Identify comorbidities associated with recurrent ED and in-patient visits

Luoluo Liu  
*Philips Research North America (PRNA)*  
Cambridge, USA  
luoluo.liu@philips.com

Eran Simhon  
*PRNA*  
Cambridge, USA  
eran.simhon@philips.com

Chaitanya Kulkarni  
*Philips Innovation India*  
Bangalore, India  
chaitanya.kulkarni@philips.com

David Noren  
*PRNA*  
Cambridge, USA  
david.noren@philips.com

Ronny Mans  
*Philips Research Europe*  
Eindhoven, Netherlands  
ronny.mans@philips.com

**Abstract**—In the hospital setting, a small percentage of recurrent frequent patients contribute to a disproportional amount of healthcare resource usage. Moreover, in many of these cases, patient outcomes can be greatly improved by reducing reoccurring visits, especially when they are associated with substance abuse, mental health, and medical factors that could be improved by social-behavioral interventions, outpatient or preventative care. Additionally, health care costs can be reduced significantly with fewer preventable recurrent visits.

To address this, we developed a computationally efficient and interpretable framework that both identifies recurrent patients with high utilization and determines which comorbidities contribute most to their recurrent visits. Specifically, we present a novel algorithm, called the minimum similarity association rules (MSAR), balancing confidence-support trade-off, to determine the conditions most associated with reoccurring Emergency department (ED) and inpatient visits. We validate MSAR on a large Electric Health Record (EHR) dataset.

**Index Terms**—Recurrent patients, high utilizers, frequent admissions, Emergency Department, inpatient admissions, association rules, confidence support trade-off

I. INTRODUCTION

Recurrent patients, also known as frequent flyers, high utilizers, or super users in hospitals, are a small group; however, they impose a disproportionately high utilization of resources [1] [2]. In fact, the top one percent contribute to 22% of health care spending, and the top 5% account for around 50% of overall costs [1]. Further, the top 15% of utilizers contribute to around 85% of total health care costs [2]. Accordingly, identifying potentially preventable visits among this group of patients could reduce hospital and health care cost significantly.

There are two major types of recurrent patients. One type includes those with mental health or substance (drug and/or alcohol) abuse conditions. It has been shown that these patients contribute to high utilization of Emergency Departments (EDs) [3–8] and inpatient visits in community hospitals [3, 9]. In 2008, mental health and substance abuse (MHSA) were the principal reasons behind 1.8 million patient hospitalizations, accounting for 4.5% of all hospitalizations in the U.S and costing $9.7 billion [9]. Additionally, a large percentage of MHSA patients lack insurance coverage, are sometimes unemployed, and have low average education levels [10] [11]. Fortunately, it has been reported that rehabilitation programs [12], accommodations [10], social support in community [13] and other outpatient programs [10] improve patient outcomes and reduce ED and inpatient re-admissions.

A second type of potentially preventable recurrent admissions relates to diseases, such as Acquired immunodeficiency syndrome (AIDS) and diabetes, which could be reduced through proactive planning and care. For instance, about half of human immunodeficiency virus (HIV) patient re-admissions could be prevented by providing better access to medical supplies, assuring adherence to follow-up tests and visits, improving treatment compliance, satisfying psychological and social needs, etc [14]. It has been shown that diabetes mellitus patients are more likely to have higher re-admission rates, and robust diabetes management, discharge planning, and post-hospital instructions could lower ED visits [15].

One of the biggest challenges in addressing recurrent/frequent visits is that there is no standard criterion for identifying these patients. In fact, there are over 180 criteria from about 100 sources based on a Google and PubMed searches [16]. In previous work, the recurrent patients definitions have been focused on one of these three types: i) resource utilization calculated from operational data elements such as 30-day readmission, number of visits, etc; ii) clinical data elements such as diagnosis codes or iii) a combination of resource utilization and clinical data elements. For an example of the third category, a previous study combined 180 previously reported rules automatically using a clustering algorithm [17]. The final rules set therefore takes into account many factors, both clinical and operational. However, it is also very complex and the number of clusters has to be tuned for each dataset in order to generate the combined rule. Additionally, the algorithm lacks interpretability, creating a barrier for adoption among users.

