KULLIYYAH OF INFORMATION AND COMMUNICATION TECHNOLOGY

CSCI 3303 MATHEMATICS FOR COMPUTING III

SECTION 3

SEMESTER 1, 2022/2023

GROUP PROJECT

PROJECT TITLE: HEATEWAVES PREDICTION IN MALAYSIA USING MARKOV

PREPARED BY

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A. **Overview**

1. Introduction

   Heatwaves are a serious problem, and they are becoming more frequent and severe in many parts of the world, including Malaysia. They are defined as periods of abnormally hot weather that can last for days or weeks. They can cause several health problems and in extreme cases, heatwaves can even be fatal. The frequency and severity of heatwaves have been increasing in recent years due to climate change. Climate change is causing the Earth's atmosphere to warm, which is leading to more extreme weather events.

   In this project, we will use the Markov chain method to analyze and predict the change probabilities of heatwave occurrences in 2 different states in Malaysia which are Kuala Lumpur and Perlis. The aim is to understand the probability of transitioning and significant differences between different heatwave states. We believe that this project will be a valuable contribution to the field of climate change research. The findings of this project will help us to better understand the impact of climate change on heatwaves. This information can then be used to develop policies and strategies to reduce the effects of heatwaves.

2. problem discussion

   Heatwaves can cause several negative impacts, including increased risk of heat-related illness and death, decreased productivity and economic activity, damage to infrastructure and crops, and increased risk of wildfires. The frequency and severity of heat waves have increased in recent years due to climate change. Thus, analyzing and predicting the probabilities of heatwaves can help in addressing that problem and give suggestions of how to decrease the heatwave probabilities.

3. Objectives

   - analyze and predict the change probabilities of Heatwave occurrences in are Kuala Lumpur and Perlis using the Markov chain method.
   - understand the probability of transitioning between different Heatwave states.

4. expected results.
   - A model that can predict the probability of heatwaves in are Kuala Lumpur and Perlis.
   - A better understanding of the factors that are most likely to contribute to heatwaves are Kuala Lumpur and Perlis.

(minimum **12** articles/references, use **Google scholar – 2015 -2022**)

Write on Similar Projects/Research, in the past or ongoing.

1. Generally, about the topic
2. Linear Algebra method(s) you plan to use, how it has been used to solve different problems.
3. Linear Algebra method(s) use to solve related problems

B. Related Work

1- Estimating the Occurrence Probability of Heat Wave Periods Using the Markov Chain Model (2015)

In this article, Markov chain model was applied. To forecast the probability of heatwaves in Iran, A dataset of daily maximum temperatures from 1980 to 2010 was used to train the model. Heatwaves may be predicted by the model with high accuracy. The Markov chain model, according to scientists, is a promising method for predicting heatwaves and might be used to develop heatwave early warning systems.

2- Markov chain analysis of the probability of days in the heat wave period (2022)

The article discusses the use of Markov chains to predict heatwaves in Hungary, it provides a good overview of the theory and methodology of Markov chains, The authors used a matrix to represent the transition probabilities between different states of the weather system. They then used a technique called eigenvector decomposition to find the equilibrium distribution of the system. The equilibrium distribution is the distribution of the weather system that is most likely to occur in the long term. The authors found that the equilibrium distribution of the weather system was strongly correlated with the occurrence of heatwaves.

3- Chasing data-driven probabilistic forecasting tools for heatwaves: the case of analog Markov chains and dimensional reduction via autoencoders (2022)

in the paper, the author studies the use of three data-driven strategies for probabilistically forecasting 14-day heatwaves. The first model is the Markov chain model, it's trained using historical weather data. The second model is a machine learning algorithm known as a deep learning-based dimensionality reduction methodology. The third approach is a combined approach that uses both the climate emulator and the dimensionality reduction technique.

4- Markov Chain: First Step towards Heat Wave Analysis in Malaysia. (2020)

This study uses a first-order Markov chain model to analyze daily maximum temperature data from 17 meteorological stations in Malaysia over a period of 24 years. The study categorizes the data into four heat wave scales and investigates the behavior of the data in terms of transitions between these scales. The study concludes that Markov chain models can be useful for analyzing climate data and predicting extreme temperatures.

5- A Multi-step-ahead Markov Conditional Forward Model with Cube Perturbations for Extreme Weather Forecasting. (2021)

In this study, the authors propose a new method for forecasting extreme weather events using Markov chains and cube perturbations. They argue that their method is more accurate than traditional methods for forecasting extreme weather events. They discussed the challenges of forecasting extreme weather events. As Extreme weather events are rare, so it is difficult to collect enough data to train a model. The authors used cube perturbation that helped them in preventing the model from overfitting the data and can improve the accuracy of the model's predictions.

6- Analysis Of Weather Changes for Estimation of Shallot Crops Fluctuation Using Hidden Markov (2022)

The authors of this study used a Hidden Markov Model (HMM) to estimate the fluctuation of shallot crops in Nganjuk Regency, East Java. The HMM is a statistical model that can be used to model sequences of events. In this case, the events were rainfall, temperature, and humidity. The HMM was trained on data from 2016 to 2020. The predicted values were then used to estimate the fluctuation of shallot crops. The authors found that the HMM had an accuracy of 80% in predicting probability of rain fall. and 60% accuracy in predicting the amount. They concluded that the HMM is a promising new method for predicting precipitation.

7- **Interval Valued Markov Integrated Rhotrix Optimization Using Genetic Algorithm for Predictive Modeling in Weather Forecasting. (2020)**

The approach in this study is based on a combination of interval-valued Markov chains, rhotrix matrices, and genetic algorithms. Interval-valued Markov chains are a type of Markov chain that allows for uncertainty in the states. This is important for weather forecasting, as the state of the weather is often uncertain. Rhotrix matrices are a type of matrix that can be used to represent the transition probabilities between states in a Markov chain. Lastly, Genetic algorithms are a type of optimization algorithm that can be used to find the best parameters for a model. This study focused on testing the interval-valued Markov integrated rhotrix optimization using genetic algorithm (IVMRIRGA) on a dataset of weather data. The results showed that the IVMRIRGA was able to predict the weather with a high degree of accuracy with handling uncertainty in the weather data and it is able to find the best parameters for the model using a genetic algorithm.

8- **Precipitation Modeling for Extreme Weather Based on Sparse Hybrid Machine Learning and Markov Chain Random Field in a Multi-Scale Subspace. (2021)**

A new approach to long-range precipitation forecasting is suggested in this paper. The strategy combines a hybrid machine learning technique with a Markov chain random field conditioning technique. While the hybrid machine learning technique learns the correlations between precipitation and other parameters, such as temperature and air pressure, the Markov chain random field conditioning method takes into consideration the spatial and temporal dependencies in precipitation data. A collection of historical precipitation data from the United States was used to assess the strategy. The findings demonstrated that, particularly in increasingly severe weather circumstances, the suggested strategy was capable of greatly enhancing the accuracy of long-range precipitation predictions.

9- **Applications of Markov Chain in Forecast. (2021)**
The article examines the use of Markov chains for weather forecasting and market share prediction. for weather forecasting, a Markov chain can be used to predict the probability of different weather conditions. In the case of market share prediction, a Markov chain can be used to predict the probability of a company's market share changing, based on its market share in the previous quarter. The author finds that Markov chains are not perfect and that their predictions can be inaccurate if the underlying assumptions are not met. For example, if the weather patterns change suddenly, or if a company's market share is affected by an unexpected event, the Markov chain's predictions may be inaccurate.

