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On the joys of perceiving: Affect as feedback for perceptual predictions

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ABSTRACT

How we perceive, attend to, or remember the stimuli in our environment depends on our preferences for them. Here we argue that this dependence is reciprocal: pleasures and displeasures are heavily dependent on cognitive processing, namely, on our ability to predict the world correctly. We propose that prediction errors, inversely weighted with prior probabilities of predictions, yield subjective experiences of positive or negative affect. In this way, we link affect to predictions within a predictive coding framework. We discuss how three key factors – uncertainty, expectations, and conflict – influence prediction accuracy and show how they shape our affective response. We demonstrate that predictable stimuli are, in general, preferred to unpredictable ones, though too much predictability may decrease this liking effect. Furthermore, the account successfully overcomes the "dark-room" problem, explaining why we do not avoid stimulation to minimize prediction error. We further discuss the implications of our approach for art perception and the utility of affect as feedback for predictions within a prediction-testing architecture of cognition.

1. Introduction

Humans continually make predictions about the environment. As early in perceptual processing as in the retina, neurons make predictions based on temporal and spatial regularities (Gollisch & Meister, 2010; Hosoya, Baccus, & Meister, 2005). Recently, a powerful inference-based framework has emerged suggesting that brain activity can be described as prediction error minimization (Clark, 2013; Friston, 2009, 2012; Hohwy, 2012). According to this *predictive coding* approach, the brain uses hierarchical Bayesian inference to build a representation of the world. Conscious experience has been described as the "best hypothesis" (Hohwy, Roepstorff, & Friston, 2008), or the model that makes the most accurate predictions about the environment. However, discrepancies between predictions and outcomes are no less important. Prediction errors signify changes in the external world or in our internal states and a need to modify our predictions. We have suggested that affect serves as feedback on our predictions, reflecting their accuracy and regulating them so that confirmed predictions are more likely to be used again (Chetverikov, 2014; Chetverikov & Kristjansson, 2015). Furthermore, if predictions are confirmed (low prediction error), feedback is weighted with inverse prior probabilities of predictions, so that more probable predictions receive less positive feedback. In other words, confirmation of more probable predictions yields less positive feedback than confirmed less-probable predictions. Notably, within this framework there is no need to invoke additional concepts, such as values or rewards, to explain the relationship between affect and predictions. Affect represents a distinct dimension in experience: in addition to our "best hypothesis" about the world, people experience a feeling of how good this hypothesis actually is. The literature describing affect from this perspective has largely been limited to the perception of art (Salimpoor, Zald, Zatorre, Dagher, & Mcintosh, 2014; van de Cruys & Wagemans, 2011). We fill this gap by providing a more general perspective within a predictive coding framework.

2. Affect as universal currency for predictions

The utility of affect as weighted prediction error lies in its ability to provide a common currency for different predictions and drive behavior out of homeostasis. Human cognition is prone to errors, leading to the problem of verification in perception. How can observers distinguish hallucinations or illusory experiences from what is actually real in the world? A recurrent idea is that even if perception does not completely correspond to the world, researchers should try to understand the mechanisms that make our picture of the world more or less realistic. Instead of looking for a single source of protection from the fragility of perception the goal would be instead to look for numerous "dirty tricks" that our cognitive system utilizes to reach the best possible result (Ramachandran, 1990).

This is a parallel processing approach, where each piece of data is scrupulously analyzed with various tools for identifying stimuli. This parallel analysis could be implemented within an inference-based framework, such as predictive coding (Clark, 2013; Friston, 2009,

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2012; Hohwy, 2012). Bayesian inference combines prior probabilities accumulated from experience (e.g., the probability of seeing a tree in a forest is high) with likelihood (how well actual input corresponds to the prediction of a tree) to determine posterior probabilities (the probability of a tree given the resemblance of sensory input to a tree and that we are in a forest). Predictive coding approaches suggest that cognitive architecture is organized in levels, each receiving predictions from higher levels that send error feedback on discrepancies between prediction and input. This information is, in turn, based on predictions that are then conveyed to lower levels, and so on (see Fig. 1, and below, for discussion of when predictions from differing levels may be in conflict).

Prediction error reflects discrepancy between prediction and input and allows comparison of qualitatively different predictions. For example, when one needs to identify an object, one could predict its identity based on recent experience, the probability of encountering it, context, color, semantic cues, shape, motion cues, and many other sources. It is hard to compare the results of such predictions directly, because they are expressed in different cognitive languages: shape, for example, involves spatial relations that are not necessary for color-based predictions. But prediction errors from differing cognitive levels can be compared, circumventing this problem, informing us which predictions are most accurate even if they are in conflict, for example, if shape analysis predicts a lamppost while context predicts a pedestrian.

Yet, prediction error may not always guide behavior optimally. As put by Clark (2013, p. 13), "staying still inside a darkened room would afford easy and nigh-perfect prediction of our own unfolding neural states" but it is obvious that this neither describes human behavior nor is this behavior adaptive. One way to solve this "dark room" problem is to posit inherent meta-priors that make dark rooms improbable with no possibility for correction of this model (Friston, Thornton, & Clark, 2012). Such meta-priors can be evolutionarily determined or learned through experience because humans are used to constant exposure to external stimulation.

We take a different approach, however, suggesting that behavior is guided by affect, defined as an experience of prediction error weighted with inverse prior probability of prediction. Prediction error is low inside the dark room while prior probabilities are high and low positive affect will therefore drive observers out of it. In the dark room, predictions become more and more accurate, but a continuous iterative weighting process of the inverse prior probabilities reduces positive affect. In contrast to the meta-priors idea we do not suggest that a high level of stimulation is always expected, but simply that low stimulation levels usually do not allow new and accurate predictions. Note that we do not reject the notion of predictions regarding stimulation levels. However, such predictions are not likely to be set in stone. For example, moving from the countryside to a big city or vice versa may lead to a troubled sleep due to changes in the level of audial stimulation. But after some time, expectations change and things return to normal.

