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Original Article

The Brain Activation-Based Sexual Image Classifier (BASIC): A Sensitive and Specific fMRI Activity Pattern for Sexual Image Processing

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Abstract

Previous studies suggest there is a complex relationship between sexual and general affective stimulus processing, which varies across individuals and situations. We examined whether sexual and general affective processing can be distinguished at the brain level. In addition, we explored to what degree possible distinctions are generalizable across individuals and different types of sexual stimuli, and whether they are limited to the engagement of lower-level processes, such as the detection of visual features. Data on sexual images, nonsexual positive and negative images, and neutral images from Wehrum et al. (2013) ($N = 100$) were reanalyzed using multivariate support vector machine models to create the brain activation-based sexual image classifier (BASIC) model. This model was tested for sensitivity, specificity, and generalizability in cross-validation ($N = 100$) and an independent test cohort ($N = 18$; Kragel et al. 2019). The BASIC model showed highly accurate performance (94–100%) in classifying sexual versus neutral or nonsexual affective images in both datasets with forced choice tests. Virtual lesions and tests of individual large-scale networks (e.g., visual or attention networks) show that individual networks are neither necessary nor sufficient to classify sexual versus nonsexual stimulus processing. Thus, responses to sexual images are distributed across brain systems.

Keywords: erotic images, machine learning prediction model, multivariate analysis, neuroimaging, sexual stimuli processing, support vector machine classification

The Brain Activation-Based Sexual Image Classifier (BASIC): A Sensitive and Specific fMRI Activity Pattern for Sexual Images

Sexual stimuli are generally believed to be associated with the (co-)activation of positive affect. For instance, the International Affective Picture System (IAPS), widely used in emotion research, assigns positive valence to sexual stimuli. Yet, psychophysiological and experimental studies on sexual desire and arousal present a more complex association between sexual responses and general positive and negative affect (Peterson and Janssen 2007). Also, neuroimaging findings suggest that parts of the brain may respond to explicit sexual stimuli in the same way as they do to nonsexual, disgust-inducing stimuli (Borg et al. 2014). The association between responses to sexual stimuli and positive and negative affect is not static either, as the same sexual stimulus can be appraised (i.e., assigned a meaning based on the stimulus in context) differently by different individuals and in different situations (Bancroft et al. 2003; Lykins et al. 2006; Brauer et al. 2009).

Visual sexual stimuli are commonly used to study processes relevant to the activation and regulation of sexual arousal. The level of sexual arousal such stimuli induce, both subjectively and in terms of genital response, varies, however, and depends on a number

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of factors, including stimulus content, intensity, and duration (for an overview, see van' t Hof and Cera 2021). Even though the presentation of sexual stimuli does not always result in high levels of sexual arousal (e.g., when presenting still images for a short duration), studying brain responses to visual sexual stimuli does provide insight into the initial appraisal of sexual stimuli, including which brain processes might be shared or distinct from those related to other affective stimuli. Previous studies using backward masking have revealed that the sexual content of a stimulus can be extracted without the need for higher-level or conscious processes, and subliminal presentations of sexual stimuli have been found to prime genital responses in both men (Janssen et al. 2000) and women (Ponseti and Bosinski 2010). A model by Janssen et al. (2000) proposes that sexual stimuli may convey more than one meaning. This (co-)activation of nonsexual affective responses to sexual stimuli can also be elicited automatically (Brauer et al. 2012; Macapagal et al. 2011). For example, women with a DSM-IV diagnosis of hyposexual desire disorder displayed less positive (but not more negative) implicit associations with sexual stimuli compared with sexually functional women (Brauer et al. 2012).

Previous neuroscientific studies have predominantly compared brain activation during sexual and neutral visual stimuli using univariate neuroimaging analysis methods. These studies demonstrated varying distributed brain activation patterns for sexual stimulus processing (for meta-analysis and reviews, see Georgiadis and Kringelbach 2012; Stoléru et al. 2012; Poeppl et al. 2016; Ruesink and Georgiadis 2017; Mitricheva et al. 2019). The results, combined, suggest that there is not one "sex nucleus" but that a distributed network of different areas is involved in sexual stimulus processing. Studies comparing brain response to sexual and general affective stimuli, specifically, both overlap and differ in their results. Both Walter et al. (2008a) and Wehrum et al. (2013) found activation in the ventral striatum (VS), hypothalamus, anterior cingulate cortex (ACC), and superior parietal lobes (SPL). However, Walter et al. (2008a) also found activation in the dorsal medial prefrontal cortex (dmPFC), ventral medial prefrontal cortex (vmPFC), precuneus, occipital cortex, and superior parietal lobes (SPL), whereas Wehrum et al. (2013) found additional activation in the orbitofrontal cortex (OFC), the middle frontal gyrus, precentral gyrus, and inferior temporal gyrus. Almost all the regions that have responded more strongly to sexual stimuli than to other affective stimuli in both studies have been linked to processing a variety of emotions. It thus remains unclear whether brain responses to sexual stimuli are robustly and reproducibly different from responses to general positive and negative affective stimuli.

In order to arrive at a more conclusive answer to the question of whether the processing of sexual stimulus is distinct from general affective stimulus processing, this study starts from the assumption that we could benefit from shifting from studying separate univariate activations to a more integrated multivariate brain model approach. Brain models have been created for many different complex psychological processes, including emotions (Kragel and LaBar 2014; Chang et al. 2015; Wager et al. 2015; Saarimäki et al. 2016), pain (Marquand et al. 2010; Wager et al. 2013), memory (Norman et al. 2006; Harrison and Tong 2009), attention (Rosenberg et al. 2015), and neurological and psychiatric disorders (for reviews, see Arbabshirani et al. 2017; Woo et al. 2017). These studies reveal a "many-to-many" mapping between brain regions and psychological processes. They also show that the brain processes and systems necessary to differentiate one stimulus category or psychological category from another are distributed across brain regions, and often across multiple large-scale systems. This advances findings from traditional activation maps by quantifying how accurately psychological categories can be "decoded" from the brain and which brain regions/systems are essential. In the field of sex research, Ponseti et al. (2012) created a brain model that can distinguish preferred from nonpreferred sexual stimuli, providing a promising objective tool that may ultimately contribute to the clinical diagnosis of pedophilia and an understanding of its brain bases. While standard univariate approaches have often led to structure-centric theories of complex mental processes (e.g., amygdala is critical for fear, anterior cingulate cortex for pain), meta-analyses have revealed that a structure-centric view is insufficient, as virtually every anatomical structure is involved in a wide array of different cognitive functions (Yarkoni et al. 2011). Multivariate approaches respect the many-to-one mapping between brain structures and mental states, allowing that populations of neurons within and across brain regions work together to create neural representations of mental states (Norman et al. 2006), in line with a long and growing literature on population coding in neuroscience (for a brief review, see Pouget et al. 2000; Kragel et al. 2018). Multivariate models can be tested for utility as neuromarkers, indicators of the presence of a particular mental state or event, by testing their sensitivity, specificity, and other measurement properties. If specificity is tested, this approach can also inform on the many-to-many mapping between brain regions and categories of mental events, shedding light on whether mental constructs can be empirically dissociated based on different multivariate brain patterns.

The current study builds on previous research on the connection between sexual and nonsexual positive and negative affect, in that its general aim is to examine whether we can distinguish sexual stimuli processing from general affective processing. We tested whether a binary multivariate classification model is capable of distinguishing between processing of sexual versus other types of (affective) stimuli in a manner generalizable

across participants. For this purpose, we first reanalyzed data from Wehrum et al. 2013; (N = 100), to date the largest neuroimaging study that included sexual, nonsexual affective (positive and negative), and neutral stimuli. We used a conjunction across several multivariate support vector machine (SVM) models to create the brain activation-based sexual image classifier (BASIC) model, which identifies a subset of regions critical for distinguishing sexual from both nonsexual negative and positive affect. We tested the sensitivity and specificity of the BASIC model in cross-validated analyses on the Wehrum et al. (2013) dataset (applied to new individuals whose data were not used in model training) and in a new, independent validation cohort that was tested only once on the final BASIC model (N = 18; Kragel et al. 2019). The BASIC model showed strong sensitivity and specificity for sexual stimulus processing, indicating that the model showed a positive response to sexual stimuli and a negative response to non-sexual affective stimuli, respectively. We then further tested to what degree the classification may be attributable to the involvement of lower-level processes and the large-scale networks to which they belong. This work shows that the BASIC model can classify, based on brain data, whether a participant was presented with a sexual or nonsexual affective/neutral stimulus with high accuracy. This pattern was generalizable across individuals and contextual factors and distributed across large-scale networks.

