

Case Study 3 Code Sup

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```
library(Sleuth3)
library(dplyr)
library(ggformula)
library(pander)
library(knitr)
library(stargazer)
library(car)
library(pander)
library(gridExtra)
library(broom)
library(ggthemes)
library(MASS)
library(leaps)
library(GGally)

library(effects)
```

After loading the necessary libraries, we also need to load the dataset of interest:

```
nes <- read.csv("http://aloy.rbind.io/data/NES.csv")
head(nes)
```

```
##   year age gender  race region  income union dem      educ
## 1 1980  70   male black     S lower 1/3   no   1 HS or less
## 2 1980  67   male white    NC middle 1/3  yes   1 HS or less
## 3 1980  47 female black     S lower 1/3   no   1 HS or less
## 4 1980  52 female white     W upper 1/3  yes   0   College
## 5 1980  30 female white    NC upper 1/3   no   1 HS or less
## 6 1980  37   male black    NC upper 1/3   no   1   College
```

```
summary(nes)
```

```
##      year      age      gender      race      region
## Min.   :1980   Min.   :18.00 female:1232  black: 281  NC:563
## 1st Qu.:1980   1st Qu.:33.00  male :1000  other: 192  NE:427
## Median :2000   Median :45.00                    white:1759  S :806
## Mean   :1991   Mean   :46.85                    W :436
## 3rd Qu.:2000   3rd Qu.:59.00
## Max.   :2000   Max.   :95.00
##      income      union      dem      educ
## lower 1/3 :799   no :1788   Min.   :0.0000  College :1179
## middle 1/3:703  yes: 444   1st Qu.:0.0000  HS or less:1053
## upper 1/3 :730                    Median :1.0000
##                                     Mean   :0.5349
##                                     3rd Qu.:1.0000
##                                     Max.   :1.0000
```

The following explains our derivation of a model:

The following code generates our baseline model for dem.

```
glm.base <- glm(dem ~ gender + region + union + income + educ + year + race + age, data = nes, family =
summary(glm.base)
```

```
##
## Call:
## glm(formula = dem ~ gender + region + union + income + educ +
##      year + race + age, family = binomial, data = nes)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.2970  -1.1065   0.4957   1.1314   1.5533
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)   -1.576601    9.492598  -0.166  0.86809
## gendermale    -0.259690    0.090771  -2.861  0.00422 **
## regionNE       0.104580    0.134548   0.777  0.43700
## regionS        0.008454    0.119120   0.071  0.94342
## regionW        0.175367    0.134395   1.305  0.19194
## unionyes       0.682129    0.120305   5.670 1.43e-08 ***
## incomemiddle 1/3 -0.258906    0.115867  -2.235  0.02545 *
## incomeupper 1/3 -0.484958    0.120274  -4.032 5.53e-05 ***
## educHS or less  0.040828    0.100289   0.407  0.68393
## year           0.001592    0.004758   0.335  0.73793
## raceother      -1.640317    0.230511  -7.116 1.11e-12 ***
## racewhite      -1.868719    0.184966 -10.103 < 2e-16 ***
## age            0.007640    0.002743   2.785  0.00535 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 3083.3  on 2231  degrees of freedom
## Residual deviance: 2856.9  on 2219  degrees of freedom
## AIC: 2882.9
##
## Number of Fisher Scoring iterations: 4
```

*# Regressing on a constant allows us to hold everything except for dem (party
identification) constant.*

```
glm.basic <- glm(dem ~ 1, data = nes, family = binomial)
```

```
stpFwd <- stepAIC(glm.basic, scope = list(lower = ~1, upper = ~ year + region + union + income + educ +
```

```
## Start:  AIC=3085.3
## dem ~ 1
##
##      Df Deviance    AIC
## + race    2   2928.3 2934.3
## + income  2   3044.9 3050.9
## + union   1   3061.7 3065.7
## + educ    1   3067.5 3071.5
```

```

## + gender 1 3072.2 3076.2
## + age 1 3077.7 3081.7
## <none> 3083.3 3085.3
## + year 1 3083.3 3087.3
## + region 3 3081.9 3089.9
##
## Step: AIC=2934.28
## dem ~ race
##
## Df Deviance AIC
## + union 1 2905.6 2913.6
## + income 2 2909.3 2919.3
## + age 1 2915.9 2923.9
## + gender 1 2918.6 2926.6
## + educ 1 2919.9 2927.9
## <none> 2928.3 2934.3
## + year 1 2928.2 2936.2
## + region 3 2925.0 2937.0
## - race 2 3083.3 3085.3
##
## Step: AIC=2913.6
## dem ~ race + union
##
## Df Deviance AIC
## + income 2 2875.9 2887.9
## + age 1 2889.7 2899.7
## + gender 1 2893.4 2903.4
## + educ 1 2899.1 2909.1
## <none> 2905.6 2913.6
## + year 1 2905.4 2915.4
## + region 3 2903.9 2917.9
## - union 1 2928.3 2934.3
## - race 2 3061.7 3065.7
##
## Step: AIC=2887.94
## dem ~ race + union + income
##
## Df Deviance AIC
## + age 1 2867.7 2881.7
## + gender 1 2867.9 2881.9
## <none> 2875.9 2887.9
## + educ 1 2875.4 2889.4
## + year 1 2875.8 2889.8
## + region 3 2873.7 2891.7
## - income 2 2905.6 2913.6
## - union 1 2909.3 2919.3
## - race 2 3007.3 3015.3
##
## Step: AIC=2881.69
## dem ~ race + union + income + age
##
## Df Deviance AIC
## + gender 1 2859.5 2875.5
## <none> 2867.7 2881.7

```

