Neural Variability and Sampling-Based Probabilistic Representations in the Visual Cortex

Highlights

- Stochastic sampling links perceptual uncertainty to neural response variability
- Model accounts for independent changes in strength and variability of responses
- Model predicts relationship between noise, signal, and spontaneous correlations
- Stimulus statistics dependence of response statistics is explained

Authors

Gergő Orbán, Pietro Berkes, József Fiser, Máté Lengyel

Correspondence

orban.gergo@wigner.mta.hu

In Brief

Orbán et al. show that linking perceptual uncertainty to neuronal variability accounts for systematic changes in variability and covariability in simple cells of the primary visual cortex. The theory also establishes a formal relationship between signal, noise, and spontaneous correlations.
Neural Variability and Sampling-Based Probabilistic Representations in the Visual Cortex

Gergő Orbán,1,2,5,6,* Pietro Berkes,3 József Fiser,3,4,5 and Máté Lengyel1,4
1Computational and Biological Learning Lab, Department of Engineering, University of Cambridge, Cambridge CB2 1PZ, UK
2MTA Wigner Research Center for Physics, Budapest 1121, Hungary
3Volen National Center for Complex Systems, Brandeis University, Waltham, MA 02454, USA
4Department of Cognitive Science, Central European University, Budapest 1051, Hungary
5Brain & Cognitive Sciences, University of Rochester, Rochester, NY 14627, USA
6Lead Contact
*Correspondence: orban.gergo@wigner.mta.hu
http://dx.doi.org/10.1016/j.neuron.2016.09.038

SUMMARY

Neural responses in the visual cortex are variable, and there is now an abundance of data characterizing how the magnitude and structure of this variability depends on the stimulus. Current theories of cortical computation fail to account for these data; they either ignore variability altogether or only model its unstructured Poisson-like aspects. We develop a theory in which the cortex performs probabilistic inference such that population activity patterns represent statistical samples from the inferred probability distribution. Our main prediction is that perceptual uncertainty is directly encoded by the variability, rather than the average, of cortical responses. Through direct comparisons to previously published data as well as original data analyses, we show that a sampling-based probabilistic representation accounts for the structure of noise, signal, and spontaneous response variability and correlations in the primary visual cortex. These results suggest a novel role for neural variability in cortical dynamics and computations.

INTRODUCTION

Neural responses in sensory cortices are notoriously variable: the same stimulus can evoke a different response on each presentation (Henry et al., 1973; Tomko and Crapper, 1974). While there have been great advances in characterizing the detailed patterns and statistical structure of cortical variability (Ecker et al., 2014; Goris et al., 2014; Kohn and Smith, 2005; Lin et al., 2015), its computational relevance has received far less attention. Indeed, the consequences of cortical variability have almost exclusively been studied from the perspective of neural coding, where variability is considered as pure noise or nuisance (Carandini, 2004; Moreno-Bote et al., 2014; Shadlen and Newsome, 1998; Tolhurst et al., 1983). Conversely, computational theories of cortical representations (Adelson and Bergen, 1985; Karlin and Lewicki, 2009; Olshausen and Field, 1996; Schwartz and Simoncelli, 2001) and dynamics (Churchland et al., 2012; Hennequin et al., 2014b; Mante et al., 2013; Rigotti et al., 2013; Rubin et al., 2015) focused only on trial-average responses, either ignoring variability altogether or considering only a simple scaling of variability with average responses (Ma et al., 2006).

Here, we argue that the rich structure of neural variability in sensory cortices reveals a key aspect of cortical computations: the representation of perceptual uncertainty. The need to represent uncertainty is the logical consequence of formalizing perception as unconscious inference (Helmholtz, 1962). For example, our retinal activations can have several different interpretations in terms of the composition and arrangement of objects in the environment, each being valid with a different probability. Thus, the uncertainty inherent in perceptual inference can be formalized as a probability distribution over possible perceptual interpretations of our input (Knill and Richards, 1996). The question is, then, how do neural activities represent probability distributions? (Fiser et al., 2010)? We propose that probability distributions are directly represented by the variability of cortical responses.

To study the implications of representing uncertainty through neural variability, we developed a model of population responses in the primary visual cortex (V1) with three main assumptions. First, we posit that neural activity patterns represent statistical samples from a probability distribution over visual features of a scene (Fiser et al., 2010; Hoyer and Hyvarinen, 2003; Lee and Mumford, 2003). Second, we specifically propose that individual samples in the model are represented by the membrane potentials (or, equivalently, the instantaneous firing rates) of neurons. Third, as the autocorrelations of membrane potentials for any static stimulus typically decay on a relatively short (~20 ms) timescale (Azouz and Gray, 1999), membrane-potential values (and consequently firing rates) separated on this timescale are considered statistically independent and therefore are modeled as independent stochastic samples from the underlying probability distribution. This naturally gives rise to within- as well as across-trial variability in the model.

This proposed representational scheme has two main implications. First, the set of responses (i.e., membrane-potential values) at any time in a population of neurons in V1 represents a combination of visual features as a possible interpretation of...
Figure 1. Schematic of the Model

(A) The generative model describing the statistical structure of image patches \( x \). Images arise as a linear combination of Gabor-filter basis functions with intensities \( y = (y_1, \ldots, y_n) \), whose contribution to the image is jointly scaled by a "contrast" variable, \( z \), plus Gaussian white noise (see Experimental Procedures for details).

(B) Probabilistic inference and the generation of membrane potentials and spike counts. The progression of four steps in the model is shown in the middle of the panel, advancing from the bottom toward the top. The activations of two example cells in red and purple (see the corresponding basis functions in A) are illustrated in two different trials using the same stimulus, \( x \) (left and right sides in B). Basis function activations, \( y \), are inferred by inverting the generative process shown in (A).

(legend continued on next page)
the input. Second, the within-trial variability of responses is such that the relative frequency with which any population pattern is visited is equal to the probability that the corresponding combination of features is a valid interpretation of the visual scene. Thus, neural response variability is directly linked to uncertainty about the stimulus: the wider the inferred range of possible feature combinations is, the wider the distribution of responses will become. In contrast to earlier proposals for how uncertainty may be represented in cortical activities (Deneve, 2008; Ma et al., 2006; Rao, 2004; Zemel et al., 1998), this establishes the mean and variability of responses as independent information channels, respectively encoding the mean and the associated uncertainty of the probability distribution over visual features. Importantly, these predictions about within-trial variability can also be tested in variability measured across trials that use the same stimulus and thus elicit the same probability distribution from which responses are sampled.