Materials and Methods

Data from Study 1, published in Wehrum et al. (2013) and Wehrum-Osinsky et al. (2014), were reanalyzed.

Participants

One hundred heterosexual, right-handed participants (50 women, 50 men, M_{age} = 25.4 years, STD = 4.8 years) with normal or corrected-to-normal vision were recruited to participate in the fMRI study. Participants with a history of psychiatric or neurological disorders, current psychotropic medication use, sexual dysfunctions, or medication influencing attention or sexual appetence were excluded. Twenty-six women were using oral hormonal contraceptives and one was using vaginal hormonal contraceptives. Of women without hormonal contraception, women were asked to indicate the beginning of their last menstrual cycle to assess duration of their menstrual cycle and actual cycle phase. Eleven women indicated that they were in the follicular phase, eleven in the luteal phase, and one woman had an irregular cycle and therefore her phase couldn't be assessed. Written informed consent was obtained after the complete procedure has been explained. The study was conducted in accordance with the Declaration of Helsinki and approved by the ethics committee of the German Psychological Society.

Experimental Design

Stimuli

A total of 120 images were selected, with 30 images for each condition: sexual, positive, negative, and neutral. Sexual and neutral images were selected from the internet (for a detailed explanation of the selection procedure, see Wehrum et al. 2013) and positive and negative images were taken from the International Affective Picture System (Lang et al. 2005). For corresponding IAPS picture numbers, see Supplementary Information 2. Sexual images depicted scenes with couples (always one man and one woman) practicing vaginal intercourse, oral or manual stimulation. Half of the sexual images depicted genitals and half did not. Neutral images depicted men and women in nonsexual interactions (e.g., during a conversation). Positive images showed nonsexual scenes typically rated as highly positively valent and medium in arousal (e.g., sport scenes and people in funfairs). Negative images showed scenes typically rated as highly arousing and highly negative (e.g., mutilated bodies). Both typically contained images of human bodies, as did the sexual images.

Experimental Design

For each participant, 30 images per condition were assigned randomly to six blocks of five images each. Each picture was presented for 3 s and the blocks were presented in pseudorandomized order. After each block, the participant rated valence, arousal, and sexual arousal on a three-button keypad attached to the MRI Table. The Self-Assessment Manikin (Bradley and Lang 1994) was used to assess valence and arousal and a nine-point Likert-type scale was used as a scale for sexual arousal. The scales were presented for a maximum of 4 s, followed by a fixation cross until the next block.

Image Acquisition

The functional and anatomical images were acquired with a 1.5 tesla whole-body MR tomography (Siemens Symphony with quantum gradient system, Siemens Medical Systems, Erlangen, Germany) with a standard head coil. Structural image acquisition was conducted prior to the functional session and consisted of 160 T1-weighted sagittal slices (1-mm slice thickness). Also prior to the functional image acquisition, a gradient echo field map sequence was acquired to obtain information for unwarping B0 distortions. For functional imaging, a total of 370 volumes were recorded using a T2*-weighted gradient echoplanar imaging sequence (EPI) with 25 axial slices covering the whole brain (slice thickness = 5 mm; gap = 1 mm; descending slice order; TA = 100 ms; TE = 55 ms; TR = 2.5 s; flip angle = 90°; field of view = 192 × 192 mm; 64 by 64 matrix). The orientation of the axial slices was paralleled to the OFC tissue–bone transition to keep susceptibility artifacts to a minimum. To minimize head movement artifacts, participants' heads were firmly fixated using the lateral clamp motion suppression system (provided by Siemens

for head imaging). The first three volumes of the EPI sequence were discarded to allow for T1 equilibration effects.

Preprocessing

Preprocessing and first-level analyses were carried out using Statistical Parametric Mapping (SPM8, Wellcome Department of Cognitive Neurology, London, UK; 2008) implemented in MATLAB 2007b (MathWorks Inc., Sherborn, MA, USA). Preprocessing included unwarping and realignment to the first volume (b-spline interpolation), slice timing correction, coregistration of functional data to each participant's anatomical image, normalization to the standard brain of the Montreal Neurological Institute, and smoothing with an isotropic three-dimensional Gaussian kernel with a full width at half maximum of 9 mm. Two male participants were excluded from further analyses due to excessive head movements, as described in Wehrum et al. (2013).

First-Level Analyses

Subject-level models were analyzed using the general linear model (GLM), which is equivalent for SPM8 and later versions to date (e.g., SPM12). Voxel time series were modeled using onsets and durations of the four experimental conditions: sexual, positive, negative, and neutral image blocks. Rating phases as well as the six movement parameters obtained from the realignment procedure were also included in the general linear model as covariates of no interest. Regressors were convolved with the canonical SPM double-gamma hemodynamic response function and a high-pass filter (256-s cutoff) was applied to the data and design. Serial correlation was modeled using SPM's approximation to the AR(1) model. Functional data were screened for outlier volumes using a distribution-free approach with thresholding for skewed data (Schweckendiek et al. 2013). Each resulting outlier volume was later modeled within the general linear model as a regressor of no interest. Custom code, written in MATLAB (2018b, The MathWorks, Inc., Natick, MA) and available from the authors' website (https://canlab.github.io), was used to visually inspect the preprocessed first-level activation parameter estimate (beta) images for potential artifacts and calculate Mahalanobis distance, a measure of multivariate distance of each first-level image from the group that can indicate outliers. Data of one male participant exceeded the threshold for Mahalanobis distance ($P < 0.05$, Bonferroni corrected) and were therefore determined to be a multivariate outlier and excluded from further analyses.

Predictive Model Development

Custom MATLAB (MATLAB 2018b, The MathWorks, Inc., Natick, MA) code available from the authors' website (https://canlab.github.io) was used for the second-level analysis, which consisted of multivariate predictive modeling applied to first-level beta images. For the development and testing of the model, three whole-brain SVMs (Gramfort et al. 2013) were trained to predict, based on brain response, whether participants were presented with either a sexual versus 1) a positive affective, 2) a negative affective, and 3) a neutral image. The three SVMs were tested using 5-fold leave-whole-participant-out cross-validation as well as an independent test cohort. To interpret the models and help evaluate their neuroscientific plausibility, we followed a recently published protocol for interpreting machine learning models (Kohoutová et al. 2020). We included analysis steps for model development, feature-level assessment, and model- and neurobiological assessment. The training and validation are described further below.

We also considered models predicting self-reported sexual arousal ratings as a continuous outcome, as participants rated their sexual arousal levels after each block of five images. However, this study did not manipulate intensity of the sexual stimuli and was hence not designed to create within-person variability. Accordingly, these ratings had little variability (mean within-subject variance was 1.05 points on a scale of 9 points). Therefore, it was not feasible to predict continuous ratings using a regression model.

Support Vector Machines and Brain Activation-Based Sexual Image Classifier

Where univariate analyses take the brain response in every voxel as the outcome of interest, multivariate analyses use the sensory experience, mental events, or behaviors as an outcome. Here, linear SVM classifiers identified multivariate patterns of brain activity discriminating sexual from neutral and nonsexual affective conditions. We trained three separate binary classifiers, one discriminating between sexual and positive affective stimuli, the second between sexual and negative affective stimuli, and the third between sexual and affectively neutral images. We then combined these into a single, final sexual versus nonsexual stimulus classifier. To estimate the predictive accuracy for each model in Study 1, we used 5-fold cross-validation blocked by participants (i.e., leaving out all images from a particular participant together), which produces an unbiased estimate of the models' performance. The classifiers were trained on whole-brain data masked with a gray matter mask. Each SVM model includes a linear pattern of weights across voxels and an intercept (offset) value.

Each of the three SVM classifiers resulted in a predictive weight map. We combined them to create BASIC, a model with a restricted set of brain features that differentiate sexual images from each of the three comparison conditions. We used bootstrap resampling (with 5000 bootstrap samples; e.g., Wager et al. 2013) to estimate voxel-wise P-values for each SVM map. We then thresholded each SVM map at $P < 0.05$ uncorrected and took the intersection of all three classifier maps. The weights for sexual versus neutral conditions masked by the overlap ($P < 0.05$ uncorrected) constituted the final BASIC model.