10- **Regional Heatwave Prediction Using Graph Neural Network and Weather Station Data (2023)**

This article is applying a new algorithm based on Graph Neural Networks (GNN), which can be used to predict regional heat waves. it was trained on weather data from 91 ground stations in North America, and it was able to predict heat waves with 90% accuracy. this method can be used to identify the key meteorological variables that lead to heatwaves and to track the spatiotemporal patterns of heatwaves across the Contiguous United States (CONUS).

11- **A Markov Chain Approach on Daily Rainfall Occurrence (2019)**
The article explores the use of a first-order Markov chain model to predict daily rainfall occurrence. It focuses on Pyin Oo Lwin, Myanmar, and highlights the model's potential in water resource management and agricultural planning. The study demonstrates the model's accuracy in forecasting precipitation probabilities and suggests future improvements for estimating rainfall amounts.

12- **Compound extremes in a changing climate –a Markov chain approach (2016)**

This study examines the succession of compound extreme events, which are simultaneous extremes involving multiple climate variables. Using Markov chains and observational data from 1951 to 2010, the research identifies regions in Europe where the ordering of these events may change in the future. Regions like southwestern France, northern Germany, Russia around Moscow, Spain, and Bulgaria are found to be particularly affected. Understanding the temporal patterns of compound extremes is crucial for developing effective adaptation and mitigation strategies in a changing climate.

C. Methodology.

Your method(s): Markov

a. General introduction/overview of the linear algebra method.

A Markov chain is a mathematical model used to describe a sequence of events or states where the probability of transitioning from one state to another depends solely on the current state. It is a stochastic process that provides a way to analyze and predict the behavior of systems that exhibit probabilistic behavior over time. A Markov chain consists of a set of states and transition probabilities. The states represent the possible conditions or situations that a system can be in, while the transition probabilities indicate the likelihood of moving from one state to another. The crucial property of a Markov chain is the Markov property, which states that the future behavior of the system depends only on its current state and is independent of its past history.

To represent a Markov chain, a square matrix called the transition matrix or stochastic matrix is used. Each element of the matrix represents the probability of transitioning from one state to another. The rows of the matrix correspond to the current state, while the columns correspond to the next state. By raising the transition matrix to a power, we can determine the probabilities of transitioning from one state to another after multiple time steps. This enables us to analyze the long-term behavior of the system. Additionally, the concept of steady-state or equilibrium distribution is often employed to determine the long-term probabilities of being in each state.

Overall, Markov chains provide a powerful framework for understanding and analyzing systems with probabilistic behavior, offering insights into their future states and long-term behavior.

b. State the general types of problems it is used to solve.

Markov chains are utilized in various problem-solving scenarios across different fields. They are commonly employed in probabilistic modelling, where they help capture the behaviour of systems with probabilistic tendencies, such as stock prices, weather patterns, population dynamics, and disease spread. Markov chains are also useful in modelling random walks, analysing queueing systems, solving optimization problems through Markov decision processes (MDPs), and performing tasks in natural language processing, such as language generation and text prediction. These applications highlight the versatility of Markov chains in analysing, predicting, and optimizing different systems and processes that involve probabilistic behaviour.

c. Write the general formulation of the equations from the textbook.

We consider a discrete-time, discrete space stochastic process which we write as

$$X(t) = X_t, \text{ for } t = 0,1,\ldots.$$

The state space S is discrete, i.e. finite or countable, so we can let it be a set of integers, as in

$$S = \{1,2,\ldots,N\} \text{ or } S = \{1,2,\ldots\}.$$

The process $X(t) = X0,X1,X2,\ldots$ is a discrete-time Markov chain if it satisfies the Markov property:

$$P(X_{n+1} = s|X_0 = x_0,X_1 = x_1,\ldots,X_n = x_n) = P(X_{n+1} = s|X_n = x_n)$$

The quantities $P(Xn + 1 = j|Xn = i)$ are called the transition probabilities. In general the transition probabilities are functions of i, j,n. It is convenient to write them as

$$pi\ j(n) = P(Xn + 1 = j|Xn = i).$$

The transition matrix at time n is the matrix $P(n) = (p_{ij}(n))$, i.e. the (i, j)th element of $P(n)$ is $p_{ij}(n)$. 1 The transition matrix satisfies:

(i) $p_{ij}(n) \geq 0 \ \forall i, j$ (the entries are non-negative)

(ii) $\sum_j p_{ij}(n) = 1 \ \forall i$ (the rows sum to 1)

Any matrix that satisfies (i), (ii) above is called a stochastic matrix. Hence, the transition matrix is a stochastic matrix.

The Markov chain $X(t)$ is time-homogeneous if $\mathbf{P(X_{n+1} = j|X_n = i) = P(X_1 = j|X_0 = i)}$, i.e. the transition probabilities do not depend on time n. If this is the case, we write

$p_{ij} = P(X_1 = j|X_0 = i)$

for the probability to go from i to j in one step, and $P = (p_{ij})$ for the transition matrix. We will only consider time-homogeneous Markov chains in this course, though we will occasionally remark on how some results may be generalized to the time-inhomogeneous case.

D. Variable & Data Sources

a. The variable and characteristics of data

- Location: The dataset includes temperature data for two locations, Kuala Lumpur and Perlis. Each location has its own set of temperature readings.
- Timeframe: The dataset covers the period from December 2022 to May 2023. The data is organized by months and days within each month.
- Temperature: The temperature values are recorded in Celsius. The dataset provides daily temperature readings for each location.
- State Label: Each temperature reading is associated with a state label indicating whether the temperature is classified as "hot" or "normal." This additional information provides a categorical description of the temperature conditions.

b. Data sources/ collection method websites

1. Temperature in Kuala Lumpur

   https://www.accuweather.com/en/my/kuala-lumpur/

2. Temperature in Perlis

   https://www.accuweather.com/en/my/kangar/

c. Process of Preparing Data

To begin, we conduct a thorough search for reliable sources, including national meteorological agencies and climate research institutions, to acquire the necessary data on the temperatures in Kuala Lumpur and Perlis. To ensure precise calculations and comparisons, we verify that all temperature values are consistently expressed in numerical unit.

Once we have obtained the data, we structure it into a tabular format, arranging the information in columns denoting the day, temperature, and the state of the temperature. We also examine the dataset for any irregularities or missing values, ensuring its suitability for subsequent analysis.

To extract meaningful insights from the dataset, we engage in diverse analytical procedures. This involves the overall trend in average mean temperature, identifying significant flunctuations in the temperature data and long-term trends. Additionally, we employ visual aids such as line charts or graphs to effectively illustrate the temperature patterns observed in both Kuala Lumpur and Perlis.

By following these systematic steps, we can proficiently process and analyze the observed average annual mean temperature data for Kuala Lumpur and Perlis. This comprehensive analysis enables us to gain a deeper understanding of the climate trends and variations within both countries throughout the studied period.

