Real-world expectations and their affective value modulate object processing

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Abbreviated title: Expectations and affect modulate object processing

Number of pages: 25
Number of figures: 3
Number of tables: 1
Number of words in the Abstract: 230
Number of words in the Significance Statement: 111
Number of words in the Introduction: 618
Number of words in the Discussion: 1431

Conflicts of interest: The authors declare no competing financial interests.

Acknowledgements: This study was funded by the Fondation Planiol (BW), by the Institut Universitaire de France (MM) and by the Social Sciences and Humanities Research Council of Canada (LC).

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Abstract

It is well known that expectations influence how we perceive the world. Yet the neural mechanisms underlying this process remain unclear. Studies have focused so far on artificial contingencies between simple neutral cues and events. Real-world expectations are however often generated from complex associations between potentially affective contexts and objects learned over a lifetime. In this study, we used fMRI to investigate how object processing is influenced by neutral and affective context-based expectations. First, we show that the precuneus and the inferotemporal cortex are more active during object recognition when expectations have been elicited a priori, irrespectively of their validity or their affective intensity. This result supports previous hypotheses according to which these brain areas integrate contextual expectations with object sensory information. Early visual areas, on the contrary, are more active during object recognition when no prior expectation has been elicited by a context. Then, we show that BOLD activity is enhanced in early visual areas when objects are less expected, but only when contexts are neutral; the reverse effect is observed when contexts are affective. This result supports recent proposals that affect modulates predictions in the brain. Lastly, the hippocampus and the parahippocampal cortex also showed an enhanced response when the object matched the preceding affective context, suggesting that predictions are initiated from these areas during object recognition. Together, our results help elucidate the neural mechanisms of real-world expectations.

Significance statement

It has been known for more than a century that expectations influence how we perceive the world. However, the precise mechanisms remain unclear and studies often used stimuli that lack ecological validity. In the present fMRI study, we assessed the effect of real-world expectations initiated by neutral and affective contexts on the neural mechanisms of object recognition. We first show evidence for previous claims that the precuneus and the inferotemporal cortex integrate contextual expectations with sensory information. We then show that the enhanced response usually observed with unexpected objects is reversed when contexts are affective. This result supports a recent proposal concerning the role of affect in the initiation of predictions.

We expect to find hairdryers in bathrooms, tombstones in cemeteries, and baguettes in bakeries, but more rarely tombstones in bathrooms, refrigerators in cemeteries and hairdryers in bakeries. That is, we live in a world where most objects are associated with specific contexts. Throughout a lifetime of experiences, we come to learn these associations, which lead us to form expectations about the objects to be encountered when we navigate the world.

Perception can be understood as the process of integrating such top-down expectations with incoming sensory information. It has been proposed that predictions from high-level areas are transmitted to adjacent lower-level areas and compared with incoming sensory signals, such that only the discrepancy between these two signals – the prediction error – is transmitted up the visual hierarchy (Friston, 2005; see also Mumford, 1992; Ullman, 1995; Rao and Ballard, 1999). In support of this model, expectation of a visual stimulus elicits a specific pattern of activity in the primary visual cortex (Kok et al., 2014, 2017; Hindy et al., 2016) and the perception of an expected stimulus results in reduced neural activity in sensory cortices (Summerfield et al., 2008; den Ouden et al., 2010; Alink et al., 2010; Kok et al., 2012a; Todorovic and de Lange, 2012; see de Lange et al., in press, for a review). Some predictions, however, may require a different mechanism than feedback from adjacent visual areas (Hindy et al., 2016): for instance, the hippocampus has been shown to play a role in the generation of predictions (Hindy et al., 2016; Kok and Turk-Browne, in press), and there is some evidence that parahippocampal (PHC) and retrosplenial (RSC) cortices initiate context-based expectations (Bar, 2003; Bar and Aminoff, 2003; Bar, 2004; Bar et al., 2006; Livne and Bar, 2016; Brandman and Peelen, 2017).

