolate was chosen!), the fact that no observed differences were found in our data suggests that the biases imposed by the cover story are quite strong.

This explanation is supported when we consider the estimates of the number of blue chocolates in these three conditions. As Figure 5 makes clear, people take the observed information into account in all conditions: regardless of whether the cover story was POSITIVE ($R^2 = .20, F(2,71) = 8.71, p < 0.001$), NEUTRAL ($R^2 = .29, F(2,63) = 12.91, p < 0.001$), or NEGATIVE ($R^2 = .39, F(2,75) = 23.52, p < 0.001$), people thought the box with two visible blue chocolates probably contained more blue chocolates, while the box with two visible red chocolates contained fewest. There is an effect of the prior cover story as well, with people who received the POSITIVE cover story consistently estimated more blue chocolates than those who received the NEUTRAL one ($t(126.82) = 2.95, p < 0.01$), and those more than the NEGATIVE one ($t(145.18) = 5.90, p < 0.001$). This is consistent with the suggestion that people are sensitive to the quantity observed evidence, but consider the cover story to be the more important factor when driving decisions in situations like these where comparatively little data is available.

Summary

The experiment suggests that participants are very sensitive to the reason given for why the ambiguity exists: it appears to exert a substantial influence on the priors people bring to the statistical inference problem that ambiguity presents. This effect is seen regardless of whether we look at which box people chose, or whether we look at their estimates of the number of chocolates in the ambiguous box. That said, ambiguity aversion is not fully explained by the combination of priors, the observed data, and estimates about the true nature of the underlying distribution of chocolates in the ambiguous box. This is evident for several reasons. First, people tended to avoid ambiguity to a similar degree regardless of whether the cover story was NEUTRAL or NEGATIVE (Figure 2), and differences in the amount of ambiguity when it was POSITIVE resulted in different levels of ambiguity aversion (Figure 2) but not differences in the estimated number of blue chocolates (Figure 3). Moreover, while differences in the *distribution* of the observed chocolates affected ambiguity aversion when the cover story was NEUTRAL, they did not affect it when the cover story was POSITIVE or NEGATIVE (Figure 4), though this may be a consequence of strong priors. As shown in Figure 5, people do use the observed data to guide their estimates in these condition, but the data never outweigh the prior.

General Discussion

It is perhaps unsurprising that ambiguity aversion is malleable when people are presented with partial data or given reasons to view ambiguity in a positive light. After all, real world decision making always involves some degree of ambiguity: it would be very strange if people could not embrace it under the right circumstances. The critical finding from our experiment, however, is that people seem to assess ambiguity in a fairly rational way: when given reasons to prefer ambiguity people do so, and when given observational data that makes the ambiguous option more favorable, people adjust their beliefs about the desirability of that option. This is consistent with findings by Güney and Newell (2011, 2015) that ambiguity aversion is related to the prior beliefs that people use to interpret the ambiguity, and is reminiscent of results showing that other decision-making effects can be manipulated by shifting the quality and quantity of information available to people (e.g. Welsh & Navarro, 2012).

Of particular interest to us is the fact that ambiguity aversion seems to be the default behavior in our experiment: despite our best efforts to create a "neutral" prior condition, participants were disposed to treat that scenario with some suspicion, and adopt a relatively negative strategy that more closely resembles the NEGATIVE cover story than the POSITIVE one. Moreover, they did so in spite of the fact that their estimates of the proportion of blue chocolates were roughly 50% on average. Does this suggest that our participants take additional information into account when making decisions about ambiguity? If so, what other cues could they be using?

One possibility is the social aspect of ambiguity aversion that has been demonstrated by several researchers. Charness, Karni, and Levin (2013) demonstrate that allowing individuals to control aspects of the experiment – reducing suspicion about the ambiguous option – reduces ambiguity aversion, whist allowing participant collusion results in a trend towards ambiguity neutrality. This effect of collusion was also demonstrated by Keck, Diecidue, and Budescu (2012), suggesting that a fruitful avenue for future work would be to examine the effect of social co-operation and competition on ambiguity preferences.

Another possibility is that participants are relying on a different decision process, one that doesn't aim to maximize expected utility. For instance, Gilboa and Schmeidler (1989) propose the Maxmin Expected Utility theory, which suggests that participants have in mind a prior range for the number of desired tokens in the ambiguous option. They will choose this ambiguous option if and only if the expected utility of the ambiguous option for the minimum of the range is less than the expected utility of the unambiguous option. If people are using this rule to make decisions, but still give estimates about the expected value of blue chocolates, this theory might explain the dissonance between decisions and inferred distribution. Future work could elicit this directly by asking participants to give an upper and lower bound for the number of blue chocolates that they expect, but would also need to explain why this is true for some but not all conditions.

More generally, a natural direction to extend this work is to consider a broader range of scenarios and mechanisms that might give rise to ambiguous data. In real life, this can happen in many different ways. The interpretation of surveys with missing data can be very different depending on whether the data are missing at random or have been systematically censored. Ambiguous phrasing in an opinion piece might be innocuous, or it might reflect an attempt to mislead with half truths. Even the ambiguity in something as simple as Ellsberg's (1961) original urn task might carry a different interpretation depending on whether participants believe the experimenter is asking a trick question. In short, when trying to construct a general theory of why people tend towards ambiguity aversion, we suggest it makes sense to ask where ambiguity arises in the real world. Is ambiguity usually associated with positive outcomes, or does the absence of key information tend to suggest something more nefarious? Our current results are ambiguous, but future work will investigate additional informative cues.

Acknowledgments

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