To test our model, we systematically compared the neural variability that our model predicted in response to various visual stimuli with the across-trial variability recorded in V1 in response to the same set of stimuli. As the parameters of our model were fundamentally determined by the statistical properties of visual scenes, rather than the properties of V1 circuits, this approach allowed a strong test of the model. Specifically, we show that the sampling-based representation of our model accounts for several key properties of response variability in V1. First, response variability not directly related to the stimulus can be so high that it dominates evoked responses (Arieli et al., 1996; Fiser et al., 2004; Vogels et al., 1989). Second, just as mean responses show systematic changes with particular attributes of the stimulus (as characterized by tuning curves), so does the variability of responses. In particular, experimental manipulations of image contrast or aperture (known to control perceptual uncertainty; Weiss et al., 2002) modulate the magnitude of variability largely independently from changes in mean responses (Churchland et al., 2010); conversely, changes in the orientation of the stimulus (which do not influence uncertainty) mainly affect the trial average of responses, and affect their relative variability much less. Third, response variability exhibits systematic patterns not only in its overall magnitude but also in its fine structure: signal correlations bear a specific relationship to noise (Ecker et al., 2010) and spontaneous correlations. Fourth, more generally, the structure of response variability during evoked activity closely resembles variability during spontaneous activity (Arieli et al., 1996; Berkes et al., 2011a; El Boustani et al., 2009; Fiser et al., 2004). In order to test and evaluate these implications of the model quantitatively, we compared model results directly to previously published experimental results whenever possible. To confirm the specific new predictions of the model about the structure and stimulus-dependent modulation of spike-count variability, we further performed novel analyses of a published dataset of V1 recordings from awake macaques (Ecker et al., 2010). These results suggest a new perspective on the functional role of variability in cortical dynamics and distinguish between previous conflicting proposals about how uncertainty is represented in the cortex.

RESULTS

From Natural Image Statistics to Neural Representations

We extended a well-known family of representational models of V1, in which the visual cortex maintains an internal model of how images are generated by underlying visual features (Figure 1A; see also Figure S1, Experimental Procedures, and Supplemental Experimental Procedures). According to this internal model, an image patch is generated by a multiplicative interaction between two terms (plus noise):

\[ \text{image} = z \times \left( \sum \text{activation}_i \times \text{basis}_i \right) + \text{noise}. \quad \text{(Equation 1)} \]

The first term, z, which we assumed for simplicity to be a single scalar, determines the global contrast level of the image patch. The second term is a linear combination of basis functions, and simple cell activations represent the coefficients with which each of these basis functions contribute to the image (Olshausen and Field, 1996; Schwartz and Simoncelli, 2001). In addition, the internal model also defines the prior probability distribution of basis function activations, P(activations), which expresses the frequency with which any combination of activations is expected to occur across different images. The role of V1 is then to invert this generative process and infer the level of activation for each feature in an image (Karklin and Lewicki, 2009; Olshausen and Field, 1996; Rao and Ballard, 1999; Schwartz and Simoncelli, 2001).

Due to noise and ambiguity in the model, y cannot be inferred from the image with certainty; hence, the result of Bayesian inference is a posterior probability distribution, P(y|x). Membrane-potential values, u, represent stochastic samples from P(y|x) through a weak non-linear transformation (inset), with independent samples drawn every ~20 ms, corresponding to typical autocorrelation timescales of V1 neurons (Azouz and Gray, 1999) (For illustration, membrane potentials are plotted after smoothing with a 7-ms Gaussian kernel here. See also Experimental Procedure). Instantaneous firing rates, r, are obtained from membrane potentials by a rectifying non-linearity (Carandini, 2004; inset). Spike counts are obtained by deterministically integrating firing rates across time over the duration of a trial: a spike is fired whenever the cumulative firing rate reaches an integer value (open circles on cumulative firing-rate traces and ticks in spike rasters, with the final spike counts shown at the right end of each raster). Note that while the distribution of neural responses (mean, variance, and covariance) remains unchanged across trials using the same stimulus, the actual time course of membrane potentials and the spike counts can vary substantially across trials due to stochastic sampling from the same underlying distribution.

(C) Statistics of the joint activity of a pair of neurons. The two sides show the membrane-potential trajectories of the pair of neurons in the two trials presented in (B) plotted against each other, revealing the higher-order statistics of the joint distribution (e.g., non-zero correlations). Colored lines correspond to the membrane-potential trajectories shown in (B) (color shade indicates elapsed time), and dashed gray ellipses show the covariance underlying the stochastic trajectories (identical for the two trials). The center shows joint spike-count distribution of the same two cells across a large set of trials (circles) for the same stimulus. The two colored circles correspond to the spike counts obtained from the two trials shown at the two sides and presented in (B). Small jitter was added to integer spike counts for illustration purposes. Photo is from istock.com/CliffParnell.
The result of inference is a posterior distribution, $P(\text{activations} | \text{image})$, expressing the probability that any particular combination of features may underlie the current input.

Despite behavioral evidence for the representation of uncertainty (Ernst and Banks, 2002; Weiss et al., 2002), most previous representational models assumed that neural activities represent a single combination of features for each input (Karklin and Lewicki, 2009; Olshausen and Field, 1996; Rao and Ballard, 1999; Schwartz and Simoncelli, 2001), such as the one with the maximum posterior probability. These models were thus unable to capture the uncertainty expressed by the extent of the posterior. In contrast, our model maintained a representation of uncertainty by neural activities encoding randomly sampled feature combinations under the posterior. That is, the relative occurrence frequency of any neural activity pattern was equal to the inferred probability that the feature combination represented by it may have generated the input image. More specifically, we assumed that samples from the posterior were represented by the fluctuating membrane potentials of V1 cells through a weak compressing non-linearity, and we derived the instantaneous firing rate of a cell as a rectified-nonlinear function of its membrane potential (Carandini, 2004; Figure 1B, top; Supplemental Experimental Procedures). Thus, we took the membrane-potential values in a population of cells at any moment in time to represent a single sample from the multidimensional posterior, so that subsequent membrane-potential responses of a pair of model neurons (Figure 2).

