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Whose statistical reasoning is facilitated by a causal structure intervention?

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Abstract

People often struggle when making Bayesian probabilistic estimates on the basis of competing sources of statistical evidence. Recently, Krynski and Tenenbaum (2007) proposed that a causal Bayesian framework accounts for peoples' errors in Bayesian reasoning, and showed that by clarifying the causal relations amongst the pieces of evidence, judgements on a classic statistical reasoning problem could be significantly improved. We aimed to understand whose statistical reasoning is facilitated by the causal structure intervention. In Experiment 1, although we observed causal facilitation effects overall, the effect was confined to participants high in numeracy. We did not find an overall facilitation effect in Experiment 2 but did replicate the earlier interaction between numerical ability and the presence or absence of causal content. This effect held when we controlled for general cognitive ability and thinking disposition. Our results suggest that clarifying causal structure facilitates Bayesian judgements, but only for participants with sufficient understanding of basic concepts in probability and statistics.

Keywords: Bayesian judgement, causal reasoning, base rate neglect, numeracy

Statistical reasoning is fundamental to a range of decisions about our health, our finances and our education. However, research consistently shows that many people struggle to appropriately interpret and integrate competing sources of probabilistic evidence when making statistical judgements (for a review see Barbey & Sloman, 2007). Interventions designed to remedy shortcomings in our statistical reasoning are, therefore, extremely important. More recently, interventions where the causal structure of the reasoning problem is made clearer have been found to lead to an increase in normatively correct statistical reasoning (Krynski & Tenenbaum, 2007). In this paper we will examine who is capable of Bayesian reasoning, and whose reasoning is helped the most by causal structure interventions. Knowing the answer to these questions will help us to evaluate theories of statistical reasoning and to target interventions designed to help people reason better about statistics.

Bayesian reasoning and causal structure

Normatively, probabilistic judgements should be calculated using Bayes Theorem, presented below.

$$P(H|E) = \frac{\mathrm{P(H)\ x\ P(E|H)}}{\mathrm{P(H)\ x\ P(E|H)} + \mathrm{P(\neg H)\ x\ P(E|\neg H)}} \qquad \text{Equation 1}$$

In Equation 1, $\mathrm{P}(H|E)$ represents the probability that an hypothesis H is true given the evidence E. To compute this, reasoners must integrate the prior probability of the hypothesis, P(H), with the likelihood that the evidence will be observed if the hypothesis is true, $\mathrm{P}(E|H)$. Reasoners must also consider the chances that the hypothesis is not true, P(¬H), and the likelihood that the evidence will still be observed even if the hypothesis is false, $\mathrm{P}(E|\neg H)$.

When asked to compute $\mathrm{P}(H|E)$ many people neglect the prior probabilities or base rates, P(H) and P(¬H).

Initial hypotheses explaining the error centred on compelling heuristics biasing reasoning (Kahneman & Tversky, 1972), with subsequent proposals focussing more on the numerical and linguistic formulation of traditional statistical reasoning problems (e.g. Gigerenzer & Hoffrage, 1995; Macchi; 2000; Sloman, Over, Slovak & Stibel, 2003). More recently, Krynski and Tenenbaum (2007) proposed a causal Bayesian framework, arguing that when reasoning statistically people begin by constructing a transient causal model of the relationships between the evidence, which is used to direct how the available data should be integrated in Bayesian terms. Thus, rather than simply extracting the statistical data and mechanically applying Bayes' Theorem, probabilistic reasoning is said to occur in a three stage process: construction of a qualitative causal model; parameterisation of the model with available statistical data; and finally calculation in accordance with Bayesian prescriptions. According to Krynski and Tenenbaum, errors such as base rate neglect occur when reasoners cannot intuitively construct the correct causal model representation of the evidence. Attempts to parameterise incorrect or incomplete causal models typically result in an incorrect integration of the given statistical data.

Evidence for base rate neglect comes from experiments on the mammography problem (Eddy, 1982) which asks for estimates of the likelihood of breast cancer in someone with a positive mammogram given information about the base rate and about hits and false positives for the test. Gigerenzer and Hoffrage (1995), for example, found that the vast majority of participants gave over-estimates between 70% and 90%, as a result of neglecting the 1% base rate. Krynski and Tenenbaum (2007) argue that the failure of the problem to specify what causes false positive tests interferes with reasoners' intuitive attempts to construct a causal model representation. In two experiments Krynski and Tenenbaum increased rates of Bayesian responding from as low as 15% on a simplified version of the mammography problem, to 45% on their causal problem. The causal problem explained that positive mammographies could also be caused by the presence of a dense but harmless cyst, but remained otherwise identical to the standard version. These, and more recent experiments (see Hayes, Newell & Hawkins, 2013; McNair & Feeney, in press), provide initial support for the idea that causal structure interventions might be a means to remedy compelling errors in statistical reasoning.