```

## + educ      1    2867.6 2883.6
## + year      1    2867.7 2883.7
## + region    3    2865.4 2885.4
## - age       1    2875.9 2887.9
## - income    2    2889.7 2899.7
## - union     1    2902.4 2914.4
## - race      2    3005.5 3015.5
##
## Step: AIC=2875.53
## dem ~ race + union + income + age + gender
##
##           Df Deviance    AIC
## <none>          2859.5 2875.5
## + year      1    2859.5 2877.5
## + educ      1    2859.5 2877.5
## + region    3    2857.2 2879.2
## - gender    1    2867.7 2881.7
## - age       1    2867.9 2881.9
## - income    2    2878.2 2890.2
## - union     1    2895.9 2909.9
## - race      2    2997.7 3009.7
summary(stpFwd)

##
## Call:
## glm(formula = dem ~ race + union + income + age + gender, family = binomial,
##      data = nes)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.3138  -1.1044   0.4946   1.1298   1.5371
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    1.648114   0.221279   7.448 9.47e-14 ***
## raceother      -1.600862   0.227855  -7.026 2.13e-12 ***
## racewhite      -1.852649   0.182748 -10.138 < 2e-16 ***
## unionyes       0.692776   0.116536   5.945 2.77e-09 ***
## incomemiddle 1/3 -0.265841   0.113745  -2.337 0.01943 *
## incomeupper 1/3 -0.491922   0.114198  -4.308 1.65e-05 ***
## age            0.007781   0.002699   2.883 0.00395 **
## gendermale     -0.258311   0.090486  -2.855 0.00431 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 3083.3  on 2231  degrees of freedom
## Residual deviance: 2859.5  on 2224  degrees of freedom
## AIC: 2875.5
##
## Number of Fisher Scoring iterations: 4

```

```

stpBk <- stepAIC(glm.base, scope = list(lower = ~1, upper = ~ year + region + union + income + educ + g

## Start: AIC=2882.94
## dem ~ gender + region + union + income + educ + year + race +
##      age
##
##           Df Deviance    AIC
## - region   3   2859.4 2879.4
## - year     1   2857.1 2881.1
## - educ     1   2857.1 2881.1
## <none>      2856.9 2882.9
## - age      1   2864.7 2888.7
## - gender   1   2865.1 2889.1
## - income   2   2873.3 2895.3
## - union    1   2889.9 2913.9
## - race     2   2992.9 3014.9
##
## Step: AIC=2879.36
## dem ~ gender + union + income + educ + year + race + age
##
##           Df Deviance    AIC
## - educ     1   2859.5 2877.5
## - year     1   2859.5 2877.5
## <none>      2859.4 2879.4
## + region   3   2856.9 2882.9
## - age      1   2867.1 2885.1
## - gender   1   2867.5 2885.5
## - income   2   2875.4 2891.4
## - union    1   2894.4 2912.4
## - race     2   2996.1 3012.1
##
## Step: AIC=2877.46
## dem ~ gender + union + income + year + race + age
##
##           Df Deviance    AIC
## - year     1   2859.5 2875.5
## <none>      2859.5 2877.5
## + educ     1   2859.4 2879.4
## + region   3   2857.1 2881.1
## - gender   1   2867.7 2883.7
## - age      1   2867.7 2883.7
## - income   2   2878.1 2892.1
## - union    1   2895.6 2911.6
## - race     2   2997.4 3011.4
##
## Step: AIC=2875.53
## dem ~ gender + union + income + race + age
##
##           Df Deviance    AIC
## <none>      2859.5 2875.5
## + year     1   2859.5 2877.5
## + educ     1   2859.5 2877.5
## + region   3   2857.2 2879.2
## - gender   1   2867.7 2881.7

```

```
## - age      1    2867.9 2881.9
## - income   2    2878.2 2890.2
## - union    1    2895.9 2909.9
## - race     2    2997.7 3009.7
```

```
summary(stpBk)
```

```
##
## Call:
## glm(formula = dem ~ gender + union + income + race + age, family = binomial,
##      data = nes)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.3138  -1.1044   0.4946   1.1298   1.5371
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    1.648114   0.221279   7.448 9.47e-14 ***
## gendermale     -0.258311   0.090486  -2.855  0.00431 **
## unionyes       0.692776   0.116536   5.945 2.77e-09 ***
## incomemiddle 1/3 -0.265841   0.113745  -2.337  0.01943 *
## incomeupper 1/3 -0.491922   0.114198  -4.308 1.65e-05 ***
## raceother     -1.600862   0.227855  -7.026 2.13e-12 ***
## racewhite     -1.852649   0.182748 -10.138 < 2e-16 ***
## age           0.007781   0.002699   2.883  0.00395 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 3083.3  on 2231  degrees of freedom
## Residual deviance: 2859.5  on 2224  degrees of freedom
## AIC: 2875.5
##
## Number of Fisher Scoring iterations: 4
```