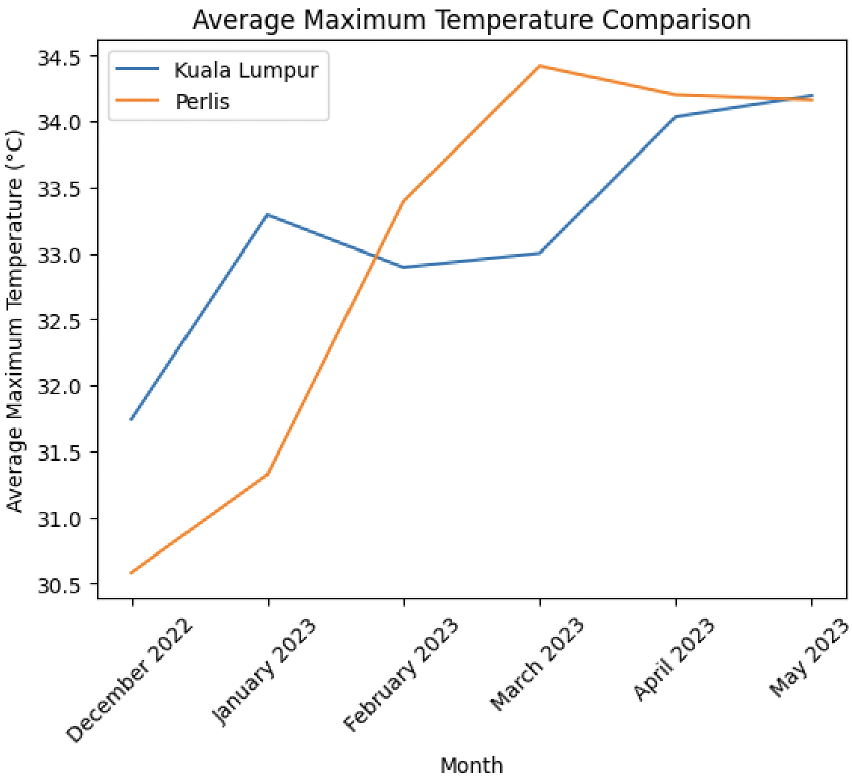

Fig 1. Shows the average max temperature of Kuala Lumpur and Perlis

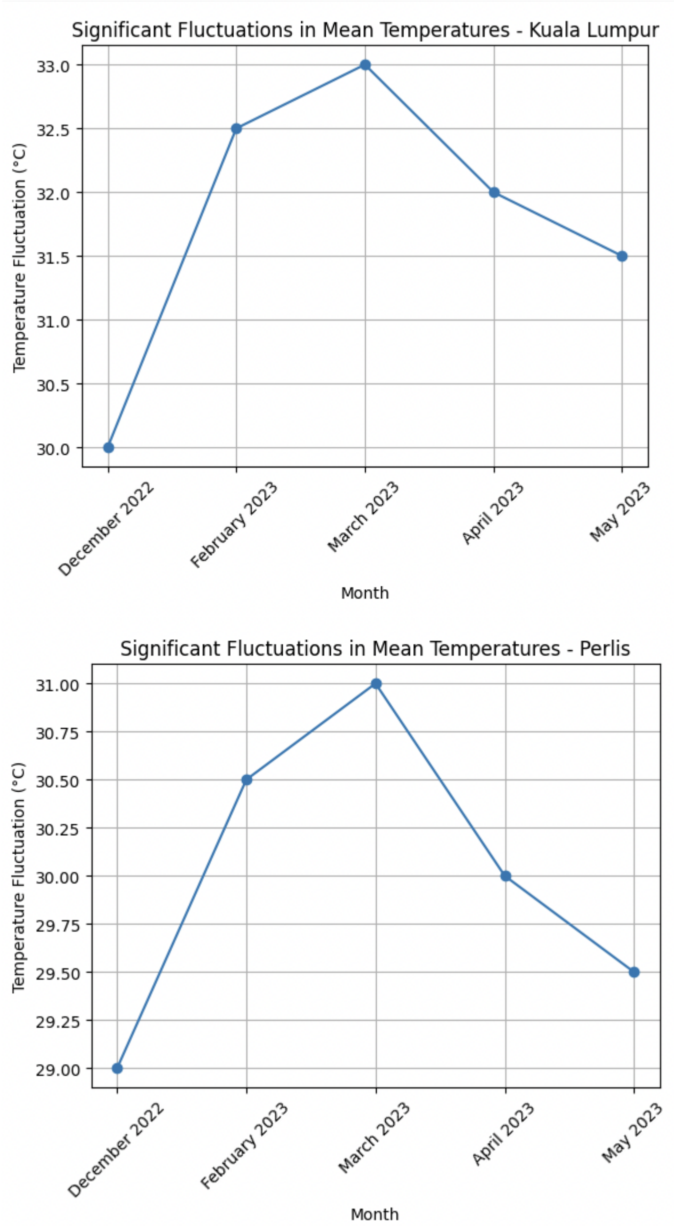

Fig 2. Show the signicant fluctuations in mean temperature of Kuala Lumpur and Perlis

Temperature degrees for Malaysia:

State	Temperature (Celsius)
Hot (heatwave) (H)	35 and above
Normal (N)	below 35

Temperature in Malaysia from December 2022 – May 2023

	Kuala Lumpur		Perlis		Perak		Malacca		Sarawak		Sabah		Terengganu		Kedah
Day	Temperature (Celcius)	State	Temperature (Celcius)	State	Temperature (Celcius)	State	Temperature (Celcius)	State	Temperature (Celcius)	State	Temperature (Celcius)	State	Temperature (Celcius)	State	Tempe (Cel
														December	
1	33	N	33	N	32	N	32	N	27	N					
2	32	N	31	N	31	N	32	N	32	N					
3	31	N	27	N	30	N	30	N	31	N					
4	32	N	30	N	32	N	33	N	31	N					
5	33	N	31	N	31	N	31	N	30	N					
6	34	N	33	N	33	N	32	N	31	N					
7	34	N	33	N	32	N	33	N	31	N					
8	32	N	31	N	32	N	31	N	30	N					
9	29	N	24	N	28	N	32	N	31	N					
10	30	N	29	N	29	N	29	N	29	N					
11	30	N	29	N	29	N	34	N	30	N					
12	31	N	30	N	29	N	30	N	30	N					
13	30	N	30	N	30	N	31	N	28	N					
14	31	N	31	N	31	N	31	N	27	N					
15	32	N	33	N	33	N	32	N	27	N					
16	35	H	33	N	34	N	29	N	31	N					
17	31	N	31	N	32	N	33	N	28	N					
18	31	N	26	N	28	N	31	N	30	N					
19	31	N	26	N	29	N	32	N	28	N					
20	33	N	30	N	31	N	33	N	30	N					
21	33	N	30	N	30	N	33	N	29	N					
22	30	N	33	N	32	N	31	N	28	N					
23	32	N	32	N	32	N	25	N	31	N					
24	33	N	32	N	33	N	29	N	30	N					
25	32	N	32	N	32	N	30	N	30	N					
26	31	N	30	N	30	N	29	N	29	N					
27	30	N	32	N	32	N	31	N	31	N					
28	29	N	32	N	33	N	31	N	27	N					
29	31	N	32	N	33	N	30	N	29	N					
30	34	N	31	N	33	N	30	N	31	N					

