Just above chance: is it harder to decode information from human prefrontal cortex BOLD signals?

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Abstract

Understanding the nature and form of prefrontal cortex representations that support flexible behavior is an important open problem in cognitive neuroscience. In humans, multi-voxel pattern analysis (MVPA) of fMRI BOLD measurements has emerged as an important approach for studying neural representations. An implicit, untested assumption underlying many MVPA studies is that the base rate of decoding information encoded in neuronal activity from BOLD activity patterns, is invariant across brain regions. Here we test this assumption by estimating these base rates from a meta-analysis of published MVPA studies. We show that this assumption is violated for the prefrontal cortex, which shows a significantly lower base rate for decoding than visual sensory cortex. Our results have implications for the design and interpretation of MVPA studies of prefrontal cortex, and raise important questions about its functional organization.

Introduction

The prefrontal cortex supports flexible, organized behavior. Patients with frontal lobe lesions struggle to coherently organize their behavior around a goal and show reduced flexibility in changing circumstances [1-3]. Theories of prefrontal cortex function emphasize its role in representing task-relevant information like rules, goals, rewards, action choices, etc. during task performance [4-10]. These task representations are hypothesized to serve as a source of top-down, contextual signals that bias processing in other brain regions, thus achieving cognitive control. Understanding the nature and form of prefrontal representations remains a key open problem in the study of cognitive control, learning, generalization, multi-tasking and decision making [11-16].

Much of our knowledge of prefrontal representations derives from single-neuron electrophysiology conducted in highly trained non-human primates. Such studies have consistently revealed rich coding of a variety of task-relevant information in the firing rate of individual prefrontal neurons [17-21], the activity patterns of ensembles of neurons [22-26] and in oscillatory synchronization of local field potentials [27].

In humans, blood-oxygenation-level dependent (BOLD) measures from functional MRI were traditionally seen as lacking the sensitivity and spatial resolution for the study of neural information coding [28]. In the past decade, however, this view has been challenged by the development of sensitive multivariate pattern analysis (MVPA) methods that employ powerful machine learning pattern classifiers to decode the information content of spatially distributed BOLD activity patterns [29-35]. MVPA has been applied to fMRI data from all over the brain, and the prefrontal cortex is no exception. Several studies have reported statistically reliable classification of task rule and other task-relevant information from regions within prefrontal cortex [36-41].

An implicit assumption in many MVPA studies is that the function relating the information content of BOLD patterns with the information content of underlying neuronal activity is invariant across different parts of the brain. In other words, all regions have similar *base rates* for decoding information from BOLD patterns, to the degree that it is encoded in the underlying neuronal activity. For example, this assumption underlies analyses comparing decoding accuracies obtained from different brain regions, or those that employ roving, whole brain 'searchlights' to discover local regions that may carry such information. However, this remains an untested assumption. Indeed, the base rate for any brain region likely depends on interactions between the underlying micro-anatomy and the haemodynamic response function, both of which may vary across regions.

For the prefrontal cortex, in particular, there is an impression among researchers with experience using MVPA that decoding information from BOLD patterns is particularly difficult. Despite the sensitivity of MVPA, typical group-mean classification accuracies reported in fMRI studies of PFC decoding often hover just above chance levels (e.g. values of 53%, 55% and 55% reported in Nelissen, et al. [42], Woolgar, et al. [37], and Bode and Haynes [38] for two-way classifications), even for task features like rules that are known to be robustly represented by the activity of prefrontal neurons in non-human primates [20,22,23,43-46]. Consistently low classification accuracies hint at a low base rate for decoding information from prefrontal BOLD patterns. A low base rate may result, in part, from methodological factors, and in that case, it would be useful to know what these factors are. Alternatively, a low base rate may raise the possibility that the prefrontal BOLD signal itself may not adequately capture the information encoded in the spiking activity of prefrontal neurons. Such an observation would raise interesting theoretical questions about why and how prefrontal cortical coding differs in its type and organization from other parts of the brain with higher base rates.

A low base rate would also have implications for experimental design and inference. First, it would suggest a small effect size, and so would require that prefrontal MVPA studies are well powered, and that power estimates are based on effects sizes obtained from the PFC itself and not from other regions of the brain. Second, a systematically lower base rate in PFC complicates the interpretation of comparisons with other brain regions, which would require a consideration of the underlying base rates of each region.

In this paper, we empirically test the assumption that the base rate of decoding information from PFC is similar to other brain regions. To this end, we carried out a systematic meta-analysis of published fMRI studies of prefrontal cortex that employed MVPA. From this analysis, we estimate the base rate of decoding information from prefrontal cortex BOLD patterns and compare it to base rates obtained from visual cortex and mid-temporal regions. We also determine the distribution of classification accuracies obtained for 'significant' and 'null' effects in PFC and ask to what extent they overlap. Based on estimates of typical classification accuracies from these distributions, we also consider whether published studies typically collect sufficient data in order to detect the small PFC effects. Finally, we identify studies that have achieved considerably better-than-average classification accuracies and ask whether they are associated with particular sub-regions of prefrontal cortex, particular task features or particular analysis methods.

Collectively, our results show that the base rate of decoding information from PFC is

systematically lower than other regions, and that this low base rate appears mostly consistent across variance in methodological approaches. We conclude by considering the potential reasons for this low base rate of prefrontal classification.

Results

Typical decoding performance in prefrontal cortex is poor

We leveraged our meta-analysis of published studies to approximately estimate the base rate of decoding information from PFC cortical BOLD patterns. To this end, we compiled all two-way, group-level mean classification accuracies reported across the 76 studies in our database. The resulting distribution is an estimate of the sampling distribution of mean classification accuracies for decoding information from PFC BOLD patterns. The mean of this distribution was 57.7% (95-CI: 56.3-59.2% **), though we observed a skew, so that more than 63.1% of the accuracies were below the mean. Therefore, we employed the median as a measure of the central tendency, arriving at a base rate of 55.7% (95-CI: 55.0-57.0%). For comparison, we also derived base rates for decoding visual information from occipital and temporal cortex BOLD patterns. These were computed from meta-analytic data previously compiled by Coutanche and colleagues consisting of 119 analyses from 52 studies[47]. Compared to prefrontal cortex base rates, both the occipital and temporal cortex (median) base rates were significantly higher at 66.6% (95-CI: 61.5-72% **) and 71.0% (95-CI: 68.0-75.0% **) respectively.