Our approach shares characteristics with other accounts linking affect to predictions (Joffily & Coricelli, 2013; Schmidhuber, 2013; Van de Cruys & Wagemans, 2011; Van de Cruys, 2014). Most commonly, affect is linked to an experience of change in prediction errors. When prediction errors increase over time, observers supposedly experience negative affect while reduction of prediction error is associated with positive affect. For example, when observers are able to perceive an image in more detail than before, reduction of prediction error will lead to more positive affect. The affect in such accounts involves a second-order prediction, that is, a prediction regarding predictions. People expect their predictions not simply to be accurate (low error for first-order predictions) but more accurate than previous predictions.

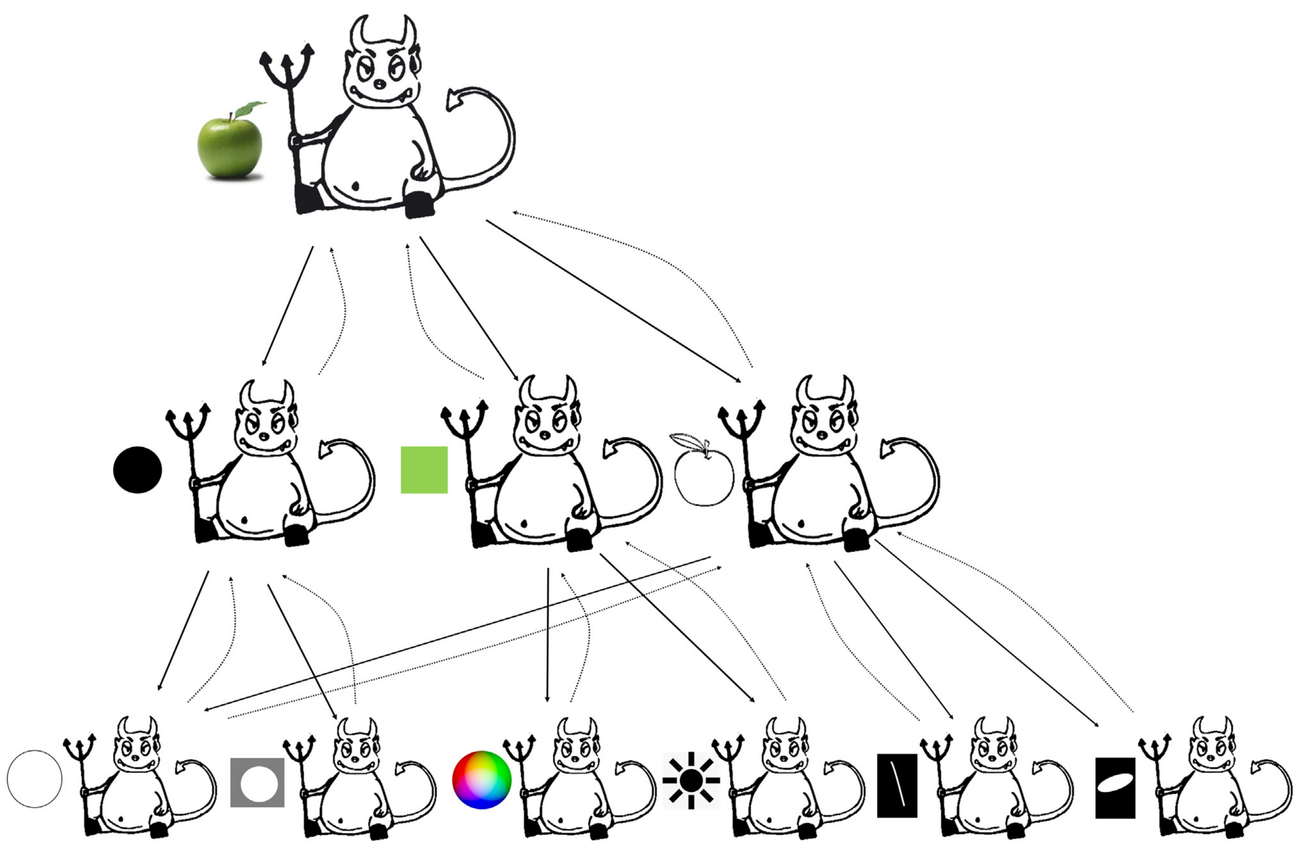

Fig. 1. Schematic representation of a predictive coding approach to perceiving an apple. A hierarchy of "predictive modules" (shown as demons echoing Selfridge's (1959) pandemonium model) are shown, with lower levels representing more granular predictions. In this example, the demons at the top level predict that one sees an apple. The prediction is translated by the second level of demons into predictions of "something circular and filled", "green" and "resembling the contours of an apple". These predictions are in turn split into simpler ones, relating to contours, lines, hue, lightness, etc. Solid arrows denote predictions, dotted arrows - prediction error. Images near the demons show the content of the predictions. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

It is unclear why such second-order predictions are special as compared to first-order (the "typical" predictions) or, for example, third-order predictions. For example, the second derivative of prediction error, the rate of change of the rate of change in prediction error is a third-order prediction. Such third-order predictions have been linked to affect as well (see e.g. Van de Cruys, 2014, p. 147) but also to specific emotions (Joffily & Coricelli, 2013). Accordingly, if prediction error decreases increasingly fast over time one should either feel stronger positive affect or experience not only positive affect but also hope.

Our approach does not require such second-order predictions, thus avoiding theoretical ambiguity and leaving particular emotional categories to be explained by other accounts (e.g., Ortony, Clore, & Collins, 1988; Russell & Barrett, 1999). Moreover, it seems clear from everyday experience that constantly high prediction error, as in constant noise, will cause irritation, while according to the aforementioned accounts this should not be the case. Note that we do not suggest that affect is not influenced by second- and higher-order predictions. We simply suggest that such predictions do not play any special role and can also be a source of affect in the same way as first-order predictions. Higher order predictions may also serve other functions, such as estimating the precision of prediction errors (Hohwy, 2012).