31	34	N	31	N	30	N	31	N	31	N
										january
1	31	N	32	N	34	N	31	N	31	N
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3	29	N	33	N	33	N	27	N	32	N
4	33	N	32	N	32	N	28	N	31	N
5	34	N	33	N	32	N	29	N	30	N
6	34	N	31	N	32	N	32	N	30	N
7	34	N	27	N	30	N	33	N	29	N
8	34	N	30	N	31	N	33	N	30	N
9	35	H	31	N	32	N	33	N	31	N
10	34	N	31	N	32	N	32	N	31	N
11	32	N	33	N	32	N	31	N	30	N
12	34	N	32	N	33	N	31	N	30	N
13	34	N	33	N	31	N	32	N	32	N
14	35	H	33	N	32	N	30	N	28	N
15	35	H	32	N	33	N	32	N	30	N
16	34	N	32	N	34	N	32	N	30	N
17	34	N	33	N	33	N	31	N	26	N
18	31	N	32	N	32	N	29	N	30	N
19	33	N	32	N	33	N	33	N	31	N
20	33	N	30	N	31	N	31	N	30	N
21	35	H	30	N	28	N	32	N	31	N
22	32	N	30	N	28	N	30	N	28	N
23	34	N	32	N	31	N	31	N	30	N
24	33	N	32	N	30	N	30	N	25	N
25	32	N	31	N	28	N	31	N	24	N
26	33	N	32	N	32	N	30	N	29	N
27	34	N	30	N	32	N	30	N	30	N
28	35	H	31	N	31	N	32	N	27	N
29	34	N	31	N	32	N	31	N	28	N
30	34	N	29	N	31	N	29	N	28	N
31	34	N	29	N	32	N	30	N	28	N
										february
1	34	N	33	N	32	N	29	N	28	N
2	34	N	31	N	31	N	32	N	30	N
3	34	N	29	N	31	N	31	N	29	N
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5	34	N	34	N	33	N	31	N	30	N
6	31	N	31	N	26	N	33	N	26	N
7	34	N	34	N	31	N	31	N	32	N
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11	29	N	34	N	33	N	32	N	30	N					
12	34	N	34	N	33	N	29	N	32	N					
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16	34	N	34	N	34	N	32	N	31	N					
17	34	N	34	N	33	N	30	N	30	N					
18	35	H	34	N	32	N	32	N	32	N					
19	35	H	34	N	32	N	31	N	32	N					
20	35	H	34	N	33	N	31	N	31	N					
21	35	H	35	H	32	N	31	N	32	N					
22	34	N	34	N	32	N	31	N	31	N					
23	34	N	34	N	32	N	31	N	31	N					
24	28	N	35	H	35	H	30	N	28	N					
25	33	N	34	N	33	N	29	N	30	N					
26	30	N	33	N	34	N	29	N	30	N					
27	32	N	34	N	33	N	28	N	30	N					
28	34	N	32	N	29	N	31	N	28	N					
														march	
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7	34	N	34	N	34	N	31	N	26	N					
8	35	H	35	H	34	N	31	N	32	N					
9	35	H	35	H	34	N	29	N	31	N					
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13	32	N	35	H	33	N	28	N	30	N					
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15	34	N	35	H	34	N	31	N	31	N					
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17	34	N	35	H	34	N	32	N	33	N					
18	34	N	36	H	34	N	28	N	32	N					
19	35	H	37	H	34	N	32	N	33	N					
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21	31	N	34	N	31	N	33	N	32	N					

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24	34	N	34	N	33	N	31	N	32	N					
25	28	N	35	H	33	N	29	N	31	N					
26	34	N	33	N	34	N	32	N	32	N					
27	34	N	35	H	33	N	33	N	31	N					
28	35	H	34	N	33	N	30	N	34	N					
29	35	H	35	H	33	N	31	N	33	N					
30	34	N	35	H	34	N	32	N	32	N					
31	35	H	36	H	34	N	32	N	32	N					
														april	
1	33	N	36	H	34	N	32	N	32	N					
2	33	N	33	N	32	N	33	N	32	N					
3	32	N	31	N	30	N	32	N	29	N					
4	34	N	33	N	34	N	33	N	29	N					
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8	35	H	36	H	34	N	32	N	31	N					
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16	35	H	34	N	35	H	34	N	33	N					
17	35	H	34	N	34	N	34	N	32	N					
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22	35	H	34	N	33	N	34	N	32	N					
23	35	H	35	H	33	N	33	N	32	N					
24	35	H	35	H	34	N	28	N	32	N					
25	34	N	36	H	33	N	34	N	33	N					
26	34	N	36	H	33	N	33	N	33	N					
27	35	H	35	H	33	N	33	N	33	N					
28	34	N	34	N	32	N	32	N	32	N					
29	34	N	34	N	33	N	33	N	32	N					
30	33	N	35	H	34	N	33	N	34	N					
														may	

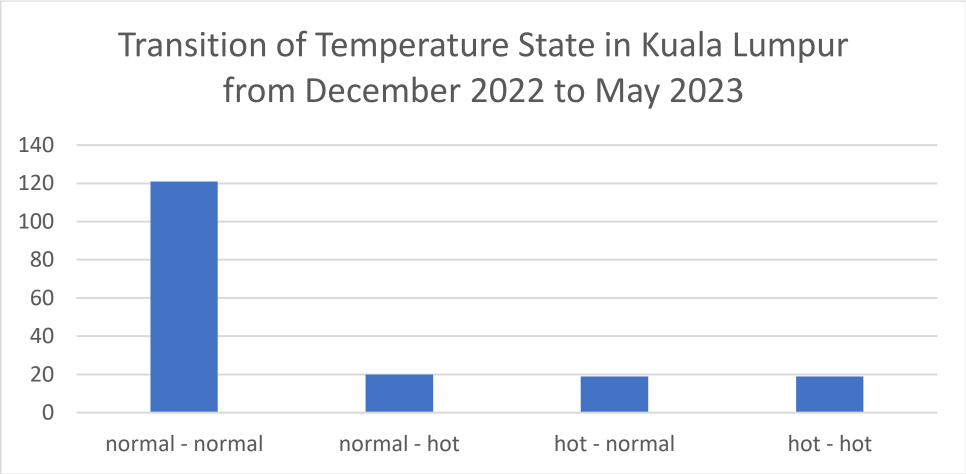
1	34	N	34	N	33	N	35	H	32	N				
2	35	H	34	N	34	N	34	N	33	N				
3	34	N	33	N	34	N	34	N	33	N				
4	34	N	34	N	33	N	34	N	32	N				
5	34	N	33	N	32	N	35	H	32	N				
6	34	N	33	N	32	N	34	N	32	N				
7	33	N	32	N	32	N	35	H	31	N				
8	35	H	33	N	35	H	32	N	33	N				
9	35	H	35	H	35	H	33	N	33	N				
10	34	N	35	H	35	H	33	N	33	N				
11	36	H	36	H	35	H	34	N	35	H				
12	35	H	36	H	35	H	35	H	34	N				
13	34	N	36	H	35	H	32	N	33	N				
14	34	N	33	N	33	N	31	N	28	N				
15	34	N	34	N	34	N	35	H	32	N				
16	35	H	34	N	35	H	35	H	34	N				
17	34	N	34	N	33	N	34	N	33	N				
18	34	N	32	N	33	N	36	H	32	N				
19	35	H	31	N	32	N	35	H	32	N				
20	35	H	33	N	35	H	35	H	32	N				
21	31	N	32	N	30	N	34	N	31	N				
22	34	N	31	N	32	N	34	N	33	N				
23	34	N	33	N	35	H	32	N	33	N				
24	34	N	32	N	33	N	32	N	33	N				
25	34	N	33	N	34	N	34	N	33	N				
26	32	N	32	N	32	N	35	H	31	N				
27	34	N	32	N	33	N	33	N	32	N				
28	34	N	33	N	33	N	34	N	33	N				
29	35	H	33	N	33	N	34	N	33	N				
30	36	H	33	N	35	H	33	N	32	N				
31	34	N	33	N	34	N	35	H	33	N				

