Project Plan for Development of a Readmission Risk Monitor Application

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**Objectives** Develop a series of predictive models derived using machine/statistical learning algorithms that target patient readmission probability and timing. Final objective is the deployment of an application through which the dynamic predictions of relative risk of patients discharged within the previous 30 days, will be delivered. This application, the *Relative Readmission Risk Monitor* or R3M (R3M) for short, is designed to assist care coordinators in prioritizing their caseload when dealing with recently discharged patients.

# Model Development

With the ultimate goal of developing a predictive algorithm targeting 30 day all cause readmission with the ACO patient population, there are three phases planned.

## Deliverables

The deliverable from each phase will be a documented model including:

* R code for training, testing, and scoring
* Description of the data set used
* Discussion of each step taken in refining the model including algorithm selection feature creation/selection
* Diagnostic metrics measuring model accuracy such as; confusion matrices, specificity and sensitivity measures, cost and risk profiles, etc.
* Discussion of potential deployment issues (Phase 3 only)

Each phase builds on the practical knowledge gained from the previous phases in terms of algorithm selection, data transformation, metric development, training and testing.

## Phase 1: Stroke Survival

This phase has been completed and a detailed description can be found in [1]. In summary, using data from the Copenhagen Stroke Study, this model targeted patient reoccurrence of stroke and/or mortality. Given the small size of the well curated data set (< 1,000 records), it was possible to carry out the development of this model on a desktop PC running R. All data transformation and manipulation was done within R, after extraction from a standard csv file.

## Phase 2: Diabetes Patient Readmission

This phase is also complete with results published in [2]. The data set consisted of some 70,000 patient records from the *Health Facts* [[1]](#footnote-1) database, a national data warehouse of clinical records gathered from US hospitals that use the Cerner Electronic Health Record System. This data set has been used in studies investigating the relationship between clinical indicators and diabetes outcomes/readmissions[2].

Development of this model built on what I learned from phase 1 while incorporating more complex metrics such as multiple diagnoses. Given the much larger size and complexity of this data set, successful development of an accurate predictive model required thoughtful development of compound metrics (i.e. for multiple diagnoses tied to multiple procedures) that enable dimensionality reduction while minimizing information loss[3].

## Phase 3: Readmission in ACO Population using (only) Administrative Claims Data

The first iteration of this phase has been completed and results published [4]. Administrative claims data is intended to be used for operational and financial planning and not for clinical interpretation or patient care optimization. These records lack the granularity or patient diagnostic details found in operational EHR systems such as Epic[[2]](#footnote-2).

In connection with administration of the Affordable Care Act, the Centers for Medicare and Medicaid Services [4] provides claims related data on patients associated with specific Accountable Care Organizations such as *Well Virginia* [5]. The goal of this third and final phase of this project is to use this data to predict the probability of individual patient readmission, and the timing of that readmission. This information can then be used to rank recently discharged ACO patients in order to optimize follow-up care, thus directly reducing costs as well as insuring that Well Virginia meet or exceed specific ACO quality of care guidelines such *ACO #8 – Risk Standardized All Condition Readmission*. A summary description for this particular measure presented in Appendix B.

There is some precedent for using this type of data to study readmission. Vernig, et. al. [6], successfully used survival analysis techniques to analyze Medicare data. This study was focused on examining specific relationships found in the data and not on predicting outcomes.

Other studies that have focused on readmission prediction have used data beyond what is available in the CMS ACO Claims database [7], [8]. In a meta-analysis conducted by the VA on readmission prediction, a number of studies were examined [9]. The nine large population-based or multicenter US studies that relied upon retrospective claims data generally had poor discriminative ability (c-statistics 0.55 – 0.65). Addition of clinical information increased the discriminative ability considerably (c-statistics 0.72 – 0.75). One study further increased discriminative ability through the additional of functional status data (available at discharge (c-statistic 0.82).

## Phase 4: Implementation of R3M Application

# Proposed Schedule



## Citations

[1] Yerex, Robert Peter, “Predicting Stroke Recurrence,” Oct. 2014.