Since there is no standard criteria for identifying recurrent
patients, our first aim was to define an algorithm to identify this group of patients. Our second aim was to develop an interpretable method to help explain frequent visits. In the EHR dataset, to find out the underlying reason for a particular visit, one could refer to chief complaints or documented reason to visits. However, for recurrent patients, the reason for any given visit might not be representative enough for recurrent visits.

In our proposal, the flagging part of the proposed algorithm only uses operational data elements collected at admission, which means that the algorithm can be triggered directly upon admission. The second part finds past comorbidities associated with recurrent visits by using a statistical method called association rules. Association rule learning [18] is a widely used statistical method that is well-suited to discovering correspondence between previous diagnoses to frequent visits. It is also advantageous due to being highly interpretable.

The conventional association rules takes the maximum confidence rule from all candidate rules exceeding a minimum support [18]. The main drawback is that, for our application, we use combinations of past comorbidities as candidates rules, and some combinations have very low support due to their rareness. Traditional AR method with a given threshold could eliminate those rules, particularly the ones corresponding to rare diseases, even if they are potentially the ones associated with recurrent visits. Association rules variants have been developed for balancing confidence and support to help resolve this issue. For example, authors in [19] use prediction of future data to determine optimal weights. In our application, however, the accuracy of prediction power for frequent visits is not relevant. Authors in [20] proposes a modification on confidence using an extra parameter. However, it requires tuning on an additional term that is hard to interpret in deployment. Instead, we propose an algorithm that improves on the conventional association rules by balancing the support and confidence trade-off, with optimal weights learnt from data which are easily adjustable to varying deployment sites.

We propose a explainable, efficient, and customizable, deployment-friendly algorithm for identifying recurrent patients and top comorbidities associated with recurrent visits. The proposed a novel association rules improvement named minimum similarity association rules (MSAR) that balances the confidence and support trade-off and learns optimal parameters from retrospective data. The proposed algorithm is particularly well suited to handle cases with a large variance in support distribution, which is crucial given that comorbidities vary widely in prevalence. The proposed solution could be used for future decisions to avoid future recurrent visits, such as recommending social-behavioral interventions, to improve patient outcome and reduce health care cost.

II. Method

The main purposes of the solution are to i) identify recurrent visits and ii) find existing conditions associated with recurrent visits. The proposed solution consists of two modules with designed functionalities. The flowchart of the solution is illustrated in Figure 1. The recurrent patient identifier module takes easily available admission timestamps. Based on three criteria, it outputs a Boolean flag indicating whether the visitor is recurrent patient. For recurrent patients, the Comorbidities Explainer gives the top three comorbidities associated with their frequent visits.

A. Recurrent Patient Solution - identifying recurrent patients

One of the challenges in reducing preventable recurrent visits is the lack of standard definition for recurrent patients. Therefore, our first task is to identify recurrent patients. Previous work have defined recurrence based on utilization, physiological states, cost factors [21]. Among these choices, utilization elements are the most easily accessible from EHR, and the algorithm can be executed at the time of admission. We decide to pick top utilization data elements from literature and combine them.

First, we use the 30-day readmission metric, which is widely used and recognized by the Centers for Medicare and Medicaid Services [22]. Second, we use the number of visits within a year, which is one of the common criteria for identify frequent users (41% out of 180 criteria) [21]. Third, we use the number of ED visits, a widely adopted metric [22].

Our proposed solution identifies recurrent visits by combining the above mentioned three criteria: if a visit satisfy one or more of the following cases: readmitted within 30-days, or more than 4 non-elective inpatient or emergency department visits within 1 year, then it is considered a recurrent visit. Figure 1 illustrates the recurrent patient identifier module. We adopt majority choices from literature for thresholds for these criteria, 4 within 1 year as the threshold for ED admissions (41% of 180 criteria) and the same threshold for inpatient admissions (44% of 180 criteria) [21]. Moreover, all thresholds are customizable by inputting user-specified values, to accommodate potential different needs in various hospitals.

