

Health study using Markov chain modeling

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Abstract

A study of health of a human being is an ever interesting and fertile one for any researcher. This is one such study in which we use Markov chain for the modeling of the problem that identifies the health status of an individual through his mood on two successive days. We have performed an empirical study for which we have collected data regarding the mood change in two successive days by making a questionnaire and identify the Markov

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chain structure from the data. Then we have analyzed the Markov chain to calculate higher order transition probabilities and steady state probabilities. Using those, we made some analytical inferences and for that we have used R language and MS Excel. Based on the data, we have found that the Markov chain, so formed is ergodic in nature with high steady state probability for happy state which is one of the six moods we have assumed when collecting the data. We have also classified the different states or moods of the data. From this study, we also infer that this is a simple way of transitioning across the states or moods of a human. Also, using this line of analysis is a robust, easy and efficient for one in calculating measures regarding moods or mood disorders.

Subject Classification: 60J10.
Keywords: Markov chain, Mood, Transition probability, Health.

1. Introduction

We can google to find that “mood is an affective state. In contrast to emotions or feelings, moods are less specific, less intense and less likely to be provoked or instantiated by a particular stimulus or event. Moods are typically described as having either a positive or negative valence.”The Plutchik-wheel which is in Figure 1 gives a glimpse of how complex it is when it comes to mood of a human being. According to Harvard Health Publishing, Harvard Medical School, there is a strong relationship between a person’s mental health and physical health or in other words a poor mental health may result in physical issues like digestive disorders, sleeping troubles and the likes. [1] is a paper studying the health, mood

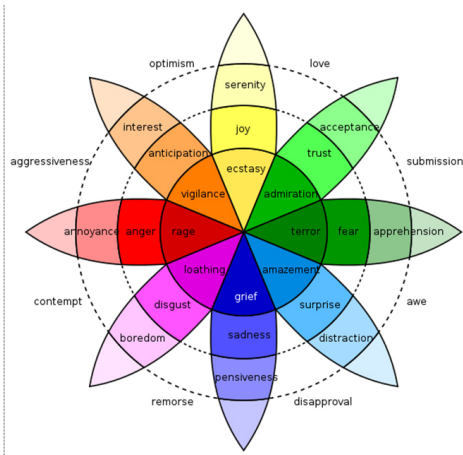


Figure 1
Plutchik Wheel

and cognitive impairment where health of an individual is assessed using many measures and SEM analysis in which they have found out that participants in the study with mood problems also had poor or fair health. [2], a report by WHO is a good starting article for learning about mental health, related issues and possible solutions. [3] is an empirical reporting study discussing course of depressive syndromes among older people in Netherland. [4] is a study which concludes that physical health and depression are closely related among elders. [5] is a study examining the basic reasons scientifically relating the mental health intervention in primary care and lists five assumptions and also evaluates them.

The above literature is sufficient to identify the connection between a person's health and mood. And we can say that studying mood is literally studying the health status of an individual. Also, the mood of an individual at the morning of a day is one of the many as seen from figure 1. But the question is, do we have the same mood everyday? does it have any significance regarding our health? are moods in successive days related?. Because of these facts, a person's mood on any given day could not be directly taken to be a significant indicator of his underlying health but change or swings in mood could be, as they are clearly observable and could be viewed as symptoms of the underlying health issues. But mood swings could be both positive and negative and so to identify a person's health issues we need something more substantial entity like mood-disorders which are clinically observable, measurable and also treatable. The prevalent mood disorders in literature are depression and bipolar disorder which can affect an individual on a daily basis.

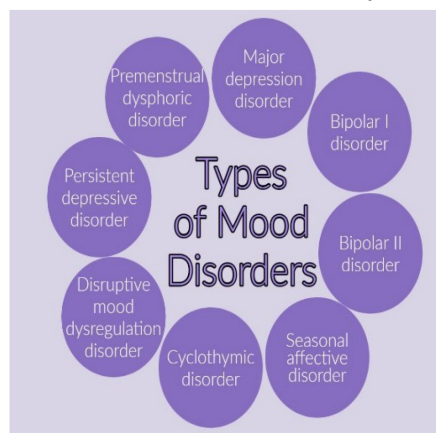


Figure 2
Mood disorder types

We can google to find out that, if a person has mood disorder, then his general emotional state or mood is distorted and inconsistent with his circumstances and also interferes in his ability to act and the general mood-disorders are in Figure 2.

