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Clinical Similarity Based Framework for Hospital Medical Supplies Utilization Anomaly Detection: A Case Study

Ning SUN[a,1], Meilin XU[b], Mingzhi CAI[c], Xudong MA[c,1], Yong QIN[a]
[a] *Ping An Health Technology, Beijing, China*
[b] *Pfizer Investment Co. Ltd. - China, Beijing, China*
[c] *Zhangzhou Municipal Hospital of Fujian Province, Fujian, China*

Abstract. Healthcare systems are costly in many countries, and hospitals have always been one of the major cornerstones of the healthcare industry. Medical supplies expense is an increasingly substantial category of hospital costs. In China, the expense of medical supplies is being controlled at the hospital level. Different from drug prescription, medical supplies utilization is not being standardized or guided by clinical guidelines. In order to achieve the goal, many hospitals directly disable the use of the most expensive medical supplies. One missing piece in consideration is the patient heterogeneity, which decides the medical necessity for a specific surgery/procedure and the associated medical supplies requirement. The other challenge is to justify the substitutability of the medical supplies being replaced. In this study, we explore a clinical similarity based framework to analyze the inpatient medical supplies use records and detect unnecessary utilization. More specifically, the inpatient stays are clustered based on patients' clinical conditions. After clustering, inpatient cases within each sub-group should have similar clinical necessities and therefore similar medical supplies utilization patterns. Thus the unnecessary medical utilization can be identified and the cost reduction suggestions can be provided accordingly. This framework will be illustrated though a case study of 3-year inpatient records from a Chinese hospital.

Keywords. medical supplies utilization, clinical similarity, anomaly detection

1. Introduction

Healthcare systems are costly in many countries. In 2016, the United States spent $3.4 trillion for healthcare, 19% of its GDP [1]. In China, healthcare expenditure in 2016 increased by 10% year-on-year to reach 1,315 billion yuan, which was 7% of its GDP [2]. Hospitals have always been one of the major cornerstones of the healthcare industry. In the US, 32% of this healthcare expenditure is attributed to hospital care in 2016. Medical supplies expense is an increasingly substantial category of hospital costs. A study showed that in 2013, U.S. hospitals on average spent $3.8 million on (tangible) supply expenses, and about 60% of the total supply expenses are medical supplies [3].

In China, the expenses in medical supplies are being controlled at the hospital level, with a requirement of 20% in the total expense excluding the expense on drugs. As this constitutes a substantial portion of the total cost structure, hospitals tend to cut the unnecessary supplies utilization to reduce costs. Different from drug prescription,

[1] Corresponding Authors. E-mail: sunning1023@yahoo.com, xudongma05@yahoo.com

medical supplies utilization is not being standardized or guided by clinical guidelines. Therefore many hospitals simply replaced the most expensive medical supplies by their "cheaper substitutes".

One missing piece in consideration is patient heterogeneity, which decides the medical necessity for a specific surgery/procedure and the associated medical supplies requirement. And for the same surgery/procedure, there are a variety of medical supplies of different qualities, technologies and prices in the market. Thus the second challenge is to justify the substitutability and cost-effectiveness of the medical supplies being used, and conduct anomaly detection to identify unnecessary utilization.

To address these challenges in medical supplies cost management, we explore a clinical similarity based analysis framework in Section 2, and conduct a case study of 3-year inpatient records from a Chinese hospital in Section 3. The conclusions are discussed in Section 4.

2. Analysis Framework

In the clinical similarity based framework, there are two stages:

- Clustering inpatient cases based on patients' clinical conditions therefore in each subgroup inpatient cases are homogeneous in terms of clinical necessities for surgeries/procedures, and accordingly medical supplies utilization;
- Identifying unusual/unnecessary medical supplies utilization patterns within each subgroup, and providing cost reduction suggestions.

2.1. Inpatient case clustering

Instead of directly using an unsupervised machine learning algorithm to cluster the patients, we need to build a clustering system to ensure the clinical meaningfulness. For this purpose, we adopt a similar design to the Diagnosis-Related Group (DRG) system. A DRG is a statistical system of classifying any inpatient case into groups for the purposes of payment. By definition, DRGs classify cases according to: principal and secondary diagnoses, patient age and sex, the presence of co-morbidities and complications and the procedures performed. Thus, cases within the same DRG are economically and medically similar [4]. Since the 1990s, payments based on DRGs have gradually become the principal means of reimbursing hospitals for acute inpatient care in most high-income countries [5]. In China, the CN-DRG pricing and payment system was released recently as an important step in the healthcare reform. The hierarchical grouping flowchart in CN-DRG is shown as the green chart in Figure 1 [6].

We design a similar grouping framework with a different ordering of the patient-specific variables as shown as the blue chart in Figure 1. The hierarchy starts from the department of an inpatient case, as this is the basic cost management unit in a hospital. The second level is the procedure (both surgical and non-surgical) performed during the inpatient stay, as this is the determinant of the medical supplies utilization. After that, we will explore if an inpatient case can be further classified by diagnoses and clinical characteristics. Diagnosis are represented in ICD-10 code or Major Diagnostic Categories (MDC) [6, 7]. The diagnoses in each MDC correspond to a single organ system or etiology and in general are associated with a particular medical specialty.

