# IAF 606, Solving Problems with Data Analytics, Final Project Report

Introduction: The diabetes dataset used for this study contains 50 variables and 101,766 observations. The data was collected over 10 years from 130 hospitals and contains information regarding patient stays in which a diagnosis of diabetes was indicated. Variables include patient information, admission and discharge information, medications and diagnostic measures and a variety of patient information. The objective of this paper is to analyze the information chosen by the authors of a research paper from the Virginia Commonwealth University (*Impact of HbA1c Measurement on Hospital Readmission Rates: Analysis of 70,000 Clinical database Patient Records*), replicate the models used and then attempt to find models that may make predictions in keeping with the goals of the research paper. The objective of the paper was to predict early readmissions (those that occurred within 30 days of discharge) and its association with HbA1c measures using the variables remaining after cleaning the data.

**Step One - Data Preparation:** The first step in the process was to prepare the data in the same way that the data was configured and cleaned by the authors of the study. Most of the variables were omitted, included medications, patient weight, payer information and a few other metrics. Diagnosis and medical specialty codes were used to consolidate categories and several other categories were reconfigured. Additionally, missing values were noted and listed as "other" in most categories. The HbA1c variable was reconfigured using the change variable to represent patients with high HbA1c measures and changed medications and those with high HbA1c measures with no change to medications. Once this variable was used to alter the HbA1c category, the change variable was also dropped.

The target variable chosen was readmissions. This category was reconfigured to be comprised of two subcategories. The first category consisted of observations with no readmissions and readmissions that occurred after a period of 30 days. The readmission category was comprised of observations where the patient was readmitted within 30 days of discharged. Additionally, to remove bias only one observation per patient was used significantly cutting the overall number of final observations. Likewise, observations where patients were discharged to a hospice or where patients died were also omitted. Once the data was cleaned 69970 observations were left and the following variables remained:

#### Continuous variables:

- Time spent in the hospital
- Age of patient (computed from age variable taking the median of the age in each category and assigning that value to a new variable)

# Categorical variables:

- HbA1c (4 categories: no test, high with meds changed, high without meds changed, and normal results)
- o Gender (2 categories: male and female)
- Discharge disposition (2 categories: discharged to home, other)
- Admission source (3 categories: admitted from emergency room, admitted from doctor or clinic referral, Other)
- Specialty of Admitting Doctor (6 categories: internal medicine, cardiology, surgery, family/general practice, missing, other)
- Primary diagnosis (9 categories: internal medicine, circulatory, diabetes, digestive, injury, musculoskeletal, genitourinary, neoplasms, other)
- o Race (4 categories: African American, Caucasian, other, missing)
- o Age (3 categories: <30, 30-60, >30
- o Readmission (2 categories: readmission, other)

**Final data set:** 69### observations - the process (programmed in python) that was used to cleaned the data is found in the "Reppert-IAF-606-Final-Project-Part 1 Cleaning Data.rmd" file.

**Building and analyzing the study model:** (code found in Reppert-IAF-606-Final-Project-Part-2 Log Regression)

#### 1. Study model (logistic regression):

a. The first step the authors used was to create a model with all variables except for HbA1c. Tests of significance of variables were obtained by looking at coefficients as variables were removed one at a time and analyzing the results. Then the HbAc1 variable was added to the core model obtained in the first step. One variable, gender, was found to not be significant and was thus removed from the model.

b. Next interactions were added to the model. Once again, this was done without HbA1c. All pairwise interactions were included and removed one at a time investigating each interaction for significance and eliminating those that were not significant. Once the best pairwise interactions were determined, HbA1c was added back into the model. The final model that was built was as follows:

Readmitted ~ Discharge + Race + Admit + Med\_spec + Time\_hosp + Age + Diag + HbA1c + Age:Med\_spec + Diag:Discharge + Race:Discharge + Discharge:Time\_hosp + Med\_spec:Discharge + Time\_hosp:Med\_spec + Time\_hosp:Diag + HbA1c:Diag

Table 4 values:

\_\_\_\_\_\_ Dependent variable: Readmitted C<u>oef.</u> DischargeTo home  $-0.\overline{262}$ , p = 0.116 0.032, p = 0.549RaceCauc RaceMissing -0.031, p = 0.8150.199, p = 0.067\* 0.017, p = 0.587 RaceOther AdmitFrom ER -0.115, p = 0.010\*\*\* AdmitOther Med specFam/GenPract -1.399, p = 0.102Med specIntMed -1.059, p = 0.156 Med specOther -1.375, p = 0.055\* Med specSurgery -1.738, p = 0.157 -0.438, p = 0.527Med specUnknown Time hosp 0.067, p = 0.002\*\*\*Age> 60 -1.224, p = 0.064\* -1.477, p = 0.027\*\*Age30-60 DiagDiabetes -0.623, p = 0.002\*\*\*-0.154, p = 0.609 DiagDig DiagGenit -0.650, p = 0.044\*\*-0.500, p = 0.167DiagInjury -0.136, p = 0.720DiagMusc/skel DiagNeoplasms -0.743, p = 0.191 DiagOther -0.125, p = 0.525DiagResp -0.512, p = 0.027\*\*HbAlcHigh no change -0.159, p = 0.320-0.150, p = 0.118HbA1cNo test HbA1cNormal -0.196, p = 0.093\*

#### Table 5 values:

 Med\_specFam/GenPract:Age> 60
 2.196, p = 0.009\*\*\*

 Med\_specIntMed:Age> 60
 1.641, p = 0.024\*\*

 Med\_specOther:Age> 60
 1.947, p = 0.006\*\*\*

 Med\_specSurgery:Age> 60
 2.662, p = 0.028\*\*

 Med\_specFam/GenPract:Age30-60
 1.010, p = 0.133

 Med\_specIntMed:Age30-60
 2.121, p = 0.012\*\*

 Med\_specIntMed:Age30-60
 2.550, p = 0.004\*\*\*

 Med\_specSurgery:Age30-60
 2.817, p = 0.021\*\*

 Med\_specUnknown:Age30-60
 2.817, p = 0.021\*\*

 Med\_specUnknown:Age30-60
 -1.092, p = 0.108

 DischargeTo home:DiagDiabetes
 -0.026, p = 0.814

 DischargeTo home:DiagDig
 -0.026, p = 0.661

 DischargeTo home:DiagMsc/skel
 -0.162, p = 0.230

 DischargeTo home:DiagNesc/skel
 -0.444, p = 0.004\*\*\*

 DischargeTo home:DiagNeoplasms
 0.139, p = 0.376

 DischargeTo home:DiagNeoplasms
 0.139, p = 0.376

 DischargeTo home:BaceCauc
 -0.013, p = 0.1007\*\*\*

 DischargeTo home:RaceCauc
 -0.018, p = 0.007\*\*

 DischargeTo home:RaceOther
 -0.285, p = 0.130

 DischargeTo home:RaceOther
 -0.285, p = 0.003\*\*\*

 DischargeTo home:Med\_specIntMed
 <td

```
-0.052, p = 0.027**
Med specOther: Time hosp
                                          -0.110, p = 0.0002***
Med specSurgery: Time hos
Med specUnknown: Time hosp
                                           -0.058, p = 0.007***
                                           0.034, p = 0.043**
Time hosp:DiagDiabetes
Time hosp:DiagDig
                                           0.0003, p = 0.987
Time_hosp:DiagGenit
                                           0.076, p = 0.0005***
                                           -0.009, p = 0.639
Time hosp:DiagInjury
Time hosp:DiagMusc/skel
                                           0.057, p = 0.023*
                                          -0.013, p = 0.590
Time hosp:DiagNeoplasms
                                          -0.023, p = 0.080*
Time hosp:DiagOther
                                           0.026, p = 0.093*
Time hosp:DiagResp
DiagDiabetes: HbAlcHigh no change
                                           0.026, p = 0.929
DiagDig:HbAlcHigh no change
                                           -0.293, p = 0.533
                                           -0.765, p = 0.252
DiagGenit: HbAlcHigh no change
DiagInjury: HbA1cHigh no change
                                           0.457, p = 0.420
DiagMusc/skel:HbAlcHigh no change
DiagNeoplasms:HbAlcHigh no change
                                          0.031, p = 0.959
                                           0.852, p = 0.298
0.399, p = 0.173
DiagOther:HbAlcHigh no change
DiagResp: HbAlcHigh no change
                                           0.061, p = 0.862
DiagDiabetes:HbA1cNo test
                                           0.542, p = 0.002***
DiagDig:HbA1cNo test
                                            0.033, p = 0.902
DiagGenit: HbA1cNo test
                                           0.102, p = 0.725
DiagInjury: HbA1cNo test
                                           0.697, p = 0.045**
                                           -0.251, p = 0.471
DiagMusc/skel:HbA1cNo test
                                           0.652, p = 0.222
DiagNeoplasms: HbA1cNo test
                                           0.278, p = 0.118
DiagOther: HbA1cNo test
                                           0.219, p = 0.291
DiagResp:HbA1cNo test
DiagDiabetes:HbA1cNormal
                                            0.595, p = 0.008*
                                           0.013, p = 0.968
DiagDig:HbA1cNormal
DiagGenit: HbA1cNormal
                                           0.375, p = 0.274
DiagInjury: HbA1cNormal
                                           0.152, p = 0.709
                                          -0.292, p = 0.483
DiagMusc/skel:HbA1cNormal
                                          0.948, p = 0.106
DiagNeoplasms: HbA1cNormal
DiagOther: HbA1cNormal
                                           0.258, p = 0.224
                                           -0.216, p = 0.399
DiagResp:HbA1cNormal
· · ·
                                       *p<0.1; **p<0.05; ***p<0.01
  Note:
```

