Assumptions

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Given our model, below are the assumptions and model assessment features that we will cover.

Assumptions:

1) Plot of binned residuals vs. predicted values
2) Plot of binned residuals vs. numeric explanatory variables
3) Influential points and multicollinearity

Model Fit:

1) Examine confusion matrix
2) Examine ROC curve

Final Model

Below, is our final model with interaction effects, after removing the obvious cases of multicollinearity.

```
final.base.model <- model.selected.interactions
kable(tidy(final.base.model), format = "markdown", digits = 3)
```

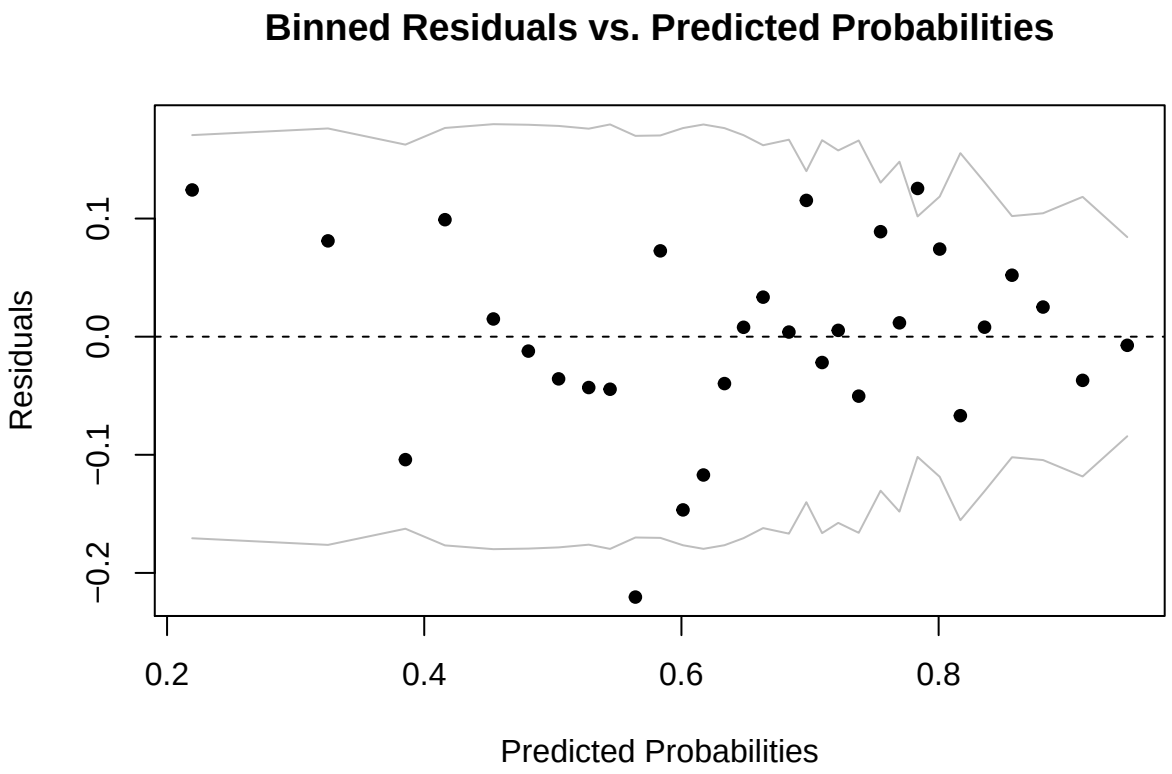
term	estimate	std.error	statistic	p.value
(Intercept)	10.392	3.518	2.954	0.003
minutes	-0.008	0.003	-2.844	0.004
ht	-0.048	0.019	-2.547	0.011
rankpoints	0.000	0.000	5.441	0.000
ace	0.110	0.040	2.764	0.006
df	-0.243	0.070	-3.474	0.001
bpSaved	-0.075	0.029	-2.548	0.011
surfaceGrass	5.285	8.299	0.637	0.524
surfaceHard	-8.048	4.294	-1.874	0.061
ht:surfaceGrass	-0.043	0.045	-0.940	0.347
ht:surfaceHard	0.040	0.023	1.710	0.087
ace:surfaceGrass	0.164	0.080	2.048	0.041
ace:surfaceHard	-0.021	0.045	-0.469	0.639
df:surfaceGrass	0.425	0.132	3.205	0.001
df:surfaceHard	0.107	0.082	1.297	0.195

Assumptions

Binned Plots with Residuals vs Predicted

```
ten <- ten %>% mutate(Residuals = residuals.glm(final.base.model,type="response"),
                      Predicted = predict.glm(final.base.model,type="response"))
```

