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Analyzing the Importance of EEG Channels for Internal and External Attention Detection

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Abstract— **For Brain-Computer Interfaces to be affordable and efficient, it is worth analyzing the importance of individual EEG channels and finding the smallest subset that still provides adequate results. In this work, we applied five different feature importance approaches to three different datasets focused on internally and externally directed attention. The methods used were: Random Forest Importance, Mutual Information, Permutation Importance, Shapley Additive Explanations, and an Ablation Study. We determined the importance of EEG channels, compared the results among the algorithms through correlation analysis, and evaluated the classification performance using different subsets of channels to validate the importance rankings. The results indicate that, in line with the existing literature, electrodes located on the right parietal cortex with the alpha frequency band appear to be the most important, followed by several channels covering the left parietal and frontal lobes. For the first dataset, we were able to reduce the number of channels from 32 to 2 while increasing the accuracy from approximately 60% to 62%. In the second dataset, we reduced the number of channels from 12 to 1 while improving the accuracy from approximately 59.5% to 64%. In the third dataset, we reduced the number of channels from 19 to 1 while only slightly decreasing the accuracy from approximately 60% to 58.5%. The results of the individual feature importance methods generally exhibit positive correlations with each other. Furthermore, we demonstrated that the rankings of channels between subjects are largely positively correlated, suggesting the presence of shared patterns of neural activity across subjects. The substantial reduction in EEG channels, identification of crucial brain regions and application of channel feature importance methods to internal/external attention data, collectively advance the development of cost-effective and efficient Brain-Computer Interfaces, paving the way for future advancements in the field.**

Brain-Computer Interfaces, Attention Recognition, Feature Importance

I. Introduction

Brain-computer interfaces (BCIs) based on EEG signals have diverse applications in research, medicine, industry, and everyday life. One useful application is detecting a person's attentional state while wearing the BCI. Attention, as defined by Chun et al. [1], involves selecting and modulating behavior-relevant information, distinguishing between external attention (incoming sensory information) and internal attention (recalled information from memory). BCIs can be employed to adapt augmented reality (AR) interfaces, reducing distractions during internal attention and enhancing thought processes [2], [3]. Monitoring attentional states using BCIs is also crucial in safety-critical activities like driving and biking, where inattention and mental fatigue can pose risks [4]–[8]. Furthermore, BCIs can be utilized in E-learning environments to monitor students' mental states and enhance their learning experiences [9]–[12]. To develop affordable and efficient BCIs, it is essential to determine the most important EEG channels for detecting attentional states. This is because the number of electrodes of an EEG device largely determines its cost and setup time. Thus, our objective is to analyze EEG channel importance for discriminating between internal and external attention using various feature importance methods. Additionally, channel importance assessment can validate machine learning models trained on EEG data by comparing with neuroscience findings to ensure model reliance on neural signals rather than artifacts. We aim to compare multiple methods to quantify channel importance and identify the smallest set of EEG channels that yield satisfactory classification scores.

Our research questions are as follows:

- What are the key channels to detect internal vs. external attention and how many channels are necessary for accurate classification?
- How do the different methods for estimating the importance of channels perform in terms of ranking?

The source code for this study is available in our GitHub repository[1].

A. Related Work

1) Neural correlates of internal and external attention: Attention is a vital cognitive function that involves the allocation and regulation of limited computational resources [1]. Alpha and theta oscillations have been extensively investigated in relation to attentional processes. Benedek et al. [13], [14] showed increased alpha power in the right parietal cortex during internally directed attention tasks, indicating the suppression of irrelevant sensory input. They also observed increased activation in the right anterior inferior parietal lobe (aIPL), bilateral lingual gyrus (parietal cortex), and cuneus (occipital lobe) for internal attention, while external attention was associated with heightened activity in the dorsal attention network (DAN). Cooper et al. [15] found heightened alpha band amplitudes during internally directed attention, indicating active blocking of external stimuli. Additionally, Braboszcz and Delorme [16] reported that alpha power correlates with low alertness and mind

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[1]https://github.com/hendrik912/EEG_channel_importance

wandering, suggesting its involvement in states of reduced external focus.

