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KM-CV-SAM: A Weighted K-Means Band Selection Method for Hyperspectral Image Classification

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Abstract Hyperspectral image (HSI) classification is an active research area with various applications, including forestry, land cover analysis, defense, and environmental monitoring. Along with numerous applications, HSI analysis is challenging due to the large number of spectral bands with high redundancy, which demands high computational cost. Band selection plays an important role in identifying compact and informative spectral band subsets. To this end, this article presents a weighted clustering-based band selection framework termed KM-CV-SAM. The proposed approach follows a two-step process. First, a weight is assigned to each band. In the second step, weighted bands are grouped into a predefined number of clusters, and representative bands are selected from each cluster. The weight for each band is computed using the Coefficient of Variation (COV) and Spectral Angle Mapper (SAM), thereby emphasizing discriminative and information-rich bands and yielding more representative and diverse subsets.

To establish the effectiveness of the proposed approach, a rigorous experimental study has been conducted on publicly available benchmark HSI datasets, including Indian Pines, Pavia University, Salinas, and WHU-Hi-LongKou, covering a wide range of land-cover classes and imaging conditions. Experimental results show that KM-CV-SAM consistently outperforms several state-of-the-art band selection techniques. The model achieves improved classification accuracy with only 5–30 selected bands with a little compromise in classifcation accuracy. The proposed framework is well suited for practical hyperspectral applications, particularly in scenarios with limited labeled samples and constrained computing resources.

Keywords Dimensionality Reduction, Band Selection, Clustering, Hyperspectral Image, K-Means

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1 Introduction

Band selection (BS) plays a crucial role in improving the performance of downstream hyperspectral image analysis tasks such as classification, detection, and material identification [1, 2]. By selecting a compact and informative subset of spectral bands, BS reduces computational complexity, and enhances model generalization. From a machine learning perspective, band selection in HSI is closely related to feature selection and can be broadly addressed using filter, wrapper, and hybrid strategies [3]. Filter methods rely on statistical, information-theoretic, or similarity-based measures to independently rank or score spectral bands without involving any classifier. Wrapper methods evaluate candidate band subsets based on their impact on classification performance, while hybrid methods combine the advantages of both filter and wrapper approaches to improve selection efficiency and robustness [4].

Band selection can be performed using supervised and unsupervised methods. Supervised methods exploit labeled samples to guide the selection process toward improved class discrimination; however, their effectiveness is limited in practical hyperspectral scenarios due to the scarcity and high cost of ground truth data [5]. Unsupervised methods, on the

other hand, depend solely on the intrinsic properties of hyperspectral data and are therefore more suitable for large-scale and operational environments. Recent developments in unsupervised band selection include information theory-based techniques [6–9], ranking approaches [10, 11], and clustering or grouping strategies [12].

Among these, clustering-based band selection has emerged as an effective strategy due to its ability to group spectrally similar bands and select representative bands from each cluster, thereby reducing redundancy while preserving essential spectral characteristics. Popular techniques such as k-means, hierarchical clustering, and spectral clustering have been widely explored in hyperspectral band grouping [12–14]. However, most existing clustering-based methods implicitly treat all spectral bands equally during clustering. In practice, different bands contribute unequally to classification performance: some bands exhibit strong spectral variability and discriminative capability, while others may be redundant or significantly corrupted by noise. Ignoring this variation may lead to suboptimal clusters and the selection of less informative representative bands, ultimately degrading classification performance. Furthermore, several recent nonlinear or deep-learning-based BS methods sacrifice computational efficiency and physical interpretability, limiting their applicability in resource-constrained or real-time systems [15].

Furthermore, although recent graph-based, subspace, higher-order, and deep learning–driven band selection methods have demonstrated improved representational capability [16–21], they often introduce increased algorithmic complexity, require large labeled datasets, and demand substantial computational resources, which limits their practicality in real-world hyperspectral applications.

