A Comparison of Signal Strength Localization Methods with Sigfox

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***Abstract*—Location-based services play an important role in Internet of Things (IoT) applications. However, a trade-off has to be made between the location estimation error and the battery lifetime of an IoT device. As IoT devices communicate over Low Power Wide Area Networks (LPWAN), signal strength localization methods can use the existing communication link to estimate their location. In this paper, we present a comparison of three proximity methods, one fingerprinting method and three ranging methods using Sigfox communication messages. To evaluate these methods, we use a ground truth Sigfox dataset which we collected in a large urban environment, as well as new evaluation data that was collected in the same urban area. With a mean estimation error of 586 m, our fingerprinting method achieves the best result compared to other signal strength localization methods.**

***Index Terms*—IoT, LPWAN, Sigfox, Localization, Signal Strength, Proximity, Fingerprinting, Ranging**

I. Introduction

As the Internet of Things (IoT) keeps growing, an enormous amount of mobile devices is being deployed all over the world. In order to develop flexible IoT applications, we want to know where these devices are located so that an application can adapt its behavior based on the device's environment. For example, a logistics company wants to prevent their assets from being stolen. If an asset leaves one of their sites without permission, the IoT application has to trigger an alert to notify security staff. In this case, location information is required to detect if an asset has left the site.

Although Global Navigation Satellite System (GNSS) solutions such as Global Positioning System (GPS), GLONASS or Galileo provide highly accurate location estimations, they are not always the best option to locate mobile IoT devices. Firstly, the high power consumption of GNSS receivers reduces the battery lifetime of an IoT device significantly. Moreover, the power consumption will increase even further if the location information has to be transmitted via wireless communication. Secondly, mobile devices can not be located in indoor environments, as GNSS is only suitable for outdoor use. Due to these flaws, other methods need to be explored to locate IoT devices in indoor and outdoor environments, while maintaining a battery lifetime of several years.

In recent years, Low Power Wide Area Networks (LPWAN) such as Sigfox [1], LoRaWAN [2] and NB-IoT [3] have been developed and deployed to allow low-power, multi-kilometer wireless communication to and from mobile IoT devices, which can be located indoor as well as outdoor. When a device transmits a message over one of these networks, network data such as the Received Signal Strength Indicator (RSSI) of each base station that received the message can be used to locate the transmitter via wireless positioning techniques. Concisely, these techniques allow us to obtain a location estimate by transmitting a single low-power LPWAN message. Contrary to GNSS solutions, the power consumption of such a transmission is very low, which benefits the battery lifetime of the transmitter. Of course, a trade-off has to be made between power consumption and location estimation error. Applications that require a very low estimation error might be better off with a GNSS method, whereas wireless positioning over LPWAN is an interesting option if battery lifetime is more critical. Although wireless positioning over LPWAN can have estimation errors of hundreds of meters, they are still suitable for several applications. For example, luggage can be provided with an LPWAN tracker. If an airline loses the luggage, we could still determine to which airport it was sent and even estimate at which terminal the luggage is located. Sigfox messages are modulated with Binary Phase Shift Keying (BPSK) and transmitted via an Ultra Narrow Band (UNB) carrier of 100 Hz. As a result, noise levels stay very limited which benefits receiver sensitivity and allows low-power transmissions of up to 10 km in urban areas and 50 km in rural areas. However, the narrow bandwidth also leads to a limited maximum data rate of 100 bit/s. Taking duty cycle regulations into account, this means that the maximal amount of uplink messages is limited to 140 12 byte messages per day. Due to the UNB characteristic of Sigfox, localization methods based on time information such as Time Difference of Arrival (TDOA) are not a viable solution [4]. Consequently, past research on localization with Sigfox has focused on signal strength based methods. Sigfox presents its own localization feature, which is based on the RSSI of the receiving base stations combined with machine learning algorithms [5]. In [6],

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messages with a 12 byte payload which contain the BSSID of the two in-range Wi-Fi networks with the highest RSSI were simulated every ten minutes. These BSSIDs where matched to open-source Wi-Fi BSSID databases to obtain a location estimate. With this experiment, the researchers illustrated that it is feasible to obtain a median location estimate of 23 m by sending a Sigfox message with context information. Of course, this method uses the entire payload of the Sigfox message for localization purposes. Sallouha et al. evaluated a fingerprinting method with Sigfox in an outdoor environment [7]. The researchers estimate the distance between a Sigfox transmitter and a receiving base station to classify the area were the transmitter is located. Within this area, location estimations are improved by estimating the distance between the transmitter and GPS anchors in the same area. However, the radius of a class was limited to 200 m to minimize the location error, as errors of over 60 m were measured for classes with a larger radius. This approach would also demand many GPS nodes, which impedes scalability.