Population and individual differences in Bayesian reasoning

Although making the causal structure of the problem more transparent may offer a means of improving statistical reasoning, it is not clear whose reasoning such a manipulation will improve. Krynski and Tenenbaum found that 45% of responses to their causal problems were Bayesian, whilst more recent experiments (McNair and Feeney, in press) consistently showed that no more than 25% of responses to various causal problems are Bayesian and sometimes failed to obtain a significant facilitation effect owing to this low rate of Bayesian responding. Owing to the fact that Krynski and Tenenbaum's samples comprised MIT students, and based on the finding that participants in top-tier Universities neglect the base rate less than participants in other Universities (Brase, Fiddick & Harries, 2006), the inconsistency between studies may be tentatively interpreted as being due to differences between the populations sampled.

Even if the conjecture about population differences is correct, the underlying factors are unclear. One potentially relevant factor is general cognitive capacity, and there is somewhat mixed evidence about its relation to Bayesian reasoning. For example, although Stanovich & West (1998) reported no differences due to general cognitive ability in people's tendency to recognise the importance of base rates, positive associations between cognitive ability and Bayesian reasoning have recently been reported (see Lesage, Navarrete and De

Neys, 2013; Sirota, Juanchich & Hagmayer, 2013). Another more specific factor is numeracy, which is known to play a role in statistical reasoning errors (see Reyna, Nelson, Han & Dieckmann, 2009). Because the role of numeracy in Bayesian reasoning has not yet been systematically investigated, the first aim of the experiments to be described here was to investigate whether numeracy is related to performance on the mammography problem. Our second aim was to examine whether numeracy mediates the facilitating effects of causal structure interventions.

Questions about population and individual differences in the effects of causal structure interventions on statistical reasoning have considerable theoretical bite as they relate to the generality of the causal Bayesian framework (Krynski and Tenenbaum, 2007) as an explanation of statistical reasoning. Some studies have shown an almost complete absence of Bayesian reasoning on typical, percentage-based problems (e.g. Brase et al., 2006) and it is possible that misunderstanding of the causal structure of the problem may be the underlying determinant of very poor statistical reasoning. Arguably, for the causal Bayesian framework to work as a general theory of statistical reasoning, this should be the case. Alternatively, poor statistical reasoners may suffer from more basic problems in thinking about statistics, which high numerates may not experience. According to this view the causal structure manipulation might have a bigger effect on the reasoning of high numerates.

Experiment 1

Method

Participants: 144 (26 males, mean age 20 years) undergraduate psychology students from Queen's University Belfast participated. Participants were expected to be of mixed mathematical ability, given that high numeracy is not a specific course requirement.

Materials, Design and Procedure: In a between subjects design we presented participants with the same Standard and Causal mammography problems used by Krynski and Tenenbaum (2007, Experiment 1). The difference between the problems is highlighted by the italicised text in the causal problem, presented below. Participants first completed Lipkus, Samsa and Rimer's (2001) 11-item numeracy scale, which assesses the ability to perform basic mathematical operations based on frequency and percentage data. All materials were distributed on paper during class. Participants were asked not to use calculators, and were given 15 minutes to complete all materials.

Causal Mammography Problem

> Suppose the following statistics are known about women at age 60 who participate in a routine mammogram screening, an X-ray of the breast tissue that detects tumours:
>
> 2% have breast cancer at the time of the screening. Most of those with breast cancer will receive a positive mammogram. About 6% of those without cancer have a dense but harmless cyst which looks like a cancerous tumour on the X-ray and thereby results in a positive mammogram.
>
> Of those that receive positive mammographies, what % would you expect to have cancer?

In the standard problem the italicised text was replaced with the following sentence: There is a 6% chance that a woman without cancer will receive a positive mammogram.

Results

Data coding: Data were coded somewhat differently from Krynski and Tenenbaum (2007), who coded only exactly correct answers of 25% as Bayesian, any estimate greater than 80% as base rate neglect, and remaining answers as "Other". Instead, to ensure that small calculation errors did not prevent us from identifying good reasoners, we coded answers within 5% of the relevant response as Bayesian or Base Rate Neglect (e.g. answers from 20% - 30% were coded as Bayesian). For brevity, our analyses focus primarily on Bayesian responses. As is common with short tests, reliability for the numeracy scale was relatively low, $\alpha = .55$. For some of the analyses involving numeracy, we carried out a median split by performance on the numeracy scale. The high levels of performance on the scale meant that we categorised participants who answered 10 (the median value) or more items correct as High numerates.