To address these challenges, this study proposes a novel weighted clustering-based band selection framework termed **KM-CV-SAM**. The proposed method integrates statistical band importance directly into the clustering process through an adaptive weighting mechanism that combines two complementary measures: the Coefficient of Variation (COV), which captures intra-band statistical variability, and the Spectral Angle Mapper (SAM), which quantifies inter-band spectral distinctiveness. By assigning higher influence to informative and distinctive bands prior to clustering, the proposed framework guides k-means toward more meaningful spectral groupings and more representative band selection. Unlike conventional clustering-based BS methods, KM-CV-SAM effectively reduces redundancy while preserving discriminative spectral information without transforming the original spectral space. The proposed approach is fully unsupervised, classifier-independent, computationally efficient, and physically interpretable, making it suitable for practical hyperspectral image analysis.

The main contributions of this work are summarized as follows:

- A novel weighted clustering-based framework for hyperspectral band selection that integrates band importance with unsupervised k-means clustering.
- An adaptive band weighting strategy based on COV and SAM that prioritizes spectrally informative and distinctive bands, overcoming the limitations of conventional equal-weight clustering methods.
- Extensive experimental validation on four benchmark hyperspectral datasets—Indian Pines, Pavia University, Salinas, and WHU-Hi-LongKou—using Support Vector Machine and Random Forest classifiers, demonstrating superior classification performance with fewer selected bands compared to state-of-the-art methods.
- A computationally efficient and scalable solution with linear complexity, suitable for high-dimensional hyperspectral data and limited-label scenarios.

The remaining part of this paper is organized as follows. Section 2 describes the proposed KM-CV-SAM framework. Section 3 presents the datasets, experimental setup, and comparative analysis in Section 4. Finally, Section 5 concludes the paper and outlines future research directions.

2 Methodology

This section presents the proposed *Weighted Band Clustering–based Band Subset Selection* framework, termed **KM-CV-SAM**, for hyperspectral image analysis. The core objective of the proposed method is to explicitly integrate band importance into the clustering process in order to identify a compact subset of representative and discriminative spectral bands. By incorporating statistical variability and spectral distinctiveness into clustering, the proposed framework effectively reduces inter-band redundancy while preserving the physical interpretability of the original hyperspectral data.

2.1 Problem Formulation

Let $X \in \mathbb{R}^{B\times N}$ denote a hyperspectral image, where B represents the number of spectral bands and N denotes the total number of pixels. Each row vector $\mathbf{x}_j \in \mathbb{R}^N$ corresponds to the spectral response of the j-th band.

The objective of hyperspectral band selection is to determine a subset of informative bands such that the selected subset preserves the discriminative spectral characteristics of the original data while minimizing spectral redundancy.

2.2 Motivation for Weighted Band Clustering

Conventional clustering based band selection methods implicitly assume that all spectral bands contribute equally dur-

ing the clustering process. However, hyperspectral data exhibit substantial variability across bands, where only a subset of bands typically carries strong discriminative information, while others may be redundant or significantly affected by noise and atmospheric disturbances. Treating all bands uniformly may therefore result in suboptimal cluster formation and the selection of less informative representatives.

To overcome this limitation, the proposed KM-CV-SAM framework introduces an adaptive band weighting mechanism prior to clustering. By assigning higher importance to bands that exhibit stronger statistical variability and spectral distinctiveness, the clustering process is guided toward more meaningful spectral groupings, leading to the selection of a compact yet discriminative band subset.

2.3 Band Weight Computation

Each spectral band is assigned a weight that reflects both its internal variability and its spectral distinctiveness with respect to other bands. This is achieved by integrating the Coefficient of Variation (COV) and the Spectral Angle Mapper (SAM).

2.3.1 Coefficient of Variation (COV)

The COV quantifies the relative dispersion of spectral intensities within an individual band and is defined as

$$\mathrm{COV}_j = \frac{\sqrt{\sum_{i=1}^{N} (x_{ij} - \overline{x}_j)^2}}{(N-1)\,\overline{x}_j}, \tag{1}$$

where x_{ij} denotes the spectral intensity of the i-th pixel in the j-th band, and $\overline{x}_j$ represents the mean intensity of the j-th band. Bands with higher COV values indicate stronger spectral variability and are more likely to possess discriminative information.