Most studies examining the effect of predictions on perception have used very simple cues such as tones (Summerfield and Koechlin, 2008; den Ouden et al., 2010; Kok et al., 2012a, 2017) or a repetition of the same object (Summerfield et al., 2008; Todorovic and de Lange, 2012). By contrast, expectations about everyday objects usually stem from other everyday

objects or from the surrounding context. Relatedly, the effect of predictions has not been considered in the setting of an ecological object recognition task. Simple detection tasks (Jiang et al., 2013), delayed discrimination tasks (Kok et al., 2012a, 2014, 2017) or categorization tasks using few alternatives (den Ouden et al., 2010; Kok et al., 2012b) are typically used. Moreover, previous studies on prediction have manipulated predictability by artificial means, either by repeating and alternating stimuli (Summerfield et al., 2008; Todorovic and de Lange, 2012), by having stimuli appearing after different cues with different probabilities during the experiment (den Ouden et al., 2010; Kok et al., 2012a, 2012b, 2014, 2017; Jiang et al., 2013), or by developing arbitrary contingencies shortly before the experiment (Hindy et al., 2016). Associations between contexts and objects formed over a lifetime of experiences may involve mechanisms distinct from these. For instance, real-world expectations are often tinted by some affective value. A visual context can elicit emotional reactions that may influence the recognition of objects in the scene (Lebrecht et al., 2012). In an emotional context (e.g., a cemetery), the affective value may be partially processed before the scene's objects (e.g., a tombstone) and in fact help predict their identities (Barrett and Bar, 2009).

In the present study, we addressed all of these shortcomings. We investigated how realistic object recognition mechanisms are influenced by task-irrelevant high-level expectations generated by a predictive or non-predictive visual context. The use of unambiguous everyday objects and scenes allowed us to use associations between objects and contexts formed over a lifetime of experiences, and to compare affective and neutral expectations.

Materials and Methods

Participants

Seventeen healthy adults (9 female; mean age = 24.8; SD = 4.3) were recruited on the campus of Aix-Marseille Université. Participants did not suffer from any neurological, psychological or psychiatric disorder and were free of medication. The experimental protocol was approved by the ethics board of CPP Sud-Méditerranée 1 and the study was carried in accordance with the approved guidelines. Written informed consent was obtained from all participants after the procedure had been fully explained, and a monetary compensation was provided upon completion of the experiment.

Stimuli

Thirty-three public domain scene color images were selected from the internet as context images. In a first validation study, an independent sample of 22 subjects identified what they thought the images represented, indicated if the context elicited an emotion and, if so, what were the valence (negative to positive, from 0 to 10) and intensity (no emotion to very intense emotion, from 0 to 10). Following this study, 32 visual scenes were selected and split in Affective (e.g., cemetery, beach, luxury hotel) and Neutral (e.g., swimming pool, airport, kitchen) categories at the median of the intensity scores (5.19).

In a second validation study, 35 different subjects were shown the context names and had to give the names of three objects with a high probability of being present in that context. Ninety-six color images of objects (three for each context) corresponding to the most cited names were selected for the experiment (e.g., swimsuit, diving board and pool ladder for swimming pool). For each context, the experimenters also chose three non-associated objects (selected from the ones that had never been associated with the context in the second validation

study). Every object was the associated object of only one context and the non-associated object of only one other context; moreover, for each context, each one of the three non-associated objects was associated with a different context.

Finally, we randomized the phases of the mean of the context images in the Fourier domain – separately for each RGB color channel – to obtain 96 different phase-scrambled images.

Data acquisition

Functional imaging data were acquired with an ADVANCE 3 Tesla scanner (Bruker Inc., Ettlingen, Germany) equipped with a 2-channel head-coil. Functional images sensitive to BOLD contrast were acquired with a T2*-weighted gradient echo EPI sequence (TR 2400 ms, TE 30 ms, matrix 64 x 64 mm, FOV 192 mm, flip angle 81.6°). Thirty-six slices with a slice gap of 0 mm were acquired within the TR; voxels were 3 x 3 x 3 mm. Between 303 and 311 volumes were acquired in each run, excluding the six dummy scans acquired at the beginning of each run for signal stabilization. Additionally, a high resolution (1 x 1 x 1 mm) structural scan was acquired from each participant with a T1-weighted MPRAGE sequence.

Experimental Design and Statistical Analysis

The LabVIEW (National Instruments Inc., Austin, TX, USA) software was used to project stimuli during the experiment. Stimuli were projected to a screen positioned in the back of the scanner using a video projector. Subjects could see the video reflected in a mirror (15 x 9 cm) suspended 10 cm in front of their face and subtending visual angles of 42 degrees horizontally and 32 degrees vertically.

