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Bayesian Discrete-Time Markov Chain Analysis of Rainfall Dynamics in Makurdi, Nigeria

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Abstract. Rainfall variability is crucial in the management of water resources, hydrological processes, and agricultural productivity, especially in climate-sensitive areas like Makurdi, Benue State, Nigeria. This paper predicts monthly rainfall occurrence using a first-order discrete-time Markov chain within a Bayesian inference framework. The Climate Research Unit Time Series (CRU TS) dataset provided monthly rainfall data from 2014 to 2023, which were transformed into binary, wet and dry states using a threshold-based transformation. Both noninformative (Beta$(1,1)$) and weakly informative (Beta$(2,2)$) prior distributions were used to estimate the transition probabilities between rainfall state. Bayesian posterior distributions of the transition probabilities were derived analytically via Beta-Bernoulli conjugacy, allowing explicit quantification of parameter uncertainty. Results revealed strong persistence in the wet state, with posterior mean probabilities showing a high probability of remaining wet after rainfall. Sensitivity analysis shows that while symmetric transitions are largely unaffected by prior choice, weakly informative priors provide regularization for highly persistent transitions. The stationary distribution indicates long-run dominance of the wet state, while mean recurrence times confirm more frequent returns to wet conditions compared to dry periods. The Bayesian Markov chain framework provides a reliable and transparent probabilistic method for simulating the occurrence of rainfall, with significant ramifications for Makurdi's water resource planning and climate risk assessment.

Keywords: Markov Chain, Bayesian Inference, Weak prior, Stationary distribution, Rainfall Occurrence

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1. Introduction

Rainfall distribution, which is essential for comprehending water availability for agriculture and hydrological planning, defines how rainfall is distributed over a particular area or time period. Designing irrigation and drainage systems

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requires a thorough understanding of both time and spatial distribution (Campos et al., 2020; Oguntunde et al., 2011). In Makurdi, the distribution of rainfall from April to October directly affects agricultural cycles, irrigation requirements, and the likelihood of droughts or floods (Akanbi, 2020). Food security and environmental stability are at risk as a result of the region's increasingly erratic rainfall patterns brought about by climate change (Akanbi, 2020).

In Makurdi, changes in rainfall patterns are driven by several interrelated factors, including climate change, alterations in land usage, and the prevalent atmospheric conditions specific to the region (Musa et al., 2021).

Regression models, time-series analysis techniques like Autoregressive Integrated Moving Average (ARIMA), and other deterministic models have been used traditionally to estimate temporal rainfall trends in Nigeria. Nevertheless, the temporal dependency and stochastic character of rainfall episodes are often overlooked by such approaches. In contrast, stochastic modeling methods—in particular, the Markov chain—offer a potent tool for capturing changes in rainfall conditions across time (Yusuf et al., 2014). Because it simulates rainfall as a probabilistic process, where the likelihood of a particular condition (such as wet or dry) depends only on the state of the preceding period, the Markov chain technique is advantageous. Because of this, it can be used to describe the inherent randomness of rainfall sequences (Yusuf et al., 2014).

Some researchers used Markov chain to estimate and model their work. Researchers such as Agada et al. (2025) focused on the annual rainfall trends in the South-South region of Nigeria from about six states from 1990 to 2020. He introduced a seven-state Markov chain model grouping rainfall from "very low" to "extremely high." According to his research, it was found that the transition probabilities across the states revealed dominant rainfall behaviors, essential for regional water management, climate adaptation strategies, and flood control measures.

Also, in the work of Ogundeji and Okemakinde (2025), they studied and adopted a Bayesian Structural Time Series (BSTS) model for rainfall forecasting. They analyzed monthly rainfall data from different stations across Nigeria, and they compared the model's forecasts with those of the traditional Seasonal Autoregressive Integrated Moving Average (SARIMA) model. Using MCMC sampling to estimate model parameters and latent components like trend and seasonality, the BSTS model skillfully captures underlying patterns and provides useful prognostic uncertainty measures.

