# ENHANCED ACCURACY IN PENETRATING POSITIONING USING UWB TECHNOLOGY BASED ON RECEIVED SIGNAL STRENGTH AND MACHINE LEARNING

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## ABSTRACT

This paper proposes a novel method to enhance accuracy in ultra-wideband penetrating positioning systems by using the raw data elimination technique combined with a machine learning model applied to received signal strength data. The emergence of ultra-wideband technology has addressed many challenges related to radio frequency spectrum scarcity, offering high precision in distance measurement and positioning. However, it still faces significant challenges such as multipath propagation, scattering, and refraction which degrade system performance. To address these issues, various signal processing approaches have been utilized, including machine learning techniques. In the proposed approach, an optimized LightGBM-based machine learning model is employed, which significantly improves the accuracy of ultra-wideband penetrating positioning systems. Computational results indicate that the proposed method reduces the mean absolute error by 28.2% to 72% compared to existing methods. This represents an effective research direction that addresses complex challenges in the field of radio-based localization and enhances the performance of both penetrating and indoor positioning systems.

# NÂNG CAO ĐỘ CHÍNH XÁC TRONG ĐỊNH VỊ XUYÊN THẤU SỬ DỤNG CÔNG NGHỆ UWB DỰA TRÊN CƯỜNG ĐỘ TÍN HIỆU THU VÀ HỌC MÁY

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**TỪ KHÓA**

Công nghệ UWB
Cường độ tín hiệu thu
Kỹ thuật định vị
Học máy
Mô hình LightGBM

## TÓM TẮT

Bài báo đề xuất một phương pháp mới nhằm tăng cường độ chính xác trong các hệ thống định vị xuyên thấu băng thông siêu rộng bằng cách sử dụng kỹ thuật loại bỏ dữ liệu thô kết hợp với mô hình học máy cho dữ liệu cường độ tín hiệu thu được. Công nghệ băng thông siêu rộng ra đời đã giải quyết nhiều thách thức liên quan đến sự khan hiếm tần số vô tuyến, đạt được độ chính xác cao trong đo khoảng cách và định vị. Tuy nhiên, vẫn tồn tại nhiều thách thức như ảnh hưởng của truyền dẫn đa đường, các hiện tượng tán xạ, khúc xạ dẫn tới làm giảm độ chính xác của hệ thống. Để giải quyết các thách thức này, các phương pháp xử lý tín hiệu khác nhau được sử dụng trong đó có kỹ thuật học máy. So với các phương pháp xử lý tín hiệu kinh điển, kỹ thuật học máy mang lại độ chính xác và hiệu suất ổn định cao hơn, đặc biệt là đối với tập dữ liệu lớn. Trong phương pháp đề xuất, mô hình học máy LightGBM tối ưu được sử dụng đã cải thiện đáng kể độ chính xác của hệ thống định vị xuyên thấu băng thông siêu rộng. Kết quả tính toán cho thấy, phương pháp đề xuất đã làm giảm sai số tuyệt đối trung bình từ 28,2% đến 72% so với các phương pháp trước đó. Đây là một hướng nghiên cứu hiệu quả góp phần giải quyết các thách thức phức tạp trong lĩnh vực định vị vô tuyến, cải thiện chất lượng các hệ thống định vị xuyên thấu và trong nhà.

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## 1. Introduction

Ultra-wideband (UWB) technology is widely known as one of the best candidate for range measurement and localization using ultra-wideband (500 MHz) radio frequency signals, particularly in indoor environments or areas where Global Positioning System (GPS) are not available [1]. By employing extremely short electromagnetic pulses that offer high spatial resolution, UWB demonstrates superior performance in many different applications, including indoor positioning, detection of buried or hidden objects (including humans) behind obstacles [2] and mine detection [3].