Generally when a person has mood-disorder, it is identified by the fact that he might be extremely sad, depressed or might have depression and happiness alternating in an unusual way. [6] is a good literature study to initiate our understanding of these. The literature convey that the scientific causes for mood-disorder are hormonal imbalances, social issues, family history or may be due to some changes in levels of neuro transmitters in the brain. Some biological conditions like Brain tumors also may lead to mood-disorders.

The common symptoms are that he will show lack of interest in almost any activities, does not eat or sleep normally, he might be anxious , may feel fatigued more. Also from some studies, it has a lifetime prevalence rate of around 10 percent with women almost at twice the risk as men. Bipolar disorder is one of the most prevalent disorders and it can even be a lifelong issue for some. These are clinically diagnosed by some proper tests like thyroid disease tests and are treated with antidepressants, mood stabilizers and like. Some are also given psychotherapy.

But as in any other disease, prevention is better than the cure and if we dwell a bit deep into the causes, we find some literature connecting mood or mood-disorder and sleep or lack of sleep. Many studies show that persons who have less sleep usually have negative moods like sadness, anger or frustration and we can even see sleeplessness as a symptom of mood-disorder. [7] is a study connecting sleep and mood disorder which says that mood disorders are found in one third to one half of patients with chronic sleep problems. It further says that attention to sleep complaints could lead to better identification of mood disorders. The general scientific guideline is that children need 9 to 10 hours of sleep and adults 8 hours per day and it can also be influenced by the level of tiredness on a particular day. But there are other studies which also say that we need not be so specific about the actual duration but we need to have a sound sleep or around 4 to 5 hours a day which can do the work, in case of adults which clearly indicate the uncertainty surrounding the duration issue. This actually raised a question in our minds, can we identify whether we had a good and sufficient sleep the previous night by factors other than the duration of the sleep which could not only solve the sleep issue but also could lead to some avenues of studying mood disorder and further about the health of a person.

Hence, we can fairly surmise that the mood of a person and its changes over a period could be an implicit interpretation of the health status of an individual and it has a fairly good connection with sleep. We can also observe that, one of the symptoms of a mood disorder is, a person feeling sad for many successive days or in other words there is no change in mood from “Sad” state for many days.

These observations from the literature convinced us to narrow our objective of the study to be about what are the different moods a normal person can be in, how often it changes, what are the chances of a person making a transition from one state to another. Also, what are the limiting state probabilities for any mood given an initial state probability as that can give us an insight into studying this problem in an analytical and efficient way. Then we sought an analytical model to suit our objective. We also felt that a stochastic process plus transitions of the stochastic process could be the apt choice from an analytical perspective. We further narrowed it to the evergreen mathematical model of Markov chain which studies transition from one state to another on two successive time point and using which we can also find the long-term state probabilities.

Having decided what kind of modelling we are interested in, we moved to the next aspect of the tools of analysis and we felt that there is something we can improve upon with respect to the tools available now. [8] is a study which summarizes and characterizes mental health using machine learning and Natural language processing tools. [9] is a paper about depression due to social media- user-generated content and how we can detect it. It is an important addition in literature for the present day scenario as most of our depression is from that avenue and that plays a significant part in the health of an individual and hence to the sleep pattern and through it in the mood when we wake up in the morning. [10] is a paper similar to [9] for our context and it uses genetic algorithm for the analytics. [11] is a very important paper for our work as it directly addresses mood state prediction, the topic of this paper, using Petri nets and we have moved into a different line of analytics from that paper and that is inspired from [12] which is a paper using Markov chain in studying the human depression. References [13], [14], [15], and [16] are the recent papers in the health study domain which have helped us in refining our objectives.