**Key Features of Neural Response Variability in the Model**

Interpreting neural population activity patterns as samples from the posterior distribution of the internal model determined by Equation 1 establishes a direct link between the parameters of the posterior and the statistics of population responses. For example, the mean and the covariance of the posterior given a particular input image respectively correspond to the average and covariance of the neural responses evoked by that image. Thus, understanding the basic properties of the posterior distribution, and their dependence on the stimulus, provides key insights about the stimulus-dependent changes of cortical variability predicted by our model, which can be most directly demonstrated in the membrane-potential responses of a pair of model neurons (Figure 2).
The variability of the average response of each cell across different stimuli is predicted by the dependence of the posterior mean on the image. As the basis functions in our model are oriented Gabor filters that are assumed to combine linearly in the image (Equation 1), the posterior mean of the activation of each basis function is largely determined by its linear overlap with the image (Experimental Procedures; Equation 5). Thus, as in earlier models (Olshausen and Field, 1996), the trial-average response for simple oriented stimuli (such as commonly used full-field gratings) depends monotonically on the similarity of the “preferred orientation” of a cell (the orientation of its basis function) and the orientation of the stimulus, resulting in orientation-dependent tuning curves (Figure S2).

Changes in image contrast lead to corresponding changes in the inferred level of contrast, z (Figure 2A). A low-contrast image provides less evidence about the exact content of the image, so inferences rely predominantly on prior expectations, P(activations). In the extreme case of a blank stimulus, z approaches zero (Figure 2A, light gray), so inferences about the basis function activations that neurons represent are unconstrained by the image (Equation 1 is constant with respect to the activations), and thus the posterior becomes entirely determined by the prior (Berkes et al., 2011a; Fiser et al., 2010). Therefore, spontaneous activity, as a special case of evoked activity recorded in response to a blank stimulus, represents the posterior becomes different from the prior mean, and will thus be specific to the particular image that gave rise to it. This implies that signal variability, the variability of the mean response across different stimuli, grows with contrast (Figures 2B–2D, insets on top). Second, the observation of a high-contrast image reduces uncertainty (on average) about basis function activations relative to the prior. Thus, the (co)variance of individual posteriors will be smaller than that of the prior, implying that noise (co)variances, the across-trial variability of neural responses to the same stimulus, must decrease with increasing contrast (e.g., red covariance ellipses across Figures 2B–2D; see also Figures 3A, 4A, 4B, and 5C). As opposed to the mean of the posterior (cf. Figure S2), its covariance does not show a strong dependence on the detailed content of the stimulus beyond its overall contrast (red versus green versus blue covariance ellipses within Figures 2B–2D; see also Figures 4C–4E). This is intuitive; for example, changing the orientation of a grating, as opposed to its contrast, does not influence our uncertainty about it.

As long as the internal model is well-adapted to the statistics of stimuli, it can be shown that its prior, P(activations) (Figures 2B–2D, gray circles), must match the average posterior, P(activations | image), averaged across the distribution of stimuli, P(image), to which it has been adapted (Gelman et al., 2013; Figures 2B–2D, gray dots). As for high-contrast images, noise variability in responses is low, but signal variability is high (see above; compare the size of the yellow covariance ellipse to that of the red-green-blue covariance ellipses in Figure 2D); most of the response variability is due to signal variability; and thus, spontaneous correlations (see above; reflecting the prior) are predicted to largely follow signal correlations (compare dark gray and black covariance ellipses in Figure 2D).
covariance ellipses in Figure 2D; see also Figure 6B). More generally, the matching of the average posterior to the prior predicts a match between the distribution of spontaneous activities and the average distribution of evoked activities (compare the scatter of empty and filled circles in Figures 2C and 2D; see also Figure 7) (Berkes et al., 2011a).

In the following, we test each of these key features of our model in neural data. For this, most parameters of the model were set according to the statistics of natural image patches, without regard to neural data, leaving only four free parameters to determine how sampled feature values under the posterior were mapped to membrane potentials and firing rates in V1 neurons (Experimental Procedures). Out of these four parameters, we determined one based on previous literature and tuned only three to fit specific experimental data recorded in V1. The experimental data to be reproduced were selected by a set of predetermined criteria regarding both the type of neural data recorded and the stimulus manipulations used in the experiments (Supplemental Experimental Procedures). Importantly, although these data included multiple species and conditions, we took a conservative approach and used a single setting of parameters across all our simulations (Table S1). For a fair comparison, in each case model responses were analyzed using the same statistical methods as those used for the analysis of the corresponding experimental dataset (Supplemental Experimental Procedures).

Figure 4. Stimulus Dependence of Neural Response Variability
(A) Across-trial SD of peak response amplitudes of a population of cells (circles) for low-contrast gratings plotted against the SD for high-contrast gratings at the preferred (blue) and non-preferred (red) stimulus orientation.
(B) Spike-count Fano factors (mean matched) for low- and high-contrast stimuli.
(C) Dependence of membrane potential SD on grating orientation at high (solid black line) and low (solid gray line) contrast. For reference, membrane potential SD during spontaneous activity recorded in response to a blank stimulus is also shown (dashed gray line).
(D and E) Mean and variance (black and blue lines in D) and Fano factor (E) of spike counts as a function of stimulus orientation relative to the preferred orientation of the cell.

