Trends in
Cognitive Sciences

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Spotlight

Explaining Negativity Dominance without Processing Bias

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In a recent study, Shin and Niv explain both negativity and positivity biases in social evaluations as a function of the diversity and low frequency of events. We discuss why negative information is indeed more diverse and less frequent, and highlight the implications beyond social evaluations.

In social evaluations, negative information dominates positive information [1]; that is, people weigh negative information more strongly than positive information. This differential weighing is well documented and has several explanations, such as negative information's attention-grabbing power or the higher diagnosticity of negative information. For example, when assessing whether someone is honest, detecting a lie garners more attention and is more diagnostic than detecting a truth [2]. Shin and Niv [3] recently complemented prior explanations with a Bayesian inference model for latent causes. They argued that people summarize similar experiences into shared latent causes. To illustrate, if a person has several positive encounters with Group A, the person infers and summarizes the encounters into the latent cause 'friendly'. This inference and summation process is parsimonious and adaptive. Instead of memorizing each positive encounter, the person can memorize 'Group A = friendly' only. Further, latent causes allow predicting behavior beyond specific events. However, negative information is generally more diverse [4]; thus, people may infer more latent causes from negative compared to positive behaviors. If averaging across these latent causes drives evaluations, negative information dominates evaluations.

The model proposed by Shin and Niv [3] therefore predicts negativity dominance in evaluations without selective or more substantive processing of negative information; instead, dominance follows from the diversity and rarity of information in the evaluative ecology. Thus, if positive information is diverse and rare, it should also dominate evaluations. Indeed, Shin and Niv showed in eight experiments that both positive and negative information can have more impact, depending on which kind of information is relatively more diverse and rarer. They also showed that a Bayesian model that infers and averages across latent causes can predict participants' evaluations.

We make three points related to the model and findings of Shin and Niv [3]. First, we offer an explanation for 'why' negative information is typically more diverse than positive information. Second, we suggest that diversity may lead to dominance in evaluations without inferring latent causes. Third, we suggest that the model is applicable beyond social evaluations.

Why Negative Information Is More Diverse

There is substantial evidence for assuming that negative information is more diverse [5], and it follows logically from the range principle [4]. Figure 1A illustrates this principle for evaluating temperature: an agreeable positive range is framed by two negative ranges of 'too hot' and 'too cold'. The principle applies to most physical dimensions influencing human comforts such as temperature (i.e., too cold, too hot), light (i.e., too dark, too bright), or fat concentration in food (i.e., too dry, too fatty). People experience 'too much' and 'too little' as negative. The agreeable and thereby positive range lies in the middle. The same is true for people's physical and social attributes (e.g., too short, too tall, too talkative, too reticent). However, the stronger the evaluative connotation of a dimension, the more extreme the location on the dimension must become to be negative (e.g., being too intelligent).

Figure 1B uses spatial distance to illustrate how the range principle translates into the assumed differential similarity for positive and negative events. The average Euclidean distance between states is much smaller for positive states. If one assumes that people actively seek comfort and avoid negative states [6], a higher frequency of positive information also follows, reinforcing the dominance of negative information.

Alternatives to Latent Causes

As discussed, traits might be meaningful latent causes for behavior. However, Shin and Niv [3] also observed dominance due to differential diversity for nonsocial evaluations (e.g., the average weight of coffee beans). Thus, one might ask about the nature of latent causes underlying such evaluations.

As Figure 1C illustrates, one might employ a sub-symbolic model that codes the observed events. In the same way that higher diversity leads to more latent cause, greater diversity requires more coding units in sub-symbolic memory models; if one sums across these units, diversity leads to dominance. For example, one might experience during a vacation a distribution of temperatures sometimes agreeable, sometimes too hot, sometimes too cold. In Figures 1A and 1C we assumed that only two positive and two negative temperatures are encoded; the positive events are fully redundant, representing extreme similarity. In the Shin and Niv model [3] these events would be coded into the same latent cause. The negative events are entirely distinct, and thus their code does not overlap. Thereby, if one sums across these vectors, negative vectors will have more influence, causing a shift towards the negative evaluation that the weather was bad.