2. Methodology

The process of study starts with the crucial aspect of connecting the Markov chain with the mood of a person or in other words how do form a

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Questions Responses Settings

surprise

What is more likely for you in two successive days, select one in every row in a suitable box. *

	Happy	Sad	Fear	Disgust	Anger	surprise
Happy	☐	☐	☐	☐	☐	☐
Sad	☐	☐	☐	☐	☐	☐
Fear	☐	☐	☐	☐	☐	☐
Disgust	☐	☐	☐	☐	☐	☐
Anger	☐	☐	☐	☐	☐	☐
Surprise	☐	☐	☐	☐	☐	☐

Number of hours you work in a day

Figure 3
Mood transition question from the Google form

Markov chain representing the mood of a human being. We dwelled on a few avenues before deciding on the statistical way of forming it through a questionnaire, as it can be more realistic and justifiable. We formed a google form of the questionnaire with some simple basic questions about how a person eats, sleeps, what are his socio-economic status etc and to have the Markov chain into the picture, we created a two dimensional question in Figure 3 from which we formed the Markov chain representing the mood transition of a person across two consecutive days. In addition, from then on our analysis started. Also, we have used only six different moods of a person, which is a way of simplification from the types discussed in the literature. We had shared the questionnaire through the social media platforms to get primary data. After getting the data pre-processed by MS-Excel, we have taken the data from this two dimensional question as the primary dataset for our Markov chain analytics. Using R platform, we formed the Markov chain for this data. Then we have obtained the single-step transition probabilities for the mood of a person and using it obtained higher order TPM's as well as the limiting probabilities and through them, the classification of states of the Markov chain is also obtained. We used these measures to derive a conclusion for the study.

3. Result and analysis

3.1 Descriptive

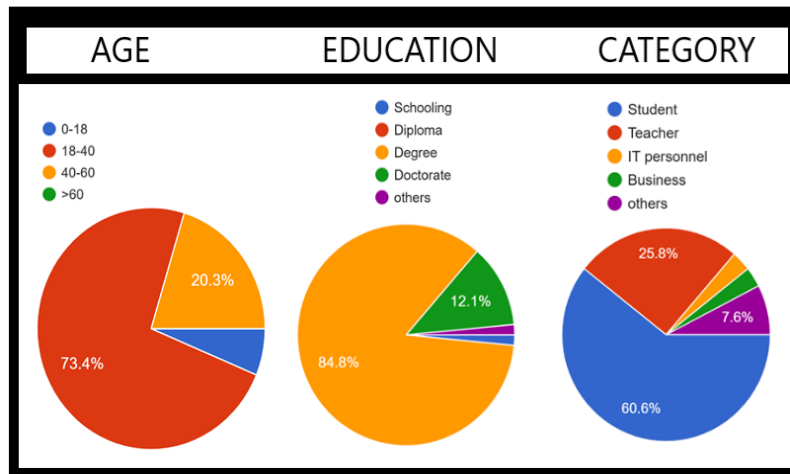


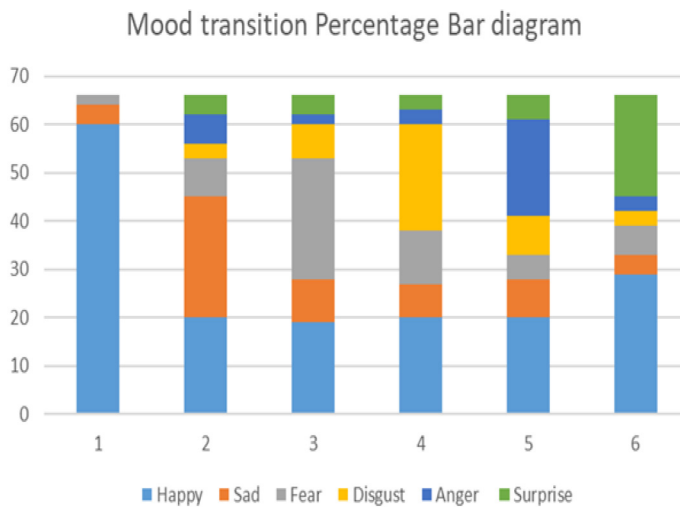
Figure 4
Descriptive of the Respondents

The questionnaire has many questions regarding the basic details of the respondents and Figure 4 is explaining the descriptive of three significant factors, the Age, Education and the category of the respondents. Age has four slabs- 0-18, 18-40, 40-60 and >60 and the biggest piece of the pie is the red one representing 18-40. Similarly the Education pie has the orange piece as the largest representing the respondents who hold a degree. The third pie is regarding the type of respondents like students, Teacher, IT personnel, Business or any other and the largest is from the student category.

