Predictive Analytics for Retention in HIV Care

Jessica Ridgway, MD, MS; Arthi Ramachandran, PhD; Hannes Koenig, MS; Avishek Kumar, PhD; Joseph Walsh, PhD; Christina Sung; Rayid Ghani, MS; John A. Schneider, MD, MPH
Big Data/Predictive Analytics

Google

Amazon

Netflix
Predictive Analytics in Healthcare

• Big Data source: Electronic medical records (EMR)
Predictive Analytics in Healthcare:
Examples of Predicted Outcomes

- In-hospital cardiac arrest
- Readmissions
- Hospital acquired infections
- Length of stay in hospital
- Missed clinic appointments
How can predictive analytics be used to improve retention in HIV care?

- Predict each client’s risk for retention in care failure before client falls out of care
- Real time, individualized assessment of risk
- Can be used to target retention resources for clients at greatest risk of falling out of care
Aim

To create a predictive model of retention in care using EMR data and electronic contextual metadata, utilizing machine learning methods
What is Machine Learning?

- Derived from computer science
- Uses historical information to identify patterns or predict future events without necessarily having pre-programmed rules
- Captures hard to detect relationships in the data
  - Scalable
  - Non linear/complex models
- Goal to maximize predictive accuracy rather than interpret regression coefficients
What is Machine Learning?

Most Common Machine Learning Tasks...

**Regression**
Using trends to predict outcomes

**Clustering**
Finding existing groups or categories

**Classification**
Labeling and sorting into groups

**Dimension Reduction**
Create a simplified abstraction of the data
Data Source

EMR data for all HIV+ patients who received care in adult ID clinic from 2008-2016:

- Appointments scheduled/attended/missed/cancelled
  - Encounters in ID and other departments
- Diagnoses
  - billing codes, problem lists, past medical history
- Social history
- Laboratory values
  - CD4, viral load
- Medications
  - ART regimen, pill burden
- Demographics, Insurance
Location Based Data: Geocoded Patient Addresses

Abbreviations: UCMC, University of Chicago Medical Center; CTA, Chicago Transit Authority
Location Based Data

- Data from American Community Survey and Chicago Open Data Portal
- Characteristics of clients’ neighborhoods
  - Average income level
  - Average education level
  - Racial/ethnic composition
  - Crime rates
Retention in Care Definition:
2 kept visits within 12 months > 90 days apart
Methods

• Machine Learning Methods used
  – Decision trees
  – Random forest
  – Logistic regression
  – Gradient boosting

• Validated using temporal cross-validation
Methods

• Compared precision of each model to baseline retention rate and to a simple logistic regression model meant to simulate expert heuristics
# Results: Patient Demographics

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>N (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N=713</td>
</tr>
<tr>
<td>Male sex</td>
<td>399 (56%)</td>
</tr>
<tr>
<td>Race</td>
<td></td>
</tr>
<tr>
<td>African American</td>
<td>585 (82%)</td>
</tr>
<tr>
<td>White</td>
<td>93 (13%)</td>
</tr>
<tr>
<td>Other</td>
<td>35 (5%)</td>
</tr>
<tr>
<td>Insurance</td>
<td></td>
</tr>
<tr>
<td>Private</td>
<td>312 (44%)</td>
</tr>
<tr>
<td>Medicaid</td>
<td>309 (43%)</td>
</tr>
<tr>
<td>Medicare</td>
<td>85 (12%)</td>
</tr>
<tr>
<td>Mean (SD)</td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>47.3 (13.6)</td>
</tr>
<tr>
<td># of attended appointments</td>
<td>19.5 (17)</td>
</tr>
</tbody>
</table>
Appointments per year in HIV care clinic
Comparison of Precision among Models

![Graph showing comparison of precision among models over years](image-url)
Best Performing Model: Random Forest Model

- Included 1,466 features

- Most important features for prediction of retention in care:
  - Previous ID encounters
  - CD4 count
  - Provider
  - Viral load
  - Substance use
  - Previous encounters in departments other than ID
Precision and Recall for Random Forest Model
Future Plans

• Incorporate natural language processing of text of provider and social work notes into the model
• Validate model using EMR data from CFAR Network of Integrated Systems (CNICS) research network
• Create interactive tool showing risk of retention failure in real time during clinical encounter
Acknowledgments

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