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Opinion

Painful Issues in Pain Prediction

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How perception of pain emerges from neural activity is largely unknown. Identifying a neural 'pain signature' and deriving a way to predict perceived pain from brain activity would have enormous basic and clinical implications. Researchers are increasingly turning to functional brain imaging, often applying machine-learning algorithms to infer that pain perception occurred. Yet, such sophisticated analyses are fraught with interpretive difficulties. Here, we highlight some common and troublesome problems in the literature, and suggest methods to ensure researchers draw accurate conclusions from their results. Since functional brain imaging is increasingly finding practical applications with real-world consequences, it is critical to interpret brain scans accurately, because decisions based on neural data will only be as good as the science behind them.

Trends

Predicting perceived pain from brain activity has enormous implications: 'pain signatures' from brain imaging data are increasingly used as evidence for pain perception in minimally conscious patients or infants, or in legal settings.

Sophisticated machine-learning algorithms are increasingly applied to functional brain-imaging data with two main objectives: (i) identifying a specific neural 'pain signature'; and (ii) predicting perceived pain from brain activity.

While machine-learning approaches hold considerable promise for pain research, they are fraught with interpretive difficulties: disregarding the tight match between machine-learning protocol design and the desired study objectives could lead to incorrect interpretation of results.

Machine Learning in Pain Research: Objectives and Protocols

Pain, as any other conscious sensation, is determined by a specific pattern of neural activity at the cortical level [1,2]. To understand the perception of pain, many researchers use non-invasive functional neuroimaging techniques [3,4], such as electroencephalography (EEG), magnetoencephalography (MEG), positron emission tomography (PET), and, especially, functional magnetic resonance imaging (fMRI). With these tools, researchers can now attempt to achieve the following key objectives: (i) identify temporal and spatial patterns of neural activity that could serve as a cortical signature for human pain perception [5–8]; and (ii) establish whether these patterns, or any other physiological measures of brain activity, can be used to reliably predict perceived pain [7,9–14]. Achieving these objectives, which would have dramatic basic and clinical implications, is increasingly attempted through the application of sophisticated **machine-learning** (see Glossary) algorithms to interpret functional brain-imaging data [15–18]. However, correct interpretation requires proper protocol design and careful inferences. Here, we highlight some of the pitfalls of applying machine-learning techniques to functional brain-imaging data related to pain perception, especially in light of recent divergent conclusions in the literature, and suggest possible remedies.

Machine learning is a scientific discipline exploiting algorithms that can learn and make **predictions** from data [19–21]. When applied to functional brain-imaging data, machine learning has the potential to: (i) identify response features that specifically encode a given experimental variable (e.g., the categories of visual objects [22]); and (ii) decode measured data to predict subjective percepts and intentions (e.g., the pain intensity reported by an individual [9]) (Box 1). Therefore, it is not surprising that machine learning has received immense interest in systems neuroscience, and it is now increasingly used in the field of human pain [7,9–14,23,24].

While machine-learning techniques hold considerable promise for pain research, investigators must take special care to match machine-learning protocol design to the desired study

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Box 1. Encoding, Decoding, and Reverse Inference

In functional brain imaging, 'encoding' refers to the identification of a statistical dependency between experimental variables (e.g., pain perception) and measured brain responses. This encoding procedure is normally achieved using the traditional voxel-by-voxel mass-univariate analysis of fMRI time series (using, for example, general linear modeling: GLM, Figure I).

In contrast, 'decoding' comprises predicting the same experimental variables based on the measured brain responses. This decoding procedure is typically achieved using machine learning (e.g., multivoxel pattern analysis, MVPA, Figure I), which is based on certain features of the fMRI response (e.g., patterns of fMRI activity distributed over many voxels).

Reverse inferences are logically flawed deductions based on affirming the consequent (e.g., if A determines B, when B is observed one infers that A has occurred). Reverse inferences are notoriously frequent in functional neuroimaging research, and typically consist in inferring a particular experimental variable (e.g., the perception of pain) from a given pattern of brain activation (e.g., the so-called 'pain matrix') [37,38]. Notably, reverse inferences have a probability of being correct, which depends on the exclusivity of the relation between the experimental variable and the recorded response (i.e., it depends on how many variables other than A determine B).

