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A Markov Chain Approach on Daily Rainfall Occurrence

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ABSTRACT

Markov modeling is one of the tools that can be used to help planners for assess precipitation. The first order Markov chain model was used to predict daily precipitation intervals using transition probability matrices. The demand for precipitation is increasing, not only for data invention, but also to provide useful information in numerous applications, including water properties organization and the hydrological and agricultural subdivisions. In this study, the objective is to predict the probability of future precipitation of the city of Pyin Oo Lwin using the Markov chain model. The system was developed on the basis of the Markov method to forecast the occurrence of precipitation. The results show that models can forecast the state of a given day by 74% on average.

KEYWORDS: *prediction, markov chain, precipitation*

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1. INTRODUCTION

Precipitation is the only source of fresh water, use and irrigation necessary for life. As a result, changes in precipitation patterns affect all ecosystems. In a tropical country like Myanmar, rainfall unpredictability is a main caution factor in hydropower generation and food production. The majority of people who work at Pyin Oo Lwin are farmers, this rain forecast will be very helpful to support at work.

Many researchers, such as Soft Computing and Data Mining, have forecast rain. Previous Soft Computing studies to predict precipitation can be seen as follows: in [1] the sequence of occurrence of daily precipitation is studied. They found that the daily rainfall occurrence for Tel Aviv data was successfully adjusted with the first-order Markov chain model. In [2], the optimal order of a Markov chain model for daily rainfall events are determined at 5 sites in Nigeria using AIC and BIC. It was concluded that caution was needed when using AIC and BIC to determine the optimal order of the Markov model. The use of time / frequency curves can provide a robust alternative method for identifying the model.

In [3], the intra-annual variation of Markov chain parameters for seven sites in Nigeria is also studied. They found that there was a systematic variation in the probability of a rainy day after a dry day when moving north and a limited regional variation. A general conclusion is that a first-order Markov model is suitable for many sites, but a second-order or higher model may be required at other sites or at certain times of the year. Meanwhile, in [5] a first order Markov chain model matched the data observed in Italy. The model was based on the assumption that the occurrence of daily precipitation was dependent on the previous day's occurrence.

In [8], GA and Fuzzy algorithm are combined for weather system for meteorological data in the Kemayoran region with an accuracy of over 90%. In [9], we conducted climate prediction surveys combining GA (genetic algorithm) and PCFNN (Partially Connected Neural Network) for Kemayoran - Jakarta Center with an accuracy of 81.52%. In [10], a comparison of GE (Grammatical Evolution) and ANFIS (Adaptive Neuro-Fuzzy Inference) algorithms was performed for the prediction of rainfall in Bandung regency with a precision of 74.35% for GE and 80% for ANFIS. In [11], implement local regression smoothing and fuzzy-grammatical evolution using Bandung regency precipitation data with an accuracy of 91.10%.

A stochastic model can be used to predict the probability of occurrence of annual precipitation. According to Taha [6], a stochastic process consisting of a random variable X_n, which characterizes the state of the system at discrete points at time t = 1,2, .. is a Markov process if the appearance of a future state depends only on the immediately preceding state. Markov chain models provide fast predictions immediately after any observation because they use only local information as predictors and require a minimum computation after data processing [6, 7].

The rest of the paper is organized as follows. Section 2 describes markov chain, and Section 3 explains illustrative example and finally, Section 4 concludes the paper and discusses the future enhancements that can be applied to the present work.

2. MARKOV CHAIN

The Markov chain appeared for the first time in an article written in 1906 by the Russian mathematician Andrei Andreevich Markov, which describes the stochastic process and provides the probability information of a transition from one state to another. The stochastic process must satisfy the property "without memory"; that is, the probability distribution of the future state is based solely on its current state and is independent of previous events in the time series. A Markov chain can be defined as a time-ordered kind of probabilistic process that changes from one state to another based on probabilistic transition instructions determined only by the current state. In other words, the possibility that a day is in a certain state (sunny or rainy) is accustomed by the states of previous stages, where the number of previous periods is called the order of the chain. When you record whether a measurable amount of rainfall has inwards in time at a specific location (time series of 2 states), the data will be in the form of a sequence of discrete states. The most generally used model for the discrete state sequence is a stationary low order Markov chain. Such models make it possible to predict the presence of certain sequences [4].

