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A System for Measuring the Neural Correlates of Baseball Pitch Recognition and Its Potential Use in Scouting and Player Development

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Abstract

In this paper we use state-of-the-art multimodal neuroimaging to tease apart the spatio-temporal sequence of neural activity that "goes through a hitter's mind" when they recognize a baseball pitch. Specifically we utilize electroencephalography (EEG) and functional magnetic resonance imaging (fMRI) to investigate the neural networks activated for correct and incorrect pitch classifications. Our previous analysis has shown where in the trajectory of a pitch the hitter's neural activity correctly discriminates a pitch type (e.g. fastball, curveball or slider). Here, we show that correct classifications correlate with a neural network including both visual and sub-cortical motor areas, likely demonstrating a link between visual identification and the required rapid motor response. Conversely, we find that not only is this activity lacking in incorrect classifications, but that it is instead replaced by prefrontal cortex activity, which has been shown to be responsible for more deliberative conflict resolution. Synthesizing these and other results, we hypothesize the potential uses of this technology in the form of a brain computer interface (BCI) to measure and enhance baseball player performance.

1 Introduction

Ted Williams called it "the hardest thing to do in sports" and Yogi Berra said it is so difficult to do that "you can't think and hit at the same time." Both of these baseball greats were referring to the act of hitting a thrown baseball. The split-second perceptual decision-making required to hit a baseball is, not only the hardest thing to do in sports but it is also, of potential interest to the neuroscience research community, in terms of what happens in a batter's brain when he/she makes this rapid decision.

Despite the richness of neuroscientific investigation in other areas of perceptual decision-making, the psychology and neuroscience communities have given relatively little attention to investigating the neural correlates underlying baseball pitch recognition. Though some studies have examined eye movements before and during pitches [1-3] and other studies have investigated some aspects of the neural responses to baseball pitches [4], our group was the first to study the time evolution and spatial distribution of the neural response for classifying baseball pitches [5].

Due to the speed of the decision process, we had used electroencephalography (EEG) with millisecond-level precision to characterize neural activity during pitch classification. EEG non-invasively measures the electrical potential due to brain activity at the scalp. In that study, we determined the precise timing of neural activity that discriminates for a given pitch class and used that information to track where in a pitch's trajectory it is classified vs. other pitches by the subject. Furthermore, we used low-resolution tomography to localize a neural generator in the frontal cortex (Brodmann Area 10) that was active across our subject population for incorrect pitch classifications.

Despite its high temporal resolution, EEG lacks high spatial resolution and so in the current study we aim to fill that void. In particular, though EEG can precisely describe "when" activity occurs it cannot tell precisely "where" in the brain activity is generated. Conversely, functional magnetic resonance imaging (fMRI), though not as temporally precise as EEG, is a true 3D imaging modality, enabling localization of specific brain regions associated with neural activations. Therefore, in this paper, we show preliminary results that used a unique combination of fMRI and EEG to provide a more detailed spatio-temporal description of the neural activity underlying baseball pitch recognition than has yet been done. Finally, in light of our analysis and preliminary results that describe the neural mechanisms of baseball pitch classification, we conclude the paper by hypothesizing the extent to which such analysis comprises the next step in player scouting, evaluation and potential means for player development.

2 Materials and Methods

Subjects and Behavioral Paradigm

Three right-handed subjects (mean age-20 years) on a division I collegiate baseball team at the time of the study participated. Informed consent was obtained for all subjects in accordance with Columbia University's Institutional Review Board.

Each subject viewed 468 simulated fastball, curveball and control pitches broken into 6 equal blocks on a computer screen while in the MRI scanner. Following our paradigm from earlier work [5], the simulated perspective was from the catcher to demonstrate our proof of concept. Pitch simulations for fastball and curveballs were created by solving a group of ordinary differential equations that describe the Newtonian mechanics of pitch trajectories (please see [5] equations 1-7). Fastballs and curveballs have well-defined individual initial conditions. To create each pitch, we only need to vary the initial velocity and the rotation angle. Each pitch was created by randomly sampling distributions of initial conditions for velocity (fastballs: mean 82±3mph; curveballs: mean 72±3mph), rotation angle, launch angle, and horizontal launch angle (see [5] for other parameter ranges). For the control pitch, we used a non-Newtonian trajectory pitch that matched the speeds of both fastballs and curveballs, but had no motion in the plane perpendicular to the initial trajectory. We added a constant 1s countdown bar before the pitch to simulate the pitcher's windup. Subjects responded with their pitch classification via a computer keyboard and were instructed to do so before the ball reached the plate.

