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Can earables support effective user engagement during weight-based gym exercises?

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ABSTRACT

We explore the use of personal 'earable' devices (widely used by gym-goers) in providing personalized, quantified insights and feedback to users performing gym exercises. As in-ear sensing by itself is often too weak to pick up exercise-driven motion dynamics, we propose a novel, low-cost system that can monitor multiple *concurrent* users by fusing data from (a) wireless earphones, equipped with inertial and physiological sensors and (b) inertial sensors attached to exercise equipment. We share preliminary findings from a small-scale study to demonstrate the promise of this approach, as well as identify open challenges.

CCS CONCEPTS

• **Information systems** → **Mobile information processing systems**; • **Applied computing** → *Health care information systems*.

KEYWORDS

Gym Exercises, Personalized Coaching, Earable, IoT

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1 INTRODUCTION

While there has been a rapid increase in the market for fitness devices and apps, relatively few solutions offer quantified and personalized feedback on an individual's overall exercise-related activities [10]. Existing technologies for fine-grained, individualized exercise tracking typically utilize video-based sensing [18], WiFi CSI information [7], or on-body wearable devices [4, 12]. However, such solutions continue to face challenges in real-world adoption. For example, video-based sensing generates significant privacy concerns, WiFi solutions suffer from poor accuracy in the presence of multiple individuals (e.g., at a gym) and individuals are reluctant to adopt custom wearable devices, *unless the wearable device is already a part of an individual's lifestyle*.

Motivated by these observations, we investigate the possibility of tapping on ear-worn (*'earable'*) devices (such as in-ear earphones) as a possible means of *capturing* a user's exercise related activities. Earables offer a compelling and attractive *mass-market* wearable platform ([16] reported a global sale of 368 million headphones and headsets in 2018). Moreover, they are also commonly used during gym activities (e.g. for listening to music while working out). They also offer the advantage of supporting *real-time*, personalized *audio-based* feedback (often preferred to alternative text-based feedback [11])–for example, to rectify incorrect exercising behavior or to motivate continuation of desirable activities.

Key Challenge: The big drawback of earables, of course, is their unfavorable on-body placement: it is indeed questionable whether ear-based inertial signals can provide *any* discriminative information about exercise motion, especially when such motion is primarily restricted to upper or lower limbs. Research on earable-based activity recognition has been confined to inferring (a) characteristics of eating or drinking [3], both of which obviously manifest in head motion, and at a stretch, (b) high-level locomotive activities [13], which also involve overall body displacement. To our knowledge, no prior work has tackled the problem of fine-grained monitoring of gym exercises using earables.

This paper introduces a novel, low-cost solution for earable-based, individual-specific *fine-grained* monitoring of gym exercises in real world scenarios, *where multiple individuals are exercising concurrently*. Our key insight is that earable-based sensing, in isolation, is too noisy and weak to directly offer accurate recognition of gym activities. To overcome this limitation, we propose a hybrid architecture (to be elaborated in Figure 1), consisting of:

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- Individuals wearing wireless earphones embedded with sensors (e.g., inertial sensors, heart rate sensor) that capture their activity and physiological context
- Individual gym equipment (e.g., dumbbells, weight machine) attached with cheap IoT sensors that capture the motion dynamics of each equipment.

Given this architecture, the problem then morphs to (a) first establishing an *association* between an individual's earable device and the corresponding gym equipment, and (b) then using this pair of (earable, equipment) sensor data to infer fine-grained aspects of the exercise being performed. While not part of this paper, our overall vision also involves the generation of personalized real-time audio-based feedback (acting as a *"virtual personalized exercise coach"*), to the exercising individual, based on such fine-grained insights.

Key Contributions: Using a very preliminary feasibility study (multiple exercise sessions conducted with two users concurrently performing identical or distinct exercises using dumbbells or weight-stack machines), we demonstrate that:

- Even though exercise-related signals are often very muted on an earable, it is indeed possible to identify related (earable, equipment) pairs from the combined inertial sensor data, via the application of sophisticated time-frequency domain statistical correlation techniques. Our resulting analysis reveals high correlation (>0.71) between the *earable* and *dumbbell* signals corresponding to the same user, and 83% accuracy in pairing the devices used by multiple *concurrent* users.
- By fusing sensor data from both the earable and equipment-embedded inertial sensors, we can obtain fine-grained insights into an individual's exercise patterns (e.g., exercise type). In particular, we show that such fusion can determine the exercise performed (among 8 candidate exercises) with an accuracy of 92%, higher than that can be achieved from either modality in isolation.