Despite the extensive research work on rainfall variability and forecasting in Nigeria, significant methodological and regional gaps remain. The majority of current research uses deterministic or classical stochastic techniques such as regression, ARIMA, and SARIMA models, which often fail to accurately capture the inherent state dependence and randomness of rainfall processes. While Markov chain models have been used to analyze rainfall in various parts of Nigeria, these studies primarily rely on frequentist estimation of transition probabilities, yielding point estimates with little consideration of parameter uncertainty arising from irregular or limited observations.

More recent Bayesian methods, such as Bayesian Structural Time Series (BSTS) models, have enhanced probabilistic rainfall forecasting by incorporating uncertainty quantification. However, these Bayesian frameworks are infrequently used in conjunction with Markov chain models for discretized rainfall states, especially at local or station-specific scales. Studies using Bayesian estimation of Markov chain transition probabilities, stationary distributions, and recurrence measures for rainfall occurrence in Makurdi, Benue State, are particularly lacking. As a result, there is still much to learn about the joint application of Markov chain modeling and Bayesian inference to rainfall occurrence in Makurdi. Closing this gap is essential to generate more trustworthy probabilistic insights into rainfall patterns and enhance uncertainty-aware decision-making for agriculture, water resource management, and climate risk adaptation in the region.

2. Materials and Methods

This study used monthly rainfall (2014–2023) data obtained from the Climate Research Unit Time Series (CRU TS) available at the Centre for Environmental Data Analysis (CEDA: http://data.ceda.ac.uk//badc/cru/data/cru$_t s/)$.
This study adopted the method of data transformation used by Shahraki et al. (2013), who converted daily rainfall data using 0.1 mm as the threshold for dry and wet days:

$$\text{Dry day} \leq 0.1 \text{ mm}, \qquad \text{Wet day} > 0.1 \text{ mm}.$$

In this research, 0.1 was multiplied by 30.044, which is the average number of days in a month, to categorize monthly rainfall data:

$$\text{Dry month} \leq 3.044 \text{ mm}, \qquad \text{Wet month} > 3.044 \text{ mm}.$$

Thus, the monthly rainfall amounts X_t were discretized into two states:

$$X_t = \begin{cases} \text{dry}, & X_{t+1} \leq 3.044 \text{ mm}, \\ \text{wet}, & X_{t+1} > 3.044 \text{ mm}. \end{cases}$$

Thus, the state space becomes dry and wet, where t represents time.
This study employs a first-order discrete-time Markov chain within a Bayesian estimation framework to model rainfall occurrence in Makurdi, Benue State, Nigeria.

2.1 *Markov Chain Model*

A Markov chain or Markov process is a mathematical system that undergoes transitions from one state to another from a finite or countable number of possible states in a chain-like manner (Strelioff et al., 2007)
The likelihood of going from state i to state j in n time steps is defined as:

$$P_{ij}^{(n)} = \Pr(X_n = j \mid X_0 = i) \tag{1}$$

and the single-step transition probability is

$$P_{ij} = \Pr(X_1 = j \mid X_0 = i) \tag{2}$$

For a time homogeneous Markov chain:

$$P_{ij}^{(n)} = \Pr(X_{k+n} = j \mid X_k = i) \tag{3}$$

and

$$P_{ij} = \Pr(X_{k+1} = j \mid X_k = i) \tag{4}$$

The Chapman-Kolmogorov equation is:

$$P_{ij}^{(n)} = \sum_{r \in S} P_{ir}^{(k)} P_{rj}^{(n-k)} \tag{5}$$

where the Markov chain has state space S.
The evolution of the process through one time step is described by

$$\Pr(X_n = j) = \sum_{r \in S} p_{rj} \Pr(X_{n-1} = r) \tag{6}$$

2.2 *Discrete-Time Markov Chains (DTMC)*

A discrete-time Markov chain $\{X_t\}$ is defined on a finite set of states

$$S = \{s_1, s_2, \ldots, s_k\}$$

such that

$$P(X_{t+1} = s_j \mid X_t = s_i, X_{t-1} = s_{i-1}, \ldots, X_0) = P(X_{t+1} = s_j \mid X_t = s_i) \tag{7}$$

The system can be represented by a Transition Probability Matrix (TPM):

$$P = [p_{ij}]$$

where

$$p_{ij} = P(X_{t+1} = j \mid X_t = i) \tag{8}$$

2.3 *Transition Counts*

In a Markov Chain, transition count refers to the quantitative frequency with which the process moves from one given state to another particular state within the chain. Given a sequence $\{X_0, X_1, \ldots, X_n\}$ of observed states, the movement to state j from state i is given by

$$P_{ijk} = \frac{n_{ijk}}{n_{ij}}, \quad \text{where} \quad n_{ij} = \sum_k n_{ijk} \quad \text{and} \quad P_{ijk} = P(X_t = k \mid X_{t-1} = j, X_{t-2} = i) \tag{9}$$

The probability is denoted by P_{ij}, and this probability does not depend on the states of the chain before the current state (Mahfuz, 2021).