Simultaneous EEG and fMRI Acquisition

Whole brain fMRI was collected on a 3T Philips Achieva MRI scanner (Philips Medical Systems, Bothell, WA) with 3mm isotropic voxel size and a repetition time of 2s (i.e., an image of the brain was recorded every 2 seconds). EEG was collected simultaneously using a custom-built MR-compatible system consisting of a multi-channel magnet-compatible differential amplifier with a 43-bipolar electrode EEG cap [6].

EEG Preprocessing and Analysis

We performed a single-trial analysis of the gradient artifact removed, filtered, and epoched EEG to discriminate between a set of stimulus and response conditions. In the simultaneous EEG-fMRI system, the MR gradients create artifacts in the EEG signal. We used a template subtraction algorithm to remove the gradient artifacts before filtering and epoching. First, we considered only behaviorally correct pitches, where the user's response was within 100ms of the end of the pitches' trajectory, and trained the classifier to classify a given pitch (e.g., a fastball) vs. pitches of the other classes (e.g., curveballs and controls). Second, we classified behaviorally correct vs. incorrect pitches (e.g., correctly identified fastballs, curveballs, and controls vs. incorrectly identified fastballs, curveballs, and controls, respectively).

Logistic regression was used as a classifier to find an optimal projection for discriminating between the chosen two conditions over a specific temporal window [7-9]. This approach has been previously applied to identify neural components underlying rapid perceptual decision-making [10-12]. Specifically, we defined a training window starting at either a pre-stimulus or post-stimulus onset time τ, with a duration of δ, and used logistic regression to estimate a spatial weighting vector $\vec{w}_{t,d}^{T}$ which maximally discriminates between EEG sensor array signals X for each class:

$$\vec{y} = \vec{w}_{t,d}^{T} X \tag{1}$$

In eqn. 1, X is an $N \times T$ matrix (N sensors and T time samples). The resulting projection is a 'discriminating component' $\vec{y}$ that is specific to activity correlated with each condition, while minimizing activity correlated with both task conditions. The term 'component' is used instead of 'source' to make it clear that this is a projection of all activity correlated with the underlying source. For our experiments, the duration of the training window (δ) was 50ms and the center the window (τ) was varied across time τ=(-200:1200) in 25ms steps for stimulus-locked epochs. This time period provided substantial time after the stimulus (i.e., the start of the pitch) to observe any electrophysiological response to the pitch. We used the re-weighted least squares algorithm to learn the optimal discriminating spatial weighting vector $\vec{w}_{t,d}^{T}$ [13].

We quantified the performance of the linear discriminator by the area under the receiver operator characteristic (ROC) curve, referred to here as A_z, using a leave-one-out procedure [14]. We used the ROC A_z metric to characterize the discrimination performance as a function of sliding our training window from -200ms pre-stimulus to 1200ms post-stimulus (i.e., varying τ). Essentially, the value of A_z indicates the predictive accuracy of our classifier given both true positives and false positives (an A_z of 1 meaning a perfectly accurate classifier and 0.5 being pure chance). We quantified the statistical significance of A_z in each window (τ) using a relabeling procedure (please see [5] for more details).

Traditional fMRI Preprocessing and Analysis

fMRI investigates neural activity by measuring changes in blood flow throughout the brain. Our body's main source of energy is glucose, but, since the brain does not store any glucose, a neuron must immediately replenish its energy supply after firing. This in turn leads to an increase in oxygen rich blood flow to the area and what we call the blood oxygenation level dependent (BOLD) response. The magnetic properties of oxygenated blood subtly change the imaging contrast in MRI, which then allows us to investigate what areas of the brain are functionally active during a given task. Thus, the MRI becomes a *functional* MRI.

We performed two types of analyses on just the fMRI data – a traditional event-related general linear model (GLM) regression and a multi-voxel pattern analysis (MVPA). Below we briefly describe fMRI GLM and MVPA analyses for those not acquainted with the techniques.