Mean Responses, Tuning Curves, and Contrast Invariance
In order to establish the validity of our model at a basic level, we first validated the model by reproducing some fundamental aspects of the mean responses of V1 simple cells. For this, we followed the method by which tuning curves are measured experimentally and computed average responses in the model for full-field grating stimuli with different orientations. As expected, our model neurons possessed clear orientation tuning for both membrane potentials and firing rates in V1 neurons (Experimental Procedures). Out of these four parameters, we determined one based on previous literature and tuned only three to fit specific experimental data recorded in V1. The experimental data to be reproduced were selected by a set of predetermined criteria regarding both the type of neural data recorded and the stimulus manipulations used in the experiments (Supplemental Experimental Procedures). Importantly, although these data included multiple species and conditions, we took a conservative approach and used a single setting of parameters across all our simulations (Table S1). For a fair comparison, in each case model responses were analyzed using the same statistical methods as those used for the analysis of the corresponding experimental dataset (Supplemental Experimental Procedures).
Response Variability and Stimulus Onset

The decrease in noise variability with contrast (Figure 2) in our model predicts that a high-contrast image following a blank period should lead to decreasing variability in V1 membrane-potential responses, and that this effect should hold regardless of whether or not the stimulus is aligned with the preferred orientation of a cell (Figures 3A–3C, top). Moreover, these changes in membrane-potential variability should carry over to changes in spike-count Fano factors even with the effects of changes in mean firing rates being factored out (Churchland et al., 2010; Figures 3D and 3E, top, two-sample t test, \( n = 90, p < 10^{-4}, t[178] = 5.4 \)). Such quenching of variability at stimulus onset is a general feature of cortical responses reported under a wide variety of experimental conditions (Churchland et al., 2010); in particular, it has been observed in recordings from V1 simple cells of anesthetized cats (Figures 3A–3C, bottom) and monkeys (Figure 3D, bottom). The decrease in model membrane-potential variability was also reflected in a decrease in spike-count Fano factors (mean matched, see Supplemental Experimental Procedures; Figure 4B, top; two-sample t test, \( n = 102, t[200] = 4.32, p < 10^{-4} \)). Our analysis of data recorded in awake-monkey V1 also showed a similar decrease in (mean matched) Fano factors with increasing contrast (Figure 4A, bottom). The decrease in membrane-potential variability was also reflected in a decrease in spike-count Fano factors (mean matched, see Supplemental Experimental Procedures; Figure 4B, top; two-sample t test, \( n = 102, t[200] = 4.32, p < 10^{-4} \)). The decrease in model membrane-potential variability was also reflected in a decrease in spike-count Fano factors (mean matched, see Supplemental Experimental Procedures; Figure 4B, top; two-sample t test, \( n = 102, t[200] = 4.32, p < 10^{-4} \)).

Contrast and Orientation Dependence of Noise Variability

Behavioral studies indicate that stimulus contrast directly affects subjective uncertainty (Weiss et al., 2002). This is consistent with the inverse scaling of posterior (co)variances with contrast in the model, which in turn predicts a similar scaling of noise (co)variances in V1 responses (Figures 2B–2D). Indeed, our model generated systematically higher membrane-potential variances for low- versus high-contrast stimuli (Figure 4A, top; paired t test, \( n = 61, t[60] = 6.02, p < 10^{-4} \)), and \( t[60] = 6.28, p < 10^{-4} \) for stimuli with preferred and non-preferred orientations, respectively). Once again, this difference between the variances at high and low contrast was present for preferred as well as non-preferred stimuli (Figure 4A, top). The same pattern of results had been obtained experimentally from V1-simple cells of anesthetized cats (Finn et al., 2007; Figure 4A, bottom). The decrease in model membrane-potential variability was also reflected in a decrease in spike-count Fano factors (mean matched, see Supplemental Experimental Procedures; Figure 4B, top; two-sample t test, \( n = 102, t[200] = 4.32, p < 10^{-4} \)). Our analysis of data recorded in awake-monkey V1 also showed a similar decrease in (mean matched) Fano factors with increasing contrast (Figure 4B, bottom; two-sample t test, \( n = 800, t[1,598] = 37.3, p < 10^{-4} \)), confirming that it could not be attributed to the confounding effects of anesthesia, in which slow, synchronized activity fluctuation can have a major impact on measures of variability (Ecker et al., 2014; Goris et al., 2014; see also Supplemental Experimental Procedures and Figure S4A). Moreover, at the same time that noise variability decreased with contrast in the model, signal variability increased (Figures 2 and S2)—in agreement with experimental data showing a general scaling of average membrane-potential and
firing-rate responses with contrast (Finn et al., 2007; Skottun et al., 1987), and in disagreement with a potentially simpler linear mechanism according to which both signal and noise variability would originate from the same form of contrast-dependent variability in the input (Moreno-Bote et al., 2014).

As opposed to contrast, the orientation of a stimulus primarily affects the mean estimate of how much the feature represented by a neuron contributes to the stimulus (reflected in the tuning curves of mean responses, Figure S2), and only much more moderately affects the uncertainty associated with this estimate (Figure 2, see also Supplemental Experimental Procedures). Confirming this observation, the membrane-potential variances in our model showed only mild modulation by stimulus orientation (Figure 4C, top). These results agreed with intracellular measurements showing a similar pattern of change in V1 simple cells of cats, with a small peak in the membrane-potential variance at the preferred stimulus orientations of neurons (Finn et al., 2007; Figure 4C, bottom).

The rectifying non-linearity that maps membrane potentials to firing rates in our model converted orientation-dependent changes in the mean membrane potential to changes in both the mean and the variance of spike counts (Figure 4D). However, as sampling resulted in the variance of membrane potentials remaining constant this time (as opposed to when contrast was changed, Figure 3), changes in spike-count variance were only as large as those in mean spike counts, such that the Fano factor of the spike-count distribution remained constant over the whole range of orientations (Figures 4C and 4E, bottom, one-way ANOVA p = 0.47, F[7,101] = 0.55). These predictions of the model have been confirmed by our analysis of awake-monkey recordings in V1 (Figures 4D and 4E, bottom, one-way ANOVA p = 0.47, F[7,101] = 0.30).

The Effect of Aperture on Response Variability, Sparseness, and Correlations

Although the generative process underlying our model specifies a relatively simple, largely linear mechanism for how natural image patches are generated as a combination of basic visual features (Equation 1; Figure 1A), inverting this process to infer the features from an image typically results in a complex posterior distribution that depends non-linearly on the image pixels. This complexity arises due to the so-called “explaining away” effect (Pearl, 1988), a common consequence of probabilistic inference, by which even distant pixel values that are unaffected by a visual feature under the generative process can indirectly influence the inferred value of that feature under the posterior. For example, in our model, all pixels in the image contribute to the inferred value of global contrast, z, which in turn influences the activity of all neurons (Figures 1 and 2), so even those portions of the image which are not part of the visual feature (basis function) represented by a neuron can change its activity.