Note that this threshold is not intended to provide strong inferences about individual voxels, but to select features likely to capture selectivity to sexual stimuli relative to multiple other conditions, and to increase the interpretability of the final model. The intersection maps for all three SVM classifiers at $q < 0.05$ FDR-corrected are shown in Supplementary Figure 1 and include many of the same regions. Performance of the final BASIC model was validated on data from Study 2 (see below).

To validate the model and assess relationships with other variables, we calculated model scores for each image type (sexual, negative, etc.) for each individual participant. We calculated these scores using the cosine similarity metric, which calculates the weighted average (the dot product) over a test data image from one participant (where the SVM model constitutes the weights) normalized by the product of the norms of the SVM pattern and the data image. For vectorized v-length SVM weight image w and v-length data image d, where v is the number of voxels in each image, $\cos(w, d) = \langle w, d\rangle / \|w\| \|d\|$. $\langle\rangle$ indicates the dot product and $\|\|$ the L2-norm. Cosine similarity is thus equivalent to the spatial correlation between the SVM pattern and the data images, but without the mean-centering operator included in the correlation. This allows overall activation intensity to contribute to the classification but normalizes the scale of each test data image.

Analysis of Confounds

To examine if the brain model responses are independent of sex and age, SVM model scores for all three classifiers were regressed on sex and age. In addition, average values for gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF) were extracted from an eroded anatomical tissue segmentation mask, and SVM model scores were regressed on GM, WM, and CSF signals. We also tested the classification performance of each of the three models after CSF and WM were regressed out; it was not meaningfully affected by controlling for these covariates.

Model-Level Assessment: Classification Performance

To examine the sensitivity, specificity, and generalizability of the BASIC model, both forced-choice and single-interval classification performance were assessed on cross-validated model scores for Study 1, and on Study 2. In forced-choice classification, the BASIC scores for two images (e.g., one sexual and one aversive) from an individual person are compared, and the one with the higher BASIC score is labeled as "sexual." Classification accuracy is the percentage of individuals for which the BASIC model yields the correct decision. In single-interval classification, the score for a single image is compared with a threshold value (e.g., BASIC response > 0.2), and scores above threshold are classified as "sexual." Forced-choice classification generally yields higher accuracy, as comparing two images from the same person matches on many sources of between-person variability (e.g., between-person differences in vasculature and brain morphometry). Single-interval classification is affected by these sources of variability. As in our previous work (Wager et al. 2013), we report both measures, and report accuracy, specificity, sensitivity, and effect sizes for all three classifiers.

For validation within Study 1, we applied whole-brain SVM models obtained during training folds to held-out participants' data (5-fold cross-validated scores). We calculated the cosine similarity between the BASIC and brain images obtained under sexual and control conditions for each of the three SVM models. Single-interval classification requires comparing scores with a specified threshold; typically, SVM scores > 0 are classified as "sexual" and scores < 0 classified as "control." Here, to obtain a single threshold for sexual versus negative, positive, and neutral conditions, we calculated the cosine similarity threshold with the optimal balanced error rate, balancing sensitivity and specificity, for each of the three comparisons, and used the highest of these three (the one most favorable to specificity) as the cosine similarity threshold for labeling a brain image as "sexual." We use this threshold for Study 1.

For prospective validation of the BASIC model, we included a second dataset (Study 2) in the analysis, independent from Study 1. This dataset consisted of neuroimaging data of 18 participants (10 females, $M_{age} = 25$) presented with sexual, positive, and negative affective images from the IAPS (Lang et al. 2005) and Geneva Affective Picture Database (GAPED) (Dan-Glauser and Scherer 2011). Aspects of this dataset were published previously (Kragel et al. 2019), but with a substantially different analysis goal. The images were presented for 4 s, with a jittered intertrial interval of 3–8 s presented in randomized order.

The content of sexual images in previous studies varies. They vary in this study as well: The stimuli do not only include nude couples engaged in sexual acts (Study 1), but also nude couples or individuals or nonexplicit images of dressed couples or individuals (e.g., Watts et al. 2017). To validate whether the BASIC model generalizes to different types of sexual image content, Study 2 included sexual IAPS images with content distinct from Study 1. The content of the sexual images consisted of a mix of nude heterosexual couples (with one showing genitals explicitly), clothed heterosexual couples, a naked man or woman (with one showing genitals explicitly), or a happy-looking clothed man or woman. This variation reduces the risk that the BASIC classifier is driven by visual characteristics, as does the location of contributing brain regions in multimodal association cortices, but this could be explored further in future studies.

All corresponding IAPS and GAPED picture numbers for Study 1 and Study 2 are presented in Supplementary Table 1. Two images in the positive condition and four in the negative condition were the same in Study 1 and

Study 2 (out of the 30 images per condition in Study 1 and 28 in Study 2). There was no overlap between sexual images used in both studies. More specific information about the participants, experimental design, and image acquisition can be found in Kragel et al. (2019).

We calculated cosine similarity scores for the BASIC model applied to sexual, positive, and negative conditions from Study 2. We used these scores to estimate the accuracy, specificity, sensitivity, and effect size for both forced-choice and single-interval classification for [sexual vs. positive] and [sexual vs. negative] comparisons to assess the classification performance of the BASIC model. While the threshold for sexual image classification developed in Study 1 would ideally be applied to Study 2, empirically the response in Study 2 was not as high as in Study 1 (see Discussion of interstudy differences below), so application of the same threshold was not practical in this case. We thus validated the BASIC model only for within-study comparisons, not for absolute comparisons across studies.

Feature-Level Assessment: Large-Scale Networks

One could argue that classification between sexual and affective/neutral conditions is driven solely by, for example, differences in visual features or in attention levels. To examine if the classifications were driven by one large-scale network, we applied a "virtual lesion" approach. We retrained each of the three SVM classifiers in Study 1 ([sexual vs. positive], and [sexual vs. negative], [sexual vs. neutral]) seven times, each time excluding voxels in one large-scale network from the training and test images. We used seven large-scale cortical networks defined based on resting-state activity in 1000 participants, including "visual," "somatomotor," "dorsal attention," "ventral attention," "limbic," "frontoparietal," and "default mode," based on Buckner et al. (2011).

In addition, we evaluated the spatial scale of information coding by constructing predictive models using signal averaged within each of 489 predefined "parcels," or macroscale regions, that covered the entire brain (the "canlab_2018 2 mm" atlas; see https://github.com/canlab/Neuroimaging_Pattern_Masks). The regions comprising the atlas are defined based on published papers considered to be high-quality parcellations of specific large-scale zones of the brain or anatomically defined nuclei, including parcellations of the cortex (Glasser et al. 2016), basal ganglia (Pauli et al. 2016), thalamus (Morel et al. 1997; Krauth et al. 2010; Jakab et al. 2012), subcortical forebrain (Pauli et al. 2018), amygdala and hippocampus (Amunts et al. 2005), specific brainstem regions (Zambreanu et al. 2005; Fairhurst et al. 2007; Keren et al. 2009; Nash et al. 2009; Beliveau et al. 2015; Bär et al. 2016; Sclocco et al. 2016; Brooks et al. 2017), cerebellum (Diedrichsen et al. 2009), and brainstem areas not otherwise covered by named parcels (Shen et al. 2013). The atlas regions do not contain fine-grained pattern information but do still allow classification based on the relative activation across the 489 constituent regions.

Overall, we compared classification accuracy for SVMs trained on 1) whole-brain voxel-wise patterns, 2) whole-brain patterns across parcel averages and 3) the voxel-wise pattern within the most predictive single region in the brain. This allowed us to test whether the information required for classification was contained at whole-brain scale (across multiple large-scale networks), within individual networks, or within a single local region. Additionally, we tested whether fine-grained voxel-wise patterns were necessary or whether parcel-wise averages were sufficient.

Biology-Level Assessment

The neurobiological plausibility and validity of a model should be regarded as an open-ended investigation that requires long-term, collaborative efforts, multimodal, and multilevel approaches (Kohoutová et al. 2020). To start this evaluation, we summarized the BASIC pattern weights as a function of 17 resting-state networks by Schaefer et al. (2018) in a wedge plot. The pattern weights in each local network were calculated with "pattern energy," related to the absolute magnitude of predictive weights:

$$E_r = \frac{\sqrt{(w^T w)}}{V + 1}$$

E_r is the root-mean-square of weights in the network mask r per cubic cm of brain tissue, w denotes the vector of weights for in-region voxels, and V is the volume of the region in cm^3. As the variance of E_r varies inversely with network volume, the constant 1 is added to regularize the volume and thus avoid noise-driven, large magnitude estimates for small regions.

