Report

2022-11-21

# Introduction

Response Variable:

* stroke:

Possible Predictors:

* smoking\_status: The smoking status of the observation. Factor variable with 3 levels: “formerly smoked”, “never smoked”, and “smokes”.

## Cleaning the data

To use this data set, we first converted variables to their correct representations and then omitted any incomplete observations.

### Notable fixes:

* The categorical variable smoking\_status was reformatted to remove the level “Unknown”, as it was used to represent unavailable data. Any cells that previously had “Unknown” were updated to reflect their unavailable status.
* The quantitative variable bmi was fixed by converting the data type from character to numeric. This change does not apply to non-numeric cells, so the cells containing “N/A” were changed to reflect their unavailable status in the now numeric column.

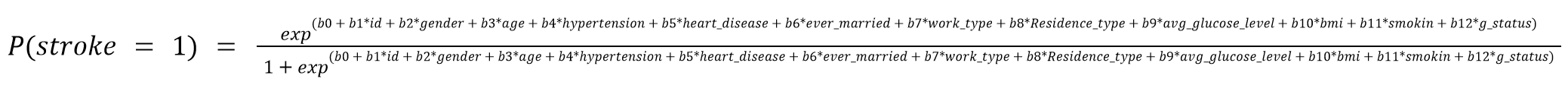
—**still need to list the rest of the variables, short description of data, and the question we want to answer**

# Logistic Regression Model

We chose to use a logistic regression model for our data because our response variable is qualitative with two classes. It was desirable to have a model predict the probability of a person having a stroke using binary classification. If linear regression is used to predict the probability of whether or not a person will have a stroke, then the model may have predicted Y values outside of our intended range of 0-1. The logistic regression model allows us to enforce this restriction of range.

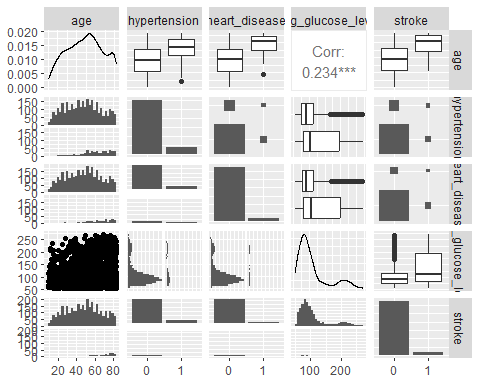
## Model Formula

Our basic logistic regression formula with all our predictors would be as follows:



## Registered S3 method overwritten by 'GGally':  
## method from   
## +.gg ggplot2

## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.  
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This is what our logistic regression formula would look like if we considered all of our predictors and the response variable being stroke. However, we automatically did not consider the unique identifier (id) as this variable is only used to identify patients, which does not have a significant influence on predicting the probability of strokes. Using the glm() function, we created our initial logistic model with stroke being the response and all the other variables as predictors (except id).

As the summary shows, the predictors age, hypertension, and avg\_glucose\_level show high levels of significance, and the predictor heart\_disease show moderate levels of significance. Since our p-values for all four predictors are less than 0.1, we can confidently reject the null hypothesis that states H0: B0 = B1= …= Bn. To confirm that these variables are significant, we used the backwards step() function to see if it would give us the same significant variables, and it did.

By removing the predictors that had little to no significance in predicting the response variable, we are able to refit our data into a second model (better.fit) with the four predictors that are significant. The original model with all predictors had an AIC of 1173.8, while the second model with the four significant predictors had an AIC of 1159.9. As there was not much of a difference between the first and second model, we decided to remove the lowest significant predictor (heart\_disease1) out of the four to perform one last model refitting of our data. This time, our AIC for the third model (best.health) came out to be 1162.1, which was a slight increase compared to the second model.

