J. Behav. Ther. & Exp. Psychiat. 56 (2017) 4–11

Contents lists available at ScienceDirect

Journal of Behavior Therapy and Experimental Psychiatry

journal homepage: www.elsevier.com/locate/jbtep

A Bayesian perspective on delusions: Suggestions for modifying two reasoning tasks

Gerit Pfuhl

Department of Psychology, University of Tromsø, The Arctic University of Norway, Norway

ARTICLE INFO

Article history:
Received 12 June 2016
Received in revised form
9 August 2016
Accepted 9 August 2016
Available online 11 August 2016

ABSTRACT

Background and objectives: There are a range of mechanistic explanations on the formation and maintenance of delusions. Within the Bayesian brain hypothesis, particularly within the framework of predictive coding models, delusions are seen as an aberrant inference process characterized by either a failure in sensory attenuation or an aberrant weighting of prior experience. Testing of these Bayesian decision theories requires measuring of both the patients' confidence in their beliefs and the confidence they assign new, incoming information. In the Bayesian framework we apply here, the former is referred to as the prior while the latter is usually called the data or likelihood.

Methods and results: This narrative review will commence by giving an introduction to the basic concept underlying the Bayesian decision theory approach to delusion. A consequence of crucial importance of this sketch is that it provides a measure for the persistence of a belief. Experimental tasks measuring these parameters are presented. Further, a modification of two standard reasoning tasks, the beads task and the evidence integration task, is proposed that permits testing the parameters from Bayesian decision theory.

Limitations: Patients differ from controls by the distress the delusions causes to them. The Bayesian Decision theory framework has no explicit parameter for distress.

Conclusions: A more detailed reporting of differences between patients with delusions is warranted.

Contents

1. Introduction

Already in the 19th century, Hermann von Helmholtz described

E-mail address: gerit.pfuhl@uit.no.

http://dx.doi.org/10.1016/j.jbtep.2016.08.006
0005-7916/

perception as an unconscious inference based on previous knowledge and incoming sensory data (1924). Seeing is believing and all seeing is influenced by what one expects to see. Indeed, one can "want to see" which means that the belief is weighted stronger than the actual information received from sensation: The perceived sensory input can be discounted to fulfil one's prediction. The influence of what one wants to see is most obvious in the somewhat different case of viewing ambiguous figures, such as the Necker cube, or the duck rabbit. Even when people entirely fail to notice that there is more than one possible interpretation of sensory data, they can deliberately switch to the alternative interpretation once told what it is. In less ambiguous situations, where one interpretation of the evidence is more strongly favoured, it takes more to go against the evidence. More of what, though? A stronger expectation that one interpretation is true (Schwartenbeck, FitzGerald, Dolan et al., 2016) or a problem with the inference process (Hemsley & Garety, 1986)? In principle, both options could cause aberrant perception and beliefs. Given that beliefs at one level are evaluated at a higher level, it is not easy to disentangle the two possibilities. What looks like aberrant inferences might be caused by too strong or too weak higher order beliefs (Mathys, Daunizeau, Friston, & Stephan, 2011). Indeed, with respect to explaining delusions an aberrant (over- or under-) weighing of belief has been postulated to be an underlying mechanism (Corlett, Frith, & Fletcher, 2009; Adams, Stephan, Brown, Frith, & Friston, 2013; Friston et al., 2015; Teufel et al., 2015). These Bayesian decision theory accounts are hierarchical. Simply said, there is a Bayesian integration at the perceptual level, as well as there is a controlling or plausibility check at a higher cognitive level (Coltheart, 2007). In the Bayesian decision theory terminology: there is an uncertainty about the precision of a belief. This uncertainty about the precision of a belief is a measure of how certain the predictions from this belief are. For example, someone picking mushrooms needs to do more than decide whether the mushroom seen now is a better match to the memory of an edible or the memory of a poisonous mushroom. It is also necessary to know how variable the appearance of both species of mushroom is, and how precisely one remembers. And although there is an objective precision that might be measured by experiment, the mushroom picker must make a subjective estimate regarding the precision, and may be uncertain regarding that precision.