In the application of detecting and locating buried objects, the UWB system functions as a penetrating radar that uses extremely short radio pulses emitted into the survey environment (soil, concrete, etc.). These pulses are reflected at objects existing inside the environment and return to the UWB receiver. The receiver captures the reflected signals and extracts parameters used by ranging and localization algorithms. In these non-line-of-sight settings, propagation distance and location of buried objects are mainly determined based on two UWB pulse parameters: received signal strength (RSS) and time of flight (ToF). ToF-based methods include Time of Arrival (ToA), Time Difference of Arrival (TDoA), Two-Way Ranging (TWR), and Round-Trip Time (RTT) measurements. ToA and TDoA techniques require a strict synchronization between the transmitter and receiver or between anchor points, require high sampling rates, precise clocks, and need line-of-sight paths to achieve accurate range estimates. Although TWR and RTT eliminate the need for synchronization between the transmitter and receiver, they still require accurate clock alignment. ToF-based methods are greatly affected by multipath propagation, which degrades the precision of propagation time estimates and the computed ranges [4]. In environments where GPS signals are blocked (underground or within building structures), RSS–based method becomes important, augmenting ToF-based methods to yield more accurate measurements [5].

Besides, the successful implementation of UWB penetrating positioning systems requires special signal processing methods. These include the wavelet transform [6], the semi-analytical mode matching algorithm, the generalized Hough transform [7], and correlation methods [8], [9]. Most of these approaches rely on time-of-arrival parameters of UWB pulses. Modern positioning algorithms prioritize the ability to select and place sensor nodes in the best possible locations to maximize connectivity, data collection, and coverage; however, these algorithms are designed for outdoor environments [10]. For other environments, range measurement and localization become much more complicated due to the need to determine the environmental properties.

Among localization techniques, RSS–based algorithms stand out for their simplicity, lower energy consumption, and cost-effectiveness. RSS measurements for ranging and localization are increasingly important and can serve as an alternative to GPS-based systems in areas where GPS signals are blocked or unavailable [11]. Therefore, in underground or in-structure environments, RSS-based positioning algorithms are particularly useful even when there is interference from other wireless devices, RSS-based methods can still provide more accurate position estimates in complex environments [12]. Although RSS-based positioning methods still have some disadvantages, such as large positioning errors in dynamic environments, the inability to avoid noise and interference from other environments. Statistical models and artificial intelligence techniques can be used to enhance its accuracy. Probabilistic and statistical localization models proposed for indoor IoT applications still suffer from limited precision [13]. Therefore, the use of machine learning (ML) algorithms represents a promising approach to solve these problems. Using ML models for penetrating UWB localization systems can significantly improve accuracy, overcoming the limitations of traditional probabilistic and statistical methods. ML algorithms can learn effectively from large datasets, enabling the system to distinguish patterns and relationships among parameters, which makes localization results more precise and reliable. Beyond improved accuracy, ML–based approaches also offer deployment flexibility. These algorithms can adapt to various environments while still ensuring cost-effectiveness because RSS data can be collected from multiple devices.

Among ML models, decision tree-based algorithms (Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Light Gradient Boosting Machine (LightGBM)) have high reliability and computational speed. Compared to RF, gradient-boosting algorithms offer faster computation and broader adoption. Based on these considerations, this paper proposes using the LightGBM model for RSS processing in UWB penetration positioning systems. The proposed method is applied to locate buried objects in environments with high accuracy.

The remainder of this paper is organized as follows. Section 2 describes the system model and methodology for the proposed approach. In Section 3, we present experimental results to evaluate the performance of the proposed method against previous techniques. Finally, Section 4 concludes the paper and outlines directions for future work.

## 2. Research methodology

### *2.1. RSS-based positioning method*

Parameter-based localization methods can be classified into four categories: distance-based, time-based, signal-based, and direction-based methods. Among them, the received signal strength-based positioning method is one of the signal-based measurement methods. In wireless systems, RSS is a potential technique used to estimate the distance between devices, as well as to detect and locate objects in indoor environments. RSS is a calculation of the actual signal power received by the receiver, usually expressed in decibel milliwatts (dBm) or milliwatts (mW) [14]. RSS can be used to estimate the distance between transmitters (Tx) and receivers (Rx) based on the difference between the transmitted and received signal power. For the scope of this paper, we adopt the log-normal model for RSS in non-line-of-sight (NLOS) transmission scenarios. According to [15], in path loss model, RSS is calculated by:

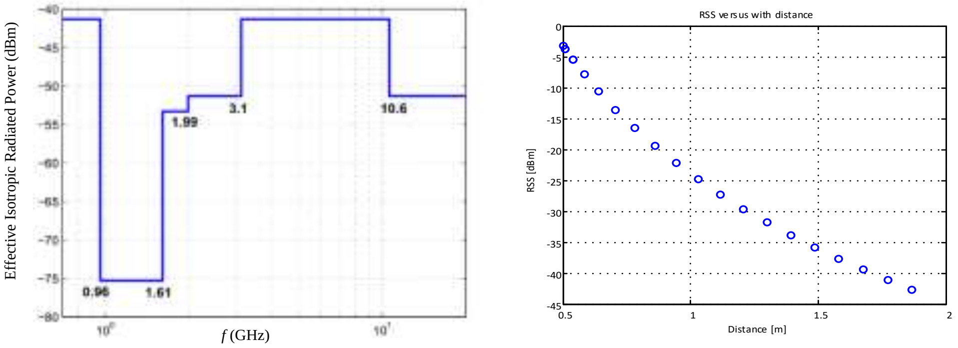
$$P_r(d) = P_t + G_t + G_r - \overline{P}(d_0) - 10\gamma \log_{10}\left(\frac{d}{d_0}\right) + \Lambda \text{ [dBm]} \tag{1}$$

In which, $P_r(d)$ epresents the RSS at distance $d$, $P_t$ is the transmitted power, $G_t$ and $G_r$ are the gains of the transmitting and receiving antennas respectively, $d_0$ is the reference distance, $\gamma$ is a constant denoted as path loss exponent whose value depends on the specific propagation environment, and $\Lambda \sim N(0,\sigma^2)$ is a zero mean, normally distributed random variable with variance $\sigma^2$ taking into account other sources of uncertainty in the transmission environment.

For penetrating positioning system, when the transmitter and receiver are placed next to each other, the received signal strength after being reflected from objects at a distance $d$ from the transceiver is rewritten in Equation (1) as:

$$P_r(d) = P_0 - 10\gamma \log_{10}\left(\frac{d}{d_0}\right) + \Lambda \text{ [dBm]} \tag{2}$$

Where $P_0$ is used to represent the total transmitted power and gain of the antennas. Because UWB signals occupy a very large spectrum and they should be used in existing narrow band systems without causing significant interferences to those systems, a series of rules of UWB systems is regulated by Federal Communications Commission (FCC). Accordingly, UWB systems must transmit impulse or non-sinusoidal wave signals below a certain energy level in order to avoid interferences with older systems in the same frequency spectrum. Specifically, the average power spectral density (PSD) shall not exceed -41.3 dBm/MHz on the frequency range of 3.1 to 10.6 GHz and must be lower outside this range depending on the specific application [16]. Figure 1 illustrates the FCC limits for indoor systems (Figure 1a) and the RSS curve varies as a function of distance in the penetrating UWB system.



*a)* *b)*

**Figure 1**. *The EIRP limits for UWB systems (a) and RSS varies as a function of distance in the penetrating UWB system (b)*

Thus, based on the RSS value, the propagation distance can be measured and the buried object can be located.

### *2.2. Proposed system model*

The proposed system model is illustrated in Figure 2 using penetrating UWB technology. This is a radio wave-based short-range wireless communication technology, similar to Bluetooth or Wi-Fi. The fact that it runs at an extremely high frequency, however, makes it easily distinct.

In Figure 2, the transmission environment has a relative permittivity of $\varepsilon$, receive and transmit antennas are placed in the same position with assumption of height of 0 m to the environment's surface, the position of the buried object is determined in two-dimensional space ($Z_T$, $Y_T$). The transmitted signal is generated by Impulse Radio Generator and denoted as $s(t)$, the reflected signal from the buried object **T** is denoted as $r(t)$, the propagation distance of the wave in the $i^{th}$ instance is denoted as $d_i$.

The transmitted signal takes the form:

$$s(t)=\sqrt{P_t}\sum_{i=0}^{N}p\left(t-iT_p\right) \tag{3}$$

Where, $P_t$ is the transmit power, $N$ is the number of transmitted pulses, $T$ is the repetitive period of the pulse and $p(t)$ is the signal pulse for IR-UWB systems, including Gaussian monocycles, Manchester monocycles and modified Hermite pulses [17].