Sunny and rainy are the states of the system. A rainy condition is well-defined as a 24-hour period with the total quantity of rain. Otherwise, the state is considered sunny. The discrete state series of rainfall can be characterized as $x_1, x_2, x_3 \ldots\ldots x_t$ for a t distance sequence, where $x_t = 0$, if day t is sunny and $x_t = 1$, if day t is rainy.

2.1. First order Markov model

The probabilities of a first-order Markov chain are defined by P $\{x_t = j \mid x_{t-1} = i\}$ i, j = 0,1

The transition probability P_{ij} ((i, j = 0, 1) is the probability that the system will be in state i in one observation, the state j in the next observation, probability, the value of all the numbers Pij is [0, 1 The primary transition probability can be expressed as follows:

$P_{ij}^{(t)} = P\{ X_t = j \mid X_{t-1} = i \}$ i,j = 0,1 (1)

For any fixed i, {i = 0, 1}, the probability must have, $P_{i0} + P_{i1} = 1$

This expresses the detail that if the system is in one of the conditions of an observation, it will surely be in one of the two states of the next observation. With these transition probabilities, a matrix of 2 × 2 P = $\{P_{ij}\}$ T can be formed, called the Markov process transition matrix, where the sum of the entries of each column of P is equal to one.

$$P = \begin{pmatrix} P_{00} & P_{01} \\ P_{10} & P_{11} \end{pmatrix} \quad (2)$$

We say that the probability directions p (n) for n = 0, 1, 2, ... are the state vectors of a Markov process, where pi (n) is the probability that the system either in state i in observation n. To be exact, the state direction p (0) is called initial probability or initial state vector of the Markov process. If P is the transition matrix and p (n) is the state vector in observation n, we can write

$$P^{(n+1)} = P^{(n)} + P \quad (3)$$

where $p^{(n+1)}$ is the state vector at the n+1th observation. From this it follows that

$$P^{(n)} = P^{(0)} + P \quad (4)$$

i.e., the initial state vector p (0) and the transition matrix P determine the state vector p (n) on day n. The transition probabilities of step n are called conditional probabilities and are indicated by P_{ij} (n), (where i, j = 0, 1) with P_{ij} (n) ≥ 0, for n = 0,1,2,3 .... and

$$\sum_{j=0}^{1} P_{ij}^{(n)} = 1 \quad (5)$$

For the 1st order Markov chain, $p^{(n)} = p^{(0)} P$ in matrix notation can be written as [4].

$$\left(p_0^{(n)}\; p_1^{(n)}\right) = \left(p_0^{(0)}\; p_1^{(0)}\right) \begin{pmatrix} P_{00} & P_{10} \\ P_{01} & P_{11} \end{pmatrix}^n \quad (6)$$

3. METHODOLOGY

3.1. Dataset

The study area is Pyin Oo Lwin in Mandalay Division in Myanmar. It is located at an altitude of 3538 feet above the sea level and is the mountain resort in Mandalay. The data was compiled by the Department of Meteorology and Hydrology (Mandalay), for a period of 10 years, from 2008 to 2017. Precipitation is usually measured with a rain gauge. It is expressed as the depth of water that accumulates on a flat surface and is measured regularly in inches. The daily precipitation of Pyin Oo Lwin is considered as an input parameter.

3.2. Modelling Markov Chain

Daily precipitation data from the weather station of Myanmar were used in this modeling study. The period from 2008 to 2016 was chosen in the evaluation of the model. A sunny state is defined with a total precipitation of 0 inches. A rainy state is defined as total precipitation greater than 0 inches. One of the main assumptions of the Markov chains is stationarity. The transitional probabilities P_{ij} of the first order were calculated as

P_{00} = P (S/S)
P_{01} = P (R/S) = 1- P_{00}
P_{10} = P (S/R)
P_{11} = P (R/R) = 1- P_{10}

where P (R/S) represents the transition probability of a sunny day and rainy day.

