國立交通大學

資訊科學與工程研究所

碩 士 論 文

中藥藥材與藥方網路分析

Network Analysis on Chinese Herb and Prescription

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中 華 民 國 九 十 七 年 七 月

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摘要

在傳統中醫醫學中，中藥藥材與藥方之間的關係可以一個網路的方式來看待。我們用一個二分關聯圖像將藥材與藥方視為兩種不同的節點，而藥材與藥方之間的連結代表藥材如果出現在藥方裡頭。在本論文中，我們以複雜網路的方式針對中醫的藥材以及藥方等系統的經驗屬性作研究。 我們探討不同年代的藥材與藥方，由分析的結果發現藥材網路的度分佈為指數分佈，藥方為常態分佈。我們提出一個進化模組以真實的藥材與藥方成長方式來模擬中醫藥材與藥方網路並給予模組模的擬結果與探討。 此外我們分析症狀以及針灸穴位網路，發現症狀網路的度分佈為指數分佈，而針灸穴位網路為常態分佈。

關鍵字：中醫醫學，網路分析，統計，度分佈，進化模組。

Network Analysis on Chinese Herb and Prescription

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National Chiao Tung University

Abstract

In Traditional Chinese Medicine (TCM), the relationships between the Chinese Herbs and prescriptions can be cast into network. We can use a bipartite graph and allow herb and prescription to be the two types of node. An edge exists between the herb and prescription if the herb appears in the prescription. In this thesis we studied the empirical properties of Chinese Herb and Prescription Network with a viewpoint of complex network. We study the herb and prescription network using the medical book from two different eras. Analytical results showing that the degree distribution of Herb Network is exponential and Prescription Network is normal distribution. We propose an evolution model using the idea of actual herb and prescription evolution to simulate the TCM network and the simulation result and discussion were given. Furthermore, we analyze the symptom and acupuncture point network and found the degree distribution of symptom network is exponential and the acupuncture point is normal distribution.

Keywords: Traditional Chinese Medicine, Network Analysis, Statistics, Degree Distribution, Evolution Model.

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1. Introduction

1.1 Historical Background

The Chinese herbs were originated from China and they were widely used for treating diseases and some Chinese cuisines. There are over three hundred herbs that are commonly being used today that have a history goes back at least 2000 years in China [1]. The first Chinese herbalist which recorded somewhere around 2000 B.C is Shennong (神農), legendarily said that he has tasted hundreds of herbs and imparted his knowledge of medicinal and poisonous plants to the people. The Shennong Bencao Jing (神農百草經), which is the first Chinese herb manual and is formally documented somewhere near the 1st century of Han dynasty, which records 365 medicines (253 are herbs, the rest were elements such as metals, rock, animals tissues, etc.). Later the Yao Xing Lun (藥性論 Treatise on the Nature of Medicinal Herbs) was successfully generated during the 7th century Tang Dynasty for more detailed on characteristic of herbs such as the qi (氣), blood (血) and meridian (歸經) of the herb, which is an extension from Shennong Bencao Jing. As for today, the most important herbal book out of these, arguably, was the Compendium of Materia Medica (本草綱目 Bencao Gangmu) was assembled and compiled during the Ming dynasty by Shizhen Li(李時珍), which is still widely used today for herbal consultation and reference.

As Today, many of the modern day drugs have been developed from these herbs such as the treatments for asthma and hay fever from Chinese ephedra (痲黃), hepatitis remedies from schizandra (五味子) fruits and liquorice (甘草) roots and a number of anticancer agents from trees and shrubs. There are several Chinese herbal drugs that invigorate the energy, nourish the blood, calm tension and regulate menstruation.

On the prescription side, *Herbology* is the Chinese art of combining medicinal herbs. In the art of combining Chinese herbs, each prescription is a combination of many herbs tailored to the individual patient or illness, customize by adjusting the ingredient if required. The Chinese herb prescription practitioner usually designs a remedy using one or two main ingredients that target the illness and then practitioner adds many other ingredients to adjust the formula to the patient's yin/yang (陰/陽) conditions. Sometimes, the practitioner will add some ingredients to cancel out the toxicity or the side-effect of the main ingredients, since some Chinese herbs have side-effects or toxic to human body. Some herbs require the use of other ingredients as catalyst so the medicine will have its effect.

Unlike the western medicine, the balance and interaction of all the ingredients are considered more important than the effect of individual ingredients. The balance and interaction requires great experience and knowledge, and make the difference between a good Chinese herbal doctor and an amateur.

During the recent years, TCM (Tradition Chinese Medicine) has gained its popularity over the world [2]. It is increasingly approval, recognized and place importance by the western culture. Despite its popularity, Chinese Medicine today has not been fully comprehended. The basic concepts of Chinese medicine, such as yin/yang (cold/hot 陰陽) , wu xing (the five elements 五行) and the qi/blood meridian theory (氣血歸經論), were too mystified and are inaccurate descriptions of the human body that were verge imaginative [3]. The TCM is based on the empirical knowledge, which is lack of scientific basis and clinical data, most research on TCM in the past is of poor quality, and is published only in Chinese medical journals without proper peer-review processes.

1.2 Different Types of Network

The term network may refer to any interconnected system which sharing information among them. The networks may be social, value, transportation or virtual, such as the Internet or human relations. A network consists of vertices and edges, where each vertex represent independent body and the edge between the vertices represent the relationship between them.

1.2.1 Random Graph

The theory of random graphs lies at the intersection between graph theory and probability theory, and studies the properties of typical random graphs. The Random graph is a graph that is generated by using some random process, it was introduced by Paul Erdős and Alfréd Rényi after Erdős discovered that probabilistic methods were often useful in tackling problems in graph theory [4,5]. Erdős and Rényi define a random graph G(n,p) as N number of nodes connect by n amount of edges, which are chosen randomly from $N(N$-1)/2 possible edges using a random connection probability p.

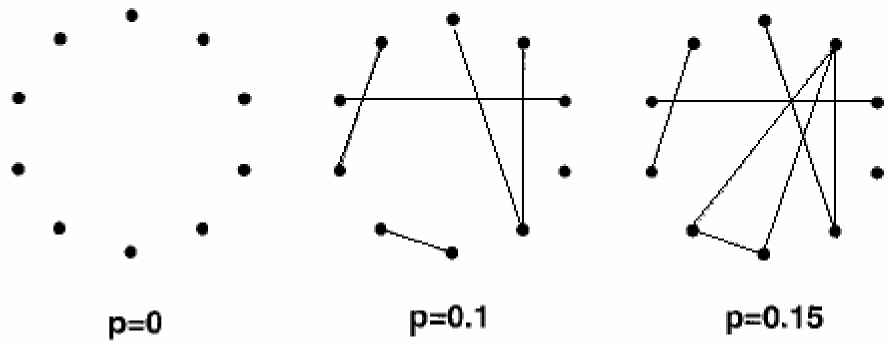

Figure 1.1 The graph evolution process of a random graph [4].

In mathematics the construction of a graph is often called the evolution of a graph. In Erdős and Rényi's Model, they start by N amount of isolated nodes (with no edge), and then the graph develops by successive addition of random edges, using a random connection probability p as the probability for introduction the edges between the nodes.

1.2.2 Small-World Network

A small-world network is a type of mathematical graph with small-world phenomenon, in which most nodes are not neighbors of one another, but most nodes can be reached from every other by a small number of hops or steps [6,7]. For example, a social relationship network where people are node and an edge is introduced between the nodes if people know each other, such network carries the small-world phenomenon.

A certain category of small-world networks were identified as a class of random graphs by using Watt-Strogatz Model. By comparing small-world network to a random graph, small-world network were similar to random graph, but they usually have higher clustering coefficient and small average path length. The Watts-Strogatz model introduces a small world structure with short average path length and high clustering coefficient.

1.2.3 Scale-free Network

A scale-free network is a noteworthy kind of complex network because many real-world networks fall into this category. In scale-free networks, some nodes act as "highly connected hubs" (node with high degree), shown in figure 1.2, the highlighted node in figure 1.2(b) were the hub nodes and most nodes in the network are of low degree [8]. For example, the Internet and the World Wide Web are a good example of scale-free network, where having some highly connected hub-like nodes and having power-law degree distribution.

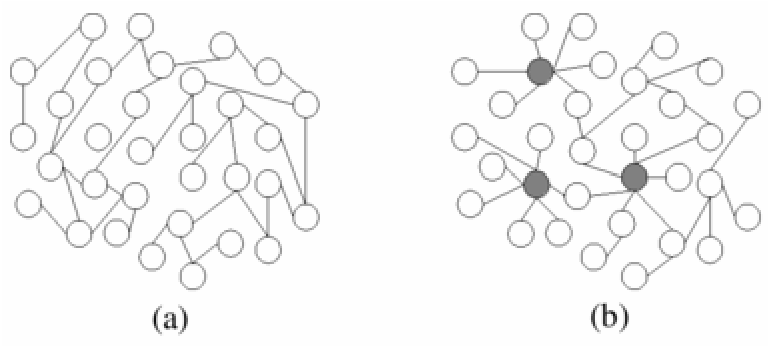

Figure 1.2 Random network (a) and scale-free network (b) [8].

The Barabási–Albert model state that the scale free nature of real networks is rooted in two generic mechanisms shared by many real networks: *Growth and Preferential Attachment.* Firstly, most of the real-world networks describe open systems that grow by the continuous addition new nodes and edges. For example, the World Wide Web grows in time by the addition of new web pages. Secondly, network models discussed so far assume that probability that two nodes are connected is independent of the nodes' degree, however, most of the real-world networks such that the likelihood of connecting to a node depends on the node's degree. For example, a web page will more likely include hyperlinks to popular documents with already high degree because the highly connected documents are easy to find thus well known. Thus a highly connected web page will result with more hyperlinks to it.

1.3 Network properties

1.3.1 Degree Distribution

Degree distribution gives the probability distribution of degrees in a network. It originates from the study of random graph and it has become an important concept which can use for describing the topology of complex networks. The degree of a node tells how many neighbors or the links the node has to other nodes. The spread in the node degrees is characterized by a distribution function $p(k)$, which give the probability that a randomly selected node from the network has exactly k edges.

Formally, degree distribution is:

$$p(k) = \sum_{v \in V \mid \deg(v)=k} 1 \quad (1)$$

Where v is a vertex in the set of the graph's vertices V, and deg(v) is the degree of vertex v. In this paper, we made a use of the complement cumulative distribution function, which is defined as:

$$F_c(k) = 1 - F(k) \quad (2)$$

Where *F(k)* is defined as:

$$F(k) = \sum_{k_i \le k} p(k_i) \quad (3)$$

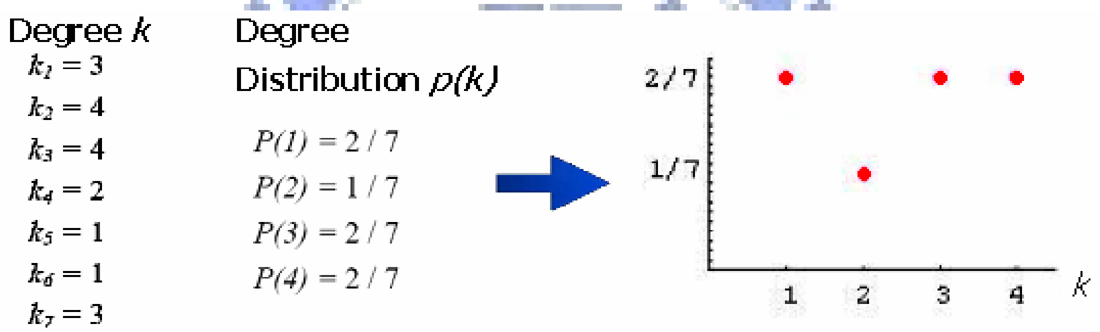

Figure 1.3 An example of Measuring the Degree Distribution of a network

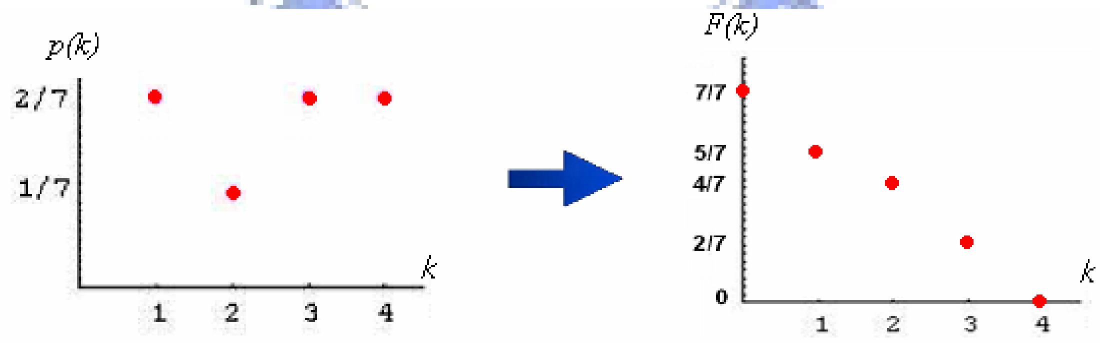

Figure 1.4 An example of Complement Cumulative Distribution Function

In a random graph with connection probability p the degree k_i of a node i follow a poisson distribution with parameters N-1 and p:

$$P(k_i = k) = C_k^{N-1} p^k (1-p)^{N-1-k} \quad (4)$$

This probability represents the number of ways in which k edges can be drawn from a certain node: the probability of k edges is p^k, the probability of the absence of additional edges is $(1-p)^{N-1-k}$, and there are C_k equivalent ways of selecting the k end points for these edges.

For small-world network, the idea presented in the small-world network model has been explored quite extensively. Indeed, several classic results in random graph theory show that even networks with no real topological structure exhibit the small-world phenomenon, some analytical results showing that the degree distribution of small-world network can be range from a power-law distribution like the scale-free network [9] or exponential distribution [10].

Distinctively, scale-free networks show a power law, long tail degree distribution:

$$P(k) \sim k^{-\gamma} \quad (5)$$

Like most real networks, network growth and preferential attachment have been shown to create networks with power law degree distributions by Barabási and Albert in 1999. In Scale-free network, most of the nodes in network have very small degree and few of the nodes in the network act as the hub of the network, with enormous high degree.

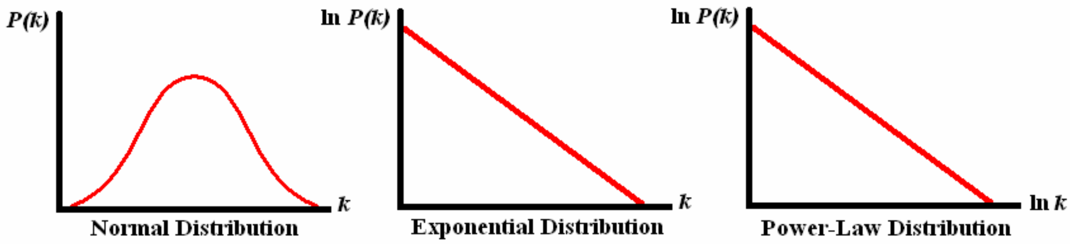

Figure 1.5 Different types of Distributions

1.3.2 Clustering Coefficient

The concept clustering is a common property of social networks that in cliques form, representing circles of fiends of acquaintances in which every member knows every other member [6]. This inherent tendency to cluster is quantified by clustering coefficient [7].

Clustering coefficient measure how close the vertex and its neighbors are from being a clique/complete graph. The *clustering coefficient* C_i for a vertex v_i is the proportion of links between the vertices within its neighborhood divided by the number of links that could possibly exist between them. In other word, it measures the neighbor connectivity for each vertex. In figure 1.6, for shaded node *i*, the black edges are edges connecting neighbors of *i*, and dotted blue edges are for unused possible edges. The clustering coefficient of the whole network is the average of all individual C_i's.

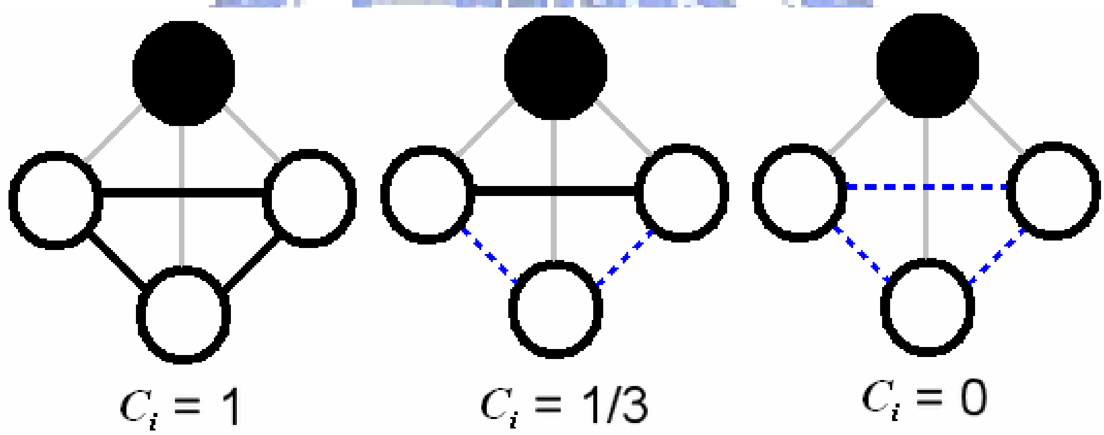

Figure 1.6 The clustering coefficient of an undirected graph.

