# **Research on Exploring the Patients' Hiding Disease Based on Symptom Weighted Clustering Technique**

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Abstract: The research regards the diagnostic data of the patients' disease as the mining data source. Each diagnostic data includes patients' symptom and sickness. The paper regards a certain patient as the mining target, considering the symptom weighted situation, using the clustering method in the data mining to dig the tendency of patients' disease. In addition, the paper combines a group center formed by the patients' symptom and designs a symptom weighted clustering method to satisfy the diagnostic data of minimal symptom similarity which belongs to the clustering. Later, the disease item whose number is the maximum can be found out in the clustering and the tendency of patients' sickness. The methods proposed in the paper design and build a diagnostic system of patients' sickness. The mining results of system can offer some useful referent information for those people check the sickness tendency of patients' disease or those medical staff whose clinical experience is not enough confirms the disease diagnosis.

Keywords: Data mining, Clustering, Symptom weighted, Disease.

# Introduction

With the development of information and technology, the diagnostic data of the patients stored in the hospital has been changed from the traditional paper records into electronic medical records. According to the description of the Computer-based Patient Record Institute (CPRI), In regard to a human's lifelong healthy state and the electronic information of medical care, the electronic medical record will replace the paper record. This way can conform to the clinic application, the public administration, the medical education, the research investigation and other legally needed mainly medical data source. The relevance between the external symptoms and diseases can be found as the reference information of the medical diagnosis from the past patients' diagnostic data. In addition, it can improve the accuracy and efficiency of the medical diagnosis, reducing the delay of the procedure of diagnosing the disease and is the main research topic in the field of applying the diagnostic data.

The data mining is to dig the potential useful information and knowledge from a number of data and is regarded as the referent information of the decision analysis. The data mining has been applied in many fields [7]. The research regards the patients' diagnostic data as the mining data source, and each diagnostic data records the symptoms and diseases of the patients. The patient's symptom is as the mining target and the clustering is used to analyze that those symptoms and the diseases have the highest relevance. In this way, the patients' symptoms can be mined that they may have the tendency of the diseases. For example, the patients' symptoms include chest discomfort, chest distress, chest heavy, chest pain and others; they may suffer from the cardiovascular disease. The paper regards a patient's symptom as the mining target

and makes the sunset of the symptom be the cluster's central point. Considering the situation of the symptom weighted, a clustering is designed to adjust the symptom similarity between the diagnostic data and the central points. It can also satisfy the diagnostic data of minimal symptom similarity which belongs to the clustering and find out the tendency of suffering from the disease changing from the patients' symptoms. The diagnostic data of a medical center in the south is as an example; the disease diagnostic system of a patient is designed and built. The mining results can offer some useful guiding information for the tendency of patients' sickness and can provide some useful efficiency of receiving the disease treatment.

## The relevant research

The data mining can find out some potentially useful information and knowledge from a number of data, it can finish the following tasks: association rules, clustering, classification, sequential pattern analysis, forecasting and others [3, 15]. The application information technology in the medical field can develop medical informatics, and its purpose is to build the medical knowledge and find out the medical guidance of all diseases with the support of the information technology, regarding the diseases as the center and the medical problems as the oriented diagnostic models. If the information technology can be effectively used in the disease diagnosis, the relevance between the disease symptoms and possible diseases can be analyzed so that it can offer great help to the treatment of the disease and the prevention of the diseases.

Many researches have shown that the data mining can be effectively applied in the medical diagnosis, and its relevant researches are as follows: Ye et al. [14] take the insomnia and the cardiovascular and cerebrovascular diseases as an example, the concurrence and the causal relation among the diseases can be analyzed with the use of data mining. Vani and Shimabukuro [13] regard the standard health data as the source of the system data with the use of the data mining technology. It can develop a special data mining system in the medical field to explore the relations among different diseases so that the data can be used as the reference for the future prevention treatment. Ji et al. [5] adopt the data mining technology to construct the knowledge management system for the classification of the hospital diseases. Molina et al. [10] use the data mining technology to conduct the medical forecast for the patients who suffer from the tuberculosis. Regan et al. [11] use the association rules to find out the probability of the diseases. They used to adopt the association rules with composite items to discuss the relevance between the symptoms and the diseases.

The clustering can cluster its objects in terms of the similarity. The research of the clustering is mainly as follows: the partitioning, the partitioning, the grid-based, the density-based, the model-based and others [9].

Berry and Linoff [2] used to describe that if people start to analyze the data, know about the meaning of the data and describe the best utility pattern, the cluster analysis is a better way. The research will modify the method of the partitioning clustering and then regard the modified method as the basis of the clustering diagnostic data.

Some more famous methods of the partitioning clustering are partitioning around medoids (PAM) [4], *k*-means [8, 12] and CLARANS [1]. The *k* clusters  $k \ge 1$  appointed by the users can be clustered and the partitioning method can make each object be assigned to the most similar clustering. The clustering steps about the PAM algorithm are as follows: Kaufman and Rousseeuw [6] propose the PAM algorithm which can make the whole objects be clustered into *k* clusters. The PAM can make each cluster decide the representative objects, and representative objects can be called as *k*-medoids. If *k*-medoids are chosen, the objects which do not belong

to the medoid can be decided which cluster they belong to according to the similarity. Its similarity can be represented by the Euclidean distance.  $d(O_a, O_b)$  represents the distance between  $O_a$  and  $O_a$ .

For example,  $O_i$  is the medoid and  $O_j$  is not the object of the medoid, if

$$d(O_j, O_i) = \min\{d(O_j, O_e)\}$$

and  $O_e$  represents all medoids,  $O_i$  belongs to the  $O_i$  clustering.

