Estimation of LOS level in hospitalization with multiple attributes: taking patients with kidney disease as an example

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Research article

Keywords: LOS, Multi-variable multi-level, Projection pursuit, Clustering and discriminant

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Abstract

Abstract: Aim: Thinking of the relationship between Multiple attributes and length of stay(LOS).This paper provide LOS level prediction method with applying a classification estimation of multi-avariables statistic,also provides suggestions of diversion management for kidney disease patients.

Methods: We use three steps to finish the estimation. Firstly, Using the correlation-coefficient between the variable and LOS to find some sensitive factors; secondly,using projection pursuit clustering analysis to find the weight of each factor, then calculation the weighting value to discriminant the LOS level.thirdly, using mean test to give the multi-level classification of LOS based on the most sensitive factor.

Results: We use 12547 kidney disease patients' data in the year 2016 from a large hospital in the Department of Nephrology to applying the estimation method. The correlations results shows that the influence of variables on LOS are ranked as disease types>age>cost.The means test results demonstrate that patients with kidney disease are divided into 3 levels between 2-20 days of los. Short-term patients (los=2-9) are mainly treated with regular treatment; medium-term patients (los=10-15) are accompanied by emergency and acute attacks; long-term patients (los=16-20) need more treatments and long hospital observation period.Tested by multi-attribute multi-level discriminant model, Indicated that the kidney patients sample data can be modeled well by the builded models.

Conclusion: We build the multi-variable multi-level discriminant model for LOS estimation, which is successively applied in kidney disease. The research offers a new way for LOS estimation through the Multi-variables.

Key words:LOS; Multi-variable multi-level; Projection pursuit; Clustering and discriminant

1.introduction

Length of stay (LOS) is an important performance indicator for costing and hospital management and a key measure of efficiency [(1)], Estimate the LOS in a large hospital in advance, and make a rehabilitation plan for the development of patients with primary care, which is extremely necessary for hospital resource management and medical insurance actuarial methods[(2)]. And plays a vital role in the strategic decision-making of health care managers [(3)].

In the study of the influencing factors of los, according to the characteristics of it, the influencing factors have certain differences. In terms of average hospitalization days, the impact dimension can be divided into three. Firstly, the patient demographic characteristics, including age, gender, and household registration; secondly, medical characteristics, including patient admission, medical equipment, treatment level, hospitalization waiting time, surgery level, hospitalization method, proportion of doctors, and bed occupancy rate Etc. Finally,the medical environment characteristics, such as fees and medical funds, affect the average hospitalization period of patients [(4-13)], among which the disease occupies an important position. In terms of over-long hospitalization, the study found that the proportion of patients

with long hospital stay was 76.03%, followed by patients (13.7%), doctors (8.51%) and others (1.77%). Di Jiebin [14]); the proportion of diseased patients was 86.83% when the los was more than 30 days (Jing Ling [15]); 85.75% of the reasons for long-term hospitalization were the cause of the disease itself [16].

In the LOS estimation based on historical data,using quantitative analysis methods most, including univariate survival function fitting method [2], multivariate regression method [17-19], and supervised machine learning method [20-22]. Using the survival function to fit the LOS distribution of a certain type of patient [23], can obtain the probability of the patient's LOS and the statistics, mean and variance in the sample group. This estimate has public health and insurance significance. But can not meet the needs of hospital operations management. In addition, when adopt the multivariate regression prediction method, los is the result of uncertainty under the influence of multiple factors. The influence of each attribute on los is nonlinear, and data acquisition is difficulty. So, it is difficult to accurately predict the los of each patient[24]. From the perspective of satisfying the patient's batch operation and care, we adopt the multi-attribute multi-level estimation method [25], only estimate the possible LOS interval of the patient,and identify the patient’s characteristics in the interval, then give the resource operation to each interval patient and care recommendations. This method can not only reduce the data requirements, but also meet the needs of hospital operation management.

In this paper, combined with the study of los influencing factors, taking kidney disease as an example, using correlation analysis to identify the key factors affecting LOS; then, using projection pursuit clustering[26] gives an estimation model of multi-level LOS, and selects typical patients for discriminant test to verify the calculation effect of the model;finally,based on the multi-factor influence matrix of LOS, using the mean test between groups to determine the multi-level of LOS.