2.3.2 Spectral Angle Mapper (SAM)

SAM measures the spectral dissimilarity between two spectral bands by computing the angle between their corresponding spectral vectors:

$$\theta(\mathbf{x}_d, \mathbf{x}_j) = \arccos\left(\frac{\mathbf{x}_d^\top \mathbf{x}_j}{\|\mathbf{x}_d\|_2 \, \|\mathbf{x}_j\|_2}\right). \tag{2}$$

For each band, the average spectral angle with respect to all remaining bands is computed as

$$S_j = \frac{1}{B-1} \sum_{\substack{d=1 \\ d \neq j}}^{B} \theta(\mathbf{x}_d, \mathbf{x}_j), \tag{3}$$

where a larger value of S_j indicates greater spectral distinctiveness and reduced redundancy.

2.3.3 Band Weight Definition

The final importance weight assigned to each spectral band is defined by jointly considering COV and SAM:

$$w_j = \frac{\exp\left(\mathrm{COV}_j \times S_j\right)}{\sum_{k=1}^{B} \exp\left(\mathrm{COV}_k \times S_k\right)}, \quad j = 1, 2, \ldots, B. \tag{4}$$

This exponential normalization emphasizes bands that simultaneously exhibit strong variability and high spectral distinctiveness, while suppressing less informative or redundant bands.

2.4 Weighted Spectral Representation

Using the computed band weights, the original hyperspectral data are transformed into a weighted spectral representation as

$$X_w = X \cdot \mathrm{diag}(w_1, w_2, \ldots, w_B). \tag{5}$$

For band-wise clustering, the weighted representation is expressed as

$$X_w^\top \in \mathbb{R}^{B \times N}, \tag{6}$$

where each row corresponds to a weighted spectral band vector. This transformation ensures that informative bands exert greater influence during the clustering process.

2.5 Band Clustering and Representative Selection

K-means clustering is applied to the weighted band vectors to partition the B spectral bands into K clusters by minimizing the intra-cluster variance:

$$\min_{\{\mathcal{C}_k\}_{k=1}^{K}} \sum_{k=1}^{K} \sum_{j \in \mathcal{C}_k} \left\| \mathbf{x}_j^{(w)} - \boldsymbol{\mu}_k \right\|_2^2, \tag{7}$$

where $\boldsymbol{\mu}_k$ denotes the centroid of the k-th cluster and $\mathbf{x}_j^{(w)}$ represents the weighted spectral vector of the j-th band.

For each cluster, a representative band is selected as the band closest to the corresponding centroid:

$$j^* = \arg\min_{j \in \mathcal{C}_k} \left\| \mathbf{x}_j^{(w)} - \boldsymbol{\mu}_k \right\|_2. \tag{8}$$

The final selected band subset $\mathcal{S}$ is formed by collecting one representative band from each cluster.

2.6 Algorithm Description

The complete KM-CV-SAM band selection procedure is summarized in Algorithm 1. The framework first computes adaptive band weights using COV and SAM, constructs a weighted spectral representation, and subsequently applies k-means++ clustering to identify representative bands.

Algorithm 1 Band Selection using KM-CV-SAM

1: **Input:** Hyperspectral image $X \in \mathbb{R}^{(m \times n) \times B}$, number of clusters K.
2: **Output:** Selected band subset $\mathcal{S}$.
3: Compute band weights w_j using COV and SAM (Eq. 4).
4: Construct the weighted band matrix $X_w^\top \in \mathbb{R}^{B \times N}$.
5: Initialize K cluster centers using the k-means++ strategy.
6: Assign each band to the nearest cluster center.
7: Update cluster centers and reassign bands.
8: Repeat until convergence.
9: Select one representative band from each cluster to form $\mathcal{S}$.

2.7 Computational Complexity Analysis

Let B denote the number of spectral bands, N the number of pixels, K the number of clusters, and T the number of k-means iterations.

- Band weight computation: $\mathcal{O}(BN)$
- K-means clustering: $\mathcal{O}(BKT)$

Since $K \ll B$ and T is typically small, the overall computational complexity scales approximately linearly with respect to the number of spectral bands and pixels, making the proposed KM-CV-SAM framework computationally efficient and suitable for large-scale hyperspectral datasets.

3 Experimental Setup

This section describes the datasets, experimental protocol, and evaluation criteria used to assess the performance of the proposed KM-CV-SAM band selection framework. Experiments were conducted on four widely used hyperspectral benchmark datasets, namely Indian Pines, Salinas, Pavia University, and WHU-Hi-LongKou, representing agricultural, urban, and UAV-based scenarios with diverse spatial and spectral characteristics.