Our approach can also explain the role of affect as a meta-cognitive regulator (Clore & Huntsinger, 2007; Huntsinger, Isbell, & Clore, 2014). Perceptual predictions leading to positive affect will be more likely in future, and those having negative feedback are less likely to be used again. Affect can therefore modify cognitive strategies (such as relying on contextual cues or using global or local information, e.g., Huntsinger, Clore, & Bar-Anan, 2010; Storbeck & Clore, 2008) with positive affect supporting currently dominant tendencies (see more detailed discussion of meta-cognitive regulation in the Discussion).

Moreover, our approach can explain affect misattribution. Just as prediction error can be used to compare qualitatively different predictions, people can experience affect from different sources and misattribute affect from one source to another (Schwarz & Clore, 1983). For example, while it is hard to mistake sight for sound, our preferences are subject to cross-modal transfer effects (van Reekum, van den Berg, & Frijda, 1999). Moreover, different kinds of positive events typically share neural correlates (Sescousse, Caldú, Segura, & Dreher, 2013). According to the present approach, affect misattribution is a necessary downside to being able to compare predictions that are based in different languages. Future predictions led by such misattribution will lead to negative affect through increased prediction error and will be eventually corrected.

In sum, our approach diverges from predictive coding accounts by suggesting that cognition is driven not by "what is most probable" (prediction error minimization) but rather by "what are the chances of learning something" represented by a balance between prediction error and prior probabilities. Affect represents a subjective experience of that balance, allowing comparison of different predictions, and drives us to explore the world rather than stay inside the "dark room".

3. Affect reflects prediction accuracy

Why do we propose that affect plays such an important role in perceptual processing? Our argument proceeds in several steps. Prediction accuracy for a given stimulus depends on several factors. Firstly, on structural properties related to perceptual organization, pertaining to stimulus *uncertainty*. Iterative build-up of a stimulus representation involves spatial predictions. This is easier if different parts are similar to each other as predictions about one part can be based on information from another. This influences how easily it is to predict a stimulus, even one never seen before. For example, it is easier to predict a stimulus in low noise. It is, however, hard to imagine completely novel stimuli. A second major factor therefore involves *expectations* stemming from previous experience. For an English speaker, Chinese ideograms will be harder to predict than Latin letters, and vice versa. Lastly, even when the stimuli are themselves perfectly predictable, predictions based on them may lead to *conflict* if they are inconsistent with data obtained later or from other predictions. If an observer sees an object clearly but incorrectly predicts its category, this may later be in conflict with other information.

The key ingredients of our new proposal are the following: if correct perceptual predictions are hard to make (uncertainty), if one is unable to predict something based on past experience (low expectations), or if one prediction does not agree with another (conflict), causing negative affect. But when one predicts something correctly, positive affect follows. Positive affect from correct predictions decreases as their prior probabilities increase. In the following three sections we review evidence for the proposal focusing on these three key ingredients.

3.1. Uncertainty

A long tradition of research originating in the Gestalt school addresses the relationship between uncertainty and preferences (Palmer, Schloss, & Sammartino, 2013; Reber, Schwarz, & Winkielman, 2004). A general finding dating back to Fechner's "principle of the aesthetic middle" (Cupchik, 1986) is the inverted U-shaped link between stimulus complexity and affect (Berlyne, 1963, 1970; Munsinger & Kessen, 1964). Complexity determines uncertainty: less complex stimuli are in general easier to predict. Predictions of an on/off signal when answering randomly will be correct at least half of the time, while predicting four such signals yields a baseline accuracy of only $0.5^4 = 6.25\%$. So for simple stimuli, predictions are usually correct but they also have high prior probabilities; for complex ones, the predictions are less likely to be correct. Accordingly, the inverted U-shaped function shows that people prefer stimuli of medium complexity. This relationship depends on observers' expertise (e.g., Orr & Ohlsson, 2005) and previous exposure.

Asymmetry and irregularity are special cases of complexity: given one part of a symmetrical object (or any regular object), it is easier to predict another, while predicting an asymmetrical or irregular object from its parts is harder. Symmetrical objects are usually rated more positively than asymmetrical ones. This holds for both natural stimuli, such as faces (Bertamini, Makin, & Rampone, 2013; Gangestad, Thornhill, & Yeo, 1994; Perrett et al., 1999; Rhodes, Sumich, & Byatt, 1999), abstract objects and simple patterns suggesting a general principle of perception (Berlyne, 1963; Cárdenas & Harris, 2006; Tinio & Leder, 2009a).

Uncertainty due to low image quality also influences preferences (see Fig. 2A). Low-contrast images are rated less positively than high-contrast ones (Reber, Winkielman, & Schwarz, 1998; Willems & Van der Linden, 2006; Willems, van der Linden, & Bastin, 2007). Decreased sharpness or increased graininess work additively with contrast reduction to decrease liking (Tinio & Leder, 2009b; Tinio, Leder, & Strasser, 2011).

Internal inconsistency also makes stimuli more difficult to predict. Seamon et al. (1995) demonstrated that "impossible" objects are rated more negatively than possible ones. Similar effects are observed for semantic inconsistency: coherent word triads are rated more positively than incoherent ones (Topolinski & Strack, 2009a,b; Whittlesea & Leboe, 2003), and logically correct syllogisms – more positively than incorrect ones (Morsanyi & Handley, 2011).

Similar principles apply to hearing. For dissonant sounds, frequency components are close but not identical and produce temporal changes in amplitude ("beating") that make acoustic signals more uncertain. Dissonant sounds are also more complex because unlike consonant sounds their frequencies cannot be approximately described as integer multiples of a common fundamental frequency. Both effects contribute to the negative affect aroused by dissonance (McDermott, Lehr, & Oxenham, 2010; McDermott, 2011), indicating that uncertain stimuli are unpleasant.