In addition, the classification performance of the BASIC model was compared with performance of an automated meta-analysis of previous studies investigating sexual stimuli processing using neurosynth.org (Wager et al. 2011; Yarkoni et al. 2011). An association test map, which displays brain regions that are preferentially related to the term 'sexual' based on an automated meta-analysis of 81 studies, was downloaded from neurosynth.org. Brain regions that were consistently reported in tables of those studies were included in this meta-analysis and maps were corrected for multiple comparisons using a false discovery rate of 0.01 (for the meta-analytic map, see Supplementary Figure 2). Note that both activations and deactivations are included in this map, as they are not separated by Neurosynth. The voxels in the brain map were used as features in an SVM classification between the sexual versus nonsexual conditions in both Study 1 and Study 2. Classification performance of this neurosynth "sexual" brain map was assessed by calculating accuracy, sensitivity, and specificity using both forced choice and single-interval methods.

Table 1. Classification performance for sexual versus neutral/affective conditions for Study 1

Condition	Method	Accuracy (%)	SE	Specificity (%)	CI	Sensitivity (%)	CI	Effect size
Sex vs. Neu	FC	100	0.0	100	100–100	100	100–100	3.29
	SI	98	1.0	97	93–100	99	97–100	3.06
Sex vs. Pos	FC	100	0.0	100	100–100	100	100–100	4.03
	SI	96	1.3	97	93–100	96	92–99	2.61
Sex vs. Neg	FC	100	0.0	100	100–100	100	100–100	3.25
	SI	95	1.5	96	92–99	95	90–99	2.22

Note: The accuracy with standard error (SE), specificity, and sensitivity with confidence interval (CI) are presented to demonstrate the performance of the three cross-validated and bootstrapped (5000 iterations) SVM classifications of Study 1 for both forced choice (FC) and single-interval (SI) classification methods. Effect size indicates Cohen's d. Condition abbreviations: sex = sexual, neu = neutral, pos = positive, neg = negative.

Self-Reported Data

Differences between conditions in self-reported valence, arousal, and sexual arousal were calculated with one-way repeated measures ANOVA in R studio 2018 (RStudio Team, Boston, MA, USA) for all participants.

Results

Model Development

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Using forced choice classification, all three classifiers performed with 100% accuracy, meaning that the cross-validated SVM scores were higher for sexual than other image types (negative, nonsexual positive, and neutral) for all 100 individuals in Study 1. Using single-interval classification, the sexual versus neutral performed with 98% accuracy, sexual versus positive with 96%, and sexual versus negative with 95%. Specificity, sensitivity, effect size, and accuracy for both forced choice and single-interval methods are presented in Table 1.

Corrected and uncorrected predictive weight maps of all three classifiers are presented in Supplementary Figure 1. Accuracy was significantly above chance (50%), as assessed with a binomial test, $P < 0.0001$ for all models. The intersection of the three thresholded predictive weight maps ($P < 0.05$) was used to create the BASIC model, with weights from the sexual versus neutral classifier retained only for voxels significant in all three models. The predictive weights map of the BASIC model is presented in Figure 1 and the included brain regions are listed in Supplementary Table 3.

Model-Level Assessment

The BASIC model was assessed by examining the classification performance between sexual and nonsexual conditions in Study 1 and Study 2. Cosine similarities between the BASIC and the sexual ($M = 0.34$, $SD = 0.0059$, $P < 0.001$, $d = 5.84$), neutral ($M = -.043$, $SD = 0.0093$, $P < 0.001$, $d = -.47$), positive ($M = 0.00020$, $SD = 0.0095$, $P = 0.98$, $d = 0.0021$), and negative ($M = 0.12$, $SD = 0.0071$, $P < 0.001$, $d = 1.75$) conditions from Study 1 are presented in Figure 2A. The classification accuracies for sexual versus positive, negative, and neutral conditions were significant ($P < 0.001$) for both forced choice and single-interval methods. Accuracy, specificity, and sensitivity for these classifications are presented in Table 2. The performance of the BASIC model on the sexual versus positive and sexual versus negative classification of Study 1 is presented in ROC plots in Figure 3A.

The highest threshold calculated with the optimal balanced error rate was 0.25 for the classification of sexual and negative images of Study 1. The threshold for the classification of both [sexual vs. positive] and [sexual vs. negative] images in Study 2 was 0.06 and did therefore not exceed the threshold from Study 1. Cosine similarities between the BASIC and sexual ($M = 0.11$, $SD = 0.15$, $P < 0.001$, $d = 1.87$), positive ($M = 0.0093$, $SD = 0.014$, $P = 0.50$, $d = 0.16$), and negative ($M = 0.0092$, $SD = 0.014$, $P = 0.52$, $d = 0.16$) conditions in Study 2 are presented in Figure 2B.

The classifications of both [sexual vs. positive] and [sexual vs. negative] conditions from Study 2, for both forced choice as well as the single-interval method, were significant ($P < 0.001$) and results are presented in Table 2. The performance of the BASIC model on the sexual versus positive and sexual versus negative classification of Study 2 is presented in ROC plots in Figure 3B.

Analysis of Sex Differences, Age, and Global Signal Confounds

No significant correlations between the three classifiers and age (sexual-neutral $r = -.00$, sexual-positive $r = 0.00$, sexual-negative $r = 0.00$) or gender (sexual-neutral $r = -.05$, sexual-positive $r = 0.04$, sexual-negative $r = -.22$) were found.

For all four conditions and all three contrasts, there was significant global activation in both CSF space/ventricles and in white matter, indicating potential global signal increases for sexual versus other image types. In each of the three models, SVM model scores with CSF and WM regressed out showed classification performance similar to that of the SVM models without nuisance regression (for forced choice: 100% accuracy, specificity, and sensitivity, effect size sexual versus neutral $d = 4.55$, sexual versus positive $d = 4.10$, sexual versus negative $d = 3.64$). The global signal thus did not contribute to the classification process and is therefore unlikely to be a confound.

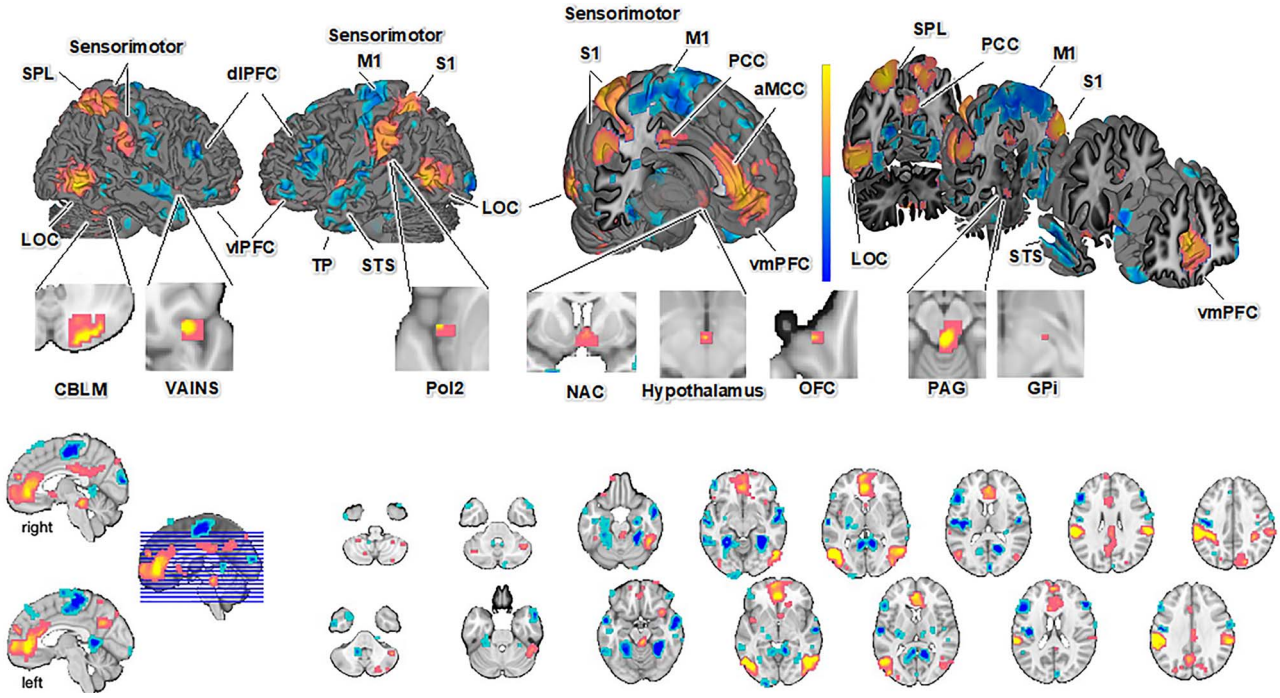

Figure 1. Predictive weight maps of the BASIC model. These brain maps represent the contribution of each voxel for the classification between sexual and neutral/affective conditions. The color bar thus represents the predictive weight value. The MNI-space anatomical underlay is adapted from Keuken et al. (2014). Upper left image represents the right hemisphere. The image next to that represents the left hemisphere.