Overall, our work provides early evidence of the promise of earable devices as a platform for capturing fine-grained context of individuals exercising in a gym.

2 SYSTEM ARCHITECTURE

A future smart gym application should have the following capabilities: (i) distinguish between multiple people exercising simultaneously in the gym, (ii) unobtrusively monitor exercises performed by each individual and obtain deeper insights on various facets of exercising, (iii) provide personalized feedback to the individuals to improve the exercise effectiveness and prevent injuries.

For realization of such a smart gym application, we assume that individuals exercising in the gym are using *earables* and the exercise equipment/machine is attached with cheap IoT sensor devices. The earables are equipped with a microphone,

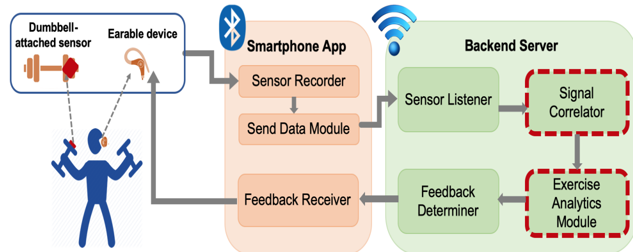


Figure 1: System Architecture

inertial sensors (accelerometer, gyroscope), bio-sensors (heart rate, body temperature) and are paired to a smartphone. The IoT device attached to the exercise equipment (e.g., dumbbells, barbells, weight machines) have embedded accelerometer, gyroscope and magnetometer sensors. A custom built smartphone application has a *Sensor Recorder* process that records the sensor data from both the devices and a *Send Data* module that periodically transmits the sensor data to a backend server over the WiFi network. This App also has a *Feedback Receiver* that receives audio inputs/feedback from the server and relays it to the earables.

The backend server performs all the smart gym analytics. In the backend, there is a *Sensor Listener* module for obtaining sensor data from both the earable and the equipment-sensor. Once the sensor data is obtained, the *Signal Correlator* module checks for the correlation between the earable sensor stream and equipment sensor stream to determine who is working out with which exercise equipment. The correlated sensor data pairs are then fed to the *Exercise Analytics* module, which identifies the type of the exercise performed and determines more fine-grained aspects such as the exercise intensity, correctness, heart rate variation for different exercises. Then, the *Feedback Determiner* module utilizes these analytics to determine the appropriate timing and the audio feedback to be sent to the earable device.

Figure 1 illustrates the architecture of the system with the sensor devices, server components and flow of the analytics pipeline. In this work, we mainly focus on the two components outlined in red-dotted lines. *Note:* For a clear representation, the figure depicts only a single-user scenario. In a practical setting, there will be multiple people exercising and thus multiple streams of both dumbbell and earable sensor will be streamed simultaneously to the backend sever.

3 EARABLE-BASED INERTIAL SENSING FOR EXERCISE ACTIVITY RECOGNITION

In this work we focus on answering the following **key research questions:**

- Does the accelerometer on the ear-worn sensor device show any discernible pattern for the common weight training exercises performed by individuals in a gym?

- Can we correlate the sensor data from the ear-worn device and the dumbbell-attached device to distinguish between individuals and identify the exercise performed by each person?

We next describe our study procedure, data collected and the overall approach of analyzing sensor data and deriving various insights on the exercises performed concurrently by multiple individuals in the gym.

Study Procedure and Data Collection

To study the feasibility of our proposed vision, we conducted multiple studies in our campus gym. For obtaining sensor data, we used the following devices: (i) eSense Earable device[1], which the subjects wore on their left ear, (ii) Cosinuss One[2] earphone, worn by subjects on their right ear and (iii) a multi-sensor device (DA14583 IoT Sensor[3]) to attach to the exercise equipment (e.g., dumbbells, exercise machines). For the eSense earable, we used only the left-side earbud which has the capability to stream inertial sensor (accelerometer and gyroscope) data as well as receive audio inputs. The Cosinuss One device has in-built sensors to record heart rate and body temperature. These devices are paired with a smartphone and we developed an android application that simultaneously connects to these devices over Bluetooth Low Energy (BLE) and records sensor data and also records ground truth labels such as exercise performed, set count and amount of weight lifted. *Note:* In this work, all the chosen free-weights exercises are performed with two arms moving at the same time and we attach a sensor device only to a single dumbbell (left-hand).