The clustering coefficient of a random graph is often found to be smaller in compare with complete graph or a small world network, since that the connections between the nodes were random, neighbors of one node can be any other nodes in the network. If we consider a node in a random graph and its nearest neighbors, the probability that two of these neighbors are connected is equal to the probability that two randomly selected nodes are connected. Consequently the clustering coefficient of a random graph is:

$$C_{rand} = p = \frac{\langle k \rangle}{N} \tag{6}$$

In small world network, clustering coefficient does not necessary depends on the size of the network. Small world network have relatively high clustering coefficient, since that one node's neighbor were mostly the neighbor one's other neighbors.

The clustering coefficient of the scale-free network is about five times higher than that of the random graph, and this factor slowly increases with the number of nodes. However, the clustering coefficient of the Barabási-Albert model decreases with the network size, while a slower decay than the $C=\langle k \rangle N^{-1}$ decay observed for random graphs, is still different from the behavior of the small-world models, where C is independent of N.

1.3.3 Average Path Length

Average path length is a concept in network topology that is defined as the average number of steps along the shortest paths for all possible pairs of network nodes. In a real network, it is a measure of the efficiency of information or mass transport on a network. Some examples are: the average number of clicks which will lead you from one website to another or the number of people you will have to communicate through, on an average, to contact a complete stranger.

The random graphs tend to have small diameters, for the connection probability p is not too small. The reason for this is that a random graph is likely to be spreading: with large probability the number of nodes at a distance l from a given node is not much smaller than $\langle k \rangle_l$. Equating $\langle k \rangle_l$ with N and finds that the average path length is proportional to $\ln(N)/\ln\langle k \rangle_l$ [8], thus it depends only logarithmically on the number of nodes.

$$\ell_{rand} \sim \frac{\ln(N)}{\ln(\langle k \rangle)} \qquad (7)$$

For small world network, it has a shorter average path length in compare with the scale-free network and for all nodes will have at least one shortest path to it. The Watts-Strogatz model is a change in the scaling of the characteristic path length l as the fraction of rewiring probability p is increased, the larger the rewiring probability p, the shorter the average path length.

In comparison with the average path length of a random graph and BA's Model, using the same size and average. While the average degree is small, average path length is smaller in the Barabási-Albert network than in a random graph for any N, indicating that scale-free is more efficient in bringing the nodes close than random graphs.

1.4 Related Work

In the past, a number of models have been proposed for the collaboration network such as the Ramasco, Dorogavtev and Pastor-Satorras (RDP) model [11] and the model presented by P. Zhang et al. [12]

The RDP model is used to simulate the movie-actor collaboration network with scale-free degree distribution. In the TDP model, the term act-size T_i refers to the amount of actors is playing in the movie i, and act-degree h_i refers to the amount of movie that actor i has played. The RDP model using a constant act-size T for all movies and the using a preferential rule of h_i for choosing the actors. The result from RDP model is that both act-degree $P(h)$ and degree distribution P(k) were both exact power-law function.

The model proposed by P. Zhang et al. is similar to the RDP with a few differences, using a fixed amount of starting nodes with constant act-size T, and having 3 different methods for choosing the node during the model time step.

The first method is using linear preferential rule, a probability proportional to the nodes act-degree h_i of each old node i. The result from this method is that both $P(h)$ and $P(k)$ were power-law function. The second method is to select nodes by random, the result was that both $P(h)$ and $P(k)$ were exponential function. The third method is to select nodes by a random probability p, and using linear preferential rule with $1-p$. The result from the third method is that both $P(h)$ and $P(k)$ were exponential function and follows a Stretched Exponential Distribution (SED).

Zhang model's simulations is in good agreement with the empirical data, such as the Collaboration Network of Hollywood Actor (CNHA), Travel Route Network of China (TRNC), Bus Route Network (BRN), Huai-Yang recipes of Chinese cooked food (HYRCCF), as well as the Traditional Chinese Herb Prescription Formulation Network (TCHPFN) [10,12]. As results of TCHPFN, they find the distribution to be exponential decays.

1.5 Problem Definition

The model used in [10] successfully simulates the herb frequency distribution and herb degree distributions in TCHPFN. The degree distribution and herb frequency distribution of the simulation were in good agreement with the empirical results. However, assuming that prescription-size T to be a constant simply means that all prescriptions were consists of same amount of herb formulation. Also that newest herb is fixed and destined to connect the newest prescription every time evolution, were unlikely to occur in real world data, that the new herb will create 1 new prescription. Thus the model by [10] lack for the actual description of the prescription size and how exactly the prescriptions should evolutes, we need a model that can correctly simulation the above two issues with regard to the evolution of the herbs and prescriptions.

In this thesis, we used network analysis method to understand more about the Traditional Chinese Medicine in Herb and Prescription, using network analysis to see if the connections between herbs, prescriptions, symptoms and acupuncture points were random, given results with discussion. We introduce an evolutionary model which can use for simulate such network, using the idea of actual growth of the Chinese herb and prescriptions and how herbs were combine to each other, with the use of prescription-size distribution and herb frequency distribution of the real world network and produce the degree distribution as result.

2. Herb and Prescription Data

2.1 Data Source

Before constructing our herb and prescription, we need to retrieve the herb and prescription information from the source. We retrieve the web pages of Chinese herbs and prescriptions using web crawler. Target source: Committee on Chinese Medicine and Pharmacy (行政院衛生署, 中醫藥委員會 - 中醫藥資訊網), The Complete Work of Jing-Yue (CWJY) [13].

Extract the primary content within each page, such as the herb information, prescription content and formulation, symptoms, etc. We extract 2064 prescriptions covering 382 herbs in total.

仲景大承氣
方劑組成
大黃，四兩。厚朴，半斤。枳實，五枚。芒硝，三合。
主治功效
治陽明太陰傷寒，譫語，五六日不大便，腹滿煩渴，並少陰舌乾口燥，潮熱脈實者。劉河間加甘草，名三一承氣湯。

Figure 2.1 An example of the primary content extract from the web page

We also retrieve an alternate source name Treatise on Febrile Diseases (TFD) [14], for comparison purposes and data robust, the TFD, which contain 289 prescriptions.

2.2 Data Cleaning and Preprocess

In order to create clean experimental result, we need to remove the noise in the database. In our herb and prescription network, we start by removing the prescriptions which contains null or incorrect values such as unrecognized font/words, and incomplete information. This is to prevent incorrect experimental results caused by noises. We remove the prescriptions which only contains a single herb, since a single herb may not be useful when we construct our network. We also remove the prescriptions which are repeated in name and ingredient so each prescription in our database is uniquely presented.

Finally, we remove the prescriptions which are supersets of the other prescriptions, i.e. if prescription A contains all herb ingredient of prescription B, such that if prescription A contains herb *a, b, c* and d and prescription B contains herb *c* and *d,* thus we say A is the superset of B, thus we remove prescription A from the database. The reason for such action is to prevent for most of the nodes in the network to form a giant cluster or a complete graph since we connect the herbs using prescriptions. Furthermore, we believe that Chinese herb prescription practitioner may design a new prescription by combining or modifying existing prescription by adding/removing herbs of the prescription. We believe by removing the prescription which are supersets of the other will be able to clean up the prescriptions to the original form.

2.3 Data Statistics

In figure 2.2 is the prescription-size (herb) distribution of the herb network, graph indicate that most of the prescriptions contain 2 herbs for CWJY. These two-herb prescriptions may be the primitive prescriptions since Chinese herb prescription practitioner usually designs a prescription start by using one or two main ingredients which target the illness. As for TFD, which is a much smaller database due to it was found at a much earlier age. The prescription-size distribution of TFD shows a shifted poison distribution, with peak a 4, representing that in TFD, most of the prescriptions contains 4 herbs rather than 2, like the CWJY does.

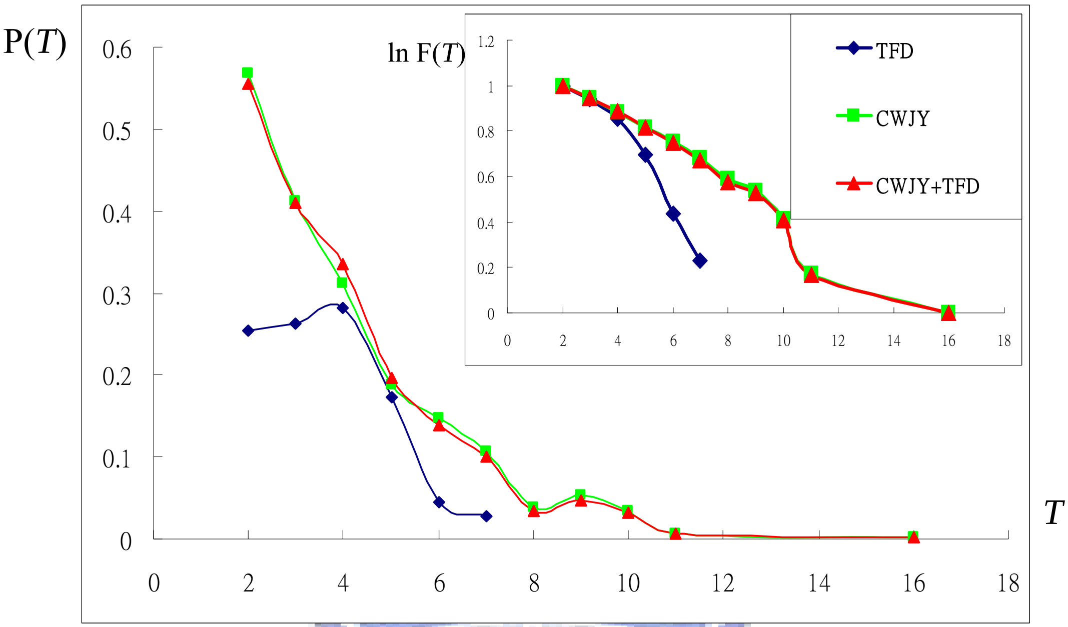

Figure 2.2 The Prescription-Size of herb network

From the distribution, we can see that the amount of prescriptions and the amount of herb per prescription are proportional to each other, thus binding between herbs in prescription is not random, since an exponential decaying distribution appeared show in the fitting of figure 2.2. No single-herb prescription exists since we have removed them during data cleaning process. Each prescription is uniquely presented and contains no subset to the other prescription. The average prescription-size $\langle T \rangle = 3.94246$, averagely each prescription consists of 4 herbs.

In figure 2.3 shows the herb frequency distribution of herb network. For CWJY, most of the herbs appeared twice among all the prescriptions. The herb with the highest herb frequency is the liquorice (甘草) and tuckahoe (茯苓), which are very commonly used for harmonize or herbal balancing of the other herbs in prescriptions and the herb with the low herb frequency were mostly the rare or uncommon herbs, some were even ores or minerals.

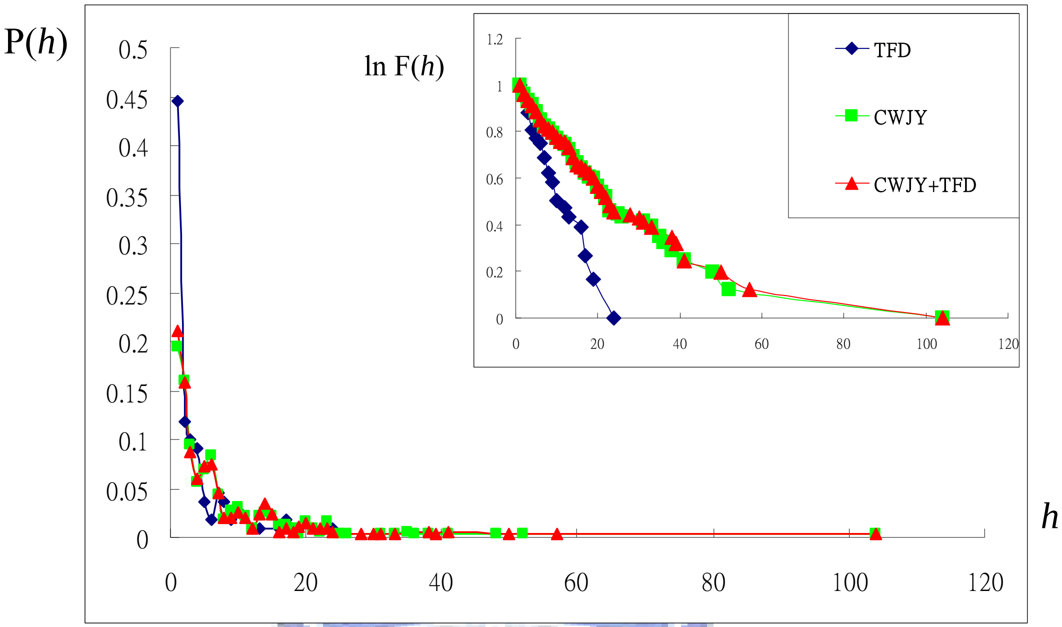

Figure 2.3 The herb frequency of the herb network

For TFD, we can see that most of the herbs in TFD (after the supersets been removed) appeared only once among all prescriptions. Again, the nodes with the highest herb frequency in the network were the herb with the most common usage in the medicine book. They are liquorice (甘草) tuckahoe (茯苓).

The herb frequency distribution is an exponential distribution, with the fitting showing the distribution in cumulative form with semi-log scale. The average herb frequency $<h>=7.32659$, averagely each herb appears 7 times.

3. Herb and Prescription Network

3.1 Bipartite Graph

A traditional unipartite (single mode) graph consist of nodes/vertices and edges/links, and the there exist an edge/link between two nodes/vertices if there exist some relationship between them. In our network, we use a bipartite graph to describe our network.

Bipartite graph has been used for describing collaboration networks such as the movie-actor collaboration network [15] .In a bipartite graph, there are two different kinds of nodes and nodes are only connects to the node of different kind. The advantage of using a bipartite graph is that is records the relationship of connection and is able to record the multi-edge or weight between the same types of node. Another advantage is that since two types of nodes in the graph are of equally importance, it is able to produce two unipartite (single mode) graphs with using the connection of two types of nodes.

For example, the bipartite graph of Herb and Prescription network shown in figure 3.1, which consists of two different types of nodes, the prescription node and the herb node. An edge exists between the herb node and prescription node if the herb appears in that prescription.

The green nodes are the prescription nodes and red nodes are the herb nodes. The herb nodes 柴胡, 大棗, 甘草, 生薑, 半夏, 人參 and 黃芩 were connected to prescription node 小柴胡湯. Here we define the two parameters: the herb frequency *h* and prescription-size *T*. The herb frequency h_i is the amount of prescription that herb *i* appeared. For example, the herb 柴胡 appears in prescription 小柴胡湯 and herb 甘草 appeared in prescription 小柴胡湯 and 芍藥湯. Thus the herb frequency for herb A is $h_{\text{柴胡}}= 1$, and B is $h_{\text{甘草}} = 2$. The prescription-size is the amount of herbs which contained in a prescription. For example, the prescription-size T for prescription 小柴胡湯 is $T_{小柴胡湯} = 7$ and prescription 大承氣湯, $T_{大承氣湯} = 4$. All herb nodes connect to the same prescription node forms a complete graph, shown in figure 3.2, converting the herb nodes from a bipartite graph to a single-mode graph, where it consists of single type of node, this can be done using prescription as node, shown in figure 3.3.

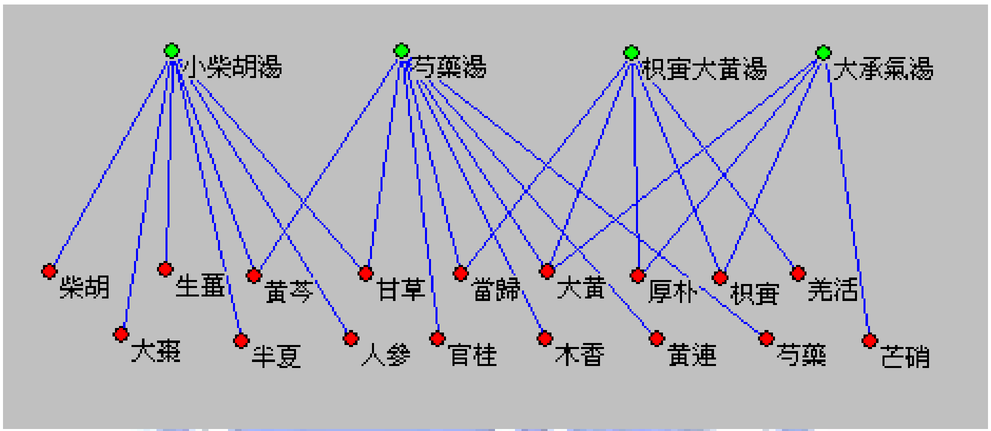

Figure 3.1 An example of bipartite graph with two types of nodes. The green nodes are the prescription nodes and the red nodes are the herb nodes

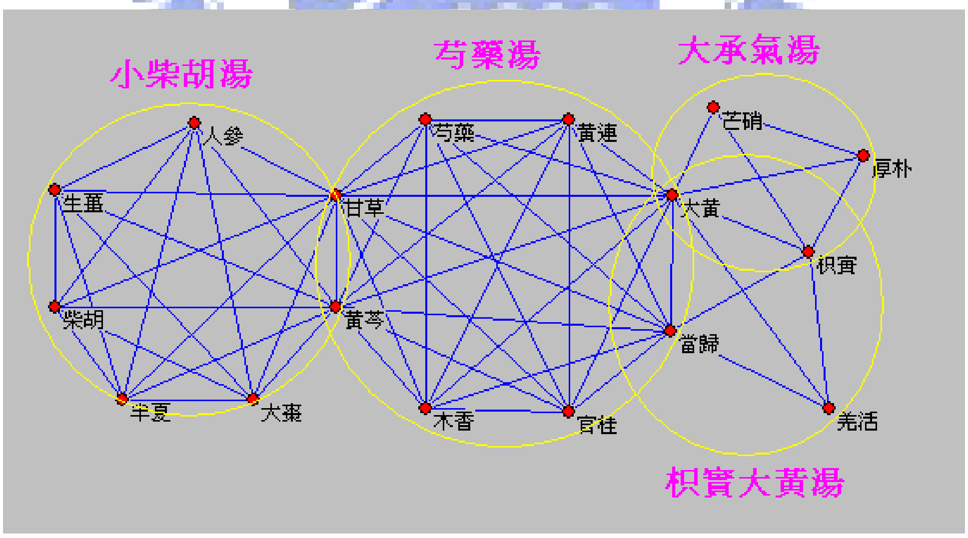

Figure 3.2 An example of a single-mode (unipartite) graph produced from a bipartite graph using herb as node.