2) Attention Classification: Putze et al. [17] achieved up to 81.2% accuracy in single trial classification of internal/external attention using EEG in an HCI context, employing the LDA classifier. Similarly, Vortmann et al. [18] used LDA for person-dependent classification and achieved an average accuracy of 70.58% on newly collected data, while their augmented reality-based experiment resulted in an average accuracy of 85.37%. Alpha and gamma bands of frontal channels were found to contain critical information for classification [19]. Vortmann and Putze [20] further investigated different models, window lengths, and person-independent classification using a shallow neural net with a window length of 4 seconds, achieving an average accuracy of 60% and 88% for selected participants. Eilts and Putze [21] achieved up to 72% accuracy in person-dependent classification with the same dataset using the Shallow Filter Bank Common Spatial Patterns Network.

3) Feature Selection: The literature offers a wide range of feature selection methods for EEG data, aiming to reduce computational costs, prevent overfitting, and enhance model interpretability by eliminating uninformative features or entire channels. These methods have been extensively explored in various tasks such as seizure detection, motor imagery, emotion recognition, mental task classification, drug effects diagnosis, and sleep state classification [22]. Some of these methods include mutual information [22], feature elimination (backward, forward, recursive) [22], short time Fourier transform (STFT) [23], and deep learning-based approaches [24]–[26]. Surprisingly, no studies have specifically focused on the internal/external attention classification task. As attention-based BCIs play a crucial role in adaptive systems, determining the most relevant electrodes is a vital step towards real-world applications. Additionally, there is a need for further research on comparing channel selection methods and datasets, which we address in this study.

II. Methods

The overall pipeline for preparing the data, calculating the feature and channel importance as well as the training of the classification models is shown in figure 1.

A. Data

We used three different datasets on attention detection for our analysis. All are based on the concept of internally- or externally-directed attention.

1) Dataset A: Dataset A was collected by Vortmann et al. [18] and consists of EEG data recorded from 12 participants during various attention tasks performed on a desktop computer. The dataset contains 94 trials of 6 seconds per subject. EEG signals were recorded using the Brainvision ActiChamp EEG system with 32 channels (10/20 layout) and a sampling rate of 500 Hz.

2) Dataset B: Vortmann et al. [19] conducted an externally and internally directed attention task in augmented reality using Microsoft HoloLens. The dataset, referred to as dataset B, includes 15 participants, each with 72 trials of 15 seconds for the internal task and 20 seconds for the external task, recorded using the g.tec Nautlius mobile 16-channel EEG system with a sampling rate of 500 Hz.

3) Dataset C: Ceh et al. [27] recorded EEG data from 36 participants during convergent and divergent thinking tasks that were divided into internally and externally directed attention by masking the task stimulus after 500ms. Data were recorded using a BrainAmp amplifier at a 1000 Hz sampling rate with 19 active electrodes placed according to the 10/20 layout. Each participant had 44 trials with an active phase of 20s (19.5s for the internal condition), and we merged the convergent and divergent trials with the same attention class, leaving two classes: internally and externally directed attention.

4) Preprocessing: We filtered each dataset with a 1-60 Hz bandpass filter and notch filtered at 50 Hz to remove power line noise, then re-referenced the data to the average of all channels. We resampled the datasets to 120 Hz to reduce computational effort and memory requirements. To remove eye, muscle and heartbeat artifacts, we used the ICLabel [28] algorithm. The datasets were segmented into non-overlapping 3-second windows. For dataset B, we excluded the broken channels and selected the subset that was present in all participants and from each trial, we considered only the range of 1-13 seconds, consistent with Vortmann et al. [19].

5) Feature Extraction: We calculate various statistical measures for power spectral densities (PSDs) of delta, theta, alpha, beta, and gamma frequency bands extracted using multitaper method, similar to Vortmann et al. [18], including mean, standard deviation, median, peak-to-peak, minimum, and maximum values. We split the frequencies as follows: δ (delta, 1-4 Hz), θ (theta, 4-8 Hz), α (alpha, 8-14 Hz), β (beta, 14-30 Hz), γ_1 (lower gamma, 30-45 Hz), γ_2 (upper gamma, 45-60 Hz). This results in a feature set with the size of number of channels $\times$ number of frequency bands $\times$ number of statistical measures.