2. Data And Methods

2.1 Data Source and Quantification

This paper selects the data of inpatients in the kidney department of a large hospital in 2016, including the los, age, cost, medical insurance (city, new rural cooperative, urban and rural, other, provincial medical insurance (this level), no medical insurance patients) and disease. The cumulative percentage of samples with LOS=2-20 is 88.8%, it is far more than half of the total and it is considered to be better representative. As shown in the Table1.

Table1. Sample capacity for different hospital stays

LOS（day）	Sample size	percentage	Cumulative percentage
2	1958	15.6%	15.6%
3	193	1.5%	17.1%
4	355	2.8%	20.0%
5	315	2.5%	22.5%
6	690	5.5%	28.0%
7	1221	9.7%	37.7%
8	965	7.7%	45.4%
9	650	5.2%	50.6%
10	108	4.8%	55.4%
11	547	4.4%	59.8%
12	533	4.2%	64.0%
13	683	5.4%	69.5%
14	753	6.0%	75.5%
15	419	3.3%	78.8%
16	295	2.4%	81.2%
17	236	1.9%	83.1%
18	254	2.0%	85.1%
19	218	1.7%	86.8%
20	252	2.0%	88.8%
>20	1402	11.2%	100%
□□	12074	100%	100%

In order to facilitate quantitative analysis, the attribute variables such as medical insurance and disease are numerically quantified, using Y, X1, X2, X3, and X4 respectively indicate LOS, disease, age, cost, and medical insurance,Among them, the disease is a keyword-based web crawler [27] high-frequency words after screening for diagnosis of medical records.The value of the variable assignment is shown in Table□.

Table□. Variable assignment

factor	variable name	Assignment
LOS	Y	Actual value
Diseases	X_1	1 = non-insulin-dependent diabetes mellitus with renal complications, 2 = chronic renal failure, uremia, 3 = chronic renal failure, 4 = lupus nephritis, 5 = chronic glomerulonephritis, 6 = nephropathy Sign
Age	X_2	Actual value
Cost	X_3	Actual value
Medical insurance	X_4	1 = city position, 2 = new rural cooperative, 3 = urban and rural, 4 = other, 5 = provincial medical insurance, 6 = no medical insurance patient

2.2 Modeling Step

(1)Identify key influencing factors. Using single factor correlation test of SPSS 24.0 software to test the correlation between influencing factors and LOS respectively,According to the significance test results to identify the key influencing factors of LOS, namely vector Xj (j=1, m), m is the key factors quantity.

(2)According to the key influencing factors of LOS,Using the projection pursuit dynamic clustering method[26] to calculate the projection pursuit value Z and as the basis for patient classification. The basic expression of projection pursuit clustering is equation (1):

$$Z = a_1X_1 + \cdots + a_jX_j + \cdots + a_mX_m \qquad (1)$$

Where “a” represents the projection direction.

3. Empirical Study

3.1 LOS Influence Factor Identification

The results of the relationship between cost, age, medical insurance, disease and los are shown in Table 1:

Table 1. Correlation between four factors and LOS

LOS Factors	Correlation coefficient	Significant（Bilateral）
Cost	0.09	0.000
Age	0.650	0.000
Medical insurance	-0.017	0.129
Diseases	0.720	0.000

According to the correlation results of Table 3-1, at the confidence level of P < 0.01, cost, age, and disease type are a significant correlation to LOS.

3.2 Projection Pursuit Clustering Discrimination

The 10672 samples of the sample data are substituted into the equation (2), and the obtained projection value function is the equation (3) ,The scatter plot of the projection values is shown in Figure.

$$Z = \text{Disease} \times 0.062320 + \text{Age} \times 0.000406 + \text{Cost} \times 0.000041 \quad (2)$$

$$Z = \text{Disease} \times 0.992878 + \text{Age} \times 0.000468 + \text{Cost} \times 0.000653 \quad (3)$$

Fig.. Projection pursuit clustering result

According to the value of “a”, the proportion of weights of each factor can be seen. The disease has the largest proportion in the LOS classification of patients, followed by age and cost again. According to the value range of the Z value in the figure, it can be clearly seen that the patients are divided into three categories. The Z value range of the first type is 0-0.3, The Z value range of the second type is 0.3-0.7. The Z value range of the third type is 0.9-1.2. Calculate the Z-means of each interval separately, as shown in Table .