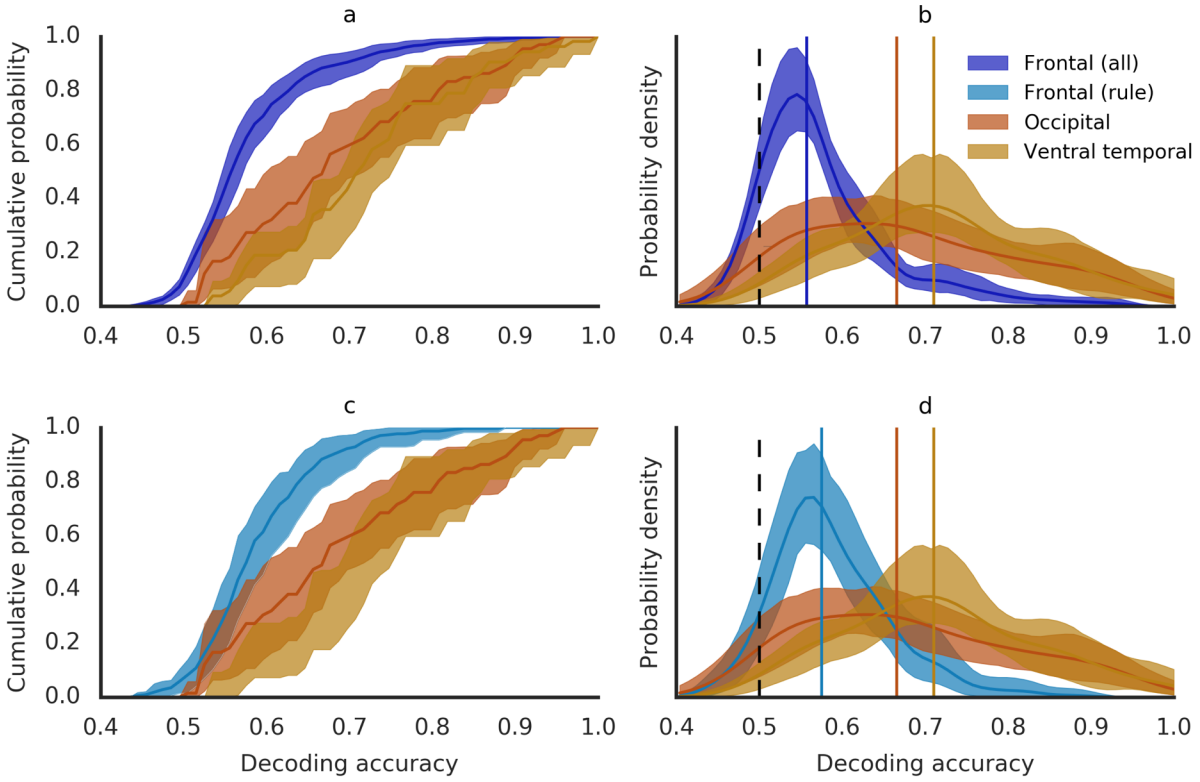

Figure 1. Decoding accuracy distributions for frontal, occipital and ventral temporal cortex. Cumulative distribution functions (a & c) and probability density functions (b & d) for visual decoding accuracies in occipital (red) and ventral temporal (orange) cortex compared with frontal decoding accuracies from all analyses (top panels, purple) and rule decoding analyses (bottom panels, aqua). Vertical lines indicate median values of 66.6% (95-CI: 61.5-72%) for occipital, 71.0% (95-CI: 68.0-75.0%) for ventral temporal, 55.7% (95-CI: 55.0-57.0%) for frontal, and 57.5% (95-CI: 56.0-60.0%) for frontal rule-decoding analyses. Shaded areas reflect 95% confidence intervals obtained from a hierarchical bootstrapping procedure.

MVPA studies of occipital and ventral temporal cortex focus exclusively on decoding information about visual stimulus attributes. This is because overwhelming evidence supports a strong prior for the hypothesis that the human occipital and ventral temporal cortices code for visual information. On the other hand, prefrontal MVPA analyses spanned attempts to decode a wide variety of information, reflecting a much less constrained hypothesis space for what information is represented in PFC. To control for this difference,

we focused on a subset of 311 analyses from 36 studies in our database that attempted to decode "rule information". Well-established deficits in rule-guided behavior have been linked to prefrontal dysfunction [48-52] and have been attributed to a loss of the ability to represent rules in working memory [7]. Moreover, there is strong evidence from macaque electrophysiology that the prefrontal neurons code for task rules [20,22,23,43-46,53]. Therefore, it is reasonable to place a strong prior on the hypothesis that task rule information is coded in the activity of human prefrontal neurons. A base rate obtained from rule decoding studies should, thus, be more comparable to the studies in Coutanche et al's database. The median of the distribution of classification accuracies from rule decoding analyses was 57.5% (56.0-60.0%), again significantly lower than both the occipital and ventral temporal base rates.

Collectively, these results demonstrate that the base rate for decoding information from human prefrontal cortex BOLD patterns is low in comparison to two sensory regions of the brain, consistent with the impression that MVPA in human prefrontal cortex is particularly difficult.

Overlaps between decoding accuracy distributions for null and significant effects

Our database of PFC decoding analyses included group mean classification accuracies of both significant (greater than chance) and null effects. This allowed us to separately compile literature-derived distributions of classification accuracies for (a) when information is successfully decoded from frontal BOLD activity patterns and (b) when no information is detected. These distributions should overlap minimally if the studies that produced the classification accuracies had high power and low false positive rates.