Analyses: Response frequencies broken down by problem and numeracy are to be found in Table 1. Participants who attempted causal problems were more likely to give a Bayesian response (13/71) than were participants who attempted the Standard problem (5/73): χ^2 (1, N = 144) = 4.32, p < .04, $\varphi_c = .17$. Separately, a greater number of High numerates gave Bayesian responses (16/79) than did lower numerates (2/65): χ^2 (1, N = 144) = 9.62, p < .01, $\varphi_c = .25$.

Table 1 here

To investigate the relative influence of each variable on Bayesian responding we conducted a binary logistic regression treating standardised numeracy scores as a continuous predictor variable alongside problem type. Given the unequal gender split in our sample, we controlled for gender. The model was statistically significant (χ^2 [4, N = 144] = 23.14, p < .001), explaining between 14.8% (Cox & Snell R^2) and 28.1% (Nagelkerke R^2) of the variance, and correctly classified 87.5% of cases. Table 2 summarises the relative contribution of each predictor in the model. Importantly, the Problem Type x Numeracy interaction accounts for a statistically significant portion of the variance in Bayesian responding.

Table 2 here

To follow up on the statistically significant interaction, we analysed separately the performance of High and Low numerates, finding that Problem Type was significantly associated with Bayesian responding in the High numerate sample (χ^2 [1, N = 79] = 6.39, $p < .02$, $\varphi_c = .28$) but not the Low numerate sample.

Discussion

Our results show that the majority of Bayesian responses occurred when reasoners were relatively high in numeracy and attempted a causal problem. Crucially, the interaction between problem type and numeracy was a better predictor of Bayesian responding than either variable alone. Participants who were low in numeracy produced almost no Bayesian responses on either problem version thus highlighting the apparent difficulty these reasoners experienced, and further supporting the hypothesis that causal facilitation is contingent upon numerical ability. However, given recent work indicating strong positive relationships between general cognitive ability and Bayesian reasoning (Lesage et al., 2013; Sirota et al., 2013), the possibility remained that any relationship between numeracy and Bayesian reasoning on the causal problem might be due to general effects of cognitive ability rather than to the specific effects of numeracy. We investigated this possibility in Experiment 2.

Experiment 2

The first aim of Experiment 2 was to replicate the association between numeracy and problem type that we observed in Experiment 1. However, because associations between certain forms of base rate neglect and both general cognitive ability (Lesage et al., 2013; Sirota et al., 2013) and thinking dispositions (Sirota et al., 2013) have recently been demonstrated, an important second aim of Experiment 2 was to examine whether the association with numeracy holds up once these other variables are controlled for. Previous demonstrations of unique effects of numeracy on judgements (Peters, Västfjäll, Slovic, Mertz, Mazzocco & Dickert, 2006), suggest that the association will hold up.

Method

Participants: 179 (26 males; mean age = 21 years) undergraduate psychology students from Queen's University Belfast participated.

Materials, Design, and Procedure: In a between subjects design we presented participants with the same causal and standard mammography problems used in Experiment 1. Owing to the high level of performance on the Lipkus et al. numeracy scale in Experiment 1, we assessed numerical ability using the 7-item form of the Berlin Numeracy Test (BNT), a scale shown to afford more discrimination than the measure we used in Experiment 1 (Cokely, Galesic, Schulz, Ghazal, & Garcia-Retamero, 2012). We also measured participants' general cognitive ability using a 9-item short form test of Raven's Standard Progressive Matrices (Bilker, Hansen, Brensinger, Richard, Gur & Gur, 2012), and their thinking dispositions using Pacini and Epstein's (1999) Rational-Experiental Inventory (REI). The REI has four sub-scales, each with 10 items, which measure rational ability, rational engagement, experiential ability and experiential engagement. All materials were presented on paper and were distributed during undergraduate lab classes. Participants were not permitted to use calculators.

Results

Data coding: Mammography problem responses were coded as in Experiment 1. Owing to a printing error, item 7 of the BNT had to be dropped from analyses so that numeracy was taken as a score out of 6. Once again, reliability of the short scales used in this experiment was somewhat low: Berlin Numeracy Test, α = .47; Raven's, α = .52. However, the subscales of the REI yielded higher reliability estimates: rational ability, α = .8; rational engagement, α =.86; experiential ability α =.81, experiential engagement, α = .67. For some of the analyses involving numeracy, we carried out a median split by performance on the numeracy scale. We categorised participants who answered 5 (the median value) or more items correct as High numerates. This resulted in a group of 50 High numerates and 129 Low numerates.