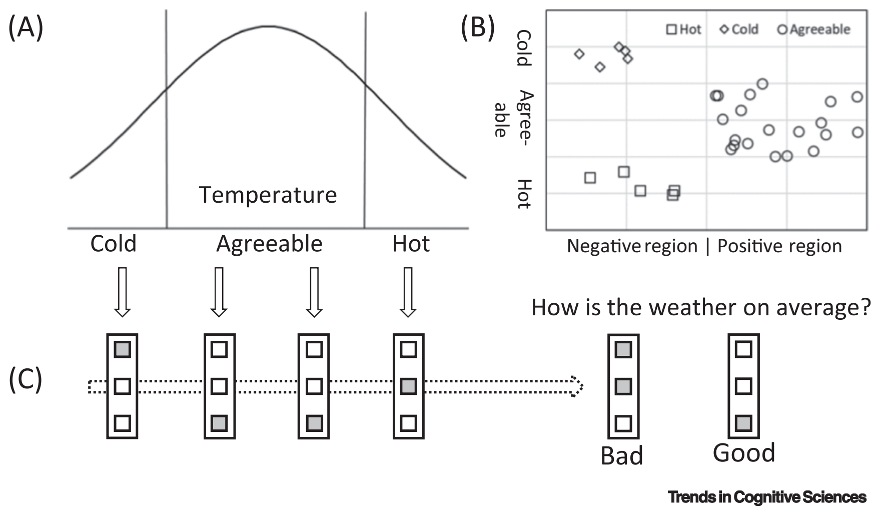

Figure 1. How the Range Principle Leads to Negativity Dominance. (A) Illustrating the range principle [4] with temperature. A middle 'good' range (here, an agreeable temperature) is framed by negative ranges of 'too little' (here, cold) and 'too much' (here, hot). (B) Illustrating the higher similarity of positive information in terms of spatial distance if one samples events from a dimension that follows the range principle. Negative states are on average farther apart than positive states. (C) Illustrating how the range principle may lead to negativity dominance if coded into sub-symbolic vectors. Because higher diversity needs more two units to code the states, the pattern across vectors will be stronger for negative than for positive information. We simplified and coded negative states as fully distinct and positive states that are fully redundant, with a single unit per state. The effect is amplified if one considers more than one dimension (e.g., temperature and humidity). Thus, if asked about the average weather, respondents are more likely to answer 'bad' [10].

The scenarios proposed by Shin and Niv [3] have no middle range, but the information that dominates evaluations, both positive and negative, always spans a broader range. However, there is no contradiction. The range principle only specifies one source of the greater diversity of negativity, and there might also be other sources. If evaluative dominance follows from diversity, one may translate the model of Shin and Niv [3] into other cognitive architectures and broaden the applicability of the basic premise.

Applications beyond Social Evaluations

Independently of whether one codes information diversity into latent causes or memory vectors, the diversity approach may explain other phenomena beyond social evaluations. For example, people typically overestimate the probability of rare cases of death (e.g., dying in a plane crash compared with dying from coronary heart disease), and there is evidence that even robust predictions from Prospect Theory such as “losses loom larger” might reverse if positive monetary events in the environment are diverse or extreme [7]. In addition, at the more basic processing levels such as memory, recognition, and priming, the diversity assumption might explain the advantages of negative information, without assuming selective attention or higher motivational engagement, due to the negative content of the information [8,9].

Concluding Remarks

The Shin and Niv model [3] aligns with an emerging perspective that conceptualizes processing differences as an interaction of cognition with the environment. The observed evaluative shifts follow not from the valence of the information but from the structure of people’s information ecologies. Thus, many negativity biases, such as negativity dominance [2], might not be “biases” after all but reflect people’s correct encoding of evaluative ecologies that are marked by the low frequency and high diversity of negative information [5].

Declaration of Interests

None are declared by the authors.

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