Readmissions Score as a Service(RaaS)

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ABSTRACT

In this paper, we describe *RaaS as a first medical risk calculator* that utilizes cloud computing capabilities to provide risk of hospital readmission score as a service. RaaS can significantly benefit both patients and providers to reduce the medical costs considerably and improve the health outcomes of the patients through exposure of the risk profiles (consisting of a risk score and the leading contributing factors) at the point of care. The service is hosted on Microsoft Azure for Research platform to enable the health providers as well as the individuals access to the service, without the need to deploy analytics infrastructure and or consume internal compute resources. Raas architecture is easily extensible to interface with other medical systems and support integration with other data sources.

1. INTRODUCTION

The health care industry is under enormous pressure to drive down costs, while maintaining and improving the quality of care. Given that $17 billion is spent annually on battling readmissions, and 75% of these readmissions are considered avoidable[1]. There exists tremendous opportunities for health providers to meet their mandates and improve outcomes as well as reduce costs, by identifying patients at high risk of readmission and adjusting care plans accordingly. Unsurprisingly, current practices for risk prediction [8, 3] rely solely upon a team of health informaticists, practitioners and data scientists to drive this effort, with solutions customized for each health system and care facility.

Understandably, while larger health organizations have the required infrastructure to bring these capabilities to bear, smaller organizations simply lack of such resources. *The novelty and societal contribution of our work is precisely around that, where, we, for the first time, bring the "Readmissions Risk as a Service" (RaaS) on cloud that is accessible ubiquitously.* RaaS is integrated with a series of machine learning models to predict risk of readmission based on an array of factors making it applicable to a variety of health system and care facility. Additionally, the need for machine learning models to continually adapt to advancements in the literature, as well as continued retraining as patient populations change and new features become available, the opportunity to leverage RaaS shows great promise. Finally, unlike traditional Electronic Medical Record (EMR) platforms such as Epic[2], that have been slow to adopt new features and capabilities, and require in-house customization for each change, Raas is adaptive to the changing population or flexible to easily incorporate the state-of-the-art machine learning models.

In this paper, we present RaaS to predict and analyze a patient's risk of hospital readmission after being discharged from an earlier stay. We invoke RaaS to predict risk score of one of the leading causes of repeated readmissions and a chronic and potentially fatal disease, namely Congestive Heart Failure[2, 7]. This service particularly focuses on generating risk profiles consisting of a risk score and the leading contributing factors that causes this risk. Our service may guide health care providers to develop better care transition interventions as well post-discharge plan to reduce the likelihood of readmission. While RaaS is invoked for Congestive Heart Failure, we underscore that our framework could be easily extended to other chronic conditions as well. We also believe that our work will encourage the informatics community to contribute more in such efforts by making them accessible to a larger population leading to higher societal impacts and better healthcare outcomes throughout the globe.

The proposed service in this paper is the extension of the Risk-O-Meter system that predicts the risk-of-readmission related to CHF [8]. Risk-O-Meter has some distinguishable characteristics in comparison with other risk calculators, such as, the Yale Model [3]. In addition to physicians and domain experts, Risk-O-Meter is also useful to patients who are unfamiliar with medical terminologies, or providers with limited information about patient. The system is flexibly designed to accept incomplete data inputs, and still predict the clinical risk. Moreover, along with the risk calculation, Risk-O-Meter also suggests meaningful explanation behind each prediction. However, similar to other risk calculators, Risk-O-Meter is a standalone system that is only accessible through a web interface and lacks the capability to interface with other systems. The next challenge is that Risk-O-Meter architecture is not extensible enough to support integration of other data sources or continual retraining or augmentation by additional prediction models as new datasets and features become available. The greatest utility of any such system, comes through exposure of the risk profiles at the point of care, this requires deep integration

[1] http://www.presidency.ucsb.edu/ws/?pid=86130

[2] 70 % of Stage 7 US Hospitals use EpicCare.(www.epic.com/recognition-stage7.php)