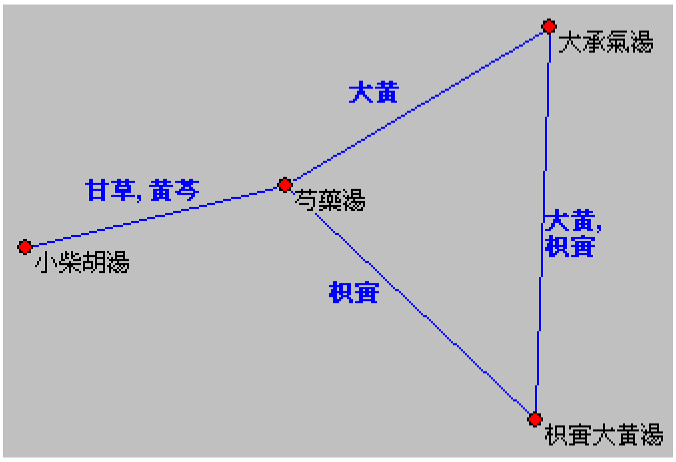

Figure 3.3 An example of a single-mode (unipartite) graph produced from a bipartite graph using the prescription as node.

3.2 Herb and Prescription Network Construction

We then give an appropriate identification for each herb then construct the herb list, for reference and identification purpose. The list is used for referencing the herb as node in the network. Then we convert the herbs and from the primary content of each web page to the identification code given previously, and then gather them together next to the prescription.

灶中黃土	1	蔓荊子	11	熟地黃	21
王不留行	2	吳茱萸	12	白豆蔻	22
生梓白皮	3	川楝子	13	草豆蔻	23
蒴藋細葉	4	自然銅	14	白蒺藜	24
五味子	5	牡丹皮	15	白蘚皮	25
蒲公英	6	山茱萸	16	白頭翁	26
九里香	7	肉蓯蓉	17	太乙禹	27
海螵蛸	8	何首烏	18	白芥子	28
百藥煎	9	佛耳草	19	白檀香	29
劉寄奴	10	青葙子	20	鼠粘子	30

Table3.1 A view of the herb list

小柴胡湯方	166 168 207 216 231 238 275
大承氣湯方	227 236 316 368
芍藥湯	128 222 140 211 122 236 367 166
枳實大黃湯	112 222 227 236
黃連解毒湯	140 166 127 249
防風湯	144 112 372 335

Table3.2 A view of our prescription and herb database

For the creation of our "Herb Network", all herb nodes appear connect to the same prescription node will form a sub complete graph.

***Example*: 4-prescriptions Herb-Prescription Network:**
"小柴胡湯" : 柴胡, 大棗, 甘草, 生薑, 半夏, 人參, 黃芩.
"大承氣湯" : 大黃, 厚朴, 枳實, 芒硝.
"芍藥湯" : 芍藥, 當歸, 黃連, 木香, 甘草, 大黃, 官桂, 黃芩.
"枳實大黃湯" : 羌活, 當歸, 枳實, 大黃.

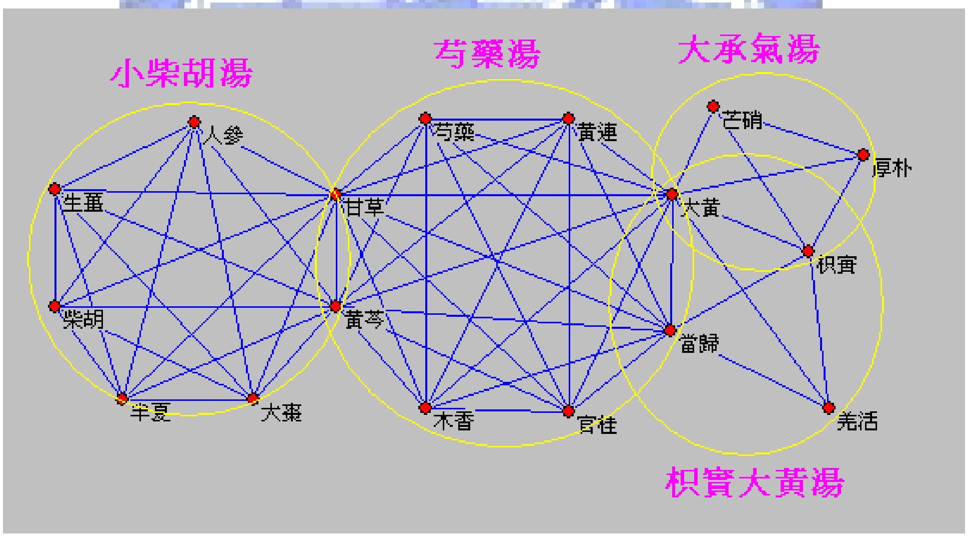

Figure 3.4 Diagram showing 4-prescriptions Herb-Prescription Network

As for the "Prescription Network", prescriptions that shared a common herb will form a complete graph.

Example: using the following 10 prescriptions : 小柴胡湯, 大承氣湯, 芍藥湯, 枳實, 大黃湯, 神保丸, 助氣丸, 大青龍湯, 瀉白散, 益元散, 白頭翁湯 to construct a Prescription Network. In figure 3.5, for each prescription as node, edge introduced among the node if there exist a common herb between the prescriptions, the amount of the herb shared between the prescriptions may be used for weighting in the later stage.

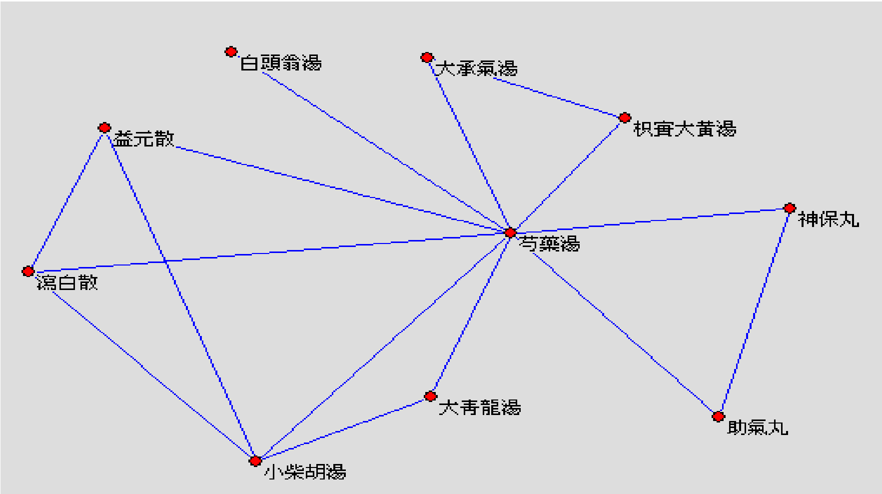

Figure 3.5 Diagram showing 10-prescriptions Prescription Network

As result from data cleaning and preprocess, removing the superset of the prescriptions, the CWJY contains 598 prescriptions and covering 320 herbs. The TFD contains 115 prescriptions covering 110 herbs. If we combine the two medicine book, result in having 643 prescriptions after the process.

We start by presenting the database of CWJY. The CWJY contains 598 prescriptions after the superset removal process.

3.3 Herb Network

We start by creating the herb network using CWJY, which contains 320 nodes, 3359 edges and average degree with 20.993. As for the degree distribution of CWJY, it appears to be long-tail shown in figure 3.6. The fitting represent distribution in cumulative function with semi-log scale. The degree distribution is exponential decay.

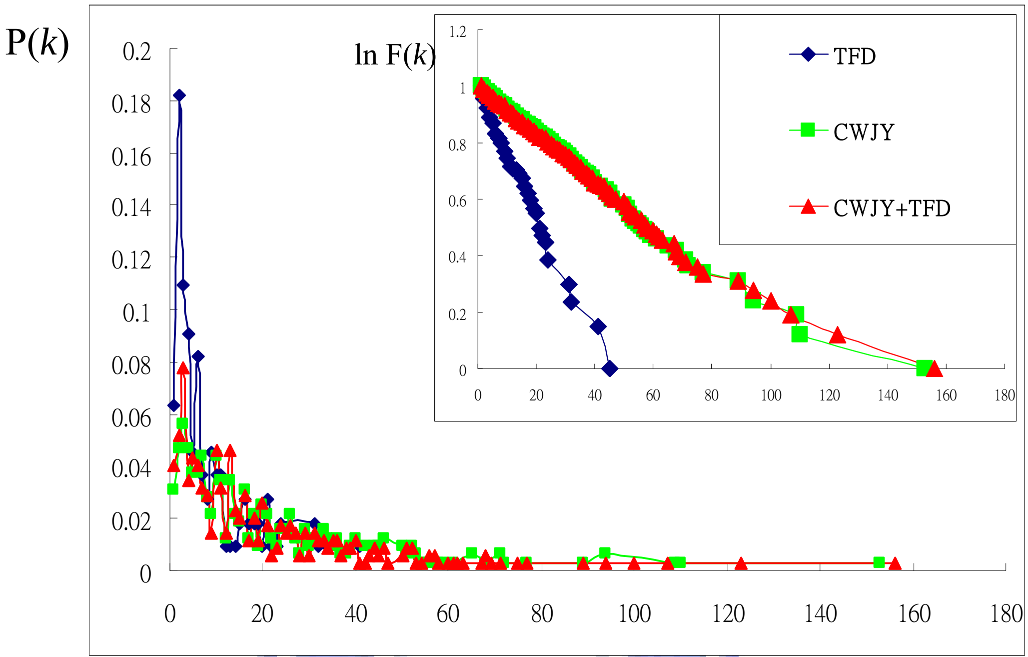

Figure 3.6 Degree Distribution of Herb Network. The Fitting represent cumulating function with semi-log scale.

The node with the highest degree is the licorice, again with the highest herb frequency. The average degree <k> is 20.993, showing that for each herb is able to combine with other 21 herbs to form the prescriptions as an average.

For the degree distribution of TFD which contains 110 nodes, 482 edges and average degree with 8.76364. Most nodes in TFD contain degree k to be 2. The fitting shows that the degree distribution is exponential when plot on a semi-log scale, which is a similar result to CWJY.

As for the degree distribution of the combined, it remains exponential like CWJY and TFD does before the combine of the two books. The distribution shows that most of the node has only a few links to the others and a few nodes with very large degree.

3.4 Prescription Network

Now we create a Prescription Network. The Prescription Network contains 643 (prescription as node) nodes, 21485 edges and average degree with 66.8274. In figure 3.7, shows a distribution with slop between degree 1~100, and then decays. The peak of the distribution was found at degree 48. The distribution suggests that the edges of the Prescription Network were formed randomly.

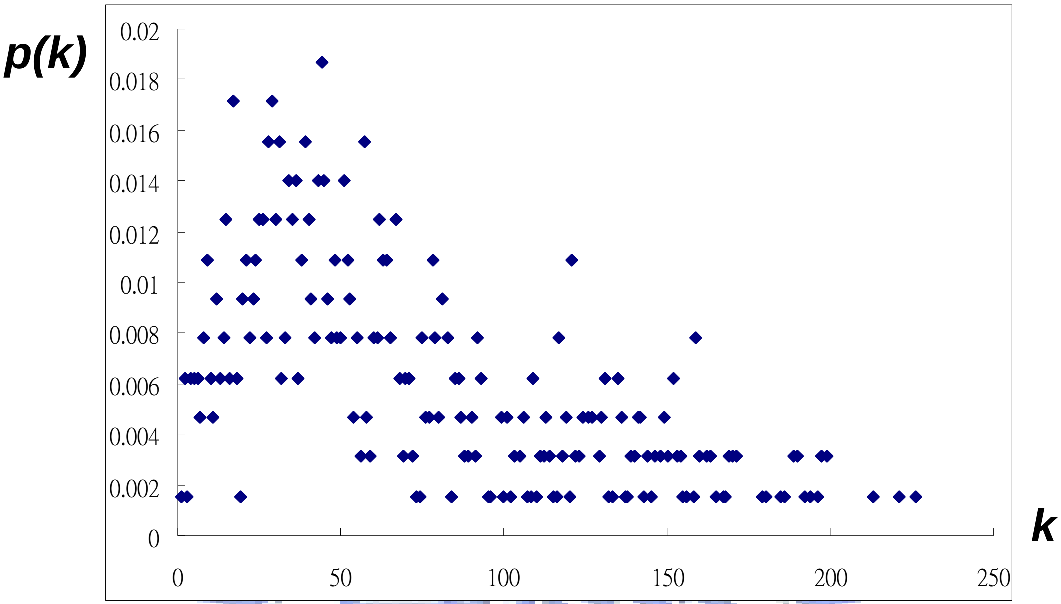

Figure 3.7 Degree Distribution of the prescription network

3.5 Clustering Coefficient and Average Path Length

The idea for measuring the clustering coefficient and the average path length of a network can be used to tell whether a network is a small world network or not.

Network	N	<k>	l	l_{rand}	C	C_{rand}
Herb	354	19.8531	2.53141	1.96405	0.523699	0.056082
Prescription	643	66.8274	2.07456	1.53878	0.136744	0.103931

Table3.3 The general characteristic of our Herb and Prescription networks.

From table 3.3, we show some properties of our network and compare them with the random network with same node size and average degree. For each network we have indicated the number of nodes N, the average degree <k>, the average path length l, and the clustering coefficient C. For a comparison we have included the average path length l_{rand} and clustering coefficient C_{rand} of a random graph of the same size and average degree. For the herb network, we see that the average path length of the real network is longer than the random network and the clustering coefficient of the real network is about 9 times bigger than the random network. Thus we conclude that herb network is a small world network.

For the prescription network, we already show that the degree distribution of network is normal distribution, and the edge connections between the nodes were connected as random.

3.6 Discussion

3.6.1 Herb Network

The degree distribution of the herb network shows that the connection between herbs was not random. There is a rule regarding the combination between herbs in the prescription. From the measuring of clustering coefficient and average path length of the herb network, we find that the herb network contains the small world phenomenon, since that the clustering coefficient is much higher (9 times bigger) than the random network with the same node size and average degree.

The degree distribution of the herb network (combine of CWJY and TFD) remains exponential, like CWJY and TFD does alone before the combine. The distribution suggesting that most of the node have only a few link to the others, where as the frequent herb such as liquorice (甘草) tuckahoe (茯苓) were appeared as hub node. These herbs were the most frequent used herbs and mostly used for balancing the negative effect or removing the toxics of the other herbs in the prescription.

3.6.2 Prescription Network

The distribution suggests that the edges of the Prescription Network were formed randomly. There is no rule regarding the sharing between herbs among the prescriptions.

3.7 Other Simulations

3.7.1 Herb Swapping Simulation

After showing that the degree distribution of herb network to be exponential, we then need to ensure that the connection between the herbs were not randomly connected, due to the combinations of herbs in the prescriptions. For such reason, we conduct an herb swapping simulations in our herb network. First, we randomly choose the herbs in the prescriptions and swap the position of herbs between the prescriptions for 100 thousand times to ensure that all herb's positions were swapped and then we compares them in degree histogram. The degree histogram is similar to degree distribution, but showing the exact amount of vertices having *k* amount of degree instead of the probability. The reason for using degree histogram to compare the two networks instead is to see the size change of the degree of the network.

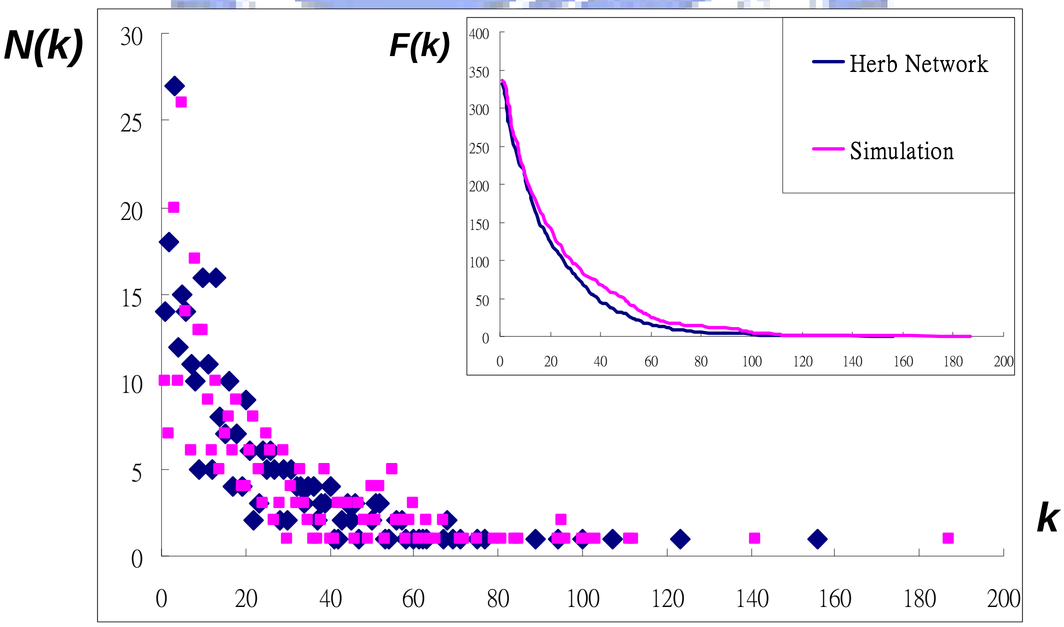

Figure 3.8 The degree histogram of the herb network and the simulation. The fitting represent the cumulative frequency of the two networks.

