Logistic Regression

Model and Description

Next, we will perform logistic regression with the remission data set. We are using logistic regression because our dependent variable is binary. With logistic regression, you are usually using your depend variables to predict odds. In using the remission data set, it appears we are using the data to predict odds of going back into remission, given some health factors. Below is the code showing that we made "remiss" (our dependent variables) a factor, and our model:

Model 1

```
`remission.(1)`$remiss<-factor(`remission.(1)`$remiss)
Deviance Residuals:
                     Median
                                  3Q
               1Q
                                           Max
                             0.74304
-1.95165 -0.66491 -0.04372
                                       1.67069
Coefficients:
           Estimate Std. Error z value Pr(>|z|)
(Intercept) 58.0385 71.2364 0.815
                                       0.4152
cell
            24.6615
                      47.8377
                              0.516
                                        0.6062
smear
           19.2936
                      57.9500 0.333
                                        0.7392
           -19.6013
                                        0.7507
infil
                     61.6815 -0.318
li.
             3.8960
                       2.3371
                               1.667
                                       0.0955 .
             0.1511
                       2.2786 0.066
blast
                                       0.9471
           -87.4339
                       67.5735 -1.294
                                        0.1957
temp
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)
    Null deviance: 34.372 on 26 degrees of freedom
Residual deviance: 21.751 on 20 degrees of freedom
AIC: 35.751
Number of Fisher Scoring iterations: 8
```

As shown above, all of our independent variables do not pass the t test, given an alpha of .05. It can be interpreted that given the log odds of "li", our results change by the estimate of 3.8960. The same aforementioned logic with "li" can be used with the other independent variables as well, although we probably wouldn't use their estimation because they do not pass the t-test. The model will be looked further into, to fix the muddy t-tests.

glm Function vs. Im function

The difference between glm and lm, is that glm is used to form generalized linear models that have symbolic (binary) descriptions in their y axis, while lm is used to form linear models that can be used to for multiple forms of regression, excluding logistic. In other words, glm is used to show the binary response variables, and lm is used for standard regression models.

Model 11

Final Logistic Model

```
glm(formula = remiss ~ li, family = "binomial", data = `remission
Deviance Residuals:
                 Median
   Min
             1Q
                               3Q
                                      Max
-1.9448 -0.6465 -0.4947 0.6571
                                   1.6971
Coefficients:
           Estimate Std. Error z value Pr(>|z|)
(Intercept) -3.777 1.379 -2.740 0.00615 **
              2.897
1i
                        1.187 2.441 0.01464 *
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)
   Null deviance: 34.372 on 26 degrees of freedom
Residual deviance: 26.073 on 25 degrees of freedom
AIC: 30.073
Number of Fisher Scoring iterations: 4
```

After removing the independent variables from highest p-value to lowest, we ended up with one independent variable that passed the t-test. Our Final model contains "li" with a p-value of .01464. It can be interpreted that given the log odds of "li", our results change by the estimate of 2.897. We can assume we would use this estimation because now it passes the t-tests.