In sum, studies of stimulus complexity show that in most cases uncertainty leads to negative affect. But interestingly, so does too little uncertainty. This relationship can be explained by prediction accuracy and

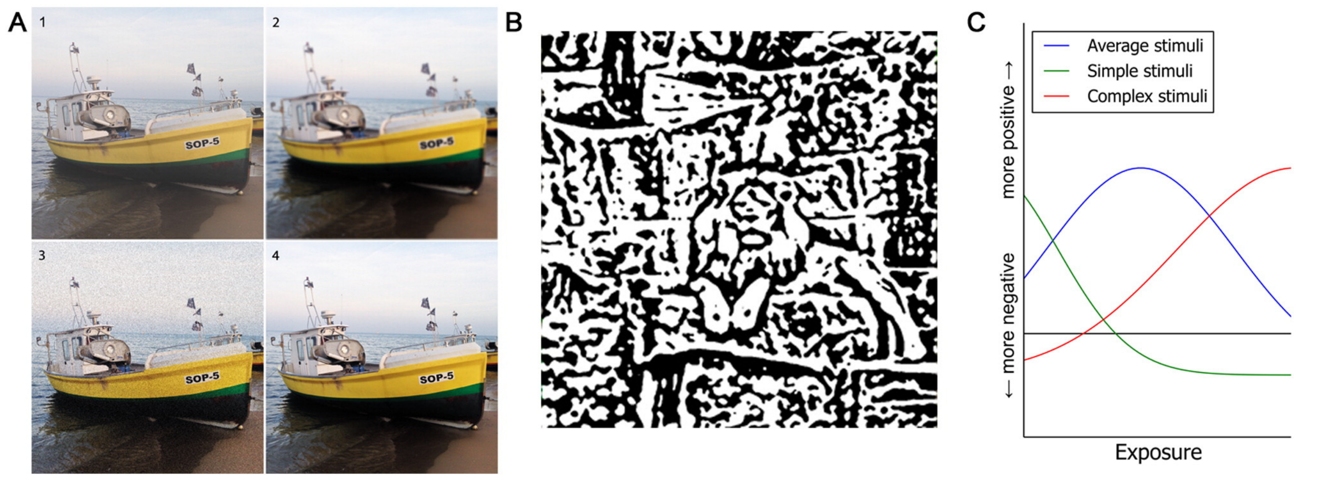

Fig. 2. Panel A: low contrast (1), blurred (2) or noisy (3) images are more difficult to perceive than originals (4) and they are liked less. Panel B: an example of degraded image used in Chetverikov and Filippova (2014). When observers are able to identify the content of such an image (the lion, in this case), they like it more, independent of the initial affective valence of the image. Panel C: schematic depiction of liking as a function of exposure. For stimuli of medium complexity, preferences first increase and then decrease with increased exposure (the inverted U-curve, see text). For simpler stimuli, this curve is shifted to the left, so exposure only serves to decrease preferences. For complex stimuli the curve is shifted to the right and preferences increase with more exposure. According to the proposed approach, both exposure and complexity influence observers' ability to correctly predict stimuli (see text).

prior probabilities - included in the proposed model. Too much uncertainty leads to large prediction errors while too little uncertainty leads to small prediction errors but positive affect is, in that case, downplayed by high prior probabilities of predictions.

3.2. Expectations

Uncertainty and unexpectedness are closely related. Seeing a stimulus once, increases, on average, the probability that it will be seen again and one therefore expects it. Perceivers are more likely to predict this stimulus and will experience more positive affect from seeing it, because predictions will be confirmed. They will also experience more positive affect from seeing this stimulus because uncertainty will be reduced: predictions regarding its structure or details are more likely to be correct. On the other hand, novelty and uncertainty can be dissociated: something novel is not necessarily unexpected (e.g., when reading about a new topic one expects to read something that was not know before) and familiar objects can appear without warning (see Barto, Mirolli, & Baldassarre, 2013; van der Helm, 2014).

Mere exposure effects involve the combined influence of these two factors. Kunst-Wilson and Zajonc (1980) and Wilson (1979) were the first to demonstrate that even subliminally presented stimuli are preferred to novel ones. A meta-analysis by Bornstein (1989) showed that the mere exposure effect is, in fact, stronger with subliminal than supraliminal exposure. This effect is a genuine emotional reaction: Harmon-Jones and Allen (2001) demonstrated that mere exposure is accompanied by the activity of zygomatic ("cheek") muscles corresponding to positive emotions, it influences mood ratings (Monahan, Murphy, & Zajonc, 2000) and has an additive effect upon affective priming (Murphy, Monahan, & Zajonc, 1995). However, affect is inversely weighted with prior probabilities of predictions and as expectations arise, increased prior probabilities of our predictions will decrease positive affect. Exposure therefore leads to similar inverted U-shaped curves as stimulus uncertainty (Bornstein, 1989; Lee, 2001). Such nonlinear effects can explain why novel stimuli are sometimes preferred to familiar ones or why reward processing can be associated with novelty as in Wittmann, Bunzeck, Dolan, and Düzel (2007).

Uncertainty and expectations may interact but are also separable. Exposure effects for stimuli of different complexity provide an example of their interaction. Complex stimuli are initially rated more negatively than simpler ones, but with repeated exposure this reverses (Berlyne, 1963, 1970). Stimuli with low uncertainty tend to be disliked with repeated exposure, moderately uncertain stimuli follow an inverted U-shaped curve, and the liking of complex stimuli increases the more the exposure (Smith & Dorfman, 1975, see also Jakesch, Leder, & Forster, 2013; see Fig. 2C). The well-known "Dalmatian in the snow", or degraded images (Fig. 2B) yield "perceptual insights" that demonstrate the effect of decreased uncertainty without prior expectations. Observers like such images more, once they perceive the camouflaged object. Remarkably, this even occurs if the image content is not pleasant (Chetverikov & Filippova, 2014; Muth & Carbon, 2013).