Each trial was built as follows: a large cue image (see below) spanning the whole screen during 1 s, a black screen during 1.5 to 4 s (duration randomly selected from a

truncated exponential distribution with mean of 2 s), a centered object image on a black background during 133 ms, a black screen during 1.5 to 4 s, and an object name on a black background shown until the subject answered or for a maximum of 1 s (Figure 1). Subjects answered by pressing one of two buttons on a hand-held response device to indicate if the name corresponded to the object, which occurred on 80% of the trials. A black screen was displayed for an additional 1 s between trials.

On a third of the trials (Predictive condition), the cue image was a scene associated with the object following it (e.g., an airport and a suitcase); on another third (Non-Predictive condition), it was a scene not associated with the object following it (e.g., a church and a tennis racket); on the final third (No-Context condition), it was a scrambled image (always a different one; see *Stimuli* section). Each object was shown once in each of these conditions, for a total of 288 trials. Furthermore, Predictive and Non-Predictive conditions were each split evenly into the Affective and Neutral subconditions, following the affective intensity of the context. There was therefore a total of 5 conditions: Predictive Affective (or Pred-Aff for short), Predictive Neutral (Pred-Neut), Non-Predictive Affective (noPred-Aff), Non-Predictive Neutral (noPred-Neut) and No-Context (noCont).

The order of trials was randomized. Randomized trials were divided in 3 fixed functional data acquisition runs of 96 trials. Each functional run lasted between 10 and 12 mins, with short breaks between them. The order of the 3 runs was counterbalanced across subjects.

For preprocessing and statistical analysis, the SPM8 software (http://www.fil.ion.ucl.ac.uk/spm/), running in the MATLAB environment (Mathworks Inc., Natick, MA, USA), was used. T1-weighted structural images were segmented into white matter, gray matter and cerebrospinal fluid, and warped into MNI space. Functional images were realigned, unwarped and corrected for geometric distortions using the field map of each

participant, slice time corrected, coregistered to the structural image of the corresponding participant, and smoothed using a 6 mm FWHM isotropic Gaussian kernel.

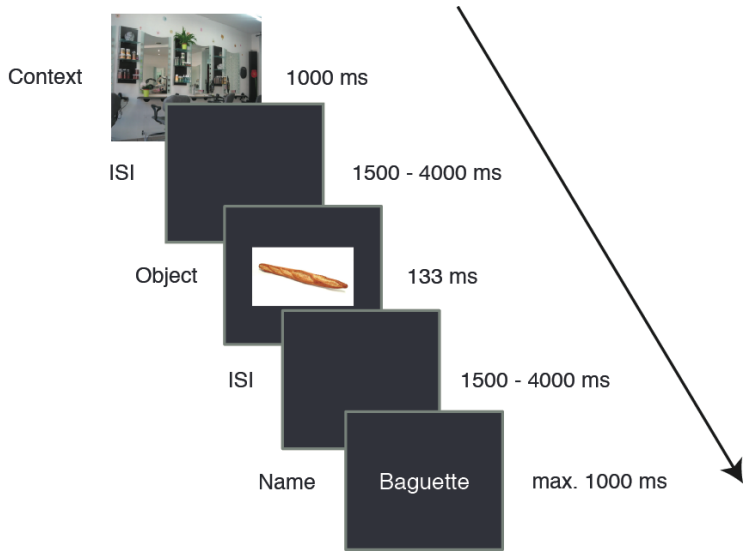

Figure 1. Example of a trial (Non-Predictive Neutral condition). The object image and name have been enlarged for better viewing.

Two different GLM analyses were performed in each subject. In a first context-and-object model, one event was modelled per trial with onset time at the beginning of the presentation of the context and offset time at the moment of the subject's response. Each condition of interest (Pred-Aff, Pred-Neut, noPred-Aff and noPred-Neut) and the noCont condition were modelled by convolving box-car functions with SPM8's canonical hemodynamic response function; the six motion parameters were also included in the model. This model was used to investigate the main effect of prediction (Pred-Aff + Pred-Neut – noPred-Aff – noPred-Neut), the main effect of affective value (Pred-Aff – Pred-Neut + noPred-Aff – noPred-Neut), and the interaction between predictive and affective values (Pred-Aff – Pred-Neut – noPred-Aff + noPred-Neut). It was possible to use the complete trials for these comparisons because the objects and contexts are the same across the conditions and only the associations between them differ; resulting activations are necessarily correlated to object recognition since the associations become clear to the subject only when the object is shown. The use of the complete trials was preferred whenever possible to increase signal-to-noise ratio.