B. Channel Importance

To calculate the importance of each EEG channel, we apply feature importance methods to the features of the datasets, which are in the form of *[channel]_[average, min, max, standard deviation, peak-to-peak]_[delta, theta, alpha, beta, gamma]*. We use model-oblique feature importance methods, which are not tied to a specific type of classifier to maintain generalizability.

1) Method 1: Random Forest Importance: Decision trees and random trees rank features by importance based on the optimization of the Gini impurity splitting criterion. The Random Forest Classifier (RFC) calculates feature importance by averaging the impurity reduction of each feature over all trees and splits [29]. In our experiment, the number

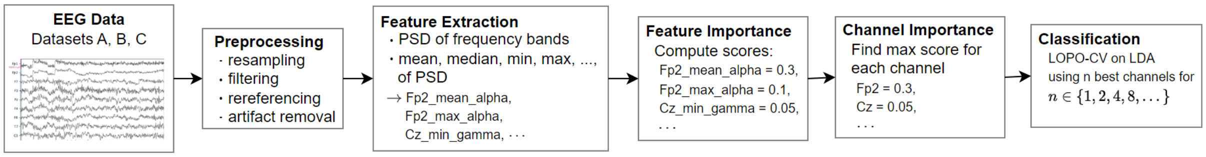

Fig. 1. Pipeline depicting the sequential stages from preprocessing of raw EEG data to LDA classifier training on the n best subsets of EEG channels. Channel importance is determined by finding the maximum value associated with each channel. For example, if features Fp2_mean_alpha and Fp2_max_alpha have scores of 0.3 and 0.1, respectively, the channel Fp2 is assigned a score of 0.3 as it represents the maximum value within that channel.

of trees in the RFC was chosen to be the square root of the number of features.

2) Method 2: Mutual Information: Mutual information measures the mutual dependence between two random variables, with 0 indicating no dependence. For feature selection, we measure the dependence between features and the label, using mutual information as a metric. We use an algorithm based on k nearest neighbor distances ($k = 3$) to estimate entropy, following the approach proposed by Ross et al. [30].

3) Method 3: Permutation Importance: We use the Permutation Feature Importance (PI) algorithm to measure the importance of a feature [31]. This involves permuting the feature's values and measuring the increase in the prediction error of a pre-trained Linear Discriminant (LDA) classifier using the accuracy metric. PI is repeated 10 times, and the importance scores are aggregated using a leave-one-person-out cross-validation (LOPO-CV) to include information about each person in the data.

4) Method 4: Ablation Study: The ablation study directly determines the importance of EEG channels by measuring the decrease in accuracy after excluding each channel. This is done for all channels using a LOPO-CV approach. The score is calculated as the difference in accuracy between the original model and a model with a channel excluded, and is averaged across CV folds.

5) Method 5: Shapely Additive Explanations (SHAP): Shapely Additive Explanations (SHAP) [32] is a cooperative game theory algorithm that computes the average expected marginal contribution of a feature using Shapely Values. We use a random forest regressor with $\approx \sqrt{\text{number of features}}$ trees as the model and perform LOPO-CV to compute the values on the test data. Finally, we concatenate the resulting Shapely values and compute the mean of the absolute values for each feature

6) Aggregation: The above methods only calculate the importance of one feature (e.g., Fp2_mean_alpha) and not the entire channel, except for the ablation study. Therefore, we need to combine the values for each feature into a single value. To find the score for the entire channel, we go through the list of importance values and find the maximum score for each channel, as described in Figure 1.

7) Comparison of Feature Importance Methods: To enable comparison of importance score vectors, obtained from different methods, we employed euclidean normalization by first subtracting the minimum value and then dividing by the square root of the sum of the squares of each value. Subsequently, we assessed the pairwise Spearman rank correlation coefficient between electrode rankings obtained from each method. Electrodes were ranked from 1 (highest) to n (total number of channels). Additionally, we evaluated the consistency of rankings within Cross Validation (CV) folds for SHAP, Permutation Importance, and the Ablation Study. This was accomplished by computing the Spearman rank correlation between rankings for each fold. Notably, this analysis was not conducted for Random Forest and Mutual Information, as their importances were not computed per CV fold.

C. Classification

Ultimately, we consider classification performance as the central measure for evaluating and comparing the different importance metrics: When selecting channels that are assigned high importance, the model should achieve a comparably high classification performance.