```
glm.square <- glm(dem ~ year + region + union + income + educ + gender + race + age +
                  I(year)^2 + I(region)^2 + I(union)^2 + I(income)^2 + I(educ)^2 + I(gender)^2 + I(race)^2 + I(age)^2,
                  data = nes, family = binomial)
```

```
glm.inter <- glm(dem ~ year + region + union + income + educ + gender + race + age +
                 age * year + age * region + age * union + age * income + age * educ + age * gender +
                 age * year * region + age * year * union + age * year * income + age * year * educ + age * year * gender +
                 age * region * union + age * region * income + age * region * educ + age * region * gender +
                 age * union * income + age * union * educ + age * union * gender +
                 age * income * educ + age * income * gender + age * educ * gender,
                 data = nes, family = binomial)
summary(glm.inter)
```

```
##
## Call:
## glm(formula = dem ~ year + region + union + income + educ + gender +
##      race + age + age * year + age * region + age * union + age *
##      income + age * educ + age * gender + age * race, family = binomial,
##      data = nes)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.4168  -1.0933   0.4528   1.1202   1.6582
```

```
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)   -6.595e+00  2.733e+01  -0.241  0.80931
## year           3.858e-03  1.370e-02   0.282  0.77818
## regionNE       1.102e+00  3.984e-01   2.766  0.00568 **
## regionS        1.730e-01  3.495e-01   0.495  0.62066
## regionW        2.172e-01  3.968e-01   0.547  0.58408
## unionyes       2.211e-01  3.802e-01   0.581  0.56094
## incomemiddle 1/3 2.062e-01  3.317e-01   0.622  0.53423
## incomeupper 1/3 8.013e-02  3.700e-01   0.217  0.82855
## educHS or less -5.212e-01  2.891e-01  -1.803  0.07141 .
## gendermale     -6.244e-01  2.673e-01  -2.336  0.01951 *
## raceother      -7.516e-01  6.687e-01  -1.124  0.26103
## racewhite      -1.397e+00  5.319e-01  -2.627  0.00862 **
## age            1.010e-01  5.517e-01   0.183  0.85479
## year:age       -4.085e-05  2.763e-04  -0.148  0.88246
## regionNE:age   -2.073e-02  7.795e-03  -2.660  0.00782 **
## regionS:age    -3.417e-03  7.006e-03  -0.488  0.62577
## regionW:age    -4.642e-04  8.192e-03  -0.057  0.95481
## unionyes:age   1.034e-02  8.180e-03   1.265  0.20602
## incomemiddle 1/3:age -9.270e-03  6.681e-03  -1.387  0.16531
## incomeupper 1/3:age -1.174e-02  7.709e-03  -1.523  0.12772
## educHS or less:age 1.188e-02  5.970e-03   1.991  0.04649 *
## gendermale:age 7.814e-03  5.424e-03   1.441  0.14967
## raceother:age  -2.264e-02  1.568e-02  -1.444  0.14888
## racewhite:age  -1.229e-02  1.248e-02  -0.985  0.32471
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##    Null deviance: 3083.3  on 2231  degrees of freedom
## Residual deviance: 2831.4  on 2208  degrees of freedom
## AIC: 2879.4
##
## Number of Fisher Scoring iterations: 4

stp.inter <- stepAIC(glm.inter, scope = list(lower = ~1, upper = ~ year + region + union + income + educ +
                                             age * year + age * region + age * union + age * income +
                                             direction = "both"))

## Start:  AIC=2879.36
## dem ~ year + region + union + income + educ + gender + race +
##       age + age * year + age * region + age * union + age * income +
##       age * educ + age * gender + age * race
##
##              Df Deviance    AIC
## - year:age    1   2831.4 2877.4
## - race:age     2   2833.5 2877.5
## - income:age   2   2834.4 2878.4
## - union:age    1   2833.0 2879.0
## <none>         0   2831.4 2879.4
## - gender:age   1   2833.4 2879.4
## - educ:age     1   2835.3 2881.3
```