#### 2. Model analysis:

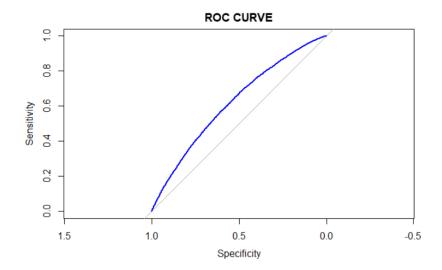
Once the model was created, the dataset was split into training and test set at a 70/30 ratio.

A sampling of model probabilities was taken and are as follows:

Based on these results a cutoff value of .1 was established for model prediction. The confusion matrix of the model is as follows:

```
glm.pred Other Readmitted
Other 10844 888
Readmitted 7943 1201
```

The model generated a ROC plot as follows:



The accuracy/efficiency calculated was 0.5769783 and the AUC score was 0.6189. The classification rate was calculated as 57.7. Other measures for this model are as follows:

Precision: 0.9243096 Specificity: 0.5749162 Sensitivity: 0.5772076 F1 Score: 0.7106393

J: 0.1521239

#### 3. Conclusions for paper model:

Overall the outcome for predictions gave mixed results. An accuracy of 0.6189 would not appear to be ideal in terms of usefulness. There were many false negatives and false positives within the confusion matrix. While the precision score was relatively high, the specificity scores and sensitivity scores were not quite as impressive leading to a relatively low Youden Index score ([]).

#### Creating my own logistic regression model:

# 1. Building the model:

In my attempts to create a better model, I tried a few approaches. The first was to experiment with a variety of interactions much in the way the paper added interactions. It became clear to me that there was potential with utilizing the admit and diagnosis variable more than the paper model used it. Additionally, I

experimented with using the numeric value for age instead of the age ranges. Several comparisons were made between various models with results reported below. All the models were constructed without the HbA1c variable. This variable was then added to the model that was determined to be best. Variables that were considered to be significant had a Pr(>Chisq) value below 0.05.

The Admit:Age variable was added and appeared to be significant with a Pr(>Chisq) of 0.008508. The ANOVA output for the model with the interaction of Admit:Age added was as follows:

```
Analysis of Deviance Table (Type II tests)
Response: Readmitted
                           LR Chisq Df Pr(>Chisq)
                              340.93 1 < 2.2e-16 ***

7.10 3 0.068780 .

9.63 2 0.008123 **

29.81 5 1.608e-05 ***
Discharge
Race
Admit
Med_spec
                                46.81 1 7.803e-12 ***
41.28 2 1.088e-09 ***
60.38 8 3.932e-10 ***
Time_hosp
Age
Diag
                                                0.000208 ***
Med_spec:Age
                                 33.70 10
                                23.88 8 0.002399 ***
14.19 3 0.002662 **
9.10 1 0.002555 **
13.65 4 0.008508 **
17.03 5 0.004445 **
Discharge:Diag
Discharge:Race
Discharge:Time_hosp
Admit:Age
Med_spec:Time_hosp
                             33.74 8 4.527e-05 ***
18.01 5 0.002938 **
Time_hosp:Diag
Discharge:Med_spec
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The results for age\_numeric substituted for the age variable did not produce a significant enough improvement over the age category (the age category's values were higher) to merit a substitution although the age\_numeric variable and interactions did have significant values.