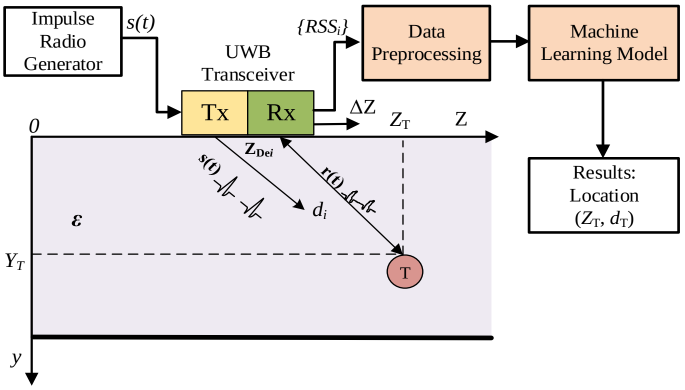


**Figure 2**. *Proposed model for locating the buried objects*

The received signal is described as:

$$r(t)=\sum_{i=1}^{M}\left[A_i s\left(t-\tau_i\right)+n_i\left(t\right)\right] \tag{4}$$

Where $M$ is the number of buried objects, $\{A_i\}_{i=1}^{M}$ represent the attenuation of the transmission environment, $\tau_i$ represents the delay time of the reflected signals from the $i^{th}$ buried object, and $n_i(t)$ is additive white Gaussian noise.

To obtain the RSS dataset, the UWB transceiver moves along the OZ axis with a shift step is $\Delta Z$ . The $i^{th}$ displacement step corresponds to the position $Z_{Dei}$ of the device, where we obtain the corresponding $RSS_i$ value for the distance $d_i$ from the device to the buried object. Mathematically, the distance $d_i$ is determined based on the coordinates of the buried object **T** ($Z_T$, $d_T$) as follows:

$$d_i = \sqrt{\left(Z_{Dei} - Z_T\right)^2 + d_T^2} \tag{5}$$

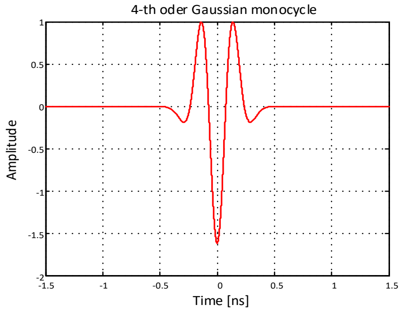
In the proposed system, the UWB pulse shape used is a 4th order Gaussian monocycle pulse with the form:

$$p_4\left(t\right) = B_{4\mathbf{p}} \frac{d^4}{dt^4} e^{-2\pi\left(\frac{t}{T_p}\right)^2} = B_{4\mathbf{p}} \left[-12\pi + 96\pi^2\left(\frac{t}{T_p}\right)^2 - 64\pi^3\left(\frac{t}{T_p}\right)^4\right] e^{-2\pi\left(\frac{t}{T_p}\right)^2} \tag{6}$$

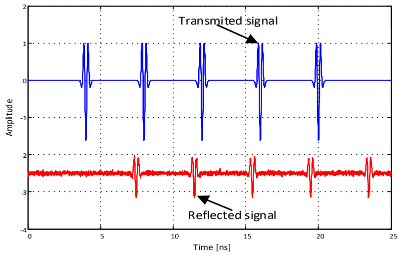
The 4th order Gaussian monocycle pulse waveform, the transmitted and received pulse shapes, and the data preprocessing technique called as raw data elimination (RDE), are shown in Figure 3. In Figure 3a and Figure 3b, the signal waveforms are presented in normalized form, with the received signal at a distance of 30 cm from the transceiver.