For the study, we obtained data from 2 subjects who performed 8 different weight training exercises across 3 days. In each session, the subjects performed 3 sets of 10 repetitions of each exercise. The exercises involved 6 dumbbell exercises: (i) Biceps Curls, (ii) Triceps Pushdown, (iii) Lateral Raise, (iv) Side Bend, (v) Squats, (vi) Lunges and 2 exercises on weight stack machines: (vii) Standing Cable Lifts (for Abs) and (viii) Bent Over Side Lateral (for Shoulders). Out of the three sets of each exercise in a session, both subjects simultaneously performed the same exercise for 2 sets and for the last set, they alternated between different exercises. Overall, we collected 144 sets (of 10 reps each) of exercise data.

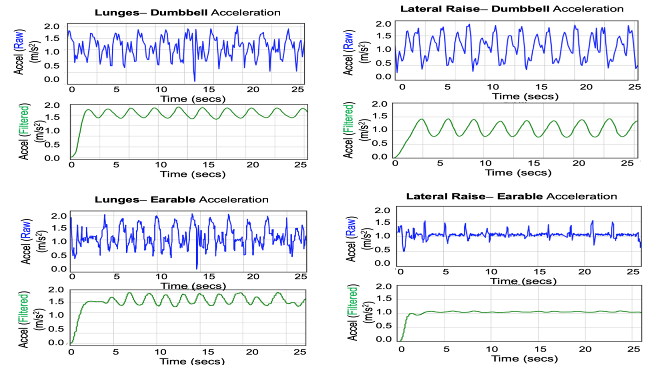
Sensor Data Analysis and Insights

We first inspect the accelerometer data recorded from the eSense left earbud and the dumbbell sensor. As expected, the dumbbell accelerometer showed clear and varying patterns for most of the exercises. For the earable, as any 'exercise-related' perturbations, if they exist, will be minor and may get swamped by various other macro-movements, we first pre-process and filter the sensor data. For this, we analyze the typical 'exercising frequency' of various exercises from the dumbbell sensor pattern. We observe that on an average the time taken to complete one repetition of a dumbbell/machine exercise is about $2 - 2.5$ seconds. As such, we use a fourth order Butterworth band pass filter with a lower cut off frequency of 0.4 Hz and a higher cut off frequency of 4 Hz to filter both streams of sensor data.

[1]eSense– http://www.esense.io/

[2]Cosinuss One– https://www.cosinuss.com/products/one/

[3]DA14583 IoT Sensor – (https://www.dialog-semiconductor.com/iotsensor)



(a) Raw (blue) and filtered (green) signals from Dumbbell (top) and Earable (bottom) for *Lunges* exercise

(b) Raw (blue) and filtered (green) signals from Dumbbell (top) and Earable (bottom) for *Lateral Raise* exercise

Figure 2: Accelerometer Sensor Patterns from Dumbbell & Earable for (a) Lunges and (b) Lateral Raise exercises

Figure 2 shows sample plots of the magnitude of the raw and filtered sensor signals for *Lunges* and *Laterl Raise* exercises. We find that exercises which involve larger body movements (for e.g., *lunges*, *squats*, *abs* exercise on machine) exhibit clear patterns in the earable signal for each exercise repetition. However, for certain upper-arm exercises (such as *biceps curls*, *lateral raise*), variations are not clearly evident in the time-domain earable signal. This makes the problem both promising and challenging and requiring further analysis of both time and frequency domain of the signals.

Identifying the Correct User-Dumbbell Pairs

In our targeted gym scenario, multiple users would perform exercises simultaneously and the *smart gym* application should monitor exercise and provide personalized feedback to each individual. As such at the server side, we would receive multiple streams of both *earable* and *dumbbell* signals and therefore, our primary goal is to identify the correct pairs of $\{earable - dumbbell\}$ sensor streams to determine who is exercising with which dumbbell.