```
Analysis of Deviance Table (Type II tests)
Response: Readmitted
                                       LR Chisq Df Pr(>Chisq)
                                           R Chisq Df Pr(Schisq)
328.85 1 < 2.2e-16 ***
7.26 3 0.0641513 .
9.32 2 0.0094898 **
24.34 5 0.0001870 ***
42.94 1 5.639e-11 ***
22.34 1 2.280e-06 ***
58.35 8 9.814e-10 ***
16.16 5 0.0064118 **
29.82 8 0.0002273 ***
14.08 3 0.0027976 ***
9.31 1 0.0022840 ***
Discharge
Race
Admit
Med_spec
Time hosp
Age_numeric
Diag
Med_spec:Age_numeric
Discharge:Diag
Discharge:Race
                                                                0.0022840 **
Discharge:Time hosp
                                                9.31
                                            34.84 16 0.0041770 **
10.76 5 0.0562980 .
36.09 8 1.690e-05 ***
7.86 2 0.0196387 *
Admit:Diag
Med_spec:Time_hosp
Time_hosp:Diag
Admit:Age_numeric
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '1
```

The Admit:Diag variable was added and appeared to be significant with a Pr(>Chisq) of 0.0060984. The ANOVA output for the model with the interaction of Admit:Diag added was as follows:

```
Analysis of Deviance Table (Type II tests)

Response: Readmitted

LR Chisq Df Pr(>Chisq)

Discharge 340.31 1 < 2.2e-16 ***
Race 7.08 3 0.0694450 .

Admit 9.63 2 0.0081230 **
Med_spec 25.20 5 0.0001277 ***
Time_hosp 41.89 1 9.674e-11 ***
Age 42.19 2 6.900e-10 ***
Diag 60.38 8 3.932e-10 ***
Med_spec:Age 33.75 10 0.0002032 ***
Discharge:Diag 24.95 8 0.0015849 **
Discharge:Race 14.01 3 0.0028879 **
Discharge:Time_hosp 8.85 1 0.0029373 **
Admit:Age 11.41 4 0.0222926 *
Med_spec:Time_hosp 16.32 5 0.0059910 **
Time_hosp:Diag 35.57 8 2.106e-05 ***
Discharge:Med_spec 17.90 5 0.0030765 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The Med\_spec:Diag variable was added and appeared to be significant with a . Pr(>Chisq) of 0.0023047. The ANOVA output for the model with the interaction of Med\_spec:Diag added was as follows:

```
Analysis of Deviance Table (Type II tests)

Response: Readmitted

LR Chisq Of Pr(>Chisq)

Discharge 339.36 1 < 2.2e-16 ***

Race 7.17 3 0.0666202.
Admit 9.16 2 0.0102667 *

Med_spec 25.20 5 0.0001277 ***

Time_hosp 40.90 1 1.601e-10 ***

Age 40.56 2 1.557e-09 ***

Diag 60.38 8 3.932e-10 ***

Med_spec:Age 25.85 10 0.0039511 **

Discharge:Diag 28.40 8 0.0004040 ***

Discharge:Race 14.38 3 0.0024342 **

Discharge:Time_hosp 8.85 1 0.0029351 **

Admit:Age 11.69 4 0.0197946 *

Med_spec:Time_hosp 13.84 8 5.260e-06 ***

Discharge:Med_spec 15.51 5 0.0080596 **

Med_spec:Diag 38.84 8 5.260e-06 ***

Discharge:Med_spec 10.002307 **

---

Signif: codes: 0 '*** '0.001 '** '0.01 '* '0.05 '.' 0.1 ' ' 1
```

Interactions that did not improve the model: Admit:Med\_Spec (Pr(>Chisq) was 0.0915773), Race:Diag (Pr(>Chisq) was 0.1112454), and Race:Admit (0.2179067). These interactions were all explored with the other interactions above due to the potential with Admit and Diag interactions being potentially significant. Nonetheless, these combinations did not produce significant values in the model results. Additionally, the interaction between time in hospital and medical specialty was removed from the model to explore if this interaction improved it since at times this value was a bit above the cutoff for significance of .05. Despite this concern the anova results demonstrated that the addition of this interaction was indeed an improve with a Pr(>Chisq) of 0.004445 with the interaction added.

The final model that was chosen was model\_tb5.4:

Readmitted ~ Discharge + Race + Admit + Med\_spec + Time\_hosp + Age + Diag + Age:Med\_spec + Diag:Discharge + Race:Discharge + Discharge:Time\_hosp + Admit:Diag + Admit:Age + Time\_hosp:Med\_spec + Time\_hosp:Diag + Med\_spec:Discharge + Med\_spec:Diag Once this model was chosen, HbA1c and the interaction HbA1c and Diagnosis were added to the model. The interaction between HbA1c and Admit (Pr(>Chisq) of 0.7501402) and the interaction between HbA1c and Medical Specialty (Pr(>Chisq) of 0.1053272 were also explored but neither interaction was significant so they were omitted. The ANOVA output for model\_tb5.4F is as follows:

```
Analysis of Deviance Table (Type II tests)

Response: Readmitted
LR Chisq Df Pr(>Chisq)
Discharge
338.31 1 < 2.2e-16 ****
Race
7.10 3 0.0689012 .
Admit 10.09 2 0.0064255 ***
Med.spec 26.35 5 7.636e-05 ****
Time.hosp 41.34 1 1.281e-10 ****
Age 37.14 2 8.621e-09 ****
Diag 61.97 8 1.911e-10 ****
HbAIc 8.04 3 0.0451569 *
Med.spec.Age 23.82 10 0.0080790 ***
Discharge:Diag 29.17 8 0.002955 ****
Discharge:Time.hosp 14.73 3 0.0024477 ***
Discharge:Time.hosp 29.17 8 0.0027680 ***
Admitt.Diag 30.02 16 0.0194053 **
Admitt.Diag 30.02 16 0.0194053 **
Admitt.Diag 40.014410 **
Med.spec.Time.hosp 14.62 5 0.0121066 **
Time.hosp:Diag 36.74 8 1.285e-05 ***
Discharge:Med.spec 15.58 5 0.0081422 **
Med.spec.Diag 09.04 40 0.0029276 ***
Diag.IBAIC 42.25 24 0.0121116 **

Signif. codes: 0 **** 0.001 *** 0.01 ** 0.05 *. 0.1 * 1 1 1
```

#### 2. Final Model:

Readmitted ~ Discharge + Race + Admit + Med\_spec + Time\_hosp + Age + Diag + HbA1c + Age:Med\_spec + Diag:Discharge + Race:Discharge +Discharge:Time\_hosp + Admit:Diag + Admit:Age + Time\_hosp:Med\_spec + Time\_hosp:Diag + Med\_spec:Discharge + Med\_spec:Diag + HbA1c:Diag

Figure 3 Results for model\_tb5.4F:

```
Dependent variable:
                                      _____
                                             Readmitted
                                          -0.212, p = 0.210
DischargeTo home
RaceCauc
                                          0.026, p = 0.624
                                          -0.040, p = 0.764
RaceMissing
RaceOther
                                          0.197, p = 0.070*
AdmitFrom ER
                                          0.156, p = 0.530
                                          0.111, p = 0.772
AdmitOther
                                          -0.925, p = 0.303
Med specFam/GenPract
                                          -0.800, p = 0.313
Med specIntMed
                                          -0.987, p = 0.195
Med specOther
Med specSurgery
                                          -1.599, p = 0.206
Med specUnknown
                                          -0.116, p = 0.875
                                           0.069, p = 0.002*
Time_hosp
Age> 60
                                          -0.873, p = 0.213
Age30-60
                                          -1.196, p = 0.090*
DiagDiabetes
                                          -0.002, p = 0.998
DiagDig
                                          -0.280, p = 0.623
                                          -0.439, p = 0.546
DiagGenit
```

```
DiagInjury
                                     0.270, p = 0.572
DiagMusc/skel
                                    -10.936, p = 0.934
                                    -12.097, p = 0.905
0.412, p = 0.200
DiagNeoplasms
DiagOther
DiagResp
                                     -0.378, p = 0.265
HbAlcHigh no change
                                     -0.166, p = 0.300
HbA1cNo test
                                     -0.142, p = 0.140
HbA1cNormal
                                     -0.202, p = 0.084*
_____
```

