Detecting phase transitions in a neural network and its application to classification of syndromes in traditional Chinese medicine

This content has been downloaded from IOPscience. Please scroll down to see the full text.
2008 J. Phys.: Conf. Ser. 96 012105
(http://iopscience.iop.org/1742-6596/96/1/012105)
View the table of contents for this issue, or go to the journal homepage for more

Download details:

IP Address: 52.27.129.95
This content was downloaded on 13/07/2015 at 21:41

Please note that terms and conditions apply.
Detecting phase transitions in a neural network and its application to classification of syndromes in Traditional Chinese Medicine

Jianxin Chen¹, Guangcheng Xi¹ and Wei Wang²

¹Key Laboratory of Complex Systems and Intelligence Science, Institute of Automation, Chinese Academy of Sciences, 100080, Beijing, China
²Beijing University of Chinese Medicine, 100029, Beijing, China

E-mail: guangcheng.xi@ia.ac.cn

Abstract. Detecting phase transitions in neural networks (determined or random) presents a challenging subject for phase transitions play a key role in human brain activity. In this paper, we detect numerically phase transitions in two types of random neural network (RNN) under proper parameters..

1. Introduction
In thermodynamics, phase transition or phase change is the transformation of a thermodynamic system from one phase to another. Combination phase transition with neural network has been a research hotspot and some achievements have been obtained during past decade [1-3]. It has been proved to play a key role in human brain activity. Hoshio and his research group detected phase transitions caused by varying weights of neurons in Hopfield network [1-2]. The literature has been proposed a network composed of infinite neurons named abstract and has been proved that phase transitions play a key role in producing thought of human brain [3]. However, in the context of random neural network, phase transitions is rarely observed, furthermore, the relation between phase transition and neuronal mechanisms, such as weights and threshold, is significantly rarely studied. In [1], the relation between phase transition and weights of neurons is recorded. But with regard to threshold of neuron, the research effort has never been made. In this paper, we try to detect phase transitions in random neural network and study the relation between phase transitions and threshold of neurons. Moreover, we try to find evidence of mathematical proof of the result to support our finding. All our finding are applied to medical application-modeling syndrome in Traditional Chinese Medicine.

Traditional Chinese medicine (TCM) is a system with its own rich tradition and over 3000 years of continuous practice and refinement through observation, testing and critical thinking. TCM can be characterized as holistic with emphasis on regulating the integrity of the human body and the interaction between human individuals and their environments [4]. TCM need to be modernized mathematically and physically and our research effort here is devoted to the issue.

¹ To whom any correspondence should be addressed.
In this paper, we declare that a syndrome is a diagnostic concept produced by means of mapping symptoms derived from Si Zhen information into brains of TCM experts. So a syndrome is a philosophical concept existing in the brain of experts. We employ homogeneous random neural network introduced in [5] to model syndrome. This article focuses on phase transitions in the random neural network and mathematically and physically interpret syndrome in TCM. The random neural network is briefly introduced in Section 2. The phase transitions are detected in Section 3, the relation between phase transitions and threshold is also given in Section 3. Section 4 is devoted to model syndrome in TCM. Conclusion is summarized in Section 5.

2. Random neural network model
The detail operation of random neural network are given in [5], we do not describe it carefully in this paper. There are two types random neural network available, one dimension RNN and two dimension RNN. For former type of RNN, the neurons are arranged in a line with one dimension. The input of the RNN is the point (neuron) on the line and the output is the limit probability of each point. The number of parameters of the one dimension RNN is four. The number of neurons, denoted as \( N \). Threshold of each neuron, denoted as \( Z(N \leq N) \). Connection from a neuron to any one of the other neurons with a fixed probability \( U \). The connection is excitatory with a probability \( V \) and inhibitory with \( 1 - V \). The limit distribution of the network can be obtained analytically [5]. For later type of RNN, the neurons are aligned as a grid with two dimensions. The number of parameters is five. Besides the four parameters introduced above, the fifth parameter is external inputs, denoted as \( M \). It is these \( M \) inputs that make the network become two dimension RNN. The neurons of the network and the external inputs are arranged on the grid with two dimensions. The probability of each point on the grid means the joint probability of one neuron and one input. The output of this type of RNN is the limit distribution of the grid and obtained numerically [5].

3. Phase transitions in the two types of RNN
We find out phase transitions in both two types of RNN. The transitions are caused by varying threshold of neurons and the critical thresholds where the phase transition takes place for two types are different. For one dimension RNN, the critical threshold is 2. For two dimensions RNN, the critical counterpart is 4.

3.1. One dimension RNN
By numerical simulation, once threshold is determined, the limit distribution is given by the RNN. When the threshold varies, the corresponding distribution is varied. As shown in Figure 1, when threshold varies from less than 2 to larger than 2, the limit distributions vary significantly, which means phase transitions occur and the critical threshold is 2. We use the mean firing rate of RNN vs threshold to visualize the phase transitions, as show in Figure 4.

3.2. Two dimensions RNN
The method to detect phase transitions is similar with method described in above subsection. As depicted in Figure 2, the distribution of neurons is obtained by computing marginal distribution of joint distribution. We can easily find that phase transitions also occur in this type RNN and the critical threshold is 4. The phase transitions can also be visualized in Figure 5.

3.3. Evidence of the finding and importance of the phase transitions
In literature [6], researchers have mathematically presented another kind of stochastic neural network- a hourglass network. They also proved a theorem to declare that for one dimension, the critical value is 2 and for two the corresponding counterpart is 4, which completely accord with the finding in this paper. Furthermore, according to the resulted proved in [3], the human brain network with phase transitions can produce thought, which is generated when two concepts in the brain transit with each
other. So in the follow section, we use this result to classify two syndromes and apply it to mathematically and physically interpret TCM to make it modernized.