In a second object-only model, two events were modelled on each trial. Object events (the regressors of interest) were modelled with onset time at the beginning of the presentation of the object and offset time at the moment of the subject's response; each condition (Pred-Aff, Pred-Neut, noPred-Aff, noPred-Neut and noCont) was modelled separately. Scene events (regressors of no interest) were modelled with onset time at the beginning of the presentation of the context and offset time at the beginning of the presentation of the object. These regressors were all modelled by convolving box-car functions with SPM8's canonical hemodynamic response function. The six motion parameters were also included in the model. Since visual scenes are different in the noCont condition, we used this model where the events of interest did not include the scene to compare the noCont condition with other conditions.

A temporal high-pass filter (cut-off of 128 s) was used to remove low-frequency drifts, and temporal autocorrelation across scans was modelled with an AR(1) process. Contrasts were then computed at the subject level and used for group analyses using one-sample *t*-tests. All voxels inside the brain were analyzed; we maintained the familywise error rate of $p < .05$, two-tailed, at the cluster level (primary threshold of $p < .001$, uncorrected) using random field theory (Friston et al., 1994). The Anatomy (Eickhoff et al., 2005) and WFU-PickAtlas (Maldjian et al., 2003) toolboxes were used to identify activated brain regions based on peak Montreal Neurological Institute (MNI) coordinates.

Results

Behavioral results

Mean accuracy was 97.1% (σ = 2.8%) for the Pred-Neut condition, 97.2% (σ = 2.1%) for the Pred-Aff condition, 96.9% (σ = 2.6%) for the noPred-Neut condition, 95.0% (σ = 2.5%) for the noPred-Aff condition and 95.7% (σ = 2.4%) for the noCont condition. When comparing

Pred, noPred and noCont together (ANOVA, n = 17), there was no effect of condition on accuracy ($F(2,16) = 2.17$, $p = .13$, $\eta^2_p = 0.12$). When comparing all conditions except noCont together (ANOVA, n = 17), there was a significant main effect of predictive value ($F(1,16) = 10.36$, $p = .005$, $\eta^2_p = 0.13$), a marginally significant main effect of affective value ($F(1,16) = 4.42$, $p = .052$, $\eta^2_p = 0.08$), and a marginally significant interaction between affective and predictive values ($F(1,16) = 3.97$, $p = .063$, $\eta^2_p = 0.10$).

Mean response time was 640 ms (σ = 121 ms) for the Pred-Neut condition, 650 ms (σ = 120 ms) for the Pred-Aff condition, 638 ms (σ = 110 ms) for the noPred-Neut condition, 636 ms (σ = 127 ms) for the noPred-Aff condition and 632 ms (σ = 116 ms) for the noCont condition. When comparing Pred, noPred and noCont together (ANOVA, n = 17), there was no effect of condition on response time ($F(2,16) = 1.53$, $p = .23$, $\eta^2_p = 0.09$). When comparing all conditions except noCont together (ANOVA, n = 17), there was no main effect of affective or predictive value and no interaction (Fs(1,16) = 1.67, 0.25 and 0.64 respectively, $p > .20$, $\eta^2_p < .03$).

fMRI results

To investigate the potential effect of the generation of explicit contextual expectations (occurring only in the Pred and noPred conditions) on brain activity, we contrasted the Pred and noPred conditions with the noCont condition using the object-only model (paired t-test, n = 17). Four clusters were significantly more activated in the Pred and noPred conditions than in the noCont condition ($p < .05$, two-tailed, corrected for family-wise error rate (FWER);