Even if decoding is the reverse prediction of experimental variables from the measured brain response, decoding is conceptually different from reverse inference: indeed, in most practical applications, decoding analysis does not require that the relation between the experimental variable and the corresponding brain response is exclusive. For example, most currently available pain prediction algorithms rely on features of the brain response that are not tested for their necessity or sufficiency for the occurrence of pain perception.

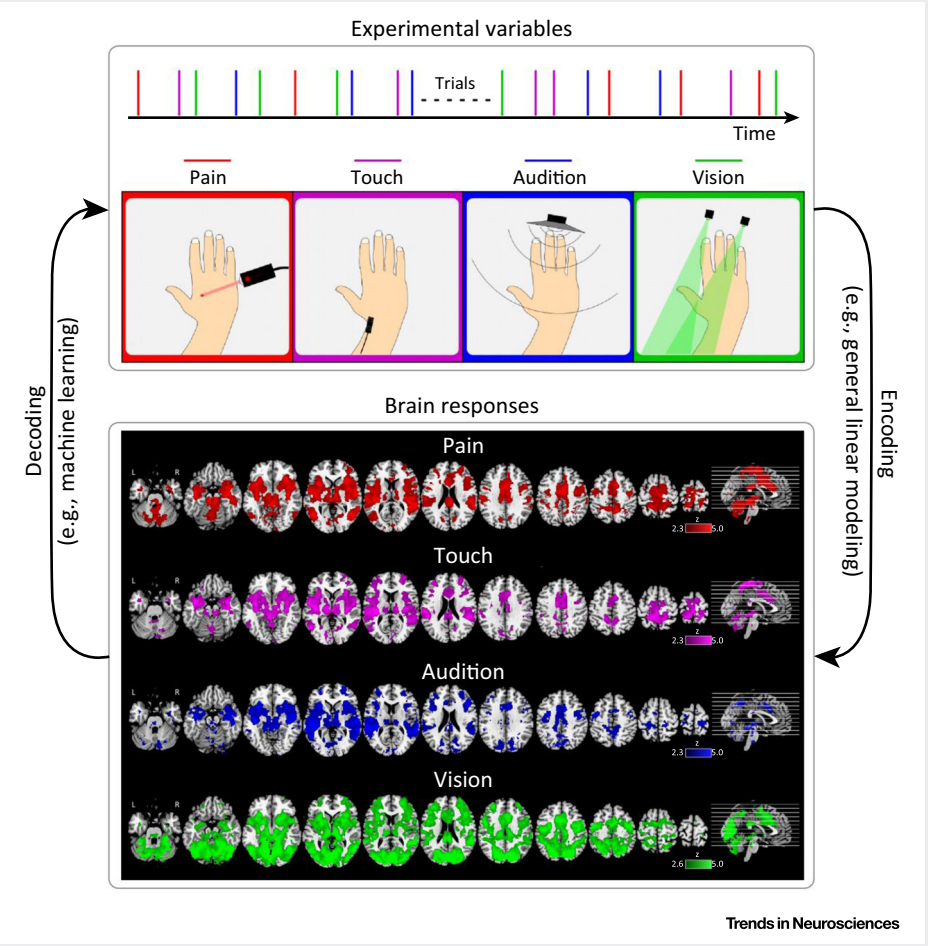

Figure I. Relationship between Encoding (Identifying the Statistical Dependency between Experimental Variables and Brain Responses) and Decoding (Predicting Unknown Experimental Variables from the Brain Responses). Bottom panel modified from [29].

Glossary

Machine-learning prediction: once machine learning has identified a response pattern associated with an experimental variable, it can be used to predict that experimental variable on the basis of the detected response pattern.

Machine learning: an analysis approach that comprises using the ability of computers to learn from, and make predictions from, different kinds of data. When applied to functional brain images, machine learning can be used to detect response patterns (e.g., intensity and spatial distribution of fMRI signals) associated with a given experimental variable (e.g., the intensity of pain perception).