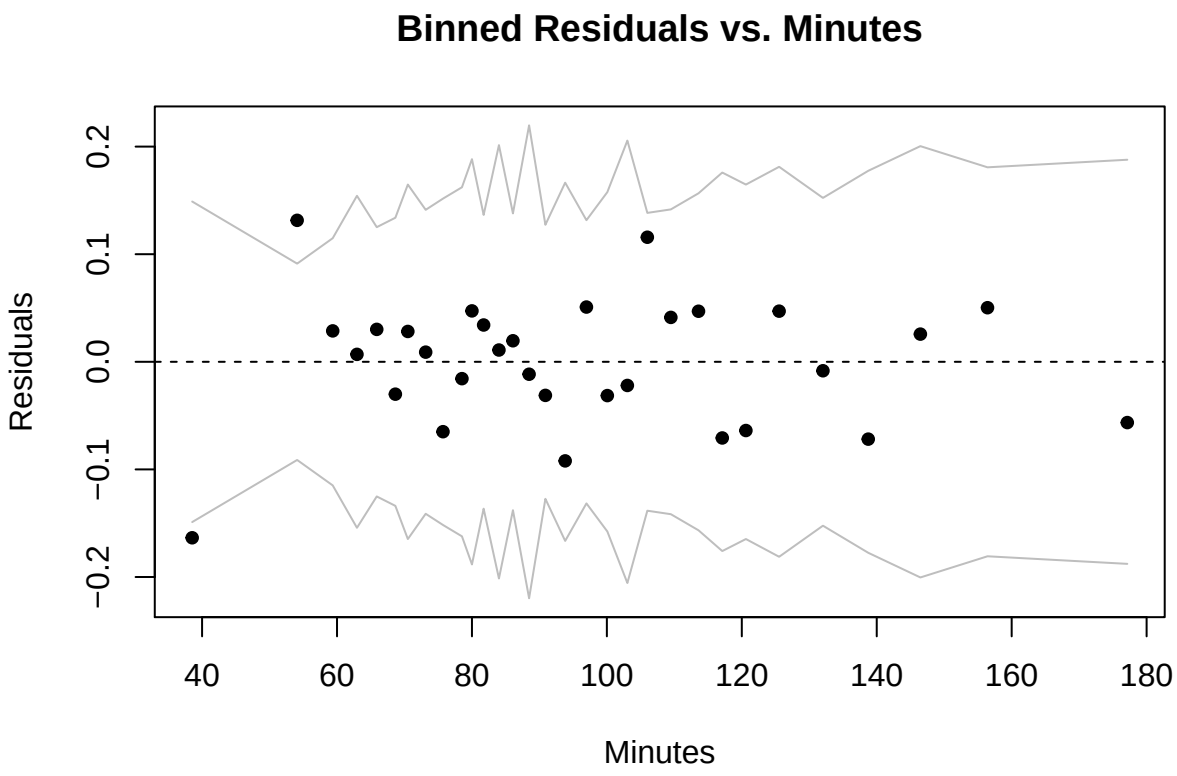
```
binnedplot(ten$Predicted, ten$Residuals,xlab="Predicted Probabilities",
           ylab="Residuals",main="Binned Residuals vs. Predicted Probabilities")
```



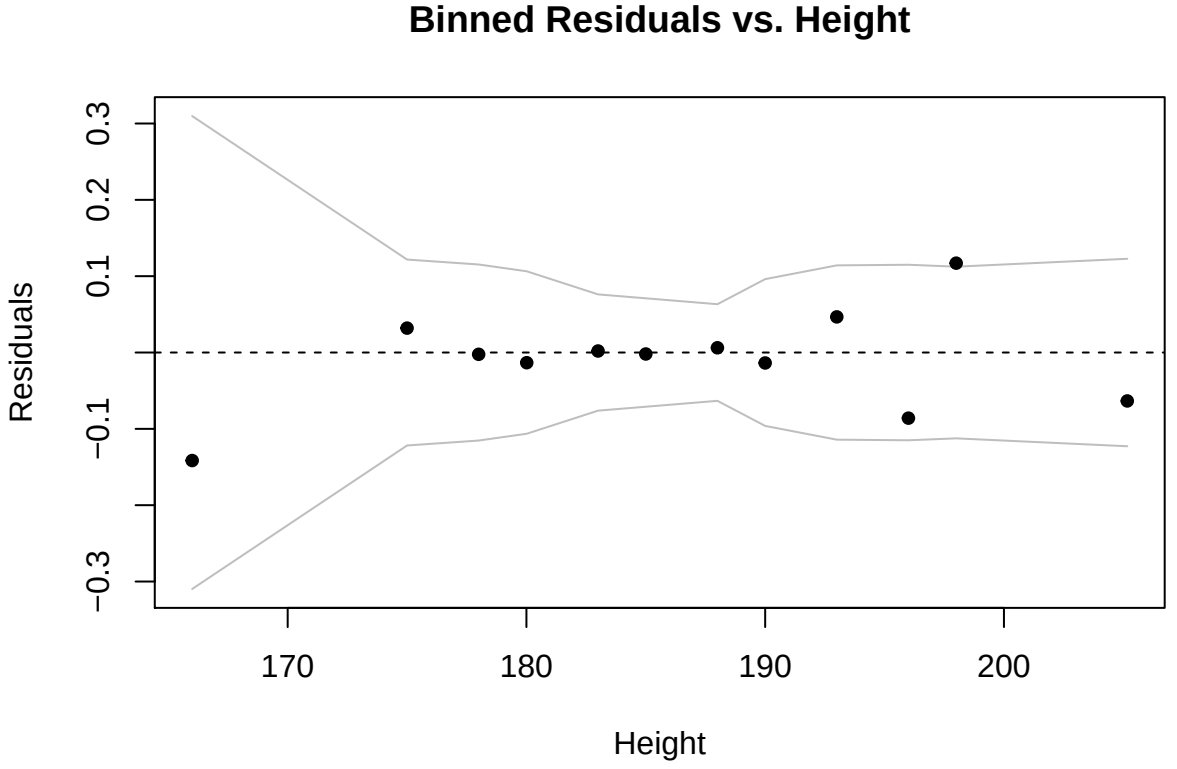
Looking at this plot, we do not see any violations of the assumptions. We see a plot that does not have a distinct pattern.