2.4 *Bayesian Estimation of Markov Chain Parameters*

Theorem 1: Posterior distribution of a transition probability. Let $X_t \geq 0$ be a discrete-time Markov chain on a finite state space

$$S = \{1, \dots, d\}$$

with transition matrix

$$P = (P_{ij})_{i,j \in S}$$

where

$$P_{ij} = P(X_{t+1} = j \mid X_t = i) \tag{10}$$

Let D denote observed transition data summarized by transition counts

$$N_{ij} = \#\{t : X_t = i, X_{t+1} = j\} \tag{11}$$

Under model M with hyperparameters θ, the posterior distribution of the transition probability is

$$P(P_{ij} \mid D, M) = \frac{1}{P(D \mid M)} \int P(D \mid P_{ij}, \theta, M) P(P_{ij} \mid \theta, M) P(\theta \mid M)\, d\theta \tag{12}$$

2.5 *Bayes' Theorem*

At the initial stage of Bayesian inference, a probabilistic model that links the observed data to the underlying parameters is established. There is a clear connection between the observed data (D), the selected model (M), and the model parameters (P_{ij}). When inference about these parameters is required, attention is focused on the posterior probability $P(P_{ij} \mid D, M)$, which represents the probability of the parameters after observing the data and specifying the model (Strelioff et al., 2007)

$$P(P_{ij} \mid D, M) = \frac{P(D \mid P_{ij}, M) P(P_{ij} \mid M)}{P(D \mid M)} \tag{13}$$

In this study, binary data (0,1: wet or dry) are modeled, and the binomial distribution is considered to be the most appropriate for this type of data.

2.6 *Likelihood of the Data (Bernoulli Trials)*

The outcome is either "0" or "1" for each step, just like a Bernoulli random variable. Thus,
Conditional on $X_t = 0$:

$$X_{t+1} \mid X_t = 0 \sim \text{Bernoulli}(p = P_{i0})$$

Conditional on $X_t = 1$:

$$X_{t+1} \mid X_t = 1 \sim \text{Bernoulli}(p = P_{i1})$$

For row 0:

$$L_0(P_{00} \mid X) = P_{00}^{N_{00}}(1 - P_{00})^{N_{01}} \tag{14}$$

Similarly, for row 1:

$$L_1(P_{10} \mid X) = P_{10}^{N_{10}}(1 - P_{10})^{N_{11}} \tag{15}$$

The full likelihood becomes:

$$L(P \mid X) = P_{00}^{N_{00}}(1 - P_{00})^{N_{01}} P_{10}^{N_{10}}(1 - P_{10})^{N_{11}} \tag{16}$$

The log-likelihood is:

$$\ell(P \mid X) = N_{00} \log P_{00} + N_{01} \log(1 - P_{00}) + N_{10} \log P_{10} + N_{11} \log(1 - P_{10}) \tag{17}$$

2.7 *Beta Prior*

Each row of the transition matrix is modeled as a Bernoulli process, so the Beta distribution is a natural conjugate prior (Assoudou and Essebbar, 2002).

$$p_{i0} \sim \text{Beta}(\alpha_{i0}, \beta_{i0})$$

The probability density function is given by

$$P(p_{i0}) = \frac{\Gamma(\alpha_{i0} + \beta_{i0})}{\Gamma(\alpha_{i0})\Gamma(\beta_{i0})} p_{i0}^{\alpha_{i0}-1}(1 - p_{i0})^{\beta_{i0}-1}, \quad 0 < p_{i0} < 1 \tag{18}$$