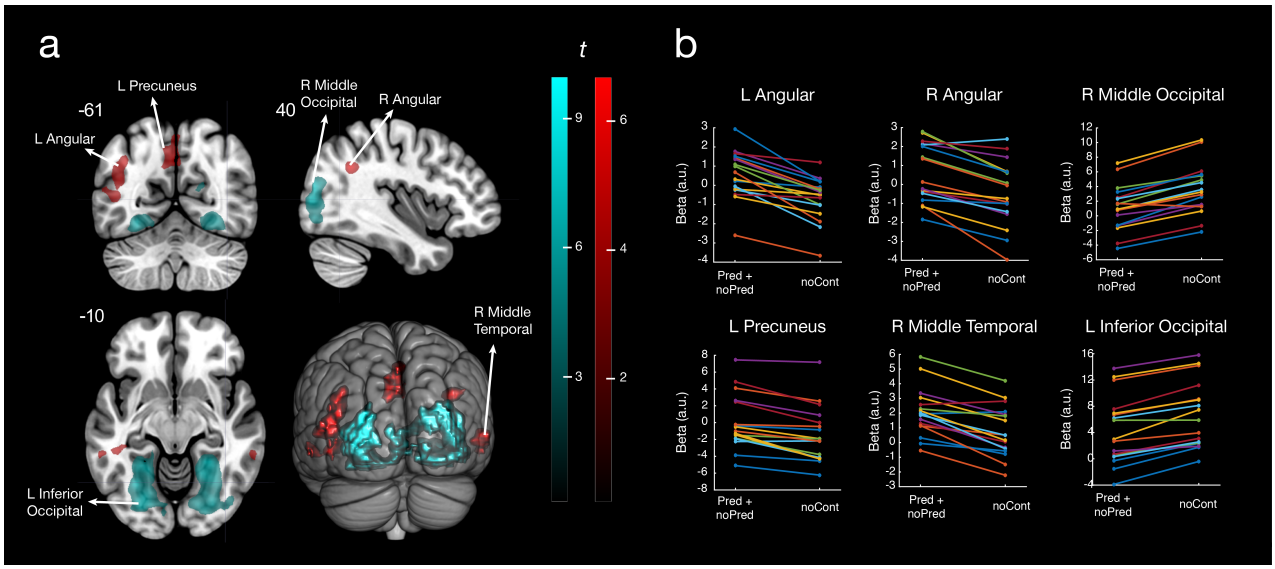

Figure 2. A) Significant clusters for the noCont > (Pred + noPred) (in red) and the (Pred + noPred) > noCont (in cyan) contrasts. **B)** Beta values of individual subjects for noCont and (Pred + noPred) conditions in peak voxels of various significant clusters.

peak Cohen's d_z = 1.62; Figure 2; Table 1): one cluster extending from the left middle temporal gyrus to the parietal cortex (angular gyrus), one in the right middle temporal gyrus, one in the right angular gyrus, and one in the precuneus. The reverse contrast revealed the specific activation of a large bilateral cluster extending from the middle occipital gyrus to the anterior fusiform, and a smaller cluster in the right calcarine gyrus ($p < .05$, two-tailed, FWER-corrected; peak Cohen's d_z = 2.42; Figure 2; Table 1).

Using the context-and-object model, we then investigated whether there was a main effect of predictive value (Pred vs noPred), a main effect of the context's affective intensity (Aff vs Neut), and an interaction between predictive and affective values on brain areas involved in object recognition (paired t-tests, n = 17). There were no significant main effects of predictive and affective values. However, there was a significant interaction between predictive and affective values for a large bilateral cluster extending from the calcarine sulci to the cuneus ($p < .05$, two-tailed, FWER-corrected; peak Cohen's d_z = 2.53; Figure 3; Table 1). When

