Classifying Diabetes Draft 2

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Introduction

Diabetes is an chronic autoimmune disease affecting millions of Americans each year. It is best described as the body's inability to properly produce insulin, or produce any at all. This is a result of either an invalid or exhausted pancreas, whose job is to secrete enough insulin to manage blood-glucose levels. Normally, insulin is released to enable cells to absorb the blood-glucose to use for energy. In this way, it acts as a "key" between blood-glucose and cells.

For a diabetic, however, this "key" doesn't occur naturally, instead taking the form of insulin injections. As such, a diabetic uses a glucose monitor to regulate their blood sugar–whose excess or lack thereof has detrimental consequences. For this reason, it is important to know whether or not someone is diabetic. In this project, I will use classification to identify diabetes.

Data Collection

The classification will be based on a Kaggle dataset derived from the CDCs Behavioral Risk Factor Surveillance System (BRFSS). The data contains 70,692 responses from the 2015 BRFSS survey, each related to risk factors like smoking, high cholesterol, and physical activity. Furthermore, the data contains an equal 50-50 split of respondents with and without diabetes.

The data is binary, meaning that the predictors take on a value one or zero depending on whether the condition is true or not. For instance, if a respondent has a smoking habit they will be marked with a 1 for the smoking column; otherwise, they will receive a 0. There are some exceptions to this like BMI and age, where the values are continuous.

Methodology

The classification will be done by binary logistic regression. As such, the response variable, diabetes, will take on two values, "yes" or "no", corresponding to whether the patient has the disease. The classification will start with a series of logistic models, each with a unique cutoff. The function will label, respectively, "yes" and "no" for the values above and below 0.5. Afterwards, these predicted values will be compared with the actual values in a table and put into a confusion matrix for evaluation. The method above will repeat itself with one large model with multiple cutoffs. The point of this is to ensure consistent results.

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
## Loading required package: lattice
```

```
## Loading required package: Matrix
```

```
##
## Attaching package: 'Matrix'
```

```
## The following objects are masked from 'package:tidyr':
##
##     expand, pack, unpack
```

```
## Loaded glmnet 4.1-8
```

```
## Warning: package 'car' was built under R version 4.3.3
```

```
## Loading required package: carData
```

```
##
## Attaching package: 'car'
```

```
## The following object is masked from 'package:dplyr':
##
##     recode
```

Load in data

Data Wrangling

```
## 'data.frame':    70692 obs. of  22 variables:
##  $ Diabetes            : Factor w/ 2 levels "no","yes": 1 1 1 1 1 1 1 1 1 1 ...
##  $ HighBP              : num  1 1 0 1 0 0 0 0 0 0 ...
##  $ HighChol            : num  0 1 0 1 0 0 1 0 0 0 ...
##  $ CholCheck           : num  1 1 1 1 1 1 1 1 1 1 ...
##  $ BMI                 : num  26 26 26 28 29 18 26 31 32 27 ...
##  $ Smoker              : num  0 1 0 1 1 0 1 1 0 1 ...
##  $ Stroke              : num  0 1 0 0 0 0 0 0 0 0 ...
##  $ HeartDiseaseorAttack: num  0 0 0 0 0 0 0 0 0 0 ...
##  $ PhysActivity        : num  1 0 1 1 1 1 1 0 1 0 ...
##  $ Fruits              : num  0 1 1 1 1 1 1 1 1 1 ...
##  $ Veggies             : num  1 0 1 1 1 1 1 1 1 1 ...
##  $ HvyAlcoholConsump   : num  0 0 0 0 0 0 1 0 0 0 ...
##  $ AnyHealthcare       : num  1 1 1 1 1 0 1 1 1 1 ...
##  $ NoDocbcCost         : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ GenHlth             : num  3 3 1 3 2 2 1 4 3 3 ...
##  $ MentHlth            : num  5 0 0 0 0 7 0 0 0 0 ...
##  $ PhysHlth            : num  30 0 10 3 0 0 0 0 0 6 ...
##  $ DiffWalk            : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ Sex                 : num  1 1 1 1 0 0 1 1 0 1 ...
##  $ Age                 : num  4 12 13 11 8 1 13 6 3 6 ...
##  $ Education           : num  6 6 6 6 5 4 5 4 6 4 ...
##  $ Income              : num  8 8 8 8 8 7 6 3 8 4 ...
```

Cross validation