Multivoxel pattern analysis (MVPA): a kind of machine-learning technique that identifies condition-specific spatial patterns of fMRI responses distributed across different voxels. These patterns of activity can be used to predict the occurrence of different experimental variables (e.g., different levels of subjective pain, or pain vs touch).

Neural signature: a feature of the brain response that is uniquely associated with a given experimental variable. To identify conclusively a neural signature, it is crucial to ensure that its relation with the experimental variable is exclusive (i.e., that other experimental variables do not produce the same pattern of brain response).

Pain prediction: the process of estimating unknown subjective intensity of pain perception using experimentally measured functional brain-imaging data. True pain prediction must not use prior knowledge about subjective reports of pain intensity when testing the prediction performance.

Prior knowledge: in the context of machine learning, refers to the information about the experimental variables that, although available, should not be used when testing the performance of the machine-learning classifier in predicting an experimental variable. The incorporation of prior knowledge into the training is a necessary aspect of machine learning. By contrast, exploiting prior knowledge when testing the algorithm performance is incorrect, and results in an artificial inflation of performance (false positive results).

objectives. Particularly in the field of pain neuroscience, disregarding the tight relation between protocol and objective can lead to inaccurate interpretation of results. In this article, we explain how incorrect conclusions can result when deviating from the allowable objective of a given machine-learning protocol. We first outline the two main objectives of machine learning in pain neuroscience, and then clarify some issues related to result interpretation. We end by providing guidelines to avoid unjustified claims.

Reverse inference: in the context of human brain imaging, reverse inference consists in inferring an experimental variable (e.g., pain perception) from a pattern of neural activity (e.g., the brain responses elicited by a nociceptive stimulus). The validity of a reverse inference drawn from neuroimaging depends on the exclusivity of the relation between the experimental variable and the brain responses. For example, the validity of the inference that a person is experiencing pain because the pattern usually seen in response to nociceptive stimuli is observed, depends on whether the same pattern is also elicited by other stimuli that do not result in painful percepts.

Objective 1: Identifying a Pain-Specific Neural Signature

A main objective of machine learning is to identify a '**neural signature**' or 'fingerprint'; that is, a neural correlate of fMRI activity that uniquely encodes a given experimental variable or perceptual experience [25,26] (Box 1). This is an appealing objective in human pain neuroscience, given that the amplitude of the fMRI signal, when analyzed with traditional mass-univariate analysis (i.e., general linear modeling, GLM [27,28]), has failed to identify a unique signature for pain [29]. Indeed, transient painful stimuli elicit graded responses within a wide array of brain regions (which has been sometimes unfoundedly labeled as a 'pain matrix'), consistently including the primary and secondary somatosensory cortices (S1 and S2), the insula, and the anterior cingulate cortex (ACC) [30–33]. However, most of these areas are also activated by equally salient, but never painful, auditory, tactile, and visual stimuli [29,34]. Given that these brain regions are also activated in situations where no pain is present, it is an incorrect reverse inference to conclude that this pattern of brain activation represents a pain signature [35–38].

Machine learning potentially offers a way forward, so long as the proper protocol is applied. Similar to traditional mass-univariate analysis, machine learning can exploit similar features of the functional neuroimaging response, such as spatial distribution and signal amplitude [39]. Yet, if machine learning simply exploits bulk differences in signal amplitude to successfully identify a given experimental variable (i.e., the perceived pain intensity), this does not reflect a unique pain signature, and the same problem of reverse inference applies to the interpretation of results [35]. Just as in mass-univariate analysis, it is valid to interpret a given result as a 'pain signature' if and only if the relation between the brain response pattern and pain is unique for pain.

To overcome this issue, machine learning should be performed using a protocol that identifies the possible relation between fine-grained spatial patterns of the brain response and pain (in this case, machine learning is named '**multivoxel pattern analysis**', MVPA [40,41]) without making use of signal amplitude. In addition, the specificity of a possible fine-grained spatial pattern should be verified against the brain responses elicited by nonpainful but isosalient stimuli, to rule out the possibility that the same spatial patterns could reflect equally salient stimuli of different sensory modalities. If these prerequisites are not satisfied, machine learning is no better than mass-univariate analysis, and the correct classification would be misinterpreted as a specific neural signature for pain.