D. Results

1. General basic descriptive statistics

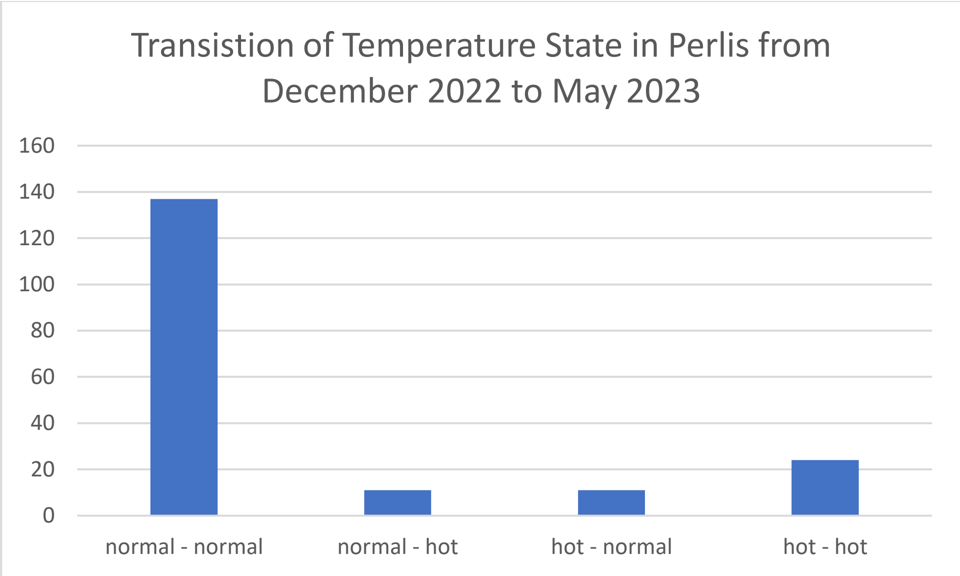
a. Transition of State of Temperature in Kuala Lumpur from December 2022 to May 2023

State	total transition
normal - normal	121
normal - hot	20
hot - normal	20
hot - hot	19



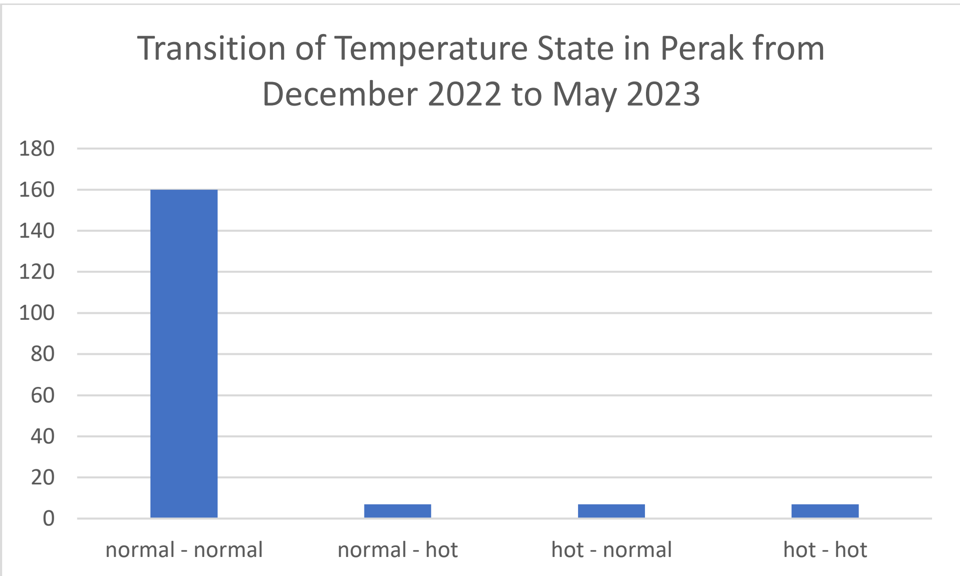
b. Transition of State of Temperature in Perlis From December 2022 to May 2023:

State	total transition
normal - normal	137
normal - hot	11
hot - normal	11
hot - hot	24



c. Transition of State of Temperature in Perak From December 2022 to May 2023:

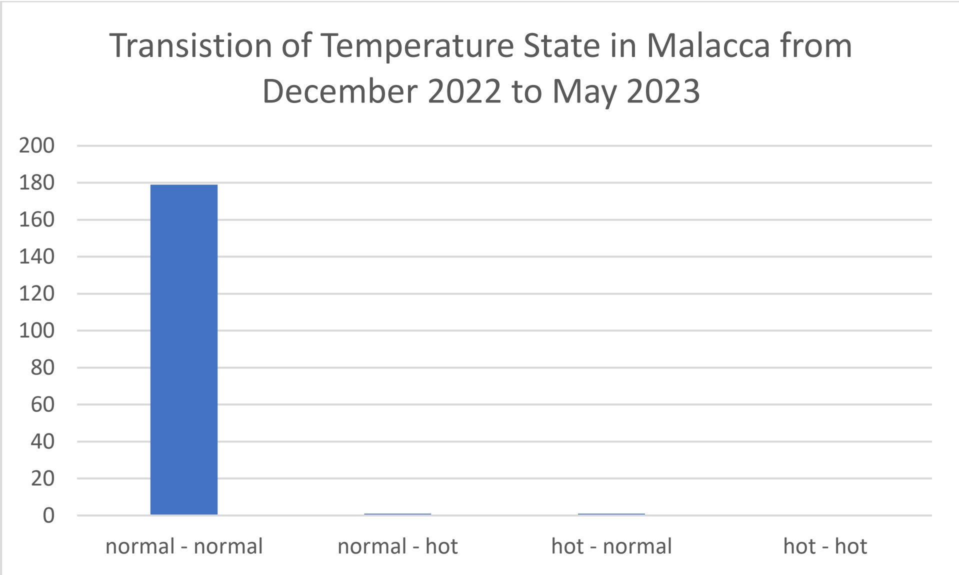
State	total transition
normal - normal	160
normal - hot	7
hot - normal	7
hot - hot	7



d. Transition of State of Temperature in Malacca From December 2022 to May 2023:

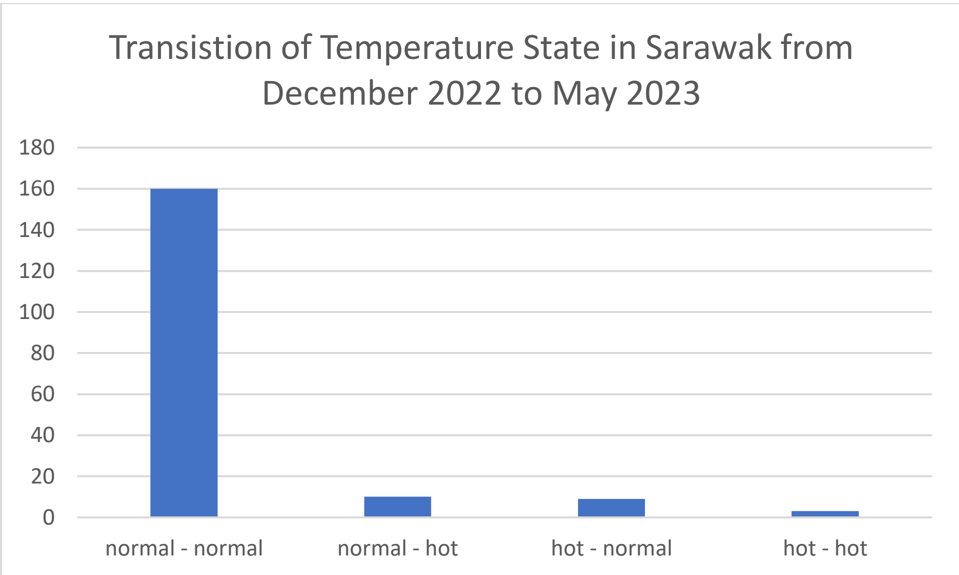
State	total transition
normal - normal	179
normal - hot	1

hot - normal	1
hot - hot	0



e. Transition of State of Temperature in Sarawak From December 2022 to May 2023:

State	total transition
normal - normal	160
normal - hot	10
hot - normal	9
hot - hot	3



2. Analysis of your results/output from your chosen method(s) Markov, Discrete Dynamic System, Least Square, Game Theory, Optimisation**:**
a. Markov Chain

1. **Kuala Lumpur**

Probability of each transition:

Normal to Normal:

$$= \frac{121}{121 + 20}$$

$$= \frac{121}{141}$$

$$= 0.858156028$$

Normal to Hot:

$$= \frac{20}{121 + 20}$$

$$= \frac{20}{141}$$

$$= 0.141843972$$

Hot to Normal:

$$= \frac{19}{19 + 19}$$

$$= \frac{19}{38}$$

$$= 0.5$$

Hot to Hot:

$$= \frac{19}{19 + 19}$$

$$= \frac{19}{38}$$

$$= 0.5$$

Transition Matrix:

	normal	hot
normal	0.858156028	0.141843972
hot	0.5	0.5

Transpose Matrix:

	normal	hot
normal	0.858156028	0.5
hot	0.141843972	0.5

Finding Eigen Value:

$$\begin{bmatrix} 0.8642-\lambda & 0.1357 \\ 0.5 & 0.5-\lambda \end{bmatrix}\begin{bmatrix} N \\ H \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\lambda^2 - 1.358156028\lambda + 0.358156028 = 0$$

$$\lambda = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$$

$$\lambda = \frac{-(-1.358156028) \pm \sqrt{(-1.358156028)^2 - 4(1)(0.358156028)}}{2(1)}$$

$$\lambda = 1, \lambda = \ 0.358156028$$

Finding steady state:

$$\lambda = 1$$

$$\begin{bmatrix} 0.8642-\lambda & 0.1357 \\ 0.5 & 0.5-\lambda \end{bmatrix}\begin{bmatrix} N \\ H \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} 0.8642-1 & 0.1357 \\ 0.5 & 0.5-1 \end{bmatrix}\begin{bmatrix} N \\ H \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} -0.141843972 & 0.5 \\ 0.141843972 & -0.5 \end{bmatrix}\begin{bmatrix} N \\ H \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} -0.141843972 & 0.5 \\ 0 & 0 \end{bmatrix}\begin{bmatrix} N \\ H \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$0.141843972\text{N} = 0.5\text{H}$$

$$N = \frac{0.5}{0.141843972}H$$

$$N = \frac{2500}{709}H$$

Eigen Vector:

$$\begin{bmatrix} Normal \\ Hot \end{bmatrix} = \begin{bmatrix} 2500 \\ 709 \end{bmatrix}$$

Normalized Eigen Vector:

$$\begin{bmatrix} Normal \\ Hot \end{bmatrix} = \begin{bmatrix} \frac{2500}{2500 + 709} \\ \frac{709}{2500 + 709} \end{bmatrix}$$

$$\begin{bmatrix} Normal \\ Hot \end{bmatrix} = \begin{bmatrix} 0.779058897 \\ 0.220941103 \end{bmatrix}$$

In the long run, there is 77.91% chances for the weather in Kuala Lumpur to be in a normal state and 22.09% chances for the weather to be in a hot or heat wave state.

2. **Perlis**

Probability of each transition:

Normal to Normal:

$$= \frac{137}{137 + 11}$$

$$= \frac{137}{148}$$

$$= 0.925675676$$

Normal to Hot:

$$= \frac{11}{137 + 11}$$

$$= \frac{11}{148}$$

$$= 0.074324324$$

Hot to Normal:

$$= \frac{11}{11 + 24}$$

$$= \frac{11}{35}$$

$$= 0.314285714$$

Hot to Hot:

$$= \frac{24}{11 + 24}$$

$$= \frac{24}{35}$$

$$= 0.685714286$$

Transition Matrix:

	normal	hot
normal	0.925675676	0.074324324
hot	0.314285714	0.685714286

Transpose Matrix:

	normal	hot
normal	0.925675676	0.314285714
hot	0.074324324	0.685714286

Finding Eigen Value:

$$\begin{bmatrix} 0.9257-\lambda & 0.3143 \\ 0.07432 & 0.6857-\lambda \end{bmatrix}\begin{bmatrix} N \\ H \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\lambda^2 - 1.6111389961\lambda + 0.611389961 = 0$$

$$\lambda = \frac{-b \pm \sqrt{b^2-4ac}}{2a}$$

$$\lambda = \frac{-(-1.611389961) \pm \sqrt{(-1.611389961)^2 - 4(1)(0.611389961)}}{2(1)}$$

$$\lambda = 1, \lambda = \ 0.611389961$$

Finding steady state:

$$\lambda = 1$$

$$\begin{bmatrix} 0.9257-\lambda & 0.3143 \\ 0.07432 & 0.6857-\lambda \end{bmatrix}\begin{bmatrix} N \\ H \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} 0.9257-1 & 0.3143 \\ 0.07432 & 0.6857-1 \end{bmatrix}\begin{bmatrix} N \\ H \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} -0.074324324 & 0.314285741 \\ 0.141843972 & -0.314285741 \end{bmatrix}\begin{bmatrix} N \\ H \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} -0.074324324 & 0.314285741 \\ 0 & 0 \end{bmatrix}\begin{bmatrix} N \\ H \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$0.074324324\mathrm{N} = 0.314285741\mathrm{H}$$

$$N = \frac{0.314285741}{0.074324324} H$$

$$N = \frac{0.3143}{0.07432} H$$

Eigen Vector:

$$\begin{bmatrix} Normal \\ Hot \end{bmatrix} \begin{bmatrix} 0.3143 \\ 0.07432 \end{bmatrix}$$

Normalized Eigen Vector:

$$\begin{bmatrix} Normal \\ Hot \end{bmatrix} \begin{bmatrix} \frac{0.3143}{0.3143 + 0.07432} \\ \frac{0.07432}{0.3143 + 0.07432} \end{bmatrix}$$

$$\begin{bmatrix} Normal \\ Hot \end{bmatrix} = \begin{bmatrix} 0.808754278 \\ 0.191245722 \end{bmatrix}$$

In the long run, there is 80.88% chances for the weather in Perlis to be in a normal state and 19.12% chances for the weather to be in a hot or heat wave state.