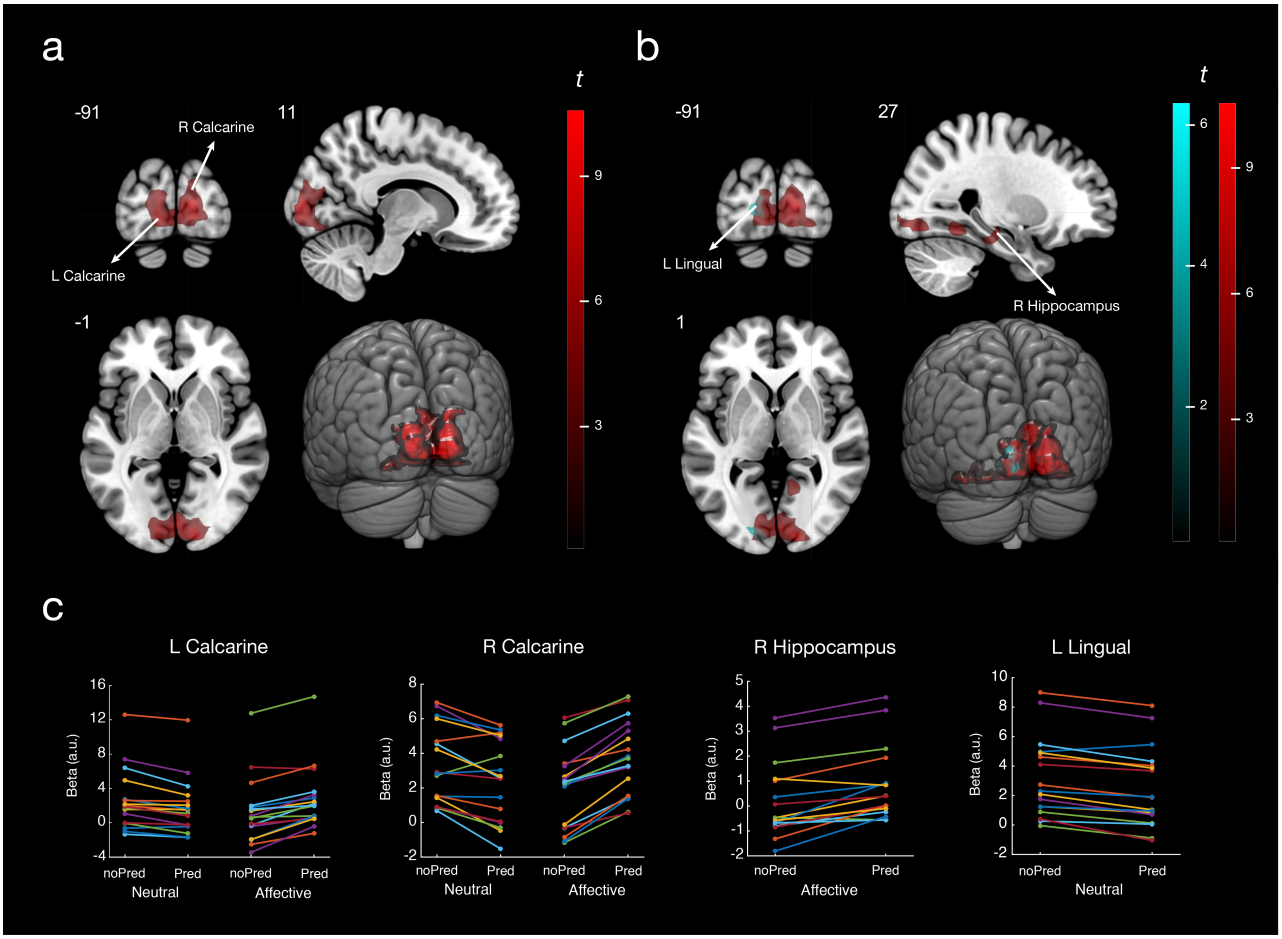

Figure 3. A) Significant clusters for the interaction between affective and predictive values (in red). **B)** Significant clusters for the Pred-Aff > noPred-Aff (in red) and the noPred-Neut > Pred-Neut (in cyan) contrasts. **C)** Beta values of individual subjects for separate conditions in peak voxels of various significant clusters.

decomposing the interaction into simple effects, these areas, along with the right fusiform gyrus and, in another cluster, the hippocampus (subiculum, CA3) and the parahippocampal gyrus, were significantly more active in the Pred-Aff condition than in the noPred-Aff condition (p < .05, two-tailed, FWER-corrected; peak Cohen's d_z = 2.56; Figure 3; Table 1). No cluster was significantly more active in the noPred-Aff condition than in the Pred-Aff condition. When looking at the neutral conditions, no cluster was significantly more active in the Pred-Neut condition than in the noPred-Neut condition, but the left lingual and superior occipital gyri were more active in the noPred-Neut condition than in the Pred-Neut condition (p < .05, two-tailed, FWER-corrected; peak Cohen's d_z = 1.53; Figure 3; Table 1). Interestingly, voxels at the intersection of the calcarine sulci, lingual gyrus and superior occipital gyrus were both part of

a cluster that was more active in the Pred-Aff condition compared to the noPred-Aff condition and part of a cluster that was more active in the noPred-Neut condition compared to the Pred-Neut condition.

Table 1. Montreal Neurological Institute (MNI) coordinates and T values for significantly activated brain regions.

