**Readmission Data is a Safety Net**

EDSA’s Data Science Innovation (DSI) is working to create new tools to predict who, among L.A. Care’s hospitalized members, is at a higher risk of returning to the hospital soon after discharge.

Readmissions 30 or fewer days after discharge can signal an underlying problem with the quality of the care a member receives. It may also indicate a missed opportunity to control costs, especially when outpatient care might have addressed the members’ needs before readmission became necessary. Additionally, it exposes frail members to hospital acquired infections for longer periods of time, and it frustrates any member who prefers to be home rather than – again – at the hospital. Accordingly, accrediting organizations commonly use readmission rates as a measure of the quality of the services that health care actors like L.A. Care render. L.A. Care in turn monitors the readmission rates of the PPGs and hospitals within its network.

Care Management nurses within L.A. Care’s Utilization Management (UM) and Care Management (CM) have the means to reduce readmission rates. They routinely reach out to members to provide them with information, resources and support to help them stay out of the hospital. Currently, they identify the members who need this assistance through professional referrals, self-referrals, and the Health Risk Assessment (HRA) survey which is administered to a subset of our membership. UM and CM have asked DSI for a new tool to calculate the risk of readmission for every hospitalized member, and to do so before claims are generated but rather as soon as a member is first admitted to hospital.

DSI produced its first readmission risk prediction tool early in Q2 of 2018. Their tool outperformed the [Lace Index](https://www.besler.com/lace-risk-score/), a widely used formula developed in Canada approximately ten years ago (see table 1):

| **Table 1: Performance of two models on cases that are distinct from those that helped to form the models.** | | | | |
| --- | --- | --- | --- | --- |
| **Model** | **Kappa1** | **AUPRC2** | **Precision3** | **Recall4** |
| L.A. Care Model 1 | 0.3803 | 0.6643 | 0.7135 | 0.6355 |
| LACE | 0.2979 | 0.6311 | 0.6845 | 0.5526 |
| 1 [Kappa](http://thedatascientist.com/performance-measures-cohens-kappa-statistic/) measures how much better the model performs compared to guesses that only take class prevalence into account. It was selected as a better measure than accuracy to train and assess the model given the moderate class imbalance between index admissions that are vs. are not followed by a readmission. 2 The Area under the Precision-Recall Curve ([AUPRC](http://www.chioka.in/differences-between-roc-auc-and-pr-auc/)) indicates the overall success of the model across levels of precision and recall. This measure does not change when better precision is solely obtained at the expense of recall or vice versa. 3 [Precision](https://en.wikipedia.org/wiki/Precision_and_recall) is the ratio of the count of stays that were correctly predicted to be followed by a readmission within 30 days over the count of all stays that were predicted (correctly or not) to be followed by readmission. 4 [Recall](https://en.wikipedia.org/wiki/Precision_and_recall) is the ratio of the count of stays that were correctly predicted to be followed by a readmission within 30 days over the count of all stays that were in fact followed by readmission. | | | | |

This first attempt took advantage of DSI’s newly acquired Cloudera Data Science Workbench. DSI used a gradient boosting algorithm to train a model on a majority of all 2017 L.A. Care member admissions; a similar method was especially successful in a recent study by [Maali et al. (2018)](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5755362/) in Australia. Developing the model using L.A. Care’s own, unique population was key to the model’s success. Indeed, DSI limited the input to what LACE requires, i.e. Length of Stay (i.e. how long a member initially stayed in the hospital), Acuity (whether the member was admitted from an emergency department), the same 14 comorbidities (including previous myocardial infarction, chronic pulmonary disease, and metastatic solid tumor), and a 6-month count of prior ER visits. On this even playing field, DSI’s model outperformed the LACE on both precision (0.71 vs. 0.68) and recall (0.64 vs. 0.55).

DSI is working on improving the quality of its predictions even more by expanding the input used to train future models. They are sourcing a list of several hundred variables that are associated with readmission in peer reviewed work. To support this sourcing work, they have become stakeholders in L.A. Care’s Health Information Exchange (HIE) projects (LANE, eConnect, EDIE PreManage, plus direct outreach to select hospitals) which are meant to bring admission data into our systems more quickly and to expand our data universe to include EMRs. Additionally, they are developing a new workflow that interleaves modeling efforts with Causal Mapping Workshops with their subject matter experts. Finally, they are collaborating with UM to build reporting tools to monitor some of the systemic drivers of readmission.

LA Care is in an advantageous position to describe a member and his or her care beyond the walls of the hospital. DSI’s readmission prediction project illustrates how the organization comes together to knit data into a safety net for members in one of the most vulnerable moments of their lives.

Version 3