```

## - region:age 3 2840.3 2882.3
##
## Step: AIC=2877.38
## dem ~ year + region + union + income + educ + gender + race +
## age + region:age + union:age + income:age + educ:age + gender:age +
## race:age
##
##          Df Deviance    AIC
## - year      1  2831.5 2875.5
## - race:age   2  2833.6 2875.6
## - income:age 2  2834.4 2876.4
## - union:age  1  2833.1 2877.1
## <none>        2831.4 2877.4
## - gender:age 1  2833.5 2877.5
## + year:age   1  2831.4 2879.4
## - educ:age   1  2835.7 2879.7
## - region:age 3  2840.3 2880.3
##
## Step: AIC=2875.54
## dem ~ region + union + income + educ + gender + race + age +
## region:age + union:age + income:age + educ:age + gender:age +
## race:age
##
##          Df Deviance    AIC
## - race:age   2  2833.7 2873.7
## - income:age 2  2834.6 2874.6
## - union:age  1  2833.2 2875.2
## <none>        2831.5 2875.5
## - gender:age 1  2833.7 2875.7
## + year       1  2831.4 2877.4
## - educ:age   1  2835.8 2877.8
## - region:age 3  2840.5 2878.5
##
## Step: AIC=2873.73
## dem ~ region + union + income + educ + gender + race + age +
## region:age + union:age + income:age + educ:age + gender:age
##
##          Df Deviance    AIC
## - income:age 2  2836.8 2872.8
## - union:age  1  2835.5 2873.5
## <none>        2833.7 2873.7
## - gender:age 1  2835.8 2873.8
## + race:age   2  2831.5 2875.5
## + year       1  2833.6 2875.6
## - educ:age   1  2838.1 2876.1
## - region:age 3  2842.4 2876.4
## - race       2  2971.7 3007.7
##
## Step: AIC=2872.75
## dem ~ region + union + income + educ + gender + race + age +
## region:age + union:age + educ:age + gender:age
##
##          Df Deviance    AIC
## - union:age  1  2837.7 2871.7

```



```

## - gender:age 1 2838.4 2872.4
## <none> 2836.8 2872.8
## + income:age 2 2833.7 2873.7
## + year 1 2836.6 2874.6
## + race:age 2 2834.6 2874.6
## - region:age 3 2845.3 2875.3
## - educ:age 1 2845.0 2879.0
## - income 2 2851.8 2883.8
## - race 2 2974.0 3006.0
##
## Step: AIC=2871.68
## dem ~ region + union + income + educ + gender + race + age +
## region:age + educ:age + gender:age
##
## Df Deviance AIC
## - gender:age 1 2839.6 2871.6
## <none> 2837.7 2871.7
## + union:age 1 2836.8 2872.8
## + year 1 2837.5 2873.5
## + race:age 2 2835.5 2873.5
## + income:age 2 2835.5 2873.5
## - region:age 3 2846.0 2874.0
## - educ:age 1 2846.3 2878.3
## - income 2 2852.8 2882.8
## - union 1 2870.4 2902.4
## - race 2 2975.3 3005.3
##
## Step: AIC=2871.6
## dem ~ region + union + income + educ + gender + race + age +
## region:age + educ:age
##
## Df Deviance AIC
## <none> 2839.6 2871.6
## + gender:age 1 2837.7 2871.7
## + union:age 1 2838.4 2872.4
## + year 1 2839.4 2873.4
## + race:age 2 2837.4 2873.4
## + income:age 2 2837.9 2873.9
## - region:age 3 2848.4 2874.4
## - educ:age 1 2848.0 2878.0
## - gender 1 2848.3 2878.3
## - income 2 2854.3 2882.3
## - union 1 2871.9 2901.9
## - race 2 2977.6 3005.6

glm.inter <- glm(dem ~ year + region + union + income + educ + gender + race + age +
+ age * union + age * income + age * educ + age * race, data = nes, family = binomial)

stp.inter <- stepAIC(glm.inter, scope = list(lower = ~1, upper = ~ year + region + union + income + educ +
age * year + age * region + age * union + age * income +
direction = "both", k = log(nrow(nes)))

## Start: AIC=2989.49
## dem ~ year + region + union + income + educ + gender + race +
## age + age * union + age * income + age * educ + age * race

```

```

##
##           Df Deviance    AIC
## - region      3   2845.6 2969.0
## - race:age     2   2844.9 2976.0
## - income:age   2   2845.3 2976.3
## - year         1   2843.2 2982.1
## - union:age    1   2844.7 2983.4
## - educ:age     1   2847.5 2986.3
## <none>         2843.0 2989.5
## - gender       1   2851.3 2990.1
## + gender:age   1   2840.3 2994.5
## + year:age     1   2843.0 2997.2
## + region:age   3   2833.5 3003.1
##
## Step:  AIC=2968.99
## dem ~ year + union + income + educ + gender + race + age + union:age +
##       income:age + educ:age + race:age
##
##           Df Deviance    AIC
## - income:age   2   2847.7 2955.7
## - race:age     2   2847.7 2955.7
## - year         1   2845.9 2961.6
## - union:age    1   2847.2 2962.8
## - educ:age     1   2850.2 2965.8
## <none>         2845.6 2969.0
## - gender       1   2853.8 2969.4
## + gender:age   1   2842.7 2973.8
## + year:age     1   2845.6 2976.7
## + region       3   2843.0 2989.5
##
## Step:  AIC=2955.65
## dem ~ year + union + income + educ + gender + race + age + union:age +
##       educ:age + race:age
##
##           Df Deviance    AIC
## - race:age     2   2849.8 2942.3
## - year         1   2848.0 2948.2
## - union:age    1   2848.6 2948.8
## - income       2   2861.0 2953.5
## <none>         2847.7 2955.7
## - educ:age     1   2855.7 2955.9
## - gender       1   2856.3 2956.5
## + gender:age   1   2845.4 2961.0
## + year:age     1   2847.7 2963.4
## + income:age   2   2845.6 2969.0
## + region       3   2845.3 2976.3
##
## Step:  AIC=2942.35
## dem ~ year + union + income + educ + gender + race + age + union:age +
##       educ:age
##
##           Df Deviance    AIC
## - year         1   2850.1 2934.9
## - union:age    1   2850.7 2935.5

```