Brain regions	Peak MNI coordinates			Nb of voxels	Peak T value
	x	y	z		
(Pred + noPred) > noCont					
L Angular	-42	-54	30	238	6.67
L Middle Temporal	-54	-48	6		5.89
L Precuneus	0	-60	39	101	5.93
R Middle Temporal	63	-42	-3	63	6.51
R Angular	39	-54	33	36	5.96
noCont > (Pred + noPred)					
R Middle Occipital	36	-81	6	1607	9.97
R Lingual	27	-45	-9		9.97
L Inferior Occipital Gyrus	-27	-81	-12		8.72
L Lingual Gyrus	-24	-48	-9		8.01
L Fusiform Gyrus	-30	-63	-9		8.01
R Calcarine	15	-51	9	59	5.58
Predict. x Affect.					
R Cuneus	15	-96	6	799	10.45
L Superior Occipital	-15	-96	9		8.17
L Calcarine	-9	-87	-6		8.16
Pred-Aff > noPred-Aff					
R Calcarine	15	-93	6	1047	10.56
L Calcarine	-3	-84	-6		7.87
R Fusiform	27	-84	-12		7.44
R Hippocampus Subiculum	27	-21	-15	44	5.61
R Parahippocampal	30	-27	-21		5.05
noPred-Neut > Pred-Neut					
L Lingual	-12	-90	0	57	6.31
L Superior Occipital	-12	-93	12		5.37

Discussion

Our first aim was to investigate how the generation of expectations about objects from a preceding context might modulate the activity of brain areas involved in object perception. We found significantly more activation in the precuneus, the middle temporal gyri and the parietal cortex, when (valid or invalid) contextual expectations were generated prior to object perception, suggesting that these high-level areas are mainly associated with object processing when expectations are generated. These activations specifically represent an interaction between contextual expectations and object bottom-up sensory information: activity related solely to object processing is cancelled out because the objects are the same in both conditions, and activity related solely to the prior presentation of the context is regressed out in the GLM.

The interaction between object and context processing observed in the middle temporal gyrus (a part of the inferotemporal cortex) supports a popular hypothesis according to which top-down contextual predictions would be combined with bottom-up sensory information to facilitate object recognition in the inferotemporal cortex (Bar, 2004). The precuneus and the parietal cortex, which are also activated in this contrast, have previously been linked to episodic memory retrieval and contextual associative processing (Lundstrom et al., 2005; Aminoff et al., 2007; Livne and Bar, 2016; Brandman and Peelen, 2017) which both require the integration of stored representations with incoming sensory information. Moreover, the precuneus of an observer that views several objects simultaneously is more activated when these objects are contextually related than when they are not (Livne and Bar, 2016); this suggests that the contextual representations elicited by some of these objects are compared to other objects. Recently, activity in the retrosplenial complex, a region comprising the precuneus, has been shown to correlate with supra-additive decoding of objects embedded in scenes, suggesting that the area is responsible for a scene-based facilitation of object representations (Brandman and Peelen, 2017). Interestingly, the interaction we observed between context and object

information in the precuneus is also supra-additive (i.e. there is a remaining positive activation after considering the main effects of object and context). We extend previous results by showing that the precuneus integrates object sensory information with valid or invalid scene-based expectations generated prior to object presentation.

The reverse contrast, associated with visual processing of objects when no expectation (neither valid nor invalid) had been generated from a context, yielded bilateral activation of lateral occipital, fusiform and lingual areas. Activated voxels may be part of areas primarily associated with the processing of sensory information shared by a majority of objects (e.g., intermediate spatial frequencies; Caplette et al., 2014), which is thus reduced when almost any object is expected.

We then investigated whether there was an effect of prediction error or match, i.e. whether some areas were more active at the presentation of the object when the object followed a predictive context or when the object followed a non-predictive context. Looking first at neutral contexts, we observed that the lingual and superior occipital gyri were more active in the non-predictive condition than in the predictive condition. This pattern of activations echoes results obtained in many studies in which activations in sensory areas when the prediction is incorrect are seen as markers of prediction error (e.g., Summerfield & Koechlin, 2008; Kok et al., 2012a, 2012b). Notably, most, if not all, of these studies also used affectively neutral cues. Combining neutral and affective contexts, we did not observe any significant difference between predictive and non-predictive conditions. A significant interaction between emotional and predictive values confirmed that the affective intensity of the prediction influenced prediction error mechanisms. This interaction was visible in a large bilateral cluster in low-level occipital areas comprising the lingual and superior occipital gyri and the calcarine sulci. The calcarine sulci showed the opposite pattern of activations when the context was emotional: they were more active when the object was predicted than when it was not.