Objective 2: Pain Prediction from Neural Activity

When the objective is instead to decode a laboratory measure of brain activity to predict a subjective painful percept (Box 1), machine learning can be performed using a protocol that exploits all signal components encoding the subjective percept (typically pain intensity, but also different qualities of pain). Therefore, both the amplitude and spatial configuration of the signal can be preserved, because they both have the potential to encode the reported pain intensity. In particular, the amplitude information should be kept and exploited, given that this information often, albeit not always, correlates well with subjective pain intensity [42–44]. Indeed, and rightly so, all studies using machine learning with the objective of predicting pain perception take advantage of the variability in signal amplitude [7,9–14,24]. It is important to note that, for the practical objective of predicting pain, the reverse inference issue highlighted

in the previous section is less important. Indeed, even if some (or all) features of the signal exploited to predict pain are not pain specific, but a good prediction is achieved, this can still be useful. Still, a practically important point is to estimate how often those features (despite not representing a unique pain signature) allow machine learning to predict pain. Indeed, most of the features that have been used to successfully predict pain (i.e., bulk signal changes in several brain regions [7,9]) are likely to fail to predict pain in some contexts. For example, failure is likely when pain intensity is dissociated from stimulus saliency, given that it has been shown that these signal changes are also determined by isosalient, but nonpainful, sensory stimuli [29,34,44].

In the following sections, we suggest some guidelines to improve the use of machine learning in interpreting fMRI data. We describe in detail key aspects of the analytical steps needed to use machine learning in relation to the two objectives outlined above. The choices for each analytical step define the potentially achievable objectives, as well as the physiological conclusions that can be inferred.

Signal Normalization

As detailed above, the response amplitude of fMRI signal in regions of the so-called 'pain matrix', although often correlated with the intensity of perceived pain, is largely not specific for pain, because nonpainful stimuli can also elicit graded brain responses that correlate with intensity of perception [29]. Therefore, if successful machine learning relies on graded levels of response amplitude, the reverse inference that these features reflect a unique 'pain signature' (Objective 1) is unlikely to be correct. Implementing a strict normalization of fMRI signal amplitude is a possible strategy to minimize the contribution of graded levels of activation to successful machine learning (Figure 1) and, therefore, increase the likelihood that the features exploited by machine learning represent a unique 'pain signature' (Objective 1). The amplitude of brain activity at each time point can be normalized across a number of voxels by subtracting from the signal of each voxel the mean signal across all voxels of a given region of interest (ROI) or the entire brain, and then dividing the result by the standard deviation of the signal from all voxels of the ROI (or the entire brain). As a result of this procedure, in each experimental condition, the voxels constituting the ROI have a mean of zero and a standard deviation of 1.

This normalization strategy minimizes the contribution of nonpain-specific graded levels of activation and, therefore, should be performed when aiming to identify a unique pain-specific spatial signature that cannot be disclosed using the mass-univariate analysis (Objective 1). By contrast, stimulus-evoked changes in signal amplitude can be preserved when aiming to predict subjective pain intensity (Objective 2), because perceived pain often correlates with signal amplitude and, therefore, removing it usually entails a reduction in the accuracy of decoding. Exactly for this reason, studies aiming to predict pain avoid such a normalization step to maximize the predictive accuracy of the machine-learning algorithm [9–12,14]. An important note of caution is that successful **pain predictions** obtained when machine learning makes use of bulk signal amplitude likely exploit nonpain-specific neural responses [7,9].

Within-Subject versus Between-Subject Prediction?