```

## - income      2    2863.3 2940.4
## <none>         2849.8 2942.3
## - educ:age    1    2858.2 2943.0
## - gender      1    2858.4 2943.3
## + gender:age  1    2847.5 2947.7
## + year:age    1    2849.8 2950.1
## + race:age    2    2847.7 2955.7
## + income:age  2    2847.7 2955.7
## + region      3    2847.2 2962.9
## - race        2    2988.5 3065.6
##
## Step:  AIC=2934.93
## dem ~ union + income + educ + gender + race + age + union:age +
##      educ:age
##
##           Df Deviance    AIC
## - union:age  1    2851.0 2928.1
## - income     2    2864.0 2933.4
## <none>        2850.1 2934.9
## - educ:age   1    2858.3 2935.4
## - gender     1    2858.7 2935.8
## + gender:age 1    2847.8 2940.3
## + year       1    2849.8 2942.3
## + race:age   2    2848.0 2948.2
## + income:age 2    2848.0 2948.2
## + region     3    2847.5 2955.4
## - race       2    2989.5 3058.9
##
## Step:  AIC=2928.1
## dem ~ union + income + educ + gender + race + age + educ:age
##
##           Df Deviance    AIC
## - income     2    2864.9 2926.6
## <none>        2851.0 2928.1
## - educ:age   1    2859.5 2928.9
## - gender     1    2859.6 2929.0
## + gender:age 1    2848.4 2933.2
## + union:age  1    2850.1 2934.9
## + year       1    2850.7 2935.5
## + race:age   2    2848.9 2941.4
## + income:age 2    2849.6 2942.1
## + region     3    2848.4 2948.7
## - union      1    2885.4 2954.8
## - race       2    2990.9 3052.6
##
## Step:  AIC=2926.6
## dem ~ union + educ + gender + race + age + educ:age
##
##           Df Deviance    AIC
## <none>        2864.9 2926.6
## + income     2    2851.0 2928.1
## - educ:age   1    2875.9 2929.8
## - gender     1    2875.9 2929.9
## + gender:age 1    2862.8 2932.2

```

```
## + union:age 1 2864.0 2933.4
## + year 1 2864.2 2933.6
## + race:age 2 2862.5 2939.6
## - union 1 2892.0 2945.9
## + region 3 2862.6 2947.4
## - race 2 3023.1 3069.4
```

```
summary(stp.inter)
```

```
##
## Call:
## glm(formula = dem ~ union + educ + gender + race + age + educ:age,
##      family = binomial, data = nes)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.2510  -1.1132   0.4908   1.1315   1.5399
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    1.800e+00  2.507e-01   7.178 7.07e-13 ***
## unionyes        5.909e-01  1.149e-01   5.141 2.74e-07 ***
## educHS or less  -6.823e-01  2.653e-01  -2.572 0.010113 *
## gendermale     -2.986e-01  9.003e-02  -3.316 0.000912 ***
## raceother      -1.672e+00  2.279e-01  -7.335 2.22e-13 ***
## racewhite     -1.956e+00  1.824e-01 -10.720 < 2e-16 ***
## age             9.047e-05  3.881e-03   0.023 0.981404
## educHS or less:age 1.745e-02  5.292e-03   3.298 0.000973 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 3083.3  on 2231  degrees of freedom
## Residual deviance: 2864.9  on 2224  degrees of freedom
## AIC: 2880.9
##
## Number of Fisher Scoring iterations: 4
```

```
stp.inter.fwd <- stepAIC(glm.basic, scope = list(lower = ~1, upper = ~ year + region + union + income +
                                                age * year + age * region + age * union + age * income,
                                                direction = "both", k = log(nrow(nes)))
```

```
## Start: AIC=3091.01
## dem ~ 1
##
##      Df Deviance    AIC
## + race 2 2928.3 2951.4
## + income 2 3044.9 3068.0
## + union 1 3061.7 3077.1
## + educ 1 3067.5 3082.9
## + gender 1 3072.2 3087.7
## <none> 3083.3 3091.0
## + age 1 3077.7 3093.1
## + year 1 3083.3 3098.7
```