1) Model: In a preliminary analysis, we compared several lightweight classification models such as the Random Forest Classifier (RFC), Linear Discriminant Analysis (LDA), Support Vector Machines (SVM), and several boosting algorithms using different hyperparameter configurations. We chose the LDA classifier with singular value decomposition (SVD) and automatic shrinkage using the Ledoit-Wolf lemma with 1 component, since it performed the best across all datasets. Due to high computation time and in line with the recommendations by [33] for small datasets, we decided against the using of deep learning algorithms.

2) Cross Validation: Performing a LOPO-CV allows for generalization across participants in EEG data. Data from one person are used for testing while data from all other participants are used for training. For each fold, accuracy is calculated and then averaged across all folds.

3) Channel Selection: We perform a LOPO-CV on the LDA classifier based on the n best channels as given by the feature importance algorithm. We iterate over different values of n, starting at 1 and double it at each iteration until the maximum is reached. In this way, we can track how the performance of the model is for each subset of channels.

4) Baseline: To test whether the rankings actually affect performance, we also compute a baseline by reversing the order of the importance rankings, thus choosing the n worst channels for each subset of channels.

5) Statistical Analysis: To assess the accuracy of the model, we used a bootstrapping approach [34] to compute the confidence interval for the accuracy metric with B = 1000 bootstrap samples and a confidence level of 0.95. To compare the accuracy of the model to a baseline, we used a paired t-test with a significance level of 0.05.

III. Results & Discussion

In the following, we use acronyms for the feature importance methods to keep the figures concise:

- RF: Random Forest Importance
- MI: Mutual Information Importance
- PI: Permutation Importance
- AS: Ablation Study
- SHAP: Shapely Additive Explanations

A. Feature Importances

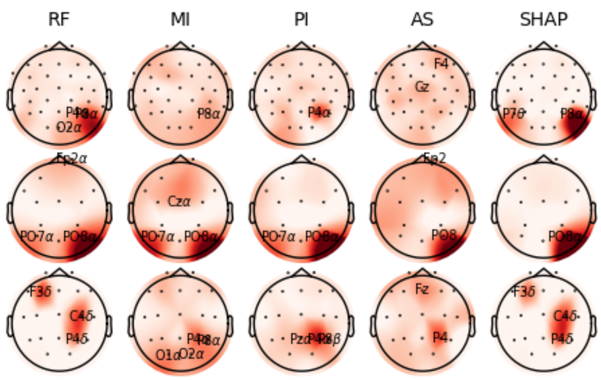

Fig. 2. Topographic map displaying the normalized importance scores for each channel and associated frequency band for all datasets A-C and all feature importance methods. Only channels with importance scores exceeding 0.3 are presented. It should be noted that the Ablation Study (AS) does not incorporate information regarding frequency bands.

Figure 2 displays the normalized importance values for each EEG channel in a topographic activation map. Only channels with importance scores exceeding 0.3 (i.e., $\geq 30\%$ of the maximum) are shown along with their associated frequency bands.

Across all datasets and methods, the right parietal, occipital, and frontal regions consistently exhibit the highest importance. Particularly noteworthy are $P8_\alpha$ and $PO8_\alpha$ in terms of their magnitude in the parietal region. Dataset B also highlights the significance of the left parietal region ($PO7_\alpha$), while dataset C focuses more on channel $P4_\delta$ instead of $P8_\alpha$. The choice of frontal channels varies between datasets and method, but $Fp2_\alpha$, $F3_\delta$ stand out.

In Figure 3 a), the cumulative importance scores across feature importance algorithms are presented. For clarity, only the frequency bands of channels with an importance score of at least 0.3 are displayed. As anticipated, P8/PO8 emerges as the highest-ranked channel for datasets A and B, whereas P4 takes precedence in dataset C and becomes the second highest-ranked channel in dataset A. P7/PO7 ranks 3rd and 2nd for datasets A and B, respectively. However, the representation of frontal channels is not as prominent as suggested by the topographic plot due to variations in frontal channels across datasets and methods. Notably, the high importance of the parietal channels (P8, PO8, P4) within the alpha frequency range is consistent with previous studies [13]–[16] that emphasize the importance of alpha bands in the right parietal lobe. The somewhat increased importance of frontal channels supports the findings of Vortmann et al. [19]. Although there are similarities between the datasets, there are also differences that may depend on the experimental setup.