To achieve encoding objectives (i.e., identifying a pain signature), machine-learning analyses should be primarily performed within subjects, while, to achieve decoding objectives (i.e., predicting pain), analyses should be primarily performed between subjects (Figure 2). Indeed, to identify a fine-grained signature (using, for example, MVPA of fMRI signals), within-subject analyses will avoid the inevitable spatial blurring of responses caused by (i) the functional and anatomical differences between individuals [45] and (ii) the lack of optimal algorithms to co-register brains from different individuals [40,41]. If performed at the between-subject level, any possible signature would be identified at least at the higher, mesoscopic scale of entire portions

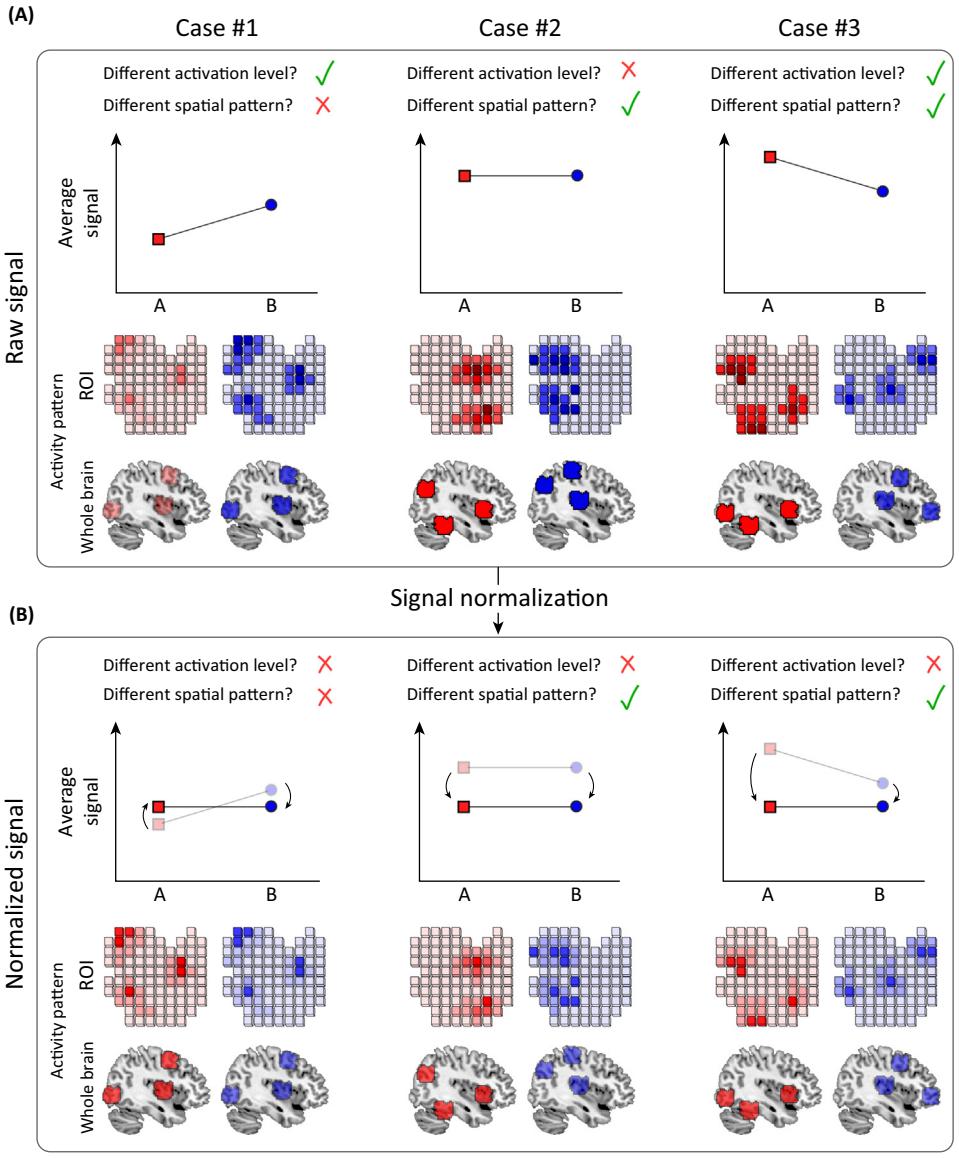

Figure 1. Effects of Signal Normalization on Spatial and Amplitude Differences in Brain Activation. Normalization of functional magnetic resonance imaging (fMRI) signal is achieved by (i) subtracting from the signal of each voxel the mean signal across all voxels of a given region of interest (ROI; or the entire brain); and (ii) dividing the result by the standard deviation of the signal from all voxels of the ROI (or the entire brain). Before signal normalization (A), brain activity in different experimental conditions could differ in signal amplitude (left column), spatial distribution (middle column), or both (right column). After signal normalization (B), brain activity mainly differs in its spatial distribution.

of brain regions. By contrast, machine learning for pain prediction is mostly performed between subjects, because, in practical applications, pain has to be predicted on new subjects, such as a patient just after hospital admission, or a healthy participant in a drug trial [9,24]. Machine learning for pain prediction can be also performed at within-subject level. Obviously, the usefulness of within-subject prediction is more limited, and the accuracy of such prediction is higher, because it is not affected by between-subject variability of the response features used to predict pain [9].