In figure 3.8 shows the differences between the Herb network and the herb swapping simulation. The distribution of the simulation appears to shift away from the degree distribution of the real network and the slop appeared higher than the herb network. Also, we notices that the total number of edges in the simulation increases as we compares the two networks. This can be explained where prescriptions of the herb network contains frequent combinations of herbs (in Chinese herbology, normally you may find a frequent used herb followed by another, which formed a frequent combination), since we've swapped the position of the herbs, thus we break the frequent combinations and resulting in new combinations. Those newly created combinations introduce new edges to the network as we create it.

The average path length of the swapping simulation is 2.58901, which is close to the average path length of the herb network (l=2.53141). Thus the average path length cannot tell the difference between the herb network and the swapping simulation.

The degree distribution alone does not tell the difference between the two networks. Here we calculated and compared clustering coefficient of the herb network and that obtain random swapping, result finding that the clustering coefficient C of the simulation is 0.0813277, which is 6 times smaller than the herb network (with C = 0.523699). The clustering coefficient shows the difference between the two networks.

As result in this experiment, we find that the edges connectivity in herb network is not random.

We than simulate the swapping network by randomly swaps the herb with different amounts of times and compare the difference between those simulations. We randomly swap the herbs in the prescriptions with 1, 10, 100, 1000, 10000, 100000, 1000000 and 10000000 amounts of swaps. Here we put edge threshold into the simulation network and compares the results in edges and nodes changes.

Network / Thresholds	T=1	T=2	T=3	T=4	T=5	T=6	T=7
Herb Network	3514	851	324	163	93	53	35
Swap1	3513	853	323	163	93	53	35
Swap10	3541	839	317	162	91	53	33
Swap100	3622	797	302	156	90	49	30
Swap1000	4002	684	216	84	39	23	13
Swap10000	4090	668	186	71	31	13	6
Swap100000	4072	664	189	69	32	17	9
Swap1000000	4125	655	161	64	30	17	8
Swap10000000	4063	659	192	80	40	17	9

3.7.2 Herb Swapping Simulation for Prescription Network

From the degree distribution of the prescription network, the initial normal distribution follows by a long tail suggest that there exist two edge connection methods in prescription network, both random and preferential.

In order to see which connection methods dominates in prescription network, we conduct a simulation by randomly swaps the herbs that each prescription were sharing then create the simulation network and plots its distribution to compares with the prescription network. The result shows in figure 3.9.

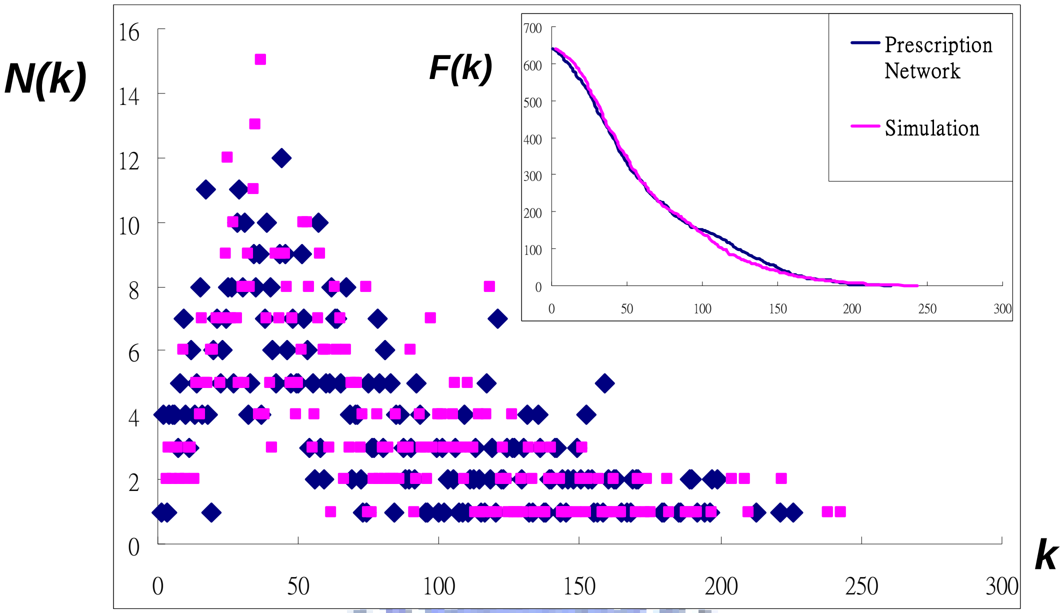

Figure 3.9 The degree histogram of prescription and swapping simulation network. The fitting represent the cumulated frequency.

From figure 3.9, shows the similarity between prescription and simulation network. Although we have randomly swapped the herb’s position, the distribution remains the same. The total degree of the simulation is close to the total degree of prescription network.

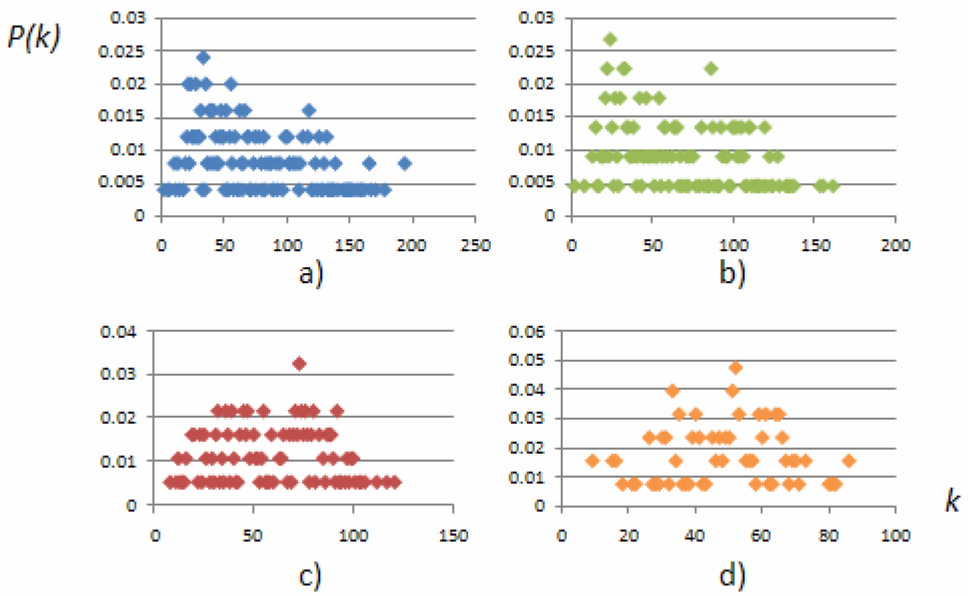

Figure3.10 The degree distribution of prescription under different threshold. Where a) Threshold > 2, b) Threshold > 3, c) Threshold > 4 and d) Threshold > 5.

Here we construct the prescription network using the amount of herb sharing among the prescriptions as different thresholds. Figure 3.10 shows the results, as the threshold increases, the tail of the distribution starts disappearing. As threshold reaches to 3, the distribution becomes a normal distribution. Therefore, the randomness between the connections dominates the preferential rules in prescription.

The average path length of the prescription swapping simulation is 1.99067 and is close to the average path length of the prescription network (l=2.07456). The average path length does not tell the difference between the prescription network and the prescription swapping simulation.

The clustering coefficient of the prescription swapping simulation is 0.110663, which is close to the clustering coefficient of the prescription network (C=0.136744). Therefore we conclude that the prescription network is a random network.

3.7.3 Randomly Chosen Prescriptions Simulation

Right now, we want to see approximately how many prescriptions will form a network with exponential distribution. Here we start by randomly choosing the prescriptions from the combined database of CWJY and TFD with the specific amounts of prescriptions and then see whether it could result an exponential decay.

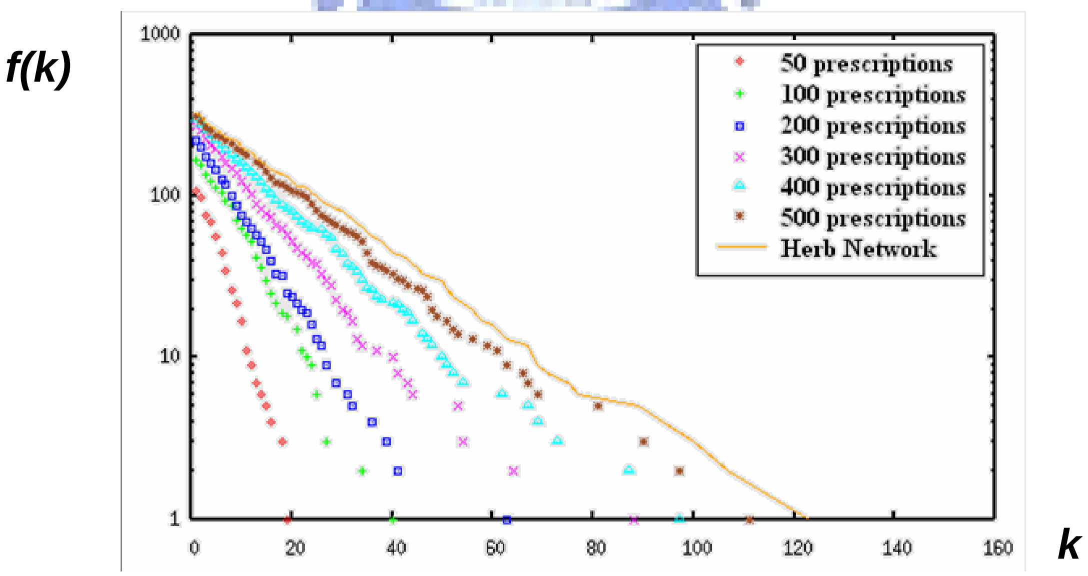

Figure3.11 Cumulative frequency of herb network in Semi-log Scale using different amounts of prescriptions

In figure 3.11, we notice when we randomly choose the prescriptions from our database, the distribution drops as well as the tail of the distribution when the amounts of prescription decreases. The less the prescriptions chosen, the earlier the tail drops and only the early stage of the distribution shows exponential. Therefore, with the result of this simulation, we finds that under the different amounts of prescriptions, herb network degree distribution remains exponential, thus the size of the prescription does not affect the distribution.

4. New Model and Simulation

4.1 The Model Description

In order to understand the growth of the herb network, we need to simulate the network using the actual evolution method of the herb and prescription. Base on this idea, we construct our model using the node selection probability of the actual network.

We propose a model which can used for simulating our herb network, using prescription-size distribution $P(T)$ for selecting the size of T and using linear preferential rule with $P(h)$ for node selection every time step. Both $P(T)$ and $P(h)$ were selected from the empirical data.

Algorithm:

- **Start with *N* herb nodes and 0 prescription initially**
- **Add 1 new prescription node each time step t and add T herb nodes in the new prescription**
- **Choosing the prescription size of T each time according to P(T)**
- **Choosing the node by "Node Selection Rule" until the T is reached**
- **All herb nodes in the same prescription formed a complete graph**

Here we have 3 Node Selection Rule:

1. **Random Probability**
2. **Linear Preferential Rule**
3. **P(h) from empirical data**

For the first method, we randomly select the herb nodes during each time step t, thus for each time step t, the network will introduce a new prescription with T edges to N amounts of herbs. Thus the growth rate of degree can be express as:

$$\frac{\partial k_i}{\partial t} = \frac{T_\alpha}{N} t \qquad (8)$$

Where T_a is a value selected from the prescription-size distribution $p(T)$. The solution of this equation with the initial condition that every node i at its introduction has $k_i(t_i)=T$-1, is:

$$k_i(t) = \frac{(T_a - 1)}{(N - 1)}\, t + c \tag{9}$$

The edge connection from the above equation resulting the randomly connection between the nodes. Where each time step t, for each node will have equal chance of receiving T-1 amount of degree (with multi-edges counted). Therefore, the formula for degree distribution for this method is:

$$p(k) = e^{-<k>} \frac{<k>^k}{k!} \tag{10}$$

From the above equation, the degree distribution is a Poisson distribution, and the average degree of the network is measure as:

$$<k> = \frac{\sum (T_i - 1)}{t} \tag{11}$$

For second method, we use Linear Preferential Rule to select the node each time step. The probability for selecting node i depends on it herb-frequency h_i. For time step t=1, we allow all nodes to have the same probability. As the prescription node increases, the node with the higher frequency will tend to have a higher probability for getting selected by the prescription node. For each time step, we increases the edge by T-1 and select the nodes by its herb-frequency h_i, thus the growth rate of the degree of node i is:

$$\frac{\partial k_i}{\partial t} = T_a \frac{h_i}{\sum_{j=1} h_j}\, t \tag{12}$$

The solution of this equation, with the initial condition that every node i at its introduction has $k_i(t_i)=T$-1, is:

$$k_i(t) = (T_a - 1)\frac{h_i}{\sum_{j=1} h_j} t + c \tag{13}$$

Whereas the average prescription-size <T> is measured as:

$$<T> = \frac{\sum(T_i-1)}{t} \sim <k> \tag{14}$$

For the third method, we use the actual herb-frequency distribution $p(h)$ as the probability for node selections during each time step. The growth rate of the degree of node i can be written as:

$$\frac{\partial k_i}{\partial t} = T_a h_a \quad t \tag{15}$$

Where variable h_a is a value selected from the herb-frequency distribution $p(h)$ of the real world network data. This equation can be analytically solved to get:

$$k_i(t) = (T_a - 1)P_i t + c \tag{17}$$

The probability P_i is the probability for selecting node i during the evolution. From the equation above shows that the degree distribution of the simulation using the third method is fairly depends on the network that the prescription-size distribution $p(T)$ and herb-frequency distribution $p(h)$ was taken from. For example, if we took the $p(T)$ and $p(h)$ from a random graph, the result of this method is that the degree distribution is poisson distribution.

4.2 The Simulation

We now use the 3 connection methods to create the simulating network in compare with their degree distribution.

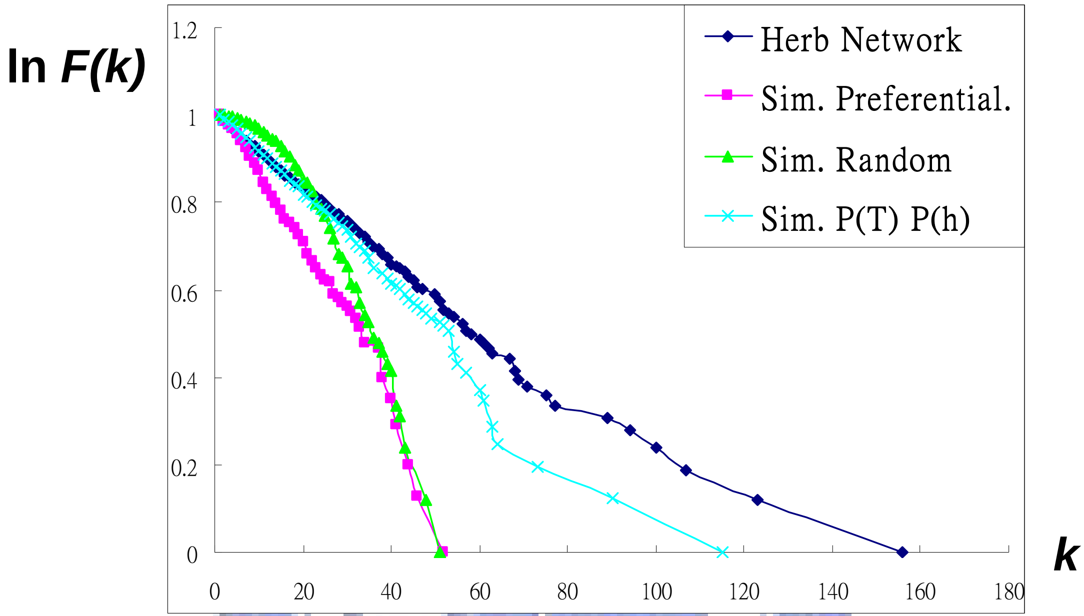

Figure 4.1 Graph showing the comparison of the degree distribution of simulating network (after the supersets been removed) and the herb network.

From figure 4.1, we show that the degree distribution of simulating network after the supersets been removed. With using the prescription-size distribution for choosing prescription's size and herb frequency distribution for node selections each time step, our model is able to simulate such network.

The clustering coefficient of the simulation using the herb frequency distribution is 0.446847, which is close to the herb network rather than random graph, showing the model is able to simulate the network with agree to the clustering coefficient of the empirical result.