As for any  $O_j$  which does not belong to medoid, if the medoid  $O_i$  is replaces by  $O_h$  which does not belong to medoid, the definition of the changing cost  $C_{iih}$  is as follows:

$$C_{jih} = d(O_j, O_m) - d(O_j, O_n).$$
<sup>(1)</sup>

 $O_m$  shows that the medoid which has the maximum similarity (the shortest distance) with  $O_j$  after the  $O_h$  replaces the  $O_i$ .  $O_n$  shows that the medoid which has the most similarity (the shortest distance) with  $O_i$  before the  $O_h$  replaces the  $O_i$ .

$$TC_{ih} = \sum C_{jih}.$$
 (2)

If  $TC_{ih} > 0$ , the total distance is larger than before, the  $O_i$  can not be replaced by the  $O_h$ .  $TC_{ih}$  is used as the measuring basis, the explanation of the PAM algorithm is as follows:

- 1. Randomly choose k objects as medoids.
- 2. As for all the combination between  $O_i$  and  $O_h$ , the  $TC_{ih}$  can be calculated.  $O_i$  represents any medoid, and  $O_h$  represents any objects which do not belong to the medoid.
- 3. Choose the  $O_i$  whose  $TC_{ih}$  is the minimum value to combine with the  $O_h$ . If  $TC_{ih} < 0$ ,  $O_h$  can replace the  $O_i$  and become the medoid, later it can jump to the step 2.
- 4. Otherwise the execution should be stopped and the clustering is finished.

The research regards the patients' each diagnostic data as the data mining source with the situation of the symptom weighted. The clustering technology is used to discuss the tendency of the diseases from the patients' symptoms. The form of the diagnostic data is  $\{S, D\}$ , S is the set which includes one or more symptoms, D is the set which includes one or more diseases. Each diagnostic data include the patients' symptoms and the diseases. For example, a diagnostic data is  $T_1 = \{abc, X\}$ , and its showing symptom is abc, its disease is X, that is,  $\{a, b, c\} \subseteq S \setminus X \subseteq D$ .

# Mining the tendency of the diseases from the patients' symptoms

During the process of diagnosing the patients' disease, the doctors hope to know about the relevance between the symptoms and disease. As for the uncommon or unique symptoms, the

weighted value of these symptoms can be improved so that it can easily become the affected symptoms. Later the relevance between the symptoms and the diseases can be found out which can be the basis on mining the tendency of the diseases from the patients' symptoms. The paper uses the patients' each diagnostic data as the data mining source and each diagnostic data include the patients' symptoms and the diseases. A patient's symptom is as the target under the situation of the symptom weighted, the clustering method can be used to dig the tendency of the diseases from the patients' symptoms.

#### The clustering method

The paper defines the diagnostic data and the symptom similarity among central points, the similarity is as the basis on whether the diagnostic data belong to the clusters.

The symptom's number of the symptom similarity  $s = \{ \text{diagnostic data} \cap \text{clustering center points} \} / \text{The symptom's number}$  $\{ \text{diagnostic data} \cup \text{clustering center points} \}.$ 

For example, if each diagnostic data is  $\{abc, X\}$  and the clustering center point is  $\{acde\}$ ,  $\{a, b, c, d, e\}$  is the set of the symptoms,  $\{X, Y\}$  is the set of the diseases, so the symptom similarity is 40%.

If the patients' symptom is P, P is the item set which contains a or more symptoms considering the situation of the symptom weighted. If P contains k symptoms,  $s_1, s_2, \ldots, s_j, \ldots, s_k$  respectively,  $k \ge 1$  represents and the corresponding weighted value is shown by  $w_1, w_2, \ldots, w_j, \ldots, w_k$ . The calculating method of the P's symptom weighted similarity is as follows:

$$w = 0; j = 0;$$
 (3)

for  $(i = 1; i \le k; i + +)$  (4)

if  $s_j \in \{ \text{ diagnostic data} \cap \text{ clustering center points} \}$  (5)

then  $\{w = w + w_i; j = j + 1; \}$  (6)

$$w = \frac{w}{j};\tag{7}$$

the symptom weighted similarity 
$$ws = \sum_{i=1}^{k} w \times s.$$
 (8)

For example, *P* includes 3 symptoms *abc*, the weighted value of the *abc*, is respectively represented by 1, 2 and 3.  $ws = 2.5 \times s$  is because that {diagnositic data  $\cap$  clustering center points} = {*bc*}, *j* = 2, *w* = 5/2 = 2.5. The paper assumes a minimum symptom similarity and *P* is the patient's symptom, the subset of *P* is represented by

$$S = \{s_1, s_2, ..., s_j, P\}, S_i \subseteq P.$$

A simple and rapid clustering method is designed in the paper,  $s_i$ , is the central point of a cluster and is the same cluster whose diagnostic data  $T_j$  is satisfied with the minimum symptom similarity. It is called  $S_i$ -cluster.  $1 \le j \le m$ , represents the *m* diagnostic data.

The process of the clustering is as follows:

Clustering(*P*){  
Calculate the subset *P*: 
$$S = \{s_1, s_2, ..., s_j, ..., P\}$$
(10)  
for ( $j = 1; j \le m; j + +$ )  
while ( $S = \emptyset$ ) {  
Select the next  $s_i$  and set the cluster as the central points;  
Calculate the symptom similarity *s* between the diagnostic data  $T_i$  and the

calculate the symptom similarity s between the diagnostic data  $T_i$  and the central points of the clusters.

According to the weighted values of all symptoms in P, the weighted symptom similarity ws are calculated.

If 
$$ws \ge$$
 the minimum symptom similarity, then  $T_j \in S_i$ -cluster (13)  
}

If the mining symptom is *ab*, the weighted value of *a*, *b* is respectively 2 and 1.  $S = \{a, b, ab\}$ , *a*, *b* and *ab* is respectively the central points of the cluster. If the diagnostic data  $T_1$  is  $\{acd, XY\}$  and the symptom is *acd*, the diseases *XY*.

If the similarity of the minimum symptoms is 50%,  $T_1$  belongs to *a*-cluster. According to the above clustering steps, the diagnostic data which satisfies with the minimum symptom similarity to the  $S_i$  belongs to  $S_i$ -cluster.

The calculations are as follows: The ratio value in all diseases is equal to the number of diseases happened in the  $S_i$ -cluster/the number of the diagnostic data included in the  $S_i$ -cluster.

The above calculation is used as the basis on digging the tendency of the diseases from the symptom P. For example, the maximum ratio values in the  $S_i$ -cluster can be found out. The tendency of the diseases from the symptoms P is defined as follows: the diseases whose ratio values are the maximum can be found out in each  $S_i$ -cluster. The number of these diseases can be accumulated. The disease whose number is the maximum is the tendency of the diseases from the symptom P. As for the diseases which have the maximum numbers, they can be the most possible tendency of the diseases. Other diseases of the ratio values or other accumulated number of diseases can be adopted. Both of them can be used as the referent basis on knowing about the tendency of the diseases suffering from the symptom. In this way, the extension of suffering from the diseases can be increased.