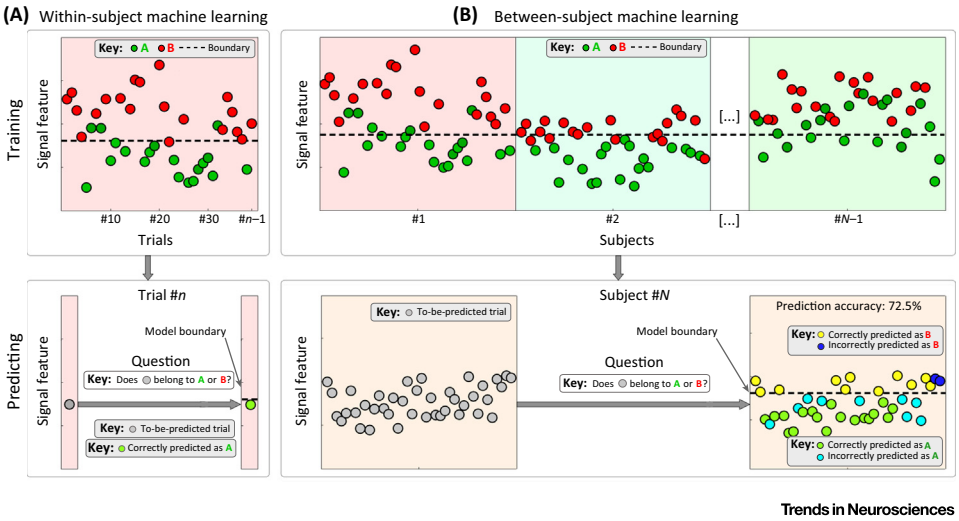

Figure 2. Comparison of Within-Subject and Between-Subject Machine-Learning Protocols. (A) Within-subject machine learning. The machine-learning model is trained on all trials except one (*n*–1), and tested on the remaining trial. The model is cross-validated using each trial as test trial once. Within-subject machine learning classifies the test trial into category A or B based on a model generated from the same subject. (B) Between-subject machine learning. The machine-learning model is trained on all trials of all subjects except one (*N*–1), and tested on all trials of the remaining subject. Cross-validation is achieved by using each subject as test subject once. Between-subject machine learning classifies each single trial of the test subject into category A or B based on a model generated from the other subjects.

Use of Prior Knowledge When Validating Prediction Performance

In basic and clinical applications of pain prediction, the quality or the intensity of subjective painful percepts are unknown variables. Obviously, to predict unknown experimental variables, the use of **prior knowledge** about which variable each trial belongs to is only allowed when training the machine-learning model, but not when testing its prediction performance (Figure 3) [19]. Therefore, the prediction performance of machine-learning models should be validated strictly without using prior knowledge about those percepts. This important requirement is satisfied only when the prediction is performed on a trial-by-trial level ('Predicting' in Figure 3) [10,11]. However, in some studies of pain prediction [7,46], trials belonging to the same experimental condition (e.g., stimulus energy) were preliminarily averaged, and both training the prediction model and testing its performance were performed using averaged brain responses with increased signal:noise ratios. This strategy ('Labeling' in Figure 3) erroneously uses prior knowledge when testing the prediction performance of the model, resulting in seemingly high accuracy of 'pain prediction' (corresponding to extremely high sensitivity and specificity; e.g., Table 1 and Figure 1 in [7]). The resulting 'prediction' accuracy is not only artificially inflated, but also does not reflect the real prediction of an unknown pain level.