Written directly in terms of both transition probabilities in row i, we have:

$$P(p_{i0}, p_{i1}) = \frac{\Gamma(\alpha_{i0} + \beta_{i0})}{\Gamma(\alpha_{i0})\Gamma(\beta_{i0})} p_{i0}^{\alpha_{i0}-1} p_{i1}^{\beta_{i0}-1}, \quad \text{with } p_{i0} + p_{i1} = 1 \tag{19}$$

In the Beta prior distribution, the parameter α is interpreted as the prior number of successes, while β represents the prior number of failures. Together, the sum

$\alpha + \beta$ can be regarded as the prior sample size, reflecting the strength of the prior information before observing the data (Akhtar and khan 2019)..

2.8 *Posterior Distribution*

To derive the posterior distribution, we begin with the joint probability of the data and the parameters. By Bayes' theorem,

$$P(P_{ij} \mid X) \propto L(P \mid X)\, P(p_{ij}) \tag{20}$$

Hence,

$$\begin{aligned} P(P_{ij} \mid X) &\propto P_{00}^{N_{00}}(1 - P_{00})^{N_{01}}\, P_{10}^{N_{10}}(1 - P_{10})^{N_{11}} \\ &\quad \times P_{00}^{\alpha_{00}-1}(1 - P_{00})^{\beta_{00}-1}\, P_{10}^{\alpha_{10}-1}(1 - P_{10})^{\beta_{10}-1} \end{aligned} \tag{21}$$

Focusing on P_{00}, the posterior is:

$$\begin{aligned} P(P_{00} \mid X) &\propto P_{00}^{N_{00}}(1 - P_{00})^{N_{01}}\, P_{00}^{\alpha_{00}-1}(1 - P_{00})^{\beta_{00}-1} \\ &= P_{00}^{N_{00}+\alpha_{00}-1}(1 - P_{00})^{N_{01}+\beta_{00}-1} \end{aligned} \tag{22}$$

By Beta–Bernoulli conjugacy,

$$P(P_{00} \mid X) \sim \mathrm{Beta}(N_{00} + \alpha_{00},\, N_{01} + \beta_{00})$$

That is,

$$P(P_{00} \mid X) \sim \mathrm{Beta}(\text{observed successes}+\text{prior successes},\, \text{observed failures}+\text{prior failure}$$

The posterior mean is:

$$E(P_{00} \mid X) = \frac{N_{00} + \alpha_{00}}{\alpha_{00} + \beta_{00} + N_{00} + N_{01}} \tag{23}$$

Non-informative prior (Uniform): A uniform prior assumes that all possible values of a parameter are equally likely before observing any data. It is used when there is no prior knowledge favoring any value. This expresses complete uncertainty and allows the data to dominate the inference. However, it may sometimes lead to unrealistic estimates when the parameter space is large (Karadavut, 2019).

$$\alpha_{00} = \beta_{00} = 1$$

$$E(P_{00} \mid X) = \frac{N_{00} + 1}{2 + N_{00} + N_{01}} \tag{24}$$

Weakly informative prior: A weakly informative prior introduces mild prior knowledge to stabilize estimation without overwhelming the data. It helps prevent extreme or implausible parameter values, especially with small samples. This prior provides regularization while still allowing the data to dominate the posterior inference (Hamra 2013).

$$\alpha_{00} = \beta_{00} = 2$$

$$E(P_{00} \mid X) = \frac{N_{00} + 2}{4 + N_{00} + N_{01}} \tag{25}$$

2.9 *Markov Chain Stationary Distribution*

Given a state S, the stationary distribution, also referred to as the steady-state or long-run distribution of a Markov chain describes the likelihood that the system will be in this specific state at an arbitrary step at infinity (Meggendorfer, 2023).

$$\pi_j \geq 0$$

and

$$\sum_{j \in S} \pi_j = 1$$

such that

$$\pi_j = \sum_{i \in S} \pi_i P_{ij} \tag{26}$$

2.10 *Mean Recurrence Time*

$$m_{ij} = E(T_j \mid X_0 = i) \tag{27}$$

where

$$T_j = \min\{n \geq 1 : X_n = j\} \tag{28}$$

then

$$m_{ij} = 1 + \sum_{k \neq j} P_{ik} m_{kj} \tag{29}$$

The mean recurrence time is

$$\mu_i = E(T_i \mid X_0 = i) \tag{30}$$

(Fabrega, 2022)

3. Results and Discussion

This section presents the empirical findings of the study based on the methodology.