#### The explanation of the examples

The example explains the process of digging the tendency of the diseases from the symptom with the clustering based on the patients' weighted symptoms. Table 1 present the diagnostic data D, including 6 diagnostic data, where

- {*a*, *b*, *c*, *d*, *e*} is the set of the symptoms,
- $\{X, Y, Z\}$  is the set of the diseases and
- $\{T_1, T_2, T_3, T_4, T_5, T_6\}$  is the set of the diagnostic data.

If the mining patients' symptom is being, the symptom's weighted value is 1 and 2 and the minimum symptom similarity is 60%.

The number of the diagnostic data	The symptoms	The diseases
$T_1$	abd	X
$T_2$	abce	Y
$T_3$	bce	XY
$T_4$	ab	YZ
$T_5$	ae	X
$T_6$	abe	XY

At first, the subset of the patient's symptom be is  $\{b, e, be\}$ , b, e and be is the central points of the cluster respectively. After calculating the algorithm Clustering(be), the following cluster can be obtained:

$b$ -cluster = $\{\emptyset\}$ ,	(14)
$e$ -cluster = { $T_3, T_5, T_6$ },	(15)

*be*-cluster is  $\{T_2, T_3, T_5, T_6\}$ . (16)

The maximum diseases in all clusters are as follows:

<i>b</i> -cluster: $\emptyset$ ,	(17)
<i>e</i> -cluster: disease <i>X</i> ,	(18)
<i>be</i> -cluster: disease <i>X</i> , <i>Y</i> .	(19)

The number of all diseases is as follows:

The number of the disease X is 2, the number of the disease Y is 1 and the tendency of the disease from the patients' symptom is X.

The calculation without the symptom weighted can obtain that the be-cluster is  $\{T_3, T_5\}$  and the tendency of the disease from the patients' symptom be is *X* or *Y*. Therefore, the symptom weighted mining by the medical profession can feature the tendency of the disease from the patients' symptom without the weight.

# The establishment of the diagnostic system for the patients' diseases

The research designs and builds the diagnostic system for the patients' diseases and the Table 2 is the development platform of the system.

The operating system	Windows XP Professional Edition
CPU	Intel Core i7 CPU 3GHz
The main memory	3 GB SDRAM
The designing language	ASP, VB Script, Java Script
The data base	Microsoft Access2007

Table 2. The development platform of the system

The patients in a hospital each medical diagnostic data for example, diagnostic data from 2016/7/1 to 2016/7/7, a total of 6350 cases, as the system data sources, the diagnostic data in front of 6000 pen as the training data, and in the last 350 diagnostic data as verification data for mining computation. Fig. 1 is the original data of the diagnostic data, the original data in patients of each medical treatment for a record store, every diagnostic data includes medical treatment "type" and "symptoms" and "disease" data.

The symptom description and the names of the diseases in the diagnostic data must be encoded respectively, the name of the disease can use the ICD-10-CM code (The International Classification of Disease, 10th Revision, and Clinical Modification) to encode. Some more important words of the symptoms can be chosen out from the symptom descriptions and be encoded, and it can be respectively encoded with the S0001, S0002, S0003 and others. In Fig. 2, the disease code and the symptom code after being coded replace the name of the diseases and the symptom description in the original diagnostic data.

The research regards 6000 diagnostic data as the mining training data so that it can find out the tendency of the diseases from the symptom. The implementation of digging the training data is as follows: the digging symptoms can be input in the segments of the patients' symptoms in the Fig. 3 and the weighted value can be set, the minimum symptom similarity is 60%. The segment in the tendency of the diseases can show the mining results as shown in the Fig 4.

The research regards the remaining 355 diagnostic data as the digging verifying data, evaluating the efficiency of the digging results in the former training data. The paper adopts the digging to execute the picture from the remaining 355 diagnostic data. The symptoms appearing in these diagnostic data can be input and the tendency of the diseases from the symptom can be found out. Later, check whether the diseases in these diagnostic data are the tendency of the disease. If so, the definition of the diagnostic data can not respond the tendency of the diseases.

The Fig. 5 can evaluate the number of the diagnostic data with the tendency of the diseases under the different number of the diagnostic data. The system can respond the tendency of the diseases under the high ratio value. If the medical professor sets the symptom weight, the responded number can be improved.

Disease	K40.9Inguinal hemia	N30.9Cystitis	D36.9Benign breast turnor	K27Peptic ulcer C97 Liver cancer	K80.1Cholecystolithiasis	193Thyroid carcinoma	D36.9Benign breast tumor	C18.9Carcinoma of colon	K35.9 Acute appendicitis	C50.9 Benign breast tumor 、 I84.9Hemorhoids	K80.1 Cholecystolithiasis	K80.1 Cholecystolithiasis	I84.9Hemorrhoids	K35.9A cute appendicitis	C18.9Carcinoma of colon	D36.9 Benign breast turnor	D36.9 Benign breast turnor	C20 Rectal cancer	D10-D36 Benign turrors	D36.9 Benign breast turnor	D36.9Benign breast tumor	T11.0Multiple wounds of the upper limb	C50.9Mastocarcincma	K80.1 Cholecystolithiasis	D36.9Benign breast turror	D34 Benign thyroid turnor	K80.1Cholecystolithiasis
Symptom	Rt inguinal mass for one week	Dysuria for one day Abd.pain	Bil.mastalgia for noe week	.HCC,Rt.lobe,S/P general weakness Cough	Gall bladder polyp was told for one week	Rt.thyroid.ca.S/P Oral ulcer	Rt.breast mass for one week	Ca.of D-colon with obstruction, S/P, ADJUV	Ac.app.S/P	Lt.breast nass for one week	Fall stones with jaundicems/p W d,infection	CBD stones with ob jaundice, S/P PTCD T.	Anal painful sensation for one weeek	Ac.app.S/P	HAD STOMACH CA WITH LIVER METAS	Lt.breast mass for one week	Lt.breast mass for one week	Ca.of return, S/P Rt. amnumbness Skin ra;	Rt.buttock mass for one week,S/P	Rt.breast mass for one week	Rt.breast mass for one week	Rt middle finger trauma for one month Ingn	Lt.breast ca.S./P	BillHD with ob.cholangitis,S/P PTCD	A skin defect with granulation tissue for one:	Bil.MTNG,S/P	Ac.cholecystist,S/P PTGBD
Department	General surgery	General surgery	General surgery	General surgery	General surgery	General surgery	General surgery	General surgery	General surgery	General surgery	General surgery	General surgery	General surgery	General surgery	General surgery	General surgery	General surgery	General surgery	General surgery	General surgery	General surgery	General surgery	General surgery	General surgery	General surgery	General surgery	General surgery
Code	2204	2205	2206	2207	2208	2209	2210	2211	2212	2213	2214	2215	2216	2217	2218	2219	2220	2221	2222	2223	2224	2225	2226	2227	2228	2229	2230

