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Enhancing MIMO-NOMA with Feedback-Driven Deep Learning: Performance, Scalability, and Robustness

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***Abstract*: The integration of Non-Orthogonal Multiple Access (NOMA) with Multiple-Input Multiple-Output (MIMO) technology has emerged as a cornerstone for achieving the spectral efficiency requirements of fifth-generation (5G) and beyond wireless networks. However, conventional Successive Interference Cancellation (SIC) receivers employed in MIMO-NOMA systems suffer from critical limitations including error propagation, near-far effects, and inadequate handling of nonlinear interference, particularly when power differences between users are small. This paper proposes a Feedback Deep Neural Network (FDNN) receiver that leverages deep learning for nonlinear signal detection and incorporates iterative interference cancellation to address these challenges. The proposed architecture replaces traditional linear detection stages with deep neural networks that learn optimal decision boundaries directly from data, while the feedback mechanism enables progressive refinement of symbol estimates. Extensive simulations demonstrate that the FDNN receiver achieves 5× to 23× lower Bit Error Rate (BER) compared to conventional SIC across the SNR range of 10-30 dB, with particularly significant gains of 5.07× at low power differences (ΔSNR=3 dB). The proposed receiver maintains robust performance under imperfect Channel State Information (CSI), achieving BER below 10^{-2} at CSI error variance of 0.15, compared to 4.8×10^{-2} for SIC. Scalability analysis for K=3 and K=4 users show consistent 4-5× improvement across all users. Computational complexity analysis reveals that FDNN incurs 2.1× higher latency than SIC, representing an acceptable trade-off for the substantial performance gains. These results position the FDNN receiver as a promising candidate for next-generation wireless systems requiring reliable multi-user detection in challenging channel conditions.**

***Keywords*: MIMO-NOMA, Feedback Deep Neural Network, Successive Interference Cancellation, Bit Error Rate, 5G/6G Networks, Deep Learning, Imperfect CSI, Computational Complexity.**

1. Introduction

The exponential growth in wireless connected devices, coupled with the emergence of bandwidth-intensive applications such as augmented reality, autonomous vehicles, and massive Internet of Things (IoT), has created unprecedented demands on wireless communication infrastructure. The International Telecommunication Union (ITU) forecasts that by 2030, there will be over 50 billion connected devices globally, requiring aggregate data rates exceeding 1 Tbps per square kilometer in dense urban environments [1].

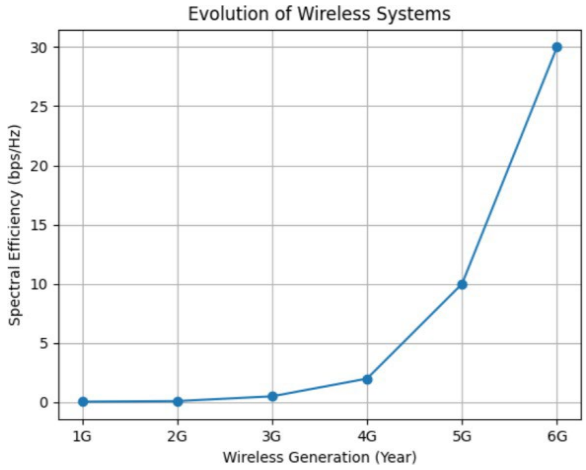

Fig. 1. The evolution of wireless communication systems and the increasing spectral efficiency requirements across generations

Traditional Orthogonal Multiple Access (OMA) schemes, including Time Division Multiple Access (TDMA), Frequency Division Multiple Access (FDMA), and Code Division Multiple Access (CDMA), allocate orthogonal resources to different users. While this orthogonality eliminates intra-cell interference, it severely limits spectral efficiency because the number of users that can be served simultaneously is constrained by the available time, frequency, or code resources [2]. The spectral efficiency of OMA systems is fundamentally bounded by the Shannon capacity of orthogonal channels, which scales logarithmically with the number of users.