5. Other TCM Network

5.1 Symptom Network

In symptom network, prescriptions and the symptoms were the two types of node, each prescription contains at least one symptoms. All symptoms connected to the same prescription forms a complete graph. To construct our symptom network, we use the symptoms from the combined prescriptions of CWJY and TFD, contains 643 prescriptions and 1954 symptoms. However, some of these symptoms may contain noises such as using different name for the same symptom or mixing the diseases name with the symptom may cause error results.

As for data cleaning and prestart process of symptom network, we remove the diseases out from the symptoms since for some of the prescriptions where they put the disease name directly before or after they describe the symptoms. For example: “headache, fever, cold body, sneeze, cough and nostrils were symptoms from a cold flu”. We also remove the prescriptions which only contains the disease name and with no symptom.

In our symptom network we have 1836 symptoms and 568 prescriptions nodes (after the data cleaning process) in the bipartite graph.

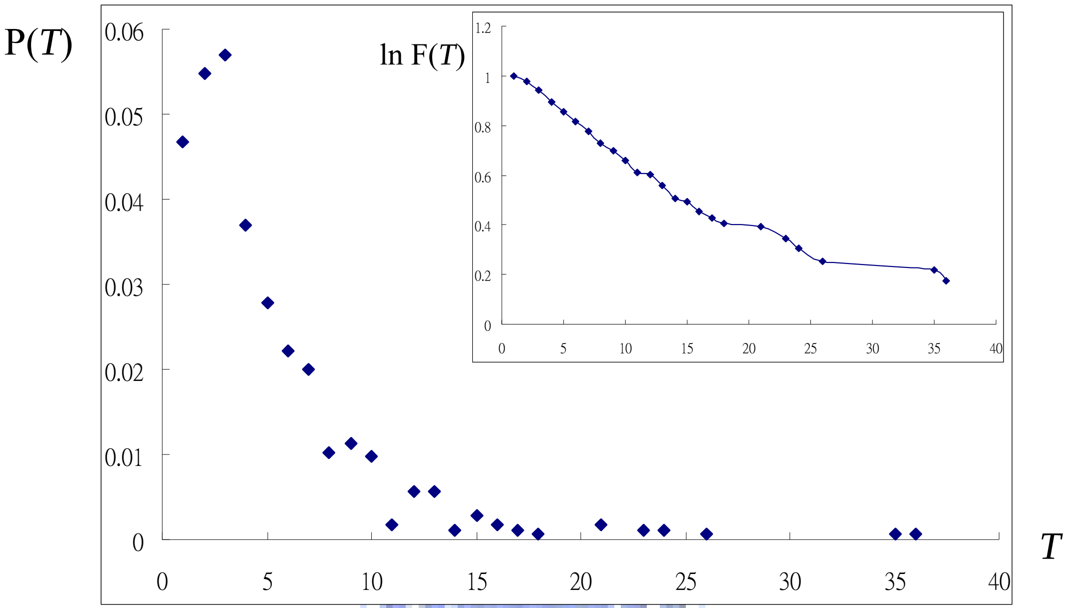

Figure 5.1 The prescription-size distribution of the symptom network. The fitting represents the cumulative function with semi-log scale.

In figure 5.1 the distribution follows a shifted poison distribution with the peak found at 3, where most of the prescriptions having 3 symptoms. The fitting of the graph shows that the prescription-size distribution of the symptom network is exponential. Other statistics such as the average prescription-size <T>=4.89626, averagely the prescriptions containing 5 symptoms.

The symptom frequency distribution of the symptom network shows a long tail distribution shown in figure 5.2, where most of the symptoms appeared once among all the prescriptions. By plotting the distribution onto a log-log scale, we find that the herb frequency distribution to be power-law distribution.

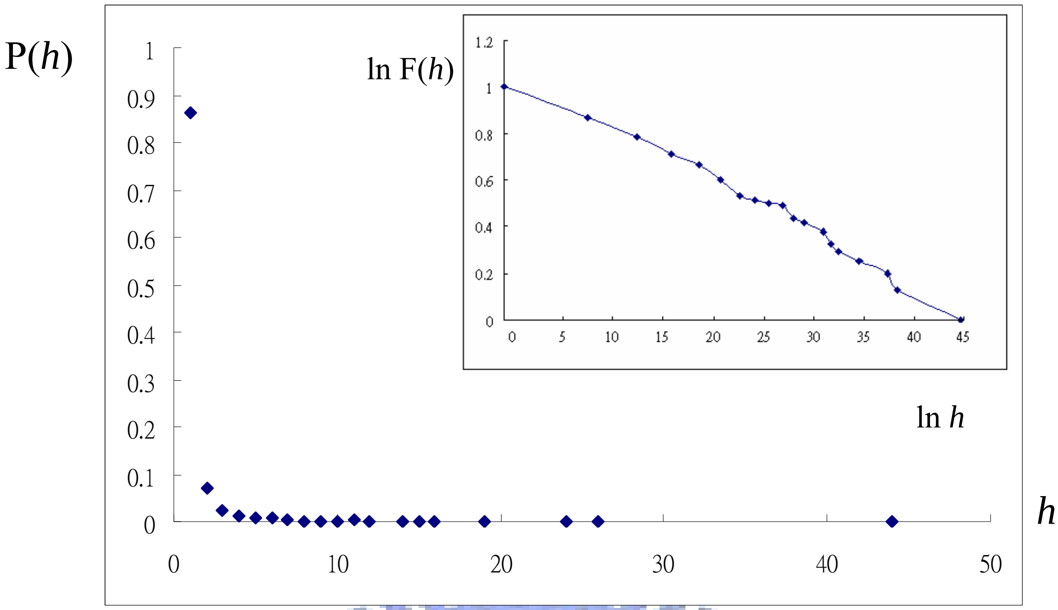

Figure 5.2 The symptom frequency distribution of the symptom network. The fitting represents the cumulative function with log-log scale.

5.2 Acupuncture Network

In the acupuncture network, the diseases and the acupuncture points were the two types of nodes. Each disease requires at least one acupuncture points for the treatment. All acupuncture point nodes connected to the same disease node forms a complete graph. As for data source of Acupuncture Network, we took the frequent used acupuncture point from 針灸甲乙經新解 by 梅翔 [16]. The acupuncture network contains 167 (combines the symmetrical acupuncture points) frequent used pressure points and 492 diseases.

For the data cleaning and prestart process, we combine the symmetrical acupuncture points, that is the acupuncture points which having the same name and same function except the location, to the right or to the left of the center of the body. For most of the cases, those symmetrical acupuncture points perform the same clinical functions. For example, the He-Koo (合谷) point, located on both left and right hand. In Chinese Acupuncture, the left He-Koo and right He-Koo performs the same function for most of the treatments, which only differs in few special cases such as the treatment of nervous pain on the skull and some qi/blood weaknesses.

Here we use Acupuncture points as one node and diseases as another node. The acupuncture network contains 167 (we combine the symmetrical acupuncture points) frequent used acupuncture points and 492 diseases. The prescription-size distribution of the acupuncture network appeared as 2 power-law distributions, shown in figure 5.3. The graph suggests that most of the disease requires only single acupuncture point for the treatment.

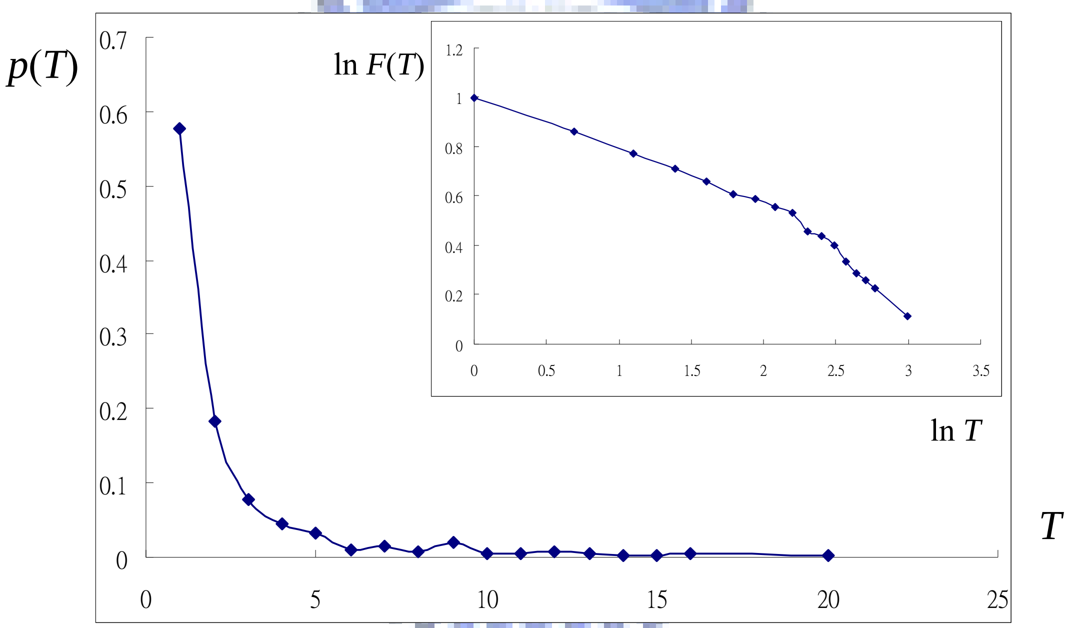

Figure 5.3 The prescription-size distribution of the acupuncture network. The fitting represents the cumulative function with log-log scale.

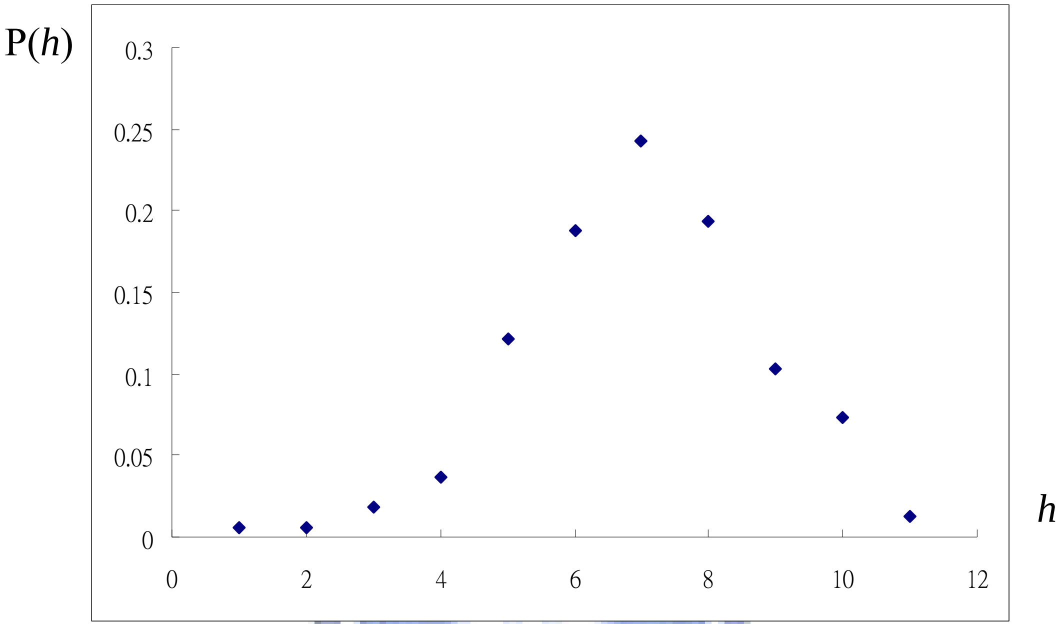

Figure 5.4 The acupuncture point frequency distribution of the acupuncture network

In figure 5.4 shows the acupuncture point frequency distribution of the acupuncture network is normal distribution, with the peak found at 7. The normal distribution of herb frequency suggests that the method for choosing the acupuncture point throughout diseases were random, i.e. the connection between each acupuncture points were randomly connected. This cause for this result can be explained that in Chinese Acupuncture, for one acupuncture points, it can be used for treating many different diseases and one acupuncture points can always be replace by the other. Also, for treating one disease, there can be many different combinations of acupuncture points, even with totally different combinations and one has no relation to each other. As long as the main acupuncture points were stunned, the rest of the acupuncture points were only there to assist the blood circulations mostly.

5.3 Degree Distribution

Here we use the symptoms from the combine of CWJY and TFD prescriptions (with supersets removed), where prescriptions and symptoms were the two kinds of node.

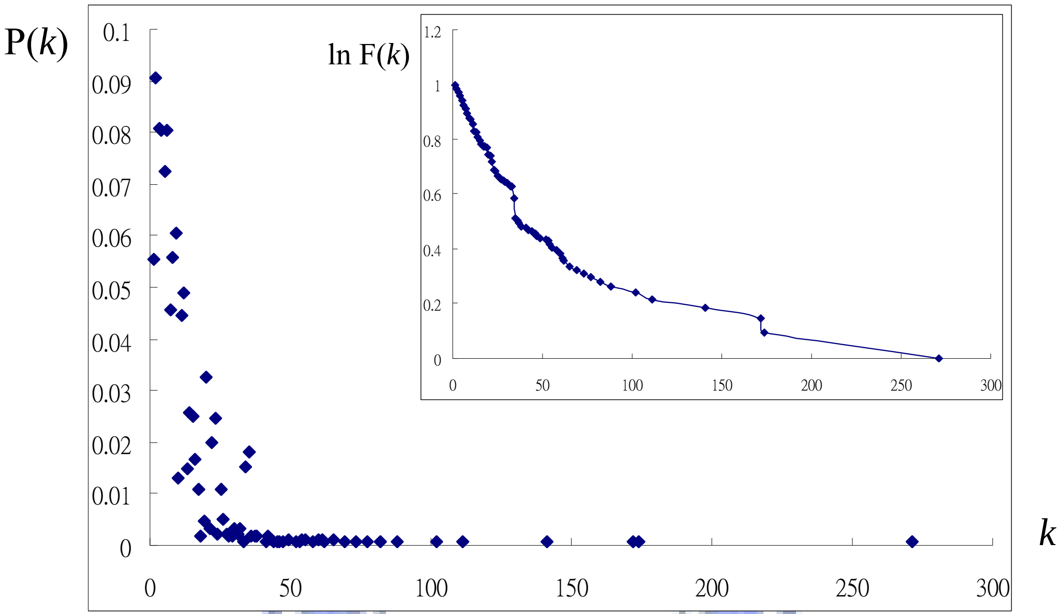

Figure 5.5 The degree distribution of the symptom network. The fitting represents the cumulative function with semi-log scale.

The long-tail degree distribution of the symptom network was found having exponential decay at the early stage of the distribution. As we can see from figure 5.5, there were few hub-like nodes in the symptom network.

In figure 5.5, the degree distribution of the acupuncture network which is similar to the herb frequency distribution, is a normal distribution. Again, showing that the connection between the acupuncture points were random.

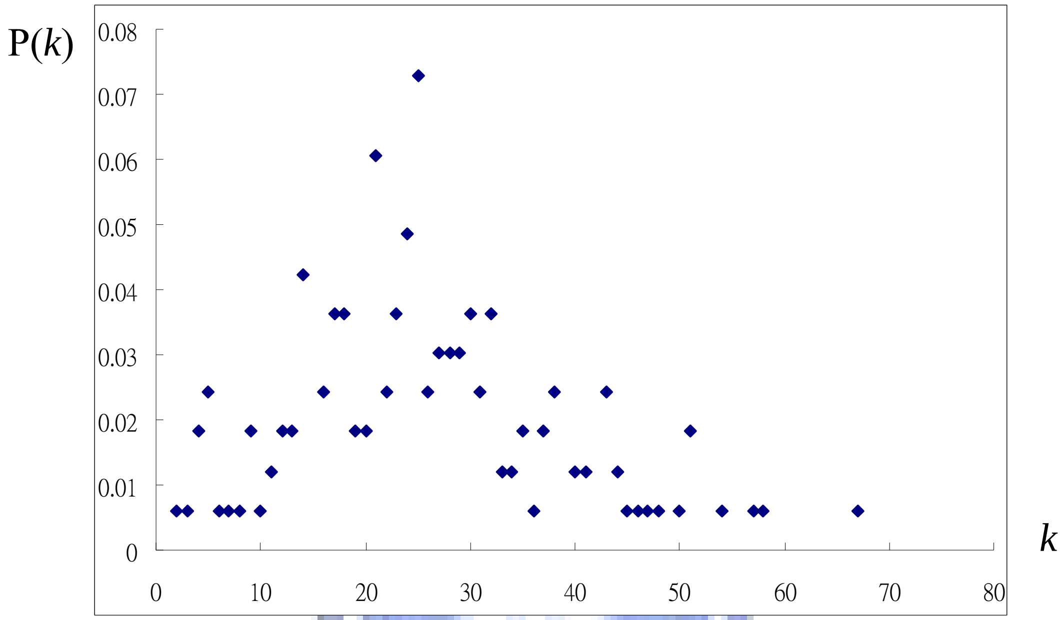

Figure 5.6 The degree distribution of the acupuncture network

In figure 5.6, the degree distribution of the acupuncture network which is similar to the herb frequency distribution, is a normal distribution. Again, showing that the connection between the acupuncture points were random.

There is no proof that a network having a normal degree distribution must be a random graph. From various empirical results [4,5] shows that the degree distribution of a random network is normal distribution and only the degree random graph can produce a normal degree distribution.

5.4 Clustering Coefficient Average Path Length

Network	N	$\langle k \rangle$	l	l_{rand}	C	C_{rand}
Symptom	1867	11.353	2.82796	3.10029	0.685585	0.006081
Acupuncture	167	25.2335	2.46108	1.58542	0.464034	0.151099

Table5.1 The general characteristic of our Symptom and Acupuncture networks.