In general, the GLM aims to "explain" the variation of a dependent variable in terms of a linear combination of several reference functions. The dependent variable corresponds to the observed fMRI time course of a voxel (volume element-3D pixel) and the reference functions correspond to time courses of expected fMRI responses for different conditions of the experimental paradigm. The reference functions are called regressors. A set of specified regressors forms the design matrix or the "model". To obtain a predictor time course, a condition 'box-car' function is convolved with a standard hemodynamic response function (i.e., a BOLD response template). A condition box-car function may be defined by setting values to 1 at time points at which the modeled condition is defined (e.g., "fastball stimulus on") and 0 at all other time points. Each predictor time course X gets an associated coefficient (β), quantifying its potential contribution in explaining the voxel time course y with some error *e*:

$$y_n = \beta_0 + X_{n1}\beta_1 + X_{n2}\beta_{n2} + \ldots X_{nk}\beta_k + e \qquad (2)$$

The GLM is solved at each voxel and t-tests are used for statistical significance testing[15]. The regressors of interest in our baseball model are the onset times and durations of each pitch class and their response times. The GLM analysis provides group level information for regions that on average correlate to the hypothesis of interest (e.g., correct fastballs, correct curveballs, etc.). The GLM is a useful post hoc technique for generating insight into what neural regions are needed to perform a task, but it is not a predictive model.

In contrast to GLM, MVPA is a predictive model, similar to our EEG-based logistic regression analysis, which allows us to develop fMRI-based classifiers for each subject and then predict pitch classifications solely from the subjects' fMRI data. Like the EEG classifiers discussed before, the output of the MVPA model is an A_z indicating classifier performance.

The data was preprocessed using traditional pipelines for both analyses [6, 9]. For the GLM analysis, we tested multiple hypotheses that were similar to our previous EEG research. In particular, we tested for what brain regions selectively activate for 1) each correctly identified pitch class and 2) correctly vs. incorrectly identifications within each pitch class. For the MVPA analysis, we only present results on correctly identified pitch types, though we plan to consider correct versus incorrect identifications in the future.

Simultaneous EEG and fMRI Single-Trial-Variability Analysis

Even though GLM and MVPA allow increased spatial resolution compared to our earlier work with EEG, we additionally sought to simultaneously leverage the complementary temporal precision of our earlier work in EEG with the increased spatial resolution that is possible with GLM and MVPA in fMRI. Therefore, we used the stimulus-locked single-trial analysis with logistic regression to classify correct and incorrect pitch identifications in EEG and, from this analysis, created fMRI regressors whose height modulated with the variation of the discriminating component in time ($\dot{y}$). This technique contrasts with the technique described earlier in which the regressor height is modulated by stimulus presence (e.g., "fastball stimulus on"). In this way, we leveraged both EEG's temporal and fMRI's spatial resolutions.

3 Results

EEG Correlates of Pitch Recognition

Continuing from our earlier work [5], we first calculated subject-mean EEG classifier performance, quantified with the area under the ROC curve (A_z) (Figure 1). The trends and peaks of these curves are consistent with our previous EEG-only recordings and analysis. The correct versus incorrect results (dark blue) show two distinct peaks: the first peak starting near 500ms and the second near 900ms. The first peak most likely represents the actual decision while the later peak may represent an error processing and/or post decision evaluation. The fastball (red), curveball (green), and control (cyan) curves all show strong discrimination past 400ms.

