

**Assignment 3**  
**Course: STAT229**  
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**Date: 2/13/2017**

4

b)

```
Call:
glm(formula = DEATH ~ AGE + INH_INJ + AGE:INH_INJ, family = "binomial",
    data = BURN1000)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.6605	-0.3861	-0.1314	-0.0583	3.5877

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-6.51007	0.52541	-12.390	< 2e-16	***
AGE	0.08434	0.00828	10.186	< 2e-16	***
INH_INJ	6.21215	0.65600	9.470	< 2e-16	***
AGE:INH_INJ	-0.06889	0.01164	-5.918	3.27e-09	***

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

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 845.42 on 999 degrees of freedom  
Residual deviance: 498.34 on 996 degrees of freedom  
AIC: 506.34

Number of Fisher Scoring iterations: 7

Table 4.1

	(Intercept)	AGE	INH_INJ	AGE:INH_INJ
(Intercept)	0.27605389	-4.188610e-03	-0.276053893	4.188610e-03
AGE	-0.00418861	6.855275e-05	0.004188610	-6.855275e-05
INH_INJ	-0.27605389	4.188610e-03	0.430335525	-7.015496e-03
AGE:INH_INJ	0.00418861	-6.855275e-05	-0.007015496	1.355111e-04

Table 4.2 covariance of variables

The four-step method is:

$(\text{INH\_INJ}=1, \text{age}) - (\text{INH\_INJ}=0, \text{age}) = \exp(\beta_1 + \beta_3 \cdot \text{age})$

$\text{OR}(\text{age}=20) = e^{(6.212 - 20 \cdot 0.069)} = 125.462$

$\text{OR}(\text{age}=40) = e^{(6.212 - 40 \cdot 0.069)} = 31.563$

$\text{OR}(\text{age}=60) = e^{(6.212 - 60 \cdot 0.069)} = 7.941$

$\text{OR}(\text{age}=80) = e^{(6.212 - 80 \cdot 0.069)} = 1.998$

$\text{Se}(\beta_1 + \beta_3 \cdot \text{age}) = \sqrt{\text{var}(\beta_1) + \text{age}^2 \cdot \text{var}(\beta_3) + 2 \cdot \text{age} \cdot \text{cov}(\beta_1, \beta_3)}$

Thus, 95% confident interval is:

	Age	Odds Ratio	95% confident interval	
1	20	125.77	51.902	304.761
2	40	31.71	17.854	56.330
3	60	8.00	4.653	13.742
4	80	2.02	0.888	4.579

Table 4.3, 95% confident interval for estimations of age

c)

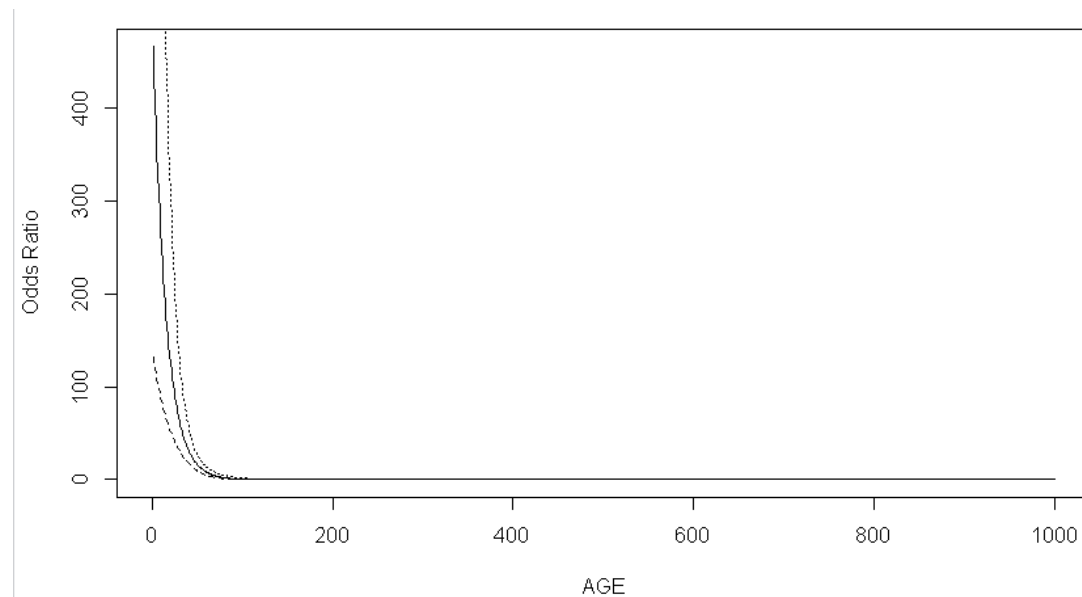


Table 4.4 inhalation injury as a function of age

5.

First the HOURS is created by summing the SPORTHR, READHR, COMPHR, STUDYHR and TVHR