Priming effects and learning demonstrate how expectations may be separated from uncertainty. For example, if an object contour is presented before the actual object, observers like this object more than otherwise (Forster, Leder, & Ansorge, 2013; Reber et al., 1998; Winkielman & Cacioppo, 2001). Showing words related to rated objects beforehand, also leads to more positive ratings (Labroo, Dhar, & Schwarz, 2008; Lee & Labroo, 2004; Reber et al., 2004). Observers asked to visualize the word "frog" liked a wine bottle with a frog on its label more than if they visualized another word, such as "ship". Similarly, Whittlesea (1993) found that words following predictable context ("The storm threatened to overturn the … boat") are rated as more pleasant than words following unpredictable context ("In the middle of the desert there was a … boat"). Categorical priming influences liking as well: not only do observers exposed to Chinese ideograms like these particular ideograms but they also like other novel ideograms more than polygons, while those exposed to polygons prefer them to ideograms (Monahan et al., 2000).

More complex learning also influences our preferences. Learning a perceptual template from a pattern of dots diverging from a prototype leads to more positive liking ratings for patterns closer to the prototype (Winkielman, Halberstadt, Fazendeiro, & Catty, 2006). "Grammatical" strings complying with previously learned artificial grammar rules, are liked more than "ungrammatical" strings (Gordon & Holyoak, 1983; Manza & Bornstein, 1995; Newell & Bright, 2001; Zizak & Reber, 2004). In contextual cueing, participants perform visual search, but unbeknownst to them, positions of targets on part of the trials are associated with positions of distractors (Chun, 2000). Following the learning phase, predictive configurations are rated more positively than nonpredictive ones, even though participants do not recognize them (Ogawa & Watanabe, 2011).

Summing up, evidence from mere exposure, priming, and learning studies indicates that people like things they expect, more than unexpected ones. We suggest that this happens because affective feedback changes as a function of prediction error and incorrect expectations lead to incorrect predictions. But affective feedback is weighted with prior probabilities and very high likelihood may result in negative affect similarly to when watching a movie with a clichéd plot where it is easy to predict what happens next, but this does not bring much joy.

3.3. Conflict

Here we consider conflict as a situation where predictions are incorrect or inconsistent with other predictions. Dreisbach and Fischer (2012) used Stroop stimuli as affective primes in an evaluative categorization task. Negative words were categorized faster following incongruent stimuli while positive ones were categorized faster following congruent stimuli. Moreover, neutral targets were more likely to be categorized as negative following incongruent than congruent primes (Fritz & Dreisbach, 2013, 2015). Importantly, observers simply viewed the primes passively.

Repeating target and distractor stimuli in sequential visual search trials typically leads to decreased reaction times (Kristjánsson & Driver, 2008; Wang, Kristjansson, & Nakayama, 2005; see review in Lamy & Kristjánsson, 2013). Chetverikov and Kristjansson (2015) found that after several repetitions, there was no difference in preferences between targets and distractors. Instead, observers selected repeated targets more often during free choice task both when they were asked about the most preferred item and when they were asked about the least preferred item – indicating a perceptual or attentional bias (see also Brascamp, Blake, & Kristjánsson, 2011). However, breaking repetition patterns by using previously distracting items as targets resulted in lower preferences for these items (see Fig. 3). This is consistent with evidence that inhibition of distractors leads to lower preferences (Fenske, Raymond, & Kunar, 2004; Fenske & Raymond, 2006; Raymond, Fenske, & Tavassoli, 2003; Raymond, Fenske, & Westoby, 2005). Yet Chetverikov and Kristjansson (2015) found that following multiple repetitions of the same distractors, when inhibition should be pronounced, negative affect occurred only if the repetition pattern was broken. It is not inhibition, but the conflict created by the need to attend to former distractors that leads to negative affect.

Even without external feedback people can evaluate the consistency of predictions based on varied sources of information (Chetverikov, 2014). Incorrect decisions should by definition have lower consistency than correct ones as they are less consistent with the available information (reminiscent of the conflict-monitoring treatment of errors, Botvinick, 2007; Yeung, Botvinick, & Cohen, 2004): errors are more probable when there is conflict. But the opposite is also true: processing of decision-related information may continue after the decision is made (Pleskac & Busemeyer, 2010), making the incorrect decision itself a source of conflict. Treating decisions as predictions, we investigated their effect on preferences. During recognition (Chetverikov, 2014), perceptual identification (Chetverikov & Filippova, 2014), and visual search (Chetverikov, Jóhannesson, & Kristjánsson, 2015) targets were rated more negatively following errors than correct answers. Moreover, following correct answers, people liked distractors less than targets while following errors targets were liked less than distractors (Chetverikov et al., 2015).

Particularly notable is that in all three studies no feedback on accuracy was provided, separating the finding from negative feedback on accuracy. The results also demonstrated that this error-related target devaluation of targets does not reflect lack of information. The devaluation was *more* pronounced with increased number of exposures to the target before recognition or increased time spent looking at targets in visual search (see Fig. 4). Negative affect following an incorrect decision *increases* as more evidence becomes available to make the correct decision.

Neurophysiological studies also demonstrate that errors are associated with negative emotions (see review in Koban & Pourtois, 2014). The error-related negativity (ERN), a negative deflection peaking within 50–100 ms following error is associated not only with trait differences (Hajcak, McDonald, & Simons, 2004; Luu, Collins, & Tucker, 2000; Simons, 2010; see review in Moser, Moran, Schroder, Donnellan, & Yeung, 2013) but also with negative emotions and momentary negative affect. For example, Aarts, De Houwer, and Pourtois (2012, 2013) found that false alarms in a Go/noGo task led to faster evaluative categorization of subsequent negative words as compared to positive words and showed that this behavioral evidence of negative affect correlates with ERN.