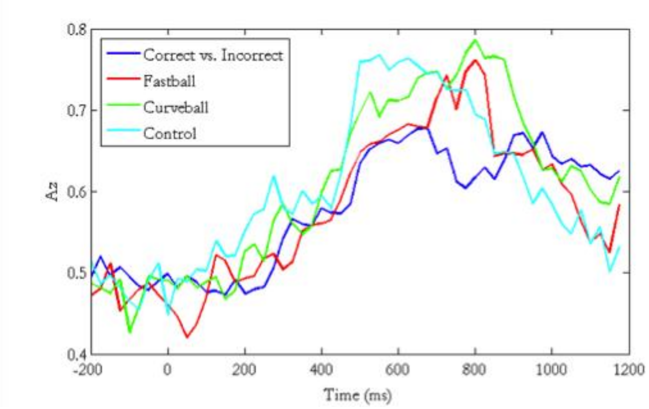
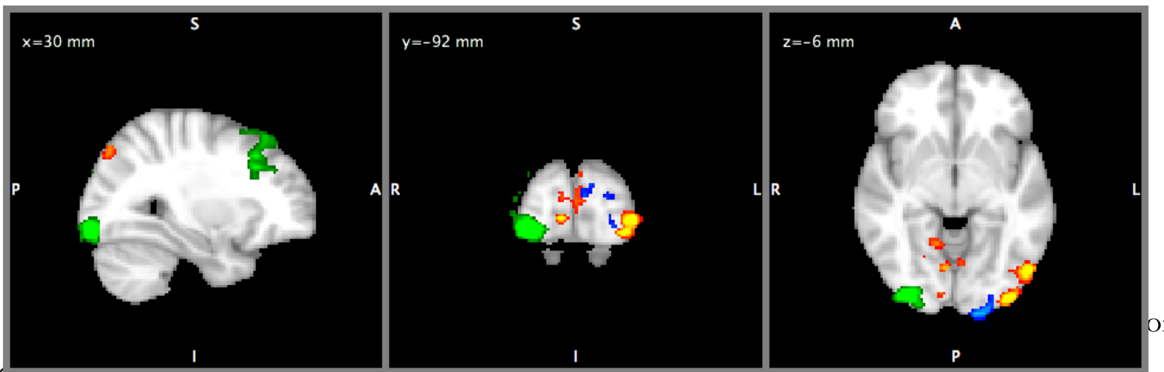


Figure 1. Mean EEG discrimination Az Plots. Mean A_z plots for each EEG comparison. 0ms is the start of the pitch.

Traditional fMRI BOLD Correlates of Pitch Recognition

Confirming our earlier findings, we then turned to GLM analysis with fMRI. The GLM analysis indicates areas of significant mean activation across all subjects and for all hypotheses tested earlier with EEG. Figure 2 shows areas of activation for the correct pitch identification hypotheses, where the results (colored areas) of the GLM pitch type identification analysis are overlaid on a standardized brain image. Regions correlating to fastball (red), curveball (blue), and control (green) pitch identifications were generally found in posterior areas of the brain mostly associated with visual processing and motion processing, specifically the lingual gyrus, lateral occipital cortex (LOC), visual area MT, and Brodmann areas 18 and 19. These regions are all part of the human visual processing stream: the lingual gyrus plays a part in visual encoding of complex images [16], Brodmann area 18 helps in interpreting an image [17], the LOC plays a major role in object recognition [18], Brodmann area 19 helps with attentional and multimodal integrating functions [19], and the MT helps the perception of motion [20]. These results show the first attempts at understanding the brain regions recruited for baseball pitch recognition.



on

Figure 2. Correct Pitch Identification Traditional BOLD Analysis. Red areas indicate regions that have higher activations during fastballs compared to other pitches, while blue areas indicate activations for curveballs, and green indicates areas activated for control pitches. All contrasts have been thresholded at Z>2.57 and family-wise error (FWE) cluster corrected at P<0.05.

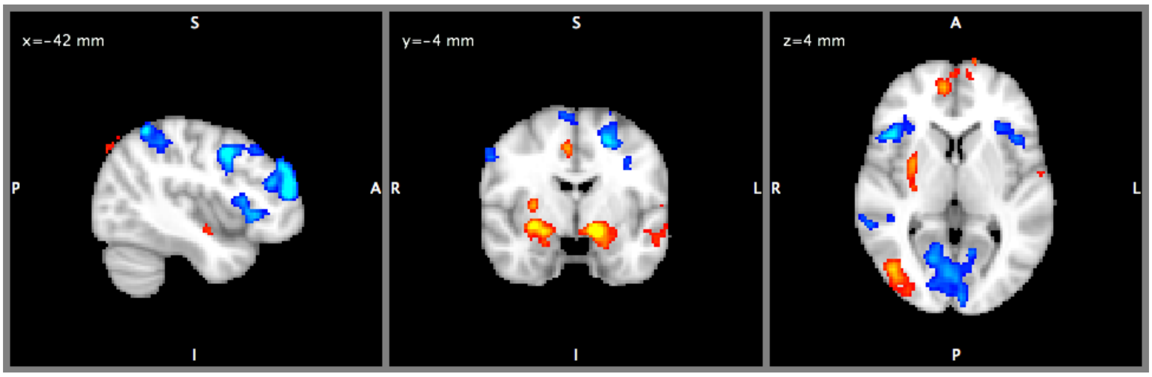


*Figure 3. Correct vs. Incorrect Traditional BOLD Analysis***.** Red areas indicate regions that have higher activations during correct trials, while blue areas indicate regions with higher activations for incorrect trials. Both contrasts have been thresholded at Z>2.57 and FWE cluster corrected at P<0.05.