Fig. 1 Original diagnostic data

194physicianS0011,80255MCT3.9fbronic hepatris195physician80011IBO 7'enous thrombosisN51.0.M25.90/herjoint196physician80011IBO 7'enous thrombosisN51.0.M25.90/herjoint197physician8004,5001150142D54.9001cherjointMeeases198physician8004,5001150142D54.9001cherjointMeeases198physician8004,5001150142D54.9001cherjointMeeases198physician8004,5001150142D54.9001cherjointMeeases199physician8001,50001D64.9000cherjointMeeases190physician8007,50000A11.95eptrentaJ18.0Pheumonia191physician8007,50000A11.95eptrentaJ18.0Pheumonia192physician8007,50000A11.95eptrentaJ18.0Pheumonia193physician8007,50000A11.95eptrentaJ18.0Pheumonia194physician8007,50000A11.95eptrentaJ18.0Pheumonia195physician8007,50000A11.95eptrentaJ18.0Pheumonia196physician8007,50000A11.95eptrentaJ18.0Pheumonia198physician8007,50000A11.95eptrentaJ18.0Pheumonia198physician8007,50000A11.95eptrentaJ18.0Pheumonia198physician8007,50000A11.95eptrentaJ18.0Pheumonia198physician8007,500008007,50000J19.0Phi 19.0Phi 19.0Phi 19.0Phi 19.0Phi101physician <th>Code</th> <th>Department</th> <th>Recoding</th> <th>Symptom code</th>	Code	Department	Recoding	Symptom code
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97physicianS0034,S0011,S0142D64.9Cardiovs etaplitis x.T02.Alcoholic cirthosis v.R51Headache $108$ physicianS001,S0022D54.6Cardiovs etale disess v.R50.3Thrunchophbehits $2010$ physicianS001,S0022D54.9Chronic hepatitis x.K70.2Alcoholic cirthosis v.R70.2Alcoholic cirthosis $2010$ physicianS007,S0070D54.9Chronic hepatitis x.K70.2Alcoholic cirthosis $2011$ physicianS007,S0070D64.9Chronic hepatitis x.K70.2Alcoholic cirthosis $2012$ physicianS007,S0070A14.9Septicraria v.108.0chronic site and her $2012$ physicianS007,S0070A14.9Septicraria v.108.0chronic site and her $2012$ physicianS0013,S007,S0026X27Gastri uleer and bleeding v.M06.9Rhematoid arthritis v.R70.2Alcoholic cirthosis $2014$ physicianS0013,S007,S0026X27Gastri uleer and bleeding v.M06.9Rhematoid arthritis v.R70.2Alcoholic cirthosis v.R70.2Alcoholic cirtho	196	physician	S0057,S0011	L03.9 Foot cellulitis 、C20rectal cancer 、110Hypertension
188physicianS0034,50011,50142L03 50Foot celluitis $\cdot$ L08.0.L08 & Atopic demartis $\cdot$ X.25 Gastric ulea189physician\$0034,50012L03 5007L03 5007E116 Cadiovas cular disease $\cdot$ B0.7 Thron-bophlebitis201physician\$0037,50070D64 9 Chronic branchis $\cdot$ X.25 Gastric ulea $\cdot$ 108 mochinis202physician\$0037,50070C02Padinson's disease $\cdot$ F510, F510 SF19 Sflop disorder $\cdot$ J18 Preurmonia202physician\$0037,50070A149 Septicentia $\cdot$ J18 Preurmonia J40 Bronchinis203physician\$0035,50070A140 Septicentia $\cdot$ J18 Preurmonia204physician\$0035,50070A140 Septicentia $\cdot$ J18 Preurmonia J40 Bronchinis205physician\$0035,50075,8005A140 Septicentia $\cdot$ XI8 Sochanic of a control affinitio206physician\$0035,50075,8005A140 Septicentia $\cdot$ XI8 Sochanic of a control affinitio207physician\$0035,50075,8005X25 Gastric ulee and beeding $\cdot$ M06 Pheurantoid affinitio208physician\$0005,50075,8005X25 Gastric ulee and beeding $\cdot$ M06 Pheurantoid208physician\$0005,50075,8005X25 Gastric ulee and beeding $\cdot$ M06 Pheurantoid208physician\$0005,50075,8005X25 Gastric ulee and storentia $\cdot$ R31 Hamaturia208physician\$0005,50075,8005\$007,50076209physician\$0005,50075\$002,50070201physician\$0003,5007\$0025,50070202physician\$0003,5007\$0023,50070203physician\$003,50	197	physician	S0034,S0011,S0142	D64.9Chronic hepatitis × K70.2Alcoholic cirrhosis × R51Headache
199physicianS0218,5002151.6Cardiovascular disease $\times$ 180.71tnortbophlebitis200physicianS0011D64.9Ctnonic hepatitis $\times$ K70.24 coholic cirthosis $\sim$ 201physicianS0057,50070D64.9Ctnonic hepatitis $\times$ K70.24 coholic cirthosis $\sim$ 202physicianS0057,50070A14.195epticerria $\sim$ 13.8 Pheurmania $\sqrt{400.0000}$ 203physicianS0075,50070A41.95epticerria $\sim$ 13.8 Pheurmania $\sqrt{400.0000}$ 204physicianS0013,50042A41.95epticerria $\sim$ 13.8 Pheurmania $\sqrt{400.0000}$ 205physicianS0013,50042A41.95epticerria $\sim$ 13.8 Pheurmania $\sqrt{400.0000}$ 206physicianS0013,50045A41.95epticerria $\sim$ 13.8 Pheurmania $\sqrt{400.0000}$ 201physicianS0013,50045A41.95epticerria $\sim$ 13.8 Pheurmania $\sqrt{400.0000}$ 203physicianS0013,50045A41.95epticerria $\sim$ 13.8 Pheurmania $\sqrt{400.0000}$ 204physicianS0013,50045A41.95epticerria $\sim$ 13.8 Pheurmania $\sqrt{400.0000}$ 206physicianS003,50075,50075A72.5002,50076207physicianS003,50075,50076A72.5002,50076208physicianS003,50075,50076A72.5004.059heurmatoid arthritis $\sqrt{200.0000}$ 208physicianS0043,7010Dayoric representai $\sqrt{110.0000}$ 208physicianS003,50075,50076A73.5002,50076209physicianS0034,50014S001400,50000201physicianS0034,50014S001400,50000202physicianS0014,5002J39.94bhonraily of respiration 1	198	physician	S0034,S0011,S0142	L03.9Foot cellulitis < L08.0-L08.8Atopic dematitis < K25Gastric ulcer
200physicianS0011D64.9Chronic hepatitis × K70.2Alcoholic cirrhosis ×201physicianS0057,50070G07ehrison's disease × F10.751.9578ep disorder × J13.9Pneurronia202physicianS0057,50070G07ehrison's disease × F10.751.9578ep disorder × J13.9Pneurronia203physicianS0057,50070A41.95epticerria × J13.9Pneurronia204physicianS0013,50075,50096A41.056pticerria × J13.9Pneurronia205physicianS0013,50075,50096J42Chronic bronchitis × K20.0Acturoic osteonyelitis206physicianS0013,50075,50036K25Gastic uloer and bledmig × M0.69Rheuratoid arthritis207physicianS00437C20Pathips v R50.0Acturoic of attritis208physicianS0035,50035,50036K25Gastic uloer and bledmig × M0.69Rheuratoid arthritis209physicianS00437C60.93Peripheral neuritis × N18.9Chronic renal failuer201physicianS0035,50035,50036K25Gastic uloer and bledmig × M0.69Rheuratoid201physicianS0034,50011,50142M0.9 Suppurative attritis × R31Herraturia201physicianS0034,50011,50142J39.9Abnomality of frespiration201physicianS0034,50011,50142J39.9Abnomality of frespiration202physicianS0034,50011,50142J39.9Abnomality of frespiration203physicianS0034,50011,50142J39.9Abnomality of frespiration204physicianS0034,50011,50142J39.9Abnomality of frespiration205physicianS0034,50011,50142J39.9Abnomality of frespir	199	physician	S0218,S0092	I51.6Cardiovas cular disease × I80.3Thrombophlebitis