4. Medical application
The data are got from a doctoral thesis [7], in which the author followed the principle of Design, Measurement and Evaluation (DME), used the method of epidemic inquiry, got the statistical data of blood stasis syndrome in five diseases, then did the Logistic regression analysis, finally determined the factors that were closely related to each disease’s blood stasis syndrome. Most of these factors are symptoms; few of them are some information of patient’s body, such as gender, age, etc. The result is showed partly in Table 1, in which we have 19 symptoms. The former 12 symptoms strongly relate to the blood stasis syndrome of coronary heart disease, namely, subtype 1, and the latter 11 symptoms fiercely associate with the blood stasis syndrome of diabetes. These two diseases’ syndromes belong to two subtypes of blood stasis syndrome and are totally different with each other although they have four same symptoms.

For the state space of the Markov chain is bespoken by a line, however, the two subtypes have four identical symptoms, so we need 19 states (12+11–4=19). We proposed a better way to encoding the symptoms. We assign the states 9,10,11,12 to four symptoms that are the overlap of two blood syndrome subtypes. With regard to other symptoms, if a symptom belongs to the first subtype, it must be assigned to one of the states that are from 1 to 8, whereas if a symptom belongs to the second subtype, then it will be assigned to one of the states that are from 13 to 19. So we can have exactly $8!\times 4\times 7!$ kinds of encoding. For example, state 1 can represent Angina, it can also be used to represent Dyspnea. But it should not be used to represent Palpitation, since Palpitation is one of the four overlap symptoms. Of course, it cannot be used to represent Frequent nocturia, since the Frequent nocturia belongs to the subtype 2. Table 1 is just one sample of $8!\times 4\times 7!$. Despite this, as shown in the following section, we find that, as long as the four overlap symptoms are aliened in states 9-12, the network can interpret the syndrome in TCM successfully, as seen in Figure 3. Each disease’s syndrome is regarded as a phase, it is also a philosophical concept existing in the brain of TCM expert. When the threshold varies, phase transitions occur, i.e., concepts transit, thought forms in the brain of TCM experts, therefore, syndrome is identified, so the “Bian Zheng” is successful. Based on this, we can conclude that syndromes in TCM can be interpreted mathematically and physically.

5. Conclusion and discussion
This paper creatively focuses on the phase transitions of the random neural network. We point out that for one dimension, the critical threshold is 2. For two dimensions, the critical counterpart is 4. It is of creativity to declare that a syndrome in TCM is a diagnosis concept of brain. Furthermore, the distillation of theory of TCM – “Bian Zheng Lun Zhi” is a high product of thought, which generates when concepts transit. The best method to encode two diseases’ symptoms as quantities of the network is brought forward. We apply it to mathematically and physically clarify the relation between the 19 symptoms and two syndrome subtypes, in which a symptom is represented by a state of state space of the network while the syndrome subtypes are denoted by the steady state probability distributions at Z=1 and Z=2 respectively. We conclude that TCM can be modernized.

6. Acknowledgement
This work has been supported by 973Projects under grant No. 2003CB517106.

7. Figures
Fig.1. The limit distribution of one dimension RNN. There is a significant variation of limit distribution when threshold varies though 2.

Fig 2. In two dimension RNN, phase transitions occur when threshold varies through 4.
Fig 3. The left figure is obtained by setting the parameters of the neural network as: $N=19, u=0.1, v=1, Z=1$ while the right figure is plotted by adjusting the threshold of the neuron to 2 and keeping other parameters invariant. The X axis is symptom, which is represented by the state of state space of the Markov process while the Y axis is the corresponding steady state probability of the state (symptom). We readily see from the figures that the random neural network model can distinguish two subtypes clearly.

Fig 4. Expectations of limit distributions (mean firing rate) for different threshold change enormously when threshold varies from 1 to 2.
Fig 5. It is easy to see that the critical threshold of two dimensions network is 4.

8. Tables

Table 1. Encoding symptoms by using states from state space of the neural network. The subtype 1 is abstract of 12 symptoms while subtype 2 is of 11 symptoms.

<table>
<thead>
<tr>
<th>State</th>
<th>Symptom</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Angina</td>
</tr>
<tr>
<td>2</td>
<td>Dyspnea</td>
</tr>
<tr>
<td>3</td>
<td>Lassitude</td>
</tr>
<tr>
<td>4</td>
<td>Squamous and dry skin</td>
</tr>
<tr>
<td>5</td>
<td>Dark eye orbit</td>
</tr>
<tr>
<td>6</td>
<td>Dysphoria with feverish sensation in the chest, palms and soles</td>
</tr>
<tr>
<td>7</td>
<td>Petechia on the tongue</td>
</tr>
<tr>
<td>8</td>
<td>Wiry pulse</td>
</tr>
<tr>
<td>9</td>
<td>Palpitation</td>
</tr>
<tr>
<td>10</td>
<td>Dark lips</td>
</tr>
<tr>
<td>11</td>
<td>Dark purple tongue marked with ecchymosis</td>
</tr>
<tr>
<td>12</td>
<td>Engorged sublingual veins</td>
</tr>
<tr>
<td>13</td>
<td>Gender</td>
</tr>
<tr>
<td>14</td>
<td>Smoking</td>
</tr>
<tr>
<td>15</td>
<td>Frequent nocturia</td>
</tr>
<tr>
<td>16</td>
<td>Unsmooth pulse</td>
</tr>
<tr>
<td>17</td>
<td>Darkish complexion</td>
</tr>
<tr>
<td>18</td>
<td>Polyoressia</td>
</tr>
<tr>
<td>19</td>
<td>Emaciate</td>
</tr>
</tbody>
</table>
References