The Indian Pines [1] dataset was acquired by the AVIRIS sensor over an agricultural region in Indiana, USA, and consists of 145×145 pixels with 224 spectral bands after removing noisy and water absorption bands, containing 16 land-cover classes. The Salinas dataset, also captured by AVIRIS over the Salinas Valley, California, USA, comprises 512×217 pixels with 224 spectral bands and includes 16 vegetation classes. The Pavia University dataset was collected by the ROSIS sensor over Pavia, Italy, and contains 610×340 pixels with 103 spectral bands after noise removal and nine urban land-cover classes. The WHU-Hi-LongKou [2] dataset is a UAV-borne hyperspectral image acquired using a Headwall Nano-Hyperspec sensor over Longkou, China. It consists of 550×400 pixels with 270 spectral bands and covers nine agricultural crop types [22].

The proposed KM-CV-SAM method was compared with several representative unsupervised band selection approaches, including BRECV [23], EFDPC [24], OCF [12], CV-BDS [25], and conventional unweighted K-Means clustering. To evaluate the discriminative capability of the selected band subsets, Support Vector Machine (SVM) with RBF kernel and Random Forest (RF) classifiers were employed. Overall Accuracy (OA) was used as the primary evaluation metric.

For each dataset, 60% of labeled samples were randomly selected for training and the remaining 40% for testing. All experiments were repeated ten times with different random splits, and the mean and standard deviation were reported. SVM hyperparameters were optimized using five-fold cross-validation. The number of selected bands was varied from 10 to 50 for sensitivity analysis, and all clustering-based methods employed k-means++ initialization. All methods were evaluated using identical training–testing splits to ensure fair comparison.

4 Results and Analysis

The experimental results demonstrate the effectiveness of the proposed KM-CV-SAM framework in selecting compact and discriminative band subsets. The influence of the number of selected bands was first examined on the Pavia University dataset by varying the band count from 10 to 50. As reported in Table 1, classification accuracy consistently increases with the number of selected bands and stabilizes beyond 30 bands. KM-CV-SAM significantly outperforms unweighted K-Means for all band configurations and achieves high classification accuracy even with a small number of bands, highlighting the advantage of incorporating band importance into the clustering process.

To analyze the diversity of selected bands, the subsets obtained for the WHU-Hi-LongKou dataset are reported in Table 2. Conventional K-Means primarily selects spectrally adjacent bands, indicating higher redundancy, whereas KM-CV-SAM selects bands distributed across the spectral range, demonstrating improved representativeness and reduced correlation among selected bands.

Further comparisons with state-of-the-art unsupervised band selection methods are presented in Table 3. Using 20 selected bands and the RF classifier, KM-CV-SAM achieves the highest classification accuracy across all datasets. The improvement is particularly evident on the Indian Pines and WHU-Hi-LongKou datasets, which are characterized by high spectral variability and complex class distributions.

The robustness of the proposed method is reflected by the low standard deviation values across ten independent runs, and paired t-tests confirmed that the performance gains

[1] https://www.ehu.eus/ccwintco/index.php/Hyperspectral_Remote_Sensing_Scenes

[2] https://rsidea.whu.edu.cn/resource_WHUHi_sharing.htm

Table 1 Overall Accuracy on Pavia University dataset (mean ± std over 10 runs)

#Bands	KM-SVM	KM-RF	KM-CV-SAM-SVM	KM-CV-SAM-RF
10	0.878±0.0014	0.890±0.0009	**0.973±0.0006**	**0.974±0.0005**
20	0.900±0.0009	0.912±0.0012	**0.979±0.0007**	**0.982±0.0003**
30	0.975±0.0007	0.978±0.0004	**0.982±0.0008**	**0.984±0.0003**
40	0.983±0.0010	0.983±0.0003	**0.986±0.0006**	**0.987±0.0006**
50	0.985±0.0011	0.984±0.0004	**0.988±0.0009**	**0.987±0.0007**