For the acupuncture network, we already show that the degree distribution of network is normal distribution, and the edge connections between the nodes were connected as random.

For the symptom network, we find that the average path length of the real network is shorter than the random network, and the clustering coefficient of the real network is about 112.7 times higher than the random network. Therefore we conclude that the symptom network is a small world network.

5.5 Model Simulation

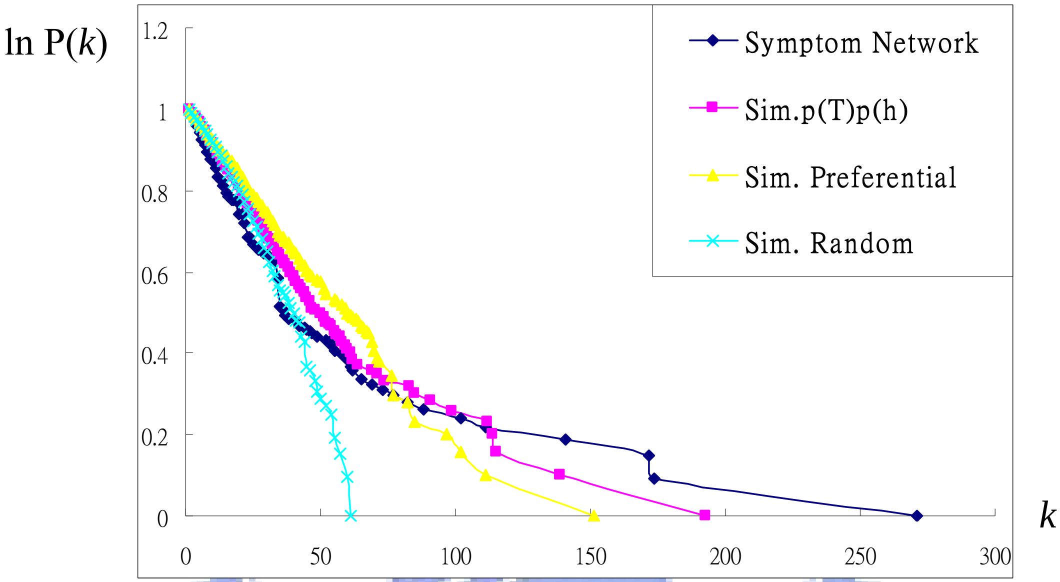

Figure 5.7 The comparison of the degree distribution between model simulation and symptom network.

From figure 5.7, we show that the degree distribution of the simulating network compares with the symptom network. Under the same amount of movie nodes, the use the prescription-size and linear preferential rule, the degree distribution were more closer to the symptom network rather than using the actual symptom frequency distribution for node selection. This occurs when there were many co-occurrence pairs existed in the symptom network, for example, in a cold flu, it is like to have headache, fever, cough or sneeze follows by one another.

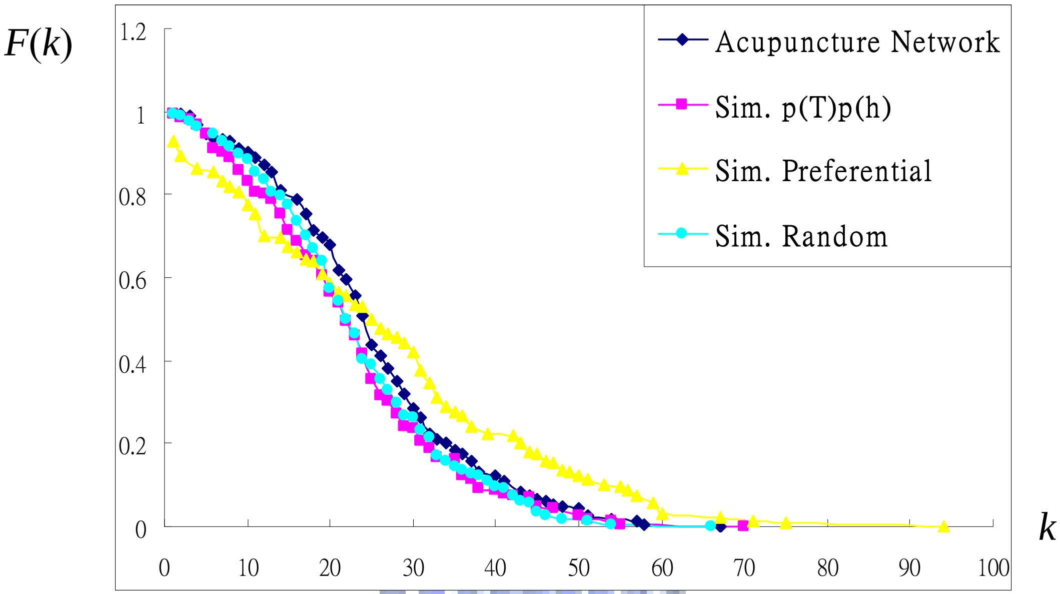

Figure 5.8 Graph showing the comparison of the degree distribution of simulating network and acupuncture network

In figure 5.8, we simulate the degree distribution of acupuncture network using the prescription-size distribution and herb frequency distribution. The distribution is very similar to the distribution using the random node connections and the acupuncture-frequency distribution P(*h*), this shows that the acupuncture network contains the property of a random graph. This was the reason due to for one disease in TCM, there are many different acupuncture points for treating such a disease, as for one acupuncture, it can be used for treating many different diseases, thus the degree distribution of acupuncture network is showing a normal distribution. However, in Chinese Acupuncture, it is okay for the whether an acupuncture point is being used as long as the main acupuncture point is stunned, the rest of the acupuncture points were mostly used for blood circulations and qi enhancement. There is also an theory for such conditions in Chinese Acupuncture, the A-Shi (阿是穴) theory, where we can randomly acupuncture the points around the place where it contains the symptom.

6. Summary

The Traditional Chinese Herb and Prescription is a complicated system, current understandings were mostly relying on experience and lack of scientific basis. Here we try to understand the relation between Chinese Herb and Prescription by casting it into networks and applying Network Analysis on such network, finding herb network's degree distribution to be exponential and the edge connectivity in prescription network were formed randomly.

The connections in prescription network were formed randomly, there is no rule regarding prescriptions should strictly sharing the same herb as the other prescription. This can be understood by saying there is nothing to stop a prescription not to use the same herb from the other prescription. The Chinese herb prescription practitioner can design many different prescriptions to target one disease and as well as one prescription may use for different diseases. This result the edges between the nodes in prescription network to be randomly connected.

Comparing the clustering coefficient and average path length of the real network and the random network, we find that herb and symptom network contains the small world phenomenon.

We showed that the combinations between herbs are not randomly combined by swapping the positions of the herb located in prescriptions. The reason for this result is that when a Chinese herb prescription practitioner designs a prescription, it takes yin/yang, blood/qi, taste and meridian into account. It follows a specific rule for which herb is to be combined with. Therefore, the connection in herb network is not randomly connected.

We compare the degree distribution of different herb network from different era and find to have the same distribution and some similar characteristics, finds that the larger databases result in larger node correlation. Ideally, if a new herb was introduced, it may create more combinations to the current available herbs now than previous age.

In acupuncture network, the result showing that the combination between the acupuncture points for treating one disease is random. This was the reason for one acupuncture point may used for treating different disease as well as for the treatment of one disease, many different combinations of acupuncture points may be used.

In the random choosing prescription experiment, we find that the degree distribution remains exponential with an earlier drop of the tail. The reason for such exponential decays is that in some of the prescriptions consist of highly frequent herb combinations, these frequent combinations causing clustering effect during the construction of the network and causing a similar effect as an evolving network with random selection of edges, with the highly frequent herb as the starting node. As result, proving that even with smaller amount of prescriptions, the herb network can still produce a degree distribution with exponential decay.

We introduced an evolutionary model that can simulate the growth of herb and prescription networks in consideration of prescription-size, herb frequency and degree distribution.

7. References

[1]. P.U. Unschuld, “Medicine in China: A History of Ideas”, *University of California Press*, ISBN 0-520-05023-1, 1985.

[2]. *Eastern Promise*, Nov 5th 1998, http://chinese-school.netfirms.com/Eastern-promise.html, *Los Angeles Chinese Learning Center.*

[3]. J. Qiu,” China Plans to Modernize Traditional Medicine”, *Nature* vol. 446, pp. 590-591, 2007.

[4]. P. Erdos , and A. Renyi, “On Random Graphs I”, *Publicationes Mathmaticae Debrecen*, vol. 6, pp. 290, 1959.

[5]. P. Erdos , and A. Renyi, "The Evolution of Random Graphs". *Magyar Tud. Akad. Mat. Kutató Int. Közl.*, vol.5, pp.17–61, 1960.

[6]. S. Milgram, ”The Small World Problem”, *Psychology Today*, vol 1, pp. 60, 1967.

[7]. D.J. Watts and S.H. Strogatz , “Collective Dynamics of 'Small-World' Networks”, *Nature*, vol. 393, pp. 440, 1998.

[8]. R. Albert R. and A.-L. Baraba´si, “Statistical mechanics of complex networks”, *Reviews of Modern Physics*, Vol. 74, pp. 47, 2002.

[9]. J Liu,Y. Dang and Z. Wang, “Multistage Random Growing Small-World Networks with Power-Law Degree Distribution”, *Chinese Physics Letters*, vol.

23, pp. 746-749, 2006.

[10]. Y. He, P. P. Zhang, J. Y. Tang, X. F. Han, R. Qiu, Q. J. Chen, Y. P. Zhou, H. Chang and D. R. He," A Collaboration Network Description on Traditional Chinese Medical Prescription Formulation System", *Science & Technology Review*, Vol.23, No.11, pp.36-39, 2005.

[11]. J.J. Ramasco, S.N. Dorogovtsev, R. Pastot-Satirrasm, "Self-organization of collaboration networks", *Physics Review E*, vol. 70, 036106, 2004.

[12]. P. P. Zhang, Y. He, T. Zhou, B. B. Su, H. Chang, Y. P. Zhou, B. H. Wang and D. R. He," A model describing the degree distribution of collaboration Networks" , *Physica A*, vol. 360, pp. 599, 2006.

[13]. 中醫中藥資訊網-景岳全書-八方藥陣, *行政院衛生署中醫藥委員會*, http://www.ccmp.gov.tw/.

[14]. 桂林古本-傷寒雜病論, *網路太醫院-民間中醫*, http://www.non-huatuo.org/index.php?op=ViewArticle&articleId=32&blogId=1.

[15]. M. E. J. Newman, S. H. Strogatz, and D. J. Watts, "Random graphs with arbitrary degree distributions and their applications", *Physics Review E*, vol. 64, 026118, 2001.

[16]. 梅翊，"針灸甲乙經新解"，*國立中國醫藥研究所*，ISBN 9570059613, 1995.

Appendix A: Herb List

編號	藥材	藥味	藥氣	毒素	編號	藥材	藥味	藥氣	毒素	編號	藥材	藥味	藥氣	毒素
1	灶中黃土	甘	平	無毒	129	黑丑	苦	寒	小毒	257	天麻	甘	平	無毒
2	王不留行	苦	平	無毒	130	薑黃	辛,苦	溫	無毒	258	硼砂	甘,鹹	涼	無毒
3	生梓白皮	苦	寒	無毒	131	靈砂	甘	溫	無毒	259	細辛	辛	溫	無毒
4	蒴藋細葉	苦	平	無毒	132	黃丹	辛	涼	無毒	260	阿魏	辛	平	無毒
5	五味子	酸,鹹	溫	無毒	133	靈脂	苦,甘	溫	無毒	261	蘿蔔	辛,甘	寒	無毒
6	蒲公英	甘,苦	寒	無毒	134	戎鹽	鹹	寒	無毒	262	芝麻	甘	溫	無毒
7	九里香	辛,苦	溫	毒	135	連翹	苦	寒	無毒	263	香附	辛,苦,甘	平	無毒
8	海螵蛸	鹹	溫	無毒	136	地榆	苦,酸	涼	無毒	264	南星	辛,苦	溫	毒
9	百藥煎	酸,甘	平	無毒	137	秦皮	苦	寒	無毒	265	乾漆	辛	溫	毒
10	劉寄奴	苦	溫	無毒	138	陳皮	辛,苦	溫	無毒	266	紫草	甘,鹹	寒	無毒
11	蔓荊子	辛,苦	寒	無毒	139	豨薟	苦	寒	小毒	267	扁豆	甘	平	無毒
12	吳茱萸	辛,苦	熱	小毒	140	黃連	苦	寒	無毒	268	遠志	辛,苦	溫	無毒
13	川楝子	苦	寒	毒	141	龍腦	辛,苦	涼	無毒	269	茯神	甘	平	無毒
14	自然銅	辛	平	無毒	142	黃柏	辛,苦	寒	無毒	270	水粉	NA	NA	無毒
15	牡丹皮	辛,苦	寒	無毒	143	滑石	甘	寒	無毒	271	杏仁	苦	溫	小毒
16	山茱萸	酸	溫	無毒	144	防風	辛,甘	溫	無毒	272	丹皮	辛,苦	寒	無毒
17	肉蓯蓉	苦,鹹	溫	無毒	145	斑蝥	辛,熱	大毒	無毒	273	附子	辛,甘	熱	毒
18	何首烏	甘,苦	溫	無毒	146	麥芽	甘	平	無毒	274	茴香	辛	溫	無毒
19	佛耳草	酸	溫	無毒	147	薄荷	辛	涼	無毒	275	半夏	辛	溫	毒
20	青葙子	苦,鹹	溫	無毒	148	雲母	甘	平	無毒	276	白粉	甘	平	無毒
21	熟地黃	甘	溫	無毒	149	麻仁	甘	平	無毒	277	藿香	辛	溫	無毒
22	白豆蔻	辛	溫	無毒	150	雞子	甘	平	無毒	278	茵陳	辛,苦	涼	無毒
23	草豆蔻	辛	溫	無毒	151	亂髮	苦	溫	無毒	279	白魚	甘	平	無毒
24	白蒺藜	辛,苦	溫	無毒	152	膽星	辛,苦	涼	無毒	280	鉛丹	辛,鹹	寒	毒
25	白蘚皮	苦	寒	無毒	153	鱉甲	鹹	寒	無毒	281	雷丸	辛,苦	寒	無毒
26	白頭翁	苦	寒	無毒	154	蘇葉	辛	溫	無毒	282	白薇	苦,鹹	寒	無毒
27	太乙禹	甘	寒	無毒	155	丁香	辛	溫	無毒	283	漏蘆	苦	寒	無毒
28	白芥子	辛	溫	無毒	156	黃耆	甘	溫	無毒	284	紅花	辛	溫	無毒
29	白檀香	辛	溫	無毒	157	艾葉	辛,苦	溫	無毒	285	鉤藤	甘	涼	無毒
30	鼠粘子	辛,苦	涼	無毒	158	硃砂	甘	涼	毒	286	豬膽	苦,鹹	涼	無毒

31	紅藍花	辛	溫	無毒	159	硫黃	酸	溫	毒	287	桃仁	苦,甘	平	無毒
32	白花蛇	甘,鹹	溫	毒	160	豬膏	甘	涼	無毒	288	棗肉	甘	溫	無毒
33	栝蔞實	苦	寒	無毒	161	知母	苦	涼	無毒	289	白芷	辛	溫	無毒
34	糖毬子	NA	NA	無毒	162	豬膚	甘	涼	無毒	290	豬苓	甘	平	無毒
35	淡竹葉	甘	寒	無毒	163	蘇木	甘,鹹	平	無毒	291	白檀	辛	溫	無毒
36	栝蔞根	甘,苦	寒	無毒	164	蓽撥	辛	熱	無毒	292	草果	辛	溫	無毒
37	天門冬	苦	平	無毒	165	蜀漆	辛	平	毒	293	蠐螬	鹹	溫	毒
38	羚羊角	鹹	寒	無毒	166	黃芩	苦	寒	無毒	294	棗仁	酸	平	無毒
39	栝蔞仁	苦	寒	無毒	167	蕪荑	辛	平	無毒	295	乾蝎	辛,鹹	平	毒
40	苦楝根	苦	寒	毒	168	柴胡	苦	寒	無毒	296	白礬	酸	寒	無毒
41	天花粉	甘,苦	寒	無毒	169	蔥白	辛	溫	無毒	297	防己	苦	寒	無毒
42	密蒙花	甘	涼	無毒	170	香薷	辛	溫	無毒	298	青黛	鹹	寒	無毒
43	鹿角膠	甘,鹹	溫	無毒	171	牡蠣	鹹	涼	無毒	299	核桃	甘	溫	無毒
44	赤石脂	甘,酸	溫	無毒	172	荊芥	辛	溫	無毒	300	青鹽	鹹	寒	無毒
45	麻黃根	甘,苦	平	無毒	173	葵子	甘	寒	無毒	301	蜀椒	辛	溫	小毒
46	麥門冬	甘,苦	寒	無毒	174	蓬朮	辛,苦	溫	小毒	302	茯苓	甘	平	無毒
47	密陀僧	辛,鹹	平	毒	175	橘皮	辛,苦	溫	無毒	303	水銀	辛	寒	毒
48	大楓子	辛	熱	無毒	176	瓜蒂	苦	寒	毒	304	白蜜	甘	平	無毒
49	大腹皮	辛	溫	無毒	177	竹葉	甘	寒	無毒	305	水蛭	苦,鹹	平	毒
50	龍膽草	苦	寒	無毒	178	紫蘇	辛	溫	無毒	306	白芨	辛,苦	平	無毒
51	胡黃連	苦	寒	無毒	179	乳香	辛,苦	溫	無毒	307	綠豆	甘	寒	無毒
52	蛇床子	辛,苦	溫	小毒	180	升麻	辛,甘	寒	無毒	308	椒目	辛,苦	寒	小毒
53	胡桃肉	甘	溫	無毒	181	蒼朮	辛,苦	溫	無毒	309	白朮	苦,甘	溫	無毒
54	赤小豆	甘,酸	平	無毒	182	蓮鬚	甘	平	無毒	310	青蒿	辛,苦	寒	無毒
55	甘菊花	甘,苦	平	無毒	183	澤漆	苦	涼	無毒	311	藜蘆	辛,苦	寒	毒
56	生地黃	甘,苦	涼	無毒	184	銅青	酸	平	小毒	312	青皮	苦,辛	溫	無毒
57	桑白皮	辛,甘	寒	無毒	185	粳米	甘	平	無毒	313	牡丹	辛,苦	寒	無毒
58	木防己	辛,苦	寒	無毒	186	前胡	辛,苦	涼	無毒	314	白蘞	甘,苦	涼	無毒
59	薑湯炒	辛	熱	無毒	187	朱砂	甘	涼	毒	315	皮硝	鹹,苦	寒	無毒
60	馬蹄香	辛,苦,甘	平	無毒	188	砂仁	辛	溫	無毒	316	厚朴	辛,苦	溫	無毒
61	骨碎補	苦	溫	無毒	189	玄參	甘,苦,鹹	涼	無毒	317	小麥	甘	涼	無毒
62	人中白	鹹	寒	無毒	190	炙草	甘	平	無毒	318	益智	辛	溫	無毒
63	土茯苓	甘	平	無毒	191	竹茹	甘	涼	無毒	319	烏藥	辛	溫	無毒
64	柏子仁	甘	平	無毒	192	金箔	辛	平	無毒	320	橘紅	辛,苦	溫	無毒
65	地骨皮	甘	寒	無毒	193	輕粉	辛	寒	毒	321	烏頭	辛,甘	熱	大毒
66	百草霜	辛	溫	無毒	194	枸杞	苦	寒	無毒	322	烏梅	酸	平	無毒
67	車前草	甘	寒	無毒	195	雄黃	辛	溫	毒	323	犀角	酸,鹹	寒	無毒