B. Comorbidity Explainer via Min-similarity association rules

We introduce the proposed algorithm: Min-similarity association rules (MSAR), for selecting the top comorbidities associated with recurrent visits. This algorithm seeks optimal solutions that balances confidence and support, learnt from retrospective data.

1) Rule candidates: Comorbidities and motivation: From EHR database, we first take International Classification of Diseases (ICD) ICD-9 and ICD–10 diagnosis codes, which, in total, contains approximately 83000 diagnosis codes [24]. To reduce the dimension while encoding such a large number of diagnosis codes, we use the Elixhauser comorbidity index [25] that maps them into comorbidity categories. Elixhauser comorbidity is a good choice for this solution because it is a updated version of widely adopted Charlson comorbidity index [26] with newly added categories for mental disorders, drug and alcohol abuse, obesity, and weight loss, which are the factors that could potentially be improved via social-behavioral interventions and outpatient care. The Hcuppy 0.0.7 [28] Python package is used to map the ICD codes to Elixhauser comorbidities.
2) **Number of comorbidities for recurrent patients:** On average, recurrent patients have 7.51 (±3.65) comorbidities from their past three visits within a year. Displaying all comorbidities associated with recurrent visits is a lot, this motivates us to develop comorbidity explainer to pick top comorbidities associated with frequent visits.

3) **Confidence and Support of a given comorbidity:** We first visualize confidence and support of one comorbidity. Figure 2 shows confidence and support for all single comorbidities. Drug abuse has the highest confidence overall. Additionally, the variance of the support across different comorbidities is large, with values ranging from 0.0045 to 0.72. There are comorbidities with low support and high confidence, such as AIDS, psychoses, weight loss, and drug abuse.

4) **Confidence increases and support decreases with increasing number of comorbidities:** From Figure 3, the range for single comorbidities is between 0.36 to 0.56, which is not very high to discriminate against recurrent patients versus non-recurrent patients. To increase the discrimination between recurrent patients versus non-recurrent patients, we increase the number of comorbidities $n$ in combination, and plot the confidence and support ranges in Fig. 3 to find a reasonable parameter for number of comorbidities $n$. As $n$ increases, the confidence range increases, and the range of supports reduces. We take comorbidities size to be $n = 3$, as the majority of their confidence are over 0.5. We therefore use association rules on combinations of 3 past comorbidities from previous up to 3 visits within last one year.

5) **Conventional association rules:** We formally introduce the definition of confidence and support in association rules. **Confidence** is the likelihood of being a recurrent patient given comorbidities combination and **support** is the prevalence of a given comorbidities combination. Here, our rule candidates are comorbidity combinations with 3 different comorbidities, taken from ICD-9, 10 codes from recent up to 3 visits. Then for a comorbidity combination of 3 comorbidities, the confidence is the likelihood of being recurrent patients (RP) given certain comorbidity combination $\{A, B, C\}$:

\[
\text{Confidence: } c(\{A, B, C\}) = P(RP|A, B, C); \quad (1)
\]

and its the support is the prevalence:

\[
\text{Support: } s(\{A, B, C\}) = P(A, B, C). \quad (2)
\]
The conventional association rules uses a user-specified threshold and then takes highest confidence rule, to make the notation shorter, we use $v$ to denote combination of comorbidities, then

$$v^*_AR = \arg \max \text{Confidence}(v), \text{s.t. } \forall v, \text{Support}(v) \geq \tau. \quad (3)$$

6) Drawbacks of conventional AR with certain threshold: Figure 2 and Figure 3 shows that there is a trade-off between confidence and support. First, in clinical applications, some diseases are more rare than others, however may have high confidence associated with recurrent visits, shown in Figure 2. Secondly, to increase the confidence of rule, increasing the number of elements (comorbidities) can boost confidence, however largely decreases the support.

Main drawbacks for conventional AR from certain threshold are: A large threshold could remove rare diseases, including the ones with high confidence. However, a too small threshold will make the algorithm very sensitive to outliers and potentially risks revealing the identification of patient with rare conditions. This drawback motivates us to develop an algorithm to balance confidence and support automatically.