This is a crucial point. Indeed, the use of prior knowledge in model testing artificially inflates the prediction accuracy and, therefore, violates a fundamental rule when machine learning is used to predict a stimulus feature or a perceptual outcome (Objective 2) [19]. By contrast, when machine learning aims to identify a spatial signature that encodes a given experimental variable (Objective 1), it is acceptable to use prior knowledge about which experimental variable (e.g., reported subjective percept) each single trial belongs to when testing the prediction performance of a model [40,47]. Therefore, although incorrect for decoding objectives such as pain prediction, testing the prediction performance of a model on trials averaged based on prior knowledge (as previously done using stimulus energy [7]) is appropriate for encoding objectives, such as identifying a new condition-specific spatial signature.

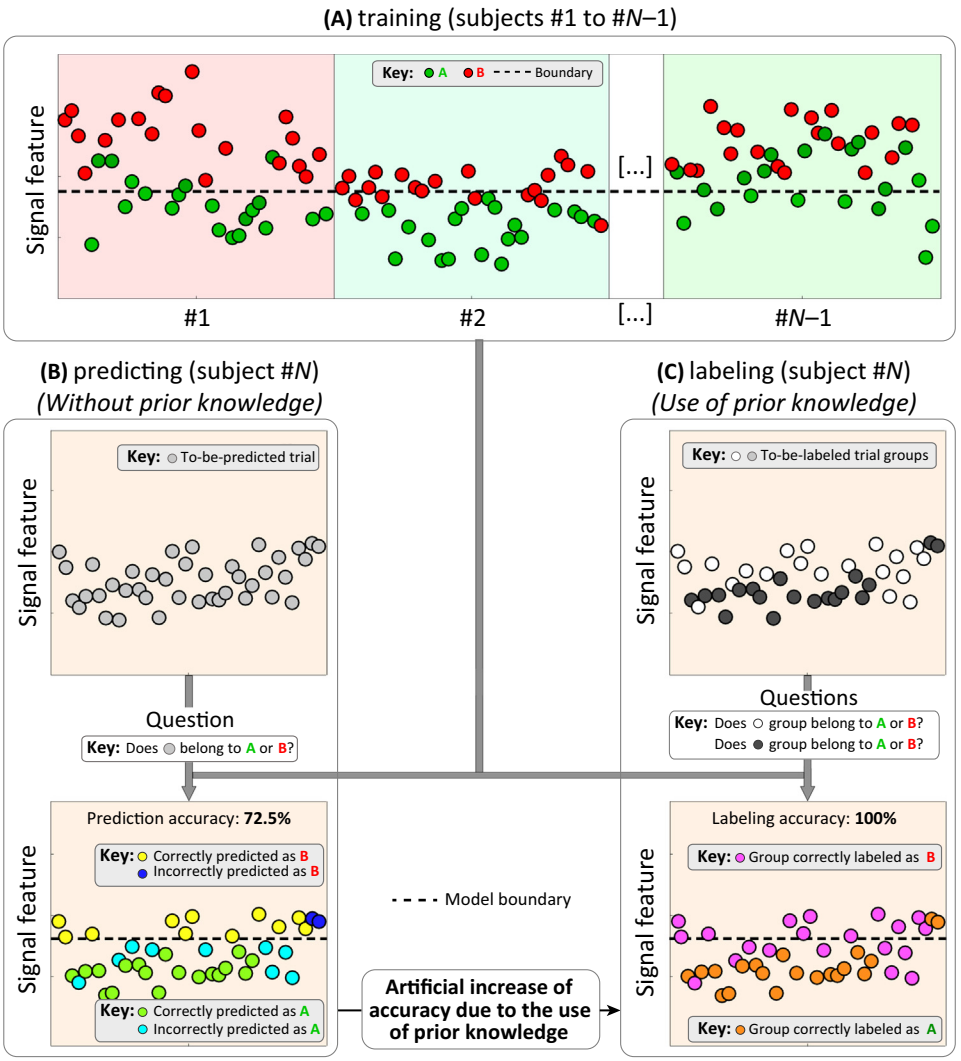

Figure 3. Predicting versus Labeling: Use of Prior Knowledge in Machine Learning. At between-subject level, the machine-learning model is trained on all trials of all subjects except one (*N*–1) (A), and tested on all trials of the remaining subject. Importantly, predicting (B) the experimental variables A or B is achieved by classifying each single trial of the test subject into category A or B based on the trained model. Predicting does not exploit prior knowledge. By contrast, labeling (C) is achieved by classifying two (or more) predefined groups (e.g., category A or B). Labeling uses prior knowledge about the experimental variable of interest, and typically results in higher accuracy than predicting (e.g., 100% versus 72.5%). Such prior knowledge is obviously unavailable in most practical applications of machine learning for pain prediction.