Table . Z-means at different LOS levels

LOS level	LOS length/Day	Projection pursuit Z-means
Short term	2-9	0.296819
Medium term	10-15	0.591746
Long term	16-20	0.973080

3.3 Discriminant Test

Using one sample to discriminant analysis of LOS levels.The process of discriminantion is as follows:

First, select any set of [X_1, X_2,..., X_m] ,("m" is the key factors quantity) and calculate the Z value by equation (3) , then refer to Table 3-2 Z is worthy of LOS^ under different LOS levels. Finally, it is tested whether the actual LOSLOS^ is established, that is, whether the LOS level estimation model is valid.

- Attribute alignment

1.Taking a group of [X_1, X_2, X_3] patient data[4, 20, 928.45]under the LOS = 2-9 level and substitute the equation (3) to calculate the Z value is 0.295466. Referring to Table 3-2 for LOS^ = 2-9 days, the actual LOS = 3 days, that is, LOS = 3 days LOS^ = 2-9 days.

2.Taking a group of [X_1, X_2, X_3] patient data [1, 61, 12083.32] under the LOS = 10-15 level and substitute the equation (3) to calculate the Z value is 0.582502. Referring to Table 3-2 for LOS^ =10-15 days, the actual LOS = 15 days, that is, LOS = 15 daysLOS ^ = 10-15 days.

3.Taking a group of [X_1, X_2, X_3] patient data [6, 68, 13511.34] under LOS = 16-20 level and substitute the equation (3) to calculate the Z value is 0.955042. Referring to Table 3-2 for LOS^ = 16-20 days, the actual LOS = 20 days, that is, LOS = 20 daysLOS ^ = 16-20 days.

- Unqualified attribute

Taking a group of [X_1, X_2, X_3]patient data [4, 34, 6478.05] substituted the equation (3) to calculated the Z value is 0.529053, Referring to Table 3-2 for LOS ^=10-15 days, the actual Los = 9 days, that is,LOS = 9 days LOS ^ = 10-15 days.

In summary, the multi-attribute multi-level LOS estimation model is effective in a limited sample case and can contribute to medical care to a certain extent.

4. Results And Discussion

4.1 Characteristic Analysis of Influencing Factors

- Disease

The average LOS of patients with disease types 1, 2, and 3 was 11.19, 10.69, and 10.91 days respectively. The average LOS of patients with disease 4 and 5 was 8.92 and 8.62 days, and the average LOS of patients with disease type 6 was 17.51 days. Referring to the results of Di Jiebin and Jing Ling [14,15], patients with LOS=2-20 days were classified according to the disease type, the patient's disease level can be divided into three categories. The classification results are shown in Table .

Table. Classification of LOS=2-20 days based on disease type

Diseases	Los/Day	Cumulative percentage/%
4、5	2-9	68.9
1、2、3	10-15	70
6	>15	—

- Age

Refer to the disease classification and statistics of the age of each patient, as shown in Table.As can be seen,when LOS is 2-9 days, the proportion of youth is the highest ,accounting for 52.1%, the age attribute is 16-45 years old;when LOS is 10-15 days,the proportion of strong year is the highest ,accounting for 41.5%, the age attribute is 46-65 years old;when LOS is 16-20 days, the proportion of old is the highest ,accounting for 43%, the age attribute is >65 years old.

Table . Proportion of LOS in the age dimension

LOS/Day	Juvenile（8-15year）	youth（16-45year）	Strong year（46-65year）	Old （>65year）	Age level/year
2-9	1.1%	**52.1%**	33.4%	13.4%	16-45
10-15	0.7%	39.5%	**41.5%**	18.3%	46-65
16-20	0.6%	20%	36.4%	**43%**	>65

- Costs

According to the value of LOS, the patients are divided into 20 groups, and the per capita cost of each group is calculated. The hospitalization days are taken as the X-axis, and the per capita cost is plotted on the Y-axis, as shown in Figure .

Fig. Scatter plot of hospital stay and per capita cost

The linear correlation and regression analysis are performed on the above two cases, and the results are shown in Table .