7) Definition of similar rules: The motivation behind conducting optimization of similar rules is that we would like to score and choose from similar rules, particularly one with higher confidence and the other one with higher support. Examples in Table 4 we have combination of first set of comorbidities: weight loss (WL), peripheral vascular diseases (PVD), hypertension, and second set of comorbidities: WL, PVD, and fluid & electrolyte disorders, those two sets have similar confidence, but support are very different. For a recurrent patient with four of those comorbidities from their past three visits, the ability to differentiate which three comorbidities to prioritize as factors of recurrent visits is fairly important, and serves as a key motivation of this solution.

Similar rules are defined as the following: for rule set $v_1$ and rule set $v_2$, both of size 3, they are similar rules if and only if there is one element difference between two sets. For example, for $v_1 = \{A, B, C\}, v_2 = \{A, B, E\}, v_3 = \{A, E, F\}$, $v_1$ and $v_2$ are similar rules, whereas $v_1$ and $v_3$ are not similar rules. In graph representation, we model each rule as a vertex in a graph, and the edge is only present if there is only one different element between the two rule sets. Figure 4 illustrates this graph structure.

8) MSAR balances confidence and support for similar rules: Then, we formulate the combined confidence and support rule: for weights $w_c, w_s \geq 0$, and the sum of weights is one: $w_c + w_s = 1$, for each rule score function on a vertex $v_i$ is as follows:

$$r(v_i) = w_c \tilde{c}(v_i) + w_s \tilde{s}(v_i), \quad (4)$$

where $\tilde{c}(v_i), \tilde{s}(v_i)$ are $z$-normalized confidence and support, respectively. Now, for an edge $e$ between vertices $v_i$ and $v_j$, we define the difference by the following:

$$\delta(e) = r(v_i) - r(v_j) = w_c \tilde{c}(v_i) + w_s \tilde{s}(v_i) - w_c \tilde{c}(v_j) - w_s \tilde{s}(v_j) = w_c (\tilde{c}(v_i) - \tilde{c}(v_j)) + w_s (\tilde{s}(v_i) - \tilde{s}(v_j)). \quad (5)$$

We use $\delta_c(e), \delta_s(e)$ to denote the difference of confidence and support between two vertices, respectively. Then, equation (5) reduces to

$$\delta(e) = w_c \delta_c(e) + w_s \delta_s(e). \quad (6)$$

We require similarity to be inversely correlated to the individual differences; specifically, we define the similarity as the overall max difference minus each individual difference: $\sim(e) = w_c (\delta_{max} - \delta_c(e)) + w_s (\delta_{max} - \delta_s(e))$, where $\delta_{max}$ is obtained by taking the max over all $\delta_c$ and $\delta_s$ in all edges from the similarity graph. Namely, $\delta_{max} = \max(\delta_c(e), \delta_s(e))$. Therefore, the minimum similarity association rules can be derived by the following:

$$\min_{w_c, w_s} \sum_{e \in G} \sim^2(e) = \sum_{e \in G} (w_c (\delta_{max} - \delta_c(e)) + w_s (\delta_{max} - \delta_s(e)))^2 \quad (7)$$

s.t. $w_s + w_c = 1, w_s, w_c \geq 0$

Equation (7) is in the form of convex quadratic programming (QP) with only 2 parameters. We use off-the-shelf MATLAB quadprog solver to solve (7). Not only is the solution efficient to obtain, but also this algorithm is easy to deploy. From retrospective data, we can calculate $w^*_c, w^*_s$ as the optimal solution from (7), and then the minimum similarity score can be calculated as the following:

$$r^*_MSAR(v_i) = w^*_c \tilde{c}(v_i) + w^*_s \tilde{s}(v_i). \quad (8)$$

The scores can be added directly to the learnt rules along with confidence and support for each rule, and customers will be able to select top ranked rules based on MSAR scores. Table 4 gives example of scores and how rules are compared during algorithm execution.
TABLE I
EXAMPLE OF COMPARISON OF THE CONVENTIONAL HIGHEST CONFIDENCE ASSOCIATION RULES (AR) WITH MSAR. BOLD ARE SELECTED RULES FROM AR AND MSAR.