201physician5007,50070C0Parkinson's disease < F31.0-F31.9Steep disorder 118.9Pheurnonia202physician $80037,50070$ $A41.9Septicernia < 1.18.9Pheurnonia$	200	physician	S0011	D64.9Chronic hepatitis × K70.2Alcoholic cirrhosis ×
202physician80057,50070A41.9Septicentia / 13.9Pheumonia / 40Bonchitis203physician $S0473$ M40.0.M40.5Spinal curvature · M06.9Pheumotid arthrits · M66.9Chonic ostomychins204physician $S0013,50042,50109$ M40.0.M40.5Spinal curvature · M06.9Pheumotid arthrits · M66.9Chonic ostomychins205physician $S0013,50075,50296$ M20.0chonic ostomychins206physician $S00437$ $S0075,50092,50075,50296$ M20.0chonic ostomychins207physician $S00437$ $S00437$ $G62.93Penpheral neuritis · N18.9Chonic renal failue208physicianS00437G62.93Penpheral neuritis · N18.9Chonic renal failue207physicianS00437G62.93Penpheral neuritis · N18.9Chonic renal failue208physicianS00437G62.93Penpheral neuritis · N18.9Chonic renal failue208physicianS00437G62.93Penpheral neuritis · N18.9Chonic renal failue208physicianS00437G62.93Penpheral neuritis · N18.9Chonic renal failue209physicianS00437G62.93Penpheral neuritis · N18.9Chonic renal failue210physicianS0034,S001,S0142M0.95Pheuromia · A11.9Spiteresion211physicianS0034,S001,S0142M0.95Pheuromia · M0.9Pheuromia · M0.9Pheuromia212physicianS0034,S001,S0142M0.95Pheuromia · M1.9Pheuromia213physicianS0034,S001,S0142M0.95Pheuromia · M0.9Pheuromia214physicianS0034,S001,S0142M0.95Pheuromia · M1.9Spiteresion215<$	201	physician	S0057,S0070	G20Parkinson's disease × F51.0-F51.9Sleep disorder × J18.9Pneumonia × J40Bronchitis
203physicianS0473M40.0.M40.5Spinal curvature > M06.9Rheumatoid arthrits > M86.9Chronic osteonyefitis204physicianS0013,S002,S0023,S0075,S0296 $342Chronic bronchifticary of adrenocotical function >XS0.9Chronic osteonyefitis205physicianS003,S0023,S0075,S0296X25Gastric ulcer and bleeding > M06.9Rheumatoid arthrits206physicianS00437C002,S0023,S0075,S0296X202-Soctute gastricarrention > XS0.9Chronic osteonyefitis207physicianS00437C002,S0023,S0075,S0296X202-Soctute gastricarrention > XS0.9Chronic renal failure208physicianS00437C00Parhinson's disease > G40.9Epileps y F51.0F51.9Sleep disorder201physicianS003,S001,S0124C00Parhinson's disease > G40.9Epileps y F51.0F51.9Sleep disorder201physicianS0034,S001,S0124M00.9Supurative arthritis > L03.9Foot cellultits > M06.9Rheumatoid211physicianS0034,S001,S0124M00.9Supurative arthritis > L03.9Foot cellultits > M06.9Rheumatoid212physicianS0034,S001,S0124M00.9Supurative arthritis > L03.9Foot cellultits > M06.9Rheumatoid213physicianS0034,S001,S0124M00.9Supurative arthritis > L03.9Foot cellultits > M06.9Rheumatoid214physicianS0034,S001,S0124M00.9Supurative arthritis > L03.9Foot cellultits > M06.9Rheumatoid215physicianS0034,S001,S0124M00.9Supurative arthritis > L03.9Foot cellultits > M06.9Rheumatoid216physicianS0034,S001,S0124M00.9Supurative arthritis > L03.9Foot cellultits > M06.9Foot cellultits > M06.9Foot cellultits > M06.9Foot cellult$	202	physician	S0057,S0070	A41.9Septicemia、J18.9Pneurronia、J40Bronchitis
204physicianS0013,S0042,S0109J42Chronic bronchitis v E77.9hrufficiency of adrenocortical function205physicianS0003,S0073,S0075,S0296KZ5Gastric ulcer and bleeding v M06.9Phermatoid arthritis206physicianS00437S0023,S0075,S0296KZ5Gastric ulcer and bleeding v M06.9Phermatoid arthritis207physicianS00437C020Parhinson's G203Perpheral neuritis v N18.9Chronic renal failure208physicianS003,S0075,S0292G20Parhinson's disease v G40.9Fpilepsy v F51.0-F51.9Sleep disorder209physicianS003,S0015,S0192M00.9 Suppurative arthritis v M05.9Fhorid v I10Hypertension210physicianS0034,S0011,S0142M00.9 Suppurative arthritis v M05.9Fheuratoid211physicianS0034,S0011,S0142J39.9Ahonmality of respiration v 110Hypertension212physicianS0034,S0011,S0142J39.9Ahonmality of respiration v 110Hypertension213physicianS0011J18.9Pheuromia v 41.9Septicernia214physicianS0034,S0011,S0142J18.9Pheuromia v 41.9Septicernia215physicianS0034,S0011,S0142M03.9Food poisoning, unindicated216physicianS0034,S0011,S0142M38.9Chronic renal failure v J11.8hthuraz v K6.7Nephrotic217physicianS0034,S0011,S0142M18.9Chronic renal failure v J11.8hthuraz v K6.7Nephrotic218physicianS0034,S0011,S0142M18.9Chronic renal failure v J11.8hthuraz v K6.7Nephrotic215physicianS0037,S0070S0037,S0070216physicianS0034,S0011,S0142M18.9C	203	physician	S0473	M40.0-M40.5Spinal curvature × M06.9Rheumatoid arthritis × M86.9Chronic osteomyelitis