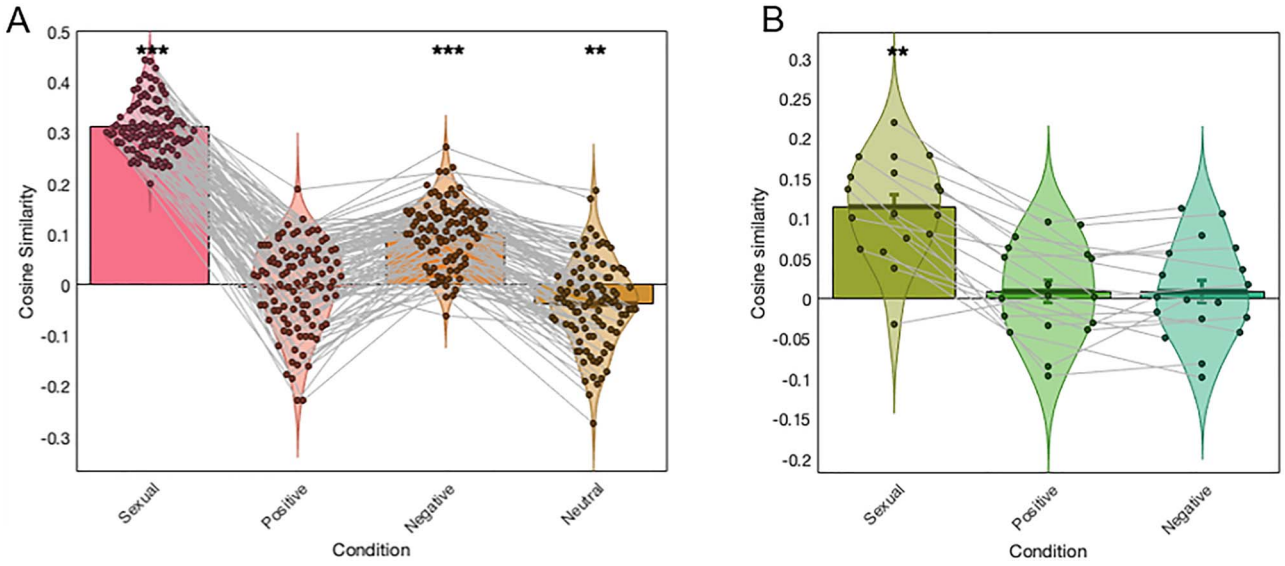

Figure 2. Cosine similarity between the BASIC and all conditions of Study 1 (A) and Study 2 (B). Lines connect data points from individual participants. The threshold calculated with optimal balanced error rate was 0.25 for Study 1 and 0.06 for Study 2. ** = $P < 0.01$, *** = $q < 0.05$ FDR.

Feature-Level Assessment: Large-Scale Networks

Feature-level assessments included 1) "virtual lesion" analyses that retrained classifiers omitting voxels in a single large-scale network and 2) tests of information coding at multiple spatial scales using retrained models and comparison of accuracy using randomly selected voxels in each single network, all voxels in each single network, all voxels averaged within parcels (see Materials and Methods), and all voxels. The latter evaluated information encoded at multiple spatial scales (see Fig. 4) and shows the highest model performance for all voxels across the whole brain (the original model). A whole-brain model averaging within parcels ("All Parcels" in Fig. 4) performed equally well, indicating that information was likely coded in the pattern of activation across gross anatomical regions (parcels) rather than fine-grained pattern information. These results were consistent across classification of sexual versus neutral, positive, and negative conditions (see Supplementary Figure 3).

For the "virtual lesion" of each of the seven Buckner Lab large-scale cortical networks (dorsal attention, default,

Table 2. Performance of BASIC between sexual versus nonsexual conditions in two datasets

Dataset	Condition	Method	Accuracy (%)	SE	Specificity (%)	CI	Sensitivity (%)	CI
Study 1	Sex vs. Neu	FC	100	0.0	100	100–100	100	100–100
		SI	100	0.0	100	100–100	100	100–100
	Sex vs. Pos	FC	100	0.0	100	100–100	100	100–100
		SI	99	0.7	99	97–100	99	97–100
	Sex vs. Neg	FC	100	0.0	100	100–100	100	100–100
		SI	97	1.2	97	93–100	97	93–100
Study 2	Sex vs. Pos	FC	94	5.4	94	81–100	94	82–100
		SI	78	6.9	78	58–95	78	55–95
	Sex vs. Neg	FC	100	0.0	100	100–100	100	100–100
		SI	78	6.9	78	56–95	78	58–95

Note: The accuracy with standard error (SE), specificity, and sensitivity with confidence interval (CI) are presented to demonstrate the performance of the BASIC model for both forced choice (FC) and single-interval (SI) classification methods. Condition abbreviations: sex = sexual, neu = neutral, pos = positive, neg = negative.

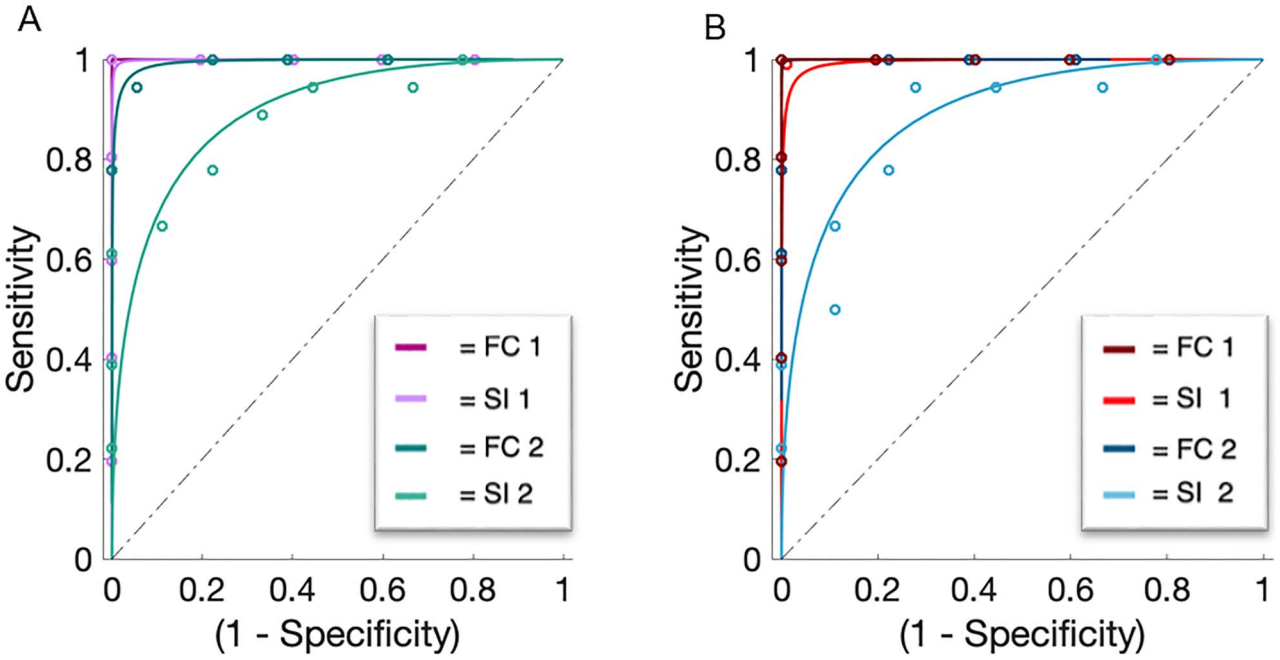

Figure 3. Receiver Operating Characteristic (ROC) plot for the BASIC model performance on sexual-positive (A) and sexual-negative (B) classification of data from Studies 1 and 2, both forced choice (FC) and single interval (SI) classification methods. The numerals 1 and 2 in the legend indicate cross-validated performance in Study 1 and generalization performance in Study 2, respectively.

frontoparietal, limbic, somatomotor, ventral attention, and visual), the forced-choice classification between sexual and nonsexual conditions from Study 1 were significant ($P < 0.001$), with perfect or near-perfect cross-validated accuracy in each case (see Supplementary Table 4 for accuracy, specificity, and sensitivity). This indicates that accurate classification did not depend on voxels in any single large-scale network.