Table 2 Band Subset for LongKou Dataset with both K-Means and KM-CV-SAM

	Band Subset
No of Bands	**KM**
30	0,124,126,122,125,123,121,127,120,128,119,118,129,117,116,130,115,114,113, 112,164,131,239,166,162,220,237,221,218,225
No of Bands	**KM-CV-SAM**
30	1,2,3,4,5,131,115,114,113,132,55,56,57,58,59,0,130,116,117,129,189,190,188, 164,191,139,144,140,143,142

Table 3 Overall Accuracy comparison across all datasets (20 bands, RF classifier)

Method	Indian Pines	Salinas
BRECV [23]	0.654±0.008	0.766±0.005
EFDPC [24]	0.672±0.007	0.812±0.004
OCF [12]	0.698±0.006	0.897±0.003
CV-BDS [25]	0.715±0.005	0.882±0.004
KM	0.641±0.012	0.894±0.004
KM-CV-SAM	**0.781±0.003**	**0.930±0.003**

are statistically significant. The computational efficiency of the proposed framework is reported in Table 4. Figure 1 provides the clear advantage of using band weight approach with clustering on various data sets. KM-CV-SAM maintains execution time comparable to unweighted K-Means and is significantly faster than optimization-based methods, indicating that the improved performance is achieved without substantial computational overhead.

The qualitative effectiveness of KM-CV-SAM is further illustrated by the classification maps shown in Figure 2. The proposed method produces more homogeneous regions and fewer misclassified pixels compared to unweighted clustering, particularly in spectrally mixed areas. Overall, the results confirm that explicitly integrating band importance into the clustering process enables KM-CV-SAM to select compact, diverse, and highly discriminative band subsets across different hyperspectral scenes.

5 Conclusion

This paper presented KM-CV-SAM, a novel weighted k-means band selection framework for hyperspectral image classification. The key innovation lies in the integration of statistical band importance—quantified through Coefficient of Variation (COV) and Spectral Angle Mapper (SAM)—into the clustering process, enabling more informed selection of representative bands. Unlike conventional clustering-based methods that treat all bands equally, KM-CV-SAM adaptively weights bands based on their discriminative potential before clustering, resulting in more diverse and informative band subsets.

Comprehensive experiments on four benchmark hyperspectral datasets demonstrated that KM-CV-SAM consistently outperforms state-of-the-art band selection methods in terms of classification accuracy, achieving improvements of 3–32% over existing approaches. The method achieves near-optimal performance with only 20–25 bands, significantly reducing dimensionality while preserving discriminative information. Furthermore, KM-CV-SAM maintains computational efficiency comparable to unweighted k-means and exhibits strong statistical stability across multiple experimental runs.

Despite its effectiveness, the current framework relies on handcrafted statistical measures for band weighting. Future work will focus on:

1. **Learning-based weighting strategies** that automatically adapt to dataset characteristics using attention mechanisms or metric learning.
2. **Integration of spatial information** to enable joint spectral-spatial band selection.
3. **Extension to online/streaming band selection** for real-time hyperspectral processing.
4. **Application to multimodal remote sensing data** combining hyperspectral, LiDAR, and SAR imagery.

The proposed KM-CV-SAM framework provides a robust, efficient, and interpretable solution for hyperspectral

Table 4 Execution time for band selection (seconds, $K = 20$)

Method	Indian Pines	Salinas	Pavia University	WHU-Hi-LongKou
BRECV	2.1	4.3	5.8	6.2
EFDPC	8.7	15.2	12.4	18.3
OCF	12.4	21.6	18.9	24.7
KM	1.4	2.8	3.9	4.1
KM-CV-SAM	**1.8**	**3.2**	**4.3**	**4.5**