```
Call:
glm(formula = MYOPIC ~ GENDER + HOURS, family = "binomial", data = myopia)
```

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.6316  -0.5700  -0.5072  -0.4674   2.2501
```

```
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -1.812237   0.326131  -5.557 2.75e-08 ***
GENDER       0.340057   0.241915   1.406   0.160
HOURS      -0.009642   0.009916  -0.972   0.331
---
signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

(Dispersion parameter for binomial family taken to be 1)

```
Null deviance: 480.08  on 617  degrees of freedom
Residual deviance: 476.77  on 615  degrees of freedom
AIC: 482.77
```

```
Number of Fisher scoring iterations: 4
```

Table 5.1

Deviance Residuals:

Min	1Q	Median	3Q	Max
-0.6607	-0.5729	-0.5419	-0.4266	2.5577

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )
(Intercept)	-1.29349	0.42952	-3.012	0.0026 **
GENDER	-0.59719	0.57685	-1.035	0.3005
HOURS	-0.02937	0.01549	-1.897	0.0579 .
GENDER:HOURS	0.03603	0.02037	1.769	0.0768 .

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signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 480.08 on 617 degrees of freedom  
Residual deviance: 473.56 on 614 degrees of freedom  
AIC: 481.56

Number of Fisher Scoring iterations: 5

Table 5.2

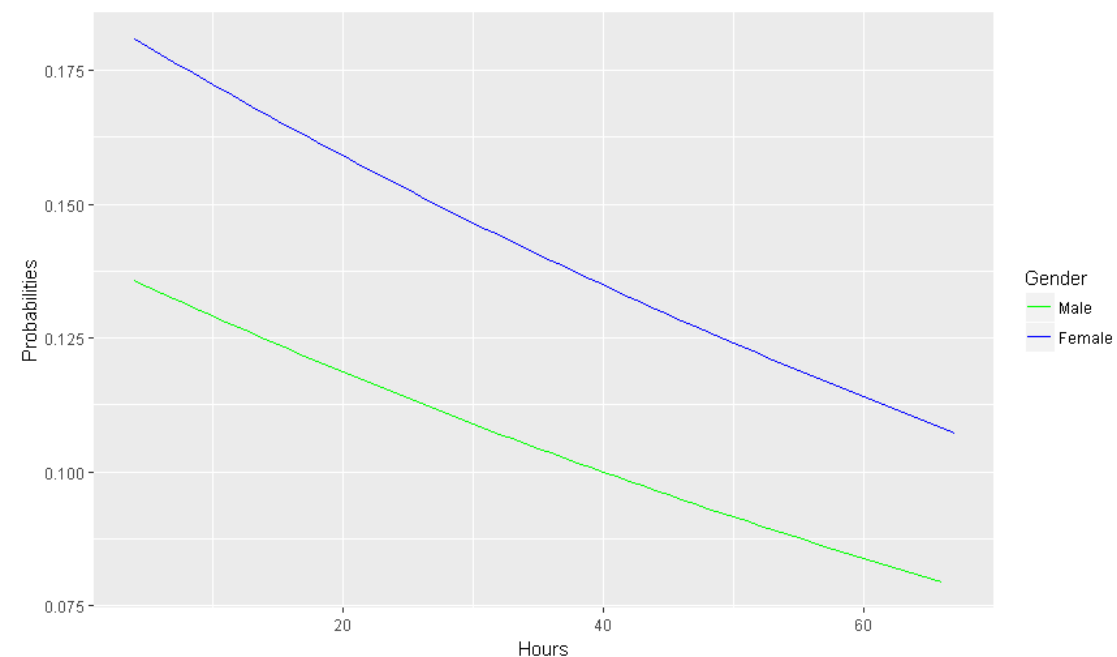


Table 5.3 Probabilities for Male and Female becoming myopic

Here shows that Male is not more likely to have myopic than Female.

### Assignment3

1. The power 2 model is chosen on the Burn data.