| Rule candidates: comorbidities combinations | Confidence | Support | AR score (the highest Confidence) | MSAR score |
|--------------------------------------------|------------|---------|----------------------------------|------------|
| 1. Weight loss, Peripheral vascular disease, Hypertension | 0.681      | 0.00871 | 0.681                            | -0.19233   |
| 2. Weight loss, Peripheral vascular disease, Fluid and electrolyte disorders | 0.675      | 0.024   | 0.675                            | 0.0543     |

| Rule candidates: comorbidities combinations | Confidence | Support | AR score | MSAR score |
|--------------------------------------------|------------|---------|----------|------------|
| 1. AIDS, Coagulopathy, Psychoses           | 0.819      | 0.000156| 0.681    | 1.0014     |
| 2. AIDS, Coagulopathy, Renal failure       | 0.748      | 0.000198| 0.748    | 0.299      |

III. NUMERIC RESULTS

We use an internal Philips Electrical Health Record (EHR) dataset to validate the proposed algorithm. It contains 8 years of previous data from over 20 community teaching hospitals in the United States.

A. Statistics for all three recurrent patient criteria

In population level among ED and inpatients, the 30-day readmission rate is 12.3%, which is within a similar range to reported values on the HCUP dataset [30]. The recurrent inpatient visits rate is 7%. The ED frequent visits rate is 21%. The percentage of total recurrent patients is roughly 25% total. For flagged visits, most of them have only one flag, and few have 2 or more flags. Noticeably, ED recurrent patients contribute to 94%, which is the majority of recurrent patients.

B. MSAR rules

To obtain past comorbidities associated with recurrent frequent visits, we first take ICD-9 and ICD-10 codes from a patient’s past visits as training data. To avoid duplicate counts of comorbidities, we only take the most recent (up to) 3 visits for both recurrent and non-recurrent patients. One patient is only counted once in training data, this process results in around 400k unique patients in training data.

Optimal weight parameters of confidence and support are learnt from retrospective data, and the numeric optimal solution is \( w_c^* = 0.778, w_s^* = 0.221 \). The weight of confidence is about 3.5 times than the weight of support. We plug back in (8) to obtain MSAR rule scores for all candidate rules.

Table I illustrates an example of two similar rules and the minimum association rules score. We compare the output of conventional association rules and MSAR. Bold text highlighted the rule that each method selects. The top examples illustrates the case that the low confidence rule has larger support than the high confidence rule, and therefore MSAR picks the slighter lower confidence rule with much higher support. The bottom example illustrates the case when the low confidence rule has lower support than the high confidence rule, and MSAR agrees with the conventional highest confidence association rules. This behavior validated the effectiveness of our proposed algorithm.

In total 3860 rules from triplets of Elixhauser comorbidities are learnt. The constant value in optimization equation (7) \( \delta_{max} \) is obtained by taking the maximum of \( z \)–normalized confidences and supports, and the value is 4.34 from our retrospective data. To understand the contributions of different comorbidities from learnt rules, we take the top 1000 (25.9%) rules and count the prevalence of each comorbidity, which is depicted in Figure 5. Top categories include drug abuse, psychoses, neurological disorders, depression, etc.; rehabilitation programs, education, follow-up treatment and other outpatient care could be introduced to reduce some future preventable visits.

IV. SUMMARY AND FUTURE WORK

In this work, we propose a recurrent patient solution that identifies recurrent patients executable upon admission and
finds the top comorbidities associated with their recurrent visits via a novel proposed algorithm MSAR that balances the trade-off between confidence and support, with optimal weights learnable from retrospective data. The proposed solution will be used to assist future decisions to avoid future recurrent visits, such as recommending social-behavioral interventions and outpatient care.

The proposed MSAR algorithm has the properties of customisable and easy to deploy in future product. Potential users of this proposal include chief operating officers, patient flow coordinators, charge nurses, house supervisors, ED nurses and managers, etc.

Future work would include combining medical risk scores such as the Acute Physiology and Chronic Health Evaluation (APACHE) score [31] and the early deterioration index [32], to find subgroups of patient with low medical risks at discharge and frequent admissions, as automatic guidance to help doctors and caregivers to recommend potential interventions that satisfy their needs such as recommendation of rehabilitation, educational programs, reminder of following prescriptions and follow-up visits, etc.

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