Binned Residuals vs Numeric Explanatory Variables

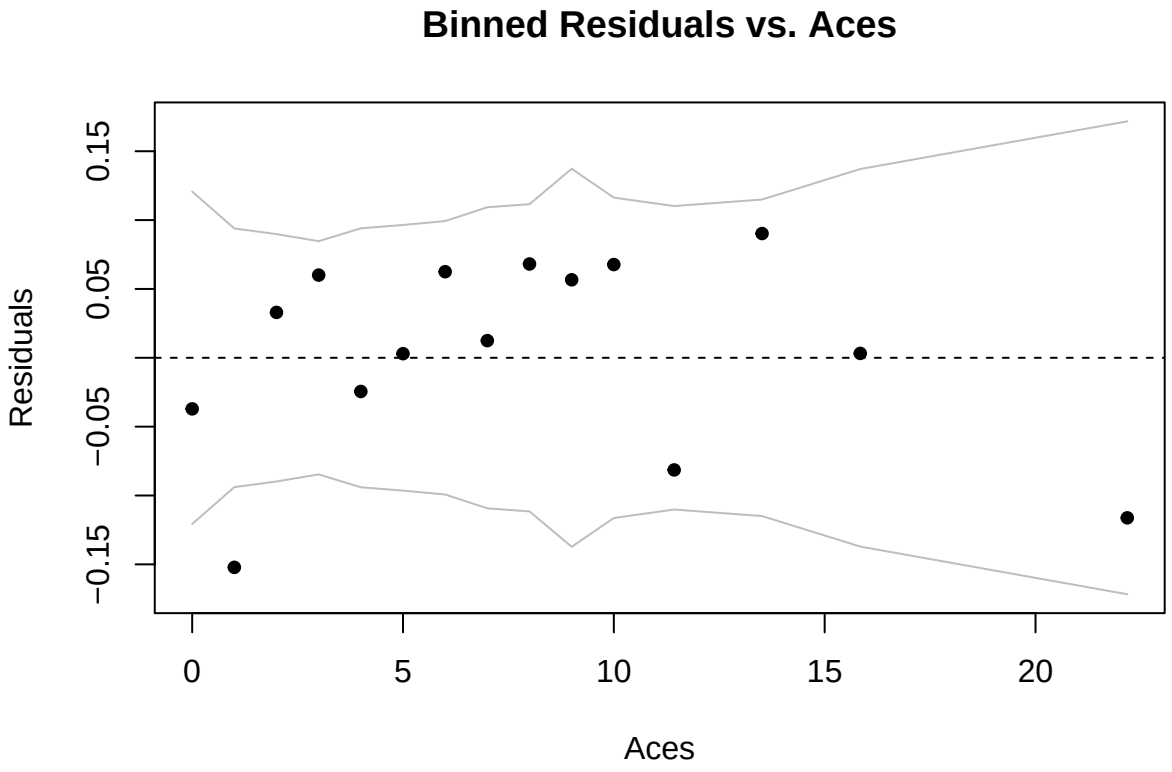
```
binnedplot(ten$minutes, ten$Residuals,xlab="Minutes",
           ylab="Residuals",main="Binned Residuals vs. Minutes")
```



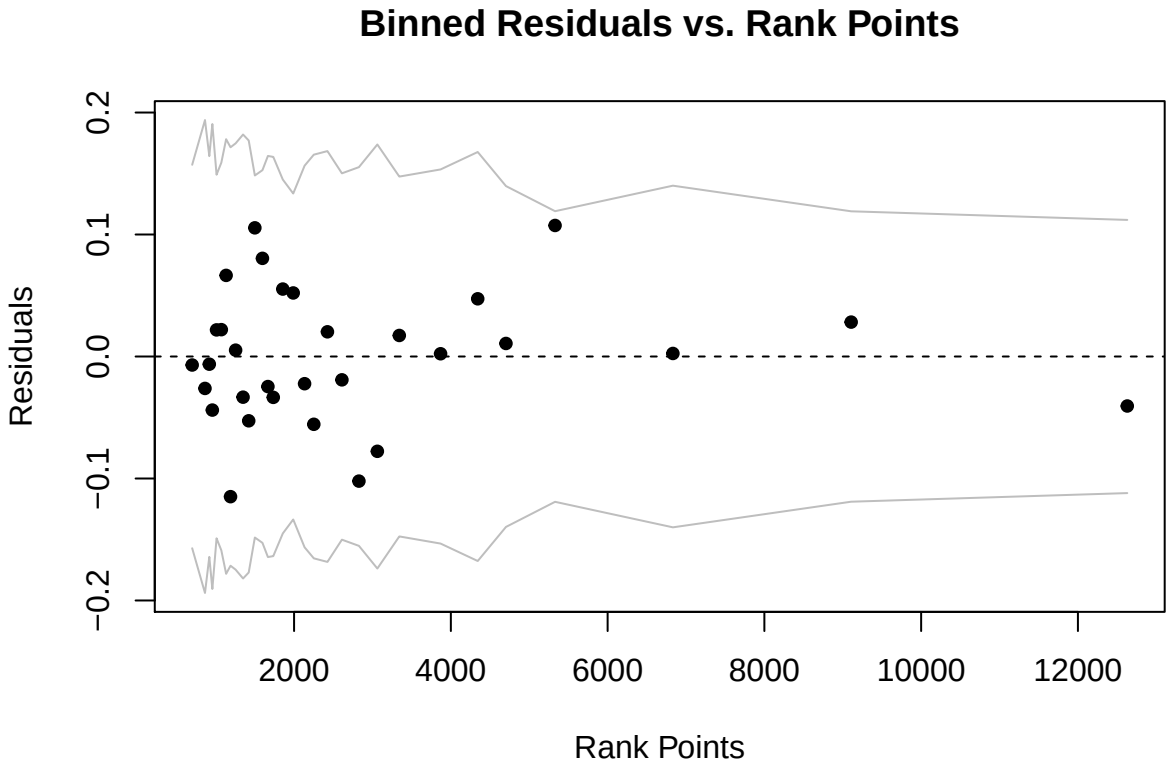

```
binnedplot(ten$ht, ten$Residuals,xlab="Height",
           ylab="Residuals",main="Binned Residuals vs. Height")
```