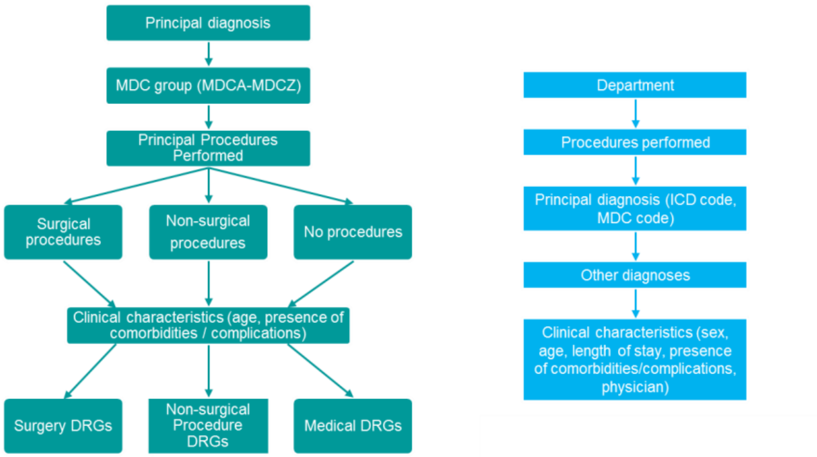

Figure 1. Left: CN-DRG grouping flowchart; Right: grouping flowchart in our framework

In our case study, grouping of each level is implemented via Classification and Regression Tree. The hierarchy of "department (dep.) -> procedure (proc.) -> diagnoses (diag.)" has been verified as the optimal hierarchy, as it returned the largest overall R-squared as shown in Table 1. The system design has also been discussed with clinical experts to ensure the clinical meaningfulness.

We have also tried multi-task learning techniques to simultaneously group patients at each level based on two tasks, their medical supplies expenses and total hospital expenses. The overall performance is not satisfying as shown in Table 1.

Table 1. Comparison of different grouping hierarchies (in the 11 departments with highest medical supplies)

	dep. -> proc.	proc. -> diag.	dep. -> diag. -> proc.	**dep. -> proc. -> diag.**
R-squared	0.385	0.423	0.403	**0.459**

2.2. Anomaly detection and intervention suggestion

After clustering, patients within each subgroup should have similar clinical necessities and similar medical supplies costs. Both point and contextual anomaly detection methods can be applied within the subgroup to identify the super users with abnormally high medical supplies costs [8]. Furthermore, the abnormal medical supplies costs can be linked to causal factors including the selections of medical supplies, operating surgeons, anesthesia methods, surgical incision types, etc. This can be established through a classification model applied on the inpatient cases. Cost reduction suggestions are provided accordingly, which target to manage these factors.

3. Case Study

3.1. Data description

Our study data is from a hospital in Fujian Province of China (average local GDP per capita was 62,507 RMB in 2016). Over the 3-year period from 2014 to 2016, there were 211,206 inpatient records of 164,164 patients in its 40 departments including departments of cardiothoracic surgery, cardiology, neurosurgery, neurology, pediatrics, gastroenterology, general surgery, stomatology, ophthalmology, orthopedics, etc.

In this case study, instead of using the amount of medical supplies expense, we use its percentage $msc\%$ in the hospital expense as the metric to evaluate the medical supplies utilization, as this is the KPI used by hospitals. More specifically, this medical supplies expense percentage is defined as $ms\% = \frac{\text{medical supplies expense}}{(\text{total hosptical expense} - \text{drug expense})}$. The metric is defined from the spending point-of-view at a hospital level (hospital $ms\%$). It can be calculated from the consumption point-of-view for any inpatient stay (individual $ms\%$) as well.

The management target of hospital $ms\%$ is 20%. In our data, the hospital aggregate $ms\%$ is 37.25% over the 3 years, with 17 departments out of 40 having $ms\%$ higher than 20%. Detailed statistics of 11 selected department with the highest medical supplies expenses are shown in Table 2, showing the significant differences across departments. Orthopedics, neurosurgery and cardiology departments tend to have the highest $ms\%$; while neurology and cardiology departments tend to have the highest coefficient-of-variation in individual $ms\%$ of each inpatient case.

Table 2. Selected hospital departments with the highest medical supplies expense and ms%

Dept.	Inpatient case #	Department ms%	Coef-of-Variation of ms%	Medical supplies expense
Neurosurgery	5386	**58.96%**	0.7127	84,869,197.59
General Surgery II	9662	51.32%	0.7275	75,634,861.37
Cardiology	6504	**58.87%**	**1.1378**	63,327,391.86
Cardiothoracic surgery	5334	52.42%	0.7123	59,103,674.61
General Surgery III	13154	42.07%	0.8938	40,520,632.93
Orthopedics I	4095	**60.55%**	0.9139	39,438,427.73
General Surgery I	10520	33.29%	0.8299	33,453,282.18
Orthopedics II	4945	51.57%	0.8727	30,908,749.28
Gastroenterology	5755	40.26%	0.9439	23,636,854.46
Neurology	6389	35.52%	**1.4880**	21,477,641.16
Ophthalmology	4634	39.62%	0.6863	11,122,949.66
p-value	< .001	< .001	< .001	< .001

3.2. Inpatient case clustering result

Figure 2 shows the hierarchical clustering result of patients in Neurosurgery Department.