The median of the classification accuracy distribution of significant effects was 58.7% (95-CI: 57.0-60.0%). Note that the values in our 'significant' distribution sample from an underlying 'true' distribution truncated at the left tail by the different significance thresholds used by specific studies. In other words, we are likely (conservatively) overestimating the center of this 'true' distribution. The distribution for the null effects had a median of 51.6% (95-CI: 51.0-52.0%). We computed the 95th percentile of this empirical 'null distribution' analogous to the typical 'critical value' used for null-hypothesis testing and obtained a value of 57.4%. Note that these values sample a putative 'true null' distribution truncated at the right tail by the significant thresholds used in each analysis. Such truncating would normally bias our estimates of central tendency and the critical value downwards. On the other hand, the studies in our database employed different sample sizes and a variety of procedures for testing significance. If a proportion of these studies were underpowered, this would bias our estimates upwards. In addition, we have only relied on published studies in this meta-analysis. Thus, it is also likely that our estimates are biased upward due to the so-called *file*

drawer effect or systematic non-reporting of null findings. In order to obtain a more conservative estimate of the critical value, we recentered the null distribution to 50%. With this approach, we obtained an estimate of 55.4 for the 95th percentile.

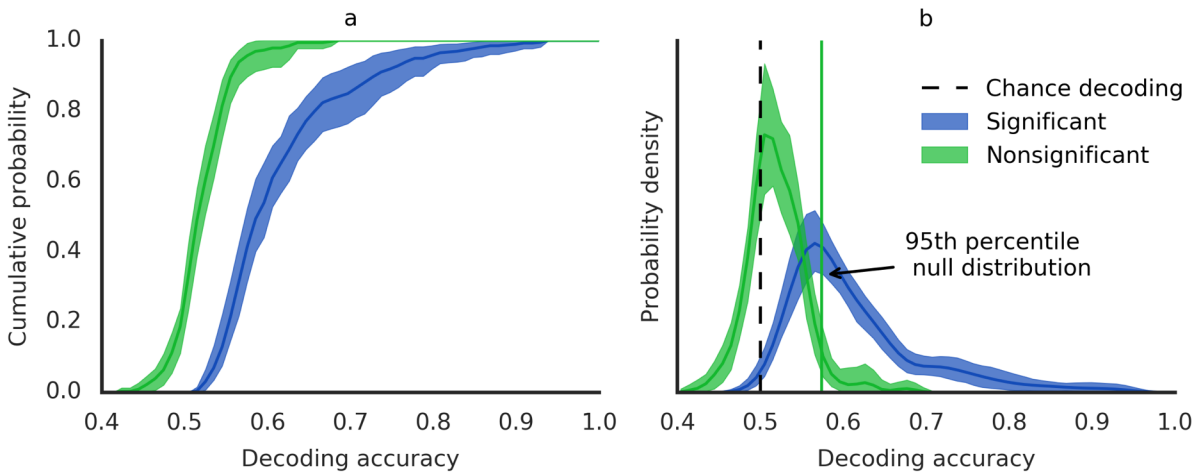

Figure 2. 'Significant' v/s 'Non-significant' decoding accuracy distributions. Cumulative distribution function (a) and probability density function (b) for frontal decoding accuracies reported as significant (blue) and non-significant (green). Dotted line in (b) reflects chance-level (50%) and solid green line indicates 95th percentile of the (uncentered) non-significant distribution at 57.4%. 36% of decoding accuracies in the significant distribution fell below this 'critical' value. Shaded areas reflect 95% confidence intervals obtained from a hierarchical bootstrapping procedure. Distributions consisted of 506 analyses from 75 studies and 349 analyses from 48 studies for significant and nonsignificant accuracies, respectively. Raw decoding accuracies are plotted in Supplementary Figure S1.

Despite these conservative adjustments, as shown in Fig 2, there was considerable overlap between the estimated 'significant' and 'null' distributions. Indeed, 36.0% (95-CI: 15.5-66.4%) of the accuracies in the 'significant' distribution fell below the 95th percentile of the uncentered null distribution of 57.5% while 23.5% fell below the centered null distribution of 55.4%. This overlap suggests that a number of previous studies were either not sufficiently powered to detect information coded in PFC BOLD patterns, or had inflated false positive rates (over the usual 5%).

However, as has been recently pointed out, the results of such tests of group-level mean accuracies against chance levels do not, in fact, support the population-level inference that

the effect is typically present in the population [54]. Instead, these tests assess the global null hypothesis [55] that *no participants* show the effect. It has been suggested that population inferences can be made based on the prevalence of an effect in a sample [54]. As a consequence, the power to detect an effect at the level of an individual participant becomes particularly important.

It has not been common practice to report individual participant data, and therefore it is difficult to get estimates of within-subject variance needed for power analysis. Nevertheless, it is possible to make some general points about power at the individual level. The empirical 'null' distribution described above gives us an estimate of the typical decoding accuracy for a participant who does not show an effect (given that in these analyses the global null hypothesis cannot be rejected). The 95th percentile of the null distribution is 55.4%. On the other hand, an estimate of the typical individual's decoding accuracy when they do show the effect may be derived from the 'significant' distribution. Comparing these two values will allow us an estimate of the size of the typical effect.

We consider two boundary conditions to derive the typical subject-level decoding accuracy. Consider the boundary condition where we assume that every significant effect reported in our database was maximally prevalent in that study's sample (i.e. every participant shows the effect). In that condition, the median of the 'significant' distribution is a good estimate of the typical participant-level decoding accuracy. Given a median of 58.7%, we are, therefore, looking to detect a difference of only 3.3% points in order to reject the null hypothesis of chance-level coding for a typical participant. If a study included test 50 trials (which is typical for MVPA designs) for each condition, this would imply a difference of less than 4 trials successfully classified. Consider another boundary condition where every significant effect reported by studies in our database show a prevalence of only 50%. A population inference requires that at least a majority of the participants show the effect. Assuming this liberal boundary condition for the studies in our database, we can estimate the typical decoding accuracy of an individual who showed the effect from the median of our significant distribution to be approximately 67.4% (assuming that half of the subjects in the study showed no effect and thus had a decoding accuracy of 50%). In that case, we would be looking to detect a 12% points difference – a difference of 12 trials successfully classified under the most liberal assumptions. These rough calculations suggest that the typical PFC MVPA effect is very small and given high levels of noise in fMRI measurements, one would require considerably more data per participant to detect such an effect reliably.