### *2.3. Data preprocessing and machine learning method*

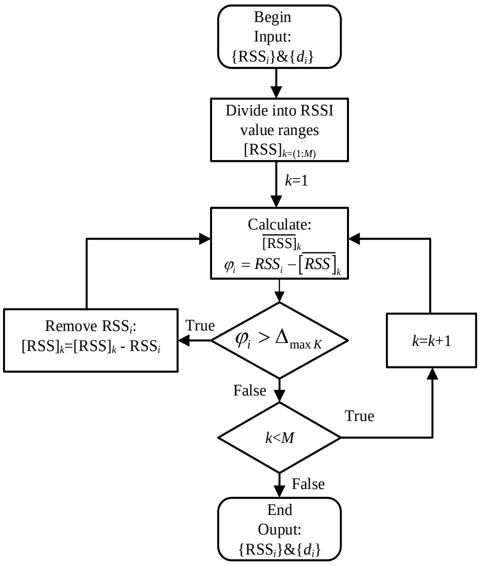
RSS data is sensitive to noise and interference from other wireless devices, so there will be many data points with low reliability. Therefore, in the proposed model, the collected RSS data is filtered to eliminate raw data and is used in an optimized machine learning model, which is called RDELGBM. As described in Figure 2, after receiving the signal and calculating the corresponding RSS, a raw data elimination technique (RDE) is applied in the data preprocessing block.



*a) The shape of the 4th oder Gaussian monocycle*



*b) The shape of transmitted and received signals*



*c) Algorithm flowchart of RDE technique*

**Figure 3**. *Transmitted and received signal waveforms used in the proposed model, algorithm diagram of the RDE technique*

The algorithm diagram for filtering and eliminating raw data is shown in Figure 3c. Accordingly, the RSS data is divided into intervals corresponding to the wave propagation distance (*M* intervals). For the $k^{th}$ RSS interval, the average value of the entire interval is calculated, and the deviation from the average value of each RSS$_i$ in that interval is determined. The maximum error $\Delta_{\max K}$ for this $k^{th}$ interval is determined according to criterion $3\sigma$ of the normal distribution. If there exists an *i* such that $\varphi_i > \Delta_{\max K}$ then the corresponding RSS$_i$ will be removed from the $k^{th}$ RSS set, and the calculation of the average value and deviation is repeated for the $k^{th}$ interval with the new set of RSS values (after removing RSS$_i$). The output of the RDE technique gives a dataset with the raw data values eliminated.

Among machine learning models, LightLGBM (LGBM) is an optimized Gradient Boosting model that enhances the efficiency and scalability of the algorithm. This model grows decision trees leaf-wise, uses a histogram-based learning method to reduce memory usage, and applies Exclusive Feature Bundling to reduce feature dimensionality. Additionally, it employs Gradient-based One-Side Sampling to prioritize samples with large gradients, preserving important training information while reducing sample size. Given the superiority of the model, LGBM is proposed to be used in our recommender system model.

## 3. Results and discussion

### *3.1. Evaluation metrics*

The performance of the proposed method is evaluated using evaluation metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Root Mean Squared Error (RMSE), calculated according to Equations (7) – (9) as belows:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|y_i - \hat{y}_i\right| \quad (7)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2 \quad (8)$$

$$RMSE = \sqrt{\sum_{i=1}^{N}\frac{\left(y_i - \hat{y}_i\right)^2}{N}} \quad (9)$$

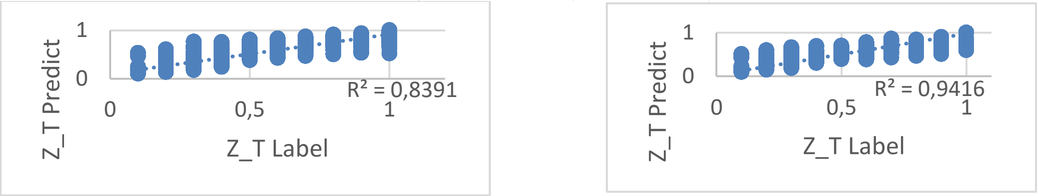
Where *N* is the total number of samples; $\hat{y}_i$ and $y_i$ represent the estimated and observed RSS$_i$ values, respectively.

RSS data was collected for different positions of the buried objects in different environments using the GPR PRO tool with $P_t = -5.4dBm, f = 5GHz$. This dataset was split into training data (80%) and testing data (20%) for the LGBM machine learning model. To optimize the model and improve its generalization performance, 5-fold cross-validation was applied to the training set using the Scikit-learn library. A Grid Search was conducted to identify the best combination of hyperparameters based on on evaluation metrics (MAE, MSE, RMSE).