```
##       Diabetes HighBP HighChol CholCheck BMI Smoker Stroke HeartDiseaseorAttack
## 36027      yes      0        0         1  32      0      0                    0
## 32605       no      1        0         1  29      1      0                    1
## 67519      yes      1        0         1  30      1      1                    0
## 41322      yes      1        0         1  24      1      0                    0
## 54098      yes      1        1         1  28      1      1                    1
## 34711       no      0        0         1  26      1      0                    0
## 27963       no      0        0         1  36      1      0                    0
## 12132       no      0        0         1  28      1      0                    0
## 11078       no      0        0         0  22      0      0                    0
## 38966      yes      1        0         1  44      0      0                    0
##       PhysActivity Fruits Veggies HvyAlcoholConsump AnyHealthcare NoDocbcCost
## 36027            1      1       1                 0             1           0
## 32605            1      0       1                 0             1           0
## 67519            1      0       1                 0             1           0
## 41322            1      1       1                 0             1           0
## 54098            1      1       1                 0             1           0
## 34711            1      1       1                 0             0           0
## 27963            1      0       1                 0             1           0
## 12132            1      1       1                 0             1           0
## 11078            1      1       1                 0             0           1
## 38966            1      1       1                 0             1           0
##       GenHlth MentHlth PhysHlth DiffWalk Sex Age Education Income
## 36027       3        0        0        0   1  11         5      7
## 32605       5        0       28        1   1   9         4      6
## 67519       5        0       30        1   1   8         6      7
## 41322       2        0        0        0   1   9         4      3
## 54098       4        0        0        0   0  13         5      6
## 34711       3        0        0        0   0   3         4      3
## 27963       3        0        2        0   1   6         5      8
## 12132       2        0        0        1   0   8         5      4
## 11078       1        0        0        0   1   6         4      3
## 38966       3        2        1        1   0   8         3      3
```

```
##
##
## |Threshold |  Accuracy| Sensitivity| Specificity|
## |:---------|---------:|-----------:|-----------:|
## |c = 0.10  | 0.5932527|   0.9930388|   0.1969014|
## |c = 0.33  | 0.7356249|   0.9041057|   0.5685915|
## |c = 0.50  | 0.7483556|   0.7675806|   0.7292958|
## |c = 0.66  | 0.7161044|   0.5726666|   0.8583099|
## |c = 0.90  | 0.5513120|   0.1128001|   0.9860563|
```

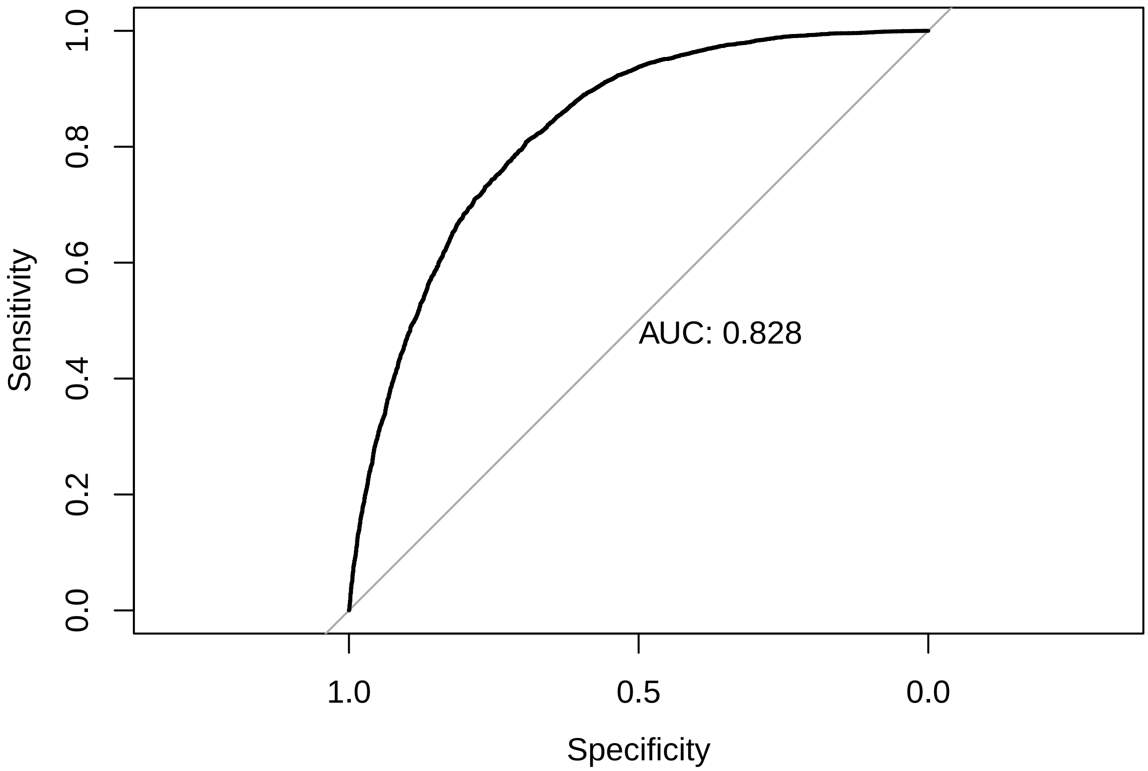
```
## Type 'citation("pROC")' for a citation.
```