[3] www.readmissionscore.org

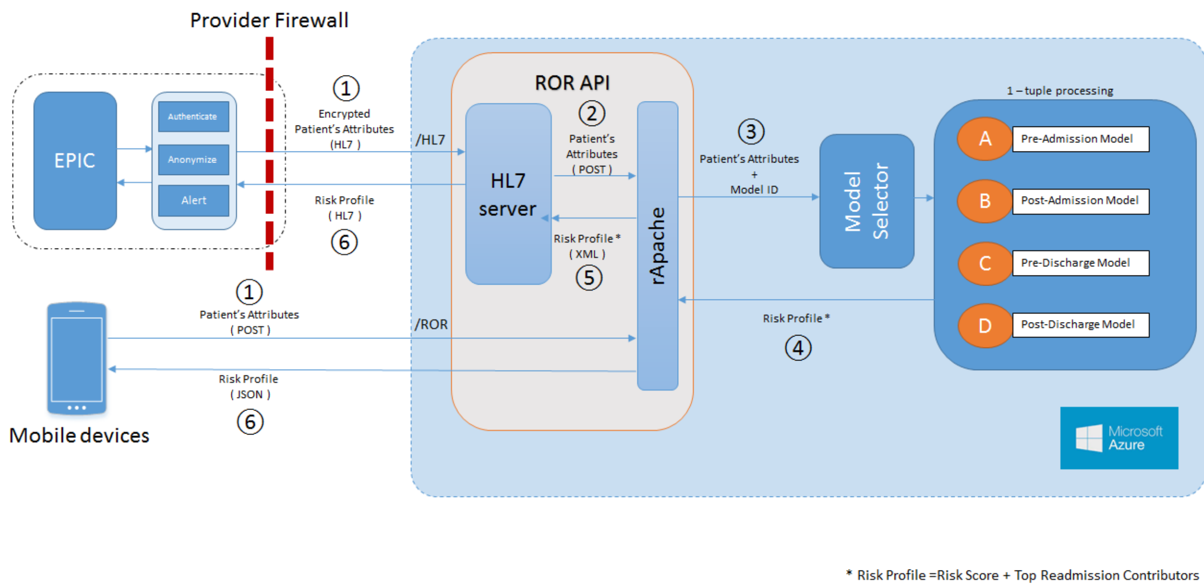

Figure 1: Illustration of the Service Architecture. (A) External Layer. (B) Communication layer. (C) Analytics layer

with the EMR and is not always feasible due to organizational and technical challenges. Therefore, we present a number of integration scenarios that could be supported by this framework, ranging from the approach previously described in [8] to a full EMR integration complete with generation of risk profiles and intervenable factors in real time. These include: (1) Accessibility via mobile app, or web interface (2) External dashboard powered by Enterprise Data Warehouse (full capabilities but time delayed) (3) External dashboard launched from within EMR (real time attributes sent to dashboard) (4) Full epic integration, panel in EPIC with graphed real time risk profiles.

While there are obvious technical challenges to any such integration, as with many new advancements, it is often not the development of the technology itself that proves the greatest challenge, but rather acceptance and deployment of that capability. The necessity of this approach was made clear to our team as we deployed the tool to MultiCare Health System. Even with early input and buy in from senior leadership and other key stakeholders, including physicians and clinical informaticists, there was significant effort spent educating the team on machine learning techniques in general, and the specific approaches used in developing RaaS. An additional challenge was leveraging cloud based solutions since the healthcare providers not only need to trust the machine learning models developed, but also to trust a third party to deliver those capabilities, on computing infrastructure that lived outside the organizations data center. While we recognized this would be an exciting challenge, we also knew that, beyond the traditional benefits of the cloud, we also needed to leverage external data sets, census, demographic, as well as other clinical data sets, to make a compelling case that this effort could bring value back to participating organizations through advanced predictive analytics capabilities.

To the best of our knowledge, RaaS is the first medical risk calculator that utilizes cloud computing capabilities to provide risk of readmission as a service, thereby extending and enhancing the health care analytics capabilities of a hospital system utilizing HIPAA compliant cloud based service. Additionally:

- Through ongoing data collection and intelligent selection of appropriate risk models, RaaS supports generation of risk profiles at multiple points throughout the encounter
- RaaS works on disparate data types (i.e. clinical and claims data). It is also extensible to support new predictive models as new datasets are made available to support those models
- RaaS can leverage continual retraining models to support changes in an organization(s) datasets.

The remainder of this paper is organized as follows: Section 2 overviews the architecture of the RaaS. Section 3 describes a demo scenario. The paper is concluded in Section 4.