Contrary to [6], where Wi-Fi BSSID databases are used, the experiments that are presented in this paper are conducted with an openly available Sigfox dataset that was presented in our previous research [8]. This dataset was built with mobile Sigfox devices that transmit their GPS coordinates from within a large urban area, allowing us to correlate ground truth location information with RSSI measurements of all receiving Sigfox base stations. Apart from this dataset, we gathered new GPS messages in the same urban area using different Sigfox hardware. Our dataset and the new messages allow us to compare multiple signal strength localization methods such as proximity, fingerprinting and ranging.

The remainder of this paper is structured as follows: Section II describes how we gathered our Sigfox data as well as the signal strength localization methods that we evaluated. Section III displays the results of our experiments, these results are discussed in Section IV. Lastly, we conclude this paper in Section V.

II. Methods and Materials

In this section, we describe the input data that was collected as well as the signal strength localization methods that are evaluated using this input data. The input data consists of an urban Sigfox dataset that was created in our previous work, as well as new evaluation data that was collected to validate optimal method parameters which were obtained using the Sigfox dataset. The urban Sigfox dataset as well as the evaluation data is used to compare several signal strength localization methods. Firstly, we evaluate three versions of proximity-based localization. Secondly, our fingerprinting implementation is explained. Finally, signal strength ranging methods based on three different urban RF propagation models are discussed.

A. Sigfox dataset

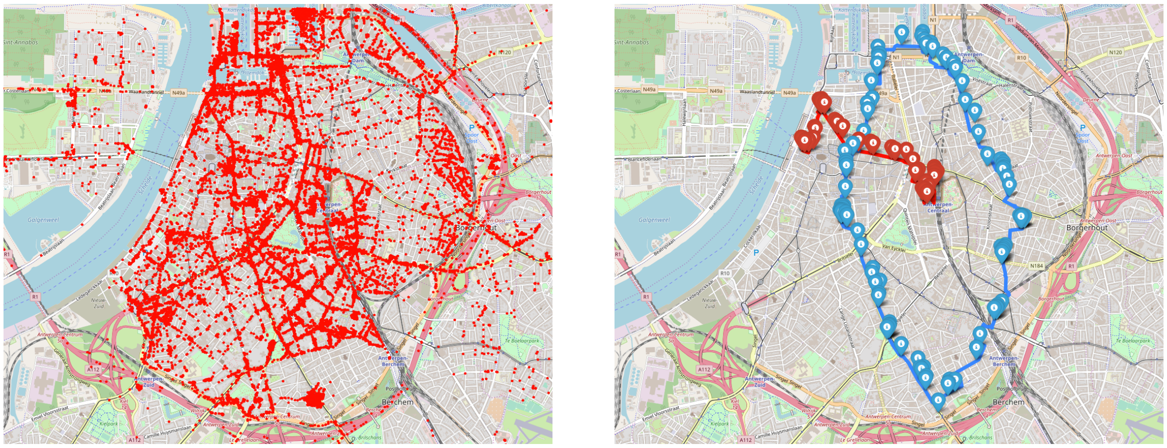
In our previous research, we have collected large ground truth LPWAN datasets in urban and rural areas. The purpose of these datasets is to provide the research community with a tool to develop and evaluate their methods for outdoor localization with long-range IoT networks [8]. In this paper, we use the urban Sigfox dataset to compare several signal strength localization methods in an urban environment. From November 2017 until February 2018, twenty cars of the Belgian postal services were equipped with OCTA-Connect hardware which contains a GPS receiver and a Sigfox modem to obtain this Sigfox dataset, this hardware can be seen in Figure 2a. Since these cars drive around the entire city center of Antwerp on a daily basis, we obtained a Sigfox dataset which has an equal spatial spread across the area of interest. The dataset that was made publicly available contains 14 378 entries but because we continued our measurement campaign during the past few months, we are able to use a much larger dataset which holds 39 313 Sigfox messages. The extended version of this dataset can be seen in Fig. 1a. In order to evaluate our proximity and fingerprinting localization methods, the dataset is randomly split up in three subsets: 70% training samples, 15% evaluation samples and 15% test samples.