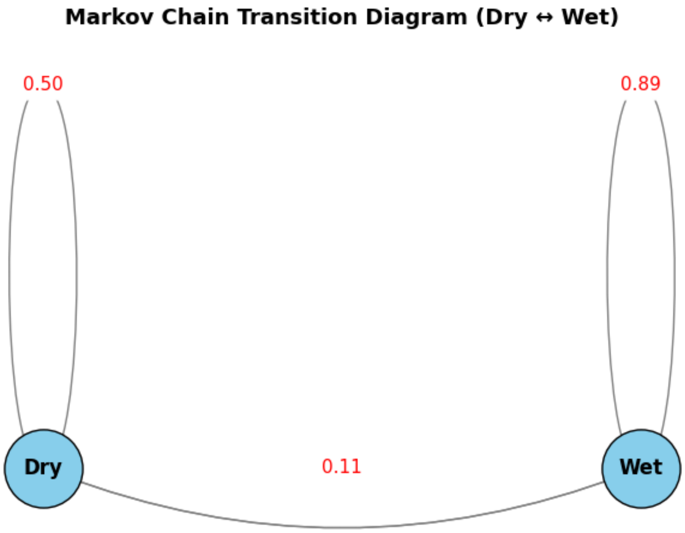

Figure 1: Markov Chain Transition Diagram

Figure 1 shows the rainfall process modeled as a two-state, first-order Markov chain with states Dry and Wet. The estimated transition probabilities indicate pronounced state asymmetry: wet conditions exhibit strong persistence, whereas dry conditions are less stable. The probability of rainfall onset following a dry period is relatively low, implying that wet spells tend to occur in clusters rather than as isolated events. Overall, the transition structure reflects strong temporal dependence in rainfall occurrence, with extended wet spells and comparatively frequent interruptions of dry spells, a pattern consistent with rainfall dynamics in tropical climates.

Table 1: Transition Probability Matrix

	Dry	Wet
Dry	0.5000	0.5000
Wet	0.1111	0.8889

Table 2: Posterior Mean Transition Matrix (Beta prior)

	Dry	Wet
Dry	0.5000	0.5000
Wet	0.1818	0.8182

Table 3: Posterior Beta Parameters and Means

Transition	Prior	Posterior	Posterior Mean
Dry $\rightarrow$ Wet	Beta(1,1)	Beta(2,2)	0.500
Dry $\rightarrow$ Wet	Beta(2,2)	Beta(3,3)	0.500
Wet $\rightarrow$ Wet	Beta(1,1)	Beta(9,2)	0.818
Wet $\rightarrow$ Wet	Beta(2,2)	Beta(10,3)	0.769

Table 3 compares posterior transition probabilities under two prior specifications, Beta(1,1) (uniform, noninformative) and Beta(2,2) (weakly informative). Under both priors, the posterior mean for the Dry to Wet transition stays at 0.50. The observed data's symmetry (one wet and one dry outcome) is reflected in this. When the likelihood is symmetric, even a weakly informative prior does not skew inference because the posterior estimate is indifferent to prior choice due to the perfectly balanced data. On the other hand, there is a clear sensitivity to the preceding in the Wet to Wet transition. The posterior mean, which closely matches the empirical proportion (8 out of 9), is 0.818 under the Beta(1,1) prior. The posterior mean drops to 0.769 when a weakly informative Beta(2,2) prior is applied. The dominating Wet to Wet tendency is maintained, although the high persistence shown by the data is tempered by this change, which signifies shrinking toward the preceding mean (0.5).

Table 4: Stationary Distribution

State	Stationary Probability
Dry	0.266667
Wet	0.733333

In Table 4, the stationary distribution represents the long-run proportion of time the system is expected to spend in each state, regardless of the initial condition. The model predicts that the system will spend approximately 26.7% of the time in the Dry state and 73.3% of the time in the Wet state. This confirms that the Wet state dominates the system's long-term behavior; the Markov chain tends to settle into a persistently wet regime.