We emphasize again that this analysis is not intended as a recommendation of trial numbers for future MVPA studies of the PFC and should not be cited as such. Rather, this analysis

merely makes concrete the point that given the low base rate decoding accuracy in PFC and given the importance of assessing prevalence, sufficiently powered studies at the individual participant level are essential. Power calculations should be based on estimates of effect sizes from classification of PFC itself and not based on samples or effect sizes observed in other regions of the brain given the differences between regions.

Analysis of outliers

Our estimate of a literature-derived decoding accuracy distribution provides a means of placing the results of any given prefrontal decoding analysis within the context of the wider literature. Studies with very high accuracies, for instance, merit attention as they may have identified classes of information that are particularly well represented in prefrontal cortex, or may have employed a particularly effectively analysis approach. At the same time, given prior findings, these effects are surprising and, therefore, also merit closer scrutiny and replication to ensure that these results are not caused by other confounding factors. For these reasons, we examined the top 5% of reported classification accuracies in our database (Table 1) to identify factors that might explain the high values.

First, as many as 18 of the 41 analyses in the top 5% decoded some form of motor response (reaching, grasping, saccades etc.). Five additional analyses involved classifying the anticipation or experience of electric shocks on very different parts of the body (arm v/s leg). Six other analyses classified ordered stimuli like speech or music versus unordered versions of the same stimuli. All of these studies manipulate conditions that likely produce univariate differences, either as a small mean-response difference across a majority of the voxels or differential activation of adjacent subregions. For example, univariate versions of ordered vs unordered stimuli are often used to localize language specific regions in prefrontal cortex [56,57]. Univariate contributions to decoding analyses do not invalidate the inference of information coding. But, they do not require the use of pattern classifiers to detect, and therefore, should not inform an assessment of the method as it is used in more typical MVPA analyses.

Two studies employed unusual measurement or analysis methods. Study 39 (5 analyses) deployed non-linear classifiers which produced significantly higher accuracies than linear classifiers on the same data. The classification accuracies obtained from the linear classifiers are much closer to the median of our distribution. Study 31 uniquely employed high-resolution scanning with a 7T magnet.

Table 1: Analyses in the top 5th percentile of the 'significant' distribution

Study ID	No. of analyses in top 5% (total 41)	Decoding accuracy range	ROI or Searchlight	Region(s)[1]	Description
48	13	76% - 93%	ROI	Right precentral gyrus; Left precentral gyrus; Left middle frontal gyrus; Right supplementary motor area; Left supplementary motor area	Classified hand v/s saccade response
66	5	79% - 90%	ROI	Right middle frontal gyrus; Left middle frontal gyrus; Bilateral anterior cingulate gyrus	Classified anticipation/experience of electric shock on arm v/s leg
39	5	76% - 82%	Searchlight	Right superior frontal gyrus; Right anterior cingulate gyrus; Bilateral medial frontal gyrus	Classified to-be-purchases objects v/s neutral objects when attended/unattended.
52	5	76% - 87%	Searchlight	Bilateral inferior frontal gyrus, pars orbitalis; Bilateral inferior frontal gyrus, pars triangularis; Bilateral inferior frontal gyrus, pars opercularis	Classified speech/music v/s re-ordered speech/music
70	4	78% - 88%	ROI	Left middle frontal gyrus; Right middle frontal gyrus; Left precentral gyrus; Right precentral gyrus	Classified tasks that involved different rules & stimuli
71	2	84% - 86%	ROI	Bilateral superior frontal &[2] gyrus & bilateral middle frontal gyrus & bilateral medial frontal gyrus & bilateral supplementary motor area; Bilateral superior frontal gyrus & bilateral middle frontal gyrus & bilateral medial frontal gyrus	Classified reactive v/s predictive eye-movement pursuit of stimuli
69	2	80% - 85%	ROI	Bilateral anterior cingulate gyrus & bilateral midcingulate area	Classified near v/s far semantic similarity of presented words
54	2	81% - 83%	ROI	Bilateral precentral gyrus	Classified execution v/s imagining/observing reaching movements
50	1	85%	Searchlight	Left inferior frontal gyrus, pars triangularis	Classified speech v/s spectrally-rotated speech
31	1	77%	ROI	Left middle frontal gyrus	Classified prospective Yes v/s No decisions across intentions (honest/dishonest)
78	1	79%	ROI	Bilateral precentral gyrus	Classified whole hand grasping v/s reaching movement

1. Regions were registered to corresponding AAL region.
2. & refers to the union of AAL regions for constructing a larger ROI used in the corresponding study.

Importantly, only 4 of these analyses, all from a single paper (Study 70), involved decoding task or rule information as posited by models of cognitive control and observed in macaque studies. However, even in these analyses, task/rule was confounded with visual information as the contrasted task conditions involved different classes of stimuli. Indeed, when task/rule was decoded after controlling stimulus differences, classification accuracies were in the mid 50s, close to the median of our distribution. Therefore, the high classification accuracies may have been driven by the additive effects of multiple sources of information.

In summary, we did not find a particular factor or approach that consistently explained these outlying decoding accuracies beyond what basic univariate analysis could provide.

Factors affecting decoding performance

We next sought to systematically examine whether particular sub-regions of frontal cortex, particular types of information, or particular methods were correlated with decoding accuracy levels. To do this, we assessed the partial influence of these factors in our full database using mixed-effects linear regression. We fit a single mixed-effects regression model with all the characteristics - region, information type, analysis procedure. All these regressors were dummy coded with one category omitted from the model. To account for covariance between observations from the same study, we also included random study intercepts. Classification accuracies reported as non-significant were excluded as they are more likely to have small or no effects.