### *3.2. Results*

The estimation results for the object's position in 2D space using the RDELGBM technique are presented as scatter plots for each coordinate component $Z_T$ and $Y_T$ on the test set shown in Figures 4 and Table 1 and Table 2. Figure 4a and Figure 4c illustrate the scatter plots of the estimated coordinates of the buried object ($Z_T$, $Y_T$) in the case without applying the RDE technique for data preprocessing, while the results obtained using the RDE technique are shown in Figure 4b and Figure 4d, respectively. The values of the evaluation metrics are illustrated in Table 1 and the comparison between the proposed method and other approaches using the MAE indicator is shown in Table 2.

Firstly, we evaluate the effectiveness of applying the RDE technique in data preprocessing. As shown in Figure 4 and Table 1, the application of the RDE technique significantly improves the accuracy of object localization, with the MAE decreasing from 8.2 (without RDE) to 2.8 (with RDE), RMSE decreasing from 12.3 to 8.2, MSE dropping from 1.5 to 0.7, and the $R^2$ score increasing from 0.81 to 0.92. Thus, applying the RDE technique in the data preprocessing step reduces the system's estimation error by approximately 65.9% (in terms of MAE) and 33.3% (in terms of RMSE) compared to the case without RDE. This improvement is achieved because raw RSS data (which are less reliable) are removed from the dataset, allowing the machine learning model to be trained on a dataset with higher reliability probability.



*a) Scatter plot of $Z_T$ estimates without RDE technique* *b) Scatter plot of $Z_T$ estimates with RDE technique*

*c) Scatter plot of $Y_T$ estimates without RDE technique* *d) Scatter plot of $Y_T$ estimates with RDE technique*

**Figure 4**. *Scatter plot of the estimation results in the two cases: RDE and without RDE technique*

**Table 1.** *Results of the evaluation metrics*

| | MAE | RMSE | $R^2$ | MSE |
|---|---|---|---|---|
| No RDE | 8.2 | 12.3 | 0.81 | 1.5 |
| RDE | 2.8 | 8.2 | 0.92 | 0.7 |

**Table 2.** *Comparison of the errors of the methods*

| Method | MAE [cm] |
|---|---|
| MPCF LSCF [20] | 7.8 |
| Multiresolution monogenic signal analysis method [19] | 5.8 |
| Wide-band chaotic [18] | 10 |
| Proposed method-RDELGBM | **2.8** |

Finally, the results of the proposed model are compared with previous research based on the MAE metric, as shown in Table 2. It can be observed that, the proposed method significantly improves the accuracy of the penetrating UWB system. Signal processing approaches based on GPR image analysis, such as wide-band chaotic [18] and multiresolution monogenic signal analysis [19], or time-of-flight signal processing methods [20], are often heavily affected by environmental propagation conditions and overlapping hyperbolas and involve high algorithmic complexity. Due to the impact of noise and the varying characteristics of the signal propagation environment, the RSS data includes numerous samples with low reliability. To address this, the RDE algorithm is applied during preprocessing to eliminate unreliable raw data points. This algorithm adaptively selects thresholds $\Delta_{\max K}$ for each data range, thereby preserving important information. Moreover, the LightGBM method employs a leaf-wise tree growth strategy, which enhances regression accuracy. However, in cases where the RSS data is affected by periodic noise with constant intensity throughout the entire data collection period, the RDE algorithm is ineffective in removing such noise. As shown in Table 2, the proposed method achieves an average MAE of 2.8 cm representing an improvement of approximately 28.2% to 72% compared to the average estimation errors of previous methods.

## 4. Conclusions

In this paper, we propose a novel method to locate buried objects in various environments using machine learning techniques for RSS data in penetrating UWB systems. Our analysis indicates that by applying raw data elimination techniques during the preprocessing of RSS datasets and using an optimal machine learning model, the limitations caused by noise and interference from nearby systems can be overcome. As a result, the accuracy of localization is significantly improved. However, the proposed method is not applicable to RSS datasets affected by periodic interference. As part of future work, we aim to incorporate advanced noise filtering techniques in combination with machine learning and deep learning approaches to further enhance system robustness and performance.

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