Table 5: Mean Recurrence Time

State	Mean Recurrence Time
Dry	3.750000
Wet	1.363636

Table 5 shows that the mean recurrence time indicates the expected number of steps required to return to a particular state once it is left. For the Dry state: On average, it takes 3.75 time steps to return once it has transitioned away. For the Wet state: On average, it takes only 1.36 time steps to return. This implies that the Wet state recurs much more frequently, while the Dry state is relatively rare and less persistent.
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Wet state: On average, it takes only 1.36-time steps to return. This implies that the Wet state recurs much more frequently, while the Dry state is relatively rare and less persistent.

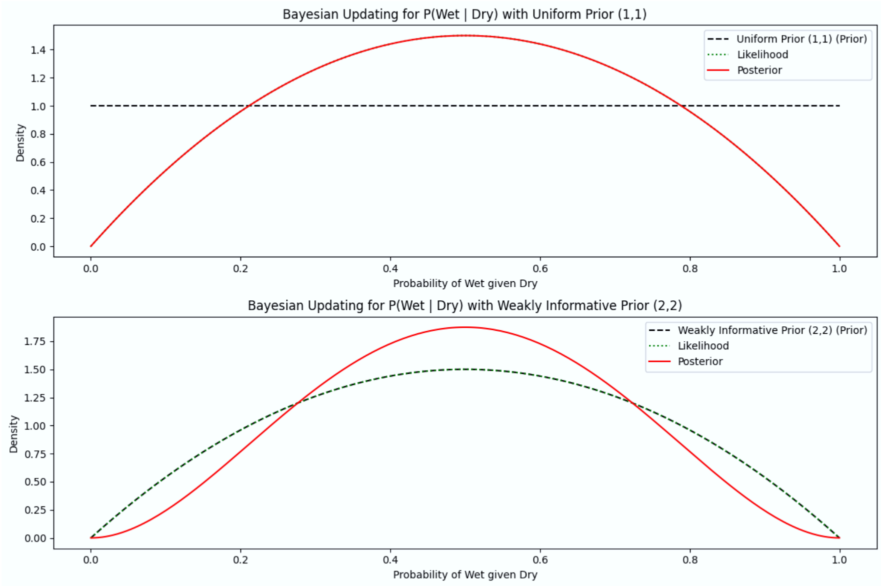

Figure 2: $P(\text{Wet}|\text{Dry})$ with Uniform and Weakly Informative Priors

The uniform prior, represented by the dashed black line, gives all values in [0,1] equal density, indicating total prior ignorance about the transition probability. Based on one wet and one dry observation, the chance is symmetrical around 0.5. Consequently, the posterior distribution (solid red curve) is Beta(2,2), with a moderate dispersion and a center of 0.5. The weakly informative prior Beta(2,2), which discourages extreme values near 0 or 1 and somewhat favors probabilities near 0.5, is represented by the dashed black curve in the bottom panel. The posterior becomes Beta(3,3) (solid red curve) when paired with the same symmetric likelihood. Compared to the uniform prior Beta(1,1), the posterior is more sharply peaked around 0.5 and less diffuse, indicating reduced uncertainty. This mirrors the regularizing effect of the weakly informative prior, which contributes pseudo-observations that stabilize inference without shifting the posterior mean from the data-supported value.

4. Conclusion

This study modeled the monthly occurrence of rainfall in Makurdi, Benue State, Nigeria, using a Bayesian discrete-time Markov chain framework. The research specifically took into account uncertainty resulting from limited observations by discretizing rainfall into wet and dry states and predicting transition probabilities using conjugate Bayesian methods. High posterior probabilities for wet-to-wet transitions, a dominant wet-state stationary distribution, and shorter mean recurrence periods for wet months all show considerable persistence of wet conditions.

A comparison of weakly informative and noninformative priors reveals that weakly informative priors successfully regularize extremely persistent transitions, lowering overconfidence without skewing data-supported inference, but symmetric transition data are mostly unaffected by prior choice. This demonstrates how Bayesian approaches are useful for stabilizing parameter estimates, especially in small or noisy datasets. Overall, by concurrently simulating rainfall dynamics and uncertainty, the Bayesian Markov chain technique offers richer probabilistic insight than conventional frequentist methods.

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