Echo-aware Transformer-based Predictive Beamforming in Bistatic Integrated Sensing and Communication Systems

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***Abstract*—Spectrum scarcity motivates integrated sensing and communication (ISAC), where radar and communication coexist in a shared band. We consider bistatic ISAC systems with spatially separated transmitter and receiver to extend coverage and suppress radar self-interference. The transmit base station (BS) sends signals, while the receive BS captures radar echo signals, predicts the beamformer, and feeds this beamformer back to the transmit BS. Then, we introduce a Transformer-based predictive beamforming scheme that converts radar echo snapshots directly into downlink beamforming without perfect channel state information. The sum rate maximization problem is formulated using a penalty relaxation method that converts the constrained problem into an unconstrained problem. The formulated problem is nonconvex, and we address this issue by employing a bistatic echo-based Convolutional Transformer Network (B-ECTNet), which consists of two CNN modules and one Transformer module. Simulation results validate that the proposed method outperforms state-of-the-art baselines, achieving enhanced spectral efficiency while satisfying the radar signal-to-interference-plus-noise ratio (SINR) constraint.**

***Index Terms*—Beamforming, deep learning (DL), integrated sensing and communication (ISAC), and vehicular networks.**

I. Introduction

Rapid growth in vehicular networks is accelerating the deployment of digital city services, autonomous driving systems, and real-time monitoring applications, which demand both gigabit-level communication links and centimeter-level sensing accuracy [1]. Base stations (BSs) that separately handle communication and sensing functionalities result in inefficient use of spectrum and redundant hardware. In contrast, integrated sensing and communication (ISAC), which combines these two functionalities, achieves an effective balance between communication and sensing performance [2]–[4].

In ISAC enabled vehicular networks, beamforming is a critical task, where large antenna arrays are utilized to design radiation patterns that maximize communication rates in desired directions while simultaneously ensuring sufficient angular coverage and Doppler resolution for radar sensing. However, optimizing these conflicting objectives, wherein narrow beams improve throughput at the expense of radar coverage and broad beams enhance radar coverage at the cost of spectral efficiency, results in an inherently non-convex optimization problem [5]. Therefore, it is crucial to jointly consider both sensing and communication requirements when designing beamformer to effectively manage these inherent trade-offs.

Recent advances in ISAC beamforming focus on joint designs that balance radar sensing accuracy with communication performance, ranging from conventional optimization problem to deep learning based techniques. In [6], a transmit beamforming algorithm for multiple-input-multiple-output (MIMO) radar improves radar metrics while meeting communication quality of service constraints. For high-mobility mmWave vehicular scenarios, where precise beam tracking and kinematic prediction at roadside units are essential, an extended Kalman filter with power allocation was proposed in [7].

To reduce signaling overhead, recent studies have explored deep learning-based predictive beamforming schemes that reduce signaling overhead by bypassing explicit channel tracking and directly inferring future beams for vehicular ISAC. In [8], convolutional neural network (CNN)-long short-term memory (LSTM) hybrids and a two-stage LSTM network for beam prediction in vehicular ISAC were proposed. The LSTM-based algorithm relies heavily on channel prediction or historical channel state information (CSI), which increases signaling overhead and limits beamforming performance. Additionally, LSTM models have limited parallel processing capabilities and insufficient spatial modeling, leading to higher latency and reduced accuracy. Therefore, a promising direction is developing a high-performance, low-overhead beamformer that bypasses CSI estimation and directly generates the beamforming matrix, as exemplified by Transformer networks [9].

Although earlier studies [8], [9] focused on monostatic ISAC beamforming, the self-interference-free bistatic architecture, in which geographically separated transmit and receive arrays provide isolation and wider sensing coverage, remains largely unexplored. To bridge this gap, we propose a bistatic echo-based CNN Transformer Network (B-ECTNet) that converts real time echo snapshots into predictive beamforming vectors, thereby boosting spectral efficiency while satisfying the required radar SINR constraint.