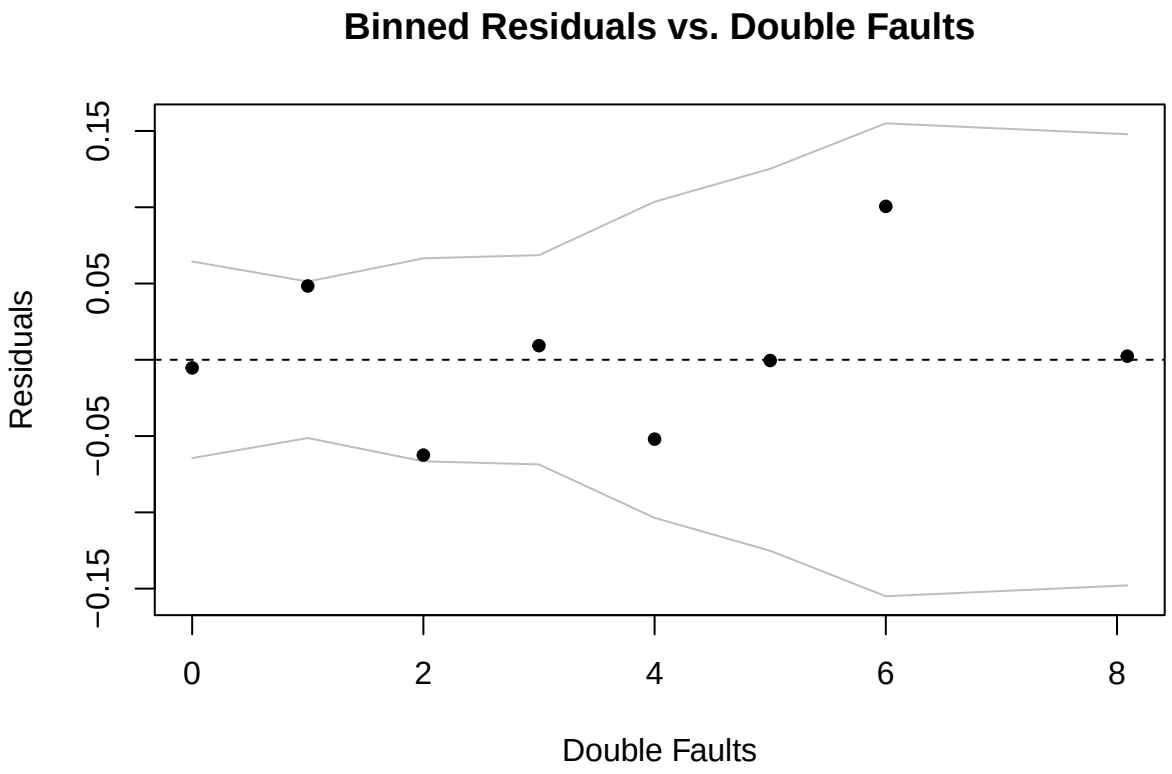

```
binnedplot(ten$ace, ten$Residuals,xlab="Aces",
           ylab="Residuals",main="Binned Residuals vs. Aces")
```




```
binnedplot(ten$rankpoints, ten$Residuals,xlab="Rank Points",
           ylab="Residuals",main="Binned Residuals vs. Rank Points")
```




```
binnedplot(ten$df, ten$Residuals,xlab="Double Faults",
           ylab="Residuals",main="Binned Residuals vs. Double Faults")
```




```
binnedplot(ten$bpSaved, ten$Residuals,xlab="Saved Break Points",
           ylab="Residuals",main="Binned Residuals vs. Saved Break Points")
```

Looking at the binned residual plots, we see that all of the plots except for the binned residuals vs. saved break point have random scatter. The binned residuals vs. saved break shows a pattern. This is a violation

of the assumptions.