Table 3. Regression analysis of hospitalization days and hospitalization cost

LOS/Day	Linear regression	t	p	Cumulative percentage	Cost level/Yuan
≤15	Y=645.416+852.245X	19.205	<0.01	0.983	645.416
>15	Y=7414.283+549.580X	1.510	>0.05	0.730	7414.283

It can be seen from Table 4-3 that when Los is 15 days, the length of hospital stay is positively correlated with the per capita cost; when LOS>15 days, the linear relationship between the two is not obvious, indicating that the longer the hospital stay, the more uncertain the cost.

(4) Comprehensive statistics

At the three levels of LOS, the characteristic properties of the above variables have certain differences, as shown in Table 4.

Table 4. Multi-attribute multi-level matrix of Los=2-20

LOS/Day	Demographic characteristics/Year	Medical characteristics	Cost level/Yuan
2-9	youth(16-45)	4、5	645.416
10-15	Strong year(46-65)	1、2、3	
16-20	Old(>65)	6	7414.283

4.2 Result Analysis

- The LOS level of patients with kidney disease is level 3, which results in the attribute factors affecting los shared decision making ranked as disease> age > cost. The reasons for this phenomenon may be:

1.The severity of the patient's condition and the characteristics of the disease seriously affect the hospitalization days of the patients. It is known from Table 4-4 that the short-term hospitalization period of disease is 4 or 5. The main features are regular treatment.The medium-term hospitalization period of disease is 1, 2, and 3, The main features are mainly characterized by emergency and acute attacks. The long-term hospitalization period of disease is 6. The main features are related to more treatment methods and longer observation period. It can be seen that the severity of the disease and the characteristics of the disease are the main factors affecting LOS, as well as the results of Di Jiebin and Jing Ling. There are also reports that LOS is related to the demographic characteristics and severity of the disease, but the factors affecting different countries, regions and different populations are completely different [19].

2.Age characteristic factors of the results of the inter-group difference test for different lengths of stay under X_2 showed that patients with different ages had different hospitalization days.This may be related

to the characteristics of elderly patients with older age, more basic diseases, slower treatment and longer recovery period. Therefore, it is particularly important to pay attention to the health of middle-aged and elderly patients.

- Analysis of attribute difference characteristics.

According to the projection pursuit clustering learning results, the most important attribute factor affecting LOS shared decision-making is the disease, followed by age, and finally cost. The reasons for this are as follows:

1.For patients with kidney disease, the severity of the disease determines the LOS,and the accurate diagnosis of the disease helps to determine the optimal treatment plan and prognosis to predict the length of LOS.

2.For patients with the same disease, the older the age, the longer the LOS. Although we can't control the age of the inpatients, by establishing an effective two-way referral mechanism, patients who are basically stable after the active treatment or who are in rehabilitation can be transferred to the lower-level medical institutions to continue the follow-up treatment and rehabilitation, How economics makes it cheaper to reduce hospitalization costs and high value-benefit ratios.

3.The cost is the smallest compared to the disease and age. The possible reason is that the proportion of China's medical insurance reimbursement policy is generally higher than that of outpatient services at present, and China is a country that implements a mixed medical payment system. At this stage, the main payment is based on service items (28). Therefore, in order to be able to get additional medical services or affordable drugs, some patients have less obvious considerations about the cost attributes than the first two attributes.

4.3 Suggestions on Patient Shunt Management

According to the attribute alignment and unqualified attribute test results of the discriminant test, we found that the estimation model of LOS under multi-attribute multi-level is effective, but the proposal to manage different levels or different attributes first ,we are based on property management and then los level management recommendations.

1.The type of disease, age, and type of medical insurance cannot be controlled and changed, and the length of patient LOS is closely related to the occupation rate of medical resources and the economic burden of patients [29]. Shortening the patient's LOS is an effective way to improve the hospital's work efficiency and service quality [30], and it also reduces the patient's economic burden and improves the patient's hospitalization treatment process, which plays a vital role in the development of the hospital [31]. Therefore, it is possible to improve hospital management, comprehensively improve medical infrastructure and medical conditions, and rationalize medical resources. It also strengthens the clinical

pathway and single disease management of the department. Uchiyama [32] and other studies have found that the implementation of the clinical pathway can not only regulate the routine diagnosis and treatment operations in the diagnosis and treatment process, reduce unnecessary and unreasonable diagnosis and treatment behaviors, but also regulate the time when the diagnosis and treatment behavior should be completed, etc. The planning of the medical treatment activities.