Biology-Level Assessment

Examining weights in established large-scale networks yielded selective profile across networks, with weights concentrated in a few networks (see Fig. 5). BASIC predictive weights were positive in "default A," "dorsal attention A & B", and "ventral attention A & B" networks (pink wedges in Fig. 5), and negative in "somatomotor A & B," "visual peripheral B," "default C," and "tempo-parietal" networks (purple wedges in Fig. 5).

Performance of the neurosynth "sexual" map was better in classifying between sexual and the nonsexual conditions in Study 1 (forced choice accuracy for [sexual vs. positive] is 77%, $P < 0.001$, [sexual vs. negative] is 57%, $P = 0.22$, and [sexual vs. neutral] is 84%, $P < 0.001$) than Study 2 (forced choice accuracy for [sexual vs. positive] is 50%, $P = 1.00$, and [sexual vs. negative] is 56%, $P = 0.81$, with chance at 50%). For detailed accuracy, sensitivity, and specificity, see Supplementary Table 2. The BASIC model thus outperformed the neurosynth "sexual" map in classifying between all contrasts in Study 1 and Study 2.

Self-Reported Data

For an overview of means and standard deviations of self-reported valence, arousal, and sexual arousal levels, see Wehrum-Osinsky et al. (2014). Omnibus tests for the ANOVA show general arousal levels were significantly

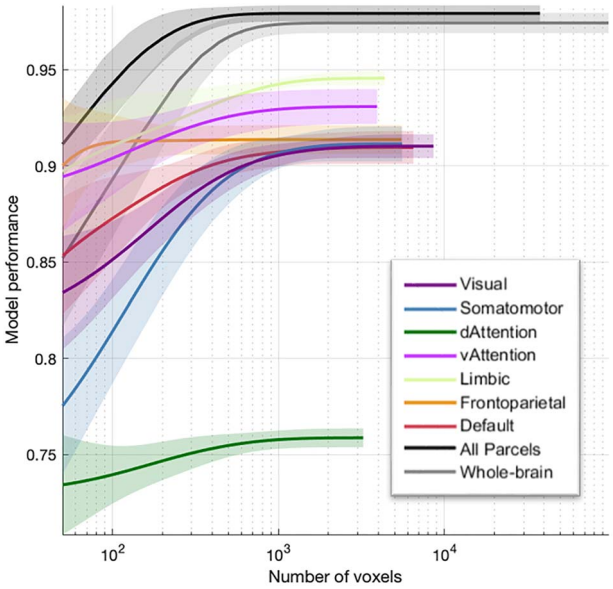

Figure 4. Spatial scale evaluation for classification between sexual and neutral conditions (for [sexual vs. positive] and [sexual vs. negative], see Supplementary Figure 3) from Study 1 on whole-brain, all parcels, and individual parcel levels, based on large-scale networks (Buckner, Krienen, Castellanos, Diaz, and Yeo 2011). This reveals that whole-brain models performed better than single-network models. In addition, the model based on brain-wide within-parcel (region) averages performed as well as the model based on voxel-level patterns, indicating that fine spatial scale pattern information is not needed for accurate performance.

different between all four conditions ($P < 0.001$), with the highest score for the negative condition. Valence levels between all four conditions, except sexual versus neutral, were significant ($P < 0.001$). Sexual arousal levels were only significant between sexual and other conditions ($P < 0.001$).

Discussion

Sexual stimulus processing is a core component of human affective and motivational systems, and part of a fundamental repertoire of motivations conserved across nearly all animal species. Previous work using sexual stimuli has made important advances (e.g., Georgiadis et al. 2006; Walter et al. 2008b; Abler et al. 2013; Borg et al. 2014; Stark et al. 2019), but these studies have generally included small sample sizes and have focused on characterizing responses in individual brain regions using standard brain-mapping approaches. Findings have been variable across studies (for meta-analyses, see Stoléru et al. 2012; Poeppl et al. 2016), and it remained unclear whether brain responses to sexual stimuli are robustly and reproducibly different from responses to nonsexual positive or negative affective stimuli.

Here, we employed a multivariate predictive model grounded in population-coding concepts in neuroscience (Pouget et al. 2000; Shadlen and Kiani 2007; Kragel et al. 2018) and systems-level characterization, based on growing evidence that various psychological processes are grounded in distributed networks rather than local regions or isolated circuits (Kamitani and Tong 2005; Kuhl et al. 2012; Arbabshirani et al. 2017). We identified a generalizable pattern of brain responses to sexual stimuli whose organization is conserved across individual participants, but which is distinct from responses to other conceptually related (nonsexual) affective images. We used cross-validated machine learning analyses to identify a brain model, which we termed the BASIC model (for purposes of sharing and reuse), that can classify sexual from neutral, positive, and negative affective images with nearly perfect accuracy in forced-choice tests, including an independent validation cohort tested on a different population (US vs. Europe), scanner, and stimulus set from those used to develop the model. Together with previous smaller-sample analyses that differentiate multivariate brain responses to romantic or sexual stimuli from responses to other types of affective and emotional events (Kassam et al. 2013; Kragel et al. 2019), our results suggest that sexual stimuli are represented by a relatively unique brain "signature" that is not shared by other types of affective stimuli.

Furthermore, our virtual lesion analysis suggests that the classifications of sexual versus neutral/affective conditions are not solely due to differences in visual or attention processing, as predictions are intact even leaving out large-scale cortical networks devoted to attention and vision. In addition, the spatial scale evaluation demonstrates that whole-brain level classification (both voxel- and parcel-wise) shows the highest model performance compared with individual large-scale network parcels. The BASIC model shows effects not only in subcortical but also in cortical areas, in line with previous human (for meta-analyses, see Stoléru et al. 2012; Poeppl et al. 2016) and animal research (for meta-analysis, see Pfaus 2009). From a basic biological perspective, this might be surprising. Evolutionarily relevant key features of sexual signals in nonhuman primates may include sex calls, pheromones, and the presentation of genitals. The sexual signals presented here are, in comparison, highly complex visual scenes containing a variety of sexual content, triggering valuation processes accompanied by neural activity on the cortical level. Even though our and previous research shows strong evidence for large cortical involvement, there still seems to be a bias in picking brain areas for region of interest (ROI) analyses toward subcortical regions. This is reflected in the neurosynth "sexual" brain map, based on an automated meta-analysis that includes coordinates from a priori ROI analyses. For example, the study with the highest loading on the term "sexual" in neurosynth (Strahler et al. 2018) used ROI analyses that included almost exclusively subcortical areas.