```
Call:
glm(formula = DEATH ~ AGEFP1 + TBSAFP1 + RACEC + INH_INJ, family = "binomial",
    data = burn)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.97653	-0.20373	-0.08907	-0.04407	3.05707

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-7.957085	0.596694	-13.335	< 2e-16	***
AGEFP1	0.086708	0.008245	10.516	< 2e-16	***
TBSAFP1	0.936365	0.087402	10.713	< 2e-16	***
RACEC	-0.608872	0.309589	-1.967	0.0492	*
INH_INJ	1.433392	0.342153	4.189	2.8e-05	***

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signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 845.42 on 999 degrees of freedom  
 Residual deviance: 321.94 on 995 degrees of freedom  
 AIC: 331.94

Number of Fisher Scoring iterations: 7

Table 3.1.1 selection of power 2 model parameters on the Burn data

Here,

$AGEFP1 = (AGE / 10)^2$

$TBSAFP1 = \sqrt{TBSA}$

```
glm(formula = DEATH ~ AGEFP1 + TBSAFP1 + RACEC + INH_INJ + AGEFP1
    INH_INJ, family = "binomial", data = burn)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.73588	-0.19395	-0.07796	-0.03850	2.96643

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-8.215445	0.631340	-13.013	< 2e-16	***
AGEFP1	0.096068	0.009583	10.025	< 2e-16	***
TBSAFP1	0.912097	0.087762	10.393	< 2e-16	***
RACEC	-0.622957	0.310032	-2.009	0.0445	*
INH_INJ	2.420008	0.545173	4.439	9.04e-06	***
AGEFP1:INH_INJ	-0.034088	0.014515	-2.349	0.0188	*

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signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 845.42 on 999 degrees of freedom  
 Residual deviance: 316.55 on 994 degrees of freedom  
 AIC: 328.55

Number of Fisher Scoring iterations: 7

3.

First, we run univariable analysis for each variables to find out whether they are significant at 25% significant level.

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-2.09139	0.76590	-2.731	0.00632	**
AGE	0.14376	0.05329	2.698	0.00698	**

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Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-1.75769	0.31389	-5.600	2.15e-08	***
BEHAV	0.29018	0.05012	5.789	7.07e-09	***

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-0.98426	0.15262	-6.449	1.13e-10	***
LOS	0.06564	0.01065	6.161	7.22e-10	***

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-26.57	22128.47	-0.001	0.999	
PLACE31	53.13	38278.41	0.001	0.999	
PLACE32	53.13	39438.81	0.001	0.999	

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-0.2271	0.1327	-1.711	0.0871	.
RACE	0.3423	0.1790	1.912	0.0559	.

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-0.1904	0.1214	-1.568	0.1168	
GENDER	0.3273	0.1786	1.832	0.0669	.

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Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-0.1144	0.1071	-1.068	0.285	
NEURO1	0.2877	0.2474	1.163	0.245	
NEURO2	0.1834	0.3867	0.474	0.635	
NEURO3	0.1978	0.3081	0.642	0.521	

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-0.1701	0.1018	-1.671	0.09469	.
EMOT	0.5616	0.2128	2.639	0.00831	**

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```

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)  -1.2528    0.3273   -3.827 0.000130 ***
DANGER1       1.4315    0.3835    3.733 0.000189 ***
DANGER2       1.4951    0.3687    4.055 5.01e-05 ***
DANGER3       1.1961    0.3550    3.369 0.000753 ***

```

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```

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.2288    0.1132   -2.021 0.04330 *
ELOPE         0.5013    0.1845    2.717 0.00659 **

```

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```

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)  -1.0365    0.1278   -8.113 4.94e-16 ***
CUSTD         2.9296    0.2497   11.733 < 2e-16 ***

```

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Table 3.3.1 univariable analysis for each variable

