



# 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**

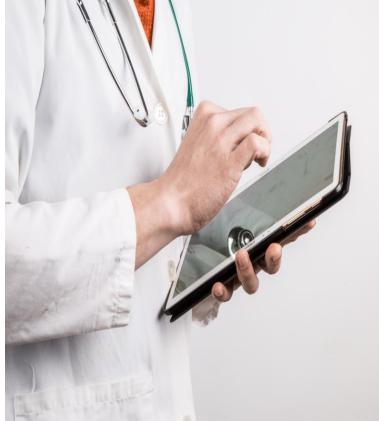




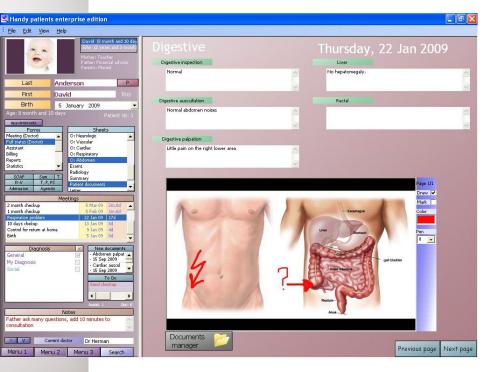


## Predictive Analytics in Healthcare

 Big Data source: Electronic medical records (EMR)



THE UNIVERSITY OF CHICAGO MEDICINE & BIOLOGICAL SCIENCES



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





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



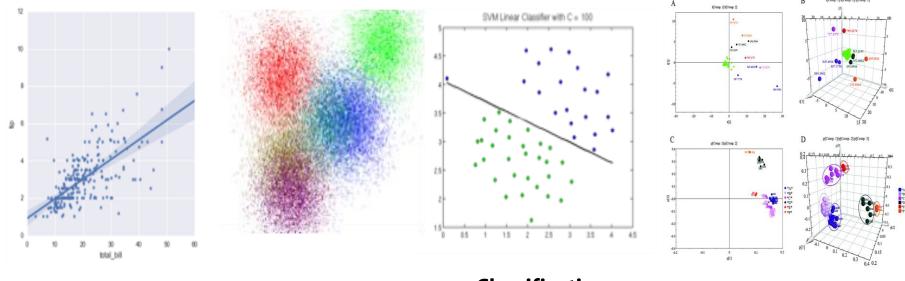
# What is Machine Learning?

- 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

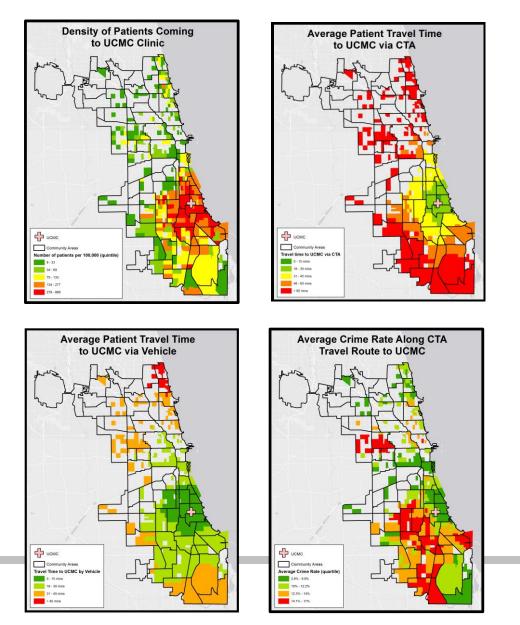
Labeling and sorting into groups **Dimension Reduction** Create a simplified abstraction of the data