2. SYSTEM ARCHITECTURE

This section describes the technical specification of the Readmissions Score as a Service (RaaS) to predict and analyze the risk of 30-day hospital readmission. The overall architecture of the system and flow of messages are illustrated in Figure 1. RaaS is hosted on Microsoft Azure and is implemented as a REST API which can receive post requests from one or more clients. Upon message consumption, the patient attributes are sent to the model selector, which is responsible to run the appropriate prediction models based on the input variables inside the request. Finally, the analytics layer generates a risk profile, consisting of risk score and top correlated factors that contribute to readmission risk and returns this to the selector layer in the requested format, where it is either returned to the calling device as JSON/XML, or converted into HL7 formatted to be sent back to the EMR system. Below, we explain the components and flow in detail. RaaS is comprised of 1) Communications Layer, which includes endpoints for HL7 messages and JSON requests, 2)

Analytics Layer which includes support for model selection, risk scoring, and generating of contributing factors.

2.1 Communication Layer

RaaS can support HL7 and JSON as inbound request formats. The first, HL7 [4] is used to support agnostic interaction with EMR systems such as Epic. These data standards are meant to allow health care organizations to easily share clinical information [4] and RaaS leverages this effort to support generation of real-time readmission risk profiles. Internally, this capability is supported through the use of Mirth Connect [1] [5]. Mirth Connect enables bi-directional sending of HL7 messages between systems and applications. Mirth Connect is configured to extract variables required by the predictive models. These data points, which include model to be used and return format of XML, are then passed along to the Risk of Readmission (RoR) API for processing. The result is then converted from XML back into HL7 and send back to the EMR.

The second, JSON is used to support interaction with web applications, mobile devices or requests from other systems utilizing REST API's. Those requests bypass Mirth Connect and are sent directly to the API in a normal API call. The Risk Profile is calculated as described above and the resulting score and contributing factors are then sent back in JSON format. There are several Proof of Concept (POC) deployments that are utilizing this flow; 1) Web Portal, currently deployed inside MultiCare's network with similar functionality to the previously referenced [8] but using more advanced API layer. 2) Android and Windows Phone mobile applications which leverage the RoR API to support the demo scenario is outlined in Section III.

RoR API is a restful API which is hosted on Microsoft Azure and accepts POST requests. The lightweight and scalable Representational State Transfer (REST) architecture is chosen for RoR API implementation to allow extremely easy integration with various web and mobile applications due to its loosely-coupled characteristics [5]. To be compliant with HIPAA[6] security regulations, a POST method is used and the sensitive information is passed in the body of the request. One of main objective of exposing RoR as a service and enabling utilization, while protecting PHI[7], is to allow hospital systems to add predictive analytics tools to their tool kits, without having to build in house capabilities. Additionally, the service can be used as a bridge until they can acquire that in house expertise. Further, the use of HIPPA compliant cloud computing services such as Microsoft Azure or Amazon EC2 allows the system to scale and respond to additional demands quickly. We utilized Azure as cloud computing service for RoR implementation because of Microsoft's early support for HIPAA certification [6]. Due to HIPAA regulations, we do not store any patient information in the server or in the application, but instead generate a key that can be used to communicate with the EMR to establish the ground truth as to whether a particular patient readmitted within 30 days.

[4]Messaging format(standards, guidelines and methodologies) by which various health care systems can communicate with each other

[5]an open source Java-based integration engine to support the ongoing interoperability effort undertaken by many health organization

[6]Health Insurance Portability and Accountability Act

[7]Protected Health Information

2.2 Analytics Layer

In this section, we present the details of the analytics layer to generate a readmission risk score. the focus of prediction is on Congestive Heart Failure (CHF) as the leading causes of readmission[3, 8]. There is an interesting dichotomy that exist in that, the earlier in the course of hospitalization to calculate readmission risk, the greater the opportunity to positively impact that risk. However, there is less information available at earlier time to perform those calculations. For that reason, we present multiple predictive models, optimized for various points in the care continuum. To better train and improve these models we generate risk profiles at admit and then track how this score may well change during the course of hospitalization as the patient undergoes treatment and care. This allows us to track how interventions can drive changes in the risk profile.

Several predictive models are integrated inside the layer and the most appropriate model can be chosen based on set of attribute values that are available at the time when health care providers uses the risk calculator. For example, during the admission we can only use the readmission model that has trained based on patient history data and current vital sign but over time, more data about the patients such as lab test result and diagnosis code may be available that enable us to use more sophisticated and effective predictive model. In the above architecture, the model selector layer is responsible to execute the chosen model based on the model ID. We currently implemented Naive Bayes classifiers using the four different set of attributes available at admission, hospitalization, pre-discharge and post-discharge time (TABLE I). Naive Bayes classifier utilizes a probabilistic method for classification by multiplying the individual probabilities of every attribute-class pair. The method has been shown as one of the effective classifiers in [9]. In addition to real-time prediction, another distinguishing characteristic is the flexibility of the system to leverage different dataset. To date, we have used two different datasets to train the models; 1) A cohort provided by MultiCare Health System [8] for the models based on clinical data, 2) State Inpatient Database [9] (SID) for the models based on claim data. The system also supports integration and training on additional data sets, and future work includes capability to predict readmission risk based on both clinical and claim data combined. Additionally, we are exploring integration of socio-economic, demographic, and other external data sources to provide a more robust risk profile.