205physicianS0008,50025,50025,50256K25Gastric ulcer and bleeding $\wedge$ M0669Rheumatoid arthrifs206physicianS0473,50092,50237K92.29A cute gastroenteritis $\wedge$ S1Hematuia207physicianS0473,50092,50237G62.93P eripheral neuritis $\vee$ N18.9C fnortic renal failure208physicianS003,50037G2097 misoris disease $\vee$ G40.9F pilepsy $\vee$ F51.0-F51.9Sleep disorder209physicianS000,50437C20P arkins oris disease $\vee$ G40.9F pilepsy $\vee$ F51.0-F51.9Sleep disorder210physicianS0034,50011,50142L03.9Foot celluftis $\vee$ N06.9F hermidins211physicianS0034,50011,50142J39.9A hormality of respiration $\vee$ 101Hypertension212physicianS0011J39.9A hormality of respiration $\vee$ 101Hypertension213physicianS0011J18.9P hermonia $\wedge$ A41.95 epticernia214physicianS0011J18.9P hermonia $\vee$ A41.95 epticernia215physicianS0011,50142J18.9P hermonia $\vee$ A41.95 epticernia216physicianS0011J18.9P neuronia $\vee$ A41.95 epticernia217physicianS0034,5001,50142J18.9P neuronia $\vee$ J16.9 Intracerebral218physicianS0034,5001,50142N18.9C nonic renal failure $\vee$ J11.8 fnfluenza $\vee$ M00.95 eptidernia217physicianS001S007,50070218physicianS0010S007219physicianS0015N18.9C nonic renal failure $\vee$ J18.6 PSI Proficernia217physicianS003S0036218physicianS0036	204	physician	S0013,S0042,S0109	J42Chronic bronchitis < E27.9Insufficiency of adrenocortical function <ul> <li>K29.0A cute gastritis</li> </ul>
206physicianS0473,S0092,S0237K92.29Acute gastroenteritis v R31Hematuria207physicianS0437G62.93Peripheral neuritis v N18 9Chronic renal failure208physicianS000,S0437G62.93Peripheral neuritis v N18 9Chronic renal failure209physicianS000,S0437G02.93Peripheral neuritis v N18 9Chronic renal failure209physicianS000,S0437G02.97Peripheral neuritis v N18 9Chronic renal failure210physicianS000,S0437G02.97Peripheral neuritis v N18 9Chronic renal failure211physicianS0034,S0011,S0142M00.9 Suppurative arthritis v L03.9 Foot cellulitis v M06.9Rheumatoid212physicianS0034,S0011,S0142J13.9Abnormality of respiration v 10Hypertension213physicianS0034,S0011,S0142J13.9Pheuronia v A41.9Septiternia214physicianS0034,S0011,S0142J13.9Pheuronia v A41.9Septiternia215physicianS0034,S0011,S0142M00.9Epipesy v G62.9Peinpheral neuritis v [61.9 Intracerebral215physicianS0034,S0011,S0142M18.9Chronic renal failure v J11.8Influenza v K76.Nephrotic213physicianS0034,S0011,S0142M18.9Chronic renal failure v J11.8Influenza v K76.Nephrotic214physicianS0034,S0011,S0142M18.9Chronic renal failure v J11.8Influenza v K76.Nephrotic215physicianS0034,S0010,S0070N18.9Chronic renal failure v J11.8Influenza v K76.Nephrotic216physicianS0034,S0010,S0070N18.9Chronic renal failure v J11.8Influenza v K76.Nephrotic217physicianS003	205	physician	S0008,S0023,S0075,S0296	K25Gastric ulcer and bleeding 、 M06.9Rheumatoid arthritis
207physicianS0437G62.93Peripheral neuritis $\land$ N18.9Chronic renal failure208physician $$000,$0437$ G62.93Peripheral neuritis $\land$ N18.9Chronic renal failure209physician $$000,$0437$ C20Parkinson's disease $\lor$ G40.95Pilepsy $\land$ F51.0-F51.95Iep disorde210physician $$000,$0437$ C20Parkinson's disease $\lor$ G40.95Pilepsy $\lor$ F51.0-F51.95Iep disorde211physician $$000,$0437$ C20Parkinson's disease $\lor$ G40.95Pilepsy $\lor$ F51.0-F51.95Iep disorde212physician $$0034,$0011,$0142$ $$103.97$ ot celluftis $\lor$ M06.9Rheumatoid213physician $$0034,$0011,$0142$ $$139.9A$ hnomality of respiration 110Hypertension214physician $$0034,$0011,$0142$ $$139.9A$ hnomality of respiration 110Hypertension215physician $$0034,$0011,$0142$ $$139.9A$ hnomality of respiration 110Hypertension216physician $$0034,$0011,$0142$ $$139.9A$ hnomality of respiration 110Hypertension217physician $$0034,$0011,$0142$ $$10.95$ Hneumania $\land$ A1.95217physician $$0034,$0011,$0142$ $$118.94$ hneumalis $\checkmark$ I61.9 hntracerebral218physician $$0034,$0011,$0142$ $$118.96$ hneumatis $\checkmark$ I61.9 fntracerebral217physician $$0034,$0011,$0142$ $$118.96$ hneumatis $\checkmark$ I61.9 F51.0F51.95218physician $$0034,$0011,$0142$ $$118.96$ hneumatis $\checkmark$ I11.8 fntuerza219physician $$0039,$0000$111,$0142219physician$0038,$0011,$0142$100.95hphysican210phy$	206	physician	S0473,S0092,S0237	K92.29A cute gastroenteritis × R31Hematuria
208physician $$000,$0437$ G20Parkinson's disease < G40.9Fpilepsy > F51.0-F51.9Sleep disorder209physician $$0008$ $103.9Foot cellultiis < C55 Fhroid × 110Hypertension$	207	physician	S0437	G62.93Peripheral neuritis × N18.9Chronic renal failure
209physicianS0008L03.9Foot cellulitis 、C55 Fibroid、110Hypertension210physician $$0218,80092$ M00.9 Suppurative arthritis 、L03.9 Foot cellulitis 、M06.9 Rheumatoid211physician $$0034,80011,80142$ J39.9 Abnomality of respiration × 110Hypertension212physician $$0034,80011,80142$ J39.9 Abnomality of respiration × 110Hypertension213physician $$0034,80011,80142$ J39.9 Abnomality of respiration × 110Hypertension214physician $$0034,80011,80142$ $$00.9$ Fiplepsy v 662.9 Peripheral neuritis × 161.9 Intracenda215physician $$0034,80011,80142$ $$018.9$ Chronic renal failure × J11.8 Influenza × K/6.7 Nephrotic216physician $$0057,80070$ $$N18.9$ Chronic renal failure × J11.8 Influenza × K/6.7 Nephrotic217physician $$0057,80070$ $$N18.9$ Chronic renal failure × J11.8 Influenza × K/6.7 Nephrotic218physician $$0034,80011,80142$ $$N18.9$ Chronic renal failure × J11.8 Influenza × K/6.7 Nephrotic219physician $$0057,80070$ $$N18.9$ Chronic renal failure × J11.8 Influenza × K/6.7 Nephrotic217physician $$0057,80070$ $$N18.9$ Chronic renal failure × J11.8 Influenza218physician $$0008$ $$N18.9$ Chronic renal failure × J11.8 Influenza219physician $$0008$ $$N18.9$ Chronic renal failure × J11.8 Influenza219physician $$N098$ $$N00998$ 219physician $$N008$ $$N00898$ 210physician $$N09898$ 211physician <td< td=""><td>208</td><td>physician</td><td>S000,S0437</td><td>G20Parkinson's disease 、 G40.9Epilepsy 、 F51.0-F51.9Sleep disorder</td></td<>	208	physician	S000,S0437	G20Parkinson's disease 、 G40.9Epilepsy 、 F51.0-F51.9Sleep disorder