Influential Points

VIF

```
tidy(vif(final.base.model))
```

```
## Warning: 'tidy.matrix' is deprecated.
## See help("Deprecated")
```

```
## # A tibble: 10 x 4
##    .rownames        GVIF    Df GVIF..1..2.Df..
##    <chr>           <dbl> <dbl>           <dbl>
##  1 minutes          1.45     1            1.21
##  2 ht               3.99     1            2.00
##  3 rankpoints       1.04     1            1.02
##  4 ace              6.82     1            2.61
##  5 df               4.02     1            2.00
##  6 bpSaved          1.32     1            1.15
##  7 surface     650920.       2           28.4
##  8 ht:surface  721588.       2           29.1
##  9 ace:surface     43.8      2            2.57
## 10 df:surface      14.7      2            1.96
```

After looking at the VIF values, we see that the VIF for `surface` is greater than 10, so we will also remove it from the model. This means we will also have to remove the interaction variables as well.

Logistic Regression Assumptions: Revised

Because one of our residuals plots has a non-linear relationship, we will remove `bpSaved` from the model and redo the assumptions. We will also remove `surface` and its corresponding interactions effects.

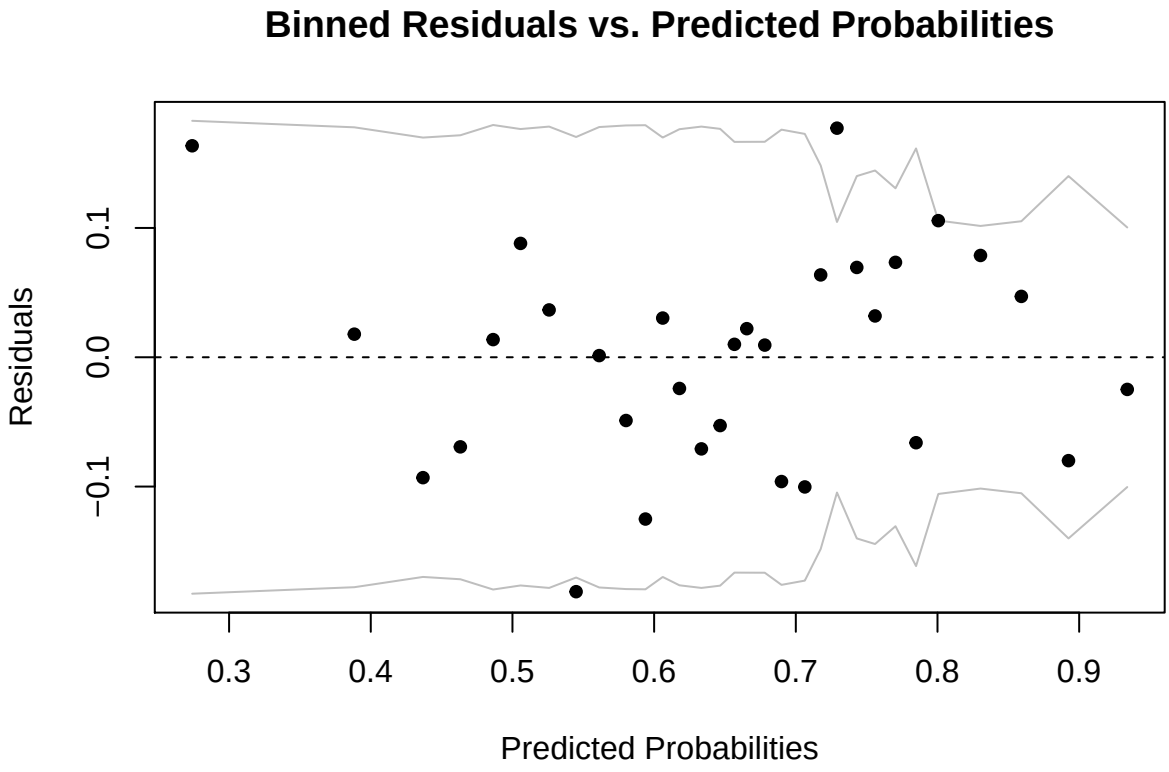
```
newten <- ten
final <- glm(status ~ minutes + ht + rankpoints + ace + df, family = binomial,
             data = newten)
kable(tidy(final), format = "markdown", digits = 6)
```

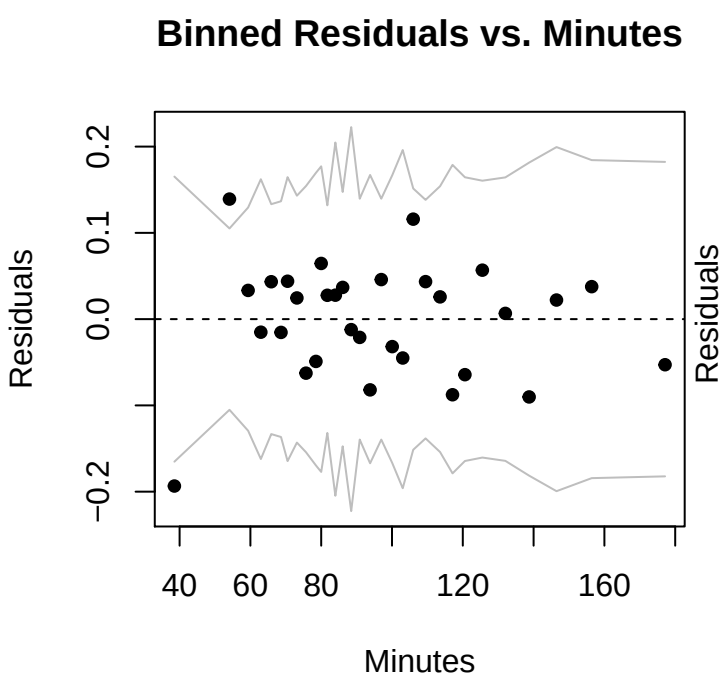
term	estimate	std.error	statistic	p.value
(Intercept)	5.197141	1.950891	2.663983	0.007722
minutes	-0.008897	0.002395	-3.714847	0.000203
ht	-0.023129	0.010416	-2.220635	0.026376
rankpoints	0.000184	0.000035	5.237843	0.000000
ace	0.094100	0.017519	5.371298	0.000000
df	-0.169342	0.035503	-4.769779	0.000002