B. Evaluation data

For our experiments, we gathered new Sigfox data in the city center of Antwerp. To collect this data, we used the Stickntrack devices of Fig. 2b that were provided by Sensolus [9]. Every 10 minutes, these devices obtain a GPS fix and transmit their current coordinates via a Sigfox message. We specifically chose the Stickntrack devices to validate that our urban Sigfox dataset can also be used with hardware that is different from the hardware that was used to collect the dataset. In Figure 1b, the data that was collected is visualized. On two different occasions, a route was followed on foot with a number of Stickntrack devices. The red trajectory was followed on June 13, 2018 with 6 devices, together they have sent 46 messages during this walk. The blue trajectory was walked on June 20, 2018 with 7 devices and resulted in 99 messages. In total we gathered 145 Sigfox messages that we used to validate our Sigfox dataset and our localization methods.

C. Proximity

We implement and evaluate three algorithms of proximity localization with the dataset proposed in Section II-A. The first proximity algorithm uses the location of the strongest receiving Sigfox base station as the estimated location. Of course, this algorithm requires that we know the location of the base station. The second proximity algorithm uses all database messages that have the same strongest receiving base station as the received message to create a cluster. The centroid of this cluster is then used as the location estimation. Consequently, this algorithm does not rely on knowing the location of the base stations. The third algorithm is the same algorithm as the second but uses a threshold value in order to improve the results. Only those database messages are selected that have the strongest receiving base station and this received signal strength is higher than the threshold. Again, the centroid of the filtered messages is used as location estimation.



(a) (b)

Fig. 1: (a) The extended urban Sigfox dataset contains 39 313 entries, which contain the GPS coordinates and RSSI measurements for each transmitted Sigfox message. (b) Extra data was collected to validate our localization methods. In total, 145 Sigfox messages were collected on two different trajectories on two different days. © *OpenStreetMap contributors*.

(a) (b)

Fig. 2: (a) The urban Sigfox dataset was collected with the OCTA-Connect hardware. (b) New evaluation data was gathered with Sensolus Sticknttrack devices [9].

To find the threshold value for the third, filtered cluster approach, an optimization is made towards the lowest location error. An evaluation set of signal strength thresholds is removed from the training samples of the database and used as input. Then, the location error of each message in the evaluation set is calculated for a range of signal strength thresholds starting from the highest received signal strength of the database until the lowest received signal strength that exists in the database. The threshold value with the lowest median location error is used as the threshold value in our experiment. This results in an optimal threshold value of −104 dBm. Note that in both cluster approaches, the clustered dataset is already created in an offline phase. In the online phase, new messages are then compared to these clusters to determine a location estimate. Hence these approaches are possible in a real-time deployment.

D. Fingerprinting

Fingerprinting is a pattern recognition localization method that allows estimating the location of a wireless device without having any knowledge of the location of the receiving base stations. In general, this method consists of two main steps: a training step and an operation step. In the training step, training data is collected in the area where we want locate our devices. To do so, messages have to be transmitted from known locations all over the area of interest to build a representative training database. Because it is easier to create such a database in small, indoor environments, fingerprinting localization has mainly been implemented in indoor environments with widely used wireless technologies such as Wi-Fi and Bluetooth [10], [11]. Nonetheless, we managed to create outdoor ground truth databases with Sigfox and LoRaWAN in our previous research [8]. As described in Section II-A, the urban Sigfox dataset is divided in training, evaluation and test subsets. We use these subsets to implement large-scale outdoor fingerprinting localization. As described in [8], all rows in such a subset represent one of the messages in the urban dataset. The last three columns represent the receiving time, latitude and longitude of a message, the columns before indicate which of the 136 Sigfox base stations in the urban area have received the message, i.e. one fingerprint has 136 dimensions. If a base station has not received the message, an out of range RSSI of -200 dB is inserted in the cell.