To assess the significance of each characteristic, regressors were dropped one at a time from the model and tested against the full model using the likelihood ratio test. Results are shown in Supplementary Fig. S2. Only the inclusion of *classifier* significantly improved model fit (Supplementary Table S4; L=17.3 p=0.004, df=5). Post-hoc pair-wise tests applied to *classifier* showed that non-linear SVM had a significantly higher accuracy than linear SVM ($t(55)$=-3.27; p=0.02, Tukey-HSD). This effect was driven by 3 out of 4 studies using non-linear SVM, each with accuracies above 70%, and was also significant in a regression using only a single mean accuracy per study (Supplementary Table S5, $F(5,59)$=4.14, p=0.003). One of these studies were also identified by our outlier analysis. However, given the non-normal distribution of group accuracies, this result should be evaluated with caution. The effects on accuracy for all other analysis characteristics can be seen in Supplementary Figure S2 and Supplementary Table S4.

The full regression model did not reveal differences in accuracy across regions (Supplementary Figure S2). However, the analysis may have been underpowered due to the large number of regions tested simultaneously and the few number of observations

associated with each region. Given that we found no effect of ROI laterality in the main model, we combined the left, right and bi-lateral portions of each ROI for a more powerful, exploratory follow up analysis, and observed that superior & middle frontal gyrus, orbital part (58.2%), and middle frontal gyrus (59.7%) were marginally lower than the grand mean (61.3%) (Supplementary Figure S3; t=-2.01, p=0.044; t=-2.21, p=0.027). Finally, we tested whether accuracy differed across regions based on the type of information decoded. Not surprisingly *response* decoding was associated with higher accuracy in superior frontal gyrus (66%, p=0.03) and marginally so in precentral gyrus & supplementary motor area (64.3%, p=0.09), and *perceptual* decoding was associated with higher accuracy in cingulate cortex (68.5%, p=0.004; Supplementary Figure S4). There were no other differences in accuracy across the rest of the regions. In summary, although these different analyses of our data suggest small differences across regions - OFC, motor, cingulate – exist, the distribution of classification accuracies is broadly similar and low across prefrontal cortex.

Discussion

Over the past decade, MVPA has emerged as a powerful method for studying information coding in the human brain with fMRI [29-34]. MVPA is a more sensitive method than traditional univariate analyses because it combines evidence across voxels to detect subtly encoded information in distributed patterns of activity. Given the many open and important questions regarding representations in prefrontal cortex, MVPA has also been enthusiastically applied to this brain region. Many MVPA studies implicitly assume that the base rate of decoding information from PFC is similar to that of other brain regions, or at the very least, does not vary systematically. This assumption underlies the comparison of decoding accuracies from PFC with other regions of the brain, the use of whole-brain searchlights to discover regions of coding, as well as choices about sample size, analysis methods, etc. This assumption has not been tested in the past and contrasts with a prevailing impression amongst practitioners (often heard at conferences) that decoding information from PFC BOLD patterns is uniquely challenging. We estimated the base rate decoding accuracy for PFC and show that it is indeed lower than sensory (visual) cortex.

Our meta-analysis of prefrontal MVPA studies identified over 800 MVPA decoding analyses across 76 studies, each reporting a group-level mean classification accuracy. This dataset includes attempts to decode a wide range of information from BOLD patterns in various sub-regions of prefrontal cortex, while employing a similarly wide range of MVPA methods. In this sense, our meta-analysis samples a space of possible approaches to classification in PFC and so permits not only an estimate of a base rate, but also if particular approaches are systematically more or less successful.

From this dataset, we estimate the base rate for decoding information from prefrontal BOLD patterns at the low value of 55.7% for two-way classifications where chance performance is 50%. Further, we observed that the PFC base rate is markedly lower than base rates for decoding visual stimulus information occipital and ventral temporal cortex BOLD patterns which were at 66.6% and 71.0% respectively. These differences are not due to the larger hypothesis space of PFC decoding studies. The differences remain stark even when we derive the PFC base rate estimates solely from analyses that decode rule or task information, which we believe is very likely to be coded by PFC neurons given evidence from primate electrophysiology and human neuropsychology. In practical terms, this low base rate means that it is likely that the difference between studies reporting successful versus unsuccessful classification may hinge on only a few trials classified better than chance. This has significant implications for experimental design and inference that we discuss further below.

Further, this base rate provides an empirically derived prior against which future decoding paradigms or methods can be compared. For example, studies that propose a new feature of the fMRI signal (for e.g. Waskom and Wagner [41] recently decoded context information from local connectivity measures), or a new decoding method as capturing a special aspect of coding in the PFC, can be evaluated for their importance relative to this base rate prior. In other words, do we see incremental gains in decoding accuracy from applying this new feature or method beyond what would be expected given the base rate distribution from PFC?

Similarly, our base rate provides a principled basis on which to highlight past studies that were unusually successful at decoding information for further scrutiny. We probed several outlier analyses in our data set that showed large classification accuracies to look for a consistent feature that explained their success. Most of these cases could be attributed to the influence of univariate effects. Beyond these effects, the few remaining outlier studies did not share a consistent approach or classification type that resulted in a marked shift in criterion. Nevertheless, our analysis places the likelihood of these outcomes in context given the broader literature. As such, these individual studies might merit further follow up and replication.

Beyond consideration of the outliers, we leveraged the meta-analysis dataset to ask whether particular information-types or methodological choices were consistently associated with higher decoding performance using regression. We found some evidence that motor information in some regions of posterior prefrontal cortex and perceptual information in cingulate cortex are associated with slightly higher decoding performance. Conversely,

regions of mid-lateral PFC closely tied to cognitive control were associated with, if anything, even lower classification success than other areas of the frontal lobe. We also found a benefit of using non-linear classifiers in the small number of studies that use them. However, this benefit may be offset by known complications associated with the use of non-linear classifiers. While they are indeed able to be able to read-out a wider variety of representational formats, non-linear classifiers are more susceptible to over-fitting. Moreover, a 'linear readout' (that a linear classifier implements) is often considered a hallmark of an *explicit* representation [58,59] under the assumption that downstream neurons usually implement a linear readout. Therefore, the results of a linear classifier can support stronger claims about representations that those of a non-linear classifier cannot. Nonetheless, the non-linear SVM approach may merit further study and replication of its advantage for PFC classification. Beyond this, we found that decoding performance was robust to variations in methods, with the one caveat that our power to detect these effects was not high. Collectively, these results suggest that the low base rate of decoding information from PFC BOLD patterns is a very general finding.