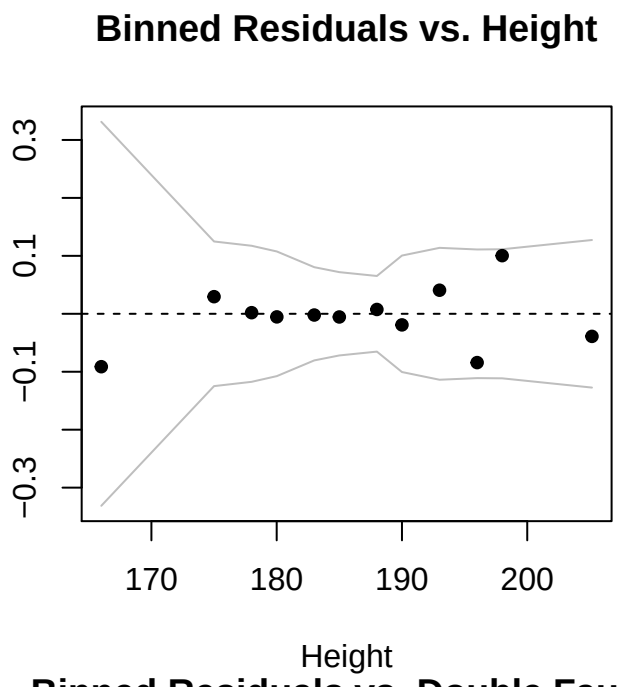
Model Assessment

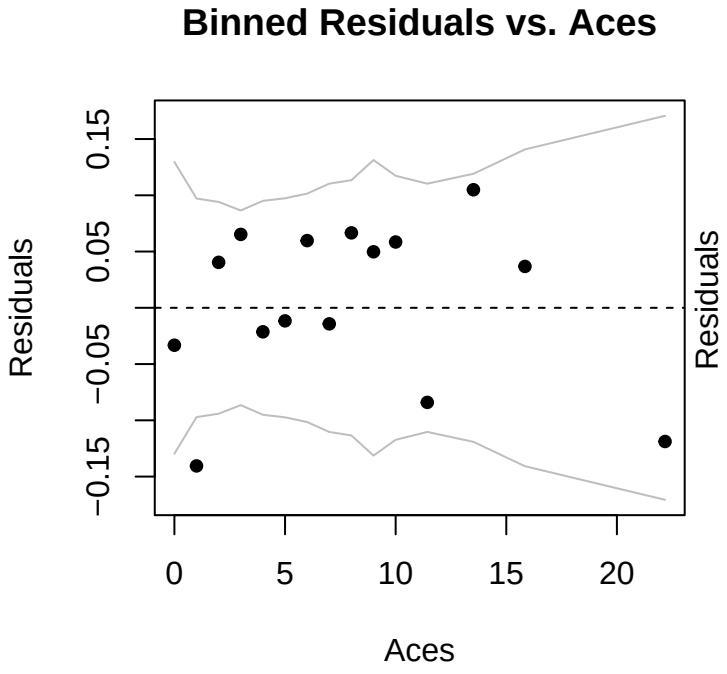
Binned Plots with Residuals vs Predicted

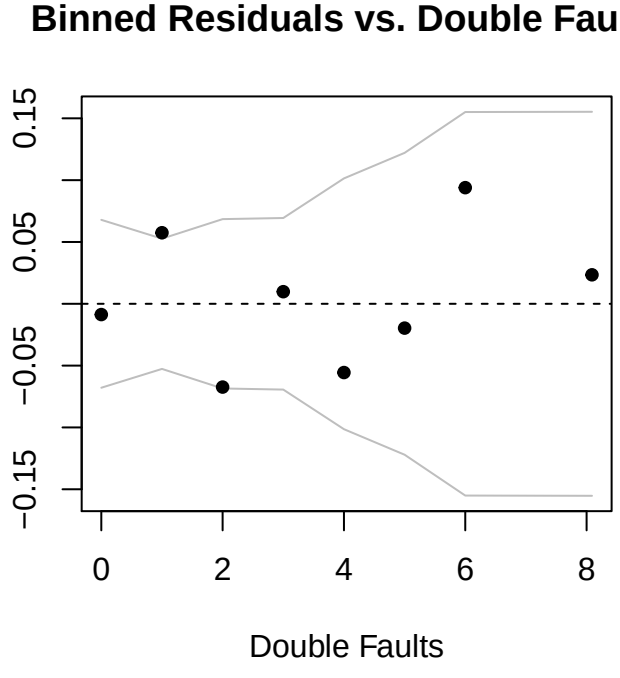
```
newten <- newten %>% mutate(Residuals = residuals.glm(final,type="response"),
                            Predicted = predict.glm(final,type="response"))

binnedplot(newten$Predicted, newten$Residuals,xlab="Predicted Probabilities",
           ylab="Residuals",main="Binned Residuals vs. Predicted Probabilities")
```