```

## + region 3 3081.9 3112.7
##
## Step: AIC=2951.41
## dem ~ race
##
##      Df Deviance    AIC
## + union 1 2905.6 2936.4
## + age 1 2915.9 2946.7
## + income 2 2909.3 2947.8
## + gender 1 2918.6 2949.4
## + educ 1 2919.9 2950.7
## <none> 2928.3 2951.4
## + year 1 2928.2 2959.1
## + region 3 2925.0 2971.3
## - race 2 3083.3 3091.0
##
## Step: AIC=2936.44
## dem ~ race + union
##
##      Df Deviance    AIC
## + income 2 2875.9 2922.2
## + age 1 2889.7 2928.3
## + gender 1 2893.4 2932.0
## <none> 2905.6 2936.4
## + educ 1 2899.1 2937.7
## + year 1 2905.4 2944.0
## - union 1 2928.3 2951.4
## + region 3 2903.9 2957.9
## - race 2 3061.7 3077.1
##
## Step: AIC=2922.21
## dem ~ race + union + income
##
##      Df Deviance    AIC
## + age 1 2867.7 2921.7
## + gender 1 2867.9 2921.8
## <none> 2875.9 2922.2
## + educ 1 2875.4 2929.3
## + year 1 2875.8 2929.8
## - income 2 2905.6 2936.4
## + region 3 2873.7 2943.1
## - union 1 2909.3 2947.8
## - race 2 3007.3 3038.2
##
## Step: AIC=2921.67
## dem ~ race + union + income + age
##
##      Df Deviance    AIC
## + gender 1 2859.5 2921.2
## <none> 2867.7 2921.7
## - age 1 2875.9 2922.2
## + union:age 1 2866.5 2928.2
## - income 2 2889.7 2928.3
## + educ 1 2867.6 2929.3

```

```

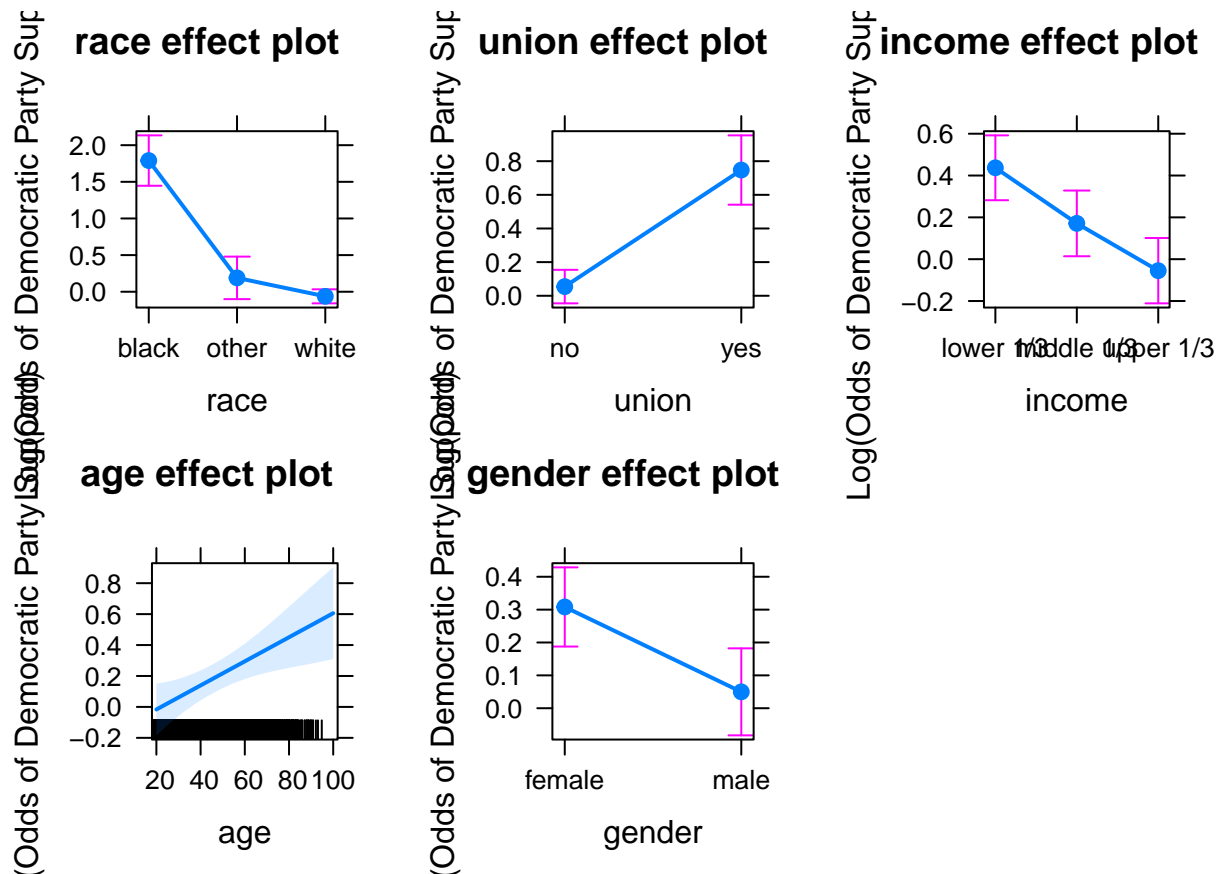
## + year      1  2867.7 2929.3
## + income:age 2  2862.8 2932.2
## + race:age   2  2865.1 2934.5
## + region     3  2865.4 2942.5
## - union      1  2902.4 2948.7
## - race       2  3005.5 3044.0
##
## Step: AIC=2921.22
## dem ~ race + union + income + age + gender
##
##           Df Deviance    AIC
## <none>           2859.5 2921.2
## - gender      1  2867.7 2921.7
## - age         1  2867.9 2921.8
## - income      2  2878.2 2924.4
## + gender:age  1  2857.1 2926.5
## + union:age   1  2858.4 2927.8
## + year        1  2859.5 2928.9
## + educ        1  2859.5 2928.9
## + income:age  2  2855.1 2932.2
## + race:age    2  2857.0 2934.1
## + region      3  2857.2 2942.0
## - union       1  2895.9 2949.8
## - race        2  2997.7 3044.0
summary(stp.inter.fwd)