As a result of explaining away, just as trial-average responses (tuning curves) were modified by suitable extra-classical

![Figure 6. Relationship between Signal, Noise, and Spontaneous Correlations](image1)

(A) Dependence of correlations during spontaneous activity, r_{spont}, on spike-count signal correlations, r_{sign}.
(B) Dependence of noise correlations during evoked activity, r_{noise}, on signal correlations. Bars show averages across cell pairs with signal correlations below or above the r_{sign} = 0.5 threshold, as shown on the x axis; error bars show SE, *p < 0.05. Insets show the distribution of noise correlations; dashed line shows the mean of the distribution. Bottom panels present analyses of data from Ecker et al. (2010) (extracellular unit recordings in awake macaque).

![Figure 7. Match between Spontaneous and Average Evoked Activity Multi-Unit Distributions Depends on Correlations and the Stimulus Ensemble Used](image2)

(A) Kullback-Leibler (KL) divergence between aEA for natural image patches (aEA_{natural} and SA (light gray bar), and between aEA_{natural} and a shuffled version of SA, preserving individual firing rates but destroying all correlations across electrodes (SA_{shuffled}, hatched bar). For reference, baseline KL divergence between two halves of SA data is also shown (dashed line).
(B) KL divergence between aEA and SA under three different stimulus conditions: natural image patches (aEA_{natural}, light gray bar, same as in (A)); random block noise images (aEA_{noise}, dark gray bar); and grating stimuli with various phases, orientations, and frequencies (aEA_{grating}, black bar). In all panels, bars show averages across animals and error bars show SE, *p < 0.05. Bottom panels present analyses of experimental data from Berkes et al. (2011a) with permission from AAAS (extracellular multi-unit recordings in awake ferrets).
receptive field (eCRF) stimuli (see above and Figure S2), so too were the higher-order statistical moments of responses subject to such eCRF effects in our model. In particular, presenting the same natural movie sequence stimulus under a larger aperture that included both the classical receptive field (CRF) and the surrounding nCRF of a cell increased the effective contrast content of the input image (total variation in pixel values over the image), and thus led to a higher inferred value of $z$ (Figure 5A, histograms). In other words, changes in aperture had effects on model inferences which were fundamentally analogous to changes in contrast (cf. Figure 2). In particular, just as when increasing contrast, an increase in inferred $z$ resulted in higher signal variance and lower noise variance in membrane potentials (Figure 5A, dotted lines and shaded areas; cf. Figure 2) and thus more reliable membrane-potential responses (Figure 5B, top, one-sample t test, $n = 54$, $t(53) = 9.18$, $p < 10^{-10}$). In turn, these opposite changes in signal and noise variability of membrane potentials meant that a larger fraction of the membrane-potential distribution of a cell lay respectively above or below the threshold for its preferred and non-preferred stimuli (frames of the movie). This increased the number of stimuli that evoked no firing in a cell while also increasing the firing rate for those stimuli that did evoke firing in it, and hence led to sparser spiking responses (Figures 5A, top solid line, and 5C, top, one-sample t test, $n = 54$, $t(53) = -20.1$, $p < 10^{-10}$). As the response of each neuron became sparser, these responses also became more de-correlated from each other, as reflected by the higher separation angles between the response vectors of neuron pairs with overlapping CRFs (Figure 5D, top, one-sample t test, $n = 1,431$, $t(1,430) = -43.4$, $p < 10^{-10}$). These results reproduced experimental data recorded in the anesthetized cat (Figures 5A–5C, bottom; Haider et al., 2010) and the awake monkey (Figure 5D, bottom; Vinje and Gallant, 2000) under similar stimulus manipulations. We found that the same mechanism also accounted for why phase scrambling of natural images, which decreased the overall local-contrast content of an image, led to less sparse responses in V1 in other experiments (Froudarakis et al., 2014; data not shown).

Next, we wanted to test whether the stimulus dependence (i.e., contrast and aperture dependence) of the variability of neural responses reproduced by our model (Figures 3–5) conveyed significant information about the stimulus beyond that information conveyed by mean responses. For this, we measured how well the stimulus could be decoded by taking into account or ignoring these stimulus-dependent variability modulations. We found that the decoding performance of an optimal decoder (which took all aspects of response distributions into account) was often substantially higher than that of a linear decoder (which assumed no changes in spike-count Fano factors; Figure S5; Supplemental Experimental Procedures). Thus, in contrast to other proposed population coding schemes for uncertainty (Ma et al., 2006), the sampling-based population code of our model was not linearly decodable in general.

**Relationship between Signal, Spontaneous, and Noise Correlations**

In the foregoing sections, we have demonstrated that the characteristics of the mean and the variance of individual model neuron responses in a sampling-based representation closely matched those found experimentally. In order to characterize the joint variability in the response distribution more completely, we also investigated the fine structure of correlations.

Our theory provided a principled link between various forms of response covariances and correlations during stimulus-evoked and spontaneous activity. In particular, it predicted a match between signal and spontaneous correlations as well as between signal and noise correlations (Figures 2 and S4; see also Supplemental Experimental Procedures). Although these similarities were most cleanly predicted for membrane potentials, directly representing samples from the posterior distribution, they also carried over to firing rates and consequently to spike counts. In particular, we found a positive relationship between signal and spontaneous correlations of spike counts in the model (Figure 6A, top, two-sample t test, $n = [27,232; 1,209]$, $t(28,439) = -19.5$, $p < 10^{-4}$), which was confirmed by our analysis of awake-monkey V1 recordings (Ecker et al., 2010; Figure 6A, bottom, two-sample t test, $n = [1,474; 189]$, $t(1,661) = -2.73$, $p = 0.0063$). A similar relationship between spontaneous and signal correlations has also been noted in the anesthetized-cat V1, but it could not be captured by previous models (Lin et al., 2015). Spike-count noise correlations also had a positive relationship with signal correlations in the model (Figure 6B, top, two-sample t test, $n = [27,457; 1,223]$, $t(28,678) = -12.0$, $p < 10^{-4}$), in line with the general finding that noise and signal correlations tend to be positively related in a variety of cortical areas (Cohen and Maunsell, 2009; Gu et al., 2011) including the awake-macaque V1 (Ecker et al., 2010; Figure 6B, bottom, two-sample t test, $n = [1,486; 172]$, $t(1,656) = -2.20$, $p = 0.028$). As our model neurons had a diverse set of receptive fields without a strong overrepresentation of any particular feature, the distribution of signal correlations was centered very close to zero (mean 0.015). As a corollary of the similarity of signal and noise correlations, the distribution of noise correlations also had a mean close to zero (Figure 6B, top inset mean 0.0074), in line with experimental findings in awake animals (Ecker et al., 2010; Figure 6B, bottom inset, mean 0.011).

