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Applying sampling theories to attitude learning in a virtual school class environment ☆

Klaus Fiedler *, Franz Wöllert, Benjamin Tauber, Philipp Heß

Department of Psychology, University of Heidelberg, Germany

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ABSTRACT

According to sampling theories of attitude formation, evaluative learning depends on the sampling in the environment. We investigated teachers' student evaluations in a simulated school class. Two experiments were designed to test distinct implications of experience-sampling models. While the model advanced by Fazio, Eiser, and Shook (2004) and Denrell (2005) led to the prediction of a negativity effect through asymmetric depolarization, another model (Fiedler, 1996) suggested a positivity effect through asymmetric polarization. Findings supported the latter contention. The selective tendency to oversample good students while neglecting weaker students was not radical enough to prevent the correction of negative impressions, precluding a negativity effect. Instead, extended selective sampling led to gradually increasing polarization of positive impressions, and facilitated detection of positive performance changes. While these findings can be reconciled with the Fazio–Denrell model, they highlight the crucial role of auxiliary psychological assumptions about attitude learning, as distinguished from the formal model itself.

Introduction

Where do attitudes and evaluative judgments come from? How can the learning of attitudes be modeled theoretically? Early approaches to attitude formation in the Hovland and Festinger traditions have emphasized the role of persuasive arguments and consistency constraints imposed, respectively, on the relationships between all attitudes. More recently, many researchers have adopted the Neobehaviorist notion that attitudes can be understood as a product of associative learning and conditioning (Fazio, 2001; Hofmann & Wilson, 2010; Wilson, Lindsey, & Schooler, 2000). However, simplistic conditioning experiments are hardly representative of realistic learning environments. To understand the process of attitude learning in reality, we have to analyze the structure of naturally occurring conditioning procedures, which are not under perfect experimental control. The stimulus input to real learning processes depends on the individual's selective attention and sampling preferences in a complex world that is replete with multiple information sources. To explain attitudes conceived as learned evaluations, we first have to understand the generation of the environmental stimulus samples that impinge on the individual's mind.

Sampling approaches to attitude formation

Inspired by this idea, researchers have recently begun to apply sampling models to attitude learning in a complex, probabilistic world. Central to this approach (cf. Denrell, 2005; Denrell & Le Mens, 2012; Fiedler, 2000; Fiedler & Juslin, 2006; Juslin & Olsson, 1997; Juslin, Winman, & Hansson, 2007; Stewart, Chater, & Brown, 2006) is the assumption that sampling filters can constrain the intra-psychic cognitive processes. Because not all stimuli are equally amenable to observation, the samples that provide the input to cognitive processes are hardly ever random or representative of latent reality. It is therefore essential to describe the nature of the sampling processes in the first place.

Implications of hedonic sampling

One intriguing sampling approach to attitude learning was suggested by Fazio et al. (2004). A similar model was formalized and simulated as a computer algorithm by Denrell (2005) and Denrell and Le Mens (2007). The idea is as simple and straightforward as Thorndike's (1898) law of effect: Individuals (or organisms in general) can be expected to continue sampling from pleasant

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* Corresponding author.
E-mail address: klaus.fiedler@psychologie.uni-heidelberg.de (K. Fiedler).

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sources but to stop sampling from unpleasant ones. This should be particularly so when sampling has hedonic consequences, that is, when sampling entails buying a product, eating a meal, or marrying a mating partner. Given such a hedonic setting, a single negative experience (e.g., a bad tasting meal in a restaurant) may prevent learners from sampling an aversive stimulus (or similar stimuli) again. As a consequence of truncated search, there is often no chance to correct for premature negative impressions. In contrast, continued sampling of positive stimuli allows for the correction of undue positive impressions. Due to this asymmetry, the most intriguing theoretical implication derived from this model is a negativity bias. A "learning asymmetry involving better learning of negatively valenced than positively valenced objects" (Fazio et al., 2004, p. 293) implies that "negative initial impressions are more stable than positive impressions" (Denrell, 2005, p. 951).

Beanfest

Pertinent evidence comes from a computer game that Fazio et al. (2004) called Beanfest. Participants were to take the role of an organism whose goal was to maximize energy intake by learning to discriminate between beans of different energy value. Upon sampling and eating every specific type of beans, each characterized by one of ten shapes and one of ten numbers of speckles, participants were either rewarded (+10 points) or punished (−10 points) if the bean's energy value was positive or negative, respectively. Participants readily learned to avoid the specific beans that had been directly experienced as negative as well as neighboring beans in the two-dimensional space, with similar shape and speckle numbers. This avoidance of negative stimuli clearly dominated the learning process.

