Predictive Analytics for Patient Mobility Using AM-PAC

Michael Crockett, Cong Mu, Anton T. Dahbura   Department of Computer Science Johns Hopkins University

Abstract

Measures of patient function are increasingly seen as important outcome measures in health care systems. Currently nurses and therapists regularly score the Activity Measure for Post-Acute Care (AM-PAC) activity and mobility short forms for all patients in JHH. These scores have been used in several operational and clinical projects to improve patient care such as mobility goal setting in the neuroscience units for the identification of patients that are more or less likely to benefit from physical therapy services. Our goal is to look for the association between measures of patient functional status and different therapy dosage regimes in order to choose optimal dynamic treatment regimes in the face of limited resources. To start with, we propose a framework to predict future AM-PAC given patients' historical data. Here we present our preliminary results and discuss future work.

Data

We test our framework on 14 days' records, which include patients' random number id, decay of 2 kinds of interventions and related outcome scores for these 2 interventions. The **intervention** and **outcome** are coded alphabetically in the original data. For **intervention**, **AA** means last intervention happened on the day of sampling, **BB** means last intervention happened 1 day prior to the day of sampling, and so on. If intervention happened 7 days or earlier (from the day of sampling), it is coded as **II**. For **outcome**, **F** = worst outcome, **G** = better, and so on. Thus we first recode the alphabetic symbol using the following rule.

Decay of Intervention		Measured Outcome	
&&, &	NA	&&, &	NA
AA	1	F	6
BB	0	G	7
...	0	...	
II	0	Z	26

Table 1: Data Recoding

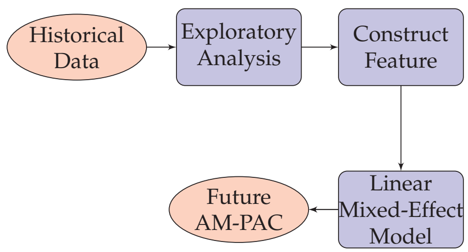
After some exploratory data analysis, we found that the influence of intervention is different for pa-tients with different initial outcomes. Thus we divide the patients into 3 groups according to their initial outcomes as shown in Table 2.

Initial Outcome	Group
$6 \sim 8$	1
$9 \sim 19$	2
$20 \sim 26$	3

Table 2: Data Grouping

Methods

We propose a framework as follows.



First, we construct the following features.

- **Initial Outcome** (X_1): First day's outcome for each patient
- **Intervention** (X_2): Whether taking intervention on the sampling day
- **Time** (X_3): Days patient is in the hospital
- **Min** (X_4): Patient's minimum score before
- **Max** (X_5): Patient's maximum score before
- **Time** $\times$ **Intervention** (X_6)
- **Group** $\times$ **Intervention** (X_7)
- **Min** $\times$ **Intervention** (X_8)
- **Max** $\times$ **Intervention** (X_9)

Then, we built a linear mixed effects model as

$$\mathbf{y}_i = \mathbf{X}_i \boldsymbol{\beta} + \mathbf{Z}_i \mathbf{b}_i + \epsilon_i,$$

where $\boldsymbol{\beta}$ would measure the fixed e ffects while $\mathbf{b}_i$ would measure the random effects. Compared with the linear model, the linear mixed effects model would consider both general effect and differences among individuals.

Results

To choose the optimal model, we try different combinations of fixed and random effects as follows.

	Fixed Effect	Random Effect	RMSE	R^2
Outcome1	X_1, X_2, X_3, X_6, X_7	X_3	2.1050	0.8438
	$X_1, X_2, X_3, X_4, X_6, X_7, X_8$	X_3	1.7001	0.8438
	$X_1, X_2, X_3, X_5, X_6, X_7, X_9$	X_3	1.2781	0.9424
	$X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8, X_9$	X_3	0.7302	0.9812
Outcome2	X_1, X_2, X_3, X_6, X_7	X_3	1.8042	0.8652
	$X_1, X_2, X_3, X_4, X_6, X_7, X_8$	X_3	1.5707	0.8652
	$X_1, X_2, X_3, X_5, X_6, X_7, X_9$	X_3	1.0435	0.9537
	$X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8, X_9$	X_3	0.7358	0.9769

Table 3: Model Comparison

Then we predict the future AM-PAC with lower and upper bounds (Figure 1) using the optimal model and examine the pattern of patients with unusual prediction (Figure 2).

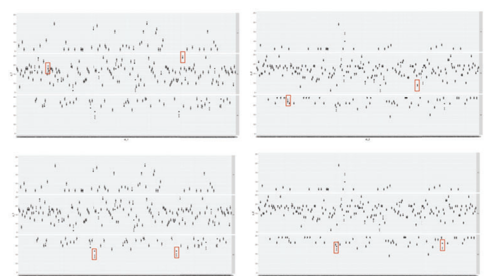


Figure 1: Predicted AM-PAC (Left: Outcome1; Right: Outcome2)

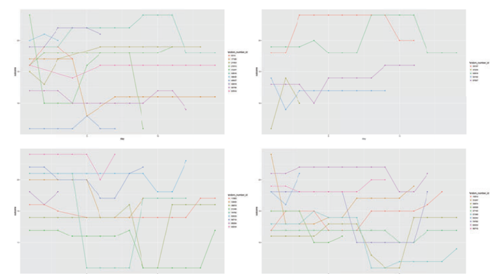


Figure 2: Historical AM-PAC of Patients with Unusual Prediction (Left: Outcome1; Right: Outcome2)

- We tracked back the patients with unusual length of the predicted interval and found that they all had some gaps in their records.
- We tracked back the patients with unusual prediction and found that: for prediction greater than upper bound, they all had a sudden drop before some flat and then a sudden increase (like a big U); for prediction less than lower bound, we found a big U that was upside down.

Future Work

What can patient mobility trajectories predict about patient outcomes (e.g. 30-day readmission, death)?

- Given patient information, output a binary "Yes/No" for being at-risk (or probability)
- Look for "archetypal" mobility trajectories with associated patient outcomes

What are the optimal dynamic treatment regimes (ODTRs) of therapy that maximize patient mobility?

- Quantify the effects that go into assigning physical therapy (propensity score)
- Calculate the average causal effect (ACE) of physical therapy