What makes decoding information from PFC BOLD patterns so difficult? Electrophysiology studies in non-human primate have provided consistent evidence for ubiquitous coding of task-relevant information in prefrontal firing rates [17-21], Thus, the finding of a low base rate of decoding such information from prefrontal BOLD patterns is surprising. Furthermore, the differences in base rates between prefrontal and occipital/ventral-temporal cortex suggest that the function relating the information content of spiking activity and that of BOLD patterns across voxels varies across regions. Of course, it is conceivable that human PFC representations have different properties than those of macaques and that prior research has simply not identified the appropriate contrasts or type of classifier to probe them. However, we deem this unlikely as a general account and suggest that PFC BOLD patterns across voxels may only weakly reflect the information encoded in the firing rate of populations of prefrontal neurons.

Another possibility we find more likely is that the particular, local functional organization and distribution of neural populations in prefrontal cortex may reduce differences between conditions at the voxel scale measured with fMRI. In a recent study, Dubois et al. (2015) examined the coding of face viewpoint and identity information using both MVPA of BOLD patterns and single-unit recordings in macaques. While both viewpoint and identity were strongly coded in single-unit firing rates, MVPA of BOLD patterns only revealed viewpoint information. The authors concluded that identity decoding suffered because identity coding neurons were only weakly clustered spatially as compared to viewpoint-coding neurons. Clustering may enable nearby blood vessels to be strongly driven by neurons selective to one

condition, thus enabling inhomogeneities in the sampling of the activity of selective neurons by voxels [60]. Most single-unit studies in primate prefrontal cortex, however, show very little evidence of clustering [61], with neurons coding different task-relevant information being heterogeneously intermixed at a fine scale e.g. [21,62,63-66] By contrast, in the visual cortex MVPA effects may depend on clustering both at the fine-scale in the form of columnar structure [60], and also at the coarse-scale in the form of asymmetric spatial distribution of columns [67-69]. This interpretation suggests that higher resolution fMRI might ultimately help this base rate issue, though this might require still higher resolution than is currently feasible. Alternately, PFC representations may perhaps be better studied by leveraging repetition suppression effects [70,71], which are not affected by the local distribution of neural populations.

A third possibility is that low decoding may be caused by MR induced or physiological noise contributions to the BOLD signal that may influence the trial-by-trial variability of BOLD patterns in a region-specific manner. Indeed, reliabilities of BOLD patterns, when they have been reported, tend to be lower in prefrontal cortex than in visual cortex [72-74]. To the extent that improved scanning methods can attenuate the effects of such noise, it may be possible to improve on the prefrontal decoding performance.

Regardless of the source of these differences, a base rate decoding difference between prefrontal and visual cortex has important implications for the interpretation of studies which rely on comparisons of classification accuracies across regions. Consider, for example, the debate surrounding the locus (prefrontal or sensory cortex) of detailed sensory information during working memory delays, which has been informed by the finding that, while classifiers readily decode sensory information from the BOLD signal recorded from visual cortex, they are much less successful in the frontal cortex reviewed in [75]. If the base rate for decoding is lower in prefrontal cortex, such a finding, on its own, would provide limited support for an exclusive sensory cortex locus of working memory representations. In order for such comparisons to be interpreted, it would be critical to first consider the base rate for decoding information for the regions in question. Indeed, while we have focused on the PFC in this study, our results highlight the more general point that knowing such base rates is critical to interpreting the findings of any MVPA study, including those employing other measurement modalities that span the brain like MEG or EEG

The empirical distribution of PFC classification accuracies that we have compiled allows any new result to be placed within the context of prior findings and for its likelihood to be computed. As also noted above, analyses that report unusually high classification accuracies should draw attention for the possibility that they may be false positives or be driven by confounding factors. Employing this logic, we compiled separate distributions of

classification accuracies for significant and null effects from our dataset and observed considerable overlap between these empirical distributions. This overlap suggests the presence of a number of analyses that either did not appropriately control false positive rates, or were insufficiently powered to reject null hypothesis of chance-level coding. Indeed, we recorded the widespread use of parametric statistics, which have been shown to inflate false positive rates for classification accuracies. We agree with recommendations that MVPA studies should rely primarily on appropriately conducted permutation testing at the individual level [76] and the assessment of the prevalence of effects at the group level [54].

Indeed, given the importance of the prevalence of MVPA effects in making population-level inferences [54], it is important to consider the power of an experimental design to detect an effect at the individual-subject level. Based on our rough estimates of typical decoding accuracies from the 'null' and 'significant' distributions, we expect that significantly more data per participant will need to be collected to detect the small PFC MVPA effects more consistently. This is particularly important as future studies move beyond demonstrating information coding to examining the factors that may influence the properties of underlying representations. With classification accuracies typically hovering in the 50%-60% range, there is little room to detect their modulation with experimental manipulation or by incorporating covariates without many more measurements. Similarly, improved statistical power will also be necessary in order to regress out the potentially confounding effects of small, idiosyncratic differences between task conditions on nuisance variables like difficulty or time-on-task [77]. The prefrontal BOLD signal is known to be sensitive to such variables [56,78] and regressing out their effects post-hoc is critical to unbiased inference.