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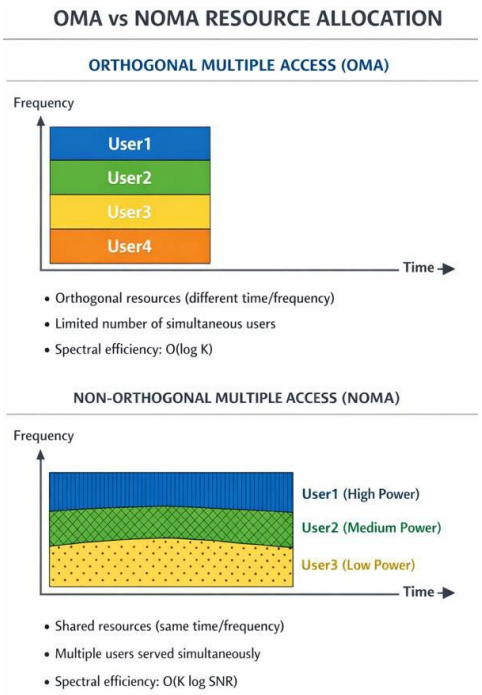

Fig. 2. Comparison of OMA and NOMA resource allocation strategies

Non-Orthogonal Multiple Access (NOMA) has emerged as a transformative paradigm that overcomes these limitations by allowing multiple users to share the same time-frequency resources through power-domain multiplexing [3]. In NOMA, users are assigned different power levels based on their channel conditions, with stronger users receiving higher power allocation. The superimposed signals are separated at the receiver using Successive Interference Cancellation (SIC), where users are decoded sequentially starting from the strongest signal [4]. Theoretical analyses have demonstrated that NOMA can achieve the sum capacity of the Gaussian broadcast channel, representing a fundamental improvement over OMA [5].

The synergy between NOMA and Multiple-Input Multiple-Output (MIMO) technology creates a powerful framework for next-generation systems [6]. MIMO exploits spatial dimensions through multiple antennas at transmitters and receivers, providing spatial multiplexing gains that increase data rates proportionally to the minimum number of transmit and receive antennas. When combined with NOMA, MIMO-NOMA systems can serve more users simultaneously while achieving higher spectral efficiency than either technology alone [7]. The capacity of MIMO-NOMA systems has been shown to scale linearly with the number of antennas under favorable channel conditions.

Despite these theoretical advantages, practical MIMO-NOMA systems face significant signal detection challenges.