For this purpose, we propose to first obtain *Continuous Wavelet Transform* (CWT) of the signals and then perform correlation analysis in the frequency domain. We choose to

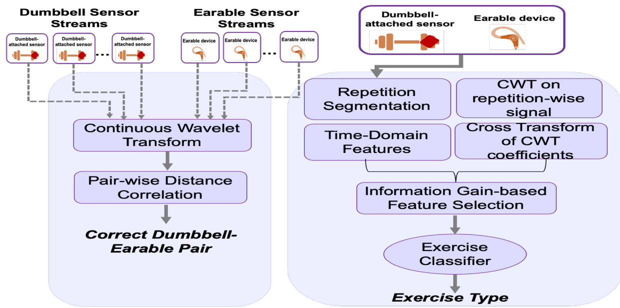


Figure 3: Steps involved in identifying the Correct *{Dumbbell-Earable}* Pair and Exercise Type

use wavelet decomposition instead of other frequency domain techniques such as Fourier Transform or Power Spectral Density because of its ability to obtain both temporal and frequency resolution of the analyzed signal.

The CWT coefficients are computed at different scales for each of the filtered earable and dumbbell sensor streams. We use the *Symlet* wavelet ('sym4') and vary the scales from 1 to 100. After performing CWT, we obtain a wavelet coefficient matrix from both sensor streams of all exercising individuals. Next, we compute *distance correlation* between all the possible pairs of the coefficient matrices. The distance correlation is a measure of dependence between random vectors and is obtained by dividing the distance covariance of two matrices by the product of their distance standard deviations [17].

To identify the correct *User-Dumbbell* pair, we further train a binary-class classifier with all combinations of CWT matrices from the dumbbell and earable signal as input. i.e., Given a dumbbell signal X and an earable signal Y, does the classifier think that (X, Y) is from the same pair or not?

Identifying Exercise Type

Once the correct dumbbell-earable pairs are determined, the next step is to identify the exercise performed by each individual. We use a supervised ML classifier trained on features extracted from both the dumbbell and earable signals (Figure 3 depicts the various steps involved). Using peak and valley detection on the filtered dumbbell sensor signal for an exercise set, we first perform repetition identification and segmentation. We assume one repetition to be the time segment between two consecutive valleys. We then compute the continuous wavelet transform of each repetition segment of both dumbbell and earable signal. Then the cross-transform/convolution of the two wavelet coefficient matrices is computed. We also compute other statistical time-domain features on both sensor streams. Using *InformationGain*-based feature selection, we found that CWT coefficients from scale 70 to 100 and 1 to 10 are the most informative. So, we ignored the features corresponding to CWT scales 11 to 69 from the feature set. The exercise classification is then performed on the new feature set with a Random Forest (RF) classifier. We also compare the performance with other machine learning classifiers (discussed later in Section 4).

4 PRELIMINARY RESULTS

In this section, we describe our early results in distinguishing between multiple exercising individuals and identifying the exercise they perform, based on the data we collected from our campus gym.

Performance of Identifying the Correct Pairs

As our system is intended for multi-user gym environments, our primary goal is to distinguish between the different people exercising in order to perform personalized exercise monitoring. We achieve this by correlating sensor signals from the dumbbell and earable in the frequency domain. As discussed earlier in Section 3, we first perform continuous wavelet decomposition of both the sensor streams. Figure 4 plots the scalogram (which is the absolute value of the CWT coefficients of a signal, plotted as a function of time and scale) of one set of *Side Bend* exercise. From the figure, we can see that the individual exercise repetitions have their energy concentrated between scales 60 to 100. We observe similar trends for other exercises as well.

As we collected data with two people exercising simultaneously, for each exercise set, we first obtain four CWT coefficient matrices (for the dumbbell and earable data from each user) and then compute the distance correlations between them. We observe that, on an average, the correct pair of signals (i.e., from same user's dumbbell and earable) have high correlation value over **0.71**.