II. System Model

We consider the vehicular networks where a transmit BS is equipped with a mmWave massive MIMO uniform linear array (ULA) consisting of N_t transmit antennas and serves K vehicle users. In a bistatic ISAC architecture, a spatially separated receive BS, located apart from the transmitter and equipped with its own N_r receive antennas, possesses high computing capability. We assume that the receive BS has high computing capability, enabling it to predict the beamformer and feed it back to the transmit BS via a backhaul connection between the receive and transmit BSs. As future work, we will investigate cases considering the limited backhaul capacity [10] between the receive and transmit BSs and analyze its impact on beamformer prediction performance. Additionally, we will explore the effect of hardware constraints due to low-resolution digital-to-analog converters (DACs) and analog-to-digital converters (ADCs) in low-power transceivers [11]–[15] as the number of antennas increases.

The BS transmits ISAC signals to the K vehicles at the n-th instant, represented as $\mathbf{s}_n(t) = [s_{1,n}(t), ..., s_{K,n}(t)]^\mathsf{T}$. At the BS, a signal $\mathbf{s}_n(t)$ is transmitted as $\mathbf{x}_n(t) = \mathbf{F}_n\mathbf{s}_n(t)$ where $\mathbf{F}_n$ is the transmit beamforming matrix. We set beamforming matrix $\mathbf{F}_n$ as $\mathbf{F}_n = [\mathbf{f}_{1,n}, ..., \mathbf{f}_{K,n}]$, where $\mathbf{f}_{k,n} \in \mathbb{C}^{N_t\times 1}$. In addition, the reflected echo signals are as follows:

$$\mathbf{r}_n(t) = \tag{1}$$

$$\psi\sum_{k=1}^{K}\beta_{k,n}e^{j2\pi\mu_{k,n}t}\mathbf{b}(\theta^{\mathsf{rx}}_{k,n})\mathbf{a}^\mathsf{H}(\theta^{\mathsf{tx}}_{k,n})\mathbf{x}_n(t-\tau_{k,n})+\mathbf{n}_r(t), \tag{2}$$

where $\psi = \sqrt{N_tN_r}$ is the antenna gain, $\beta_{k,n} = \phi/(4\pi d^{\mathsf{rx}}_{k,n}d^{\mathsf{tx}}_{k,n})$ is the reflection coefficient, $d^{\mathsf{rx}}_{k,n}$ is distance between the receive BS and the vehicle, $d^{\mathsf{tx}}_{k,n}$ is distance between the transmit BS and the vehicle, ϕ is the fading coefficient, $\theta^{\mathsf{rx}}_{k,n}$ is the receive angle of the k-th vehicle with the receive BS at the n-th instant, $\theta^{\mathsf{tx}}_{k,n}$ is the transmit angle of the k-th vehicle with the BS at the n-th instant, $\mu_{k,n}$ is the Doppler frequency, $\tau_{k,n}$ is the time-delay, and $\mathbf{n}_r(t) \in \mathbb{C}^{N_r\times 1}$ is the complex additive white Gaussion noise with zero mean and variance of σ^2, i.e., $\mathbf{n}_r(t) \sim \mathcal{N}(0, \sigma_r^2)$. Furthermore, we assume that a line-of-sight (LOS) channel is employed and the steering vectors of the transmit and receive antenna array are

$$\mathbf{a}(\theta^{\mathsf{tx}}_{k,n}) = \sqrt{\frac{1}{N_t}}[1, e^{-j\pi\cos\theta^{\mathsf{tx}}}, ..., e^{-j\pi(N_t-1)\cos\theta^{\mathsf{tx}}}]^\mathsf{T} \tag{3}$$

and

$$\mathbf{b}(\theta^{\mathsf{rx}}_{k,n}) = \sqrt{\frac{1}{N_r}}[1, e^{-j\pi\cos\theta^{\mathsf{rx}}}, ..., e^{-j\pi(N_r-1)\cos\theta^{\mathsf{rx}}}]^\mathsf{T}, \tag{4}$$

respectively.