##   
## Call:  
## glm(formula = stroke ~ ., family = "binomial", data = health)  
##   
## Deviance Residuals:   
## Min 1Q Median 3Q Max   
## -1.2163 -0.3357 -0.1914 -0.1051 3.1357   
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -1.911e+01 4.775e+02 -0.040 0.968076   
## genderFemale 7.625e-02 1.681e-01 0.454 0.650091   
## genderOther -1.234e+01 3.956e+03 -0.003 0.997511   
## age 7.304e-02 6.958e-03 10.497 < 2e-16 \*\*\*  
## hypertension1 5.694e-01 1.828e-01 3.114 0.001845 \*\*   
## heart\_disease1 3.906e-01 2.211e-01 1.767 0.077249 .   
## ever\_marriedYes -1.795e-01 2.627e-01 -0.683 0.494366   
## work\_typeGovt\_job 1.092e+01 4.775e+02 0.023 0.981747   
## work\_typeNever\_worked -2.958e-01 1.157e+03 0.000 0.999796   
## work\_typePrivate 1.117e+01 4.775e+02 0.023 0.981339   
## work\_typeSelf-employed 1.081e+01 4.775e+02 0.023 0.981936   
## Residence\_typeUrban -4.830e-03 1.624e-01 -0.030 0.976276   
## avg\_glucose\_level 4.696e-03 1.377e-03 3.409 0.000651 \*\*\*  
## bmi 6.501e-03 1.292e-02 0.503 0.614789   
## smoking\_statusnever smoked -7.476e-02 1.894e-01 -0.395 0.692999   
## smoking\_statussmokes 3.151e-01 2.305e-01 1.367 0.171639   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## (Dispersion parameter for binomial family taken to be 1)  
##   
## Null deviance: 1411.0 on 3425 degrees of freedom  
## Residual deviance: 1141.8 on 3410 degrees of freedom  
## AIC: 1173.8  
##   
## Number of Fisher Scoring iterations: 16

##   
## Call:  
## glm(formula = stroke ~ age + hypertension + heart\_disease + avg\_glucose\_level,   
## family = "binomial", data = health)  
##   
## Deviance Residuals:   
## Min 1Q Median 3Q Max   
## -1.1420 -0.3357 -0.1927 -0.1072 3.1976   
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -7.632810 0.439480 -17.368 < 2e-16 \*\*\*  
## age 0.067773 0.006359 10.659 < 2e-16 \*\*\*  
## hypertension1 0.568379 0.181386 3.134 0.001727 \*\*   
## heart\_disease1 0.453704 0.216660 2.094 0.036253 \*   
## avg\_glucose\_level 0.004701 0.001334 3.524 0.000426 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## (Dispersion parameter for binomial family taken to be 1)  
##   
## Null deviance: 1411.0 on 3425 degrees of freedom  
## Residual deviance: 1149.9 on 3421 degrees of freedom  
## AIC: 1159.9  
##   
## Number of Fisher Scoring iterations: 7

##   
## Call:  
## glm(formula = stroke ~ age + hypertension + avg\_glucose\_level,   
## family = "binomial", data = health)  
##   
## Deviance Residuals:   
## Min 1Q Median 3Q Max   
## -1.0523 -0.3398 -0.1939 -0.1058 3.2054   
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -7.750124 0.437181 -17.728 < 2e-16 \*\*\*  
## age 0.070099 0.006262 11.194 < 2e-16 \*\*\*  
## hypertension1 0.579247 0.180838 3.203 0.001359 \*\*   
## avg\_glucose\_level 0.004932 0.001326 3.720 0.000199 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## (Dispersion parameter for binomial family taken to be 1)  
##   
## Null deviance: 1411.0 on 3425 degrees of freedom  
## Residual deviance: 1154.1 on 3422 degrees of freedom  
## AIC: 1162.1  
##   
## Number of Fisher Scoring iterations: 7

## Null Deviance Residual Deviance R^2 AIC BIC  
## health.glm 1411.002 1141.806 0.1907835 1173.806 1272.032  
## health2.glm 1411.002 1149.914 0.1850374 1159.914 1190.609  
## health3.glm 1411.002 1154.069 0.1820928 1162.069 1186.625

## [1] 0.05275447

## [1] 0.05080292

## [1] 0.00000000 0.00000000 0.03225806 0.00000000 0.00000000 0.00000000  
## [7] 0.00000000 0.00000000 0.00000000 0.00000000

## [1] 0.003225806

## [1] 1 1 1 1 1 1 1 1 1 1

## [1] 1

explain model choice  
write model equation  
test/train models  
test error rate  
interpretation of full model in regards to our question: which factors demonstrate statistical significance in relation to having a stroke?

# Conclusion