B. Classification

Figure 3 b) illustrates accuracy values obtained from different feature importance methods. The error bars represent the 95% confidence interval, and the numbers denote statistical significance (paired t-test, $p < 0.05$) compared to the baseline accuracy. For dataset A, statistically significant highest average accuracies of approximately 63% are achieved by the MI and SHAP methods when utilizing 8 channels. Notably, reducing the number of channels to 2 (RF, $p = 0.019$) maintains an average accuracy of approximately 62%, employing channels $P8_\alpha$ and $P4_\alpha$. Dataset B exhibits the highest accuracies when using a single channel, specifically $PO8_\alpha$ ($0.009 \leq p \leq 0.012$). Accuracy decreases as additional electrodes are incorporated. In dataset C, the AS method attains the highest accuracy of 60% using 16 channels ($p = 0.032$). However, the difference in accuracy for varying numbers of channels is only marginally better than selecting a single electrode (approximately 58.5%). The choice of electrode varies between P4, C4, and F3. Thus, effectively reducing the number of channels to 1 or 2 does not result in a significant performance loss. It is important to note the low overall accuracy compared to related studies of the datasets, limiting the generalizability of the results. This discrepancy arises from employing a person-independent training approach, aiming to identify channels and features of high importance across all subjects. Consequently, activity that may be relevant but specific to individual participants is omitted.

C. Correlation

Figure 4 a) presents the pairwise Spearman rank correlations between feature importance methods, as a measure of their agreement. The correlations range from absent to moderate, with mostly positive values across all datasets. However, AS in dataset A and B exhibits negative correlations compared to MI and PI, respectively. Dataset C demonstrates a higher degree of low to absent correlation in the rankings. These correlation patterns align with the different activity patterns observed in Figure 2. Notably, dataset C shows a high correlation and similar channel importance patterns between RF and SHAP. Figure 4 b) displays the correlations between rankings obtained from each LOPO-CV-fold, which were used to calculate the importance for PI, AS, and SHAP. Generally, the rankings appear consistent across subjects for datasets A to C, except for AS, which exhibits more variability. Notably, the rankings of SHAP in dataset C demonstrate a high level of consistency, as it assigns a weight of zero to most channels, preserving the initial order for the remaining channels. Overall, these findings suggest the