That errors are related to preferences is consistent with recent theories of reward. Reward-related brain regions (ventral striatum) are active even when extrinsic reward is not provided (Daniel & Pollmann, 2012, 2014; Satterthwaite et al., 2012). Conflict monitoring allows the estimation of answer accuracy without external feedback and may provide positive (correct answers) or negative (errors) reinforcement. Moreover, errors, violations of expectations, and reward may share neural substrates (Bromberg-Martin & Hikosaka, 2009, 2011) further linking error-related negative affect with effects of expectations. In

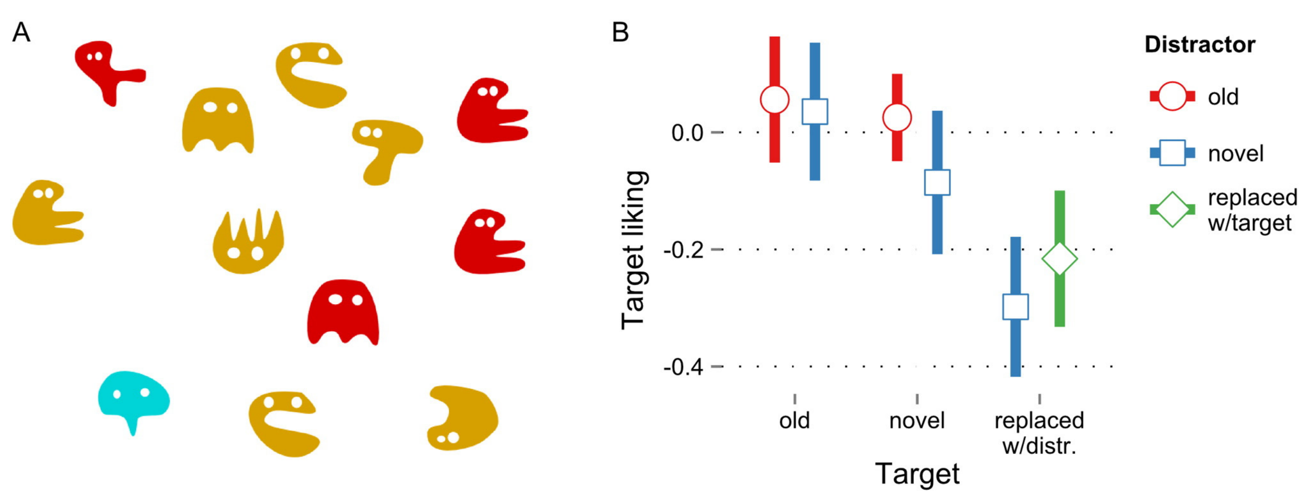

Fig. 3. Panel A: an example search display from Chetverikov and Kristjansson (2015). Observers looked for a uniquely colored "monster". Following four priming trials with the same colors of target and distractor sets, on a fifth, critical trial, color of target, one of the distractor sets, or both could be changed to novel colors or switched. Panel B: liking of targets following critical trial. When target color is replaced with previously distracting colors, targets are rated negatively. Error bars show 95% confidence intervals. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

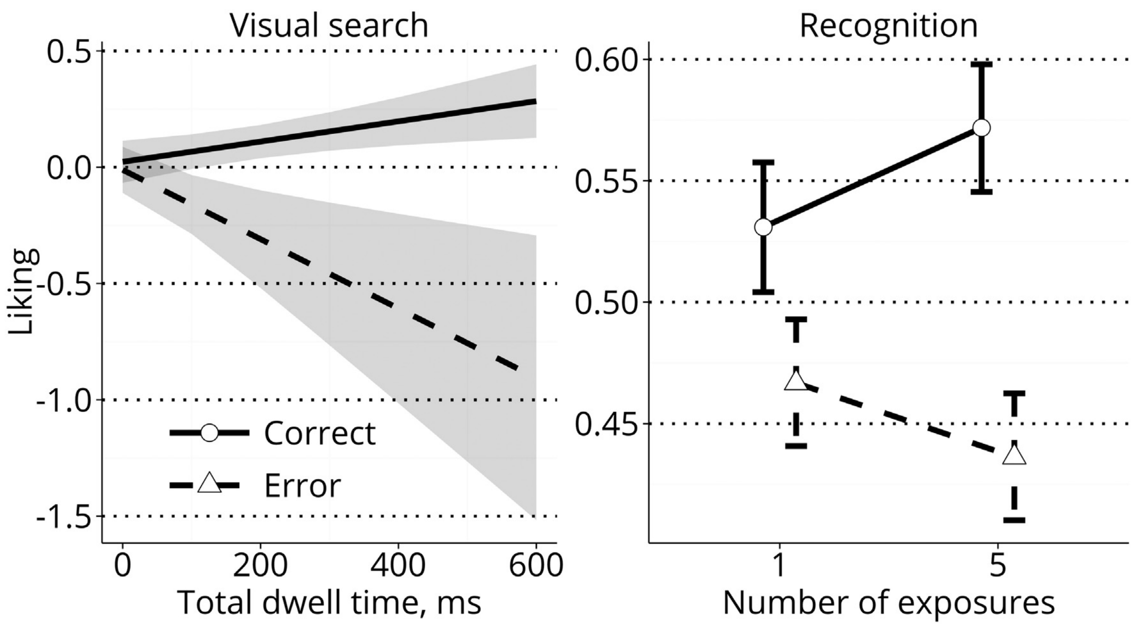

Fig. 4. Liking as a function of answer accuracy and the amount of information available for the decision. During visual search (Chetverikov et al., 2015) the amount of information was measured with eye-tracking as total dwell time on target. In the recognition task (Chetverikov, 2014), information was controlled by the experimenter via the number of exposures before recognition. Shaded regions and error bars show 95% confidence intervals.

sum, the evidence reviewed above shows that conflict occurring when particular predictions are inconsistent with other predictions, leads to negative affect, consistent with our proposal.

