## Improved Predictive Models for Readmission of Patients with Diabetes Chathurangi Heshani Karunapala Pathiravasan(chathurangi@siu.edu), R. W. M. A. Madushani, PhD(<u>anusha.wasalamudiyanselage@medicine.ufl.edu</u>), Gabrielle LaRosa (<u>gal41@pitt.edu</u>) Southern Illinois University, University of Florida, University of Pittsburgh



### **Problem Statement**

Examining the historical patterns of diabetics care is very essential which leads to improvements in patient safety and prevent future readmissions.



This improves the quality of health care and reduces the medical expenses on readmission.

# Goals and Objectives

- To build accurate predictive models for hospital readmission of patients with diabetes.
- Identifying key contributing factors of readmission.



The data set is obtained from UCI machine learning repository and it is highly imbalanced and contains multiple patient visits. We used ROC and AUC to compare models.



• We use 19 predictors (8 continuous predictors and 11 categorical predictors). Results

#### Model

GLM 1 (Base Model)

GLM 2 (with 19 predictors)

GLM 3 (backward elimination sub model)

GAM (all excluding number of procedure)

Model

LDA (Linear Discriminant A

QDA (Quadratic Discrimina

MM (Marginal Models with

**GLMM** (Generalized Linear with repeated data)



AIC	AUC	
24733.7	0.6034	
24509.1	0.6255	
24491.3	0.6239	
24482.4	0.6291	
		AUC
nalysis)		0.6016
int Analysis)		0.6018
n repeated data)		0.6480
Mixed Models		0.6470

#### Model

NB (Naïve Bayes) RF1 (Random Forest without repeated data) RF2:Dealing with imbalanced (without repeated) Over Sampling Under Sampling RF3 (Random Forest with repeated data) SVM (Support vector machine: 19 Predictors)

### EGB(Extreme gradient boosting)



Top 10 varaibles Importance of RF3 (with repeated data)

number_inpatient		num_lab_procedures	
discharge_disposition	o	num_medications	
num_medications	·····o	primary_diagnosis	······
primary_diagnosis	····· 0	time_in_hospital	······
number_emergency	·····0····	number_inpatient	······
time_in_hospital	0.	medical_specialty	······
number_diagnoses	··· 0	number_diagnoses	······
age	-0	num_procedures	······
number_outpatient	-0	admission_type	
num_lab_procedures	0	number_outpatient	······
	5 10 15 20 25 30 35 40	)	0 200 400 600 80
	MeanDecreaseAccuracy		MeanDecreaseGini





### Conclusions

- Compared to the base model GLM model 2 has more predictability.
- GAM model is a better fit (AIC lower) and it has more predictive power than GLM models.
- Naïve Bayes model has better predictability compared to GLM.
- Substantial improvement in the predictability, when we consider marginal and mixed effect models.
- Random Forests performs well compared to other machine learning approaches.
- Number of lab procedures, number of medications, time in hospital, number of diagnoses, number of procedure, primary diagnosis and medical specialty are the main contributing factors of readmission.

## References

[1] B. Strack, et al.. Impact of hba1c measurement on hospital readmission rates: analysis of 70,000 clinical database patient records. BioMed research international, 2014.

[2] A. Frank and A. Asuncion, UCI Machine Learning Repository, University of California, School of Information and Computer Science, 2010.

### Acknowledgement

This project is under the grant NSF **CCF0939370: Center for Science of** Information (https://www.soihub.org)