Then, we define the received signal to interference plus noise ratio (SINR) of the receive BS as follows:

$$\xi_{k,n}(\mathbf{f}_{k,n}) \tag{5}$$

$$= \frac{\psi^2|\beta_{k,n}|^2|\mathbf{a}^\mathsf{H}(\theta^{\mathsf{tx}}_{k,n})\mathbf{f}_{k,n}|^2}{\sum_{i\neq k}^{K}\psi^2|\beta_{i,n}|^2|\mathbf{b}^\mathsf{H}(\theta^{\mathsf{rx}}_{k,n})\mathbf{b}(\theta^{\mathsf{rx}}_{i,n})|^2|\mathbf{a}^\mathsf{H}(\theta^{\mathsf{tx}}_{k,n})\mathbf{f}_{i,n}|^2+\sigma_r^2}. \tag{6}$$

The received signal of k-th vehicle at the n-th instant is

$$y_{k,n}(t) \tag{7}$$

$$= \sqrt{N_r\alpha_{k,n}}e^{j2\pi\nu_{k,n}t}\mathbf{a}^\mathsf{H}(\theta^{\mathsf{tx}}_{k,n})\sum_{i=1}^{K}\mathbf{f}_{i,n}x_{i,n}(t) + n_{k,n}(t), \tag{8}$$

where $\alpha_{k,n}$ is given by $\alpha_0(d^{\mathsf{tx}}_{k,n}/d_0)^{-\eta}$, $\nu_{k,n}$ is the Doppler frequency, and $n_{k,n}(t)$ is the noise which follows a complex Gaussian distribution with zero mean and unit variance. Here, α_0 is the path loss at a reference distance d_0 and η is the path loss exponent. Then, we define SINR of the k-th vehicle at the n-th instant can be presented as follows:

$$R_{k,n}(\mathbf{f}_{k,n}) = \frac{|\mathbf{h}^\mathsf{H}_{k,n}\mathbf{f}_{k,n}|^2}{\sum_{i\neq k}^{K}|\mathbf{h}^\mathsf{H}_{k,n}\mathbf{f}_{i,n}|^2+\sigma^2}, \tag{9}$$

where $\mathbf{h}^\mathsf{H}_{k,n} = \sqrt{N_t\alpha_0(d^{\mathsf{tx}}_{k,n}/d_0)^{-\eta}}\mathbf{a}^\mathsf{H}(\theta^{\mathsf{tx}}_{k,n})$ represents the channel vector between the BS and the vehicle.

A. Problem Formulation

We formulate an optimization problem to maximize the overall communication sum rate while satisfying the total transmit power budget and the radar SINR threshold. Accordingly, the optimization problem can be formulated as follows:

$$\underset{\mathbf{F}_n}{\text{maximize}}\ \mathbb{E}_{\mathbf{r}_{n-1}}\left[\sum_{k=1}^{K}\log_2(1+R_{k,n}(\mathbf{f}_{k,n}))\right] \tag{10}$$

$$\text{subject to}\ \ \mathrm{Tr}\left(\mathbf{F}_n\mathbf{F}_n^\mathsf{H}\right) \leq P_t \tag{11}$$

$$\xi_{k,n}(\mathbf{f}_{k,n}) \geq \Gamma_{k,n}, \tag{12}$$

where P_t denotes the maximum transmission power, the objective function includes the term $\mathbb{E}_{\mathbf{r}_{n-1}}$ that presents the ergodic average with respect to $\mathbf{r}_{n-1} = [r_{1,n-1}, \ldots, r_{K,n-1}]$, (11) is transmit power constraint of the BS, and (12) is the minimum tolerable SINR threshold to ensure sensing performance. Subsequently, we recast the optimization problem in (10) into an equivalent unconstrained form as follows:

$$\underset{\mathbf{F}_n}{\text{maximize}}\ \mathbb{E}_{\mathbf{r}_{n-1}}\left[\sum_{k=1}^{K}\log_2(1+R_{k,n}(\mathbf{f}_{k,n}))\right] \tag{13}$$

$$-\lambda_1\left(\min(0, \xi_{k,n}(\mathbf{f}_{k,n}) - \Gamma_{k,n})\right)^2 \tag{14}$$

$$-\lambda_2\left(\max(0, \mathrm{Tr}\left(\mathbf{F}_n\mathbf{F}_n^\mathsf{H}\right) - P_t)\right)^2, \tag{15}$$

where λ_1 and λ_2 are penalty parameters used to determine the magnitude of the penalty term.