4. Discussion

Our key proposal is that affect is inherent in perceiving. A wealth of evidence shows how affect can play a key role in shaping interpretations of the perceptual environment. Humans need to make predictions about the environment, and depending on how accurate these predictions are, they receive affective feedback. This feedback influences future predictions, ultimately playing a critical role in perception, memory, and learning.

We believe that the evidence for this proposal that we review above is strong. Properties of stimuli, such as complexity, determine the uncertainty that influences prediction accuracy. For low levels of uncertainty, predictions are likely to be correct but they are, at the same time, too obvious, while for high levels of uncertainty, predictions are the least obvious but are not likely to be correct. Average levels of uncertainty that are likely to result in correct but not too obvious predictions yield the most positive affect. Studies on different forms of priming demonstrate that expected stimuli are preferred. However, mere exposure effects tell a cautionary tale: positive effects of exposure on preferences are observed only for relatively complex stimuli. Previous exposure decreases uncertainty of stimuli, so that for simple stimuli less exposure means more positive preferences, and for stimuli of medium complexity average levels of exposure are optimal and provide more positive affect. In addition to expectations and uncertainty, stimuli that lead to correct predictions are also preferred. Conversely, observers tend not to like stimuli leading to errors or conflicting predictions. Note that even in the absence of explicit instructions, some processes, such as recognition and categorization, are inherently present in perception. It is therefore possible that accuracy in such ubiquitous tasks may account for some of the effects attributed to expectation.

Three general objections could be raised against the proposed model:

1) pleasant unpredicted events occur, such as a surprise party;
2) humans perceive predictable but unpleasant things such as a clearly visible spider;
3) most of the time humans live in a stable and predictable environment, yet do not experience a constant stream of positive affect.

These objections fail to undermine our model, however. For the surprise party puzzle, one needs to consider events as they unfold in time. Initial emotional reaction to unexpected events is negative as studies of facial expressions show (Noordewier & Breugelmans, 2013; Topolinski & Strack, 2015). But, later, one may reassess the situation, depending on the consistency with more general predictions. In addition, prediction error may provide an opportunity to explore something new, to make correct predictions, leading in the end to positive affect.

Predictable but unpleasant things, such as clearly visible spiders, are rarely evaluated positively. But the more relevant question is whether they are more or less unpleasant than unpredictable and unpleasant things. The intuitive answer is that they are less unpleasant, and that intuition corresponds to the experimental data on affective reactions to uncertain pleasant and unpleasant stimuli. In Chetverikov and Filippova (2014), observers judged the category of a noisy image (an animal, a human, or an object) and indicated their preferences afterwards. The images had either positive or negative valence (e.g., snakes vs. puppies, or happy vs. angry people). The results showed that while negative images are generally rated lower than the positives ones, correctly categorized negative images are preferred to incorrectly categorized ones while correctly categorized positive images were preferred to incorrectly categorized ones. Unpleasant stimuli could therefore be less or more unpleasant depending on observer's predictions regarding them. When observers categorize images correctly, it means that they were able to make correct predictions regarding stimuli, leading to a more positive affect even in relation to less pleasant stimuli.

Finally, in predictable environments correct predictions will yield only mild positive affect as they are inversely weighted with high prior probabilities. Positive but relatively weak affect should therefore be dominant. This idea finds support in studies demonstrating that people have a tendency to experience positive affect in the absence of strong emotional events (Cacioppo & Bernston, 1999; Diener, Kanazawa, Suh, & Oishi, 2015; Norris, Larsen, Crawford, & Cacioppo, 2011).

Our proposal can also explain cognitive regulation provided by affect. If affect does indeed function as feedback for predictions, then it should not only reflect their accuracy but also influence whether they are used. According to the affect-as-information account[1] (Clore & Huntsinger, 2007; Clore & Storbeck, 2006; Huntsinger et al., 2014), affect provides information about the value of currently dominant information-processing strategies. For example, if we tend towards local perception ("trees before forest"), this tendency will be strengthened by positive affect and weakened by negative affect. The reverse is also true: when global perception is prioritized, it is facilitated by positive affect and inhibited by negative affect (Huntsinger, 2013). Similarly, positive affect makes interpretative tendencies created by priming stronger, while negative affect weakens them (Storbeck & Clore, 2008). Happy participants are influenced more by priming than those in a neutral mood, who, in turn, are more influenced by priming than sad participants. These findings are in sharp contrast to previous ideas, such as that negative affect leads to more local and positive affect to more global perception (e.g. Derryberry & Tucker, 1994). By the current account, affect has a flexible influence, conveying value for the currently dominant interpretative tendencies. It is also important that not only is affect used for automatic regulation of cognitive processing as described above, but is also utilized in meta-cognitive monitoring. For example, confidence ratings correlate with mood (Chetverikov & Filippova, 2014; Efklides & Petkaki, 2005; Sanna, 1999). The present account provides a rationale for these findings: given that affect is essentially an experience of prediction error and accuracy, its flexible regulatory role is expected. It can be implemented through the modification of weights within a "predictive modules" hierarchy, making modules that provide more positive affect weigh more in future predictions.