**Spontaneous and Evoked Response Distributions**

In the previous sections, we have shown how a sampling-based representation accounted for differences in both neural variability and correlations between spontaneous and stimulus-evoked activities as responses recorded at zero and full contrast. However, sampling also implied specific similarities between spontaneous and stimulus-evoked activities (Figure 2D, bottom). In particular, it implied that the distribution of spontaneous activity (SA) must match the average distribution of evoked activities (aEAs). Importantly, this match was only expected to hold for stimuli to which the model has been adapted, i.e., for natural images but not for artificial images. Indeed, computing the dissimilarity between SA and the respective aEAs for natural images (aEA_{natural}) block noise patterns (aEA_{noise}), and drifting gratings (aEA_{grating}) confirmed these relationships in our model (Figures 7 and S6). More specifically, the divergence between aEA_{natural} and SA was not different from a baseline divergence computed between the two halves of SA representing the minimal
Distinguishing Different Probabilistic Representations

Our results provide a way to distinguish between previous conflicting proposals about the neural underpinning of probabilistic representations in the cortex (Fiser et al., 2010). These proposals broadly fall into two classes. In one class, both the mean of a probability distribution and the associated uncertainty are represented by time-average neural responses. In this class of models, changes in response variability are directly linked to changes in average responses and thus do not serve as an independent information channel (Deneve, 2008; Ma et al., 2006; Rao, 2004; Zemel et al., 1998). In the second class, which is based on sampling, the average and variability of responses encode different and complementary aspects of a probability distribution: average responses encode the mean, while variability and co-variability encode higher-order moments, such as variances and covariances, of the distribution (Fiser et al., 2010; Hoyer and Hyvarinen, 2003; Lee and Mumford, 2003). Therefore, the main empirically testable difference between sampling-based and most other types of probabilistic representations, such as probabilistic population codes (Ma et al., 2006), is that variability is controlled independently of mean responses in the former, while in the latter the mean and variance are coupled by a fixed constant of proportionality. Nevertheless, despite the fundamental differences in, e.g., how the mean and variability of responses are coupled in these two classes of models, no prior work attempted to link either of them directly to the rich structure of neural variability in sensory cortices.

We have shown here that a sampling-based representation correctly predicted that particular stimulus manipulations result in systematic, mean-independent modulations of variability in V1. Further analysis also revealed that these modulations of variability in the model, though they sometimes appeared to be subtle, in fact conveyed substantial amounts of information about the stimulus and thus could be expected to be functionally relevant for downstream computations (Supplemental Experimental Procedures; Figure S5). Crucially, models that couple response means and variances cannot capture these effects (Ma et al., 2006). Moreover, sampling also provided a parsimonious account of the similarity of noise, signal, and spontaneous correlations, as well as the similarity between evoked and spontaneous activities, which do not naturally emerge without additional assumptions in alternative models of probabilistic representations (Deneve, 2008; Ma et al., 2006; Rao, 2004; Zemel et al., 1998).

Key Model Assumptions

Our results were obtained by representing the result of inference over variables encoding basis function activations \( \eta \) and not those that encode contrast \( z \) in Equation 1. This choice can be justified in two ways, both of which have precedents in previous representational models of V1 (Berkes et al., 2009; Karklin and Lewicki, 2009; Schwartz and Simoncelli, 2001). First, although such contrast variables are part of the generative model of natural images we considered, this does not imply that they also need to be explicitly included in the “recognition” model that the cortex uses to invert the generative model. Instead, they may be implicitly integrated out during inference. Note that even the posterior over basis function activations shows strong contrast dependence (both in its mean and covariance);
therefore, without an explicit representation of the contrast variable, contrast can be decoded from population activity should this decoding be necessary. Second, statistical arguments suggest that the number of contrast-like variables needs to be far lower than the number of those representing basis function activations, and so the experimental recordings which we use to test the theory are likely to be largely probing the latter. Nevertheless, were contrast-like variables represented explicitly in V1 and identifiable in experimental recordings (perhaps in inhibitory interneurons), we predict that their activity during spontaneous activity should not reflect the prior and, consequently, also should not match their average evoked-activity distribution.

In line with previous approaches (Karklin and Lewicki, 2009; Olshausen and Field, 1996; Schwartz and Simoncelli, 2001), our model took the posterior to be static compared to the timescale of inference, although under natural conditions, the posterior distribution itself may be changing due to both bottom-up and top-down effects. Bottom-up-driven changes in the posterior occur because the visual stimulus is changing, while top-down factors include changes in attention, cortical state (Goris et al., 2014; Harris and Thiele, 2011), and interactions with other sensory modalities (Driver and Noesselt, 2008). Thus, our results apply to standard visual electrophysiological experiments in which these factors are either well-controlled, by using the same stimulus and ensuring a homogeneous attentional state across multiple trials (Ecker et al., 2010), or averaged out, by pooling data over long time windows (Berkes et al., 2011a; Fiser et al., 2004). Furthermore, because the synchronized cortical state is characterized by large-amplitude fluctuations in membrane potentials and overall activity of cortical neurons, which are generally hard to control, our predictions are most directly testable in the desynchronized state characteristic of cortical populations processing the attended stimulus (Harris and Thiele, 2011; see also Supplemental Experimental Procedures and Figure S4).

**Sampling and Neural Circuit Mechanisms**

While our theory defines a neural representational scheme, it remains agnostic as to the neural circuit dynamics that give rise to such representations. As such, it accounts for the stationary distribution of neural network dynamics (as the posterior distribution that needs to be sampled) which is most readily testable in variability at slow timescales, e.g., across trials. However, anchoring the representation computationally in this way also provides useful constraints for mechanistic models that explicitly examine the underlying cellular- and network-level dynamics and thus make predictions about correlations at shorter timescales.