3.2 Question

What is more likely for you in two successive days, select one in every row in a suitable box.

Figure 5 is percentage values of the transitions from one state to another across two days. That is the first bar indicates the percentage of transition from Happy state on one day to every other state on the next day. Similarly the other following bars represent the other states

**Figure 5**

Percentage Bar diagram of the Mood transition on two successive days

Table 1**Frequency Distribution of the Mood Transition**

	Happy	Sad	Fear	Disgust	Anger	Surprise
Happy	60	4	2	0	0	0
Sad	20	25	8	3	6	4
Fear	19	9	25	7	2	4
Disgust	20	7	11	22	3	3
Anger	20	8	5	8	20	5

Table 1 is the frequency distribution of the two-dimensional question, Figure 3, and this is the basic table from which we construct our one step transition probability matrix for the mood study, Table 2 . The transition diagram of the mood TPM is given by Figure 6 and we can clearly observe the amount of complexity even with the restricted consideration of only six predominant moods and we had drawn this using the R programming platform.

Table 2 is the Four step Transition probability matrix of the Mood MC which helps us identify many characters of the Mood MC. From Table 2, immediate clear observation is that all the transition probabilities are positive and hence the mood MC is irreducible. Also, as there are loops

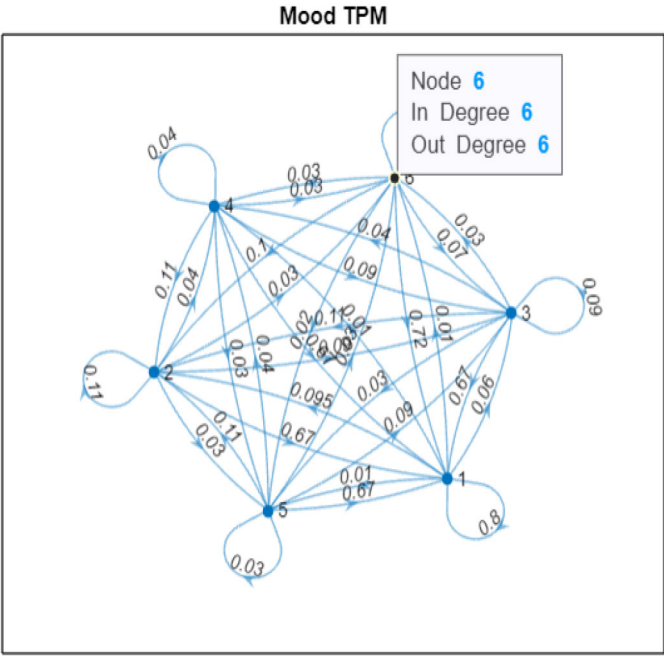


Figure 6
Transition diagram of the mood MC

Table 2
Four Step Transition Probability Matrix

	Happy	Sad	Fear	Disgust	Anger	Surprise
Happy	0.8008	0.095	0.0606	0.0157	0.0144	0.0135
Sad	0.6762	0.1184	0.0919	0.043	0.035	0.0355
Fear	0.6703	0.1156	0.0995	0.0472	0.0317	0.0357
Disgust	0.6735	0.1137	0.0969	0.0499	0.0315	0.0343
Anger	0.6782	0.1129	0.0903	0.0467	0.0362	0.0357
Surprise	0.7259	0.1031	0.0799	0.0333	0.0252	0.0325

with positive probabilities, the MC is aperiodic. As the MC is finite and irreducible, all its states are non-null recurrent. Hence, being an aperiodic irreducible MC, it is ergodic. To obtain the steady state probabilities, first we form the equation using Table 1 as,