```
##
## Attaching package: 'pROC'
```

```
## The following objects are masked from 'package:stats':
##
##     cov, smooth, var
```

```
## Setting levels: control = no, case = yes

## Setting direction: controls < cases
```



The table above contains regression models with varying cutoffs. The model with a 0.5 cutoff appears to have the most balanced trade-off between Accuracy, Specificity, and Sensitivity, exhibiting characteristics of a valid classifier. Furthermore, the ideal values for Sensitivity and Specificity align with the values for the 0.5 model as seen the ROC curve.

Test errors

```
## [1] 0.2516444
```

Comparing test and train data to test over-fitting.

```
##
##
## |Type        |     Error|
## |:-----------|---------:|
## |Train Error | 0.2518346|
## |Test Error  | 0.2516444|
```

Test for class imbalance

We can rule out the possibility of a class imbalance.

Test for multicollinearity

```
##
##
## |                     |        x|
## |:--------------------|--------:|
## |HighBP               | 1.127726|
## |HighChol             | 1.058458|
## |CholCheck            | 1.015735|
## |BMI                  | 1.111790|
## |Smoker               | 1.070270|
## |Stroke               | 1.060868|
## |HeartDiseaseorAttack | 1.120413|
## |PhysActivity         | 1.129877|
## |Fruits               | 1.096395|
## |Veggies              | 1.094426|
## |HvyAlcoholConsump    | 1.017290|
## |AnyHealthcare        | 1.098121|
## |NoDocbcCost          | 1.151400|
## |GenHlth              | 1.563787|
## |MentHlth             | 1.265825|
## |PhysHlth             | 1.611370|
## |DiffWalk             | 1.437037|
## |Sex                  | 1.099854|
```

```
## |Age                    | 1.274132|
## |Education              | 1.291934|
## |Income                 | 1.472285|
```

Evaluate

Address the tendency for the model to overfit

The above model exhibits different levels of Accuracy, Sensitivity, and Specificity at different cutoffs. This implies a change the amount of positive and negative cases captured, (i.e., 1 for positive, 0 for negative) meaning that the values for Accuracy, Specificity, and Sensitivity are a direct reflection of however many positive and negative cases there are. For example, it is no surprise that the first model captures 99 percent of true positives under a 0.10 cutoff. It practically only captures positive cases. The inverse is true for the last model.

With that said, the model with the most balanced trade-off between Accuracy, Sensitivity, and Specificity is the model with a 0.5 cutoff. It differs from the other models in the sense that it doesn't skew toward one metric, making for a unbiased classifier. Furthermore, the ROC curve hugs the top-left around the 0.50 mark, where the model exhibits its highest true positive and negative rates. The overall performance of the model is 0.82, meaning that it has a solid ability to discriminate between diabetics and non-diabetics.

Conclusion