Further, at any time, there is not just one belief. As in hypothesis testing there are alternative options to believe in, each with its "strength". A person's model of the world contains many beliefs. The aim is to reduce uncertainties, find the appropriate model and hence make better predictions (Friston, 2005). Accordingly, there is ongoing learning. And how fast one learns depends on many factors. The difference in learning rate (attention, interests) leads to differences in the kind of beliefs (belief formation) one has as well as differences in the persistence of well-functioning beliefs (conviction stage). One may cling to some believes more than to others as some beliefs apply across various environments (are universal) whereas other beliefs are part of unstable environments (e.g. friendships). These two basic stages of belief formation and belief conviction also apply to delusion (see also Moritz, Pfuhl, Lüdtke, Menon, Balzan & Andreou, 2017).

In the next part, this article will illustrate belief formation and maintenance on a fictional example. This example shows that it is not the inference process itself that is aberrant. Rather, it appears to be a weak reflective, metacognitive assessment of the reliability of a belief that prevents the calibration of false beliefs and belief flexibility (Buck, Warman, Huddy, & Lysaker, 2012; Coltheart, 2007; Moritz & Woodward, 2006). That is, patients with delusions show epistemic irrationality, but intact instrumental rationality, i.e. they act according to their beliefs (Barch et al., 2013). Thereafter, I will describe modifications to two classical paradigms: the beads task and the evidence integration task. Knowing which parameter is impacted by delusions may provide individually tailored metacognitive therapy but also provide objective measures of treatment outcomes. It will allow measuring when all parameters are "normal".

2. Delusions as aberrant statistical inference

An advance from a descriptive towards a mechanistic understanding of delusions is crucial to advance understanding and treatment of this condition. The "Bayesian brain" framework provides such a mechanistic approach. In this view, all information processing in the brain is seen as an integration of previous knowledge with incoming new information. Continuously, knowledge/belief, is accumulated over various timescales: Prior experience and beliefs can be evolutionarily acquired (e.g. light comes from above), learned within the lifetime of an individual (e.g., chocolate is tasty) or fluctuate quickly on the order of seconds (e.g., the bird changed flight direction). Stereotypes or religions are examples of strongly learned beliefs: They can be held with great precision and be strongly robust against conflicting information. Mathematically, beliefs can conveniently be modelled as probability distributions over the space of possible events, allowing the study of the rather abstract concept of a "belief" in concrete terms. When representing beliefs as probability distributions the most likely value is its expectation.[1] Information about uncertainty of this parameter is contained in a dispersion parameter indexing the width of the distribution, its variance (the inverse of the variance is called precision). The stronger a belief, the more precise or narrow its corresponding distribution. A critical assumption of (Bayesian) reasoning is that beliefs are updated after perceiving new data. Further, probability distributions over the likelihood of different beliefs can be specified (beliefs about beliefs), expressing how reliable or appropriate one belief is compared to another. It follows that each belief also has a precision, and also a reliability in the precision of the belief. That is, the reliability is here how certain the agent is regarding the distribution of the belief, its shape, mean and variance. This reliability is a measure of how resistant a belief is to change. Reliabilities are thought to be set by sufficient experience, i.e. optimal agents become correctly calibrated (Huys, Guitart-Masip, Dolan, & Dayan, 2015; Pfuhl, Tjelmeland, & Biegler, 2011).

Data, in the form of novel observations, impact the internal representation of the world (the "model") by changing the associated probability distribution of the parameters by way of their "likelihood" (the probability of the data given the model). Depending on the (perceived) precision of this data as well as the current estimate of reliability, the internal update of a belief will be strong (in case of highly trustworthy or precise data) or weak. Any deviation between a predicted outcome based on one's belief, i.e. how children will react to a cyclist, and data, i.e. how did the children react, is the prediction error. Any prediction error leads to a re-evaluation of the reliability and precision of the belief.

2.1. How are delusions explained in terms of Bayesian inference?

The discussion of Bayesian inference so far has centered on inference processes as assumed in healthy individuals. In the following scenario, I will illustrate how such Bayesian reasoning can go wrong and result in delusional beliefs. Consider the following belief Julie may hold about herself: Julie believes that all

[1] In the special case of a normal distribution the expectation is the mode, median and mean.