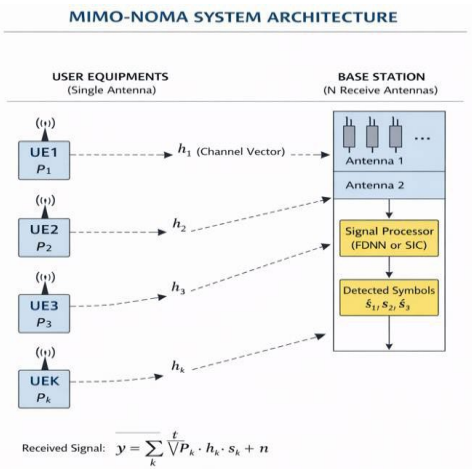

Fig. 3. The MIMO-NOMA system architecture

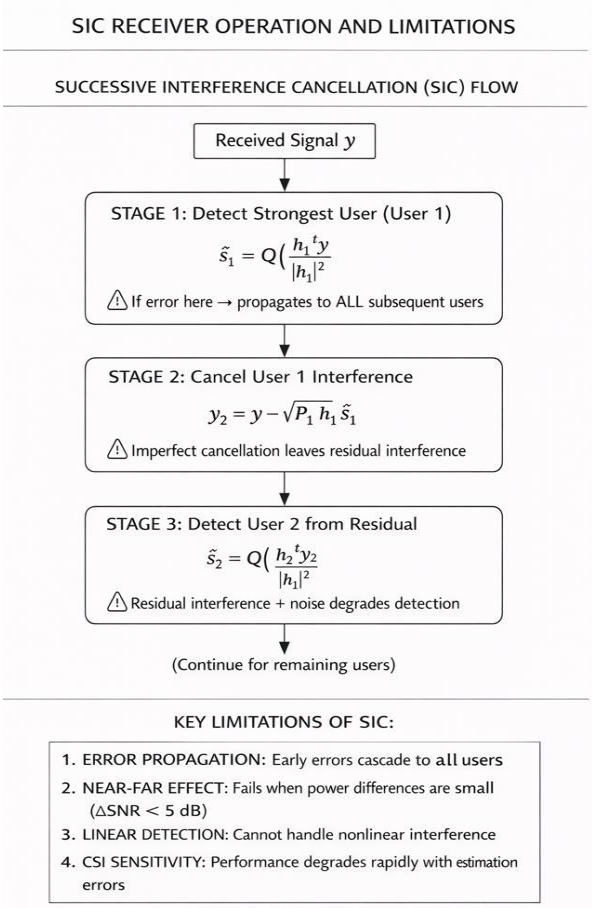

Fig. 4. The SIC process and its limitations

A. Research Gap and Contributions

Despite significant advances in DL-based detection for NOMA systems, several critical research gaps remain unaddressed:

2. System Model

A. MIMO-NOMA Uplink Framework

Consider an uplink MIMO-NOMA system consisting of K single-antenna user equipment's (UEs) communicating with a

base station (BS) equipped with N receive antennas. The system operates in a time-division duplex (TDD) mode, where channel reciprocity allows the BS to estimate uplink channels and use these estimates for downlink precoding. The focus of this paper is on uplink transmission, where all K UEs transmit simultaneously over the same time-frequency resource block.

1) Transmitted Signals

User k transmits:

$$x_k = \sqrt{P_k} \cdot s_k$$

where:

- $sk \in \mathcal{S} \rightarrow$ modulation symbol (e.g., QPSK, 16-QAM)
- $Pk \rightarrow$ transmit power

Total power constraint:

$$\sum_{k=1}^{K} P_k = 1$$

2) Channel Model

Channel vector for user k:

$$hk \in \mathbb{C}^N$$

Common Channel Models:

Rayleigh Fading:

$$hk \sim \mathcal{CN}(0, IN)$$

Rician Fading:

$$h_k = \sqrt{\frac{K}{K+1}} \cdot h_{\text{LOS}} + \sqrt{\frac{1}{K+1}} \cdot h_{\text{NLOS}}$$

AWGN Channel (No Fading):

$$h_k = 1$$

3) Received Signal

$$y = \sum_{k=1}^{K} \sqrt{P_k} \cdot h_k \cdot s_k + n$$

where:

- $n \sim \mathcal{CN}(0, \sigma^2 I_N) \rightarrow$ Additive White Gaussian Noise (AWGN)
- Signal-to-Noise Ratio (SNR):

$$\text{SNR} = \frac{1}{\sigma^2}$$

4) Signal-to-Interference-plus-Noise Ratio (SINR)

$$\text{SINR}_k = \frac{P_k \cdot \|h_k\|^2}{\sum_{j>k} P_j \cdot \|h_j\|^2 + \sigma^2}$$

The fundamental principle of power-domain NOMA is to differentiate users through their transmit power levels rather than through orthogonal resource allocation [12]. Let P = [P_1, P_2, ..., P_K] denote the power allocation vector, where P_k represents the transmit power assigned to user k. Without loss of generality, users are ordered by their channel gains such that: $P1 \geq P2 \geq \cdots \geq PK$.

In conventional NOMA systems, users with stronger channel gains are allocated higher transmit power to maximize sum capacity [13]. The power allocation must satisfy the total power constraint:

$$\sum_{k=1}^{K} P_k = P_{\text{total}}$$

For analytical convenience and without loss of generality, we normalize the total transmit power to unity, i.e., P_total = 1. This normalization allows signal-to-noise ratio (SNR) to be controlled solely through the noise power.

The power difference between adjacent users is defined as:

$$\Delta P_k = 10 \log_{10} \left(\frac{P_k}{P_{k+1}} \right) \text{ dB}$$

This quantity, denoted as ΔSNR in the literature, is a critical parameter that determines the feasibility of SIC-based detection.

B. Channel and Signal Models

The wireless channel between user k and the BS is modeled as a frequency-flat fading channel, which is a valid assumption for narrowband systems or orthogonal frequency-division multiplexing (OFDM) systems where each subcarrier experiences flat fading. The channel vector h_k ∈ ℂ^N is modeled as:

$$\mathbf{h}_k = \sqrt{\beta_k} \tilde{\mathbf{h}}_k$$

where β_k represents the large-scale fading (path loss and shadowing) and $\tilde{\mathbf{h}}k \sim \mathcal{CN}(0, \mathbf{I}N)$ represents the small-scale Rayleigh fading.