In the operation step, the received signal strength of new transmitted messages is compared to the training database to estimate the location of the wireless transmitter. This comparison can be done with algorithms such as k Nearest Neighbors (kNN), Support Vector Machines (SVM) or Neural Networks (NN). In our previous research, we implemented kNN to evaluate outdoor fingerprinting in LPWAN [8], [12]. This paper intends to compare signal strength localization methods, rather than optimizing our previous work. Therefore, we apply the kNN algorithm in this research as well. With this algorithm, we look for the k samples in the training database that have the smallest distance in signal space to the new received message [13]. The centroid of these k training samples is then used as the location estimate for the transmitter. As stated in previous research on indoor fingerprinting localization, the distance in signal space between two signal strength vectors can be calculated in different ways, and there are multiple alternatives to represent signal strength values [14]. With the extended version of our Sigfox dataset, we repeated a parameter sweep that was conducted in our previous research to determine an optimal set of fingerprinting parameters [12]. This way, we determine which combination of distance metric, RSSI representation and k-value result in the lowest mean estimation error for our urban Sigfox fingerprinting dataset. The evaluation subset is used to conduct a parameter sweep of 31 distance metrics, 4 RSSI representations and 16 values for k. As a result, we find that we can achieve a mean estimation error of 287 m when k equals 5, the RSSI is represented exponentially and the distance between signal strength vectors is computed with the Sørensen formula [15]. We validate this optimal parameter set with the remaining test subset, which results in a mean estimation error of 283 m. Finally, we use this optimal parameter set to compare the evaluation data of Figure 1b to the training subset. The results of this evaluation are discussed in Section III.

E. Ranging

Signal strength ranging methods use radio propagation loss models to calculate the distance between a transmitter and its receivers. Generally, such models take the distance between transmitter and receiver as well as the transmitted power and the frequency into account to determine the received signal strength [16]. As the path loss of a signal strongly depends on the environment, numerous propagation models have been proposed to accommodate all different types of use cases. Because our evaluation data is recorded in a dense urban environment, we evaluate three outdoor urban propagation models. For the same reason, only Sigfox base stations within the urban environment are taken into account in our ranging experiments. As we know the TX power and the RX power of the signal, we can rewrite the urban propagation model formulas to estimate the distance between transmitter and receiver. Firstly, we implement the urban Hata model, which is based on the widely used Okumura model [17]. Eq. (1) shows how distance d is calculated by rewriting the formula for this model:

$$\begin{aligned} d = 10 \exp \big\{ \big(& PL - 69.55 \\ & -26.161 \log_{10}(f) + 13.82 \log_{10}(h_R) + a(h_T) \big) \\ & / \big(44.9 - 6.55 \log_{10}(h_R) \big) \big\}, \end{aligned} \tag{1}$$

with:

$$a(h_T) = 3.2[\log_{10}(11.75 h_T)]^2 - 4.97, \tag{2}$$

where PL represents the known received signal strength in dBm, f describes the radio frequency, h_T and h_R indicate the height of the transmitter and receiver respectively. The parameter $a(h_T)$ is a correction factor to fit the propagation model for the specific transmitter height in urban environments. In our experiments, we use 868 MHz as a fixed value for f and 1.5 m for h_T. The value for h_R differs for each receiving base station.

Secondly, the COST231-Hata model is evaluated, which is an extended version of the Hata model [17]. Eq. (3) illustrates how distance d is estimated. $a(h_T)$ is calculated in the same way as shown in Eq. (2) [18].

$$\begin{aligned} d = 10 \exp \big\{ \big(& PL - 46.3 \\ & -33.9 \log_{10}(f) + 13.82 \log_{10}(h_R) + a(h_T) - 3 \big) \\ & / \big(44.9 - 6.55 \log_{10}(h_R) \big) \big\}. \end{aligned} \tag{3}$$