$$\begin{aligned}
\pi_1 &= 0.9091 \pi_1 + 0.303 \pi_2 + 0.2879 \pi_3 + 0.303 \pi_4 + 0.303 \pi_5 + 0.4394 \pi_6 \\
\pi_2 &= 0.0606 \pi_1 + 0.3788 \pi_2 + 0.1364 \pi_3 + 0.1061 \pi_4 + 0.1212 \pi_5 + 0.0606 \pi_6 \\
\pi_3 &= 0.0303 \pi_1 + 0.1212 \pi_2 + 0.3788 \pi_3 + 0.1667 \pi_4 + 0.0758 \pi_5 + 0.0909 \pi_6 \\
\pi_4 &= 0 \pi_1 + 0.0455 \pi_2 + 0.1061 \pi_3 + 0.3333 \pi_4 + 0.1212 \pi_5 + 0.0455 \pi_6 \\
\pi_5 &= 0 \pi_1 + 0.0909 \pi_2 + 0.0303 \pi_3 + 0.0455 \pi_4 + 0.303 \pi_5 + 0.0455 \pi_6 \\
\pi_6 &= 0 \pi_1 + 0.0606 \pi_2 + 0.0606 \pi_3 + 0.0455 \pi_4 + 0.0758 \pi_5 + 0.3182 \pi_6
\end{aligned}$$

Then we have used the R programming platform to solve these simultaneous equations by performing 100 iterations and that resulted in Table 3 values.

Table 3
Four Step Transition Probability Matrix

	Happy	Sad	Fear	Disgust	Anger	Surprise
π_i	0.773	0.0995	0.0681	0.0223	0.0186	0.0185

The values in Table 3 are plotted as a pie diagram for easier analysis, Figure 7. It is clearly observable that being in the happy state is the

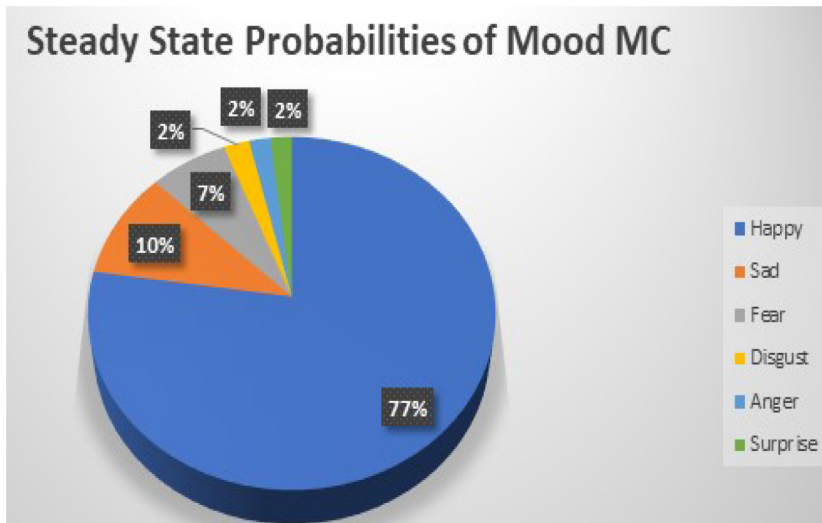


Figure 7
Steady state probabilities of Mood MC

predominant one with 77% and the Sad state comes a distant second with 10 %. All the other states are relatively speaking , not as significant as the first two. From this, we could deduce that , in the longer run, we are most likely to be in a Happy state of mood as compared to any other mood. But the limitation of this deduction is that this is only with respect to the data collected for the study.

4. Conclusion

As the Markov chain of the moods is ergodic, it is possible to make a transition from any state (mood) to any other state (mood) and that too in an aperiodic fashion, which is very much in line with the reality. In addition, because of this ergodic nature, we can derive many things regarding the moods, change in mood and through that the health status of a person. For example, if we know the current mood of a person as “Sad”, using the TPM we can obtain the chances of the person making a transition to a “Happy” state. We can also obtain, what are the expected number of days it might take that person for that transition and this sounds quite a lot of fun and scientific, even a bit more logical than the traditional ways of finding this kind of information. Also, we can clearly observe that the steady state probability of the “Happy” state is the largest among the moods and we can fairly say that whatever the current mood, in the longer run every individual is going to be happy and this sounds a lot more positive, refresh-ing and encouraging. Objectively looking at the whole study we do feel that we should go for a larger dataset with a wider class of individuals to see whether these results stand the test of size and variety and this forms our future study.

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