3. **Perak**

Probability of each transition:

Normal to Normal:

$$= \frac{160}{160 + 7}$$

$$= \frac{160}{167}$$

=0.958083832

Normal to Hot:

$$= \frac{7}{160 + 7}$$

$$= \frac{7}{167}$$

=0.041916168

Hot to Normal:

$$= \frac{7}{7 + 7}$$

$$= \frac{7}{14}$$

$$= 0.5$$

Hot to Hot:

$$= \frac{7}{7+7}$$

$$= \frac{7}{14}$$

$$= 0.5$$

Transition Matrix:

	normal	hot
normal	0.958083832	0.041916168
hot	0.5	0.5

Transpose Matrix:

	normal	hot
normal	0.958083832	0.5
hot	0.041916168	0.5

Finding Eigen Value:

$$\begin{bmatrix} 0.958083832 - \lambda & 0.5 \\ 0.041916168 & 0.5 - \lambda \end{bmatrix} \begin{bmatrix} N \\ H \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\lambda^2 - 1.4580083832\lambda + 0.458083832 = 0$$

$$\lambda = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$$

$$\lambda = \frac{-(-1.458083832) \pm \sqrt{(-1.458083832)^2 - 4(1)(0.458083832)}}{2(1)}$$

$$\lambda = 1, \lambda = \ 0.458083832$$

Finding steady state:

$\lambda = 1$

$$\begin{bmatrix} 0.958083832 - \lambda & 0.5 \\ 0.041916168 & 0.5 - \lambda \end{bmatrix} \begin{bmatrix} N \\ H \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} 0.958083832 - 1 & 0.5 \\ 0.041916168 & 0.5 - 1 \end{bmatrix} \begin{bmatrix} N \\ H \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} -0.041916168 & 0.5 \\ 0.041916168 & -0.5 \end{bmatrix} \begin{bmatrix} N \\ H \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} -0.041916168 & 0.5 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} N \\ H \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$0.041916168\mathrm{N} = 0.5\mathrm{H}$$

$$N = \frac{0.5}{0.041916168} H$$

Eigen Vector:

$$\begin{bmatrix} Normal \\ Hot \end{bmatrix} = \begin{bmatrix} 0.5 \\ 0.041916168 \end{bmatrix}$$

Normalized Eigen Vector:

$$\begin{bmatrix} Normal \\ Hot \end{bmatrix} = \begin{bmatrix} \dfrac{0.5}{0.041916168 + 0.5} \\ \dfrac{0.041916168}{0.041916168 + 0.5} \end{bmatrix}$$

$$\begin{bmatrix} Normal \\ Hot \end{bmatrix} = \begin{bmatrix} 0.922651934 \\ 0.077348066 \end{bmatrix}$$

In the long run, there is 92.27% chances for the weather in Perak to be in a normal state and 7.73% chances for the weather to be in a hot or heat wave state.

4. **Malacca**

Probability of each transition:

Normal to Normal:

$$= \frac{179}{179 + 1}$$

$$= \frac{179}{180}$$

$$= 0.994444444$$

Normal to Hot:

$= \frac{1}{179 + 1}$

$= \frac{1}{180}$

$= 0.005555556$

Hot to Normal:

$= \frac{1}{1 + 0}$

$= \frac{1}{1}$

$= 1$

Hot to Hot:

$= \frac{0}{0 + 1}$

$= \frac{0}{1}$

$= 0$

Transition Matrix:

	normal	hot
normal	0.994444444	0.005555556
hot	1	0

Transpose Matrix:

	normal	hot
normal	0.994444444	1
hot	0.005555556	0

Finding Eigen Value:

$$\begin{bmatrix} 0.994444444 - \lambda & 1 \\ 0.005555556 & 0 - \lambda \end{bmatrix} \begin{bmatrix} N \\ H \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$\lambda^2 - 0.994444444\lambda - 0.005555556 = 0$

$$\lambda = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$$

$$\lambda = \frac{-(-0.994444444\lambda) \pm \sqrt{(-0.994444444\lambda)^2 - 4(1)(-0.005555556)}}{2(1)}$$

$$\lambda = 1, \lambda = \ -0.005555556$$

Finding steady state:

$$\lambda = 1$$

$$\begin{bmatrix} 0.994444444 - \lambda & 1 \\ 0.005555556 & 0 - \lambda \end{bmatrix} \begin{bmatrix} N \\ H \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} 0.994444444 - 1 & 1 \\ 0.005555556 & 0 - 1 \end{bmatrix} \begin{bmatrix} N \\ H \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} -0.005555556 & 1 \\ 0.005555556 & -1 \end{bmatrix} \begin{bmatrix} N \\ H \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} -0.005555556 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} N \\ H \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$0.005555556\mathrm{N} = 1H$$

$$N = \frac{1}{0.005555556} H$$

Eigen Vector:

$$\begin{bmatrix} Normal \\ Hot \end{bmatrix} = \begin{bmatrix} 1 \\ 0.005555556 \end{bmatrix}$$

Normalized Eigen Vector:

$$\begin{bmatrix} Normal \\ Hot \end{bmatrix} = \begin{bmatrix} \frac{1}{1 + 0.005555556} \\ \frac{0.005555556}{1 + 0.005555556} \end{bmatrix}$$

$$\begin{bmatrix} Normal \\ Hot \end{bmatrix} = \begin{bmatrix} 0.994475138 \\ 0.005524862 \end{bmatrix}$$

In the long run, there is 99.45% chances for the weather in Malacca to be in a normal state and 0.55% chances for the weather to be in a hot or heat wave state.

5. **Sarawak**

Probability of each transition:

Normal to Normal:

$$= \frac{160}{160 + 10}$$

$= \frac{160}{170}$

$= 0.941176471$

Normal to Hot:

$\frac{10}{160 + 10}$

$= \frac{10}{170}$

$= 0.058823529$

Hot to Normal:

$= \frac{9}{9 + 3}$

$= \frac{9}{12}$

$= 0.75$

Hot to Hot:

$= \frac{3}{9 + 3}$

$= \frac{3}{12}$

$= 0.25$

Transition Matrix:

	normal	hot
normal	0.941176471	0.058823529
hot	0.75	0.25

Transpose Matrix:

	normal	hot
normal	0.941176471	0.75
hot	0.058823529	0.25

Finding Eigen Value:

$$\begin{bmatrix} 0.941176471 - \lambda & 0.75 \\ 0.058823529 & 0.25 - \lambda \end{bmatrix} \begin{bmatrix} N \\ H \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\lambda^2 - 1.191176471\lambda + 0.191176471 = 0$$

$$\lambda = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$$

$$\lambda = \frac{-(-1.191176471) \pm \sqrt{(-1.191176471)^2 - 4(1)(0.191176471)}}{2(1)}$$

$$\lambda = 1, \lambda = 0.191176471$$

Finding steady state:

$$\lambda = 1$$

$$\begin{bmatrix} 0.941176471 - \lambda & 0.75 \\ 0.058823529 & 0.25 - \lambda \end{bmatrix} \begin{bmatrix} N \\ H \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} 0.941176471 - 1 & 0.75 \\ 0.058823529 & 0.25 - 1 \end{bmatrix} \begin{bmatrix} N \\ H \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} -0.058823529 & 0.75 \\ 0.058823529 & -0.75 \end{bmatrix} \begin{bmatrix} N \\ H \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} -0.058823529 & 0.75 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} N \\ H \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$0.058823529\text{N} = 0.75H$$

$$N = \frac{0.75}{0.058823529} H$$

Eigen Vector:

$$\begin{bmatrix} Normal \\ Hot \end{bmatrix} = \begin{bmatrix} 0.75 \\ 0.058823529 \end{bmatrix}$$