#### Figure 5 results for model\_tb5.4F:

```
Dependent variable:
                                                                         _____
                                                                                       Readmitted
   _____
Med_specIntMed:Age30-60
Med_specOther:Age30-60

      Med_specOther:Age30-60
      1.746, p = 0.018**

      Med_specSurgery:Age30-60
      2.600, p = 0.036**

      Med_specUnknown:Age30-60
      0.878, p = 0.219

      DischargeTo home:DiagDiabetes
      -0.011, p = 0.919

      DischargeTo home:DiagGenit
      0.128, p = 0.355

      DischargeTo home:DiagGenit
      0.128, p = 0.305*

      DischargeTo home:DiagMusc/skel
      -0.498, p = 0.002***

      DischargeTo home:DiagNeoplasms
      0.169, p = 0.288

      DischargeTo home:DiagResp
      -0.145, p = 0.143

      DischargeTo home:RaceCauc
      -0.018, p = 0.802

      DischargeTo home:RaceOther
      -0.287, p = 0.129

      DischargeTo home:Time_hosp
      0.028, p = 0.003***

      AdmitFrom ER:DiagDiabetes
      -0.174, p = 0.166

      AdmitFrom ER:DiagDiabetes
      0.029, p = 0.871

      AdmitFrom ER:DiagDig
      -0.086, p = 0.494

      AdmitOther:DiagDiag
      0.196, p = 0.263

                                                                                1.746, p = 0.018**
2.600, p = 0.036**
0.878, p = 0.219
AdmitFrom ER:DiagDig
                                                                                  0.196, p = 0.263
 AdmitOther:DiagDig
 AdmitOther:DiagDig

AdmitFrom ER:DiagGenit
                                                                                 -0.290, p = 0.055*
                                                                                 0.027, p = 0.905
 AdmitOther:DiagGenit
 AdmitGrom ER:DiagInjury
AdmitFrom Ex.DIS
AdmitOther:DiagInjury
AdmitFrom ER:DiagMusc/skel
**Other:DiagMusc/skel
                                                                                 0.123, p = 0.341
                                                                                -0.022, p = 0.908
                                                                                  0.171, p = 0.340
                                                                                 0.027, p = 0.900
                                                                                 0.320, p = 0.060*
 AdmitOther:DiagNeoplasms
                                                                                  0.212, p = 0.436
 AdmitFrom ER:DiagOther
                                                                                 -0.281, p = 0.003***
 AdmitOther:DiagOther
                                                                                 -0.055, p = 0.665
 AdmitFrom ER:DiagResp
                                                                                 -0.187, p = 0.113
 AdmitOther:DiagResp
                                                                                 -0.047, p = 0.770
 AdmitOther:DiagResp
AdmitFrom ER:Age> 60
                                                                                 -0.057, p = 0.815
                                                                                 -0.320, p = 0.395
 AdmitOther:Age> 60
                                                                                 -0.080, p = 0.745
 AdmitFrom ER:Age30-60
                                                                                -0.029, p = 0.940
 AdmitOther:Age30-60
 Med specFam/GenPract:Time hosp -0.062, p = 0.018**
 Med specIntMed:Time hosp
                                                                                 -0.039, p = 0.098*
```

```
Med specOther:Time hosp
Med specSurgery:Time hosp
Med specSurgery:Time hosp
Med specSurgery:Time hosp
Med specSurgery:Time hosp
Time hosp Diagniabetes

10.030, p = 0.001***

10.030, p = 0.001***

10.030, p = 0.001***

10.030, p = 0.002**

10.030, p = 0.020**

10.030, p = 0.003***

10.030, p = 0.031**

10.030,
```

```
DiagOther: HbA1cNo test
                                             0.241, p = 0.176
                                             0.222, p = 0.287
DiagResp:HbA1cNo test
DiagDiabetes: HbA1cNormal
                                             0.582, p = 0.010***
DiagDig:HbA1cNormal
                                             0.022, p = 0.945
DiagGenit: HbA1cNormal
                                             0.358, p = 0.297
DiagInjury:HbA1cNormal
                                             0.164, p = 0.686
DiagMusc/skel:HbA1cNormal
                                            -0.267, p = 0.523
DiagNeoplasms: HbA1cNormal
                                             1.001, p = 0.090*
DiagOther: HbA1cNormal
                                             0.256, p = 0.229
DiagResp: HbA1cNormal
                                            -0.203, p = 0.428
Observations
                                        *p<0.1; **p<0.05; ***p<0.01
Note:
```

# 3. Final Model Analysis

Once the model was created, the dataset was split into training and test set at a 70/30 ratio.

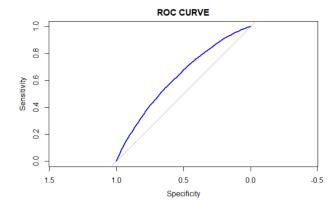
A sampling of model probabilities was taken and are as follows:

```
4 5 8 11 15 16 19 22 26 27 0.05426014 0.10427214 0.09861913 0.10693170 0.06085263 0.15663704 0.09788592 0.05015426 0.03415239 0.10391974
```

Based on these results a cutoff value of .1 was established for model prediction. The confusion matrix of the model is as follows:

```
glm.pred2 Other Readmitted
Other 10859 873
Readmitted 7897 1225
```

The model generated a ROC plot as follows:



The accuracy/efficiency calculated was 0.5794572 and the AUC score was 0.6251. The classification rate for the final model (model\_tb5.4F) was 57.95. Other measures for this model are as follows:

Precision: 0.9255881 Specificity: 0.5838894 Sensitivity: 0.5789614 F1\_Score: 0.7123458

J: 0.1628508

#### 3. Conclusions for paper mode

Overall, the outcome for predictions still was rather lackluster. The quantitative measures for the "improved model" showed some small improvements but there were still deficits in the model performance. There were still many false negatives and false positives within the confusion matrix (although there were less). The precision score was still relatively high, but the specificity scores and sensitivity scores were only a little higher than the paper model with a slightly higher Youden Index score of 0.1628508. Overall, more readmissions were predicted, which is good, however total readmissions predicted correctly is still, in my opinion, not a very strong number.