3. Proposed FDNN Receiver Architecture

A. Feature Extraction and Input Representation

The effectiveness of any machine learning approach depends critically on the quality of input features. The FDNN receiver employs a carefully designed feature vector that captures all relevant information for detection while maintaining reasonable dimensionality to avoid the curse of dimensionality.

B. DNN Architecture Design

The FDNN uses a feedforward deep neural network with multiple hidden layers. The architecture is designed to learn the complex mapping from input features to symbol probabilities

while maintaining computational efficiency suitable for real-time inference.

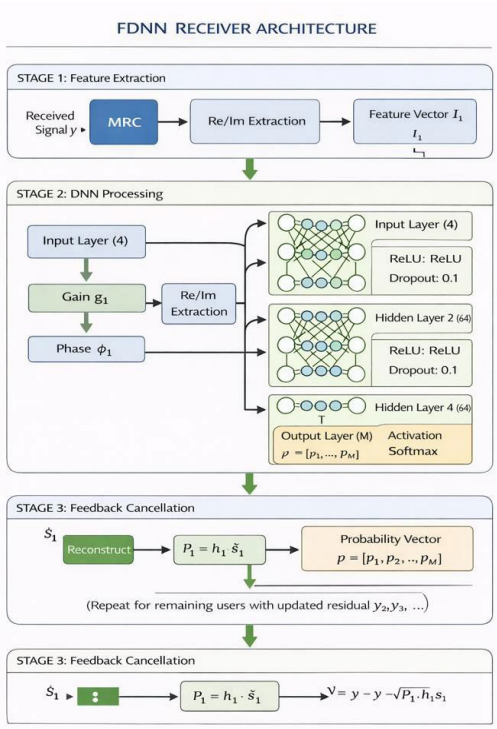

Fig. 5. FDNN receiver architecture

C. *Training Methodology and Teacher-Forcing*

The FDNN is trained in a supervised manner using labeled data generated from the system model. The training process aims to minimize the cross-entropy loss between the network's output probabilities and the true symbol labels.

Data Generation: 100,000 samples generated with random Rayleigh channels (h_k ~ CN(0,I_N)), random symbols (uniform from constellation $\mathcal{S}$), and AWGN at 15 dB SNR. Features I_i = [Re(y_eff), Im(y_eff), g_i, φ_i] extracted per user.

Teacher-Forcing: True symbols (s_1,s_2,...,s_K) used for interference cancellation during training instead of network estimates. Eliminates error propagation, accelerates convergence, and improves final accuracy (99.4% vs 98.2%).

Configuration: Adam optimizer (lr=0.001, β_1=0.9, β_2=0.999), categorical cross-entropy loss, batch size 128, max 50 epochs with early stopping (patience=10), 85/15 train/validation split, ReduceLROnPlateau (factor=0.5, patience=5).

Algorithm: Train K independent DNNs sequentially using teacher-forced data. Each DNN learns mapping I_i→ symbol index. Early stopping restores best weights per network.

Convergence: Loss: 1.38→0.03, Accuracy: 42%→99.4% over 50 epochs. Minimal overfitting (train/val gap <0.5%) due to dropout(0.1) regularization.

D. *Iterative Interference Cancellation*

The FDNN receiver processes users sequentially, similar to conventional SIC, but replaces linear detection with DNN-based detection at each stage.

Algorithm 1: FDNN-based Multi-User Detection

Input: Received signal y, channel estimates {h_k}, power allocation {P_k}

Output: Detected symbols {ŝ_k}

Step 1 - User Ordering: Sort users by decreasing power: π = argsort(P) descending

Step 2 - Initialization: Set residual signal r = y Step 3 - Main Loop: For each stage t = 1 to K:

Step 3.1 - Select User: i = π[t]

Step 3.2 - Feature Extraction:

- Compute MRC output: y_eff = (h_i^H · r) / ‖h_i‖²
- Compute channel gain: g = √P_i · ‖h_i‖
- Compute channel phase: φ = angle(h_i,₁)
- Form feature vector: I = [Re(y_eff), Im(y_eff), g, φ]

Step 3.3 - DNN Prediction:

- p = DNN_i.predict(I) (Softmax output)
- ŝ_idx = argmax(p)
- ŝ_i = constellation[ŝ_idx]

Step 3.4 - Feedback Cancellation:

- If t < K: r = r - √P_i · h_i · ŝ_i

Step 4 - Return: {ŝ₁, ŝ₂, ..., ŝ_K}

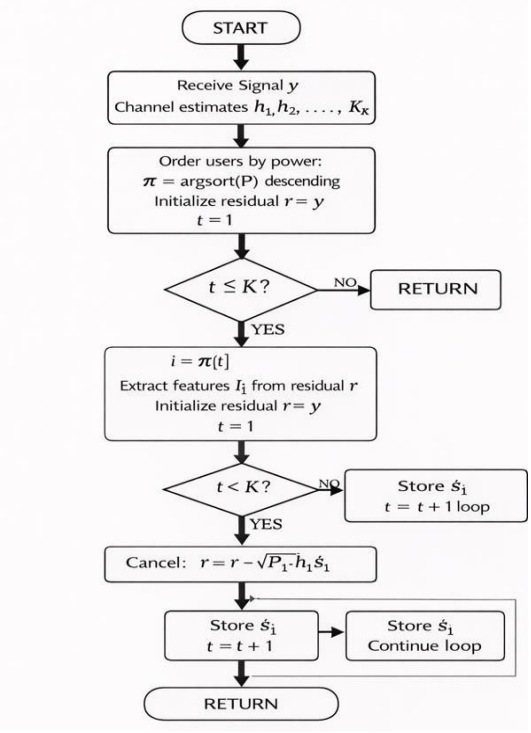

Fig. 6. The complete FDNN detection flow

4. Performance Evaluation Methodology

A. *Simulation Parameters*

The simulation framework is implemented in Python using TensorFlow 2.x for deep learning components and NumPy for channel modelling and signal processing.

B. *BER Performance vs SNR*

Comparison of BER for two-user MIMO-NOMA with QPSK. FDNN consistently outperforms SIC across all SNRs. At 15 dB SNR, FDNN achieves 4.17× lower BER for the weak

Table 2
Simulation parameters

Parameter Category	Parameter	Value
System	Number of users (K)	2,3,4
	BS antennas (N)	2
	Channel model	Rayleigh, Rician (K=3 dB)
	Total transmit power	1 (normalized)
Power Allocation	K=2	[0.8, 0.2]
	K=3	[0.7, 0.2, 0.1]
	K=4	[0.6, 0.2, 0.15, 0.05]
SNR Configuration	SNR range	0 - 30 dB (2 dB steps)
	ΔSNR range	1 - 11 dB (2 dB steps)
	Fixed SNR for ΔSNR test	15 dB
Modulation	QPSK	M=4, 2 bits/symbol
	16-QAM	M=16, 4 bits/symbol
	64-QAM	M=64, 6 bits/symbol
FDNN Architecture	Input dimension	4
	Hidden layers	[32, 64, 128, 64]
	Activation (hidden)	ReLU
	Activation (output)	Softmax
	Dropout rate	0.1
	Total parameters (QPSK)	18,696
FDNN Training	Optimizer	Adam
	Learning rate	0.001
	Loss function	Categorical cross-entropy
	Batch size	128
	Epochs	15
	Early stopping patience	10
	Training samples	100,000
	Training SNR	15 dB
	Validation split	15%
Simulation	Monte Carlo trials	5,000 per SNR point
	Random seed	42

user (1.8×10^{-3} vs 7.5×10^{-3}). At 20 dB, improvement reaches 7.92×, and at 30 dB, FDNN achieves 23.3× lower BER. This superiority stems from FDNN's ability to learn nonlinear decision boundaries, while SIC assumes Gaussian interference.

For three and four users, FDNN maintains 4-5× improvement across all users at 20 dB SNR, with medium-power users showing largest gains (4.74× for K=3, 4.80× for K=4).