Many types of validation are beyond the scope of this study, but we were able to provide validation of several key elements. First is the application to a new cohort with different population characteristics, equipment, and paradigm details, with large effect sizes for sexual versus nonsexual affective images. Second, we investigated the effects of globally distributed signal in white matter and

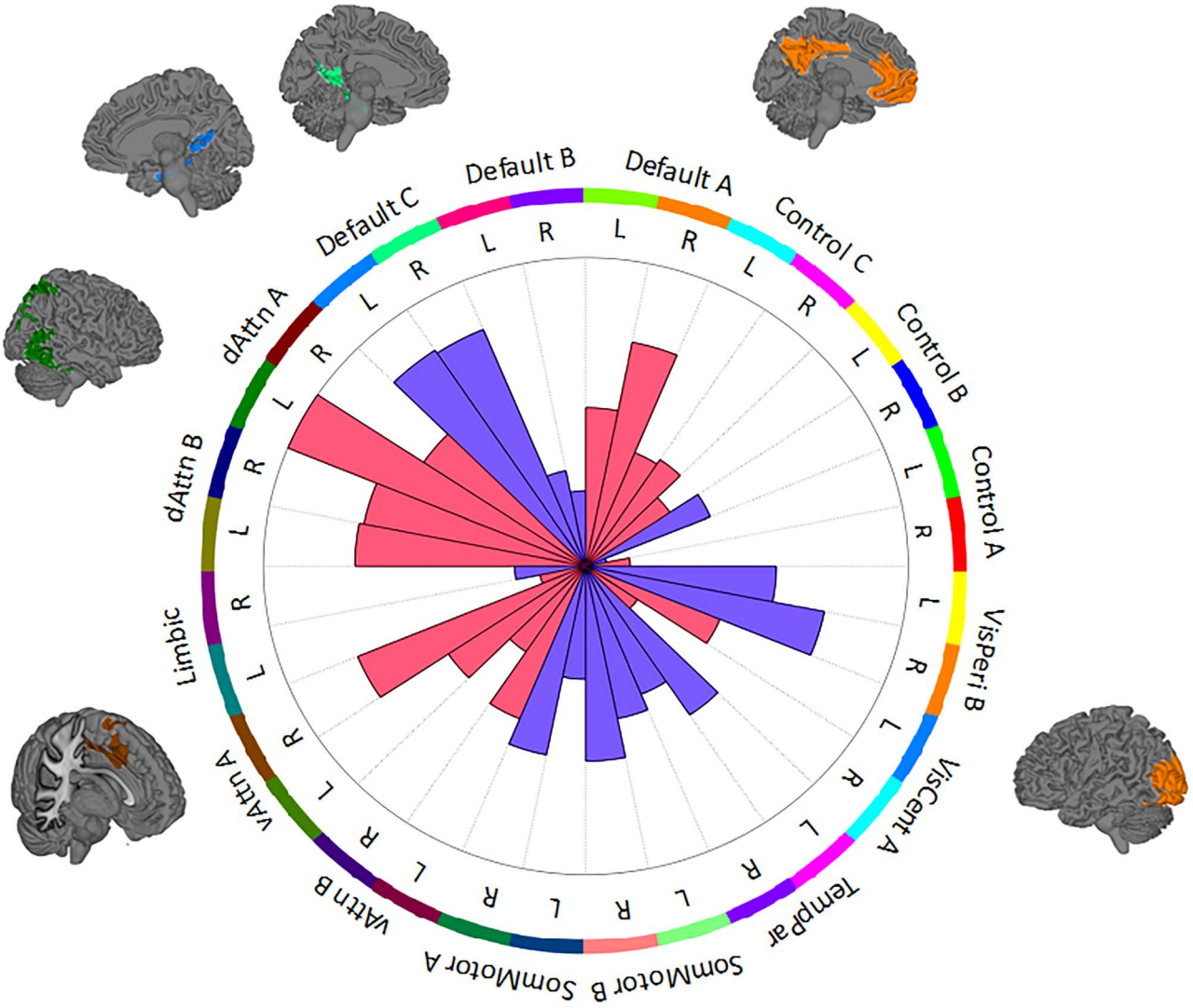

Figure 5. Cortical network profile for BASIC model. Pattern energy in resting-state cortical networks by Schaefer et al. (2018) is distributed unevenly. Wedges represent positive (pink) and negative (purple) weights and corresponding networks are presented for the networks with the highest and lowest average weights.

ventricle spaces, which can capture complex effects of head movement and task-correlated physiological noise and have been found to drive some multivariate predictive models in the past. Lack of relationships with these non–gray matter areas, along with significant contributions to the model in known affective/motivational systems, increases confidence that the model is driven by neuroscientific relevant systems. Third, we investigated whether the model showed differential effects for male versus female subgroups or varied with age. It did not, supporting the notion that despite individual differences there is a generalizable brain response across individuals (note, this study did not include nonheterosexual, noncis individuals, and individuals of different age groups). This is in line with the findings of previous neuroimaging meta-analyses that revealed common "unisex" brain responses to sexual stimuli (Poeppl et al. 2016; Mitricheva et al. 2019).

Interpretation of a machine learning–based model is complex because the classification is not explained by one region or network, but by a combination across regions. One set of regions may encode one aspect, for example the positive valance aspect, another set may encode the arousal aspect, and yet another set the concept of personal closeness. All these sets then jointly contribute to the overall discrimination of sexual from general affective images. The studies we analyzed do not have sufficient information to link specific brain areas to specific component processes underlying response to sexual images, but we do evaluate our model in light of previous neuroscientific literature here to examine the neurobiological plausibility of the model (Kohoutová et al. 2020).

Brain areas included in the BASIC model are also present in the most recent meta-analytical model of brain responses to sexual stimuli (Stoléru et al. 2012), although the BASIC model presents a more comprehensive and precisely specified set of hypotheses about which voxels, with which relative activity pattern across them, to test and validate in future studies.

In terms of resting-state networks (see Fig. 5), we see positive and negative weight effects emerge: negative weights (relative decreases in activity associated with sexual image processing) in somatomotor networks and positive weights (relative increases) in dorsal and ventral attention networks. In addition, weights in the default mode network (DMN) are near-zero when averaging across the entire DMN. However, when looking at default mode subnetworks, DMN A (ventral medial PFC and posterior cingulate areas) shows strong positive weights, whereas DMN C (hippocampal and more posterior occipital areas) shows strong negative weights. This relates to previous research linking DMN to drug, gambling, and food craving and their regulation, which generally involve DMN A regions, and the vmPFC and NAc in particular (Hare et al. 2009; Kober et al. 2010; Hutcherson et al. 2012; Kearney-Ramos et al. 2018; Aronson Fischell et al. 2020; Schmidt et al. 2020). Both these areas are involved in the BASIC model, in line with previous research linking these areas to sexual stimuli. For instance, previous studies have reported significant vmPFC activation during sexual compared with monetary rewards (Schmidt et al. 2020), and neural reactivity to sexual stimuli in the NAc was positively correlated with sexual arousal ratings (Klein et al. 2020). In addition, activation of both regions to food and sex cues has been found to predict subsequent risky sexual behavior (Demos et al. 2012).

The BASIC model included positive weights (a higher likelihood that the image was sexual with increasing activity) in several additional regions thought to be important for sexual responses: the hypothalamus, amygdala, somatomotor cortices, and insula. The hypothalamus is a small area near the ventricles and sinus spaces, and this likely introduces substantial variability. A preliminary study by Walter et al. (2008b) using ultra high-resolution imaging at 7 T, which is likely to have superior ability to detect hypothalamic activity, found signal dropouts in ventral subcortical structures such as the hypothalamus. Similar dropout may have limited sensitivity in the hypothalamus in this study. However, findings of hypothalamic activation in sexual stimulus processing have varied across studies. The meta-analysis by Stoléru et al. (2012) found that 37.8% of studies reported hypothalamic responses to visual sexual stimuli. A motivational role for hypothalamus is included in the model of Stoléru et al. (2012) as well, although this has only been found in animal studies. Responses of the hypothalamus have been related to the regulation of autonomic responses, and in particular the physiological aspect of sexual arousal (Ferretti et al. 2005). Here, we did not measure genital responses and can therefore not know if the stimuli triggered a physiological response. Further research, including genital response measures, could therefore shed more light on the role of the hypothalamus in sexual behavior.

The amygdala and somatomotor cortices are part of the emotional component of the model of sexual stimuli processing by Stoléru et al. (2012). All these show positive weights in the BASIC model. Within the amygdala, positive weights were found in the corticomedial division, in contrast from emotions more generally, which most often show central nucleus and sometimes basolateral activation (Wager et al. 2008; Yarkoni et al. 2010). The insula has previously been reported to sex, food, and drug craving (Pelchat et al. 2004; Yokum et al. 2011; Murdaugh et al. 2012; Tang et al. 2012), as well as interoception (Paulus and Stewart 2014). The insula is, however, large and heterogeneous region. Within the insula, the BASIC model included positive weights in two areas: the right ventral anterior insula and posterior insula PoI2 (from Glasser et al. 2016). The posterior insula is held to be important for somatosensory representations, multisensory information, and pleasant touch (Olausson et al. 2002; Cera et al. 2020). The anterior insula seems to play a role in visceral information processing and subjective feelings (Craig 2002; Uddin 2015). However, the ventral anterior insula is distinct from the dorsal anterior insula identified in most studies and has stronger associations with ventromedial prefrontal and subcortical structures including the amygdala, and functional associations with emotion and gustation (Chang et al. 2013; Wager and Barrett 2017).