Analyses: Table 3 presents a breakdown of response frequencies by problem type and numeracy level. There were more Bayesian responses to causal problems (17%) than to standard problems (11%), but the association between response and problem type was not significant, χ^2 (1, N = 179) = 1.37, p = .28, φ_c = .09. Although this finding indicates that we have not replicated the causal facilitation effect overall, it is in line with previous findings that the effect is weaker than initially thought and is sometimes not observed (see McNair & Feeney, in press). The association between numeracy and Bayesian responses was significant: χ^2 (1, N = 179) = 5.81, p < .02 φ_c = .25. As may be seen from Table 3, proportionally more Bayesian responses were given by High numerates than by Low numerates.

Table 3 here

To investigate whether the causal facilitation effect is associated with numeracy we conducted a binary logistic regression with Bayesian responses as the criterion, treating standardised numeracy, Raven's, and REI scores as continuous predictors and problem type as a categorical predictor. As previously, we also controlled for gender. The model was significant (χ^2= 37.78 [14, N = 179], $p < .01$), correctly classifying 89% of cases and explaining between 18% (Cox & Snell R^2) and 33% (Nagelkerke R^2) of the variance. Table 4 summarises the relative contribution of each predictor in the model.

Table 4 here

Results in Table 4 replicate those observed in Experiment 1, indicating that controlling for cognitive ability and thinking dispositions, a significant portion of the variance in Bayesian responding was uniquely predicted by an interaction between numeracy and problem type. In addition, collapsing across problem type, the tendency to give a Bayesian response was associated with higher cognitive ability.

We followed up the significant interaction between numeracy and problem type by testing for causal facilitation effects in High and Low numerates separately; analysis again indicated that although we did not observe a causal facilitation effect overall, the effect did appear in High numerates, χ^2 (1, N = 50) = 7.06, $p < .01$, $\varphi_c = .37$, but not in Low numerates, replicating the key finding from Experiment 1.

Discussion

The results of this study replicate our finding that whether information about causal structure facilitates reasoning is dependent on the numerical ability of the sample: a facilitation effect is observed in High but not in Low numerates. Importantly, this effect holds even when general cognitive ability and thinking dispositions have been controlled for. It is also noteworthy that we did not find a causal facilitation effect overall. These results support previous suggestions (McNair & Feeney, in press) that the causal facilitation effect is not as strong as originally thought, and show for the first time that relatively high levels of numeracy are required for the effect to be observed. Furthermore, results were also in line with recent findings (Lesage et al., 2013; Sirota et al., 2013) indicating a unique predictive role for general intelligence in Bayesian reasoning.

General Discussion

Our aims at the outset were to investigate the role of numeracy in (a) Bayesian statistical reasoning and (b) the causal facilitation effect. Although participants in Experiment 1 who were more numerate were more likely to give Bayesian answers, this pattern did not hold in Experiment 2 when general ability and thinking dispositions were controlled for. Instead, general cognitive ability was uniquely associated with reasoning performance. However, in both experiments a causal facilitation effect was observed only in High numerates, and this effect held even when we controlled for the other variables. Thus, relatively high numeracy appears to be a pre-requisite for a facilitating effect of causal information on statistical reasoning.

The significant interaction we have observed between the presence or absence of additional causal information and numeracy suggests that misunderstanding the causal structure of the problem is only one of several causes of non-Bayesian statistical reasoning. For example, only 13 out of the 21 High numerates in the causal condition of Experiment 2 correctly solved the problem, and almost none of the Low numerates in either experiment solved the problem correctly, even when given information about causal structure. Thus, provision of additional information about causal structure is not a universal cure by which the statistical reasoning of the majority can be improved. This observation has theoretical and practical implications.

That general cognitive ability, but not numeracy, was uniquely associated with overall Bayesian responding suggests that the more general measure may be sensitive to a variety of factors, such as misunderstanding of statistics, failure to consider the alternative hypothesis, inability to integrate the statistics, and calculation errors, which prevent a Bayesian response. The interaction between numeracy and problem type, on the other hand, suggests that the efficacy of the causal structure intervention, which helps participants construct an integrated representation of the data, is dependent on more basic understanding of numerical and statistical concepts (for additional evidence of experimental manipulations that differentially affect low and high numerates, see Johnson & Tubau, 2013). Because a causal structure intervention cannot remedy basic misunderstandings, causal model accounts are thus unlikely to suffice as general explanations for people's problems with statistical reasoning.