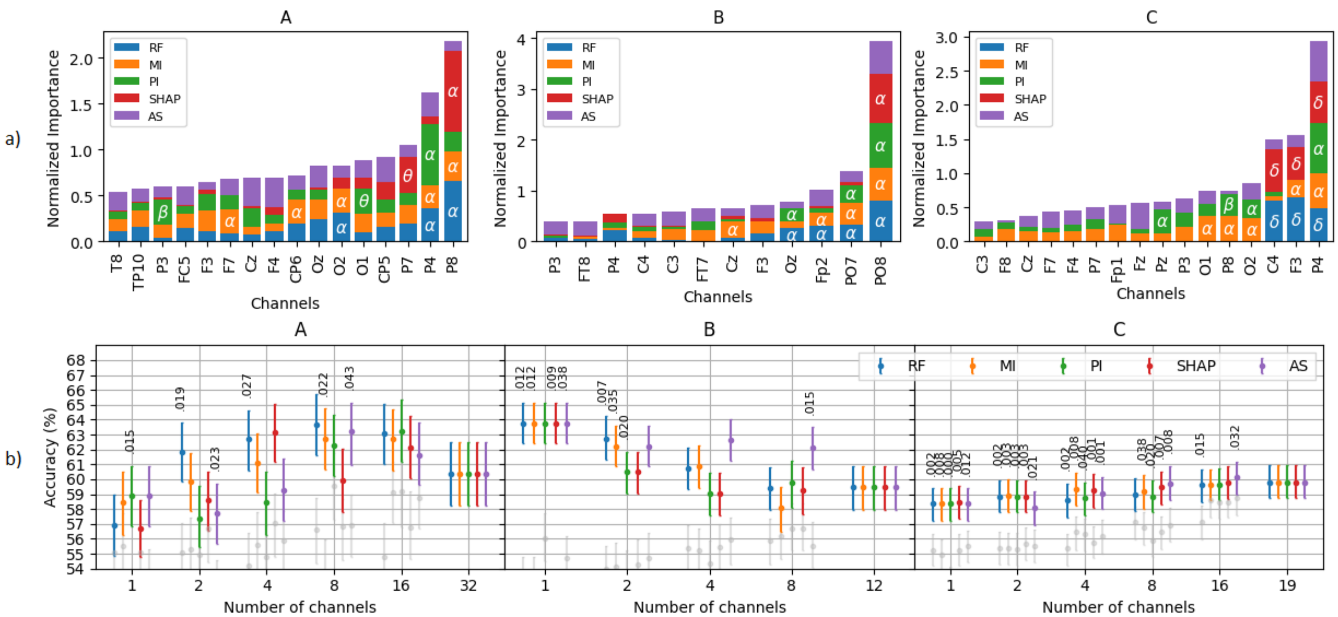

Fig. 3. **a)** Stacked bar chart displays normalized feature values for each method applied to EEG channels, arranged by ascending importance scores. Greek symbols denote frequency bands, excluding AS. Only bands with importance values ≥ 0.3 are shown. Scores range from 0 to 1, with a maximum cumulative score of 5. **b)** Accuracy values and confidence intervals for channel subsets based on importance rankings. Gray error bars represent baseline. Numerical values indicate significant differences from the baseline ($p < 0.05$, paired t-test).

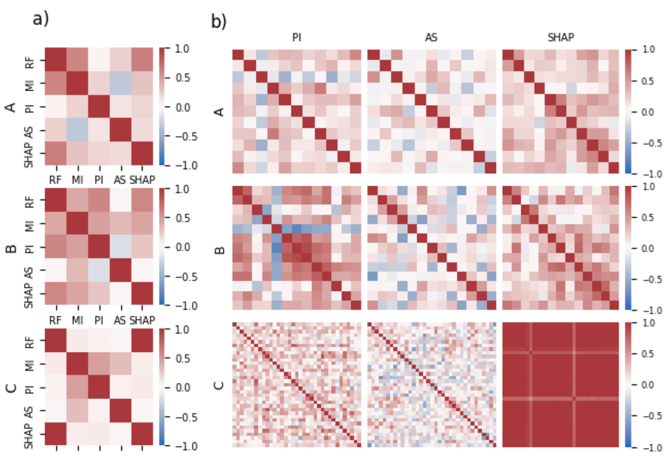

Fig. 4. **a)** Spearman Rank Correlation between the rankings of feature importance methods. **b)** Spearman Rank Correlation between the channel rankings of each LOPO-CV-fold.

presence of significant similarities among participants, albeit to varying degrees.

IV. Conclusion

Across all datasets, the right parietal region (P8, PO8, P4) emerges as the most important for the internal/external attention task. Additionally, some importance is observed for the left parietal, occipital, and frontal regions. Our analysis encompassed three distinct datasets, and while there were slight variations, the overall results were similar. This suggests that the observed importance is influenced by the attentional state itself rather than solely being dictated by the specific experimental design. Furthermore, our findings demonstrate that significant reduction in the number of channels (1-2 channels) can be achieved while maintaining satisfactory classification performance across all datasets and even increasing it substantially for datasets A and B. By reducing the number of channels, computational costs can be minimized, overfitting can be prevented, and model interpretability can be improved. Importantly, this study represents the first investigation into the feature importance for internal/external attention. By filling this research gap, we provide novel insights into the specific channels that contribute significantly to the classification of attention states. Regarding the rankings of the feature importance methods, positive correlations were observed among the rankings for all datasets, except for the ablation study, which displayed negative correlations in isolated cases. This indicates a consistent pattern in the rankings of channel importance across the employed methods.

A. Future Work

In future work, we will consider deep learning methods on larger data sets. For these, we will face the challenge of feature interpretability for architectures which process raw EEG data. Furthermore, we want to investigate the creation of custom minimal electrode setups for real-world attention-related BCIs based on right-parietal and frontal electrodes. Available low-cost headset (such as InteraXon Muse) often focus on frontal electrodes alone, which this work shows is not optimal for all applications.

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