We also tested for areas that are associated with correct and incorrect pitch identifications (within pitch type). Our earlier EEG work found an area in the frontal region of the brain called Brodmann area 10 that is more active during incorrect pitch identifications. The preliminary fMRI results (Figure 3) confirm this previous finding as we see a large activation for incorrect trials (blue) in Brodmann area 10. While the pitch identification activations are mostly located in the visual processing areas, the average activations for correct and incorrect trials are located throughout the brain. The average correct trial activation pattern (red) has clusters of activation located in the MT, LOC, globus pallidus, putamen, and frontal pole regions. Regions in the MT and LOC indicate that there is higher activation in these late-stage visual processing areas when the subjects are able to identify the pitches correctly. The putamen and globus pallidus are important regions for motor control and processing [21]. The frontal pole regions found in this task have been implicated in top-down processing of reward and subjective value. Conversely, the activation pattern for incorrect classifications closely matches the neural networks related to task difficulty [22], even though there is also substantial activation in the early visual processing areas. The implication is that for incorrect pitch identifications the subject is "seeing" the pitch but the information is not being passed or decoded correctly in the higher visual processing areas (e.g., MT, LOC) for the subject to answer correctly. Furthermore, the lack of sub-cortical activation in involuntary and complex movement motor areas, such as the putamen and globus pallidus, point to a disconnect in the motor sequence of events required to respond correctly. Finally, the broad activation of the prefrontal cortex indicates an attempt by the subjects to call upon their executive decision-making and conflict resolution mechanisms to classify the pitch. As a whole, this analysis further elucidates which brain areas are both important for baseball pitch recognition and indicative of when it fails.

MVPA classification

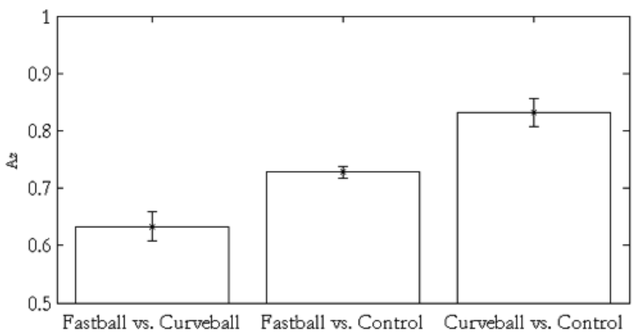


Figure 4. Mean MVPA A_z results with standard error bars.

We then turned to predicting fMRI activity using multi-voxel pattern analysis (MVPA). The MVPA resulted in substantially above-chance A_z values (Figure 4) for all subjects and pitch comparisons. The classifier for fastballs versus curveballs (mean A_z = 0.63) was the least accurate classifier. This was expected because discriminating between a fastball and a curveball in this experiment is the most difficult distinction. The classifiers for fastball versus control (mean A_z = 0.73) and curveball versus control (mean A_z = 0.83) performed well and followed the task difficulty of each comparison. The EEG results earlier showed our ability to discriminate pitches based solely on the electric scalp potentials with high temporal resolution but with poor spatial resolution, now with MVPA we are able to show comparable classification results with high spatial resolution. Our future work will attempt to link these two classifiers to achieve high temporal and spatial resolution.

Simultaneous EEG-fMRI Correlates of Pitch Classification

The previous results analyzed either the EEG or fMRI data separately. Below, we present preliminary results combining the complementary nature of EEG's temporal and fMRI's spatial resolutions to further elucidate the temporal cascade of neural events underlying classification of a baseball pitch.