2.The hospital should focus on the diseases of middle-aged and elderly patients, strengthen the diagnosis and treatment techniques of related diseases, and continuously improve the care for elderly patients, thus shortening the LOS for middle-aged and elderly patients.

3.Strengthen the application of information technology, optimize the admission process, and promote the improvement of medical efficiency, thus shortening the LOS. By establishing an effective two-way referral mechanism, the hospital can transfer patients who are basically stable after the active treatment or enter the rehabilitation treatment period to the lower-level medical institutions to continue the follow-up treatment and rehabilitation. Establish trust between doctors and patients, and make joint decisions on this basis to achieve optimal medical care [33].

5. Conclusions

On the one hand, this paper gives the data-driven LOS attribute recognition method; on the other hand, it gives the multi-attribute decision Los multi-level, after attribute alignment, attribute non-homogeneous test, multi-attribute multi-level hospitalization time LOS estimation model effective. The limitation of the research is that the indicators included in this study have limited dimensions, and the research results have certain limitations, The results of hospitals in different regions or cities and different levels may differ, so only the results of this sample are reflected. The next step is to further collect data from multiple regions, multiple hospitals, and multi-dimensional samples to further investigate the impact of other factors on LOS to explain predictive factors.

Declarations

- **Ethics and Consent to participate**: Not applicable
- **Consent for publication**: Not applicable
- **Availability of Data and Materials**: The data in this manuscript was obtained from the inpatient and outpatient departments of the West China Hospital of Sichuan University. It could only be used for the research detailed in the manuscript and cannot be shared.
- **Competing interests**: The authors declare that they have no competing interests.
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- **Authors' contributions**: The data were collected by Xue Shen. The preliminary and final drafts were written by Xue Shen. The drafts were critiqued by Xinli Zhang. The results were analysed by Xinli Zhang

and Xue Shen. The research and key elements of the models were reviewed by Xinli Zhang and Xue Shen. Writing portions of the manuscript and major revisions of the paper were completed by Xinli Zhang .

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Figures

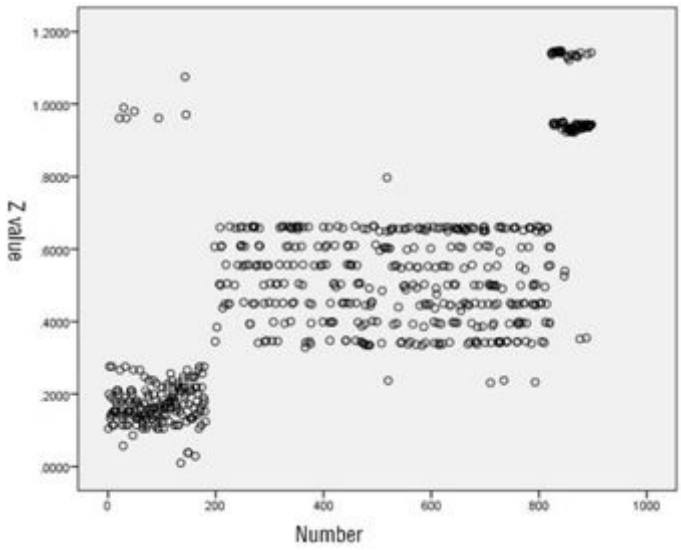

Figure 1

Projection pursuit clustering result

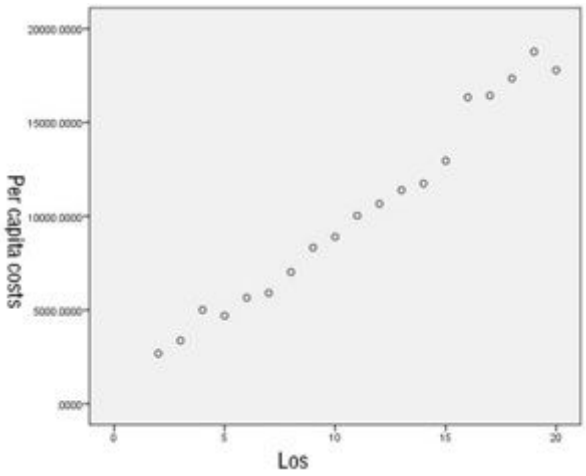

Figure 2

Scatter plot of hospital stay and per capita cost