To automatically classify the correct and incorrect pairs, we train a Random Forest classifier and evaluate the performance using 10-fold cross validation. We obtain an accuracy of **83%** in identifying the correct pair. Upon analyzing the incorrectly classified instances, we gather two insights: (i) several of the mis-classified instances belongs to the sets where both subjects were concurrently performing the "same" exercise and (ii) sets of *biceps curls* and *lateral raise* exercises (which involve limited head motion) have comparatively more number of mis-classifications.

Performance of Identifying Exercise Performed

We next evaluate the accuracy of classifying the 8 exercises (dumbbell and machine exercises) from a total of 144 sets of exercise data collected. We have a balanced set of data as we collected equal number of sets for each exercise. We then perform 10-fold cross-validation and report the average performance metrics in Table 1, for a number of machine learning algorithms in Weka.

We observe that the highest performance is obtained with a Random Forest classifier, with an average accuracy of **92.9%**,

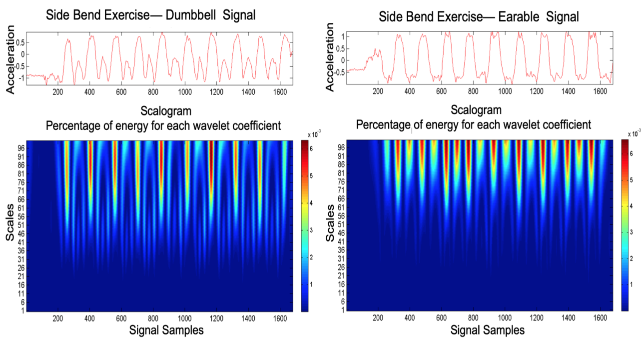


Figure 4: Continuous Wavelet Transform of Dumbbell (*left*) and Earable (*right*) Signal for *Side-Bend* Exercise

	Accuracy	Precision	Recall	F-Score
Naive Bayes	79.23%	0.792	0.79	0.79
Random Forest	**92.94%**	**0.93**	**0.929**	**0.929**
Decision Tree	83.98%	0.84	0.84	0.84
SVM	71.04%	0.71	0.71	0.71
Logistic	72.98%	0.73	0.73	0.73

Table 1: Exercise Classification accuracy using different machine learning algorithms

precision of 0.93 and recall of 0.929 in classifying the 8 exercises. On inspecting the confusion matrix, we found that the classification errors occurred primarily for the following exercises: *triceps pushdown* & *lateral raise* (dumbbells) and *bent over side lateral* (machine), which has comparatively lesser head movements involved.

We next investigate the performance of exercise classification when only *either* of the dumbbell or earable sensor data is used to train the model. We obtain an average accuracy of *85.20%* and *54.58%* by considering only dumbbell or only earable data, respectively. Although the average accuracy obtained with earable is quite low, we observe that classification of certain exercises (e.g., lunges, side bend) achieves a higher precision of ≈ 0.78 with earables. This shows that combining both dumbbell and earable data helps to increase the performance of classifying exercises.

5 DISCUSSION

Our initial results are promising, but admittedly based on a small scale study conducted with only two users. Further extensive studies with a larger population and more number of people exercising simultaneously needs to be conducted to validate our approach. There are several other aspects and open questions that we are actively pursuing to make this vision an eventual reality.

Real-time audio feedback: Providing personalized feedback on the exercise progress and correctness could help improve exercise effectiveness as well as retain motivation to continue exercising. Prior studies [11] have reported that "auditory feedback" is ranked top among feedback features based on a review of physical activity apps. Based on real-time sensing and analysis of the multi-modal sensor data, we intend to provide incremental feedback in the form of short audio instructions or "beep" sounds, based on the performance and progress of users. The system could also provide positive, motivating feedback after completing each exercise set and at the end of the gym workout for the day. Motivated by prior work [13], we shall also investigate if we can use music to regulate the 'exercise tempo' of users.

Integrating physiological sensor data: Besides inertial sensor data, additional physiological signals (e.g., heart rate or breathing rate) from earables may enable more sophisticated monitoring or intervention strategies. For example, the physiological data could reveal the user-perceived intensity of the current exercises and enable the delivery of appropriate corrective feedback–e.g., alerting the user to slow down if the heart rate exceeds the maximum active heart rate. More interestingly, such physiological signals may provide additional temporal markers for better matching of {earable-dumbbell} pairs, especially for exercises with imperceptible head motion–e.g., if the inhalation/exhalation times match with the exercise repetition dynamics.