Along with the risk calculation, each model also suggests meaningful explanation behind such prediction. We used Apriori association rules mining to identify contributing factors that may associated with high/low risk of readmission. For each model, we extracted rules of high support and confidence scores based on the available attribute set. At prediction time we then find the matched rules at real-time based on input data and the chosen model.The ROR service primarily used R language to implement statistical analysis, predictive modeling, and association rules mining. The choice of the implementation allows us to combine extensible data mining algorithms and statistical analysis tools.

[8]http://www.multicare.org/

[9]http://www.hcup-us.ahrq.gov/sidoverview.jsp

Figure 2: Screenshots of the RaaS service on mobile application: a) Patient view b) Physician view

Table 1: Predictive Models Specification

Model	Attribute Set	Dataset
Pre-Admission	demographic (age,gender,...), vital sign (blood pressure,BMI,..), historical data	Clinical
Post-Admission	demographic, vital sign, historical data, medical test result(Glucose level, Ejection Fraction value), diagnosis codes	Clinical
Pre-discharge	demographic, vital sign, historical data, lab test result, diagnosis code, discharge parameter (length of stay, risk of mortality, severity of illness)	Clinical
Post-Discharge	demographic, social factors, ,diagnosis code, length of stay, comorbidities and coding attributes	Claim

3. DEMONSTRATION SCENARIO

This section illustrates a mobile version of our service on Windows phone. Mobile application supports 2 level of profiles namely patient and physician profile(figure 2).

3.1 Patient Scenario

Imagine Mike's father was admitted to hospital because of congestive heart failure and couple of days back he was discharged. Now, Mike is worried about his father being readmitted to the hospital. In order to know the probability of his father being readmitted, Mike opens up Risk-O-Meter application in his mobile and navigates to Patient profile:

(1) He enters information regarding his father ranging from demographics to lab results. (2) Risk-O-Meter app takes all the values entered by Mike, forms a POST request and sends it to ROR API. (3) API calculates risk profile for his father and returns result in a JSON format. (4) Upon receiving the result from API, Risk-O-Meter app converts information in the JSON into a meaningful graphical component and displays the result (5) Now Mike knows the his father risk profile and they can make some interventions to reduce the risk score.

3.2 Physician Scenario

Consider Dr. Amy. who is traveling to a health care conference and wants to knows how her patients are doing. She ses Risk-O-Meter mobile application and navigates to the Physician profile:

(1)She enters credentials given by the hospital. (2) After successful log in, she is directed to a personalized dashboard. (3) In the dashboard, she can see alerts as well as patient list. (4) She is interested in alerts, so if "Alert" icon is tapped, it will show all recent notifications. Furthermore, she can also browse individual patients. Dr. Amy can contact the hospital with this application with specific instructions for a patient. (5) To get overall view of her patients, she clicks on the "Monitor Patient" icon. A broad overview containing respective current risk score of each patient, any changes in risk score, and time stamp of each event is displayed.

4. CONCLUSION

In this paper, we propose RaaS to predict and analyze hospital readmission risk. This service can help health providers to identify patients likely to transition into a higher risk category and guide them to undertake more appropriate interventions to reduce the likelihood of a readmission. There are several practical advantages in RaaS implementation in comparison with previous efforts: First of all, the service has been deployed on the cloud which enables the health providers to access the service without the need to deploy analytics infrastructure and or consume internal compute resources. Secondly, the API is generic enough to support different systems such as EPIC or other EMR's, as well as web-based dashboards and mobile application. Moreover the service architecture is flexible enough to extend the analytic layers by deploying additional predictive models as new datasets support these efforts. Finally, though the current version of RaaS evaluates 30-day risk of hospital readmission for Congestive Heart Failure, the proposed service framework is applicable to general clinical risk prediction through on boarding of additional models and datasets.

5. ACKNOWLEDGMENT

We acknowledge Multicare Health Systems and Microsoft Azure for Research for their generous supports in this research.

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