From table 3.3.1 we found NEURO and PLACE3 are not significant, thus we have a multivariable analysis for other significant variables.

```

Deviance Residuals:
      Min       1Q   Median       3Q      Max
-3.1901  -0.5571  -0.2023   0.4748   2.4748

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```

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)  -7.54089    1.45440   -5.185 2.16e-07 ***
AGE           0.17649    0.08378    2.107 0.03515 *
BEHAV         0.25585    0.09810    2.608 0.00911 **
LOS           0.07482    0.01352    5.533 3.14e-08 ***
RACE          0.69803    0.27608    2.528 0.01146 *
GENDER        0.51187    0.30546    1.676 0.09378 .
NEURO.1       0.16742    0.35729    0.469 0.63938
EMOT          0.44776    0.32869    1.362 0.17311
DANGER1       1.02227    0.62475    1.636 0.10178
DANGER2       0.46298    0.69615    0.665 0.50601
DANGER3       0.34618    0.68149    0.508 0.61147
ELOPE         -0.02616    0.29826   -0.088 0.93012
CUSTD         3.43088    0.30961   11.081 < 2e-16 ***
VIOL          -0.11684    0.45465   -0.257 0.79719

```

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Table 3.3.2 multivariable analysis for significant variables

From table 3.3.2 we found AGE, BEHAV, LOS, RACE, GENDER, CUSTD are significant,

```

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)  -7.06221    1.37833   -5.124 3.00e-07 ***
AGE           0.19593    0.08218    2.384 0.01712 *
BEHAV         0.22694    0.07207    3.149 0.00164 **
LOS           0.07507    0.01330    5.643 1.67e-08 ***
RACE          0.64793    0.27115    2.390 0.01687 *
CUSTD         3.48410    0.30057   11.592 < 2e-16 ***
GENDER        0.42622    0.28505    1.495 0.13484

```

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signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Table 3.3.3 reduced model

From table 3.3.3, GENDER is not significant.

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-6.77033	1.36217	-4.970	6.69e-07	***
AGE	0.18003	0.08163	2.205	0.02743	*
BEHAV	0.25539	0.06954	3.673	0.00024	***
LOS	0.07441	0.01316	5.656	1.55e-08	***
RACE	0.62555	0.26959	2.320	0.02032	*
CUSTD	3.43495	0.29513	11.639	< 2e-16	***

---

signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Table 3.3.4 reduced model

Then we check the confounder of the variables

AGE: 2.0057794%

BEHAV: -0.1797928%

LOS: -0.5479818%

RACE: -10.3835079%

CUSTD: 0.1186285%

It shows none of the parameters are bigger than 20%, thus, there is no confounder.

Then we add the variables which are not significant in the 1<sup>st</sup> step into this model.

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-6.95902	1.36949	-5.081	3.75e-07	***
AGE	0.17165	0.08155	2.105	0.035309	*
BEHAV	0.26063	0.07036	3.704	0.000212	***
LOS	0.07290	0.01302	5.598	2.17e-08	***
RACE	0.62176	0.27431	2.267	0.023413	*
CUSTD	3.59239	0.30931	11.614	< 2e-16	***
NEURO1	0.38894	0.36539	1.064	0.287122	
NEURO2	0.68738	0.52172	1.318	0.187664	
NEURO3	1.11993	0.42998	2.605	0.009197	**

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signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

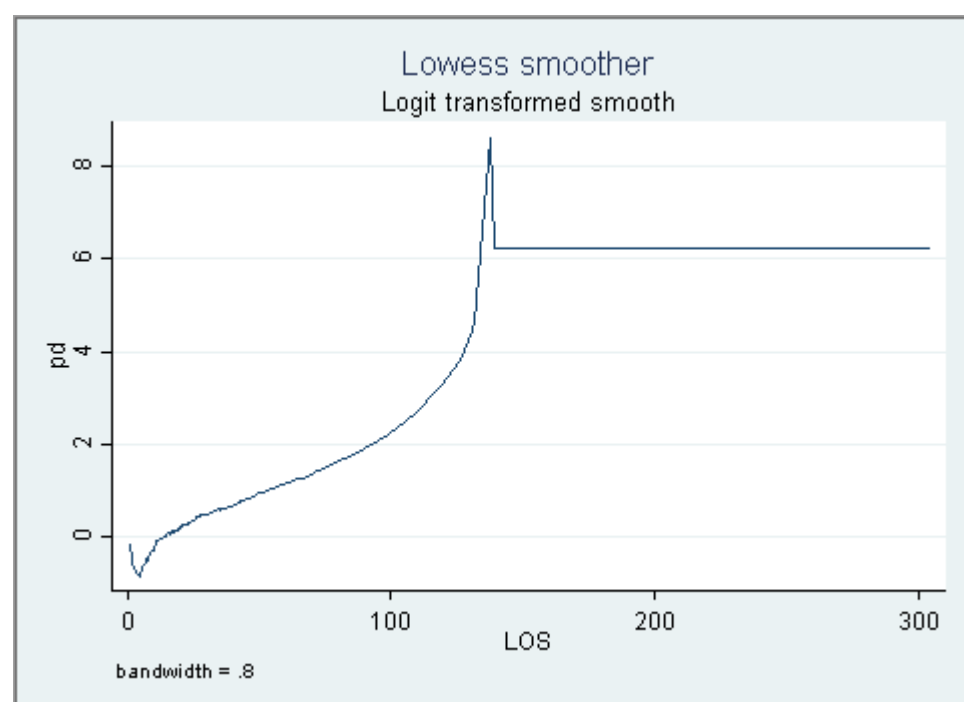
(Dispersion parameter for binomial family taken to be 1)