Achieving the desired trade-off between communication rate and sensing accuracy depends on the careful design of

TABLE I
HYPERPARAMETERS OF THE PROPOSED B-ECTNET

Input: $\bar{\mathbf{r}}_{n-1}$ and $\bar{\mathbf{F}}_{n-1}$ with the size of $[B,2,K]$ and $[B,2N_t,K]$		
Layers/Modules/Blocks	**Parameters**	**Values**
Concatenate layer	Output shape	$[B,2+2N_t,K]$
Convolutional layer (CNN)	Kernel size	$[2{+}2N_t,\ 2N_t,\ 3]$
Activation layer (CNN)	Function	ReLU
Attention mechanism (Encoder)	Output shape	$[B,2N_t,K]$
FNN (Encoder)	Output shape	$[B,2N_t,K]$
Convolutional layer (CNN)	Kernel size	$[2N_t,\ 2N_t,\ 3]$
Activation layer (CNN)	Function	ReLU
Output: $\bar{\mathbf{F}}_n=[\mathrm{Re}\{\mathbf{F}_n\},\mathrm{Im}\{\mathbf{F}_n\}]$ with the size of $[B,2N_t,K]$		

the beamforming matrix $\mathbf{F}_n$. In addition, the reformulated unconstrained optimization problem in (15) is still non-convex. Accordingly, we propose B-ECTNet, a lightweight predictive beamforming architecture that integrates two symmetrical CNN branches for local spatial feature extraction with a Transformer encoder block for capturing global dependencies.

III. PROPOSED ALGORITHM

We first introduce the input layer of the proposed B-ECTNet. The complex echo signal $\mathbf{r}_{n-1}\in\mathbb{C}^{1\times K}$ and the previous beamformer $\mathbf{F}_{n-1}\in\mathbb{C}^{N_t\times K}$ are first decomposed into their real and imaginary components as follows:

$$\bar{\mathbf{r}}_{n-1}=\mathcal{F}\big(\mathrm{Re}\{\mathbf{r}_{n-1}\},\mathrm{Im}\{\mathbf{r}_{n-1}\}\big)\in\mathbb{R}^{B\times 2\times K} \tag{16}$$

and

$$\bar{\mathbf{F}}_{n-1}=\mathcal{M}\big(\mathrm{Re}\{\mathbf{F}_{n-1}\},\mathrm{Im}\{\mathbf{F}_{n-1}\}\big)\in\mathbb{R}^{B\times 2N_t\times K}. \tag{17}$$

Here, $\mathcal{F}(\cdot):\mathbb{R}^{B\times K}\rightarrow\mathbb{R}^{B\times 2\times K}$ and $\mathcal{M}(\cdot):\mathbb{R}^{B\times N_t\times K}\rightarrow\mathbb{R}^{B\times 2N_t\times K}$ represent the mapping function, where B denotes the batch size. Then, the output of concatenated layer is

$$\mathbf{X}_{n-1}=[\bar{\mathbf{r}}_{n-1};\bar{\mathbf{F}}_{n-1}]\in\mathbb{R}^{B\times(2+2N_t)\times K}. \tag{18}$$

This serves as the unified input to the first CNN module, ensuring that spatial features related to both the echoes and the beamformer are jointly exploited in subsequent layers.

In addition, the encoder block duplicates the CNN feature map to form the query, key, and value tensors $\mathbf{Q},\mathbf{K}$, and $\mathbf{V}\in\mathbb{R}^{B\times 2N_t\times d_k}$. Here, d_k denotes the dimensionality of the query and key vectors. Then, we apply scaled-dot self-attention, $\mathrm{softmax}(\mathbf{QK}^{\mathsf{T}}/\sqrt{d_k})\times\mathbf{V}$, to capture global dependencies. The attention output passes through a position-wise feed-forward network (FNN) and layer normalization, with identity skip connections around both sub-layers to stabilize gradients and accelerate convergence. Then, the optimzed predicted beamforming matrix using B-ECTNet algorithm can be formualted as follows:

$$\mathbf{F}_n=\mathcal{F}^{-1}(f_\omega(\bar{\mathbf{r}}_{n-1},\bar{\mathbf{F}}_{n-1})). \tag{19}$$

Here, the function $f_\omega(\cdot)$ is the nonlinear mapping employed by B-ECTNet, processing the input data together with the network parameters and producing the optimized beamformer and $\mathcal{F}^{-1}(\cdot)$ is inverse mapping function. The hyperparameters of the proposed network are provided in Table I.