The idea that prediction accuracy influences affect corresponds well with studies of art and aesthetics. It is difficult to explain why people prefer one arrangement of colored patches over another. Such preferences require invoking some idea of temporal or spatial relationships between them, which leads to accounts quite consistent with the current one. For example, Huron (2006) demonstrated how pleasure from music depends on anticipation ranging from expecting the continuation of simple ascending or descending pitch sequences to culturally-learned patterns (see Salimpoor et al., 2014). Van de Cruys and Wagemans (2011) show that perception of visual art often depends on decreases of prediction error initially created by artistic deviation of a depicted object from the real one. An intriguing possibility is that artists create images corresponding more accurately to our predictions than real ones, exaggerating the relevant features. Ramachandran and Hirstein concisely formulated this proposal as "all art is caricature" (1999, p. 18). All three factors described here (uncertainty, expectations, and conflict) may influence art perception. For example, increased predictability due to previous exposure results in higher liking (Cutting, 2006). Interestingly, medium levels of uncertainty are preferred in art (Jakesch & Leder, 2009). Moreover, preference for ambiguity has been repeatedly demonstrated in art perception (Jakesch et al., 2013; Muth, Hesslinger, & Carbon, 2015). Note that Muth et al. (2015) show how increases in complexity could lead to perceptual insights which in turn are related to liking. It may, therefore, not be complexity per se, but the opportunity to make correct predictions (that is, gain "perceptual insights") that creates positive affect. Also note that complexity is a relative concept. For example, Belke, Leder, and Carbon (2015) demonstrate that observers appreciate more challenging portraits to more fluent ones. Crucially, in several experiments this difference was pronounced for observers with low art expertise only on repeated evaluation. For the experts, however, it was already evident during the first viewing and the experts also showed more appreciation for challenging portraits than other observers but not for fluent ones. Apart from the ambiguity studies described above, the impact of conflict created by incorrect or inconsistent predictions is less well studied. Leder's influential model of aesthetic appreciation and aesthetic judgments (Leder, Belke, Oeberst, & Augustin, 2004; Leder & Nadal, 2014) suggests that the ability to implicitly and explicitly classify art plays an important role in observers' reactions. Accordingly, the affective feedback approach suggests that consistency and accuracy of predictions involved in such classification will influence appreciation of art. In general, the recent revival in interest into art perception from the perspective of cognitive science and neuroscience, suggests that this topic will provide further insights in the mechanisms of affective feedback (see reviews in Muth & Carbon, 2016; Van de Cruys & Wagemans, 2011).

If affect is a secondary variable to predictions, it is not surprising that specific manipulations intended to influence affective ratings do not always bring the intended consequences. For example, while most studies support the idea that moderate uncertainty or confirming expectations bring positive affect, not all do. For example, Albrecht and Carbon (2014) found that liking ratings due to matching primes increased only for positive targets while for negative ones the effect was reversed. They argued that matching stimuli increase fluency of processing that amplifies the effect of valence. In contrast, Gerger, Forster, and Leder (2016) found increased preference ratings with increased duration for abstract patterns while the reverse was found for faces – independent of valence. A probable reason for this inconsistency is that not only are predictions by themselves complex phenomena but affect also be a result of different predictions tested in parallel. For example, changes in response times due to priming could be different for positive and negative stimuli due to differences in the density of associative networks (Unkelbach, Fiedler, Bayer, Stegmüller, & Danner, 2008). Because "all positive stimuli are alike, while negative information is negative in its own way" (Unkelbach et al., 2008, p. 46) predictions based on partial representation of negative stimuli might be more prone to errors.

Moreover, the main problem for studying predictions and, consequently, affective feedback for predictions, is that prediction is an active process. It depends on current goals and task context. The key difference between stimuli presented for 50 and 500 ms, for example, is not the exposure time in itself – it is what observers are able and willing to do within this time. While it seems relatively safe to say that for abstract patterns or neutral everyday objects the predictive activity is limited to perception, for other stimuli this is unlikely. Predictions, for example, can involve comparisons with already familiar perceptual templates: a conflict between predictions when faces that simultaneously resemble two highly familiar faces leads to decreased preferences (Halberstadt, Pecher, Zeelenberg, Ip Wai, & Winkielman, 2013). Furthermore, depending on the task at hand, observers devaluate different "face blends": when required to categorize faces based on emotional expressions, they dislike faces showing mixed emotions and so on (Halberstadt & Winkielman, 2014; Winkielman, Olszanowski, & Gola, 2015). Although such goal- and task-dependence greatly complicates the study of cognitive antecedents of preferences, it cannot be ignored and must be controlled for in studies of affect.

4.1. Future directions

Importantly, our proposal leads to a large number of questions that can be used to generate testable hypotheses. Among the most pertinent are the following:

1) Does negative affect associated with incorrect predictions imply that people are aware that their predictions are incorrect? Or may they persist, making incorrect predictions while continuing to receive negative feedback? Is there a threshold for such negative feedback, at which point the prediction is abandoned?
2) Are all incorrect predictions created equal? Are unconfirmed predictions processed in the same way as predictions contradicting other predictions or novel data? Our study on visual search (Chetverikov

[1] The "affect-as-information" account was renamed "affect-as-cognitive-feedback" (Huntsinger et al., 2014). To avoid confusion with our account, we use the former name.

& Kristjansson, 2015) and recent neurophysiological data (Hsu, Bars, & Ha, 2015) suggests that it this is not the case, but what is the key difference?
3) At which processing stages are prediction errors experienced as affect?
4) How do observers determine the source of affective feedback? At any moment humans make many predictions and sometimes fail to attribute feedback from them to the correct source, potentially leading to affect "diffusion" or "misattribution". What mechanisms are used to avoid this?
5) Are there individual differences in the effects of affective feedback?
6) Finally, note that there can be a difference between something that is novel and something that is unexpected, and the inherent value of these two scenarios may differ.

We suggest that perceptual predictions yield feedback involving subjective experience of prediction error that is inversely weighted with prior probabilities of these predictions. These predictions color our perception of the world. As put by Robert Zajonc, "We do not just see 'a house': we see 'a handsome house,' 'an ugly house,' or 'a pretentious house.'" (Zajonc, 1980, p. 154). The handsomeness or ugliness does not come from nowhere: perception is inseparable from predictions and feedback from predictions is experienced as positive or negative affect. Similarly, we do not just remember or think of "a house". All cognitive activity entails affect. In sum, being right feels good, and, according to our account, especially when we do not expect to be right.

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