68	爐甘石	甘	平	無毒	196	百合	甘	涼	無毒	324	山梔	苦	寒	無毒
69	旋覆花	辛,苦,鹹	溫	無毒	197	柏葉	甘	溫	無毒	325	新絳	苦	寒	無毒
70	石蓮肉	苦	寒	無毒	198	良薑	辛	熱	無毒	326	山藥	甘	平	無毒
71	款冬花	辛	溫	無毒	199	貝母	辛,甘	涼	無毒	327	沒藥	辛,苦	平	無毒
72	肉豆蔻	辛	溫	無毒	200	訶子	苦,酸	溫	無毒	328	粟殼	酸	涼	毒
73	白扁豆	甘	溫	無毒	201	沙參	苦	涼	無毒	329	萹蓄	苦	涼	無毒
74	冬瓜子	甘	寒	無毒	202	柏皮	苦	平	無毒	330	葶藶	辛,苦	寒	無毒
75	益母草	辛,苦	寒	無毒	203	乾薑	辛	溫	無毒	331	蜈蚣	辛,鹹	溫	毒
76	茵陳蒿	甘	涼	無毒	204	續斷	辛,苦	溫	無毒	332	樟腦	辛	溫	無毒
77	商陸根	辛,酸	平	無毒	205	射干	甘	平	毒	333	山楂	酸,甘	溫	無毒
78	桑寄生	甘,苦	平	無毒	206	續隨	辛	溫	毒	334	三七	甘,苦	溫	無毒
79	馬兜鈴	苦	涼	無毒	207	人參	甘,苦	平	無毒	335	川芎	辛	溫	無毒
80	郁李仁	辛,苦,甘	平	無毒	208	血竭	甘,鹹	平	小毒	336	膠飴	甘	溫	無毒
81	大豬膽	苦,鹹	寒	無毒	209	辛夷	辛	溫	無毒	337	川椒	辛	溫	無毒
82	穿山甲	鹹	涼	無毒	210	沉香	辛,苦	溫	無毒	338	川烏	辛,苦	熱	大毒
83	蒼耳子	辛,苦	溫	無毒	211	木香	辛,苦	溫	無毒	339	狼毒	辛	平	大毒
84	破故紙	辛	熱	無毒	212	羊肉	甘	溫	無毒	340	狼牙	苦	寒	無毒
85	金銀花	甘	寒	無毒	213	蚯蚓	鹹	寒	無毒	341	三棱	辛,苦	平	無毒
86	地黃汁	甘,苦	寒	無毒	214	甘遂	苦	寒	毒	342	真珠	甘,鹹	寒	無毒
87	金櫻子	酸,甘	平	無毒	215	木通	苦	涼	無毒	343	葛根	辛,甘	平	無毒
88	訶黎勒	苦	溫	無毒	216	生薑	辛	溫	無毒	344	巴豆	辛	熱	毒
89	威靈仙	辛,鹹	溫	無毒	217	木鱉	苦,甘	溫	毒	345	肉桂	辛,甘	熱	無毒
90	菟絲子	甘	溫	無毒	218	芡實	甘	平	無毒	346	紫菀	辛,苦	溫	無毒
91	車前子	甘	涼	無毒	219	松香	苦,甘	溫	小毒	347	石脂	甘	平	無毒
92	禹餘糧	甘	寒	無毒	220	芫花	辛,苦	寒	無毒	348	海粉	甘,鹹	寒	無毒
93	花蕊石	酸	平	無毒	221	龍骨	甘	平	無毒	349	牛膝	苦,酸	平	無毒
94	玄明粉	鹹,苦	寒	無毒	222	當歸	辛,甘	溫	無毒	350	側柏	苦	寒	無毒
95	山豆根	苦	寒	無毒	223	木賊	甘,苦	平	無毒	351	巴霜	辛	熱	毒
96	酸棗仁	甘,酸	平	無毒	224	木瓜	酸	溫	無毒	352	牛黃	甘	涼	無毒
97	海金沙	甘	寒	無毒	225	蓮肉	甘	平	無毒	353	海藻	苦,鹹	寒	無毒
98	桑螵蛸	甘,鹹	平	無毒	226	雲苓	甘	平	無毒	354	竹瀝	甘	寒	無毒
99	蘇合油	辛,甘	溫	無毒	227	枳實	辛,苦,酸	溫	無毒	355	硇砂	辛,苦,鹹	溫	毒
100	紫河車	甘,鹹	溫	無毒	228	殭蠶	辛,鹹	平	無毒	356	桂枝	辛,甘	溫	無毒
101	白附子	辛,甘	熱	小毒	229	枳殼	苦,辛,酸	溫	無毒	357	石灰	辛	溫	毒
102	五加皮	辛	溫	無毒	230	薏仁	甘	涼	無毒	358	桔梗	辛,苦	溫	小毒
103	代赭石	苦,甘	寒	無毒	231	甘草	甘	平	無毒	359	石膏	辛,甘	寒	無毒
104	使君子	甘	溫	無毒	232	薏苡	甘	涼	無毒	360	萆薢	辛,苦	平	無毒

105	延胡索	辛,苦	溫	無毒	233	秦艽	辛,苦	平	無毒	361	芎藭	辛	溫	無毒
106	蝸牛	鹹	寒	小毒	234	貫眾	苦	涼	無毒	362	苦參	苦	寒	小毒
107	韭菜	甘,辛	溫	無毒	235	神麴	辛,甘	溫	無毒	363	杜仲	辛,甘	溫	無毒
108	麝香	辛	溫	無毒	236	大黃	苦	寒	無毒	364	石斛	甘	涼	無毒
109	蟾酥	辛	溫	毒	237	鹿茸	甘,鹹	溫	無毒	365	巴戟	辛,甘	溫	無毒
110	鬱金	辛,苦	寒	無毒	238	大棗	甘	溫	無毒	366	菖蒲	辛	溫	無毒
111	蓖麻	辛,甘	平	小毒	239	麥冬	甘,苦	涼	無毒	367	官桂	辛,甘	熱	無毒
112	羌活	辛,苦	溫	無毒	240	蜘蛛	酸,鹹	涼	小毒	368	芒硝	鹹,苦	寒	無毒
113	地黃	甘,苦	寒	無毒	241	麻黃	辛,苦	溫	無毒	369	朴硝	苦,鹹	寒	無毒
114	虎骨	甘,辛	溫	無毒	242	胡椒	辛	熱	無毒	370	䗪蟲	苦	涼	毒
115	文蛤	鹹	平	無毒	243	阿膠	甘	平	無毒	371	硝石	苦	寒	無毒
116	鶴虱	辛,苦	平	小毒	244	大戟	苦	寒	小毒	372	獨活	辛,苦	溫	無毒
117	瞿麥	苦	寒	無毒	245	童便	鹹	寒	無毒	373	香蒲	甘	平	無毒
118	蜂房	甘	平	無毒	246	龜板	甘,鹹	寒	無毒	374	全蝎	辛	平	毒
119	血餘	苦	平	無毒	247	香豉	苦	寒	無毒	375	揀參	NA	NA	無毒
120	蟬蛻	苦	寒	無毒	248	韭子	辛,甘	溫	無毒	376	蒲灰	辛	溫	無毒
121	澤蘭	辛,苦	溫	無毒	249	梔子	苦	寒	無毒	377	蒲黃	甘	平	無毒
122	檳榔	辛,苦	溫	無毒	250	皂角	辛	溫	無毒	378	蟲	NA	NA	無毒
123	歸尾	辛,甘	溫	無毒	251	皂莢	辛,鹹	溫	小毒	379	蒜	辛	溫	無毒
124	澤瀉	甘	溫	無毒	252	決明	鹹	平	無毒	380	豉	苦	寒	無毒
125	蘆薈	苦	寒	無毒	253	紫參	苦	寒	無毒	381	蜜	甘	涼	無毒
126	琥珀	甘	平	無毒	254	丹參	苦	涼	無毒	382	蔥	辛	平	無毒
127	黃檗	辛,苦	寒	無毒	255	天雄	辛	溫	大毒					
128	芍藥	甘,苦,酸,鹹,	平,寒	無毒	256	牽牛	辛	溫	毒					

Appendix B: Prescription name and Herb Formulation

藥方	藥材	藥方	藥材	藥方	藥材
大造丸	100 326 246 127 363 349 37 46 188 302 5	瘋犬傷人	195 108	仲景小陷胸湯	275 140 39
蝸牛膏	106 108	雄黃解毒丸	195 110 351	半硫丸	275 159
熨痞方	108 260 368	嗽煙筒	195 157	潔古漿水散	275 273 345 231 198
麝礬散	108 296	神仙薰照方	195 158 208 327	豬苓丸	275 290
通天再造散	110 236	紫白癜風歌	195 159 132 47 264	蝎螯毒	275 296 331
枯痔水澄膏	110 306 140	三味牛黃丸	195 256	木賊煎	275 312 223 316 181 122
地黃黃柏秦皮茯苓澤瀉湯方	113 124 137 142 302	痘疔散	195 266	香朴散	277 316 138 275 231
地黃黃柏黃連半夏湯方	113 140 142 275	雄黃兌散	195 287 20 140 362	茵陳薰法	278 150
地黃知母黃連阿膠湯方	113 140 161 243	雄黃解毒散	195 296	茵陳蒿湯	278 236 324
地黃黃柏茯苓栝蔞湯方	113 142 302 36	解藜蘆毒	195 382	茵陳飲	278 249 124 312 231 55
大黃黃芩地黃牡丹湯方	113 15 166 236 313	搽牙散	195 51 259 322	茵陳湯	278 249 302 330 227 231
人參地黃龍骨牡蠣茯苓湯方	113 171 207 221 302	百合貝母茯苓桔梗湯方	196 199 302 358	化蟲散	281 122 116 104 193
地黃半夏牡蠣酸棗仁湯方	113 171 275 96	百合丸	196 9 271 200 232	控涎丹	28 244 214
百合地黃湯方	113 196 86	槐花散	197 172 229	漏蘆湯	283 156 231 135 210 236
玉關丸	115 200	柏葉阿膠湯方	197 203 243 313	豬膽汁方	286 81
紫金錠	115 244 108	赴筵散	198 259 172	潤腸丸	287 112 123 236 233
玉鎖丹	115 302 221	鐵刷散	198 274 181 231	桃仁湯	287 163 56 378 305
圍藥鐵井欄	115 306 199	團魚丸	199 186 161 271 168	吹鼻六神散	289 195 179 327
吳茱萸湯方	12 207 216 238	當歸貝母苦參丸方	199 222 362	集香散	289 277 263 144 211 231
五德丸	12 211 203 72 319	二母散	199 245 161 216	玉容散	289 306 228 101 41 307 144
宣風散	122 138 231 256	白散方	199 344 358	面鼻雀斑	289 55
檳蘇散	122 224 138 231 263 178	貝母丸	199 381	白芷散	289 8
吳茱萸湯	12 224	草烏揭毒散	199 41 264	箭鏃竹木刺方	293 378
奪命丹	12 245 124	澀腸散	200 44 221	七福飲	294 268

涼血化毒湯	123 128 56 215 135 284 266 358 95	潤肺丸	200 5 231	如神千金方	296 132
洗肝散	123 144 236 112 335 147 249 231	射干丸	205 231 180 236 217 271	白礬散	296 159 179
通瘀煎	123 263 284 319 312 211 124	七寶丸	206 187 195	東垣椿皮散	296 231
益陰腎氣丸	123 272 326 16 168 302 124	調氣散	207 138 211 277 263 231	吐痰方	296 381
牡蠣澤瀉散方	124 165 171 330 353 36 77	茯神湯	207 156 294 64 5 269 231	千金化毒丸	296 382
澤瀉湯方	124 309	地骨皮散	207 156 56 65 168 302 359 161	飛礬散	296 66
五寶丹	126 231 158 211	二味參蘇飲	207 163	青火金針	298 335
琥珀膏	126 289 144 222 217 215 155 158 211 219	大續命湯	207 166 354	諸癬疥頑瘡	299 48 332 303
金花煎	127 140 249	黃芽丸	207 203	葛氏青白散	300 337
正氣湯	127 161 231	王荊公妙柏散	207 221 318 269 302 268 231 187	沉香散	302 210 155 211 277 316 231
丹溪大補陰丸	127 161 246	團參散	207 222	金鎖匙丹	302 269 268 221 171
東垣滋腎丸	127 161 345	小溫金散	207 225 365 318 156 381 239 302 360 231	威喜丸	302 290
丹溪二妙散	127 181	柴胡散	207 231 239 50 144 168	射干鼠粘子湯	30 231 180 205
大補地黃丸	127 222 326 194 161 16 128 17 189	保元湯	207 231 345 156 381	竹葉湯	302 46 166
二黃膏	127 236	十味安神丸	207 269 46 326 187 231	硃砂膏	303 158
細辛黃檗散	127 259	一氣丹	207 273	水銀棗子膏	303 288
錢氏黃檗膏	127 307 231	釀乳法	207 277 211 210 138 235 146 155 178	護心散	307 179
真珠粉丸	127 342 298	人參胃愛散	207 302 231 155 277 178 224	遇仙無比丸	309 122 144 129 47 145 231
柳華散	127 377 298 62	平和飲子	207 302 231 180	芍藥枳朮丸	309 128 227 138
白蠶黃檗散	127 381 228	木防己去石膏加茯苓芒硝湯方	207 302 356 359 368 58	朮連丸	309 140
綠雲散	127 381 298	人參理中丸	207 309 231	白朮防風湯	309 156 144
排膿散方	128 227 358	固陰煎	207 326 16 268 231 90	白朮散	309 166
芍藥甘草湯方	128 231	七珍散	207 366 335 259 144 187	王母桃	309 18 365 231 194
清化飲	128 239 272 302 166 364	延年益嗣丹	207 37 46 21 56 302 65 18	四聖散	309 188 243
犀角地黃湯	128 272 323	二味沉附湯	210 273	倍朮丸	309 203
桂枝茯苓丸方	128 287 302 313 356	福建香茶餅	210 291 108	嚴氏實脾散	309 302
芍藥散	128 345 263	地黃醴	210 291 194	經驗豬肚丸	309 362 171
王瓜根散方	128 356 378	七聖丸	211 122 335 345 112 80 236	敦阜糕	309 84
遇仙丹	129 122 236 341 211	四神丸	211 12 263	七珍湯	310 157 83
追蟲丸	129 122 281 211 278 250 307	生肌散	211 193 132	掃蟲煎	312 274 122 319 12 322 231 158 195
青木香丸	129 164 211 122	十香丸	211 210 124 319 138 155 274 263 250	厚朴方	316 203
子和禹功散	129 274 211 216	神保丸	211 242 295 344	蟲牙痛	317 220