A. B-ECTNet Algorithm

We divide the B-ECTNet into three steps: offline training, where the network learns the echo-to-beamformer mapping; offline validation, which assesses model generalization by detecting overfitting or underfitting; and online prediction, where the trained model uses current echoes and the previous beamformer to generate the next beamforming matrix in real time, thereby enhancing overall system performance.

1) Offline Training: During offline training, an unlabeled set $\mathcal{X}=\{(\bar{\mathbf{r}}_{n-1}^{(i)},\bar{\mathbf{F}}_{n-1}^{(i)})\}_{i=1}^{B}$ is applied to B-ECTNet. Then, using (15), the formulated loss function is as follows:

$$L_{\mathsf{B-ECTNet}}(\omega) \tag{20}$$
$$=-\frac{1}{B}\sum_{i=1}^{B}\sum_{k=1}^{K}\log_2\left(1+\frac{|\mathbf{h}_{k,n}^{\mathsf{H}}\mathbf{f}_{k,n}^{(i)}(\omega)|^2}{\sum_{i\neq k}^{K}|\mathbf{h}_{k,n}^{\mathsf{H}}\mathbf{f}_{i,n}^{(i)}(\omega)|^2+\sigma^2}\right) \tag{21}$$
$$+\lambda_1\frac{1}{B}\sum_{i=1}^{B}\left[\left(\min(0,\xi_{k,n}(\mathbf{f}_{k,n}^{(i)}(\omega))-\Gamma_{k,n})\right)^2\right] \tag{22}$$
$$+\lambda_2\frac{1}{B}\sum_{i=1}^{B}\left[\left(\max(0,\mathrm{Tr}\left(\mathbf{F}_n^{(i)}(\omega)(\mathbf{F}_n^{(i)}(\omega))^{\mathsf{H}}\right)-P_t)\right)\right], \tag{23}$$

where $\mathbf{f}_{k,n}^{(i)}(\omega)$ is k-th and i-th batch column of $\mathbf{F}_n$. Accordingly, we iteratively refine the parameters ω via back-propagation to minimize the loss. When the convergence is reached, the trained proposed model can be written as

$$f_{\omega^\star}\left(\bar{\mathbf{r}}_{n-1},\bar{\mathbf{F}}_{n-1}\right)=\mathbf{F}_n^\star. \tag{24}$$

Here, $f_{\omega^\star}$ is the mapping function of the optimal iteration mapping.

2) Offline Validation: Let us assume a validation set defined as

$$\mathcal{V}=\left\{(\ddot{\mathbf{r}}_{n-1}^{(1)},\ddot{\mathbf{F}}_{n-1}^{(1)}),(\ddot{\mathbf{r}}_{n-1}^{(2)},\ddot{\mathbf{F}}_{n-1}^{(2)}),\ldots,(\ddot{\mathbf{r}}_{n-1}^{(B)},\ddot{\mathbf{F}}_{n-1}^{(B)})\right\}.$$

Evaluating the B-ECTNet output with loss function in (23) allows us to assess its generalization performance and identify potential overfitting or underfitting.

3) Online Prediction: Finally, we test the proposed algorithm using a test example $(\bar{\mathbf{r}}_{m-1}^{(test)},\bar{\mathbf{F}}_{m-1}^{(test)})$. In this regard, the optimized predicted beamformer is formulated as follows:

$$\mathbf{F}_n^\star=\mathcal{F}^{-1}(f_{\omega^\star}(\bar{\mathbf{r}}_{n-1},\bar{\mathbf{F}}_{n-1})). \tag{25}$$

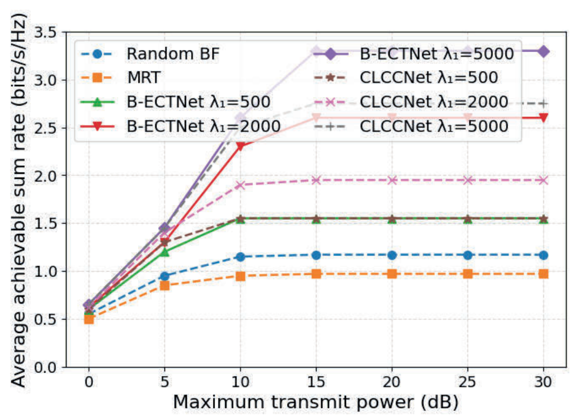
The overall proposed algorithm is summarized in Algorithm 1.