Experience-sampling

A pessimistic interpretation of a regular and robust negativity bias might suggest that evaluative learning favors negative over positive attitudes, thus affording a generalized account of prejudice and disparaging social judgments. However, a closer look at Denrell's (2005) model clarifies that the prediction of a clear-cut negativity bias is qualified by distinct boundary conditions that may not always be met in reality. The model assumes (a) that on each feedback trial of a sequential sampling process, the current evaluation x of a stimulus object is updated as a weighted average of its prior value and the evaluative impact of the new feedback; and (b) that the probability p of sampling the stimulus on the next trial is a sigmoid function of the negative versus positive past experience with x. Specifically, the new evaluation, after experiencing the valenced outcome v_{t+1} on trial $t + 1$, is $x_{t+1} = (1 - b)\cdot x_t + b\cdot v_{t+1}$, and the function relating p to x is specifies as $p = e^{c+Sx}/1 + e^{c+Sx}$. Hereby b is a weighting parameter of the most recent outcome; c and S specify the baserate and the impact of the current baseline evaluation on the sampling probability.

In Denrell's (2005) basic simulation, setting these parameters to $b = 0.5$, $c = 0$ and $S = 3$ yielded a pronounced negativity bias, due to an almost stepwise p function predicting a radical decline from very high to a very low p when the evaluation x is getting only slightly negative (see solid curve for $S = 3$ in Fig. 1). Such a radical reduction in p over a small range of x, together with the high weight ($b = 0.5$) given to recent outcomes, can of course explain that a few negative experiences may cause severe negative oscillations in x, resulting in truncated sampling and irreversible negative impressions. However, the psychological question that guided the present investigation is whether these parametric assumptions, which apparently applied to the typical behavior in the Beanfest (Fazio et al., 2004), also apply to the formation of social attitudes toward human targets in reality. As also shown in Fig. 1, different parameter settings ($S = 1$ or $S = 0.25$) create much flatter p functions that do not reach $p = 0$, rendering radical truncation less likely and the correction of negative evaluation much more likely. As a result, attitude learning may not reflect a negativity bias but, as will soon be apparent, may actually exhibit a reverse positivity effect.

Experience sampling in the learning of teachers' student evaluations

For several reasons, indeed, any hedonically motivated decline in the sampling probability p should be less abrupt in real social settings than in the Beanfest. As discussed by Denrell (2005) with reference to Blau (1962), negativity in social evaluation can be evaded when small group-settings and epistemic goals encourage people to interact regardless of negative hedonic experience. Moreover, human attitude objects are different from exchangeable food or consumption objects that lack any individuality. A generally shared theory of mind (Wimmer & Perner, 1983) implies that human individuals are complex entities whose future behavior is not determined by a few observations. A student may fail on one or two tasks and still turn out to be gifted, mastering the most difficult tasks and outperforming most others. Human entities have the right to show more variance and context-dependence in their behavior than beans. They are subject to motivation shifts, free will, and social rules guiding their social interactions. Ethical and legal norms oblige us not to be prejudiced against individuals who happen to fail once or twice. A teacher cannot just drop or discard a student due to a single failure or disappointment. Wisdom of life tells us to maintain faith in every individual's potential for increment and improvement (Dweck, 2012).

Moreover, the learning of social attitudes in general, and teachers' student evaluations in particular, is not solely determined by hedonic motives but also by epistemic interest. A teacher's primary epistemic goal is to diagnose students' performance, in addition to a hedonic preference for pleasant feedback about positive performance of the class. This hedonic motive can be expected to increase when her class is being evaluated by the school

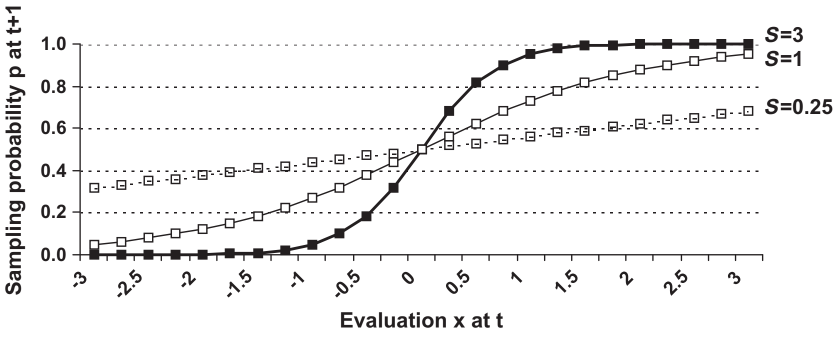

Fig. 1. Sampling probability at the time $t + 1$ as a function of the value x of the stimulus source at t for different S parameters according to Denrell's (2005) model.