薑黃散	130 289 259	復元通氣散	211 274 312 138 289 231 199 82 283	七德丸	319 12 203 181 211 302
蠲痺消毒散	130 63 372 309 222 128 289	香橘餅	211 312 138 316 235 146	琥珀散	319 222 174
桃花散	132 359	匀氣散	211 312 333	縮泉丸	319 318
小安腎丸	13 263 338 337	木香餅	211 56	神效開結散	320 210 211
失笑散	133 377	湧泉散	2 117 46 221	如聖散	322 203
梔子連翹甘草栝蔞湯方	135 231 249 36	貞元飲	21 231 222	香梅丸	322 289 9
連翹阿膠半夏赤小豆湯方	135 243 275 54	大黃甘遂阿膠湯方	214 236 243	龍腦上清丸	322 29 154 258
連翹飲子	135 335 39 312 231 287	大陷胸湯方	214 236 368	寧肺散	322 328 381
四味地榆散	136 128 140 312	導赤散	215 231	烏巴丸	322 351
地榆丸	136 222 243 140 200 211 322	木通散百	215 312 261 274 13 344 143 211	白花蛇膏	32 257 172 147
白頭翁湯方	137 140 142 26	明目地黃丸	21 56 349 364	加味清胃散	323 135
秦皮散	137 143 140	火龍膏	216 179 327 108	犀角地黃湯	323 15 128 166 180
安胃飲	138 146 215 124 166 364	桂枝生薑枳實湯方	216 227 356	清神湯	323 268 25 366 207 231
丹溪疝氣神方	138 159	甘露湯	216 231	犀角丸	323 44 369 228 147
徒薪飲四	138 166 239 128 127 302 15	蟠桃果	218 225 288 53	旋覆花湯方	325 382 69
清膈煎	138 199 152 28 215	金瘡降真散	219 115	右歸飲	326 16 194 231 363 345 273
排氣飲	138 211 277 263 229 124 319 316	如神散	219 296	右歸丸	326 16 194 43 90 363 59 222 345 273
子和通經散	138 222 214	疥癬光	219 303 159 332	濟陰地黃丸	326 16 222 194 365 239 17 5 55
大和中飲	138 227 188 146 316 124	秘元丹	221 200 188 131	歸腎丸	326 16 302 222 194 363 90
六安煎	138 275 302 231 271 28	龍骨散	221 222 263	左歸丸	326 194 16 349 90
解肝煎	138 275 316 302 154 128 188	天雄散方	221 255 309 356	左歸飲	326 194 231 302 16
小和中飲	138 302 316 231 267	玉鎖丹	221 322	滋陰八味丸	326 272 302 16 124 127 21 161
溫中化痰丸	138 312 198 203	龍骨散	221 44 132 8	泄瀉經驗方	326 337
黃連丸	140 12	靈脂丸	22 146 133 188 174 312 320 104	萬金散	327 231
六味肥兒丸	140 138 13 235 167	決津煎	222 124 349 345 319	七灰散	328 75
黃連人參膏	140 207	玄胡當歸散	222 128 10 327 229	桔梗湯	330 161 65
木香丸	140 211 316 200	豬腰湯	222 128 247 382	上清散	335 110 128 172 368 147
黃連散	140 221	沒藥丸	222 128 287 327 378 305	大芎黃湯	335 112 166 236
黃連粉方	140 231	當歸沒藥丸	222 133 327	秘方茶調散	335 147 289 172 259 11
七味肥兒丸	140 235 211 122 104 146 72	金水六君煎	222 138 275 302 231	赤火金針	335 195 179 327 359
阿膠丸	140 243 302	五味當歸散	222 166 171 128	點頭散	335 263
黃連丸	140 271 322	歸柴飲十七	222 168 231	如神散	337 118
小陷胸湯方	140 275 33	神效瓜蔞散	222 179 327	取牙不犯手	337 259

吹口丹	140 298	大營煎	222 194 231 363 349 345	椒紅丸	337 56
化　丸	140 301 40	消痞核桃	222 28 315 348 299	損傷敷夾法	338 216
黃連朴硝散	140 369 296 147	清涼膏	222 289 217 127 179 132	愈風餅子	338 335 289 144 259 257 112 172 147
痔漏腸紅方	140 66 322	固齒雄鼠骨散	222 300 259	紅丸子	341 174 312 320 203 242
龍腦黃連膏	141 140	豕膏	222 304	三棱散	341 309 174 222 211 122
梅蘇丸	141 147 322 29 154	當歸地黃飲	222 326 363 349 16 231	三棱丸	341 312 146 275
龍腦膏	141 308 271	牛膝散	222 349 128 287 15 211	助氣丸	341 312 320 309 211 122 229
梔子柏皮湯方	142 202 231 249	濟川煎	222 349 17 124 180 229	葛根解毒湯	343 180 56 46 41 231
大黃硝石湯方	142 236 249 368 371	調經飲	222 349 263 312 302	葛根牛蒡湯	343 231 380
滑石散	143 127	赤豆當歸散方	222 54	陳米三棱丸	344 138 341 188 146
滑石亂髮白魚散方	143 151 279	神效當歸膏	222 56	三合散	344 145
退火丹	143 187	加減駐景丸	222 90 194 91 5 337	烏金膏	344 179
百合滑石散方	143 196	厚朴枳實白朮甘草湯方	227 231 309 316	東垣雄黃聖餅子	344 195
經驗滑石散	143 304	梔子大黃湯方	227 236 249 380	外臺走馬湯	344 271
滑石散	143 91 173	七寶散	228 258 195 374	褊銀丸	344 303 108
防風湯	144 112 372 335	開關散一	228 296	大已寒丸	345 203 198
七貼方	144 120 135 102 172 82 224 228 230 63	烏梅丸	228 322	安腎丸	345 302
清心湯	144 140	枳殼湯	229 140	紫菀茸湯	346 71 196 271 243 199 275 377 207 323 231
陳氏解毒防風湯	144 166 65 128 172	熏熨脫肛方	229 144	牛膝湯	349 108
立效散	144 180 231 259	廓清飲	229 316 49 28 261 302 124 138	桂心散	349 117 222
防風湯	144 241 367 180 215 249 359	桂枝散	229 356	牛膝煎	349 222 138
防風天麻丸	144 257 180 101 259 335 207 254 362 189 253 11 89 82 18 331	甘草小麥大棗湯方	231 238 317	三味牛膝湯	349 222 166
二味消風散	147 120	甘草粉蜜湯方	231 276 381	鎮陰煎	349 231 124 345 273
冰檗丸	147 127 258	明膠飲子	231 320	牛膝酒	349 335 112 102 363 231 65 230 56
蜀漆散方	148 165 221	桔梗湯方	231 358	備急丸	351 236 203
麻仁白蜜煎方	149 304	瀉白散	231 57 65	萬氏龍腦安神丸	352 141
雞子黃連膏	150 140	薏苡仁湯	232 15 287	四聖丹	352 187
百合雞子黃湯方	150 196	草豆蔻湯	23 277 138 229 309 326 155	消癭酒	353 210 195 8
木防己湯方	150 207 356 359 58	解毒丸	234 298 231	玉壺散	353 281 300
苦酒湯方	150 275	丹溪保和丸	235 138 275 302 333 135 261	海藻散堅丸	353 50 317
雞子清飲	150 368	仲景大黃黃連瀉心湯	236 140	勝金散	356 133 222
豬膏髮煎方	151 160	梅仁湯	236 15 368 323	桂枝加黃耆湯	356 156

黃芩牡丹皮栝蔞半夏枳實湯方	15 166 227 275 33	隱君滾痰丸	236 166 210	桂枝加大黃湯	356 236
九還金液丹	152 187 228 317 381	當歸導滯散	236 222	栝蔞桂枝湯	356 36
桂枝當歸牡丹皮桃仁枳實湯方	15 222 227 287 356	茵陳蒿湯方	236 249 76	金瘡方	357 334
膽星天竺丸	152 275 101 257 144	行藥方	236 256 122 231 193	三聖膏	357 367 236
化痰丸	152 275 227 108	大陷胸丸方	236 271 330 368	冰玉散	359 228
大黃湯	15 287 236 368	抵當湯方	236 287 305 370	玉露散	359 231
補脬飲	15 306	大黃牡丹湯方	236 287 313 368 74	玉女煎	359 239 161 349
升麻鱉甲去雄黃蜀椒湯方	153 180 195 222 231 301	下瘀血湯方	236 287 378	軟石膏丸	359 275 263 249
中蟹毒	154 178 379	宣毒散	236 289	生鐵落飲	359 302 144 189 233
濕疝陰丸作痛	154 337	防己椒目葶藶大黃丸方	236 297 308 330	石膏散	359 335 289
消積丸	155 188 322 344	厚朴大黃湯方	236 316	石膏升麻散	359 65 180
二仙散	155 203	固齒將軍散	236 363 300	土萆薢湯	360 63
嚴氏柿蒂湯	155 216	二神散	236 369	洗瘍方	362 172 144 289 112 372
神香散	155 22 188	治大孔蟲癢方	238 303 378	錢氏苦參丸	362 24 18 172
丁香散	155 231 198	當歸養心湯	239 207 231 180	河間苦參丸	362 254 201 207 144 102 11 246 114 189
丁香溫中湯	155 275	錢氏安神丸	239 302 326 231 187 141	保孕丸	363 204
丁香柿蒂散	155 312 138	蜘蛛散方	240 356	胡蘆巴丸	365 338 13 274 12
丁香丸	155 335 289 231	如聖散	241 108	菖蒲散	366 250
三香散	155 337	鼻塞方	241 251 259 376	小便不通經驗方	369 274 213
替針丸	155 355 327 179	麻黃附子細辛湯方	241 259 273	大硝石丸	371 236 207 231
鼠粘子湯	156 168 166 135 65	稀痘酒	241 266	硝石散	371 62
黃耆當歸湯方	156 222	半夏麻黃丸方	241 275	節齋化痰丸	37 166 348 39 320 135 263 358 298 368
四味排膿散	156 289 5 207	桂枝麻黃各半湯方	241 356	三才封髓丹	37 21 207 127 188 231
黃耆湯	156 335	蒺藜散	24 144 112	陰陽散	372 128 289 366
四生散	156 372 101 24	八味還睛散	24 144 231 223 324 252 20 120	趙府膏	374 228 331 145 77 179 327 208 221 108
托裏黃耆湯	156 381 231 41	去星	242 107	碧雪	377 298 258 231
斷癇丹	156 381 285 259 231 120 352	紅丸子	242 260 312 341	寸金散	377 352
牡蠣散	156 381 45 171	神應散	242 274	獨蒜通便方	379 249
小己寒丸	157 181 12 138	膠艾湯	243 157	塞耳聾	379 344
柏葉湯方	157 197 203	棗變百祥丸	244 288	羚羊角散	38 156 166 252 91 180 144 236 368

良方>四生丸	157 197 56	固真散	248 221	熏洗脫肛方	382 107 48 144 44
守病丸	158 195 258 193 351 355 179	家韭子丸	248 237 17 349 222 90 365 363 364 203	下蟲丸	40 234 122 287 167 211 116 193 104
薰疥方	158 195 48 217	黃芩清肺飲	249 166	抑陽散	41 130 289 128
硫黃膏	159 289 41 270 374 120	仲景梔子蘗皮湯	249 231 127	下胎方	41 345 349 380
養正丹	159 303 187	仲景梔子豆豉湯	249 247	天花散	41 56 46 5 231
硫黃散	159 5	皂角散	250 172	密蒙花散	42 112 24 223 252
硫黃湯	159 90 12 52	海藏愈風丹	250 362 32	羊肝散	42 20 252 91
花蕊石散	159 93	大青膏	257 298 101 108	針頭散	44 193 108 179 155 132 331
治誤吞水蛭	160 344 307	硼砂丸	258 108 231	桃花丸	44 203
百合知母湯方	161 196	絳雪	258 187	烏頭湯	45 157
陳氏二母散	161 199 207 287 302	硼砂散	258 298 141 147 359	服蠻煎	46 128 366 364 272 269 138 215 161
酸棗仁湯方	161 231 302 361 96	上清丸	258 322 199 200	萬氏清肺飲	46 358 172 41 161 366 200
太清飲	161 364 215 359	辰砂膏	258 94 374 108	滅瘢散	47 101 228 289
薛氏加減八味丸	16 326 124 302 15	治八般頭風	259 132	救苦滅瘢散	47 143 289
河間黃芩芍藥湯	166 231	通關散	259 147 250	坐板瘡	47 236
如聖丸	167 140 51 104 108	東垣明目細辛湯	259 241 112 11 144 335 172 302 56 123	密陀膏	47 245
四味肥兒丸	167 235 146 140	神愈散	259 289 144 112 222 275 358 138 302 147	瘡二方	48 217 52 303
獵蟲丸	167 281 287 265 195 250 122 104 193	醍醐散	259 335 147 338 289 231	大蘆薈丸	51 140 125 167 281 211 312 116 108
七味龍膽瀉肝湯	168 124 91 215 50	二辛煎	259 359	胡黃連丸	51 140 187
加減小柴胡湯	168 166 128	東垣芎辛散	259 361 11 231 289 144	五味子散	5 12
七宣丸	168 227 200 211 231 287 236	丹溪阿魏丸	260 34 140 135	四味肉蓯蓉丸	5 17 90 326
加味小柴胡湯	168 229 171	褐子丸	261 138 312 122 133 174 256 302 211	五味子丸	5 231 115
退熱湯	168 50 310 161 239 231	止鼻衄歌	261 221 67	洗藥神效散	52 369
柴胡麥門冬散	168 50 46 231 207 189	仲景白頭翁湯	26 140 127 137	蛇床子散	52 372 362 144 172
解射工溪毒	169 380 343 180	麻仁丸	262 271 236 324	三痘湯	54 307
燥囊牡蠣散	171 195 159 362 52	天仙藤散	263 138 231 319	生地黃湯五	56 136 231
白朮散方	171 301 309 361	消乳丸	263 188 138 235 231 146	生地黃散	56 166 243 197
止汗散	171 317	香鹽散	263 300	化陰煎	56 21 349 290 124 127 161 307 50 91
牡蠣丸	171 44	擦牙通關散	264 108 228 331	火府丹	56 215 166
爛腿瘡久不愈方	172 144 336	抑陰散	264 128 289 345	地芝丸	56 229 55
洗損傷方	172 222 382 216	玉真散	264 144	五福化毒丹	56 37 46 189 21 231 298

消毒散	172 231	清涼膏	264 172 9 115	生地黃散	56 46 71 138 271 231
荊芥散	172 359	粉紅丸	264 187	冰白散	62 271
葵子茯苓散方	173 302	辰砂化痰	264 275	馬鳴散	62 296
橘皮湯方	175 216	萬病丸	265 349	楊梅癰漏方	63 85 110 222 303
厚朴四物湯方	175 227 275 316	紫草散	266 156 231	柏子仁丸	64 349 121 204 21
萬氏橘皮湯	175 275 302	紫草化毒散	266 180 231	敷藥方	67 139 85
瓜蒂散方	176 54	紫草飲子	266 207 229 333 215 82 120	白虎丹	67 7 60 194
碧油膏	179 208 132	搜毒煎	266 65 166 215 135 120 128	旋覆花湯	69 335 259 302 186
乳香定痛散	179 327 143	銀白散	267 309 231 155 277	四神丸	72 211 274
正骨丹	179 327 163 14 338 208 221	虎睛丸	268 323 366 236 239	二神丸	72 84
三品錠子	179 327 352	面瘡二方	271 150	白扁豆散	73 298 231 344
升麻湯	180 181 46 241 166 359 35	臘梨 E	271 169 381	益母丸	75 257
升麻湯	180 207 269 144 112 323 38 345	綿花瘡點藥	271 193	通聖散	82 108
東垣清胃散	180 222 272 140	薛氏加味小柴胡湯	272 249	白粉散	8 306 193
東垣白牙散	180 359 289 108	冷香飲子	273 138 292 231	蒼耳散	83 209 147 289
辟邪丹	181 140 179 259	理中加丁香湯	273 155	鎖精丸	84 300 302 5
固元丹	181 274 337 321 13	十補丸	273 211 365 367 274 84	加味羌活湯	85 135
丹溪龍虎丹	181 289	椒附丸	273 221 98 16 237	消毒散	85 312 41 168 228 199 222 289
七寶美髯丹	18 349 84 262 302 222 194	韓氏小茵陳湯	273 231 278	螵蛸散	8 62
蘭香散	184 193	復陽丹	273 242 231	收淚散	8 68
前胡枳殼湯	186 229 302 231 236	奪命丹	273 265 15	經驗水陸二仙丹	87 218
五癇丸	187 195 303	附子理中丸	273 309	菟絲子丸	90 17 171 273 5 237 98
金薄鎮心丸	187 207 302 231 326 108	十補丸	273 326 16 272 237 302 124	固真丸	90 171 87 302
子和朱砂滾涎丸	187 296 371 44	七棗湯	273 338	五子丸	90 248 318 274 52
楊氏消食丸	188 138 235 146 341 174 263	二至丸	273 363 237 300	固脬丸	90 274 98 273 134
縮砂散	188 140 223	蜜附子	273 381	茯菟丸	90 302 70
通氣散	189 335 311	訶梨勒丸	273 72 211 12 221 302	神仙六子丸	90 5 194 52 18 349 65 274 224
竹茹半夏湯方	191 275 302 36	三層茴香丸	274 13 201 211	齒縫出血	9 109
瘡隔紙膏	193 179 327	去鈴丸	274 216 300	傅爛弦歌	9 193
飛丹散	193 270	金鎖丹	274 221 211 53		
利驚丸	193 298 256	赤石脂禹餘糧湯方	27 44 92		
杖丹膏	193 303	丹溪腎氣丸	274 84 12 211		
醉仙丹	194 11 24 362 41 144	豬肚丸	274 84 13 155		
玄武豆	194 274 17 300	半夏茯苓湯	275 138 188 302 231		