IV. SIMULATION RESULTS

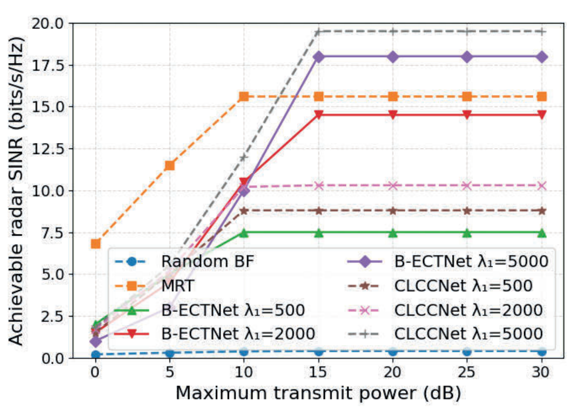
We adopt the hyperparameter configuration described in [9]. In addition, we set the path-loss exponent $\eta=2$, the reference path loss $\alpha_0=-70$ dB, the carrier frequency $f_c=30$ GHz, and noise variance $\sigma=-30$ dBm. We place the transmit BS at the origin at $(0,0)$, locate the receive BS at $(10,0)$, and uniformly distributed each vehicle users within a circular region

Algorithm 1: B-ECTNet Predictive Beamforming

initialize: $t_1 = 0$, $E_t = N_{\max}$, random weight ω, and training set $\mathcal{X}$
Unsupervised Offline Training:
  Input: Training set $\mathcal{X}$
    while $t_1 < N_{\mathsf{max}}$ **do**
      Update ω to minimze $L_{\mathsf{B-ECTNet}}(\omega)$ in (23)
  Output: Well-trained $f_{\omega^\star}(\cdot)$ in (24)
Offline Validation:
  Input: Validation set $\mathcal{V}$
    while $t_2 < N_{\mathsf{max}}$ **do**
      Save $L_{\mathsf{B-ECTNet}}(\omega)$
  Output:$L_{\mathsf{B-ECTNet}}(\omega)$
Online Beamforming Prediction:
  Input: Test sample set $(\bar{\mathbf{r}}_{m-1}^{(test)}, \bar{\mathbf{W}}_{m-1}^{(test)})$
    do Beamforming Prediction using $f_{\omega^\star}(\cdot)$
  Output: Predicted Beamforming $\mathbf{F}_n^\star$ in (25)
return $\mathbf{F}_n^\star$.



(a) Communication Performance



(b) Radar Performance

Fig. 1. The sum rate and radar SINR versus the maximum transmit power for $N = 16$ BS antennas, SINR radar threshold $\Gamma_{k,n} = 15$ dB, and $K = 4$ users.

of radius 10 m centered on the BS. We consider the following benchmarks for comparison. 1) Random beamforming (BF). 2) Maximum ratio transmission (MRT). 3) LSTM-based Net (CLCCNet), reconstructed following the method in [8].

In Fig. 1, we consider $N_t = 16$ transmit BS antennas, $N_r = 16$ receive BS antennas, $K = 4$ users, and $\Gamma_{k,n} = 15$ dB radar SINR threshold. We plot the average communication sum rate in Fig. 1(a) and the radar SINR in Fig. 1(b) varying the radar SINR penalty constraint λ_1. As shown in Fig. 1, the proposed B-ECTNet algorithm attains the highest performance compared to the other baseline methods satisfying the radar SINR constraint. While the LSTM-based CLCCNet outperforms conventional methods, its modeling is restricted to short-term temporal patterns, whereas the proposed algorithm of global self-attention captures long-range spatio-temporal dependencies across the entire echo sequence, resulting in superior performance.

V. Conclusion

In this paper, we introduced a Transformer-based predictive beamforming scheme for bistatic ISAC vehicular networks and a transmission protocol that eliminates the need for the BS to obtain CSI or historical channel data, thereby reducing signaling overhead. We formulated an optimization problem to maximize the communication sum rate, converting it into an unconstrained problem via a penalty method. A B-ECTNet, combining a convolutional front end and a global self-attention module, was developed to extract both local and global echo features for predictive beamforming. Simulations demonstrate that the proposed approach consistently surpasses state-of-the-art beamformers in communication and radar performance.

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