**Creating a random forest model:** (code found in file - Reppert-IAF-606-Final-Part-3-Random-Forest.rmd)

#### 1. Building the model:

The model chosen for further exploring the diabetes dataset was the Random Forest model. The first step in the model building process was to fit the model with all of the variables. The same cutoff parameters were used (.10) so that the analysis of all models would be consistent. Some time was spent using the caret package model for random forest in order to do parameter tuning to find best mtry values and the best number of trees. In the end, after running several tests, it was found that the default values showed the best results. Most of these tests took several hours to run even with additional cores allocated to them using a parallel package to assign 6 additional cores to the model creation. For that reason this code, since it was not used in the final model, is not included. The random forest package in R was used instead since this package had a much more efficient means of creating models that only took a few minutes per model.

The dataset was split into training and test sets at a 70/30 ratio and the model was run using the training set. Predictions were then made using the test set. These predictions were used to create a confusion matrix to analyze results. The model was also used to find variable importance values in order to ascertain

which variables were rated as most important in the model. Based on this information, subsequent models were created by removing the variable with the smallest variable importance value, one at a time.

Results of the full model (Model 1) with training set:

```
Call:
randomForest(formula = Readmitted ~ ., data = train, importance = TRUE,
Type of random forest: classification
Number of trees: 500
No. of variables tried at each split: 3

OOB estimate of error rate: 17.97%
Confusion matrix:
Other Readmitted class.error
Other 39523 5068 0.1136552
Readmitted 3734 666 0.8486364
```

The full model (Model 1) was used to produce a confusion matrix after using the model to make predictions. The model is quite overfitted with all the variables but still has a pretty high error rate in the training set. The quantitative measures are as follows:

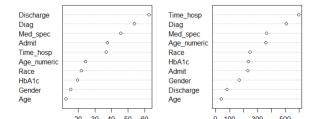
```
Confusion Matrix and Statistics
Reference
Prediction Other Readmitted
Other 16864 1612
Readmitted 2247 273
     Accuracy : 0.8162
95% CI : (0.8109, 0.8214)
No Information Rate : 0.9102
P-Value [Acc > NIR] : 1
                             Kappa : 0.0237
 Mcnemar's Test P-Value : <2e-16
                   Sensitivity: 0.8824
              Specificity: 0.1448
Pos Pred Value: 0.9128
Neg Pred Value: 0.1083
                                          0.1083
                      Precision
                           Recal1
                                       : 0.8824
                                       : 0.8973
: 0.9102
: 0.8032
: 0.8800
                                  F1
    Prevalence
Detection Rate
Detection Prevalence
         Balanced Accuracy : 0.5136
            'Positive' Class : Other
```

Other <dbi></dbi>	Readmitted <dbl></dbl>
7.523115	7.523115
6.558730	6.558730
3.652420	3.652420
29.947925	29.947925
15.849180	15.849180
19.059204	19.059204
20.543162	20.543162
22.757935	22.757935
9.137579	9.137579
5.457839	5.457839
	7.523115 6.558730 3.652420 29.947925 15.849180 19.059204 20.543162 22.757935 9.137579

#### Variable Importance Plot:

MeanDecreaseAccuracy

#### Youden Index:



MeanDecreaseGini

rf1

Sensitivity 0.8824237 Specificity 0.1448276 J: 0.0608244 The least important variable in both cases is the age variable (three categories) followed by discharge and gender. A variety of combinations were tried in addition to removing one variable at a time; however, none of the various combinations had measures that were preferable to that of the full model and most had significantly poorer quantitative measures. In particular, after removing anything other than the age category (either numeric or categorical) the specificity measure fell significantly. Ultimately, these observations led to utilizing all of the selected variables but removing the categorical variable for age.