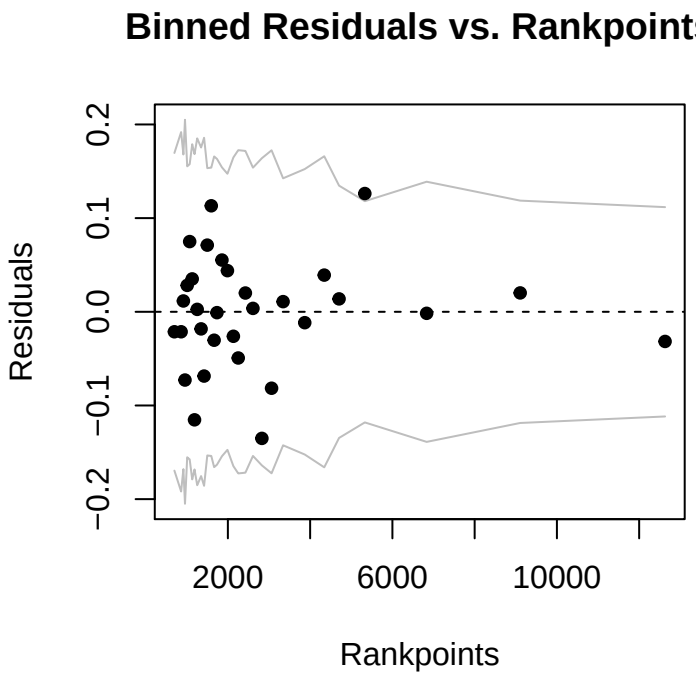



Binned Residuals vs. Minutes
Residuals
0.2
0.1
0.0
−0.2
40
60
80
120
160
Minutes

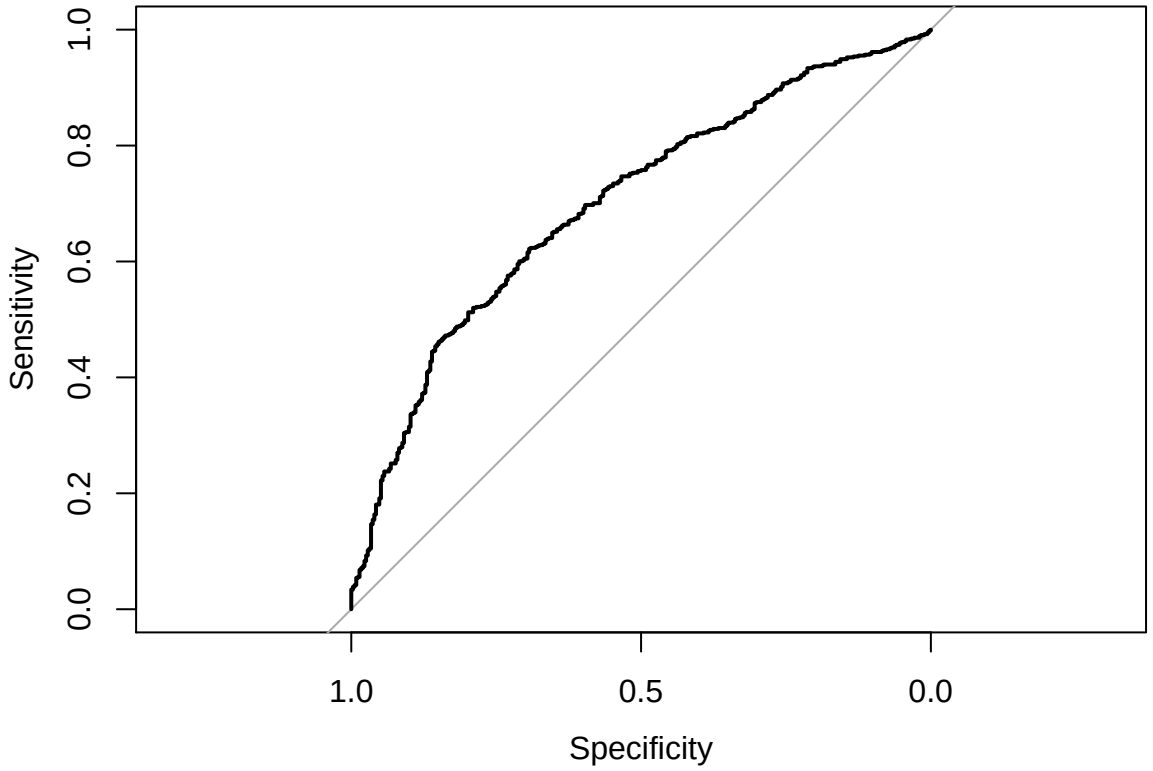

Binned Residuals vs. Height
0.3
0.1
−0.1
−0.3
170
180
190
200
Height


Binned Residuals vs. Aces
Residuals
0.15
0.05
−0.05
−0.15
0
5
10
15
20
Aces


Binned Residuals vs. Double Faults
0.15
0.05
−0.05
−0.15
0
2
4
6
8
Double Faults




```
ROC.newten <- roc(newten$status,newten$Predicted,plot=T)
```




```
ROC.newten$auc
```

```
## Area under the curve: 0.6996
```

```
threshold = 0.30
table(newten$status, newten$Predicted > threshold)
```

```
##
##     FALSE TRUE
##   0    10  342
##   1    10  638
```

```
(342 + 10)/(342 + 10 + 10 + 638)
```