The single-trial-variability analysis for the correct and incorrect pitch identifications revealed multiple clusters in several different time windows. For brevity, we show a subset of the potential analysis. In particular, we show the positive correlations between single-trial variability ($\dot{y}$) and the BOLD for only two windows (Figure 5). The earlier cluster (675ms) is located in the posterior cingulate while later clusters (925ms) are located in the superior frontal and paracingulate gyri. These areas have been shown to be active for positive salient events [23] and introspection [24], both of which are likely to exist in post-response time windows for correct pitch classifications.

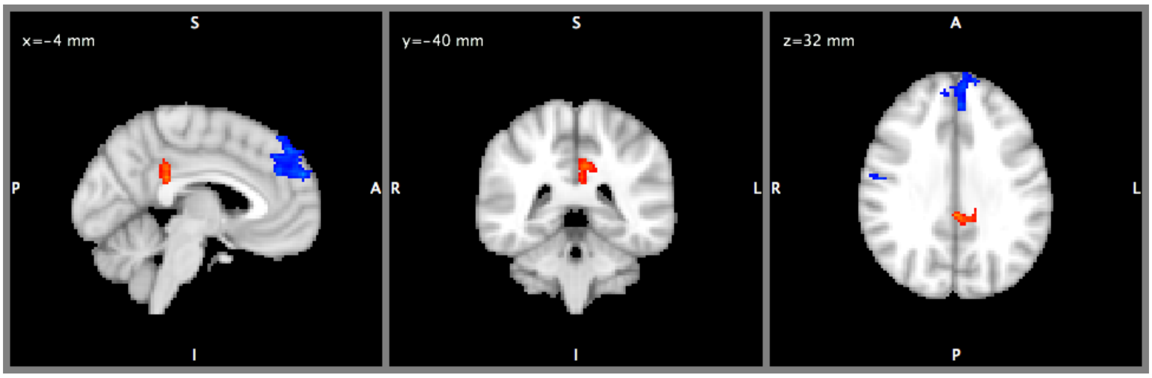


Figure 5. Correct vs. Incorrect Single-Trial-Variability BOLD Analysis. Areas that show a significant positive correlation with the single-trial-variability discriminating component for correct trials at 675ms (red) and 925ms (blue) windows. Z>2.57 and FWE cluster corrected at P<0.05.

4 Beyond Statistics: Hypothesized Applications and Conclusions

Though the ability to classify an incoming pitch is an important aptitude for a good hitter, the implications of our results and this work go beyond the specific task and stimuli used in our experimental paradigm. Rather, the ability to characterize the spatio-temporal neural activity of any player in this regard goes beyond the statistical revolution in baseball analytics by showing how the individual nervous system of a player is tuned (or not) to respond to situations of strategic importance in baseball. This neural response is the foundation for the player's response that manifests itself in a swing, a take, a bunt, a steal, or any other aspect of the game that requires split-second decision-making. Consequently, our neuroimaging methodology could serve as a better direct metric of player performance, or potential performance, compared to current statistical measures of past performance. In what follows, we propose some areas of application for this novel technique, including baseball player evaluation, training and potential performance augmentation.

The most immediate application of this work is to create a neural profile of a player from the perspective of how well his/her nervous system tackles the problem of hitting a baseball. What if a player has trouble with a curveball, or a split-finger pitch? With this technology, a coach could see where in the course of the trajectory that happens and what areas of the brain are activated or not (e.g., correct vs. incorrect analysis, as shown earlier). Alternatively, a young prospect could be highly undervalued due to lack of physical strength, but quite valuable due to an acute nervous system that can recognize a breaking ball early in its trajectory. With this technology, that ability would be traceable and consequently known to the scout or organization possessing such a tool to measure the performance of the player's nervous system.

Another application of this work comes from the other side of the game, i.e., from pitching. For instance, with this technology, a pitcher could see where in the trajectory of his/her pitches a hitter identified them. Perhaps this information can mediate the development of new pitches and/or their sequencing in an at-bat?

Finally, this work points towards a neural means of feedback and, hence, non-chemical performance enhancement. Knowing the neural circuits involved in the rapid decision-making that occurs in baseball opens up the possibility for players to train themselves using their own neural signatures. While our work has not proposed any rigorous means to do so, the neural activity detailed here and in subsequent studies that utilize these analyses will likely rest at the foundation of these attempts to augment baseball player performance.

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