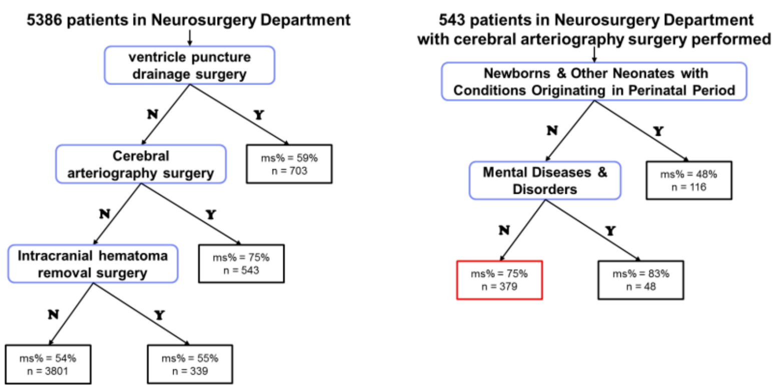

Figure 2. An example of inpatient case clustering in Neurosurgery Department.

The department $ms\%$ is 58.96%, with the average individual $ms\%$ of 39.15%.The left is the first-level clustering based on procedures performed. Three major surgeries significantly influencing $ms\%$ are identified: ventricle puncture drainage, cerebral arteriography and intracranial hematoma removal. The right is the second-level clustering based on the principal diagnosis in the cases with cerebral arteriography. Mental diseases and disorders (MDC 19) are shown to increase the $ms\%$ significantly.

3.3. Anomaly detection result

As an example, look at the highlighted subgroup in red with 379 inpatient cases in Figure 2. The group $ms\%$ is 75%, with an average individual $ms\%$ of 61%. A point anomaly detection method, the density based technique Local Outlier Factor (LOF) [9] is applied to detect the cases with abnormally high $ms\%$ or medical supplies cost. 21 abnormal cases are identified with an average individual $ms\%$ of 85%. Other anomaly detection method can also been applied.

Furthermore, a decision tree is built over the 379 cases, with the 21 abnormal cases labeled as 1, to identify the specific medical supplies use which is the major cause of the high cost. From the model, the use of a specific guide catheter priced at 1,400 RMB is *identified, although it is not the most expensive device used in the cerebral arteriography* surgery. And as in the same surgery, most patients not using this catheter have lower $ms\%$'s, the catheter can be considered to be replaceable. Furthermore, 3 surgeons are identified to use this catheter far more frequently than the others, with an average of 1.9 vs. 0.2 catheters per surgery. Other factors including anesthesia method and surgical incision type have no significant effect on the medical supplies use.

4. Conclusion and Discussion

This study propose a clinical similarity based framework to analyze inpatient medical supplies use records, identifying the abnormally high expenses due to unnecessary medical supplies utilization and providing actionable cost reduction suggestions. The framework has been illustrated through a real case study.

Due to limited space, we only demonstrate the analysis results of inpatient cases in the Neurosurgery Department. The analysis will be conducted for all departments to provide hospital-level cost saving suggestions. Furthermore, the current hierarchical clustering framework is implemented though iterative tree building, which is not convenient for global parameter optimization. An integrated algorithm should be developed to fulfill the task.

References

[1] Centers for Medicare & Medicaid Services, 2016-2025 Projections of National Health Expenditures Data Released, 2017, Retrieved from www.cms.gov/Newsroom/MediaReleaseDatabase/Press-releases/2017-Press-releases-items/2017-02-15-2.html

[2] english.gov.cn/news/video/2017/02/09/content_281475563130303.htm

[3] Y. Abdulsalam, and E.S. Schneller. Hospital supply expenses: An important ingredient in health services research. *Medical Care Research and Review*, 2017, 1–13.

[4] I. Mathauer, F. Wittenbecher. Hospital payment systems based on diagnosis-related groups: experiences in low- and middle-income countries. Bull World Health Organ. 91(2013), 10, 746 - 56A.

[5] J.C. Langenbrunner, C. Cashin, S. O'Dougherty, editors. *Designing and implementing provider payment systems: how to manuals*. Washington: The World Bank; 2009.

[6] *CN-DRGs 分组方案(2014 版),* 中国医药科技出版社; 2014

[7] https://www.cms.gov/icd10manual/fullcode_cms/P0001.html

[8] V. Chandola, A. Banerjee, and V. Kumar, Anomaly detection: A survey, *ACM computing surveys (CSUR)*, 41 (2009), 3, 15.

[9] M. M. Breunig, H.P. Kriegel, R. T. Ng, and J. Sander, Lof: identifying density-based local outliers, *ACM Sigmod Record*, 29 (2000), 2, 93–104.