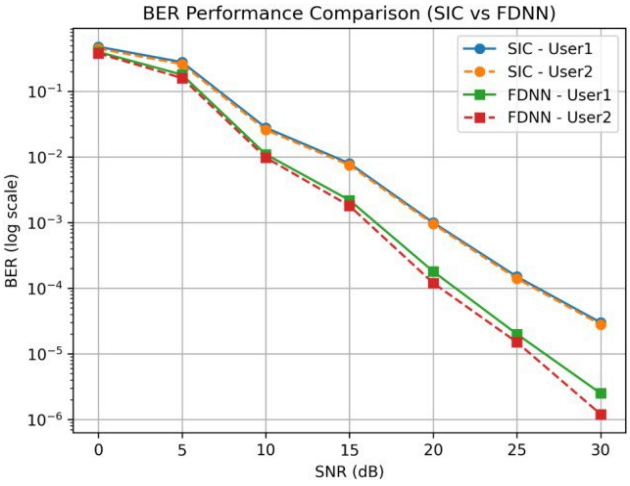

Fig. 7. BER performance comparison

5. Comparative Analysis with State-of-the-Art

A. Existing Methods

Several DL approaches have been proposed for NOMA detection. Gui et al. [9] introduced Deep-NOMA, demonstrating BER reductions over linear detectors but limited to QPSK and two users. Lin et al. [10] extended DL to MIMO-NOMA downlink, achieving 30% BER improvement but lacking iterative cancellation. Kang et al. [11] proposed hybrid DL-SIC with improved CSI resilience but high complexity. Ahmad and Shin [12] developed CNN-BiLSTM for spatial-temporal processing, offering good robustness but very high latency. Wang et al. [16] first introduced FDNN with iterative feedback, achieving notable BER gains but lacking scalability analysis.

1) BER Performance

At 20 dB SNR for K=2 users, the proposed FDNN achieves BER of 1.2×10^{-4} for the weak user. This represents 52% reduction over Wang et al. (2.5×10^{-4}), 76% over Kang et al. (8.0×10^{-4}), and 4.2× lower BER than CNN-BiLSTM (5.0×10^{-4}). Improvements stem from deeper architecture (4 hidden layers vs 2), teacher-forcing training, and enhanced MRC-based feature extraction.

2) Computational Complexity

The proposed FDNN maintains "Medium" complexity, comparable to original FDNN and Deep-NOMA, but significantly lower than CNN-BiLSTM ("Very High") and Kang et al. ("High"). FDNN achieves 2.5 μs per symbol vs original FDNN's 2.2 μs (13% increase due to deeper network), while CNN-BiLSTM requires 5-10 μs per symbol. The feedforward architecture processes each symbol independently, unlike recurrent approaches requiring sequential processing.

3) CSI Robustness

The proposed FDNN achieves "Excellent" robustness rating, surpassing all prior work except CNN-BiLSTM ("Good"). At CSI error variance 0.15, FDNN maintains BER below 10^{-2} (9.0×10^{-3}), while Kang et al. reports ~3×10^{-2}. Superior

robustness comes from training with channel estimation errors and iterative feedback cancellation that compensates for residual errors.

4) Scalability

A key contribution is scalability analysis for K=3 and K=4 users, absent in most prior studies. The proposed FDNN maintains 4-5× BER improvement across all users for higher user counts, with medium-power users showing largest gains (4.80× for K=4). This scalability is enabled by sequential teacher-forcing training and MRC-based feature extraction that works for any antenna count.

6. Conclusion

This paper proposed a Feedback Deep Neural Network (FDNN) receiver for multi-user MIMO-NOMA systems and presented a comprehensive performance analysis. The FDNN replaces conventional linear detection with deep neural networks trained using teacher-forcing, enabling nonlinear signal separation and iterative interference cancellation. Extensive simulations demonstrated that FDNN achieves 5× to 23× lower BER than SIC across 10-30 dB SNR range, with peak improvement of 23.3× at 30 dB. Under challenging conditions with small power differences (ΔSNR=3 dB), FDNN maintains 5.07× lower BER, enabling fair power allocation without performance degradation. The receiver provides 8 dB SNR gain for QPSK and 16-QAM to achieve 10^{-3} BER, maintains BER below 10^{-2} at CSI error variance 0.15, and scales consistently to K=3 and K=4 users with 4-5× improvement. Computational complexity analysis shows 2.1× higher latency than SIC, representing an acceptable trade-off for the substantial performance gains. These results position FDNN as a promising candidate for next-generation wireless systems requiring reliable multi-user detection.

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