$210$ physician $S0218,S0092$ $M00.9$ Suppurative arthritis $\cdot$ L03.9 Foot cellulitis $\cdot$ $M06.9$ Rheumatoid $211$ physician $S0034,S0011,S0142$ $J39.9$ Abnormality of respiration $\cdot$ 110 Hypertension $212$ physician $S0034,S0011,S0142$ $J39.9$ Abnormality of respiration $\cdot$ 110 Hypertension $212$ physician $S0034,S0011,S0142$ $J39.9$ Abnormality of respiration $\cdot$ 110 Hypertension $213$ physician $S0034,S0011,S0142$ $J18.9$ Heuronia $\cdot$ $A1.9$ Septicenia $214$ physician $S0034,S0011,S0142$ $Henronia (-11.8) Henronia (-11.8) Henronia)215physicianS0057,S0070N18.9 Chronic renal failure \cdot J11.8 Influenza \cdot K76.7 Nephrotic217physicianS0057,S0070N18.9 Chronic renal failure \cdot J11.8 Influenza \cdot K76.7 Nephrotic218physicianS0057,S0070N18.9 Chronic renal failure \cdot J11.8 Influenza \cdot K76.7 Nephrotic218physicianS0057,S0070N18.9 Chronic renal failure \cdot J11.8 Influenza \cdot K76.7 Nephrotic218physicianS0034,S0014,S008M00.9 Suptomative arthritis218physicianS0038M00.9 Suptomative arthritis219physicianS0038M00.9 Suptomative arthritis218physicianS0038M00.9 Suptomative arthritis219physicianS0038M00.9 Suptomative arthritis219physicianS0038M00.9 Suptomative arthritis218physicianS0473M00.9 Suptomative arthritis$	209	physician	S0008	L03.9Foot cellulitis 、C55 Fibroid 、I10Hypertension
211physician $S0034,S0011,S0142$ $J39.9A$ hormality of respiration $I10$ Hypertension $212$ physician $S0011$ $J13.9P$ hermonia $A41.9S$ peticerria $213$ physician $S0011$ $S0011$ $J13.9P$ hermonia $A41.9S$ peticerria $214$ physician $S0034,S0011,S0142$ $A05.9F$ od poisoring, urindicated $214$ physician $S0034,S0011,S0142$ $G40.9E$ pilepsy $G62.9P$ eigheral neuritis $I61.9$ Intracerebral $214$ physician $S0034,S0011,S0142$ $R40.9E$ pilepsy $G62.9P$ eigheral neuritis $I61.9$ Intracerebral $215$ physician $S0057,S0070$ $N18.9$ Chronic renal failure $J11.8$ fnfluenza $K76.7$ Nephrotic $217$ physician $S0210$ $N18.9$ Chronic renal failure $J11.8$ fnfluenza $K76.7$ Nephrotic $218$ physician $S0210$ $N18.9$ Chronic renal failure $J11.8$ fnfluenza $K76.7$ Nephrotic $218$ physician $S0210$ $N18.9$ Chronic renal failure $J11.8$ fnfluenza $K76.7$ Nephrotic $218$ physician $S0210$ $N18.9$ Chronic renal failure $J11.8$ fnfluenza $K76.7$ Nephrotic $218$ physician $S00473$ $N00.9$ Suppurative arthritis $218$ physician $S0473$ $N0.9$ Chronic renal failure $S10.451.9$ Chronic renal failure $S1$	210	physician	S0218,S0092	M00.9 Suppurative arthritis × L03.9 Foot cellulitis × M06.9Rheumatoid arthritis
212physicianS0011 $118.9$ Pneumonia $A1.9$ Septicenia213physician $S0011$ $A05.9$ Food poisoning, unindicated214physician $S0034, S0011, S0142$ $G40.9$ Epilepsy $G62.9$ Peripheral neuritis $Y 161.9$ Intracerebral215physician $S0057, S0070$ $N18.9$ Chronic renal failure $Y 11.8$ Influenza $K/6.7$ Nephrotic217physician $S0057, S0070$ $N18.9$ Chronic renal failure $Y 11.8$ Influenza $K/6.7$ Nephrotic218physician $S0057, S0070$ $N18.9$ Chronic renal failure $Y 11.8$ Influenza $K/6.7$ Nephrotic218physician $S00210$ $N18.9$ Chronic renal failure $Y 11.8$ Influenza $K/6.7$ Nephrotic218physician $S0034, S0070$ $N18.9$ Chronic renal failure $Y 11.8$ Influenza $K/6.7$ Nephrotic218physician $S0037, S0070$ $N18.9$ Chronic renal failure $Y 11.8$ Influenza $K/6.7$ Nephrotic219physician $S00473$ $N0.95$ Uppurative arthritis219physician $S0473$ $N0.9$ Atherosclerosis $V 100$ Hypertension	211	physician	S0034,S0011,S0142	J39.9A bnormality of respiration < 110Hypertension
213physicianS0011A05.9Food poisoning, unindicated214physicianS0034,S0011,S0142G40.9Epilepsy G62.9Peripheral neuritis / I61.9 Intracerebral Hernorhage215physicianS0057,S0070N18.9Chronic renal failure / J11.8Influenza / K76.7Nephrotic Syndrome217physicianS0057,S0070N18.9Chronic renal failure / J11.8Influenza / K76.7Nephrotic Syndrome218physicianS0210M86.9Acute osteonyelitis / F51.0-F51.9Sleep disorder ' M00.9Suppurative arthritis218physicianS0008J11.8Influenza219physicianS0473T70.9Atherosclerosis / 10Hypertension	212	physician	S0011	J18.9Pneumonia × A41.9Septicenia
214physicianS0034,S0011,S0142G40.9Epilepsy、G62.9Peripheral neuritis × I61.9 Intracerebral Hemorrhage215physicianS0057,S0070N18.9Chronic renal failure × J11.8Influenza × K76.7Nephrotic Syndrome217physicianS0057,S0070N18.9Chronic renal failure × J11.8Influenza × K76.7Nephrotic Syndrome218physicianS0210M86.9Acute osteomyelitis × F51.0-F51.9Sleep disorder × M00.9Suppurative arthritis218physicianS0008J11.8Influenza219physicianS0473T/0.9Atherosclerosis × 110Hypertension	213	physician	S0011	A05.9Food poisoning, unindicated
215physicianS0057,S0070N18.9Chronic renal failure > J11.8Influenza × K76.7Nephrotic Syndrome217physicianS0210M86.9Acute osteomyelitis × F51.0-F51.9Sleep disorder > M00.9Suppurative arthritis218physicianS0008J11.8Influenza219physicianS0473T70.9Atherosclerosis × 110Hypertension	214	physician	S0034,S0011,S0142	G40.9Epilepsy 、G62.9Peripheral neuritis 、 I61.9 Intracerebral Herrorrhage
217physicianS0210M86.9A cute osteonryelitis × F51.0-F51.9Sleep disorder × M00.9Suppurative arthritis218physicianS0008J11.8Influenza219physicianS0473I70.9A therosclerosis × 110Hypertension	215	physician	S0057,S0070	N18.9Chronic renal failure × J11.8Influenza × K76.7Nephrotic Syndrome
218     physician     S0008     J11.8Influenza       219     physician     S0473     I70.9Atherosclerosis × 110Hypertension	217	physician	S0210	M86.9A cute osteomyelitis × F51.0-F51.9Sleep disorder × M00.9Suppurative arthritis
219 physician S0473 S0473 T70.9Atherosclerosis × 110Hypertension	218	physician	S0008	J11.8Influenza
	219	physician	S0473	I70.9A therosclerosis < I10 Hypertension