Null deviance: 704.04 on 507 degrees of freedom  
Residual deviance: 364.84 on 499 degrees of freedom  
AIC: 382.84

Table 3.3.5

We found NEURO3 is significant.

Then check the continuous variables by using Lowess Smooth.





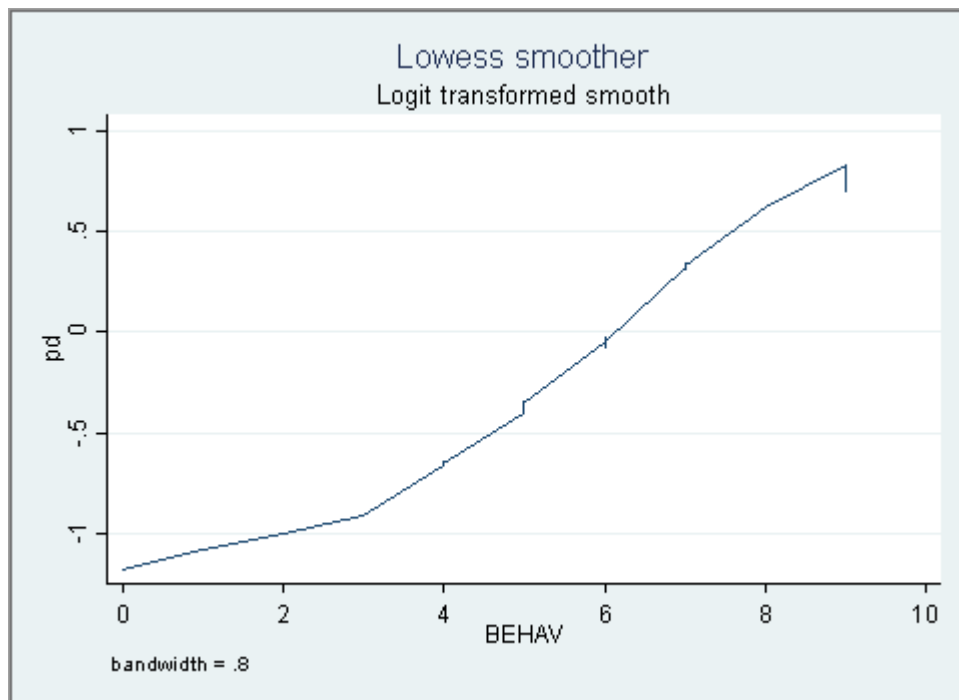


Table 3.3.6 Checking the linearity of three variables

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
(Intercept)	-7.5799	1.4659	-5.171	2.33e-07	***
AGE.s	2.0802	0.8550	2.433	0.01498	*
BEHAV.s	2.3369	0.7672	3.046	0.00232	**
LOS.s	0.9238	0.1671	5.530	3.20e-08	***
RACE	0.4691	0.2930	1.601	0.10935	
CUSTD	4.2339	0.4365	9.699	< 2e-16	***
NEURO.n	-3.9787	2.0702	-1.922	0.05462	.
LOS.s:CUSTD	-0.6442	0.2607	-2.470	0.01349	*
RACE:NEURO.n	2.6525	1.0803	2.455	0.01408	*
BEHAV.s:NEURO.n	5.2577	2.5346	2.074	0.03805	*

---

signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 704.04 on 507 degrees of freedom  
Residual deviance: 354.53 on 498 degrees of freedom  
AIC: 374.53

Number of Fisher Scoring iterations: 7

Table 3.3.7

Then we filter the interactions and at last here is the fitted model.