Table1. Some Rainfall Data

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
1 June	7	2	2	0	2	0	0	0	22	4
2 June	2	3	0	0	0	36	0	0	11	1

$$\begin{array}{cc} & \begin{array}{cc} \text{Sunny} & \text{Rainy} \end{array} \\ \begin{array}{c} \text{Sunny} \\ \text{Rainy} \end{array} & \begin{bmatrix} 3 & 1 \\ 2 & 3 \end{bmatrix} \end{array}$$

$$\begin{array}{c c} & \begin{array}{cc} \text{Sunny} & \text{Rainy} \end{array} \\ \begin{array}{c} \text{Sunny} \\ \text{Rainy} \end{array} & \begin{bmatrix} 3/4 & 1/4 \\ 2/5 & 3/5 \end{bmatrix} \end{array}$$

$$\begin{array}{c c} & \begin{array}{cc} \text{Sunny} & \text{Rainy} \end{array} \\ \begin{array}{c} \text{Sunny} \\ \text{Rainy} \end{array} & \begin{bmatrix} 0.75 & 0.25 \\ 0.4 & 0.6 \end{bmatrix} \end{array}$$

1 June 2017 => Rainy => $x^{(0)} = [0\ 1]$

The weather on 2 June 2017 can be predicted by
$x^{(1)} = x^{(0)} P = [0\ 1] \begin{pmatrix} 0.75 & 0.25 \\ 0.4 & 0.6 \end{pmatrix} = [\ 0.4\ 0.6]$

Thus, there is a 60% chance that 2nd June will also be rainy. There is a 40% chance that 2nd June will be sunny. As a result, there is a 60% chance that June 2 will also be rainy.

There is a 40% chance that June 2nd will be sunny.
In the current 10-year data approach, 9-year data were used to estimate transition probabilities. The remaining year was considered as the year observed and was used to calculate the initial probabilities as well as the prognostic controls.

3.3. System Flow of Rainfall Prediction

The system flow diagram shows the one-day prediction of the system and as shown in Fig 1. The system uses rainfall data set from Pyin Oo Lwin. The input of the system is weather data of 2017 in this city. In this system, Markov chain approach is used. The system counts the states using the previous 9 years dataset. The output of the system is the probability of rainfall in the following days. The system is implemented by using Java Programming.

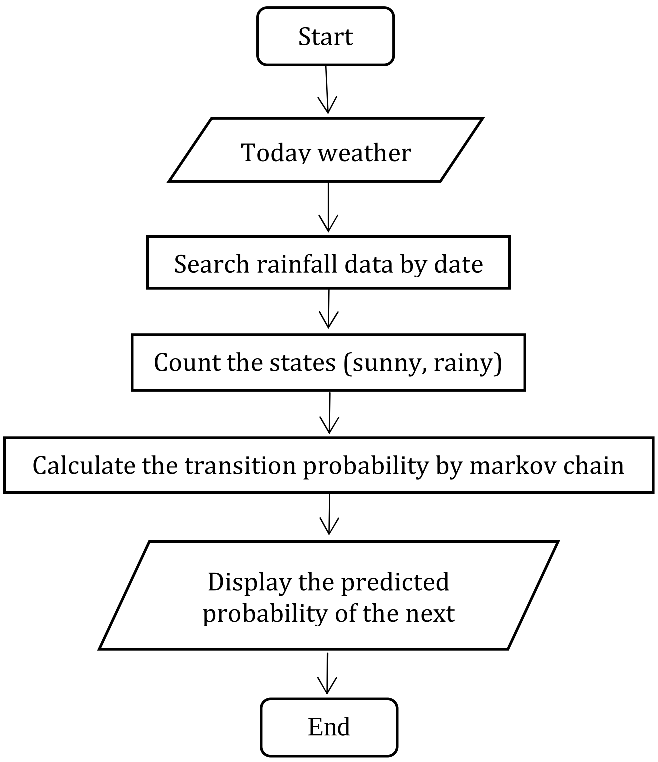

Fig 1 Flow chart for predicting rainfall

4. CONCLUSIONS

In this study, in which the daily precipitation probabilities for Pyin Oo Lwin are determined, the Markov chain model is established and the results are evaluated. The amount of total daily precipitation observed for the year 2017 was compared with the values obtained with the model to prove the accuracy of the model. Precipitation range with a good chance of occurrence based on model result for 2017 with 74%. Although the predicting model described here is only used to predict the probability of rain, the same frame of the Markov chain can be further developed to predict rainfall quantities.

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