These results are not compatible with the proposal that a subject's internal affective state is altering the content of their predictions about object identities (Barrett and Bar, 2009). According to this idea, the affective value of a preceding context (or even a simultaneous context or the object itself; see Barrett and Bar, 2009) would alter the subject's bodily state and bring additional information that could be used by the brain to predict the identity of perceived objects. Consequently, a similar pattern of results should be visible for neutral and emotional contexts, with only a greater difference in activation between predicted and unpredicted objects for emotional contexts than for neutral contexts (due to the additional emotional information).

Our results are compatible, however, with the general idea that affect interacts with predictive processing (Barrett and Simmons, 2015; Miller and Clark, 2018). One possibility recently put forward by some authors is that, rather than contributing to the content of the predictions, a subject's internal affective state modulates the precision of the predictions (Miller and Clark, 2018). In recent formulations of predictive coding (Feldman and Friston, 2010), the prediction error is weighted by the reliability, or precision, of sensory information. When precision is low, prediction errors are down-weighted and observers rely more on predictions; when it is high, prediction errors are up-weighted and observers rely more on the sensory input. Because this weighting only occurs for neurons representing prediction error and not for neurons representing predictions (Friston, 2009; Kok et al., 2012b), it should lead to an interaction between prediction error and precision (Rao, 2005; Friston, 2009; Kok et al., 2012b), exactly like the one we observed between predictive and affective values.

Kok and colleagues (Kok et al., 2012b) reported a similar reversal of the prediction error effect in the early visual cortex for task relevant stimuli. They argued that this effect was caused by endogenous attention enhancing the precision of the predictions (Rao, 2005; Feldman & Friston, 2010). This cannot be the cause of the effect we observed however, since attention was not manipulated in our study and our stimuli were all similarly task relevant. Furthermore,

reaction times and accuracies were similar for affective and neutral contexts; in fact, there even was a tendency toward lower rather than higher recognition rates for affective contexts (p = .052; see also Caplette et al., 2014). This indicates that exogenous attention was also similar between the conditions and implies that the prediction error reversal in our study was not caused by an increase in attention.

We also observed significantly more activation in the medial temporal lobe, specifically in the hippocampus and parahippocampal cortex, when an object was following a predictive emotional context compared to when it was following a non-predictive emotional context. Higher-level areas have been shown to display enhanced activation when there is a match between expectation and sensory information (Murray et al., 2002; Harrison et al., 2007; Summerfield et al., 2006; Summerfield & Koechlin, 2008); this is expected in the predictive coding framework because higher-level areas should "complete" sensory information in lower areas with the predictions they represent (Summerfield & Koechlin, 2008). Moreover, the parahippocampal cortex is known to represent contextual information (Epstein & Kanwisher, 1998; Bar & Aminoff, 2003; Aminoff et al., 2013) and has been hypothesized to initiate predictions based on contextual information (Bar, 2004). The hippocampus has also been shown to be the source of top-down predictions (Davachi & DuBrow, 2015; Hindy et al., 2016; Kok and Turk-Browne, in press). Here, we show that the parahippocampal cortex and the hippocampus are more activated when the object matches the context-based expectation, suggesting that predictions originate from these areas during object recognition.

In summary, real-world expectations initiated by contexts, irrespectively of their degree of validity, led to more activation of high-level areas and less activation of low-level areas during subsequent object recognition. Furthermore, the context's affective value interacted with the validity of the prediction it had initiated: classical prediction error effects were only observed with neutral contexts, and a complete reversal of these effects was observed when

contexts were emotional. This result is not compatible with the idea that the affective value of a stimulus, and the ensuing internal bodily state of the subject, are contributing to the creation of predictions (Barrett and Bar, 2009); but it is compatible with a modulatory role of affective value over the weight of predictions in perception (Miller and Clark, 2018). Finally, hippocampal and parahippocampal areas were selective to matches between affective contexts and objects, suggesting that contextual predictions are initiated in these areas (Bar, 2004; Kok and Turk-Browne, in press). In conclusion, our results deepen our understanding of predictive coding in an ecological setting by showing that the mere presence of explicit expectations, and their affective content, modulate object recognition.

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