Robust and generalized pairing: We will need to extend our 'matching' technique to scenarios with a larger number of concurrent users. Moreover, we would have to incorporate practical situations where all exercising individuals may not be wearing earable devices–in such cases, we would obtain M earable and N dumbbell sensor streams ($M < N$). To tackle such scenarios, we plan to first assign 'confidence scores' to different {earable-dumbbell} pairs, and then apply *inexact bipartite matching* techniques to improve the association of users to specific exercise equipment.

Extending to other exercise types and scenarios: In this work, we focus only on weight training exercises (both free-weights and machine weights). However, we believe that the ear-worn sensing platform can be used to monitor other types of gym exercise (e.g., cardio, body-weight exercises) and other outdoor exercises or sports. Additionally, the proposed approach of real-time sensing of activities and bio-signals using in-ear sensors can also be extended to other lifestyle activities such as monitoring cognitive state and well-being of people in office environments.

6 RELATED WORK

We highlight recent work on monitoring gym exercises, as well as work that is most closely related to our vision of using ear-worn sensors for activity recognition.

Pervasive Monitoring of Gym Exercises: In the recent years, several commercial mobile applications (e.g., Trackmyfitness [19], JEFIT [9]) and wearable devices (e.g., Apple Watch, Nike Fuelband) have spawned in the fitness space with the goal to digitally track and encourage physical activity among individuals. However, a review of such physical activity apps found that only 2% provided evidence-based guidelines for gym exercises training and people find it not helpful [10].

Existing pervasive technologies for providing quantified insights into an individual's gym activity rely primarily on on-body wearable devices (e.g., [4, 12, 15]) and video-based sensing [8, 18]. However, each of these approaches have different drawbacks such as usability concerns with wearables and the reluctance to wear such additional devices while exercising in gym, the overly intrusive nature and privacy concerns associated with videos. Guo et al. [7] uses Wi-Fi CSI information to analyze workouts within a home/work environment. However, WiFi-based systems may not work in a multi-user gym environment and in non line-of-sight scenarios. We believe that earables present a compelling alternative because of its form-factor as well as the wide use of earphones by exercisers during gym activity. The FEMO [5] system and the recently proposed JARVIS system [14] rely on the idea of attaching sensors to exercise equipment (dumbbell or weight machine) to track various aspects of specific class of gym exercises. In our work, we propose a hybrid approach of combining sensor data from earables as well as equipment attached sensor device to obtain accurate and fine-grained tracking of the exercises performed in a gym.

Ear-worn Sensing for Activity Recognition: While prior works have explored the use of microphones in ear-worn devices to capture chewing sounds [1] and eating episodes [3], not many has explored the use of inertial sensors on ear-worn devices for complex activity recognition. Atallah et al. [2] proposed using an ear-worn accelerometer for gait monitoring while exercising on a treadmill. Nirjon et al. [13] proposed the 'MusicalHeart' system which uses a sensor-equipped ear-worn device that monitors heart rate and provides music recommendation based on user's activity levels. Gil et al. [6] developed a prototype of an ear-worn device that can measure cardiovascular and sweat parameters during physical exercise.

7 CONCLUDING REMARKS

In this work, we have introduced a vision of using ear-worn devices as the *preferred*, mass-market wearable platform, for both (a) individualized, fine-grained monitoring of gym exercise activities, and (b) subsequent real-time, context-aware feedback on exercise dynamics. As exercise-driven motion signals are often too weak to be distinctly captured by a earable device, we propose a novel, hybrid architecture for multi-user gym environments, where joint statistical analysis of equipment-mounted IoT and earable sensor data are used to match individuals to specific gym equipment. We showed that, in spite of the significant signal dampening on the earable, it is possible to extract salient frequency components of exercise-related motion, and that there exists strong correlation (> 0.71) between the relevant earable and equipment features. Early experimental results suggest that such correlation can be used to accurately identify (user, equipment) pairings among current users (83% of such pairings were correctly identified). Furthermore, the combined inertial signals from ear-worn and equipment-mounted sensors can be used to classify exercises (from among 8 distinct choices) with 92% accuracy, a notable improvement over the accuracy achieved from either device alone.

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