## 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

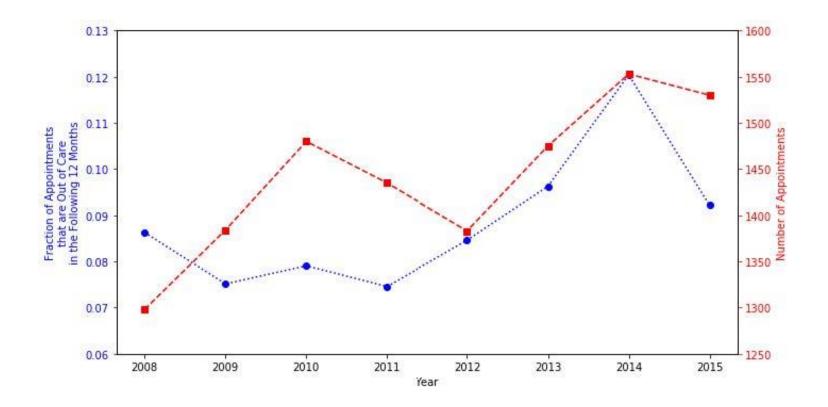


# **Results: Patient Demographics**

| Characteristics                              | N (%)<br>N=713                     |
|--|------------------------------------|
| Male sex                                     | 399 (56%)                          |
| Race<br>African American<br>White<br>Other   | 585 (82%)<br>93 (13%)<br>35 (5%)   |
| Insurance<br>Private<br>Medicaid<br>Medicare | 312 (44%)<br>309 (43%)<br>85 (12%) |
|  | Mean (SD)                          |
| Age  | 47.3 (13.6)                        |
| # of attended appointments                   | 19.5 (17)                          |

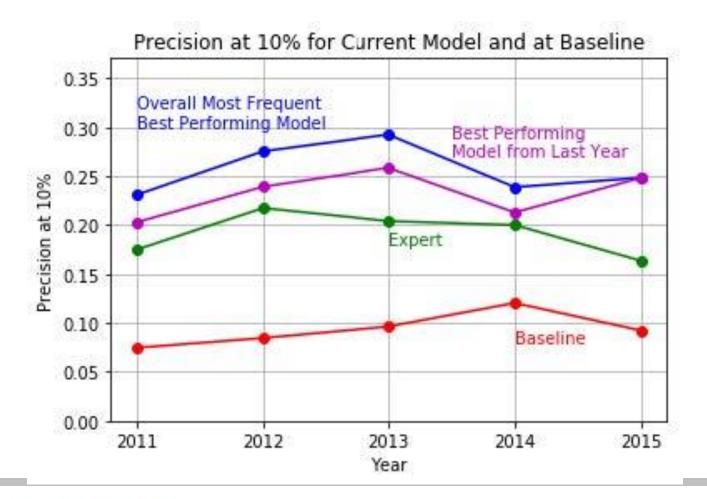


### Appointments per year in HIV care clinic





## Comparison of Precision among Models



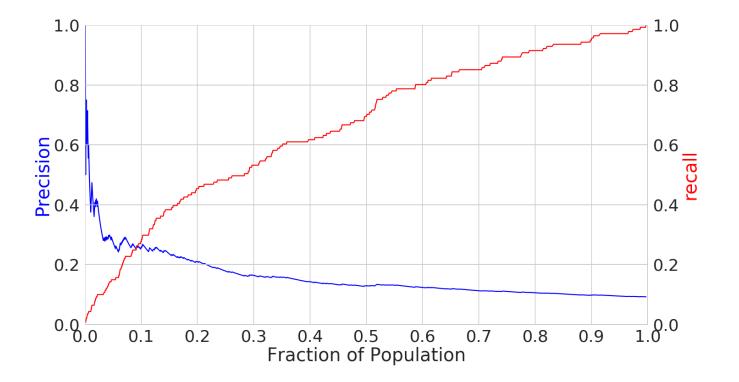


Best Performing Model: Random Forest Model

- 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

#### **Center for Data Science and Public Policy**





Funding provided by pilot award from the Third Coast Center for AIDS Research (CFAR), an NIH funded center (P30 AI117943).