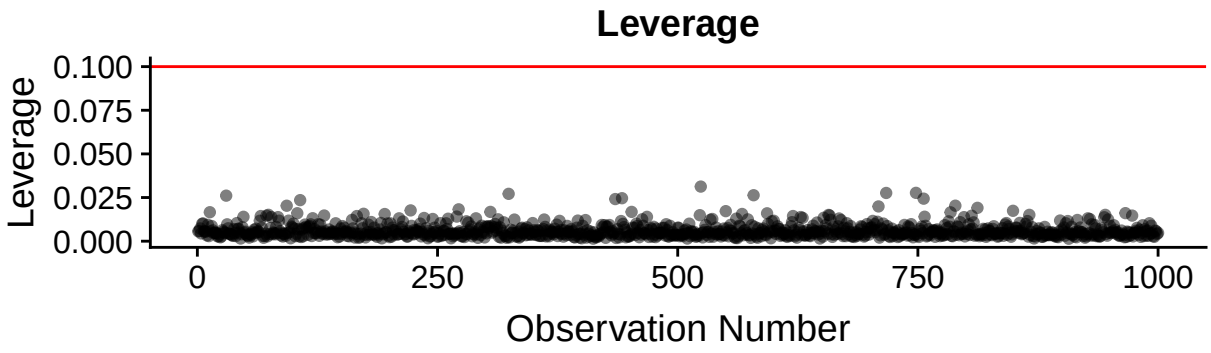
```
## [1] 0.352
```

Influential Points

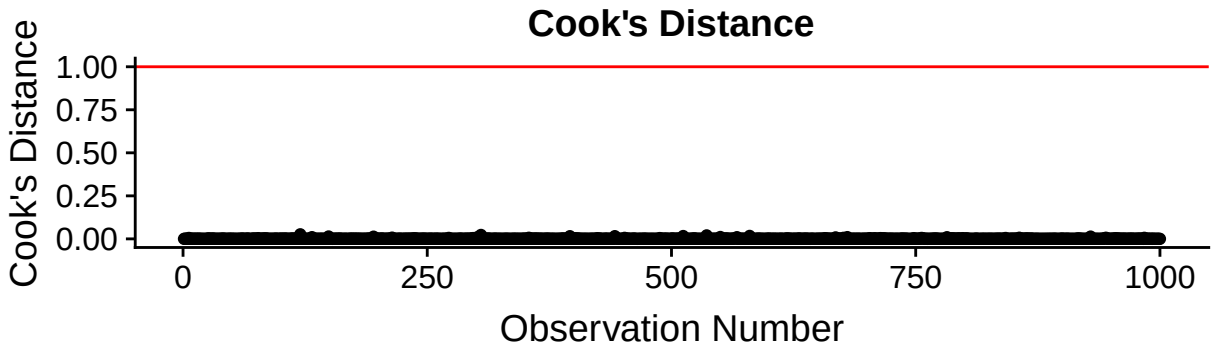
```
newten <- newten %>%
  mutate(leverage = hatvalues(final),
         cooks = cooks.distance(final),
         stand.resid = rstandard(final),
         obs.num = row_number())
```

Leverage and Cook's Distance

```
ggplot(data=newten, aes(x=obs.num,y=leverage)) +
  geom_point(alpha=0.5) +
  geom_hline(yintercept=0.1,color="red")+
  labs(x="Observation Number",y="Leverage",title="Leverage")
```




```
ggplot(data=newten, aes(x=obs.num,y=cooks)) +
  geom_point() +
  geom_hline(yintercept=1,color="red")+
  labs(x="Observation Number",y="Cook's Distance",title="Cook's Distance")
```



VIF

```
tidy(vif(final))
```

```
## Warning: 'tidy.numeric' is deprecated.
## See help("Deprecated")
```

```
## # A tibble: 5 x 2
##   names          x
##   <chr>      <dbl>
## 1 minutes     1.19
## 2 ht          1.28
## 3 rankpoints  1.02
## 4 ace         1.41
## 5 df          1.08
```

Conclusion

With VIF values less than 10, observations that are under the leverage and Cook's distance line, and binned residual plots that complete the assumptions, we have cleared model assessment and assumptions for the following final model:

```
kable(tidy(final), format = "markdown", digits = 6)
```

term	estimate	std.error	statistic	p.value
(Intercept)	5.197141	1.950891	2.663983	0.007722
minutes	-0.008897	0.002395	-3.714847	0.000203
ht	-0.023129	0.010416	-2.220635	0.026376
rankpoints	0.000184	0.000035	5.237843	0.000000
ace	0.094100	0.017519	5.371298	0.000000
df	-0.169342	0.035503	-4.769779	0.000002