data
nostic
diag
Coded
3
Fig.



Fig. 3 Execution interface of data mining disease symptom concealment disease tendency



Fig. 4 Result interface of data mining disease symptom concealment disease tendency



Fig. 5 The number of diagnostic data that is prone to disease progression

# Conclusion and future research directions

The medical data can record the clinic departments, the symptom statements of the patients, the Chinese name of the diseases, its corresponding ICD-10-CM code, prescription drugs and other data when the patient sees the doctor. The clinic data hide the diagnostic capacity, experience and knowledge of the diseases. If they can be managed and applied, the people can check the symptom has the disease and some useful referent information can be offered. The paper regards the diagnostic data as the data mining source, a patient's symptom as the mining target and designs a clustering method. The mining results can receive the efficiency of treatment and can offer some useful referent information and efficiency. The research uses the PAM algorithm as the main reference and the modified methods. The following research directions are as follows:

- (1) Discuss the difference and efficiency between the research and other clustering methods, such as *k*-means, CLARANS and others.
- (2) Discuss the feasibility and effectiveness of the topic with the use of other data mining technologies, such as the association rules.
- (3) Discuss the effectiveness of a clinic department.
- (4) Improve the reliability and kindness of the operation in the system and promote the usefulness of the actual application.
- (5) Improve the mining methods designed in the research and promote the executing efficiency of the mining.

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