In addition, another subcortical region little discussed in the Stoléru et al. (2012) meta-analysis but involved in the BASIC model is the midbrain periaqueductal gray (PAG). The PAG is best-known for its role in pain and defensive behaviors, but animal literature also shows effects of lesions on sexual behavior (Lonstein and Stern 1998), particularly lordosis. Many PAG neurons express estrogen receptors, and areas where these neurons are concentrated are targeted by inputs from the hypothalamus (Bandler and Shipley 1994). This and related pathways through the PAG are thought to be involved in sexual readiness (Holstege and Georgiadis 2004). In humans, nearby areas of the midbrain are activated during male ejaculation (Holstege et al. 2003; Georgiadis et al. 2009), though precise localization is difficult, and other studies have related human PAG activity more to bonding than sex (Ortigue et al. 2010).

The overlap of areas in BASIC model with some drug- and food-cue reactivity studies, but not others, suggests that different types of appetitive stimuli and responses may activate dissociable systems in some cases. Exploring these differences in depth is beyond the scope of this study but very interesting for future studies. An interesting next step, for instance, would for example be to test BASIC model on a different set of rewarding stimuli.

Thus, future validation for BASIC model can involve testing it on many other types of stimuli but our work already shows that based on brain data, we can distinguish sexual from general affective processing. Previous research has associated sexual stimuli with positive affect, as the wide use of IAPS, where sexual images are placed under positive affect, indicates. This strong link

between positive affect and sexual stimuli might be the result of the assessment method of affect. Most studies have used a bipolar scale (i.e., negative to positive affect/valence) but when using to separate unipolar scales, both positive and negative affect have been reported during sexual stimuli (Peterson and Janssen 2007). Here, we show that the BASIC model has the highest cosine similarity with the sexual condition as expected (see Supplementary Figure 1) but shows more cosine similarity to the negative condition in Study 1 than the positive condition. Hence, in line with previous research, this work therefore demonstrates that the intuitive link between positive affect and sexual stimuli is much more complicated.

In addition to the link between sexual stimuli and general affect, we were able to gain some insight into whether the BASIC model captures general arousal or valence. To examine the role of general arousal and valence in the prediction of BASIC model, we adopted two strategies. First, we measured valence and arousal in Study 1 and performed a sensitivity analysis, testing whether the BASIC model was sensitive to valence and arousal of nonsexual images. Second, we applied the BASIC model to an independent test dataset (Study 2), in which sexual and nonsexual images were matched on valence and arousal. Regarding the first strategy, the self-reported data showed that sexual images had a significantly lower arousal than the negative images, but significantly higher BASIC responses. In addition, positive images had a higher valence than neutral or negative images but did not produce higher BASIC responses. Regarding the second strategy, the BASIC model responded more strongly to sexual than nonsexual images matched on valence and arousal and did not respond to either positively or negatively valenced nonsexual images. In addition, the strong classification performance was replicated in both Study 1 and Study 2 despite differences in the content of sexual images (Study 1 showed explicit sex scenes with couples, whereas Study 2 showed both clothed and naked couples and individuals) and likely general arousal levels. Together, these findings indicate that it is not sensitive to general arousal and valence per se but is instead sensitive to sexual content. This is in line with a previous study by Walter et al. (2008a), demonstrating that during a sexual stimulus, activation patterns modulated by general emotional arousal differed from activation patterns modulated by sexual stimulus intensity.

Sexual stimuli have often been used by researchers to study sexual arousal, although it is unclear if a state of sexual arousal is elicited by short visual sexual stimuli and therefore whether it was present during conditions used in BASIC model. In Study 1, the sexual images consisted of heterosexual couples engaged in sexual interactions, and self-reported sexual arousal was significantly higher in the sexual conditions versus the other conditions. Based on these results, we might suspect that the images, although presented for a short duration, might have induced a certain level of sexual arousal, at least at the subjective self-report level. However, in Study 2, participants were presented not only with couples, but also sexual or romantic images of an individual man or woman. Assuming that not all participants were bisexual, participants were presented with sexual images depicting both individuals consistent and inconsistent with their preferred sex. Thus, even though the images might not have induced high levels of sexual arousal in all participants, we can distinguish sexual from general affective processing in the brain, which was the aim of our study. For future research, it would be interesting to examine whether the BASIC model can also differentiate between longer visual sexual stimuli, whether sexual arousal is more likely to be induced by long than short-duration, and whether the BASIC model responds to sexual stimuli of other modalities, for example, sensory (genital stimulation), cognitive (fantasy), or auditory.

Ponseti et al. (2012) conducted one of the few studies on sexual stimulus processing that used multivariate analysis. They classified preferred and nonpreferred (e.g., child nudity vs. adult nudity) sexual stimuli based on brain data in participants with and without pedophilia using nude frontal images of adults and children. This classification might be more linked to sexual arousal, although it is still hard to evaluate whether sexual arousal was induced. In order to gain additional insight into sexual arousal specifically, future research could examine if sexual arousal is elicited during sexual image presentation, and to identify the brain processes generating it, multivariate analysis could be used to predict sexual arousal ratings based on brain data collected during sexual image presentation. In our study, this was not possible due to a lack of within-subject variability in the sexual arousal ratings during the sexual image blocks. Parada et al. (2016) presents large variability of sexual arousal ratings and, using a parametric modulation analysis, found various subregions of the parietal cortex that showed significant changes in activation corresponding to the degree of self-reported sexual arousal with no gender differences. Future studies could further examine role of the parietal cortex in the subjective experience of sexual arousal.

Besides self-reported sexual arousal, genital responses are often assessed in psychophysiological studies to examine sexual arousal (Rosen and Beck 1988; Janssen and Prause 2016). The assessment of genital response in neuroimaging studies is sparse (Arnow et al. 2009; Parada et al. 2018). Parada et al. (2018) presents several brain regions (supramarginal gyri, frontal pole, lateral occipital cortex, and middle frontal gyri in men; same regions plus the ACC/PCC, right cerebellum, insula, frontal operculum, and paracingulate gyrus) to be correlated with changes in genital response, with a stronger brain–genital relation in women compared with men in several regions. Assessment of genital response during fMRI research could improve our understanding

of the interaction between brain and genital and the gender differences between this interaction. In addition, multivariate analysis could be used to predict genital arousal levels and self-reported sexual arousal based on brain data, and these patterns could be compared. This type of study design would allow for a mediation analysis, which could give more insight into the brain organization by examining the distributed, network-level patterns that mediate the stimulus intensity effects on sexual arousal (Geuter et al. 2020).

A limitation of this study is that although the BASIC model can accurately classify sexual and nonsexual images with forced choice tests, we did not identify one absolute threshold that could be used as a quantitative measure across studies. Future studies thus have to establish a threshold in a study-specific manner and make relative comparisons across conditions within-study, which is a limitation. However, we do show that the BASIC model can be generalized to individuals studied in other research centers with forced choice tests, though the absolute scale of the response is likely to vary across studies as a function of scanner field strength, signal-to-noise ratio, and other signal properties.

To summarize, in this study, we applied multivariate neuroimaging analyses to investigate sexual stimulus processing in the brain. This approach allowed for the development of the BASIC model, which can accurately classify sexual versus neutral and positive and negative affective images in two separate datasets, consisting of different types of sexual stimuli and individuals. The BASIC model includes a precisely specified pattern of cortical and subcortical areas, some of which have received relatively little attention in the literature on human sexual responses (e.g., cortical networks). Some may be shared across other appetitive responses (e.g., vmPFC and NAc for drug cues), but the BASIC model may also diverge from studies of other appetitive responses as well (e.g., in the insula). The work gives insight into the complex processing of sexual stimuli and supports the notion that processing sexual stimuli is a neurologically complex, potentially unique mental event that involves multiple networks distributed in the brain. There are many avenues open for future validation and further development, such as testing the BASIC model to nonsexual rewarding stimuli or sexual stimuli of other modalities, and linking the work to sexual arousal.

Supplementary Material

Supplementary material is available at *Cerebral Cortex* online.

Conflict of Interest

None declared.

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