Normalized Eigen Vector:

$$\begin{bmatrix} Normal \\ Hot \end{bmatrix} = \begin{bmatrix} \dfrac{0.75}{0.75 + 0.058823529} \\ \dfrac{0.058823529}{0.75 + 0.058823529} \end{bmatrix}$$

$$\begin{bmatrix} Normal \\ Hot \end{bmatrix} = \begin{bmatrix} 0.927272727 \\ 0.072727273 \end{bmatrix}$$

In the long run, there is 92.73% chances for the weather in Sarawak to be in a normal state and 7.27% chances for the weather to be in a hot or heat wave state.

b. Identifying the worst-case predictions, best case predictions, optimum cases, etc

1) **Worst-Case Prediction:**

   a. **Kuala Lumpur:**

      The worst-case prediction for the weather in Kuala Lumpur is, there are 22.09% chances of heat wave occurring there.

   b. **Perlis:**

      The worst-case prediction for the weather in Perlis is, there are 19.12% chances of heat wave occurring there.

   c. **Perak:**

      The worst-case prediction for the weather in Perak is, there are 7.73% chances of heat wave occurring there.

   d. **Malacca:**

      The worst-case prediction for the weather in Malacca is, there are 0.55% chances of heat wave occurring there.

   e. **Sarawak:**

      The worst-case prediction for the weather in Perlis is, there are 7.27% chances of heat wave occurring there.

   f. **Sabah:**

      The worst-case prediction for the weather in Sabah is, there are % chances of heat wave occurring there.

   g. **Terengganu:**

      The worst-case prediction for the weather in Terengganu is, there are % chances of heat wave occurring there.

   h. **Kedah:**

      The worst-case prediction for the weather in Kedah is, there are % chances of heat wave occurring there.

   i. **Selangor:**

      The worst-case prediction for the weather in Selangor is, there are % chances of heat wave occurring there.

   j. **Johor:**

      The worst-case prediction for the weather in Johor is, there are % chances of heat wave occurring there.

   k. **Penang:**

      The worst-case prediction for the weather in Penang is, there are % chances of heat wave occurring there.

   l. **Kelantan:**

      The worst-case prediction for the weather in Kelantan is, there are % chances of heat wave occurring there.

   m. **Pahang:**

      The worst-case prediction for the weather in Pahang is, there are % chances of heat wave occurring there.

   n. **Negeri Sembilan:**

      The worst-case prediction for the weather in Negeri Sembilan is, there are % chances of heat wave occurring there.

2) **Best-Case Prediction:**

a. **Kuala Lumpur:**

The best-case prediction for the weather in Kuala Lumpur is, there are 77.91% chances of heat wave occurring there.

b. **Perlis:**

The best-case prediction for the weather in Perlis is, there are 80.88% chances of heat wave occurring there.

c. **Perak:**

The best-case prediction for the weather in Perak is, there are 92.27% chances of heat wave occurring there.

d. **Malacca:**

The best-case prediction for the weather in Malacca is, there are 99.45% chances of heat wave occurring there.

e. **Sarawak:**

The best-case prediction for the weather in Perlis is, there are 92.73% chances of heat wave occurring there.

f. **Sabah:**

The best-case prediction for the weather in Sabah is, there are % chances of heat wave occurring there.

g. **Terengganu:**

The best-case prediction for the weather in Terengganu is, there are % chances of heat wave occurring there.

h. **Kedah:**

The best-case prediction for the weather in Kedah is, there are % chances of heat wave occurring there.

i. **Selangor:**

The best-case prediction for the weather in Selangor is, there are % chances of heat wave occurring there.

j. **Johor:**

The best-case prediction for the weather in Johor is, there are % chances of heat wave occurring there.

k. **Penang:**

The best-case prediction for the weather in Penang is, there are % chances of heat wave occurring there.

l. **Kelantan:**

The best-case prediction for the weather in Kelantan is, there are % chances of heat wave occurring there.

m. **Pahang:**

The best-case prediction for the weather in Pahang is, there are % chances of heat wave occurring there.

n. **Negeri Sembilan:**

The best-case prediction for the weather in Negeri Sembilan is, there are % chances of heat wave occurring there.

c) Do general comparison of the scenarios, individual variable, several variables, and overall variables, to see different view. You may present in tables for comparison.

Comparison of Steady State of Heat Wave Occurrence in Malaysia:

Steady State in Kuala Lumpur: $\begin{bmatrix} Normal \\ Hot \end{bmatrix} = \begin{bmatrix} 0.779058897 \\ 0.220941103 \end{bmatrix}$	Steady State in Perlis: $\begin{bmatrix} Normal \\ Hot \end{bmatrix} = \begin{bmatrix} 0.808754278 \\ 0.191245722 \end{bmatrix}$	Steady State in Perak: $\begin{bmatrix} Normal \\ Hot \end{bmatrix} = \begin{bmatrix} 0.922651934 \\ 0.077348066 \end{bmatrix}$
Steady State in Malacca: $\begin{bmatrix} Normal \\ Hot \end{bmatrix} = \begin{bmatrix} 0.994475138 \\ 0.005524862 \end{bmatrix}$	Steady State in Sarawak: $\begin{bmatrix} Normal \\ Hot \end{bmatrix} = \begin{bmatrix} 0.927272727 \\ 0.072727273 \end{bmatrix}$	Steady State in Sabah: $\begin{bmatrix} Normal \\ Hot \end{bmatrix} = [\quad]$
Steady State in Terengganu: $\begin{bmatrix} Normal \\ Hot \end{bmatrix} = [\quad]$	Steady State in Kedah: $\begin{bmatrix} Normal \\ Hot \end{bmatrix} = [\quad]$	Steady State in Selangor: $\begin{bmatrix} Normal \\ Hot \end{bmatrix} = [\quad]$
Steady State in Johor: $\begin{bmatrix} Normal \\ Hot \end{bmatrix} = [\quad]$	Steady State in Penang: $\begin{bmatrix} Normal \\ Hot \end{bmatrix} = [\quad]$	Steady State in Kelantan: $\begin{bmatrix} Normal \\ Hot \end{bmatrix} = [\quad]$
Steady State in Pahang: $\begin{bmatrix} Normal \\ Hot \end{bmatrix} = [\quad]$	Steady State in Negeri Sembilan: $\begin{bmatrix} Normal \\ Hot \end{bmatrix} = [\quad]$	

E. Conclusion

In conclusion, we can observe that both states in Malaysia have the same steady states of the heatwave occurrence. From the result we can conclude that, most of the day in Malaysia, there will be no heatwave phenomena that will happen in future. However, there are still chances of heatwave occurrence in Malaysia with a smaller chance.

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