Whilst some people appear to give a non-Bayesian answer because, as the causal Bayesian framework (Krynski & Tenenbaum, 2007) suggests, they cannot construct an accurate causal model based on the statistics presented in the problem, others commit errors for some other, perhaps more basic, reason. Basic difficulties are to be seen in the results on the numeracy scale employed in Experiment 1. For example, the majority of people incorrectly answered item 10 in the Lipkus et al. (2001) numeracy scale, which asks how many out of 10,000 people would contract a viral infection if the chance of getting it is .0005. Post hoc analysis revealed that amongst those who answered this item correctly there was a causal facilitation effect, χ^2 (1, N = 62) = 5.36, p < .03, whereas those who answered the question incorrectly did not show the effect, χ^2 (1, N = 82) = .21. Failure to answer this question correctly, which is associated with absence of the causal facilitation effect, reveals an inability to reason about very basic concepts in probability.

From a practical perspective, one important goal of all interventions designed to reduce base rate neglect is helping people make better statistical judgements (see Sedlmeier, 1999). Facilitation effects with statistical format manipulations (see Cosmides & Tooby, 1996) have recently been shown to also be contingent upon numerical ability (e.g. Chapman

& Liu, 2009; Sirota & Juanchich, 2011). That work, alongside our own, demonstrates how important it is to determine exactly whose reasoning is facilitated by particular interventions, and suggests that there is a pressing need for the development of techniques designed primarily to help people understand the statistics in the problem. Only when we are confident that reasoners understand the statistics with which they have been presented is it likely to be useful to consider their understanding of how those statistics should be integrated. In the meantime, our results suggest that causal structure interventions have positive implications for statistical reasoning but that on their own, such interventions are best targeted at individuals and populations who are relatively numerate.

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Tables

Table 1

Overall frequencies of Response Types across Problem Type according to Numeracy for Experiment 1

Numeracy	**Problem**	Bayesian	BRN	Other	Total
Higher	Causal	12	5	20	37
	Standard	4	15	23	42
	Total	16	20	43	79
Lower	Causal	1	5	28	34
	Standard	1	9	21	31
	Total	2	14	49	65

Note: BRN = base rate neglect

Table 2

Binary Logistic Regression predicting likelihood of Bayesian responding in Experiment 1

							95% CI	
	B	**S.E.**	**Wald**	**DF**	**P**	**Exp(B)**	**Low**	**Up**
Gender	.54	.86	.39	1	.54	1.71	.32	9.26
Problem	.05	.8	.01	1	.95	.95	.2	4.54
Numeracy	.31	.51	.36	1	.55	.73	.27	2.01
Problem*Numeracy	2.06	.91	5.08	1	.02	.13	.02	.76

Table 3

Overall frequencies of Response Types across Problem Type according to Numeracy for Experiment 2

Numeracy	**Problem**	Bayesian	BRN	Other	Total
Higher	Causal	9	1	11	21
	Standard	3	9	17	29
	Total	12	10	28	50
Lower	Causal	6	7	54	67
	Standard	7	15	40	62
	Total	13	22	94	129

Note: BRN = base rate neglect

Table 4

Binary Logistic Regression predicting likelihood of Bayesian responding in Experiment 2

							95% CI	
	B	**S.E.**	**Wald**	**DF**	**P**	**Exp(B)**	**Low**	**Up**
Gender	-1.35	.76	3.14	1	.08	.26	.06	1.16
Problem	.33	.75	.19	1	.66	1.39	.32	6.11
Numeracy	-.2	.35	.34	1	.56	.82	.41	1.62
Raven's	1.19	.6	3.99	1	.05	3.3	1.02	10.63
REI Rational Ability	-.13	.49	.07	1	.79	.88	.34	2.29
REI Rational Engagement	.61	.45	1.80	1	.18	1.83	.75	4.44
REI Experiential Ability	.59	.53	1.24	1	.27	1.8	.64	5.04
REI Experiential Engagement	-.07	.43	.03	1	.87	.93	.4	2.16
Problem* Numeracy	2.18	.71	9.37	1	<.01	8.86	2.19	12.14
Problem*Raven's	-.75	.7	1.16	1	.28	.47	.12	1.85
Problem*REI Rational Ability	-.4	.67	.35	1	.55	.67	.18	2.51
Problem*REI Rational Engagement	-.04	.7	.01	1	.95	.96	.24	3.78
Problem*REI Exp. Ability	-1.19	.79	2.28	1	.13	.31	.07	1.42
Problem*REI Exp. Engagement	.36	.65	.30	1	.58	1.43	.4	5.08