Lastly, we assess the 3GPP Macro-cell model. In previous research, this propagation model was validated by Bellekens et al. for the IEEE 802.15ah communication standard [19]. The rewritten formula can be seen in Eq. (4):

$$d = 10 \exp \frac{PL - 8}{37.6}. \tag{4}$$

After using these formulas to estimate the distances between the Sigfox transmitter and all receiving base stations, we can use this information to estimate the location of the transmitter. A common technique to do this is deriving an equation system from the base station locations as well as the estimated distances from the transmitter to the base stations, and solving this system with a least-squares approach [20]. During our ranging experiments, we noticed that this method resulted in high estimation errors. Therefore, we did not continue with this method. Due to its simple implementation, we chose to evaluate another method called the Min-Max algorithm. Basically, this algorithm draws a bounding box for every base station, the size of such a box is based on the location of the base station and its estimated distance to the transmitter. To find the location estimate, the minimum and maximum coordinates of all bounding boxes are stored, and a new bounding box is defined using the maximum of all minimum coordinates and the minimum of all maximum coordinates. The center of this new bounding box is then used as the estimated location of the transmitter [21].

III. RESULTS

In this section, we list the results that we obtained with the aforementioned signal strength localization methods. As a reference, we also include the estimation error of the Spot'it feature which is developed by Sigfox. It has to be noted that we do not have insight in the Spot'it algorithm itself, we only receive a location estimate which we compare to the actual GPS coordinates of the Sigfox transmitter. Fig. 3 displays the cumulative distribution function for every localization method. Table I shows the mean and median estimation errors per method, as well as the 75th percentile error. Because Sigfox advises to combine their Spot'it feature with GPS or Wi-Fi localization if estimation errors below 500 m are required, Table I also illustrates for every method the amount of estimation errors that are lower than 500 m [5]. All results were calculated using the 145 validation messages that were described in Section II-B.

TABLE I: Overview of our signal strength localization results

	Proximity Base Station	Proximity Cluster	Proximity Filtered Cluster	Fingerprinting	Ranging Hata	Ranging COST231-Hata	Ranging 3GPP Macro	Spot'it
Mean error [m]	808	880	803	**586**	721	760	722	676
Median error [m]	577	774	658	**443**	617	657	598	476
75th percentile [m]	1025	1134	961	**648**	922	957	890	836
Errors below 500 m [%]	36	16	28	**57**	43	38	46	52

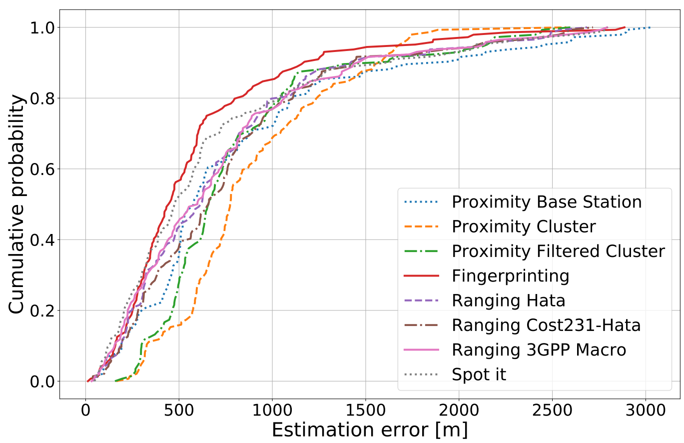


Fig. 3: Estimation errors for the signal strength localization methods

A. Proximity

In Section II-C, we introduce three versions of proximity localization. Table I displays the results of these implementations. First, we use the Sigfox base station with the highest receiving signal strength as the location estimate for the transmitter. This results in a mean estimation error of 808 m, a median error of 577 m, a 75th percentile error of 1025 m and 36% of the estimation errors stay below 500 m. Second, we propose to cluster all messages in the dataset of Section II-A that have the same strongest receiving base station, and use the centroid of this cluster as the location estimate. This implementation results in a mean error of 880 m, a median error of 774 m, a 75th percentile error of 1134 m and 16% of the errors is lower than 500 m. Lastly, we optimize the cluster implementation by purging all cluster messages of which the signal strength is lower than a defined optimal threshold. The mean error with this approach is 803 m, the median error is 658 m, the 75th percentile error is 961 m and 28% of the estimation errors is lower than 500 m.

B. Fingerprinting

Fig. 3 and Table I show that our fingerprinting implementation results in a mean estimation error of 586 m, a median error of 443 m and a 75th percentile error of 648 m. Finally, 57 % of the 145 location estimations achieve an error below 500 m.