In conclusion, we provide an estimate of the base rate of decoding information from PFC BOLD patterns and show that the assumption of a comparable base rate across brain regions is unwarranted. Our low estimate supports the prevailing impression that using MVPA to decode information in PFC is particularly challenging. The reasons for this difficulty remain open, and we suspect may reflect an important property of neural coding in the PFC, such as their spatial organization and distribution. Though we cannot provide a reason for this difference, our results have concrete implications for the design and interpretation of future studies – we recommend more data per participant, the use of permutation tests, reporting of prevalence at the group-level, and a consideration of base rate when making comparisons across regions. Finally, this study provides an example of how meta-analyses of MVPA data can provide unique insights that are not available in single studies. To facilitate future investigations, we are sharing our database and code publicly via the Open Science Framework (OSF) (https://osf.io/8dvzr/).

Methods

Literature Search and Study Inclusion

We conducted a comprehensive search of the literature to identify all published studies between the years of 2001 and 2016 that employed multivariate methods to decode information from fMRI BOLD patterns in the prefrontal cortex. In summary, we queried the PubMed database for articles whose abstracts contained at least one term related to (i1) functional imaging, (i2) multivoxel pattern analysis, (i3) frontal cortex. In addition, we explicitly excluded articles whose abstracts contained terms related to patient samples and non-human primates. A full list of terms employed for the search are shown in Fig 3.

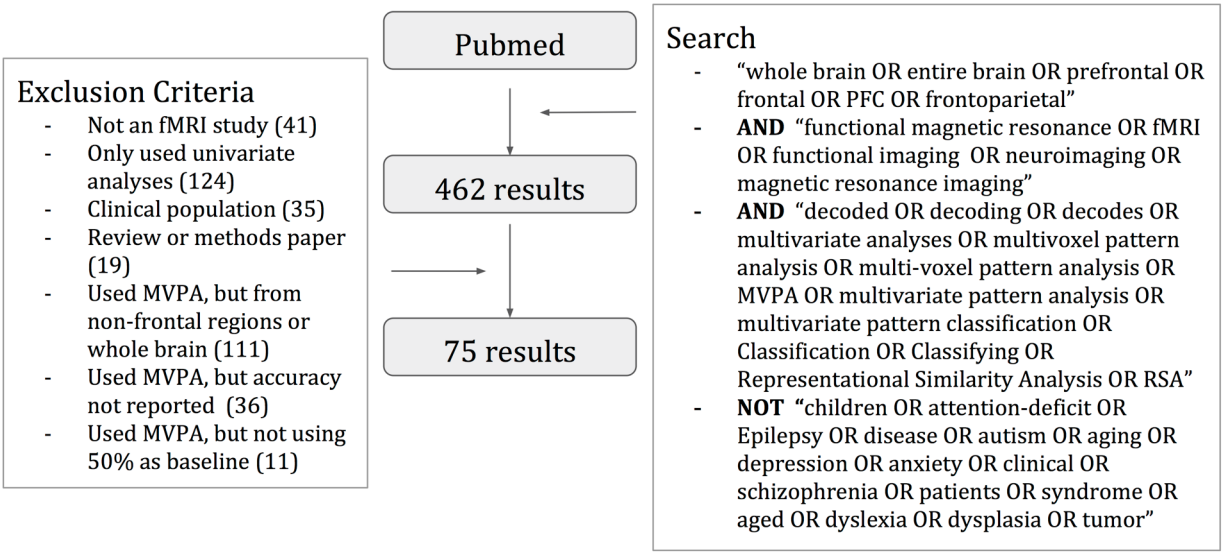

Figure 3. Search terms employed for literature search. The final literature search was conducted on 09/03/2016. The search string above was entered into Pubmed's advanced search (https://www.ncbi.nlm.nih.gov/pubmed/advanced), additionally restricting the year of publication to be between 2001 and 2016.

This search resulted in a set of 462 studies that employed multivariate fMRI analysis, including classification analysis and representational similarity analysis. Across approaches, there was further variability in the metrics used to report the strength of decoding, including

significance statistics, correlation coefficients, single-subject mean classification accuracies, group-level mean classification accuracies, etc. To allow for comparison and aggregation across studies, we focused on the largest subset of studies, those that employed a cross-validated classification approach for decoding and reported group-level summary classification accuracies. We define the cross-validated classification approach as one in which unseen and unlabeled BOLD patterns are assigned labels by a 'classifier' trained on independent data, and the success of this classification is reported in terms of classification accuracies. We further restricted our dataset to the studies that reported decoding analyses with two classes (i.e. those that had 50% as chance level). This left us with 76 studies that reported a total of 877 decoding accuracies. The list of papers can be found in Supplementary Table 1.

Within Study Extraction

Studies reported a variable number of decoding analyses, ranging from 1-96 per study Some studies decoded the same information from different PFC regions, while other studies decoded different types of information from the same region. A few studies also applied the same analysis to data from different time points within a single trial. As a rule, we separately recorded all reported group-level summary classification accuracies. However, there were some exceptional cases in which it was either infeasible or undesirable to record all the reported classification accuracies. For example, analyses that attempt to classify stimulus information at each TR over a window of time would be likely to yield highly correlated classification accuracies, due to the autocorrelation in fMRI BOLD signal. Therefore, in such cases, we only recorded the maximum decoding accuracy from the entire window. Another case concerns analyses conducted in both a single region and its constituent sub-regions, such as right, left, and bilateral dorsolateral PFC. We recorded only the sub-regions to reduce redundancy in our dataset. Finally, in cases where the goal of an analysis was to test whether the number of included voxels influenced the result, we again only recorded the maximum accuracy achieved. Thus, in general, we sought to include independent classification attempts in prefrontal cortex, and where classifications were non-independent, to favor inclusion of the one with the highest classification accuracy. Note that this latter inclusion criterion biases against the hypothesis that it is difficult to classify prefrontal cortex BOLD.

Another concern regarding the independence of observations relates to the intrinsic spatial smoothness of fMRI datasets. If decoding accuracies are obtained from two regions that are close enough to each other to show spatial correlation, the observations would not be independent. Given that papers do not report intrinsic spatial smoothness, we employed a threshold of 10mm as the minimum separation required for decoding accuracies to be considered separate. We found no cases of two analyses from the same study, decoding the

same information, focused on regions that were less that 10mm apart. In addition, we conducted a second analysis where we averaged all accuracies from a study if they were associated with the same AAL region. This did not affect our results.