In particular, our model requires that the dynamically evolving membrane-potential or firing-rate traces of neurons represent sequences of stochastic samples from a posterior distribution. There have indeed been several neural circuit models proposed recently in which single neuron properties together with feedforward and recurrent connections shape either intrinsic or extrinsic noise in a network, such that for any particular input its dynamics produce samples from a computationally appropriate posterior distribution of activities (Buesing et al., 2011; Hennequin et al., 2014a; Savin et al., 2014). Such network models establish important proofs of the principle that neural circuit dynamics can give rise to sampling-based representations, and will be useful for making predictions about correlations on faster, within-trial timescales.

While the same stationary distribution can be attained by many different sampling algorithms, these will be different in their transient behaviors (so-called “burn-in”) and non-equilibrium properties (i.e., whether and how they violate detailed balance), and so data about autocorrelations, including characteristic oscillations, fast timescale cross-correlations, and transients (Azouz and Gray, 1999; Ray and Maunsell, 2010), should reveal hallmarks of the specific sampling dynamics employed by the cortex (Hennequin et al., 2014a). For example, our preliminary results indicate that the stimulus-onset-related transients and the contrast-dependent oscillation frequency of V1 responses may be accounted for by a specific class of sampling-based neural circuit dynamics that is both computationally efficient and neurally plausible (Aitchison and Lengyel, 2014), in that it accommodates separate classes of excitatory and inhibitory neurons which most previous approaches eschewed (Buesing et al., 2011; Savin et al., 2014).
compatible with a drastic, orders-of-magnitude change in perceptual confidence (Supplemental Experimental Procedures; Figures S3E and S3F).

Sampling through Time
As inferences in our model are represented by sequentially generated samples at the rate of one new statistically independent sample every few tens (for membrane potentials) or hundreds of milliseconds (for spike counts), we expect this to limit the resolution of the representation of uncertainty. (Although, by using over-complete representations, in which many neurons effectively code for the same variable, even one sample of a population activity pattern may represent multiple samples of the relevant variables, such that the effective rate of sampling can be faster than expected from neural time constants; see, e.g., Savin and Denève, 2014, and also Supplemental Experimental Procedures.) Indeed, such a gradual buildup of the representation of uncertainty over time within individual trials has been recently described (Lengyel et al., 2015). Moreover, it has been suggested that human-level performance in a range of behavioral tasks is indeed achievable by collecting a limited number of samples from a probability distribution given either static (P. Berkes et al., 2011b, COSYNE, conference; Vul et al., 2009) or dynamic stimuli (Levy et al., 2009). It has also been shown that specific patterns of perceptual variability in bi-stable percepts can be directly accounted for by sampling-based dynamics (Moreno-Bote et al., 2011). Our work complements these behavioral results by identifying the neural signatures of a sampling-based representation in V1, and demonstrates that the structure of neural variability and covariability provides useful clues for understanding the underlying probabilistic computations and representations utilized by the cortex.

EXPERIMENTAL PROCEDURES

The Gaussian Scale Mixture Model
We used a Gaussian scale mixture (GSM) model (Wainwright and Simoncelli, 2000) to define a generative model of image patches (Figure 1A). Each patch was represented by a vector of pixel values $x$ and assumed to be generated by a scaled, linear combination of features plus additive Gaussian white noise (see also Equation 1).

$$P(x|y,z) = N(x;z\ A y; \sigma^2_y I) \quad \text{(Equation 2)}$$

where $y$ describes the activation of features in $A$ for that image, $z$ is an independent variable scaling the output of these features, and $\sigma^2_y$ is the variance of observation noise independently affecting the intensity of every pixel of the image. The multiplicative interaction between $z$ and the basis functions captures two important aspects of natural images: first, that the effective contribution of each basis function (its activation level, $y$, multiplied by $z$) is sparsely distributed, and second, that the magnitude of basis-function contributions within the same local image patch tends to be correlated (Schwartz and Simoncelli, 2001).

The prior of activations was a multivariate normal distribution with a mean of zero and covariance matrix $C$,

$$P(y) = N(y; \ 0 \ C) \quad \text{(Equation 3)}$$

and the prior distribution of the scale variable $P(z)$, was a Gamma distribution with parameters $k$ and $\theta$.

The posterior distribution over feature activations could be obtained in a closed form for the scale variable $z$ and, conditioning on $z$, also for the feature activations $y$.

$$P(z | x) = \frac{P(x|z)N(z; 0 2^\gamma \ C_0^{1/2} \ A^T + \sigma^2_z I)}{Z} \quad \text{(Equation 4)}$$

and

$$P(y | z; x) = N(y; \mu(z; x); \Sigma(z)) \quad \text{(Equation 5)}$$

where the posterior mean and covariance of feature activations is

$$\Sigma(z) = \left( C^{-1} + \frac{z^2}{\sigma^2_z} A^T A \right)^{-1} \quad \text{and} \ \mu(z; x) = \frac{z}{\sigma^2_z} \sum(z) A^T x.$$

As it was not necessary to represent the posterior distribution of $z$ explicitly, we marginalized over this variable in order to express $P(y|x) = \int P(z|y|x)P(y|x)dz$.

Membrane potentials (dimensionless), $u$, were taken to represent a weakly non-linear function of visual feature activations $y$ (Figure 1B, bottom): $u = \text{sign}(y/y^\text{thresh})$. (Equation 6)

Firing rates were generated by first sampling membrane-potential values and then transforming them using a standard, rectified non-linearity (Carandini, 2004) (Figure 1B, middle): $r = m(u - U\text{thresh})^+$. (Equation 7)

For sampling consecutive firing-rate values, we approximated autocorrelation timescales by regarding the firing rate of a cell to be constant within each 20 ms time bin and independently sampling across bins. Spike counts, $n$, were generated simply by integrating instantaneous firing rates over time, starting from a random value distributed uniformly between zero and one (Figure 1B, top). Spike counts were computed over trial durations that matched those used in the corresponding experiments.

See Supplemental Experimental Procedures for a justification of model choices and more details of the model, including the setting of parameters, criteria used to select relevant experimental data to test the model, and procedures for analyzing neural responses in the model and in experimental data. Code for the model is available at https://github.com/gergoorban/sampling_in_gsm.