C. Ranging

In our ranging experiments, we evaluated three propagation models to estimate the distances between a Sensolus Stick-ntrack transmitter and its receiving base stations. The Min-Max algorithm was then used to estimate the location of the transmitter, based on the known locations of the receiving base stations and the distance estimates. With the Hata propagation model, we obtained a mean estimation error of 721 m, a median error of 617 m, a 75th percentile error of 922 m and 43 % of the estimation errors was lower than 500 m. The COST231-Hata model resulted in a mean, median and 75th percentile error of 760 m, 657 m and 957 m respectively, and 38 % of the estimation errors lay below 500 m. Lastly, the 3GPP Macro-cell model achieved a mean error of 722 m, a median error of 598 m, a 75th percentile error of 890 m, and 46 % of the errors was lower than 500 m.

IV. Discussion

Firstly, we take a look at our results for proximity localization. Clearly, the cluster implementation leads to significantly higher estimation errors compared to all other signal strength localization methods. Filtering the clusters based on an optimal signal strength threshold certainly improves this implementation, although the estimation errors remain relatively high compared to other methods. Using the location of the Sigfox base station with the highest receiving signal strength generates results that are similar to the filtered cluster approach. However, information about the locations of the base stations is required in order to implement this method, whereas the cluster-based proximity methods do not need this information. Overall, we can state that proximity localization methods induce the highest estimation errors because they use a naive approach to obtain a location estimate.

Secondly, we discuss our fingerprinting results. By looking at the results in Table I, it becomes clear that our fingerprinting method achieves the lowest estimation errors compared to the other localization methods that we evaluate in this paper. We think this is mainly because fingerprinting utilizes a high amount of actual signal strength information from the area of interest as well as a specific optimal parameter set, whereas other methods such as ranging use generic theoretical models to obtain a location estimate.

Lastly, we analyze the results of the three signal strength ranging implementations. We notice that the COST231-Hata propagation model induces the highest estimation errors compared to the other ranging implementation, whereas the Hata and 3GPP Macro-cell models achieve very similar results. Contrary to the Hata and COST231-Hata models, the 3GPP Macro-cell model does not require height information from the transmitter and receiver. Due to its simple implementation, the 3GPP Macro-cell model seems more interesting for ranging localization.

V. Conclusion

In this paper, we compare eight signal strength localization methods using Sigfox messages. With our results, we can conclude that fingerprinting localization in a large urban area can achieve the lowest estimation errors compared to the other signal strength localization methods that were evaluated in this paper, as well as the Spot'it algorithm. However, fingerprinting calls for an extensive measurement campaign to collect a usable training database, which has proved to be a challenging task in large outdoor environments [8]. Such a training database is also required to implement the cluster-based proximity localization methods that we propose in this paper. On the other hand, proximity localization based on the base station with the strongest link require knowledge of the locations of the receiving base stations, whereas fingerprinting and cluster-based proximity methods do not need this information. Ranging methods also need information about the base station locations, but they do not require a time-consuming measurement campaign. In general, the methods that we discuss in this research result in estimation errors of 586 m and more. Although these errors are high, the methods are still usable for some applications, e.g. the luggage tracker that is proposed in the introduction of this paper. Also, these methods can serve as a baseline for more complex localization algorithms, were context such as application data, map information, etc. is implemented.

In our future work, we will study the effect of multiple parameters on the magnitude of our estimation errors. For the ranging methods, we will experiment with other urban RF propagation models, and include suburban and rural base stations as well. Also, we will compare our results with the Cramer-Rao Lower Bound (CRLB) of these methods. For our fingerprinting approach, other pattern matching techniques such as SVM and NN can be evaluated as an alternative for the kNN algorithm that we are using now. Moreover, we will experiment with different training set sizes, and we will research how we can optimize our datasets for localization purposes. Another important part of our future research includes analyzing the correlation between estimation error, the number of receiving base stations and the base station density. Also, our future work will include evaluations in other urban and rural areas, and with other LPWAN standards such as LoRaWAN and NB-IoT. Furthermore, we will research multi-modal localization. On the one hand, this can be achieved by switching between localization methods based on context information, e.g. using fingerprinting in urban areas and ranging in rural areas. On the other hand, we can switch between communication standards, e.g. using Sigfox fingerprinting in outdoor environments and switch to another mid-range sub-GHz communication standard such as DASH7 for indoor localization [22].

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