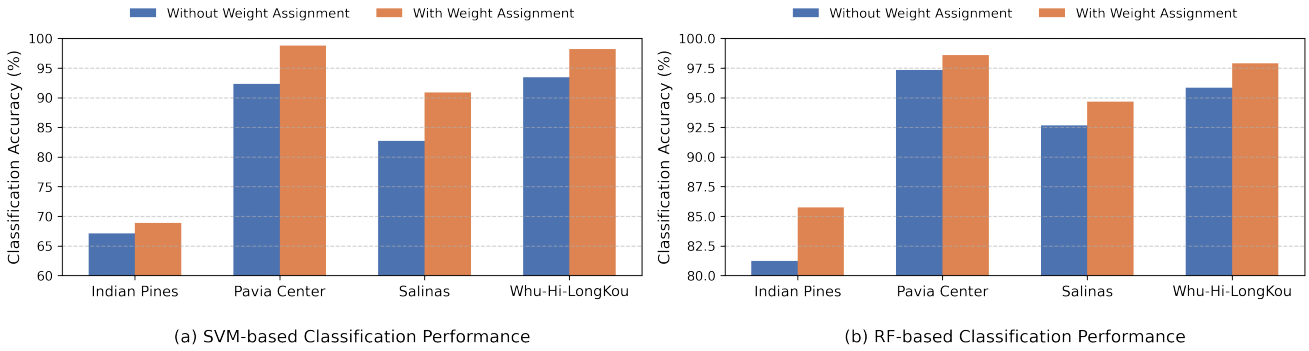


Fig. 1 Classification Accuracy of the proposed method KM-CV-SAM on various datasets using SVM and RF

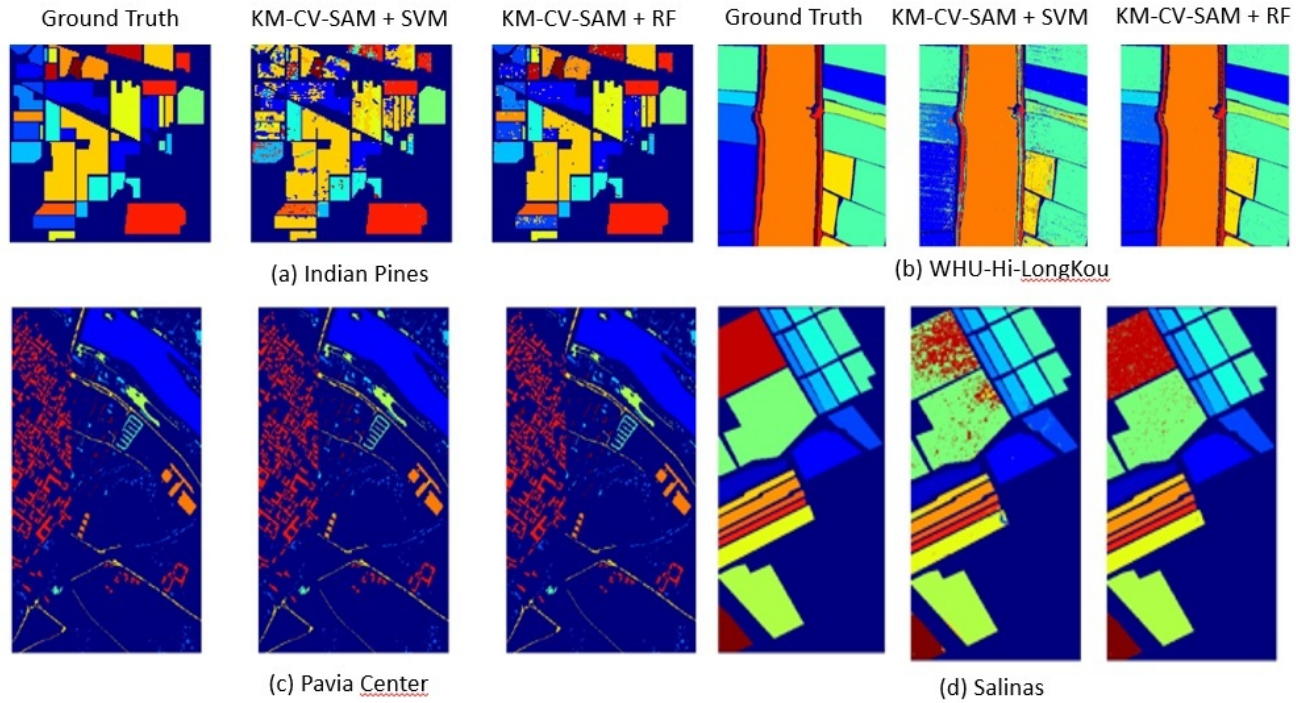


Fig. 2 Classification Maps obtained using KM-CV-SAM

band selection, particularly valuable in scenarios with limited labeled data and constrained computational resources. Code and experimental details will be made publicly available to facilitate reproducibility and further research.

6 Declarations

6.1 Funding

Not Applicable

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