[2] B. Strack, J. P. DeShazo, C. Gennings, J. L. Olmo, S. Ventura, K. J. Cios, and J. N. Clore, “Impact of HbA1c Measurement on Hospital Readmission Rates: Analysis of 70,000 Clinical Database Patient Records,” *BioMed Res. Int.*, vol. 2014, p. e781670, Apr. 2014.

[3] C. E. Shannon, “Probability of Error for Optimal Codes in a Gaussian Channel,” *Bell Syst. Tech. J.*, vol. 38, no. 3, pp. 611–656, May 1959.

[4] C. for Medicare, M. S. 7500 S. B. Baltimore, and M. Usa, “Centers for Medicare and Medicaid Services,” 17-Sep-2014. [Online]. Available: http://www.cms.gov/Regulations-and-Guidance/HIPAA-Administrative-Simplification/Affordable-Care-Act/. [Accessed: 30-Oct-2014].

[5] SL5VS, “Well Virginia - UVA’s Accountable Care Organization — UVA Health System.” [Online]. Available: http://www.healthsystem.virginia.edu/pub/well-virginia/home.html. [Accessed: 30-Oct-2014].

[6] A. A., Kind S, Mesler DE Virnig BA, “Survival analysis using Medicare data: example and methods.,” *Health Serv. Res.*, vol. 35, no. 5, pp. 86–101, 2000.

[7] A. G. Au, F. A. McAlister, J. A. Bakal, J. Ezekowitz, P. Kaul, and C. van Walraven, “Predicting the risk of unplanned readmission or death within 30 days of discharge after a heart failure hospitalization,” *Am. Heart J.*, vol. 164, no. 3, pp. 365–372, Sep. 2012.

[8] J. J. Holloway, S. V. Medendorp, and J. Bromberg, “Risk factors for early readmission among veterans.,” *Health Serv. Res.*, vol. 25, no. 1 Pt 2, pp. 213–237, Apr. 1990.

[9] D. Kansagara, H. Englander, A. Salanitro, D. Kagen, C. Theobald, M. Freeman, and S. Kripalani, *Risk Prediction Models for Hospital Readmission: A Systematic Review*. Washington (DC): Department of Veterans Affairs (US), 2011.

# Appendix A: ACO Measure #8

**Unit of Measurement:** Accountable Care Organization (ACO)

**Measurement Duration:** Calendar Year

**Measurement Period:** Calendar Year

**Measure Type**: Outcome

**Measure Scoring:** Risk-standardized readmission rate (RSRR)

**Payer source:** Medicare Fee-for-Service

**Improvement notation:** Lower RSRR scores are better

**Measure description and Rationale**Risk-adjusted percentage of Accountable Care Organization (ACO) assigned beneficiaries who were hospitalized who were readmitted to a hospital within 30 days following discharge from the hospital for the index admission.  
Readmission following an acute care hospitalization is a costly and often preventable event. During 2003 and 2004, almost one-fifth of Medicare beneficiaries – more than 2.3 million patients – were readmitted within 30 days of discharge. A Commonwealth Fund report estimated that if national readmission rates were lowered to the levels achieved by the top performing regions, Medicare would save $1.9 billion annually.

Hospital readmission is also disruptive to patients and caregivers, and puts patients at additional risk of hospital-acquired infections and complications. Some readmissions are unavoidable, but readmissions may also result from poor quality of care, inadequate coordination of care, or lack of effective discharge planning and transitional care.

Since studies have shown readmissions within 30 days to often be related to quality of care, coordination of care, or other factors within the control of health care providers, interventions have been able to reduce 30-day readmission rates for a variety of medical conditions, and high readmission rates and institutional variations in readmission rates indicate an opportunity for improvement, it is important to consider an all-condition 30-day readmission rate as a quality measure.

1. Cerner Corporation, Kansas City, MO [↑](#footnote-ref-1)
2. Epic Systems Corporation, Verona, WI [↑](#footnote-ref-2)