SUPPLEMENTAL INFORMATION

Supplemental Information includes Supplemental Experimental Procedures, six figures, and two tables and can be found with this article online at http://dx.doi.org/10.1016/j.neuron.2016.09.038.

AUTHOR CONTRIBUTIONS

M.L. conceived the theoretical framework. G.O. and M.L. developed the model and conducted the mathematical analyses. G.O. performed the numerical simulations. G.O., P.B., J.F., and M.L. discussed the results and wrote the manuscript.

ACKNOWLEDGMENTS

We thank R. Turner and G. Hennrein for useful discussions; D. Wolpert, R. Aslin, and A. Ecker for comments on a previous version of the manuscript; and especially A. Ecker, P. Berens, M. Bethge, and A. Tolias for making their data publicly available. This work was supported by an EU-FP7 Marie Curie Intra-European Fellowship, a Lendület Award of the Hungarian Academy of Sciences (G.O.), the Swartz Foundation (P.B. and J.F.), the Swiss National Science Foundation (P.B.), the NSF (J.F.), EU-FP7 Marie Curie CIG (J.F.), and the Wellcome Trust (M.L.).

Received: March 22, 2016
Revised: July 27, 2016
Accepted: September 6, 2016
Published: October 19, 2016
Mante, V., Sussillo, D., Shenoy, K.V., and Newsome, W.T. (2013). Context-dependent computation by recurrent dynamics in prefrontal cortex. Nature 503, 78–84.

Moreno-Bote, R., Knill, D.C., and Pouget, A. (2011). Bayesian sampling in visual perception. Proc. Natl. Acad. Sci. USA 108, 12491–12496.

Moreno-Bote, R., Beck, J., Kanitscheider, I., Pitkow, X., Latham, P., and Pouget, A. (2014). Information-limiting correlations. Nat. Neurosci. 17, 1410–1417.

Olshausen, B.A., and Field, D.J. (1996). Emergence of simple-cell receptive field properties by learning a sparse code for natural images. Nature 381, 607–609.

Pearl, J. (1988). Probabilistic Reasoning in Intelligent Systems (Morgan Kaufmann).

Pouget, A., Beck, J.M., Ma, W.J., and Latham, P.E. (2013). Probabilistic brains: knowns and unknowns. Nat. Neurosci. 16, 1170–1178.

Rao, R.P.N. (2004). Bayesian computation in recurrent neural circuits. Neural Comput. 16, 1–38.

Rao, R.P.N., and Ballard, D.H. (1999). Predictive coding in the visual cortex: a functional interpretation of some extra-classical receptive-field effects. Nat. Neurosci. 2, 79–87.

Ray, S., and Maunsell, J.H.R. (2010). Differences in gamma frequencies across visual cortex restrict their possible use in computation. Neuron 67, 885–896.

Rigotti, M., Barak, O., Warden, M.R., Wang, X.-J., Daw, N.D., Miller, E.K., and Fusi, S. (2013). The importance of mixed selectivity in complex cognitive tasks. Nature 497, 585–590.

Roelfsema, P.R., Lamme, V.A.F., and Spekreijse, H. (2004). Synchrony and covariation of firing rates in the primary visual cortex during contour grouping. Nat. Neurosci. 7, 982–991.

Rubin, D.B., Van Hooser, S.D., and Miller, K.D. (2015). The stabilized supralinear network: a unifying circuit motif underlying multi-input integration in sensory cortex. Neuron 85, 402–417.

Salakhutdinov, R., and Hinton, G. (2012). An efficient learning procedure for deep Boltzmann machines. Neural Comput. 24, 1967–2006.

Savin, C., and Denève, S. (2014). Spatio-temporal representations of uncertainty in spiking neural networks. In Advances in Neural Information Processing Systems, Volume 27, Z. Ghahramani, M. Welling, C. Cortes, N.D. Lawrence, and K.Q. Weinberger, eds. (Curran Associates, Inc.), pp. 2024–2032.

Savin, C., Dayan, P., and Lengyel, M. (2014). Optimal recall from bounded metastable synapses: predicting functional adaptations in hippocampal area CA3. PLoS Comput. Biol. 10, e1003489.

Schwartz, O., and Simoncelli, E.P. (2001). Natural signal statistics and sensory gain control. Nat. Neurosci. 4, 819–825.

Shadlen, M.N., and Newsome, W.T. (1998). The variable discharge of cortical neurons: implications for connectivity, computation, and information coding. J. Neurosci. 18, 3870–3896.

Skottun, B.C., Bradley, A., Sclar, G., Ohzawa, I., and Freeman, R.D. (1987). The effects of contrast on visual orientation and spatial frequency discrimination: a comparison of single cells and behavior. J. Neurophysiol. 57, 773–786.

Tolhurst, D.J., Movshon, J.A., and Dean, A.F. (1983). The statistical reliability of signals in single neurons in cat and monkey visual cortex. Vision Res. 23, 775–785.

Tomko, G.J., and Crapper, D.R. (1974). Neuronal variability: non-stationary responses to identical visual stimuli. Brain Res. 79, 405–418.

Vinje, W.E., and Gallant, J.L. (2000). Sparse coding and decorrelation in primary visual cortex during natural vision. Science 287, 1273–1276.

Vogels, R., Spijkers, W., and Orban, G.A. (1989). The response variability of striate cortical neurons in the behaving monkey. Exp. Brain Res. 77, 432–436.

Vul, E., Goodman, N.D., and Griffiths, T.L. (2009). One and done? Optimal decisions from very few samples. In Proceedings of the 31st Annual Conference of the Cognitive Science Society, N. Taatgen and H. van Rijn, eds., pp. 66–72.

Wainwright, M.J., and Simoncelli, E.P. (2000). Scale mixtures of Gaussians and the statistics of natural images. In Advances in Neural Information Processing Systems, Volume 12, S.A. Solla, T.K. Leen, and K.-R. Muller, eds. (MIT Press), pp. 855–861.

Weiss, Y., Simoncelli, E.P., and Adelson, E.H. (2002). Motion illusions as optimal percepts. Nat. Neurosci. 5, 508–504.

Zemel, R.S.S., Dayan, P., and Pouget, A. (1998). Probabilistic interpretation of population codes. Neural Comput. 10, 403–430.