To ensure that classification accuracy values were reliably recorded from each paper we conducted a validation procedure in which an independent investigator (blinded to the initially coded value and without authorship incentive) re-coded the accuracy values from each paper. In each case where the two values were different, the values were re-checked and corrected in the record.

All recorded raw decoding accuracies are plotted in Supplementary Figure S1.

Estimating Distributions

To compare decoding accuracy across regions (frontal v/s occipital or mid-temporal) and between significant and non-significant data we estimated distributions for the group mean data. First, the accuracies were pooled across studies and kernel density estimates were applied (using Scott's rule for bandwidth). To obtain confidence intervals, we applied hierarchical bootstrapping which accounts for the dependence among analyses from the same study. Analyses from the same study share features that may influence classification accuracy such as sample size, data quality, preprocessing methods, etc. Studies were first randomly sampled with replacement and then group-level analyses were randomly sampled with replacement from these selected studies. Similar credible intervals were obtained by fitting Bayesian hierarchical Gaussian models to the data, though these models had to additionally assume a parametric family for the data.

In Study 70, mean decoding accuracies were reported in a bar graph and it was unclear whether decoding accuracies not significantly different from chance were excluded. Therefore, we excluded data from Study 70 from the estimation of the significant and non-significant distributions. Study 31 used 99.99% confidence intervals, reporting two accuracies at 63% and 64% within this interval. To be conservative, we did not count these accuracies in the estimation of the non-significant distribution.

Regression Analysis

A regression analysis was employed to examine how decoding accuracy across the studies in our database depended on brain region within frontal cortex, the type of information decoded, and the analysis methods used. The coding of these factors for the regression is described below.

Region: We examined classification performance as a function of brain region. Individual analyses reported location using a number of different atlases. Therefore, to compare accuracy in a single space, we mapped all reported locations to the AAL atlas. Analyses that were reported with centroid coordinates, from either an ROI or a roaming searchlight were assigned to AAL regions by coordinate-lookup in SPM12's AAL template image. Analyses that did not report coordinates used ROIs coming from one of several common brain atlases: Brodmann [79], Destrieux [80], Desikan-Kellaney [81], Oxford-Harvard (FSL). These analyses were assigned within AAL by a region-to-region correspondence table constructed by visually comparing the non-AAL atlases to the AAL atlas in MRICRON (Supplementary Table 2)

Within this region coding scheme, analyses with small ROIs or those that reported peak coordinates were each assigned to one AAL region, whereas analyses with larger ROIs were assigned to two or more AAL regions. 53%, 32%, 15% of the analyses were assigned to one, two, and three or more regions respectively. In most cases where accuracies were assigned to two AAL regions, these were the left and right hemisphere counterparts of the same AAL region. Therefore, for the main regression, analyses that had been assigned to two AAL regions were assigned to a bilateral region regressor. The accuracies not assigned to a bilateral ROI or assigned to more than 2 regions were omitted from the main analysis to maintain mutual exclusivity, leaving 82% of the original data. These accuracies were included in follow-up analyses described in the results and in the supplements.

Information Type: The type of information decoded in each analysis can be broadly categorized as either *perceptual, response, rule, or value.* We categorized an analysis as *perceptual* if trials were separated into classes so that they shared either a low-level perceptual feature such as color, or a high-level feature such as object category. Importantly, trials or patterns from the same class would be associated with different actions. In contrast, we categorized an analysis as *response* if trials from the same class contained the same action but different perceptual features. We categorized an analysis as *rule* if trials from the same class shared the same abstract goal, task or set of stimulus-response mappings. For example, one class of trials might require objects to be judged on their size, while the other class of trials might require judgments of shape. We considered an analysis as *value* if different classes of trials were associated with different levels of subjective value. For example, classes of trials might be distinguished based on a participant's desire to purchase an object, or whether they experienced a win or loss outcome. Examples of each type of analysis can be seen in Supplementary Table 3.

Analysis Procedure: MVPA analyses varied along several dimensions at each step in the analysis pipeline from data collection and preprocessing to classification that could

ultimately affect outcome. We recorded the following for each analysis at each step of the procedure: scanner strength, number of subjects, coregistration, smoothing, temporal averaging, response normalization, and classifier used. Specific codes used and their definitions are elaborated below.

Coregistration. Coded as 0-1 and refers to whether the decoding analysis was conducted in native-subject space or a standard space such as MNI.

Smoothing. Coded as 0-1 and refers to whether or not any smoothing kernel was applied to the fMRI data prior to the decoding analysis.

Temporal Averaging. Coded as one of four types, referring to how multiple fMRI images are combined into a single pattern corresponding to an experimental event. The four levels were:

1. *no temporal averaging*: uses every TR (repetition time) on every trial as a pattern
2. *averaging across trials*: averages data across trials, but maintains a separate pattern for each TR;
3. *averaging across TRs*: averages data across TRs but maintains a separate pattern for trial (or event)
4. *averaging across TRs and trials*: averages data across both trials and across TRs. This last category has the largest degree of temporal compression, often leading to only a few training examples per class.

Response normalization. Coded into 3 levels: no normalization, temporal normalization, and spatial normalization. Temporal normalization de-means each voxel across time and divides by the standard deviation either within class or across all classes. Examples using this method are Studies 36, 25, 4. Spatial normalization de-means each voxel using the average response of the surrounding voxels. An example using this method is Study 3.

Classifiers. Coded as one of 6 types: Gaussian naive Bayes (gnb), logistic regression (logreg), linear discriminant analysis (lda), linear support vector machines (svm-lin), nonlinear support vector machines (svm-nonlin), and correlation (correlation). Correlation accuracy is determined by assessing whether the within class correlation is higher than the between class correlation in random splits of the data.

Data and Code Availability:

Our meta-analysis database and analoysis code is publicly available via the Open Science Framework (OSF) (https://osf.io/8dvzr/).

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