##
## Call:
## glm(formula = dem ~ race + union + income + age + gender, family = binomial,
##      data = nes)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.3138  -1.1044   0.4946   1.1298   1.5371
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    1.648114   0.221279   7.448 9.47e-14 ***
## raceother      -1.600862   0.227855  -7.026 2.13e-12 ***
## racewhite      -1.852649   0.182748 -10.138 < 2e-16 ***
## unionyes       0.692776   0.116536   5.945 2.77e-09 ***
## incomemiddle 1/3 -0.265841   0.113745  -2.337 0.01943 *
## incomeupper 1/3 -0.491922   0.114198  -4.308 1.65e-05 ***
## age            0.007781   0.002699   2.883 0.00395 **
## gendermale     -0.258311   0.090486  -2.855 0.00431 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 3083.3  on 2231  degrees of freedom
## Residual deviance: 2859.5  on 2224  degrees of freedom
## AIC: 2875.5
##

```

```
## Number of Fisher Scoring iterations: 4
# In order to do some preliminary investigation into whether there are
# associations between gender and party preference,
# between region and party preference,
# and between unionized status and party preference,
# I have created some plots of gender, region, and union.

plot(allEffects(stp.inter.fwd), rows = 2, cols = 3, type = "link",
     ylab = "Log(Odds of Democratic Party Support)")
```



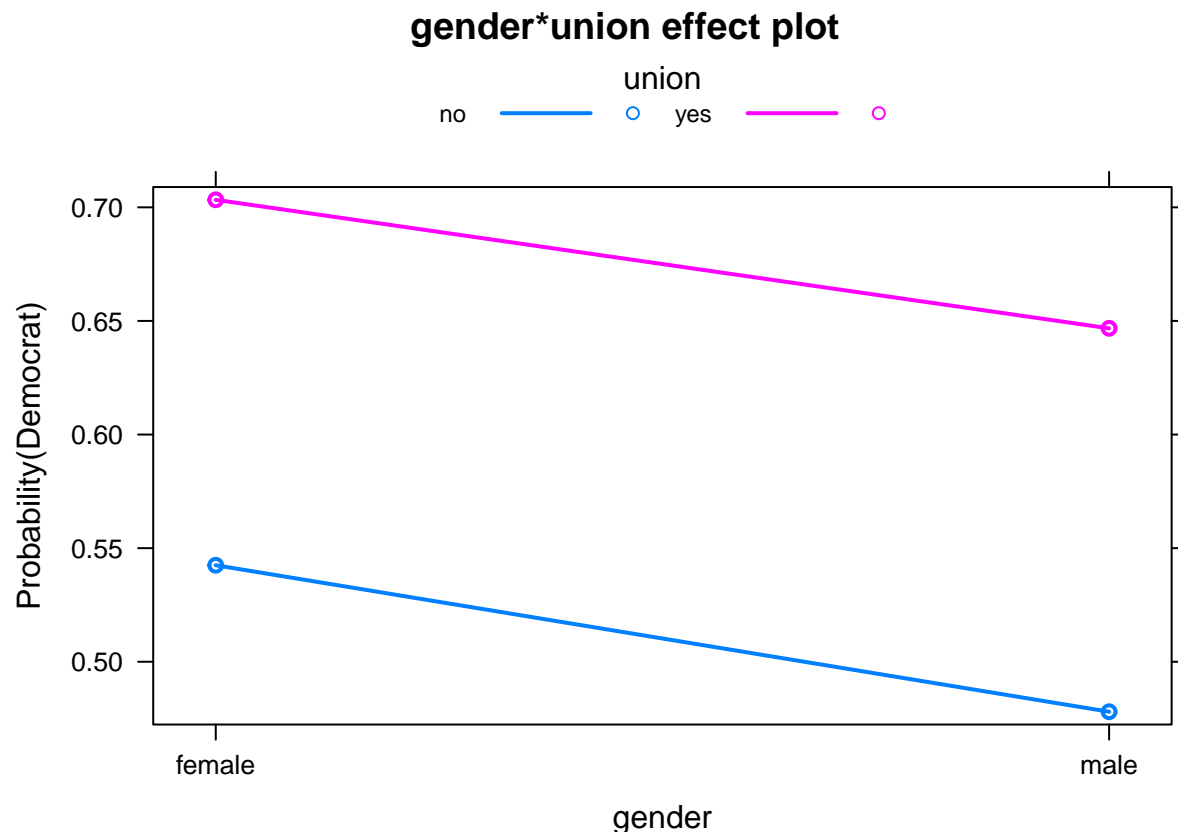
As we can see from the plots, males have lower odds of supporting the Democratic party.

Although people in North Carolina and the Southern region have lower odds of supporting the Democratic party, our model has been simplified such that these do not matter.

Those who are not in unions also have lower odds of supporting the Democratic party.

For further analysis of the probability that any given individual supports the Democrats, we can use the following code:

```
plot(Effect(c("gender", "union"), stp.inter.fwd), multiline = TRUE, type = "response", ylab = "Probability")
```



This code allows us to more clearly see that Support of the Democratic Party tends to come from people who are in unions and who are female.

More specifically, Unionization seems to have the largest effect on support, followed by Gender and then Region.

NOW, we need to assess the significance of these effects regardless of time.

```
for (i in c(2, 3, 4, 5, 6, 7, 8)) {
  coefficient <- coef(stp.inter.fwd)[i]
  standardError <- sqrt(vcov(stp.inter.fwd)[i,i])
  waldStat <- (coefficient / standardError)^2
  print(1-pchisq(waldStat, df = 1))
}
```

```
##      raceother
## 2.128298e-12
##      racewhite
##          0
##      unionyes
## 2.768933e-09
## incomemiddle 1/3
##      0.01943014
## incomeupper 1/3
##      1.650271e-05
##          age
## 0.003945303
##      gendermale
```



```
## 0.00430756
```

Based off these p-values, we can reject the null hypothesis that the coefficients are zero. We can reject them for small p-values. Specifically, unionyes and gendermale seem to have an undeniable impact at an alpha level of 0.05.

If we also want to look at the significance of the union variable,

```
gender_only <- glm(dem ~ union, family = binomial, data = nes)
anova(gender_only, glm.base, test = "Chisq")
```

```
## Analysis of Deviance Table
```

```
##
```

```
## Model 1: dem ~ union
```

```
## Model 2: dem ~ gender + region + union + income + educ + year + race +
```

```
## age
```

```
## Resid. Df Resid. Dev Df Deviance Pr(>Chi)
```

```
## 1 2230 3061.7
```

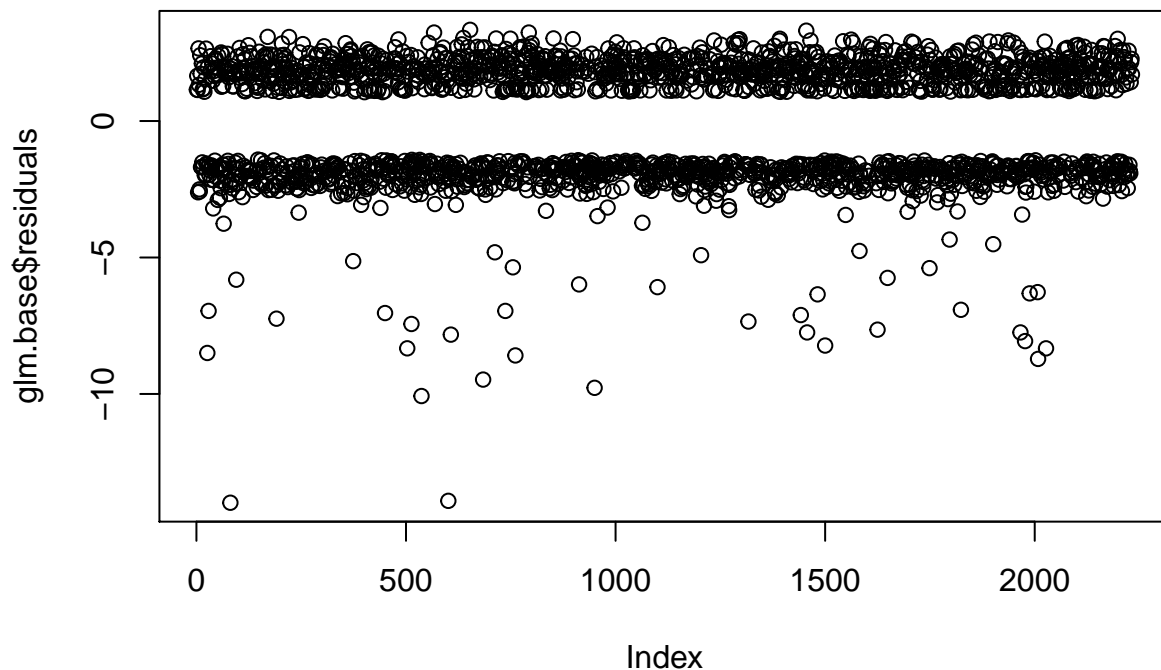
```
## 2 2219 2856.9 11 204.72 < 2.2e-16 ***
```

```
## ---
```

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

shows that we can reject the notion that the other coefficients are not necessary.

```
plot(glm.base$residuals)
```



The residuals plot shows that our model generally fits the data.