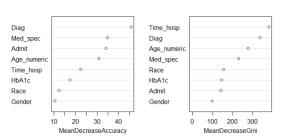
# Examples of some other model attempts:

Model with discharge omitted:

Training output:

#### Test output:





rf3

Sensitivity 0.9510753 Specificity 0.05676393 J3: 0.00783923

Youden Index:

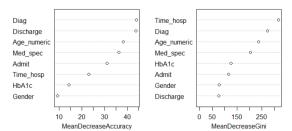
# Model 4 (removing gender):

# Training output:

# Test output:

Confusion Matrix and Statistics  Reference Prediction Other Readmitted Other 18214 Readmitted 897 103			
Accuracy : 0.8724 95% CI : (0.8678, 0.8769) No Information Rate : 0.9102 P-Value [Acc > NIR] : 1			
Карра : 0.0098			
Mcnemar's Test P-Value : <2e-16			
Sensitivity: 0.95306 Specificity: 0.05464		Other «dbl»	Readmitted «dbl»
Pos Pred Value : 0.91088 Neg Pred Value : 0.10300	Time_hosp	11.735735	11.735735
Precision : 0.91088	Diag	17.551729	17.551729
Recall : 0.95306 F1 : 0.93150	Med_spec	14.706231	14.706231
Prevalence : 0.91022	Age_numeric	13.058630	13.058630
Detection Rate : 0.86750	Gender	4.589535	4.589535
Detection Prevalence : 0.95237 Balanced Accuracy : 0.50385	HbA1c	6.098576	6.098576
balanceu Acculacy . 0.30363	Admit	12.974454	12.974454
'Positive' Class : Other	Discharge	19.201083	19.201083

rf4



Sensitivity 0.9530637 Specificity 0.05464191 J4: 0.00770561

Youden Index:

# 2. Final random forest model analysis:

The only model that appeared to be preferable to the full model was the model where categorical age was dropped:

Readmitted ~ Time\_hosp + Diag + Med\_spec + Age\_numeric + Race + HbA1c + Admit + Gender + Discharge

This model had a higher balanced accuracy and did succeed to correctly classify more readmissions leading to a specificity rate that was higher than the other models. The higher specificity rate appeared to come at a cost of a lower sensitivity rate. Although the Youden Index was lower for this model (0.0427076) the other quantitative measures led me to choose this model over the full model.

3. Final random forest model quantitative measures:

Training output for final model:

#### Test output and confusion matrix:

#### Youden Index:

```
Reference
Prediction Other Readmitted
Other 16399 1537
Readmitted 2712 348

Accuracy: 0.7976
95% CI: (0.7921, 0.803)
No Information Rate: 0.9102
P-Value [Acc > NIR]: 1

Kappa: 0.0333

Mcnemar's Test P-Value: <2e-16

Sensitivity: 0.8581
Specificity: 0.1846
Pos Pred Value: 0.9143
Neg Pred Value: 0.1137
Precision: 0.9143
Recall: 0.8581
Specificity: 0.8581
Prevalence: 0.9102
Detection Rate: 0.7811
Detection Prevalence: 0.9102
Detection Rate: 0.7811
Detection Prevalence: 0.8543
Balanced Accuracy: 0.5214

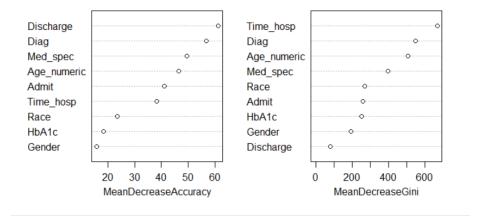
'Positive' Class: Other
```

Sensitivity 0.8580922 Specificity 0.1846154 J2: 0.0427076

# Final Model Feature Importances:

	Other <dbl></dbl>	Readmitted <dbl></dbl>
Time_hosp	19.777130	19.777130
Diag	25.318087	25.318087
Med_spec	23.569592	23.569592
Age_numeric	16.030257	16.030257
Race	8.237336	8.237336
HbA1c	8.725223	8.725223
Admit	17.377268	17.377268
Gender	8.098224	8.098224
Discharge	29.634945	29.634945

rf2



#### **Final Conclusions:**

Overall, the improved logistic regression model appeared to be able to accurately predict more readmissions than either the paper model (although not by a large margin). The logistic regression model proved to be far more effective than the random forest model.

For future study, it could be possible to improve the random forest model by adding in some of the dataset variables that were omitted by the paper. More variable choices could lead to a better performance using the random forest model. Another possible problem with the random forest model might have been the imbalance of the target value.

Once possible solution to this imbalance that could be explored would involve subsetting the data in some fashion and exploring models with a smaller more

balanced set of data. The HbA1c variable could also be used to subset the data by selecting out only the observations where an HbA1c test was performed. It could be possible that some results could be identified by the random forest model given some of these adjustments to the dataset.