Concluding Remarks and Implications for the Assessment of Previous Studies

Machine learning is extremely promising in pain research because it can identify response features that cannot be detected using mass-univariate analyses [23]. However, simply using machine-learning algorithms is not sufficient; the protocols must match the objectives to avoid erroneous conclusions. For example, given that machine learning can also exploit bulk differences in response amplitude, when these differences are not removed, a successful classification could simply rely on the same information identified by mass-univariate analyses [9]. This is acceptable if machine learning aims to predict pain (Objective 2), but it represents a significant issue if machine learning aims to identify a unique signature for pain (Objective 1).

Outstanding Questions

Do the functional neuroimaging features used to predict pain truly reflect neural activities that are causally related to the emergence of pain percepts? Or, do they reflect neural activities related to the consequences of painful percepts, but not directly involved in their emergence (e.g., attentional orienting, autonomic responses, or motor preparation)?

Which of these two kinds of neural activity (causally specific for pain versus pain byproducts) is more likely to provide a reliable pain prediction?

Will it be possible to use a machine-learning classifier trained on functional neuroimaging data to predict perceived pain in real-life situations (e.g., when an individual is admitted to hospital)?

Should functional neuroimaging data be used as conclusive evidence of an experiential state of pain in medicolegal cases?

Should the scientific community agree on guidelines for avoiding the conflation of the objectives of pain prediction versus the identification of pain signatures?

Indeed, the validity issues of reverse inferences made from mass-univariate analyses of pain neuroimaging data [35,36,48] equally apply to the interpretation of the results obtained using machine learning. A given machine-learning result can be interpreted as reflecting a 'pain signature' (Objective 1) if and only if the relation between the brain response pattern and pain is unique for pain.

The conclusions we draw here warrant more careful assessment of the interpretations of some recent machine-learning results in pain neuroscience [7,46,49]. Indeed, one particular study used a single, mixed machine-learning protocol: machine learning was performed on non-normalized fMRI data, at a between-subject level, and made use of prior knowledge when estimating the prediction accuracy [7]. Using this approach, the authors claimed to have achieved the two objectives of machine learning together. Indeed, they affirmed to have identified: (i) a specific neurological pain signature ('NPS') relying on fine-grained spatial scales, which (ii) can 'reliably predict pain across different experiments' with extremely high accuracy.

However, the claim of having discovered a unique NPS that relies on fine-grained spatial scales is not entirely justified, because the machine-learning protocol used violates the requirements needed to identify a unique brain signature of pain (see sections 'Signal Normalization' and 'Within-Subject versus Between-Subject Prediction?') [7,46]. Furthermore, the seemingly impressive pain prediction accuracy was obtained by making use of prior knowledge when decoding the brain responses, a procedure that is incorrect when aiming to predict unknown experimental variables (see section 'Use of Prior Knowledge When Validating Prediction Performance').

Such sweeping conclusions were only possible by incorrectly conflating encoding (Objective 1) versus decoding (Objective 2) protocols, which must be applied separately to achieve those objectives (Box 1). Machine learning is a promising tool, but only by careful application can one take advantage of its full power to advance pain research (see Outstanding Questions). The stakes are high: functional brain imaging is increasingly finding practical applications with real-world consequences [49]. A neural 'pain signature' could serve as a biomarker for drug development, as evidence for pain perception in minimally conscious patients (or other patients that cannot report pain, such as infants [50]), or as an objective measure of pain to be used in legal cases. Therefore, it is critical to interpret brain scans accurately, because decisions based on neural data will only be as good as the science behind them.

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